

Interpreting the seasonality of atmospheric methane

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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

25 **Abstract**

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

37

38 **Plain Language Summary**

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

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55

56 **1 Introduction**

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

66

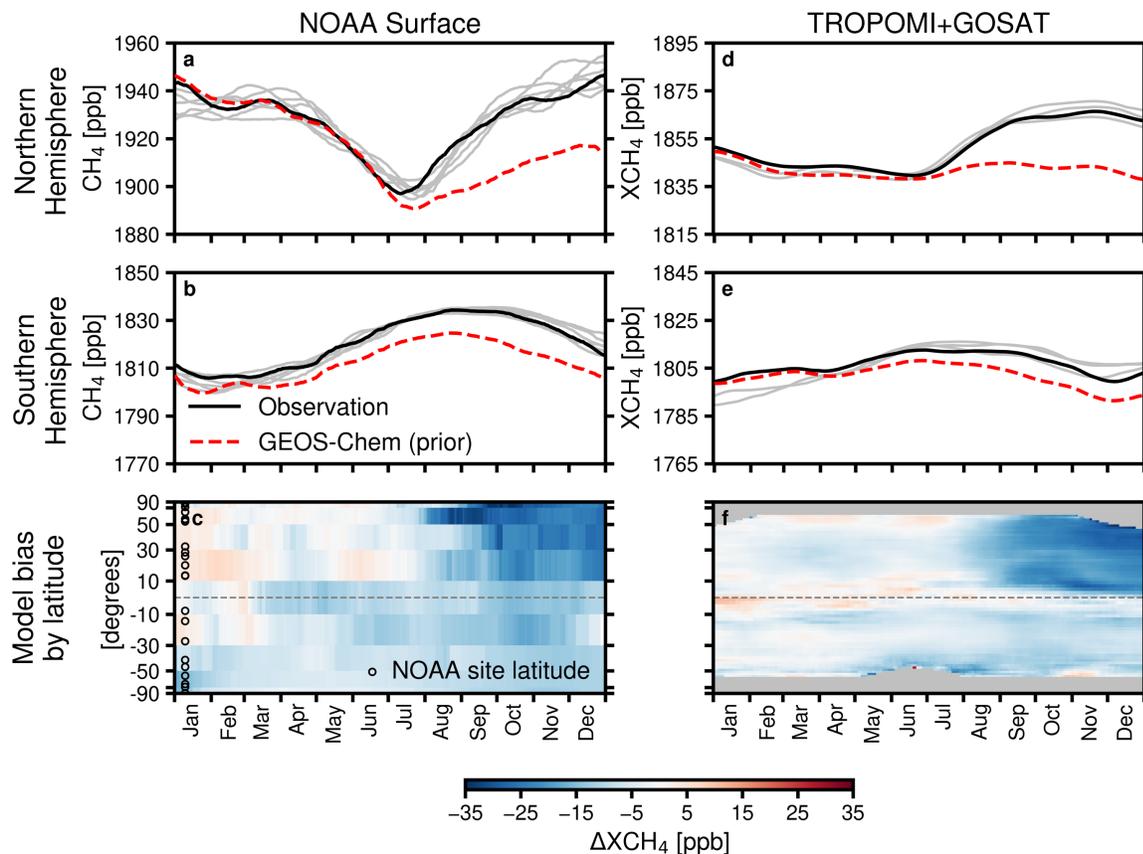
67 The observed seasonality of atmospheric methane offers important information on the methane
68 budget (Chandra et al., 2017; Dowd et al., 2023; Kivimäki et al., 2019; Warwick et al., 2016) because
69 several budget terms have strong seasonal variations, including emissions from wetlands (Delwiche et al.,
70 2021; Ito et al., 2023; Parker et al., 2020; Rocher-Ros et al., 2023), rice cultivation (Zhang et al., 2016a;
71 Zhang et al., 2020), manure (Chadwick et al., 2011), and fires (Van Der Werf et al., 2017), as well as
72 losses to oxidation by the hydroxyl radical (OH) (Dlugokencky et al., 1997; Naus et al., 2021) and soil

73 uptake (Murguia-Flores et al., 2018; Nazaries et al., 2013). Global chemical transport models used as
74 forward models in inverse analyses have difficulty reproducing the observed seasonality of atmospheric
75 methane (Maasackers et al., 2019; Pickett-Heaps et al., 2011; Warwick et al., 2016).

76
77 Inverse analyses either seek to correct the seasonalities of the methane budget terms or treat them
78 as parameters, meaning that they are not optimized and are instead considered to be part of the forward
79 model error. Treating seasonalities as model parameters provides more power for the inversion to
80 constrain other aspects of the methane budget, but bias in the prior estimate can persist to the inversion
81 results (Yu et al., 2021). Even when seasonalities are optimized in the inversion, the associated error
82 covariances between budget terms can complicate the optimization (Bergamaschi et al., 2018; Tsuruta et
83 al., 2023; Zhang et al., 2021), and

84
85 Here, we use global surface and satellite observations of the seasonality of atmospheric methane,
86 simulated with the GEOS-Chem chemical transport model, to better understand the roles of different
87 methane budget terms in driving the seasonality and the implications for inverse analyses. Surface
88 observations are from the remote sites of the NOAA network (Schuldt et al., 2023) and satellite
89 observations are from a blended TROPOMI+GOSAT dry air column mole fraction (XCH_4) retrieval that
90 combines the observational density of the TROPOMI instrument with the precision of the GOSAT
91 instrument (Balasus et al., 2023). GEOS-Chem is widely used as forward model in global and regional
92 inverse analyses (e.g., Chen et al., 2023; Feng et al., 2023; Worden et al., 2022; Zhang et al., 2022). We
93 show that GEOS-Chem driven by its default prior budget terms has a large seasonal bias in the northern
94 hemisphere. We then explore the contribution of individual budget terms to this bias using simulation
95 ensembles. This leads us to recommend improved choices of prior budget terms for use in inverse
96 analyses.

97



98

99 **Figure 1:** Seasonality of atmospheric methane concentrations in the Northern and Southern
 100 Hemispheres. The 2019 observations from the NOAA remote surface sites
 101 (<https://gml.noaa.gov/ccgg/mbl/mbl.html>) and from blended TROPOMI+GOSAT satellite retrievals of
 102 the dry air column mole fraction XCH₄ (Balasus et al., 2023) are compared to the GEOS-Chem model
 103 driven by its default budget terms (Table 1) and sampled in the same way as the observations. Panels (a)
 104 and (b) show the daily hemispheric averages from the NOAA Marine Boundary Layer (MBL) Reference,
 105 constructed from the mean of each day’s observations across all sites in the hemisphere. Panels (d) and (e)
 106 show valid TROPOMI+GOSAT observations over land, discarding observations above 60°N and below
 107 60°S, which are affected by high uncertainty. To create the curves, satellite retrievals are first binned and
 108 then averaged into GEOS-Chem 2° × 2.5° grid cells each day. Daily, area-weighted zonal means are then
 109 created from the binned data. Curves in (a, b, d, e) show results from two passes of a 30-day moving
 110 average filter, with black curves denoting observations and red dashed curves representing model results.
 111 Grey lines denote interannual variability for 2015 – 2021 NOAA measurements and for May 2018 –
 112 December 2021 TROPOMI+GOSAT retrievals (the TROPOMI record starts in May 2018), with the
 113 annual averages adjusted to match the 2019 mean. Panel (c) shows the model bias (model minus
 114 observations) in surface concentrations compared to NOAA MBL observations in 20° latitude bands, and
 115 panel (f) shows the same compared to TROPOMI+GOSAT XCH₄. Data in (c) and (f) is plotted as sine
 116 latitude. Note different y-axes in panels a, b, d, e.

117

118 2 Seasonality of atmospheric methane

119 Figure 1 (a and b) shows the observed seasonal variations of surface methane in the Northern
 120 Hemisphere (NH) and Southern Hemisphere (SH). Observations are methane surface flask samples

121 between 2015 and 2021 from the NOAA Marine Boundary Layer (MBL) Reference (NOAA GML, 2023)
 122 accessed via CH₄ GLOBALVIEWplus v5.1 ObsPack (Schuldt et al., 2023). The seasonality is highly
 123 consistent from year to year. The SH February-March minimum and August-September maximum can
 124 simply be explained by the OH sink, and are similar to those of methyl chloroform, which is commonly
 125 used as a global OH proxy (Patra et al., 2021). The NH seasonality is more complex, featuring a sharp
 126 July minimum rather than a smooth seasonal cycle in opposite phase to the SH.

127

Table 1: Global methane budget¹

Budget term	GEOS-Chem default (2019)	Global Carbon Project (2017)
Sources (Tg a⁻¹)	528	747 [602-896]
Wetlands*	147 ²	145 [100-183]
Other natural sources ³	14	222 [143-306]
Agriculture & waste	240 ⁴	213 [198-232]
Enteric fermentation & manure	121	115 [110-121]
Enteric fermentation	109	
Manure management*	12	
Landfills, wastewater	81 ⁴	68 [64-71]
Rice cultivation*	38 ⁴	30 [24-40]
Fossil fuels	84 ⁵	135 [121-164]
Other anthropogenic	24 ⁴	
Fires*	19 ⁶	29 [24-38]
Sinks (Tg a⁻¹)	545	625 [500-798]
Chemical loss (sink)*	511 ⁷	595 [498-749]
Tropospheric OH *	471	
Stratospheric loss*	37	
Tropospheric Cl*	3	
Soil uptake (sink)*	34 ⁸	30 [11-49]
Lifetime against tropospheric OH (years)	11.2	

* Assumed to be seasonally varying in GEOS-Chem.

¹ GEOS-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)² WetCHARTs version 1.3.3 ensemble (Bloom et al., 2017), using the mean of the nine best performing ensemble members (Ma et al., 2021)³ Termites 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)⁴ EDGAR v6 (Crippa et al., 2020) superseded by national estimates for the US, Canada, and Mexico (Maasakkers et al., 2016; Scarpelli et al., 2020; Scarpelli et al., 2022a)⁵ GFEI v2 (Scarpelli et al., 2022b) based on national totals reported to the United Nations Framework Convention on Climate Change (UNFCCC).⁶ GFED version 4 (Van Der Werf et al., 2017)⁷ Chemical 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).⁸ MeMo v1.0 global model (Murguia-Flores et al., 2018)

128

129 Figure 1 also compares the NOAA observations to the methane seasonality simulated by GEOS-

130 Chem for 2019 with its default sources and sinks used as prior estimates in recent inverse analyses.

131 GEOS-Chem is sampled at the NOAA sites and the hemispheric means are computed with the same

132 procedure used with the observational data. Table 1 shows the methane sources and sinks used in the

133 default simulation, and compares with the multi-model bottom-up estimates for 2017 compiled by the

134 Global Carbon Project (Saunio et al., 2020). The GCP has a larger global source mainly because it

135 assumes large emissions from lakes, but these are not supported by top-down inversion estimates

136 (Saunio et al., 2020). We use GEOS-Chem version 14.1.0 (doi.org/10.5281/zenodo.7600404) at

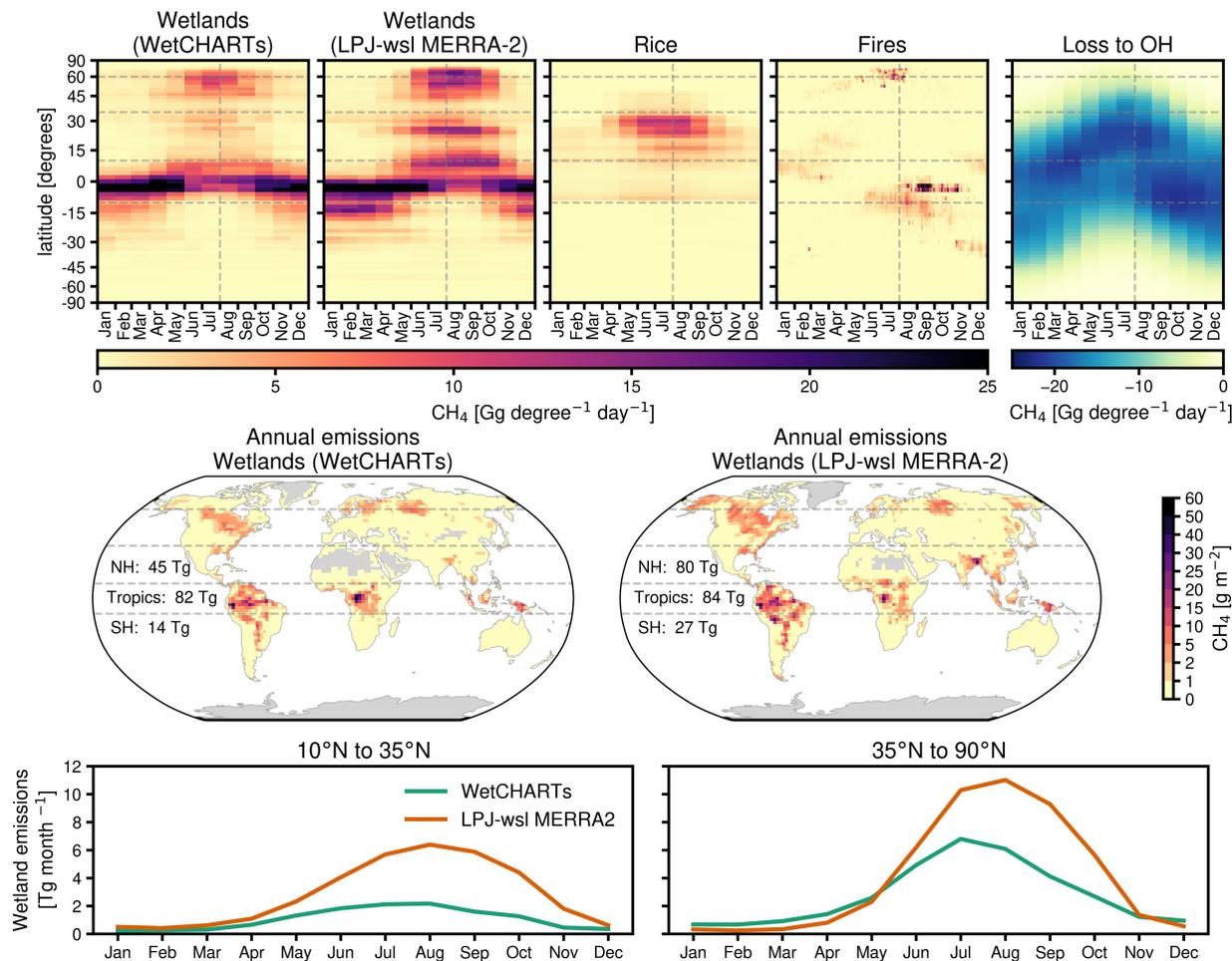
137 $2^\circ \times 2.5^\circ$ horizontal resolution with NASA MERRA-2 assimilated meteorological data. Initial conditions
138 on December 1, 2018, are from a 34-year GEOS-Chem simulation that uses time-varying gridded NOAA
139 surface methane observations as its lower boundary condition. We do this to properly initialize the
140 stratosphere, in which transport time scales are several years (Mooring et al., 2024). To account for
141 regional emissions-driven methane enhancements not adequately resolved by the surface boundary
142 condition, we conduct a 1-month spinup for December 2018 and then apply a bias correction to the 3-D
143 methane mole fractions at the spinup's last timestep using zonally averaged TROPOMI+GOSAT
144 observations over land grid cells. The resulting initialization is unbiased with respect to surface and
145 satellite methane observations in the NH and SH.

146
147 The GEOS-Chem seasonality in the SH is consistent with the NOAA observations (Figure 1b).
148 There is a gradual departure from the observations that can be attributed to a global bias in the default
149 bottom-up sources and/or sinks used in GEOS-Chem. Such a bias is expected (Saunio et al., 2020) and
150 would be corrected in an inversion (Zhang et al., 2021). The lack of seasonal dependence of the bias
151 indicates that the driver of SH seasonality – mainly loss to OH – is well represented in the model. On the
152 other hand, the GEOS-Chem seasonality in the NH does not capture the sharp rise starting in July and the
153 resulting offset persists for the rest of the year (Figure 1a).

154
155 Figure 1 (d and e) shows the seasonality of XCH_4 in each hemisphere for the blended
156 TROPOMI+GOSAT satellite observations (Balasus et al., 2023) and for GEOS-Chem sampled at the
157 same locations. The seasonality is similar to that in the NOAA data. The satellite data have a smaller
158 relative seasonal amplitude because of their lower range of latitudes and because of the dominance of the
159 lower troposphere for the methane sink resulting from the strong temperature dependence of the $CH_4 +$
160 OH rate constant. The model matches the observed seasonality until July but fails to reproduce the sharp
161 rise starting that month.

162
163 Figure 1 (c and f) further shows the seasonal and latitudinal dependence of the model bias relative
164 to the NOAA and TROPOMI+GOSAT observations. The SH shows a weak negative bias slowly growing
165 with time versus both surface and satellite. The NH bias versus the NOAA data starts with a sharp onset
166 at $50^\circ N$ - $70^\circ N$ in August that then spreads within a month to the rest of the hemisphere. No such
167 latitudinal structure in the bias is found for the TROPOMI+GOSAT data (restricted to south of 60°),
168 where onset of the bias is in August across the NH.

169 **3 Drivers of methane seasonality**



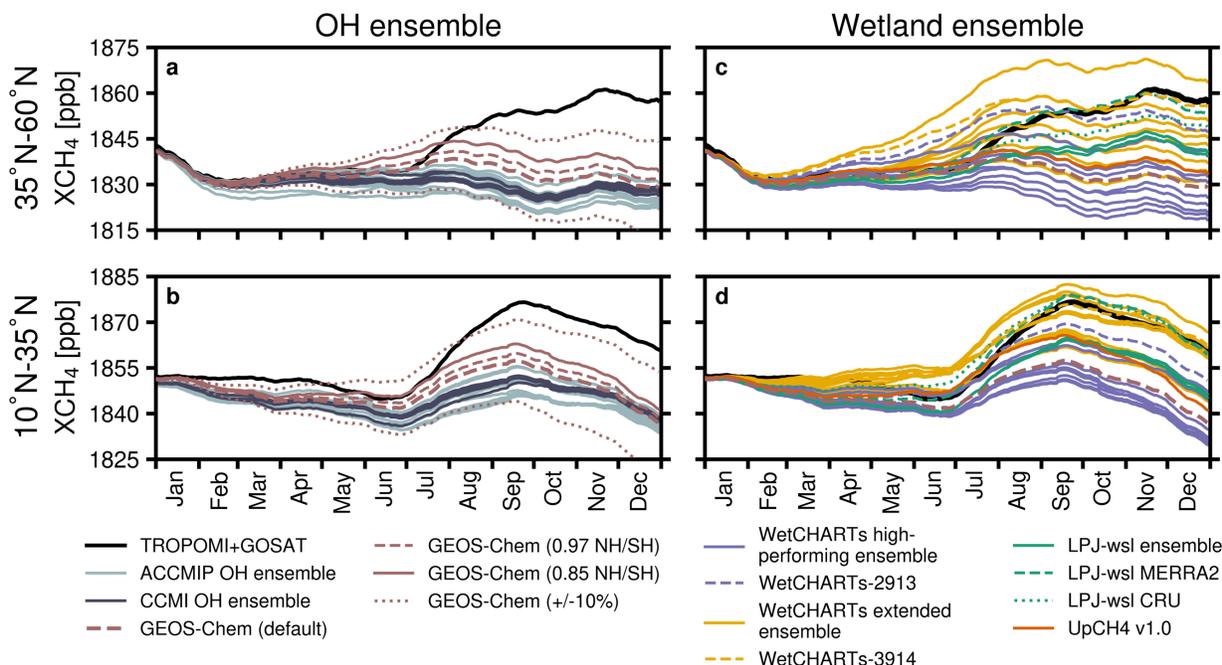
170
 171 **Figure 2:** Seasonal cycles of major seasonally varying terms in the GEOS-Chem methane budget for
 172 2019. Top row shows monthly zonal sums plotted versus latitude. Horizontal dashed lines at 10°S, 10°N,
 173 35°N, and 60°N delimit the latitude bands used in the analysis, and the vertical dashed line is at August
 174 1st. The WetCHARTs wetland emissions are the mean of the nine best-performing ensemble members
 175 (Ma et al., 2021). Maps show the distribution of annual emissions from WetCHARTs (mean of the nine
 176 members of the high-performing ensemble) and LPJ-wsl MERRA-2, with annual total emissions for
 177 latitude bands 90°S-10°S, 10°S-10°N, and 10°N-90°N inset. The bottom row shows the corresponding
 178 monthly wetland emissions in the 10°-35°N and 35°-60°N latitude bands.

179
 180 Here we aim to understand the drivers of the methane seasonality in the NH and the cause of the
 181 sharp mid-summer rise. Figure 2 shows the seasonal and latitudinal distributions of seasonally varying
 182 budget terms in GEOS-Chem including emissions from wetlands, rice cultivation, and fires, and loss to
 183 tropospheric OH. We focus on OH and wetlands as the dominant seasonally varying terms and use
 184 ensembles of independent estimates of these terms as estimates of uncertainty. We compare the resulting
 185 simulations to the TROPOMI+GOSAT observations, which are of particular value for inversions,
 186 focusing on the 10°-35°N and 35°-60°N latitude bands where discrepancies between model and
 187 observations are most prominent.

189 Loss by OH

190 Figure 3 compares TROPOMI+GOSAT XCH₄ observations to XCH₄ calculated by an ensemble
191 of GEOS-Chem simulations using global 3-D monthly mean OH concentrations archived from 17
192 different atmospheric chemistry models that contributed to the Atmospheric Chemistry and Climate
193 Model Intercomparison Project (ACCMIP) (12 models; Naik et al., 2013) and the Chemistry-Climate
194 Model Initiative (CCMI) Phase-1 (5 models; Hegglin et al., 2015; Orbe et al., 2020). Individual models
195 are listed in Table S1 and are described in Lamarque et al. (2013) for ACCMIP and Morgenstern et al.
196 (2017) for CCMI. All OH fields are scaled so that methane's tropospheric lifetime due to loss to OH
197 matches the best estimate derived from methyl chloroform observations of 11.2 years (Prather et al.,
198 2012). We do this for each archived OH field by performing a 1-year GEOS-Chem simulation without
199 scaling OH, calculating the methane lifetime, and then applying a single global scaling factor to adjust
200 OH concentrations to yield the expected methane lifetime of 11.2 years. This ensures that differences
201 between the OH fields in our ensemble are due to their seasonality and distribution, and not due to
202 differences in methane lifetime. In addition, we perform two simulations with the GEOS-Chem default
203 OH field perturbed $\pm 10\%$, representing an estimate of the uncertainty for global mean OH (Prather et al.,
204 2012).

205
206 Figure 3 shows that all OH models yield the same methane seasonality in the NH. All models
207 capture the observed methane seasonality in the first half of the year and none capture the mid-summer
208 rise, which would require a sharp decrease in OH not simulated by any of the models. However, there is
209 evidence that lower model NH/SH OH interhemispheric ratios can lead to a better comparison against
210 observations. The model NH/SH OH ratios range from 1.07 to 1.40 (Table S1 and Figure S1; 1.07 for the
211 GEOS-Chem default), while methyl chloroform observations imply a ratio of 0.97 ± 0.12 (Patra et al.,
212 2014). We investigate this possibility by applying hemispheric scale factors to the GEOS-Chem OH fields
213 to achieve annual mean NH/SH ratios of 0.97 and 0.85 in two separate simulations. This is accomplished
214 by adjusting NH OH concentrations to get the desired annual mean NH/SH ratio, and then performing a
215 GEOS-Chem simulation to calculate a global scaling factor which is applied to yield a tropospheric
216 methane lifetime to OH of 11.2 years, as before. Figure 3 shows that lower OH concentrations in the NH
217 allow for an increase of NH methane in mid-summer, leading to a better match at $10^\circ - 35^\circ\text{N}$. However, at
218 $35^\circ - 60^\circ\text{N}$ the increase starts earlier than the observations, and the underestimate of observations later in
219 the summer is merely delayed. In addition, bias in the SH gets worse with higher OH in that hemisphere
220 (Figure S2). Figure 3 also shows that decreasing global OH by 10% produces a better match to end-of-
221 year observations in our simulations, but the seasonal cycle amplitude is severely underestimated.
222 Adjusting OH within its $\pm 10\%$ uncertainty does not improve simulations of methane's seasonality.
223



224
 225 **Figure 3:** Seasonality of dry air column mole fraction of methane (XCH_4) for ensembles of OH and
 226 wetland simulations, compared to TROPOMI+GOSAT observations (black curves) for the $10^\circ N-35^\circ N$
 227 and $35^\circ N-60^\circ N$ latitude bands. Panels (a) and (b) show results for the OH ensemble with colored curves
 228 representing results from different model simulations, and panels (c) and (d) show results for the wetland
 229 emissions ensemble. All OH concentrations except for the dotted lines ($\pm 10\%$) have been normalized to
 230 yield a methane lifetime of 11.2 years against oxidation by tropospheric OH. Brown curves in panels (a)
 231 and (b) show GEOS-Chem with its default OH which has a NH/SH ratio of 1.07, simulations with global
 232 mean OH adjusted $\pm 10\%$, and additional simulations with the NH/SH ratio adjusted to 0.97 and 0.85.
 233 Dashed and dotted curves in panels (c) and (d) show XCH_4 simulated with selected wetland ensemble
 234 members including WetCHARTs-2913, WetCHARTs-3914, LPJ-wsl MERRA-2, and LPJ-wsl CRU.

235 Emissions from wetlands

236 We conducted an ensemble of 24 simulations with different monthly wetland emission
 237 inventories. In addition to the base run, the ensemble includes (1) four inventories from the Lund–
 238 Potsdam–Jena Wald Schnee und Landschaft (LPJ-wsl) dynamic global vegetation model (Zhang et al.,
 239 2016b) driven with assimilated meteorological data from either MERRA-2, CRU, ERA5, or ERA5 with
 240 MSWEP precipitation; (2) 18 inventories from the full WetCHARTs v1.3.3 ensemble (Bloom et al.,
 241 2017), including the nine highest-performing (HP) WetCHARTs members identified in Ma et al. (2021);
 242 and (3) the UpCH4 v1.0 inventory applying machine learning to generalize flux tower observations
 243 (McNicol et al., 2023). The inventory in our base run is the mean of the HP WetCHARTs members. Table
 244 S2 gives the annual wetland emissions for each member and the peak month for boreal emissions north of
 245 $35^\circ N$.

247 Figure S2 shows methane in the Southern Hemisphere and the tropics for the wetland emissions
 248 ensemble. The simulations all exhibit similar seasonality to the GEOS-Chem default. In the tropics
 249 ($10^\circ S - 10^\circ N$), LPJ-wsl MERRA-2 performs best among all flux estimates, while LPJ-wsl CRU and
 250 several members of the WetCHARTs extended ensemble are notably high-biased throughout the year.

252 Figure 3 (c and d) shows NH methane simulated with the wetland ensemble. The spread of
 253 seasonality is much larger than for the ensemble of OH models, reflecting differences in the latitude-

254 dependent timing and magnitude of wetland emissions. We find that the LPJ-wsl MERRA-2 is uniquely
255 successful in reproducing the observed seasonality in the two latitude bands. LPJ-wsl CRU simulates
256 10°N – 35°N seasonality well but underestimates observations north of 35°. UpCH4 is biased low
257 throughout the NH and does not replicate observed seasonality at 35°-60°N. WetCHARTs members 2913
258 and 3914, symbolized with dashed lines in Figure 3, perform best among the WetCHARTs ensemble
259 members. However, both exhibit a large spring high bias at 35°-60°N, and WetCHARTs-2913 results in a
260 subsequent underestimate compared to observations.

261
262 Several features in the magnitude and timing of emissions from LPJ-wsl MERRA-2 distinguish it
263 from the other estimates. First, it has larger NH emissions than any of the other inventories, with 80 Tg
264 north of 10°N and over half of those emissions occurring north of 35°N. Second, larger regional
265 emissions from South Asia compared to the other inventories, particularly in July – October, contribute to
266 better seasonality at 10°-35°N. Third, LPJ-wsl's boreal emissions have a delayed emissions onset, an
267 August peak (versus a July peak in WetCHARTs and UpCH4), and larger emissions through the boreal
268 autumn.

269
270 The inventories differ in their meteorological inputs and the degree to which they represent
271 physical processes controlling emissions. LPJ-wsl's delayed summer peak and sustained autumn boreal
272 emissions, in line with observed high-latitude wetland dynamics (Bao et al., 2021; Warwick et al., 2016)
273 and global wetland methane flux observations (Chang et al., 2021), are due to its permafrost module
274 (Zhang et al., 2016b) which allows the use of soil temperature for estimating heterotrophic respiration. In
275 contrast, WetCHARTs' methanogenesis and heterotrophic respiration parameterizations (Bloom et al.,
276 2016) rely on air temperature. Soil temperature seasonal changes lag air temperature changes, allowing
277 LPJ-wsl to better represent freeze-thaw and permafrost dynamics (Wania et al., 2009), which in turn
278 control the timing and magnitude of boreal wetland emissions through changes in soil moisture and
279 temperature (Olefeldt et al., 2013; Treat et al., 2018). In addition, LPJ-wsl explicitly simulates snow-
280 cover, which may suppress spring boreal wetland emissions (Pickett-Heaps et al., 2011). Although
281 emissions from rice and wetlands are difficult to distinguish in South Asia (Peters et al., 2017), LPJ-wsl
282 MERRA-2's higher emissions may stem from better representation of wetland area through its inundation
283 model and rice cultivation masking (Portmann et al., 2010). WetCHARTs, using GLWD as its wetland
284 map, may underestimate wetland extent in the region. Among LPJ-wsl members, NH emissions driven by
285 MERRA-2 meteorology are larger than those driven by CRU, ERA5, or ERA5-MSWEP because of
286 differences in precipitation and temperature (Zhang et al., 2018).

287

288 Other potential drivers of methane seasonality

289
290 Rice emissions are concentrated in the 10°-35°N latitude band of South Asia, and EDGAR v6
291 emissions used in GEOS-Chem by default peak in July (Figure 2). Inversions of GOSAT and TROPOMI
292 satellite data indicate that peak emissions should be shifted to later in the season (Palmer et al., 2021; Yu
293 et al., 2023). We tested shifting EDGARv6 rice emissions seasonality to July-October and increasing their
294 magnitude, as shown in Figure S3, but the effects are limited by the relatively small magnitude of rice
295 emissions. Increasing this magnitude further would not be consistent with the range of Global Carbon
296 Project estimates (Table 1). In addition, Figure 1 shows no indication that the NH bias is initiated at rice-
297 growing latitudes.

298 Boreal wildfires are a NH source of atmospheric methane with a seasonal peak in late summer to
299 fall (Liu et al., 2020; Nelson et al., 2021; Turetsky et al., 2004), but the source is relatively small
300 (Figure 2). Carbon monoxide (CO) observations at the NOAA sites show interannual variability
301 associated with high fire years but we cannot detect correlated interannual variability for methane in the
302 NOAA data.

303 The soil sink for methane has a seasonality largely controlled by temperature, and the northern
304 mid-latitudes exhibit the largest seasonal variations with peak uptake in summer (Curry, 2007; Murguia-
305 Flores et al., 2018; Priemé & Christensen, 1997). Soil uptake in the NH north of 10°N is estimated at 19
306 Tg per year (Murguia-Flores et al., 2018), which is too small to significantly affect the methane
307 seasonality. Emissions from landfills may vary seasonally and these variations need to be better
308 understood, but the amplitude would likely be insufficient to account for the methane seasonality and they
309 are often assumed aseasonal in global and regional inventories (e.g. Crippa et al., 2020; Maasakkers et al.,
310 2023). Emissions due to building energy consumption peak in NH winter but are relatively small at an
311 estimated 12 Tg a⁻¹ (Crippa et al., 2020). Emissions from manure management are also relatively small
312 (Table 1) and depend on temperature in a way that is well understood (Chadwick et al., 2011). GEOS-
313 Chem model transport errors at the 2° × 2.5° resolution used here show no indication of systematic bias
314 (Stanevich et al., 2020). Biases in non-seasonal sources can affect the magnitude of the seasonal bias but
315 not significantly its phase.
316

317 **3 Conclusions**

318 Surface and satellite observations of atmospheric methane show a sharp mid-summer increase in
319 the Northern Hemisphere (NH) that is not reproduced by the GEOS-Chem chemical transport model
320 driven by its default representations of sources and sinks. Such a bias could affect global inverse analyses
321 of atmospheric observations using these sources and sinks as prior estimates. Using an ensemble of model
322 simulations, we find that the seasonality and latitudinal distribution of NH wetland emissions are the most
323 likely causes of the seasonal methane bias. In contrast, the seasonality of the OH sink is consistent across
324 models. Other seasonal terms in the methane budget are not sufficiently large to have significant effect on
325 the bias. Of the 24 wetland emission inventories considered in our ensemble, we find that the LPJ-wsl
326 with MERRA-2 meteorology is the only one that reproduces the observed NH seasonality of atmospheric
327 methane in different latitude bands. This is because of two attributes: (1) a large emission of 80 Tg a⁻¹
328 from NH wetlands north of 10°N, including a significant contribution at 10°-35°N from South Asia, and
329 (2) the timing of boreal emissions with a delayed spring start, an August peak, and persistence into
330 autumn, reflecting the use of soil temperature to estimate heterotrophic respiration and the representation
331 of freeze-thaw dynamics and snow cover. These insights can inform studies of past and future
332 atmospheres. Prior wetland emission estimates used for inverse modeling should reflect the two attributes
333 named above. Optimization of OH concentrations as part of these inversions should separate the two
334 hemispheres, with appropriate error correlations (Penn et al., 2023).

335

336 **Acknowledgments**

337 This work was supported by the NASA Carbon Monitoring System (CMS) and the NOAA AC4
338 programs. Portions of this research were carried out at the Jet Propulsion Laboratory, California Institute
339 of Technology, under a contract with the National Aeronautics and Space Administration. We
340 acknowledge the modeling groups participating in ACCMIP and CCMi for making their simulations
341 available for this analysis, the joint WCRP SPARC/IGAC Chemistry-Climate Model Initiative (CCMI)
342 for organizing and coordinating the model data analysis activity, and the British Atmospheric Data Centre
343 (BADc) for collecting and archiving the CCMi model output.
344

345

346

347 **Open Research**

348 The ACCMIP OH distributions can be downloaded from
 349 <http://catalogue.ceda.ac.uk/uuid/ded523bf23d59910e5d73f1703a2d540> (Shindell et al., 2011). The
 350 CCMI-1 OH distributions can be downloaded from
 351 <https://catalogue.ceda.ac.uk/uuid/9cc6b94df0f4469d8066d69b5df879d5> (Hegglin et al., 2015). The
 352 blended TROPOMI+GOSAT methane satellite data can be downloaded from
 353 <https://dataverse.harvard.edu/dataverse/blended-tropomi-gosat-methane> (Balasus, 2023). The NOAA
 354 surface observations can be downloaded from <https://gml.noaa.gov/ccgg/data/ch4.html> (Schuldt et al.,
 355 2023). The GEOS-Chem code used in this study is archived at <https://zenodo.org/records/7600404>
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