



Assessment of Technologies for Estimating Methane Destruction Removal Efficiency of Flares

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Executive summary

Flaring remains a significant operational practice in the upstream oil and gas sector and will continue beyond 2030 despite global commitments to reduce routine flaring. While flaring prevents the uncontrolled release of methane—one of the most potent greenhouse gases—recent evidence shows that its climate impact has been consistently underestimated. Traditional assumptions that flares destroy more than 98% of methane are increasingly contradicted by field data and large-scale experiments.

Accurate assessment of flare performance is therefore essential for climate mitigation, regulatory design, and investment decisions. Yet measurement of combustion efficiency (CE) and methane destruction removal efficiency (DRE) in real-world operating conditions remains challenging. These quantities are never measured directly; rather, they are inferred using instrument models that link observable data—such as gas concentrations or infrared radiance—to flare performance. The models are derived by making simplifying assumptions about plume behavior, species distributions, and mixing processes, all of which introduce uncertainty into the CE/DRE estimate. Spatial and temporal variability, including fuel stripping caused by crosswinds and intermittent “rogue events,” further complicate measurement.

There is no “best solution” or “golden bullet”. Instead, both the diversity and capability of measurement technologies are expanding rapidly, driven by advancements in sensor minimization, autonomous vehicles, new light sources and detectors, and computational power. Technologies differ in their capabilities, data requirements, and sensitivity to plume dynamics, and many report only local CE/DRE, which cannot be assumed representative of global performance. Moreover, no internationally recognized protocol exists for validating CE/DRE measurements or for quantifying their uncertainty.

In this context, global efforts to mitigate methane emissions from flaring require a better understanding of measurement physics, sources of uncertainty, improved transparency, and harmonized methodological standards. This report provides a detailed survey of measurement approaches, reviews the underlying physical and modeling challenges, and proposes a pathway toward standardized uncertainty quantification.

Key Findings

- **No technology measures CE/DRE directly.** All approaches rely on instrument models to convert observables into performance metrics. Model assumptions—rather than sensor precision—are the principal source of error.
- **Flare CE/DRE is difficult to measure.** Crosswinds, fuel composition, assist gas, and turbulent mixing produce strong spatial and temporal variability that cannot be captured using near-instantaneous measurements, measurements made at a single point, or measurements made along a line-of-sight.
- **Local CE/DRE values differ fundamentally from global values.** While many instruments measure the local CE or DRE, one cannot just “average” these values to obtain a reliable picture of global CE/DRE or overall flare emissions.
- **Uncertainty is rarely quantified adequately.** Most reported CE/DRE values exclude model error and plume variability, leading to a systematic underestimation of uncertainty.

- **A harmonized methodology is urgently needed** to ensure comparability of measurements across technologies, operators, and jurisdictions.

Key Challenges

1. **Instrument-model dependency:** All CE/DRE instrument models are derived by making assumptions about plume structure, mixing, and correlation between the species-of-interest (e.g., methane, carbon dioxide) that are seldom validated at full scale.
2. **Plume heterogeneity and intermittency:** Spatial variability, fuel stripping, and intermittency lead to large deviations between local (at one location or along one line of sight) and global (overall) combustion efficiency.
3. **Limited benchmark data:** Direct sampling is difficult, expensive, and itself subject to uncertainty, restricting opportunities for rigorous validation.
4. **Lack of standardized uncertainty frameworks:** Most current uncertainty estimates are derived from benchmark studies, which are subject to their own uncertainties. Without clear methods for quantifying uncertainty, CE/DRE values cannot support transparent reporting or enforcement.

Recommendations

1. **Standardize definitions** of local and global CE/DRE and require explicit disclosure of which metric is being reported.
2. **Mandate defensible uncertainty intervals** for all CE/DRE estimates, including sensor uncertainty, model error, and plume variability. The methodology used for obtaining these uncertainty estimates must be transparent and traceable.
3. **Develop and adopt a unified uncertainty-quantification framework**, based on Bayesian inference, suitable for diverse measurement technologies and synthesizing information from multiple sources.
4. **Strengthen validation protocols**, including use of controlled testing, multi-point or imaging-based measurements, and, where appropriate, high-fidelity computational modeling (e.g., CFD-LES).
5. **Encourage transparent instrument models**, with clear documentation of assumptions, data inputs, and limitations.
6. **Promote technologies that sample the plume more comprehensively**, particularly imaging systems or multi-transect approaches capable of capturing heterogeneity.
7. **Support international harmonization** of flare-measurement standards to improve comparability across jurisdictions and to inform global methane-mitigation strategies.

Conclusion

Improving the accuracy and transparency of flare-emissions measurement is essential for designing effective methane-mitigation policies and for supporting countries and operators in their commitments to reduce greenhouse-gas emissions. While a wide range of measurement technologies exists, all are limited by instrument-model dependency and plume variability. A standardized framework for uncertainty quantification is critical for ensuring that CE/DRE measurements are scientifically credible, policy-relevant, and comparable across global contexts. This report provides the technical foundation and recommended pathway toward achieving that objective.

Abstract

Globally, the upstream oil and gas industry flared more than 150 billion m³ of natural gas in 2024. Flaring has traditionally been assumed to oxidize nearly all high global warming potential (GWP) constituents of flare gas—chiefly methane—into carbon dioxide and water vapor, which have lower GWPs. However, increasing evidence shows this assumption is not always valid. Growing awareness of flaring’s climate impact has driven the development of performance-based regulations, voluntary reporting frameworks, and a rapidly evolving set of techniques for measuring flare emissions. These techniques may quantify emission rates directly, but more commonly assess combustion performance in terms of combustion efficiency (CE) or destruction removal efficiency (DRE) for species such as methane. The definitions of CE and DRE vary across technologies, which complicates the interpretation of these quantities, while the uncertainties associated with many estimates remain unvalidated or absent altogether. This report reviews the quantities used to characterize flare performance, explains the challenges of measuring these parameters under field conditions, surveys current and emerging measurement approaches, and concludes with a recommended procedure for establishing uncertainty in CE/DRE estimates—an essential step for ensuring that reported values are scientifically meaningful and policy-relevant. The capabilities and operating parameters of the most relevant technologies available for measuring flare emissions are summarized in an annex.

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List of Acronyms

AFTIR	Active FTIR
AVIRIS-NG	Airborne visible/infrared imaging spectrometer-next generation
AI	Artificial intelligence
BC	Black carbon
CE	Combustion efficiency
CFD	Computational fluid dynamics
CRDS	Cavity ringdown spectrometer
DCS	Dual comb spectroscopy
DIAL	Differential absorption LiDAR
DRE	Destruction removal efficiency
FTIR	Fourier transform infrared
GAO	Global airborne observatory
GPS	Global positioning system
GUM	Guide to the expression of uncertainty in measurement
GWP	Global warming potential
HC	Hydrocarbons
IFTS	Imaging Fourier transform spectrometer
IMACC	Industrial monitor and control corporation
LES	Large eddy simulation
LiDAR	Light detection and ranging
LOS	Line-of-sight
LWIR	Long-wavelength infrared
ML	Machine learning
MIA	Multiwavelength image analysis
MODIS	Moderate resolution imaging spectrometer
MWIR	Mid-wavelength infrared
NASA	National Aeronautics and Space Administration
NDIR	Non-dispersive infrared
NIR	Near infrared
NHV _{CZ}	Net heating value in the combustion zone
NIST	National Institute of Standards and Technology
NMVOCs	Non-methane VOCs
NPL	National Physics Laboratory
PFTIR	Passive FTIR
PMM	Parametric model method (type of ML algorithm)
OGI	Optical gas imaging
QoI	Quantity (quantities)-of-interest
ROI	Region of interest
SLSTR	Sea and land surface temperature radiometer
TCEQ	Texas Commission on Environmental Quality
TDL	Tunable diode laser
TDLAS	Tunable diode laser absorption spectroscopy
TROPOMI	Tropospheric monitoring instrument
TSD	Temporal standard deviation
UAV	Uncrewed aerial vehicle

US EPA	United States Environmental Protection Agency
VIIRS	Visible infrared imaging radiometer suite
VISR	Visible imaging spectro-radiometry
VOC	Volatile organic compounds

List of Symbols

A	Area
$\mathbf{b}$	Data vector
C	Parameter that accounts for fuel stream composition, Eq. (9)
I_η	Spectral intensity ($\text{W}/(\text{m}^2 \cdot \text{sr} \cdot \text{cm}^{-1})$)
$I_{\eta,d}$	Detected spectral intensity ($\text{W}/(\text{m}^2 \cdot \text{sr} \cdot \text{cm}^{-1})$)
$\dot{m}_k$	Mass flow rate of species k , kg/s
$\dot{m}_C$	Mass flow rate of carbon affixed to species k , kg/s
n_k'	Column number density of species k (ppm·m)
$\mathbf{n}$	Unit normal vector
$\mathbf{u}$	Velocity vector (m/s)
$\mathbf{x}$	Unknown vector
y_X	Mole fraction of species X
η	Wavenumber (cm^{-1})
κ_η	Spectral absorption coefficient (m^{-1})
λ	Wavelength (μm)
ρ	Density (kg/m^3)
ρ_k'	Column density of species k (kg/m^2)

1 Introduction

The upstream oil and gas industry uses flaring to dispose of methane (CH_4) and other flammable hydrocarbon (HC) gases in a number of scenarios. These include initial start-up flaring, in which the gas is used to test the functionality of new processes and equipment; continuous production flaring, in which associated natural gas cannot be commodified due to economic or operational limitations; and non-routine/emergency flaring, caused by equipment failure and other unexpected production issues. While the majority of the upstream oil and gas industry have committed to the World Bank’s “Zero Routine Flaring by 2030” initiative, there remain situations in which flaring is unavoidable; accordingly, this practice will continue for the foreseeable future.

While flaring is preferable to venting the gas due to safety concerns and, especially, to the large global warming potential of CH_4 (the main constituent of associated gas), emissions from flaring, which include particulate matter and unburned HCs arising from incomplete combustion or situations in which the flare is unlit, are a growing concern. The efficiency with which flaring converts HCs into more benign species (mainly carbon dioxide, CO_2) is quantified by the combustion efficiency (CE), or, when focusing on a particular species like CH_4 , the destruction removal efficiency of that species (DRE_{CH_4}).

While flaring has long been assumed to take place with a DRE_{CH_4} of 98% [1–4], a recent aircraft survey of over 300 flares in the Bakken, Eagle Ford, and Permian basins suggests this number may be closer to 95% [5]. When unlit flares are included in this assessment, the effective DRE_{CH_4} drops to 91%. This amounts to underestimating annual CH_4 emissions by roughly 480 gigagrams per year in the United States alone [5]. Given that global flare volumes exceed 138 billion cubic meters of gas, the majority from upstream oil and gas operations, any uncertainty in DRE (both DRE_{CH_4} and DRE for other HC species) has profound implications for the planet.

Concerns about flare emissions have motivated the development of regulations and reporting initiatives around the world that require producers to monitor flare performance, usually in terms of DRE_{CH_4} [6–8]. Flare equipment manufacturers also need DRE estimates to assess the performance of new designs and practices for reducing flare emissions. Environmental scientists and policymakers need DRE estimates to understand the impact of flaring on climate change.

Motivated by these needs, a diverse range of equipment and techniques have been developed to measure flare emissions, often in terms of CE/DRE. They can broadly be categorized as sampling-based techniques, in which flare emissions are inferred from samples extracted from the flare plume, and remote-sensing techniques that rely on spectroscopy of the plume or the flame. None of these techniques measure flare DRE directly; instead, they relate the observed quantities (e.g., concentrations measured at a specific location in the plume using a drone or spectrally resolved intensity measurements recorded with an open-path spectrometer) to a *quantity-of-interest* (QoI), e.g., DRE_{CH_4} , via an *instrument model*. Because the observed quantities are related to the flare DRE in an indirect manner, the instrument model must “fill the gap” with assumed information about the flare operating state, for example, by assuming that the flare species are distributed in a spatially uniform way, or that the CO_2/CH_4 concentration ratio is constant as a function of time.

However, the heterogeneity and nonstationary nature of the turbulent flare plume, coupled with the fact that the plume of an operating flare is difficult and sometimes impossible to access directly, leads to unavoidable differences between the “measurement” from the instrument model and the real-world state of the flare plume. These differences manifest as *model error*, which corrupt the inferred DRE. While many uncertainty estimates focus on propagating sensor

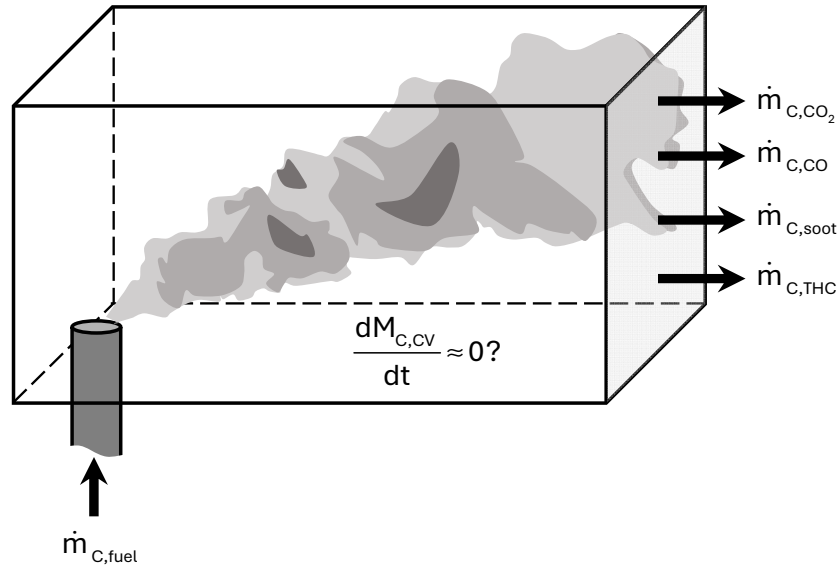


Figure 1: Control volume used to define the global CE of a flare. The analysis assumes that the mass of carbon within the CV is invariant with time, which is only true for long averaging times and if the flare is operated in a steady manner.

uncertainty and calibration error through the instrument equations (e.g., Refs. [9,10]), in most cases model error has a much larger impact on DRE estimates. Moreover, while sensor uncertainty and calibration error can be unbiased and random, the structure of model error introduces a bias in the estimated flare state.

The objective of this report is to present a comprehensive survey and taxonomy of techniques and instrumentation for measuring CE/DRE from flares and to assess what is known about the uncertainty of those measurements. Without uncertainty, we cannot answer key questions that directly impact CH₄ and other HC emissions from flaring worldwide. These include:

- From the regulator's perspective: What is a reasonable CE/DRE goal? If we implement performance-based regulations, how can the regulation be enforced if we cannot measure it?
- From the policymaker's perspective: What is the actual impact of flaring on climate change?
- From the producer's perspective: What is the cost-benefit analysis of various measurement technologies?
- From the flare equipment manufacturer's perspective: What improvement do various innovations offer, and are they worthwhile?

The scope of the report focuses on open flares in upstream environments as opposed to enclosed ground combustors, although many of the techniques included in this review may be applied to both types of flares. While particulate emissions are also a concern [11], they fall outside of the scope of this review. Finally, while the report focuses on lit flares, many of the techniques may also be used to detect unlit flares, which contribute significantly to CH₄ emissions from flaring operations.

The report begins by defining CE and DRE, followed by a review of why measuring these quantities in working flares is challenging. The report then provides a summary of technologies for measuring CE and DRE and their basic operating principles, evaluates what is known about measurement uncertainty, and comments on potential sources of model error contributing to

that measurement uncertainty. It concludes with a discussion of how one could develop standardized uncertainty estimates for these CE/DRE values. The capabilities and operating parameters of the most relevant technologies are summarized in Annex A.

This report summarizes a more detailed analysis presented in *Progress in Energy and Combustion Science (PECS)*, published in April 2025 [12]. Given the urgency of understanding flare emissions and the rapidly evolving regulatory landscape, several commercial systems for estimating DRE are included in this report that were unavailable at the time the *PECS* paper was submitted. We also note two other reports contemporaneous to our review that summarize available technologies for measuring CH₄ emissions from flares: “Recommended practices for emissions detection and quantification technologies – upstream” [13] and “Recommended practices for CH₄ emissions detection and quantification – combustion efficiency and flaring destruction” [14]. The present report is an important addition to this canon as it provides a more thorough discussion of the physical principles that underly the measurements, a critical analysis of the uncertainty of the measurements, particularly their susceptibility to model error, and a suggested methodology for quantifying the uncertainty across measurement technologies.

2 Combustion efficiency and Destruction Removal Efficiency¹

Both CE and DRE can be defined on a *local* or *global* basis. A local value refers to CE/DRE measured at a location within the plume or along a line-of-sight (LOS) that transects the plume. A global value refers to the overall CE/DRE from the entire flare plume and is the most relevant quantity to policy makers, regulators, equipment manufacturers, producers, and measurement technology companies. As we discuss in this section, local values of CE/DRE in a flare plume are not the same as the global CE/DRE values of the entire flare plume. Determining global CE/DRE from a single, local measurement or set of local measurements is a significant source of measurement uncertainty in global CE/DRE estimates.

2.1 Global CE and DRE

Both CE and DRE are based on mass balances using the control volume in Figure 1 and are closely linked to the quantification of CH₄ emissions. Global CE is defined as [15,16]

$$CE = \frac{\dot{m}_{C,CO_2}}{\dot{m}_{C,fuel}} \quad (1)$$

where $\dot{m}_{C,CO_2}$ and $\dot{m}_{C,fuel}$ are the mass flow rates of carbon affixed to CO₂ leaving the flare plume and carbon affixed to the fuel entering the flare stack. A drawback of Eq. (1) is that both the composition and mass flow rate of the fuel entering the flare must be known, which may not be the case due to a lack of information about the underlying flaring process (e.g., fence-line measurements). However, some of the technologies that are reviewed in Sec. 5 can quantify the concentrations of all the carbon-containing species in the flare plume and the local gas velocities at the point of measurement. In this case, CE can be defined by totalling the mass flow rates of carbon in the CO₂, CO, unburned HCs, and soot leaving the control volume rather than using the mass flow rate of carbon in the fuel. For non-smoking flares, the mass flow rate of soot is negligible and thus ignored [1,2,17]. With these approximations, CE is defined as

¹ CO₂ concentrations, column densities, and mass flow rates used to define global and local CE represent enhancements over background amounts, caused by combustion. It is sometimes necessary to account for background CO₂ levels, particularly when plume concentrations are low, although this may not be straightforward.

$$CE = \frac{\dot{m}_{C,CO_2}}{\sum_k \dot{m}_{C,k}} \quad (2)$$

where $\dot{m}_{C,k}$ is the mass flow rate of the carbon affixed to the k th species leaving the flare plume.

While CE is a convenient way to define the overall ability of a flare to convert HC fuel to CO_2 , often the focus is on the destruction of a particular species such as CH_4 . In this scenario the relevant performance metric is the DRE of species X , defined as

$$DRE_X = 1 - \frac{\dot{m}_{X,plume}}{\dot{m}_{X,fuel}} \quad (3)$$

In contrast to CE, DRE cannot be inferred using the plume composition and gas velocities alone; some information must be known or assumed about the concentration and velocity (to compute mass flow rate) of species X in the vent gas [18,19]. If DRE_{CH_4} is given, flare CH_4 emissions are directly determined by multiplying the mass flow rate of vent gas by $1 - DRE_{CH_4}$. For an unlit methane flare, $DRE_{CH_4} = 0$.

Comparing Eqs. (1) and (2) shows that the DRE for a specific component of the vent gas will always be greater than or equal to the CE [16,20]. For a methane flare operating with a CE of 98%, the DRE_{CH_4} is typically 1.5% higher, e.g. 99.5% [21,22].

2.2 Local CE and DRE

Several of the technologies and methodologies presented in Sec. 5 provide either local concentrations of the gas phase species or, in the case of remote-sensing approaches, column densities along LOSs that transect the plume. For example, the local CE is often defined based on the concentrations of species at a particular location within the plume, e.g. [18]

$$CE_{local} = \frac{[CO_2]}{[CO_2] + [CO] + [CH_4] + \dots} \quad (4)$$

where $[\cdot]$ denotes any concentration unit, e.g. parts per million (ppm), moles/ m^3 , etc. In the case of imaging-based techniques, CE_{local} may be defined as

$$CE_{local} = \frac{\rho'_{C,CO_2}}{\rho'_{C,CO_2} + \rho'_{C,CO} + \rho'_{C,CH_4} + \dots} \quad (5)$$

where $\rho'_{c,x}$ is the column density of carbon mass (kg/m^2) associated with species X that is integrated along a path that traverses the plume normal to the image plane. Equivalently, Eq. (5) can be written in terms of column number densities, n'_k (ppm·m).

It is also commonplace to use a concentration-based DRE,

$$DRE_{X,local} = 1 - \frac{y_{X,out}}{y_{X,fuel}} \quad (6)$$

where $y_{X,fuel}$ and $y_{X,out}$ denote the fraction of carbon in the form of X in the fuel stream entering the flare and at some location in the plume, respectively [18]. The carbon mole or mass fraction is usually inferred through point concentration measurements.

2.3 Implications of local versus global CE/DRE

Local CE/DRE values are frequently assumed to be, or are converted into, global values by the technology provider. These assumptions and conversions introduce additional uncertainty that has largely been overlooked in the literature. We emphasize that, in general, *global CE is not equivalent to local CE (CE_{local}) and global DRE is not equivalent to local DRE (DRE_{local})*. Assuming that these quantities are equal may be a significant source of uncertainty that is unaccounted for by many measurement techniques.

Recognizing why these quantities differ is key to understanding the challenge of assessing flare performance. First, the numerator in Eq. (2) accounts for the mass flux (mass flow rate divided by area) of CO_2 while the denominator accounts for the mass fluxes of all carbon-containing species over the control-volume surface (the box in Figure 1.) Mass flux accounts for the spatial variation in the density and velocity across the plume surface. Area elements with more mass flow (more gas species emissions) will be weighted more than area elements with less mass flow in computing global CE. In contrast, with local CE values as defined by Eqs. (4) or (5), the CO_2 concentration/column density is normalized by the total concentration/column density of all carbon-containing species at a given location. If a suite of these local CE values measured across the plume are simply averaged to obtain a global CE (e.g., Ref. [23]), the area elements containing more carbon mass do not have a greater influence than those with less carbon mass as they should. Second, concentrations and column densities (used for local CE calculations) do not capture the effect of nonuniform gas velocities throughout the plume and thus may be poor approximations of CE/DRE in regions of the flare plume where there is significant spatial variation in velocity. Only if the plume is well mixed and spatially uniform and if the quantities in Eq. (2) are time-averaged over a window sufficiently long to capture stationary-state behavior (if such a state exists) are the global CE, Eqs. (1) and (2), and local CE values, Eqs. (4) and (5), equivalent. This statement also applies to the definitions of global DRE, Eq. (3), and local DRE, Eq. (6). However, we will show in the next section that these conditions are rarely if ever satisfied.

Additionally, while Eqs. (1)-(3) represent the most relevant definitions of flare performance and emissions, in practice it is extremely challenging to estimate these parameters under operational conditions, for reasons outlined in Sec. 3. Even in so-called “validation experiments”, in which the plume of a full-scale flare is sampled using an extractor like the one in Figure 2 [23], questions often arise as to whether the entire plume has been sampled adequately. Laboratory experiments conducted in a sealed, recirculating wind tunnel only claim the ability to measure CE/DRE within 1% [24] (i.e., they cannot distinguish a CE above 99%), so any claim made by a technology provider suggesting a lower uncertainty under far more challenging operational conditions must be treated with skepticism. Current methods for estimating uncertainty are discussed in Sec. 4 while a more robust and rigorous uncertainty quantification procedure is proposed in Sec. 6.2.

3 Challenges of Measuring CE and DRE

For decades, techniques for obtaining accurate CE and DRE estimates from flares operating in open environments have been a highly sought after yet elusive goal. From the extractive sampling measurements of the late 20th century [1,25] to the sophisticated imaging methods of today [26–29], the goal has been to determine the real-world state of a flare given limited information. We begin this section by introducing the concept of the instrument model that converts the observed quantity being measured by the sensor into the QoI (CE, DRE, or CH_4 emission rate). We then evaluate some of the real-world phenomena that are difficult to capture by the instrument models and lead to model error that corrupts the QoI estimates.

3.1 What is a measurement?

Flare measurements such as species concentrations, mass flow rates, CE and DRE (the QoIs) are not directly observable data. Rather, these “measurements” are inferred from data that is observable such as spectroscopic measurements of light emitted by the hot combustion products in the flare plume. The QoIs are related to the observable data (as measured by the instrument sensor) by an *instrument model* according to the schematic in Figure 3. A detailed instrument model specific to a measurement technology may be available or deducible based on information in the open literature (e.g., a patent), although the instrument-model algorithm is proprietary/confidential in many cases. Every measurement technique reviewed in this report has an instrument model associated with it; in other words, every “measurement” is the result of applying an instrument model to an observable (or multiple observables).

As shown in Figure 3, there are multiple sources of uncertainty that contribute to the overall uncertainty in the QoI: (1) uncertainty in the observables results from sensor uncertainty and calibration error; and (2) uncertainty in the instrument model results from model error (due to uncertain instrument model parameters and/or model equations that do not adequately capture the physical processes that produce the observable data). The uncertainty in the observables is propagated through the model but is not part of the model uncertainty.

Even extractive-sampling “validation” measurements, like the one shown in Figure 2, rely on an instrument model to connect the species concentrations measured in the extracted gases to the flare operating state. An example of an extractive-sampling instrument model is detailed in a report by Allen and Torres summarizing the 2010 Texas Commission on Environmental Quality (TCEQ) flare study [10]. Samples were extracted via a sample collector at the center of the flare plume and far enough downwind that combustion reactions were complete (similar to the setup shown in Figure 2) and sent through a series of analyzers and instruments. The instrument model for computing CE/DRE included the calibration models for the gas analyzers measuring gas-phase species concentrations, a time-series data analysis to distinguish constituents in the flare plume from those same constituents in the ambient background, and a carbon-balance method using measurements of any carbon-containing species of “significant abundance”; it did not include an analysis of sampling error (relationship of sample collector to location in the plume).



Figure 2: Even in the case of full-scale validation experiments, the CE or DRE of the flare is connected to the measurements (plume gas composition) by an instrument model derived from assumptions and simplifications, e.g., that the sampled gases represent the overall flare emissions [23].

The instrument models for remote-sensing measurement technologies link spectroscopic data to CE/DRE “measurements”. They consist of many equations, parameters, and simplifying assumptions, as discussed in more detail in Sec. 5, all of which are potential sources of model error. An example of one such instrument model is described in a report for the Marathon Petroleum Consent Decree [30]. The experimental team used a Passive Fourier Transform Infrared (PFTIR) spectrometer (Sec. 5.2.3) pointed at a location two flame lengths downwind from the flare tip to infer column densities of various species along an LOS through the flare plume. The test report provides detailed descriptions of the measurement procedure and of aspects of the instrument model used to convert infrared radiance spectra to species concentrations and then to local CE (see Appendices A.4 and A.5 of Ref. [30]); however, proprietary software is required for some of the analysis.

The form of the instrument model depends on the specific definition of CE or DRE that is being used, the observable(s) being measured, the location of the measurement in the plume, and the spatial and temporal averaging being applied. Due to the paucity of available data, all CE and DRE instrument models are built on a number of simplifying assumptions, and it is these assumptions (“model error”), rather than the sensitivity of the sensors being used (“sensor uncertainty”), that tend to dominate the uncertainty in the QoI.

3.2 Spatial heterogeneity and fuel stripping

It is common practice to approximate the global CE/DRE with a local CE/DRE made at “representative” locations in the plume. In this case, the spatial inhomogeneity of the flare plume needs to be considered.

Multiple researchers have noted the inhomogeneity of flare plumes [2,25,31] with the impact of spatial inhomogeneity on global CE estimates increasing as CE decreases [32]. Consider the instantaneous CE field shown in Figure 4, obtained from a computational fluid dynamics/large eddy simulation (CFD-LES) of a steam-assisted flare operating at high turndown [33]. Contours show the local CE for each computational cell in the two-dimensional slice through the midplane of the simulation, calculated using Eq. (4). According to US Environmental Protection Agency (EPA) rules [22], a flare operating under these conditions should have a global DRE_{CH₄} of 98%, corresponding to a global CE of 96.5%.

In experiments conducted with this steam-assisted flare, the remote-sensing instrument for determining local CE, a PFTIR, was aimed at a location two flame lengths from the flare tip

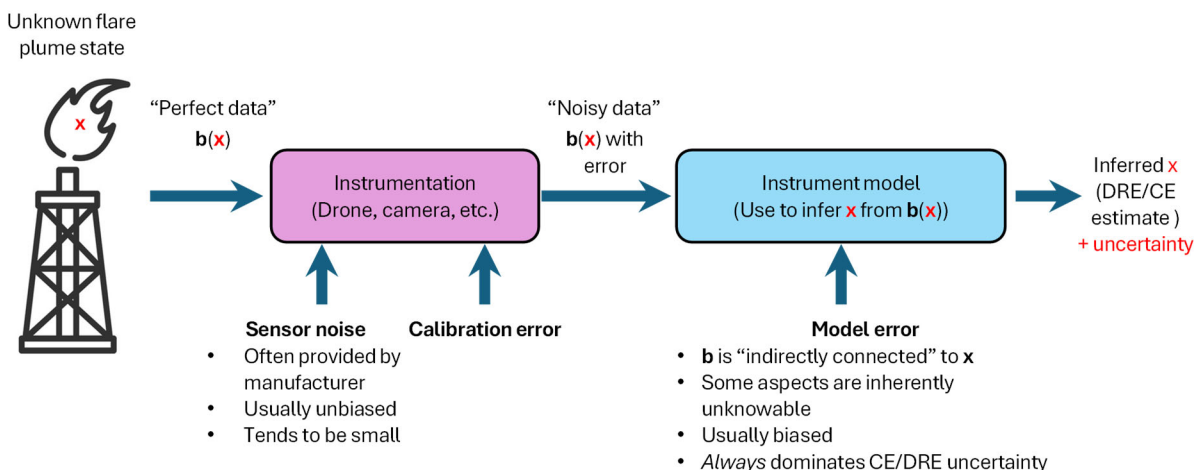


Figure 3: Definition of a measurement. The measurement, known as the QoI (CE or DRE; x), is related to observed data in vector b by an instrument model.

[30,34]. This location, approximated using the time-averaged temperature field, is indicated with a crosshair in the figure. The circle surrounding the crosshair represents the PFTIR field-of-view in the experiment, which subtends a region of high local CE while completely missing the region of low CE in the wake of the flare stack. This low CE region results from fuel stripping, which occurs when fuel is diverted from the combustion zone by vortices formed in the wake of the flare stack, resulting in a region of unburned fuel beneath the reaction zone in the buoyant combustion plume [17]. In this scenario the true CE would be lower than the PFTIR estimated value.

Crosswind-induced fuel stripping was first proposed by Johnson et al. [17,35]. Their wind tunnel experiments on 1" (25.4 mm) and 3" (76.2 mm) diameter flare tips revealed a strong, nonlinear relationship between CE and crosswind speed. The fuel-stripping mechanism involves the formation of complex, transient structures downwind of the flare where intense local mixing of fuel with air dilutes the fuel below its lower flammability limit [17]. Recent work by Burt et al. [24] in a larger, closed-loop wind tunnel with 4" (101.6 mm) diameter flare tips, a regime that overlaps with full-scale flares, lends credence to the hypothesis that crosswind-induced fuel stripping impacts the performance of operating flares.

3.3 Temporal variability and rogue events

Real-world flares exhibit a high degree of temporal variation that needs to be accounted for when estimating global CE/DRE_{CH₄}. Pohl et al. refer to this temporal variability as *intermittency*, the fraction of time that the flare plume is present in a particular location [2]. They propose an equation for computing the global CE from local CE measurements that includes an intermittency factor and weighting by the velocity and area from which the probe sampled. Because of this intermittency, the local CE (measured along the axis of the flare tip) overestimates the global CE of the flare, although in their experimental scenario, the authors

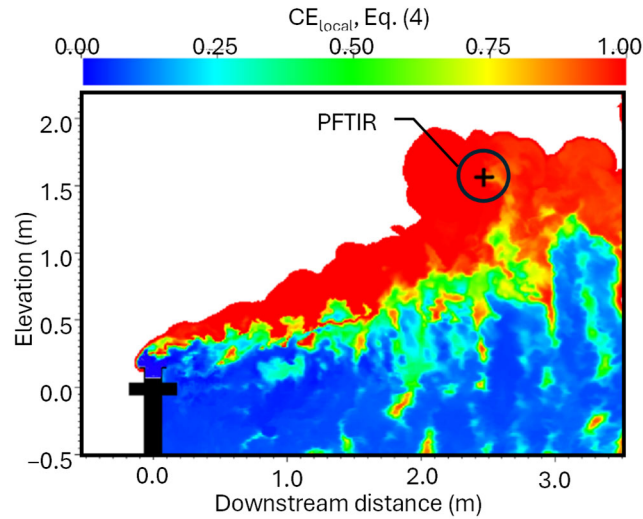


Figure 4: CFD-LES data of a steam-assisted flare burning natural gas, showing the instantaneous local CE along the simulation midplane. The local CE field is calculated for cells having CH₄ mass fractions exceeding 10⁻⁵. Fuel is stripped from the combustion zone and pulled into a region beneath the flare plume through crosswind-induced aerodynamics. The crosshairs and circle mark the field of view for a PFTIR measurement aligned two visible flame lengths downwind of the flare tip. In this configuration, the PFTIR measurement would not capture the fuel-rich region beneath the flare plume. Adapted from Ref. [33].

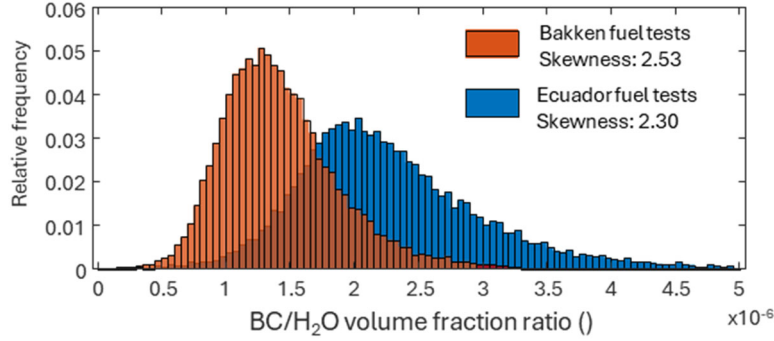


Figure 5: Histograms showing instantaneous black carbon to H_2O column densities across the plume of a laboratory diffusion flare burning two fuel types. The high degree of skewness calls into question the validity of instrument models that assume that the species concentration ratios used to derive local CE or DRE are highly correlated. Adapted from Ref. [36].

determine that the error is usually less than 50% of combustion inefficiency, $(1-CE)$ [2]. Johnson et al. [17,35] also note the highly intermittent and spatially variable fuel-stripping process by which unburned fuel (CH_4 or propane) is ejected from low-momentum, jet diffusion flames under crossflow conditions.

Another aspect of temporal variability was investigated by Seymour and Johnson [36]. It is the assumption that underlies many instrument models: a carbon balance for computing CE/DRE can be closed using the relative concentrations of species measured at one location in the flare plume. Often this treatment is justified by arguing that (1) the plume is well mixed and thus the species are well correlated, or (2) the number of measurements is sufficient to minimize any bias or uncertainty resulting from this assumption. To investigate, Seymour and Johnson made measurements of black carbon (BC) and H_2O concentrations in laboratory flares (1" or 3" diameters) burning synthetic flare gas. Figure 5 shows positive skewness and variability in the instantaneous BC/ H_2O ratios that call these assumptions into question and suggest that the amount of temporal and/or spatial averaging needed to obtain the "true" BC/ H_2O ratio for the flare should be considered carefully. The skewed distribution implies that a BC/ H_2O ratio calculated from a small sample size would likely be biased toward low ratio values, thus missing the infrequent bursts of BC production observed by the authors. Consequently, inadequate sampling would cause the CE/DRE to be biased toward higher values. The broader implication is that the wide variation in the instantaneous, LOS species concentration ratios introduces considerable uncertainty into measurements that assume these ratios are fixed.

A final consideration regarding the temporal variability of flares is that of rogue events, defined as infrequent phenomena that have an outsized effect on the mean outcome of a system. The infrequent bursts of BC production in laboratory-scale flare plumes [36] evidenced by the positive skewness in BC/ H_2O ratios in Figure 5, are one such example. These bursts populate the distribution's long tail and have an outsized influence on the mean value. In the case of industrial-scale flares, a rogue eddy rich in unburned CH_4 or in BC may exit the combustion zone of the flare by the fuel-stripping mechanism described above. Conrad and Johnson [37] characterized rogue events during measurement campaigns on nine field flares. Eight of the nine flares exhibited positive skewness, which the authors attributed to intermittent bursts of high BC production within localized areas of the plume.

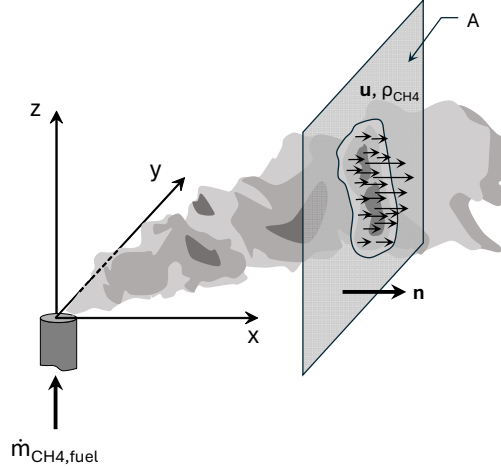


Figure 6: Local quantities used to derive DRE_{CH_4} through Eq. (7).

3.4 Connecting local DRE to global DRE

Most of the technologies used to measure DRE_{CH_4} do not distinguish between local DRE_{CH_4} and global DRE_{CH_4} . Instead, the local DRE_{CH_4} “measurement,” inferred from observations made at a “representative” point or LOS, is taken to be the global value. As seen in Figure 4, the local CE (and thus DRE) values may vary throughout the plume in a manner that depends on system parameters such as vent gas composition and flow rate, crosswind velocity, and assist gas flow rate. What distribution of DRE_{CH_4} would we obtain if we were to make measurements at more locations in the plume? How many measurements would be required to adequately describe the distribution? How should we determine the global CE/DRE from these local data?

According to Eq. (3), global DRE_{CH_4} is defined based on the mass flow rate of unreacted CH_4 exiting the boundary of the flare plume (where no further reaction occurs) relative to the mass flow rate of CH_4 in the fuel entering through the flare tip. Accordingly, the global DRE_{CH_4} may be written in terms of local concentrations and velocities in the flare plume as

$$DRE_{CH_4} = 1 - \frac{\int_A \rho_{CH_4} \mathbf{u} \cdot \mathbf{n} dA}{\dot{m}_{CH_4, fuel}} \quad (7)$$

where A is the area of the downwind face, ρ_{CH_4} is the local density of CH_4 , $\mathbf{u}$ is the velocity vector at the downwind face, $\mathbf{n}$ is the unit normal vector pointing out of the control-volume face, and $\dot{m}_{CH_4, fuel}$ is the mass flow rate of CH_4 entering the flare tip as fuel. These quantities are shown in Figure 6. In practice, the concentrations and velocities are never known as continuous functions and can only be sampled at a limited number of locations in the plume (e.g., [2,25]).

It is important to note that Eq. (7) is not equivalent to integrating local values of DRE_{CH_4} , defined by Eq. (6), over the downwind face of the control volume. First, area elements containing more CH_4 mass should have a greater influence on the global DRE_{CH_4} , but this is not the case when averaging the local DRE values over the total area. Second, averaging the local DRE_{CH_4} estimates does not account for the nonuniform projected velocity profile on the control-volume face.

In the case of remote sensing, various instrument models have been proposed to compute global CE from local CE measurements. In the PFTIR approach (Sec. 5.2.3), a local CE consistent with Eq. (5) written in column-number-density form is computed based on the spectrally

resolved intensity measured along an LOS located at a prescribed distance downwind of the visible flame; this local CE is taken to be representative of the global CE [34]. In the VISR/FlareGuardian™ technique (Sec. 5.2.4), local CE values are computed for multiple pixels within a region of interest outside a flame envelope and then averaged to obtain a global CE value [23,26,38]. Both approaches introduce potentially significant errors in the computation of global CE values by not considering mass weighting and the impact of nonuniform projected velocity profiles. A similar argument could be made for the computation of global DRE_{CH_4} from DRE instrument models.

The integrand in the numerator of Eq. (7) may be estimated by converting spectrally resolved intensity measurements into column densities and combining these with 2D velocity fields inferred through feature tracking between successive plume images. This technique is possible using imaging Fourier transform spectrometers, as discussed in Sec. 5.2.4. However, inferring the local species concentrations along each LOS involves approximations that also introduce uncertainty in the global DRE_{CH_4} estimate.

4 Calibration, Validation, and uncertainty quantification

As flare emission regulations are growing more stringent, the accuracy and uncertainty attached to flare emission estimates are becoming more important. Previously, US EPA rules were written so that if certain operating conditions were met (e.g., minimum net heating value in the combustion zone, NHV_{cz} , minimum flare tip velocity, presence of a pilot flame), the flare was assumed to operate with a global DRE of 98% [4]. In new US EPA rules effective 2024, flares burning associated gas from new wells must achieve DREs for CH_4 and volatile organic carbon (VOC) emissions of 95%, although it is unclear how these DREs will be determined [39]. Nevertheless, any reported DRE without an associated uncertainty estimate inevitably has very limited value.

4.1 CE and DRE as distributions

As discussed in Sec. 3 there is not one CE/DRE value for a given flare. Instead, these estimates should be thought as random variables that obey a distribution like the one shown in Figure 7, due to physical phenomena including intermittency, rogue events, fuel stripping, variable wind conditions, changing vent gas composition, etc., as well as sensor uncertainty, calibration error, and model error. In this example figure, the most probable value of DRE_{CH_4} is 90%, but there is a

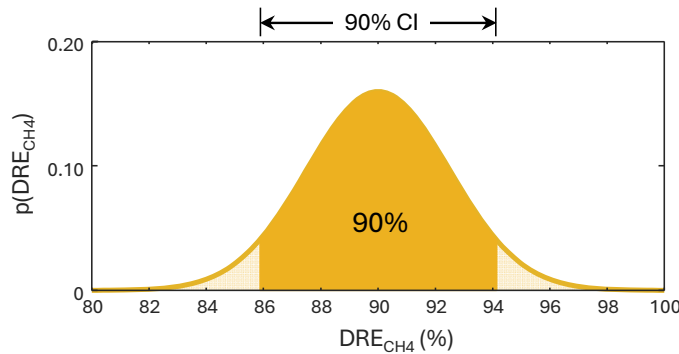


Figure 7: The quantity-of-interest (here DRE_{CH_4}) is envisioned as a random variable that obeys a probability density function. The width of the pdf reflects the uncertainty of the estimate and is a consequence of both sensor uncertainty and model error, see Figure 3. The uncertainty can be summarized by a confidence interval (Bayesian: credibility interval) that contains the “true” answer with a fixed probability, here 90%.

smaller probability that DRE_{CH_4} could hold any value between 80 and 100%. The distribution width reflects the uncertainty attached to the DRE_{CH_4} estimate resulting from the error sources discussed in Sec. 4.3 and Figure 3. It is commonplace to express a confidence interval (called a “credibility interval” in Bayesian inference) that may be interpreted as containing the “true” QoI with a certain probability.

The impact of uncertainty in determining the global impact of flaring is conveyed in Figure 8. A large uncertainty interval for DRE_{CH_4} corresponds to a large uncertainty in the CH_4 emission rate. Flares operating with $DRE_{CH_4} = 99\%$ will have 50% fewer CH_4 emissions than those operating at 98%. Conversely, a flare operating with $DRE_{CH_4} = 91.1\%$ will have four times the emissions of a flare operating at a DRE of 98%.

4.2 Definitions of calibration, validation, and uncertainty quantification

In the context of this report, we apply the following definitions of calibration, validation, and uncertainty quantification.

- *Calibration* is “the process of adjusting physical modeling parameters in the computational model to improve agreement with experimental data” [40]. Calibration of the sensor requires data obtained using a calibration device (e.g. a blackbody calibration source). Calibration of the instrument model requires benchmark data that may be used as a basis to calibrate the uncertain model parameters. In the context of flaring, benchmark data is usually taken as extractive-sampling data, but this standard is subject to inaccuracy and bias.
- *Validation* is “the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model” [40]. In the specific context of flaring, a recent report published by the Energy Institute defines validation as “the ability of technologies to give measurement values that match the actual measurements from a trusted method, such as extractive sampling...” is the process of comparing experimental data for DRE_{CH_4} computed from the instrument model of a specific technology to benchmark data that approximates the “true values” to determine the degree to which they agree [14].
- *Uncertainty quantification*: The objective of a flare measurement is to transform measured observables (e.g., spectroscopic data) into an estimate of the QoI with quantified uncertainty based on what is known about the instrument model from the calibration and validation steps. Bayarri et al. [41] state that “...we do not focus on

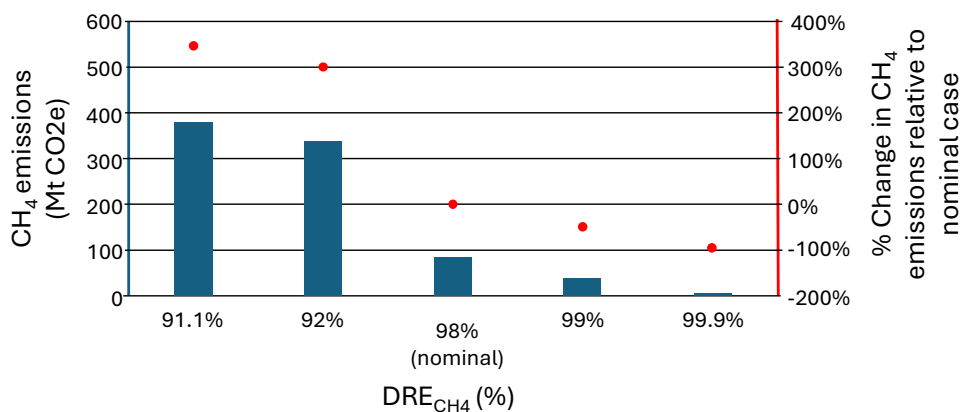


Figure 8: Small changes/uncertainties in flare DRE correspond to large changes in CH_4 emissions relative to the nominal case of $DRE_{CH_4} = 98\%$. (Adapted from Ref. [44]).

answering the yes/no question ‘Is the model correct?’ but rather on assessing accuracy of predictions in uses of the model.” They suggest using tolerance bounds representing the specified chance (say 95%) that the true value of the QoI lies within the given bounds, as per Figure 7. They emphatically add that, “Such tolerance bounds should be given whenever predictions are made, i.e., they should routinely be included along with any predictions arising from use of the model” [41]. We agree with this statement and adopt their definition of uncertainty quantification as predicting the range in which the true value of the QoI is most likely to lie. Experimental values (i.e., instrument model predictions) of DRE_{CH_4} obtained using any of the measurement technologies described in this report should necessarily include uncertainty bounds (determined using an accepted, standardized approach) for them to be considered relevant for estimating flare emissions.

4.3 *Leading uncertainty sources*

Uncertainty intervals are frequently estimated by propagating the uncertainty in the observed data (sensor uncertainty) through the instrument model. However, this approach overlooks the often (much) larger uncertainties (model error) arising from imperfectly known model parameters and from the simplifications and “missing physics” in the instrument model.

The impact of an uncertain model parameter depends on both the level of uncertainty associated with the parameter as well as the sensitivity of the QoI to the parameter. If the sensitivity of the QoI to parameter X and the uncertainty of parameter X are both large, that parameter will be a large source of uncertainty in the value of the QoI predicted by the instrument model (the “measurement”). Sensitivity is also amplified by the complexity of the instrument model. Generally, the more indirect the connection between the observables and the QoI, the more sensitive the estimated QoI is to uncertainties in both the observed data (sensor uncertainty) and the instrument model (model error).

Other sources of instrument model uncertainty may include relevant physics that either are excluded to keep the model tractable or are unknown altogether. Model uncertainties are particularly important in the context of the measurement challenges outlined in Sec. 3: spatial heterogeneity in the plume, fuel stripping resulting from the interaction of crosswind with the flare, temporal variability (including intermittency and rogue events), and the simplifications made to infer a global DRE from a single (or set of) local DRE measurement(s). All of these phenomena are potentially large sources of model error.

As an example, the concentration of CH_4 in a sample extracted from a flare plume by a drone may be measured to sub-ppm levels by an instrument onboard the drone (sensor uncertainty), but the velocity field used to calculate the mass flow rate is far less certain, particularly given temporal fluctuations in wind and concentrations during the drone measurement (model error resulting from temporal variability). If the uncertainty in the QoI is determined solely by propagating the sensor uncertainty from the onboard instrument measuring CH_4 concentration, a large source of error is excluded from the CE or DRE estimate.

Model errors often manifest as a systematic bias. An example of systematic bias for flares in crosswind is the fuel-stripping phenomenon identified by Johnson et al. [17,35]. Researchers who compare remote-sensing results to the benchmark of extractive sampling (e.g., [23,32]) may be missing the region downstream of the flare stack and below the level of the flare tip where unburned HCs are most likely to be found. In this case, both the instrument models used in remote-sensing and extractive-sampling systems may introduce a bias by missing regions of stripped fuel, depending on the capability of the spectroscopic system and the sampling location.

4.4 Current methods of estimating uncertainty

There is no internationally recognized protocol for determining the accuracy (e.g., estimating the uncertainty) of CE/DRE measurements in flares [13,14]. Technology providers may use the words “accurate” or “verified” or “validated,” but without an assessment standard, it is impossible to compare uncertainties across technologies and to decide which technology most accurately represents the true but unknown distribution of CE/DRE values. Ideally, a methodology for determining uncertainty in CE/DRE_{CH₄} measurements would address the current inconsistencies in the literature and among manufacturers, be cost-effective to implement, and be applicable to a wide range of flare types and flaring scenarios. We propose such a methodology in Sec. 6.2 of this report.

In this section, we summarize common techniques for evaluating CE/DRE uncertainty. *While all these methods provide an estimate of uncertainty, none of them fully capture the extent of model error that we believe to exist in flare CE/DRE estimates, resulting in an underestimation of uncertainty by all the methods summarized below.* One important effect that is excluded by all techniques described here concerns the extrapolation of uncertainty. All uncertainty quantification methods apply to a particular set of conditions. However, these uncertainty estimates are often extrapolated to other conditions which may differ from the conditions used in the original uncertainty estimate. It is unlikely that the uncertainties computed for a flare on a test pad, where operating inputs such as fuel composition and flow rate, exit velocity, and assist-gas flow rate are carefully controlled and monitored and data are not taken if ambient wind speeds exceed a certain value [42], are directly translatable to DRE uncertainty in an operating flare.

4.4.1 Propagation of observed data uncertainty

Discussions of uncertainty in plume sampling are often limited to the accuracy and precision of the sensors in the instruments used to examine the sampled gas. Allen and Torres [10] and Wormhoudt et al. [32] applied this method to data obtained from the plumes of industrial-scale, steam- and air-assisted flares. A sample collector placed in the flare plume drew a large sample that was homogenized and sent to a series of analyzers. They propagated the uncertainty of measured ratios of various carbon-containing species in the flare plume into their definition of CE. Because they only propagated sensor uncertainty, the uncertainty they computed likely underestimates the total uncertainty (including model error). In other words, uncertainty in CE/DRE derived from extractive measurements is almost certainly dominated by flare plume dynamics that cannot be captured due to the limited spatial and temporal resolution of probing in both ground-based and aircraft- or drone-based measurements, as opposed to the uncertainty in the composition of the gas sample.

To address the limitations of this type of error propagation, Allen and Torres [10] presented a detailed analysis of other potential uncertainty sources for CE in Section 7 of their report. Wormhoudt et al. [32] acknowledged that their nominal error bars on CE values from extractive sampling did not include “systematic” errors. Nevertheless, they concluded that their error bars were adequate for explaining most of the differences between CE measurements obtained from remote sensing and from extractive sampling. In an aircraft-based, extractive-sampling study, Gvakharia et al. [43] found that the calculated DRE values for plumes sampled from a single flare on the same day or over multiple days were inconsistent. They addressed this variability by deriving an overall uncertainty that included both the threshold sensitivity of the onboard sensors to CH₄ and CO₂ (sensor uncertainty) and the statistical variability of the concentration enhancements of carbon-containing gases in the plume relative to background values (see Sec. 5.1.2) measured from the set of transects by the aircraft through the plume (model error).

4.4.2 Basic GUM approach – standard error propagation

The internationally accepted framework for evaluating and expressing measurement uncertainty is the Guide to the Expression of Uncertainty in Measurement (GUM) approach [44]. This framework focuses on three basic steps: (1) identify all significant sources of uncertainty, (2) develop an instrument model, and (3) combine the identified uncertainties into a total uncertainty estimate by taking a root sum of squares of all identified errors using sensitivities obtained from the instrument model. By focusing on uncertainty in the instrument model in addition to observed-data uncertainty, this framework provides a more rigorous assessment of uncertainty than the propagation of observed-data uncertainty alone.

As an example, a recent study by Evans et al. focused on measuring the CE/DRE of three different flare tips under various mass flow rates, NHV_{cz} values, and crosswind conditions [45]. The CE/DRE values were inferred from concentration measurements of combustion gases sampled via an extractor located downwind of the visible flame. The extractor inlet was instrumented with three thermocouples, and the hood was located to ensure that the average temperature remained between 300°–700°F (149°–371°C) to ensure that the extractor was sampling combustion products and that the combustion process was complete. Evans et al. estimated the overall CE/DRE uncertainty by combining the uncertainty associated with the resolution of the online sensors with a replication uncertainty meant to capture the effect of plume intermittency and heterogeneity using this standard error propagation approach [45]. They found the uncertainty in their estimates to scale with combustion inefficiency; for $DRE_{HC} > 98\%$, the median 68% confidence interval was $\pm 0.11\%$ DRE but for $DRE_{HC} < 98\%$, the uncertainty grew rapidly, mainly due to intermittency.

Corbin and Johnson used this framework to quantify the uncertainty associated with the CE of a modular burner with a large exhaust hood centered over it [46]. They developed two instrument models, one based on a carbon-balance approach and the other on a tracer-gas approach, and derived the partial derivatives needed to compute the sensitivities of these models to the uncertain inputs. The uncertainty was much greater with the tracer-gas method ($\pm 5\%$ CE) than with the carbon-balance method ($< \pm 0.1\%$ CE), which they attributed to uncertainties in the measured concentrations of tracer gas and CO_2 in the plume diluted by ambient air.

In a third example of this approach, researchers using an uncrewed aerial vehicle (UAV, “drone”) (Sec. 5.1.1) computed an estimate of DRE_{CH_4} in which the mass flow rate of the CH_4 entering the fuel stream was informed from CH_4 and CO_2 mass flow rates through a “flux wall” located downstream of the flare [47]. In their definition of DRE_{CH_4} ,

$$DRE_{CH_4} = 1 - \frac{\dot{m}_{CH_4}}{\dot{m}_{CH_4, fuel}} \approx 1 - \frac{\dot{m}_{CH_4}}{C \cdot \dot{m}_{CO_2} + \dot{m}_{CH_4}} \quad (8)$$

C is a parameter that accounts for the fuel stream composition (i.e., all the components that could produce CO_2 if burned completely) and the molecular masses of CH_4 and CO_2 . The mass flow rates, $\dot{m}_k$, were found by combining CH_4 and CO_2 point concentration measurements and anemometry measurements made with sensors on the UAV. A standard error propagation analysis of three sources of uncertainty (computed mass flow rates of CH_4 and CO_2 , flare gas composition expressed as C^2) showed that [47]

² In Ref. [47] variable C is expressed as $M_{CH_4}/M_{CO_2} \cdot X$, where M_{CH_4} and M_{CO_2} are the molecular masses of methane and carbon dioxide, respectively, and X depends on the composition of the flare gas.

$$\Delta DRE_{CH_4} = \frac{(1-DRE)}{1 + \dot{m}_{CH_4}/(C \cdot \dot{m}_{CO_2})} \sqrt{\left(\frac{\Delta \dot{m}_{CH_4}}{\dot{m}_{CH_4}}\right)^2 + \left(\frac{\Delta \dot{m}_{CO_2}}{\dot{m}_{CO_2}}\right)^2 + \left(\frac{\Delta C}{C}\right)^2} \quad (9)$$

The relative error in C was typically an order of magnitude smaller than those of the computed mass flow rates; the relative error in mass flow rates was ~ 10 -30% depending on meteorological conditions, as discussed in Sec. 5.1.1. Equation (9) shows that the absolute error in DRE_{CH_4} approaches zero as DRE_{CH_4} approaches 100%, a trend observed in many benchmarking studies.

There are several drawbacks to this approach of error propagation. First, because the GUM approach relies on the analyst to inventory every known uncertainty source, it is susceptible to *unknown* uncertainty sources, e.g., in the event of crosswind-induced fuel stripping, the fuel-rich region beneath the flare may not be sampled adequately if the extractor is not placed correctly. Second, the analyst must estimate the uncertainty of all identified sources *a priori* [24,46] rather than inferring the uncertainties from the available data. There is no mechanism in the GUM approach to learn from the data, i.e., to use newly observed data to update the uncertainty estimate. Third, if improvements are made to an instrument model (i.e., additional physics are included), more uncertain parameters are introduced, which results in increased overall uncertainty using standard error propagation. This result is the opposite of what one would expect with a higher-fidelity model; as model fidelity increases, the overall uncertainty should decrease [48]. These shortcomings are addressed through the Bayesian approach proposed in Sec. 6.2.

4.4.3 Alternative GUM approach – Monte Carlo propagation

An alternative to the basic GUM framework is to propagate probability distributions of inputs through the instrument model using a Monte Carlo method. This approach applies to an instrument model with multiple uncertain inputs (observables, model parameters) but a single output (the QoI) [49].

Burt et al. [24] used a Monte Carlo approach to compute the uncertainty of CE and CH_4 emission estimates for a flare operating within a closed-loop wind tunnel. They applied their instrument model to a synthetic data set that modeled a wind tunnel with a volume of 2000 m³, large infiltration/exfiltration rates (10 changes of air per hour), and a range of flare gas flow rates. The simulated data was distorted with several types of errors (precision, bias, etc.) to test the robustness of their methodology. For each simulated test condition, they drew values of all uncertain input variables to the instrument model from representative distributions. They performed 10,000 such draws at each condition to calculate 95% confidence intervals for the QoIs. This Monte Carlo uncertainty and sensitivity analysis demonstrated that overall uncertainties (combined bias and precision) of $< 1\%$ CE were achievable from this carefully controlled experiment, implying that CE measurements taken under more challenging, real-world conditions with reported accuracy of $\leq 1\%$ CE should be viewed with skepticism.

While this approach to quantifying uncertainty accounts for the fact that uncertain parameters are random variables best represented by distributions, it shares the same drawbacks as the standard GUM approach: (1) the analyst must identify the sources of uncertainty, thus excluding *unknown* (and potentially large) sources from the analysis, (2) the analyst must define the magnitude of each source of uncertainty rather than learning the uncertainties from the data *priori* [24,46] and (3) improvements to the instrument model (which inevitably introduces additional uncertain parameters) results in increased uncertainty estimates due to error propagation of the new parameters rather than decreased uncertainty that one would expect from a model that better represents the real world [48].

4.4.4 Comparison with benchmark data

Near-field, direct-sampling measurements are generally considered the most accurate benchmark data for determining flare plume composition and are routinely used to quantify flare CE/DRE, e.g., [1–3,19,42,45,50] and to “validate” the accuracy of remote-sensing technologies [10,23,32]. However, “Strictly speaking, what can be assessed is the agreement between the two methods, not the accuracy of either method because the true flare CE is unknown” [51].

In a single blind study conducted by Allen and Torres [10], the technology providers of remote-sensing instruments (PFTIR, Sec. 5.2.3; AFTIR, Sec. 5.2.3) collected their observables and then used their instrument models to determine CE/DRE without receiving any additional information about direct-sampling results. Mean differences between the direct-sampling and remote-sensing CE measurements ranged from 1.1–20.2% CE. Zeng et al. [23] measured CE using two methods: an extractive-sampling apparatus and their hyperspectral infrared imager (the “video imaging spectro-radiometry” or VISR method) with its proprietary instrument model. In a subset of 28 tests corresponding to high CE conditions, the mean difference between the two types of measurements was 0.5% CE, although it should be noted that this was not a blind test.

The drawback of this approach is the lack of a well-defined, well-analyzed set of benchmark data that can be used for calibration and validation due to the challenges inherent to measuring a full-scale, open flare. While sample extraction from a flare plume and the subsequent analysis of gas-phase species concentrations in the sample are generally regarded as the most reliable way to compute CE/DRE, the location of the extractor relative to the plume, the effect of sample dilution, the sample size, the sampling time, and other factors all contribute to a measurement uncertainty that has never been adequately evaluated.

4.4.5 Uncertainty propagation in expert systems

There is a growing trend towards using artificial intelligence (AI) and its subset, machine learning (ML), in the form of “expert systems” to determine DRE in field flares. These expert systems, a type of instrument model developed from training data, may exploit subtle and sometimes hidden relationships among readily observable quantities about the operating state (fuel flow rate, fuel composition, exit velocity, air/steam assist, ambient wind conditions, etc.) to infer DRE without interrogating the flare emissions directly [42,52,53]. The DRE “training data” is obtained from multiple sources including extractive-sampling, PFTIR, and VISR measurements [42,52,53] as well as CFD-LES simulations of conditions that are difficult to achieve during testing [42].

Tao et al. [42] performed a validation test of their expert-system instrument model, the parametric model method (PMM), by comparing with “benchmark” data from extractive-sampling tests. They conducted both types of GUM uncertainty analysis (Sec. 4.4.2 and Sec. 4.4.3) with their PMM measurements [42] and used the standard error propagation method (Sec. 4.4.2) with their extractive-sampling measurements [45] to obtain DRE_{HC} uncertainty estimates. The uncertainty of both types of DRE_{HC} measurements was correlated with the difference between the PMM and extractive sampling predictions (measurement discrepancy); both uncertainty and discrepancy increased as NHV_{cz} (and thus DRE_{HC}) decreased. For $NHV_{cz} \geq 300$ BTU/scf (11.2 MJ/m³), the DRE_{HC} generally exceeds 98%; under these conditions the discrepancy was negligible and the uncertainty for the benchmark and the PMM data was approximately $\pm 0.40\%$ DRE_{HC} . For cases in which $170 < NHV_{cz} < 250$ BTU/SCF ($6.3 \text{ MJ/m}^3 < NHV_{cz} < 9.3 \text{ MJ/m}^3$), scenarios in which $DRE_{HC} < 98\%$, the discrepancy was 10.6% DRE_{HC} and the average

uncertainties for both PMM and extractive-sampling DRE_{HC} estimates were both approximately 11% DRE_{HC} .

While this detailed analysis shows self-consistency between the PMM and extractive-sampling DRE measurements, it is important to remember that expert systems are subject to considerable instrument model uncertainty associated with the training datasets; bias in the training data produces bias in the PMM-generated values of DRE_{HC} . In addition, their generalizability has not been adequately probed in the open literature.

5 Technologies and methodologies for measuring CE/DRE

This section summarizes the technologies and methodologies that may be used to measure the CE or DRE of operating flares in upstream oil and gas applications. One-page summaries of the capabilities and operating parameters of the most relevant technologies are included in Annex A.

The scope of the review is defined as follows:

- The review focuses on technologies for measuring the CE/DRE of elevated flares, although many of these technologies are also applicable to enclosed combustors/ground flares.
- The review excludes sampling-based systems that are suitable only for validation tests, such as the one shown in Figure 2. These types of systems require a much higher degree of access to the flare plume than is typically afforded under operational conditions.
- Although the review focuses on techniques for measuring the CE/DRE of lit flares, we note the ones that can also measure emissions of unlit flares and that can determine whether the flare is lit (e.g., pilot monitoring).
- While some of the technologies use instrument models derived in part using data from validation tests or CFD studies, the review excludes “expert systems” that rely solely on measurement of the operating state (fuel flow rate, fuel composition, air/steam assist, wind measurements) to estimate flare CE/DRE without interrogating the flare emissions directly [42,52,53]. As noted in Sec. 4.4.5, in our opinion, these types of instrument models are subject to considerable model errors associated with the training data set and their robustness has not been defined adequately in open literature.
- The review focuses on technologies that can infer flare CE/DRE via Eqs. (1)-(6), which requires simultaneous measurements of CH₄, CO₂, and often CO, or explicit knowledge of the flare gas composition. However, our review also includes some technologies that can only measure CH₄ emissions.

Technologies for measuring flare CE/DRE may be most broadly categorized as sampling-based or remote-sensing approaches.

5.1 Sampling-based approaches

All techniques used to estimate flare CE/DRE or the emission rate of a particular species of interest require some means to determine the flare plume composition. The most direct way to do this is to identify the composition and concentration of species within samples of the gas phase. Concentrations are then related to the composition of the flare plume at the sample location, and, in some cases, may be converted to a global emission estimate. These approaches can be subdivided into near-field techniques, which sample the plume close to the flame, and far-field techniques that operate further downstream.

5.1.1 Near-field sampling techniques

Near-field sampling techniques have historically been associated with validation tests in which the flare plume is sampled using a large air extractor [23,32] or smaller point sensors that are either fixed in place or traversed through the plume on a rake. As already noted, these measurements require a far higher degree of plume access than can be obtained from operating

flares, so they are useful only for conducting scientific investigations of flares and obtaining the benchmark data described in Sec. 4.

However, the growing affordability and increasing payload of UAVs (or drones), coupled with the miniaturization of instrumentation, presents new opportunities for deploying near-field sampling techniques on operating flares. A typical instrumentation payload consists of a GPS for locating the drone and sensors for measuring plume species' composition, pressure, temperature, relative humidity, as well as wind speed and direction. The drone flies repeated plume transects, typically 20-100 m downwind of the flame depending on flare size and wind speed. Concentrations of CH_4 , CO_2 , and potentially other species of interest, like CO and non-methane VOCs (NMVOCs), are measured at a frequency between 1-5 Hz. Carbon dioxide concentrations are typically measured using a non-dispersive infrared (NDIR) sensor, while CH_4 concentrations are inferred to sub-ppm precision with a compact tunable-diode-laser-absorption-spectroscopy (TDLAS) sensor. (These sensors are founded on the spectroscopic principles discussed in Sec. 5.2.1.) Preliminary research that examines the potential of UAVs for measuring flare CE/DRE has been carried out by Festa-Bianchet et al. [54] and there are at least two commercial systems that have recently become available: the Explicit ApS [55] and Aeromon's BH-12 sensor payload [56]. Typically, the drone is used to conduct a preliminary survey of the plume structure and composition prior to undertaking data collection required for a CE or DRE calculation. This survey sometimes reveals plumes from other nearby sources, and, under some conditions, UAV measurements reveal two distinct plumes: a buoyant plume consisting of hot CH_4 mixed with the combustion products, and a cold plume containing fuel stripped from the combustion zone.

Several techniques can be used to convert these concentration measurements into a CE or DRE estimate. The most obvious approach is to transform the concentrations measured at a given location into a local CE estimate using Eqs. (4) or (6). Alternatively, global DRE estimates may be obtained from CH_4 emission rates found by flying repeated transects within an imaginary plane or multiple planes oriented perpendicularly to the wind direction (Figure 9). Methane concentrations measured during the transects are then combined with drone-based anemometry data (mass-balance method [57] or results from reverse-dispersion modeling [58]) to obtain the mass flow rate of CH_4 , $\dot{m}_{\text{CH}_4}$. Typically, the CH_4 mass flow rate will also be calculated through an upwind surface and then subtracted from the mass flow rate through the downwind surface to isolate the flare contribution. The inferred CH_4 mass flow rates are then used to calculate DRE_{CH_4} via Eq. (3).

A typical mass balance measurement requires approximately 10 minutes for the drone to complete the required transects. Ideally, this duration would be sufficient to capture intermittent plugs of unburned CH_4 associated with incomplete combustion (see Sec. 3.2). However, local CE estimates obtained from simultaneous CO_2 and CH_4 concentrations would be more susceptible to the imperfect correlation between these two variables, as described in Sec. 3.3 [37].

While neither commercial instrument has a defensible, publicly available procedure for quantifying uncertainty attached to DRE estimates, both companies have developed internal practices that focus on the uncertainty of the CH_4 flow rate calculation. For smaller flares and lower CH_4 concentrations the sensor uncertainty plays an important role in the mass flow rate uncertainty, while for larger flares and higher concentrations it is dominated by the model error associated with the mass-balance method [57]. The levels of uncertainty inferred from benchmark studies suggest drone-derived mass flow rates may be subject to uncertainties of between 15%-30% under favorable conditions [59,60]. Uncertainty depends strongly on factors like wind fluctuations and therefore should be calculated for each measurement scenario.

Conservative uncertainty estimates may be derived by applying the GUM methodology to Eq. (3) assuming the errors in the CH_4 , CO_2 and CO mass flow rate estimates are uncorrelated [47].

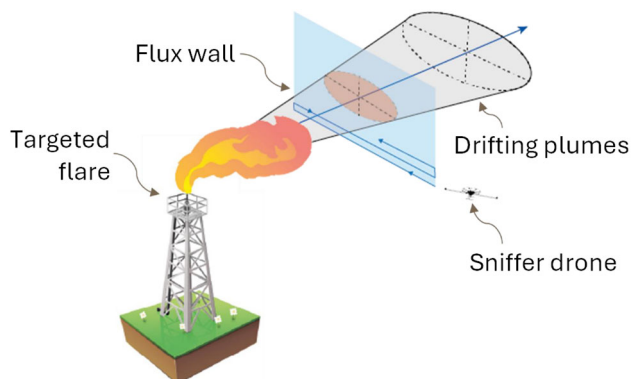


Figure 9: Commercial UAV systems work by flying repeated transects across one or multiple planes through the flare plume. Concentration maps are then used to infer mass flow rates through reverse dispersion modeling or the mass balance method. These mass flow rates are then converted into a DRE estimate via Eq. (3). Adapted from Ref. [47].

5.1.2 Far-field sampling techniques

Far-field sampling is often conducted as part of large-scale environmental monitoring campaigns, as opposed to focusing on a particular flare or facility. The key distinction between near- and far-field measurements is the additional mixing that occurs as the plume travels downstream. Consequently, the assumption of a homogeneous plume may be more reasonable for far-field sampling, and the inferred CE/DRE may not be as sensitive to rogue events and temporally uncorrelated fluctuations in species concentrations that severely impact near-field measurements (Sec. 3.3). The drawbacks of far-field measurements are the inherently lower concentrations of target species caused by air entrainment and dilution, and the possibility that part of the plume may be excluded from the sampling. A further challenge concerns distinguishing the species emitted by a particular flare from contributions from other local sources, which is generally not a concern when conducting near-field sampling.

Instrument models developed for far-field sampling include methods for determining enhancements to CO_2 (ΔCO_2 , the increase in CO_2 concentration measured in the plume relative to measurements made outside the plume) and other carbon-containing species. In the case of DRE estimates, some assumptions must be made about the composition of the flare vent gas since it is generally unknown for a specific flare, a potentially large source of error.

Downstream measurements may be made from the ground or in the air. For example, Wood et al. [18] conducted ground-based mobile measurements of flare plumes in the Houston area using an Aerodyne Mobile Laboratory, which was stationary during measurements. They assumed that the plume was released from a height of 65–70 m and then transported to the ground through atmospheric mixing. Measurements were made approximately 400–800 m downstream of the flare; this distance is a trade-off between being far enough away to ensure the plume is well mixed at ground level but sufficiently close to avoid contributions from other nearby emission sources. The CE was estimated using Eq. (4), with concentrations scaled and regressed versus the CO concentrations to distinguish the concentrations of carbon-containing species within the flare exhaust from background concentrations, which may be considerable

in an industrial area. The authors also evaluated flare DREs for several C_{2+} hydrocarbons on a concentration basis via Eq.-(6).

Aircraft are increasingly being used to measure flare CE/DREs [5,43,61,62]. Typically, the aircraft conducts multiple transects of a single plume. The start and end of the transect should be far enough from the influence of the plume to experience background CH_4 conditions. The sensor package onboard the aircraft often includes a cavity ringdown spectrometer (CRDS), which is highly sensitive to CH_4 , C_2H_6 , and CO_2 along with other sensors to measure NO_x and particulate matter.

The enhancements to CO_2 ($[\Delta CO_2]$) and CH_4 ($[\Delta CH_4]$) concentrations (and other species) in the plume are determined relative to background concentration measurements made outside of the plume (Figure 10 (a)). By regressing ΔCH_4 versus ΔCO_2 , as shown in Figure 10 (b), the CH_4 emission factor (ppm CH_4 /ppm CO_2) is obtained as the slope of the regression line; emission factors are a measure of flare efficiency in addition to CE and DRE. Assuming the plume is well mixed in the far field and using the computed peak enhancements, DRE_{CH_4} is often approximated in these studies by

$$DRE_{CH_4} = 1 - \frac{[\Delta CH_4]}{y_{CH_4, fuel} [\Delta CO_2] + [\Delta CH_4]} \quad (10)$$

This approach employs a carbon mass balance to estimate the $\dot{m}_{CH_4}/\dot{m}_{CH_4, fuel}$ term in Eq. (3) where the mass fraction of CH_4 in the fuel stream, $y_{CH_4, fuel}$, may be obtained from the flare operator, or more often, is assumed based on the typical associated gas composition for a particular geological formation. The uncertainty of this measurement is derived from the noise threshold of the onboard sensors to CH_4 and CO_2 [62] (lowest detectable signal level that can be reliably distinguished from background noise), along with the statistical variability of the concentration enhancements measured from the set of transects.

A similar approach was used by Shaw et al. [61] in their aircraft survey of oil and gas flares in the North Sea, although they defined the enhancements by integrating the concentration along the flight path for a given transect (e.g., ppm-m). They argued that their approach reduced potential errors with temporal misalignment among the sensors (sampling at slightly different times for each species) compared with the peak enhancement approach used by other authors.

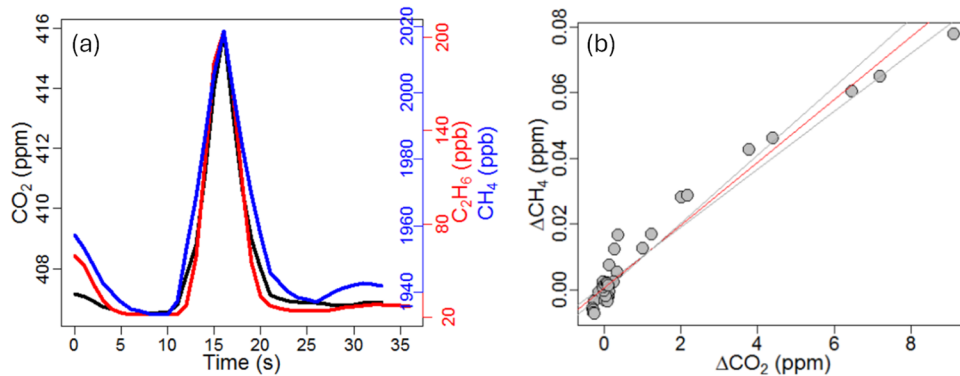


Figure 10: (a) Example concentrations measured during a plume transect. The enhancement is taken as the difference between the peak concentration and background concentration measured outside of the plume. (b) A linear regression is conducted on enhancements from multiple plume transects to obtain a robust DRE estimate via Eq. (9). Adapted from Ref. [43].

Temporal misalignment is an example of an instrument model error that may or may not be accounted for in the instrument model being used for the “measurement.”

The accuracy of the CE/DRE values obtained from far-field sampling hinges on the validity of the assumptions that the plume is well mixed and steady and that it originates only from the flare. As noted by Gvakharia et al., a major challenge is the ability to discern CO₂ enhancements relative to background concentration, which impacts the uncertainty of high CE/DRE estimates [43]. Accordingly, the transect distance should be far enough downwind to provide a clear plume profile, but close enough to be within the noise threshold of the CO₂ sensor. Gvakharia et al. also stated that it would be difficult to distinguish DRE measurements greater than 99% due to the background variability of both the CO₂ and CH₄ sensors [43]. Plant et al. examined the impact of inert CO₂ that may be present in the flare gas and products of incomplete combustion and found that both these effects produced a small overestimation of DRE_{CH₄} of approximately 0.1% [5]. Nevertheless, a particular concern for aircraft-based plume sampling is the possibility that crosswind-induced fuel stripping could lead to a segregated plume of cold, unburned fuel closer to the ground and a second plume of hot, buoyant combustion products that are presumably measured by the aircraft. As noted in Sec. 5.1.1, separate plumes are sometimes observed using UAVs, and that fact that these less-buoyant plumes may be missed by aircraft may explain the perceived insensitivity of CE/DRE estimates to crosswinds reported in some of the aircraft-based surveys [5]. If this is the case, there may be systematic bias in aircraft-based surveys leading to the overestimation of flare DRE.

While aircraft-based sampling is not expected to provide the same accuracy or degree of specificity as UAV near-field sampling, an important attribute is the efficiency with which large numbers of flares may be measured in a single campaign. To date, the most complete and reliable overall assessment of flaring emissions comes from Plant et al., who surveyed over 300 flares in three geological formations using aircraft [5]. Arguably, the only other way to measure a similar number of flares is via high-altitude and satellite-based remote sensing (Sec. 5.2.2), although these instruments currently lack the spatial and spectral resolution to measure CE/DRE of individual flares.

A key conclusion from airborne surveys of upstream flares is that flare CE and DRE in each region exhibit wide distributions, with poorly performing flares having a pronounced effect on overall emissions. When the QoI is the mean or median flare performance, the contrast between the results of Caulton et al. [62], Gvakharia et al. [43], and Plant et al. [5] highlight that a leading uncertainty source is likely to be sampling error. Accordingly, the true environmental impact of upstream flaring can only be understood through large-scale measurement campaigns. In this regard, while aircraft-based sampling may have a lower sensitivity compared to UAV sampling, it is ideally suited to measuring large numbers of flares over wide geographic areas, exemplifying our assertion that there is no “one-size-fits-all” solution to measuring flare performance.

5.2 Remote sensing

Remote-sensing techniques work by inferring the efficiency of the combustion process through remote (e.g., fenceline or stand-off) radiometric measurements. There are clear advantages to stand-off techniques, particularly given the challenges inherent to sampling the plume gases directly. Stand-off measurements are also often safer, less expensive, more amenable to fenceline monitoring, and may permit automated, continuous monitoring of flare performance, as increasingly required under regulations and reporting initiatives.

5.2.1 Measurement principle

Spectrally resolved intensity measurements are made on the flame or, more often, on the hot plume gases generated by the flame. In the former category, the QoIs are inferred from radiometric temperature and visible flame shape mainly via instrument models derived empirically using reported flaring volumes or “calibration” measurements done through extractive sampling or CFD. Radiometric measurements on the plume gases, in contrast, provide a more direct connection to the gas-phase species emitted by the flare, and the instrument models are derived from physical principles.

Understanding the basic processes responsible for the measured intensity is paramount to appreciating the operating principles and limitations of these instruments³. Radiometric techniques measure the thermal radiation along lines-of-sight that transect the flare plume and/or flame at some distance away from the flare. The “strength” of thermal radiation at a given wavenumber⁴, η , is given by its *spectral intensity*, I_η . As shown in Figure 11, the measured spectral intensity entering the instrument aperture, $I_{\eta,d}$, is due to thermal emission from the flare plume, transmitted radiation from the background (e.g., the sky, the sun, or an active light source), and emitted and absorbed radiation by the atmospheric layer between the plume and the sensor. The amount of thermal radiation absorbed along a given pathlength through the medium depends on the *spectral absorption coefficient*, κ_η , in units of m^{-1} , while the amount of emitted thermal radiation depends on both κ_η and the temperature of the medium via Planck’s blackbody distribution [63].

Often the spectral intensity detected by the sensor is modeled by approximating the plume gases and the atmosphere between the plume and instrument as layers or “slabs” that are homogeneous in both composition and temperature. While this assumption is usually reasonable for the atmosphere layer, this is less likely to be the case for flare plume, as

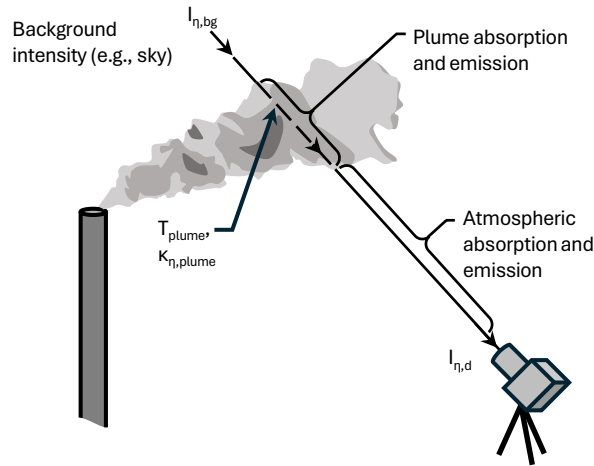


Figure 11: For a line-of-sight (LOS) that transects the flare plume, the spectral intensity entering the instrument aperture, $I_{\eta,d}$, is due to transmitted intensity from the background, emitted and absorbed intensity by the plume gases, and the transmission and emission of the atmospheric layer between the plume and the instrument.

³ For a more detailed discussion, the reader is referred to Ref. [12].

⁴ Wavenumber is the reciprocal of wavelength and is often used when quantifying thermal radiation in molecular gases, having a standard unit of cm^{-1} .

discussed in Sec. 3.2. Consequently, this approximation introduces model error into the CE/DRE estimate.

Radiometric measurements made on the plume exploit the fact that the plume species of interest, including CO_2 , CO , and HCs, have distinct absorption features over infrared wavenumbers that arise from transitions between the quantized vibrational-rotational molecular energy states. Each transition corresponds to an absorption “line” at a specific wavenumber; the lines are grouped together into vibrational-rotational “bands” (typically 3-4) over the infrared spectrum, with each band containing millions of lines. This structure arises from the unique spacing of the quantized energy levels of the molecule, so κ_i acts like a “fingerprint” for each species. Therefore, spectral variations in intensity may be leveraged to identify species in the flare plume and to develop a quantitative estimate of the amount of each species along the corresponding LOS. Example absorption spectra for these species are shown in Figure 12. These spectra appear as “absorption lines” or “emission lines” depending on the relative magnitude of the emitted intensity (plume temperature) to the background intensity.

The detection spectrum chosen for characterizing the flare plume depends on the location of absorption/emission features, the operating principle of the instrument (based on absorbed radiation or radiation emitted by the plume), and the transmittance of the atmospheric layer between the plume and the instrument. Techniques based on the absorption of solar radiation, like satellites, are aligned with the $1.65\text{ }\mu\text{m}$ (6060 cm^{-1}) CH_4 vibrational-rotational band in the near infrared (NIR), where solar intensity is high and atmospheric interference is low. Sensors that measure thermal emission from the plume gas focus on CH_4 features at $3.34\text{ }\mu\text{m}$ (3105 cm^{-1}) bands in the mid-wavelength infrared (MWIR) and at $7.8\text{ }\mu\text{m}$ ($\sim 1300\text{ cm}^{-1}$) bands in the long-wavelength infrared (LWIR), since blackbody emission from the plume gases ($\sim 4\text{--}600\text{ K}$) is more pronounced over these wavelengths.

Some radiometric instruments, like the TDLAS and CRDS sensors mentioned in Sec. 5.1.1 and the dual comb spectroscopy (DCS) system in Sec 5.2.7, focus on the absorption of laser light by particular lines, while other systems, like the NDIR sensor and two of the cameras discussed in Sec. 5.2.4, measure absorbed and emitted spectral intensity integrated over wider detection bands. The detection bands are usually aligned to capture a portion, or all, of the vibrational-rotational band of a species of interest.

Thermal radiation emitted by the luminous flame is typically dominated by incandescence from the soot, which has a broadband (spectrally flat) character. In this scenario the spectral distribution of detected intensity may be used to infer the flame temperature directly.

5.2.2 *Satellite-based and high-altitude observations*

While satellite-based sensors cannot measure flare CE or DRE directly, they play a critical role in assessing global flaring activities and flare gas volumes and thus merit discussion. Recent surveys of the history and state-of-the-art in satellite-based flare measurements are provided by Faruolo et al. [64] and Anejionu [65].

Flares may be observed using a suite of satellite-based sensors that measure irradiance over multiple bands across the visible and NIR spectra due to the high solar intensity and the absence of water lines that would otherwise interfere with the signal over the long atmospheric pathlengths involved in the measurement. In this context, plume gases appear as “shadows” over the reflected intensity spectrum since incident solar intensity is far greater than emitted intensity over NIR wavelengths. Sensors include the National Oceanic and Atmospheric

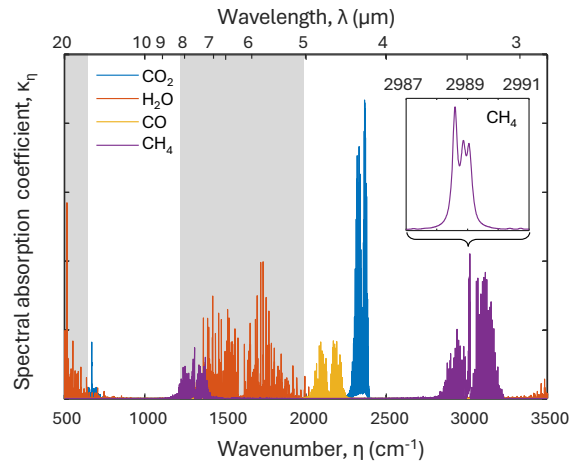


Figure 12: Absorption spectra of gas species relevant to flare CE and DRE. Most gases have 3-4 absorption bands over the infrared spectrum, each containing 10^6 - 10^7 lines. Each line is associated with a specific rotational/vibrational energy transition. Shaded areas denote portions of the atmospheric layer that have low transmittance and are therefore avoided. The scale of κ_η is adjusted for each species so they may be plotted on the same graph.

Administration's Visible Infrared Imaging Radiometer Suite (VIIRS), the National Aeronautics and Space Administration's (NASA's) Moderate Resolution Imaging Spectrometer (MODIS), and, most recently, the European Space Agency's Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR). Potential flares may be identified as "hot spots" through multispectral image analysis. Once identified, the flame temperature is estimated through Planck's law by comparing intensities measured at multiple channels; flares are distinguished from other incandescent sources (e.g., biomass combustion) based on their temperature. Flare measurements are usually made at night because the sensors are more sensitive compared to daytime operation and solar reflection is avoided, although increasingly sophisticated sensors and data processing may enable daytime detection of flares under some conditions [66]. Infrared imaging sensors on satellites have spatial resolutions much larger than the size of the visible flame of a single flare (e.g., ~ 70 m for VIIRS), so detection of individual flares over the infrared spectrum is currently not possible. However, spatial resolution may be enhanced by combining nighttime observations with synthetic aperture radar [67] or high-resolution daytime imaging [66], which is an area of ongoing research. It is worth noting that satellite-based sensors cannot observe unlit flares or enclosed combustors.

While early studies estimated flaring activity based on the numbers of flares in a given area, more sophisticated multispectral analysis may be used to estimate flare gas volumes in two ways: using empirical instrument models developed by correlating satellite-observed quantities (e.g., flame temperature or radiance) with flaring volumes reported by producers [68,69] or physiochemical instrument models that account for the heating value of the fuel, flare CE/DRE, and radiant fraction (the portion of combustion enthalpy converted to thermal emission) [70,71]. In both techniques, BC and greenhouse gas emission estimates derived from satellite imagery require specification of flare CE or DRE and not vice versa (i.e., it is a parameter, not an outcome, of the instrument model), highlighting the need for the measurement techniques reviewed in this study. In the case of large flares, however, it may be possible to exploit a correlation between flare temperature and CE, since low flame temperatures often indicate inefficient combustion [72]. Were this approach viable, it would rely on "micro-scale" calibrations between satellite

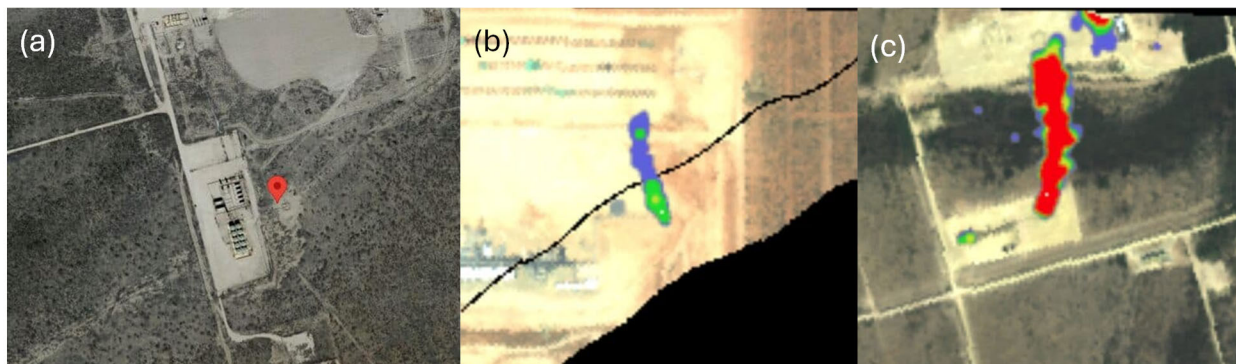


Figure 13: Image of CH_4 emissions from flares in the Permian Basin recorded using the GAO system: (a) no visible CH_4 plume, suggesting a high DRE_{CH_4} ; (b) a visible CH_4 plume, suggesting a low DRE_{CH_4} ; and (c) an unlit flare [74].

data and CE or DRE measurements made locally [71]. Emerging satellite-based hyperspectral imaging would be particularly useful in this regard.

Another approach is to combine visible and infrared emission measurements made mainly at night with daytime observations of backscattered sunlight, which may be used to infer column densities (in $\text{ppm}\cdot\text{m}$) of NO_2 , CH_4 , aerosols, and other pollutant species of interest along a LOS. The Ozone Monitoring Instrument (OMI) [73], and more recently TROPOMI (TROPOSPheric Monitoring Instrument) [66], launched in 2004 and 2017, respectively, are particularly useful in this regard. However, the low spatial resolution of these sensors (on the order of 20 km for OMI and 5 km for TROPOMI) means that emissions may be attributed to flaring activities at the gas-field or facility level, but not at the level of individual flares.

As noted above, the key impediment to using satellites to observe flare emissions directly is the limited spatial resolution afforded by the infrared sensors needed to see the absorption features of the relevant gases via reflected sunlight over the NIR spectrum. As a rule of thumb, spatial resolution is inversely proportional to wavelength and to distance between the sensor and the target. Hence, while satellites in low Earth orbit may obtain visible images with sub-meter resolution, this is not the case over the infrared spectrum.

To a certain extent, NASA's Airborne Visible/Infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) and the Global Airborne Observatory (GAO) systems fill this gap. Hyperspectral cameras (see Sec. 5.2.4) are deployed on aircraft that operate at lower altitudes and therefore higher spatial resolutions than can be obtained using satellites. Accordingly, these instruments can observe CH_4 plumes [74] and, under favorable conditions, they can also quantify the CH_4 and CO_2 concentrations needed to derive CE [75].

Figure 13 shows CH_4 plumes from flares in the Permian Basin measured using the GAO sensor at an altitude of 4.5 km and a spatial resolution of 4.5 m [74]. The obvious drawbacks of aircraft-based sampling are the limited duration of the measurement compared to the quasi-continuous observation platform of satellites and an operation window defined by daytime hours with clear skies.

5.2.3 Open-path FTIR spectroscopy

Open-path FTIR (Fourier transform infrared) spectroscopy was the first remote-sensing technique used to quantify flare CE/DRE. In this approach, a telescope-equipped FTIR spectrometer measures the spectral intensity along a LOS that transects the flare. The measured spectrum is then used to infer species column number densities, and the CE may be found via Eq. (5). A similar column-density-based definition may be used to infer DRE_{CH_4} .

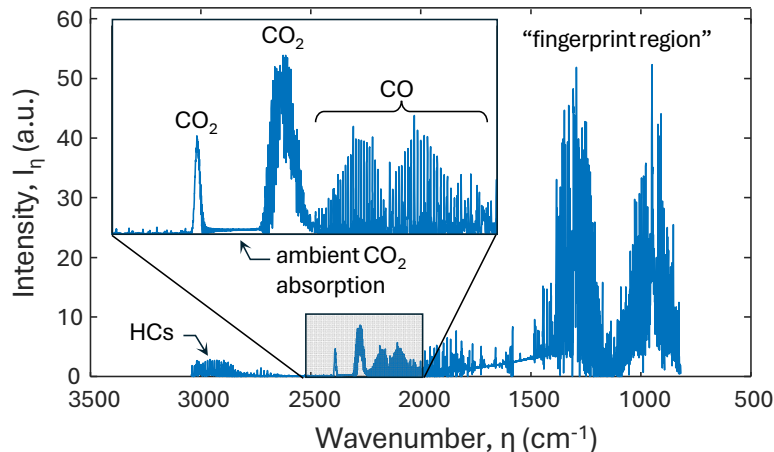


Figure 14: Simulated flare plume emission spectrum representative of PFTIR data at 0.5 cm^{-1} resolution. The “fingerpint region” is useful for determining complex hydrocarbons. While the CO_2 band at $2,349\text{ cm}^{-1}$ appears as a continuous “hump” in Figure 12, the detected CO_2 emission spectrum appears as two “spikes” due to the absorptance of the atmosphere between the flare plume and the instrument.

A dedicated instrument for measuring flare plumes, the open-path, passive FTIR, was developed in 1984 by Industrial Monitor and Control Corporation (IMACC) and subsequently refined through field deployments in 2003 and 2009, as well as the TCEQ measurement campaign in 2010, by IMACC and later Clean Air Engineering [10,32,76]. In 2000, Blackwood used open-path FTIR measurements to infer DRE_{CO} of two flares simultaneously [77]. The technique was also proposed independently by Haus et al. [3], who used their instrument to measure concentrations of CH_4 , CO_2 , CO , NO and H_2O in natural gas flares in Europe. The open-path, passive FTIR technology is currently provided by Spectrum Environmental Solutions and Clean Air Engineering, while Bruker, Inc. sells a commercial, general-purpose, open-path active FTIR instrument (Bruker OPS).

The FTIR spectrometers resolve broadband infrared radiation into its spectral components using interferometry. Light from a broadband source is directed into a Michelson interferometer, where it is split into two beams: one reflected by a fixed mirror and the other by a moving mirror. The recombined beams interfere, producing an intensity pattern (interferogram) that varies with the moving mirror’s position. Applying a Fourier transform to the interferogram yields the sample’s infrared absorption or emission spectrum.

Open-path FTIRs typically capture a considerable portion of the infrared spectrum, e.g., 500 cm^{-1} ($\sim 20\text{ }\mu\text{m}$) to 4000 cm^{-1} ($\sim 2.5\text{ }\mu\text{m}$), which includes key absorption features of CO , CO_2 , CH_4 and NMVOCs, although analysis is typically confined to the atmospheric windows ($200\text{--}300\text{ cm}^{-1}$, $650\text{--}1250\text{ cm}^{-1}$, see Figure 12) which are relatively free of H_2O lines. The measured spectrum amounts to a convolution of the true intensity and an instrument lineshape function that “blends” the shape of the lines, thereby determining the spectral resolution of the data. A typical spectral resolution is 0.5 cm^{-1} , sufficient to resolve key absorption lines. Spectra are integrated over 1-min intervals [34] and may be further averaged over time, e.g., over 15 min [32], to improve the signal-to-noise ratio.

Open-path FTIR may be operated in one of two modes. In the passive mode (PFTIR), the instrument consists only of a receiver. Figure 11 represents a typical measurement configuration and Figure 14 shows a typical measurement spectrum. Background intensity (typically sky) is found by comparing intensity measurements made through the plume and

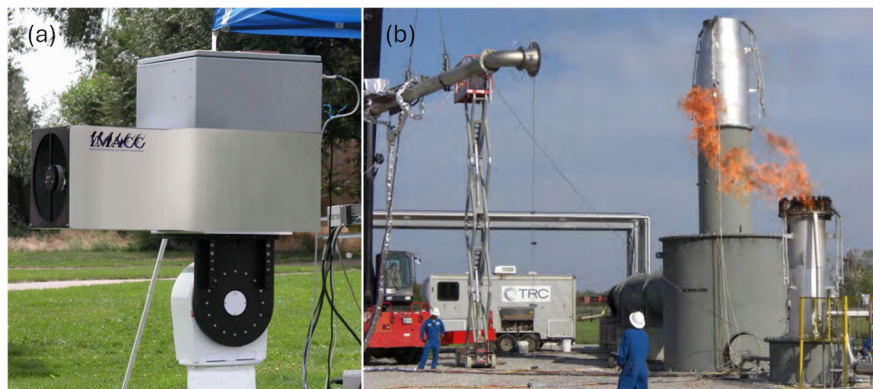


Figure 15: In the AFTIR configuration, the beam path is defined by a transceiver unit and a retroreflector. (a): The transceiver unit [76]; (b) A retroreflector mounted on a scissor lift configured for a large-scale test [31] behind the sampler.

outside of the plume, while the atmospheric transmittance is obtained by measuring the spectrum of a blackbody calibration source located at a similar distance away from the instrument. The plume temperature is calculated from temperature-sensitive features of the absorption spectrum, e.g., a Boltzmann plot of the “hot lines” at the wings of the $2,150\text{ cm}^{-1}$ CO band [34]. Finally, the path-integrated species concentrations are found by regressing a modeled plume transmittance to the one inferred from the FTIR intensity spectrum using an RTE model, often based on the two-slab model described in Sec. 5.2.1.

In the active configuration (AFTIR), the background intensity in Figure 11 comes from an active light source or a retroreflector. Haus et al. used a steady infrared light source [3], while the commercial Spectrum and Bruker OPS instruments combine a time-modulated light source and FTIR into a single transceiver unit and terminate the path with a retroreflector behind the plume (Figure 15). The modulation is used to isolate the transmitted portion of the spectrum (“AC” component) from the emission and background (“DC” components), which increases the sensitivity of the instrument and avoids additional calibration steps. The obvious challenge of deploying the AFTIR configuration is the need to position a source or retroreflector behind the flare plume, which is feasible for large-scale testing scenarios in which the flare tip is close to the ground (e.g., [10,32]) but less so for operating flares. While Clean Air Engineering has attempted to overcome this challenge using a drone-based retroreflector [78], it is unclear whether this approach is practical for routine testing.

The measured intensity spectra are then interpreted using an instrument model that assumes the plume to be homogeneous in composition and temperature. Since these instruments only measure intensity along a single LOS through the plume, a key question concerns how the instrument should be aimed. The IMACC/Clean Air Engineering/Spectrum procedure is to aim the telescope “one visible flame length away” from the visible flame tip [34], as shown in Figure 4, reasoning that at this location the reactants in the flare vent gas have been consumed completely. Ideally the optical path is perpendicular to the wind direction, so that the plume may be modeled as homogeneous. The Cassegrain telescope used in this instrument has a divergence of 0.5 mrad , so a measurement made 100 m away from the plume corresponds to a spot diameter of 30 cm , as indicated in Figure 4.

A key advantage of FTIR-based approaches is the ability to fingerprint and quantify a wide range of species. As an example, in 2014 the US EPA deployed the IMACC PFTIR instrument and Telops Hyper-Cam MW imaging Fourier transform spectrometer (IFTS) (Sec. 5.2.4) to measure

the CE of enclosed ground combustors via Eq. (5) [79]. The PFTIR instrument provided column densities (ppm·m) of C_4H_{10} , C_2H_2 , C_3H_6 , CH_4 , CO , CO_2 , H_2O , NO , and NO_2 within the exhaust plumes. Plumes from enclosed ground combustors are a particularly challenging target compared to flares due to their lower temperature and heterogeneity.

There are several challenges inherent to open-path FTIR that contribute to uncertainty in measured CE and DRE. While CO_2 is abundant in flare plumes as a combustion product, it is also present in the atmosphere and, depending on the stand-off distance and the concentration and temperature of the CO_2 in the flare plume, it may be difficult to calculate the CO_2 column density accurately. As shown in Figure 14, CO_2 in the flare plume is only detectable based on the temperature-sensitive “hot lines” at the wings of the $2,325\text{ cm}^{-1}$ band, which appear as “spikes” on either side of the band; the center is completely absorbed by the atmospheric layer between the plume and the camera.

Most importantly, the assumption of a temporally steady and spatially homogeneous plume that underlies this technique is not realistic, as discussed in Secs. 3.2 and 3.3. Wormholdt et al. [32] compared CE estimates derived from PFTIR and extractive-sampling measurements during the 2010 TCEQ Study. They found PFTIR-derived values to match those determined from extractive sampling within specified error bars at high CE but saw greater variability and larger differences between these methods at lower CE, when the flare may be “sputtering”. This was particularly the case for over-steamed flares and was attributed to greater plume inhomogeneities under those operating conditions. Propylene-fueled flares exhibited the largest differences between PFTIR and extractive CE estimates; possible reasons included challenges inherent in measuring propylene in the extracted sample, errors in the spectroscopic model used to analyze the PFTIR data, cold fuel that was undetected by the PFTIR instrument, plume inhomogeneity, or some combination of these factors. Wormholdt et al. [32] observed that fluctuations in individual species column densities were much larger than fluctuations in CE estimates since species column densities were highly temporally correlated. They argue that this makes open-path, FTIR-inferred CE estimates more robust compared to individual column density estimates, although this finding conflicts with other observations showing that species column densities may not be temporally correlated [36] (Sec. 3.3).

Even for flares operated at high CE, it is not clear that open-path FTIR would be capable of capturing the fuel-rich region beneath the plume that may arise from fuel stripping, as is visible in Figure 4. First, the FTIR LOS is aligned immediately downstream of the visible flame tip to capture the hot plume gases from the combustion region but not *beneath* the visible flame, where the colder, more dense stripped fuel is likely to accumulate. Second, the cold-fuel region may not have sufficient thermal contrast with the background to be visible. Given that the performance of open-path FTIR methods has been validated by extractive sampling conducted downstream of the flare plume and not beneath it (Figure 15 (b)), both PFTIR and extractive-sampling approaches may systematically overestimate the flare CE.

5.2.4 Multispectral and hyperspectral infrared imaging

The main drawback of open-path FTIR is that its narrow field-of-view may lead to strongly biased CE or DRE estimates due to plume heterogeneity. Accordingly, there is an increasing trend towards whole-plume imaging techniques, which infer CE or DRE based on images of the flare plume viewed in profile, albeit with lower spectral (and sometimes temporal) resolution. Most approaches focus on the MWIR spectrum ($3\text{--}5\text{ }\mu\text{m}$, $3,333\text{--}2,000\text{ cm}^{-1}$), which contains vibrational-rotational bands for CO_2 , CO , and HCs, and, importantly, excludes strong H_2O lines that are not of interest and could obscure or confound measurement of the species needed to estimate CE. However, recent research has demonstrated the viability of hyperspectral imagers

that operate over the LWIR spectrum (7.4-12.5 μm , 1,350-800 cm^{-1}) [29,80]. The advantage of conducting measurements over the LWIR spectrum is an increased sensitivity to CH_4 , particularly at low temperatures, although the drawback is that it may be challenging to distinguish the CH_4 from the abundant (and hot) H_2O in the flare plume without adequate spectral resolution.

It is important to highlight the technical challenge of generating near simultaneous images of a flare plume over different wavelength ranges. Multispectral cameras based on uncooled “warm” filters placed over the instrument aperture cannot be used to develop quantitative CE or DRE estimates, since blackbody emission from the opaque portion of these filters would dominate the part of the signal from the flare plume. This consideration limits the candidate equipment for estimating CE or DRE to specialized instruments that have only become commercially available within the last decade.

In this section, we summarize three groups of whole-plume imaging techniques operating over the MWIR and LWIR spectra: light-field and line-scan cameras, coaxial multicamera systems, and IFTSs. We do not include standard, single-band optical gas imaging (OGI) cameras in our summary; these cameras are useless for measuring CE/DRE since they cannot distinguish between emissions from unburned CH_4 and hot H_2O in the flare plume. These instruments may be used to quantify emissions from unlit flares, however, provided there is sufficient thermal contrast between the plume and the background.

Light-field and line-scan cameras: In 2012 Zeng et al. [26,38] proposed the “Visible imaging spectro-radiometry” or VISR technique based on a multispectral camera capable of measuring spectrally integrated intensity over four bands, each aligned to a vibrational-rotational band of a species of interest: CO_2 (4.2–4.3 μm), CO (4.7–4.8 μm), HCs (3–4 μm), and a background measurement. These signals are related to the column densities through spectrally averaged absorption cross-sections using a simplified two-slab model (Sec. 5.2.1). Nominally, the measured intensity depends on both local number density of the species of interest and the temperature along each LOS; however, by assuming that the blackbody intensity is the same for all channels and by calculating the molecular absorption cross-section at a “representative” plume temperature, the local CE for each pixel in the image can be approximated without knowing the plume temperature. The local CE estimates are converted to an overall flare CE, e.g., Eq. (1), by averaging the local CE values for pixels over a VISR region of interest (ROI) that extends outwards from the flame envelope to a contour where the signal-to-noise ratio becomes too large to make a reliable measurement [23]. A key benefit of this simplified radiometric model is that flare CE estimates may be generated in real-time, without the post-processing required for other techniques. This attribute is critical for real-time flare monitoring, and the technique has recently been recognized by the US EPA as a non-regulatory “other test method” [81].

This concept was prototyped using a Surface Optics Corporation SOC750 commercial hyperspectral (line-scan) camera [23]. The instrument generates a 3D data cube consisting of 42 images, each integrated over uniform spectral intervals between 2 and 5 μm as shown in Figure 16 (a). For each experiment, the camera acquired data for 30 s, generating 11 data cubes per second (256 pixels $\times$ 240 pixels $\times$ 42 bands) for a total of 325 cubes per measurement. These cubes were averaged to reduce measurement variance, and the single, averaged data cube was used to calculate the CE [23].

Zeng et al. [23] assessed the accuracy of this technique by comparing VISR-derived CE values with those found through plume sampling (Figure 2) for 28 cases consisting of both steam- and air-assisted flares. The results of this comparison are plotted in Figure 17. The average difference between these datasets was 0.50% CE when all data points were included

and 0.10% CE when a subset of 18 data points with lower O₂ content was considered, rationalizing that the samples were less diluted and thus more representative of the actual plume composition. Thirteen of these tests were replicated, and the maximum difference between the VISR-derived and plume-sampling CE values was 0.2% CE, excluding two outliers. They found greater disagreement between the datasets at low CE, with the VISR-derived CE values being larger than those derived from sampling; indeed, Figure 17 shows that the regression line does not intercept the origin for this reason. This finding is similar to the difference between PFTIR-derived CE values and those found through extractive sampling on similar flare types [32]. In subsequent work, Providence Photonics identified a “systematic negative bias of -0.8% ... in the VISR results when compared to the extractive results” [82]. They assumed the extractive results to be correct and adjusted the VISR instrument model accordingly to remove the bias. Given that the underlying uncertainty of CE values obtained from near-field extractive measurements is almost certainly larger than this discrepancy, this treatment raises questions about the accuracy of the VISR-derived CE estimates.

While the SOC750 is a convenient, general-purpose, hyperspectral imager, Figure 16 (a) shows that only a minority of its 42 spectral bins are aligned with vibrational-rotational bands of the species of interest. Furthermore, the moving components of the line-scan camera constrain the minimum time needed to generate an image. Accordingly, Providence Photonics, Surface Optics Corporation, and Zeeco, Inc. partnered to develop the FlareGuardian™ system; instead of a line-scan camera, it uses a light-field hyperspectral imager, which can acquire images at intervals of 33–91 ms. The measurement spectrum has been reduced to 3–5 μm and divided into a similar number of bins as the SOC750; however, the bins are distributed nonuniformly according to the spectral features of the species of interest (CO, CO₂, HCs). This spectral resolution is sufficient to capture some coarse features of the emission spectrum, e.g., CO₂ emission features on either side of the 4.26 μm atmospheric absorption band, often called CO₂ “red” and “blue” spikes, but inadequate to estimate temperature or identify unburned or partially pyrolyzed species in the flare plume. It may be an important limitation in the case of downstream flaring, which often involves more complex fuels, or even in upstream flaring when the associated gas is not dominated by one species. While it may be possible to develop a

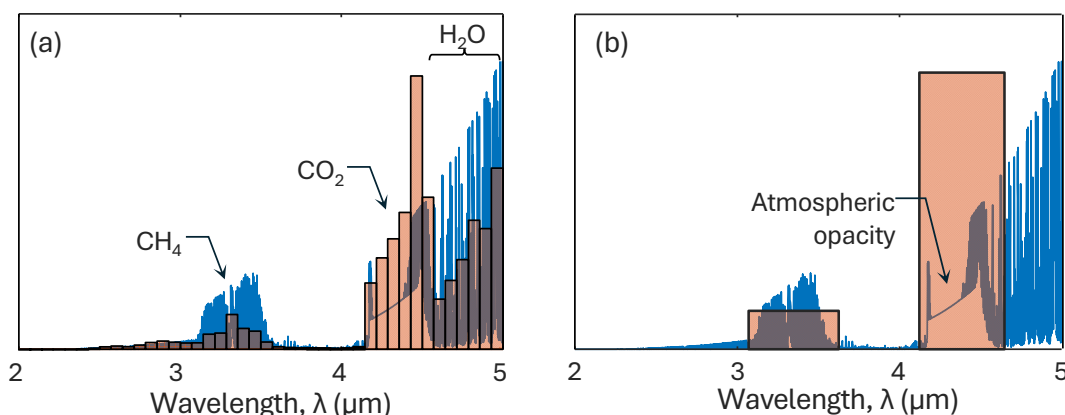


Figure 16: Simulated flare plume emission spectrum and multispectral bins used by (a) the original VISR prototype (SOC750) [23] and (b) the Sensia Agni™ system [27]. The commercialized FlareGuardian™ system uses a microlens array to generate a more optimized set of bins over a narrower (3–5 μm) spectrum. Diagram is by the authors and is generated using information available in the literature.

IR cameras containing cold filters roughly aligned to the absorption bands of HCs (3.2–3.4 μm) and CO_2 (4.2–4.4 μm) as shown in Figure 16 (b). The dual-band radiance is compared against a dataset of synthetic signals to retrieve the CO_2/HC ratio that best matches the observed signal. These synthetic signals are generated from CFD simulations of plumes arising from flares of various sizes and flowrates in a manner similar to Kaveh et al. [83]. Like VISR, AgniTM can account for HCs other than CH_4 via a correction factor derived from the corresponding absorption cross-sections of the relevant species, provided the fuel composition is known.

In contrast to VISR, however, AgniTM does not generate a pixelwise CE or DRE. Instead, an embedded AI/ML engine is trained on this dataset to link the radiance patterns to global CE and DRE with sufficient rapidity to permit continuous monitoring. When the system is deployed on operating flares, it undergoes an additional calibration step to adjust for flare geometry and other site-dependent factors. Like the FlareGuardianTM, the manufacturer claims a “0.5% accuracy”, although this uncertainty is based on standard error propagation through the radiometric model (Sec. 4.4.2). As already noted, this procedure does not address systematic model errors, likely similar in type and magnitude as those that affect the FlareGuardianTM system. Particular concerns include the limited information contained in only two channels and the inability of MWIR optics to image a segregated stream of cold fuel that may arise due to over-assistance or crosswind stripping.

Imaging Fourier transform spectrometers (IFTSs): Commercial MWIR and LWIR IFTSs developed in the mid-2000s by Telops, Inc. have been used extensively to measure combustion-generated gas plumes. The operating principle of an IFTS is similar to that of an open-path FTIR spectrometer in passive mode; whereas the FTIR works on a beam of light and generates a single spectrum, the IFTS preserves the image through the interferometer and produces a data cube containing hundreds of images, each at a specific wavenumber. The spectral resolution (usually $\sim 1 \text{ cm}^{-1}$) is lower than a typical PFTIR measurement (0.5 cm^{-1}) but much higher than a light-field or line-scan hyperspectral camera (e.g., $\sim 70 \text{ cm}^{-1}$ near 3.5 μm for the SOC750). Figure 18 shows example IFTS data from a steam-assisted flare obtained with a Telops Hyper-cam iMW (3–5.4 μm). The spectra for a subset of pixels are then analyzed to recover column number densities, and it is often possible to fingerprint species within plumes of uncertain composition. The richness of the data allows for a more sophisticated spectroscopic model compared to the ones used by the FlareGuardianTM and AgniTM systems. However, it remains necessary to parameterize the temperature and species mole fraction distributions along each pixel LOS, e.g., using a top-hat or Gaussian profile. The visible plume width in the image plane may inform the width of these distributions by modeling the plume as axisymmetric. Computing this regression for each pixel LOS is time-consuming, mainly due to the expense of calculating the temperature-dependent absorption cross-sections. Consequently, rather than generating a full 2D column density map, column densities are solved only for pixels along one or several “integration lines” that define a transecting plane normal to the image plane, like the one in Figure 6.

While each interferogram takes $\sim 30 \text{ s}$ to several minutes to assemble, depending on the spectral resolution, the individual images within the interferogram are recorded at hundreds of frames per second. These images may be normalized and processed using feature tracking algorithms to obtain a near-instantaneous, intensity-weighted 2D velocity field. Each column density is then multiplied by the corresponding velocity component and the pixel height. Summing over the pixels gives the mass flow rates needed to calculate CE via Eq. (2).

Lapeyre et al. [28] used the Telops Hyper-cam iMW to measure the plumes from a natural gas flare, an enclosed ground combustor, and a steam-assisted flare at a refinery. Overall, IFTS-inferred carbon mass flow rates for the enclosed ground combustor matched the fuel supply

rate. However, quantitative analysis of both exposed flares was affected by lens flare artifacts emanating from the hot CO_2 in the combustion region, a common problem in high-dynamic-range imaging. Flare-plume measurements made using a LWIR IFTS (Telops mini xLW, 7.4–12.5 μm) were free of this artifact [29,80], since the spectral absorption cross-section of CO_2 over this wavelength range is much smaller compared to the other species of interest. Instruments that measure intensity over the LWIR spectrum have a significantly higher capacity to detect CH_4 at ambient temperatures compared to those that operate over the MWIR spectrum due mainly to the higher blackbody intensity, which peaks at $\sim 10\ \mu\text{m}$ for near-ambient temperatures. As already noted, the main impediment to operating over this spectrum is the presence of strong H_2O lines, but the spectral resolution of the IFTS is sufficient in most cases to distinguish the contributions of H_2O and other species, including CH_4 . This is potentially an important attribute in the context of measuring CH_4 slip as well as emissions from unlit flares.

To the best of our knowledge, there has yet to be a rigorous quantification of the uncertainties of the CE/DRE values obtained from an IFTS or of the underlying mass flow rates used in Eq. (1). The uncertainty in the mass flow rates arises from at least two sources: uncertainties in the column densities found by inverting the spectroscopic model, and uncertainties in the projected velocity field used to convert the column densities into a mass flow rate. Both Miguel et al. [85] and Lapeyre et al. [28] benchmarked the performance of the IFTS by quantifying CO_2 and CH_4 mass flow rates from a heated vent. The IFTS-derived mass flow rates were generally within 10% of the imposed mass flow rates, similar to the uncertainty associated with UAV-derived mass flow rates (Sec. 5.1.1). If these mass flow rates were used to derive the CE via Eq. (2), the corresponding uncertainty would be smaller because the mass flow rate errors are correlated by the velocity field (i.e., the same velocity field is used to calculate the two mass flow rates, so the errors “cancel out” to some extent.)

The uncertainties in the column-density values depend on the sensitivity of the IFTS-measured spectra to the species in the plume, which in turn are functions of the spectral resolution, the presence of other plume species that absorb and emit over the same spectrum, the transmittance of the atmosphere between the plume and the IFTS, and, especially, the parameterization of the temperature and species concentration along each LOS. Lapeyre et al. recently explored how camera noise propagates into uncertainty in the mass flow rates using Bayesian analysis [86]. They found that the posterior probability densities inferred from the IFTS data generally overlapped with those from the mass flow controller. Their results also highlighted that the parameterization used for the temperature and species concentration along each LOS has a pronounced effect on the inferred mass flow rate, so this model error must be considered when assessing uncertainty.

The major drawbacks of the IFTS are cost, complexity, and a very low time resolution compared to the AgniTM and FlareGuardianTM systems. These latter instruments have been developed for continuous monitoring, and they can produce real-time, or near real-time, CE/DRE estimates without user interaction. In contrast, while the broadband camera within the IFTS operates at $\sim 1\ \text{kHz}$, between 30 s and several minutes is needed to assemble a single interferogram, and multiple interferograms must be recorded and combined to mitigate scene change artifacts caused by the turbulent motion of the plume as each interferogram is assembled. Consequently, an IFTS measurement captures the average plume state over ~ 10 minutes. Moreover, while the large amount of data (on the order of gigabytes for a single measurement) allows a far more robust estimate of species column temperature than can be

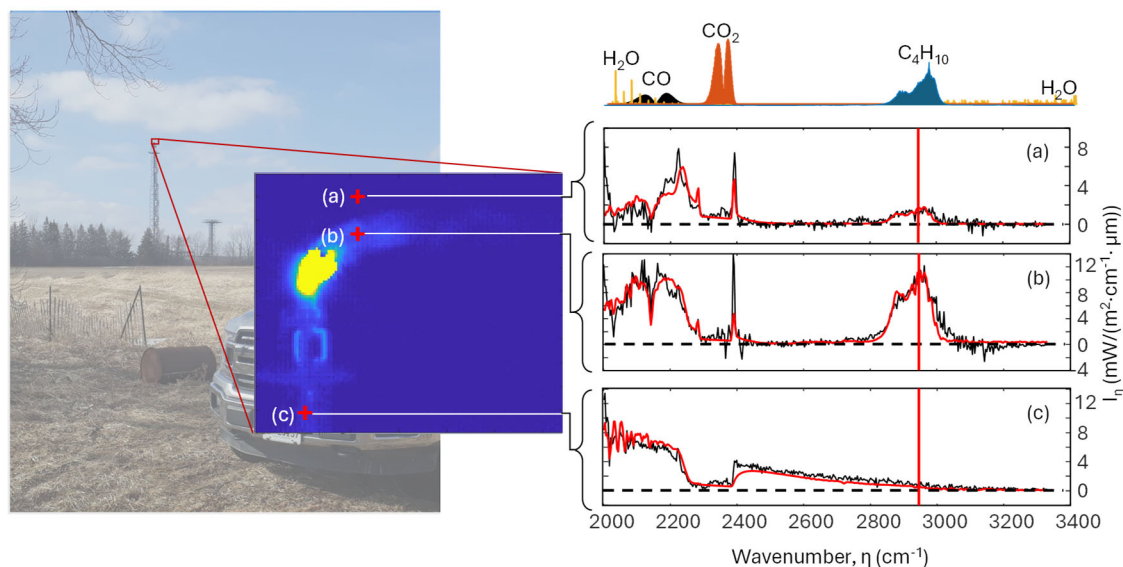


Figure 18: Hyperspectral image of a flare at 2949 cm^{-1} , along with spectra corresponding to pixels (a) above and (b) within the plume, as well as (c) from the flare stack. [28].

obtained using either the Agni™ or FlareGuardian™ systems, the time required to process this data is on the order of hours using high performance computing, and data processing demands specialized knowledge on the part of the analyst. While this picture is changing with AI/ML and cloud computing, at the current time the IFTS should mainly be considered as a research tool which could be used to develop other techniques more adaptable to continuous monitoring.

5.2.5 Visible-flame spectroscopy

A major drawback of whole-plume imaging techniques is that they require costly and specialized equipment to capture the MWIR or LWIR spectra needed to quantify the plume species. An alternative approach is to image the flame over visible wavelengths using less expensive equipment and then correlate these images to the CE or DRE, exploiting the fact that hotter, brighter flames tend to be more efficient. Since the visible appearance of the flame is only indirectly connected to the plume composition, however, this approach is strongly “data-driven” and relies on training data obtained through extractive measurements or CFD simulations.

Castiñeira et al. [87] proposed a multiwavelength image analysis (MIA) technique based on simultaneous flame images recorded over the red, blue, and green channels of a visible camera. They used a principal component analysis to reduce the images into candidate feature variables that included the area of the luminous region, peak flame brightness, uniformity of flame brightness, and average brightness of the nonluminous area. These features became the basis of a regressive model for flame CE.

This approach was deployed on a subset of experimental measurements conducted on steam- and air-assisted flares operated under 20 distinct scenarios (7 for steam-assisted flares, 13 for air-assisted flares) during the 2010 TCEQ study [10]. In this case, the feature variables included the flame area, angle, brightness, and hue. A partial least squares regression was conducted using time-resolved images collected at 1 Hz for 5 min per test. Two training schemes were used: in Scheme A, half of the entire image data for one scenario was used to train the model and the other half was used to assess the model, while in Scheme B, the model for each scenario was trained using data from the other scenarios (steam-assist or air-assist) while excluding the current scenario (cross-validation).

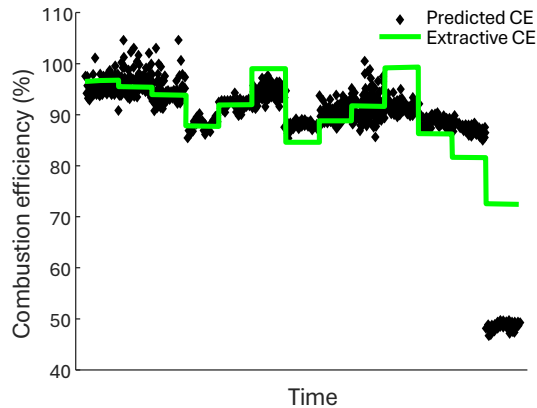


Figure 19: Comparison of CE predictions using visible image spectroscopy on an air-assisted flare using Scheme B with those found through near-field extractive sampling [87].

Figure 19 compares CE values found by applying Scheme B to visible images of an air-assisted flare to those found through extractive sampling. Scheme B is more representative of real-world applications, since the operating point and environmental conditions of a flare are unlikely to perfectly match those used to construct the training dataset. Nevertheless, Castiñeira et al. [87] showed that Scheme A has a better predictive capability than Scheme B, highlighting that the effectiveness of this approach hinges on the availability of a training dataset that includes flares operating under similar conditions. Particularly notable is the poor predictive performance of the MIA algorithm for the last case shown in Figure 19, which was severely over-assisted; the flare operating parameters for this case were highly distinct from the others, so the training model was inadequate. This outcome highlights the challenge of data-driven measurement models.

A similar approach was recently proposed by Boumaraf et al. [88], wherein an ML algorithm was developed using data obtained from an oil and gas flare instrumented with the Baker-Hughes FlareIQ™ system and an RGB camera. The procedure consists of three main stages: preprocessing, feature-learning, and regression. In the preprocessing step, the algorithm is trained to label and segment flame and smoke from the visible image in order to delineate an ROI from the image. A temporal standard deviation (TSD) image is then generated over the ROI, wherein the intensity of each pixel represents the standard deviation of the RGB intensity of the same pixel over a time-series of images. Physically, regions of high intermittency (high TSD) often correspond to low CEs. An ML algorithm is then trained using the normalized TSD images and the corresponding data collected from the FlareIQ™ system, which includes both the operating and environmental parameters as well as the CE/DRE predictions from the FlareIQ™ ML algorithm. (The FlareIQ™-derived CE/DRE estimates are interpreted as “perfect” in this exercise.) The ML algorithm can reconstruct the predictions of the FlareIQ™ algorithm with an R^2 score of $\sim 95\%$, although the flare in this study is limited to a CE of 97% or greater, thus excluding problematic low CE cases that may be harder to predict.

In 2023 Providence Photonics introduced Mantis Lite™, marketed as a more cost-effective version of the full FlareGuardian™/VISR approach described in Sec. 5.2.4 [89]. Based on the very sparse technical information about this approach available in the open literature, the method appears to use multispectral image analysis of the combustion zone to estimate the NHV_{cz} , which is then used to estimate a range of probable CE values based on a calibration curve. Conceptually, then, this method is aligned with visible flame spectroscopy. However,

details about the instrument model, its performance, and its susceptibility to environmental factors are not presently available.

An obvious drawback of visible flame spectroscopy is its strong reliance on training data sets, which are subject to their own (often considerable) uncertainties. In our opinion a significant measurement campaign would be required to develop reliable CE predictions along with defensible uncertainty estimates. As is the case for all ML algorithms, it is also critical to understand the generalizability of this approach, including lighting and camera placement, among other factors. To the best of our knowledge, this approach has not been developed beyond the academic prototype stage.

5.2.6 Differential Absorption LiDAR (DIAL)

Differential absorption LiDAR (DIAL) has been used in several flare emission measurement campaigns [90–92]. A DIAL system consists of a transceiver unit that contains multiple laser light sources, launch and collection optics, and data logging equipment. Two laser pulses of several nanoseconds in duration are emitted simultaneously along a LOS that transects the plume. The wavelength of one pulse is aligned with an absorption line of the species of interest (“on-resonant”), while the other is a nearby wavelength transparent to the species of interest (“off resonant”). The intensity of the light backscattered by aerosol particles (infrared wavelengths) or nitrogen molecules (ultraviolet wavelengths) is captured using a telescope. The delay between pulse emission and backscatter detection is related to the backscatter location along the LOS by the speed of light, while the ratio of on- and off-resonant backscattered signals indicates the column density of the target gas between the backscattering event and the detector. These data are then deconvolved in space/time to obtain the target gas distribution along the LOS; the spatial resolution depends in part on the minimum pulse length, but also on the signal-to-noise ratio. By traversing the laser through an arc, a plume cross-section may be generated as shown in Figure 20. Finally, local species concentrations are combined with anemometric data to obtain the mass flow rate of the target species.

This technique can measure many species with high precision and selectivity. Typically, NO_x , SO_2 , O_3 , benzene, and toluene are measured using UV laser pulses, while the IR pulses are used for HCs [90,92]. Few et al. describe 14 measurement campaigns conducted by the UK's

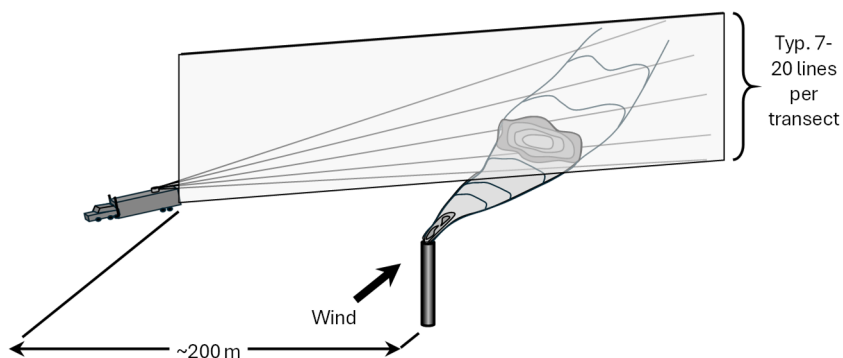


Figure 20: Schematic of a DIAL measurement of a flare plume. In an ideal measurement scenario, the transceiver unit is located with an unobstructed view upstream and downstream of the plume. A concentration map is generated by traversing the transceiver through an arc and solving the LiDAR equation at each angle. The concentration profile is then combined with a logarithmic wind profile to obtain the mass flow rate.

National Physics Laboratory (NPL) between 1983 and 2015 [90]. The NPL mobile DIAL system is mounted in a truck typically positioned ~200 m away from the plume. It uses a combination of Nd:YAG and dye lasers to generate tunable infrared and ultraviolet wavelengths, respectively. Backscattered light is collected by a telescope, converted to an electronic signal, and then digitized using a high-speed oscilloscope that gives a theoretical resolution of ~4 m, although in practice it is ~20–30 m due to noise. Signals are averaged over 250 shots to reduce variance. Typically, each plume scan consists of between 7 and 20 transects, with 10 being a typical value, and requires 10–15 min to complete [91]. This time window is much longer than the time scales relevant to the intermittent/rogue events that may dominate flare CE as discussed in Sec. 3.3, so the field should be considered as time averaged.

A further advantage of DIAL is that it can sample both inside and outside the plume in a single measurement, allowing it to capture background concentrations simultaneously. The DIAL signal returns can be combined with doppler techniques to perform simultaneous wind and concentration measurements [93].

The instrument has been used to estimate CE for scenarios in which the fuel flow rate is known. Uncertainties are usually reported based on the standard deviation of repeated scans [90,91], with the assumption that the main sources of error are random and unbiased. Innocenti et al. present a more detailed uncertainty analysis in which the signal noise is propagated through the DIAL equations to obtain a concentration uncertainty, which is then combined with uncertainty in wind speed and wind direction to obtain an overall mass flow rate uncertainty [91]. Typical uncertainties in the mass emission rates and concentrations are on the order of 10 % [91], although this depends on the mass flow rates, ambient meteorological conditions, number of scans, and the range between the transceiver and the plume. Controlled-release studies have shown that DIAL-inferred mass flow rates are within 5-20% of the known emission source [91,94], which is consistent with the theoretical prediction and similar to the uncertainty attached to mass flow rate estimates obtained using UAVs (Sec. 5.1.1) and IFTSs (Sec. 5.2.4).

While DIAL may be used to obtain reliable concentrations and mass emission rates for species that otherwise have a trace presence in the atmosphere, measuring CO₂ is difficult due to its large atmospheric abundance. Over the long pathlengths typical of a DIAL measurement, the enhancement of CO₂ concentration from a flare plume may represent a very small fraction of the overall column density and it becomes “lost” in the noise when the LiDAR equation is deconvolved. Only recently have systems been developed that could potentially be used to measure CO₂ emissions from flare plumes. Robinson et al. extended the capabilities of the NPL DIAL system by targeting the 1572.46 nm CO₂ absorption feature [95]; this line is sufficiently strong to have good sensitivity but not so strong that the atmosphere between the plume and the instrument becomes opaque. This wavelength also avoids interference from nearby H₂O lines. A proof-of-concept measurement was made on exhaust plumes at a coal-fired power plant [95]. The National Institute of Standards and Technology (NIST) also developed a DIAL system capable of measuring CO₂ and H₂O in industrial plumes [96]. Rather than targeting a single “on-resonant” line, the NIST system covers 10 wavelengths that span a CO₂/H₂O line pair centered at 1571.9 nm; the absorptances obtained from these wavelengths are then used to fit a theoretical line shape for the individual CO₂ and H₂O column densities. This technique was demonstrated to measure CO₂ and H₂O emission rates from a natural gas power plant [96].

Despite these innovations, at the time of writing the enhanced capabilities of the NPL system have not been leveraged to obtain a CE estimate independent of the known vent flow rate and composition, and the current NIST system for measuring CO₂ and H₂O cannot measure HCs. However, it is questionable whether the capacity to measure CO₂ is important for DIAL measurements of flares, since the cost, size, and complexity of these systems limit their use to

dedicated measurement campaigns in which the vent gas flow rate is likely to be known. Moreover, the long scan time means that temporal variations in CO₂ and HC concentrations that may provide insight into the cause of low CE performance are out of reach for this instrument. Nevertheless, this instrument is likely the most accurate and reliable means to obtain a time-averaged concentration field within a flare plume and will remain a critical part of future measurement campaigns.

5.2.7 Existing and emerging methane-only approaches

In scenarios where the vent gas flow rate is inferred through a carbon mass balance on the flare plume, the requirement to measure all carbon-containing species in the flare plume is a significant challenge for remote-sensing systems since these species absorb and emit radiation at different wavelengths. However, if the objective is to quantify only CH₄ emissions from flares, other specialized technologies for measuring CH₄ emissions from ambient sources may potentially be adapted for characterizing flare emissions.

Laser-based systems: Tunable diode lasers (TDL) operating at NIR wavelengths are among the most accurate means to quantify CH₄ column density. These lasers target a single CH₄ absorption line, or potentially a pair of neighboring lines. The transmitted light may be detected using a photosensor that terminates the beam path, or the detector may be collocated with the laser in a common transceiver unit if the laser light is reflected off an intermediate surface. In most cases the laser wavelength is sinusoidally modulated across the line by controlling the supply current, and a locked-in amplifier is used to demodulate the signal, resulting in a highly sensitive CH₄ column density estimate. As an example, Bridger Photonics's airborne Gas Mapping LiDAR system [97] uses a TDL that scans the 1651 nm line and a second laser operating at a nearby, non-absorbing wavelength to account for ground reflection and to determine pathlength via LiDAR. The lasers oscillate as the aircraft flies over the target, generating an elliptical scan pattern over the ground. Ground-reflected laser light is detected using an onboard sensor and transformed into a CH₄ column density. A similar ground-based system developed by SLB has recently been introduced that scans a solid angle and generates a column density "image" of a CH₄ plume based on backscattered returns [98]. At first glance, these systems would seem ideally suited for measuring the unburned CH₄ within a flare plume, since they are highly sensitive to CH₄ and insensitive to H₂O and other species. However, open-path TDL measurements are subject to "beam steering," in which the optical path is "bent" by temperature-induced gradients in the refractive index within the plume; while this effect may be manageable over short pathlengths, handling beam deflections over the longer pathlengths required for stand-off flare observations would be more difficult. A further challenge, in the case of the SLB system, is that the camera, which relies on ground-reflected laser light, is necessarily downward-looking and is typically positioned below the height of most elevated flare plumes.

Coburn et al. proposed [99] using a DCS system to characterize DRE_{CH₄} of a flare. While a conventional laser produces light at a single wavelength (or scans a narrow band in the case of a TDL), a frequency comb produces light at thousands of evenly spaced wavenumbers. In a DCS system, two mode-locked lasers with slightly different repetition rates each generate a comb. When the two combs are interfered on a detector, each pair of comb "teeth" beats together to create a unique radio-frequency signal. This process effectively maps the optical spectrum (hundreds of THz) down into the radio-frequency domain (MHz to GHz), where it can be recorded with standard electronics. The result is a broadband, high-resolution optical spectrum acquired rapidly, without moving parts, and with absolute frequency calibration. This approach has been commercialized as the LongPathTM system to measure CH₄ column densities arising from upstream oil and gas facilities over long measurement paths [100]. Coburn et al. envision using

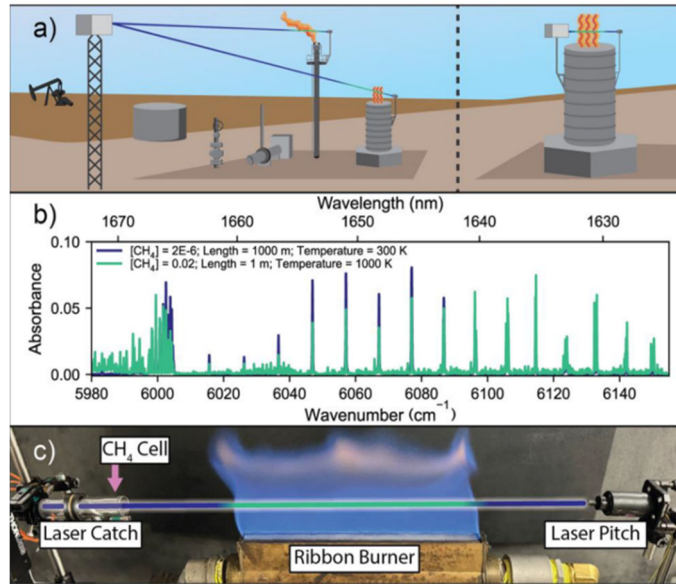


Figure 21: (a) Potential configuration of a DCS system for measuring flare DRE_{CH_4} ; (b) simulated spectra for CH_4 at ambient temperatures (blue) and elevated temperatures (green) over the DCS detection spectrum; (c) experimental setup consisting of a ribbon burner that represents the flare plume and a CH_4 gas cell to simulate absorption of the laser by ambient

this system to measure unburned CH_4 in the flare plume (Figure 21 (a)), exploiting the fact that the spectral resolution is sufficient to measure both CH_4 column density and its temperature since absorption line intensities are temperature sensitive to varying degrees (Figure 21 (b)). This attribute would allow the system to distinguish hot CH_4 within the flare plume over a short pathlength (e. g., 20,000 ppm, 1000 K over 1 m) from background CH_4 over a much longer pathlength (e.g., 2 ppm, 300 K, 1 km). Coburn et al. developed a laboratory-scale, proof-of-concept experiment that measured CH_4 and H_2O temperatures and column densities within a ribbon burner simultaneously, with a separate, adjacent gas cell containing CH_4 at ambient temperatures and a concentration representative of a 1 km measurement path (Figure 21 (c)) [99]. This study shows some promise, but a number of issues would need to be addressed for this system to be useful in a practical setting: (1) the aerodynamic fuel-stripping mechanism suggests that, under crosswind conditions, a significant amount of CH_4 emissions would be at low temperature and therefore difficult to distinguish from background CH_4 ; (2) beam steering would likely be a challenge over long pathlengths; and (3) the single measurement path would share the same weakness as PFTIR, i.e., it could not account for plume heterogeneity (Sec. 3.2).

Multispectral NIR cameras: Over the last decade, several commercial systems have been developed that image CH_4 plumes over the NIR spectrum, mostly using reflected sunlight. The NIR spectrum is mostly free of interfering species such as CO_2 and H_2O , although the CH_4 absorption features are weaker than those in the MWIR and LWIR, and measurements can only take place during daylight hours and under clear-sky conditions.

These systems may be airborne or ground based. In addition to the AVIRIS-NG and GAO systems (Sec. 5.2.2), which are primarily research tools, there are at least two aircraft-based commercial systems: the GHGSat-AV ($\sim 1.65 \mu m$) [101] and the Kairos Aerospace Leak Surveyor ($2.2\text{-}2.5 \mu m$) [102]. These systems can reliably detect plumes on the order of 5 kg/hr [103], which could be representative of an unlit flare, but it seems unlikely that either system could quantify the much lower column densities typical of a lit but inefficient flare.

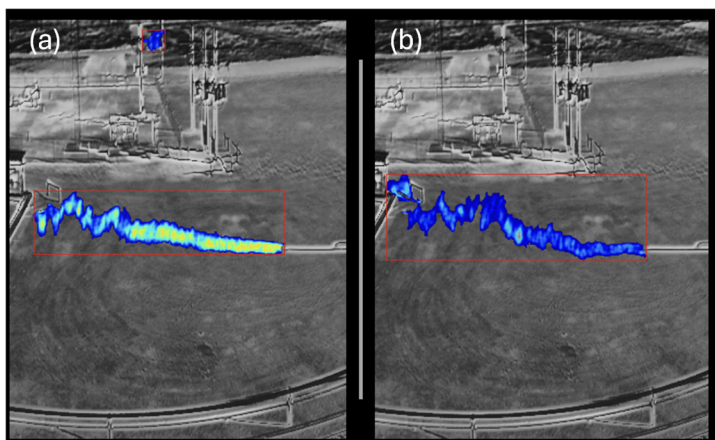


Figure 22: Unburned CH_4 emanating from (a) an unlit flare; and (b) an inefficient flare imaged by the Kuva GC1360 system. This instrument detects CH_4 plumes based on absorption over the $1.65\ \mu\text{m}$ CH_4 band in ground-reflected sunlight using a fixed, downward-looking sensor. (Courtesy of Robert Ward, Kuva Systems.)

Fixed, ground-based imaging systems that target fugitive CH_4 may also be used to identify unlit and poorly performing flares and would have greater sensitivity due to their proximity to the flare plume. Figure 22 shows unburned CH_4 detected in the shadow of a flare plume using a Kuva GC1360 OGI, which detects CH_4 plumes based on the absorption of ground-reflected sunlight over the $1.65\ \mu\text{m}$ band imaged using a fixed, downward-looking, multiband, short-wavelength infrared sensor [104]. While these systems may be able to distinguish among efficient flares, inefficient flares, and unlit flares, it is unclear whether they would be able to develop a reliable, quantitative estimate of CH_4 column density within the plume.

5.3 Summary of state-of-the-art and emerging trends for measuring flare CE/DRE

Growing awareness of the environmental impact of flare emissions, coupled with introduction of new regulations and voluntary reporting initiatives and the availability of new optoelectronics, algorithms, and computing power, is rapidly changing how flare CE/DRE is measured. We highlight three of the most important trends below.

5.3.1 MWIR imaging- based approaches for continuous monitoring

Remote-sensing technologies based on intensity measurements made along a single LOS (e.g., PFTIR) have been superseded by whole-plume imaging, enabled by the availability of low cost MWIR cameras and the computational power needed to process the images on a nearly instantaneous basis. Both the FlareGuardianTM and AgniTM systems are direct responses to new regulations [8] and reporting initiatives [6] that require continuous monitoring, but they achieve this at the expense of low spectral resolution, which leads to model errors. The low spectral resolution also confines these systems to the MWIR spectrum, since they would be unable to distinguish overlapping CH_4 and H_2O features over the LWIR spectrum. The AgniTM system partially compensates for the low spectral resolution through AI training data (see Sec. 5.3.3). We identify two major concerns with these systems: (1) the simplified instrument models introduce model errors that have not been fully characterized in the peer-reviewed literature; and (2) it is unclear whether any MWIR system could capture “cold” unburned CH_4 segregated from the hot combustion products, e.g., crosswind-induced fuel stripping. Such “problem cases” are likely to be the main contributors to CH_4 emissions from flaring [5], and accurate quantification of these sources is therefore of paramount importance.

5.3.2 Uncrewed aerial vehicles

The increasing payload of UAVs, coupled with the miniaturization of sensors like TDL spectroscopy systems, has presented a significant opportunity for measuring flare emissions. Controlled-release studies of CH₄ over the past five years have shown a significant improvement in the accuracy of the “flux wall” approach used to infer the mass flow rates needed to estimate CE/DRE (Figure 9). The uncertainty associated with these estimates is well-understood compared to other approaches and may be incorporated into CE/DRE estimates, e.g., Eq. (9). Furthermore, recent regulatory changes that now permit beyond-visible-range flying and advances in autonomous navigation offer the possibility of using these systems to measure remote flares with limited human intervention. However, the chief drawback of UAVs is that the mass flow rates are not instantaneous, but rather are temporally and spatially averaged, and are therefore unlikely to capture brief and infrequent “rogue events” that may dominate emissions from some flares (Sec. 3.3). Moreover, this approach cannot provide a continuous measurement of flare CE/DRE. Finally, we note that UAV-derived CE/DRE estimates have not yet been benchmarked against validation tests based on extractive sampling to the same extent as remote-sensing approaches (e.g., [10,23,32]), at least in the open literature, although the outcomes of these tests should be interpreted in the context of the uncertainty attached to the validation measurements.

5.3.3 Artificial intelligence/machine learning

As we note in Sec. 3, estimating flare CE/DRE is an inherently challenging undertaking due to several factors, including the intermittency and inhomogeneity of the flare plume and the limited access offered under operating conditions. This task is tantamount to solving an “inverse problem” wherein the objective is to infer the flare CE/DRE via indirect and incomplete data. These problems are notoriously ill-posed, meaning that, due to an *information deficit*, a large range of CE/DRE values exist that could explain the observations with a reasonable likelihood. The ill-posedness of the problem materializes as a wide probability density function as shown in Figure 7. Artificial intelligence and machine learning synthesize the information contained in observations with other “prior” information, e.g., from CFD simulations or validation tests, in a computationally expedient manner. Both the Angi™ dual-channel MWIR system and the visible-flame spectroscopy techniques (Sec. 5.2.5) rely on this approach to compensate for the incomplete and indirect nature of the measurement data obtained from the sensors. Given the ill-posed nature of the problem and the complexity of the physical models that connect the observations to the flare state (particularly for remote sensing), AI/ML is likely to become an essential component for any continuous monitoring system for measuring flare CE/DRE.

There are, however, important nuances in how these systems are implemented and validated. ML-based vision systems are notoriously sensitive to nuisance artifacts, such as changes in camera settings, viewing geometry, or background reflections, which can produce large errors even when the flare itself is unchanged. Also, the training data sets are subject to their own uncertainties, which are often overlooked. Finally, and invariably, the training dataset is unlikely to include the operating conditions of each flare, and scenarios that depart from training conditions (crosswinds, over-assistance, low NHV gases) may be subject to large errors (e.g., Figure 19). Again, these “non-ideal” operating conditions are likely to account for a disproportionate amount of overall flare emissions, and it is precisely these cases that need to be measured accurately.

6 Summary and next steps

Through the efforts of World Bank's Zero Routine Flaring initiative [7] and Global Flaring and Methane Reduction Partnership [105], as well as the United Nations Environment Programme's Oil & Gas Methane Partnership 2.0 (UNEP OGMP 2.0, [6]), the environmental impact of flaring is receiving considerable attention. To better understand the impact of this flaring on carbon budgets and climate change, we need methods for measuring CH₄ emissions from flares that are robust, low-cost, implementable across a broad range of flaring scenarios, and, most importantly, have quantifiable uncertainty. In this section we summarize why uncertainty is critical and suggest a path forward for determining uncertainty across technology platforms.

6.1 Importance of uncertainty

As detailed in this report, a wide range of techniques are being developed to estimate flare CE/DRE, but these measurements remain challenging because of limited access to flares plumes in the near field, lack of information about flare volume and composition, flare intermittency and heterogeneity resulting from flame interactions with the ambient conditions (e.g., wind speed and direction), and unavoidable simplifications and assumptions made in instrument models that convert observed quantities to the QoIs (CE/DRE). Most importantly, there is little understanding of uncertainty in these measurements and no standardized method for estimating uncertainty across methodologies. Reports contemporaneous to this one have also raised this issue. The report entitled "Recommended practices for methane emissions detection and quantification technologies – upstream" acknowledges, "Uncertainty of methane measurements is a complex topic, and methods to calculate these uncertainties are not fully resolved and implementable with a widely agreed upon method. Therefore, many open research questions remain in this area" [13]. Reference [14], which focuses on flares and other combustion-generated plumes, highlights the importance of transparency: "To enhance transparency in evaluating technology capabilities, it is beneficial to have robust, parameterized, and publicly available analyses of quantification performance. Technologies that have published results for these parameters provide more reliable performance indications compared to those without public data" [14]. Establishing uncertainty in CE/DRE estimates is an essential step for ensuring that reported distributions are scientifically meaningful and policy relevant.

6.2 Generalizable method for quantifying uncertainty in DRE_{CH₄} estimates

We have highlighted the challenges of providing more accurate CH₄ emission rates from gas flaring without a standardized and transparent procedure for determining DRE_{CH₄} across the wide range of technologies that are currently available. In this section, we propose a method for quantifying DRE_{CH₄} uncertainty that uses *a priori* testing with synthetic data [106–108]. *A priori* testing was developed in the turbulence community to assess the strengths and weaknesses of candidate turbulence models by comparing model predictions to high-quality numerical data. Because model deficiencies are highlighted by *a priori* testing, more accurate and robust models can then be developed. Our proposed methodology, which uses this approach, is broadly generalizable and can be applied to any of the measurement technologies summarized in this report.

Step 1: Generate synthetic data sets to use as benchmark data: In the current benchmark data sets for calibration/validation, DRE_{CH₄} is computed from direct-sampling measurements of gases in the flare plume [10,23,42]. Due to the high probability of bias and other instrument model uncertainties associated with this method, we propose that the new benchmark data set

be a suite of synthetic data generated by CFD-LES simulations in a design space that may include flare type, crosswind speed, vent gas flow rate and composition, flare tip design, etc. This suite will be small enough to be manageable given time and budget constraints but sufficiently large to capture the design/operating space of the majority of upstream flares worldwide. For this methodology to be useful in determining CE/DRE_{CH4} uncertainty in real-world scenarios and to identify instrument-model deficiencies associated with each measurement technology, the simulated data need only approximate the behavior of an actual flare. For example, does the flare in crosswind exhibit the fuel-stripping behavior observed by Johnson et al. [17,35]? Does decreasing the NHV_{cz} lead to flame instability/reduced DRE_{CH4} [42]?

Step 2: Provide more rigorous definition of global DRE: A rigorous, standardized definition of global DRE_{CH4} allows measurements made with different instruments to be evaluated on the same basis. The definition should account for the impacts of intermittency, heterogeneity, and rogue events that skew the distribution of outcomes. For example, should DRE_{CH4} be computed based on time-averaged values in the flare plume or defined as the median of a distribution of short-time-scale samples? Seymour and Johnson [36] showed that ~100 measurements were required for the median value of BC/H₂O ratios measured in field flares to be within 10% of the true mean. With a standardized definition, each technology provider may then adjust their instrument model to best match the definition given the constraints of their technology.

Step 3: Conduct a blind a priori test of DRE: For the blind *a priori* test, the technology provider is given a synthetic CFD data set for each case in the test suite. They apply their instrument model to the data to compute a prediction of global DRE_{CH4}. The simulation team computes the actual global DRE_{CH4} using the definition from Step 2 applied directly to the synthetic data. The *a priori* testing then involves the comparison of the predicted to the actual DRE_{CH4} mean values and/or distributions to learn about instrument model accuracy and robustness. A recent example of this approach applied to CE measurements in gas flares is described by Kaveh et al. [83]. The authors developed an instrument model for the VISR technique [23,38] based on information they found in patents and published papers. They used an equation for spectral intensity incident on the camera aperture together with the simulated temperature and species' concentration profiles along an LOS to generate synthetic spectral intensities that they then contaminated with white noise representative of the camera sensor. Finally, they applied their VISR instrument model to these intensities to obtain local and global mean values of CE. The CEs inferred from the VISR instrument model differed by more than 10% DRE_{CH4} from the actual global DRE_{CH4} values (computed directly from the whole-plume synthetic data using a specific definition of CE) in the four scenarios that were tested, and in some cases the difference exceeded 50%.

Step 4: Use Bayesian inference to compute uncertainty for real-world measurements: According to Clayton, "Inferential probabilities go from data to hypothesis: Given what we observed, what can we conclude and with what certainty?" [109]. For example, given a set of observed quantities (e.g. spectra in the case of flares), what can we conclude about the "true" global DRE_{CH4} of the flare and with what degree of certainty? The application of Bayes' Law and its inferential probability allow us to compute global DRE_{CH4} with quantified uncertainty for a given measurement technology deployed to a real-world flare. In other words, we extrapolate uncertainty rather than a QoI, so the uncertainty varies with changes in scenario, as it should.

In the Bayesian viewpoint, the measurements of observed, indirect quantities and the parameters in the instrument model that translate those observed quantities into the QoI are viewed, not as single, deterministic values, but rather as random variables characterized by a

probability density function (Figure 7). As a result, there is no single DRE_{CH_4} for a flare; rather, one may state that the global DRE_{CH_4} belongs to a given interval (e.g. 98-100%) with a certain probability (e.g., 90%). Probability represents our state of knowledge, and that state of knowledge is continually improving as new information becomes available. The two sources of information available to estimate flare DRE_{CH_4} are experimental data (usually radiometric observations), $\mathbf{b}^{exp}$, and simulation data, $\mathbf{b}^{mod}$. However, experimental data obtained from any of the instruments (and their associated models) described in this report as well as simulation data from a high-fidelity, physics-based flare model are only approximations; each source has unquantified bias due to limitations of the chosen model [48]. As we have limited information as to the source of the uncertainty (experimental instrument model or simulation model), we treat both sources of data as the truth and elucidate the overall uncertainty from their difference, $\mathbf{b}^{mod} - \mathbf{b}^{exp}$, also known as the defect, within the framework of Bayesian calibration. The advantage of this methodology is that we do not have to identify all the sources of error and provide estimates of the uncertainty ranges for each uncertain variable as with the GUM approaches (Secs. 4.4.2 and 4.4.3). Rather, we infer the overall error by solving the Bayesian inverse problem with the defect computed from the available data [48,110]. Through this technique, we can compute flare DRE_{CH_4} with quantified uncertainty.

6.3 *Moving forward*

For the foreseeable future, flaring will continue to be an unavoidable part of oil and gas production, particularly in the developing world. Given the time, money, and effort that have been spent by governments, non-governmental organizations, producers, equipment manufacturers, measurement technology providers, and academics to characterize and reduce emissions from industrial flares, now is the time to address the unaddressed critical issue impacting forward progress – developing a standardized method for quantifying uncertainty of flare DRE_{CH_4} measurements.

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Annex A: Technology Summary Sheets
(CE, DRE, Lit/Unlit Flares, and Methane Emissions)

This annex summarizes classes of technologies that are used to monitor flare emissions. While most technologies measure CE/DRE, some are only capable of measuring methane emissions or concentrations, or are used to estimate flaring activity (i.e., flare gas volumes). The summary sheets address the following questions. The answers contained herein are intended for informational purposes and are provided according to the authors' best judgement.

1. Capital and deployment costs (high, medium, low)
2. Expertise needed to deploy (expert, intermediate, low)
3. Deployment frequency (intermittent, continuous monitoring)
4. Time required to process data (real time, intermediate, long)
5. Mode of deployment (direct sampling, standoff)
6. Commercialization/Technology Readiness Level (TRL)
7. Can it measure an unlit flare?
8. Availability of uncertainty estimates

Open-path Fourier transform infrared (PFTIR/AFTIR) spectroscopy

1. Capital and deployment costs
Medium (Capital cost est. ~\$200 K. Fee-for-service with PFTIR is ~\$100 K per deployment, while that of AFTIR is ~\$130 K due to expense of flying the drone to hold retroreflector).
2. Expertise needed to deploy
Expert needed to aim/calibrate system and to analyze and interpret spectra. Available as fee-for-service.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign).
4. Time required to process data
Near real-time acquisition. Data can be post-processed within hours and can be done on-site. Not automated⁵.
5. Mode of deployment
Stand-off, single line-of-sight at one visible flame length away from the flame tip.
6. Commercialization/Technology Readiness Level (TRL)
PFTIR, TRL 9 (commercially available). AFTIR (with drone for retroreflector), TRL 7. Service provided by Spectrum Environmental Solutions and Clean Air Engineering. Only a handful of instruments are presently available.
7. Can it measure an unlit flare?
PFTIR could potentially measure a partially lit fuel stream but would likely not detect a completely unlit stream. AFTIR could measure an unlit fuel stream provided correct location of the retroreflector. As these technologies are not intended for continuous monitoring, open-path FTIR is unlikely to be used to detect unlit flares.
8. Availability of uncertainty estimates
 - Evaluated as part of the 2010 TCEQ flare study⁶, showed good reproducibility and consistency with extractive measurements at high CE (~99%), but greater deviation at lower CE (higher assistance, lower $NHVCZ$). Attributed to plume heterogeneity and flame instability.
 - Concern about whether extractive measurements and test regime captured fuel stripping scenarios.

⁵ Clean Air Engineering. (2020, October 26). PFTIR flare testing: Technology and method summary (Revision 0). Clean Air Engineering

⁶ Wormholdt et al., *Ind. Eng. Chem. Res.* 2012, 51, 12621–12629 dx.doi.org/10.1021/ie202783m

Multispectral mid-wavelength infrared (MWIR) plume imaging

1. Capital and deployment costs
Medium/high (Capital cost est. \$300-400 K for Sensia Agri™, \$800 K for VISR/FlareGuardian™. VISR fee-for-service is ~\$20 K per day).
2. Expertise needed to deploy
Low (after installation). Both instruments are intended as automated systems for continuous monitoring. The instruments are less sensitive to alignment compared to telescope systems but need to be installed and calibrated by experts.
3. Deployment frequency
Continuous monitoring, VISR/FlareGuardian™ may be deployed as part of measurement campaigns and deployed as fee-for-service.
4. Time required to process data
Provides real-time or near-real-time CE/DRE estimates.
5. Mode of deployment
Stand-off imaging of the flare plume.
6. Commercialization/Technology Readiness Level (TRL)
TRL 9 (commercially available). Commercial providers are Sensia (Agni™, two channel) and Zeeco/Providence Photonics (VISR/FlareGuardian™, ~40 channels). FlareGuardian™ is an approved EPA alternative testing method⁷.
7. Can it measure an unlit flare?
Both systems are capable of pilot monitoring. However, MWIR imaging may not be able to visualize a cold plume of methane except under clear-sky conditions. Sensia offers other cameras for measuring cold fuel streams.
8. Availability of uncertainty estimates
 - VISR/FlareGuardian™: Evaluated against extractive measurements⁸. Technology provider claims “0.5% accuracy” based on these results. Kaveh et al. casts doubt on this claim, however, due mainly to the process used to convert the local CE to a global CE⁹.
 - Sensia Agni™: Technology provider claims within 0.5% accuracy based on propagation of sensor uncertainty (noise) through the instrument model¹⁰ (but this ignores model error). Validation experiments were in progress at the time of this report.

⁷ U.S. Environmental Protection Agency. (2024, July 12). *Approval of the Simplified Video Imaging Spectro-Radiometry (VISR) method (OTM-56) as an alternative test method under § 60.5417b(d)(8): ATM approval letter ALT-156*. Air Emission Measurement Center. Retrieved September 7, 2025, from EPA.gov.

⁸ Zeng, Y., Morris, J., & Dombrowski, M. (2016). Validation of a new method for measuring and continuously monitoring the efficiency of industrial flares. *J. Air Waste Manag. Assoc.*, 66(1), 76–86. <https://doi.org/10.1080/10962247.2015.1114046>

⁹ Kaveh, A., Spinti, J., Lapeyre, P., Bonarens, M., & Daun, K. J. (2025, June 9). Viability of video imaging spectro-radiometry (VISR) for quantifying flare combustion efficiency. *J. Air Waste Manag. Assoc.*, 75(7), 522–539.

¹⁰ Personal correspondence with Alejandra Motta, August 4, 2025

Imaging Fourier transform spectrometer (IFTS) plume imaging

1. Capital and deployment costs
High (Capital cost est. \$750 K-\$1 M). Likely done as fee-for-service, ~\$30,000 per week.
2. Expertise needed to deploy
Expert.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign).
4. Time required to process data
Several days to several weeks.
5. Mode of deployment
Stand-off imaging of the flare plume.
6. Commercialization/Technology Readiness Level (TRL)
Telops Hyper-Cam™ iMW, xLW mini, xMW mini

TRL 7 (system prototype demonstration in an operational environment). General purpose instruments for many applications. In the context of flaring, currently a research tool for understanding combustion physics.
7. Can it measure an unlit flare?
LWIR yes, MWIR is unlikely due to low thermal contrast with background. All systems could likely image a pilot flame.
8. Availability of uncertainty estimates
 - No validation with extractive measurements to date. (Telops Hyper-Cams were included in 2010 TECQ study but were unable to process the data in the allocated time¹¹.)
 - Comparison with laboratory controlled-release studies suggest inferred mass flow rates within 10-30% of controlled release¹².
 - Measurements on enclosed ground combustor demonstrated carbon mass balance with prescribed fuel flow rate¹³.

¹¹ The University of Texas at Austin, Center for Energy & Environmental Resources. (2011, August 1). *TCEQ 2010 flare study: Final report* (Report No. PGA No. 582-8-86245-FY09-04). Texas Commission on Environmental Quality.

¹² Lapeyre, P., Narayanan, N. S., Larivière-Bastien, M., & Daun, K. J. (2024). *Quantifying flare combustion efficiency using a long wave infrared Fourier transform spectrometer. Proceedings of the Combustion Institute, 1-4*, 105554. <https://doi.org/10.1016/j.proci.2024.105554>.

¹³ Lapeyre, P., Miguel, R. B., Nagorski, M. C., Gagnon, J.-P., Chamberland, M., Turcotte, C., & Daun, K. J. (2024). Quantifying flare combustion efficiency using an imaging Fourier transform spectrometer. *Journal of the Air & Waste Management Association*, 74(5), 319-334. <https://doi.org/10.1080/10962247.2024.2319773>.

Differential adsorption LiDAR (DIAL)

1. Capital and deployment costs
High (Capital cost est. \$750 K-\$1 M). Likely done as fee-for-service or as a scientific measurement campaign.
2. Expertise needed to deploy
Expert.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign).
4. Time required to process data
Data acquisition and post-processing times of 10-15 minutes. CE/DRE estimates require that vent gas flow rate and composition be known.
5. Mode of deployment
Stand-off, line-of-sight that transects flare plume. Plume scan consists of 7-20 transects.
6. Commercialization/Technology Readiness Level (TRL)
Prototype systems developed by the UK's National Physical Laboratory¹⁴, the US National Institute of Standards and Technology¹⁵, and France's ONERA and Total¹⁶.

TRL 8 (actual technology completed and qualified through tests and demonstration). Used for measuring many species in flare plumes with high precision and selectivity, but not for commercial purposes.
7. Can it measure an unlit flare?
Yes, it can sample both inside and outside the methane plume simultaneously, thereby differentiating between the plume and the ambient background.
8. Availability of uncertainty estimates
 - Uncertainties are usually reported based on standard deviation of repeated scans^{10,17}.
 - Combining sensor uncertainty propagated through DIAL equations (model error ignored) with uncertainty in wind speed and wind direction yields uncertainties in mass emission rates and concentrations on the order of 10%¹⁷ (depending on environmental factors.)
 - Controlled release studies demonstrate estimated mass flow rates are within 5-20 % of known values^{16,18}.

¹⁴ Few, J., Gardiner, T., & Smith, T. (2019). *Review of differential absorption LiDAR flare emission and performance data: Chief Scientist's Group report* (Report No. SC150026/R). Environment Agency.

¹⁵ Stroud, J. R., Dienstfrey, W. J., & Plusquellic, D. F. (2023). Study on local power plant emissions using multi-frequency differential absorption LIDAR and real-time plume tracking. *Remote Sens.*, 15(17), 4283. <https://doi.org/10.3390/rs15174283>.

¹⁶ Cezard, N., Le Méhauté, S., Le Gouët, J., Valla, M., Goular, D., Fleury, D., Planchat, C., & Dolfi-Bouteyre, A. (2020). Performance assessment of a coherent DIAL-Doppler fiber lidar at 1645 nm for remote sensing of methane and wind. *Opt. Express*, 28(15), 22345–22364. <https://doi.org/10.1364/OE.395093>.

¹⁷ Innocenti, F., Gardiner, T., & Robinson, R. (2022). Uncertainty assessment of differential absorption lidar measurements of industrial emissions concentrations. *Remote Sens.*, 14(17), 4291. <https://doi.org/10.3390/rs14174291>.

¹⁸ Gardiner, T., Helmore, J., Innocenti, F., & Robinson, R. (2017). Field validation of remote sensing methane emission measurements. *Remote Sens.*, 9(9), 956. <https://doi.org/10.3390/rs9090956>.

Visible-flame spectroscopy

1. Capital and deployment costs
Low (Capital cost est. \$50-\$150 K). Equipment costs are lower than instruments that need MWIR imaging.
2. Expertise needed to deploy
Low/intermediate after installation (need expertise to process training data).
3. Deployment frequency
Continuous monitoring, intended as an automated system.
4. Time required to process data
Near-real-time data acquisition and data post-processing to produce DRE/CE estimates.
5. Mode of deployment
Stand-off imaging of visible flame. Simultaneous flame images recorded over the red, blue, and green channels.
6. Commercialization/Technology Readiness Level (TRL)
Machine learning techniques: TRL 6 (system/subsystem model or prototype demonstration in a simulated environment). Methodology demonstrated with data from image analysis and machine-learning tools¹⁹. Also demonstrated using data from both an RGB camera and the Baker-Hughes FlareIQ™ system²⁰.

VISR/Mantis Lite™ technology: TRL 9 (commercially available).
7. Can it measure an unlit flare?
No as it depends on visible features of a flame.
8. Availability of uncertainty estimates
 - Evaluated against extractive measurements¹⁹ but uncertainty not quantified. Poor CE estimates for flare operating outside range of training dataset.
 - Trained with and evaluated against CE/DRE predictions of the FlareIQ™ algorithm (which are interpreted as “truth” for purposes of uncertainty quantification). The R^2 score is ~95% when CE is $\geq 97\%$ ^{Error! Bookmark not defined.}. No uncertainty estimates for harder-to-predict low CE cases.
 - VISR/Mantis Lite™ technology provides only rough estimates of CE/DRE bands. No information available about instrument model for further uncertainty analysis.

¹⁹ Castiñeira, D., Rawlings, B. C., & Edgar, T. F. (2012). Multivariate image analysis (MIA) for industrial flare combustion control. *Ind. Eng. Chem. Res.*, 51(36), 12642–12652. <https://doi.org/10.1021/ie3003039>.

²⁰ Boumaraf, S., Li, P., Al Radi, M. K., Abdelhafez, F. O., Behouch, A., Al Awadhi, K. Y., Karki, H., Javed, S., Dias, J., & Werghi, N. (2025). Optimized flare performance analysis through multi-modal machine learning and temporal standard deviation enhancements. *IEEE Access*, 13, 34362–34377. <https://doi.org/10.1109/ACCESS.2025.3540558>.

Near-field sampling (UAVs)

1. Capital and deployment costs
Low (Capital costs est. \$150 K for drone + sensors). Fee-for-service is approximately \$50 K per deployment.
2. Expertise needed to deploy
Intermediate-high to operate, low for fee-for-service. Likely provided as fee-for-service.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign).
4. Time required to process data
Real-time preliminary feedback from a minimum of 24 hours to several days/weeks for a complete analysis that includes correlation with wind data.
5. Mode of deployment
Near-field sampling of flare plume requires some degree of site access.
6. Commercialization/Technology Readiness Level (TRL)
TRL 9 (commercially available). Commercial systems are the Explicit ApS and Aeromon's BH-12 sensor payload.
7. Can it measure an unlit flare?
Yes, if the sampling region coincides with the flare plume.
8. Availability of uncertainty estimates
 - Mass flow rate uncertainty results from sensor noise (particularly for smaller flares and lower CH₄ concentrations) and from model error associated with the mass balance method (for larger flares and higher CH₄ concentrations)²¹.
 - Level of uncertainty in drone-derived mass flow rates, inferred from benchmark studies, are between 15%-30% under favorable conditions^{22,23}. Uncertainty depends strongly on factors like wind fluctuations and should be calculated for each measurement scenario.

²¹ Shaw, J. T., Shah, A., Yong, H., & Allen, G. (2021). Methods for quantifying methane emissions using unmanned aerial vehicles: A review. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, 379(2210), 20200450. <https://doi.org/10.1098/rsta.2020.0450>.

²² Liu, Y., Paris, J. D., Broquet, G., Bescós Roy, V., Fernandez, T. M., Andersen, R., Russu Berlanga, A., Christensen, E., Courtois, Y., Dominok, S., Dussenne, C., Eckert, T., Finlayson, A., Fernández de la Fuente, A., Gunn, C., Hashmonay, R., Hayashi, J. G., Helmore, J., Honsel, S., Innocenti, F., ... Bousquet, P. (2024). Assessment of current methane emission quantification techniques for natural gas midstream applications. *Atmos. Meas. Tech.*, 17(9), 1633–1649. <https://doi.org/10.5194/amt-17-1633-2024>.

²³ Morales, R., Ravelid, J., Vinkovic, K., Korbeñ, P., Tuzson, B., Emmenegger, L., Chen, H., Schmidt, M., Humbel, S., & Brunner, D. (2022). Controlled-release experiment to investigate uncertainties in UAV-based emission quantification for methane point sources. *Atmos. Meas. Tech.*, 15(5), 2177–2198. <https://doi.org/10.5194/amt-15-2177-2022>.

Far-field sampling

1. Capital and deployment costs
High (Capital cost est. \$500 K-\$1M for instrumentation on ground or as payload). For airborne-sampling, flight time is a significant cost (~\$3 K/h).
2. Expertise needed to deploy
Expert (deploying onboard sensors, devising flight paths, data processing).
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign).
4. Time required to process data
Near-real-time preliminary feedback to several weeks for a complete analysis that includes correlation with wind data.
5. Mode of deployment
Ground-based or airborne-based far-field sampling of flare plume does not require site access.
6. Commercialization/Technology Readiness Level (TRL)
Ground based: TRL 9 (commercially available). Aerodyne Mobile Laboratory is a ground-based suite of instrumentation.

Airborne sampling: TRL 8 (actual technology completed and qualified through tests and demonstrations). For airborne-based sampling, sensor packages are designed for specific applications and include commercial instruments such as cavity ringdown spectrometers (for measuring CH₄, C₂H₆, and CO₂) and NO_x analyzers.
7. Can it measure an unlit flare?
Yes, if the sampling region coincides with the flare plume. Sampling region is more difficult to determine in case of unlit flare.
8. Availability of uncertainty estimates
 - Accuracy of CE/DRE values hinges on validity of assumptions: (1) plume is well mixed and steady and (2) it originates only from flare being measured. Potential for bias error is high as less-buoyant plumes of cold, unburned fuel may be missed by aircraft.
 - Uncertainty presented as 95% confidence intervals (CI) based on statistical analysis of data (e.g. DREs > 90 % with CI of $\sim \pm 1\%$ DRE²⁴, CH₄ emissions factor estimates of 0-70 ppm CH₄/ppm CO₂*1000 with CI of ± 1 -25²⁵).
 - Comparing results of Caulton et al.²⁶, Gvakharia et al.²⁵, and Plant et al.²⁴ highlights likelihood that leading uncertainty source is sampling error.

²⁴ Plant, G., Kort, E. A., Brandt, A. R., Chen, Y., Fordice, G., Gorchov Negron, A. M., Schwietzke, S., Smith, M., & Zavala-Araiza, D. (2022). Inefficient and unlit natural gas flares both emit large quantities of methane. *Science*, 377(6614), 1566–1571. <https://doi.org/10.1126/science.abq0385>.

²⁵ Gvakharia, A., Kort, E. A., Brandt, A., Peischl, J., Ryerson, T. B., Schwarz, J. P., Smith, M. L., & Sweeney, C. (2017). Methane, black carbon, and ethane emissions from natural gas flares in the Bakken shale, North Dakota. *Environ. Sci. Technol.*, 51(9), 5317–5325. <https://doi.org/10.1021/acs.est.6b05183>

²⁶ Caulton, D. R., Shepson, P. B., Cambaliza, M. O. L., McCabe, D., Baum, E., & Stirr, B. H. (2014). Methane destruction efficiency of natural gas flares associated with shale formation wells. *Environ. Sci. Technol.*, 48(16), 9548–9554. <https://doi.org/10.1021/es500511w>

Satellite-based sensors
(Assessment of flaring activity only; no CE/DRE)

1. Capital and deployment costs
Very high (Program cost est. \$500 M-\$1 B; inclusive of manufacture, testing, delivery, integration, and post-launch support of instruments providing environmental monitoring). Programs launching these satellites have thus far been funded by governments.
2. Expertise needed to deploy
Expert.
3. Deployment frequency
Quasi-continuous monitoring. Nighttime observations of visible and infrared emissions, daytime observations of backscattered sunlight.
4. Time required to process data
Several hours to several days. Data processing contract given to university²⁷.
5. Mode of deployment
Multispectral (visible and infrared) imaging from space. The spatial resolution is inadequate to resolve the plume of a single flare over the infrared spectrum.
6. Commercialization/Technology Readiness Level (TRL)
TRL 9 (commercially available). Service provided by NOAA (VIIRS), NASA (MODIS), ESA (SLSTR, OMI, TROPOMI).
7. Can it measure an unlit flare?
Unlikely due to limited spatial resolution at infrared wavelengths and low thermal contrast between flare and surroundings. Could detect the absence of a lit flare from a known flare site.
8. Availability of uncertainty estimates
 - CE/DRE are input parameters, not outputs.
 - CH₄ enhancements cross-validated using data from TROPOMI. Errors in wind speed and direction estimated from data. Overall uncertainty estimates in CH₄ emissions rates of $\sim\pm 25\%$ Error! Bookmark not defined..

²⁷ NASA. (2020, June 26). *NASA awards contract for Earth observing satellite instrument*. Retrieved from <https://www.nasa.gov/news-release/nasa-awards-contract-for-earth-observing-satellite-instrument/>

Tunable diode lasers (TDL) at near-infrared (NIR) wavelengths
(CH₄ emissions only)

1. Capital and deployment costs
Fee-for-service (monthly monitoring of several sites) with airborne system is ~\$80K per year. Medium for ground-based system (Capital cost est. \$200 K + \$100 K per year for continuous on-site monitoring support).
2. Expertise needed to deploy
Low for airborne system (operated entirely by technology provider). Low for ground-based system (after installation). Intended as an automatic system.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign) for airborne system. Continuous monitoring for ground-based system. Designed to run autonomously.
4. Time required to process data
Provides near-real-time estimates of CH₄ emissions rates.
5. Mode of deployment
Ground-based and airborne-based stand-off systems. Ground-reflected laser light is detected and transformed into CH₄ column density.
6. Commercialization/Technology Readiness Level (TRL)
TRL 9 (commercially available). Commercial providers include Bridger Photonics (airborne LiDAR system) and QLM Technology Ltd (ground-based TDL + DIAL systems).
7. Can it measure an unlit flare?
Yes, it is one of most accurate means to quantify CH₄ column density by targeting a single CH₄ absorption line or pair of neighboring lines.
8. Availability of uncertainty estimates
 - Analysis of CH₄ emissions rates using ground-based system showed average percentage error of ~50 % between the computed and the true values²⁸.
 - In single-blind test conducted by Bridger Photonics, single-measurement uncertainty (one standard deviation) is in 15-21% range depending on source of wind measurement, while the aggregated “bias” error for all measurements is ~4%²⁹.

²⁸ Titchener, J., Millington-Smith, D., Goldsack, C., Harrison, G., Dunning, A., Ai, X., & Reed, M. (2022). Single photon lidar gas imagers for practical and widespread continuous methane monitoring. *Appl. Energy*, 306, 118086. <https://doi.org/10.1016/j.apenergy.2021.118086>.

²⁹ Bridger Photonics. (2021, June 7). *Performance of Gas Mapping LiDAR™ for quantification of very high methane emission rates* (White Paper No. 210607). Bridger Photonics, Inc. https://www.bridgerphotonics.com/sites/default/files/inline-files/BridgerPhotonics_HighControlledReleaseRates.pdf

Multispectral near-infrared (NIR) cameras (CH₄ emissions only)

1. Capital and deployment costs
Low for ground-based system (Capital cost est. ~\$100 K. Fee-for-service est. cost of \$100 K per year for continuous monitoring). With airborne system, fee-for-service cost est. is \$50 K per day.
2. Expertise needed to deploy
Low for airborne system (operated entirely by provider). Low for ground-based system (after installation). Intended as an automatic system.
3. Deployment frequency
Intermittent (not continuous monitoring, but dedicated measurement campaign) for airborne systems.

Continuous monitoring with autonomous daytime operation for ground-based systems.
4. Time required to process data
Provides near-real-time estimates of CH₄ emissions rates with analysis of emission events requiring several days to process.
5. Mode of deployment
Stand-off CH₄ plume imaging (either airborne or ground based).
6. Commercialization/Technology Readiness Level (TRL)
TRL 9 (commercially available). Aircraft-based commercial systems include GHGSat-AV (~1.65 µm) and Kairos Aerospace Leak Surveyor (2.2-2.5 µm). A ground-based system is Kuva GC1360 OGI.

TRL 7 (system prototype demonstration in an operational environment). Research tools (also aircraft-based) include NASA's Airborne Visible/Infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) and ESA's Global Airborne Observatory (GAO).
7. Can it measure an unlit flare?
Yes, cameras detect plumes of 5 kg/h³⁰ (representative of an unlit flare) and may distinguish among efficient, inefficient and unlit flares. Unlikely that they can be used for quantitative estimates of CH₄ column densities within plumes of inefficient flares.
8. Availability of uncertainty estimates
 - In single-blind test, error in computed methane emissions rate is ~30%–40% of rate value.
 - Accuracy of single frame analysis is low, but averaging frames over a CH₄ release event yields 1.5-28 % error³¹.

³⁰ El Abbadi, S. H., Chen, Z., Burdeau, P. M., Rutherford, J. S., Chen, Y., Zhang, Z., Sherwin, E. D., & Brandt, A. R. (2024). Technological maturity of aircraft-based methane sensing for greenhouse gas mitigation. *Environ. Sci. Technol.*, 58(15), 9591–9600. <https://doi.org/10.1021/acs.est.4c02439>

³¹ McArthur, T. (2024). *RPT F0160829 – Kuva Final Report: Methane imaging solution for continuous leak detection and quantification for tank emissions and facility monitoring* (Final Outcomes Report, Project ID F0160829). Kuva Canada Inc.; Emissions Reduction Alberta. <https://www.eralberta.ca/wp-content/uploads/2024/12/RPT-F0160829-Kuva-Final-Report-Public-8-30.pdf>