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1 **Modeled production, oxidation and transport processes of wetland**
2 **methane emissions in temperate, boreal, and Arctic regions**

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Abstract

87 Wetlands are the largest natural source of methane (CH₄) to the atmosphere. The eddy covariance
88 method provides robust measurements of net ecosystem exchange of CH₄, but interpreting its
89 spatio-temporal variations is challenging due to the co-occurrence of CH₄ production, oxidation,
90 and transport dynamics. Here we estimate these three processes using a data-model fusion
91 approach across 25 wetlands in temperate, boreal, and Arctic regions. Our data-constrained model
92 – iPEACE – reasonably reproduced CH₄ emissions at 19 of the 25 sites with normalized root mean
93 square error of 0.59, correlation coefficient of 0.82, and normalized standard deviation of 0.87.
94 Among the three processes, CH₄ production appeared to be the most important process, followed
95 by oxidation in explaining inter-site variations in CH₄ emissions. Based on a sensitivity analysis,
96 CH₄ emissions were generally more sensitive to decreased water table than to increased gross
97 primary productivity or soil temperature. For periods with leaf area index (LAI) of $\geq 20\%$ of its
98 annual peak, plant-mediated transport appeared to be the major pathway for CH₄ transport.
99 Contributions from ebullition and diffusion were relatively high during low LAI (<20 %) periods.
100 The lag time between CH₄ production and CH₄ emissions tended to be short in fen sites (3 ± 2
101 days) and long in bog sites (13 ± 10 days). Based on a principal component analysis, we found that
102 parameters for CH₄ production, plant-mediated transport, and diffusion through water explained
103 77% of the variance in the parameters across the 19 sites, highlighting the importance of these
104 parameters for predicting wetland CH₄ emissions across biomes. These processes and associated
105 parameters for CH₄ emissions among and within the wetlands provide useful insights for
106 interpreting observed net CH₄ fluxes, estimating sensitivities to biophysical variables, and
107 modeling global CH₄ fluxes.

108

109 Running title: Estimating processes for wetland CH₄ emissions

110 **Keywords:** Methane emissions, Eddy covariance, Bayesian optimization, Multi-site synthesis,
111 Methane model, Data-model fusion

113 **1. Introduction**

114 Wetlands are the largest natural source of methane (CH₄) – a potent greenhouse gas contributing
115 to climate warming. Methane emissions from wetlands contribute approximately 20% of total
116 annual CH₄ emissions (Saunois et al., 2020). Despite their importance, estimates of wetland CH₄
117 emissions are highly uncertain (Bohn et al., 2015; Melton et al., 2013) because direct
118 measurements of CH₄ emissions (Delwiche et al., 2021) are far fewer than those of carbon dioxide
119 (CO₂) fluxes (Pastorello et al., 2020). In particular, the variability in CH₄ emissions appears high
120 across spatial and temporal scales (Knox et al., 2019; Delwiche et al., 2021). As a result of the
121 associated uncertainties, current estimates of the global CH₄ budget contain large discrepancies
122 between top-down and bottom-up approaches (Saunois et al., 2020; Jackson et al. 2020).

123 Methane emissions from wetlands also exhibit a wide range of magnitudes and responses to
124 biophysical variables. Because CH₄ is primarily produced by anaerobic methanogens and oxidized
125 by aerobic bacteria (Bridgham et al., 2013; Conrad 2009), water table depth (WTD) has been
126 identified as an important thermodynamic boundary and thus potential predictor of wetland CH₄
127 emissions (Brown et al., 2014; Moore and Roulet, 1993; Rinne et al., 2018). Methanogens produce
128 CH₄ using substrates both from carbon recently fixed through photosynthesis (Whiting and
129 Chanton, 1993) and previously fixed carbon (Glaser et al., 2004; Karofeld and Tönisson, 2014).
130 Thus, CH₄ emissions are often correlated with plant primary production and/or soil respiration
131 (Turetsky et al., 2014; Villa et al., 2020; Whiting and Chanton, 1993). Because temperature affects
132 CH₄ production kinetics, soil temperature is typically correlated with CH₄ emissions (Knox et al.,
133 2019; Yvon-Durocher et al., 2014), albeit substantial seasonal hysteresis was reported to occur in
134 many sites, likely due to substrate-temperature driver interactions (Chang et al. 2020, 2021). In
135 addition to production and oxidation, transport pathways are also crucial in modeling CH₄
136 emissions. Because CH₄ in soils is transported through plant aerenchyma, ebullition bubbles
137 through standing water, and/or diffusion, CH₄ emissions were shown to be often correlated with
138 leaf area index (LAI), latent heat flux, and/or barometric pressure (PA) (Kwon et al., 2017;
139 Sturtevant et al., 2016; Tokida et al., 2005; Ueyama et al. 2020).

140 To better understand wetland CH₄ emissions, the eddy covariance (EC) method has been
141 widely used at various wetlands along with measurements of other ancillary covariates such as
142 WTD and soil temperature (Morin, 2018; Knox et al., 2019; Delwiche et al., 2021). The EC method
143 provides quasi-continuous measurements of CH₄, CO₂, and energy exchanges between the land

144 surface and the atmosphere (Baldocchi, 2014). The direct measurements have been used to
145 evaluate magnitudes of CH₄ emissions, their interannual variations, and their responses to various
146 biophysical variables (Chang et al., 2021; Chu et al., 2014; Knox et al., 2019; Rinne et al., 2018;
147 Yuan et al., 2022). Previous studies have identified biophysical variables such as soil and air
148 temperature and WTD as the primary drivers for the temporal and spatial variations in CH₄
149 emissions (Knox et al., 2019; Turetsky et al., 2014; Yuan et al., 2022), but their importance varies
150 substantially among wetlands and across time scales (Koebsch et al., 2015; Knox et al., 2021).
151 Furthermore, complex interactions hinder the use of simple correlation analyses for disentangling
152 responses of CH₄ emissions to biophysical variables, leading to large uncertainties when
153 interpreting observations (Chang et al. 2020; Sturtevant et al., 2016; Knox et al., 2021). Recently,
154 the FLUXNET-CH₄ database was curated for supporting synthesis of wetland CH₄ emissions using
155 the EC methods (Knox et al., 2019; Delwiche et al., 2021) and, for example, was used to evaluate
156 inter-site variations in CH₄ emissions (Chang et al. 2021; Knox et al., 2021, 2021; Yuan et al.,
157 2022).

158 To improve the mechanistic understanding and accurate modeling of CH₄ emissions, the
159 relative contributions of CH₄ emission pathways have been measured or estimated with various
160 field measurements (Table 1). These measurements include chamber techniques (Korrensalo et al.,
161 2022; Tokida et al., 2007a, b), bubble traps (Stanley et al., 2019), isotope techniques (Dorodnikov
162 et al., 2011), and dissolved CH₄ concentrations in pore water (McNicol et al., 2017). Recently, a
163 wavelet analysis of EC measurements examined the contribution of ebullition to total CH₄
164 emissions (Göckede et al., 2019; Iwata et al., 2018; Hwang et al., 2020; Richardson et al., 2022;
165 Schaller et al., 2018). These analyses revealed that plant-mediated transport was the most
166 important pathway for wetland CH₄ emissions (up to 98% of the total emissions), but the other
167 two pathways were also important under environmental conditions such as flooded wetlands
168 without emergent vegetation and shallow ponds. Many process-based models (Table 1) have also
169 shown that CH₄ emissions occur mostly through plant-mediated transport (Castro-Morales et al.,
170 2018; Ma et al., 2017; Peltola et al., 2018; Susiluoto et al., 2018; Wania et al., 2010), although one
171 model found ebullition was the dominant pathway (Ito, 2019). Although previous studies
172 conducted across relatively few wetland sites are useful for understanding CH₄ transport pathways,
173 comparisons of transport mechanisms across multiple wetlands remain challenging. The challenge
174 lies in uncertainties in measurement techniques, spatial representation of measured processes in

175 the field, and different model structures in process-based models.

176 Data-model fusion approaches have recently been used for evaluating wetland CH₄ emissions
177 (Ma et al., 2017; Müller et al., 2015; Salmon et al., 2022; Susiluoto et al., 2018; Ueyama et al.,
178 2022). These methods use observed data for constraining process-based models that are often
179 difficult to calibrate, and can be used to evaluate processes of CH₄ emissions and their sensitivity
180 to biophysical drivers. To reduce the uncertainties in a process-based model, Müller et al. (2015)
181 used observed data for constraining a model for CH₄ dynamics and found that detailed process-
182 based models were not well constrained owing to the complexity of the model. Susiluoto et al.
183 (2018) calibrated a detailed model using nine years of EC-based CH₄ flux data in a northern fen.
184 Their results suggested that CH₄ production was the most important factor responsible for the
185 interannual variations in CH₄ emissions, whereas plant-mediated transport was the most important
186 CH₄ transport pathway. Data-model fusion approaches to study CH₄ emissions have been applied
187 only for a limited number of individual sites; thus, their applicability should be evaluated across
188 wide arrays of wetland sites and biomes.

189 Recently, Ueyama et al. (2022) developed a process-based model (i.e., inferring Processes for
190 Ecosystem-Atmosphere CH₄ Exchange – iPEACE) for partitioning CH₄ emissions using a data-
191 model fusion approach for a cool temperate bog in Japan. Their approach constrained the model
192 using CH₄ emissions and associated biophysical variables from the EC tower with the goal to
193 determine a parameter set for reproducing daily CH₄ emissions under various environmental
194 conditions. These conditions included growing and dormant seasons, wet and dry conditions, high
195 and low LAI, and various ranges of gross primary production (GPP), soil temperature, and PA.
196 The model reasonably identified processes that were qualitatively consistent with previous field
197 experiments to shed light on processes in the bog. Findings include: 1) ebullition and plant-
198 mediated transport as the important CH₄ transport pathways, 2) high contributions of the deep
199 organic layer (i.e., <30 cm) to total CH₄ emissions due to very low CH₄ concentrations in the
200 surface organic layer (Tokida et al., 2007a), and 3) gaseous-bubble accumulation in deep organic
201 layer (Tokida et al., 2005, 2007a, b). A chamber-based study further suggested that contributions
202 of bubble transport to total CH₄ emissions ranged from 67-95% during the snow-free season in the
203 bog (Tokida et al., 2005, 2007a, b), which was close to the iPEACE model estimates (64%).

204 Here, we modified iPEACE to simulate CH₄ fluxes and infer processes related to CH₄
205 emissions (i.e., production, oxidation, and transport pathways) from 25 wetlands across mid- to

206 high-latitudes included in the FLUXNET-CH₄ database. Applying the data-model fusion method
207 (Ueyama et al., 2022) across these wetland sites spanning temperate, boreal, and Arctic regions,
208 our objectives were to: 1) evaluate the model's suitability for simulating CH₄ emissions across
209 wetland types, 2) quantify inter-site variations in estimated processes related to CH₄ emissions, 3)
210 evaluate the sensitivities of CH₄ emissions to GPP, soil temperature, and WTD, and 4) examine
211 inter-site variations in parameters for improved predictions of wetland CH₄ emissions.

212

213 **2. Materials and methods**

214 *2.1 Dataset and model inputs*

215 We used daily EC CH₄ flux data archived in the FLUXNET-CH₄ database (Delwiche et al., 2021).
216 We selected all mid- to high-latitude freshwater wetland sites from the database (Table 2) that
217 contained all relevant forcing variables (i.e., soil and air temperature, WTD, PA, and GPP). The
218 selected 25 sites represent wetland types of bog (ombrotrophic), fen (minerotrophic), marsh, wet
219 tundra, and rice paddy in temperate, boreal, and Arctic regions. The mean annual air temperature
220 ranged from -5 °C to 17 °C across the sites, and minimum WTD ranged from -0.62 m to 0.68 m.

221 We used daily gap-filled CH₄ fluxes and the ancillary biophysical variables at the tower sites.
222 The daily mean values of the gap-filled half-hourly variables were provided in the FLUXNET-
223 CH₄ database (Delwiche et al., 2021). We used two types of daily CH₄ fluxes (i.e., FCH4_F and
224 FCH4_F_ANN_median) in the database. FCH4_F was gap-filled using a multidimensional scaling
225 (MDS) approach in REddyProc (Delwiche et al., 2021), but still contained periods of time with
226 long data gaps (<2 months). FCH4_F_ANN_median was gap-filled based on an artificial neural
227 network method, which fills all data gaps (Knox et al., 2019). As input drivers from the
228 FLUXNET-CH₄ database, daytime-based GPP (GPP_DT) in the database (Lasslop et al., 2010),
229 air temperature (TA_F), barometric pressure (PA_F), soil temperature (TS), and WTD (WTD_F)
230 were used. The gaps in the meteorology (i.e., TA_F, and PA_F) were filled using the ERA-Interim
231 reanalysis data (Vuichard and Papale, 2015), whereas those of WTD and soil temperatures were
232 filled using the MDS method. We used soil temperature at two depths for representing the surface
233 and deep layers in the model. For sites affected by permafrost (RU-Ch2, US-Ics, and US-Uaf), we
234 assumed that the deepest soil temperature measurement was representative of the bottom of the
235 active layer. Data for RU-Ch2, US-Ics, US-Bzf, and US-Bzb sites did not include WTD data in
236 the FLUXNET-CH₄ database, but WTD data were directly provided from principal investigators.

237 Since WTD for RU-Ch2 was based on discrete manual measurements, we linearly interpolated the
238 data to the daily timescale.

239 We prepared daily LAI as a model input based on satellite-based LAI smoothed using GPP.
240 First, the four-day LAI data (MCD15A3H; collection 6) was downloaded from MODIS land
241 products subsets. The spatial resolution of the product is 500 m. We used a single grid cell of data
242 centered on the site location. The LAI data were first set to zero for the snow periods, and were
243 then smoothed using a Savitzky-Golay filter (Chen et al., 2004). The snow conditions were
244 determined based on the MODIS reflectance products (MCD43A4; collection 6) from the MODIS
245 land products subsets. Because smoothed LAI often failed to explain seasonal peaks when peak
246 LAI was missing, daily LAI was then modeled using the smoothed LAI and daily GPP normalized
247 with a maximum GPP ($nGPP$). LAI at day (i) was modeled with a non-centered moving mean of
248 the normalized GPP multiplying a scale factor.

249

$$250 \quad LAI_i = L_s \sum_{j=i-D}^i nGPP_j / (D + 1) \quad (1)$$

251

252 Two empirical parameters of the scale factor for explaining maximum LAI (L_s) and moving
253 window for explaining a lag between GPP and LAI (D) were the parameters determined based on
254 a differential evolution method. Since there was no clear relationship between LAI and GPP for
255 NZ-Kop, LAI for NZ-Kop was estimated simply based on 10-day moving mean of the satellite-
256 based LAI. The smoothed LAI well mimicked the satellite-derived LAI, where mean and standard
257 deviation of root mean square error (RMSE) and correlation coefficient (R) were 0.46 ± 0.24 and
258 0.84 ± 0.11 , respectively, across the sites.

259 2.2 The iPEACE model

260 Partitioning CH_4 emissions from the EC measurements was conducted by optimization of a
261 process-based model with the data. We used the iPEACE model (Ueyama et al., 2022), which was
262 originally proposed to infer CH_4 dynamics at a temperate bog in Japan, but has been generalized
263 for the current analysis (Fig. 1).

264 The iPEACE model consists of two soil layers, a surface layer susceptible to oxic conditions
265 and a deep layer prone to anoxic conditions, and considers CH_4 production and oxidation in each
266 layer, as well as three transport pathways: plant-mediated transport, ebullition, and diffusion. The

267 modeled mechanisms are similar to those used in current process-based models (Ralvonen et al.,
268 2017; Walter and Heimann, 2000; Wania et al., 2010; Riley et al., 2011). The simple formulation
269 of iPEACE allows to effectively fit the model to data at reduced computational costs. The model
270 is driven with GPP for substrate availability, LAI for transport potential through plant stems, soil
271 temperature in the two layers for driving kinetics, oxygen (O₂) concentration for redox potential,
272 WTD for diffusivity and hydrostatic pressure that drives ebullition, and PA for ebullitive transport.
273 The O₂ concentration was not included in the FLUXNET-CH₄ database, and thus was determined
274 from WTD. When the water table position is above or below a soil layer, the layer is assumed to
275 be anoxic or fully oxic, respectively. When WTD is within a soil layer, O₂ concentration in that
276 layer is linearly related to that fraction of the layer that is inundated between fully oxic to anoxic
277 conditions.

278 To explore the underlying processes, the model contains 10 parameters and two initial values
279 of the CH₄ pools in each soil layer (mol-CH₄ m⁻³), which are calibrated with data (Table 3). For
280 adapting the model to the current analysis, the thickness of the surface layer and root fraction
281 (described below) in the surface layer are calibrated for each site, whereas the previous study
282 (Ueyama et al., 2022) used a fixed value.

283 Thickness of the surface layer (z_{surf} , m) is the parameter constrained by the data. Thickness of
284 the deep layer is calculated as the difference between total soil thickness (1 m, except for
285 permafrost sites) and the thickness of the surface layer. For sites affected by permafrost, total soil
286 thickness is defined as the active layer depth (0.5 m for RU-Ch2, 1.0 m for US-ICs, and 0.6 m for
287 US-Uaf). Seasonal changes in soil thickness associated with soil thaw are not considered in the
288 model for simplicity. Surface root fraction (f_{root}) is the parameter explaining how roots are
289 concentrated in the surface layer relative to the total roots. The model assumes that root density is
290 higher in the surface layer than the deep layer.

291 Methane production is assumed to depend on substrate availability from GPP, kinetics as
292 determined by soil temperature, and anaerobic status as determined by O₂ concentration. The
293 fraction of GPP to CH₄ substrate ($p_{\text{production}}$; mmol-CH₄ g⁻¹ C) and temperature sensitivity (Q_{10}) are
294 both empirical parameters. Modeled CH₄ production increases with soil temperature and substrate
295 availability but decreases with increased O₂ concentration. The $p_{\text{production}}$ parameter is the
296 aggregated parameter for explaining the fraction of root exudates from GPP and the efficiency
297 from exudates to CH₄ production and relates to the base production rate in a Q_{10} equation (Chen,

298 2021). The model does not explicitly consider anaerobic peat decomposition; thus, CH₄ production
299 by decomposition are implicitly incorporated through a decrease in the CH₄ pools. Partitioning of
300 CH₄ substrate in each soil layer is assumed to be a function of the root distribution between the
301 surface and deep soil layers. CH₄ oxidation is calculated with a Michaelis-Menten equation (Wania
302 et al, 2010) with CH₄ concentration and O₂ concentration, where the maximum CH₄ oxidation rate
303 ($p_{\text{oxidation}}$; mol-CH₄ m⁻³ s⁻¹) is a calibrated parameter.

304 Plant-mediated transport is calculated by the concentration gradient between a soil layer and
305 the atmosphere, root fraction in each layer, and LAI. The transfer efficiency under a given
306 concentration gradient (p_{plant} ; 10⁻³ d⁻¹) is a calibrated parameter. The model does not consider CH₄
307 transport by dead plants, which are not accounted for by LAI, with the assumption that collapsed
308 aerenchymatous tissue in senesced leaves has low transport capacity (Korrensalo et al., 2022).

309 Ebullitive transport is calculated based on a concentration threshold scheme (Peltola et al.,
310 2018), which has two empirical parameters: nondimensional conductivity for bubble transport
311 ($p_{\text{ebullition}}$) and a parameter for explaining episodic CH₄ bubble transport driven by barometric
312 pressure changes (p_{pressure} ; hPa⁻¹). Since the model assumes that CH₄ is not immediately emitted as
313 ebullition but accumulated as bubbles, $p_{\text{ebullition}}$ represents the transport efficiency of bubbles. The
314 p_{pressure} parameter empirically explains the sensitivity to decreasing barometric pressure, i.e., the
315 relative increase in ebullition per 1 hPa decrease in mean PA. In the model, the ebullition flux from
316 each layer is assumed to be directly transported to the atmosphere, when WTD is within the top
317 10 cm of the soil based on a field study (Stanley et al., 2019). When WTD is deeper than 10 cm,
318 CH₄ transport through ebullition is added to the surface layer CH₄ pool, which is a modification
319 from the original model of Ueyama et al. (2022).

320 Diffusive flux is calculated using Fick's first law. The diffusion coefficients for gas and water
321 are calculated based on Riley et al. (2011), and then their calibrated correction factors ($p_{\text{diffusion-gas}}$
322 and $p_{\text{diffusion-water}}$) are multiplied to the respective diffusion coefficients.

323 2.3 Model applications

324 The model parameters, initial conditions, and model error (σ) were determined from the observed
325 data by the Bayesian method as follows:

326

$$327 F_{OBS} \sim \text{Normal}(F_{MODEL}, \sigma^2) \quad (2)$$

328

329 where the function *Normal* represents the normal distribution, F_{OBS} is the observed CH₄ emission,
330 and F_{MODEL} is the modeled CH₄ emission. The *a priori* distribution of σ was assumed to be a log
331 normal distribution with mean of $\log(0.5)$ mg CH₄ m⁻² d⁻¹ and standard deviation of 0.1 mg CH₄
332 m⁻² d⁻¹, where the hierarchical structure was used to reduce computational costs. Equation 2
333 assumes that variance for the model-observation mismatch was temporally uniform without
334 incorporating temporal correlation in the observed data.

335 The *a priori* distributions of the parameters were generally assumed to be uniform (Table 3).
336 The range of uniform distributions were determined by adding plus/minus to the values determined
337 by the differential evolution method for each site (Table S1). The pre-constraint of *a priori*
338 distribution effectively reduces computational costs without decreasing model performance and
339 improves model convergence, based on a preliminary analysis. For constraining the behavior that
340 root density must be higher in the surface layer than the deep layer in the Bayesian optimization,
341 the thickness of the surface layer and root distribution were determined without results from the
342 mathematical optimization. For the parameter optimization, we did not assume the hierarchy in the
343 statistical model.

344 The posterior distributions of the parameters were estimated using a Markov Chain Monte
345 Carlo (MCMC) method with the No-U-Turn Sampler (NUTS). NUTS is an extension of
346 Hamiltonian Monte Carlo and provides very effective samples without requiring user intervention
347 or costly tuning runs (Hoffman and Gelman, 2014). The efficiency of NUTS was more than 1,000
348 times that of Metropolis or Gibbs sampling. Posterior distributions of the parameters were
349 estimated using four chains with 1,000 samples after warm-up based on 1,000 sampling. Bayesian
350 inference was performed using the PyStan library (version 2.19.1.1). Owing to a complex and
351 multimodal parameter space, consistent solutions from each chain were not obtained or some
352 chains were not converged for some sites. In this case, we used results from chains that estimated
353 the lowest model errors. The conservative treatment was required because bad chains seem to
354 converge to local minima rather than to mathematically meaningful multimodal distributions and
355 the problem was not fixed using different *a priori*, different initial values or further sampling. The
356 trace plots and probability density functions for all parameters in all sites are shown in Fig. S1,
357 which shows that at least two chains were well converged. Convergence of MCMC was evaluated
358 by the Gelman–Rubin method with the potential scale reduction factor (PSRF), which showed that

359 all parameters for all sites were well converged (PSRF < 1.05) except slightly high PSRF for two
360 parameters for US-Uaf (PSRF < 1.12; [Table S3](#)). Computational costs of the Bayesian inference
361 ranged from 0.35 hours to 2.5 days per site with an average of 6.16 hours ([Table S4](#)).

362 Model parameters were estimated using daily CH₄ fluxes and the ancillary biophysical
363 variables. Specifically, we used daily gap-filled CH₄ flux (FCH4_F), which contained only long
364 data gaps (>2 months), and did not assume embedded functional relationships. In addition, we
365 used FCH4_F_ANN_median when uncertainties in the neural network (FCH4_uncertainty) were
366 less than absolute of FCH4_F_ANN_median. The use of gap-filled fluxes with low uncertainties
367 could prevent propagating uncertainties associated with long-term gap-filling data into the
368 parameter estimation. We also evaluated how the gap-filled data influenced modeled processes,
369 where we eliminated data records where daily CH₄ emission contained more than 80% gaps in
370 half-hourly data, in constraining the model. Apart from this issue, some high-latitude and rice
371 paddy sites provided only growing-season fluxes, which hampered constraining the model for cold
372 non-growing and fallow seasons, respectively. We also found that flux data for the first few days
373 of a model run were important for constraining the initial CH₄ pools (i.e., initial conditions).
374 Without the data, initial conditions were not well converged, and estimated dormant season
375 emissions were unrealistic. Consequently, when FCH4_F was missing, we used the gap-filled CH₄
376 flux (FCH4_F_ANN_median) during the first six days of a model run and for the winter period
377 (air temperature < -10 °C). The benefits of selectively using gap-filled data could outweigh the
378 propagation of gap-filled errors, where unrealistic CH₄ emissions were not estimated.

379 The model constraints for each site were evaluated by RMSE normalized by mean, R, and
380 normalized standard deviation (SD) in daily CH₄ flux. For further interpreting and analyzing
381 modeled results, we eliminated unconstrained site-data where normalized RMSE was >0.9, R was
382 <0.6, normalized SD was <0.7, or normalized SD was >1.3.

383 The sensitivities to the forcing variables were performed using the models successfully
384 constrained for each site. First, we applied perturbations to the inputs of: 1) 1 °C increase to the
385 observed soil temperatures, 2) 10% increase in GPP and LAI, 3) 10 cm increase in WTD, and 4)
386 10 cm decrease in WTD with all other inputs held at measured conditions. Next, we examined the
387 changes in modeled CH₄ emissions with unperturbed input (control experiment). We conducted
388 the sensitivity analysis for sites spanning at least three years of data because the uncertainties are
389 high in models constrained by short-term data ([Ueyama et al., 2022](#)).

390 To understand the variabilities in the estimated parameters across the sites, we applied
391 principal component analysis (PCA) toward seven parameters: $p_{\text{production}}$, $Q_{10\text{production}}$, $p_{\text{oxidation}}$,
392 $p_{\text{ebullition}}$, p_{plant} , $p_{\text{diffusion-water}}$, and p_{pressure} . The parameter for gas diffusion ($p_{\text{diffusion-gas}}$) was not
393 included in the PCA because $p_{\text{diffusion-gas}}$ did not show a bell-shaped density curve at approximately
394 half of the sites (Fig. S1). The parameters were first standardized with mean and SD and then
395 compressed into two principal components (PC) using the scikit-learn library in python. We chose
396 two principal components because they explained more than 70% of the variance in the parameters
397 across the sites.

398 3. Results

399 3.1. Model performance

400 Across the 25 sites, 19 sites had reliable performance that satisfied the criterion for normalized
401 RMSE, R, and normalized SD (section 2.3). According to the Taylor diagram (Fig. 2), model-data
402 agreement was the best ($R > 0.9$) for RU-Ch2, FI-Lom, SE-Deg, FI-Sii, and CA-SCB. Among the
403 accepted 19 sites, the median of normalized RMSE, R, and normalized SD were 0.59, 0.82, and
404 0.87, respectively. Except for the five sites with good model fit noted above, the model
405 underestimated the SD of CH_4 flux, where the mean and SD of the normalized SD was 0.84 ± 0.13
406 across all sites. For the six sites excluded from subsequent analyses due to low performance (US-
407 Sne, DE-Hte, DE-Zrk, DE-Sfn, US-Bzf, and US-Wpt), the mean seasonality was inconsistent
408 between observations and models (Fig. 3), despite a moderate R and normalized RMSE. The low
409 performance may represent a lack of important processes in the model and insufficient data to
410 constrain the model. For example, US-Sne is a newly restored wetland and has a heterogeneous
411 surface of open water and emergent vegetation, which make it difficult to constrain the processes
412 based only on measured CH_4 fluxes for three years. Overall, there was no significant difference in
413 the model performance in terms of wetland type and the number of years used for calibration.

414 In general, there were no obvious differences in modeled results with the optimized data
415 containing fully gap-filled data or data when excluding days with $>80\%$ gaps. However, five sites
416 (US-Sne, DE-Hte, DE-Zrk, FR-LGt, and NZ-Kop) did not meet the standard for a well constrained
417 model with the non-gap-filled data (Fig. S2). The median of normalized RMSE, R, and normalized
418 SD were 0.57, 0.83, and 0.90, respectively, in the model with the data not containing fully gap-
419 filled data. The estimated CH_4 transport, production, and oxidation were also consistent among the

420 two models constrained with two data criteria, except for sites having low record numbers (e.g.,
421 RU-Ch2 and JP-Mse) (Fig. S3). Other results, including inter-site differences in CH₄ emission
422 processes and sensitivity to biophysical drivers, were generally consistent among the two models
423 constrained with two data criteria.

424 3.2. Estimated transport processes

425 Based on model results, plant-mediated transport and ebullition were more important pathways
426 for CH₄ emissions than diffusive transport across sites (Fig. 3, 4; Table 2). In most cases, plant-
427 mediated transport tended to be the major pathway for fen sites (72% ± 10%, n = 8; mean ± SD)
428 and bog sites (55% ± 16%, n = 8; mean ± SD) (Fig. 4). Ebullition accounted for 27% ± 10% of the
429 total emission for the fen sites and 26% ± 10% for the bog sites. In contrast, ebullition was
430 estimated to be the major pathway at the two tundra sites (64% ± 4%) owing to shallow WTD (Fig.
431 4). Because the modeled plant-mediated transport increased with LAI, relative contribution of
432 ebullition and/or diffusion was found high during periods of low LAI. When LAI was ≥20% of
433 the annual peak, plant-mediated transport was the major pathway (70% ± 14%), except for three
434 sites (RU-Ch2, US-Bzb, and KR-Crk) during the growing season (Fig. 3; Table 2). Diffusion was
435 a minor pathway at most sites, but tended to be high in two marsh sites (US-Myb and US-Tw1)
436 and a bog site (SE-Sto). For the three sites, the model predicted an anoxic surface layer, negligible
437 oxidation, and high CH₄ concentrations in the surface layer at high WTD sites, allowing for surface
438 diffusion. Since US-Myb was a restored wetland, the contribution of diffusion was approximately
439 half of the CH₄ emissions in open water conditions (2010-2011) and then decreased to 31% ± 6%
440 with the expansion of emergent vegetation from 2012 to 2018.

441 Based on cross-correlation analysis, CH₄ emissions lagged CH₄ production by 1-32 days (Fig.
442 5). There was more than a 30-day lag between CH₄ production and CH₄ emissions at US-Uaf.
443 Lags tended to be, on average, longer in bogs (13 ± 10 days; n = 7; mean ± SD) than in fens (3 ±
444 2 days; n = 5), rice paddies (11 ± 3 days; n = 2), or tundra (6 ± 3 days; n = 2). Even in a long-
445 lagged site (> 30 days for US-Uaf), the correlation between CH₄ production and CH₄ emission was
446 good (R > 0.70), indicating that CH₄ production controlled temporal variations in CH₄ emission.

447 Inter-site variations in CH₄ production explained inter-site variations in CH₄ emissions (R² =
448 0.72; p = 0.01), except for sites where the ratio of oxidation to production was high (Fig. 6a). For
449 sites with high oxidative fraction to production, CH₄ emissions were relatively low considering

450 their production (Fig. 6a). These sites with high oxidation generally exhibited low minimum WTD
451 (Fig. 6b). CH₄ production and emission were positively correlated with soil temperature and GPP
452 across the sites having low oxidation (Fig. 6c-f). This result is unexpected because the model was
453 constrained in each site using temporal variations in the variables, as there was no assumption
454 about inter-site variations in constraining the model. Based on the variable importance analysis
455 using random forest regression, soil temperature and GPP almost equally explained the inter-site
456 variations in CH₄ production. In contrast to production and oxidation, inter-site variations in three
457 transport pathways did not correlate with CH₄ emissions.

458 3.3. Estimated parameters

459 Most parameters in our model were well converged (Table S3), but $p_{\text{diffusion-gas}}$ did not show a bell-
460 shaped density curve with a single peak at 8 of the 19 sites (Fig. S1). Substrates for CH₄ production
461 per GPP ($p_{\text{production}}$) were converged on the lower end of *a priori* range (median = 1.1 mmol m⁻²
462 gC⁻¹ m²) over the 19 sites. The median and SD of Q₁₀ of CH₄ production was 3.7 ± 1.9, where
463 there was a weak negative correlation between $p_{\text{production}}$ and Q₁₀ across the sites ($R^2 = 0.31$; $p =$
464 0.01). The maximum oxidation parameter was estimated to be in the middle of the prescribed upper
465 and lower range at most sites. Estimated $p_{\text{ebullition}}$ and p_{plant} were not correlated with contributions
466 from ebullition and plant-mediated transport to CH₄ emission, respectively. Ebullition from 9 sites
467 had a marginal sensitivity to pressure decline (< 2% hPa⁻¹), where there was no correlation between
468 p_{pressure} and contributions of ebullition to the total emission across the sites. There was no
469 significant difference ($p < 0.05$) in all parameters aggregated by aerenchymatous and moss
470 vegetation.

471 Based on the PCA analysis, 77% of the variance in the parameters among the sites was
472 compressed with two PCs (Fig. 7). The first PC represented a tradeoff of two parameters for CH₄
473 production between high $p_{\text{production}}$ and low Q₁₀ and *vice versa*, representing 61% of the parameter
474 distribution across the sites. The second PC explained 16% of the distribution and represented a
475 tradeoff between CH₄ production and transport through plants and gas diffusion. There were weak
476 clusters for bog sites with relatively high Q₁₀, tundra sites with low transport parameters, and rice
477 paddies with high transport parameters. No clusters were apparent for fen and marsh sites.

478 The thickness of the surface layer, z_{surf} , was the conceptual depth separating surface oxic and
479 deeper anoxic layers, and thus negatively correlated to WTD for sites where minimum WTD was

480 below -0.1 m ($z_{\text{surf}} = -1.2 * \text{WTD} - 0.05$ m; $R^2 = 0.48$; $p=0.03$; $n = 10$). The regression analysis
481 showed that z_{surf} was close to minimum WTD. In contrast, there was no significant trend in the
482 surface layer thickness for sites with high mean annual WTD (> -0.1 m). For sites with high WTD
483 (i.e., always above the ground surface), the thickness of the soil layers did not control the degree
484 of redox conditions for the two layers because the surface layer was always anaerobic.

485 3.4. Sensitivity to biophysical variables

486 Based on the sensitivity analysis, CH_4 emissions increased by 9.6% or $3.5 \text{ gCH}_4 \text{ m}^{-2} \text{ yr}^{-1}$ (median
487 relative increase), with 10% increase in GPP across the sites, with the increases higher in the sites
488 with high annual soil temperatures (Fig. 8a). The sensitivity analysis was performed on sites that
489 had at least three years of data (14 sites) among the 19 sites. The sensitivities aggregated for high
490 or low WTD sites (sites having mean water table position above or below the ground surface)
491 indicated that the relative increases in CH_4 emissions did not differ significantly between the two
492 WTD classes ($p = 0.35$ in Welch's t test; inset in Fig. 8a).

493 The 1°C increases in soil temperatures increased CH_4 emissions by 6.6% or $2.5 \text{ gCH}_4 \text{ m}^{-2} \text{ yr}^{-1}$
494 (median relative increase) (Fig. 8b). The increases were similar in magnitude to those from the
495 10% increase in GPP. Compared with the sensitivity to GPP, the increased magnitudes appeared
496 to not be clearly related to the mean annual soil temperatures and WTD, likely because temperature
497 sensitivity (Q_{10}) for CH_4 production differed by site. The increases in CH_4 emissions also did not
498 differ significantly between the two WTD classes ($p = 0.80$; inset in Fig. 8b).

499 The increase in CH_4 emissions with 1°C increases were lower than those estimated based on
500 an empirical Q_{10} relationship between daily mean soil temperature and CH_4 emissions (Fig. 9).
501 Eight of the 14 sites were estimated to have higher CH_4 emission sensitivity using the empirical
502 Q_{10} model than iPEACE. Across all 14 sites, the relative increases in CH_4 emissions tended to be
503 higher in the empirical Q_{10} model (12%) than the iPEACE model (8%) across the sites ($p = 0.12$)
504 (US-Uaf was not included in relative changes in emission owing to the small magnitude in
505 emission).

506 Decreased CH_4 emissions associated with a 10 cm decrease in WTD were greater than
507 increased CH_4 emissions with a 10 cm increase in WTD (Fig. 8c, d). A decrease in WTD decreased
508 CH_4 emissions at most sites and *vice versa*, where the median changes by the decrease and increase
509 in WTD were -31% and +6.5%, respectively. A site with a WTD permanently well above the

510 ground surface (US-Myb) did not exhibit significant responses to changing WTD, as WTD always
511 remained above the surface. The relative changes in CH₄ emissions did not differ significantly
512 between sites with low and high WTD with 10 cm increases in WTD (inset in Fig. 8c; $p = 0.34$)
513 and 10 cm decrease in WTD (inset in Fig. 8d; $p = 0.15$).

514 There were two mechanisms for reduced CH₄ emissions by decreased WTD. The first
515 mechanism is associated with changes in the frequency with which the surface layer becomes oxic
516 conditions. In this mechanism, CH₄ production from the surface layer decreases when the WTD
517 decreases with the perturbed input mostly fluctuating within the surface layer throughout the year.
518 The second mechanism is related to the long-lasting change in redox conditions in the deep layer.
519 We argue that reduced anaerobic conditions in the deep layer, which was rarely affected by oxic
520 conditions with the unperturbed WTD, but was affected by the perturbed decrease in WTD. Owing
521 to the loss of anaerobic conditions, CH₄ in the deep layer was consumed through oxidation; thus,
522 the effects were relatively long-lasting until CH₄ concentrations built-up again. The median
523 decrease in CH₄ production was $-6.9 \text{ gCH}_4 \text{ m}^{-2} \text{ yr}^{-1}$, and median increase in CH₄ oxidation was
524 $12.9 \text{ gCH}_4 \text{ m}^{-2} \text{ yr}^{-1}$, indicating that the second mechanism was the major process responsible for
525 the reduction in CH₄ emissions. As an exceptional response examined at NZ-Kop, the decreased
526 WTD could change sustained anoxic conditions to oxic conditions in the deep layer, resulting in
527 decreased CH₄ production, reduced CH₄ pool, and finally decreased oxidation.

528

529 **4. Discussion**

530 The estimated processes for CH₄ emissions provide meaningful insights for interpreting observed
531 data and estimating sensitivities to the forcing variables. The current analysis aims to shed light on
532 the relative importance of processes involved in CH₄ production, transport, and oxidation across
533 25 freshwater wetland sites in temperate, boreal, and Arctic regions. The observed data included
534 in the FLUXNET-CH₄ database were used to constrain a process-based model which has a similar
535 structure used in previous modeling studies (Walter and Heimann, 2000; Wania et al., 2010; Riley
536 et al., 2011). Flux partitioning is typically applied to net CO₂ fluxes for estimating GPP and
537 ecosystem respiration (Reichstein et al., 2005), and has successfully provided deeper insights on
538 their biotic and abiotic controls (Jung et al., 2017; Mahecha et al., 2010). Compared to the
539 partitioning of CO₂ fluxes, more complex models are required to explain wetland CH₄ emissions
540 and partition net CH₄ flux observations (Wania et al., 2010; Riley et al., 2011; Grant et al., 2019;

541 [Chen 2021](#)). Partitioned CH₄ fluxes can be useful for evaluating inter-site differences in fluxes
542 ([Figs. 3, 4](#)), time lags between surface emissions and production ([Fig. 5](#)), different responses of
543 CH₄ processes (e.g., production, oxidation, and transport) to biophysical variables ([Figs. 6 and 8](#)),
544 and model parameterizations ([Fig. 7](#)). Key processes and parameters estimated in this study need
545 to be better constrained with further long-term observations and different data streams.

546

547 *4.1. Inter-site variations in estimated processes*

548 The inter-site variations in CH₄ emissions were found to be primarily associated with those in CH₄
549 production rather than those in oxidation and transport ([Fig. 6](#)), especially for sites with high WTD
550 and low CH₄ oxidation. These results could explain the correlation of annual CH₄ emissions with
551 mean annual air or soil temperature across global wetlands in the FLUXNET-CH₄ database ([Knox
552 et al., 2019; Delwiche et al., 2021](#)), where temperature was found to be an important driver of
553 methanogenesis substrates ([Chang et al. 2021](#)) and CH₄ production ([Yvon-Durocher et al., 2014](#)).
554 In contrast, oxidation increased with decreasing WTD ([Fig. 6b](#)), resulting in oxidation as the
555 second most important process for explaining inter-site variations in CH₄ emissions. These results
556 are also consistent with global syntheses, which showed that a positive correlation between CH₄
557 emissions and WTD was only detected in sites with relatively low WTD (i.e., mean annual WTD
558 was below the soil surface) ([Knox et al., 2019, 2021](#)).

559 Transport processes were estimated to regulate the time-lag between CH₄ production and
560 emissions ([Fig. 5](#)), albeit we found no significant effect on total CH₄ emissions because annual
561 emissions were mainly controlled by CH₄ production ([Fig. 6](#)). The lag between production and
562 emission occurred due to the time required to increase the CH₄ concentrations to drive CH₄
563 transport. The lag of CH₄ emissions to soil temperature or GPP was reported in studies using
564 FLUXNET-CH₄ ([Chang et al., 2019; Delwiche et al., 2021; Knox et al., 2021; Yuan et al., 2022](#)).
565 For example, [Knox et al. \(2021\)](#) estimated that on average CH₄ emissions lagged soil temperature
566 and GPP by 5.4 days and 20.7 days, respectively, across wetlands globally. The lag between CH₄
567 emission and production ([Fig. 5](#)) nonetheless partly explained the lag between emission and
568 biophysical variables, as time is required for building up sufficient CH₄ concentrations driving
569 CH₄ emissions.

570

571 *4.2. Sensitivities of CH₄ emissions to biophysical drivers*

572 The estimated sensitivity of CH₄ emissions to GPP (Fig. 8a, b) indicates the importance of
573 substrate availability. A strong relationship between net ecosystem production and CH₄ emissions
574 was previously reported across wetlands extending from subarctic peatlands to subtropical marshes
575 associated with substrate availability (Whiting and Chanton, 1993). The estimated sensitivity
576 occurred because CH₄ production in iPEACE was driven by GPP and soil temperature, reflecting
577 the concept that increased GPP will increase substrate availability and thereby CH₄ emissions. The
578 strong relationship with GPP (Fig. 8a) was unexpected, however, because the sensitivity to GPP
579 ($p_{\text{production}}$) was calibrated in each site and thus was expected to show high variability among the
580 sites. It is worth noting that the estimated sensitivity to GPP might be caused by model assumptions.
581 The model assumed that substrates for CH₄ were only provided by GPP, but old peat previously
582 fixed is also known to be a substrate for CH₄ production (Chasar et al., 2000). Substrates from
583 recent primary production and peat organic carbon should be incorporated into future modeling
584 with iPEACE.

585 Based on our sensitivity analyses, CH₄ emissions were sensitive to a decrease in WTD for most
586 sites (Fig. 8). The most important mechanism associated with decreased WTD was increased
587 oxidation at the deep layer. Because the buildup of the CH₄ pool after loss of anaerobic conditions
588 is time consuming, the effects can be long-lasting. This result is consistent with previous studies.
589 Brown et al. (2014) indicated that a long recovery time was required for CH₄ emissions after re-
590 wetting following a drop in WTD at a site where the mean WTD was below the surface. They
591 proposed a reason for the long recovery time as breaking the critical zone for CH₄ emissions by
592 low WTD conditions. Simultaneously, when increased WTD resulted in aerobic layers switching
593 to anaerobic conditions, CH₄ emissions increased, but the response was smaller than those to a
594 decreasing WTD. This difference occurs because increased WTD increased the frequency of
595 anoxic conditions at the surface layer, but the surface layer was still susceptible to oxic conditions
596 even with perturbation increase in WTD, resulting in limited increases in CH₄ concentration. When
597 deep soil remained anaerobic owing to shallow WTD, increases in soil temperature and GPP were
598 equally important drivers of CH₄ emissions through kinetics and substrate availability, respectively
599 (Fig. 8).

600

601 4.3. Comparison of estimated processes to observations from previous studies

602 Estimated transport flux was compared to EC measurements at various sites (Table 1). The high

603 ebullition (50% of total emissions) was measured with chamber measurements at JP-Bby (Tokida
604 et al., 2007a, b), which was consistent with the current study. Windham-Myers et al. (2018)
605 measured ebullition with a static chamber during five days in summer at US-Tw1, and ebullition
606 contributions to the total emission (10-30%) were comparable to those by the current study (26%).
607 In contrast, plant-mediated transport estimated with chambers for FI-Sii (31%) and FI-Si2 (21%)
608 was smaller than our model estimates (91% for FI-Sii and 67% for FI-Si2). However, Susiluoto et
609 al. (2018) reported contributions similar to the current study based on process-based models also
610 constrained using EC data (75-95%) for FI-Sii. Kwon et al., (2017) measured lower contributions
611 of plant-mediated transport (25%) and ebullition (2%) in RU-Ch2 than the model estimates.
612 McNicol et al. (2017) measured ebullition by bubble traps (< 1.3%) and diffusion by dissolved
613 CH₄ (< 4.1%) from open water bodies within the flux footprint US-Myb, values which are smaller
614 than the current estimates (18% and 24%, respectively). One reason for the inconsistency might
615 be the spatial heterogeneity at US-Myb. Their study did not consider areas of emergent vegetation
616 where contributions by ebullition can be higher (Villa et al., 2021). Hwang et al. (2020) estimated
617 smaller ebullition (10-17%) than the current study (61%) based on the wavelet analysis of EC data
618 at KR-Crk. For KR-Crk data in the FLUXNET-CH₄ database, WTD under drainage was provided
619 as 0 cm; thus, the model predicted more saturated conditions at the surface than the actual
620 conditions, resulting in higher contributions by ebullition.

621 Based on the site-scale validation, iPEACE estimates were consistent with production,
622 ebullition, or diffusive flux observations at two sites, but inconsistent with observations from four
623 sites. A comprehensive validation of estimated transport fluxes is challenging at the site scale
624 owing to limited sites with both EC data and process studies available at the same location (Table
625 1). Furthermore, no study has in-situ measured the three transport fluxes simultaneously, resulting
626 in uncertainties in how transport fluxes by process studies are consistent with CH₄ emissions
627 measured with EC towers. Plant-mediated transport could be the priority for in-situ measured
628 transport fluxes to validate CH₄ emissions, since it was estimated to be a major pathway in most
629 sites (Table 2) and in other modeling studies (Table 1). Differences in spatial representativeness
630 between EC towers and process studies could also contribute to inconsistencies.

631 Our estimated wetland CH₄ emissions were within the range of those measured or predicted
632 with process-based models regardless of difficulties in direct comparisons at the site scale.
633 Although the contributions of each transport flux were highly variable among previous studies

634 (Table 1), plant-mediated transport and ebullition tended to be major transport pathways,
635 consistent with our current estimates (Fig. 4). Previous models also estimated plant-mediated
636 transport as the major pathway (Table 1), although the VISIT model predicted ebullition as the
637 major pathway for Arctic wetlands (Ito, 2019). In contrast, iPEACE tended to estimate higher
638 contributions from ebullition and lower contributions from diffusion. This difference could be
639 caused by the assumption that ebullition occurs when WTD is greater than 10 cm below the ground
640 (Stanley et al., 2019). The contribution of plant-mediated transport was similar to previous
641 modeling studies because of similar model structure, but tended to be higher than measurements
642 (Table 1). Rhizospheric oxidation (Bansal et al., 2020; Korrensalo et al., 2022) is a potential reason
643 for low CH₄ emissions through vegetation, which was not considered in the current version of
644 iPEACE.

645

646 *4.4. Toward refined parameterizations*

647 Based on the PCA (Fig. 7), modeling wetland CH₄ emissions could be improved with refined
648 parameterization and representation of CH₄ production, plant-mediated transport, and diffusion
649 through water. The importance of parameterizations for production and plant-mediated transport
650 was also estimated in a study constraining a global CH₄ model with observed CH₄ emissions at 16
651 wetland sites (Müller et al., 2015). The high explanatory power in the first PC by the production
652 parameters suggests that CH₄ production was important for inter-site variations in CH₄ emissions.
653 Considering the structure of iPEACE, sites with high $p_{\text{production}}$ could be more limited by substrate
654 availability, whereas sites with high Q_{10} could be more limited by kinetics. The second PC
655 explained CH₄ emissions that are limited by production and/or transport. A similar trade-off
656 between parameters of production and plant-mediated transport was also inferred in an optimized
657 process-based model (Salmon et al., 2022). These results suggest that a model for explaining
658 variabilities in parameters of production and plant-mediated transport across wetlands is needed
659 for refined simulations rather than determining one set of parameters.

660

661 *4.5. Next steps in modeling wetland CH₄ emissions*

662 The estimated processes were the most likely processes for explaining observed CH₄ emissions
663 under the model structure of iPEACE (section 2.2), suggesting that careful interpretation is
664 required. iPEACE considers important processes to explain CH₄ emissions that have been

665 incorporated in some previous modeling studies (Walter and Heimann, 2000; Wania et al., 2010;
666 Riley et al., 2011). However, definitions and formulations of CH₄-related processes are often
667 different among models (Melton et al., 2013). For instance, iPEACE does not include processes
668 included in more mechanistic models (e.g., Salmon et al., 2022; Susiluto et al., 2018). We need to
669 better define processes in the model and to validate modeled processes, where the model-data
670 fusion could be useful to bridge model and observation.

671 To improve our understanding of CH₄ emissions from wetlands, future improvements are
672 possible with increased availability of EC data, additional observations, and by incorporating more
673 processes into the model. First, in-situ observations of transport fluxes and production parameters
674 with incubations would be useful to constrain the model because Bayesian optimization can
675 effectively incorporate the additional constraints from observations. Second, more long-term data
676 are required for better constraining the model. The period of the current study ranged from one to
677 nine years with a median of four years. Ueyama et al. (2022) indicated that long-term data (e.g.,
678 >3 years) effectively constrained the partitioned fluxes. Furthermore, we did not focus on tree-
679 dominated wetlands (e.g., swamps) owing to the importance of unaccounted processes, such as
680 CH₄ transport to the atmosphere by tree stems (Pangala et al., 2012), or from O₂ transport to the
681 rhizosphere via aerial roots (Purvaja et al., 2004). In this study, we predicted O₂ concentration in
682 the soil based on WTD, but the relationship between O₂ concentrations and WTD is complex
683 (Ueyama et al., 2020). Thus, measurements of WTD and O₂ concentrations are strongly
684 recommended for evaluating CH₄ emissions in wetlands. The current model considers a 1 m thick
685 soil, but anaerobic peat deeper than 1 m could play a role in CH₄ emissions (Tokida et al., 2007a,
686 b; Peltola et al., 2018). Since flux tower measurements did not continuously monitor the O₂ and
687 CH₄ concentrations in the deep peat, constraining processes at the deep peat were difficult in this
688 study. Finally, refined modeling wetland CH₄ emission will be possible by evaluating how
689 partitioned emissions are consistent across different models constrained with the same data.

690 The Bayesian inference in this study might be improved after considering the outlined
691 limitations. We did not obtain reliable results for 6 of 23 sites. The inability could be caused by
692 lack of important processes, but might be resolved with improved mathematical techniques. The
693 error distribution was assumed with Gaussian distribution, which lacked the ability to fit long-tail,
694 such as data containing outliers. Use of other error distributions might improve posterior inference
695 (Hamura et al., 2022). For 12 sites, at least one chain was not well converged (Fig. S1), possibly

696 due to a problem of slow convergence associated with complex multimodal parameter distributions.
697 Introducing Extended Ensemble Monte Carlo (Iba, 2001), such as the replica exchange method,
698 could improve convergence. The techniques for complex parameter distributions could improve
699 the parameter optimization, where some parameters in the current study hit the range of prior
700 distributions (Fig. S1) possibly owing to the equifinality problem (Schulz et al., 2001).

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730

731 **Data availability statement**

732 The data that support the findings of this study are available in the FLUXNET-CH₄ Community
733 Product, available at <https://fluxnet.org/data/fluxnet-ch4-community-product/>. DOIs for
734 individual site data are provided in Table 2. The iPEACE source code is available upon request to
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736

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1033

1034 Figures and table captions

1035 Fig. 1. Schematic representation of the model structure for methane (CH_4) flux. The model consists
1036 of two soil layers: a surface layer susceptible to oxic conditions and a deep layer prone to anoxic
1037 conditions. Ecosystem-atmosphere CH_4 fluxes are the net result of CH_4 production ($p_{\text{production}}$
1038 and Q_{10}), oxidation ($p_{\text{oxidation}}$), and transport processes. Transport is the sum of diffusion ($p_{\text{diffusion-}}$
1039 gas and $p_{\text{diffusion-water}}$), plant-mediated transport (p_{plant}), and ebullition ($p_{\text{ebullition}}$ and p_{pressure}).
1040 Substrate for CH_4 production associated with gross primary productivity (GPP) is divided into
1041 surface and deep layers (z_{surf}), considering root distribution (f_{root}). The model is driven by
1042 biophysical variables: soil temperature (T_s) in the two soil layers, water table depth (WTD), leaf
1043 area index (LAI), GPP, and barometric pressure (PA). Calibrated parameters are shown with
1044 parentheses, and dashed lines represent a major flow of causality.

1045
1046 Fig. 2. Taylor diagram of the model performances in daily methane (CH_4) fluxes for each site. The
1047 benchmark corresponding to observations is shown as Obs with red dots. RMSE = root mean
1048 square error.

1049
1050 Fig. 3. Mean seasonal variations of observed and modeled methane (CH_4) fluxes and the transport
1051 components of plant-mediated transport, ebullition, and diffusion. The seasonality is calculated
1052 as a mean across years, and then a seven-day moving mean is applied for smoothing. Note
1053 differences in y-axis ranges among panels. Frames colored by blue are the sites having
1054 acceptable model performance (normalized root mean square error was >0.9 , correlation
1055 coefficient was <0.6 , normalized standard deviation was <0.7 , or normalized standard deviation
1056 was >1.3), and those colored by brown are the sites having low performance.

1057
1058 Fig. 4. Ternary plot for modeled annual methane (CH_4) transport pathways of plant-mediated
1059 transport, ebullition, and diffusion.

1060
1061 Fig. 5. Lag time between modeled methane (CH_4) production and CH_4 flux based on a cross-
1062 correlation analysis, plotted against the correlation coefficient between CH_4 fluxes and lagged
1063 CH_4 production.

1064

1065 Fig. 6. Relationships between modeled methane (CH_4) production and CH_4 flux (a), between
1066 minimum water table position and ratio of oxidation to production (b), between mean annual
1067 soil temperature and modeled CH_4 production (c), between gross primary productivity (GPP)
1068 and modeled CH_4 production (d), between soil temperature and modeled CH_4 flux (e), and
1069 between GPP and CH_4 flux (f). Annual mean or minimum for the study period are shown. Blue
1070 lines in (a, c, d, e, f) represent linear regression (all $p < 0.001$) based on sites where modeled
1071 oxidation contributed less than 70% of CH_4 production, where shading represents the prediction
1072 interval ($p = 0.1$). Dashed line in (a) represents the 1:1 line between production and flux. The
1073 high CH_4 production for NZ-Kop ($525 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$) is too high to fit the range in the figure
1074 (a, c, d). Points represent mean values over the observation period, and their colors represent the
1075 ratio of CH_4 oxidation to production.

1076

1077 Fig. 7. Biplots showing the first and second components based on the principal components (PC)
1078 of the estimated parameters across the sites: methane (CH_4) production per gross primary
1079 productivity ($p_{\text{production}}$), Q_{10} for CH_4 production, maximum CH_4 oxidation rate ($p_{\text{oxidation}}$),
1080 nondimensional conductivity for gaseous transfer ($p_{\text{ebullition}}$), diffusion coefficient for plant-
1081 mediated transport (p_{plant}), diffusion coefficient multiplier for water ($p_{\text{diffusion-water}}$), and
1082 sensitivity of ebullition to barometric pressure (p_{pressure}).

1083

1084 Fig. 8. Modeled sensitivity of annual mean methane (CH_4) flux to perturbed input of 10% high
1085 gross primary productivity (GPP) (a), biased input of 1°C high soil temperatures (Ts) (b), 10 cm
1086 high water table position (WTP) (c), and 10 cm low WTP (d). The changes in fluxes were shown
1087 on climate space of mean annual soil temperature and mean annual WTP over the observation
1088 period for each site. Boxplots represent the relative changes in flux for aggregated sites having
1089 annual high and low mean WTP (higher and lower above the ground, respectively), where dots
1090 represent outliers. The relative changes by boxplots did not include US-Uaf, because the flux
1091 was too low and the ratio was anomalously high due to low denominator. The sensitivity
1092 analysis was done for sites having at least three years of data.

1093

1094 Fig. 9. Change in methane (CH_4) flux estimated with a perturbed input of 1°C increase in soil
1095 temperatures for the empirical Q_{10} model and iPEACE model. The colors in plots represent the

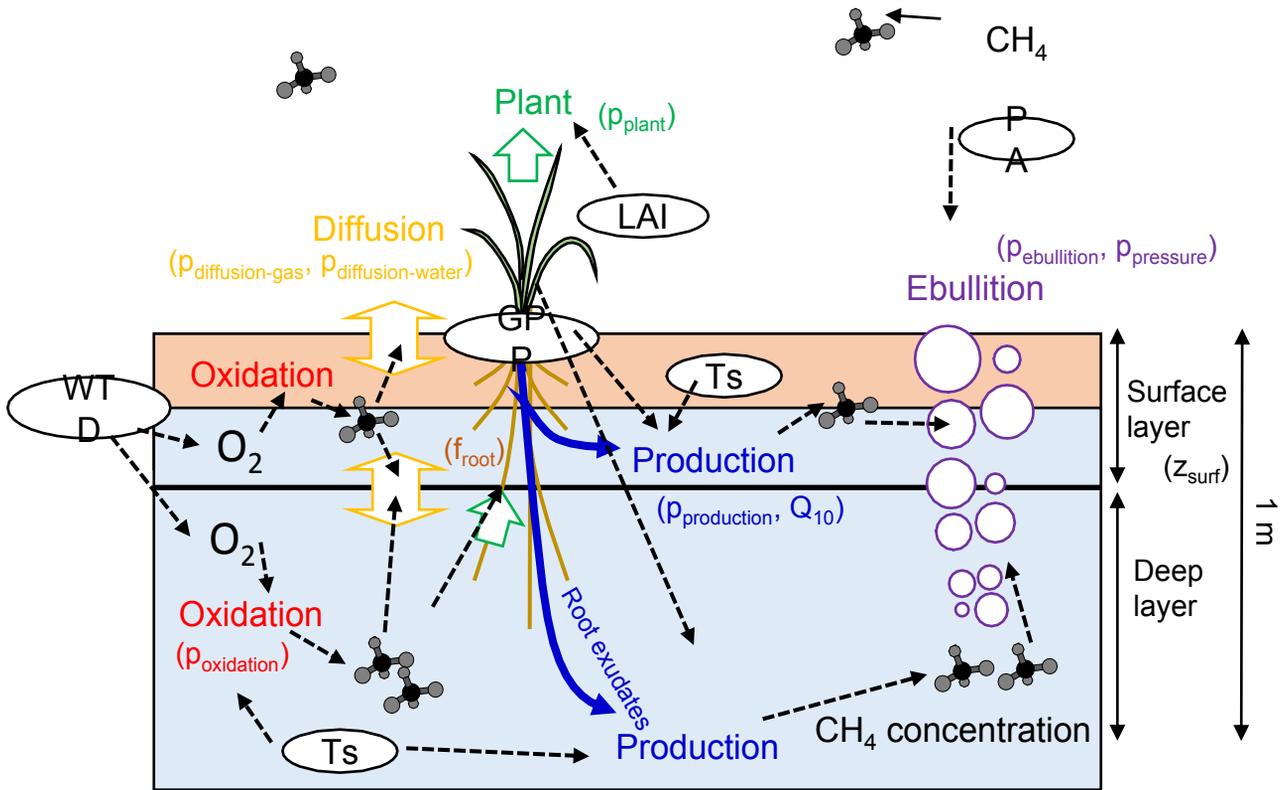
1096 empirical Q_{10} value between daily CH_4 flux and soil temperature for the surface layer. Boxplots
1097 represent the relative changes in flux for aggregated sites having annual high and low mean
1098 water table positions (higher and lower above the ground, respectively). The relative changes
1099 by boxplots did not include US-Uaf, because the flux was too low and the ratio was anomalously
1100 high due to low denominator.

1101
1102 Table 1. Literature survey for partitioned methane (CH_4) emissions from wetlands (i.e., ebullition
1103 diffusion, and plant-mediated transport) based on field observations and modeling.

1104
1105 Table 2. Description of study sites, showing wetland type, location, dominant vegetation type
1106 (DOM_VEG), mean annual air temperature (TAVE), GPP, annual maximum monthly leaf area
1107 index (LAI) (MCD15A3H), mean annual soil temperature (TS), water table depth during the
1108 period when soil was thaw (WTD gs), and modeled partitioned methane (CH_4) emissions during
1109 the growing season when LAI was higher than 20% of the annual maximum.

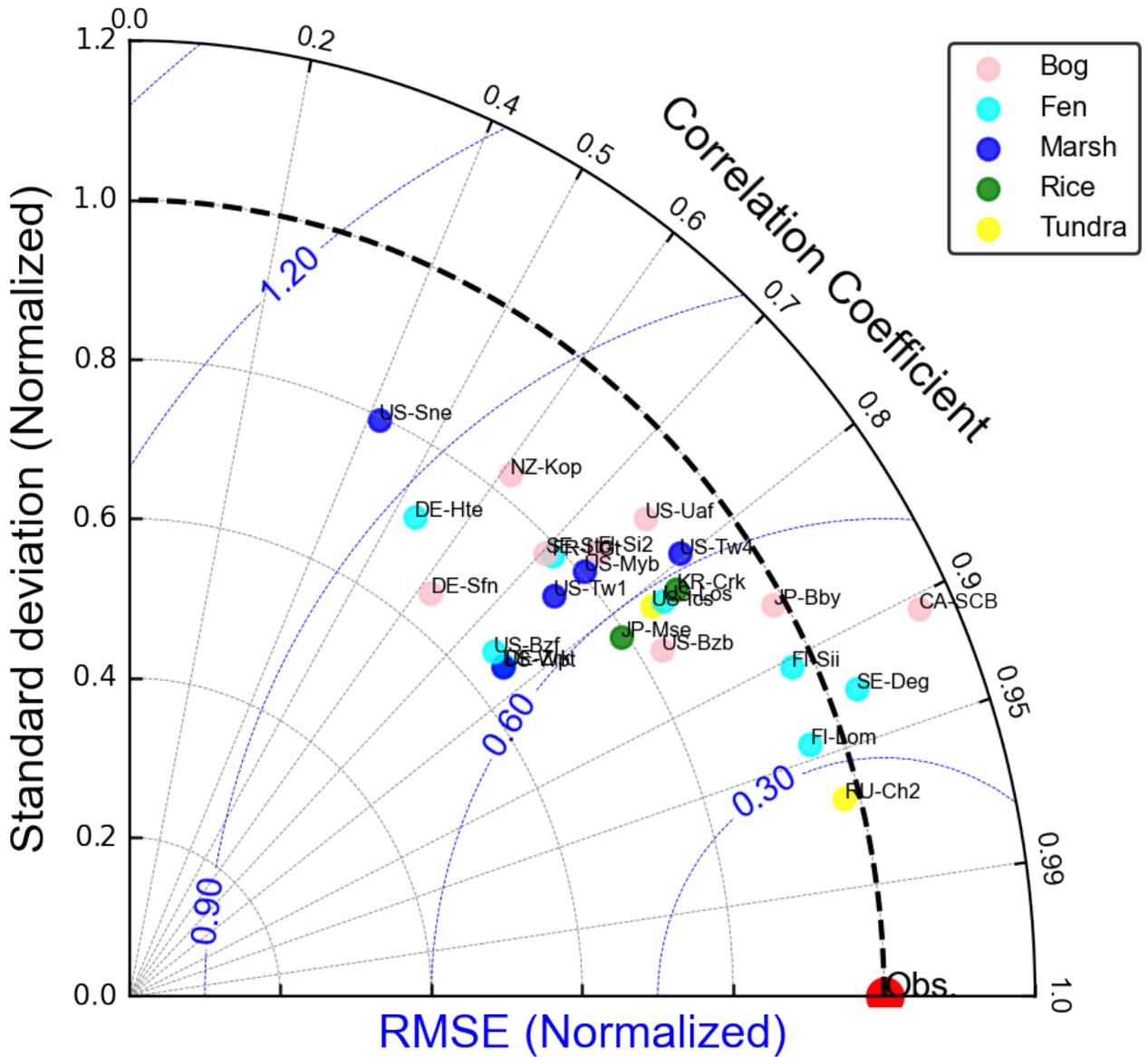
1110
1111 Table 3. Ranges of parameters for mathematical optimization and prior distributions for Bayesian
1112 optimization for the iPEACE model. The range of uniform distributions were determined by
1113 adding plus/minus to the values determined by the differential evolution method for each site
1114 ([Table S1](#)).

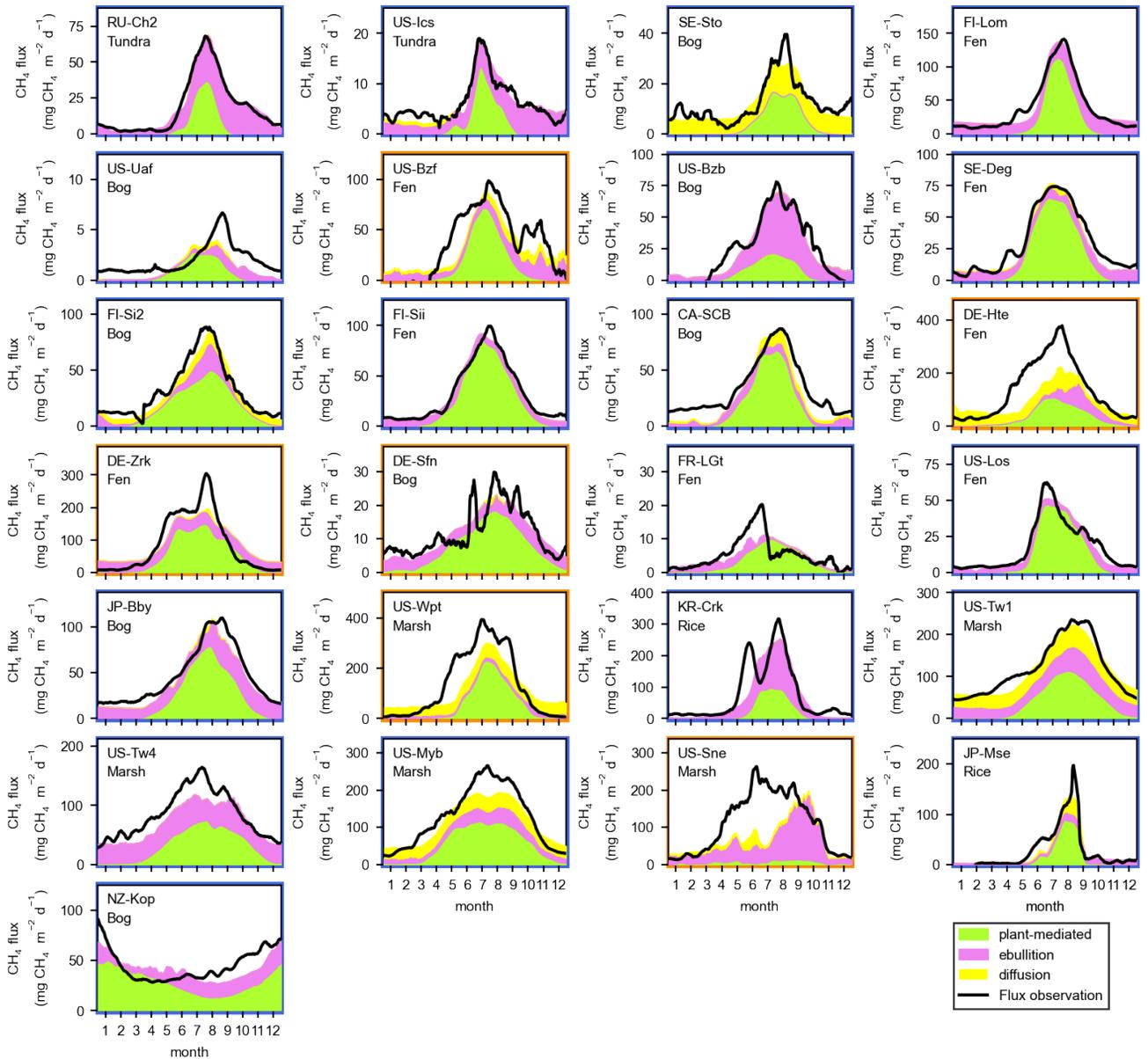
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Schematic representation of the model structure for methane (CH₄) flux. The model consists of two soil layers: a surface layer susceptible to oxic conditions and a deep layer prone to anoxic conditions. Ecosystem-atmosphere CH₄ fluxes are the net result of CH₄ production ($p_{\text{production}}$ and Q_{10}), oxidation ($p_{\text{oxidation}}$), and transport processes. Transport is the sum of diffusion ($p_{\text{diffusion-gas}}$ and $p_{\text{diffusion-water}}$), plant-mediated transport (p_{plant}), and ebullition ($p_{\text{ebullition}}$ and p_{pressure}). Substrate for CH₄ production associated with gross primary productivity (GPP) is divided into surface and deep layers (z_{surf}), considering root distribution (f_{root}). The model is driven by biophysical variables: soil temperature (T_s) in the two soil layers, water table depth (WTD), leaf area index (LAI), GPP, and barometric pressure (PA). Calibrated parameters are shown with parentheses, and dashed lines represent a major flow of causality.

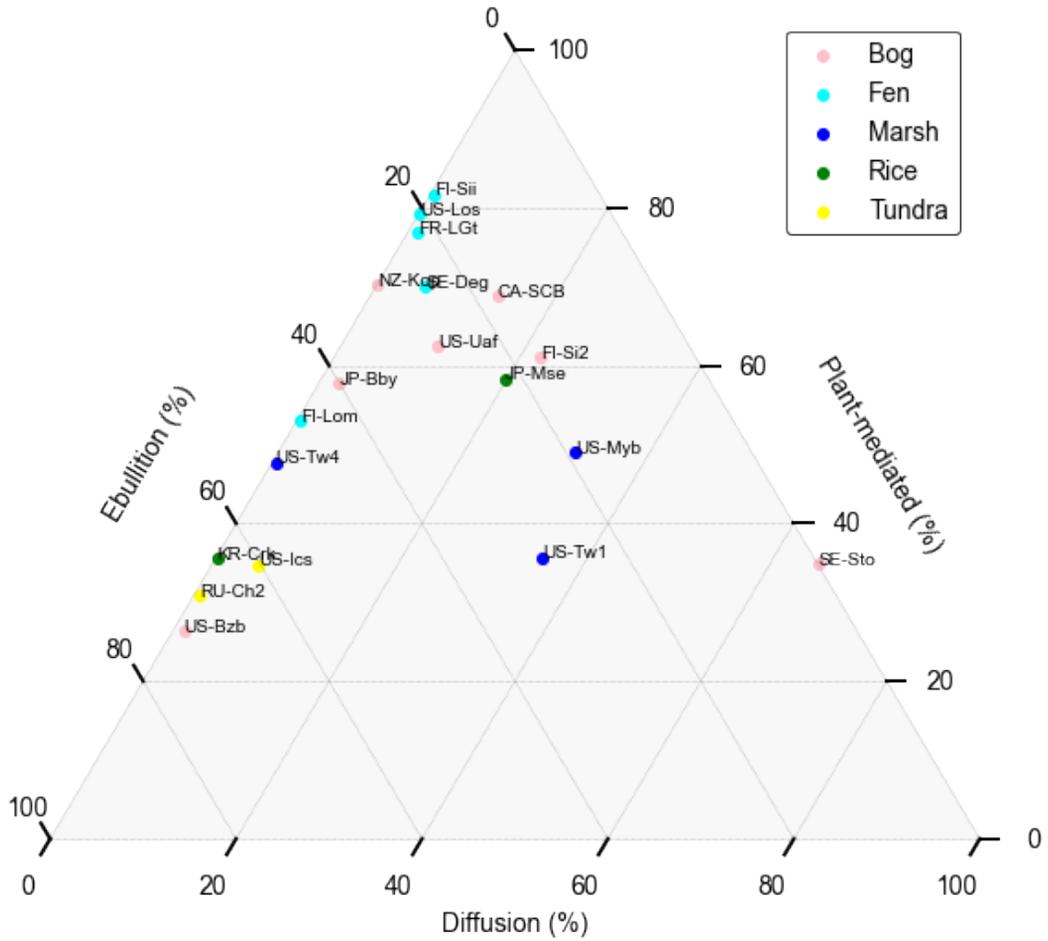
Figure 2



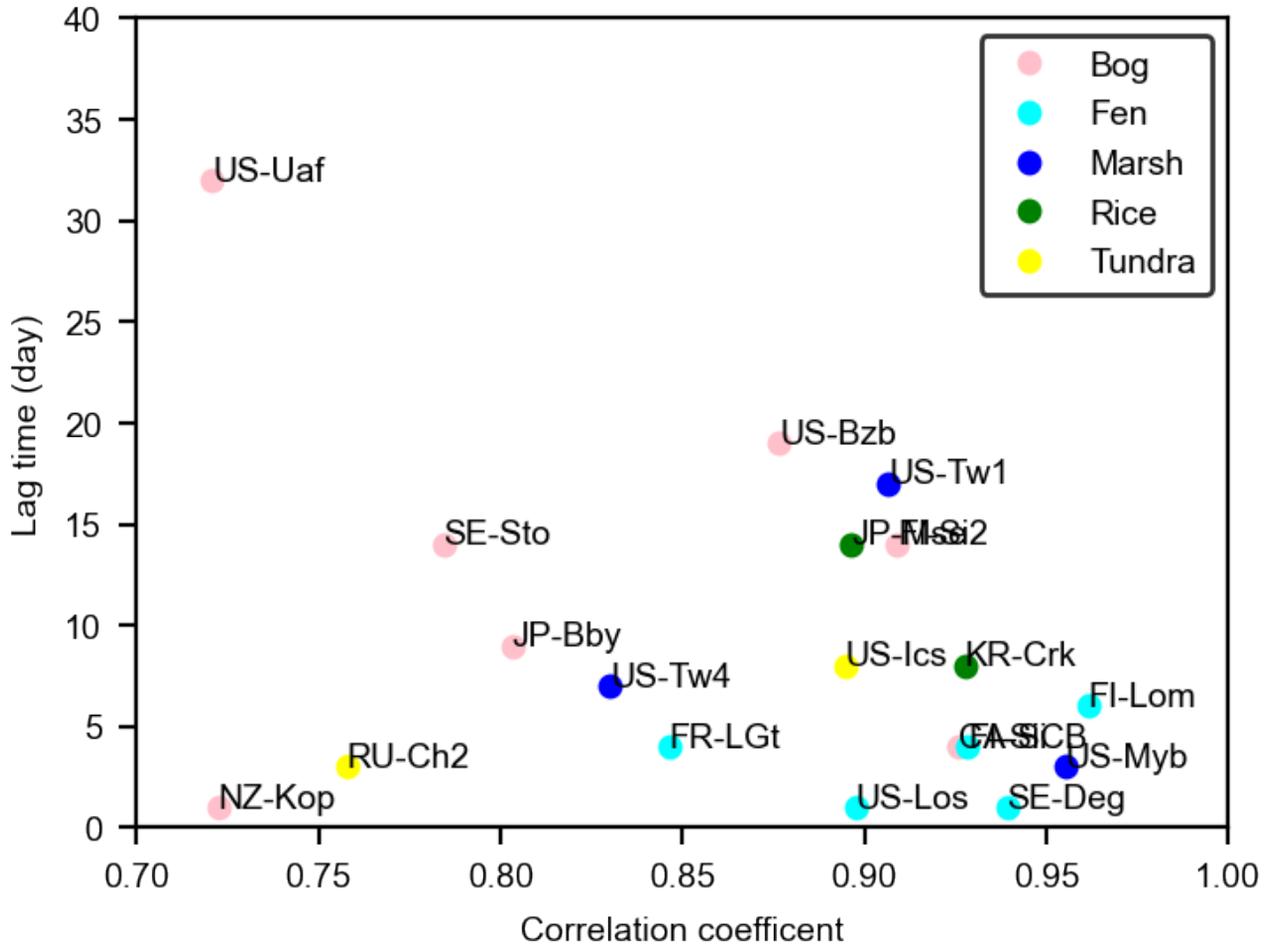


Mean seasonal variations of observed and modeled methane (CH_4) fluxes and the transport components of plant-mediated transport, ebullition, and diffusion. The seasonality is calculated as a mean across years, and then a seven-day moving mean is applied for smoothing. Note differences in y-axis ranges among panels. Frames colored by blue are the sites having acceptable model performance (normalized root mean square error was >0.9 , correlation coefficient was <0.6 , normalized standard deviation was <0.7 , or normalized standard deviation was >1.3), and those colored by brown are the sites having low performance.

Figure 4

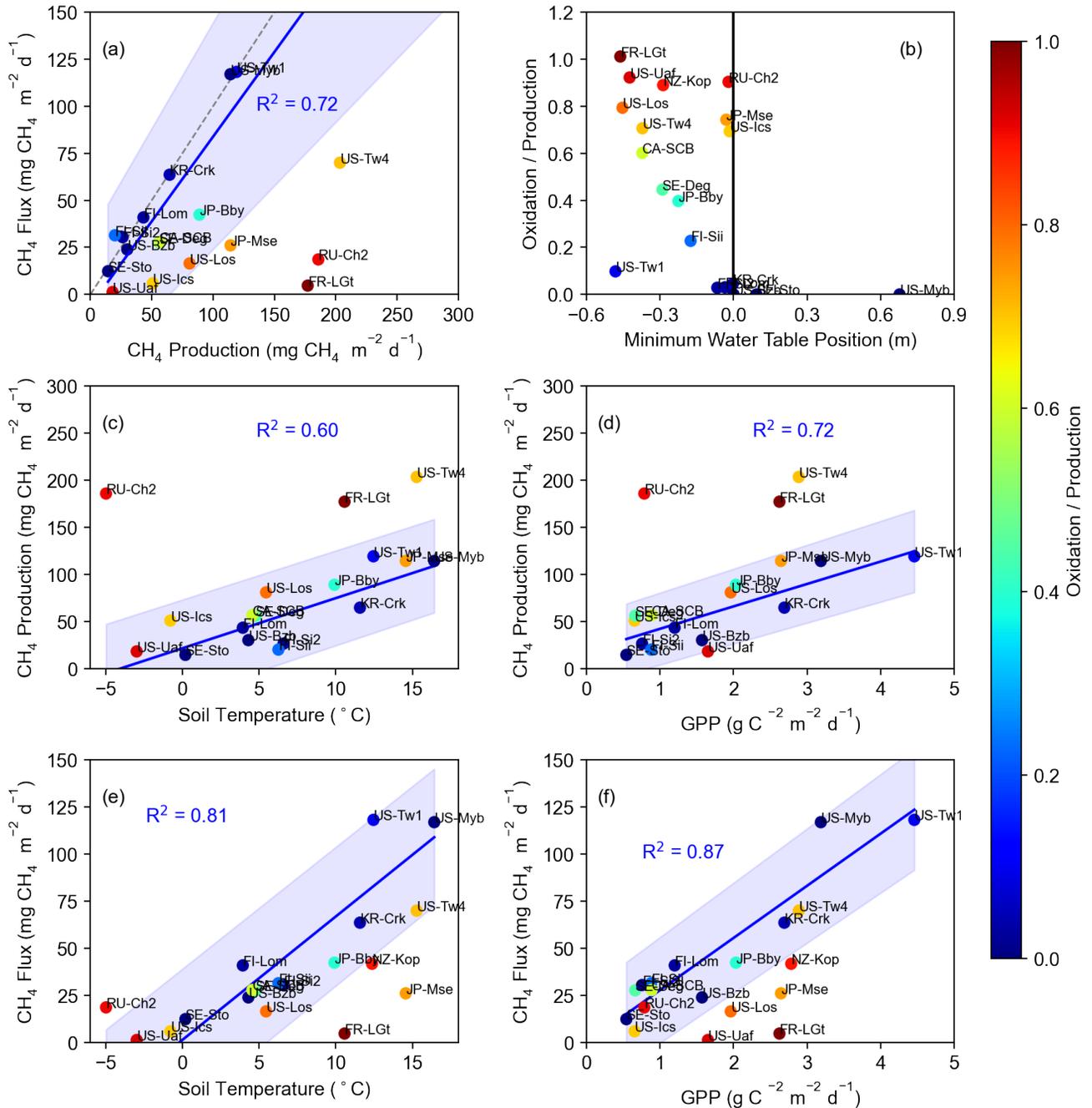


Ternary plot for modeled annual methane (CH₄) transport pathways of plant-mediated transport, ebullition, and diffusion.

Figure 5

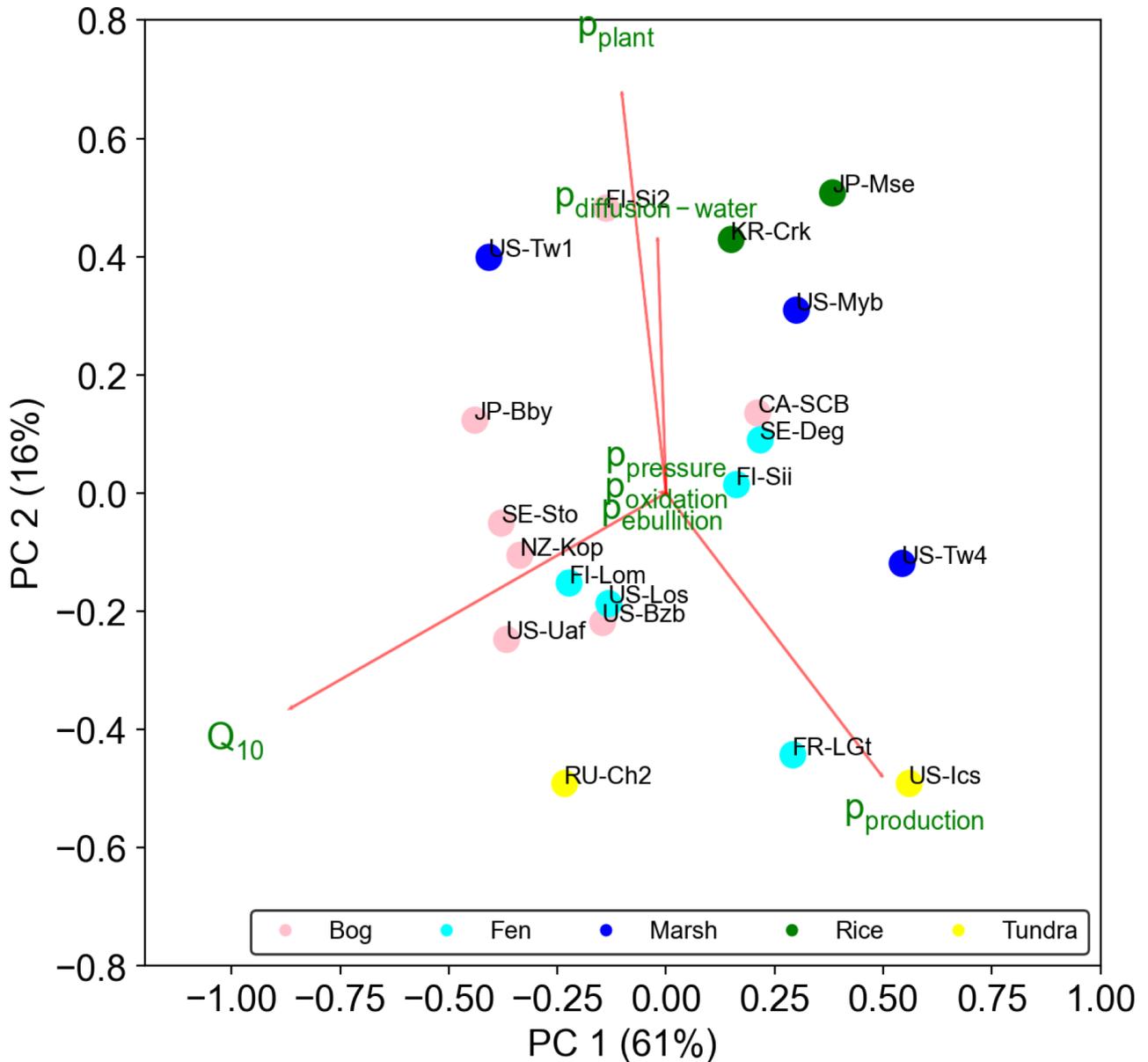
Lag time between modeled methane (CH_4) production and CH_4 flux based on a cross-correlation analysis, plotted against the correlation coefficient between CH_4 fluxes and lagged CH_4 production.

Figure 6



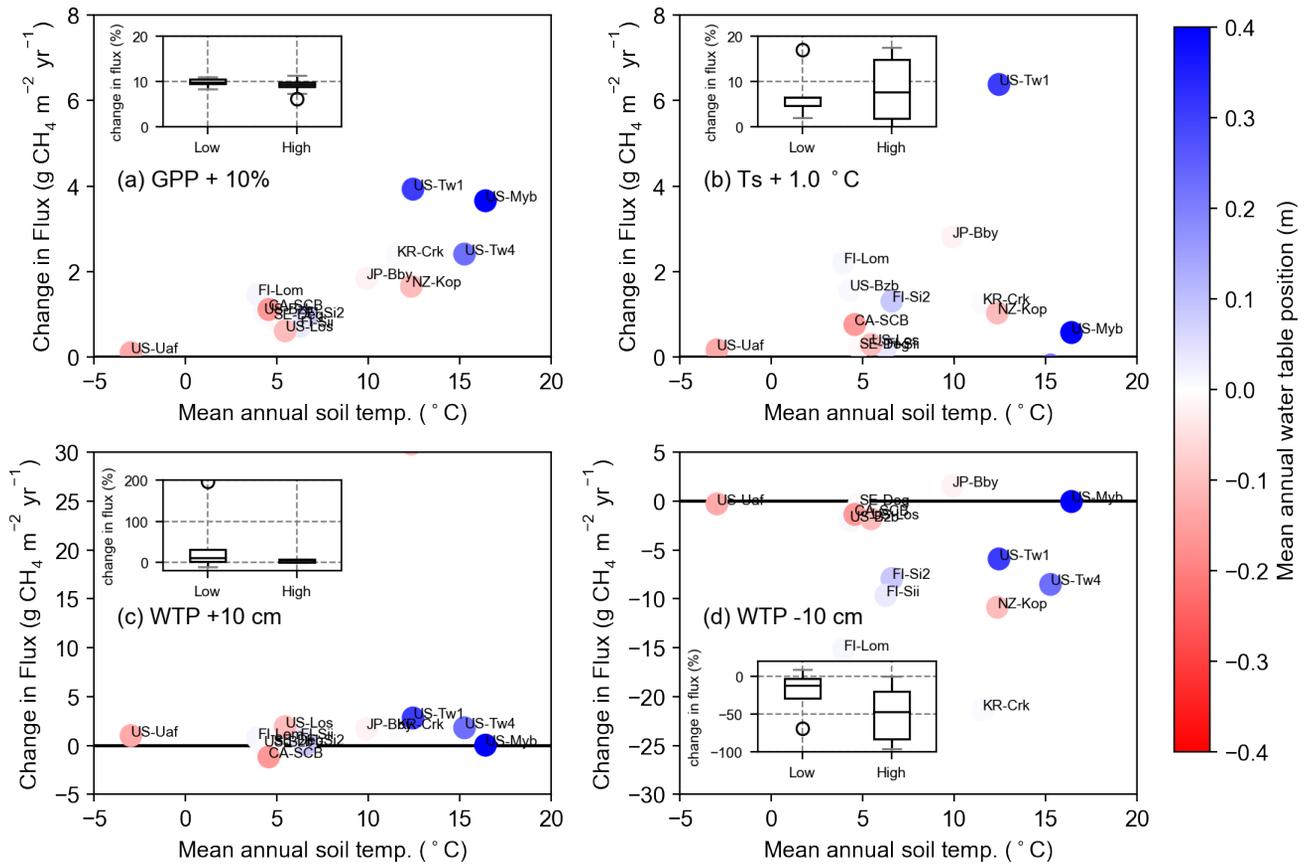
Relationships between modeled methane (CH₄) production and CH₄ flux (a), between minimum water table position and ratio of oxidation to production (b), between mean annual soil temperature and modeled CH₄ production (c), between gross primary productivity (GPP) and modeled CH₄ production (d), between soil temperature and modeled CH₄ flux (e), and between GPP and CH₄ flux (f). Annual mean or minimum for the study period are shown. Blue lines in (a, c, d, e, f) represent linear regression (all $p < 0.001$) based on sites where modeled oxidation contributed less than 70% of CH₄ production, where shading represents the prediction interval ($p = 0.1$). Dashed line in (a) represents the 1:1 line between production and flux. The high CH₄ production for NZ-Kop (525 mg CH₄ m⁻² d⁻¹) is too high to fit the range in the figure (a, c, d). Points represent mean values over the observation period, and their colors represent the ratio of CH₄ oxidation to production.

Figure 7

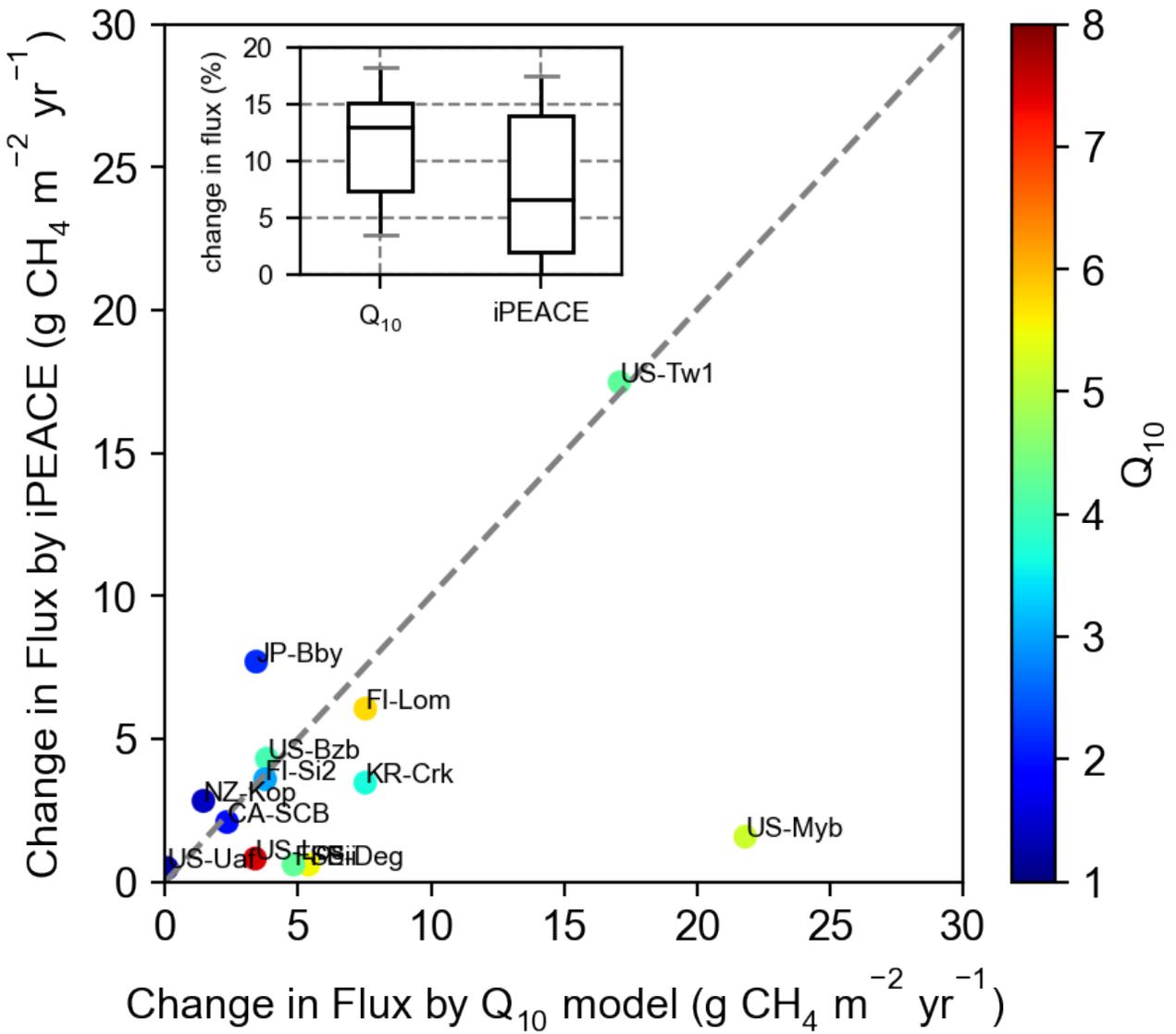


Biplot showing the first and second components based on the principal components (PC) of the estimated parameters across the sites: methane (CH_4) production per gross primary productivity ($p_{\text{production}}$), Q_{10} for CH_4 production, maximum CH_4 oxidation rate ($p_{\text{oxidation}}$), nondimensional conductivity for gaseous transfer ($p_{\text{ebullition}}$), diffusion coefficient for plant-mediated transport (p_{plant}), diffusion coefficient multiplier for water ($p_{\text{diffusion-water}}$), and sensitivity of ebullition to barometric pressure (p_{pressure}).

Figure 8



Modeled sensitivity of annual mean methane (CH_4) flux to perturbed input of 10% high gross primary productivity (GPP) (a), biased input of 1°C high soil temperatures (Ts) (b), 10 cm high water table position (WTP) (c), and 10 cm low WTP (d). The changes in fluxes were shown on climate space of mean annual soil temperature and mean annual WTP over the observation period for each site. Boxplots represent the relative changes in flux for aggregated sites having annual high and low mean WTP (higher and lower above the ground, respectively), where dots represent outliers. The relative changes by boxplots did not include US-Uaf, because the flux was too low and the ratio was anomalously high due to low denominator. The sensitivity analysis was done for sites having at least three years of data.



Change in methane (CH₄) flux estimated with a perturbed input of 1°C increase in soil temperatures for the empirical Q₁₀ model and iPEACE model. The colors in plots represent the empirical Q₁₀ value between daily CH₄ flux and soil temperature for the surface layer. Boxplots represent the relative changes in flux for aggregated sites having annual high and low mean water table positions (higher and lower above the ground, respectively). The relative changes by boxplots did not include US-Uaf, because the flux was too low and the ratio was anomalously high due to low denominator.

Table 1. Literature survey for partitioned methane (CH₄) emissions from wetlands (i.e., ebullition diffusion, and plant-mediated transport) based on field observations and modeling.

Obs./Model	Wetland Type	Site	Ebullition	Diffusion	Plant	Method	Period	Reference
Observation	Arctic Tundra					92-98 Chamber	Summer	Morrissey and Livingston, 1992
Observation	Arctic Tundra				66 (polygon center)	Chamber	August	Kutzbach et al., 2004
Observation	Arctic Tundra	RU-Ch2	2		27 (polygon rim)	Chamber	Summer	Kwon et al., 2017
Observation	Boreal bog	FI-Si2	2-8		25 (wet sites)	Bubble trap	Growing season	Männistö et al., 2019
Observation	Boreal fen	FI-Sii			0 (dry sites)	Chamber		Korrensalo et al., 2022
Observation	Boreal fen				38 (hummocks)	Chamber		Korrensalo et al., 2022
Observation	Boreal fen				31 (lawns)	¹⁴ C pulse labeling of mesocosms	12 days	Dorodnikov et al., 2011
Observation	Temperate bog	JP-Bby	50		51 (hollows)	Chamber	Summer	Tokida et al., 2007a, b
Observation	Temperate bog		14-16			Bubble trap	Growing season	Stamp et al., 2013
Observation	Temperate bog				64-90	Chamber	May-December	Shannon et al., 1996
Observation	Temperate fen		38			Bubble trap	Spring & summer	Stanley et al., 2019
Observation	Temperate fen		~ 10			Eddy covariance for isoflux	two days in summer	Santoni et al., 2012
Observation	Temperate fen (<i>Eriophorum vaginatum</i>)	FR-LGt	54.7 in May			Chamber	two months	Gogo et al., 2011
	Temperate fen (<i>Sphagnum</i> spp. & <i>Betula</i> spp.)		40.7 in March					
			negligible					
Observation	Temperate marsh (open water)	US-Myb	~ 1.3	~ 4.1		Combined eddy covariance and process study	Annual	McNicol et al., 2017
Observation	Temperate marsh (open water)		50	50 Not consier		Bubble trap in open water area within the flux footprint		
Observation	Temperate marsh (floating vegetation)		50	50 Not consier		Gas concentration in water for open water area		
Observation	Temperate marsh (emergent vegetation)		99	1 Not consier		Chamber at water surface not including vegetation	September	Villa et al., 2021
Observation	Temperate marsh (emergent vegetation)	US-Tw1	10-30			Chamber at water surface not including vegetation		
Observation	Rice paddy		9			Static chambers	Aug. 29- Sep. 2	Windham-Myers et al. (2018)
Observation	Rice paddy	KR-Crk	10-17			Eddy covariance + Wavelet analysis	Growing season	Richardson et al., 2022
Observation	Rice paddy			marginal		Eddy covariance + Wavelet analysis	Growing season	Hwang et al., 2020
Observation	Rice paddy		4	marginal		Chamber	Growing season	Butterbach-Bahl et al., 1997
Observation	Rice paddy					96 Chamber	Growing season	Kajiura and Tokida, 2021
Model	pan-Arctic wetland (regional mean)		51.5	1		47.5 VISIT	Annual	Ito 2019
Model	Boreal bog		0.6	3.4		96 TECO calibrated with chamber data	Annual	Ma et al., 2017
Model	Boreal fen	FI-Sii	0	37		63 HIMMELI calibrated with eddy covariance data	Annual	Peltola et al., 2018
Model	Boreal fen	FI-Sii	5	30		75-95 sqHIMMELI calibrated with eddy covariance data	Annual	Susiluoto et al., 2018
Model	Arctic Tundra near RU-Ch2		4.2	34.8		61.0 JSBACH-methane	Annual	Castro-Morales et al., 2018
Model	Alpine tundra (Ruoergai)		0.3	28.8		70.8 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Subarctic mire (Abisko)		0	15.5		84.5 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Boreal fen (BOREAS)		0.9	29.2		69.9 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Boreal fen (Salmisuo)		1.4	30.9		67.8 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Boreal fen (Degero)		0.8	25.7		74.3 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Temperate bog (Michigan)		0	24.4		75.6 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Temperate fen (Minnesota)		0.4	22.9		76.7 LPJ-WHyMe v 1.3.1	Annual	Wania et al., 2010
Model	Temperate fen	US-Los	0.0	23.7		76.3 ORCHIDEE-PEAT revision 7020	Annual	Salmon et al., 2022
Model	Boreal bog	US-Bzb	0.0	0.9		99.1 ORCHIDEE-PEAT revision 7020	Annual	Salmon et al., 2022
Model	Temperate fen	FR-LGt	0.0	-0.1		100.1 ORCHIDEE-PEAT revision 7020	Annual	Salmon et al., 2022
Model	Boreal fen	FI-Lom	0.8	-1.6		100.8 ORCHIDEE-PEAT revision 7020	Annual	Salmon et al., 2022
Model	Temperate Marsh	US-Wpt	0.0	0.0		100.0 ORCHIDEE-PEAT revision 7020	Annual	Salmon et al., 2022

Table 2 Description of study sites, showing wetland type, location, dominant vegetation type (DOM_VEG), mean annual air temperature (TAVE), GPP, annual maximum monthly leaf area index (LAI) (MCD15A3H), mean annual soil temperature (TS), water table depth during the period when soil was thaw (WTD gs), and modeled partitioned methane (CH₄) emissions during the growing season when LAI was higher than 20% of the annual maximum.

Site	Wetland type	Latitude	Longitude	DOM_VEG	TAVE (°C)	GPP (g C m ⁻² yr ⁻¹)	LAI (m ² m ⁻²)	TS (°C)	WTD gs (m)	WTD min (m)	Start year	End year	Ebullition (%)	Plant (%)	Diffusion (%)	References
RU-Ch2	Tundra	68.617	161.351	aerenchymatous	-10.6	284	2.0	-5.0	-0.01	-0.02	2014	2015	50	49	1	Goeckede (2020)
US-Ics	Tundra	68.606	-149.311	aerenchymatous	-5.9	237	1.7	-0.8	-0.01	-0.02	2015	2016	35	65	0	Euskirchen et al. (2020)
SE-Sto	Bog	68.356	19.0452	aerenchymatous	0.7	197	1.4	0.2	0.09	0.09	2014	2015	0	53	47	Knox et al. (2019)
FI-Lom	Fen	67.99724	24.20918	aerenchymatous	-0.4	434	2.0	3.9	0.02	-0.04	2006	2010	23	77	0	Lohila et al. (2020)
US-Uaf	Bog	64.86627	-147.8555	moss_sphagnum	-2.9	599	1.4	-3.0	-0.14	-0.42	2011	2018	18	70	12	Iwata et al. (2020)
US-Bzf	Fen	64.703733	-148.3133	aerenchymatous	-0.2	581	2.3	4.7	0.00	-0.01	2015	2016	--	--	--	Euskirchen and Edgar (2020a)
US-Bzb	Bog	64.695547	-148.3208	eri_shrub	-0.7	570	1.5	4.3	0.02	0.00	2014	2016	68	31	1	Euskirchen and Edgar (2020b)
SE-Deg	Fen	64.182029	19.556539	moss_sphagnum	2.5	241	2.2	4.8	-0.01	-0.29	2014	2018	12	84	5	Nilsson and Peichl (2020)
FI-Si2	Bog	61.837459	24.169896	moss_sphagnum	5.1	275	2.2	6.6	0.09	-0.07	2012	2016	16	67	17	Vesala et al. (2020a)
FI-Sii	Fen	61.832562	24.192933	moss_sphagnum	4.7	319	2.4	6.2	0.03	-0.17	2013	2018	9	91	0	Vesala et al. (2020b)
CA-SCB	Bog	61.308	-121.299	moss_sphagnum	-1.5	312	2.9	4.6	-0.16	-0.37	2014	2017	11	78	11	Sonntag and Helbig (2020)
DE-Hte	Fen	54.210278	12.17611	aerenchymatous	10.0	774	4.9	10.6	-0.27	-0.62	2011	2018	--	--	--	Koebisch and Jurasinski (2020)
DE-Zrk	Fen	53.8759	12.88901	aerenchymatous	9.5	598	2.8	10.9	0.23	-0.12	2013	2018	--	--	--	Sachs and Wille (2020)
DE-Sfn	Bog	47.806389	11.3275	tree	8.3	772	2.9	7.8	-0.07	-0.24	2012	2014	--	--	--	Schmid and Klatt (2020)
FR-LGt	Fen	47.32291	2.284102	aerenchymatous	11.0	952	4.6	10.5	-0.23	-0.46	2017	2018	12	87	1	Jacotot et al. (2020)
US-Los	Fen	46.0827	-89.9792	eri_shrub	4.9	712	6.5	5.4	-0.11	-0.45	2014	2018	9	91	0	Desai (2020)
JP-Bby	Bog	43.323006	141.8107	aerenchymatous	7.0	737	2.7	9.9	-0.02	-0.23	2015	2018	27	70	2	Ueyama et al. (2020)
US-Wpt	Marsh	41.464639	-82.99616	aerenchymatous	11.3	636	2.8	13.4	0.38	0.14	2011	2013	--	--	--	Chen and Chu (2020)
KR-Crk	Rice	38.2013	127.2506	aerenchymatous	10.9	975	2.0	11.5	0.01	0.00	2015	2018	61	39	0	Ryu et al. (2020)
US-Tw1	Marsh	38.107	-121.647	aerenchymatous	15.1	1617	1.7	12.4	0.30	-0.48	2011	2018	26	45	29	Valach et al. (2020b)
US-Tw4	Marsh	38.103	-121.641	aerenchymatous	15.5	1048	1.3	15.3	0.23	-0.37	2013	2018	42	57	0	Eichelmann et al. (2020)
US-Myb	Marsh	38.05	-121.765	aerenchymatous	15.5	1157	2.1	16.4	1.23	0.68	2010	2018	18	58	24	Matthes et al. (2020)
US-Sne	Marsh	38.037	-121.755	aerenchymatous	15.0	329	1.8	16.9	0.10	-0.58	2016	2018	--	--	--	Shortt et al. (2020)
JP-Mse	Rice	36.054	140.0269	aerenchymatous	13.7	960	2.1	14.5	-0.01	-0.03	2012	2012	12	65	23	Iwata (2020)
NZ-Kop	Bog	-37.388	175.554	aerenchymatous	13.7	1017	5.0	12.4	-0.10	-0.29	2012	2015	30	70	0	Campbell and Goodrich (2020)

Table 3. Ranges of parameters for mathematical optimization and prior distributions for Bayesian optimization for the iPEACE model. The range of uniform distributions were determined by adding plus/minus to the values determined by the differential evolution method for each site (Table S1)

Parameter	Unit	Lower range in mathematical optimization	Upper range in mathematical optimization	Prior range in Bayesian inference	Prior distribution
Initial CH ₄ value at the surface layer	mol-CH ₄ m ⁻³	0	0.5	±0.1	uniform
Initial CH ₄ value at the deep layer	mol-CH ₄ m ⁻³	0	4	±0.2	uniform
Base production rate per gross primary productivity (p _{production})	mmol-CH ₄ g C ⁻¹	1	6	±0.5	uniform
Temperature sensitivity of CH ₄ production (Q _{10production})	--	0.00001	5	±1	uniform
Maximum CH ₄ oxidation rate (p _{oxidation})	mol-CH ₄ m ⁻² s ⁻¹	0.000000125	0.000125	±log(1.0)	uniform
Nondimensional conductivity for gaseous transfer (p _{ebullition})	--	0	0.01	b	uniform
Diffusion coefficient for plant-mediated transport (p _{plant})	10 ⁻³ d ⁻¹	0.001	3	±1	uniform
Diffusion coefficient multiplier for water (p _{diffusion-water})	--	0.001	2	±0.3	uniform
Diffusion coefficient multiplier for gas (p _{diffusion-gas})	--	0.001	2	±0.3	uniform
Sensitivity of ebullition to barometric pressure (p _{pressure})	hPa ⁻¹	0	1	±0.05	uniform
Thickness of the surface layer (z _{surf})	m	0.05	0.80	0.05-0.80	uniform
Surface root fraction (f _{sroot})	--	0.05	1.00	0.05-1.00	uniform
Residuals of the model	mg CH ₄ m ⁻² d ⁻¹	--	--	--	log normal