A global methane model for rice cropping systems

Final Report

Working Paper No. 365

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

It has been estimated that rice production accounts for up to 55% of the total greenhouse gas (GHG) emissions budget from agricultural soils. Finding efficient ways to mitigate these emissions without adversely impacting yield is crucial as rice is a major cereal crop for half of the world's population and with production being estimated to increase by up to 40% by 2040 to meet demands. Emissions are challenging to measure and thus finding field-specific mitigation options is difficult; many therefore rely on GHG tools to explore suitable mitigation strategies. We have collected field data from across the world from peer-reviewed publications pre-2021, by evaluating the influence of different factors on methane (CH_4) fluxes, and using a step-down approach, a new CH_4 model was created using the linear mixed model in Rstudio. The new model has five additional factors and uses a different climate classification compared to existing models. Baseline emission factors (EFs) were estimated using the predicted data. Result shows that the difference between tropical and temperate regions needs to be considered when calculating an EF. By having different pre-season water management as a baseline, more accurate EFs can be estimated, particularly for temperate and American rice regions as the existing EF uses a baseline of short drainage, which is not common in these regions that typically have a long drainage duration and only one rice crop cycle per year. Evaluation of the new model against existing models shows the new model performs better, with R values of 0.602 while other models produce R^2 in the range of 0.11-0.37. The new model could be more sensitive to capture management practice differences between tropical and temperate rice and their impact on CH_4 emission.

Keywords

Agriculture; climate change; food systems; food security; rice; methane; greenhouse gas emissions.

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Contents

Acronyms

AIC	Akaike information criterion
AWD	Alternate wetting and drying
C	Carbon
CF	Continual flooding
CFT	Cool Farm Tool
CH_4	Methane
CO_2	Carbon dioxide
DDS/DWS	Direct dry/wet seeded
EF	Emission Factor
GHG	Greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
N	Nitrogen
N_2O	Nitrous oxide
RMSE	Root mean square error
SD	Single drainage
SF	Scaling factor
SOC	Soil organic carbon

TP	Transplant
WF	Winter flooding

Introduction

Rice cultivation

Rice is produced in all continents of the world except Antarctica and is a major cereal crop for almost half of the world's population, accounting for up to two thirds of the daily calories for nearly 3 billion people. Asia is the main rice producer and consumer (Khush., 2005; Mosleh et al., 2015; Wang et al., 2017); with populations rapidly increasing in countries which have rice as their staple food, it has been predicted that the production must increase with 8-10 million tons per year (Seck et al., 2012) and with as much as 40% by 2040 to meet demands (Wang et al., 2017). With this comes challenges not only in sourcing land to grow rice on and water availability, but also when it comes to making rice production more efficient in terms of increasing yields, minimizing water usage and greenhouse gases (GHGs) emissions. Rice production is considered a potent source of anthrophonic GHGs, with the IPCC estimating that it accounts for up to 55% of the total GHG emission budget from agricultural soils (IPCC, 2013); thus there are concerns related to increased production which will lead to higher emissions, particularly from the potent GHGs of methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) with rice accounting for 10-12% of the global CH_4 emissions from anthropogenic sources (Ciais et al., 2013).

Cultivation practices varies from country to country. Similarities can however be found for those countries that have similar climate. European rice paddies are often direct seeded, fallow or winter flooded and have a temperate climate with exception of some regions with arid climate. Rotation with upland crop such as wheat or legumes can occur (Lagomarsino et al., 2018). Rice producing regions of the USA, and South American countries such as Brazil and Uruguay have very similar management as European rice fields which are mostly irrigated; however, crop rotation with soybean is more common than with wheat, and South American fields are mostly rainfed instead of irrigated. Though less-developed South American countries such as Bolivia, Colombia and Mexico will not be irrigated or have upland crop rotations, fields are left waterlogged to allow for cattle grazing after harvest and have a more tropical climate than Brazil and Uruguay (Chauhan et al., 2017). In Asia, eastern Asia has the most similar management and climate conditions to Mediterranean and American countries; however, transplanting is the main planting method in all the Asian countries. Crop rotation varies depending on climate. Japan and South Korea have the coldest climate and either operate with rice-fallow or rice-upland crops such as wheat. China is a large country and main rice producer and represents all types of crop rotations and planting methods, though it has an arid or temperate climate. Southeast and South Asia has the warmest climate. These tropical countries often have double or triple cropping either as rice-rice, rice-upland or rice-rice-upland with rice-rice being the most common. In south Asia, India has varied climate regions e.g., tropical, arid and temperate climates where rice is grown and thus the rotation and crop duration vary. European and North American rice paddies have the longest crop duration which is reflected by rice-fallow being most common due to the cooler climate, while Southeast Asian countries has the shortest crop duration as seen in Table 1 (Adviento-Borbe and Linquist, 2016; Lagomarsino et al., 2016; Chauhan et al., 2017; Martinez-Eixarch et al., 2018).

Mitigation of Greenhouse Gas emissions

It is important to find technical measures that will reduce emissions and minimize environmental impact without yield reduction and financial loss to rice growers. Mitigating GHG emissions from rice is difficult due to the trade-off between different gases in which N_2O increases when CH_4 decreases and vice versa while the soil can be used to store CO_2 by implementing organic materials such as manure and straw, which in turn will lead to increased emissions of CH_4. Finding suitable mitigation options is a complex process where many factors will have to be considered, because of this inverse relationship in which mitigating one gas may lead to the increase in emissions of another (Ghosh et al., 2003; Linquist et al., 2012). The most common form of mitigation is through changes in water management practices, fertilizer type and amount, incorporation of organic material or changes in tillage practices. Other mitigation options include nitrification inhibitors, dual cropping, change of cultivar and more advanced water management/saving practices such as alternate wetting and drying (AWD), where the quantity of water and drainage period follows the plant's growth stages. Recent studies have shown that AWD reduces CH_4 emissions while having a lower yield penalty than the more traditional water mitigation options, such as midseason drainage or multiple drainage. It also reduces the arsenic levels in the soil and may reduce irrigation costs for the producer by reducing the amount of total water use by as much as 42% compared to continuously flooded fields (Linquist et al., 2015; LaHue et al., 2016; Chidthaisong et al., 2017). However, the traditional water management strategies are still useful mitigation strategies in areas where AWD might not be suitable. For instance, Wang et al., (2018)'s statistical analysis of data collected from peer reviews pre-2017 showed a decrease in CH_4 emissions of 29% when using single drainage and 41% with use of multiple drainage compared to fields which were continuously flooded. Implementing water management changes through more frequent drainage will, however, lead to increased N_2O emissions. Nayak et al., (2015) found that single drainage would increase N_2O emissions by 48% while decreasing CH_4 by 30%, while Meijide et al., (2011) showed an increase of 30% in N_2O emissions and up to a 45% decrease in CH_4 fluxes under single drainage. The total greenhouse gas balance for multiple drainage or alternate wetting and drying (AWD) will often still be lower even if N_2O fluxes increases (Meijide et al., 2016). This is supported by Linquist et al., (2012) which recorded a greenhouse gas balance and yield-scaled greenhouse gas balance reduction of up to 35% through drainage of rice paddies without significantly influencing yields. Nitrification inhibitors can thus be used to further reduce the total net greenhouse gas balance by reducing N_2O emissions through slowing down the conversion of NO_3 to N and thus limit available N for denitrification (Zou et al., 2005; Hillier et al., 2012; Akiyama et al., 2010). The application of N inhibitors can reduce both CH_4 and soil N_2O emissions by 21% and 24%, respectively (Nayak et al., 2015). According to FAOSTAT (2010), the use of synthetic fertilizers accounted for 60% of all N_2O emissions from Chinese agriculture; minimizing use of fertilizers, implementing N inhibitors or changing the type of fertilizer used may thus prove suitable mitigation options for reducing N_2O emissions.

Table 1. Summary of management practices for different rice producing regions, the data used for this table is derived from summary of all peer-reviews used in creating the database for this model development and thus may vary slightly from real rice farms as many of these are located at rice research fields and with set experiments.

Country	**Region**	**Climate**	**Crop rotation**	**Crop duration**	**Planting method**
Italy	Europe	Temperate	Rice-Fallow Rice-Upland	123	DDS or DWS
Portugal	Europe	Temperate	Rice-Fallow	152	DDS
Spain	Europe	Arid/ temperate	Rice-Fallow	156	DDS or DWS
USA	North America	Temperate	Rice-Fallow Rice-Upland	133	DDS or DWS
Brazil	South America	Temperate/ Tropical	Rice-Upland	129	DDS, Transplant (TP) tropical
Uruguay	South America	Temperate	Rice-Fallow	113	DDS
China	Eastern Asia	Temperate/ Cold	Rice-Upland Rice-Rice Rice-Fallow Rice-Rice-Upland (In descending order)	111	TP mostly occasional DDS and DWS
Japan	Eastern Asia	Temperate/ Cold	Rice-Fallow	113	TP
South Korea	Eastern Asia	Cold	Rice-Fallow Rice-Upland	126	TP
Indonesia	Southeast Asia	Tropical/ Temperate	Rice-Rice mostly Rice-Rice-Upland Rice-Upland	99	TP mostly occasional DDS and DWS
Myanmar	Southeast Asia	Tropical	Rice-Rice Rice-Upland	101	TP
Philippines	Southeast Asia	Tropical	Rice-Rice mostly Occasional Rice-Upland	101	TP most common, some DDS
Thailand	Southeast Asia	Tropical	Rice-Rice mostly some Rice-Upland	127	TP, DDS, DWS
Vietnam	Southeast Asia	Tropical/ Temperate	Rice-Rice Rice-Rice-Upland	90	TP, DDS
Bangladesh	South Asia	Tropical	Rice-Rice	114	TP

India	South Asia	Tropical/Arid /Temperate	Rice-Rice, Rice-Upland, some Rice-Fallow	111	TP, some DDS and DWS

Incorporation of organic material may not be the most suitable practice when it comes to reduction in emissions from rice with Nayak et al., (2015) showing an increase of up to 108% in CH_4 emissions when straw is applied. On a global scale however, improving soil carbon sequestration is one of the best countermeasures for mitigating agricultural GHGs with soils storing 2 to 3 times more carbon (C) than the atmosphere (Minasny et al., 2017; Begum et al., 2018b). Rice cultivation is thought to be able to sequester more C than upland crops due to the long-term reduction of microbial decomposition (Begum et al., 2018a). By applying straw, Nayak et al., (2015) found that it could increase SOC content by 0.99% annually and reduce N_2O emissions by 21%. Synthetic fertilizer application can also influence and improve soil C sequestration while tillage practices such as ploughing tend to lead to an increase in CO_2 emissions from the soil. An alternative for improving soil sequestration while minimizing emissions, is to time the incorporation of organic material correctly, with Wang et al., (2018) suggesting that CH_4 emissions from straw incorporation immediately after harvest in the previous season was half of the emissions than when straw was applied right before transplanting. Thus, incorporating straw directly after harvest in the previous season, or compositing while having fields drained in the fallow season, could effectively reduce CH_4 emissions. Mitigation of GHGs from rice should therefore be carefully considered, with a focus on the reduction of a fields total net greenhouse gas balance without yield penalty, since a reduction in yield may result in a more GHG intense production elsewhere to meet demand (Smith, 2012). Each mitigation option needs to be evaluated for the individual region or site to account for environmental and financial differences (Smith, 2012) as some regions will not have irrigation systems but rely on rainwater, and some may not be able to remove straw due to transport issues and thus will need to incorporate it into the soil.

Greenhouse Gas Tools & models

Measuring GHG emissions is difficult, costly and time consuming and thus many farmers and supply chain managers rely on GHG calculators to estimate emissions and select suitable mitigation options. Such software tools can be used to inform growers on how best they can contribute to minimizing the environmental footprint of their products without 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, considering the wide variation in management practices which vary greatly across the globe. There are, at present, many different models for predicting CH_4 emissions, both empirical and process based. However, many are too regionally specific to work across different continents or lack the ability to provide adequate mitigation options by only considering a handful of parameters that influence these emissions. The Cool Farm Tool (CFT) rice CH_4 model is a model which is widely used both by growers and supply chain managers across the world. The tool aims to produce a representative GHG footprint and net GHG emission estimates and uses a mix of IPCC Tiers ranging from Tier 1 to Tier 3 (Hillier et al., 2011). The IPCC Tier 1 2006 model used for rice in the CFT was originally derived from the Yan et al., (2005) empirical model on CH_4 emissions from Asian rice paddies but is currently being updated with the IPCC 2019 model which is based on the Wang et al., 2018 model, which includes data collected from temperate regions, though data from temperate regions are still greatly under-represented. These models, however, still have difficulties in accurately predicting emissions as they lack sensitivity to key variables such as soil texture, cultivar and certain management practices, raising concerns about the relevance of the existing models for estimating EFs globally. Impact of planting method, pre-season water status e.g., winter flooding, differ widely in temperate regions and inclusion of these parameters might improve model performance. As many countries rely on the IPCC Tier 1 or Tier 2 methods for estimating emissions for their national greenhouse gas emission reports, the accuracy of these models is crucial for estimating GHG emissions and setting reduction targets for each country. Our aim is therefore to produce a global model for quantifying rice based CH_4 emissions which considers factors such as soil texture, planting method and the wide range of management practices that differ between countries and climate regions. Based on this, new EFs will be created for CH_4 emission estimates from rice at country scale.

Materials & methods

Evaluation of existing empirical models and IPCC methods

We evaluated 4 existing CH_4 models with use of independent data (data from peer reviewed papers that were not used in the development of these models) resulting in 631 measurements from 70 publications, the location of the data used can be seen in Figure 1. Four different approaches; Yan et al., (2005); IPCC (2006); Wang et al., (2018) and IPCC (2019) were considered for comparison. Evaluation was done for all global regions in which Asia was divded into South, South-East and East (Table). With use of an excel-based model performance statistical package (MODEVAL; Smith and Smith, 2007) data was used to check for significant association between the observed and simulated fluxes for each of the models and if they were over or underestimating the observed data. The sample correlation coefficient was used to compare the relationship between the observed and modelled values and a linear regression analysis was used to determine the relationship between the two. Further statistical analysis was done in which the significance of r correlation coefficient and mean difference (M) was tested by using the F-test (p=0.05) and the Student's two-tailed t-test (critical at 2.5%). The R value represents the relationship between measured and observed value between -1 and 1 in which the closer it is to 1, the better the model. Student's t test shows the variation between the dataset in which the bias of the variation is shown as the mean difference, *M*, (Smith and Smith, 2007; Addiscott and Whitmore (1987). The modelled and measured datasets were then compared against each other to determine the total error of the model compared to observations by calculating the root mean square error (RMSE).

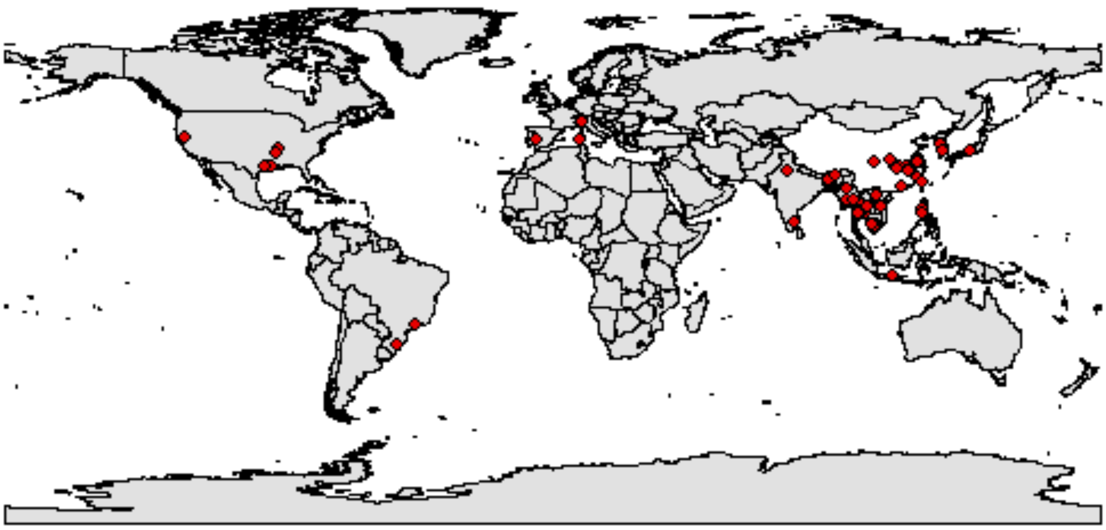


Figure 1. Location of data used for model evaluation

Table 2. Grouping of countires into regions

Regions	Country in regions

Europe	Italy, Portugal, Spain
East Asia	China, South Korea
South-East Asia	Indonesia, Myanmar, Vietnam, Philippines, Thailand
South Asia	Bangladesh, India
South America	Brazil
North America	United States (USA)

The two IPCC models which have been derived from the Yan 2005 and Wang 2018 models use scaling factors (SFs) and emission factors (EFs) in their models. The IPCC 2019 model also has an additional pre-season water regime class; non-flooded pre-season >365 d. Apart from this the classes for all parameters are the same though SFs differ slightly. The SFs and EFs for the IPCC methods vary according to different regions and/or management practices (IPCC, 2019; IPCC, 2006), and EFs are calculated considering water regime during the plant growing season and organic amendments applied for the different regions (Equation 1). The Yan et al., (2005) (Equation 2) and Wang et al., (2018) (Equation 3) models consider all the parameters included in the IPCC models as well as soil organic carbon (SOC), pH and climate. These EF and SF values along with the statistical models below have been used for our evaluation, and as input parameters for our analysis.

IPCC 2006 & IPCC 2019:

$$EF_i = SF\ EF_c \times SF_p \times SF_w \times SF_o \qquad \text{Equation 1}$$

Where:

EF_i = Daily emission factor (kg CH_4 day^{-1} ha^{-1}).

EF_c = Region specific for baseline emission factor (continuous flooding without organic amendment).

SF_p = Scaling factor accounting for the difference in water regime before the rice growing season.

SF_w = Scaling factor accounting for the difference in water regime during the rice growing season.

SF_o = Scaling factor accounting for the difference in organic amendment application.

$$Ln(flux) = constant + a \times ln(SOC) + pH_m + PW_i + WT_j + CL_k + OM_l \times ln\,(1 + AOM_l) \qquad \text{Equation 2}$$

$$Ln(flux) = constant + a \times ln(SOC) + pH_h + PW_i + WR_j + AEZ_k + OM_l \times ln\,(1 + AOM_l)$$ Equation 3

Where:

Ln(flux) = natural log of average CH4 flux (mg m2 h-1) during growing season
Constant = Intercept

SOC = Soil organic carbon (a is the effect of SOC)

pHm / pHh = The effect of pH in which m/h is for each individual class.

PWi =Effect of pre-season water regime (i is for each individual class)

WTj/WRj =Effect of water regime during growing period (j is for each individual class)

CLk/AEZk = The effect of climate/agroecological zones (AEZ)

OMl x ln (1 + AOMl) = OA is effect of added organic material while AOM is the effect of the amount applied (l is for each individual class/amount t/ha^{-1}.

Database collation

Data on CH_4 emissions from rice and influencing factors were collected using peer-reviewed papers published before 2021 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 FAOSTAT (FAO, 2018). 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 not included. For a paper to be deemed suitable to be included in the database it needed to contain data and information for certain key parameters. These parameters were soil pH, soil organic carbon (SOC), water management practice during growing season and previous season, organic amendment where applicable and cumulative CH_4 emission. In total, 220 publications comprising 2098 measurements fit the quality criteria. Of these, 183 with 1758 measurements were used for model creation, while 124 datapoints from 19 publications were collected later and used for evaluation of the model.

The new database has recorded CH_4 emissions from all rice growing continents in the world with exception of Africa and Oceania with country search being done based on FAOSTAT’s list of rice producing countries (FAO, 2018). For each individual study a range of data were collected such as CH_4 emissions and water regime during and pre-rice-crop, planting method, organic amendment types and amount, fertilizers and use of nitrification inhibitors as well as climatic conditions and soil properties. The data collection methodology is similar to Wang et al., (2018) and full list of data collated are provided in Table . Where data was missing unknown or -9999 was used for most parameters, while missing geographic coordinates, climate and soil data were obtained for the location using online resources. Missing climate data was obtained from https://en.climate-data.org/ The coordinates were put into ArcGIS along with GIS files from Beck et al., (2018) to determine the climate groups for each location using the Köppen-Geiger climate classification maps. We chose to use the 2nd level climate class group which resulted in 13 climate groups. Location and climate group for the collated data is provided in **Error! Reference source not found.** while the description of each group is provided in **Error! Reference source not found.** with full list in Beck et al., 2018 (Table 2).

Soil texture where clay, sand and silt percentage had been recorded was found with use of the United States department of agriculture (USDA) soil classification triangle and further grouped into broad classes based on USDA soil texture classes (FAO, http://www.fao.org/fishery/docs/CDrom/FAO_Training/FAO_Training/General/x6706e/x6706e06.htm). Soil texture was included, as studies have indicated that the soil texture influences CH_4 emissions e.g., Baldock and Skjemstad (2000) showed soils with high clay content have lower CH_4 emission than those rich in sand or silt. Soil organic carbon was recoded in %. If papers provided soil organic matter (SOM), it was converted to SOC % using Bemmelen index value of 0.58 times the SOM value, and if given in g kg^{-1} total organic carbon it was divided by 10; similar approach was used for soil nitrogen (N) to convert it from g kg^{-1} to percentage. Carbon:Nitrogen and bulk density was recorded when available, however not all papers record a comprehensive list of soil properties and thus pH and organic carbon was considered as the baseline of what a paper needed to have on soil properties.

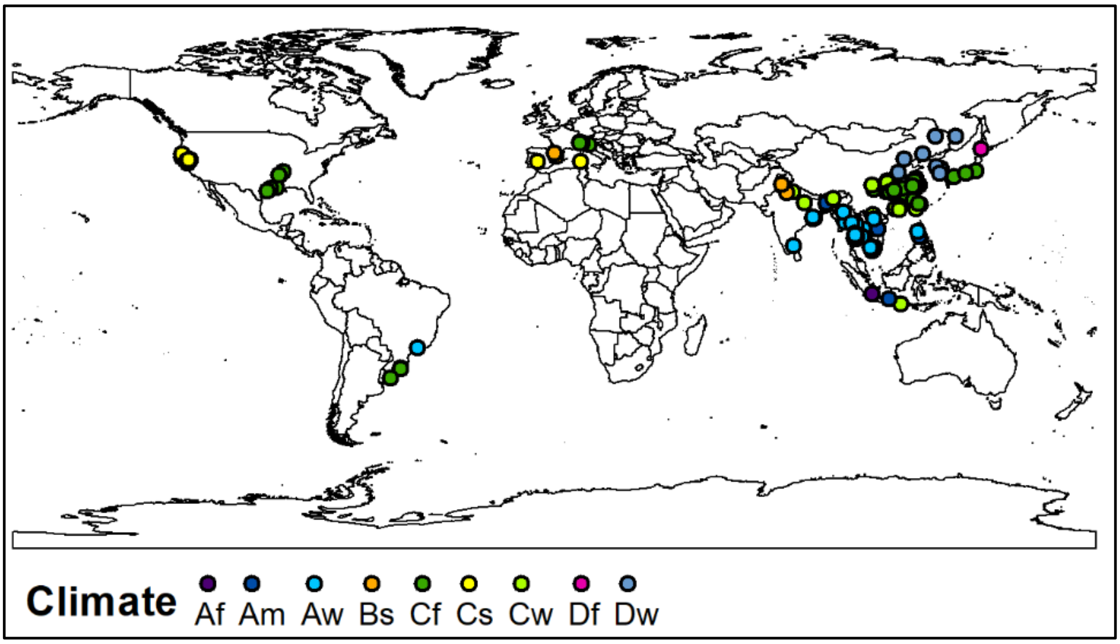


Figure 2. World map showing location of each experiment and climate distribution across continents.

Table 3. Definition and criterion for climate groups. Full list including those climates in 2nd group class not in our database and additional subgroups can be found in Beck et al., 2018 table 2.

Climate group (2nd)	Definition	Criterion
Tropical		Not (B) & $T_{cold} \geq 18$
Af	Rainforest	$p_{dry} \geq 60$
Am	Monsoon	Not (Af) & $P_{dry} \geq 100$-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) & $T_{hot}>10$ & $T_{cold} \leq 0$
Dw	Dry summer	$P_{sdry}<40$ & $P_{sdry} < P_{wwet}/3$
Df	Without dry season	Not (Ds) or (Dw)

The organic amendments were classed into the groups of manure, biochar, straw (grass, wheat and rice straw, on-season or off-season based on application time), green manure, farmyard manure and compost. Straw application was classed as either on or off season since timing of straw incorporation affects CH_4 emissions, in which on-season was defined as straw incorporation right before planting or transplanting of rice while off-season if incorporated directly after harvest or in previous season with a different crop. 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. Amount of organic amendment was extracted, and where not already in the correct weight format, was converted into dry weight for straw and fresh weight for compost and manures. In cases where moisture content of wet rice straw was not recorded, we used IRRI's moisture estimate for straw in which the moisture content at harvest ranged between 15-18% (IRRI, 2014). Method of organic amendment application were also recorded and grouped into following classes: incorporated, surface-applied, burnt, none or unknown. If paper said left on field or applied, it was classed as surface applied.

Table 4. List of all parameters collected and consider

Parameters	Acronym	Model terms
Experiment identification	Exp.ID	Covariate
Location	Country	Factor
	Region	Factor
	Latitude	Factor
	Longitude	Factor
	Elevation	Factor
Mean annual temperature	Mean_an_temp	Covariate
Mean annual precipitation	Mean_an_prec	Covariate
Sample year	Sample year	Covariate
Reference	Reference	Covariate
Soil texture	Unknown, Fine, Moderately_Fine (medium fine), Medium, Moderately_Coarse, Coarse	Factor
Soil texture %	Sand, Silt and Clay %	Covariate
Soil organic carbon	SOC%	Factor
pH	pH	Covariate
pH group	Acidic, Neutral, Alkaline	Factor
Sulphate in soil	Sulphate	Covariate
Soil Nitrogen %	Soil N%	Covariate
Carbon:Nitrogen ratio	C:N ratio	Covariate
Bulk density	Bulk density	Covariate
Experiment/treatment	Treatment	Covariate
Growing type	Single, Late, Early, Unknown	Factor
Rotation type	Rice_Fallow, Rice_Rice, Rice_Rice_Upland, Rice_Upland, Unknown	Factor
Cultivar	Crop type	Factor
Planting method	DDS (Direct dry seeded), DWS (Direct wet seeded), TP (Transplant)	Factor
Sowing date	Sowing date	Covariate
Transplanting date	Transplanting date	Covariate
Harvest date	Harvest date	Covariate
Crop period	Crop length (duration from sowing/transplanting to harvest)	Factor
Crop length	Short, Medium, Long	Factor
Yield	Yield (t/ha^{-1})	Dependent
Pre-season water	FD (flooded), LD (long drainage), SD (single drainage), WF (winter flooded), Unknown	Factor
Water depth (cm)	Water_depth_cm	Covariate
Current water regime	CF (continuous flooding), SD (single drainage), MD (multiple drainage), RFW (rainfed wet season), RFD (rainfed dry season), AWD (alternate wetting and drying), Saturated (SA), deep water (DW)	Factor
Organic amendment (OA)	Yes, No, Unknown	Factor
Residue type	Manure (green manure, Farmyard manure, compost), straw (on or off season), Biochar, Combined (when mix of previous), NONE	Factor
OA method	Incorporated, burned, broadcasted, NONE, Unknown	Factor
Amount of OA	t/ha (dry weight for straw, fresh for manure and compost)	Covariate

OA carbon content	OA_C_Amount	Covariate
OA nitrogen content	OA_N_Amount	Covariate
Fertilizer information	Fertilizer type (a)	Factor
	N rate, P rate, K rate, Other	Covariate
	No. splits	Covariate
Sulphur in fertilizer	With or without sulphur	Factor
CH_4 flux	Per hour (mg/m^2/h), day (mg/m2/d), season (g/m2)	Dependent

For water regime, we used the IPCC classification groups which were continuously flooded (CF), single/mid-season drainage (SD), multiple drainage, dry and wet season rainfed, deep water or unknown. In addition to this, we added two new water regime groups; alternate wetting and drying (AWD), as research suggest if implemented accurately AWD can reduce CH_4 emissions, while not impacting yield significantly (Linquist et al., 2015. When field was moist but not flooded, the water regime was classified as saturated. In cases where field had a single drainage event, mid-season and then a drainage event at the end of season it was classed as single drainage, as fields most commonly are drained before harvest including those classed as CF. Flooding depth (cm) was also recorded as studies have shown that there is a potential threshold line for ideal water depth when it comes to CH_4 emissions, particularly with the use of AWD (Linquist et al., 2015) The pre-season water regimes were grouped into flooded, short drainage, long drainage or unknown as per IPCC (IPCC, 2006, 2019). We also added winter flooded (WF) as a parameter as some rice paddies in Europe and North America leave fields flooded during the fallow season. In locations with double cropping where preseason water was not described, sowing/transplanting and harvest dates were used for calculating the number of days between cropping. We then used the IPCCs (2006) "timeframe" in their 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 sowing/transplanting and harvesting dates were not provided, we assumed that if double cropping late rice often would often be planted directly after early rice in which the preseason water regime for the late crop would be classed as flooded. If they had a single crop planting, and no indication of flooding in the winter, it was classed as long drainage. In some instances, there were too little information provided to class growing season and preseason water regime, in these circumstances, we left it as unknown.

Many of the collected variables were divided into broader groups to reduce classes, such as soil texture and organic amendment types and cultivar type to make analysis easier. CH_4 emissions were extracted directly from text or tables within the publications and converted to seasonal, daily and hourly emission values based on crop duration or recorded measurement period. In cases where crop duration or measurement period were not accurately recorded with dates of sowing/transplanting and harvest or with days after sowing/transplanting an 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 late-April to mid-September it was calculated to be number of months multiplied by 30 plus half a month (15 days). If both measurement and crop duration were recorded, then measurement period was used for converting and calculation the emissions. In publications where date of sowing, transplanting and harvest or emission or yield values were missing, but presented in graphs or figures, an online tool was used for extracting the data (Rohatgi, 2021).

Additional parameters such as cultivar type, planting method and yield were also recorded. For cultivar we divided them into short, medium and long duration as there were too many different cultivar types to divide by name. Rice cultivar varieties have differential effect on CH_4 emission which is mostly due to different morphological and physiological characters. For instance, Linquist et al., (2018) stated that hybrid rice cultivars had lower emission than semi-dwarf cultivars in the US, while other studies have suggested that high yielding cultivars have lower CH_4 emissions. We attempted to divide the cultivars into type such as Jasmine, Japonica, Indica, Hybrid etc. but not enough information was available to do so. However, we used crop duration as a proxy to include impact of rice cultivar varieties. Planting method is considered important as it is related to water management practises, and thus influence CH_4 and N_2O emissions, due to removal or adding of water during germination or transplantation of rice creating either anaerobic or aerobic conditions which forms ideal conditions for the formation of CH_4 through methanogenesis or N_2O through denitrification and nitrification processes. Studies by Linquist et al., (2015) and LaHue et al., (2016) show that dry-seeded systems decreased CH_4 emissions by up to 60% compared to direct seeding carried out in water (wet seeding). There are generally three types of planting method used; these are transplanting (seeds are germinated off site, once they reach preferred height they are planted in the field), direct wet seeding (seeds are broadcast into flooded fields, then the fields are drained to allow germination and then reflooded) and direct dry seeding (seeds are drill seeded or broadcast to dry fields). In cases where papers mentioned direct seeding and did not mention whether or not the field was flooded it was classed as unknown. Yield data was collated to study influence of management practices on rice yield as mitigation technologies that reduces yield will have financial impact of the grower and with projected increased demand for rice meaning that a reduction in yield will have a significant impact on supply and thus food security.

Statistics & final parameter selection for new model

Data were collected based on their availability and not through a single study, thus being unbalanced. Histogram plots showed the emissions to be right skewed and thus needed transforming to achieve a normal distribution. 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 fifth root appeared to normalize the distribution best, particularly for the kg per ha per day which were used for the model creation. Since CH_4 emission depends on multiple factors, some fixed while others random, a linear mixed model (LMER) was thought to be the best approach when categorial, continuous, fixed and random factors need to be considered to best assess the variables impact on the emissions. Rstudio (2020) was used for the creation of the model, first data was transformed, and factors labelled. Correlation and boxplot were created to study the impact of individual parameters on emissions (S.1). A stepdown approach for selection of variables was used by first adding all influencing parameters and then removing one by one of those who showed no significance (NCSS, n.d.). We then assessed which parameters would be random within which Country, and Climate was determined to be our random factor. Several steps were required to determine the preferred model based on The Akaike information criterion (AIC) values, r^2 and the normality of the residuals. From all the variables listed in table 2, only 9 were included in the final selection, all of which had a significant effect on CH_4 emissions. Country and climate were included as random factors. The response variable was fifth root of CH_4 kg ha^{-1} d^{-1} and explanatory variables were pre-season water, water regime, crop duration, organic amendment type, method and total amount, pH, nitrogen fertilizer amount, soil texture with country and climate as random factors.

$$CH_4{}^{0.2} = Constant + Psw_a + Pm_b + Wr_c + Cd + Gs_d + pH + Na + OAt_e{:}\,tOA + St_f + (1|Co_g) + (1|Cl_h) \quad \text{Equation 4}$$

Where:

P sw = pre-season water, a = class (short drainage, long drainage, flooded, winter flooded)

Pm = planting method, b = class (transplanted, direct dry seeded, direct wet seeded)

Wr = water regime during crop season, c = class (continuously flooded, single drainage, multiple drainage, alternate wetting and drying, rainfed wet or dry season, deep water, saturated

Cd = Crop duration

Gs = growing season, d = class (single, late, early, wet, dry)

pH = value

Na = Nitrogen fertilizer amount

OAt = Organic amendment type, e = class (straw on or off season, compost, farmyard manure, green manure, biochar or none)

tOA = total organic amendment amount

St = soil texture, f = class (fine, medium fine, medium, medium coarse, coarse, unknown)

1|Co = 1| = random factor, Co = Country, g = specific country

Development of regional and country specific EFs using predicted data

Descriptive analysis of predicted data was performed using both Rstudio (2020) and IBM Corp. (2020) statistical packages, and baseline emission factors were calculated from the predicted data. We used two baselines, in which only pre-season water status differed. For all Asian countries, with the exception of 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, we used a pre-season water management of long drainage, the rest remained the same. These countries were the European countries, countries in the Americas as well as Japan and South Korea. Based on this, default EFs (kg CH_4 ha^{-1} day^{-1}) were estimated at both regional and country scale.

Result & Discussion

Evaluation of existing models

Results show that the existing models lack some sensitivity to predict emissions accurately and that the recently updated models, particularly for IPCC (2019) only had minor improvements compared to the original models. On regional scale, the modelled emissions were much lower than the measured emissions for most regions. However, for southeast Asia (Philippines/Thailand and Indonesia/Myanmar/Vietnam) Yan et al., (2005) and Wang et al., (2018) seems to overestimate the smaller observed values, but underestimates the higher values, while the IPCC models underestimate the higher observed values, with a few overestimates of the lower values (Fig. 3). For the Chinese data, the models also underestimate emissions for all measured emissions over 2 kg CH_4-C ha^{-1} d^{-1}. Like Southeast Asia, Japanese and South Korean emissions were underestimated for the larger observed values and lower emissions were overestimated by both the Yan and Wang models, while the IPCC models estimate the same value for all of the range, with everything being estimated between 0.5 and 1.5 while observed data ranged from around 0.2 to circa 2.8 (Fig. 4). The models still underestimate data from American rice paddies for both Brazil (Fig. 8) and USA, in which the IPCC models do not capture the trend of the American rice paddies, estimating most values to be right below 1 (Fig. 5), while their performance is more spread for the European data (Fig. 6). For India, the models performed quite well but the emission range is small, with all observed data lower than 1 CH_4-C kg ha^{-1} d^{-1}, which makes the model appear better. However, there was still some over- and under-estimation by the model compared to the observed data. For Bangladesh, the existing models significantly underestimated the emissions (Fig. 7). This could be due to low sample number in Wang et al., (2018) database for this country. However, if India and Bangladesh were combined to form South Asia, this would cause a substantial over- or under-estimation of emissions for each country when EFs are produced with our database having India as the country with the lowest mean CH_4 emission (mean 1.24 kg ha^{-1} d^{-1}) while Bangladesh has the third highest emissions of all countries (mean 4.10 kg ha^{-1} d^{-1}), as shown in figure 7 below. Based on these findings, questions arose on how best to group the different countries as Wang et al., (2018) had grouped Asian data into climatic zones, while it had not been done for European, North American and South American data and grouping them into the above regions would also influence the accuracy of using the model EFs at country scale. Mean CH_4 emissions (kg ha^{-1} d^{-1}) at country scale and regional scale for India is 1.24 kg CH_4 ha^{-1} d^{-1}, for Eastern Asia it is 2.20 kg CH_4 ha^{-1} d^{-1}, for Bangladesh the value is double, 4.10 kg CH_4 ha^{-1} d^{-1} (Fig. 7). However, baseline EFs are similar, and thus the type of studies included, and for example the use of organic amendments, may influence the mean emission value. A descriptive analysis using Modeval, and standard deviation is provided in the supplemental material (S3).

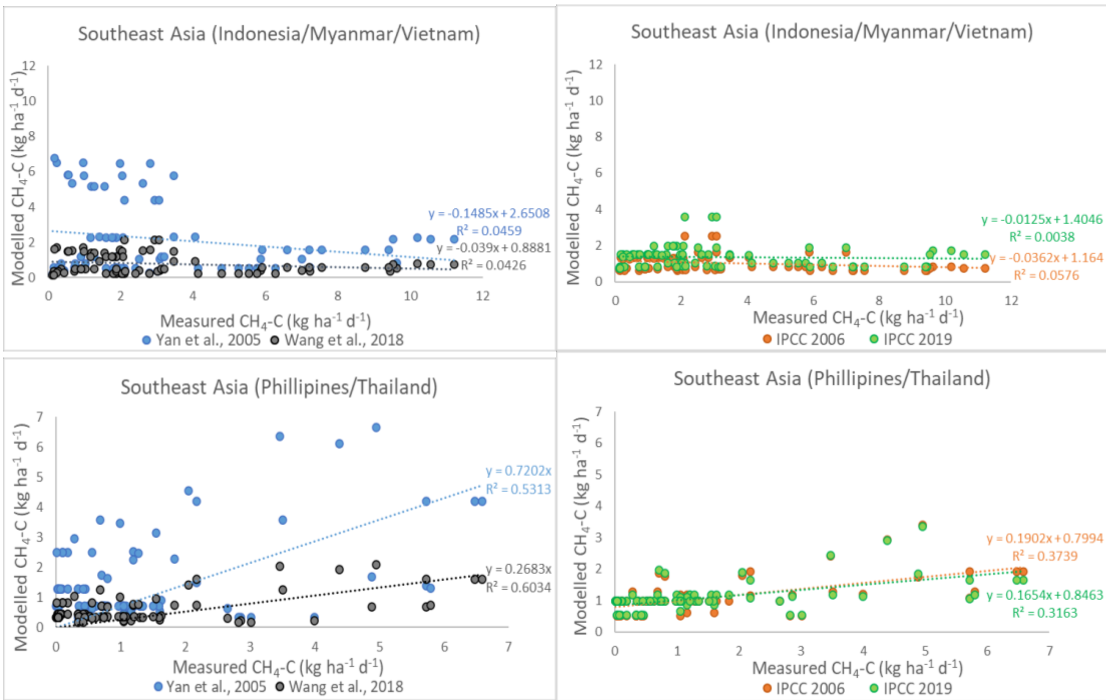


Figure 3. Model performance for Southeast Asia. The region is divided based on mean emission value with the three highest in one graph and the two countries with the lowest mean emission in the other to better assess model performance. However, the figure shows that all models underestimate emissions for larger observed values while particularly Yan et al., 2005 model overestimates smaller values for Indonesia, Myanmar and Vietnam data.

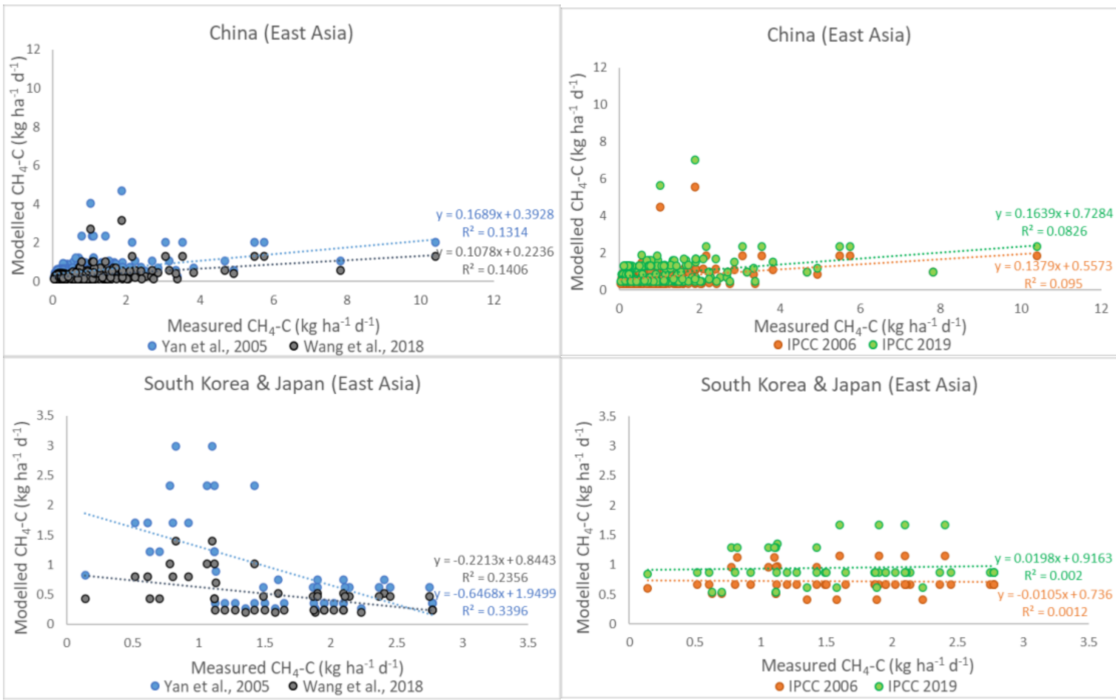


Figure 4. In East Asia, models perform quite well for the Chinese data, with the exception of some higher values.

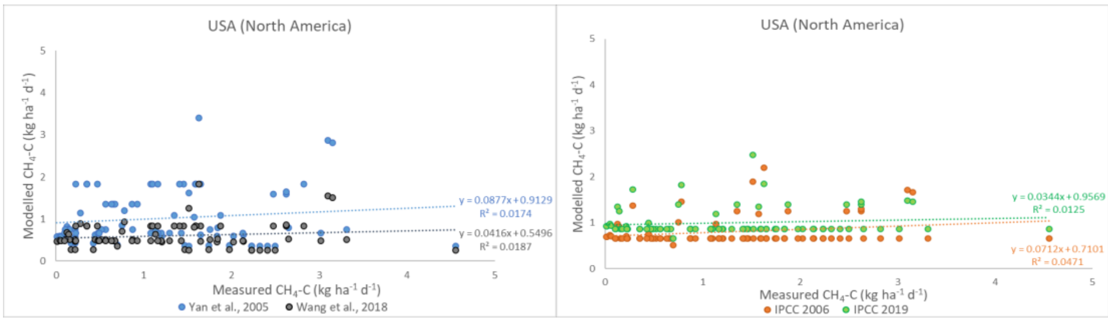


Figure 5. Figure shows that the models underestimate emissions for USA. Here the updated IPCC model (2019) performs slightly better than the original (2006) model, while for the other two the new model (Wang et al., 2018) performs worse than the original (Yan et al., 2005) model.

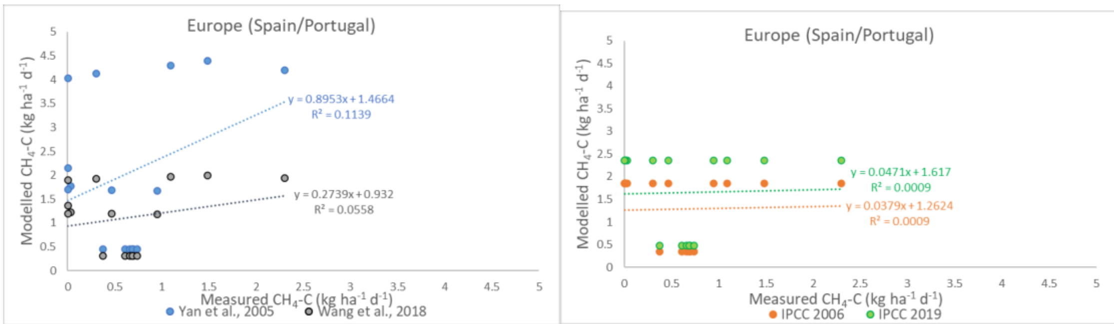


Figure 6. The original Yan et al., 2005 model overestimates emissions for the European data while the updated Wang et al., 2018 model is more accurate. The model performance is, however, better for the European data than for most of the other regions. For the two IPCC models, neither capture the trend well.

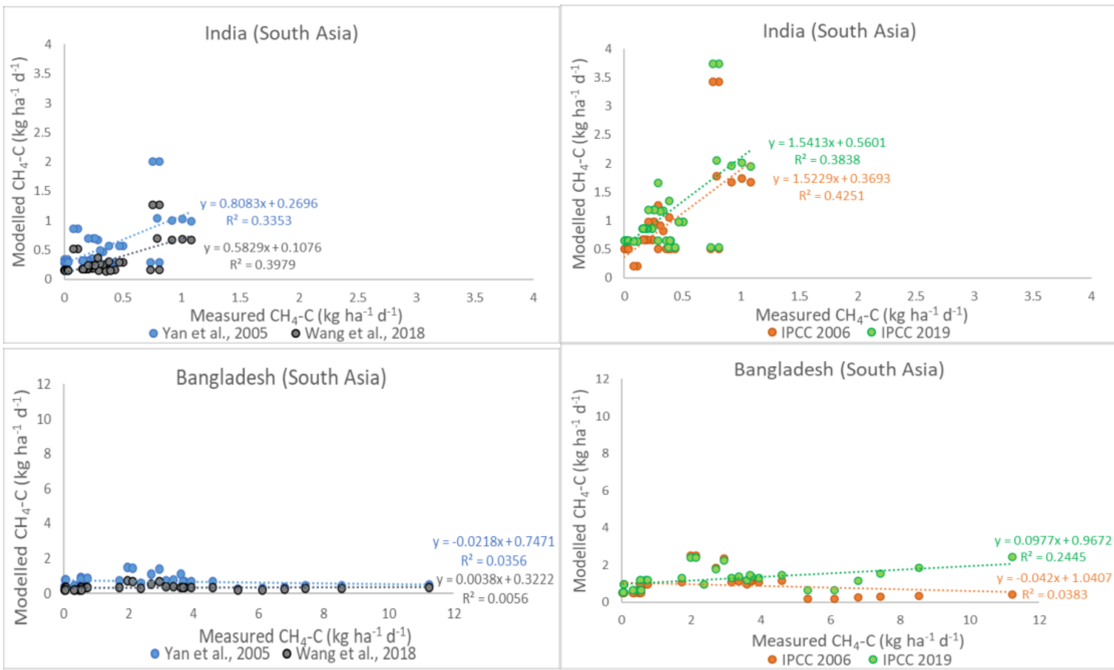


Figure 7. The models performed for these two countries, underestimating emissions for Bangladesh, but performing well for India.

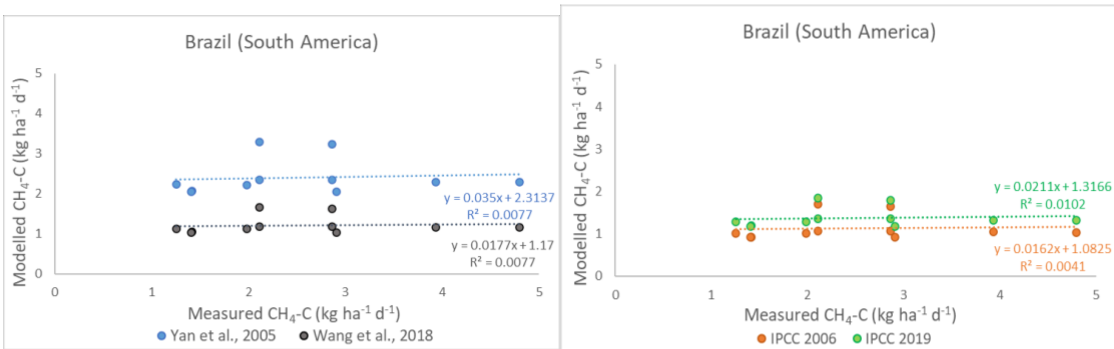


Figure 8. The newer Wang et al., 2018 model performs worse than the original Yan et al., 2005 and thus the new model does not improve emission estimation. All models underestimate emissions overall, particularly the IPCC models.

Considered variables and their impact on the model

Linear mixed models can handle both random and fixed factors and have the advantage of being capable of analyzing unsystematic data (Wang et al., 2018; Jørgensen and Fath, 2011; Yan et al., 2005). Only a handful of countries used empirical or process-based models (IPCC tier 2 or 3) for estimating their emissions from rice for national reports submitted to the UNFCCC Conference of the Parties, while the majority rely on default EFs through an IPCC tier 1 approach (Wang et al., 2018; UNFCCC, 2017). In addition to the existing explanatory variables included in previous CH_4 models used by IPCC, additional variables considered in this model (Equation 4) where soil texture, planting method, growing season, N fertilizer, crop duration as a proxy to include impact of rice cultivars and organic amendment method, as well as a different classification of climate group, the Köppen-Geiger climate classification (Beck et al., 2018).

The most common soil parameters recorded in published literature are SOC and pH as they are considered as most significant parameters affecting CH_4 emissions. However, evaluations have showed that there is a significant relationship between soil texture and CH_4. We tried developing the models using clay/silty/sand content as covariates and soil texture class as factors. 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 significant impact on emissions. The production of CH_4 is sensitive to pH changes with methanogens being most active in slightly acidic soil (Garcia et al., 2000; Aulakh et al., 2001; Wang et al., 2018) which supports our data with highest emissions being recorded under slightly acidic pH between 5.5 and 6 which also corresponds to previous models and their results (Yan et al., 2005; Wang et al., 2018). SOC had no significant impact on emissions in our database and was therefore not included in the final model. Even though it is considered a key parameter, and with previous studies suggesting that it can influence emissions as well as improving the model output, we did not include it in the model as it has no significant impact.

Using Anova and chi-square tests on the fixed factors in Rstudio we determined the different variables association with CH_4 emissions (table 5). This showed that water regime during crop growing season had the highest impact (166.3 chi-square) on emissions followed by soil texture (145.7) and growing season (118.4). Organic amendment amount is thought to have a significant impact on emissions, with previous CH_4 models results showing it being closely related to CH_4 fluxes (Wang et al., 2018). In our model. we have linked it together with type of organic amendment and thus this could have impacted the chi-square value (112.8) which shows it not being the most influencing factor, though the overall results shows that it does have a significant impact on emissions. Results show that use of nitrogen fertilizer had the smallest impact on emissions (10.7) while application method of organic amendment and pH has similar effects (29.8 and 36.6, respectively). This corresponds well with previous models which had water regime during the rice crop season as one of the main factors controlling CH_4 fluxes with CF field having the highest average emissions (Wang et al., 2018). All factors used in the model had a significant impact on emissions (table 5). Diagnostic plots of the final model (Fig. 9) show the overall performance of the model is good, with an AIC value of -923.9 (S2).

Table 5. Descriptive statistics showing the different parameters impact on CH4 emissions in which water regime is the most controlling factor.

Anova of fixed factors				
Factors	**Chisq**	**Df**	**Pr(>Chisq)**	
Pre-season water	69.887	4	<0.001	***
Crop duration	66.738	1	<0.001	***
Planting method	48.912	2	<0.001	***
Water regime	166.282	7	<0.001	***
Growing season	118.372	4	<0.001	***
pH	29.756	1	<0.001	***
Oa method	36.574	4	<0.001	***
N amount	10.705	1	<0.01	**
Soil texture	145.668	5	<0.001	***
Oa type: tot oa	112.835	6	<0.001	***

Significance Codes: 0’***’, 0.001 ‘**’, 0.01 ‘*’, 0,05 ‘.’ 0.1’’ 1

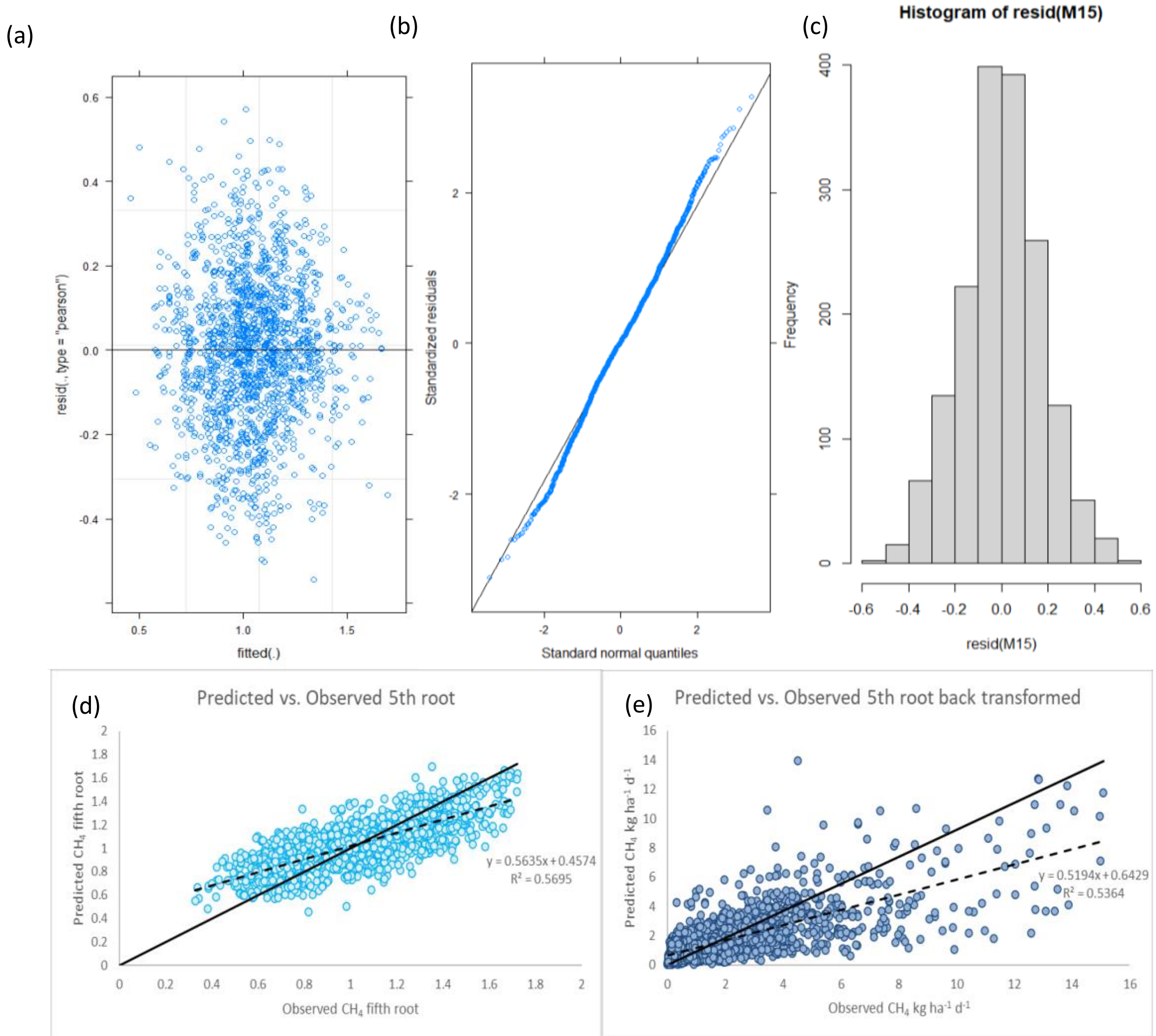


Figure 9. Diagnostic plots of the LMER model reported in Equation 4. The residual versus fitted values (a) suggest an almost constant variance with increasing means. The normal Q-Q graph (b) is close to following a straight line, indicating that the data distribution of cube root was reasonable. The histogram of residuals is close to normality (c) while the correlation between observed and predicted emissions shows a decent model performance with R^2 value of 0.97 in cube root format (d) and R^2 values of 0.73 when back transformed to mean CH_4 kg ha^{-1} d^{-1} (e) where the solid line is the reference line.

Descriptive statistics of modelled CH_4 emission

Mean CH_4 emissions for predicted data were 1.75 CH_4 ha^{-1} d^{-1}, with highest mean value being recorded for Vietnamese rice paddies and lowest for rice fields in Portugal (5.05 vs 0.58 kg ha^{-1} d^{-1}). Crop length varied from 64 days to 205 days, with Vietnam having the shortest average crop duration of 90 days, while Spain had the longest of 156 days followed by Portugal (152 days); mean crop duration across all data was 114 days. For organic amendment types, compost and green manure had the highest emissions. Application of straw off season and biochar may reduce CH_4 emission significantly. Impact of organic amendment is a function of type, amount and methodology of organic manure application. Comparing straw on and off season, there is a significant difference, with straw on season emitting 33% more than if straw was applied off season. This supports Wang et al., (2018)'s findings, which showed that applying straw off season compared to on-season is a good way to reduce emissions (S2).

For pre-season water regime, flooded rice paddies had the highest mean emissions (2.77 kg ha^{-1} d^{-1}) while WF had the lowest (1.18 kg ha^{-1} d^{-1}). Often, information on pre-season water regime which can be inferred from crop rotation information for the whole season, is not reported in the publication; however, in many instances this could be drawn from regional crop patterns. Rice grown in temperate regions such as Europe, North America, Japan and South Korea have long drainage between crop, as rice is sown only during the summer months with the occasional rotation of upland crops that do not require flooding such as wheat or soybean or with winter flooded fields, which is common in some European countries and North American regions. Many of the rice production sites in the Mediterranean regions of Europe have soil rich in clay and poor drainage and thus it is common that the fields remain water logged through most of the year through rainwater or irrigation systems (Meijide et al., 2011) while some, particularly in Spain are kept flooded in the fallow season to maintain soil salinity and biodiversity (Martínez-Eixarch et al., 2018). Prolonged anaerobic conditions in the winter, just after incorporating the straw, might result in greater emissions in both fallow season and the following rice season (Wang et al., 2018). However, emissions from rice paddies during growing season in these countries is low compared to other rice producing countries. Table 6 shows the overall results from the predicted data in which WF fields showed a 33%, and long drainage fields a 17%, reduction in CH_4 emissions compared to short drainage fields. However, rice fields with flooded pre-season water status have a significantly higher average emissions compared to those from short, drained fields (being 36% higher; S2).

Table 6. Relative CH_4 fluxes (kg ha d^{-1}) for pre-season and crop-season water management regimes. Values based on continuously flooding and short drainage being set to 1 and calculated for full database.

			95% confidence interval	
Variables	**Mean flux (CH_4 kg^{-1} d^{-1})**	**Relative flux**	**Lower**	**Upper**
Water regime during crop growth				
Continuously flooded	2.02	1	1	1
Single drainage	2.69	1.33	1.17	1.47
Multiple drainage	1.37	0.68	0.20	0.40
Deep water	1.33	0.66	0.33	0.95
Rainfed wet season	1.24	0.61	0.44	0.76
Alternate wetting and drying	1.00	0.49	0.41	0.57
Rainfed dry season	0.62	0.31	0.20	0.40
Saturated	0.45	0.22	0.15	0.29
Pre-season water				
Flooded	2.77	1	1	1
Short drainage	1.76	0.64	0.63	0.64

Long drainage	1.46	0.53	0.54	0.52
Winter flooded	1.18	0.43	0.39	0.45

Several studies have shown that CF during the growing season emit the most CH_4 compared to other water management practices. Our data, however, shows that single drainage (SD) has a higher mean CH_4 kg ha^{-1} d^{-1} value than CF fields. The high mean emissions from SD are mainly due to Trinh et al, (2017), which was carried out in Vietnam with a predicted emission range between 6.74 and 12.71 kg ha^{-1} d^{-1}; the original emission range was 6.6 and 15.09 kg ha^{-1} d^{-1}. If Trinh et al., (2017) was excluded, average CH_4 flux from SD fields was 1.69 kg CH_4 ha^{-1} d^{-1} which is significantly lower than the 2.69 kg CH_4 ha^{-1} d^{-1} if Trinh et al., 2017 is included, and lower than the CF mean of 2.02 kg CH_4 ha^{-1} d^{-1}, but higher than rainfed wet season and multiple drainage of 1.24 and 1.37 kg CH_4 ha^{-1} d^{-1}. This is more consistent with research focused on emissions from different water regimes and previous CH_4 models from Wang et al., (2018), which has the highest relative flux from CF fields followed by SD then RFW. If we did not consider the outliers caused by individual studies but looked across all data collected, then emissions decrease by as much as 51% for AWD fields and 78% for Saturated fields compared to continuously flooded fields (Table 6).

The five new explanatory variables included in this model were planting method, growing season, soil texture, N fertilizer and organic amendment method. For planting method direct wet seeded (DWS) plots had the highest average emission while direct dry seeded (DDS) had the lowest (2.35 vs. 1.44 kg CH_4 ha^{-1} d^{-1}). Transplanted (TP) rice paddies had an average emission of 1.76 kg CH_4 ha^{-1} d^{-1}, though the majority of data collected used this planting method (1284 compared to 330 for DDS and 139 samples for DWS). Using DDS as planting method can reduce emissions by 18% compared to TP, however using DWS increases emissions by 25% compared to TP. For growing season, Dry season had the lowest emissions while late season rice was highest. CH_4 emission during dry season were 37% lower than r wet season and emissions during early rice was 28% less than late rice season. Fields growing only one rice crop classified as single season had the third lowest emissions, with mean CH_4 flux of 1.66 kg CH_4 ha^{-1} d^{-1}, which was 22% higher than dry season rice. For soil texture, moderately fine soil had the highest emissions (4%, 21% and 21% higher than moderately coarse, coarse and medium soil textures respectively), emitting twice as much methane as those soils that had fine texture (50% lower). For organic amendment method, the variance between the methods was quite small, with incorporated organic amendment having the highest emissions (2.40 kg CH_4 ha^{-1} d^{-1}), with burned being 12% lower at 2.10 and surface applied emitting 11% less than incorporated, with mean emissions being 2.15 kg CH_4 ha^{-1} d^{-1} (S2).

Regional and country scale emission factors from descriptive analysis of data

Baseline emission factors for CH_4 emissions estimated for rice paddy has commonly been calculated using pre-season status of short drainage, continuously flooding as growing season water regime and no organic amendment (Wang et al., 2018). After careful analysis of the data, and traditional management practises, climate and other crop related patterns as seen in table 1, we have used country specific pre-season water management. For all European and American rice paddies as well as the Japanese and South Korean data we used long drainage for pre-season water management, as in these countries only one rice crop is grown annually and the fields are not waterlogged in non-rice growing season (table 1); the data collated for the remaining Asian countries had mostly short or flooded pre-season based on different crop rotation and thus the baseline used for EF estimates for these countries remains similar to the IPCC 2019 EF calculation baseline. For estimating EF 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 crop management and pre-season water method.

Globally, for continuously flooded fields with no organic amendment, the EF was estimated to 1.42 kg CH_4 ha^{-1} d^{-1} with an error range of 1.31-1.53 kg ha^{-1} d^{-1}, which is higher than the EF presented by IPCC (2019) derived from Wang et al., (2018) of 1.19 kg CH_4 ha^{-1} d^{-1} and for IPCC 2006 of 1.30 kg CH_4 ha^{-1} d^{-1}, we did not consider pre-season water status for the global EF estimate (Table 7 and 8). Not only does our database have an increased number of field measurements compared to previous models, but it also considers variation in management practices between the different rice growing regions worldwide. Previous studies have mainly focused on Asian rice paddies. Even though the updated models considered temperate regions outside Asia, they still derive EFs according to the most common management in Asia, which likely leads to some bias. This we can see particularly well for European and American rice paddies, in which our updated EFs are significantly higher, more than double for North America than the IPCC 2019 EFs. The new EF corresponds better to national inventory reports, with EFs being 2.0 and 2.7 kg CH_4 ha^{-1} d^{-1} for single and multiple drainage for the Italian Greenhouse Gas Inventory (2018) which is close to our EF estimate of 1.91 kg CH_4 ha^{-1} d^{-1} which is based on continuously flooded fields (table 7). Both the Spanish and Portuguese national communications used the IPCC (2006) default EF of 1.30 kg CH_4 ha^{-1} d^{-1} (National Inventory Report of Portugal, 2021, National Inventory Report of Spain, 2020). For Spain EF was created using winter flooding (WF) for pre-season drainage as this is most commonly used, while for Portugal all fields had multiple drainage as water management and thus an EF was not created at present. The new EF of kg 1.14 kg CH_4 ha^{-1} d^{-1} for Spain is similar to those used by IPCC 2019 of 1.13 kg CH_4 ha^{-1} d^{-1}. For American rice paddies, our EFs were 1.01 kg CH_4 ha^{-1} d^{-1} for USA and 1.45 kg CH_4 ha^{-1} d^{-1} Uruguay, as we did not have any data from Brazil with the correct management for EF creation (table 7). Compared to previous EFs, the new EFs (give value) are higher than the existing EFs of 0.65 and 1.27 kg CH_4 ha^{-1} d^{-1} for North and South America.

Table 7. Statistical summary of CH_4 emissions (kg ha-1 d-1) and CH_4-EF (%) at country and regional scale. C.I is the 95% confidence interval range.

		Daily CH_4 emission (kg CH_4 ha^{-1} d^{-1})				Annual CH_4-EF (kg CH_4 ha^{-1} d^{-1})			
				C.I.				C.I.	
		Mean	**Median**	**Lower**	**Upper**	**Mean**	**Median**	**Lower**	**Upper**
World		1.844	1.187	1.726	1.964	1.418	1.116	1.308	1.527
Region	South Asia[a]	0.805	0.609	0.695	0.914	1.081	0.919	0.902	1.261
	Southeast Asia[a]	2.309	1.366	2.074	2.545	1.745	1.169	1.394	2.095
	China	1.604	1.257	1.506	1.701	1.825	1.697	1.181	2.470
	Eastern Asia[b]	2.547	2.003	2.239	2.856	2.359	2.432	2.121	2.598
	Europe	2.430	1.705	1.800	3.060	1.914	1.796	1.770	2.058
	North America[b]	1.083	1.027	0.996	1.171	1.011	1.002	0.897	1.125
	South America[b]	2.831	3.268	2.542	3.120	1.447	1.476	0.995	1.899
Country	Bangladesh[a]	1.535	1.083	1.129	1.941	1.425	1.409	1.317	1.534
	China[a]	1.604	1.257	1.506	1.701	1.825	1.697	1.181	2.470
	India[a]	0.622	0.444	0.548	0.696	0.967	0.864	0.769	1.165
	Indonesia[a]	2.761	1.982	2.386	3.136	2.595	2.085	2.041	3.148
	Philippines[a]	0.988	0.742	0.843	1.134	0.839	0.786	0.691	0.987
	Thailand[a]	1.542	1.366	1.249	1.836	0.901	0.557	0.299	1.504
	Italy[b]	3.379	2.484	2.462	4.297	1.914	1.796	1.770	2.058
	Japan[b]	1.256	1.264	1.078	1.433	0.772	0.522	-0.410	1.953
	South Korea[b]	3.420	3.022	3.026	3.814	2.496	2.485	2.301	2.690
	Uruguay[b*]	1.040	0.986	0.553	1.527	1.447	1.476	0.995	1.899
	USA[b*]	1.083	1.027	0.996	1.171	1.011	1.002	0.897	1.125
	Brazil[b]	3.100	3.338	2.875	3.325	Other water management			
	Portugal[b]	0.583	0.583	0.515	0.650	Other water management			
	Myanmar[a]	1.432	1.615	0.945	1.920	No data fitting baseline			
	Spain[b]	1.146	1.330	0.748	1.545	All winter flooded 1.14 using WF as pre-ses			
	Vietnam[a]	5.047	4.000	4.199	5.894	No data fitting baseline			

[a]Short drainage, continuously flooded, no organic amendment
[b]Long drainage, continuously flooded, no organic amendment. Note Japan and South Korea put under here, the plots have similar climate as the European and American plots and long drainage has been recorded for these fields.

Table 8. Showing new regional and country specific baseline EF factors compared to the existing EF's as precented in IPCC 2019.

Region	**New EF**	**IPCC/Wang EF**	**Error range**
World	1.42	1.19	0.80-1.76
East Asia*	2.36	1.32	0.89-1.96
China*	1.83	1.32	0.89-1.96
Southeast Asia	1.75	1.22	0.83-1.81
South Asia	1.08	0.85	0.58-1.26
Europe	1.91	1.56	1.06-2.31
North America	1.01	0.65	0.44-0.96
South America	1.45	1.27	0.86-1.88
Country	**New EF**	**IPCC/Wang EF**	**Error range**
Bangladesh[a]	1.43	0.97	0.65-1.53

China[a]	1.83	1.30	0.88-1.93
India[a]	0.97	0.85	0.57-1.25
Indonesia[a]	2.60	1.18	0.80-1.74
Philippines[a]	0.84	0.60	0.41-0.89
Thailand[a]	0.90	NA	NA
Italy[b]	1.91	1.66	1.12-2.46
Japan[b]	0.77	1.06	0.72-1.56
South Korea[b]	2.50	1.83	1.24-2.71
Uruguay[b*]	1.45	0.80	0.54-1.18
USA[b*]	1.01	0.65	0.44-0.96
Brazil[b]	NA	1.62	1.10-2.40
Portugal[b]	NA	NA	NA
Myanmar[a]	NA	NA	NA
Spain[b]	NA	1.13	0.77-1.68
Vietnam[a]	NA	1.13	0.76-1.67

[a]Short drainage, continuously flooded, no organic amendment
[b]Long drainage, continuously flooded, no organic amendment.

For Asia, estimated EFs are higher for all regions compared to IPCC EFs (table 8). The calculated EFs are higher for all countries, except for Japan, where the new EF is 0.77 kg CH_4 ha^{-1} d^{-1} compared to 1.06 kg CH_4 ha^{-1} d^{-1} in IPCC 2019. As previously discussed, the existing models significantly underestimated emissions, particularly for Bangladesh, with IPCC EFs for Bangladesh being based on a single study (Wang et al., 2018). Comparing Bangladesh and India EFs, the original IPCC EFs were very similar for the two, while new estimated EFs are much higher for Bangladesh than for India (1.43 compared to 0.97 kg CH_4 ha^{-1} d^{-1}). According to India's third biennial update report (BUR), 33.2% of all rice is produced under drought prone conditions, while 15.9% is produced under continuously flooded fields, and 16.4% under single drainage with rice cultivation being responsible for 17.49% of the country's total GHG emissions. India used the IPCC tier 2 and country specific EF approach (MOEFCC, 2021). For Bangladesh, the Second National Communication report from 2012 used baseline EF based on data from Indian rice paddies of 10g/m^2 which is approximately 0.877 kg CH_4 ha^{-1} d^{-1} if assuming average crop duration of 114 days (MOEFCC, 2018). The EF recorded in Bangladesh's NCR for 2012 is 0.55 kg CH_4 ha^{-1} d^{-1} lower than our estimates of 1.43 kg CH_4 ha^{-1} d^{-1} and closer to the IPCC 2019 estimate of 0.97 kg CH_4 ha^{-1} d^{-1} which is 0.093 kg CH_4 ha^{-1} d^{-1} higher than their recorded EF (MOEFCC, 2018).

EFs for Southeast Asian countries varied between 0.84 and 2.60 kg CH_4 ha^{-1} d^{-1} for Philippines and Indonesia, respectively. Thailand has previously not been included in previous models. The new estimated EF of 0.90 kg CH_4 ha^{-1} d^{-1} is derived from 4 datapoints from one single paper; however, mean daily estimated emission was 1.54 kg CH_4 ha^{-1} d^{-1} and thus may underestimate the country's EF. For Indonesia, their first BUR had an emission range from 0.67 to 79.86 g CH_4 m-^{2} $season^{-1}$ and an average default value of 160.9 kg CH_4 ha^{-1} $season^{-1}$ (MoEFCC, 2015), while our seasonal average for Indonesia was estimated at 256.2 kg CH_4 ha^{-1} which is much higher. Both Vietnam and the

Philippines used IPCC default values for their NIC reports to UNFCCC (MNRE, 2020). Our EF estimate for the Philippines is higher than the IPCC 2019, but lower than those estimated by Yan et al., (2003) which had an EF of 3.46 kg CH_4 ha^{-1} d^{-1}. It is, at present, not possible to calculate EFs for Myanmar and Vietnam, as they did not have any data fitting the baseline with the two papers collected from Myanmar those that had no OA and CF had LD for pre-season. Out of the 69 datapoints collected from Vietnam only two had no OA both with unknown pre-season, one with AWD and the other with CF.

The new EFs for the three countries in East Asia where 1.83, 2.50 and 0.77 kg CH_4 ha^{-1} d^{-1} for China, South Korea and Japan, respectively. While the new EF is lower for Japan, it is higher for both China and South Korea as compared to IPCC 2019 (Table 8). For national EF estimates, Japan used the IPCC Tier 3 approach to derive county-specific EFs using DeNitrification-DeComposition-Rice model (DNDC-Rice model) in which EFs were simulated for different regions, and under different organic amendment and water management methods (National Inventory Report of Japan, 2021). China typically also used the Tier 3 approach but using a process-based model called CH4MOD. Approximately 1/3 of all data were collected from China, but only 17 out of the 663 datapoints collected from China fit the baseline for EF estimates, which is only 2.56% of total data. Mean daily emissions for China, across all managements, was calculated to be 1.83 kg CH_4 ha^{-1} d^{-1} Which is higher compared to the IPCC 2019 EF of 1.30 kg CH_4 ha^{-1} d^{-1}.

Evaluation of the New CH_4 Model

Data from 19 publications those were not used for model development were used to evaluate the new CH_4 model. Modelled CH_4 emission was estimated in transformed scale (fifth root) and was back transformed to original scale (kg CH_4 m^{-2} d^{-1}) for comparison with the measured data. RMSE of the back transformed simulated data used for evaluation of the new model was 76.04 with a correlation coefficient of 0.60. RMSE for transformed fifth root data was 17.55% with correlation coefficient of 0.61 (Table 9). Compared to the existing models, and IPCC models, the new model performs better with R values of 0.605 for transformed scale (fifth root) and 0.602 for mean CH_4 kg CH_4 ha^{-1} d^{-1}, compared to the other models for which R value varied between 0.111 and 0.371, with the data being expressed in kg CH_4-C ha^{-1} d^{-1} (Fig. 10).

The model accuracy of simulated emissions is determined based on plots fitted on the 1:1 line and will show any outliers, systematic shift of measured against simulated values, as well as variability in the trend between the two variables (Smith and Smith, 2007). When evaluating the model for all data in the independent dataset, we can clearly see some outliers, particularly when the data is back transformed (11a-11b), but also for data in 5th cube root value (11c-11d); Figure 11b and 11d shows the individual datapoints that are not captured well by the model. When looking at individual publications, we can get a better overview of model performance, such as for Cowan et al., (2021) in Figure 12a-b showing only small outliers with RMSE of 8.77% and 39.90% for fifth root and back transformed data repetitively and correlation coefficient of 0.84 and 0.87 (Table 10). Here, for the evaluation more detailed information on standard error and number of replications was included, and thus provides a more detailed evaluation. This indicates that the model is capable of performing well for some of the data, but still lacks some sensitivity to particularly large emission values. For both figures, the effect of transforming the data on RMSE can be seen, indicating that bias correction is needed to back transform the data accurately.

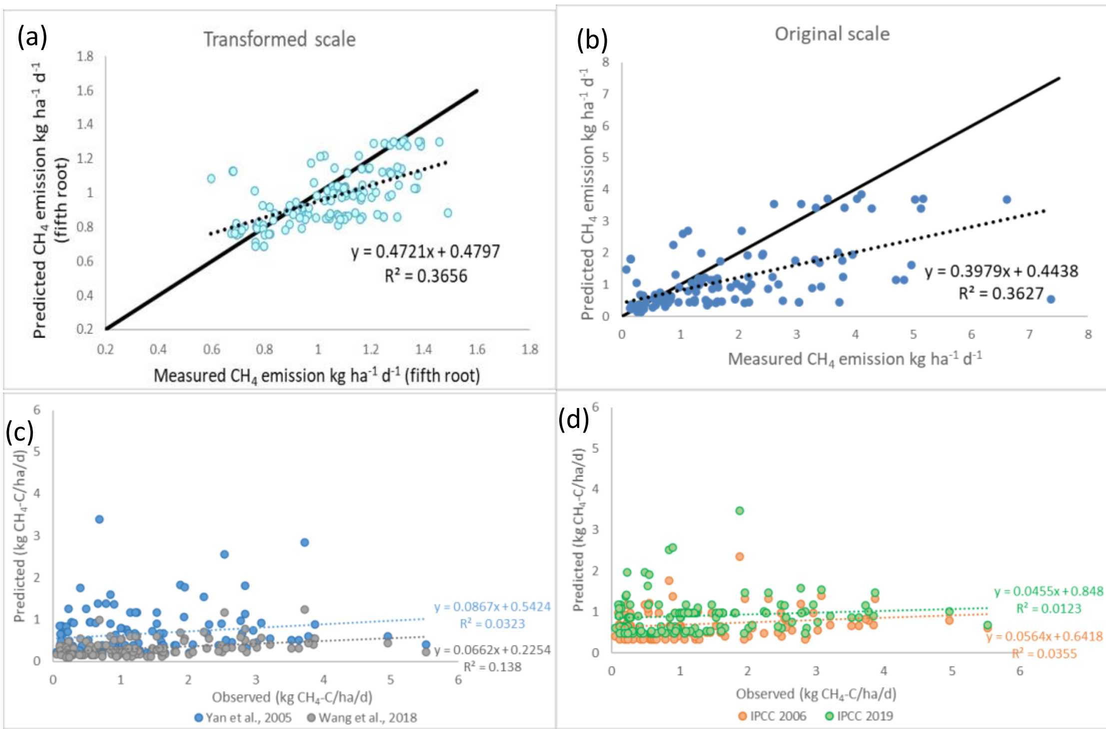


Figure 10. (a) Predicted vs. observed data for new model for transformed data (CH_4 fifth root), (b) Predicted (a) vs. observed data for new model for back-transformed data (CH4 kg ha-1 d-1), (c), Yan et al., (2005) and Wang et al., (2018), (d) and IPCC (2006) and IPCC (2019) (d).

Table 9. Modeval output for fifth root (left) and back transformed (kg ha^{-1} d^{-1}) data (right).

	CH_4 (Fifth root)	CH4 (back transformed)
r = Correlation Coeff.	0.605	0.602
Assuming no model parameters adjusted, (i.e.k=1), ...		
F = ((n-2) r^2) / (1-r^2)	70.31	69.42
F-value at (P=0.05)	3.92	3.92
Significant association?	Yes - Good	Yes - Good
RMSE = Root mean square error of model	17.55%	76.04%
M = Mean Difference	0.07	0.62
t = Student's t of M	4.94	5.78
t-value (Critical at 2.5% - Two-tailed)	1.98	1.98
Significant bias?	Yes - Bad	Yes - Bad
LOFIT = Lack of Fit	12.6176299	673.5988167
F = MSLOFIT/MSE	0.0296550	0.3381643
F (Critical at 5%)	1.24	1.24
Significant error between simulated and measured values?	No - Good	No - Good
ME = Maximum Error. Best = ABS(M)	0.48	3.70
RMSE * Obar/100	0.18	1.35
Number of Values	124	124

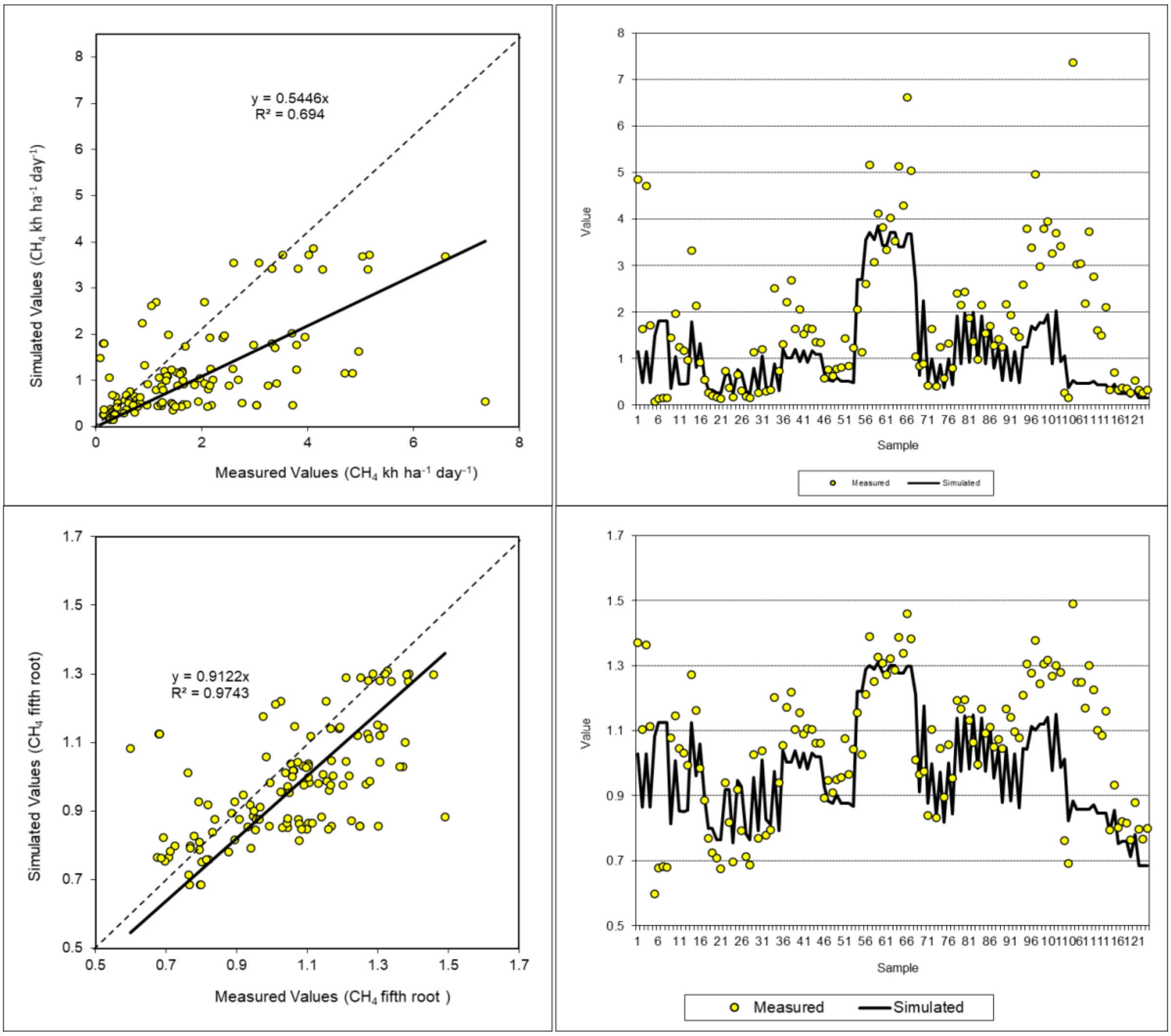


Figure 11. Modeval plots used to check model accuracy on simulated emission values for all collected data in independent dataset.

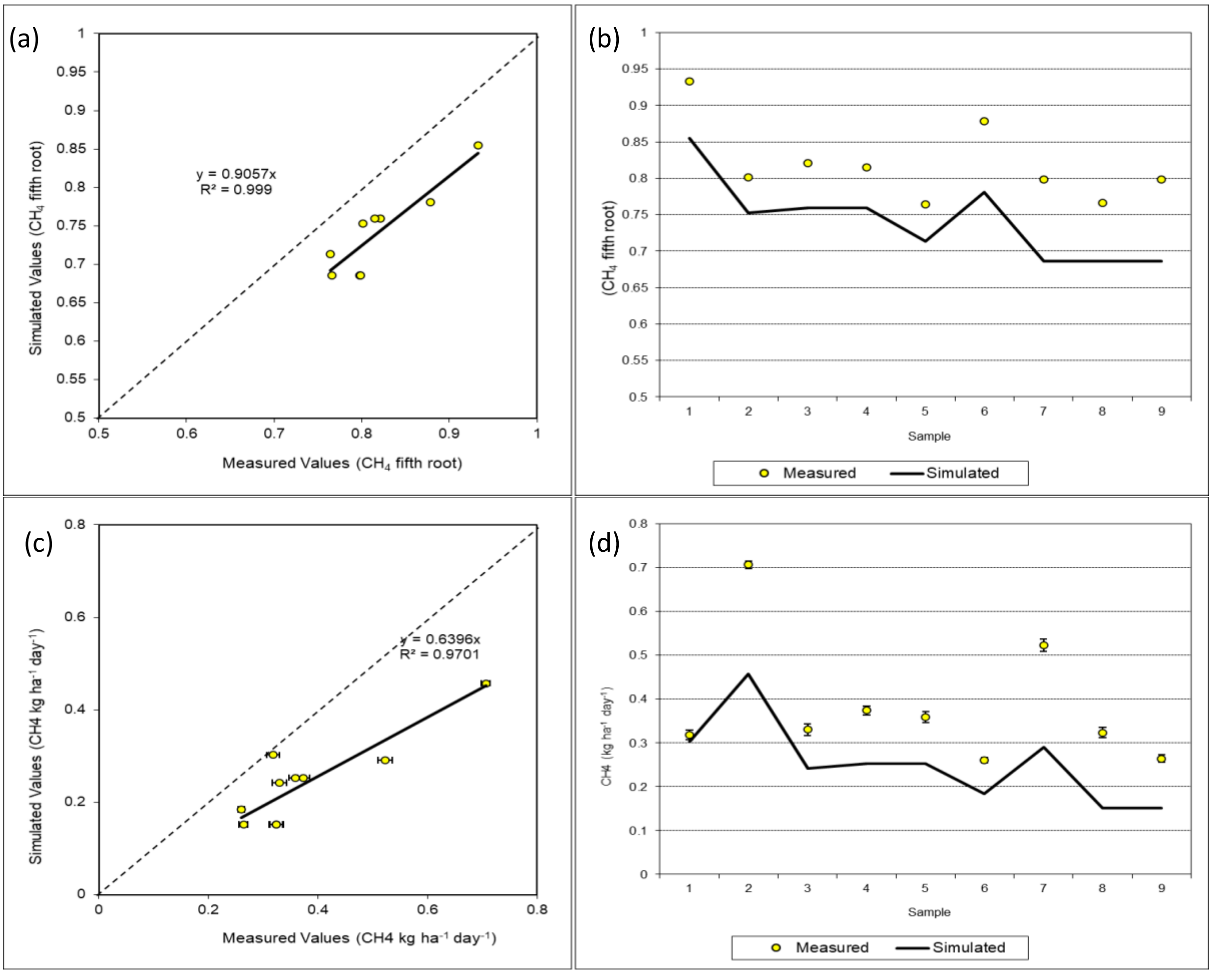


Figure 12. Modeval plots used to check model accuracy on simulated emission values for independent dataset from Cowan et al., 2021 with inclusion of variance of CH_4 emission

Table. 10. Modeval output for Cowan et al., 2021 with use of standard error and replicate number for fifth root (left) and back transformed (kg ha^{-1} d^{-1}) data (right).

	CH4 (fifth root)	CH4 (kg ha^{-1}day^{-1})
r = Correlation Coeff.	0.840	0.867
Assuming no model parameters adjusted, (i.e.k=1), ...		
F = ((n-2) r^2) / (1-r^2)	16.78	24.32
F-value at (P=0.05)	5.59	5.32
Significant association?	**Yes - Good**	**Yes - Good**
RMSE = Root mean square error of model	8.77%	39.90%
RMSE (95% Confidence Limit)	#DIV/0!	37.34%
Significant total error?	#DIV/0!	Yes - Bad
M = Mean Difference	0.07	0.13
t = Student's t of M	#NUM!	#NUM!
t-value (Critical at 2.5% - Two-tailed)	2.36	2.31
Significant bias?	#NUM!	#NUM!
E = Relative Error	8.03	35.58
E (95% Confidence Limit). = +/-	#DIV/0!	#NUM!
Significant bias?	#DIV/0!	#NUM!
LOFIT = Lack of Fit	0.1197594	0.6831981
F = MSLOFIT/MSE	0.0054882	0.2703229
F (Critical at 5%)	2.19	2.03
Significant error between simulated and measured values?	**No - Good**	**No - Good**
ME = Maximum Error. Best = ABS(M)	0.11	0.25
RMSE * Obar/100	0.07	0.15
Number of Values	10	10

Table 11. Modeval output for Yan et al., 2005, IPCC 2006, Wang et al., 2018 and IPCC 2019 models.

Statistics	Yan et al., 2005	IPCC 2006	Wang et al., 2018	IPCC 2019
r = Correlation Coeff.	0.180	0.189	0.371	0.111
Assuming no model parameters adjusted, (i.e., =1)				
F = ((n-2) r^2) / (1-r^2)	4.08	4.50	19.53	1.52
F-value at (P=0.05)	3.92	3.92	3.92	3.02
Significant association?	Yes - Good	Yes - Good	Yes - Good	No - Bad
RMSE = Root mean square error of model	100.31%	95.12%	110.54%	92.97%
RMSE (95% Confidence Limit)	0.00%	0.00%	0.00%	0.00%
Significant total error?	Yes - Bad	Yes - Bad	Yes - Bad	Yes - Bad
M = Mean Difference	0.66	0.61	1.01	0.42
t = Student's t of M	6.46	6.13	10.61	4.01
t-value (Critical at 2.5% - Two-tailed)	1.98	1.98	1.98	1.98
Significant bias?	Yes - Bad	Yes - Bad	Yes - Bad	Yes - Bad
E = Relative Error	49.99	45.46	76.20	30.90
E (95% Confidence Limit).	0.00	0.00	0.00	0.00
Significant bias?	Yes - Bad	Yes - Bad	Yes - Bad	Yes - Bad
LOFIT = Lack of Fit	659.4592741	592.9556527	800.7932533	556.4414595
F = MSLOFIT/MSE	0.5885522	0.5291993	0.7146895	0.5055360
F (Critical at 5%)	1.24	1.24	1.24	1.24
Significant error between simulated and measured values?	No - Good	No - Good	No - Good	No - Good
ME = Maximum Error. Best = ABS(M)	3.12	2.97	3.31	2.77
RMSE * Obar/100	1.33	1.26	1.47	1.23
Number of Values	124	124	124	124

Study Limitations

The literature search only considered studies written in English, and therefore may have missed papers written in other languages. Evaluation of the existing models shows that a good R^2 value may not always be representative of good model performance; even though it captures the trend of emissions, it may under- or over-estimate emissions. Back transformation of data to original scale has led to some bias and mostly the predicted values are lower than measured values, and thus requires bias correction which is not yet implemented. The large number of fields with zero organic amendment in the dataset may influence the model prediction for fields which has used organic amendment, resulted in the simulated emissions being underestimated compared to the observed data. We will investigate this in the future and look into ways on how this can be improved. Inclusion of new factors which are strikingly different among rice growing regions have improved the sensitivity of new model and enables it to capture emission more accurately. Country specific baseline EF can be calculated using management practices used in the specific country e.g., using long drainage instead of short drainage for temperate rice will result in more accurate EFs. However, winter flooding is also common in some European countries and in the USA. Our EFs are extracted using a baseline from back transformed predicted data. The way we have calculated our EFs could also be the reason why the Chinese EFs are so much higher than those used in current IPCC models, as China is the largest country with a wide variety of climate zone, crop rotation management types, as well as representing 1/3 of all the data collected. We will in the future look into this, and how we best can back transform data to represent the model better. A detailed evaluation using Modeval with standard error and replication number when available will also be beneficial for further assessment of the model in the future.

References

Addiscott TM, Whitmore AP. (1987). 'Computer simulation of changes in soil mineral nitrogen and crop nitrogen during autumn, winter and spring'. *Journal of Agriculture Science*, 109: 141–157.

Akiyama H, Yan X, Yagi K. 2010. 'Evaluation of effectiveness of enhanced-efficiency fertilizers as mitigation options for N_2O and NO emissions from agricultural soils: meta-analysis'. *Global Change Biology*, 16, 1837– 1846. DOI: https://doi.org/10.1111/j.1365-2486.2009.02031.x

Aulakh MS, Wassmann R, Rennenberg H. (2001). Methane emissions from rice fields – quantification, mechanisms, role of management, and mitigation options. *Advanced Agronomy*, 70, 193–260. DOI: https://doi.org/10.1016/S0065-2113(01)70006-5

Baldock JA, Skjemstad JO. (2000). 'Role of the soil matrix and minerals in protecting natural organic materials against biological attack'. *Organic Geochemistry*, 31(7–8), 697–710. DOI: https://doi.org/10.1016/S0146-6380(00)00049-8

Beck HE, Ximmermann NE, McVicar TR, Vergopolan N, Berg A, Wood EF. (2018). 'Present and future Köppen-Geiger climate classification maps at 1-km resolution'. *Scientific Data,* 5:180214. https://doi.org/10.1038/sdata.2018.214

Begum K, Kuhnert M, Yeluripati JB, Ogle S, Parton W, Kader MA, Smith P. (2018a). 'Model Based Regional Estimates of Soil Organic Carbon Sequestration and Greenhouse Gas Mitigation Potentials from Rice Croplands in Bangladesh'. *Land*, 7(3), 82. https://doi.org/10.3390/land7030082

Begum K, Kuhnert M, Yeluripati JB, Ogle S, Parton W, Kader MA, Smith P. (2018b). 'Soil organic carbon sequestration and mitigation potential in a rice cropland in Bangladesh—a modelling approach'. *Field Crop Research*, 226, 16–27. https://doi.org/10.1016/j.fcr.2018.07.001

Chauhan, Jabran, Mahajan. (2017). Rice Production Worldwide. International, Springer, pp. 33-184.

Chidthaisong A, Cha-un N, Rossopa B, Buddaboon C, Kunuthai C, et al. (2018). 'Evaluating the effects of alternate wetting and drying (AWD) on methane and nitrous oxide emissions from a paddy field in Thailand'. *Soil Science and Plant Nutrition*, 64:1, 31-38. https://doi.org/10.1080/00380768.2017.1399044

Ciais P, Sabine C, Bala G, Bopp L, Brovkin V, et al. (2013). 'Carbon and Other Biogeochemical Cycles'. Climate Change 2013 –The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, 465–570

Clift R, Keller E, King H, Lee J, Mila-i-Canals L. (2014). 'Challenges of scale and specificity in greenhouse gas calculators', Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector, (October), pp. 241–247. http://lcafood2014.org/papers/59.pdf

Cowan N, Bhatia A, Jain N, Singh R, Tomer R, et al. (2021). 'Experimental comparison of continuous and intermittent flooding of rice in relation to methane, nitrous oxide and ammonia emissions and the implications for nitrogen use efficiency and yield'. *Agriculture, Ecosystems and Environment,* 319, 107571. https://doi.org/10.1016/j.agee.2021.107571

FAO. (2018). FAOSTAT [Online]. Food and Agricultural Organization of the United Nations (FAO). Available from: http://www.fao.org/faostat/en/#data/GR/visualize

FAO. (2018) FAOSTAT: Soil Texture [Online]. Food and Agricultural Organization of the United Nations (FAO). Available from: http://www.fao.org/fishery/docs/CDrom/FAO_Training/FAO_Training/General/x6706e/.!53884!x6706e06.htm

Garcia J-L, Patel BK, Ollivier B. (2000). 'Taxonomic, Phylogenetic and Ecological Diversity of Methanogenic Archaea'. Anaerobe, 6, 205–226. https://doi.org/10.1006/anae.2000.0345

Ghosh S, Majumdar D, Jain MC. (2003). 'Methane and nitrous oxide emissions from an irrigated rice of North India', *Chemosphere*, 51(3), pp. 181–195. https://doi.org/10.1016/S0045-6535(02)00822-6

Hillier J, Walter C, Malin D, Garcia-Suarez T, Mila-i-Canals L, Smith P. (2011). 'A farm-focused calculator for emissions from crop and livestock production'. *Environmental Modelling and Software*, 26(9), pp. 1070–1078. https://doi.org/10.1016/j.envsoft.2011.03.014

Hillier J, Brentrup F, Wattenbach M, Walter C, Garcia-Suarez T. et al. (2012). 'Which cropland greenhouse gas mitigation options give the greatest benefits in different world regions? Climate and soil-specific predictions from integrated empirical models'. *Global Change Biology,* 18(6), 1880–1894. https://doi.org/10.1111/j.1365-2486.2012.02671.x

IBM Corp. (2020). IBM SPSS Statistics for Windows, Version 27.0. Armonk, NY: IBM Corp

IPCC. (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Volume 4 - AFOLU. Intergovernmental Panel on Climate Change (IPCC), Institute for global Environmental Strategies, Tokyo, Japan. Available at: http://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html

IPCC. (2013). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

IPCC. (2019). IPCC 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change (IPCC), Institute for global Environmental Strategies, Tokyo, Japan. Available at: https://www.ipcc-nggip.iges.or.jp/public/2019rf/index.html

IRRI. (2014). Rice Knowledge Bank. Rice Straw. International Rice Research Institute (IRRI). Available at: http://www.knowledgebank.irri.org/step-by-step-production/postharvest/rice-by-products/rice-straw

Jørgensen SE, Fath BD. (2011) 'Fundamentals of Ecological Modelling: Applications in Environmental Management and Research'. Elsevier, Amsterdam, 2011.

Khush. (2005). What it will take to Feed 5.0 billion Rice consumers in 2030. *Plant Molecular Biology*, 59:1-6. https://doi.org/10.1007/s1103-005-2159-5

Lagomarsino A, Agnelli AE, Linquist B, Adviento-Borbe MA, Agnelli A, et al. (2016) .'Alternate Wetting and Drying of Rice Reduced CH_4 Emissions but Triggered N_2O Peaks in a Clayey Soil of Central Italy'. *Pedosphere*, 26(4), 533–548. https://doi.org/10.1016/S1002-0160(15)60063-7

LaHue GT, Chaney RL, Adviento-Borbe MA, Linquist BA. (2016). 'Alternate wetting and drying in high yielding direct-seeded rice systems accomplishes multiple environmental and agronomic objectives'. Agriculture, Ecosystems and Environment, 229, 30–39. DOI: https://doi.org/10.1016/j.agee.2016.05.020

Linquist, B.A., Groenigen, K. J., Adviento-Borbe, M.A., and Kessel, C., (2012) 'An agronomic assessment of greenhouse gas emissions from major cereal crops'. Global Change Biology, 18(1), pp. 194–209. https://doi.org/10.1111/j.1365-2486.2011.02502.x

Linquist BA, Anders MM, Adviento-Borbe MAA, Chaney RL, Nalley LL, et al. (2015). 'Reducing greenhouse gas emissions, water use, and grain arsenic levels in rice systems'. *Global Change Biology*, 21(1), 407–417. https://doi.org/10.1111/gcb.12701

Linquist BA, Marcos M, Arlene Adviento-Borbe M, Anders M, Harrell D, et al. (2018). 'Greenhouse gas emissions and management practices that affect emissions in US rice systems'. *Journal of Environmental Quality*, 47(3), 395–409. https://doi.org/10.2134/jeq2017.11.0445

Martinez-Eixarch M, Alcaraz C, Viñas M, Noguerol J, Aranda X, et al. (2018). 'Neglecting the fallow season can significantly underestimate annual methane emissions in Mediterranean rice fields'. *PLoS ONE,* 13(5). https://doi.org/10.1371/journal.pone.0198081

Meijide A, Manca G, Goded I, Magliulo V, Tommasi P, Saufert G, Cescatti A. (2011). 'Seasonal trends and environmental controls of methane emissions in a rice paddy field in Northern Italy', *Biogeosciences*, 8(12), pp. 3809–3821. https://doi.org/10.5194/bg-8-3809-2011

Meijide A, Gruening C, Goded I, Cescatti A. (2016). 'Water management reduces greenhouse gas emissions in a Mediterranean rice paddy field', *Agriculture, Ecosystems and Environment*. https://doi.org/10.5194/bg-8-3809-2011

Minasny B, Malone BP, McBratney AB, Angers DA, Arrouays D, et al. (2017). 'Soil carbon 4 per mille'. *Geoderma*. 292:59–86. https://doi.org/10.1016/j.geoderma.2017.01.002

MNRE. (2020). Third Biennial Update Report to the United Framework Convention on Climate Chang: Report on National GHG Inventory for 2016. Ministry of Natural Resources and Environment of Vietnam (MNRE). https://unfccc.int/documents/271503

MoEFCC. (2015). First Biennial Update Report under the United Nations Framework Convention on Climate Change of Indonesia. Ministry of Environment and Forestry of Indonesia (MOEFCC). https://unfccc.int/documents/180649

MoEFCC. (2012). Second National Communication of Bangladesh to the United Nations Framework Convention on Climate Change. Ministry of Environment and Forests of Bangladesh (MoEFCC). http://unfccc.int/national_reports/non-annex_i_natcom/items/10124.php

MoEFCC. (2018). Third National Communication of Bangladesh to the United Nations Framework Convention on Climate Change. Ministry of Environment and Forests of Bangladesh (MoEFCC). Available at: https://unfccc.int/documents/192278 Accessed: 25.08.2021

MoEFCC. (2021). Third Biennial Update Report to the United Framework Convention on Climate Change of India. Ministry of Environments, Forests and Climate Change of India (MoEFCC). https://unfccc.int/documents/268470

Mosleh MK, Hassan QK, Chowdhury EH. (2015). 'Application of Remote Sensors in Mapping Rice Area and Forecasting Its Production: A Review'. Sensors 2015, 15(1), 769-791. https://doi.org/10.3390/s150100769

National Inventory Report of Italy: Italian Greenhouse Gas Inventory 1990–2018. https://unfccc.int/documents/223571

National Inventory Report of Japan: National Greenhouse Gas Inventory report of Japan. https://unfccc.int/documents/271503

National Inventory Report of Portugal: National Inventory of Emissions of Greenhous Gases 1990–2021. https://unfccc.int/documents/271508

National Inventory Report of Spain: National Inventory of Emissions of Greenhous Gases 1990–2018. https://unfccc.int/documents/228014

Nayak D, Saetnan E, Cheng K, Wang W, Koslowski F. et al. (2015). 'Management opportunities to mitigate greenhouse gas emissions from Chinese agriculture', Agriculture, Ecosystems and Environment. Elsevier B.V., 209, pp. 108–124. DOI: 10.1016/j.agee.2015.04.035

NCSS. N.d. NcSSstatistical software, stepwise Regression. https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Stepwise_Regression.pdf

RStudio Team. (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA. http://www.rstudio.com/

Rohatgi A. (2021). WebPlotDigitizer Version 4.5 available at: https://automeris.io/WebPlotDigitizer/

Seck PA, Diagne A, Mohanty S, Wopereis MCS. (2012) 'Crops that feed the world 7: Rice'. *Food security*, 4:7-24. https://doi.org/10.1007/s12571-012-0168-1

Smith J, Smith P. (2007). Environmental Modelling: An Introduction. Oxford University Press.

Smith P. (2012). 'Agricultural greenhouse gas mitigation potential globally, in Europe and in the UK: What have we learnt in the last 20 years?'. *Global Change Biology*, 18(1),35–43. https://doi.org/10.1111/j.1365-2486.2011.02517.x

Trinh MV, Tesfai M, Borrell A, Nagothu US, Bui TPL, et al. (2017). 'Effect of organic, inorganic and slow-release urea fertilisers on CH_4 and N_2O emissions from rice paddy fields'. *Paddy Water Environment,* 15:317-330. https://doi.org/10.1007/s10333-016-0551-1

Wang C, Lai DYF, Sardans J, Wang W, Zeng C, Peñuelas J. (2017) 'Factors related with CH_4 and N_2O emissions from a paddy field: Clues for management implications'. *PLoS ONE*, 12(1), 1–23. https://doi.org/10.1371/journal.pone.0169254

Wang J, Akiyama H, Yagi K, Yan X. (2018). 'Controlling variables and emission factors of methane from global rice fields'. *Atmospheric Chemistry and Physics*, 18(14), 10419–10431. https://doi.org/10.5194/acp-18-10419-2018

Yan X, Yagi K, Akiyama H, Akimoto H. (2005). 'Statistical analysis of the major variables controlling methane emission from rice fields'. *Global Change Biology*, 11(7), 1131–1141. https://doi.org/10.1111/j.1365-2486.2005.00976.x

Zou J, Huang Y, Jiang J, Zheng X, Sass RL. (2005). 'A 3-year field measurement of methane and nitrous oxide emissions from rice paddies in China: Effects of water regime, crop residue, and fertilizer application'. *Global Biogeochemical Cycles*, 19(2), 1–9. https://doi.org/10.1029/2004GB002401

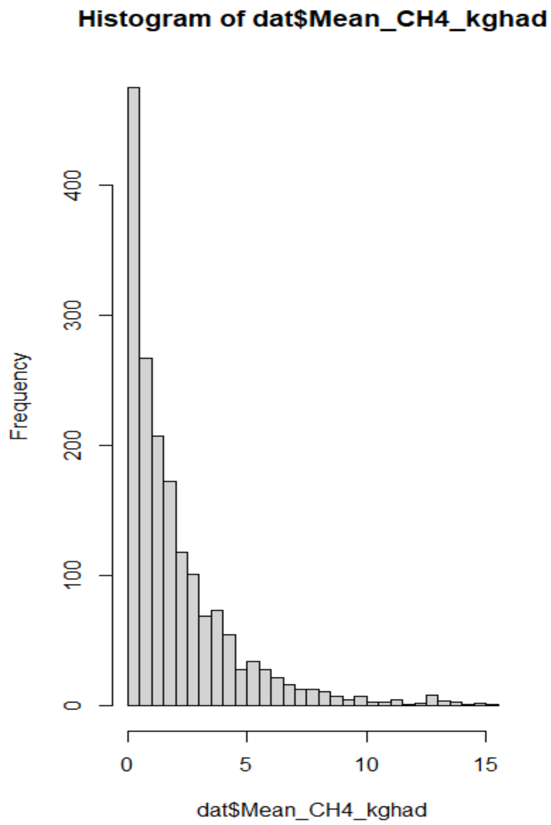
Supplementary Information

S1. Descriptive statistics of collated data

Country	Daily mean emission	Seasonal mean emission	Min/Max emission	Sample n (after -9999 removed)
Bangladesh	2.386	260.03	3.15/1648.5	45
Brazil	3.388	380.75	46/671.5	40
China	2.084	213.92	3.15/219.7	663 (650)
India	0.679	70.36	0.50/353.3	180
Indonesia	2.990	266.44	26/722	136 (128)
Italy	2.939	387.09	8.43/816	42 (36)
Japan	1.535	150.76	6/544	50
Myanmar	1.946	188.30	15/419	8
Philippines	1.438	141.52	0.9/952	139
Portugal	0.836	126.33	79/156	6
South Korea	3.885	485.11	89.16/1560	74
Spain	1.886	236.88	0.73/972	18
Thailand	2.146	244.27	1.70/939	73
Uruguay	1.140	166.95	93.3/249.4	6
USA	1.396	158.58	2.27/1360	204 (168)
Vietnam	5.536	455	31/1192	69
Climate				
Af	5.162	428.35	216/722	58 (50)
Am	1.798	180.99	0.90/1649	212
Aw	2.705	257.35	1.7/1192	224 (220)
Bs	0.638	69.54	0.5/972	104
Cf	2.192	230.2	2.27/1435	766 (711)
Cs	1.295	168.9	0.73/1360	82
Cw	1.203	126.2	3.33/780	176
Df	3.169	273.8	53.87/544	5
Dw	2.862	351.5	3.15/1560	126
Soil texture				
Unknown	3.055	299.6	0.5/1435	322 (312)
Coarse	2.235	263.1	11.9/540	20 (18)
Moderately coarse	2.306	254.7	5.91/1649	218
Medium	1.766	201	0.73/1560	449 (422)
Moderately fine	2.406	227	3.33/1260	404 (385)
Fine	1.265	138	0.90/952	340 (335)
Planting method				
TP (transplanted)	2.181	219	0.9/1649	1284 (1263)
DDS (direct dry seeded)	1.682	186.4	0.5/804	330 (290)
DWS (direct wet seeded)	2.671	312.5	8.39/1360	139 (137)
Growing season				
Single	1.941	229.2	0.73/1560	662 (615)
Early	2.005	188.5	4.12/1431	209 (205)
Late	2.764	277.8	3.33/1525	215 (211)
Wet	2.374	224.3	0.5/1649	431 (428)
Dry	1.717	163.7	0.9/939	236 (231)
Pre-season water				
SD (short drainage)	2.306	215.5	0.9/1649	414 (402)
UN (unknown)	2.488	227.8	0.5/1192	194 (194)
FL (flooded)	3.271	305.4	17.7/1435	193 (189)
LD (long drainage)	1.757	204.3	2.27/155.8	887 (840)
WF (winter flooded)	1.534	193.2	0.73/972	65
Water regime				

CF (continuously flooded)	2.356	246.6	1.7/1560	871 (823)
AWD (alternate wetting and drying)	1.488	143.2	2.2/652	82
DW (deep water)	1.474	198.2	18/868	20
MD (multiple drainage)	1.730	181	0.5/1260	501 (486)
SA (saturated)	1.071	119.5	0.73/804	54
SD (single drainage)	2.990	284.2	2.67/1192	157
RFW (rainfed wet)	2.202	239.7	2.93/1649	52
RFD (rainfed dry)	0.931	88.5	5/634	16
Organic amendment type				
None	1.501	154.2	0.5/1415	912 (880)
Biochar	1.778	156.6	17.7/995	54
GM (green manure)	3.491	375.4	2.27/1560	136
FYM (farmyard manure)	2.646	275.1	4.15/1266	150
Compost	3.497	334.3	15/1649	65 (62)
Straw off season	1.965	212.9	6/1435	211 (191)
Straw on season	3.325	347.9	6.28/1260	225 (217)
Organic amendment method				
None	1.501	154.2	0.5/1415	912 (880)
Unknown	2.852	267.9	6/972	96 (94)
Incorporated	2.855	297	2.27/1649	629 (600)
Burned	2.821	274.6	16.4/1220	30
Surface applied	2.367	287.6	6.28/741	86

Country	**Average crop duration**	**Min/Max**
Bangladesh	114.09	91/134
Brazil	129.23	105/150
China	110.80	68/162
India	111.01	77/158
Indonesia	98.53	74/137
Italy	123.40	103/153
Japan	113.36	64/147
Myanmar	101.25	95/104
Philippines	100.96	84/129
Portugal	151.50	144/159
South Korea	126.42	111/140
Spain	156.11	141/163
Thailand	127.05	88/205
Uruguay	113.33	110/119
USA	133.03	69/171
Vietnam	90.12	78/113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400
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10
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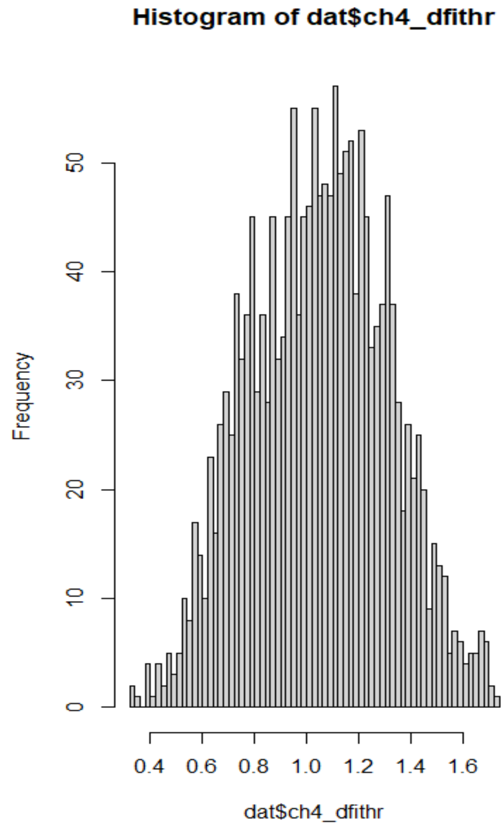
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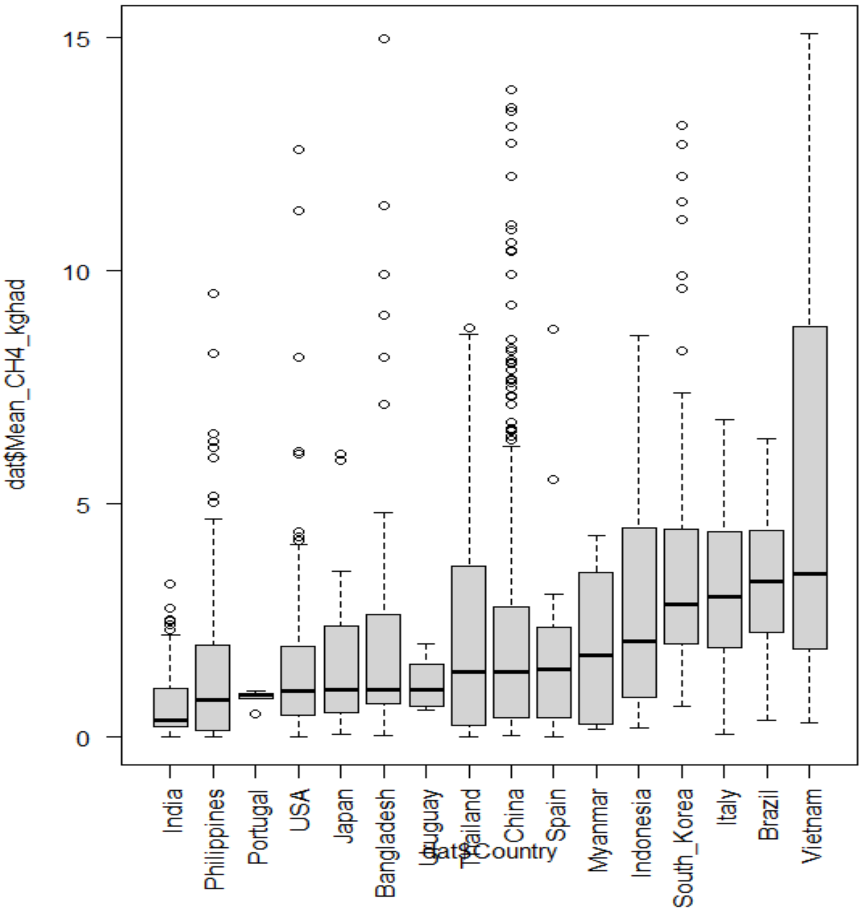
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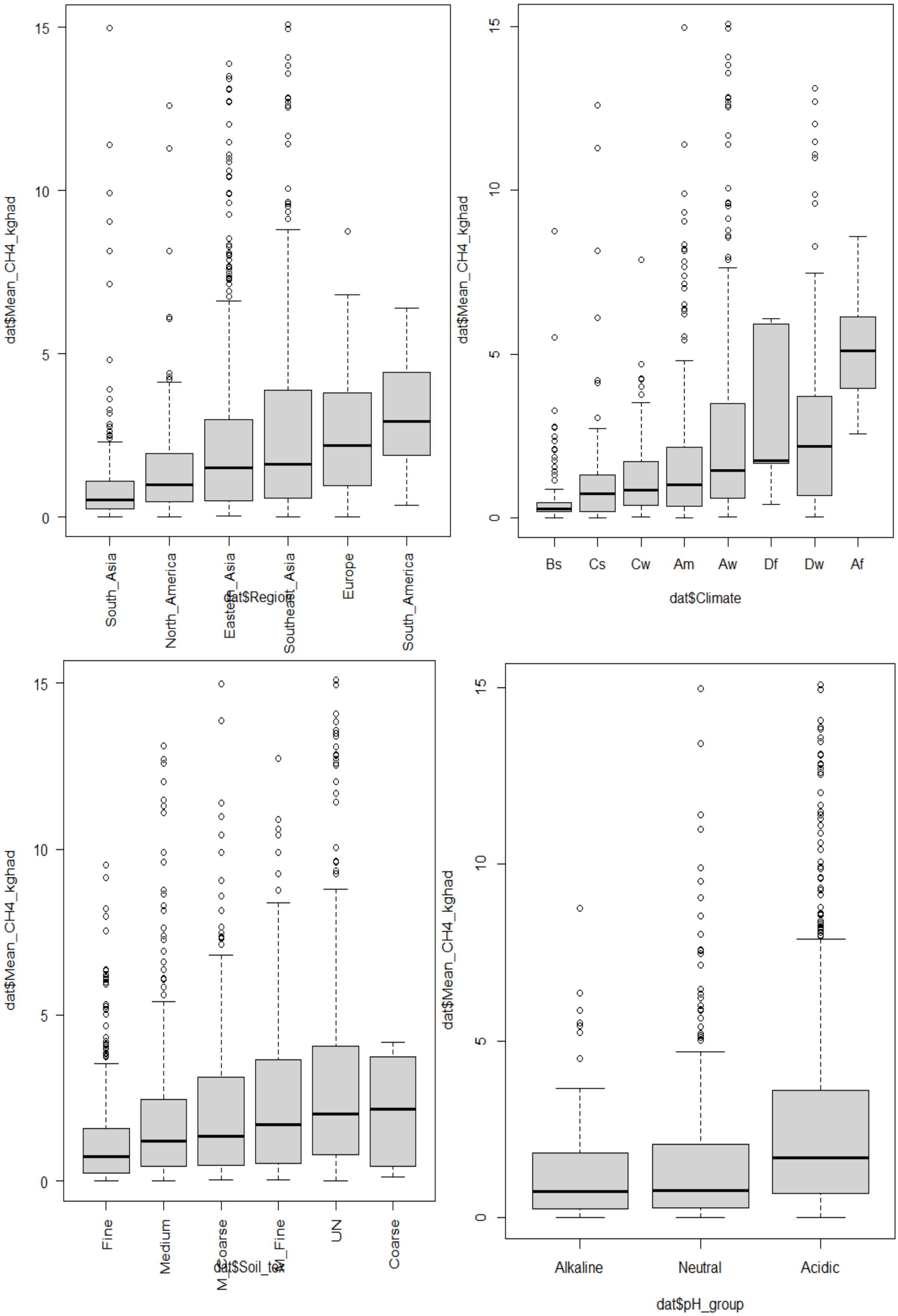
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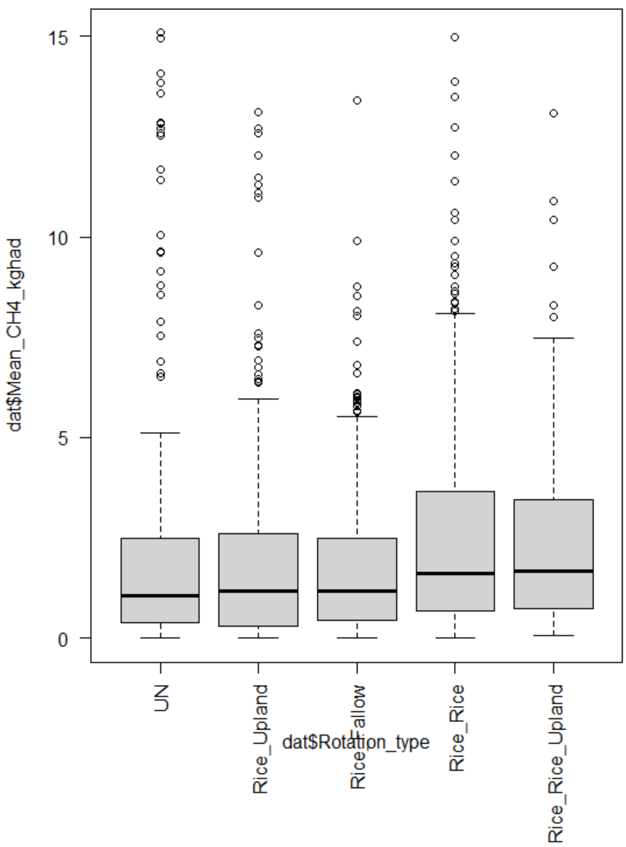
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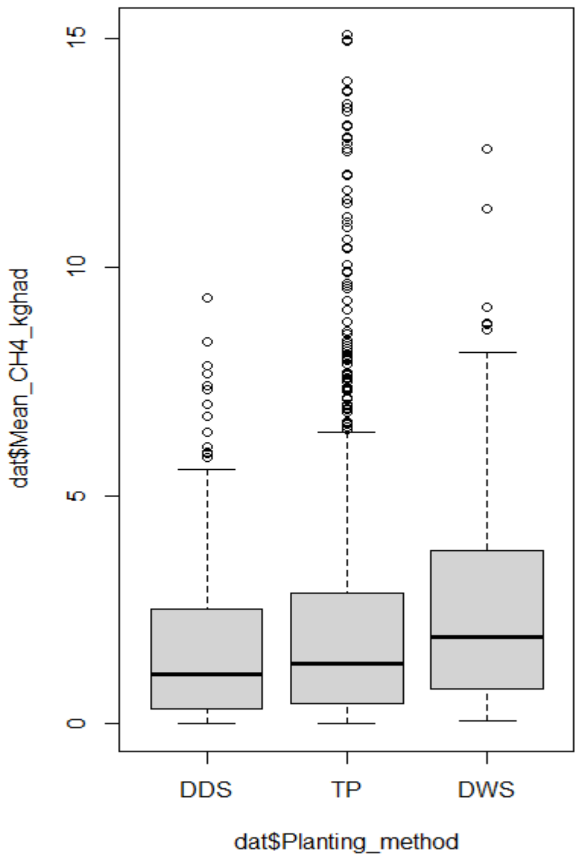
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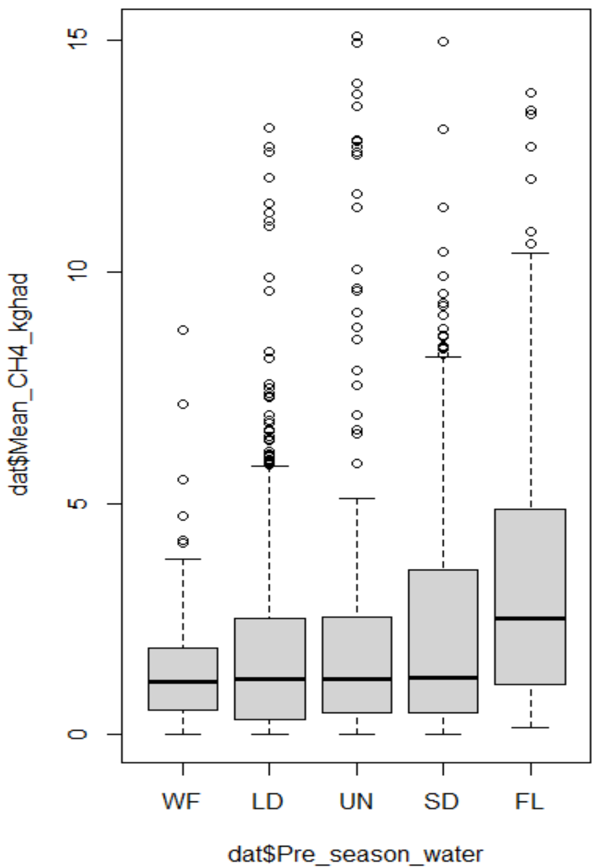
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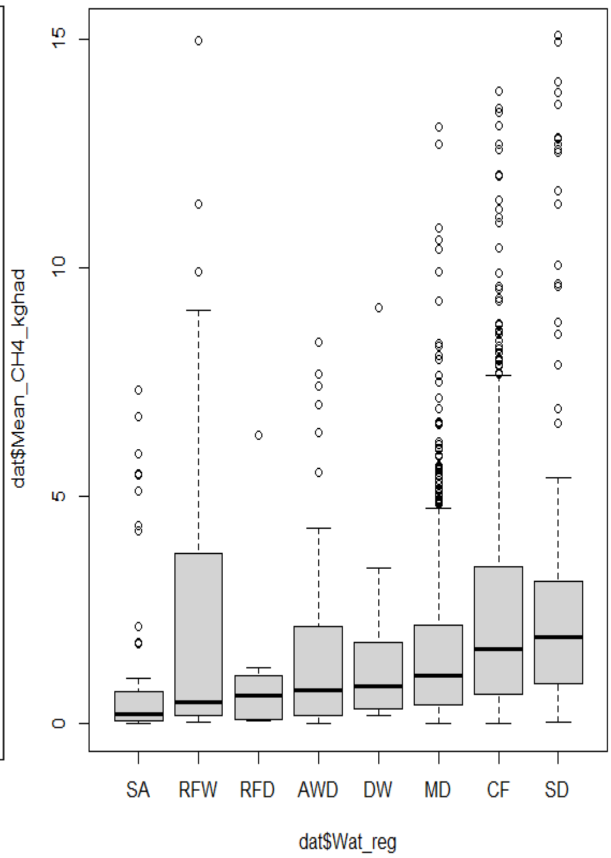
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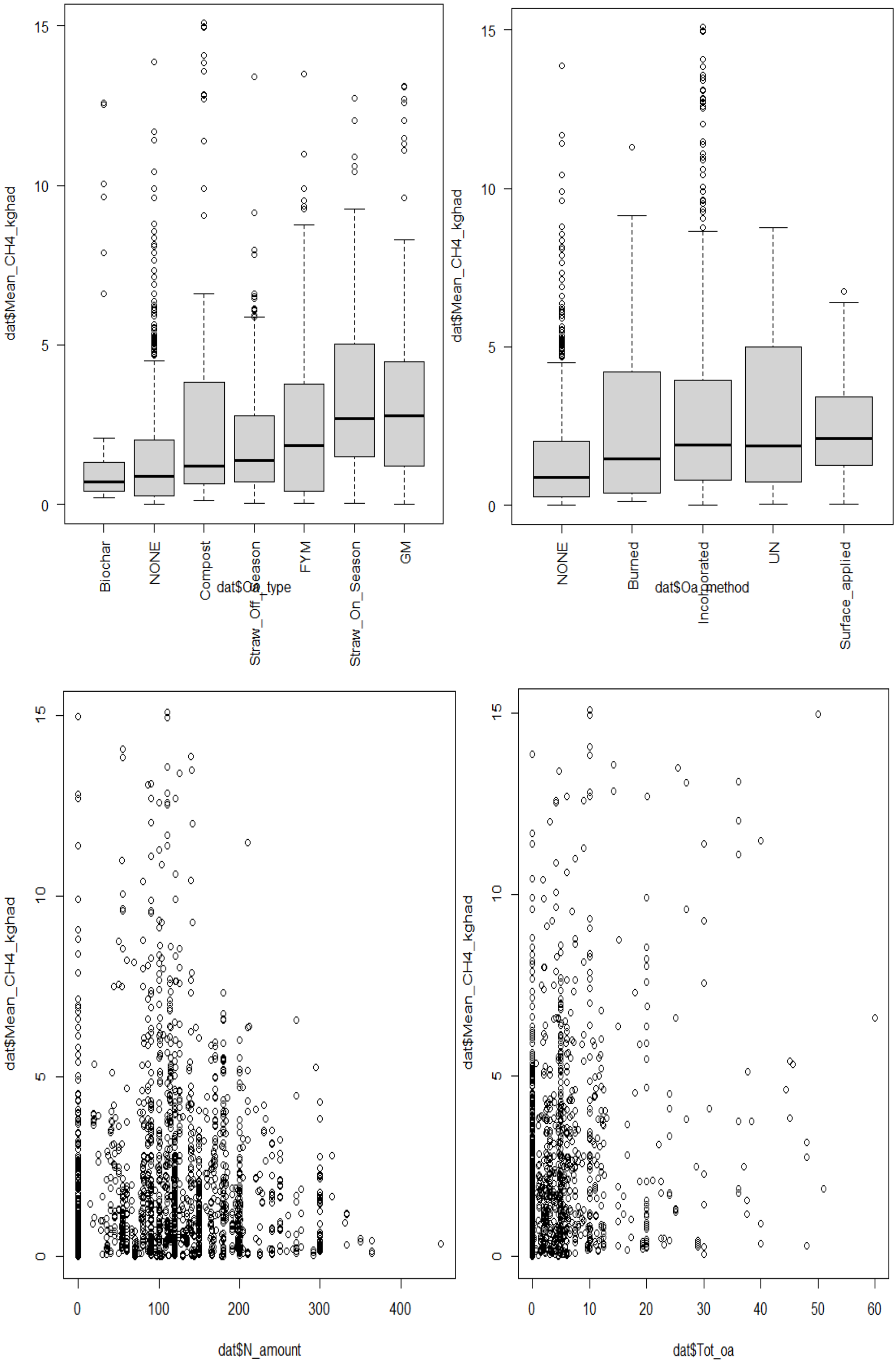
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Incoorporated
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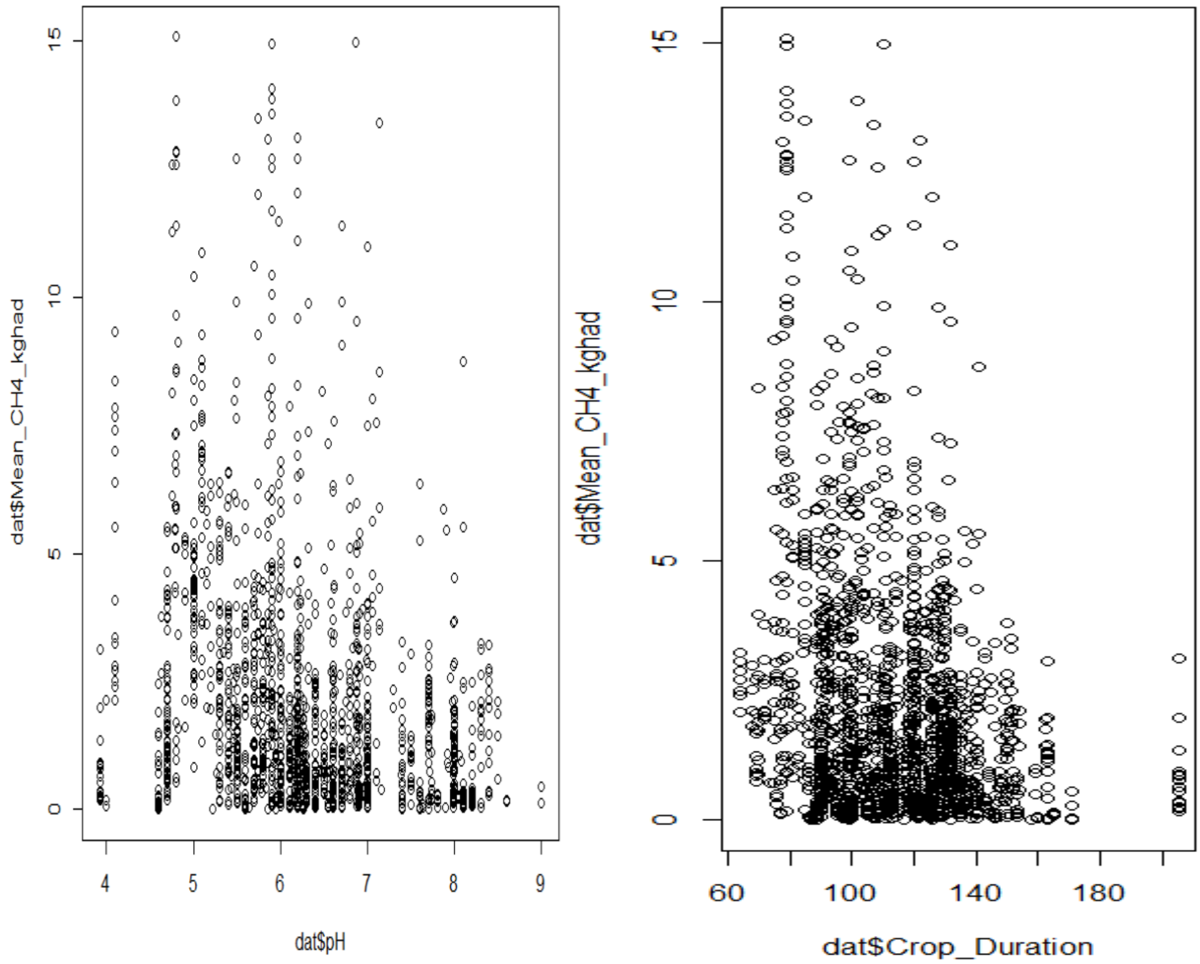

S2. Summary information for the new CH4 model provided in Equation 4

Formula:

ch4_dfithr ~ Pre_season_water + Planting_method + Wat_reg + Growing_season + pH +

Oa_type:Tot_oa + Oa_method + N_amount + Soil_tex + (1 | Country) + (1 | Climate) Data:dat

AIC	BIC	Loglik	Deviance	Df. resid
-923.9	-712.1	501.0	-1001.9	1651

Descriptive statistics model results for fixed and random effects through fitting the model to fifth cube transformed CH_4 fluxes (kg ha^{-1} d^{-1}).

	Estimate	Std. Error	T value
Fixed effects			
Intercept	1.651e+00	9.372e-02	17.620
pH	-4.362e-02	7.996e-03	-5.455
N amount	-2.287e-04	6.989e-05	-3.272
Crop duration	-2.426e-03	2.970e-04	-8.169
Pre-season water			
SD (single drainage)	0[c]		
UN (unknown)	-3.199e-02	2.061e-02	-1.552
FL (flooded)	1.295e-01	2.038e-02	6.354

LD (long drainage)	-1.264e-02	1.772e-02	-0.713
WF (winter flooding)	1.408e-01	4.400e-02	3.199
Planting method			
TP (transplanted)	0[c]		
DDS (direct dry seeded)	-6.235e-02	2.011e-02	-3.100
DWS (direct wet seeded)	1.157e-01	2.682e-02	4.132
Water regime			
CF (Continuous flooded)	0[c]		
AWD (Alternate wetting and drying)	-1.642e-01	2.266e-02	-7.245
DW (deep water)	-3.987e-02	5.458e-02	-0.731
MD (multiple drainage)	-7.395e-02	1.365e-02	-5.416
SA (saturated)	-1.987e-01	2.786e-02	-7.133
SD (single drainage)	2.560e-02	1.830e-02	1.399
RFW (rainfed wet)	-2.062e-02	2.935e-02	-7.025
RFD (rainfed dry)	-1.435e-01	4.799e-02	-2.991
Growing season			
Single	0[c]		
Early	-8.262e-02	1.984e-02	-4.164
Late	-5.451e-02	2.027e-02	-2.689
Wet	1.156e-01	3.204e-02	3.606
Dry	-4.892e-02	3.417e-02	-1.432
OA method			
None	0[c]		
UN (unknown)	-3.007e-02	2.387e-02	-1.260
Incorporated	6.723e-02	1.444e-02	4.656
Burned	2.059e-02	3.874e-02	0.531
Surface applied	7.882e-02	6.989e-02	-3.272
Soil texture			
UN	0[c]		
Coarse	1.477e-01	4.769e-02	3.097
M_coarse (Moderately coarse)	1.300e-01	1.952e-02	6.658
Medium	1.115e-02	1.725e-02	0.646
M_Fine (Moderately fine)	-3.099e-02	1.604e-02	-1.932
Fine	-1.211e-01	2.241e-02	-5.404
Oa_type:Oa_method			
Biochar:tot_oa (total organic amendment)	-7.066	1.690e-03	-4.182
GM:tot_oa (green manure)	7.212e-03	1.158e-03	6.229
FYM:tot_oa (Farmyard manure)	3.052e-03	1.100e-03	2.775
Compost:tot_oa	5.782e-03	1.598e-03	3.618
Straw off season:tot_oa	8.878e-03	3.077e-03	2.885
Straw on season:tot_oa	1.953e-02	2.758e-03	7.081

Random Effect (Best Linear Unbiased Predictions)

Country	Intercept	Climate	Intercept
Bangladesh	-0.0366	Af	0.3124
Brazil	0.1611	Am	0.0370
China	0.0326	Aw	0.1179
India	-0.2202	Bs	-0.1526
Indonesia	-0.2089	Cf	-0.0261
Italia	-0.1471	Cs	-0.2692
Japan	-0.0231	Cw	-0.0999
Myanmar	-0.2122	Df	0.1436
Philippines	-0.1026	Dw	-0.0631
Portugal	0.4304		
South Korea	0.2373		

Spain	0.0831
Thailand	-0.1954
Uruguay	0.1055
USA	0.0357
Vietnam	0.0604

Descriptive statistics of predicted value using Equation 4

Variables	Mean flux (CH_4 kg-1 d-1)	Relative flux	95% confidence interval	
			Lower	Upper
Water regime during crop growth				
Continuously flooded	2.024	1	1	1
Alternate wetting and drying	1.001	0.49	0.41	0.57
Deep water	1.331	0.66	0.33	0.95
Single drainage	2.687	1.33	1.17	1.47
Saturated	0.452	0.22	0.15	0.29
Multiple drainage	1.370	0.68	0.20	0.40
Rainfed wet season	1.235	0.61	0.44	0.76
Rainfed dry season	0.620	0.31	0.20	0.40
Pre-season water				
Flooded	2.771	1	1	1
Long drainage	1.463	0.53	0.54	0.52
Short Drainage	1.763	0.64	0.63	0.64
Winter flooded	1.178	0.43	0.39	0.45
Soil texture				
Moderately fine	1.949	1	1	1
Coarse	1.547	0.79	0.67	0.90
Moderately coarse	1.879	0.96	0.91	1.01
Medium	1.542	0.79	0.78	0.80
Fine	0.969	0.50	0.49	0.51
Planting method				
Direct wet seeded	2.345	1	1	1
Transplanted	1.760	0.75	0.83	0.69
Direct dry seeded	1.435	0.61	0.64	0.59
Organic amendment type				
Compost	3.099	1	1	1
Green manure	2.925	0.94	1.23	0.80
Biochar	2.114	0.68	0.67	0.69
Farmyard manure	1.757	0.57	0.73	0.48
Straw on season	2.798	0.90	1.19	0.75
Straw off season	1.886	0.61	0.80	0.51
Organic amendment method				
Incorporated	2.400	1	1	1
Burned	2.104	0.88	0.63	1.10
Surface applied	2.146	0.89	0.86	0.93
Growing season				
Late season	2.149	1	1	1
Early season	1.546	0.72	0.71	0.73
Wet season	2.040	0.95	0.93	0.96
Dry season	1.288	0.60	0.59	0.61
Single season	1.658	0.77	0.80	0.75

S3. Modeval evaluation of existing model

Model evaluation using Modeval. N/B = no/bad, Y/G = yes/good, Y/B= yes/bad, N/G = no/good. Correlation coefficient, significant association, significant total error, mean difference, student's t of m, t-value (critical at 2.5% - two-tailed), significant bias

Model evaluation	**Europe (n:16)**															
	R = corr coeff.	**F = (n-2) r^2 / (1-r^2)**	**F-value at (p=0.05)**	**Sig. assoc**	**RMSE %**	**RMSE (95%conf)**	**Sig. tot error?**	**Mean dif**	**Stud t of M**	**T-val**	**Sig. bias**	**E = Rel error**	**E (95%)**	**Sig. bias**	**LOFIT**	**F=MDLO FIT/MSE**
Yan et al., 2005	0.34	1.80	4.60	N/B	312.5	0	Y/B	-1.40	3.60	2.14	Y/B	-215.08	40.44	Y/B	184.4	4.983
Wang et al., 2018	0.24	0.83	4.60	N/B	140.7	0	Y/B	-0.46	2.20	2.14	Y/B	-70.75	40.44	Y/B	34.58	0.935
IPCC 2006	0.03	0.01	4.60	N/B	172.7	0	Y/B	-0.64	2.61	2.14	Y/B	-97.98	40.44	Y/B	50.23	1.358
IPCC 2019	0.03	0.01	4.60	N/B	224.6	0	Y/B	-1.00	3.53	2.14	Y/B	-153.4	40.44	Y/B	85.82	2.320
Model evaluation	**North America (n:81)**															
	R = corr coeff.	**F = (n-2) r^2 / (1-r^2)**	**F-value at (p=0.05)**	**Sig. assoc**	**RMSE %**	**RMSE (95%conf)**	**Sig. tot error?**	**Mean dif**	**Stud t of M**	**T-val**	**Sig. bias**	**E = Rel error**	**E (95%)**	**Sig. bias**	**LOFIT**	**F=MDLO FIT/MSE**
Yan et al., 2005	0.13	1.40	3.96	N/B	86.76	0	Y/B	0.25	2.09	1.99	Y/B	19.75	58.67	N/G	298.3	0.482
Wang et al., 2018	0.14	1.50	3.96	N/B	92.09	0	Y/B	0.67	6.29	1.99	Y/B	52.81	58.67	N/G	336.1	0.542
IPCC 2006	0.22	3.91	3.96	N/B	82.65	0	Y/B	0.48	4.53	1.99	Y/B	37.28	58.67	N/G	270.8	0.437
IPCC 2019	0.11	1.00	3.96	N/B	79.06	0	Y/B	0.28	2.55	1.99	Y/B	21.63	58.67	N/G	247.8	0.382
Model evaluation	**East Asia (n:254)**															
	R = corr coeff.	**F = (n-2) r^2 / (1-r^2)**	**F-value at (p=0.05)**	**Sig. assoc**	**RMSE %**	**RMSE (95%conf)**	**Sig. tot error?**	**Mean dif**	**Stud t of M**	**T-val**	**Sig. bias**	**E = Rel error**	**E (95%)**	**Sig. bias**	**LOFIT**	**F=MDLO FIT/MSE**
Yan et al., 2005	0.27	19.80	3.88	Y/G	115.3	0	Y/B	0.52	6.92	1.97	Y/B	45.97	105.5	N/G	1274	0.620
Wang et al., 2018	0.32	28.12	3.88	Y/G	122.3	0	Y/B	0.77	10.73	1.97	Y/B	68.35	105.5	N/G	1434	0.698
IPCC 2006	0.29	23.33	3.88	Y/G	109.9	0	Y/B	0.42	5.79	1.97	Y/B	37.59	105.5	N/G	1159	0.564
IPCC 2019	0.27	20.01	3.88	Y/G	108.7	0	Y/B	0.22	2.93	1.97	Y/B	19.72	105.5	N/G	1134	0.552
Model evaluation	**South Asia (n:77)**															
	R = corr coeff.	**F = (n-2) r^2 / (1-r^2)**	**F-value at (p=0.05)**	**Sig. assoc**	**RMSE %**	**RMSE (95%conf)**	**Sig. tot error?**	**Mean dif**	**Stud t of M**	**T-val**	**Sig. bias**	**E = Rel error**	**E (95%)**	**Sig. bias**	**LOFIT**	**F=MDLO FIT/MSE**
Yan et al., 2005	0.06	0.24	3.97	N/B	169.4	0	Y/B	0.76	3.02	1.99	Y/B	55.43	18.68	Y/B	1241	0.812

Wang et al., 2018	0.12	1.01	3.97	N/B	175.9	0	Y/B	1.05	4.24	1.99	Y/B	76.83	18.68	Y/B	1338	0.875
IPCC 2006	-0.03	0.08	3.97	N/B	170.9	0	Y/B	0.46	1.76	1.99	N/G	33.83	18.68	Y/B	1263	0.779
IPCC 2019	0.34	9.91	3.97	Y/G	150.7	0	Y/B	0.22	0.95	1.99	N/G	16.32	18.68	N/G	982.2	0.642
Model evaluation	**South-East Asia (n:159)**															
	R = corr coeff.	**F = (n-2) r^2 / (1-r^2)**	**F-value at (p=0.05)**	**Sig. assoc**	**RMSE %**	**RMSE (95%conf)**	**Sig. tot error?**	**Mean dif**	**Stud t of M**	**T-val**	**Sig. bias**	**E = Rel error**	**E (95%)**	**Sig. bias**	**LOFIT**	**F=MDLOFIT/MSE**
Yan et al., 2005	0.06	0.48	3.90	N/B	132.7	0	Y/B	0.44	1.84	1.98	N/G	19.16	15.54	Y/B	4447	0.793
Wang et al., 2018	0.10	1.73	3.90	N/B	130.9	0	Y/B	1.62	8.04	1.98	Y/B	71.44	15.75	Y/B	4330	0.773
IPCC 2006	0.10	1.60	3.90	N/B	123.1	0	Y/B	1.25	6.30	1.98	Y/B	54.11	15.54	Y/B	3906	0.674
IPCC 2019	0.25	10.84	3.90	Y/G	118.0	0	Y/B	1.08	5.39	1.98	Y/B	46.95	15.95	Y/B	3408	0.624

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