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Key Points:

- Northern Hemisphere atmospheric methane shows a summer increase not replicated by the GEOS-Chem model with its default sources and sinks
- The summer increase's timing and magnitude is determined by the magnitude, seasonality, and spatial distribution of NH wetland emissions
- Inversions of atmospheric methane observations should use a suitable wetland emission inventory and optimize hemispheric OH concentrations

Supporting Information:

Supporting Information may be found in the online version of this article.

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Interpreting the Seasonality of Atmospheric Methane

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Abstract Surface and satellite observations of atmospheric methane show smooth seasonal behavior in the Southern Hemisphere driven by loss from the hydroxyl (OH) radical. However, observations in the Northern Hemisphere show a sharp mid-summer increase that is asymmetric with the Southern Hemisphere and not captured by the default configuration of the GEOS-Chem chemical transport model. Using an ensemble of 22 OH model estimates and 24 wetland emission inventories in GEOS-Chem, we show that the magnitude, latitudinal distribution, and seasonality of Northern Hemisphere wetland emissions are critical for reproducing the observed seasonality of methane in that hemisphere, with the interhemispheric OH ratio playing a lesser role. Reproducing the observed seasonality requires a wetland emission inventory with $\sim 80 \text{ Tg a}^{-1}$ poleward of 10°N including significant emissions in South Asia, and an August peak in boreal emissions persisting into autumn. In our 24-member wetland emission ensemble, only the LPJ-wsl MERRA-2 inventory has these attributes.

Plain Language Summary The amount of methane, a powerful greenhouse gas, has been growing in Earth's atmosphere during the last decade, and scientists disagree about which methane sources and sinks are responsible for the growth. One clue into understanding methane's sources and sinks is their seasonality—their month-to-month cycles that happen every year. Measurements of atmospheric methane taken at the Earth's surface and using satellite instruments show a steep increase each summer in the Northern Hemisphere that is not replicated when methane is simulated in a global chemical transport model, indicating missing information about source and sink seasonalities. To investigate, we use that model to simulate 24 representations of methane's largest source, emissions from wetlands, and 22 representations of its largest sink, chemical loss by the hydroxyl radical (OH). We find that OH is unlikely to cause the summer increase and model bias, but the amount, spatial distribution, and seasonal cycles of global wetland emissions are the strongest drivers. We suggest that these characteristics are linked to the underlying mechanisms determining wetland area and methane production in wetland models. The results unveil the role of global wetlands in driving methane's seasonality and inform research to analyze methane's long-term trends.

1. Introduction

Methane (CH_4) is a greenhouse gas with a global warming potential 80 times that of CO_2 on 20-year time scales, and an atmospheric abundance that has been increasing at an accelerated pace in recent years (IPCC, 2021). Uncertainty in the methane budget makes it difficult to identify drivers of methane's recent growth (Kirschke et al., 2013; Saunio et al., 2020; Turner et al., 2017). Inverse analyses using atmospheric methane observations have been used extensively to quantify methane sources and sinks (Houweling et al., 2017; Jacob et al., 2016; Palmer et al., 2021), but require prior assumptions regarding the seasonality of these sources and sinks. Here, we show that the observed seasonality of atmospheric methane places basic constraints on the methane budget that should be reflected in prior estimates used for inversions.

The observed seasonality of atmospheric methane offers information on the methane budget (Chandra et al., 2017; Dowd et al., 2023; Kivimäki et al., 2019; Warwick et al., 2016) because several budget terms have strong seasonal variations, including emissions from wetlands (Delwiche et al., 2021; Ito et al., 2023; Parker

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et al., 2020; Rocher-Ros et al., 2023), rice cultivation (Zhang, Tian, et al., 2016; Zhang et al., 2020), manure (Chadwick et al., 2011), and fires (Van Der Werf et al., 2017), as well as losses to oxidation by the hydroxyl radical (OH) (Dlugokencky et al., 1997; Naus et al., 2021) and soil uptake (Murguía-Flores et al., 2018; Nazaries et al., 2013). Global chemical transport models used as forward models in inverse analyses have difficulty reproducing the observed seasonality of atmospheric methane (Maasakkers et al., 2019; Pickett-Heaps et al., 2011; Warwick et al., 2016).

Inverse analyses either seek to correct the seasonalities of the methane budget terms or treat them as parameters, meaning they are not optimized and are instead considered part of the forward model error. Treating seasonalities as model parameters provides more power for the inversion to constrain other aspects of the methane budget, but bias in the prior estimate can persist to the inversion results (Yu et al., 2021). Even when seasonalities are optimized in the inversion, associated error covariances between budget terms can complicate the optimization (Bergamaschi et al., 2018; Tsuruta et al., 2023; Zhang et al., 2021).

Here, we use global surface and satellite observations of the seasonality of atmospheric methane, simulated with the GEOS-Chem chemical transport model, to better understand the roles of different methane budget terms in driving the seasonality and the implications for inverse analyses. Surface observations are from the remote sites of the NOAA network (Schuldt et al., 2023) and satellite observations are from a blended TROPOMI + GOSAT dry air column mole fraction (XCH_4) retrieval that combines the observational density of TROPOMI with the precision of GOSAT (Balasus et al., 2023). GEOS-Chem is widely used as forward model in global and regional inverse analyses (e.g., Chen et al., 2023; Feng et al., 2023; Worden et al., 2022; Zhang et al., 2022). We show that GEOS-Chem driven by its default prior budget terms has a large seasonal low bias in the Northern Hemisphere. We then explore the contribution of individual budget terms to this bias using simulation ensembles. This leads us to recommend improved choices of prior budget terms for inverse analyses.

2. Seasonality of Atmospheric Methane

Figures 1a and 1b shows the observed seasonal variations of surface methane in the Northern Hemisphere (NH) and Southern Hemisphere (SH). Observations are methane surface flask samples between 2015 and 2021 for years with at least 10 observations from the NOAA Marine Boundary Layer (MBL) Reference (NOAA GML, 2023) accessed via CH_4 GLOBALVIEWplus v5.1 ObsPack (Schuldt et al., 2023). The seasonality is highly consistent from year to year. The SH February–March minimum and August–September maximum can simply be explained by the OH sink, and are similar to those of methyl chloroform, which is commonly used as a global OH proxy (Patra et al., 2021). The NH seasonality is more complex, featuring a sharp July minimum rather than a smooth seasonal cycle in opposite phase to the SH.

Figure 1 also compares the NOAA observations to the methane seasonality simulated by GEOS-Chem for 2019 with its default sources and sinks used as prior estimates in recent inverse analyses. GEOS-Chem is sampled at the NOAA sites and the hemispheric means are computed with the same procedure used with the observational data. Table 1 shows the methane sources and sinks used in the default simulation, and compares with the multi-model bottom-up estimates for 2017 compiled by the Global Carbon Project (Saunois et al., 2020). The GCP has a larger global source mainly because it assumes large emissions from lakes, but these are not supported by top-down inversion estimates (Saunois et al., 2020). We use GEOS-Chem version 14.1.0 (<https://doi.org/10.5281/zenodo.7600404>) at $2^\circ \times 2.5^\circ$ horizontal resolution with NASA MERRA-2 assimilated meteorological data. Initial conditions on 1 December 2018, are from a 34-year GEOS-Chem simulation that uses time-varying gridded NOAA surface methane observations as its lower boundary condition. This initializes the stratosphere, in which transport time scales are several years (Chabrillat et al., 2018; Mooring et al., 2024). To account for regional emissions-driven methane enhancements not resolved by the surface boundary condition, we conduct a 1-month spinup for December 2018. Then, we calculate the XCH_4 bias at the last timestep as zonally averaged TROPOMI + GOSAT land observations minus GEOS-Chem, apply a $3^\circ \times 3^\circ$ rolling mean, and subtract that bias from the modeled XCH_4 . The resulting initialization concentrations are unbiased compared to surface and satellite methane observations in the NH and SH.

The GEOS-Chem seasonality in the SH is consistent with the NOAA observations (Figure 1b). A gradual departure from observations can be attributed to a global bias in the default bottom-up sources and/or sinks used in GEOS-Chem. Such a bias is expected (Saunois et al., 2020) and would be corrected in an inversion (Zhang et al., 2021). The lack of seasonal dependence of the bias indicates that the driver of SH seasonality—mainly loss

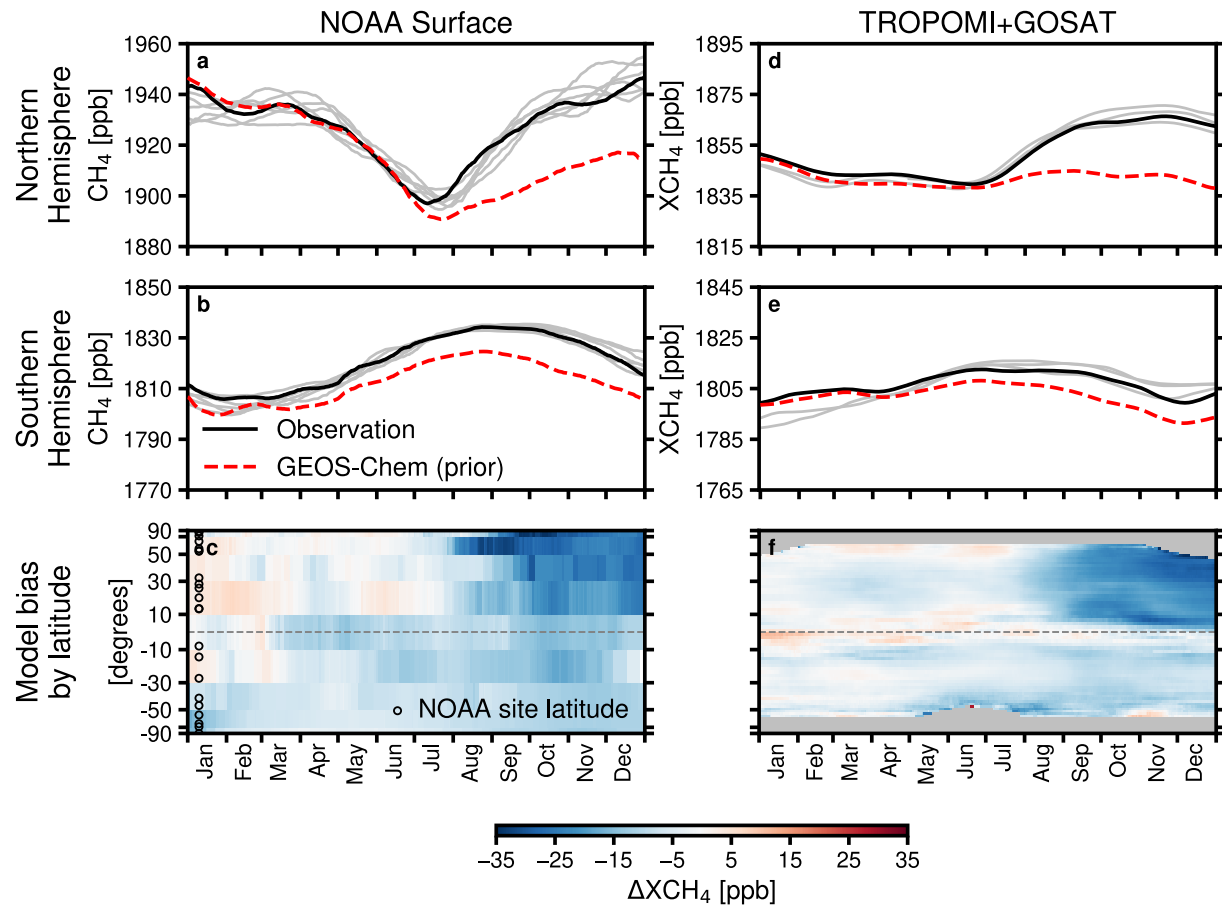


Figure 1. Seasonality of atmospheric methane concentrations in the Northern and Southern Hemispheres. The 2019 observations from the NOAA remote surface sites (<https://gml.noaa.gov/ccgg/mb1/mb1.html>) and from blended TROPOMI + GOSAT satellite retrievals of the dry air column mole fraction XCH₄ (Balasus et al., 2023) are compared to the GEOS-Chem model driven by its default budget terms (Table 1) and sampled in the same way as the observations. Panels (a) and (b) show the daily hemispheric averages from the NOAA Marine Boundary Layer (MBL) Reference, constructed from the mean of each day's observations across all sites in the hemisphere. Panels (d) and (e) show valid TROPOMI + GOSAT observations over land, discarding observations above 60°N and below 60°S, which have high uncertainty. To create the curves, satellite retrievals are binned and then averaged into GEOS-Chem 2° × 2.5° grid cells each day. Daily, area-weighted zonal means are then created from the binned data. Curves in (a, b, d, e) show results from two passes of a 30-day moving average applied to the raw data, with black curves denoting observations and red dashed curves representing model results. Gray lines denote interannual variability for 2015–2021 NOAA measurements and for May 2018–December 2021 TROPOMI + GOSAT retrievals (the TROPOMI record starts in May 2018). Each year's data are uniformly adjusted so that year's annual mean matches the 2019 annual mean, removing the interannual trend while maintaining the seasonal cycle. Panel (c) shows the model bias (model minus observations) in surface concentrations compared to NOAA MBL observations in 20° latitude bands, and panel (f) shows the same compared to TROPOMI + GOSAT XCH₄. Data in (c) and (f) is plotted as sine latitude. Note different y-axes in panels (a, b, d, e).

to OH—is well represented in the model. On the other hand, the GEOS-Chem seasonality in the NH does not capture the sharp rise starting in July and the resulting offset persists for the rest of the year (Figure 1a).

Figures 1d and 1e shows the seasonality of XCH₄ in each hemisphere for the blended TROPOMI + GOSAT satellite observations and for GEOS-Chem sampled at the same locations. The blended retrieval improves TROPOMI's biases versus GOSAT and TCCON XCH₄, with downward corrections over winter land scenes north of 40°N due to low surface albedo (Balasus et al., 2023). Satellite retrievals poleward of 60° are discarded due to their uncertainty and seasonally inconsistent coverage. The seasonality is similar to that of the NOAA data. The satellite data have a smaller relative seasonal amplitude because of their lower range of latitudes and because of the dominance of the lower troposphere for the methane sink resulting from the strong temperature dependence of the CH₄ + OH rate constant. The model matches the observed seasonality until July but fails to reproduce the sharp rise starting that month.

Figures 1c and 1f further shows the seasonal and latitudinal dependence of the model bias relative to the NOAA and TROPOMI + GOSAT observations. The SH shows a weak negative bias slowly growing with time versus

Table 1
Global Methane Budget^a

Budget term	GEOS-Chem default (2019)	Global carbon project (2017)
Sources (Tg a ⁻¹)	528	747 [602–896]
Wetlands ^b	147 ^c	145 [100–183]
Other natural sources ^d	14	222 [143–306]
Agriculture and waste	240 ^e	213 [198–232]
Enteric fermentation and manure	121	115 [110–121]
Enteric fermentation	109	
Manure management ^b	12	
Landfills, wastewater	81 ^e	68 [64–71]
Rice cultivation ^b	38 ^e	30 [24–40]
Fossil fuels	84 ^f	135 [121–164]
Other anthropogenic	24 ^e	
Fires ^b	19 ^g	29 [24–38]
Sinks (Tg a ⁻¹)	545	625 [500–798]
Chemical loss (sink) ^b	511 ^h	595 [498–749]
Tropospheric OH ^b	471	
Stratospheric loss ^b	37	
Tropospheric Cl ^b	3	
Soil uptake (sink) ^b	34 ⁱ	30 [11–49]
Lifetime against tropospheric OH (years)	11.2	

Note. Indented categories and values are subcategories and subtotals. ^aGEOS-Chem default sources and sinks used as prior estimates in inversions, and bottom-up central estimates and ranges from the Global Carbon Project (GCP) (Saunio et al., 2020). ^bSeasonally varying in GEOS-Chem. ^cWetCHARTs version 1.3.3 ensemble (Bloom et al., 2017), using the mean of the nine best performing ensemble members (Ma et al., 2021). ^dTermites and other wild animals, water bodies, and geological seeps. The large GCP bottom-up estimate is due mostly to lakes and is not supported by top-down estimates (Saunio et al., 2020). ^eEDGAR v6 (Crippa et al., 2020) superseded by national estimates for the US, Canada, and Mexico (Maasakkers et al., 2016; Scarpelli et al., 2020; Scarpelli, Jacob, Moran, et al., 2022). ^fGFEI v2 (Scarpelli, Jacob, Grossman, et al., 2022) based on national totals reported to the United Nations Framework Convention on Climate Change (UNFCCC). ^gGFED version 4 (Van Der Werf et al., 2017). ^hChemical losses computed from GEOS-Chem oxidant fields including tropospheric OH from Wecht et al. (2014), stratospheric oxidants from Eastham et al. (2014), tropospheric Cl from Wang et al. (2019). GEOS-Chem has an atmospheric methane lifetime of 11.2 years from oxidation by tropospheric OH, consistent with the lifetime of 11.2 ± 1.3 years inferred from methyl chloroform observations (Prather et al., 2012). ⁱMeMo v1.0 global model (Murguía-Flores et al., 2018).

both surface and satellite. The NH bias versus the NOAA data starts in August with a sharp onset at 50°N–70°N, where four NOAA sites sample the North American and Asian air masses, and then spreads within a month to the rest of the hemisphere. No such latitudinal structure in the bias is found for the TROPOMI + GOSAT data, where onset of the bias is in August across the NH.

3. Drivers of Methane Seasonality

Here we aim to understand the drivers of the methane seasonality in the NH and the cause of the sharp mid-summer rise. Figure 2 shows the seasonal and latitudinal distributions of seasonally varying budget terms in GEOS-Chem including emissions from wetlands, rice cultivation, and fires, and loss to tropospheric OH. We focus on OH and wetlands as the dominant seasonally varying terms and use ensembles of independent estimates of these terms as estimates of uncertainty. We compare the resulting simulations to the TROPOMI + GOSAT observations, which are of particular value for inversions, focusing on the 10°–35°N and 35°–60°N latitude bands where discrepancies between model and observations are most prominent.

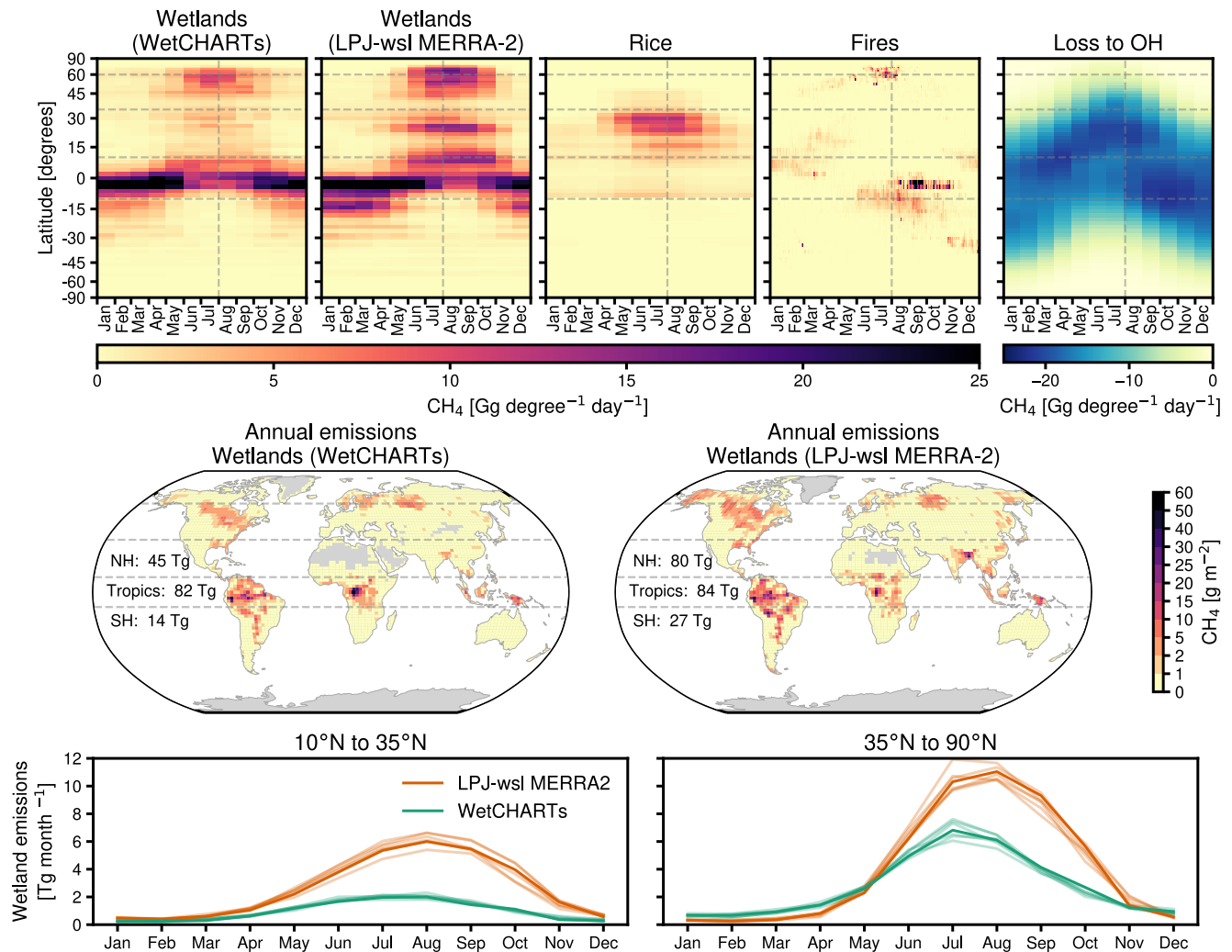


Figure 2. Seasonal cycles of the principle seasonally varying terms in the GEOS-Chem methane budget. Top row shows monthly zonal sums for 2019 plotted versus latitude. Horizontal dashed lines at 10°S, 10°N, 35°N, and 60°N delimit the latitude bands used in the analysis, and the vertical dashed line is at August 1st. The WetCHARTs wetland emissions are the mean of the nine best-performing ensemble members (Ma et al., 2021). Maps show the distribution of 2019 annual emissions from WetCHARTs (mean of the nine members of the high-performing ensemble) and LPJ-wsl MERRA-2, with annual total emissions for latitude bands 90°S–10°S, 10°S–10°N, and 10°N–90°N inset. The bottom row shows the corresponding monthly wetland emissions in the 10°–35°N and 35°–60°N latitude bands for 2015–2021 with 2019 in bold.

3.1. Loss by OH

Figure 3 compares TROPOMI + GOSAT XCH_4 observations to XCH_4 calculated by an ensemble of GEOS-Chem simulations using global 3-D monthly mean OH concentrations archived from 17 atmospheric chemistry models that contributed to the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP) (12 models; Naik et al., 2013) and the Chemistry-Climate Model Initiative (CCMI) Phase-1 (5 models; Hegglin et al., 2015; Orbe et al., 2020). Individual models are listed in Table S1 in Supporting Information S1 and described in Lamarque et al. (2013) for ACCMIP and Morgenstern et al. (2017) for CCMI. All simulations use the default WetCHARTs wetland emissions. All OH fields are scaled so that methane's tropospheric lifetime due to loss to OH matches the best estimate derived from methyl chloroform observations of 11.2 years (Prather et al., 2012). We do this for each archived OH field by performing a 1-year GEOS-Chem simulation without scaling OH, calculating the methane lifetime, and then applying a single global scaling factor to adjust OH concentrations to yield the expected methane lifetime of 11.2 years. This ensures that differences between the OH fields in our ensemble are due to their seasonality and distribution rather than different

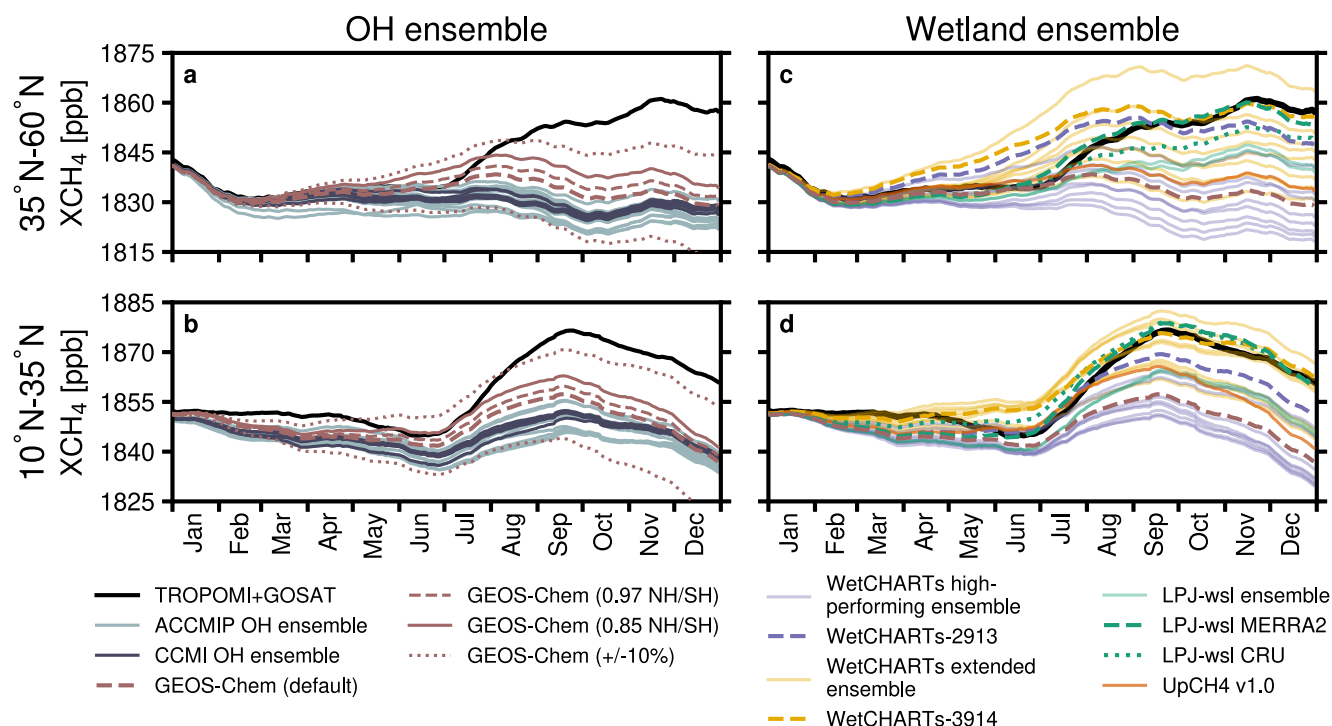


Figure 3. Seasonality of dry air column mole fraction of methane (XCH_4) for ensembles of OH and wetland simulations, compared to TROPOMI + GOSAT observations (black curves) for the $10^\circ N$ – $35^\circ N$ and $35^\circ N$ – $60^\circ N$ latitude bands. Panels (a) and (b) show results for the OH ensemble with colored curves representing results from different model simulations, and panels (c) and (d) show results for the wetland emissions ensemble. All OH concentrations except for the dotted lines ($\pm 10\%$) have been normalized to yield a methane lifetime of 11.2 years against oxidation by tropospheric OH. Brown curves in panels (a) and (b) show GEOS-Chem with its default OH which has a NH/SH ratio of 1.07, simulations with global mean OH adjusted $\pm 10\%$, and additional simulations with the NH/SH ratio adjusted to 0.97 and 0.85. Dashed and dotted curves in panels (c) and (d) show XCH_4 simulated with selected wetland ensemble members including WetCHARTs-2913, WetCHARTs-3914, LPJ-wsl MERRA-2, and LPJ-wsl CRU.

methane lifetimes. We also perform two simulations with the GEOS-Chem default OH field perturbed $\pm 10\%$, representing an estimate of global mean OH uncertainty (Prather et al., 2012).

Figure 3 shows that all OH models yield the same methane seasonality in the NH. All models capture the observed methane seasonality in the first half of the year and none capture the mid-summer rise, which would require a sharp decrease in OH not simulated by any of the models. Lower model NH/SH OH interhemispheric ratios could lead to a better comparison against observations. The model NH/SH OH ratios range from 1.07 to 1.40 (Table S1 and Figure S1 in Supporting Information S1; 1.07 for the GEOS-Chem default), while methyl chloroform observations imply a ratio of 0.97 ± 0.12 (Patra et al., 2014). We investigate this possibility by applying hemispheric scale factors to the GEOS-Chem OH fields to achieve annual mean NH/SH ratios of 0.97 and 0.85 in two separate simulations. This is accomplished by adjusting NH OH concentrations to get the desired annual mean NH/SH ratio, and then performing a GEOS-Chem simulation to calculate a global scaling factor which is applied to yield a tropospheric methane lifetime to OH of 11.2 years, as before. Figure 3 shows that lower OH concentrations in the NH allow for an increase of NH methane in mid-summer, leading to a better match at 10° – $35^\circ N$. However, at 35° – $60^\circ N$ the increase starts earlier than the observations, and the underestimate of observations in both latitude bands later in the summer is merely delayed. In addition, bias in the SH gets worse with higher OH in that hemisphere (Figure S2 in Supporting Information S1). Figure 3 also shows that while decreasing global OH by 10% produces a better match to end-of-year observations, it does not improve simulation of methane's seasonality.

3.2. Emissions From Wetlands

We conducted an ensemble of 24 simulations with different monthly wetland emission inventories. The ensemble includes the base run, (a) four inventories from the Lund–Potsdam–Jena Wald Schnee und Landschaft (LPJ-wsl) dynamic global vegetation model (Zhang, Zimmermann, et al., 2016) driven with assimilated meteorological data from either MERRA-2, CRU, ERA5, or ERA5 with MSWEP precipitation; (b) 18 inventories from the full

WetCHARTs v1.3.3 ensemble (Bloom et al., 2017), including the nine highest-performing (HP) WetCHARTs members identified in Ma et al. (2021); and (c) the UpCH4 v1.0 inventory applying machine learning to generalize flux tower observations (McNicol et al., 2023), all using the default GEOS-Chem OH concentrations. The base run inventory is the mean of the HP WetCHARTs members. Table S2 in Supporting Information S1 gives annual wetland emissions for each member and the peak month for boreal emissions north of 35°N.

Figure S2 in Supporting Information S1 shows methane in the SH and tropics for the wetland emissions ensemble. The simulations all exhibit similar seasonality to the GEOS-Chem default. In the tropics (10°S–10°N), LPJ-wsl MERRA-2 performs best among all flux estimates, while LPJ-wsl CRU and several members of the WetCHARTs extended ensemble are notably high-biased throughout the year.

Figures 3c and 3d shows NH methane simulated with the wetland ensemble. The spread of seasonality is much larger than for the ensemble of OH models, reflecting differences in the latitude-dependent timing and magnitude of wetland emissions. We find that the LPJ-wsl MERRA-2 is uniquely successful in reproducing the observed seasonality in the two latitude bands. LPJ-wsl CRU simulates 10°N–35°N seasonality well but underestimates observations north of 35°. UpCH4 is biased low throughout the NH and does not replicate observed seasonality at 35°–60°N. WetCHARTs members 2913 (ERA-Interim precipitation, GLWD wetland extent, and 170 Tg global emissions (Bloom et al., 2017)), and 3914 (ERA-Interim precipitation, GLOBCOVER wetland extent, and 208 Tg global emissions), both symbolized with dashed lines in Figure 3, perform best among the WetCHARTs ensemble members. However, both exhibit a large spring high bias at 35°–60°N, and WetCHARTs-2913 results in a subsequent underestimate compared to observations.

Several features in the magnitude and timing of emissions from LPJ-wsl MERRA-2 distinguish it from the other estimates. First, it has larger NH emissions than any of the other inventories, with 80 Tg north of 10°N and over half of those emissions occurring north of 35°N. Second, it has larger regional emissions from South Asia, with 5.3 Tg emitted over Bangladesh annually and 3.4 Tg in July–October versus 0.8 Tg and 0.4 Tg for WetCHARTs, contribute to better seasonality at 10°–35°N. Third, LPJ-wsl's boreal emissions have a delayed emissions onset, an August peak (vs. a July peak in WetCHARTs and UpCH4), and larger emissions through the boreal autumn, with 15 Tg in September–October north of 35°N versus 7 Tg for WetCHARTs.

The inventories differ in their meteorological inputs and representation of physical processes controlling emissions. LPJ-wsl's delayed summer peak and sustained autumn boreal emissions, in line with observed high-latitude wetland dynamics (Bao et al., 2021; Warwick et al., 2016) and global wetland methane flux observations (Chang et al., 2021), are due to its permafrost module (Zhang, Zimmermann, et al., 2016) which uses soil temperature for estimating heterotrophic respiration. In contrast, WetCHARTs' methanogenesis and heterotrophic respiration parameterizations (Bloom et al., 2016) rely on surface skin temperature. Soil temperature seasonal changes lag surface skin temperature changes, allowing LPJ-wsl to better represent freeze-thaw and permafrost dynamics (Wania et al., 2009), which in turn control the timing and magnitude of boreal wetland emissions through changes in soil moisture and temperature (Olefeldt et al., 2013; Treat et al., 2018). In addition, LPJ-wsl explicitly simulates snow cover as suppressing spring boreal wetland emissions (Pickett-Heaps et al., 2011). Although emissions from rice and wetlands are difficult to distinguish in South Asia (Peters et al., 2017), LPJ-wsl MERRA-2's higher emissions may stem from its inundation model and rice cultivation masking (Portmann et al., 2010). GLWD and GLOBCOVER used by WetCHARTs to define wetland area estimate smaller wetland maximum extent in the region compared to SWAMPS-GLWD used by LPJ-wsl (Ma et al., 2021; Poulter et al., 2017; Zhang et al., 2017). Comparing inundation extents reveals that WetCHARTs reports less inundated area than LPJ-wsl MERRA-2 in the region throughout the year. Among LPJ-wsl members, NH emissions driven by MERRA-2 meteorology are larger than those driven by CRU, ERA5, or ERA5-MSWEP because of differences in precipitation and temperature (Zhang et al., 2018).

3.3. Other Potential Drivers of Methane Seasonality

Rice emissions are concentrated in the 10°–35°N latitude band of South Asia, and EDGAR v6 emissions used in the GEOS-Chem default peak in July (Figure 2). Inversions of GOSAT and TROPOMI satellite data indicate that peak emissions should be shifted to later in the season (Palmer et al., 2021; Yu et al., 2023). We tested shifting EDGARv6 rice emissions seasonality to July–October and increasing the global annual total from 38 to 40 Tg and 42 Tg, as shown in Figure S3 in Supporting Information S1, but the effects are limited by the relatively small magnitude of rice emissions. Increasing the magnitude further would not be consistent with the range of Global

Carbon Project estimates (Table 1; Saunio et al., 2020) with its upper estimate of 40 Tg. In addition, Figure 1 shows no indication that the NH bias is initiated at rice-growing latitudes. Boreal wildfires are a NH source of atmospheric methane with a seasonal peak in late summer to fall (Liu et al., 2020; Nelson et al., 2021; Turetsky et al., 2004), but the source is relatively small (Figure 2). Carbon monoxide (CO) observations at the NOAA sites show interannual variability associated with high fire years but we cannot detect correlated interannual variability for methane in the NOAA data.

The soil sink for methane has a seasonality largely controlled by temperature, and the northern mid-latitudes exhibit the largest seasonal variations with peak uptake in summer (Curry, 2007; Murguia-Flores et al., 2018; Priemé & Christensen, 1997). Soil uptake in the NH north of 10°N is estimated at 19 Tg per year (Murguia-Flores et al., 2018), too small to significantly affect methane's seasonality. Emissions from landfills may vary seasonally and these variations need to be better understood, but the amplitude would likely be insufficient to account for methane's seasonality and they are often assumed aseasonal in global and regional inventories (e.g., Crippa et al., 2020; Maasakkers et al., 2023). Emissions due to building energy consumption peak in NH winter but are relatively small at an estimated 12 Tg a⁻¹ (Crippa et al., 2020). Manure management emissions are also relatively small (Table 1) and have well understood temperature dependence (Chadwick et al., 2011). GEOS-Chem model transport errors at the 2° × 2.5° resolution used here show no indication of systematic bias (Stanevich et al., 2020). Biases in non-seasonal sources can affect the magnitude of the seasonal bias but not significantly its phase. The results are not sensitive to choice of year due to the small interannual variability of wetland seasonalities (Figure 2).

4. Conclusions

Surface and satellite observations of atmospheric methane show a sharp mid-summer increase in the Northern Hemisphere (NH) not reproduced by the GEOS-Chem chemical transport model driven by its default representations of sources and sinks. Such a bias could affect global inverse analyses of atmospheric observations using these sources and sinks as prior estimates because errors propagate to optimized emissions (Yu et al., 2021). Using an ensemble of model simulations, we find that the seasonality and latitudinal distribution of NH wetland emissions are the most likely causes of the seasonal methane bias. In contrast, the seasonality of the OH sink is consistent across models. Other seasonal terms in the methane budget are not sufficiently large to have significant effect on the bias. Of the 24 wetland emission inventories considered in our ensemble, we find that the LPJ-wsl with MERRA-2 meteorology is the only one that reproduces the observed NH seasonality of atmospheric methane in different latitude bands. This is because of two attributes: (a) a large emission of 80 Tg a⁻¹ from NH wetlands north of 10°N, including a significant contribution at 10°–35°N from South Asia, and (b) the timing of boreal emissions with a delayed spring start, an August peak, and persistence into autumn, reflecting the use of soil temperature to estimate heterotrophic respiration and the representations of freeze-thaw dynamics and snow cover. Inverse analyses of atmospheric methane observations should check the seasonality of their prior simulation against the observations and select a wetland emission inventory that reproduces the observed seasonality. They should also optimize OH concentrations separately in the two hemispheres, with appropriate error correlations (Penn et al., 2023), because of the impact on the methane seasonality.

Data Availability Statement

The ACCMIP OH distributions can be downloaded from <http://catalogue.ceda.ac.uk/uuid/ded523bf23-d59910e5d73f1703a2d540> (Shindell et al., 2011). The CCMI-1 OH distributions can be downloaded from <https://catalogue.ceda.ac.uk/uuid/9cc6b94df0f4469d8066d69b5df879d5> (Hegglin et al., 2015). The blended TROPOMI + GOSAT methane satellite data can be downloaded from <https://dataverse.harvard.edu/dataverse/blended-tropomi-gosat-methane> (Balasus, 2023). The NOAA surface observations can be downloaded from <https://gml.noaa.gov/ccgg/data/ch4.html> (Schuldt et al., 2023). The GEOS-Chem code used in this study is archived at <https://zenodo.org/records/7600404> (Yantosca et al., 2023).

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