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Methane emissions from rice paddies globally: A quantitative statistical review of controlling variables and modelling of emission factors

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ABSTRACT

Greenhouse gas (GHG) modelling tools or the Intergovernmental Panel on Climate Change (IPCC) inventory methods are often used to identify suitable mitigation strategies for GHG emissions from rice, since measuring them in field is challenging and costly. Here we report an up-to-date quantitative review on methane (CH_4) emission from rice paddies using information obtained from peer-review articles. Statistical analysis was conducted on the factors controlling CH_4 emissions and a generalised additive model (GAM) was developed to estimate emission factors (EFs). Results showed that emissions were strongly linked to water regime, soil texture and organic amendment practices. Fields that were rainfed during the dry season or saturated emitted 70% and 56% that of continuously flooded fields, while applying straw off-season instead of within-season could decrease emissions by 48%. An independent dataset was used to evaluate the new model performance against existing models with the new model showing R^2 values of 0.47 (n: 169), compared to 0.01–0.09 (n: 169) for the existing models. New baseline EFs was estimated at global, regional, and Country scale with result showing that using different pre-season water management when calculating baseline EFs at country level is vital in order to reflect the variation between tropical and temperate rice regions accurately. Our findings shows that the new model is more sensitive in capturing differences in management practices between tropical and temperate rice, and their impacts on CH_4 emissions with baseline EF calculations accounting for these differences providing sound mitigation strategies.

1. Introduction

Rice is a major cereal crop for half of the world's population accounting for two thirds of the daily calories for nearly three billion people (Mosleh et al., 2015; Wang et al., 2017). Its production is a potent source of anthropogenic greenhouse gases (GHG), accounting for up to 55% of the total GHG emission budget from agricultural soils (IPCC et al., 2013) and for 6–11% of the global methane (CH_4) emissions from anthropogenic sources (Smith et al., 2021). With production increasing to meet the demand of a growing population, rice paddies will contribute to increased emissions from agricultural soils. The rising concerns of climate change will require climate smart management and increased consideration on use of resources, particularly through water management practices with traditional rice paddy management relying on large amounts of water (Tian et al., 2021). Studies carried out by Maraseni et al., (2018) covering eight rice producing countries in Asia show that the emissions per kilogram of rice decreased by 44–69% from 1961 to 2014 due to improved productivity and crop intensity. However, with rice production, on average, requiring 2500 L of water per kilogram of rice, which is two to three times more than for other cereal crops (Bouman, 2008), and with CH_4 emission being driven by flooding of fields (Yan et al., 2009; Smith et al., 2021), further research on climate smart management is needed to support reductions in emissions intensity.

Water management and system of rice intensification are predicted to be the main factors for producing more rice with less energy, water and land resources in the future (Maraseni et al., 2018) with water management being one of the most common interventions for mitigating

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emissions from rice paddies along with alterations to type and amount of fertilizer used, use of nitrification inhibitors, cultivar selection, incorporation of organic material or changes in tillage practices (Nayak et al., 2015; Wang et al., 2018). Optimising water usage for rice paddy fields can therefore lead to a reduction in GHG emissions, and reduced pressure on local water resources, with rice production using up to 40% of global water resources (Lampayan et al., 2015; He et al., 2020). Recent studies have shown that alternate wetting and drying, where the quantity of water and drainage period follows the plant's growth stages, reduces CH_4 emissions while having a lower yield penalty than the more traditional water mitigation options. It also reduces arsenic uptake by rice plants (Lagomarsino et al., 2016; Linquist et al., 2015; Norton et al., 2017) and may reduce irrigation costs by reducing the amount of water use by 42% compared to continuously flooded fields (Linquist et al., 2015; LaHue et al., 2016; Chidthaisong et al., 2018). Studies by Sriphirom et al. (2019) showed that alternate wetting and drying could reduce emissions by up to 23.1% during the dry season in Thailand compared to continuously flooded fields, while Lagomarsino et al. (2016) showed a reduction of up to 97% in Italy. Studies from California, North America showed a reduction in CH_4 of 60–87% (LaHue et al., 2016). Traditional water management strategies are, however, still useful mitigation strategies in areas where alternate wetting and drying might not be suitable. Studies have showed that single drainage can decrease CH_4 fluxes by 45% compared to continuously flooded fields (Meijide et al., 2011), while the application of nitrogen (N) inhibitors could reduce both CH_4 and soil N_2O emissions by 21% and 24%, respectively (Nayak et al., 2015). Water usage during pre-season, and time between crop cycles, also influence emissions and should be included when considering mitigation strategies from rice paddies, with studies on a winter flooded rice site in the Mediterranean showing that 63.1% of CH_4 were emitted during the flooded fallow season (Martínez-Eixarch et al., 2021). Wang et al. (2018) showed at sites with multiple rice cropping, that leaving the field drained for less than 30 days between crop cycles emitted 2.4 to 4.1 times more than fields which had longer durations of drainage.

Incorporation of organic material may not be the most suitable for reducing emissions from rice as increased soil carbon leads to increased CH_4 emissions with CH_4 being a product of anaerobic organic matter decomposition (Meijide et al., 2017), however, carbon sequestration is one of the best countermeasures for mitigating agricultural GHGs, with soils storing two to three times more C than the atmosphere (Minasny et al., 2017; Begum et al., 2018a). Options for improving soil sequestration while minimising emissions include timing the incorporation of organic material correctly, e.g. incorporating straw immediately after harvest in the previous season, which can halve CH_4 emissions compared to the application of straw just prior to transplanting (Wang et al., 2018). Management, soil and climatic conditions are highly variable across regions and as such mitigation of GHGs from rice should be carefully considered, for the individual region or site, with focus on the reduction of a field's total net GHG balance without yield penalty (Smith, 2012) with rice having a bottom-up mitigation potential of 10.6 Tg CH_4 y^{-1} (Smith et al., 2021).

GHG emissions are difficult, costly and time consuming to measure and thus many farmers and supply chain actors rely on GHG calculators to estimate their emissions and provide suitable mitigation options. The tools can be used to inform growers on how they best can minimise their environmental footprint without it having a negative impact on their finances (Hillier et al., 2011; Clift et al., 2014). For the tools to be effective, it is crucial that they can provide accurate estimates and mitigation options at a regional scale by considering the wide variation in management practices across the globe. There are, at present, several different models for predicting CH_4 emissions from rice from the more advanced process-based models of DeNitrification-DeComposition (DNDC) and DayCent (Li et al., 2004, Cheng and Ogle, 2014) to the empirical tier 3 models of Wang et al. (2018) and the tier 1 IPCC (2019) methods. The process-based models are often too site specific to work on a global scale due to the amount of input parameters required (Del Grosso et al., 2011; Cheng and Ogle, 2014; Begum et al., 2018b) and as such the empirical models are more commonly used due to their simplicity.

Studies done by Nikolaisen et al. (2023) showed that the empirical models for most rice-producing countries, could predict emission trends and management effects, but struggled to predict the magnitude of emissions, suggesting that the models lack sensitivity to key variables. As such, the ability to provide adequate mitigation options by only considering a handful of variables that influence these emissions may be limited, particularly if such models are prone to geographical bias. Soil texture, planting method, cultivar type and variation between single and dual cropping have not previously been included in CH_4 emission models for rice. Water management practices, such as alternate wetting and drying or winter flooding in pre-season or use of biochar are also excluded, and emission data from temperate regions are greatly under-represented, raising concerns about the relevance of the existing models for estimating EFs globally. As many countries rely on the IPCC tier 1 methods for estimating emissions for their national reports, the accuracy of these models is crucial when it comes to GHG mitigation and reduction targets for each country. Our aim, therefore, is to produce a global empirical model for quantifying rice based CH_4 emissions with the objectives being to (1) consider factors such as soil texture, planting method and the wide range of management practices that differ between countries, (2) emphasis on collection of data from non-Asian rice paddies and (3) estimate updated baseline EFs and how these are currently calculated. Based on the new model, the updated EFs will be compared to existing, global, regional, and country-specific EFs, and the model will be evaluated against existing models using an independent dataset.

2. Method

2.1. Database collation

Data on CH_4 emissions from rice and influencing factors were collected using peer-reviewed articles published before 2022 through a comprehensive literature search. Google Scholar, Scopus and ISI-Web of Science were searched for the following keywords in various combinations; "Rice", "Paddy", "Methane", "CH_4", "emission", "greenhouse gas", "GHG" and each rice producing country based on Food and Agriculture Organization of the United Nations (FAOSTAT) list (FAO, 2019a). Only original data which directly measured CH_4 emissions from fields were included; studies which involved use of greenhouses, laboratories, pots, or computer modelling in the data collection process were excluded. For a paper to be deemed suitable it needed to contain information on soil pH, soil organic carbon (SOC), water management practice during growing season, organic amendment where applicable and cumulative CH_4 emission. In addition to the key variables, a range of additional data were collected when available (A.1). In total, 245 publications comprising 2301 measurements fit the quality criteria. Of these, 225 with 2132 measurements were used for model creation, while papers published 2020 or later (169 datapoints from 20 publications) were held back for model evaluation.

CH_4 emissions were extracted directly from text, tables or figures within the publications and converted to seasonal, daily, and hourly emission values based on crop duration or recorded measurement period. If both measurement and crop duration were recorded, then measurement period was used for converting and calculating the emissions. In cases where crop duration was not mentioned, estimation was made based on the same cultivar from the same country, or if months of sowing/transplanting and harvest where given, the number of months would be counted and multiplied by 30. If it was expressed as early, mid, or late in a month it was calculated by number of months multiplied with 30 plus half a month (15 days). In publications where data were presented in graphs or figures rather than text, the online tool, Webplot digitizer, was used for extracting the data (Rohatgi, 2021). To distinguish the climate zone of a location, the Köppen-Geiger climate classification maps and 2nd level climate class groups (Beck et al., 2018) were used as shown in Fig. 1 with group description in Table 1.

In some cases, variables were aggregated into fewer classes. For soil texture, the United States Department of Agriculture (USDA) soil texture classification system was used. Based on sand, silt and clay content or soil texture description in individual studies they were divided into five classes: coarse, moderately coarse, medium, moderately fine, fine (FAO, 2019b). Growing season was divided into single, early, late, wet, and dry season based on crop information for each study. Planting method was divided into three groups; 'transplanted' when seeds are germinated off site and planted in the field once they have reach preferred height, 'direct wet-seeding' when seeds are broadcasted into flooded fields before fields are drained to allow seeds to germinate before fields are reflooded, and 'direct dry-seeding' for when seeds are drill seeded or broadcast on dry fields. Organic amendment was classed into the groups of biochar, green manure, farmyard manure, compost, and straw. Straw application was classed as either on (within) or off (outside) season since timing of straw incorporation affects CH_4 emissions, in which on season was defined as straw incorporation right before (trans)planting of rice while off season if incorporated directly after harvest. If straw was left on field after harvest, but not incorporated before the start of the next planting, then it was classed as on season (Wang et al., 2018). Organic amendment was also classified by application methods of incorporated, surface-applied, burnt, or unknown. Amount of organic amendment was extracted and converted into dry weight for straw and fresh weight for compost and manures (t/ha) when necessary. In cases where moisture content of wet rice straw was not recorded, we used IRRI's moisture estimate for straw which ranged between 15 and 18% (Jenkins, 1998; International rice research institute, 2005). The total amount of organic amendment applied for each plot was log transformed using ln(totOA + 1), to decrease the influence of individual extreme input values.

For water regime, the IPCC (2019) classification groups were used, that is, continuously flooded, single/mid-season drainage, multiple drainage, dry and wet season rainfed, deep water or unknown. In addition to this, we added two new water regime groups: saturated for when fields where moist but not flooded, and alternate wetting and drying. The pre-season water regimes were grouped into flooded, short drainage, long drainage or unknown as per IPCC (2019). In addition, winter flooded was added as a variable to include European and North American fields that are left flooded during the fallow season. Where fields had double cropping and pre-season water was not described, sowing and harvest dates were used for calculating the number of days between cropping. We then used the IPCC (2019) pre-season water regime classification to determine the class; flooded if less than 30 days prior to planting, long drainage if left bare for more than 180 days or short drainage if less than 180 days. In cases where (trans)planting and harvesting dates were not provided, we assumed that if double cropping, late rice would often be planted directly after early rice in which the pre-season water regime for the late crop would be classed as flooded (less than 30 days). If single crop planting occurred with no indication of winter flooding, it was classed as long drainage. In some instances,

Table 1
Definition and criteria for climate groups. Full list including those climates not included in our database and additional subgroups can be found in Beck et al. (2018) Table 2.

Climate group (2nd)	Definition	Criterion
	Tropical	Not (B) & $T_{cold}\geq18$
Af	Rainforest	$p_{dry}\geq60$
Am	Monsoon	Not (Af) & $P_{dry}\geq100$-Map/25
Aw	Savannah	Not (Af) & $P_{dry<}100$-Map/25
	Arid	Map<10x$P_{threshold}$
Bs	Steppe	Map≥5x$P_{threshold}$
	Temperate	Not (B) & $T_{hot}>10$ & $0<T_{cold}<18$
Cs	Dry summer	$P_{sdry}<40$ & $P_{sdry}<P_{wwet}/3$
Cw	Dry winter	$P_{wdry}<P_{swet}/10$
Cf	Without dry season	Not (Cs) or (Cw)
	Cold	Not (B) & $T_{hot}>10$ & $T_{cold}\leq0$
Dw	Dry summer	$P_{sdry}<40$ & $P_{sdry} < P_{wwet}/3$
Df	Without dry season	Not (Ds) or (Dw)

Table 2
Anova test of fixed effects showing the different variables impact on CH_4 emissions.

Parametric terms:	df	F	P-value	
Pre-season water	4	12.04	1.16e-10	
Planting method	2	12.09	6.10e-06	
Water regime	7	24.57	<2e-16	
Crop duration	1	37.57	1.08e-09	
Growing season	4	28.80	<2e-16	
Oa method	4	7.03	1.29e-05	
Soil texture	5	4.06	0.001	
Approximate significance of smooth terms:				
	Edf	**Ref.df**	**F**	**p-value**
S(pH)	5.35	6.09	3.15	0.004
S(Tot_oa): straw on season	2.74	3.33	47.28	<2e-16
S(Tot_oa): straw off season	1.00	1.00	49.87	<2e-16
S(Tot_oa): compost	2.15	2.62	9.84	9.84e-06
S(Tot_oa): green manure	1.65	1.99	56.60	<2e-16
S(Tot_oa): farmyard manure	2.18	2.64	25.73	<2e-16
S(Country)	8.52	16.00	471.07	0.000
S(Climate)	6.23	8.00	461.84	0.053
S(studyid)	208.13	258.00	12.28	<2e-16

Oa = Organic amendment.

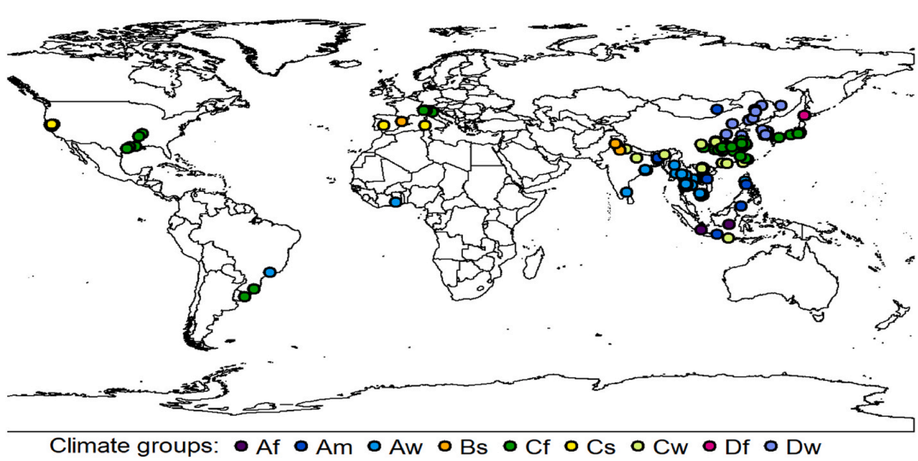

Fig. 1. World map showing location of each experiment and climate distribution across continents.

where information was limited, or there was an indication of dual cropping, but no mention of it, we could not determine the pre-season duration and it was left as unknown.

2.2. Statistics and final selection of variables for the new model

Data were collected based on their availability and as a result were unbalanced. Histogram plots showed the emissions to be right skewed and were therefore transformed to achieve a normal distribution (B.1). Different transformations from natural log to root square, fifth root and cube root were performed on the CH_4 emissions data to find the best normality fit. The cubed root appeared to normalise the distribution best, particularly for the variable kg CH_4 per ha per day and was therefore adopted for the model. Since CH_4 emissions depend on multiple factors, some categorical, some fixed while others random or continuous, a generalised additive model (GAM) was selected as the best approach as it allows modelling of both the linear and smooth non-linear effects of multiple covariates (Wood, 2006). R version 4.2.1, (R Core Team, 2022), RStudio version 2022.07.1–554 (RStudio Team, 2020) and mixed gam computation vehicle (mgcv) package version 1.8–40 (Wood, 2006) was used for the creation of the model. A forward selection procedure was used to better understand the difference and interactions between the parameters, adding one at the time starting with the highest corelation coefficient to the response variable first. Akaike Information Criterion (AIC) was used to compare model value by evaluating model fit to data and parsimony, with the lower AIC value suggesting a better model. Restricted maximum likelihood (REML) estimation was used for estimating the random effects standard deviation and degree of smoothing (Wood, 2006). Modelling assumptions were assessed using residuals and fitted values against observed values (Fig. 2).

Published experiments usually included one or more control replicates, serving as a reference for one or more types of organic amendment treatments. By definition, these controls do not belong to a specific type of organic amendment and were thus labelled as OA_type = “None”, meaning that no conventional OA types include data with zero amounts. To precisely estimate the effects of each type of OA when amendment amounts approach zero, we constrained the marginal effects for each OA type to be zero for OA amount = 0, such that the predicted value at zero was that of the reference type, defined to be the control treatment. Of the 2132 datapoints, 56 were removed when the amount of organic amendment applied was unknown, leaving 2076 datapoints for model fitting. From all the factors listed in supplement A.1, nine were included in the final selection, all of which had a significant effect on CH_4 emissions ($p < 0.001$). The response variable was the cube root of CH_4 kg ha^{-1} d^{-1} and the explanatory variables were: pre-season water, water regime, crop duration, organic amendment method, soil texture, with smoothers being applied to pH, country, climate and study id as well as organic amendment amount by organic amendment type. The best candidate GAM was:

$$E\left(CH_4^{(1/3)}\right) = \alpha_0 + \beta_{Psw} + \gamma_{Pm} + \delta_{wr} + \theta \times Cd + \mu_{Gs} + \pi_{OAm} + \rho_{St} + f_1(pH) + f_{2,OAt}(log(tOA+1)) + f_3(Co) + f_4(Cl) + f_5(St)$$

Equation 1

where.

Psw = Pre-season water class (short drainage, long drainage, flooded, winter flooded)
Pm = Planting method class (transplanted, direct dry-seeded, direct wet-seeded)
Wr = Water regime during crop season (continuously flooded, single drainage, multiple drainage, alternate wetting and drying, rainfed wet or dry season, deep water, saturated
Cd = Crop duration
Gs = Growing season class (single, late, early, wet, dry)

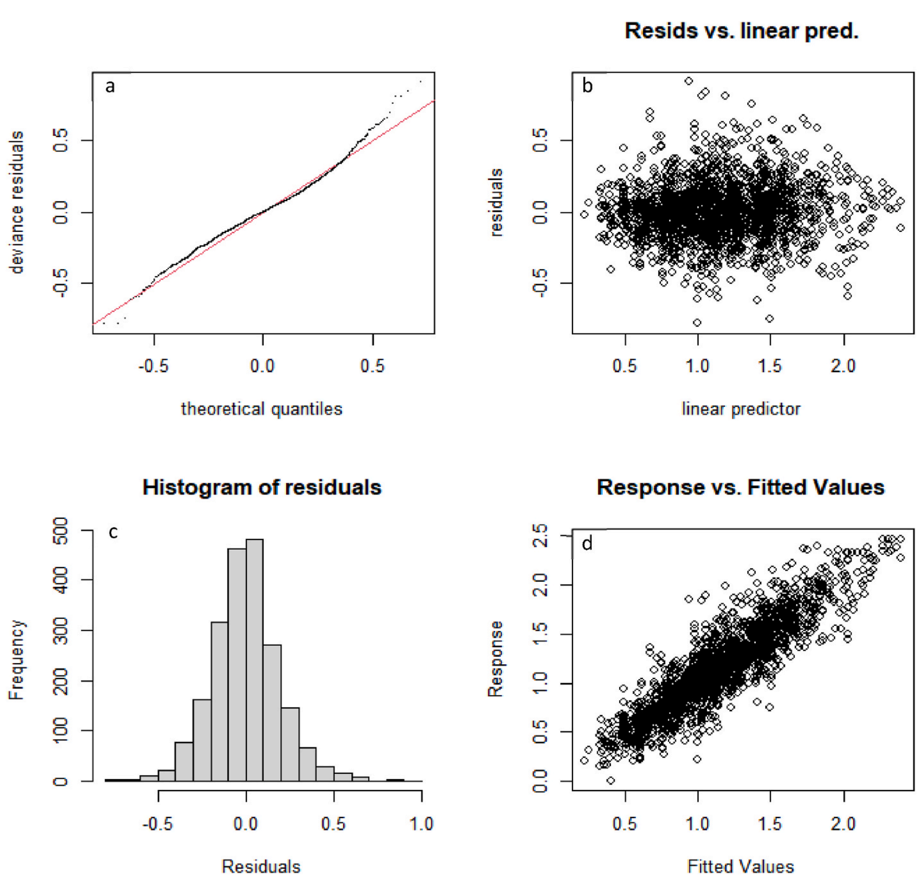

Fig. 2. Diagnostic plots of the GAM model reported in Equation (1). The normal Q-Q graph (a) is close to linear, indicating that the data distribution of cube root was approximately normal. The residual versus fitted values (b) suggest an almost constant variance with increasing means. The histogram of residuals is close to normality (c) while the correlation between observed and predicted emissions shows an acceptable model performance with R^2 value of 0.82 in cube root format (d) where the solid line is the reference line.

OAm = Organic amendment method (Incorporated, surface applied, burned, unknown, none), with a point constraint at zero (setting "pc = 0")
St = Soil texture class (fine, medium fine, medium, medium coarse, coarse, unknown)

For the smoothers below f_x are non-parametric penalized thin plate regression splines, while bs = "re" is the smoothed random effects.

f_1(pH) is a penalized thin plate regression spline ("*tprs*") of pH value
$f_{2,OAt}(tOA)$ is a *tprs* function of tOA (total organic amendment amount), estimated for each level of Organic amendment type *OAt* (straw on or off season, compost, farmyard manure, green manure, biochar or none), with a point constraint at zero (setting "pc = 0")
$f_3(Co)$ is a random intercept for Country
$f_4(Cl)$ is a random intercept for Climate group (Bs, Cs, Cw, Am, Aw, Df, Dw, Af)
f_5(Si) is a random Study id intercept

2.3. Evaluation of models

For model evaluation, both the above model and four existing models were evaluated using independent data (*test dataset*). The four models used were: Yan et al., 2005; Wang et al., 2018; IPCC 2006; IPCC 2019. However, for prediction using the new model the study id was excluded. With use of an Excel-based model performance statistical package (ModEval: Smith and Smith, 2007), the measured and predicted CH_4 emissions were compared for the different models by calculating the sample correlation coefficient (R) to test for association between predicted and observed data, the root mean square error (RMSE) for total difference between the observed and predicted values, mean error (E) and mean difference (M) between observation and simulation for bias in the modelled results (Smith and Smith, 2007).

2.4. Development of global, regional, and country specific EFs using predicted data

Descriptive analysis of predicted data was performed using both R version 4.2.1, (R Core Team, 2022) and IBM SPSS version 28.0.0 (IBM Corp. Released, 2021) statistical packages. Global, regional, and country scale baseline EFs (kg CH_4 ha^{-1} day^{-1}) were estimated from the predicted data and estimated effects of the variables combining the data from both the training and test dataset, using three baselines in which only pre-season water status differed. For all Asian countries, apart from Japan and South-Korea, the baselines were short drainage in pre-season, continuously flooded during growing period and no organic amendment. However, for countries that operated with single crop cycles, mostly in temperate regions such as Europe. American, Japan and South Korean rice paddies, we used a pre-season water management of long drainage, while Spain had winter flooded in pre-season, the remaining variables remained the same except study id and climate which was excluded for the EF predictions. The baseline EF (kg CH_4 ha^{-1} day^{-1}) values were derived using the following equation (equation (2)):

$$\boldsymbol{EF(CH_4{}^{(1/3)}) = \alpha_0 + \beta_{Psw} + \gamma_{Pm} + \delta_{wr} + \theta \times Cd + \mu_{Gs} + \pi_{OAm} + \rho_{St} + f_1(pH) + f_{2,OAt}(log(tOA+1)) + f_3(Co)} \quad \text{Equation 2}$$

Pre-season water were classed as short drainage for most Asian countries, long drainage for all North and South American countries, Portugal, Japan and South Korea and winter flooded for Spain.

Water regime during crop season was classed as continuously flooded for all plots.

Organic amendment type was classed as none for all plots.

All remaining parameters followed same principles as equation (1).

3. Results

3.1. Summary of the generalised additive model and modelled CH_4 emission

The selected variables had a significant impact on emissions at probability levels $p < 0.01$ or $p < 0.001$ (Table 2). All variables that had smoothing applied had a highly significant ($p < 0.01$) impact on emissions, except climate which was significant at the $p = 0.05$ level. The estimated effects of pH on CH_4 emissions indicate lowest emissions at a pH level around 7, and increasing on either side of pH 7, for both more alkaline and more acidic soils. Below pH 5 and above pH 8, the confidence intervals widen such that the impact on CH_4 emissions cannot be confidently estimated from the present data (Fig. 3, Table 2). For the organic amendment (Fig. 4) emissions tend to increase with amendment amount for all amendment types. The impact of straw on season amount increases up until approximately 6.4 t/ha (2 on the transformed scale), but beyond this value, the effect on emissions becomes highly uncertain due to the widening of the confidence intervals visible in Fig. 4a.

Predicted CH_4 emissions across the dataset were 1.98 CH_4 ha^{-1} d^{-1} with highest mean value being predicted for Vietnamese rice paddies and lowest for rice fields in India (Table 3). Crop duration varied from 64 days to 205 days across all data, with Vietnam having the shortest average seasonal crop duration of 97 days, while Spain had the longest of 156 days followed by Portugal (152 days); mean crop duration across all data was 114 days (C.1). For organic amendment types, straw on season and green manure resulted in the highest emissions, biochar the lowest. Emissions of CH_4 when straw was applied on season were 38% higher than if straw was applied off season. For pre-season water regime, fields which were winter flooded or with long drainage showed a 38% and 23% reduction in CH_4 emissions respectively when compared to fields with short drainage. Rice fields which were flooded pre-season emitted the most, with mean emissions of 3.29 kg ha^{-1} d^{-1} being 35% higher than those from short drained fields. Water regime during crop growing season showed continuously flooded fields having highest mean emissions followed by single drained fields; 2.29 and 2.14 kg ha^{-1} d^{-1} respectively, while emissions decrease by as much as 38% for alternate wetting and drying, 66% for saturated and 70% for rainfed dry season fields, compared to continuously flooded fields.

The four new explanatory variables included in this model were planting method, growing season, soil texture and organic amendment method. For planting method, direct wet-seeded plots had the highest average emissions while direct dry-seeded had the lowest (2.67 vs. 1.56 kg CH_4 ha^{-1} d^{-1}). Transplanted rice paddies had an average emission of 2.00 kg CH_4 ha^{-1} d^{-1}, though most data collected used this planting method (1574 compared to 338 for direct dry-seeded and 163 samples for direct wet-seeded). Using direct dry-seeded as the planting method can reduce emissions by 28% while direct wet-seeded increases emissions by 25% compared to plants being transplanted. For growing seasons, dry season had the lowest emissions, being 35% lower than wet season, while late season rice had the highest emissions at 29% more than early rice. Fields growing only one rice crop (classified as single season) had the second lowest emissions, with mean CH_4 flux of 1.73 kg CH_4 ha^{-1} d^{-1}, which was 9% higher than dry season rice. For soil texture, moderately fine soil had the highest emissions; 5%, 9% and 31% higher than moderately coarse, coarse, and medium soil textures respectively, emitting almost twice as much CH_4 as fine textured soils (44% reduction). For organic amendment method, incorporation had the highest emissions (2.72 kg CH_4 ha^{-1} d^{-1}) with burned (1.79 kg CH_4 ha^{-1} d^{-1}) and surface applied (2.15 kg CH_4 ha^{-1} d^{-1}) emitting 34% and 21% less (Table 3).

3.2. Evaluation of the new CH_4 model & existing models

The new CH_4 model was evaluated using independent data from 20 publications. Modelled CH_4 emissions were estimated in transformed

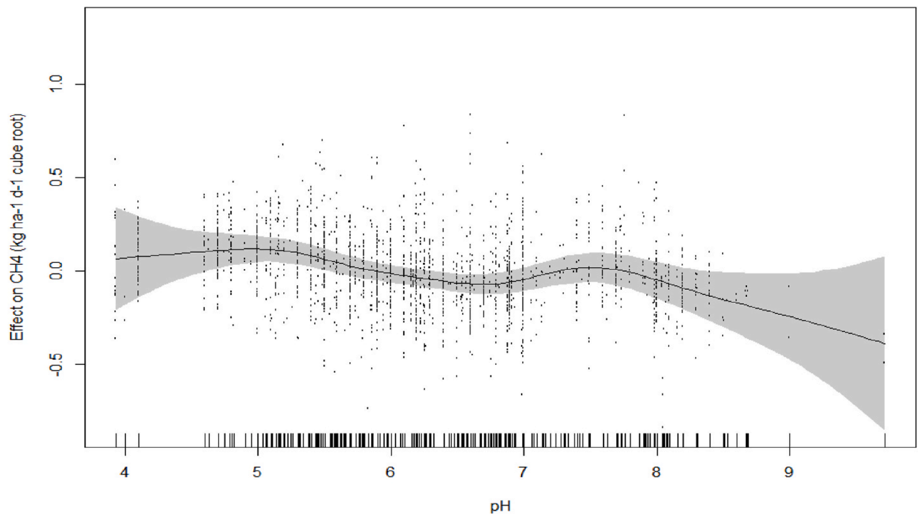

Fig. 3. Estimated pH effect with grey shadow representing 95 CI%, dots and rug marks represent partial residuals and observed pH values in the data respectively.

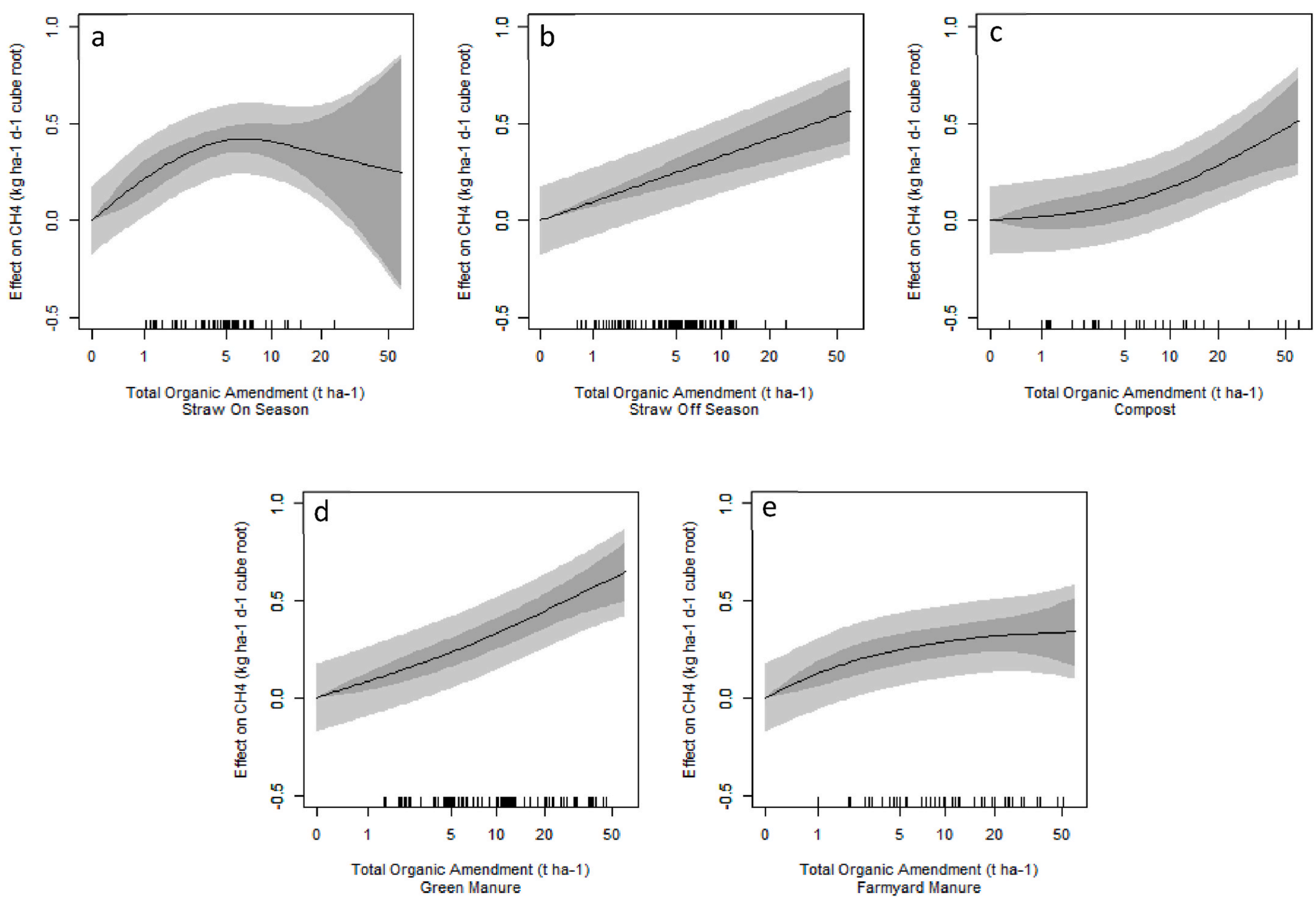

Fig. 4. Estimated effect total organic amendment amount for each organic amendment type. Straw on season (a), straw off season (b), compost (c), green manure (d) and farmyard manure (e). Grey shades are 95% confidence bands representing uncertainty in the effect of total organic amendment alone (dark grey) and combined uncertainty in the effect of total organic amendment and the baseline estimate (light grey). Rug marks represent observed total organic amendment for each organic amendment type.

scale (cubed root) and back transformed to the original scale (kg CH_4 ha^{-1} d^{-1}) for comparison with the measured data. The R values of the new model were 0.56 (n:169) for transformed and 0.47 (n:169) for back transformed predicted data (Fig. 5a–b) with existing methods ranging between 0.01 (n:169) and 0.09 (n:169) (Fig. 4a–b). When evaluating the model, we can clearly see some outliers, particularly when the data is back transformed but also for cube root values (Fig. 5a–b). However, compared to the existing models (Fig. 6a–b) the new model performs

Table 3
Relative CH_4 fluxes (kg ha^{-1} d^{-1}) for different growing season water regime, pre-season water status, soil texture, planting method, organic amendment type and method and rice growing season. Values based on model predictions.

Variables	Mean flux	Lower 95% CI	Upper 95% CI	Relative flux	Lower 95% CI	Upper 95% CI	Nr.Samples
				(kg CH_4 ha^{-1} d^{-1})			
Database summary	1.98	1.89	2.07				2076
Water regime during crop growth							
Continuously flooded	2.24	2.12	2.37	1.00	1.00	1.00	992
Alternate wetting and drying	1.39	1.07	1.71	0.62	0.51	0.72	93
Deep water	1.26	0.65	1.87	0.56	0.30	0.79	20
Single drainage	2.19	1.87	2.51	0.98	0.88	1.06	273
Saturated	1.00	0.59	1.41	0.44	0.28	0.59	62
Multiple drainage	1.69	1.55	1.83	0.75	0.73	0.77	561
Rainfed wet season	1.87	1.12	2.61	0.83	0.53	1.10	59
Rainfed dry season	0.68	0.40	0.97	0.30	0.19	0.41	16
Pre-season water							
Flooded	3.29	3.01	3.56	1.00	1.00	1.00	219
Long drainage	1.65	1.56	1.74	0.50	0.52	0.49	1079
Short Drainage	2.14	1.93	2.34	0.65	0.64	0.66	489
Winter flooded	1.32	1.05	1.59	0.40	0.35	0.45	64
Soil texture							
Moderately fine	2.27	2.09	2.46	1.00	1.00	1.00	467
Coarse	2.08	1.41	2.75	0.91	0.67	1.12	20
Moderately coarse	2.16	1.89	2.43	0.95	0.91	0.99	239
Medium	1.56	1.43	1.69	0.69	0.69	0.69	552
Fine	1.28	1.17	1.39	0.56	0.56	0.57	425
Planting method							
Direct wet-seeded	2.67	2.38	2.97	1.00	1.00	1.00	163
Transplanted	2.00	1.89	2.10	0.75	0.80	0.71	1574
Direct dry-seeded	1.56	1.40	1.72	0.58	0.59	0.58	338
Organic amendment type							
Straw on season	3.36	3.05	3.67	1.00	1.00	1.00	255
Green manure	3.29	2.92	3.66	0.98	0.96	1.00	138
Biochar	1.36	0.96	1.76	0.40	0.31	0.48	109
Farmyard manure	2.42	2.15	2.70	0.72	0.71	0.73	181
Compost	2.86	2.05	3.68	0.85	0.67	1.00	86
Straw off season	2.08	1.87	2.29	0.62	0.61	0.62	225
Organic amendment method							
Incorporated	2.72	2.54	2.89	1.00	1.00	1.00	758
Burned	1.79	0.86	2.71	0.66	0.34	0.94	22
Surface applied	2.15	1.93	2.38	0.79	0.76	0.82	84
Growing season							
Late season	3.09	2.70	3.48	1.00	1.00	1.00	129
Early season	2.184	1.87	2.50	0.71	0.69	0.72	138
Wet season	2.442	2.20	2.69	0.79	0.81	0.77	501
Dry season	1.481	1.31	1.66	0.48	0.48	0.48	309
Single season	1.73	1.63	1.83	0.56	0.60	0.52	999
Country							
Vietnam	4.23	3.66	4.79	1.00	1.00	1.00	129
Brazil	3.22	2.92	3.51	0.76	0.80	0.73	40
South Korea	3.15	2.83	3.48	0.75	0.77	0.73	106
Indonesia	3.06	2.64	3.48	0.72	0.72	0.73	164
Italy	3.04	2.58	3.50	0.72	0.70	0.73	37
Bangladesh	2.25	1.34	3.17	0.53	0.36	0.66	45
Ghana	1.94	1.39	2.49	0.46	0.38	0.52	5
Thailand	1.92	1.51	2.33	0.45	0.41	0.49	73
China	1.85	1.73	1.97	0.44	0.47	0.41	799
Myanmar	1.89	0.61	3.18	0.45	0.17	0.66	8
Japan	1.66	1.28	2.04	0.39	0.35	0.43	71
Spain	1.57	0.81	2.33	0.37	0.22	0.49	18
USA	1.35	1.16	1.54	0.32	0.32	0.32	192
Philippines	1.16	0.99	1.34	0.27	0.27	0.28	157
Uruguay	1.10	0.62	1.59	0.26	0.17	0.33	6
Portugal	0.73	0.65	0.82	0.17	0.18	0.17	6
India	0.65	0.56	0.73	0.15	0.15	0.15	220

better and has reduced the outliers.

All models were evaluated using the statistical routines suggested by Smith and Smith (2007). Model evaluation allows us to determine the behaviour and accuracy of model predictions; the full list of statistical measures calculated using ModEval, and plots of observed and simulated values for each model, can be seen in supplement (Table E1). The evaluation of the new CH_4 models shows a significant association between the measured and observed data with correlation coefficients of 0.68 (n: 169) for the back transformed data. RMSE shows that the total difference between the observed and measured data is 63.70% with a relative error of 14.14 and mean difference of 0.20 for the back transformed data (Table 4). Plots and evaluation of data which had uncertainty recorded (standard deviation) for the individual publications was also assessed to capture the impact of management and how model performance improved when uncertainty was available (E.1-E.6) with ModEval statistical analysis showing a reduction in RMSE, relative error and mean difference along with improved correlation coefficients (Table 4, Fig. 7).

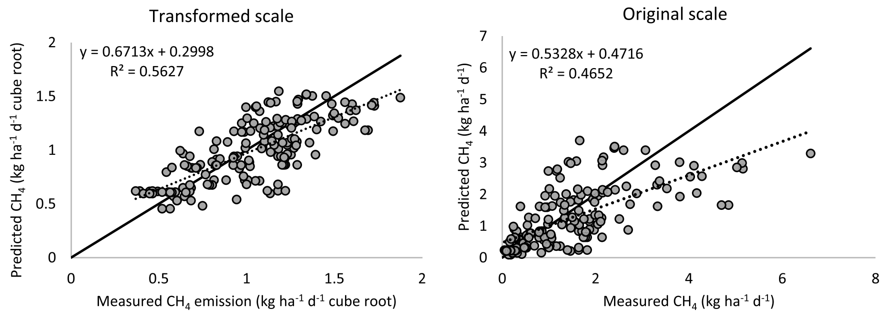

Fig. 5. Model performance for the new model; (a) predicted vs. observed data for new model for transformed data (CH_4 cube root), (b) predicted vs. observed data for new model for back-transformed data (CH_4 kg ha^{-1} d^{-1}). Solid line = reference line (1:1), dashed line = Ordinary Least Square estimate.

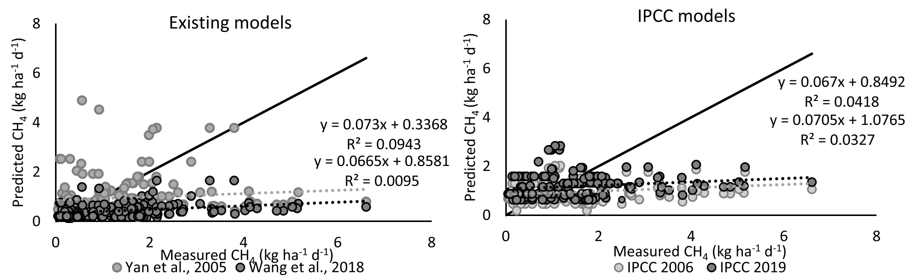

Fig. 6. Model performance of existing models (a) Yan et al., 2005 and Wang et al., 2018, (b) IPCC 2006 and IPCC 2019 (CH_4 kg ha^{-1} d^{-1}). Solid line = reference line (1:1), dashed line = Ordinary Least Square estimate.

Table 4
ModEval output for all models showing differences in statistical performance between the five models.

	CH_4 (cube root)	CH_4 SD (cube root)	CH_4 (kg ha^{-1} day^{-1})	CH_4 SD (kg ha^{-1} day^{-1})
r = Correlation Coeff.	0.75	0.79	0.68	0.65
Root mean square error of model	21.58%	18.11%	63.70%	60.69%
M = Mean Difference	0.04	0.03	0.20	0.23
E – Relative error	3.99	2.38	14.14	12.90
	Yan et al., 2005	IPCC 2006	Wang et al., 2018	IPCC 2019
		Kg CH_4 ha^{-1} d^{-1}		
r = Correlation Coeff.	0.10	0.204	0.31	0.18
Root mean square error of model	102.94%	89.96%	106.14%	86.62%
M = Mean Difference	0.49	0.50	1.00	0.27
E – Relative error	34.06	34.62	69.42	18.55

3.3. Modelled baseline EFs

CH_4 baseline EFs were estimated based on all fields being continuously flooded with no organic amendment and with country specific pre-season water management. This meant that Japanese, South Korean and most of European and American rice paddies were assumed to have long drainage for pre-season water management, while Spain had winter flooding, since these fields have one crop rotation with rice. The remaining Asian and African countries mostly had short or flooded pre-season based on different crop rotations and thus the baseline used for EF estimates were set to short drainage. For estimating EFs at regional scale, East-Asia was divided into two regions in which China was separated from Japan and South Korea due to the differences in climate, crop management and pre-season water method. The mean modelled emission was 1.97 CH_4 kg ha^{-1} d^{-1} (1.93–2.01) globally, with Africa having the highest regional predicted EF while South Asia had the lowest at 2.54 (2.54–2.54) and 1.16 (1.08–1.34) respectively. (Table 5, Fig. 8).

4. Discussion

4.1. Model advantages and the impact of variables on emissions

Generalised Additive Models (GAMs) can account for both random and fixed factors and are thus suitable for analysing unsystematic data (Hastie and Tibshirani, 1990; Berk, 2017). Random effects enabled us to account for multiple scales of geographical and experimental clustering in the data, while smoothing splines provided the necessary flexibility for capturing ad-hoc non-linear relationships between the response and explanatory variables. Our model can estimate total emissions based on current practices and environmental conditions and predict response to management interventions, with associated uncertainty. In addition to the existing explanatory variables included in previous CH_4 models used by IPCC, our model (Eq. (1)) includes effects of soil texture, planting method, growing season, organic amendment method, crop duration as a proxy to include impact of rice cultivars and a global classification system for climate groups (Beck et al., 2018). These new variables were added as they were all priori expected to influence CH_4 emissions, and we found these effects to be supported by the available data. We also added additional classes to pre-season water and water regime during crop growth as research suggests they either affect CH_4 emissions or more accurately represent the management in a country (such as winter flooding in pre-season which is common in parts of the USA and European countries either to maintain soil salinity and biodiversity (Martínez-Eixarch et al., 2018) or because of soil being rich in clay and having poor drainage (Meijide et al., 2011; Pittelkow et al., 2014)).

Planting method was considered important as it relates to water management practices and thus influence CH_4 and N_2O emissions by creating anaerobic or aerobic conditions which forms ideal conditions for the formation of CH_4 through methanogenesis or N_2O through

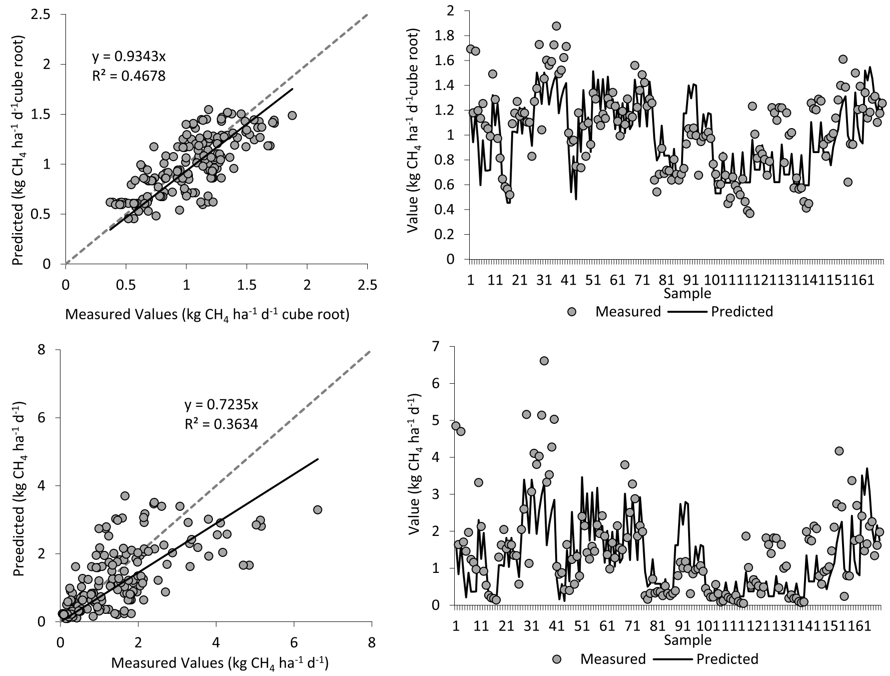

Fig. 7. ModEval plots used to check model accuracy on predicted emission values for all collected data in independent dataset. Where a and b are cube root values, c and d are back transformed values in kg ha^{-1} d^{-1}.

denitrification and nitrification processes. For instance, studies have showed that direct dry-seeding systems decreased CH_4 emissions by up to 60% compared to wet direct-seeding (Nayak et al., 2015; Wang et al., 2018) which supports our findings of a 42% decrease in emission when using direct dry-seeding compared to direct wet-seeding. Soil texture was included as studies have indicated that the soil texture influences CH_4 emissions with soils high in clay content having lower CH_4 emission than those rich in sand or silt (Baldock and Skjemstad, 2000). Using soil texture class instead of silt, sand or clay content improved the AIC value of the model and allowed for more data points to be included as some papers had expressed soil texture by name and not by % of silt, sand, or clay. PH was another soil characteristic factor used in the model as it has a substantial impact on emissions and is, together with soil organic carbon (SOC) thought to be the most common soil variables recorded in published literature. The production of CH_4 is sensitive to pH changes with methanogens being most active around neutral to slightly alkaline conditions (Garcia et al., 2000; Aulakh et al., 2001; Wang et al., 2018) which supports our findings that suggests CH_4 emission being lowest at neutral levels, peaking at pH levels around 5.5 and 7.5 and could be caused by water management with pH neutralising during flooded conditions while emissions peak under the same conditions (Minasny et al., 2016; Ding et al., 2019). Effects of pH below 5 or above 8 (Fig. 3) were comparatively highly uncertain, so our model should be used with caution when seeking absolute emission estimates or when making comparisons between pH levels in these extreme ranges of pH values. Given that CH_4 emissions are a product of the consumption, production, and transfer of methanotrophs and methanogens from soil into the atmosphere which processes are tolerant to pH variations (Bodegom et al., 2001; Wang et al., 2018) the correlation between the emissions and pH may be driven by other factors within the soil as well as water management.

SOC is often considered a key variable for soil conditions with several studies indicating an impact on CH_4 emissions (Shang et al., 2011; Zhan et al., 2011), however SOC had no significant impact on emissions in our database and was therefore not included in the final model. Wang et al. (2018) model showed SOC having the smallest contribution on variance of all variables considered though still having a significant impact on emissions. They further stated that the controlling effect of SOC on CH_4 emissions may be outweighed by other variables with the weak relation between the two being controlled by labile carbon substrate from both inherent and external sources. Thus, with our model having significantly more variables included, the effect of SOC on CH_4 emissions may be negligible with the positive relationship between the increase in emission and SOC for some experiments likely being related to increased carbon stock caused by the application of organic amendment and readily mineralizable carbon (Yagi and Minami, 1990; Wang et al., 2018) meaning more carbon being available for methanogens, leading to increase in CH_4 emitted.

Organic amendment amount is another factor thought to have a significant impact on emissions, with results from previous CH_4 models showing it being closely related to CH_4 fluxes (Wang et al., 2018). In our model, we linked it with organic amendment type as the impact of organic amendment is a function of type, amount, and methodology of organic manure application, while application method was kept as a separate factor. The overall results show a significant impact on CH_4 emissions for all three factors ($p < 0.001$, Table 2) in which applying straw off season, compared to straw on season, would be a good mitigation strategy, supporting previous model findings (Wang et al., 2018).

4.2. Evaluation of models

For model evaluation, the model accuracy of predicted emissions was determined using RMSE, E and M, calculating mean error and bias (Smith and Smith, 2007) using out-of-sample prediction. Overall, the model performs well, however it fails to accurately predict extreme observations, particularly when the data is back transformed on the original measurement scale. This is in line with the large unexplained variation within and between studies (about 50%), which is by definition unpredictable. A separate evaluation was done for those papers that included standard error and number of replications, thus providing a more detailed evaluation than for the full database (E.1-E.2). The comparison between the models show that including the new factors which are strikingly different among rice growing regions improved the sensitivity of the new model and enabled it to capture emission more

Table 5
Statistical summary of CH_4 emissions (kg ha^{-1} d^{-1}) and CH_4-EF (%) at country and regional scale.

		Daily CH_4-EF (kg CH_4 ha^{-1} d^{-1})									Daily CH_4-EF (kg CH_4 ha^{-1} d^{-1})						
			C.I.									C.I.					
		Mean	Median	Lower	Upper	Snr	Orig	Snr			Mean	Median	Lower	Upper	Snr	Orig	Snr
Region	**World**	1.97	1.97	1.93	2.01	2238	1.77	334	**Country**	**Bangladesh**[a]	2.08	1.83	1.85	2.31	54	0.85	4
	S.Asia[a]	1.16	0.99	1.08	1.23	296	0.65	40		**China**[a]	2.41	2.50	2.38	2.46	850	2.61	21
	S.E.Asia[a]	1.91	1.55	1.81	2.02	629	1.86	90		**India**[a]	0.95	0.94	0.90	1.00	242	0.62	36
	China[a]	2.41	2.50	2.38	2.46	850	2.61	21		**Indonesia**[a]	1.96	1.84	1.87	2.04	164	2.68	44
	Africa[a]	2.54	2.54	2.54	2.54	5	NA			**Philippines**[a]	0.97	0.87	0.91	1.02	171	0.89	34
										Thailand[a]	1.27	1.27	1.15	1.39	145	1.27	11
										Myanmar[a]	1.49	1.64	1.13	1.85	8	NA	NA
										Vietnam[a]	3.60	3.19	3.36	3.84	149	5.35	1
										Ghana[a]	2.54	2.54	2.54	2.54	5	NA	NA
	E.Asia[b]	2.03	2.07	1.93	2.12	194	2.09	67		**Italy**[b]	2.21	2.47	2.03	2.39	41	2.38	15
	Europe[b]	2.16	2.47	2.00	2.33	69	2.21	25		**Portugal**[b]	1.36	1.15	0.91	1.82	10	NA	NA
	N.America[b]	1.25	1.16	1.19	1.30	204	1.64	88		**Spain**[c]	2.51	2.51	2.18	2.84	18	1.94	10
	S.America[b]	2.04	1.99	1.94	2.15	46	1.61	3		**Japan**[b]	1.53	1.39	1.38	1.67	82	1.69	19
										South Korea[b]	2.39	2.32	2.31	2.47	112	2.25	48
										USA[b]*	1.25	1.16	1.19	1.30	204	1.64	88
										Uruguay[b]*	1.49	1.47	1.23	1.74	6	1.61	3
										Brazil[b]	2.13	2.12	2.04	2.22	40	NA	NA

EF = Emission factor.
C.I is the 95% confidence interval range.
Mean original (orig); mean CH_4 (kg ha^{-1} day^{-1}) from original data with the data available that fit the baseline EF categories of pre-season water condition, continuously flooded and no organic amendment.
[a] Short drainage, continuously flooded, no organic amendment.
[b] Long drainage, continuously flooded, no organic amendment.
[c] Winter flooded, continuously flooded, no organic amendment.

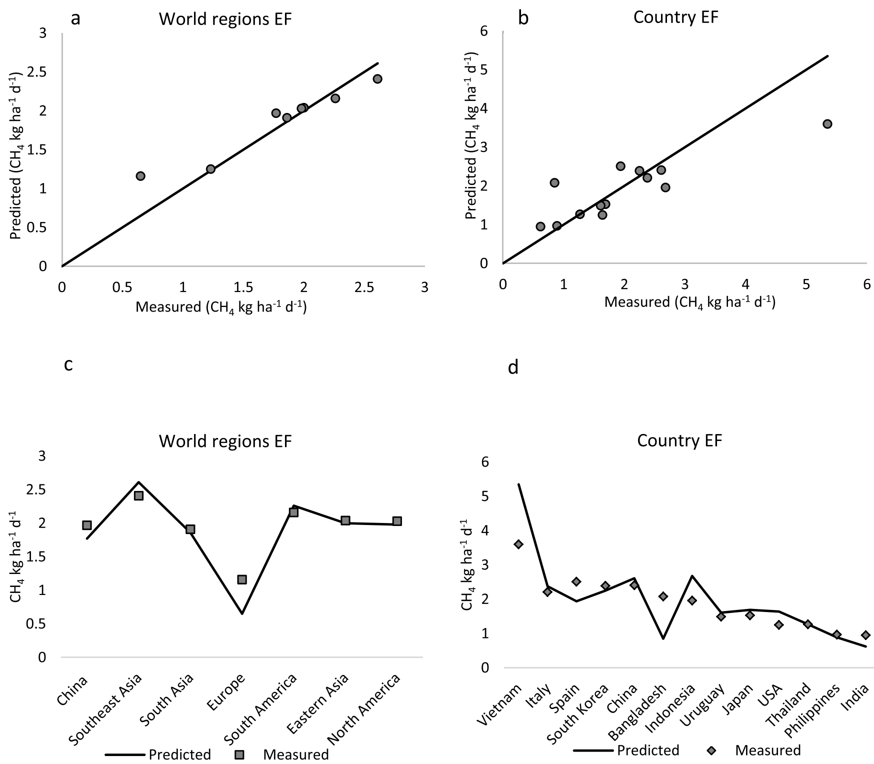

Fig. 8. Comparison of predicted EF at global, regional and country scale against those calculated based on original data that fit the baseline variables selection of the three pre-season regions, continuously flooded, no organic amendment. In figure a and b Solid line = reference line (1:1), dashed line = Ordinary Least Square estimate.

accurately than the existing models. This supports the overall finding that the model can perform well for some of the data, but still lacks some sensitivity to particularly large emission values. Back transformation of data to the original scale has led to some bias with the predicted values mostly being lower than measured values. Using a bias correction to back transform the data could therefore result in more accurate data and model performance (Strimbu et al., 2018), though the model can predict emissions well.

4.3. Global, regional, and country EFs

Only a handful of countries use empirical or process-based models (IPCC tier 2 or 3) for estimating their emissions from rice for national reports submitted to the United Nations Framework Convention on Climate Change (UNFCCC), while the majority rely on baseline EFs through an IPCC tier 1 approach. EFs for rice based CH_4 emissions have commonly been calculated using pre-season status of short drainage, continuously flooded as water regime during crop cycle and no organic amendment (Wang et al., 2018). After initial analysis of the data, management practices, climate, and other crop related patterns, we concluded that country specific pre-season water management should be used as existing method may have led to some bias considering same baseline EF calculation for all countries (Yan et al., 2005; Wang et al., 2018). This meant that Japanese, South Korean, American and European rice paddies had long drainage for pre-season water management as these countries commonly grow one rice crop annually with winter being left fallow or with upland crops, with exception of Spain where winter flooding is a common practice. For North America long drainage was chosen when calculating EFs as all states except California which commonly are winter flooded has long flooding or upland crop rotation in winter season (LaHue et al., 2016). Globally, the new estimated baseline EF was higher than those presented by IPCC (2019).

The change in baseline calculation for pre-season water management impact on country scale EFs can be seen particularly well for Italy in which the new EF of 2.21 kg CH_4 ha^{-1} d^{-1} (Table 5) corresponds better to national inventory reports EF of 2.0 and 2.7 kg CH_4 ha^{-1} d^{-1} for single and multiple drainage (National Inventory Report of Italy, 2020) than those currently used by IPCC (1.66 kg CH_4 ha^{-1} d^{-1}). Both the Spanish and Portuguese national communications reports (NCR) used the IPCC (2006) baseline EF of 1.30 kg CH_4 ha^{-1} d^{-1} (National Inventory Report of Spain, 2020; National Inventory Report of Portugal, 2021), however, the new estimated baseline EF for Spain is significantly higher at 2.51 kg CH_4 ha^{-1} d^{-1} while for Portugal it is almost the same as IPCC default at 1.36 kg CH_4 ha^{-1} d^{-1} (Table 5). Leaving fields flooded in winter as the common practice in Spain lead to higher emissions in the next rice season, particularly if organic amendment is applied off season (Martínez-Eixarch et al., 2018)). The high EF calculated for Spain is significantly higher than the mean measured emission and could be caused by the model accounting for the high application of farmyard manure of 15.2 and 51 t/ha^{-1} for some of the Spanish plots (Maris et al., 2016).

Our EF is higher than the existing EFs of 0.65 and 1.27 kg CH_4 ha^{-1} d^{-1} for North and South America, as is the case for all other rice regions all our EF estimated where higher than the existing ones used by IPCC 2019 and at country scale compared to Wang et al. (2018) at 1.25 and 2.04 kg CH_4 ha^{-1} d^{-1} respectively (Table 5). This difference results from the increased number of field measurements compared to previous models as well as the new way of estimating EFs. Approximately one third of all data were collected from China which mean daily emission were 2.02 while the estimated EF were calculated to 2.41 kg CH_4 ha^{-1} d^{-1}, (Table 5). The new EF for China is significantly higher than the existing one of 1.30 kg CH_4 ha^{-1} d^{-1} from Wang et al. (2018), but closer to the mean daily emission. IPCC EFs for Bangladesh and India are very similar at 0.85 and 0.97 kg CH_4 ha^{-1} d^{-1} (Table 5), respectively, while the new estimated EF are much higher for Bangladesh than for India (2.08 compared to 0.95 kg CH_4 ha^{-1} d^{-1}, Table 5). According to India's second biennial update report (BUR), the IPCC tier 2 and country specific EF approach was used for rice with seasonal EF estimate of 159.74 kg/ha for continuously flooded fields (Ministry of Environment, Forest and Climate Change, Government of India, 2018) which is higher than our seasonal EF estimate of 107.40 kg/ha using average crop duration of 113 days based on mean crop duration from collated data for India (C.1). For Bangladesh, the 3rd National Communication Report (2018) used IPCC EF of 0.97 kg CH_4 ha^{-1} d^{-1} which is significantly lower than our EF estimates. Both Vietnam and the Philippines used IPCC default values for their NIC reports (Ministry of Natural Resources and Environment, Government of Philippines, 2014, Ministry of National Resources and Environment, Government of Vietnam, 2020). Our EF estimate of 0.97 kg CH_4 ha^{-1} d^{-1} (Table 5) for the Philippines is higher than Wang et al. (2018) of 0.60, but lower than those estimated by Yan et al. (2003), which had an EF of 3.46 kg CH_4 ha^{-1} d^{-1}. While Vietnam, which had an EF of 1.13 from Wang et al. (2018) is significantly higher at 3.60 kg CH_4 ha^{-1} d^{-1} (Table 5) as our database contained 149 datapoints while Wang et al. (2018) had 14 datapoints from Vietnam. The increase in EF value could therefore be due to increased sample number and variability in experiments. Ghana, Myanmar, and Thailand have not been included in previous models. We estimated the EF to be 1.27 kg CH_4 ha^{-1} d^{-1} for Thailand, 1.49 for Myanmar and 2.54 for Ghana. For Thailand (145 samples) the updated the EF corresponds well with EF estimated of original data of 1.27 kg CH_4 ha^{-1} d^{-1} (11 samples, Table 5). For Ghana, pre-season water status is unknown and for Myanmar the experiments either had organic amendment application or long drainage in pre-season as measurements were done in wet season only, and thus EF calculation could not be performed on original data. The last two countries only have small sample number of five for Ghana and eight for Myanmar. The EF may therefore change as more publications become available.

5. Conclusion

Our findings show that consideration of key variables such as soil texture, planting method, and growing season, along with a global climate classification and additional classes to existing parameters, all have a significant impact on CH_4 emissions from rice fields. The new parameters are, therefore, needed to reflect the impact of soil, environment, and management practices on emission globally with the existing models for predicting CH_4 emission from rice paddies lacking sensitivity to some of these factors. Moreover, our results shows that it is crucial to acknowledge the differences between temperate and tropical regions to provide accurate baseline EF estimates at regional and country scale in the future. Our results also include estimates for four new countries, and as such, not only provide an updated list of baseline emission and scaling factors globally but can improve the submission process of national inventory reports for these countries in the future. Our findings will provide nations with more accurate EF estimates which reflects the local management and environmental conditions. Particularly for temperate rice regions with updated scaling factors and baseline EFs on average being higher than the existing factors produced by the Wang et al. (2018) and IPCC 2019 models. The inclusion of additional parameters and the large sample number collected has produced a new model which reflects the magnitude of the emissions more accurately than previous models and as such can aid countries in their aim to reach GHG reduction goals by setting more realistic emission estimates and mitigation objectives.

CRediT authorship contribution statement

Marte Nikolaisen: co-designed the research, collected the dataset, and, Writing – original draft, designed the modelling approach and performed the statistical analysis. **Thomas Cornulier:** advised on the study design, Writing – original draft, and approved the final version of the manuscript. **Jonathan Hillier:** designed the modelling approach and performed the statistical analysis, advised on the study design, Writing – original draft, and approved the final version of the manuscript. **Pete Smith:** advised on the study design, Writing – original draft, and approved the final version of the manuscript. **Fabrizio Albanito:** advised on the study design, Writing – original draft, and approved the final version of the manuscript. **Dali Nayak:** designed the modelling approach and performed the statistical analysis, advised on the study design, Writing – original draft, and approved the final version of the manuscript.

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.

Data availability

Data and model code has been uploaded as supplements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.137245.

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