Journal Pre-proof

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PII: S2667-0100(26)00118-6
DOI: https://doi.org/10.1016/j.envc.2026.101524
Reference: ENVC 101524

To appear in: *Environmental Challenges*

Received date: 27 March 2026
Revised date: 13 May 2026
Accepted date: 14 May 2026

Highlights

- Tier 1, Tier 2, and Tier 3 comparison for CH_4 estimation in Vietnamese rice fields
- Tier 3 applies two biogeochemical process-based models: DNDC and LandscapeDNDC
- Tier 2 remains a practical choice with acceptable accuracy under limited data
- Tier 3 shows marked superiority when detail management data are available
- Process-based models show rising potential as national activity datasets are improving

Quantifying methane emissions from rice cultivation in Vietnam: A site-level evaluation of IPCC Tier 1–3 approaches for inventory design

Chien Nguyen[a,b], David Kraus[a,*], Tanh Nguyen[a,c,f], Reiner Wassmann[d], Klaus Butterbach-Bahl[a,e], Thi Bach Thuong Vo[d], Van Trinh Mai[b], Thi Phuong Loan Bui[b], Ralf Kiese[a]

[a] Institute of Meteorology and Climate Research – Atmospheric Environmental Research, Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany
[b] Institute for Agricultural Environment, Vietnam Academy of Agricultural Sciences, Hanoi, Vietnam
[c] Climate Change Institute, An Giang University, An Giang, Vietnam
[d] International Rice Research Institute (IRRI), Los Baños, Laguna, Philippines
[e] Pioneer Center Land-CRAFT, Department of Agroecology, University of Aarhus, Aarhus, Denmark
[f] Vietnam National University, Ho Chi Minh City, Vietnam

[*] Corresponding author. E-mail address: david.kraus@kit.edu, Address: Kreuzeckbahnstraße 19, 82467 Garmisch-Partenkirchen, Germany

Abstract:

Rice cultivation is the largest source of CH_4 emissions in Vietnam's agricultural sector, making robust quantification essential for national GHG inventories and mitigation planning. This study compares three IPCC approaches for estimating CH_4 emissions from Vietnamese rice systems: Tier 1 (global emission factors, EFs), Tier 2 (national EFs), and Tier 3 (two process-based biogeochemical models, DNDC and LandscapeDNDC). Model estimates were evaluated against a site-level CH_4 dataset, grouped by the availability of local soil data and full-year management records. Tier 1 underperformed across all sites. Tier 2 showed moderate and relatively stable agreement with observations for both the full dataset (R^2 = 0.31; NSE = 0.27) and better-documented sites (R^2 = 0.27; NSE = 0.21). In contrast, Tier 3 accuracy depended strongly on information from both the evaluated and preceding season. For DNDC, NSE (R^2) improved from 0.25 (0.30) at data-limited sites to 0.41 (0.47) at better-documented sites; for LandscapeDNDC, NSE (R^2) increased from 0.24 (0.44) to 0.65 (0.71). Under complex water management (e.g. multiple drainage events), Tier 3 performance declined; a simple input perturbation showed that uncertain soil hydrologic properties strongly affect simulated CH_4, making it difficult to determine whether the reduced performance reflects model limitations or input uncertainty. For inventory design, Tier 2 currently offers a practical balance between accuracy and data requirements and should remain the backbone of national reporting. Targeted Tier 3 applications can add value where full-year management information and basic soil data are available, especially for analysing temporal emission dynamics and evaluating mitigation options.

Keywords: GHG inventory; CH4 emissions; rice cultivation; IPCC Tier approaches; process based models; DNDC; LandscapeDNDC

1. Introduction

Rice is the primary staple food for over half the world's population. It is grown in over 100 countries, and supplies up to 50% of daily caloric intake for Asian populations [1–3]. In Vietnam, rice has been cultivated for over 4,000 years and has become a deeply rooted part of the nation's history and culture [4]. In 2023, Vietnam recorded a harvested rice area of about 7.1 million hectares and a production of over 43 million tons [5], ranking third in the region of SE Asia [6]. Rice production accounts for 30% of the total value of Vietnam's agricultural production and thus is a major component of the agricultural sector, which contributes 24% to the GDP and 20% to total exports [7]. In terms of volume, Vietnam is the world's fifth-largest producer and third-largest rice exporter, with 8.13 million metric tons exported globally in 2023 [8].

Beyond its socio-economic importance, rice cultivation has also become a focal point in discussions on environmental sustainability. Globally, irrigated rice cultivation is recognized as one of the largest anthropogenic sources of methane (CH_4), resulting from the anaerobic decomposition of organic matter in submerged soils [9]. Emissions of CH_4 from rice cultivation during 2008–2019 are consistently estimated at 25 – 38 Tg CH_4 yr^{-1}, accounting for 7–10 % of total anthropogenic methane release [10,11]. In Vietnam, the latest national greenhouse gas (GHG) inventory estimated CH_4 emissions from rice cultivation at 1.8 Tg in 2016, accounting for approximately 11.6% of the total GHG emissions [12]. CH_4 emissions show strong spatial and seasonal variability, with the average daily emission rate ranging from 1.7 to 3.9 kg CH_4 ha^{-1} d^{-1} across regions and cropping seasons, reaching higher values in late-year crops and in the Mekong River Delta [13].

Given its high GHG emissions, potential mitigation practices have been introduced and applied in Vietnam's rice systems, including alternate wetting and drying (AWD), mid-season drainage, and optimized residues and fertilizer application [14–16]. Additionally, the Vietnamese government has made notable efforts to develop the institutional framework required to fulfill its international climate commitments, including the national goal of achieving net-zero emissions by 2050. Recently, two major programs have further operationalized national policy framework for low-emission rice production: Decision No. 1490/QD-TTg (2023), which targets to develop one million hectares of high-quality, low-emission rice in the Mekong Delta by 2030 and to reduce GHG emissions by at least 10 % compared with conventional cultivation [17]; and the Decision No. 4024/QD-BNNMT (2025), which sets a nationwide target to cutdown GHG emissions from crop production by at least 15 % by 2035 relative to 2020 levels [18]. However, implementing such targeted mitigation strategies requires an in-depth understanding of the sources, timing, and drivers of CH_4 emissions, which in turn relies on an accurate quantification of the emissions and underlying management data [19].

The Intergovernmental Panel on Climate Change (IPCC) provides methodologies to help countries consistently and transparently quantify and report their national GHG emissions from rice cultivation. The IPCC guidelines distinguish three tiers of calculation approaches, which vary in complexity and data requirements. Tier 1 applies a set of global default emission factors (EF), providing coarse but accessible estimates under limited activity data availability. Tier 2 improves accuracy by incorporating country-specific emission factors that better reflect local to regional conditions of climate, soil types, and management practices, and, if available, season-specific data. Although IPCC Tier 1 and Tier 2 EFs are primarily developed for regional or national-scale estimations [9], they are currently applied at site or household scale in Vietnam due to constraints in financial and technical resources [20,21]. Applying Tier 1 and Tier 2 across multiple sites, rather than at a single field, can help reveal systematic biases relative to observations and provides more robust insight than purely site-specific use. However, a methodological gap for quantifying emission reductions remains, as such applications do not meet the eligibility and environmental integrity requirements of international carbon standards (e.g., Verra or Gold Standard), making it difficult for smallholder mitigation efforts to translate into tradable carbon credits [20]. Tier 3 methods use models that simulate site-specific biogeochemical processes affecting GHG emissions. In the case of this study, in rice paddies at up to a daily time scale. This approach offers the highest potential accuracy but requires high-quality comprehensive input data on agricultural practices, soil conditions, and climate, as well as advanced modeling capabilities [22–24].

Several process-based models have been developed to estimate site-level GHG emissions. These models offer capabilities ranging from site-specific simulations to regional-scale applications. Examples include the DeNitrification-DeComposition (DNDC) model, which originated from US cropping system simulations [25,26] and is the most widely applied model for quantifying CH_4 emissions from paddy rice systems in Asia [27], the Daycent model [28], which has been implemented for Tier 3 emissions reporting in the US [29] and the LandscapeDNDC model [30,31], which is currently being developed within Germany's national GHG inventory system. Each model incorporates different representations of soil, crop, and microbial processes, which can offer advantages or pose limitations depending on the specific application and context. For LandscapeDNDC, it was demonstrated that field management data, such as irrigation regimes and residue incorporation, are the most influential determinants of GHG emission estimates in rice systems at the national scale [22]. Since this dependency on data availability is likely shared by other process-based models, a significant challenge arises because such detailed field-level data are often incomplete or unavailable. Consequently, the question remains regarding the actual advantage of complex process models over simpler EF approaches in upscaling GHG emissions to national scale, particularly in the presence of high uncertainties in model input data.

This study utilizes a comprehensive site-level dataset of measured CH_4 emissions from rice production systems across Vietnam to assess the performance of emission estimates derived from different IPCC Tier approaches. Specifically, two different process-based biogeochemical models—DNDC and LandscapeDNDC—were set up to compare their simulation results with corresponding Tier 1 and Tier 2 EF-based estimates. The advantages and disadvantages of each method and model are then discussed, alongside an evaluation of the opportunities and challenges of integrating process-based models into Vietnam's GHG inventory for rice cultivation, as national mitigation policies are expanding in scope and ambition.

2. Materials and Methods

2.1. Experimental dataset

A total of 13 experimental sites were selected from previously published studies, covering the major rice-growing regions of Vietnam: the Northeast (NE), Red River Delta (RRD), South-Central Coast (SCC), and Mekong River Delta (MRD). Across these sites, 23 cropping seasons were monitored, providing a basis for a country-scale evaluation of the different IPCC Tier approaches in Vietnamese rice systems (*Figure 1*). Site selection was guided by the adequacy of CH_4 flux observations, specifically requiring sampling intervals shorter than 12 days, in line with national guidelines [32]. Fields under saline conditions were excluded because such conditions are not yet represented in the Tier 3 models used here. The resulting dataset captures a broad range of geographical, climatic, edaphic, and management conditions. Soil properties at the observation sites are summarized in *Table 1*. The MRD, Vietnam's largest rice-growing region, exhibits the highest soil organic carbon contents (3.07–4.27%), followed by the RRD (1.26–2.61%), the second-largest rice region. Regional climate characteristics relevant to this study are provided in the Supporting Information (*Appendix S1*).

Figure 1 shows the locations of the experimental sites and monitored seasons across northern (6 sites / 12 seasons), central (2 sites / 2 seasons), and southern Vietnam (6 sites / 9 seasons) during 2011–2021. Details on sampling procedures, gas analysis, and flux calculations are reported in Vo et al. [13]. Briefly, CH_4 emissions were measured using manual closed chambers and laboratory analysis of CH_4 concentration. Cumulative CH_4 emissions were calculated using the trapezoidal rule over all sampling intervals. Where monitoring did not cover the entire cropping period, cumulative emissions were scaled by the ratio of monitored to total cropping days to estimate seasonal totals.

Process-based models such as DNDC and LandscapeDNDC simulate continuous time periods, including a multi-year spin-up prior to the season of interest, and therefore require time-resolved management data not only for the target season but also for preceding seasons to represent legacy effects of hydrology and residue management. They also depend on initial soil properties, which are often incompletely documented.

To account for data availability when evaluating the Tier approaches, this study applied a binary site-level classification: a site was considered data-sufficient if both of the following conditions were met:

(i) Complete cropping season management information (flooding and drainage dates, residue and fertilizer inputs, and planting/harvest dates) was available for all rice seasons within the year used in the simulation

(ii) At least five out of six key soil properties were reported: soil organic C concentration, total N concentration, bulk density (needed to derive C and N stocks), sand and clay content (for texture), and pH (*Table 1*).

Sites not meeting these criteria were classified as data-limited. The six variables were chosen because they control soil C and N stocks, redox dynamics, and hydrologic behaviour, are routinely measured in field studies, and are used as primary inputs in process-based models, making them critical for CH_4 simulations.

Table 1. Soil properties, climate conditions, and group classification of selected sites

ID	Region	Source	Climate class	pH	Bulk density (g/cm^3)	Clay (%)	Sand (%)	OC (%)	Total N (%)	Observed cropping seasons	Irrigation regime	Group
N1	NE	Vu et al. (2015) [16]	Cfa	5.30	1.24*	2*	28*	0.75	0.13	Mid 2011, Early 2012	MD	Data-limited
N2[c]	RRD	Chu et al. (2020) [33]	Cwa	5.56	1.24*	13	50	2.00	0.20	Early 2018, Mid 2018	CF	Data-sufficient
N3[c]	RRD	Chu et al. (2020) [33]	Cwa	4.80	1.24*	20	31	2.61	0.27	Early 2018, Late 2018	CF	Data-sufficient
N4[c]	RRD	Chu et al. (2020) [33]	Cwa	5.04	1.24*	16	27	2.29	0.27	Early 2018, Late 2018	CF	Data-sufficient
N6	RRD	Tariq et al. (2017) [14]	Cfa	5.16	1.16	22	33	1.30	0.11	Early 2016, Late 2016	CF	Data-sufficient
N8	RRD	Pandey et al. (2014) [34]	Cfa	5.70	1.37	27	22	1.26	0.16	Late 2012, Early 2013	CF	Data-sufficient
C5	SCC	Vu et al. (2018) [35]	Aw	5.90	1.19*	29	40	1.90	0.20	Early 2014	CF	Data-sufficient
C13	SCC	Tirol-Padre et al. (2017) [36]	Am	4.59	1.19*	27	19	1.19	0.11	Mid 2011	CF	Data-limited
S6	MRD	Vo et al. (2018) [37]	Aw	5.92	1.24*	38*	31*	1.51	0.08	Late 2013	CF	Data-limited
S8	MRD	Vo et al. (2018) [37]	Aw	4.90	1.24*	35*	33*	2.20	0.11	Early 2013, Mid 2013	CF	Data-limited
S9	MRD	Vo et al. (2018) [37]	Aw	4.63	1.10*	37*	31*	4.27	0.28	Early 2013	CF	Data-limited
S10	MRD	Vo et al. (2018) [37]	Aw	5.40	1.00*	36*	29*	4.90	0.20	Early 2016	CF	Data-limited
S24	MRD	Vo et al. (2024) [15]	Aw	5.20	1.10*	41*	25*	3.92	0.37	Early 2020, Early 2021	CF, AWD	Data-limited

Notes: Ids are kept consistent with the meta-analysis of Vo et al. (2020) [13], except for S24 which was taken from study by Vo et al. (2024) [15]; small letters or symbols indicate: [c] sites that were part of the 2018 national dataset (15 sites total) used for the development of Vietnam's Tier 2 emission factors; * soil data from the ISRIC-WISE global Soil Database [38] due to missing local data. *Source* lists the original experimental studies synthesized in the research of of Vo et al. (2020) [13], except for S24. *Climate class* follows the Köppen-Geiger classification [39]: Cfa (Humid subtropical climate); Cwa (Monsoon-influenced humid subtropical climate); Am (Tropical monsoon climate); and Aw (Tropical savanna climate). *Observed cropping seasons* names follow a unified convention (early, mid, and late year) to avoid confusion across regional/ local terminology, as applied by Vo et al. (2020) [13]. Irrigation regime includes mid-season drainage (MD), continuous flooding (CF), and alternate wetting drying (AWD).

2.2. Tier 1 and 2 – Emission factors

Tier 1 and Tier 2 approaches employ the same methodology for estimating CH_4 emissions and differ only in the choice and detail of the applied emissions factor. Seasonal CH_4 emissions were calculated by multiplying adjusted daily emission factors (EF_i, unit: kg CH_4 ha^{-1} d^{-1}) by the cultivation period (days). The values of EF_i were determined by multiplying a baseline emission factor (EF_c) by various scaling factors. The baseline condition refers to continuously flooded rice fields without organic amendments. The scaling factors SF_w, SF_p, and SF_o account for water-regime variations during the cropping period, pre-season conditions, and the type and amount of organic amendments, respectively. Detailed calculations for EF_i and the specific scaling factors are provided in the Supporting Information, *Appendix 2*.

For Tier 1, EF_c represents the regional default for Southeast Asia, as specified in Table 5.11, IPCC 2019, with a value of 1.22 kg CH_4 ha^{-1} d^{-1} [9]. For Tier 2, EF_c corresponds to the country-specific emission factors that vary across regions and cropping seasons within each region. According to Decision No. 2626/QD-BTNMT, EF_c values for the North are 1.61 and 3.43 kg CH_4 ha^{-1} d^{-1} for the early and late seasons, respectively. In the Central, these values are 1.92 and 1.91 kg CH_4 ha^{-1} d^{-1} and in the South, EF_c values for the early, mid, and late seasons are 1.95, 1.83, and 2.20 kg CH_4 ha^{-1} d^{-1}, respectively [40]. These national Tier 2 EFs were originally derived from measurements at 15 sites established in 2018. Three of the 13 sites used in our evaluation were part of that dataset, while the remaining 10 sites are independent of the EF derivation. The overlapping sites are indicated in *Table 1*.

2.3. Tier 3 – The biogeochemical process models DNDC and LandscapeDNDC

DNDC

The DNDC model [25,26] can simulate C and N cycling in agroecosystems and has undergone a long process of evolution, with several versions created for different research purposes [41]. For this study, DNDC version 9.5 was used, which is accessible at https://www.dndc.sr.unh.edu/. Key simulation processes include soil organic matter turnover, nitrification, and denitrification, which predict the emissions of carbon dioxide (CO_2), methane (CH_4), ammonia (NH_3), nitric oxide (NO), nitrous oxide (N_2O), and dinitrogen (N_2) from plant-soil systems [42].

The mechanisms by which the DNDC model estimates soil CH_4 emissions from rice fields have been widely reported in previous studies [43–46]. In DNDC, total CH_4 flux results from three processes: production, oxidation, and transport. CH_4 production depends on DOC derived from SOC decomposition and the soil redox potential (Eh); once Eh drops to –150 to –300 mV under saturated conditions, methanogenesis begins and is calculated using Michaelis–Menten kinetics. Produced CH_4 can be oxidized in aerobic layers, with oxidation rates also governed by Michaelis–Menten kinetics. Remaining CH_4 diffuses between soil layers, escapes via ebullition when supersaturated, or is transported through rice aerenchyma. All processes are simulated in a 1-D soil column (5-cm layers to 50 cm depth) at a daily time step [25,27].

LandscapeDNDC

The LandscapeDNDC (LDNDC) model [30,31] was developed to assess carbon, nitrogen, and water fluxes of terrestrial ecosystems. It integrates vegetation growth, soil biogeochemistry, and management practices to assess GHG emissions (CO_2, N_2O, CH_4), nutrient cycling, and plant productivity across different land-use types such as forests, grasslands, croplands, and paddy rice. For this study, the LandscapeDNDC version 1.37 was used, which is accessible from the LandscapeDNDC website (https://ldndc.imk-ifu.kit.edu).

The model represents ecosystems as a set of interacting domains (Microclimate, Vegetation, Watercycle, Soil–Biogeochemistry), each resolved by configurable, domain-specific sub-models. For simulating CH_4 emissions from paddy rice systems, the LandscapeDNDC setup [47,48] employs CanopyECM for microclimate, WatercycleDNDC for water dynamics [49], PlaMo^x for plant C–N processes, and MeTr^x [30] for microbially mediated soil C–N cycling and GHG production and consumption. LandscapeDNDC–MeTr^x explicitly represents redox-sensitive electron acceptors, dynamic soil O_2 profiles under anaerobic conditions, and litter pools partitioned into lignin, cellulose, and soluble fractions, as well as floodwater biomass processes. The vertical soil discretization is user-defined, typically 1–2 cm within the plough layer and 5–10 cm below, and simulations are performed at an hourly time step.

2.4. Model setups

2.4.1. Input data and model setup

A 10-year spin-up was applied at each site, and the same climate, soil, and management data sources were used for both models, despite differences in input format. Climate data, including daily maximum/minimum/average temperature, precipitation, wind speed, air humidity, and solar radiation, were obtained from the ERA5 climate database [50]. Local soil data were collected from published articles of each respective site (*Table 1*). Essential soil information for model setup that was not available from site measurements was extracted from the ISRIC-WISE global Soil Database [38]. Management data include information on cultivation schedules, fertilizer applications, irrigation regimes, yields, and straw treatments. Except for N1, which applied mid-season drainage and site S24, which included AWD, the remaining sites apply continuous flooding.

2.4.2. Crop parametrization

Various rice varieties were cultivated at the test sites, which are not parameterized as standard in either DNDC or LandscapeDNDC. Variety-specific modeling was not feasible because actual variety information was often unavailable, the model's spatial units typically encompassed multiple fields planted with different varieties, and field data were insufficient to derive robust variety-specific parameters. A generalized rice variety was used in both models and adjusted for each region by calibrating phenology with growing degree days to match observed maturity.

DNDC

The DNDC model was calibrated using crop parameters based on observed data regarding rice yield and seasonal CH_4 emissions, as suggested by [51,52]. The crop parameters include maximum biomass production, biomass fractions for grain, leaf, stem, and root, biomass C/N ratios for grain and root, and required thermal degree days (TDD) to reach maturity. Due to the differing climate conditions in the North, Central, and South, as detailed in *Table 1*, TDD was modified separately for each region.

LandscapeDNDC

For the LDNDC model, the crop type "padr" standing for general paddy rice was used. Site-specific crop parameters included the required growing degree days (comparable to TDD in DNDC) for the phenological crop development. These parameters were dynamically determined during the initial spin-up phase, subject to the constraint of crop maturity at the harvest date, which was set as a constant value according to the input data.

2.4.3. Model evaluation

Model performance was evaluated by comparing observed and simulated values using the coefficient of determination (R^2), root mean squared error (RMSE), Nash–Sutcliffe efficiency (NSE), and percent bias (PBIAS), calculated according to Eqs. (1)– (4) [52,53]. R^2 (0–1) and the linear regression (y = ax + b) describe the agreement between simulated (y) and observed (x) values. RMSE (0, ∞) quantifies the absolute deviation, with lower values indicating better accuracy. NSE (−∞, 1) measures performance relative to the mean of observations. Model performance was evaluated based on the criteria recommended by Moriasi et al. (2007) [54] and Moriasi et al. (2015) [55] for nitrogen and field-scale simulations. Performance was classified as 'Satisfactory' if NSE > 0.35, R^2 > 0.30, and PBIAS ≤ ±70%. Higher ratings were assigned as follows: 'Good' (NSE > 0.50, R^2 > 0.60, PBIAS ≤ ±30%) and 'Very Good' (NSE > 0.65, R^2 > 0.75, PBIAS ≤ ±15%). These refined and relaxed thresholds are justified by the high inherent variability of Carbon and Nitrogen cycles in rice paddies and the challenges of discontinuous GHG monitoring, which often result in lower correlation metrics compared to continuous hydrological flows.

$$R^2 = \left(\frac{\sum_{i=1}^{n} (M_i - \bar{M})\,(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (M_i - \bar{M})^2 \sum_{i=1}^{n} (S_i - \bar{S})^2}} \right)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_i - M_i)^2}{n}} \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (M_i - \bar{M})^2} \quad (3)$$

$$PBIAS = 100 \times \frac{\sum_{i=1}^{n} (S_i - M_i)}{\sum_{i=1}^{n} M_i} \quad (4)$$

In Eqs. (1)-(4), M and S denote measured and simulated values, $\bar{M}$ and $\bar{S}$ their respective means and i = 1, 2, …, n the number of paired values. CH_4 emissions from the Tier approaches were compared with observed seasonal emissions across 23 sites, followed by separate evaluations for data-sufficient (N = 11) and data-limited sites (N = 12). All the statistical analyses were conducted in Visual Studio Code version 1.101.2 using Python 3.10.

3. Results

3.1. Comparison of IPCC Tier approaches for seasonal CH_4 emissions

The statistical performance measures of simulated and observed CH_4 emissions improved progressively from Tier 1 to Tier 3. The Tier 1 approach (*Figure 2a*) showed no predictive performance (R^2 = 0.001) and substantial bias (RMSE = 182.73 kg CH_4 ha^{-1}, NSE =

–1.09, PBIAS = –49.54%). On average, Tier 1 significantly underestimated seasonal CH_4 emissions, predicting about 133.44 kg CH_4 ha^{-1} compared to the observed value of 264.44 kg CH_4 ha^{-1}.

For the Tier 2 approach (*Figure 2b*), applying country-specific EFs reduced the overall bias, yielding a mean estimate of 239.84 kg CH_4 ha^{-1}, closer to the observed value than Tier 1. Compared to Tier 1, all performance measures were improved, R^2 and NSE increased to 0.31 and 0.27, while RMSE and PBIAS reduced to 108.23 kg CH_4 ha^{-1} and –9.3%, respectively.

For the Tier 3 approaches, both process-based biogeochemical models showed better agreement with observations than Tier 1, while the improvements relative to Tier 2 were moderate. The mean seasonal CH_4 emissions simulated by DNDC and LandscapeDNDC (245.06 and 270.02 kg CH_4 ha^{-1}, respectively) were closer to the observed mean than Tier 1. As for Tier 2, NSE values for both Tier 3 models approached the satisfactory threshold, and PBIAS values fell within the 'Very good' category. While both models produced NSE and RMSE values slightly less favorable than those of Tier 2, the LandscapeDNDC model (*Figure 2d*) showed the strongest correlation with seasonal observations (R^2 = 0.44).

The subgroup analysis showed that, for both DNDC and LandscapeDNDC, model performance generally improved at data-sufficient sites compared to the full dataset. The most pronounced improvement was observed for LandscapeDNDC (*Figure 2h*): R^2 increased from 0.44 to 0.71, while NSE rose from 0.24 to a 'Good' level of 0.65. Furthermore, RMSE decreased to 87.69 kg CH_4 ha^{-1}, and PBIAS remained consistently within ± 5%. For DNDC (*Figure 2g*), R^2 and NSE increased from 0.30 to 0.47 and from 0.25 to 0.41, respectively, whereas RMSE slightly increased from 109.91 to 113.36 kg CH_4 ha^{-1} and PBIAS shifted to –11.16%, indicating a somewhat stronger systematic underestimation.

Besides these improvements, several data points within the data-sufficient group still deviate from the 1:1 line in both models, and the residual scatter is particularly pronounced for LandscapeDNDC (*Figure 2h*), suggesting that even under better data conditions, substantial variability remains unexplained.

Under data-limited conditions, the performance of the Tier 3 models was lower than that of the Tier 2 approach. (*Figure 2g, h*). The most distinctive performance gap appeared in the NSE values; while both process-based models exhibited negative results, Tier 2 provided a more stable and positive estimate (NSE = 0.19). In addition, the coefficient of determination for Tier 2 changed only slightly between data-sufficient and data-limited sites (R^2 = 0.27 and 0.24, respectively). Negative PBIAS values across all Tiers indicate a general tendency toward underestimation; however, with the exception of Tier 1, all approaches remained within the 'Very good' category.

3.2. Comparison of Tier 3 process-based models for yield and seasonal CH_4 emissions

Beyond seasonal CH_4 emissions, the Tier 3 process-based models also predict rice yield, an important variable for evaluating GHG mitigation strategies. For the full dataset, DNDC (*Figure 3a*) showed moderate agreement with observed yields (R^2 = 0.51) and fair model efficiency (NSE = 0.29). LandscapeDNDC (*Figure 3b*) performed somewhat less well with R^2 = 0.33 and NSE = 0.22. DNDC had a lower RMSE (0.97 t ha^{-1}) but a lager negative PBIAS (−9.11%), indicating a stronger systematic underestimation. In contrast, LandscapeDNDC showed a higher RMSE (1.02 t ha^{-1}) but a near-zero PBIAS (−0.34%), suggesting largely compensating errors. Consequently, the simulated mean yield by LandscapeDNDC (5.69 t ha⁻

^{1}) was closer to the observed mean (5.71 t ha^{-1}) than the 5.19 t ha^{-1} estimated by DNDC. Inter-model comparison (*Figure 3c*) revealed a higher consistency (R^2 = 0.55, RMSE = 0.87 t ha^{-1}) than their individual performance against observations, with LandscapeDNDC generally predicting higher yields than DNDC. Under data-sufficient conditions, model performances improved, consistent with the pattern found for CH_4. For DNDC (*Figure 3d*), R^2 increased to 0.72, RMSE decreased to 0.80 t ha^{-1}, and NSE rose to 0.68. LandscapeDNDC also improved (*Figure 3e*), though less strongly (R^2 = 0.42, RMSE = 1.12 t ha^{-1}, and NSE = 0.36). The agreement between the two models (*Figure 3f*) also increased, with R^2 = 0.68, RMSE = 0.77 t ha^{-1}, and NSE = 0.40.

Both models reproduced the expected inverse relationship between simulated yield and seasonal CH_4 emissions (*Figure 4*), with LandscapeDNDC (r = –0.41) showing a correlation closer to the observed value (r = –0.54) than DNDC (r = –0.17). The distributions of simulated yields were similar between models, with DNDC ranging from 3.1 to 7.0 t ha^{-1} and LandscapeDNDC from 4.0 to 7.5 t ha^{-1}; DNDC thus produced slightly broader yield variability. In contrast, DNDC simulated a narrower range of seasonal CH_4 emissions (146.9–418.4 kg CH_4 ha^{-1}) than LandscapeDNDC (102.9–702.3 kg CH_4 ha^{-1}). For the data-sufficient subset, the negative yield–CH_4 relationship strengthened, with correlation coefficients of –0.24 for DNDC, –0.54 for LandscapeDNDC, and –0.61 for observations.

3.3. Comparison of Tier 3 process-based models for daily CH_4 emission patterns

In Vietnam, rice is primarily a short-duration crop, completing its growth cycle in approximately 100 days. Since local names and seasonal timings vary significantly across regions, this study adopts the generic terms for the three consecutive seasons: early (October to June), mid (May to November), and late (June to December), following the definition by Vo et al. [13]. Across these seasons, observed CH_4 emissions exhibited distinct phenological patterns. In the early season (*Figure 5a*), emissions and their variability were highest from stem elongation through to flowering. In the mid season (*Figure 5b*), peak emissions occurred around tillering. In the late season (*Figure 5c*), emissions were high from rooting onwards and then decreased over the remainder of the season.

LandscapeDNDC reflected this shift in the timing of higher emissions to some extent: simulated fluxes at the start of the cropping season increased from early to mid and late seasons, broadly following the observed tendency toward earlier and higher emissions in the later seasons. By contrast, DNDC simulated a similar temporal pattern in all seasons, with the highest emissions consistently centred in the middle of the cropping period. In the early season, the spread of DNDC and LandscapeDNDC simulations (shaded area) overlapped well with the interquartile range of observed daily fluxes, and both models performed best in terms of RMSE (DNDC: 1.06 kg CH_4 ha^{-1} d^{-1}; LandscapeDNDC: 0.97 kg CH_4 ha^{-1} d^{-1}). In the mid season, both models underestimated emissions during the early growth stages, where observations indicated a pronounced increase between rooting and tillering, but agreement improved from stem elongation onwards. The RMSE values were: 2.86 kg CH_4 ha^{-1} d^{-1} (DNDC) and: 2.06 kg CH_4 ha^{-1} d^{-1} (LandscapeDNDC). In the late season, both models substantially underestimated emissions during rooting, tillering, and stem elongation, resulting in the highest RMSE values (DNDC: 5.23 kg CH_4 ha^{-1} d^{-1}; LandscapeDNDC: 4.07 kg CH_4 ha^{-1} d^{-1}).

Across all three seasons, DNDC simulated negligible CH_4 fluxes immediately after transplanting, whereas LandscapeDNDC produced higher initial emissions closer to observations. The phenological stage–specific means (*Table 2*) show that both models perform more consistently at intermediate growth stages (especially stem elongation, panicle initiation, and booting), but differ systematically in their representation of early-season CH_4 dynamics and legacy effects of pre-season hydrology and residue management.

Table 2. Comparison of mean CH_4 emissions (kg CH_4 ha^{-1} d^{-1}) by rice growth stage of DNDC and LandscapeDNDC (LDNDC) with observation.

Season	Model	Rooting	Tillering	Stem elongation	Panicle initiation	Booting	Flowering	Ripening	Maturity
Early	DNDC	0.23	0.43	2.14	3.62	3.60	2.97	2.34	0.65
	LDNDC	0.60	0.59	2.24	2.86	3.22	3.22	2.85	1.15
	Observed	*1.19*	*1.33*	*2.15*	*2.02*	*2.56*	*1.79*	*0.98*	*1.24*
Mid	DNDC	0.00	0.28	2.49	4.31	4.49	3.58	2.82	0.86
	LDNDC	1.24	1.50	2.84	2.77	3.04	3.09	2.70	0.68
	Observed	*3.19*	*6.75*	*3.45*	*3.68*	*3.32*	*2.07*	*2.08*	*0.73*
Late	DNDC	0.45	0.85	3.53	5.63	4.71	3.42	2.41	0.44
	LDNDC	3.39	3.03	5.42	5.39	4.94	4.71	4.10	1.00
	Observed	*13.46*	*6.85*	*7.15*	*5.57*	*4.73*	*2.66*	*2.51*	*1.41*

Beyond these aggregated patterns, the Mekong Delta site (N1) with improved water management (*Figure 6*) illustrates daily-scale behaviour. Although observed seasonal CH_4 emissions (243.28 kg ha^{-1}) agreed well with DNDC (244.32 kg ha^{-1}) and LandscapeDNDC (238.35 kg ha^{-1}), the daily emission pattern revealed a difference between models and observations. While both models captured a drainage-induced decline at 28–32 DAT (*Figure 6a*), observations showed an earlier emissions decrease that began at 20 DAT and reached its lowest level at 26 DAT (*Figure 6c*). Additionally, *Figure 6a* shows that the two models maintained distinct water-level dynamics despite being set up with 10 cm flooding, with further details provided in the Supporting Information (*Appendix S3*).

For AWD, measurements were available for two consecutive years at the same site (S24 in *Table 1*). DNDC showed a systematic underestimation, yielding approximately 44.6 kg CH_4 ha^{-1} in both years. LandscapeDNDC produced higher and more variable estimates, with 143.40 and 234.31 kg CH_4 ha^{-1}, whereas the corresponding observed values were 114.50 and 117.28 kg CH_4 ha^{-1}. As illustrated for the second year (*Figure 6b, d*), the models exhibited differing water-level dynamics. In DNDC, the fixed thresholds (−5 to +5 cm) and a constant drainage/pumping rate of 2.5 cm d^{-1} triggered frequent and rapid wet–dry cycles, which likely suppressed anaerobic conditions and led to consistently low CH_4 emissions. In contrast, LandscapeDNDC utilized flexible water-level settings aligned with the experimental schedule, resulting in fewer drying events and higher simulated emissions.

4. Discussion

4.1. Rice yield–CH_4 relationship

Although both models show limitations in simulating rice yield—partly because a generalized cultivar parameterization was applied across all sites—DNDC reproduces observed yields more accurately than LandscapeDNDC. Additional uncertainty in the observed yields (site-level variability, measurement and sampling errors, and methodological differences in yield estimation) likely contributes to model–data discrepancies.

Our dataset shows an overall negative relationship between yield and CH_4 emissions, consistent with earlier work by Denier van der Gon et al. [56], who found that increased CH_4

emissions were associated with reduced grain filling, indicating that optimizing grain production can lower CH_4 emissions. However, this relationship may depend on how yield is achieved. Asif et al. [57] showed that yield gains via more spikelets per panicle tend to decrease CH_4 emissions by favouring carbon allocation to grains, whereas yield increases driven mainly by higher grain weight were positively associated with CH_4 emissions. Qian et al. [58] reviewed that rice plants influence CH_4 emissions through two main mechanisms: (i) supply of substrates for methanogenesis via rhizodeposition and (ii) release of oxygen into the rhizosphere via aerenchyma, which promotes CH_4 oxidation. Thus, the net effect of high yield is not automatically lower methane emissions, but this depends on the specific trait combinations that are present.

In addition, factors independent of yield further weaken the statistical yield–CH_4 relationship. Different cultivars express different trait combinations, and management and environmental conditions can override any underlying yield–emission signal. For example, sites with relatively low yields may still exhibit high CH_4 emissions due to prolonged flooding, residue management (e.g. straw incorporation vs. removal), or high soil organic C stocks, all of which can enhance CH_4 production irrespective of yield.

Despite its poorer yield prediction, LandscapeDNDC captured the observed negative correlation between rice yield and seasonal CH_4 emissions more effectively than DNDC (*Figure 4*). This may indicate that its internal linkage between yield, carbon release, and oxygen transport in the rhizosphere is more consistent with the dominant trait and management combinations in our dataset, although this interpretation is tentative given the limited trait information available.

Taken together, these findings explain why the yield–CH_4 relationship in our data is weak and context-dependent. For process-based modelling, they imply that (i) a reasonable representation of yield is necessary but not sufficient for robust CH_4 simulations, because yield integrates only part of the plant traits that control rhizodeposition, aerenchyma development, and oxygen transport; and (ii) model development and calibration should more explicitly account for carbon allocation patterns, root and aerenchyma traits.

4.2. Tier 1 and Tier 2 Emission Factors in Methane Inventory Reporting

IPCC introduced Tier 1 as the most straightforward approach for countries where CH_4 emissions from rice cultivation are not a key category or where country-specific EFs are unavailable [9]. Previously, IPCC 2006 reported a single global baseline EF of 1.30 kg CH_4 ha^{-1} d^{-1}, derived from 554 measurements at 53 Asian sites [59]. The 2019 Refinement expanded this to 1,089 measurements from 122 sites and provided region-specific EFs, including a default EF of 1.22 kg CH_4 ha^{-1} d^{-1} for Southeast Asia [9,60]. Nevertheless, our results, together with those of Reavis et al. [61] and Katayanagi et al. [62] show that, even acknowledging that Tier 1 is not intended to capture site-specific variability, substantial discrepancies persist between its generalized estimates and observed site-scale emissions.

To improve national inventory accuracy, Vietnam has developed and, since 2020, officially applied country-specific Tier 2 EFs for rice [40]. Our analysis indicates that Tier 2 improves agreement with observations relative to Tier 1. Compared with the process-based Tier 3 models, Tier 2 also has practical advantages, particularly in providing stable estimates when activity data are unavailable or incomplete (*Figure 2f*). Given that Tier 3 approaches are data- and resource-intensive, Tier 2 currently represents a practical and robust option for many countries, balancing methodological complexity and feasibility. However, Tier 2 EFs are essentially static, whereas CH_4 emissions are sensitive to evolving climate conditions and management practices [61,63,64]. Consequently, their representativeness may be limited when applied across diverse regions or over extended time scales in national inventories. The variability of Tier 2 EFs for Vietnam reported in the literature illustrates this challenge (*Figure 7*). Official national EFs (1.61–3.43 kg CH_4 ha^{-1} d^{-1}) were derived from measurements at 15 sites, whereas extending the spatial and temporal coverage to 36 sites yielded a wider range of 1.72–3.89 kg CH_4 ha^{-1} d^{-1} [13]. In addition, global compilations by Wang et al. [60] and Nikolaisen et al. [63] report country-level EFs for Vietnam of 1.13 and 3.60 kg CH_4 ha^{-1} d^{-1}, respectively. These differences emphasize that EF estimates are sensitive to data coverage, site selection, and analytical choices. They also raise the question of whether Vietnam's current Tier 2 EFs—derived primarily from 2018 field measurements under IPCC baseline conditions—will remain representative for future inventories in the context of rapid changes in mitigation practices, climate, and irrigation water availability. The wide range of EFs (*Figure 7*) obtained by selecting different data subsets reveals an arbitrary element that is inherently embedded in the site selection for EF determination. Vo et al. [15] further exemplified this issue by reporting variety-specific EFs in the Mekong River Delta (2.52–3.96 kg CH_4 ha^{-1} d^{-1}), that are notably higher than the nationally adopted defaults [40] for the same region (1.83–2.20 kg CH_4 ha^{-1} d^{-1}).

4.3. Seasonal and daily CH_4 emission with Tier 3 process-based models

In this study, discrepancies between simulated and observed site-level CH_4 emissions can be traced primarily to three sources: model parameterization, input data limitations, and observational uncertainties. First, generalized rice variety parameters were applied rather than site-specific calibration to preserve model transferability across a diverse national dataset. This choice inevitably neglects cultivar-specific traits (e.g. differences in root exudation and phenology), and thus constrains model performance at individual sites. Second, the scarcity of local input data adds further uncertainty. The lack of on-site meteorological observations and incomplete soil information for some experiments required the use of regional climate products and pedotransfer-based soil estimates, which may not fully capture local conditions. Third, the observational data themselves are subject to considerable uncertainty. This is because seasonal emissions are inferred from infrequent, manual, closed-chamber measurements with limited spatial representativeness, which can introduce substantial errors in observed CH_4 fluxes on the order of 40–60% [65,66]. This is reflected in the wide error bars in *Figure 6c*, particularly during early growth stages, when the transition to anaerobic conditions often leads to patchy CH_4 production [67], and short-lived ebullition events may be missed.

Despite improvements from Tier 1 to Tier 3 and from data-limited to data-sufficient sites, several data-sufficient sites still deviate markedly from the 1:1 line for both Tier 3 applications, DNDC and LandscapeDNDC, indicating that substantial variability remains unexplained even under comparatively good data conditions. Additional analyses (Supporting Information, *Appendix S4*) show that combining both models can reduce these residual errors. Using the mean of DNDC and LandscapeDNDC improves performance to R^2 = 0.46 and NSE = 0.44, and an ex-post choice of the better-performing model at each site increases these metrics further to R^2 = 0.70 and NSE = 0.67 (*Appendix S4*). Although such "best-model" selection is opportunistic, it may suggest a degree of complementarity between DNDC and LandscapeDNDC, in that each tends to perform better at different sites. Similar behaviour has been reported in crop-growth modelling, where multi-model ensembles often outperform individual models [68]. For CH_4 emissions from rice, comparable ensemble approaches that benefit from structural diversity among models have not yet been explored. In this study, structural differences between DNDC and LandscapeDNDC contributed to performance differences, especially at the start of the cropping season. Simulating CH_4 fluxes at the onset of flooding remains intrinsically challenging because of the rapid decline in soil redox potential and the lag in methanogenic activity as anaerobic conditions become established [44,69]. Fumoto et al. [44] showed that DNDC's empirical representation of Eh makes it relatively insensitive to the dynamics of alternative electron acceptors (AEA) such as reducible Fe^{3+}. Combined with its assumption of homogeneous soil conditions and simplified treatment of microscale heterogeneity, this can lead DNDC to underestimate early-season CH_4 fluxes more strongly (*Figure 5*). In contrast, LandscapeDNDC explicitly simulates AEA pools and their redox cycles: during flooding, AEAs are reduced and compete with methanogenesis for available carbon, whereas during drainage they are re-oxidized, with the extent of re-oxidation depending on the drainage duration and intensity. At the beginning of the season, emissions also depend on how pre-season residues are represented. In DNDC, stubbles are incorporated into the soil immediately after harvest, while in LandscapeDNDC stubbles remain on the surface with limited decomposition until incorporation at the first tillage of the new season. If tillage occurs shortly before the start of the next season, this promotes higher CH_4 emissions in LandscapeDNDC. Together, these structural differences help explain why DNDC tends to simulate negligible fluxes at transplanting, whereas LandscapeDNDC produces higher initial emissions closer to observations.

Water management adds further complexity. Both models generally captured emission reductions during mid-season drainage, but reproducing flux responses under alternate wetting and drying (AWD) was more challenging. AWD requires models to simulate sharp, timing-sensitive declines in flux and short-lived emission peaks driven by rapid redox shifts [70,71]. Representing these dynamics depends on both model structure and the quality of soil and water input data. A simple input perturbation under AWD showed that LandscapeDNDC is highly sensitive to soil hydrologic properties, which control water table dynamics and CH_4 emissions, whereas DNDC is much less responsive (Supporting Information, *Appendix S5*). This could also mean that part of the apparent model–data mismatch under AWD arises from uncertain soil and water management inputs rather than from model limitations alone. Reducing field capacity and wilting point roughly halved simulated emissions in LandscapeDNDC and brought them close to observed values, while hardly affecting DNDC. Because the AWD site belongs to the data-limited group with poorly constrained soil hydrologic and water-management information, the mismatch likely reflects a combination of structural differences and input uncertainty. The strong influence of soil properties on the CH_4 reduction potential of AWD is generally consistent with previous work, which reports a wide range of mitigation (≈20–90% reduction relative to continuous flooding; Sander et al. [72]). For Tier 3 applications under AWD, accurate characterization of soil hydrologic properties is therefore as critical as model choice, and apparent model–data discrepancies cannot be attributed to either soil inputs or model structure alone.

4.4. Tier 3 process-based models at the national scale

The findings of this study (*Figure 2g, h*) indicate that, given sufficiently reliable input data, process-based models can generate CH_4 emission estimates that are more representative of local conditions, improving upon the Tier 1/2 approaches. In line with this, Perugini et al. [73] highlighted that process-based modeling can improve the accuracy of GHG inventories by simulating complex emission pathways in the plant soil system and supporting the development of more detailed and scientifically grounded emission factors. However, as Umemiya et al. [74] emphasized, reliable activity data and a robust data management system are essential for producing accurate and consistent GHG inventories. Therefore, the advantage of Tier 3 approach can only be achieved when countries ensure high-quality input and activity data and transparent documentation of methods and assumptions. Zhang et al. [75] further highlight a trade-off between model performance and activity data availability: although models with higher process representation can reduce uncertainties in simulated CH_4 emissions, these uncertainties may increase when input data are scarce, as more detailed information is required to achieve improved performance.

For upscaling to the national scale, process-based models require extensive, high-resolution input data, including detailed information on water management, soil characteristics, organic amendments, rice varieties, and local climate conditions. However, unless supported by harmonized and spatially explicit datasets, the high spatial and temporal variability of these factors remains challenging to represent, leading to substantial uncertainty in the model results. Upscaling studies from the Philippines and Vietnam likewise indicate that the primary constraint on applying Tier 3 models at the national scale is the availability and quality of activity data. When such information is incomplete or inconsistent, models are often forced to rely on idealized assumptions - such as optimal crop yields and irrigation levels - which substantially increases the uncertainty of the resulting emission estimates [22,48].

The limited availability of high temporal resolution field measurements and consistent spatial environmental datasets, such as weather, soil, and land-use data, can constrain the parameterization and validation of process-based models at the regional or national scale. As shown in *Table 3*, varying input data and model structures lead to a wide divergence in upscaling of CH_4 estimation for Red River Delta, ranging markedly from 0.08 to 0.93 Mt CH_4 yr^{-1}.

Table 3. Effect of input data differences among Tier 3 DNDC studies on CH_4 emission estimates for the Red River Delta, Vietnam

	Torbick et al. [76]	*Butterbach-Bahl et al. [22]*	*Bui and Mai [77]*
Model	DNDC v9.5	LandscapeDNDC	DNDC v9.5
Main approach	Applied remote sensing to generate model inputs (rice extent, irrigation, crop calendar) for the DNDC simulation of GHG emissions	Applied LDNDC model integrated with GIS databases to estimate national-scale GHG emissions from rice systems	Applied DNDC model to estimate GHG emissions from rice and upland crops under different soil and climatic conditions
Climate data	Not specified	ECMWF Reanalysis v5 (ERA5) climate database	Compiled from 28 local weather stations for the period 2010–2020
Soil map	Harmonized World Soil Database v1.1 (FAO/IIASA)	ISRIC-WISE Soil Properties Database v1.2 (ISRIC)	SFI Soil Map 2016 (Vietnam Soil and Fertilizer Institute)
Rice map	Generated using a machine learning classifier trained on multiscale SAR and optical imagery in 2015	Extracted from Annual land-use/cover from 1990 to 2020 dataset [78]	Extracted from the 2015 Land-use map provided by MONRE
Activity data	Crop calendar and Irrigation regime were extracted from multitemporal Synthetic	Crop calendar was created based on RiceAtlas [79]; Irrigation	Combined field experiment data with information from

	Aperture Radar (SAR) imagery. Fertilizer and residue management were assigned based on regional average practices.	regime was assumed continuous flooding Fertilizer and residue management were varied by around ±50% regional averages using Latin Hypercube Sampling	national agricultural guidelines and reports.
Emission rate	427 kg CH_4 ha^{-1} yr^{-1} for the year 2015	408–654 kg CH_4 ha^{-1} yr^{-1} for the period 2010–2019	72–859 kg CH_4 ha^{-1} yr^{-1} for the period 2010–2020
Total emission*	0.46 Mt CH_4 yr^{-1}	0.44–0.71 Mt CH_4 yr^{-1}	0.08–0.93 Mt CH_4 yr^{-1}

Note: * Total CH_4 emissions were calculated based on a rice harvested area of 1,078,783 ha in the Red River Delta (2015) for cross-study comparison.

4.5. Policy implications and Pathway for Tier 3 Implementation in Vietnam

Vietnam has adopted ambitious methane-reduction targets for rice, including the one-million-hectare low-emission rice program in the Mekong Delta [17,80]. However, the evaluation of these mitigation efforts continues to rely on a hybrid approach that combines Tier 2 emission factors combined with Tier 1 scaling factors, even at site and project scale. As shown in this study, such applications do not resolve local management dynamics and can leave substantial variability unexplained, limiting their suitability for high-integrity MRV and carbon crediting.

The findings of this study provide concrete implications for inventory design and Tier 3 deployment. First, temporal completeness over at least one full year is important for model reliability. We recommend that the minimum dataset for effective Tier 3 implementation should cover at least one continuous year and include the timing of key management events (tillage, planting/transplanting, fertilization, irrigation and drainage, residue management, harvest) for rice and relevant upland crops. In addition, basic soil information (SOC, texture, bulk density, and pH) should be measured to estimate carbon stocks and derive hydrologic properties.

Second, the Mekong Delta is the most viable region for pilot Tier 3 implementation, particularly within the one-million-hectare high-quality rice program. The region's emerging digital ecosystems, such as RiceMoRe (https://ricemore.org/map) and cooperative data platforms, already provide a basis for storing cultivation data and can, in principle, link field-level management logs with digitized soil and meteorological databases, thereby reducing data-collection barriers for Tier 3 modelling.

Third, the results point to the potential value of model ensembles for CH_4 estimation, as DNDC and LandscapeDNDC show partly complementary behaviour across sites. In the longer term, a small ensemble of process-based models calibrated against Vietnamese benchmark sites could provide a more robust basis for deriving emission factors and assessing mitigation options than reliance on a single model. Japan provides a relevant example of how such model-based information can be integrated into national inventories. Tier 2 CH_4 EFs developed in the 1990s did not adequately account for variation in fertilizer inputs, drainage regimes, or temperature, leading to large uncertainties [81]. To address this, Fumoto et al. [44] developed DNDC-Rice, which is now used to derive CH_4 emission factors within a modified Tier 2 framework in Japan's national inventory [82]. A similar, but potentially ensemble-based, approach would allow Vietnam to move toward a transparent, science-based reporting system.

4.6. Limitations and implications for generalizability

Several limitations affect the generalizability of the results and point to priorities for future work. While the dataset spans the major rice-growing regions, the number of sites implementing advanced water-saving regimes is limited. Most observations stem from continuously flooded or simple mid-season drainage systems, with only few AWD cases. As a result, model performance under improved irrigation practices is less well constrained. Future studies should expand the site network, particularly for AWD and other mitigation-oriented water-management regimes.

The use of gridded environmental data (ERA5 climate and ISRIC-WISE soils) introduces additional uncertainty at the site scale. The coarse resolution of these datasets may not capture local rainfall patterns, micro-climate, or site-specific soil characteristics that are important for CH_4 dynamics. This spatial mismatch between grid-based inputs and field-scale processes is an inherent limitation when upscaling models to national applications and could be reduced by integrating more on-site meteorological and soil measurements in future work.

Manual closed-chamber measurements constrain both the temporal and spatial representativeness of observed CH_4 fluxes. As discussed earlier, low sampling frequency can miss short-lived ebullition events and other episodic peaks, while sampling only a few plots per field leads to large uncertainty due to small-scale heterogeneity. These observational uncertainties not only weaken model evaluation, but also complicate calibration of process-based models, which requires high-quality datasets with consistent management records and flux responses. If key events (e.g. drainage episodes or residue inputs) are not documented, or if short-lived peaks are missed, there is a risk that models will be tuned to reproduce emissions driven by processes that are not properly represented in the input data. This will result in parameter sets that may be 'right for the wrong reasons'. Future studies would therefore benefit from complementing chamber measurements with automated, higher-frequency techniques (e.g. eddy covariance or laser-based systems) where feasible, to provide more reliable calibration and evaluation datasets.

5. Conclusion

CH_4 emissions from rice cultivation remain the dominant source of agricultural GHG emissions in Vietnam, underscoring the need to understand how different IPCC approaches perform under realistic data conditions. Using a diverse set of experimental sites, this study compared Tier 1, Tier 2, and Tier 3 (DNDC and LandscapeDNDC) estimates against observations. Tier 1, based on global default emission factors, produced unexpectedly low CH_4 estimates, confirming its limited suitability for national reporting in Vietnam. Tier 2, using country-specific emission factors, substantially improved agreement with observations and showed only modest sensitivity to data completeness. Where full-year management records and basic soil information were available, the Tier 3 models either matched or outperformed the Tier 2 models. However, where such information was incomplete, the Tier 3 models performed no better and sometimes worse than the Tier 2 models. This finding highlights the necessity of temporal data integrity for the effective application of Tier 3. A structured comparison of Tier-specific strengths and limitations is provided in *Appendix S6*.

The results of this study support a differentiated use of IPCC Tiers. Tier 2 currently offers a practical balance between accuracy and resource requirements for national CH_4 inventories. Tier 3 can add value where high-quality, spatially explicit activity data and inputs with full-year temporal integrity are available, and where policy questions require high-resolution dynamics and process understanding. Maintaining data integrity over at least a full annual cycle ensures effective model application by capturing critical biogeochemical legacy effects, such as soil redox states, across seasonal transitions. Accordingly, we recommend that policymakers prioritize high-tier implementation where the digital infrastructure supports comprehensive data recording. In such contexts, Tier 3 models can be used both to refine Tier 2 emission factors and to support highly integrated MRV systems for climate protection projects. This targeted use of Tier 3 models supports national climate protection goals and forms the basis for transparent, scientifically sound participation in carbon markets, where reliably quantified emission reductions are a prerequisite.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary information includes a description of regional climatic conditions across major rice-growing regions in Vietnam (Appendix S1); detailed methodology for IPCC Tier-based emission factor calculations (Appendix S2); detailed explanations of structural differences in water-table dynamics and residue management between DNDC and LandscapeDNDC (Appendix S3); comparison of observed and Tier 3 simulated seasonal CH_4 emissions using (i) the mean and (ii) the ex-post choice of the better-performing model (Appendix S4); an assessment of model responses to alternate wetting and drying and their sensitivity to soil hydrologic properties (Appendix S5); and a synthesis of key differences across Tier-based approaches for rice CH_4 estimation (Appendix S6).

Data availability

The data that support the findings of this study are available from the corresponding author upon request.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used GPt – 5.1 in order to improve the langauge. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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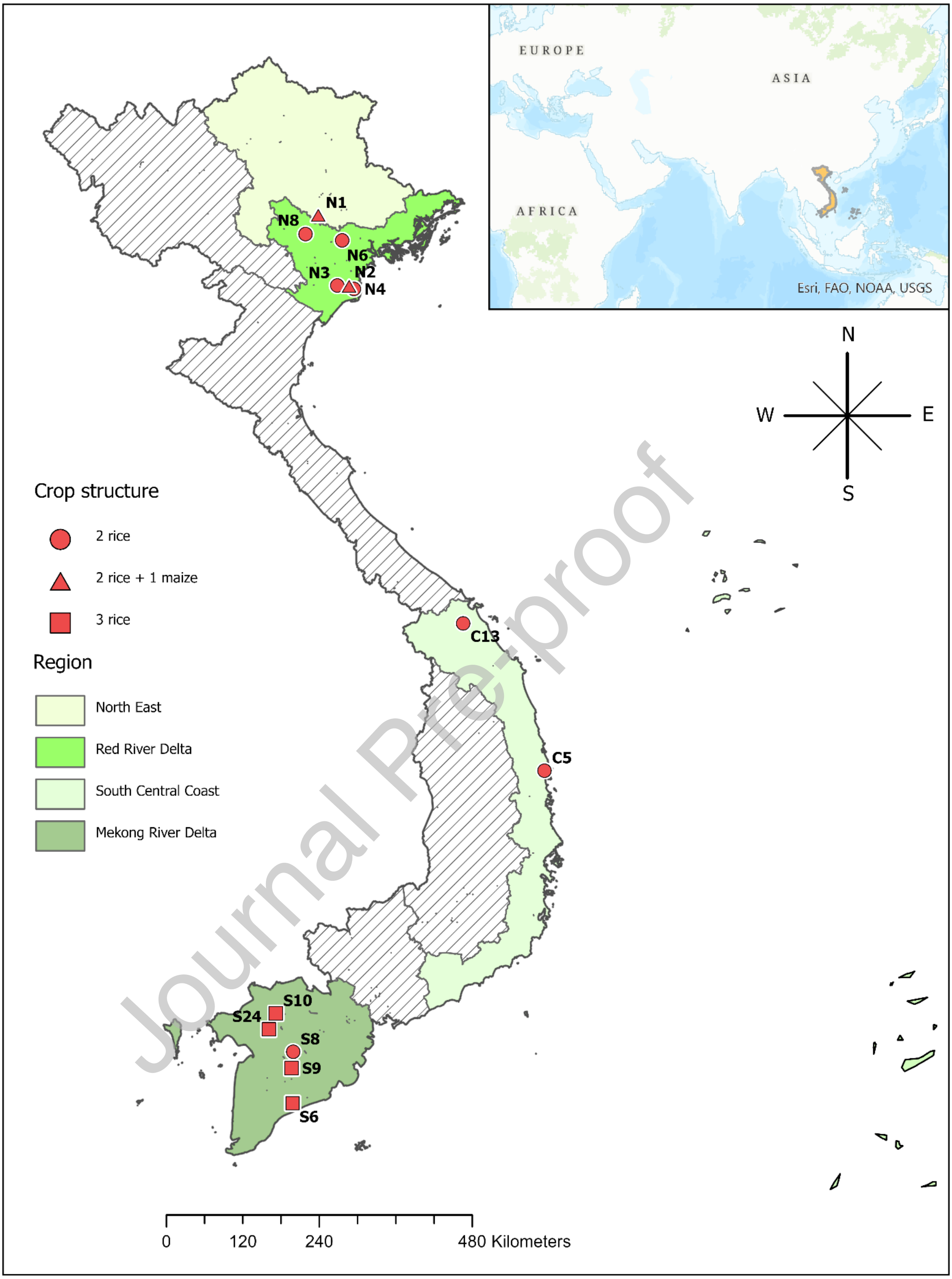

Figure 1. Study sites and rice cropping systems across agro-ecological regions in Vietnam

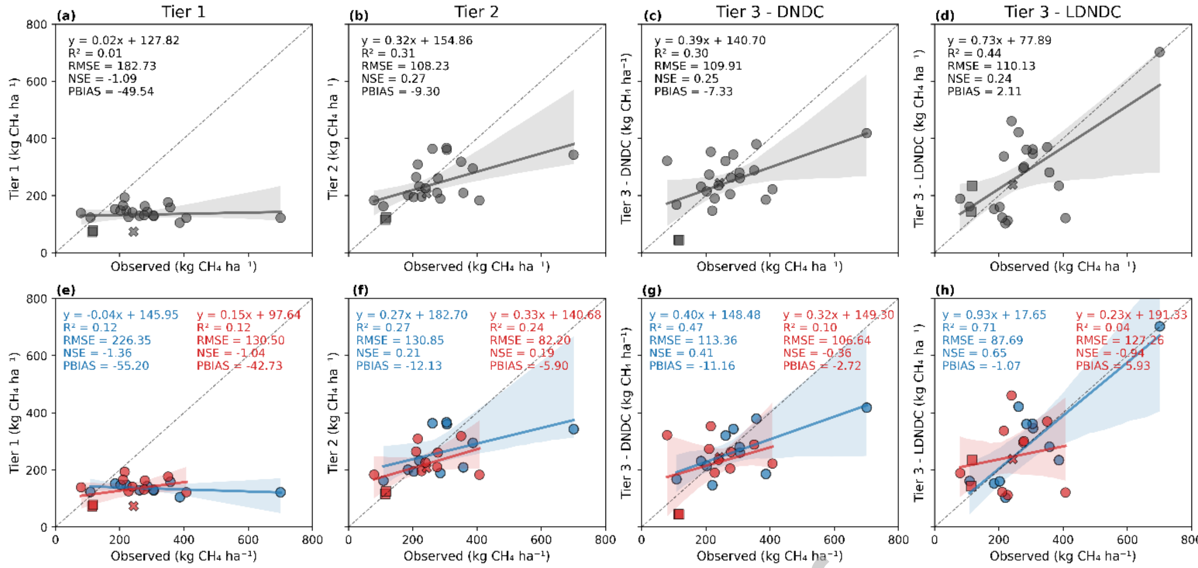

Figure 2. Top row: Comparison of observed seasonal CH_4 emissions with different IPCC Tier approaches across all sites. Bottom row: Comparison of observed seasonal CH_4 emissions with different IPCC tier approaches separately for data-sufficient (blue) and data-limited groups (red) (criteria see 2.1). In each scatter plot, circles indicate continuous flooding, squares Alternate Wetting and Drying (AWD) and crosses mid-season drainage (MD), the dashed line represents the 1:1 line, the solid line represents the fitted regression line, and the shaded area shows the 95% confidence interval

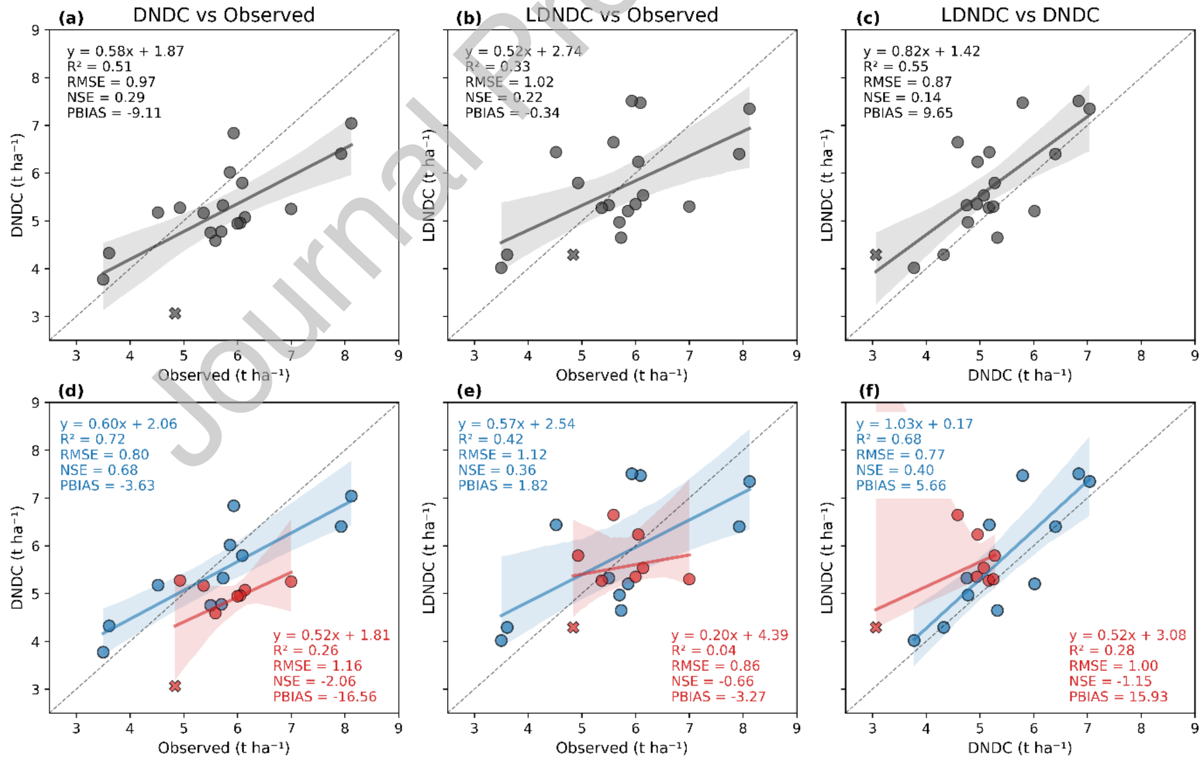

Figure 3. Top row: Comparison of simulated and observed rice yields of DNDC and LandscapeDNDC (a and b), and between LandscapeDNDC and DNDC (c). Bottom row: Comparison of rice yield performance of two models separately for data-sufficient (blue) and data-limited groups (red). In each scatter plot, circles indicate continuous flooding, crosses

indicate mid-season drainage (MD), the dashed line represents the 1:1 line, the solid line represents the fitted regression line, and the shaded area shows the 95% confidence interval

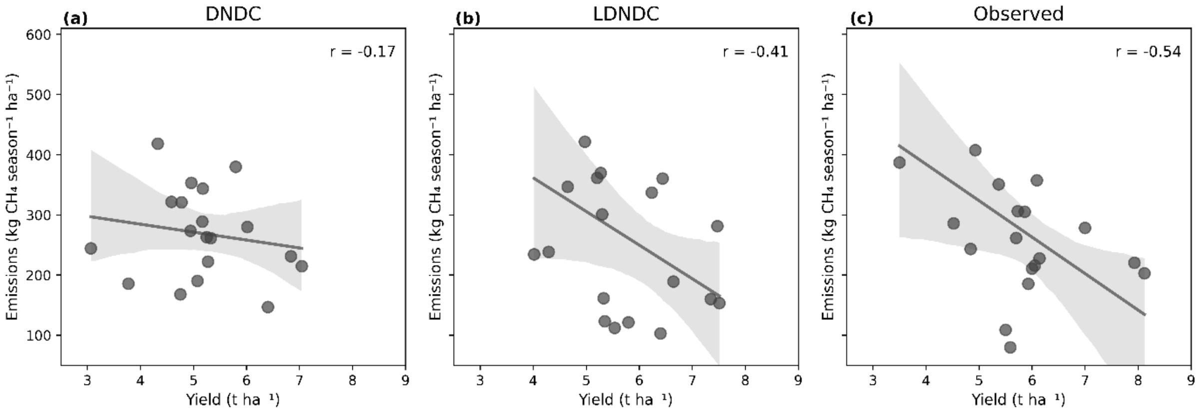

Figure 4. Relationship between simulated yield and seasonal CH_4 emission for DNDC (a), LandscapeDNDC (b), and Observed data (c). In each scatter plot, circles indicate individual sites, the dashed line represents the 1:1 line, the solid line represents the fitted regression line, and the shaded area shows the 95% confidence interval

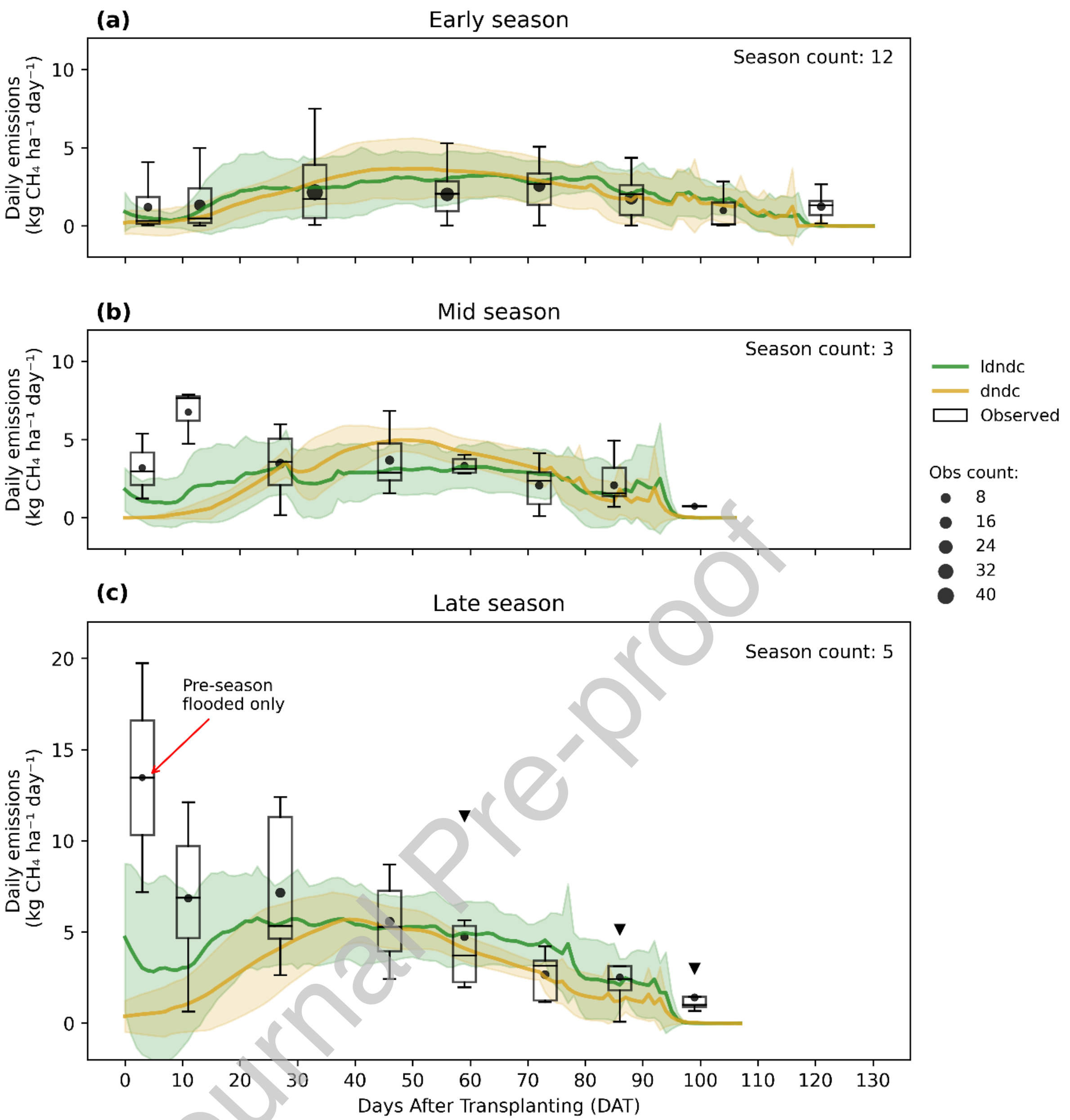

Figure 5. Comparison of daily CH_4 emissions simulated by DNDC and LandscapeDNDC for three rice seasons of all continuously flooded sites: early (a), mid (b), and late (c). In each subplot, solid lines represent the mean daily fluxes simulated by the two models, and shaded areas denote ± 1 standard deviation across sites. Boxplots show observed CH_4 fluxes grouped into eight rice growth stages: Rooting, Tillering, Stem elongation, Panicle initiation, Booting, Flowering, Ripening, and Maturity. Circles indicate the mean observed flux for each stage, with symbol size proportional to the number of observations, while inverted triangles denote outliers

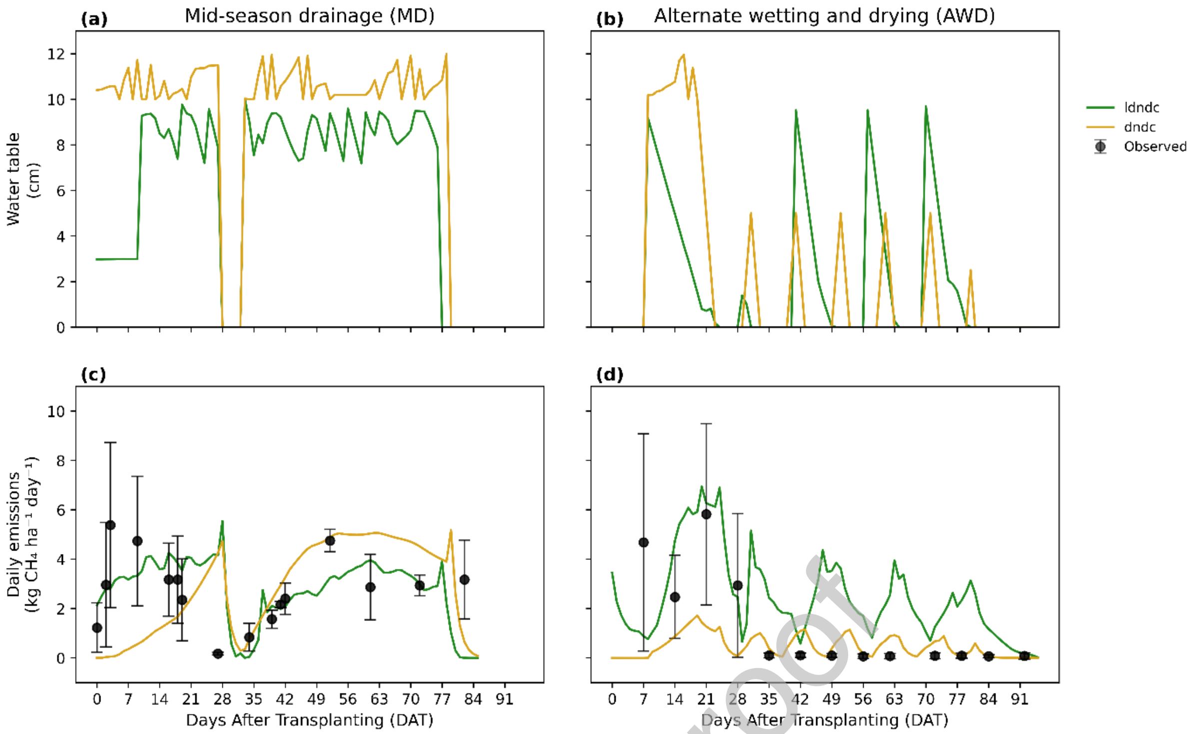

Figure 6. Comparison of simulated water table (a–b) and CH_4 emissions (c–d) by DNDC (orange) and LandscapeDNDC (green). Panels (a) and (c) represent mid-season drainage (MD), while panels (b) and (d) represent alternate wetting and drying (AWD). Observed daily means are shown as circles, with error bars indicating standard deviations

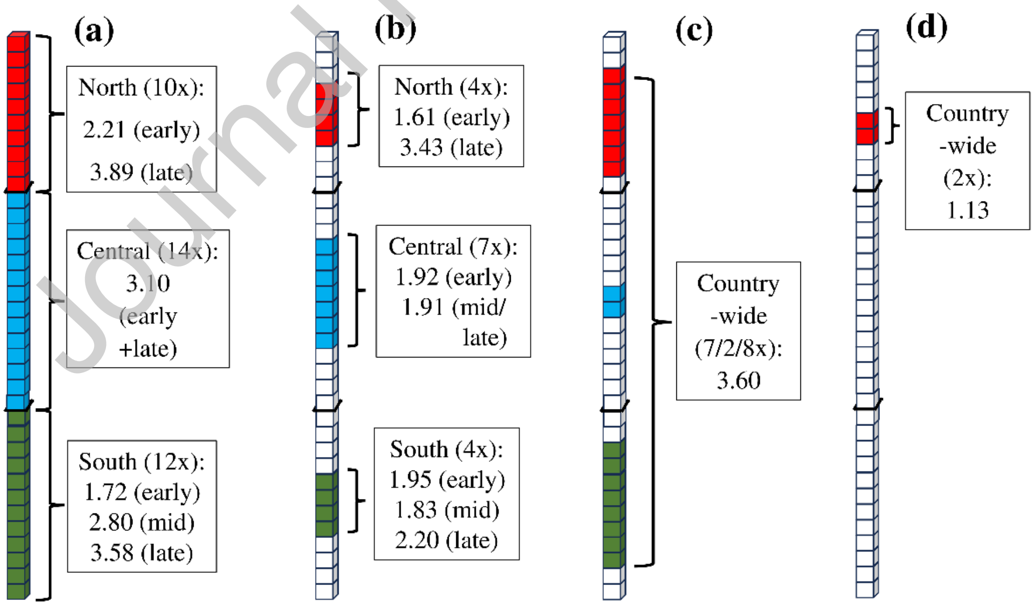

Figure 7. Schematic presentation of the variation in EFs through site selection from a given dataset described in a) Vo et al. (2020) and subsets in b) IAE (unpublished), c) Nikolaisen et al. (2023) and d) Wang et al. (2018); regional and national EFs (kg CH_4 ha^{-1} day^{-1}) are specified per season; color-coding for North (red), Central (blue) and South (green); number of sites (x) given in brackets; EFs were developed under IPCC baseline conditions: Continuously flooded during crop, short drainage before season (<30 days), no organic amendment

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: