

Satellite-based Quantification of NO_x Emissions from Global Oil and Gas Fields

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Abstract

Identifying air pollutant sources and quantifying related emissions provides crucial information towards improving global air quality and public health. Emission inventories commonly used for oil and gas (OG) activities inadequately represent nitrogen oxide (NO_x) emissions, with notable discrepancies identified in the past. Satellite remote sensing provides a unique vantage point to map and quantify several key multi-pollutant species on a routine basis across the global scale. Here, we quantify annual NO_x emissions from 44 major OG basins distributed globally, utilizing TROPOspheric Monitoring Instrument (TROPOMI) nitrogen dioxide (NO₂) observations with the divergence flux method. In addition, we use the spaceborne Visible Infrared Imaging Radiometer Suite (VIIRS) natural gas flaring detections to further constrain satellite-derived NO_x emissions. The divergence flux method, which addresses 3D topography corrections and chemical loss of NO_x while accounting for wind-induced flux smearing, provides a robust approach for estimating NO_x emissions. Our findings reveal a substantial level of NO_x emissions from individual OG facilities and major production clusters as well as flaring activity, which serve as valuable data for assessing emission inventories. Subsequently, we conducted a comparative analysis between our TROPOMI-derived NO_x emissions and those obtained from the existing EDGARv6.1 and CAMS-GLOB-ANT_v5.3 global emission inventories. This evaluation underscored a noteworthy disparity, with existing inventories significantly reporting lower emissions from the OG sector relative to TROPOMI-derived data. Specifically, EDGAR exhibited a substantially lower estimate of onshore emissions by 61%, and CAMS displayed an even pronounced lower estimate by 78%, compared to TROPOMI-derived data from this study. For offshore emissions, EDGAR showed a similar pattern, albeit to a lesser extent, with a 26% underestimation, while CAMS showed a considerable underestimation of 92%. These findings hold significance for enhancing global NO₂ emission inventories, particularly from OG fields, and therefore address gaps in current bottom-up inventories. Additionally, our approach yields detailed spatial emission maps, enhancing granularity in depicting NO_x distribution. We further explore the variations in the correlation between NO_x emissions with OG production volumes and CH₄ concentrations across the different OG basins in North America, shedding light on their emissions characteristics and providing insights into the observed co-locations of methane and NO_x emissions from oil and gas activity.

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Abstract

Identifying air pollutant sources and quantifying related emissions provides crucial information towards improving global air quality and public health. Emission inventories commonly used for oil and gas (OG) activities inadequately represent nitrogen oxide (NO_x) emissions, with notable discrepancies identified in the past. Satellite remote sensing provides a unique vantage point to map and quantify several key multi-pollutant species on a routine basis across the global scale. Here, we quantify annual NO_x emissions from 44 major OG basins distributed globally, utilizing Tropospheric Monitoring Instrument (TROPOMI) nitrogen dioxide (NO₂) observations with the divergence flux method. In addition, we use the spaceborne Visible Infrared Imaging Radiometer Suite (VIIRS) natural gas flaring detections to further constrain satellite-derived NO_x emissions. The divergence flux method, which addresses 3D topography corrections and chemical loss of NO_x while accounting for wind-induced flux smearing, provides a robust approach for estimating NO_x emissions. Our findings reveal a substantial level of NO_x emissions from individual OG facilities and major production clusters as well as flaring activity, which serve as valuable data for assessing emission inventories. Subsequently, we conducted a comparative analysis between our TROPOMI-derived NO_x emissions and those obtained from the existing EDGARv6.1 and CAMS-GLOB-ANT_v5.3 global emission inventories. This evaluation underscored a noteworthy disparity, with existing inventories significantly reporting lower emissions from the OG sector relative to TROPOMI-derived data. Specifically, EDGAR exhibited a substantially lower estimate of onshore emissions by 61%, and CAMS displayed an even pronounced lower estimate by 78%, compared to TROPOMI-derived data from this study. For offshore emissions, EDGAR showed a similar pattern, albeit to a lesser extent, with a 26% underestimation, while CAMS showed a considerable underestimation of 92%. These findings hold significance for enhancing global NO₂ emission inventories, particularly from OG fields, and therefore address gaps in current bottom-up inventories. Additionally, our approach yields detailed spatial emission maps, enhancing

40 granularity in depicting NO_x distribution. We further explore the variations in the correlation
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44
45

46 **1 Introduction**

47 Emissions of air pollutants including nitrogen oxides (NO_x), from various oil and gas (OG)
48 sources, such as venting, flaring, combustion machinery, and leakage, have raised growing
49 environmental concerns (Banerjee & Toledano, 2016; Duncan et al. 2016; Elvidge et al., 2018).
50 Emissions of NO_x, comprising nitrogen monoxide (NO) and nitrogen dioxide (NO₂), are of utmost
51 concern due to their central role in atmospheric chemistry, air quality, and climate. They serve as
52 precursors to ground-level ozone (O₃), a key air pollutant with severe health implications, and
53 contribute to the production of secondary aerosols and tropospheric ozone. Increased levels of
54 tropospheric ozone, which result from NO_x and volatile organic compound (VOC) emissions, can
55 have effects on respiratory and cardiovascular health issues (WHO, 2019). Additionally, elevated
56 NO₂ levels pose direct health risks (Jacob, 1999). Given that anthropogenic activities linked to oil
57 and gas extraction, refining, and combustion stand as an important source of NO_x emissions, there
58 is a strong need for comprehensive assessment and monitoring. To mitigate these emissions and
59 their adverse effects on the environment and public health, policy interventions and regulatory
60 measures have been enacted within the fossil fuel energy sector (Falkner, 2016; Keohane &
61 Oppenheimer, 2016). These efforts are crucial not only for mitigating climate change but also for
62 promoting data transparency, a fundamental requirement under the Paris Agreement framework
63 (Falkner, 2016)

64 The need to accurately track and quantify changes in air pollution and greenhouse gas
65 emissions from OG operations has led to the development of independent observational methods
66 (Alvarez, 2018; de Gouw et al., 2020; Dix et al., 2020, 2022; Edwards et al., 2014; Fedkin et al.,
67 2024; Francoeur et al., 2021; Lauvaux et al., 2022; Omara et al., 2022, 2023; Shen et al., 2022;
68 Zhang et al., 2019; Varon et al., 2024). Existing bottom-up emission inventories are often based
69 on reported activities and dated emission factors and can lag behind regular monitoring
70 observations. Therefore, satellite measurements, like those from TROPOspheric Monitoring
71 Instrument (TROPOMI), can serve as important tool for providing regular and up-to-date
72 information about emissions. Satellite-based approaches may offer valuable insights into the
73 effectiveness of OG regulation and policy implementation. Notably, satellite-based observations
74 have emerged as a reliable means of monitoring anthropogenic emissions, including those
75 stemming from OG activities (Duncan et al., 2016; Fioletov et al., 2013; Li et al., 2016; Majid et
76 al., 2017; McLinden et al., 2012, 2016; Zhu et al., 2014; Zhang et al. 2018). Such observations
77 complement ground-based monitoring efforts (Alvarez, 2018; Gilman et al., 2013; Simpson et al.,
78 2010; Zavala-Araiza et al., 2015).
79 Satellite observations offer a unique advantage in providing complementary information about

80 emission sources, allowing for a more comprehensive understanding of underlying emission
81 activity. For instance, spaceborne observations using the Ozone Monitoring Instrument (OMI)
82 identified numerous large SO₂ sources, including offshore OG production clusters in the southern
83 Gulf of Mexico and the Persian Gulf, which were absent from bottom-up emission inventories
84 (McLinden et al., 2016; Zhang et al., 2019). Similarly, satellite-based studies have revealed
85 increasing trends in NO₂ column densities in several North American OG production areas, such
86 as Bakken, Eagle Ford, Permian, Niobrara-Codell in the United States, and Athabasca in Canada,
87 largely attributed to expanding production between 2005 and 2020 (Dix et al., 2020, 2022;
88 Laughner & Cohen, 2019; Li et al., 2016; Majid et al., 2017; Zhang et al., 2019)]

89 Satellite-based measurements utilize spectrally resolved observations, such as those
90 acquired by the TROPospheric Monitoring Instrument (TROPOMI) aboard the Sentinel-5
91 Precursor satellite. With its relatively high spatial resolution of 3.5 km x 3.5 km and daily global
92 coverage, TROPOMI enables the identification of NO_x point sources with unprecedented accuracy
93 (ATBD, [https://sentinels.copernicus.eu/documents/247904/2476257/Sentinel-5P-TROPOMI-](https://sentinels.copernicus.eu/documents/247904/2476257/Sentinel-5P-TROPOMI-ATBD-NO2-data-products)
94 [ATBD-NO2-data-products](https://sentinels.copernicus.eu/documents/247904/2476257/Sentinel-5P-TROPOMI-ATBD-NO2-data-products), last access: 7 April 2023), (Van Geffen et al., 2022). Consequently,
95 TROPOMI has facilitated a series of studies examining the variability of NO_x in various regions,
96 leading to the identification of specific emission sources and their emissions. The data from
97 TROPOMI, and its predecessors, have offered valuable insights into NO_x point source emissions,
98 allowing for more precise control of emission inventories and enhancements to existing data
99 (Beirle et al., 2019, 2021, 2023). The application of a method based on the divergence of NO₂
100 column fluxes has been pivotal in quantifying NO_x emissions from point sources, along with the
101 development of a fuel-based inventory for oil and gas operations by Francoeur et al., (2021),
102 showcasing the potential of spaceborne data for emission estimation (Beirle et al., 2019; Goldberg
103 et al., 2019; Lorente et al., 2019). These top-down approaches, which do not rely on complex
104 atmospheric chemistry models, have proven to be computationally efficient and independent,
105 providing annually updated emission estimates.

106 This study aims to estimate NO_x emissions originating from global oil and gas operations by
107 leveraging TROPOMI retrievals. Our distinctive approach involves integrating natural flaring
108 detection data from Visible Infrared Imaging Radiometer Suite (VIIRS) with TROPOMI-derived
109 tropospheric NO₂ to identify global oil and gas (OG) operations on a global scale. Building upon
110 previous research, our approach utilizes the flux-divergence method, used for the detection and
111 quantification of NO_x emissions from point sources like power plants, as well as to calculate area
112 emissions attributed to oil and gas fields. By harnessing the high spatial resolution and frequent
113 coverage of TROPOMI data, we aim to provide detailed and up-to-date information on NO_x
114 emissions from this sector. Moreover, we compare the TROPOMI-derived NO_x emissions with
115 those from inventories such as EDGARv6.1 and CAMS-GLOB-ANT_v5.3 to assess emissions
116 through the bottom-up approach. We also addressed the uncertainties associated with TROPOMI-
117 derived NO_x emissions. The outcomes of our study will serve as a valuable resource for air quality
118 management and policy-making, helping targeted reduction strategies and enabling effective
119 monitoring of progress toward emission reduction goals.

120

121 **2 Datasets**

122 **2.1 TROPOMI NO₂**

123 The TROPospheric Monitoring Instrument (TROPOMI), launched as part of the European Space
124 Agency's Copernicus Sentinel 5 Precursor (S5P) satellite mission on October 13, 2017, is a
125 pioneering Earth observation instrument. It orbits at an altitude of 825 kilometers in a sun-
126 synchronous, low-Earth orbit, crossing the Equator at 13:30 local solar time. TROPOMI quantifies
127 total column densities of trace gases across ultraviolet-visible-near-infrared (UV-VIS-NIR) and
128 shortwave infrared (SWIR) spectral regions. TROPOMI offers exceptional spatial precision, with
129 pixel sizes initially at 3.5 x 7 km², later refined to 3.5 x 5.5 km², covering a swath width of 2600
130 kilometers (Van Geffen et al., 2020, 2022). Its operational efficiency enables rapid Earth surface
131 scans, providing global coverage in about 100 minutes daily.

132 NO₂ slant column densities from radiance measurements acquired within the 405–465 nm
133 spectral range of the UV-VIS-NIR spectrometer. Tropospheric vertical column density data,
134 representing the integrated number of NO₂ molecules per unit area from the surface to the
135 tropopause, is derived by subtracting the stratospheric component and converting the tropospheric
136 slant column into a vertical column employing an air mass factor (AMF). The AMF, a
137 dimensionless quantity, depends on various parameters, including satellite viewing angles, solar
138 angles, the effective cloud radiance fraction, atmospheric pressure, and the vertical distribution of
139 NO₂ as simulated using the TM5-MP chemical transport model at a 1 x 1° resolution (Williams et
140 al., 2017), and surface reflectivity (climatological Lambertian-equivalent reflectivity data at a 0.5
141 x 0.5° resolution; (Kleipool et al., 2008). It is noteworthy that operational AMF computation does
142 not explicitly incorporate aerosol absorption effects, as these are addressed within the effective
143 cloud radiance component.

144 For our analysis, we use the level 2 NO₂ tropospheric VCD (TVCD) from the v2.3.1 Product
145 Algorithm Laboratory (PAL) product, which was released in December 2021 (Data was sourced
146 from the S5P Pre-operations Data Hub, accessible at <https://s5phub.copernicus.eu/dhus/>). In
147 contrast to earlier versions, this PAL product incorporates an enhanced FRESCO algorithm, which
148 yielded notable improvements: higher cloud altitudes, reduced air mass factors (AMFs), and
149 elevated tropospheric NO₂ columns. Furthermore, a refinement has been introduced involving a
150 surface albedo correction based on observed reflectance, tailored explicitly for cloud-free scenes.
151 This alteration has resulted in a general upswing in tropospheric NO₂ columns, particularly
152 pronounced over regions characterized by higher pollution levels. According to findings reported
153 by (Van Geffen et al., 2021), the net effect of this transition from v1.3 to v2.3.1 manifests as a
154 roughly 13% increase in tropospheric vertical column NO₂ for cloud-free scenes, exhibiting spatial
155 variability and accentuated elevations in areas with heightened pollution levels. To ensure data
156 quality, TROPOMI NO₂ VCDs undergo filtering with a quality assurance threshold (> 0.75) and a
157 solar zenith angle (SZA ≤ 65°) to mitigate potential errors arising from the stratospheric correction
158 and low-light conditions. Furthermore, to ensure optimal viewing conditions, selecting TROPOMI

159 pixels restricts the viewing zenith angles (VZA), limiting them to values below 56° . This criterion
160 helps avoid less favorable viewing conditions, particularly at the edges of the satellite's swath. As
161 a result, this restriction effectively limits the maximum pixel width across the track to 11 km.
162 Subsequently, the filtered data are gridded onto a regular latitude/longitude grid with a spatial
163 resolution of $0.01^\circ \times 0.01^\circ$ using an optimal algorithm.
164

165 2.2 VIIRS Natural Gas Flaring Detections

166 We use natural gas flaring detection data from the Visible Infrared Imaging Radiometer Suite
167 (VIIRS) instrument onboard the Suomi-National Polar-orbiting Partnership (S-NPP) satellite, a
168 joint endeavor between NASA and NOAA, launched in October 2011 as a proxy to identify NO_2
169 plumes from OG sites. VIIRS offers observations twice daily near the equator, with extended
170 coverage at higher latitudes due to orbit overlaps. These observations occur at approximately 1:30
171 p.m. (ascending node) and 1:30 a.m. (descending node), ensuring regular and comprehensive
172 monitoring. The significance of VIIRS extends beyond its observational frequency. Notably, the
173 S-NPP afternoon overpass aligns closely with the Sentinel-5P satellite's orbit, allowing for
174 synergistic observations that enhance the accuracy and scope of our research.

175 For the detection of gas flares, (Elvidge et al., 2013) developed an algorithm that takes
176 advantage of VIIRS nighttime capabilities in recording data in near- to short-wave infrared
177 channels, particularly the VIIRS 750 m short-wave infrared ($1.61 \mu\text{m}$) channel and Day-Night
178 Band (DNB) data. By focusing on nighttime observations, the algorithm effectively eliminates the
179 influence of sunlight and pinpoints the radiant emissions of gas flares. Specifically, the algorithm
180 capitalizes on the SWIR channel at $1.61 \mu\text{m}$, which captures the peak radiant emissions from gas
181 flares. Additionally, the $4\text{-}\mu\text{m}$ channel, commonly used for satellite fire detection, can identify
182 larger flares. To underscore the global relevance of VIIRS Natural Gas Flaring Detections,
183 (Elvidge et al., 2015) conducted a comprehensive survey of natural gas flaring. This survey
184 provides valuable information, including estimates of gas-flared volumes for 7,467 individual
185 sites. Users interested in annual global estimates up to 2020 can access this data
186 at https://eogdata.mines.edu/download_global_flare.html. We harness VIIRS nighttime natural
187 gas flaring data for our analysis in conjunction with TROPOMI tropospheric NO_2 VCDs. This
188 combined dataset empowers us to identify emissions from oil and gas facilities, as depicted in
189 *Figure 1*. However, it's imperative to acknowledge that while VIIRS data offers invaluable
190 insights, certain limitations and uncertainties may be associated with its accuracy.
191

192 2.3 Meteorological Data

193 In addition to the TROPOMI NO_2 VCD data, meridional and zonal wind components, pressure,
194 and temperature are required to determine the NO_x emission and lifetimes. The wind and
195 meteorological parameters are provided by the ERA-5 reanalysis dataset from the European Centre
196 for Medium-Range Weather Forecasts (ECMWF) on an hourly basis with a spatial resolution of
197 $0.25^\circ \times 0.25^\circ$ latitude/longitude. To align the wind and meteorological data with TROPOMI

198 observations, we interpolated the ERA-5 data onto the NO₂ spatial grid. We also performed
199 temporal interpolation to match the local TROPOMI overpass for each study region. (Beirle et al.,
200 2011) examined the influence of wind data level height on estimated NO_x emissions and lifetimes.
201 Findings indicated a slight impact, with emissions and lifetimes changing less than 2% (5%) on
202 average when wind data was taken from 200 meters (1000 meters) instead of 500 meters, with
203 individual sources showing variations below 15%. Therefore, we use the horizontal winds at 100
204 and 10 meters from the ERA5 reanalysis data. The 100-meter wind was used to characterize
205 horizontal transport in the planetary boundary layer, while the 10-meter wind represented the near-
206 surface wind. Furthermore, we spatiotemporally interpolated horizontal winds at 100 and 10
207 meters from the ERA5 reanalysis to match TROPOMI Level 2 observations. By leveraging the
208 ERA5 reanalysis dataset, we obtained the necessary meteorological variables to analyze
209 atmospheric dynamics and transport patterns accurately.
210

211 *2.4 Ozone Climatology*

212 Ozone mixing ratios, used for the scaling of NO₂ to NO_x, were obtained from the Earth System
213 Chemistry integrated Modelling (ESCiMo) project (Jöckel et al., 2016), using a specified dynamics
214 simulation RD1SD-base-01. RD1SD-base-01 simulation is similar to the RC1SD-base-10
215 simulation but with an updated ECHAM5/MESSy Atmospheric Chemistry (EMAC) version,
216 nudged (by Newtonian relaxation) towards ECMWF ERA-5 reanalysis data (Hersbach et al.,
217 2020), and with boundary conditions (primarily emission inventories) according to the Chemistry
218 -Climate Model Initiative (CCMI)-2 protocol (P. Jöckel, personal communication). The data has
219 been online (i.e. during the simulation) sampled along the Sentinel 5P orbit as described by (Jöckel
220 et al., 2010) (in section 5.4, submodel SORBIT). To accurately assess the NO_x/NO₂ ratio near the
221 surface, it was essential to consider O₃ concentrations extracted from the lowest layer of the model.
222 This selection played a critical role in capturing the sensitivity of divergence to additional NO_x
223 emissions at the emission source.
224

225 *2.5 Emission Inventories*

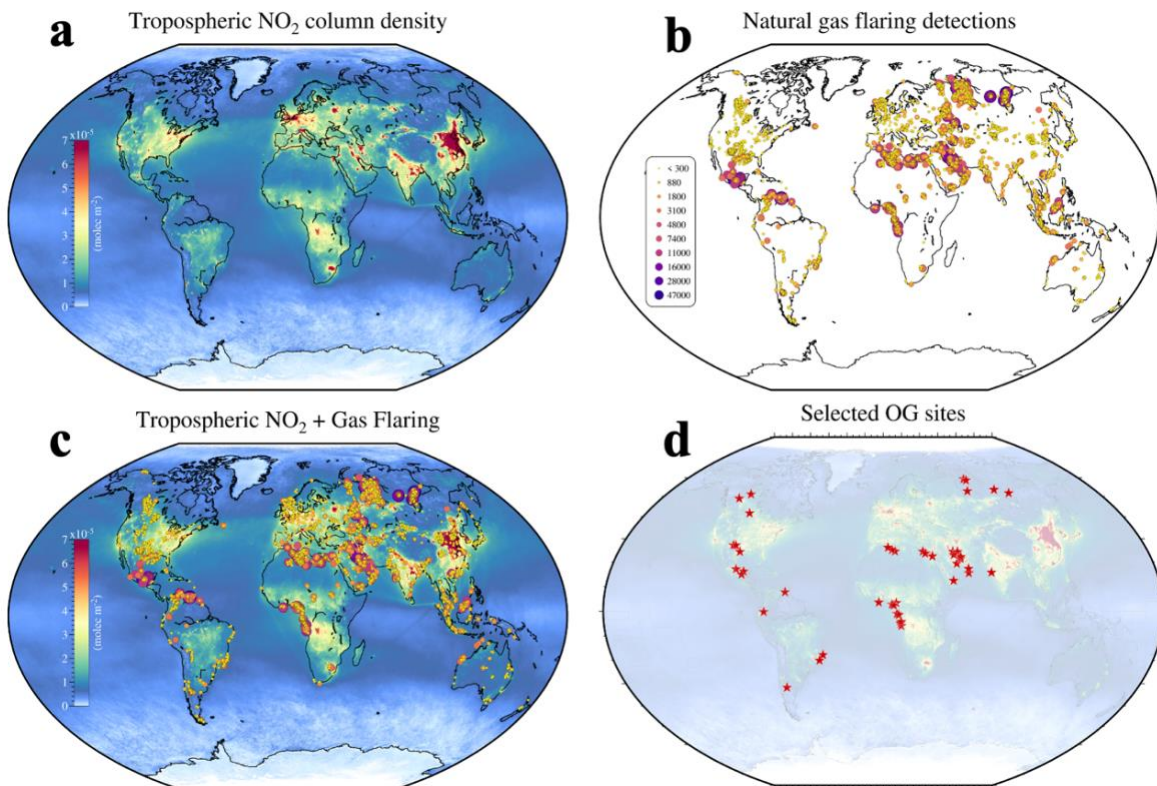
226 The Emissions Database for Global Atmospheric Research (EDGARv6.1) and the CAMS global
227 anthropogenic emissions (CAMS-GLOB-ANT_v5.3) are both global emission inventories that
228 provide monthly gridded emissions at a resolution 0.1°×0.1° across various sectors. EDGARv6.1
229 utilizes the activity data acquired from the International Energy Agency (IEA) and the Food and
230 Agriculture Organization (FAO), covering various factors, including population, energy
231 production, fossil fuel extraction, industrial processes, and agricultural statistics. Emissions in
232 EDGARv6.1 are computed based on corresponding emission factors alongside national and
233 regional data regarding technology mix and end-of-pipe measurements. This database
234 encompasses the years from 1970 to 2018. CAMS-GLOB-ANT_v5.3 is a product developed
235 within the Copernicus Atmospheric Monitoring Service framework, as comprehensively detailed
236 by (Granier et al., 2019). In constructing this emissions inventory, NO_x emissions primarily draw

237 from various sectors outlined in the EDGARv5.0 emissions dataset, encompassing data up to 2015,
238 which are extrapolated to 2021 relies on sector-specific trends gleaned from the Community
239 Emissions Data System (CEDs) inventory, as expounded by (Hoesly et al., 2018) through 2019.
240 Notably, sector nomenclature and definitions may exhibit variances when transitioning between
241 different inventories. Both EDGARv6.1 and CAMS-GLOB-ANT_v5.3 implement a
242 comprehensive methodology for estimating emissions at the country level. This methodology
243 encompasses considerations such as technology deployment and the influence of emission factors
244 contingent on fuel types and combustion conditions, in addition to activity data and low-resolution
245 emission factors, as elucidated by (Janssens-Maenhout et al., 2019).
246

247 3 Methodology

248 3.1 Identification of OG sites

249



250

251

252 **Figure 1** (a) Global distribution of TROPOMI-based tropospheric NO₂ VCD for the period
253 January-December 2022, (b) global distribution of natural gas flaring detection from VIIRS
254 observations, (c) collocated tropospheric NO₂ VCD and natural-gas flaring detections for
255 identifying the oil and gas operations globally. (d) selected 44 OG sites, both offshore and onshore,
256 for quantification of NO_x emission.
257

258

259 The worldwide network of oil and gas infrastructure is extensive, intricate, and multifaceted.
Identifying the NO_x emissions directly from TROPOMI datasets for OG sites poses challenges.

260 Consequently, we adopt VIIRS nighttime natural gas flaring data as a proxy for NO₂ plume
261 detection, combined with TROPOMI tropospheric NO₂ VCDs, to discern NO₂ emissions
262 originating from OG sites from January to December 2022. A two-step process is implemented to
263 exclude NO₂ plumes resulting from transient occurrences like biomass burning or fire events.
264 Initially, both TROPOMI and VIIRS data are subjected to annual averaging to pinpoint persistent
265 NO₂ plume locations. Subsequently, these identified NO₂ plumes are cross-referenced with daily
266 datasets to validate their persistence. Once the definitive NO₂ plumes associated with Oil and Gas
267 (OG) sites are confirmed, their precise origin is visually verified using Google Maps to ensure that
268 they emanate exclusively from OG sites. *Figure 1* illustrates the globally annual mean picture of
269 TROPOMI tropospheric NO₂ VCDs (*Figure 1a*), VIIRS-based intensity of natural gas flaring
270 detections (*Figure 1b*), collocated image of TROPOMI NO₂ VCD and VIIRS natural gas flaring
271 detections (*Figure 1c*).

272 The natural gas flaring detections provide valuable spatial information on global upstream,
273 midstream, and downstream natural gas flaring, revealing flaring hotspots in major oil and gas-
274 producing countries, including those for which limited open-source data on oil and natural gas well
275 locations are available (*Figure 1b*, *Figure 1c*). Detections were reported at over 10,000 facilities
276 or groups of facilities worldwide (as seen in *Figure 1c*). This extensive dataset facilitates the
277 identification of emission sources precisely and regional-scale emission characterization, as
278 exemplified in recent studies by (Ialongo et al., 2021; Lyon et al., 2021; Shen et al., 2022; Zhang
279 et al., 2020). These datasets are part of the Oil and Gas Infrastructure Mapping database (OGIM)
280 V1 datasets (Omara et al., 2023). Nonetheless, it is worth noting that the VIIRS instrument operates
281 at an approximate spatial resolution of about 750 m x 750 m at its nadir point (Elvidge et al., 2015).
282 This presents challenges when attempting to associate VIIRS detections with specific oil and gas
283 facilities, especially in regions like the Permian Basin in southern New Mexico and western Texas
284 (USA), known for their high density of oil and gas infrastructure. Accurately attributing detections
285 to individual facilities in spatially concentrated oil and gas regions demands additional
286 investigation and research. The primary goal of this study is not to pinpoint the individual facilities
287 or quantify NO_x emissions precisely. Instead, we aim to demonstrate the potential of modern
288 satellite remote sensing technology in delineating the OG sites and mapping the extent of NO_x
289 emissions across these areas. For this purpose, we have identified 44 specific OG sites (listed in
290 *Table 1*), both onshore and offshore, illustrated in *Figure 1d*, for our subsequent analysis aimed at
291 estimating NO_x emissions from space.

292

293 3.2 Flux divergence method

294 The typical outflow pattern of NO₂ TVCD, characterized by a signal decay with distance
295 from the source point, reflects the interplay of atmospheric transport and nonlinear chemical
296 processes. To address this, Beirle et al., (2019) proposed a flux divergence method aimed at
297 estimating NO_x emissions and lifetimes by multiplying the mean NO₂ VCDs with the horizontal
298 wind component. This method consists of applying the continuity equation in a steady state
299 framework, where the combination of mass inflow into a specific pixel and emissions equals the

300 combination of mass outflow from the pixel and chemical loss. We employ a modified flux
 301 divergence method Beirle et al., (2019, 2021) to derive top-down NO_x emission maps. The central
 302 concept lies in the divergence of mass flux, which characterizes alterations in mass flow. A positive
 303 divergence value serves as an indication of a source. Consequently, we quantify NO_x emissions
 304 (E_{NO_x}) by aggregating the contributions from both sources and sinks, as follows:
 305

$$E_{NO_x} = f_{NO_x} \left(\nabla(V \cdot u) + \frac{V}{\tau} \right) \quad (1)$$

306 Here, the divergence term (D) were obtained by multiplying NO₂ VCDs (V) with the horizontal
 307 wind field (u) (along and across the swath tracks). The sink term is dominated by the chemical loss
 308 due to the reactions of NO₂ with OH, with a constant lifetime (τ). TROPOMI derived NO₂ VCD
 309 is scaled to NO_x by multiplying the scaling factor (f_{NO_x}). Analyzing the flux divergence results in
 310 an emission estimate expressed in units of molec cm⁻² s⁻¹. A step-by-step explanation of the
 311 emission estimation algorithm is provided in the subsequent sections.
 312

313 3.2.1 Upscaling NO₂ to NO_x

314 In our study, we first converted the observed NO₂ columns for every TROPOMI pixel into the NO_x
 315 columns from which NO_x emissions are calculated directly instead of applying the fixed NO_x/NO₂
 316 ratio of 1.32. To achieve this, we determine the scaling factor f_{NO_x} (in Eq. 1) by employing the
 317 principle underlying the photostationary steady state for polluted airmasses.
 318

$$\frac{[NO_x]}{[NO_2]} = 1 + \frac{[NO]}{[NO_2]} = 1 + \frac{J}{k[O_3]} \quad (2)$$

319
 320 With the photolysis frequency of NO₂ (J) and the rate constant for the reaction of NO with O₃
 321 ($k[O_3]$) (Seinfeld & Pandis, 2016). Ozone data are taken from a multi-year climatology model by
 322 ESCiMO (as described in section 2.4) simulation and converted into concentrations based on
 323 temperature and pressure from ERA5.

324 The photolysis frequency in the boundary layer for clear-sky conditions is parameterized
 325 as $J = 0.0167 \times \exp(-0.575 / SZA) \text{ s}^{-1}$, as proposed by (Dickerson et al., 1982), with solar zenith
 326 angle (SZA) taken from TROPOMI data product. The rate constant is parameterized as $k[O_3] =$
 327 $2.07 \times 10^{-12} \times \exp(-1400/T) \text{ cm}^{-3} \text{ molec}^{-1} \text{ s}^{-1}$, as recommended by (Atkinson et al., 2004), with
 328 temperature T (in kelvin) from ERA5 reanalysis data. ERA5 reanalysis data were interpolated to
 329 TROPOMI overpass time and oversampled to the same spatial resolution.
 330

331 3.2.2 Divergence

332 The divergence of the flux ($F = u \cdot V$) in Eq. 1 is calculated as the derivative of horizontal wind (u)
 333 scaled NO_x column fluxes (V) (Beirle et al., 2019, 2021). The annual flux divergence, derived from

334 daily NO_x flux calculations, serves as an emission indicator in the planetary boundary layer (PBL),
 335 assuming a relatively constant free tropospheric NO_x fraction above the PBL, minimizing its
 336 impact on the divergence.
 337

$$D = \nabla \cdot \mathbf{F} = \nabla \cdot (\mathbf{u}V) = \mathbf{u} \cdot \nabla V + V \cdot \nabla \mathbf{u} \quad (3)$$

338 The first term ($\mathbf{u} \cdot \nabla V$) is represents advection (A) in meteorology, defined as the scalar product of
 339 horizontal wind vector and the spatial gradient of the TCVD. The second term ($V \cdot \nabla \mathbf{u}$)
 340 characterizes the divergence of wind fields scaled by the NO_x TVCD. However, our primary
 341 interest is on flux changes resulting from local NO_x emissions. Consequently, we calculate
 342 advection directly from Eq. 4 while explicitly excluding the influence of non-vanishing divergence
 343 of wind field. Nonetheless, the mean values of A and D exhibit remarkable similarity since the
 344 divergence of wind field is practically negligible over time.
 345

$$A = \mathbf{u} \cdot \nabla V \quad (4)$$

346 Beirle et al., (2021) identified systematic artifacts in divergence maps over mountainous regions,
 347 hindering NO_x quantification. In contrast, Sun (2022) introduced the "topography-wind" term (as
 348 seen in Eq. 5) to correct for these 3D transport effects, improving accuracy in emission estimates.
 349 The topography-wind term is calculated as:
 350

$$C_{topo} = V/H_{sh} \cdot w_0 \cdot \nabla Z_0 \quad (5)$$

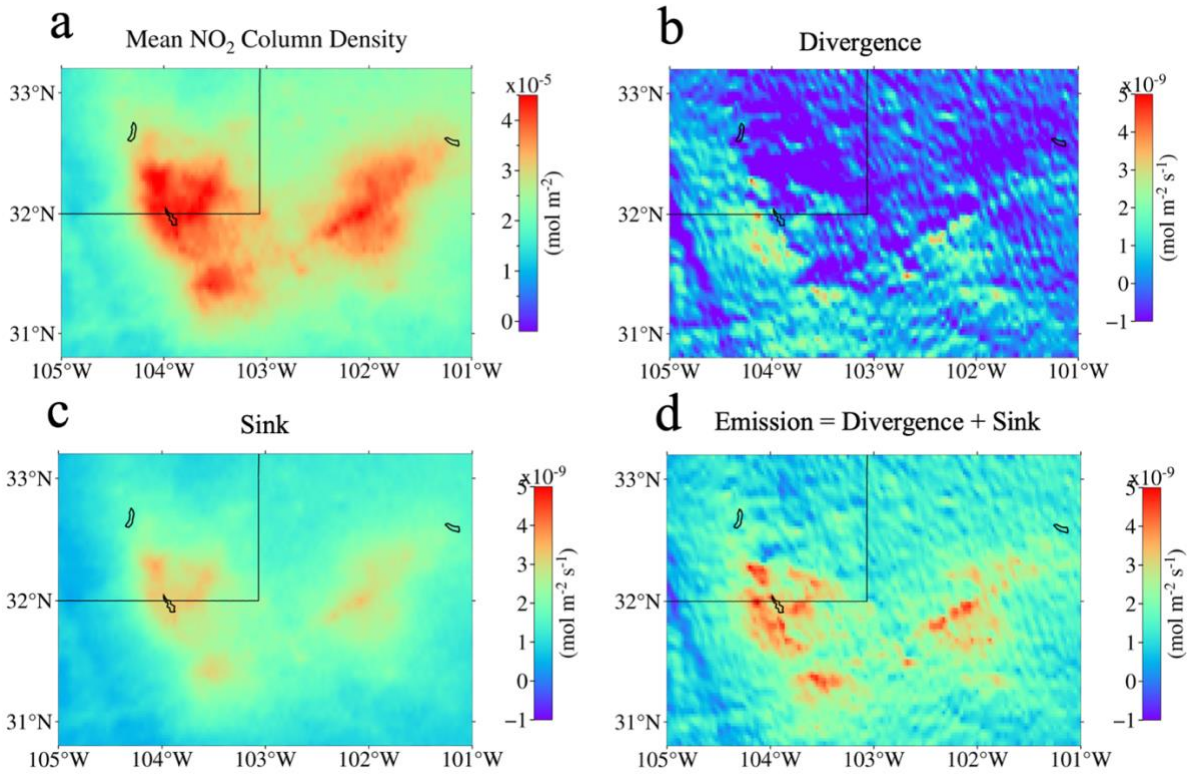
351
 352 with NO_x TVCD (V), H_{sh} , w_0 , z_0 are the NO_x scale height, surface wind speed at 10 m and surface
 353 elevation, respectively. This correction term, known as the topography-wind term (C_{topo}) is
 354 calculated for each TROPOMI pixel using provided z_0 and w_0 at 10 m within the data product,
 355 assuming NO_x scale height of 1 km.
 356

357 The topography-corrected advection (divergence as per Eq. 1) is then derived as:
 358

$$A^* = A + f \cdot C_{topo} \quad (6)$$

359 The scaling factor (f) is empirically determined as 1.5, equivalent to a net NO_x scale height of 1/1.5
 360 km = 667 m, to reducing the topography effects.

361 In Figure 2, we showcase a divergence map (computed using Eq. 6) for the Permian Basin,
 362 a largest OG production region in the United States. Positive values signify emission sources, while
 363 negative values are primarily associated with chemical loss, to be addressed in the sink term.
 364 Nevertheless, negative values could also result from factors like violation of steady state, statistical
 365 noise, or errors in the wind fields.
 366
 367



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Figure 2: Calculation of NO_x emission using TROPOMI NO_2 and the flux divergence method. (a) annual mean tropospheric NO_2 vertical column density, (b) calculated divergence, (c) calculated sink, (d) Calculated NO_x emissions (divergence and sink). The data shown here are an average over the full data set from January – December 2022.

374 3.2.3 Sink

375 The sink process is primarily governed by the chemical loss of NO_x through the reaction
376 with the hydroxyl radical (OH). Sinks of NO_x are included in the Eq. 1 by adding TVCD (V)
377 divided by the atmospheric lifetime (τ) of NO_x . The effective lifetime (τ) can be approximated as
378 the first-order loss to OH:
379

$$\tau = 1/(k_{\text{OH}+\text{NO}_2} \cdot [\text{OH}]) \quad (7)$$

380 The Master Chemical Mechanism (MCM; Jenkin et al., 2003; Saunders et al., 2003) scheme is
381 used to calculate the rate constant $k_{\text{OH}+\text{NO}_2}$ using pressure and temperature from ERA5. Despite
382 the intricate nature of the instantaneous NO_x lifetime, constant NO_x lifetimes effectively link
383 observed NO_2 TVCDs with NO_x emissions (Beirle et al., 2011; Goldberg et al., 2019; F. Liu et al.,
384 2016). We determine OH concentrations using the method described by Dix et al., (2022), which
385 relies on the empirical relationship between ozone photolysis frequency $J(\text{O}(^1\text{D}))$ and OH
386 concentrations, as established by Rohrer & Berresheim, (2006). The empirical correlation reveals
387 a primarily linear relationship between $J(\text{O}(^1\text{D}))$ and OH, consistently observed across various

388 seasons and locations, albeit with slight variations in slope and offset for the applied line fits. In
389 our study, we utilize line fit parameters averaged from all documented campaigns:
390

$$OH = 3.38 \times 10^6 \cdot \left(J(O^1(D)) \cdot 10^5 \right)^{0.956} + 0.162 \times 10^6 \quad (8)$$

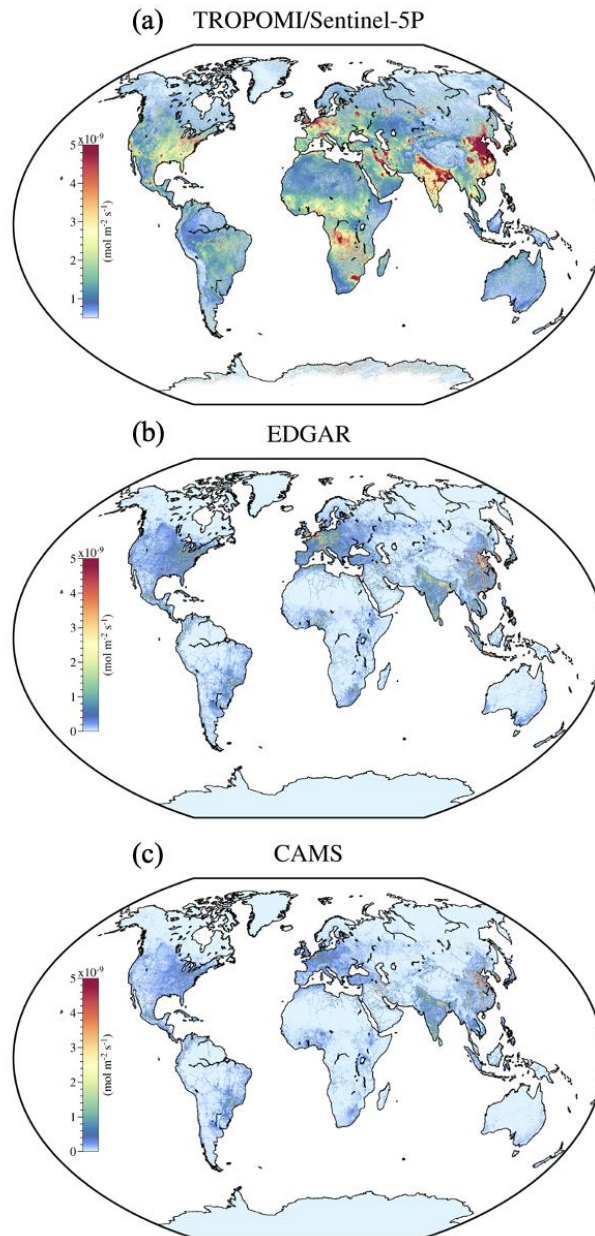
391 OH and $J(O^1(D))$ are expressed in units of 10^6 cm^{-3} and 10^{-5} s^{-1} , respectively. The calculation of
392 $J(O^1(D))$ depends on solar zenith angle. We have excluded both the lifetime and background
393 corrections, as performed in Beirle et al., (2019) and Dix et al., (2022), to eliminate free-
394 tropospheric NO_x with a prolonged lifetime and different $f\text{NO}_x$. This exclusion has no impact on
395 divergence calculation since additive terms are nullified.

396
397

398 **4 Comparing Satellite-derived NO_x emission with existing emission inventories**

399 In our extensive global assessment, we analyzed NO_x emissions as derived from TROPOMI and
400 conducted a rigorous comparative analysis against two prominent emission inventories, namely
401 EDGARv6.1 for the year 2018 and CAMS-GLOB-ANT_v5.3 spanning 2019-2022. Notably, the
402 year 2020 is omitted from the CAMS dataset due to a substantial reduction in NO_x emissions
403 attributable to the COVID-19 pandemic. Utilizing a $0.1^\circ \times 0.1^\circ$ sectorial gridding approach for both
404 inventories, we aggregated emissions across various activity sectors to directly obtain estimates of
405 anthropogenic NO_x emissions over the same geographic domain. Our examination encompassed a
406 global scale, and Figure-3 offers a comprehensive visualization of the comparative emissions data
407 from TROPOMI, EDGAR, and CAMS. The outcomes of our analysis revealed noteworthy
408 discrepancies between the emission estimates originating from TROPOMI and those from the
409 established EDGAR and CAMS inventories. Particularly, CAMS-GLOB-ANT reported lower
410 average emissions, while EDGAR's NO_x emission estimates contrasted with TROPOMI's
411 assessments. These disparities bring to the forefront the intricacies and variations inherent in the
412 methods employed for quantifying emissions between TROPOMI and conventional inventory
413 systems. The dissimilarities in reported emission levels underscore the diverse underlying
414 assumptions, data sources, and methodologies applied in the estimation of NO_x emissions. Such
415 variations in estimation approaches carry significant implications for the interpretation and
416 utilization of emissions data, underscoring the imperative need for comprehensive and precise
417 emission quantification to effectively inform policy decision-making. In our comprehensive
418 analysis, we particularly emphasized the oil and gas sectors due to their pivotal role in emissions
419 management. The variances observed in the sectoral allocation of emissions in these inventories
420 further underline the necessity for enhanced accuracy and consistency in emission inventories,
421 with particular attention to sectors as critical as oil and gas.

422

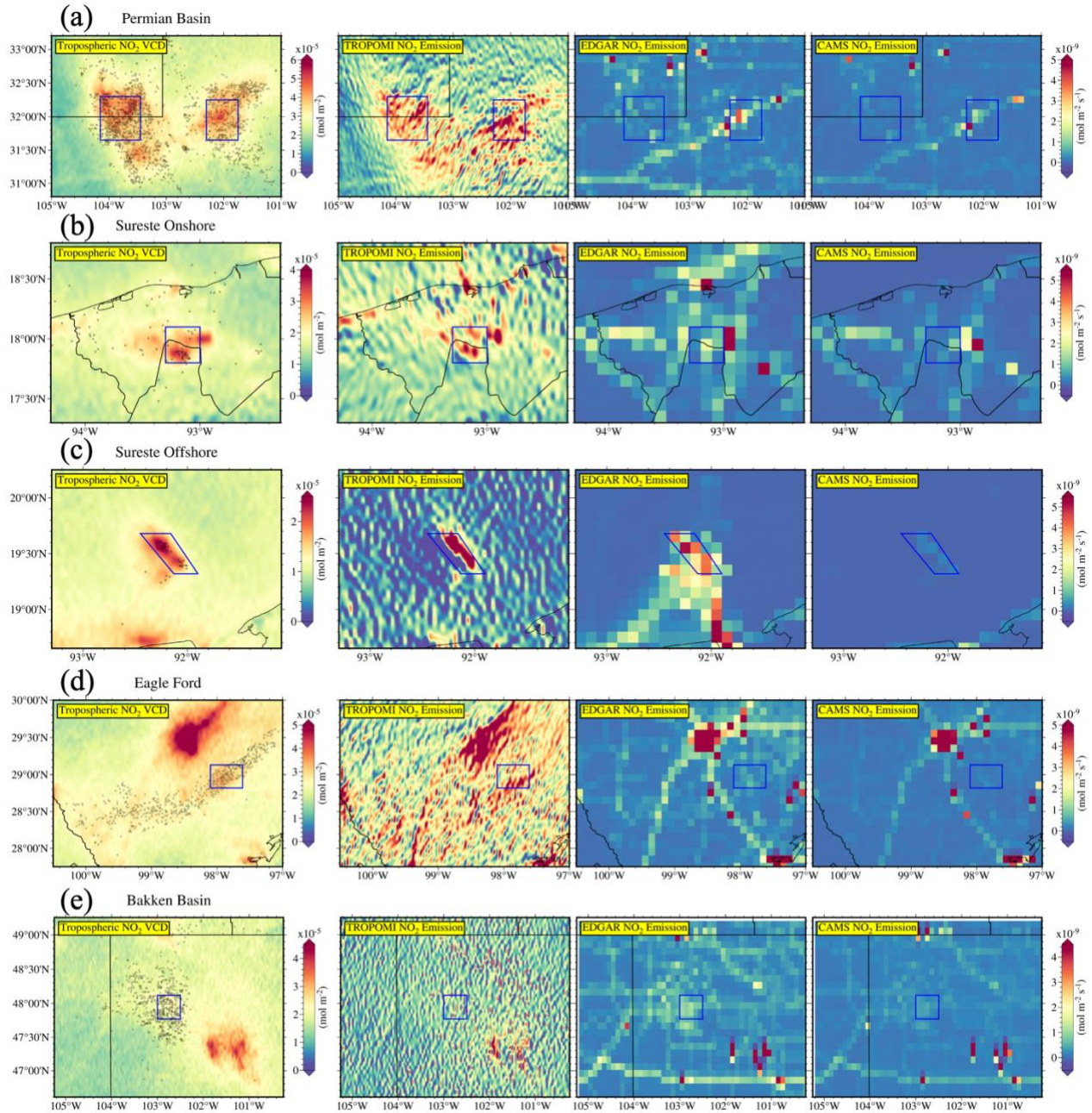


423
 424 **Figure 3:** (a) Calculated NO_x emission using TROPOMI observations using flux divergence
 425 method, (b) NO_x emission from EDGAR (EDGARv6.1) inventory, (c) NO_x emission from CAMS
 426 (CAMS-GLOB-ANT_v5.3) inventory.
 427

428 4.1 Comparing regional NO_x emissions

429 Utilizing the method described in section 3.2, we computed the annual average NO_x
 430 emissions for the year 2022 across 44 oil and gas production regions worldwide. The net NO_x
 431 emissions for each study area are quantified as the sum of emissions above zero within the region
 432 of interest. The borders of each study area were optimized to include significant signals over OG
 433 production areas and exclude other significant NO_x sources, but some contamination from other

434 sources might remain. The results are visually presented in Figure 4 & 5 and S1-S4 and their NO_x
 435 emissions from TROPOMI, EDGAR and CAMS and their relative differences are listed in Table
 436 1. For instance, Figure-4 represents the tropospheric NO₂ vertical column density (VCD) following
 437 by corresponding NO_x emission from TROPOMI, EDGAR and CAMS in subsequent panels,
 438 focusing on three (a. Permian Basin, USA, b. Sureste onshore, Mexico, c. Sureste offshore,
 439 Mexico, d. Eagle Ford, USA and e. Bakken Basin, USA) oil and gas fields.



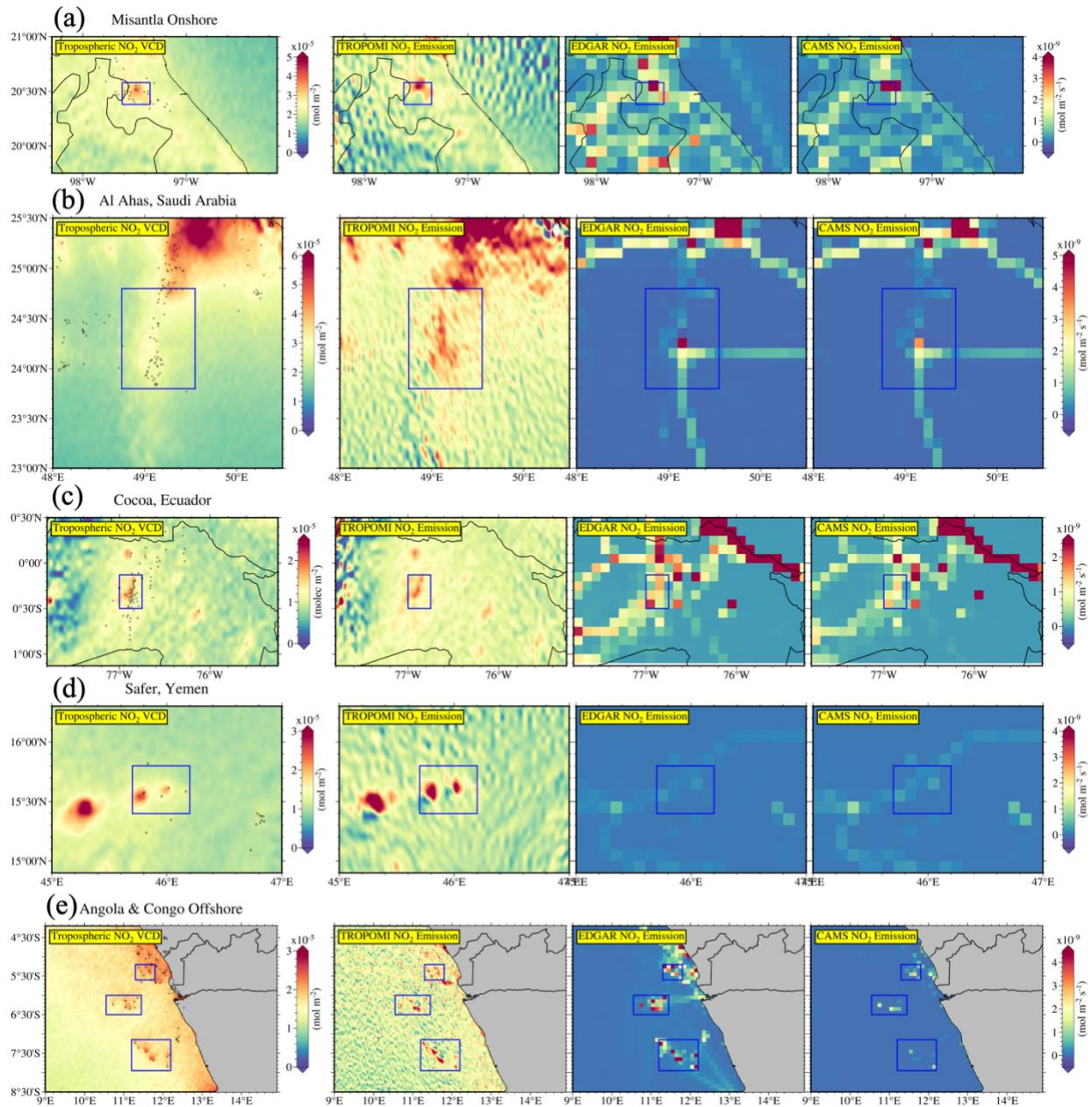
440
 441 **Figure 4:** Spatial distribution of tropospheric NO₂ vertical column density as derived from
 442 TROPOMI is presented in the initial panel, followed by the corresponding NO_x emissions from
 443 TROPOMI, EDGAR, and CAMS in subsequent panels. This analysis is centered on three (a.

444 *Permian Basin, USA, b. Sureste onshore, Mexico, c. Sureste offshore, Mexico, d. Eagle Ford, USA*
445 *and e. Bakken Basin, USA) oil and gas fields.*
446

447 Emissions from TROPOMI analysis ranged between 2,370 and 131,346 T yr⁻¹ across the
448 33 onshore sites globally (seen in Table 1). The EDGAR NO_x emissions data generally
449 underestimate the magnitude when compared to NO_x emissions derived from our TROPOMI
450 analysis, with discrepancies ranging from 48% to 91% across the onshore OG regions examined.
451 These discrepancies may be attributed to the inherent limitations of bottom-up inventories, which
452 rely on reported data and may not fully account for the dynamic and complex nature of local OG
453 activities. On the other hand, it appears that CAMS contains limited information to capture the
454 NO_x emissions. . The CAMS data indicates its own set of underestimations, with deviations
455 ranging from 65% to 96% assss compared to TROPOMI derived NO_x emissions. The Permian
456 (Figure 4a) and Bakken (Figure 4e) basins, which are major oil producing basins in the US,
457 exhibited notably high NO_x emissions (Permian is the largest oil producing basin in the US). The
458 most substantial underestimations were observed in the Delaware sub-basin of the Permian basin
459 (Figure 4a), where NO_x emissions reported by EDGAR and CAMS were approximately 91% and
460 95% lower, respectively, than those derived from TROPOMI. Similarly, other OG regions such as
461 Al Ahas in Saudi Arabia (Figure 5b) and Safer in Yemen (Figure 5d), exhibited high NO_x
462 emissions and considerable discrepancies between TROPOMI-derived NO_x emissions and those
463 reported by EDGAR and CAMS. Varon et al., (2024) also detected and reported the elevated NO_x
464 emissions from power plants in the Al Ahas sites in Saudi Arabia. These noteworthy discrepancies
465 may be reasonably ascribed to variations in local OG production activities, effectively captured by
466 TROPOMI's high-resolution measurements but posing challenges for existing inventories with
467 coarser spatial resolution to detect. In addition, the Athabasca OG basin in Canada (Figure S1)
468 displayed underestimations of around 70% and 87% for EDGAR and CAMS, respectively. Our
469 analysis considered a typical low bias of approximately 20% in TROPOMI-derived tropospheric
470 NO₂ measurements in heavily polluted regions, potentially even greater when estimating near-
471 surface NO_x emissions. Consequently, our calculated NO_x emissions should be regarded as
472 conservative estimates, representing a lower limit.

473 Nevertheless, specific OG sites, including Bakken (Figure-4e), Misantla (Figure 5a) and
474 Cocoa (Figure 5c) basins, which exhibited elevated NO_x emissions, shows relatively minimal
475 deviations between TROPOMI-derived NO_x emissions and those reported by EDGAR and CAMS.
476 The Misantla basin in Mexico displayed relatively small deviations between TROPOMI NO_x
477 emissions and those reported in EDGAR and CAMS, with an underestimation of approximately
478 6% and 9%, respectively. This can be attributed to the remote location of the Misantla basin, which
479 experiences limited influence from urban or other emission sources. Likewise, the Bakken basin
480 displayed relatively minor discrepancy in NO_x emissions between TROPOMI and EDGAR,
481 amounting to around 25%, but a substantial variation of approximately 73% was found between
482 TROPOMI and CAMS. Despite its considerable distance from urban areas in this study, there was
483 a 25% underestimation of NO_x emissions in EDGAR. However, CAMS had difficulty to capture
484 OG sources, perhaps because of the proximity of the basin to mountain ranges. In the case of the

485 Cocoa basin, there was an underestimation of approximately 18% and 45% in EDGAR and CAMS,
 486 respectively. This remarkable discrepancy can be attributed to the remote location of the Cocoa
 487 basin, which experiences limited influence from urban or other emission sources.



488
 489 **Figure-5:** Spatial distribution of tropospheric NO_2 vertical column density as derived from
 490 TROPOMI is presented in the initial panel, followed by the corresponding NO_x emissions from
 491 TROPOMI, EDGAR, and CAMS in subsequent panels. This analysis is centered on three (a.
 492 Misantla Onshore, Mexico, b. Al Ahas, Saudi Arabia, c. Cocoa, Ecuador, d. Safer, Yemen and e.
 493 Angola & Congo Offshore) oil and gas fields

494
 495 Our in-depth analysis underscores the variability in NO_x emissions across these OG sites
 496 and emphasizes the critical importance of employing high-resolution measurements, such as those

497 provided by TROPOMI. These high-resolution measurements can accurately assess and monitor
498 these emissions, especially in regions where substantial discrepancies exist between bottom-up
499 inventories like EDGAR and CAMS. Moreover, the observed differences between TROPOMI and
500 EDGAR can be attributed to multiple factors. Cloud and solar zenith angle filtering in TROPOMI
501 may lead to uneven data statistics in NO₂ VCDs, leaving some areas within a region under-
502 sampled. Furthermore, drilling rigs in OG activities are not stationary sources of NO_x emissions,
503 as the drilling process involves moving from one well site to another, which can result in uneven
504 sampling of NO₂ VCDs and missing drilling-related emissions. On the other hand, discrepancies
505 associated with the EDGAR inventory may arise because it assumes emissions to be consistent
506 throughout a 24-hour daily cycle, which may not hold true in reality. Additionally, the distribution
507 of state-level fuel volumes to individual wells in the EDGAR inventory can introduce
508 uncertainties. Despite these potential sources of discrepancies, TROPOMI-derived emission maps
509 offer valuable information on the spatial distribution of NO_x emissions resulting from oil and gas
510 production activities, particularly in areas characterized by higher emission levels. These findings
511 are important for enhancing our understanding of emissions, supporting effective air quality
512 management, and informing policymaking by providing high-resolution observations of emissions
513 from oil and gas activities.

514 In contrast to onshore sites, we broaden our investigation to encompass eleven offshore oil
515 and gas (OG) production sites spanning across the globe (seen in Figure 4c, 4e and few more
516 shown in supplementary figures S1 – S5). What emerges from this comprehensive examination is
517 a strikingly diverse range of NO_x emissions, quantified by TROPOMI, with values spanning from
518 2,898 to 37,892 T yr⁻¹ across these offshore OG regions. One of the most intriguing aspects of our
519 findings lies in the substantial high estimates observed in the NO_x emissions calculated by
520 TROPOMI when compared to those derived from the EDGAR and CAMS inventories. This
521 consistent pattern most notably pronounced at offshore sites where the influence of urban areas is
522 almost nonexistent, suggests that TROPOMI data are effective in reliably capturing the spatial
523 distribution of NO_x emissions stemming from offshore OG activities. This result implies that
524 TROPOMI's high-resolution measurements are particularly effective in regions where urban
525 influence is minimal. The contrasting performance of the EDGAR inventory at offshore sites,
526 compared to its performance at onshore sites, merits further exploration. At onshore sites, EDGAR
527 tends to underestimate emissions by 14% to 57%. However, the data reveal that at offshore sites,
528 EDGAR provides relatively better agreement with TROPOMI, implying less underestimation in
529 comparison to onshore sites. Several factors contribute to this intriguing outcome: the isolation of
530 offshore sites from urban areas, resulting in reduced urban influence; the more stable and
531 consistent nature of offshore emissions due to more stationary offshore drilling platforms; and the
532 distinct wind patterns that characterize offshore areas, facilitating the efficient dispersion of
533 emissions. These factors collectively contribute to the improved agreement between TROPOMI
534 and EDGAR in the context of offshore emissions. In contrast, a significant discrepancy arises in
535 the performance of CAMS, which consistently struggles to capture the NO_x emissions from
536 offshore OG sites. Consequently, CAMS NO_x emissions are found to be severely underestimated,

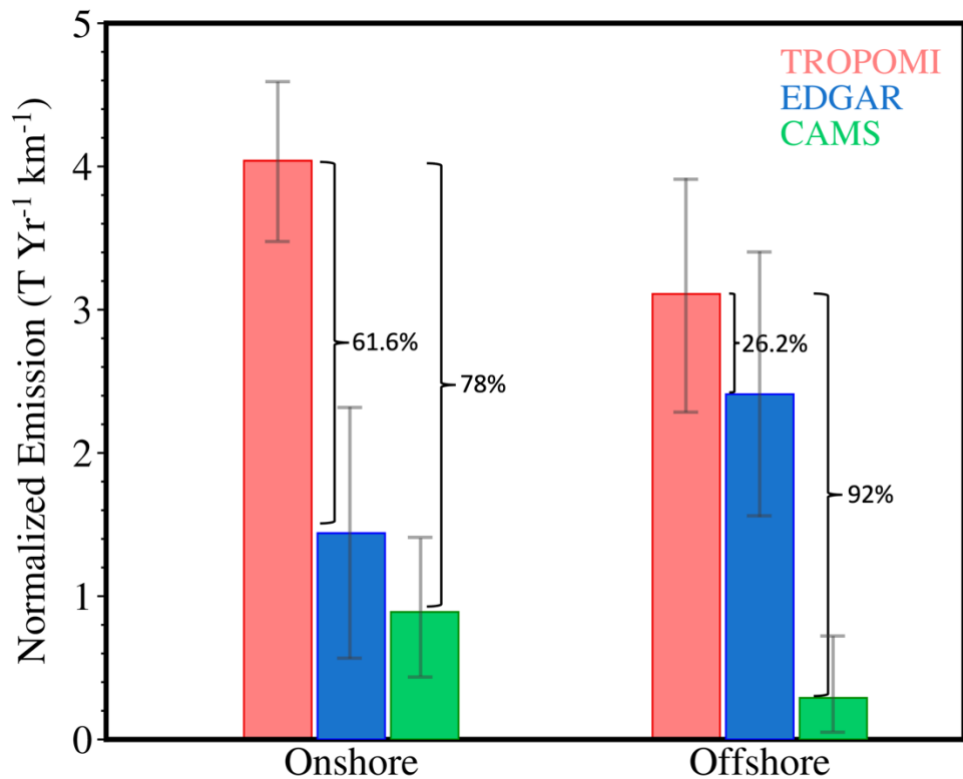
537 with underestimations exceeding 90% across all sites, and even surpassing 97% in 85% of offshore
538 OG sites. This substantial underestimation underscores limitations of CAMS in representing NO_x
539 emissions from offshore locations accurately.

540 In conclusion, our expanded analysis not only highlights the variability in NO_x emissions
541 from offshore OG sites but also underscores the crucial role of high-resolution measurements, such
542 as those provided by TROPOMI, in comprehensively assessing and monitoring emissions.
543 Additionally, it emphasizes the significance of urban influence and wind patterns in influencing
544 the discrepancies between TROPOMI, EDGAR, and CAMS measurements.

545 *Table 1: Comprehensive summary of NO_x emissions derived from TROPOMI, EDGAR, and CAMS for 44 oil and gas (OG) sites*
546 *worldwide. The last two columns detail the relative percentage differences in NO_x emissions between TROPOMI and EDGAR, as well*
547 *as TROPOMI and CAMS, offering insights into the variations in emission estimates across these datasets.*

OG Sites	Country	Lat Long	Area (in km ²)	TROPOMI NO ₂ emission (T yr ⁻¹)	EDGAR NO ₂ emission (T yr ⁻¹)	CAMS NO ₂ emission (T yr ⁻¹)	Percentage Difference (TROPOMI - EDGAR) (%)	Percentage Difference (TROPOMI - CAMS) (%)
Offshore	Angola	-7.55 11.70	10159.41	27207.9	11549.0	668.3	57.55	97.54
Offshore	Cameroon	4.27 8.38	1658.99	6061.8	6505.0	2667.5	-7.31	55.99
Offshore	Democratic Republic of the Congo	-6.25 11.00	5747.28	15956.3	8654.0	999.2	45.76	93.74
Elborma	Algeria	30.95 8.10	3006.48	7886.7	247.0	46.8	96.87	99.41
Offshore	Gabon	-1.35 8.75	1946.62	5309.8	1493.7	231.8	71.87	95.63
Divangui	Gabon	-1.92 9.90	1298.12	4327.6	482.6	200.7	88.85	95.36
Offshore	Ghana	4.55 -2.87	3483.51	8366.0	7206.6	191.1	13.86	97.72
Hassi Messaoud	Algeria	31.70 6.05	2291.55	9581.3	4926.3	2272.8	48.58	76.28
Hassi R'mel	Algeria	32.90 3.25	4569.87	12955.6	3522.6	2097.5	72.81	83.81
Offshore1	Nigeria	3.48 5.56	929.84	2898.8	2000.2	79.7	31.00	97.25
Offshore2	Nigeria	3.14 6.80	2389.13	6211.2	5031.9	23.5	18.99	99.62
Offshore	Republic of Congo	-5.40 11.55	2585.46	8583.3	6358.6	1055.8	25.92	87.70
Athabasca Basin	Canada	57.18 -111.63	9938.61	43270.5	12712.1	5488.9	70.62	87.31
Grande Prairie Basin	Canada	54.50 -118.60	3366.17	4721.5	1278.6	1024.8	72.92	78.30
Mumbai Offshore	India	19.40 71.33	2867.91	9910.8	6254.9	9.6	36.89	99.90
Misantla	Mexico	20.48 -97.49	810.03	3211.8	3009.5	2914.9	6.30	9.24
Sureste Offshore	Mexico	19.50 -92.18	2756.00	12042.6	13174.8	734.7	-9.40	93.90
Sureste Onshore	Mexico	17.95 -93.15	1284.35	5025.5	1702.2	737.3	66.13	85.33
Agiba-Meleiha	Egypt	30.75 27.05	4764.94	9591.3	4918.6	1729.0	48.72	81.97
Matrouh	Egypt	29.70 28.60	4415.75	9895.3	3047.8	962.8	69.20	90.27
Rasgarib	Egypt	28.20 33.25	15682.06	62917.4	45139.2	3821.9	28.26	93.93
Alahas	Saudi Arabia	24.30 49.15	11061.69	39264.3	4283.4	3264.7	89.09	91.69
Ar Rumaylah	Iraq	30.43 47.55	6700.75	131346.7	33234.7	29657.2	74.70	77.42
Gachsaran	Iran	30.20 50.65	6178.78	24453.9	7711.3	5734.6	68.47	76.55

Southpars	Iran	27.63 52.40	11110.92	138724.8	55185.3	68514.2	60.22	50.61
Mukhaizna	Oman	19.35 56.35	4727.47	9121.0	1096.5	290.8	87.98	96.81
Saihrawl	Oman	21.55 56.55	6677.41	14668.8	6771.1	3292.7	53.84	77.55
Safer	Yemen	15.60 45.95	2673.57	6033.0	196.6	237.5	96.74	96.06
Wafra-Burgan	Kuwait	28.80 47.90	5234.89	79905.2	23368.8	8940.6	70.75	88.81
Offshore	Persian Gulf	26.70 52.10	6817.10	21480.0	23326.3	2804.4	-8.60	86.94
Evenkiysky	Russia	60.40 96.35	3734.49	4121.1	135.5	4.1	96.71	99.90
Nadymsky	Russia	66.95 75.55	3546.75	3384.3	101.2	0.4	97.01	99.99
Khanty-Mansi	Russia	60.73 72.75	8263.37	12583.3	5957.5	1139.8	52.66	90.94
Yamalo-Nenets	Russia	66.25 77.05	14421.47	17088.3	20064.1	18765.4	-17.41	-9.81
Ust-Kutsky	Russia	58.10 106.70	5853.97	6810.7	2278.3	51.5	66.55	99.24
Cocoa	Ecuador	-0.32 -76.88	1216.16	2370.8	1943.4	1289.8	18.03	45.60
Maturin	Venezuela	9.66 -63.52	498.29	2851.5	1383.0	820.5	51.50	71.23
Neuquen	Argentina	-38.40 -68.68	3034.49	6325.8	6091.9	1195.7	3.70	81.10
Offshore	Rio de Janeiro	-22.35 -40.00	14935.29	24653.3	26391.8	518.3	-7.05	97.90
Offshore	São Paulo	-25.15 -42.70	20970.13	37892.6	18439.9	461.6	51.34	98.78
Eagle Ford	USA	28.98 -97.86	2299.88	10280.4	1416.1	746.1	86.23	92.74
Bakken Basin	USA	47.95 -102.75	3386.36	7849.4	5864.2	2108.9	25.29	73.13
Delaware, Permian Basin	USA	31.95 -103.75	5585.45	32363.7	2897.4	1543.0	91.05	95.23
Midland, Permian Basin	USA	32.00 -102.08	4169.19	22516.4	4864.4	8000.5	78.40	64.47



550

551

552 **Figure 6:** Comparison of normalized NO_x emission from TROPOMI, EDGAR, and CAMS over the
 553 44 onshore and offshore OG sites distributed globally (33 onshore and 11 offshore) . The
 554 normalized emissions are calculated firstly by dividing the individual site-wise NO_x emission by
 555 their total area in km^2 and then averaged annually. Later, the sites are segregated into offshore and
 556 onshore sites and averaged the normalized emission values. Gray semi-transparent bars shows the
 557 standard deviation in the normalized emissions within the various OG sites included in the
 558 particular category.

559

560 4.2 Global NO_x comparisons

561 In our comprehensive assessment of NO_x emissions from 44 Oil and Gas sites across the
 562 globe, we systematically categorized these sites into onshore and offshore locations, with 33 and
 563 11 sites, respectively. To facilitate meaningful comparisons, we calculated normalized emissions
 564 by dividing TROPOMI-derived NO_x emissions for each site by their corresponding areas. These
 565 normalized emissions were then averaged separately for onshore and offshore sites. Figure 6
 566 illustrates the comparison of annually averaged normalized NO_x emissions from TROPOMI,
 567 EDGAR, and CAMS, grouped into onshore and offshore sites. Subsequently, we contrasted our
 568 findings with the NO_x emissions estimates provided by established bottom-up inventories,
 569 specifically EDGAR and CAMS. The results presented a significant contrast between onshore and
 570 offshore sites (as seen in Figure 6). For onshore sites, both EDGAR and CAMS exhibited
 571 significant underestimations, with EDGAR underestimating by 61% and CAMS by a stronger 78%

572 compared to TROPOMI-derived NO_x emissions. This substantial discrepancy between satellite-
573 detected emissions and inventory-based estimates may be attributed to several factors. Onshore
574 areas are more susceptible to the influence of background NO_x emissions, originating from urban
575 centers and recurrent fire events. The urban environment contributes significantly to the pool of
576 NO_x emissions, and these emissions can skew inventory-based estimates, leading to substantial
577 underestimations. However, the situation differs for offshore sites. Emission estimates from
578 EDGAR for offshore sites are notably closer to the actual TROPOMI-derived NO_x emissions,
579 underestimating by 26%. This closer comparison can be attributed to the reduced influence of
580 background emissions in offshore areas. These sites are more remote and less impacted by urban
581 centers and associated emissions, thereby resulting in more accurate EDGAR-based estimates. In
582 contrast, CAMS exhibits a much higher underestimation for offshore sites, at 92%, compared to
583 TROPOMI-based emissions. This significant underestimation may be due to inherent limitations
584 of CAMS in capturing emissions from such offshore areas accurately. In summary, the discernible
585 discrepancies in underestimation between onshore and offshore sites underscore the intricate
586 interplay between emissions from various sources and background contributions, necessitating the
587 implementation of region-specific environmental management strategies.
588

589 4.3 *Uncertainties in TROPOMI-derived tropospheric NO₂ and NO_x emissions*

590 Quantification of NO_x emissions from global oil and gas fields using TROPOMI datasets
591 with the flux divergence method is a complex endeavor that may be affected with uncertainties.
592 These uncertainties stem from various sources, including the TROPOMI datasets, the NO₂
593 retrieval algorithm, assumptions made during algorithm development, limitation of the divergence
594 flux method, and parameter estimation. To gain a comprehensive understanding of the
595 uncertainties associated with this approach, we delve into these sources of uncertainty in detail:

596 4.3.1 *Uncertainties in TROPOMI dataset*

597 The precise estimation of tropospheric NO₂ column density data using TROPOMI is an
598 invaluable resource for emissions quantification; however, it is accompanied by inherent
599 uncertainties that warrant thorough consideration. These uncertainties originate from various
600 facets of the retrieval process and significantly influence the robustness of the data. Firstly, the
601 accuracy of slant column density (SCD) measurements is challenged by measurement noise and
602 spectral fitting errors, which are well-documented sources of uncertainty in satellite-based
603 observations (Boersma et al., 2004). Accurately distinguishing between stratospheric and
604 tropospheric NO₂ is a crucial step in the retrieval process, and errors in this separation process can
605 introduce significant uncertainties (Boersma et al., 2007). One of the most substantial contributors
606 to the overall uncertainty is the calculation of tropospheric air mass factors (AMF), which are
607 highly dependent on several parameters. These include surface albedo, a priori NO₂ profile, cloud
608 fraction, and cloud pressure (Boersma et al., 2004; De Smedt et al., 2018). A crucial factor to
609 consider is the impact of aerosols on the measurement. Errors in aerosol fraction assumptions,
610 particularly near the Earth's surface compared to the true vertical profile, can lead to an

611 overestimation of tropospheric AMF, consequently resulting in an underestimation of tropospheric
612 NO₂ vertical column density (VCD) (Boersma et al., 2004). It is also important to note that
613 systematic underestimations of high NO₂ concentrations have been observed, particularly in highly
614 polluted regions, due to spatial variability and inherent retrieval challenges (Shaiganfar et al.,
615 2011). While temporal and spatial averaging can mitigate random errors, systematic errors are
616 expected to persist if not adequately accounted for. As a whole, these uncertainties can range from
617 30% - 60% (Liu et al., 2021), underlining the critical necessity of acknowledging and quantifying
618 these uncertainties to ensure the accurate interpretation of TROPOMI-derived data for emissions
619 estimation and the consequential policy and decision-making processes. Continuous efforts to
620 refine retrieval algorithms and enhance data quality aim to reduce these uncertainties over time.

621 The use of satellite data introduces a systematic clear-sky bias, as it relies on measurements
622 from predominantly cloud-free days, limiting specific emission patterns from cloudier days. This
623 limitation also impacts estimates of chemical lifetimes, resulting in systematic underestimations
624 due to increased photolysis rates on cloudless days. Additionally, emissions and lifetimes are
625 derived from early afternoon measurements, introducing a temporal bias. To delve deeper into
626 temporal variability, future sensors on geostationary satellites could offer valuable insights.

627 Moreover, it is imperative to recognize that TROPOMI retrievals exhibit biases due to air
628 mass factor estimation challenges and local effects, especially under varying vertical conditions.
629 Recent versions of TROPOMI datasets (v2.x) indicate tropospheric vertical column densities 10-
630 40% larger than earlier versions (v1.x), dependent on pollution levels and seasons (Van Geffen et
631 al., 2021). The use of the TM5 chemical transport model in operational TROPOMI data retrieval
632 results in systematic underestimations of surface pollution and overestimations of NO₂ at higher
633 altitudes (Riess et al., 2022). These biases, while not insignificant, can contribute to discrepancy
634 between estimates and inventories, with variations in surface albedo in different terrains potentially
635 exacerbating the issue.

636 4.3.2 *Limitations of divergence flux method*

637 The Divergence Flux method has emerged as a powerful tool for quantifying global NO_x
638 emissions using TROPOMI-derived NO₂ column density. However, like any methodology, it has
639 limitations and uncertainties. In this section, we shed light on these aspects, underlining the critical
640 points of consideration for researchers and policymakers.

641 In our quest for estimating NO_x emission from oil and gas operations, we navigate a
642 landscape of uncertainties inherent to the divergence flux method. Previous studies have
643 highlighted the relatively minor impact of wind-level altitude and the NO_x to NO₂ scaling factor
644 on potential errors in emission estimates (Beirle et al., 2019, 2021). In contrast, more significant
645 errors are associated with the background correction process, the selection of wind fields, and
646 variations in OH lifetime, further emphasizing the complexity of accurate NO_x emission
647 calculations (Dix et al., 2022). The uncertainty stemming from background correction serves as an
648 essential indicator for assessing potential errors in emissions quantification. This uncertainty holds
649 more weight in smaller study areas and regions with dynamically changing topography. To
650 counteract its impact, adapting the background region becomes imperative. Furthermore, errors in

651 wind fields may lead to inaccuracies in divergence maps and hinder the spatial alignment of
652 calculated emissions with actual sources. To address these challenges, a topography-wind”
653 correction term was introduced (as outlined in Eq. 5) to effectively accounts for 3D transport
654 effects. Employing the topography-wind term helps reduce uncertainties and enhance the accuracy
655 of emission estimates. This approach aligns with a broader effort to improve the reliability of
656 emissions data in complex terrains, providing a valuable tool for emissions quantification in
657 challenging geographic regions. Furthermore, incorporating the topography-wind correction term
658 with a scaling factor (f) of 1.5, representing an estimated net NO_x scale height of 667 meters, is a
659 practical approach when regional-specific NO_x scale height information is lacking. As highlighted
660 by Beirle et al., (2023), an assumed relative uncertainty of 33% (equivalent to f values ranging
661 from 1.0 to 2.0 or NO_x scale heights between 500 and 1000 meters) is attributed to this topographic
662 correction term. This uncertainty is subsequently propagated to the corrected advection map
663 following Eq. 6.

664 Utilizing the divergence method for NO_x emission calculation relies on the premise of a
665 steady state, implying consistent wind direction and uniform NO_x emissions within the region of
666 interest. However, this daily divergence calculation assumption isn't universally valid. Regions
667 characterized by systematic diurnal wind direction variations or intricate mesoscale meteorological
668 dynamics beyond the spatial resolution of wind fields are ill-suited for the application of
669 divergence method. Such areas pose challenges to the accuracy and suitability of method.

670 Tropospheric NO_2 columns are profoundly influenced by wind fields, significantly
671 impacting the computation of NO_x emissions and lifetimes. To enhance data reliability, we
672 implemented a filtering criterion, exclusively incorporating measurements associated with wind
673 speeds exceeding 2 m s^{-1} . Given the limited lifetime of NO_2 , satellite-based NO_2 distributions
674 primarily reflect wind conditions during overpasses. Nevertheless, days with swiftly changing
675 wind directions can distort spatial patterns, particularly manifesting as curved plumes. This
676 distortion, more pronounced during extended lifetimes, significantly impacts single-day estimates.
677 However, this influence diminishes when analyzing larger averages unaffected by frequent wind
678 direction shifts. Despite the importance of wind conditions, it remains a substantial source of
679 uncertainty, with reported variations of up to 20% in emissions when wind speeds are altered by
680 20%. Accurate global wind data is challenging to acquire, carrying an estimated 30% uncertainty.
681 Uncertainties related to wind fields may vary across source regions, with an overall assumption of
682 30% uncertainty in our analyses (Beirle et al., 2011; Lorente et al., 2019).

683 For estimating NO_x emission, we implemented a novel approach involving the conversion
684 of each TROPOMI pixel from NO_2 column density to NO_x column density. Our approach
685 employed leverages the Leighton photostationary state principle to characterize the dynamic of
686 polluted air masses (Karl et al., 2023; Leighton, 1961). This approach offers a great precision
687 relative to conventional approaches that rely on constant conversion factors (~ 1.32). This
688 improvement provides a significant advantage for our extensive analysis spanning a wide
689 latitudinal gradients and seasonal variations. However, it is important to acknowledge that the
690 parameterization of photolysis rates, coupled with the application of temperature-dependent rate

691 constants and ozone concentrations obtained from the ESCiMO dataset interpolated to the Sentinel
692 5P overpass time, introduces systematic uncertainties in the conversion process from NO₂ to NO_x.

693 In the assessment of NO_x emissions, it is imperative to consider the susceptibility of sink
694 term to uncertainties in OH lifetimes. An erroneous estimation of the sink term could lead to
695 erroneous negative emissions in various regions or, conversely, non-emitting areas with artificially
696 elevated NO_x emissions. Although annual averaged emissions appear stable, daily and monthly
697 maps reveal noteworthy patterns, with certain periods exhibiting negative emissions in some
698 territories, while others display anomalous spikes in emissions, especially over deserts and seas
699 during the summer. This suggests potential underestimations in the sink term during winter and
700 spring and overestimations during summer, likely linked to OH estimation errors or additional
701 sinks in the warmer months. Taking this into consideration, while the averaged emissions for the
702 year 2022 remain unaffected, it serves to diminish the seasonal variations in emissions. A
703 sensitivity analysis in the Delaware basin by (Dix et al., 2022) demonstrates a minor 13% deviation
704 between parameterized OH values and WRF-Chem OH, despite the latter has higher variability.
705 Consequently, the inclusion of this factor aids in alleviating errors in the calculated NO_x emissions,
706 as it adjusts the proportion attributed to the sink term within the total emissions.

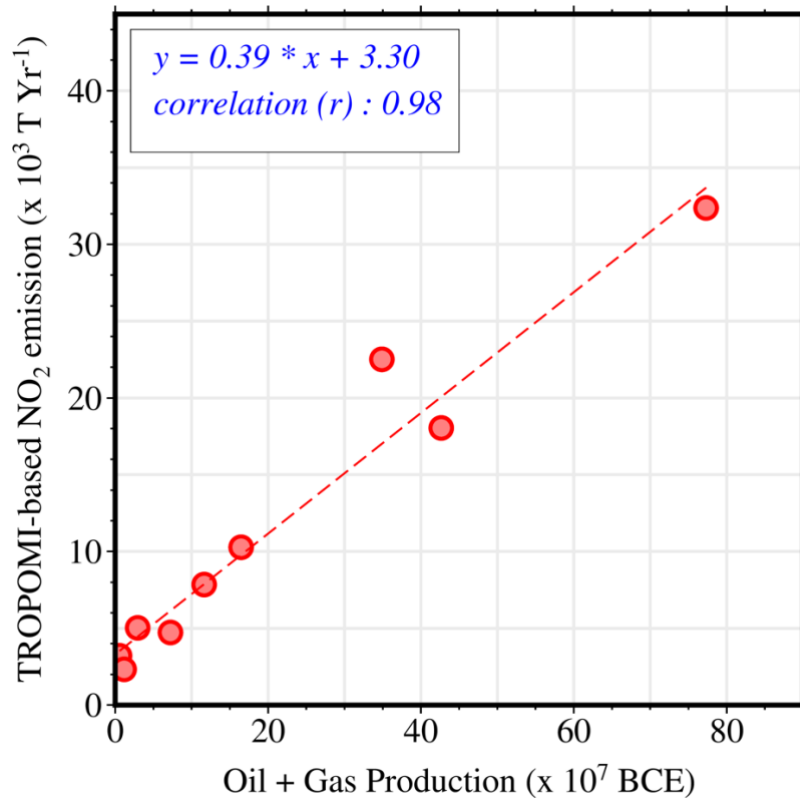
707 In summary, the comprehensive evaluation of NO_x emissions and lifetimes derived from
708 TROPOMI NO₂ data grapples with a spectrum of error sources, primarily systematic in nature.
709 These errors remain unaffected by extended temporal averaging, invariably leading to a consistent
710 underestimation in estimated emissions. This underestimation predominantly stems from
711 systematic discrepancies embedded in the TROPOMI NO₂ tropospheric column (30%–60%) and
712 the wind field (30%). Furthermore, the variability in area size contributes an estimated 10%
713 uncertainty, introducing a tendency for low-biased emissions and lifetimes. Other factors,
714 encompassing uncertainty in the measurement time, clear-sky bias, and assumptions regarding
715 sources, tend to accentuate this underestimation. Unraveling these intricacies necessitates in-depth
716 investigations. Aggregating these error components, computed as squared values, yields an overall
717 uncertainty estimate spanning the 40%–50% range.

718

719 **5 Exploring the relationship: NO_x emission, Oil & Gas production and methane** 720 **enhancement**

721 In recent environmental research, the intricate relationship between emissions and production
722 volumes in the OG sector has garnered significant attention. Seminal studies by (Omara et al.,
723 2022) and (de Gouw et al., 2020) have been instrumental in shaping this disclosure, primarily
724 elucidating the interconnected dynamics between methane emissions and OG production. Omara
725 et al., (2022) notably focused on methane emission at low-production OG sites, emphasizing the
726 pivotal role of equipment maintenance in mitigating emissions. Conversely, (de Gouw et al.,
727 2020)) conducted an extensive examination of the Permian Basin, revealing correlated columnar
728 methane with OG production. Their findings highlighted the intricate correlation between
729 emission, specifically methane and the volume of OG produced. Building upon the insights from
730 these refence studies, our current research advances this exploration into a critical yet less-explored

731 dimension — the correlation between NO_x emissions and OG production volumes. NO_x is
732 predominantly associated with combustion processes inherent in various facets of OG operations.
733 Drawing inspiration from the previous studies, our study seeks to unravel the correlation between
734 tropospheric NO_x emission and the intricate production dynamics of the OG industry, focusing on
735 flaring activity.
736



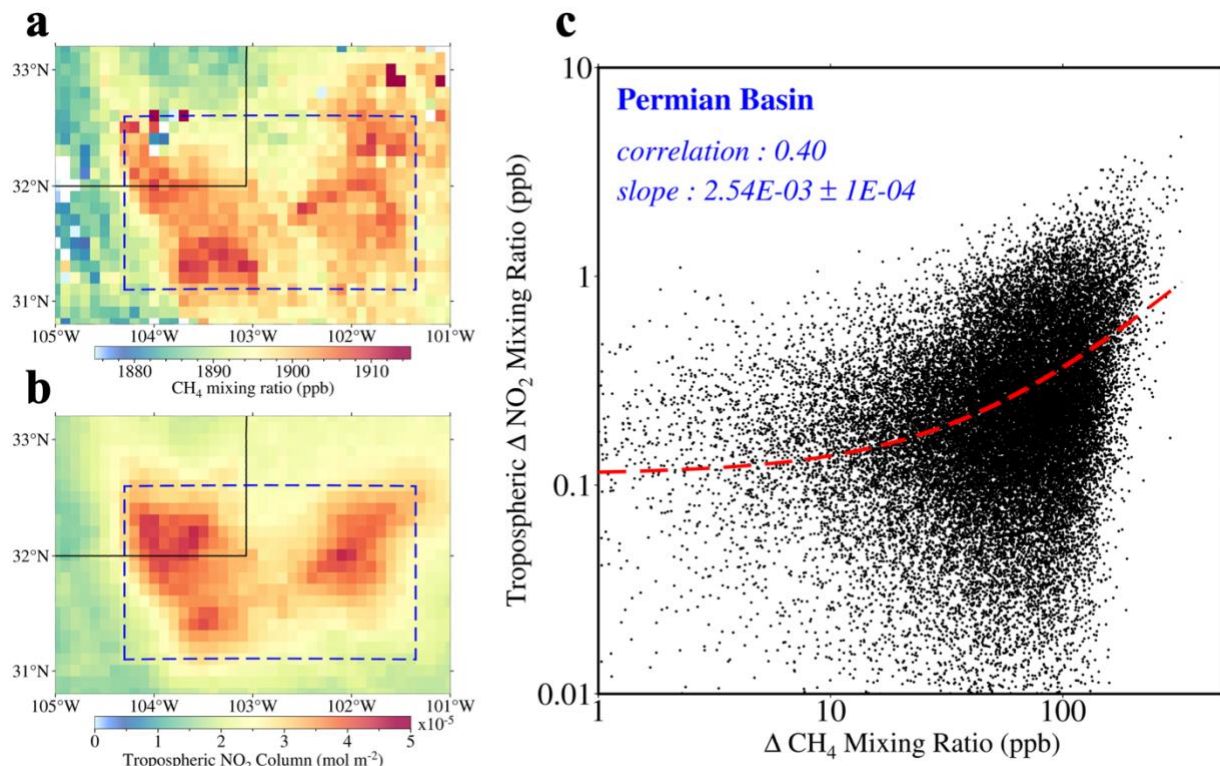
737
738 **Figure 7:** Correlation between TROPOMI-derived NO_x emissions and the oil and gas productions
739 from the various OG sites.
740

741 To facilitate this investigation, we acquired area-aggregated OG production data and well
742 count information for the year 2022 from Enverus Prism (Enverus, 2023) and the Mexico
743 Government's National Hydrocarbons Commission (CNH, 2023). This dataset, spanning nine
744 discrete OG sites across the United States, Canada, and Mexico, offers a diversified representation
745 of production activities within North America. The analytical emphasis revolves around comparing
746 the annual mean production of oil and gas with the annual mean of NO_x emissions derived from
747 TROPOMI observations. Our empirical findings revealed a robust correlation ($r = 0.98$ with $p \lll$
748 0.001) between TROPOMI-derived NO_x emissions and the integrated oil and gas productions for
749 the selected OG sites (as seen in Figure 7). Notably, the site with the maximum OG productions
750 exhibited the highest NO_x emission. This robust correlation, akin to prior observations on methane,
751 underscores the intrinsic association between emissions and production volumes. These
752 preliminary insights contribute substantively to the advancing discourse on emissions emanating

753 from OG operations. Our research delves beyond methane-centric investigations, uncovering the
 754 boarder environmental impact of OG activities. Understanding the crucial link between NO_x
 755 emissions and production volumes is pivotal for informed environmental management and policy
 756 decisions. This preliminary analysis sets the stage for more in-depth investigations, warranting
 757 consideration of additional factors and potentially expanding the scope of the study to other
 758 regions.

759 **5.1 Exploring the relation: NO_2 with CH_4 enhancement**

760 The above exploration has also suggested that NO_x emissions from oil and gas operations may
 761 be accompanied by CH_4 emissions which is associated with OG production (Alvarez et al. 2018),
 762 which we explore in this study. NO_x and CH_4 emissions follow distinct routes: NO_x arises from
 763 combustion processes, while CH_4 results from fugitive or vented sources or gas flaring activity.
 764 While originating from distinct sources (Warneke et al., 2014), CH_4 and NO_x emissions in oil and
 765 gas operations exhibit a spatial correlation due to their close proximity during release (de Gouw et
 766 al., 2020; Gorchov Negron et al., 2018). This proximity creates a perception of emissions from a
 767 single source, impacting atmospheric measurements.



768 **Figure 8:** Correlation between CH_4 and NO_2 columns in the Permian Basin using TROPOMI
 769 datasets. TROPOMI-derived (a) CH_4 mixing ratio and (b) tropospheric NO_2 column density over
 770 the Permian basin averaged from January - December 2022. (c) Correlation between
 771 enhancements of NO_x and CH_4 boundary layer mixing ratio across the Permian basin (highlighted
 772 by the thick red dashed line) observed from TROPOMI measurements during the period 2022.
 773 Linear fit (red dashed lines), the 95% confidence intervals of the slopes, and corresponding
 774 correlation values are shown.
 775

776

777 Figure 8a and 8b illustrate the averaged NO₂ column density and CH₄ mixing ratio over the
778 Permian basin (area covered within blue box) encompassing the entire year of 2022. NO₂ and CH₄
779 exhibit elevated concentrations across the Delaware sub-basin in the western region and the
780 Midland in the eastern sector of the Permian basin. The annual average for NO₂ and CH₄ displayed
781 a correlation with a coefficient of 0.41, aligning closely with the correlation value reported by de
782 Gouw et al., (2020) for the December 2018 to March 2019 period. We systematically explore the
783 connection within the boundary layer between NO₂ and CH₄. We initiate our approach by deducing
784 background values for both NO₂ and CH₄, aligning with the methodology presented by de Gouw
785 et al. (2020). This process entails the calculation of the 10th percentile for each species. Following
786 this initial step, we proceed to convert the NO₂ columns and CH₄ mixing ratios into boundary layer
787 mixing ratios, by assuming a boundary layer thickness of 100 hPa. For CH₄, we adjust the column
788 mixing ratio by dividing the surface pressure by 100 hPa, while for NO₂, this transformation
789 involves a shift from number concentrations to mixing ratios. Subsequently, we employ orthogonal
790 least-squares fitting to establish a linear correlation between the NO₂-CH₄ data points. Prior to
791 conducting this fitting, we apply a scaling procedure to normalize both NO₂ and CH₄ values within
792 the range of 0–1. Importantly, it's worth noting that this comprehensive analysis is tailored to days
793 when over 10 sets of NO₂-CH₄ data are available, ensuring the robustness of our findings.

794 The analysis of the annual average $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratio in the Permian Basin for the year 2022
795 yielded a value of $(2.54 \pm 0.1) \times 10^{-3}$. This result is lower than previously reported ratios, where
796 Gorchoy Negron et al., (2018) observed a considerably higher ratio of $(9.0 \pm 0.2) \times 10^{-3}$ through
797 airborne measurements. Similarly, de Gouw et al., (2020) documented values of $(4.9 \pm 0.2) \times 10^{-3}$
798 for January 31, 2019, and approximately 3.0×10^{-3} for the December 2018 to March 2019
799 timeframe utilizing TROPOMI datasets. The variations in the observed $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios may be
800 attributed to multiple factors. The variations in emission sources and their temporal dynamics
801 across the different study periods could account for these differences. The 2022 timeframe may
802 have witnessed alterations in emission patterns, or the development of the basins compared to the
803 earlier periods under examination. In addition, the differences in the observed ratio can be
804 explained by the composition of NO_x. NO_x encompasses both NO and NO₂, and the photochemical
805 removal of NO_x can be significant during the atmospheric transport process across the basin. This
806 removal process could lead to a reduction in the observed $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratio in this study compared
807 to the earlier studies. These findings contribute to a more comprehensive understanding of
808 emission pattern from the OG fields.

809

810 **Table 2:** Summary of observed $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios across the individual oil and gas basins over
811 the period 2022.

Basin	$\Delta\text{NO}_x/\Delta\text{CH}_4$ ratio ($\times 10^{-3}$)
Delaware (Permian basin), USA	3.0 ± 0.3
Midland (Permian basin), USA	2.5 ± 0.2

Eagle Ford, USA	6.2 ± 1.0
Bakken, USA	1.4 ± 1.0
Sureste onshore, Mexico	6.8 ± 2.0
Sureste offshore, Mexico	1.1 ± 0.5
Misantla onshore, Mexico	3.5 ± 1.0
Athabasca basin, Canada	5.2 ± 2.0
Grande Prairie, Canada	0.5 ± 1.3

812
813 In 2022, the TROPOMI-based observations unveiled distinctive $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios across
814 various oil and gas basins in North America (Table 2), each offering a unique perspective on the
815 regional emissions landscape. We examined the $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios separately for two regions
816 within the larger Permian basin: Delaware and Midland. The Delaware basin displayed a relatively
817 balanced ratio of $(3.0 \pm 0.3) \times 10^{-3}$. In contrast, the Midland basin, also part of the Permian basin,
818 showed a slightly lower ratio of $(2.5 \pm 0.2) \times 10^{-3}$, emphasizing a greater prevalence of CH_4
819 emissions. On the other hand, the Eagle Ford basin in the U.S. reported a notably higher ratio of
820 $(6.2 \pm 1.0) \times 10^{-3}$, indicating a prominent role of NO_x in emissions, warranting closer
821 environmental scrutiny. Meanwhile, the Bakken basin displayed a low ratio of $(1.4 \pm 1.0) \times 10^{-3}$,
822 signaling relatively modest emissions of both pollutants. In Mexico, the Sureste onshore region
823 displayed a high $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratio of $(6.8 \pm 2.0) \times 10^{-3}$, likely associated with industrial activities.
824 Conversely, the Sureste offshore area had a low ratio of $(1.1 \pm 0.5) \times 10^{-3}$, while the Misantla
825 onshore area showed a balanced ratio of $(3.5 \pm 1.0) \times 10^{-3}$. In Canada, the Athabasca basin indicated
826 significant NO_x emissions with a ratio of $(5.2 \pm 2.0) \times 10^{-3}$, while Grande Prairie in Canada had
827 the lowest ratio of $(0.5 \pm 1.3) \times 10^{-3}$, suggesting minimal emissions of both pollutants. These
828 variations in $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios provide insights into the diverse emissions characteristics across
829 these basins, contributing to our understanding of methane and NO_x emissions in the region.
830

831 6 Conclusion

832 In this comprehensive research study, we delve into the characteristics of NO_x emissions,
833 focusing on 44 oil and gas production sites distributed across the globe. Leveraging the capabilities
834 of satellite observations, we combine NO_2 data from TROPOMI with VIIRS-derived natural gas
835 flaring detection, effectively pinpointing natural gas flaring hotspots. Drawing from established
836 methodologies, we merge TROPOMI tropospheric NO_2 vertical column measurements with wind
837 data sourced from ECMWF ERA5 reanalysis, applying the divergence flux method to uncover the
838 nuanced dynamics of NO_x emissions. Benefitting from the high spatial resolution and high signal-
839 to-noise ratio of TROPOMI measurements, our analysis encompasses the entire year of 2022,
840 allowing us to analyze both the geographically diverse oil and gas emission sources that have
841 rarely been explored previously and the temporal variability over short-term intervals. This study

842 encompasses a total of 44 oil and gas production fields located in diverse regions across the globe,
843 providing a comprehensive examination of NO_x emissions in this critical industry.

844 Our extensive global assessment compared NO_x emissions derived from TROPOMI with two
845 established inventories, EDGARv6.1 (2018) and CAMS-GLOB-ANT_v5.3 (2019-2022).
846 Notably, our findings revealed significant discrepancies between TROPOMI-based estimates and
847 the inventories. TROPOMI reported higher emission levels, likely indicating the need for
848 improved accuracy in emission inventories, particularly within the oil and gas sectors. We then
849 delved into site-specific comparisons, analyzing 44 oil and gas production regions worldwide. The
850 outcomes emphasized the benefits of high-resolution measurements from TROPOMI in assessing
851 emissions, especially in regions with discrepancies between inventories. The differences were
852 attributed to various factors, including the influence of urban areas, dynamic nature of emissions,
853 and wind patterns. Furthermore, in our analysis comparing onshore and offshore oil and gas
854 production sites, distinct quantitative findings emerged, shedding light into the performance of
855 emission inventories (EDGAR and CAMS) in these different settings. For onshore sites, where the
856 influence of urban areas and associated emissions is more pronounced, both EDGAR and CAMS
857 exhibited substantial underestimations in comparison to TROPOMI-derived NO_x emissions.
858 Specifically, EDGAR underestimated emissions by an average of approximately 61%, while
859 CAMS showed a more significant underestimation, averaging around 78%. Conversely, for
860 offshore sites, characterized by their remote location and reduced impact from urban emissions,
861 EDGAR's performance notably improved. It exhibited a much lower average underestimation of
862 approximately 26% compared to TROPOMI-derived NO_x emissions. In contrast, CAMS
863 continued to struggle with offshore sites, displaying a substantial underestimation of
864 approximately 92% on average. These quantitative differences underscore the intricate interplay
865 between emissions from various sources and background contributions, highlighting the necessity
866 of implementing region-specific environmental management strategies. These findings may
867 provide valuable insights for policymakers and environmental scientists seeking to enhance
868 emission inventories related to oil and gas operations, emphasizing the importance of tailored
869 approaches for onshore and offshore settings. Moreover, the divergence method applied in this
870 study to satellite data offers an effective solution to address the inherent challenges associated with
871 general bottom-up emission inventories in the context of oil and gas operations. Its benefits include
872 the provision of near-real time emissions data for applications such as chemistry transport models,
873 the critical role of evaluating existing emission inventories, and the ability to furnish granular
874 insights into the spatial distribution of NO_x emissions, thus reducing uncertainties.

875 Our study has rigorously examined uncertainties in estimating NO₂ and NO_x emissions from
876 global oil and gas fields using TROPOMI datasets and the flux divergence method. These
877 uncertainties, originating from both data sources and the method itself, are essential to
878 acknowledge for reliable emissions data. The quantification of these uncertainties is paramount
879 for ensuring the accuracy and reliability of emissions data, which, in turn, informs critical policy
880 and decision-making processes. Precisely estimating tropospheric NO₂ column density confronts
881 challenges, including measurement noise, spectral fitting errors, and distinguishing between

882 stratospheric and tropospheric NO₂. Calculating tropospheric air mass factors amplifies
883 uncertainties, influenced by surface albedo, cloud fraction, and aerosol assumptions, ranging from
884 30% to 60%. This underscores the ongoing need for data quality and retrieval algorithm
885 enhancements. Satellite data use introduces biases, such as clear-sky bias, temporal bias, and those
886 tied to air mass factor estimation and local effects. Recent TROPOMI versions exhibit variable
887 tropospheric vertical column densities, adding complexity. We explore limitations in the
888 divergence flux method, encompassing uncertainties in background correction, wind field
889 selection, OH lifetime variations, and daily divergence calculations. Wind fields present
890 substantial uncertainties affecting NO_x emission accuracy and divergence map reliability.
891 Furthermore, our novel approach converts NO₂ to NO_x column density, stressing precision.
892 However, this process introduces systematic errors related to photolysis frequencies, rate
893 constants, and ozone concentrations. OH lifetime uncertainties affect the sink term, potentially
894 leading to erroneous emissions. In summary, the assessment of NO_x emissions and lifetimes from
895 TROPOMI NO₂ data consistently reveals systematic errors, resulting in underestimations of
896 emissions by 40% to 50%. Recognizing and quantifying these uncertainties are pivotal for
897 enhancing data accuracy and informed decision-making in environmental policies.

898 Furthermore, we explored the correlation between tropospheric NO_x emissions and oil and
899 gas (OG) production volumes. Analyzing data from nine diverse North American OG sites, a
900 robust correlation ($r = 0.98$) between TROPOMI-derived NO_x emissions and integrated oil and
901 gas production highlights the intrinsic link between emissions and production volumes, offering
902 crucial insights for environmental management and policy decisions in the OG sector. In addition,
903 our study underscores the co-emission of NO_x and CH₄ from oil and gas operations, despite their
904 distinct sources. Through an analysis of $\Delta\text{NO}_x/\Delta\text{CH}_4$ ratios, we have identified variations in
905 emissions characteristics, shedding light on the intricate interplay between pollutants and their
906 sources. Our findings contribute to a more comprehensive understanding of methane and NO_x
907 emissions in diverse geographic regions, providing insights of continuous monitoring and region-
908 specific strategies for air pollution management and mitigation efforts.

909

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911

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922

923 **Data Availability**

924

925 The TROPOMI NO₂ product is publicly available on the TROPOMI Open hub
926 (<http://www.tropomi.eu/data-products/data-access>, TROPOMI DataHub, 2022). The European
927 Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis be downloaded from
928 the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means>, ECMWF, 2022b). EDGARv6.1 emissions are provided by
929 https://edgar.jrc.ec.europa.eu/emissions_data_and_maps. CAMS-GLOB-ANT_v5.3 emissions are
930 available at <https://eccad3.sedoo.fr>. CAMS data can be downloaded from the Copernicus Climate
931 Data Store (<https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-atmospheric-composition-forecasts>, ECMWF, 2022a).

934

935 **Author contributions.** PNP and RG designed the study. PNP performed the analysis and
936 interpretation of the various satellite and emission datasets used in the study. RG supervised the
937 study and contributed to the data analysis and interpretation. MO contributed to the data analysis
938 of flaring and production data. PNP wrote the draft with inputs from all coauthors.

939

940 **Competing interests.** The authors declare that they have no conflict of interest.

941

942

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