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Permalink

<https://escholarship.org/uc/item/4vt1d7fh>

Journal

Environmental Science and Technology, 60(1)

ISSN

0013-936X

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Publication Date

2026-01-13

DOI

10.1021/acs.est.5c08745

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Seasonality and Declining Intensity of Methane Emissions from the Permian and Nearby US Oil and Gas Basins

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Cite This: <https://doi.org/10.1021/acs.est.5c08745>



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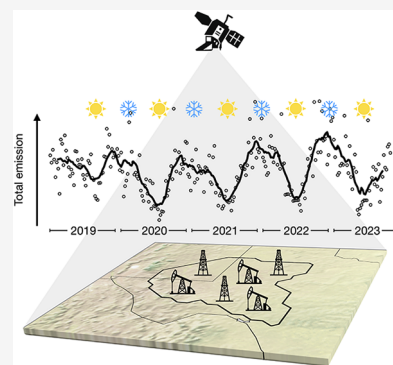
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ABSTRACT: We quantify weekly methane emissions and trends from oil and gas production in the US Permian Basin for 2019–2023, and in nearby basins for 2022–2023, by analytical inversion of Tropospheric Monitoring Instrument (TROPOMI) satellite observations with the Integrated Methane Inversion (IMI) at 25 km resolution. Permian oil and gas emissions averaged $4.0 \pm 1.1 \text{ Tg a}^{-1}$ over 2019–2023, with large seasonal variation but little interannual variability. Methane intensity fell from 5.2 to 3.2% as production surged. Intensity in the New Mexico Permian fell from 4.5 to 2.1%, approaching the state's 2026 target of <2%. Emissions were on average $50 \pm 10\%$ higher in winter than summer, which we corroborate with Permian Basin Tower Network measurements, Insight M aircraft data, and GHGSat satellite observations. This seasonality may be driven in part by higher winter emissions from liquid storage tanks due to decreased separator efficiency in cold conditions. Similar but weaker seasonality along with decreasing emissions and intensities is found in weekly inversions for the Anadarko, Barnett, Eagle Ford, and Haynesville basins in 2022–2023. Our work suggests that better weatherization of oil and gas facilities could significantly reduce methane emissions.

KEYWORDS: Permian, methane, seasonality, TROPOMI



1. INTRODUCTION

Curbing methane emissions is a powerful lever to slow near-term warming. Anthropogenic methane emissions come from a wide range of activities in the agriculture, fossil fuel, and waste sectors.¹ Emissions from oil and gas production have been identified as a priority for mitigation in part because the captured gas can be sold and because relatively few companies control the means of production.² Satellite observations of atmospheric methane offer a means to quantify emissions and their trends in oil and gas production regions worldwide.^{3,4} The Tropospheric Monitoring Instrument (TROPOMI) aboard the Sentinel-5P satellite provides a uniquely dense record of global methane concentrations with up to $7 \times 5.5\text{-km}^2$ pixel resolution and daily global coverage from May 2018 to present.^{5,6} This dense spatiotemporal sampling lends itself to high-frequency monitoring of methane emissions at regional scales⁷ and could be of great value for tracking mitigation efforts.

The Permian Basin in Texas and New Mexico is a prolific oil and gas field that accounts for more than 40% of US oil production.⁸ Strong methane emissions from Permian oil and gas activities have been extensively documented by satellite,^{9,10} aircraft,^{11,12} and ground measurement platforms.¹³ The

methane intensity of Permian oil and gas production, defined here as the ratio of emitted to produced gas across the basin, is much higher than the Oil and Gas Climate Initiative (OGCI) industry target of <0.2%,¹⁴ with estimates in the literature ranging from ~3% to more than 9% depending on the study region and period.^{9,12,15} These high intensities have been attributed to venting and incomplete combustion of by-produced gas in the primarily oil-producing basin.^{12,16}

There has been strong interest in monitoring Permian methane emissions over time to improve understanding of their drivers and to determine whether emissions and intensity are decreasing. Lu et al.¹⁶ inferred annual Permian methane emissions from 2010 to 2019 from GOSAT satellite observations and reported a decrease in intensity from 7 to 3%. Varon et al.¹⁷ demonstrated weekly continuous monitoring of Permian methane emissions with TROPOMI from May

Received: July 3, 2025

Revised: November 18, 2025

Accepted: November 19, 2025

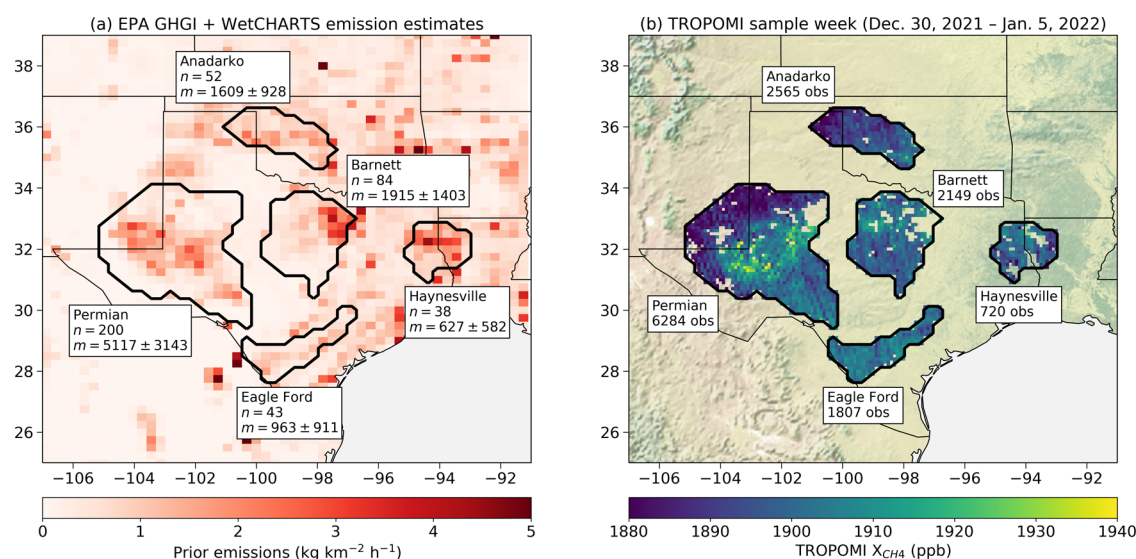


Figure 1. Oil and gas production regions in the south-central US. (a) 2020 bottom-up methane emission estimates on the $0.25^\circ \times 0.3125^\circ$ GEOS-Chem grid from the gridded version of the US EPA Greenhouse Gas Inventory (GHGI) version 2 Express Extension²⁴ and from the mean of the WetCHARTS v1.3.1 wetlands inventory ensemble.²⁵ The black contours delineate the regions of interest optimized in the inversion, with the state vector consisting of the $0.25^\circ \times 0.3125^\circ$ grid cells within the regions. Legends give the number n of state vector elements and the weekly average number m ($\pm$ standard deviation) of TROPOMI observations within the region contour over the 2019–2023 period. (b) Blended TROPOMI + GOSAT X_{CH_4} observations,²² referred to in the text as TROPOMI, averaged over a typical sample week (December 30, 2021–January 5, 2022) on a $0.1^\circ \times 0.1^\circ$ grid, with the number of within-region observations for that week indicated for each region of interest.

2018 through October 2020 and also reported decreasing intensity, from 6 to 3%. They found that the intensity decreases were due to emissions remaining flat while production increased, and that gas prices and drilling of new wells were better predictors of emissions than production.¹⁷

Here we extend the weekly analysis of Varon et al.¹⁷ to five full years, from 2019 to 2023, to evaluate more recent trends in Permian methane emissions and intensity, and to analyze a large, unexpected seasonality in emissions that corroborates recent findings by Vanselow et al.¹⁸ and Hu et al.¹⁹ We use the open-source Integrated Methane Inversion (IMI) framework^{20,21} to infer weekly emissions at $0.25^\circ \times 0.3125^\circ$ (≈ 25 km) resolution from TROPOMI satellite observations. We evaluate our results with independent methane measurements from the Permian Basin Tower Network, and from Insight M aerial surveys and GHGSat satellite observations of methane point sources. We also perform weekly methane inversions over two years (2022–2023) for four other high-emitting oil and gas basins in the south-central United States—the Anadarko, Barnett, Eagle Ford, and Haynesville basins—to compare emissions and trends with those in the Permian.

2. MATERIALS AND METHODS

The IMI is an open-source cloud-computing facility for inferring methane emissions at up to 25 km resolution for any region and period of interest based on an analytical Bayesian inverse analysis of TROPOMI satellite observations. It is available as a free product on the Amazon Web Services (AWS) cloud and can be downloaded and run locally (<https://carboninversion.com/>). IMI 2.0 introduced a capability for users to continuously monitor emissions from a region of interest using a Kalman filter with user-selected update frequency (e.g., weekly, monthly).^{17,21} We describe our configuration of the IMI Kalman filter in more detail below.

2.1. TROPOMI Satellite Observations. We use satellite observations of column-average methane mixing ratio X_{CH_4}

[ppb] from the Balasus et al.²² blended TROPOMI+GOSAT retrieval product. The blended product uses a machine learning model to correct differences between TROPOMI and GOSAT observations based on predictor variables from the operational (v02.04.00) TROPOMI retrieval. The model is trained on more than 150,000 pairs of colocated TROPOMI and GOSAT observations and adjusts TROPOMI to be more consistent with the GOSAT data, which are about 200 times sparser than TROPOMI but less prone to artifacts. It shows improved agreement with the Total Column Carbon Observing Network (TCCON) relative to the operational TROPOMI product in terms of variable bias (<5 ppb) and precision (<12 ppb).²² Differences between the operational and blended TROPOMI retrieval products are too small to be of concern over the Permian and nearby oil/gas basins (Figure S1).

Figure 1 shows the Permian, Anadarko, Barnett, Eagle Ford, and Haynesville regions of interest for our inversions, along with prior emission estimates and a sample week of TROPOMI observations. Weekly observation counts m (mean $\pm$ standard deviation) within the region contours range from 627 ± 582 for the Haynesville Basin to 5117 ± 3143 for the Permian. Outside observations are also used in the inversions, primarily to constrain the boundary conditions and emissions adjacent to the regions of interest (see Section 2.4). TROPOMI observations are lacking for 28 July–18 August 2022 and 10–24 August 2023 due to failure of the VIIRS instrument, which provides cloud masks for the TROPOMI methane retrieval.²³

2.2. GEOS-Chem Forward Model. The IMI uses the nested GEOS-Chem chemical transport model (here v14.2.3)²⁶ as the forward model for regional inversions. The model is driven by assimilated meteorological data from NASA's Goddard Earth Observing System Forward Processing (GEOS-FP) product. It has $0.25^\circ \times 0.3125^\circ$ resolution and 47 vertical layers, reduced from the 72 native layers of GEOS-FP

by combining layers in the upper stratosphere and mesosphere. Boundary conditions for the nested domain are from a global boundary condition data set distributed with the IMI, which is based on a $2^\circ \times 2.5^\circ$ GEOS-Chem simulation corrected to match spatiotemporally smoothed TROPOMI observations.^{20,21} The model is initialized from a 1-month spin-up simulation using the boundary condition data set as initial conditions.

The IMI uses a TROPOMI observation operator to sample the 3D GEOS-Chem methane output fields at the locations and times of the TROPOMI observations.²⁰ This generates pseudo-observations for comparison with the real ones. The IMI TROPOMI operator accounts for variable footprint geometry and vertical averaging kernel vectors as reported in the operational TROPOMI retrieval product. In IMI 2.0, individual TROPOMI observations are averaged by orbit into superobservations on the $0.25^\circ \times 0.3125^\circ$ GEOS-Chem grid for computational expediency and better accounting of errors.

2.3. Prior Emission Estimates. We use the default IMI 2.0 prior emission estimates described by Estrada et al.²¹ and shown in Figure 1. Anthropogenic emissions are from the gridded version of the US Environmental Protection Agency (EPA) Greenhouse Gas Inventory (GHGI), version 2 Express Extension with up to monthly resolution.²⁴ Oil/gas emissions are aseasonal in the GHGI. Monthly wetland emissions are from the WetCHARTS v1.3.1 ensemble mean²⁵ and daily fire emissions are from GFED4.²⁷ Emissions from geological seeps are from Etiope et al.²⁸ scaled to 2 Tg a^{-1} globally following Hmiel et al.²⁹ Emissions from termites are from Fung et al.³⁰ Methane losses from soil absorption and oxidation by OH and Cl are included in the GEOS-Chem forward model through prescribed oxidant concentration fields and the MeMo soil methanotrophy model.³¹ Losses are relatively uniform across our regional inversion domains and are thus effectively optimized through correction to the boundary conditions as described in the next section.

2.4. State Vectors. The black contours in Figure 1 outline the emission state vectors (2D gridded methane emissions) optimized in our inversions. The emission state vectors have native 25 km resolution within the basin boundaries. They also include 16 coarse buffer elements (not shown in Figure 1), which are collections of 25 km grid cells extending 3° outside the region of interest that serve to adjust external emissions and pad out the rectangular inversion domain.^{17,20,32}

Regional inversions are sensitive to errors in the boundary conditions, which can alias into the solution for emissions.³³ While the buffer emission elements provide some protection against this, and the TROPOMI boundary conditions data set is on average unbiased, we also optimize the boundary conditions directly in our inversions by including in the state vector four additional elements representing adjustments to be applied to the methane concentrations along the edges of the inversion domain in each cardinal direction. The inversion can in this manner effectively separate in-domain emissions from the boundary conditions while correcting for upwind emissions from the different directions.³³ The state vectors for our weekly inversions thus contain $n + 16 + 4$ elements: $n \in [38, 200]$ high-resolution emission elements within the region of interest (shown inset in Figure 1), 16 coarse buffer emission elements outside the region of interest, and 4 boundary condition elements.

2.5. Inversion. We use the IMI 2.0 continuous emission monitoring (Kalman filter) feature developed by Varon et al.¹⁷

and Estrada et al.²¹ to infer weekly methane emissions from our regions of interest. For a given week and region, we seek to optimize the state vector $\mathbf{x}$ (emissions and boundary conditions) to better match the satellite observations $\mathbf{y} = \mathbf{F}(\mathbf{x}) + \boldsymbol{\epsilon}$ by inverting the forward model $\mathbf{F}$ while accounting for model and observation errors $\boldsymbol{\epsilon}$. The problem is generally underconstrained due to observation/model errors and gaps in coverage, which can be addressed by regularizing the solution with prior estimates $\mathbf{x}_A$. Assuming normally distributed error probability density functions (pdfs) on $\mathbf{x}$ and $\mathbf{y}$, the problem is then to minimize the cost function³⁴

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_A)^T \mathbf{S}_A^{-1} (\mathbf{x} - \mathbf{x}_A) + \gamma (\mathbf{y} - \mathbf{K}\mathbf{x})^T \mathbf{S}_o^{-1} (\mathbf{y} - \mathbf{K}\mathbf{x}) \quad (1)$$

where $\mathbf{K} = \text{d}\mathbf{F}/\text{d}\mathbf{x}$ is the Jacobian matrix representing the sensitivity of the observations to the state variables, $\mathbf{S}_A$ is a prior error covariance matrix describing uncertainties in the prior estimates, $\mathbf{S}_o$ is an observational error covariance matrix describing the combined model and observation errors, and γ is a regularization parameter to prevent overfitting in the solution. We use the default IMI 2.0 settings²¹ for these parameters, taking $\mathbf{S}_A$ and $\mathbf{S}_o$ to be diagonal with uniform error standard deviations $\sigma_A = 50\%$ for emissions ($\sigma_A = 10$ ppb for boundary conditions) and $\sigma_o = 15$ ppb for observations (scaled down for superobservations with accounting for error correlations³⁵) as in previous studies.^{17,20,21} The number of observations over a weekly period is sufficiently small that overfitting is not a concern and so we use the IMI default setting²¹ $\gamma = 1$. The optimized (posterior) emissions $\hat{\mathbf{x}}$ are obtained analytically by solving $\text{d}J(\mathbf{x})/\text{d}\mathbf{x} = \mathbf{0}$ for $\mathbf{x}$

$$\hat{\mathbf{x}} = \mathbf{x}_A + (\gamma \mathbf{K}^T \mathbf{S}_o^{-1} \mathbf{K} + \mathbf{S}_A^{-1})^{-1} \gamma \mathbf{K}^T \mathbf{S}_o^{-1} (\mathbf{y} - \mathbf{K}\mathbf{x}_A) \quad (2)$$

In the IMI 2.0 Kalman filter inversion, the prior estimates $\mathbf{x}_A$ evolve from week to week based on the latest posterior solution in combination with the original prior estimate¹⁷

$$\mathbf{x}_A^i = \lambda (\alpha \mathbf{x}_A^0 + (1 - \alpha) \hat{\mathbf{x}}^{i-1}) \quad (3)$$

Here $\mathbf{x}_A^i$ is the prior estimate for the current week $i \geq 1$, $\mathbf{x}_A^0$ is the original prior estimate, $\hat{\mathbf{x}}^{i-1}$ is the most recent weekly posterior estimate (with $\hat{\mathbf{x}}^0 = \mathbf{x}_A^0$), $\alpha = 0.1$ assigns 10% weight to the original prior and 90% weight to the most recent posterior, and λ is a scale factor to ensure that $\mathbf{x}_A^i$ has the same mean emission as $\hat{\mathbf{x}}^{i-1}$. This update is applied only to emissions within the region of interest; prior estimates for buffer emission elements are not updated from week to week, and prior estimates for the boundary conditions follow the time-dependent IMI boundary condition data set. If no observations are available during week i , the inversion returns $\hat{\mathbf{x}}^i = \mathbf{x}_A^i$. The posterior distribution of source sectors in each grid cell follows that of the prior.

IMI 2.0 provides an option to use log-normal error pdfs for emissions in the inversion,²¹ which has the advantage of enforcing positivity in the posterior emission solution and reflects the well-documented heavy tail of methane emissions.³⁶ We use this option in our inversions for the Permian Basin. With log-normal errors, eq 1 is solved in log space ($\mathbf{x} \rightarrow \mathbf{x}' = \ln \mathbf{x}$) and becomes nonlinear, so that the Jacobian matrix ($\mathbf{K} \rightarrow \mathbf{K}' = \text{d}\mathbf{F}/\text{d} \ln \mathbf{x}$) must be updated iteratively to converge to a solution. IMI 2.0 uses the Levenberg–Marquardt optimization algorithm as described by Rodgers³⁷ for this purpose. We only optimize the emissions within the region of interest in log space; the boundary condition and buffer

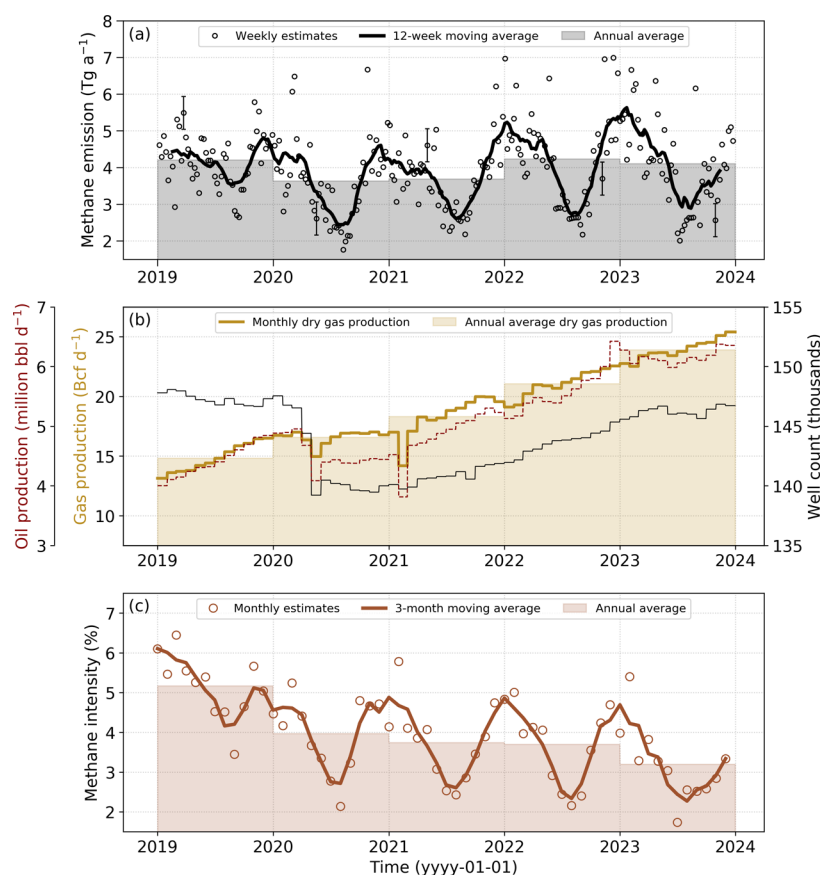


Figure 2. Total oil and gas methane emissions, gas production, active well count, and methane intensity for the Permian, 2019–2023. Tick marks on the x -axes indicate January 1 of each year. (a) Weekly methane emissions inferred from TROPOMI data along with 12-week and annual averages. Error bars on select points represent the estimated error standard deviation of 0.45 Tg a^{-1} (see text). (b) Monthly dry gas production data, oil production, and well count from Enverus Drillinginfo⁴⁰ along with annual average dry gas production. (c) Monthly methane intensity (ratio of methane emitted to methane gas produced) derived from panels (a) and (b) along with 3-month and annual averages, assuming 80% methane content for Permian gas.⁹ To compute the monthly intensity, we resample our weekly emission estimates to daily values and then compute monthly emission averages for comparison with the monthly production data.

emission elements of the state vector are optimized with normally distributed error pdfs, because they are intended to correct boundary condition errors and need not be strictly positive. The prior emission error covariances in the log-normal inversion become geometric error variances $(\ln \sigma_g)^2$, where σ_g is the geometric error standard deviation. We set $\sigma_g = 2.0$, reflecting a factor-of-two uncertainty in the prior emission estimates.

While the normal inversion solves for the mean of a Gaussian distribution, the log-normal inversion solves for the median of a log-normal distribution. The prior estimates $\mathbf{x}_A$, which reflect mean emission values, therefore need to be adjusted to reflect medians, and the IMI does so following Hancock et al.,³⁸ by applying the formula

$$\mathbf{x}_{\text{median}} = \mathbf{x}_{\text{mean}} \exp \left(- \frac{(\ln \sigma_g)^2}{2} \right) \quad (4)$$

such that $\mathbf{x}_A \rightarrow \mathbf{x}'_A = 0.79 \ln \mathbf{x}_A$. The reverse correction is then applied to the posterior emission solution to recover a mean value that can be compared with the prior inventory estimates.

3. RESULTS AND DISCUSSION

3.1. Permian Methane Emissions and Intensity. Figure 2 shows time series of total oil and gas methane emissions, gas

production, active well count, and methane intensity for the Permian from 2019 to 2023. Our inversions begin in July 2018, but we discard the first six months of results as a burn-in period following Varon et al.¹⁷ to address low bias in the EPA GHGI (our prior estimate), which reports Permian methane emissions of only 1.1 Tg a^{-1} with 0.9 Tg a^{-1} from oil and gas production. We find that Permian emissions averaged $4.9 \pm 1.3 \text{ Tg a}^{-1}$ (weekly mean $\pm$ standard deviation) over the 2019–2023 period, nearly five times higher than the GHGI, with $4.0 \pm 1.1 \text{ Tg a}^{-1}$ from oil and gas. Varon et al.¹⁷ estimated an error standard deviation of 0.45 Tg a^{-1} for their weekly 2018–2020 Permian emission estimates based on a collection of six IMI Kalman-filter inversions varying input parameters, and we take this to represent the precision of our weekly estimates for 2019–2023. A strong seasonal variation is apparent in the oil and gas posterior emissions, which are on average $50 \pm 10\%$ higher in the winter (December, January, February; DJF) than summer (June, July, August; JJA). We discuss this seasonality further in Section 3.

Interannual variability of emissions is considerably weaker. Emissions fell $14 \pm 5\%$ from 2019 to 2020 despite increasing production, likely due to the reduction in commissioning of new wells during the COVID-19 pandemic,^{17,39} but then rebounded with the number of active wells. The large increase in oil and gas production during the study period, from 4.4

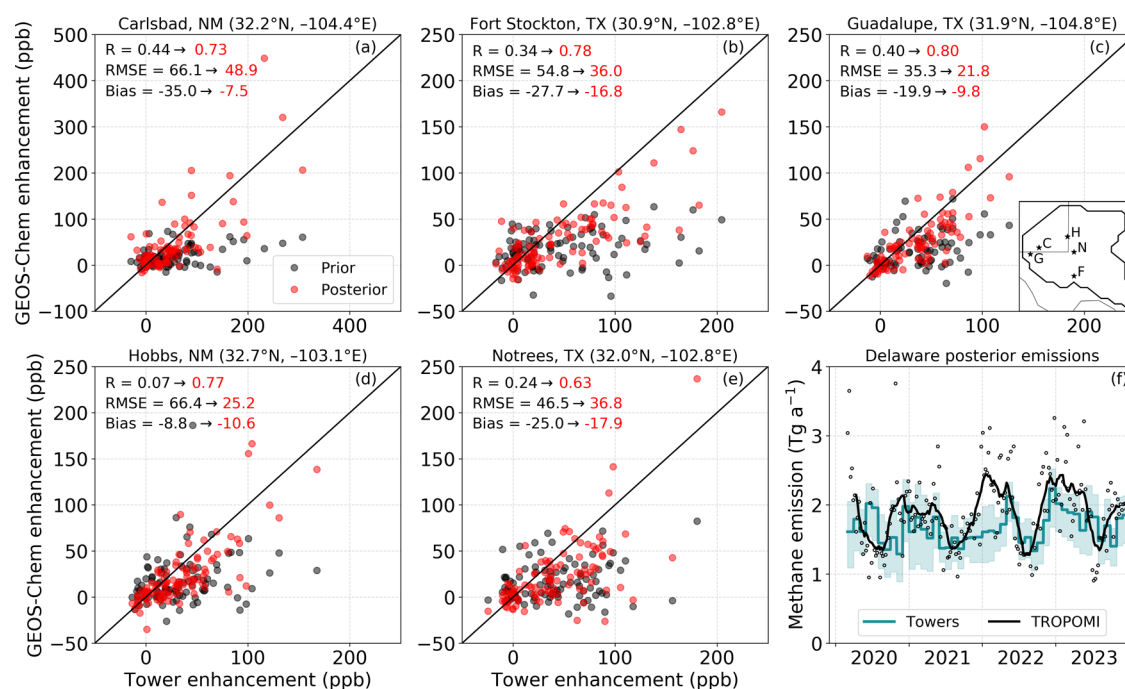


Figure 3. Evaluation of our weekly inversions with in situ methane measurements from the Permian Basin Tower Network. Panels (a–e) compare simulated methane enhancements relative to the seasonal background from GEOS-Chem using prior emissions and posterior (weekly updated) emissions to observations from five tall towers (2022–2023). Enhancements are shown as weekly mean afternoon (20:00–24:00 UTC) values. Legends give the Pearson correlation coefficient R , root-mean-square error (RMSE), and mean bias. The inset map in panel (c) shows the tower locations labeled by leading letter (e.g., C = Carlsbad). The 1:1 line is shown in black. Panel (f) compares our weekly inversions (black circles, with 12-week moving average as black line) with monthly inversions of the tower observations (blue line, with blue shading showing the range of results from a sensitivity analysis adjusting inversion parameters) described by Barkley et al.¹³ for March 2020 to December 2023. Emissions are for a $200 \times 200 \text{ km}^2$ rectangular domain around the Permian Delaware sub-basin (30.82°N to 32.89°N, -104.99°E to -102.71°E). Tick marks on the x -axis indicate January 1 of each year.

million bbl d⁻¹ and 13 Bcf d⁻¹ in early 2020 to 6.2 bbl d⁻¹ and 25 Bcf d⁻¹ by the end of 2023, did not produce a similar trend in emissions. Methane intensity averaged $4.0 \pm 1.1\%$ and fell steadily from $5.2 \pm 0.8\%$ in 2019 to $3.2 \pm 0.9\%$ in 2023. The decline in methane intensity continues to reflect increasing production, not decreasing emissions.

In 2021 and 2022, New Mexico introduced new state policies to reduce oil and gas methane emissions, requiring that operators achieve methane intensities of less than 2% by 2026,⁴¹ and separately requiring reduced air pollution from oil and gas activities for better compliance with the national ambient air quality standard for ozone.⁴² We examined whether emissions and intensity declined in response to these policies by separating our posterior emission estimates for Texas and New Mexico (Figure S2). Methane intensity in the New Mexico Permian decreased rapidly during the study period, from $4.5 \pm 1.3\%$ in 2019 to $2.1 \pm 0.7\%$ in 2023, approaching the state's target of 2% as growth in production outpaced that in emissions. However, most of the decrease occurred before 2021. Methane intensity in the Texas Permian decreased more slowly, from $5.2 \pm 0.7\%$ in 2019 to $3.6 \pm 1.0\%$ in 2023.

3.2. Evaluation with Independent Observations.

Independent observations of methane concentrations in the Permian Basin can verify the emission trends we infer from TROPOMI. We evaluate our results using independent ground-based observations from the Permian Basin Tower Network, aerial surveys of methane point sources from Insight M, and satellite observations of point sources from GHGSat.

3.2.1. Tall Tower Measurements. The Permian Basin Tower Network has measured in situ methane concentrations since March 2020.^{13,43} Five towers operated continuously throughout 2022 and 2023. Figure 3a–e compares weekly averages of methane enhancements at each tower with those simulated by the GEOS-Chem forward model using either prior or posterior emissions. The averages are for afternoon hours (20:00–24:00 UTC) when the mixed layer is fully developed.¹³ Enhancements are defined relative to a seasonally varying background concentration, which we obtain by fitting the lower envelopes of the observed and simulated time series of methane concentrations at each tower with a natural smoothing spline. At all towers, the posterior GEOS-Chem simulation improves agreement with the observations as diagnosed by the Pearson correlation coefficient R and root-mean-square error (RMSE). The mean bias improves at all towers except Hobbs.

Figure 3f compares our results with independent monthly inversions of the tower observations quantifying emissions from a $\sim 200 \times 200 \text{ km}^2$ rectangular domain around the Permian Delaware sub-basin.¹³ The inversions use a constant prior estimate from the measurement-based “EI_{ME}” inventory developed by Zhang et al.^{9,13} Mean emissions of 1.7 Tg a⁻¹ for the towers and 1.9 Tg a⁻¹ for TROPOMI for the period March 2020 to December 2023 agree to within 10–15%. The towers suggest a stronger summer 2020 uptick in emissions than TROPOMI and a weaker 2022 winter uptick, leading to a weaker seasonal variation with emissions on average $14 \pm 6\%$ higher in winter than summer. TROPOMI infers a larger average variation of $57 \pm 11\%$ for the same region and period,

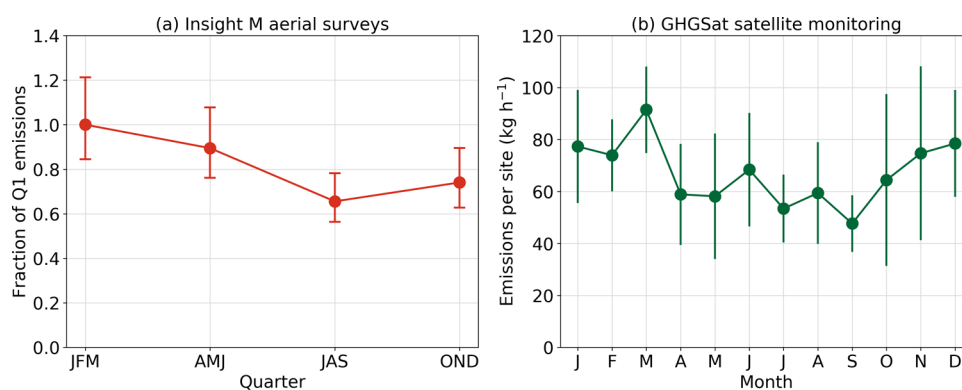


Figure 4. Seasonality of Permian point source emissions based on (a) Insight M aerial surveys and (b) targeted GHGSat satellite monitoring of oil and gas infrastructure in the Permian. (a) Quarterly total emissions detected by Insight M from 2021 to 2023,⁴⁴ normalized to emissions in the first quarter of each year and averaged over all three years. Error bars represent 95% confidence intervals. (b) Monthly mean emissions per source location monitored by GHGSat from 2022 to 2024.⁴⁵ Error bars represent the standard deviation of daily values within each month.

and Hu et al.¹⁹ inferred from ground and aircraft observations an average variation of $\sim 40\%$ for continental-US oil and gas emissions from 2008 to 2021.

3.2.2. Aircraft and Satellite Observations of Methane Point Sources. Next, we compare our results with methane point source observations from wide-area Insight M aerial remote sensing surveys⁴⁴ (Text S1) and targeted GHGSat satellite monitoring⁴⁵ (Text S2) in the Permian. The Insight M surveys ran from 2021 to 2023 and covered infrastructure accounting for 47–89% of total natural gas production in the Permian depending on the year. We compute total aerally detected emissions per year following the approach of Sherwin et al.⁴⁴ and considering infrastructure surveyed at least once per quarter (Text S1 and Figure S3). GHGSat monitored 1041 distinct source locations from 2022 to 2024 with a constellation of 5–10 satellites and detected 1629 plumes from 1098 clear-sky acquisitions targeting domains of size 12×15 to 12×40 km². We applied the methodology of Jervis et al.⁴⁵ to quantify daily emissions and detections per source location from 2022 to 2024 (Text S2 and Figure S4). Source locations were defined by attributing to a new location any detected plume origin not within 300 m of another plume origin.

Figure 4 plots the quarterly variability in total point source emissions detected by Insight M from 2021 to 2023, and the monthly variability in total emissions per source location monitored by GHGSat from 2022 to 2024. Both platforms find emission maxima in the first quarter (JFM) and minima in the third quarter (JAS). Insight M emissions were on average roughly 50% higher in JFM than JAS. GHGSat emissions were also on average 50% higher in JFM than JAS, and 30% higher in winter (DJF) than summer (JJA). These fluctuations are similar to the 50% fluctuation in total emissions we infer from TROPOMI.

3.3. Drivers of Permian Emission Seasonality. Understanding the drivers of seasonal variability of Permian methane emissions could help identify mitigation opportunities. The economic predictors identified by Varon et al.¹⁷ including gas price, new well development, flaring, and oil/gas production cannot explain the seasonal variation. Rapid withdrawal of gas from underground storage facilities to meet winter heating demand could lead to higher throughput and emissions from combustion slip at compressor stations, but Permian storage volumes are too low (<80 Bcf in 2022⁴⁶) for this to be a strong effect, and their seasonal cycle does not align with that of

emissions.¹⁹ Seasonal trends in equipment malfunction and maintenance events in the Permian are also an unlikely explanation, as those events are more frequently reported by operators in summer than winter^{47,48} (Figure S5). Winter highs in urban methane emissions have been attributed to increased gas consumption and postmeter leakage,^{49,50} which could also occur in US oil and gas basins,¹⁹ but the seasonal fluctuation in the Permian (~ 2 Tg a⁻¹) is many times larger than observed in cities (order 10 Gg a⁻¹)⁵⁰ despite a much lower population density. We hypothesize here that the winter maximum in Permian methane emissions could be partially driven by increased liquid storage tank emissions in cold conditions, caused by inadequate weatherization of wellhead separators.

Unweatherized equipment is prone to malfunction at low temperatures. Hydrate formation and icing of control valves can occur in production, gathering, and transmission systems at freezing temperatures, and even above freezing,⁵¹ due to the Joule-Thomson effect. In 2022, the Railroad Commission (RRC) of Texas introduced a new Weather Emergency Preparedness Standards rule requiring winter weatherization of critical natural gas facilities.⁵² RRC recommends using a combination of heating blankets, line heaters, catalytic heaters, and other solutions to prevent equipment from freezing in cold conditions,⁵³ but some Permian oil and gas infrastructure remains unweatherized.⁵⁴ Line and catalytic heaters, turned on in the fall and off in the spring and fueled by natural gas, could themselves represent a seasonal source of methane emissions. Festa-Bianchet et al.⁵⁵ found that catalytic heaters at upstream production facilities in British Columbia, Canada vented about 40% of incoming gas during winter operations, much higher than the standard assumption of 2% (98% efficiency) for combustion processes. The relatively small number of catalytic heaters in the Permian, however—at most 23,000 units (0.18 per well) in 2023 according to US Greenhouse Gas Reporting Program data for small combustion units⁵⁶—cannot explain the 50% seasonal fluctuation we observe with TROPOMI.

The seasonal variability in Permian methane emissions may be more strongly driven by emissions from storage tanks for produced liquids including water and liquid hydrocarbons. Emissions from these liquids could increase during the winter if they contain more dissolved gas under cold conditions, as one would expect from equilibrium thermodynamics (Henry's Law). Production facilities use separators to divide the well stream into its liquid and gaseous components. The liquids are

stored in tanks at atmospheric pressure before being transported away by pipeline or truck, and the drop in pressure between separator and tank leads to the release of the dissolved gases in a process called “tank flashing”.^{57,58} Poorly weatherized separators operating at cold temperatures would send more dissolved gas to liquid storage tanks, which periodically vent when the tank pressure exceeds a near-atmospheric threshold. Cold weather could therefore lead to increased methane emissions from the storage of produced liquids across the basin.

To test this hypothesis, we analyzed thermodynamic simulations of separator efficiency and tank flashing emissions by Cardoso-Saldaña et al.⁵⁹ for different temperatures, pressures, and well stream compositions (wide range of gas-to-oil ratios and liquid hydrocarbon densities based on field measurements). The simulations are for a single-stage, unheated separator with water and liquid hydrocarbon tanks. Salt content and entrainment of hydrocarbon liquids into the water storage tank are not considered. Figure 5 plots the

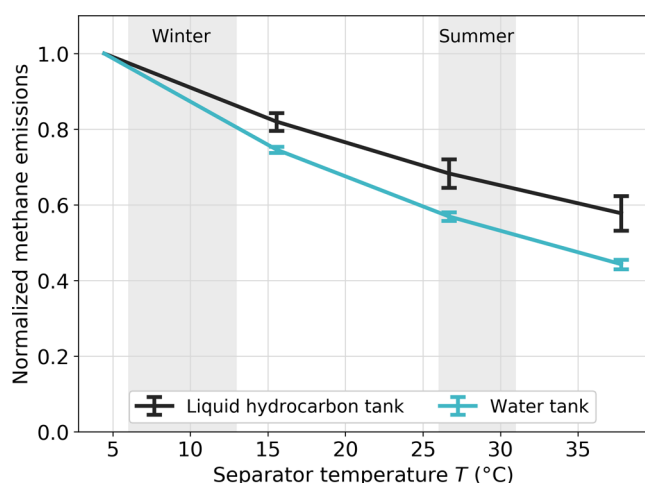


Figure 5. Tank flashing emissions from liquid hydrocarbon and water storage tanks for different separator temperatures T , normalized to emissions at $T = 4.4\text{ }^{\circ}\text{C}$ ($40\text{ }^{\circ}\text{F}$), based on thermodynamic simulations by Cardoso-Saldaña et al.⁵⁹ The vertical bars represent the interquartile range of results for different combinations of separator pressure (20–1400 psia) and well stream composition (wide range of gas-to-oil ratios and liquid hydrocarbon densities). The shaded areas are ranges of monthly average surface temperatures for Midland, Texas in the winter and summer months from 2019 to 2023.⁶⁰

expected tank emissions at different ambient/separator temperatures. As expected, tank emissions decrease with increasing temperature as the level of dissolved gas decreases. For example, methane emissions from liquid hydrocarbon tanks are 39–55% higher at $4\text{ }^{\circ}\text{C}$ than at $27\text{ }^{\circ}\text{C}$ (normalized emissions of 1 at $4\text{ }^{\circ}\text{C}$ vs $0.65\text{--}0.72$ at $27\text{ }^{\circ}\text{C}$) and emissions from water tanks are 72–79% higher.

Monthly average surface temperature in Midland, Texas ranged from 26 to $31\text{ }^{\circ}\text{C}$ during the summer months and 6 to $13\text{ }^{\circ}\text{C}$ during the winter months from 2019 to 2023.⁶⁰ We see from Figure 5 that ~50% higher tank flashing emissions in winter are plausible. Liquid storage tanks accounted for 33% of total emissions detected in a September–November 2019 aerial survey of 1100 Permian methane point sources by Cusworth et al.¹¹ and a similar fraction of total emissions modeled by Sherwin et al.¹² for year-round surveys, in both

cases the most of any source type. The temperature dependence of tank flashing emissions could thus explain much of the seasonal trend observed in the Permian.

3.4. Anadarko, Barnett, Eagle Ford, and Haynesville Basins. To determine whether the seasonal variation in emissions is unique to the Permian, we apply IMI continuous emission monitoring to four other south-central US oil and gas production regions: the Anadarko, Barnett, Eagle Ford, and Haynesville basins (Figure 1). These basins accounted for 11% (25%) of US oil (gas) production in 2023⁴⁰ and have been identified as high emitters in previous analyses of satellite observations.^{16,61} We perform weekly regional inversions for each basin over two years from 2022 to 2023 and report total methane emissions and intensities. Our inversions assume normal error statistics on emissions and begin in July 2021, but as for the Permian we discard the first six months of results as a burn-in period.¹⁷

Figure 6 shows the resulting oil and gas methane emission estimates for the four basins as annual and 12-week moving averages, along with time series for oil and gas production, methane intensity, and active well count. Mean 2022–2023 emissions average $0.76 \pm 0.15\text{ Tg a}^{-1}$ for Anadarko, $0.40 \pm 0.10\text{ Tg a}^{-1}$ for Barnett, $0.46 \pm 0.09\text{ Tg a}^{-1}$ for Eagle Ford, and $0.46 \pm 0.11\text{ Tg a}^{-1}$ for Haynesville. These values are similar to those reported by Shen et al.⁶¹ based on analysis of TROPOMI observations for 2018–2020. Mean annual emissions declined respectively by 11 ± 3 , 14 ± 12 , 3 ± 11 , and $26 \pm 3\%$ in these basins from 2022 to 2023. Seasonal trends are weaker than observed in the Permian, but broadly consistent in the Anadarko, Barnett, and Haynesville basins where the mean winter-to-summer emission ratios are respectively 1.25 ± 0.12 , 1.14 ± 0.09 , and 1.49 ± 0.15 . Differences in seasonal variations, such as for the Eagle Ford where the mean winter-to-summer ratio is 0.99 ± 0.12 , may reflect different seasonal conditions and practices, or simply the shorter study period. They do not appear to reflect differences in the basins’ oil-to-gas production ratios.

The methane intensities in Figure 6 are computed here as in Figure 2, but assuming 90% methane gas content for all four basins.⁶² Average methane intensity was $2.1 \pm 0.5\%$ in the Anadarko, $2.6 \pm 0.6\%$ in the Barnett, $1.1 \pm 0.2\%$ in the Eagle Ford, and $0.5 \pm 0.1\%$ in the Haynesville. These intensities are a factor of 2–3 lower than estimated by Lu et al.¹⁶ for the years 2010–2019 based on GOSAT satellite observations, except for the Barnett, where we both estimate 2.6% intensity. The higher intensity in the Barnett despite its relatively low emissions likely reflects low and declining production.⁶³ The Haynesville’s much lower intensity likely reflects more efficient practices in the primarily gas-producing basin. Intensity declined in all basins from 2022 to 2023, reflecting decreasing emissions and increasing production everywhere except the Barnett, which saw declines in both. Annual intensity decreased by $0.3 \pm 0.1\%$ in the Anadarko (from 2.3 to 2.0%), $0.3 \pm 0.4\%$ in the Barnett (from 2.8 to 2.5%), $0.2 \pm 0.1\%$ in the Eagle Ford (from 1.2 to 1.0%), and $0.2 \pm 0.02\%$ in the Haynesville (from 0.6 to 0.4%).

In summary, five years of weekly TROPOMI methane inversions for the Permian basin (2019–2023) reveal declining methane intensity and strong seasonal variability in total oil and gas emissions, $50 \pm 10\%$ higher in winter than summer. The decreasing intensity is driven by increasing production, not decreasing emissions, and the seasonality is corroborated by independent tower, aerial, and facility-level satellite

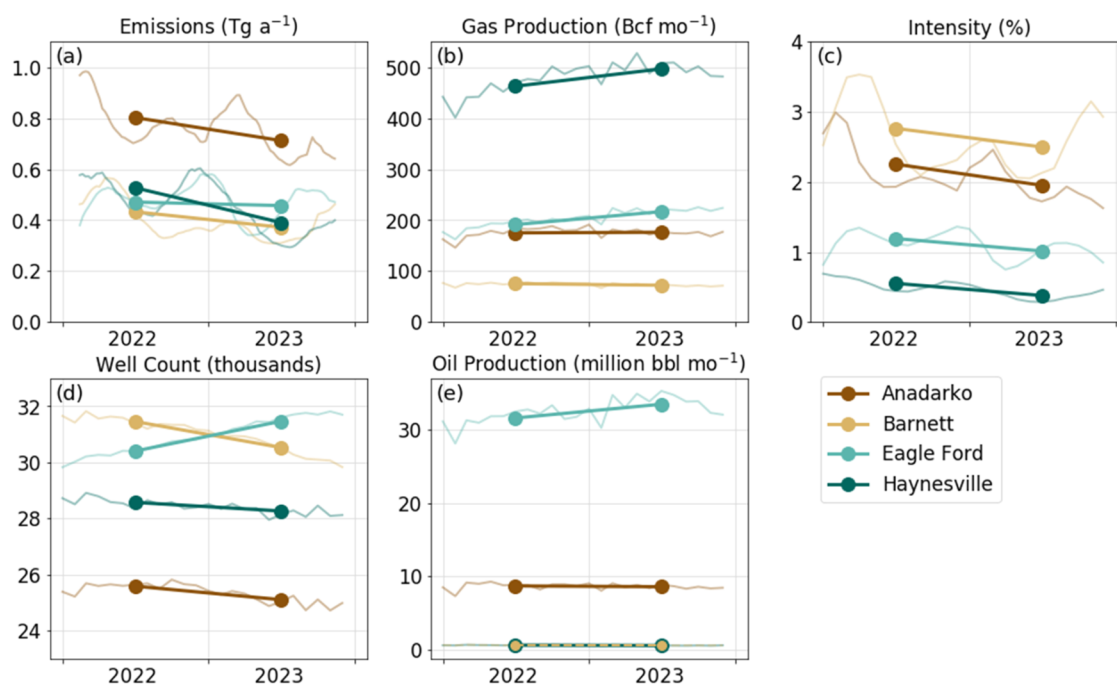


Figure 6. (a) Total methane emissions, (b) dry gas production, (c) methane intensity, (d) active well counts, and (e) oil production in the US Anadarko, Barnett, Eagle Ford, and Haynesville basins, in 2022 and 2023. Data for production and well counts are from Enverus Drillinginfo.⁴⁰ Thin light lines show (a) 12-week moving average emissions, (b) monthly dry gas production, (c) 3-month moving average methane intensity computed as in Figure 2 but assuming 90% methane gas content,⁶² (d) monthly average well count, and (e) monthly oil production. The thick dark markers show annual averages.

observations. Two years (2022–2023) of weekly inversions for the nearby Anadarko, Barnett, Eagle Ford, and Haynesville basins reveal similar but weaker seasonal fluctuations and declining intensity. The winter maximum may be driven in part by higher emissions from produced-liquids storage tanks due to decreased separator efficiency in cold conditions. Better weatherization of facilities could significantly decrease emissions.

■ ASSOCIATED CONTENT

SI Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.5c08745>.

Additional description of Insight M and GHGSat emission analysis (Texts S1 and S2; Figures S3 and S4) and additional figures for differences between the Operational and Blended TROPOMI retrieval products (Figure S1), TX/NM emission estimates (Figure S2), TX/NM excess emission reporting data (Figure S5), and prior sectoral emission estimates (Figure S6) (PDF)

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Author Contributions

D.J.V. and D.J.J. designed the study. D.J.V. performed the satellite inverse analysis and wrote the first draft of the manuscript. Z.B. performed the tower inverse analysis. E.D.S. and H.K. performed the Insight M emission analysis. D.J. performed the GHGSat emission analysis. F.C.S. analyzed the thermodynamic simulations of separator efficiency. All authors contributed to the interpretation of results and writing the manuscript.

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work was supported by the Harvard Initiative on Reducing Global Methane Emissions, the National Aeronautics and Space Administration (NASA) Carbon Monitoring System, the NASA Jet Propulsion Laboratory initiative for the US GHG Center, Environmental Defense Fund, GHGSat Inc., and ExxonMobil Technology and Engineering Company. Part of this research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under contract with NASA (80NM0018D0004). This work was partially supported by the California Energy Commission (SUMMATION project, agreement number PIR-17-015). It does not necessarily represent the views of the Energy Commission, its employees, or the State of California. The Energy Commission, the State of California, its employees, contractors, and subcontractors make no warranty, express or implied, and assume no legal liability for the information in this report; nor

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