

# Analysis of Oil and Gas Ethane and Methane Emissions in the Southcentral and Eastern United States Using Four Seasons of Continuous Aircraft Ethane Measurements

Z. R. Barkley<sup>1</sup>, K. J. Davis<sup>1</sup>, S. Feng<sup>1</sup>, Y. Y. Cui<sup>1</sup>, A. Fried<sup>2</sup>, P. Weibring<sup>2</sup>, D. Richter<sup>2</sup>, J. G. Walega<sup>2</sup>, S. M. Miller<sup>3</sup>, M. Eckl<sup>5</sup>, A. Roiger<sup>5</sup>, A. Fiehn<sup>5</sup>, J. Kostinek<sup>5</sup>

<sup>1</sup>The Pennsylvania State University, University Park, PA, USA

<sup>2</sup>Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO, USA

<sup>3</sup>Department of Environmental Health and Engineering, Johns Hopkins University

<sup>4</sup>National Aeronautics and Space Administration, Langley Research Center, Hampton, VA, USA

<sup>5</sup>Deutsches Zentrum für Luft- und Raumfahrt e.V., Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany

## Key Points:

- This study uses ethane observations to quantify both ethane and methane emissions from the United States oil and gas sector.
- Ethane emissions in the central and eastern United States are larger than existing inventories by more than a factor of 2.
- Ethane-methane ratios indicate that the US EPA methane inventory is underestimating leak rates from the oil and gas sector by at least 50%.

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Corresponding author: Zachary R. Barkley, [zrb5027@psu.edu](mailto:zrb5027@psu.edu)

## Abstract

In the last decade, much work has been done to better understand methane ( $\text{CH}_4$ ) emissions from the oil and gas (O&G) industry in the United States. Ethane ( $\text{C}_2\text{H}_6$ ), a gas that is co-emitted with thermogenic sources of  $\text{CH}_4$ , is emitted in the US almost entirely by the O&G sector. In this study, we perform an inverse analysis on 300 hours of atmospheric boundary layer  $\text{C}_2\text{H}_6$  measurements to estimate  $\text{C}_2\text{H}_6$  emissions from the US O&G sector. Measurements were collected from 2017-2019 as part of the Atmospheric Carbon and Transport (ACT) America aircraft campaign and encompass much of the central and eastern United States. We find that for the fall, winter, and spring campaigns,  $\text{C}_2\text{H}_6$  data consistently exceeds values that would be expected based on EPA O&G leak rate estimates.  $\text{C}_2\text{H}_6$  observations from the summer 2019 dataset show significantly lower  $\text{C}_2\text{H}_6$  enhancements in the southcentral region that cannot be reconciled with data from the other three seasons, either due to complex meteorological conditions or a temporal shift in the emissions. Converting the fall, winter, and spring season posterior  $\text{C}_2\text{H}_6$  emissions estimate to an inventory of O&G  $\text{CH}_4$  emissions, we estimate that O&G  $\text{CH}_4$  emissions are larger than EPA inventory values by more than 50%. Uncertainties in the gas composition data limit the effectiveness of using  $\text{C}_2\text{H}_6$  as a proxy for O&G  $\text{CH}_4$  emissions. These limits could be resolved retroactively by increasing the availability of industry-collected gas composition data.

## Plain Language Summary

Methane is a potent greenhouse gas responsible for a quarter of the warming the climate has experienced thus far. The oil and gas sector is a significant source of methane through leaks in its infrastructure. Recent studies of individual basins have found emissions from oil and gas in the US to be greater than inventory estimates, but difficulties arise with source attribution in broader scale studies due to the numerous potential sources of methane. This study quantifies methane emissions from oil and gas by looking at atmospheric ethane, a gas whose emissions stem almost entirely from oil and gas in the US. Hundreds of hours of ethane observations were collected via aircraft over the course of 4 seasons between 2017-2019. These observations are compared with model-projected ethane values based on our current knowledge of ethane emissions, and those emissions are adjusted to best match the observed data. We find ethane emissions are grossly underestimated in the US. Because ethane is co-emitted with oil and gas methane sources, this underestimation of ethane reflects similar underestimations in oil and gas methane emissions. We conclude that US inventories are underestimating methane emissions from oil and gas by more than 50%.

## 1 Introduction

Methane ( $\text{CH}_4$ ) is an important greenhouse gas with 28-35 times the warming potential of carbon dioxide over a 100 year period (Myhre et al., 2013). Global  $\text{CH}_4$  concentrations in the atmosphere have nearly tripled since pre-industrial times, mainly driven by anthropogenic activity and are responsible for a fourth of the increased radiative forcing on the planet (Myhre et al., 2013). Although  $\text{CH}_4$  concentrations stabilized for a brief period in the early 2000s, global concentrations began increasing again by 2007, with an increasing growth rate continuing through present date (Nisbet et al., 2019).

Efforts to understand causes for increasing global  $\text{CH}_4$  trends are hampered by difficulties related to source attribution (Saunio et al., 2020).  $\text{CH}_4$  has numerous anthropogenic sources, including animal agriculture, fossil fuel extraction, and waste management. In addition to anthropogenic emitters, there are natural sources of  $\text{CH}_4$  emissions that play a large role in the global  $\text{CH}_4$  budget. Of particular importance to the global  $\text{CH}_4$  budget are emissions from anaerobic respiration in wetlands, which create unique challenges to  $\text{CH}_4$  source attribution. Unlike most anthropogenic sources, whose emis-

sions can be spatially mapped out using inventory techniques and are relatively consistent in magnitude on an annual timeframe, wetland emissions are more difficult to describe, with an uncertain spatial pattern and large seasonal variability in emissions based on soil temperature and moisture (Yvon-Durocher et al., 2014). Many prior studies have examined seasonal emissions and magnitudes of local wetland sources using flux tower measurements (Grant & Roulet, 2002; Matthes et al., 2014), but extrapolating these results to a continental or global scale is challenging.

Difficulties with source attribution extend into the United States, where both anthropogenic and natural sources play a large role in the country’s  $\text{CH}_4$  budget. In the US, greenhouse gas emissions from anthropogenic sources are quantified through a bottom-up inventory created by the United States Environmental Protection Agency (EPA). The largest sources of anthropogenic  $\text{CH}_4$  emissions projected by this inventory are from leaks in oil and gas (O&G) infrastructure, enteric fermentation and manure management related to livestock, and anaerobic respiration occurring in landfills (US Environmental Protection Agency, 2020). These sources were responsible for 83% of US anthropogenic  $\text{CH}_4$  emissions in the 2018 inventory estimate. Natural sources in the US are dominated by wetlands and are not tracked by the EPA’s inventory. WetCHARTs, a global wetland emissions ensemble, is generally used as the prior for  $\text{CH}_4$  emissions from wetlands in the US (Bloom et al., 2017; Sheng et al., 2017; Maasakkers et al., 2016). WetCHARTs ensemble members estimates the country’s wetland emissions to vary from values that are insignificant to totals rivaling those from anthropogenic emissions, with seasonal dependence and spatial variability between ensemble members, resulting in large uncertainties in the overall US  $\text{CH}_4$  budget.

Contrary to recent global increases in the atmospheric growth rate of  $\text{CH}_4$ , the EPA’s inventory estimates of anthropogenic  $\text{CH}_4$  emission in the US show a 10% decrease in the last decade, from 28 Tg in 2008 to 25 Tg in 2018. This decrease is driven primarily by projected decreases in emissions from the energy sector, despite a 50% increase in gas production and a >200% increase in oil production during the 10 year period (US Energy Information Administration, 2020b). Over the last several years, various atmospheric studies monitoring emissions from O&G from individual wellpads (Rella et al., 2015; Robertson et al., 2017; Caulton et al., 2019), basins (Karion et al., 2015; Barkley et al., 2017; Peischl et al., 2018), and entire regions (Barkley et al., 2019b) have consistently found emission rates larger than the EPA inventory, raising concerns of a broad underestimation of leaks from the O&G sector (Alvarez et al., 2018). However, large-scale  $\text{CH}_4$  inversion studies involving the US have not been as conclusive, with differing opinions, as to the accuracy of inventory emissions from O&G, animal agriculture, and wetlands (Sheng et al., 2018; Yu et al., 2020; Maasakkers et al., 2019). The enormous spread of uncertainty regarding the magnitude, spatial distribution, and seasonality of  $\text{CH}_4$  emissions from wetlands, as well as the numerous other potential sources of  $\text{CH}_4$ , poses a challenge to large scale studies attempting source attribution of detected  $\text{CH}_4$  signals.

One common method to disaggregate certain sources is to measure both  $\text{CH}_4$  and ethane ( $\text{C}_2\text{H}_6$ ) concentrations (McKain et al., 2015; Barkley et al., 2019a). Sources of  $\text{C}_2\text{H}_6$  coincide with thermogenic  $\text{CH}_4$  emitters (O&G extraction, biomass burning), but not biogenic sources (wetlands, animal agriculture, landfills). Thus, a correlation (or lack of) between  $\text{C}_2\text{H}_6$  and  $\text{CH}_4$  can provide information on the sector responsible for observed  $\text{CH}_4$  enhancements. While global  $\text{C}_2\text{H}_6$  emissions are split between the energy sector and biomass burning (Xiao et al., 2008), the National Emissions Inventory (NEI) 2011  $\text{C}_2\text{H}_6$  inventory attributes 95% of  $\text{C}_2\text{H}_6$  emissions in the US to the energy sector, making it a simple tracer for identifying O&G emissions in the region ((US Environmental Protection Agency, 2014)). This technique has been used in various smaller-scale aircraft mass balance studies across individual O&G basins to verify that the measured enhancements are associated with O&G activity (Peischl et al., 2018; Roscioli et al., 2015). Sim-

ilarly,  $\text{C}_2\text{H}_6$  concentrations from a network of flask measurements have been used to infer trends in emissions from O&G emissions on broader scales (Xiao et al., 2008; Tzompa-Sosa et al., 2017).

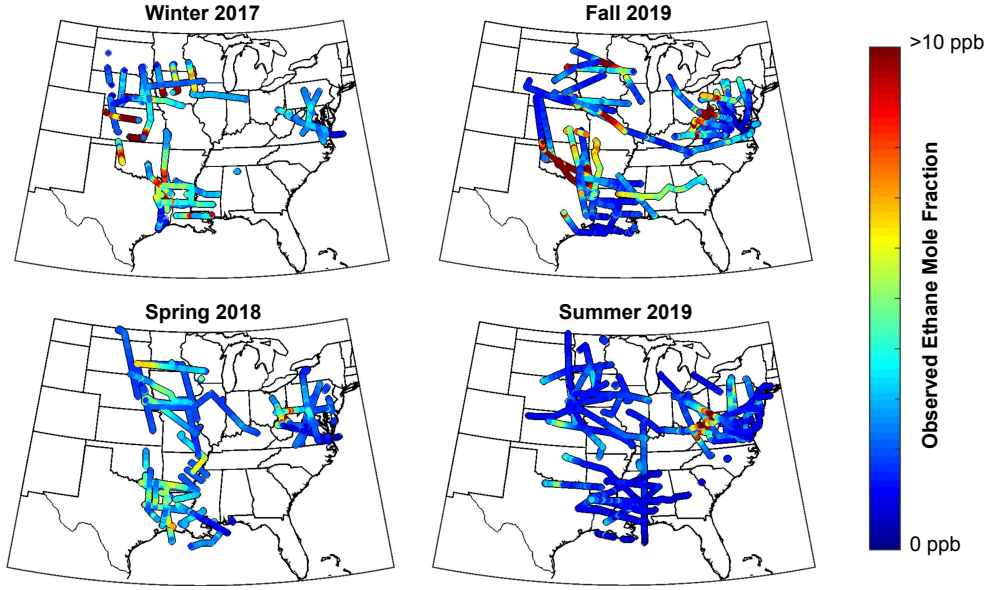
Advancements in technology have resulted in the increased availability of instrumentation capable of measuring  $\text{C}_2\text{H}_6$  concentrations precisely at high temporal resolution (Weibring et al., 2020; Kostinek et al., 2019; Yacovitch et al., 2014), expanding our capabilities of solving for  $\text{C}_2\text{H}_6$  emissions. The Atmospheric Carbon and Transport - America (ACT-America) mission was a 5-season aircraft campaign across the central and eastern US designed to examine various trace gases and their transport in the atmosphere. During four of the seasonal campaigns, continuous  $\text{C}_2\text{H}_6$  measurements were collected, producing more than 500 hours of  $\text{C}_2\text{H}_6$  data capable of capturing various plume structures related to O&G activity on a regional scale. In this study, we examine the characteristics of this unprecedented dataset and use it to quantify  $\text{C}_2\text{H}_6$  emissions compared to bottom-up inventory estimates. These  $\text{C}_2\text{H}_6$  emissions are then combined with US gas composition data to infer  $\text{CH}_4$  leak rates from major US O&G basins.

## 2 Methods

### 2.1 ACT-America Aircraft Campaign and Observational Dataset

The ACT-America campaign was a NASA Earth Venture suborbital aircraft mission with flight activities spanning summer 2016 to summer 2019. During this time, 5 individual campaigns covering all 4 seasons (summer twice) were conducted using two aircraft collecting meteorological, greenhouse gas, and trace gas data within fair weather and frontal weather patterns. For all 5 campaigns, continuous  $\text{CH}_4$  data were collected on both aircraft using a commercial PICARRO G2401-m instrument adapted with a custom inlet system for drying and conditioning the sample air (DiGangi et al., 2018). During the Winter 2017, Fall 2017, Spring 2018, and Summer 2019 campaigns, continuous  $\text{C}_2\text{H}_6$  data were collected on the B200 aircraft using the CAMS-2 (Compact Airborne Multi-Species Spectrometer) instrument (Weibring et al., 2020). The CAMS-2  $\text{C}_2\text{H}_6$  measurements when averaged over time and linearly regressed versus NOAA portable flask packages collected during the flights yielded slopes in the 0.990 to 1.031 range across seasonal campaigns, with  $r^2$  values between the two measurements of 0.996 (Baier et al., 2020; Weibring et al., 2020), providing high confidence in the accuracy of its measurements. Additionally, during the Fall 2017 and Summer 2019 campaigns, the C130 aircraft was equipped with a quantum and interband cascade laser spectrometer (QCLS) capable of continuous in situ  $\text{C}_2\text{H}_6$  measurements (Kostinek et al., 2019). The QCLS instrument performed in-flight two-point calibrations every three to ten minutes, ensuring accurate measurements throughout the flights. Altogether, the entire  $\text{C}_2\text{H}_6$  dataset contains more than 500 hours of continuous airborne  $\text{C}_2\text{H}_6$  observations, of which 300 hours were within the atmospheric boundary layer (ABL), making it an ideal dataset to study atmospheric  $\text{C}_2\text{H}_6$  plumes and structures throughout the central and eastern US.

From the observational dataset, large  $\text{C}_2\text{H}_6$  plumes were consistently observed downwind of Texas/Oklahoma/Louisiana in the southcentral US and along the western Appalachians in the northeast, corresponding with O&G activity in each of these regions (Figure 1).  $\text{C}_2\text{H}_6$  plumes associated with southcentral O&G sources could be observed in the midwestern flights as far north as Minnesota when consistent southerly winds were present.  $\text{C}_2\text{H}_6$  mixing ratios within the plumes were largest during the fall and winter campaign, likely related to the low boundary layer mixing depth during those seasons. During the Summer 2019 campaign, large  $\text{C}_2\text{H}_6$  plumes were detected in the western Appalachian similar to other seasons, but signals in the southcentral were substantially smaller in a way that boundary layer depth alone cannot explain. Additionally, boundary layer

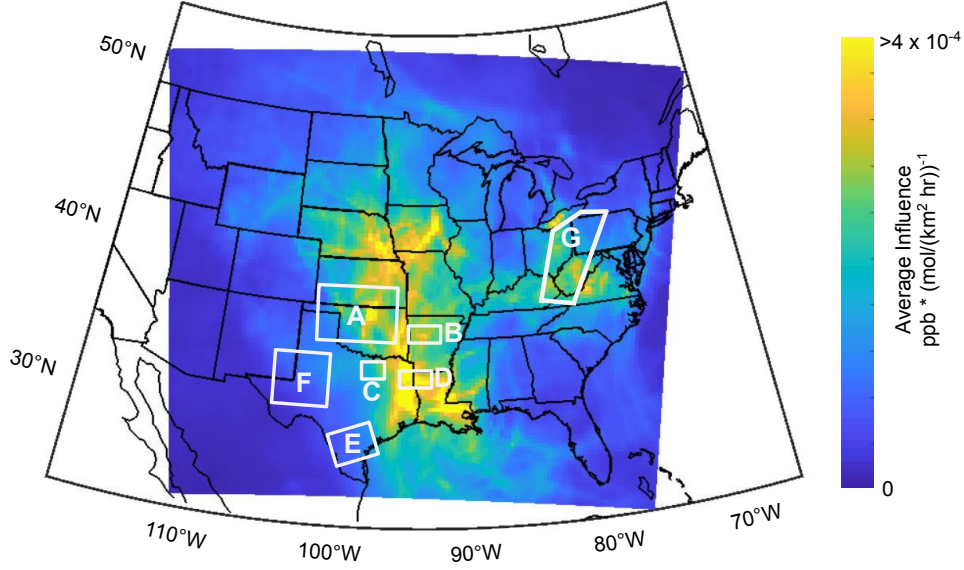


**Figure 1.** Continuous boundary layer  $C_2H_6$  measurements collected by the B200 and C130 aircraft during each seasonal campaign. Only data within the atmospheric boundary layer ( $\leq 1000$  m AGL) are shown.

$C_2H_6$  concentrations in the summer were often similar in value to their free tropospheric counterparts, a trait not observed during other seasons (Figure S2).

Influence functions for observations were created using the Lagrangian particle dispersion model FLEXPART-WRF (Brioude et al., 2013) to provide information on the area captured by the ACT-America  $C_2H_6$  dataset. The model was run at 27 km resolution over the North American domain and was meteorologically driven using WRF-Chem simulations developed as part of the ACT-America campaign (Feng et al., 2019). Every 30 seconds of flight time, 5,000 particles were released from the aircraft location and traced back 10 days in time. Further details on the development of the influence functions can be found in Cui et al. (2015).

Averaging the influence functions provides information on which O&G basins have substantial coverage by the ACT flight campaign (Figure 2). Much of the midwestern and southcentral US is captured across all four seasons, encompassing many of the major O&G basins including Haynesville, Fayetteville, Anadarko, Eagle Ford, Woodford, and the Barnett. A sharp decrease in the influence map can be observed west of central Texas. For this reason, we do not include the Permian basin in western Texas/New Mexico in our analysis of the southcentral US and consider it and other western basins (Bakken, Denver-Julesburg, four-corners region, California) to be outside the scope of this study. In the northeast, many flight tracks were designed to fly downwind of the Marcellus and Utica gas basins in the western Appalachian regions of West Virginia and western Pennsylvania, and thus this area has significant coverage in the influence maps. An exception to this occurs during the winter campaign, where many of the downwind measurements were performed by the C130 aircraft which did not have an  $C_2H_6$  instrument at the time, resulting in only 3 flights with direct  $C_2H_6$  measurements downwind of the region (see Figure S3 for a seasonal breakdown of the influence functions).



**Figure 2.** Averaged influence function from the boundary layer observations used in the  $\text{C}_2\text{H}_6$  inversion. Brighter colors indicate areas whose surface interactions were captured more frequently by the boundary layer observations. O&G basins pertinent to this study are highlighted in boxes and are labeled as follows: (A.) Anadarko. (B.) Fayetteville. (C.) Barnett. (D.) Haynesville. (E.) Eagle Ford. (F.) Permian. (G.) Appalachia.

## 2.2 Inversion Framework

Observational  $\text{C}_2\text{H}_6$  data collected from the ACT-America campaign is used in this study to perform an inversion and learn about  $\text{C}_2\text{H}_6$  emissions from O&G sources in the flight domain. The basic inversion framework used is similar to previous work (Lauvaux et al., 2012; Sheng et al., 2018) and is expressed by cost function,

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{y} - \mathbf{H}\mathbf{x})^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}\mathbf{x}) + \frac{1}{2}(\mathbf{x} - \mathbf{x}_0)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_0) \quad (1)$$

In this equation, we solve for a posterior emissions grid  $\mathbf{x}$  that minimizes the cost function  $J$  using influence functions ( $\mathbf{H}$ ) that translate the flux field to a modelled enhancement ( $\mathbf{H}\mathbf{x}$ ). In the cost function, two terms control the solution. The first term is a cost related to the mismatch between the posterior modelled enhancements versus observed concentrations ( $\mathbf{y}$ ), with greater discrepancies resulting in a larger cost term. Here,  $\mathbf{R}$  is the observation error covariance matrix, and weights the first term based on the confidence in the observations and model transport. The second term in the cost function equation is a cost related to the change between the posterior flux ( $\mathbf{x}$ ) and the prior flux ( $\mathbf{x}_0$ ), with larger changes resulting in a greater cost. Here,  $\mathbf{B}$  is the flux error covariance matrix, and weights the second term based on the confidence in the prior flux field. Minimizing the cost function with respect to  $\mathbf{x}$  yields

$$\mathbf{x} = \mathbf{x}_0 + \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}(\mathbf{y} - \mathbf{H}\mathbf{x}_0) \quad (2)$$



and solving for  $\mathbf{x}$  yields the posterior flux field. For this study, observations from each season are grouped together and an posterior flux map is solved for each of the seasonal flight campaigns.

A best guess  $\text{C}_2\text{H}_6$  emissions map was created to serve as a prior for the inversion (Figure 4). To create this prior,  $\text{CH}_4$  emissions from the O&G sector of the EPA Grid-  
ded 2012  $\text{CH}_4$  Emissions Inventory (Maasakkers et al., 2016) were multiplied by expected  
molar  $\text{C}_2\text{H}_6/\text{CH}_4$  ratios of each basin (Table S2), resulting in an  $\text{C}_2\text{H}_6$  emissions map.  
For Eagle Ford, Haynesville, Fayetteville, Barnett, Permian, Denver-Julesburg, and the  
Bakken O&G basins, atmospheric measurements from NOAA aircraft studies were avail-  
able to derive observed basin-wide  $\text{C}_2\text{H}_6/\text{CH}_4$  ratios (Peischl et al., 2015, 2018; Tzompa-  
Sosa et al., 2017). For the Anadarko and Appalachian region where representative at-  
mospheric measurements were not available, data from the United States Geological Sur-  
vey were used to create a spatial map of  $\text{C}_2\text{H}_6/\text{CH}_4$  ratios to apply to these regions (US  
Geological Survey, 2018; Kitanidis, 1997)(See supplemental section S1 for additional info).  
For all emissions related to transmission, storage, and distribution, an  $\text{C}_2\text{H}_6/\text{CH}_4$  ratio  
of 0.027 was applied (Plant et al., 2019). For prior  $\text{C}_2\text{H}_6$  emissions in Canada and Mex-  
ico, we use  $\text{CH}_4$  emissions from O&G facilities provided in Sheng et al. (2017) and ap-  
ply the mean  $\text{C}_2\text{H}_6/\text{CH}_4$  ratio from the USGS database of 0.085 to convert it to  $\text{C}_2\text{H}_6$  emis-  
sions. These sources outside the US have minimal representation in our influence func-  
tions and have no impact on the overall solution. Although biomass burning and bio-  
fuels are also significant sources of  $\text{C}_2\text{H}_6$  on a global scale, these sources are estimated  
to be only a few percent of the total  $\text{C}_2\text{H}_6$  emissions in the US (Tzompa-Sosa et al., 2017).  
Overall, this  $\text{C}_2\text{H}_6$  emissions map represents our best guess as to representing  $\text{C}_2\text{H}_6$  emis-  
sions based on the EPA’s bottom-up O&G  $\text{CH}_4$  emissions inventory, and will be referred  
to as the "Default" map henceforth.

Two additional  $\text{C}_2\text{H}_6$  emission maps were created to test the sensitivity of the in-  
version to different priors. The first alternative map was created by taking the EPA  $\text{CH}_4$   
emissions map used in the creation of the Default inventory and applying a flat  $\text{C}_2\text{H}_6/\text{CH}_4$   
ratio of 0.085. This ratio preserves the total  $\text{C}_2\text{H}_6$  emissions from the "Default" map but  
redistributes them in a way that removes knowledge of the unique gas compositions of  
different basins, and is referred to henceforth as the "Flat Rate" inventory. The second  
alternative map is based on ethane emissions provided by the US National Emissions In-  
ventory 2011 inventory (NEI2011)  $\text{C}_2\text{H}_6$ , an  $\text{C}_2\text{H}_6$  map available in GEOS-Chem and used  
in Tzompa-Sosa et al. (2017). In addition to having a different spatial distribution com-  
pared to the Default inventory, total emissions in the NEI2011 inventory are roughly half  
the Default total.  $\text{C}_2\text{H}_6$  emissions from the Emissions Database for Global Atmospheric  
Research (EDGAR) v4.3.2 were originally considered as well for this analysis, but to-  
tal emissions were 8 times lower than our Default inventory and were decided to be too  
inaccurate to serve as a useful prior (Huang et al., 2017).

Continuous boundary layer  $\text{C}_2\text{H}_6$  measurements from the ACT-America campaign  
were used as observational input for this study, with their associated FLEXPART-derived  
influence functions used for  $\mathbf{H}$  in the inversion (section 2.1). Observations greater than  
1000 meters above ground level were not included in the analysis to remove any data above  
the ABL. For this study, we restrict the domain of our inversion to the area within the  
4 corners (23.7°N, 110.72°W), (23.0°N, 77.5°W), (49.9°N, -67.3°W), (51.1°N, -119.0°W,  
domain shown as the colored region in Figure 2). Because the influence functions only  
provide a local enhancement inside the study domain, for each flight date a background  
value is determined to represent the  $\text{C}_2\text{H}_6$  mixing ratios entering the domain. This value  
is chosen by taking the 5th percentile of the observed boundary layer  $\text{C}_2\text{H}_6$  concentra-  
tions on a given flight and subtracting it from the observations, producing an observed  
 $\text{C}_2\text{H}_6$  enhancement. The 5th percentile of model-projected enhancements along the flight  
track is then added onto the observed enhancements in order to align the modelled and  
observed background values. This final step is necessary in rare scenarios where mod-

elled O&G enhancements are influencing the entire aircraft transect, thus impacting the observed background concentrations (see Barkley et al. (2019b) for more details). In calculating the modelled  $\text{C}_2\text{H}_6$  enhancements for this study, we treat  $\text{C}_2\text{H}_6$  as an inert gas rather than a reactive one due to its long average lifetime (weeks to months) relative to the length of time the local plumes travel from the source to the aircraft (hours to days). For more information on the possible influence of  $\text{C}_2\text{H}_6$  loss rates, see supplemental section S1.

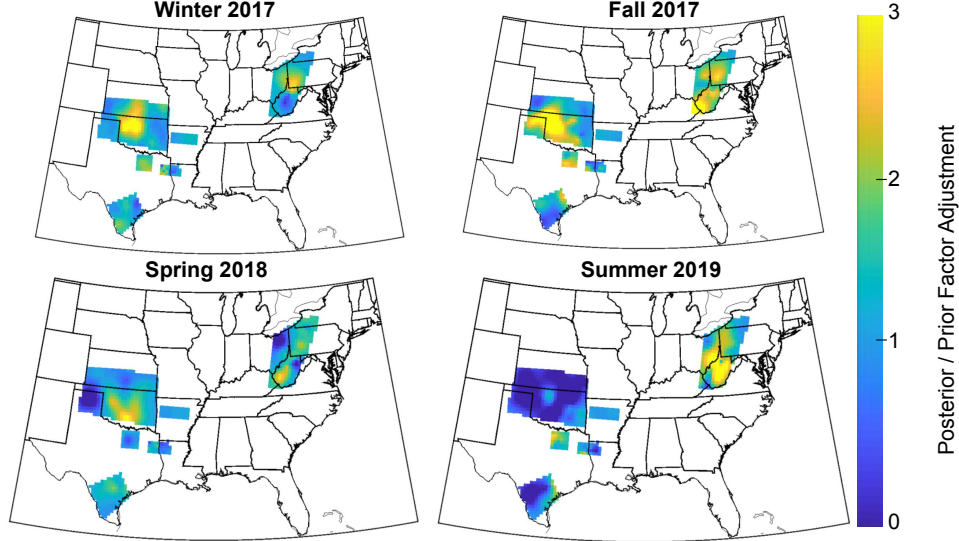
To run an inversion, values must be assigned to the  $\mathbf{R}$  and  $\mathbf{B}$  matrices related to the uncertainty in the observation/transport and prior flux fields respectively. For the observational/transport uncertainty matrix  $\mathbf{R}$ , we use a method similar to the residual error method discussed in Sheng et al. (2017). For each flight, modelled enhancements are first scaled by a constant to have the same overall enhancement as the observed enhancements. This step is performed to remove any existing overall bias that may exist in the prior inventory for the calculation of  $\mathbf{R}$ . After removing this bias, the residual errors are calculated between the model and observation and the standard deviation of this error is used to represent the  $\mathbf{R}$  value along its diagonal for a given flight, with no value assigned for the off-diagonals. Values for the diagonal elements of  $\mathbf{R}$  varied across flights, but seasonal averages for the standard deviation of the error ranged from 0.7 ppb in the spring to 1.8 ppb in the fall. This process results in flights with large observational and transport uncertainty on days with large enhancements and poor correlations between the observed and modelled values, thus giving these flights less weight in the inversion solution. Similarly, flights where observed and modelled plume structures align have a smaller  $\mathbf{R}$  value assigned and thus are given greater weight in the overall solution. This method for classifying transport uncertainty is particularly effective for an  $\text{C}_2\text{H}_6$  inversion study, since the locations of the sources (i.e. O&G infrastructure) are known with high confidence such that misaligned plumes would most likely be caused by errors in the transport rather than problems with the spatial mapping of the flux.

For the flux uncertainty matrix  $\mathbf{B}$ , there lacks a clear answer on what the uncertainty of the prior fluxes should be. Since the primary source of  $\text{C}_2\text{H}_6$  in the US is from O&G production and processing, the location of  $\text{C}_2\text{H}_6$  emitters in the US should be accurate. However, leak rates from O&G activity have been shown in various studies to be beyond the uncertainty bounds of the EPA 2012 Gridded  $\text{CH}_4$  Inventory (Alvarez et al., 2018; Maasakkers et al., 2016). For this reason, a value for the flux uncertainty  $\mathbf{B}$  is selected based on mathematical constraints of the inversion rather than an understanding of the prior flux map. Specifically, all flux grids are assigned an error as a percentage of their prior, where the percent uncertainty is selected using a chi-squared metric, defined as

$$\chi^2 = \frac{1}{m}(\mathbf{y} - \mathbf{H}\mathbf{x}_0)^T(\mathbf{H}\mathbf{B}\mathbf{H}' + \mathbf{R})^{-1}(\mathbf{y} - \mathbf{H}\mathbf{x}_0) \quad (3)$$

where  $m$  is the number of observations and  $\chi^2$  is the chi-squared metric used to assess whether the inversion errors satisfy a Gaussian distribution. Here, we select a percent error for the flux uncertainty in  $\mathbf{B}$  that brings  $\chi^2$  close to 1. For the Default, Flat Rate, and NEI2011 inventory, the assigned flux errors along the diagonal of  $\mathbf{B}$  were 50, 50, and 80 percent of the total grid emissions respectively. Additionally, a correlation length with an e-folding decay length of 50 km is assigned to the off-diagonal elements in  $\mathbf{B}$ . This added correlation provides consistent shifts in the emissions within a basin, while allowing changes across basins to behave uniquely. Implications of the  $\mathbf{R}$  and  $\mathbf{B}$  matrices selected for this study are explored further in the sensitivity analysis (Table S4).





**Figure 3.** Fractional changes between the Default posterior and prior  $\text{C}_2\text{H}_6$  flux map created by an inversion conducted for each individual season. Only basins within the scope of this study are shown on the map.

### 3 Results and Discussion

#### 3.1 $\text{C}_2\text{H}_6$ Inversion Results

For each season, posterior  $\text{C}_2\text{H}_6$  flux maps were successful in reducing both the error and bias and increasing the correlation between the observed and modelled signal for that season (Table 1, Figures S4-S9). Notably, across all 4 seasons there was an overall low bias between the modelled prior and observed  $\text{C}_2\text{H}_6$  enhancements, resulting in seasonal posterior maps that generally increased  $\text{C}_2\text{H}_6$  emissions in order to compensate. Regionally, observed  $\text{C}_2\text{H}_6$  plumes were underestimated the largest in the western Appalachian region across all 4 seasons (Figure 3). In this region, posterior  $\text{C}_2\text{H}_6$  emissions were increased by 50 to 150% more than the prior to correct for the underestimation. In the southcentral US, a similar low bias was observed in the winter, fall, and spring campaign. This led to posterior solutions for these three seasons that show a systematic increase to the total posterior flux of 50%. This increase is mostly uniform across the individual O&G basins, with a notable exception for the Haynesville basin whose posterior is consistently within 11% of the Default prior across all seasons.

Observations from the southcentral and midwestern US during the Summer 19 campaign behave like outliers compared to the rest of the dataset. Of the 87 flights used in the inversion analysis, only 12 had an overall negative bias when comparing the observed  $\text{C}_2\text{H}_6$  to the model prior (observed enhancement less than modelled enhancement), 8 of which occurred in the southcentral and midwestern portion of the Summer 19 campaign. These low observations have a profound effect on the posterior emissions in the southcentral US for the Summer 19 campaign, with total emissions from this region that are less than a third of posterior emission maps from the other three seasonal campaigns. To demonstrate how unrepresentative the Summer 19 results are compared to the rest of the dataset, we take the posterior inventory derived for each season and apply it to the entire 4 season dataset (Table 2). In doing this, we find that the winter, fall, and spring posteriors all produce similar statistical improvements to the overall dataset compared

	Default Inventory Winter 2017 Performance		Default Inventory Fall 2017 Performance		Default Inventory Spring 2018 Performance		Default Inventory Summer 2019 Performance	
	Prior	Posterior	Prior	Posterior	Prior	Posterior	Prior	Posterior
Southcentral Total $C_2H_6$ (mol $s^{-1}$ )	488	709	488	777	488	601	488	199
Western Appalachia Total $C_2H_6$ (mol $s^{-1}$ )	125	184	125	294	125	185	125	269
Mean Absolute Error (ppb)	1.39	0.99	1.65	1.16	0.68	0.54	0.85	0.59
Mean Bias (ppb)	1.20	0.61	1.50	0.76	0.55	0.37	0.25	0.20
y,Hx Correlation	0.85	0.90	0.75	0.83	0.61	0.72	0.44	0.74

**Table 1.** Table describing the performance of each of the seasonal posteriors relative to the observations from that season.

to the prior. However, when applying the summer  $C_2H_6$  posterior to the 4 season dataset, not only does it perform substantially worse than each of the other seasonal posteriors, it also performs worse than the prior, with increases to the absolute error, bias, and a substantial decrease in the model-obs correlation coefficient from 0.71 to 0.50.

One possible explanation for the discrepancy in summer could be related to errors in the model transport simulation. The mean absolute error in the modelled boundary layer wind direction compared to flight observations were on average 30 degrees per flight in the summer campaign versus 15 in each of the other three seasons, likely related to the slower wind speeds observed during summer (Table S3). These directional transport errors can create misalignments in observed versus modelled plumes, leading to an overall reduction in the posterior emissions relative to the truth. Compounding on these wind issues is the possibility of increased convective activity in summer. While boundary layer statistics are tracked in the model and compared to observations, it is more difficult to assess how much of the signal is lost out the top of the boundary layer due to summertime convective processes. Another, non-transport related possibility is that there could be a non-trivial loss of  $C_2H_6$  due to an increase in the OH chemical sink during the summer months. In this study, the impacts of  $C_2H_6$  loss were not considered, as  $C_2H_6$  has an average lifetime of two months and most plumes were captured within 48 hours of release from the source (Burkholder et al., 2015). However, in conditions with excessive heat and large OH concentrations that can occur in the summer, the lifetime of  $C_2H_6$  can be reduced to as little as four days in the most extreme conditions (see supplemental section S2 for more details). Even so, a lifetime of four days would only have minor impacts on local plumes, and the extreme conditions leading to high  $C_2H_6$  loss would only exist for a short period in the afternoon hours. Furthermore, summer  $C_2H_6$  observations from the northeast were elevated to levels similar to those observed during the other seasons, seemingly unaffected by summertime conditions. For these reasons, it is unlikely that a chemical loss could be responsible for the low values observed in the south-central US. One final possibility is that the low  $C_2H_6$  enhancements observed in the Summer 19 campaign are due to a real and significant temporal change in  $C_2H_6$  emissions in the southcentral US during this period, particularly in the Anadarko basin. However, the near-zero emission rate solution provided by the inversion posterior in the Anadarko lacks any sort of real-world explanation for such a large shift compared to previous sea-

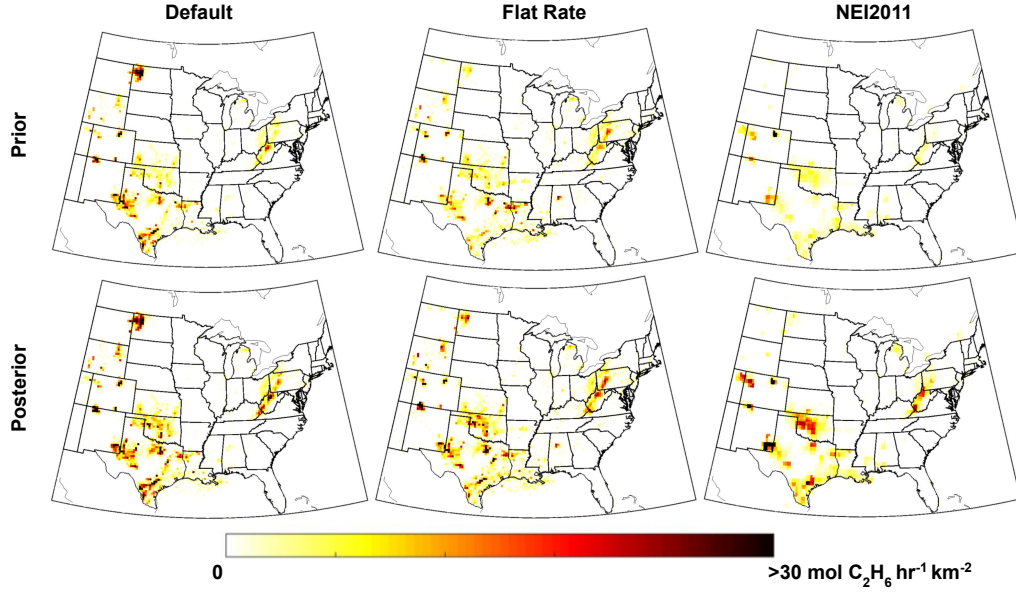
	Default Inventory Prior	Default Inventory Winter 2017 Posterior	Default Inventory Fall 2017 Posterior	Default Inventory Spring 2018 Posterior	Default Inventory Summer 2019 Posterior
<b>Southcentral Total <math>C_2H_6</math> (mol <math>s^{-1}</math>)</b>	488	709	777	601	199
<b>Western Appalachia Total <math>C_2H_6</math> (mol <math>s^{-1}</math>)</b>	125	184	294	185	269
Four Season Mean Absolute Error (ppb)	1.15	1.02	0.96	1.04	1.18
Four Season Mean Bias (ppb)	0.86	0.21	0.23	0.58	0.94
Four Season y,Hx Correlation	0.71	0.73	0.78	0.71	0.50

**Table 2.** Table describing the performance of each of the individual seasonal posterior fluxes when each is applied relative to all four seasons of observations. Green areas highlight statistical improvement compared to the prior, whereas red boxes show degradation.

sons. Production data shows the Anadarko basin was at its peak O&G production rates during the period (US Energy Information Administration, 2020a). Regardless of the reason, the low  $C_2H_6$  observations measured in the southcentral during the Summer 19 months are not representative of data from the winter, fall, and spring campaigns, which show strong consistency in the location and expected magnitudes of regional  $C_2H_6$  enhancements. For this work, we choose to discard summer data in evaluating our best estimate of US  $C_2H_6$  emissions, but consider it a source of uncertainty and intrigue for future research.

To create our best guess regarding  $C_2H_6$  emissions across the southcentral and eastern US, we weight the Default posterior flux maps from winter, fall, and spring with equal confidence and average them together (Figure 4). This averaged posterior solution provides consistent improvement compared to the prior, reducing the absolute error between the model and observations in 84% of flights, providing confidence that this averaged solution serves as an improvement to a large majority of the observational data for the three seasons it represents.  $C_2H_6$  emissions from the 3 season posterior are almost universally increased compared to the prior, with a 43% increase overall in the southcentral US and a 76% increase in the Appalachia. With these large increases in the emissions the mean obs-model bias is reduced, decreasing from 1.14 ppb to 0.70 ppb. The inability to eliminate this bias is a natural result of errors in the transport preventing the inversion from solving for misaligned observed plumes, and thus the emission increases in the 3 season posterior are likely still an underestimation of the true emissions.

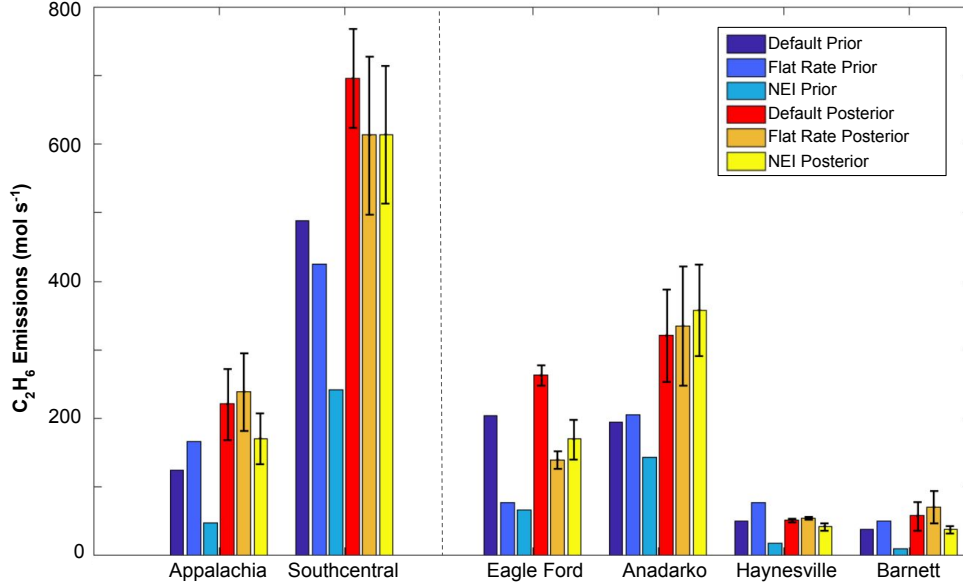
To better understand the sensitivity of our 3 season posterior to the prior, the inversion was rerun using the two alternative prior maps discussed in section 2.2 and a 3 season posterior was created from each set of priors (Figures 4 and 5) For every basin, posteriors from the three inventories converged towards a similar solution compared to their priors. An example of this is the Haynesville basin, where the two alternative prior inventories have a factor of 4 spread between their emissions, but their posteriors con-



**Figure 4.** Prior C<sub>2</sub>H<sub>6</sub> inventories used in this study and their respective 3 season mean posteriors. "Default" represents the best guess prior from this study based on multiplying the O&G sector of the Gridded EPA 2012 CH<sub>4</sub> Emissions Inventory by projected C<sub>2</sub>H<sub>6</sub>/CH<sub>4</sub> ratios of individual basins. "Flat Rate" multiplies the same CH<sub>4</sub> inventory by a flat rate C<sub>2</sub>H<sub>6</sub>/CH<sub>4</sub> ratio of 0.085, producing a similar total as "Default" with a different spatial representation. "NEI2011" comes from the NEI 2011 C<sub>2</sub>H<sub>6</sub> inventory.

verge to within 20% of the Default posterior solution. Ultimately, the 2 alternative posteriors produced solutions for the entire southcentral US that were within 1 mol/s of each other, despite starting 183 mol/s apart. Their similar solutions for the southcentral region are 12% lower than the posterior calculated using the Default inventory. This difference is driven primarily by the Eagle Ford basin, which had the largest absolute spreads between prior inventories and whose western portion lies on the edge of the region of influence captured by the ACT-America flights (Figure 2), making it more difficult for the inversion to constrain using the available dataset. In the northeast, there was a similar consensus among the three inventories of a substantial increase in emissions required to recreate the large plumes observed there. While the emissions in the NEI2011 posterior do not increase to the same levels as the other two priors (171 vs 221 and 239 mol/s), the NEI2011 prior in the northeast was missing nearly all of the emissions from conventional gas activity in western Pennsylvania, resulting in a posterior map that still appears to be underestimating the sources in that region even after substantial increases given the large positive bias between the observations and modelled posterior. Overall the NEI2011 prior, whose total C<sub>2</sub>H<sub>6</sub> emissions are 53% less than the Default prior, leads to a total posterior C<sub>2</sub>H<sub>6</sub> emissions estimate that is only 14% lower than the Default posterior.

In addition to testing the sensitivity of the inversion posterior to different priors, we also test its sensitivity to numerous other conditions, including adjustments to the magnitude of the prior, changes to the selection of the background C<sub>2</sub>H<sub>6</sub> term, elimination of the length correlations applied to the prior flux uncertainty, adjustment of the observation matrix error term to a constant (giving equal uncertainty to all observations), and solving for a posterior solution using all three seasons of data simultaneously rather

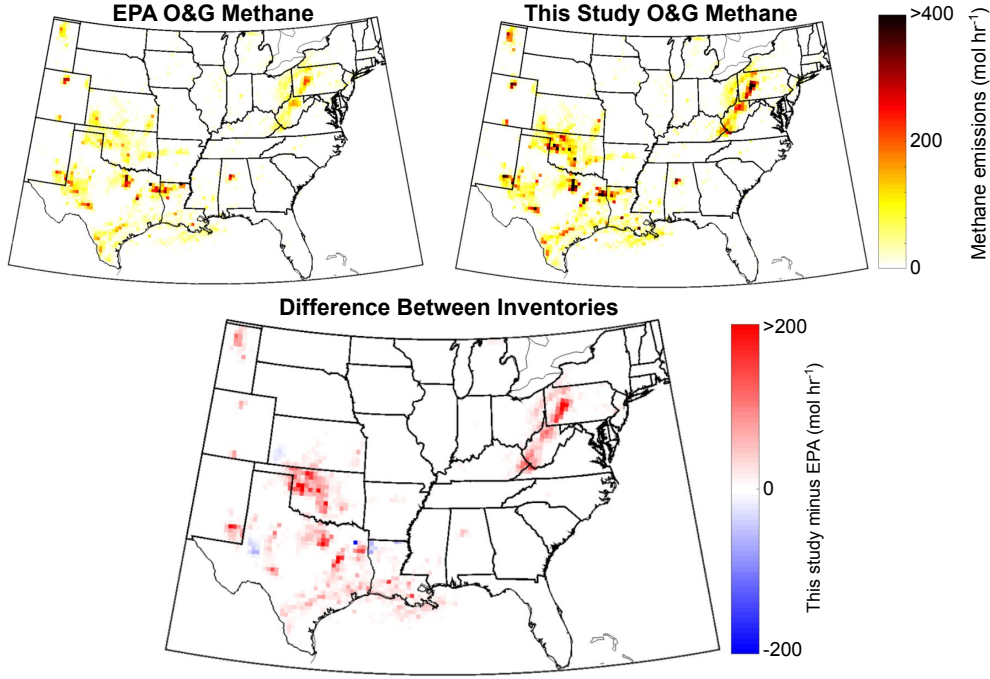


**Figure 5.** Priors and their respective 3 season posterior C<sub>2</sub>H<sub>6</sub> emissions for major basins in this study. "Southcentral" is the sum of Eagle Ford, Anadarko, Haynesville, and Barnett. Error bars show the standard deviation of the individual season solutions for each basin.

than averaging 3 unique posterior maps (Table S4). All resulting posteriors produce similar results compared to the Default posterior, providing further confidence in the solution. In particular, using our Default prior multiplied by a factor of 3 converged to a similar solution as our Default posterior, reducing concerns that using a prior with a low bias could be resulting in an large underestimation of the solution. One source of uncertainty that is difficult to address in our sensitivity tests are errors in the transport used to create the influence functions. Average flight wind speed biases were under 1.3 m/s and wind direction absolute errors were close to 15 degrees for the winter, fall, and spring campaigns when compared to ACT-America boundary layer aircraft data (Table S3). However, modelled boundary layer heights were 15 to 22 percent lower on average seasonally compared to observations. A negative bias in the modelled boundary layer would result in an equally proportionally higher value in the influence functions and model-projected enhancements. Applying a correction factor to the influence functions relative to the mean bias for each season and rerunning the inversion produces an overall posterior that is 22% higher than the Default posterior. Consistent with our past work that has applied corrections to simulated errors in ABL depth and winds (Barkley et al., 2017, 2019a, 2019b), we consider the posterior created using the ABL depth correction to be an equally plausible solution in our best estimate of the C<sub>2</sub>H<sub>6</sub> emissions, as the boundary layer bias is a source of error with a known and somewhat correctable bias on the solution. The boundary layer bias, along with a negative enhancement bias still present in the model versus observational comparison of the posterior C<sub>2</sub>H<sub>6</sub> enhancements, are both potential reasons to suspect the Default posterior on its own may still be underestimating overall C<sub>2</sub>H<sub>6</sub> emissions despite the large increase in the emissions relative to the prior.

### 3.2 Interpretation of CH<sub>4</sub> Emissions from the O&G Sector

The Default prior inventory developed in this study is created by multiplying the EPA 2012 Gridded CH<sub>4</sub> Emissions Inventory for O&G sources by the suspected C<sub>2</sub>H<sub>6</sub>/CH<sub>4</sub>



**Figure 6.** Top-left: Oil and gas CH<sub>4</sub> emissions from the EPA 2012 Gridded CH<sub>4</sub> Inventory. Top-right: Oil and gas CH<sub>4</sub> emissions estimated from the C<sub>2</sub>H<sub>6</sub> posterior in this study. Bottom: Difference between the two inventories.

ratio of each grid's emissions. If the assumed ratios are correct, and emissions primarily occur in situations where the gas content is unaltered (i.e. processes unrelated to gas separation), then changes between the posterior and prior Default C<sub>2</sub>H<sub>6</sub> inventory should proportionally reflect changes in the EPA 2012 CH<sub>4</sub> inventory for O&G. Thus, we can use our Default posterior C<sub>2</sub>H<sub>6</sub> inventory to create our best interpretation of O&G CH<sub>4</sub> emissions in the southcentral and eastern US.

Using the converted C<sub>2</sub>H<sub>6</sub> posterior as a proxy for O&G CH<sub>4</sub> emissions, our inventory projects that O&G CH<sub>4</sub> emissions are almost universally larger than the 2012 EPA Inventory estimates (Figure 6). In the southcentral US, we estimate emissions to be 48% higher than inventory estimates (77% using the ABL-adjusted posterior). Of this increase, two-thirds of it is driven by increases in the Anadarko basin, which had the largest proportional change in the C<sub>2</sub>H<sub>6</sub> posterior and is the largest source of CH<sub>4</sub> emissions in the region. Of the four remaining southcentral basins captured in this study, the Haynesville basin is the only basin that did not see a significant increase in its emissions relative to the prior. As noted in section 2.1, our solution does not include potential changes from the Permian basin which is outside of the region of influence captured by ACT-America campaign. O&G production in the Permian has increased by more than a factor of 3 since 2012 and some of the largest CH<sub>4</sub> signals from the basin have been measured using satellite observations in the area (Zhang et al., 2020). As such, it is likely that emissions in the Permian follow a similar pattern of underestimation observed for other southcentral basins in our study.

In the Appalachians, we estimate CH<sub>4</sub> emissions to be 77% higher than EPA 2012 inventory estimates (105% using the ABL-adjusted posterior), the largest difference of any basin in this study. Part of the discrepancy between inventory results and the posterior may be related to the increased presence of unconventional natural gas activity



in the Marcellus shale. Between 2012 and 2018 Pennsylvania and West Virginia underwent some of the largest gas production growth in the US, with annual production tripling during the period (US Energy Information Administration, 2020a), a change that would not be captured in the EPA 2012 inventory. However, Pennsylvania state inventories, which provide annual inventory estimates of unconventional natural gas activity in the state using methodologies similar to the EPA, show  $\text{CH}_4$  emissions from unconventional activity only increased by 20% during this period, and that these unconventional wells only represent a portion of O&G emissions in the region (Omara et al., 2016), with much of the emissions coming from pre-existing conventional activity. Thus, it is unlikely that changes in unconventional activity between 2012 and the time of this study would be responsible for the 77% increase in regional emission rates found from the inversion results relative to the EPA 2012 Gridded Inventory, and that the discrepancy would still be present in an updated EPA inventory.

The  $\text{CH}_4$  inventory estimates for individual basins from this study generally align with mass balance studies of corresponding basins. In the Haynesville basin we calculate an O&G emission rate of 43 Mg/hr, compared to 42 Mg/hr from Peischl et al. (2018) and 76 Mg/hr from Cui et al. (2017), which includes non-O&G values in its total as well. In the Barnett, we calculate emissions to be 57 Mg/hr, larger than 46 Mg/hr found in Peischl et al. (2018) but close to the 60 Mg/hr found in Karion et al. (2015). In Eagle Ford, both the western and eastern basin in this study had a combined emission rate of 68 Mg/hr versus 83 Mg/hr in Peischl et al. (2018). Additionally, the large values observed in the Appalachian match findings that show emissions from unconventional O&G infrastructure in the Marcellus are greatly underestimated by EPA inventory values (Barkley et al., 2019a; Caulton et al., 2019).

The interpretation of O&G  $\text{CH}_4$  emissions using  $\text{C}_2\text{H}_6$  observations has a unique advantage compared to more traditional methodologies that rely on  $\text{CH}_4$  measurements due to the simplicity of  $\text{C}_2\text{H}_6$  sources. In the US where  $\text{CH}_4$  emissions have near equal contributions from fossil fuels, agriculture, and wetlands, each of which have their own uncertainties,  $\text{C}_2\text{H}_6$  emissions are dominated almost entirely by the O&G sector. Furthermore, there is high confidence in the spatial mapping of O&G sources in the US due to extensive documentation of the various components associated with O&G extraction, simplifying interpretation of atmospheric  $\text{C}_2\text{H}_6$  data. As an example, in the ACT-America campaign, the majority of aircraft flight tracks were hundreds to thousands of kilometers away from O&G basins. Despite this, the model prior was able to consistently track  $\text{C}_2\text{H}_6$  enhancements from these sources in the winter, fall, and spring, with correlations between the model vs observed boundary layer  $\text{C}_2\text{H}_6$  enhancements of 0.85, 0.75, and 0.61 respectively. The high skill in tracking enhancements from a single sector with well-defined locations creates a scenario where a stable posterior solution can be generated through various inverse methodologies (Table S4).

Despite high confidence in the  $\text{C}_2\text{H}_6$  posterior, the conversion of this posterior to O&G  $\text{CH}_4$  emissions is entirely dependent on the quality and availability of information related to the  $\text{C}_2\text{H}_6/\text{CH}_4$  ratio for each basin. During the time observations from this study were collected, there were numerous recent flights available from a separate study that captured the  $\text{C}_2\text{H}_6/\text{CH}_4$  ratios of various basins (Peischl et al., 2018), providing confidence in our  $\text{C}_2\text{H}_6$  to  $\text{CH}_4$  conversions for those locations. However, basins that are geographically broad, such as the Anadarko and Marcellus, are more difficult to characterize a ratio for using atmospheric data. Furthermore, the average gas composition of a basin can change over time, making ratios found in older studies less applicable (Lan et al., 2019). Publicizing upstream gas composition data collected by major O&G companies would be one immediate solution and effectively eliminate any uncertainty introduced in an  $\text{C}_2\text{H}_6$  to  $\text{CH}_4$  inventory conversion.

One other source of uncertainty related to the  $\text{C}_2\text{H}_6$  to  $\text{CH}_4$  inventory conversion presented in this study is the presence of coal mines in the Appalachia that overlap with

regional gas production. These mines are a dominant source of  $\text{CH}_4$  emissions in the region, but little information is available regarding  $\text{C}_2\text{H}_6$  emissions associated with them. For this study, we treat  $\text{C}_2\text{H}_6$  emissions from these sources to be negligible based measured values from a 1973 geological survey that found little to no  $\text{C}_2\text{H}_6$  in many of the mines relevant to this study (Kim, 1973). However, ratios as high as 0.08 have been observed in western Kentucky (Strapoć et al., 2007), raising the possibility that some portion of the  $\text{C}_2\text{H}_6$  observed in this study in the Appalachia could be attributable to underground mines. Air from major coal ventilation shafts is sampled 4 times each year to quantify the amount of  $\text{CH}_4$  present for safety precautions (US Environmental Protection Agency, 2017). Measuring  $\text{C}_2\text{H}_6$  mixing ratios in these samples would provide additional information to expand our understanding of  $\text{C}_2\text{H}_6$  emissions in the northeastern US.

## 4 Conclusion

Using the largest collection of airborne boundary layer  $\text{C}_2\text{H}_6$  data to date, an inversion was performed to estimate  $\text{C}_2\text{H}_6$  and  $\text{CH}_4$  emissions from various O&G basins across the eastern US. From this dataset, we estimate that a large portion of  $\text{C}_2\text{H}_6$  emissions cannot be explained using O&G emission data from the EPA 2012 Gridded  $\text{CH}_4$  Inventory and existing  $\text{C}_2\text{H}_6$  to  $\text{CH}_4$  emissions ratio data. We conclude that the EPA  $\text{CH}_4$  emissions inventory significantly underestimates  $\text{CH}_4$  emissions from O&G sources. From this dataset, our results yield  $\text{CH}_4$  emissions estimates similar in magnitude to national estimates in Alvarez et al. (2018). In particular, this study finds the largest discrepancies occurring in the Anadarko and western Appalachian O&G plays, though all basins other than Haynesville showed an increase in expected  $\text{C}_2\text{H}_6$  emissions relative to the prior. We also find  $\text{C}_2\text{H}_6$  emissions from O&G that are much higher than existing  $\text{C}_2\text{H}_6$  inventories, a fact that should be taken into account in any future efforts to investigate O&G  $\text{CH}_4$  emissions using atmospheric  $\text{C}_2\text{H}_6$  observations, as well as studies relying on existing  $\text{C}_2\text{H}_6$  inventories to account for certain chemical reactions.

This study reveals the potential to use broad-scale continuous  $\text{C}_2\text{H}_6$  data to constrain  $\text{CH}_4$  emissions from the O&G sector on a nationwide scale. Our confidence in the spatial distribution of emissions associated with the O&G sector and the dominant role of O&G in US  $\text{C}_2\text{H}_6$  emissions allows for modelling and interpretation of observed signals without large concerns for source attribution. Furthermore, misalignment in observed versus modelled plumes may serve as a useful diagnostic of model transport errors due to the well-documented spatial knowledge of  $\text{C}_2\text{H}_6$  emitters in the US. One current weakness with relying on  $\text{C}_2\text{H}_6$  observations to understand  $\text{CH}_4$  emissions from O&G is the requirement of knowing the  $\text{C}_2\text{H}_6$  to  $\text{CH}_4$  ratio of gas composition and basin emissions in order to convert  $\text{C}_2\text{H}_6$  emissions into  $\text{CH}_4$  emissions. Gas composition data is collected by individual companies but not shared publicly. Should some form of this information be made available for the public, it would greatly enhance the confidence of  $\text{CH}_4$  emission estimates of the O&G industry using  $\text{C}_2\text{H}_6$  and other trace gases.

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