METHODS FOR ESTIMATING GREENHOUSE GAS EMISSIONS FROM CROPLANDS IN INDIA

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# Summary of Methods

The analysis estimates district-level GHG emissions from croplands in India: methane from rice, nitrous oxide from nutrient additions; and nitrous oxide and methane from crop residue burning for data derived from the period 2015-2021. The analysis provides district-level estimates of emissions from each source disaggregated by 44 crop types (total, per hectare and per kg of harvest product), landholding size class (5 size categories from <1 to 10 ha), and irrigation status (irrigated and rainfed). Estimates and uncertainty ranges are based on ensemble modeling using Monte Carlo simulations from a range of emission factor-based and empirical models obtained from the literature. Input data for the models is derived from publicly available data sources from the Government of India.

The purpose of the analysis is to identify the geographic locations, crop types, and farm types that provide opportunities to reduce emissions through changes in management with a focus on water, nutrient and residue management. This analysis does not include emissions from livestock, although literature estimates for these emissions are available and future work could apply a similar Monte Carlo approach to constrain the geographic distribution of emissions from livestock.

Data sets and code for running the analysis are in a single SQL Server database, which will be made available when publishing these results.

Nitrous oxide emissions from nutrient additions

## Nitrous oxide emissions models

A literature review yielded seven papers that contained published sets of emission factors (EF) in addition to the IPCC tier one method1 (Table 1). The models stratify emission factors according to different dimensions including country, climate, fertilizer type, crop, water regime for rice, and soil properties. The chosen models include both proportional and non-linear relationships between nitrogen inputs and emissions. Some models include background levels of nitrous oxide (Table 1). The models were chosen to represent important dimensions within the input data so that the ensemble would capture the underling variability from different models and input data sets.

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| Table : Models for nitrous oxide emissions from nutrient additions. See Appendix A for emission factors from each reference. | | |
| **Reference** | **Method** | **Emission factors sets for models** |
| Albanito et al (2017)2 | EF linear | Country level |
| Crop type |
| Fertilizer |
| Aliyu et al (2019)3 | EF linear with background N2O | Crop type |
| Hergoualc’h et al (2021)4 | EF linear | Climate (dry/wet) |
| Fertilizer |
| Irrigation |
| Crop type (Perennial, Annual) |
| N application rate |
| Soil alkalinity |
| Soil carbon content |
| Soil texture |
| Akiyama et al (2005)5 | EF linear with background N2O | Rice water regime |
| Mathivanan et al (2021)6 | EF linear | Fertilizer type |
| Shcherbak et al (2014)7 | EF non-linear with background N2O | Fertilizer type |
| Crop |
| Yue et al (2019)8 | EF sets derived from three empirical models. | Model 1: crop and fertilizer types |
| Model 2: crop and fertilizer types |
| Model 3: crop type |
| IPCC 20191 | EF linear | IPCC standard method, 2019 update |

Input data

The input data for the EF based estimates was obtained mainly from the [Input Survey from 2016-17](https://inputsurvey.dacnet.nic.in/)9, a district-level representative sample survey based on the Agriculture Census 2015-16. The input survey provides district-level quantity of fertilizer applied to different crops. Each crop is further stratified by 5 landholding size groups which are further disaggregated by irrigated and unirrigated area. District-level, crop-specific total nitrogen application was derived by combining data on synthetic and organic fertilizer (farmyard and green manure) application from the Input Survey (Table 2).

Input data on soil carbon content and soil pH was computed as the median value of all valid soil health card data from 2015-21 at the district level. Soil texture data was estimated from soil pH and soil carbon content classified as fine, medium, and coarse textures in accordance with the CCAFS Mitigation Options Tool 10 (CCAFS MOT) model by using the Euclidean distance between the district median soil parameters and CCAFS MOT’s soil parameters for their simplified soil classification, see Appendix D Table 31 10

Climate zone data (wet/dry) used the Agro-Ecological Sub-Regions dataset11 from WRIS based on which zone covers the majority area of the district. Look-up tables to assign climate zones to wet or dry categories and rice water regimes to continuous flooding/midseason drainage/all water regimes categories are in Table 27 of Appendix D for the respective models.

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| Table : Input data for models used in estimating nitrous oxide emissions. | | | | |
| **DATA SOURCE** | **PARAMETER USED IN EMISSION MODELS** | **SCALES** | **YEAR** | **COMMENTS** |
| Table 4: Usage of fertilizer for different crops in 2016-17 [Input Survey](https://inputsurvey.dacnet.nic.in/districttables.aspx)9 | Area treated by one or more fertilizer; area irrigated and non-irrigated | District, crop, size group, irrigation | 2016-17 | To compute the amount of nitrogen applied per hectare on average, the area from Table 4 was used in the denominator. |
| Table 4a: Usage of different fertilizers for different crops 2016-17 [Input Survey](https://inputsurvey.dacnet.nic.in/districttables.aspx)9 | Total quantity of fertilizer applied; nitrogen application rate | District, crop, size group, irrigation | 2016-17 |
| Table 5e: Usage of FYM/compost for different crops 2016-17 [Input Survey](https://inputsurvey.dacnet.nic.in/districttables.aspx)9 | Area under the crop treated with the manure; total quantity of the manure applied | District, crop, size group, irrigation | 2016-17 |  |
| Table 5la. Usage of green manure for different crops 2016-17 [Input Survey](https://inputsurvey.dacnet.nic.in/districttables.aspx)9 | Area under the crop treated with manure | District, crop, size group, irrigation | 2016-17 | Quantity of green manure per hectare was implemented as a constant at 7.5 ton ha-1 (based on expert opinion) |
| [WRIS](https://arc.indiawris.gov.in/server/rest/services/SubInfoSysLCC/Agro_Regions/MapServer/2): Agro-Ecological Sub-Regions11 | Climate (wet/dry) | District | NA | See Table 27 in Appendix D |
| [Soil health cards](https://soilhealth.dac.gov.in/piechart) | Soil Alkalinity (pH) | Sub-district (tehsil) | 2015-21 | Accessed 2021-01\* |
| Soil Carbon Content (organic carbon) |
| Soil Texture | Derived from pH and OC |
| [IRRI South Asia rice map](https://web.archive.org/web/20150810010620/http:/irri.org/our-work/research/policy-and-markets/mapping/remote-sensing-derived-rice-maps-and-related-publications) 12 | Rice water regime | Sub-district (tehsil) | 2000-01 | % of area of each water regime in each tehsil |
| \* The specific report of soil health cards from which the data was generated is no longer available on-line. The resulting data is contained in the table [rice,crop]\_median\_soil\_inputs within the database. | | | | |

Model implementation

We used a total of 20 emission factor models (Table 1) to estimate nitrous oxide emissions from nitrogen additions. The models were all implemented as a table(s) of factors, table of results and a SQL stored procedure (see Table 14 in Appendix A for a list of database objects used to implement the models). The SQL stored procedure for each model first creates the input data required by aggregating the fertilizer specific nitrogen applied to each crop to the level of the emission factors. Crop and fertilizer factors used lookup tables to map between the standard crop names in the input data and the crop names in the model factor sets (Table 28 in Appendix D). Similarly standard fertilizer names in the input data were mapped to model fertilizer factor names (Table 29 in Appendix D). The aggregated nitrogen amounts were then mapped to the correct emission factor to create an input dataset for the model. Next the stored procedure used a loop to implement a Monte Carlo simulation. The first step was to sample the emission factors from an appropriate distribution. Beta distributions were typically used to sample the EFs as they were constrained between 0 and 1. When background emission values were included in the models, they were sampled from normal or gamma distributions depending whether the confidence interval was skewed. The sampled EF was then used to compute the kg ha-1 emissions of N2O with the result, inputs and the index of the iteration stored in the results table. The stored procedure takes the number of simulations desired as an input parameter. One thousand simulations were used for each model. The resulting data from all 20 models was then summarized to create ensemble results and uncertainty ranges. For each model, the mean, standard deviation, and the 2.5th, 25th 50th, 75th and 97.5th percentile were computed from the ensemble. The final ensemble was created by combining all the model simulations into a single distribution and then computing the results. The results were then used to create the district level results of total emissions Mg N2O yr-1 and emission per unit of production kg N2O kg product-1 for each crop and farm size with uncertainty ranges. The database objects use to implement the nitrous oxide models are documented in Table 14 of Appendix A. Detailed description of each model and its EF value can be found in Tables 6 through 13 in Appendix A.

Methane emissions from rice

Methane emissions models

The literature review yielded five papers that contained emission factors (EF) or empirical models for estimating rice methane emission. The IPCC 2019 updated methodology 1 was also implemented. The models ranged from the simple EF based models 13, that only accounted for water regime to complex Generalized Additive Mixed Models (GAMM) 14 that accounted for a range of variables including climate data, soil carbon content, soil pH, soil texture, the season the crop was grown in, preseason water status, water regime, organic fertilizer type, organic fertilizer amount, method of applying the organic fertilizer, method used to plant the rice, and crop duration. Other models contained scaling factors for water regime, preseason water status and organic amendments. Two models 13,15 were India specific and contained factors for drought prone rice. Drought prone rice is also included in the IPCC 2019 updated methodology1. Drought prone rice is important in India as a large amount of rice production occurs in drought prone areas and has significantly less emissions than rice grown in non-drought areas. The ensemble of models represents a range of methodologies applicable to the available data to use and ensemble approach to estimate uncertainties.

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| Table : Models for estimating methane emissions from rice | | |
| **REFERENCE** | **DESCRIPTION** | **INPUT DATA REQUIRED** |
| Bhatia et al (2013)13 | India NATCOM EF model | Water regime, crop duration |
| Gupta et al (2009)15 | India specific EF model with scaling factors for organic amendments | Water regime, crop duration, organic fertilizer |
| IPCC 2019 Update1 | Standard IPCC method, 2019 update | Water regime, pre-season water status, organic fertilizer, crop duration |
| Nikolaisen et al (2023)14 | GAMM model | climate, preseason water status, water regime, soil texture, pH and organic carbon, organic inputs type, amount and application method, season grown in, and type of planting |
| Wang et al (2018)16 | GAM model | Soil organic carbon, pH, ecological zone, organic fertilizer, pre-season water status, water regime, crop duration, organic fertilizer |
| EF mode with non-linear equations for organic amendments | Organic fertilizer |
| Yan et al (2005)17 | GAM model (same as Wang et al (2018) 16 with different coefficients and climate data) | Same as Wang et al (2018) 16 |

## 

Input data

Input data (in addition to data for organic fertilizer; soil pH, organic carbon content, and texture; and water regime described in nitrous oxide emissions section) for rice methane emissions consists of:

*Crop duration*: Crop duration data was obtained from the [SeedsNet database](https://seednet.gov.in/Index.aspx) 18 for rice varieties released to the states. The rice crop durations for each state were computed from the proportion of the number of varieties of the given crop duration (days, using mid-point of duration) to total number of varieties in the state (see Table 21) on rice crop varieties in Appendix B). Each district within a state was assigned the state rice crop duration distribution.

*Water regime:* The water regime was estimated as the proportion of each water regime class within a district using the irrigated and non-irrigated area reported in the Input Survey, disaggregated by the area of the water regime classes reported in Gumma et al (2010)12. Models typically estimated results for several irrigated water regimes that include continuous flooding, single aeration, and multiple aeration. There was no data available to spatially quantify the area of the different irrigated water regimes, so they were averaged to estimate the methane emissions for an irrigated hectare. Rainfed area of rice production was disaggregated using the Gumma et al (2010)12 data into deepwater, rainfed in the wet season and upland area. Deepwater area was considered static while the other two classes were used to proportionally disaggregate the remaining non-irrigated area reported in the input survey. The model estimate for each rainfed class was then weighted by its area to estimate the average per hectare rainfed methane emissions. Mapping between the different model water regime names used in the models and the names in the Gumme et al (2010)12 data can be found in the lookup Table 30 in Appendix D

*Pre-season water status:* The pre-season water status was estimated from the APY19 data using the seasons in which rice was grown to determine the length of drainage before the rice was planted. The APY 19 data contains the area planted in each season ranging from one to three seasons. It was assumed that rice grown in different seasons was planted on the same land. The area where rice was only grown once was assigned the pre-season water status of “Long drainage”. The area where rice was grown more than once was assigned the pre-season water status of “Short drainage”. Other pre-season water status specified in the models were not considered to be applicable. The proportion of each pre-season water status was then used as weighting factors to estimate average results for each district.

*Climate and agro-ecological zone (AEZ):* Climate date was obtained from the WRIS GIS layer Agro-ecological Sub-Regions 11 was used to develop district level climate variable for Yan et al (2005) 17 and Wang et al (2018) 16 empirical models. The data was reclassed according to the lookup table in Table 27 of Appendix D. The climate class with the majority area within the district was assigned to the district. Yan et al (2005) 17 used the IRRI climate classification while Wang et al (2018) 16 used a system that differentiated the tropics from the subtropics. The GAMM model of Nikolaisen et al (2023)14 used the Köppen-Geiger climate20(Appendix B, Figure 1).

*Organic input type:* The quantity for farmyard and green manure is taken from the input survey for each crop using the lookup table for mapping APY crop names to the names used in the models (Table 28, Appendix D).

*Application method of organic amendments:* The Nikolaisen (2023) 14 GAMM model required the categorical variable for the method of application of organic amendments with the classes incorporated, surface applied, burned, unknown, and none. Due to lack of data, this variable was assumed to be “incorporated”.

*Season grown (dry/wet):* The Nikolaisen (2023) 14 GAMM model required the categorical variable on the season the rice was planted (dry or wet). Emissions were estimated, then weighted by proportion of rice grown in the kharif (monsoon) for the wet season estimate and the proportion or rice grown in non-kharif season for the dry season estimate.

*Type of planting:* The Nikolaisen (2023) 14 GAMM model used a categorical variable for planting type that included the classes transplanted, direct dry seeding, direct wet seeding. Due to lack of data, estimates were made for each class and the results were averaged using equal weights for the three planting methods.

*Drought-prone rice water regime:* The rainfed water regime class in the Gumma (2010)12 data was further divided into drought-prone and regular/flood-prone classes as required by the Gupta (2009)15, Bhatia (2013)13 and IPCC models 1 (Appendix D, Table 30). The India Meteorological Department (IMD) New (0.25X0.25 degree) Long Period (1901-2022) Daily Gridded Rainfall Data Set 21 Over India was used to classify districts as either drought-prone or not on a yearly basis from 1901 to 2022. Drought-prone districts were defined as areas receiving less than 750mm of rain per annum. The years were then aggregated to compute the proportion of years the district was drought prone. The models were used to estimate both rainfed classes and then average emissions were weighted by the proportion or years.

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| Table : Input data used to estimate methane emissions from rice production. | | | |
| **SOURCE** | **INPUT DATA REQUIRED FOR MODELS** | **SPATIAL SCALE** | **YEAR** |
| See Table 2 | Rice water regime | Sub-district (tehsil) | 2000-01 |
| SeedsNet, [(Central Varieties)](https://seednet.gov.in/Index.aspx) report18 | Crop duration | State | 1970-2023 releases |
| See Table 2 (Table 5e and 5la from input survey)9 | Organic fertilizer | District | 2016-117 |
| [WRIS, Agro-Ecological Sub-regions](https://arc.indiawris.gov.in/server/rest/services/SubInfoSysLCC/Agro_Regions/MapServer/2)11  & [Beck et al (2019)](https://www.gloh2o.org/koppen/)20 | Climate and ecological zone | NA |  |
| See Table 2 | Soil texture | Sub-district (tehsil) | 2015-21 |
| See Table 2 | Soil pH | Sub-district (tehsil) | 2015-21 |
| See Table 2 | Soil organic carbon | Sub-district (tehsil) | 2015-21 |
| Assumed “incorporated” | Application method | NA | NA |
| Area, Production, Yield Report 19 | Season grown, pre-season water status | District | 2015 |
| Averaged over classes, assumed equal weights as there is not data available. | Type of planting (transplanted, direct seeded wet, direct seeded dry) | NA | NA |
| [IMD, Yearly Gridded Rainfall](https://imdpune.gov.in/cmpg/Griddata/Rainfall_25_Bin.html)  21 | Drought/non-drought water regime | 0.25x0.25 degree | 1901-present |

Model implementation

A total of seven models were implemented to estimate methane emission from rice production. Four models were factor based while three were empirical. All but Nikolaison et al (2023) were implemented as SQL stored procedure that referenced factor or coefficient tables stored in the database. The Nikolaison et al (2023) 14 GAMM model was implemented by creating an input dataset for the R code distribution in the supplemental material of the paper. The R code was used to predict estimates and confidence intervals of daily methane emissions. The predictions were imported into the database where Monte Carlo simulations were implemented in an SQL stored procedure to estimate season methane emissions and its uncertainty by sampling the daily predictions from a normal distribution built from the confidence intervals and multiplying by crop duration from a categorical distribution as described in the *Crop duration* section under *Input Data*.

The SQL stored procedure for the other models were implemented in a similar manner to the emission factor models for nitrous oxide. This included sampling the emission factors or empirical model coefficients from either beta (for EFs) and gamma and normal for scaling factors and coefficients to implement the Monte Carlo simulations to estimate the uncertainty of the methane emission estimate. Only Gupta (2005) 15 and Bhatia (2013)13 estimated season methane flux. For these models the seasonal methane emission was multiplied by a crop duration scaler to adjust for the different growing lengths between districts. The crop duration scaler was computed by sampling a crop duration from a categorical variable and dividing it by the national average rice crop duration. For the models that estimated daily methane flux the season emission were estimated by multiplying the result by the crop duration sample.

Each model was simulated 1000 times as with N2O models and the results were summarized using the same metrics as with N2O. To create the summary results for each district the simulated results first had to be collapsed over the water regime and preseason water status as described in the Input data section for each variable before computing the model and ensemble summary metrics. The database objects used to implement the methane emission models are documented in Table 22. Detailed implementation descriptions for each model along with their equations, emission factor values and coefficient value can be found in Appendix B.

Emissions from crop residue burning.

Crop residue burning emissions models.

The models used to estimate emissions from residue burning all followed the same general formulation represented by Equation 1, Equation 2 and Equation 3. The main difference between the equations is the estimate of biomass. Equation 1 estimates biomass from crop yield, Equation 2 from harvested area and Equation 3 as a function of yield. In equations 1, 2 and 3, *Eij* represents emissions for gas *i*, for crop *j*. In Equation 1, *RPRj*is the ratio of production (yield) to residue for crop *j*. In Equation 2, *RARj* is the amount (ton) of residue for crop j per hectare. In Equation 3, *f(Yj)* represents a crop-specific function that estimates residue biomass from crop yield. In all equations, *DMj* is the dry matter fraction for crop *j*, *SFj*is the residue left on the field for crop *j*, *BEj* is the burn efficiency and *EFi*is the emission factor for gas *i*.

|  |  |
| --- | --- |
|  | Equation |
|  | Equation |
|  | Equation |

Input data

Table 5 lists the data used to estimate emissions from crop residue burning.

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| Table : Input data for models to estimate emissions from crop residue burning. | | | |
| **PARAMETER** | **SOURCE** | **SCALES** | **YEAR** |
| Crop yield | Area, Production, Yield Report (APY)19 | District | 2016 |
| Harvested area | District | 2016 |
| Crop residue (kg residue per kg of harvest) | [National Biomass Atlas of India version 2](https://www.nibe.res.in/biomass-atlas.php) 22 | By Crop (63) | NA |

*Crop residue:* Three different methods were used to estimate total crop residue after harvest. The first method estimated total crop residue as a ratio of crop yield (RPR) with data taken from the APY dataset for the year 2015 (Table 5) for each crop (Equation 1). The second approach estimated total residue per hectare per crop (Equation 2) with values derived from the literature. The crop specific residue to production ratios and the residue per hectare values were compiled from the literature (see Appendix C, Table 23 for list of references for each variable of the model). Where crop specific factors were not available, a crop class factor was used that was constructed from the other crop specific factors (Appendix C, Table 24). Where no standard deviation was reported for the factor, the standard deviation was borrowed from the crop class standard deviation or constructed from the available data (Appendix C, Table 24). The final method implemented the functions that estimate RPR from crop yield published in Karan et al (2021) 23 (Equation 3). The functions represent non-proportional residue amounts with increase in yield. The RPR functions were only implemented for 31 crops due to lack of functions for some crops (Appendix C, Table 26).

The ensemble of residue estimates made from the three models include four distinct sets of values, a set or RPR and RAR values derived from the literature, the functions reported in Karan et al (2021) 23 and the Indian Biomass Atlas v2.0. The National Biomass Atlas of India (Biomass Atlas v2.0) 22 represent a study conducted by Ministry of New and Renewable Energy that published crop residue amounts for 63 different crops. The Atlas represents a mix of both RPR and RAR values depending on the crop and represents the most complete crop specific values that are regional to India. For this reason, it was implemented as its own set of results as it mixed both Equation 1 and Equation 2. The Biomass Atlas v2.0 22 did not report ranges for their estimates so values from the RPR and RAR value sets were used. The values and standard deviations use for the RPR, RAR and Biomass Atlas v2.0 can be found in Appendix C, Table 25

*Residue dry matter fraction (DM):* Dry matter fraction converts the fresh residue mass to a dry matter basis. Dry matter fraction was taken from the literature (Appendix C, Table 23). The standard deviation was taken from the literature or computed from the total set of dry matter fraction crop values that did not contain estimates of uncertainty. Few studies reported the n for the reported uncertainty values precluding the ability to weight the individual studies when computing the average values and standard deviations. Using all available data, means and standard deviations were computed for each reported crop, the crop class and all the data. Where possible crop specific values were used with missing values filled from crop class or full dataset values. See Appendix C, Table 24 and Table 25 for the values and their respective sources.

*In-field residue fraction (SF):* In-field residue fraction represents the amount of residue left in the field that is not used for some other purpose and is available to be burnt. Values were compiled from the literature (Appendix C, Table 23). The standard deviation was taken from the literature or computed from the total set of in-field residue fractions that didn’t contain estimates of uncertainty as for dry matter fraction. The source for both the mean and standard deviation for each crop can be found in Table 24 and the values can be found in Table 25 of Appendix C.

*Residue burn efficiency (BE):* Burn efficiency represents the proportion of residue dry matter that is combusted. Crop-specific values were obtained from the literature (Appendix C, Table 23). The mean and standard deviations used for the Monte Carlo simulation to estimate uncertainty were developed in same way as for the above with sources reported in Table 24 and values in Table 25 of Appendix C.

*Residue burning emission factors (EF):* Crop-specific residue burning emission factors for nitrous oxide and methane were compiled from the literature (Appendix C, Table 23). The crop specific values were compiled in the same manner as above with sources reported in Table 24 and mean and standard deviations reported in Table 25 of Appendix C.

Model implementation

The implementation of the crop burning residue models used SQL stored procedures. A single stored procedure implemented the Monte Carlo simulations for Equation 1 and Equation 2. The model RPR and RAR values along with the methane and nitrous oxide EF values were sampled from normal distributions. The in-field fraction, burn efficiency fraction, and dry matter fraction values were sampled from normal distributions truncated between zero and one. The stored procedure was run 1000 times for the Kg/Kg yield (RPR) set of value, the T/Ha (RAR) set of values and the Biomass Atlas v2.0 set of values for each district.

The Karan et al (2021) 23 RPR function was implemented as a table valued function that returned all function RPR values published in the paper for the supplied crop and yield sampled from a normal distribution constructed from the supplied standard deviation. The table valued function was then called within a stored procedure that implemented the Monte Carlo simulations.

The results of running the four parameter sets were summarized following the same methodology as with the other modules for nitrous oxide emissions and methane emissions from rice production.

Implementation, Reproducibility and Distribution

The ensemble modeling of India’s agriculture GHG emissions has been implemented as a self-contained SQL Server database. The database contains all the input data generated from the other input databases. The statistical probability distribution sampling routines have been implemented in the database as CLR functions built from the [Math.NET](https://numerics.mathdotnet.com/) open-source library24. The stored procedure, functions and result tables used to implement the Monte Carlo simulations are all contained in the data as are the routines used to summarize the simulation results as described in the individual module implementation sections. Database views are used to create spatial tables that represent per hectare, per kg of product and total emissions by crop, irrigation status and landholding size with additional views aggregating the results across the dimensions of crop, irrigation, and landholding size. Implementing the estimation of India’s agriculture GHG emissions in this manner allows both the data and code used to create the results to be encapsulated into a single system.

The results can be easily reproduced by rerunning the stored procedures within the database to rerun the Monte Carlo simulations for each model and then running the stored procedures to compute the ensemble results. Rerunning the simulations will yield different but comparable results as the simulations are a stochastic process. The input data can be changed to produce new results for different time periods and/or additional crops. The database can be easily altered to compute estimates of other regions of interest or to add additional models to the ensemble.

The database can be distributed easily as a single file. Additionally, the database can be used as the backend for web-based applications. The web-based applications can be tailored to dynamic visualization of the results or to facilitate the importation of input data and the running of the simulations.

The design of the system has been optimized for computing Monte Carlo simulated results for multiple models and aggregating them into ensemble results for a large number of simulated units. Running the Monte Carlo simulations and summarizing the results is computer intense. Tests were carried out that determined that implementing the models and conducting the Monte Carlo simulations within the database had substantial performances advantages over using other programming paradigms. The process can take serval days to complete depending on the number of simulated units. The size of the database is large when the simulation result tables are filled. The current simulation of 1000 results per analytical unit yields a result table with ~1.5 billion records. Once the summary tables are created, the simulation results can be deleted. The simulation data can also be added to if the initial number of simulations is found to be inadequate at representing the distribution of possible outcomes. The final design of the system took several development iterations to achieve the performance necessary to generate ensemble results from Monte Carlo simulations while achieving a flexible design that can be further developed to meet evolving needs.

APPENDIX A. Implementation of nitrous oxide models

Albanito et al(2017) 2 published three sets of emission factors by country(Equation 4), crop type(Equation 5) and fertilizer(Equation 6), see Table 6. *EDistrict* is the district level N2O emissions for a crop, landholding size and irrigation status that represents the disaggregation of the input data. In Equation 6 the emissions for each fertilizer class area summed to create the total emission. To estimate uncertainty using Monte Carlo simulations the emission factors were sampled from beta distributions constructed from the mean and confidence intervals reported in Table 6.

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| Table : Albanito et al (2017) emission factors for India, crop type and fertilizer type. | | |
| **Class** | **Description** | **Factor** |
| Country (Equation 4) | India | 0.012(0.0001-0.078) |
| Crop Type (Equation 5) | Annual | 0.012(0.0001-0.078) |
| Perennial | 0.012(0.0001-0.067) |
| Fertilizers (Equation 6) | Ammonium Nitrate | 0.021(0.0006-0.067) |
| Other N Fertilizers | 0.011(0.0002-0.078) |
| Urea | 0.011(0.0002-0.078) |
| Urea & NI | 0.007(0.0001-0.029) |

Aliya (2017) published emission factors and background emissions values for different crops which were used in Equation 7 to estimate seasonal N2O emissions. *Ncrop* is the nitrogen applied to the crop, *EFcrop* is the emission factor from Table 7 and *BGcrop* is the background emission for the crop from Table 7. The means and standard deviations in Table 7 were used to construct sampling distributions for Monte Carlo simulations to estimate uncertainty. *BGcrop* used a normal distribution while the *EFcrop* used a beta distribution.

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| Table : Aliya (2017) emissions factors for different crops (Equation 7). | | | |
| **Crop** |  | **Direct Emission Factor** | **Background emission kg N ha-1 yr-1** |
| Cabbage |  | 0.0077(±0.0021) | 1.9(±0.69) |
| Celery |  | 0.0057(±0.0044) | 2.6(±0.74) |
| Cucumber |  | 0.0028(±0.0005) | 0.82(±0.38) |
| Maize |  | 0.0071(±0.001) | 0.63(±0.09) |
| Others |  | 0.0166(±0.0088) | 0.53(±0.08) |
| Paddy rice |  | 0.0048(±0.0005) | 0.43(±0.07) |
| Peanut |  | 0.0022(±0) | 1(±0) |
| Rapeseed |  | 0.0055(±0.0007) | 0.3(±0.14) |
| Soybean |  | 0.009(±0.0038) | 1.25(±0.62) |
| Tomato |  | 0.0041(±0.0017) | 1.75(±0.85) |
| Upland rice |  | 0.0087(±0.0041) | 0.38(±0.07) |
| vegetable |  | 0.0054(±0.0021) | 1.8673(±0.6764) |
| Wheat |  | 0.0059(±0.0009) | 0.63(±0.16) |

Akiyama et al(2005) 5 published N2O emission factors and background emissions values (Table 8) for different rice water regimes that were used in Equation 8 to estimate seasonal N2O emissions. The background emissions were sampled from a normal distribution while the EF was sampled from a beta distribution during the Monte Carlo simulations to estimate uncertainty.

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| Table : Akiyama et al(2005) emission factors for different rice water regimes (Equation 8). | | |
| **Water Regime** | **Background emission kg N ha-1 yr-1** | **Emission Factor** |
| Continuous flooding | 0.211(±0.143) | 0.0022(±0.0024) |
| Midseason drainage | 0.372(±0.284) | 0.0037(±0.0035) |
| All water regimes | 0.325(±0.258) | 0.0031(±0.0031) |

## 

Hergoualc’h et al (2021) 4 published a series of emissions factors sets for nitrous oxide for a variety of factors (Table 9). further disaggregated by wet or dry climate. The climate factor was implemented by mapping India’s agro-ecological sub-regions (climate zones) according to Table 27 in Appendix D. The fertilizer form was implemented by assigning green manure and farmyard manure to organic fertilizer and all other fertilizers to the synthetic and mixed fertilizer class. Landcover (crop type) used to lookup Table 28 in Appendix D. The soil texture used the CCAFS MOT class in Table 31, Appendix D mapping to the soil properties using the minimum Euclidean distance. Soil carbon context, soil alkalinity and nitrogen application rate variables were reclassed to fit the EF definition listed in Table 9.

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| Table : Hergoualc’h et al (2021) emission factor sets disaggregated by climate and a number of other factors. | | | |
| **Class** | **Climate** | **Description** | **Factor** |
| Climate  (Equation 9) | Dry | dry | 0.005(0-0.011) |
| Wet | wet | 0.014(0.011-0.017) |
| Fertilizer form  (Equation 10) | Dry | organic fertilizer | 0.005(0.002-0.008) |
| synthetic and mixed fertilizer | 0.005(0.003-0.008) |
| Wet | organic fertilizer | 0.006(0.001-0.011) |
| synthetic and mixed fertilizer | 0.016(0.013-0.019) |
| Irrigation  (Equation 11) | Dry | irrigation | 0.004(0.003-0.006) |
| rainfed (unirrigated) | 0.001(-0-0.003) |
| Wet | irrigation | 0.004(0.003-0.006) |
| rainfed (unirrigated) | 0.001(-0-0.003) |
| Landcover/crop type  (Equation 12) | Dry | annual croplands and bare soils | 0.014(0.011-0.017) |
| perennial systems | 0.009(0.005-0.013) |
| Wet | annual croplands and bare soils | 0.017(0.013-0.021) |
| perennial systems | 0.01(0.006-0.015) |
| N application rate  (Equation 13) | Dry | (0-100] kg N ha-1 | 0.015(0.011-0.018) |
| (100-200] kg N ha-1 | 0.011(0.007-0.015) |
| (200-300] kg N ha-1 | 0.013(0.009-0.018) |
| >300 kg N ha-1 | 0.01(0.005-0.015) |
| Wet | (0-100] kg N ha-1 | 0.018(0.013-0.022) |
| (100-200] kg N ha-1 | 0.012(0.007-0.016) |
| (200-300] kg N ha-1 | 0.015(0.01-0.02) |
| >300 kg N ha-1 | 0.011(0.005-0.017) |
| Soil alkalinity  (Equation 14) | Dry | acid soils (pH < 7) | 0.002(-0-0.004) |
| basic soils (pH ≥ 7) | 0.005(0.003-0.007) |
| Wet | acid soils (pH < 7) | 0.015(0.011-0.019) |
| basic soils (pH ≥ 7) | 0.007(0.002-0.013) |
| Soil C  (Equation 15) | Dry | high soil C (=2%) | 0.015(0.012-0.019) |
| low and medium soil C 2%) | 0.007(0.004-0.01) |
| Wet | high soil C (=2%) | 0.016(0.012-0.02) |
| low and medium soil C 2%) | 0.009(0.005-0.013) |
| Texture class  (Equation 16) | Dry | fine texture | 0.001(-0-0.006) |
| medium and coarse texture | 0.006(0.003-0.008) |
| Wet | fine texture | 0.027(0.021-0.033) |
| medium and coarse texture | 0.011(0.007-0.015) |

Mathivanan et al (2021) 6 fertilizer emission factors and ranges (Table 10) where used in Equation 17 to estimate the seasonal N2O emissions. Durning Monte Carlo simulation to estimate uncertainty the *EFfert*was sampled from a beta distribution constructed from the mean and confidence interval reported in Table 10: Mathivanan et al (2021) emission factors for different fertilizer types (Equation 17).

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| Table : Mathivanan et al (2021) emission factors for different fertilizer types (Equation 17). | |
| **Description** | **Factor** |
| Inorganic N fertilizers | 0.0061(0.0042-0.0084) |
| Animal manure applied to soils | 0.0066(0.0046-0.009) |
| Sewage sludge applied to soils | 0.0057(0.0041-0.0077) |
| Other organic fertilizers applied to soils | 0.0065(0.0045-0.0087) |
| (digestates)Crop residues | 0.0059(0.0041-0.0081) |

Shcherbak et al (2014) 7 used Equation 18 and Equation 19 to estimate N2O for two sets of emission factor listed in Table 11. The Emission factors are disaggregated by crop or fertilize type and mapped to the input data using the lookup table in Appendix D, Table 28 and Table 29. *EN0* is the background emission of N2O and *EFdelta* is the change in emissions for each additional kg of nitrogen added. This creates a non-linear flux of N2O as nitrogen additions area increased. The was drawn from a normal distribution while the was drawn from a beta distribution during the Monte Carlo sample to estimate uncertainty.

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| Table : Shcherbak et al (2014) emission factors for background emission and direct emission from fertilizer application. EN0 is background emissions of N2O. Emission factor delta is for each additional kg of fertilizer applied. | | | | |
| **Class** | **Description** | **EN0** | **EF** | **EFdelta** |
| Crop Type  (Equation 18) | N-fixers | 1.2116( 0.7605) | 0.0145( 0.0203) | 1.85E-04( 3.24E-04) |
| Rice | 0.2877( 0.4057) | 0.0081( 0.0155) | 9.01E-06( 1.09E-05) |
| Upland Grain | 1.1822( 0.5763) | 0.011( 0.0145) | 2.30E-05( 1.25E-04) |
| Fertilizer Type  (Equation 19) | Urea | 0.6509( 0.6264) | 0.0108( 0.0186) | 2.03E-05( 9.06E-05) |
| Calcium ammonium nitrate | 2.027( 0.5309) | 0.0136( 0.0142) | 3.12E-05( 7.00E-05) |
| Manure | 0.8783( 0.667) | 0.0091( 0.0101) | 1.06E-04( 2.28E-04) |
| Mixed | 0.3975( 0.65) | 0.0018( 0.0007) | 4.12E-05( 7.30E-05) |
| Controlled-release urea | 0.7914( 0.4894) | 0.0091( 0.005) | 5.92E-08( 1.33E-05) |
| Ammonium nitrate | 1.4755( 0.6196) | 0.013( 0.0113) | 1.08E-04( 2.42E-04) |

Yue et al (2019) 8 estimated emission factors using three different empirical models that disaggregated N2O emissions by crop and fertilizer types for models 1 and 2 and only crop for model 3. Equation 20 was used for the EFs for model 1 and 2. The *c,f* subscript denotes the factor is for a combination of crop and fertilizer type. Equation 21 was used for the EFs produced from model 3 that only disaggregate the data by crop.

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| Table : Yue et al (2019) Click or tap here to enter text.emission factors for the three models. Models 1 and 2 have emission factors disaggregated by crop and fertilizer type while model 3 is only disaggregated by crop. | | | | |
| **Crop** | **Fertilizer** | **Model 1 EF**  **(**Equation 20**)** | **Model 2 EF**  **(**Equation 20**)** | **Model 3 EF**  **(**Equation 21**)** |
| cotton | Mineral | 0.796(±0.584) | 0.778(±0.644) | 0.37(±0.205) |
| legume | Min & Org | 0.17(±0.07) | 0.17(±0.07) | 0.14(±0.165) |
| legume | Mineral | 0.189(±0.063) | 0.178(±0.057) |
| legume | Organic | 0.101(±0.069) | 0.067(±0.043) |
| maize | Min & Org | 0.604(±0.501) | 0.245(±0.175) | 0.6(±0.05) |
| maize | Mineral | 0.546(±0.401) | 0.565(±0.13) |
| maize | Organic | 0.564(±0.364) | 0.438(±0.287) |
| other | Min & Org | 0.443(±0.327) | 0.35(±0.132) | 0.476(±0.064) |
| other | Mineral | 0.483(±0.424) | 0.481(±0.119) |
| other | Organic | 0.386(±0.32) | 0.23(±0.182) |
| rapeseed | Mineral | 0.41(±0.206) | 0.416(±0.042) | 0.51(±0.165) |
| rice | Min & Org | 0.218(±0.188) | 0.221(±0.074) | 0.35(±0.05) |
| rice | Mineral | 0.31(±0.396) | 0.331(±0.08) |
| rice | Organic | 0.1(±0.07) | 0.06(±0.16) |
| vegetable | Min & Org | 0.652(±0.446) | 0.611(±0.141) | 0.42(±0.03) |
| vegetable | Mineral | 0.642(±0.564) | 0.59(±0.169) |
| vegetable | Organic | 0.573(±0.681) | 0.285(±0.245) |
| wheat | Min & Org | 0.408(±0.249) | 0.396(±0.159) | 0.59(±0.06) |
| wheat | Mineral | 0.573(±0.507) | 0.542(±0.126) |
| wheat | Organic | 0.35(±0.14) | 0.14(±0.07) |

IPCC 2019 update methodology 1 used Equation 22 with the emission factors and ranges reported in Table 13 to estimate N2O emission from the application of fertilizer. EF1,c is the emission factor for the climate of the district (Dry or Wet) in Table 13. The ranges for EF1,c in Table 13 were used to construct beta distribution to sample from during the Monte Carlo simulation to estimate uncertainty.

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| Table : IPCC 2019 updated methodology emission factors. | | |
| **Emission Factor** | **description** | **Factor** |
| EF1 | All N inputs in dry climates | 0.005(0-0.011) |
| EF1 | Other N inputs in wet climates | 0.006(0.001-0.011) |
| EF1 | Synthetic fertilizer inputs in wet climates | 0.016(0.013-0.019) |

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| Table : Database objects used to model estimations of nitrous oxide and its uncertainty. | | |
| **Model** | **Database object** | **Description** |
| Albanito et al (2017) 2 EF Models | n2o\_albanito\_2017 | Table of emission factors |
| n2o\_albanito\_2017\_country\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for country level factors |
| n2o\_albanito\_2017\_country\_results | Table that holds the results of the Monte Carlo simulations of the model for country level factors |
| n2o\_albanito\_2017\_crop\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model of crop specific factors |
| n2o\_albanito\_2017\_crop\_results | Table that holds the results of the Monte Carlo simulations for model of crop specific factors. |
| n2o\_albanito\_2017\_fertilizer\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for fertilizer specific factors |
| n2o\_albanito\_2017\_fertilizer\_results | Table that holds the results of the Monte Carlo simulations of the model for fertilizer specific factors |
| Albanito et al (2017) 2 GAMM model | vwR\_n2o\_albanito\_2017\_gamm\_data | View of input data for the Albanito et al (2017) 2 GAMM model in R |
| n2o\_albanito\_2017\_gamm\_predict | Table of the predictions from the GAMM model in R |
| Aliyu et al (2019) 3 EF Models | n2o\_aliyu\_2019 | Table of emission factors |
| n2o\_aliyu\_2019\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| n2o\_aliyu\_2019\_results | Table that holds the results of the Monte Carlo simulations |
| Hergoualc’h et al (2021) 4 EF Models | n2o\_hergoualch\_2021 | Table of emission factors |
| n2o\_hergoualch\_2021\_climate\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for climate classes |
| n2o\_hergoualch\_2021\_climate\_results | Table that holds the results of the Monte Carlo simulations the model for climate classes |
| n2o\_hergoualch\_2021\_fertilizer\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for fertilizer specific factors |
| n2o\_hergoualch\_2021\_fertilizer\_results | Table that holds the results of the Monte Carlo simulations of the model for fertilizer specific factors |
| n2o\_hergoualch\_2021\_irrigation\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for irrigation status factors |
| n2o\_hergoualch\_2021\_irrigation\_results | Table that holds the results of the Monte Carlo simulations for irrigation status factors |
| n2o\_hergoualch\_2021\_landcover\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for crop types (landcover) |
| n2o\_hergoualch\_2021\_landcover\_results | Table that holds the results of the Monte Carlo simulations of the model for crop types (landcover) |
| n2o\_hergoualch\_2021\_n\_rate\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model nitrogen application rates |
| n2o\_hergoualch\_2021\_n\_rate\_results | Table that holds the results of the Monte Carlo simulations of the model for nitrogen application rates |
| n2o\_hergoualch\_2021\_soil\_alkalinity\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model soil alkalinity classes |
| n2o\_hergoualch\_2021\_soil\_alkalinity\_results | Table that holds the results of the Monte Carlo simulations of the model for alkalinity classes |
| n2o\_hergoualch\_2021\_soil\_c\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model soil carbon content |
| n2o\_hergoualch\_2021\_soil\_c\_results | Table that holds the results of the Monte Carlo simulations of the model for for soil carbon content |
| n2o\_hergoualch\_2021\_soil\_texture\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for soil texture classes |
| n2o\_hergoualch\_2021\_soil\_texture\_results | Table that holds the results of the Monte Carlo simulations of the model for of soil texture classes |
| Akiyama et al (2005) 5 EF Model | n2o\_hiroko\_akiyama\_2005\_background\_n2o\_emission\_gn\_ha\_1 | Table of background emission values |
| n2o\_hiroko\_akiyama\_2005\_fertilizer\_induced\_n2o\_emission\_factor\_perc | Table of emission factors |
| n2o\_hiroko\_akiyama\_2005\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| n2o\_hiroko\_akiyama\_2005\_results | Table that holds the results of the Monte Carlo simulations |
| IPCC 2019 Updated Methodology 1 | n2o\_ipcc\_2019 | Table of emission factors |
| n2o\_ipcc\_2019\_climate\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| n2o\_ipcc\_2019\_climate\_results | Table that holds the results of the Monte Carlo simulations |
| Mathivanan et al (2021) 6 EF Model | n2o\_mathivanan\_2021 | Table of emission factors |
| n2o\_mathivanan\_2021\_fertilizer\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| n2o\_mathivanan\_2021\_fertilizer\_results | Table that holds the results of the Monte Carlo simulations |
| Shcherbak et al (2014) 7 Non-linear EF Model | n2o\_shcherbak\_2014 | Table of data from Shcherbak (2014) used to create emission factors for the model |
| n2o\_shcherbak\_2014\_crop\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model for crop types |
| n2o\_shcherbak\_2014\_crop\_results | Table that holds the results of the Monte Carlo simulations of the model for crop types |
| n2o\_shcherbak\_2014\_fertilizer\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model of the model for fertilizer types |
| n2o\_shcherbak\_2014\_fertilizer\_results | Table that holds the results of the Monte Carlo simulations of the model for fertilizer types |
| Yue et al (2019) 8 EF Model | n2o\_yue\_2019\_crop\_m1 | Table of emission factors of the model 1 |
| n2o\_yue\_2019\_crop\_m1\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model 1 |
| n2o\_yue\_2019\_crop\_m1\_results | Table that holds the results of the Monte Carlo simulations of the model 1 |
| n2o\_yue\_2019\_crop\_m2 | Table of emission factors of the model 2 |
| n2o\_yue\_2019\_crop\_m2\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model 2 |
| n2o\_yue\_2019\_crop\_m2\_results | Table that holds the results of the Monte Carlo simulations of the model 2 |
| n2o\_yue\_2019\_crop\_m3 | Table of emission factors of the model 3 |
| n2o\_yue\_2019\_crop\_m3\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model 3 |
| n2o\_yue\_2019\_crop\_m3\_results | Table that holds the results of the Monte Carlo simulations of the model 3 |
| vwR\_n2o\_yue\_2019\_crop\_m1\_m2 | Transformed view of Yue et al (2019) 8 model 1 and 2 emission factors |
| vwR\_n2o\_yue\_2019\_crop\_m3 | Transformed view of Yue et al (2019) 8 model 1 and 2 emission factors |

APPENDIX B. Implementation of models to estimate methane from rice production.

The Bhatia et al (2013) 13 model was the simplest model and used the Equation 23 to estimate seasonal methane.

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|  | Equation |

*Eci* represents methane seasonal flux in kg ha-1 for crop *c* for unit of estimation *i*. Unit *i* represents a tehsil, landholding size and irrigation status. EFwr equals the emission factor kg ha-1 for a given water regime (Appendix B). *CD*is the crop duration. The Monte Carlo simulation drew samples from a normal distribution for the *EFwr* and from a categorical distribution for the CD to estimate the uncertainty. The emission factor values, and standard deviations used to construct the sampling distributions for the Monte Carlo simulation are reported in Table 15.

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| Table : Bhatia et al (2013) emission factor values for estimating methane emissions from rice. Standard deviation in parentheses were used to create sampling distributions for Monte Carlo simulation to estimate uncertainty. | | |
| **Ecosystem** | **Water Regime** | **EF (kg ha-1)** |
| Irrigated | Continuous flooding | 162(±28) |
| Deepwater | Deepwater | 190(±60) |
| Rain-fed | Drought-prone | 66(±4) |
| Rain-fed | Flood-prone | 190(±60) |
| Irrigated | Multiple aeration | 18(±5) |
| Irrigated | Single aeration | 66(±10) |
| Upland | Upland | 0 |

The Gupta et al (2009) 15 emission factor-based model was implemented with Equation 24.

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|  | Equation |

*EFwr* is the water regime emission factor (Appendix B). *OAscalar* is the organic amendment scalar. *CD* is as in Bhatia et al (2013) 13. Uncertainty was estimated using Monte Carlo simulations drawing the *EFwr* and *OAscalar,* from a normal distribution, and the *CD* as described above for Bhatia et al (2013) 13. The factor values and standard deviations used to create the sampling distributions for the Monte Carlo simulation are presented in Table 16.

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| --- | --- | --- | --- | --- | --- |
| Table : Gupta et al (2009) emission factors for water regimes and organic amendment scalars. Standard deviations in parathesis were used to create sampling distributions for Monte Carlo simulations to estimate uncertainty. | | | | | |
| **Water Regime** | **EF (kg ha-1)** | **Low (<0.7%) SOC, No Organic Amendments (kg ha-1)** | **Low (<0.7%) SOC, With Organic Amendments (kg ha-1)** | **High (≥0.7%) SOC, No Organic Amendments (kg ha-1)** | **High (≥0.7%) SOC, With Organic Amendments (kg ha-1)** |
| Continuous flooding | 174.8(±40.0) | 150(±30) | 120(±40) | 260(±70) | 630(±170) |
| Deepwater | 190.0(±60.0) | 190(±60) | 260(±86.67) | 190(±60) | 260(±86.67) |
| Drought-prone | 69.5(±18.6) | 70(±40) | 130(±43.33) | 80(±20) | 193.85(±52.31) |
| Flood-prone | 190.0(±60.0) | 190(±60) | 352.86(±117.62) | 217.14(±55.68) | 300(±80.95) |
| Multiple aeration | 20.1(±14.9) | 20(±10) | 50(±16.67) | 60(±15.38) | 210(±56.67) |
| Single aeration | 66.2(±18.9) | 70(±40) | 130(±43.33) | 80(±20) | 190(±51.27) |
| Upland | 0 | 0 | 0 | 0 | 0 |

The IPCC 2019 update methodology 1 was implemented with Equation 25.

|  |  |
| --- | --- |
|  | Equation |

The *EFregion* is the emission factor for South Asia (Appendix B). WR is the water regime and PW is the preseason water status scaling factors. *FYMcf* and *GMcf*are the conversion factors for farmyard manure and green manure respectively for the amount of farmyard manure and green manure applied in ton ha-1 respectively. The Monte Carlo simulation drew samples from gamma distributions for all parameters besides the crop duration which was drawn from a categorial distribution as described above. The coefficient values and ranges used to construct the sampling distributions are presented in Table 17.

|  |  |  |  |
| --- | --- | --- | --- |
| Table : IPCC 2019 updated methodology methane emission and scaling factors. The factor ranges were used to construct sampling distributions for Monte Carlo simulations to estimate uncertainty. | | | |
| **Parameter** | **Description** | **Value** | **Units** |
| Country | South Asia | 0.85(0.58-1.26) | kg CH4 ha-1 day-1 |
| Water Regime | Continuously Flooded | 1.00(0.73-1.27) | scalar |
| Deep water | 0.06(0.03-0.12) |
| Drought prone | 0.16(0.11-0.24) |
| Multiple Drainage Periods | 0.55(0.41-0.72) |
| Regular Rainfed | 0.54(0.39-0.74) |
| Single Drainage period | 0.71(0.53-0.94) |
| Upland | 0 |
| Preseason Water Status | Flooded preseason (>30 days) | 2.41(2.13-2.73) | scalar |
| Non flooded preseason (<180 days) | 1.00(0.88-1.12) |
| Non flooded preseason (>180 days) | 0.89(0.8-0.99) |
| Non-flooded preseason (>365 days) | 0.59(0.41-0.84) |
| Organic Amendments | Farmyard Manure | 0.21(0.15-0.28) | conversion factor |
| Green manure | 0.45(0.36-0.57) |

The Yan et al (2005) 17 empirical model used Equation 26.

|  |  |
| --- | --- |
|  | Equation |

*SOC* is the soil organic carbon, *pHk* is the soil pH class coefficient (Appendix B). *PWi* is the preseason water coefficient. *WRj* is the water regime coefficient. *AEZk* is the coefficient for the agricultural climatic zone. *FYM and GM* represent farmyard manure and green manure organic amendments type coefficients respectfully and *FYMamt* and *GMamt* represent the amount (ton ha-1) of the organic amendment. The Monte Carlo simulation to estimate uncertainty sampled all the values for the model from normal distributions other than the crop duration which was sampled as described above. The coefficients and standard deviations used for constructing the sampling distributions for the Monte Carlo simulations are presented in Table 18.

|  |  |  |
| --- | --- | --- |
| Table : Yan et al (2005) empirical model coefficients and standard errors used to construct the sampling distribution for the Monte Carlo simulations. | | |
| **Parameter** | **Description** | **Coefficient** |
| Contant | α | 0.363(±0.259) |
| SOC | β | 0.3371(±0.048) |
| Climat | AEZ 1 | 0.89580(±0.45962) |
| AEZ 2 | 0.10720(±0.10865) |
| AEZ 3 | -0.40760(±0.09975) |
| AEZ 5 | -0.04512(±0.22189) |
| AEZ 6 | 0.34440(±0.08740) |
| AEZ 7 | 0.32660(±0.08910) |
| AEZ 8 | 0.00000(±0.00000) |
| pH | 0.0-4.5 | 0.18720(±0.282700) |
| 4.5-5.0 | 1.16640(±0.222900) |
| 5.0-5.5 | 1.32730(±0.212600) |
| 5.5-6.0 | 0.44360(±0.212845) |
| 6.0-6.5 | -0.01575(±0.209675) |
| 6.5-7.0 | -0.14580(±0.211850) |
| 7.0-7.5 | -0.09750(±0.227450) |
| 7.5-100.0 | -0.30370(±0.116450) |
| Water Regime | Continuous flooding | 1.1739(±0.11640) |
| Deepwater | 0.0000(±0.00000) |
| Multiple drainage | 0.5132(±0.12100) |
| Rainfed, wet season | -0.1013(±0.14425) |
| Single drainage | 0.6709(±0.14200) |
| Upland | 0.0000(±0.00000) |
| Preseason Water Status | Long drainage | -0.6968(±0.08090) |
| Short drainage | -0.3082(±0.06555) |
| Organic Amendments | Farmyard manure | 0.2055(±0.03335) |
| Green manure | 0.3954(±0.03335) |

The Wang et al (2018) 16 empirical model used the same equation as Yan et al (2005) 17 but with different coefficients Table 19. The climate classes also deferred as shown in Figure 1.

|  |  |  |
| --- | --- | --- |
| Table : Wang et al (2018) empirical model coefficients and ranges used to construct sampling distributions for Monte Carlo simulations to estimate uncertainty. | | |
| **Parameter** | **Description** | **Coefficient** |
| Constant | α | -0.478(±0.168) |
| SOC | β | 0.19(±0.0295) |
| Climate | AEZ 1 | 1.5230(0.528-2.518) |
| AEZ 2 | 1.0050(0.829-1.180) |
| AEZ 3 | 0.3070(0.163-0.451) |
| AEZ 5 | 0.5250(0.334-0.717) |
| AEZ 6 | 1.1270(0.989-1.265) |
| AEZ 7 | 0.6050(0.455-0.754) |
| pH | 0.0-4.5 | 2.045(1.634-2.456) |
| 4.5-5.0 | 1.124(0.916-1.332) |
| 5.0-5.5 | 1.299(1.116-1.483) |
| 5.5-6.0 | 0.825(0.647-1.004) |
| 6.0-6.5 | 0.312(0.146-0.477) |
| 6.5-7.0 | 0.151(-0.021-0.323) |
| 7.0-7.5 | 0.181(-0.010-0.372) |
| 7.5-8.0 | 0.099(-0.083-0.280) |
| 8.0-100.0 | 0.000(0.000-0.000) |
| Water Regime | Continuous flooding | 0.851(0.580-1.122) |
| Deep water | -1.897(-2.503--1.291) |
| Multiple drainage | 0.247(-0.032-0.525) |
| Rainfed, wet season | 0.236(-0.081-0.552) |
| Single drainage | 0.505(0.218-0.793) |
| Upland | 0.000(0.000-0.000) |
| Preseason Water Status | Long drainage | -0.228(-0.335--0.122) |
| Short drainage | -0.116(-0.237-0.004) |
| Organic Amendments | Farmyard manure | 0.247(0.193-0.302) |
| Green manure | 0.400(0.349-0.450) |

The Wang et al (2018) 16 emission factor model used Equation 26. *EFc* is the country specific emission factor for India. *PWscalar* is the preseason water status scaling factor. *WRscalar* is the water regime scaling factor. *FYMscalar* and *GMscalar* are the organic amendment scaling factor for farmyard manure and green manure respectfully. The organic amendments used non-linear equations to estimate a scaling factor which were estimated for farmyard manure and green manure using Equation 27 and Equation 28 where OAamt is the amount of organic amendment in ton ha-1.

|  |  |
| --- | --- |
|  | Equation |
|  | Equation |

The Monte Carlo simulation for the Wang (2019) empirical model drew samples for model coefficients from normal distributions other than the crop duration parameter. While the Wang (2019) emission factor model Monte Carlo simulation drew samples for gamma distributions, estimated from the parameter confidence intervals. The crop duration for both models was draw from a categorical distribution as described above.

|  |  |  |
| --- | --- | --- |
| Table : Wang et al (2018) emission factors and ranges used to implement sampling distributions for Monte Carlo simulations to estimate uncertainty. | | |
|  | | |
| **Description** | **Value** | **Units** |
| India | 0.85(0.57-1.25) | kg CH4 Ha-1 Day-1 |
| Flooded | 2.41(2.13-2.73) | scaling |
| Long drainage | 0.89(0.80-0.99) |
| Short drainage | 1.00(1.00-1.00) |
| Two drainages | 0.59(0.41-0.84) |
| Continuously flooded | 1.00(1.00-1.00) | scaling |
| Deep water | 0.06(0.03-0.12) |
| Multiple drainage | 0.55(0.41-0.72) |
| Rainfed, dry season | 0.16(0.11-0.24) |
| Rainfed, wet season | 0.54(0.39-0.74) |
| Single drainage | 0.71(0.53-0.94) |

The Nikolaisen et al (2023) 14 model was implemented using the R code and data provided in the supplemental material of the paper. An input dataset was created for the input variables using the data described in the Input data section. The R code was used to refit the model and then predict methane flux kg ha-1 day-1 along with estimates of the 95% confidence interval. The predicted results were then imported back into the database. Within the database Monte Carlo simulations were used to estimate the seasonal methane flux and its uncertainty. The estimate of daily methane flux and the 95% confidence interval were used to construct a gamma distribution to sample for the Monte Carlo simulation. The Monte Carlo simulation drew the crop duration sample using a categorical distribution as described above.

For models requiring crop duration to estimate methane emissions from rice, the following are the paddy variety crop duration released to the states.

|  |  |  |  |
| --- | --- | --- | --- |
| Table : Rice crop durations counts and probabilities for the varieties released to the states. The probabilities are used to construct categorical distributes of crop duration used in the Monte Carlo simulations to estimate rice methane emissions. | | | |
| **State** | **Crop Duration** | **Count of Varieties Released to the State** | **Proportion** |
| A AND N ISLANDS | 116 | 1 | 0.5 |
| 120 | 1 | 0.5 |
| ANDHRA PRADESH | 85 | 1 | 0.0227 |
| 100 | 1 | 0.0227 |
| 102 | 1 | 0.0227 |
| 105 | 1 | 0.0227 |
| 115 | 5 | 0.1136 |
| 120 | 2 | 0.0455 |
| 125 | 2 | 0.0455 |
| 126 | 1 | 0.0227 |
| 128 | 5 | 0.1136 |
| 130 | 3 | 0.0682 |
| 131 | 1 | 0.0227 |
| 132 | 1 | 0.0227 |
| 133 | 1 | 0.0227 |
| 135 | 3 | 0.0682 |
| 136 | 1 | 0.0227 |
| 138 | 1 | 0.0227 |
| 140 | 7 | 0.1591 |
| 145 | 1 | 0.0227 |
| 150 | 2 | 0.0455 |
| 155 | 2 | 0.0455 |
| 160 | 1 | 0.0227 |
| 180 | 1 | 0.0227 |
| ARUNACHAL PRADESH | 125 | 1 | 1 |
| ASSAM | 100 | 1 | 0.0526 |
| 115 | 2 | 0.1053 |
| 120 | 3 | 0.1579 |
| 122 | 1 | 0.0526 |
| 125 | 1 | 0.0526 |
| 128 | 1 | 0.0526 |
| 130 | 1 | 0.0526 |
| 131 | 1 | 0.0526 |
| 135 | 1 | 0.0526 |
| 138 | 1 | 0.0526 |
| 145 | 1 | 0.0526 |
| 152 | 1 | 0.0526 |
| 160 | 1 | 0.0526 |
| 163 | 1 | 0.0526 |
| 165 | 1 | 0.0526 |
| 181 | 1 | 0.0526 |
| BIHAR | 86 | 1 | 0.0149 |
| 90 | 3 | 0.0448 |
| 95 | 1 | 0.0149 |
| 100 | 5 | 0.0746 |
| 105 | 1 | 0.0149 |
| 109 | 1 | 0.0149 |
| 110 | 1 | 0.0149 |
| 113 | 1 | 0.0149 |
| 115 | 3 | 0.0448 |
| 118 | 1 | 0.0149 |
| 120 | 4 | 0.0597 |
| 122 | 2 | 0.0299 |
| 125 | 3 | 0.0448 |
| 126 | 2 | 0.0299 |
| 128 | 2 | 0.0299 |
| 130 | 20 | 0.2985 |
| 135 | 1 | 0.0149 |
| 140 | 4 | 0.0597 |
| 142 | 1 | 0.0149 |
| 145 | 1 | 0.0149 |
| 147 | 1 | 0.0149 |
| 150 | 2 | 0.0299 |
| 155 | 2 | 0.0299 |
| 166 | 1 | 0.0149 |
| 170 | 1 | 0.0149 |
| 180 | 1 | 0.0149 |
| 181 | 1 | 0.0149 |
| CHHATTISGARH | 86 | 1 | 0.0256 |
| 100 | 1 | 0.0256 |
| 105 | 1 | 0.0256 |
| 109 | 1 | 0.0256 |
| 110 | 1 | 0.0256 |
| 115 | 4 | 0.1026 |
| 120 | 4 | 0.1026 |
| 125 | 4 | 0.1026 |
| 126 | 2 | 0.0513 |
| 127 | 1 | 0.0256 |
| 128 | 1 | 0.0256 |
| 130 | 6 | 0.1538 |
| 132 | 1 | 0.0256 |
| 135 | 6 | 0.1538 |
| 140 | 4 | 0.1026 |
| 170 | 1 | 0.0256 |
| DELHI | 82 | 1 | 0.1111 |
| 120 | 1 | 0.1111 |
| 128 | 1 | 0.1111 |
| 130 | 1 | 0.1111 |
| 135 | 2 | 0.2222 |
| 138 | 1 | 0.1111 |
| 144 | 1 | 0.1111 |
| 145 | 1 | 0.1111 |
| GOA | 125 | 1 | 0.05 |
| 130 | 18 | 0.9 |
| 133 | 1 | 0.05 |
| GUJARAT | 100 | 1 | 0.0357 |
| 105 | 1 | 0.0357 |
| 113 | 1 | 0.0357 |
| 115 | 3 | 0.1071 |
| 120 | 3 | 0.1071 |
| 125 | 1 | 0.0357 |
| 126 | 1 | 0.0357 |
| 128 | 1 | 0.0357 |
| 130 | 4 | 0.1429 |
| 131 | 1 | 0.0357 |
| 132 | 2 | 0.0714 |
| 135 | 5 | 0.1786 |
| 136 | 1 | 0.0357 |
| 140 | 2 | 0.0714 |
| 142 | 1 | 0.0357 |
| HARYANA | 82 | 1 | 0.025 |
| 115 | 1 | 0.025 |
| 116 | 1 | 0.025 |
| 117 | 1 | 0.025 |
| 119 | 1 | 0.025 |
| 120 | 7 | 0.175 |
| 122 | 1 | 0.025 |
| 125 | 1 | 0.025 |
| 128 | 2 | 0.05 |
| 130 | 5 | 0.125 |
| 131 | 1 | 0.025 |
| 135 | 2 | 0.05 |
| 138 | 1 | 0.025 |
| 139 | 1 | 0.025 |
| 140 | 3 | 0.075 |
| 141 | 1 | 0.025 |
| 143 | 1 | 0.025 |
| 144 | 1 | 0.025 |
| 145 | 1 | 0.025 |
| 155 | 3 | 0.075 |
| 160 | 2 | 0.05 |
| 165 | 1 | 0.025 |
| 166 | 1 | 0.025 |
| HIMACHAL PRADESH | 112 | 1 | 0.1429 |
| 120 | 1 | 0.1429 |
| 125 | 2 | 0.2857 |
| 127 | 1 | 0.1429 |
| 128 | 1 | 0.1429 |
| 140 | 1 | 0.1429 |
| JAMMU&KASHMIR | 115 | 1 | 0.125 |
| 125 | 2 | 0.25 |
| 128 | 1 | 0.125 |
| 130 | 2 | 0.25 |
| 135 | 1 | 0.125 |
| 144 | 1 | 0.125 |
| JHARKAND | 70 | 1 | 0.0455 |
| 90 | 1 | 0.0455 |
| 95 | 2 | 0.0909 |
| 105 | 1 | 0.0455 |
| 110 | 1 | 0.0455 |
| 115 | 2 | 0.0909 |
| 120 | 3 | 0.1364 |
| 125 | 2 | 0.0909 |
| 128 | 2 | 0.0909 |
| 130 | 1 | 0.0455 |
| 131 | 1 | 0.0455 |
| 135 | 1 | 0.0455 |
| 145 | 1 | 0.0455 |
| 150 | 1 | 0.0455 |
| 170 | 1 | 0.0455 |
| 199 | 1 | 0.0455 |
| KARNATAKA | 100 | 1 | 0.0217 |
| 112 | 1 | 0.0217 |
| 120 | 3 | 0.0652 |
| 128 | 4 | 0.087 |
| 130 | 22 | 0.4783 |
| 132 | 2 | 0.0435 |
| 133 | 1 | 0.0217 |
| 135 | 4 | 0.087 |
| 138 | 1 | 0.0217 |
| 140 | 1 | 0.0217 |
| 145 | 2 | 0.0435 |
| 155 | 1 | 0.0217 |
| 165 | 1 | 0.0217 |
| 170 | 1 | 0.0217 |
| 180 | 1 | 0.0217 |
| KERALA | 109 | 1 | 0.0588 |
| 115 | 1 | 0.0588 |
| 120 | 3 | 0.1765 |
| 128 | 2 | 0.1176 |
| 130 | 1 | 0.0588 |
| 135 | 3 | 0.1765 |
| 140 | 2 | 0.1176 |
| 145 | 1 | 0.0588 |
| 160 | 1 | 0.0588 |
| 172 | 1 | 0.0588 |
| 175 | 1 | 0.0588 |
| MADHYA PRADESH | 85 | 1 | 0.0455 |
| 100 | 1 | 0.0455 |
| 110 | 1 | 0.0455 |
| 115 | 1 | 0.0455 |
| 120 | 4 | 0.1818 |
| 125 | 3 | 0.1364 |
| 128 | 2 | 0.0909 |
| 130 | 3 | 0.1364 |
| 131 | 1 | 0.0455 |
| 135 | 2 | 0.0909 |
| 140 | 2 | 0.0909 |
| 160 | 1 | 0.0455 |
| MAHARASHTRA | 108 | 1 | 0.0149 |
| 109 | 1 | 0.0149 |
| 113 | 1 | 0.0149 |
| 115 | 6 | 0.0896 |
| 120 | 7 | 0.1045 |
| 125 | 3 | 0.0448 |
| 126 | 1 | 0.0149 |
| 128 | 3 | 0.0448 |
| 130 | 25 | 0.3731 |
| 132 | 2 | 0.0299 |
| 135 | 11 | 0.1642 |
| 140 | 3 | 0.0448 |
| 147 | 1 | 0.0149 |
| 150 | 1 | 0.0149 |
| 199 | 1 | 0.0149 |
| MANIPUR | 100 | 1 | 0.1667 |
| 120 | 1 | 0.1667 |
| 125 | 1 | 0.1667 |
| 128 | 1 | 0.1667 |
| 135 | 1 | 0.1667 |
| 180 | 1 | 0.1667 |
| MEGHALAYA | 100 | 1 | 0.25 |
| 120 | 1 | 0.25 |
| 127 | 1 | 0.25 |
| 135 | 1 | 0.25 |
| ODISHA | 70 | 1 | 0.0122 |
| 100 | 3 | 0.0366 |
| 105 | 3 | 0.0366 |
| 110 | 2 | 0.0244 |
| 113 | 1 | 0.0122 |
| 115 | 6 | 0.0732 |
| 117 | 1 | 0.0122 |
| 120 | 8 | 0.0976 |
| 125 | 1 | 0.0122 |
| 128 | 5 | 0.061 |
| 130 | 20 | 0.2439 |
| 131 | 1 | 0.0122 |
| 135 | 3 | 0.0366 |
| 137 | 1 | 0.0122 |
| 138 | 1 | 0.0122 |
| 140 | 6 | 0.0732 |
| 145 | 3 | 0.0366 |
| 147 | 1 | 0.0122 |
| 148 | 1 | 0.0122 |
| 150 | 5 | 0.061 |
| 155 | 1 | 0.0122 |
| 160 | 3 | 0.0366 |
| 163 | 1 | 0.0122 |
| 165 | 3 | 0.0366 |
| 180 | 1 | 0.0122 |
| PUDUCHERRY | 116 | 1 | 0.0435 |
| 119 | 1 | 0.0435 |
| 120 | 1 | 0.0435 |
| 130 | 18 | 0.7826 |
| 133 | 1 | 0.0435 |
| 135 | 1 | 0.0435 |
| PUNJAB | 110 | 1 | 0.05 |
| 118 | 1 | 0.05 |
| 120 | 4 | 0.2 |
| 128 | 2 | 0.1 |
| 130 | 4 | 0.2 |
| 135 | 3 | 0.15 |
| 138 | 1 | 0.05 |
| 140 | 1 | 0.05 |
| 144 | 1 | 0.05 |
| 145 | 1 | 0.05 |
| 155 | 1 | 0.05 |
| RAJASTHAN | 128 | 1 | 0.0455 |
| 130 | 19 | 0.8636 |
| 135 | 1 | 0.0455 |
| 145 | 1 | 0.0455 |
| TAMILNADU | 85 | 1 | 0.0175 |
| 100 | 1 | 0.0175 |
| 105 | 1 | 0.0175 |
| 108 | 1 | 0.0175 |
| 109 | 1 | 0.0175 |
| 110 | 1 | 0.0175 |
| 115 | 3 | 0.0526 |
| 116 | 1 | 0.0175 |
| 120 | 5 | 0.0877 |
| 125 | 2 | 0.0351 |
| 126 | 1 | 0.0175 |
| 128 | 6 | 0.1053 |
| 130 | 20 | 0.3509 |
| 132 | 1 | 0.0175 |
| 135 | 7 | 0.1228 |
| 140 | 2 | 0.0351 |
| 150 | 1 | 0.0175 |
| 155 | 2 | 0.0351 |
| TELANAGANA | 105 | 1 | 0.1111 |
| 107 | 1 | 0.1111 |
| 115 | 2 | 0.2222 |
| 120 | 2 | 0.2222 |
| 127 | 1 | 0.1111 |
| 130 | 1 | 0.1111 |
| 138 | 1 | 0.1111 |
| TRIPURA | 122 | 1 | 0.0385 |
| 130 | 18 | 0.6923 |
| 131 | 1 | 0.0385 |
| 160 | 2 | 0.0769 |
| 163 | 1 | 0.0385 |
| 166 | 2 | 0.0769 |
| 180 | 1 | 0.0385 |
| UTTAR PRADESH | 82 | 1 | 0.0147 |
| 100 | 2 | 0.0294 |
| 105 | 1 | 0.0147 |
| 115 | 2 | 0.0294 |
| 117 | 1 | 0.0147 |
| 120 | 6 | 0.0882 |
| 121 | 1 | 0.0147 |
| 122 | 1 | 0.0147 |
| 125 | 4 | 0.0588 |
| 128 | 3 | 0.0441 |
| 130 | 21 | 0.3088 |
| 131 | 2 | 0.0294 |
| 135 | 7 | 0.1029 |
| 140 | 2 | 0.0294 |
| 145 | 5 | 0.0735 |
| 148 | 1 | 0.0147 |
| 150 | 1 | 0.0147 |
| 152 | 1 | 0.0147 |
| 155 | 1 | 0.0147 |
| 163 | 1 | 0.0147 |
| 166 | 2 | 0.0294 |
| 180 | 1 | 0.0147 |
| 181 | 1 | 0.0147 |
| UTTARAKHAND | 116 | 1 | 0.0625 |
| 120 | 2 | 0.125 |
| 122 | 1 | 0.0625 |
| 125 | 1 | 0.0625 |
| 127 | 1 | 0.0625 |
| 128 | 2 | 0.125 |
| 130 | 2 | 0.125 |
| 131 | 1 | 0.0625 |
| 135 | 3 | 0.1875 |
| 145 | 1 | 0.0625 |
| 165 | 1 | 0.0625 |
| WEST BENGAL | 100 | 2 | 0.0333 |
| 105 | 1 | 0.0167 |
| 108 | 2 | 0.0333 |
| 114 | 1 | 0.0167 |
| 116 | 2 | 0.0333 |
| 118 | 1 | 0.0167 |
| 120 | 3 | 0.05 |
| 122 | 2 | 0.0333 |
| 124 | 1 | 0.0167 |
| 125 | 2 | 0.0333 |
| 128 | 4 | 0.0667 |
| 130 | 21 | 0.35 |
| 132 | 1 | 0.0167 |
| 135 | 3 | 0.05 |
| 140 | 2 | 0.0333 |
| 142 | 1 | 0.0167 |
| 145 | 1 | 0.0167 |
| 147 | 1 | 0.0167 |
| 148 | 1 | 0.0167 |
| 150 | 2 | 0.0333 |
| 155 | 1 | 0.0167 |
| 160 | 1 | 0.0167 |
| 165 | 1 | 0.0167 |
| 166 | 2 | 0.0333 |
| 180 | 1 | 0.0167 |

|  |  |  |
| --- | --- | --- |
| Table : Database objects used to estimate methane emission from rice production and their uncertainty. | | |
| **Model** | **Object Name** | **Description** |
|  |  |  |
| Bhatia et al (2013) 13 EF Model | ch4\_bhatia\_2013\_ef | Table of emission factors |
| ch4\_bhatia\_2013\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_bhatia\_2013\_ef\_results | Table that holds the results of the Monte Carlo simulations |
| Gupta et al (2009) 15 EF Model | ch4\_gupta\_2009\_ef | Table of emission factors |
| ch4\_gupta\_2009\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_gupta\_2009\_ef\_results | Table that holds the results of the Monte Carlo simulations |
| IPCC 2019 update methodology 1 | ch4\_ipcc\_2019\_country\_ef | Table of country level emission factors |
| ch4\_ipcc\_2019\_organic\_amendments\_ef | Table of organic amendments scaling factors |
| ch4\_ipcc\_2019\_preseason\_water\_status\_ef | Table of preseason water status scaling factors |
| ch4\_ipcc\_2019\_water\_regime\_ef | Table of water regime scaling factors |
| ch4\_ipcc\_2019\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_ipcc\_2019\_ef\_results | Table that holds the results of the Monte Carlo simulations |
| Nikolaisen et al (2013) 14 empirical model | ch4\_nikolaisen\_2023\_emperical\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_nikolaisen\_2023\_emperical\_results | Table that holds the results of the Monte Carlo simulations |
| ch4\_nikolaisen\_2023\_input | Table of input data for the empirical model run in R |
| ch4\_nikolaisen\_2023\_predict | Table of prediction from the empirical model run in R |
| Wang et al (2018) 16 Climate data | ch4\_wang\_2018\_climate | Table of climate classes used in Wang et al (2018) 16 models |
| vwM\_ch4\_wang\_2018\_climate\_map | Map of climate classes used in Wang et al (2018) 16 models |
| Wang et al (2018) 16 EF Model | ch4\_wang\_2018\_ef | Table of emission factors |
| ch4\_wang\_2018\_aez | Table of climate scaling factors |
| ch4\_wang\_2018\_preseason\_water\_status\_scaler | Table of preseason water status scaling factors |
| ch4\_wang\_2018\_water\_regime\_scaler | Table of water regime scaling factors |
| ch4\_wang\_2018\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_wang\_2018\_ef\_results | Table that holds the results of the Monte Carlo simulations |
|  | ch4\_wang\_2018\_aez\_coef | Table of climate coefficients |
| ch4\_wang\_2018\_organic\_amendments\_coef | Table or organic amendment coefficients |
| ch4\_wang\_2018\_ph\_coef | Table of soil pH coefficients |
| ch4\_wang\_2018\_preseason\_water\_status\_coef | Table of preseason water status model coefficients |
| ch4\_wang\_2018\_water\_regime\_coef | Table of water regime model coefficients |
| ch4\_wang\_2018\_emperical\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_wang\_2018\_emperical\_results | Table that holds the results of the Monte Carlo simulations |
| Yan et al (2005) 17 Empirical Model | ch4\_yan\_2005\_aez\_coef | Table of climate coefficients |
| ch4\_yan\_2005\_organic\_amendments\_coef | Table or organic amendment coefficients |
| ch4\_yan\_2005\_ph\_coef | Table of soil pH coefficients |
| ch4\_yan\_2005\_preseason\_water\_status\_coef | Table of preseason water status model coefficients |
| ch4\_yan\_2005\_water\_regime\_coef | Table of water regime model coefficients |
| ch4\_yan\_2005\_ef\_monte\_carlo | Procedure that implements the Monte Carlo simulation of the model |
| ch4\_yan\_2005\_emperical\_results | Table that holds the results of the Monte Carlo simulations |

A screenshot of a computer screen

Description automatically generated

Figure : Maps of the different climate datasets used in the modeling of rice methane emissions.

APPENDIX C. Parameters used in the estimation of emissions from crop residue burning.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table : References used to assemble the database of factors used for the different variables used to estimate emissions from crop residue burning. | | | | | |
| **Reference** | **Residue Amount (ratio and per ha)** | **Dry Matter Fraction** | **In-field Residue Faction** | **Burn Efficiency Factor** | **Burn EF (N2O and CH4)**  **(g kg-1)** |
| Akagi et al (2011) 25 |  |  |  |  | 🗸 |
| Andreae et al (2019) |  |  |  |  | 🗸 |
| Andreae Merlet et al (2001)26 |  |  |  |  | 🗸 |
| Bhupendas Das et al (2020)27 | 🗸 | 🗸 |  | 🗸 |  |
| Biomass Altas V2.022 | 🗸 |  |  |  |  |
| Chauhan et al (2012)28 | 🗸 |  | 🗸 |  |  |
| Daioglou et al (2016)29 | 🗸 | 🗸 |  |  |  |
| Dennis et al (2002)30 |  |  |  |  | 🗸 |
| FAO BEFS RA31 | 🗸 |  |  |  |  |
| Gupta et al (2004) | 🗸 |  |  |  |  |
| Hayashi et al (2014)32 |  |  |  |  | 🗸 |
| Hiloidhari et al 2011)33 | 🗸 |  | 🗸 |  |  |
| Hiloidhari et al (2014)34 |  |  | 🗸 |  |  |
| Jagtar Singh et al (2008)35 | 🗸 | 🗸 |  |  |  |
| Jain et al (2014)36 | 🗸 | 🗸 |  |  |  |
| Ji Gao et al (2016)37 | 🗸 | 🗸 |  |  |  |
| Jing Li et al (2016)38 | 🗸 |  |  |  |  |
| Jolli et al (2005) | 🗸 |  |  |  |  |
| Jolli et al (2005) (T Ha) | 🗸 |  |  |  |  |
| Kanabkaew et al (2011)39 | 🗸 | 🗸 |  |  |  |
| Kang et al (2020)40 | 🗸 |  |  |  |  |
| Karan et al (2021) 23 |  | 🗸 |  |  |  |
| Kumar et al (2014)41 |  |  | 🗸 |  |  |
| Li-Qun Ji et al (2015)42 | 🗸 |  |  |  |  |
| Lu Yang et al (2013)43 | 🗸 |  |  |  |  |
| Lui et al (2008)44 | 🗸 |  |  |  |  |
| Miura Kanno et al (1997)45 |  |  |  |  | 🗸 |
| Quanfeng Jin et al (2018)46 | 🗸 |  |  | 🗸 |  |
| R Lal et al (2005)47 | 🗸 |  |  |  |  |
| R Lal et al (2005) 47 (Mg Ha) | 🗸 |  |  |  |  |
| Ravindra et al (2019)48 | 🗸 | 🗸 | 🗸 | 🗸 |  |
| Romasanta et al (2017)49 |  |  |  |  | 🗸 |
| Scarlat et al (2010)50 | 🗸 |  |  |  |  |
| Shivraj Sahai et al (2007)51 |  |  |  |  | 🗸 |
| Singh et al (2022)52 | 🗸 |  |  |  |  |
| Streets et al (2003)53 | 🗸 | 🗸 | 🗸 |  |  |
| Suresh Chauhan et al (2010)54 |  |  | 🗸 |  |  |
| Suresh Chauhan et al (2012)28 | 🗸 |  | 🗸 |  |  |
| Thorenz et al (2019)55 | 🗸 |  |  |  |  |
| Travis et al (2023)56 |  |  |  |  | 🗸 |
| Venkatramanan et al (2021)57 | 🗸 | 🗸 | 🗸 |  |  |
| Wei Jia et al (2018)58 | 🗸 |  |  |  |  |
| Wietshel et al (2019)55 | 🗸 |  |  |  |  |
| Wirsenius et al (2000)59 | 🗸 |  |  |  |  |
| Xiaohui Zhang et al (2019)60 |  |  |  |  | 🗸 |
| Xin Huang et al (2012)61 |  |  |  | 🗸 |  |
| Xinghua Li et al (2007)62 |  |  |  |  | 🗸 |
| Yang et al (2008)63 | 🗸 |  |  |  |  |
| Yokelson et al (2011)64 |  |  |  | 🗸 | 🗸 |
| Zhang et al (2013)65 | 🗸 | 🗸 | 🗸 | 🗸 |  |

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table : Source of the estimated mean and standard deviations used in crop residue burning models. **C** is crop specific, meaning the value for the crop was reported in the literature. **CL** is crop class, meaning the values were estimated from grouping similar crops similar to the crop. **AC** equals all crops mean the values came from aggregating all the reported crop values. | | | | | | | | | | | | | | | | |
| **Crop** | **Residue Ratios** | | | | | | **Dry Matter Fraction** | | **In-field Residue Fraction** | | **Burn Efficiency** | | **N2O EF** | | **CH4 EF** | |
| **Biomass Atlas v2.0** | | **Kg/Kg Yield** | | **T/Ha** | |
|  | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| Arecanut | C(T/Ha) | CL(T/Ha) | CL | CL | CL | CL | AC | AC | C | CL | AC | AC | AC | AC | AC | AC |
| Arhar/Tur | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | C | C | C | CL | CL | C | CL | CL | CL | AC | AC | CL | CL |
| Bajra | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | CL | CL | C | C | CL | CL | CL | CL | CL | CL |
| Banana | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | CL | AC | C | C | AC | AC | AC | AC | AC | AC |
| Barley | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | CL | C | CL | C | C | C | C |
| Cardamom | C(T/Ha) | AC (T/Ha) | CL | CL | CL | CL | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Cashewnut | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | AC | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Coconut | C(Kg/Kg Yield), C(T/Ha) | CL(Kg/Kg Yield), CL(T/Ha) | C | C | CL | CL | AC | AC | C | C | AC | AC | AC | AC | AC | AC |
| Coriander | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Cotton(lint) | C(Kg/Kg Yield), C(T/Ha) | CL(Kg/Kg Yield), global(T/Ha) | C | C | C | C | C | C | C | C | C | C | AC | AC | C | AC |
| Dry chillies | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Garlic | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | CL | C | C | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Ginger | C(Kg/Kg Yield) | C(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | CL | AC | CL | AC | AC | AC | AC | AC |
| Gram | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | C | C | C | C | CL | C | CL | CL | CL | AC | AC | CL | CL |
| Groundnut | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | CL | AC | AC | CL | CL |
| Horse-gram | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | CL | CL | CL | CL | AC | AC | CL | CL |
| Jowar | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | CL | CL | C | C | CL | CL | CL | CL | CL | CL |
| Jute | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | C | C | C | C | C | C | AC | AC | CL | AC |
| Linseed | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | CL | CL | C | CL | CL | CL | AC | AC | AC | AC |
| Maize | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | C | C | C | C | C |
| Masoor | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | CL | CL | CL | CL | CL | CL | CL | CL | CL | AC | AC | CL | CL |
| Mesta | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | C | C | C | C | C | CL | AC | AC | CL | AC |
| Moong(Green Gram) | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | C | CL | CL | C | CL | CL | CL | CL | CL | AC | AC | CL | CL |
| Moth | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | CL | CL | CL | CL | AC | AC | CL | CL |
| Niger seed | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | C | CL | CL | CL | AC | AC | AC | AC |
| Onion | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | CL | C | C | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Other Cereals | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | C | CL | CL | CL | CL | CL | CL | CL | CL | CL |
| other oilseeds | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | C | C | C | C | CL | C | CL | CL | CL | AC | AC | AC | AC |
| Peas & beans (Pulses) | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | C | C | C | C | C | C | CL | CL | CL | AC | AC | CL | CL |
| Potato | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | CL | AC | C | AC | AC | AC | AC | AC |
| Ragi | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | C | CL | CL | CL | CL | CL | CL | CL |
| Rapeseed &Mustard | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | C | AC | AC | AC | AC |
| Rice | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | C | C | C | C | C |
| Safflower | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | CL | CL | C | CL | CL | CL | AC | AC | AC | AC |
| Small millets | C(Kg/Kg Yield) | C(Kg/Kg Yield) | C | CL | CL | CL | CL | CL | C | CL | CL | CL | CL | CL | CL | CL |
| Soyabean | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | C | C | C | C | C | CL | AC | AC | C | CL |
| Sugarcane | C(Kg/Kg Yield) | AC(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | C | AC | AC | C | AC |
| Sunflower | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | CL | C | CL | CL | CL | AC | AC | AC | AC |
| Sweet potato | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | CL | CL | AC | CL | AC | AC | AC | AC | AC |
| Tapioca | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | CL | CL | C | CL | CL | AC | CL | AC | AC | AC | AC | AC |
| Tobacco | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | CL | CL | AC | AC | AC | AC | AC | AC |
| Turmeric | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | AC | CL | CL | AC | AC | AC | AC | AC | AC |
| Urad | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | CL | CL | CL | CL | CL | CL | CL | CL | CL | CL | AC | AC | CL | CL |
| Wheat | C(Kg/Kg Yield) | CL(Kg/Kg Yield) | C | C | C | C | C | C | C | C | C | C | C | C | C | C |

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| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table : Variables means and standard deviations used in the equations to compute crop residue burning emissions for methane and nitrous oxide. | | | | | | | | |
| **Crop** | **Residue Ratios** | | | **Dry Matter Fraction** | **In-field Residue Faction** | **Burn Efficiency Factor** | **N2O EF** | **CH4 EF** |
| **Biomass Atlas v2** | **Kg/Kg Yield** | **T/Ha** |
| Bajra | 2.33(0.639) Kg/Kg Yield | 2.317(0.315) | 5.501(1.911) | 0.802 (0.171) | 0.25 (0.057) | 0.887 (0.038) | 0.172 (0.197) | 2.891 (0.714) |
| Barley | 1.3(0.639) Kg/Kg Yield | 1.889(0.479) | 4.513(1.858) | 0.875 (0.039) | 0.125 (0.12) | 0.82 (0.038) | 0.023 (0.002) | 3.01 (0.286) |
| Jowar | 2.2(0.639) Kg/Kg Yield | 1.917(0.419) | 5.501(1.911) | 0.802 (0.171) | 0.244 (0.064) | 0.887 (0.038) | 0.172 (0.197) | 2.891 (0.714) |
| Maize | 2.3(0.639) Kg/Kg Yield | 1.724(0.759) | 6.159(2.895) | 0.635 (0.251) | 0.248 (0.037) | 0.92 (0.056) | 0.14 (0.03) | 4.05 (0.98) |
| Other Cereals | 1.497(0.639) Kg/Kg Yield | 1.393(0.318) | 5.501(1.911) | 0.886 (0.171) | 0.385 (0.12) | 0.887 (0.038) | 0.172 (0.197) | 2.891 (0.714) |
| Ragi | 1.3(0.639) Kg/Kg Yield | 1.813(0.619) | 5.501(1.911) | 0.802 (0.171) | 0.111 (0.12) | 0.887 (0.038) | 0.172 (0.197) | 2.891 (0.714) |
| Rice | 3(0.639) Kg/Kg Yield | 1.524(0.468) | 5.442(2.599) | 0.873 (0.029) | 0.417 (0.166) | 0.902 (0.024) | 0.153 (0.201) | 2.441 (0.88) |
| Small millets | 1.12(0.106) Kg/Kg Yield | 1.3(0.619) | 5.501(1.911) | 0.802 (0.171) | 0.167 (0.12) | 0.887 (0.038) | 0.172 (0.197) | 2.891 (0.714) |
| Wheat | 1.8(0.639) Kg/Kg Yield | 2.293(0.822) | 4.823(0.986) | 0.865 (0.032) | 0.289 (0.096) | 0.86 (0.056) | 0.236 (0.226) | 3.107 (0.664) |
| Cotton(lint) | 3.8(3.304) T/Ha | 2.847(1.008) | 3.818(2.185) | 0.822 (0.035) | 0.374 (0.173) | 0.85 (0.071) | 0.162 (0.17) | 3.5 (1.432) |
| Jute | 5(2.034) Kg/Kg Yield | 2.002(0.94) | 3.818(2.185) | 0.8 (0) | 0.201 (0.085) | 0.9 (0.056) | 0.162 (0.17) | 3.5 (1.432) |
| Mesta | 2.05(2.034) Kg/Kg Yield | 3(0.58) | 3.818(2.185) | 0.8 (0.102) | 0.25 (0.088) | 0.9 (0.045) | 0.162 (0.17) | 3.5 (1.432) |
| Linseed | 1.47(7.195) Kg/Kg Yield | 1.564(0.456) | 2.413(0.679) | 0.862 (0.045) | 0 (0.238) | 0.84 (0.04) | 0.162 (0.17) | 3.477 (1.432) |
| Niger seed | 2.28(7.195) Kg/Kg Yield | 2.555(0.608) | 2.413(0.679) | 0.862 (0.045) | 0 (0.238) | 0.84 (0.04) | 0.162 (0.17) | 3.477 (1.432) |
| other oilseeds | 8.384(12.947) Kg/Kg Yield | 2.418(1.01) | 0.939(0.679) | 0.891 (0.045) | 0.125 (0.238) | 0.84 (0.04) | 0.162 (0.17) | 3.477 (1.432) |
| Rapeseed &Mustard | 1.8(7.195) Kg/Kg Yield | 2.438(0.559) | 2.918(0.389) | 0.855 (0.049) | 0.343 (0.061) | 0.82 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Safflower | 3(7.195) Kg/Kg Yield | 2.2(1.131) | 1.8(0.679) | 0.862 (0.045) | 0.833 (0.238) | 0.84 (0.04) | 0.162 (0.17) | 3.477 (1.432) |
| Sunflower | 2.4(7.195) Kg/Kg Yield | 2.747(0.566) | 1.8(0.679) | 0.9 (0.045) | 0.158 (0.238) | 0.84 (0.04) | 0.162 (0.17) | 3.477 (1.432) |
| Arecanut | 3(3.202) T/Ha | 1.172(0.655) | 2.486(0.816) | 0.821 (0.102) | 0.333 (0.103) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Cashewnut | 1.667(0.569) Kg/Kg Yield | 1.172(0.655) | 2.486(0.816) | 0.821 (0.102) | 0.431 (0.103) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Coconut | 4(3.202) T/Ha | 1.113(1.722) | 2.486(0.816) | 0.821 (0.102) | 0.479 (0.084) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Arhar/Tur | 1.8(0.99) Kg/Kg Yield | 2.56(0.085) | 4.286(1.032) | 0.827 (0.083) | 0.194 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Gram | 1.167(0.115) Kg/Kg Yield | 1.22(0.254) | 2.12(1.032) | 0.897 (0.083) | 0.25 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Groundnut | 2(0.49) Kg/Kg Yield | 1.398(0.326) | 2.729(2.706) | 0.851 (0.059) | 0.238 (0.087) | 0.8 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Horse-gram | 1.3(0.49) Kg/Kg Yield | 1.583(0.417) | 2.289(1.032) | 0.827 (0.083) | 0.289 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Masoor | 1.8(0.49) Kg/Kg Yield | 1.52(0.417) | 2.289(1.032) | 0.827 (0.083) | 0.289 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Moong(Green Gram) | 1.1(2.928) Kg/Kg Yield | 1.33(0.407) | 2.289(1.032) | 0.8 (0.083) | 0.289 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Moth | 1.8(0.49) Kg/Kg Yield | 1.583(0.417) | 2.289(1.032) | 0.827 (0.083) | 0.289 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Peas & beans | 1.184(0.759) Kg/Kg Yield | 1.381(0.312) | 2.01(0.4) | 0.923 (0.037) | 0.692 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Soyabean | 1.7(0.49) Kg/Kg Yield | 1.927(0.59) | 2.289(1.032) | 0.804 (0.109) | 0.297 (0.045) | 0.68 (0.1) | 0.162 (0.17) | 3.8 (0.071) |
| Urad | 1.1(0.49) Kg/Kg Yield | 1.583(0.417) | 2.289(1.032) | 0.827 (0.083) | 0.289 (0.144) | 0.748 (0.1) | 0.162 (0.17) | 3.85 (0.071) |
| Ginger | 0.794(1.053) Kg/Kg Yield | 0.479(0.212) | 2.165(0.552) | 0.588 (0.263) | 0.25 (0.088) | 0.9 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Potato | 0.81(0.61) Kg/Kg Yield | 0.426(0.189) | 2.96(0.552) | 0.497 (0.286) | 0.25 (0.088) | 0.9 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Sweet potato | 0.1(0.61) Kg/Kg Yield | 0.608(0.283) | 2.96(0.552) | 0.877 (0.263) | 0.25 (0.088) | 0.9 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Tapioca | 0.75(0.61) Kg/Kg Yield | 0.311(0.332) | 2.165(0.552) | 0.71 (0.263) | 0.25 (0.088) | 0.9 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Sugarcane | 0.05(2.928) Kg/Kg Yield | 0.261(0.181) | 6.53(0.694) | 0.75 (0.161) | 0.374 (0.151) | 0.77 (0.156) | 0.162 (0.17) | 3.76 (1.432) |
| Banana | 3(0.95) Kg/Kg Yield | 2.667(0.577) | 2.367(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Cardamom | 0.64(3.304) T/Ha | 0.721(0.456) | 2.367(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Coriander | 1.15(0.95) Kg/Kg Yield | 0.721(0.456) | 2.367(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Dry chillies | 1.5(0.95) Kg/Kg Yield | 1.075(0.813) | 2.12(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Garlic | 0.3(0.95) Kg/Kg Yield | 0.5(0.456) | 2.12(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Onion | 0.05(0.95) Kg/Kg Yield | 0.5(0.456) | 2.12(1.149) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Tobacco | 1(0.95) Kg/Kg Yield | 1.215(0.369) | 2.9(0.208) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |
| Turmeric | 0.3(0.95) Kg/Kg Yield | 0.721(0.456) | 2.367(0.739) | 0.965 (0.102) | 0.357 (0.089) | 0.843 (0.056) | 0.162 (0.17) | 3.477 (1.432) |

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| Table : Karan et al (2021)23 list of functions used to estimate the residue to production ratio for different crops. | | |
| **Crop Class** | **Crop** | **Function** |
| Cereal Crops | Bajra | rpr = -0.55\*yield\_kg\_ha+4.55 |
| Cereal Crops | Bajra | rpr = 2.302\*exp(-0.100\*yield\_kg\_ha) |
| Cereal Crops | Barley | rpr = 1.822\*exp(-0.149\*yield\_kg\_ha) |
| Cereal Crops | Barley | rpr = -0.2751\*log(yield\_kg\_ha)+1.3796 |
| Cereal Crops | Barley | rpr = 0.769-0.129\*atan((yield\_kg\_ha)-6.7)/1.5 |
| Cereal Crops | Barley | rpr = -0.27\*yield\_kg\_ha+2.77 |
| Cereal Crops | Jowar | rpr = -0.55\*yield\_kg\_ha+4.55 |
| Cereal Crops | Jowar | rpr = 2.302\*exp(-0.100\*yield\_kg\_ha) |
| Cereal Crops | Maize | rpr = -0.1807\*log(yield\_kg\_ha)+1.3373 |
| Cereal Crops | Maize | rpr = 2.656\*exp(-0.103\*yield\_kg\_ha) |
| Cereal Crops | Maize | rpr = -0.13\*yield\_kg\_ha+2.20 |
| Cereal Crops | Ragi | rpr = -0.55\*yield\_kg\_ha+4.55 |
| Cereal Crops | Ragi | rpr = 2.302\*exp(-0.100\*yield\_kg\_ha) |
| Cereal Crops | Rice | rpr = -1.2256\*log(yield\_kg\_ha)+3.845 |
| Cereal Crops | Rice | rpr = 2.450\*exp(-0.084\*yield\_kg\_ha) |
| Cereal Crops | Rice | rpr = -0.22\*yield\_kg\_ha+2.56 |
| Cereal Crops | Small millets | rpr = -0.55\*yield\_kg\_ha+4.55 |
| Cereal Crops | Small millets | rpr = 2.302\*exp(-0.100\*yield\_kg\_ha) |
| Cereal Crops | Wheat | rpr = -0.3629\*log(yield\_kg\_ha)+1.6057 |
| Cereal Crops | Wheat | rpr = 0.769-0.129\*atan((yield\_kg\_ha)-6.7)/1.5 |
| Cereal Crops | Wheat | rpr = 2.186\*exp(-0.127\*yield\_kg\_ha) |
| Cereal Crops | Wheat | rpr = -0.14\*yield\_kg\_ha+1.96 |
| Oil Crops | Linseed | rpr = 2.148\*exp(-0.200\*yield\_kg\_ha) |
| Oil Crops | other oilseeds | rpr = 2.580\*exp(-0.200\*yield\_kg\_ha) |
| Oil Crops | other oilseeds | rpr = -1.1097\*log(yield\_kg\_ha)+3.2189 |
| Oil Crops | other oilseeds | rpr = -0.70\*yield\_kg\_ha+3.85 |
| Oil Crops | Rapeseed &Mustard | rpr = 3.028\*exp(-0.200\*yield\_kg\_ha) |
| Oil Crops | Rapeseed &Mustard | rpr = -0.452\*log(yield\_kg\_ha)+3.2189 |
| Oil Crops | Safflower | rpr = 2.148\*exp(-0.200\*yield\_kg\_ha) |
| Oil Crops | Soyabean | rpr = 3.869\*exp(-0.178\*yield\_kg\_ha) |
| Oil Crops | Soyabean | rpr = -0.80\*yield\_kg\_ha+3.90 |
| Oil Crops | Sunflower | rpr = 2.580\*exp(-0.200\*yield\_kg\_ha) |
| Oil Crops | Sunflower | rpr = -1.1097\*log(yield\_kg\_ha)+3.2189 |
| Oil Crops | Sunflower | rpr = -0.70\*yield\_kg\_ha+3.85 |
| Protein Crops | Peas & beans (Pulses) | rpr = 3.232\*exp(-0.300\*yield\_kg\_ha) |
| Roots and Tubers | Potato | rpr = 1.916\*exp(-0.108\*yield\_kg\_ha) |
| Roots and Tubers | Potato | rpr = -0.01\*yield\_kg\_ha+1.10 |
| Roots and Tubers | Potato | rpr = 1.916\*exp(-0.108\*yield\_kg\_ha) |

APPENDIX D: Lookup Tables

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| Table : Lookup table for climate classes to the Agro-Ecological Sub-Region data of WRIS | | | |
| **India Agro-ecology Zone**11 | **Hergoualc’h et al (2021)** 4 | **Yue et al (2019)** 8 | **Wang et al (2018)** 16 |
| Arid (hyper) | Dry | Warm arid and semiarid subtropics with summer rainfall | subtropic Arid (hyper)(AEZ 5) |
| tropic Arid (hyper)(AEZ 1) |
| Arid (typic) | Dry | Warm arid and semiarid subtropics with summer rainfall | subtropic Arid (typic)(AEZ 5) |
| tropic Arid (typic)(AEZ 1) |
| Humid | Wet | Warm humid tropics | subtropic Humid(AEZ 7) |
| subtropic Perhumid(AEZ 7) |
| tropic Humid(AEZ 3) |
| Humid to Perhumid | Wet | Warm humid tropics | subtropic Humid to Perhumid(AEZ 7) |
| subtropic Subhumid (dry) to Subhumid (moist)(AEZ 6) |
| tropic Humid to Perhumid(AEZ 3) |
| Perhumid | Wet | Warm humid tropics | subtropic Perhumid(AEZ 7) |
| tropic Perhumid(AEZ 3) |
| Semi-arid (dry) | Dry | Warm arid and semiarid tropics | subtropic Semi-arid (dry)(AEZ 5) |
| tropic Semi-arid (dry)(AEZ 1) |
| tropic Semi-arid (moist)(AEZ 1) |
| Semi-arid (dry) To Subhumid (dry) | Dry | Warm arid and semiarid tropics | subtropic Semi-arid (dry) To Subhumid (dry)(AEZ 5) |
| Semi-arid (moist) | Wet | Warm arid and semiarid tropics | subtropic Semi-arid (moist)(AEZ 5) |
| tropic Semi-arid (moist)(AEZ 1) |
| Semi-arid (moist) To Subhumid (dry) | Wet | Warm subhumid subtropics with summer rainfall | subtropic Semi-arid (moist) To Subhumid (dry)(AEZ 6) |
| Subhumid (dry) | Dry | Warm subhumid tropics | subtropic Subhumid (dry)(AEZ 6) |
| tropic Semi-arid (moist) To Subhumid (dry)(AEZ 2) |
| tropic Subhumid (dry)(AEZ 2) |
| Subhumid (dry) to Subhumid (moist) | Wet | Warm subhumid tropics | subtropic Subhumid (dry) to Subhumid (moist)(AEZ 6) |
| tropic Subhumid (dry) to Subhumid (moist)(AEZ 2) |
| Subhumid (moist) | Wet | Warm subhumid tropics | subtropic Subhumid (moist)(AEZ 6) |
| tropic Subhumid (moist)(AEZ 2) |

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| Table : Lookup table for crop names to the standard crop names used in the input data to the models. | | | | | |
| **APY Crop Name** | **Albanito et al (2017)** 2 **Crop Type** | **Aliyu et al (2019) 3 Crop Type** | **Shcherbak et al (2014) 7 Crop Name** | **Hergoualc’h et al (2021)** 4 **Crop Type** | **Yue et al (2019)** 8 **Crop Name** |
| Arecanut | PC | Others | Upland Grain | perennial systems | other |
| Arhar/Tur | PC | Others | N-fixers | perennial systems | Legume |
| Bajra | AC | Maize | Upland Grain | annual croplands and bare soils | other |
| Banana | PC | Others | Upland Grain | perennial systems | other |
| Barley | AC | Wheat | Upland Grain | annual croplands and bare soils | other |
| Cardamom | PC | vegetable | Upland Grain | perennial systems | Vegetable |
| Cashewnut | PC | Others | Upland Grain | perennial systems | other |
| Coconut | PC | Others | Upland Grain | perennial systems | other |
| Coriander | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Cotton(lint) | AC | Others | Cotton | annual croplands and bare soils | Cotton |
| Dry chillies | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Garlic | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Ginger | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Gram | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Groundnut | AC | Peanut | Upland Grain | annual croplands and bare soils | other |
| Horse-gram | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Jowar | AC | Maize | Upland Grain | annual croplands and bare soils | other |
| Jute | AC | vegetable | Upland Grain | annual croplands and bare soils | other |
| Linseed | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Maize | AC | Maize | Maize | annual croplands and bare soils | Maize |
| Masoor | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Mesta | AC | vegetable | Upland Grain | annual croplands and bare soils | other |
| Moong(Green Gram) | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Moth | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Niger seed | AC | vegetable | Upland Grain | annual croplands and bare soils | other |
| Onion | AC | vegetable | Upland Grain | annual croplands and bare soils | Vegetable |
| Other Cereals | AC | Wheat | Upland Grain | annual croplands and bare soils | other |
| Other oilseeds | AC | Rapeseed | Upland Grain | annual croplands and bare soils | other |
| Peas & beans (Pulses) | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |
| Potato | AC | Others | Upland Grain | annual croplands and bare soils | other |
| Ragi | AC | Maize | Upland Grain | annual croplands and bare soils | other |
| Rapeseed &Mustard | AC | Rapeseed | Rapeseed | annual croplands and bare soils | Rapeseed |
| Rice | AC | Upland rice | Rice | annual croplands and bare soils | Rice |
| Rice | AC | Paddy rice | Rice | annual croplands and bare soils | Rice |
| Safflower | AC | Others | Upland Grain | annual croplands and bare soils | other |
| Small millets | AC | Maize | Upland Grain | annual croplands and bare soils | other |
| Soyabean | AC | Soybean | N-fixers | annual croplands and bare soils | Legume |
| Sugarcane | AC | Others | Upland Grain | annual croplands and bare soils | other |
| Sunflower | AC | Rapeseed | Upland Grain | annual croplands and bare soils | other |
| Sweet potato | AC | Others | Upland Grain | annual croplands and bare soils | other |
| Tapioca | PC | vegetable | Upland Grain | perennial systems | other |
| Tobacco | AC | vegetable | Upland Grain | annual croplands and bare soils | other |
| Turmeric | AC | vegetable | Upland Grain | annual croplands and bare soils | other |
| Urad | AC | vegetable | N-fixers | annual croplands and bare soils | Legume |

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| Table : Lookup table for fertilizer names used in the models mapped to the standard fertilizer names used in the input data. | | | | |
| **Input Census Fertilizer Name** | **Albanito et al (2017)** 2 **Fertilizer** | **Hergoualc’h et al (2021)** 4 **Fertilizer** | **Mathivanan et al (2021)** 6 **Fertilizer** | **Shcherbak et al (2014)** 7 **Fertilizer** |
| AMM. PHOS. SUL./N. PHOS. | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| AMMONIUM CHLORIDE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| AMMONIUM MOLYBDATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| AMMONIUM N. PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Ammonium nitrate |
| AMMONIUM PHOS. SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| AMMONIUM SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| BONE MEAL (RAW) | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| BONE MEAL (STEAMED) | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| CALCIUM AMMONIUM NITRATE | AN | synthetic and mixed fertilizer | Inorganic N fertilisers | Calcium ammonium nitrate |
| Cattle farmyard manure | Other N Fertilizers | organic fertilizer | Animal manure applied to soils | Manure |
| COPPER SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| DI-AMMONIUM PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| FERROUS SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| Green manure | Other N Fertilizers | organic fertilizer | Other organic fertilisers applied to soils | Manure |
| GYPSUM | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| MANGANESE SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| MONO AMMONIUM PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| MURATE OF POTASH | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| N P K MIXTURE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| NITRO PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| NITRO PHOSPHATE POTASH | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| POTASSIUM SULPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| ROCK PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| SINGLE SUPER PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| SODIUM TETRABORATE(BORAX) | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| SOLUBOR | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| TRIPLE SUPER PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| UREA | Urea | synthetic and mixed fertilizer | Inorganic N fertilisers | Urea |
| Urea & NI |  | Controlled-release urea |
| UREA AMMONIUM PHOSPHATE | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |
| ZINC SUL. HEP. HYD/M.HYD. | Other N Fertilizers | synthetic and mixed fertilizer | Inorganic N fertilisers | Mixed |

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| Table : Lookup table of rice water regimes used in the models mapped to the water regime in Gumme (2010) dataset. used to compute the proportions of water regimes in the districts. | | | | | | | |
| **Water Regime** | **Akiyama et al (2005)** 5 | **Bhatia et al (2013)** 13 | **Gupta et al (2009)** 15 | **Wang et al (2018)** 16 | **Yan et al (2005)** 17 | **Nikolaisen et al (2023)** 14 | **IPCC 2019 Update** 1 |
| Irrigated | Continuous flooding | Continuous flooding | Continuous flooding | Continuously flooded | Continuous flooding | CF | Continuously Flooded |
| Irrigated | Midseason drainage | Multiple aeration | Multiple aeration | Multiple drainage | Multiple drainage | MD | Multiple Drainage Periods |
| Irrigated | Midseason drainage | Single aeration | Single aeration | Single drainage | Single drainage | SD | Single Drainage period |
| deepwater | All water regimes | Deepwater | Deepwater | Deep water | Deepwater | DW | Deep water |
| rainfed | Rain-fed, wet season | Drought-prone | Drought-prone | Rainfed, wet season | Rainfed, wet season | RFW | Drought prone |
| rainfed | Rain-fed, wet season | Drought-prone | Flood-prone | Rainfed, wet season | Rainfed, wet season | RFW | Drought prone |
| rainfed | Rain-fed, wet season | Flood-prone | Drought-prone | Rainfed, wet season | Rainfed, wet season | RFW | Drought prone |
| rainfed | Rain-fed, wet season | Flood-prone | Flood-prone | Rainfed, wet season | Rainfed, wet season | RFW | Drought prone |
| rainfed | Rain-fed, wet season | Drought-prone | Drought-prone | Rainfed, wet season | Rainfed, wet season | RFW | Regular Rainfed |
| rainfed | Rain-fed, wet season | Drought-prone | Flood-prone | Rainfed, wet season | Rainfed, wet season | RFW | Regular Rainfed |
| rainfed | Rain-fed, wet season | Flood-prone | Drought-prone | Rainfed, wet season | Rainfed, wet season | RFW | Regular Rainfed |
| rainfed | Rain-fed, wet season | Flood-prone | Flood-prone | Rainfed, wet season | Rainfed, wet season | RFW | Regular Rainfed |
| upland |  | Upland | Upland |  | Upland |  | Upland |

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| Table : CCAFS-MOT simplified soil class, use the map soil texture to India's soil health cards. | | | | | |
| **Soil texture** | **Description** | **Soil organic C** | **Soil N content** | **Soil pH** | **Bulk density** |
| Coarse | Light soil (e.g. sandy), low SOC | 1.2 | 0.12 | 7 | 1.7 |
| Medium | Medium soil | 2 | 0.2 | 6 | 1.3 |
| Fine | Heavy soil (e.g. clay), high SOC | 6 | 0.6 | 5 | 1.5 |

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