**High-resolution US methane emissions inferred from an inversion of TROPOMI satellite data: contributions from livestock, individual states, and urban areas**

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We quantify 2019 methane emissions in the contiguous United States (CONUS) at 0.25° × 0.3125° resolution by inverse analysis of atmospheric methane columns measured by the Tropospheric Monitoring Instrument (TROPOMI). A gridded version of the U.S. Environmental Protection Agency (EPA) methane inventory serves as prior estimate for the inversion. We optimize emissions and quantify observing system information content through analytical minimization of a Bayesian cost function. We achieve high resolution with a reduced-rank characterization of the observing system that preserves information content by optimizing emissions only where observing system errors are sufficiently low. This decreases computational cost by an order of magnitude relative to a full-rank 0.25ox0.3125o inversion while optimizing 80% of anthropogenic emissions in CONUS. Our optimal (posterior) estimate of anthropogenic emissions in the US is 30.9 (30.0 - 31.8) Tg a-1, where the values in parentheses is the spread of an 8-member inversion ensemble. This is a 15% increase from the most recent EPA Greenhouse Gas Inventory (GHGI) estimate for 2019 of 26.8 Tg a-1. We decompose emissions by sector as livestock 10.4 Tg a-1, oil and natural gas 10.4 Tg a-1, coal 1.5 Tg a-1, landfills 6.9 Tg a-1, wastewater xx Tg a-1, and others xx Tg a-1. We find a 52% increase and 30% decrease from the GHGI for landfills and coal. The GHGI livestock emissions increase of 11% correlates with hog and dairy cattle operations, suggesting underestimated manure management emissions. We exploit the high resolution of our inversion to quantify emissions for all individual states and compare to EPA’s new state-level inventories as well as independent inventories produced by state agencies. Our posterior emissions are on average 38% larger than these inventories in the largest 10 methane-producing states, with the largest upward adjustments in states with large oil and natural gas emissions and the largest downward adjustments in states with large contributions from coal emissions. We also calculate emissions for 219 geographically diverse urban areas. We find a 69% increase relative to the EPA inventory in the largest 10 methane-producing cities. The addition of post-meter natural gas emissions to the latest version of the GHGI could largely account for this correction.

**1 Introduction**

All modeled pathways that prevent global warming above 1.5°C require methane emissions reductions (IPCC SR5). The United Nations Framework Convention on Climate Change (UNFCCC) requires member parties to report methane emissions. The bottom-up approaches used to generate these emission inventories use information on sectoral activity levels and emission factors, but considerable uncertainty can exist in these values. Top-down evaluations of bottom-up inventories use observations of atmospheric methane together with an atmospheric transport model to relate observed concentrations to emissions through inverse analyses. These top-down emission estimates are most useful if they can achieve high spatial resolution with sufficient information content including error characterization. Here we use column methane observations from the TROPOMI satellite instrument in a reduced-rank analytical inversion to infer methane emissions and the associated information content at 0.25° × 0.3125° (≈25 × 25 km2) resolution over North America for 2019, allowing detailed analysis of US sectoral, state, and urban emissions.

Satellite observations of atmospheric methane column concentrations inferred from measurement of backscattered sunlight in the shortwave infrared have been extensively used in inverse analyses of methane emissions (Streets et al., 2013; Jacob et al., 2022). Past satellite instruments were limited by large pixel sizes (SCIAMCHY, 2003 – 2012) or sparse observations (GOSAT, 2009 – present). The Tropospheric Monitoring Instrument (TROPOMI) aboard the Sentinel-5 Precursor satellite now provides daily, global observations of atmospheric methane columns at 5.5 km × 7 km nadir pixel resolution over land (Hu et al., 2018; Lorente et al., 2021) with a 3% success rate limited by cloud cover, optically dark surfaces, and heterogeneous terrain (Hasekamp et al., 2019). Inversions of TROPOMI data allow for high-resolution emission quantification but require understanding the actual information content of the observations.

Inverse analyses optimize methane emissions (the state vector) by fitting observations to simulated concentrations from a chemical transport model (CTM). This is typically done by minimizing a Bayesian cost function regularized by a prior emissions estimate given by a bottom-up inventory. When a linear relationship exists between emissions and concentrations, as in the case of methane, the optimal (posterior) solution and the associated errors and information content can be found analytically. This method also supports the generation of inversion ensembles. However, it requires explicit construction of the Jacobian matrix that represents the relationship between emissions and concentrations in the CTM, This is a computationally expensive task, typically done by conducting a perturbation CTM simulation for each emission element, and limits either the spatial resolution of the optimized emissions or the size of the inversion domain. .In Nesser et al. (2021), we presented an alternative method that approximates the Jacobian matrix by perturbing leading emission patterns guided by both the prior information and the observations. This method maximizes the exploitation of the information content available from the observations towards quantifying emissions at the highest resolution possible, trading high resolution against the rank of the problem (that is, defaulting to the prior estimate in regions of low emissions are where the observations do not provide sufficient information).

Quantifying methane emissions from the US is of particular interest. Several inverse studies conducted on the national scale have found large discrepancies between bottom-up emissions estimates from the U.S. Environmental Protection Agency’s Greenhouse Gas Inventory (GHGI) and inferred emissions from satellite, aircraft, and in situ observations. Lu et al. (2022) found mean 2010 – 2017 anthropogenic emissions of 36.0 (32.5 - 37.8) Tg a-1 compared to the 2021 EPA GHGI estimate of 26.0 Tg a-1 for the same period from an inversion of GOSAT data, which they attributed largely to oil emissions over the south-central US. They also found increases in livestock (15%) and landfill (24%) emissions relative to the GHGI but were unable to explain the source of the increase, due in part to the coarse resolution of the inversion over those source regions. Deng et al. (2022) determined national methane emissions from the Global Carbon Project inversion ensemble (Saunois et al., 2020), and found median 2017 emissions of 26.5 (20.8 - 38.7) Tg a-1 for GOSAT inversions and 31.9 (23.9 - 43.1) Tg a-1 for inversions of in situ data. However, the large range prohibits accurate source attribution.

Higher resolution regional studies have targeted specific aspects of US emissions. Alvarez et al. (2018) used aircraft and in situ observations from Shen et al. (2022) conducted an inversion of TROPOMI data over North American oil and natural gas basins from May 2018 to February 2020 and found emissions 80% larger than the EPA GHGI for 2021. Chen et al. (2018) and Yu et al. (2021) inverted in situ and aircraft observations over the upper Midwest and found an 80% and 24% increase, respectively, from the Gridded EPA (GEPA) inventory based on the 2016 EPA GHGI for 2012. Sheng et al. (2018) found good agreement with GEPA in an inversion of SEAC4RS aircraft observations over the Southeast US, but they found large regional variability. Plant et al. (2019) used aircraft observations of methane, CO2, and CO together with CO2 and CO emission inventories to infer methane emissions from six East Coast urban areas more than two times larger than GEPA. While these regional studies provide insight into some of the sources of the observed discrepancy with EPA estimates, they are hindered by their limited domain.

Here we use the method of Nesser et al. (2021) in a continental-scale analytical inversion of 2019 TROPOMI observations at 0.25o×0.3125o resolution for North America, using national inventories reported to the UNFCCC as prior estimates. Several filters are applied to the TROPOMI data to avoid spatial biases. We focus our analysis of inversion results on the US with specific attention to the livestock sector to the quantification of emissions for individual states and metropolitan areas. The most recent version of the US EPA GHGI resolves emissions and our inversion is an opportunity to evaluate these emissions.

**2** **Data and methods**

We conduct an ensemble of inversions of 2019 TROPOMI methane observations over North America using the GEOS-Chem CTM as forward model applied to the continental-scale domain shown in Figure 1 (9.75° -60°N, 130°-60°W).. The ensemble is described in Section 2.7. The TROPOMI observations are fit to simulated GEOS-Chem concentrations to optimize a state vector of mean methane emissions for 2019 on the 0.25° × 0.3125° GEOS-Chem grid. This yields a state vector of . 23691 grid cells including all grid cells with prior methane emissions larger than 0.1 Mg km-2 a-1, representing over 99% of methane emissions in North America. We also optimize the boundary conditions for the GEOS-Chem simulation in the four cardinal directions (north, south, east, and west). Methane chemical and soil sinks are not optimized because they are slow compared to the domain ventilation timescale and also relatively uniform.

**2.1 Reduced-rank analytical inversion**

The inversion optimizes the state vector of gridded emissions assuming normal errors by minimizing a Bayesian cost function

where and are the prior emissions estimate and error covariance matrix, respectively; and are the vector of observed concentrations and the associated error covariance matrix, respectively; and is the reduced-rank Jacobian matrix that represents the sensitivity of concentrations to emissions in the CTM (Rodgers, 2000). The relationship between emissions and concentrations is linear, therefore **K** fully describes the CTM for the purpose of the inversion. The error covariance matrices are assumed diagonal in the absence of better information, and is a regularization factor to correct for the absence of covariance in (Chevallier et al., 2014).

The reduced-rank Jacobian matrix is constructed with the GEOS-Chem CTM by finite-difference perturbations of a number *k* < *n*  of leading emission patterns as described in Section 2.6. The leading emission patterns are selected on the basis of the prior emission estimates and the information content of the TROPOMI observations. This maximizes the computational efficiency of the inversion and enables the optimization of the state vector on the native 0.25° × 0.3125° grid of GEOS-Chem. But it also means that the resulting Jacobian matrix is of rank *m×k* rather than *m×n*.

Analytical minimization of the cost function following Rodgers (2000) yields the optimal (posterior) state vector estimate , error covariance matrix , and information content given by the averaging kernel matrix , which describes the sensitivity of the posterior estimate to the true state vector. The diagonal elements of are commonly referred to as averaging kernel sensitivities and their sum (trace of ) gives the degrees of freedom for signal (DOFS) representing the number of pieces of information independently quantified by the observing system ). The computations of   and involve operations on **K** but its reduced rank causes numerical instabilities in the *n*-dimensional space.

Here we use a reduced-rank approximation following Bousserez and Henze (2018) to obtain the solution on an orthonormal basis that optimally spans the information content of the satellite–forward model observing system. The basis is given by the eigendecomposition of the prior-preconditioned Hessian of the forward model

where the columns of are the eigenvectors and is a diagonal matrix with entries equal to the eigenvalues. The reduced-rank approximation is then generated using the largest eigenvalues and the associated eigenvectors :

Here, approximates the full-rank (FR) posterior by minimizing the difference between the two, and and are the optimal posterior error covariance and averaging kernel matrices for an inversion solved with the reduced-rank observing system. We choose to match the rank of the reduced-rank Jacobian matrix, which is chosen to maximize the DOFS within the available computational resources (section 2.8). The reduced-rank inversion does not attempt to optimize low-information emission patterns, as revealed by very small averaging kernel sensitivities on the 0.25° × 0.3125° grid. We default to the prior estimate for grid cells with averaging kernel sensitivities less than 0.05.

**2.2 Prior estimates and errors**

Figure 1 shows the prior emission estimates for the different sectors. Anthropogenic emissions for the United States, Mexico, and Canada are from the spatially disaggregated versions of the EPA GHGI for the US in 2012 (GEPA; Maasakkers et al., 2016), the INECC inventory for Mexico in 2015 (Scarpelli et al., 2020), and the ECCC inventory for Canada in 2018 (Scarpelli et al., 2021). We update GEPA oil/gas emissions in the US to 2018 following Shen et al. (2022). The GEPA is known to greatly underestimate oil/gas emissions in the Permian basin, which is the largest production field in the US, and we use for that basin the Environmental Defense Fund’s inventory for 2019 (Zhang et al., 2020). We treat oil and natural gas as a single sector in our analysis due to significant source co-location and uncertainty in the partitioning of oil and gas wells. Anthropogenic emissions for Central America and the Caribbean islands are provided by the EDGAR v4.3.2 global emission inventory for 2012. All , anthropogenic emissions are assumed aseasonal except for manure management and rice cultivation, for which we apply monthly scaling factors as described by Maasakkers et al. (2016) and Zhang et al. (2016), respectively.

Wetlands are the dominant natural source of methane emissions (Bloom et al., xxxx). We use the high-performance subset of xx members from the WetCHARTs ensemble version 1.3.1selected for its ability to match global GOSAT inversion results (Ma et al. 2021). Lu et al. (2022) previously found that this high-performance subset overestimated wetland emissions in their GOSAT inversion for North America, particularly at high latitudes. Here we remove the two members that are most responsible for this overestimate. Other minor natural methane emissions include open fires, termites, and geological seeps, for which we follow the emissions described in Lu et al. (2022).

We assume uniform relative prior error standard deviations for emissions of between 50% and 100% in our inversion ensemble, with no error covariance between grid cells. The 50% relative error follows previous inversions that optimized methane emissions over North America (Maasakkers et al., 2021; Lu et al., 2022). We inflate errors up to 100% to account for displacement errors and increased error covariance at high resolution (Maasakkers et al. 2016).

**2.3 Forward model**

We use the nested version of the GEOS-Chem CTM 12.7 at 0.25° × 0.3125° resolution over North America as the forward model for the inversion. Earlier versions of the methane simulation were described by Wecht et al. (2014) and Turner et al. (2015). The model is driven by GEOS-FP meteorological fields from the NASA Global Modeling and Assimilation Office (GMAO). Methane loss from OH, Cl, soil uptake, and stratospheric oxidation is described in Maasakkers et al. (2019) and is included in our simulation but is of no consequence because ventilation of the domain by the boundary conditions is much faster. Initial conditions for January 1, 2019 and 3-hourly boundary conditions for the year are specified by methane concentration fields from a global GEOS-Chem simulation at 2° × 2.5° resolution using optimized emissions from a global inversion of TROPOMI observations (Qu et al., 2021). These concentration fields are unbiased with respect to the global TROPOMI data

**2.4 TROPOMI observations**

TROPOMI has provided daily, global observations of dry column methane mixing ratios at 7 × 7 km2 nadir pixel resolution since May 2018 and at 5.5 × 7 km2 nadir pixel resolution since August 2019 (citation). TROPOMI measures backscattered solar radiation at 2.3 μm from a sun-synchronous orbit with a local overpass time of 13:30 (Veefkind et al. 2012). Methane concentrations are inferred from a full-physics retrieval that can fail due to cloud cover, variable topography, low or heterogeneous albedo, and high aerosol loading (citation). As a result, TROPOMI has a xx% retrieval success rate over North America for 2019. We use the retrieval described by Lorente et al. (2021), which has a -3.4 ± 5.6 ppb bias relative to the Total Carbon Column Observing Network (TCCON). We use only high-quality retrievals as indicated by the quality assessment flag.

Previous analyses of TROPOMI data have pointed out the presence of surface artifacts (Barré et al., 2021) and spatially variable biases relative to the more accurate but much sparser GOSAT data (Qu et al., 2021; Chen et al., 2023). Here we filtered the TROPOMI data using the blended albedo product introduced by Lorente et al. (2021) to remove scenes with blended albedo > 0.75 in non-summer seasons when they are indicative of snow or ice. We also remove scenes with shortwave albedo less than 0.05 following de Gouw et al. (2020), which account for most of the remaining unphysical TROPOMI observations (XCH4 < 1700 ppb), and scenes north of 50°N in winter.

Figure 2 shows the final 2919358 observations used for the inversion on the GEOS-Chem 0.25o×0.3125o grid. The filters preserve 69% of the high-quality retrievals of TROPOMI version xxxx. and increase the GOSAT – TROPOMI correlation in all seasons, with the largest increases in winter and spring. Seasonal regional biases decrease by between 7% and 21% and are always within the one standard deviation range of both the TROPOMI and GOSAT data. Comparison to the GEOS-Chem simulation with prior emissions shows a mean negative GEOS-Chem bias of 9.1 ppb over the North America domain, which can be fit as a linear function of latitude (degrees) as l . This bias and its latitudinal structure could be caused by the boundary conditions and we correct it in our inversion ensemble members either as a continental mean or latitude-dependent adjustment to the GEOS-Chem concentrations.

**2.5 Observing system errors**

The observing system error covariance matrix (equation 1), includes contributions from the forward model, the instrument, and representation error (Brasseur and Jacob, 2017). We calculate the error variances using the residual error method (Heald et al. 2004). This method assumes that the mean difference between the TROPOMI observations and the prior GEOS-Chem simulation, which we calculate on a seasonal 2° × 2° grid, is caused by errors in emissions that will be corrected by the inversion. The standard deviation of the residual errors after subtracting the mean gridded errors then gives the observational errors. We set a minimum error of 10 ppb, which applies to 32% observations. We find a mean observational error standard deviation of 11.5 ppb, with larger errors in winter and at high latitudes. The resulting variances are the diagonal elements of . Off-diagonal terms are assumed zero in the absence of better information, which we account for by introducing the regularization factor (Chevallier et al., 2007). We describe the choice of in section 2.7.

**2.6 Jacobian matrix**

The Jacobian matrix **K** is normally constructed column by column by perturbing individual elements of the state vector in the forward model. However, conducting 1-year perturbation simulations in GEOS-Chem for the *n* =23691 grid cells optimized by our inversion is computationally intractable. We construct the Jacobian matrix at substantially decreased computational cost using the reduced-rank method introduced by Nesser et al. (2021) and taking advantage of the heterogeneous information content of the TROPOMI observations. This method updates an initial, low-cost estimate of the Jacobian matrix by perturbing the patterns that best explain the information content of the observing system, constructing a reduced-rank *m×n* Jacobian matrix while optimally preserving information content.

We construct the initial estimate of the Jacobian matrix using the mass-balance approach introduced by Nesser et al. (2021). We assume that a perturbation of methane emissions Δ*xj* in grid cell *j* produces column mixing ratio enhancements Δ*yi* in observation grid cell *i* according to

where is a dimensionless coefficient providing a crude representation of turbulent diffusion, and are the molecular weights of dry air and methane, respectively, is a ventilation length scale equal to the square root of the grid cell area, is gravitational acceleration, is the wind speed taken here as 5 km h-1, and is the surface pressure taken here as 1000 hPa. The simplest approach would be to simply collocate the column mixing enhancement with the emission, with α*ij* = 0 and Δ*yi*/Δ*xj* = 0 for *i ≠ j* resulting in a diagonal **K**(0), but we found in Nesser et al. (2021) that some off-diagonal structure is important for **K**(0) to serve as an effective first guess. To provide this off-diagonal structure we apply a simple isotropic turbulent diffusion allowing the influence of emissions to spread to the concentric ring of neighboring grid cells. This is represented as , where gives the absolute value of the difference in latitude or longitude grid cell index between and , 36 is the sum of values, and gives the number of grid cells in the corresponding concentric ring. This decreases the sparsity of , increasing its value as a first estimate.

We use in combination with the error covariance matrices **SA** and **SO** to select the initial patterns of information content to be perturbed in the forward model as described in Section 2.1. We calculate the prior pre-conditioned Hessian (equation 2) and complete its eigendecomposition. The resulting matrix of eigenvectors is related to the patterns of information content via , which is equivalent to the eigenvectors of the averaging kernel matrix calculated with (Bousserez and Henze, 2018). We perturb the = 434 eigenvectors that capture 50% of the DOFS generated with . We then apply an optimal operator that restores the original state dimension and minimizes information content loss to yield an updated reduced-rank Jacobian matrix estimate . We then recompute the eigenvectors, perturb the = 1952 eigenvectors that explain 80% of the initial DOFS, and construct the updated reduced-rank Jacobian matrix for use in the inversion. This iterative update scheme optimizes the information content of the posterior solution while reducing the computational cost by an order of magnitude (Nesser et al., 2021).

**2.7 Inversion ensemble**

The posterior error covariance matrix resulting from Bayesian optimization underestimates the actual errors in the posterior solution by failing to account for systematic observational errors or errors in the inversion parameters (Houweling et al., 2014). We estimate the effect of these errors by generating a quality-controlled ensemble of inversions, summarized in table 1. We use four sets of inversions by including or not the latitudinal correction to the model – observation difference and the use of boundary condition corrections. For each of these sets, we construct a further subset of members by varying the prior error standard deviation (50%, 75%, or 100%). For each member, we adjust the regularization factor (between 0.175 and 0.5) so that the prior term of the cost function evaluated at the posterior solution averages to 1 across all grid cells optimized by the reduced-rank inversion, which is the expected value from the narrow chi-square distribution (Lu et al., 2021). This yields an ensemble of 8 quality-controlled inversions that we consider to all be equally valid. We report the mean posterior emissions for that ensemble, with uncertainty ranges given by the ensemble range.

**2.8 Source attribution**

The high resolution of the inversion facilitates the attribution of the posterior emission estimates to different source categories including sectors, states, and urban areas. We aggregate the native resolution emissions estimate and associated errors to find the corresponding quantities for each source category by using a summation matrix , where is the number of source categories. The rows of are given by the relative contribution of each grid cell to a given source category. For sectoral attribution, the rows are given by the relative contribution of each sector to a grid cell in the prior emissions estimate. For state and urban area attribution, the rows are given by the fraction of each grid cell within the state or urban area, respectively. The reduced-dimension posterior estimate and associated posterior covariance and averaging kernel matrices are then given by

where is the Moore-Penrose pseudo inverse (Caliesi et al., 2005). This approach to source attribution assumes that the prior fractional sectoral contributions are correct in each grid cell and that emission sources are evenly distributed in grid cells that cross state or urban lines. The high resolution of the inversion decreases the chance of source co-location or significant distributional errors across boundaries.

**3 Results and discussion**

Figure 3 shows the ensemble mean posterior correction factors relative to the prior emissions estimate (left) and the corresponding averaging kernel sensitivities (right). Grid cells unoptimized by any inversion (mean averaging kernel sensitivity < 0.05) are left blank. We find 772 (421 - 1279) DOFS across the domain, where the values in parentheses are the ensemble minimum and maximum, respectively. Of these DOFS, 37 (15 - 69) are in Canada, 641 (350 – 1058) in CONUS, and 86 (53 - 134) in Mexico. This represents a large increase in information content relative to past inversions over North America. For example, Lu et al. (2022) found 114 DOFS in a joint inversion of data from GOSAT and NOAA’s ObsPack, while Shen et al. (2022) found 201 DOFS in an inversion of TROPOMI observations over 14 oil and natural gas basins. This increase reflects both the improved constraint provided by TROPOMI and our use of 0.25o×0.3125o resolution on the continental scale. Here we focus our analysis on CONUS where the information from the inversion is the greatest, and isolate anthropogenic emissions by removing contributions from wetlands and other natural sources following Section 2.8.

The mean posterior emissions when used in GEOS-Chem decrease the root mean squared error of the simulated observations with the TROPOMI data by xx% relative to the prior GEOS-Chem simulation. [Insert posterior evaluation.] We also compare the prior and mean posterior simulations to in situ surface and aircraft observations from the GLOBALVIEWplus CH4 ObsPack v(xx) database maintained by the National Oceanic and Atmospheric Administration (NOAA) Global Monitoring Laboratory (cite). [Insert independent posterior evaluation.]

We further evaluate the reduced-rank inversion by comparing our mean posterior emissions to a full-rank regional inversion of TROPOMI observations for May 2018 to February 2020 to quantify emissions from major oil and natural gas producing regions (Shen et al., 2022). Using the same basin boundaries, we find broadly consistent posterior emissions with Shen et al. (2022), with all posterior emissions within 0.25 Tg a-1 and all but five basins within 0.10 Tg a-1. We find small but significant differences in six basins (the Delaware, the Marcellus, Eagle Ford, California, Wyoming, and the Uinta), with posterior emissions exceeding the 0.5 Tg a-1 threshold defined by Shen et al. (2022) for successful quantification of basin emissions by TROPOMI only in the Delaware. These differences could result from the different time periods examined. The broad agreement found indicates that the reduced-rank approach reproduces full-rank results.

**3.1 CONUS sectoral emissions**

We find posterior anthropogenic emissions of 30.9 (30.0 - 31.8) Tg a-1 in CONUS, an 8% (5% - 11%) increase from our prior estimate of 28.7 Tg a-1 and a 15% (12% - 19%) increase from the most recent EPA Greenhouse Gas Inventory (GHGI) estimate of 26.8 Tg a-1 for 2019. Lu et al. (2022) found larger anthropogenic methane emissions of 36.2 (32.1 – 37.6) Tg a-1 over the same domain for 2017 by optimizing emissions and trends in a joint inversion of GOSAT and in situ observations for 2010 - 2017. Deng et al. (2022) reviewed an ensemble of global GOSAT and in situ inversions and found median posterior anthropogenic methane emissions for the United States in 2019 of 26.5 (20.8 – 38.7) Tg a-1 for GOSAT inversions and 31.9 (23.9 - 43.1) Tg a-1 for in situ inversions.

We allocate our national total to the emission sectors described in section 2.2 using the attribution method described in section 2.8. From the off-diagonal structure of (equation 8), we find very low posterior error correlation between the sectors (mean error correlation coefficients less than 0.2 in all cases), indicating that we can successfully separate sectoral emissions. Figure 4 and Table 2 summarize the results. Livestock, oil/gas, and landfills dominate the national emissions. Our posterior emissions for these three sectors are higher than the EPA(2022) GHGI for 2019 (henceforth “GHGI”). However, we find lower values than the GHGI for coal. occur in anthropogenic sectors, including landfills, livestock, oil and natural gas, and coal. For these sectors, we find sectoral averaging kernel sensitivities between 0.47 and 0.91, significantly larger than the values found by Lu et al. (2022) from GOSAT and in situ data. We find a small but significant increase in wetland emissions that is consistent with the large range found by Lu et al. (2022). However, the observing system constrains a relatively small fraction of wetland grid cells.

Landfill emissions show the largest relative and absolute increase from GHGI. We find posterior emissions of 6.9 (6.4 - 7.5) Tg a-1, an increase of 52% (41% - 65%) relative to the GHGI. EPA has reported a downward trend in landfill emissions since 1990 due to increased landfill gas collection and decreased organic material in landfills. Lu et al. (2022) found similar mean posterior landfill emissions of 7.5 (5.9 – 7.7) Tg a-1 for 2017. We attribute the increase to underestimated urban emissions, including both direct landfill emissions and co-located post-meter natural gas emissions, which we discuss in section 3.4.

Livestock emissions show the second largest absolute increase from the prior emissions estimate, with posterior emissions of 10.4 (10.0 - 10.7) Tg a-1 representing an increase of 13% (9% - 16%) from GEPA and 11% (6% - 14%) from the GHGI. The smaller discrepancy with respect to the GHGI reflects the increase in CONUS cattle populations since 1990. Lu et al. (2022) found similar mean posterior livestock emissions of 10.4 (8.8 - 11.6) Tg a-1 over CONUS for 2017. Yu et al. (2021) conducted a seasonal inversion of aircraft observations over the north central United States and south central Canada to find mean posterior livestock emissions of 5.5 (5.1 - 6.2) Tg a-1, which agrees with our posterior livestock estimate of 5.4 (5.1 - 5.6) Tg a-1 over the same region. We attribute the low GHGI value to underestimated manure management emissions, which we discuss in section 3.2.

TROPOMI provides the strongest constraint for oil and gas emissions, with sectoral averaging kernel sensitivity of 0.91, because these emissions are concentrated in arid regions where TROPOMI is most successful at observing. Posterior oil and natural gas emissions are 10.4 (10.1 - 10.7) Tg a-1, an increase of 11% (7% - 14%) from the GEPA inventory updated for 2018 combined with the high-resolution EDF inventory over the Permian and 18% (14% - 22%) from the GHGI. Lu et al. (2022) found much larger posterior emissions of 4.8 (3.1 - 4.9) Tg a-1 for oil and 8.9 (8.0 - 9.8) Tg a-1 for natural gas in 2010-2017. However, they found decreasing natural gas emissions beginning in 2014. Compared to Lu et al. (2022), Shen et al. (2022) found lower oil and natural gas emissions of 12.6 ± 2.1 Tg a-1 from an inversion of TROPOMI data over 14 basins extrapolated to the national scale for May 2018 to 2020, which is consistent with continued emissions decreases into 2019. Coal mining emissions exhibit the largest decline in sectoral emissions, decreasing 48% (34% - 59%) from GEPA and 30% (11% - 44%) from the GHGI. Lu et al. (2022) found much larger posterior emissions of 2.9 (2.3 - 3.4) Tg a-1 for 2017, but our decrease is consistent the 30% decrease in CONUS coal production since 2012 (USGS). Deng et al. (2022) found cumulative fossil fuel emissions of 9.8 (8.1 - 13.7) Tg a-1 from an ensemble of GOSAT inversions and 12.6 (8.0 - 16.7) Tg a-1 for an ensemble of in situ inversions in 2019, both of which are consistent with our result.

**3.2 Livestock emissions**

[Insert work on identifying the cause of the livestock increase.]

**3.3 State emissions**

We partition emissions, excluding offshore emissions, to each of the 48 states in CONUS as described in section 2.8 and compare the results to GEPA, the EPA’s new state inventory, which is scaled to match the GHGI (henceforth “state GHGI”), and inventories prepared independently by state governments. Figure 5 shows prior and posterior emissions for the 29 states responsible for 90% of posterior CONUS anthropogenic emissions, excluding offshore emissions, and Table S1 shows the full results. TROPOMI provides a strong constraint at this resolution, with averaging kernel sensitivity larger than 0.5 in most states. Our reduced-rank inversion also constrains emissions in most states: we optimize an average of 80% of prior emissions in each of the top 25 methane producing states.

We find a large increase in state emissions compared with EPA estimates, with state posterior emissions on average 6% larger than GEPA and 12% larger than the state GHGI. The bigge

st increases from the state GHGI occur in 8 of the top 10 methane-producing states of Figure 5, where state posteriors are on average 24% larger than GEPA and 38% larger than the state GHGI. These states are responsible for 55% of posterior CONUS methane emissions, These include states dominated by oil and natural gas production (Texas, New Mexico, Louisiana, and Oklahoma), livestock (California and Iowa), and landfills (Florida and Illinois). Significant state emission decreases relative to the GHGI are limited to coal-producing states including Wyoming, West Virginia, and Pennsylvania.

We consider in more detail Texas and California, which are responsible for 21% and 6% of posterior US anthropogenic emissions respectively. Our posterior emission for Texas of 6.3 (6.1 - 6.5) Tg a-1is 69% higher than the state GHGI mainly because of the oil and gas sector. Half of all posterior emissions in Texas are from the Permian basin., the largest oil and natural gas producing region in CONUS (Zhang et al., 2020). We find Permian emissions of 2.9 Tg a-1 that are consistent with recent studies (Zhang et al., 2020; Schneising et al., 2020; Liu et al., 2021; Shen et al., 2022; Varon et al., in review).

Our posterior emission for California is 2.1 (2.0 - 2.1) Tg a-1. This is a 33% increase from the state GHGI and a 32% increase from the independent estimate prepared by the California Air Resource Board (CARB). Relative to the CARB inventory, 78% of the inferred increase is attributable to livestock and 14% to oil and natural gas. We find good agreement with the sectoral partitioning in both the state GHGI and the CARB inventory. Livestock explain 54% of emissions in the posterior, 50% in the state GHGI, and 54% in the CARB inventory, while landfills explain 25%, 23%, and 21% of emissions, respectively. We find slightly smaller relative contributions from oil and natural gas, which is responsible for 11% of posterior emissions compared to 20% and 17% of state GHGI and the CARB inventory respectively. This partitioning differs from that found in Wecht et al. (2014), where 30% of emissions were attributed to livestock, 38% to landfills, and 22% to oil and natural gas. As above, the discrepancy could be due to temporal or seasonal differences, or from the coarser resolution (1/2° × 2/3°) of the CalNex inversion.

We also compare our posterior emissions to other available state greenhouse gas inventories for the year closest to 2019 where the observing system provides a strong constraint (state averaging kernel sensitivity greater than 0.5). Of the inventories of Colorado, Iowa, Louisiana, and Pennsylvania, our posterior agrees only with Pennsylvania. However, we find a source shift from fossil fuels (from 73% in the prior and 76% in the inventory to 63% in the posterior) to landfills and livestock (from 25% in the prior to 34% in the posterior). We find that the state inventory of Iowa is too low due to underestimate of livestock emissions, and the state inventory of Louisiana is too low due to underestimate of oil/gas and rice emissions. On the other hand, the Colorado state inventory is 65% higher than our posterior estimate mainly because oil and natural gas emissions are more than twice higher.

**3.4 Urban area emissions**

We calculate the posterior emissions for 219 urban areas across CONUS, providing the first comprehensive national-scale analysis of urban emissions. Urban areas are defined using the U.S. Census Urban Areas for 2010, and populations greater than 1 million people. according to the 2010 Census . We limit our attention tourban areas for which the inversion achieves averaging kernel sensitivities greater than 0.2, a relatively low threshold because TROPOMI provides limited spatial information on the scale of cities. We still find significant corrections: urban anthropogenic posterior emissions are 2.4 (2.2 - 2.7) Tg a-1, 29% (16% - 44%) larger than GEPA. These emissions represent 8.3% (7.7% - 7.2%) of anthropogenic emissions, equivalent to almost a quarter of CONUS oil and natural gas emissions. The top 10 methane-producing cities, shown in figure 6 and described in table S2, have a larger mean urban averaging kernel sensitivity of 0.40 and are responsible for 40% (39% - 42%) of urban posterior emissions. We find a mean increase relative to GEPA of 69% in these cities and emissions more than twice as large as the inventories from New York City and Philadelphia, the only available methane emission estimates among these cities.

We compare our results to 17 studies of ten urban areas published since 2015. These studies tended to quantify emissions in coastal metropolitan centers, with only three studies quantifying emissions in smaller, non-coastal cities: Kansas City (Plant et al., 2022) and Indianapolis (Lamb et al., 2016 and Jones et al., 2021). On average, we find lower emissions than past studies, which may result in part from the weaker constraint generated by TROPOMI and in part from from our restrictive definition of urban extent. We find the largest discrepancies over coastal cities, including San Francisco (Fairley and Fischer, 2015; Jeong et al., 2016, 2017; Guha et al., 2022), Washington (D.C.) and Baltimore (Huang et al., 2016; Ren et al., 2018; Lopez-Coto et al., 2020; Plant et al., 2019, 2022), Boston (Plant et al., 2019, 2022; Sargent et al., 2021), and Los Angeles (Cui et al., 2015; Jeong et al., 2016; Wunch et al., 2016; Yadav et al., 2019; Cusworth et al., 2022). In Philadelphia (Plant et al., 2019, 2022) and Atlanta (Plant et al., 2022), emissions estimated using observed methane-carbon monoxide ratios together with carbon monoxide inventories were consistent with our posterior. However, the confidence intervals in both studies spanned more than 200 Gg a-1, and Plant et al. (2019) found Philadelphia emissions significantly larger than our estimate using methane-carbon dioxide ratios. We find consistent results with most surveyed studies in New York City and Indianapolis (Plant et al., 2019, 2022; Pitt et al., 2022; Lamb et al., 2016; Jones et al., 2021).

While the observed increase in urban emissions is likely an underestimate, it still suggests that landfill emissions or natural gas distribution or post-meter emissions are too low. The EPA added post-meter emissions of 456 Gg a-1 to the GHGI in 2022. This addition explains 82% (57% - 130%) of the increase from GEPA in urban areas. We are unable to attribute the remaining discrepancy to a particular sector due to source co-location. We also find no correlations between the posterior increase from GEPA and 2010 urban area population, population change from 2000 to 2010, population density, or surface area. Indeed, the three largest cities by population (New York, Los Angeles, and Chicago) have the smallest per capita methane emissions among the top 10 methane-producing cities, while the two smallest cities by population (Detroit and Indianapolis) have the largest per capita emissions. The lack of correlation reflects the variability of methane emission sources and trends between urban areas. Floerchinger et al. (2021) found “dramatically different” emission profiles in an aircraft survey of methane and ethane over seven U.S. cities, with the fraction of emissions attributable to natural gas ranging from 0.32 to 1.0. Sargent et al. (2021) surveyed 12 studies spanning six cities and found that natural gas contributions to urban emissions ranged from 43% to 88%. Both studies included geographically diverse cities with a range of populations. Plant et al. (2019) used aircraft data over six cities on the East Coast of CONUS and found that on average between 80% and 110% of emissions in each city were explained by natural gas emissions. However, their confidence intervals ranged from 45% to 170% of urban emissions.

**4 Conclusions**

[Insert.]