

1 A top-down evaluation of bottom-up estimates to reduce uncertainty 2 in methane emissions from Arctic wetlands

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11 **Abstract.**

12 Wetlands are a major natural source of atmospheric CH₄, however, accurately estimating their emissions is difficult due
13 to the complex biogeochemical interactions and spatial heterogeneity of wetland environments. This study explores how a
14 combination of atmospheric inverse and process-based modelling can reduce the discrepancy in Arctic wetland estimates
15 between bottom-up and top-down approaches. We employed the Jena CarboScope global inversion system, incorporating prior
16 wetland fluxes simulated by the JSBACH land surface model, which is part of the Max Planck Institute Earth System Model
17 (MPI-ESM). We conducted a series of inversion experiments, each incorporating JSBACH-generated CH₄ fluxes based on
18 different CH₄ production Q₁₀ values, which represents the temperature dependence of CH₄ production. Additionally, we
19 examined the impact of changing the baseline f_{CH_4} fraction value, which defines the fraction of anaerobically mineralized
20 carbon converted to CH₄, while keeping all other JSBACH and inversion settings constant. Our findings show that, at a pan-
21 Arctic scale, using a CH₄ Q₁₀ value of 1.8 produces the best agreement between the two approaches. However, no single Q₁₀
22 value yielded optimal agreement between the simulated fluxes and the fluxes inferred from atmospheric observations across
23 all subregions. Instead, the best performance varied spatially, with different CH₄ production Q₁₀ values and baseline
24 f_{CH_4} fraction leading to a better flux agreement in specific areas. These results highlight the importance of using regionally
25 specific parameters to more accurately estimate wetland CH₄ emissions, and the potential of employing atmospheric inversions
26 to guide bottom-up process models towards regionally representative parameter settings.

27 **1. Introduction**

28 Methane (CH₄) is the second most important anthropogenic greenhouse gas and it is emitted from both natural and
29 anthropogenic sources. Combined wetlands and inland freshwaters are the largest natural source of CH₄ to the atmosphere,
30 accounting for about 28-37% (by bottom-up and top-down estimates, respectively) of the global total CH₄ emissions (Sauniois
31 et al., 2025). However, quantifying these emissions remains challenging due to the complexity of biogeochemical processes

32 and the spatial variability of these ecosystems. Constraining CH₄ budgets is particularly relevant in the Arctic-Boreal region,
33 which is warming faster than most other regions (Rantanen et al., 2022), and at the same time contains extensive wetlands and
34 permafrost landscapes storing significant amounts of soil carbon (Hugelius et al., 2024). Under warming conditions, this carbon
35 can be mobilized and potentially release substantial amounts of CH₄ into the atmosphere. Large uncertainties in Arctic CH₄
36 emission estimates limit our ability to quantify the region's contribution to the global CH₄ budget and its climate feedbacks.

37 Global and regional CH₄ emissions are estimated using both bottom-up or top-down approaches. Bottom-up methods,
38 including inventories, data-driven ecosystem flux upscaling and process-based models, provide detailed information with fine-
39 scale resolution for both, processes and spatial heterogeneity. Process-based models simulate CH₄ emissions by mathematically
40 representing ecosystem dynamics, biogeochemical cycles, and physical processes. However, extrapolating these estimates to
41 regional or global scales is challenging due to the strong spatial variability in wetland characteristics (e.g., extent, hydrology
42 and vegetation), as well as sensitivity of the models to parameterizations. Top-down approaches estimate net surface-
43 atmosphere CH₄ fluxes using atmospheric observations (in situ, flask and/or satellite measurements) in combination with prior
44 flux information (from process-based models and/or inventories), and atmospheric transport and chemistry models to link
45 surface sources with atmospheric observations. Their ability to provide accurate estimates of net surface-atmosphere fluxes is
46 limited by sparse observational coverage, particularly in remote regions, as well as by uncertainties in atmospheric transport,
47 prior flux estimates, and atmospheric CH₄ sink processes (Houweling et al., 2017). These limitations can lead to significant
48 uncertainties in the magnitude and spatial distribution of inferred emissions, which makes attributing fluxes to specific sources
49 or processes challenging. Still, despite these limitations, the inverse modeling approach allowed us to derive important
50 constraints on the global sources and sinks of CH₄ (Houweling et al., 2017).

51 Although both approaches are widely used, substantial discrepancies exist between bottom-up and top-down estimates of
52 CH₄ emissions. From 2010 to 2019, top-down approaches estimated global CH₄ emissions at 575 TgCH₄ y⁻¹ (553-586 TgCH₄
53 y⁻¹), whereas bottom-up estimates were approximately 15% higher, at 669 TgCH₄ y⁻¹ (512-849 TgCH₄ y⁻¹) (Saunio et al.,
54 2025). Similar differences are evident in the high-northern latitudes regions, where wetlands and inland waters dominate
55 emissions. In the Arctic-Boreal region, bottom-up estimates of 50 TgCH₄ y⁻¹ (29-71 TgCH₄ y⁻¹) contrast with top-down
56 estimates of 20 TgCH₄ y⁻¹ (15-24 TgCH₄ y⁻¹) (Hugelius et al., 2024).

57 Mechanistic modeling of net surface CH₄ emissions requires capturing a range of complex, interacting processes (Conrad,
58 1999; Moser et al., 2026; Riley et al., 2011). As a key parameter, the net CH₄:CO₂ production ratio is determined by the relative
59 importance of several biogeochemical processes, which in turn are dependent on environmental conditions, and a large range
60 of this production ratio has been observed (Knoblauch et al., 2018). As a consequence, global-scale land surface models often
61 represent anaerobic CH₄ production in a simplified way, i.e. as a first-order decay of soil organic matter with adjusted rate
62 constants, applying a fixed ratio of CH₄ versus CO₂ production (Guimberteau et al., 2018; Kleinen et al., 2020; Moser et al.,
63 2026; Ricciuto et al., 2021; Sellar et al., 2019). Here, the models can differ in whether the ratio applies to the CH₄ production
64 or emission.

65 Biogeochemical process models require balancing the inclusion of key mechanisms with limitations such as structural and
66 parameter uncertainty, spatial heterogeneity, sparse observational data, uncertain initial and boundary conditions, and
67 computational constraints (Riley et al., 2011). Regarding the simulation of CH₄ emissions, a higher CH₄:CO₂ ratio indicates a
68 greater dominance of CH₄ in production and emission relative to CO₂ (Chinta et al., 2024), while a higher CH₄ production Q₁₀
69 indicates that CH₄ production increases more rapidly with rising temperatures. As regional model sensitivity varies and site-
70 specific measurements may not be representative across broader areas, both the CH₄:CO₂ ratio and the CH₄ production Q₁₀ are
71 uncertain at large spatial scales. For example, increasing CH₄ production Q₁₀ in high-latitude regions can reduce simulated
72 CH₄ emissions by more than half, because the temperature-dependent component, scaled relative to a reference temperature of
73 295 K, leads to a decline in CH₄ production rate at the lower temperatures typical of these regions (Riley et al., 2011). As many
74 large-scale land surface models still rely on simplified, fixed CH₄ production fractions, their ability to accurately represent
75 observed spatiotemporal variability in CH₄:CO₂ production ratios across Arctic landscapes is therefore limited (Moser et al.,
76 2026). These differences in model structure, parameterization and initialization contribute strongly to relative high
77 uncertainties in wetland estimates (Poulter et al., 2017).

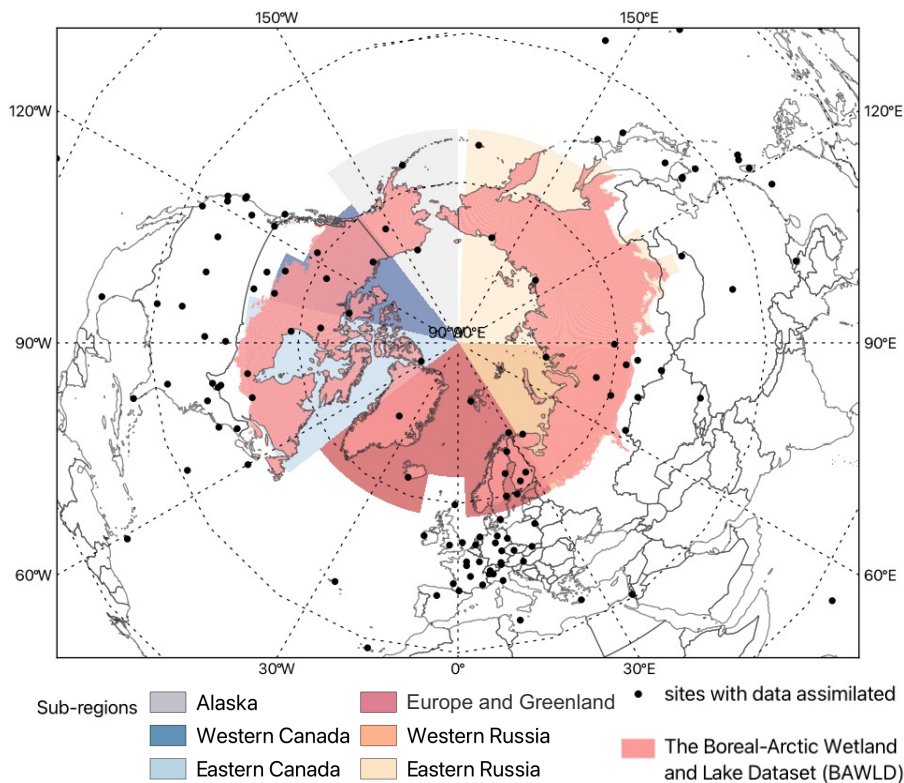
78 The JSBACH v3.2 model (Reick et al., 2021) that we apply in this study is taking the first approach and mechanistically
79 distinguish between methanogenesis and methanotrophy. In JSBACH v3.2, anaerobic decomposition and CH₄ oxidation are
80 temperature dependent and the CH₄:CO₂ production ratio is also assumed to follow a Q₁₀ temperature sensitivity (Kleinen et
81 al., 2020). This formulation allows the relative importance of the above-mentioned underlying biogeochemical processes
82 changes in space and time depending on the soil temperature. In addition, making the CH₄:CO₂ production ratio temperature
83 dependent allows us to additionally tune CH₄ versus CO₂ production across bioclimatic zones. Still, the optimum parameter
84 setting of the Q₁₀ value for this temperature dependency of the CH₄:CO₂ production ratio is still highly uncertain.

85 This study therefore explores novel concepts for using atmospheric inverse modeling to constrain parameter settings in
86 bottom-up estimates of wetland CH₄ emissions in the Arctic-Boreal region. Using the Jena CarboScope global inversion
87 system, we employed prior fluxes from the JSBACH land surface model (a component of the MPI Earth System Model) and
88 systematically varied key parameters that govern CH₄ production. Specifically, we tested a range of Q₁₀ values, which define
89 the temperature sensitivity of CH₄ production, and different f_{CH_4} baseline values, which determine the proportion of
90 anaerobically mineralized carbon converted to CH₄. However, a portion of the produced CH₄ is oxidized to CO₂. Since
91 transport pathways determine how much CH₄ is exposed to oxidation on its way to the surface, they reduce the resulting
92 CH₄:CO₂ emission ratio. We kept other model settings constant throughout these tests. Integrating these parameter sensitivity
93 experiments into the inversion framework allowed us to assess which parameterizations yield the most consistent fluxes with
94 atmospheric observations. This approach enables us to identify regionally representative parameter settings and guide
95 parameterizations that could improve the consistency between bottom-up process models and top-down constraints on Arctic-
96 Boreal wetland CH₄ emissions.

97 2. Methods

98 2.1. Region and time period of interest

99 Our Arctic-Boreal domain was defined based on The Boreal-Arctic Wetland and Lake Dataset – BAWLD (Olefeldt et al.,
100 2021), and we divided this region into 6 sub-regions for more detailed spatial analyses (Alaska, western Canada, eastern
101 Canada, Europe including Greenland, western Russia, eastern Russia, Fig. 1). In recent decades, the atmospheric observation
102 network suitable for inverse modeling has expanded across the Arctic, with a considerable increase in available sites after 2010
103 (Vogt et al., 2025). However, due to data-sharing disruptions associated with the ongoing conflict involving Russia and
104 Ukraine, observational data from Russian stations has been limited since 2022. Consequently, this study focuses on the period
105 from 2010 to 2021, when data coverage from surface stations was more consistent across the full domain.
106



107

108 Figure 1: Geographic distribution of surface sites operated by different network providers where flask-based and/or continuous
109 in-situ CH₄ measurements are available for assimilation into the inverse model (black dots; Supplementary Table 1). The
110 colored boxes delineate the Arctic-Boreal regions (Alaska, western Canada, eastern Canada, Europe including Greenland,
111 western Russia, eastern Russia), as defined based on The Boreal-Arctic Wetland and Lake Dataset (BAWLD) (Olefeldt et al.,
112 2021).

113 2.2. Wetland estimates used as prior fluxes in the inverse modelling

114 In this study, we utilize the JSBACH model (Reick et al., 2021), the land component of the MPI-ESM (Mauritsen et al.,
115 2019), to estimate bottom-up wetland CH₄ emissions. JSBACH is run in standalone mode at T63 resolution (approximately
116 1.85°, or 185 km) and driven by CRUJRA2.3 (Harris, 2019) climate forcing. Soil hydrology and thermodynamics follow the
117 multilayer formulation of Hagemann and Stacke (2015), with permafrost-related processes implemented as described by Ekici
118 et al. (2014). Soil organic carbon (SOC) decomposition is simulated as a first-order decay process that depends on surface air
119 temperature, water availability, and litter size, following the YASSO model formulation (Tuomi et al., 2011) and its
120 implementation in JSBACH by Goll et al. (2015).

121 The wetland area fraction of the grid is determined using TOPMODEL (Beven and Kirkby, 1979), a conceptual rainfall-
122 runoff model that estimates inundation based on the compound topographic index (CTI). If the inundated fraction of the grid
123 is non-frozen (depending on the soil temperature), it is considered a CH₄-emitting area. The methodology for wetland CH₄
124 production and transport is adopted from Riley et al. (2011), and the details of the TOPMODEL and its implementation for
125 wetland CH₄ within JSBACH are outlined in Kleinen et al. (2020).

126 Methane production and the transport pathways that move CH₄ to the surface (diffusion, plant-mediated aerenchyma and
127 ebullition) follow the scheme of Riley et al. (2011), as implemented in JSBACH by Kleinen et al. (2020). Under anaerobic
128 conditions, a proportion of SOC (f_{CH_4}) is converted to CH₄, while the remaining is converted to CO₂. The temperature
129 dependence of f_{CH_4} is represented using a Q₁₀ formulation.

$$130 \quad f_{CH_4} = f_{CH_4,baseline} \cdot Q_{10}^{(T_{soil}-295)/10K} \quad \text{Equation 1}$$

131

132 Oxidation reduces the amount of CH₄ that reaches the atmosphere. Consequently, the net CH₄:CO₂ emission ratio depends
133 on production and oxidation rates, as well as transport pathways, which control the amount of CH₄ exposed to oxidation. A
134 simplified conceptual relationship is as follows:

$$135 \quad CH_4:CO_2 = \frac{f_{CH_4}P - O_{CH_4}}{(1-f_{CH_4})P + O_{CH_4}} \quad \text{Equation 2}$$

136

137 where P is gross anaerobic SOC decomposition and O is the amount of CH₄ oxidized before emission.

138 To evaluate how sensitive CH₄ wetland emission estimates are to key parameters, we conducted nine experiments in which
139 we varied only the Q₁₀ coefficient for CH₄ production and the baseline f_{CH_4} fraction (Fig. 2b). Specifically, we tested three
140 different Q₁₀ values ranging from 1.4 to 2.2, consistent with commonly used values reported in literature review (Moser et al.,
141 2026), and baseline f_{CH_4} fractions from 0.33 to 0.38. These combinations are summarized in Table 1 and were chosen to identify
142 parameter sets that best align with the observed atmospheric data. All other carbon decomposition, hydrological, transport, and
143 oxidation processes follow the standard JSBACH configuration.

144 2.3. Inverse modeling setup

145 We used the Jena CarboScope Inversion System (Rödenbeck, 2005) to quantify CH₄ emissions between the surface and
146 the atmosphere globally from 2010 to 2021, with the evaluation and interpretation of fluxes focused on the Arctic-Boreal
147 region. This is a linear Bayesian framework that infers surface-atmosphere CH₄ fluxes by combining prior flux estimates with
148 atmospheric CH₄ mole fraction measurements and accounting for their respective uncertainties. The flux vector f represents
149 the net flux per grid cell per time step. The Jena CarboScope enables f to be represented as the sum of different flux components,
150 each of which is modelled independently using its own statistical linear flux model. These independent a priori error covariance
151 structures allow deviations from the prior flux estimate to be attributed to specific components during the inversion process.
152 In this study, the a priori shape uncertainty was defined as 100% of the prior flux for each flux category. All flux categories
153 were optimized, assuming spatial correlation lengths of ~500 km and temporal correlation lengths of about 15 days. Temporal
154 and spatial fluxes are optimized within a Bayesian inversion framework that minimizes a cost function combining prior and
155 observational constraints. The solution is obtained analytically using the linear Bayesian approach, which yields maximum
156 posterior flux estimates and their associated uncertainties. Details of the cost function formulation and solution method can be
157 found in the CarboScope technical report (Rödenbeck, 2005).

158 A total of 154 stations were assimilated for the global domain (Fig.1; Supplementary Table 1). These CH₄ observations
159 were obtained from multiple global and regional networks (ICOS RI et al., 2024; Panov et al., 2021; Sasakawa et al., 2010,
160 2025; Schuldt et al., 2023), with the majority of sites located in the Northern Hemisphere, including 33 stations within the
161 Arctic-Boreal domain. Most observational data used in this study were accessed through NOAA GML ObsPack (Schuldt et
162 al., 2023), ICOS Carbon Portal (ICOS RI et al., 2024), World Data Centre for Greenhouse Gases (WDCGG) database
163 (https://doi.org/10.50849/WDCGG_CH4_ALL_2023), and JR-STATION network (Sasakawa et al., 2010, 2025); further
164 details are provided in the “Data Availability section”. Detailed information on the stations with assimilated data is given in
165 Supplementary Table 1. For tower sites with multiple intake heights available, we assimilated only data from the highest height
166 in the inversion, and for the continuous data, we use only daytime measurements. The transport model used in CarboScope is
167 the TM3 global atmospheric tracer model, an Eulerian transport model that solves the continuity equation (and
168 parameterizations of boundary layer and convective mixing) for atmospheric tracers in a three-dimensional grid over the globe
169 (Heimann and Körner, 2003). The model has a spatial resolution of approximately 3.8° latitude by 5° longitude, with 19 vertical
170 layers, and it is driven by meteorological inputs from the NCEP reanalysis dataset (Kalnay et al., 1996). Flux inversions were
171 conducted at the TM3 spatial resolution and a daily temporal resolution. Since the model is initialized with a homogeneous
172 background concentration of methane, it is run for at least one year before to the period of interest to avoid any impact resulting
173 from the model spin-up. To account for model-data mismatch, including the representation error of the measurements within
174 the transport model, each station is assigned a weekly error value based on how well the atmospheric transport model can
175 capture local atmospheric dynamics. For example, for mountain sites and stations near shores samples are assigned a smaller
176 error of 15 ppb, whereas surface sites in regions with complex circulation patterns receive a larger error of 30 ppb. Additionally,

177 to ensure balanced representation across observational sites, particularly between continuous and sparse time series, we applied
178 a data density weighting scheme, assigning equal influence to each weekly period, regardless of data frequency. Without this
179 adjustment, sites with high-frequency data would dominate the cost function solely because of the greater number of
180 observations. To avoid this, the uncertainty of each measurement is multiplied by the number of observations per week. This
181 corresponds to the assumption that errors are correlated on weekly timescales, meaning that one week of hourly data provides
182 roughly the same amount of independent information as one weekly flask sample (Rödenbeck, 2005).

183 Prior CH₄ flux estimates include five source categories, all of which were optimized: wetlands, other natural sources,
184 anthropogenic, ocean and fire emissions. The monthly mean emissions from wetlands and fires were obtained from the
185 JSBACH model (Kleinen et al., 2020), as previously described. Fire emissions represent the simulated biomass burning
186 emissions of JSBACH and were prescribed as monthly varying prior fluxes. Additional natural sources, such as termites and
187 wild animal emissions taken from JSBACH (Kleinen et al., 2020) and geological emissions from Etiope et al. (2019) were
188 combined as the “other natural source” category. Emissions from oceans were obtained from Weber et al. (2019) and
189 implemented as a non-seasonal climatology. Anthropogenic emissions were obtained from the EDGAR inventories database
190 (<https://edgar.jrc.ec.europa.eu>) version 8 (Crippa et al., 2023) and are provided as monthly global fluxes. This category
191 includes emissions from agriculture, livestock, waste management, fossil fuel exploitation and other minor anthropogenic
192 sources except biomass burning. Emissions of CH₄ from inland water (freshwater) were not included as a separate prior
193 category and are therefore not explicitly optimized in the inversion framework.

194 CH₄ chemical loss includes loss due to OH and Cl in the troposphere, as well as OH, Cl, and O(¹D) in the stratosphere.
195 For tropospheric OH, we use the monthly three-dimensional OH fields calculated by Spivakovsky et al. (2000), which are
196 based on observed climatological distributions of OH precursors and scaled to match the observed CH₃CCl₃ lifetime. The
197 monthly climatological loss rates of CH₄ in the stratosphere due to OH, Cl, and O(¹D) were derived from a simulation of the
198 ECHAM5/MESy1 chemistry transport model (Jöckel et al., 2006). Additionally, tropospheric Cl loss is simulated using a
199 recent model-derived estimate of tropospheric Cl (Hossaini et al., 2016). The surface sink from upland soils and the ocean was
200 implemented as a zeroth-order reaction with prescribed reaction rates that occur only in the surface-most model layer. Reaction
201 rates for the microbial oxidation of atmospheric CH₄ in soil were based on the uptake estimates from the LPJ-Bern model
202 (Spahni et al., 2011).

203 **2.4. Evaluating Bottom-Up Emissions Using Top-Down Constraints**

204 Previous studies have used atmospheric inversion models to evaluate different bottom-up estimates and determine which
205 one best reproduces observed atmospheric CH₄ data (Kim et al., 2011; Miller et al., 2016), providing an effective framework
206 for model evaluation. In this study, we evaluated the performance of different JSBACH parameterizations by using the CH₄
207 wetland emission outputs from each experiment as wetland prior fluxes in a top-down atmospheric inversion framework. The
208 inversion then generated posterior fluxes, reflecting the adjustments needed to align the prior emissions with atmospheric CH₄

209 observations. These adjustments take into account uncertainties in atmospheric transport, observational errors, and model
210 representation. In this study, we used the model adjustment defined as the difference between posterior and prior fluxes,
211 calculated as the mean monthly and mean annual values across the Arctic-Boreal region from 2010 to 2021. First, we identified
212 the parameterization resulting in the lowest mean model adjustment across the entire domain.

213 For the monthly analysis, we first computed the mean monthly prior flux and the mean monthly posterior flux, and then
214 defined the model adjustment as the difference between these two means. For the annual analysis, we calculated the mean
215 annual prior and posterior fluxes and again defined the adjustment as their difference. This allowed us to determine which
216 JSBACH configuration provided the best overall agreement with atmospheric constraints at the pan-regional scale and
217 investigate temporal variability.

218 Next, we examined spatial variability of the difference between posterior and prior fluxes using different JSBACH
219 parameterizations as wetland priors. At the grid-cell level, we identified the parameter combination that minimized annual
220 model adjustment, thereby providing the best match to the top-down atmospheric constraints. To conduct this analysis, an
221 ensemble of posterior fluxes was calculated based on each CH₄ production Q₁₀ value from the prior wetland flux. This approach
222 was supported by the observation that CH₄ production Q₁₀ significantly influenced CH₄ emission estimates compared to the
223 baseline f_{CH_4} fraction. Additionally, posterior fluxes from priors with different baseline f_{CH_4} fraction scenarios remained highly
224 similar for a given Q₁₀ value. As a result, maps were created by calculating the absolute difference between the posterior
225 ensemble of the respectively Q₁₀ value and prior CH₄ fluxes for each experiment at each grid-cell. Then, the annual mean
226 adjustment was calculated and we identified the parameterization that resulted in the smallest adjustment at each grid-cell. In
227 summary, each grid-cell shows the experiment that best matched the atmospheric CH₄ observations.

228 3. Results and Discussion

229 3.1 Sensitivity of JSBACH CH₄ wetland emission estimates to CH₄ production Q₁₀ and baseline f_{CH_4} fraction in the 230 Arctic–Boreal region

231 Table 1 summarizes the experiments and parameters combinations that have been tested in the JSBACH model and used
232 as a wetland prior in the atmospheric inversions. Across the Arctic-Boreal region, our nine experiments produced annual mean
233 CH₄ wetland estimates ranging from 13.8 to 33.5 TgCH₄ y⁻¹. These estimates are consistent with previously published bottom-
234 up estimates of ~15-50 TgCH₄ y⁻¹, with most studies reporting mean values near 20-25 TgCH₄ y⁻¹ (Christensen et al., 1996;
235 Ying et al., 2025; Yuan et al., 2024; Zhang et al., 2025). It should be noted that these studies consider different spatial domains
236 and time periods. The estimates obtained using a Q₁₀ value of 1.8 align most closely with this published range among our
237 experiments.

238

239 Table 1. Summary of JSBACH wetland CH₄ estimates used as prior fluxes in the inversions and posterior fluxes estimates for
240 each respective model run.

JSBACH parameterization		Arctic-Boreal annual mean CH ₄ emission (TgCH ₄ y ⁻¹)*		
Baseline f_{CH_4} fraction	Q ₁₀ model	JSBACH estimates (prior)	Posterior estimates	Mean model adjustment
0.33	1.4	31.7 ± 1.1	25.0 ± 1.4	-6.7
0.33	1.8	20.0 ± 0.7	22.9 ± 1.1	2.9
0.33	2.2	14.6 ± 0.5	21.2 ± 0.9	6.6
0.35	1.4	29.7 ± 0.9	24.8 ± 1.5	-5.0
0.35	1.8	18.9 ± 0.6	22.7 ± 1.1	3.8
0.35	2.2	13.8 ± 0.5	20.9 ± 0.9	7.1
0.38	1.4	33.5 ± 1.0	25.2 ± 1.6	-8.2
0.38	1.8	21.3 ± 0.7	23.3 ± 1.2	2.0
0.38	2.2	15.5 ± 0.5	21.6 ± 1.0	6.1

*The annual mean between 2010 and 2021, with the standard deviation representing interannual variability.

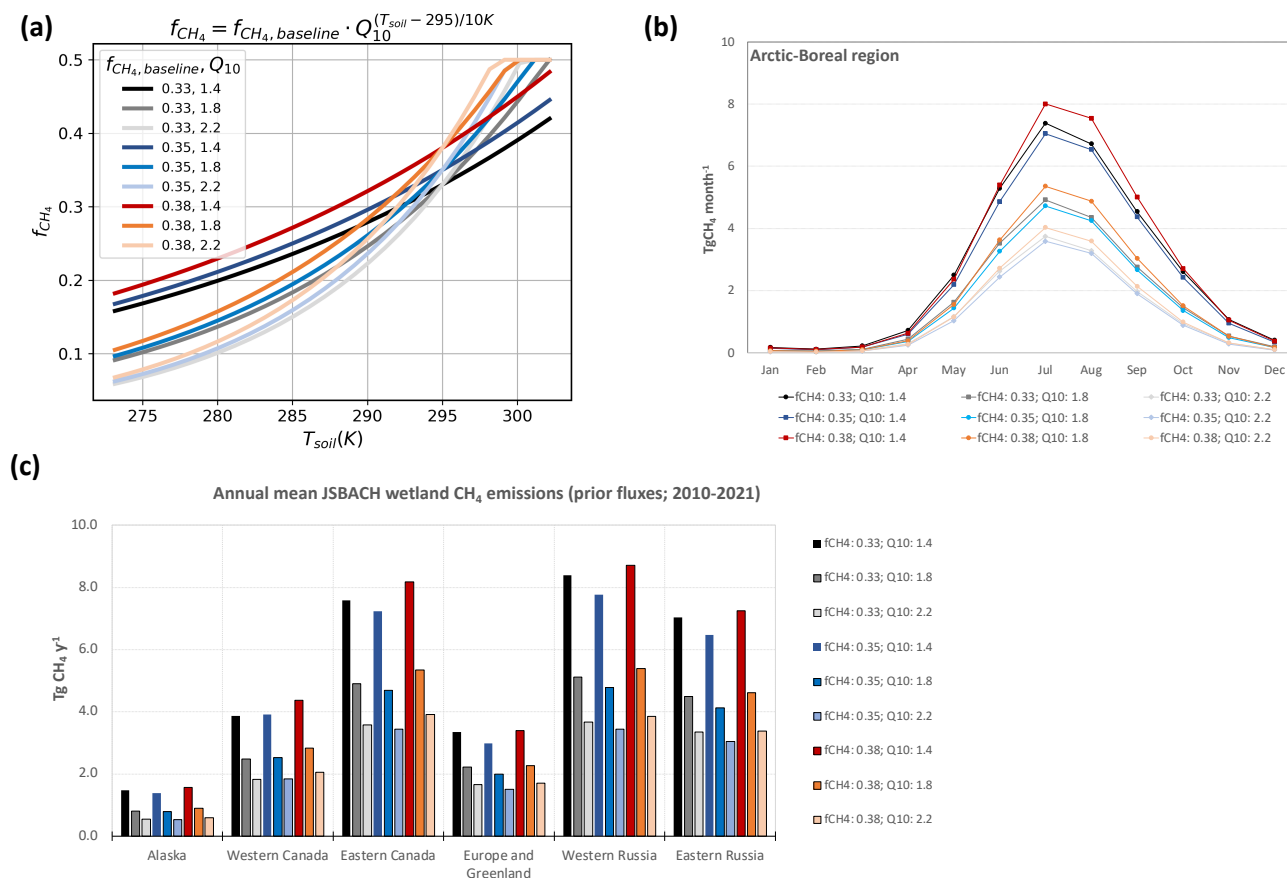
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242

243 Emissions peaked during the summer months (July-August), with a mean emission ranging from 6.8 to 15.5 TgCH₄ y⁻¹
244 (Fig. 2b). These larger emissions were followed by spring (May-June; range of 3.5-7.8 TgCH₄ y⁻¹), autumn (September-
245 October; range of 2.8-7.7 TgCH₄ y⁻¹), and winter with the lower emissions (November-April; range of 0.7-2.7 TgCH₄ y⁻¹). The
246 timing of the peak in wetland emissions aligns with previous bottom-up estimates (Ying et al., 2025). At the sub-regional scale,
247 emissions showed substantial spatial variability (Fig. 2c). The highest annual mean fluxes were found in western Russia (3.4-
248 8.7 TgCH₄ y⁻¹, depending on the parameter set), followed by eastern Canada (3.4-8.2 TgCH₄ y⁻¹), eastern Russia (3.1-7.2
249 TgCH₄ y⁻¹), western Canada (1.8-4.4 TgCH₄ y⁻¹), Europe including Greenland (1.5-3.4 TgCH₄ y⁻¹), and Alaska (0.5-1.6 TgCH₄
250 y⁻¹).

251 In general, increasing the baseline value of the f_{CH_4} fraction from 0.33 to 0.38 increases CH₄ production. However, an
252 increase in the CH₄ production Q₁₀ parameter decreases CH₄ production for temperatures below 295 K (the reference
253 temperature) and increases it for temperatures higher than 295 K. This means that increasing Q₁₀ values from 1.4 to 2.2 reduces
254 wetland CH₄ emissions in the comparatively cold Arctic region (Table 1 and Fig. 2). The sensitivity of wetland CH₄ to the Q₁₀
255 temperature response and the baseline f_{CH_4} fraction is evident when comparing seasonal cycles over the Arctic-Boreal domain
256 (Fig. 2b). For example, contrasting the simulations with baseline f_{CH_4} fraction equaling 0.33 and varying CH₄ production Q₁₀
257 values (from 1.4 to 2.2), shows that increasing Q₁₀ significantly reduces annual wetland mean CH₄ emission in this region by
258 ~ 54% (~17 TgCH₄ y⁻¹). This reduction is not uniform throughout the year. Although winter emissions are relatively low,
259 increasing Q₁₀ from 1.4 to 2.2 results in a ~70% decrease compared to a ~50-59% decrease during the summer, spring and fall.
260 Similarly, the influence of the baseline f_{CH_4} fraction can be observed by keeping Q₁₀ constant, for example at 1.4, and varying

261 the baseline f_{CH_4} fraction from 0.33 to 0.38. This increase leads to an increase of up to 6% in the annual wetland CH_4 emissions
 262 for the region. In general, our parameter sensitivity tests show that CH_4 production Q_{10} has a stronger effect on emission
 263 variability than the baseline f_{CH_4} fraction. These wetland CH_4 emission estimates with different parameterizations were
 264 subsequently integrated into the Jena CarboScope atmospheric inversion framework as wetland prior fluxes to determine the
 265 combination that closest align with atmospheric CH_4 observations, which means those requiring the minimum adjustment to
 266 fluxes from prior to posterior.

267



268
 269 Figure 2. (a) Sensitivity of f_{CH_4} production fraction to the chosen range of input parameters for this study. The y-axis represents
 270 the fraction of anaerobic carbon mineralization allocated to CH_4 production, calculated using the equation displayed at the top
 271 of the panel and in Equation 1. In the legend, the first number denotes the f_{CH_4} baseline fraction and the second number denotes
 272 the CH_4 production Q_{10} value. (b) Mean seasonal cycle of Arctic-Boreal wetland CH_4 emissions for each experiment used in
 273 the inversion as the wetland prior flux. (c) Annual mean wetland fluxes from each experiment estimated by JSBACH model.
 274

275 3.2 Evaluation of JSBACH CH_4 Fluxes Using Inverse Modeling

276 Our nine inverse model estimates produce an annual mean total emission (i.e. including natural and anthropogenic
 277 sources) for the Arctic-Boreal region ranging from 44.2 to 47.1 $TgCH_4 y^{-1}$, with wetland emissions being the main CH_4 source

278 to the atmosphere. Depending on the parameter set in the prior flux setup by JSBACH, the annual mean wetland emission
279 ranges from 20.9 to 25.0 TgCH₄ y⁻¹ (47-54% of total emissions). The largest posterior wetland CH₄ emissions were estimated
280 for western Russia (range of 6.9-8.4 TgCH₄ y⁻¹, depending on the parameter set), followed by eastern Russia (range of 6.0-7.5
281 TgCH₄ y⁻¹), eastern Canada (range of 4.3-4.9 TgCH₄ y⁻¹), western Canada (range of 1.7-1.8 TgCH₄ y⁻¹), Alaska (range of 1.0-
282 2.0 TgCH₄ y⁻¹) and Europe including Greenland (range of 0.7-0.8 TgCH₄ y⁻¹)

283 At the pan-Arctic scale, posterior wetland fluxes are higher than prior fluxes in the experiments using CH₄ production
284 Q₁₀ values of 1.8 (8-22% higher than prior) and 2.2 (37-54% higher), see Table 1 and Fig. 3a. This suggests that these prior
285 estimates underestimate CH₄ emissions in the Arctic-Boreal region relative to the observation-constrained posterior fluxes.
286 However, prior fluxes estimated using a Q₁₀ value of 1.4 are higher than posterior fluxes (16-25% higher than posterior),
287 indicating overestimation of CH₄ emissions in this case. When comparing the model adjustment for the three experiments
288 (varying only the Q₁₀ parameters), the prior flux using Q₁₀ values of 1.8 produces the best agreement between prior and
289 posterior flux budgets, meaning that a minimum adjustment in the inverse model optimization is required when considering
290 annual mean emissions in the entire Arctic-Boreal region. Additionally, when comparing the different baseline f_{CH_4} fractions
291 (using the Q₁₀ value with the best fit: 1.8), the minimum adjustment in the inverse model optimization is required for the prior
292 flux with the largest baseline f_{CH_4} fraction (0.38), with posterior flux being 8% (2.0 TgCH₄ y⁻¹) higher than the prior.

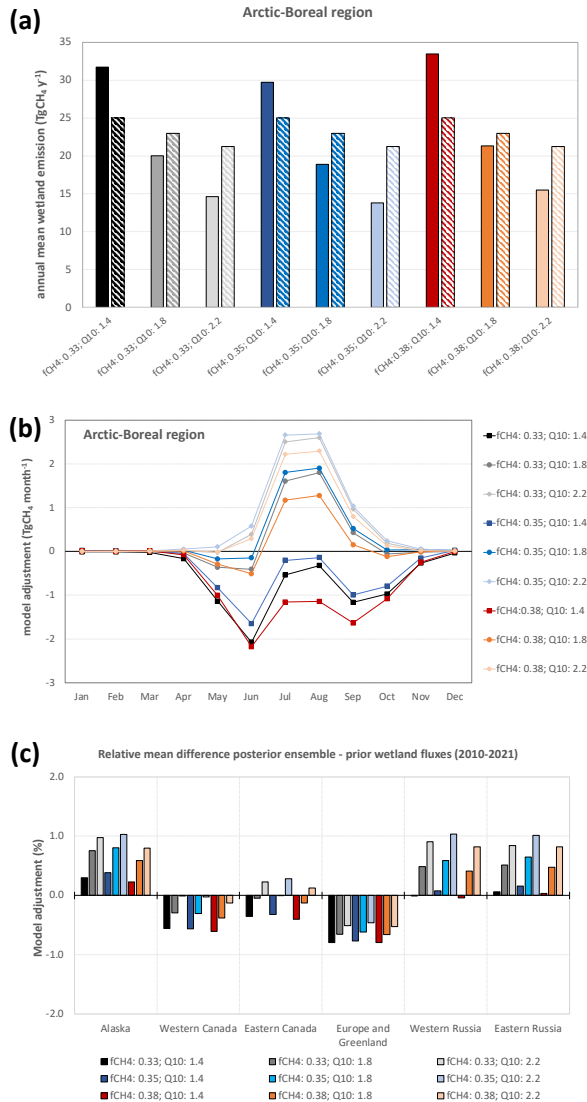
293 Our posterior estimates of CH₄ emissions from wetlands are similar to previous Arctic-Boreal estimates. Using a process-
294 oriented ecosystem model, Christensen et al. (1996) estimated a total CH₄ emissions from northern wetlands and tundra (>
295 50°N) to be 20 ± 13 TgCH₄ y⁻¹. Yuan et al. (2024) reported a mean annual emission of 20.3 ± 0.9 TgCH₄ y⁻¹ from Boreal-
296 Arctic wetland based on upscaled flux observations for the period 2002-2021. The Global Carbon Project estimated a mean
297 annual wetland (including inland freshwaters) CH₄ emission for regions north of 60°N at 24 (9-53) TgCH₄ y⁻¹, while top-down
298 approaches resulted in a lower estimate of 9 (7-17) TgCH₄ y⁻¹ for the same region (Saunois et al., 2025). Recently, Ying et al.
299 (2025) estimated an annual mean CH₄ emissions from vegetated wetlands north of 45°N during 2016-2022 at
300 22.8 ± 2.4 TgCH₄ y⁻¹, ranging from 15.7 ± 1.8 TgCH₄ y⁻¹ to 51.6 ± 2.2 TgCH₄ y⁻¹, depending on the wetland dataset used in the
301 machine-learning-based upscaling approach. Although our posterior estimates are within the range of previous Arctic-Boreal
302 estimates, direct comparisons are difficult because of differences in the study period, methodological approach, and
303 inconsistent or unclear definitions of the spatial domain.

304

305 **3.3 Seasonal variability in optimum CH₄ production Q₁₀ settings**

306 Before analyzing regional differences in optimum CH₄ production Q₁₀ settings, we first focused on a clear seasonal
307 pattern in the adjustments between prior and posterior CH₄ emissions, which showed a peak of changes occurring during
308 summer. We therefore assessed whether the Q₁₀ value resulting in the minimum adjustment remained constant throughout the
309 year or varied by season. At a pan-Arctic scale, seasonal variations were evident: estimates using CH₄ production Q₁₀ equaling
310 1.8 aligned better with atmospheric observations in spring and fall but substantially underestimated summer emissions (Fig.
311 3b). In contrast, estimates using a Q₁₀ of 1.4 best aligned with the atmospheric observation during summer, reducing the

312 discrepancy between top-down and bottom-up estimates during the growing season, but strongly overestimating emissions in
 313 spring and fall (Fig. 3b). This pattern is primarily driven by wetlands in Russia. Bergman et al. (2000) found temporal variation
 314 in Q_{10} at peatland sites, suggesting that factors such as the availability of easily degradable compounds (e.g., root exudates)
 315 and the activity of anaerobic microbial biomass influence CH_4 production rates alongside temperature.
 316



317
 318 Figure 3. (a) Annual mean CH_4 emissions (prior: full color bars; posterior: dashed color bars) for the entire Arctic-Boreal
 319 region using all nine inversion scenarios with the different values of Q_{10} parameter and baseline f_{CH_4} fraction in JSBACH
 320 wetland emissions. (b) adjustment of prior fluxes at monthly timesteps for the same model configurations as used in (a). (c)
 321 relative annual mean model adjustment as percentage of prior (posterior ensemble minus prior flux) for each one of the sub-
 322 regions. Positive values indicate regions where prior estimates underestimated emissions compared with posterior estimates,
 323 while negative values represent areas where prior emissions overestimate CH_4 emissions compared with the posterior
 324 estimates.

325 3.4. Spatial patterns of best-fit model results based on posterior fluxes

326 CH₄ emissions exhibited spatial variability, and model adjustments were not uniform across the domain. This suggests
327 that the optimal parameterization varies by region and seasons (as discussed in Section 3.3). In some areas, Q₁₀ values of 1.4
328 or 2.2 resulted in minimal adjustments (Fig. 3c), outperforming the model using a Q₁₀ equaling 1.8 that was shown to work
329 best as an average setting across the entire domain. To better evaluate this variability and explore ways to reduce uncertainty
330 in specific regions, we assessed the best parameterization fit with observations at the per grid-cell level (Fig. 4).

331 In our first analysis, we evaluated the spatial best fit model by keeping the baseline constant at a value of 0.35 and varying
332 the CH₄ production Q₁₀ values (Fig. 4a). This spatial analysis showed that, in general, in regions with large wetland areas and
333 high annual CH₄ emissions (for example the Western Siberian Lowlands, Supplementary Fig. 1 and 2) a Q₁₀ value of 1.4
334 resulted in the smallest model adjustment. As an increase in the Q₁₀ parameter decreases CH₄ production for temperatures
335 below 295 K, a higher Q₁₀ value in these regions results in an underestimation of emissions. In contrast, regions such as Europe
336 and northern Canada showed, in general, minimum model adjustments with a Q₁₀ value of 2.2, suggesting that lower Q₁₀ value
337 would overestimate wetland CH₄ emissions in these regions. Interestingly, we observed adjustments with different signs in
338 eastern Canada depending on the parameterization. For example, positive adjustments were associated with Q₁₀ value of 2.2,
339 as the prior emissions were underestimated compared with the estimated flux inferred from atmospheric observations.
340 Additionally, we analyzed the effect of varying baseline flux values while keeping Q₁₀ constant as 1.8, which showed that in
341 high-emission areas, for example the Western Siberian Lowlands (Supplementary Fig. 1 and 2), in general a larger baseline
342 flux value led to the smallest model adjustments (Fig. 4b). When considering the model adjustment for all sensitivity tests
343 (varying both CH₄ production Q₁₀ and baseline f_{CH_4} fraction) as shown in Fig. 4c, we also found a consistent pattern that
344 confirmed the above findings varying only single parameters: the combination of higher baseline fluxes and lower Q₁₀ value
345 (Q₁₀ = 1.4) best captured CH₄ dynamics in CH₄ hotspots, as the Western Siberia Lowlands.

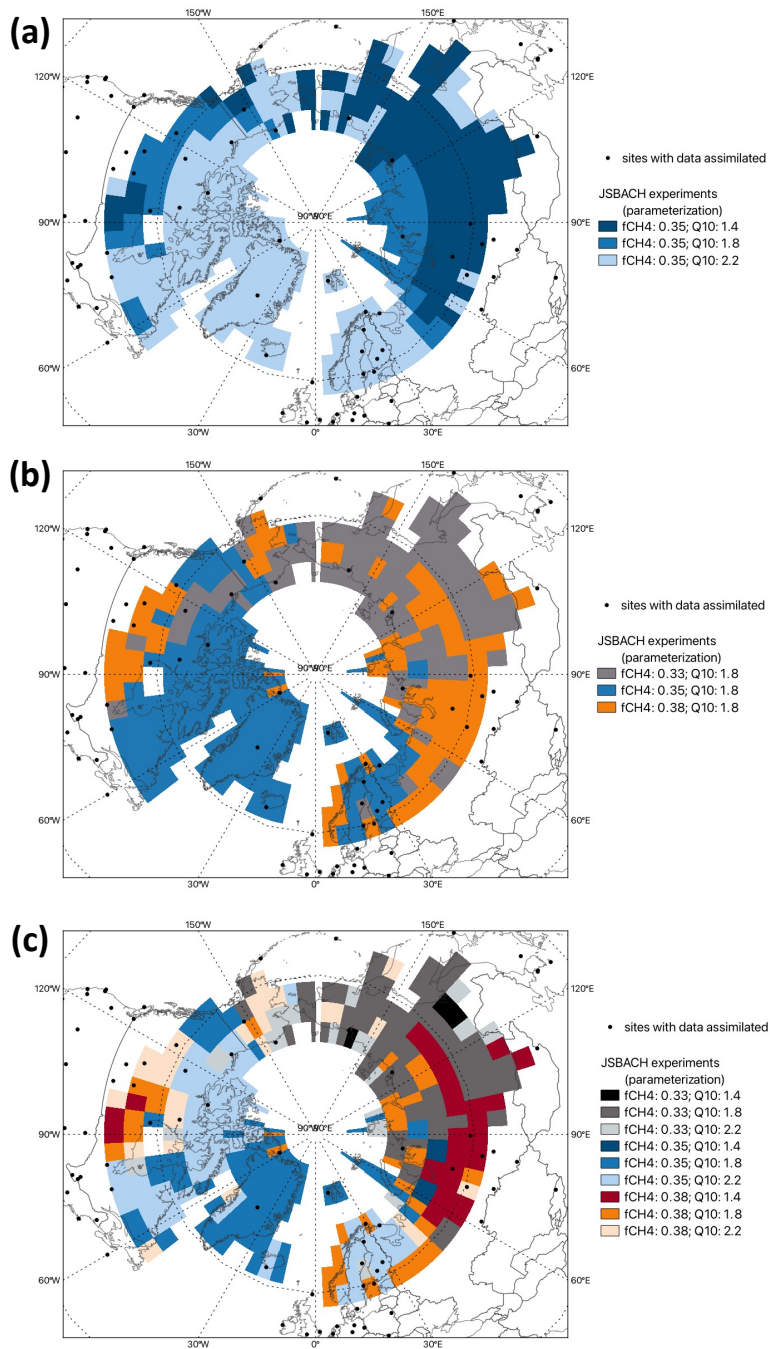
346 The wide range of reported incubation-based Q₁₀ values for CH₄ production in Arctic and northern wetlands depending
347 on the site, substrate, and season, shows that the temperature sensitivity of CH₄ production varies considerably across
348 environments (Bergman et al., 2000; Roy Chowdhury et al., 2015; Treat et al., 2015). This variability, which could be driven
349 by factors such as vegetation type, organic matter quality, and microbial activity, emphasizes the necessity of models to account
350 for spatial differences in process rates. For example, one synthesis study reported a mean Q₁₀ value of 1.18 for CH₄ production
351 under Arctic soil conditions (Roy Chowdhury et al., 2015; Treat et al., 2015). Roy Chowdhury et al. (2015) used anoxic
352 laboratory incubations of active layer and permafrost samples from the Barrow Environmental Observatory in Alaska and
353 reported a range of Q₁₀ values from 1.8 to 22. Lupascu et al. (2012) reported that Q₁₀ values describing the CH₄ production
354 response of peat to a 10 °C temperature change ranged from 1.9 to 3.5 in sedge sites and from 2.4 to 5.8 in *Sphagnum* mire
355 sites, and suggested that using spatially variable CH₄ production Q₁₀ values could improve the accuracy of CH₄ flux modeling
356 in northern wetlands. Furthermore, Bergman et al. (2000) found that the seasonal average Q₁₀ values ranged from
357 approximately 4.6 to 9.2 depending on the plant community of the various peat types. Here, our intent is not to directly compare
358 our results with reported incubation-based values, since our adjustments in the CH₄ production Q₁₀ refer to the Q₁₀ of the

359 CH₄:CO₂ production ratio, as represented in the model, and could not directly be comparable with CH₄ production Q₁₀ from
360 the literature review. In JSBACH, the Q₁₀ applied to CH₄ production controls the fraction of CH₄ generated, but the surface
361 emission ratio may still be lower due to oxidation and transport pathways. Together, these examples highlight that CH₄
362 production is strongly temperature dependent, and that the degree of this dependency can differ across regions and time periods.
363 However, most current models cannot fully capture the influence of these factors due to structural limitations or a lack of
364 detailed input data that is both spatially and temporally resolved. Consequently, these environmental drivers are often
365 oversimplified or overlooked. Adjusting the CH₄ production Q₁₀ values, as we do here, offers a useful initial approach, but it
366 should not be seen as a long-term solution. Ideally, future model and data developments will enable CH₄ production Q₁₀ values
367 to adjust dynamically in response to underlying biophysical conditions, such as shifts in vegetation or organic matter
368 characteristics. This will allow models to operate with a more generalizable formulation that still captures observed
369 heterogeneity. Recent studies have demonstrated the potential of methane data assimilation techniques to optimize process-
370 model parameters using observational constraints (Bernard et al., 2025; Monteil et al., 2025); however, regional and seasonal
371 optimization remains largely unexplored. While our model experiments identified a single CH₄ production Q₁₀ value that best
372 agrees with observations at the pan-Arctic scale, they also showed that CH₄ emissions and model adjustments vary regionally.
373 Some areas showed a substantial response to different Q₁₀ values, which further demonstrates that an approach using a single
374 parameter value is not sufficient. This highlights the need for future data assimilation frameworks that allow for regional, and
375 potentially seasonal, parameter optimization.

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380 Figure 4. Map of the prior flux setting leading to minimum model adjustment (posterior ensemble minus prior fluxes) for the
 381 annual mean fluxes at each grid-cell for the Arctic-Boreal region varying the (a) CH₄ production Q₁₀ parameter only, (b)
 382 baseline f_{CH_4} fraction only and (c) both Q₁₀ parameter and baseline f_{CH_4} fraction. As mentioned in Section 3.2, the configuration
 383 with Q₁₀ = 1.8 and f_{CH_4} = 0.38 provides the best fit at the pan-Arctic scale. However, regional results show that this
 384 configuration does not minimize flux adjustments everywhere.

385
386

3.5. Limitations of Top-Down CH₄ estimates

387 Our analysis shows that atmospheric inverse modeling is a useful tool for evaluating and guiding process-model
388 parameterizations when estimating wetland CH₄ emissions. However, it is important to note the limitations of the top-down
389 approach, especially its relatively coarse spatial resolution. Global inversions usually operate at spatial scales larger than the
390 process models, limiting their ability to resolve fine-scale heterogeneity, local emission hotspots, and small-scale processes.
391 Consequently, grid-cell-level emission estimates represent aggregated signals and cannot fully capture localized variability.

392 Additionally, top-down estimates rely heavily on the spatial and temporal distribution of atmospheric observations
393 assimilated into the model. Regions with sparse coverage, such as central and eastern Russia, can limit the ability to accurately
394 identify emission sources and increase dependence on prior estimates. Furthermore, most surface observation sites at high
395 latitudes only started providing measurements in the early 2010s. This limits the ability to assess multi-decadal changes in CH₄
396 emissions (Vogt et al., 2025).

397 At the grid-cell scale, assimilating only atmospheric CH₄ observations reflect the combined influence of all sources and
398 sinks, making it difficult to distinguish overlapping source sectors. However, differences in the spatial patterns and seasonality
399 of emissions can be constrained by atmospheric CH₄ observations in inversions that solve for different source categories
400 (Saunio et al., 2025). Furthermore, errors in atmospheric transport model can propagate into emission estimates (Houweling
401 et al., 2017; Locatelli et al., 2013; Schuh et al., 2019). Despite these limitations, our approach demonstrated a strong potential
402 to help reduce the discrepancy between bottom-up and top-down estimates, therefore improving the accuracy of wetland CH₄
403 emission estimates.

404 4. Conclusions

405 Overall, our parameter sensitivity tests of bottom-up wetland emissions indicate that CH₄ production Q_{10} has a stronger
406 effect on emission variability than the baseline f_{CH_4} fraction. Our bottom-up estimates showed that increasing CH₄ production
407 Q_{10} from 1.4 to 2.2 decreased the annual mean wetland CH₄ emission in the Arctic–Boreal region by half. In addition, our
408 analysis shows that a single Q_{10} value cannot capture the complexity of CH₄ emission dynamics across the Arctic-Boreal
409 region. CH₄ production Q_{10} values of 1.8 and 2.2 underestimate hotspot emissions, mainly during summer. In contrast, a Q_{10}
410 value of 1.4 overestimates emissions in regions with lower annual mean wetland emissions, such as e.g., Europe and northern
411 Canada. Furthermore, a baseline f_{CH_4} fraction value of 0.38 led to the smallest model adjustments in CH₄ hotspots. These
412 findings emphasize the importance of selecting appropriate parameterizations to accurately represent wetland emissions,
413 especially in regions with substantial CH₄ release. Future models should incorporate dynamic, data-driven adjustments to
414 reflect underlying environmental controls more accurately. If a varying CH₄ production Q_{10} value approach is not feasible for
415 this region due to computational cost or model setup constraints, using a Q_{10} value of 1.8 provides the more similar CH₄
416 emission estimates compared to the atmospheric data across the entire Arctic-Boreal region.

417 Our results demonstrate that, despite the inherent limitations of top-down approaches when it comes to resolving fine scale
418 heterogeneity, combining atmospheric inversions and process-models provides an important tool for reconciling discrepancies
419 between bottom-up and top-down estimates, thereby improving constraints on large-scale wetland methane emissions.
420 Guidance by atmospheric inversion could therefore be instrumental to ensure the regional representativeness, and where
421 applicable temporal variability, of process model parameter settings.

422 **5. Authors contributions**

423 LSB, MG, GG, VB designed the methodology. LSB wrote the first version of the manuscript and performed analysis and CH₄
424 inversions. GG performed and provided the JSBACH simulations. CR provided guidance and technical support for the inverse
425 modelling. CB provided additional input on the discussion of results. All authors contributed with analysis and text. MG
426 supervised and acquired funding.

427 **6. Data and code availability**

428 The prior and posterior mean Arctic-Boreal CH₄ fluxes on the CarboScope model horizontal resolution are publicly available
429 on Zenodo (Basso et al., 2026) <https://doi.org/10.5281/zenodo.19201813>. Observations from the NOAA GML network can be
430 downloaded from the dedicated Observation Package (ObsPack) web server at <http://doi.org/10.25925/20231001>. The dataset
431 “European atmospheric CO₂, CH₄ and N₂O Mole Fraction data product – 2024” analyzed during the current study was
432 downloaded from the ICOS Carbon portal, DOI: <https://doi.org/10.18160/KDMT-V6CG>. The observations from the WDCGG
433 dataset are available at https://doi.org/10.50849/WDCGG_CH4_ALL_2023. ATTO tower data can be request at
434 <https://www.attodata.org/>. Observations from the Japan-Russia Siberian Tall Tower Inland Observation Network (JR-
435 STATION (Sasakawa et al., 2010) can be downloaded from <https://doi.org/10.17595/20231117.001>,
436 <https://doi.org/10.17595/20231117.002>, <https://doi.org/10.17595/20231117.004>, <https://doi.org/10.17595/20231117.005>,
437 <https://doi.org/10.17595/20231117.006>, <https://doi.org/10.17595/20231117.007>, <https://doi.org/10.17595/20231117.008>. CH₄
438 observations from the western Taimyr Peninsula (Siberia) can be downloaded from <http://doi.org/10.17632/gcts3dddrh.1>.

439 **7. Competing interests**

440 The authors declare that they have no conflict of interest.

441 **8. Acknowledgements**

442 The authors were funded by the European Research Council (ERC synergy project Q-Arctic, grant agreement no. 951288), the
443 German Federal Ministry of Research, Technology and Space (MOMENT project, support code 03F0931G), and the AMPAC-

444 net initiative (European Space Agency, grant no. 4000137912/22/I-DT). The authors would also like to thank Dr. Santiago
445 Botía at MPI-BGC/BSI for his valuable comments and suggestions, which helped us to improve this manuscript. The authors
446 would like to acknowledge the contributions of Tonatiuh Nunez Ramirez, who designed the CH₄ chemistry model for
447 CarboScope inversion system used in this work.

448 We would like to thank all Principal Investigators and supporting staff for setting up and maintaining observation sites around
449 the world, particularly in the Arctic, and for making the data available through different databases, including NOAA Obspack,
450 ICOS RI, WDCGG and JR-STATION. The ICOS activities at Ricerca sul Sistema Energetico (PRS) station are financed by
451 the Research Fund for the Italian Electrical System under the Three-Year Research Plan 2025-2027 (MASE, Decree n.388 of
452 November 6th, 2024), in compliance with the Decree of April 12th, 2024. Although not fundamental to our study, we use
453 ATTO methane data from 2012 to 2019 and for this we want to acknowledge Jost Lavric and the ATTO consortium for making
454 the data available. This work is based on use of Large Research Infrastructure CzeCOS supported by the Ministry of Education,
455 Youth and Sports of CR within the CzeCOS program, grant number LM2023048.

456 Parts of the text was language-edited for grammatical correctness using DeepL. The authors have reviewed and verified the
457 content as needed and take full responsibility for it.

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