



CLM-Wet-MS v1.0: A Community Land Model with Wetland-Adapted Plant Physiology and Microbial Soil Decomposition for Simulating Carbon Dioxide and Methane Fluxes at Temperate Riverine Wetlands

5 Hyunyoung Oh¹, Justine Missik², Gil Bohrer², Vonihannitranaina D.Z. Andriamanantena. R.¹, Minseok Kang³, Hojeong Kang⁴, and Yeonjoo Kim¹

¹Department of Civil and Environmental Engineering, Yonsei University, South Korea

²Department of Civil, Environmental, and Geodetic Engineering, The Ohio State University, USA

³Department of Atmospheric and Environmental Sciences, Kangwon National University Gangneung Campus, South Korea

10 ⁴North China University of Water Resources and Electric Power, China

Correspondence to: Yeonjoo Kim (yeonjoo.kim@yonsei.ac.kr)

Abstract. Temperate inland riverine wetlands contribute meaningfully to regional carbon cycling, yet they remain poorly represented in land surface models. This study introduces CLM-Wet-MS, a modified version of the Community Land Model version 5 (CLM5) that incorporates a dedicated wetland landunit with wetland-adapted soil hydrology and a microbial soil decomposition scheme. The model was applied at Bibong wetland, a freshwater riverine wetland in South Korea, dominated by *Phragmites australis*. Hydrological representation is a dominant control on simulated carbon fluxes. The simulation configuration with observation-driven prescribed soil moisture is the only one that realistically reproduce the observed aerenchyma-dominated CH₄ transport. The microbial decomposition scheme reduces a persistent winter respiration bias that parameter optimization alone could not correct. Bayesian-based hierarchical parameter optimization was then performed against eddy covariance observations of gross primary productivity (GPP), ecosystem respiration (ER), and methane flux (FCH₄). Optimization reduced root-mean-square error (RMSE) by 57.8% (GPP), 37.1% (ER), and 31.2% (FCH₄), with optimized parameters consistent with wetland-adapted C3 grass physiology and soil biogeochemistry. Comparison with plot-scale chamber measurements show that flux estimates diverge according to their spatial coverage, highlighting the influence of observation scale on model evaluation in heterogeneous wetlands. The CLM-Wet-MS model provides an optimized baseline for wetland modeling within CLM5 that can be extended to regional-scale simulations incorporating multiple land cover types.

1 Introduction

Wetlands cover only a small fraction of the Earth's land surface, roughly 2% to 6%, yet they store a disproportionately large amount of terrestrial carbon—approximately 1,500 PgC in soil reservoir (Whiting and Chanton, 2001; Kayranli et al., 2009; Villa et al., 2019). Wetlands function as long-term carbon sinks because high plant productivity is coupled with suppressed decomposition under saturated, anaerobic conditions. Yet, the same condition can also promote methanogenesis, making



wetlands the largest natural source of CH₄. Whether a given wetland acts as an overall net carbon source or sink therefore depends on the balance between these two opposing fluxes (Whiting and Chanton, 2001; Limpert et al., 2020). This balance, however, is inherently difficult to constrain. Wetlands are spatially heterogeneous, with plant community composition, soil biogeochemistry, and gas transport pathways shifting in response to seasonal and interannual hydrological variability (Villa et al., 2019). At larger scales, the global areal extent of wetlands also remains poorly quantified (Kirschke et al., 2013; Zhang et al., 2017). Climate change adds a further layer of uncertainty as suggested by multi-model ensemble projections showing that the expansion of boreal wetland extent and rising temperatures could substantially amplify natural methane emissions over the 21st century (Melton et al., 2013; Zhang et al., 2017; Saunois et al., 2025). Largely because of these uncertainties, wetland carbon feedbacks have not been fully incorporated into global assessments such as the IPCC Fifth Assessment Report. Their consequences extend beyond scientific assessment, limiting our ability to assess whether wetland conservation and restoration can serve as an effective long-term negative emission strategy (Valach et al., 2021). Process-based modeling frameworks offer a way forward to move beyond these limitations, as they can represent the complex interactions governing wetland carbon dynamics and projecting their response to future environmental change. Land surface models (LSMs) provide such a framework, representing the complex interactions among vegetation, hydrology, and soil biogeochemistry (Friedlingstein et al., 2006; Fisher and Koven, 2020; LaFond-Hudson and Sulman, 2023).

Simulating wetland carbon fluxes with LSMs, however, remains highly challenging, primarily due to two dominant sources of uncertainty: structural differences in how key processes are represented, and the parameter values governing those representations. The processes that are most difficult to represent fall into three broad categories: (i) hydrological controls, including seasonal water table variability and short-term water elevation fluctuations (Rosenberry and Winter, 1997; Tamea et al., 2010; Li et al., 2024; Tang et al., 2025); (ii) soil biogeochemical processes, such as microbial decomposition under varying redox conditions, salinity, and soil temperature (Chambers et al., 2016; Bian et al., 2020; Rezanezhad et al., 2020); and (iii) vegetation structural adaptations to inundated environments, notably aerenchyma tissue that facilitates gas transport (Villa et al., 2020; van den Berg et al., 2024). These representational challenges are evident in model intercomparisons, where estimates from multiple land surface models diverge substantially even after differences in wetland extent are accounted for (Melton et al., 2013; Saunois et al., 2025). In land surface models, these numerous physical and biological processes are described by parameters. Ideally, these parameters should represent properties of the ecosystem that are static in time and space (Hourdin et al., 2017). However, determining the values of these parameters is extremely challenging in terrestrial ecosystems with high spatial and temporal variation, and especially in wetlands, where hydrological dynamics further compound spatial and temporal ecosystem variation. Despite numerous optimization approaches (LeBauer et al., 2013; Fer et al., 2018; Raoult et al., 2025), the high dimensionality of the parameter space often leads to equifinality, where multiple parameter sets produce equally good fits to data (Tang and Zhuang, 2008; Keetz et al., 2025). This problem is compounded by the fact that biases in one component of a complex model can undermine effective calibration of other components (Fisher and Koven, 2020). Furthermore, key ecosystem properties are determined by the traits of organisms, which vary across functional types and shift dynamically in response to environmental change. Identifying fixed values to represent the temporal dynamics



65 of plant community composition, functional diversity, and demographic responses to changing climate and resource competition remains an open challenge in land surface modeling (Moorcroft et al., 2001; Scheiter et al., 2013; Fisher et al., 2018; Longo et al., 2019a, b). Model predictions have shown high sensitivity to the representation of vegetation composition and phenological controls across ecosystems ranging from tropical forests to temperate mixed forests, and Arctic tundra (Kim et al., 2012; Kim et al., 2021; Kim et al., 2022).

70 Beyond these general challenges, wetland modeling faces a more basic structural limitation. A key limitation with current LSMs, including Community Land Model (CLM) and the Energy Exascale Earth System Model Land Model (ELM), is that they do not assign wetlands an explicit landunit type. Instead, wetland processes are represented through inundated soil biogeochemical processes activated within the inundated fraction of dry-land ecosystem landunits. Vegetation and other process parameters are derived from properties of dry-land plant functional types. While site-level parameterizations can be

75 adjusted to represent wetland vegetation, their values cannot be generalized because no corresponding wetland plant functional types exist in the models (Yazbeck and Bohrer, 2023). Several efforts have been made to address this problem in process-based models, each with different emphases and limitations. The Denitrification-Decomposition model for wetlands (Wetland-DNDC) integrated hydrology, soil biogeochemistry, and vegetation processes for forested wetlands, but its standalone design limits applicability within global modeling frameworks (Zhang et al., 2002). A peat-enabled version of the Joint UK Land

80 Environment Simulator (JULES) improved the sensitivity of soil carbon decomposition to moisture and nitrogen availability in temperate peatlands, though wetland vegetation dynamics were not addressed and were identified as a necessary future development (Chadburn et al., 2022). A coupled ELM–Process-based reactive transport model (ELM-PFLOTRAN) framework enabled simulation of redox reactions, pH dynamics, and methane cycling in tidal marshes, yet the parameterization of its complex reaction networks remains difficult to constrain with available observations (Sulman et al., 2024). Among these

85 efforts, the wetland-enabled ELM (ELM-Wet) represents the most comprehensive attempt to date to solve this problem. It introduces a dedicated wetland landunit (wet-landunit) whose vegetation patch types integrate both vegetation and soil characteristics, together with an aerenchyma conductivity scaling revised to scale with leaf area index. To represent hydrological heterogeneity, it further assigns each patch type a maximal inundation depth and modifies the runoff scheme so that sustained, within-site inundation can be resolved or prescribed (Yazbeck et al., 2025).

90 A further gap in current wetland modeling processes concerns the representation of soil microbial processes. Most LSMs rely on first-order kinetics to describe soil organic matter decomposition, without explicitly representing microbial biomass, enzyme dynamics, or carbon use efficiency (Tao et al., 2025). There is growing recognition that microbial-explicit representations improve the simulation of soil carbon dynamics and their response to environmental change. Recent developments include the microbe-enabled Community Land Model (CLM-Microbe), which incorporates fungal and bacterial

95 biomass dynamics (He et al., 2021); the Reaction-network-based model of Soil Organic Matter and microbes coupled into ELM (ELM-ReSOM), which integrates microbial dynamics with organo-mineral interactions (Tao et al., 2025); the Microbial-Mineral Carbon Stabilization model (MIMICS) (Wieder et al., 2015); and a microbe-mediated decomposition module coupled into the Organizing Carbon and Hydrology in Dynamic Ecosystems model (ORCHIMIC) (Huang et al., 2018, 2021). Microbial



processes are central to both carbon decomposition and methane production in wetlands, as the balance between methanogenic and methanotrophic communities directly determines net CH_4 emissions. Extensions of the Terrestrial Ecosystem Model (TEM) that explicitly represent microbial dynamics have demonstrated substantial improvements in simulating wetland methane fluxes. One extension incorporating methanotroph and methanogen dynamics improved the reproduction of observed methane emission and consumption across Arctic wetlands (Oh et al., 2020), while a subsequent isotope-enabled extension not only better reproduced the observed latitudinal isotopic gradient of methane, but also successfully attributed recent increases in wetland methane emissions to methanogen community dynamics. Despite these progresses, explicit microbial representations remain largely absent from the wetland components of major LSMs including CLM (Oh et al., 2022).

Geographic and ecosystem-type coverage of existing model development and evaluation efforts is another limitation to concern. Much of the research has been concentrated on northern peatlands, leaving mineral soil, temperate, and tropical wetlands comparatively under-represented despite their substantial contribution to global CH_4 emissions (Bridgman et al., 2013; Delwiche et al., 2021). A recent multi-model evaluation against FLUXNET- CH_4 flux tower observations found that most conventional wetland CH_4 models perform adequately for boreal and arctic tundra sites but exhibit significant biases for temperate and tropical wetlands (Zhang et al., 2023). Temperate mineral soil wetlands along river floodplains are a particularly notable gap: they are hydrologically dynamic, subject to periodic inundation, and biogeochemically distinct from the peatland systems around which most models have been designed (Zehetner et al., 2009; Bernal and Mitsch, 2012; Boye et al., 2017). Since different wetland types can be governed by distinct environmental controls on their carbon fluxes (Hodson et al., 2011; Spahni et al., 2011), incorporating these under-represented wetland areas into model development is critical for reducing biases in regional and global carbon flux estimates. Site-level investigations are essential for characterizing these controls and for integrating vegetation-specific parameters into models (Yazbeck and Bohrer, 2023).

To address this gap, this study develops CLM-Wet-MS, a modified version of the CLM version 5 (CLM5) adapted for temperate freshwater riverine wetlands. Korean wetlands are predominantly temperate, freshwater, mineral soil systems situated along river floodplains — a wetland type that remains poorly represented in both observational datasets and model development efforts yet contributes meaningfully to regional carbon cycling. Our objectives are: (1) to develop CLM-Wet-MS by introducing a dedicated wetland landunit with wetland vegetation parameterizations, wetland-adapted soil hydrology, and a microbial soil decomposition scheme; (2) to evaluate the extent to which these process representations reduce uncertainty in simulated CO_2 and CH_4 fluxes compared to the original CLM5; and (3) to establish an optimized baseline for wetland land surface modeling that can be refined with longer observational records and extended to regional-scale simulations incorporating multiple land cover types. By improving the realism and reducing the uncertainty of wetland process representations within CLM, this work provides a foundation that can be extended to temperate riverine wetlands in other regions, contributing to more reliable carbon flux estimates at regional and global scales.



130 2 Materials and Methods

2.1 Site descriptions

Bibong wetland is a temperate inland riverine wetland located in Gyeonggi Province, South Korea, within the Sihwa constructed wetland, which has been operational since 2002 (Fig. 1a). The site is vegetated predominantly with *Phragmites australis* (Fig. 1b), and the underlying soil is silty clay loam according to the soil analysis conducted at the site. During the study period in 2024, no surface inundation was observed, indicating predominantly unsaturated surface conditions at the site. The site has a humid continental climate with a mean annual temperature of 13.7°C and annual precipitation of approximately 1103 mm in 2024. Precipitation is concentrated during the wet season from June to September, driven by the East Asian monsoon. The eddy covariance tower has been operational since May 2023; however, waterway construction in November 2024 substantially altered the local hydrology and site conditions, restricting the undisturbed observation period used in this study to only 2024.

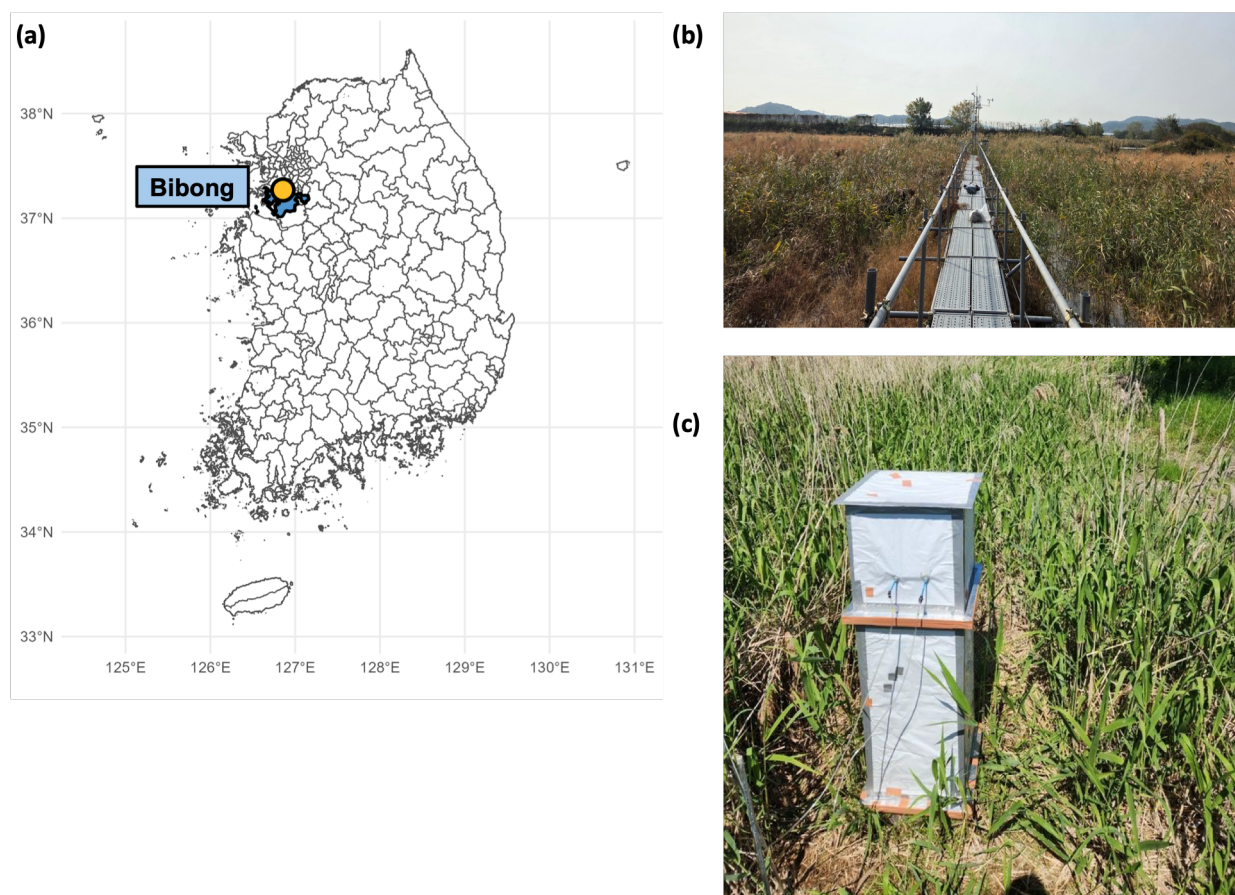


Figure 1: The Bibong wetland study site. (a) Location of Bibong wetland in South Korea; (b) view of the wetland, showing the *Phragmites australis* canopy and the eddy covariance tower with its boardwalk; (c) an opaque static chamber deployed for flux measurements.



145 2.2 Observation data

2.2.1 Eddy covariance flux measurements

An eddy covariance (EC) flux tower has been operational at Bibong wetland since May 2023 (37.270°N, 126.856°E). The tower is equipped with a three-dimensional sonic anemometer (WindMaster Pro, Gill Instruments Limited, UK) at 5.8 m for wind speed, wind direction, and sensible heat flux measurements, paired with an enclosed-path CO₂/H₂O gas analyzer (LI-7200, LI-COR, Inc., USA) and an open-path CH₄ analyzer (LI-7700, LI-COR, Inc.) at the same height. A four-component net radiometer (CNR4, Kipp & Zonen B.V., The Netherlands) and an air temperature and relative humidity probe (HMP155, Vaisala, Inc., Finland) are installed at 5.5 m, along with a quantum sensor for photosynthetically active radiation (LI-190, LI-COR, Inc.). A tipping-bucket rain gauge (TR-525M, Texas Electronics, Inc., USA) is mounted at 2.5 m. Soil temperature and moisture are measured at 0.1, 0.3, and 0.5 m below the surface using CS655 sensors (Campbell Scientific, Inc., USA).

All variables are stored as 30-min averages. EC flux data are sampled at 10 Hz, while other micrometeorological variables are recorded at 1 s intervals. These raw data are processed in real time using an on-site SmartFlux 2 system, including coordinate rotation (double rotation, McMillen, 1988), frequency response correction (Fratini et al., 2012; Horst and Lenschow, 2009), and sonic temperature humidity correction (van Dijk et al., 2004) with additional Webb-Pearman-Leuning (WPL) and spectroscopic corrections applied for CH₄ flux (Burba, 2013), followed by quality control procedures such as steady-state and developed turbulent condition tests (Mauder and Foken, 2011). Post-processing, including quality control, gap-filling, and flux partitioning, follows the standardized protocol of KoFlux, the Korean flux monitoring network (Kang et al., 2018). Gaps in CO₂, CH₄, and energy fluxes are filled using marginal distribution sampling (MDS, Reichstein et al., 2005), while meteorological variables are gap-filled through linear interpolation or linear regression against data from the Korea Meteorological Administration (KMA). Net ecosystem exchange is partitioned into GPP and ER using the modified moving point test method (MPTm, Kang et al., 2019) with a temperature response function. The Level 2 (gap-filled) data products used for model validation include latent and sensible heat fluxes, net ecosystem exchange, ER, GPP, and FCH₄.

2.2.2 Static chamber flux measurements

Monthly chamber measurements of CO₂ and CH₄ fluxes were conducted from January to September 2024 (Oh et al., 2026a). Four measurement points were established along the deck connected to the flux tower, two on each side, to capture soil microbial and vegetation respiration and methane emissions. Permanent soil collars were installed at each point one month prior to the first measurement. An opaque chamber (0.25 m² base area, 1.5 m height) was deployed on each collar to enclose representative *Phragmites* individuals, with the opaque material preventing photosynthesis during measurements so that only ecosystem respiration was captured (Fig. 1c). Each chamber was sealed at the base to isolate interior air from the surrounding atmosphere, and two battery-powered fans attached inside the chamber ensured uniform air mixing (Maier et al., 2022).

Changes in CO₂ and CH₄ concentrations during 5-minute closure period were measured using a LI-7810 CH₄/CO₂/H₂O Trace



Gas Analyzer (LI-COR Biosciences, Lincoln, NE, USA) at 1 Hz sampling frequency. All four replicates were measured sequentially during each site visit between 10:00 and 14:00 local time to represent peak daytime fluxes.

From each 5-minute measurement period, we used a sliding window linear regression with 1-second increments to identify the 150-second (2.5-minute) window that yielded the highest coefficient of determination (R^2). The window was evaluated independently for CO_2 and CH_4 , allowing each gas to have a different optimal window from the same chamber closure when concentration dynamics differed between gases. All candidate windows were required to have full coverage of the 150-second span to be considered valid. Selected windows for each chamber replicate were then screened as follows. Replicates with $R^2 \geq 0.80$ and a significant concentration–time slope were retained directly. For measurements with $R^2 < 0.80$, the significance of the concentration–time slope and the root-mean-square error (RMSE) of the linear fit were evaluated. Those with a significant slope ($p < 0.001$) and $\text{RMSE} \leq 1$ ppm for CO_2 or ≤ 10 ppb for CH_4 were retained, as a weak linear fit in these cases is attributable to low signal-to-noise ratios associated with near-zero fluxes rather than to experimental failure (Sanders-DeMott et al., 2022). Measurements where the slope was not significantly different from zero ($p \geq 0.001$) were assigned a flux of zero rather than excluded, as these represent valid observations of minimal gas exchange. Measurements that failed all of the above criteria were rejected and excluded from subsequent analyses. Because the study site was not surface-inundated during the measurement periods, ebullition was not observed and no bubble-related corrections were applied.

Final flux calculation was done using the R package *fluxfinder* (Wilson et al., 2024), which supports reproducible flux calculations from static chamber measurements. Concentration data (ppm for CO_2 ; ppb for CH_4) were converted to molar quantities using the ideal gas law at standard conditions ($T = 20^\circ\text{C}$, $P = 101,325$ Pa) and normalized by chamber dimensions (area = 0.25 m^2 , headspace volume = 0.375 m^3). The rate of concentration change from the best-fit window was then converted to area-based fluxes using the “*ffi_compute_fluxes*” function in the package, which estimates flux from the linear model slope and its associated standard error. For each monthly measurement, the representative site flux was calculated as the inverse-variance weighted mean of all retained replicates, with weights defined as the inverse of the squared standard error of each individual flux estimate. The 95% confidence intervals were calculated as the weighted mean ± 1.96 times the weighted standard error.

2.3 Community Land Model

Our model development builds upon the Community Land Model (CLM), which serves as the land surface component of the Community Earth System Model (CESM) and is employed across various global and regional carbon flux simulations (Zhang et al., 2016; Birch et al., 2021; Cheng et al., 2021; Fu et al., 2023; Duarte et al., 2025). CLM version 5 (CLM5) functions as the default land component within CESM2 (Lawrence et al., 2019). The model employs a subgrid hierarchy in which each grid cell may contain multiple land units, and each land unit may comprise several columns. Each column may support multiple patches, each associated with a distinct plant functional type (PFT). For this study, we performed single-point simulations, which simulate a specific latitude/longitude point with its own surface characteristics and atmospheric forcings. We employed CLM5 coupled with the Functionally Assembled Terrestrial Ecosystem Simulator (FATES; Fisher et al., 2015). FATES is a



cohort-based model of vegetation competition and coexistence that represents the vegetated land surface as a dynamic mosaic of successional stages, with height-structured cohorts of different PFTs competing for light. Below is a brief description of how the key carbon fluxes targeted in this study, GPP, ER, and FCH₄, are represented in CLM5.

Photosynthesis for C₃ plants follows the biochemical model of Farquhar et al. (1980), with modifications by Collatz et al. (1991). Within FATES, the photosynthesis scheme computes stomatal conductance, photosynthesis, and respiration across a three-dimensional matrix indexed by canopy level, plant functional type, and leaf layer. At each layer, gross photosynthesis is determined as the minimum of three potentially limiting factors: carboxylation, electron transport, and export limitation. Stomatal conductance is calculated using the Ball–Berry model (Ball et al., 1987). Plant respiration is computed as the sum of maintenance and growth respiration. Maintenance respiration is calculated as the sum of respiration from four plant tissue pools: leaf, fine root, coarse root, and stem, parameterized following Atkin et al. (2017). Growth respiration is then calculated as a fixed fraction of the carbon remaining after maintenance respiration has occurred. Soil decomposition is represented using a Century-based decomposition cascade, which employs a discrete pool structure where decomposition proceeds via first-order kinetics (Koven et al., 2013). Organic material first enters litter and coarse woody debris (CWD) pools from plant tissue turnover, and is subsequently transferred through a series of progressively recalcitrant pools, with a fraction of carbon lost as heterotrophic respiration at each transition. Plant autotrophic and heterotrophic respiration are added to constitute ecosystem respiration.

In the current version of CLM5, methane biogeochemistry is represented using the CLM4Me module (Riley et al., 2011), which simulates the soil methane cycle through a transient reaction–diffusion equation. The module is activated over the saturated soil fraction, and accounts for methane production in the anaerobic soil fraction, ebullition, aerenchyma transport, aqueous and gaseous diffusion, and oxidation. Because the CLM4Me module in CLM5 is a property of the dry-land PFTs, it does not explicitly represent wetland-specific plant functional types or soil biogeochemical processes. Instead, the model relies on gridcell-averaged decomposition rates as proxies for wetland fluxes. Specifically, the module assumes methane production is proportional to heterotrophic respiration, with a portion corrected for soil temperature, pH, redox potential, and seasonal inundation. Aerenchyma transport parameters are scaled by stem and root area of the dryland PFT that characteristically occupies the patch when it is not inundated.

2.4 CLM-Wet-MS

As mentioned above, wetlands are not represented as a distinct landunit in the Community Land Model version 5 (CLM5). Instead, they are treated as an inundated fraction of vegetated land, without accounting for wetland-specific vegetation or soil biogeophysics. For more realistic wetland representation, we introduced a dedicated landunit for wetlands, the wet-landunit, derived from the vegetated landunit, retaining its vertical soil discretization and vegetation structure, while incorporating modified soil hydrology to maintain saturation. A key challenge in representing wetland hydrology is that wetlands are generally characterized by persistent near-saturated soil conditions sustained by groundwater connectivity or lateral riverine/coastal water inputs (Zeng et al., 2018; Felfelani et al., 2021; Sadat-Noori et al., 2025). Thus, representing their



hydrology requires appropriate boundary conditions maintaining high soil moisture locally beyond the prediction derived from the model pixel average vertical precipitation, evaporation, and infiltration water balance (Joris and Feyen, 2003; Maxwell et al., 2005; He et al., 2021). Since CLM5 does not simulate lateral flow, these boundary conditions cannot be established prognostically. In ELM-Wet, sustained inundation was addressed by introducing an impermeable bottom soil layer, switching runoff off until inundation reach a patch-characteristic maximum inundation depth, and either prognostically determining water table or inundation following local water budget or forcing it directly from observations by prescribing inflow as a negative runoff (inflow) term (Yazbeck et al., 2025). However, neither approach is suitable at Bibong wetland, as surface inundation was rarely observed during the measurement period and water table depth was not directly measured at the site. Instead, we constrained the wetland landunit using observed volumetric soil moisture. Soil moisture was measured at three depths (0.1, 0.3, and 0.5 m) below the surface. Given the negligible diurnal variability and intermittent gaps in the half-hourly records, daily mean values at each measurement depth were used. These values were then linearly interpolated onto the CLM5 soil layer discretization, and full saturation was assumed for all layers below the deepest measurement depth. The interpolated volumetric soil moisture was prescribed to the model by overwriting the prognostic soil moisture at every time step.

Soil decomposition with a microbial carbon pool was implemented following the scheme proposed by Tao et al. (2023). This scheme accounts for microbial carbon transformations including CO₂ mineralization through respiration and assimilation for soil organic carbon accumulation, governed by carbon use efficiency (CUE) (Tan et al., 2025). The major modification was to the soil organic matter pool structure and carbon transfer pathways. The previous structure comprising active, slow, and passive pools was reformed into dissolved organic carbon (DOC), mineral-associated soil organic carbon (MSOC), microbial biomass carbon (MBC), and extracellular enzyme (EXE) pools. Carbon transfers are now divided into two types: non-microbial transfer and microbial carbon transfer with respiration. Within the soil organic carbon pools, only the MBC pool has a fraction of carbon respired. The detailed structure of the new carbon pools and transfer pathways is shown in Fig. 2. In contrast to the default Century-based decomposition model, the newly introduced microbial decomposition employs nonlinear Michaelis-Menten kinetics for the DOC and MSOC pools, where the decomposition rate is dynamically adjusted based on the current state of the carbon pool. The substrate term in the denominator causes the effective rate to slow as substrate accumulates relative to the enzyme or microbial pool, whereas greater microbial biomass or enzyme availability increases the rate. Equations for the decomposition rate coefficient of DOC and MSOC pools (k_{DOC} , and k_{MSOC} , respectively) are shown in Eqs. (1) and (2). Hereafter, we refer to this modified version as *CLM-Wet-MS*.

$$k_{DOC} = \frac{1}{\tau_{s1}} \cdot \frac{C_{MBC}}{K_{assim} + C_{DOC}} \cdot f_T \cdot f_W \cdot f_D \cdot f_O, \quad (1)$$

$$k_{MSOC} = \frac{1}{\tau_{s4}} \cdot \frac{C_{EXE}}{K_{decom} + C_{MSOC}} \cdot f_T \cdot f_W \cdot f_D \cdot f_O, \quad (2)$$

where τ_{s1} and τ_{s4} are the baseline turnover times for the DOC and MSOC pools, respectively; C_{MBC} and C_{EXE} are the microbial biomass and extracellular enzyme pool carbon; C_{DOC} and C_{MSOC} are the DOC and MSOC pool carbon; K_{assim} and

K_{decom} are the Michaelis–Menten half-saturation coefficients for assimilation and decomposition; and f_T, f_W, f_D , and f_O are scalar functions for temperature, water stress, depth, and oxygen availability.

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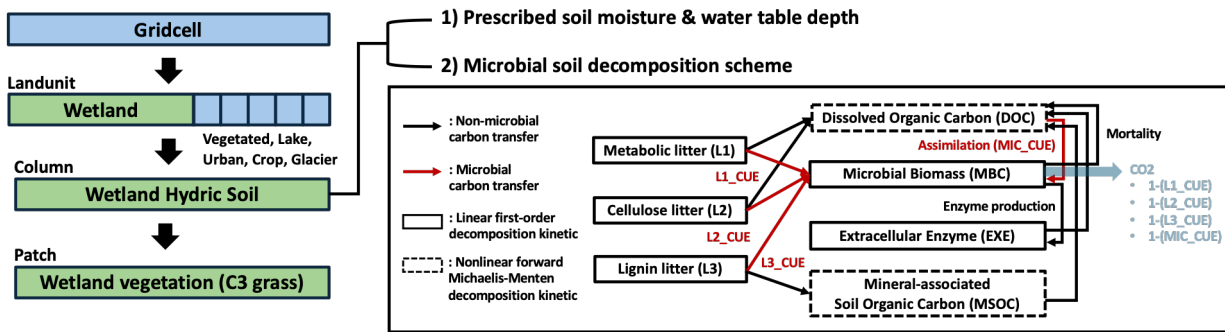


Figure 2: Schematic of the CLM-Wet-MS model structure

2.5 Simulation setup

2.5.1 CLM5-FATES setup

We used CLM5 (CTSM version 5.1) coupled with FATES (CLM5-FATES). The simulation was configured as a single-point run at the same latitude and longitude as the eddy covariance tower at the Bibong wetland site. Half-hourly atmospheric forcing data were derived from the tower measurements, including air temperature, air pressure, incoming longwave and shortwave radiation, precipitation, relative humidity, and wind speed, with local time converted to UTC. For the surface data, vegetation was prescribed as a single plant functional type of C3 grass for site-specific vegetation parameterization, and soil texture was set to silty clay loam.

The simulation was conducted in two stages. In the first stage, the model was spun up for 500 years using the atmospheric forcing data of the year 2024 to stabilize soil and vegetative carbon. Using the resulting state as the initial conditions, the model was run for an additional 30 years for final stabilization before using the last cycle for the analysis (Fleischer et al., 2019; Holm et al., 2020; Liu et al., 2024; Shu et al., 2025). Then, the model was optimized against the observation from January 1st to December 31st, 2024. All model outputs were generated at a half-hourly time step.

2.5.2 Numerical experiments

To isolate the effect of structural modifications from parameter optimization, we first compared flux simulations across different model configurations prior to optimization. We tested three approaches to handling soil moisture for wetland hydrology: (1) no wetland-specific boundary condition, where soil moisture is fully prognostic (*no_wet*), (2) imposing full saturation by setting the volumetric water content to the porosity value at and below a specified soil layer at each time step, while allowing soil moisture above that layer to evolve prognostically, and (3) directly prescribing observed volumetric soil



moisture. The first setting represents the default model behavior and serves as a baseline to demonstrate why wetland-specific boundary conditions are necessary. For the second approach, we tested saturation boundaries at soil layers 2, 4, 6, 8, 10, and 12 (*wtd_2*, *wtd_4*, *wtd_6*, *wtd_8*, *wtd_10*, *wtd_12*). The resulting water table depths for each configuration are shown in Fig. 4a. *wtd_2*, *wtd_4*, and *wtd_6* produced water table depths too close to the surface, indicating conditions wetter than the reality. Water table depths closest to the observations were obtained by the *wtd_8*, and selected for further comparison. Then, we denoted the model run with and without the microbial decomposition scheme as *_micro* and *_nomicro* to isolate its effect.

2.6 Parameter optimization

Key parameters for optimization and their range were selected based on a literature review to cover the primary parameters governing each target carbon flux: gross primary production, autotrophic and heterotrophic respiration, and methane emissions. All new parameters introduced through the microbial soil decomposition scheme were also included. The full list of optimized parameters is provided in Table 1. The range for the optimization was determined based on literature reviews. When there is no literature reference, $\pm 50\%$ of the original value was used or defined manually according to the site condition (Post et al., 2017). Parameter optimization was performed using the Bayesian Optimization for Anything (BOA) framework (Scyphers et al., 2023; Scyphers et al., 2024). BOA is a software package that provides a set of Bayesian optimization functions applicable to models written in any programming language. A CLM-specific wrapper was developed for this study, where the objective function was defined as the minimization of root mean square error (RMSE) between simulated and observed fluxes. The optimization was carried out using BOA tools from the BoTorch library (Balandat et al., 2020). The optimization followed a hierarchical approach, reflecting the sequential dependencies among the target fluxes (Yazbeck et al., 2025). In the first stage, parameters controlling photosynthesis were optimized against observed GPP. Then, since heterotrophic respiration serves as a proxy for methane production in the model, obtaining a reliable respiration estimate is necessary before proceeding to methane flux optimization. Therefore, in the second stage, parameters related to respiration were optimized against observed ER. In the final stage, methane production and transport parameters were optimized against observed total methane fluxes (Fig. 3).

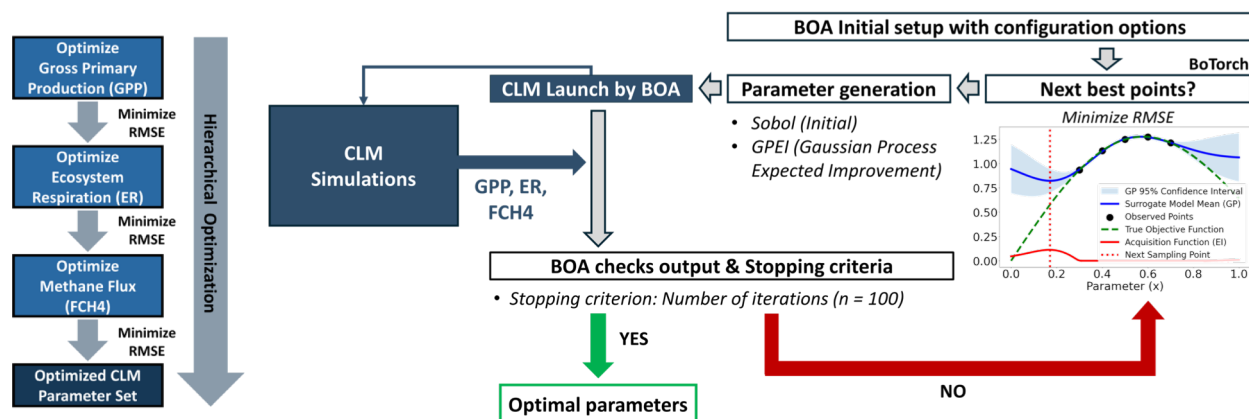


Figure 3: Hierarchical optimization scheme with CLM-specific Bayesian Optimization for Anything (BOA)



Table 1: Parameters subjected to optimization for each target flux, including descriptions and literature-based upper and lower limits.

Target flux	Parameter name	Descriptions	Range	References
GPP	fates_leaf_vmax25top	Maximum carboxylation rate of rubisco at 25°C at canopy top (umol CO ₂ /m ² /s)	[100, 190]	Hu et al., 2010; Qian et al., 2021
	fates_leaf_slatop	Specific leaf area at top of canopy (m ² /gC)	[0.01, 0.10]	Post et al., 2017; Jesnen et al., 2024
	fates_leaf_stomatal_slope_ballberry	Stomatal slope parameter for Ball-Berry model	[5, 8]	Lin et al., 2015; Miner and Bauerle, 2017
	fates_phen_mindayson	Minimum leaf-on duration required before leaf-drop (days)	[70, 170]	Author-defined range
	fates_phen_coldtemp	Vegetation temperature threshold defining a cold-day for cold-deciduous leaf-drop (°C)	[12, 25]	Author-defined range
ER	tau_s2_death	Turnover time governing microbial biomass loss through mortality (1/yr)	[1.2, 40.0]	Tao et al., 2023
	tau_s2_enz	turnover time governing microbial biomass allocation to enzyme production (1/yr)	[1.2, 40.0]	
	l1_cue	Carbon use efficiency of metabolic litter pool	[0.1, 0.9]	
	l2_cue	Carbon use efficiency of cellulosic litter pool	[0.1, 0.9]	
	l3_cue	Carbon use efficiency of lignin litter pool	[0.1, 0.9]	
	mic_cue	Carbon use efficiency of microbial biomass pool	[0.1, 0.9]	Post et al., 2017; Wang et al., 2017; Niu et al., 2024
	fates_q10_mr	Q10 for maintenance respiration	[0.1, 3.0]	
	mino2lim	Minimum fraction of aerobic decomposition rate maintained under fully anaerobic conditions	[0.05, 0.8]	
FCH4	q10ch4	Q10 for methane production	[1.0, 40.0]	Inglett et al., 2011; Zhao et al., 2018; Fan et al., 2022
	q10ch4base	Reference temperature at which the methane production fraction equals the baseline value of f _{ch4} (K)	[305.0, 310.0]	Author-defined range
	f_ch4	Fraction of total carbon mineralization produced as methane	[0.05, 0.8]	Riley et al., 2011
	q10_ch4oxid	Q10 oxidation constant	[0.95, 2.85]	± 50% original value
	porosmin	Minimum aerenchyma porosity	[0.025, 0.4]	Smirnov and Crawford, 1983; Visser and Bögemann, 2006
	rob	Ratio of root length to vertical depth (root obliquity)	[0.5, 4.0]	Riley et al., 2011; Post et al., 2017



2.7 Model evaluation

Simulated GPP, ER, and FCH4 were evaluated against the EC tower observations using root mean square error (RMSE), the Nash–Sutcliffe efficiency (NSE), and the slope of the linear regression of simulated against observed values. While RMSE served as the objective function during optimization, NSE and the regression slope were used as complementary diagnostics of model performance. NSE was calculated as follows:

$$NSE = 1 - \frac{\sum_i (O_i - S_i)^2}{\sum_i (O_i - \bar{O})^2}, \quad (3)$$

where O_i and S_i are the observed and simulated values, and $\bar{O}$ is the observed mean. NSE ranges from $-\infty$ to 1, where 1 indicates perfect agreement, 0 indicates that the simulation performs no better than the observed mean, and negative values indicate that it performs worse than the observed mean. The regression slope of the linear fit between model and observations characterizes over- or underestimation, while RMSE summarizes the mean magnitude of model error. Evaluations were carried out separately for CLM-Wet-MS with default parameter values and with optimized parameters, to quantify the improvement attributable to parameter optimization alone.

3 Results

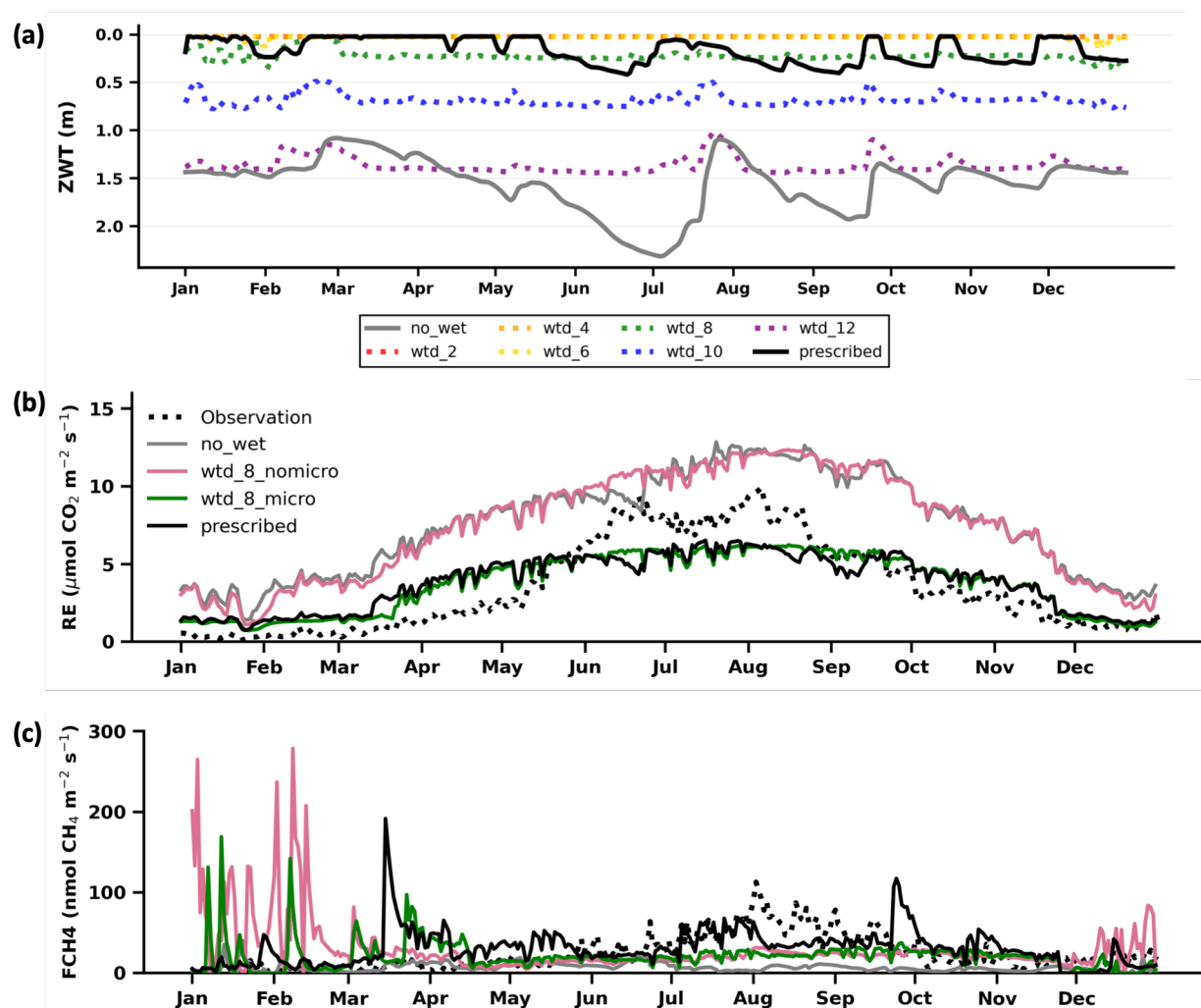
3.1 Impact of the structural improvement

We first assessed how each structural improvement affects simulated fluxes by comparing configurations that isolate the representation of wetland hydrology (*no_wet*, *wtd_8*, and *prescribed*) and the microbial decomposition scheme (*wtd_8_nomicro* versus *wtd_8_micro*; Fig. 4). Among the simulated fluxes, methane was most sensitive to how wetland hydrology was represented (Fig. 4c). *no_wet* configuration produced very limited methane emissions throughout the period, most notably failing to capture the summer peak when observed fluxes were highest. Capturing this summer peak is critical, as it represents the dominant period of methane emission and should carry greater weight in evaluating model performance. Introducing water table dynamics in *wtd_8* improved the seasonal pattern, but directly prescribing observed soil moisture (*prescribed*) reproduced the summer peak more closely still, despite producing unrealistically high fluxes in winter. This bias is attributable to uncalibrated parameters governing the temperature sensitivity of methane fluxes, rather than the structural change itself, which is addressed in the subsequent site-specific parameter optimization.

The microbial soil decomposition scheme had its clearest effect on CO_2 flux, particularly heterotrophic respiration (Fig. 4b). Holding wetland hydrology fixed, *wtd_8_nomicro* overestimated respiration relative to observations, whereas *wtd_8_micro* suppressed decomposition under cold, wet conditions and brought respiration closer to the observations, albeit with an underestimated summer peak. This remaining summer bias can likewise be corrected during optimization by adjusting parameters governing carbon transfer and respiration rates. Because the direction of this effect is independent of wetland



hydrology, we carried the microbial scheme into the prescribed soil moisture configuration (*prescribed*), which we selected for subsequent site-specific parameter optimization.



360 Figure 4: Comparison of flux simulations across different model structural configurations prior to parameter optimization. (a)
 365 Simulated water table depth (ZWT) under different saturation threshold configurations (*wtd_2*, *wtd_4*, *wtd_6*, *wtd_8*, *wtd_10*, and
wtd_12), alongside the *no_wet* configuration and the prescribed observed water table depth (*prescribed*); (b) Simulated heterotrophic
 respiration (HR) (RE) under the *no_wet*, *wtd_8* configuration with and without microbial decomposition scheme (*wtd_8_micro*, and
wtd_8_nomicro, respectively), and *prescribed* configurations; (c) Simulated methane flux (FCH4) under the same configurations as
 in (b).



3.2 Optimized model evaluation

3.2.1 CO₂ fluxes

Model performance for GPP and ER was assessed with RMSE, R^2 , and the slope of the regression (Sect. 2.7), before and after parameter optimization (Table 2). Before optimization, CLM-Wet-MS substantially overestimated GPP throughout the growing season ($R^2 = -0.256$, RMSE = $5.62 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$; Fig. 5a). The model initiated photosynthetic activity approximately two months ahead of the observed green-up, reached a strongly overestimated peak, and sustained elevated GPP into late autumn. Optimization considerably improved reproduction of the seasonal cycle, raising R^2 to 0.778 and reducing RMSE to $2.37 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$. The regression slope changed little, indicating that the improvement arose from reduced phase and magnitude errors rather than from a change in slope. The early onset bias was corrected by a more gradual increase in GPP, and the summer peak magnitude matched observations more closely. A notable remaining discrepancy was an abrupt drop in GPP around early October, sharper than the observed gradual decline. This was attributable to the model phenology scheme, which prescribes a complete leaf-off event rather than progressive senescence.

For ER, the model captured the general seasonal pattern reasonably well without optimization ($R^2 = 0.672$), but consistently underestimated its magnitude, with a regression slope of 0.519 and RMSE of $1.67 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ (Fig. 5b). Simulated ER stayed below $6 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ during summer, whereas observations exceeded $8 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$. Optimization substantially narrowed this gap, improving R^2 to 0.870, reducing RMSE to $1.05 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$, and increasing the regression slope to 0.773. The optimized model reproduced the summer peak better and followed the observed trajectory more closely from spring through autumn. Some overestimation during the early growing season remained, driven by the premature leaf onset (also evident in the GPP simulation), which elevated autotrophic respiration before the observed growing season began.

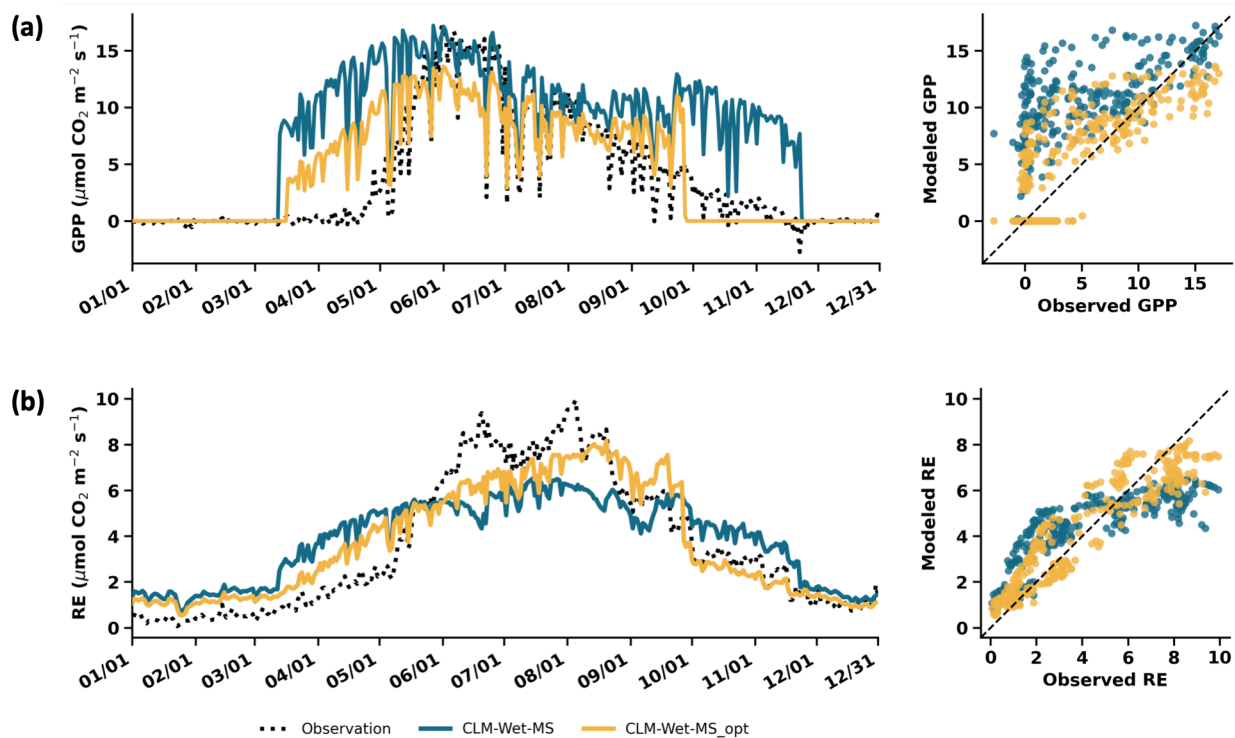


Figure 5: Comparison of simulated and observed carbon dioxide fluxes before and after parameter optimization. (a) Time series (left) and scatter plot (right) of gross primary production (GPP) before and after optimization (CLM-Wet-MS, and CLM-Wet-MS_opt, respectively) against eddy covariance observations (black dotted line); (b) Time series (left) and scatter plot (right) of ecosystem respiration (ER) under the same configurations as in (a). Scatter plots show modeled versus observed daily values, with the 1:1 line (dashed) indicating perfect agreement. Units are $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$.

Table 2: Summary of model performance metrics for gross primary production (GPP), ecosystem respiration (ER), and methane flux (FCH4) before (Default) and after parameter optimization (Optimized). Metrics include root mean square error (RMSE; μmol



CO₂ m⁻² s⁻¹ for GPP and ER, nmol CH₄ m⁻² s⁻¹ for FCH₄), the Nash–Sutcliffe efficiency (NSE), and the slope of the linear regression between modeled and observed values.

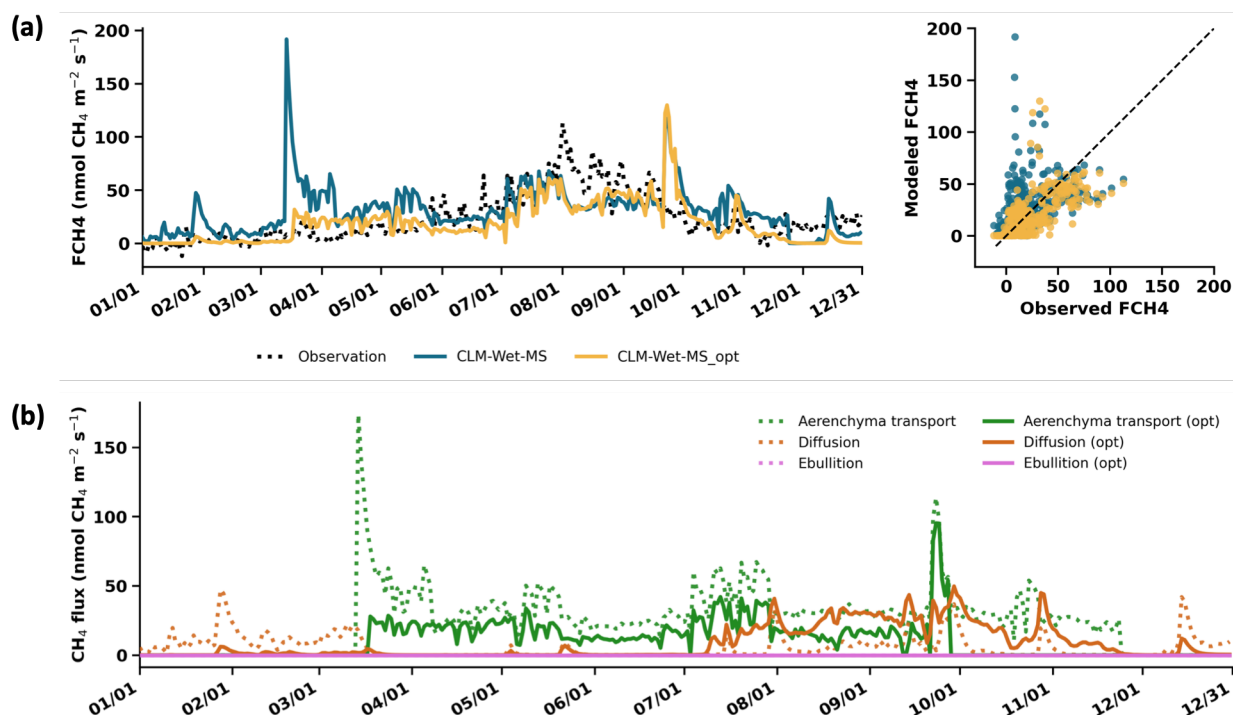
	GPP		ER		FCH ₄	
	Default	Optimized	Default	Optimized	Default	Optimized
RMSE	5.62	2.37	1.67	1.05	27.08	18.64
NSE	-0.256	0.778	0.672	0.870	-0.497	0.291
Slope	0.791	0.762	0.519	0.773	0.320	0.561

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3.2.2 CH₄ fluxes

The optimization results for FCH₄ are shown in Fig. 6a. Before optimization, the model performed poorly (NSE = −0.497, RMSE = 27.08 nmol CH₄ m⁻² s⁻¹), producing sporadic large peaks during winter and early spring, particularly around March, while substantially underestimating observed summer emissions from July through October. Optimization raised R² to 0.291 and reduced RMSE to 18.64 nmol CH₄ m⁻² s⁻¹, largely suppressing the winter overestimation and better capturing the gradual increase in emissions from April to August.

The effect of optimization on individual methane transport pathways is shown in Fig. 6b. Aerenchyma transport decreased substantially in magnitude after optimization, with the winter spikes largely eliminated, although it still exhibited elevated peaks in late September and early October, consistent with the GPP overestimation during the senescence period. Diffusive flux also decreased substantially from January to March but became relatively more prominent from late August to December, following vegetation senescence period. This shift suggests that optimization rebalanced the partitioning among pathways rather than simply scaling total flux. Ebullition remained negligible in both configurations, consistent with the absence of prolonged surface inundation at this site that would enable bubble-mediated release. While NSE 0.291 remained modest compared to GPP and ER, the shift from a negative to a positive value represents a meaningful advance, given that methane flux is inherently more difficult to constrain owing to the interactions among soil moisture, temperature, substrate availability, and transport pathway partitioning. The model nonetheless continued to underestimate peak emissions during late summer and early autumn, a persistent bias linked to underestimated respiration during the peak growing season, which constrains methane production in the model.



415 **Figure 6: Comparison of simulated and observed methane fluxes before and after parameter optimization. (a) Time series (left) and**
scatter plot (right) of total methane fluxes (FCH4) before and after optimization ('CLM-Wet-MS', and 'CLM-Wet-MS_opt',
respectively) against eddy covariance observations (black dotted line). The scatter plot shows modeled versus observed daily values,
with the 1:1 line (dashed) indicating perfect agreement; (b) Individual methane transport pathways — plant aerenchyma transport
(green), diffusion (orange), and ebullition (pink) — before (dotted) and after (solid) optimization. Units are $\text{nmol CH}_4 \text{ m}^{-2} \text{ s}^{-1}$.

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3.3 Optimized parameters

The optimized parameters represent site-specific adjustments for Bibong wetland and provide a baseline for future refinement with longer records and additional sites. The full set of default and optimized values is provided in Appendix A (Table A1). Here we summarize the main parameter changes and relate these changes to the flux improvements described in the previous section. Among GPP-related parameters, the largest adjustments were in photosynthetic capacity and phenology. The maximum carboxylation rate ($v_{\text{cmax25top}}$) was raised (78 to $100 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$), indicating that the default underestimated the photosynthetic capacity of the wetland vegetation at this site, while specific leaf area (slatop) was reduced, corresponding to thicker leaves with lower area per unit mass. The stomatal conductance slope ($\text{stomatal_slope_ballberry}$) remained at its default, suggesting the Ball-Berry relationship was not sensitive to this parameter at this site, probably due to the sustained high moisture. The phenology threshold changed most markedly. Both the minimum leaf-on duration (phen_mindayson) and the cold-day temperature threshold (phen_coldtemp) were increased, which together shortened the active growing season by

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delaying leaf flush. These phenology adjustments are the direct counterpart of the corrected early-onset bias seen in the GPP simulation before optimization.

For ER, the microbial soil decomposition scheme introduced several parameters without default CLM5 counterparts, governing the turnover of the microbial biomass and extracellular enzyme pools and the carbon use efficiency (CUE) of each substrate pool. The optimized CUE varied across pools, with lower values for cellulose and microbial biomass indicating that a larger fraction of carbon from these pools was respired rather than assimilated. Among parameters with existing defaults, the increase in the maintenance respiration Q_{10} (1.5 to 3.0) and the reduction in the minimum anaerobic decomposition fraction (*mino2lim*) together sharpened the temperature and redox dependence of respiration, consistent with the improved suppression of decomposition under cold, wet conditions.

For FCH₄, the most prominent changes were in methane production. The Q_{10} for methane production (*q10ch4*) and the fraction of mineralized carbon allocated to methane (*f_ch4*) both increased substantially, directing more decomposed carbon to methane production under anaerobic conditions, while the Q_{10} for the methane oxidation (*q10_ch4oxid*) was reduced, dampening the temperature sensitivity of oxidation. Among plant-mediated transport parameters, the minimum aerenchyma porosity (*porosmin*) was reduced and the root-length-to-depth ratio (*rob*) increased, together reshaping the effective pathway for gas transport through plant tissue and root system. These adjustments are consistent with the improved capture of the summer emission increase and the rebalanced pathway partitioning described in Sect. 3.2.2.

3.4 Evaluation against chamber measurements

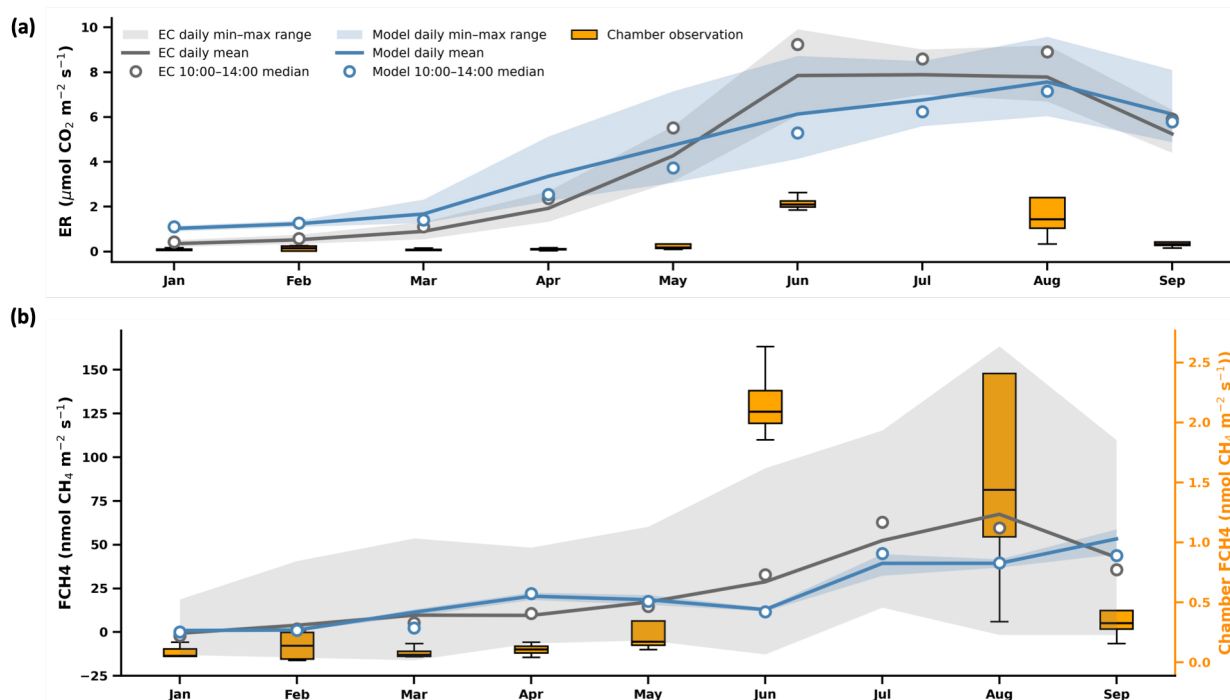
To evaluate the optimized model across observation scales, we compared simulated ER against monthly chamber measurements alongside EC observations (Fig. 7a). The chamber measurements represent fluxes from four replicate plots within the EC tower footprint. For a consistent comparisons, the EC and EC and modeled ER were aggregated to monthly values over the midday period (10:00–14:00) during which the chamber measurements were made. We compared the three estimates at their native spatial scales without upscaling the chamber measurements to the footprint scale.

From January to March, all three estimates agreed closely, with ER remaining below 2 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$. A gap between the chamber and EC estimates emerged in April and persisted throughout the growing season. In summer, the chamber medians stayed near 2 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ while the EC midday medians reached 8–9 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$, and the chamber values remained the lowest of the three through September. The optimized model tracked the EC observations more closely than the chamber measurements throughout the year. During the growing season, the modeled values were slightly lower than the EC observations, consistent with the underestimated summer respiration peak noted in Sect. 3.2.1.

We compared simulated FCH₄ against the chamber and EC observations following the same approach as for ER (Fig. 7b). All three estimates showed a clear seasonal cycle, low in winter and rising through the growing season. The chamber medians tracked this seasonality but were substantially smaller than the EC and modeled fluxes throughout, reaching slightly negative values (net CH₄ uptake) at the four plots during winter. The larger relative difference in winter reflects the very low absolute



465 fluxes then rather than a meaningful divergence. As in the respiration comparison, the optimized model followed the EC seasonal cycle while underestimating the summer magnitude.



470 **Figure 7: Evaluation of the optimized model against monthly chamber measurements and eddy covariance (EC) observations for (a) ecosystem respiration (ER) and (b) methane flux (FCH4). Gray shading and lines show the EC daily min–max range, daily mean, and the median over the midday period (10:00–14:00); blue shows the corresponding model quantities. Orange boxplots show the chamber observations from four replicate plots (box, interquartile range; center line, median; whiskers, range). In (b), the chamber fluxes are plotted on a separate axis (right) owing to their much smaller magnitude than the EC and modeled fluxes.**

4 Discussions

4.1 Sensitivity of wetland carbon fluxes to hydrological representation

475 Water table depth (or inundation depth) is the primary control on wetland biogeochemistry because it determines the boundary between aerobic and anaerobic zones within the soil column. Above the water table, oxygen availability permits aerobic decomposition, while below it, saturated conditions restrict oxygen diffusion and shift decomposition pathways toward anaerobic processes including methanogenesis (Hassett et al., 2024). Our results demonstrate this sensitivity directly: contrasting flux responses across simulation configurations arise not only from changes in soil moisture magnitude, but from shifts in the vertical redox structure and the partitioning of methane transport pathways.

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Methane emissions respond primarily to changes in water table position through modulation of (i) the anaerobic soil volume available for methanogenesis and (ii) the thickness of the overlying oxidized layer available for methane oxidation (Fig. 8a).



In the fully prognostic *no_wet* configuration, the water table remains deep for most of the growing season, fluctuating between 1 and 2.5 m depth (Fig. 8b). This creates a thick unsaturated zone above the anaerobic layer, enhancing methane oxidation and preventing substantial flux to the atmosphere. Even when soil temperatures increase in summer, the persistence of a deep oxidized layer limits effective methane emission. Without a hydrological constraint to maintain shallow groundwater, the model cannot sustain the anaerobic conditions required for methane production and transport. The soil moisture profile in this configuration shows a broad, gradual vertical gradient without a well-defined saturated zone, further indicating that the default model structure does not reproduce the hydrological characteristics of a wetland environment.

In contrast, both the *wtd_8* and prescribed soil moisture configurations (*prescribed*) maintain shallow water tables during the growing season, reducing the vertical extent of the oxidized layer. However, the two configurations differ substantially in how they achieve this. The *wtd_8* configuration produces a nearly uniformly saturated soil profile with the water table locked near 0.2–0.3 m depth (Fig. 8b). While this activates methane production and transport, the lack of vertical moisture variability leads to unrealistic flux behavior. Diffusion-driven spikes reach 140–170 nmol CH₄ m⁻² s⁻¹, far exceeding observed values (Fig. 8a). These episodic bursts appear to result from the fixed saturation boundary maintaining a thin but persistent unsaturated layer above the water table, which is thick enough to permit rapid diffusive transport yet too shallow to allow significant methane oxidation before the gas reaches the atmosphere. Aerenchyma transport in this configuration remains relatively limited and episodic, failing to establish the observed seasonal pattern.

The *prescribed* simulation case, by contrast, produces a soil moisture profile with clear seasonal variation, including dynamic wetting and drying cycles that more realistically represent the hydrological regime of the site (Fig. 8b). This temporal variability in water table position translates directly into variability in aerenchyma flux (Fig. 8a). Periods of rising water table correspond to rapid increases in plant-mediated methane transport, whereas drawdown events suppress emissions by expanding the oxidized zone. Importantly, aerenchyma transport in this configuration exhibits a coherent seasonal pattern that tracks observations more closely than either of the other configurations. The dominance of plant-mediated transport under these conditions indicates that methane emissions at this vegetated wetland are governed more by vegetation–hydrology coupling than by diffusive or ebullition processes. These dynamics highlight that methane sensitivity arises from vertical redistribution of redox boundaries rather than from bulk soil moisture changes alone.

The absence of significant ebullition across all configurations suggests that methane accumulation in Bibong porewater rarely exceed the solubility thresholds required for bubble formation, either due to relatively low production rates or that sustained plant-mediated release prevents sufficient gas pressure buildup in the soil pore space. This finding is in stark contrast to observations reported in another temperate site, dominated by sparse floating leaves and open water (Villa et al., 2021), though that site has an extremely high methane production rate. Our results reinforce the hypothesis of flux transport tradeoff, i.e., while the transport pathway may change, methane production rates dominate the total flux, with little sensitivity to which pathway ultimately carries it (Yazbeck et al., 2024). Within this tradeoff, we hypothesize that in densely vegetated freshwater wetlands, aerenchyma can be the dominant transport pathway, reducing the relative importance of ebullition without altering the total flux set by production.



The hydrological representation also propagates into CO₂ flux simulation through its effect on the water stress scalar (w_scalar), which modulates the decomposition rate at each soil layer (Fig. 8c). The vertical distribution of w_scalar broadly follows that of soil moisture (Fig. 8d). The *prescribed* produces a w_scalar profile with clear seasonal dynamics, including reduced values during observed drying events that temporarily lower w_scalar in the upper soil layers and reduce decomposition rates accordingly (Fig. 8d). This captures a key feature of the observed respiration pattern: heterotrophic respiration is suppressed in response to episodic changes in soil moisture. The resulting respiration in the *prescribed* simulation case tracks observations more closely than in the other two configurations. Combined with the microbial soil decomposition scheme, which limits the respired fraction of decomposed carbon, the hydrological constraint and w_scalar jointly regulate heterotrophic respiration — the former controlling the seasonality and the latter governing the magnitude. This complementary effect is visible around mid-June and early September (Fig. 8c), where the prescribed soil moisture configuration shows brief drops in respiration that coincide with observed drying events. Because methane production in the model is computed from the heterotrophic respiration, this improvement in the respiration seasonality propagates directly into the methane simulation. A more realistic respiration results in a more realistic pool of substrate for methanogenesis, which the transport pathways then partition into the emitted flux.

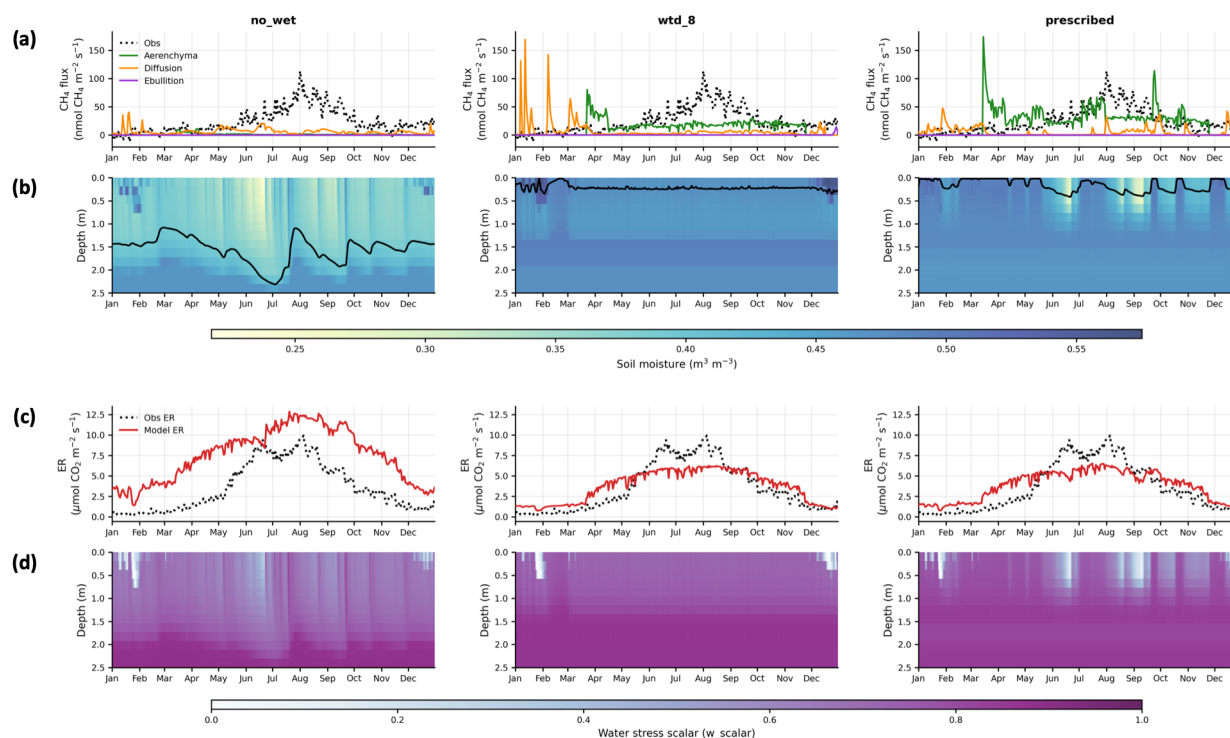


Figure 8: Sensitivity of wetland carbon fluxes to hydrological representation across three model settings: 'no_wet' (left column), 'wtd_8' (center column), and 'prescribed' (right column). (a) Simulated methane flux partitioned into aerenchyma transport, diffusion, and ebullition, compared with eddy covariance observations; (b) Vertical soil moisture profiles ($\text{m}^3 \text{ m}^{-3}$) with simulated water table depth (black line); (c) Simulated ecosystem respiration (ER) compared with eddy covariance observations; (d) Vertical profiles of the water stress scalar (w_scalar).



4.2 Physical interpretations of optimized parameters

4.2.1 Parameters governing CO₂ fluxes

The optimization of GPP-related parameters reveals that the default CLM5 parameterization is poorly suited for wetland
 540 vegetation at this site, particularly in phenology and leaf properties. The increase in *vcmax25top* is consistent with observations
 that productive C3 herbaceous wetland species maintain high carboxylation rates under nutrient-rich, saturated conditions.
vcmax values for C3 herbaceous species span a broad range from 6 to 194 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (Wullschlegel, 1993), with particularly
 high values observed in wetland grasses such as *Arundo donax* ($\sim 117 \mu\text{mol m}^{-2} \text{s}^{-1}$; Webster et al., 2016) and *Phragmites*
australis (Nguyen et al., 2013; An et al., 2020). These values considerably exceed the default CLM5 parameterization for
 545 *vcmax* in the C3 grass PFT, which is calibrated for broader grassland conditions and does not account for the enhanced
 photosynthetic capacity of wetland-adapted species. The high nutrient availability typical of wetland soils, particularly nitrogen,
 provides a mechanistic basis for elevated *vcmax*, as leaf-level carboxylation capacity scales strongly with leaf nitrogen content
 (Walker et al., 2014). The decrease in specific leaf area reflects characteristics typical of tall emergent wetland grasses, which
 develop leaves with greater mass per unit area than the default C3 grass in CLM5. Measured specific leaf area values for
 550 *Phragmites australis* range from approximately 0.012 to 0.024 $\text{m}^2 \text{g}^{-1}$ depending on genotype and habitat (Nguyen et al., 2013;
 Li et al., 2014), well below the CLM5 default for C3 grass (0.03 $\text{m}^2 \text{g}^{-1}$). This lower specific leaf area arises from biomechanical
 constraints: tall emergent wetland plants require structurally reinforced, erect shoots and leaves to support their
 canopy above the water surface (Zhao et al., 2015). Additionally, because wetland emergent grasses are typically exposed to
 full sun without canopy shading, they tend to develop thicker, more structurally reinforced leaves (Poorter et al., 2009).
 555 *Phragmites australis* in temperate regions generally maintains an active green-leaf period of roughly 150–180 days, with
 shoots typically emerging in April and leaves remaining photosynthetically active through September or early October before
 senescence progresses (Lessmann et al., 2001; Karunaratne et al., 2003; Packer et al., 2017). The optimized lengthening of the
 phenological active period thus reflects the actual life cycle of the dominant wetland vegetation at this site. Furthermore, the
 increase in the cold temperature threshold from 7.5°C to 24°C for triggering senescence is consistent with site conditions,
 560 where air temperatures remain well above 25°C during midday in September when vegetation begins to senesce — the default
 cold-signal parameterization would prematurely terminate the growing season under these conditions.

The optimized ER parameters provide insight into the decomposition dynamics of the wetland soil. The slower enzyme
 turnover relative to microbial mortality (40 days versus 27.19 days) means that extracellular enzymes persist in the soil after
 microbial cells die, maintaining decomposition activity beyond the lifespan of individual microbial populations. This pattern
 565 may reflect the stabilizing effect of saturated soil conditions on enzyme longevity. Adsorption of extracellular enzymes to soil
 minerals and organic matter is known to protect them against degradation and extend their functional lifetime; laboratory
 studies have shown that free extracellular enzymes can persist with substantial activity for up to 100 days in solution, with
 mineral adsorption further modulating their longevity (Olagoke et al., 2020). In wetland soils specifically, persistently
 anaerobic and waterlogged conditions help maintain enzymatic stability, buffering against the rapid shifts in edaphic properties



570 and enzyme degradation that occur in aerobic upland soils (Ferronato et al., 2019; Zhu et al., 2025). The "enzyme latch" hypothesis further suggests that the lack of oxygen in saturated soils suppresses oxidative enzyme activity (phenol oxidase), allowing hydrolytic enzymes to persist and accumulate, thereby regulating organic matter decomposition differently from aerobic systems (Freeman et al., 2001). Together, these mechanisms provide a physical basis for the optimized enzyme turnover time exceeding microbial mortality at this site.

575 The CUE values across substrate pools reveal a distinct pattern of carbon partitioning (Table A1). The litter pool has the highest CUE, meaning that microbes assimilate fresh litter most efficiently, with only about 33% of consumed carbon respired as CO₂. This is consistent with litter being the most labile substrate, requiring less enzymatic effort to decompose, and aligns with the general understanding that microbial CUE is higher when processing readily available substrates (Manzoni et al., 2012; Sinsabaugh et al., 2013). The lignin CUE exceeds the cellulose CUE, which is less intuitive from a substrate quality perspective

580 since cellulose is generally more biodegradable than lignin. This ordering may reflect parameter compensation within the optimization rather than a direct mechanistic relationship. The microbial biomass CUE is the lowest among all pools, meaning that about 75% of carbon from microbial turnover is respired. This is consistent with the understanding that recycling of dead microbial biomass (necromass) is energetically costly, with low assimilation efficiency (Geyer et al., 2016; Liang et al., 2017). The low CUE for necromass recycling also aligns with observations that microbial necromass reprocessing involves substantial

585 respiratory losses, with microbial biomass turnover rate being a key control on soil carbon dynamics (Liang et al., 2017; Woolf and Lehmann, 2019). Collectively, the direction and magnitude of the optimized parameter shifts consistently reflect the distinct ecophysiological and biogeochemical characteristics of a temperate vegetated wetland, suggesting that the optimization has converged on a physically coherent parameterization rather than an arbitrary numerical fit.

4.2.2 Parameters governing CH₄ fluxes

590 The optimized parameters for methane fluxes reveal important characteristics of the methane production and transport regime at Bibong wetland. The increase in q_{10ch4} from 1.33 to 3.37, combined with the shift in $q_{10ch4base}$ from 295 to 307.22 K, fundamentally reshapes the temperature response curve of methane production. The higher Q_{10} creates a steeper exponential relationship between temperature and production rate, while the elevated reference temperature shifts the curve so that the prescribed f_{ch4} ratio of respiration is realized at a warmer temperature. The optimized Q_{10} of 3.37 falls well within the range

595 reported for wetland methane production. Measured Q_{10} values for methanogenesis are highly temperature sensitive, spanning a range from 1.7 to 28 (Dunfield et al., 1993). Field measurements from *Phragmites australis* marshes yielded mean Q_{10} values of 3.38 ± 0.46 (Wang et al., 2015), and laboratory incubations of subtropical wetland soils produced Q_{10} values for methane production ranging from 1.4 to 3.6 (Inglett et al., 2011). A compilation of temperature-response studies using wetland soils reported an average Q_{10} of 4.1 for methane production (Segers, 1998), and the higher temperature sensitivity of methanogenesis

600 relative to other decomposition processes is well established. The increase in f_{ch4} from 0.2 to 0.54 indicates that more than half of the anaerobically mineralized carbon is allocated to methane production at the reference temperature, compared to only 20% in the default setting. This substantial increase suggests that the default ratio significantly underestimates the



methanogenic potential of this wetland system. In densely vegetated wetland soils like our study site, root exudates and decomposing plant material provide readily available carbon substrates that stimulate microbial activity and fuel methanogenesis (Whiting and Chanton, 1993; Waldo et al., 2019), creating more favorable conditions for high methanogenic conversion rates. The decrease in $q_{10_ch4oxid}$ from 1.9 to 1.15 indicates that methane oxidation at this site is nearly temperature-insensitive. This contrasts with the strongly temperature-dependent production, creating an asymmetry where production responds sharply to warming while oxidation remains relatively constant. Dunfield et al. (1993) reported Q_{10} values for methane oxidation ranging from 1.4 to 2.1 in northern peat soils, notably lower than the corresponding values for production (5.3–16), confirming that methanotrophy is inherently less temperature-sensitive than methanogenesis. The near-unity value of Q_{10} for oxidation at Bibong wetland suggests that methanotrophic activity in the thin oxidized layer above the water table is limited primarily by oxygen and methane substrate availability rather than by temperature, which is physically plausible in a system where the oxidized layer thickness fluctuates with water table position.

For plant-mediated transport, the decrease in minimum aerenchyma porosity from 0.05 to 0.025 reduces the minimum gas transport capacity of the plant tissue. This tighter constraint on porosity means that during periods of low plant activity, less methane escapes through the aerenchyma pathway. Aerenchyma porosity is a key trait controlling methane transport capacity, as species with higher tissue porosity and larger internal gas spaces offer less resistance to gas movement and exhibit higher transport rates (Brix et al., 1992; Andresen et al., 2017; Vroom et al., 2022). The optimized lower porosity is consistent with the observation that plant-mediated methane transport varies substantially among wetland species and is modulated by stomatal conductance and plant phenology (Chanton and Whiting, 1996; Kim et al., 1999; Vroom et al., 2022), suggesting that a single default porosity value may overestimate transport capacity for certain vegetation types and seasons. The increase in the ratio of root length to vertical depth (rob) lengthens the effective path that gas must travel from the anaerobic zone to the atmosphere through the root system. A more oblique root structure increases the residence time of methane within the root–soil interface, potentially enhancing the opportunity for partial oxidation during gas transport. Rhizosphere methane oxidation is well documented in vegetated wetlands, where oxygen leaking from roots into the surrounding soil sustains methanotrophic communities which can consume a substantial fraction of the methane before it reaches the atmosphere (Laanbroek, 2010; Sutton-Grier and Megonigal, 2011). A longer transport path through the root zone would increase the exposure of methane to these oxidizing conditions. Together, these transport parameter adjustments reduce the overall efficiency of plant-mediated methane release, which is consistent with the optimization suppressing the overestimated winter aerenchyma fluxes.

4.3 Remaining challenges and future directions

While CLM-Wet-MS reproduces the observed carbon fluxes well, several aspects of the framework can be further improved. In this study, we chose to prescribe observed soil moisture to represent wetland hydrology. This isolates the newly developed biogeochemical components from uncertainties in the model's hydrological prediction, enabling their evaluation independently of hydrological biases (Kim et al., 2015). The trade-off is that it currently limits application to sites where continuous soil moisture observations are available. For broader application, a prognostic watershed-resolving approach to wetland hydrology



would be necessary. The saturation boundary method tested in this study (e.g. *wtd_8*) represents one such approach, but our results demonstrate that fixing the water table at a single depth introduces biases in the vertical soil moisture structure, leading to unrealistic flux partitioning, particularly the dominance of diffusion over aerenchyma transport. Future development should explore coupling the wetland landunit with lateral flow or shallow groundwater schemes capable of prognostically maintaining dynamic near-saturated conditions without requiring observational constraints. Recent advances in representing lateral subsurface flow and wetland-groundwater interactions within land surface models (e.g. Swenson et al., 2019; Felfelani et al., 2021) offer potential pathways for such integration.

The model phenology scheme presents a second structural limitation. The simulated abrupt leaf-off event in early October, driven by CLM's seasonal-deciduous phenology that drops all leaves simultaneously once the cold temperature threshold is met, produces a sharper decline in both GPP and ER than observed. This abrupt transition also propagates into the methane simulation, as the sudden loss of leaf area reduces carbon availability, aerenchyma conductivity and plant-mediated transport. The affected period corresponds to the autumn “shoulder-season”, the transition between peak growing-season and dormant conditions, during which fluxes are disproportionately sensitive to the timing and pace of senescence and are frequently misrepresented by threshold-based phenology schemes. In high-latitude ecosystems, shoulder-season non-growing-season CO₂ and CH₄ exchange has been shown to contribute substantially to annual carbon budget, yet remains underestimated by land models and undersampled by observations (Zona et al., 2016; Bao et al., 2021; Arndt et al., 2023). Although these findings derive from Arctic and boreal ecosystems, the same difficulty applies to our temperate riverine wetland, where CLM's threshold-driven leaf-off compresses the autumn transition into a single abrupt event. Developing a progressive senescence scheme that allows partial and gradual leaf area reduction rather than a single threshold-triggered event would improve the representation of this transition period and its cascading effects on autotrophic respiration and plant-mediated methane transport.

Methane flux simulation remains the most challenging aspect of the framework. Despite substantial improvement after optimization, the model still underestimates peak emissions during late summer and early autumn. This persistent bias likely reflects limitations in both the production and transport representations. On the production side, the strong temperature-dependent parameterization concentrates emissions into the warmest periods but may not fully capture substrate-driven pulses of methanogenesis associated with fresh carbon inputs — from lateral DOC transport through riverine and subsurface flows, and locally from root exudates or litter decomposition (Li et al., 2025). The temperature sensitivity of methanogenesis is known to vary seasonally, with higher Q_{10} values often observed during cooler months than during warmer months (Wang et al., 2015; Röbger et al., 2022), suggesting that a static Q_{10} value may not adequately represent the full seasonal dynamics of the methane producing microbial community. In terms of methane transport, the resulting parameterization with its very low temperature sensitivity of methane oxidation may oversimplify the dynamics of methanotrophic activity, which can vary with water table fluctuations and oxygen availability in the rhizosphere (Laanbroek, 2010; Sutton-Grier and Megonigal, 2011). Further refinement of the methane module, potentially incorporating substrate-explicit production pathways and dynamic oxidation responses linked to water table position, would be needed to resolve the remaining gap between modeled and observed fluxes.



670 The physical interpretation of optimized parameters also reveals areas where equifinality through parameter compensation may be occurring. The counterintuitive ordering of cellulose and lignin CUE, and the near-unity Q_{10} for methane oxidation, may partly reflect parameter values absorbing structural biases from other model components rather than representing true process characteristics. Independent laboratory or field measurements of process-level microbial parameters such as CUE under controlled substrate conditions, methane oxidation kinetics at varying oxygen concentrations, and the temporal dynamics of methane concentration, production, and oxidation at different soil depths, would help disentangle parameter compensation from genuine site-specific behavior and provide tighter constraints for future calibration efforts.

The comparison against chamber measurements illustrates how strongly observation scale shapes model evaluation. Evaluated against the EC data, the optimized model slightly underestimates the summer respiration and methane peaks; evaluated against the plot-scale chambers, the same model appears to overestimate both by a wide margin. This divergence arises because the two measurements sample different spatial supports — the EC flux integrates over a footprint extending well beyond the four chamber plots — rather than from any error in either measurement, and we deliberately compared them without upscaling. The contrast is larger for methane than for respiration, consistent with the greater spatial heterogeneity of methane emission in vegetated wetlands. This scale dependence has a direct bearing on the regional application envisioned for CLM-Wet-MS: validating wetland flux models against single plot-scale observations can be misleading, and representative evaluation will require either footprint-matched observations or explicit treatment of within-site spatial heterogeneity. It also reinforces the need for multi-plot or multi-site sampling to constrain the spatial variability that a single tower or chamber cannot capture. A further constraint concerns the temporal extent of the calibration data. Calibration was based on a single year (2024) of observations. Continuous flux monitoring has been maintained at the site, but waterway construction in November 2024 substantially altered the local hydrology and elevated methane emissions, so that later years no longer reflect the undisturbed baseline used here. Extending the calibration to multiple undisturbed years, once the site re-stabilizes, remains an important direction for future work.

Despite these limitations, this study establishes a process-based modeling framework for wetland carbon flux simulation in Korean wetlands. As the first such effort targeting a temperate inland riverine wetland within a land surface model, CLM-Wet-MS provides an optimized baseline that can be refined as longer observational records become available and as the structural limitations identified above are addressed. Because CLM5 inherently represents multiple land cover types within its sub-grid hierarchical structure, this wetland-specific scheme can be embedded within regional-scale simulations alongside other land covers, enabling more realistic carbon flux estimates that account for wetland contributions alongside those of upland ecosystems. Extension of this framework to other Korean wetland sites and wetland types would further test the generalizability of the structural modifications and provide additional constraints for regional carbon budget assessments.



700 5 Conclusions

705 This study developed CLM-Wet-MS, a modified version of CLM5 incorporating a dedicated wetland landunit, wetland-adapted soil hydrology, and a microbial soil decomposition scheme, and applied it at Bibong wetland, a temperate inland riverine wetland in South Korea. Structural comparisons across hydrological configurations demonstrated that the representation of soil moisture is a dominant control on simulated carbon fluxes, fundamentally determining methane transport pathway partitioning and the seasonal dynamics of ecosystem respiration. The microbial decomposition scheme addressed a structural overestimation of winter respiration that could not be corrected through parameter optimization alone, confirming that process-level modifications are necessary beyond recalibration of existing model structures. Sequential optimization substantially improved model performance for all three targeted fluxes, and the optimized parameters were shown to be physically consistent with wetland vegetation traits, soil microbial dynamics, and methane biogeochemistry. The structural comparison further indicated that plant-mediated aerenchyma transport, rather than diffusion or ebullition, dominates methane emission at this vegetated site. Despite remaining challenges, CLM-Wet-MS establishes a process-based baseline for wetland carbon flux modeling in Korean wetlands. Because the framework is embedded within CLM5's sub-grid hierarchy, it can be extended to regional-scale simulations that integrate wetland and upland land cover types, contributing to the broader effort of improving the representation of temperate inland wetlands in process-based land surface models.



715 Appendix A

Table A1: Default and optimized parameter values for the CLM-Wet-MS

Flux	Parameter	Default	Optimized
GPP	fates_leaf_vmax25top	78	100
	fates_leaf_slatop	0.03	0.01
	fates_leaf_stomatal_slope_ballberry	8.0	8.0
	fates_phen_mindayson	90	170
	fates_phen_coldtemp	7.5	24
ER	tau_s2_death	-	27.19
	tau_s2_enz	-	40.0
	l1_cue	-	0.67
	l2_cue	-	0.36
	l3_cue	-	0.53
	mic_cue	-	0.25
	fates_q10_mr	1.5	3.0
	mino2lim	0.2	0.07
FCH4	q10ch4	1.33	3.37
	q10ch4base	295	307.22
	f_ch4	0.2	0.54
	q10_ch4oxid	1.9	1.15
	porosmin	0.05	0.025
	rob	3.0	4.0

Code and data availability

The exact version of CLM-Wet-MS (v1.0) used in this study is preserved at <https://doi.org/10.5281/zenodo.21866744> (Oh et al., 2026b), and developed openly at https://github.com/yonsei-hecl/clm-wet-ms_v1.0. CLM-Wet-MS was developed based on the Community Earth System Model (CESM) version 2.2.2 (<https://github.com/ESCOMP/CESM/tree/release-cesm2.2.2>). Model output and processing scripts used in this study are available at <https://doi.org/10.5281/zenodo.21868272> (Oh et al.,



2026c). Eddy covariance data of the site, provided by National Center for AgroMeteorology (NCAM), and chamber flux data are also available at <https://doi.org/10.5281/zenodo.21868272> (Oh et al., 2026c). BOA software (Scyphers et al., 2024) code is available through <https://zenodo.org/records/12797033> (Scyphers et al., 2023) with a corresponding open-access GitHub repository <https://github.com/madeline-scyphers/boa/tree/0.11.0>.

Author contributions

HO and YK conceptualized the study. HO developed the model code, performed the simulations and analyses, conducted the field measurements, and prepared the manuscript with contributions from all co-authors. JM and GB provided the conceptual basis for the model development from their prior work on ELM-Wet and the Bayesian optimization framework. VDZAR carried out the chamber measurements together with HO. MK provided and processed the eddy covariance data. HK designed and funded the chamber measurement campaign. YK supervised the research and acquired funding.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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