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Key Points:

- Bayesian flux inversion combining TROPOMI observations and an ML emulator of transport resolves methane emissions across the Permian Basin
- Emissions correspond with the spatial pattern of gas production infrastructure: wells, pipeline corridors, and midstream infrastructure
- Permian Basin methane emissions remained stable from 2018 through 2025 and the methane intensity declined from 5% to 2%

Supporting Information:

Supporting Information may be found in the online version of this article.

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Observing Methane Emissions From Oil and Gas Infrastructure in the Permian Basin Using TROPOMI

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Abstract The Permian Basin is one of the largest methane sources in the United States, yet quantifying emissions at scales needed to attribute them to specific infrastructure remains challenging. Here we present a methane flux inversion from 2018 through 2025 using TROPOMI retrievals and a machine learning surrogate for atmospheric transport (FootNet). We estimate emissions at $1 \times 1 \text{ km}^2$ spatial resolution and weekly time resolution over the Permian Basin, jointly solving for background concentrations. We find total Permian Basin emissions of $2.6 \pm 0.5 \text{ Tg/yr}$ (structural uncertainty range: $1.7\text{--}3.2 \text{ Tg/yr}$), a factor of 2.4 higher than the EPA inventory, with strong spatial correspondence to gas wells, pipelines, storage tanks, compressor stations, and processing facilities. Permian sub-basins have distinct drivers of methane emissions: gas wells in the Delaware, midstream infrastructure in the Midland. Despite a $2\text{--}3\times$ increase in production, total emissions remained stable, driving a decline in methane intensity from 5% to 2%.

Plain Language Summary Methane is a potent greenhouse gas, and oil and gas operations in the Permian Basin of Texas and New Mexico are a major source. Pinpointing exactly where those emissions come from is difficult because they vary significantly over short distances. We used satellite measurements and a machine learning model of atmospheric transport to estimate methane emissions at kilometer-scale resolution across the Permian Basin from 2018 through 2025. Our total emission estimate is 2.4 times higher than the official EPA inventory. Our estimated emission patterns closely match the locations of gas wells, major pipelines, and related facilities such as compressor stations and storage tanks, and show low emissions in areas lacking this infrastructure, like the city of Midland, TX. Although oil and gas production in the basin roughly tripled over our study period, total methane emissions stayed relatively flat, and the fraction of methane leaked per unit of gas produced declined from 5% to 2%. These results demonstrate that satellite data combined with machine learning can track emissions at the scale of individual infrastructure corridors and could be extended to other major oil and gas producing regions globally.

1. Introduction

Methane is the second most important anthropogenic greenhouse gas after carbon dioxide, contributing approximately 30% of the cumulative radiative forcing since the pre-industrial era (IPCC, 2023). A major source of uncertainty in projecting future warming is the incomplete characterization of methane emission sources, which are often highly heterogeneous in space and time and difficult to resolve with existing coarse resolution flux inversion frameworks. Improved understanding of methane sources and sinks is therefore crucial for constraining future climate trajectories. A significant portion of anthropogenic methane emissions arise from oil and gas production, making this sector a critical focus for improved quantification and mitigation efforts.

The Permian basin in Texas and New Mexico is the largest oil-producing region in the United States (EIA, 2024) and a major source of methane emissions. Oil and gas production in the basin has increased steadily over the past decade (EIA, 2024), intensifying the need for accurate emission quantification. However, substantial discrepancies persist between bottom-up inventories (Maasakkers et al., 2016, 2023) and top-down estimates of methane emissions in the Permian with top-down studies often reporting emissions that are a factor of two to four higher than bottom-up estimates (range: $2.3\text{--}4.0 \text{ Tg/yr}$), depending on inversion configurations, prior estimates, and study period (Barkley et al., 2023, 2025; Liu et al., 2021; Lyon et al., 2021; McNorton et al., 2022; Schneising et al., 2020; Shen et al., 2022; Varon et al., 2023, 2026; Zhang et al., 2020). These differences are often attributed to strong spatiotemporal variability in emissions across sub-basins, as well as inconsistencies in observational sampling (Barkley et al., 2025; Cusworth et al., 2022; Lyon et al., 2021; Varon et al., 2023).

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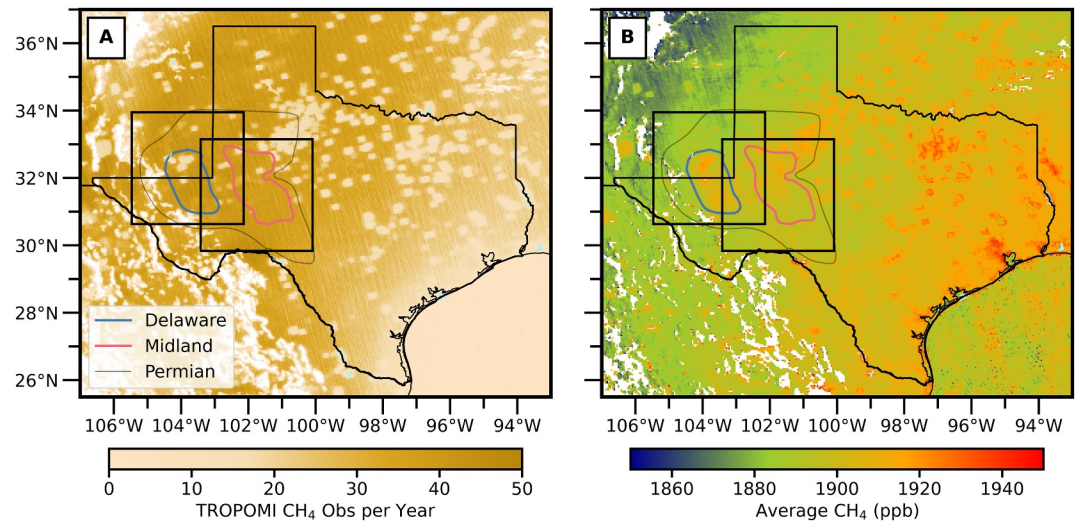


Figure 1. TROPOMI methane observation density and mean methane concentrations in the Permian Basin and surrounding region. (Panel a) Shows the TROPOMI observations per year for each pixel in the Permian and the nearby region. (Panel b) Shows mean methane concentrations for each pixel in the Permian and the nearby region, averaged from 2019 through 2025. The black squares represent $400 \times 400 \text{ km}^2$ inversion domains focusing on Delaware and Midland sub-basins.

Resolving this variability requires both high spatial resolution to capture localized emission sources and dense observational coverage to adequately constrain emissions (e.g., Hamilton et al., 2024; Jacob et al., 2016, 2022). Satellite instruments such as Tropospheric Monitoring Instrument (TROPOMI; Veefkind et al., 2012) provide daily global methane observations, offering unprecedented measurement density. However, leveraging these data in high-resolution frameworks remains challenging due to the high computational cost of atmospheric transport modeling. Recent advances in machine learning (ML)-based emulators of atmospheric transport provide a pathway to overcome these limitations by enabling fast and scalable computation of surface sensitivities of measurements or “footprints” (Cartwright et al., 2023; Dadheech & Turner, 2026b; Dadheech et al., 2025; Fillola et al., 2026; He et al., 2025).

Here we present a kilometer-scale methane inversion framework that combines TROPOMI satellite observations with an ML-based atmospheric transport model to quantify emissions across the Permian basin from 2018 through 2025. Previous work using TROPOMI over the Permian has operated at coarse spatial scales of $10 \times 10 \text{ km}^2$ or larger, limiting the ability to attribute emissions to specific infrastructure. By estimating emissions at high-resolution, we show strong spatial correspondence with gas wells, major pipeline corridors, and associated midstream facilities, and track how methane intensity has evolved over nearly a decade of rising production. These results demonstrate that satellite observations, combined with ML-based transport modeling, can resolve methane emissions at spatial scales not accessible with conventional inversion frameworks.

2. Atmospheric Inversion Framework

We use column-averaged methane observations from TROPOMI, which provides global daily observations of methane beginning in May 2018, with an average spatial resolution of $5.5 \times 5 \text{ km}^2$ and an overpass time of approximately 13:30 local solar time. To ensure data quality, we exclude retrievals with quality assurance values less than or equal to 0.5. Figure 1 shows the mean methane concentrations and spatial density of TROPOMI measurements over the Permian Basin and surrounding regions. These dense observations provide the primary constraint on methane emissions in our inversion framework.

These TROPOMI observations can be related to the surface fluxes through a linear transport operator in the flux inversion as:

$$\mathbf{y} = \mathbf{H}\mathbf{x}, \quad (1)$$

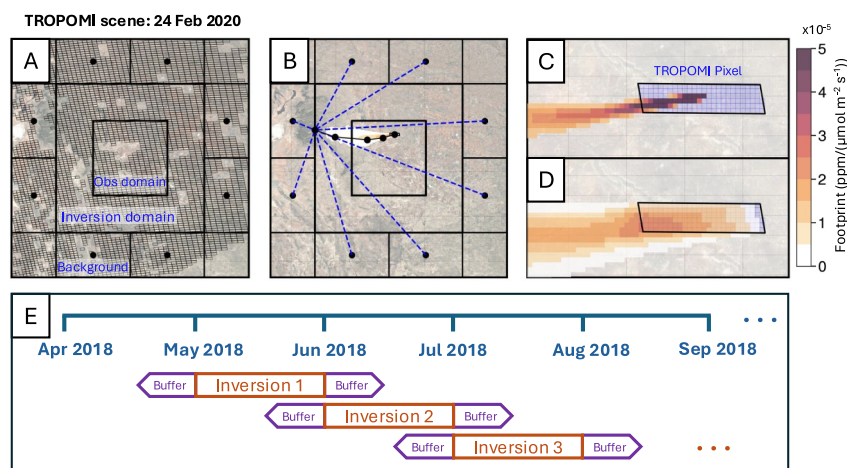


Figure 2. Schematic of the inversion framework. (Panel a) Shows TROPOMI measurements observed on 24 February 2020 over the Delaware domain. Small black boxes show the spatial extent of individual TROPOMI pixels, and empty areas indicate failed retrievals on that day. (Panel b) Shows the back trajectory for a measurement, its exit point, and the distance of centroids of each background region from the exit point. (Panels c and d) Show the kilometer-scale subpixel and averaged kilometer-scale footprints for a TROPOMI pixel. (Panel e) Shows each of temporal window of each flux inversion. Inversions are done at weekly time resolution. They cover overlapping 6-week windows with an operational window of 1 month and a 1 week buffer on both ends.

where $\mathbf{y} \in \mathbb{R}^n$ is the vector of satellite observations and n is the number of observations. $\mathbf{x} \in \mathbb{R}^{m+dT}$ is the state vector comprising m surface flux elements and background methane concentrations for $d = 8$ “background” regions over T time steps (Figure 2a). The Jacobian matrix $\mathbf{H} \in \mathbb{R}^{n \times (m+dT)}$ represents the sensitivity of observations to the state vector elements: the first m columns correspond to surface sensitivities of the observations, while the remaining dT columns represent sensitivities to the background concentration in the d directional sectors at each of the T time steps. We construct the surface sensitivities component of the $\mathbf{H}$ matrix with a Lagrangian approach by populating the first m columns of $\mathbf{H}$ matrix row by row.

We construct the surface sensitivity component of $\mathbf{H}$ using FootNet (<https://footnet-uw.github.io/>; Dadheech & Turner, 2026b; Dadheech et al., 2025; He et al., 2025), an ML-based emulator of atmospheric transport, driven by meteorological fields from the NOAA High Resolution Rapid Refresh (HRRR). FootNet takes meteorological fields as input and produces source-receptor relationships (also known as “footprints”) that map surface fluxes to column-averaged concentrations at kilometer-scale resolution. The model is trained on a million footprints representing both surface and column-averaged measurements at kilometer-scale spatial resolution. These training samples were randomly distributed across the contiguous United States and uniformly sampled over 2020–2021 at hourly resolution. Dadheech and Turner (2026b) demonstrated that FootNet generalizes well to out-of-sample regions and can outperform the physics-based STILT model in a flux inversion. This generalization capability enables real-time, high-resolution greenhouse gas flux inversion in new domains without requiring retraining or precomputed footprint libraries.

TROPOMI observations have a native spatial resolution of $5.5 \times 5 \text{ km}^2$ and previous work using TROPOMI has focused on coarse spatial scales of $10 \times 10 \text{ km}^2$ or larger. However, we posit that TROPOMI observations contain information at finer scales for two reasons. First, TROPOMI’s 16-day orbit cycle means that different ground scenes are sampled on different days, so temporal aggregation over monthly windows effectively provides multiple independent views of the same surface area with different viewing geometries. Second, sensitivity to surface fluxes varies spatially across a single TROPOMI ground scene: that is, footprints computed for subpixels on the upwind edge of the scene would be more sensitive to nearby surface emissions than those on the downwind edge. The first point is an idea that has yielded meaningful information at sub-grid scales via oversampling in related applications (e.g., Turner et al., 2020, 2021). To exploit both effects, we subdivide each TROPOMI pixel into 1-km subpixels and compute footprints for each subpixel using FootNet. The footprint corresponding to the TROPOMI observation is then obtained by averaging the subpixel footprints using a uniform (top-hat) spatial response, such that each subpixel contributes equally to the pixel-averaged methane column. Figure 2c shows an

example footprint computed for a single 1-km subpixel, while Figure 2d shows the resulting footprint for the full TROPOMI observation obtained by averaging the footprints from all of the blue 1-km subpixels shown in panel c. This approach accounts for spatial variability in transport sensitivity across the TROPOMI ground scene while remaining consistent with the spatial extent of the TROPOMI observation, and may improve the representation of subpixel-scale emission heterogeneity. This process is performed on every TROPOMI observation. Ultimately, this allows the inversion to resolve emission variability at a finer scale than the native TROPOMI resolution. This approach described here is computationally demanding, increasing the cost by up to two orders of magnitude compared to the naive approach of running a single footprint per TROPOMI observation. However, FootNet provides a 3+ order of magnitude computational speedup compared to physics-based transport models such as STILT (Dadheech et al., 2025), enabling efficient implementation of these kilometer-scale footprint calculations.

Previous studies have shown that inverse problems are optimally formulated on the highest practical spatial resolution grid to minimize aggregation and representation error, provided that the prior error covariance appropriately represents the spatial error structure (e.g., Bocquet, 2009; Bocquet & Wu, 2011; Bocquet et al., 2011; Bousseres & Henze, 2018; Turner & Jacob, 2015). Accordingly, we formulate the inversion on a 1-km grid to exploit high-resolution information that may be available from TROPOMI while emphasizing that this computational grid spacing should not be interpreted as the independently resolvable spatial resolution of the inferred emissions. The resolvable spatial resolution is ultimately determined by the combination of the observational information content, atmospheric transport, and prior error covariance matrix. The effective resolution of the posterior fluxes is ~5–20 km (see Text S8 in Supporting Information S1).

We perform a Bayesian flux inversion over two overlapping 400×400 km² domains centered on the Delaware and Midland sub-basins (Figure 1). The inversion is conducted at weekly temporal resolution on overlapping 6-week windows, with an operational period of 1 month and a 1-week buffer on either side to reduce edge effects (Figure 2e). Background methane concentrations are estimated using eight surrounding “background” regions and incorporated directly into the state vector, allowing for joint optimization of emissions and boundary conditions. The prior value for each of these background regions is taken as the average of the TROPOMI observations within them and their uncertainties are computed based on the standard deviation of those observations. Figure 2a shows the $d = 8$ background regions. For each observation, we compute both the trajectory exit location and the corresponding exit time at the domain boundary using domain-averaged winds. The background concentration is then estimated as a distance-weighted combination of the surrounding regions using TROPOMI observations corresponding to the estimated boundary-entry time. Figure 2b shows an example of this distance weighting. In this example, the trajectories entered the domain from the west. Therefore, we put more weight on the western background region. However, we also note that this particular box is partially obscured by clouds on this particular day (Figure 2a shows fewer TROPOMI retrievals in this domain). As such, this method will incorporate information from other background regions if the nearest exit region is obscured and is therefore robust to cloud effects. The observational error covariance matrix is constructed using the residual error method (Heald et al., 2004). Further, we prescribe a temporal correlation length of 1 year and a spatial correlation length of 10 km for the flux part of the prior error covariance, with an emission uncertainty of 500% and a scaling factor of 2.5. Additional details on the inversion framework, including the construction of the state vector, Jacobian matrix, and error covariance matrices, is included in Text S1 in Supporting Information S1.

3. High-Resolution Posterior Fluxes

The gridded US EPA bottom-up inventory (Maasackers et al., 2023) is available on a 10×10 km² grid (Figure 3c). The total Permian Basin methane emissions in the EPA inventory are 1.1 Tg/yr, with 86% coming from the oil and gas sector, 11% from livestock and agriculture, 2% from landfills and wastewater, and 1% from other sources. Although elevated emissions are evident in both Delaware and Midland sub-basins in the EPA inventory, the emissions show little correspondence with the underlying oil and gas infrastructure in the region (Figures 3a and 3b). Previous studies have reported that the EPA inventory underestimates methane emissions in the Permian Basin (e.g., Barkley et al., 2023; Shen et al., 2022; Varon et al., 2023, 2026) and broadly attributed the underestimate to the oil and gas sector due to its out-sized contribution to the inventory. However, the coarse spatial resolution of previous flux inversions (10×10 km² or coarser) makes it difficult to robustly discern meaningful relationships with the underlying oil and gas infrastructure.

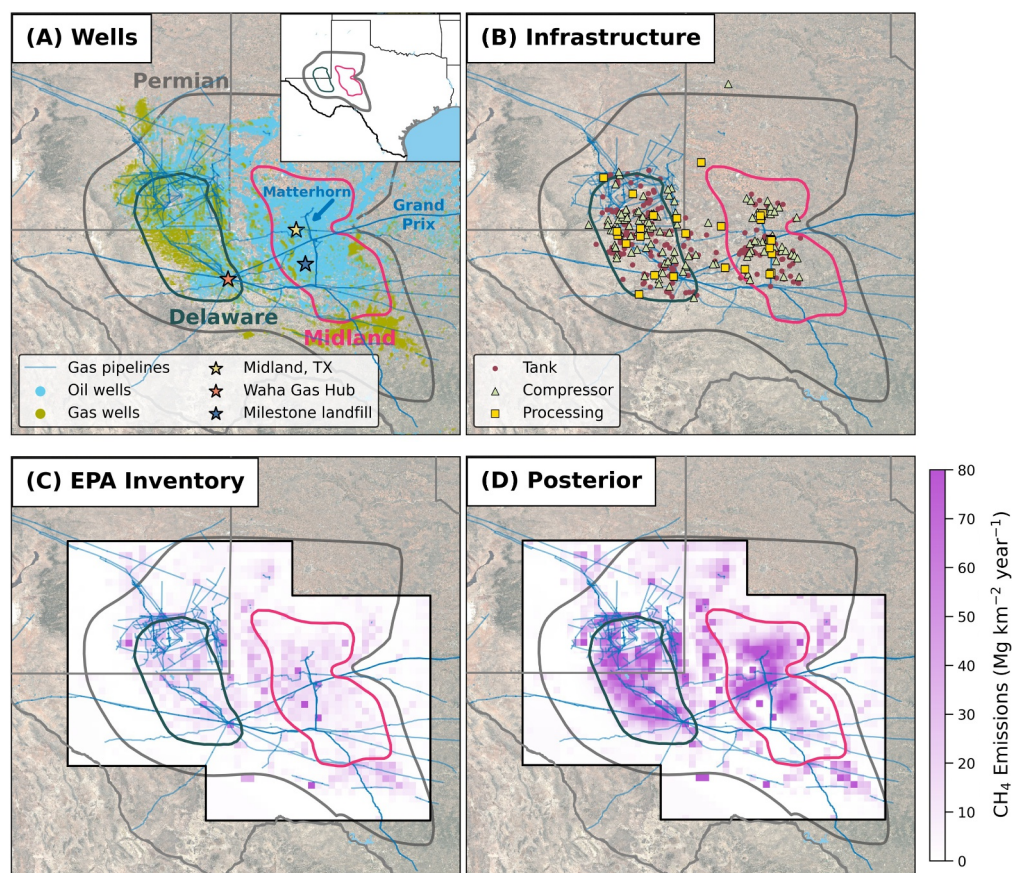


Figure 3. Spatial correspondence between posterior methane fluxes and oil and gas infrastructure in the Permian basin. (Panel a) Shows the location of oil and gas wells. Blue lines indicate major gas pipelines with diameters greater than 800 mm (31 inches). Oil and gas well locations are obtained from data sets provided by the Railroad Commission of Texas and Petroleum Recovery Research Center, while pipeline locations are from O'Brien et al. (2025). (Panel b) Shows the locations of storage tanks, compressor stations, and processing facilities; these sources are filtered to include only those with emissions greater than or equal to 200 kg/hr. These midstream infrastructure locations are from Cusworth et al. (2021). (Panel c) Shows the EPA methane emission inventory overlaid with major gas pipelines. (Panel d) Shows the inferred posterior emission fluxes averaged from April 2018 through December 2025 overlaid with the same pipeline network.

Here we use a scaled version of the EPA bottom-up inventory as our prior emissions in a Bayesian flux inversion. We use a scaled version of the EPA inventory because of previous findings that the inventory underestimates the emissions, a similar approach was adopted by Shen et al. (2022). A scaling factor of 2.5 was selected based on two diagnostic criteria: the domain-wide pattern of posterior corrections relative to the prior, and predictive skill on withheld observations (see Text S5 in Supporting Information S1 for details). We ultimately aim to estimate fluxes at $1 \times 1 \text{ km}^2$ spatial resolution. As such, we subdivide each $10 \times 10 \text{ km}^2$ grid cell from the EPA inventory into one hundred $1 \times 1 \text{ km}^2$ elements all with the same emissions, thus preserving the spatial pattern from the EPA inventory without interpolation. This allows the inversion to update the spatial pattern and magnitude of emissions based on observational constraints, transport, and prior uncertainties. This formulation is similar in spirit to using a spatially uniform prior inventory.

Figure 3d shows the average posterior emissions over 7 years (April 2018 through December 2025) inferred from our flux inversion using TROPOMI observations. We estimate emissions that are substantially higher than the EPA inventory and show spatial patterns that are distinct from the prior. Our total emissions for the Permian Basin are $2.6 \pm 0.5 \text{ Tg/yr}$, compared to 1.1 Tg/yr in the EPA inventory and $2.3\text{--}4.0 \text{ Tg/yr}$ for previous top-down studies (Liu et al., 2021; Lyon et al., 2021; McNorton et al., 2022; Schneising et al., 2020; Shen et al., 2022; Varon et al., 2023, 2026; Zhang et al., 2020). This estimate reflects a prior scaling factor of 2.5 (see Section 2 and Text S5 in Supporting Information S1); sensitivity tests using scaling factors from 1 to 4 yield a structural uncertainty

range of 1.7–3.2 Tg/yr, which exceeds the posterior statistical uncertainty of ± 0.5 Tg/yr that conditions on this scaling factor choice. The two most prominent features we observe are: (a) large emissions on the western flank of the Delaware sub-basin and (b) a J-shaped emission pattern in the Midland sub-basin. Notably, these features are not simple refinements of the prior but instead reflect newly resolved structures emerging from observational constraints. Further, these spatial patterns are robust to the choice of scaling factor (Figure S5 in Supporting Information S1). This raises the question “Are the emission patterns observed in the posterior fluxes real?”

To evaluate the efficacy of the inferred fluxes, we first perform cross-validation by withholding 10% of the observations from each inversion run and using them as an independent validation data set. Methane enhancements were simulated using both the prior and posterior fluxes. The enhancements were combined with the background concentrations and compared against the held-out observations. In the Delaware domain, the mean squared error (MSE) improved from 299 ppb² for the prior to 229 ppb² for the posterior and the R^2 improved from 0.64 to 0.72. In the Midland domain, the MSE improved from 236 ppb² to 179 ppb² and the R^2 improved from 0.71 to 0.79 (see Figure S7 in Supporting Information S1). These reductions in MSE and corresponding increases in R^2 demonstrate that the posterior fluxes provide a better fit to independent observations than the EPA-based prior, indicating improved predictive skill of the inferred fluxes.

In addition to cross-validation, we compare the posterior emissions with the distribution of oil and gas wells. Figure 3a shows that the Delaware sub-basin contains a mixture of both oil and gas production with the gas wells being predominantly located on the western side. In contrast, the Midland sub-basin is almost exclusively comprised of oil wells. The spatial pattern of the gas wells within the Delaware sub-basin is strongly correlated with the posterior emissions we infer. This spatial correspondence with gas wells in the Delaware sub-basin both indicates that the inversion is capturing emissions associated with gas production infrastructure and that gas production is likely dominating the methane emissions within the Permian Basin.

While the distribution of gas wells largely explains the spatial pattern of emissions in the Delaware sub-basin, it does not explain the patterns observed in the Midland basin. We examined the spatial distribution of oil and gas infrastructure. The blue lines in Figure 3 show the locations of major gas pipelines with diameters larger than 800 mm (31 inches). The Grand Prix pipeline is one of the largest gas pipelines in the Permian Basin that connects the Waha Gas Hub in the Delaware sub-Basin to Mont Belvieu, TX and runs East-West through the middle of the Midland sub-basin. Another major gas pipeline is the Matterhorn pipeline that runs North-South through the Midland sub-basin. We observe large emissions along these pipelines, and they largely track the J-shaped feature mentioned earlier. These spatial correspondences suggest that large-scale transport and handling infrastructure play a significant role in shaping the methane emission patterns in the Permian basin. We are not arguing that these pipelines are directly leaking methane, but we posit that there is oil and gas infrastructure along these large pipelines that may be driving the emissions we infer.

Figure 3b shows the location of storage tanks, compressor stations, and processing facilities. As posited above, this infrastructure is concentrated in the vicinity of the major gas pipelines. The localized emission enhancements observed along the pipeline corridors are likely associated with this supporting infrastructure. These sources contribute to the concentrated emission hotspots observed in the posterior emissions. This is prevalent in both the Delaware and Midland sub-basins. For example, elevated emissions in northeastern Delaware, central Midland, and along the Matterhorn pipeline coincide with clusters of such infrastructure. This finding of emissions co-located with dense oil and gas infrastructure gives credence to the spatial patterns inferred here. Furthermore, the ability to resolve these localized features highlights the advantage of kilometer-scale inversions for capturing emissions from heterogeneous and spatially clustered sources.

The most compelling validation of the posterior emissions comes from regions where infrastructure is absent. One of the few areas exhibiting posterior emissions that are lower than the EPA inventory is centered directly on the city of Midland, TX. An examination of Figure 3b confirms an absence of oil and gas infrastructure within the city boundary, and we observe the major gas pipeline routed south specifically to bypass the city (see Figure S8 in Supporting Information S1 for an expanded view). The low posterior emissions in this urban area, coinciding with the absence of infrastructure and pipelines, strongly support the interpretation that the inferred posterior emissions are driven by the spatial distribution of oil and gas infrastructure. A further test is provided by the region surrounding the Milestone landfill. Although the Milestone landfill is one of the largest sources in the EPA inventory, our posterior emissions show a general reduction in this area, again coinciding with an absence of oil and

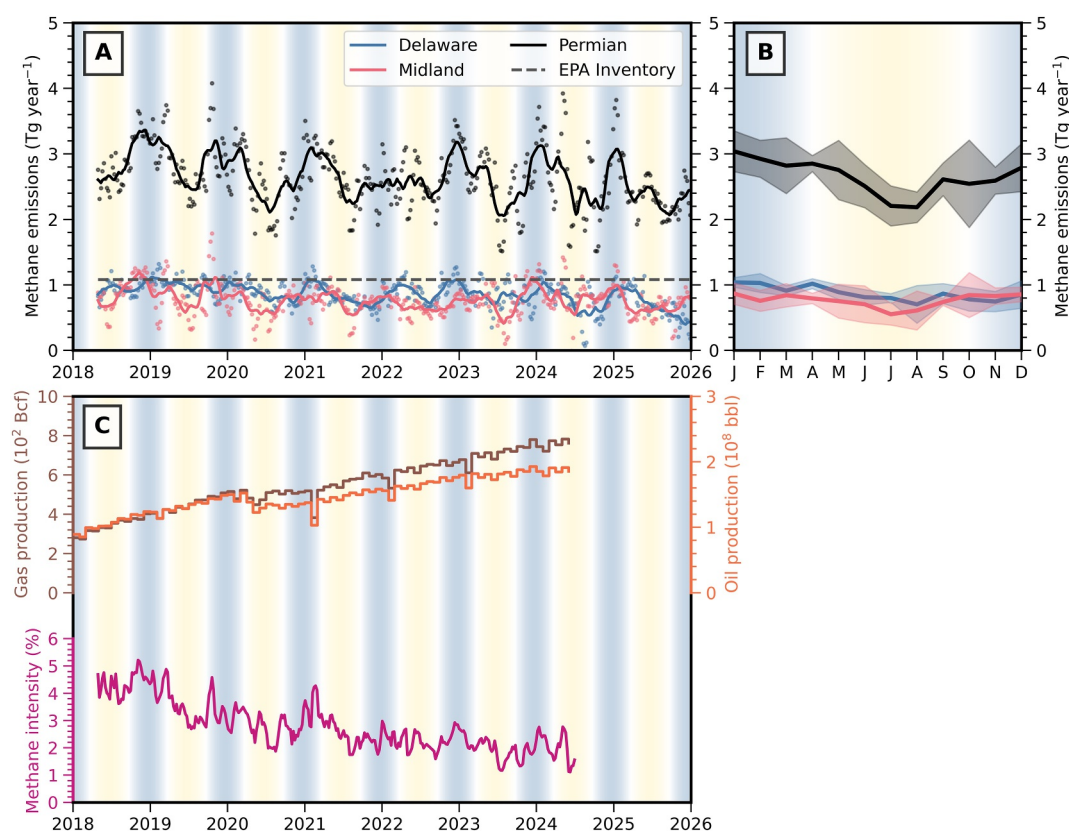


Figure 4. Timeseries of methane emissions, oil and gas production, and methane intensity. (Panel a) Shows the time series of methane emissions in the Permian (black), Delaware (blue), and Midland (pink) basins. Solid lines are a 12-week moving average. (Panel b) Shows the seasonal cycle of the methane emissions. (Panel c) Shows the timeseries of oil (orange) and gas (brown) production and the timeseries of methane intensity (purple) for the Permian Basin. We assume 80% methane content for the natural gas produced in the Permian basin. Background shading indicates summer and winter as discerned by $\cos(\text{SZA})$.

gas infrastructure. We emphasize that the spatial patterns of infrastructure (i.e., information shown in Figures 3a and 3b) are not used in our flux inversion, our prior emissions are a scaled version of the EPA inventory. Taken together, the spatial correspondence in regions of both high and low infrastructure density, none of which is used as input to the inversion, provides strong independent validation of the posterior emission patterns.

Figure 4a shows the time series of posterior methane emission fluxes from May 2018 through December 2025, highlighting substantial differences between the prior and posterior estimates over the Permian Basin. The prior, derived from constant bottom-up EPA emissions, appears as a flat time series, whereas the posterior fluxes exhibit pronounced temporal variability, with peaks reaching up to 4.0 Tg/yr and minima of 1.6 Tg/yr. These peaks and minima are 3.6 $\times$ and 1.5 $\times$, respectively, higher than the EPA inventory. Across the record, we find comparable emissions in the Delaware and Midland sub-basins. The difference between emissions from the Delaware and Midland sub-basins is not statistically significant. The comparable emissions across sub-basins is notable as the spatial pattern of emissions in the Delaware sub-basin follows the location of gas wells whereas the pattern of emissions in the Midland sub-basin follows the location of infrastructure such as storage tanks, compressor stations, and processing facilities. Together, these results indicate that the inversion captures both temporal variability and basin-scale differences that are not represented in the EPA inventory.

Figure 4b shows the mean seasonal cycle of emissions over the full record. Mean emissions are generally higher during winter and early spring, and an F-test indicates that the seasonal cycle is statistically significant ($p < 0.01$). Previous studies have also reported elevated wintertime emissions (Barkley et al., 2023; Hu et al., 2025; Vanselow et al., 2024; Varon et al., 2026), and Varon et al. (2026) suggest that this wintertime enhancement is driven by increased emissions from liquid storage tanks resulting from reduced separator

efficiency under colder conditions. The inferred strength of the seasonal cycle, however, varies substantially across studies. The seasonal cycle found here is weaker than reported in Varon et al. (2026) and more consistent with that of Barkley et al. (2023). Varon et al. (2026) use a coarse-resolution inversion ($25 \times 25 \text{ km}^2$) whereas Barkley et al. (2023) use a $3 \times 3 \text{ km}^2$ inversion. Our results suggest that the seasonal cycle of methane emissions from oil and gas infrastructure may be more modest than previously inferred from coarse-resolution analyses, motivating further investigation into its robustness and potential drivers.

Methane intensity, defined as the fraction of methane emitted relative to total methane gas production, provides a normalized measure of production efficiency. Figure 4c shows the time series of methane intensity for the Permian Basin, assuming an 80% methane content in produced natural gas. We observe a clear decline in methane intensity from approximately 5% in 2018 to 2% in 2024, consistent with previous studies (Lu et al., 2023; Varon et al., 2026). This decrease is primarily driven by increasing natural gas production over time, while total methane emissions remain relatively stable. These results suggest that the observed reduction in methane intensity reflects improved production scaling rather than a proportional reduction in absolute emissions.

4. Conclusion

In this study, we developed a kilometer-scale methane inversion framework that combines TROPOMI observations with the ML-based FootNet transport model to quantify emissions across the Permian Basin from 2018 through 2025. Total Permian Basin methane emissions averaged $2.6 \pm 0.5 \text{ Tg/yr}$ (structural uncertainty range of 1.7–3.2 Tg/yr) over the study period, a 2.4× increase relative to the EPA inventory. The inferred posterior fluxes reveal strong spatial correspondence with oil and gas infrastructure, including gas wells, major pipeline corridors, and associated facilities, while showing reduced emissions in urban areas and regions devoid of gas infrastructure. Critically, this infrastructure information was not used as input to the inversion, providing independent validation of the spatial patterns. We further identify persistent basin-scale differences in the drivers of the emissions, with elevated emissions in the Delaware sub-basin co-located with gas wells and elevated emissions in the Midland sub-basin co-located with storage tanks, compressor stations, and processing facilities. We find a statistically significant seasonal cycle in methane emissions across the Permian Basin with elevated wintertime emissions, but the seasonal cycle is notably weaker than reported by previous work. Despite a 2–3× increase in oil and gas production over the study period, total methane emissions remained relatively stable, driving a decline in methane intensity from approximately 5% in 2018 to 2% in 2024. This reduction in methane intensity reflects improved production scaling rather than absolute emission reductions. Together, these results demonstrate that combining satellite observations with ML-based transport emulation enables robust, fine-scale emission estimates at spatial scales substantially finer than those achieved in previous regional TROPOMI inversion frameworks. This framework provides a pathway for improved attribution and monitoring of methane emissions in complex oil and gas basins and can be extended to other major production regions globally.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

TROPOMI methane observations are available at <https://www.earthdata.nasa.gov/data/tools/earthdata-search> (last accessed: 15 May 2026). Oil and gas wells locations can be obtained from Railroad Commission of Texas (2026) (last accessed: 15 May 2026) and Petroleum Recovery Research Center (PRRC) (2026) (last accessed: 15 May 2026). The EPA bottom-up inventory for methane emissions is available at McDuffie et al. (2023) (last accessed: 15 May 2026). The code for the flux inversion and footprint computation is available at https://github.com/nd349/TROPOMI_flux_inversion (last accessed: 19 October 2026). Our weekly posterior methane emission estimates and code are available at Dadheech and Turner (2026a) (last accessed: 19 October 2026).

References

- Barkley, Z., Davis, K., Miles, N., Richardson, S., Deng, A., Hmiel, B., et al. (2023). Quantification of oil and gas methane emissions in the Delaware and Marcellus basins using a network of continuous tower-based measurements. *Atmospheric Chemistry and Physics*, 23(11), 6127–6144. <https://doi.org/10.5194/acp-23-6127-2023>

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- Barkley, Z., Davis, K. J., Miles, N. L., & Richardson, S. J. (2025). Examining daily temporal characteristics of oil and gas methane emissions in the Delaware basin using continuous tower observations. *Journal of Geophysical Research: Atmospheres*, 130(6), e2024JD042050. <https://doi.org/10.1029/2024JD042050>
- Bocquet, M. (2009). Toward optimal choices of control space representation for geophysical data assimilation. *Monthly Weather Review*, 137(7), 2331–2348. <https://doi.org/10.1175/2009mwr2789.1>
- Bocquet, M., & Wu, L. (2011). Bayesian design of control space for optimal assimilation of observations. Part II: Asymptotic solutions. *Quarterly Journal of the Royal Meteorological Society*, 137(658), 1357–1368. <https://doi.org/10.1002/qj.841>
- Bocquet, M., Wu, L., & Chevallier, F. (2011). Bayesian design of control space for optimal assimilation of observations. Part I: Consistent multiscale formalism. *Quarterly Journal of the Royal Meteorological Society*, 137(658), 1340–1356. <https://doi.org/10.1002/qj.837>
- Bousserez, N., & Henze, D. K. (2018). Optimal and scalable methods to approximate the solutions of large-scale Bayesian problems: Theory and application to atmospheric inversion and data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 144(711), 365–390. <https://doi.org/10.1002/qj.3209>
- Cartwright, L., Zammit-Mangion, A., & Deutscher, N. M. (2023). Emulation of greenhouse-gas sensitivities using variational autoencoders. *Environmetrics*, 34(2), e2754. <https://doi.org/10.1002/env.2754>
- Cusworth, D. H., Duren, R. M., Thorpe, A. K., Olson-Duvall, W., Heckler, J., Chapman, J. W., et al. (2021). Intermittency of large methane emitters in the Permian basin. *Environmental Science and Technology Letters*, 8(7), 567–573. <https://doi.org/10.1021/acs.estlett.1c00173>
- Cusworth, D. H., Thorpe, A. K., Ayasse, A. K., Stepp, D., Heckler, J., Asner, G. P., et al. (2022). Strong methane point sources contribute a disproportionate fraction of total emissions across multiple basins in the United States. *Proceedings of the National Academy of Sciences*, 119(38), e2202338119. <https://doi.org/10.1073/pnas.2202338119>
- Dadheech, N., He, T.-L., & Turner, A. J. (2025). High-resolution greenhouse gas flux inversions using a machine learning surrogate model for atmospheric transport. *Atmospheric Chemistry and Physics*, 25(10), 5159–5174. <https://doi.org/10.5194/acp-25-5159-2025>
- Dadheech, N., & Turner, A. (2026a). Observing methane emissions from oil and gas infrastructure in the Permian basin using tropomi [Code & Dataset]. *Zenodo*. <https://doi.org/10.5281/zenodo.20192538>
- Dadheech, N., & Turner, A. J. (2026b). Simulating out-of-sample atmospheric transport to enable flux inversions. *Atmospheric Chemistry and Physics*, 26(1), 427–441. <https://doi.org/10.5194/acp-26-427-2026>
- EIA. (2024). U.S. energy information administration drilling productivity report. Retrieved from <https://www.eia.gov/petroleum/drilling/>
- Fillola, E., Santos-Rodriguez, R., Tunnicliffe, R., Clark, J. N., Keshtmand, N., Ganesan, A., & Rigby, M. (2026). Enabling fast greenhouse gas emissions inference from satellites with gates: A graph-neural-network atmospheric transport emulation system. *Geoscientific Model Development*, 19(5), 1893–1915. <https://doi.org/10.5194/gmd-19-1893-2026>
- Hamilton, S. D., Wu, D., Johnson, M. S., Turner, A. J., Fischer, M. L., Dadheech, N., & Jeong, S. (2024). Estimating carbon dioxide emissions in two California cities using Bayesian inversion and satellite measurements. *Geophysical Research Letters*, 51(20), e2024GL111150. <https://doi.org/10.1029/2024GL111150>
- He, T.-L., Dadheech, N., Thompson, T. M., & Turner, A. J. (2025). Footnet v1.0: Development of a machine learning emulator of atmospheric transport. *Geoscientific Model Development*, 18(5), 1661–1671. <https://doi.org/10.5194/gmd-18-1661-2025>
- Heald, C. L., Jacob, D. J., Jones, D. B. A., Palmer, P. I., Logan, J. A., Streets, D. G., et al. (2004). Comparative inverse analysis of satellite (MOPITT) and aircraft (TRACE-P) observations to estimate Asian sources of carbon monoxide. *Journal of Geophysical Research*, 109(D23). <https://doi.org/10.1029/2004JD005185>
- Hu, L., Andrews, A. E., Montzka, S. A., Miller, S. M., Bruhwiler, L., Oh, Y., et al. (2025). An unexpected seasonal cycle in U.S. oil and gas methane emissions. *Environmental Science & Technology*, 59(20), 9968–9979. <https://doi.org/10.1021/acs.est.4c14090>
- IPCC. (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. The Australian National University.
- Jacob, D. J., Turner, A. J., Maasakkers, J. D., Sheng, J., Sun, K., Liu, X., et al. (2016). Satellite observations of atmospheric methane and their value for quantifying methane emissions. *Atmospheric Chemistry and Physics*, 16(22), 14371–14396. <https://doi.org/10.5194/acp-16-14371-2016>
- Jacob, D. J., Varon, D. J., Cusworth, D. H., Dennison, P. E., Frankenberg, C., Gautam, R., et al. (2022). Quantifying methane emissions from the global scale down to point sources using satellite observations of atmospheric methane. *Atmospheric Chemistry and Physics*, 22(14), 9617–9646. <https://doi.org/10.5194/acp-22-9617-2022>
- Liu, M., van der A, R., van Weele, M., Eskes, H., Lu, X., Veeckind, P., et al. (2021). A new divergence method to quantify methane emissions using observations of Sentinel-5P TROPOMI. *Geophysical Research Letters*, 48(18), e2021GL094151. <https://doi.org/10.1029/2021GL094151>
- Lu, X., Jacob, D. J., Zhang, Y., Shen, L., Sulprizio, M. P., Maasakkers, J. D., et al. (2023). Observation-derived 2010–2019 trends in methane emissions and intensities from US oil and gas fields tied to activity metrics. *Proceedings of the National Academy of Sciences*, 120(17), e2217900120. <https://doi.org/10.1073/pnas.2217900120>
- Lyon, D. R., Hmiel, B., Gautam, R., Omara, M., Roberts, K. A., Barkley, Z. R., et al. (2021). Concurrent variation in oil and gas methane emissions and oil price during the COVID-19 pandemic. *Atmospheric Chemistry and Physics*, 21(9), 6605–6626. <https://doi.org/10.5194/acp-21-6605-2021>
- Maasakkers, J. D., Jacob, D. J., Sulprizio, M. P., Turner, A. J., Weitz, M., Wirth, T., et al. (2016). Gridded national inventory of U.S. methane emissions. *Environmental Science & Technology*, 50(23), 13123–13133. <https://doi.org/10.1021/acs.est.6b02878>
- Maasakkers, J. D., McDuffie, E. E., Sulprizio, M. P., Chen, C., Schultz, M., Brunelle, L., et al. (2023). A gridded inventory of annual 2012–2018 U.S. anthropogenic methane emissions. *Environmental Science & Technology*, 57(43), 16276–16288. <https://doi.org/10.1021/acs.est.3c05138>
- McDuffie, E. E., Maasakkers, J. D., Sulprizio, M. P., Chen, C., Schultz, M., Brunelle, L., et al. (2023). Gridded EPA U.S. anthropogenic methane greenhouse gas inventory (gridded GHGI). *Zenodo*. <https://doi.org/10.5281/zenodo.8367082>
- McNorton, J., Bousserez, N., Agustí-Panareda, A., Balsamo, G., Cantarello, L., Engelen, R., et al. (2022). Quantification of methane emissions from hotspots and during COVID-19 using a global atmospheric inversion. *Atmospheric Chemistry and Physics*, 22(9), 5961–5981. <https://doi.org/10.5194/acp-22-5961-2022>
- O'Brien, M., Omara, M., Himmelberger, A., & Gautam, R. (2025). Oil and gas infrastructure mapping (OGIM) database [Dataset]. *Zenodo*. <https://doi.org/10.5281/zenodo.15103476>
- Petroleum Recovery Research Center (PRRC). (2026). All wells data [Dataset]. *Collected and compiled by the Industry Service Outreach Group*. [Dataset provided primarily by the New Mexico Oil Conservation Division (NMOCD) and updated monthly] Retrieved from https://gotech.nmt.edu/gotech/Petroleum_Data/allwells.aspx.Socorro,NM:NewMexicoInstituteofMiningandTechnology.GO-TECH
- Railroad Commission of Texas. (2026). Data sets available for download [Dataset]. Retrieved from <https://www.rrc.texas.gov/resource-center/research/data-sets-available-for-download/>

- Schneising, O., Buchwitz, M., Reuter, M., Vanselow, S., Bovensmann, H., & Burrows, J. P. (2020). Remote sensing of methane leakage from natural gas and petroleum systems revisited. *Atmospheric Chemistry and Physics*, 20(15), 9169–9182. <https://doi.org/10.5194/acp-20-9169-2020>
- Shen, L., Gautam, R., Omara, M., Zavala-Araiza, D., Maasakkers, J. D., Scarpelli, T. R., et al. (2022). Satellite quantification of oil and natural gas methane emissions in the US and Canada including contributions from individual basins. *Atmospheric Chemistry and Physics*, 22(17), 11203–11215. <https://doi.org/10.5194/acp-22-11203-2022>
- Turner, A. J., & Jacob, D. J. (2015). Balancing aggregation and smoothing errors in inverse models. *Atmospheric Chemistry and Physics*, 15(12), 7039–7048. <https://doi.org/10.5194/acp-15-7039-2015>
- Turner, A. J., Köhler, P., Magney, T. S., Frankenberg, C., Fung, I., & Cohen, R. C. (2020). A double peak in the seasonality of California's photosynthesis as observed from space. *Biogeosciences*, 17(2), 405–422. <https://doi.org/10.5194/bg-17-405-2020>
- Turner, A. J., Köhler, P., Magney, T. S., Frankenberg, C., Fung, I., & Cohen, R. C. (2021). Extreme events driving year-to-year differences in gross primary productivity across the US. *Biogeosciences*, 18(24), 6579–6588. <https://doi.org/10.5194/bg-18-6579-2021>
- Vanselow, S., Schneising, O., Buchwitz, M., Reuter, M., Bovensmann, H., Boesch, H., & Burrows, J. P. (2024). Automated detection of regions with persistently enhanced methane concentrations using Sentinel-5 precursor satellite data. *Atmospheric Chemistry and Physics*, 24(18), 10441–10473. <https://doi.org/10.5194/acp-24-10441-2024>
- Varon, D. J., Jacob, D. J., Estrada, L. A., Balasus, N., East, J. D., Pendergrass, D. C., et al. (2026). Seasonality and declining intensity of methane emissions from the Permian and nearby US oil and gas basins. *Environmental Science & Technology*, 60(1), 425–435. <https://doi.org/10.1021/acs.est.5c08745>
- Varon, D. J., Jacob, D. J., Hmiel, B., Gautam, R., Lyon, D. R., Omara, M., et al. (2023). Continuous weekly monitoring of methane emissions from the Permian basin by inversion of TROPOMI satellite observations. *Atmospheric Chemistry and Physics*, 23(13), 7503–7520. <https://doi.org/10.5194/acp-23-7503-2023>
- Veefkind, J., Aben, I., McMullan, K., Förster, H., de Vries, J., Otter, G., et al. (2012). TROPOMI on the ESA Sentinel-5 precursor: A GMES mission for global observations of the atmospheric composition for climate, air quality and ozone layer applications. *Remote Sensing of Environment*, 120, 70–83. <https://doi.org/10.1016/j.rse.2011.09.027>
- Zhang, Y., Gautam, R., Pandey, S., Omara, M., Maasakkers, J. D., Sadavarte, P., et al. (2020). Quantifying methane emissions from the largest oil-producing basin in the United States from space. *Science Advances*, 6(17), eaaz5120. <https://doi.org/10.1126/sciadv.aaz5120>

References From the Supporting Information

- Nesser, H., Bowman, K. W., Thill, M. D., Varon, D. J., Randles, C. A., Tewari, A., et al. (2025). Predicting and correcting the influence of boundary conditions in regional inverse analyses. *Geoscientific Model Development*, 18(23), 9279–9291. <https://doi.org/10.5194/gmd-18-9279-2025>
- Yadav, V., & Michalak, A. M. (2013). Improving computational efficiency in large linear inverse problems: An example from carbon dioxide flux estimation. *Geoscientific Model Development*, 6(3), 583–590. <https://doi.org/10.5194/gmd-6-583-2013>