








EVALUATIONS OF EXISTING METHODS

Uncertainty in aquatic greenhouse gas flux estimates arises from subjective processing of floating chamber time series

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Abstract

Accurate quantification of greenhouse gas (GHG) fluxes from aquatic systems is essential for constraining regional and global carbon budgets. Closed floating chambers are widely used to measure carbon dioxide (CO₂) and methane (CH₄) fluxes at the water–air interface, yet large uncertainties persist due to subjective processing of chamber time series. In particular, the treatment of nonlinear patterns and abrupt events such as ebullition often relies on expert judgment, which may strongly influence flux estimates. We present the first quantitative assessment of bias arising from expert subjectivity in the processing of floating chamber measurements. Seventeen researchers, all of whom participated in field sampling, independently evaluated a common dataset of 794 incubations from 36 European coastal wetlands. Each expert visually selected valid data segments and flagged abnormal time series prior to flux calculation. In total, 2679 manual inspections were compared with fully automated flux estimates based on untrimmed time series. Experts showed substantial variability in flagging abnormal measurements and handling nonlinear or irregular concentration patterns. While flux variability was generally low for most CO₂ and CH₄ incubations, disagreements exceeded 100% for curved or temporally complex time series. For CH₄, ebullition was a major source of divergence, but marked variability also occurred when ebullition contributed only marginally to total fluxes. This methodological experiment demonstrates that expert judgment introduces significant, previously unquantified uncertainty into aquatic GHG flux estimates. We advocate for transparent, standardized, and reproducible data-processing workflows, including automated tools for objective identification and treatment of nonlinearities.

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Coastal and inland water habitats are collectively an important source of greenhouse gases (GHGs) to the atmosphere (Lauerwald et al. 2023). In the context of climate change and the urgent need to reduce GHG emissions, accurate quantification of carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O) fluxes is therefore essential for constraining regional and global carbon budgets, informing climate

models, and supporting mitigation strategies (Regulation (EU) 2021). The accuracy and reliability of these flux estimates strongly depend on the measurement techniques employed in the field and subsequently used to inform upscaling models (Lauerwald et al. 2023).

Aquatic GHG fluxes are measured using a wide range of techniques and protocols, each with distinct advantages and limitations. Common approaches include floating chambers, which provide direct flux estimates at high temporal resolution; eddy covariance systems, which integrate fluxes over larger spatial scales; and dissolved-gas methods such as headspace equilibrations, mass balance approaches, or membrane-based sensors that infer air–water gas exchange indirectly. While this methodological diversity offers flexibility, it also results in substantial heterogeneity in sampling designs, data-processing choices, and reporting standards. Consequently, there remains a clear need for consistent, standardized protocols that enable more reliable comparison among studies.

Among available approaches, the closed floating chamber technique is widely used to estimate in situ short-term GHG fluxes at the water–atmosphere interface (e.g., Mannich et al. 2019; Martinsen et al. 2018; Vachon et al. 2010; Xiao et al. 2016). This method isolates a defined air volume directly above the water surface (the chamber headspace) for a limited incubation period, typically lasting 5–20 min. During this time, changes in GHG concentrations within the chamber headspace are monitored and used to infer fluxes across the boundary layer. Flux time series obtained using floating chambers coupled to portable gas analyzers are now commonly available; however, many earlier measurements relied on discrete syringe sampling followed by laboratory gas analysis, an approach that is still used by several research groups. Experts generally assume constant diffusive fluxes during short-term incubations (< 15 min) and therefore commonly fit chamber concentration time series with linear regressions. While this assumption has been strongly debated within the soil science community for the processing of static chamber measurements (Hutchinson and Mosier 1981; Pirk et al. 2016; Hüppi et al. 2018; Maier et al. 2022), aquatic scientists often overlook nonlinear patterns (Silva et al. 2015), which can lead to severe underestimation of actual fluxes (Kutzbach et al. 2007). Indeed, several studies report nonlinear or abrupt patterns in short chamber time series (e.g., Hoffmann et al. 2017; Sørensen et al. 2024; Villa et al. 2021; Żygadłowska et al. 2024). Such behavior may reflect the non-steady-state conditions inherent to closed chambers (Mannich et al. 2019), as well as short-term variability in the processes controlling GHG fluxes. For example, turbulence at the air–water interface is inherently unsteady, resulting in fluctuating gas-exchange velocities over short time scales (Zappa et al. 2007; Wang and Liao 2016; Perolo et al. 2021).

For CH₄, which is poorly soluble in water, emissions can occur not only through molecular diffusion, but also via

nondiffusive pathways such as ebullition, whereby gas bubbles formed in water-saturated sediments escape to the surface. This additional transport mechanism adds further complexity to CH₄ flux dynamics and frequently produces abrupt jumps in concentration time series of floating chamber measurements (e.g., Gerardo-Nieto et al. 2019; Sørensen et al. 2024; Varadharajan and Hemond 2012). Several studies have attempted to separate the diffusive and ebullitive components of CH₄ fluxes (Hoffmann et al. 2017; Sørensen et al. 2024), yet methodological inconsistencies persist.

Despite these well-documented challenges, there is no clear consensus on how floating chamber incubation time series should be processed. In practice, GHG flux calculations often rely on expert visual inspection and subjective selection of observations deemed suitable for regression analysis. This subjectivity raises several important questions:

- i. How do experts treat nonlinear patterns in CO₂ and CH₄ chamber time series?
- ii. To what extent do experts agree on how such patterns should be handled?
- iii. Under which conditions is consensus among experts stronger or weaker, and does this differ between CO₂ and CH₄?

In this study, we explore these questions by assessing the degree of agreement among experts in GHG data processing. By comparing expert decisions and the resulting flux estimates, we quantify the extent to which subjective choices influence results. Finally, we provide guidance on implementing more objective and transparent methodologies for processing GHG chamber time series.

Materials and procedure

A database of in situ floating chamber incubations

A total of 794 floating chamber incubations were performed seasonally across 36 coastal wetland sites (Minaudo et al. 2025), including a large freshwater lagoon (Curonian Lagoon, Lithuania), freshwater ponds and marshes (Camargue, France), freshwater ponds and lakes (Danube Delta, Romania), brackish marshes (Marjal dels Moros, Spain), intertidal salt marshes (Oosterschelde and Grevelingen Deltas, the Netherlands), and seagrass beds (Ria de Aveiro, Portugal). These sites represent a wide range of ecological conditions, from natural and well-preserved systems to heavily impacted or restored environments.

All in situ measurements followed a standardized protocol (Minaudo et al. 2023). Incubations lasted up to 12 min and were conducted at water depths > 10 cm without emergent vegetation inside the chamber. Chambers were flushed before and after each incubation, and trained operators were instructed to minimize any disturbance of the chamber. Opaque floating chambers (Supporting Information Fig. S1) were used to prevent overheating; all had identical dimensions

(half-sphere, radius 19 cm, area 1134 cm², volume 14.37 L). Three portable gas analyzers were employed for direct CO₂ and CH₄ flux measurements: a Picarro GasScouter G4301, a LiCOR LI-7810, and a Los Gatos GLA132-GGA. These three different instruments are based on cavity ring-down spectroscopy. This technique quantifies trace gas concentrations by measuring the decay time of laser light within a highly reflective optical cavity, which is proportional to molecular absorption in the sample (Crosson 2008). Each incubation provided high-frequency (every second) simultaneous measurements of CO₂, CH₄, and H₂O concentrations in the chamber headspace. All CO₂ and CH₄ time series were corrected for water vapor, expressed on a dry-gas basis, and compiled into a single database.

Tracking experts' selection of valid data

Among the team members who participated in the sampling campaigns, 17 researchers reported having sufficient experience to process incubation time series. All were familiar with collecting and processing this type of datasets and with deriving flux estimates from high-resolution incubation time series. Hereafter, we refer to this group as “experts.” All experts received the same R scripts as described in Minaudo (2026). After installing the necessary dependencies, experts were instructed to run the main script, *expert_vs_automatic_processing.R*. This script loaded the dataset of incubation time series and randomly selected 10 incubations for each program run. All participant names were anonymized, and a unique ID was assigned to each expert to prevent potential bias during analysis.

Experts were asked to:

- i. visually inspect CO₂ and CH₄ incubation time series;
- ii. flag time series exhibiting abnormal patterns that prevented safe CO₂ and CH₄ flux calculation (independently for each gas);
- iii. select data segments considered valid for flux calculation;
- iv. for CH₄, specifically identify the segment of the time series suitable for estimating the diffusive flux component only.

To proceed with data selection, plots of raw CO₂ or CH₄ concentrations were shown (Supporting Information Fig. S1.2), and experts clicked on the start and end points of the selected segments. Each expert was asked to repeat this process until at least 100 incubations had been visually inspected. During the random draw of incubations, the script first prioritized incubations not yet evaluated by any expert and then favored those with the fewest prior assessments, ensuring that most incubations were reviewed by at least three experts. At the end of each program run, selected start and end times were stored in a dedicated table.

Flux calculations

For each manual selection, CO₂ and CH₄ fluxes were calculated using the *goFlux* package (Rheault et al. 2024) with both a linear model and the nonlinear Hutchinson–Mosier model

(Hutchinson and Mosier 1981) using the HMR procedure described in Pedersen et al. (2010). Selection of the best model followed the default objective criteria implemented in *goFlux*. The nonlinear model was favored unless:

- The ratio between nonlinear and linear estimates (*g.factor*) was ≥ 2 .
- Curvature thresholds (*k.ratio* = 1) were exceeded;
- Sensor-based minimum detectable flux criteria were violated.
- The model with the smallest mean absolute error (MAE) was selected. If both models had MAE values smaller than the instrument precision, the nonlinear flux was chosen by default. If the MAE exceeded instrument precision, a warning indicated that the measurement was likely noise-dominated.

The total CH₄ flux ($F_{CH_4 tot}$) was calculated with a two-point method where the flux resulted from the net concentration change during the incubation. To avoid miscalculations due to noisy or highly variable measurements at the beginning or end of the incubation time series, the minimum and maximum values of the smoothed time series were extracted from the first and last 30 data points, respectively (*see* Supplement S2). Their difference was divided by the incubation duration ($t_{incubation}$) and multiplied by a correction factor (*flux.term*) to account for atmospheric pressure, air temperature, water vapor, chamber volume, and chamber surface area, as specified in *goFlux* (Eq. 1).

$$F_{CH_4 tot} = \frac{\max(C_{last\ 30\ s}^{smoothed}) - \min(C_{first\ 30\ s}^{smoothed})}{t_{incubation}} \cdot \text{flux.term} \quad (1)$$

The diffusive CH₄ flux ($F_{CH_4 diff}$) was estimated by applying the linear model from *goFlux* to the expert-selected diffusive segment. The ebullitive flux ($F_{CH_4 ebull}$) was calculated by difference between the total and the diffusive flux (Eq. 2).

$$F_{CH_4 ebull} = F_{CH_4 tot} - F_{CH_4 diff} \quad (2)$$

Fluxes derived from expert data selection were compared with a fully automated data processing, here considered as a benchmark model, in which no trimming of the time series was applied—that is, all observations from the measurements were retained and processed into flux estimates as described above. This fully automated calculation processed the entire dataset uniformly across all incubations. Hereafter, in both the text and figures, flux estimates based on expert data selection are denoted as $F_{variable}^{expert}$, and those derived from automatic processing as $F_{variable}^{auto}$ where variable refers to CO₂, CH_{4 tot}, CH_{4 diff}, or CH_{4 ebull}.

In the specific case of $F_{CH_4}^{auto}$ calculations, additional functions were developed to calculate the total flux and separate diffusive and ebullitive components. This was achieved using

a running-variance model to identify bubbling events and an iterative linear model to detect diffusion patterns, building on previous approaches (Hoffmann et al. 2017; Sørensen et al. 2024). First, CH₄ concentration within the chamber headspace was normalized by the mean concentration over the incubation period. Then, for a moving window of 10 data points, the running variance of the normalized concentration was computed. All observations corresponding to a running variance exceeding the 75th percentile of the variance time series (or an arbitrary minimum threshold of 10⁻⁴) were flagged as part of a probable ebullition event. Flagged data segments separated by fewer than 10 data points were merged. Flagged segments shorter than five data points were discarded.

It was considered possible for an incubation to begin with an ebullition event. In such cases, the sudden increase in CH₄ concentration within the chamber headspace may induce diffusion of CH₄ back into the water, thereby increasing the uncertainty of diffusion estimates once the rate of change in concentration stabilizes. For this reason, when a probable ebullition event was detected within the first 20 s of an incubation, diffusion and ebullition were not separated, and only the total flux was retained. Otherwise, when no bubbling event was detected during the first 20 s of an incubation, the first linear segment of the time series was used to estimate $F_{\text{CH}_4\text{diff}}^{\text{auto}}$. Fully automated $F_{\text{CH}_4\text{tot}}^{\text{auto}}$ was computed using the smoothed full time series without any trimming of the time series. The ebullitive flux $F_{\text{CH}_4\text{ebull}}^{\text{auto}}$ was calculated by subtracting $F_{\text{CH}_4\text{diff}}^{\text{auto}}$ from $F_{\text{CH}_4\text{tot}}^{\text{auto}}$ (Eq. 2).

Flux comparisons across expert and automated estimates

For each incubation assessed by at least three different experts, the mean, standard deviation, and coefficient of variation (CV) of flux estimates were computed. This enabled an objective quantification of the variability in flux estimates across expert assessments. Mean expert fluxes were also compared with the fully automated flux estimates for CO₂, CH₄ tot, CH₄ diff, and CH₄ ebull.

Nonlinearity in the incubation time series was assessed by calculating the mean absolute error (LM.MAE) of a linear regression using all available observations (i.e., without trimming). Large LM.MAE values indicate poor model fits with the linear model, reflecting either nonlinear patterns or abrupt concentration changes during the measurement period.

All data preparation, processing, and analyses were performed in R 4.5.2 (R Core Team 2025).

Assessment

Overview of experts' contributions

A total of 764 incubations were included in the dataset, which collectively underwent 2679 manual inspections by the 17 experts (Fig. 1). On average, each expert evaluated 157 incubations, with individual contributions ranging from 100 to 384. Of all incubations, 532 were inspected multiple times by different experts, receiving between 3 and 10 independent

assessments; only 3 incubations reached the maximum of 10 assessments. Some incubations were also assessed multiple times by the same expert; this occurred 221 times, of which 209 involved two assessments by the same expert and only 12 involved three or more assessments.

During these inspections, 158 time series were flagged as abnormal by at least one expert, including 73 for CO₂ and 85 for CH₄. Overall, 23 incubations were identified as abnormal for both gases. None of the incubations inspected at least three times were flagged as abnormal by all experts; in every case, at least one expert considered part of the time series suitable for flux calculation. Experts 3 and 7 were more likely than others to classify measurements as abnormal, particularly for CH₄ (Fig. 1a). To ensure consistency, we adopted a conservative approach in subsequent analyses: any incubation flagged as abnormal by at least one expert was discarded. This decision had no substantial effect on the distribution of incubations assessed more than three times. The final working dataset comprised 629 incubations.

On average, experts retained 84% of the original CO₂ measurements and 71% of CH₄ measurements (Fig. 2). Experts preserved at least 90% of the original measurements in 57% of CO₂ and 41% of CH₄ assessments. Segments shorter than half of the original record were selected in 9% of CO₂ assessments and 26% of CH₄ assessments. In the most heavily trimmed cases, experts generally retained data from the first half of the incubation, discarding later observations. Conversely, only 2% of CO₂ and 6% of CH₄ assessments involved discarding the entire first half of the record.

The data segments selected by different experts for flux calculation revealed substantial subjectivity and contrasting methodological strategies. For example, for a highly fluctuating CO₂ time series (Fig. 3a), three experts selected an extended segment of the record, whereas the other three restricted their selection to a later, more linear segment. For a curved CO₂ time series (Fig. 3b), one expert selected only the first linear segment (first 85 s), while six others retained the second half of the record. These examples highlight differing tolerance for curvature, with most experts excluding the visibly nonlinear portion.

Corresponding CH₄ time series revealed similar variability (Fig. 3c,d), with incubation 34 showing typical ebullition-related patterns (Fig. 3c) and incubation 140 displaying strong curvature similar to its CO₂ counterpart (Fig. 3d). In both cases, experts either selected the earliest linear portion as a conservative estimate of CH₄ diffusion or favored a longer linear segment later in the record. These pronounced discrepancies underscore the high subjectivity in data selection and highlight the resulting uncertainty in flux estimates.

Impact of subjective data selection on CO₂ and CH₄ flux estimates

After retaining the 498 CO₂ and CH₄ incubations that were assessed at least three times and never flagged as abnormal, we

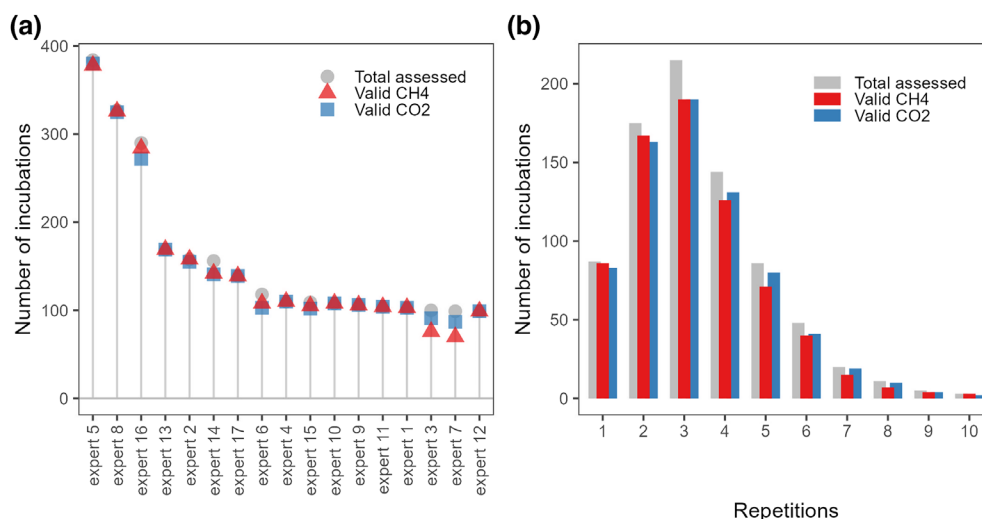


Fig. 1. Overview of experts' contributions. Total number of incubations inspected and considered valid by each of the 17 experts (a), and frequency distribution of the number of inspections per incubation for all incubations and for those considered valid (b).

evaluated how agreement among experts influenced flux estimates.

Flux estimates ranged from -0.3 to $1.0 \mu\text{mol m}^{-2} \text{s}^{-1}$ for CO_2 and from -15 to $860 \text{ nmol m}^{-2} \text{s}^{-1}$ for CH_4 tot (Fig. 4). Across all expert assessments, absolute flux variability increased with flux magnitude (Fig. 4a,d). When variability was expressed relative to the mean flux estimates (Fig. 4b), F_{CO_2} generally exhibited low variability, with the CV below 0.1 in 74% of the CO_2 time series and exceeding 0.5 in only 5% of the time series. For $F_{\text{CH}_4 \text{ tot}}$, variability was slightly higher, with $\text{CV} < 0.1$ in 68% of the time series and $\text{CV} > 0.5$ in 5% (Fig. 4e).

In some cases, experts strongly disagreed on data selection, resulting in markedly different flux estimates. Eleven F_{CO_2} and eight $F_{\text{CH}_4 \text{ tot}}$ estimates exhibited $\text{CV} > 1$, indicating major discrepancies among expert-derived fluxes. These disagreements were not associated with flux magnitude, but rather with time series characterized by high LM.MAE values, that is, poor linear model fits (Fig. 4). This suggests that the highest uncertainty arose from nonlinear behaviors, where interpreting concentration patterns was less straightforward. Despite these cases, there was overall good agreement between fluxes derived from expert data selection and those obtained using fully automated calculations that included all data points in the regression (Fig. 4c,f). This consistency indicates that, for most cases, expert-driven data selection and fully automated full-series approaches yielded comparable CO_2 and CH_4 flux estimates, with only a limited subset of nonlinear time series leading to substantial divergence. For both gases, the difference between experts' fluxes and the fully automated flux estimates was minimal when the simple fitting of incubation time series with a linear model produced low errors (Supporting Information Fig. S1.3). Conversely, when high

values of LM.MAE indicated nonlinearity, discrepancies between experts' flux estimates and the fully automated flux estimates were the highest.

Influence of ebullition on expert variability

In the dataset, ebullition contributed more than 10% of the total CH_4 flux in 81 incubations and exceeded 50% in 46 of them. Variability across $F_{\text{CH}_4 \text{ ebull}}$ estimates was not clearly related to the relative contribution of ebullition to the total flux (Fig. 5a) and remained consistently high, with a CV of 0.8 ± 0.65 (mean \pm standard deviation). For both diffusive and total CH_4 fluxes, the variability among expert assessments increased with the magnitude of the ebullition contribution (Fig. 5b,c). When ebullition accounted for 10–50% of the total CH_4 flux, the CV of $F_{\text{CH}_4 \text{ diff}}^{\text{expert}}$ was 0.24 ± 0.30 and it was 0.13 ± 0.24 for $F_{\text{CH}_4 \text{ tot}}^{\text{expert}}$. In contrast, when ebullition contributed more than 50% of the total CH_4 flux, variability rose markedly, with CV values of 0.57 ± 0.79 and 0.35 ± 0.43 for $F_{\text{CH}_4 \text{ diff}}^{\text{expert}}$ and $F_{\text{CH}_4 \text{ tot}}^{\text{expert}}$, respectively. Notably, many CH_4 time series showed minor ebullition contributions to total fluxes yet still exhibited substantial variability among experts' flux estimates.

Across the dataset, the CV of expert-derived F_{CO_2} increased with those for $F_{\text{CH}_4 \text{ tot}}$, indicating that variability within a given incubation was often mirrored across both gases (Fig. 6a). A total of 39 incubations showed a $\text{CV} > 0.4$ for $F_{\text{CH}_4 \text{ tot}}$. These incubations were all associated with moderate to high variability in F_{CO_2} , with a mean CV of 0.67. We identified that 15 of these incubations (i.e., 38%) corresponded to cases where ebullition contributed most to the total CH_4 flux. This pattern likely reflects rapid pressure changes inside the chamber headspace, a sudden change in gas composition, or spectral interference in cavity ring-down spectrometry during

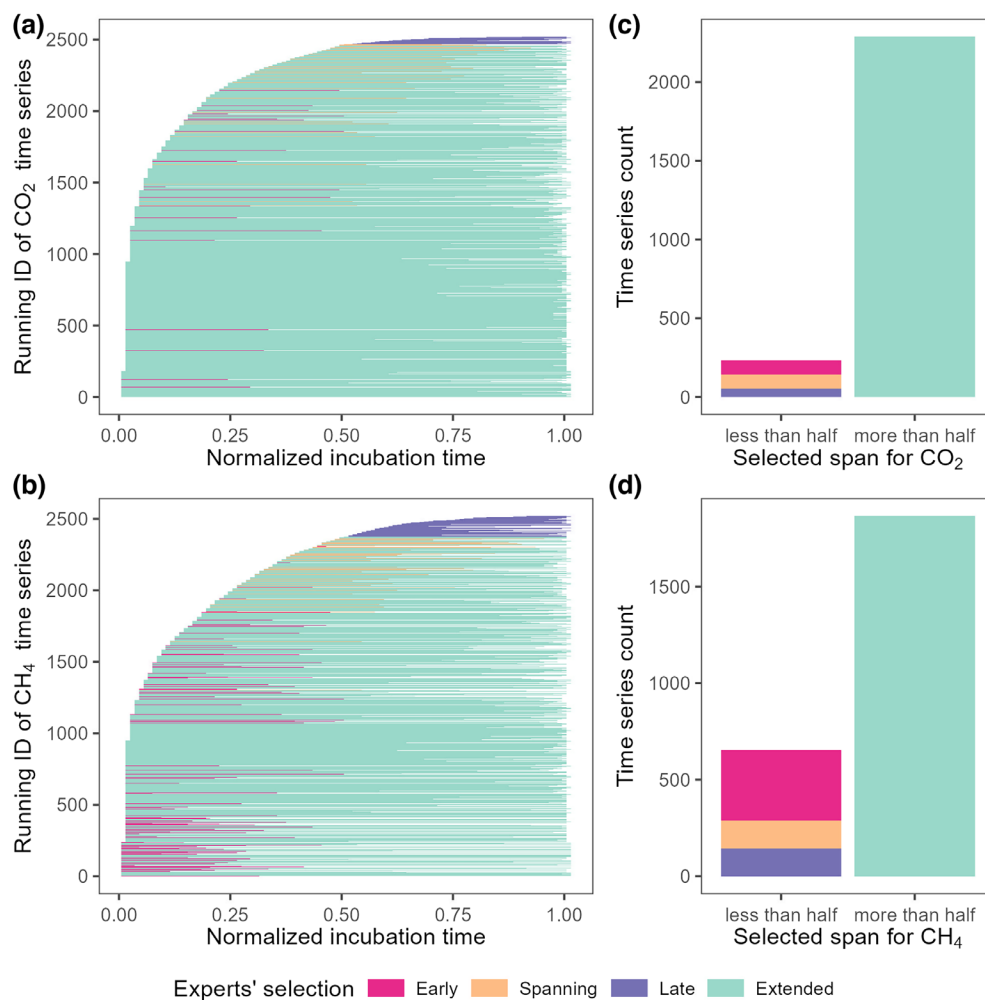


Fig. 2. Experts' selection of valid time series segments for all CO₂ (a) and CH₄ (b) incubations, ordered by the starting time of the selected data segments, normalized from 0 (start) to 1 (end). Colors indicate whether > 50% ("Extended") or < 50% of the original measurement was retained. Subcategories for < 50% indicate whether selections occurred in the early, late, or spanning portions of the time series. (c, d) Counts for each selection category.

strong CH₄ ebullition events, which can distort CO₂ concentration readings (Zhao et al. 2022) and thereby increase variability in derived CO₂ flux estimates, as illustrated by incubation 34 in Fig. 6b,c. To our knowledge, no previous studies have reported this technical issue in CO₂ flux measurements at the air–water interface of aquatic ecosystems, while our observations show this must be accounted for. High variability in flux estimates for both gases could not always be attributed to ebullition, as shown by incubation 140 in Fig. 6b,c, which exhibit a clear nonlinear pattern for both gases, leading to highly variable experts' flux estimates.

Discussion

Prevalent nonlinearities lead to high flux uncertainties

This methodological experiment provides a quantitative demonstration that expert judgment introduces substantial

uncertainty in GHG flux estimates, particularly when incubation time series exhibit nonlinear patterns. When faced with such complexities, experts adopt markedly different strategies for data selection, leading to high variability in final flux estimates. This variability highlights a critical gap in standardized guidelines and training for the processing of floating—and, by extension, static chamber data. These findings underscore the need for transparent, reproducible, and harmonized procedures to minimize subjectivity in GHG flux estimation.

Experts showed heterogeneous criteria for flagging abnormal time series. Some applied highly conservative approaches, fully discarding incubations that displayed irregular or erratic concentration changes. Others adopted more permissive criteria, retaining data segments of the time series they considered sufficiently reliable for flux calculation. Such discrepancies reveal the subjective nature of expert-driven quality

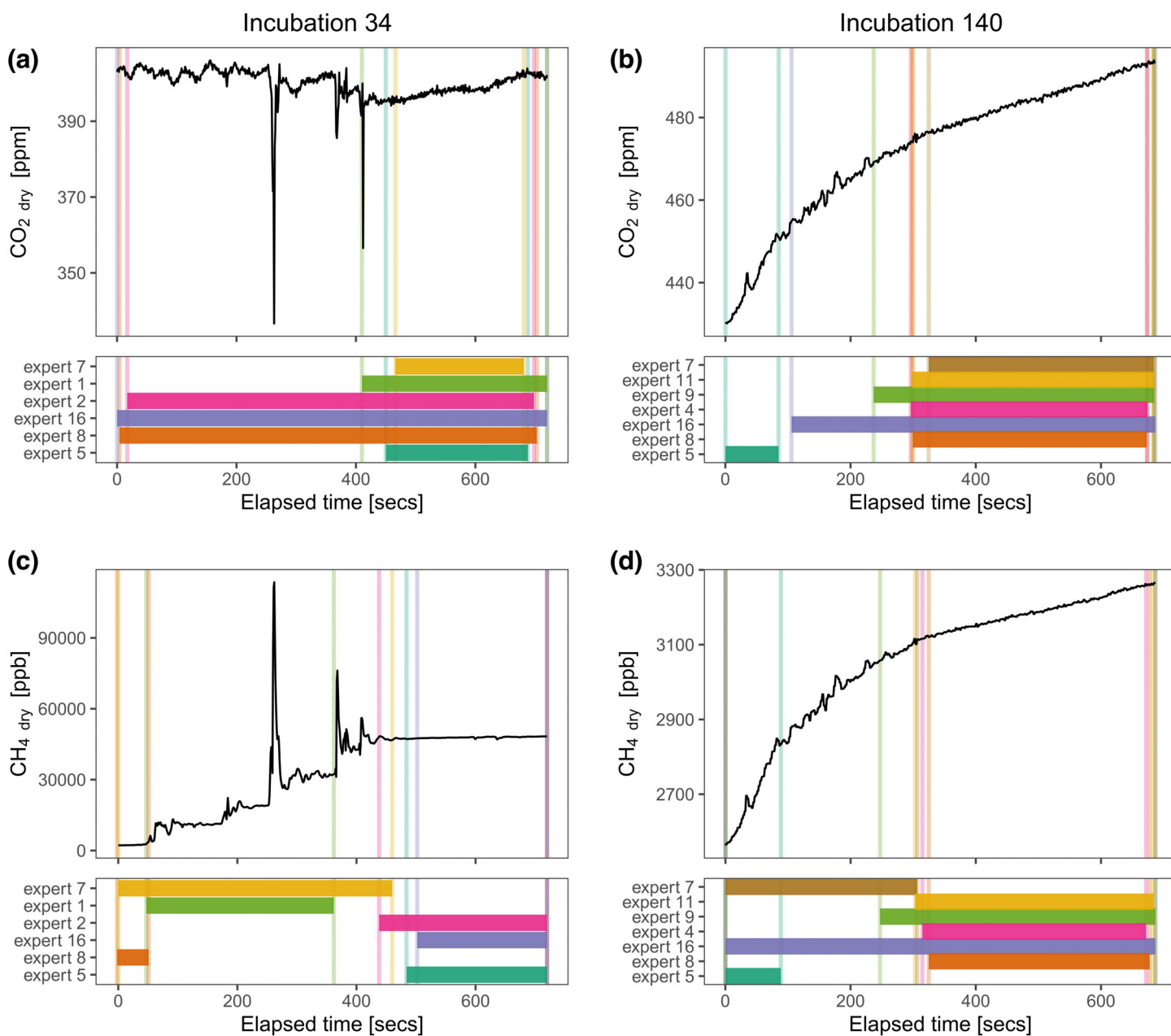


Fig. 3. Example of experts' data selection for two incubations (given IDs are 34 and 140). (a, b) CO₂ selections; (c, d) selections for estimating CH₄ diffusion. Vertical lines and horizontal bands denote each expert's start and end points.

control, which, in the absence of formal criteria, can substantially affect the reproducibility of flux datasets.

Once CO₂ or CH₄ incubation time series deviated from a strictly linear trend, expert strategies diverged further. Some relied on shortened linear fits, others manually trimmed suspect data points, while a few accepted nonlinear curve-fitting approaches. Importantly, experts did not systematically select the first linear portion of the record; in many cases, later segments were preferred if they appeared more stable or better behaved. These differing practices produced flux estimate

variabilities ranging from 10% to more than 100% across identical measurements. For CO₂, disagreements were mostly related to gradual nonlinearities, which were previously reported in several static chamber studies for both soil and aquatic measurements (e.g., Hüppi et al. 2018; Kutzbach et al. 2007; Silva et al. 2015; Xiao et al. 2016) but for which no consensus treatment currently exists for aquatic ecosystems. The lack of agreement on how to interpret curvature in concentration–time relationships remains a major source of uncertainty in CO₂ flux estimation in aquatic ecosystems

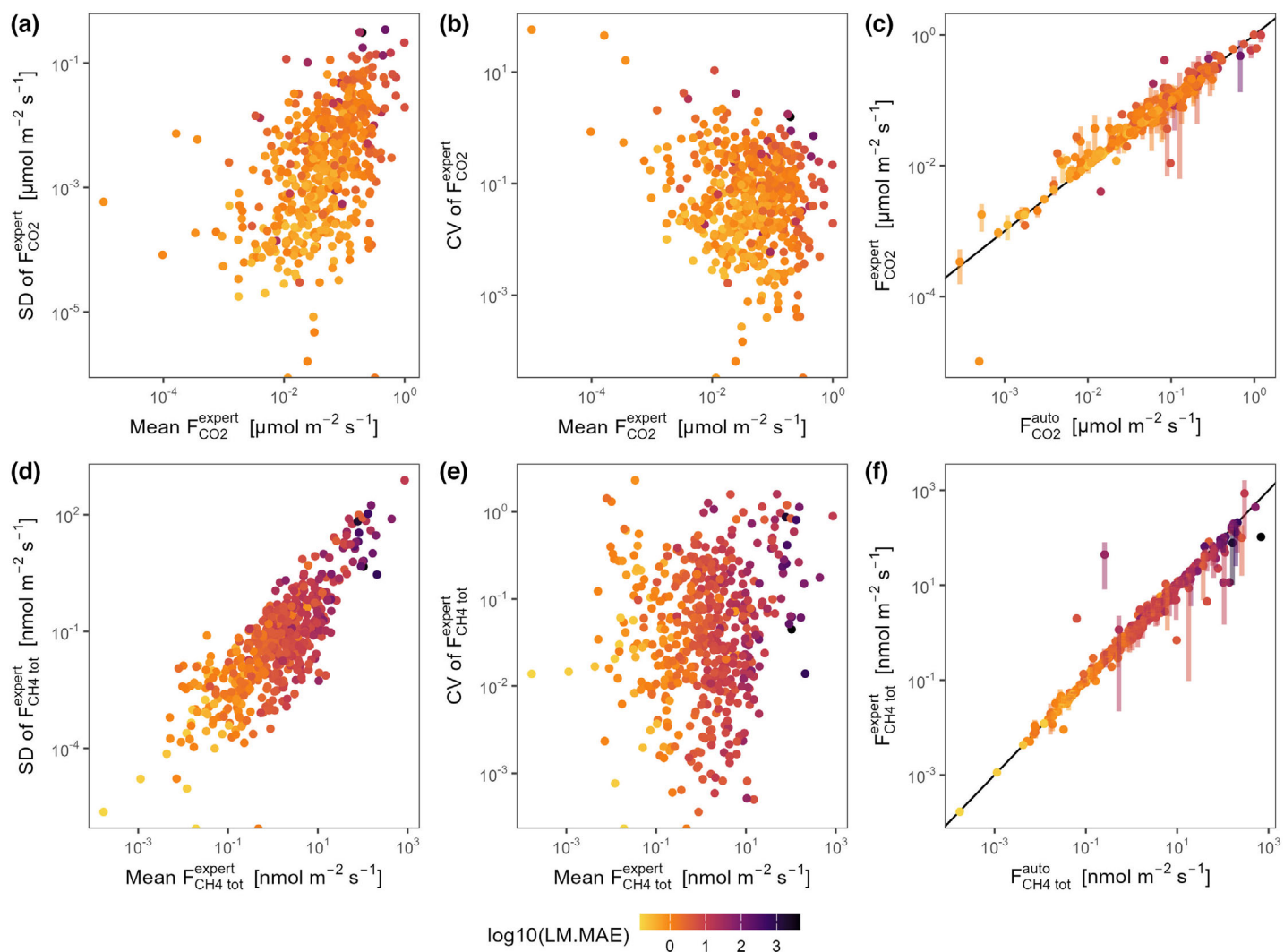


Fig. 4. Variability in expert-derived CO_2 and CH_4_{tot} flux estimates. **(a, d)** Standard deviation vs. mean; **(b, e)** CV vs. mean; **(c, f)** expert vs. fully automated estimates with 1 : 1 line indicated in solid black. Color scale indicates LM.MAE of the untrimmed incubation time series.

(Silva et al. 2015). Unlike soil chambers, where gas transport is primarily diffusion-controlled and fluxes tend to stabilize over time (Maier et al. 2022), aquatic chambers are subject to additional sources of short-term variability, including fluctuating turbulence, surface renewal processes, and rapid changes in photosynthetic and respiratory activity. These hydrodynamic and biogeochemical dynamics assume steady-state conditions—and thus linear behavior—far less tenable in aquatic systems.

For CH_4 , the situation is further complicated by ebullition, a dominant driver of abrupt, nonlinear changes in concentration time series. Differences in expert judgment when isolating diffusive patterns led to large uncertainties in both diffusive and ebullitive flux estimates. Nonetheless, even when ebullition played only a minor role, substantial variability persisted among expert-derived total and diffusive CH_4 fluxes, indicating that nonbullitive processes (e.g., fluctuating turbulence, short-term

variability in gas exchange) also contributed to interpretative divergence.

Toward an automated processing pipeline for more objectivity and reproducibility

Overall, the results of this study demonstrate that expert subjectivity can substantially influence GHG flux estimates, particularly when incubation data deviate from ideal linear behavior. These discrepancies highlight the urgent need to establish standardized, transparent data processing protocols that reduce interpretative bias. The development and adoption of automated or semi-automated processing pipelines capable of objectively identifying and addressing nonlinearities would represent a major step forward in ensuring the comparability, reproducibility, and robustness of GHG flux data across studies and ecosystems.

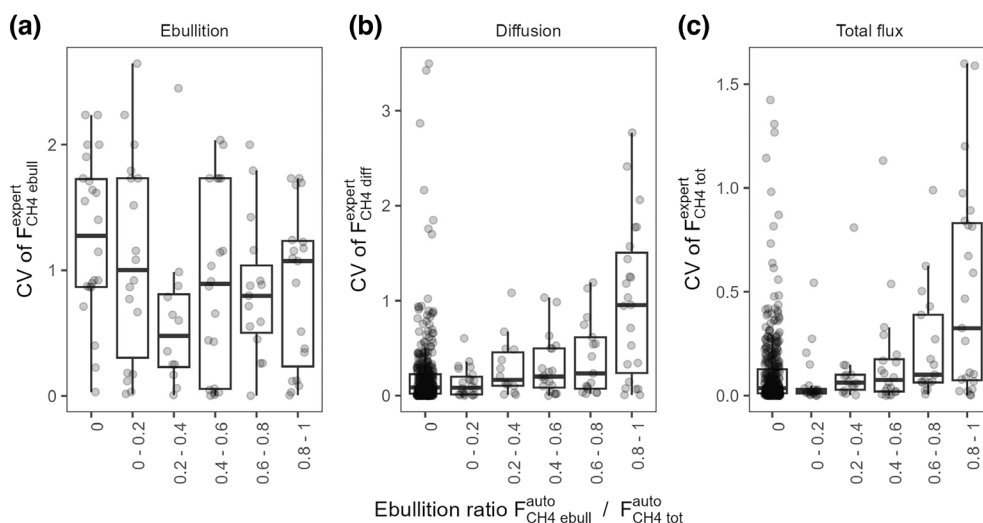


Fig. 5. Coefficient of variation of expert-derived CH₄ fluxes for different levels of ebullition contribution to the total CH₄ flux. Ebullition ratio was calculated according to the fully automated data processing.

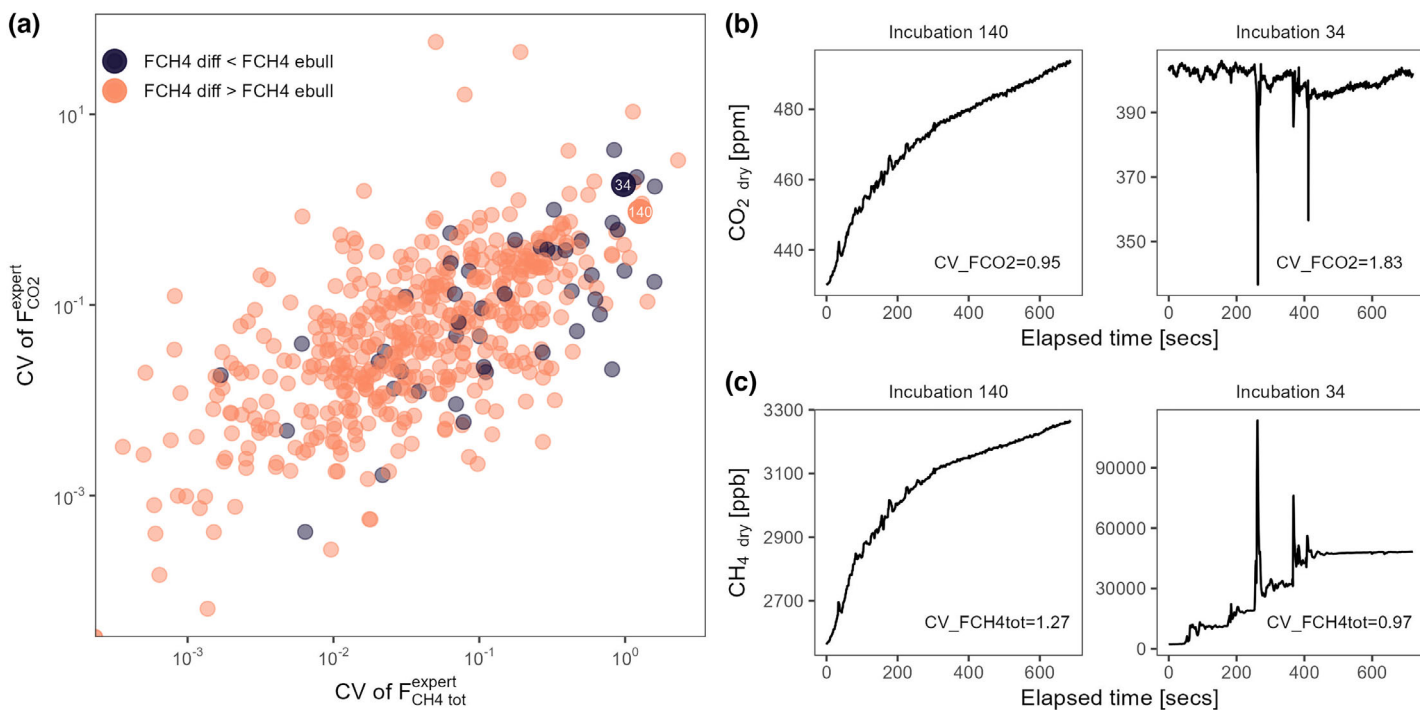


Fig. 6. (a) Coefficient of variation of expert-derived F_{CO_2} vs. CV of $F_{CH_4\ tot}$ estimates. Colors indicate diffusion-dominated (orange) or ebullition-dominated (purple) incubations. (b, c) Examples of CO₂ and CH₄ measurements corresponding to high variability in experts' flux estimates for both gases: incubation 140 (diffusion-dominated, curved) and 34 (ebullition-dominated, nonlinear pattern).

Several existing R packages, such as goFlux (Rheault et al. 2024), fluxfinder (Wilson et al. 2024), and fluxible (Gaudard et al. 2025), already incorporate algorithms designed to handle both linear and nonlinear patterns in GHG concentration time series from closed chamber measurements. These tools follow clear and reproducible workflows to automatically load and process raw measurements and derive flux estimates.

They typically include features for detecting abnormal measurements or outliers, fitting multiple candidate models, and comparing statistical performance metrics to select the most appropriate model for flux estimation. Such structured approaches substantially reduce operator influence, ensuring that results can be consistently reproduced and objectively compared across datasets.

While some degree of subjectivity remains—particularly in the selection of models or the criteria used to determine the best fit—the reproducibility of the computational workflow itself is guaranteed (Gaudard et al. 2025). This reproducibility is essential to building confidence in flux estimates, especially when results are used to upscale site-level observations to ecosystem, regional, national, or global assessments. Since international regulations request the reporting of complete national inventories of GHG fluxes from all sources, including ecosystems (e.g., European Union Regulation 2021/1119, 2021), transparent and standardized pipelines therefore play a key role in improving both the credibility and traceability of aquatic GHG budgets.

It is important to note, however, that all these tools were originally developed for terrestrial ecosystem measurements, and none are yet fully tailored to the specific characteristics of aquatic environments. Differences in turbulence dynamics, boundary-layer processes, and the prevalence of phenomena such as ebullition require adaptation and careful parameterization. As such, there is a clear need for the aquatic research community to reach consensus on best practices for implementing, validating, and potentially extending these automated frameworks. Doing so would facilitate the development of a harmonized, community-endorsed pipeline for flux data processing, enhancing both scientific rigor and cross-study comparability in aquatic GHG research.

Conclusions and recommendations

In the context of global change, effective climate action relies on robust and transparent data to inform policy and guide mitigation strategies. Inland waters contribute significantly to GHG emissions, yet their role remains under-constrained, in part due to methodological inconsistencies. This study demonstrates that expert judgment in the processing of floating-chamber incubations can introduce substantial and previously unquantified uncertainty.

Building on the insights from this methodological experiment, we propose the following practical guidelines to enhance consistency, transparency, and reproducibility in the processing of aquatic GHG incubation time series:

1. Understand the theoretical foundations of chamber-based flux estimation.

Researchers should ensure a sound understanding of the physical and mathematical principles underlying static and floating chamber techniques. A comprehensive overview is provided by Xiao et al. (2016), who detail the assumptions and limitations associated with different modeling approaches. Such theoretical grounding is essential for correctly interpreting concentration–time relationships and identifying cases where standard assumptions (e.g., steady-state diffusion) may be violated.

2. Tolerate curved patterns and explicitly justify model selection.

Nonlinear concentration changes are common in chamber measurements, and linear regressions can substantially underestimate fluxes when curvature is present (Silva et al. 2015; Xiao et al. 2016). Rather than automatically discarding nonlinear series, researchers should explore multiple models (e.g., exponential, quadratic) and document the criteria used to justify the final model choice. Reporting such criteria enhances transparency and allows others to reproduce or reassess flux estimates.

3. Recognize and appropriately treat complex measurement patterns.

Portable gas analyzers can produce noisy or unstable readings, especially under fluctuating field conditions, typical of aquatic environments. Abrupt variations in concentration data do not necessarily invalidate the entire incubation. For example, in CH₄ measurements, ebullition events can generate short-lived spikes, yet total fluxes can still be computed and, under reasonable conditions (see Guideline 4 below), it may remain possible to separate fluxes into diffusive and ebullitive components. Researchers should therefore carefully assess whether noise reflects instrument artifacts or real environmental dynamics before rejecting data.

4. Use the early linear segment to estimate diffusive CH₄ fluxes.

When ebullition occurs, back-diffusion of CH₄ in the chamber headspace can bias diffusion flux estimates if a linear pattern later in the time series is used. To avoid this, researchers should rely on the first linear segment of the time series to estimate the diffusive flux component. We do not recommend any attempt for diffusion/ebullition separation if an incubation time series starts immediately with an ebullition event.

5. Consider cross-gas interference from ebullition events.

Ebullition can also affect CO₂ time series, particularly as highly elevated CH₄ concentration and rapidly changing pressure and moisture during ebullition events interferes with CO₂ readings of cavity ring-down spectrometers (Zhao et al. 2022). In such cases, the underlying diffusive CO₂ signal often remains recoverable between ebullition events, and identifying these stable intervals can preserve valuable information otherwise lost through complete data exclusion.

6. Apply established, standardized data processing tools.

Several R packages now provide frameworks for data harmonization, quality control, and flux estimation, including goFlux (Rheault et al. 2024), fluxfinder (Wilson et al. 2024), and fluxible (Gaudard et al. 2025). These tools implement reproducible workflows for reading raw data, identifying

outliers, and fitting models. Despite prior works on the automatic separation of methane flux into diffusion and ebullition components (Hoffmann et al. 2017; Sørensen et al. 2024), there is currently no framework for the automatic processing of floating chamber time series. The scripts developed for the purpose of the present study can serve as a basis for this (see Data and code availability section below).

7. Prefer harmonized workflows over ad hoc treatments.

Whenever possible, use a consistent data processing pipeline for all incubations rather than relying on subjective, case-by-case decisions. Harmonized workflows not only improve comparability between datasets but also reduce the risk of hidden biases introduced by individual interpretation.

8. Ensure transparency and reproducibility to improve accuracy.

Finally, all steps in data selection, model fitting, and flux estimation should be fully documented and reproducible, ideally through shared code and raw and processed data. Transparent methodologies are essential for building confidence in flux estimates and for enabling robust data synthesis across research groups and ecosystems.

Although this study focuses on variability arising from data processing, it is important to recognize that uncertainty in GHG flux estimates also originates from earlier stages of the measurement process. Standardized operating procedures are needed throughout all steps preceding and during field measurements, including the selection of chamber dimensions and materials (Mannich et al. 2019), the deployment setup, and the duration and timing of incubations. Variability in these parameters can influence chamber temperature, mixing dynamics, and gas accumulation rates, ultimately affecting flux estimates. Establishing clear methodological standards alongside automated data-processing pipelines would therefore ensure greater comparability and reproducibility of GHG flux measurements across studies and ecosystems.

Author Contributions

Camille Minaudo: conceptualization, methodology, software, formal analysis, investigation, writing—original draft. Miguel Cabrera-Brufau and Jorge Juan Montes-Pérez: methodology, validation. All authors: resources, data curation, writing—review and editing. Daniel von Schiller: supervision.

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Data Availability Statement

All the raw incubation time series are made available in a dedicated Zenodo repository (<https://doi.org/10.5281/zenodo.17828220>). All R scripts to proceed with the data preparation, the interactive data selection, and the data processing for this manuscript are accessible in a dedicated GitHub repository archived at <https://doi.org/10.5281/zenodo.18710431>.

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Supporting Information

Additional Supporting Information may be found in the online version of this article.

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