Advances in UAV-Based Methane Emission Monitoring: Sensors, Sampling Geometry, and Quantification

Nabin Bhandari, Akshansha Chauhan[1], Simit Raval[1], *

[1] School of Minerals and Energy Resources Engineering, University of New South Wales, Sydney, Kensington, 2052, NSW, Australia

Emails: nabin.bhandari@unsw.edu.au; akshansha.chauhan@unsw.edu.au; simit@unsw.edu.au

*Correspondence: simit@unsw.edu.au

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School of Minerals and Energy Resources Engineering, University of New South Wales, Sydney, Kensington, 2052, NSW, Australia

*simit@unsw.edu.au

Abstract

Unmanned aerial vehicles (UAVs) are one key platforms for monitoring methane due to their flexible deployment with spatial scales between ground-based sensors and crewed aircraft This review synthesises research on UAV sensing technologies, flight and sampling strategies, quantification methods, and validation practices. It finds that quantitative performance depends on the combined choice of sensor, platform, flight geometry, wind measurement, and estimation method. The key UAV-deployable sensor categories are contrasted based on sensitivity, response, payload restrictions, and field of use, which includes open-path tunable diode laser absorption spectroscopy (TDLAS) and closed-path TDLAS, quantum cascade laser absorption spectroscopy (QCLAS), active AirCore, non-dispersive infrared (NDIR), and thermal imaging sensors. Multirotor UAVs support repeated transects and vertical plume sampling, while fixed-wing platforms are primarily suited to broader-area screening. Mass-balance and Gaussian inversion methods can estimate emission rates, but their results are sensitive to wind uncertainty and incomplete plume coverage. Tracer-based approaches can reduce direct reliance on wind measurements when tracer and methane plumes disperse together. Controlled-release studies also show that small average bias can coexist with substantial errors in individual flights. Across sectors, methods are more developed for oil and gas facilities, landfills, and coal-mine ventilation shafts than for agriculture and wastewater. The literature reviewed identified no dedicated peer-reviewed UAV methane quantification study at an active surface coal mine. Wider use of UAVs for emissions assessment will require survey designs matched to source characteristics, stronger field validation, and more consistent uncertainty reporting.

Keywords: Methane emissions; Uncrewed aerial vehicles (UAVs); Plume sampling; Emission quantification; Uncertainty assessment

1. Introduction

Advances in unmanned aerial platforms, miniaturized gas sensors, and onboard data systems have opened new possibilities for UAV-based methane monitoring over the last 10 years. Small UAVs are now small enough to be easily portable and operationally adaptable for use in hazardous, inaccessible, or logistically challenging areas to support a standard ground survey. More recent projects have demonstrated effective uses of UAVs for gas and oil leakage monitoring, landfill emissions mapping, and agricultural methane monitoring, (Yong et al., 2024; Shaw et al., 2021; Fosco et al., 2024). UAVs can bridge the gap between local ground measurements and more global perspectives from airborne or satellite measurements as an intermediate-scale observation platform (Fox et al., 2019; Shaw et al., 2021; Li et al., 2025). Besides scientific benefits, UAV-based systems offer operational benefits, such as quick hotspot screening and support for near-real-time mitigation efforts (Zavala-Araiza et al., 2015; Fox et al., 2019). As a result, recent years have seen rapid growth in interest in UAV-based sensing systems and their applications in methane detection.

Despite this progress, many technical issues still hinder reliable, widespread operational use in the observation and quantification of methane. The major concerns are the selection of sensors, the integration of platforms sampling strategy, quantification approach, and validation, since the sensing modality significantly affects field performance (Shaw et al., 2021). Open-path and closed-path tunable diode laser

absorption spectroscopy (TDLAS), quantum cascade laser absorption spectroscopy (QCLAS), active AirCore, non-dispersive infrared (NDIR) methane sensors, and thermal imaging technologies have recently become UAV-deployable technologies (Asher et al., 2021; Tuzson et al., 2020; Andersen et al., 2018; Shah et al., 2019; Fosco et al., 2024). These systems vary significantly in sensitivity, accuracy, response time, payload weight, power consumption, and endurance (Kwaśny and Bombalska, 2023; Li et al., 2025; Hollenbeck et al., 2021; Shaw et al., 2021). Additionally, the sampling strategy, namely the UAV's direction and path relative to the source of emissions. As opposed to fixed instruments, UAVs are capable of sampling various sections of a plume in space, and the effectiveness of sampling is highly dependent on the design of flight paths, the geometry of plume interception, and the meteorological conditions during survey (Nathan et al., 2015; Yang et al., 2018; Golston et al., 2018).

A third difficulty is transforming raw methane measurements into useful products such as emission maps, source-localization results, or source emission rate estimates (Mohammadloo et al., 2024). Some quantification methods have been applied to UAV-based methane data, such as mass-balance models, Gaussian plume inversion, tracer flux ratio (TFR) models, and, more recently, machine-learning frameworks (Scheutz et al., 2025; Tiemann et al., 2025). However, these methods of quantification are sensitive to wind conditions, plume structure, background concentration, and sensor response (Mohammadloo et al., 2024; Morales et al., 2022; Wietzel et al., 2025). Incomplete plume capture, uncertain wind characterization, sensor lag, and spatial interpolation errors can all propagate directly into the final emission estimate.

Another issue is validation and reporting. Due to the relatively new field, methane sensing by UAV systems lacks a solid framework for validating measurements and reporting uncertainties, and as a result, comparing studies becomes difficult and inaccurate (Dooley et al., 2024; Shaw et al., 2021). By contrast, more developed methods of measuring methane, which include tracer flux release measurement, and eddy covariance measurements, with crewed-aircraft mass balance surveys, tend to adhere to more developed methods of uncertainty assessment and bias measurements (Lamb et al., 1995; Roscioli et al., 2015; Daube et al., 2019). Studies on UAVs based observation are more based on controlled-release experiments, simulation benchmarks, and intercomparison exercises (Morales et al., 2022; Dooley et al., 2024). The necessity to standardize validation procedures, mitigate uncertainty, and standardize performance reporting is the focus of the further evolution of UAV-based methane monitoring.

Existing UAV methane studies have mainly focused on oil and gas facilities, ventilation shafts, landfills, agricultural sources, with broader methodological development, including sensing technologies, flight strategies, and quantification frameworks (Shaw et al., 2021; Yong et al., 2024; Fosco et al., 2024; Li et al., 2025). This development has, however, not yet extended to for the surface coal mines. The recent studies focusing on methane in the coal-mining industry are largely based on satellite and crewed-aircraft methods as opposed to UAV-cantered observation and measurements (Sadavarte et al., 2021; Borchardt et al., 2025; Harris et al., 2026). Borchardt et al. (2025) has mentioned that the literature on verification of methane emissions on open-cut coal mines is still underdeveloped and lacks the well-constrained quantification in mine-scale studies. Likewise, Harris et al. (2026) demonstrated aircraft-based top-down estimations and reported emissions of coal mines on the surface did not agree well in the Bowen Basin, which means that the existing methods of estimating surface coal mines still need significant enhancement. Thus, to the best of our knowledge, the peer-reviewed research dedicated solely to UAV-based observation and quantification of methane of surface coal mines still does not exist.

Against this background, the present review examines UAV-based methane detection and quantification through four interlinked themes: sensing modalities, flight-path patterns and sampling strategies, quantification approaches, and validation/uncertainty assessment. To guide this review, the following research questions are addressed:

1. What sensing modalities have been integrated into UAVs for methane monitoring, and what constraints shape their field performance?
2. How do UAV flight patterns and sampling geometries align with different monitoring objectives and source types, and how do trajectory choices affect detection capability?
3. What inference methods are used to convert UAV methane measurements into emission maps or emission-rate estimates, and what are their principal assumptions and limitations?
4. What validation and uncertainty assessment practices are employed in UAV-based methane studies?

Through these themes, the review evaluates current capabilities, identifies existing limitations, and highlights methodological gaps that must be addressed for broader UAV application, including future deployment in surface coal mine methane monitoring.

2. Study Selection

Given the rapid developments and open challenges outlined above, this article presents a comprehensive review of UAV-based methane emission detection, with particular attention to how sensor technology, deployment strategies, analytical techniques, and validation practices interact to determine measurement performance. The literature was identified through a structured database search, with the search strategy and selection criteria summarized in Table 1. The time window was chosen to span the early adoption of lightweight gas sensors on small UAV platforms through to recent advances in quantification and inverse modelling, while the inclusion of conference papers and book chapters alongside journal articles ensured that emerging applied work was captured together with peer-reviewed methodological developments.

Table 1: Search Strategy and Criteria

Item	Source / Criteria
Database	Scopus
Keywords	UAV AND Methane
Time Range	2010–2025
Document Type	Article, Review, Conference Paper, Book Chapter
Language	English

3. UAV Platform Selection

Platform selection is important in UAV-based methane monitoring because it directly influences sensor payload capacity, endurance, maneuverability, plume-interception geometry, onboard wind measurement, and the suitability of different quantification approaches. So, platform should be taken as a methodological factor that interacts with sensing modality, sampling strategy, and uncertainty, rather than as a standalone hardware description. In the literature on methane quantification, there are two high-priority UAV platform classes: multirotor and fixed-wing UAVs. The most commonly used platform for quantitative flux estimation is a multirotor system, as it can hover, repeat horizontal transects, and perform vertical profiling of the area with high positional precision while integrating different types of methane sensors, Fig. 1. An example of this is the DJI Matrice 600 Pro hexa-rotor, which carries a mid-infrared laser absorption spectrometer and a 3D ultrasonic anemometer to measure both methane concentration and wind direction, enabling direct mass balance computation (Andersen et al., 2021). Multi-level downwind curtain transects across both point sources and distributed sources (such as landfills and wastewater treatment plants) can be done using such systems with payloads up to 6 kg and flight times of approximately 18-25 min (Andersen et al., 2021).

Figure 1: Drone integrated with: a) AirCore and QCLAS sensors, b) Falcon Plus TDLAS, c) MIRA Strato, d) Tether connected to ground-based sensor

Conversely, fixed-wing UAVs have primarily been used for detection and screening rather than for accurately measuring flux (Barchyn et al., 2017; Dooley et al., 2024; Bretschneider et al., 2024). Their superior speed on the cruise and their lengthier duration render them efficient in pipeline examination and scan-scale reconnaissance, yet their ineffectiveness in hovering or undertaking thick crosswind transects limits the applicability of the mass-balance method. Therefore, research that utilizes fixed-wing platforms typically focuses on frequency and detection of anomalies of plume encounters (Barchyn et al., 2017). The comparisons made between the two classes of platforms further suggest that the multirotor UAVs offer more valid wind measurements due to their lower relative airspeed, as the aerodynamic distortion of onboard anemometers is reduced, unlike in the fixed-wing platforms, which have a stronger flow perturbation, making it difficult to retrieve the wind on the ground (Andersen et al., 2021). As a result, multirotor UAVs have been dominant in quantitative methane flux estimation, as they allow simultaneous quantification of wind, position, and methane concentration within a quasi-Eulerian sampling frame. Future development is directed toward hybrid VTOL-fixed-wing designs and onboard autonomy; existing findings indicate that maneuverability and hovering help to achieve near-field plume observation and quantification.

4. Sensing Technology

4.1. Open Path TDLAS

Open-path TDLAS measures methane along an atmospheric beam path rather than in a sampling cell, so its output is a path-integrated concentration, commonly reported in ppm-m, rather than a true local point concentration. It operates on the principle of simple, selective absorption of methane by a tunable near-infrared diode laser, which follows the Beer-Lambert law, typically with wavelength modulation to improve sensitivity and eliminate noise. It includes a diode laser that emits approximately 1.65 μm, laser current regulation, temperature regulation, transmitting and receiving optics or a reflector/backscatter

target system, a photo detector, and digital signal-processing (Well et al., 2005; Wang et al., 2019). The sensor in open-path mode measures the attenuation of a laser beam that has been shot through the air surrounding it and reflected off a surface, and therefore does not sample air in a cell, giving a column-integrated methane signal, Fig. 2. It is at the core of remote leak detectors, and the backscatter-TDLAS concept has been proven useful for detecting methane even when the returned signal strength varies due to changes in surface reflectance, dust, and motion (Gao et al., 2006). The main advantages of open-path TDLAS are its non-contact operation, fast response, high methane selectivity, and ability to cover large areas without pumps, tubing, or sampling cells. Commercial examples of this sensing class include the MSA Senscient ELDS open-path methane detector, the Boreal Laser Gas Finder family, such as GasFinder3-AB and GasFinder3-VB, and remote laser methane detectors such as the Pergam Laser Falcon and LMF G2, which have been used in ground based and UAV-related methane-inspection workflows. As soon as small aerial platforms became reliable, open-path laser sensing naturally transferred to airborne methane research. One important step was to demonstrate that high-rate open-path measurements could indeed reflect the true variability of a facility structure rather than a single "snapshot" of emissions. Nathan et al. (2015) found a broad dynamic range of observed emissions between flights using an aircraft making repeated passes around a compressor station, and that seeing large temporal variations at a mean and median rates, and temporal peaks of orders of magnitude, suggested that temporal intermittency is a first-order challenge to methane monitoring and repeated sampling often provides more value than single flights carefully flown transects. This framing translated directly into UAV work, where the same sensing principle was packed into lightweight remote methane leak detectors and mounted on multirotor. Yang et al. (2018) described a UAV-mounted mini remote methane leak detector (RMLD) system based on backscatter TDLAS, in which a downward-facing sensor measured column-integrated methane. Their controlled-release experiments showed distinct methane enhancement peaks above background during UAV surveys, demonstrating the suitability of this configuration for leak detection and preliminary quantification. Building up on this, Golston et al. (2018) formalized the operational workflow, which consists of detection, localization, and rate estimation and demonstrated that, given enough repeated passes as well as spatial averaging, it is possible to localize at scales down to the meter and maintain sensitivity to small, controlled leakages; multiple flights, in practice, localized the error down to 1 m in aggregate. Because open-path sensors measure a line-integrated signal, emission estimates depend strongly on sampling geometry, wind conditions, and plume coverage; repeated passes are therefore often used to improve robustness (Golston et al., 2018; Yang et al., 2018; Cossel et al., 2023). Another recent corroboration of the same open-path absorption concept can be seen through trade-space as a specific example: Cossel et al. (2023) demonstrated a ground-to-UAV open-path configuration in which a ground-based spectrometer measured total column methane along the path to a retroreflector mounted on a UAV, allowing emission quantification without placing the gas analyser onboard the aircraft. Their results showed that reliable quantification depended less on the instrument's intrinsic sensitivity than on adequate sampling of the plume structure through repeated scans and appropriate flight geometry. Collectively, the literature on open-path TDLAS has an obvious progression: Early experiments in robust backscatter absorption sensing, then airborne experiments in strong temporal variability, then operationalizing detection and localization with meter-scale performance, and most recently, more complex architectures (including gimballed pointing and long-standoff geometries) in which sensor aiming, flight pattern and inversion method are considered to be a design issue. Open-path TDLAS continues to be a workhorse in modern UAV-based methane monitoring, with tools used to find and localize leaks, and is also capable of quantifying when combined with wind-aware sampling approaches and repeated cross-plume measurements, although the most effective designs are those explicitly tailored to the fact that a sensor is used to measure a column rather than a point.

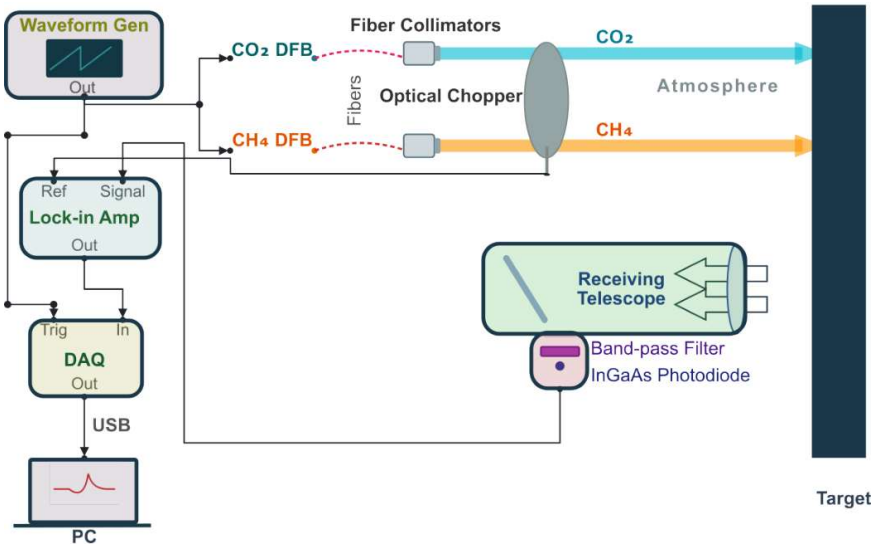

Figure 2: Working of Open Path TDLAS sensor, (Siozos et al., 2022)

4.2. Closed Path TDLAS

In closed-path TDLAS, the measurements of methane occur within an enclosed optical cell following drawdown of the gas sample into the analyser and therefore, unlike open-path systems that provide path-integrated concentrations, it measures local point concentration. These systems are typically active at 1.65 μm absorption region as it is the spectral range. Kwaśny and Bombalska (2023) mentioned that it is one of the most significant optical tools of detecting methane since they possess high selectivity, fast responses, and an adequate match with practical equipment. The absorption of methane occurs within a controlled chamber with a known optical path length and a regulated gas flow, which enhances repeatability and minimizes the effects of ambient optical disturbances compared to open-path measurements in closed-path operation, Fig. 3.

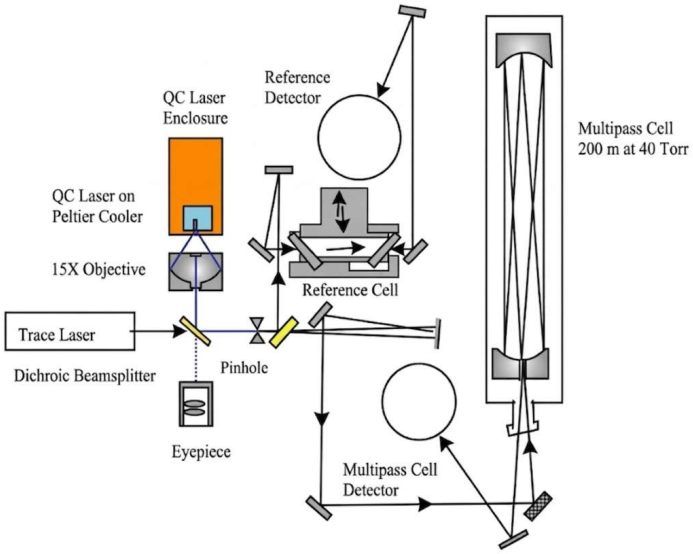

Figure 3: Working of Close Path TDLAS sensor, (McManus et al., 2002)

A closed-path TDLAS methane analyser typically requires a near-infrared diode laser, control of laser current and temperature, a gas inlet, filters, a pump or forced-flow, an enclosed absorption cell, a photodetector, and digital signal-processing electronics. Kong et al. (2024) showed that closed-path

methane sensors use compact multi-pass cells to increase the effective optical path length while keeping the cell volume small enough for practical response times. In their system, a two-mirror multi-pass cell provided an optical path length of 23.4 m within a cell volume of only 233.3 cm^3. Using this design, they reported a methane detection limit of 0.37 ppm. In closed-path TDLAS, methane absorption within the enclosed gas cell can be retrieved either by direct absorption spectroscopy (AS/DAS) or by wavelength modulation spectroscopy (WMS). Among these, WMS is often preferred because it improves sensitivity and signal-to-noise performance compared with direct absorption measurements. Liu et al. (2015) did the same with compact, dense-pattern multi-pass cell designs earlier, demonstrating that designs capable of achieving path-length enhancement were a central design principle in closed-path TDLAS. Since methane is measured inside an enclosed sampling cell rather than along an atmospheric beam path, closed-path TDLAS is generally less sensitive than open-path TDLAS to rain, fog, dust, beam-pointing instability, and variations in target reflectivity. So, it is common in fixed-station methane monitoring, process analysis, chamber studies, and the UAV in situ sampling of the plume. Scheutz et al. (2025) mentioned that a small Axetris LGD Compact-A closed-path TDLAS sensor can be incorporated into a UAV to measure methane emissions by integrating point measurements of methane output with onboard wind data. Their research revealed that small, closed-path TDLAS sensors now go beyond mere methane detection to support field-capable UAV-based emission measurements. Examples of commercial closed-path TDLAS methane sensors include the Axetris LGD Compact-A CH_4, the Axetris LGD Compact-A CH_4/C_2H_6, the Cubic Gasboard-2502, the Senovol TDL-LELM-1000, and the industrial Mettler Toledo GPro 500 CH_4. These instruments range from small to larger industrial analysers, but they all use the same basic closed-path TDLAS design: a near-infrared diode laser, a sealed gas cell, and wavelength-selective methane measurement. Once small UAVs proved reliable, closed-path TDLAS was widely adopted for airborne methane studies. It was demonstrated by Scheutz et al. (2025) that this type of configuration is applicable in real-world UAV emission research, and Kwaśny and Bombalska (2023) have made a more general point, saying that laser methane sensors are desirable in those cases when quick, selective, and field-deployable measurements are needed. A benefit of closed-path sensing in this application is that the methane signal can be immediately filled in, unlike an open-path signal, which is filled in by path integration. The key benefits of closed-path TDLAS are thus that it offers high selectivity to methane, point-concentration accuracy, reduced susceptibility to external optical perturbations, and direct integration with wind-coupled inversion techniques. Kong et al. (2024) gives a clear hardware example: the sensor uses a long optical path inside a small cell, which improves sensitivity without needing the laser beam to travel through open air. Another point highlighted by Shemshad et al. (2012) is that the availability of near-infrared diode lasers at near-room temperature is also a key factor that enabled the widespread adoption of methane TDLAS points in useful systems. The primary shortcomings are associated with gas manipulation and not with the spectroscopy per se: the tubing and pump add weight and power, the filters and cells need upkeep, the residence time either in the inlet or the cell can even out temporarily spikes of methane, and narrow or wavy plumes might be missed if the path of the sampling is improperly designed. That is, closed-path TDLAS makes methane measurements easier, but the sampling coverage and atmospheric transport uncertainties that continue to dominate the accuracy of field emission-rate measurements remain.

4.3. QCLAS

QCLAS differs from standard TDLAS mainly in the laser source and spectral region. QCLAS commonly operates in the mid-infrared, where methane has much stronger fundamental absorption bands than in the near infrared. The key innovation was the quantum cascade laser (QCL): Faist et al. (1994) demonstrated the property of 4.2 um pulsed lasing and realized the characteristic of QCLs -wavelength control through quantum-well band-structure engineering, not bandgap selection, that led to a straightforward way to compact mid-IR sources in which the methane absorption is inherently intense, Fig. 4. The second facilitating milestone in UAV-class spectrometers was the ability to reduce the optical path length to a

small size without compromising the stability. Graf et al. (2018) developed a mechanically rigid and optically stable cell concept of a segmented circular multi-pass that has up to 10 m effective path length, and a long-standing limit of multi-pass cell size was eliminated: they can be deployed in a mobile setting.

Based on these component improvements, the initial UAV-based QCLAS systems demonstrated that it is possible to achieve ppb-level methane precision at 1 Hz during flight without the need for lab-like facilities. A small, autonomous QCLAS specifically intended to operate on a drone was also reported by Tuzson et al. (2020), with a QCL at 7.83 um and a 10 m segmented circular multi-pass cell and the entire system In stable laboratory conditions, the instrument demonstrated 1.1 ppb (1s) accuracy at 1 s which was later flown in over 60 flights in a massive oil-and-gas campaign, demonstrating its operational realism. The design philosophy, highlighted by Tuzson et al. (2020), is to minimize heavy gas handling and, wherever possible, avoid pressure-controlled cells, which are beneficial for maintaining fast-time response and minimizing contamination risk. Practical benefits when it is desired to capture sharp and turbulent plume structures, but not the substantially averaged background signals. Coexisting with "classic" QCLAS, purpose-built mid-IR laser absorption payloads designed for field ruggedness are now common in UAV methane measurements, the most notable among them being the Aeris MIRA Pico family. When used in a validated UAV system, Dooley et al. (2024) explains that the MIRA Pico is a compact mid-IR laser analyser with a multi-pass absorption cell with a spectral bandpass of 2.5-4.7 um to measure CH_4 and C_2H_6 simultaneously. They provide precisions of about 1 ppb s -1 on CH_4 and about 0.5 ppb s -1 on C_2H_6, and point out an operational consideration that is important when using UAV plume assays: a phase lag of about 2 s is introduced by the inlet tube, so before mass-balance calculations are applied, methane/ethane time series must be synchronized to the wind and position streams. What finally identifies QCLAS-class sensors in the UAV literature is that they have now been adopted for high-resolution mapping and controlled-release validation of the emission-rate retrieval. Morales et al. (2022) used a fast-response QCLAS and an active AirCore sampler installed on a commercial UAV and calculated the flux with a multi-altitude curtain in a vertical plane downwind of the source in a dedicated uncertainty study. More importantly, they introduced cluster-based kriging to reconstruct the plume-plane and discovered that it performed better in quantification compared to ordinary kriging; overall, the average bias at the plane was 1 percent and the average residual of the single errors was 54 percent, meaning that in the area of the sensor precision, the ppb scale, the rest of the uncertainty is due to sampling geometry and meteorology and not the noise of the analyser. Their

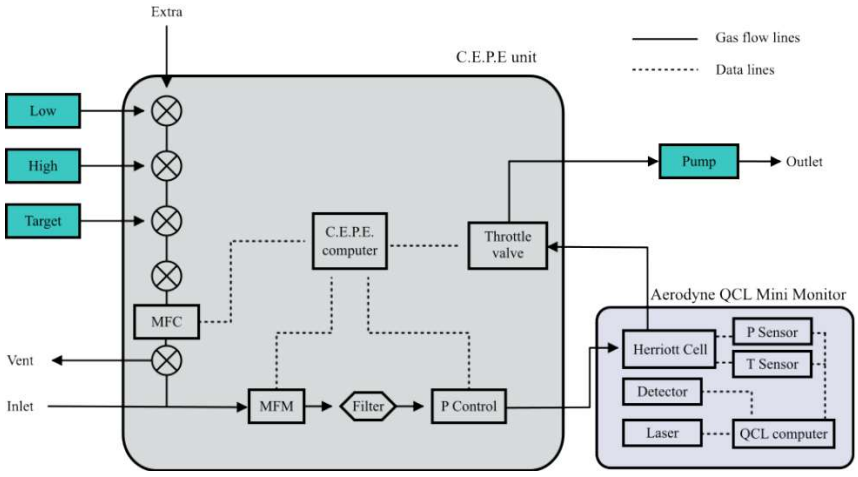

Figure 4: Working of Aerodyne QCLAS sensor, (Pitt et al., 2016)

direct comparison further indicates why QCLAS is commonly regarded as the onboard "reference": AirCore time series were smoothed down to an average lag of about 7 s and actually possessed an average

lag of about 20 s to the QCLAS signal, i.e. plume peaks and gradients are better maintained when retrieval of the onboard signal is required to be based on a sophisticated reconstruction of the narrow plume structure.

4.4. Active AirCore

Active AirCore is a UAV-adapted sampling method that separates air collection from high-precision lab analysis, enabling the sampling of methane plumes without carrying a full spectrometer on board the UAV. The active AirCore described by Andersen et al. (2018) (including 50 m stainless-steel tubing that requires dryer, micro-pump, and data logger) has a weight of 1.1 kg that is appropriate for small payload carrying UAVs and is housed in a carbon-fibre shell. The working protocol is standardized whereby the pump is activated just before take-off and switched off upon the completion of the quantification flight to confine the sampled time to gather the samples and suitable analysis performed on site cavity ring-down spectroscopy, which is shown in Fig. 5. In practice, the main trade-off of AirCore is that it captures the realistic variability of plumes but delivers a smoothed methane Y signal compared to quick, in-situ monitors. As demonstrated by Morales et al. (2022), due to turbulence, instantaneous methane structures are non-Gaussian and patchy, thus are sharpened up by a fast-response QCLAS analyser but smeared in AirCore, and since they are simultaneously flighted in Fig. 4, their comparison is presented on the same. To measure and correct this Morales et al. (2022) derive and compute a shift-stretch-smooth, 3S transformation, which then extracts parameters to scale high-resolution QCLAS time series to the lower-resolution AirCore response; the air mixing in the CRDS cavity is identified as the dominant contributor to the smoothing process and further contributions are made by molecular diffusion and storage in storage and Taylor diffusion and sampling/analysis in analysis.

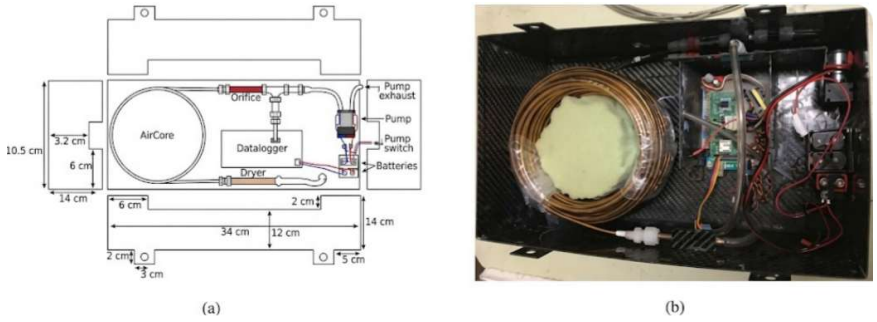

Figure 5: AirCore Sensor in UAV a) Diagram, b) Image, (Andersen et al., 2018)

Since AirCore is a sampling system rather than a visual depiction or direct image of the plume, the crucial element of its success in quantifying the sampled air is its spatiotemporal mapping of the sampled plume relative to the UAV track. The previous data confirms that the ability of standard UAV GPS in the vertical direction is only up to +-0.5m, which is not enough to construct the plume plane precisely is the concern that prompts the implementation of RTK-GPS to achieve the centimetre-level positional accuracy and coordinate timings among instruments and navigation records (Morales et al., 2022).

4.5. NDIR

Non-dispersive infrared (NDIR) sensing is one of the oldest and most common technologies for detecting methane and is the historical basis for most portable and UAV-based methane detectors. It can be traced back to the way its development occurred in industrial analysis of gases related to gas society work and the mid-20th century, employing infrared absorption to sense the presence of the gas in a particular band to identify the makeup of gases like CO_2 and CH_4. SJH-5B-SL NDIR-based sensor can detect 0 -5 % Volume concentration of methane. NDIR works on the principle of broadband absorbing infrared governed by the Beer-Lambert law where an infrared source emits radiation within a fixed optical chamber, there is

a narrow optical filter that isolates a band of methane absorption usually near 3.3 μm, and a thermopile or pyroelectric detector is used to measure an attenuation rate that is dependent on methane concentration, which is represented in Fig. 6. NDIR is also insensitive to individual absorption lines, unlike laser-based methods. This method of work ensures that a single bandpass filter measures the total absorption across the bandpass, making the hardware simpler, but it diminishes spectral selectivity and sensitivity. This became possible with miniaturized IR sources and compact detectors developed in the early 2000s, which enabled NDIR modules to be lightweight and low-power, and therefore some of the early methane sensors were placed on small unmanned aerial vehicles. Initial mapping of UAV methane in landfills, agricultural areas, and local industries that leaked nearby showed that NDIR systems were both mechanically durable and affordable, and sensitive enough to detect significant increases in methane. Nevertheless, with further advances in the research of UAV methane instruments to a stage of quantitative emission-rate recovery, NDIR limitations increasingly became clear. The most common limits of detection are in the tens of ppm range, with an accuracy of ±30 ppm, depending on the design and environmental stability. Since ambient methane levels are about 1.9 ppm, NDIR would not be able to detect subtle enhancement of the plume on top of ambient with a strong near-source gradient (Fosco et al., 2024), (Li et al., 2025).

Experiments have shown that NDIR measurements are also vulnerable to changes in temperature, pressure, and humidity, and algorithms based on compensation methods are needed, though there is no guarantee that rapidly changing atmospheric conditions will not drift over time. This slow reaction speed of 1-5 sec can flatten sharp plume gradients observed during UAV survey trails, resulting in erroneous mass-balance flux estimates in a mass-balance flux algorithm. The presence of cross-sensitivity with all other hydrocarbons and water vapor also makes the interpretation of the methodology more difficult, especially in mixed-emission conditions. Therefore, although NDIR is still quite appropriate for hotspot determination, rapid screening, and low-cost screening programs, it is seldom used as the primary method in controlled-release quantification studies that require ppb-level accuracy and high response.

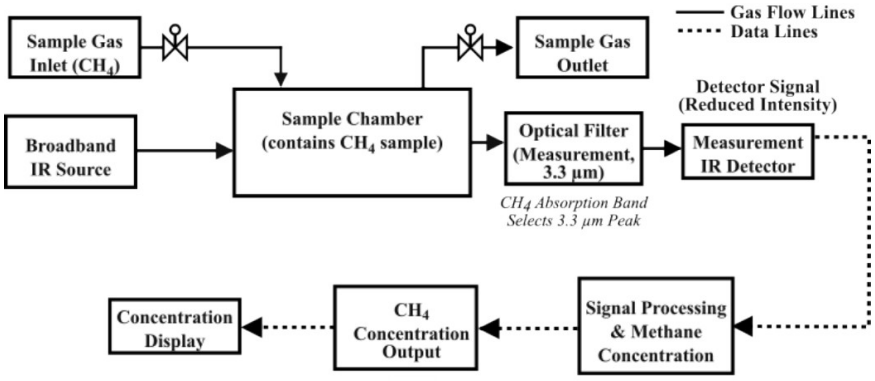

Figure 6: Simplified working-principal schematic of a single-channel NDIR methane sensor, showing infrared transmission through a methane-containing sample chamber, wavelength selection near the 3.3 µm absorption band, detector response, and concentration calculation.

Compared with mid-infrared QCLAS and cavity-enhanced methods like CRDS or OA-ICOS, NDIR is at the lower end of the figure of merit, but offers size, weight, power consumption, and operational ease as advantages. It does not need high-finesse optics, wavelength control, or sensitivity to vibration, and it is more tolerant of small UAV platforms. Primarily, in current UAV methane quantification systems, NDIR is used as a detection device, as a complementary sensor, or in experiments where anticipated methane improvements are large (>50-100 ppm), but more generally in experiments in which the goal is to accurately measure the rate of emission inversion.

4.6. Thermal Infrared

Studies related to Thermal Infrared methane sensing has evolved infrared thermography into a wider family that also, or at least includes, optical gas imaging (OGI) and hyperspectral IR plume detection, all sharing a common basis that a methane has diagnostically useful absorption/emission characteristics throughout the infrared (including both MWIR and LWIR bands) which can be utilized to detect remote plumes under radiometric contrast conditions. In its conventional thermography form (which was widespread at landfills prior to the deployment of UAVs), the sensor would not directly measure the mole fraction of methane but would directly measure emitted long-wave infrared radiance and refer this to surface temperature, attempting to identify spatial patterns that were consistent with the expected warm landfill gases pathways or perturbed heat exchange as in early landfill applications by field tests of the use of IR thermography to control biogas Madruga et al. (2007) and in later close-range aerial thermographic researcher Fjelsted et al. (2019) tested a UAV-carrying TIR camera to map out hotspots of landfill-gas emissions and specifically optimized the acquisition to give a high level of thermal contrast (acquisition images taken before sunrise) using a TIM450 camera (Micro-Epsilon; 7.5-13 um band, approximately 382 x 288 pixels, 0.04 $°C$ temperature resolution, ± 2 $°C$ system accuracy) and flying at an altitude of approximately 20-25 A. When thermography was used to screen for potential methane sources, reliable detection with the TIR camera under Danish conditions required both sufficient radiometric (thermal) contrast and a hotspot covering at least 1 m^2. The method therefore shows some promise, but only when conditions are favorable. Plume-visualization modality is designed to make gas clouds a contrast feature using spectral filtering and scene/background radiance instead of temperature alone on surfaces; though its effectiveness and reliability at detection strongly depend on environmental radiance, temperature contrast, range, and operator/algorithm settings, this is why this modality has been critically scrutinized in the methane context (Ravikumar et al., 2017). Active differential IR imaging utilization direct visualization of methane distribution at a time: MacGruer et al. (2025) show an example of using a UAV to carry a methane imaging system which intermittently switches laser diodes on and off a 1.6 um methane line and compares backscatter images with the camera to visualize gas distributions, which exemplifies the continuing shift in the paradigm between "thermal anomaly screening" and more spectrally specific imaging methods of localizing gas distributions rapidly.

Following Table 2 summarizes all the sensor type, with UAV implication, sensitivity and field performance notes

Table 2: Summary of UAV-deployable methane sensing approaches, including representative implementations, reported sensitivity or precision, and key field-performance characteristics.

Sensor type	Representative UAV implementations	Sensitivity / precision	Field performance notes
Open-path TDLAS	Fixed-wing transceiver–retroreflector open-path TDLAS; multirotor scanning/path-integrated TDLAS (e.g., AiLF U10); handheld/open-path systems such as Laser Falcon, (Xu et al., 2025)	5 ppm-m at 40 Hz for AiLF U10; Laser Falcon reported with a 0–50,000 ppm measurement range, (Xu et al., 2025)	Well suited to rapid, large-area screening, but path-integrated measurements have lower spatial resolution than point concentration measurements. Scanning TDLAS is efficient but lower-resolution than point-sampling approaches, (Xu et al., 2025).
QCLAS	Commercial systems (e.g., Aeris MIRA Pico) on small multirotor mapping platforms; custom compact QCL spectrometers for mobile sensing and controlled-release studies, (Gålfalk et al., 2021; Tuzson et al., 2020)	Commercial MIRA Pico: 0.84 ppb s^{-1} at 1 Hz, with accuracy better than 5 ppb after stabilization; custom compact QCLAS: 1.1 ppb (1σ) in 1 s and 0.1 ppb at 100 s averaging time under stable laboratory conditions,	QCLAS offers very high sensitivity for UAV-based methane mapping and quantification. Reported limitations include long-term and semi-periodic drift at the ppb level, while field flux uncertainty is often dominated by meteorological conditions and sampling design rather than intrinsic sensor

Sensor type	Representative UAV implementations	Sensitivity / precision	Field performance notes
		(Gålfalk et al., 2021; Tuzson et al., 2020)	precision, (Gålfalk et al., 2021; Tuzson et al., 2020).
Closed-path TDLAS	UAV-mounted closed-path TDLAS modules with multi-pass gas cells (e.g., Axetris LGD Compact-A), (Olaguer et al., 2022)	0.4 ppm lower detection limit, 2 Hz sampling frequency, and 10 ppb resolution reported for an LGD Compact-A implementation, (Olaguer et al., 2022)	High selectivity and reduced dependence on surface reflectivity; performance depends on inlet design, flow stability, and residence time, (Olaguer et al., 2022).
Active AirCore	UAV-based active AirCore sampling followed by ground-based CRDS analysis, (Morales et al., 2022)	Better than 0.7 ppb (1σ) at 0.25 Hz for the CRDS analysis, (Morales et al., 2022)	Useful for controlled-release and farm-scale quantification studies. Temporal filtering can bias retrievals unless corrected, and field uncertainty depends strongly on wind regime and sampling strategy, (Morales et al., 2022).
NDIR	Low-cost UAV methane sensing, mainly in screening and proof-of-concept studies, (Shah et al., 2019)	±1.16 ppm at 1 Hz Allan-deviation precision reported for a UAV-deployed methane NDIR sensor, (Shah et al., 2019)	Lower precision than laser-based sensors and more susceptible to background fluctuations; generally better suited to coarse screening than rigorous flux quantification. Existing NDIR approaches are also sensitive to water vapor, drift, temperature, and pressure effects, (Shah et al., 2019).
Thermal IR	UAV-mounted thermal-IR cameras for landfill hotspot screening, (Fjelsted et al., 2019)	Minimum observable hotspot reported at about 150 g CH_4 m^{-2} d^{-1} from areas larger than 1 m^2; associated thermal anomalies were typically 0.7–1.2 ° C, (Fjelsted et al., 2019)	Best used for screening and hotspot targeting, not direct quantitative flux quantification. Performance is strongly site-dependent and influenced by meteorology and barometric pressure, (Fjelsted et al., 2019).

Note: Reported sensitivity or precision values are representative of selected studies and may vary depending on the specific sensor model, optical path design, sampling configuration, calibration state, ambient temperature, pressure, humidity, platform-induced flow effects, and other operating conditions.

5. Quantification Methods

Quantifying methane emissions from airborne measurements is fundamentally an inverse problem: emissions must be inferred from imperfect, sparse observations of concentration within a turbulent flow field. At the altitudes typical of UAV operations, plumes are strongly intermittent and can meander laterally under variable winds, leading to cross-section measurements that may under-sample peak concentrations or miss plume filaments.

5.1. Mass-Balance

Mass balance is one of the most common top-down methods for estimating methane emissions using UAVs. This procedure helps measure the concentration of methane in the vertical plane or a curtain of the source downwind and uses wind information to convert the enhancements into a methane flux across the plane. On the assumption that methane acts as a chemically inert tracer on the small scale on which a specific sample is taken and that the flow is approximately constant across the sample duration, Morales et al. (2022); Mohammadloo et al. (2024) mentioned that the rate of source emission is assumed to be the net excess of methane that is flowing across that downwind plane. This renders the technique particularly appealing for UAV use, since it estimates the entire source emission rate based on observed atmospheric quantities rather than just the number of equipment or emission factors. In a typical practical UAV survey, Vinković et al. (2022) flew the aircraft perpendicular to the direction of the mean wind at multiple altitudes as the plume is subsequently covered in both lateral and vertical directions. Background methane has been estimated either by measuring upwind or by portions of the transect off the plume, and the rate of emission is then determined by integrating the concentration of background minus the transect with the wind part perpendicular to the plane of sampling. The most convenient expression is represented by following, Eq 1.

$$Q_{CH_4} = \int_z \int_y \left(C(y,z) - C_{bg}(y,z)\right) u_{\perp}(y,z)\, dy\, dz \quad (1)$$

where, C is the methane concentration, C_{bg} is the background concentration, and $u_{\perp}$ is the wind speed perpendicular to the measurement plane. In discrete UAV applications, this integral is estimated from a combination of measured samples along sequential horizontal transects or curtain flight lines (Morales et al., 2022; Xu et al., 2025). This fundamental framework has been used with closed-loop even-sampling systems, active AirCore, QCLAS, and open-path TDLAS on multirotor UAVs.

One of the most significant advantages of the mass-balance approach is its directness and integration with sources. While estimating total emissions from any sources, this method does not require a detailed prior description of every individual leak point. This is the reason why it has been used effectively in most methane sources. Andersen et al. (2021) study of coal mine shafts and Vinković et al. (2022) study of dairy farms, Gålfalk et al. (2021) study of wastewater/agriculture, and Yong et al. (2024) study of landfill emissions, all indicate that operational-scale estimates of methane can be performed with UAV measurements of a mass-balance approach.

One more significant benefit is that UAVs provide an opportunity to apply the classical concept of aircraft mass balance in near-field and hard-to-reach areas. Multirotor UAVs can cruise at low speed, hover, revisit transects, and sample near the plume, thereby enhancing spatial resolution compared to large and medium-sized conventional aircraft. Newer systems also integrate methane and wind measurements on board and do not rely on remote weather stations. Dooley et al. (2024), have also reported a UAV-based system with simultaneous CH4, and vector-wind measurements capable of measuring sources with a range of 0.04 to 1500 kg/h and Gålfalk et al. (2021) have demonstrated a lightweight QCLAS Aeries MIRA sensor system that utilized plume cross-sections to model a simple system, with all measurements made onboard the drone, without requiring supplementary ground-based instruments.

Regardless of these benefits, the mass-balance method is still highly reliant on the completeness of measurement and quality of wind fields. The plume should be taken in full, across the full width and height, the flux is underestimated. Morales et al. (2022) demonstrated that plume reconstruction and interpolation are paramount, and an advanced cluster-based kriging strategy was more effective than the standard kriging. During their controlled-release trials, the stabilized bias was approximately 1% on average, but the stabilized residual of the individual errors was 54 %, indicating that low bias did not always entail low scatter in individual flights. Andersen et al. (2021) also discovered that inverse Gaussian inversion was better than mass balance in their coal mine shaft emissions case, although they did emphasize that mass balance could not cope in circumstances where plume sampling was incomplete, or where sparse data would become significant in their interpolations.

In the literature, the leading sources of uncertainty always include wind speed, wind direction, background concentration, flight spacing, and plume reconstruction. Vinković et al. (2022) discovered that both horizontal wind speed and wind-direction angle are dominant, and onsite wind measurements greatly enhanced the estimation. In the low altitude box sampling method by Xu et al. (2025) in small oilfield sources, the average relative error was calculated to be 18.5 %, and the average uncertainty was 55.75% with wind speed being the greatest source of uncertainty, then directions of the wind next causing the uncertainty followed by background methane. Yong et al. (2024) further notes that spatially distributed, heterogeneous emissions complicate estimations, highlighting that background definition, interpolation methods, and onboard wind measurements are critical factors for accuracy.

Some recent validation efforts indicate that this approach provides useful accuracy, but single-flight data should be interpreted with some caution. The results of Scheutz et al. (2025) tested a drone flux technique relative to the control releases of 2.18 or 3.59 kg/h. and had an error rate of between +33 % to 35 %. In a real biogas-plant comparison, the drone method gave 25.3 ± 6.2 kg/h, while the tracer gas dispersion

method gave 25.7 ± 4.4 kg/h over the same interval, whose uncertainty is 46 % when a single flight was quantified: they too indicated that 2 or 3 flight replicas could theoretically reduce the uncertainty to 33 % and 27 %, respectively.

5.2. Gaussian Plume Inversion

Gaussian plume inversion (GPI) is a top-down, model-based method for estimating methane emission rates from concentration enhancements measured downwind of a source. Plume is supposed to be a time-averaged Gaussian distribution in crosswind directions as well as vertical direction, and estimation of the source strength is performed through fitting the plume model to the observed results. In methane sensing with UAVs, this approach is usually used with downwind transects, vertical profiling or flux-plane sampling along with local wind measurements. Shah et al. (2019) developed a near-field Gaussian plume inversion (NGI) model of UAV measurements at the close vicinity of point sources, whereas Shaw et al. (2021) mentioned that it is one of the best quantification approaches for local-scale UAV-based methane quantification studies. The general form of gaussian inversion model at a point *(x,y,z)* is expressed as, Eq 2:

$$\Delta C(x,y,z) = \frac{Q}{2\pi U \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right)\left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right] \quad (2)$$

where Q denotes the methane emission rate, U represents the mean wind speed, H is the effective height of the source, and σ_y and σ_z are the lateral and vertical dispersion parameters, respectively. In inversion mode, the emission rate is determined by minimizing the difference between the predicted and observed concentrations. Shaw et al. (2021) reported that implementing more advanced approaches can improve the estimation of source location and dispersion parameters, which is particularly beneficial when there is uncertainty in the source position or in the meteorological data. In the case of UAVs, the workflow typically includes removing a background methane concentration, translating the observations into a source-relative frame based on the mean wind direction, and fitting a Gaussian model to the observed plume. The approach followed by Shah et al. (2019, 2020) uses the fit of the methane flux density over a vertical plane rather than concentration for turbulent near-source sampling. Subsequently, Shi et al. (2022a) created a genetic algorithm-interior point penalty function (GA-IPPF) inversion that is the best way of the Gaussian-dispersion parameters and has less dependency on the highly accurate auxiliary inputs. Yang et al. (2025) also demonstrated that the multi-source gambling plume inversion may be extended to large facilities with multiple emitting units. One of the biggest advantages of Gaussian plume inversion is that it presents a physical meaning of the plume description in terms of parameters. Since it does not directly integrate measurements, and it should only accommodate a plume model, which is suitable even when UAV sampling is constrained spatially. Nathan et al. (2015) once again measured early UAV-based measurements of methane in the surroundings of a compressor station, Andersen et al. (2021) measured UAV-based AirCore measurements of inverse Gaussian frameworks, and Yang et al. (2025) measured emitters in a wastewater treatment facility between many sources. These papers show that Gaussian inversion can help estimate emissions and localize sources. The other advantage is that the Gaussian inversion is computationally efficient and operationally practical. It is quicker to implement in field studies than more complex atmospheric transport models and thus useful for near-real-time decision support systems when UAV surveys are conducted. It can also work with various sensing architectures, such as in situ analysers, AirCore systems, and mobile concentration measurements.

Irrespective of the above advantages, the Gaussian plume inversion is more assumption-based than measurement-based approaches, which require constant wind conditions. As Shaw et al. (2021) highlighted, very near-field measurements of UAVs can resolve a turbulent plume in an instant instead of an averaged plume over time, particularly inside the range of 100 m from the source, which is important in the close-range UAV sampling. Shah et al. (2019) demonstrated that negative bias and high variability

may occur due to incomplete sampling of plumes, insufficient capability to sample close to the ground, and a short flight time in the retrieved fluxes. Kumar et al. (2024) have also observed that Gaussian inversions of landfill emissions were highly dependent on source representation and deteriorated with complex terrain, as well as with source-measurement distance and terrain-induced flow effects, which are relevant in complex locations with buildings, slopes, or intersecting plumes.

Additionally, wind characterization is a critical parameter, since the retrieved emission rate is directly proportional to wind speed; wind errors are therefore highly transferred to the final estimate of flux. The results of Wietzel et al. (2025) demonstrated that inaccurate wind data may lead to a significant error and suggested that onsite measurements of wind are vital in making a robust quantification. They also discovered that measurements too close to the source are less reliable and suggested using a greater source-measurement distance and repeated transects to reduce uncertainty.

5.3. Tracer Flux Ratio (TFR) Methods

Tracer Flux Ratio (TFR) techniques are controlled-release, top-down techniques in which a known rate of tracer introduction is added near/with the source of methane, and the rate of methane discharge is estimated from the ratio of the downwind increase in methane to the increase in tracer. The technique was applied to methane since studies of atmospheric tracers by (Lamb et al., 1995). In practice, most studies consider the ratio of the combined methane and tracer plumes rather than the instantaneous point ratio, since this is typically more robust to turbulence and less prone to imprecise overlap between the two plumes. Shah et al. (2025) explicitly reports that tracer-based methods of quantifying methane can be conducted without measurements of wind, and that integrated-plume ratios are more accurate compared to simpler ratio methods. The simplest expression for the methane flux estimation using TRF is expressed as, Eqn. 3.

$$Q_{\mathrm{CH_4}} = Q_{\mathrm{tr}} \frac{\Delta C_{\mathrm{CH_4}}}{\Delta C_{\mathrm{tr}}} \tag{3}$$

where Q_{tr} is the value of the known tracer release rate, ΔC_{CH4} and ΔC_{tr} are methane and tracer-gas concentration enhancement above background, respectively. One of the biggest strengths of TFR is that it does not rely directly on local wind-field estimation, which can also be among the biggest sources of uncertainty of other top-down approaches. It is also an integrated source approach; hence, it can measure emissions from entire facilities or parts of the site, rather than just a single leak point. To illustrate, the dual-tracer model of the facility, results collection, and processing by Roscioli et al. (2015) had facility-specific uncertainties of approximately 20% to 47%, whereas Daube et al. (2019) used airborne TFR around dairy farms and found that whole-site methane fluxes agreed well with existing ground-based tracer and mass-balance estimates.

The primary weakness of TFR is that methane and tracer should be subjected to nearly identical transport and dilution. Unless the tracer is properly collocated with the methane source, the resulting flux will be biased. Mønster et al. (2014) demonstrated that the placement of tracers should be correct, and the highest credible results were obtained when the ratio of the integrated plume was utilized. Delre et al. (2018) also demonstrated that a misplacement of upwind tracer by approximately 150 m led to an overestimation of nearly 50%, and discrepancies among instrument and tracer-gas combinations resulted in an estimate of methane emissions that varied by up to 18%. In the same study, high detection frequency, good precision, and a high tracer-release-to-noise ratio were found to be significant for making an application reliable.

In UAV-based methane sensing, TFR is appealing due to its physical simplicity, allowing it to operate without wind data, and its application to different sampling strategies and the quality of dual-gas sensing are highly dependent on each other. Recent small-UAV research by Alaba et al. (2025) demonstrated that arc-like flight paths enhanced plume capture as compared to conventional patterns, and a cumulative-sum estimator had relative error as low as 3.3% when the mixing was ideal, which is further discussed in 6.3.

Nonetheless, the same study also indicated that performance is very sensitive to whether co-dispersion is achieved and whether the UAV is sampling a sufficient portion of the plume structure.

5.4. Thermal Imaging Quantification

Quantification by thermal imaging determines the degree of methane emissions via infrared imaging without direct concentration measurement, a technique known as passive optical gas imaging. In this method, the plume is visualized in the infrared, or in UAV thermal mapping of surface anomalies, where inferred visual reports of methane leakage are generated. Kang et al. (2022) mentioned that passive optical gas imaging can be used to perform detection and localization, but quantification is more challenging, as the recorded signals are more dependent on the temperature of the background and the orientation of the sensor.

One of the greatest strengths of thermal imaging is its remote, fast, and broad spatial coverage. It is capable of scanning across a wide area, identifying leak locations, and controlling follow up measurements, which are particularly valuable when UAVs fly over multiple sources. Nevertheless, more recent reviews also indicate that quantification of methane by UAV-based thermographic imaging is still not as well developed as direct gas-sensing methods, and quantitative uncertainties remain rather high (Fosco et al., 2024).

UAV thermal imaging is not strictly a method for quantifying methane and is most frequently used in landfill applications as an indirect screening method. Fjelsted et al. (2019) demonstrated that a UAV-based thermal infrared camera possessed certain potential in the determination of methane hotspots when the conditions were favourable, with the minimum observable surface flux of approximately 150 /$m^2 d$ being observed in regions larger than 1 m^2. Tanda et al. (2020) also suggested a thermal-imaging technique founded on a surface energy balance and indicated that observed anomalies were approximately 3 K to 4 K hotter than adjacent soil and even mentioned the resulting estimates of methane as a preliminary analysis.

Some of the more recent studies of quantitative optical gas imaging by Ilonze et al. (2024), 75 % of the measurements had a factor of 3 difference to the actual methane release rate, with an individual error of -90 % to +831 %, which shows its accuracy depends strongly on release rate, wind condition, and background concentration.

6. Flight Patterns

Flight pattern design is a defining element of UAV-based methane monitoring, directly controlling detection probability, quantification bias, and uncertainty propagation. Unlike fixed monitoring platforms, UAVs introduce an explicit coupling between sampling geometry, atmospheric transport, and inference method, such that the flight path itself becomes part of the measurement model. As a result, sampling design should be viewed not as a logistical detail but as a statistical and physical choice that shapes what emissions can be detected, localized, or quantified. Across the literature, flight patterns have evolved from simple exploratory surveys toward increasingly structured geometries tailored to source type, wind regime, and inference objective. This section synthesizes dominant flight-pattern classes and their methodological implications.

6.1. Plume Tracking for Source Localization

Plume-tracking strategies are primarily used for source localization and leak detection, particularly when emission locations are unknown a priori or multiple potential emitters coexist. In this mode, UAVs operate reactively, adjusting their trajectories based on real-time methane enhancements relative to background levels. Common implementations include upwind–downwind gradient-following, zigzag search patterns, and gradient-ascent logic, in which the vehicle iteratively moves toward increasing concentration signals (Golston et al., 2018). These approaches are especially effective for identifying intermittent or spatially

compact leaks, such as fugitive pipeline releases or discrete venting points, where static sensors or coarse satellite pixels may miss short-lived plumes. However, plume tracking is inherently sensitive to wind variability and turbulence. Meandering plumes can generate false gradients, leading to oscillatory or biased localization paths (Ayasse et al., 2024). As a result, several studies emphasize the need for temporal smoothing, repeated upwind confirmation passes, or hybrid strategies that combine exploratory tracking with structured transects once a candidate source is identified (Golston et al., 2018). Barchyn et al. (2017) mentioned that a practical hybrid pattern appears in along-asset surveys where detection triggers a re-sampling manoeuvre, where a fixed-wing open-path methane system demonstrates this pattern family and operationalizes loopback logic: anomalies (higher than the predefined threshold) found during along-track sampling trigger a loopback re-flight to confirm plume consistency, Fig. 7. This design is explicitly positioned for industrial leak detection, where the signal is expected to be >2–3 ppm-v anomalies and where the priority is rapid screening rather than precise emission quantification, providing sensor-performance context relevant to pattern selection: an Allan deviation analysis suggests a minimum stable averaging timescale, which constrains how aggressively the UAV can manoeuvre while maintaining reliable concentration interpretation. In practice, this is a key differentiator between fixed-wing along-asset screening, which includes fast, long-endurance aircraft, and multirotor quantification, which can build dense cross-sections.

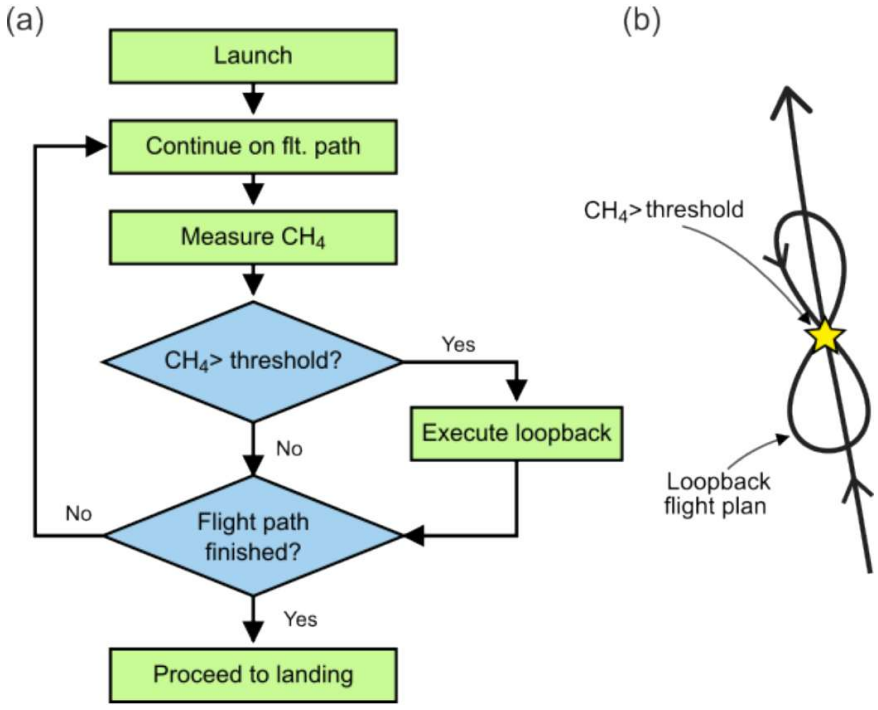

Figure 7: a) Flowchart to trigger the loopback in the presence of a higher concentration than the predefined threshold, otherwise continue the predefined flight path, b) Loopback pattern when triggered, (Barchyn et al., 2017)

6.2. Curtain Transects for Point-Source Flux Estimation

Curtain-style sampling, consisting of multiple horizontals transects flown perpendicular to the mean wind direction at successive altitudes downwind of a source, forms the methodological backbone of point-source methane quantification, particularly in coal-mine shafts and oil-and-gas operations. AirCore-based and in situ analyser systems commonly use these transects to reconstruct plume cross-sections, from which fluxes are derived using inverse Gaussian or mass-balance formulations, (Andersen et al., 2021) and (Andersen et al., 2023). Dooley et al. (2024) validated UAV-based quantification workflow showing strong agreement between UAV-derived flux and independently metered emissions across repeated flights.

Additionally, the author illustrated how the curtain logic extends to complex sites: for a landfill with a non-uniform emission structure, it uses longer transects and wider vertical coverage to cope with distributed emitters, reporting an example estimated flux of 1.33 ± 0.58 kg/h for that flight Fig. 8. Vertical extent is equally critical, as the curtain must fully span the plume rise and the effective mixing layer; failure to capture the full vertical plume results in a low bias, a contrast evident when comparing a well-defined point-source curtain with a distributed landfill case requiring much wider vertical coverage. Wind non-stationarity handling further differentiates high-and low-accuracy implementations: studies that segment flights or resample transects in response to plume meanders achieve lower errors than those that assume steady winds, as illustrated by the transect segmentation logic. Finally, georeferencing sensitivity, particularly the choice of altitude reference, positional accuracy, and measurement of wind speed, directly affects measurement of concentration, which measurably creates differences in emission estimation as well, Fig. 9.

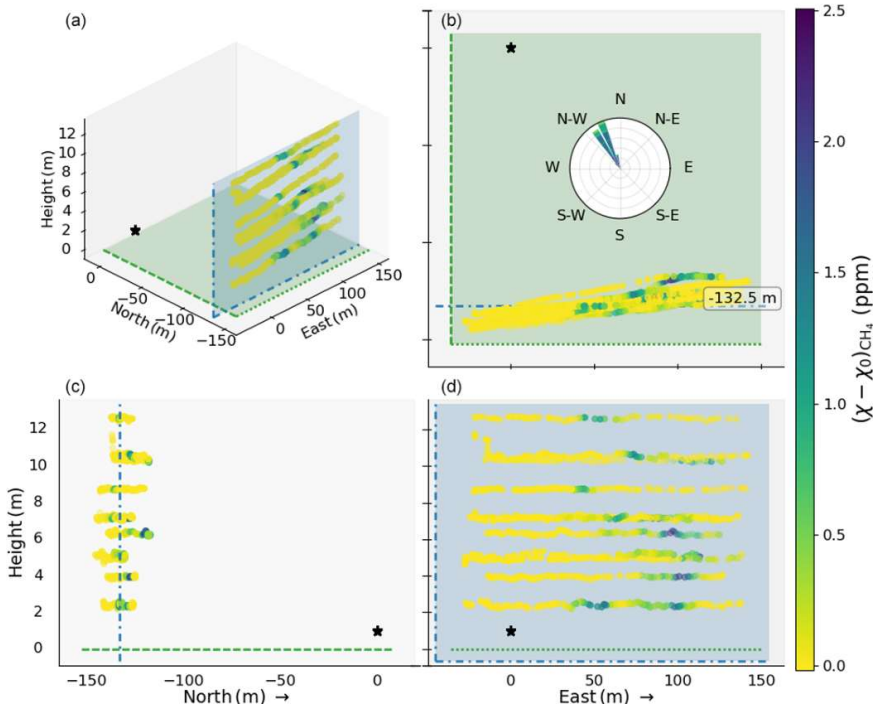

Figure 8: UAV methane plume-transect flight geometry for a controlled-release experiment: (a) three-dimensional view of the sampled flight curtain, (b) top view of the transects with the horizontal wind rose, (c) east-view projection, and (d) south-view projection. Marker colour denotes methane enhancement above background, $(\chi - \chi_0)_{CH4}$, while the black square indicates the approximate source location, (Barchyn et al., 2017)

Collectively, these comparisons show that curtain accuracy is not determined by a single factor, but by the coordinated design of sampling density, vertical coverage, wind-aware segmentation, and precise georeferencing.

6.3. Circular/Cylindrical and Arc sampling

At facility-scale or diffuse multi-source sites, such as compressor stations, landfills, or processing plants, curtain transects become less effective due to overlapping plumes and spatially distributed emissions. In these contexts, circular/cylindrical, and arc-shaped flight patterns have emerged as preferred alternatives. A rotary-wing UAV methodology for oil and gas facilities employs concentric circular sampling around the site, combined with a top-down retrieval algorithm that integrates concentration enhancements across azimuthal angles to estimate aggregate emissions (Xu et al., 2025).

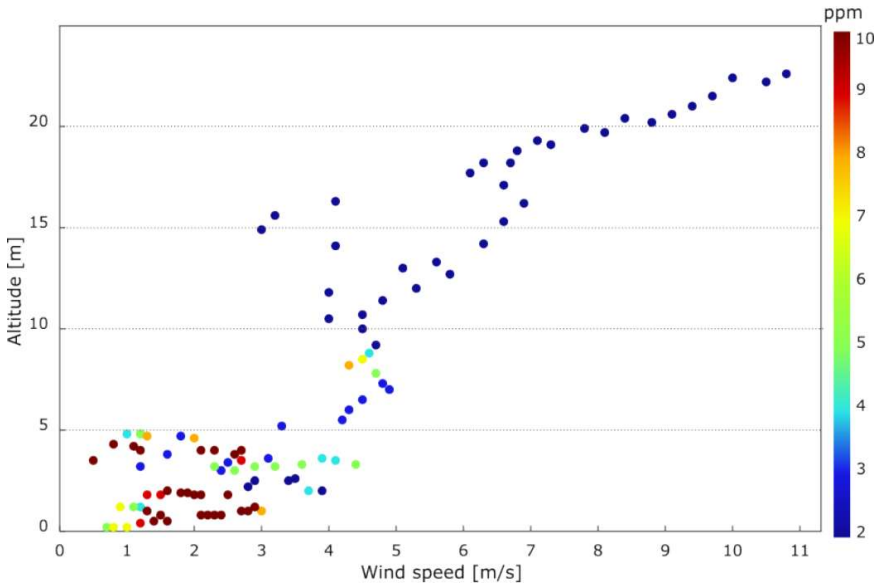

Figure 9: Vertical profile of wind speed and CH_4 concentration during UAV ascent and descent from 0 to 23 m above ground level, (Gålfalk et al., 2021)

A tracer-flux-ratio (TFR) focused study provides one of the clearest quantitative demonstrations that flight geometry fundamentally controls quantification accuracy and robustness, rather than serving merely as an operational choice. In this work, circular, cylindrical, and arc-shaped sampling patterns are explicitly compared, with the corresponding geometries illustrated in Fig. 10 and their performance summarized through heat-map comparisons in Fig. 11.

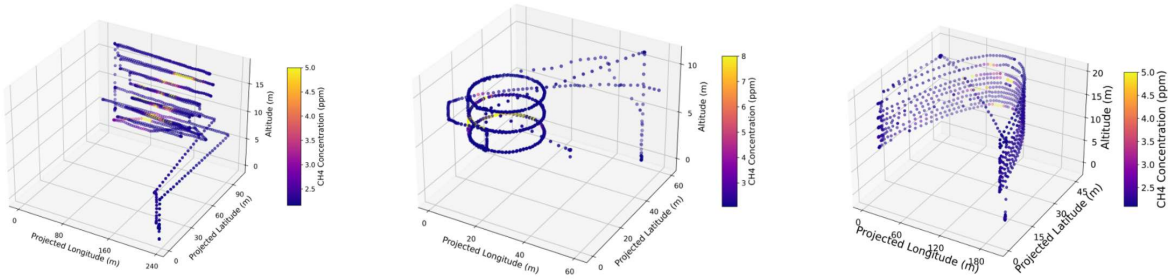

Figure 10: 3-D space concentration level in different flight patterns (a) Curtain flight pattern. (b) Cylindrical flight pattern. (c) Arc flight pattern, (Alaba et al., 2025)

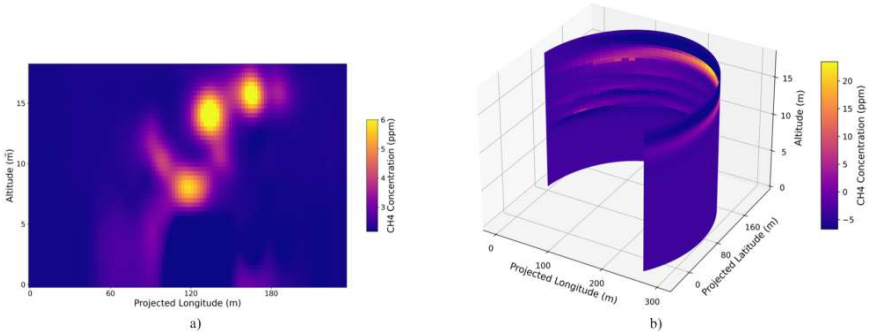

Figure 11: Flight path-based concentration data comparison (a) Curtain heat map. (b) Arc heat map, (Alaba et al., 2025)

Under idealized conditions characterized by favourable mixing, limited plume meander, and well-constrained tracer release arc sampling, a cumulative-sum estimator combined with a cumulative-sum estimator achieved a relative error of only 3.31 %, corresponding to an absolute uncertainty of 6.22 SLPM, representing the best-performing configuration evaluated in the study. When the experimental setup was made more challenging by introducing spatial separation between the tracer and methane release points, arc sampling maintained comparatively strong performance, with relative errors ranging from −39.93 % to +8.8 %, indicating substantially greater robustness to source separation and plume distortion than more conventional geometries. In contrast, curtain-style sampling exhibited pronounced sensitivity to plume geometry and alignment, producing very large negative biases in at least one tested configuration, with relative errors reaching −59.17 %, highlighting the vulnerability of linear cross-section approaches when plume structure deviates from underlying model assumptions. The same study further demonstrates that vertical sampling extent is a first-order control on accuracy: extending the vertical range of the sampling pattern reduced relative error from 8.8 % to as low as 0.38 % in one scenario, underscoring the importance of capturing the full vertical plume structure even in tracer-based methods, Fig. 12.

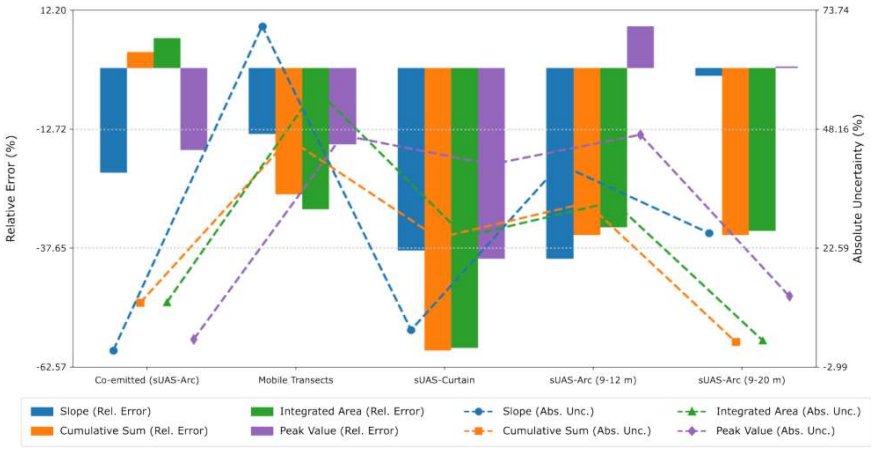

Figure 12: Comparison of relative error and absolute uncertainty in CH_4 emission estimates across different analytical methods and sampling strategies. Solid bars denote relative error (%) referenced to the left y-axis, while dashed lines with markers indicate absolute uncertainty (%) referenced to the right y-axis. Four analytical methods, namely Slope (blue), Cumulative Sum (orange), Integrated Area (green), and Peak Value (purple), are evaluated for different measurement approaches, including Co-emitted, sUAV-Arc, Mobile Transects, and sUAV-Curtain, (Alaba et al., 2025).

Complementing these findings, a method-focused synthesis of UAV methane quantification frames flight pattern choice as an explicit uncertainty-control strategy rather than a neutral design decision. This work aggregates results across multiple deployments and reports order-of-magnitude uncertainty ranges associated with different pattern families, noting that simple designs such as single transects often exhibit uncertainties on the order of ±60–100 %, while single-screen approaches typically fall in the ±30–80 % range, with wind estimation errors and concentration variability dominating the uncertainty budget (Xu et al., 2025). Through example site layouts and representative flight paths Xu et al. (2025), this research illustrates how increasing geometric redundancy and spatial averaging can systematically reduce sensitivity to wind non-stationarity and plume intermittency. Taken together, these studies reinforce the conclusion that sampling geometry directly shapes estimator variance, bias, and robustness, and that comparative evaluation of flight patterns must be grounded in quantitative error behaviour rather than operational convenience.

Table 3 compares the UAV flight patterns used for methane source localization and quantification in terms of flight pattern, quantification method, primary objective, key design parameters, and reported accuracy or uncertainty.

Table 3: Comparison of UAV flight patterns used for methane source localization and quantification.

Flight pattern	Quantification method	Primary objective	Key design parameters reported as important	Accuracy / uncertainty outcomes reported
Plume tracking for source localization	Inverse atmospheric gas-dispersion modelling applied to methane path-integrated measurements from a drone-tracked retroreflector system (Soskind et al., 2023).	Locate the emitting source and, secondarily, estimate leak rate from reconstructed plume geometry (Soskind et al., 2023).	Active tracking of a drone-mounted retroreflector; path lengths of about 40–150 m; multiple radial views of the plume; inversion quality depends on plume reconstruction geometry (Soskind et al., 2023).	Source localization was reported to ±1 m for drone-assisted tracking and ±7 m for stationary mapping; leak-rate estimates were reported within ±30% for low-flow controlled releases (Soskind et al., 2023).
Curtain transects	Mass-balance / integrated flux-plane methods; inverse-Gaussian plume fitting has also been used with stacked downwind transects (Andersen et al., 2021; Morales et al., 2022).	Direct emission-rate quantification of point sources or distributed emitters by sampling a vertically resolved downwind plume cross-section (Andersen et al., 2021; Dooley et al., 2024).	Transects flown perpendicular to mean wind with sufficient vertical coverage; favourable conditions included wind speed $\geq$ 2.3 m s^{-1}, wind-direction variability $\leq$ 33.1°, and downwind distance < 75 m (Morales et al., 2022). For distributed sources, longer transects and a wider altitude range may be required; Dooley et al. report a landfill case about 0.5 km downwind with transects up to ~500 m and altitude range up to 50 m (Dooley et al., 2024).	Under screened favourable conditions, RMSE was 39% and absolute error was 29%, compared with 69% and 54% for all flights (Morales et al., 2022). Dooley et al. also reported strong agreement with metered releases across eight validation flights and a distributed-landfill example of 1.33 ± 0.58 kg h^{-1} (Dooley et al., 2024).
Circular / cylindrical and Arc	Tracer flux ratio (TFR) methods using downwind arc-shaped flights; single-height concentric circular scanning with path-integrated TDLAS has also been reported for well-site quantification (Alaba et al., 2025; Xu et al., 2025).	Robust facility-scale quantification where conventional planar transects may miss portions of the plume or where source geometry and access constraints limit simple curtain sampling (Alaba et al., 2025; Xu et al., 2025).	For arc-based TFR, adequate vertical coverage, strong methane–tracer co-dispersion, and flight geometry that captures the downwind plume envelope were identified as key (Alaba et al., 2025). For concentric circular scanning, Xu et al. report repeated circular scans, radius range of 100–240 m, and circle spacing of 20–30 m; to keep release-rate deviation below 30%, they report wind-direction deviation < 40° and wind speed > 5.5 m s^{-1} for their well-site case (Xu et al., 2025).	Arc flights produced the lowest relative error and uncertainty across the tested TFR configurations; under ideal mixing, the cumulative-sum estimator achieved relative error as low as 3.3%, and increasing vertical coverage improved performance (Alaba et al., 2025). For single-height concentric circular scanning, Xu et al. reported an average deviation of 33.4% relative to on-site direct measurement, a maximum deviation of 53.5%, and a scenario-specific minimum quantification limit of about 0.404 kg h^{-1} (Xu et al., 2025).

Note: The arc-pattern results are based on tracer-flux-ratio experiments, whereas the circular-pattern results are based on single-height concentric scanning with path-integrated TDLAS at oil and gas well sites. Reported performance is therefore method- and scenario-specific.

7. Data Processing

7.1. Signal Pre-processing and Noise Reduction

The initial processing of data captured by UAV-mounted sensors is critical for ensuring temporal and spatial accuracy, particularly when integrating high-frequency gas measurements with flight telemetry. Temporal synchronization is achieved by performing cross-correlations between the internal GPS clocks of high-precision analysers (such as QCLAS or MIRA systems) and the primary UAV flight controller to correct for clock drift (Dooley et al., 2024) and (Morales et al., 2022). A significant engineering challenge involves phase lag correction; for instance, the Aeris MIRA Pico sensor experiences a measurement delay of approximately 2 seconds due to the constant pump flow rate through its intake tubing (Dooley et al., 2024). More pronounced lags are observed in AirCore systems, which typically exhibit an average time lag of 7 seconds and require a 20-second smoothing correction to align with faster-response analysers (Morales et al., 2022).

To mitigate electronic and atmospheric noise, raw concentration data are often filtered using statistical methods. This includes three-point smoothing of raw mixing ratios to decrease high-frequency fluctuations before further analysis. Figure. 13 illustrates the methane time-series preprocessing workflow used to isolate plume enhancements from background variability. The procedure includes smoothing, gradient-based identification of plume-affected samples, segment-wise outlier removal, and polynomial fitting of

the remaining background signal. This process is essential for reducing noise and drift prior to methane enhancement and flux estimation.

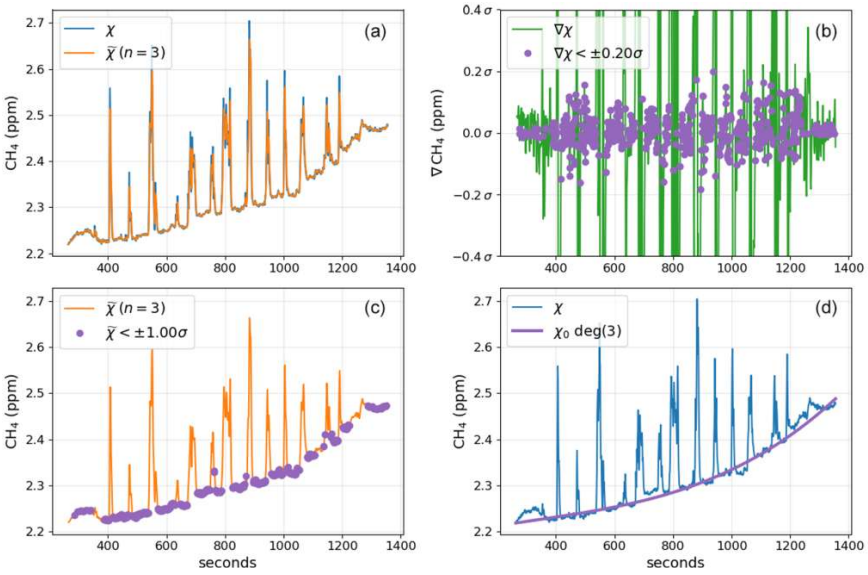

Figure 13: Methane time-series preprocessing workflow showing smoothing, gradient-based plume detection, background-sample filtering, and polynomial background fitting used for noise reduction and background correction prior to flux estimation, (Dooley et al., 2024).

For path-integrated TDLAS sensors, Fig. 14 illustrates the preprocessing workflow applied to methane measurements at different flight altitudes, including Kalman filtering and false-positive removal. This step was performed prior to background concentration estimation to reduce noise and eliminate spurious peaks that could bias the derived methane enhancement during the flight.

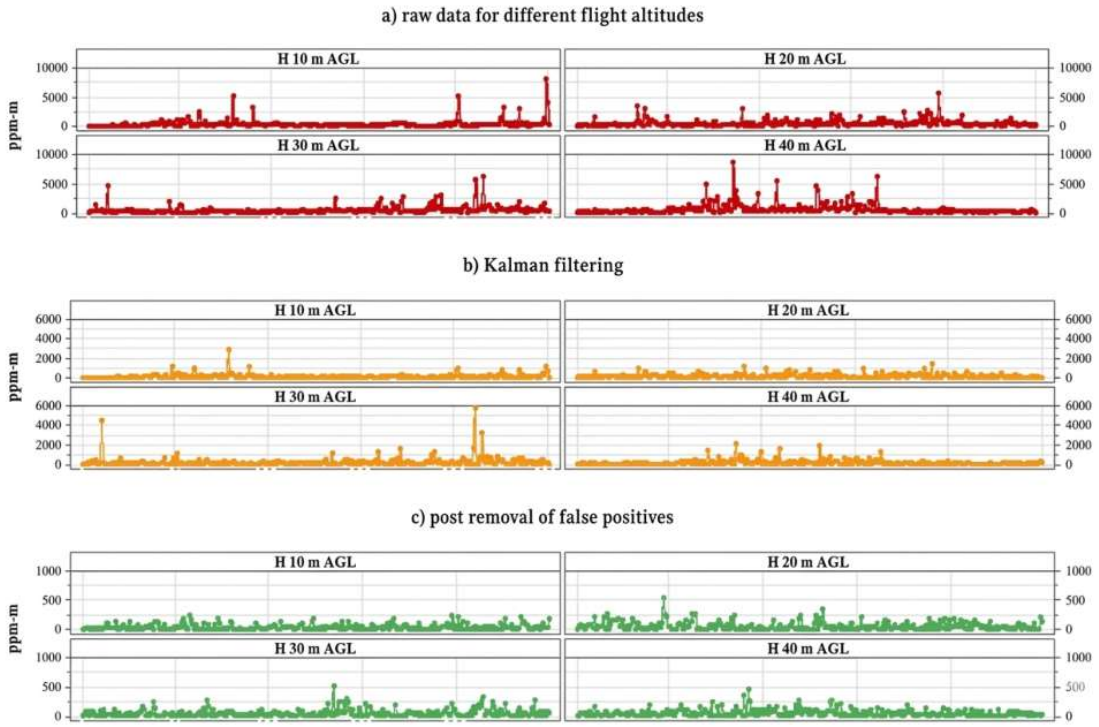

Figure 14: Methane concentration time series at four flight altitudes showing successive preprocessing stages: (a) raw measurements, (b) Kalman-filtered data, and (c) data after false-positive removal. The sequence illustrates the signal-cleaning procedure applied prior to background concentration and emission analysis, (Fosco et al., 2025a).

In the context of real-time methane imaging, pre-processing is even more intensive, utilizing Gaussian filters to smooth infrared frames and persistence filters that require a signal to appear in the same spatial location for six consecutive frames to be classified as a true detection rather than a motion artifact (MacGruer et al., 2025). Furthermore, in hazardous mining environments, high-frequency cut-off filters are used to distinguish between salt dust particles and true structural obstructions in LiDAR datasets (Nordström et al., 2025).

7.2. Background Concentration Estimation

Isolating source-specific enhancements from the ambient regional background is fundamental for accurate emission quantification. A prevalent technique involves polynomial fitting, where a variable-order polynomial is applied to measurements outside the plume. To isolate these "inter-plume" samples, a gradient filter is used to detect abrupt mixing ratio changes indicative of plume entry or exit; samples where the gradient exceeds a threshold, such as $\pm 0.2\sigma$, are removed to leave only background values for the fit Fig. 13. Alternatively, the Robust Extraction of Baseline Signal (REBS) algorithm utilizes local regression to correct for variability in background levels across the flight path, yielding determined background averages such as 2.09 ± 0.19 ppm in some validation campaigns (Morales et al., 2022).

In landfill applications where diffuse emissions are widespread, statistical parameters like the median or 25th percentile of the measured dataset are used as representative background values, particularly when the plume occupies a significant portion of the scanned plane. For regional source attribution, the Keeling plot method is employed, where or values are plotted against the reciprocal of concentration ($1/CH_4$); this linear regression allows researchers (Fosco et al., 2025a; Andersen et al., 2023) to interpolate the unique isotopic signature of the source endmember.

7.3. Wind Vector Transformation

UAV-mounted anemometers measure wind relative to a moving platform, so raw vectors must be transformed into a static, Earth-fixed coordinate system. This is achieved via a Galilean transformation using counterclockwise (CCW) Euler rotation matrices based on the instantaneous UAV heading and velocity. For flux calculations, researchers generally compare two primary meteorological models: the Scalar Wind (SW) approach, which applies to a normal component uniformly across a measurement plane, and the Logarithmic Wind (LW) profile, represented by Eqn. 4. Morales et al. (2022) considered the LW model to be more robust as it uses a theoretical profile to vertically extrapolate measurements from a reference height typically 2 m to the UAV's altitude, accounting for atmospheric stability and surface roughness (z_0).

$$\mathbf{u} = \mathbf{R}(\phi)\,\mathbf{u}_m + \mathbf{V}_s$$

$$\mathbf{u} = \begin{bmatrix} \cos(\phi) & \sin(\phi) & 0 \\ -\sin(\phi) & \cos(\phi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_m \\ v_m \\ w_m \end{bmatrix} + \begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} = \begin{bmatrix} u \\ v \\ w \end{bmatrix} \tag{4}$$

Here, $\mathbf{u}_m = [u_m, v_m, w_m]^T$ denotes the TWS-measured wind vector, $\mathbf{u} = [u, v, w]^T$ is the adjusted wind velocity in Earth-fixed coordinates, and $\mathbf{V}_s = [V_x, V_y, V_z]^T$ is the instantaneous UAV velocity. $\mathbf{R}(\phi)$ is the counterclockwise (CCW) Euler rotation matrix about the vertical axis ($\hat{z}$), where ϕ represents the heading (yaw) angle of the quadcopter UAV. Validation experiments highlight the superiority of the LW approach, which has demonstrated an average recovery rate of 98% across all downwind distances. In contrast, the SW approach can lead to 20% overestimation at 20 meters because it fails to capture the velocity gradients inherent in the atmospheric surface layer (Fosco et al., 2025b). Advanced systems also utilize Projected Wind (PW), which synchronizes 1-second average wind components with the UAV's exact GPS location to account for real-time wind gusts during the monitoring period (Fosco et al., 2024).

7.4. Spatial Interpolation and Mapping

Since UAV measurements provide discrete data points, spatial interpolation is required to reconstruct the full 2D or 3D morphology of an emission plume. Ordinary Kriging is a common stochastic method that assumes spatial stationarity; however, it often over-smooths plumes in turbulent environments (Fosco et al., 2024). To overcome this, cluster-based kriging has been developed, which uses Gaussian Mixture Models (GMM) to partition data into "background" and "elevated" clusters. Separate kriging models are then trained for each cluster and combined using membership probabilities as weights, a technique shown to reduce the mean absolute error by approximately 12 % (Morales et al., 2022). For landfill and wastewater mapping, data are often resampled onto a regular 1 × 1 m² grid using bilinear interpolation or nearest-neighbour interpolation to facilitate mass-balance integration (Gålfalk et al., 2021). In large-scale surveys, heat maps are generated in GIS environments by considering the concentration at each GPS point and neighbouring points within a 5 m radius to visualize high-density leakage zones. In the mining sector, mapping involves change detection through 3D point-to-voxel comparisons of LiDAR data, allowing for the automatic identification of wall expansions or muck pile volumes within 0.3 to 1 second of processing time (Nordström et al., 2025).

8. Validation, and Uncertainty

8.1. Validation Methodologies

Validation of UAV-based methane quantification is primarily achieved through controlled-release experiments, in which quantified fluxes are compared with a metered "ground truth" to determine system accuracy across varying emission scales. A prominent example is the MATRIX (Methane Release Experiment) conducted in Dübendorf, Switzerland, which utilized controlled releases to benchmark a

miniaturized QCLAS system. This study demonstrated that a refined cluster-based kriging approach integrated with projected wind (CKPW) yielded an average bias of only −1%, although individual error residuals averaged 54% (Morales et al., 2022). Similarly, validation campaigns in Casa Grande, Arizona, utilized single-blind and unblinded releases ranging from 1.7 to 1500 kg/h to test a hexa-rotor platform's dynamic range. These tests confirmed by Dooley et al. (2024) that adopting an LW profile approach yields a robust average recovery rate of 98%, significantly outperforming constant-scalar wind models, which frequently resulted in 20% overestimation at downwind distances of 20 meters.

Beyond controlled releases, Morales et al. (2022) validation involves inter-method comparisons with established ground-based techniques. UAV-based mass balance estimates have been cross-validated against the OTM-33A stationary method, showing that both approaches typically capture the true release within their respective uncertainty bounds. In landfill environments, validation against the flux chamber method of Fosco et al. (2025a) revealed that UAV measurements were 2 to 4 times higher than ground-based results. This discrepancy is attributed to the aerial platform's ability to capture diffuse hotspots and extraction-well leaks that are often inaccessible or missed by traditional chambers. Furthermore, inter-instrumental validation between fast-response analysers and AirCore systems has identified a characteristic 7-second time lag and 20-second smoothing effect in AirCore data, the correction of which improves quantification accuracy by approximately 3%.

8.2. Uncertainty Quantification and Mitigation

Uncertainty in UAV methane sensing is dominated by meteorological variability, which has been identified as the primary source of error in multiple studies. The study Xu et al. (2025) shows that wind speed and direction fluctuations often account for 60% to 97.8% of the total uncertainty in landfill emission estimates. The researcher Xu et al. (2025) mentioned that the quantification accuracy drops significantly when wind speeds are below 2.3 m/s or when directional variability exceeds 33.1°. These unstable conditions violate the steady-state assumptions of Gaussian and mass-balance models, leading to "storage-and-release" events that can result in quantification deviations of up to 53.4%. To mitigate these effects, researchers Dooley et al. (2024) recommend selecting narrow sampling windows with high solar insulation and mean wind speeds between 2 and 6 m/s.

Platform-induced disturbances, particularly propeller down-wash, represent another critical source of uncertainty that can distort the morphology of the methane plume. To mitigate this, Dooley et al. (2024) and Xu et al. (2025) typically mounted sensors or sample inlets on masts extending 37-85 cm above or below the UAV's rotors to place them outside the shallow inflow layer. Positional and altitude drift also contribute to error; standard UAV-GPS units can exhibit a vertical drift of 0.10 to 0.11 cm/s, accumulating a 0.6 m error over a 10 min flight. Nathan et al. (2015) mitigated this by using RTK-GPS systems, which provide centimetre-level accuracy (1.5 cm vertical), thereby preventing artificial distortion of the emission plume during spatial reconstruction. Additionally, for path-integrated TDLAS sensors, the signal-to-noise ratio is highly sensitive to altitude; increasing flight height beyond the manufacturer's optimal range can degrade precision and increase instrumental uncertainty, (Fosco et al., 2025a). Advanced spatial interpolation techniques like cluster-based kriging further reduce uncertainty by partitioning data into "background" and "elevated" clusters, as shown in (Dooley et al., 2024), reducing the mean absolute error by 12% compared to standard ordinary kriging.

9. Application Domain: Field Specific Development

To complement the above discussion of sensors, flight plans, quantification, and uncertainty, this section compares UAV-based methane monitoring in the significant areas of application. The objective is to demonstrate the differences in methodological maturity with the source type as each area has different

plume behaviour, operational limits and validation issues. Table 4 shows the domain-specific platforms and sensors used, the quantification methods employed, the main sources of uncertainty, and the maturity stage. Subsections below thus examine the main sectors individually, highlighting typical source characteristics, commonly used UAV approaches, current strengths, and remaining research gaps.

Table 4: Cross-domain comparison of UAV-based methane observation and quantification applications.

Domain	Platform Type	Main sensing modalities	Quantification approaches	Uncertainty	Maturity
Landfill	Multirotor, Fixed wing	Thermal IR, TDLAS	Mass balance, Gaussian inverse modelling, backward dispersion	Often wind/background dominated	Intermediate to advanced pilot
Oil & gas	Multirotor, fixed wing	TDLAS, QCLAS	Mass balance, tracer flux ratio	Poor wind, background instability	Advanced for detection, intermediate for quantification
Agriculture	Multirotor	Active AirCore, TDLAS	Mass balance, inverse Gaussian, Lagrangian mass balance, Bayesian inversion	Wind direction variability and non-simultaneous vertical sampling dominate, low-emission rate	Early to intermediate pilot
Wastewater	Multirotor	TDLAS	Mass balance	Sludge diffuse sources	Early to intermediate pilot
Coal-mine ventilation shafts	Multirotor	Active AirCore + CRDS	Inverse Gaussian, mass balance, GA-IPPF inversion	Wind variability and vertical coverage	Intermediate
Surface coal mines	—	—	—	—	Pre-pilot / gap

9.1. Landfill

Landfills were among the earliest real-world applications where UAV-based methods on methane tracking progressed beyond leak detection to site-scale emission estimation. This development happened in a clear sequence. Firstly, there was screening: Fjelsted et al. (2019) demonstrated that a UAV-based thermal infrared camera could identify landfill-gas hotspots, whereas Tanda et al. (2020) further believed that thermal anomalies could be used as a diagnostic proxy of fugitive biogas escapes over municipal landfills. Meanwhile, Allen et al. (2019) were one of the first to demonstrate complete-site UAV methane-flux demonstrations, with crosswind sampling, wind data, and co-emitted CO_2 serving as a methane proxy to obtain instantaneous landfill fluxes. Daugela et al. (2020) later broadened this approach by integrating UAV mapping products into methane-focused landfill monitoring, though their study was diagnostic rather than quantitative. Taken together, these studies mark a shift in drone applications from locating hotspots to characterizing entire sites.

The second phase was method consolidation under messy field conditions. Olaguer et al. (2022) combined drone-mounted TDLAS and meteorology, with the inverse model and mobile CRDS measurements at two Michigan landfills and found total emissions as high as 500 kg/h with uncertainties near 50 % concluding active faces and leaking gas-collection systems both as important sources of methane. Abichou et al. (2023) demonstrated that with backward dispersion in SEM2Flux drone-based surface emission monitoring could statistically recapture whole-site emissions, which were statistically consistent with tracer-correlation estimates at two landfills. Then Yong et al. (2024) gave a "failure-aware" field paper: in a UK landfill survey, in which they provided insight into methodological aspects: background definition, geospatial

interpolation and most importantly: the difficulty of measuring the onboard wind measurements for a large, heterogeneous source.

The primary difficulties of landfills are now very clear. Background concentration may change over a survey window and flight geometry is forced to compromise vertical completeness with battery life and regulatory altitude limits, which is 120 m. Background variability and wind speed were found to be the most significant contributors to uncertainty, not instrument noise, (Allen et al., 2019); complex terrain and source multiplicity have the potential to inflate total uncertainty in Olaguer et al. (2022), and data processing choices have a significant impact on flux results in Yong et al. (2024).

Recent landfill studies have responded with three kinds of solutions. First, they minimize geometry-based error by using denser, well-defined flight curtains and explicit interpolation or inverse models rather than relying on transects alone. Second, they accelerate data turnaround: Fosco et al. (2025a) observed a mass-balance workflow running fast with just two short downwind flights and processing them on site at an Italian landfill, whereas in one study, drone-derived rates of emissions improved by 2-4 times the flux-chamber estimates. Third, they enhance source localization and interpretation of maps: Guerra et al. (2025) suggested a geostatistical source identification tool to identify methane sources clusters in drone surveys, and Tassielli et al. (2024) demonstrated that the background noise in the surveys with TDLAS increased with the height of the surface, its type, the amount of solar loading, and the background estimation.

Landfills are thus at the stage that can be said to be intermediate-to-advanced pilot readiness. Nowadays, UAVs are used widely in landfill hotspots screening, remedial targeting, and even whole-site top-down estimation, particularly when used in conjunction with inverse or hybrid techniques. The open gaps are less about whether UAVs work than about standardization: survey design under nonuniform wind, treatment of spatially distributed sources, reconciliation with traditional surface methods, and repeatability across operators. Landfill as a practice currently resembles the field where UAVs would be most likely to be applied on a regular basis, but not yet one with universally interchangeable methods

9.2. Oil and gas

UAV based methane observation in oil-and-gas developed earlier than most other domains because the practical value of finding and quantifying discrete leaks oil and gas plant is important and immediate. The 2018 literature established two complementary paradigms. Yang et al. (2018) detailed the RMLD-UAV system, which is a downward-seeing open-path design that highlights the use of real-time characterization of leaks via mass-balance approach, indicating that estimates smaller than about 1 SCFH were unreliable as GPS accuracy, wind quality, and constant survey elevation had a significant influence over the error. Golston et al. (2018) created a different path-integrated method that pays attention to the localization and emission rate recovery and is supported by over 200 controlled release trials. When repeated flights were spatially averaged, their system accurately sorted leak and no-leak cases down to 2 SCFH and localized sources to a mean absolute error of about 1.2 m. Later, Tuzson et al. (2020) presented a lightweight mid-infrared QCLAS that can be easily carried by UAVs, pushing the limit of precision of in situ methane measurements. Iwaszenko et al. (2021) subsequently demonstrated that the ability to detect UAV leaks could be generalized to a real pipeline leak, and operationally, lower altitudes of 4–15 m were found to be optimal with their laser-based sensor. By contrasting miniature TDLAS systems on fixed-wing aircraft and multirotor aircraft and demonstrating through controlled release and field measurements that quantification on the scale matched in facilities could be obtained with average errors of the order of 16 % on perimeter polygons and of the order 25 % on downwind flux planes in their test cases, Corbett and Smith (2022) pushed the sector toward uncertainty-conscious deployment. Morales et al. (2022) further refined best practice by demonstrating that favourable wind conditions, a low variability in wind direction, and close enough downwind sampling are conditions to enable a confident quantification of point-source. Xu et al. (2025) addressed diffuse emissions at oilfield well sites using scanning TDLAS with concentric flight

paths and a top-down retrieval algorithm. Alaba et al. (2025) showed that arc-shaped flights and cumulative-sum estimation can improve tracer flux ratio methods at complex oil and gas facilities.

The key challenges in oil and gas are source multiplicity, intermittency, and attribution. Facilities often contain multiple valves, hatches, tanks, separators, and vents operating simultaneously, while background or nearby biogenic sources can further complicate interpretation. This is why oil-and-gas literature puts lots of effort to control releases, uncertainty wraps and co-emitted tracers. Yang et al. (2018); Golston et al. (2018); Corbett and Smith (2022) demonstrated that wind, GPS noise, flight pattern choice, raw sensor noise and incomplete capture of the plume can be directly related to rate error.

The present capability is advanced for detection and leak localization, but still intermediate for universal quantification. Practically, the field already has operational UAV workflows to identify leaks and to an extent for top-down asset-level quantification, including offshore and large-facility applications. What remains open is the transferability of the method across source classes and atmospheric regimes; a method that works for one small leak may not work equally well for a larger site or a mixed-source environment.

9.3. Agriculture

The methane studies in agriculture came later than those in landfills and oil-and-gas since the sources are frequently biologically diffuse, time-varying and encased in operationally complex farms. Vinković et al. (2022) were the first to demonstrate convincingly the efficacy of farm-scale deployment of the UAV-based active AirCore system by presenting total farm rates of methane emissions. They showed that most tracer-release errors came from local wind uncertainty and the angle between the wind and the flight path, and that tracer correction improved both inverse Gaussian and mass-balance estimates. The literature then branched out in two directions. One of them remains near to the farm infrastructure. In a peer-reviewed conference paper, Becciolini et al. (2023) provided real-time UAV measurements of gaseous and particulate emissions in livestock buildings and manure stores using multi-sensor UAV monitoring approach. The second branch grew to open grazing systems where the geometry of the sources is more problematic. Using a Lagrangian mass-balance framework and a UAV-based air-sampling system, Yang et al. (2025) compared the emissions of beef, dairy, and sheep pastures and quantified them using UAV-based sensors; the authors specifically compared results UAV-based measurements of greenhouse-gas emissions with dynamic flux-chamber measurements. van Hove et al. (2025) went even deeper, by integrating drone observations with tower observations to a Bayesian dispersion model of the African livestock systems, discovering that the practical use of the Bayesian framework was superior to non-stationary winds when compared to conventional mass balance, as well as able to estimate weak sources of about 100 g/h. Agricultural methane studies face different challenges from industrial ones. The emissions depend on the location of the herds, feeding, manure management, and ventilation, whilst plumes are weak and short-lived. Vinković et al. (2022) demonstrated that a significant limitation to the accurate farm-scale quantification is that nonsimultaneous vertical sampling. Yang et al. (2025) demonstrated that attempting to implement longer sampling probes can resolve rotor-wash issues, to some degree, and validation issues.

It is at the early-to-intermediate capability stage. UAVs are also capable of measuring methane in dairy plants and, more recently, pasture-based systems though there is yet to have been harmonization between the method and agriculture like in landfill or late oil-and-gas operations. The open gaps are source separation, repeated seasonal validation, and robust treatment of very weak, mobile and distributed biological sources. To this end, agriculture could perhaps best be regarded as a field of application where UAV methane approaches are rapidly becoming scientifically credible faster than they are becoming standardized into operation.

9.4. Wastewater

Wastewater is one of the least-studied UAV methane domains in the peer-reviewed literature. The field's first strong methane-specific demonstration was Gafalk et al. (2021), who presented a highly sensitive drone-based methane mapping method that did not require supplementary ground-based wind measurements and used a wastewater-treatment sludge deposit as a key case study. The paper showed that multiple short UAV flights could map hotspots and quantify total methane flux from the source, which was important because sludge surfaces are exactly the kind of extended. In methodological terms, this paper was the wastewater analogy of the early landfill breakthrough: it showed that a drone could create a "virtual wall" around a complex source field without the heavy infrastructure of fixed towers or manned aircraft. Gafalk and Bastviken (2025) used drone-based measurements at wastewater treatment plants with anaerobic digestion and showed that combined methane and nitrous-oxide climate impacts were 2.4-fold higher than IPCC-recommended emission-factor estimates. Critically, they found sludge-related emissions to be a major previously underrepresented source. This is a pivotal result for the sector because it shifts UAV relevance from "hotspot mapping" to "inventory correction".

The wastewater challenge is that facilities contain both compact process leaks and large diffuse surfaces, and the most climate-relevant emissions may arise from sludge handling rather than from the treatment stage operators expect. This makes source attribution and method choice unusually consequential. Gafalk et al. (2021) showed that drone-based virtual-wall mapping can work for diffuse sludge deposits; Gafalk and Bastviken (2025) showed that those diffuse sources can dominate total greenhouse-gas budgets.

Unlike landfills, wastewater has only recently developed a peer-reviewed UAV methane base, but the newest studies are already sector-relevant because they target inventory bias and utility mitigation. The largest remaining gaps are intercomparison across instruments, extension beyond anaerobic-digestion plants, and standardization of multi-gas flux mapping over wet, thermally variable, and topographically cluttered process units. Most grey literature in this area comes from vendors or utility demonstrations of drone LDAR and mapping at full-scale plants. These reports show growing adoption, but the peer-reviewed evidence is still limited.

9.5. Coal-mine ventilation shafts

Coal-mine ventilation shafts are one of the clearest examples of a UAV methane application that is not merely convenient, but structurally well matched to the source. Initially Andersen et al. (2018) developed the UAV-based active AirCore system and analysed it later using CRDS. The authors made specific observations of potential opportunities of methane hotspots, including landfills and wetlands, but the most productive future use of the system was found to be in methane-saturated mine-vent plumes. Andersen et al. (2021) became the first to fly perpendicular flights in several heights 150–350 m downwind of a single Upper Silesian ventilation shaft and built a two-dimensional methane curtain. They compared a mass-balance method with an inverse Gaussian method and found that the inverse Gaussian approach performed better in simulations, especially when the vertical spacing was large relative to plume spread. The methane estimates for the shaft covered a wide range, but the main methodological result was clear: strong point sources with relatively steady plume rise are well suited to repeated UAV curtain sampling. Shi et al. (2022b) then used UAV AirCore data to the same genetic algorithm–interior point penalty function inversion, which minimized the dependency on diffusion parameters and accuracy of auxiliary-data. Andersen et al. (2023) generalized the concept to region by scaling five ventilation shafts in the regional scale of the Upper Silesian Coal Basin and estimated basin-wide emissions but highlighted that repeated flights and increased shafts are needed to reduce upscaling uncertainty.

The main issues of the sector have become clear. First, high-intensity plumes still need sufficient vertical sampling density; Andersen et al. (2021) demonstrated that transects that are too coarse in comparison to

plume depth degrade retrieval accuracy. Second, even for relatively favourable point sources, wind variability remains as the primary source of uncertainty at the individual-flight level. Third, the comparison of inventories is not trivial due to the possibility of large divergence of hourly and annual mine emissions; actually, the correlation between UAV measurements of the shaft rates and the annual average inventories is very low, which is exactly why these measurements are useful (Andersen et al., 2023). Shi et al. (2022a) have tackled some of this issue by employing a more adaptable inversion framework that can self-determine dispersion parameters based on the concentration field itself.

The solutions here are more mature conceptually compared to other domains. The source remains quasi-point, and the emission rate is facility-based, as opposed to being distributed over a large area. This gives UAVs a clear advantage over ground-only methods. Curtain flights, stacked-altitude sampling, and inversion-based retrievals have all been shown to work well. The remaining questions are mainly practical: how many flights are needed to estimate a reliable average shaft emission rate, how UAV data should be combined with mine operational data, and how results from a few shafts can be scaled to an entire mining basin. In general, coal-mine ventilation shafts can be considered currently one of the most powerful examples of intermediate UAV quantification maturity of strong point sources.

9.6. Surface coal mines

Unlike ventilation shafts, active surface coal mines remain a significant gap in the UAV methane literature. The peer-reviewed sources obtained to conduct this review had no specific study that employed the use of UAV methane measurements to determine the emissions of a busy surface coal mine. The recent peer-reviewed literature is, instead, dominated by non-UAV methods: inventory reform and mine-specific modelling, aircraft-based top-down measurements, satellite-based analyses, and inversions based on surface observations. Alarcon Vigil et al. (2025) contended that current reporting of surface coal mine methane is not satisfactory and there are better methods of estimating the open-cut metallurgical coal mines. Borchardt et al. (2025) then demonstrated with two independent manned aircraft-based measurements at an Australian open-cut coal mine that reported emissions of methane were significantly greater than those reported by the operators. Similarly, Lu et al. (2025) demonstrated through surface observations and inversion to the coal-mine of Shanxi that the amount of methane released by coalmines was higher than the expectation of the inventory. This is important since it redefines what would have been required to solve in the missing UAV literature. Surface coal mines are not compact point sources such as ventilation shafts nor are they relatively confined surface sources such as landfills. Emission rate is highly dependent on exposed coal surfaces, fractured overburden, blast-disturbed strata, pits with strong thermal and topographic effects, and possibly a variety of active areas within a large coal mine area. The combination of Borchardt et al. (2025) and Alarcon Vigil et al. (2025) suggests that the industry urgently requires facility-scale atmospheric verification, yet they also mentioned the deployment of UAVs is challenging due to the source field is diffuse and spatially variant, with complex aerodynamics.

The current stage is therefore at initial phase of peer-reviewed UAV quantification of methane although the sector is obviously in need of improved measurements. The open gaps are abnormally basic: no standard sampling geometry is yet in place regarding an open-cut mine; it is not yet understood whether crosswind curtains or circular scans or tracer-assisted techniques will prove to be most robust in deep pits or high-walls; nor again has any controlled-release analogy as yet been published in this context. In a nutshell, surface coal mines cannot be addressed as a fully-grown UAV solution that simply requires streamlining, but as a high-priority research area in which non-UAV evidence has already revealed that current inventories are already insufficient. References to the use of UAVs are usually conference, utility or industry reports, rather than peer-reviewed methane-quantification literature.

10. Commercial Landscape of UAV-Based Methane Sensing

The commercial UAV-based methane sensing market has grown rapidly, comprising full-scale methane monitoring services, autonomous inspection, sensor manufacturers, and systems integrators.

These companies can be listed in a single list under the broader term UAV methane monitoring; however, their technical services are not quite equivalent. Companies that provide end-to-end solutions to identify a leak, its source, measure the emissions, visualize them, or conduct compliance-oriented inspections. Such a distinction is crucial when comparing commercial capabilities, where the term UAV methane sensing can refer to radically different levels of measurement maturity, ranging from simple anomaly detection to site-scale emissions quantification. Table 5 summarizes selected leading commercial companies in UAV-based methane sensing and compares their core technological capabilities.

The first group comprises companies that orient their systems toward measuring and quantifying methane. Some of the examples of this category are Seekops, Flylogix, Bridger, Photonics, Aeromon, and AIRMO. Although their technical approaches and areas of operation differ, SeekOps and Flylogix are focused on laser-based methane detection for offshore and industrial systems. While Bridger Photonics is interested in expanding commercial markets to LiDAR-based gas imaging to locate and measure gas over large distances. The same can be said of Aeromon and AIRMO, which refer to the enhanced applicability of quantification-oriented workflows, particularly in cases involving case reporting models such as the OGMP and EU methane regulations.

The second group is dominated by compliance-based and imaging-based inspection solutions. This category has Percepto, ChampionX, MFE Inspection Solutions, AerialOGI, Vision Aerial, and SENSIA. Such systems are based on optical gas imaging (OGI), quantitative OGI, or related imaging-guided solutions, and have application in the inspection of industry leaks, LDAR programs, and regulatory compliance. Their major commercial advantages are rapid detection of visual leaks, operational efficiency, and the ability to inspect hard or unsafe infrastructure with repeatable UAV flights. However, direct concentration-measurement systems are more likely to be optimized for detection and localization than imaging-based methods.

A third category comprises companies specialized in applications or enabling technologies. Sniffer Robotics is important for monitoring conditions in landfills and surface emissions; near-ground methane mapping and flux-oriented workflows are especially valuable. Aeris Technologies offers high-sensitivity analysers that are typically used to aid concentration mapping across different UAV types, but SPH Engineering, Pergam, and Purway Innovation highlight the significance of integrator and payload vendors in the commercial ecosystem. The importance of these companies is that they increase deployment flexibility and reduce the cost of UAV-based methane operations, though they may not necessarily provide an end-to-end quantification service.

Table 5: Commercial UAV-based methane sensing companies and their core technology characteristics.

Company	Platform	Sensor	Sensing principle	Used for	Used sector	Highlight
AerialOGI	DJI M350, Sony Airpeak, Freefly Astro, Vision Aerial Switchblade and others	AerialOGI payload using Sierra-Olympia core	OGI with TDLAS	Detect + localize	Oil & gas, LDAR, industrial leak inspection	Turnkey drone-agnostic OGI integration across multiple UAV platforms
Aeris Technologies	Light/heavy-lift drones	MIRA Pico/Strato/Ultra	QCLAS	Detect + concentration mapping	Oil & gas, landfills, waste, biogas	High-sensitivity analysers for concentration mapping across multiple platforms

Company	Platform	Sensor	Sensing principle	Used for	Used sector	Highlight
Aeromon	Heavy-lift drones	BH-12 modular	Pumped-sample modular sensing	Detect + localize + quantify	Oil & gas, industrial emissions, OGMP-style reporting	Flexible modular platform with reporting-oriented quantification workflows
AIRMO	Heavy-lift drones	Proprietary UAS TDLAS sensor	TDLAS with OGI and FID	Detect + localize + quantify	Oil & gas, landfill, OGMP / EU methane reporting	Lightweight compliance-oriented system aligned with OGMP/EU needs
Bridger Photonics	Heavy-lift drones	Gas Mapping LiDAR (GML)	TDLAS with LiDAR & gas imaging	Detect + localize + quantify	Oil & gas, LNG, offshore, remote assets	LiDAR-based wide-area localization and quantification over complex sites
ChampionX	Heavy-lift drones	AOGI / OGI platform	Open-path TDLAS with OGI	Detect + localize	Oil & gas LDAR and aerial surveys	Strong commercial LDAR and aerial inspection experience
Flogistix / Flowco	Heavy-lift drones	U-10 laser, sniffer, and Purway sensors	TDLAS with OGI	Detect + localize	Oil & gas, midstream, well pads, compressor stations, storage	Multi-sensor service model adaptable to varied oil and gas assets
Flylogix	FX2 fixed-wing BVLOS UAV	SeekIR	TDLAS	Detect + localize + quantify	Offshore oil & gas	Long-range BVLOS offshore monitoring over remote assets
MFE Inspection Solutions	DJI M300/M350	MFE Detect LW	Long-wave infrared (LWIR) with OGI	Detect + localize	Oil & gas, tank farms, landfills, industrial sites	Practical drone-mounted LWIR OGI payload for industrial surveys
Percepto	Percepto Air Max/OGI	Sierra-Olympia Ventus OGI AI camera	Optical Gas Imaging (OGI)	Detect + localize	Oil & gas, industrial compliance inspections	Autonomous drone-in-a-box OGI inspections with compliance focus
Pergam	Light/Heavy UAV, and fixed-wing options	HC G5, Falcon G2, LMF G2	TDLAS with OGI	Detect + localize	Pipelines, gas utilities, infrastructure inspection	Broad payload range across light, heavy, and fixed-wing UAVs
Purway Innovation	DJI Matrice 200 / 300 / 350	Laser Methane Leak Detector /Model II/III	TDLAS with visible-camera integration	Detect + localize	Pipelines, gas storage, natural gas plants, hard-to-reach infrastructure	Compact methane-specific payload for hard-to-access infrastructure inspection
SeekOps	Most enterprise UAVs; DJI Matrice 400; FX2 fixed wing	SeekIR	TDLAS	Detect + localize + quantify	Offshore oil & gas, utilities, RNG, waste	Mature full-stack methane quantification with strong offshore and industrial deployment
SENSIA	Heavy-lift drones	Mileva / Caroline Camera Families with RedLook analytics	OGI / Quantitative optical gas imaging (QOGI) with TDLAS	Detect + localize + camera-based quantification	LDAR, OGMP reporting, oil & gas environmental compliance	Strong quantitative OGI and analytics-oriented methane imaging workflow
Sniffer Robotics	Gen II adapted to DJI M300/350	SnifferDRONE ™ (Gen I / II)	NDIR / TDLAS	Detect + localize + quantify + flux studies	Landfills, waste, biogas, land-based emissions	Strong landfill surface-emission mapping and flux-oriented workflows
SPH Engineering	DJI M300/M350, SkyFront, Wispr, Harris	Falcon Plus	TDLAS	Detect + localize	Pipelines, oil & gas, landfill screening	Strong integration ecosystem for rapid methane screening missions
Vision Aerial	SwitchBlade-Elite	OGI Scout with Sierra-Olympia Ventus OGI core	OGI	Detect + localize	Oil & gas, LDAR, industrial inspection	Purpose-built UAV platform optimized for industrial OGI payloads

Note: This table includes selected prominent commercial companies for comparison and is not exhaustive; other companies and market solutions also exist

11. Conclusions

Methane monitoring of UAVs has provided a valuable contribution between ground-based measurements and airborne or satellite measurements. This review demonstrates that system performance is a function of platform selection, sensing modality, flight geometry, and quantification method, rather than sensor capability alone. The multirotor UAVs are still preferred for quantitative studies due to their hovering capability and high plume-interception precision. Among the various sensing methodologies, QCLAS and closed-path TDLAS are currently the best technologies for UAVs, enabling high-quality quantification, whereas open-path TDLAS is efficient for remote locations and screening, and NDIR, thermal infrared, and other low-cost solutions are more suitable for screening and hotspot localization.

This review further highlights that the design of flight and the interpretation of data are the focus of reliable quantification of methane. The most used methods are mass-balance and Gaussian plume inversion, whereas tracer-based techniques have benefits when the uncertainty in the wind can be mitigated through controlled co-dispersion. In all solutions, the main sources of uncertainty are generally meteorological variability, incomplete plume coverage, background estimation, temporal synchronization, characterization of the wind field, and sensor accuracy. Across application domains, oil and gas, landfills, and coal-mine ventilation shafts have progressed further toward operational quantification, whereas agriculture and wastewater remain less standardized, and surface coal mines still lack dedicated peer-reviewed UAV quantification studies. Although controlled-release studies demonstrate that UAV systems can provide useful methane emission estimates under favourable conditions, broader operational adoption will require more standardized validation protocols, clearer reporting of uncertainty, and better integration of sensing, wind measurement, and flight autonomy.

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The data will be provided on request.

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