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RESEARCH ARTICLE

Methane fluxes in tidal marshes of the conterminous United States

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Abstract

Methane (CH_4) is a potent greenhouse gas (GHG) with atmospheric concentrations that have nearly tripled since pre-industrial times. Wetlands account for a large share of global CH_4 emissions, yet the magnitude and factors controlling CH_4 fluxes in tidal wetlands remain uncertain. We synthesized CH_4 flux data from 100 chamber and 9 eddy covariance (EC) sites across tidal marshes in the conterminous United States to assess controlling factors and improve predictions of CH_4 emissions. This effort included creating an open-source database of chamber-based GHG fluxes (https://doi.org/10.25573/serc.14227085). Annual fluxes across chamber and EC sites averaged 26 ± 53 g CH_4 $m^{-2}year^{-1}$, with a median of 3.9 g CH_4 $m^{-2}year^{-1}$, and only 25% of sites exceeding 18 g CH_4 $m^{-2}year^{-1}$. The highest fluxes were observed at fresh-oligohaline sites with daily maximum temperature normals (MATmax) above 25.6°C. These were followed by frequently inundated low and mid-fresh-oligohaline marshes with MATmax ≤25.6°C, and mesohaline sites with MATmax >19°C. Quantile regressions of paired chamber CH_4 flux and porewater biogeochemistry revealed that the 90th percentile of fluxes fell below 5 ± 3 nmol $m^{-2}s^{-1}$ at sulfate concentrations $>4.7 \pm 0.6$ mM, porewater salinity $>21 \pm 2$ psu, or surface water salinity $>15 \pm 3$ psu. Across sites, salinity was the dominant predictor of annual CH_4 fluxes, while within sites, temperature, gross primary productivity (GPP),

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and tidal height controlled variability at diel and seasonal scales. At the diel scale, GPP preceded temperature in importance for predicting CH_4 flux changes, while the opposite was observed at the seasonal scale. Water levels influenced the timing and pathway of diel CH_4 fluxes, with pulsed releases of stored CH_4 at low to rising tide. This study provides data and methods to improve tidal marsh CH_4 emission estimates, support blue carbon assessments, and refine national and global GHG inventories.

KEYWORDS
contiguous United States, eddy covariance, flux chamber, methane, open-source database, predictors, synthesis, tidal wetlands

1 | INTRODUCTION

Tidal wetlands play a critical role in global carbon (C) cycling (Bianchi, 2006; Odum, 2002). They have the potential to provide major feedbacks to the Earth's climate system as they exchange greenhouse gasses (GHGs) with the atmosphere, store large soil C pools, and have the potential to sequester C through continuous vertical accretion, allochthonous sediment deposition, and biomass accumulation (Duarte et al., 2013). Low rates of organic matter decomposition in their waterlogged soils promote the preservation of large quantities of soil organic C (also known as blue carbon) for centuries to millennia, contributing to the long-term removal of carbon dioxide (CO_2) from the atmosphere (Chmura et al., 2003).

However, the anaerobic conditions that promote soil C storage also lead to microbial methane (CH_4) production (Megonigal et al., 2004). Methane, with 32–45 times the warming potential of CO_2 over a 100-year time horizon, is second behind CO_2 in contributing to increases in atmospheric GHGs associated with recent warming (Forster et al., 2021; Neubauer & Megonigal, 2015). When considered in the timeframe relevant to meeting the Paris Agreement's target of limiting warming to 1.5°C, the CH_4 global warming potential is even higher, reaching 75 times that of CO_2 (Abernethy & Jackson, 2022). A recent compilation of global CH_4 emissions identified wetlands as among the primary natural sources of atmospheric CH_4, second only to freshwaters, with emissions ranging between 150 and 180 Tg CH_4 $year^{-1}$ (Saunois et al., 2020) and likely contributing to growing atmospheric CH_4 concentrations as the climate becomes warmer and wetter (Zhang et al., 2023), and anthropogenic wetland modifications increase (Kroeger et al., 2017; Rosentreter, Borges, et al., 2021). Global atmospheric CH_4 contributions from coastal wetlands, like tidal marshes, have been less studied (Rosentreter, Borges, et al., 2021), and recent bottom-up estimates (1–3.5 Tg CH_4 $year^{-1}$; Saunois et al., 2020) are not well constrained due to the lack of systematic observations, data quality (i.e., primarily discrete measurements with few high-frequency continuous measurements), uncertainties associated with coastal wetland area, and the risk of double counting of ecosystem types (e.g., tidal and non-tidal riverine, floodwater or estuarine wetlands) (Rosentreter et al., 2023; Rosentreter, Borges, et al., 2021; Roth et al., 2022; Saunois et al., 2020).

Global-scale controls on wetland CH_4 dynamics are reasonably known, including climatic zones, the presence of permafrost, peat, or mineral soils, groundwater, and surface water inputs in addition to precipitation, and the influence of salinity (Bridgham et al., 2013; Turetsky et al., 2014). These large spatial-scale characteristics subsequently control plant composition and the soil attributes that drive anaerobic C cycling and CH_4 dynamics. However, in tidal wetlands, where the tidal influence can dominate over other global factors, it remains unclear whether CH_4 responses to commonly studied predictors in non-tidal freshwater wetlands also apply. Tidal wetlands experience unique spatial and temporal variation in tides, redox conditions, and the influence of seawater (Cloern & Jassby, 2012; Seyfferth et al., 2020). These variations contribute to spatial gradients in plant species and traits, microbial communities, and processes such as soil accretion, primary production, respiration, and decomposition (Borde et al., 2020; Campbell & Kirchman, 2013; Morris et al., 2002; Watson & Byrne, 2009). Any or all of these factors substantially influence CH_4 emissions, highlighting the complexity of predicting CH_4 fluxes from these ecosystems.

On a local scale, rates of methanogenesis in wetland soils are primarily governed by the balance of electron donors and terminal electron acceptors. In general, saline tidal wetlands have high concentrations of porewater sulfate, typically leading to low rates of methanogenesis as acetate and hydrogen, primary substrates for methanogens, are utilized by sulfate reducers to decompose organic matter anaerobically (Megonigal et al., 2004). However, other pathways like methylotrophic methanogenesis can also be important in saline environments where non-competitive substrates are degraded to methyl compounds, producing CH_4 even when sulfate reduction co-occurs (Oremland et al., 1982; Seyfferth et al., 2020). Once CH_4 is produced, it can reach the atmosphere by physical (diffusion and ebullition) and plant-mediated processes. Some plants efficiently vent CH_4 to the atmosphere through aerenchymatous tissue. For example, in species such as *Phragmites australis*, *Typha latifolia*, *and T. angustifolia*, convective gas transport during light conditions allows CH_4 produced in soils to bypass CH_4 oxidation zones and escape to the atmosphere at greater rates (Bendix et al., 1994; Sanders-Demott et al., 2022; Van der Nat & Middelburg, 1998; Vroom et al., 2022).

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Previous syntheses have identified important drivers of CH_4 emissions in tidal wetlands, including salinity and sulfate concentrations (Poffenbarger et al., 2011), temperature, and the quality and quantity of organic matter (Al-Haj & Fulweiler, 2020). Additionally, tidal pumping (Call et al., 2015; Trifunovic et al., 2020), dominant vegetation types and hydrology (Derby et al., 2022), plant phenological phases (Vázquez-Lule & Vargas, 2021), and functional trait composition (Mueller et al., 2020; Tong et al., 2018; Van der Nat & Middelburg, 1998) have been shown to play significant roles. While recent syntheses (Al-Haj & Fulweiler, 2020; Rosentreter, Al-Haj, et al., 2021; Rosentreter, Borges, et al., 2021) have qualitatively discussed these biogeochemical (e.g., salinity, temperature, organic matter) and biotic (e.g., plant-mediated transport) drivers, they have not resolved the relative influence of overlapping predictors in a quantitative fashion. This may be partly attributed to the reliance of syntheses on literature values, which often represent summarized flux averages or temporally upscaled estimates that can mask a wealth of processes and important variations evident in original disaggregated measurements. In contrast, this study focuses on original, disaggregated data and metadata obtained directly from researchers, allowing for a more detailed and in-depth analysis of CH_4 fluxes and their influencing factors.

Measuring CH_4 emissions from tidal marshes has primarily depended on chamber methods, especially static chambers sampled manually, due to their low cost, simplicity of application, and ease of deployment in areas without power (Rolston, 1986; Yu et al., 2013). The fine spatial resolution of chamber flux measurements, their generally low detection limits, and their compatibility with concurrent surface and porewater sampling of relevant analytes (salinity, pH, dissolved gas concentrations, or alternate electron acceptors) have made them an invaluable resource for process-based research and for measuring small fluxes and instances of net CH_4 oxidation. However, due to logistical constraints, chamber methods introduce limitations as they encourage sampling at low tide, during daylight hours, and on an intermittent sampling schedule (typically monthly). As a result, pulse events triggered by diurnal and tidal cycles, changes in atmospheric pressure, or sediment disturbances are often unobserved or filtered out to remove ebullition (Altor & Mitsch, 2006; Morin et al., 2014; Podgrajsek et al., 2014; Rosentreter et al., 2018).

To address the low resolution of daytime static chamber measurements, some studies have employed custom gas exchange models that incorporate continuous air temperature or water table depth, among other factors, to model CH_4 fluxes between sampling events (Krauss et al., 2016; Neubauer, 2013; Sanders-Demott et al., 2022; Schultz et al., 2023; Weston et al., 2014). In the absence of continuous measurements of predictor variables, others have used scaling factors to convert average daily fluxes into annual emissions (Bartlett & Harriss, 1993; Bridgham et al., 2006; Poffenbarger et al., 2011). These factors are based on studies that report both annual and daily rates and represent the ratio of annual CH_4 flux to average daily flux (Bridgham et al., 2006).

On the contrary, the continuous, high-frequency eddy covariance (EC) technique offers promising datasets for understanding tidal marsh CH_4 fluxes, which often involve nonlinear and asynchronous processes across multiple timescales (Reid et al., 2013; Sturtevant et al., 2016). However, EC studies in tidal marshes are less common than chamber studies and are not as widespread as in other ecosystems, such as inland freshwater wetlands, rice paddies, and tundra. Unlike chambers, EC systems are less effective in discerning the influence of factors operating at small spatial scales, such as plant traits and microtopography, and often lack supporting water level (Knox et al., 2019), salinity (Delwiche et al., 2021), and porewater data such as sulfate or nitrate concentrations that may pose important controls on CH_4 production. Nevertheless, they offer ecosystem-scale fluxes and are better suited for assessing the influence of plant C assimilation on CH_4 fluxes and pulsed events.

Drawing on data from both flux monitoring techniques increases the quantity of data available and leverages the benefits of both approaches to better understand the variability of CH_4 fluxes across time and space (Yuan et al., 2024). However, while EC data are available through global and national networks such as AmeriFlux and FLUXNET, chamber fluxes disaggregated by sampling event and supporting environmental covariates remain widely dispersed and frequently unavailable. In the context of the Coastal Carbon Network (CCN) Methane Working Group, we compiled, synthesized, and standardized chamber-based CH_4 fluxes across the conterminous United States (CONUS) and created an open-source database focused on tidal marsh ecosystems that host chamber-based GHG fluxes with supporting observations and porewater biogeochemistry (Arias-Ortiz et al., 2024).

Our primary objective was to assess controlling factors and improve predictions of CH_4 emissions in tidal marshes across CONUS. Here, we provide an in-depth analysis of tidal marsh CH_4 flux patterns and the factors influencing the variation in flux magnitudes and timing. Specifically, we address the following questions: (i) What are the primary predictors of CH_4 flux in tidal marshes across sites in CONUS? (ii) How does the variability in CH_4 fluxes change across daily to seasonal timescales, and what are the dominant predictors at each timescale? (iii) Can improved scaling factors for annualizing discrete chamber measurements be developed, and to what extent do daily and seasonal variations in CH_4 fluxes affect these factors? Finally, (iv) how can the identified relationships and gained information be used to improve monitoring and predictions of CH_4 emissions in tidal marshes?

2 | METHODS

2.1 | Dataset description

The database contains 35 contributed CH_4 flux datasets of 122 tidal marsh sites measured with chambers across CONUS (Arias-Ortiz et al., 2024). Details on the data acquisition process and database structure can be found in Supporting Information sections 1 and 2.

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For the analysis in this study, we selected chamber plots without any experimental treatment, except for those involving salinity. These treatments consisted of slight changes from fresh to oligohaline conditions, resembling the seasonal variations in salinity that tidal marshes may naturally experience. This resulted in a total of 100 marsh sites with discrete CH_4 flux measurements disaggregated by sampling event, spanning from 1 day to 4 years, and accompanied by ancillary data, including porewater biogeochemistry. Analyses of the chamber dataset were complemented with nine independent EC tidal marsh datasets available through FLUXNET-CH_4 (US-LA1, US-LA2, US-Srr), AmeriFlux (US-EDN, US-Dmg, US-StJ), and tower-site PIs (US-MRM, US-HPY, and US-PLM) (Table S1), all of which adhere to standards and data QA/QC procedures explained elsewhere (Chu et al., 2023; Delwiche et al., 2021; Knox et al., 2019). Gap-filled fluxes were obtained from site PIs if missing in the original datasets. Likewise, when absent, water quality parameters, including conductivity or salinity and dissolved nitrate concentrations, were sourced from the USGS National Water Information System or National Estuarine Research Reserves online databases (NOAA, 2023; USGS NWIS 11180770, 2023). See Supporting Information section 1 and Table S1 for details on tower sites, including fraction of gap-filled CH_4 flux data.

Eddy covariance and chamber sites were classified using a multi-faceted classification system described in Table 1 and the Supporting Information section 2. The definition of "site" differs between chamber and EC studies. Eddy covariance sites are represented by the flux footprint rather than by gradients in biotic and abiotic factors such as elevation, species composition, or substrate type (channel, mudflat, or vegetated area). In this study, we defined chamber sites as distinct locations within a tidal wetland that could consist of several chamber plots. Adjacent areas, if composed of different wetland vegetation, salinity, elevation, or disturbance classes, were considered different chamber sites in our database.

2.1.1 | Chamber flux QA/QC and filtering

Submitted chamber-based CH_4 fluxes were assigned quality flags based on details reported during the data submission process or in the original publication (Table 2). These flags indicate if any thresholds (R^2 and/or p-value) were used to test, modify, or remove flux rates in the original studies. 65% of the submitted CH_4 fluxes were accompanied by R^2 and/or p-values (24% had both reported), and 35% had no associated statistics. Chamber flux measurements across studies in the synthesis varied in methodology. Some were based on syringe headspace samples, while others used continuous gas analyzers, which provide a more accurate assessment of concentration changes over time. To harmonize data quality control procedures across the dataset for analysis in this study, we filtered the data using percentiles (to remove outliers) and flux quality flags (Table 2). For the entire dataset, CH_4 fluxes below and above the 1st and 99th percentiles were excluded if statistics supporting these extreme values were not reported or if the R^2 of the regression was lower than 0.90 (Figure S2a). Furthermore, CH_4 flux rates flagged as "Not Significant" or "Not Tested" with reported statistics were further filtered out based on p-values, R^2, and the number of sample points (n) used to fit the regression model, all conditional on flux magnitude. Briefly, CH_4 flux rates with a p-value >0.10 were filtered out if they exceeded 10 nmol $m^{-2} s^{-1}$ (the mean flux rate estimated for fluxes flagged as not significantly different from zero). If p-values were not provided but R^2 and n were available, we filtered out fluxes exceeding 10 nmol $m^{-2} s^{-1}$, those with $R^2 < 0.80$ and $n < 4$, or $R^2 < 0.55$ and $n < 6$. Rates <10 nmol $m^{-2} s^{-1}$ were retained even if they did not meet the R^2 requirements because samples with low CH_4 concentrations generally have low R^2 values reflecting the low fluxes from those chambers rather than a poor measurement quality. Of 8980 individual chamber CH_4 fluxes, 156 were filtered out because they exceeded the 1st and 99th percentiles with no supporting statistics. An additional 60 measurements were discarded based on p, R^2, and n values (Figure S2b). The result is a vetted dataset without unsubstantiated outliers of 8764 observations. We acknowledge that fluxes driven by nonlinear processes such as ebullition may be underrepresented.

2.2 | Annual CH_4 flux estimates and scaling factors

We estimated annual tidal marsh CH_4 fluxes where there was a full year of tower or chamber data. At EC sites, we calculated annual sums using gap-filled data. At chamber sites, we used published estimates where available. At sites where CH_4 fluxes had been measured across all months but annual estimates had not been reported, we integrated daytime fluxes using linear interpolation between year-round measurements after calculating the median of CH_4 flux rates within replicate chambers.

Most chamber sites (82 out of 100) did not have a full year of sampling coverage (i.e., one or more monthly measurements were missing). Additionally, two EC sites did not have a full year of data (US-PLM) or lacked gap-filled meteorological and flux variables (US-HPY). For these and the chamber sites lacking annual CH_4 flux measurements, we developed scaling factors to upscale measurements to annual estimates. Scaling factors were calculated from the ratio between annual flux (in units of g CH_4 m^{-2} $year^{-1}$) and average daily flux (in mg CH_4 m^{-2} day^{-1}) using sites with a full year of sampling coverage (Bridgham et al., 2006). Scaling factors were calculated for both chamber and EC sites. At EC sites, we used non-gap-filled mean daily flux measurements against the annual sum calculated with gap-filled data. If a specific site-year had more than 2 consecutive months of missing data, we excluded it from the computation of scaling factors.

Particularly, we were interested in developing a scaling factor specific to the peak emission period (annual flux/average daily flux between June and August) since chamber studies in temperate marshes do not often include winter sampling when plant productivity is at its lowest (e.g., Bartlett, 1985; Weston et al., 2014) and most sites in the database met the condition of having data

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TABLE 1 Attribute categories used to classify chamber and EC sites in according to wetland type, vegetation, salinity, relative elevation, and disturbance conditions.

Attribute	Code	Description
Wetland type	Palustrine tidal	Wetlands dominated by trees, shrubs, or emergents that occur in tidal areas where salinity is <0.5 psu (Cowardin et al., 1979)
	Estuarine intertidal	Tidal wetlands usually semi-enclosed by land but have open, partly obstructed, or sporadic access to the open ocean, and in which ocean water is diluted by freshwater runoff from the land. Salinities >0.5 psu (Cowardin et al., 1979)
Vegetation Class	Mudflat	Describes unvegetated areas exposed and flooded by tides
	Emergent	Describes wetlands dominated by persistent emergent vascular plants
	Scrub/Shrub	Describes wetlands dominated by woody vegetation ≤5 m in height
	Forested	Describes wetlands dominated by woody vegetation >5 m in height
Salinity class	Fresh	<0.5 psu
	Oligohaline	0.5–5 psu
	Mesohaline	5–18 psu
	Polyhaline	18–30 psu
	Mixoeuhaline	30–40 psu
Elevation Class	High	Elevation above the Mean Highwater mark (MHW), inundated infrequently. Could be defined by vegetation communities (e.g., *Spartina patens*, *Distichlis spicata*, *Salicornia* sp., *Juncus* sp., and bulrush species)
	Mid	Elevation in the relative middle of the tidal frame, frequently inundated, typically defined by vegetation communities (e.g., *Spartina patens*)
	Low	Elevation relatively low in the tidal frame, frequently inundated, typically defined by vegetation communities (e.g., *Spartina alterniflora*)
	Levee	Study-specific definition of a relatively high elevation zone built up on the edge of a river, creek, or channel
	Back	Study-specific definition of a relatively low elevation zone behind a levee
Disturbance class	Undisturbed	No disturbance or management has occurred on the site
	Tidally restored	Tidal flow has been restored by removing an artificial obstruction
	Tidally restricted	Tidal flow is muted or blocked by built structures. Includes impoundment
	Ditched	Tidal hydrology is altered because artificial ditches have been cut to promote tidal flooding and drainage
	Species invasion	Establishment of non-native species that compete with, displace, or even eliminate native species
	Submergence-Salinization	Caused by sea level rise and saltwater intrusion
	Storm disturbance	Major storms, including unusually high precipitation and/or wind events
	Removal of invasive plants	Natural plant communities have been restored by actively removing invasive plant species
	Revegetation	Wetland vegetation has been reintroduced by replanting on unvegetated surfaces
	Wetland construction	Constructed wetland using sediments such as dredge spoils or other sediment source

during this period. For sites lacking annual CH_4 flux measurements, we provided a first-order estimation of their annual CH_4 flux using the scaling factor derived from June–August mean daily CH_4 fluxes (without gap-filling for EC sites). We refrained from scaling mean daily CH_4 fluxes to annual estimates at chamber sites with a study duration ≤1 day (sites = 4). We averaged annual fluxes when there was more than 1 year of data for a given chamber or EC site. Additionally, we added two sites for which disaggregated data could not be synthesized (i.e., not in the dataset) but measured annual CH_4 fluxes had been published (Neubauer et al., 2000; Segarra et al., 2013).

We treated annual CH_4 flux estimates from chambers and EC as comparable, making no distinction between the two when estimating mean, median, and geometric mean annual CH_4 fluxes across tidal marshes in the CONUS. Previous synthesis works have also combined chamber and EC annual CH_4 flux estimates due to the limited number of EC sites in tidal or coastal settings compared with those of chambers (Al-Haj & Fulweiler, 2020; Rosentreter et al., 2023).

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TABLE 2 Flagging criteria for chamber CH_4 flux analysis based on their statistical significance and treatment in original studies.

Flag	Description
"Not Tested" (NT)	Assigned to flux rates missing statistics or any flux not censored or modified based on R^2 or *P*-values, even if these were provided in the original publication
"Not Significant" (NS)	Assigned to flux rates considered not significantly different from zero by the authors, divided into two subcategories NS_0: Used when authors replaced non-significant flux rates with zero NS_NA: Assigned when authors removed non-significant flux rates at specific sampling events
"Significant" (S)	Assigned to all flux rates accompanied by linear regression statistics and considered significantly different from zero by authors, regardless of study-specific thresholds

Scaling factors and CH_4 flux data had non-normal distributions; thus, we focused on comparing medians and used non-parametric tests such as paired-sample Signed test (S) for paired comparisons (i.e., year-round vs. June–August scaling factors), Mann–Whitney test (U) for two-group comparisons (e.g., scaling factors between EC and chambers), or a Kruskal–Wallis Dunn's test (H) using the Benjamini–Hochberg correction for multiple comparisons (i.e., fluxes between salinity, elevation, and disturbance classes). All statistical analyses were done at a level of significance of $\alpha < 0.05$.

2.3 | Analysis of predictors of CH_4 fluxes across sites

2.3.1 | Predictors of annual CH_4 fluxes using broadly available data

To evaluate the predictors of annual CH_4 fluxes across sites in CONUS, we combined chamber and EC annual CH_4 flux estimates and used qualitative (e.g., salinity and elevation class) and long-term climatological data (i.e., climate normals), which were broadly available at all sites. These data were fit to classification and regression trees such as Conditional Inference Trees (CTree) (Hothorn et al., 2006) and Random Forests (RF) (Breiman, 2001). CTrees use a significance test procedure to select variables at each split to reduce overfitting and selection bias. The stopping criterion is implemented when the global null hypothesis of independence between the response and any of the covariates cannot be rejected at a nominal level α, set at 0.05. The tree was constructed using the function "ctree" in the R package "Partykit" (Hothorn & Zeileis, 2015), limiting the tree depth to five levels. CTrees provide direct visualization of the splits at decision nodes, helping the interpretability of predictors, and are similar to binary partitioning methods used for analyzing soil CO_2 efflux measurements in terrestrial ecosystems (Vargas et al., 2010). However, they may suffer from issues associated with single trees, such as overfitting, high variance, or bias toward dominant classes.

For this reason, we added RF to our analysis. We trained a RF algorithm for annual CH_4 fluxes using R's "caret" package (Kuhn, 2008). Similar to CTrees, the RF model was trained on all available data (i.e., we did not create training and test data splits) since our objective was to determine the hierarchy of predictor importance of CH_4 fluxes in tidal wetlands rather than to identify a predictive model that can generalize to new conditions (Knox et al., 2021). Hyperparameter tuning was performed for mtry (number of predictors randomly sampled at each decision node, selected at 6), and the number of trees was set to 400. For CTrees and RF models, we provide out-of-bag model fit metrics (coefficient of determination, mean absolute error, and root mean squared error) to further evaluate relative confidence in results.

Long-term average normals included in CTree and RF analyses were mean annual temperature and precipitation (MAT and MAP), mean daily maximum annual temperature and vapor pressure deficit (MATmax and VPDmax), and mean total daily shortwave solar radiation (Soltotal), which were extracted from PRISM using specific site coordinates (PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu, data generated November 10, 2022). For these analyses, back and levee elevation classes (Table 1) were grouped within the low and high elevation classes, respectively, due to their low representation (less than three sites each) across the dataset. Salinity class was converted to numeric format to run the RF algorithm. Mean annual surface water or porewater salinity was calculated at sites with available data, while the midpoint of the salinity class range was used at sites with no salinity data.

2.3.2 | Predictors of CH_4 fluxes using discrete chamber measurements

To evaluate predictors of CH_4 flux across sites using chamber-disaggregated CH_4 fluxes by sampling event and time-specific environmental parameters, we employed generalized additive models (GAMs) (Hastie & Tibshirani, 1990). We chose GAMs over regression trees like RF because we prioritized interpretability

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over predictive performance. Additionally, discrete chamber data present challenges due to patchiness in recorded variables, highlighting a lack of standardization across chamber studies and, consequently, the need for developing models for each recorded variable individually when using the entire dataset. GAMs can describe linear and nonlinear relationships between CH_4 fluxes and predictor variables, and they have the advantage of not needing data transformation. Before running GAMs and any of the following analyses, we transformed periodic variables such as day of year (DOY) and sample hour using their sine and cosine transformations instead of their original values to linearize their cyclical pattern. First, we developed GAMs of CH_4 flux using each predictor individually. Relative predictor importance was determined by comparing the deviance explained among predictors. From the entire database, we selected predictors that were available in five or more studies. Then multivariate GAMs were implemented using a combination of predictors that individually explained the largest variance and were present in at least five studies. Models were fit with restricted maximum likelihood (REML), and study ID (i.e., publication) was included as a random factor to account for non-independence of multiple chamber fluxes extracted from the same study. Additionally, the presence or absence of flux R^2 or p-values was used as an estimate of precision and was applied to weight flux rates so that studies in which statistics had supported CH_4 fluxes were given a higher weight (0.8 vs. 0.2). All GAMs were implemented using the R *"mgcv"* package (Wood, 2011).

Leveraging nonlinear quantile regression, we established quantitative relationships between CH_4 emissions and the top-ranked predictor variables identified by GAMs, and estimated thresholds above which CH_4 fluxes were negligible. Quantile regression is valuable when assumptions like normality are not met. Additionally, this approach is adept at resisting the influence of outliers and is well suited for handling heteroscedasticity (i.e., where the variance of the CH_4 fluxes varies across different levels of a predictor, e.g., salinity) (Koenker, 2005). It allows for more accurate modeling of the varying spread of CH_4 fluxes by estimating multiple slopes that describe the relationships between specific quantiles of the CH_4 flux distribution and a predictor that regression methods, focused solely on predicting mean values, would otherwise overlook (Cade & Noon, 2003). Quantile regressions were fitted for the 0.1, 0.5, and 0.9 quantiles of CH_4 fluxes using the nlrq() function within the R package *"quantreg"* (Koenker, 2023) due to the observed nonlinear relationships between CH_4 fluxes and the tested predictor variables. The slopes of the fitted conditional quantile regressions were used to estimate the predictor level required to decrease CH_4 fluxes by half, based on an exponential decay relationship (i.e., $X_{1/2} = \ln(2)/\text{slope}$). Subsequently, threshold values were estimated as seven times $X_{1/2}$, representing a 99% reduction of CH_4 fluxes through interactions with increasing predictor levels. We calculated these thresholds for the 50th and 90th percentiles of the conditional distribution of CH_4 fluxes, representing the predictor thresholds below which the 50% and 90% of the highest CH_4 fluxes occur, respectively.

2.4 | Analysis of predictors of CH_4 fluxes across timescales

Half-hourly EC datasets were used to assess CH_4 flux magnitude fluctuations at diel to seasonal scales and their controlling factors. Additionally, they provided insights into the significance of predictor variables not often evaluated in chamber studies, such as plant activity through GPP, net ecosystem exchange, or latent heat, as well as the effects of tidal pulsing on modulating CH_4 exchange.

We employed wavelet time series decomposition to identify major timescales of variation within the continuous CH_4 flux time series. Then, we used mutual information (I) to find the relative importance of each predictor variable and identify both synchronous and asynchronous interactions (Ruddell et al., 2013). Mutual information (I) measures the amount of information shared by two variables, X and Y, or the reduction in uncertainty of one variable given the knowledge of the other variable (Fraser & Swinney, 1986). The degree of mutual information between X and Y is increased by adding a time lag (positive or negative) in series Y relative to X, thereby allowing the identification of both synchronous and asynchronous interactions. Using the ProcessNetwork Software (v1.5, Ruddell et al., 2008) and the Wavelet Methods for Time Series Analysis (WMTSA) toolkit (Cornish et al., 2003), we decomposed gap-filled CH_4 flux and explanatory variables in four general timescales of variation: hourly (1–2 h), diel (4 h–1.3 days), multiday (2.7–21.3 days), and seasonal (42.7–341 days). These timescales of variation represented short-term perturbations such as wind gusts or overpassing clouds, day-night changes in meteorological variables and tidal fluctuations, neap-spring tidal cycles, and seasonal courses of solar movement and vegetation phenology, respectively. Wavelet decomposition was performed on gap-filled, half-hourly data using the maximal overlap discrete wavelet transform (MODWT), summing the detail over adjacent scales to yield the latter four timescales of variation (details in Sturtevant et al., 2016). Wavelet decomposed data were then used to compute the mutual information between CH_4 fluxes and biophysical variables within each timescale over a range of time lags (from half a day at the diel scale to 60 days at the seasonal scale). Original gaps in the reconstructed time series were reintroduced before mutual information calculation for all except the seasonal analysis following (Knox et al., 2021). Results were interpreted using the relative mutual information (I^R) metric, a normalized measure of the statistical dependence of CH_4 flux on a range of predictor variables, with larger values indicating higher dependence. To determine the relative importance of each predictor variable, we ranked the normalized I^R values across sites, and we did that within each timescale of interest. In this study, we followed the methods described by Knox et al. (2021) (i.e., 10 bins and 50 random reshufflings to calculate significance thresholds at each lag) and focused on results for the predictors of diel, multiday, and seasonal timescales. The hourly wavelet scale is often dominated by noise (Hollinger & Richardson, 2005) and was only produced to show the distribution of CH_4 flux variability across timescales.

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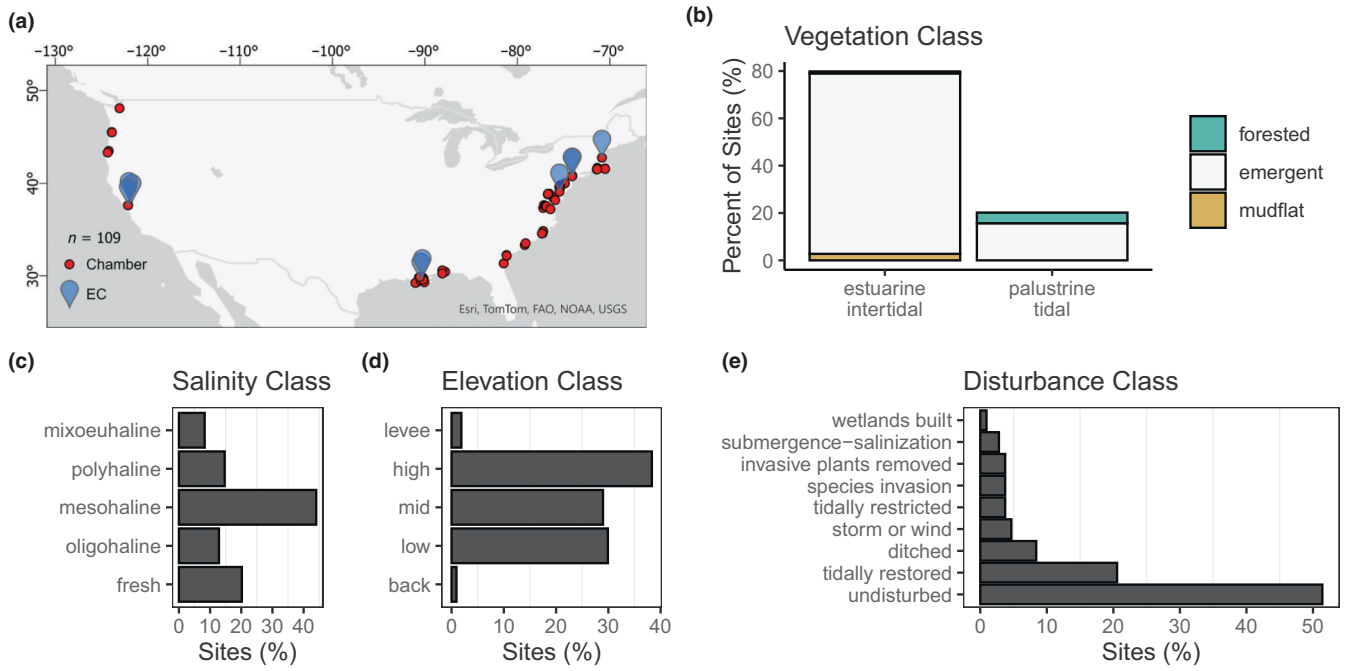

FIGURE 1 Location of sites included in this synthesis (a) and characteristics of CH_4 flux rates contained in the database. Sites are classified based on wetland vegetation type (b), salinity (c), elevation (d), and disturbance (e).

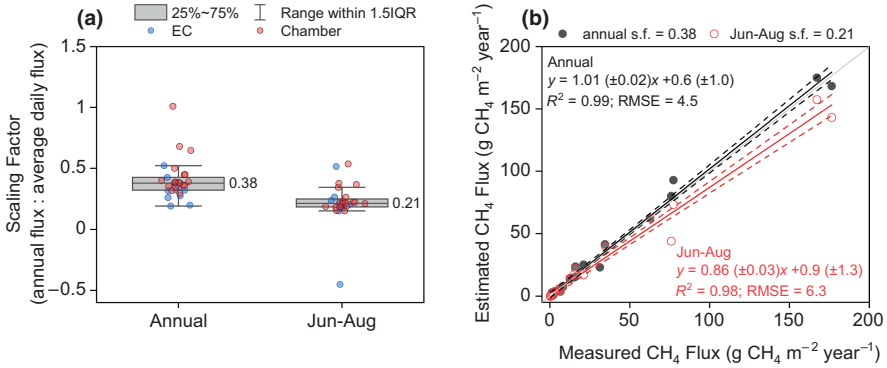

FIGURE 2 Annual CH_4 flux scaling factors. Scaling factors estimated using average daily fluxes over the course of a year and from June to August (a). Relationship between measured and estimated annual CH_4 flux using the annual (solid circles) or the June–August scaling factor (open circles) (b). Linear regression fits show 95% confidence bands. Results in panels (a) and (b) include EC and chamber datasets with a year of sampling coverage.

3 | RESULTS

The final database contained 44 contributed datasets with 109 (100 chamber and 9 EC) tidal marsh sites, with measurements from 1980 to 2022. The dataset was dominated by CH_4 fluxes from tidal mesohaline wetlands with emergent vegetation, predominantly located on the US East Coast (Figure 1). Similar proportions (~30%–40%) of high, mid, and low tidal marsh environments were represented, with fewer sites located in environments affected by banks, berms, or levees. Half of the sites corresponded to undisturbed tidal marshes, followed by tidally restored (20%), ditched (8%), and other disturbance classes with a minority representation (<5%), including tidally restricted sites and species invasion (4%). Chamber-based data were unequally distributed throughout the year, with more observations concentrated from June to August (Figure S3). Five of the nine EC tower sites had paired chamber CH_4 flux measurements. Carbon dioxide and N_2O fluxes were also compiled alongside CH_4 and are available in 52% and 30% of the sites, respectively, but they were not the focus of this synthesis.

3.1 | Scaling factors

A total of 29 site-years (11 from EC, 18 from chambers) had data covering all months of the year; hence, they were used to compute annual CH_4 flux scaling factors. Median scaling factors (s.f.) differed significantly when calculated based on daily fluxes averaged year-round (0.38, IQR = 0.10) compared to when considering

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June–August daily average fluxes (0.21, IQR = 0.06) ($S = 3$, $z = 3.97$, $P < 0.001$) (Figure 2a). Scaling factors estimated using year-round daily averages were significantly lower for EC (s.f. = 0.32) than for chamber measurements (s.f. = 0.39) ($U(N_{EC} = 11, N_{chamber} = 18) = 42$, $z = -2.54$, $p = .01$), but no significant differences in the scaling factor were observed between methods when using daily averages from June to August ($U(N_{EC} = 10, N_{chamber} = 18) = 69$, $z = -0.98$, $p = .33$). For the 29 site-years (EC and chamber combined), the annual CH_4 fluxes estimated using the June–August scaling factor closely agreed with the measured values (Figure 2b). We did not find significant differences in annual scaling factors between wetland types ($U(N_{estuarine\ intertidal} = 23, N_{palustrine\ tidal} = 5) = 53$, $z = -0.24$, $p = .81$), salinity classes ($H(4) = 2.0$, $p = .74$), elevation classes ($H(4) = 2.8$, $p = .60$), or disturbance classes ($H(4) = 4.8$, $p = .30$) (Tables S2–S5).

3.2 | Tidal Marsh annual CH_4 flux estimates

Using available full site-year data, published fluxes, and scaling factors at sites where the sampling coverage was shorter than a year, we estimated annual CH_4 fluxes from tidal marshes in CONUS. From a total of 108 sites including chamber and EC datasets, mean ± SD annual CH_4 fluxes were 26 ± 53 g CH_4 m^{-2} $year^{-1}$, but the central tendency of the estimates represented by the median and the geometric mean were seven to five times lower, at 3.9 and 5.4 g CH_4 m^{-2} $year^{-1}$, respectively (note that the geometric mean excludes sites with negative or zero annual CH_4 fluxes) (Figure 3a). Median CH_4 fluxes were significantly higher at freshwater sites than at mesohaline, polyhaline, and mixoeuhaline marshes ($H(4) = 28.06$, $p < .001$) (Figure 3b). Statistical overlap of annual CH_4 fluxes existed between fresh and oligohaline, oligohaline and mesohaline, and polyhaline and mixoeuhaline conditions. However, when using chamber flux data disaggregated by sampling event, differences between salinity classes were more pronounced, with only fresh and oligohaline conditions showing statistical overlap ($z = -1.93$, $p = .27$) (Figure 3c). The variance of CH_4 fluxes at fresh and oligohaline sites was 27, 700, and >5000 times larger than at mesohaline, polyhaline, and mixoeuhaline sites, respectively. No statistical differences were observed between the distributions of chamber- and EC-derived annual fluxes across CONUS or when aggregated by salinity class (Table S6).

The wide numerical range and the right-skewed nature of the CH_4 flux data were also observed in annual CH_4 fluxes when separated by salinity class, which additionally showed a slight bimodal distribution (Figure S4). In fresh-oligohaline and mesohaline conditions, there was a trend of higher CH_4 fluxes in low than high marsh environments, but this pattern was not observed in more saline sites (Figure S5). The assessment of disparities in CH_4 flux between disturbance classes was limited due to the uneven distribution of sites across salinity classes. When sites were grouped by salinity, tidally restored mesohaline marshes exhibited significantly lower CH_4 fluxes than *Phragmites*-invaded sites (Figure S5). Upon exploring chamber CH_4 fluxes disaggregated by sampling event grouped by salinity and species, chambers featuring *Phragmites* exhibited higher CH_4 fluxes than those where other species were present (Figure S6). This trend was only notable in mesohaline and polyhaline marshes, where most data were available. However, the generalizability of these results to CH_4 fluxes from other salinity classes could not be assessed due to the incomplete representation of disturbance classes in non-mesohaline salinity conditions.

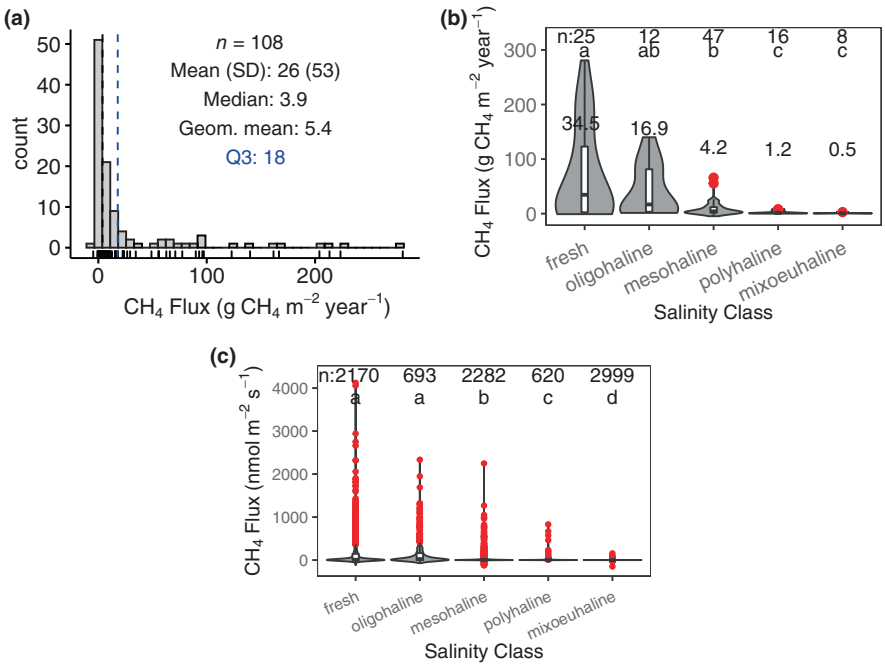

FIGURE 3 Tidal marsh CH_4 fluxes. Histogram of annual CH_4 fluxes (a), annual CH_4 fluxes grouped by salinity class (b), and chamber-based CH_4 fluxes disaggregated by sampling event grouped by salinity class (c). Panel (a) and (b) combine results from chamber and eddy covariance sites. On panel a, vertical lines (or rug) across the *x*-axis project individual data points and their distribution. On panels b and c, red dots indicate outliers and different lower-case letters represent significant differences between salinity classes as a result of a Kruskal–Wallis Dunn's multiple comparison test with $p < .05$ adjusted using the Benjamini–Hochberg procedure ($p < \alpha/2$). Values on the box plot in panel (b) represent median annual CH_4 fluxes at each salinity class.

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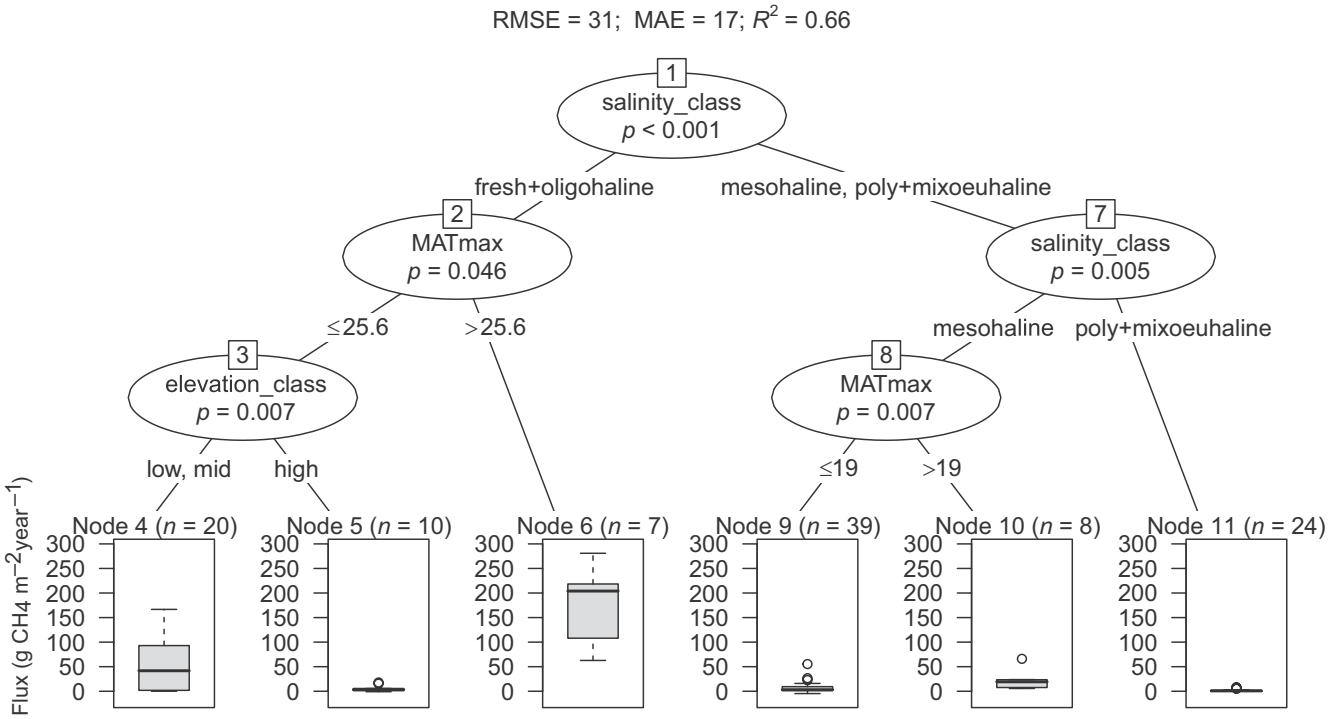

FIGURE 4 Conditional inference tree based on salinity class (with fresh and oligohaline, and polyhaline and mixoeuhaline classes combined), long-term mean daily maximum annual temperature (MATmax) and elevation class. MATmax represents the "normal" or average maximum temperature for each day of the year based on 30-year historical data. Box plots show annual CH_4 flux in g CH_4 m^{-2} $year^{-1}$. Results of the CTree include eddy covariance and chamber data.

3.3 | Predictors of CH_4 flux across sites

3.3.1 | Predictors of annual CH_4 flux

Results of both the CTree and RF methods were similar, ranking salinity as the most important predictor of the magnitude of annual CH_4 fluxes, followed by mean daily maximum annual temperature (MATmax) and, to a minor extent, elevation class and mean daily maximum annual vapor pressure deficit (Figure 4; Figure S7). These rankings were obtained using EC and chamber-based annual estimates combined. Average model performance was highest for RF with an out-of-bag R^2 of 0.94, MAE (mean absolute error) of 7.9 g CH_4 m^{-2} $year^{-1}$, and RMSE of 14 g CH_4 m^{-2} $year^{-1}$ (Figure S7). The best resulting CTree (R^2 = 0.66, MAE = 17, RMSE = 31 g CH_4 m^{-2} $year^{-1}$) was achieved when fresh and oligohaline, and polyhaline and mixoeuhaline classes were combined. This CTree was composed of 11 decision nodes, with salinity at the root of the tree, followed by MATmax and elevation class. The highest annual CH_4 fluxes were observed at fresh and oligohaline sites with MATmax above 25.6°C, followed by frequently inundated low and mid-fresh-oligohaline marshes with MATmax ≤25.6°C, and mesohaline sites with MATmax above 19°C. Methane fluxes at sites with salinities >18 psu were consistently low regardless of MATmax or elevation class (Figure 4). The representation of elevation classes was similar among fresh-oligohaline systems with MATmax ≤25.6°C, mesohaline sites with MATmax ≤19°C, and polyhaline and mixoeuhaline marshes (Figure S8). However, elevation could not be assessed as a predictor of annual CH_4 fluxes at warmer fresh-oligohaline (>25.6°C) and mesohaline (>19°C) sites due to the lack of variation in elevation classes within these categories.

While the mean difference between predicted and observed values was roughly equal to the average of annual CH_4 fluxes across the dataset, CTree binary partitioning enabled a breakdown of annual CH_4 fluxes across marsh categories based on salinity and daily maximum annual temperature, with additional consideration of elevation class specifically within the fresh-oligohaline category (Table 3).

3.3.2 | Predictors of CH_4 fluxes from disaggregated chamber data

We used chamber-based disaggregated data to understand CH_4 flux variability across sites and to establish quantitative relationships between CH_4 fluxes and predictor variables, particularly porewater biogeochemistry. Results from GAM models showed that porewater CH_4, porewater sulfate concentrations, and porewater salinity explained the highest percentage of the variance (27%–16%), followed by surface water salinity and air temperature (13%–8%) (Table 4). Similar results were obtained if CH_4 flux data were filtered to consider emissions only (i.e., CH_4 fluxes >0) (Table S7). Surface and porewater nitrate concentrations and porewater temperature also explained some percentage of the deviance in CH_4 fluxes (26%, 10%, and 18%, respectively); however, these results were based on a limited number of studies (n < 5) (Table S7). Adding study ID as a random

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TABLE 3 Summary of annual CH_4 fluxes (g CH_4 m^{-2} $year^{-1}$) grouped by salinity class, MATmax, and elevation class from the Conditional Inference Tree in Figure 4.

Salinity class	MAT max	Elevation class	N	Distribution	Mean	SD	SE	Median	Geom. mean	geoSD
Fresh-oligohaline	>25.6		7	Normal	171.5	79.4	30	204	153	1.7
Fresh-oligohaline	≤25.6	Low, mid	20	Square root-normal	54.9	56	12.5	41.5	15	10.5
Fresh-oligohaline	≤25.6	High	10	Log-normal	5.3	6.3	2	3.2	3.8[a]	2.7
Mesohaline	>19		8	Log-normal	21.5	19.5	6.9	19.2	15.8	2.3
Mesohaline	≤19		39	Log-normal	6.9	10.3	1.7	3.1	3.4[a]	3.6
Poly-mixoeuhaline			24	Log-normal	1.8	2.3	0.5	0.7	1.2[a]	2.9

Note: *N* is number of sites, SD and SE are standard deviation and error, respectively, geom.mean refers to geometric mean, and geoSD is the standard deviation of the latter.

[a]Negative flux values ($n=1$ high fresh-oligohaline ≤25.6; $n=1$ mesohaline ≤19°C) and fluxes equal to zero ($n=1$; mesohaline ≤19°C; $n=3$ poly-mixoeuhaline) were removed to compute the geometric mean.

TABLE 4 General additive model (GAM) results for chamber-disaggregated CH_4 fluxes against time-specific predictor variables.

Variable	R^2	Deviance explained (%)	d.f.	AIC	# studies
Porewater CH_4	0.27 [0.33]	27 [34]	879	8420 [8336]	11
Porewater SO_4^{2-}	0.21 [0.27]	22 [29]	310	4200 [4177]	6
Porewater salinity	0.16 [0.20]	16 [22]	1162	16,734 [16,680]	15
Surface water salinity	0.12 [0.46]	13 [46]	760	9463 [9088]	6
Air temperature	0.08 [0.26]	8 [26]	6729	88,747 [87,337]	28
cosHour	0.05 [0.32]	5.1 [32]	6229	85,370 [83305]	18
Porewater SO_4^{2-} and porewater CH_4	0.67 [0.71]	69 [73]	239	2097 [2065]	5
Surface water salinity and air temperature	0.60 [0.66]	61 [67]	654	7632 [7514]	5
Porewater salinity and porewater CH_4	0.32 [0.36]	34 [39]	347	3594 [3576]	7

Notes: In brackets are GAM results with Study ID as a random effect. Results shown include relationships that explain >5% of the deviance in CH_4 fluxes, focusing on variables available in at least five studies. Table S7 contains GAM results for CH_4 emissions (i.e., >0) against all time-specific predictor variables with a significant relationship ($p<.05$). d.f. stands for degrees of freedom, AIC is the Akaike information criterion, and # studies indicate the number of studies that recorded each predictor variable (the total number of studies is 35).

effect increased the model performance between 6 and 32%, with the lowest increase observed for porewater salinity and the highest increase observed for surface water salinity. This highlights the intrinsic site-specific variability of CH_4 fluxes when predicted using surface water salinity. It also emphasizes the disconnect between surface and porewater salinity. Multivariate GAM models combining porewater CH_4 and sulfate concentrations, or surface salinity and air temperature, achieved the best performance with the highest deviance explained, 73% and 67%, respectively. However, these models were representative of only five studies (Table 4).

To estimate effect sizes, we examined the individual relationships between CH_4 fluxes and porewater concentrations of CH_4, sulfate, and salinity. All these variables, except for porewater CH_4, had significant effects on the magnitude of CH_4 fluxes, as shown by nonlinear quantile regression fits (Figure 5; Table S8). We observed a significant exponential decrease in CH_4 fluxes as surface and porewater salinity or sulfate concentrations increased. Moreover, as salinity and sulfate concentrations increased, the range of CH_4 fluxes decreased, suggesting that the effects of salinity and sulfate on CH_4 emissions were not consistent across all study sites. At the median quantile, CH_4 fluxes were significantly reduced when porewater sulfate and porewater salinity exceeded 2.8 ± 0.5 mM and 9.6 ± 1.1 psu, respectively. A 90% response, indicated by a significant reduction of the 0.9 quantile of the CH_4 fluxes, was achieved when sulfate concentrations reached 4.7 ± 0.6 mM, and porewater and surface water salinity reached 21 ± 2 and 15 ± 3 psu, respectively (Figure 5). These values represent the mean estimated cutoff points below which either the 50% or 90% of the highest CH_4 fluxes occur.

Analysis of the quantile regression model residuals revealed that CH_4 fluxes were not dependent on only one predictor variable. Several environmental covariates could explain variability in model residuals of the porewater or surface water salinity-CH_4 relationship. Primarily, the residual variance in CH_4 fluxes modeled from surface water salinity was notably influenced by porewater sulfate and CH_4 concentrations. Likewise, sulfate concentrations and porewater temperature influenced the remaining variance in fluxes modeled

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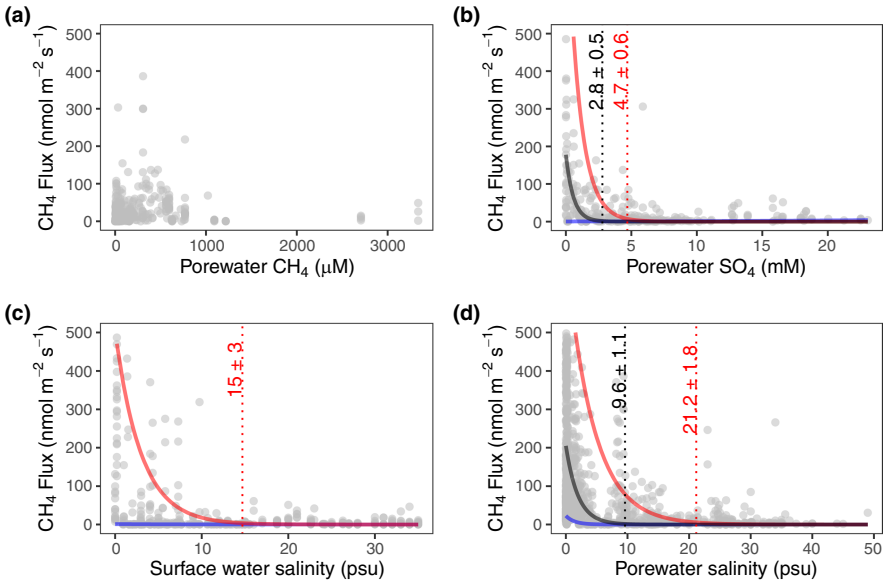

FIGURE 5 Quantiles of CH_4 fluxes as a function of best-ranked predictors in general additive models with the solid blue, black, and red lines representing the fitted regression for the 0.1, 0.5, and 0.9 quantiles of CH_4 fluxes, respectively. Only lines for significant fits are shown. Statistics for the regression lines are summarized in Table S8. Vertical dashed lines represent thresholds of predictor variables below which the highest 50% and 90% of CH_4 fluxes occur. Data in the figure represent chamber-based CH_4 fluxes disaggregated by sampling event with matching porewater data. Points with emissions above 500 nmol m^{-2} s^{-1} are not displayed.

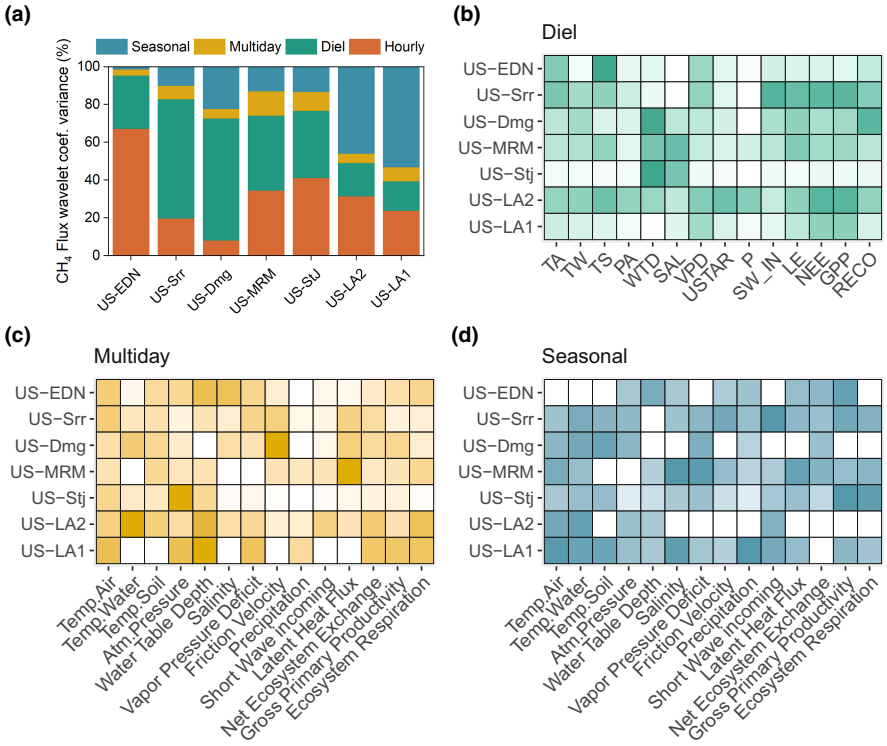

FIGURE 6 Variance of CH_4 flux and dominant predictor variables across timescales. Variance of CH_4 flux wavelet coefficients at each timescale of interest as a percentage of the total variance for all eddy covariance tower sites with at least a full year of gap-filled data (a). Heatmap of normalized (0 to 1 scale), maximum relative mutual information (I^R) between methane flux and biophysical variables within sites for the (b) diel, (c) multiday, and (d) seasonal scale. All analyses were conducted on wavelet-transformed data. Light colors represent the lowest normalized I^R, dark colors the highest normalized I^R and non-significant I^R values are shaded white. See Table S1 for tower site information. Predictor codes in (b) are spelled out in panels (c) and (d).

from porewater salinity (Figures S9 and S10). In contrast, no predictor variable was found to explain the variability in model residuals of the sulfate-CH_4 flux relationship.

3.4 | Predictors of CH_4 flux across timescales

Mutual Information analysis using wavelet decomposed EC datasets revealed that CH_4 responses to environmental covariates exhibited nonlinearity and were characterized by asynchronous interactions, particularly at the multiday and seasonal scales (compare maximum I^R heatmaps in Figure 6 with those of synchronous I^R in Figure S11).

The diel timescale generally dominated CH_4 flux variability across tidal marsh EC sites, except for microtidal sites in Louisiana (US-LA1 and US-LA2), where the seasonal scale prevailed (Figure 6a). For some sites, the proportion of variance in CH_4 flux at the hourly scale appeared large (e.g., US-EDN). This was generally due to the higher signal-to-noise ratio at sites with low CH_4 fluxes or their low variation at other scales. The variance in CH_4 fluxes at the multiday scale was the lowest across all tidal marsh EC sites.

To assess the relative importance of CH_4 flux predictors at each timescale, we first normalized relative mutual information (I^R) values (Figure S12) within each site and then averaged normalized I^R across sites. We did that within each timescale of interest (Figure 6b–d). At

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the diel scale, the main predictors of CH_4 flux were GPP, net ecosystem exchange, and soil temperature. Latent heat and water table depth ranked 4th and 5th in importance. On a multiday scale, the hierarchy of predictors was led by air temperature, water table depth, and atmospheric pressure. At the seasonal scale, water and air temperature were among the top predictors, followed by GPP and incoming shortwave radiation. Vapor pressure deficit and salinity ranked 5th and 6th, respectively, while water table depth was last in importance.

Heatmaps in Figure 6b–d provide a more detailed depiction of the primary predictors determined by maximum I^R between CH_4 flux and biophysical variables. These heatmaps reveal site-specific patterns not evident when averaging normalized I^R values across sites. Notably, water table depth and GPP emerged as dominant predictors at sites with large CH_4 flux variance at the diel scale. Diurnal patterns, characterized by peak CH_4 fluxes during midday hours and lower fluxes at night, as well as pulses of CH_4 flux occurring within 0 and 90 min after low tide, were commonly observed at these sites (Figures 7a–c and S13). On a multiday scale, increased CH_4 fluxes aligned with either spring tide cycles (US-EDN) or atmospheric pressure lows (US-LA1, US-LA2, US-StJ). At the seasonal scale, the dominance of water and air temperature, followed by GPP was apparent in most sites (Figure 6c). In some cases, lows in dissolved oxygen (at US-StJ) or high precipitation, bringing pulses of fresh water (US-LA1), manifested as key controls of CH_4 flux (Figure 7g,i).

While the influence of temperature (air, soil, or water) and effects of plant activity (through GPP, net ecosystem exchange or latent heat) on CH_4 fluxes were apparent across timescales and sites, the presence of a diel cycle marked by plant activity was site-specific. Heatmaps in Figure 6 support the point that there may not be a universal explanation for flux variability; rather, CH_4 fluxes appear to be conditional on time and location. Salinity was not a top predictor in continuous EC datasets when averaging normalized I^R values across sites. However, it emerged as an important predictor at the seasonal timescale at sites that experienced a freshening during the growing season months (US-LA1, US-MRM, and US-EDN) (Figure S14), or at the diel scale where it correlated with water table depth (US-StJ or US-MRM).

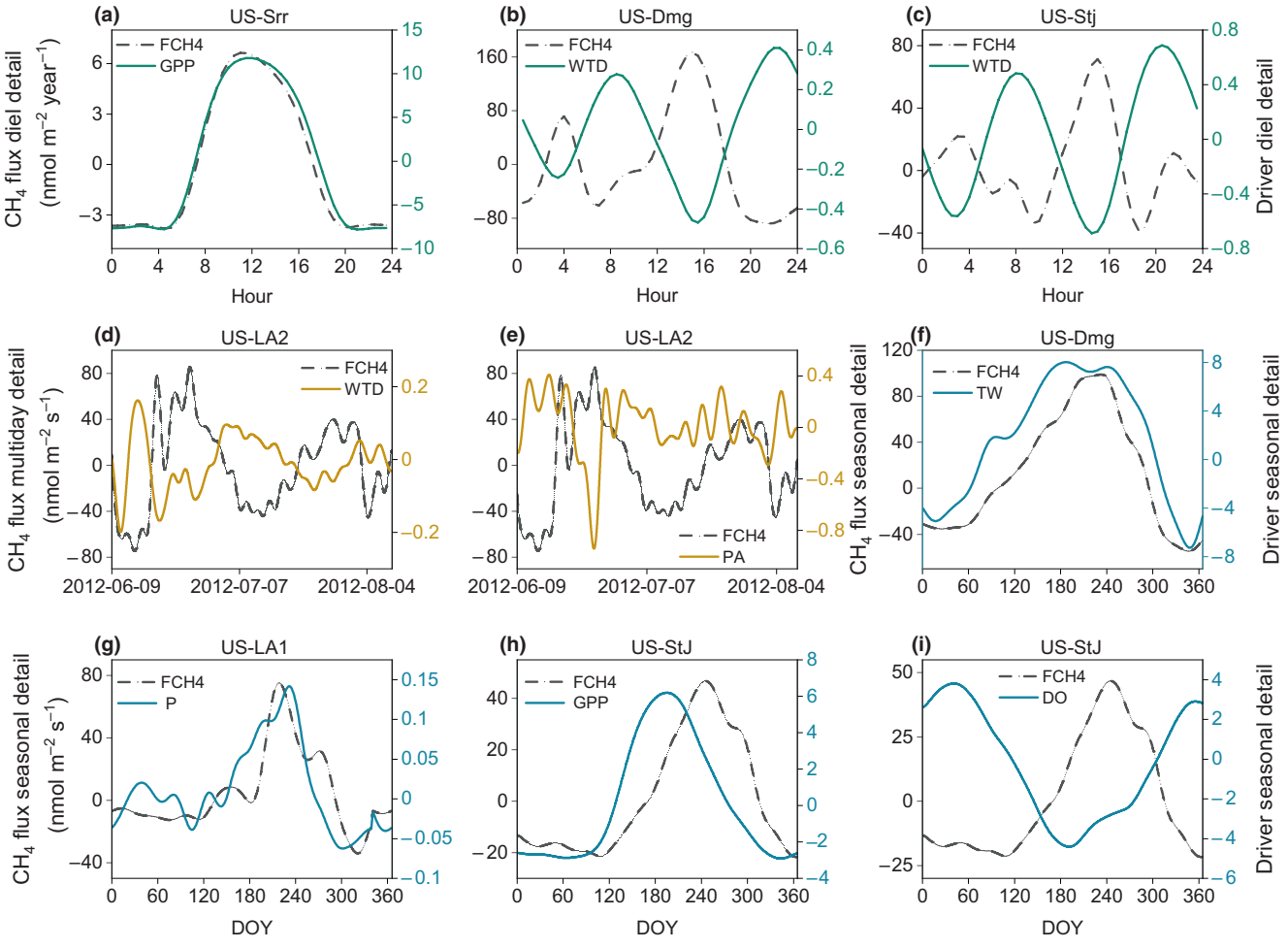

FIGURE 7 Examples of diel and seasonal variation in the wavelet detail reconstruction for CH_4 flux and predictor variables. Note that the mean is removed in wavelet detail reconstructions; therefore, the y-axes are relative rather than absolute. Panels (a) through (c) illustrate diel wavelet details, panels (d) and (e) show examples of multiday wavelet details, and panels (f) through (i) show seasonal wavelet details. Predictor variable abbreviations are those introduced in Figure 6. DO stands for dissolved oxygen. Wavelet details for CH_4 flux, water table depth, and salinity at the diel and seasonal scales across all eddy covariance sites are in Figures S13 and S14, respectively.

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4 | DISCUSSION

Our primary goal was to improve predictions of CH_4 emissions from tidal marshes in CONUS. This discussion focuses on four research questions that align with this goal. Firstly, we identify the primary predictors of CH_4 flux in tidal marshes across sites using broadly available data. Secondly, using EC sites with continuous CH_4 flux data, we assess the effects of predictors across varying timescales. Third, we discuss the application of scaling factors to annualize short-term static chamber measurements and their limitations, considering daily and seasonal flux variations. Lastly, we highlight how the identified relationships and gained information can be applied to improve monitoring and predictions of CH_4 emissions in tidal marshes, supporting blue carbon assessments and advancing our ability to constrain estimates of GHG emissions across diverse tidal wetlands.

4.1 | Dominant predictors of CH_4 flux in tidal marshes across CONUS

In our analysis of tidal marsh CH_4 fluxes across CONUS, we observed a wide range of flux magnitudes, varying from −150 to 4120 nmol $m^{-2} s^{-1}$, with an average of 82 nmol $m^{-2} s^{-1}$ and a median significantly lower at 5.8 nmol $m^{-2} s^{-1}$. When compared to available estimates from a recent synthesis, the median instantaneous CH_4 flux per unit area aligns with values reported for North American saltmarshes, yet it is approximately half of that observed for mangroves, and about 10 times higher than figures reported for seagrasses (Rosentreter et al., 2023). Annual CH_4 fluxes showed a positive skew with a mean of 26 ± 53 g CH_4 $m^{-2} year^{-1}$ and median and geometric means significantly lower, a reflection of the predominant data from mesohaline tidal marshes as well as the notoriously variable behavior of CH_4, with hotspots of activity. This raises a question about the reliability of arithmetic, median, or geometric mean values as estimates for representing the regional scale magnitude of annual CH_4 emissions in tidal marshes or their emission factors globally. The adequacy of these metrics will largely depend on the actual distribution and proportion of various marsh salinity classes across different climatic zones (e.g., Table 3). However, at finer spatial and temporal scales, factors such as hydrology, plant activity, and porewater biogeochemistry may become more influential than salinity in determining tidal marsh CH_4 fluxes.

4.1.1 | Influence of salinity, temperature, relative elevation, and alternate electron acceptors on CH_4 fluxes

Across CONUS, we observed significant differences in median annual CH_4 fluxes among salinity classes, with a ~ threefold decrease in median CH_4 fluxes for each increase in salinity class from fresh to mixoeuhaline (Figure 3b). Median CH_4 fluxes in tidal freshwater marshes were 2, 8, 29, and 69 times higher than those of oligohaline, mesohaline, polyhaline, and mixoeuhaline marshes, respectively. Previous studies by Bartlett et al. (1987) and Poffenbarger et al. (2011) demonstrated a significant relationship between CH_4 fluxes and salinity. Sites with salinities above 18 psu had significantly lower CH_4 fluxes than less saline marshes, but this relationship was found to be less predictive at sites with salinities fresher than 18 psu (Poffenbarger et al., 2011; Windham-Myers et al., 2018). This agrees with our results when data were summarized at the annual level. When examining the data at the disaggregated level, CH_4 fluxes from freshwater and oligohaline marshes (0–5 psu) were the only groups showing statistical overlap (Figure 3c). This suggests that the attenuation of CH_4 fluxes by salinity primarily occurs beyond the oligohaline threshold (>5 psu) and that variables other than salinity may dominate CH_4 flux variance in fresh-oligohaline conditions.

Consistent with Poffenbarger et al. (2011), who found substantial dispersion in annual CH_4 fluxes at low salinities below 5 psu, we observed a great deal of variation in CH_4 fluxes with the magnitude of the variance decreasing as salinity increased (Figure 3b,c). At fresh to mesohaline sites, variability in annual CH_4 fluxes was partially attributed to temperature. Additionally, elevation class, a qualitative measure of inundation frequency, also contributed to the variability in annual CH_4 fluxes across fresh-oligohaline sites. The highest fluxes were observed at fresh and oligohaline sites experiencing a daily maximum annual temperature normal (MATmax) above 25.6°C (~204 g CH_4 $m^{-2} year^{-1}$). These were followed by frequently inundated low and mid-fresh-oligohaline marshes with MATmax ≤25.6°C (~42 g CH_4 $m^{-2} year^{-1}$), and mesohaline sites with MATmax above 19°C (~19 g CH_4 $m^{-2} year^{-1}$) (Table 3). The fact that elevation class emerged as an important explanatory variable for CH_4 fluxes at low salinity levels may reflect the decrease in soil oxygen availability as flooding increases from high to low elevations (Kirwan et al., 2013), enhancing methanogenesis and suppressing methanotrophy. This pattern, however, did not emerge in saline systems, possibly due to the overriding influence of sulfate availability compared to fresh sites (DeLaune et al., 1983; Martens & Berner, 1974). In saline environments, CH_4 fluxes could remain low regardless of inundation, as sulfate reduction precedes methanogenesis. However sample size limitations and high variability within groups could have also played a role.

Synthesizing chamber-disaggregated flux and ancillary variables by sampling event allowed us to evaluate further the effects of salinity, temperature, and porewater biogeochemistry on the magnitude and variability of CH_4 fluxes in tidal wetlands. As per the well-established CH_4 response to salinity observed in other studies (Bartlett et al., 1987; DeLaune et al., 1983; Poffenbarger et al., 2011; Sanders-Demott et al., 2022; Schultz et al., 2023; Windham-Myers et al., 2018), chamber flux data disaggregated by sampling event also showed a significant exponential decrease with increasing salinity, for both surface water and porewater (Figure 5c,d). Across the range of sites, fitted median CH_4 fluxes fell below 1.6 ± 1.3 nmol $m^{-2} s^{-1}$ at porewater salinities above 9.6 ± 1.1 psu. However, some instances of high CH_4 emissions

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(50–170 nmol m^{-2} s^{-1}) were still evident above this threshold. A more conservative threshold was identified at porewater salinities of 21 ± 2 psu, incorporating the 90th percentile of the CH_4 fluxes. The latter threshold was 15 ± 3 psu if surface water salinity was considered instead. Surface water and porewater salinity are not always well correlated at a site, as surface water salinity is often more variable than porewater salinity (Wilson et al., 2015). Indeed, the salinity measured on the surface may not accurately reflect the salinity conditions experienced by methanogens or, more precisely, their competition with sulfate-reducing bacteria. Surface inputs of salts are modified by plant transpiration, while sulfate inputs are modified by the balance between consumption by sulfate-reducing bacteria and production by sulfide oxidation. Such process may explain the reduced predictability of CH_4 emissions when using surface water salinity as a standalone predictor; thus, porewater salinity is preferred. Methane emissions significantly decreased with increasing porewater salinity across all conditional quantile levels, whereas surface salinity only explained changes in CH_4 emissions at the 90th percentile of the flux distribution (Table S8; Figure 5).

Causes of CH_4 flux variation at low salinities have previously been explained by microsite spatial and temporal variability in the presence of alternate electron acceptors and the sensitivity of methanogens to variations in their availability (Brooker et al., 2014; Galand et al., 2003). Because of the high abundance of sulfate in seawater, salinity has been used as a proxy of sulfate availability in tidal and salt marsh studies. However, we observed considerable variability in sulfate concentrations at a given salinity level, particularly when surface salinity was used to infer porewater sulfate concentrations (Figure S15a,b). Sulfate concentrations can change independently of salinity due to local sulfate depletion, leading to high CH_4 emissions despite high salinity levels, as observed in Wilson et al. (2015), and at high (>10 psu) porewater salinities in this synthesis (Figure 5d).

The general inverse relationship between sulfate concentration and CH_4 emissions is well-supported and upheld by studies through time (Bartlett et al., 1987; DeLaune et al., 1983; Martens & Berner, 1974; Poffenbarger et al., 2011). However, it is not well defined if there is a specific sulfate concentration above which tidal marsh CH_4 emissions are negligible. Poffenbarger et al. (2011) found that porewater CH_4 concentrations were negligible at sulfate concentrations >4 mM in marsh soils. However, they did not relate porewater sulfate concentration to CH_4 emissions due to the lack of paired data to evaluate such a relationship. Our analysis suggests that median CH_4 emissions were low across sites at porewater sulfate concentrations >2.8 ± 0.5 mM. However, considering the large spread of the response of CH_4 emissions to sulfate at low (<5 mM) sulfate concentrations, a more stringent threshold of 4.7 ± 0.6 mM delineated CH_4 emissions in the lowest 90th percentile of the data (Figure 5b). CH_4 emissions displayed significant responses to sulfate concentrations at all quantile levels and exhibited a third of the residual variance observed in CH_4 flux responses to porewater salinity. Residual analysis revealed that the modeled salinity–CH_4 relationship tended to overestimate CH_4 emissions as porewater sulfate concentrations decreased, particularly within 0 to 5 mM, indicating a greater sensitivity to increasing sulfate availability than to increasing salinity. A similar trend was observed for residuals fitted to porewater CH_4 concentrations, particularly within the range 0–100 μM CH_4, highlighting the activity of sulfate reducers as a primary control on CH_4 production in surface soils (0–30 cm).

We did not find a consistent significant relationship between porewater CH_4 concentrations and CH_4 fluxes (Figure 5a; Table S8). The discrepancy between CH_4 production and emissions may be attributed to several factors. These include bacterial-mediated aerobic CH_4 oxidation near the sediment surface during low tide or facilitated by plant rhizosphere oxygenation (Megonigal & Schlesinger, 2002; Van der Nat & Middelburg, 1998). Additionally, non-diffusive emission pathways like ebullition and plant-mediated transport (Hill & Vargas, 2022) are not always accounted for in chamber studies, as chambers may not include tall vegetation or headspace concentrations may be filtered to remove pulsed or erratic emissions. Furthermore, tidal flooding could drive lateral transport of dissolved porewater CH_4 from the marsh, which would be missed by chamber and eddy flux methods (Kelley et al., 1995; Tong et al., 2010; Trifunovic et al., 2020).

Porewater nitrate concentrations are typically low in most coastal marshes (Valiela & Teal, 1974), but surface water concentrations can be notably high at some sites due to agricultural intensification and other anthropogenic sources (Galloway et al., 2003; Pardo et al., 2011) (Figure S15). Nitrate is a thermodynamically favorable electron acceptor used by anaerobic bacteria shown to enhance soil organic matter decomposition (Bulseco et al., 2019). Similarly to sulfate, methanogenesis can be inhibited in the presence of nitrate. In this synthesis, signals of this process might be observed from the decrease in EC and chamber-based CH_4 fluxes with increasing dissolved nitrate concentrations (Figure S15c,d). However, the extent of CH_4 emission reduction was less pronounced for nitrate than for porewater sulfate. This pattern emerged despite a small dataset ($n = 3$ studies), suggesting that nitrate inhibition of methanogenesis by nitrate reducers (denitrifiers) is a very strong biogeochemical signal that should be explored further given the fact that the process may also produce nitrous oxide (N_2O), a potent GHG. Our dataset lacked contemporaneous measurements of N_2O emissions at these sites.

4.2 | Tidal marsh CH_4 fluxes across timescales

Methane fluxes in tidal marshes, as measured by EC, exhibited strong variation at the diel scale (Figure 6a), although most of the CONUS sites experience a strongly seasonal temperate climate. Among the seven EC sites analyzed, US-Srr exhibited a unique diel pattern in CH_4 flux wavelets. Peak fluxes occurred from late morning to mid-afternoon and were correlated with GPP, net ecosystem exchange, or incoming shortwave radiation. This pattern was likely due to its high marsh elevation, not frequently inundated in the flux footprint. In contrast, most sites showed less symmetric diel

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patterns influenced by diurnal and tidal interactions, with additional peaks often lagging lows of sinusoidal tidal patterns (Figure 7a–c; Figure S13), representing the release of stored CH_4 during brief and localized periods at low tide.

Higher daytime CH_4 fluxes could stem from several factors, increased soil and air temperatures (Bansal et al., 2018), enhanced root exudation with GPP stimulating methanogens and microbial priming (Bridgham et al., 2013), or CH_4 transport mediated by plants. This plant-mediated transport could either be driven by a pressure gradient that intensifies during daylight and coincides with active photosynthesis (Bansal et al., 2020; Dacey & Klug, 1979; Vroom et al., 2022) or by stomatal control of diffusive transport (Garnet et al., 2005). The former might be particularly relevant in *Phragmites*-dominated marshes (van den Berg et al., 2020; Van der Nat & Middelburg, 1998). Evidence from local studies focusing on individual site locations suggested that both impoundment and *Phragmites* invasion, separately or combined, could markedly increase CH_4 fluxes (Martin & Moseman-Valtierra, 2015; Mueller et al., 2016; Sanders-Demott et al., 2022).

The dominance of the diel scale over the seasonal scale in CH_4 flux variance is not limited to EC sites included in this synthesis; it has also been documented in other tidal ecosystems, such as in a subtropical estuarine mangrove (Liu et al., 2022). Chamber studies that conducted measurements over 12–24 h periods or consisted of automated chambers also noted diel CH_4 fluctuations of varying frequency and nature. For instance, Kelley et al. (1995) noted that CH_4 fluxes were higher when tidal waters were closest to the soil surface. Diefenderfer et al. (2018) observed that CH_4 flux was greater at night, likely due to the effects of hydrostatic pressure on diffusion and ebullition processes influenced by water surface elevation dynamics. Capooci and Vargas (2022) found that confluences of peak daily temperatures and low to rising tides could cause CH_4 pulses throughout the day. Tong et al. (2013) reported that plant activity controlled CH_4 emissions during neap tide days when sites were exposed; when sites were flooded, other factors dominated. These findings suggest that while diel CH_4 flux variability is expected in tidal marshes, the presence and strength of a daily cycle are site-specific depending on species, temperature, and tidal forcings.

Microtidal sites in Louisiana do not experience large tidal amplitudes nor the sinusoidal pattern with tides; thus, peaks in wavelet analysis were not observed at diel scales related to semidiurnal tides or fortnightly neap-spring tidal cycles (Figure S13). Sites in Louisiana are wind- and river-influenced, and atmospheric pressure changes and freshwater pulses driven by synoptic and mesoscale weather played a more significant role in CH_4 flux variability. These results suggest that CH_4 fluxes and their drivers at microtidal sites may align more closely with those of non-tidal wetlands found elsewhere (Knox et al., 2021; Sturtevant et al., 2016). In contrast, where tides are significant, they may strongly modulate the timing and pathway of CH_4 emissions.

At the seasonal scale, water and air temperatures were the primary predictors of CH_4 flux, followed by GPP. Salinity ranked 6th in importance, demonstrating greater relevance at this scale compared with other timescales. This may reflect the limitations of using surface water salinity at EC sites to explain diel CH_4 flux responses. It may also suggest that seasonal, rather than shorter-term diel changes in surface water salinity are required to affect CH_4 emissions significantly. Seasonal salinity changes, driven by reduced freshwater flow and increased seawater intrusion, typically elevate salinity during the summer and growing season. However, higher temperatures and enhanced GPP during these periods could offset potential CH_4 flux inhibition due to increased sulfate availability. A distinct observation was that CH_4 fluxes were largely enhanced when reduced salinity aligned with peak growing season conditions (Figure 7; Figure S14).

4.3 | Daytime chamber CH_4 fluxes: Temporal upscaling and limitations

Only a few chamber studies have shown the significant variability of CH_4 fluxes at daily scales (Capooci & Vargas, 2022; Diefenderfer et al., 2018; Kelley et al., 1995; Tong et al., 2013), highlighting the limitations of temporally upscaling CH_4 fluxes from discrete static chamber measurements (Hill & Vargas, 2022; Vargas & Le, 2023). Static chambers, predominantly deployed at low tide, are limited in their sensitivity to sudden pulse events and may not effectively capture CH_4 responses to GPP dynamics. Assessments of GPP require consecutive measurements under both light and dark conditions that can be affected by chamber heating or an incomplete physiological adaptation (e.g., stomatal closure) to dark conditions. While static chamber measurements offer the advantage of capturing CH_4 flux variability across sites, they are not well suited to capture the temporal variability of CH_4 fluxes and their influencing factors.

However, most flux measurements in tidal marshes are derived from static chambers, often paired with sporadic recordings of temperature, water table depth, or porewater geochemistry. Lacking continuous predictor variables that would allow for confident temporal scaling of discrete CH_4 flux measurements, we estimated scaling factors based on sites with a full year of sampling coverage. Significant differences emerged between factors derived from EC (s.f. = 0.32) and chamber (s.f. = 0.39) methods when cumulative annual fluxes were compared against daily measurements averaged year-round. Daytime static chamber measurements hardly integrate diel variations in CH_4 fluxes, which likely introduces bias into annual estimates (Vargas & Le, 2023). Diel variations not only refer to fluctuations between day and night due to temperature and plant activity but can represent variations with tides, carbon substrates, and/or ebullition. At sites with overlapping chamber and EC measurements, chamber measurements were generally lower than EC, except at microtidal sites in Louisiana (Figure S16). This difference suggested that chamber measurements often miss episodic CH_4 flux events due to infrequent sampling and differing footprints, leading to site-level CH_4 flux discrepancies between methods. However, with chamber estimates of CH_4 fluxes ranging from less than half (Hill & Vargas, 2022) to about twice as high as EC estimates (Krauss

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et al., 2016), disparities appeared to be site-specific and difficult to reconcile at the regional level.

Building on the scaling factors discussed earlier, Bridgham et al. (2006) found a similar ratio between annual and mean daily CH_4 fluxes from chamber measurements in non-tidal freshwater (s.f. = 0.36) and estuarine (s.f. = 0.34) wetlands across North America, suggesting there is a ~360-day emission season. Seasonality in CH_4 fluxes is evident in many tidal wetland datasets (Figure S14a) (e.g., Derby et al., 2022; Neubauer, 2013; Vázquez-Lule & Vargas, 2021), with CH_4 fluxes typically being low during winter. However, a substantial fraction (~15%) of annual CH_4 fluxes may occur during cooler months, as observed in this study for sites with year-round data and in temperate freshwater wetlands in Delwiche et al. (2021). Specifically, in our dataset, CH_4 fluxes during January–March and October–December accounted for 9 ± 5% and 20 ± 6% of annual CH_4 fluxes, respectively, highlighting the significance of winter fluxes in the annual CH_4 budget.

Most static chamber studies in temperate marshes typically exclude winter sampling. Traditionally, a common approach was to annualize the average daily fluxes from the growing season, applying a 150-day emissions season and assuming negligible winter emissions (Bartlett & Harriss, 1993; Magenheimer et al., 1996). More recently, scaling factors, as described in Bridgham et al. (2006), have been used to calculate annual CH_4 fluxes from mean daily fluxes sampled during the growing season (Bridgham et al., 2006; Poffenbarger et al., 2011). However, this approach may lead to an apparent overestimation of annual CH_4 fluxes of up to ~50% due to the relative seasonal increase in CH_4 fluxes compared with baseline (Figure S17). According to our results, an emission season of 210 days (or a s.f. = 0.21) may be more accurate to consider if fluxes are sampled during the peak emission period (June–August) (Figure 2). The variance of the June–August scaling factor across sites was lower than that observed for the ratio of annual flux: mean daily flux averaged year-round. Additionally, no significant differences were detected in the June–August scaling factors between chamber and EC sites. This might be due to the lower variability in within-site CH_4 fluxes during the peak emission season compared with that observed year-round. Consequently, the ratio of annual flux to June–August mean daily flux may be less affected by how well the length and amplitude of the seasonal cycle are captured by discrete chamber measurements.

4.4 | Advancing CH_4 flux assessments in tidal marshes

Results of the present study could improve predictions of CH_4 emissions in tidal marshes at the local and regional levels in various ways. Porewater sulfate and salinity concentration thresholds below which 90% of the highest CH_4 fluxes occur (4.7 ± 0.6 mM SO_4^{2-} and 21 ± 2 psu, respectively) may help determine whether a site's CH_4 responses should be included in blue carbon assessments, wetland restoration monitoring, or GHG inventories. Above these thresholds, CH_4 emissions may be considered negligible. Despite porewater sulfate concentrations more accurately representing the competition between methanogens and sulfate-reducing bacteria, the practicality of porewater sulfate as a proxy for widespread application may be limited due to the challenges associated with its measurement. On the contrary, porewater salinity, which is relatively easy to measure and also represents conditions experienced by methanogens, could be more applicable in real-world scenarios for estimating the magnitude of CH_4 fluxes across a range of sites.

Estimated median annual CH_4 fluxes among salinity classes (Figure 3b), which showed a consistent ~threefold decrease for each increase in salinity class, could serve as CONUS-specific Tier 2 estimates, offering a more detailed approach to better constrain CH_4 emissions factors beyond the global Tier 1 factors of the IPCC Wetlands Supplement (IPCC, 2014). The current Tier 1 emission factor relies on an 18 psu salinity threshold, below which CH_4 emissions are set at 19 g CH_4 m^{-2} $year^{-1}$ (based on range 1.1–539 g CH_4 m^{-2} $year^{-1}$), and above it are set at zero. However, the primary limitation of the salinity–CH_4 flux relationship in predicting CH_4 fluxes lies in the substantial variability in flux magnitudes observed at low salinity conditions (< 18 psu). Our results suggest that the daily maximum annual temperature normal (MATmax), along with elevation class, could be used to improve the accuracy of this relationship. Table 3 proposes a new categorization of annual CH_4 fluxes that distinguishes between warmer and cooler fresh-oligohaline and mesohaline marshes. Additionally, it incorporates marsh elevation classes within fresh-oligohaline conditions to better constrain CH_4 fluxes at low salinity levels. This categorization, specific to US data, could further improve Tier 2 estimates. This approach would adjust median emission factors for fresh-oligohaline marshes with MATmax >25.6°C to be 8–10 times higher than the current Tier 1 factor, while those for frequently inundated, low- and mid-elevation fresh-oligohaline marshes with MATmax below 25.6°C would be increased by two times. Emission factors for warm mesohaline marshes (MATmax >19°C) would remain unchanged. Conversely, the revised median estimate for infrequently inundated colder fresh-oligohaline high marshes (MATmax ≤25.6°C), and mesohaline marshes (MATmax ≤19°C) would be one-sixth of the current Tier 1 factor. These emission factors could be viewed as Tier 2 estimates for implementing national inventories rather than precise predictions of tidal marsh CH_4 fluxes across temporal and spatial scales. Eddy covariance datasets identified GPP as a main predictor of CH_4 fluxes. If GPP data were available across more tidal marsh sites, it could improve annual CH_4 flux predictions and offer valuable insights for future studies. Likewise, the hydrologic setting, often reported qualitatively as either "high" or "low" marsh environments, could be made a stronger predictor of annual CH_4 fluxes across sites by including a quantitative metric of relative tidal elevation, such as elevation normalized to tidal amplitude in future research (e.g. Z^*_{MHW}, Holmquist & Windham-Myers, 2022).

Daytime chamber measurements during the growing season currently represent the majority of available CH_4 flux data from tidal wetlands and are likely to remain prevalent. Therefore, developing carbon exchange models that combine discrete chamber CH_4 fluxes

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with continuous predictor variables or robust scaling factors to annualize daytime chamber measurements would support the continuation of chamber monitoring approaches. This would enhance efforts to achieve Tier 2 national inventories and implement carbon finance protocols by reducing the data collection effort, which is generally less available than carbon sequestration data. Despite its limitations, we provide a scaling factor (s.f. = 0.21) that can be used to upscale growing season chamber-based CH_4 fluxes to first-order annual CH_4 flux estimates. However, we caution about the limitations of manual measurements in capturing the temporal variability of CH_4 fluxes. The presence and symmetry of a diel cycle appeared to be site-specific, suggesting that scaling factors should ideally be assessed carefully on a site-specific basis. We propose that when feasible, CH_4 flux measurements be collected over a 24-h cycle or continuously using automated chambers or EC towers to capture the diurnal variability of CH_4 flux, identify important site-specific drivers, and improve scaling factors.

5 | CONCLUSIONS

We compiled, standardized, and synthesized chamber-based CH_4 fluxes across tidal wetlands in CONUS and created an open-source database (Arias-Ortiz et al., 2024, https://doi.org/10.25573/serc.14227085). Chamber flux data disaggregated by sampling event combined with available EC datasets improved the representation of CH_4 fluxes and their variability across time and space in tidal marshes. Porewater sulfate and salinity, along with mean daily maximum annual temperatures and elevation, were important predictors of CH_4 emissions across sites. However, temperature, plant activity (through GPP), and tidal height significantly contributed to the variability of CH_4 fluxes within individual sites, with tidal height influencing the timing and pathways of CH_4 fluxes at the diel scale. Our analysis shows the large diel CH_4 flux variance observed in tidal wetlands, emphasizing the need for integrated measurement approaches to capture the complexity of tidal marsh CH_4 dynamics.

AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST STATEMENT

The authors claim no conflicts of interest.

DATA AVAILABILITY STATEMENT

Chamber flux data supporting the findings of this study are openly available in figshare at https://doi.org/10.25573/serc.14227085. Eddy covariance data is available at https://doi.org/10.6084/m9.figshare.26411305, from the FLUXNET-CH4 Community Product https://fluxnet.org/data/fluxnet-ch4-community-product/ or at AmeriFlux at https://ameriflux.lbl.gov/. DOIs for individual eddy covariance site data are provided in Table S1.

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