Lagged Wetland CH_4 Flux Response in a Historically Wet Year

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Key Points:

- Analyzed lagged response of methane flux to different driver variables at two closely located fen wetlands in Wisconsin
- Air-temperature normalization of methane flux was crucial for interpretation of lagged responses, especially in wet year
- Lagged response of methane flux to gross primary productivity surpassed sixty days and had weaker correlation during wet year at both sites

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Abstract

While a stimulating effect of plant primary productivity on soil carbon dioxide (CO_2) emissions has been well documented, links between gross primary productivity (GPP) and wetland methane (CH_4) emissions are less well investigated. Determination of the influence of primary productivity on wetland CH_4 emissions (FCH_4) is complicated by confounding influences of water table level and temperature on CH_4 production, which also vary seasonally. Here, we evaluate the link between preceding GPP and subsequent FCH_4 at two fens in Wisconsin using eddy covariance flux towers, Lost Creek (US-Los) and Allequash Creek (US-ALQ). Both wetlands are mosaics of forested and shrub wetlands, with US-Los being larger in scale and having a more open canopy. Co-located sites with multi-year observations of flux, hydrology, and meteorology provide an opportunity to measure and compare lag effects on FCH_4 without interference due to differing climate. Daily average FCH_4 from US-Los reached a maximum of 47.7 ηmol CH_4 $m^{-2}\cdot s^{-1}$ during the study period, while US-ALQ was more than double at 117.9 ηmol CH_4 $m^{-2}\cdot s^{-1}$. The lagged influence of GPP on temperature-normalized FCH_4 (T_{air}-FCH_4) was weaker and more delayed in a year with anomalously high precipitation than a following drier year at both sites. FCH_4 at US-ALQ was lower coincident with higher stream discharge in the wet year (2019), potentially due to soil gas flushing during high precipitation events and lower water temperatures. Better understanding of the lagged influence of GPP on FCH_4 due to this study has implications for climate modeling and more accurate carbon budgeting.

Plain Language Summary

Research on what controls wetland methane emissions is continually advancing, and while this is beneficial for predicting future climate scenarios, there is still a need to understand how changes in plant productivity will influence wetland methane emissions. In this study, we investigated the strength and lag time of the relationship between gross primary productivity due to photosynthesizing plants and wetland methane flux in two closely situated sites. We also looked at how hydrology might change that relationship. We found the total amount of methane emitted in an extremely wet year was less than what was emitted in the following drier year at both wetlands potentially because of less carbon provided to the soil by photosynthesizing plants. The difference in methane emissions from one year to the next could be influenced by wetland hydrology, water temperature, or other conditions that impact methane-producing bacteria. Results from this study will help scientists better predict methane emissions following high precipitation years which may become more common in a changing climate.

1 Introduction

By the year 2100, mean global annual CH_4 flux (FCH_4) from natural wetlands is projected to increase from 172 Tg CH_4 yr^{-1} to anywhere between 222 and 338 Tg CH_4 yr^{-1} depending on the climate scenario (Zhang et al., 2017). Under the best climate scenario of strong climate mitigation (RCP 2.6), wetland methane (CH_4) emissions are projected to decline in the 2050s after peaking at ~225 Tg CH_4 yr^{-1}. Radiative forcing feedback from wetland CH_4 could account for a large portion of the total radiative forcing change from CH_4, accounting for 0.04 ± 0.002 Wm^{-2}, and global mean temperature would increase slightly as a result (Zhang et al., 2017). Ecosystem-scale controls over microbial activity and resulting wetland CH_4 emissions are difficult to include in climate projection models despite their importance as a major climate feedback. Specifically, there is a need to understand and include the impact of shifting spatial patterns of vascular plants on CH_4 transport from soil into atmosphere, and biogeographical distribution of methanogen communities and their metabolic processes, which could be leading to current underestimation of CH_4 emissions with certain models. A better understanding of the relationship between gross primary productivity (GPP) and FCH_4 in fen wetlands is crucial to understanding the potential impacts of a longer growing season, higher GPP, and the shifting distribution of terrestrial ecosystems due to a changing climate (Zhang et al., 2017). In this study, we take a close look at the lagged effect of GPP on FCH_4 from two closely located north temperate fen wetlands.

Global syntheses of eddy covariance flux data and improved earth system models have contributed to a better understanding of FCH_4 drivers and variability across sites (Knox et al., 2019; Delwiche et al., 2021; Knox et al., 2021), but there is room to improve understanding even further through regional site comparisons. Driver analysis on this small-scale has the potential to explain variability in FCH_4 in locations undergoing the same synoptic meteorology on the scale of hundreds to thousands of kilometers (e.g., low pressure systems), some overlapping mesoscale meteorology at the scale of a few to hundreds of kilometers (e.g., thunderstorms), but separate microclimates under the scale of a kilometer (e.g., structure and function of vegetation and its influence on local climate variables).

Some prior studies have found no significant relationship between GPP and FCH_4 (Sturtevant and Oechel, 2013; Davidson et al., 2016). However, certain physical mechanisms should cause GPP and FCH_4 to be linked in wetland ecosystems, either synchronously or lagged. GPP can influence FCH_4 directly through plant-mediated transport of gas from porewater to the atmosphere (Dannenberg and Conrad, 1999; Dorodnikov et al., 2011) or indirectly through plant C fixation to soil methanogens during photosynthesis (Hatala et al., 2012). Aerenchymatous wetland plants transport dissolved CH_4 from porewater, through roots, into the root cortex, and then out through leaf sheath micropores in the lower part of the shoot (Nouchi et al., 1990; Henneberg et al., 2012). Root area is therefore an important determinant of plant-mediated CH_4 transport and will increase CH_4 production in anoxic conditions. Ecosystem-scale FCH_4 is more difficult to predict given that flux varies among plants of the same genus (Ding et al., 2005). CH_4 oxidation rate will also peak at different times of the season depending on plant type (Welsch and Yavitt, 2007).

The lag time between plant C assimilation and soil CO_2 efflux (i.e., microbial decomposition & root respiration) takes less than one day for grasses and up to 5 days for mature trees (Kuzyakov and Gavrichkova, 2010). Due to plant metabolism, one would expect, in anoxic soil conditions, a similar lagged influence of GPP on soil FCH_4, which has been detected and discussed in some studies (Mitra et al., 2020; Bridgham et al., 2013; Updegraff et al., 2001) but not others (Villa et al., 2019) or may disappear after temperature-normalization (Rinne et al., 2018; Chen et al., 2020). Methane emission can be stimulated by plant shoot clipping (which results in the growth of new roots) in as few as three days, although the short duration of mesocosm experiments limits measurement of maximum total lag time (Rietl et al., 2017). Another experiment found a six-day lag between soaking a rice field and a rise in CH_4 emissions and a clear change in the magnitude of the FCH_4 diel cycle depending on plant growth phase (Centeno et al., 2017).

In this study we compare FCH_4 and related environmental variables of two co-located fen wetlands in Wisconsin to answer two questions: (1) What is the influence of plant C fixation on FCH_4 as measured by the lagged effect of GPP at two north temperate fen wetlands when removing the known influence of air temperature (T_{air})? (2) How do factors relating to wetland hydrology as indicated by wetland stream discharge, stream temperature (T_{stream}), and water table depth (WTD), mediate the GPP-FCH_4 relationship at both sites? We hypothesize GPP will have a strong but short-term lagged influence on temperature-normalized FCH_4 (T_{air}-FCH_4) at both sites because of allocation of recently fixed C to roots, followed by methanogenesis. Removing the influence of T_{air} will be critical to the interpretation of results. We expect wetland stream discharge to correspond with increasing FCH_4, assuming it is indicative of a higher WTD. Finally, FCH_4 should be similar but not identical at the two sites in this study given that they are co-located fens with mixed vegetative cover but possess unique physical and hydrological features, discussed below.

2 Methods

2.1 Site descriptions

Our study focuses on two sites in northern Wisconsin that are located approximately 29 km apart: US-Los and US-ALQ. US-Los (46.082777, -89.978611) is larger in scale (flux footprint radius 1,033 m), features more open canopy vegetation, and is dominated by broad-leaved deciduous shrub vegetation (20% of flux footprint). US-ALQ (46.030759, -89.606730) is smaller in scale (flux footprint radius 238 m), features more sheltered canopies, and is dominated by broad-leaved deciduous or evergreen shrub vegetation (30% of flux footprint). Both sites are mixed sedge meadow, forest, and shrub wetland. Both sites are fen wetlands, as they are surface water and groundwater sourced and have peat soil, and each is bisected by a headwater stream (Lost Creek at US-Los; Allequash Creek at US-ALQ). Detailed site descriptions are available for US-Los in Sulman et al. (2009) and for US-ALQ in Anderson and Lowry (2007). It should be noted that Allequash Creek (flowing through US-ALQ) is a groundwater-fed stream (Pint et al., 2003) and thus flows year-round.

2.2 Flux data

CH_4 and CO_2 eddy covariance flux data for US-ALQ (doi: 10.3389/fenvs.2019.00179) and US-Los (doi:10.17190/AMF/1246071) are available on Ameriflux (Olson, B. 2020; Desai, A. 2020; https://ameriflux.lbl.gov/).). All data analyzed in this study were collected during

January 1, 2019 through Dec 31, 2020. Instrumentation at both sites included a sonic anemometer (Campbell Scientific, Inc., Logan, 188 UT, CSAT-3), open path infrared gas analyzer, and methane flux sensor (LI-COR, Lincoln, NE, LI7700). There was a different radiation sensor at US-Los (Kipp & Zonen 197 North America, Sterling, USA, Kipp-Zonen CNR4) than US-ALQ (Apogee Instruments Inc., Logan, UT, SN-500). There was also a different air temperature and relative humidity sensor at US-Los (Campbell Scientific, Inc., Logan, UT, CS215) than at US-ALQ (Campbell Scientific, Inc., Logan, UT, Vaisala HMP45C 190 platinum-resistance thermometer). A quantum photosynthetically active radiation (PAR) sensor was installed only at US-Los (LI-COR, Lincoln, NE, LI-190). More information on flux tower height, footprint, and instrumentation for both sites can be found in Turner et al. (2019).

Typical in eddy covariance studies, there were portions of data missing from the continuous record that required gap-filling. There were more missing half-hourly FCH_4 data at US-ALQ than US-Los (49% vs. 34%). Fewer data were missing during the typical CO_2 uptake period from April to October (US-ALQ 44%, US-Los 23%) than during the rest of the year for both sites (US-ALQ 57%, US-Los 48%). There were more data gaps in 2019 (US-ALQ 63%, US-Los 45%) than 2020 (US-ALQ 36%, US-Los 22%). FCH_4 was gap-filled with the machine learning random forest algorithm using the “randomForest” R package (Liaw and Wiener, 2001) and gap-filling script (Kim, 2020; Kim et al., 2020). This approach was selected because it outperforms marginal distribution sampling, artificial neural networks, and support vector machine for gap-filling of eddy covariance FCH_4 data.

Net ecosystem exchange of CO_2 (NEE) was gap-filled and partitioned into GPP and ecosystem respiration (R_{eco}) using the Desai-Cook flux partitioning model (Cook et al., 2004; Desai et al., 2007), which utilizes a non-linear regression of daytime R_{eco} to PAR and is comparable to many other regressions based on moving window flux partitioning algorithms. R_{eco} in the model is calculated from a non-linear regression of nighttime NEE to T_{air}. Once again, there were more data gaps in 2019 (US-ALQ 37%, US-Los 49%) than in 2020 (US-ALQ 29%, US-Los 33%), for NEE. Fewer data were missing during the CO_2 uptake period from April to October (US-ALQ 29%, US-Los 34%) than during the rest of the year (US-ALQ 38%, US-Los 51%). No missing data remained after gap-filling NEE for US-ALQ during either year. No missing data remained after gap-filling NEE for US-Los in 2019, but a small amount of missing data remained after gap-filling in 2020 (US-Los 94%).

2.3 Meteorological and hydrological data

Daily total precipitation data were from Lakeland Field Station at Lakeland Airport in Woodruff, WI (45.927222, -89.730836), located 26.1 km away from US-Los and 15.4 km from US-ALQ (NOAA, 2021). Rhinelander, WI, a city located 56 km from the study sites, received nearly 110 cm of total precipitation in 2019, making it the wettest year on record from 1908 to 2020 (Rhinelander Weather Recs., 2021). The average annual precipitation for Rhinelander during that time was 80 ± 15 cm (standard deviation). Meanwhile, the city received only 90 cm of precipitation in 2020. Stream temperature and temperature data for US-ALQ were from the National Water Information System (USGS, 2020a; https://waterdata.usgs.gov/nwis). US-ALQ lacked water table depth data during the time of study. WTD was used in place of stream discharge to understand the impact of hydrology on FCH_4 at US-Los. The water level sensor used to measure WTD was a Campbell Scientific CS451.

2.4 GPP-FCH_4 Lag analysis

Lag analysis involved multiple steps. First, we utilized a built-in function in MATLAB that performed a circular shift of the data ("xcorr") to estimate the direction of the strongest lag correlation based on cross correlation of the two variables of interest. Lag analysis was then performed in the direction of the strongest lag correlation as in Rinne et al. (2018). The driver variable was lagged with respect to the response variable one step at a time. Rows with missing driver variable data were removed. Correlation and significance between variables were measured at each step. Variables analyzed for lags included GPP & FCH_4, GPP & T_{air}-FCH_4, WTD & FCH_4, WTD & T_{air}-FCH_4, and WTD & GPP. The lag was not measured past 200 days. MATLAB scripts for creating the lag analysis plots and all other plots used in this study are available online (turner-j, 2020). All lag analysis was performed with daily average data.

2.5 Temperature normalization of FCH_4

Covariates must be taken into careful consideration when analyzing data for FCH_4 drivers that are interrelated. One such covariate that has a noticeable impact on FCH_4 is temperature, but whether it is the soil, air, or water temperature which dominantly influences FCH_4 varies among sites (Rey-Sanchez et al., 2018; Chu et al., 2014). Removing the influence of temperature on FCH_4 before performing lag analysis with GPP should be done to eliminate any trends solely due to temperature as a driving force (Chen et al., 2020). We removed the influence of T_{air} on FCH_4 by fitting observed FCH_4 to an exponential model with T_{air} as a predictor. Non-linear regression was used to find the coefficients β_1 and β_2 in equation (1) below. Observed FCH_4 from both years was then divided by predicted FCH_4 based on observed T_{air} as in equation (2) below. T_{air} dependence of FCH_4 was therefore modeled and removed using the following equations:

$$(1)\ F = \beta_1 \times \exp(\beta_2 \cdot T)$$

$$(2)\ T_{air}FCH_4 = \frac{daily\ average\ FCH_4}{F}$$

3 Results

3.1 Meteorology and stream discharge

The two study sites, US-ALQ and US-Los, had equal means of daily average incoming radiation ($p = 0.054$) and linearly correlated but unequal means of air temperature ($r = 1$, $p << 0.01$) and vapor pressure deficit ($r = 0.97$, $p << 0.01$). Resulting differences in the variables we compare and analyze in this study at each site could therefore be due to the impacts of mesoscale or microscale meteorology; differences in magnitude of stream discharge, air temperature, or vapor pressure deficit; or abiotic or biotic site characteristics other than those previously mentioned.

The water table at US-Los was closer to the surface in 2019 than 2020 (-0.26 vs. -0.29 m below surface). Additionally, stream discharge at US-ALQ was linearly related to WTD at US-Los ($r = 0.45$, $p = << 0.01$) and was slightly higher in 2019 (0.15 m^3s^{-1}) than 2020 (0.16 m^3s^{-1}).). There was a low covariance (cov = 0.0045) and a significant, positive two-day lagged effect of precipitation at Lakeland Airport on WTD at US-Los ($r = 0.11$). Precipitation covaried with stream discharge at US-ALQ (cov = 0.01). Precipitation also covaried with T_{stream} at US-ALQ (cov = 0.56) and T_{air} at US-Los (cov = 0.81) and US-ALQ (cov = 0.91).

3.2 CH_4 and CO_2 fluxes in wet (2019) and dry (2020) years

FCH$_4$ gap-filling performance was higher with US-ALQ than US-Los (R^2 = 0.85 vs. 0.70). No FCH$_4$ data were missing at either site after gap-filling (Fig 1). US-ALQ emitted more than double the daily average FCH$_4$ as US-Los during the entire study period (approx. 19.6 versus 6.7 ηmol m^{-2} s^{-1}). Daily average FCH$_4$ reached a maximum of 47.7 ηmol CH_4 m^{-2} s^{-1} at US-Los and 117.9 ηmol CH_4 m^{-2} s^{-1} at US-ALQ. More carbon as CH_4 (C-CH_4) was emitted and less carbon as CO_2 (C-CO_2) was taken up annually at US-ALQ than US-Los in both years (Table 1). Both sites exhibited lower daily mean FCH$_4$ in the historically wet year of 2019 (5.5 ηmol CH_4 $m^{-2}s^{-1}$ US-Los; 13.5 ηmol CH_4 $m^{-2}s^{-1}$ US-ALQ) than in 2020 (7.8 ηmol CH_4 $m^{-2}s^{-1}$ US-Los; 25.8 ηmol CH_4 $m^{-2}s^{-1}$ US-ALQ). Cumulative annual C-CH_4 emission at both sites was only a fraction of C-CO_2 uptake. US-ALQ had the highest cumulative annual FCH$_4$ in comparison to FCO$_2$, at 10.31% in 2020. US-Los had the lowest cumulative annual FCH$_4$ in comparison to FCO$_2$, at approximately 1% in 2019.

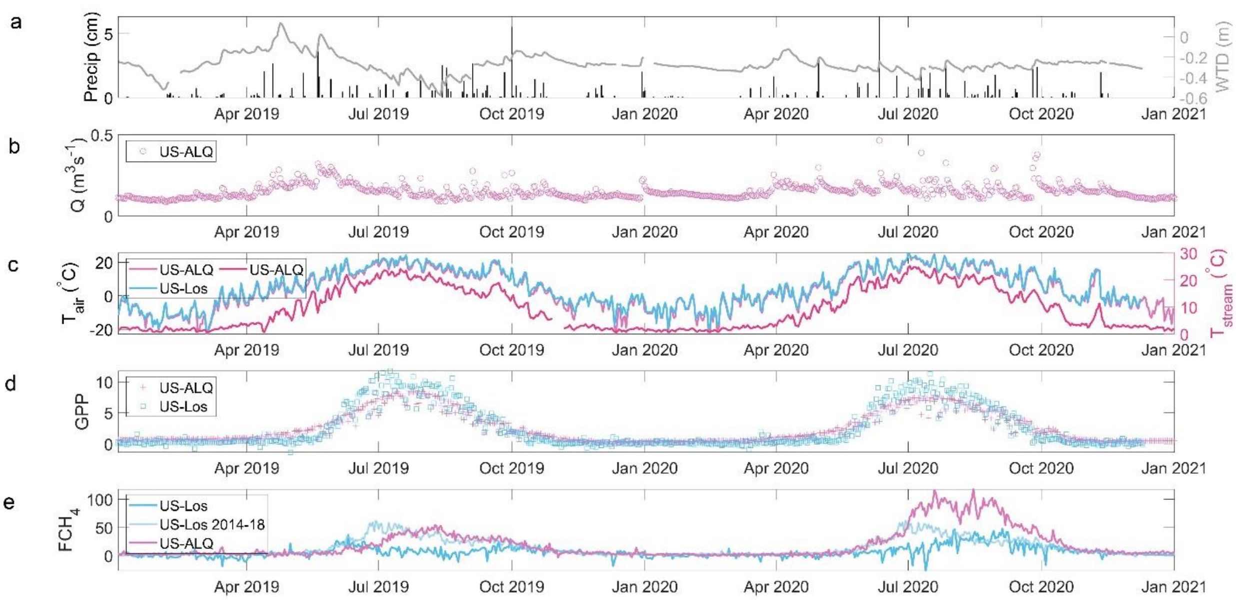

Fig 1. (A) Bar plot of precipitation at Lakeland Airport and timeseries of water table depth (WTD) at US-Los, (B) stream discharge (Q) at US-ALQ, (C) air temperature in degrees C at both sites and stream water temperature at US-ALQ, (D) GPP at both sites in µmol CO_2 $m^{-2}s^{-1}$, and (E) FCH$_4$ at both sites in ηmol CH_4 $m^{-2}s^{-1}$ and historic average FCH$_4$ at US-Los from 2014 to 2018.

Table 1. Cumulative annual FCH_4 and FCO_2 as C from US-ALQ and US-Los in 2019 and 2020.

	FCH_4 (g C-CH_4 m^{-2} yr^{-1})		FCO_2 (g C-CO_2 m^{-2} yr^{-1})	
	2019	2020	2019	2020
US-ALQ	5.08 ± 0.10	9.79 ± 0.21	-78.36 ± 2.59	-94.92 ± 2.52
US-Los	2.08 ± 0.04	2.98 ± 0.06	-202.61 ± 5.79	-148.73 ± 4.69

Note: Values are shown with standard error of the mean. Negative values indicate a C sink from the atmosphere. Positive values indicate a C source to the atmosphere.

3.3 GPP-FCH_4 relationship

FCH_4 preceded GPP by approximately 20 days at US-Los in 2019 (Fig 2A). Removing the influence of air temperature ("normalized" in Figs 2,3) resulted in a stronger lagged correlation where FCH_4 followed GPP starting after 40 days in 2019, and the strength of the correlation continued to grow up until at least 100 days (Fig 2B). The lag relationships between FCH_4 and GPP, as well as T_{air}-FCH_4 and GPP, were both weakly correlated in 2019 ($r < 0.4$). The lagged influence of GPP on FCH_4 at US-Los peaked at 40 days in 2020 (Fig 2C). The lagged influence of GPP on T_{air}-FCH_4 at US-Los was shorter than that of FCH_4 in 2020, with a broad peak lasting 40-60 days ($r = 0.65$).

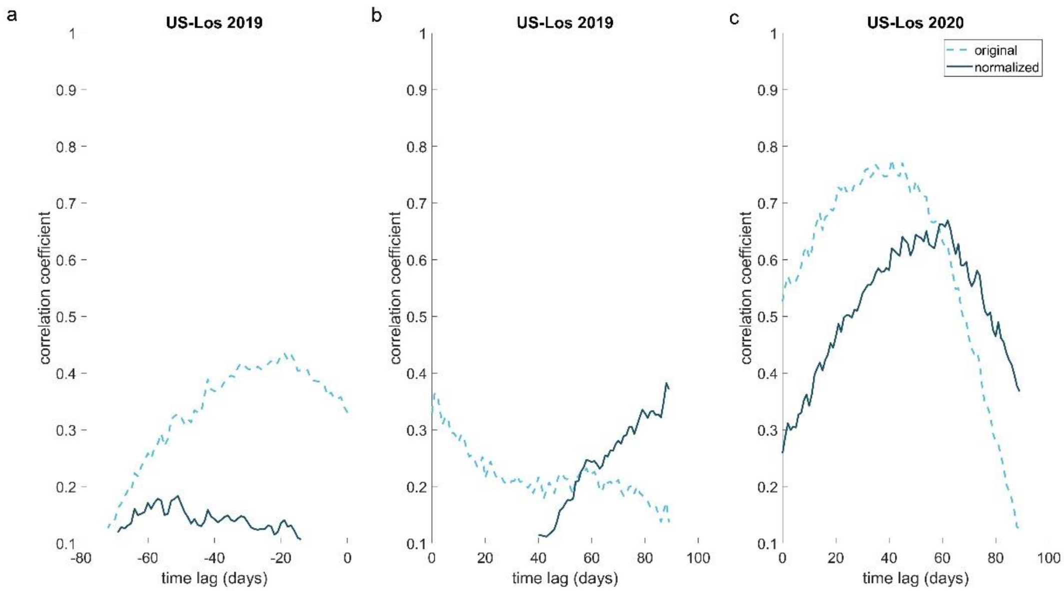

Fig 2. Lagged influence of GPP on FCH_4 and temperature-normalized FCH_4 at US-Los. (A) FCH_4 preceding GPP in 2019. (B) FCH_4 following GPP in 2019. (C) FCH_4 following GPP in 2020. Positive values indicate FCH_4 follows GPP. Only significant ($p < 0.05$), positive lags ($r > 0$) shown.

GPP preceded FCH_4 by approximately 20 days at US-ALQ in 2019 (Fig 3A). Removing the influence of air temperature on FCH_4 revealed that the strongest correlation between GPP and T_{air}-FCH_4 occurred around 60 days and plateaued until at least 100 days, meaning that GPP was not correlated with FCH_4 for at least 2 months ($r = 0.52$). The lag relationship was slightly shorter in 2020, with GPP leading FCH_4 by roughly 20 days and GPP leading T_{air}-FCH_4 by approximately 35-50 days ($r = 0.78$, Fig 3B). The lagged influence of GPP on T_{air}-FCH_4 was shorter, stronger, and more closely related to that of GPP and FCH_4 in 2020 than 2019 for both sites.

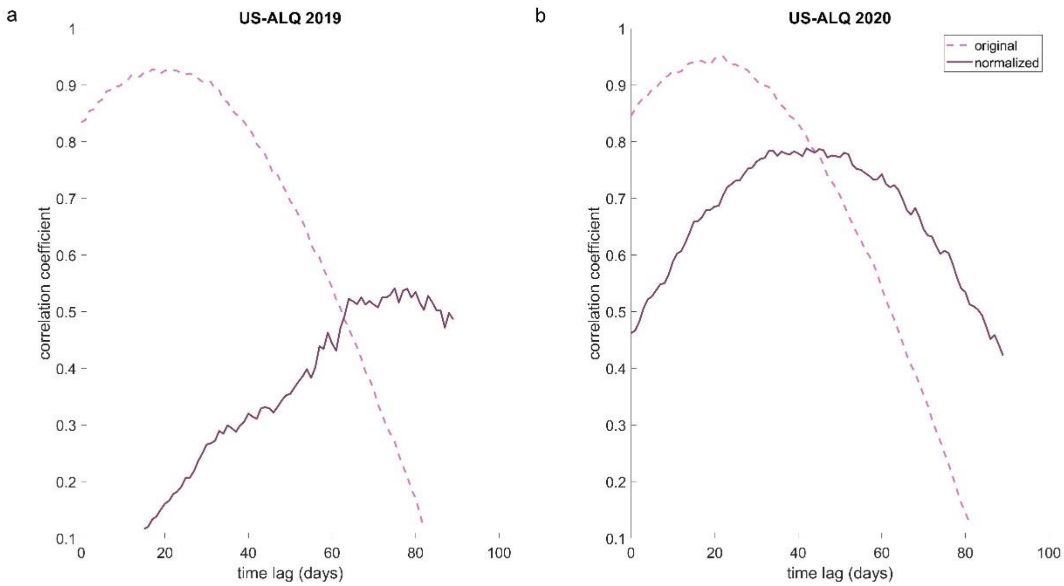

Fig 3. Lagged influence of GPP on FCH_4 and temperature-normalized FCH_4 at US-ALQ in 2019 and 2020. Only significant ($p < 0.05$), positive lags ($r > 0$) shown.

3.4 Influences of hydrology

FCH_4 at both sites was correlated with T_{air}, but the relationship was stronger at US-ALQ ($R^2 = 0.53$) than US-Los ($R^2 = 0.25$) (Figs 4A & 5A). The relationship between WTD and T_{air}-FCH_4 at US-Los was not linear in either year (Fig 4B & C). There was a significant inverse relationship between discharge and T_{air}-FCH_4 at US-ALQ during 2019 ($R^2 = 0.73$) (Fig 5B). However, there was no significant relationship between discharge and T_{air}-FCH_4 at US-ALQ in 2020 (Fig 5C).

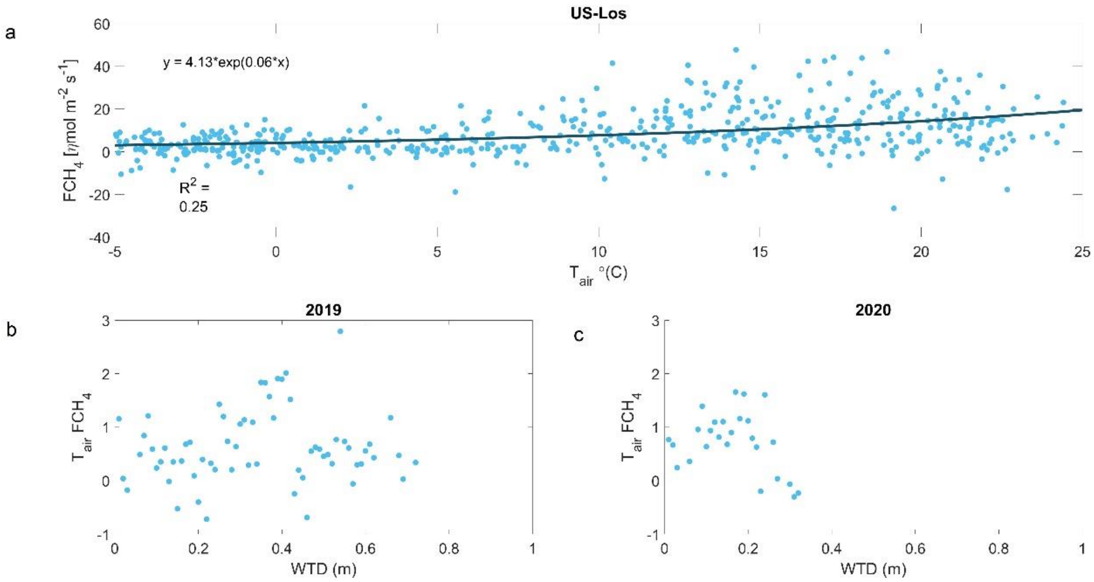

Fig 4. (A) Air temperature sensitivity of FCH_4 in both years combined, and (B) WTD versus temperature-normalized FCH_4 using daily average data at US-Los during 2019 and (C) 2020. R^2 displayed on the first subplot is the coefficient of determination between the best fit of the relevant model (second order polynomial) and observations. Best fit lines show significant relationships ($p < 0.05$). T_{air}- FCH_4 was bin averaged according to discharge rounded to the nearest 0.01 m.

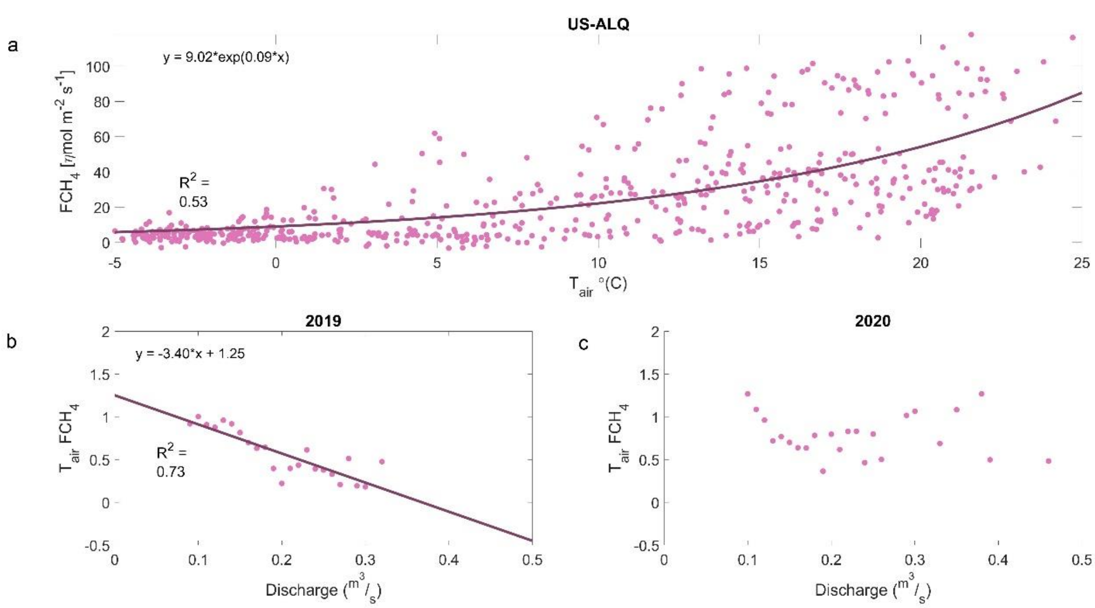

Fig 5. (A) Air temperature sensitivity of FCH_4 in both years and (B) Discharge versus T_{air}- FCH_4 using daily average data at US-ALQ during 2019 and (C) 2020. R^2 displayed on each plot is the coefficient of determination between the best fit of the relevant model (first or second order polynomial) and observations. Best fit lines show significant relationships ($p < 0.05$). T_{air}- FCH_4 was bin averaged according to discharge rounded to the nearest 0.01 m^3s^{-1}.

There was a significant lagged influence of WTD on FCH_4 at US-Los in 2019 (Fig 6A). Removing the influence of T_{air} did not greatly change the relationship (Fig 6B). The lagged effect of WTD on T_{air}-FCH_4 lasted 5-52 days with a peak at 24 days and a correlation coefficient of 0.27. No significant, positive correlation was detected between WTD and FCH_4 or T_{air}-FCH_4 at US-Los during 2020 (data not shown).

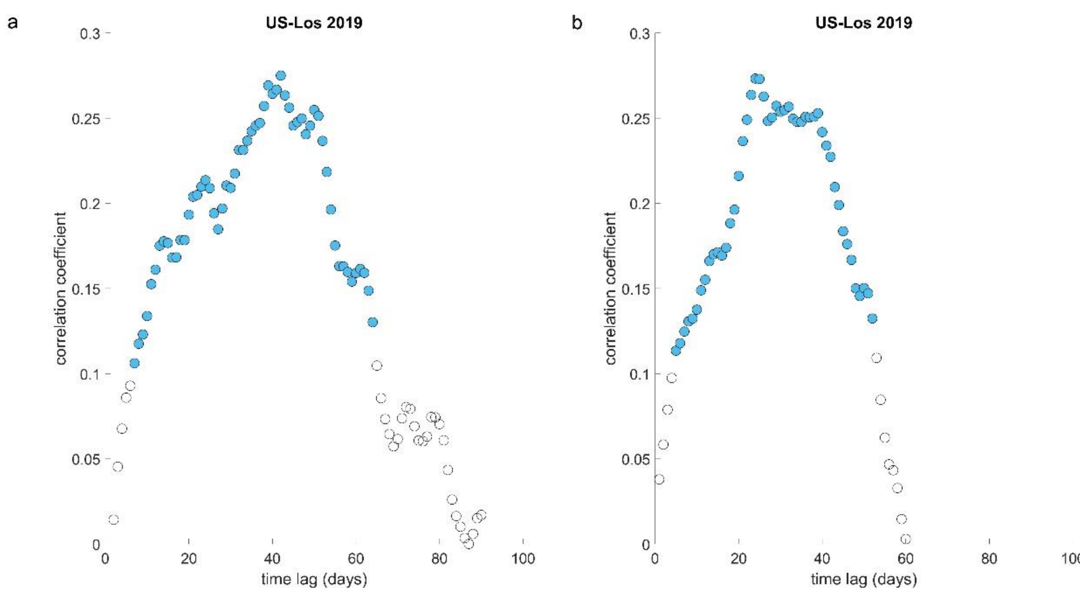

Fig 6. Lagged effects of water table depth (WTD) on (A) FCH_4 and (B) T_{air}-FCH_4 at US-Los in 2019. Filled blue circles represent significant ($p < 0.05$), positive ($r > 0$) lag correlations. Empty circles are not significant and/or do not represent positive correlations.

WTD variability at US-Los was lower in 2020 (var = 0.002) than 2019 (var = 0.016). Discharge variance was consistently low at US-ALQ, remaining at 0.002 in both years.

Discharge was also low but typical for the stream, ranging from 0.086-0.32 m^3s^{-1} in 2019 and from 0.10-0.46 m^3s^{-1} in 2020 at US-ALQ. There was also a significant, positive ($p< 0.05$, $r>0$) lagged effect of WTD on GPP at US-Los with a very long duration of 43-140 days with a peak at 92 days ($r = 0.81$) in 2019 (Fig 7A). The lag effect was similar in 2020 but did not begin until around 60 days and had a lower peak correlation ($r = 0.42$, Fig 7B).

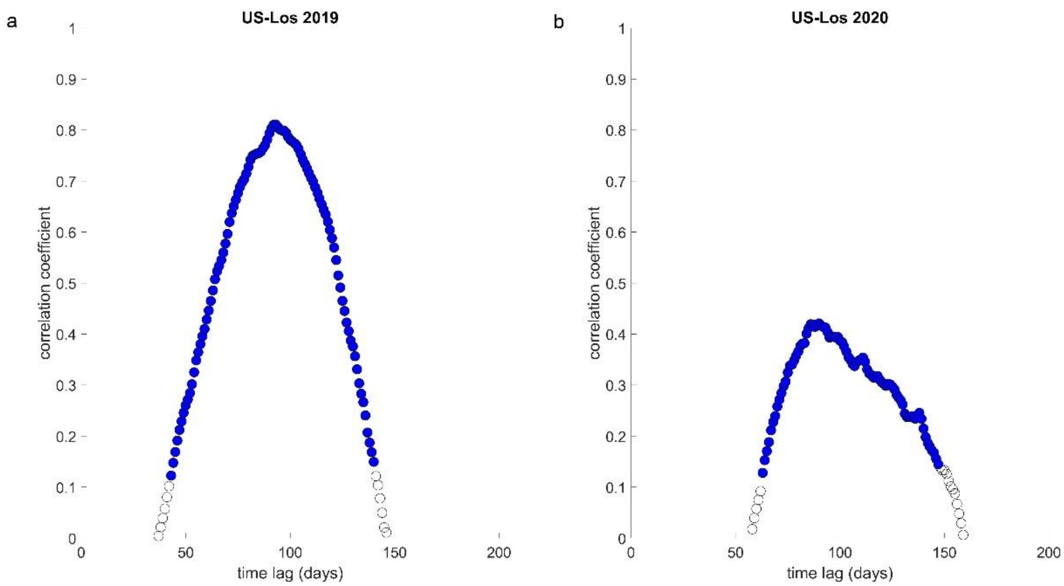

Fig 7. Lagged effects of water table depth (WTD) on GPP in (A) 2019 and (B) 2020 at US-Los. Filled blue circles represent significant ($p < 0.05$), positive ($r > 0$) lag correlations. Empty circles are not significant and/or do not represent positive correlations.

Higher T_{stream} was significantly positively correlated ($r = 0.15$, $p = 0.003$) with higher T_{air}-FCH_4 at US-ALQ from April to October but negatively correlated with T_{air}-FCH_4 during the rest of the year ($r = -0.28$, $p = 0$) during both years combined (Fig 8 A & B). However, the linear model demonstrated a poor fit to the data in both cases ($R^2 < 0.1$). Stream temperature did not surpass 5 °C during months outside April to October. Average yearly water temperature in the creek was slightly lower in 2019 than 2020 (9.3 vs. 9.6 °C).

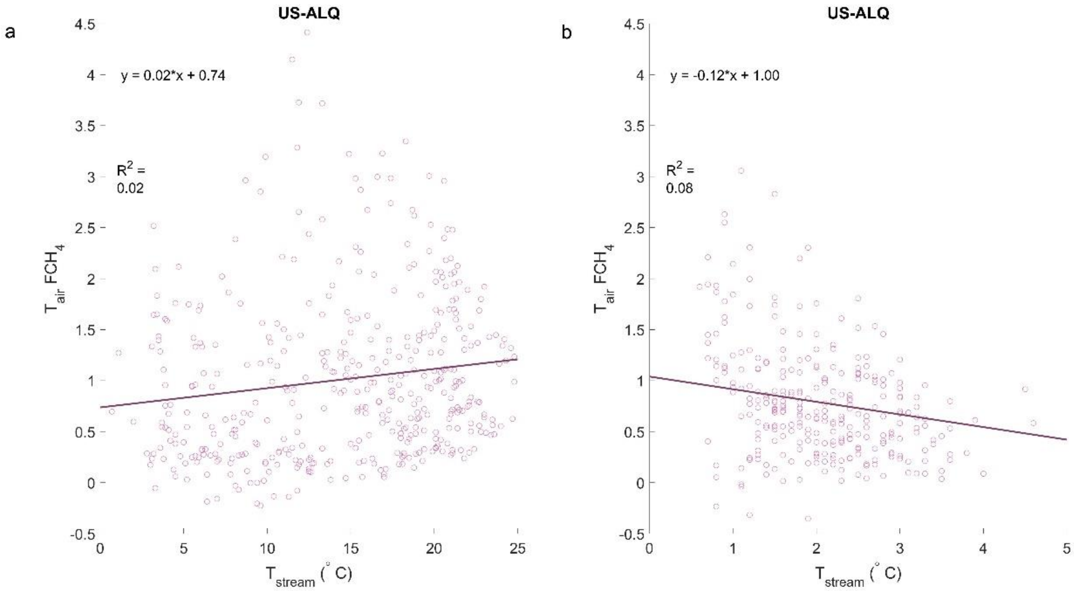

Fig 8. The influence of T_{stream} on T_{air}-FCH_4 at US-ALQ during (A) April to October and (B) all other months for both years combined. Solid lines represent the first-order linear regression. R^2 is the coefficient of determination between the linear regression and observations.

4 Discussion

4.1 CH_4 limitations in a historically wet year

Daily average FCH_4 for both sites was on the lower end of what is expected for wetlands in general (Nicolini et al., 2013), but cumulative annual FCH_4 aligned well within the wetland type of fens (Knox et al., 2019). Daily average FCH_4 and cumulative annual FCH_4 for both sites were lower in the historically wet year than in the following dry year (Table 1, Figure 1E). This is a noteworthy finding given that an earlier study in the same region, but from a landscape-level tall tower, concluded a dry year with a longer growing season and warmer conditions cut FCH_4 by 28% (Desai et al., 2015). These decreases in FCH_4 in unusually wet and dry years suggest environmental extremes could reduce cumulative annual FCH_4 at these sites. The results of this study also strengthen the idea of a critical inundation level past which wetland CH_4 emissions begin to decline due to a number of possible reasons (e.g., lower light attenuation, diluted organic substrate, etc.) (Calabrese et al., 2021). However, more hydrological data from both sites is needed.

4.2 GPP-FCH_4 lagged relationship

At both sites, the lag between GPP and FCH_4 was weaker and took longer in 2019 than in 2020. The GPP-FCH_4 lag relationship observed at both sites during the study is supported by Delwiche et al. (2021), which found a lag relationship between FCH_4 and GPP in 83% of global freshwater wetlands, and the 20.7-day lag observed in Knox et al. (2021). T_{air} normalization of FCH_4 was critical for observation of the severe shifts in the lag effect in this study during a historically wet year, as normalization shifted the GPP-FCH_4 relationship at US-ALQ backwards by roughly twenty days in 2019. The lag correlation between GPP and subsequent T_{air}-FCH_4 observed at both sites in 2019 superseded the amount of time needed for photosynthesis, soil C fixation, and root growth, indicating the influence of another factor not considered in this study or a process that needs to be further explored.

The extremely long lagged influences of GPP on T_{air}-FCH_4 at both sites, and WTD on GPP at US-Los in comparison with the much shorter lag between WTD and FCH_4, indicate that root respiration was not a strong driver of FCH_4 in the beginning of 2019. One possible explanation is substrate limitation for methanogenesis caused by a lack of recently fixed labile C or older, more recalcitrant soil organic carbon (Oikawa et al., 2017).

In a year characterized by historical levels of precipitation, WTD fluctuated from approximately 0.2 m to -0.6 m from May to August of 2019 at US-Los. This brings into question the potential of plant stress to limit GPP, as high water level fluctuations will increase plant biomass allocation to roots rather than shoots and can have a negative impact on propagation (Wei et al., 2019) and photosynthetic potential (Ballantyne et al., 2014). Additionally, in flood years following droughts, maximum growing season GPP could decline due to plant stress or change in vegetation composition (Olefeldt et al., 2017), and the expected consequential increase in FCH_4 would not occur. Plant stress response and the resulting impact on gas flux is an area worthy of further research especially as extreme precipitation becomes more common.

4.3 WTD

Pugh et al. (2018) investigated WTD and monthly average FCH_4 at US-Los and found no correlation when accounting for T_{air}, but our analysis of daily average fluxes in a historically wet year revealed a lag effect of the two variables that lasted 5-52 days but reached peak correlation at 24 days. Peak lag correlation of WTD and FCH_4 in 2019 aligned well with other sites from the FLUXNET-CH4 database, which averaged approximately 18.3 days (Knox et al., 2021). The response of GPP did not follow until nearly 40 days later at US-Los in 2019, a year that was characterized by historic precipitation.

High water table level will reduce seedling establishment, growth, and survival in wetlands if it occurs during seedling establishment or for a prolonged period of time (Zacks et al., 2019). Although some plants are more resilient to flooded conditions, permanently flooded conditions cause oxygen deprivation and higher CO_2 storage in plant tissues and at the cellular level (Pedersen et al., 2017). A shallower water table (i.e., closer to the surface) should increase FCH_4 by increasing GPP of hydric vegetation (Gomez-Casanovas et al., 2020; Musarika et al., 2017). Other studies disagree, demonstrating that a deeper water table (i.e., farther below the surface) will increase GPP in the absence of moisture stress by improving the availability of O_2 for photosynthesis in roots (Ballantyne et al., 2014).

Analysis of twenty-three sites from the FLUXNET-FCH4 database has shown that T_{air} controls FCH_4 at sites with lower WTD variability, but WTD controls FCH_4 at sites with lower T_{air} variability (Knox et al., 2019; Delwiche et al., 2021). The lack of correlation between lagged WTD and FCH_4 at US-Los in 2020, a year with more WTD variability, supports this. However, the positive relationship between WTD variability and FCH_4 appears to be species-specific (Radu and Duval, 2018).

4.4 Study limitations

Among the variables considered in this study, there are expected covariate relationships between precipitation, T_{air}, T_{stream}, WTD, and stream discharge, and seasonal cycles for each. WTD and temperature may alter the GPP-FCH_4 relationship because their covariance can appear like a cause and effect (direct relationship) when it is instead evidence of an indirect relationship. For example, the negative relationship between T_{stream} and T_{air}-FCH_4 outside of the months April-October (Fig 8B) demonstrated how shifting seasonal patterns may mask the relationship of GPP and FCH_4.

The interactions of precipitation and T_{air} are evidenced in Dinsmore et al. (2013), where essentially all interannual variability in the export of dissolved organic carbon from a peatland catchment was explained by interactions between the two variables. Additionally, interannual variability of total aquatic carbon (POC, DOC, DIC) concentration in a stream draining a peatland was strongly connected to GPP, but the main source of evaded CO_2 (unclear whether from stream or wetland) was suspected to be deep within the soil profile and disconnected from surface processes to some extent. This supports the idea that terrestrially-derived CO_2 in groundwater is a dominant source (other than soil) of total dissolved gas flux from riverine and wetland ecosystems (Olde, 2017). Other studies have aligned with a deep soil source (below 20 cm) of CH_4 as well (Peng et al., 2017). Flow regime and soil water content also has a clear impact on instream and riparian GPP within a forested biome (Dodd, 2018). Stream discharge and WTD should therefore be carefully considered in comparative FCH_4 driver analysis due to their interactions.

Although data were gap-filled, the fraction of missing or low-quality data that was removed was typical of eddy covariance flux data. Gap filling did not appreciably change conclusions. Where results did change as a result of gap-filling, it was the product of unequal sample sizes across years.

4.5 Future work

Further research at US-ALQ and US-Los could help pinpoint the magnitude and extent of FCH_4 from wetlands and wetland streams and quantify the variability in wetland FCH_4 in closely located sites due to random effects, such as differing microbial communities and their resulting rates of methanogenesis. Stream discharge and T_{stream} are tied to wetland FCH_4 but have strong spatial variability. Taking more frequent measurements of these variables and sampling different locations within the wetland and within the water column or peat profile may reveal relationships that were previously masked by spatial or temporal variability.

5 Conclusions

Here, we presented FCH_4 and corresponding hydrological measurements from two wetland sites to determine (1) the importance of plant C fixation measured by the lagged effect of GPP on FCH_4 and (2) how factors relating to wetland hydrology (i.e., stream discharge,

T_{stream}, and WTD) mediate the GPP-FCH_4 relationship. This study showed that two closely located wetlands can produce vastly different FCH_4 and demonstrate different seasonal cycles of FCH_4 because of different plant and microbial communities and responses, especially during a year with extreme precipitation. During a year with historically high precipitation, there was lower cumulative annual and daily average FCH_4 from the wetlands compared to the following drier year. Both wetlands displayed a longer lagged effect of GPP on FCH_4 during the wet year. US-ALQ demonstrated a decrease in T_{air}-FCH_4 with increasing stream discharge in 2019 and not in 2020, but US-Los exhibited no significant linear trend between WTD and T_{air}-FCH_4 in either year unless a lag was introduced. Lag analysis showed that FCH_4 response to WTD preceded GPP response to WTD at US-Los. A potential explanation is microbial respiration was more reliant on preexisting soil organic matter as a C source earlier in the season but was sourced by recently fixed plant C later in the season.

To answer to the second question of our study, we considered indicators of wetland hydrology and analyzed their relationship with FCH_4. As previously mentioned, there was a shorter lagged response of FCH_4 to WTD than GPP to WTD at US-Los. However, there was no relationship between FCH_4 and WTD in 2020. The analysis of stream discharge or WTD alone can potentially mask the influence of groundwater flow or precipitation on T_{water} and resulting daily average FCH_4. It was important to consider the influence of T_{stream} during the on-season and off-season separately, and to remove the influence of T_{air} on FCH_4 when looking at the impact of stream discharge. Questions remain on whether larger fluctuations in WTD caused or indicated conditions that could have caused plant or microbial stress and lowered FCH_4 during 2019 at US-Los in comparison to US-ALQ, which emitted more CH_4 and displayed a stronger seasonal cycle. Additional work of linking lags between productivity and FCH_4 along with accounting for temperature and discharge effects will help clarify and constrain the role of wetland biogeochemistry in a changing (e.g., wetter or drier) climate.

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