



Satellite Remote Sensing of Methane Point Sources: A Review of Capabilities and Applications

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Abstract. The ability to remotely sense methane point sources continues to grow, driven by new satellite launches, newly discovered detection capabilities in satellites not originally intended for methane observation, and increasingly mature data processing and delivery pipelines. We review current and anticipated satellite remote sensing capabilities, including a description of instrument specifications, sampling strategies, and data availability. We detail algorithms that drive general methane plume processing pipelines and associated validation experiments across multiple product levels. We describe categories of stakeholder and science driven use cases that use satellite point source datasets. In particular, we detail several mitigation programs that use satellite point source detections to inform leak detection and verification (e.g., IMEO Methane Alert and Response System; California Satellite Methane Project). We also summarize research to date that incorporates point source datasets to inform practices to reduce emissions and aid aggregate accounting of emissions from facilities to regional scales. Continued work to establish common validation standards and reference sites to make detection and quantification



performance comparable across instruments is recommended for building increased confidence in plume datasets. However, the successful integration of satellite point source imager observations into stakeholder workstreams demonstrates that these datasets are equipped today to support climate policy, operator response, and emissions accounting.

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1 Introduction

Methane is a key contributor to the global warming realized since the pre-industrial period (0.6° C). Methane is emitted from several source categories, including both natural sources (wetlands) and anthropogenic sources (e.g., fossil fuel, waste, agriculture) (Saunio et al., 2025). The primary sink of methane is via reaction with the hydroxyl radical (OH), other
50 minor sinks include reaction with chlorine in the marine boundary layer, excited oxygen atoms O(¹D) and chlorine in the stratosphere, and uptake in soils through consumption by methanotrophic bacteria (Guerrero-Cruz et al., 2021). Due to methane's large global warming potential and relatively short lifetime (~10 years), reduction of methane emissions presents a near-term climate mitigation lever. The Global Methane Pledge of 2021, signed by almost 160 countries, commits to methane emission reductions of 30% below 2020 levels globally by 2030. However, annual global methane concentrations have
55 continued to rise monotonically since 2007, with global background concentrations exceeding 1940 ppb as of September 2025 (NOAA GML, 2025). The relative contributions of that growth from source emission sectors and changes in the atmospheric sink remain uncertain (e.g., Turner et al., 2017; Rigby et al., 2017; Turner et al., 2019; Ciais et al., 2026).

Methane emissions manifest as either discrete point sources (e.g., unlit gas flares, pipeline leaks), more diffusive area sources (e.g., wetlands, rice cultivation), or both (e.g., landfills), which complicates their detection and quantification by some
60 observing systems. Local scales (e.g., oil & gas facilities) are where direct anthropogenic methane mitigation generally occurs, often in the form of leak detection and repair (LDAR), increasing process efficiency, or through other remediation efforts. Methane observing satellites play a role in quantifying local to global distributions of emissions across sectors, identifying areas underlying causes prime for mitigation, and supporting emission reduction programs. Here we review satellite capabilities for monitoring point sources and user applications of the data.

Monitoring of methane sources through atmospheric observation (satellite or otherwise) serves two major use cases:
65 (1) aiding accounting of aggregate emissions across sites, regions, sectors, etc., generally over a fixed time period and (2) direct monitoring of specific infrastructure types and facilities to attribute and root cause individual emission events (e.g., LDAR). Systems focused on Type (1) monitoring support the creation of bottom-up inventories and emissions reporting programs. Inventories are developed at national and subnational levels to track methane emissions over time, give an estimate
70 of total emissions across all source and sector categories for jurisdictions, provide baselines for climate commitments, and for compliance with international agreements, including for emission reporting to the United Nations Framework Convention on Climate Change (UNFCCC, 2026). Bottom-up inventories quantify emissions through accounting and estimation of activity across sector categories, and applying specific emission factors to these activity datasets. Traditionally, atmospheric measurements may enter into these inventories through quantification of emission factors. For example, field surveys across



75 multiple infrastructure and sector categories underpin emission factors used within the US EPA Greenhouse Gas Inventory (US EPA, 2024).

Private companies, particularly in the oil & gas sector, also engage with Type (1) monitoring for voluntary or regulatory reporting frameworks. For example, the Oil & Gas Partnership (OGMP) 2.0 is the United Nations Environment Programme (UNEP) voluntary program for oil & gas operators to reduce methane emissions through a measurement-based reporting framework. Companies can achieve an OGMP Level 5 reporting status when they report measurement-based emission estimates at a source- and facility-level for all material assets, disclosing the methodology used to prove sufficient justification of measurement protocols, selected technologies, and applicability to the different facility types within an operator's portfolio (UNEP, 2026). Companies can also achieve the OGMP "Gold Standard" if they keep that reporting level for 3 and 5 years for operated and non-operated assets, respectively. Another example of industry led emission tracking and reporting initiative is the GTI Veritas protocol (Garg et al., 2023). Related, emission certification programs exist to provide standards for companies to show evidence of producing clean energy. Examples include ERM's Equitable Origin's EO100 Standard and MiQ's Standard for Methane Emission Performance (Garg et al., 2023). These standards use a combination of company reports and measurements to evaluate and differentiate operator performance with respect to methane emissions. Other sectors outside of oil & gas are increasingly motivated to also engage with Type (1) monitoring to support Monitoring, Reporting, and Verification (MRV) requirements for carbon markets, biogas production, or other initiatives (US EPA, 2022)

Systems designed for Type (2) monitoring generally prioritize detection of single plumes and precise attribution of emission sources over precise quantification of emission rates over fixed time periods (e.g., annual averages). For example, in the United States, landfills of a certain size category are required to perform surface emissions monitoring (SEM) surveys, typically once per quarter with handheld methane detectors to find hotspots across various cover types and operations at landfills. Similar monitoring requirements exist in the oil & gas sector in the United States, where specific infrastructure types are required to be monitored by EPA approved technologies at specific cadences for the purpose of finding and fixing leaks (US EPA, 2026). Recently, several Type (2) monitoring efforts have been created or expanded to incorporate large emission releases detected specifically by satellite or other remote sensing platforms. Updates to EPA oil & gas regulations included the addition of a Super-Emitter Program (SEP) where third party large methane detections ("super-emitters" >100 kg/h) detected by EPA-approved technology and reporters could be submitted to EPA and would require a response from the identified operator (US EPA, 2025). The UNEP International Methane Emissions Observatory (IMEO) implemented in 2023 the Methane Alert and Response System (MARS) to notify countries of large methane emission satellite detections to promote direct mitigation (UNEP, 2025). The State of California in 2025 instituted the California Satellite Methane Project (CalSMP) to monitor and notify operators of large emission events detected by satellites (CARB, 2026). Other Type (2) monitoring programs that use a variety of atmospheric observations (satellites, aircraft, drone, ground-based observation) are under development (e.g., CCAC, 2026).

Satellites provide an opportunity to support both Type (1) and Type (2) monitoring with global coverage. Satellite instruments that measure solar backscattered radiation in key methane absorbing wavelengths, typically the shortwave infrared



(SWIR), use that signal to infer column concentrations of methane, which may then be used to estimate emissions at some spatial scale and level of precision. Previous reviews have described in detail the capabilities of satellites for methane emission quantification (Jacob et al., 2016; Jacob et al., 2022). For this review, we distinguish between two overlapping observing capabilities: (1) area-flux mapping and (2) point-source imaging. The distinction reflects an instrument’s primary coverage, retrieval precision, spatial resolution, and intended application. For clarity, we generally assign instruments to their primary observing mode throughout this review, while recognizing that individual satellite systems may serve dual purpose, with differing levels of capability. Area flux mapping satellite instruments (GOSAT series, Sentinel-5p TROPOMI, MethaneSAT, CO2M constellation) provide very precise measurements of column methane concentration ($<15\text{--}30$ ppb) by measuring radiance over large spatial areas (0.3–25 km). Through the use of an atmospheric transport model, these area-flux mapping measurements are used to estimate total top-down methane emission fluxes. Several studies have performed these analyses using area-flux mapping satellites to compare top-down emission estimates to bottom-up inventories (Worden et al., 2022; Qu et al., 2021; East et al., 2025), noting areas of agreement and disagreement, and serving as an additional estimate of country- and regional- level emissions. In this manner, area-flux mapping satellites are of great utility in servicing Type (1) monitoring efforts.

Point source imagers trade high precision of methane column measurements typical for area-flux mapping instruments for fine spatial resolution (10s of meters). Many point source imaging satellites and aircraft instruments were not originally designed for methane mapping. In fact, high spatial resolution methane detection capability was first discovered using the hyperspectral land imaging instrument AVIRIS over the Coal Oil Point offshore oil & gas platforms in California (Roberts et al., 2010). The high spatial resolving ability of point source imagers allows for attribution of enhanced methane concentrations (i.e., plumes) to specific facilities, operators, and sectors. Individual plume detections can also be quantified for emissions. There are several trade-offs for application of plume imager data from remote sensing systems. First, plume imagers historically only provide “snapshots” in time of emission events, with some caveats to be discussed by this review. Second, plume imaging satellites are only sensitive to a fraction of all emission events, often described as “super-emitters,” which though significant, only represents a subset of total global methane emissions, and tend to mostly manifest in the fossil fuel, waste, and agriculture sectors. The attribution and quantification ability of point source imagers has resulted in incorporation of these datasets into many Type (1) studies and applications (Naus et al., 2023; Jervis et al., 2025; Zhang et al., 2025), as well as Type (2) monitoring programs, including the aforementioned EPA SEP, UNEP’s IMEO MARS, and CalSMP programs.

Jacob et al. (2022) presented an update on launched and announced area-flux and point source imaging satellite missions. Since then, many of those missions have been launched, new missions have been proposed, and other existing satellites have demonstrated success in detecting point sources at some limit of detection. Data products from point source imaging satellites during this time frame have further matured and have become integrated into several science analyses and stakeholder workflows. Across satellites and data providers, many validation experiments have been performed to verify predicted performance against stated performance (Worden et al., 2025). The focus of this review is to update the current and planned capabilities of point source imaging satellite missions, describe the processes and workflows to estimate methane



emissions from these datasets with associated uncertainties, describe existing validation procedures, and synthesize the collection of applied science analyses that have used these datasets.

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2 Point source imaging capability

There exist over 20 satellites that currently or when launched are predicted to have some methane point source observing capability (Table 1). These satellites have distinct instrument design and revisit intervals, which directly influences how much of the total methane point source budget a single instrument can directly observe (Jacob et al., 2022). Understanding these differences is key for anticipating performance against potential applications. Furthermore, given the complexity of public agencies, private companies, and non-governmental organizations (NGOs) that maintain or process information from these instruments, the availability of data varies across missions and data processing levels. This section clarifies key instrument differences, revisit cycles, and data availability across the growing catalog of satellite point source datasets.

2.1 Point source imaging satellite missions

Table 1. Instrument design specification for current CH₄ point source imaging satellites

	Satellite Instrument	Organization	Operational Dates	Imaging approach ^a	Methane Band(s) (nm) ^b	Spectral Sampling (nm)	Spatial Resolution at nadir (m)	Retrieval Precision (%) ^c	References
Multispectral	Landsat (4-9)	USGS	1982-present	Global mapper	2110-2290	180	30	30-90%	Ehret et al. (2022); He et al. (2024)
	Sentinel-2	ESA	2015-present	Global mapper	2011-2361	175	20	21-49%	Varon et al. (2021)
	Sentinel-3	ESA	2016-present	Global mapper	2230-2280	50	500		Pandey et al. (2023)
	VIIRS	NOAA, NASA	2011-present	Global mapper	2230-2280	50	750	4.3-44%	de Jong et al. (2025)
	PACE OCI	NASA	2024-present	Global mapper	2222-2295	73	1200		He et al. (2026)
	GOES ABI	NOAA, NASA	2016-present	Regional mapper	2225-2275	50	2000	9%	Watine-Guiu et al. (2023)
	MTG-FCI	ESA, EUMETSAT	2024-present	Regional mapper	2225-2275	50	500-1000		Zhou et al. (2026)
	Worldview-3	Vantor	2014-present	Tasked-Global	2235-2285	50	3.7	6.7%	Sanchez-Garcia et al. (2022)
	iSIM-90 (GEI-SAT Precursor)	SATLANTIS	2023-present	Tasked-Global	450-1700		13		Ubierna et al. (2022); Montesino-SanMartin et al. (2025)
	iSIM-170 (GEI-SAT Constellation)	SATLANTIS	Planned	Tasked-Global	up to 2300		9		Ubierna et al. (2022)
Wide-band hyperspectral	Gaofen-5 AHSI	CNSA	2018-present	Tasked-Global	2000-2500	10	30	1.7-2.5%	Irakulis-Loitxate et al. (2021); Li al. (2026)



	Hyperion EO1	NASA	2000-2017	Tasked-Global	2000-2500	10	30		Thompson et al. (2016)
	ZY1 AHSI	CNSA	2019-present	Tasked-Global	2000-2500	20	30	3.8%	Irakulis-Loitxate et al. (2021); Li et al. (2026)
	EMIT	NASA	2022-present	Tasked-Restricted	2000-2500	7.4	60	1.0-2.3%	Thorpe et al. (2023); Li et al. (2026); Ayasse et al. (2024)
	EnMAP	DLR	2022-present	Tasked-Global	2000-2500	8.4	30	1.8%	Roger et al. (2024); Li et al. (2026)
	PRISMA	ASI	2019-present	Tasked-Global	2000-2500	10	30	3.3-10%	Guanter et al. (2021)
	GHOST	Orbital Sidekick	2023-present	Tasked-Global	2000-2500	5	8		Sanders et al. (2024)
	Tanager	Planet and Carbon Mapper	2024-present	Tasked-Global	2000-2500	5	30	0.94-1.9%	Duren et al. (2025)
Narrow-band hyperspectral	GESat	Absolut Sensing	2025-present	Tasked-Global	1625-1660	1	50	~6%	Pignol et al. (2026)
	GHGSat-C	GHGSat, Inc	2021-present	Tasked-Global	1650	0.1	27	1.4-2.9%	Ramier et al. (2025)
	MethaneSAT	MethaneSAT	2024-2025	Tasked-Global	1650	0.08	110 · 400	1.1%	Chan Miller et al. (2026); Williams et al. (2026)
	Sentinel-5p TROPOMI	ESA	2018-present	Global mapper	2305-2385	0.25	5500 x 7000	0.64%	Lorente et al. (2021); Schuit et al. (2023)
	Sentinel-5	ESA, EUMETSAT	2025-present	Global mapper	2305-2385	0.25	7500		Pérez Albiñana et al. (2017)
	GOSAT-GW	JAXA, NIES, MOE	2025-present	Global mapper	1650	<0.2	10000 (Wide); 1000 x 3000 (Focus)	1.6%	Tanimoto et al. (2025)
	AIRMO	AIRMO	Planned	Tasked-Global			50		EnduroSat/AIRMO (2026)
	NarSha	Nara Space	Planned	Tasked-Global	1625-1670	<1	30		Koo et al. (2025)
	SWIRSAT Imager	LatConnect 60	Planned	Tasked-Global	1600-1750		8.7		LatConnect 60 (2026)
	TANGO-Carbon	ISISpace, ESA	Planned	Tasked-Global	1590-1675	0.15	300		Charuvil Asokan et al. (2025)
	CO2-Image	DLR	Planned	Tasked-Global	1950-2450	1.0-1.3	50		Krutz et al. (2022)

^aImaging approach refers to the mode that the satellite executes imaging. “Global mapper” means all land area is imaged on a routine cadence. “Tasked-Global” means the satellite has access to any global area but only images through direct tasking of areas of interest. “Tasked-restricted” means the satellite does not have global access and only acquires data over areas of interest. “Regional mapper” means a satellite that has full mapping coverage over limited regions.

^bBands used primarily for methane retrievals. Not necessarily all bands and wavelengths an instrument observes.

^cRepresents a diversity of surface and environmental conditions described in the referenced studies. In cases where retrieval precision is reported in units XCH₄ (ppb), we convert to percentage, assuming 1850 ppb background.

Table 1 lists and Figure 1 shows the current status of launched and operational satellite instruments that have demonstrated capability for detection, quantification, and attribution of methane point sources. The satellites listed in Table 1 all measure solar backscattered radiation either at wavelengths that include 1650 nm or 2300 nm (or both) to infer column concentrations of methane. The table is divided into three general instrument groups: “multispectral” instruments that observe a small number of wavelengths bands at coarse spectral resolution (50-180 nm); “wide-band hyperspectral” which observe



over a large wavelength range (e.g., 400-2500 nm) at medium spectral resolution (5-20nm); “narrow-band hyperspectral” which observe over a small wavelength window (e.g., 1590-1675 nm) at fine spectral resolution (0.25-1 nm). Given the existence of many exceptionally large super-emitting sources globally (Lauvaux et al., 2022; Ehret et al., 2022; Jervis et al., 2026), almost any sensor with sensitivity in these two wavelength regions may detect large methane plumes even when methane monitoring was not a primary mission objective. Since a previous review (Jacob et al., 2022), new studies have discovered some methane remote sensing capability of existing or previous satellite missions that were not originally designed for this application. In particular, He et al. (2024) and Irakulis-Loitxate et al. (2022a) analyzed the back catalog of Landsat 4-5 datasets in Turkmenistan, finding methane plumes spanning back to 1986. The coarse spatial resolution (500-750m) imagers VIIRS and Sentinel-3 have demonstrated some capability for plume detection (Pandey et al., 2023; de Jong et al., 2025). The geostationary suite of GOES and MTG weather satellites have also shown some plume detection capability for exceptionally large emission sources (>100 tons/hr), and due to the high temporal revisit (minutes to hours), have shown capability of estimating durations of these events (Watine-Guiu et al., 2023; He et al., 2026; Zhou et al., 2026).

Several new satellites have launched since previous review including the NASA EMIT satellite onboard the International Space Station (Thorpe et al., 2023), the GHOSSt constellation of hyperspectral satellites (Sanders et al., 2024), the MethaneSAT satellite (Guanter et al., 2025a), the first of the Tanager constellation of satellites (Duren et al., 2025), as well as additional launches of GHGSat satellites (Jervis et al., 2025). The EMIT and GHOSSt satellites house multi-purpose hyperspectral instruments sensitive to wavelengths between 400-2500nm similar to other hyperspectral missions like PRISMA, EnMAP, and the AHSI instruments onboard ZY1 and Gaofen-5 satellites. Tanager is also a hyperspectral instrument sensitive to 400-2500nm wavelengths, but whose primary mission is methane and carbon dioxide point source mapping, which influenced its operational design (Duren et al., 2025). MethaneSAT and GHGSat are purpose built for methane monitoring.

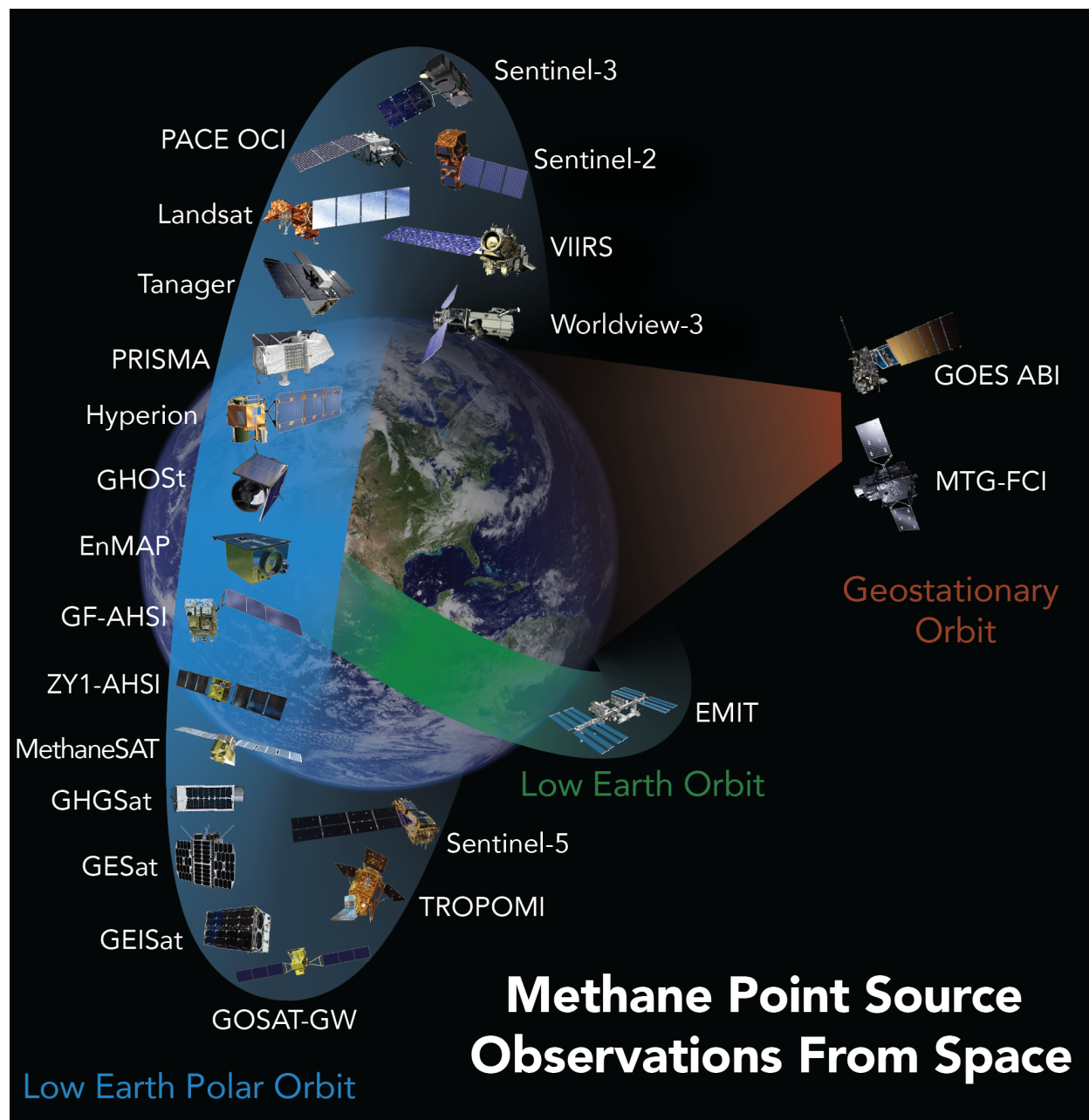


Figure 1: Satellite instruments for observing methane point sources that have launched by the time of this review. Specifications for instruments are provided in Table 1. Icons for satellite images were obtained from the following sources: <https://space.skyrocket.de/> for Landsat, PACE OCI, VIIRS (JPSS-2 satellite), GEISat; Wikimedia Commons for Sentinel-2, Sentinel-3, GOES ABI, MTG-FCI, TROPOMI (Sentinel-5p), Hyperion (EO-1 satellite), EMIT (International Space Station), GF-AHSI (Gaofen-5), ZY1-AHSI; <https://www.eoportal.org/> for WorldView-3, PRISMA, GHOST, GESat, GOSAT-GW; <https://www.planet.com> for Tanager; <https://www.enmap.org> for EnMAP; <https://www.methanesat.org> for MethaneSAT; <https://www.ghgsat.com> for GHGSat; Sentinel-5 from <https://www.esa.int/>.



2.2 Target revisit

Estimating revisit intervals for single satellite instruments is complicated by the observational strategies deployed and the satellite's observational design and execution. Pure nadir-looking pushbroom sensors in sun-synchronous orbits with continuous along track data collection have revisit intervals set by the satellite altitude, the latitude/longitude of an imaging target, the instrument's field of view, and the satellite's downlink capacity. This is the general imaging operation for Sentinel-2/3, Landsat, and VIIRS and results in a predictable revisit interval and image acquisition on the scale of days to weeks. Other sun-synchronous orbiting satellites employ tasking, often using dynamic satellite pointing agility to collect targets of interest. A satellite tasking and scheduling system balances competition between targets, weather forecasts, and user-set priorities in determining which targets to acquire in an overpass. Therefore, although the satellite orbit may revisit a given target on the scale of a week, it may not image that specific target during every available window due to its limited spatial footprints and the prioritization of the full set of targets. For example, Cusworth et al. (2022) tasked a collection of 30 globally distributed coal fired power plants weekly over the course of two years with the PRISMA satellite. Though PRISMA technically has a target revisit rate of 7 days (Loizzo et al., 2018), the study managed a range of only 1-15 observations per power plant over the two year study, with actual data acquisition limited by competing tasking priorities and poor weather forecasts, in particular cloudy conditions which limit retrieval and detection.

Other satellite systems employ non-sun-synchronous orbits, which influence revisit and collection capabilities. The EMIT satellite instrument is integrated on the International Space Station (ISS), which employs a near-circular orbit with an inclination of 51.6 degrees to the Equator. This only allows for image acquisition at latitudes between 52S and 52N. The instrument images in nadir pushbroom mode, but acquires data only over specific targets of interest. Quantifying a revisit rate for specific targets is difficult given frequent changes in operational orbital maneuvers of the ISS. Also, given the non-sun-synchronous orbit for EMIT, data acquisition may occur across any daylight hour. Satellites in geostationary orbits (e.g., GOES-R) image a fixed area on Earth's surface near continuously, providing high temporal resolution (minutes) of detected emissions sources (Watine-Guiu et al., 2023). A constellation of geostationary satellites could provide frequent coverage across much of the low- and mid-latitude global regions.

For all satellite instruments observing in the SWIR, data acquisition is also affected by the presence of clouds or high aerosol loading. In perpetually cloudy regions (e.g., the Amazon), actual data acquisition may be severely limited. Point source imaging satellites with fine spatial resolution (30-300 m), can offset some of this issue by identifying sources within scattered cloud conditions (Duren et al., 2025; Frankenberg et al., 2024). However, other adverse conditions like complex terrain, low sun elevation angles in wintertime, and low albedo surface conditions (water, snow) can severely limit data acquisition and quality. An emerging capability for some satellite systems is to task offshore regions under sun glint conditions. Here the satellite viewing geometry of a ground target is aligned to maximize specular reflection of solar radiation off the ocean surface, meaning that the satellite viewing zenith angle roughly matches the solar zenith angle. When these conditions align, satellites



have demonstrated the ability to detect and quantify large methane plumes from offshore oil & gas infrastructure (Irakulis-
 235 Loitxate et al., 2022b; MacLean et al., 2024; Roger et al., 2024; Duren et al., 2025)

2.3 Data availability

Satellite data pipelines and products follow multiple processing steps and product levels (Figure 2). Depending on mission objectives, business model, or funding available for a data provider, data products may or may not be available to a common user for free, for a fee, and with limited or expansive data redistribution rights at each product level. Table 2 lists data
 240 availability of current and future satellite point source imaging satellites. Generally, “L1” data refers to radiance, “L2” refers to retrieved concentrations or concentration enhancements, “L3” refers to plume detections, and “L4” refers to emission rate quantification. Section 3 describes in more detail the methods associated with each of these product levels of the processing chain. The satellites listed in Table 2 represent a diversity of operators: public agencies, private companies, and non-profits.
 245 For satellite instruments launched by many international space agencies, radiance datasets (i.e., Level 1 products) are made publicly available to any user with generally broad license and redistribution terms (e.g., PRISMA, EnMAP, EMIT, Landsat, Sentinel, GOES). As methane detection and quantification is not the primary mission driver for these satellites, outside of EMIT, the agencies who launch and maintain these satellites do no additional methane processing. However, other entities – academic researchers, for-profit data providers, non-profits – may take the radiance data, apply additional methane plume
 250 detection processing, and then disseminate in the literature, sell to customers, or provide publicly as a service. The data that gets processed and released by these downstream entities may only represent a subset of the full radiance data archive acquired by the satellite system, and delivery of fully processed methane data may occur at various levels of latency, depending on the provider. One exception is EMIT, where the mission operations team also delivers full scene concentration imagery, segmented plume masks, and emission rates to a Distributed Active Archive Center (DAAC).

Privately funded satellites, both by for-profit and non-profit companies, employ a variety of data availability and licensing terms (GHGSat, GHOSat, Tanager, WorldView-3, MethaneSAT). GHGSat provides customers with retrieved methane concentration fields, associated uncertainty estimates, plume masks, and source emission-rate estimates. Radiance data are not provided because of the measurement architecture of GHGSat’s wide-angle Fabry–Pérot (WAF-P) instrument (Jervis et al 2021). Selected GHGSat data are also available to academic researchers through NASA’s Commercial Satellite
 260 Data Acquisition Program and ESA’s Third Party Missions program. Orbital Sidekick (GHOSat), Planet (Tanager), Vantor (Worldview-3), offer radiance data to customers as well as a methane plume product. Carbon Mapper has a data agreement with Planet to process all radiance data from Tanager for methane plume detection and quantification and release all methane data (retrievals, detections, non-detection, quantification) publicly on its portal 30 days post observation. Worldview-3 radiance data can also be acquired via the ESA Third Party Missions program. MethaneSAT provides radiance data and
 265 retrieved concentrations and methane plume detections on its portal or via Google Earth Engine.

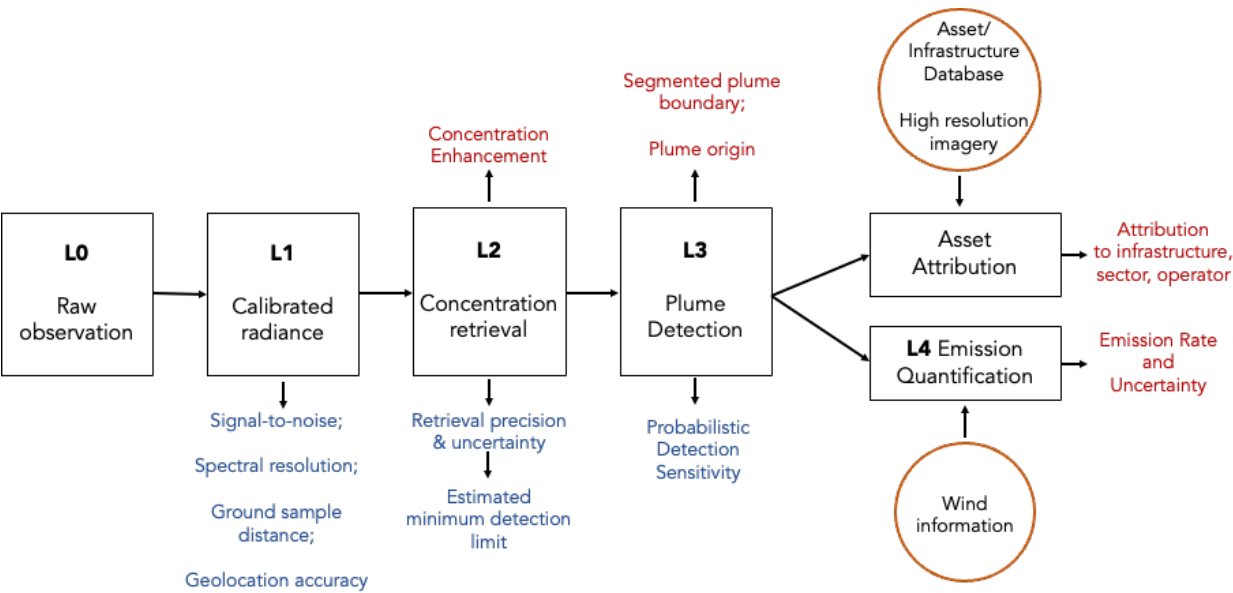


Figure 2. General methane plume processing pipeline for point source imaging sensors. The figure shows commonly used data naming conventions, L1 to L4, for product levels. Blue text represents metrics derived from components of the processing pipeline, red text represents product outputs from each step, and orange circles represent ancillary datasets commonly used for the associated processing step. Figure is adapted from Worden et al., (2025).

Table 2. Data availability at several data product levels across satellite missions

Satellite Instrument ^a	Organization	L1 data availability	L2 data availability	L3 data availability	L4 data availability
Landsat	USGS	Made available by mission; full archive	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution
Sentinel-2	ESA	freely accessible and redistributable			
Sentinel-3	ESA				
VIIRS	NOAA/NASA				
PACE OCI	NASA				
GOES ABI	NOAA/NASA				
MTG-FCI	ESA				
EnMAP	DLR				
PRISMA	ASI				
Hyperion EO1	NASA				



Gaofen-5 AHI ZY1 AHSI	CNSA CNSA	Made available by mission; part of the archive freely available under request. Redistribution under request.	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution
EMIT	NASA	Made available by mission; full archive freely accessible and redistributable	Made available by mission; full archive freely accessible and redistributable	Made available by mission; full archive freely accessible and redistributable	Partial archive available via 3 rd parties; variable pricing, latency, and redistribution
GHOST Worldview-3 GESAT	OSK Vantor Absolut Sensing	Available for purchase	Available for purchase by mission or 3 rd party	Available for purchase by mission or 3 rd party	Available for purchase by mission or 3 rd party
GHGSat	GHGSat, Inc	Not applicable	Available for purchase and/or available through CSDA, ESA TPM	Available for purchase and/or available through CSDA, ESA TPM	Available for purchase and/or available through CSDA, ESA TPM
Tanager	Planet and Carbon Mapper	Available for purchase	Available for noncommercial redistribution 30 days post observation by Carbon Mapper	Available for noncommercial redistribution 30 days post observation by Carbon Mapper	Available for noncommercial redistribution 30 days post observation by Carbon Mapper
MethaneSAT	MethaneSAT	Available by establishing an account and paying cloud download cost	Available by establishing an account and paying cloud download cost	Available by establishing an account and paying cloud download cost	Full archive freely accessible and redistributable
TROPOMI	ESA	Made available by mission; full archive freely accessible and redistributable	Made available by mission; full archive freely accessible and redistributable	Archive available in part of fully via 3 rd parties; variable pricing, latency, and redistribution	Archive available in part or fully via 3 rd parties; variable pricing, latency, and redistribution

^aTable includes satellites that launched at time of this review.



3 Methane Point Source Processing Pipeline

In this section we describe a general methane plume processing workflow employed in part or in whole by many data providers and researchers (Figure 2). Some proposed processing workflows circumvent one or more of these steps, for example
 285 Kumar et al. (2023) proposed a machine learning algorithm to estimate emission rates directly from radiance. For clarity, we treat each processing step in Figure 2 independently. We also describe a set of commonly accepted calibration or validation procedures that may exist at each processing level, or in some cases, highlight key existing gaps at these levels.

3.1 Calibrated Radiance

290 The methane plume processing pipeline starts at the raw level of observation: a digital number (DN) that corresponds to an uncalibrated measure of light intensity per pixel per wavelength that is measured by the instrument. The DN is then calibrated to a measure of electromagnetic radiation, or radiance (e.g., units $[W\ cm^{-2}\ sr^{-1}\ nm^{-1}]$), that represents the quantity of radiation that was reflected, scattered, or emitted somewhere along the path from the sun to the instrument. This conversion from DN to radiance is generally determined during pre-launch on-ground instrument calibration in laboratory settings using
 295 known and traceable standards (Thompson et al., 2024). Additional calibration is also often performed vicariously in the field at calibration sites where the surface spectroscopy is well known, and where ancillary ground-instruments may be deployed for comparison and validation (Carmona et al., 2023). In addition to estimating the conversion of DN to radiance, calibration procedures are also performed to correct biases resulting from electronic and other optical effects (Eckert et al., 2024). A separate step, geometric calibration, is also performed in lab and vicariously to ensure geospatial accuracy for each observed
 300 pixel (Schneider et al., 2012)

For the methane plume application in particular, a few key instrument design parameters are verified and characterized through the calibration step. These parameters have significant downstream effects on how well an observation can lead to a plume detection. One parameter is spectral sampling, which estimates the central wavelength and width of the wavelength band where the instrument measures radiance. This parameter is originally set by the design of the instrument, but may shift
 305 slightly as the instrument is built and aligned. Calibration recovers an improved estimate of the actual wavelength positions. Another related but separate parameter is spectral response, often summarized by the full-width at half-maximum (FWHM). This parameter represents the sensitivity of a measurement at a central wavelength to incident radiation at that and at adjacent wavelengths. A third key parameter is the signal-to-noise ratio (SNR), which results from the optical throughput of the instrument, electronics (read noise and dark current), photon shot noise, stray light, integration time, and the detector's
 310 sensitivity. Geometric calibration also characterizes spatial information for point source applications: geolocation accuracy, interband co-registration, and spatial response functions influence the contrast/blurring of a plume image, and influence the accuracy of an inferred source origin.



315

3.2 Retrievals

Methane column concentrations or column concentration enhancements are estimated, or “retrieved,” from calibrated radiance. Methane absorbs nearly uniformly in the troposphere at SWIR wavelengths (Balasus et al., 2023). This functionally means that a SWIR satellite instrument is sensitive to excess methane concentrations in the atmosphere regardless of where that concentration is located vertically. However, it also means that SWIR instruments cannot provide a reliable estimate of vertical structure of any observed plumes. Column concentrations are summarized generally using a variety of units: column-averaged dry-air mixing ratio (XCH_4 , units ppb), pathlength column enhancement (ppm-m), and column density (units moles m^{-2} , molecules m^{-2} , $kg\ m^{-2}$, etc). Conversion among units requires general assumptions about the density of air in the column, whether the unit is a total column concentration or column enhancement, and whether the conversion is applied to a vertical column (ground to sensor) or along the full light path length (sun to sensor).

Retrievals take several forms, and are often informed by the instrument’s design, a candidate retrieval’s performance for plume detection, and computational cost. One class of retrieval, full-physics algorithms, estimate column concentrations by employing a radiative transfer model (RTM) and surface reflectivity parameterization. These retrievals are often applied to area-flux mapping satellites (Lorente et al., 2021), but can also be applied to point source imagers. The algorithm uses an initial, or prior, estimate of parameters (e.g., methane, water vapor, albedo) to serve as input to a RTM that simulates radiance. Those initial estimates are then adjusted until the state minimizes a cost function that balances radiance residuals against departures from the prior, with the relative weighting determined by the measurement and prior error covariance matrices. Often this optimal state is derived through a maximum a posteriori (MAP) Bayesian formulation (Rodgers, 2000), which also produces error characterization and information content of retrieved values. Full-physics retrievals estimate total column concentrations which include contributions from background methane and enhancements from discrete plume sources. These algorithms are typically computationally slow, which limits their operational deployment for wide-band, high spatial resolution imaging spectrometers (Ayasse et al., 2023), though RTM emulation through machine learning may provide a pathway for greater computational efficiency (Bréon et al., 2022; Lamminpää et al., 2025). One common retrieval algorithm for plume imagers is the Iterative Maximum A Posteriori – Differential Optical Absorption Spectroscopy (IMAP-DOAS) algorithm, whose radiative transfer model assumes that a radiance spectrum can be decomposed and modeled into a high frequency term (mostly representing absorption from gases), and a low frequency term (mostly representing surface reflectance) (Frankenberg et al., 2005; Thorpe et al., 2017). Narrow-band spectrometers that observe near 1650 nm may also employ a light-path CO_2 proxy methane retrieval, which reduces potential retrieval bias due to light path interference (e.g., aerosol scattering) through comparison of CO_2/CH_4 retrievals (Jacob et al., 2016; Chan Miller et al., 2026). A N_2O light path proxy has been proposed for methane retrievals for theoretical narrow-band hyperspectral instruments that utilize the 2000-2400 nm methane absorption feature given the close spectral proximity of N_2O and CH_4 absorption in that range (Frankenberg et al., 2025)

Matched filters represent different but commonly used retrieval algorithms often applied to wide-band hyperspectral instruments (Thorpe et al., 2013; Thompson et al., 2016; Pei et al., 2023; Feng et al., 2024; Foote et al., 2020; Roger et al.,



2024). Hyperspectral instruments measure radiance across a detector array, and each element in the detector array corresponds to a pixel on the ground that is measured. As the instrument measures along an orbital track, each element collects many pixel spectra while the instrument is imaging. This collection of along-track pixel spectra per detector element is often called a column, though the usage of “column” in this context is distinct from vertical column concentration that is retrieved. The classical linearized matched filter runs a retrieval for each pixel using statistics derived from all pixels in the column:

$$\hat{\alpha} = \frac{(x - \mu)^T \Sigma^{-1} t}{t^T \Sigma^{-1} t} \quad (1)$$

Where $\hat{\alpha}$ is the retrieved value of vertical column enhancement for a given pixel, x is the radiance spectrum of a given pixel generally restricted to methane-absorbing wavelengths, μ is the average radiance spectrum for all pixels per column (often called the reference spectrum), Σ is the covariance for all pixels per column, and t is a quantity called the unit or target absorption spectrum (e.g., units $[\text{W cm}^{-2} \text{ sr}^{-1} \text{ nm}^{-1} \text{ ppm-m}^{-1}]$). The vector t is derived from offline radiative transfer simulations and effectively maps a perturbation in radiance to a concentration enhancement value (Foote et al., 2020).

There are several advantages of deploying column-wise matched filter retrievals. First, they account for nonlinear detector responses, variability in pixel-to-pixel gain, and inconsistent instrument line shapes across detector array elements, which can manifest as sources of systematic radiance bias or along-track striping patterns in full-physics retrievals. Using a column mean and covariance as part of the retrieval generally normalizes out this type of systematic retrieval error. Second, matched filters are significantly more computationally efficient than full-physics retrievals. Fast full-physics retrievals may take several seconds to run for a single spatial pixel depending on the retrieval complexity, while matched filters generally take minutes to run for all pixels in an image. Third, as a signal boosting algorithm (Equation 1), matched filters tend to exhibit more contrast between foreground and background concentrations than full physics retrievals, potentially enabling detection of smaller plumes (Guanter et al., 2025b). This fact is attributed to the localized computation of μ and Σ – i.e., small background methane gradients are removed through the averaging of spectra.

Matched filters also have limitations. Because the retrieved values for each pixel rely on column statistics, problematic spectra within the column (specular reflectors, clouds, water) can bias the retrieval, sometimes severely. Matched filters also do not provide full error characterization like a MAP full-physics retrieval, though some work has been proposed to better estimate pixel-level uncertainties in matched filter retrievals as they relate to deviation from the reference spectrum (Fahlen et al., 2024). To account for some of these retrieval issues, several variants of the matched filter retrieval have been proposed: lognormal (Pei et al., 2023), albedo corrected (Foote et al., 2020), multi-modal (Cusworth et al., 2021a), surface-controlled (Elder et al., 2021), sparsity constrained (Foote et al., 2020), bias-corrected (Fahlen et al., 2024), Kalman filter adjusted (Feng et al., 2024), and the Differential Matched Filter (Bue et al., 2026). These variants either adapt Equation 1 or adapt the calculation of μ or Σ through selective removal of problematic spectra, or apply additional bias correction for factors like surface reflectivity.



380 Another common retrieval approach, specifically used with multiband imagers is to apply classical band-differencing among bands with known methane absorption and without methane absorption (Varon et al. 2021, Ehret et al., 2022). One example of this approach is the multi-band single-pass (MBSP) algorithm (Varon et al., 2021), which takes the following form:

$$\Delta R = \frac{cR_a - R_n}{R_n} \quad (2)$$

Where ΔR is the normalized band difference (in units of radiance) calculated from the radiance in a methane absorbing band (385 R_a) and radiance from a non-absorbing band (R_n). The coefficient c is fit to correct for scene-wide signal differences between each of those bands. A column enhancement concentration can be estimated from ΔR through an RTM, specifically the retrieved methane concentration is the value that reproduces ΔR in a model simulation. Several variants of this band differencing approach exist – for example the multi-band multi-pass (MBMP) aims to reduce retrieval artifacts by differencing MBSP retrievals over the same area from two different satellite overpasses (Varon et al., 2021). While the MBMP approach (390 typically provides less noisy retrievals in areas with low temporal variability, such as desert regions with little activity on the surface, the MBSP retrieval is often preferable for surfaces that vary significantly between observations, such as offshore areas due to wave motion, or areas with high vegetation or crops (Gorroño et al., 2023; Irakulis-Loitxate et al, 2022b). Other approaches calculate a systematic artifact field by combining many previous image acquisitions for background quantification (e.g., Ehret et al., 2022).

395 Concentration retrievals for point source imaging satellites are currently extremely difficult to validate. This differs from area-flux mapping satellites: networks of surface based, high precision spectrometers have been deployed globally for validation of area-flux mapper retrievals (Sha et al., 2021). Unlike point source imagers, area-flux mappers require high precision in total column concentrations as downstream flux products derived from these satellite measurements require precise knowledge of very small regionally varying background gradients in order to quantify the full emission field rather than a (400 single source. Point source imagers do not require accurate knowledge of total column concentrations, but instead require that the concentration gradient within an individual plume is not biased. This presents a challenge for validation, as to date there has not been a successful prototype of plume-level concentration retrieval validation experiment. Most teams infer bias through application to synthetic datasets (Pei et al. 2023, Fahlen et al., 2024), through visual inspection of retrieval bias, or by inference through other validation procedures that occur further downstream in the processing pipeline.

405 A key parameter estimated at this processing step is retrieval noise. Retrieval noise is a consequence of instrument design and calibration parameters (SNR, FWHM, spectral sampling) and the choice of applied retrieval. Retrieval noise provides a general estimate of a minimum level of plume detectability: the minimum detection limit for a methane plume is a function of wind speed, spatial resolution, and retrieval noise (Jacob et al., 2016; Bruno et al., 2024). Many workflows quantify retrieval noise as a standard deviation of background concentrations in the vicinity of a methane plume (e.g., Guanter et al., (410 2021; Bruno et al., 2024; He et al., 2024; Duren et al., 2025; Ramier et al., 2025). This is different from many area-flux mapping satellites that estimate retrieval error through comparison to surface based measurements. Data providers of plume-



imagers generally prefer background standard deviation as a metric as it more closely aligns with plume detection: plumes are only detected by an analyst if they exhibit significant concentration above background concentration distributions.

3.3 Plume Detection

Plume detection is often performed by a human through visual inspection of concentration imagery, though may be aided through deployment of supervised machine learning algorithms or thresholding algorithms. To detect a plume of methane gas from concentration imagery requires a level of expert knowledge and judgement. Analysts must discern plume-like structures from potential retrieval artifacts or clustered noise features (Figure 3). This discernment is complicated by a variety of factors. First, plume morphology follows the wind direction and eddy-scale atmospheric transport which can be highly turbulent and result in a large diversity of characteristic plume shapes. Second, plume morphology depends on emission source characteristics. Third, the colloquial use of “plume” may refer to multiple atmospheric manifestations of a gas (NIST, 2024). For example, any cluster of truly enhanced methane concentrations visually discernible in retrieval imagery may be classified as a plume. However, some clusters of enhanced methane may actually be a downwind manifestation of a short-lived discrete “puff” of gas that is no longer visibly attached to its source. For some use-cases, it may be worthwhile to detect and track this downwind concentration enhancement. The data provider, tuned to their use-case, uses expert judgement when classifying plumes.

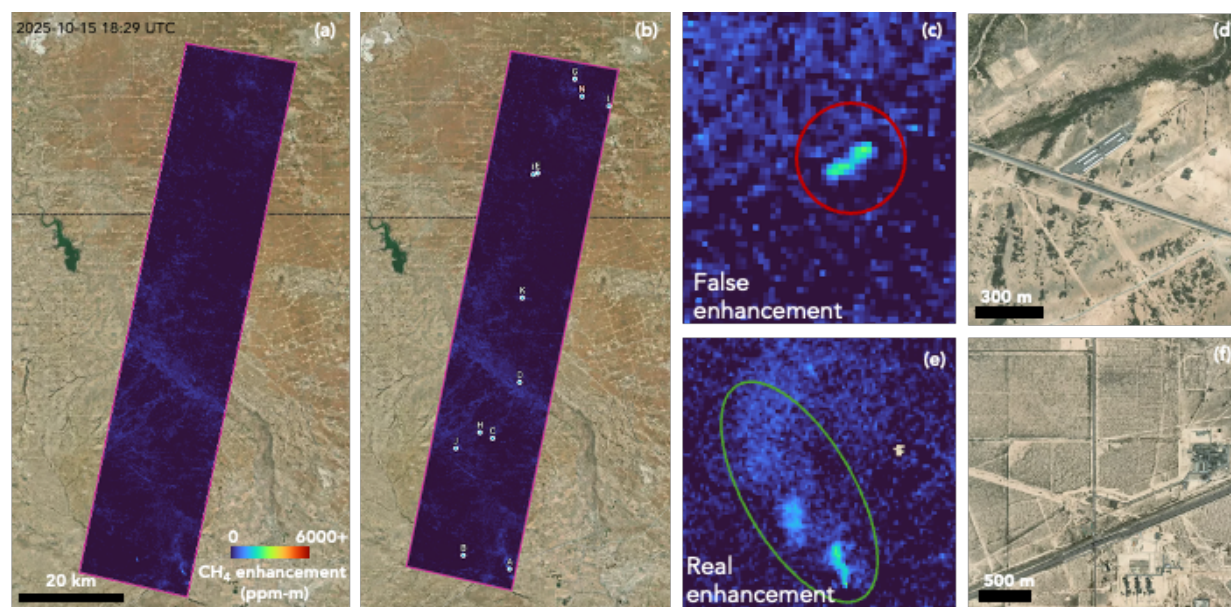


Figure 3. Visualization of plume detection process. Panel (a) represents a full scene concentration enhancement Tanager image (L2 product level) derived through a matched filter algorithm (Section 3.2). Panel (b) represents locations where several human analysts identified candidate plume detections. Panels (c) shows a false enhancement caused by confusing surface features shown in high resolution visible imagery in panel (d). Panel (e) shows a real enhancement attributed to infrastructure at a gas processing plant, visualized in panel (f). Visible basemaps in Panels



435 **a, b, d, f are provided from Mapbox, ©Mapbox, ©OpenStreetMap. All data for this figure is accessible via Carbon Mapper's data platform (data.carbonmapper.org).**

Methane plumes detected by point source imagers generally represent a small area relative to the total area that may be imaged in a scene. For example, even in basins where super-emitters make up a significant fraction of total emissions, the spatial frequency of these sources may be low. For example, in the Permian Basin, an aircraft survey found roughly 2 super-emitters ($>100 \text{ kg h}^{-1}$) per 100 km^2 surveyed (Cusworth et al., 2026). That frequency will vary basin to basin and sector by
 440 sector, but the result is that most satellite imagery does not contain large plumes. Many studies have shown potential for reducing latency in the plume detection process by employing machine learning algorithms based on a diversity of training datasets. In localized environments, models applied to diverse instruments have shown some promise for plume detection (Bruno et al., 2024; Růžicka et al., 2023; Vaughan et al., 2024; Jongaramrungruang et al., 2022; Bue et al., 2026; Mateo-Garcia
 445 et al., 2025). However, these models rarely generalize well globally because observing conditions, emission sectors, and plume morphologies are extremely diverse and training samples are still relatively small across and among all instruments listed in Table 1 (i.e., 10s of thousands of plume examples). To augment training datasets, some studies have leveraged synthetic plume datasets, generated via Gaussian plume models, Large eddy simulations (LES), or through other means. These have been shown to improve in some cases train/test performance, but have also been shown to not generalize well globally due to lack
 450 of diversity in plume shapes (Bue et al., 2026), and have been shown to result in significant false positives when applied to real-world controlled releases without sufficient quality screening (Reuland et al., 2026; Batchu et al., 2026). Still, the quantity of imagery collected from plume imagers is surely set to increase in the coming decade, increasing training examples, and likely improving the performance of automated detection systems.

Validation of plume detection is possible but in practice difficult to perform with high certainty. In addition to
 455 validating emission rates, single-blind controlled release studies evaluate the ability for a detection process to correctly identify plumes given ground-truth emission rates (Sherwin et al., 2023; Sherwin et al., 2024a; Reuland et al., 2026). The results of these experiments have been used to probabilistically estimate detection limits for instrument, retrieval, detection algorithms (Conrad et al., 2023, Ramier et al., 2025). Other validation experiments leverage co-observation of potential emission sources in near-simultaneity, using a more sensitive instrument (e.g., an aircraft) to validate detection performance of a less sensitive
 460 instrument (e.g., satellite) (Ayasse et al., 2024, Duren et al., 2025). In both these scenarios, the data provider knows the potential sources of emissions, which may produce overly optimistic detection performance compared to actual field performance (Jervis et al., 2026; Worden et al., 2025; Cusworth et al., 2026). “Blind-blind” or source-location-blind experiments where the data provider is unaware of release locations could potentially reduce this bias, although this is complicated to execute for tasked satellites where a priori knowledge of priority tasking areas are required to schedule image
 465 acquisition. Controlled release experiments that simulate more challenging observing environments and more typical operational conditions have been demonstrated at oil&gas and landfill facilities (e.g., McManemin et al., 2026; Hossain et al., 2026). Further expansion of this class of experiment is recommended to continue to build a diversity of validation datasets.

Another potential validation mechanism is to compare plume detections to operator information (supervisory control and data acquisition (SCADA) systems, operator maintenance logs, etc) (Zimmerle et al., 2024). However, such analysis would need to balance uncertainties in both atmospheric observations and operator reporting to assess detection capability.

3.4 Attribution

Related but distinct from plume detection is the process of attribution of a plume to an emission source. Broadly, attribution is the process that relates the detected plume to some underlying feature or source. This process is generally performed through a level of manual inspection of a plume's concentration gradient relative to surface features visible using other geospatial datasets (high resolution visible imagery, GIS databases, etc.) (Cusworth et al., 2026; Warren et al., 2025), although some research has explored automating this process through machine learning or decision tree algorithms (Wilson et al., 2026; Rafiq et al., 2020). Both manual and automated processes require a level of expert knowledge to perform this inference, and can be complicated by several factors. Attribution of a plume to a source may be performed by associating a plume to a point (e.g., GPS coordinate), a specific piece of equipment (e.g., unlit flare), a site/facility (e.g., landfill), an operator, or a general sector (e.g., coal) (e.g., Irakulis-Loitxate et al., 2022a). The accuracy of attribution can be limited by the quality of datasets available to the entity (or automation) performing the attribution. Visual imagery and GIS databases can become outdated quickly as new facilities are constructed or removed. Geospatial datasets available in the public domain are limited in comparison to proprietary datasets owned by the industry or operator of the facilities being observed, such that attribution results may differ based on the resources and expertise available to the performing entity. Similarly, no consensus standard exists for "site," "facility," or "source," and may be defined by specific user-needs or use-cases pertinent to that data provider. Table 3 contains facility, source, and site definitions used in some reporting programs, but this may not necessarily be the common definition applied by all data providers for all emission sectors for the sake of attribution. Furthermore, a facility may have several individual sources of emission, but a data provider may perform plume attribution at a facility or sub-facility scale, or not at all, depending on their data processing system.

Table 3. Definitions of Facility, Site, and Source used in common reporting frameworks

Term	Program	Definition	Reference
Facility	EPA GHGRP	Any physical property, plant, building, structure, source, or stationary equipment located on one or more contiguous or adjacent properties in actual physical contact or separated solely by a public roadway or other public right-of-way and under common ownership or common control, that emits or may emit any greenhouse gas.	Subpart A, General Provisions, found at 40 CFR 98.6
Site/Facility	UNEP OGMP 2.0	All sources within a physical unit (e.g., production battery, compressor station, processing plant,	UNEP, 2020



		transmission station, pipeline segment, liquefaction plant, etc.). Site-level measurement (i.e. Level 5) reporting would consider sites as the appropriate level to reasonably and transparently reconcile Level 4 and Level 5, but not to introduce needless complexity or cost in reporting below a venture level (e.g. combined wells and gathering systems comprising a production asset, not each individual well pad or pipeline).	
Source	UNEP OGMP 2.0	A component within a process or equipment that releases methane to the atmosphere either intentionally or unintentionally, intermittently or persistently.	UNEP, 2020

495 A second complicating factor for attribution is the fundamental spatial resolving ability of the instrument against the spatial manifestation of a plume in the atmosphere. The point source imagers in Table 1 observe with spatial resolution that varies from 3m to 7000m. Spatial resolution is related to the scale which one can attribute to a single point, facility, etc. The bottom row of Figure 4 shows an example of a plume imaged consecutively within the same hour by the AVIRIS-3 airborne imaging spectrometer, Tanager, and EMIT. The visual representation of the plume, and thus the level of confidence in attribution, changes with spatial resolution and retrieval precision variations among instruments.

500 Spatial resolution is not the only driver of attribution uncertainty, as the manifestation of a gas in the atmosphere is a function of transport conditions at the time of observation and the nature of the emission source. For example, under turbulent or very low wind conditions, a plume may appear amorphous or globular, whereas under steady turbulent flow conditions, a plume may appear more conical or gaussian (top row of Figure 4). If attribution is performed at the infrastructure or site-level, confidence in the attribution process will depend on the density of candidate infrastructure in the near vicinity of the plume, 505 the visual shape and concentration distribution of the plume (including any potential continuity “breaks” due to changes in wind direction, intermittency of sources, etc.), and the spatial resolution of the instrument.

Validation for plume attribution follows a similar approach as plume detection (controlled releases, instrument intercomparison, comparison with operational data), though may vary based on the level of attribution performed by the provider. Little has been published to assess quantitative uncertainties in attribution (Eldering et al., 2026). One avenue to 510 reduce uncertainties in attribution, at least for persistent sources, is through repeat observation of the same area. Multiple plume observations of varying morphology and wind conditions aids the expert reviewer (Figure 4). More work is needed to more robustly quantify uncertainties in attribution. However, even with existing levels of unquantified uncertainty, attribution is a critical step in the processing pipeline as it unlocks a number of key stakeholder applications and scientific analyses. For example, the EPA SEP program requires attribution to operator and GPS source origin coordinate for third party reporters. 515 Leak detection programs like IMEO MARS and the CalSMP send notification based on attributed datasets. Studies to



understand root causes of super-emitter distributions use attribution to infrastructure and operator to differentiate performance across basins (Hmiel et al., 2023).

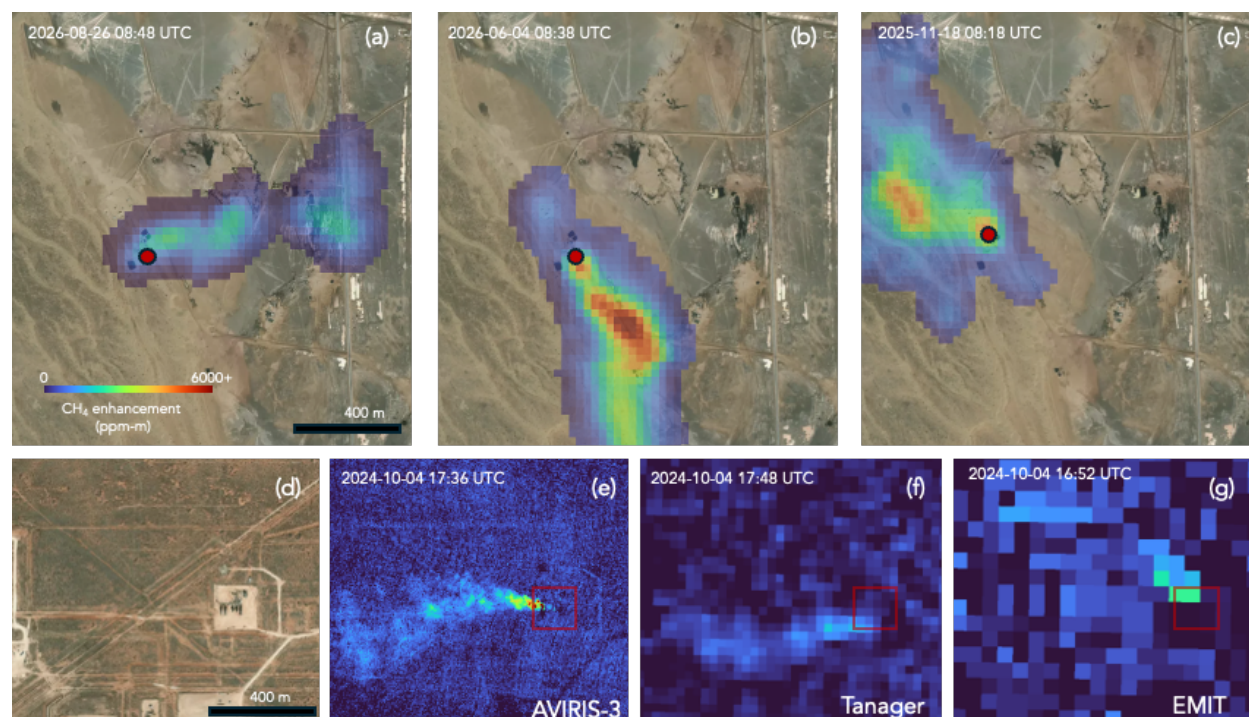


Figure 4. Visualization of factors that influence the attribution process. Panels (a)-(c) show segmented plumes detected by Tanager at a site of persistent emission (38.266, 54.025) over multiple days, demonstrating how changing atmospheric conditions may influence the attribution of each plume to an origin. Red dots represent analyst-attributed origins. Panels (d)-(g) show a different site (32.227, -103.744) imaged by the AVIRIS-3 airborne imaging spectrometer, Tanager, and EMIT within 1 hour of one another, demonstrating how spatial resolution of an instrument may influence the attribution process. Panels (e)-(g) show matched filter concentration enhancements, where the red box in each panel represents the boundary of the site where plumes were detected. Visible basemaps in Panels (a)-(d) are provided from Mapbox, ©Mapbox, ©OpenStreetMap. All data for this figure is accessible via Carbon Mapper's data platform (data.carbonmapper.org).

3.5 Segmentation

Emission rate quantification for a source (Section 3.6) usually relies on a critical pre-processing step, called plume segmentation, also referred to as plume masking. This is the process of determining and delineating plume concentration from background concentrations. For idealized conditions, assuming Gaussian noise distributions of background concentration fields, the application of smoothing filters and thresholds may adequately separate enhanced and connected concentrations from the background (Varon et al., 2018; Zhang et al., 2026). However, this process is complicated by a variety of factors in more general real-world settings. First, plume morphology and concentration intensity varies across emission sources: e.g.,



landfill plumes tend to manifest as more distributed and dispersed sources than oil & gas sources. Second, structured noise or artifacts in concentration imagery complicates segmentation as false enhancements may be incorrectly associated with a plume (e.g., Figure 3). Related, changes in albedo may affect the apparent morphology of a plume, e.g., a plume that starts on land but travels over a dark surface, like a water body, may appear to “drop out.” Third, plumes may exhibit separation depending on atmospheric transport conditions, topography, and intermittency of the emission source.

Factors that complicate the visual manifestation of plume morphologies also challenge systematic segmentation algorithms. Data providers, especially working to provide high volumes of plume datasets, must apply algorithms that attempt to accommodate these factors across the diversity of plumes. Several approaches have been implemented across data providers: Gaussian + median filtering (Varon et al., 2018); watershed algorithms (Zhang et al., 2025); dynamic noise and clustering (Duren et al., 2025), semantic segmentation via deep learning (e.g., Bruno et al., 2024; He et al., 2024); hand-labeling (EMIT Plume viewer: <https://earth.gov/ghgcenter/data-tools/view/emit-plume-viewer>; IMEO MARS portal, <https://methanedata.unep.org/>; MethaneBench: <https://bench4.uw.atmos.edu>). Figure 5 shows an example of a variety of plume segmentation algorithms applied to the same EMIT observed plume image (Eldering, 2026). Based on the assumptions of the algorithm or approach, a wide range of segmentation masks are estimated. As downstream quantification algorithms depend heavily on key parameters from the segmentation masks (plume length, spatial area to integrate mass enhancement), variability in segmentation approach can have significant impact on quantification.

Segmentation masks are difficult if not impossible to validate directly. A plume extent observed by an imager is smaller than the true spatial extent of a plume; what is visible in concentration imagery is ultimately a function of methane retrieval precision and environmental conditions. Given that segmentation masks generally serve as an input for emission rate quantification (Section 3.6), general best practices for segmentation prioritize consistency in algorithm application. Uncertainties for segmentation algorithms are often quantified by varying the hyper-parameters that drive the segmentation algorithm or using ensembles of segmentation algorithms (Guanter et al., 2021; He et al., 2024). Segmentation approaches that apply hand-labeled or drawn information do not typically report uncertainties, which may result in an underestimate in uncertainty on emission rate quantification.

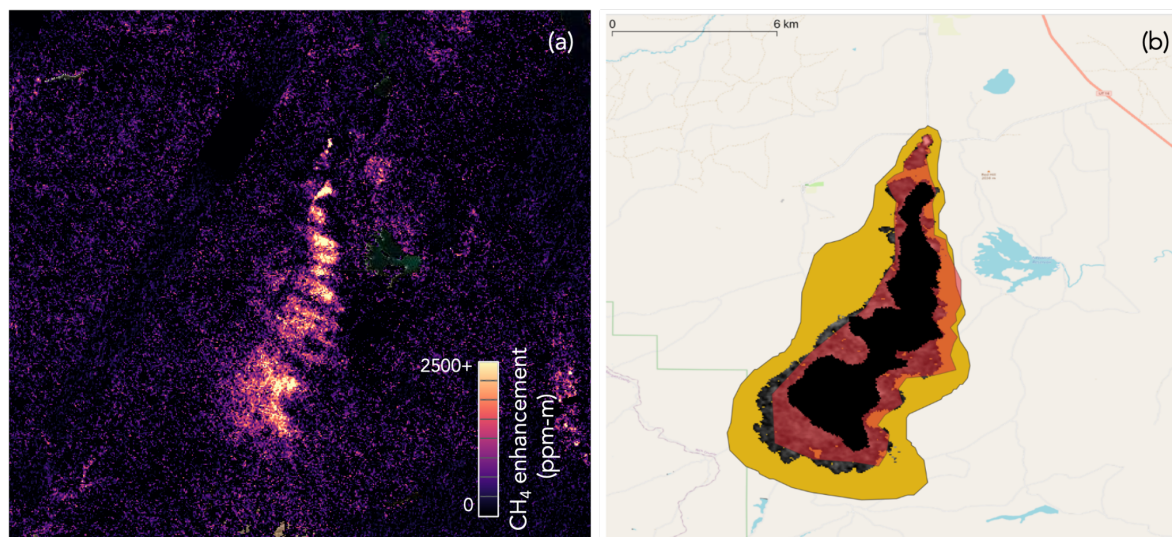


Figure 5. Variation in plume segmentation approaches. Panel (a) shows retrieved EMIT plume concentration enhancements over a large emission source detected on June 12, 2023 in Utah, USA available on the LP DAAC data archive (Thorpe et al., 2025). Panel (b) shows the segmentation masks applied by several human analysts as part of an intercomparison analysis. Panel (b) is reproduced from Eldering et al. (2026).

3.6 Quantification

The final step in the plume processing pipeline described by Figure 2 is emission rate and emission rate uncertainty calculation. In this step, segmented plume concentration masks are used in conjunction with wind information to estimate flow rate. Jacob et al. (2022) describes in detail several approaches to estimate emission rates from segmented plumes. A summary of commonly used emission rate quantification methods is summarized in Table 4. Of the variety of possible methods to estimate plume emission rates, generally three approaches are adopted operationally by data providers: The Gauss Integral or Divergence Integral (DI) method (Krings et al., 2011; Chulakadabba et al., 2023), The Cross Section Flux (CSF) method (Varon et al., 2018), and the Integrated Methane/Mass Enhancement (IME) method (Varon et al., 2018; Frankenberg et al., 2016). Other methods, like Gaussian Plume model (Pasquill, 1961; Gifford, 1961), Local mass balance (Jacob et al., 2022), Angular width (Jongaramrungruang et al., 2019), and deep learning approaches (Jongaramrungruang et al., 2022) are used in more limited capacity or for other trace gases (Nassar et al., 2021). New algorithms to update Gaussian plume modeling for point source imagers have been proposed (Fahlen et al., 2026). All the approaches listed in Table 4 assume that the magnitude of the methane enhancement of the plume is related to Q divided by U , meaning that independent information for U is required in order to quantify emission rates.



585 **Table 4. Commonly applied quantification methods for point sources**

Method Name	Formula ^a	Reference
Gaussian Plume	$Q = U \Delta\Omega(x, y) \sqrt{2\pi} \sigma_y(x) e^{-\frac{y^2}{2\sigma_y(x)^2}}$	Pasquill, 1961; Gifford, 1961; Nassar et al., 2021; Fahlen et al., 2026
Gauss theorem / Divergence Integral (DI)	$Q = \int_s \Delta\Omega(s) \vec{U} \cdot \vec{n} ds$	Krings et al., 2011; Chulakadabba et al., 2023
Cross-Section Flux (CSF)	$Q = U \int_a^b \Delta\Omega(x, y) dy$	Varon et al., 2018
Integrated Methane / Mass Enhancement (IME)	$Q = \frac{IME}{L} U^*$	Varon et al., 2018; Frankenberg et al., 2016

^aHere U represents wind speed (m s^{-1}), $\Delta\Omega$ represents column concentration enhancement (kg m^{-2}), σ_y represents the horizontal standard deviation of the emission distribution (m), and L represents the plume length (m).

590 The CSF algorithm requires an estimate of a major plume axis along the direction of the mean flow of the wind. For a perpendicular transect, emissions are estimated as the product of wind speed and integrated mass along that transect. Multiple plume transects along the major plume axis provide multiple estimates of plume emission rates, which is also used to estimate uncertainties. Similarly, the DI approach integrates mass around a contour instead of a plume axis, and multiple contours around the plume are used to estimate uncertainties. Both CSF and DI algorithms are attractive in their physics-based explainability, and because they do not require plume-masking and the inherent uncertainties based on how the mask boundary is drawn. However they can be difficult to deploy in practice as irregular plume shapes and uncertain wind directions
 595 complicate precise estimation of plume axes or integration boundaries.

A widely used emission quantification approach is the IME method. The IME method is attractive for many data providers due to its simplicity in implementation, and robustness against validation experiments (Sherwin et al., 2024a; Reuland et al., 2026). Unlike CSF and DI approaches, the IME method generally does not explicitly require any knowledge of
 600 plume direction. IME (unit kg) is calculated through integration of plume mass within a segmented plume mask:

$$IME = \alpha \sum_{i=1}^N \Delta\Omega_i A_i \quad (3)$$

Where $\Delta\Omega$ represents a plume concentration enhancement (e.g., ppm-m, ppm, kg m^{-2}), A represents the area of a pixel (m^2), and N is the number of pixels in the plume mask. The value α is a unit conversion term from the unit of the retrieval to



kilograms per pixel area. If the retrieval output is in units of pathlength or column enhancement (e.g., ppm-m via the matched
 605 filter method), then the pathlength assumed during the retrieval step must also be assumed when α is calculated.

The source emission rate is proportional to the IME, wind speed, and shape of the segmented plume mask:

$$Q \propto \frac{IME}{L} U \quad (4)$$

Where L (unit m) is a length metric of the plume and U (unit m s^{-1}) is the wind speed. The proportionality in Equation 4 can
 be made an explicit equality if L is estimated as the downwind distance from the origin to the end of the plume mask and the
 610 wind is assumed constant and uniform. The proof is derived through the Gaussian plume model, where concentrations
 downwind of an emission source are represented by the following relationship (Turner, 2020):

$$C(x, y, z) = \frac{Q}{U \sqrt{2\pi} \sigma_y \sigma_z} e^{(-\frac{y}{2\sigma_y})^2} e^{(-\frac{z}{2\sigma_z})^2} \quad (5)$$

For the application of total column concentrations, we integrate along the z direction, noting that the integral of a normal
 distribution equals one:

$$615 \quad C_{col}(x, y) = \frac{Q}{U \sqrt{2\pi} \sigma_y} e^{(-\frac{y}{2\sigma_y})^2} \quad (6)$$

We can estimate IME from C_{col} in Equation 6 through integration for some linear distance D downwind of the origin of the
 emission:

$$IME = \int_{x=0}^{x=D} \int_{y=-\infty}^{y=\infty} C_{col}(x, y) dy dx = \int_{x=0}^{x=D} \int_{y=-\infty}^{y=\infty} \frac{Q}{U \sqrt{2\pi} \sigma_y} e^{(-\frac{y}{2\sigma_y})^2} dy dx \quad (7)$$

$$IME = \frac{Q}{U} D \quad (8)$$

620 Which reproduces Equation 4 as an equality.

Other IME implementations do not explicitly relate IME to Q through a plume transport model derivation. Varon et
 al. (2018) asserts that the IME , L , and U terms in Equation 4 only need to be correlated to the true emission rate, and the actual
 physical relationship and interaction between these terms can be characterized through a parameterization, often called the
 “effective wind” (U^* ; also commonly written as U_{eff}), such that the relationship from Equation 4 becomes explicit:

$$625 \quad Q = \frac{IME}{L} U^* \quad (9)$$

In practice, the U^* term is estimated by first choosing some estimate for L for a specific segmentation algorithm, and
 also choosing some wind speed estimate (e.g., the 10-m wind speed from reanalysis datasets). Using these choices for L and
 U , one calculates a preliminary emission estimate following Equation 4, and compares against a truth dataset, which is often
 derived from large eddy simulations (LES). The U^* term is then defined and derived as the parametric transformation of U
 630 (e.g., $U^* = aU + b$) that reduces aggregate bias between the true emission rates and calculated emission rates.



Though a statistically derived U^* model is performed in practice, U^* can also be understood through a Gaussian plume model, assuming L is estimated as the square root of area of the segmented plume mask (Varon et al., 2018). The Pasquill-Gifford formulation of the Gaussian plume model asserts the following form for σ_y :

$$\sigma_y(x) = R_y x^{0.894} \quad (10)$$

635 Where R_y is a constant based on atmospheric stability classes: values range from 0.443 (extremely unstable) to 0.071 (extremely stable) (Turner, 2020). Choosing a value of 0.216 (Class B; moderate stability for winds around 2-3 m/s), results in $\sigma_y(x) = 0.216x^{0.894}$. Under the Gaussian plume assumption, we can assume that the shape of a plume seen from above resembles a triangle, therefore $A = D^*W$ where W is the half-width (perpendicular cross section) of the plume at a distance D downwind of a plume. Also under Gaussian assumptions, 97% of the plume mass at a cross section is represented by $2^*\sigma_y$, so
 640 $W \approx 2\sigma_y$, and therefore $A \approx 0.432D^{1.894}$ and $\text{sqrt}(A) \approx 0.657D^{0.947} \approx 0.657D$. This would imply that $U^* = 0.465U$. Under different stability conditions or using a different value for W (e.g., $W \approx \sigma_y$), the scalar relationship changes, highlighting that the U^* representation is both a function of wind stability and plume segmentation algorithm. U^* equations derived from comparison to LES across a range of wind speeds using the $\text{sqrt}(A)$ for L are mostly derived through simple least squares regression – e.g., a U^* for PRISMA is estimated as $U^* = 0.34*U_{10} + 0.44$ (Guanter et al., 2021). This shows general
 645 agreement with what is derived through the Gaussian plume arguments listed above, with the exception of a fitted intercept, which is needed as the Gaussian plume derived U^* relationship breaks down as U goes to zero. More research connecting this U^* parameterization to physical explanations is needed to better generalize and understand uncertainties with this method.

Uncertainties in wind speeds generally are the largest driver of quantified emission rate uncertainties, driven both by uncertainties or error in independent wind products (e.g., global reanalyses) and model transport uncertainties driven by
 650 quantification algorithms described in Table 4. Some new methods, particularly through the use of geostationary observations, circumvent the need to use a wind speed estimate directly in the IME formulation (Watine-Guiou et al., 2023). In this case, given the rapid revisit of a site (minutes), the change in IME with respect to time can be used directly to estimate a source rate, however this assumes that excess mass cannot escape the plume, which likely can only be assumed during early stages of plume development. Likewise, preliminary assessments of rapid revisit of a controlled release site with the AVIRIS aircraft
 655 point source imager showed capability of optical flow methods for retrieving wind speed directly from changes in plume morphology seen in closely temporally spaced plume images (Eastwood et al., 2025). A constellation of point source imagers flown in formation in low earth orbit could both offer the ability of rapid plume imaging, potentially circumventing the need for a wind or effective wind estimate, while maintaining high detection sensitivity.

Validation of source emission rate quantification is performed through various experiments, including controlled
 660 releases, instrument intercomparison, comparison to well characterized known sources, distributional assessments, and comparison to synthetic datasets (e.g., LES). Comparison of quantified emission rates to metered emission rates during controlled release experiments allows for an assessment of bias and correlation of a quantification approach. Several experiments have been performed to test quantification performance for satellite point source imagers (Sherwin et al., 2023;



Sherwin et al., 2024a; McManemin et al., 2026; Reuland et al., 2026; Ramier et al., 2025). These experiments are of high value for validation, but incur significant costs, do not yet represent diverse observing conditions, and require long deployments to acquire sufficient samples to statistically interrogate quantification bias given the sometimes long revisit times of some satellite imaging systems. Increasing the number, geographic diversity, and meteorological range of controlled release experiments with the appropriate level of financing will undoubtedly improve the performance of satellite point source processing teams to produce unbiased quantification results.

In absence of controlled releases, other experiments are useful for building confidence in emission quantification algorithms. Simultaneous aircraft underflights campaigns coordinated with satellite overpasses in regions of high density of large point sources (e.g., Permian Basin) can be used to test the similarity in quantification performance for plumes detected by both systems (Ayasse et al., 2023; Duren et al., 2025). These intercomparisons have also been performed in limited capacity for independent satellite systems: joint tasking of satellites at the same target at nearly the same time (NASA, 2024). Outside of single plume detections, comparison of distributions of point source emission rates across similar regions can reveal systematic agreement or disagreement between point source imaging systems (Jervis et al., 2026). Studies have also assessed the agreement in emission rate quantification among teams processing the same point source imaging data (Eldering et al., 2026; Guanter et al., 2026). The process to reconcile divergent emission estimates across teams without the presence of ground truth is an open question. Lastly, synthetic datasets like LES simulations have been used to validate quantification performance. However, these comparisons are complicated by the fact that to date, they have represented idealized plume conditions. Also, teams that derive a U^* value from synthetic data can no longer independently generalize quantification performance using those same simulations.

4 Characterizing Detection Performance

The processing and validation procedures described in Section 3 enable overall performance characterizations for an instrument processing pipeline. We describe in this section key performance metrics used across data providers and satellites to differentiate point source detection, quantification, and observing performance.

4.1 Detection Sensitivity

A key metric for point source imagers is the quantitative estimate of detection performance, which not only informs instrument completeness but also enables robust statistical treatment of observational data to provide higher-level inferences such as source persistence, emissions inventories, etc. As described in Section 3.3, plume detection is a function of retrieval noise, presence of retrieval artifacts within a scene, the magnitude of the methane enhancement within the plume, plume morphology, spatial resolution, and other environmental conditions at the time of observation. Plume concentration enhancement and morphology are generally related to the magnitude of an emission rate and the wind speed. Noise is related to both the instrument design and the instrument's treatment of light, albedo, and solar illumination conditions at the time of



observation. Given these relationships, a dimensionless metric of plume observability (O_{ps} ; Bruno et al., 2024) can be assumed to correlate with a limit of detection (LOD) and takes the following form:

$$O_{ps} = \frac{Q}{UW\sigma} \quad (11)$$

700 Where σ represents retrieval noise, and W represents the dimension of a single pixel (m). The O_{ps} metric represents the plume SNR signal, which relates to a theoretical minimum detection limit (MDL; units kg h^{-1}) following Jacob et al. (2016):

$$MDL = \frac{M_{CH_4}}{M_a} \frac{UWpq\sigma}{g} \quad (12)$$

705 Where M represents the molar mass of CH_4 or dry air, p represents atmospheric pressure, and g represents acceleration due to gravity. The value q can be chosen as the number of plume pixels needed for detection, which was defined as $q=2$ in Jacob et al. (2016). Figure 6 shows the results of Equation 12 for various satellites where details are available, assuming 3 m s^{-1} wind speed. Single scan point source detections of $<100 \text{ kg h}^{-1}$ are possible for some satellite instruments (Tanager, GHGSat, Worldview-3), however, across the suite of point source imagers, predicted MDLs range from 60 to 42000 kg h^{-1} . Several studies cite retrieval precision for point source imagers across a diversity of observing conditions, however, given the strong linear dependence of MDL on retrieval precision in Equation 12, comparisons of MDLs across satellites may be severely
 710 complicated when observing conditions are not identical. Therefore, it is a recommendation for future analysis to define reference observations to more consistently assess retrieval precision for comparison.



Point source imager detection performance

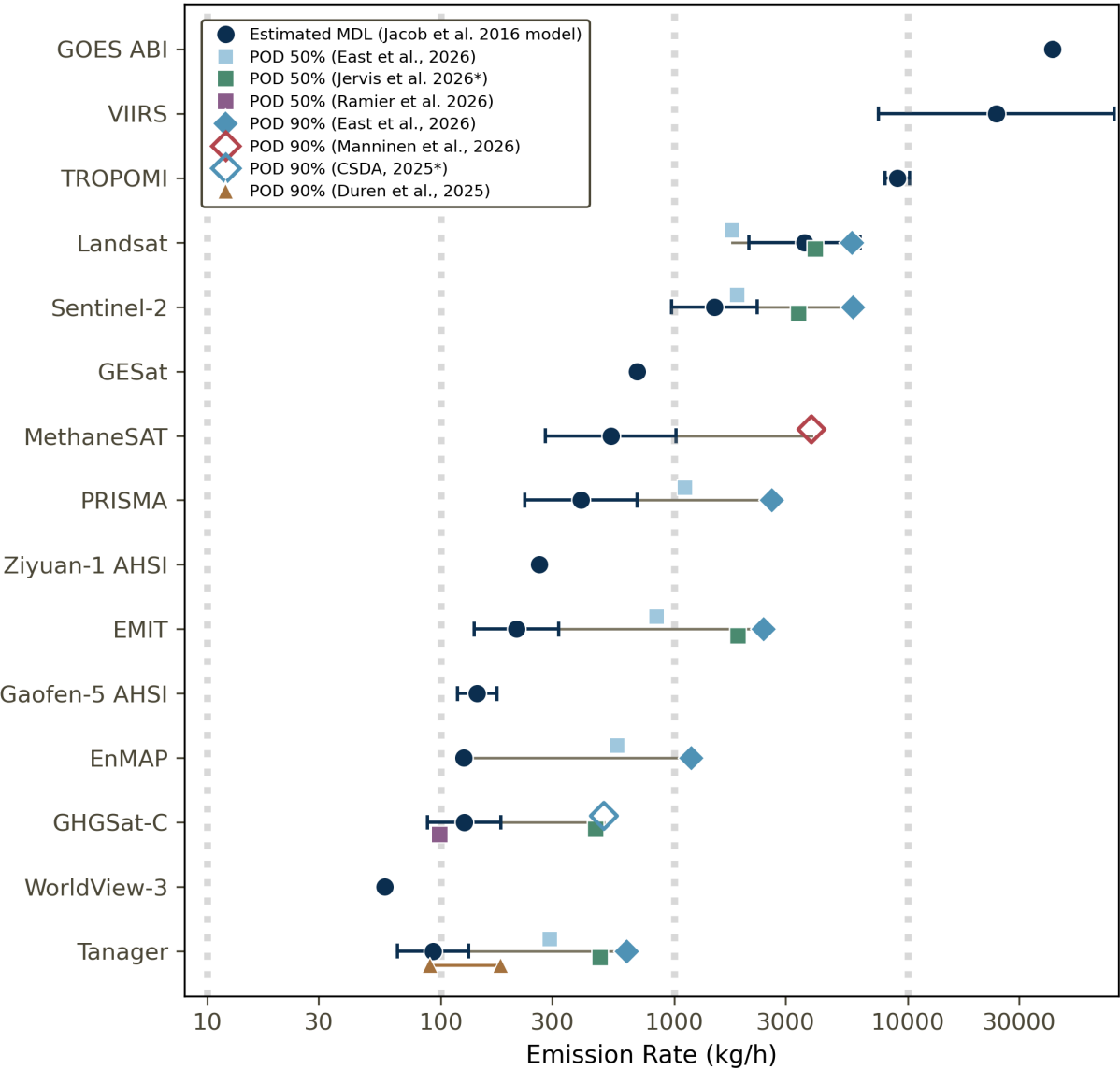


Figure 6. Detection performance for point source imaging satellites. Dots represent a theoretical minimum detection limit described by Equation 12 and using retrieval precision and spatial resolution metrics described in Table 1. Square, triangular, or diamond markers represent probabilistic detection limits for some instruments as estimated from published studies. All detection limit estimates assume 3 m s^{-1} wind speed, unless indicated by an asterisk in the legend.

The MDL metric is of limited utility in practice because it does not convey the range of emission rates that a satellite processing pipeline reliably detects across diverse environmental conditions. Alternative probabilistic estimates of detection



720 limit provide a more useful characterization of detection performance. The probability of detection (POD) is defined as the likelihood of detecting a plume for a given experiment or observing environment. As POD represents a true positive rate, a simple formulation for POD is to count the number of correctly identified true positives (TP) and false negatives (FN) against a ground truth (e.g., controlled release or comparison to more sensitive instrument) against a range of detections:

$$POD = \frac{TP}{TP + FN} \quad (13)$$

725 In practice, to characterize instrument and retrieval performance, it is useful to go beyond the POD formulation in Equation 13 and instead estimate the emission rate threshold where there is high probability of detection (e.g., 90% POD), given a set of environmental conditions and noise factors impacting detection (Conrad et al., 2023; Ayasse et al., 2024; Ramier et al., 2025). A POD estimate for a detection technology can be derived by fitting a probabilistic model to ground truth data. To do this, a candidate model for detectability (F) is made by adapting Equation 11, which is then used to estimate POD. In
 730 its most general form:

$$F(Q, U, \sigma, W) = \frac{\phi_9(Q + \phi_5)^{\phi_1}}{(U + \phi_6)^{\phi_2}(\sigma + \phi_7)^{\phi_3}(W + \phi_8)^{\phi_4}} \quad (14)$$

$$POD(F) = 1 - (1 + F^2)^{-1.5} \quad (15)$$

with each coefficient ϕ_i being nonnegative, ensuring that F itself is nonnegative. Equation 15 is a Burr cumulative distribution
 735 function (CDF), but any form of inverse link function that maps F to the range 0-1 in a monotonically increasing way can be used (e.g., lognormal CDF, error function, etc.) assuming it fits sufficiently well to the data. The coefficients ϕ in Equation 14 represent fitting parameters that are optimized by comparison to ground truth datasets of TP and FN detections. Assuming $\phi = 1$ for coefficients ϕ_1 to ϕ_4 and $\phi_i = 0$ for coefficients ϕ_5 to ϕ_8 recovers the righthand side of Equation 11 and effectively assumes that each of the variables that influence detection in Equation 14 vary linearly with POD. In all studies that include
 740 ϕ_1 to ϕ_8 in their formulation, one or more of these coefficients has statistically improved the model (Conrad et al., 2023; Thorpe et al., 2024; Ramier et al., 2025). Examples of 50% and 90% POD models estimated through Equations 14-15 are shown in Figure 6 for Tanager, GHGSat, and MethaneSAT (Duren et al., 2025; Ramier et al., 2025; Manninen et al., 2026).

Deriving a POD model following Equations 14-15 may produce overly optimistic performance results if fit to data in controlled release experiments. During single-blind controlled release testing, data providers are generally aware of the
 745 potential for emissions (i.e., controlled releases) at a given geographic location. For manual plume detection/identification approaches, this foreknowledge may impact an analyst's decision during the detection process, leading to more optimistic detection yields than what a manual processing pipeline produces outside of controlled environments (Kunkel et al., 2023). This can be seen through analysis of emissions distributions quantified in field campaigns (Duren et al., 2019; Irakulis-Loitxate et al., 2021; Lauvaux et al., 2022; Sherwin et al., 2024b; Chen and Sherwin, 2022). Plotting a CDF of quantified emission
 750 sources on logarithmic axes shows the expected relationship in the region of large emissions and therefore perfect detection sensitivity, which is consistent with the upper tail of parametric emission rate distributions. At lower emission rates, a

divergence from this relationship is observed as the core of the distribution and the detection limit of the instrument are simultaneously approached (Lauvaux et al., 2022; Ehret et al., 2022; Cusworth et al., 2026). Figure 7 shows an example of this process for the EnMAP instrument, processed and available on the IMEO MARS portal (<https://methanedata.unep.org/>). The distribution appears roughly linear on logarithmic axes from 10,000 kg h⁻¹ until around 900 kg h⁻¹, suggesting that the EnMAP instrument with the associated processing algorithms experiences reduced detectability somewhere below 900 kg h⁻¹.

To create POD estimates for standard processing pipelines without relying on controlled releases, some studies analyze distributions of detected and quantified emissions (e.g., as seen in Figure 7), primarily in the oil & gas sector. Assuming that a distribution of quantified emission sources and an instrument's POD can be modeled parametrically, then the parameters of a candidate POD model can be inferred by Bayesian methods, and therefore more closely represent typical performance for an instrument and data provider under standard operating conditions. Examples of this POD estimation are shown in Figure 6, applied to multiple instruments (Jervis et al., 2026; East et al., 2026). This method, though more representative of actual detection performance, can become biased if quantification uncertainties are not considered, and if candidate POD models and emission rate distributions cannot capture reality. If systemic bias in a quantification system cannot be corrected, this approach will bias POD estimates proportionally. Therefore, continuing to build a diversity of controlled testing sites and prioritizing blinded studies is crucial for performance characterization.

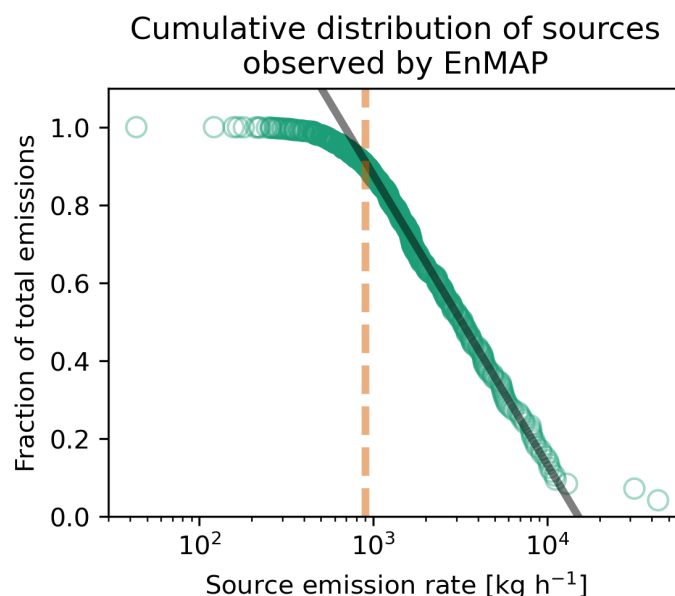


Figure 7. Cumulative distribution of average oil & gas source-averaged emissions (not including non-detections) as observed by EnMAP and quantified on the IMEO MARS portal (<https://methanedata.unep.org/>). The dashed orange line represents visually where the distribution begins to diverge from linearity (black solid line), representing potential reduced detection sensitivity. The shape of this distribution can be used to estimate detection sensitivity for the instrument and applied data processing pipeline.



Figure 6 shows the estimated detection limits for instruments in Table 1 based on published studies applying one to many of the MDL and POD characterization approaches described above. Point source imaging instruments have wide ranges of detection performance given variable ambient and surface conditions and methods to assess detection sensitivity. These ranges are important to understand and characterize especially as it comes to application of point source imaging satellites to a variety of use-cases (Section 5). Continued development of methods and standards to characterize detection performance of instruments is recommended especially as point source imager datasets are increasingly being incorporated into regulatory, reporting, and other workstreams.

5 Applications

Data from point source imaging satellites serve a variety of use-cases, which can be broadly classified into (1) direct mitigation guidance and verification (e.g., leak detection, source identification, etc) and (2) emission quantification and accounting. Here we provide a short review of published studies and existing programs that utilize these datasets.

5.1 Mitigation guidance and verification

A primary advantage of point source imagers is their ability at times to localize individual super-emitter events within tens of meters of a true emission event while covering large spatial areas in single image acquisitions, depending on the satellite. These capabilities lend themselves naturally to leak detection and repair use cases. There are several documented cases of operators or regulators across jurisdictions taking action on satellite detections of plumes (Dowd et al., 2024; Duren et al., 2025; CARB, 2026; OGCI, 2025).

Given direct mitigation potential, several government or industry/NGO led initiatives have emerged to connect satellite detections to operators to facilitate mitigation and to verify mitigation after action takes place. Examples include the IMEO MARS program which routinely processes datasets from publicly available satellites and notifies countries when plumes are detected. These notifications have resulted in many documented and verified mitigated sources (UNEP, 2026; Figure 8). In a regulatory context, the United States EPA Super-Emitter Program (SEP) allows for an approved third-party provider to provide super-emitter detections derived from EPA-approved technology (including remote sensing systems) to EPA within 15 days from observations. EPA then notifies operators who have 15 days to respond to EPA. Detections and operator responses are then posted publicly (<https://echo.epa.gov/trends/methane-super-emitter-program/data-explorer>). To date, several notifications and responses have been logged into the program. Related, as of 2024, oil & gas regulations in California require oil & gas operators to respond to satellite detections of methane plumes. The California Air Resources Board (CARB) initiated the California Satellite Methane Project (CalSMP) to actively task and notify operators of detections. For sectors outside oil & gas, CARB still notifies operators and asks for responses on a voluntary basis, and a summary for all responses from regulated sources are posted publicly (<https://ww2.arb.ca.gov/our-work/programs/california-satellite-methane-project/calsmp-dashboard>). CalSMP builds on years of prototype field campaigns to connect data to operators (CARB, 2026), and to date, the CalSMP program has motivated many mitigation successes (Figure 8). Key to the success of these programs

include the fidelity of the data product (source geolocation accuracy; source rate quantification; minimal false positive identification), the delivery mechanism and latency of the product, and the receptivity or regulatory ecosystem that encourages or requires operator action. The nonprofit Carbon Mapper works to connect the methane emissions data made public through their data portal directly to regulators and operators through a mitigation initiative (Carbon Mapper, 2026).

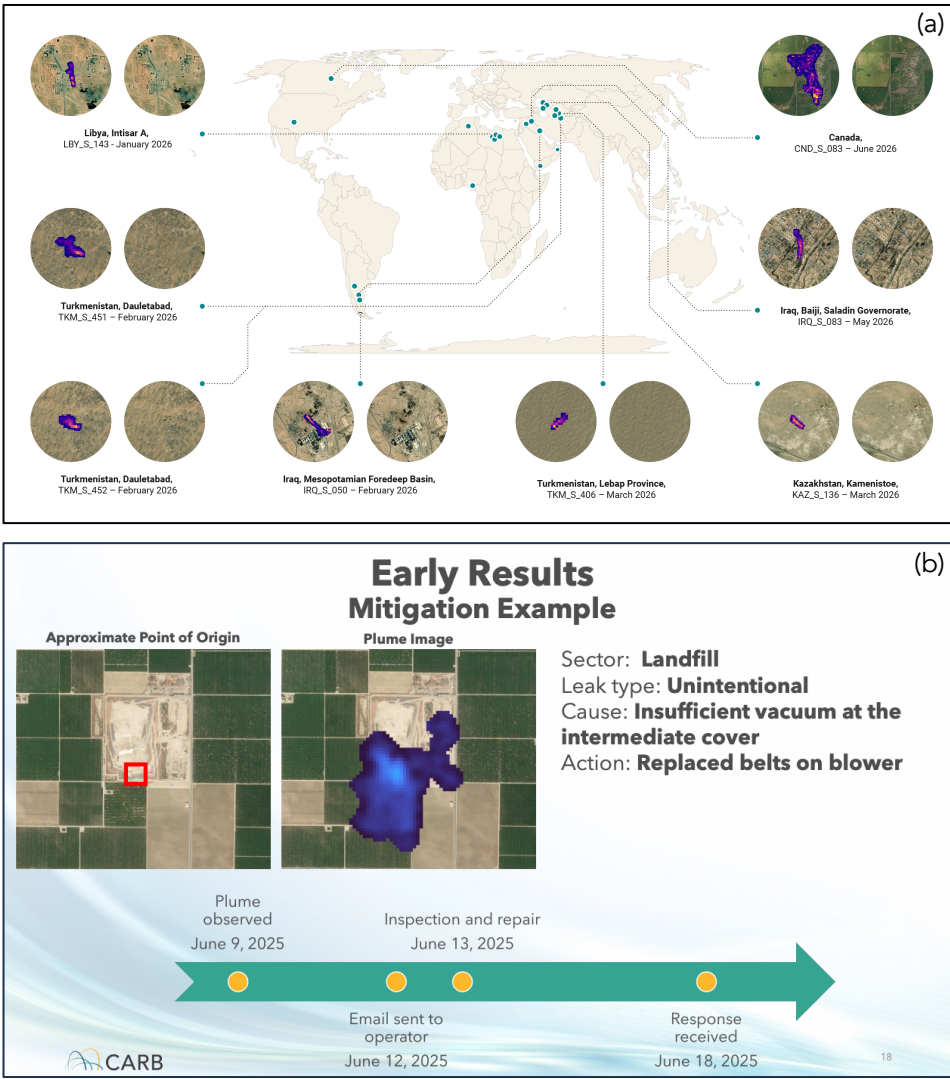


Figure 8. Mitigation case study examples. Panel (a) shows a selection of emission sources identified by satellites by the UNEP’s IMEO MARS program, then sent to operators who acted on the data to mitigate emissions. Follow up satellite observations resulted in non-detections. The figure is reproduced from UNEP, 2025. Panel (b) shows an early mitigation example of the California CalSMP program, where a satellite plume detection at a landfill was sent to an operator who took action. The figure is reproduced from CARB, 2025.



820 Given the vast and complex networks of potentially methane super-emitting infrastructure, tip-and-cue with multiple
 satellites may more efficiently identify potential emission hotspots (Schuit et al., 2023). In this framework, a globally mapping
 coarser resolution satellite (e.g., TROPOMI) identifies an exceptionally large methane hotspot at coarse kilometer scale
 resolution. This detection then triggers follow-up tasking or processing of finer resolution satellites to localize the potential
 emission source. The MARS system operationally utilizes this model by leveraging TROPOMI detected hotspots (following
 825 the machine learning approach described in Schuit et al. and long-term TROPOMI analysis), which triggers processing and
 tasking of 30-m resolution publicly available satellite data. Růžicka et al. (2026) describes a proof-of-concept method to detect
 via deep learning a class of highly credible sources with the EMIT satellite with very low latency, thus providing a daily digest
 of credible detections based on new observations. This model was proof-tested with Tanager satellite data, where a Tanager
 follow up to an anomalously large EMIT detection was performed two days post initial observation. A challenge with tip-and-
 830 cue is that generally less sensitive instruments trigger follow-up observations, meaning that only a subset of all super-emissions
 are detected via this approach. A related challenge is that publicly available satellites that exhibit more frequent revisit (e.g.,
 Sentinel-2) are less sensitive generally than tasked satellites (EnMAP, PRISMA), but tasked satellites, given competing
 observational priorities, tend to have longer revisit intervals than these global mappers.

835 The fine spatial resolution of point source imagers can help identify certain infrastructure classes or processes, which
 is helpful for informing best practices, prioritizing investment, improving operational efficiency, or verifying remediation
 action. Through attribution of satellite retrieved concentrations to visible imagery at landfills, Zhang et al (2025) and Dogniaux
 et al. (2025) identified that for a class of landfills, large emission sources could be attributed to the landfill working face, i.e.,
 the disposal area at a landfill. The attribution of large emission sources to the landfill working face is behavior also identified
 in previous airborne point source imaging studies (Scarpelli et al., 2024; Cusworth et al., 2020), and highlights an area for
 840 increased emphasis in landfill design and construction. Similarly, Scarpelli et al. (in review), worked with a landfill operator
 in California to connect airborne and satellite methane observations to gas collection well installation, and found that emissions
 significantly decreased post well installation in a recent disposal area. In the oil & gas sector, several studies (e.g., Conrad et
 al. (in review); Irakulis-Loitxate et al., 2022a; Irakulis-Loitxate et al., 2021) attributed hundreds of satellite detections across
 oil & gas basins globally, identifying infrastructure categories most responsible for a region's super-emissions. Distributions
 845 vary considerably from basin-to-basin: for example, the near entirety of Algeria's super-emissions come from pipelines and
 flaring/venting, whereas in the San Joaquin Valley (California), most super-emissions come from well-sites. Understanding
 these regional distributions may be helpful in targeted investment and mitigation strategies.

5.2 Aggregate emission accounting

850 A key observing challenge for point source imaging satellites is the non-continuous “snapshot” observational nature
 of most systems, combined with a high detection limit. Jacob et al. (2022) introduced the concept of Observing System
 Completeness, which relates the detectability of a global fraction of methane point sources for an observing system to that



system's instrument detection limit, temporal sampling, and spatial coverage. Duren et al. (2025) and Jervis et al. (2026) further describe methods to estimate these completeness parameters using data from several point source imaging satellites. Systems with high Observing System Completeness identify a large number of potential mitigation opportunities, serving direct mitigation use-cases. Other quantification use cases have related but separate requirements, in particular for long-term averaging of facility-level and basin-scale emissions.

For source to facility level quantification of long-term (e.g. annual) average emission rates, minimum sampling requirements need to be met given the often variable and intermittent nature of anthropogenic sources (Jacob et al., 2022). Geostationary satellites overcome sampling issues through rapid minute-scale revisit. However, the detection limit for the current suite of geostationary satellites is such that they can only detect and quantify a small fraction of global sources. However, for these detected sources, these instruments provide a near-continuous estimate (restricted to daylight hours) of emissions (He et al., 2026). Constellations of more sensitive low earth orbiting satellite observations can still potentially satisfy sampling requirements for long-term average emission quantification. Studies of quantification of exceptionally large events (e.g., gas well blowouts) show that multiple satellites imaging or specifically tasked at a source for the duration of an event capture variability and provide a quantification of the total emission from the event (Guanter et al., 2024; Cusworth et al. 2021b, Maasakkers et al., 2022a; Harris et al., 2025).

Less extreme, albeit persistent sources have also been observed systematically with satellite observations. Multi-sensor tasking and quantification of a set of globally distributed landfills using GHGSat, EMIT, EnMAP, and PRISMA show disagreement with bottom-up inventories (Dogniaux et al., 2025; Zhang et al., 2025). These studies highlight and point to the need for reconciliation of modeling to be consistent within the uncertainties of satellite-based estimates. Using a combination of intensively tasked Tanager, GHGSat, and aircraft remote sensing observations in the U.S., Howell et al. (2025) compared bottom-up and top-down landfill emission estimates and found that although top-down and bottom-up emission estimates disagree, there is close correlation of top-down estimates with key parameters that drive bottom-up models (e.g., methane generation, recovered gas volumes), indicating a pathway to reconcile and improve inventory reporting. In the coal sector, Penn et al. (2026) and Karacan et al. (2025) found agreement between remotely sensed estimates of coal ventilation shaft emissions with bottom-up measurements. Penn et al. (2026) also found that these estimates could be used to derive emission factors consistent with IPCC Tier-2 inventory protocols. A key benefit of point source imagers for these studies is the ability to directly attribute emission sources to facilities and infrastructure, which is more challenging for area-flux mapping satellites due to their coarser spatial resolution.

Estimating emissions for a larger regional scale requires a different sampling approach for point source imagers. Given high detection limits, point source imagers can rarely, if ever, produce a total basin level estimate, however aggregate quantification of total emissions from large point sources helps characterize the impact of these large sources on regional budgets. Studies across a variety of basins globally have shown that for regions of large fossil fuel production, super-emitting methane sources can make up a substantial proportion of net emissions (Naus et al., 2023; Cusworth et al., 2022; Jervis et al., 2025; Conrad et al., in review). Maasakkers et al. (2022b) and Lama et al. (2026) show similarly that for some urban areas,



point sources quantified at landfills make up a significant fraction of total urban emissions. These results follow similar findings derived from wide area surveys performed with aircraft remote sensing platforms (Sherwin et al., 2024b; Donahue et al., 2026; Johnson et al., 2023). In those studies, remote sensing platforms sampled infrastructure across large swaths of oil & gas basins in the U.S. and Canada with limited revisit, but leveraged large ensemble spatial statistics to derive their basin-total estimate. Here the key assumption is that temporally disparate snapshot sums of emissions represent an unbiased estimator of true basin total emissions. This can be written in a simple formulation:

$$\hat{E} = \sum_i^N X_i(t_i) \approx E = \sum_i^N \mu_i \quad (16)$$

Where $\hat{E}$ represents the estimated basin total point source emission rate, E represents the true basin total emission rate, X_i is a function representing a source-level emission rate for source i , N represents the total infrastructure counts in a basin, and μ_i represents the true long term average emission rate for source i . Here, the expected value of $\hat{E}$ equals E if and only if each process X_i is stationary. This is a difficult condition to establish in oil & gas basins because the time evolution of source emission rates may trend or vary based on operational, seasonal, or economic conditions.

Even under non-stationarity of individual sources within a basin, the population distribution of sources within a basin may exhibit stationarity, which allows for aggregate emissions to be calculated assuming a critical amount of infrastructure is measured. Here it is assumed that X_i is associated with a stable population distribution (P), i.e.,

$$X_i \sim P(\mu, \sigma). \quad (17)$$

Under this assumption, we rewrite E using the following form:

$$E = N * E[X] = N * \mu_P \quad (18)$$

Where μ_P represents the population mean from the distribution P . Now $\hat{E}$ is an unbiased estimator of E if the population distribution P is stationary. This is a weaker condition than requiring stationarity for every individual source. Instead, what's required is the stationarity of the following empirical measure (Gray, 2009):

$$\hat{P} = \frac{1}{N} \sum_{i=1}^N \delta_{X(t)} \approx P \quad \forall t \quad (19)$$

Which asserts that any snapshot of sources at time t approximates the true distribution. However, in reality, regional emission distributions may not be stationary. For example, Varon et al. (2026) and Hu et al. (2025) assessed trends in basin-total emissions across multiple basins in the U.S. using area-flux mapping satellites, and ground+airborne measurements, respectively, and found strong seasonal trends. The timescales over which population distributions may drift is an open question and likely depends on regionally specific conditions. Future study with the growing constellation of point source imaging satellites can help diagnose variability in observed emission distributions in specific regions, helping inform appropriate sampling requirements for basin-level point source emission accounting. However, results from studies that aggregate point source measurements (e.g., Donahue et al., 2026; Sherwin et al., 2024b; Johnson et al., 2023) show general agreement with basin-level estimates derived from area flux mapping satellites (e.g., Shen et al., 2022; Williams et al., 2026)



suggesting that, for the regions and observing periods studied, variability in the basin-level source distribution was sufficiently constrained to support regional point-source emission estimates within the reported uncertainties.

920 Generalizing beyond stationarity, Pandey et al. (2025) relates the sum of emissions quantified from a point source instrument i (y_{ics}) to total emissions (x_{cs}):

$$y_{ics} = \tau_{ics} \kappa_{is} \eta_{ic} x_{cs} \quad (20)$$

Where τ_{ics} , κ_{is} , η_{ic} represent factors that account for quantified emission rates against a total emissions on the scale of a basin or domain “ c ” for each emission sector “ s ”: κ_{is} represents temporal sampling bias to account for the non-continuous
 925 measurement of the instrument, η_{ic} represents the fraction of spatial area observed by the instrument, and τ_{ics} represents the instrument sensitivity, i.e., how much of total emissions the instrument would observe if it had complete spatiotemporal coverage over c . Estimation of τ_{ics} , κ_{is} , η_{ic} through inverse modeling or other approaches provides a mechanism to estimate total emissions for a region from point source imager observations.

Point source data can be integrated directly into regional quantification frameworks that leverage area-flux mapping
 930 satellites. Area-flux mappers derive regional emissions by connecting downwind satellite observations to emission fluxes by inversion of a chemical transport model, where the optimal solution is conditioned by a prior emission estimate (Jacob et al., 2022). One approach to merge information from area-flux and point source imagers is to use the spatial information from point source detections to help constrain prior distributions (e.g., Naus et al. 2023). East et al. (2025) estimates country-level methane emissions using inversion of TROPOMI observations along with a prior partially informed by GHGSat global plume
 935 detections. Another approach is to refine post-hoc sector attribution of inverse fluxes through the use of point source datasets. Williams et al. (2026) estimates methane intensities for several basins globally using MethaneSAT, and uses Tanager plume datasets in addition to other prior inventories to partition fluxes to the emission sector. A third approach (Pandey et al., 2025), builds on the point and total emission relationship from Equation 20 to estimate total basin-level emissions through Bayesian assimilation of point source observations while using TROPOMI derived area-fluxes or gridded bottom-up inventories as a
 940 prior. The analysis shows that summed plume emissions contain information on the spatial and temporal variability of area-scale emissions and that plume assimilation can refine prior estimates. Future work could extend this sequential framework to simultaneous or hierarchical assimilation of concentration and plume observations, with explicit propagation of uncertainty in sampling, detectability, plume quantification, and resolution-dependent source aggregation.

945 6 Conclusion

Methane point source imaging has matured rapidly since the last comprehensive review of these capabilities (Jacob et al., 2022), with several new satellite missions launched, established retrieval and detection methods refined, and a growing body of applied science demonstrating the value of these datasets for both mitigation and emissions accounting. This review synthesizes currently understood capabilities of point source imaging missions, describes data pipelines and data availability,
 950 approaches to validate detection and quantification performance, and summarizes several examples of how these datasets are being applied across mitigation and quantification use cases.



The fleet of point source imaging satellites has expanded considerably, with new launches from purpose-built missions (GHGSat, Tanager, MethaneSAT) joining a growing set of multi-purpose hyperspectral instruments (EMIT, GHST, EnMAP) and an expanding list of sensors found to have incidental plume-detection capability (Landsat's back-catalog, VIIRS, Sentinel-3, and the geostationary GOES/MTG constellations). This diversity comes with tradeoffs: revisit frequency is governed as much by tasking competition, orbital geometry, and weather as by nominal repeat cycles, and data availability and licensing terms vary widely across public agencies, commercial providers, and non-profits. This fragmentation of access and format is itself a barrier to broader community use, and standardizing how availability is communicated across providers would benefit users trying to compare or combine datasets to obtain deeper insights into emissions.

Across the processing pipelines, a variety of retrieval, detection, and quantification algorithms exist and are being actively researched. Some segments of the plume processing chain, like retrieval algorithms, are difficult to validate directly. However, an increasing number of controlled release experiments and instrument data intercomparison projects provide testbeds for evaluating downstream data products like source emission rates and probabilistic detection limit estimates. Increasing the geographic and source morphology diversity of controlled releases globally and expanding intercomparison datasets is recommended for further validation of algorithm processing pipelines. Some residual sources of error, in particular due to wind, might be irreducible in current emission rate quantification pipelines due to reliance on available global reanalysis datasets. Some work using rapid revisit plume imaging potentially circumvents these issues, but requires further investigation.

Applications of point source imaging data fall broadly into two categories: direct mitigation guidance and verification (Type 2 monitoring), and emissions quantification and accounting (Type 1 monitoring). On the mitigation side, government and industry programs (UNEP's IMEO MARS, the EPA's Super-Emitter Program, California's CalSMP) have demonstrated that timely, geolocated detections can drive real operator action, with tip-and-cue strategies helping to extend coverage despite the detection-limit constraints of any single instrument. On the quantification side, initial studies using point source data have shown the capability to reconcile top-down and bottom-up emission estimates at the facility and basin level, and to characterize the outsized contribution of super-emitters to regional totals, complementing, rather than replacing, area-flux mapping and inventory-based approaches.

Looking ahead, several priorities stand out: establishing common validation standards and reference sites to make detection and quantification performance genuinely comparable across instruments, providers, and diverse environmental conditions; deeper integration of point source detections into area-flux inversion frameworks, so that facility-level attribution and regional flux totals are estimated within a single consistent framework; and continued expansion of the observing fleet, which will improve both detection sensitivity and revisit frequency. However, the existing demonstrated capabilities and integration of point source imager observations into stakeholder workstreams shows that these datasets and frameworks are ready today to support climate policy and direct action.

Author Contributions



985 DHC wrote the manuscript with contributions from DJV, DJ, JM, AJT, CF, JRW, AKT, JF, SP, JDM, IA, AE, RMD, BMC, TRS, DMB, MH, IIL, LG, JS, BH, EDS, SC, EAK, AB, FR, MS, JDE, and DJJ. JDE created Figure 7, and DHC created or adapted all other Figures.

Competing Interests

990 The authors declare no competing interests

Data Availability

Tanager, EMIT, and AVIRIS derivative data required to reproduce Figure 3 and Figure 4 are available via Carbon Mapper's data portal (data.carbonmapper.org). EnMAP derivative data required to reproduce Figure 7 is available on the IMEO MARS portal (<https://methanedata.unep.org/>). Data to reproduce Figure 6 is contained within Table 1.

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