

1 **Satellite-based surveys reveal substantial methane point-source emissions in major oil & gas basins of**  
2 **North America during 2022-2023**

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35 **Key Points:**

- 36 • The new Chinese Gaofen5-01A/02 hyperspectral satellite missions have great capability in  
37 methane mapping.
- 38 • We find a substantial methane point-source emissions in Permian Delaware Tight US after  
39 COVID-19 during 2022-2023.
- 40 • Satellite-based survey can effectively improve bottom-up regional methane emissions  
41 inventories.

42 **Plain Language Summary**

43 Reducing methane (CH<sub>4</sub>) leaks from Oil & Gas (O&G) production is crucial for abating climate  
44 change. However, detecting these abnormal CH<sub>4</sub> emissions globally is challenging as they often  
45 occur unexpectedly. Satellite remote sensing with hyperspectral imaging spectrometer provides a  
46 novel approach for top-down monitoring. These instruments produce CH<sub>4</sub> plume maps, enabling  
47 the quantification of emissions. In this research, we conduct a comprehensive survey in major  
48 O&G basins of North America during 2022-2023 using the new Chinese Gaofen5-01A/02  
49 satellite. Through repeated observations by high-resolution satellites, we capture CH<sub>4</sub> emission  
50 dynamics in sample basins and quantify their contribution to regional methane budget. Our  
51 results demonstrate the value of high-resolution satellite observations in reducing uncertainties in  
52 quantifying anthropogenic CH<sub>4</sub> emission and supporting strategies for emission mitigation.

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54

## 55 **Abstract**

56 Utilizing imaging spectroscopy technology to identify methane super-emitters plays a vital role  
57 in mitigating methane emissions in the Oil & Gas (O&G) sector. While earlier research has  
58 uncovered significant point-source methane emissions from O&G production in the US and  
59 Canada, which are key regions with large methane emissions, a comprehensive post-COVID-19  
60 survey has been notably absent. Here, we perform a detailed survey of methane super-emitters  
61 across multiple basins of North America (Marcellus Shale US, Haynesville/Bossier Shale US,  
62 Permian Delaware Tight US and Montney Play Canada) using the new Chinese Gaofen5-01A/02  
63 (GF5-01A/02) satellite measurements during 2022-2023. We detect 48 extreme methane point-  
64 source emissions with flux rates of 646 to 16071 kg h<sup>-1</sup>. These emissions exhibit a highly  
65 skewed and heavy-tailed distribution, constituting approximately 30% of the total flux in sample  
66 region, with a range of 13% to 63%. Moreover, we observe a 66.7% reduction in methane  
67 emissions in Permian Delaware Tight region during COVID-19, followed by fluctuations until  
68 spring 2022. By summer 2023, methane emissions rebound to previous magnitude ( $0.66 \pm 0.20$   
69 Tg a<sup>-1</sup>). Using these point-source surveys, we further quantify a regional methane emission of  
70  $1.08 \pm 0.02$  Tg a<sup>-1</sup> in Delaware subbasin. This estimation closely aligns with top-down inversions  
71 ( $0.86 \pm 0.03$  Tg a<sup>-1</sup>) from TROPOMI. The upscale estimation underscores the effectiveness of  
72 high-resolution remote sensing measurements in improving bottom-up emissions inventories and  
73 refining regional methane emission assessments. Our results highlight the potential climate  
74 benefits derived from regular monitoring and specific remediation efforts focused on relatively  
75 few strong point-source emissions.

## 76 **1 Introduction**

77 Prompt detection of abnormal methane (CH<sub>4</sub>) emissions in Oil & Gas (O&G) field, coal  
78 mine and liquefied natural gas terminal would enable action for climate change mitigation. CH<sub>4</sub>  
79 emissions from O&G facilities predominantly emanate from key infrastructures, including  
80 wellheads, compressor stations, tank batteries, pipelines and flares (Lyon et al. 2016), forming  
81 easily recognizable "point-source emissions". Numerous studies indicate that CH<sub>4</sub> emissions  
82 from O&G facilities exhibit a heavy-tailed distribution with a small number of large point  
83 sources contributing significantly to total emissions (e.g., Brandt et al. 2014; Cusworth et al.  
84 2021; Duren et al. 2019). This disproportionate contribution often stems from malfunctions and  
85 abnormal operating conditions, such as fugitive emissions from leakage, venting, and facility  
86 blowouts (Lyon et al. 2021; Rutherford et al. 2021; Zavala-Araiza et al. 2021). Detecting these  
87 unexpected emissions of relatively small sizes globally poses a significant challenge (Cusworth  
88 et al. 2021). Additionally, the duration, quantity, and frequency of these leaks have large  
89 variations in different regions and periods (Irakulis-Loitxate et al. 2021; 2022b).

90 Spaceborne imaging spectroscopy offer a unique observational approach for mapping  
91 CH<sub>4</sub> point-sources emissions. These instruments, utilizing the radiance in the SWIR range, can  
92 discern subtle signal changes from methane absorption (Frankenberg et al. 2005; Jacob et al.  
93 2016; Jacob et al. 2022). Recent advancements in hyperspectral satellites have demonstrated  
94 their potential to map and quantify point-source methane emissions. Hyperspectral imaging  
95 spectrometers, with ~10 nm spectral resolution and 30~60 m spatial resolution, such as those  
96 onboard the PRISMA (PRecursores IperSpettrale della Missione Applicativa) (Guanter et al.  
97 2021), EnMAP (Environmental Mapping and Analysis Program) (Roger et al. 2024), EMIT  
98 (Earth Surface Mineral Dust Source Investigation) (Thorpe et al. 2023a), GF5-01-AHSI

99 (Gaofen5-01) and ZY1-02D-AHSI (Ziyuan-1 02D) (Liu et al. 2019), exhibit significant ability  
100 for mapping CH<sub>4</sub> point-sources in O&G basins and coal mining areas. The recently operational  
101 GF5-01A/02 missions, launched on 7 Sep.2021 and 9 Dec. 2022 respectively, offer an  
102 opportunity to enhance our ability to quantify methane point-source emissions. However, the  
103 capabilities of these latest missions for methane mapping remain unclear in comparison to the  
104 high performance of the first-generation AHSI on board China GF5 (GF5-01-AHSI) in detecting  
105 methane point-source emissions.

106 As the largest O&G producer globally, the US contributes 15% of the global O&G CH<sub>4</sub>  
107 emissions for 2019 (8.1 Tg a<sup>-1</sup>) (Scarpelli et al. 2022), making it a major methane emitter in the  
108 O&G industry. The Permian Basin with the largest oil production in the US, responsible for over  
109 40% of the country's oil and gas production (FRBD, 2022), has garnered increased attention for  
110 estimations of methane emissions. Despite previous studies utilizing satellite imaging  
111 spectroscopy for high-resolution surveys of methane point emitters in individual O&G basins,  
112 these have mainly focused on a few observations (Esparza et al. 2023; Irakulis-Loitxate et al.  
113 2021). However, considering the impact of the COVID-19 pandemic on CH<sub>4</sub> emissions (Thorpe  
114 et al. 2023b), it remains unclear if the observed temporary reductions extend across the entire  
115 O&G supply chain, all basins, and sectors. Further surveying efforts are needed to address this  
116 uncertainty.

117 In this work, we aim to evaluate the impact of the COVID-19 pandemic on methane  
118 emissions in various North American O&G basins (Marcellus Shale US, Haynesville/Bossier  
119 Shale US, Permian Delaware Tight US, and Montney Play Canada) from 2022 to 2023.  
120 Employing GF5-01A/02, we identify CH<sub>4</sub> point sources, quantify emission flux, and attribute  
121 contributions to specific facilities in these regions. Additionally, we estimate regional methane  
122 budgets exclusively using point source observations in Permian Delaware Tight US and compare  
123 them to regional methane flux inversions based on TROPOMI/GOSAT XCH<sub>4</sub>. Through this  
124 comprehensive approach, we aim to discern the contribution of these significant point sources to  
125 the regional methane budget. Ultimately, we leverage satellite observations to enhance bottom-up  
126 inventories and highlight opportunities for emission reduction.

## 127 **2 Material and Methods**

### 128 2.1 Satellite imaging spectroscopy data

129 The GF5-01A/02 satellites are the 2<sup>nd</sup> generation satellites of the Gaofen-5 series  
130 (Chinese civilian remote sensing satellites) and were launched on 7 Sep.2021 and 9 Dec.2022,  
131 respectively. They have been operation over two years with a large number of global  
132 observations to date. GF5 satellite is configured with six types of payloads including  
133 hyperspectral and directional polarization instruments, designed for environmental monitoring,  
134 encompassing aerosol, cloud and greenhouse gas monitoring (Chen et al. 2022). The Advanced  
135 Hyperspectral Imager (AHSI) aboard the GF5 is a groundbreaking spaceborne hyperspectral  
136 camera. It employs both an improved three-concentric-mirror (Offner) configuration and a  
137 convex-grating spectrophotometry. Covering a spectral window from 400 to 2500 nm, the AHSI  
138 achieves a spatial resolution of 30 m with a swath of 60 km. It comprises 330 spectral bands with  
139 5 and 10 nm spectral resolution in the VNIR and SWIR, respectively (Liu et al. 2019). The  
140 distinctive features of wide coverage, fine spatial resolution, high signal-to-noise ratio (SNR)  
141 (500 in the SWIR bands), and excellent spectral uniformity set GF5-01A/02 apart from other

142 hyperspectral imaging spectrometers. These characteristics provide significant advantages in  
 143 mapping point-source CH<sub>4</sub> emissions (Irakulis-Loitxate et al. 2021). In addition to the GF5-  
 144 01A/02, NASA’s EMIT, launched on 14 July 2022, and is operational on the International Space  
 145 Station. EMIT have 285 distinct wavelengths at a spectral resolution of 7.4 nm, ranging from 381  
 146 to 2493 nm. It achieves 60 m spatial resolution, an 80 km swath, and a SNR from 500 to 750 in  
 147 most bands. This makes EMIT also well suited for identifying methane super-emitters (Thorpe et  
 148 al. 2023a). More details of these satellites can be seen in Table 1.

149 In this work, we integrated a set of 27 images obtained from GF5-01A/02 and EMIT to  
 150 cover major O&G basins in North America. The acquisitions employed in this study  
 151 predominantly spanned from February 2022 to September 2023. We use L1 level datasets from 3  
 152 scenes of GF5-01A, 20 scenes of GF5-02 and 4 scenes of EMIT, with the EMIT scenes serving  
 153 as supplementary data (see Table A1).

## 154 2.2 Principles in the retrievals of methane column concentration enhancement

155 Methane column concentration enhancement ( $\Delta X_{CH_4}$ ) can be retrieved through the  
 156 application of the Matched Filter (MF) method. It characterizes the background radiance as a  
 157 multivariate Gaussian with mean ( $\mu$ ) and covariance ( $\Sigma$ ), under the assumption that each input  
 158 radiance is expressed as the average radiance plus the perturbation resulting from a variation in  
 159 methane column concentration (Thompson et al. 2016):

$$160 \quad x = \mu + \Delta X_{CH_4} \cdot t \quad (1)$$

161 where  $x$  represents the radiance spectrum at sensor, and  $t$  is the target signature, defining the  
 162 radiance spectrum equivalent to the absorption of one unit of methane concentration in relation  
 163 to background.  $t$  is derived from the product of the unit methane absorption ( $k$ ) spectrum and the  
 164 background mean.  $k$  is calculated from a Look-Up Table linking CH<sub>4</sub> transmittance spectra,  
 165 obtained from the HITRAN database, to methane concentration (Gordon et al. 2017). Figure 1a  
 166 shows an illustrative example of a  $k$  target unit absorption spectrum. By maximizing the  
 167 likelihood of Eq.1 (Eismann 2012),  $\Delta X_{CH_4}$  can be described as follows:

$$168 \quad \Delta X_{CH_4} = \frac{(x - \mu)^T \Sigma^{-1} t}{t^T \Sigma^{-1} t} \quad (2)$$

169 The application of the MF to the strong CH<sub>4</sub> absorption bands at 2300 nm is a widely  
 170 adopted approach (Dennison et al. 2013; Foote et al. 2020; Thompson et al. 2015). Hence, we  
 171 apply the MF technique for the strong CH<sub>4</sub> absorption bands within the 2100-2450 nm. Despite  
 172 the 1700 nm absorption bands generally exhibiting higher radiance levels, the CH<sub>4</sub> absorption is  
 173 significantly weaker (see Figure 1 (b) and (c)), leading to more noise in methane retrievals.

## 174 2.3 Methane plume detection and quantifications

175 The identification of CH<sub>4</sub> plumes initiates with a visual examination of the  $\Delta X_{CH_4}$  maps  
 176 obtained. Distinguishing the plumes from the background is usually straightforward in maps with  
 177 minimal random noise, thanks to the distinctive shape of the plumes. After the initial  
 178 identification of plumes, their shape is cross-verified with the GEOS-FP 10 m wind direction  
 179 data to ensure consistency. Once confirmed, the plumes are matched with high-resolution images  
 180 to precisely locate the infrastructure responsible for the emissions.

181 The subsequent step in the detection process focuses on each identified plume, separating  
 182 it from the surrounding background to calculate the whole emission area. Here, a semi-

183 automated approach is employed. The plume is segregated using a mask set at a 95% confidence  
 184 level and further refined with a square dilation mask spanning multiple pixels. Like the median  
 185 filter method, this dilation mask guarantees the inclusion of the plume tails in the identified area.  
 186 This method not only minimizes discontinuities arising from the spatial pattern of a CH<sub>4</sub> plume  
 187 but also ensures a more cohesive selection of the plume. Lastly, feature selection techniques are  
 188 employed to eliminate any detected outliers in close proximity to the plumes (Szeliski, 2022).

189 After identifying the CH<sub>4</sub> plumes, we use the integrated mass enhancement (IME) method  
 190 to quantify the flux rate for each methane plume (Frankenberg et al. 2016; Varon et al. 2018).  
 191 The IME is calculated in kg units, representing the overall excess mass of CH<sub>4</sub> present in the  
 192 plume:

$$193 \quad IME = k \sum_{i=1}^{n_p} \hat{\alpha}(i) \quad (3)$$

194 where  $k$  is a scaling factor ( $5.155 \times 10^{-3} \text{ kg/ppb}$ ), and  $n_p$  is the number of pixels within the plume  
 195 The scaling factor  $k$  transforms the sum of pixel-wise CH<sub>4</sub> concentration in  $ppb$  to  $kg$ ,  
 196 considering Avogadro's law, the molecular weight of CH<sub>4</sub> and the 30-m pixel size.  $Q$  is derived  
 197 as follows:

$$198 \quad Q = \frac{U_{eff} \cdot IME}{L} \quad (4)$$

199 where  $L$  is the plume length scale determined as  $L = \sqrt{A}$ .  $A$  is the square root of the area of the  
 200 detectable plume.  $U_{eff} = f(U_{10})$  is an effective wind speed. The  $U_{eff}$  term is computed from the  
 201 local 10-m wind speed ( $U_{10}$ ) in Eq. 5 (Li et al. 2023):

$$202 \quad U_{eff} = 0.38 \cdot U_{10} + 0.41 \quad (5)$$

203 This linear relationship is from the large-eddy simulations (LES) that are specifically  
 204 tailored for the spatial resolution and  $\Delta X_{CH_4}$  retrieval precision similar to satellite data. A linear  
 205 model is found to provide the best fit (Varon et al., 2018, Cusworth et al. 2019).  $U_{10}$  data are  
 206 extracted from the GEOS-FP dataset.

207 The accuracy of satellite-based methane point-source emissions detection and  
 208 quantification has been validated against a few controlled CH<sub>4</sub> release experiments (Sherwin et  
 209 al. 2023a; Sherwin et al. 2023b). Quantification error across all satellites and participants are  
 210 generally low. In the case of all identified emissions using hyperspectral instruments, the parity  
 211 lines for each satellite team consistently align closely with the ideal 1:1 line. The accuracy of  
 212 mean estimates for all combinations of satellite teams exceeds 80%, and the R<sup>2</sup> values for linear  
 213 fits for fully blinded estimates range from 0.89 to 0.97. These validations demonstrate the good  
 214 performance of MF method in identifying and measuring methane point-source emissions.

#### 215 2.4 Methane point sources attribution

216 The abundant spatial detail provided by high resolution satellite data facilitates the  
 217 detection of CH<sub>4</sub> point sources, including those within O&G extraction facilities, and tank  
 218 batteries or compressor stations. We leverage high spatial resolution satellite images from  
 219 platforms like Google Earth, Esri Map, and Bing Maps, co-registered with  $\Delta X_{CH_4}$  maps, to assign  
 220 point sources to specific facilities. In instances where high-resolution imagery data are

221 unavailable for the detected methane plume's time and location, Sentinel-2A/2B images are  
222 utilized as a substitute.

223 We have gathered specific details about O&G extraction platforms in the interactive  
224 PermianMAP provided by the Environmental Defense Fund. Others not available in  
225 PermianMAP have been obtained through Global Energy Monitor and visual interpretation of  
226 Sentinel-2A/2B historical images. With this information, we can pinpoint the emission facilities  
227 associated with the detected plumes.

## 228 2.5 Estimation of integrated emission rate and regional methane budget

229 Our plume detections capture specific moments when emissions exceed  $500 \text{ kg h}^{-1}$  during  
230 satellite overpasses, providing snapshots in time. To facilitate a meaningful comparison, we  
231 convert emissions from per-hour to per-year units (Irakulis-Loitxate et al., 2021). Recognizing  
232 the intermittent nature of most point-source emissions, we make the assumption that the leakage  
233 facility emits consistently throughout the entire event with a relatively constant flux (Irakulis-  
234 Loitxate et al. 2022a). The detected point-sources serve as a representative ground sample of  
235 significant emitters on the regional scale, allowing us to scale up and generate a comprehensive  
236 annual estimation of  $\text{CH}_4$  emissions.

237 Moreover, we derive the regional methane emissions based on point-source observations  
238 in Permian Delaware Tight US. This estimation involves employing Kriging interpolation with a  
239 spherical semi-variogram model, using a maximum radius setting of  $12 \beta$  values. Considering  
240 that the interpolation results can be influenced by the grid size and spatial density of point  
241 sources, and to prevent overfitting while minimizing interpolation errors, we adopt a  $0.3125^\circ \times$   
242  $0.3125^\circ$  grid sample unit to encompass the entire Delaware subbasin. This choice closely aligns  
243 with the spatial resolution of atmospheric inversion results.

244 Additionally, we have conducted a comparison between the individual point-source  
245 emissions we identified and the area-integrated emission estimates derived from both the bottom-  
246 up emission inventory of GFEI v2/EPA v2 (Maasackers et al., 2023; Scarpelli et al., 2022) and  
247 the top-down inversions of TROPOMI/GOSAT (Lu et al., 2023; Shen et al., 2022). It should be  
248 noted that such comparison between single-point and area-integrated  $\text{CH}_4$  emissions is solely  
249 intended to offer additional context on the level of the extreme  $\text{CH}_4$  point-source emissions.  
250 Details of the emission inventory and inversion estimates are provided in Table 2.

## 251 3 Results

### 252 3.1 Characteristic of observed methane point-source emissions

253 Utilizing the methodologies outlined earlier, we perform a high-resolution survey of all  
254 detectable  $\text{CH}_4$  point-source emissions across major O&G basins in North America. This survey  
255 incorporates all accessible imagery captured by GF5-01A/02 & EMIT from Feb.2022 to  
256 Sep.2023. In total, we identify 48 extreme point sources, and their spatial distribution along with  
257 emission magnitudes are illustrated in Figure 2. The majority, specifically 40, are located in  
258 Permian Delaware Tight US, while the remaining point source emissions are relatively dispersed  
259 across other basins, including Montney Play Canada (4 plumes), Marcellus Shale US (2 plumes),  
260 and Haynesville/Bossier Shale US (2 plumes). Of the 48 methane plumes observed during this  
261 survey, the average emission is  $3,575 \pm 1,249 \text{ kg h}^{-1}$  and the total emission is  $171,617 \pm 59,937$   
262  $\text{kg h}^{-1}$ . Furthermore, out of the detected 48 plumes, 35 are identified by the GF5-01A/02

263 satellites, showcasing outstanding performance of the GF5 series satellite in detecting extreme  
264 methane point-source emissions.

265 Figure 3 shows some examples of individual methane plumes observed using GF5-  
266 01A/02 instruments across multiple basins and various facilities (Fig. S1 and Table S2 for  
267 comprehensive details of all emission locations, flux rates and type of facility). The emissions  
268 exhibit considerable variability in both source types and flux rates. For instance, plume A  
269 represents a substantial emission with high flux rates ( $Q = 6,452 \pm 2,422 \text{ kg h}^{-1}$ ) from a  
270 malfunctioning flare, while plume Q corresponds to a source emission ( $Q = 3,392 \pm 967 \text{ kg h}^{-1}$ )  
271 attributed to incomplete combustion of a flare in a well pad. Additionally, plume T ( $Q$   
272  $= 1,844 \pm 464 \text{ kg h}^{-1}$ ) and plume V ( $Q = 1,313 \pm 436 \text{ kg h}^{-1}$ ) are associated with leakage from a tank  
273 battery. It is important to note that our plume detections capture snapshots of emissions with flux  
274 rates exceeding  $500 \text{ kg h}^{-1}$  when satellite overpass. Most emission sources detected align  
275 serendipitously with the space-borne missions (Fig. S1). More comprehensive statistics for these  
276 basins will emerge as additional data is analyzed, allowing for targeted assessments during  
277 subsequent missions.

278 We further analyze the characteristic of flux rates stemming from identified point source  
279 emissions (Figure 4). The emissions from these point sources exhibit a markedly skewed  
280 distribution, typically falling within the range of  $500$  to  $4,000 \text{ kg h}^{-1}$ . As displayed in the inset  
281 plot of Figure 4, relatively substantial extreme point emitters are detected ( $>1,000 \text{ kg h}^{-1}$ ) that  
282 account for more than 78% of the whole  $\text{CH}_4$  emission rates in each survey. Combining all  
283 surveys, it is noteworthy that a mere 8.33% of emitters contributed to over 30% of the whole  
284 emissions detected in the studied region, with the largest plume notably contributing 9.36% of  
285 the total methane detected.

286 Figure 5 illustrates the comparisons of methane point source emissions from our study  
287 during 2022 and 2023 with previous surveys. The observed emission intensities in this study  
288 (ranging from  $646$  to  $16,071 \text{ kg h}^{-1}$ ) exceed the median values ( $299 \text{ kg h}^{-1}$ ) in comprehensive  
289 regional airborne surveys of the US from 2019 to 2021 (Cusworth et al. 2022), exceeding earlier  
290 airborne survey findings as well (Duren et al. 2019). In addition, our study identifies a higher  
291 number of methane extreme emitters compared to US airborne surveys, at a median emission  
292 flux rate of  $2,050 \text{ kg h}^{-1}$ . Our results also indicate higher emission intensities compared to a  
293 previous satellite survey in the Permian region from 2019 to 2020 (median of  $1,850 \text{ kg h}^{-1}$ )  
294 (Irakulis-Loitxate et al., 2021), potentially suggesting a rebound in methane emissions after  
295 COVID-19. This comparison contextualizes the emission magnitudes of identified super  $\text{CH}_4$   
296 emitters, affirming that our surveys align with that observed from field campaigns.

297 We also examine the cumulative distribution of methane point-source emissions during  
298 2022 and 2023, comparing them with previous studies in the Permian basin (Figure 6). The  
299 smallest emission rate identified during 2022 and 2023 is  $646 \text{ kg h}^{-1}$  (Figure 6), with emissions  
300 exceeding this threshold contributing to 22% of the total  $\text{CH}_4$  emissions from airborne surveys in  
301 the Permian Basin (Cusworth et al., 2022). The coarser spatial resolution of spaceborne  
302 instruments makes them less sensitive to low  $\text{CH}_4$  emissions, making them to capture a large  
303 number of  $\text{CH}_4$  emissions significantly larger than those observed in airborne surveys.  
304 Consequently, the distribution of spaceborne observations skews towards larger emissions with  
305 respect to airborne surveys (e.g., AVIRIS-NG and GAO) conducted in multiple US regions.  
306 Notably, the cumulative distribution of emission rates during 2022-2023 is also shifted towards  
307 larger emissions compared to spaceborne surveys in 2019-2020 (Irakulis-Loitxate et al. 2021).



308 This finding reaffirms the substantial CH<sub>4</sub> emissions in the Permian Basin after the COVID-19  
309 period.

310 In addition, we assess the contribution of emissions from these super emitters on the  
311 regional methane budget (Figure 7), by comparing to both bottom-up inventories (US EPA  
312 inventory) and top-down inversions (Lu et al. 2023; Maasakkers et al. 2023; Shen et al. 2022).  
313 Our findings indicate that these super emitters contribute an average of 30% to each basin's total  
314 emissions with a range of 13% to 63% across all basins and time periods. Notably, we attribute  
315 63% of the regional emissions to point sources in Permian Delaware Tight US. Furthermore, the  
316 bottom-up inventory tends to underestimate the overall CH<sub>4</sub> flux compared to estimates derived  
317 from GOSAT or TROPOMI, aligning with previous findings from top-down analyses (Alvarez  
318 et al. 2018).

### 319 3.2 Estimation of regional methane budgets from point sources observations

320 We quantify regional methane budgets by integrating point-source observations and  
321 spatial interpolation in the methane-intensive Permian Delaware Tight US. In Figure 8, our  
322 regional estimation is compared with (1) total methane fluxes obtained from a top-down  
323 inversion from TROPOMI XCH<sub>4</sub> (Shen et al. 2022) and (2) bottom-up emission inventories for  
324 O&G sectors (US EPA inventory) (Maasakkers et al. 2023). TROPOMI XCH<sub>4</sub> measurements  
325 indicate significant methane enhancements, reaching ~30 ppb above the background, over the  
326 Delaware basin from February 2022 to October 2023 (Figure 8a). The spatial distribution of  
327 methane emission from atmospheric inversion (Shen et al. 2022) reveals a single-branch  
328 distribution over the Delaware basin, corresponding to the major O&G production region (Figure  
329 8b). As can be seen in the regional-scale methane enhancements and methane emissions  
330 generated from TROPOMI observations and inversion estimate (Figure 8a and b), the regions  
331 exhibiting the highest density of super emitters in our satellite-based survey align with the most  
332 substantial methane enhancements and the highest methane fluxes over the central and eastern  
333 regions of Delaware subbasin.

334 Regarding the regional methane budget, we estimate methane emissions at  $1.08 \pm 0.02$  Tg  
335 a<sup>-1</sup> in the Delaware basin during 2022 and 2023. Notably, our regional estimation solely based on  
336 point-source observations closely aligns with top-down atmospheric inversions ( $0.86 \pm 0.03$  Tg a<sup>-1</sup>)  
337 from TROPOMI, even though the time periods differ (refer to Figure 8b and c). The spatial  
338 distribution of methane emissions demonstrates remarkable consistency between our spatial  
339 interpolation and atmospheric inversions, emphasizing that the emissions predominantly  
340 originate from significant point-source emitters in the Delaware subbasin. In contrast, the EPA  
341 greenhouse gas inventory significantly underestimates the total methane flux for the Delaware  
342 subbasin (Figure 8d), providing a mere estimation of 0.18 Tg a<sup>-1</sup>. The inventory generally falls  
343 short of the total CH<sub>4</sub> emissions inverted from GOSAT or TROPOMI, as shown in previous top-  
344 down analyses (Alvarez et al. 2018). These comparisons underscore the effectiveness of  
345 upscaling estimations from high-resolution satellite data in overcoming regional inversion  
346 uncertainties. These findings also highlight the importance of satellite point-source observations  
347 in the estimation of regional methane emission, providing an additional bottom-up approach to  
348 mitigate the underestimation inherent in bottom-up inventories.

### 3.3 Temporal evolution of methane point source emissions

Utilizing multi-period satellite surveys enables us to examine the temporal trends of methane point-source emissions in these O&G basins during 2022 and 2023. In Figure 9(a), methane emission rates and the number of detected point sources are presented based on multi-month space-borne surveys. From February 2022 to October 2023, variations in the number of observed point sources are evident, reaching a maximum of 10 plumes in a single day. Correspondingly, point-source aggregated emissions range between  $0.013 \text{ Tg a}^{-1}$  and  $0.583 \text{ Tg a}^{-1}$ . Notably, we observe that the number of detected point sources does not consistently correlate with the magnitude of methane emissions. A few super-emitters can significantly contribute to the overall leak volume.

We then compare methane emission rates in the Permian Delaware Tight US for different time period. In Figure 9 (b), emissions from various airborne/spaceborne surveys in the Delaware subbasin are compared before and after COVID-19. Notably, point-source  $\text{CH}_4$  emissions in fall 2019 are significantly higher ( $0.84 \pm 0.27 \text{ Tg a}^{-1}$ ) than that in subsequent surveys from winter 2020 to spring 2022 (ranging from  $0.24 \pm 0.11 \text{ Tg a}^{-1}$  to  $0.52 \pm 0.15 \text{ Tg a}^{-1}$ ) during the COVID-19 period. However, methane emissions in summer 2023 rebound to levels similar to fall 2019. The sharp decline in emissions after fall 2019 may be attributed to factors such as the impact of COVID-19 and changes in the oil market, leading to decreased flaring activities and well completions. Additionally, the diverse characteristics of operators and supply chain activities in Permian contribute to high variability in emissions, as observed in aggregated airborne point-source emissions during fall 2019 (Cusworth et al. 2021). Therefore, a more comprehensive and extended analysis is required to distinguish long-term trends from the changes of point-sources  $\text{CH}_4$  emission in the Permian Delaware Tight US.

### 3.4 Attribution of emission sources

The high spatial resolution of remote sensing data enables us to precisely associate the identified point sources with specific infrastructure. We categorize emissions based on the emission source (tank battery, compressor station, flaring, wellhead and unknown) and the sector of the emitting infrastructure (O&G, coal mining, electricity generation, livestock and solid waste). A breakdown of the characteristics of the emitting infrastructure detected by spaceborne instruments is presented in Figure 10 (a) (see Table A1 for more details), and emission sectors with point source characteristics detected by airborne instruments is displayed in Figure 10 (b). Whether viewed from emission sources in spaceborne surveys or emission sectors in airborne surveys, we observe a surprisingly high proportion of  $\text{CH}_4$  emissions from the O&G sector, ranging from 87% to 98%. In comparison to a previous Permian survey (Irakulis-Loitxate et al. 2021), the proportion of methane leaks from wellheads and tank batteries has increased, while the proportion from compressor stations and flaring has decreased. Our source analysis indicates that wellheads have become significant emitters (22.9%) during the post-COVID-19 survey, potentially due to recently developed wells, associated infrastructures, and increased productivity. Furthermore, the flux rates of detected emissions from wellheads, tank batteries, and compressor stations range from 646 to  $14,156 \text{ kg h}^{-1}$  (refer to table S1). This range encompasses our entire emission distribution (Fig. 4), with high emissions exceeding  $4,000 \text{ kg h}^{-1}$  possibly resulting from accidents or malfunctioning equipment. These findings are useful to help mitigate the design and regulation of O&G production activities in North America.

## 392 4 Discussion

### 393 4.1 Methane point-source emissions monitoring

394 In this study, we utilize spaceborne imaging spectroscopy data to perform a survey of  
395 individual methane super emitters in North America, a prominent global methane hotspot,  
396 spanning the years 2022 to 2023 after COVID-19. Most detected plumes are located in Permian  
397 Delaware Tight US, the rest of plumes are relatively dispersed across other basins. This  
398 distribution aligns with the regions of highest CH<sub>4</sub> emission identified in top-down inversions by  
399 Shen et al. (2022) but shows less correlation with the bottom-up inventory from the updated  
400 Global Fuel Exploitation Inventory (GFEI-v2) (Scarpelli et al. 2022) (Fig. A2). Methane  
401 emissions observed by GF5-01A/02-AHSI and EMIT from individual plumes range from 646 to  
402 16,071 kg h<sup>-1</sup>, closely aligning with previous findings in the Permian region (522~18,492 kg h<sup>-1</sup>)  
403 (Irakulis-Loitxate et al. 2021). Methane emissions exceeding 646 kg h<sup>-1</sup> contribute to 22% of the  
404 total emissions measured in US airborne surveys (Cusworth et al. 2022), underscoring the  
405 potential of the recently launched GF5-01A/02-AHSI to map large regions inaccessible to  
406 airborne surveys. Notably, some emissions detected by GF5-01A/02-AHSI fall below minimum  
407 detection thresholds determined in other studies utilizing multispectral satellite data (Ehret et al.  
408 2022; Irakulis-Loitxate et al. 2022a; Pandey et al. 2023; Varon et al. 2021), highlighting the  
409 significance of these advanced technologies in detecting emissions that may be missed in surveys  
410 relying solely on publicly available remote sensing datasets.

411 In comparison to prior surveys in North America (Cusworth et al. 2022; Irakulis-Loitxate  
412 et al. 2021), the methane point-source emissions identified in this study show a shift toward  
413 larger emissions, with a higher median CH<sub>4</sub> emission flux of 2050 kg h<sup>-1</sup> (refer to Figure 5 and  
414 Figure 6). This shift indicates an increase in methane emissions in North America following the  
415 COVID-19 period, possibly influenced by the resurgence of O&G prices and production in the  
416 post-COVID-19 period (Thorpe et al. 2023b). These findings suggest that the average emission  
417 rate per source has indeed risen, and the production activity have recovered following the  
418 COVID-19 pandemic.

419 Furthermore, the pronounced heavy-tailed emission distribution observed in this study  
420 underscores the significant contribution of a few "super-emitters" to the overall methane  
421 emissions, consistent with prior research in the US O&G sector (Cusworth et al. 2021;  
422 Frankenberg et al. 2016; Irakulis-Loitxate et al. 2021; Yu et al. 2022). It is anticipated that as  
423 ongoing monitoring in North America continues, the emission distribution will progressively  
424 exhibit a heavier tail with more sample size, capturing more super emission events.  
425 Consequently, this implies that a substantial portion of the detected methane emissions from  
426 these basins could be alleviated by promptly addressing a small number of leaks (Mayfield et al.  
427 2017). With 30% of regional methane emissions detected over these basins originating from  
428 these super-emitters, rapid detection and repair of these significant CH<sub>4</sub> leaks could significantly  
429 reduce the environmental impact with less additional labor.

### 430 4.2 Implications for estimation of regional methane budget from satellite-based point- 431 source observations

432 In Permian Delaware Tight US, our upscaling estimate based on extrapolation of limited  
433 satellite-detected methane emissions ( $1.08 \pm 0.02$  Tg a<sup>-1</sup>) closely align with the atmospheric  
434 inversion results with TROPOMI observations ( $0.86 \pm 0.03$  Tg a<sup>-1</sup>) (Figure 8). However, there

435 are more than four times lower in the EPA inventory data ( $0.18 \text{ Tg a}^{-1}$ ). Our results indicate that  
436 current bottom-up inventories for national  $\text{CH}_4$  emissions in the United States underestimate real  
437 emissions, highlighting the potential of high spatial resolution remote sensing measurements to  
438 offer a more accurate representation. Our results affirm that remote sensing technologies, such as  
439 hyperspectral satellite, can significantly enhance bottom-up emissions inventories, refine  
440 regional methane emission estimation, and mitigate uncertainties.

441 Prior research proposes potential explanations for the disparity between bottom-up and  
442 top-down methane emission estimation. One factor is the oversight of unexpected leaks or point  
443 source emitters in inventories (Alvarez et al. 2018), with these super-emitters being recognized  
444 contributors to total methane emissions as shown in this study. Another contributing factor is the  
445 utilization of outdated emission factors in inventories, and updating these factors has proven  
446 effective in minimizing the divergence (Rutherford et al. 2021). However, emission factors can  
447 vary across regions, and those from a single region may not be used in other regions or countries  
448 (Rutherford et al. 2021). Spatiotemporal misalignment is another potential reason for  
449 discrepancies (Vaughn et al. 2018), as the timing of measurements have important impact on the  
450 accuracy due to the variable nature of methane emissions over time. It is crucial to point out the  
451 uncertainties in top-down inversions, which may overestimate actual emissions. Combining  
452 inventory data with satellite-based surveys as shown in this study is essential to mitigate these  
453 uncertainties and inconsistencies.

#### 454 4.3 Monitoring the temporal evolution of point-sources $\text{CH}_4$ emissions

455 A prior study indicates a continuous rise in O&G production until the COVID-19  
456 pandemic (e.g., Lyon et al., 2021). Consequently, methane emissions reached their peak by fall  
457 2019 ( $0.84 \pm 0.27 \text{ Tg a}^{-1}$ ). During the pandemic, methane emissions experienced a significant  
458 decline, followed by fluctuations from winter 2020 to spring 2022 (from  $0.24 \pm 0.11 \text{ Tg a}^{-1}$  to  
459  $0.52 \pm 0.15 \text{ Tg a}^{-1}$ ). Upon entering the post-COVID-19 period in 2023, methane emissions  
460 rebounded alongside increased O&G prices and production ( $0.66 \pm 0.20 \text{ Tg a}^{-1}$  in the summer of  
461 2023). These findings underscore the capability of hyperspectral imaging spectroscopy to capture  
462 variations in methane emissions associated with long-term trends such as the epidemic. This  
463 highlights the significant potential of remote sensing measurements to quantify methane  
464 emissions and depict temporal trends, thereby enhancing our comprehension of regional methane  
465 budgets. Considering the substantial rise in global atmospheric  $\text{CH}_4$  growth rates post-2020  
466 (Tollefson 2022), there is an urgent demand for methane mitigation facilitated by using satellite  
467 imaging spectroscopy techniques.

#### 468 4.4 Limitations and outlook

469 The GF5-01A/02-AHSI missions contribute significantly by offering extensive coverage  
470 and fine spatial resolution, paving the way for potential identification of fugitive emissions. This  
471 study presents the initial instances of GF5-01A/02-AHSI imaging spectrometer observations  
472 capturing methane emissions from the O&G sector across North America. Additionally, we  
473 showcase the instrument's capability to map and quantify various emission sources, attributing  
474 them to specific facilities. These capabilities, driven by the 30 m spatial resolution and 60 km  
475 swath, are crucial for accurately assessing regional methane budgets (Jacob et al. 2022).  
476 Nevertheless, this study offers only a two-year snapshot of multi-basin methane emissions, with  
477 the initial GF5-01A/02-AHSI observations lacking complete spatial coverage and repeat

478 mapping essential for assessing persistence. Despite these limitations, the preliminary findings  
479 from the spaceborne survey reveal significant regional variability in methane emissions,  
480 shedding light on areas with substantial emissions and incomplete activity reporting.

481 Future studies combining measurements from various airborne/spaceborne instruments  
482 can enhance global coverage and revisit frequency (Chulakadabba et al. 2023; Pandey et al.  
483 2023), a critical step in determining emission persistence and reducing uncertainty in the regional  
484 to global CH<sub>4</sub> budget (Mayfield et al. 2017). More specifically, a number of high-resolution and  
485 hyperspectral satellite missions currently in orbit (i.e., Chinese ZY1-02D/02E satellites, Italian  
486 PRISMA satellite, German EnMAP mission and Canadian GHGSat constellation) and upcoming  
487 spaceborne imaging spectroscopy missions (i.e., Carbon Mapper, CHIME and SBG missions)  
488 will contribute to a comprehensive scenario for point-source methane mapping. In addition, daily  
489 observations from TROPOMI and the soon-to-be-launched MethaneSAT mission, along with  
490 long time-series observations from multispectral systems (GF5-01/02-VIMS, Sentinel-2/3,  
491 Landsat-8/9, WorldView-3) can be served as complementary data. As we approach the Paris  
492 target, the collaborative utilization of these missions holds the promise of a breakthrough in  
493 mitigating unintended methane leakages from the Oil & Gas industry in the coming years and  
494 has significant implications for measuring global methane pledges.

## 495 **5 Conclusions**

496 In this work, we demonstrate the potential of Chinese new hyperspectral satellites (GF5-  
497 01A/02-AHSI) in detecting and quantifying methane point-source emissions across multiple  
498 North American basins from 2022 to 2023. The identification of 48 methane super-emitters, with  
499 flux rates between 646 and 16071 kg h<sup>-1</sup>, reveals a skewed and heavy-tailed emission  
500 distribution from O&G infrastructures. Specifically, the wellhead emerges as a major emitter  
501 (22.9%) post-COVID-19. Regional methane estimation indicates that point sources contribute  
502 approximately 30% of the total methane flux (13 to 63% range). In Permian Delaware Tight US,  
503 methane emissions decline by 66.7% after COVID-19, then rebound to previous levels by  
504 summer 2030 ( $0.66 \pm 0.20$  Tg a<sup>-1</sup>). Our upscaling estimates ( $1.08 \pm 0.02$  Tg a<sup>-1</sup>) from point-  
505 source observations closely align with atmospheric inversion results ( $0.86 \pm 0.03$  Tg a<sup>-1</sup>). The  
506 findings underscore the value of hyperspectral imaging spectroscopy in enhancing bottom-up  
507 inventories, refining regional methane estimates, and reducing uncertainties. Integrating bottom-  
508 up data with satellite data holds the potential to provide a better understanding of methane  
509 emissions, thereby enabling targeted CH<sub>4</sub> emission mitigation strategies to reduce their impact  
510 on climate change.

## 511 **Open Data Sources**

513 All data underpinning this publication are openly available.

514 GF5-01A/02-AHSI L1 data are available here: <https://data.cresda.cn/>.

515 EMIT L1B data are available here: <https://search.earthdata.nasa.gov/search>.

516 Updated global fuel exploitation inventory (GFEI v2) are available here:

517 <https://doi.org/10.7910/DVN/HH4EUM>.

518 EPA greenhouse gas inventory (EPA v2) are available here:

519 <https://www.epa.gov/ghgemissions/us-gridded-methane-emissions>.

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521 <https://github.com/luxiaoatchemsysu/Data-USoilgasCH4>.

522 Top-down flux inversion with TROPOMI observations is available here:

523 <https://doi.org/10.18170/DVN/JPKFU6>.

524 Sentinel-2A/2B data are available here: <https://dataspace.copernicus.eu/>.

525 Global Oil & Gas (O&G) infrastructure database are available here:

526 <https://globalenergymonitor.org/>.

527 GEOS-FP data are available here: <https://portal.nccs.nasa.gov/datashare/gmao/geos-fp/das/>.

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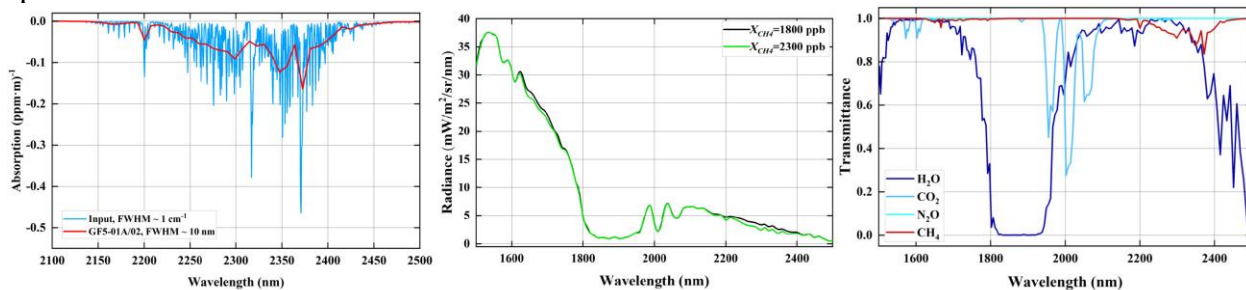
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706 **Figure 1.** Sensitivity of GF5-01A/02-AHSI shortwave infrared (SWIR) measurements to  
 707 methane. (a) Example of a unit methane absorption spectrum  $k$  used as target signature by  
 708 the matched filter retrieval method used in this study. (b) Simulated top-of-atmosphere  
 709 radiance spectra in the SWIR as measured by GF5-01A/02-AHSI. (c) Two-way  
 710 transmittance of greenhouse gases with the highest absorption in the SWIR part of the  
 711 spectrum.



(a) Unit methane absorption spectrum

(b) Sensitivity to CH<sub>4</sub> enhancements

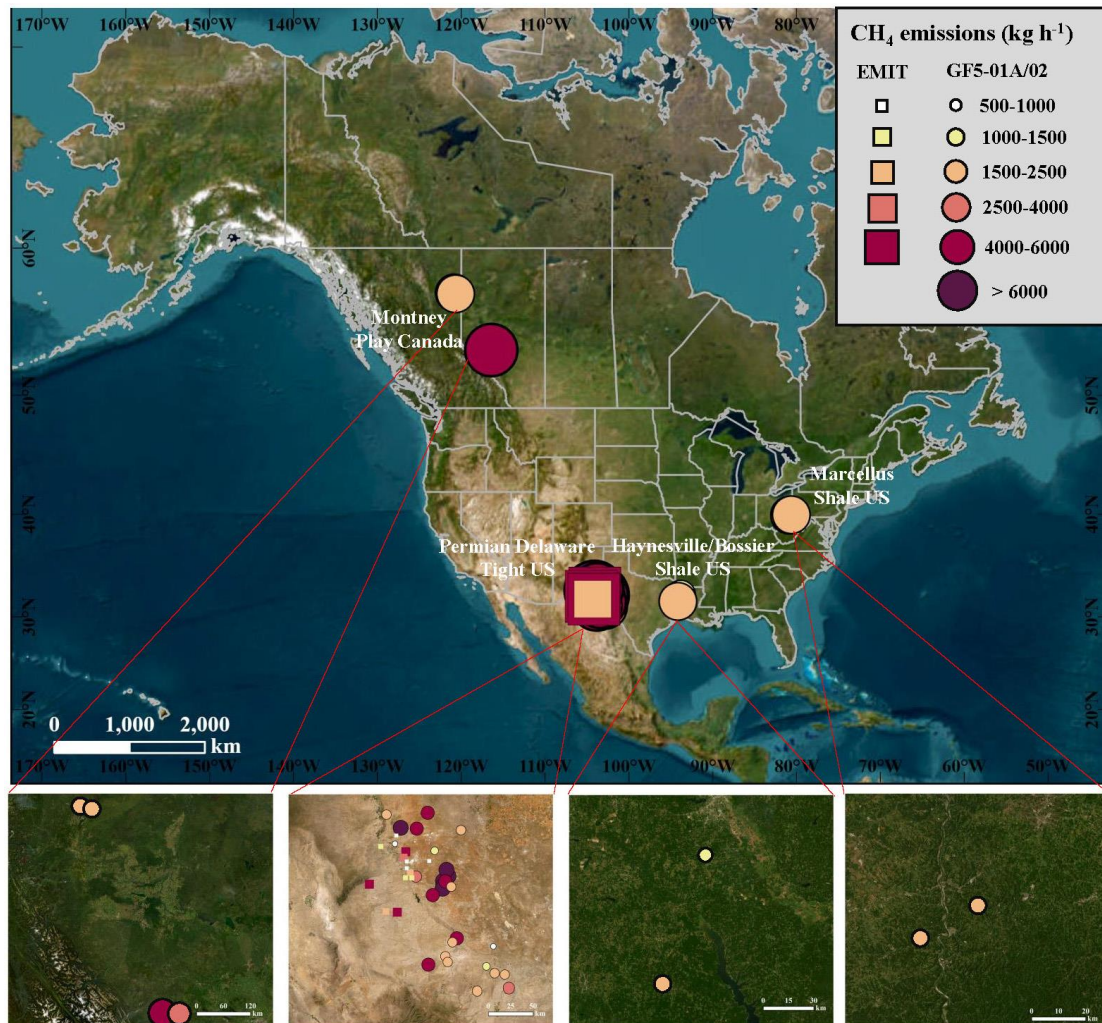
(c) Two-way transmittance of greenhouse gases

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**Figure 2.** Major basins surveyed between 2022 and 2023 with the spaceborne imaging spectrometers. Subpanels show the location and intensity of the detected methane point source emissions.

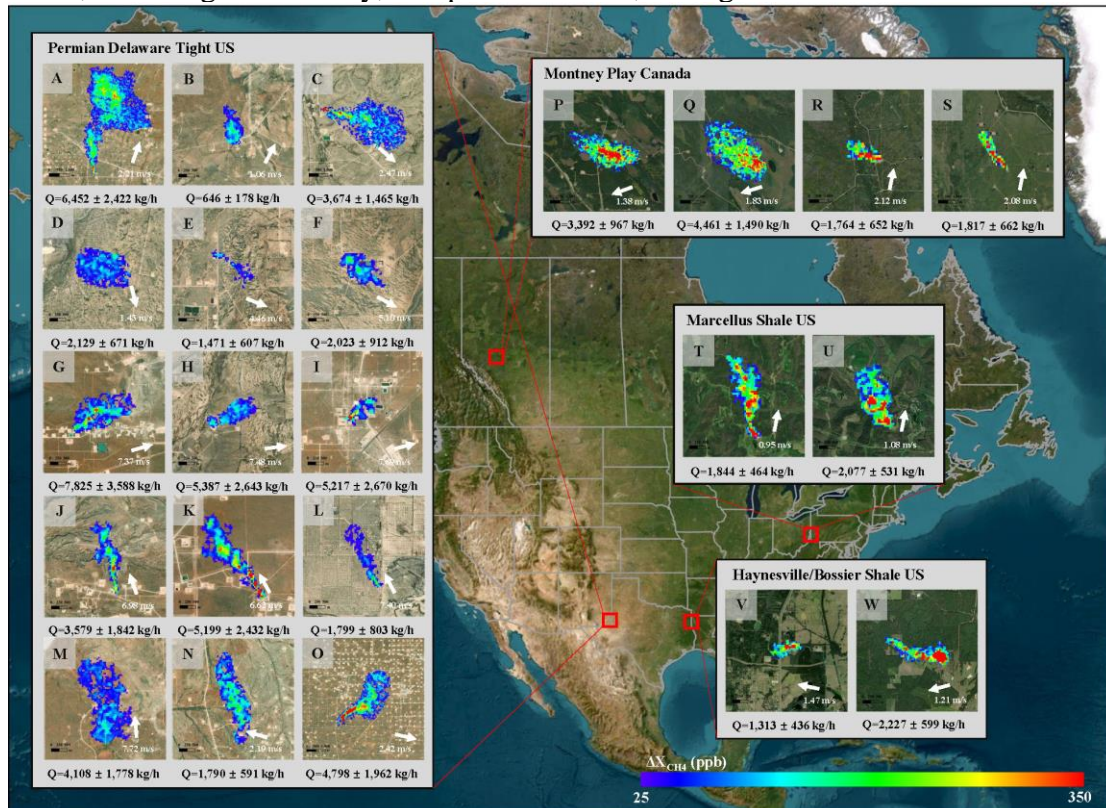


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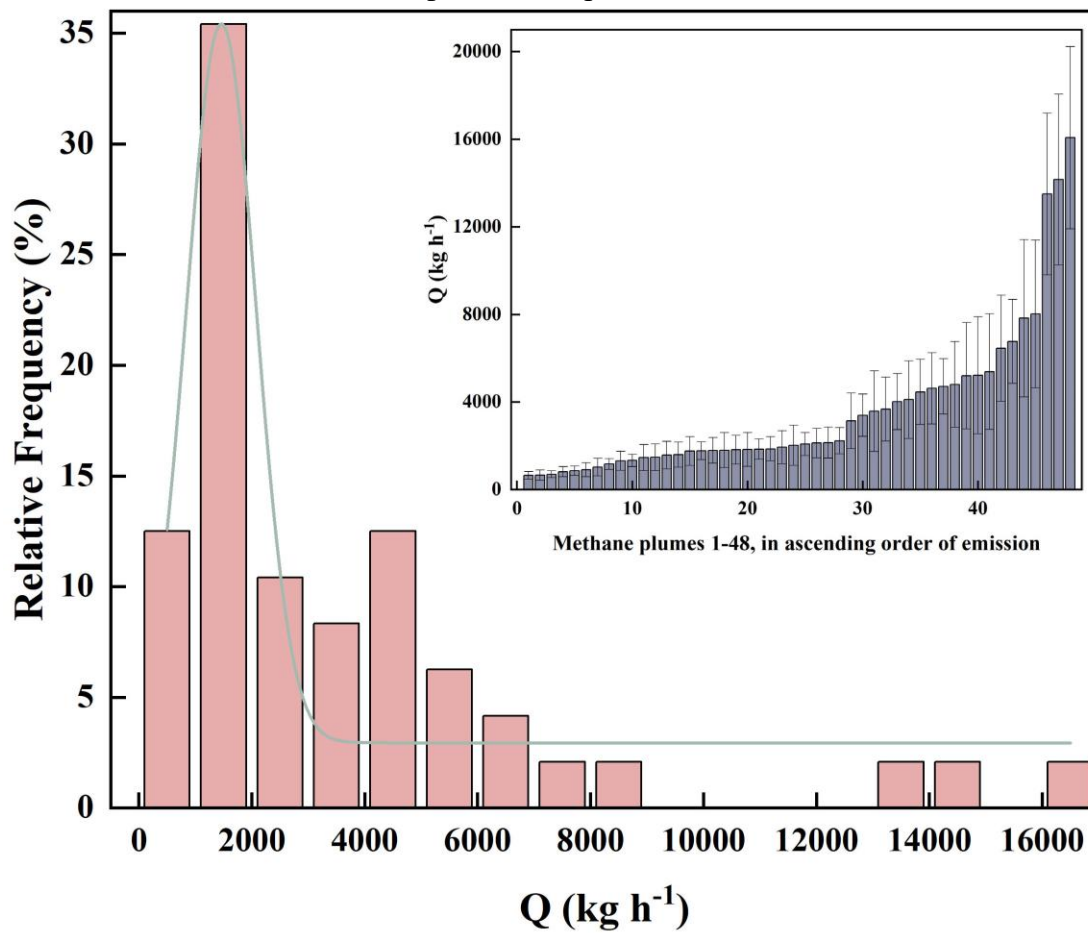
**Figure 3.** The representative methane plumes from various emission sources in North America, including tank battery, compressor station, flaring and wellhead.



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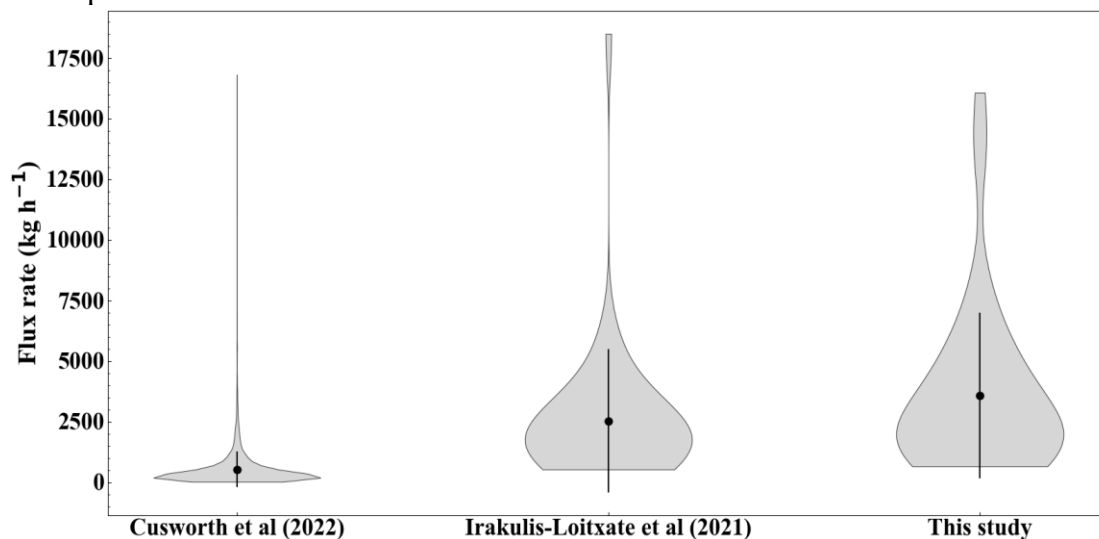
**Figure 4.** Relative frequency for the 48 methane plumes detected over North America with satellite imaging spectroscopy. The inset bar shows a comparison of methane point source emissions. Vertical error bars correspond to 1- $\sigma$  precision errors in in flux rate calculation.



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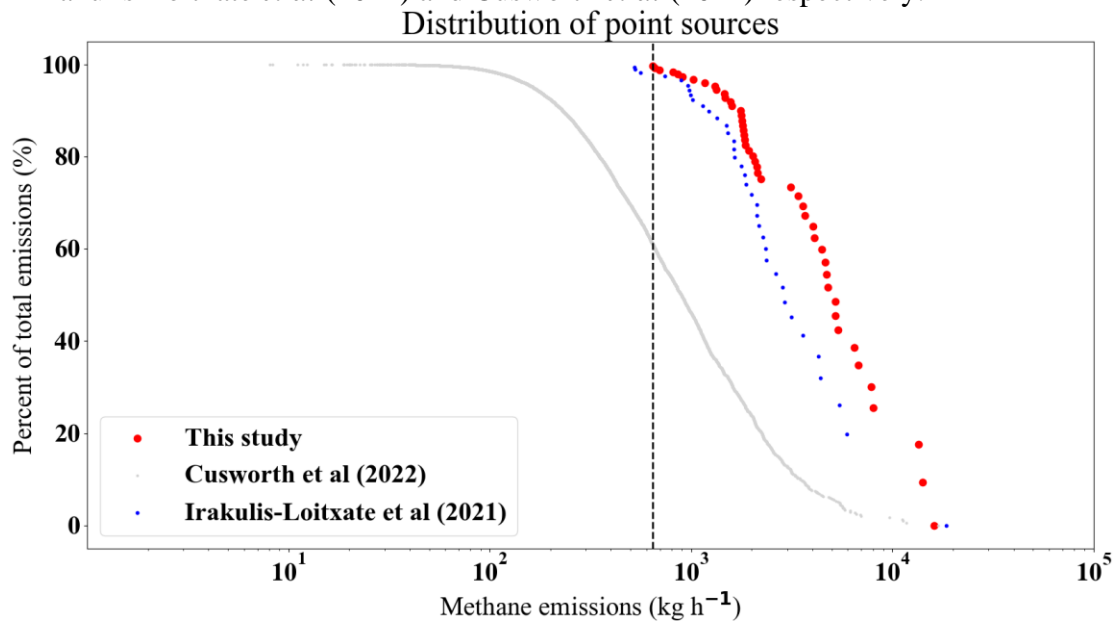
732 **Figure 5.** Comparison of emission estimates of methane plumes between surveys. The  
733 surveys for the multiple basins in the US are selected as the references. They report 5593  
734 and 37 methane plumes, while our survey attempts 48 plumes. Violin plots show statistical  
735 distributions of methane plume emission rates for these surveys. For each survey, the black  
736 dot represents the median value. The shading represents the number distribution of the  
737 methane plumes with different emission rates.



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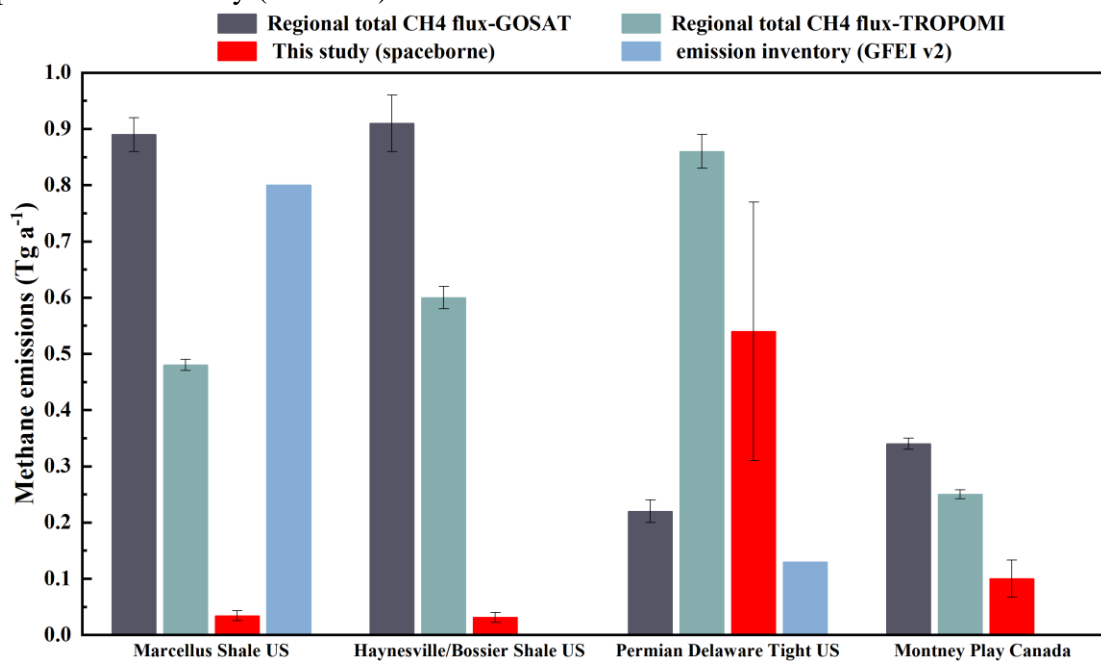
741 **Figure 6.** The cumulative distribution of methane point-source emissions quantified for  
742 each survey. Data for Permian 2019-2020 and multiple basins 2019-2021 in the US come  
743 from Irakulis-Loitxate *et al* (2021) and Cusworth *et al* (2022) respectively.



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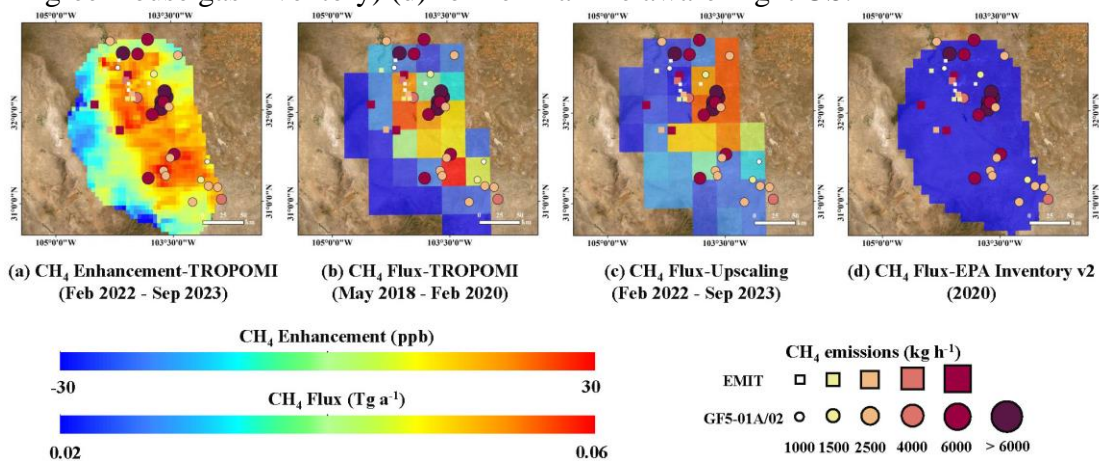
747 **Figure 7.** Summary statistics for each basin surveyed between 2022 and 2023. Comparison  
 748 between aggregated point-source emissions for each survey with a top-down flux inversion  
 749 with GOSAT/TROPOMI observations and bottom-up emission from the updated global fuel  
 750 exploitation inventory (GFEI v2).



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754 **Figure 8.** Comparison of regional methane enhancement (a), TROPOMI-based flux  
 755 inversions (b), Kriging interpolation-based flux inversions (c) and bottom-up inventory  
 756 (EPA greenhouse gas inventory) (d) for Permian Delaware Tight US.

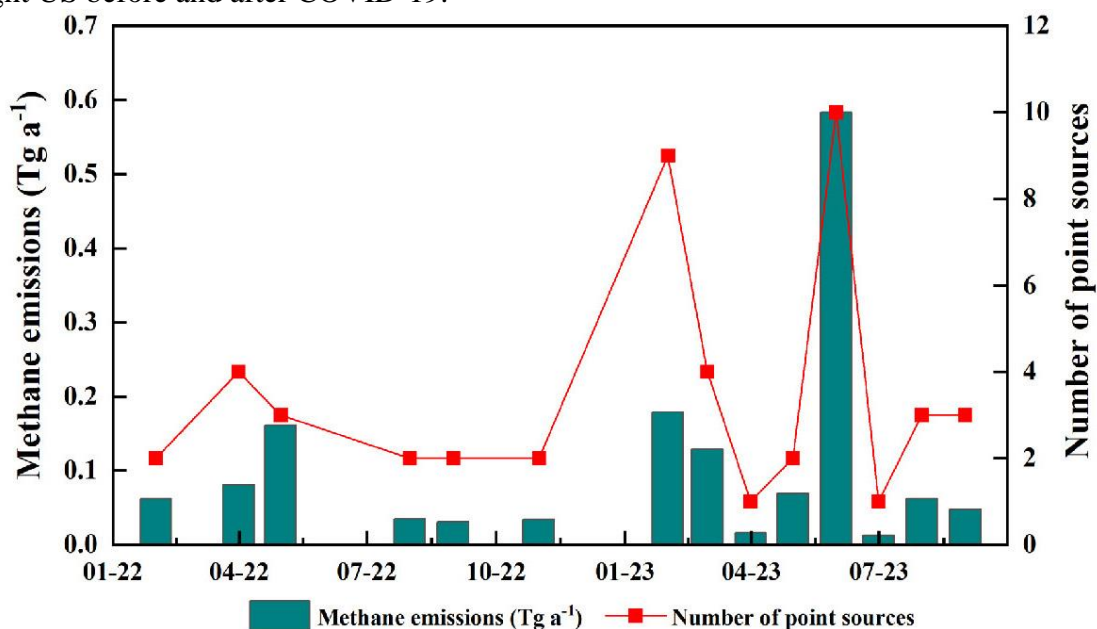


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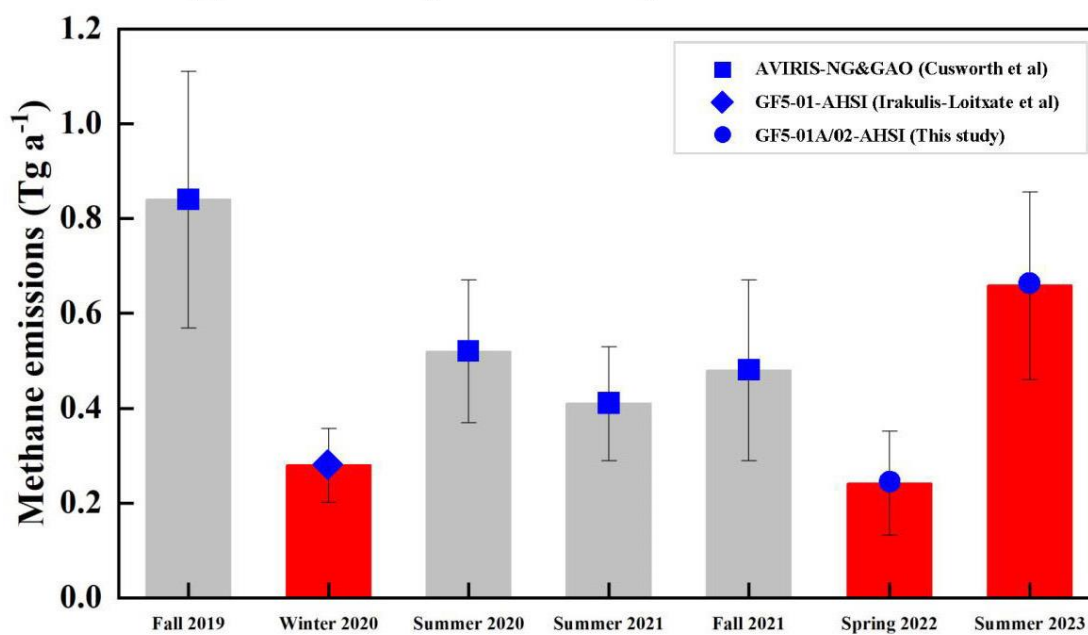
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**Figure 9.** Distribution of methane emissions for multiple basins over the North America with spaceborne/airborne imaging spectroscopy. (a) Multi-month spaceborne surveys in North America. (b) Comparisons of airborne/spaceborne surveys in Permian Delaware Tight US before and after COVID-19.



(a) Multi-month spaceborne surveys in North America

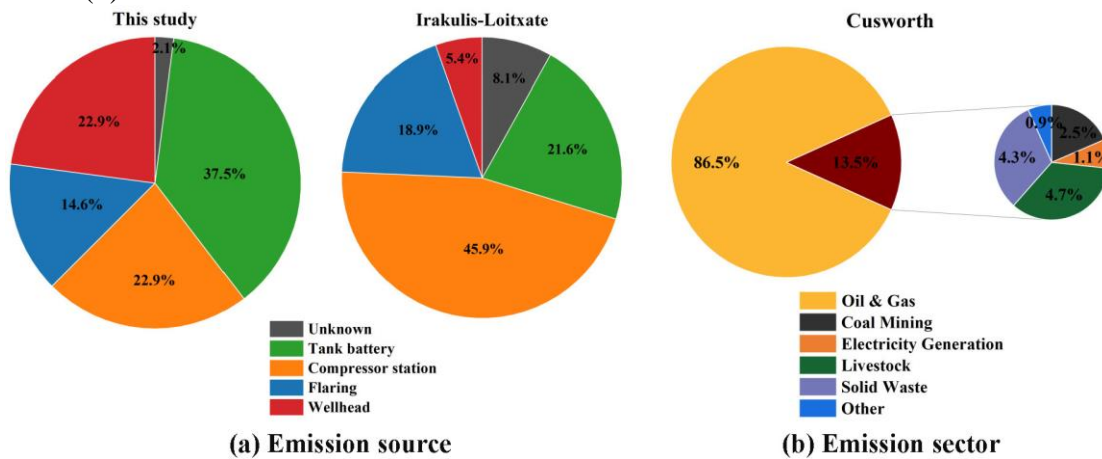


(b) Comparisons of airborne/spaceborne surveys in Permian Delaware Tight US

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**Figure 10.** Breakdown of spaceborne/airborne-detected methane emissions in North America. Emissions are classified in terms of the emission source (a) and of the emission sector (b).



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**Table 1.** Satellite instruments for mapping methane point-source emissions used in this study.

Mission	Spatial resolution	Spectral resolution	Spatial coverage	Temporal resolution	Period of operation
GF5-01A	30 m×30 m	10 nm	60 km×60 km	51 days	Dec.2022 - present
GF5-02	30 m×30 m	10 nm	60 km×60 km	51 days	Sep.2021 - present
EMIT	60 m×60 m	7.4 nm	80 km×80 km	36.5 days	Jul.2022 - present

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**Table 2.** The list of bottom-up emission inventory and top-down emission estimate.

Data	Mission	Spatial resolution	Time	Data sources
Bottom-up emission inventory	GFEI v2	0.1°×0.1°	2019	HARVARD Dataverse ( <a href="https://doi.org/10.7910/DVN/HH4EUM">https://doi.org/10.7910/DVN/HH4EUM</a> )
	EPA v2	0.1°×0.1°	2020	United States Environmental Protection Agency ( <a href="https://www.epa.gov/ghgemissions/us-gridded-methane-emissions">https://www.epa.gov/ghgemissions/us-gridded-methane-emissions</a> )
Top-down emission estimate	TROPOMI	0.25°×0.3125°	05/2018 ~02/2020	Peking University Open Research Data ( <a href="https://doi.org/10.18170/DVN/JPKFU6">https://doi.org/10.18170/DVN/JPKFU6</a> )
	GOSAT	0.5°×0.625°	2019	GitHub ( <a href="https://github.com/luxiaoatchemsysu/Data-USoilgasCH4">https://github.com/luxiaoatchemsysu/Data-USoilgasCH4</a> )