LETTER

Attribution of the 2020 surge in atmospheric methane by inverse analysis of GOSAT observations

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Abstract

Atmospheric methane mixing ratio rose by 15 ppbv between 2019 and 2020, the fastest growth rate on record. We conduct a global inverse analysis of 2019–2020 Greenhouse Gases Observing Satellite observations of atmospheric methane to analyze the combination of sources and sinks driving this surge. The imbalance between sources and sinks of atmospheric methane increased by 31 Tg a$^{-1}$ from 2019 to 2020, representing a 36 Tg a$^{-1}$ forcing (direct changes in methane emissions and OH concentrations) on the methane budget away from steady state. 86% of the forcing in the base inversion is from increasing emissions (82 ± 18% in the nine-member inversion ensemble), and only 14% is from decrease in tropospheric OH. Half of the increase in emissions is from Africa (15 Tg a$^{-1}$) and appears to be driven by wetland inundation. There is also a large relative increase in emissions from Canada and Alaska (4.8 Tg a$^{-1}$, 24%) that could be driven by temperature sensitivity of boreal wetland emissions.

1. Introduction

Methane (CH$_4$) is a potent greenhouse gas. Its atmospheric concentration has almost tripled since preindustrial time, resulting in a 1.2 W m$^{-2}$ radiative forcing and a 0.6 °C increase in global mean surface air temperature (Szopa et al. 2021). The concentration plateaued in 2000–2007 but has since resumed its increase with acceleration in recent years (Nisbet et al. 2019). The annual rise in methane in 2020 was a record high of 13 ppbv, 50% larger than the 10 ppbv a$^{-1}$ growth rate between 2015 and 2019 (Blunden and Boyer 2020, NOAA 2021a, 2021b). Here we use an inversion of Greenhouse Gases Observing Satellite (GOSAT) observations of atmospheric methane to analyze the factors driving the 2020 surge.

Major anthropogenic sources of atmospheric methane include fossil fuels (oil, gas, and coal), livestock farming, rice cultivation, and waste management (Saunois et al. 2020). Other sources include wetlands, wildfires, and termites. Both wetlands and open fires have large interannual variability and may respond strongly to climate change (Ciais et al. 2013, Saunois et al. 2020). Loss of methane is mainly by atmospheric oxidation by the hydroxyl radical (OH) in the troposphere, which is determined by complex chemistry and is also subject to interannual variability (Holmes 2018). COVID-19 shutdowns in 2020 were a major perturbation to economic activity but the effect on methane is unclear. Oil/gas production declined which would be expected to decrease methane emission in some regions (Lyon et al. 2021), but reduced maintenance of infrastructure could have
caused increases (Laughner et al. 2021). Decreases in emissions of nitrogen oxides (\(NO_x \equiv NO + NO_2\)) from fuel combustion led to decreases in free tropospheric ozone (Bouarar et al. 2021, Steinbrecht et al. 2021), which would decrease OH concentrations (Miyazaki et al. 2021) and hence the methane sink (Laughner et al. 2021).

Satellite observations of column-averaged dry methane mixing ratios \(X_{CH4}\) by solar backscatter in the shortwave infrared offer a unique resource to investigate the global changes in methane sources and sinks through inverse analysis (Jacob et al. 2016). The GOSAT has been providing stable high-quality data since 2009 (Kuze et al. 2009, 2016, Buchwitz et al. 2015, Parker et al. 2020) and has been used extensively in inversions (Monteil et al. 2013, Cressot et al. 2014, Alexe et al. 2015, Pandey et al. 2016, Janardanan et al. 2020, Stanевич et al. 2021). The recently launched TROPOSpheric Monitoring Instrument (TROPOMI) provides a much higher data density of atmospheric methane (Hu et al. 2018, Lorente et al. 2021) but regional biases in the retrieval still limit its capability for global inversions (Qu et al. 2021). In this work, we use the GOSAT \(X_{CH4}\) retrieval in a Bayesian analytical inversion to quantify the methane emissions and OH concentrations in 2019 and 2020, and their differences, in order to explain the 2020 surge.

2. Methods

2.1. Observations and model

We use the University of Leicester version 9.0 GOSAT methane retrieval (Parker and Boesch 2020). This product shows good consistency (3.9 ppbv regional bias) with ground-based methane column measurements from the total carbon column observing network (TCCON) (Parker et al. 2020) and good consistency with surface data in estimating global methane sources through inversions (Lu et al. 2021, 2022). We use observations over both land and ocean, the latter in glint mode (Parker et al. 2020). We only include high-quality retrievals that pass the cloud-screening and post-retrieval quality filtering (‘\(xch4\_quality\_flag\) = 0’) (Parker et al. 2020).

We use the GEOS-Chem chemical transport model version 12.5.0 (10.5281/zenodo.3403111) at 2° \(\times\) 2.5° grid resolution to relate methane emissions to \(X_{CH4}\) as retrieved by GOSAT. Model transport is driven by NASA MERRA-2 archived meteorological fields. The model is essentially linear except for a small nonlinearity from the optimization of OH concentrations (Maasakkers et al. 2019).

We use the same prior emission estimates for 2019 and 2020 in the simulations, including the Global Fuel Exploitation Inventory version 2.0 (Scarpelli et al. 2022) for oil, gas, and coal exploitation; the EDGAR v4.3.2 inventory (Janssens-Maenhout et al. 2019) for other anthropogenic sources; and monthly mean 2019 wetland and lake emissions from the nine highest-performance members of the WetCHARTs v1.3.2 inventory ensemble (Ma et al. 2021). Other natural sources include open fire emissions in 2019 from the Global Fire Emissions Database version 4 (van der Werf et al. 2017), termite emissions from Fung et al. (1991), and geological seepage from Etiope et al. (2019) scaled to a global magnitude of 2 Tg a\(^{-1}\) from Hmiel et al. (2020). Loss of methane from oxidation by tropospheric OH is calculated with archived 3D climatological monthly fields of OH concentrations from a GEOS-Chem full-chemistry simulation (Wecht et al. 2014), with a corresponding methane lifetime of 10.5 years. Other minor sinks from oxidation by tropospheric Cl and in the stratosphere, and from uptake by soils, are the same as in Qu et al. (2021). Initial model concentrations of methane on 1 January 2019 and 1 January 2020 are obtained from a standard GEOS-Chem simulation using the prior emissions and a ten year spin-up and are adjusted by a global scaling factor of 0.97 and 1.01 respectively to match GOSAT \(X_{CH4}\). This scaling ensures consistent atmospheric concentrations between the model and observations at the beginning of each one-year simulation, and subsequent deviation of the model from the observations over the course of simulation year can then be attributed to errors in emissions and/or OH concentrations for that year. We use the quadratic regression in Turner et al. (2015) to remove high-latitude biases between GEOS-Chem and GOSAT.

2.2. Inverse analysis

We perform two independent Bayesian analytical inversions to estimate the sources and sinks of methane for 2019 and 2020. The inversions draw on GOSAT observations \(y\) together with the above prior estimates for emissions and OH concentrations. Because these prior estimates are the same for 2019 and 2020, and we do not update the prior error covariance matrix from one year to the next (see below), the differences in 2019 and 2020 inversion results are solely driven by observations. For each year, the inversion optimizes a state vector \(x\) consisting of (a) annual mean non-wetland methane emissions for land-containing 2° \(\times\) 2.5° grid cells (4020 elements), (b) monthly wetland methane emissions for 14 subcontinental regions (168 elements), and (c) annual methane loss frequency against oxidation by tropospheric OH (1 element). Previous work has shown that inversion of GOSAT observations can provide independent information on global emissions and OH concentrations as indicated by inspection of the posterior error correlation matrix (Maasakkers et al. 2019, Zhang et al. 2021) and can constrain the global tropospheric OH concentration with an accuracy of 3% (Zhang et al. 2018).

For each year, we perturb each of the state vector elements in 4189 GEOS-Chem simulations to construct the full Jacobian matrix \(K\). Since the relationship between \(x\) and \(y\) is approximately linear, \(K\)
describes the sensitivity of the methane observations to the state vector as simulated by GEOS-Chem. The posterior estimate with Gaussian error statistics is obtained by minimizing the scalar cost function $J(x)$:

$$J(x) = (x - x_a)^T S_a^{-1} (x - x_a) + \gamma (y - Kx)^T S_o^{-1} (y - Kx),$$  \hspace{1cm} (1)

where $x_a$ is the prior estimate of the state vector, $S_a$ is the prior error covariance matrix, $S_o$ is the observational error covariance matrix assumed to be diagonal, and $\gamma$ is a regularization parameter that accounts for the effect of unresolved correlation in the observational error. $S_o$ is constructed assuming a 10% error standard deviation for annual mean OH concentrations and a 50% error standard deviation for all emissions. Prior error correlations for monthly wetland emissions in the 14 subcontinental regions follow the calculation using the WetCHARTs model ensemble as described in Bloom et al (2017) and Zhang et al (2021). We do not allow results from the 2019 inversion to inform the 2020 inversion, so that the same $S_a$ applies to both years. Diagonal elements of $S_o$ are calculated using the residual error method (Heald et al 2004), resulting in a mean observational error standard deviation of 14 ppb. $\gamma$ is chosen to be 0.5 based on the L-curve test (figure S1).

The best posterior estimate of $x$ is given by (Rodgers 2000):

$$\hat{x} = x_a + (\gamma K^T S_o^{-1} K + S_a^{-1})^{-1} \gamma K^T S_o^{-1} (y - Kx_a),$$  \hspace{1cm} (2)

with posterior error covariance matrix $\hat{S}$:

$$\hat{S} = (\gamma K^T S_o^{-1} K + S_a^{-1})^{-1},$$  \hspace{1cm} (3)

The posterior solution can also be presented in reduced aggregated form for emission sectors and regions with a matrix $W$ to represent the linear transformation from the full state vector to the reduced state vector. The posterior estimate of the reduced state vector ($\hat{x}_{red}$) is computed as

$$\hat{x}_{red} = W \hat{x},$$  \hspace{1cm} (4)

and its posterior error covariance is given by

$$\hat{S}_{red} = W S W^T.$$  \hspace{1cm} (5)

The posterior error covariance matrix estimates error statistics under the assumption that the prior error covariance and other inversion parameters are correct, but there is uncertainty in these parameters. The assumption that prior errors on anthropogenic emissions are spatially uncorrelated can lead to an underestimate of posterior errors when aggregating emissions. As a complementary approach to estimate errors, we conducted an inversion ensemble varying parameters from our base inversion one at a time, including prior error standard deviations for anthropogenic emissions (30% and 60%), wetland emissions (20% and 60%), and OH concentrations (5% and 20%), and different regularization parameters ($\gamma = 0.1$ and 1). This results in a nine-member inversion ensemble including the base inversion, as listed in table S1. We take the standard deviation of results for that ensemble as a better estimate of the error on our posterior estimates.

### 3. Results

Figure 1 shows the global distribution of GOSAT annual mean $X_{CH4}$ differences between 2019 and 2020. The global mean increase from 2019 to 2020 is 13.4 ppbv. Some continental regions show particularly large increases including Central Africa, Europe, northern Brazil, and North America. China, the largest anthropogenic methane source (Janssens-Maenhout et al 2019), shows weaker increases. However, such year-to-year comparisons in methane concentrations may have sampling bias and not necessarily relate to changes in emissions because atmospheric transport also drives interannual variability (Bruhwiler et al 2017, Feng et al 2021). The inversion allows us to correct for the effect of transport and isolate the contributions from changes in sources and sinks.

Table 1 summarizes our inversion results. GEOS-Chem simulations using posterior emission and OH estimates show a 42 Tg increase (0.8%) in the atmospheric mass of methane from 2019 to 2020, corresponding to a global mean 13.7 ppbv increase in $X_{CH4}$ as would be sampled by GOSAT. Methane emissions increase by 31 Tg a$^{-1}$ from 2019 to 2020 in the base inversion while the sink from oxidation by tropospheric OH decreases by 1.0 Tg a$^{-1}$. $\hat{S}_{red}$ (equation (5)) shows that 2019–2020 changes in methane sources and sinks have a strong error correlation ($r = 0.97$) but that the posterior errors are small, with 90% confidence that the increase of methane emission is in the range of 25–37 Tg a$^{-1}$ and that the change in the methane sink due to changes in OH is in the range of −6–4 Tg a$^{-1}$. As pointed out above, this could underestimate the actual uncertainty in the solution. Analysis of the inversion ensemble as individual realizations of the solution, shown in tables 1 and S1, confirms the dominance of increase in methane emissions (mean ± standard deviation: 30 ± 5.5 Tg a$^{-1}$) as a principal driver for the 2019–2020 rise in methane concentrations, while finding that the change in the methane sink is a minor contributor (−2.6 ± 6.7 Tg a$^{-1}$).

The results from the inversion can be interpreted with a simple mass balance analysis. The global growth rate of tropospheric methane mass $dmn/dt$ is
Table 1. Global 2019–2020 methane budget from inverse analysis of GOSAT data.

| Component                  | 2019  | 2020  | 2020–2019$^a$ |
|----------------------------|-------|-------|---------------|
| Atmospheric mass (Tg)      | 5197  | 5238  | 41 (42 ± 0.67) |
| Total sources (Tg a$^{-1}$)| 572   | 603   | 31 (30 ± 5.5)  |
| Total sinks (Tg a$^{-1}$)  | 544   | 544   | −0.2 (−1.8 ± 6.7) |
| Tropospheric OH            | 469   | 468   | −1.0 (−2.6 ± 6.7) |
| Others$^b$                 | 75    | 76    | 0.8 |
| Growth rate (Tg a$^{-1}$)  | 28    | 59    | 31 (31 ± 1.2)  |
| Lifetime (OH) (a)$^d$      | 11.06 | 11.21 | 0.15 (0.20 ± 0.17) |

$^a$ Difference between 2020 and 2019. Values are from the base inversion, with means and standard deviations from the nine-member inversion ensemble in parentheses.

$^b$ Including oxidation in the stratosphere and by tropospheric Cl, and uptake by soils. These minor sinks are not optimized in the inversion and their small increase from 2019 to 2020 (same for all inversion ensemble members) is due solely to the increase in methane mass driving an increase in the oxidation loss rate.

$^c$ Growth rate in atmospheric methane as determined by the imbalance between sources and sinks.

$^d$ Lifetime of total atmospheric methane against oxidation by tropospheric OH.

determined by a balance between methane emission $E$, oxidation by tropospheric OH (loss frequency $k$), and other minor losses $L$ not optimized in the inversion:

$$\frac{dm}{dt} = E - km - L. \tag{6}$$

The change in imbalance or acceleration of methane growth ($d^2m/dt^2$) between 2019 and 2020 can be expressed as:

$$\frac{d^2m}{dt^2} = \frac{dE}{dt} - m\frac{dk}{dt} - k\frac{dm}{dt} - \frac{dL}{dt}, \tag{7}$$

where $dE/dt = E_{2020} - E_{2019}$ is the change in methane emissions, $dm/dt = m_{2020} - m_{2019}$ is the change in methane mass, $dk/dt = k_{2020} - k_{2019}$ is the change driven by OH, and $dL/dt = L_{2020} - L_{2019}$ is the change due to other minor sinks. We define the first two terms in equation (7) as the forcing on the methane budget:

$$F = \frac{dE}{dt} - m\frac{dk}{dt}, \tag{8}$$

which describes the changes in methane emissions and OH concentrations that force the methane concentration away from first-order relaxation to steady state. $F$ can be largely derived from observations since it is given equivalently by $F = \frac{d^2m}{dt^2} + kdm/dt + dL/dt$. The other two terms in equation (7) represent the changes in methane loss due simply to changes in methane mass.

The base inversion results as given in table 1 show a 5.4% increase in global methane emissions ($dE/dt$) from 2019 to 2020 and a 1.2% decrease in area-weighted global mean tropospheric OH concentrations, which accounts for adjustments from both meteorological factors and emissions. The decrease in OH drives a $5 \text{Tg a}^{-1}$ ($−mdk/dt$) forcing of the methane budget to offset the increase in methane mass, which for constant OH would cause an increase in the sink of $4 \text{Tg a}^{-1}$ ($km/dt$). The $dL/dt$ term for other methane losses is small ($1 \text{Tg a}^{-1}$) and is in the model solely determined by increase in methane mass (no forcing). The forcing on the methane budget from 2019 to 2020 is thus $36 \text{Tg a}^{-1}$, of which $31 \text{Tg a}^{-1}$ (86%) is from emissions and $5 \text{Tg a}^{-1}$ (14%) is from the decrease in tropospheric OH in our base inversion. Changes in methane mass offset the forcing by $5 \text{Tg a}^{-1}$ and lead

Figure 1. Methane changes from 2019 to 2020 measured by the GOSAT satellite instrument as the difference in annual mean dry column mixing ratio ($X_{CH4}$) mapped on a $4^\circ \times 5^\circ$ grid. The global mean increase is 13.4 ppbv. 5% of the $4^\circ \times 5^\circ$ grid cells show decreases from 2019 to 2020. Areas in grey do not have observations in either 2019 or 2020.
to a methane growth rate of 31 Tg a\(^{-1}\). For our nine-member inversion ensemble, the contribution to the 36 Tg a\(^{-1}\) forcing from emissions is 30 ± 5.5 Tg a\(^{-1}\) (82 ± 18%), with OH contributing the remainder.

The 1.2% OH decrease from 2019 to 2020 in our base inversion (1.6 ± 1.5% in the nine-member inversion ensemble) is lower than the 2%–4% decrease inferred by Miyazaki \textit{et al} (2021) for the first half of 2020 based on chemical data assimilation of satellite observations and attributed to NO\(_x\) emission decreases from COVID-19 lockdowns. These lockdowns relaxed in the second half of 2020 and OH could have recovered. Laughner \textit{et al} (2021) found in a box model analysis that a 3% reduction in global mean OH concentration in 2020 could account for only half of the observed methane increase, which is consistent with our results that OH changes cannot explain most of the 2020 methane surge. Stevenson \textit{et al} (2021) argue that most of the methane increase from 2019 to 2020 is due to a 15% reduction in global NO\(_x\) emissions, based on model sensitivities of methane to NO\(_x\), but they did not consider the offsetting impact of reductions in CO emissions (Fry \textit{et al} 2012). In addition, a 15% reduction applied to global annual NO\(_x\) emissions in 2020 is likely excessive.

We went on to further analyze the GOSAT inversion results in terms of the sources contributing to the global 2019–2020 change in methane emissions. We find from the posterior error correlations and the spread of results in the inversion ensemble that we cannot robustly quantify the changes in the spatial distribution of emissions on the 2° × 2.5° model grid resolution, nor can we separate the contributions from different emission sectors including anthropogenic versus wetlands. However, we can separate the contributions from individual continental regions. Figure 2 and table 2 show those results. \(S_{red}\) for the base inversion finds only moderate error correlation between different regions (figure 2(a)) and the inversion ensemble also indicates consistent results for the major regions driving the change (table 2).

Figure 2(b) shows that Africa is the largest single contributor to the 2020 surge. It accounts for 48% of the global increase in methane emissions from 2019 to 2020 with the rest spread across other continental regions. Some regions show a decrease including China, the Contiguous United States (CONUS), South America, and Russia. These results are consistent across the inversion ensemble (table 2). Africa shows an increase of 15 Tg a\(^{-1}\) in methane emissions from 2019 to 2020, consistent with the 13 Tg a\(^{-1}\) increase reported in another inverse analysis of GOSAT observations (Feng \textit{et al} 2022). We attribute most of the increase to wetland emissions in East Africa (30° E–50° E, 15° S–10° N) due to the increases in rainfall by 20% (46 mm) in the first three seasons from 2019 to 2020 according to the tropical applications of meteorology using SATEllite and ground based observations (TAMSAT) (www.tamsat.org.uk/index.php/data). Consistent with the increase in rainfall, the water flows of the Congo-Oubangui River, which goes through wetlands in the Congo Basin, were much higher in 2020 than in previous years (World Meteorological Organization 2021). Flooding in 2020 was widespread, affecting 50% more East Africans than in 2019 (BBC 2020). Wetland methane emission in the tropics is dominantly controlled by water table depth, and interannual variability is primarily driven by precipitation and inundation (Bloom \textit{et al} 2010, Lunt \textit{et al} 2019). The rapid increase in livestock emissions in East Africa (Zhang \textit{et al} 2021) could also contribute to the surge.

Other regions also show significant changes from 2019 to 2020. The large relative increase of methane...
Table 2. Regional methane emissions and 2020–2019 differences.

| Region                        | Prior (Tg a⁻¹) | 2019 (Tg a⁻¹) | 2020 (Tg a⁻¹) | 2020–2019 (Tg a⁻¹) | (%) |
|-------------------------------|---------------|---------------|---------------|-------------------|-----|
| South America                 | 92            | 120           | 117           | −0.7 (−2.8 ± 0.98) | −2.3 (−2.4 ± 0.87) |
| Africa                        | 81            | 80            | 95            | 15 (14 ± 1.6)     | 18 (18 ± 1.9) |
| Oceania                       | 26            | 32            | 35            | 3.2 (2.7 ± 1.7)   | 10 (8.6 ± 5.4) |
| Europe                        | 34            | 32            | 37            | 4.6 (4.4 ± 0.68)  | 14 (14 ± 2.1) |
| Russia                        | 32            | 39            | 38            | −1.1 (−1.1 ± 0.39) | −2.9 (−2.7 ± 1.0) |
| China                         | 64            | 51            | 47            | −3.9 (−3.7 ± 0.47) | −7.8 (−7.3 ± 1.0) |
| India + Pakistan              | 38            | 47            | 50            | 3.5 (3.5 ± 0.53)  | 7.4 (7.4 ± 1.1) |
| CONUS                         | 34            | 44            | 42            | −2.0 (−1.8 ± 0.29) | −4.6 (−4.2 ± 0.57) |
| S + SE Asia                   | 22            | 29            | 31            | 2.0 (1.9 ± 0.40)  | 6.7 (6.5 ± 1.3) |
| Canada + Alaska               | 19            | 20            | 25            | 4.8 (4.9 ± 0.16)  | 24 (24 ± 0.81) |
| Middle East                   | 17            | 21            | 24            | 2.5 (2.5 ± 0.13)  | 12 (12 ± 0.64) |
| Mexico + Central America       | 14            | 19            | 19            | −0.49 (−0.54 ± 0.34) | −2.6 (−2.8 ± 1.8) |
| Central Asia                  | 11            | 16            | 18            | 2.5 (2.3 ± 0.35)  | 16 (15 ± 1.9) |
| Rest of the world             | 23            | 24            | 25            | 1.7 (1.4 ± 1.1)   | 7.3 (6.0 ± 4.5) |

*Values from the base inversion, with means and standard deviations from the nine-member inversion ensemble in parentheses. Prior and posterior emissions include both anthropogenic and natural sources.

emissions in Canada and Alaska (4.8 Tg a⁻¹ or 24%) can be attributed to a temperature-driven increase in wetland emissions as shown by WetCHARTs (figure S2). The decrease in China could reflect the continued decline of emissions from coal mines (Zhang et al 2021) and rice (Zhang et al 2020). The decrease in CONUS could reflect the continued decline of emissions from the oil/gas sector (Lu et al 2022). Although surface temperature increased in Siberia in 2020, which would lead to an increase in wetland emissions (figure S2), the posterior methane emissions show a slight decrease, consistent with Feng et al (2022). This could possibly be explained by a decrease of anthropogenic emissions. The increase in Europe could be explained by oil and gas leakage due to the lack of maintenance during the COVID-19 shutdown (S&P Global Commodity Insights 2020, Clean Air Task Force 2021).

4. Conclusions

We conducted a global inverse analysis of 2019–2020 GOASAT observations to analyze the factors driving the 2020 surge in atmospheric methane concentrations. The inversion shows an increase in the methane growth rate from 28 Tg a⁻¹ in 2019 to 59 Tg a⁻¹ in 2020, consistent with observations. This implies a forcing on the methane budget away from a steady state by 36 Tg a⁻¹ from 2019 to 2020, 86% (82 ± 18% in the nine-member inversion ensemble) of which is from the increase in emissions between the two years and the rest is from the decrease in tropospheric OH. Changes in methane mass offset the forcing by 5 Tg a⁻¹. The global mean OH concentration decreases by 1.2% (1.6 ± 1.5%) from 2019 to 2020, which could be due to reduced NOx emissions from COVID-19 decreases in economic activity but accounts for only a small fraction of the methane surge. We find that half of the increase in methane emissions from 2019 to 2020 is due to Africa. High precipitation and flooding in East Africa leading to increased wetland methane emissions could explain the increase. We also find a large relative increase in Canadian emissions, also apparently driven by wetlands. Our finding of wetlands as the principal driver for the 2020 surge could be a harbinger for the response of atmospheric methane to climate change.

Data availability statement

The GOSAT methane retrieval is available at www.leos.le.ac.uk/data/GHG/GOSAT/v9.0/CH4_GOS_OCP_R_v9.0_final_nceo_2009_2020.tar.gz (last accessed 3 May 2022).

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5285/18ef8247f52a4cb6a14013f8235cc1eb.

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