An event-based framework for estimating, tracking, and managing annual methane emissions from upstream oil and gas sites

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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 group multi-scale emissions data into discrete events using the concept of Allen's interval algebra and spatial proximity. Following event creation, emissions are categorized into three groups—resolved (known emission rate and duration), partially resolved (known emission rate but unknown duration), and unresolved (unknown emission rate and duration)—to facilitate different management and emissions estimation approaches. Three Monte Carlo-based approaches are developed under the framework. They 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 distributions. The methodology enables emissions to be reported and verified at the group level rather than individual observation. To demonstrate estimating emissions using this framework, we created two scenarios and performed emissions estimation using synthetic emission observations based on real emissions data for an upstream O&G site. The proposed framework can be implemented in voluntary initiatives such as Veritas 2.0 and the Oil & Gas Methane Partnership (OGMP) 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: This study addresses the fundamental data integration challenges in emissions estimation and well-suited for aligning with the MMRV framework.

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 [1]. This effort gained significant momentum following the launch of the Global Methane Pledge [2] at the 2021 United Nations Climate Change Conference (COP26), which set an ambitious goal of reducing methane emissions by 30% from 2020 levels by 2030. Since then, stakeholders 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 [3,4] to help achieve these reduction targets.

The Measuring, Monitoring, Reporting, and Verification (MMRV) framework is widely recognized as one of the most effective frameworks for managing emissions in the oil and gas (O&G) sector and tracking annual emissions [5,6]. Measuring refers to deploying 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 track emission activity. Reporting refers to standardized documentation and disclosure of emissions data and methodologies applied to calculate emissions to regulatory bodies (e.g., EU) or voluntary programs (e.g., UNEP OGMP 2.0). Verification refers to reviewing and validating reported emissions [5, 6].

To date, MMRV is still an ongoing effort, and the equivalent frameworks have primarily been adopted by voluntary initiatives such as the Oil and Gas Methane Partnership (OGMP) 2.0, the MiQ standard, and Veritas 2.0 [7-9]. Some regulatory initiatives, such as Air Quality Control Commission Regulation 7, Part B, implemented by the Colorado Department of Public Health and Environment (CDPHE), have also incorporated similar frameworks [10]. 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 measurement-based inventory (MBI) and/or measurement-informed inventory (MII), and assessing overall carbon intensity across the supply chain [5, 6].

Various technical challenges and inherent emissions characteristics hinder the effective implementation of MMRV by O&G operators. These challenges include the missing emissions from abnormal events from emissions reporting, the 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 the lack of unified measurement scales for emissions data [5,11–13].

To address these challenges and generate a more accurate emissions inventory, the scientific community has been actively developing hybrid approaches that integrate both BU and TD data to maximize emissions data utilization, which includes combining measurements results by using multi-scale remote sensing technologies, applying advanced statistical methods, and developing simulation approaches [14–19]. However, a framework and emissions data model to spatiotemporally assimilate emissions data from different measurement scales and estimate emissions that are not measured is still under development. Such a framework can improve emissions management, increase reporting transparency, and enhance uncertainty estimations.

This work introduces a novel framework that includes 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, and it integrates with the OGC Sensor Web Enablement suite [20–22]. In the following sections, we will first introduce EEDM and three types of emissions events. Next, we outline the methodology for calculating emissions and uncertainties associated with each type of emission event. Third, we introduce 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 a fictitious site and synthetic emissions data.

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 occurred and the quantity (how much) emitted. This information helps attribute each emission observation to a specific physical source (e.g., equipment) and a cause (e.g., fugitive emissions, tank venting, etc.). However, emission observations 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, EEDM (Figure 1b) was proposed based on the OGC standards, including ISO/OGC's Observations and Measurements 19156:2023/OGC 20-082r4 [20] and W3C/OGC Semantic Sensor Networks [22]. EEDM provides a consistent foundation aimed at enhancing the estimation of emissions duration and capturing their dynamic aspects, such as the lifecycle of leaks.

As illustrated in Figure 1a, emissions observations (EOs) are grouped into events as part of the measurement and monitoring process, allowing each event to serve as a container for managing emissions and their associated sources. Each event is then verified to assess its completeness and accuracy. Since different types of EO have different characteristics and are constrained by different factors (for example, satellite measurements are impacted by cloud cover), and different regulatory or voluntary initiatives may have different quality assurance processes, no specific QA/QC threshold is set in EEDM. However, EEDM does require the uncertainty of each EO to be included. For example, the MIQ protocol follows ISO 14044 to evaluate the quality of EOs [8].

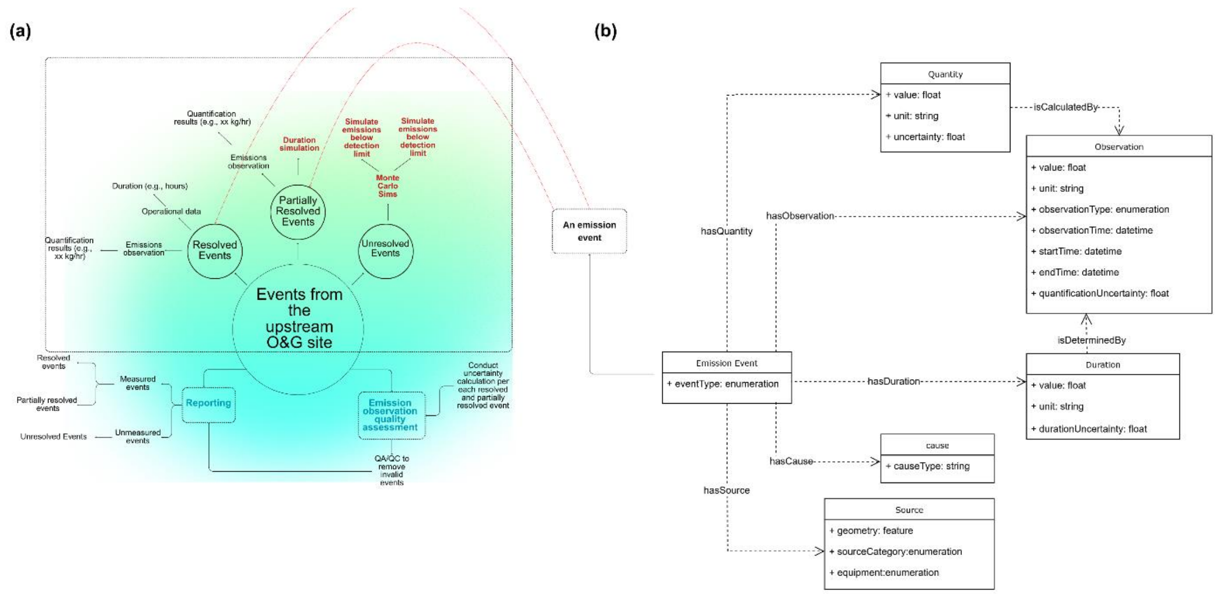

Figure 1. **(a)** Schematic view of event-based framework; **(b)** The entities and properties of the EEDM and their relationships. The formal definition can be found in S1 of the Supporting Information (SI).

2.2 Spatial and Temporal Correlation of Emissions Event (EE)

An emission event (EE) may consist of either a single observation or multiple observations capturing the same emission. To determine whether multiple observations can be grouped in both space and time, we apply spatial proximity [23] and Allen's interval algebra [24]. Spatial proximity assesses whether observations are geographically close or attributed to the same source (e.g., Compressor No. 1), while Allen's interval algebra (See Table S1) determines the temporal relationships between observations. If 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 observe the same emission event.

As illustrated in Table S1, 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* [24]. Except for *precedes* and *preceded by*, if two or more EOs or EEs 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 EEDM, we treat intermittent events as separate events.

In addition to EO, an EE consists of four other primary components: source, cause, duration, and quantity (Figure 1b). The source refers to any equipment or activity that emits methane, and EOs can be attributed to a specific physical source (e.g., Compressor No. 1), a source category (e.g., fugitive emissions, tank venting), or both (e.g., hydraulic fracturing from a gas well). The cause of an emission event ties 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 observation has its measurement result, associated unit, type of observation (e.g., aircraft flyover - Bridger), observation time that describes when the observation was conducted, start and end time if the observation was reported as a period and quantification uncertainty is quantification is the measurement result.

The duration of EE can be either directly measured using CMS (e.g., start and end times) or estimated through indirect observations, such as the absence of emissions or null detection. Both measured and estimated duration have associated uncertainty. Lastly, the quantity represents the total amount of methane emitted during the event. When an event includes multiple measured emissions observations, the observation with the lowest quantification uncertainty is selected to calculate the quantity. When an event includes both calculated and measured emissions, the appropriate quantity should be selected based on the quality, reliability, and relevance of the available data. Some standards, such as Veritas 2.0 [9], guide whether measured or calculated emission results should be used. Such standards can be integrated into the EEDM to determine the quantity for each event. Since quantity is estimated by combining emissions rate quantification and duration estimates, its overall uncertainty reflects the propagation of errors from both sources.

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

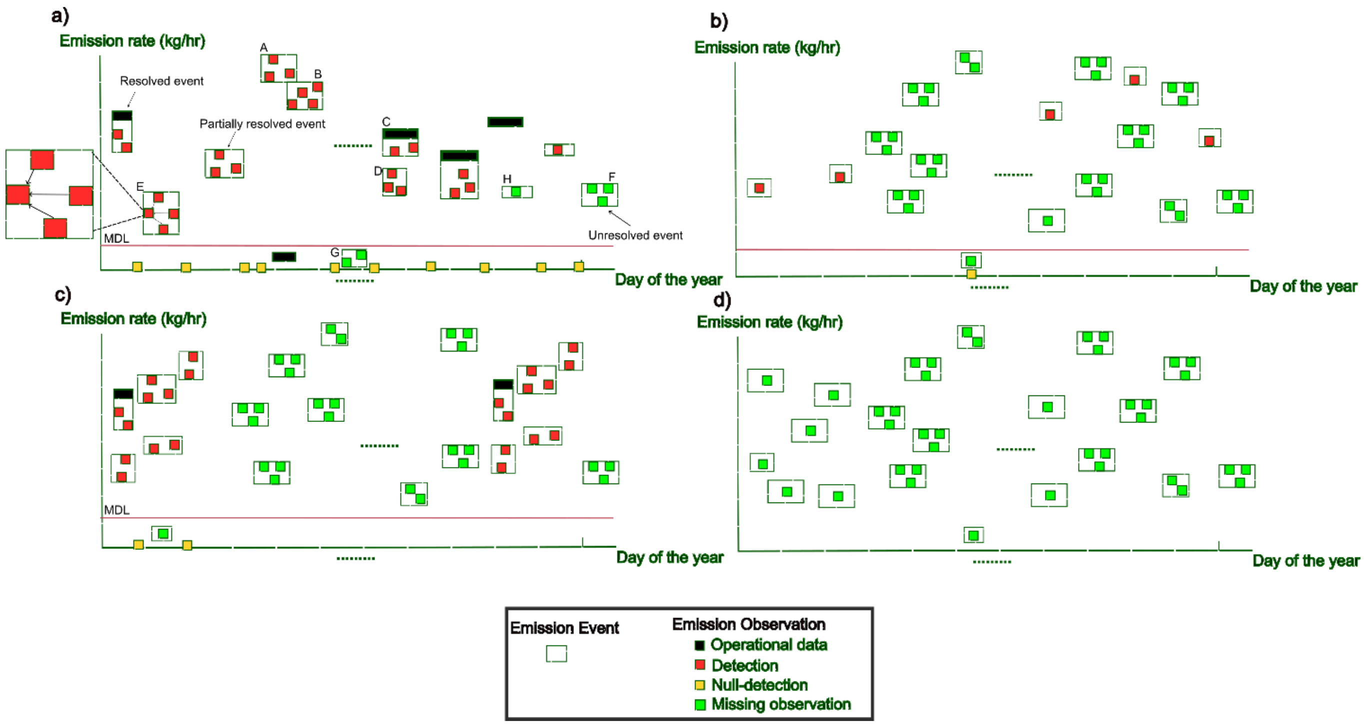

Figure 2. Representation of resolved, partially resolved, and unresolved emission events for four sites under different monitoring scenarios throughout the year. The x-axis represents the quantifications of EO associated with each EE. The y-axis represents when emissions are measured and how long they persist in a year. 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

We classify EE into three types (see Table 1): resolved events (REs), partially resolved events (PREs), and unresolved events (UEs). REs include EOs from data sources such as operational logs, which can be directly used to estimate duration, attribute sources, and perform root cause analysis. In contrast, PREs consist solely of EO from measurement technologies. They may require additional information to determine their duration and root cause, such as estimating duration using null detections from aircraft flyovers or routine leak detection and repair (LDAR) surveys that do not identify emissions. The unmeasured and undocumented emissions are classified as unresolved events (UEs), which 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. Since the emission rates of both events cannot be separated, Type 3 UEs are typically omitted. Since they are not

measured, the reported emissions usually include only the emissions from the large operational event and neglect the small fugitive emissions.

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 (or equipment) has a unique event within each period, we apply spatial proximity and Allen's interval algebra again to merge events. For example, event A and event B can be merged if event A overlaps with event B. Similarly, event C and event D can be merged if event C contains event D, as shown in Figure 1a. After the merging, the duration and quantity are re-calculated. 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 monthly or yearly, and both instantaneous screening technology and continuous monitoring systems are deployed to the site (Figure 2a), then the annual emissions quantity can be calculated by 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} is zero, and emissions from REs will be instead simulated as E_{UE}. Thus, annual emissions will be calculated by summing E_{PRE} and E_{UE}.
- **Measurement campaign only**: If a site has only been surveyed during an annual or bi-annual measurement campaign (Figure 2c) and emissions are also only reported during the measurement campaign, only limited numbers of REs and PREs are measured during the measurement campaign. Thus, E_{UE} 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.

2.4 Generic emissions estimation equation for EE

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.

2.5 Resolved Event (RE)

For REs, the uncertainties associated with each event primarily arise from rate estimation uncertainty. While operational data can be used to estimate event durations, the associated uncertainties are difficult to estimate and are highly variable across different operational practices [25]. 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 (was known as Kairos) aircraft system is found to be approximately ±40% [26]. By incorporating the quantification uncertainty (U_{Q_RE}), the emission 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 from measurement technology with the associated emission rate's quantification uncertainty (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. 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 calculated based on measured CH_4 concentrations. However, studies have shown that the resulting durations can significantly differ from actual durations [27, 28]. Addressing this uncertainty requires time series analysis of in-situ wind direction and CH_4 concentration measurements, such as the Probabilistic Duration Model [27]. In contrast, the duration of PREs based solely on instantaneous observations is often estimated using rules or times derived from the preceding null-detects time (PNDT) and succeeding null-detects time (SNDT) [29]. 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 models such as LDAR-Sim and FEAST [30-32].

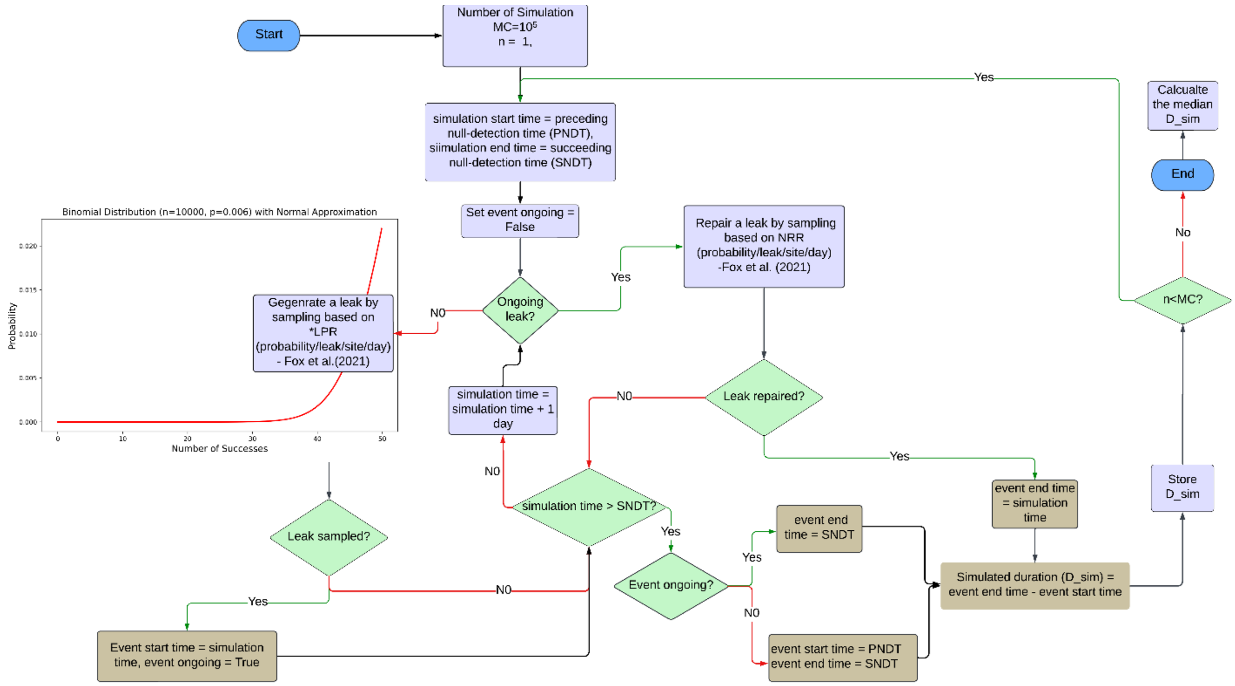

Figure 3. The Monte Carlo simulation workflow simulates the duration of a PRE based on the preceding null-detection and succeeding null-detection of the event. In the simulation, the units of LPR and NRR are per site per day. Here, we present an example binomial distribution with a probability of 0.006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

As shown in Figure 3, a Monte Carlo simulation ($M = 10^5$ iterations) is performed to simulate the duration to ensure the stationary distribution of results. The start and end times of the simulation were bounded by the preceding null-detection time (PNDT) and succeeding null-detection time (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 [30]. If an emission is sampled, the timestamp of the simulation becomes the start time of the emission event, the simulation updates the status of event as ongoing, and the simulation 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 [30], is used to perform daily random sampling to determine event cessation. If the event is stopped, the simulation timestamp is saved as the simulated end time of the event; if not, the process continues to the next day until either the timestamp exceeds the SNDT, or an end time has been successfully determined. 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 and start times. 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 [33].

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:

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

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

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

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:

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

To combine both uncertainties from quantification and duration estimations, the error propagation equations described by IPCC [34] can be used to calculate U_{E_PRE}:

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

The *Eq.8* assumes that duration estimation uncertainty and quantification uncertainty are uncorrelated. However, this assumption may not always be valid. For instance, in a PRE with a CMS measurement, the emission rate and duration are both measured by the same sensor, introducing potential dependencies between the two uncertainties. 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 [15] into our EEDM framework, 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)

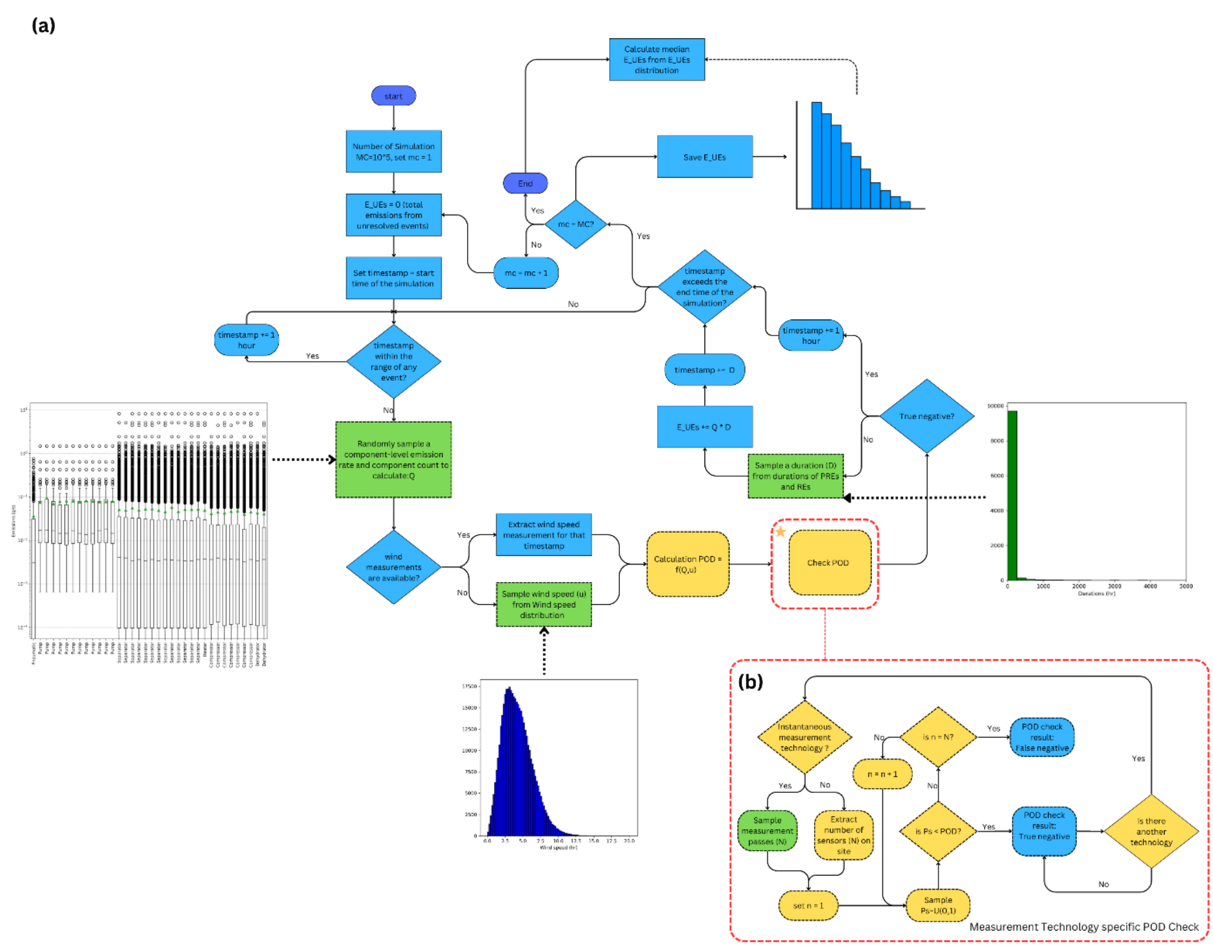

Figure 4. Monte Carlo simulation workflow to estimate total emissions from unresolved events for a given site that is monitored by flyover and CMS. This workflow specifically illustrates the scenario where emissions are measured by one type of aircraft flyover and one CMS; more probability of detection (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 [14]. [b]Different aircraft systems require different equations to calculate POD based on different parameters. For instance, Conrad et al. [35] 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. [28] derived POD equations for multiple CMSs in METEC based on 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 no emission event occurs in a given timestamp, 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. Wind speed and flight passes for each flyover survey at the site location are also randomly sampled.

In Figure 4, we are using a site measured by both flyover and CMS as an example. The simulation determines the false negative and identifies if any measurement technology fails to detect an emission independently. Probability of detection (POD)s are calculated using the sampled emission rate and wind speed. Each calculated PODs are 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 occurred in the real world, it would not be detected). If the POD is smaller than ξ, it indicates a true negative (i.e., if the sampled emission occurred in the real world, it would be detected). This comparison is done for each flyover path and each sensor installed on the site. If either the flyover or CMS POD check returns false negative, the sampled emission rate is multiplied by a sampled duration (t_u) to consolidate a UE. Then, the resulted emissions are 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} distributionare 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

A significant limitation in estimating emissions from UEs through the simulation of POD and identifying false negatives is the requirement for extensive temporal coverage of emissions measurements (i.e., either via continuous monitoring systems or frequent instantaneous screening surveys). However, not all sites are monitored sufficiently in the real world. To address this issue, we developed a second simulation approach that simulates UEs based on the probability of emission event occurrence rather than relying 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.

Equipment data and bottom-up inventory are necessary to enhance the simulation results and prevent extrapolating emissions from incorrect source categories. For example, equipment or infrastructure on site can be used to determine the possible emission sources (e.g., emissions from flaring should not be extrapolated for a separator). Similarly, an accurate bottom-up inventory can also be used to constrain the simulation. For example, if liquid unloading never occurred, the simulation should not extrapolate emissions from liquid unloading.

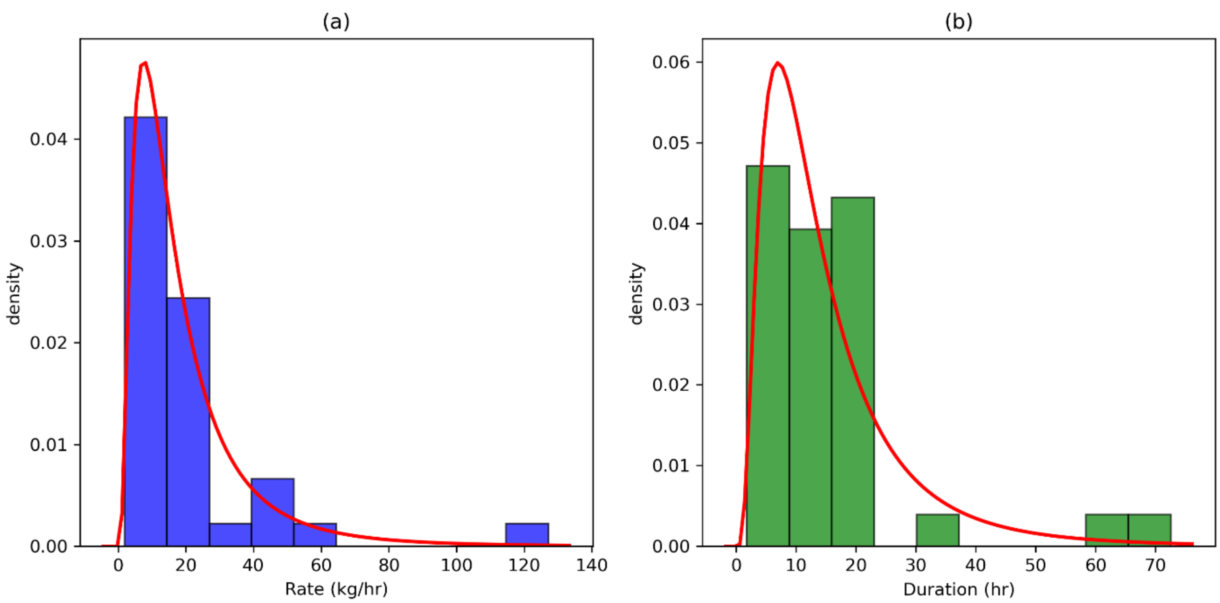

Figure 5. Example of using *Eq.9* to fit empirical rate (a) and duration (b) distributions

Since emission rates and durations tend to follow right-skewed distributions, we use a log-normal probability density functions to fit the empirical 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 [36] 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.

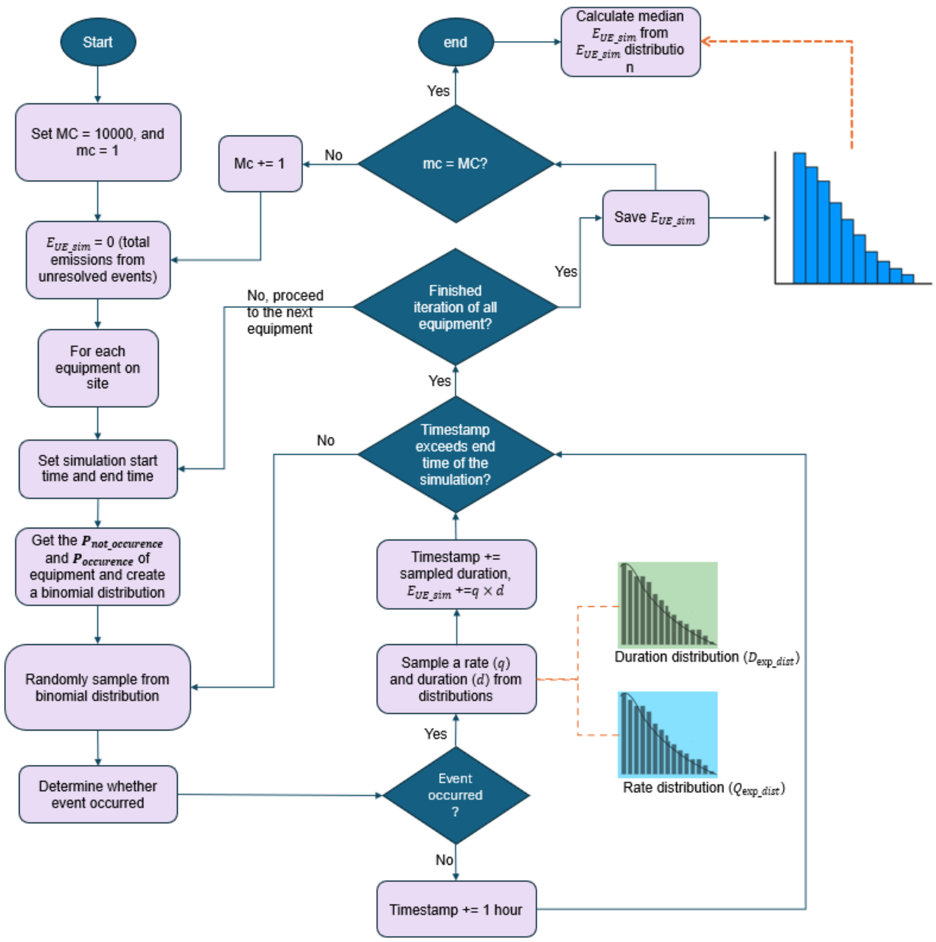

Figure 6. A workflow of simulating emissions from UEs by sampling events.

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.

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:

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

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 did not detect any plume), four OGI inspection records (two did not find any leaks), and 49 venting data points. Due to sufficient EOs and all four months being monitored 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 for three unmonitored months. Case Studies 1 and 2 correspond to Scenarios 1 (Figure 2a) and 3 (Figure 2c), respectively, as described in Figure 2. All synthetic emission observations can be found in Section S2 of the Supporting Information.

These two case studies demonstrate the EEDM's capabilities and provide examples of how annual emissions and their uncertainties can be estimated within the proposed framework. 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

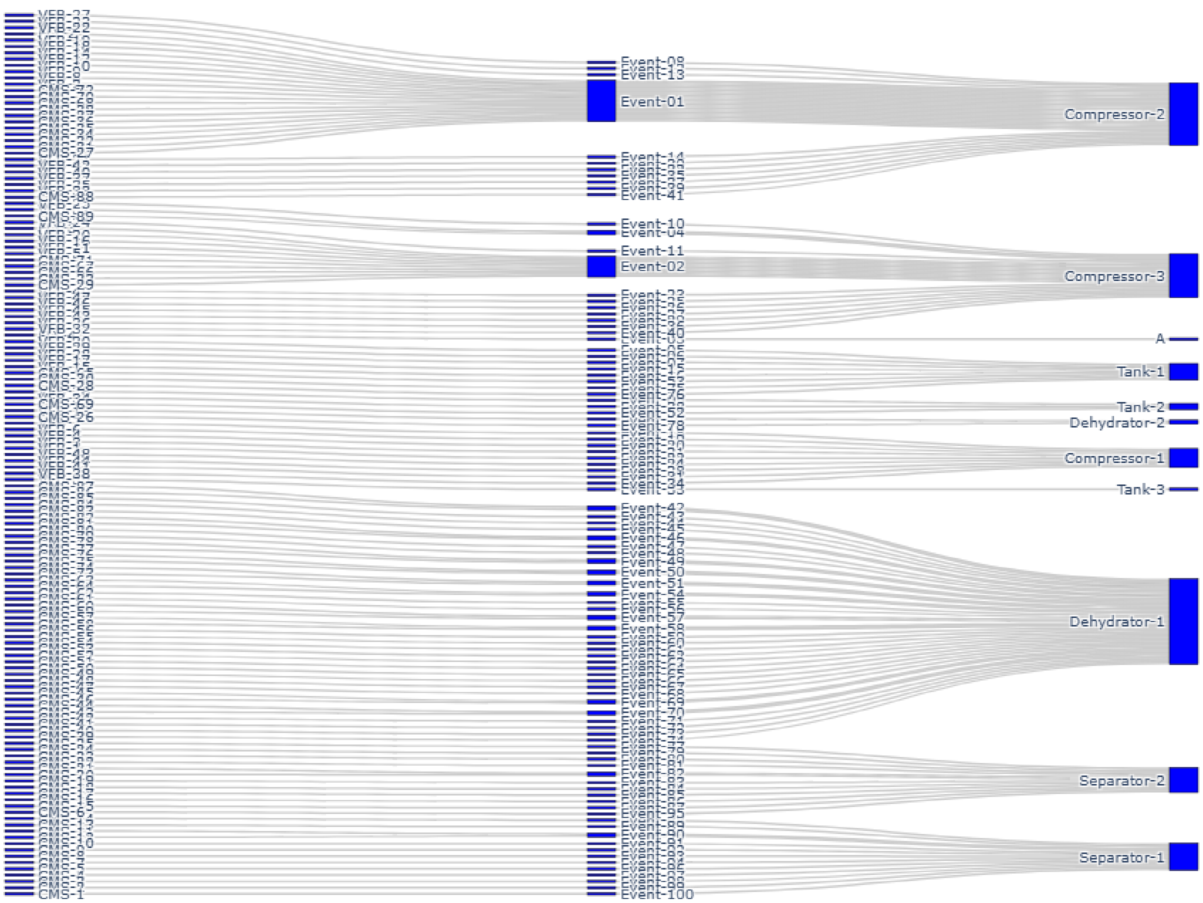

Figure 7. Sankey diagram describing how EOs are merged to EEs and are attributed to equipment in case study No.1.

For case study No.1, we initiated 92 PREs and 49 REs. By 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 7).

To demonstrate the proposed equations, we assume a quantification uncertainty of +/-60% across all events. After merging the events, only one PRE requires duration to be estimated using our proposed duration simulation. The following parameters and assumptions are used to simulate the duration of this PRE: 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 measured start and end times from CMS observations. Following the findings from Daniels et al. [27], the associated duration uncertainties were assumed to range from 0 to twice the measured durations.

The simulation of emissions below the MDL was applied to estimate total emissions from UEs. The following parameters, datasets, and assumptions were used: five CMS sensors were installed on-site; wind speed data from the Permian Basin were obtained from ERA5 [37]; three flight passes were conducted; component-scale emission rates were sampled from empirical component measurements [14]; and POD equations were derived from previous studies [35,38].

Figure 8a illustrates the total emissions and their associated uncertainties. After merging the events, only one PRE had its duration estimated using null detections. The resulting distribution of simulated durations was right-skewed, with a median duration of 116.75 hours and a 95% confidence interval (CI) of [4.75, 606.75]. The total emissions over four months are 43922.09 kg, with 95% CI [37336.08, 65408.83]. The breakdown of emissions from REs and PREs are 19167.56 kg (95% CI [15959.26, 22375.86]) and 24719.31 kg (95% CI [18967.67, 45945.20]).

Case studies No.2

In the second case study, 36 CMS synthesized observations over a month, initiated 36 PREs. Similar to Case Study 1, we assumed quantification and duration uncertainties of 60% and 200%, respectively, across all PREs. Using Eqs. 9, 10, 14, and 15, the total emissions from PREs were estimated at 12,752.90 kg, with a 95% confidence interval (CI) of [10,318.35, 21,225.40]. After adding 890,185.12 kg of simulated emissions from UEs using the second simulation approach, the total four-month emissions for the fictitious site were 902,938.02 kg, with a 95% CI of [847,296.82, 983,393.09].

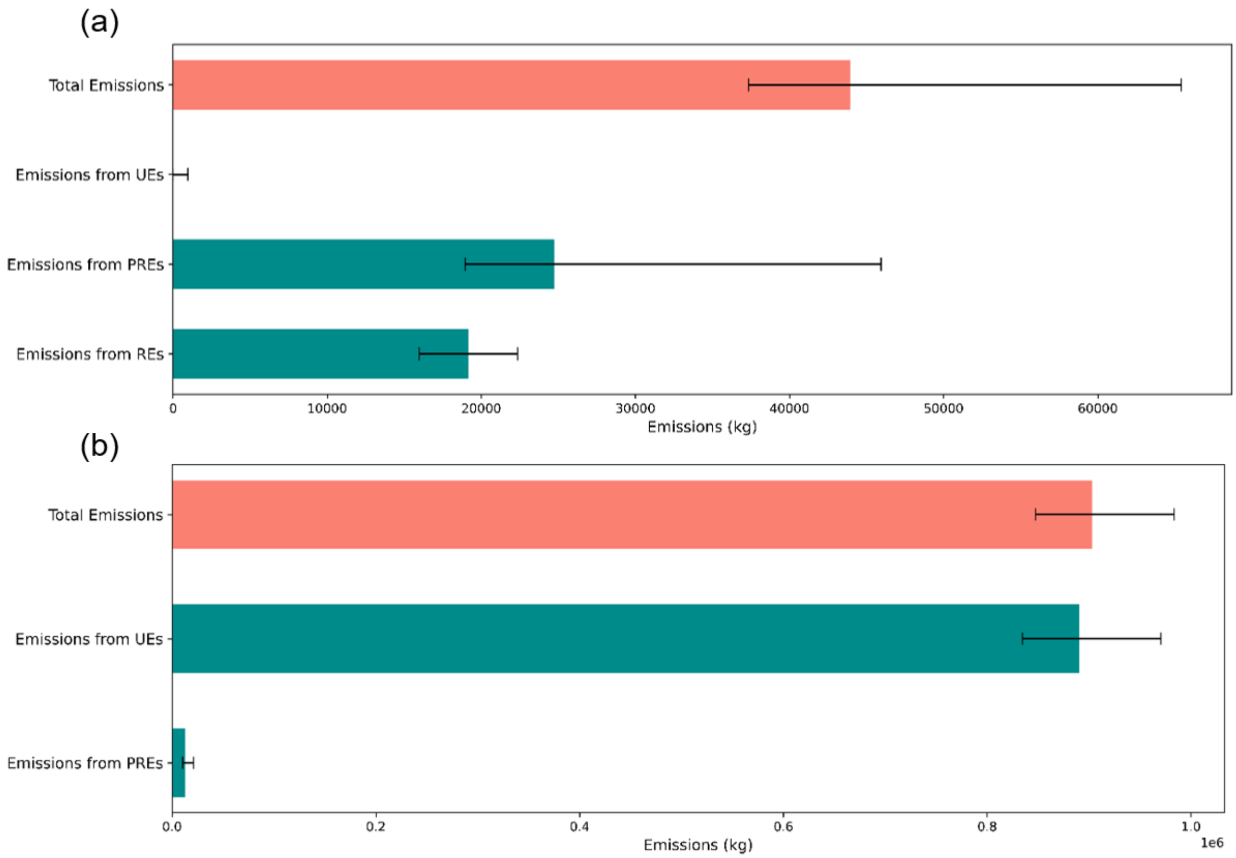

Figure 8. The bar chart shows the total site-level emission estimates and breakdown of REs, PREs, and UEs emissions from (a) case study No.1 and (b) case study No.2.

4. Implication & Conclusion

We introduce a new framework integrating multi-scale measurements and O&G operational data to construct emission events. Adopting ISO and OGC standards ensures that emission events are compatible across diverse technologies. This integration enhances source attribution and root cause analysis by combining sensor data with operational records. It highlights the following key implications:

- The EEDM represents a simplified data model developed by 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 source attribution and cause analysis—two of the most important follow-up actions for emissions data. A formal data model will be developed through collaborative group efforts [39].

- Differentiating between REs and PREs improves uncertainty assessments. Past studies have found that most operational events are of short duration [17]. Partitioning emissions from an intermittent source into multiple short-duration events can significantly reduce overall uncertainties associated with its annual emissions estimation, as mathematically, most of the uncertainty in short-duration events stems from quantification rather than both quantification and duration. While measurements from CMSs help reduce duration uncertainty compared to using only snapshot screening technologies, such as aircraft systems, the duration uncertainty associated with CMSs should also be addressed. This is particularly important because surface wind directions often vary on-site, especially at locations with complex infrastructure. Incorporating routine and non-routine operational activity details into the emission event model can further improve the accuracy of duration estimation.
- We integrated emission events into the methodology developed by Johnson et al. [15], 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 these should be based on results from controlled release tests.
- Extrapolation is typically required in two primary 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 calculate probabilities. Both distributions are expected 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 determine sites with the same characteristics so that CMS data from unmonitored sites can be used to infer emissions from unmonitored sites.
- 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.
- Beyond site-level emission estimates, EEDM is also suited for responding to the Super-Emitter Program under US EPA regulations [3, 40]. EEDM can more effectively track the source and results from root cause analysis. The start and end times can be more clearly defined by grouping a super-emitter observation (e.g., flyover) and OGI follow-up into a single event.
- 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 (one class of EEDM). For instance, an MII-based emission factor and its associated uncertainty for flaring can be calculated by dividing the total emissions by the total number of flaring events. To fully align with MMRV, the remaining

gap in the framework is the lack of a standard QA/QC process to validate input EOs for emissions quantification and duration estimation. Adding such a standard could ensure that only valid information is included in creating EEs (e.g., using only duration measurements from CMS).

This study provides an alternative framework that can be used to estimate annual site-level emissions estimation for the upstream O&G sector. By integrating multiscale emissions observations and operational data using EEDM, annual emissions and associated uncertainties are estimated per each event by combining both quantified rate 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. Adding an event-based QA/QC process could enhance the framework's credibility. Moreover, 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

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Disclosure statement

No potential conflict of interest was reported by the author (s).

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.

Supporting Information for:

An event-based framework for estimating, tracking, and managing annual methane emissions from upstream oil and gas sites

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S1. Emissions event data model (EEDM) and Allen's time algebra

The UML definition of the emissions event data model (EEDM) can be expressed as follows:

```
class EmissionsEvent {
   - eventType: enumeration
   - hasDuration: Duration
   - hasCause: Cause
   - hasSource: Source
   - hasQuantity: Quantity
   - hasObservation: Observation[*]
}

class Duration {
   + value: float
   + unit: string
}

class Cause {
   + causeType: string
}

class Source {
   + geometry: feature
   + sourceCategory: enumeration
   + equipment: enumeration
}

class Quantity {
   + value: float
   + unit: string
   - isCalculatedBy: Observation
   - isDeterminedBy: ObservationF
}

class Observation {
   + value: float
   + unit: string
   + observationType: enumeration
   + observationTime: datetime
   + startTime: datetime
   + endTime: datetime
}

class EventGrouping {
   - spatialProximity: boolean
   - temporalRelationship: enumeration
   - groups: EmissionsEvent[*]
}
```

Where *Obervation[*]* in EE allows multiple emissions observations (EOs) to be associated with a single EE. *EventGrouping* class is not included in the Figure 1 of main paper. It represents the logic of grouping EOs using spatial proximity and Allen's interval algebra. The *groups* tracks merged emission events.

To group EOs into a single EE or merge multiple EEs into one EE, the model uses spatial proximity to indicate if observations are geographically close or directly/indirectly attributed to the same physical emission sources (equipment). The *temporalRelationship* indicates the temporal relations between EOs or EEs based on Allen's Interval Algebra [1].

Table S1: Illustration of Allen's interval algebra logic between two-time intervals.

Relation	Illustration
T1 precedes T2 T2 precededBy T1	T1 T2
T1 meets T2 T2 metBy T1	T1 T2
T1 overlaps T2 T2 overlappedBy T1	T1 T2
T1 starts T2 T2 startedBy T1	T1 T2
T1 during T2 T2 contains T1	T1 T2
T1 finishes T2 T2 finishedBy T1	T1 T2
T1 equals T2	T1 T2

As illustrated in Table S1, 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* [1]. Except for *precedes* and *preceded by*, if two or more EOs or EEs 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. For example, we can conclude that the CMS alarm and VFB can be correlated as the same event, when a CMS alarm indicating emissions from Compressor A between 2024-07-05T09:00:00 and 2024-07-05T11:00:00 *contains* Compressor rod packing venting reported for Compressor A from 2024-07-05T10:20:00 to 2024-07-05T10:50:00.

EEDM uses a network of nodes and edges to identify temporal rules based on relationships between emission observations within the same event. Each observation is a node within an event, while edges represent the spatiotemporal correlations between them. The observation with the earliest timestamp is defined as the parent, and all other observations are considered child observations. When two events merge, child and parent observations are redefined accordingly.

The parent observation plays a crucial role in PREs that contain only instantaneous measurement observations, particularly when duration must be inferred from preceding and succeeding null detections.

S2. Synthetic emissions observations

Table S2. Synthetic CMS measurements in the case study No.1.

ID	site	equipment	start time	end time	rate (kg/hr)
CMS-89	A	Compressor-3	01-01-2024 2:16	01-01-2024 18:46	13.43743062
CMS-88	A	Compressor-2	01-01-2024 17:12	02-01-2024 0:32	11.0537834
CMS-87	A	Dehydrator-1	02-01-2024 8:38	03-01-2024 2:14	6.485984945
CMS-86	A	Dehydrator-1	03-01-2024 1:20	03-01-2024 17:55	9.745295575
CMS-85	A	Dehydrator-1	03-01-2024 23:33	04-01-2024 3:06	5.279977194
CMS-84	A	Dehydrator-1	04-01-2024 12:02	04-01-2024 20:25	44.44340994
CMS-83	A	Dehydrator-1	05-01-2024 12:21	05-01-2024 14:09	26.4754512
CMS-82	A	Dehydrator-1	05-01-2024 18:40	06-01-2024 15:03	10.2931667
CMS-81	A	Dehydrator-1	06-01-2024 12:55	07-01-2024 6:39	22.90488356
CMS-80	A	Dehydrator-1	07-01-2024 3:28	07-01-2024 7:34	4.38235222
CMS-79	A	Dehydrator-1	07-01-2024 15:50	08-01-2024 5:10	15.68792648
CMS-78	A	Dehydrator-1	08-01-2024 21:11	09-01-2024 5:36	23.01335768
CMS-77	A	Dehydrator-1	09-01-2024 4:54	09-01-2024 15:33	16.46214129
CMS-76	A	Dehydrator-1	09-01-2024 20:05	10-01-2024 10:21	6.575924082
CMS-75	A	Dehydrator-1	10-01-2024 9:17	11-01-2024 20:43	9.97428315
CMS-74	A	Dehydrator-1	12-01-2024 8:57	15-01-2024 9:31	39.60280338
CMS-73	A	Dehydrator-1	15-01-2024 9:19	15-01-2024 12:30	4.631917288
CMS-72	A	Compressor-2	15-01-2024 11:46	16-01-2024 6:06	127.1398731
CMS-71	A	Compressor-3	16-01-2024 11:53	17-01-2024 3:15	50.81348771
CMS-70	A	Compressor-2	17-01-2024 10:29	19-01-2024 23:15	9.865365612
CMS-69	A	Tank-2	20-01-2024 17:49	21-01-2024 0:07	7.830741333
CMS-68	A	Compressor-2	21-01-2024 7:16	22-01-2024 0:02	7.280364451
CMS-67	A	Compressor-3	22-01-2024 2:24	22-01-2024 7:15	1.872333732
CMS-66	A	Compressor-3	22-01-2024 6:48	23-01-2024 1:56	11.11957246
CMS-65	A	Tank-1	22-01-2024 13:05	23-01-2024 2:59	15.78909064
CMS-63	A	Dehydrator-1	23-01-2024 16:02	24-01-2024 8:27	19.49150927
CMS-64	A	Dehydrator-1	23-01-2024 16:02	24-01-2024 6:27	27.31177958
CMS-62	A	Dehydrator-1	24-01-2024 15:06	25-01-2024 1:46	17.92923359
CMS-61	A	Dehydrator-1	25-01-2024 16:45	26-01-2024 5:08	19.41097409
CMS-60	A	Dehydrator-1	26-01-2024 13:50	27-01-2024 6:36	22.35054016
CMS-59	A	Dehydrator-1	27-01-2024 1:45	27-01-2024 8:08	13.98306741
CMS-57	A	Dehydrator-1	27-01-2024 10:10	28-01-2024 3:15	13.09969511
CMS-58	A	Dehydrator-1	27-01-2024 10:10	27-01-2024 23:37	16.04159662
CMS-56	A	Dehydrator-1	28-01-2024 15:43	28-01-2024 23:59	10.05147194
CMS-55	A	Dehydrator-1	29-01-2024 15:48	30-01-2024 0:36	12.67874941

CMS-54	A	Dehydrator-1	31-01-2024 17:15	01-02-2024 3:30	60.47970498
CMS-53	A	Dehydrator-1	01-02-2024 13:45	01-02-2024 22:38	10.77638599
CMS-52	A	Dehydrator-1	02-02-2024 23:30	03-02-2024 6:10	24.7853662
CMS-51	A	Dehydrator-1	03-02-2024 11:03	03-02-2024 15:53	17.19845255
CMS-50	A	Dehydrator-1	04-02-2024 13:38	05-02-2024 8:05	23.45762222
CMS-49	A	Dehydrator-1	07-02-2024 4:05	07-02-2024 9:11	14.86192301
CMS-48	A	Dehydrator-1	07-02-2024 17:09	07-02-2024 21:40	13.72649872
CMS-47	A	Dehydrator-1	08-02-2024 8:39	08-02-2024 14:27	17.22924512
CMS-45	A	Dehydrator-1	08-02-2024 17:30	09-02-2024 4:10	11.86600299
CMS-46	A	Dehydrator-1	08-02-2024 17:30	09-02-2024 4:10	14.76924197
CMS-44	A	Dehydrator-1	10-02-2024 6:47	10-02-2024 16:31	6.821435342
CMS-43	A	Dehydrator-1	10-02-2024 14:50	10-02-2024 23:17	28.89126158
CMS-42	A	Dehydrator-1	11-02-2024 15:45	12-02-2024 5:38	123.3328614
CMS-41	A	Dehydrator-1	16-02-2024 11:51	16-02-2024 16:46	14.83360889
CMS-40	A	Dehydrator-1	22-02-2024 2:22	22-02-2024 9:08	17.60689626
CMS-39	A	Dehydrator-1	22-02-2024 11:25	23-02-2024 4:36	33.41612275
CMS-38	A	Compressor-2	23-02-2024 14:04	24-02-2024 3:23	18.51180616
CMS-37	A	Compressor-2	24-02-2024 8:34	24-02-2024 18:34	11.69312178
CMS-36	A	Compressor-2	27-02-2024 10:58	27-02-2024 15:44	14.44655555
CMS-35	A	Compressor-2	01-03-2024 17:52	01-03-2024 23:27	16.77220239
CMS-34	A	Compressor-2	03-03-2024 4:38	03-03-2024 22:15	17.15981442
CMS-33	A	Compressor-3	07-03-2024 5:57	07-03-2024 10:56	11.42898031
CMS-32	A	Compressor-2	07-03-2024 7:16	07-03-2024 15:02	16.23481555
CMS-31	A	Compressor-2	08-03-2024 12:23	10-03-2024 0:18	14.71608663
CMS-29	A	Compressor-3	14-03-2024 9:15	14-03-2024 23:52	15.29498708
CMS-30	A	Tank-1	14-03-2024 9:15	14-03-2024 23:52	14.74954203
CMS-28	A	Tank-1	15-03-2024 7:54	15-03-2024 19:43	10.83058592
CMS-27	A	Compressor-2	18-03-2024 15:35	19-03-2024 1:32	13.08735161
CMS-25	A	Separator-2	21-03-2024 16:45	22-03-2024 2:54	12.4923744
CMS-26	A	Dehydrator-2	21-03-2024 16:45	22-03-2024 2:54	15.49997366
CMS-24	A	Separator-2	22-03-2024 11:45	23-03-2024 4:40	19.45596602
CMS-23	A	Separator-2	23-03-2024 15:56	24-03-2024 8:16	20.77621499
CMS-22	A	Separator-2	29-03-2024 12:10	29-03-2024 18:10	50.5477992
CMS-21	A	Separator-2	05-04-2024 14:08	05-04-2024 17:58	19.2303107
CMS-20	A	Separator-2	05-04-2024 15:40	05-04-2024 20:41	53.27457756
CMS-19	A	Separator-2	06-04-2024 1:59	06-04-2024 5:50	18.95548269
CMS-18	A	Separator-2	09-04-2024 8:27	09-04-2024 19:36	18.53332709
CMS-17	A	Separator-2	10-04-2024 14:25	11-04-2024 0:11	140.6241274
CMS-16	A	Separator-2	11-04-2024 15:06	11-04-2024 22:43	55.89072104
CMS-15	A	Separator-2	12-04-2024 14:09	12-04-2024 22:15	29.79022037
CMS-14	A	Separator-1	13-04-2024 0:00	13-04-2024 8:05	14.72482916
CMS-13	A	Separator-1	14-04-2024 1:54	14-04-2024 5:54	16.01493411
CMS-11	A	Separator-1	16-04-2024 4:25	16-04-2024 10:40	13.04163146

CMS-12	A	Separator-1	16-04-2024 4:25	16-04-2024 10:40	9.677583744
CMS-10	A	Separator-1	17-04-2024 5:04	17-04-2024 14:09	24.53500301
CMS-9	A	Separator-1	18-04-2024 13:26	18-04-2024 20:51	14.93944563
CMS-8	A	Separator-1	18-04-2024 22:32	19-04-2024 2:41	17.65106764
CMS-7	A	Separator-1	19-04-2024 14:49	20-04-2024 2:49	35.81272269
CMS-6	A	Separator-2	20-04-2024 14:10	20-04-2024 16:35	77.00366334
CMS-5	A	Separator-1	22-04-2024 14:00	23-04-2024 10:07	77.63196097
CMS-4	A	Separator-1	26-04-2024 10:15	26-04-2024 16:38	10.80466042
CMS-3	A	Separator-1	27-04-2024 6:05	27-04-2024 13:57	16.03540446
CMS-2	A	Separator-1	28-04-2024 7:12	28-04-2024 19:16	11.16171355
CMS-1	A	Separator-1	29-04-2024 23:25	30-04-2024 4:48	29.86309642

Table S3. Synthetic flyover measurements in the case study No.1.

ID	site	equipment	detection time	detection	survey time	rate (kg/hr)
FLY-1	A			FALSE	07-01-2024 17:31	1538.3
FLY-2	A	Compressor-2	22-02-2024 19:40	TRUE	22-02-2024 15:40	53
FLY-3	A	Compressor-3	22-03-2024 19:40	TRUE	22-03-2024 16:40	64
FLY-4	A		05-04-2024 19:14	TRUE	05-04-2024 16:14	38.5

Table S4. Synthetic OGI measurements in the case study No.1.

ID	site	equipment	detection	survey time	number of leaks
OGI-1	A		FALSE	01-01-2024 17:31	0
OGI-2	A	Compressor-2	TRUE	01-02-2024 15:40	2
OGI-3	A	Separator-2	TRUE	01-03-2024 16:40	4
OGI-4	A		FALSE	01-04-2024 16:14	0

Table S5. Synthetic venting events in the case study No.1.

ID	site	equipment	start time	end time	total emissions (kg)
OP-1	A	Compressor-3	01-01-2024 4:25	01-01-2024 4:35	182.79626
OP-2	A	Tank-1	01-01-2024 13:34	01-01-2024 13:40	231.25869
OP-3	A	Tank-1	02-01-2024 6:50	02-01-2024 6:57	159.22217
OP-4	A	Tank-1	03-01-2024 15:15	03-01-2024 15:20	263.07187
OP-5	A	Compressor-2	05-01-2024 7:30	05-01-2024 7:35	339.0873
OP-6	A	Tank-2	06-01-2024 0:40	06-01-2024 0:50	263.41729
OP-7	A	Compressor-3	06-01-2024 11:30	06-01-2024 11:35	263.41729
OP-8	A	Compressor-3	06-01-2024 17:25	06-01-2024 17:30	333.67572
OP-9	A	Compressor-2	07-01-2024 1:30	07-01-2024 1:35	537.58866
OP-10	A	Compressor-2	07-01-2024 9:30	07-01-2024 9:35	3515.5696
OP-11	A	Compressor-2	07-01-2024 11:00	07-01-2024 11:05	335.88641

OP-12	A	Compressor-3	08-01-2024 9:35	08-01-2024 9:40	311.91426
OP-13	A	Compressor-2	10-01-2024 7:30	10-01-2024 7:35	390.3246
OP-14	A	Compressor-2	10-01-2024 9:50	10-01-2024 9:55	401.44712
OP-15	A	Tank-1	12-01-2024 9:45	12-01-2024 10:35	606.50225
OP-16	A	Compressor-3	23-01-2024 7:10	23-01-2024 7:15	416.32321
OP-17	A	Tank-1	25-01-2024 9:00	25-01-2024 10:00	432.74218
OP-18	A	Compressor-2	03-02-2024 7:40	03-02-2024 7:45	339.84722
OP-19	A	Dehydrator-2	05-02-2024 14:14	16-02-2024 11:45	2.0650047
OP-20	A	Compressor-2	10-02-2024 8:41	10-02-2024 8:45	307.9995
OP-21	A	Compressor-3	10-02-2024 9:04	10-02-2024 9:07	480.05704
OP-22	A	Compressor-2	10-02-2024 10:14	10-02-2024 10:16	541.158
OP-23	A	Compressor-2	10-02-2024 11:00	10-02-2024 11:03	423.1395
OP-24	A	Compressor-2	13-02-2024 8:30	13-02-2024 9:10	382.33676
OP-25	A	Compressor-1	25-02-2024 7:22	25-02-2024 7:24	413.12232
OP-26	A	Compressor-1	26-02-2024 14:35	26-02-2024 14:37	615.999
OP-27	A	Compressor-3	29-02-2024 17:20	29-02-2024 17:25	309.03576
OP-28	A	Compressor-1	01-03-2024 11:45	01-03-2024 11:50	278.43155
OP-29	A	Compressor-1	16-03-2024 11:10	16-03-2024 11:15	347.5616
OP-30	A	Compressor-2	18-03-2024 9:10	18-03-2024 9:15	212.77872
OP-31	A	Compressor-1	20-03-2024 14:45	20-03-2024 14:47	513.98496
OP-32	A	Compressor-3	02-04-2024 10:23	02-04-2024 10:26	454.11216
OP-33	A	Compressor-1	06-04-2024 9:20	06-04-2024 9:26	245.70876
OP-34	A	Compressor-3	20-04-2024 13:19	20-04-2024 13:24	288.05024
OP-35	A	Compressor-3	22-04-2024 3:03	22-04-2024 3:14	123.09513
OP-36	A	Compressor-3	22-04-2024 6:40	22-04-2024 6:45	320.91821
OP-37	A	Compressor-1	23-04-2024 8:20	23-04-2024 8:25	415.77054
OP-38	A	Compressor-3	23-04-2024 11:40	23-04-2024 11:45	385.90322
OP-39	A	Compressor-2	26-04-2024 0:12	26-04-2024 0:35	53.88552
OP-40	A	Compressor-1	26-04-2024 22:20	26-04-2024 22:30	119.37715
OP-41	A	Compressor-2	27-04-2024 8:24	27-04-2024 8:35	147.85023
OP-42	A	Tank-3	27-04-2024 15:08	27-04-2024 15:24	122.45859
OP-43	A	Compressor-1	29-04-2024 23:13	29-04-2024 23:20	176.32869
OP-44	A	Compressor-2	29-04-2024 23:20	29-04-2024 23:26	229.5124
OP-45	A	Compressor-3	30-04-2024 2:05	30-04-2024 2:13	266.69303
OP-46	A	Compressor-2	30-04-2024 4:10	30-04-2024 4:19	221.6445
OP-47	A	Tank-2	30-04-2024 6:37	30-04-2024 6:50	1152.1794
OP-48	A	Compressor-2	30-04-2024 8:12	30-04-2024 8:23	109.69702
OP-49	A	Compressor-3	30-04-2024 9:50	30-04-2024 9:58	182.61204

Table S6. Synthetic CMS measurement in the case study No.2.

ID	site	equipment	start time	end time	rate (kg/hr)
CMS-1	B	Compressor-3	01-01-2024 2:16	01-01-2024 18:46	13.43743062
CMS-2	B	Compressor-2	01-01-2024 17:12	02-01-2024 0:32	11.0537834
CMS-3	B	Tank-1	02-01-2024 8:38	03-01-2024 2:14	6.485984945
CMS-4	B	Dehydrator-1	03-01-2024 1:20	03-01-2024 17:55	9.745295575
CMS-5	B	Tank-1	03-01-2024 23:33	04-01-2024 3:06	5.279977194
CMS-6	B	Separator-1	04-01-2024 12:02	04-01-2024 20:25	44.44340994
CMS-7	B	Dehydrator-1	05-01-2024 12:21	05-01-2024 14:09	26.4754512
CMS-8	B	Separator-2	05-01-2024 18:40	06-01-2024 15:03	10.2931667
CMS-9	B	Dehydrator-1	06-01-2024 12:55	07-01-2024 6:39	22.90488356
CMS-10	B	Separator-3	07-01-2024 3:28	07-01-2024 7:34	4.38235222
CMS-11	B	Tank-1	07-01-2024 15:50	08-01-2024 5:10	15.68792648
CMS-12	B	Dehydrator-1	08-01-2024 21:11	09-01-2024 5:36	23.01335768
CMS-13	B	Dehydrator-1	09-01-2024 4:54	09-01-2024 15:33	16.46214129
CMS-14	B	Dehydrator-1	09-01-2024 20:05	10-01-2024 10:21	6.575924082
CMS-15	B	Dehydrator-1	10-01-2024 9:17	11-01-2024 20:43	9.97428315
CMS-16	B	Tank-1	12-01-2024 8:57	15-01-2024 9:31	39.60280338
CMS-17	B	Dehydrator-1	15-01-2024 9:19	15-01-2024 12:30	4.631917288
CMS-18	B	Compressor-2	15-01-2024 11:46	16-01-2024 6:06	127.1398731
CMS-19	B	Compressor-3	16-01-2024 11:53	17-01-2024 3:15	50.81348771
CMS-20	B	Compressor-2	17-01-2024 10:29	19-01-2024 23:15	9.865365612
CMS-21	B	Tank-2	20-01-2024 17:49	21-01-2024 0:07	7.830741333
CMS-22	B	Compressor-2	21-01-2024 7:16	22-01-2024 0:02	7.280364451
CMS-23	B	Compressor-3	22-01-2024 2:24	22-01-2024 7:15	1.872333732
CMS-24	B	Wellhead	22-01-2024 6:48	23-01-2024 1:56	11.11957246
CMS-25	B	Tank-1	22-01-2024 13:05	23-01-2024 2:59	15.78909064
CMS-26	B	Dehydrator-1	23-01-2024 16:02	24-01-2024 8:27	19.49150927
CMS-27	B	Compressor-1	23-01-2024 16:02	24-01-2024 6:27	27.31177958
CMS-28	B	Dehydrator-1	24-01-2024 15:06	25-01-2024 1:46	17.92923359
CMS-29	B	Separator-2	25-01-2024 16:45	26-01-2024 5:08	19.41097409
CMS-30	B	Dehydrator-1	26-01-2024 13:50	27-01-2024 6:36	22.35054016
CMS-31	B	Dehydrator-1	27-01-2024 1:45	27-01-2024 8:08	13.98306741
CMS-32	B	Separator-2	27-01-2024 10:10	28-01-2024 3:15	13.09969511
CMS-33	B	Compressor-1	27-01-2024 10:10	27-01-2024 23:37	16.04159662
CMS-34	B	Separator-2	28-01-2024 15:43	28-01-2024 23:59	10.05147194
CMS-35	B	Dehydrator-1	29-01-2024 15:48	30-01-2024 0:36	12.67874941
CMS-36	B	Tank-2	31-01-2024 17:15	01-02-2024 3:30	60.47970498

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