

Annual mean methane emissions from individual oil-gas point
sources worldwide inferred from multi-satellite plume-imaging
observations

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Abstract

Plume-imaging satellite instruments routinely reveal large methane point source emissions from oil and gas systems. But the observations are for instantaneous plumes, and the instruments have limited detection and revisit capabilities, making it challenging to infer time-averaged emission rates as needed for emission inventories and reporting. Here we develop a general method to infer the probability of detection (POD) of any plume-imaging instrument, over any surface, and to estimate the time-averaged point source emission rates on the basis of a limited collection of data. Applying this method to 12080 plume observations from the Sentinel-2, Landsat, EnMAP, PRISMA, EMIT, and Tanager instruments for each year in 2022-2025, we find that PODs are lower than commonly reported from controlled releases conducted under favorable conditions. We quantify annual mean emission rates for 1924 individual oil and gas point sources worldwide, estimate that point sources detected by these instruments emitted 7.6 Tg y^{-1} in 2025, identify 245 sources that emitted more than 1 ton h^{-1} on an annual basis, and show 2022-2025 trends for illustrative individual sources. 18% of sources emit for only one year and subsequently cease. Accounting for sub-detection-threshold emissions reveals higher source persistence (averaging 56%) than previously reported for oil-gas sources globally.

Significance Statement

Methane is a potent greenhouse gas responsible for 0.6°C of warming since preindustrial times and it is the primary component of natural gas. Large methane releases to the atmosphere from the oil and gas industry are frequently observed by satellite instruments and are often missing from national emission inventories reported under the Paris Agreement. Here, we develop a method to characterize satellite sensitivity to release size at any location worldwide and to model the time-averaged emission rate of point source releases using a limited collection of satellite observations. Applying the method to six instruments orbiting during 2022-2025, we quantify annual mean emissions for 1924 point sources.

Introduction

Atmospheric methane is the second most important anthropogenic greenhouse gas, 80 times more powerful than CO₂ per unit mass on a 20-year time scale (IPCC, 2021). Emissions from the oil and natural gas (oil-gas) sector including extraction, processing, and distribution account for about 20% of the anthropogenic methane source (Saunio et al., 2025), and are an attractive mitigation target due to the economic value of natural gas and the feasibility of emission controls (IMEO, 2025a). However, annual bottom-up emission inventories based on oil-gas activities and emission factors are typically much lower than top-down estimates from satellite observations (East et al., 2025; Scarpelli et al., 2022), suggesting missing sources that must be identified for effective mitigation.

Aircraft and satellite point source imagers have revealed widespread occurrences of large oil-gas methane point sources missing from current inventories (Duren et al., 2019; Ehret et al., 2022; Frankenberg et al., 2016; Irakulis-Loitxate et al., 2022; Johnson et al., 2023). These instruments detect atmospheric methane columns Ω_{CH_4} (kg m⁻²) by solar backscatter in the shortwave infrared (SWIR) under clear-sky conditions, and quantify methane column enhancements $\Delta\Omega_{\text{CH}_4}$ in the point source plumes relative to background. By imaging the plume and with independent information on wind speed, they enable inference of instantaneous point source emissions at the time of observation (Jacob et al., 2022). However, repeated observations show that point sources are generally transient, intermittent, and highly variable (Cusworth et al., 2026; Wang et al., 2022; Watine-Guiu et al., 2023), making it difficult to quantify time-averaged emissions relevant to emission inventories.

A growing constellation of satellite point source imagers observes methane point sources worldwide (IMEO, 2025a; Jacob et al., 2022), providing repeated observations of individual sources from which to infer time-averaged emissions. However, these instruments have limited and variable detection capability (Cusworth et al., 2019) as described by the probability of detection (POD) for an emission of a given rate. The POD is a function of the instrument's precision, the wind speed, and the local surface heterogeneity driving background spectral noise in the viewing scene (Bruno et al., 2024). Reported instrument PODs are typically derived from controlled-release experiments but may be over-optimistic because these experiments are conducted under favorable meteorological and surface conditions, with the instrument teams informed of the location and timing of the releases (Conrad et al., 2023; Sherwin et al., 2023, 2024a). Time-averaged emissions for a given point source are generally estimated from repeated observations with a given instrument by multiplying the mean observed emissions by the persistence, defined as the fraction of time that the source is detectable (Cusworth et al., 2024; Jervis et al. 2025a; Varon et al., 2021). However, this assumes a binary model where the source is either on or off, not accounting for emissions below the POD.

Here we develop a general method to infer the POD of any point source imager, over any surface, on the basis of the worldwide collection of its observations. We apply this method to estimate PODs for the ensemble of satellite point source imagers currently providing open-access observations including Sentinel-2, Landsat, EMIT, PRISMA, EnMAP, and Tanager-1. We combine the PODs with the reported 2022-2025 observations of instantaneous point source emissions from these instruments for 1924 individual oil-gas point sources worldwide, including non-detections, to infer time-averaged annual methane emission rates from the individual sources. We compare our results to the Global Fuel Exploitation Inventory v3 (Scarpelli et al., 2025), a spatially explicit bottom-up inventory based on national reports to the United Nations

Framework Convention on Climate Change (UNFCCC), and to a previous estimate of time-averaged emissions from proprietary GHGSat satellite observations (Jervis et al., 2025).

Results

We use databases of individual oil-gas point source observations worldwide compiled by the International Methane Earth Observation (IMEO) of the United Nations Environment Programme (IMEO, 2025b) for the Sentinel-2, Landsat, EnMAP, PRISMA, and EMIT instruments, and by Carbon Mapper (CM, 2025) for the Tanager instrument (Table 1). The IMEO database covers 2022-2025 while the Tanager observations are for 2024-2025 only. The databases give for each observation the point source location, the source type, the 10-m wind speed u , and the instantaneous point source rate q computed with the integrated mass enhancement (IME) method along with uncertainty (Frankenberg et al., 2016; Varon et al., 2018). They also include for each instrument the clear-sky non-detections for each point source. The non-detections are manually validated for a given instrument by human analysts using the ensemble of clear-sky scenes at the locations of point sources with at least one plume detected by that instrument over its observation record. The EMIT data further include $\Delta\Omega_{\text{CH}_4}$ for all pixels within an observation scene and this allows quantification of background noise.

Properties of each instrument are listed in Table 1 (Materials and Methods). Sensitivity for plume detection is largely determined by spectral resolution and signal-to-noise ratio (SNR) (Cusworth et al., 2019; Jacob et al., 2022). Tanager has the finest spectral resolution (5 nm) and hence the lowest detection limit. EnMAP, PRISMA, and EMIT have hyperspectral resolution (7.4-10 nm) that still allows spectral fitting in the 2.3 μm methane absorption band (Cusworth et al., 2019). Sentinel-2 and Landsat only have multi-spectral resolution (200 nm bands) but can still detect very large plumes with a band-differencing retrieval (Varon et al., 2021).

Point source locations and numbers of observations for each instrument over the 2022-2025 period are shown in Fig. 1. Here we have discarded observations with $u < 1 \text{ m s}^{-1}$ for which quantification of emissions is too uncertain (Varon et al., 2018) and those at sources with fewer than three total observations (including non-detections). Most observations are in North Africa, the Middle East, and the U.S. Permian Basin. Tropical oil-gas basins are less observed because of extensive cloudiness. Low sun angles and seasonal darkness limit high-latitude observations. Offshore point sources are excluded due to the uncertainty associated with the sun glint observations necessary for viewing them. EnMAP and PRISMA report the smallest number of plumes because they only task upon request. Tanager has a relatively small number of observations because it was only launched in August 2024.

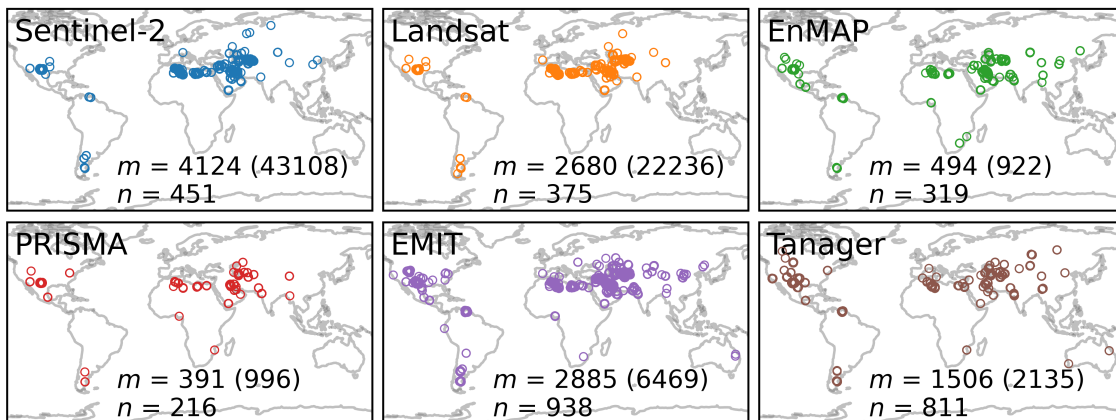


Figure 1: Locations of oil-gas point sources observed in 2022-2025 by satellite point source imagers with open-access data. Total numbers of point source locations (n) and plume detections (m) are given inset, with total number of clear-sky non-detections in parentheses.

2.1 Nominal probability of detection (POD) for individual instruments

We use emission rates from the instantaneous plume detections of Fig. 1 to estimate a nominal probability of detection (POD) for each instrument based on their global data. The observed plume enhancements $\Delta\Omega_{\text{CH}_4}$ depend on the ratio q/u_{eff} , where u_{eff} is an effective wind speed for the plume that depends linearly on u (Varon et al., 2021). The POD applies therefore to the normalized source rate $x = q/u$, which is what the instruments effectively measure (Jacob et al., 2022). The plume observation can only inform x , and independent information on u is needed to infer q . Let $\rho(x)$ represent the global frequency distribution of normalized point source rates for all active point sources in a given instrument's database, including all sources observed at least once but excluding periods when the sources are inactive (as would happen if the sources are turned on or shut off over part of the record). This on/off switch will be modeled as persistence in Section 2.3 using the observed non-detections combined with the instrument POD.

We find that ρ is best modeled as a log-normal distribution with mean μ and geometric standard deviation σ (see Materials and Methods):

$$\rho(x; \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} \quad \text{Eq. 1}$$

This global frequency distribution is observed by the instrument with a $\text{POD}(x; x_{50}, s) \in [0, 1]$ modeled as a lognormal cumulative distribution function (CDF) (Jervis et al., 2026) with x_{50} defining the 50% detection probability and s the sharpness of the POD:

$$\text{POD}(x; x_{50}, s) = \frac{1}{2} \text{erfc}\left(-\frac{\ln x - \ln x_{50}}{s\sqrt{2}}\right) \quad \text{Eq. 2}$$

The global frequency distribution $f(x)$ of individual, normalized point source rates observed by the instrument and excluding non-detections is then modeled by combining the instrument's POD and the underlying point source rate distribution:

$$f(x; x_{50}, s, \mu, \sigma) = \frac{\text{POD}(x; x_{50}, s)\rho(x; \mu, \sigma)}{C(x_{50}, s, \mu, \sigma)} \quad \text{Eq. 3}$$

where C is a normalization factor so that $\int_0^\infty f(x)dx = 1$. We find the rate distribution parameters x_{50} , s , μ , and σ , and the resulting POD, by fitting $f(x)$ to the observed emission rate frequency distribution using Bayesian inference with a Markov-Chain Monte Carlo method (see Materials and Methods). Parameters are optimized independently for each instrument because each instrument samples its own collection of point sources. Deriving the POD from the global database of observations describes the mean performance of the instrument over the range of observing conditions. It is conditioned on the instrument's detections and it therefore necessarily yields higher detection probability than the instrument's true global POD, which would include locations where plumes were never detected. We call this global mean value the nominal POD.

Fig. 2A-F shows $f(x)$ and $\rho(x)$ along with the actual observed frequency distributions for each instrument. $f(x)$ closely fits the observed frequency distributions. $\rho(x)$ is shifted toward lower values of x for the most sensitive instrument (Tanager) and toward higher values for the least sensitive instruments (Sentinel-2, Landsat), reflecting the range of sources that they are able to

detect at least once. $\rho(x)$ varies between instruments also due to unbalanced coverage by the satellites of different regions.

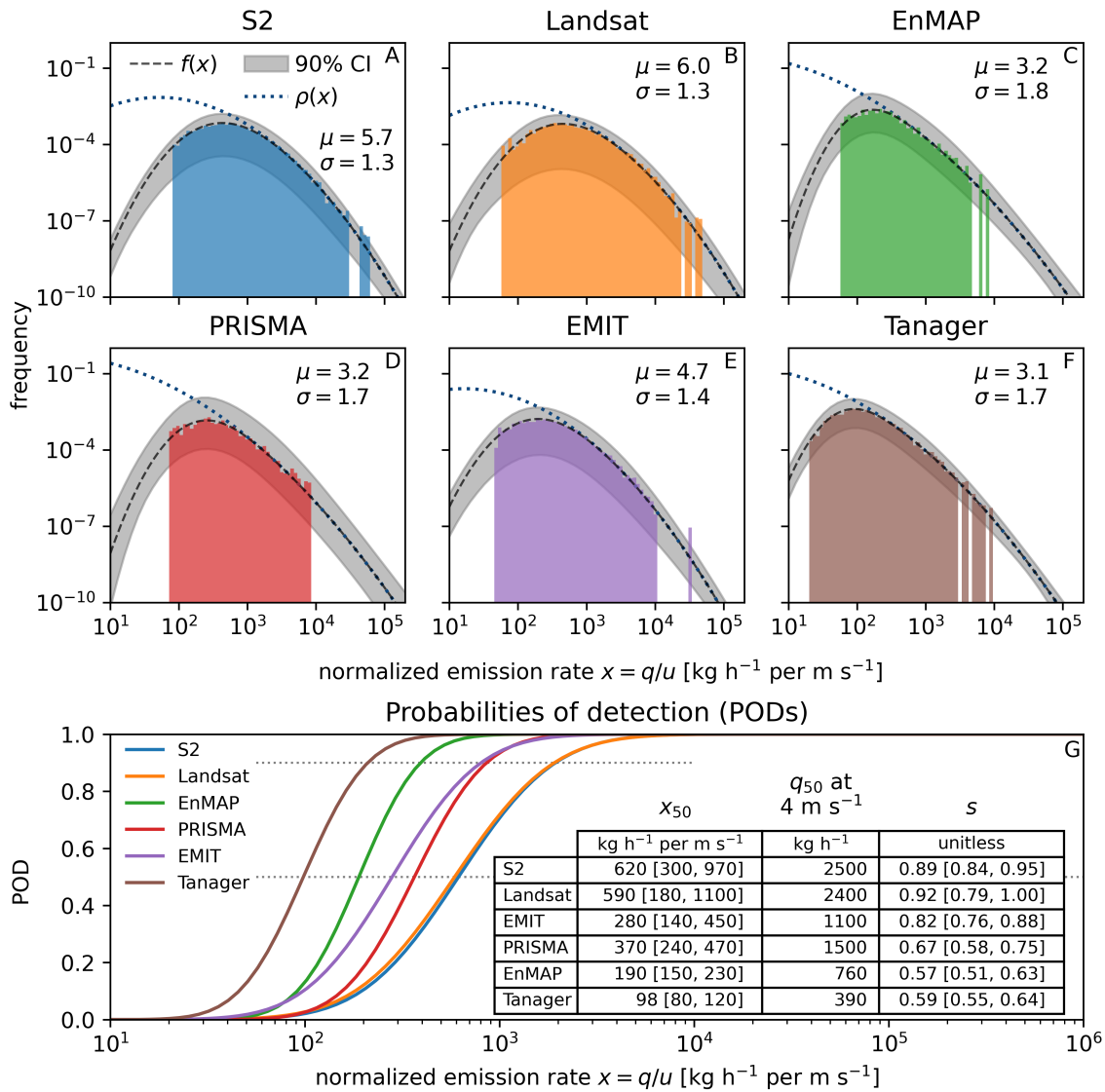


Figure 2: (A-F): Global frequency distributions of wind-normalized emission rates from point sources observed by different satellite instruments. Colored bars show the observed frequency distributions from the point source observations in Fig. 1. Dashed black line shows the observed emission rate distribution $f(x)$ (Eq. 3) fit to the observations with 90% equal-tailed credible interval (CI). Dotted blue line shows the complete log-normal distribution of emissions $\rho(x)$ (Eq. 1) with parameters (μ, σ) inset. (G): Nominal probability of detection (POD) curves for the different instruments based on global observations and for 10-m wind speeds u larger than 1 m s^{-1} . PODs for the wind-normalized point source rates (x) are given by Eq. 2 with parameters x_{50} (50% detection threshold) and s (sharpness of the POD) fit to Eq. 3 and given inset. Bracketed values for x_{50} and s are the 68% equal-tailed CIs. Inset Table also shows the 50% threshold emission rate q_{50} (kg h^{-1}) for a representative 10-m wind speed of 4 m s^{-1} .

Fig. 2G shows the nominal POD curves for each instrument derived from their global observations following Eq. 2 and with parameters x_{50} (50% detection probability) and s

(sharpness of the curve) inset in the figure. Also shown is the emission rate q_{50} with 50% detection probability when the 10-m wind is 4 m s^{-1} . The POD curves align with the precisions and SNRs of the instruments (Table 1, Materials and Methods). Tanager is the most sensitive instrument, due to its higher spectral resolution and oversampling capabilities, followed by the hyperspectral imagers EnMAP, EMIT, and PRISMA. EnMAP and PRISMA have similar characteristics (see Table 1), but EnMAP has a higher SNR (Roger et al., 2024b). Although EMIT's spectral resolution is second only to Tanager, its sensitivity falls between that of EnMAP and PRISMA due to its coarser pixel resolution. Sentinel-2 and Landsat are less sensitive than others due to their low spectral resolution.

Our nominal PODs translate to x_{50} values that are systematically larger than minimum detections reported from controlled releases (Sherwin et al., 2023, 2024a), which is expected because the releases were conducted under favorable surface and meteorological conditions and with known timing and location. PODs for the minimum detections reported by Sherwin et al. (2024a) for PRISMA (414 kg h^{-1}), Landsat (1400 kg h^{-1}), and Sentinel-2 (1200 kg h^{-1}) are 3%, 16%, and 8%, respectively, assuming 3 m s^{-1} wind speed. These emissions are unlikely to be detected without prior knowledge of the emission location and over less favorable surfaces worldwide, and therefore do not reflect the instruments' global capabilities. EnMAP's minimum detection of 1100 kg h^{-1} with detection probability 83% is more representative. Our q_{50} estimate of 1100 kg h^{-1} for EMIT at wind speed of 4 m s^{-1} is comparable to the estimate of 900 kg h^{-1} from Ayasse et al. (2024) over the Permian Basin, where the favorable surface is expected to decrease the threshold for detection by 20% relative to the nominal average (Section 2.2). Tanager's pre-launch predicted 90% POD of 180 kg h^{-1} at 3 m s^{-1} wind speed, 25% albedo, and 35° solar zenith angle (Duren et al., 2025) was calculated using idealized conditions whereas our 90% POD estimate of 630 kg h^{-1} at that wind speed reflects the range of observed conditions. Our POD estimates for Tanager, Sentinel-2, Landsat, and EMIT are by contrast 20-40% smaller than those of Jervis et al. (2026) who used a similar statistical method but for q instead of x , a dataset five times smaller, and $\rho(x)$ estimated jointly across instruments. Our estimates of s , the sharpness of the POD representing the transition from the non-detection to detection region, indicate a broader transition region (larger s) for Sentinel-2, Landsat, and EMIT and a narrower transition region for Tanager compared to those of Jervis et al. (2026). PODs have not been published previously for EnMAP and PRISMA.

2.2 Local POD for individual instruments

The ability of a satellite instrument to detect a point source within a given scene depends on the normalized source rate $x = q/u$ (kg h^{-1} per m s^{-1}), the instrument pixel resolution W (m), and the methane column background noise ΔB (kg m^{-2}) in the scene which depends in turn on the instrument precision and SNR, and on the surface properties of the scene. This can be encapsulated in a single dependence on the point source observability dimensionless number O_{ps} (Bruno et al., 2024):

$$O_{ps} = \frac{x}{W\Delta B} \quad \text{Eq. 4}$$

Bruno et al. (2024) define ΔB as the standard deviation of $\Delta\Omega_{\text{CH}_4}$ in the plume-masked scene (excluding the plume). O_{ps} determines the POD across all viewing conditions (Manninen et al., 2026), allowing instrument nominal PODs to be translated to local PODs through ΔB . We

leverage Eq. 4 to derive the local $x_{50,L}$ from the local background noise ΔB_L and the previously derived nominal x_{50} for the instrument:

$$x_{50,L} = x_{50} \frac{\Delta B_L}{\Delta B_G} \quad \text{Eq. 5}$$

where ΔB_G is a global mean background noise, calculated for each instrument by sampling ΔB at the instrument's detection locations.

Here we use EMIT and Sentinel-2 to derive local-to-global background noise ratios $\Delta B_L/\Delta B_G$ in Eq. 5, and assume that these ratios apply linearly to all hyperspectral and multispectral instruments, respectively. We take advantage of the complete pixel-level information on methane column enhancements $\Delta\Omega_{\text{CH}_4}$ within viewing scenes for EMIT and Sentinel-2, where $\Delta\Omega_{\text{CH}_4}$ for Sentinel-2 is derived by the multi-band multi-pass (MBMP) method (Varon et al., 2021). We define ΔB_L as the median absolute deviation of $\Delta\Omega_{\text{CH}_4}$ within a given scene (Materials and Methods), and derive from there the $\Delta B_L/\Delta B_G$ ratio. Although instruments with different precisions have different ΔB values, the ratio $\Delta B_L/\Delta B_G$ should be much less variable. Hyperspectral and multispectral instruments have different ratios because of the completely different retrieval methods.

The global distributions of EMIT (hyperspectral) and Sentinel-2 (multispectral) background noise ratios ($\Delta B_L/\Delta B_G$) are shown in Fig. 3. EMIT ratios are gridded to 0.25° latitude $\times$ 0.3125° longitude ($\approx 25 \times 25 \text{ km}^2$) and Sentinel-2 ratios are gridded to 1° latitude $\times$ 1.25° longitude ($\approx 100 \times 100 \text{ km}^2$). Cloudy scenes are excluded from both. Background noise in a scene is mainly due to surface heterogeneity and the resulting variability in SWIR surface reflectance (Ayasse et al., 2018; Cusworth et al., 2019). The background noise ratio in Fig. 3 is <1 in arid (bright) regions, and >1 in forested (dark) and heterogeneous regions, consistent between EMIT and Sentinel-2. Background noise variability as shown in Fig. 3 helps explain the satellite observing locations in Fig. 1, which are concentrated in lower noise regions, especially North Africa and the Middle East, while noisy regions with significant oil-gas activity such as Venezuela and the Appalachian Basin in North America have limited observations. The ΔB map for EMIT extends only from -51.6° to $+51.6^\circ$ latitude due to EMIT's inclined orbit on the International Space Station, but few plumes are observed outside this latitude range by any of the instruments.

Figs. 3C and 3D show the distribution of the local-to-global background noise ratio $\Delta B_L/\Delta B_G$ in selected basins. The mean ratio over the Permian Basin is 0.8 (0.7) for hyperspectral (multispectral) instruments, and is 0.9 over the controlled-release site of Sherwin et al. (2024) and Reuland et al. (2026) in Arizona. The Appalachian basin, a forested region of the Eastern U.S. with complex terrain, is 1.5 (1.7) times more difficult to observe than the median globally. Turkmenistan and Algeria have favorable detectability. Venezuela, including the Orinoco Belt with significant oil extraction activity, has lower-than-average detection probability. Its background

noise ratio distribution is centered around one for multispectral retrievals because cloud cover prevents successful retrievals in large areas of the country.

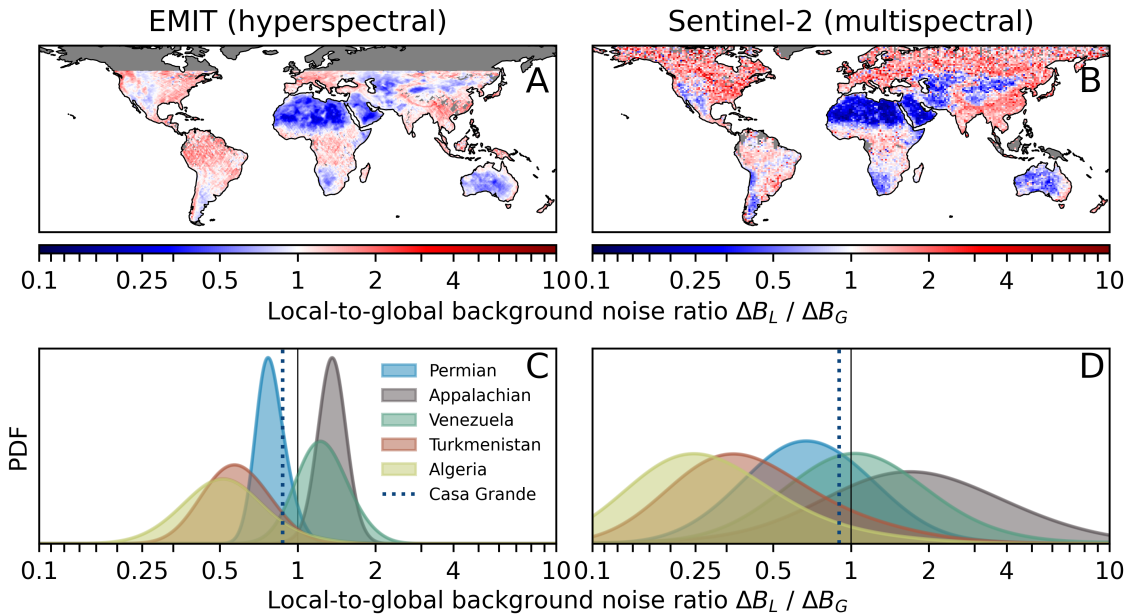


Figure 3 (A, B): Local-to-global background noise ratio $\Delta B_L / \Delta B_G$ used to determine the local probability of detection (POD) of point sources using hyperspectral and multispectral instruments. The ratios are determined from full-scene observations available from EMIT and Sentinel-2, and are gridded to $0.25^\circ \times 0.3125^\circ$ (A) and $1^\circ \times 1.25^\circ$ (B). (C-D): Distribution of $\Delta B_L / \Delta B_G$ in selected oil-gas producing basins and countries plotted with Gaussian kernel smoothing. Casa Grande, Arizona, USA is the controlled-release testing site of Sherwin et al. (2024) and Reuland et al. (2026).

2.3 Annual average emissions from individual point sources

We derived in Section 2.1 a global frequency distribution $\rho(x)$ of wind-normalized source rates for emitting point sources detected at least once by a given instrument. This can be converted into a frequency distribution $\rho_S(x)$ for an individual point source S with adjusted parameters (μ_S, σ_S) based on actual observations of that point source, using Bayesian inference and combined observations for all instruments viewing that source (Materials and Methods). The local wind speed distribution $U_S(u)$ is based on the local observations and a Weibull distribution (Materials and Methods). The product of the wind speed at the source and the wind-normalized emission rate gives the source rate. We also account for the source being completely off for part of individual years in the 2022-2025 period. The probability of a source being on is represented as the probability distribution of the persistence parameter $z_S \in [0, 1]$ (unitless) having expected value $\langle z_S \rangle$. z_S is derived from the observed frequency of clear-sky observations without methane plumes (non-detections) for that source in comparison to the frequency distribution $\rho_S(x)$ and the local instrument POD, again using Bayesian inference (Materials and Methods). The annual-

average emission rate Q_s of a source is then obtained from the expected values of the normalized emission rate x_s , the wind speed at the source u_s , and the source persistence z_s :

$$Q_s = \frac{\langle x_s \rangle}{\langle 1/u_s \rangle} \langle z_s \rangle \quad \text{Eq. 6}$$

Because of dependence between x_s and u_s coming from the definition $x = q/u$, the product of their expectations would produce a biased estimate of Q_s , but using the expected value of the inverse of u_s avoids this bias. The dependence also implies that constructing the temporal frequency distribution of emissions from a given source cannot be done from an ensemble of satellite observations taken over a range of wind speeds.

We calculate in this manner the annual time-averaged emission rates accounting for persistence for each individual point source observed by the collection of instruments (Figure 1) and for each year in 2022-2025. Each year, we include only those sources with at least one plume and three total observations including non-detections. In total across the 4 years, we have a collection of 1924 unique point sources from 12080 observations of plumes.

We estimate the error on our calculated Q_s by propagating the error in x_s due to the lognormal curve fit (parametric uncertainty on μ_s and σ_s), the error in wind speed, and the error on z_s (Materials and Methods). The resulting error on Q_s averages 67% for the ensemble of sources and is in the range 44-95% for 95% of sources. It is dominated by the error in the lognormal curve fit (50% of total error on average) followed by wind speed error (29%), and persistence error (21%).

Figure 4 maps all point sources and their annual mean emission rates Q_s in 2025, the year with the most observations because of the launch of Tanager-1. We find that 18% of the sources detected in any one of 2022-2024 were not detected in subsequent years, pointing to the ephemeral nature of many point sources. Of the 78 sources detected in 2022, 47 show sustained detections in all four years. Examples for Yemen and Turkmenistan are shown in Figs. 4D and E, respectively. The point source in Yemen comes from the Marib Central Production Unit, an oil refinery in the Block 18 oil-gas field, and shows a decreasing trend over time from $3.6 \pm 1.3 \text{ t h}^{-1}$ in 2022 to $1.1 \pm 0.6 \text{ t h}^{-1}$ in 2025. The source falls below the detection limits of Landsat and Sentinel-2 in 2025 with few multispectral detections and continued non-detections during the year but is still detectable by the hyperspectral instruments. The Turkmenistan point source is a large facility operating in the Ekizak oil-gas field with substantial and increasing emissions, rising from $5.9 \pm 1.9 \text{ t h}^{-1}$ in 2023 to $14.0 \pm 6.9 \text{ tons h}^{-1}$ in 2025, the largest source in our database.

Figure 4F shows the cumulative distribution function (CDF) of Q_s by year for all sources in our database. The distribution is heavy-tailed, as is typically found (Brandt et al., 2016; Cusworth et al., 2026; Ehret et al., 2022; Lauvaux et al., 2022; Sherwin et al., 2024b; Zavala-Araiza et al., 2015), with 17% of sources emitting more than 1 ton h^{-1} (245 sources) in 2025 and accounting for 53% of emissions. The CDF is more heavy-tailed in 2022 because 84% of detections that year are by Sentinel-2 and Landsat. The portion of sources smaller than 1 t h^{-1} increases in 2025 with the launch of Tanager.

Our calculation of the persistence of a source within a given year accounts for undetected emissions due to the instrument POD (Materials and Methods). We find a mean persistence of $51 \pm 24\%$ across all sources. Our calculated persistence is higher than previous estimates (Cusworth et al., 2022; Jervis et al., 2025) that did not account for undetected emissions. A consequence is that our calculated annual mean emissions is higher than these estimates.

East et al. (2025) previously inferred global oil-gas emissions in 2023 on a $0.25^\circ \times 0.3125^\circ$ grid by inversion of TROPOMI satellite data. Starting from the bottom-up Global Fuel Emissions

Inventory (GFEI) v3 (Scarpelli et al., 2025) as prior estimate, they found a global emission of 58 Tg y⁻¹ as compared to the GFEI value of 43 Tg y⁻¹. Here we estimate total emissions from all oil-gas point sources in our database in 2023 to be 4.3 Tg y⁻¹, representing 7% of the global 2023 oil-gas emissions inferred by East et al. (2025) and up to 28% for Turkmenistan. Our total goes up to 7.6 Tg y⁻¹ in 2025, reflecting the larger number of plumes in the IMEO database and the launch of the Tanager instrument.

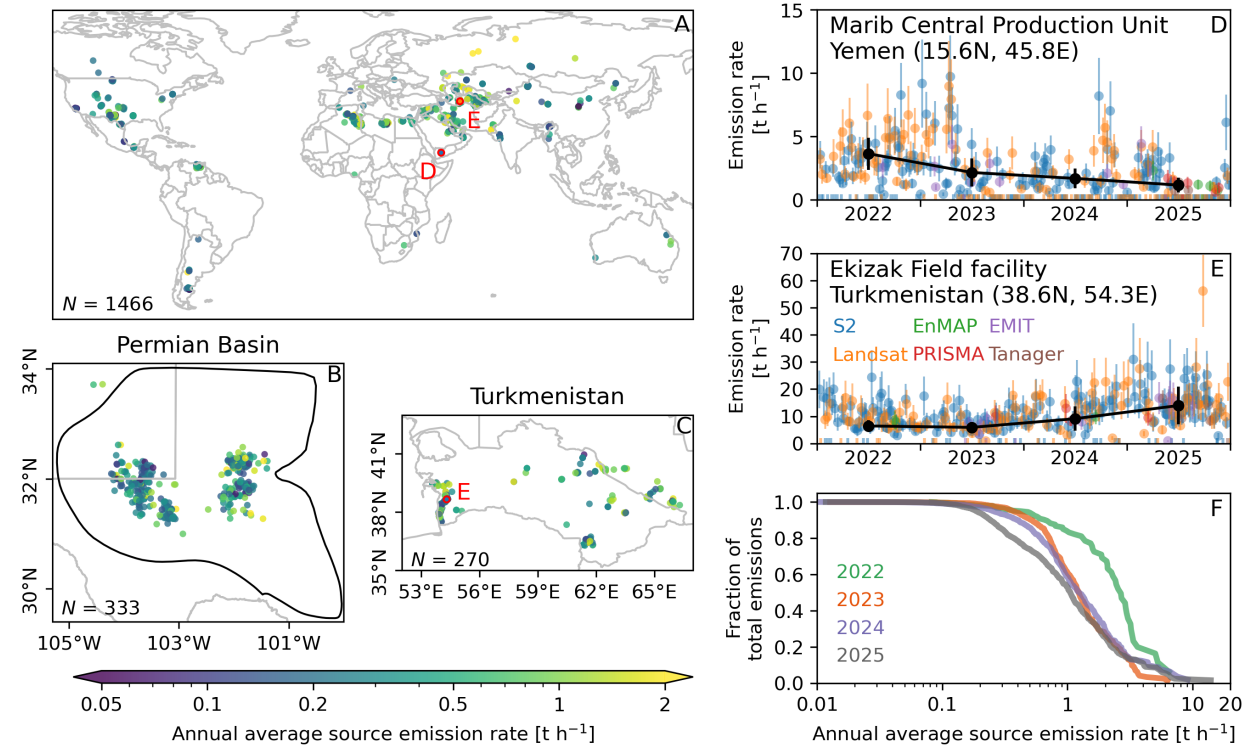


Figure 4: Annual average point source emission rates Q_s compiled in our database from open-source satellite data for 2022-2025. 2025 values are shown in (A-C) for the globe, the Permian Basin, and Turkmenistan. Points on the maps are colored by their annual average emission rate. Also shown are time series of instantaneous source rates, uncertainties, and non-detections reported by the different instruments (colored by instrument) at the Marib Central Production Unit in Yemen (D) and an oil-gas facility at the Ekizak field in Turkmenistan (E), together with annual average emission rates Q_s as black symbols with uncertainty bars, and black lines added for visualization of trends. Dash marks along the x-axis are non-detections (clear sky observations without plumes), colored by instrument. Locations of the selected point sources are circled and labeled in red in panels (A-C) and inset in (D-E). (F) shows the cumulative distributions of annual average emissions by year for all sources globally.

GHGSat, Inc. has been launching a growing fleet of satellite point source imagers starting in 2016 and with 15 instruments in orbit as of 2026 (Ramier et al., 2026). The data are not publicly available and therefore not included in our analysis, but we compare our results in 2023 to those of Jervis et al. (2025) who used 8 instruments in the GHGSat fleet for their own compilation of annual mean point source rates during 2023. Fig. 5 compares our Q_s estimates worldwide to the GHGSat estimates on a $0.25^\circ \times 0.3125^\circ$ grid, and to bottom-up GFEI v3 estimates (Scarpelli et al., 2025) on a $0.1^\circ \times 0.1^\circ$ grid. We find modest correlation ($r = 0.36$) with GHGSat and agreement to within a factor of four for 66% of sources. GHGSat's emission estimates are calculated as the mean of the observed plumes at each source, multiplied by the source's persistence estimated from counts of its plumes and non-detections, and adjusted by a

continental-scale prior persistence estimate created from sources with ≥ 20 observations (Jervis et al., 2025). Our estimates tend to be higher with a 0.7 t h^{-1} average difference, and systematically so for GHGSat source rates $< 100 \text{ kg h}^{-1}$. Such a difference may be expected since the GHGSat estimate does not account for emissions below the POD in its persistence-weighted source rates. The difference is reflected in persistence; our mean persistence in 2023 is 56%, much larger than the 16% of Jervis et al. (2025) due to accounting for sub-detection-threshold emissions.

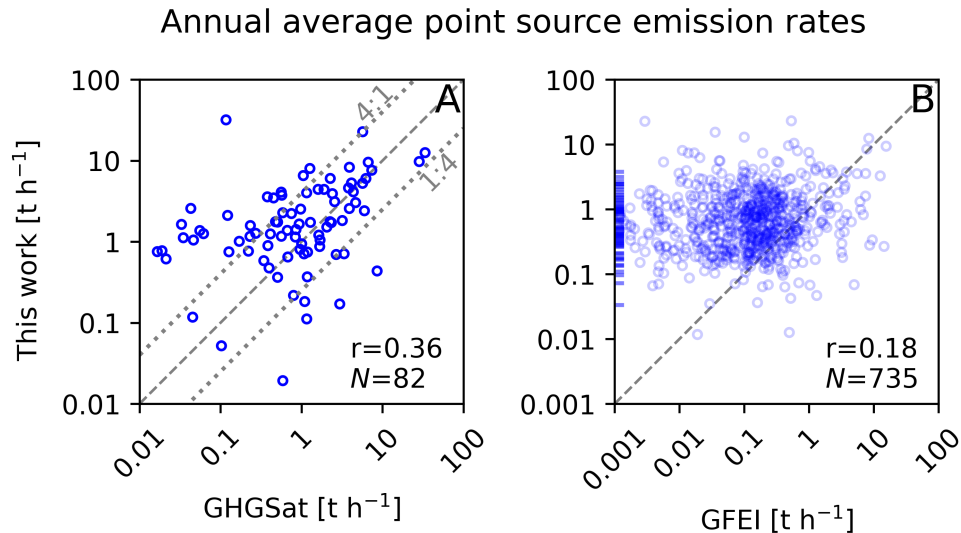


Figure 5: Comparison of our annual average estimates of oil-gas point source rates to the 2023 GHGSat (A) and GFEI (B) datasets. The GHGSat dataset of point sources is from Jervis et al. (2025) on a $0.25^\circ \times 0.3125^\circ$ grid and the bottom-up Global Fuel Exploitation Inventory (GFEI) v3 is from Scarpelli et al. (2025) on a $0.1^\circ \times 0.1^\circ$ grid. We sum our 2023 estimates on the corresponding grids, and each point on the plots represents an annual average emission for a given grid cell. Also shown are the Pearson correlation coefficient r and the number N of comparison grid cells, excepting GFEI grid cells with emissions less than 1 kg h^{-1} (66 closely spaced dashes along the y axis).

Correlation with GFEI is weak ($r = 0.18$) and we estimate emissions to be 2.5-fold larger on average for our observed grid cells. We detect emissions in 13 $0.1^\circ \times 0.1^\circ$ grid cells that have emissions lower than 1 kg h^{-1} in GFEI. Adding missing point sources to the GFEI would increase it by 5.8 Tg y^{-1} (14%). The difference with GFEI could reflect in part an uncertainty in the location of oil-gas infrastructure, but it is also consistent with the large underestimate of oil-gas emission inventories previously reported in inversions of satellite observations (Deng et al., 2022; East et al., 2025; Shen et al., 2023; Tibrewal et al., 2024; Williams et al., 2026; Yu et al., 2026). The GFEI inventory is calibrated to UNFCCC reporting for individual countries, and this reporting typically uses IPCC methods that do not account for large intermittent point sources.

In summary, we have developed a method to infer the probability of detection (POD) of oil-gas point sources for any satellite instrument and over any surface worldwide, and to estimate the time-averaged emissions for individual point sources from limited multi-instrument collections of instantaneous plume observations including non-detections. Our POD estimates are lower than commonly estimated from controlled-release observations under favorable conditions. We inferred annually averaged emission rates for 1924 individual oil-gas point sources worldwide from instantaneous publicly available observations by six different instruments (Sentinel-2, Landsat, EnMAP, PRISMA, EMIT, Tanager) reported by the International Methane Earth Observation (IMEO) and Carbon Mapper (CM). The corresponding total from detected pointed sources is 7.6 Tg y^{-1} for 2025 with 245 sources emitting more than 1 ton h^{-1} on an annual basis.

18% of sources emit for only one year. Within a given year we find that point sources emit on average 51% of the time (persistence), much higher than previous estimates that do not account for emissions below the POD, and resulting in higher annual mean emissions than these previous estimates. Our estimated annual mean emissions are thus 29% higher on average than a recent estimate from proprietary GHGSat satellite data, with moderate correlation for individual co-observed sources ($r = 0.34$). As the constellation of point source imagers increases, the number of detected point sources will increase, and our method can be applied to infer the corresponding annual mean emissions as input to emission inventories. Indeed, we find that many of the point sources that we detect are greatly underestimated or missing in the GFEIv3 bottom-up inventory derived from UNFCCC reporting of national oil-gas emissions

Our dataset of annual-average estimates from individual point sources for each year of 2022-2025 is available in NetCDF and CSV format at <https://doi.org/10.5281/zenodo.22651608> and can be automatically updated with the gradual addition of new IMEO and CM data. It includes for each source and year the emission rate with its uncertainty, latitude/longitude location, average persistence, average wind speed, number of plumes and non-detections observed, unique source identifier, and the IMEO source ID from IMEO's Eye on Methane Data Platform (<https://methanedata.unep.org/>) for sources where such IDs are available. Results are displayed on an interactive portal showing a global map of point sources with a time series of their emissions at <https://eastjames.github.io/pointsource-dashboard/>.

Materials and Methods

Satellite observations

Table 1 lists specifications of the different instruments used in this work. EMIT is in inclined orbit and the others are in polar sun-synchronous orbit with equatorial overpass local solar times of 1030-1300. All use the 2.3 μm methane absorption band observed in solar backscatter mode and measure plume enhancements $\Delta\Omega_{\text{CH}_4}$ of the dry-air methane column. Sentinel-2 and Landsat are multispectral instruments from which $\Delta\Omega_{\text{CH}_4}$ is retrieved from the contrast between two SWIR bands (Varon et al., 2021). The other instruments are hyperspectral with ability to resolve the 2.3 μm band (Cusworth et al., 2019; Roger et al., 2024a). The spectral resolution largely defines the

precision of the instrument (Cusworth et al., 2019), which together with the SNR defines the local POD for a given emission rate.

Table 1: Satellite point source imagers.

Instrument	Agency	Pixel resolution (m ²)	Revisit time (days)	Spectral resolution (nm)	Precision (%) ^a	SNR
<i>Multi-spectral</i>						
Sentinel-2 (A, B, C) ^{b,c}	ESA	20 × 20	5 ^d	200	30-90	100 ^e
Landsat (8, 9) ^f	USGS/NASA	30 × 30	8 ^d	200	30-90	325 ^g
<i>Hyper-spectral</i>						
EnMAP ^h	DLR	30 × 30	4-27 ⁱ	10	3-9	300 ^h
PRISMA ^j	ASI	30 × 30	7-29 ⁱ	10	3-9	150 ^h
EMIT ^k	NASA	60 × 60	24-122 ^m	7.4	2-6	500 ⁿ
Tanager-1 ^p	Carbon Mapper	30 × 30	2-8 ^q	5	0.9-2.0 ^r	400-800 ^p

^a For retrievals of Ω_{CH_4} . Estimates reported by Jacob et al. (2022) except for Tanager.

^b The Sentinel-2 suite includes three identical instruments with the same local overpass times in different orbits.

^c Varon et al. (2021)

^d Revisit time for Sentinel-2 and Landsat is the combined revisit time for all instruments in the fleet

^e Drusch et al. (2012)

^f Ehret et al. (2022)

^g Knight and Kvaran (2014)

^h Roger, Irakulis-Loitxate et al. (2024)

ⁱ PRISMA and EnMAP operate in target-mode, meaning that the instrument is pointed to view a specific scene. The lower end of the range is the minimum revisit time with targeting.

^j Guanter et al. (2021)

^k Thorpe et al. (2023)

^m EMIT is in inclined orbit and has variable overpass time of day and revisit times.

ⁿ Thompson et al. (2024)

^p Duren et al. (2025)

^q Minimum revisit time using target-mode operation as reported in Duren et al. (2025) and dependent on latitude.

^r The range in Tanager precision comes from operation in standard mode vs. maximum sensitivity mode (Duren et al., 2025).

Potential plumes are identified by IMEO using machine-learning models applied to Ω_{CH_4} images from Sentinel-2, Landsat, EnMAP, PRISMA, and EMIT, and are then confirmed by two human analysts (Mateo-Garcia et al., 2025; Růžicka et al., 2025). For Tanager, plumes are identified by CM human analysts from Ω_{CH_4} images and then undergo automated delineation (Duren et al., 2025). Plumes and non-detections are assigned to individual uniquely identified point sources by human analysts using RGB imagery and GIS data. Emission rates are obtained by the IME method using independent wind speed data. IMEO and CM have separate lists of sources to which individual plumes are assigned. We unify the separate lists of unique source locations by

assigning CM sources within 250 m of an IMEO source to that IMEO source location, and keeping the CM source alone otherwise.

Although the instruments report emission rates q (kg h^{-1}), the plume enhancements that they detect actually depend on the wind-normalized emission rate $x = q/u$ (Jacob et al., 2022). The IME approach fits x to the observed plume enhancements (Varon et al., 2021). Both q and u are given for individual plumes in the IMEO and CM data. Considering that error in u can be a major contributor to error in q (Conrad and Johnson, 2025; Gorroño et al., 2023; Varon et al., 2018), and that the instrument POD depends on x rather than q , we focus on x in our analysis. Further, due to large quantification uncertainty for $u < 1 \text{ m s}^{-1}$ (Varon et al., 2018), we drop all observations with $u < 1 \text{ m s}^{-1}$ and consider the PODs valid only for $u \geq 1 \text{ m s}^{-1}$. We also drop unrealistically small point sources, diagnosed by comparison to the instrument minimum detection threshold which we calculate as in Jacob et al. (2016). This drops $<1\%$ of the detected plumes. For the POD analysis we use all available plume observations in the IMEO and CM databases up to the end of 2025 using the filtering described above, totaling 15037 observations with contributions from the instruments of 6036 (Sentinel-2), 3175 (Landsat), 602 (EnMAP), 412 (PRISMA), 2973 (EMIT), and 1839 (Tanager). For estimating point source emission rates, we further restrict observations to those in 2022-2025 and only estimate sources with at least three observations including non-detections.

Empirically derived probability of detection

We estimate parameters x_{50} , s , μ , and σ of Eqs. 1-3 for each instrument using the global ensemble of the instrument's point source observations. The normalization factor C of Eq. 1 is

$$C(x_{50}, s, \mu, \sigma) = \int_0^\infty \text{POD}(x; x_{50}, s) \rho(x; \mu, \sigma) dx \quad \text{Eq. 7}$$

where the parameters x_{50} , s , μ , and σ are from Eqs. 1-3. C also has a physical meaning as the instrument's global detection fraction. From Bayes theorem, the inferred posterior parameter distributions are proportional to the product of their joint prior distributions and their likelihood given observations x . This is given in log space by

$$\ln p(x_{50}, s, \mu, \sigma | x) \propto \ln p(x_{50}, s, \mu, \sigma) + \ln L(x_{50}, s, \mu, \sigma; x) \quad \text{Eq. 8}$$

where $p(x_{50}, s, \mu, \sigma | x)$ is the joint posterior distribution of the parameters given the plume observations x , and $p(x_{50}, s, \mu, \sigma)$ is the joint prior distribution for the parameters. The likelihood $L(x_{50}, s, \mu, \sigma; x)$ describes the likelihood of observing x under all possible values of the parameters according to their prior distributions. We construct $p(x_{50}, s, \mu, \sigma | x)$ using the No U-Turn Sampler implementation of Markov-Chain Monte Carlo (MCMC) (Hoffman and Gelman, 2014). Parameter prior distributions are uniform distributions spanning $1\text{-}3000 \text{ kg h}^{-1} \text{ per m s}^{-1}$ for x_{50} , $0.2\text{-}2.0$ for s , $0.1\text{-}8.0$ for μ , and $0.5\text{-}2.5$ for σ , and are the same for all instruments. We perform the inference independently for each instrument.

The likelihood $L(x_{50}, s, \mu, \sigma; x)$ is defined as the product of all values of $f(x; x_{50}, s, \mu, \sigma)$ computed at N observations of x :

$$L(x_{50}, s, \mu, \sigma; x) = \prod_{j=1}^N f(x; x_{50}, s, \mu, \sigma) \quad \text{Eq. 9}$$

After substituting Eq. 1, its log is:

$$\ln L(x_{50}, s, \mu, \sigma; x) = -N \ln C(x_{50}, s, \mu, \sigma) + \sum_{j=1}^N \ln(\rho(x; \mu, \sigma)) + \sum_{j=1}^N \ln(\text{POD}(x; x_{50}, s)) \quad \text{Eq. 10}$$

We then generate parameter estimates by using MCMC to sample the posterior distribution in Eq. 8 uniquely for each instrument's observations x . We tested for $\rho(x)$ either the lognormal

distribution of Eq. 1 or a power-law distribution $\rho(x; \alpha) = x^{-\alpha}$, both chosen to describe the heavily right-skewed temporal frequency distributions of source emission rates (Allen et al., 2022; Chen et al., 2022; Daniels and Hammerling, 2026; Daniels et al., 2025; Khaliukova et al., 2025; Kunkel et al., 2023). From the resulting two sets of parameters, we choose that which minimizes the Widely Applicable Information Criterion (WAIC) score (Watanabe, 2010), a measure of the variance in $f(x)$ coming from variance in $p(x_{50}, s, \mu, \sigma|x)$. We find that using the log-normal rate distribution for $\rho(x)$ minimizes the WAIC for all instruments so we use that for the analysis. Parameter values are then taken as the expected value of their marginal posterior distributions and define the POD for each instrument.

Background noise

Calculation of the background noise ΔB requires statistics on pixel-level column enhancements $\Delta\Omega_{\text{CH}_4}$ outside of the plumes. EMIT is the only hyperspectral instrument providing that information as $\Delta\Omega_{\text{CH}_4}$ across its viewing scenes, and we obtain it from the EMITL2BCH4ENH V002 data product (Thorpe et al., 2025) for August 2022 through 2025. We obtain that information for Sentinel-2 by using 68500 globally distributed MBMP retrievals outside of detected plumes (Varon et al., 2021). Although ΔB is instrument-specific because of its dependence on instrument precision, the local-to-global ratio $\Delta B_L/\Delta B_G$ (Eq. 5) should largely eliminate that dependence, except between multispectral and hyperspectral instruments. Our approach is therefore to construct global gridded maps of the ratio $\Delta B_L/\Delta B_G$ from EMIT and Sentinel-2 data, and then apply the local ratio through Eq. 5 to derive the local POD for multispectral instruments (Sentinel-2 and Landsat) using ΔB from Sentinel-2, and for hyperspectral instruments (EnMAP, PRISMA, EMIT, Tanager) using ΔB from EMIT.

For each EMIT 75×75 km tile and each Sentinel-2 scene, we compute a ΔB value as the median absolute deviation (MAD) of the pixel enhancements for all pixels j :

$$\Delta B = \text{median}(|\Delta\Omega_j - \bar{\Delta\Omega}|) \quad \text{Eq. 11}$$

where $\Delta\Omega_j$ is the column enhancement in individual pixels j reported by the instrument, and $\bar{\Delta\Omega}$ is the median enhancement in the scene. The MAD is robust to outliers in the data and so it effectively excludes plumes. For each instrument, the global background noise ΔB_G is computed by sampling the EMIT or Sentinel-2 ΔB maps in Fig. 3 at all plume locations and taking the median, because the instruments sample differently over the globe. Few plumes are observed outside EMIT's latitudinal range by any of the hyperspectral instruments but in those cases we use the nearest-neighbor value in the calculation.

Point source wind-normalized emission rate frequency distribution

To compute the distribution of x for an individual source S observed by an instrument, we use $f(x)$ of Eq. 1 after its fit to global observations as a prior estimate and then perform a Bayesian update to the individual source parameters μ_S and σ_S using plume observations x_S by the instrument. We do not update the POD parameters x_{50} and s , instead using $x_{50,L}$ calculated in Eq. 5 and keeping s from the MCMC global inference. We compute the joint posterior distribution of μ_S and σ_S using Bayes' Theorem:

$$p(\mu_S, \sigma_S | x_S) = \frac{p(\mu_S, \sigma_S) L(\mu_S, \sigma_S; x_S)}{\int \int p(\mu_S, \sigma_S) L(\mu_S, \sigma_S; x_S) d\mu d\sigma} \quad \text{Eq. 12}$$

where $L(\mu_S, \sigma_S; x_S)$ is the log-likelihood of Eq. 10 computed using the N observations x_S for source S rather than all global observations, and $p(\mu_S, \sigma_S)$ is the joint prior distribution for the parameters, for which we use the joint posterior distribution from Eq. 8. The computation is done by Bayesian grid approximation. The update is performed uniquely for each instrument with observations at the source. Then, at each source, we combine the posterior distributions of μ_S and σ_S across

instruments into source-level posterior mixture distributions μ_s and σ_s . Each instrument's contributions to the posterior mixture distributions μ_s and σ_s is inverse-weighted by the variance in its instrument-specific distributions of μ_s of σ_s . We then create the source-specific rate distribution estimate $\rho_s(x; \mu_s, \sigma_s)$, using the medians of the μ_s and σ_s marginal distributions. This approach trades spatial variability for temporal variability by the ergodic assumption (Birkhoff, 1931), which is frequently invoked for reconciling oil-gas point source instantaneous emissions with time-averaged emission rates (Chen et al., 2022; Daniels and Hammerling, 2026; Gorchoff Negron et al., 2023; Kamdar et al., 2025; Tullios et al., 2021).

Source-level wind speed distributions

We model the 10-m wind speed distribution U using a Weibull function, known to be a good fit for observed wind speeds (Burton et al., 2011):

$$U(u; \lambda, k) = \frac{k}{\lambda} \left(\frac{u}{\lambda}\right)^{k-1} e^{-(u/\lambda)^k} \quad \text{Eq. 13}$$

where λ (m s^{-1}) is the Weibull scale parameter that describes a characteristic wind speed and k (unitless) is the Weibull shape parameter that describes variability. Their prior estimates are found by fitting Eq. 14 to the distribution of all wind speeds u (m s^{-1}) in our dataset across all instruments including non-detections using Maximum Likelihood Estimation (MLE), yielding global values $\lambda_G = 4.5 \text{ m s}^{-1}$ and $k_G = 1.9$, representing overpass-time wind distribution. The global average wind speed $\bar{u}$ is 4.0 m s^{-1} and the mode is 3.2 m s^{-1} .

We construct the wind speed distribution at individual source locations by updating λ using all wind speeds observed at source s . By Bayes Theorem:

$$p(\lambda_s | u_s) = \frac{p(\lambda_s) L(\lambda_s)}{\int p(\lambda_s) L(\lambda_s) d\lambda} \quad \text{Eq. 14}$$

where λ_s is the source-specific Weibull scale parameter, $p(\lambda_s | u_s)$ is the posterior distribution of λ_s given source wind speeds u_s , $p(\lambda_s)$ is its prior distribution which is a uniform distribution from 0.5 to 20, and $L(\lambda_s)$ is the likelihood function:

$$L(\lambda_s) = \prod_{j=1}^N U(u_s, \lambda_s) \quad \text{Eq. 15}$$

where $U(u_s, \lambda_s)$ is the Weibull distribution truncated at 1 m s^{-1} to match our data filtering. $L(\lambda_s)$ is computed for N wind speed observations u_s at the site. The Weibull shape parameter k is held constant at its MLE estimated value k_G because there is more variation in λ across sites. The best posterior estimate for λ_s is the mean of the posterior distribution. The source wind speed distribution is then $U_s(u) = U(u; \lambda_s, k_G)$.

Source persistence

The lognormal distribution ρ_s of wind-normalized source rates for a given point source assumes that the source is on. However, the source may be off part of the time (Cusworth et al., 2026; Khaliukova et al., 2025; Schissel and Allen, 2022). The clear-sky observations without plumes (non-detections) in our database cannot represent this because they cannot distinguish whether the source is off or emitting below a level detectable by the instrument. We therefore construct a

multi-instrument, source-level persistence estimate z_S that accounts for the instruments' PODs and is built from all observations at the source by applying Bayes Theorem:

$$p(z_S|d) = \frac{p(z_S)L(z_S)}{\int p(z_S)L(z_S)dz} \quad \text{Eq. 16}$$

where $d = 1$ for a detection and 0 for a non-detection, $z_S \in [0, 1]$ is the source persistence variable, and $p(z_S)$ is the prior distribution of z_S . For N total observations at site S , the likelihood function is built from the binomial distribution:

$$L(z_S) = \prod_{j=1}^N (z_S \pi_j)^{d_j} (1 - z_S \pi_j)^{1-d_j} \quad \text{Eq. 17}$$

where π_j is the probability that an active source would have been detected on observation j . It is computed for each observation j from the instrument- and source-specific POD and rate distribution ρ_S applicable to that observation:

$$\pi_j = \int_0^{\infty} POD_{i,S}(x) \rho_S(x) dx \quad \text{Eq. 18}$$

where the subscript i refers to the instrument. For the prior $p(z_S)$, we use a uniform distribution spanning $[0, 1]$. This allows information about the source persistence to come exclusively from $L(z_S)$. We compute z_S for each year that a source is active and take its mean as the average value of $p(z_S|d)$. z_S is a Beta distribution and has variance $\sigma_z^2 = \alpha\beta/((\alpha + \beta)^2(\alpha + \beta + 1))$, where α is the number of detections +1, and β is the number of non-detections +1.

Error analysis

We calculate errors on the annual emission estimates Q_S for individual sources from the error standard deviations of x_S (σ_x), wind speed (σ_u), and persistence (σ_z). The relative error standard deviation σ_x/x_S for each source is the coefficient of variation (CV) of the mean $\langle x_S \rangle = \exp(\mu_S + \sigma_S^2/2)$ computed from sampling the joint log-normal source distribution (μ_S, σ_S) , with CV computed as the median absolute deviation over the median of the samples of $\langle x_S \rangle$. Wind speed relative error standard deviation σ_u/u is 30% (Varon et al., 2018). Persistence relative error variance is as defined in the previous section. Assuming that the errors in x_S , u_S , and z_S are uncorrelated, the relative error standard deviation on Q_S is obtained by adding the error variances in quadrature:

$$\frac{\sigma_{Q_S}}{Q_S} = \sqrt{\left(\frac{\sigma_{x_S}}{x_S}\right)^2 + \left(\frac{\sigma_{u_S}}{u_S}\right)^2 + \left(\frac{\sigma_{z_S}}{z_S}\right)^2} \quad \text{Eq. 19}$$

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References

- Allen, D. T., Cardoso-Saldaña, F. J., Kimura, Y., Chen, Q., Xiang, Z., Zimmerle, D., Bell, C., Lute, C., Duggan, J., and Harrison, M.: A Methane Emission Estimation Tool (MEET) for predictions of emissions from upstream oil and gas well sites with fine scale temporal and spatial resolution: Model structure and applications, *Science of The Total Environment*, 829, 154277, <https://doi.org/10.1016/j.scitotenv.2022.154277>, 2022.
- Ayasse, A. K., Thorpe, A. K., Roberts, D. A., Funk, C. C., Dennison, P. E., Frankenberg, C., Steffke, A., and Aubrey, A. D.: Evaluating the effects of surface properties on methane retrievals using a synthetic airborne visible/infrared imaging spectrometer next generation (AVIRIS-NG) image, *Remote Sensing of Environment*, 215, 386–397, <https://doi.org/10.1016/j.rse.2018.06.018>, 2018.
- Ayasse, A. K., Cusworth, D. H., Howell, K., O'Neill, K., Conrad, B. M., Johnson, M. R., Heckler, J., Asner, G. P., and Duren, R.: Probability of Detection and Multi-Sensor Persistence of Methane Emissions from Coincident Airborne and Satellite Observations, *Environ. Sci. Technol.*, 58, 21536–21544, <https://doi.org/10.1021/acs.est.4c06702>, 2024.
- Birkhoff, G. D.: Proof of the Ergodic Theorem, *Proc. Natl. Acad. Sci. U.S.A.*, 17, 656–660, <https://doi.org/10.1073/pnas.17.2.656>, 1931.
- Brandt, A. R., Heath, G. A., and Cooley, D.: Methane Leaks from Natural Gas Systems Follow Extreme Distributions, *Environ. Sci. Technol.*, 50, 12512–12520, <https://doi.org/10.1021/acs.est.6b04303>, 2016.
- Bruno, J. H., Jervis, D., Varon, D. J., and Jacob, D. J.: U-Plume: automated algorithm for plume detection and source quantification by satellite point-source imagers, *Atmos. Meas. Tech.*, 17, 2625–2636, <https://doi.org/10.5194/amt-17-2625-2024>, 2024.
- Burton, T., Jenkins, N., Sharpe, D., and Bossanyi, E.: *Wind energy handbook*, 2nd ed., Wiley, Chichester, West Sussex, 1 p., <https://doi.org/10.1002/9781119992714>, 2011.
- Carbon Mapper: Carbon Mapper Data, <https://carbonmapper.org/data> (last access: 3 July 2025), 2025.
- Chen, Y., Sherwin, E. D., Berman, E. S. F., Jones, B. B., Gordon, M. P., Wetherley, E. B., Kort, E. A., and Brandt, A. R.: Quantifying Regional Methane Emissions in the New Mexico Permian Basin with a Comprehensive Aerial Survey, *Environ. Sci. Technol.*, 56, 4317–4323, <https://doi.org/10.1021/acs.est.1c06458>, 2022.
- Conrad, B. M. and Johnson, M. R.: Accounting for spatiotemporally correlated errors in wind speed for remote surveys of methane emissions, <https://doi.org/10.5194/egusphere-2025-3924>, 8 September 2025., 2025.
- Conrad, B. M., Tyner, D. R., and Johnson, M. R.: Robust probabilities of detection and quantification uncertainty for aerial methane detection: Examples for three airborne technologies, *Remote Sensing of Environment*, 288, 113499, <https://doi.org/10.1016/j.rse.2023.113499>, 2023.
- Cusworth, D. H., Jacob, D. J., Varon, D. J., Chan Miller, C., Liu, X., Chance, K., Thorpe, A. K., Duren, R. M., Miller, C. E., Thompson, D. R., Frankenberg, C., Guanter, L., and Randles, C. A.: Potential of next-generation imaging spectrometers to detect and quantify methane point sources from space, *Atmos. Meas. Tech.*, 12, 5655–5668, <https://doi.org/10.5194/amt-12-5655-2019>, 2019.
- Cusworth, D. H., Thorpe, A. K., Ayasse, A. K., Stepp, D., Heckler, J., Asner, G. P., Miller, C. E., Yadav, V., Chapman, J. W., Eastwood, M. L., Green, R. O., Hmiel, B., Lyon, D. R., and Duren, R. M.: Strong methane point sources contribute a disproportionate fraction of total emissions across multiple basins in the United States, *Proc. Natl. Acad. Sci. U.S.A.*, 119, e2202338119, <https://doi.org/10.1073/pnas.2202338119>, 2022.
- Cusworth, D. H., Duren, R. M., Ayasse, A. K., Jiorle, R., Howell, K., Aubrey, A., Green, R. O., Eastwood, M. L., Chapman, J. W., Thorpe, A. K., Heckler, J., Asner, G. P., Smith, M. L., Thoma, E., Krause, M. J., Heins,

- 679 D., and Thorneloe, S.: Quantifying methane emissions from United States landfills, *Science*, 383, 1499–
680 1504, <https://doi.org/10.1126/science.adi7735>, 2024.
- 681 Cusworth, D. H., Bon, D. M., Varon, D. J., Ayasse, A. K., Asner, G. P., Heckler, J., Sherwin, E. D., Biraud, S.
682 C., and Duren, R. M.: Duration of super-emitting oil and gas methane sources, *Nat Commun*, 17, 2011,
683 <https://doi.org/10.1038/s41467-026-68804-7>, 2026.
- 684 Daniels, W. and Hammerling, D.: Sampling variability under extreme skewness: sample size guidance for
685 future methane measurement campaigns, <https://doi.org/10.31223/X5MR0K>, 4 February 2026., 2026.
- 686 Daniels, W. S., Kidd, S. G., Yang, S. L., Stokes, S., Ravikumar, A. P., and Hammerling, D. M.:
687 Intercomparison of Three Continuous Monitoring Systems on Operating Oil and Gas Sites, *ACS EST Air*, 2,
688 564–577, <https://doi.org/10.1021/acsestair.4c00298>, 2025.
- 689 Deng, Z., Ciais, P., Tzompa-Sosa, Z. A., Saunio, M., Qiu, C., Tan, C., Sun, T., Ke, P., Cui, Y., Tanaka, K.,
690 Lin, X., Thompson, R. L., Tian, H., Yao, Y., Huang, Y., Lauerwald, R., Jain, A. K., Xu, X., Bastos, A., Sitch,
691 S., Palmer, P. I., Lauvaux, T., d'Aspremont, A., Giron, C., Benoit, A., Poulter, B., Chang, J., Petrescu, A. M.
692 R., Davis, S. J., Liu, Z., Grassi, G., Albergel, C., Tubiello, F. N., Perugini, L., Peters, W., and Chevallier, F.:
693 Comparing national greenhouse gas budgets reported in UNFCCC inventories against atmospheric
694 inversions, *Earth Syst. Sci. Data*, 14, 1639–1675, <https://doi.org/10.5194/essd-14-1639-2022>, 2022.
- 695 Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti,
696 P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., and Bargellini, P.: Sentinel-2: ESA's Optical
697 High-Resolution Mission for GMES Operational Services, *Remote Sensing of Environment*, 120, 25–36,
698 <https://doi.org/10.1016/j.rse.2011.11.026>, 2012.
- 699 Duren, R. M., Thorpe, A. K., Foster, K. T., Rafiq, T., Hopkins, F. M., Yadav, V., Bue, B. D., Thompson, D. R.,
700 Conley, S., Colombi, N. K., Frankenberg, C., McCubbin, I. B., Eastwood, M. L., Falk, M., Herner, J. D.,
701 Croes, B. E., Green, R. O., and Miller, C. E.: California's methane super-emitters, *Nature*, 575, 180–184,
702 <https://doi.org/10.1038/s41586-019-1720-3>, 2019.
- 703 Duren, R. M., Cusworth, D., Ayasse, A., Howell, K., Diamond, A., Scarpelli, T., Kim, J., O'Neill, K., Lai-
704 Norling, J., Thorpe, A., Zandbergen, S. R., Shaw, L., Keremedjiev, M., Guido, J., Giuliano, P., Goldstein, M.,
705 Nallapu, R., Barentsen, G., Thompson, D. R., Roth, K., Jensen, D., Eastwood, M., Reuland, F., Adams, T.,
706 Brandt, A., Kort, E. A., Mason, J., and Green, R. O.: The Carbon Mapper emissions monitoring system,
707 *Atmos. Meas. Tech.*, 18, 6933–6958, <https://doi.org/10.5194/amt-18-6933-2025>, 2025.
- 708 East, J. D., Jacob, D. J., Jervis, D., Balasus, N., Estrada, L. A., Hancock, S. E., Sulprizio, M. P., Thomas, J.,
709 Wang, X., Chen, Z., Varon, D. J., and Worden, J. R.: Worldwide inference of national methane emissions by
710 inversion of satellite observations with UNFCCC prior estimates, *Nat Commun*, 16, 11004,
711 <https://doi.org/10.1038/s41467-025-67122-8>, 2025.
- 712 Ehret, T., De Truchis, A., Mazzolini, M., Morel, J.-M., d'Aspremont, A., Lauvaux, T., Duren, R., Cusworth, D.,
713 and Facciolo, G.: Global Tracking and Quantification of Oil and Gas Methane Emissions from Recurrent
714 Sentinel-2 Imagery, *Environ. Sci. Technol.*, 56, 10517–10529, <https://doi.org/10.1021/acs.est.1c08575>,
715 2022.
- 716 Frankenberg, C., Thorpe, A. K., Thompson, D. R., Hulley, G., Kort, E. A., Vance, N., Borchardt, J., Krings,
717 T., Gerilowski, K., Sweeney, C., Conley, S., Bue, B. D., Aubrey, A. D., Hook, S., and Green, R. O.: Airborne
718 methane remote measurements reveal heavy-tail flux distribution in Four Corners region, *Proc. Natl. Acad.*
719 *Sci. U.S.A.*, 113, 9734–9739, <https://doi.org/10.1073/pnas.1605617113>, 2016.
- 720 Gorchoy Negron, A. M., Kort, E. A., Chen, Y., Brandt, A. R., Smith, M. L., Plant, G., Ayasse, A. K.,
721 Schwiethke, S., Zavala-Araiza, D., Hausman, C., and Adames-Corraliza, Á. F.: Excess methane emissions
722 from shallow water platforms elevate the carbon intensity of US Gulf of Mexico oil and gas production, *Proc.*
723 *Natl. Acad. Sci. U.S.A.*, 120, e2215275120, <https://doi.org/10.1073/pnas.2215275120>, 2023.

- 724 Gorroño, J., Varon, D. J., Irakulis-Loitxate, I., and Guanter, L.: Understanding the potential of Sentinel-2 for
725 monitoring methane point emissions, *Atmos. Meas. Tech.*, 16, 89–107, [https://doi.org/10.5194/amt-16-89-](https://doi.org/10.5194/amt-16-89-2023)
726 2023, 2023.
- 727 Guanter, L., Irakulis-Loitxate, I., Gorroño, J., Sánchez-García, E., Cusworth, D. H., Varon, D. J., Cogliati, S.,
728 and Colombo, R.: Mapping methane point emissions with the PRISMA spaceborne imaging spectrometer,
729 *Remote Sensing of Environment*, 265, 112671, <https://doi.org/10.1016/j.rse.2021.112671>, 2021.
- 730 Hoffman, M. D. and Gelman, A.: The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian
731 Monte Carlo, *Journal of Machine Learning Research*, 15, 1593–1623, 2014.
- 732 IMEO: An Eye on Methane 2025: From Measurement to Momentum, United Nations Environment
733 Programme, <https://wedocs.unep.org/handle/20.500.11822/48664>, 2025a.
- 734 IMEO: Eye on methane data platform. UN Environment Programme., <https://methanedata.unep.org/> (last
735 access: 3 July 2025b), 2025.
- 736 IPCC: Summary for Policymakers, in: *Climate Change 2021: The physical science basis. Contributions of*
737 *Working Group 1 to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited
738 by: Masson-Demotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y.,
739 Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K.,
740 Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., Cambridge University Press, 2021.
- 741 Irakulis-Loitxate, I., Guanter, L., Maasackers, J. D., Zavala-Araiza, D., and Aben, I.: Satellites Detect
742 Abatable Super-Emissions in One of the World's Largest Methane Hotspot Regions, *Environ. Sci. Technol.*,
743 56, 2143–2152, <https://doi.org/10.1021/acs.est.1c04873>, 2022.
- 744 Jacob, D. J., Turner, A. J., Maasackers, J. D., Sheng, J., Sun, K., Liu, X., Chance, K., Aben, I., McKeever,
745 J., and Frankenberg, C.: Satellite observations of atmospheric methane and their value for quantifying
746 methane emissions, *Atmos. Chem. Phys.*, 16, 14371–14396, <https://doi.org/10.5194/acp-16-14371-2016>,
747 2016.
- 748 Jacob, D. J., Varon, D. J., Cusworth, D. H., Dennison, P. E., Frankenberg, C., Gautam, R., Guanter, L.,
749 Kelley, J., McKeever, J., Ott, L. E., Poulter, B., Qu, Z., Thorpe, A. K., Worden, J. R., and Duren, R. M.:
750 Quantifying methane emissions from the global scale down to point sources using satellite observations of
751 atmospheric methane, *Atmos. Chem. Phys.*, 22, 9617–9646, <https://doi.org/10.5194/acp-22-9617-2022>,
752 2022.
- 753 Jervis, D., Girard, M., MacLean, J.-P. W., Marshall, D., McKeever, J., Strupler, M., Ramier, A., Tarrant, E.,
754 Young, D., Maasackers, J. D., Aben, I., and Scarpelli, T. R.: Global energy sector methane emissions
755 estimated by using facility-level satellite observations, *Science*, 390, 1151–1155,
756 <https://doi.org/10.1126/science.adv3183>, 2025.
- 757 Jervis, D., MacLean, J.-P. W., McKeever, J., Ramier, A., and Strupler, M.: Joint Estimation of the Global
758 Facility-Scale Oil–Gas Methane Emission Rate Distribution and Survey-Mode Detection Probabilities from
759 Multiple Satellite Systems, *Environ. Sci. Technol.*, 60, 14961–14970,
760 <https://doi.org/10.1021/acs.est.5c17089>, 2026.
- 761 Johnson, M. R., Conrad, B. M., and Tyner, D. R.: Creating measurement-based oil and gas sector methane
762 inventories using source-resolved aerial surveys, *Commun Earth Environ*, 4, 139,
763 <https://doi.org/10.1038/s43247-023-00769-7>, 2023.
- 764 Kamdar, H., Kruguer, J., Weller, Z., Sherwin, E., Chen, Y., Romo, J., Owens, L., Yakolev, P., Wetherley, E.,
765 and Berman, E.: Creating Accurate Methane Emission Inventories through Data-Driven Airborne Survey
766 Strategies, <https://doi.org/10.46855/energy-proceedings-11754>, 6 February 2025., 2025.
- 767 Khaliukova, O., Zhu, Y., Daniels, W. S., Ravikumar, A. P., Ross, G. B., Roman-White, S. A., George, F. C.,
768 and Hammerling, D. M.: Investigating Aerial Data Preanalysis Schemes and Site-Level Methane Emission

- 769 Aggregation Methods at Liquefied Natural Gas Facilities, ACS EST Air, 2, 1009–1019,
770 <https://doi.org/10.1021/acsestair.4c00301>, 2025.
- 771 Knight, E. and Kvaran, G.: Landsat-8 Operational Land Imager Design, Characterization and Performance,
772 Remote Sensing, 6, 10286–10305, <https://doi.org/10.3390/rs61110286>, 2014.
- 773 Kunkel, W. M., Carre-Burritt, A. E., Aivazian, G. S., Snow, N. C., Harris, J. T., Mueller, T. S., Roos, P. A.,
774 and Thorpe, M. J.: Extension of Methane Emission Rate Distribution for Permian Basin Oil and Gas
775 Production Infrastructure by Aerial LiDAR, Environ. Sci. Technol., 57, 12234–12241,
776 <https://doi.org/10.1021/acs.est.3c00229>, 2023.
- 777 Lauvaux, T., Giron, C., Mazzolini, M., d'Aspremont, A., Duren, R., Cusworth, D., Shindell, D., and Ciais, P.:
778 Global assessment of oil and gas methane ultra-emitters, Science, 375, 557–561,
779 <https://doi.org/10.1126/science.abj4351>, 2022.
- 780 Manninen, E., Chulakadabba, A., Sargent, M., Zhang, Z., Kamdar, H., Warren, J., Roche, S., Chan Miller,
781 C., Kyzivat, E., Benmergui, J., Pittman, J., Walker, E., Bushey, J., Samra, J., Hawthorne, J., Luo, B., Nasr,
782 M., Sun, K., Franklin, J., Liu, X., Chen, J., and Wofsy, S.: Probabilities of Detection of Methane Plumes by
783 Remote Sensing and Implications for Inferred Emissions Distributions, [https://doi.org/10.5194/egusphere-](https://doi.org/10.5194/egusphere-2026-115)
784 2026-115, 3 February 2026., 2026.
- 785 Mateo-Garcia, G., Allen, A., Irakulis-Loitxate, I., Martin, M. M.-S., Watine, M., Randles, C., Mokalled, T.,
786 Raunak, A., Castañeda-Martinez, C., Jonhson, J. E., Gorroño, J., Requeima, J., Cifarelli, C., Guanter, L.,
787 Turner, R. E., and Caltagirone, M.: Artificial intelligence for methane detection: from continuous monitoring
788 to verified mitigation, <https://doi.org/10.48550/ARXIV.2511.21777>, 2025., 2025.
- 789 Ramier, A., Deglint, H., Deslieres, A., Formenti, L., Girard, M., Jervis, D., Marshall, D., MacLean, J. P.,
790 McKeever, J., McKell, A., Strupler, M., and Tarrant, E.: Performance validation of the GHGSat Methane
791 Constellation via controlled releases, <https://doi.org/10.31223/X5N78R>, 20 June 2026., 2026.
- 792 Reuland, F., Adams, T., Sherwin, E., Abbadi, S. E., Kort, E., and Brandt, A. R.: Unlocking credible space-
793 based methane sensing through a year-long single-blind test, <https://doi.org/10.21203/rs.3.rs-9110475/v1>,
794 22 April 2026., 2026.
- 795 Roger, J., Guanter, L., Gorroño, J., and Irakulis-Loitxate, I.: Exploiting the entire near-infrared spectral range
796 to improve the detection of methane plumes with high-resolution imaging spectrometers, Atmos. Meas.
797 Tech., 17, 1333–1346, <https://doi.org/10.5194/amt-17-1333-2024>, 2024a.
- 798 Roger, J., Irakulis-Loitxate, I., Valverde, A., Gorroño, J., Chabrilat, S., Brell, M., and Guanter, L.: High-
799 Resolution Methane Mapping With the EnMAP Satellite Imaging Spectroscopy Mission, IEEE Trans. Geosci.
800 Remote Sensing, 62, 1–12, <https://doi.org/10.1109/TGRS.2024.3352403>, 2024b.
- 801 Růžička, V., Mateo-García, G., Irakulis-Loitxate, I., Johnson, J. E., Martín, M. M. S., Allen, A., Raunak, A.,
802 Castaneda, C., Guanter, L., and Thompson, D. R.: Operational machine learning for remote spectroscopic
803 detection of CH₄ point sources, <https://doi.org/10.48550/ARXIV.2511.07719>, 2025., 2025.
- 804 Saunio, M., Martinez, A., Poulter, B., Zhang, Z., Raymond, P. A., Regnier, P., Canadell, J. G., Jackson, R.
805 B., Patra, P. K., Bousquet, P., Ciais, P., Dlugokencky, E. J., Lan, X., Allen, G. H., Bastviken, D., Beerling, D.
806 J., Belikov, D. A., Blake, D. R., Castaldi, S., Crippa, M., Deemer, B. R., Dennison, F., Etiope, G., Gedney,
807 N., Höglund-Isaksson, L., Holgerson, M. A., Hopcroft, P. O., Hugelius, G., Ito, A., Jain, A. K., Janardanan,
808 R., Johnson, M. S., Kleinen, T., Krummel, P. B., Lauerwald, R., Li, T., Liu, X., McDonald, K. C., Melton, J.
809 R., Mühle, J., Müller, J., Murguía-Flores, F., Niwa, Y., Noce, S., Pan, S., Parker, R. J., Peng, C., Ramonet,
810 M., Riley, W. J., Rocher-Ros, G., Rosentreter, J. A., Sasakawa, M., Segers, A., Smith, S. J., Stanley, E. H.,
811 Thanwerdas, J., Tian, H., Tsuruta, A., Tubiello, F. N., Weber, T. S., Van Der Werf, G. R., Worthy, D. E. J.,
812 Xi, Y., Yoshida, Y., Zhang, W., Zheng, B., Zhu, Q., Zhu, Q., and Zhuang, Q.: Global Methane Budget 2000–
813 2020, Earth Syst. Sci. Data, 17, 1873–1958, <https://doi.org/10.5194/essd-17-1873-2025>, 2025.
- 814 Scarpelli, T. R., Jacob, D. J., Grossman, S., Lu, X., Qu, Z., Sulprizio, M. P., Zhang, Y., Reuland, F., Gordon,
815 D., and Worden, J. R.: Updated Global Fuel Exploitation Inventory (GFEI) for methane emissions from the

- oil, gas, and coal sectors: evaluation with inversions of atmospheric methane observations, *Atmos. Chem. Phys.*, 22, 3235–3249, <https://doi.org/10.5194/acp-22-3235-2022>, 2022.
- Scarpelli, T. R., Roy, E., Jacob, D. J., Sulprizio, M. P., Tate, R. D., and Cusworth, D. H.: Using new geospatial data and 2020 fossil fuel methane emissions for the Global Fuel Exploitation Inventory (GFEI) v3, *Earth Syst. Sci. Data*, 17, 7019–7033, <https://doi.org/10.5194/essd-17-7019-2025>, 2025.
- Schissel, C. and Allen, D. T.: Impact of the High-Emission Event Duration and Sampling Frequency on the Uncertainty in Emission Estimates, *Environ. Sci. Technol. Lett.*, 9, 1063–1067, <https://doi.org/10.1021/acs.estlett.2c00731>, 2022.
- Shen, L., Jacob, D. J., Gautam, R., Omara, M., Scarpelli, T. R., Lorente, A., Zavala-Araiza, D., Lu, X., Chen, Z., and Lin, J.: National quantifications of methane emissions from fuel exploitation using high resolution inversions of satellite observations, *Nat Commun*, 14, 4948, <https://doi.org/10.1038/s41467-023-40671-6>, 2023.
- Sherwin, E. D., Rutherford, J. S., Chen, Y., Aminfard, S., Kort, E. A., Jackson, R. B., and Brandt, A. R.: Single-blind validation of space-based point-source detection and quantification of onshore methane emissions, *Sci Rep*, 13, 3836, <https://doi.org/10.1038/s41598-023-30761-2>, 2023.
- Sherwin, E. D., El Abbadi, S. H., Burdeau, P. M., Zhang, Z., Chen, Z., Rutherford, J. S., Chen, Y., and Brandt, A. R.: Single-blind test of nine methane-sensing satellite systems from three continents, *Atmos. Meas. Tech.*, 17, 765–782, <https://doi.org/10.5194/amt-17-765-2024>, 2024a.
- Sherwin, E. D., Rutherford, J. S., Zhang, Z., Chen, Y., Wetherley, E. B., Yakovlev, P. V., Berman, E. S. F., Jones, B. B., Cusworth, D. H., Thorpe, A. K., Ayasse, A. K., Duren, R. M., and Brandt, A. R.: US oil and gas system emissions from nearly one million aerial site measurements, *Nature*, 627, 328–334, <https://doi.org/10.1038/s41586-024-07117-5>, 2024b.
- Thompson, D. R., Green, R. O., Bradley, C., Brodrick, P. G., Mahowald, N., Dor, E. B., Bennett, M., Bernas, M., Carmon, N., Chadwick, K. D., Clark, R. N., Coleman, R. W., Cox, E., Diaz, E., Eastwood, M. L., Eckert, R., Ehlmann, B. L., Ginoux, P., Ageitos, M. G., Grant, K., Guanter, L., Pearlshtien, D. H., Helmlinger, M., Herzog, H., Hoefen, T., Huang, Y., Keebler, A., Kalashnikova, O., Keymeulen, D., Kokaly, R., Klose, M., Li, L., Lundeen, S. R., Meyer, J., Middleton, E., Miller, R. L., Mouroulis, P., Oaida, B., Obiso, V., Ochoa, F., Olson-Duvall, W., Okin, G. S., Painter, T. H., Pérez García-Pando, C., Pollock, R., Realmuto, V., Shaw, L., Sullivan, P., Swayze, G., Thingvold, E., Thorpe, A. K., Vannan, S., Villarreal, C., Ung, C., Wilson, D. W., and Zandbergen, S.: On-orbit calibration and performance of the EMIT imaging spectrometer, *Remote Sensing of Environment*, 303, 113986, <https://doi.org/10.1016/j.rse.2023.113986>, 2024.
- Thorpe, A. K., Green, R. O., Thompson, D. R., Brodrick, P. G., Chapman, J. W., Elder, C. D., Irakulis-Loitxate, I., Cusworth, D. H., Ayasse, A. K., Duren, R. M., Frankenberg, C., Guanter, L., Worden, J. R., Dennison, P. E., Roberts, D. A., Chadwick, K. D., Eastwood, M. L., Fahlen, J. E., and Miller, C. E.: Attribution of individual methane and carbon dioxide emission sources using EMIT observations from space, *Sci. Adv.*, 9, eadh2391, <https://doi.org/10.1126/sciadv.adh2391>, 2023.
- Thorpe, A. K., Brodrick, P., Chadwick, D., Lopez, A., Villanueva-Weeks, C., Fahlen, J., Jensen, D., Bender, H., Vinckier, Q., Xiang, C., Olson-Duvall, W., Chlus, A., Lundeen, S., Thompson, D., and Green, R.: EMIT L2B Methane Enhancement Data 60 m V002, <https://doi.org/10.5067/EMIT/EMITL2BCH4ENH.002>, 2025.
- Tibrewal, K., Ciais, P., Saunio, M., Martinez, A., Lin, X., Thanwerdas, J., Deng, Z., Chevallier, F., Giron, C., Albergel, C., Tanaka, K., Patra, P., Tsuruta, A., Zheng, B., Belikov, D., Niwa, Y., Janardanan, R., Maksyutov, S., Segers, A., Tzompa-Sosa, Z. A., Bousquet, P., and Sciare, J.: Assessment of methane emissions from oil, gas and coal sectors across inventories and atmospheric inversions, *Commun Earth Environ*, 5, 26, <https://doi.org/10.1038/s43247-023-01190-w>, 2024.
- Tullos, E. E., Stokes, S. N., Cardoso-Saldaña, F. J., Herndon, S. C., Smith, B. J., and Allen, D. T.: Use of Short Duration Measurements to Estimate Methane Emissions at Oil and Gas Production Sites, *Environ. Sci. Technol. Lett.*, 8, 463–467, <https://doi.org/10.1021/acs.estlett.1c00239>, 2021.

- 863 Varon, D. J., Jacob, D. J., McKeever, J., Jervis, D., Durak, B. O. A., Xia, Y., and Huang, Y.: Quantifying
864 methane point sources from fine-scale satellite observations of atmospheric methane plumes, *Atmos. Meas.*
865 *Tech.*, 11, 5673–5686, <https://doi.org/10.5194/amt-11-5673-2018>, 2018.
- 866 Varon, D. J., Jervis, D., McKeever, J., Spence, I., Gains, D., and Jacob, D. J.: High-frequency monitoring of
867 anomalous methane point sources with multispectral Sentinel-2 satellite observations, *Atmos. Meas. Tech.*,
868 14, 2771–2785, <https://doi.org/10.5194/amt-14-2771-2021>, 2021.
- 869 Wang, J. L., Daniels, W. S., Hammerling, D. M., Harrison, M., Burmaster, K., George, F. C., and Ravikumar,
870 A. P.: Multiscale Methane Measurements at Oil and Gas Facilities Reveal Necessary Frameworks for
871 Improved Emissions Accounting, *Environ. Sci. Technol.*, 56, 14743–14752,
872 <https://doi.org/10.1021/acs.est.2c06211>, 2022.
- 873 Watanabe, S.: Asymptotic Equivalence of Bayes Cross Validation and Widely Applicable Information
874 Criterion in Singular Learning Theory, *Journal of Machine Learning Research*, 11, 3571–3594, 2010.
- 875 Watine-Guiu, M., Varon, D. J., Irakulis-Loitxate, I., Balasus, N., and Jacob, D. J.: Geostationary satellite
876 observations of extreme and transient methane emissions from oil and gas infrastructure, *Proc. Natl. Acad.*
877 *Sci. U.S.A.*, 120, e2310797120, <https://doi.org/10.1073/pnas.2310797120>, 2023.
- 878 Williams, J. P., Benmergui, J., Knapp, M., Omara, M., Himmelberger, A., Kyzivat, E., Weatherby, K., Lyke,
879 B., Warren, J., MacKay, K., Ayvazov, S., Russi, M., LoFaso, N., Melendez, T., Miller, C. C., Roche, S.,
880 Sargent, M., Franklin, J., Nasr, M., Zhang, Z., Miller, D. J., Luo, B., Guanter, L., Hamburg, S. P., Wofsy, S.
881 C., and Gautam, R.: Methane intensity and emissions across major oil and gas basins and individual
882 jurisdictions using MethaneSAT observations, *Atmos. Chem. Phys.*, 26, 5961–5981,
883 <https://doi.org/10.5194/acp-26-5961-2026>, 2026.
- 884 Yu, X., Canadell, J. G., Henze, D. K., Patra, P. K., Saunio, M., Cen, X., Lan, X., Riddell-Young, B.,
885 Röckmann, T., and Jackson, R. B.: Incorporating methane isotopologues alters tropical and subtropical
886 methane emission estimates, *Nat Commun*, 17, 6002, <https://doi.org/10.1038/s41467-026-72668-2>, 2026.
- 887 Zavala-Araiza, D., Lyon, D. R., Alvarez, R. A., Davis, K. J., Harriss, R., Herndon, S. C., Karion, A., Kort, E.
888 A., Lamb, B. K., Lan, X., Marchese, A. J., Pacala, S. W., Robinson, A. L., Shepson, P. B., Sweeney, C.,
889 Talbot, R., Townsend-Small, A., Yacovitch, T. I., Zimmerle, D. J., and Hamburg, S. P.: Reconciling divergent
890 estimates of oil and gas methane emissions, *Proc. Natl. Acad. Sci. U.S.A.*, 112, 15597–15602,
891 <https://doi.org/10.1073/pnas.1522126112>, 2015.
- 892