

# *Understanding the Opportunity and Limitation of Source-Based Aerial Methane Measurements:*

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# The Multi-scale Methane Challenge

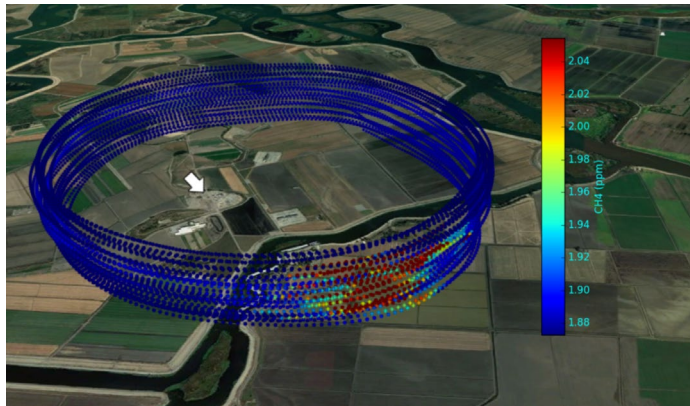
- Basin-level to global scale
  - Total inventories & tracking aggregate reductions
- Site/facility-level quantification
  - Total inventories & tracking aggregate reductions
  - Screening for mitigation opportunities
  - Compliance with regulations
- Source-level measurement & mitigation
  - Source-specific regulations (e.g. tanks, unlit flares, compressors)
  - Actual mitigation occurs at sources





# The First Revolution of Airborne Measurement Technologies

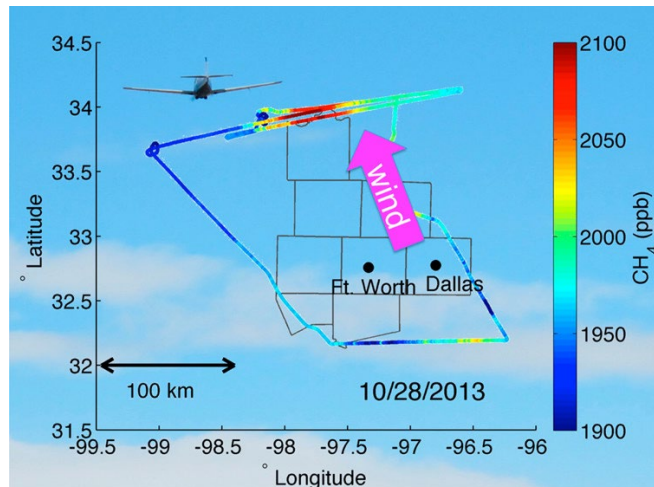
## ■ Mass-Balance Approaches



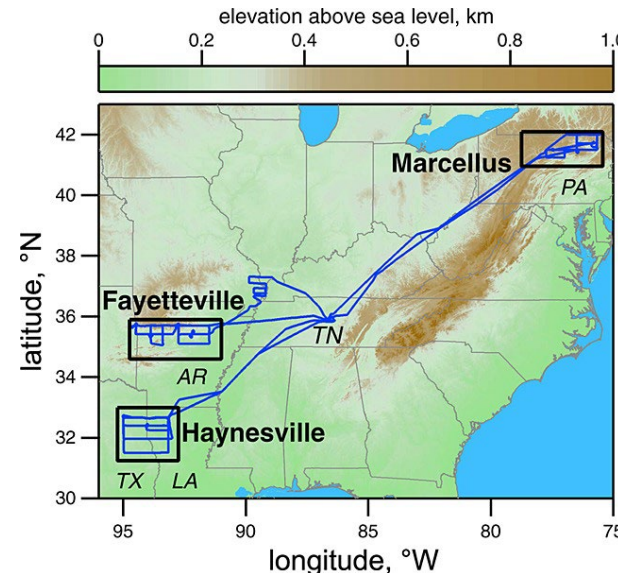
(Conley et al., AMT 2017)



(Johnson et al., EST 2017)



(Karion et al., EST 2015)



(Peischl et al., JGR 2015)

### RESEARCH

#### GREENHOUSE GASES

## Assessment of methane emissions from the U.S. oil and gas supply chain

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Methane emissions from the U.S. oil and natural gas supply chain were estimated by using ground-based, facility-scale measurements and validated with aircraft observations in areas accounting for ~30% of U.S. gas production. When scaled up nationally, our facility-based estimate of 2015 supply chain emissions is  $13 \pm 2$  teragrams per year, equivalent to 2.3% of gross U.S. gas production. This value is ~60% higher than the U.S. Environmental Protection Agency inventory estimate, likely because existing inventory methods miss emissions released during abnormal operating conditions. Methane emissions of this magnitude, per unit of natural gas consumed, produce radiative forcing over a 20-year time horizon comparable to the CO<sub>2</sub> from natural gas combustion. Substantial emission reductions are feasible through rapid detection of the root causes of high emissions and deployment of less failure-prone systems.

Methane (CH<sub>4</sub>) is a potent greenhouse gas, and CH<sub>4</sub> emissions from human activities since preindustrial times are responsible for 0.57 W m<sup>-2</sup> of radiative forcing, as compared to 1.7 W m<sup>-2</sup> for carbon dioxide (CO<sub>2</sub>) (1). CH<sub>4</sub> is removed from the atmosphere much more rapidly than CO<sub>2</sub>, thus reducing CH<sub>4</sub> emissions can effectively reduce the near-term rate of warming (2). Sharp growth in U.S. oil and natural gas (O/NG) production beginning around 2005 (3) raised concerns about the climate impacts of increased natural gas use (4, 5). By 2012, disagreement among published estimates of CH<sub>4</sub> emissions from U.S. natural gas operations led to a broad consensus that additional data were needed to better characterize emission rates (4–7). A large body of field measurements made between 2012 and 2016 (table S1) has markedly improved understanding of the sources and magnitude of CH<sub>4</sub> emissions from the industry's operations. Brandt et al. summarized the early literature (8); other assessments incorporated elements of recent data (9–17). This work synthesizes recent studies to provide an improved overall assessment of emissions from

the O/NG supply chain, which we define to include all operations associated with O/NG production, processing, and transport (materials and methods, section S1.0) (22).

Measurements of O/NG CH<sub>4</sub> emissions can be classified as either top-down (TD) or bottom-up (BU). TD studies quantify ambient methane enhancements using aircraft, satellites, or tower networks and infer aggregate emissions from all contributing sources across large geographies. TD estimates for nine O/NG production areas have been reported to date (table S2). These areas are distributed across the U.S. (fig. S1) and account for ~33% of natural gas, ~24% of oil production, and ~14% of all wells (23). Areas sampled in TD studies also span the range of hydrocarbon characteristics (predominantly gas, predominantly oil, or mixed), as well as a range of production characteristics such as well productivity and maturity. In contrast, BU studies generate regional, state, or national emission estimates by aggregating and extrapolating measured emissions from individual pieces of equipment, operations, or facilities, using measurements made directly at the emission point or, in the case of facilities, directly downwind.

Recent BU studies have been performed on equipment or facilities that are expected to represent the vast majority of emissions from the O/NG supply chain (table S1). In this work, we integrate the results of recent facility-scale BU studies to estimate CH<sub>4</sub> emissions from the U.S. O/NG supply chain, and then we validate the results using TD studies (materials and methods). The probability distributions of our BU methodology are based on observed facility-level emissions, in contrast to the component-by-component approach used for conventional inventories. We thus capture enhancements pro-

duced by all sources within a facility, including the heavy tail of the distribution. When the BU estimate is developed in this manner, direct comparison of BU and TD estimates of CH<sub>4</sub> emissions in the nine basins for which TD measurements have been reported indicates agreement between methods, within estimated uncertainty ranges (Fig. 1).

Our national BU estimate of total CH<sub>4</sub> emissions in 2015 from the U.S. O/NG supply chain is  $13 (+2.1/-1.6, 95\% \text{ confidence interval})$  Tg CH<sub>4</sub>/year (Table 1). This estimate of O/NG CH<sub>4</sub> emissions can also be expressed as a production-normalized emission rate of 2.3% (+0.4%/-0.3%) by normalizing by annual gross natural gas production [33 trillion cubic feet (23), with average CH<sub>4</sub> content of 90 volume %]. Roughly 85% of national BU emissions are from production, gathering, and processing sources, which are concentrated in active O/NG production areas.

Our assessment does not update emissions from local distribution and end use of natural gas, owing to insufficient information addressing this portion of the supply chain. However, recent studies suggest that local distribution emissions exceed the current inventory estimate (14–16), and that end-user emissions might also be important. If these findings prove to be representative, overall emissions from the natural gas supply chain would increase relative to the value in Table 1 (materials and methods, section S1.5).

Our BU method and TD measurements yield similar estimates of U.S. O/NG CH<sub>4</sub> emissions in 2015, and both are significantly higher than the corresponding estimate in the U.S. Environmental Protection Agency's Greenhouse Gas Inventory (EPA GHGI) (Table 1 and materials and methods, section S1.3) (17). Discrepancies between TD estimates and the EPA GHGI have been reported previously (8, 18). Our BU estimate is 63% higher than the EPA GHGI, largely due to a more than twofold difference in the production segment (Table 1). The discrepancy in production sector emissions alone is ~4 Tg CH<sub>4</sub>/year, an amount larger than the emissions from any other O/NG supply chain segment. Such a large difference cannot be attributed to expected uncertainty in either estimate: The extreme ends of the 95% confidence intervals for each estimate differ by 20% (i.e., ~12 Tg/year for the lower bound of our BU estimate can be compared to ~10 Tg/year for the upper bound of the EPA GHGI estimate).

We believe the reason for such large divergence is that sampling methods underlying conventional inventories systematically underestimate total emissions because they miss high emissions caused by abnormal operating conditions (e.g., malfunctions). Distributions of measured emissions from production sites in BU studies are invariably "tail-heavy," with large emission rates measured at a small subset of sites at any single point in time (19–22). Consequently, the most likely hypothesis for the difference between the EPA GHGI and BU estimates derived from facility-level measurements is that measurements used to develop GHGI emission factors

(Alvarez et al., *Science* 2018)



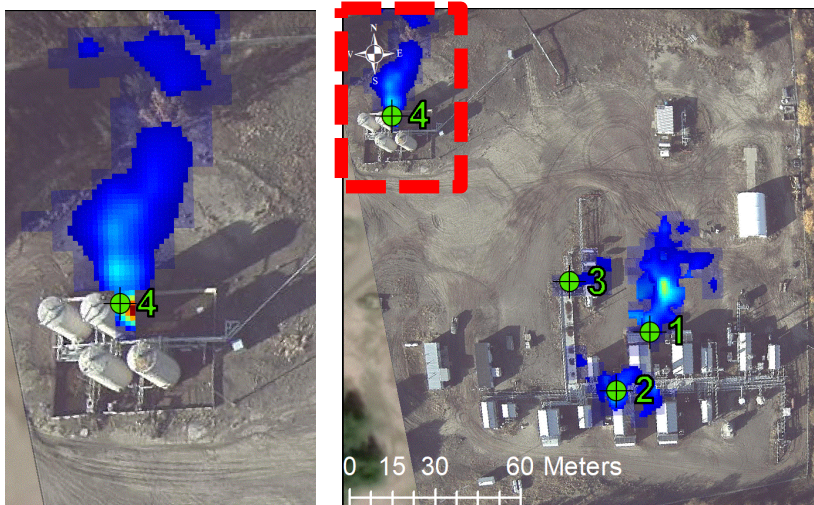
# Recent Emergence of Source-Level Airborne Measurement Approaches

- A second revolution in possibilities?

## Bridger Photonics

### Gas Mapping LiDAR (GML)<sup>™</sup>

- Active laser-based sensor
  - ~1m resolution
  - ~100m swath width

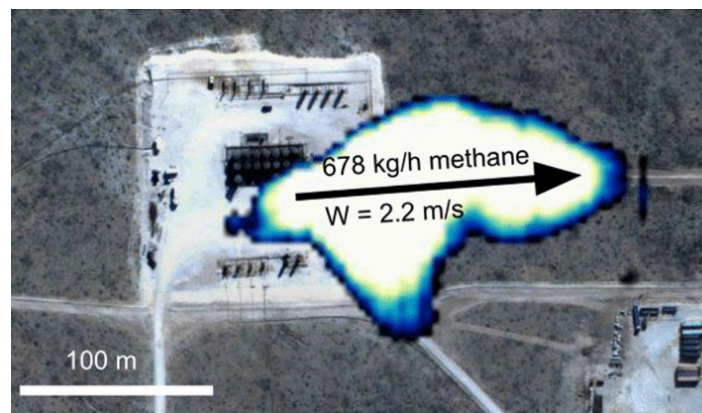


(Tyner & Johnson, EST 2021)

## Kairos Aerospace

### LeakSurveyor<sup>™</sup>

- Passive imaging spectrometer
  - ~3m resolution
  - ~800m swath width

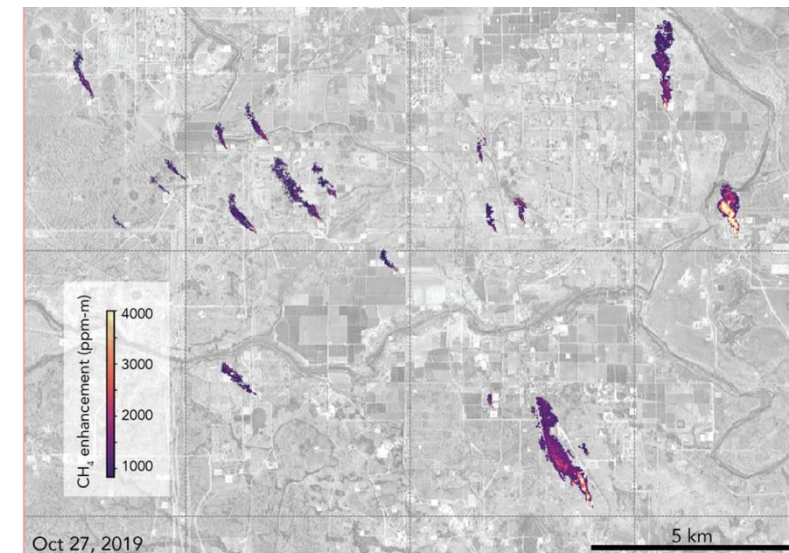


(Chen et al., EST 2022)

## NASA/JPL

### AVIRIS-NG

- Passive imaging spectrometer
  - ~3m resolution @3000m AGL
  - ~1800m swath width @3000m AGL



(Cusworth et al., Energy & Climate 2021)



# Robust, Critical Evaluation of Measurement Technologies



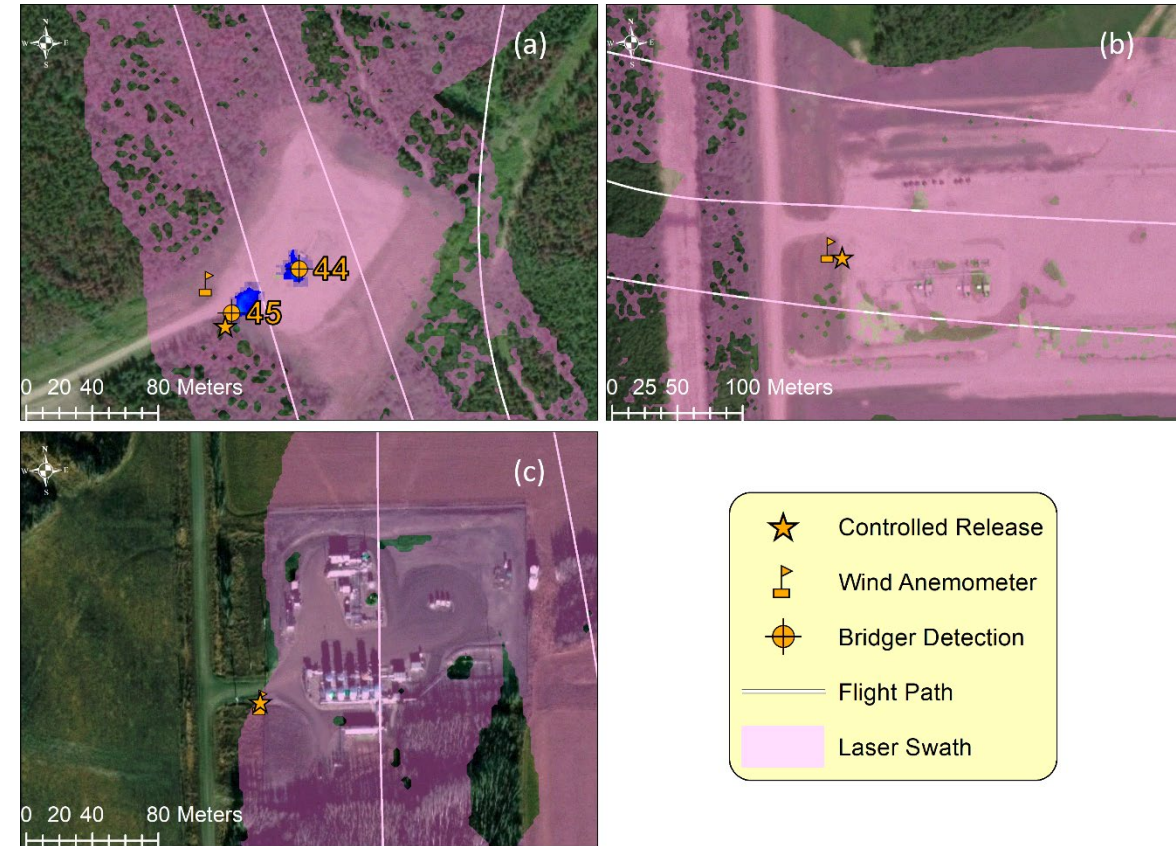
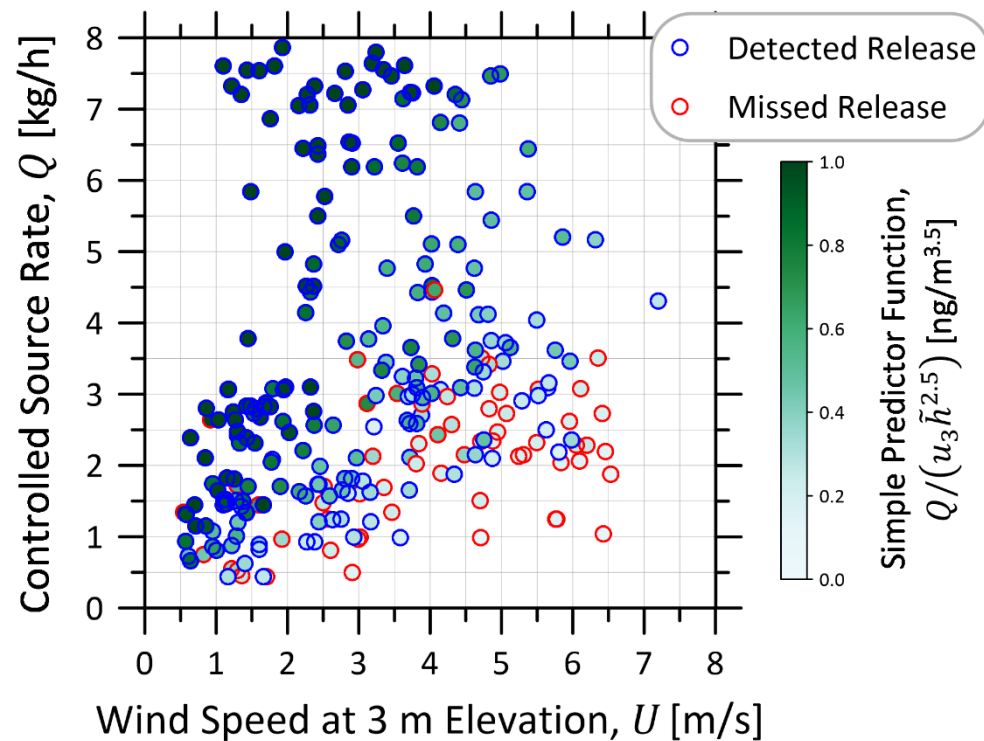
- Fully- and semi-blinded controlled release testing

- B.M. Conrad, D.R. Tyner, M.R. Johnson (2022) **Robust Probabilities of Detection and Quantification Uncertainty for Aerial Methane Detection: Examples for Three Airborne Technologies**, *Remote Sensing of Environment* (under review: [preprint](#))
- M.R. Johnson, D.R. Tyner, A.J. Szekeres (2021) **Blinded evaluation of airborne methane source detection using Bridger Photonics LiDAR**, *Remote Sensing of Environment*, 259:112418. (doi: [10.1016/j.rse.2021.112418](https://doi.org/10.1016/j.rse.2021.112418))



# 1. Fully-Blinded Controlled Release Testing of Sensitivity Limits

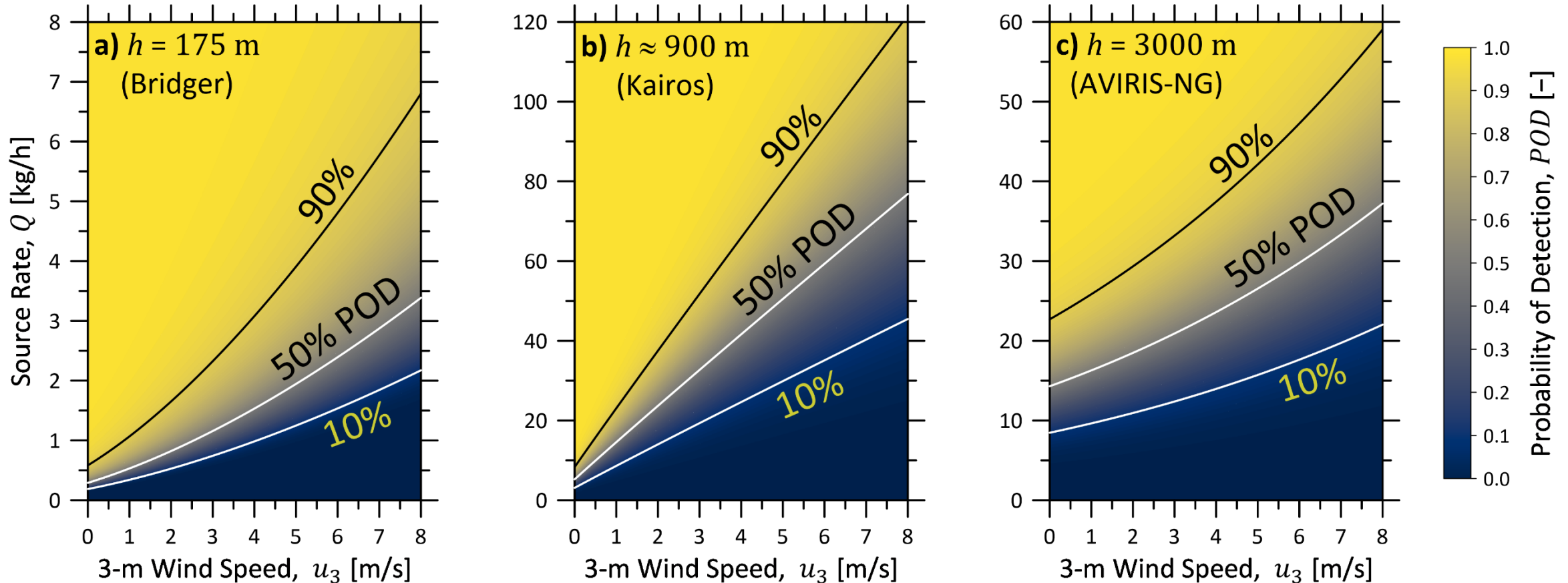
- Conducted under cover of parallel survey of oil and gas facilities
  - Airplane has no knowledge they are even being tested



M.R. Johnson, D.R. Tyner, A.J. Szekeres (2021) Blinded evaluation of airborne methane source detection using Bridger Photonics LiDAR, *Remote Sensing of Environment*, 259, 112418. (doi: [10.1016/j.rse.2021.112418](https://doi.org/10.1016/j.rse.2021.112418))



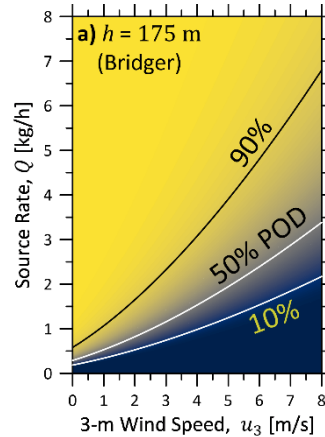
# Continuous Probability of Detection (POD) Functions



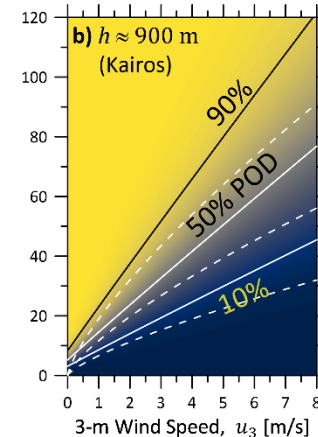
- Probability of detection any source  $Q$  for a given wind speed  $u$  and altitude  $h$

# Continuous Probability of Detection (POD) Functions

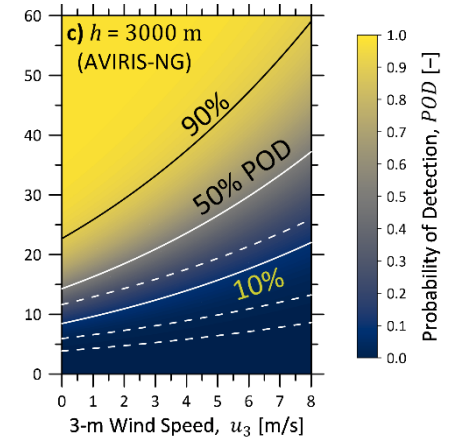
Bridger GML™



Kairos LeakSurveyor™



NASA AVIRIS-NG



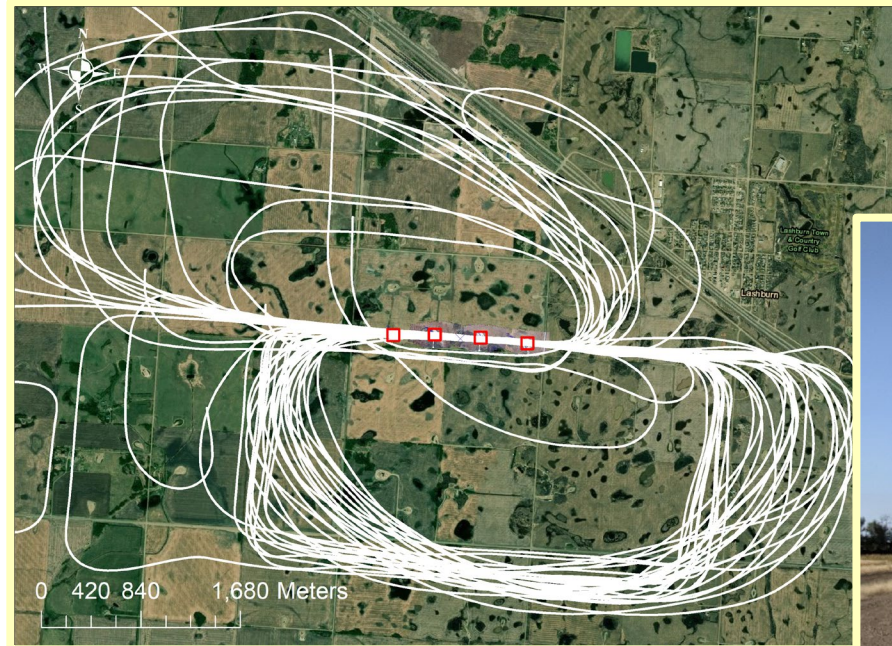
Typical Altitude:	175 m	900 m	3000 m
50% POD @ 3m/s:	1.2 kg/h	32.6 kg/h	20.4 kg/h
Measurement Swath:	97 m	800 m	1830 m

- Probability of detection any source  $Q$  for a given wind speed  $u$  and altitude  $h$



## 2. Semi-Blinded Controlled Release Testing of Quantification Accuracy

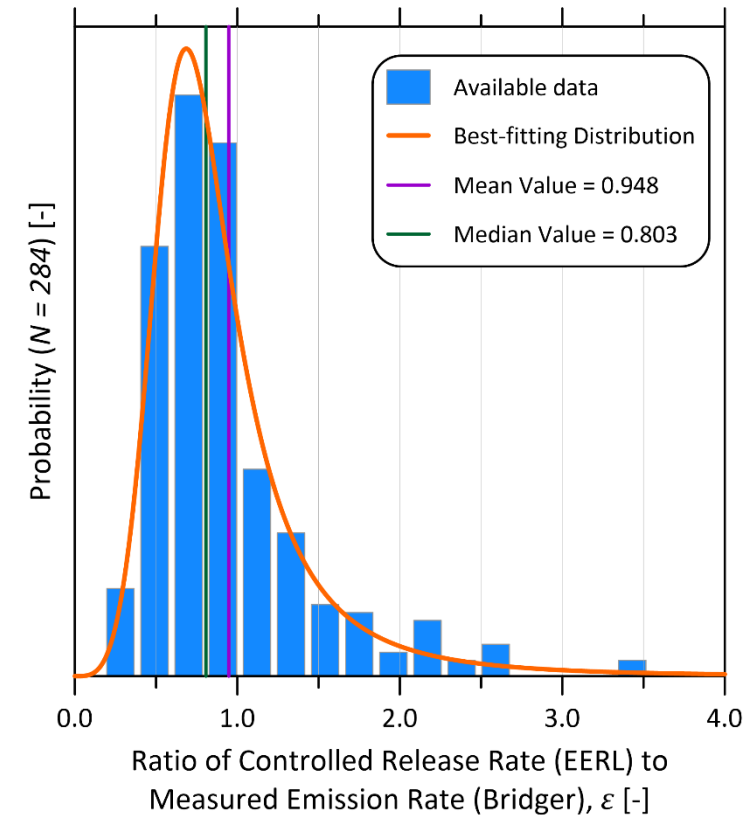
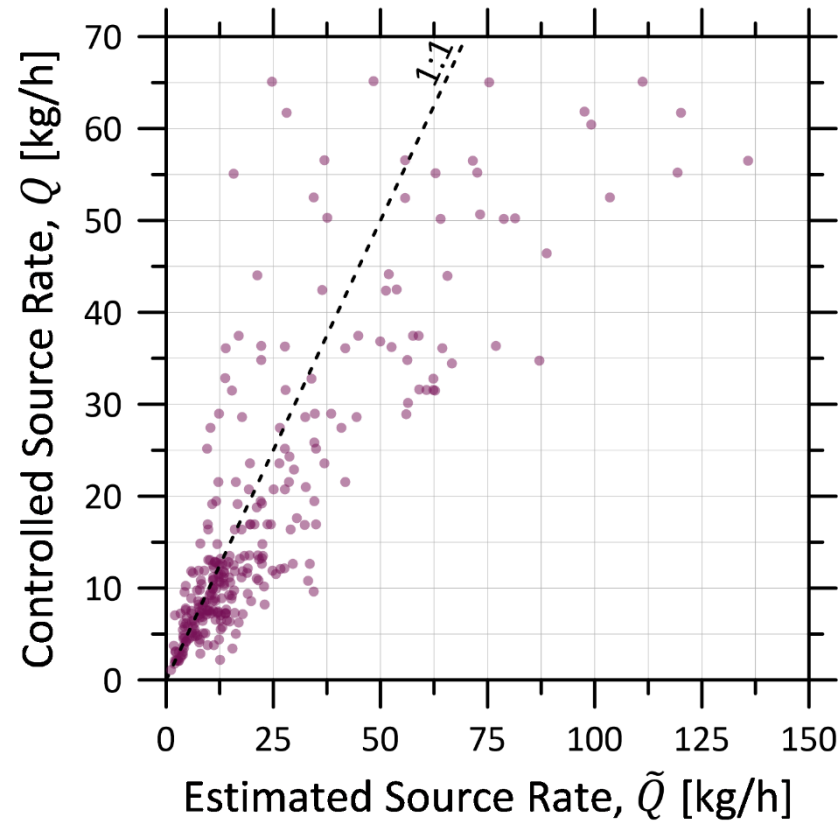
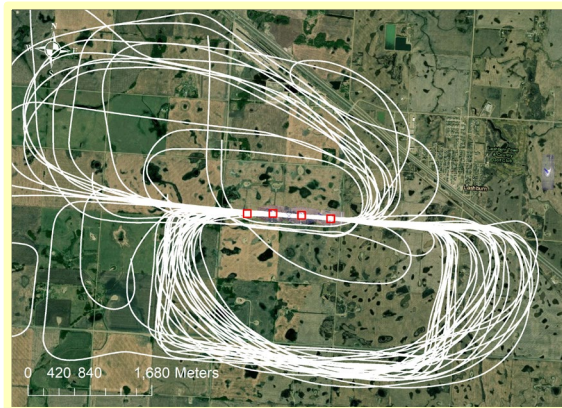
- Semi-blinded (collaborative) controlled release tests
  - Plane flies laps over controlled release points and quantifies
  - Actual release rates are not shared with plane



## 2. Semi-Blinded Controlled Release Testing of Quantification Accuracy

### ■ Semi-blinded (collaborative) controlled release tests

- Plane flies laps over controlled release points and quantifies
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B.M. Conrad, D.R. Tyner, M.R. Johnson (2022) Robust Probabilities of Detection and Quantification Uncertainty for Aerial Methane Detection: Examples for Three Airborne Technologies, *Remote Sensing of Environment* (under review: [preprint](#))



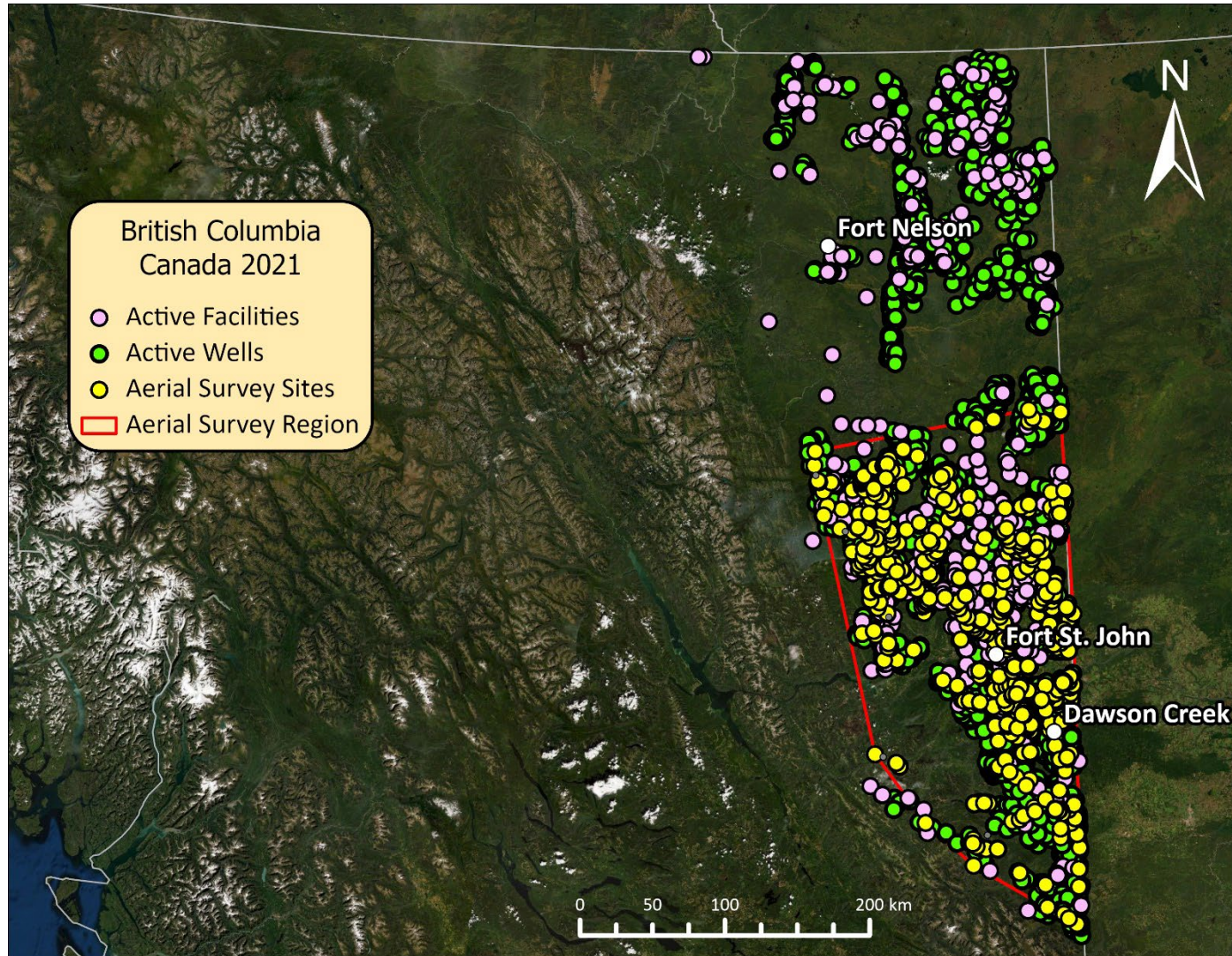
# A Measurement-Based Methane Inventory for British Columbia (BC), Canada

- Demonstrate feasibility of measurement-based methane inventories using aerial measurements
- Key enabling pieces:
  - Technology with sufficient sensitivity to capture majority of sources
  - Detailed probability of detection (POD) functions in varying conditions
  - Detailed uncertainty model for technology
  - Bottom-up data for unmeasured sources





# A Measurement-Based Methane Inventory for British Columbia (BC), Canada



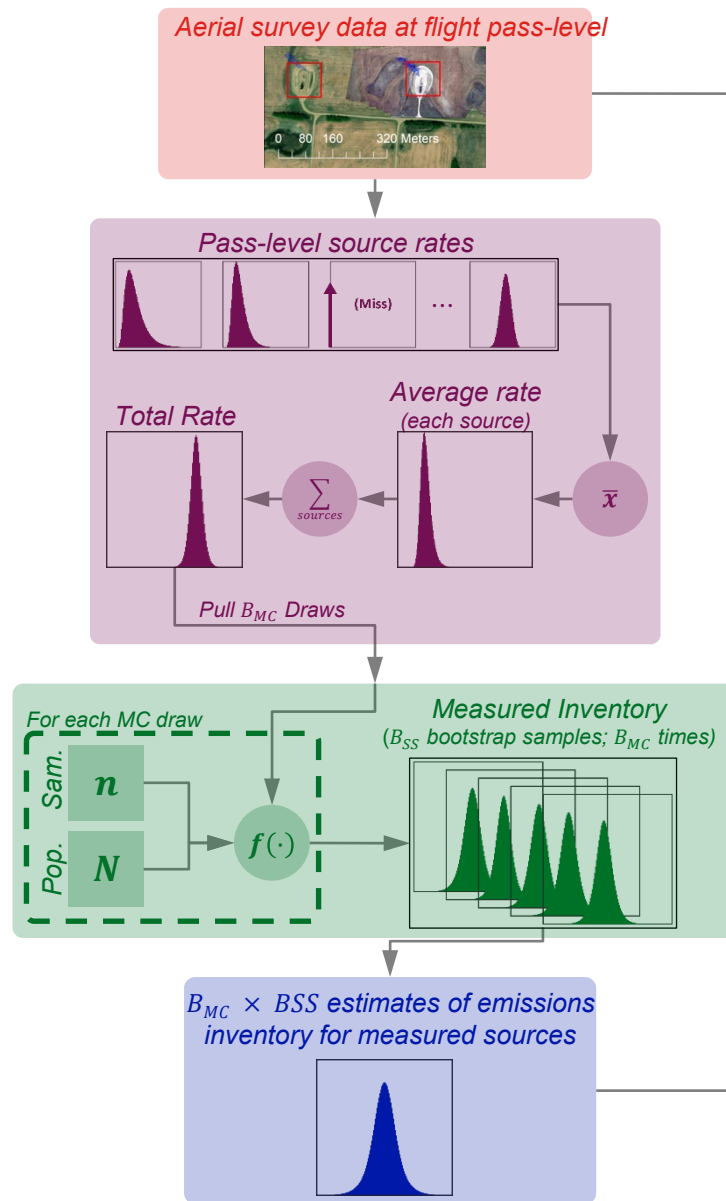
- Survey includes:
  - 59% of all active facilities
  - 8% of all active wells



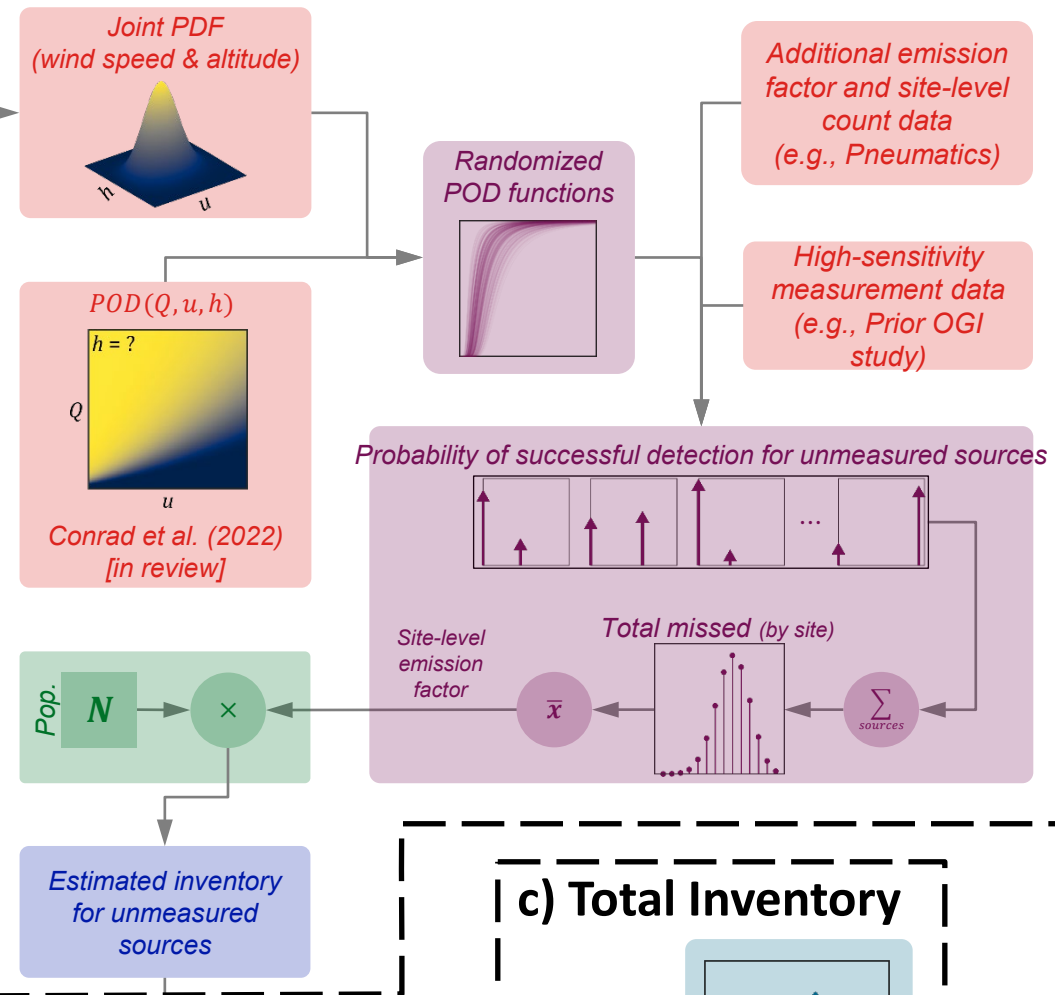


# Protocol to Create a “Hybrid” Bottom-Up Measurement-Based Inventory

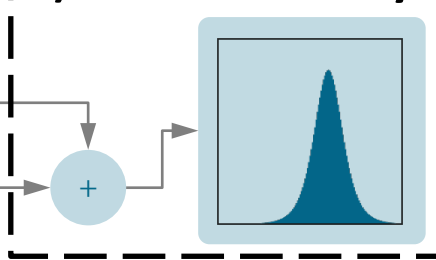
## a) Measured Sources



## b) Unmeasured Sources



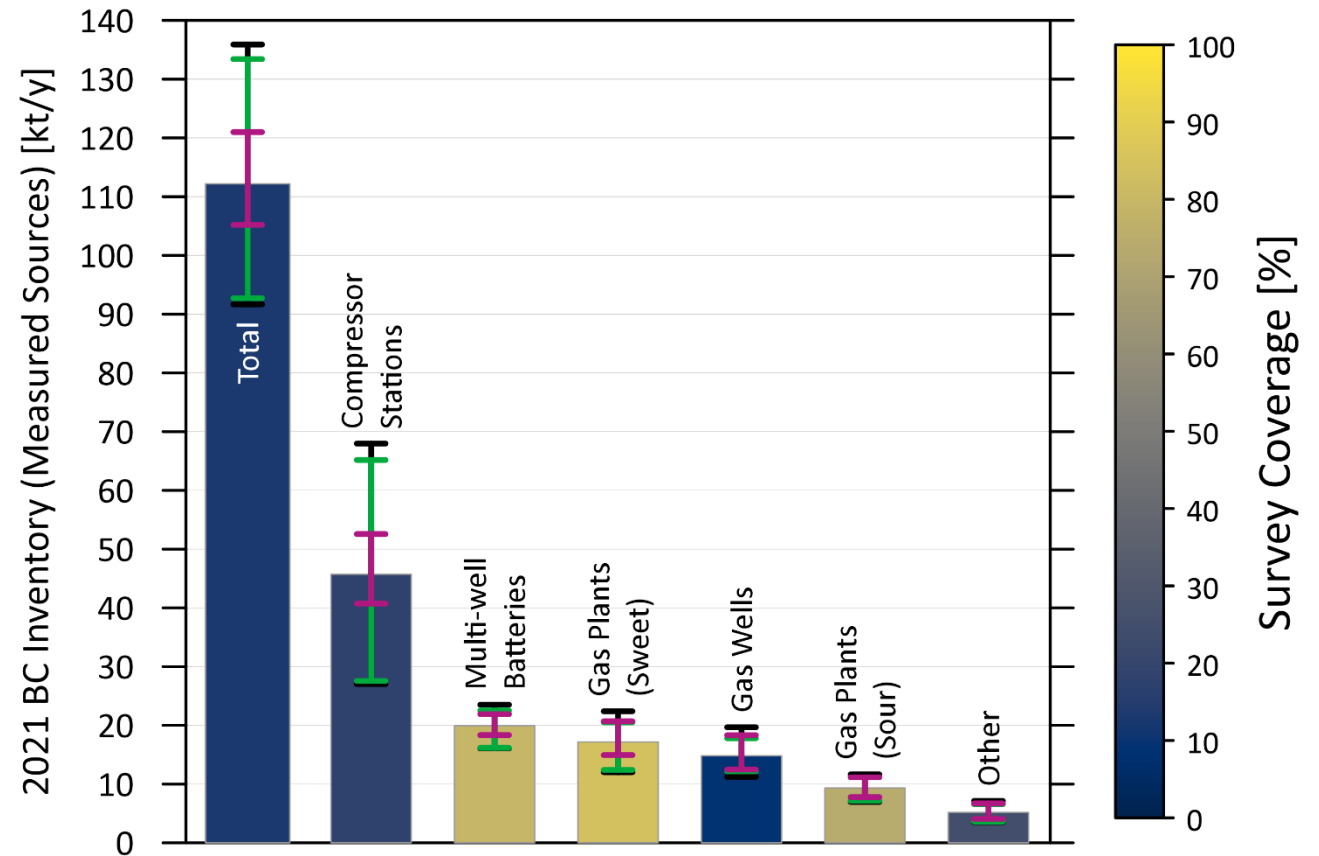
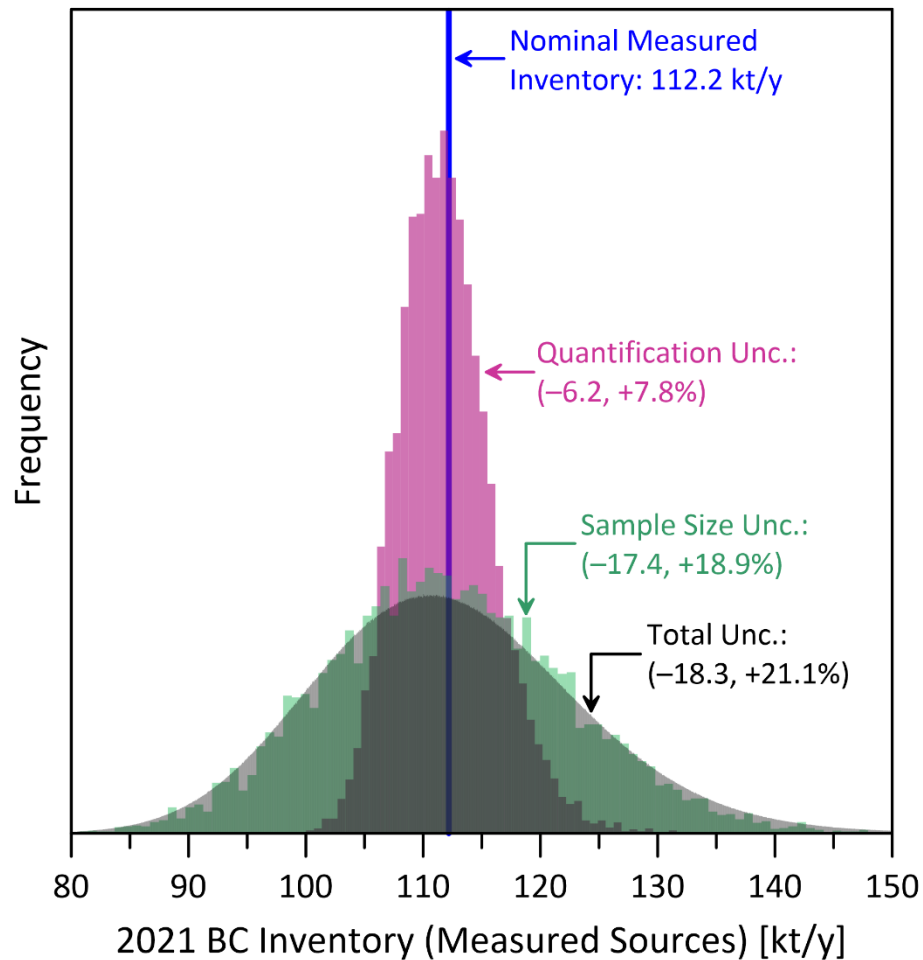
## c) Total Inventory



### Legend

- Bridger GML characteristics and assorted data
- Monte Carlo analysis of quantification uncertainty and detection sensitivity
- Population scaling, including bootstrap analysis of sample size effects
- Estimated partial inventory; measured and unmeasured sources
- Estimated total inventory

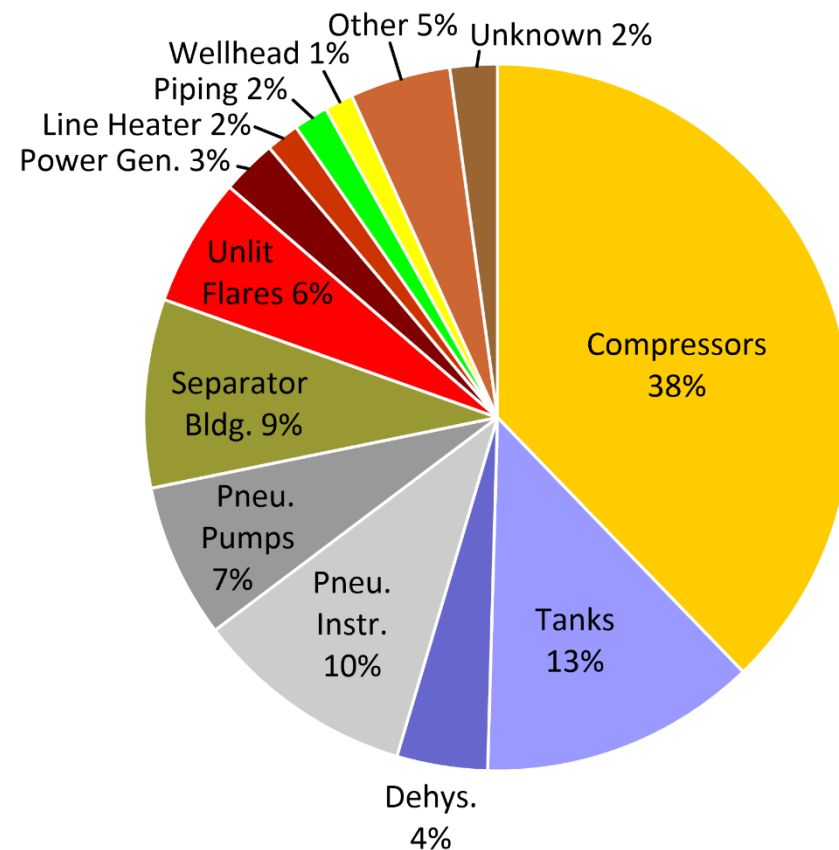
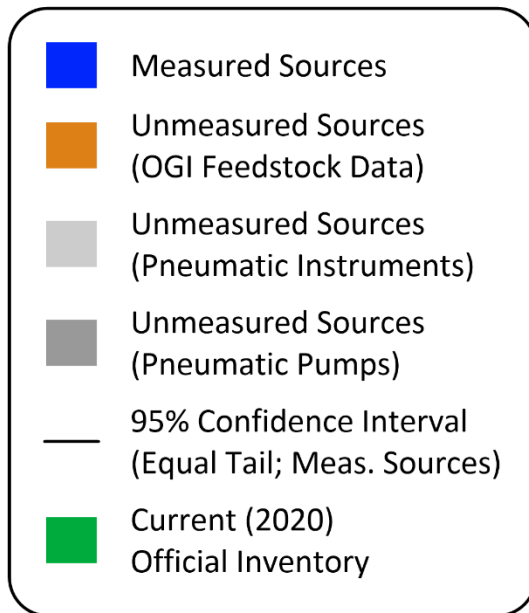
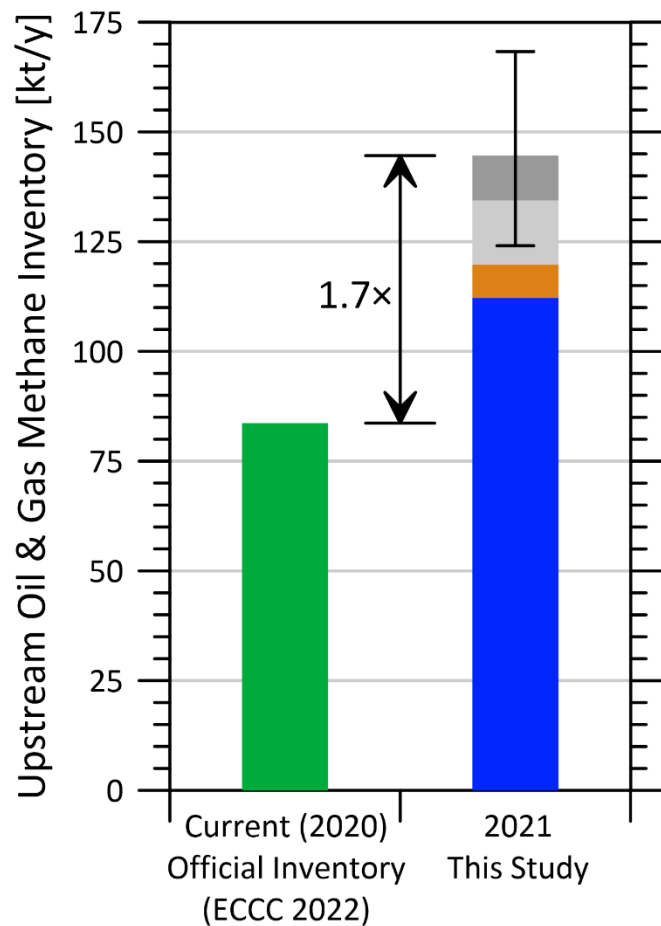
# Quantification and Sample Size Uncertainties in Measured Inventory Sources



- Very powerful approach to quantify, analyze, and *minimize* uncertainty



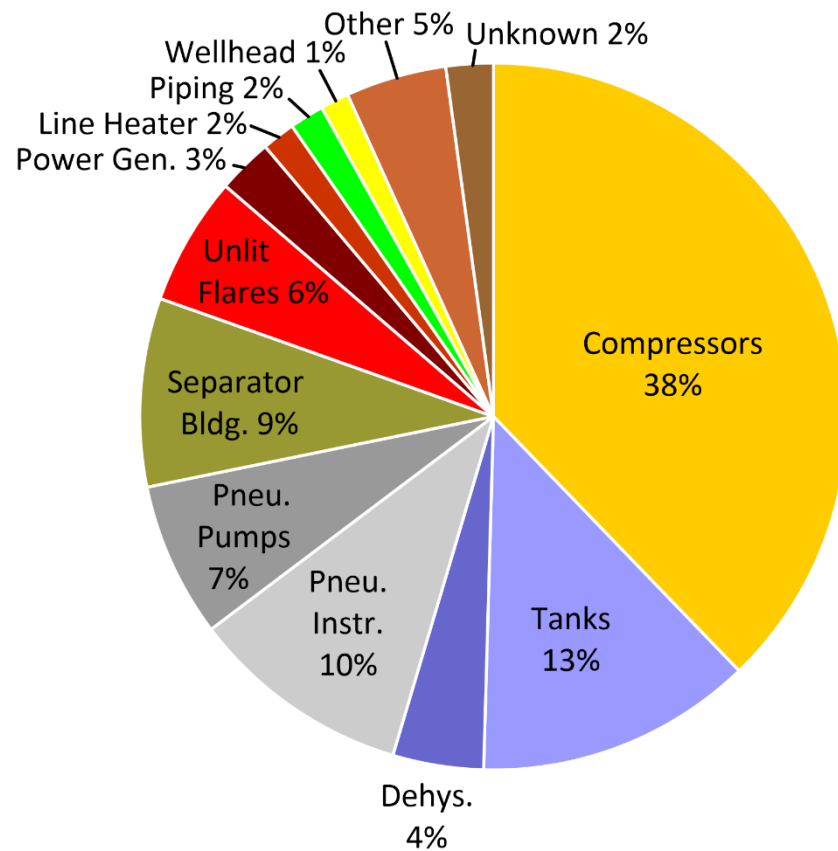
# 2021 Measurement-Based Methane Inventory for BC



# Contrast Sources in Measured(Hybrid) vs. Current Bottom-Up Inventory

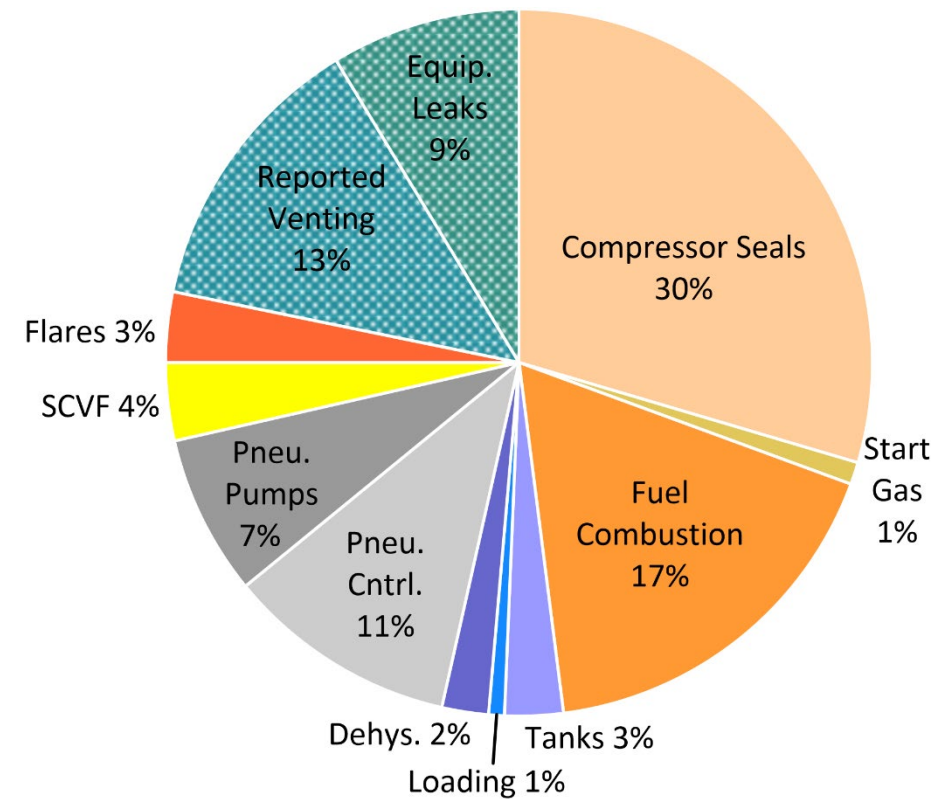
**2021 EERL Meas.-Based Inventory**

*British Columbia Inventory by Source*



**Current Official (ECCC) 2020 Inventory**

*British Columbia Inventory by Source*



- Regulations won't work if they tackle the wrong problem



# Conclusions

- New aerial technologies are a revolution in possibilities, but:
  - Robust, independently-proven, probabilistic sensitivity and uncertainty models are critical
  - Protocols for interpreting data, leveraging POD and uncertainty models, equally important
  - Critical to understand where different technologies fit and how they may best be used
- Oil and gas sector emission patterns are/will rapidly evolve
  - We must expect inventories and source distributions to be changing rapidly year-over-year
  - As we seek to push emissions lower toward zero, measurements will only become more critical
- Measurement-based inventories and policy are essential to achieving mitigation targets

# Acknowledgements



Natural Resources  
Canada

Ressources naturelles  
Canada

Canada



Environment and  
Climate Change Canada

Environnement et  
Changement climatique Canada

Carleton  
University



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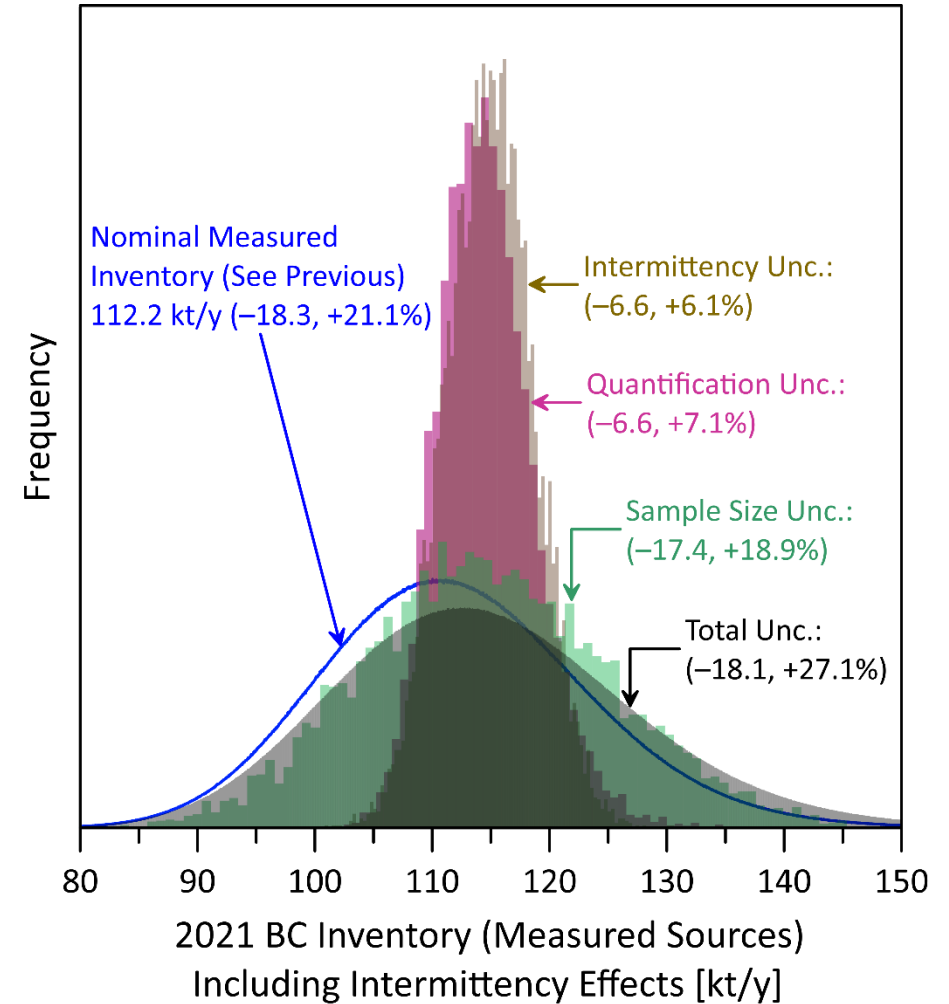


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- D.R. Tyner, M.R. Johnson\* (2018), **A Techno-Economic Analysis of Methane Mitigation Potential from Reported Venting at Oil Production Sites in Alberta**, *Environmental Science & Technology*, 52(21):12877-12885 (doi: [10.1021/acs.est.8b01345](#))

# What About Source Variability / Intermittency?

- A novel approach to bounding the potential uncertainties
- Premise:
  - Grossly overestimate variability using empirical raw data assuming pass-by-pass data
  - Bootstrap values assuming they have no uncertainty
  - Then run complete analysis adding back in quantification plus sample size uncertainties

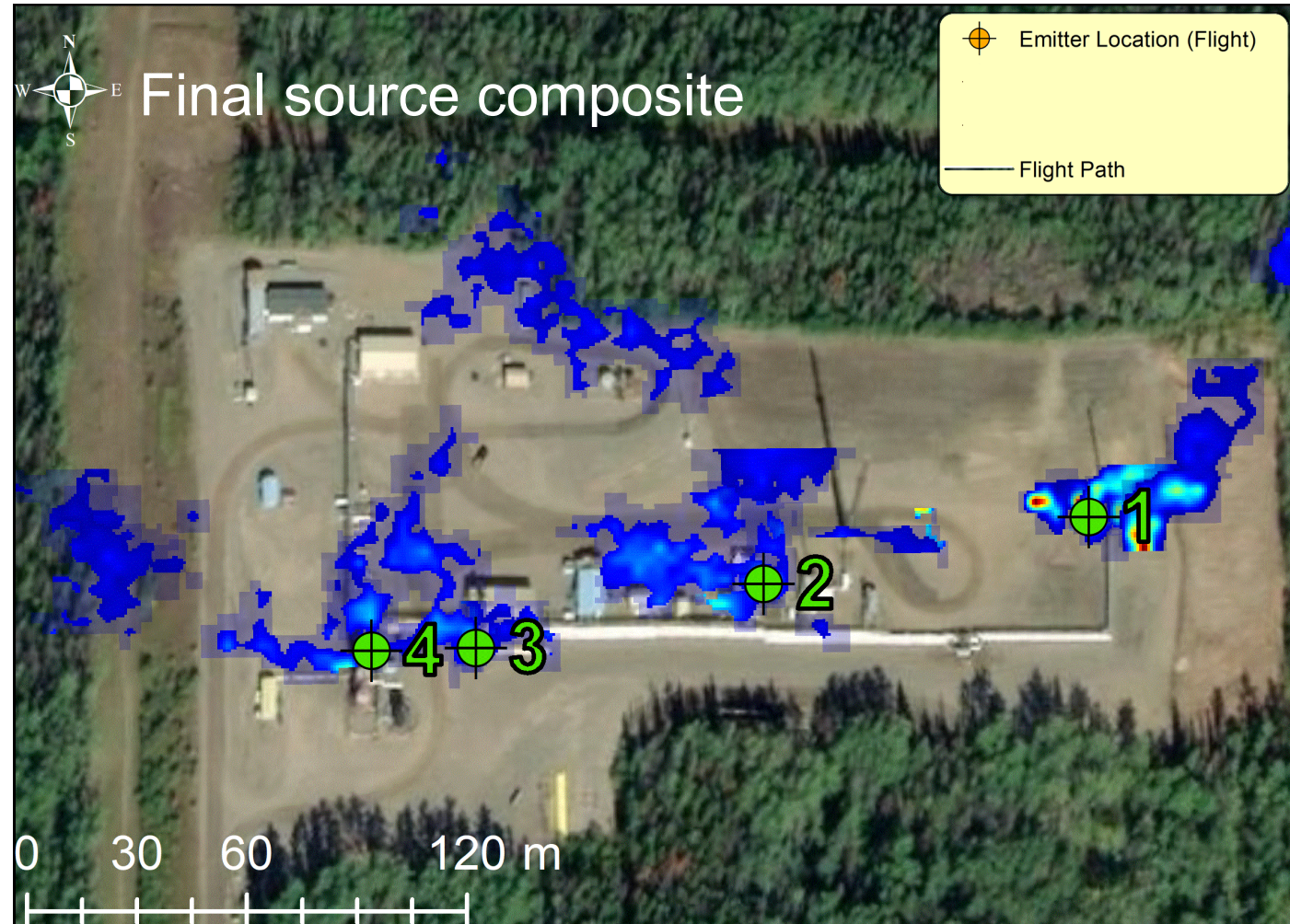






# Example Aerial Technology: Bridger Photonics Gas Mapping LiDAR

- Sites have one or more passes
- Flights with detected emissions are revisited in a subsequent day
- Source quantification for inventory development purposes requires interpretation of data from each pass



Tyner & Johnson, *Environ. Sci. Technol.*, 2021  
(doi: [10.1021/acs.est.1c01572](https://doi.org/10.1021/acs.est.1c01572))



# Source Attribution: Geo-locating Aerial Survey Imagery

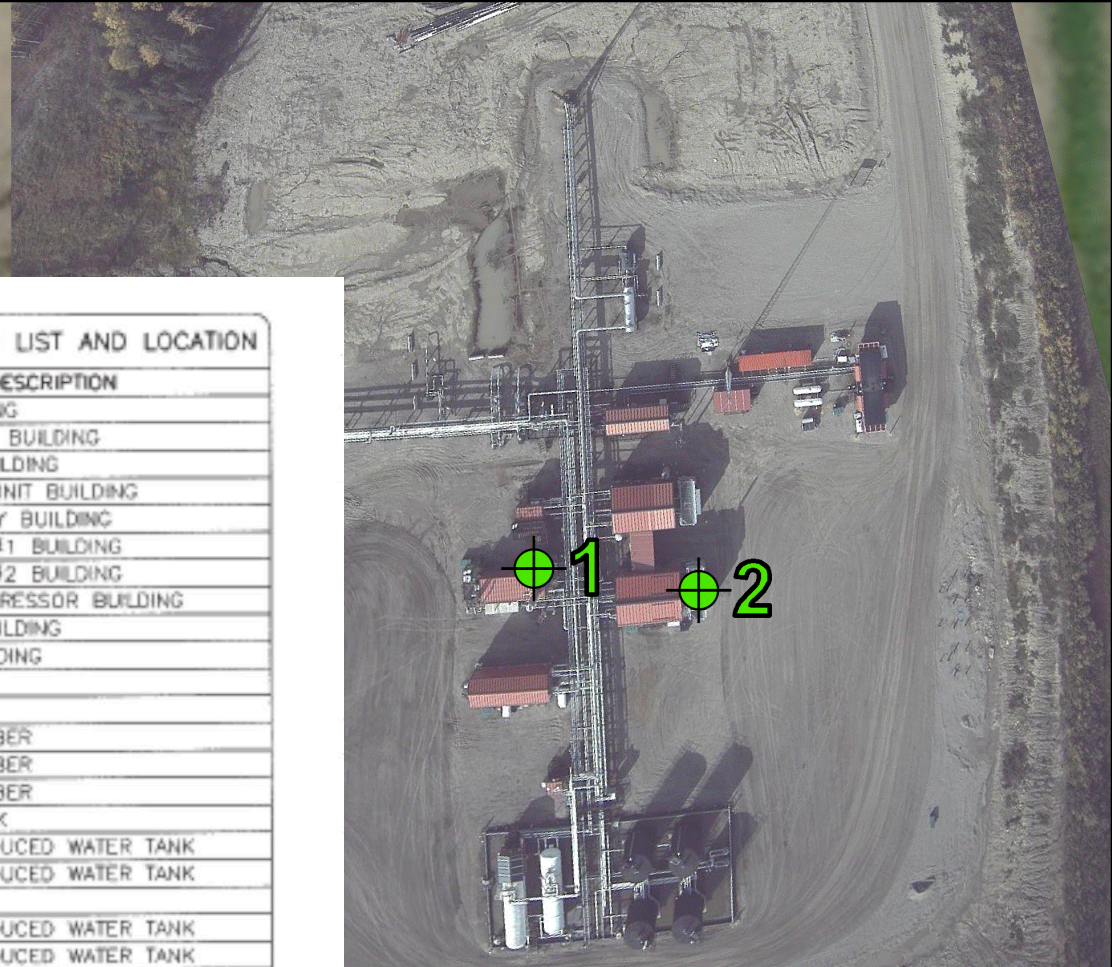
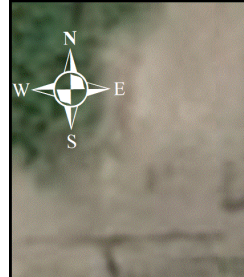
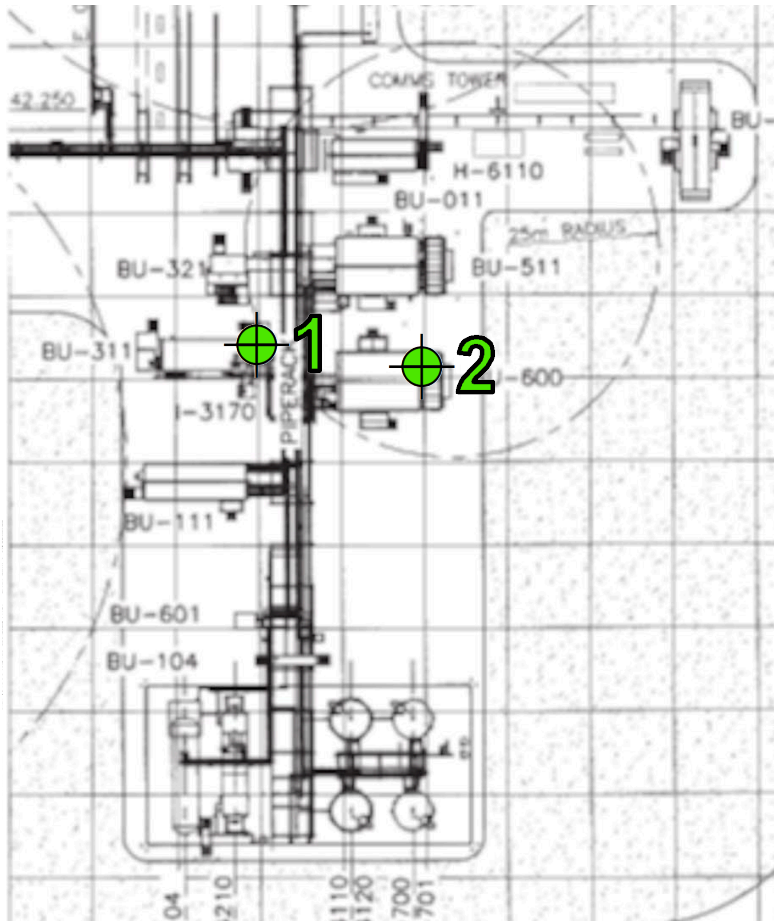
- Combining satellite imagery, geo-located aerial photos, plot plans, & ground survey data to attribute





# Source Attribution: Match Sources to Plot Plans

- Plot Plans provide a site schematic and equipment list
- Match Sources to Plot Plan



EQUIPMENT/BUILDING LIST AND LOCATION	
TAG NO.	DESCRIPTION
BU-011	MCC/IA BUILDING
BU-111	SLUG CATCHER BUILDING
BU-131	SEPARATOR BUILDING
BU-311	DEHYDRATION UNIT BUILDING
BU-321	FUEL GAS DEHY BUILDING
BU-511	COMPRESSOR #1 BUILDING
BU-521	COMPRESSOR #2 BUILDING
BU-541	RECYCLE COMPRESSOR BUILDING
BU-921	GENERATOR BUILDING
BU-931	METERING BUILDING
FS-9110	FLARE STACK
I-3170	INCINERATOR
M-4410	ODOUR SCRUBBER
M-4420	ODOUR SCRUBBER
M-4430	ODOUR SCRUBBER
S-1340	METHANOL TANK
S-4110	750 BBL PRODUCED WATER TANK
S-4120	750 BBL PRODUCED WATER TANK
H-6110	TBO
TK-700	750 BBL PRODUCED WATER TANK
TK-701	750 BBL PRODUCED WATER TANK
S-4210	CONDENSATE STORAGE TANK
V-104	CONDENSATE STORAGE TANK
S-9330	CORROSION INHIBITOR TANK
V-9120	LP FLARE KNOCK-OUT DRUM
V-9130	HP FLARE KNOCK-OUT DRUM



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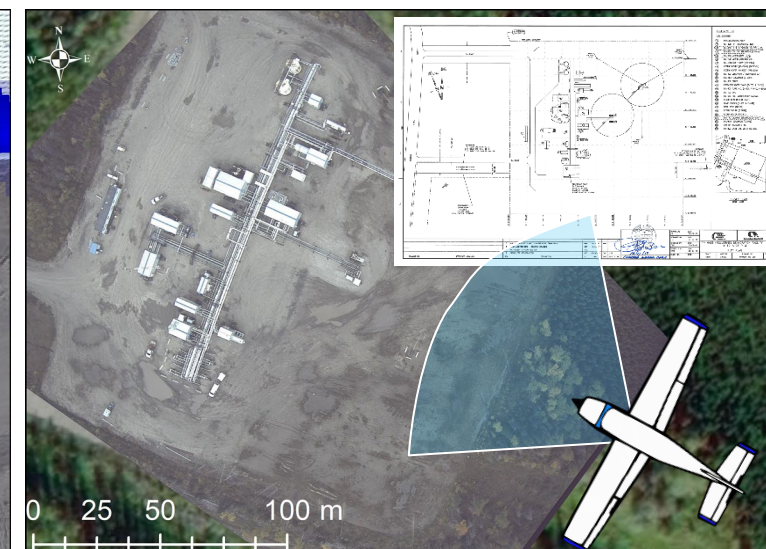
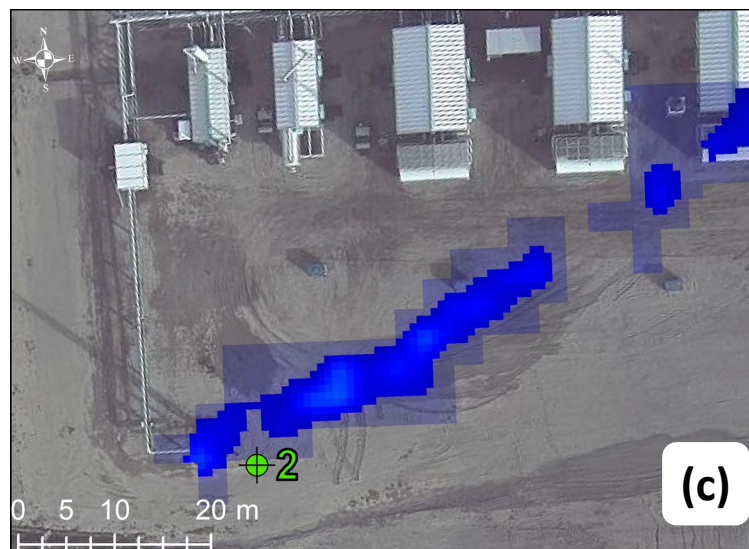
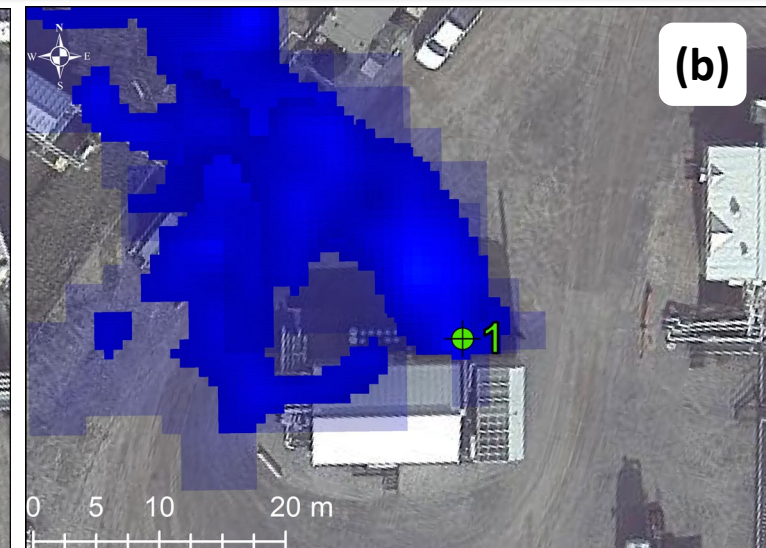
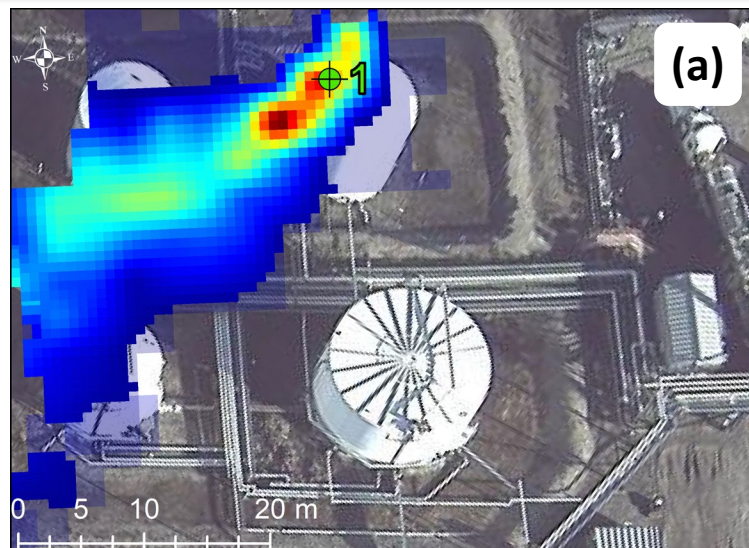


ENERGY AND  
EMISSIONS  
RESEARCH  
LABORATORY



# High Resolution (~1m) Data Enables Attribution to Specific Sources

- Key sources:
  - Tanks
  - Compressors
  - Unlit flares

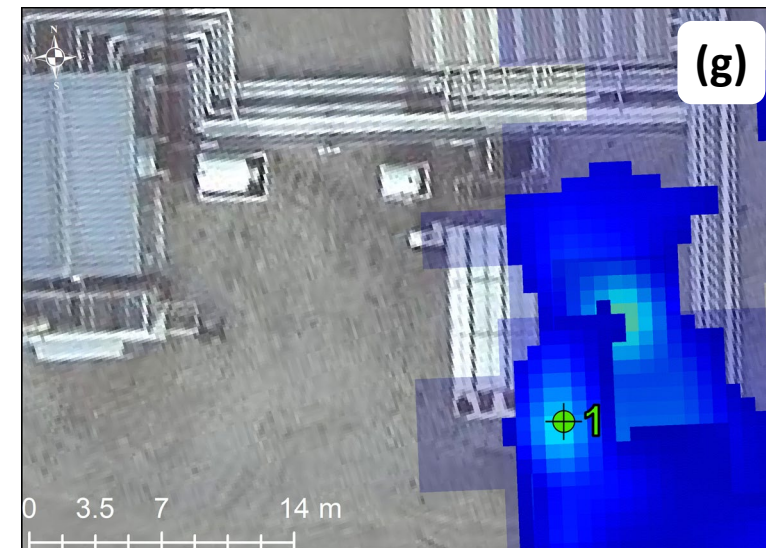
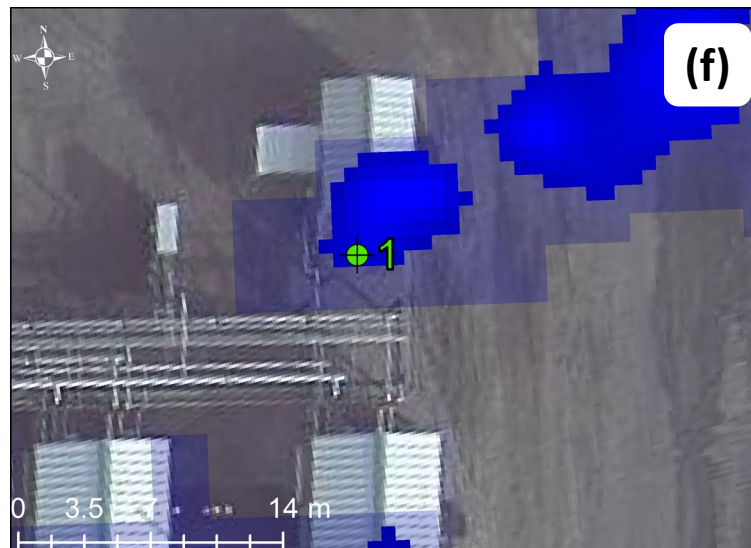
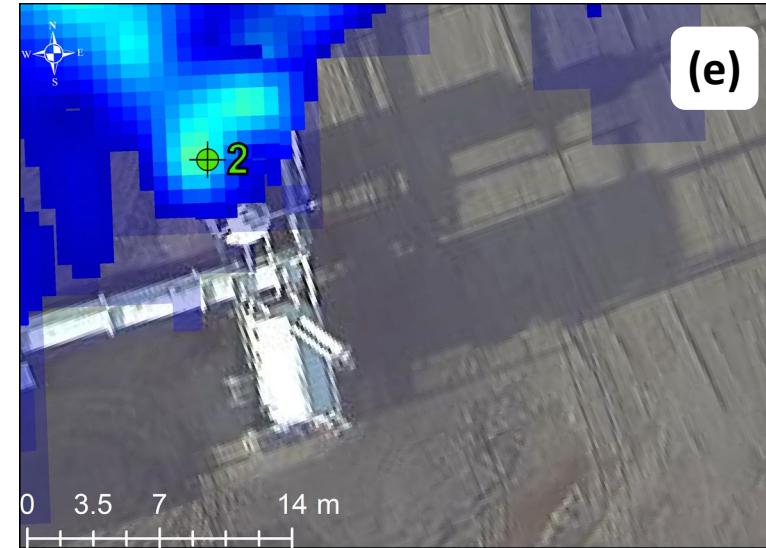
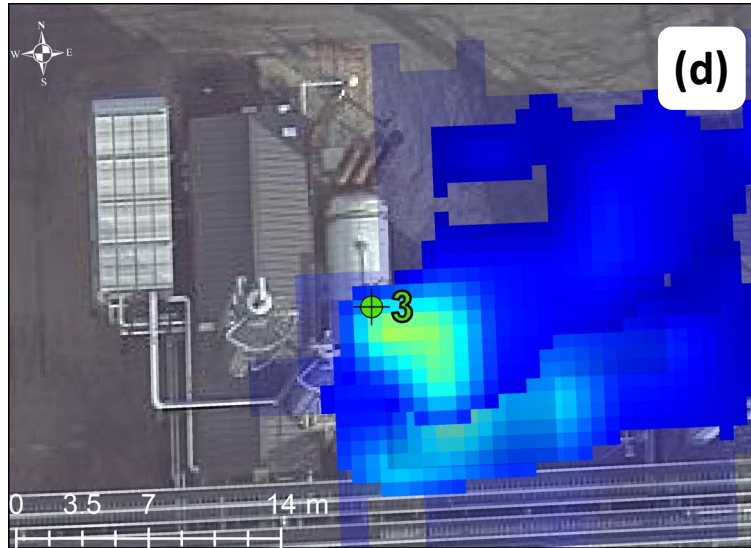


Tyner & Johnson, *Environ. Sci. Technol.*, 2021  
(doi: [10.1021/acs.est.1c01572](https://doi.org/10.1021/acs.est.1c01572))



# High Resolution (~1m) Data Enables Attribution to Specific Sources

- Other detected sources in BC:
  - d) Amine boiler unit
  - e) Dehydrator
  - f) Generator
  - g) Cooler
  - h) Etc.

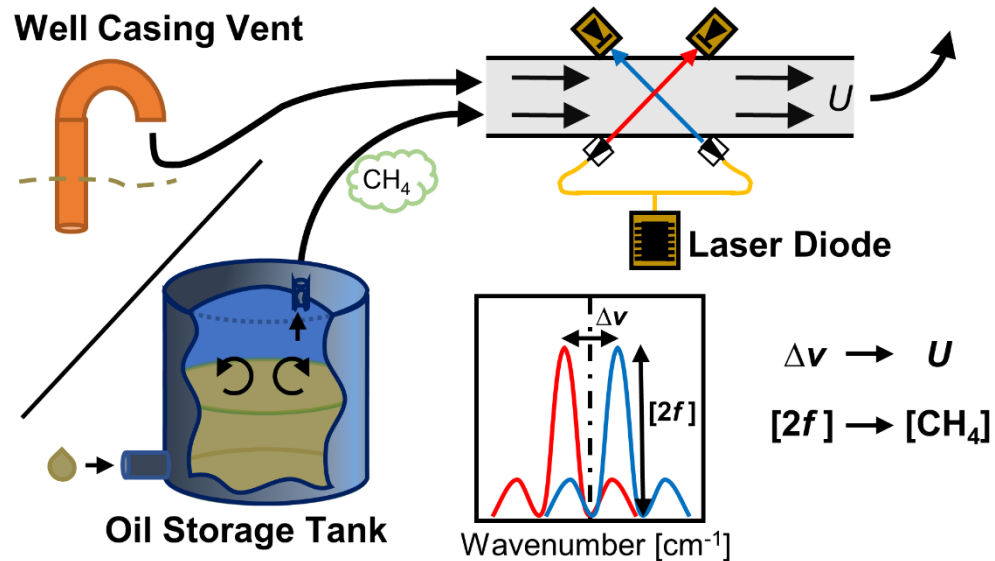


Tyner & Johnson, *Environ. Sci. Technol.*, 2021  
(doi: [10.1021/acs.est.1c01572](https://doi.org/10.1021/acs.est.1c01572))



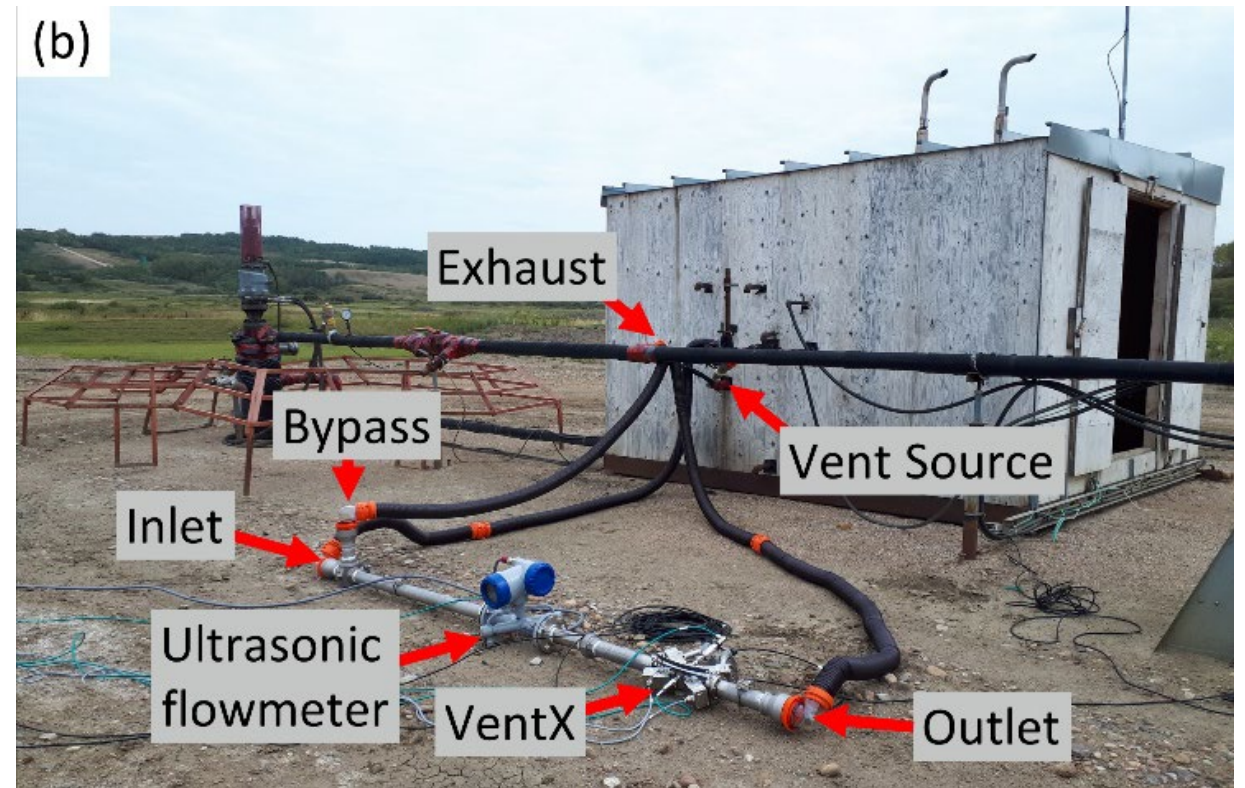
# Parallel On-Site Measurements of Key Sources

- “VentX” Measurements of Unsteady Methane Vent Sources
  - Engine shed vents (CHOPS) in Saskatchewan



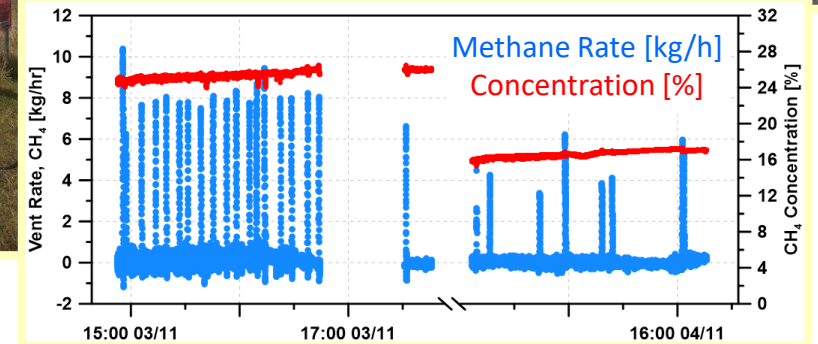
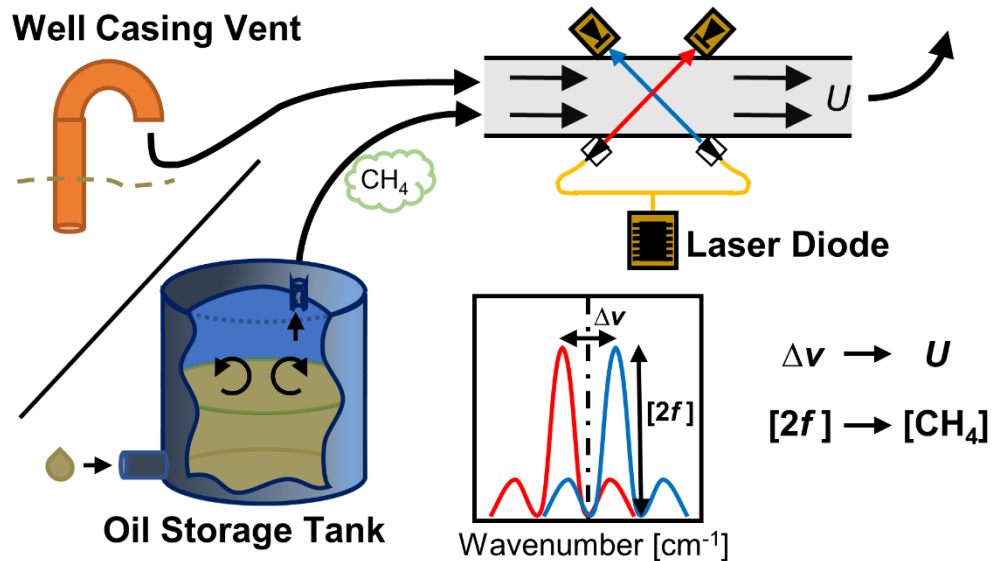
Festa-Bianchet et al. (2022), *Sensors* (doi: [10.3390/s22114175](https://doi.org/10.3390/s22114175)).

Seymour et al. (2022), *Sensors* (doi: [10.3390/s22166139](https://doi.org/10.3390/s22166139)).



# Parallel On-Site Measurements of Key Sources

- “VentX” Measurements of Unsteady Methane Vent Sources
  - Engine shed vents (CHOPS) in Saskatchewan
  - Tank vents in Alberta




Festa-Bianchet et al. (2022), *Sensors* (doi: [10.3390/s22114175](https://doi.org/10.3390/s22114175)).

Seymour et al. (2022), *Sensors* (doi: [10.3390/s22166139](https://doi.org/10.3390/s22166139)).



# 2021 Carleton-EERL National Methane Survey

- National-scale effort
  - ~8200 sites across 4 provinces

 Natural Resources Canada / Ressources naturelles Canada

**Canada**

**EDF**  
ENVIRONMENTAL DEFENSE FUND

**BC OGRIS**  
BC Oil and Gas Research and Innovation Society

**UN** environment programme  
50 1972-2022

**BC Oil & Gas COMMISSION**

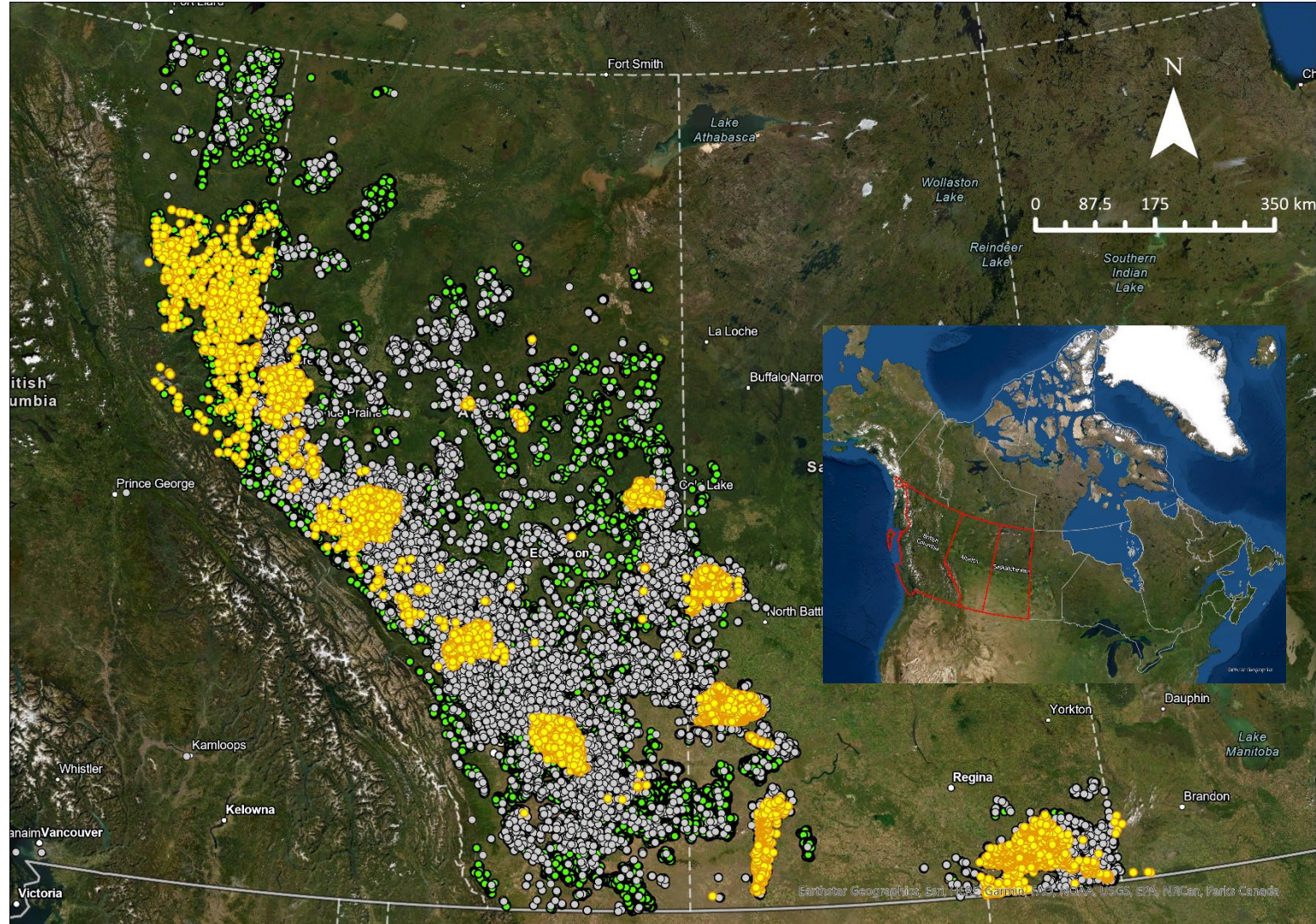
**NSERC CRSNG**

 Environment and Climate Change Canada / Environnement et Changement climatique Canada

**BRIDGER**  
PHOTONICS

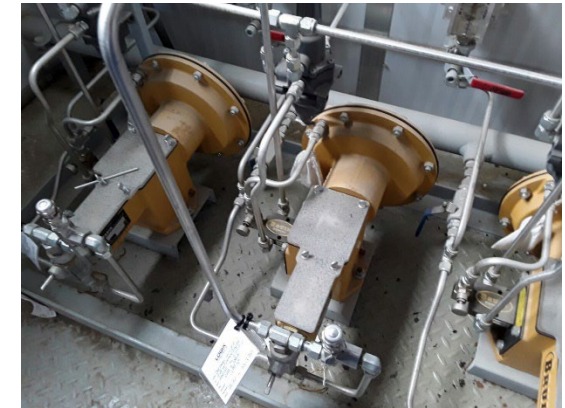
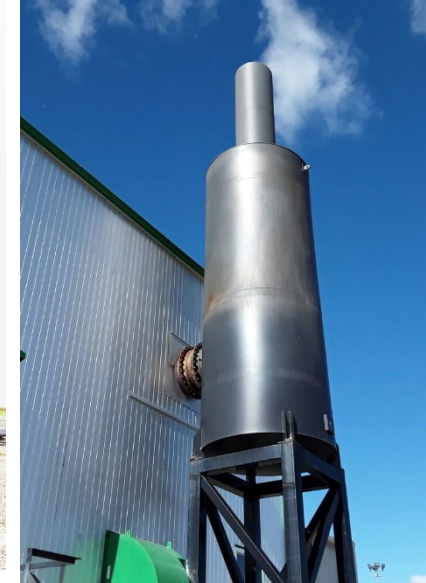
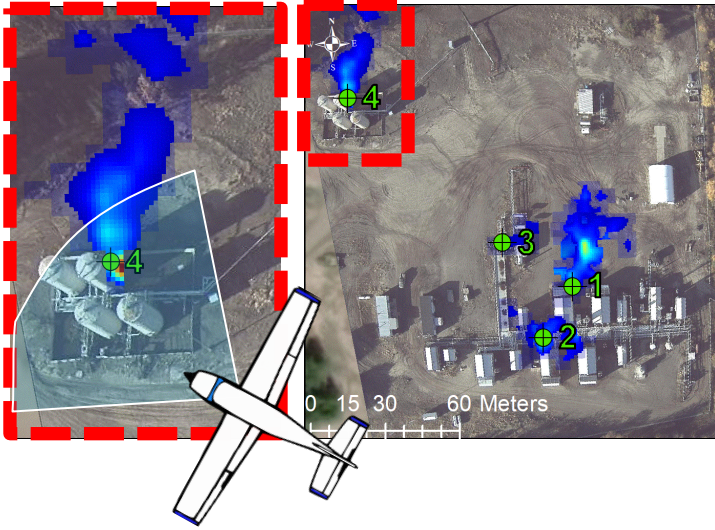
**GREENPATH ENERGY LTD**

**Carleton University**  **eerl** ENERGY AND EMISSIONS RESEARCH LABORATORY



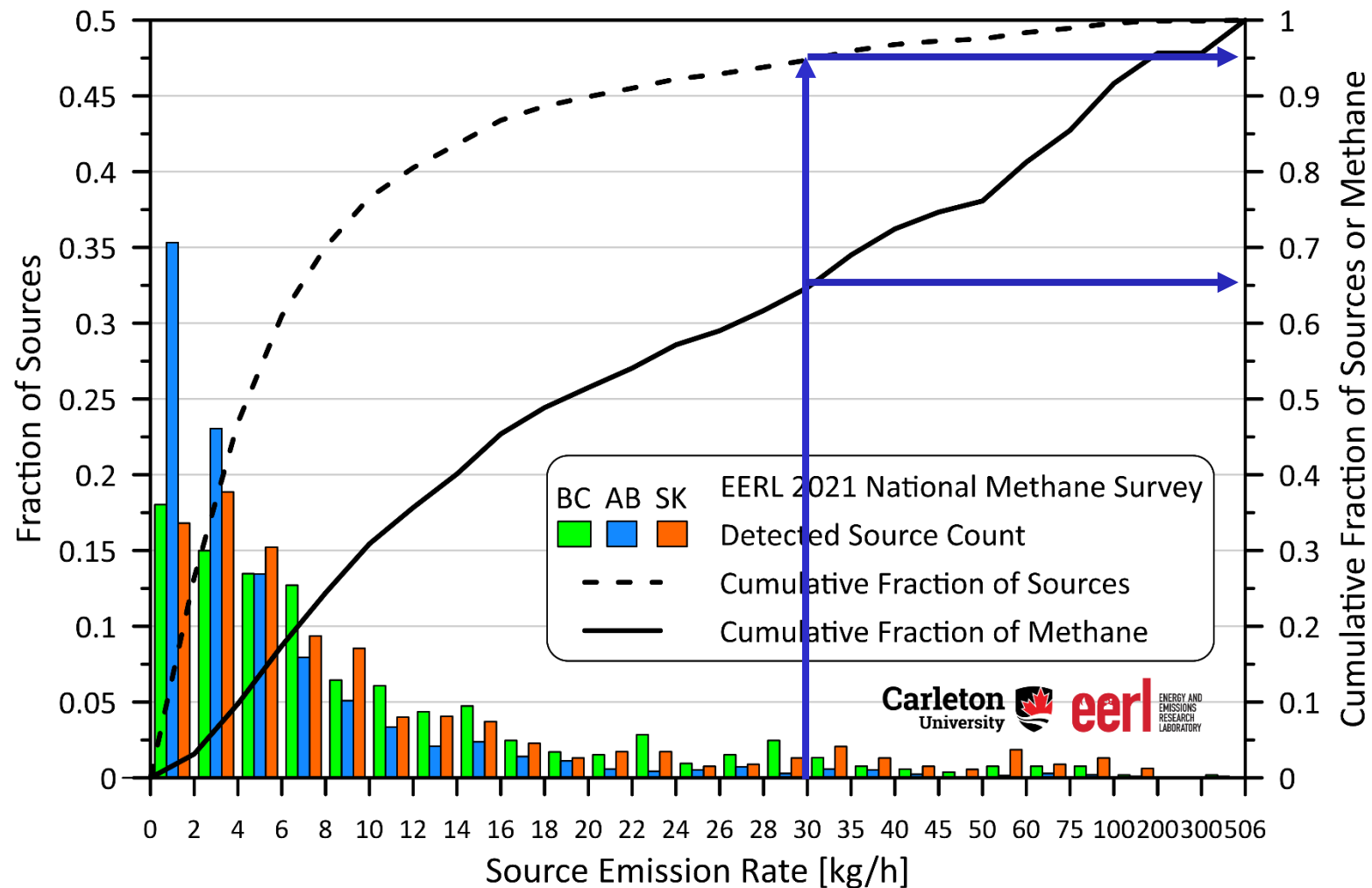


# On Site Follow-ups and Root Cause Analysis



# EERL 2021 National Survey: Distributions of Detected Sources

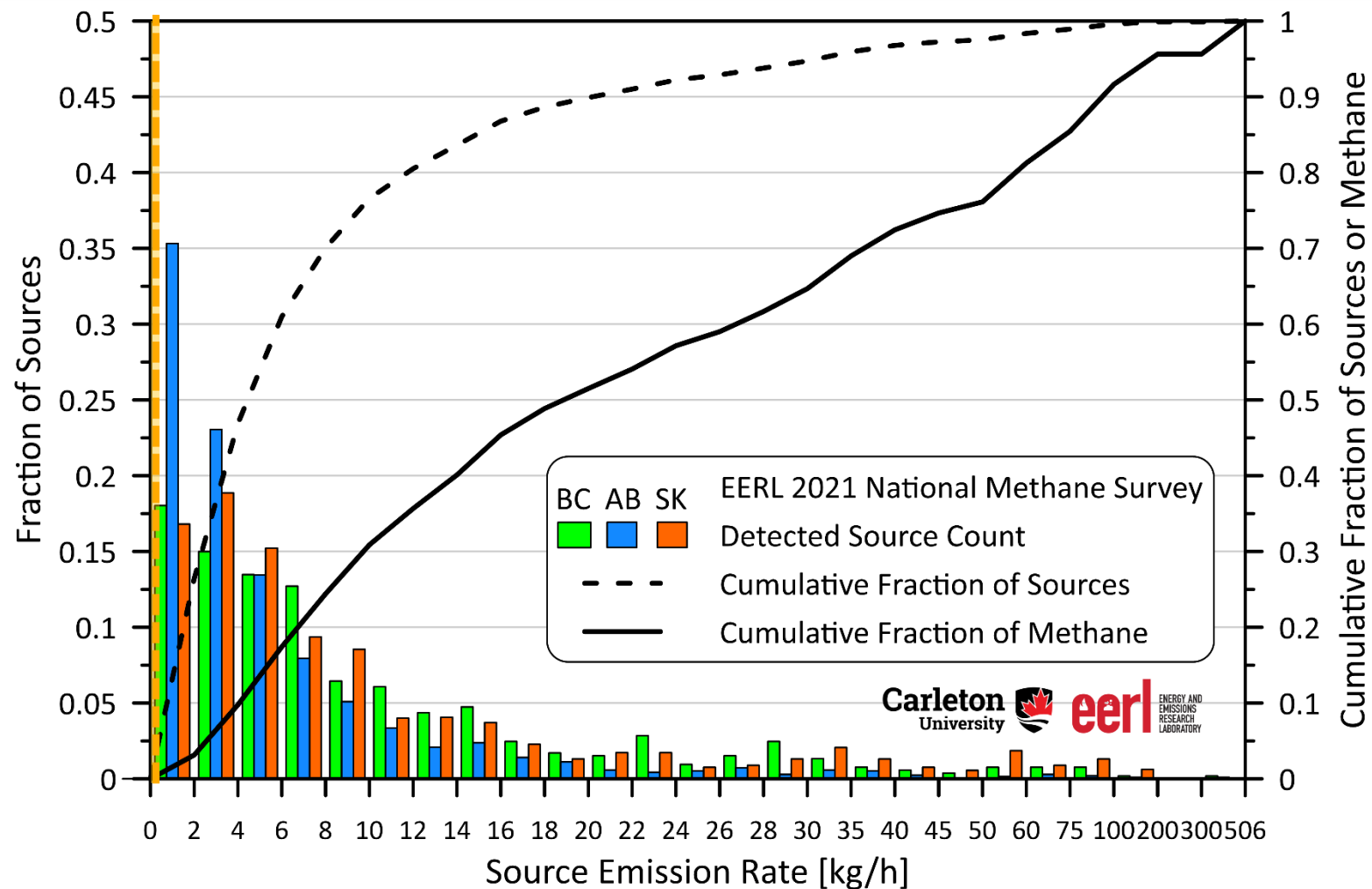
- Similar, highly-skewed distributions across all provinces
  - Note these measured sources are ~80% of total methane (shown later)
- 95% of GML measured sources less than 30 kg/h
  - 2/3 of measured methane / ~81% of all methane
  - Not just about “super-emitters”
  - Mid-sized source key and will become more important as mitigation efforts succeed





# EERL 2021 National Survey: Distributions of Detected Sources

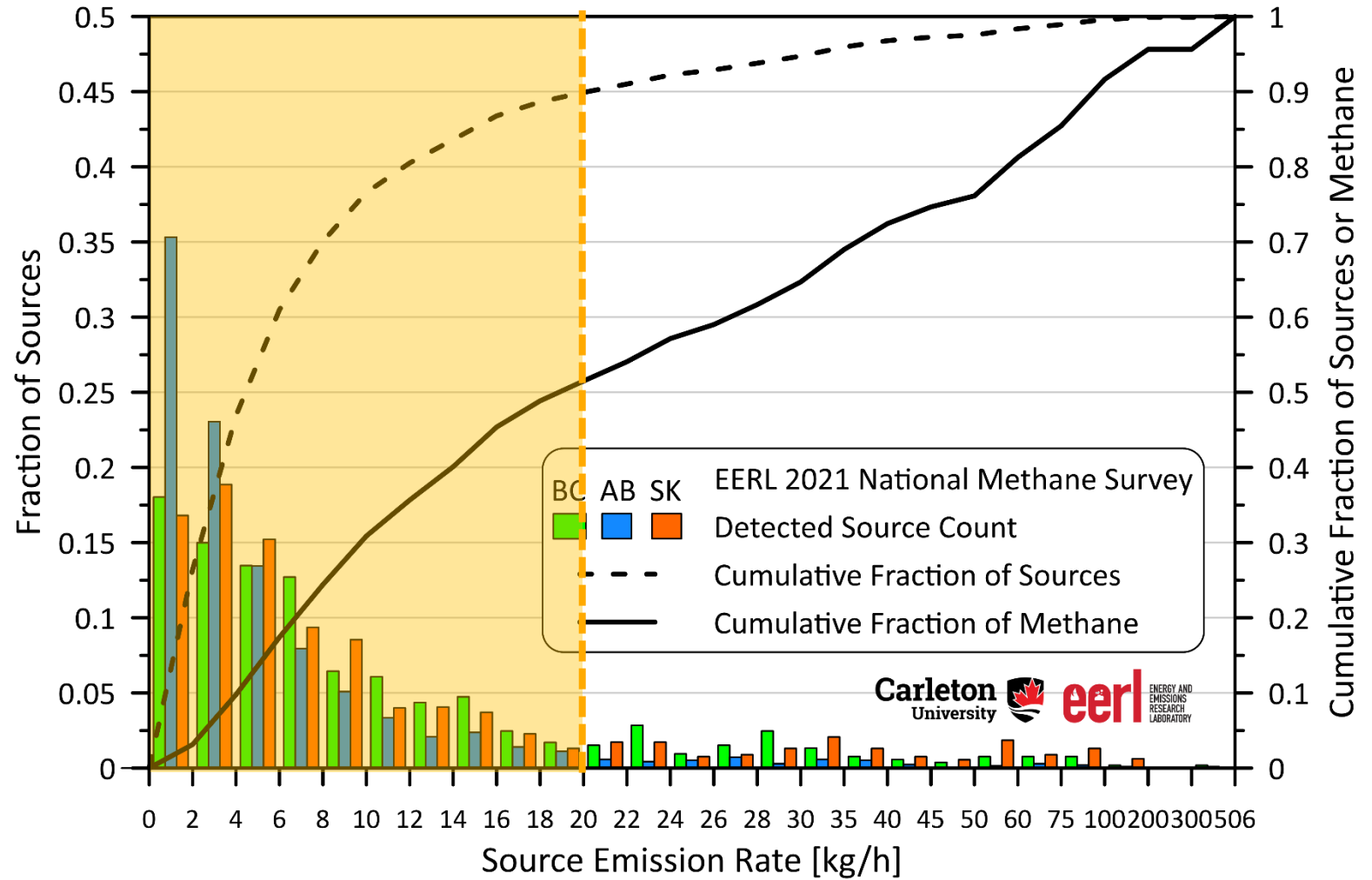
- Measured distributions represent ~80% of total methane (*shown later*)





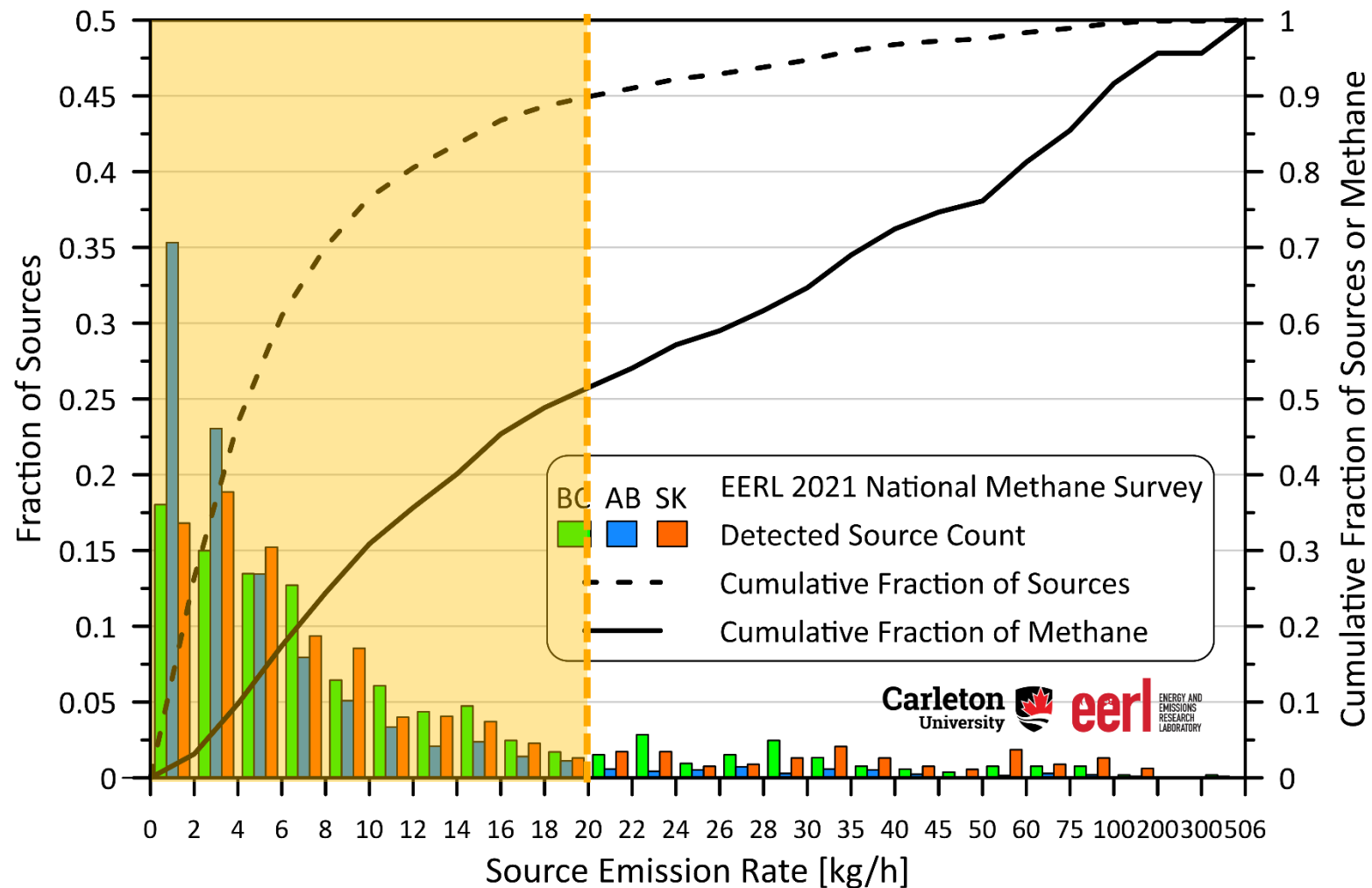
# EERL 2021 National Survey: Distributions of Detected Sources

- Measured distributions represent ~80% of total methane (*shown later*)
- At 20 kg/h sensitivity can see:
  - ~10% of these sources / 48% of this methane
  - ~38% ( $0.48 \times 0.8$ ) of all methane



# EERL 2021 National Survey: Distributions of Detected Sources

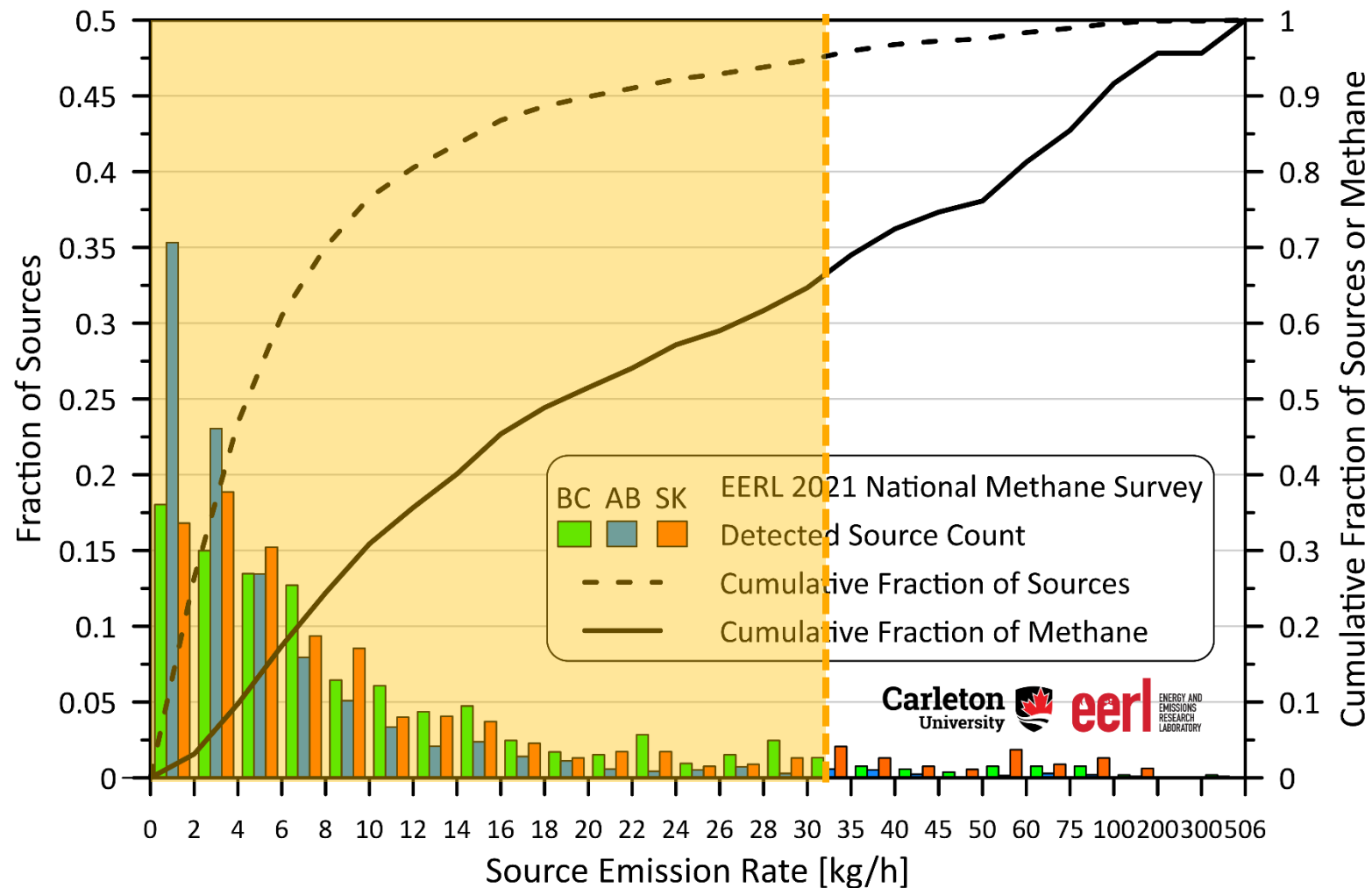
- Measured distributions represent ~80% of total methane (*shown later*)
- At 20 kg/h sensitivity can see:
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  - ~38% ( $0.48 \times 0.8$ ) of all methane
- At 32 kg/h sensitivity can see:





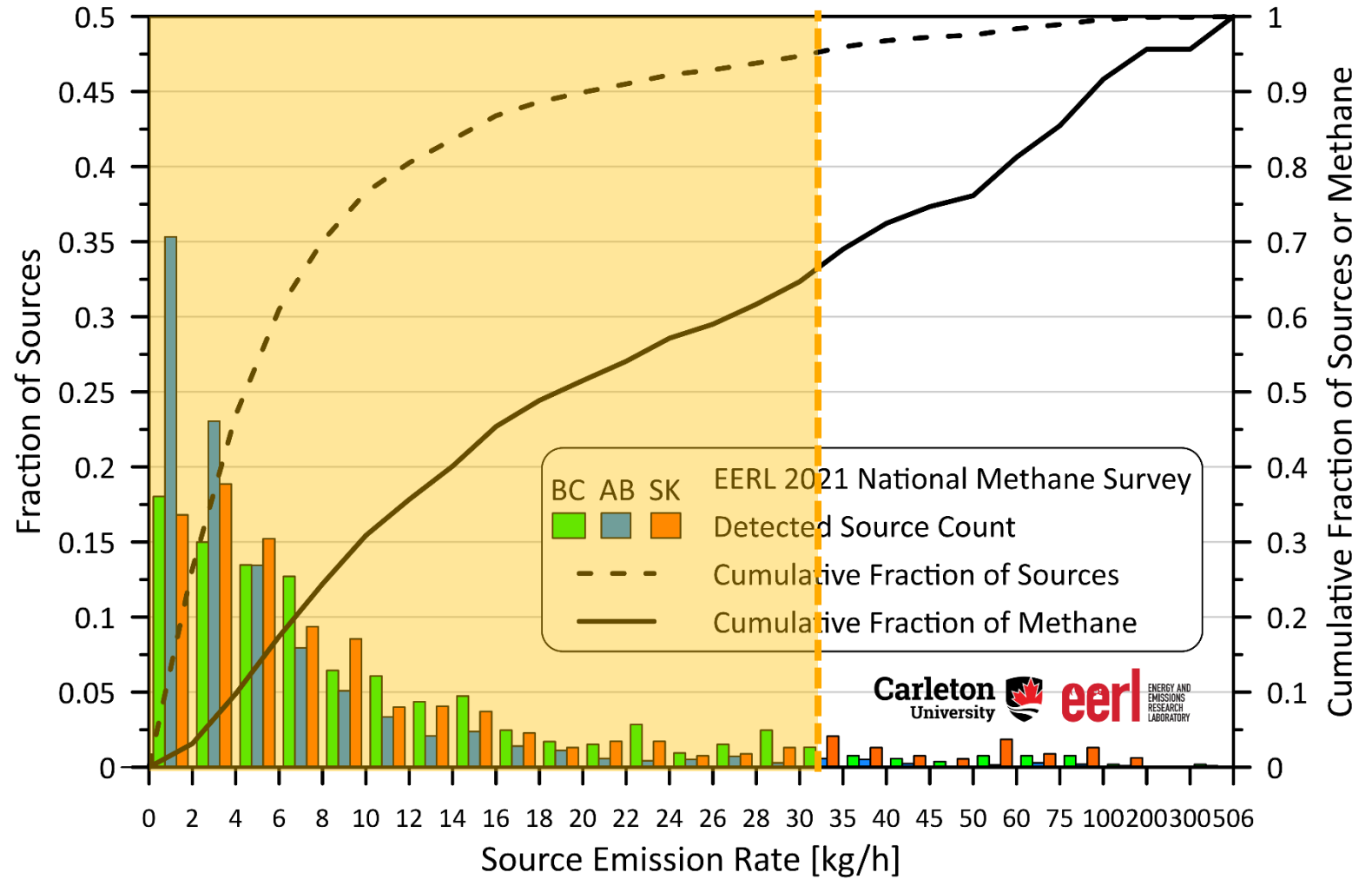
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- At 20 kg/h sensitivity can see:
  - ~10% of these sources / 48% of this methane
  - ~38% ( $0.48 \times 0.8$ ) of all methane
- At 32 kg/h sensitivity can see:
  - ~5% of these sources / 33% of this methane
  - ~26% ( $0.33 \times 0.8$ ) of all methane



# EERL 2021 National Survey: Distributions of Detected Sources

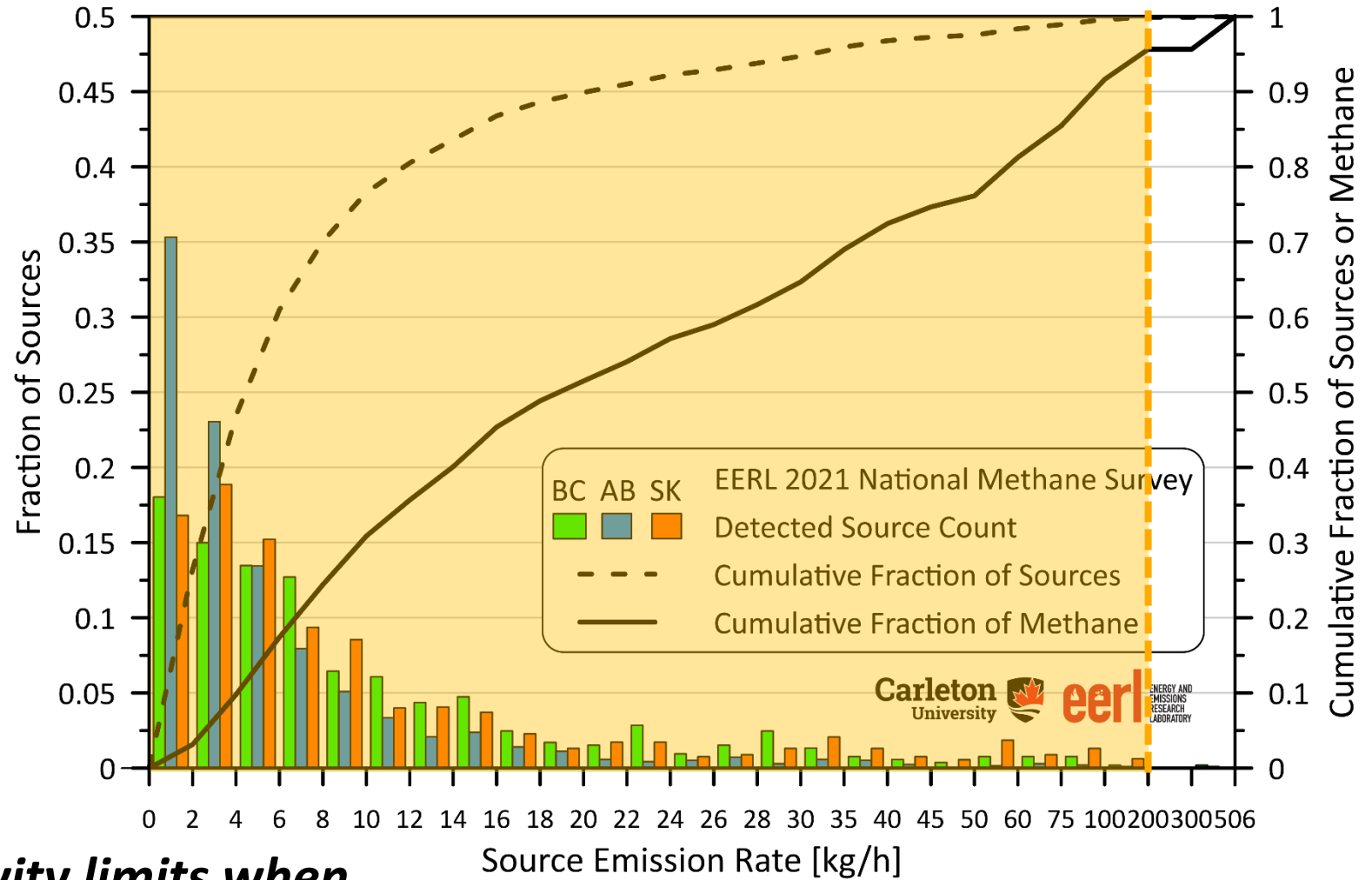
- Measured distributions represent ~80% of total methane (*shown later*)
- At 20 kg/h sensitivity can see:
  - ~10% of these sources / 48% of this methane
  - ~38% ( $0.48 \times 0.8$ ) of all methane
- At 32 kg/h sensitivity can see:
  - ~5% of these sources / 33% of this methane
  - ~26% ( $0.33 \times 0.8$ ) of all methane
- At 200 kg/h sensitivity can see:





# EERL 2021 National Survey: Distributions of Detected Sources

- Measured distributions represent ~80% of total methane (*shown later*)
- At 20 kg/h sensitivity can see:
  - ~10% of these sources / 48% of this methane
  - ~38% ( $0.48 \times 0.8$ ) of all methane
- At 32 kg/h sensitivity can see:
  - ~5% of these sources / 33% of this methane
  - ~26% ( $0.33 \times 0.8$ ) of all methane
- At 200 kg/h sensitivity can see:
  - <1% of these sources / 5% of this methane
  - ~4% ( $0.05 \times 0.8$ ) of all methane



- ***Critical to understand sensitivity limits when incorporating measurements from different technologies***