An Event-Based Framework for Estimating Annual Methane Emissions and Managing Emissions Data from Oil and Gas Facilities

Mozhou Gao[1,4], Zahra Ashena[1,3], Steve H.L. Liang[1,3], Sina Kiaei[1,3], and Sara Saeedi[1,2]

[1]GeoSensorWeb Lab, Department of Geomatics Engineering, Schulich School of Engineering, University of Calgary, 2500 University Dr. NW, Calgary, AB, Canada

[2]Department of Electrical and Software Engineering, Schulich School of Engineering, University of Calgary, 2500 University Dr. NW, Calgary, AB, Canada

[3]SensorUp Inc., Calgary, AB, Canada

[4]Kuruktag Emissions Ltd., Coquitlam, BC, Canada

Email: mozhou.gao@ucalgary.ca

Abstract

Accurate reporting of annual site-level methane emissions is increasingly required under emerging regulatory and voluntary frameworks in the oil and gas (O&G) sector. In this study, we present an event-based framework for estimating and tracking annual methane emissions from upstream O&G operations. The framework applies the Emission Event Data Model (EEDM) to spatiotemporally aggregate multi-scale emissions data into discrete events using the concept of Allen's interval algebra and spatial proximity. Following the creation of events, emissions are categorized into three groups: resolved (with a known emission rate and duration), partially resolved (with a known emission rate but an unknown duration), and unresolved (with an unknown emission rate and duration) to facilitate various management and emissions estimation approaches. Three Monte Carlo-based approaches are developed within the framework. These include (1) estimating durations for partially resolved events using null detection, leak generation, and natural repair processes; (2) estimating emissions from unresolved events based on the minimum detection limit of deployed technologies; and (3) estimating emissions from unresolved events using probabilistic occurrence and best-fit rate and duration distributions. This methodology enables emissions to be reported and verified at a uniform level rather than at the individual observation level. To demonstrate the estimation of emissions using this framework, we created two case studies. In both studies, we performed emissions estimation using emission observations synthesized from real emissions data from an upstream O&G site. The proposed framework and methodologies can be implemented in voluntary initiatives such as Veritas 2.0 and the Oil & Gas Methane Partnership 2.0 and applied as a data management framework for the Measurement, Monitoring, Reporting, and Verification (MMRV) framework.

Keywords: Oil and Gas Methane, Greenhouse Gases, Emissions Data model, Emissions Management, Methane Emissions Reconciliation, Measurement-informed Inventory, MMRV Framework

Highlights:

1. This study addresses the fundamental challenges of data integration in estimating annual methane emissions.
2. This study presents the first event-based framework to assimilate multi-scale methane emissions measurements and oil and gas operational data.
3. This study focuses not only on the rate of emissions but also on the duration and uncertainties in emissions estimation.
4. This study presents two new Monte Carlo–based approaches to estimating unmeasured methane emissions.
5. The presented data model and methodology will help oil and gas operators better understand and track their emissions mitigation progress.

1. Introduction

Reducing methane (CH_4) emissions from the oil and gas (O&G) sector is internationally recognized as one of the most cost-effective strategies for mitigating global warming (IEA, 2023). This effort gained significant momentum following the launch of the Global Methane Pledge at the 2021 United Nations Climate Change Conference (COP26), where 159 countries pledged to reduce methane emissions by 30% from 2020 levels by 2030 (UNFCCC, 2021). Since then, participants worldwide have made substantial efforts to develop innovative measurement technologies and emissions estimation frameworks. Regulators, such as the U.S. Environmental Protection Agency (EPA) and the European Commission (EC), have further tightened regulatory requirements in recent years to help achieve these reduction targets (Directorate-General for Energy, 2024; US EPA, 2024).

The Measuring, Monitoring, Reporting, and Verification (MMRV; also with a variant that emphasizes the importance of quantification, known as framework or Measuring, Quantification, Reporting and Verification framework) is widely recognized as one of the most effective and transparent frameworks for tracking annual emissions in the oil and gas (Allen, Ravikumar and Tullos, 2023; US Department of Energy, 2024b). Measuring and quantification refer to the deployment of measurement technologies to directly measure and quantify emissions, including remote sensing systems and close-range instruments. For emission sources that have already been identified, monitoring is conducted either through continuous monitoring systems or revisits using snapshot technologies to assess the emission source and its activity. Reporting refers to the standardized documentation and disclosure of emissions data, along with the methodologies applied to calculate emissions, to regulatory bodies (e.g., the EU) or voluntary programs (e.g., UNEP OGMP 2.0). Verification refers to validating emissions across the supply chain and providing verified results for both total emissions and intensity from production (Allen, Ravikumar and Tullos, 2023; US Department of Energy, 2024a).

To date, MMRV remains an ongoing effort, and equivalent frameworks are also being adopted by voluntary initiatives, such as the Oil and Gas Methane Partnership (OGMP) 2.0, the MiQ standard, and Veritas 2.0 (GTI Energy, 2023; MIQ, 2024a; Oil and Gas Methane Partnership 2.0, 2022). Some regulatory initiatives, including Air Quality Control Commission Regulation 7, Part B, implemented by the Colorado Department of Public Health and Environment (CDPHE), have also incorporated similar frameworks (CDPHE, 2025). The key objectives of integrating MMRV into emissions reporting and management include guiding the development of measurement technology, establishing an internationally recognized standard to enhance the credibility of emissions reporting, enabling better reconciliation between emissions estimates from bottom-up (BU) and top-down (TD) approaches, creating a more accurate inventory, and generating credible assessments of overall carbon intensity across the supply chain (e.g., US Department of Energy, 2024b).

Various technical challenges and inherent emissions characteristics hinder effective implementation of MMRV by O&G operators. These challenges include missing emissions from abnormal events in emissions reporting, limited availability of measurement data that captures routine operational events, insufficient temporal and spatial coverage of remote O&G sites, undocumented operational activities, inaccuracies in emissions attribution, and lack of unified measurement scales for emissions data (Allen, Ravikumar and Tullos, 2023; Brandt, Heath and Cooley, 2016; Scarpelli et al., 2022; Vaughn et al., 2018).

To address these challenges and generate a more accurate emissions estimation, the scientific community has been actively developing hybrid approaches that integrate both BU and TD data to maximize the utilization of emissions data. This includes combining measurement results through multi-scale remote sensing technologies, applying advanced statistical methods to create measurement-informed inventories, and developing simulation approaches (Daniels et al., 2023; Johnson, Conrad and Tyner, 2023; MacKay et al., 2024; Riddick et al., 2024; Rutherford et al., 2021; Scarpelli et al., 2022; Wang et al., 2022). However, no data integration methodology or data model has been developed to spatiotemporally assimilate emissions data from different measurement scales and estimate emissions, along with their associated uncertainty estimates.

This work introduces a novel event-based framework that utilizes the Emissions Event Data Model (EEDM), designed to spatially and temporally integrate multi-scale emissions measurements with O&G operational data. The model is developed based on the International Organization for Standardization (ISO) 19156:2023 and the Open Geospatial Consortium (OGC) 20-082r4 standards, integrating with the OGC Sensor Web Enablement suite (Carl et al., 2013; ISO, 2023).

In the following sections, we first introduce EEDM and three types of emissions events. Next, we outline the methodology for calculating emissions and the uncertainties associated with each type of emission event. Third, we present two Monte Carlo approaches for estimating total emissions from unmeasured events (defined as unresolved events in our framework). Finally, we present two case studies to demonstrate our framework using synthetic emissions data and O&G sites.

2. Method and Materials

2.1 Emissions Event Data Model (EEDM)

Conventionally, methane emission data are modeled and managed for each emissions observation (EO). This process captures any form of detection, null-detection, or operational data indicating the presence or absence of CH_4 pollutants in the atmosphere, along with the timing (when) and location (where) of emissions, as well as the quantity (how much) emitted. This information helps attribute each EO to a specific physical source (e.g., equipment) and a cause (e.g., fugitive emissions, tank venting, etc.). However, EOs are typically discrete in time and space, captured at different scales, and quantified using different algorithms. For example, snapshot emission observations, such as aircraft flyover measurements, provide a more accurate quantification of emissions from a site. In contrast, point-based CMS have lower detection limits and capture emission duration but only measure CH_4 at a fixed location, making them less accurate than aircraft flyovers in quantifying emissions.

To address the challenges, an event-based framework (Figure 1a) and an emissions event data model (Figure 1b) were proposed based on the OGC standards, including ISO/OGC's Observations and Measurements 19156:2023/OGC 20- 082r4 (Carl et al., 2013; ISO, 2023). EEDM provides consistent classes aimed at capturing the dynamic aspects of rate and duration from a given source, such as the lifecycle of leaks for a pneumatic valve.

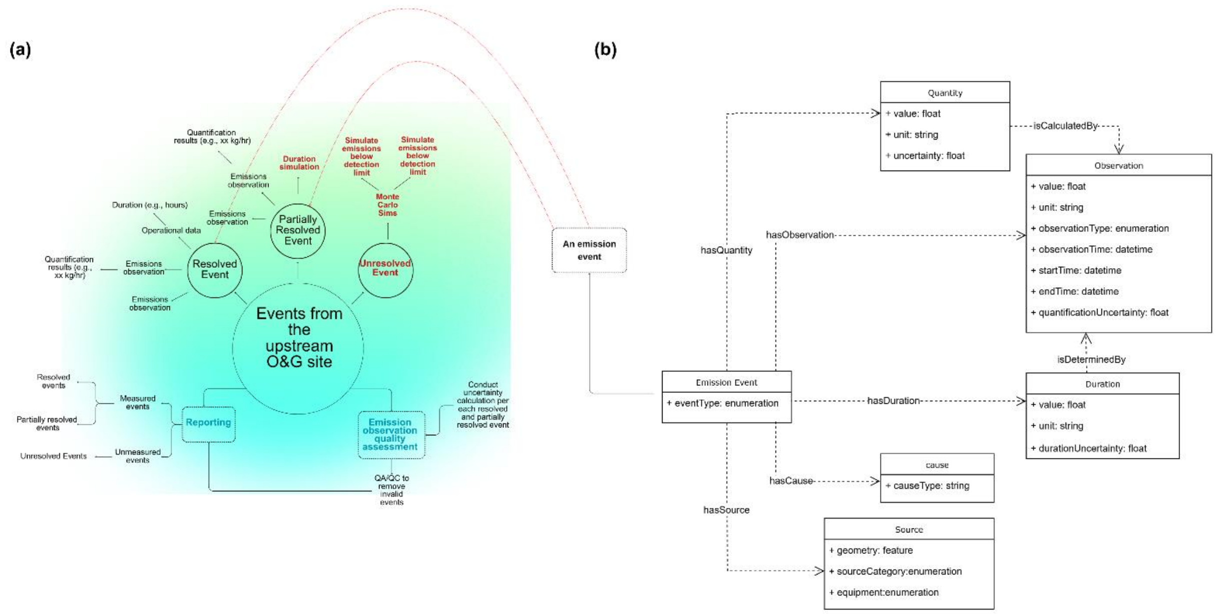

Figure 1. **(a)** Schematic view of event-based framework; **(b)** The entities and properties of the EEDM and their relationships. The formal definition can be found in S1 of the Supporting Information (SI).

2.2 Spatial and Temporal Correlation of Emissions Event (EE)

An emission event (EE) may consist of either a single EO or multiple EOs (Figure 1a). We use spatial association (Anselin, 1995) and Allen's interval algebra (Allen, 1983) to determine whether multiple EOs can be grouped into the same event and resolved both spatially and temporally. Spatial association assesses whether two or more EOs observe the same phenomenon (Anselin, 1995). In this case, the geographical location associated with EOs (i.e., latitude and longitude) should be the same or close. If the coordinates are not available, two EOs should be attributed to the same source (e.g., Compressor No. 1) or carry the same location indicator with the same scale (e.g., facility ID, 001).

Temporally, Allen's interval algebra (Table S1) is used to determine the temporal relationships between EOs. In total, thirteen fundamental temporal relationships are defined: *precedes, preceded by, meets, met by, overlaps, overlapped by, contains, during, starts, started by, finishes, finished by,* and *equals* [Allen, 1983]. Except for the "precedes" and "precededBy" relationships, if any two or more observations satisfy any of the other eleven relationships and are also spatially close (or attributed to the same equipment), they are more likely to originate from the same emission within the same emission event. It is important to highlight that *precedes* and *precededBy* are specifically applied to intermittent emission events that have stopped and started again. In this study, we treat intermittent events as separate events.

In addition to EO, an EE consists of four other primary classes: source, cause, duration, and quantity (Figure 1b). The source refers to equipment that emits methane or activities that lead to emissions. An EO can be attributed to a specific physical source (e.g., Compressor No. 1), a source category (e.g., fugitives), or both (e.g., hydraulic fracturing from a gas well). The cause of an emission event is tied to the results of a root cause analysis and is not limited to predefined categories. All observations within the same event should share a common cause. Each EO has its quantification result, associated unit, type of observation (e.g., aircraft flyover - Bridger), observation time, which describes when the observation was conducted, and start and end times if the observation is reported as a period, as well as quantification uncertainty. Quantification uncertainty represents the measurement result.

The duration of EE can be obtained either directly from the operational data (e.g., scheduled venting from 10:00 am to 10:15 am), based on measurements from CMS (e.g., start and end times of alarms), or estimated indirectly through observations, such as the absence of emissions or null detection. Lastly, the quantity represents the total amount of methane emitted during the event and can be calculated by multiplying the quantified rate by duration (see Eq. 2). When an event comprises multiple measured emissions observations, the observation with the lowest quantification uncertainty is chosen for quantity calculation. For scheduled events, the associated operational data may include calculated emission results using engineering equations. For instance, Eq. W-7A from 40 CFR Part 98, Subpart W, computes the emissions from single-well liquid unloading (US EPA, 2025). Standards like Veritas 2.0 provide guidance on whether to use measured or calculated emission results (GTI Energy, 2023). Since the calculated emissions quantity significantly depends on the equation applied, our framework focuses solely on the measured emissions quantity. The overall uncertainty of the measured emissions quantities results from error propagation from both quantification results and duration estimation. The following subsection discusses the mathematical equations used to calculate emission quantities and their associated uncertainties through error propagation.

2.3 Resolved Event, Partially Resolved Event, and Unresolved Event

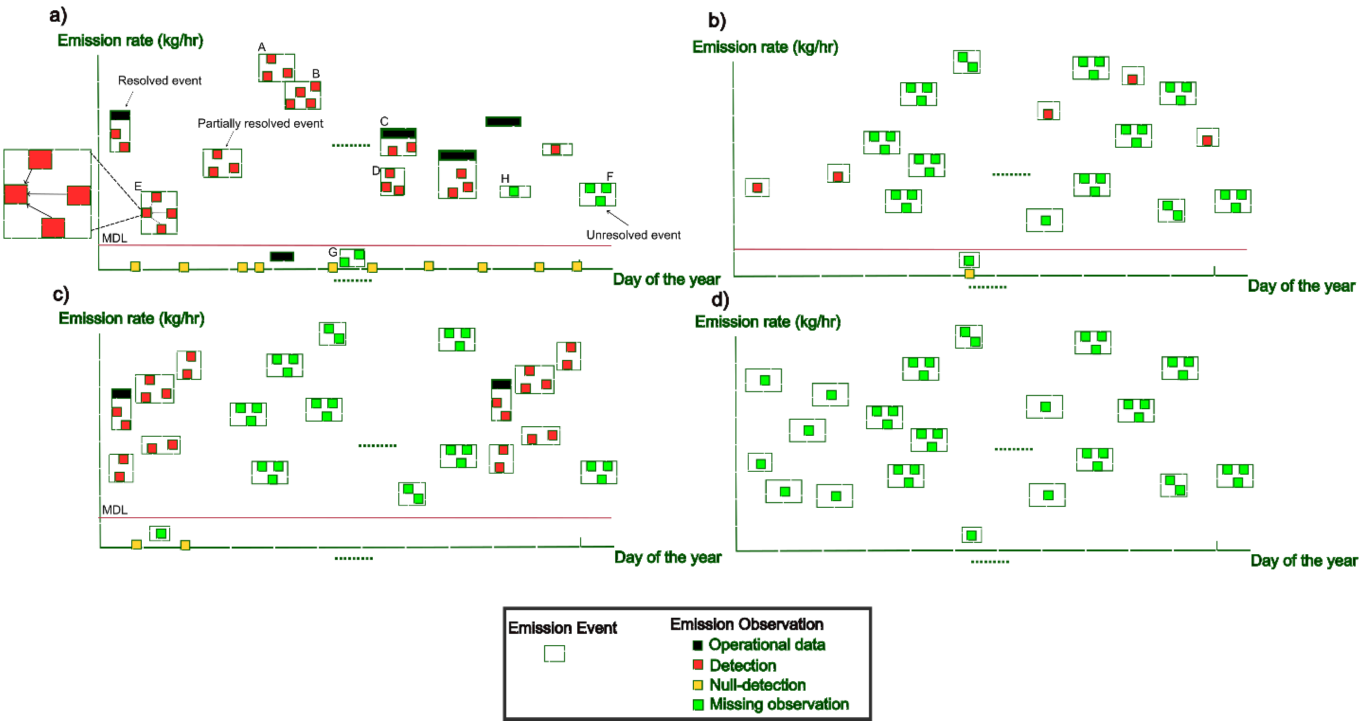

Figure 2. Representation of resolved, partially resolved, and unresolved emission events for four sites under different monitoring scenarios throughout the year. The x-axis represents the quantifications of EO associated with each EE. The y-axis represents the time at which emissions are measured, and the total width of the rectangle indicates the duration of the event. Distinct colors, including operational data, detections, null-detections, and missing observations, indicate various observation types. Green dashed square boxes represent emission events. (a) A site with CMS measuring emissions 24 hours a day; (b) A site monitored through flyover surveys conducted every few months; (c) A site with a measurement campaign in which emissions are only measured during the campaign; and (d) A site without any monitoring

Table 1: Three categories of emission event types.

Emission Event Type	Definition	Duration Determination	Emissions Quantity from Events	Uncertainty
Resolved Event (RE)	Events with durations determined using operational data/log	Extracted from operational data/log	Calculated	Only quantification uncertainty is considered
Partially Resolved Event (PRE)	Events with duration that are either measured by remote sensing technologies or estimated using null-detection and rules	Simulated by using proceedings and succeeding null-detection times	Calculated	Quantification uncertainty and duration estimation uncertainty
Unresolved Event (UE)	Events that are missing from annual emissions data	Simulated	(1) Simulate emissions that are not detected using POD checks (2) Simulate emissions by random sample RE and PRE	Estimated in the simulations

As shown in Figure 1a, we classify EE into three types: resolved events (REs), partially resolved events (PREs), and unresolved events (UEs). Table 1 lists the descriptions of each type of EE. REs include EOs from data sources such as operational logs, which typically contain information on duration, known emissions sources (for scheduled events), and causes. In contrast, PREs consist solely of EOs from measurement technologies. They may require additional information to determine their duration, source, and cause, such as estimating duration using data from routine leak detection and repair (LDAR) surveys that do not identify emissions. The unresolved events (UEs) represent all other unmeasured and undocumented emissions and can be further classified into three types:

- **Type 1** occurs when emissions are present, but their rate falls below the deployed technology's minimum detection limit (MDL) (e.g., event G in Figure 2a). This type of UE, also known as a false negative, represents an undetected emission event.
- **Type 2** happens when no measurement technology is deployed to detect the emission (e.g., event F in Figure 2a).
- **Type 3** occurs when a small fugitive emission coincides with a large operational event (e.g., event H in Figure 2a) from the same equipment. Emissions from Type 3 events are typically small and are often omitted since fugitive measurement will not be conducted during the operational event occurrence.

Based on the above definitions, we can define the three types of EE mathematically based on the following expressions:

Let:

E be the set of all emission events.

RE, PRE and UE be the subsets of E corresponding to Resolved Events, Partially Resolved Events, and Unresolved Events, respectively.

EO_m be the set of emissions observations from measurement technologies.

EO_o be the set of emissions observations from operational logs.

N be the set of null-detection data (including from screening survey or LDAR inspection).

U be the set of emissions data that are not captured by any emissions observations.

Then we can define each emission event type as:

For resolved events (REs):

$$RE = \{e \in E \mid e \text{ } has \text{ } at \text{ } least \text{ } one \text{ } observation \text{ } from \text{ } EO_o\}$$

For partially resolved events (PREs):

$$PRE = \{e \in E \mid e \text{ } has \text{ } at \text{ } least \text{ } one \text{ } observation \text{ } from \text{ } EO_m \text{ } but \text{ } lacks \text{ } EO_o\}$$

For unresolved event (UEs):

$$UE = \{e \in E \mid e \notin RE \cup PRE\} = \{e \in E \mid e \text{ } has \text{ } no \text{ } observation \text{ } from \text{ } EO_m \text{ } or \text{ } EO_o\}$$

To ensure that every EE falls into exactly one category:

$E = RE \cup PRE \cup UE$,

$RE \cup PRE = \emptyset$,

$RE \cup UE = \emptyset$,

$PRE \cup UE = \emptyset$,

To ensure that each physical emission source (i.e., equipment) has a unique event within each period, we once again apply spatial association and Allen's interval algebra to merge events. For example, event A and event B can be merged if event A overlaps with event B. Likewise, event C and event D can be merged if event C contains event D, as illustrated in Figure 1a. After merging, the duration and quantity are recalculated. By following the structure of RE, PRE, and UE, annual emissions quantities across all events for a given site (E_{total}) can be calculated as follows:

$$E_{Total} = \sum_{i_{RE}=1}^{N_{RE}} E_{RE_i} + \sum_{i_{PRE}=1}^{N_{PRE}} E_{PRE_i} + \sum_{i_{UE}=1}^{N_{UE}} E_{UE_i} \qquad Eq.1$$

where N_{RE}, N_{PRE} and N_{UE} indicates the number of resolved, partially resolved, and unresolved events, respectively. The E_{RE}, E_{PRE} , and E_{UE} represents total CH_4 emissions quantity from each resolved, partially resolved, and unresolved event, respectively.

Based on how measurement technologies are deployed on-site, an upstream O&G site can be measured or monitored under the following scenarios:

- **Instantaneous screening technology and continuous monitoring systems:** If operational events are reported and both instantaneous screening technology and continuous monitoring systems are deployed at the site (Figure 2a), then the annual emissions quantity can be calculated using all three types of EE.
- **Instantaneous screening survey only**: If a site has only been surveyed using snapshot measurement technologies, such as bi-monthly flyovers (Figure 2b). In that case, no REs are available and total emissions from E_{RE} are zero; instead, emissions from REs will be simulated as E_{UE}. Thus, annual emissions are calculated by summing E_{PRE} and E_{UE}.
- **Measurement campaign only**: If a site has only been surveyed during an annual or biannual measurement campaign (Figure 2c) and emissions are also only reported during the measurement campaign, only a limited number of REs and PREs are measured during the campaign. Thus, E_{UE} needs to be simulated for periods outside the measurement campaign.
- **No Emissions data available:** If a site has no measurements at all (Figure 2d), both E_{PRE} and E_{RE} are zero, and E_{UE} needs to be simulated for the entire year (or reporting time range).

<u>2.4 Generic emissions estimation equation for EE</u>

The generic equation of calculating emissions quantity (E) of an event can be described as follows:

$$E = Q \times D \qquad Eq.\ 2$$

where, Q and D are emission rate, and duration of the event, respectively.

<u>2.5 Resolved Event (RE)</u>

For REs, the uncertainties associated with each event primarily arise from uncertainties in rate estimation. While operational data can be used to estimate event durations, the associated uncertainties are challenging to quantify and exhibit significant variability across different operational practices (Higgins et al., 2024). Thus, we omit duration uncertainty for REs. However, quantification uncertainty should be accounted for, either by utilizing uncertainty estimates provided by technology vendors or by simulating or calculating it through engineering methods. For example, the quantification uncertainty of the Insight M (previously known as Kairos Aerospace) aircraft system is approximately ±40% (Sherwin et al., 2021). By incorporating the quantification uncertainty (U_{Q_RE}), the emissions quantity estimation of a RE (E_{RE}) can be expressed as follows:

$$E_{RE} = Q_{RE} \times D_{opt} \pm U_{Q\_RE} \times D_{opt} \qquad \textit{Eq. 3}$$

where the emission rate (Q_{RE}) is obtained either from engineering calculations or quantified using measurement technology, along with the associated uncertainty in quantification of the emission rate (U_{Q_RE}). The duration (D_{opt}) is associated with operational data. Therefore, the uncertainty of emissions quantity of RE (U_{E_RE}) can be calculated by multiplying the quantification uncertainty by the duration. *Eq. 3* can also be rewritten as follows:

$$E_{RE} = Q_{RE} \times D_{opt} \pm U_{E\_RE} \qquad \textit{Eq. 4}$$

It should be noted that some engineering equations directly calculate emissions quantity (E_{RE}). In such cases, the uncertainty should be determined based on the equation used in the calculation.

2.6 Partially Resolved Event (PRE)

Unlike REs, the uncertainty of PREs must account for both quantification and duration uncertainties. For PREs that include observations from CMS, start and end times are typically calculated based on the time when measured CH_4 concentrations exceed the background methane concentration (Daniels, Jia and Hammerling, 2024). However, studies have shown that the measured durations can differ significantly from actual durations (Bell et al., 2023; Daniels, Jia, and Hammerling, 2024). Addressing this uncertainty requires time series analysis of in-situ wind direction and CH_4 concentration measurements, such as the Probabilistic Duration Model (Daniels, Jia and Hammerling, 2024). In contrast, the duration of PREs is often estimated using rules or times derived from the preceding null-detects time (PNDT) and succeeding null-detects time (SNDT) (Government of Canada, 2025). As a result, these duration estimates may either overestimate or underestimate actual durations.

To improve duration accuracy for this type of PRE, we developed an event-based Monte Carlo simulation workflow that integrates the leak production rate (LPR) and null repair rate (NRR), both of which are implemented in established stochastic emissions models such as LDAR-Sim and FEAST (Fox et al., 2021; Kemp, Ravikumar and Brandt, 2016).

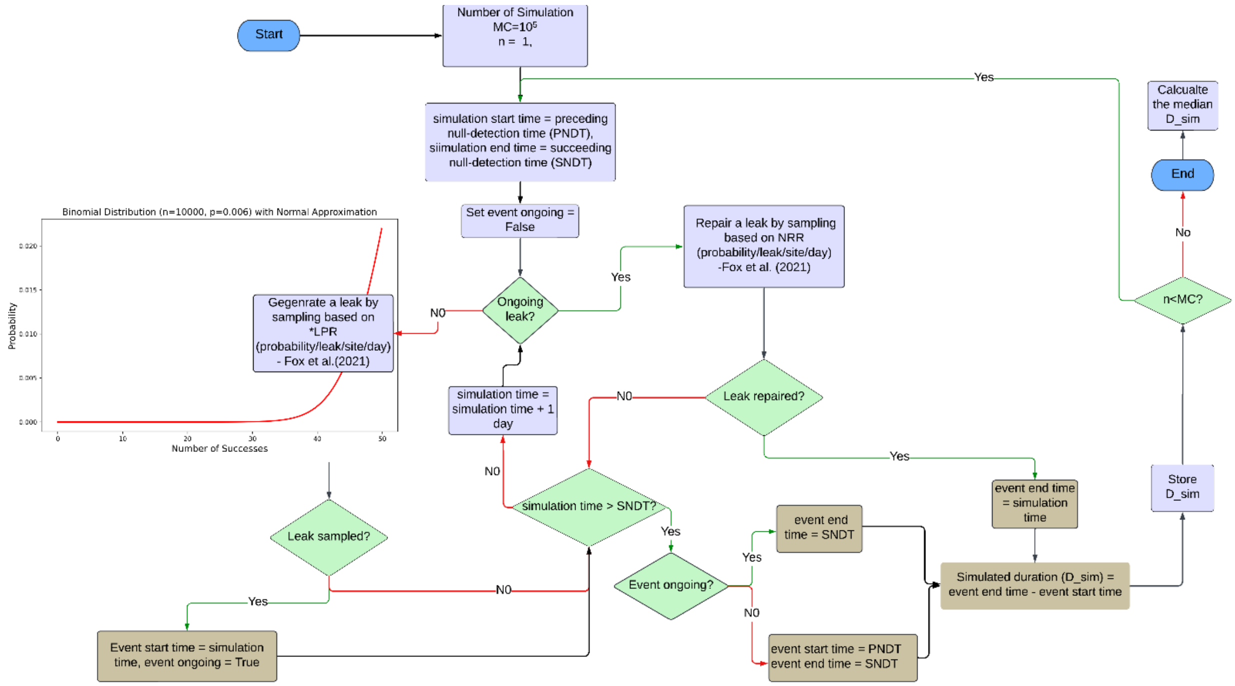

Figure 3. The Monte Carlo simulation workflow simulates the duration of a PRE based on the preceding null detection and succeeding null detection of the event. In the simulation, the units of LPR and NRR are per site per day. In the flowchart, we present an example binomial distribution with a probability of 0.006 to sample leaks across 10^5 iterations. * If LPR and NRR are calculated by equipment or component, the leak sampling and repair processes iterate through each equipment or component based on the number of equipment or components.

As shown in Figure 3, a Monte Carlo simulation (M = 10 ^5 iterations) is performed to simulate the duration and ensure the stationary distribution of the results. The start and end times of the simulation were bounded by PNDT and SNDT, respectively. Each simulation iteration initializes the emission event as "not occurring." To determine the start time of the emission event, the simulation randomly samples from a binomial distribution based on an emission probability calculated using the LPR equation (Fox et al., 2021). If an emission is sampled, the simulation's timestamp becomes the start time of the emission event, the simulation updates the event's status to 'ongoing', and it proceeds to the next day. Otherwise, the simulation directly proceeds to the next day and repeats the sampling process. Once an emission event is ongoing, a second binomial distribution, based on a probability calculated using the NRR equation (Fox et al., 2021), is used to perform daily random sampling to determine when the event will cease. If the event is stopped, the simulation timestamp is saved as the event's end time; otherwise, the process continues to the next day until the timestamp exceeds the SNDT. At the end of each simulation run, the simulated end time is set to the SNDT if the emission event remains ongoing. If no emission event occurred during the simulation, both the simulated start and end times are set to the PNDT and SNDT, respectively. The simulated duration is then calculated as the difference between the simulated end time and start time. After 10^5 iterations, the mean ($\overline{D_{sim}}$) and 2 times standard deviation of the differences between simulated and estimated durations are calculated to represent the uncertainty in duration and the uncertainty from random sampling under the 95% confidence interval. If simulation results are non-normally distributed, we use median and 2.5- ($D_{sim\_2.5\%}$) and 97.5-percentiles ($D_{sim\_97.5\%}$) to represent simulated duration and uncertainty (Koehler, Brown and Haneuse, 2009).

By integrating both the uncertainty from duration estimation and the uncertainty from quantification (U_{E_PRE}), the emissions quantity of each PRE (E_{PRE}) can be calculated by using the below equation:

$$E_{PRE} = Q_{PRE} \times D_{PRE} \pm U_{E\_PRE} \qquad Eq.5$$

where the D_{PRE} can be either calculated or simulated:

$$D_{PRE} = \begin{cases} T_{end} - T_{start}, & if\ determined\ using\ CMS\ measurement \\ \overline{\mathrm{D_{sim}}}, & if\ determined\ using\ null\ detect\ or\ rule \end{cases} \qquad Eq.6$$

U_{E_PRE} represents uncertainties associated with the emissions quantity estimated for each PRE. It consists of both quantification uncertainty ($U_{Q_{PRE}}$) and duration estimation uncertainty ($U_{D_{PRE}}$), which can be calculated as follows:

$$U_{D_{PRE}} = \begin{cases} PDM(T_{end}, T_{start}, C_{CH4}), & if\ determined\ using\ CMS\ measurement\ [27] \\ [D_{sim\_2.5\%}, D_{sim\_97.5\%}], & if\ determined\ using\ nondetect\ or\ rule \end{cases} \qquad Eq.7$$

To combine uncertainties from quantification and duration estimations, the error propagation equations described by IPCC (IPCC, 2019) are used to calculate U_{E_PRE}:

$$U_{E\_PRE} = \sqrt{\left(U_{Q_{PRE}}\right)^2 + (U_{D_{PRE}})^2} \qquad Eq.8$$

The *Eq.8* assumes that duration estimation uncertainty and quantification uncertainty are uncorrelated. However, the rate and duration from CMS could generated from the same algorithm based on concentration measured from the same sensor. While this correlation is important, a detailed investigation is beyond the scope of this study.

2.7 Estimating emissions and uncertainty from UEs

We developed two distinct simulation approaches to estimate emissions from UEs at a given site. The first simulation integrates a published methodology (Johnson, Conrad and Tyner, 2023) into the event, using a probability of detection (POD) equation and a stochastic process to identify UEs below the minimum detection limit (MDL) of the deployed technologies. The second simulation addresses scenarios in which measurements are insufficient to calculate the annual emissions of a given site (e.g., the third and fourth scenarios in Figure 2). Instead of relying on POD, it simulates UEs based on the likelihood of emission event occurrence and precalculated expected emissions rate and duration distributions.

2.7.1 Simulating Emissions from UEs using probability of detection (POD)

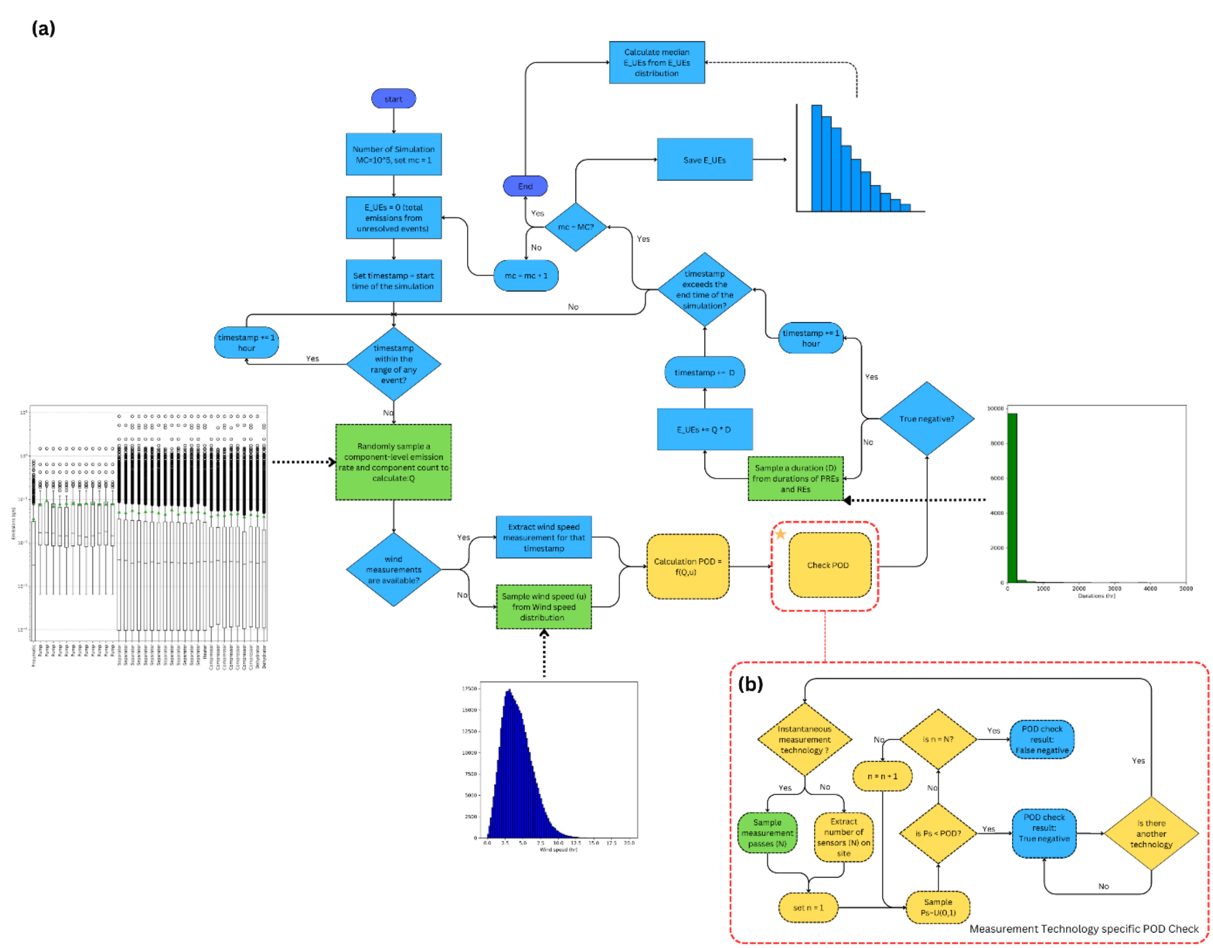

Figure 4. Monte Carlo simulation workflow to estimate total emissions from unresolved events for a given site that is monitored by flyover and CMS. This workflow illustrates explicitly the scenario where emissions are measured by one type of aircraft flyover and one CMS; more probability of detection (POD) checks are required if other types of technology are also deployed for emission monitoring. [a]Component-level emissions distributions should be derived from real measurements (Rutherford et al., 2021). [b]Different aircraft systems require different equations to calculate POD based on different parameters. For instance, Conrad, Tyner and Johnson (2023) provided POD equations for three different aircraft systems. Here, the flowchart only assumes the POD is affected by wind speed. [c]Similarly, Bell et al. (2023) derived POD equations for multiple CMSs in METEC based on a single-blind test. It is also dependent on wind speed. They are

applicable in CMS POD checks as well. [d]The duration distributions are based on empirical data from partially resolved events (PREs) of the site or sites with similar characteristics.

As illustrated in Figure 4, the simulation workflow begins by initializing the simulation time to the start of the reconciliation period (usually the first day of the year for the annual reconciliation) and setting possible emissions from UEs (E_{UE_sim}) to 0. At each hourly timestep, the simulation checks if the current timestamp falls within the range of any emission event (both RE and PRE). If the timestamp exceeds the simulation range (e.g., the last day of the year), the simulation proceeds to the next iteration. If the simulation time is not included by any REs and PREs, a component-scale emission rate and component counts are sampled from either the inventory or database containing component-scale measurements to obtain an equipment-scale emission rate. Next, wind speed and flight passes for each flyover survey at the site location are also randomly sampled. The former is used to calculate POD, and the latter is used to determine the number of survey attempts.

Subsequently, the simulation determines the false negative and identifies whether any measurement technology fails to detect an emission independently for each survey attempt. Based on the calculated POD, it is then compared to a randomly generated probability (ξ) between 0 and 1. If the POD exceeds ξ, it indicates a false negative (i.e., if the sampled emission had occurred in the real world, it would not have been detected). If the POD is smaller than ξ, it indicates a true negative (i.e., if the sampled emission had occurred in the real world, it would have been detected). This comparison is done for each flyover path and each sensor installed on the site. If either the flyover or CMS POD check indicates a false negative, the sampled emission rate is multiplied by a sampled duration to consolidate the emissions quantity of the sampled UE. Then, the simulated emissions quantity is added to the cumulative E_{UE_sim}. The sampled duration is also added to the time step in the simulation. If POD checks from flyover and CMS both return true negative, meaning no emissions occurred at the time step, the simulation proceeds to the next hour. This process is repeated until the timestamp exceeds the simulation period. Then, the Monte Carlo counter is incremented, and we repeat the whole process until 10^5 iterations are completed. Finally, the mean ($\bar{E}_{UE\_sim}$) and the 2.5th and 97.5th percentiles of the E_{UE_sim}distribution are calculated across all simulation iterations to represent the emissions from UEs and their uncertainty.

2.7.2 Simulating Emissions from UEs using probability of emission event occurrence

identifying false negatives is the requirement of sufficient temporal coverage of emissions measurements (i.e., either through continuous monitoring systems or frequent instantaneous screening surveys). However, in reality, not all sites are monitored sufficiently. To tackle this challenge, we developed a second simulation approach that models UEs based on the probability of emission event occurrence rather than depending on the POD of deployed measurement technologies.

Prior to simulation, the following distributions are required to be created from the REs and PREs:

- The emission rate distribution (Q_{dist}) represents the expected emission rates for a given potential emission source category or equipment.
- The emission duration distribution (D_{dist}) represents the expected durations for a given potential emission source category or equipment.
- The probabilities represent the likelihood of an emission event occurrence ($P_{occurence}$) and not occurrence ($P_{not\_occurence}$) for a given potential emission source category or equipment based on D_{dist}. Since multiple pieces of equipment can emit simultaneously and the emission of one piece is independent of another, sites with more equipment are more likely to have a higher probability of emissions occurring.

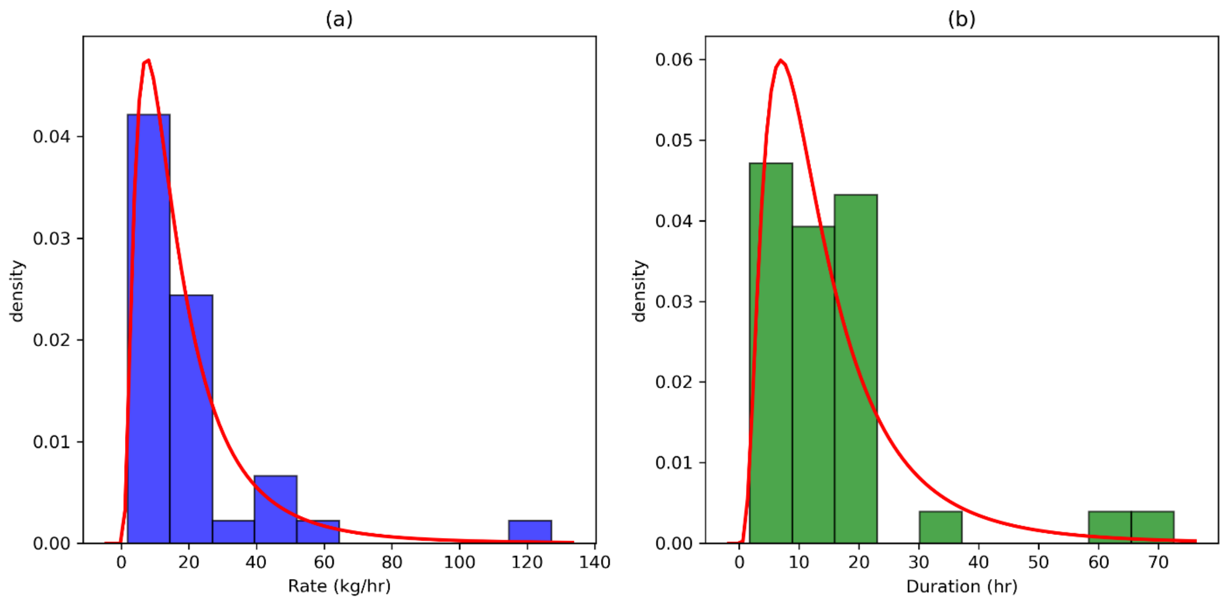

Figure 5. Example of using *Eq.9* to fit empirical rate (a) and duration (b) distributions

Since emission rates and durations tend to follow right-skewed distributions, we use a log-normal probability density functions to fit the empirical measured Q_{dist} and D_{dist} from REs and PREs (e.g., Figure 5).

$$P(v) = ae^{v^b} \qquad Eq.9$$

Where v is the rate or duration sampled under the probability $P(v)$, and a and b are parameters required to fit the rate and duration for each source category or equipment type.

After fitting, the log-normal PDF with optimal a and b are used to create the expected rate and duration distributions, $Q_{\exp\_dist}$ and $D_{\exp\_dist}$, for UEs.

Unlike creating probability density functions, the combination of an emission event occurrence. Creating binomial distribution based on two probabilities: $P_{occurence}$ and $P_{not\_occurence}$ can be described as follows:

$$B(x) = \binom{n}{x} P_{occurence}{}^{x} P_{not\_occurence}{}^{n-x} \qquad Eq.10$$

Where x is the proportion of time that a source can have an emission event in a given period (n). Since the probability is calculated using duration, $P_{occurence}$ and $P_{not\_occurence}$, it also describes how frequently a source can have an emission event.

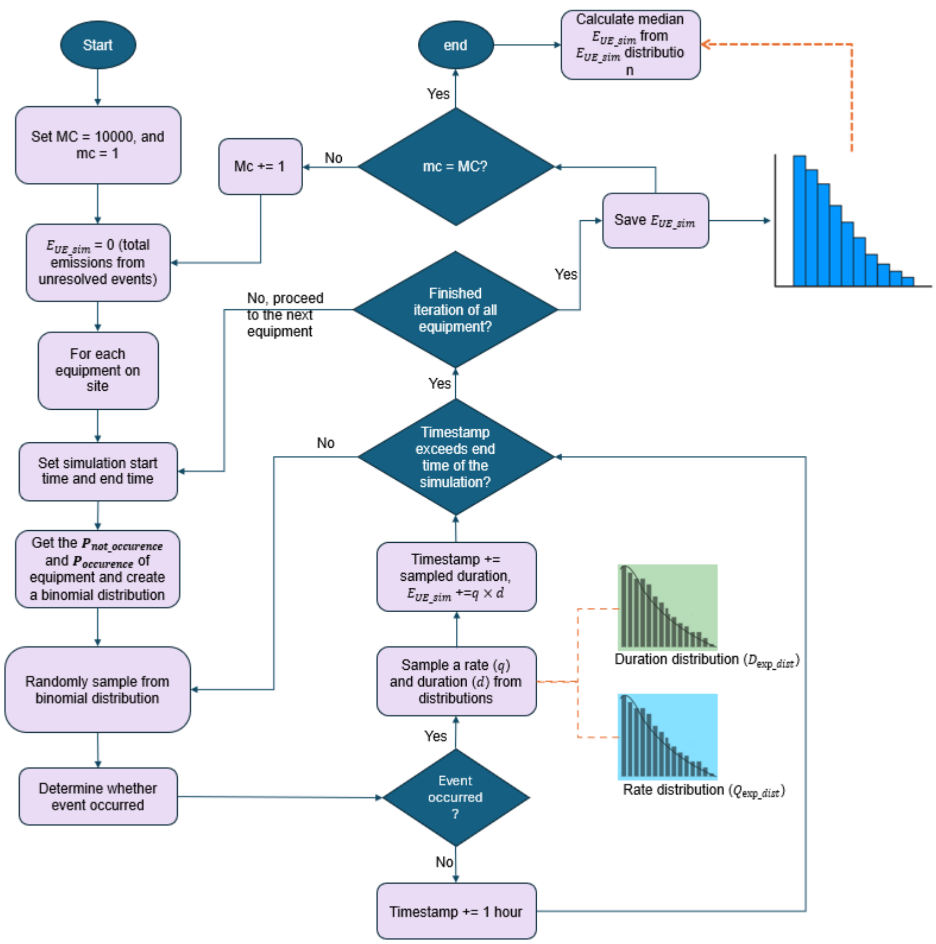

Figure 6. A workflow of simulating emissions from UEs by sampling events.

Figure 6 describes the workflow of simulations. The Monte Carlo simulation begins by setting the timestamp to the start time of the simulation and initializing emissions from UEs (E_{UE_sim}) to 0 kg. For each piece of equipment (source category), the simulation proceeds hourly, evaluating the likelihood of emission occurrence by sampling a binary outcome (0 or 1) based on the precalculated $P_{occurence}$ and $P_{not\_occurence}$ of that equipment. If an emission occurs, the emission rate (q) and duration (d) are sampled from the rate ($Q_{\exp\_dist}$) and duration ($D_{\exp\_dist}$) distributions, respectively, to define a UE. The E_{UE_sim} then updated by adding the emissions calculated from multiplying q and d, and the simulation time is incremented by d. If no emission event occurs, the simulation time advances by one hour. This process is repeated until the end of the simulation time for each piece of equipment. The E_{UE_sim} is calculated by summing emissions from all sampled UEs across all equipment. The simulation is repeated for 10^5 iterations, and the median ($\bar{E}_{UE\_sim}$), along with the 2.5th and 97.5th percentiles of the E_{UE_sim} distribution, are calculated to represent the simulated emissions from UEs and their associated uncertainty.

For this methodology, equipment data and bottom-up inventory are essential to improve the simulation results and avoid extrapolating emissions from inaccurate or nonexistent source categories. The emissions sampling mechanism can align with the site's infrastructure and activities. For example, emissions from flaring should not be extrapolated for a separator; similarly, if liquid unloading never occurred, the simulation should not extrapolate emissions from liquid unloading.

2.8 Estimating emissions and uncertainties across all EEs

By integrating the simulated emissions from UEs ($\bar{E}_{UE\_sim}$), *Eq. 4* and *Eq. 5* into *Eq. 1,* it can be rewritten as

$$E_{Total} = \sum_{i_{RE}=1}^{N_{RE}} Q_{RE_i} \times D_{opt_i} + \sum_{i_{PRE}=1}^{N_{PRE}} Q_{PRE_i} \times D_{PRE_i} + \bar{E}_{UE\_sim} \qquad Eq.11$$

By following the uncertainty equation suggested by IPCC [33], the uncertainties associated with emissions quantity of all REs (U_{E_REs}) and PREs (U_{E_PRE}) can be expressed as follows:

$$U_{E\_REs} = \frac{\sqrt{(U_{E\_RE_1} \times E_{RE_1})^2 + (U_{E\_RE_2} \times E_{RE_2})^2 + \ldots + (U_{E\_RE_{N_{RE}}} \times E_{RE_{N_{RE}}})^2}}{\left| E_{\_RE_1} + E_{RE_2} + \cdots + E_{RE_{N_{RE}}} \right|} \qquad Eq.12$$

and

$$U_{E\_PREs} = \frac{\sqrt{(U_{E\_PRE_1} \times E_{PRE_1})^2 + (U_{E\_PRE_2} \times E_{PRE_2})^2 + \ldots + (U_{E\_PRE_{N_{PRE}}} \times E_{PRE_{N_{PRE}}})^2}}{\left| E_{PRE_1} + E_{PRE_2} + \cdots + E_{PRE_{N_{RE}}} \right|} \qquad Eq.13$$

where U_{E_RE} and U_{E_PRE} are calculated in *Eq.3* and *Eq.8*, respectively.

By combining *Eq 12-13*, the total uncertainty (U_{E_total}) associated with E_{Total} can be calculated as follows:

$$U_{E\_total} = \frac{\sqrt{(U_{E\_REs} \times E_{REs})^2 + (U_{E\_PREs} \times E_{PREs})^2 + (U_{E\_REs} \times E_{UEs})^2}}{\left| E_{REs} + E_{PREs} + E_{UEs} \right|} \qquad Eq.14$$

3. Case studies and results

To demonstrate our methodologies, we developed two distinct case studies to estimate total emissions from a fictitious site with ten pieces of equipment from January 1, 2024, to April 30, 2024. The first case study utilizes 146 simulated emission observations, including 89 CMS measurements, four flyover survey records (one of which did not detect any plume), four OGI inspection records (two of which did not find any leaks), and 49 venting data points. Due to the availability of sufficient EOs and the monitoring of all four months by CMS, we decided to simulate emissions from UEs using a POD-based approach. The second case study extrapolates emissions based on the probability of EE occurrence, using only 36 synthetic CMS observations spanning a single month. In this case, emissions from UEs are simulated based on the probability of an emission event occurring over three unmonitored months. Case Studies 1 and 2 correspond to Scenarios 1 (Figure 2a) and 3 (Figure 2c), respectively, as described in Figure 2. Table S1 to S5 are synthetic emission observations for case study No.1 and Table S6 is the synthetic emission observations for case study No.2.

These two case studies demonstrate how annual emissions, and their uncertainties can be estimated by using EEDM framework and associated methodology. However, real-world applications may require adjustments to the parameters, equations, and simulation logic presented here. For example, it may be necessary to exclude certain months from simulations if sites are shut in during those periods to more accurately reflect operational realities.

3.1 Case study No.1

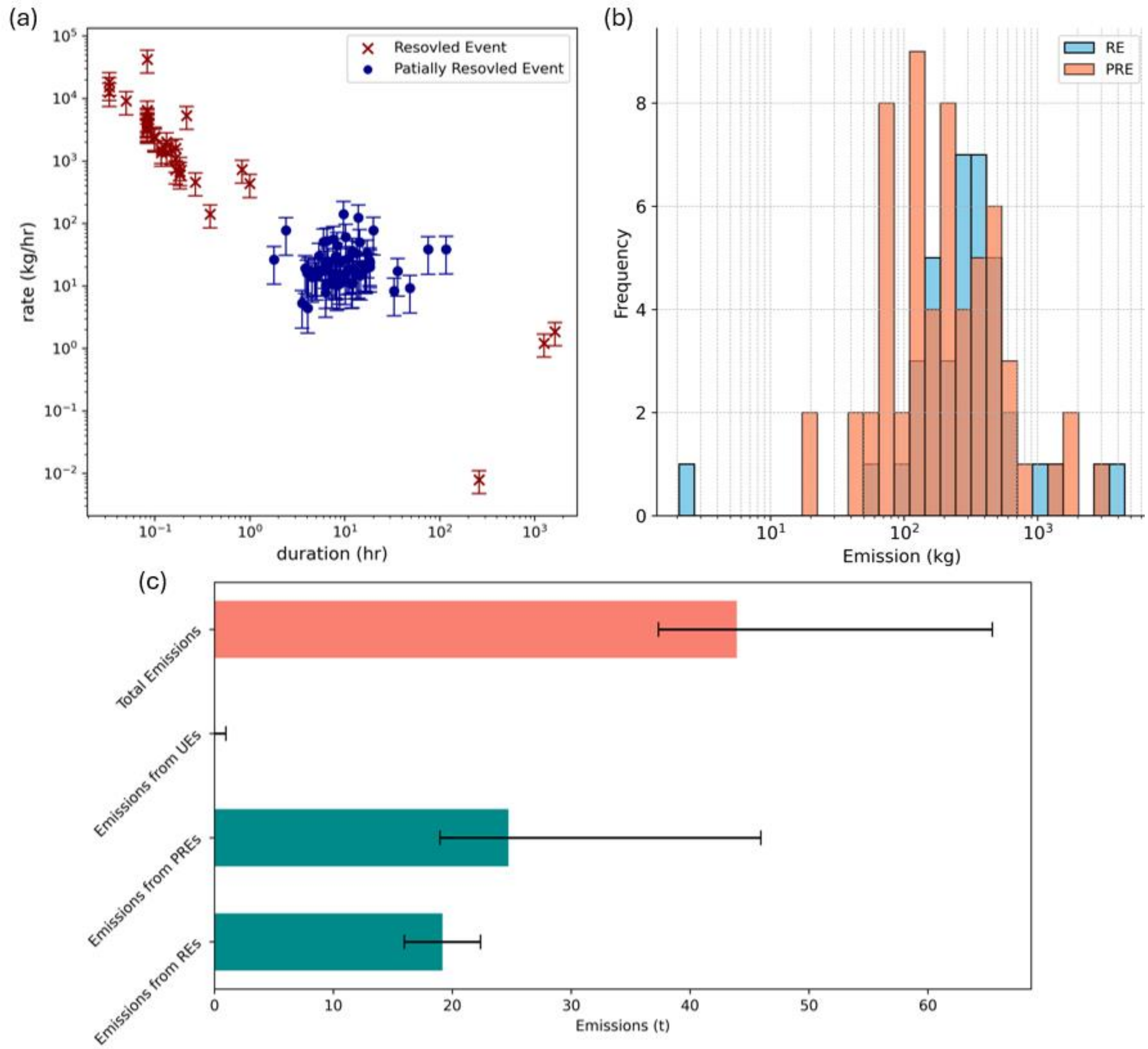

Figure 7. Results from the case study No.1: (a) Scatter plot of rates, durations, and associated uncertainties of REs and PREs after spatial association and Allen's interval algebra are applied; (b) Emissions quantities for REs and PREs after spatial association and Allen's interval algebra are applied (logarithmic scale); (c) The bar chart shows the total site-level emission estimates and breakdown of REs, PREs, and UEs emissions.

For case study No.1, we initiated 92 PREs and 49 REs. To demonstrate the proposed equations, we assume a quantification uncertainty of ±60% across all events. After merging the events, only one PRE requires duration simulation. The parameters and assumptions used to simulate the duration of this PRE include a default LPR of 0.006 leaks/day/site, a 7-day visitation interval, one leak per site at initialization, 10 global leaks, one active leak, and an operator bonus of 0.5. For the remaining PREs, durations were determined based on the measured start and end times from CMS observations. Following the findings from Daniels et al. (2024), the associated duration uncertainties of all CMS PREs are twice the measured duration.

After applying Allen's interval algebra and source attribution results, we merged 41 events, reducing the total number of events to 100, consisting of 61 PREs and 39 REs (Figure S1). The rate and duration distributions of both REs and PREs are skewed to the right with a weak correlation. The medians of rates and durations for REs and PREs are 2312.59 kg/hr and 0.1 hour and 18.53 kg/hr and 9.1 hours, respectively. However, events are clearly clustered, and their rate and duration are negatively correlated after both are converted to a logarithmic scale. As indicated in Figure 7a, all synthetic PREs (which contain only observations from either the flyover survey or CMS) vary between 0 and 100 kg/hr and persist for less than 1 hour to 4 days. The negative correlation indicates that most synthetic events have either short duration or low rate. It matches what was found by Wang et al. (2022), as the REs include operational data, which usually have large emissions rates but shorter periods. Due to the right-skewed durations and rate distributions, without considering uncertainties, the top four REs and six PREs contributed to 47.9% and 42.1% of the total emissions quantities of REs and PREs, respectively (see Figure 7b).

The simulation of emissions below the MDL was applied to estimate total emissions from UEs. The following input parameters, datasets, and assumptions were used: five CMS sensors were installed on-site; wind speed data from the Permian Basin were downloaded from ERA5 (Hersbach et al., 2023); the flight passes were default to three passes; component-scale emission rates were sampled from empirical component measurements (Rutherford et al., 2021); and POD equations were derived from previous studies (Conrad, Tyner and Johnson, 2023; MIQ, 2024b). The visualizations of input data for case study No.1 can be found in Figure S2.

Only one PRE had its duration estimated using proceeding and succeeding null detections. The resulting distribution of simulated durations was right-skewed (see Figure S3a), with a median duration of 115.75 hours and a 95% confidence interval (CI) of [4.75, 607.75].

Since both CMS and flyover are deployed for Case Study No. 1, the simulated emissions below the MDL of both technologies are significantly lower than the emissions quantities from RE and PREs (see Figure 7c). The median emissions quantities for all UEs is 31.73 kg (95% CI [3.34, 1016.00]; see Figure S3b).

Figure 7c illustrates the total emissions and breakdown emissions per each type of events. The total emissions over four months are 43.92 tonnes, with 95% CI [37.34, 65.41]. The breakdown of emissions from REs and PREs are 19.17 tonnes (95% CI [15.96, 22.38]) and 24.72 tonnes (95% CI [18.97, 45.95]).

3.2 Case study No.2

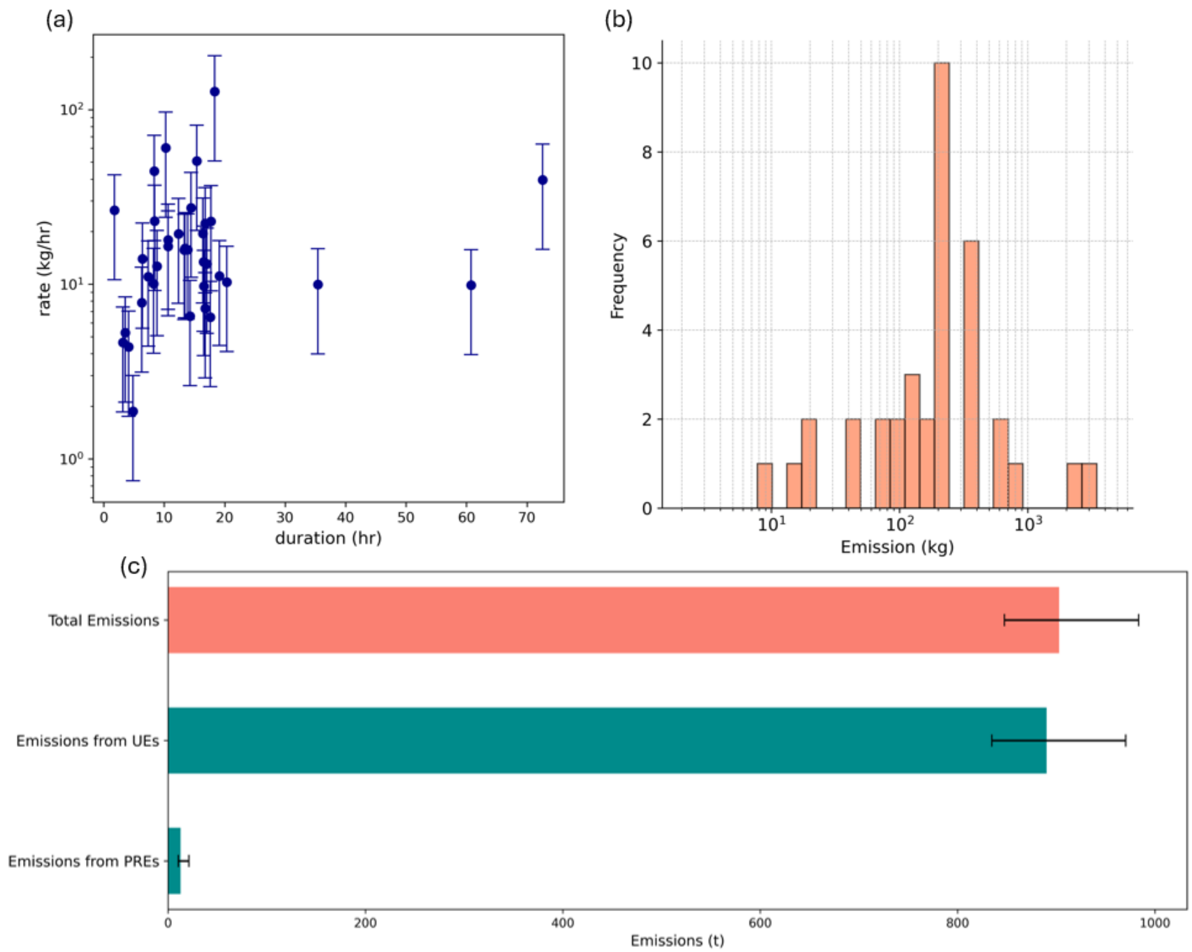

Figure 8. Results from case study No.2: (a) Scatter plot of rates, durations, and associated uncertainties of PREs; (b) Distribution of emissions quantities for PREs created using synthetic CMS emissions observations (logarithmic scale); (c) The bar chart shows the total site-level emission estimates and breakdown of PREs and UEs emissions.

In the second case study, 36 CMS synthesized observations over a month and initiated 36 PREs. Since all of them are neither spatially associated nor satisfy Allen's temporal algebra, no PREs are merged. These PREs are attributed to eight pieces of equipment from four equipment types on our fictitious upstream O&G site (see Table S6).

Similar to Case Study 1, we assumed quantification and duration uncertainties of 60% and 0-200%, respectively. As shown in Figure 8a, no significant trend is detected between the rate and duration of synthetic PREs for case study No. 2. The medians of the rates and durations are approximately 13.71 kg/hr and 13.68 hours, respectively. By extracting rates and durations from

REs, we created expected rate and duration distributions per each equipment type (see Figures S4 and S5). The emissions quantity distribution is right-skewed (see Figure 8b and 8c), with approximately the top four PREs contributing to 51.80% of total emissions (12.75 tonnes, with a 95% confidence interval (CI) of [10.32, 21.23]).

As shown in Figure 8c, by applying our proposed second simulation technique, the total simulated unmeasured emissions amount to 890.19 tonnes, with a 95% confidence interval (CI) of [834.60, 970.19]. This total includes 36.93 tonnes from Compressor-1, 36.80 tonnes from Compressor-2, 37.03 tonnes from Compressor-3, 27.60 tonnes from Dehydrator-1, 29.59 tonnes from Tank-1, 29.52 tonnes from Tank-2, 10.11 tonnes from Separator-1, 10.09 tonnes from Separator-2, 10.11 tonnes from Separator-3, and 80.85 tonnes from the Wellhead. The distribution of simulated unmeasured emissions for each piece of equipment is shown in Figure S6. Since the expected distributions are generated by equipment type, the simulated unmeasured emissions are nearly identical across different pieces of equipment of the same type. After adding the simulated emissions from UEs to the emissions from synthetic PREs, the total four-month emissions for our fictitious site are 903.29 tonnes, with a 95% CI of [847.30, 983.39].

4. Implication & Conclusion

We introduce an event-based framework and associated annual emissions estimation methodologies that integrates multi-scale measurements and oil and gas operational data to construct emission events. By adopting ISO and OGC standards, we ensure that emission events are generic across different scales of technologies. It highlights the following key implications:

- The EEDM represents a simplified data model developed in accordance with the ISO 19156 / OGC 20-082r4 standard and the OGC Sensor Web Enablement suite of standards. It ensures basic compatibility and interoperability for assimilating sensor data across diverse measurement technologies. It supports duration estimation, source attribution, and cause analysis, which are usually three follow-up actions required for O&G operators to respond to emissions. A formal data model will be developed through collaborative group efforts (Open Geospatial Consortium, 2024).
- Differentiating between REs and PREs enhances uncertainty assessments. Previous studies indicate that most operational events are of short duration (Wang et al., 2022). Partitioning emissions from an intermittent source into several short-duration events can significantly reduce the overall uncertainties associated with estimating its annual emissions. Mathematically, most uncertainty in short-duration events arises from quantification rather than from both quantification and duration. Although measurements from CMSs help decrease duration uncertainty compared to relying solely on snapshot

screening technologies, such as aircraft systems, the duration uncertainty associated with CMSs also needs to be addressed. This is particularly critical because surface wind directions often fluctuate on-site, particularly at locations with complex infrastructure. Incorporating details of routine and non-routine operational activities into the emission event model can further enhance the accuracy of duration estimation.

- We integrated emission events into the methodology developed by Johnson et al. (2023), which is sensitive to the PODs of the deployed measurement technologies. Our case studies are based on POD equations derived for InsightM's aircraft flyovers and Qube's CMS. If other technologies are simulated, different POD equations should be used, and simulated UEs will also be different.
- Extrapolation is generally required in two main scenarios: (1) sites with limited measurements and (2) sites with no events. For sites with limited measurements, accuracy is highly sensitive to the sample size of events (i.e., the number of REs and PREs) used to create the expected rate and duration distributions and to calculate probabilities. Both distributions are anticipated to improve as more events become available for fitting. Future research aims to determine the minimum number of events required to achieve relatively accurate simulation results. Site clustering analysis is often necessary to identify sites with similar characteristics, allowing CMS data from unmonitored sites to be used for inferring emissions from these unmonitored locations.
- In Case Study 2, distributions and probabilities are calculated for each equipment unit. These metrics can also be derived for individual activities or source categories to align with reporting frameworks, such as OGMP 2.0.
- Our model supports the creation of an MII and is compatible with known voluntary initiative frameworks, such as Best-Measured vs. Best-Calculated from Veritas 2.0 and OGMP 2.0 Level 4 and 5 emissions reporting. REs and PREs can be grouped by source to classify events for each source category. For instance, an MII-based emission factor and its associated uncertainty for flaring can be calculated by dividing the total emissions from flaring events by the total number of flaring events.
- Currently, our framework lacks a standard QA/QC process to validate input EOs. Adding such a standard in the future could ensure that only valid information is included in creating EEs (e.g., using only duration measurements from CMS).

This study presents an alternative framework for estimating annual site-level emissions in the upstream oil and gas (O&G) sector. By integrating multiscale emissions observations and operational data using EEDM, annual emissions and associated uncertainties are estimated for each event by combining both quantified rates and estimated durations. The proposed framework has a substantial contribution to ongoing efforts aimed at creating a measurement-informed inventory, improving methane mitigation strategies, and supporting the global objective of reducing methane emissions in the O&G sector. Expanding the scope of our framework to include more types of methane emission data and diverse operational conditions will further enhance its reliability. Future studies will also focus on demonstrating this methodology using real-world data across multiple sites to evaluate its feasibility and effectiveness on a broader scale.

Code and Data availability

The analysis was programmed in Python with standard packages. The results can be reproduced by employing the equations, explanations, and parameters provided in the main text. Additional code and data will be made available upon request

References

Allen, D., Ravikumar, A. and Tullos, E. (2023). Scientific Challenges of Monitoring, Measuring, Reporting, and Verifying Greenhouse Gas Emissions from Natural Gas Systems. *ACS Sustainable Resource Management*, 1(1), pp.10–12. doi:https://doi.org/10.1021/acssusresmgt.3c00132.

Allen, J.F. (1983). Maintaining knowledge about temporal intervals. *Communications of the ACM*, [online] 26(11), pp.832–843. doi:https://doi.org/10.1145/182.358434.

Anselin, L. (1995). Local Indicators of Spatial Association-LISA. *Geographical Analysis*, 27(2), pp.93–115. doi:https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Bell, C.S., Chiemezie Ilonze, Duggan, A. and Yuan, S. (2023). Performance of Continuous Emission Monitoring Solutions under a Single-Blind Controlled Testing Protocol. *Environ. Sci. Technol*, 57, pp.5794–5805. doi:https://doi.org/10.1021/acs.est.2c09235.

Brandt, A.R., Heath, G.A. and Cooley, D. (2016). Methane Leaks from Natural Gas Systems Follow Extreme Distributions. *Environmental Science & Technology*, 50(22), pp.12512–12520. doi:https://doi.org/10.1021/acs.est.6b04303.

Carl, R., Mike, B., George, P. and John, D. (2013). OGC® Sensor Web Enablement: Overview And High Level Architecture. *Ogc.org*. [online] doi:https://doi.org/07-165r1.

CDPHE (2025). *5 CCR 1001-9 REGULATION NUMBER 7 CONTROL OF EMISSIONS FROM OIL AND GAS EMISSIONS OPERATIONS*. [online] cdphe.colorado.gov. Available at: https://www.sos.state.co.us/CCR/DisplayRule.do?action=ruleinfo&ruleId=2341&deptID=16&agencyID=7&deptName=Department%20of%20Public%20Health%20and%20Environment&agencyName=Air%20Quality%20Control%20Commission&seriesNum=5%20CCR%201001-9.

Conrad, B.M., Tyner, D.R. and Johnson, M.R. (2023). Robust probabilities of detection and quantification uncertainty for aerial methane detection: Examples for three airborne technologies. *Remote Sensing of Environment*, 288, pp.113499–113499. doi:https://doi.org/10.1016/j.rse.2023.113499.

Daniels, W.S., Jia, M. and Hammerling, D.M. (2024). Estimating Methane Emission Durations Using Continuous Monitoring Systems. *Environmental Science & Technology Letters*, 11(11), pp.1187–1192. doi:https://doi.org/10.1021/acs.estlett.4c00687.

Daniels, W.S., Wang, J.L., Ravikumar, A.P., Harrison, M., Roman-White, S.A., George, F.C. and Hammerling, D.M. (2023). Toward Multiscale Measurement-Informed Methane Inventories: Reconciling Bottom-Up Site-Level Inventories with Top-Down Measurements Using Continuous Monitoring Systems. *Environmental Science & Technology*, 57(32), pp.11823–11833. doi:https://doi.org/10.1021/acs.est.3c01121.

Directorate-General for Energy (2024). *New EU Methane Regulation to reduce harmful emissions from fossil fuels in Europe and abroad*. [online] energy.ec.europa.eu. Available at: https://energy.ec.europa.eu/news/new-eu-methane-regulation-reduce-harmful-emissions-fossil-fuels-europe-and-abroad-2024-05-27_en.

Fox, T.A., Gao, M., Barchyn, T.E., Jamin, Y.L. and Hugenholtz, C.H. (2021). An agent-based model for estimating emissions reduction equivalence among leak detection and repair programs. *Journal of Cleaner Production*, 282, p.125237. doi:https://doi.org/10.1016/j.jclepro.2020.125237.

Government of Canada (2025). *Regulations Respecting Reduction in the Release of Methane and Certain Volatile Organic Compounds (Upstream Oil and Gas Sector) (SOR/2018-66)*. [online] Justice Laws Website. Available at: https://laws-lois.justice.gc.ca/eng/regulations/SOR-2018-66/ [Accessed 13 Jun. 2025].

GTI Energy (2023). *Veritas: Home*. [online] Available at: https://veritas.gti.energy/.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J-N. (2023): ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), DOI: 10.24381/cds.adbb2d47 (Accessed on DD-MMM-YYYY)

Higgins, S., Arsineh Hecobian, Munkhbayar Baasandorj and Pacsi, A.P. (2024). A Practical Framework for Oil and Gas Operators to Estimate Methane Emission Duration Using Operational Data. *SPE Journal*, 29(5). doi:https://doi.org/10.2118/219445-pa.

IEA (2023). *Global Methane Tracker 2023 – Analysis*. [online] IEA. Available at: https://www.iea.org/reports/global-methane-tracker-2023.

IPCC (2019). *IPCC - Task Force on National Greenhouse Gas Inventories*. [online] Iges.or.jp. Available at: https://www.ipcc-nggip.iges.or.jp/public/2006gl/.

ISO (2023). *ISO 19156:2023*. [online] ISO. Available at: https://www.iso.org/standard/82463.html#lifecycle [Accessed 12 Jun. 2025].

Johnson, M.R., Conrad, B.M. and Tyner, D.R. (2023). Creating measurement-based oil and gas sector methane inventories using source-resolved aerial surveys. *Communications earth & environment*, [online] 4(1). doi:https://doi.org/10.1038/s43247-023-00769-7.

Kemp, C.E., Ravikumar, A.P. and Brandt, A.R. (2016). Comparing Natural Gas Leakage Detection Technologies Using an Open-Source 'Virtual Gas Field' Simulator. *Environmental Science & Technology*, 50(8), pp.4546–4553. doi:https://doi.org/10.1021/acs.est.5b06068.

Koehler, E., Brown, E. and Haneuse, S.J.-P. . A. (2009). On the Assessment of Monte Carlo Error in Simulation-Based Statistical Analyses. *The American Statistician*, 63(2), pp.155–162. doi:https://doi.org/10.1198/tast.2009.0030.

MacKay, K., Seymour, S.P., Li, H.Z., Zavala-Araiza, D. and Xie, D. (2024). A Comprehensive Integration and Synthesis of Methane Emissions from Canada's Oil and Gas Value Chain. *Environmental Science & Technology*, 58(32), pp.14203–14213. doi:https://doi.org/10.1021/acs.est.4c03651.

MIQ (2024a). *The MiQ Standard - MiQ*. [online] MiQ. Available at: https://miq.org/the-technical-standard/.

MiQ (2024b). *Monitoring Technology Compatibility Assessment Qube Axon*. [online] MIQ. Available at: https://miq.org/document/qube-compatibility-assessment-2.

Oil and Gas Methane Partnership 2.0 (2022). *OGMP 2.0 – The Oil & Gas Methane Partnership 2.0*. [online] The Oil and Gas Methane Partnership 2.0. Available at: https://ogmpartnership.com/.

Open Geospatial Consortium (2024). *OGC to Form Emission Event Modeling Language Working Group: Public Comment Sought on Charter*. [online] Available at: https://www.ogc.org/requests/ogc-to-form-emission-event-modeling-language-working-group-public-comment-sought-on-charter/

Riddick, S.N., Mbua, M., Anand, A., Kiplimo, E., Santos, A., Aashish Upreti and Zimmerle, D.J. (2024). Estimating Total Methane Emissions from the Denver-Julesburg Basin Using Bottom-Up Approaches. *Gases*, 4(3), pp.236–252. doi:https://doi.org/10.3390/gases4030014.

Rutherford, J.S., Sherwin, E.D., Ravikumar, A.P., Heath, G.A., Englander, J., Cooley, D., Lyon, D., Omara, M., Langfitt, Q. and Brandt, A.R. (2021). Closing the methane gap in US oil and natural gas production emissions inventories. *Nature Communications*, 12(1). doi:https://doi.org/10.1038/s41467-021-25017-4.

Scarpelli, T.R., Jacob, D.J., Grossman, S., Lu, X., Qu, Z., Sulprizio, M.P., Zhang, Y., Reuland, F., Gordon, D. and Worden, J.R. (2022). Updated Global Fuel Exploitation Inventory (GFEI) for methane emissions from the oil, gas, and coal sectors: evaluation with inversions of atmospheric methane observations. *Atmospheric Chemistry and Physics*, 22(5), pp.3235–3249. doi:https://doi.org/10.5194/acp-22-3235-2022.

Sherwin, E.D., Chen, Y., Ravikumar, A.P. and Brandt, A.R. (2021). Single-blind test of airplane-based hyperspectral methane detection via controlled releases. *Elementa: Science of the Anthropocene*, 9(1). doi:https://doi.org/10.1525/elementa.2021.00063.

UNFCC (2021). *The Imperative for Methane Action*. [online] Globalmethanepledge.org. Available at: https://www.globalmethanepledge.org/imperative-methane-action.

US Department of Energy (2024a). *Greenhouse Gas Supply Chain Emissions Measurement, Monitoring, Reporting, Verification Framework*. [online] Energy.gov. Available at: https://www.energy.gov/fecm/greenhouse-gas-supply-chain-emissions-measurement-monitoring-reporting-verification-framework.

US Department of Energy (2024b). *International MMRV Working Group Reaches Milestone in Developing a Credible Framework for Measuring Natural Gas Supply Chain Emissions to Drive Continuous Reductions in Methane and Carbon Dioxide Emissions in the Global Natural Gas Market*. [online] US Department of Energy. Available at: https://www.energy.gov/fecm/articles/international-mmrv-working-group-reaches-milestone-developing-credible-framework [Accessed 12 Jun. 2025].

US EPA (2024). *Methane Emissions Reduction Program and GHGRP Subpart W (Petroleum and Natural Gas Systems)*. [online] US EPA. Available at: https://www.epa.gov/inflation-reduction-act/revisions-ghgrp-subpart-w-petroleum-and-natural-gas-systems.

US EPA (2025). *40 CFR Part 98 Subpart W -- Petroleum and Natural Gas Systems*. [online] Ecfr.gov. Available at: https://www.ecfr.gov/current/title-40/chapter-I/subchapter-C/part-98/subpart-W.

Vaughn, T.L., Bell, C.S., Pickering, C.K., Schwietzke, S., Heath, G.A., Pétron, G., Zimmerle, D.J., Schnell, R.C. and Nummedal, D. (2018). Temporal variability largely explains top-down/bottom-up difference in methane emission estimates from a natural gas production region. *Proceedings of the National Academy of Sciences*, 115(46), pp.11712–11717. doi:https://doi.org/10.1073/pnas.1805687115.

Wang, J.L., Daniels, W.S., Hammerling, D.M., Harrison, M., Burmaster, K., George, F.C. and Ravikumar, A.P. (2022). Multiscale Methane Measurements at Oil and Gas Facilities Reveal Necessary Frameworks for Improved Emissions Accounting. *Environmental Science & Technology*, 56(20), pp.14743–14752. doi:https://doi.org/10.1021/acs.est.2c06211.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

M.G and S. L designed the research. M.G. directed and performed the analyses. M.G. and Z. A. wrote the paper. M.G., S.L., Z.A., S.S. and S. K. edited the paper.