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BRIDGING MEASUREMENT AND MODELLING: HYBRID PATHWAYS FOR ACCURATE RESERVOIR GHG QUANTIFICATION

Research paper

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Abstract: Reservoir greenhouse gas (GHG) quantification remains methodologically difficult because emissions are spatially heterogeneous, temporally dynamic and distributed among diffusion, ebullition, degassing and downstream pathways. Field measurements provide indispensable process-level evidence but are difficult to extrapolate, whereas empirical and process-based models extend estimates beyond sampled locations at the cost of structural and input uncertainty. This conference paper develops a focused measurement-to-model framework for integrating these complementary information streams. Building on recent comparative evidence, the proposed pathway combines targeted field observations, Earth-observation products, reservoir and catchment descriptors, mechanistic constraints and data-driven inference within an iterative validation and uncertainty-assessment loop. Particular attention is given to pathway-specific calibration because model–measurement disagreement is not uniform: methane ebullition and carbon dioxide diffusion can be substantially less predictable than methane diffusion. A three-tier implementation strategy is proposed, progressing from low-cost screening through targeted field validation to adaptive hybrid monitoring, reporting and verification (MRV). The framework is intended to preserve site specificity where it matters while enabling spatial and temporal scaling across reservoir portfolios. Rather than replacing measurements with models, hybrid quantification uses measurements to constrain model behaviour and models to direct subsequent observations. This architecture offers a practical route toward more transparent, updateable and decision-relevant reservoir GHG estimates for hydropower sustainability assessment and climate reporting.

Key words: reservoir emissions, methane, carbon dioxide, hybrid modelling, remote sensing, machine learning, uncertainty

INTRODUCTION

Hydropower is commonly treated as a low-carbon electricity source, yet the climate performance of individual reservoir systems can differ markedly. Flooded organic matter, catchment-derived carbon and in-reservoir production are transformed under reservoir-specific thermal, redox and hydrodynamic conditions, generating carbon dioxide (CO_2) and methane (CH_4) that may reach the atmosphere through several distinct pathways. Diffusive exchange at the water surface, CH_4 ebullition, degassing at turbines and spillways, and downstream emissions operate at different spatial and temporal scales and respond differently to climate, morphology and reservoir operation. Consequently, a single emission factor or a short field campaign cannot be assumed to represent the full reservoir carbon signal (Deemer et al., 2016; Prairie et al., 2021; Seth et al., 2026).

The central methodological problem is therefore not simply how to measure reservoir emissions, but how to connect observations made at limited locations and times with models capable of representing unobserved conditions. Direct measurements remain essential because they resolve actual fluxes and provide the reference against which other methods are tested. Their spatial footprint, however, is restricted and intensive monitoring is expensive. Empirical models are readily transferable but simplify dynamic controls; process-based models preserve mechanistic relationships but require extensive parameterisation; remote sensing broadens spatial and temporal coverage but mostly observes environmental proxies rather than GHG flux directly; and machine-learning (ML) methods can learn nonlinear relationships

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while remaining dependent on representative training data and explicit validation (Seth et al., 2026).

Recent model–measurement comparisons illustrate why integration is necessary. Across six hydropower reservoirs in the southeastern United States, Pilla et al. (2025) found that agreement depended strongly on the emission pathway: CH_4 diffusion was comparatively well constrained, whereas CH_4 ebullition and CO_2 diffusion showed substantially greater disagreement and uncertainty. At a different decision scale, Janus et al. (2025) demonstrated that incorporating reservoir-emission models into hydropower planning can alter project portfolios and reduce the carbon footprint of new development. These studies point to the same requirement: emission estimates must be sufficiently scalable for planning, but their confidence depends on observations that expose pathway-specific model weaknesses.

This paper develops a concise hybrid framework for reservoir GHG quantification designed specifically around that measurement–model interface. Unlike a broad review of available methods, the objective is to define how complementary data streams can be organised into an iterative workflow for screening, calibration, validation, spatial–temporal scaling and uncertainty reporting. The proposed architecture is intended as a practical basis for reservoir-level assessment and for monitoring, reporting and verification (MRV) systems that can be updated as new observations become available.

METHODOLOGICAL BASIS

Reservoir emission pathways and observation requirements

Reservoir GHG assessment is complicated by the fact that the principal emission pathways are not sampled in the same way. Surface diffusion is commonly quantified from floating chambers, eddy-covariance systems or dissolved-gas concentrations combined with gas-transfer formulations. Ebullition is episodic and spatially clustered and therefore requires approaches capable of resolving bubbles and sediment-associated hotspots. Degassing depends on dissolved gas concentrations and hydraulic passage through turbines or spillways, while downstream emissions require measurements below the dam and consideration of gas exchange along the receiving river. A monitoring design that resolves only one pathway may therefore provide a precise but incomplete estimate of the reservoir total.

As illustrated in Fig. 1, reservoir GHG release is the end result of interacting external drivers, biogeochemical production processes and several transport pathways. This process-oriented view is important because diffusion, ebullition and downstream degassing respond differently to environmental forcing and therefore should not be treated as interchangeable components of a single bulk flux.

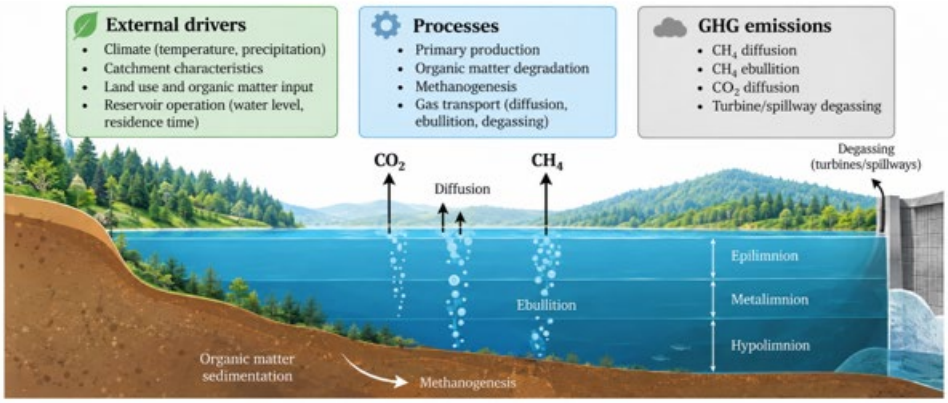


Fig. 1. *Key processes and pathways of GHG emissions from reservoirs*

From method comparison to functional integration

The value of a hybrid framework lies in assigning a specific function to each information source rather than combining methods indiscriminately. Field observations should anchor flux magnitude and pathway partitioning. Earth-observation products can characterise variables that are spatially continuous or repeatedly observable, including reservoir surface area, water-surface temperature, catchment land cover and selected optical water-quality indicators. Reservoir morphology, hydrology, meteorology and operational data provide additional explanatory variables. Process knowledge then constrains physically implausible relationships, while statistical or ML components can capture residual nonlinearities and extend inference to unsampled periods or reservoirs. This division of roles reduces the risk that a flexible model merely reproduces correlations without respecting reservoir processes.

Table 1. *Functional roles of complementary components in a hybrid reservoir GHG framework*

Component	Primary contribution	Main limitation	Best role in hybrid system	Uncertainty control
Field measurements	Observed fluxes and pathway partitioning	Sparse spatial/temporal coverage	Calibration and independent validation	Replication; seasonal coverage; QA/QC
Remote sensing	Spatially repeated environmental descriptors	Mostly indirect proxies of GHG flux	Scaling and hotspot stratification	Cloud/sensor screening; cross-validation
Empirical models	Rapid screening with limited inputs	Static relationships; domain dependence	First-pass estimates and benchmarks	Report applicability domain
Process-based models	Mechanistic and time-resolved representation	High data and calibration demand	Physical constraints and scenario analysis	Parameter sensitivity; mass-balance checks
ML / data-driven models	Nonlinear integration of heterogeneous predictors	Training bias and limited interpretability	Residual learning and spatial–temporal scaling	Independent testing; XAI; domain checks

PROPOSED HYBRID MEASUREMENT–MODEL PATHWAY

The proposed architecture is organised as a closed loop rather than a one-way progression from data collection to prediction (Figure 2). Four input groups are considered: (i) field observations of fluxes and dissolved gases; (ii) Earth-observation variables; (iii) mechanistic knowledge describing gas production, transport and exchange; and (iv) auxiliary information describing climate, catchment, morphology, hydrology and operation. These inputs converge in a hybrid inference layer in which mechanistic constraints and data-driven relationships are combined. Model outputs are then subjected to independent validation and explicit uncertainty analysis. The resulting diagnostics are used to identify where additional measurements are most informative, thereby updating the next monitoring cycle.

The integration logic shown in Fig. 2 follows this complementarity: field observations provide calibration and validation, remote sensing and auxiliary information extend spatial and temporal coverage, and empirical, process-based and machine-learning models provide alternative inference structures. Their combination is most useful when bias correction and uncertainty propagation are retained as explicit steps rather than applied only after model fitting.

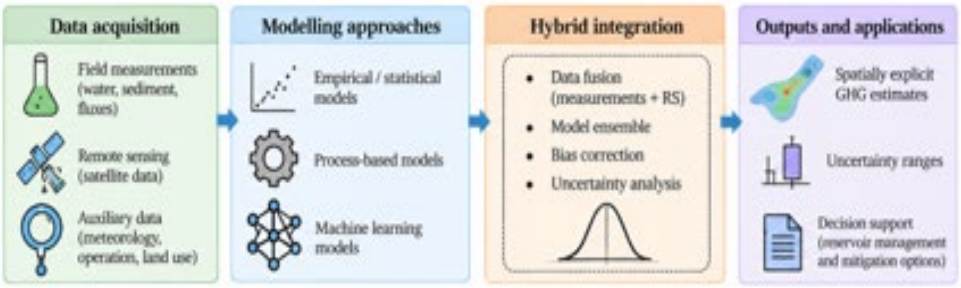


Fig. 2. *Conceptual framework for integrating measurements and modeling for reservoir GHG quantification*

Pathway-specific calibration and validation

A central design principle is that validation should be performed by emission pathway before reservoir totals are aggregated. This follows directly from empirical evidence showing that model performance can differ substantially among diffusion, ebullition and degassing. Pilla et al. (2025), for example, reported relatively low sensitivity of CH_4 diffusion to the choice of modelled versus observed data source, while CH_4 ebullition exhibited much greater variability and CO_2 diffusion showed systematic disagreement between G-res estimates and field surveys at the six reservoirs examined. Aggregating pathways too early can conceal compensating errors: an apparently plausible total may arise from overestimation of one component and underestimation of another. Hybrid calibration should therefore retain pathway-resolved outputs wherever the available data allow.

Mechanistic constraints and data-driven correction

Hybridisation can occur at several levels. In a sequential configuration, a process-based or empirical model provides a baseline estimate and ML is trained on residual errors using meteorological, hydrological, optical or operational predictors. In a constrained-learning configuration, known physical relationships or feasible ranges are incorporated into the model structure or loss function. A third option is ensemble inference, in which several models contribute to a combined estimate weighted by their validation performance and domain similarity. For reservoir applications, the first two configurations are particularly attractive because they preserve a traceable baseline while allowing the model to respond to environmental conditions not represented adequately by static emission factors.
Explainability should be treated as part of validation rather than as a cosmetic post-processing step. Feature-attribution methods can identify whether predictions are controlled by variables that are scientifically plausible, such as temperature, organic-carbon availability, water level, residence time or catchment characteristics. Such diagnostics cannot prove causality, but they can reveal unstable or non-transferable model behaviour before estimates are used for reporting or planning. The model should also report whether a prediction lies within the environmental domain represented by the training data; extrapolation to novel climates or reservoir types should carry a correspondingly larger uncertainty.

A TIERED IMPLEMENTATION STRATEGY

Not every reservoir requires the same monitoring intensity. A practical programme can therefore be organised into three tiers (Figure 3). Tier 1 uses existing reservoir descriptors, climate data and Earth observation to generate screening estimates and identify systems likely to warrant additional attention. Tier 2 adds targeted field campaigns designed around seasons, spatial zones and emission pathways that contribute most to uncertainty. Tier 3 is reserved for high-priority reservoirs, where repeated or continuous observations support adaptive model

updating and formal MRV. Movement between tiers should be driven by uncertainty and decision relevance rather than reservoir size alone.

Figure 3 is intentionally illustrative rather than a new empirical result. It summarizes two recurring features reported across the reservoir literature: pronounced seasonal variation in methane pathways and substantial between-method dispersion. The purpose is to show why temporally sparse measurements and single-model estimates can produce different reservoir-scale conclusions, thereby motivating the hybrid framework proposed here.

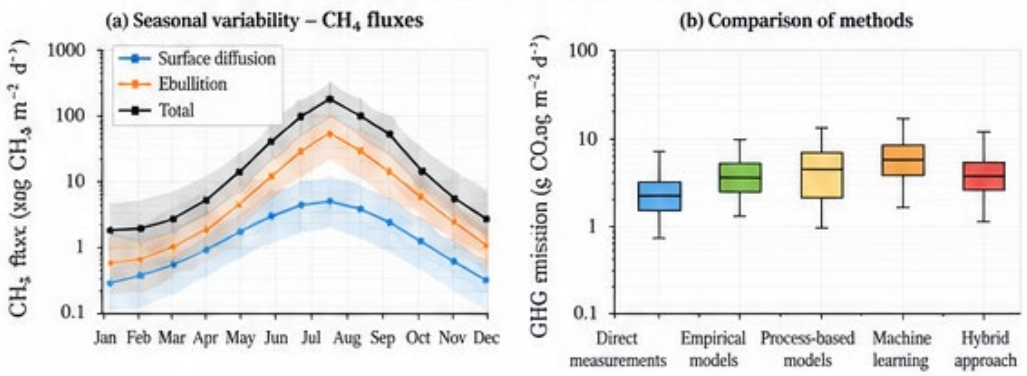


Fig. 3. *Schematic illustration of (a) seasonal variability in CH_4 emission pathways and (b) inter-method variability in reservoir GHG estimates. The graphical ranges are illustrative and are intended to represent patterns commonly reported in the literature rather than a quantitative meta-analysis*

Table 2. Suggested minimum information and outputs across implementation tiers.

Tier	Typical inputs	Field effort	Principal output	Decision use
1 Screening	Climate, morphology, catchment, operation, EO	None or legacy data	Prior emission range + hotspot/data-gap flag	Portfolio prioritisation
2 Targeted validations	Tier 1 + seasonal pathway-resolved measurements	Campaign-based	Calibrated site estimate + pathway uncertainty	Project assessment / model correction
3 Adaptive MRV	Tier 2 + repeated/continuous sensing and model updates	Long-term / adaptive	Time-resolved estimate + auditable uncertainty	Reporting, mitigation and operational management

DISCUSSION

The proposed framework differs from a conventional method-selection exercise in one important respect: it assumes from the outset that no single method should be expected to satisfy simultaneously the requirements for local accuracy, spatial representativeness, temporal resolution, interpretability and scalability. This position is consistent with the comparative synthesis of Seth et al. (2026), but the present framework translates that conclusion into an operational sequence. Measurements are not treated as an alternative to modelling; they constrain the model, test its failure modes and determine where subsequent observations should be placed. Conversely, models are not used merely to fill gaps; they organise the monitoring problem by indicating which variables, locations and periods are most informative.

The need for this iterative structure is reinforced by the magnitude and direction of model–measurement discrepancies reported in recent studies. Pilla et al. (2025) observed that the

same reservoir could appear differently depending on the emission pathway and data source, with particularly high uncertainty for ebullition and marked disagreement in CO_2 diffusion. Such results caution against validation based only on total CO_2-equivalent emissions. They also support spatially stratified sampling near inflows, shallow productive zones, deep-water areas and dam outlets, because these locations represent different biogeochemical and hydraulic controls. Long-term measurements are equally important where seasonality or episodic events dominate the annual budget.

Remote sensing and ML are valuable primarily because they can extend this sparse observational foundation. Satellite data can provide repeated information on reservoir extent, thermal conditions, catchment state and optically detectable water properties over large areas, while ML can integrate these variables with field and operational records. Nevertheless, remote sensing generally does not measure reservoir GHG flux directly, and a highly accurate statistical fit within the training dataset does not guarantee transferability to a new climatic or morphological domain. Hybrid models should therefore retain explicit provenance for every input, separate calibration from independent testing, and accompany predictions with uncertainty and applicability-domain information.

For hydropower planning, the benefit of improved quantification is not limited to more accurate inventories. Janus et al. (2025) showed that reservoir-emission modelling can be incorporated directly into project planning and portfolio optimisation, demonstrating that emissions information can influence infrastructure choices before impoundment. The same principle can be extended to existing reservoirs: pathway-resolved models can help identify whether mitigation should focus on organic-matter inputs, water-level management, turbine withdrawal depth, degassing zones or other operational controls. In this sense, a hybrid MRV system becomes not only an accounting tool but also a learning system for mitigation.

Several limitations should be recognised. First, the framework presented here is conceptual and does not prescribe a universal algorithm. The appropriate model architecture depends on the quantity and quality of available observations. Second, uncertainty cannot be eliminated through data fusion; poorly characterised inputs may instead propagate through several model layers. Third, methodological complexity must remain proportional to the decision being supported. A screening assessment for a large reservoir portfolio does not require the same monitoring density as a site-specific carbon-accounting study. The tiered structure is intended to make that distinction explicit.

CONCLUSION

Reliable reservoir GHG quantification requires a transition from isolated methods toward an integrated measurement–model system. Field observations provide the empirical anchor, mechanistic models preserve process consistency, Earth observation expands environmental coverage, and data-driven methods support nonlinear scaling across space and time. Their combination is most useful when validation remains pathway-specific, uncertainty is propagated transparently and model applicability is checked before extrapolation.

The three-tier strategy proposed here offers a practical route from broad screening to targeted validation and adaptive MRV. Its central principle is iterative: observations constrain models, model diagnostics direct new observations, and both are updated as reservoir conditions and available data evolve. Such a framework can improve the credibility of reservoir carbon accounting while keeping monitoring effort aligned with decision relevance. Future work should test the architecture across contrasting climatic regions and reservoir types using harmonised, openly documented datasets and independent validation periods.

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