# VALIDATION REPORT

Project VCS 2590: Regenerative agriculture in rice-wheat-maize system for income generation

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# 1. Project summary

Our current project "Regenerative agriculture in Rice-Wheat-Maize system for income generation", is a greenhouse gas (GHG) removal and emission reduction project, under the methodology, VM0042 Version 1.0. The project aims to reduce net emissions of $CO_2$, $CH_4$, and $N_2O$ and enhance soil organic carbon (SOC) sequestration in agricultural lands through the adoption of regenerative agricultural land and crop management activities.

The project is currently being implemented in the states of Punjab and Haryana, primarily focusing on Rice-Wheat-Maize cropping system. The project design aims to increase the adoption of regenerative practices among farmers by incentivizing their enrolment in the project and thus gain access to carbon market incentives. It will be the first of its kind in India, rewarding smallholder farmers for adopting regenerative agricultural practices and contributing to reduction of GHG emissions via carbon offset projects.

Scientifically proven regenerative agricultural practices known to reduce GHG emissions (CH4, N2O and CO2) and improve SOC are being promoted in the project area to enable generation of income through carbon markets. The regenerative agriculture practices selected for promotion in the project area for this monitoring period (2019-2021) are (i) reduced tillage / zero tillage (ZT) and (ii) direct seeding of rice (DSR). The map of the project area is given in Figure 1. This is a grouped project, with a geographical reach of Punjab and Haryana, and practices that may vary on some farms.

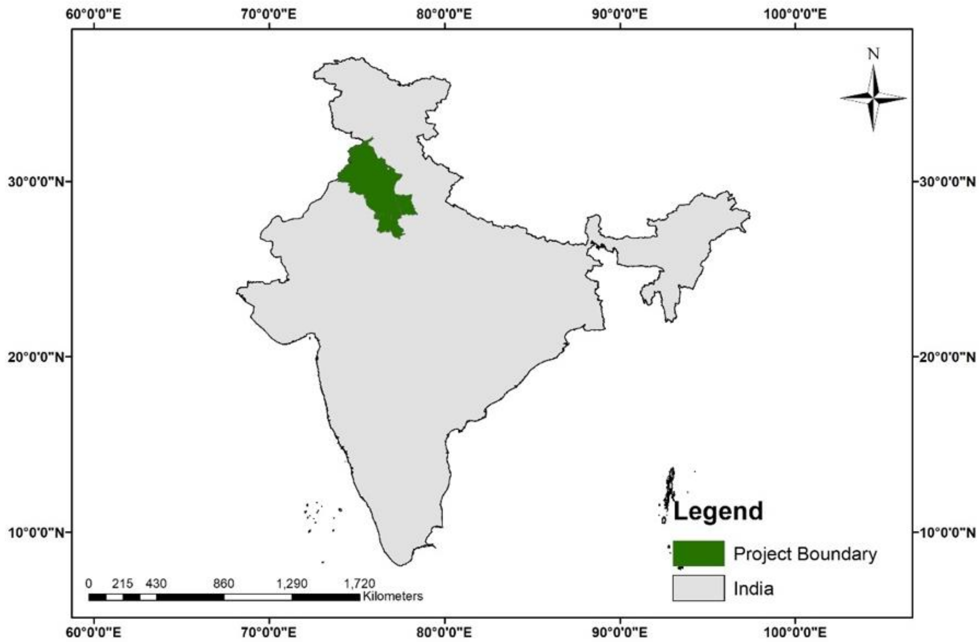



**Figure 1: Project boundary on the map of India**

## 1a. Project activities

Project activities are changes in agricultural land management activities that are expected to increase SOC storage and reduce emissions of CO2, CH4, and/or N2O over the crediting period of a field. Each project activity whose effect could be quantified through the combination of modelling and default equations, and for which the model is validated, are incentivized by a payment for a reduction in GHG emissions or increase in SOC storage. The effect of the project activities is quantified through the combination of modelling and default equations as per the guidelines of VM0042 v1.0 and VMD0053 v1.0. Quantification approach 1 (measure and model) was followed in this project.

The Rice-Wheat-Maize system in project area accounts for a significant portion of the food supply in the country. The crop planting methods are predominantly, puddled transplanted rice (TPR) followed by intensively tilled (CT) wheat which is also the lifeline for millions of people in our project area. Several sustainability issues are associated with TPR and CT practices in Rice-Wheat (R–W) cultivation system, including decline in crop, water, and land productivity, deterioration of soil health, emissions of GHG caused by flooding, tillage and residue burning, deepening of groundwater levels and quality, and shifts in weeds. Promoting ZT and substituting TPR with DSR in combination with effective weed-control methods will contribute to a GHG reduction of about 8 to 15 million tons CO2e per year.

Project activities for currently enrolled fields in the project resulted in one or more practice changes, i.e., either TPR→DSR or CT→ZT, or both. . Grazing has not been included in the project due to the absence of grazing on the project fields and fossil fuel contribution to GHG emissions has not been quantified during this monitoring period.

### 1b. Methodology version

The current project and analysis follow VM0042 V1.0 and VMD0053 V1.0 methodologies.

## 2. Biogeochemical modelling

### 2a. Model Selection and Model Version

As per the VMD0053 Model Requirements, the biogeochemical model selected for calibration, validation and quantification of GHGs in the project is the Denitrification-Decomposition (DNDC) model, version DNDC 9.5 (http://www.dndc.sr.unh.edu/model/DNDC95.zip). DNDC is a process-oriented computer simulation model of carbon and nitrogen biogeochemistry in agroecosystems. The DNDC model incorporates the driving factors of the ecological environment and aims to simulate the carbon and nitrogen cycle in the terrestrial ecosystem. The entire model forms a bridge between the C and N biogeochemical cycles and the primary ecological drivers.

DNDC model has been shown to be highly valid across a wide range of management practices and geographic area and needs to be explicitly calibrated with empirical data. DNDC has also been widely tested against several field observations regarding trace gas emissions and SOC dynamics and in agroecosystems worldwide (Cai et al., 2003; Brown et al., 2002; Zhang et al., 2002; Li, 2000). The empirical data requirement is necessary because the quantification of uncertainty around modelled results can only be done with local and specific data.

### 2b. DNDC Model Description

The model consists of two components. The first component, consisting of the soil climate, crop growth and decomposition sub-models, predicts soil temperature, moisture, pH, redox potential (Eh) and substrate concentration profiles driven by ecological drivers (e.g., climate, soil, vegetation and anthropogenic activity). The second component, consisting of the nitrification, denitrification and fermentation sub-models, predicts emissions of carbon dioxide (CO2), methane (CH4), ammonia (NH3), nitric oxide (NO), nitrous oxide (N2O) and dinitrogen (N2) from the plant-soil systems.

The DNDC model accommodates six sub-models and describes soil C and N cycles in agricultural systems (Li et al., 1992, 2000). DNDC95 was calibrated to simulate Rice-wheat cropping system, and the sensitivity of the model to different input parameters was investigated as described in Pathak et al., 2005. Region specific climate, soil and crop input parameters were adopted to simulate Kharif Rice-Rabi Wheat cropping systems in this project.

In the current project, two key management practices were modelled and quantified;

i. DSR for achieving CH4 and N2O emission reductions, and
ii. ZT for SOC sequestration

DSR practice allows avoidance of the flooding or inundated conditions for cultivation of rice paddy and thus reducing CH4 emissions. Whereas ZT practice involves reduced number of tillage operations before planting and retaining/incorporation of crop residues in the field.

### 2c. Model Initialization

The DNDC model was initialized for a ten years historical period, after selecting weather records and designating crop management practices specific to a site at IARI, New Delhi (located in Indo Gangetic Plains (IGP) region) (Table 1, Figure 2). Soil and crop parameters were allowed to be populated by default values. For example, selecting a soil texture results in default values of porosity, hydraulic conductivity, field capacity, and wilting point. Soil parameters supplied under the default scenario were texture class, while soil pH, Bulk density (BD) and initial SOC content (0.53%) were measured values at the site (Bhatia et al., 2011, studies were conducted in 2004-2005). This was the SOC value closest to the beginning of the year of initialization in our project (for the year 2006). Cropping parameters supplied included cropping system information, planting and harvest dates, tillage events, fertilization conditions, manure or compost applications, and flooding/irrigation schedules common to IGP region (Package of practices for crops of Punjab, Kharif, https://www.pau.edu/content/ccil/pf/pp_kharif.pdf). Weather data was gathered from NASA POWER website (https://power.larc.nasa.gov/docs/methodology/).

**Table 1: Initialization of the DNDC Model**

| Year -10 to -3 | Year -3 to 0 | Year 0 to 1 | Year 1 to 2 | Year 2 to 3 |
|---|---|---|---|---|
| Historical period | Baseline | Crediting period | | |
| Model equilibration | t-3 to t | Period 1 | Period 2 | Period 3 |

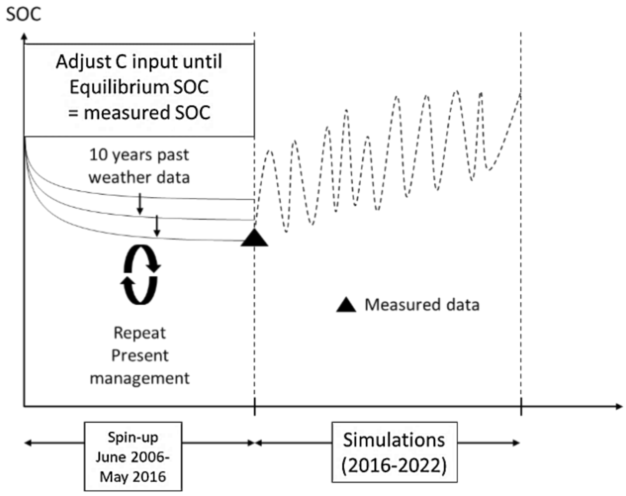



**Figure 2: Spin-up initialization with C adjustment.** *(Figure adapted from Rie Nemoto,2014)*

T he DNDC model allocates SOC among several pools (i.e. residues, microbial biomass, humads, and humus), and the initial composition of the SOC affects the simulation results. To determine the initial SOC composition, we assumed that the soil has already reached a steady state because rice-wheat cropping had been conducted for many years at the site (IARI, New Delhi). However, to achieve a similar steady state in the model for the carbon pools, we ran the model for 10 years (Table 1, Figure 2) (June 2006-May 2016) with rice-wheat cropping system under conventional practices of continuous flooding and tillage. For the preliminary run, we assumed that rice straw was routinely applied at a rate of 1200-3000 kg C $ha^{-1}$ $yr^{-1}$, following the typical local practices for rice-wheat farming. We adjusted the C input during the spin-up run period until the equilibrium SOC could match the measured SOC value (Figure 3). However, model simulated SOC results remained about 8-10% underestimated from measured values. It is to be noted that measured values were also from different studies in time (but from the same site). The simulation results further indicated only fair results for SOC stocks prediction (Figure 3, $R^2$ value 0.42).

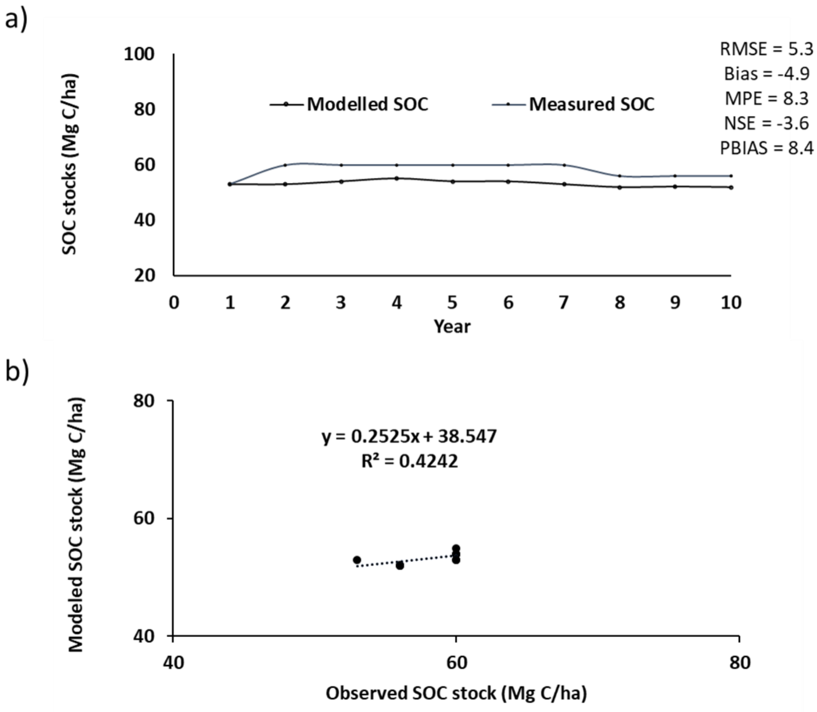



**Figure 3: Spin-up initialization and observed vs. simulated change in SOC stocks**

## 2d. Model sensitivity

A great amount of field observations on C sequestration and trace gas emissions from croplands have been accumulated worldwide, but datasets for Indian conditions are still very limited. A set of sensitivity simulations were tested with DNDC, in which a series of model runs were conducted in rice growing regions, in Karnal (Haryana) and Delhi in the north. For the sensitivity analyses, the parameters being evaluated were set within predefined range, commonly observed in agricultural soils of IGP region, while all other model parameters and inputs were held constant as standard values (Table 2). Simulated seasonal CH4 and N2O flux sensitivities were evaluated for soil textures (clay content from 3 to 63%), and soil organic C contents (3-6g $kg^{-1}$ soil). Model sensitivity was also evaluated for management parameters, fertilizer amounts and degree of flooding/ draining floodings/ irrigations (3-35), sowing and harvesting dates (+15 to -15 days of prescribed dates in the states by the respective governments).

**Table 2: Baseline and project parameters studied for evaluating model sensitivity**

| Scenario | Condition variations |
|---|---|
| **Baseline** | Rice-Wheat rotation (R-W),<br>Continuous flooding (CF),<br>Conventional tillage (tilling twice to depth 20 cm)<br>Rice optimum yield 6500 kg dry grain/ha,<br>Fertilizer 80-250 kg urea-N/ha per year;<br>Annual average temperature 17.2°C,<br>Annual precipitation 1000 mm, N concentration in rainfall 2 ppm, |
| **Management Alternatives** | |

| | |
|---|---|
| **Crop rotation, Tillage, Fertilizers** | Rice-wheat crop (R-W), and rice-fallow (RF)<br>conservation tillage (depth 10 cm) (CST), and ZT<br>Fertilizer types- Urea, DAP, nitrate, ammonium bicarbonate (AB) |
| **Soil Factor** | |
| **Soil textures**<br>**SOC content** | Loam, Loamy sand, sandy loam, clay loam, silty clay and clay<br>SOC content 0.42-0.50% (0.0042-0.005 kg c/kg soil) |

***Sensitivity analysis***

***Influence of soils properties***

The sensitivity of simulated CH4 emissions from rice fields to soil properties varied with site characteristics. At the two sites viz. Delhi, and Karnal the model is sensitive to soil texture. Soil texture has been documented to affect CH4 emission from rice fields, with emissions decreasing with an increase in clay content. Such diffusion limitations would ultimately lead to substrate limitations. The modelled data showed that the DNDC was more sensitive to temperature in climatic factors followed by initial SOC and clay content in soil properties over the ten simulated years. Increase in temperature accelerated SOC loss. Literature results also support our findings and confirm that DNDC model was more sensitive to temperature, initial SOC, and clay content (Zhang et al., 2019).

***Influence of management practices***

Water management, tillage, straw addition and fertilizer N application rates (urea-N) were tested for its influence on GHG emissions. Direct seeding of rice, alternative wetting and drying and intermittent wetting and drying decreased methane emissions upto ≥50%. The N2O emissions increase >50% during direct seeding of rice to that emitted during transplanted method of rice crop establishment. Increase in straw addition/crop residue incorporation 1200-3000 kg C $ha^{-1}$ $yr^{-1}$ and ZT practices increased CH4 emissions due to the increase in soil organic matter (SOM) content. Although simulated CH4 emissions increased with increased fertilizer-N application, the sensitivity of simulated CH4 emissions from rice fields to soil properties varied with site characteristics (temperatures, rainfall and soil textures).

**Influence of depth of top soil with uniform SOC content setting of DNDC** DNDC simulations were conducted with the uniform-topsoil depth set to 0.2 m (model default) and 0.3m (VM0042 quantification requirement). Over a 10-year period, the cumulative 0–30 cm soil-carbon stock gain showed no material difference between these settings (08_Sensitivity_analysis). Accordingly, within this range, modeled 0–30 cm SOC change is effectively insensitive to the DNDC uniform-depth parameter.

## 2e. Documentation Of Model Parameter Sets

**Input Parameters**

As per the Model Requirements and Guidance in VMD0053, parameter set was defined as "the set of mathematical values and constants contained in a model that characterize the biophysical and biogeochemical system being represented". Crop management practices implemented before project start, form the "baseline" scenario, and is thus unambiguously defined by fixing the following values ("key input parameters") ex-ante, in the project document:

**Climate parameters**

Data for atmospheric background CO2 concentration and the daily climate files (daily weather data – Minimum and maximum temperature and precipitation) were obtained from public sources of information such as from regional/local weather stations, from NASA power (https://power.larc.nasa.gov/), and from IARI weather station, where the literature studies were conducted/reported (Table 3).

DNDC provides default values for the following atmospheric background concentrations of ammonia (NH3) and carbon dioxide (CO2).

a. N concentration in rainfall mg N/l or ppm = 0
b. Atmospheric background NH3 concentration (μg N/m3) = 0.06
c. Atmospheric background CO2 concentration ppm = 350
d. Annual increase rate of atmospheric concentration (ppm/yr) = 0

However, for Calibration and Validation, input parameters for atmospheric background concentrations need to be applied based on the year of the experimental studies (published literature). In the current project, the data points applied for atmospheric background CO2 concentration are specific to the years for which the simulations were conducted;

a. Atmospheric background CO2 concentration ppm = range 350 - 404.41 (over the simulations time period)
b. Annual increase rate of atmospheric concentration (ppm/yr) =1-3.75 (over the simulations time period)

**Table 3: Input parameters specific to climate conditions**

| Input parameter | Unit |
|---|---|
| J day (julian day) | Day of the year |
| MaxT<br>(maximum temperature) | °C |
| MinT<br>(minimum temperature) | °C |
| Precipitation | mm $day^{-1}$ |

**Soil parameters**

1. Land-use type- rice paddy field

2. Soil Texture: Soil type was based on area of the experimental studies or field site. The soil textures applied for calibration included (1) loam (2) loamy sand and (3) silty clay loam. For GHG quantification amongst the sample fields, the soil textures applied were based on soil measurements/analyses (from each of the sampled field areas). These soils are very commonly found in Haryana and Punjab.
3. Bulk density (g/cm^3): Bulk density (BD) of topsoil (0-10 cm) for calibration and validation was used as reported in the published literature (BD measured and reported in the experimental studies). BD used for sample quantification was from measured soil samples.
4. Soil pH: For Calibration and Validation soil pH parameters were from literature whereas for quantification, data from soil sampling measurements were applied.
5. Clay fraction of soil by weight: default clay content was applied.
6. Field Capacity (0-1): Water-filled porosity (WFPS) at soil field capacity. The default values of DNDC obtained after the selection of soil texture were applied.
7. Wilting Point (0-1): Water-filled porosity (WFPS) at soil wilting point. The default values of DNDC obtained after the selection of soil texture were applied.
8. Hydro-conductivity (m/hr): Hydrological saturation conductivity in m/hr, was default value. The default values of DNDC obtained after the selection of soil texture were applied.
9. Porosity (0-1): a default porosity value was used. The default values of DNDC obtained after the selection of soil texture were applied.
10. SOC at surface soil (0-10cm) (kg C/kg soil): for Calibration and validation, literature values were applied.
11. Initial NO3(-) concentration at surface soil (mg N/kg): Fixed values of 10 and 12 were used for loam soils and silty loam soils whereas in soils with clay content (silty clay loam or sandy clay loams) a higher initial NO3- concentration value of 18 was applied. This is because NO3- leaching is higher in loamy or silty loam soils and lower in soils with clay content.
12. Initial NH4(+) concentration at surface soil (mg N/kg): a fixed value of 2 was used for Calibration, Validation and Quantification.

**Management parameters**

1. Total years: For calibration and validation, 1–3-year simulations were performed (as per the experimental duration).
2. Number of cropping systems applied during the total simulated years: 1 cropping system for calibration, validation and quantification exercises.
3. Duration of this cropping system (yrs): 7.

**Crop parameters**

1. Crop type: Annual
2. Seeding procedures: Transplanting (TPR), DSR.

3. Tillage information (no of applications): Varied from 3-5 tills for TPR-CT and 0-1 for Reduced/Zero till.
4. Tilling #: Sequential number of each application.
5. Month/Day: Date of the tilling application.
6. Tilling method: Defined tilling depths by selecting the default methods as (1) no-till (i.e., only mulching) (0 cm), (2) ploughing slightly (5 cm), (3) ploughing with disk or chisel (10 cm), (4) ploughing with moldboard (20 cm), or (5) deep ploughing (30 cm).
7. Fertilization information: options for fertilization: Manual application of fertilizers was opted with only surface application (typically broadcasting method of fertilizer application).
8. Number of applications in the year was added as per the surveyed data of the sample fields.
9. Fertilization #: Sequential numbers were provided for each application.
10. Application date: month/Day: Dates of each application were applied.
11. Application depth: Surface or injection applications was specified.
12. Applied amount of fertilizers (kg N/ha): actual amount of fertilizers applied.
13. Flooding: Flooding practice applied for paddy rice.
14. Number of flooding applications in the year was provided.
15. Flooding #: Sequential number of each application. Frequency and duration of flooding for the rice crop (if any) was provided.
16. Start on month/day: Starting date of each flooding application was applied.
17. End on month/day: End date of each flooding application was applied.

**Key Input Parameters**

All parameters that are related to the project activities were named "key management parameters" (Table 4) and were fixed ex-ante. In other words, values of key management parameters must be identical ex-ante and ex- post. Specific parameters representing TPR and DSR practices were input into the model as shown in Table 5, and Table 6.

**Table 4: Key crop management parameters as per crop establishment**

| Baseline/Project activity | Key input parameters |
|---|---|
| Transplanted/ Dry seeding (DSR) | Sowing date<br>Harvesting date<br>Fertilization schedule<br>Irrigation schedule |
| Conventional/ Reduced tillage (ZT) | Tillage events<br>Sowing date<br>Harvesting date<br>Fertilization schedule<br>Irrigation schedule |

Crop management data were also taken from the literature studies to support calibration/validation of the model (Table 5).

**Table 5: Qualitative and Quantitative parameters as per crop management practices**

| Agricultural management practice | Qualitative | Quantitative |
|---|---|---|
| Crop planting and harvesting | Transplanted or Direct seeded rice | Sowing date<br>Harvesting date<br>Fertilization schedule<br>Irrigation schedule |
| Tillage management | Conventional or Zero/reduced tillage | Depth of tillage<br>Frequency of tillage |
| Water management | Irrigation<br>Flooding | Irrigation type<br>No of Irrigation events<br>Flooding (height of water level maintained)<br>No. of Flooding events |

**Table 6: Input parameters applied for TPR and DSR representation in DNDC**

| Input category | Input | Default values used? | Parameters added for TPR | Parameters added for DSR |
|---|---|---|---|---|
| **Area** | Site | | ✓ | ✓ |
| | Latitude | | ✓ | ✓ |
| **Climate/weather** | Daily mean or max/min. air temperature(°C) | | ✓ | ✓ |
| | Daily precipitation(cm) | | ✓ | ✓ |
| | Humidity (%) | | ✓ | ✓ |
| | Daily solar radiation (MJ/m2/day) | | | |
| | N concentration in precipitation (mgN/l or ppm) | | ✓ | ✓ |
| | Atmospheric background CO2 concentration (ppm) | | ✓ | ✓ |
| | Atmospheric background NH3 concentration (µg N/m3) | ✓ | | |
| | Annual increase rate of atmospheric CO2 concentration (ppm/year) | | ✓ | ✓ |
| **Soil** | Land use type[a] | | ✓ | ✓ |

| Input category | Input | Default values used? | Parameters added for TPR | Parameters added for DSR |
|---|---|---|---|---|
| | Soil texture[b] | | ✓ | ✓ |
| | Bulk density (g/cm3) | | ✓ | ✓ |
| | pH | | ✓ | ✓ |
| | SOC at surface (kg C/kg soil) | | ✓ | ✓ |
| | SOC partitioning (fraction & C/N ratio of litter, humads, humus and char C) | ✓ | | |
| | SOC profile: depth of top soil with uniform SOC content (m); | | ✓ (value applied 0.2m) | ✓ (value applied 0.2m) |
| | SOC decrease rate below topsoil (0.5–5) | | ✓ (value applied "2") | ✓ (value applied "2") |
| | Clay fraction (0–1) | | ✓ | ✓ |
| | Soil structure: Bypass flow rate (0–1); depth of water retention layer (m); drainage efficiency (0–1) | ✓ | | |
| | NO3- concentration at surface soil (mg/kg) | | ✓ | ✓ |
| | NH4 + concentration at surface soil (mg/kg) | | ✓ | ✓ |
| | Field capacity (WFPS; 0–1) | | ✓ | ✓ |
| | Wilting point (WFPS; 0–1) | | ✓ | ✓ |
| | Porosity (0–1) | | ✓ | ✓ |
| | Hydro-conductivity (m/hr) | | ✓ | ✓ |
| | Microbial activity index (0–1) | ✓ | | |
| | Slope (0–90°) | ✓ | | |
| | Soil salinity index (0–100) | ✓ | | |
| | Rainwater collection index (0–1) | ✓ | | |

| Input category | Input | Default values used? | Parameters added for TPR | Parameters added for DSR |
|---|---|---|---|---|
| | Use SCS and MUSLE functions (yes/no) | | NA | NA |
| **Farming management practices** | | | | |
| **Crop** | Type (62 default types) | | ✓ selected from dropdown list of DNDC | ✓ selected from dropdown list of DNDC |
| | Crop rotation (no. crops per year | | ✓ | ✓ |
| | Planting and harvest date | | ✓ | ✓ |
| | Transplanting (Yes/No) | | Yes | No |
| | Cover crop (yes/no) | | NA | NA |
| | Perennial crop (yes/no) | | NA | NA |
| | Fraction of leaves & stems left in field after harvest (0–1) | ✓ | | |
| | Annual N demand (kg N/ha/year) | ✓ | | |
| | C/N ratio of grain, leaf, stem & root | ✓ | | |
| | Biomass fraction of grain, leaf, stem & root (0–1) | ✓ | | |
| | Maximum biomass production (kg/C/ha/ year) | | ✓ | ✓ |
| | Thermal degree days for maturity (days) | ✓ | | |
| | Water demand (g water/g dry matter) | ✓ | | |
| | Optimum temperature for crop growth (°C) | ✓ | | |
| | N fixation index (crop N/N from soil) | ✓ | | |
| | Vascularity index for wetland plants (0-1) | ✓ | | |
| **Fertilizer** | Type, method, rate, no. of applications, dates, depth | | ✓ | ✓ |

| Input category | Input | Default values used? | Parameters added for TPR | Parameters added for DSR |
|---|---|---|---|---|
| **Manure** | Type, method, rate, no. of applications, dates, depth | | NA | NA |
| | C/N ratio of manure | | | |
| **Tillage** | Method, no. of applications, dates | | ✓ | ✓ |
| **Grazing or cutting** | No. of grazing/cutting applications, dates; grazing livestock type, grazing hours per day & stocking rate | | NA | NA |
| **Irrigation** | Method, rate, no. of applications, dates | | NA | NA |
| **Flooding** | Method, dates, N in flood water, water leaking rate | | ✓ | ✓ |

[a]Upland crop field, rice paddy field, moist grassland/pasture, dry grassland/pasture, wetland, tree plantation.
[b]Sand, loamy sand, sandy loam, silt loam, loam, sandy clay loam, silty clay loam, clay loam, sandy clay, silty clay, clay, organic soil.

## 2f. Justification for Splitting Experimental Data

Research papers selected for the calibration of the model were mainly focused on setting the key soil parameters such as soil textures common to IGP and the relevant soil characteristics (conductivity, clay fraction, porosity, wilting point, and water filled pore space, initial nitrogen concentration and microbial activity index 1) and crop management parameters specific to IGP region, i.e., crop establishment practice of "transplanting", other water management practice of rice crop- flooding along with other water management practices such as Intermittent wetting and drying (IWD), Alternate wetting and drying (AWD) and Organic amendments (FYM) for simulating the corresponding emissions fluxes .

The datasets selected for validation exercise include research studies capturing the GHG fluxes specifically from regenerative agricultural practices such as DSR and ZT practices specific to IGP region. These studies also reported emission fluxes and SOC changes and thus enable validating our sampled fields that adopted these regenerative practices.

## 2g. Model Calibration

The DNDC model was calibrated for loamy soils that are predominant in the Indo Gangetic Plain region of Northern India that includes Punjab and Haryana (project area). To calibrate DNDC95, measured data from 15 field studies was extracted from 9 published research papers that measured GHG ($CH_4$ and $N_2O$) emissions in R-W cropping systems, within the Indo Gangetic Plain (IGP) region (Table 7). The model was calibrated to simulate Methane ($CH_4$) and Nitrous Oxide ($N_2O$) emissions from transplanted Rice (TPR) crop during Kharif (June-October) and from Wheat (winter wheat) crop during Rabi (October-April) season. Detailed climate, soil parameters and management routines were obtained from the publications that represented common crop management practices, predominant soil textures, and climatic conditions within the IGP region (Table 7).

***Calibration Procedure***

Model calibration for $CH_4$ and $N_2O$ emissions was mainly done by optimizing a combination of different climate, soil and crop management parameters (Table 8). To run the DNDC model, climate data specific to the year of the publication/study in the IGP region was acquired from NASA power website (https://power.larc.nasa.gov/docs/methodology/) and added as "weather files" into the model. These weather files included the data for the parameters mentioned in Table 3. Crop management data provided in the publications including sowing and harvesting dates, N fertilizer additions, water management (flooding) and tillage information were added as inputs into the cropping module.

However, before we conducted the calibration procedure, we began by an initial testing of the default parameterization present in the model (model generated/default values) for climate (Initial background atmospheric N concentration), soil (textural default values and initial N concentration in the form of $NO_3^-$ and $NH_4$ default values) and crop management parameters (Table 8) for comparing their impact on simulated and observed daily/cumulative $CH_4$ and $N_2O$ fluxes.

***Variable data applied for Climate Parameters***

The climate parameters, maximum and minimum temperature and precipitation data were obtained on site-by-site basis from NASA POWER website (https://power.larc.nasa.gov/docs/methodology/). Site latitude information as per studies applied for calibration, and weather data specific to each year of the research study were input in text format as required by DNDC model.

***Default data applied for climate parameters***

N concentration in rainfall (0 ppm) and atmospheric background $NH_3$ concentration (ug $N/m^3$) of 0.06 (default value by DNDC) were applied (Table 8).

***Variable data applied for soil parameters***

Soil parameters such as SOC, pH and Bulk density were variable parameters. The variable data for soil parameters SOC, pH and bulk density were applied from publications to simulate GHG emissions from the R-W cropping system (Table 7).

***Default Soil Parameters***

Model generated data for soil textural parameters such as Field capacity (wfps), Wilting point (wfps), Clay fraction (0-1), Conductivity (m/hr), Porosity (0-1), Initial Nitrate $NO3^-$ (mg N/kg), and Initial Nitrate $NH4^+$ (mg N/kg) were applied when testing the effect of default values on GHG emission flux simulations.

***Variable data for Crop Management Parameters***

Key crop information obtained from each site included, seeding and harvest dates, N fertilizer input, number of irrigation/flooding events and tillage events. These were applied from the publications (References for calibration are in Appendix 3).

***Default data applied for Crop Management Parameters***

Model generated values for Maximum/potential biomass production for grain, root, stem and leaf (kg C/kg ha) were applied (Table 9).

***Water management***

Water input was tested initially by opting continuous flooding in order to test the effectiveness of Continuous flooding (as practiced in TPR production) on GHG emissions and actual grain yields in the DNDC model.

**Table 7: Characterization of field sites and soil and crop management parameters applied for calibration**

| S.No. | Reference | Year | Season | Cropping system | Tillage | Crop establishment/ Water management/Fertilizer | Soil Bulk Density ($g/cm^3$) | Soil Texture | Soil pH | SOC (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Bhatia et al. (2005) | 2001-02 | Kharif | Rice-wheat | CT | TPR, Flooded, organic amendments (FYM, GM and residues), NPK | 1.4 | Loam | 8 | 0.59 |
| 2 | Bhatia et al. (2011) | 2004-2005 | Kharif, Rabi | Rice-wheat | CT | TPR, NPK, Zn | 1.49 | Silty clay loam | 8.04 | 0.53 |
| 3 | Cowan et al. (2021) | 2016 | Kharif | Rice-wheat | CT | TPR, CF, IF, NPK, FYM | 1.38 | Silty clay loam | 8.01 | 0.42 |
| 4 | Ghosh et al. (2003) | 1999 | Kharif | Rice-wheat | CT | TPR, NPK, DCD | 1.38 | Sandy loam | 7.6 | 0.45 |
| 5 | Jain et al. (2009) | 2009 | Kharif | Rice-wheat | CT | TPR, NPK, FYM | 1.49 | Loam | 8.04 | 0.53 |
| 6 | Malla et al. (2005) | 2001-02 | Kharif, Rabi | Rice-wheat | CT | TPR, Urea, Neem oil coated urea, DCD | 1.38 | Loam | 8.04 | 0.42 |
| 7 | Pathak et al.(2002) | 1999-2000 | Kharif, Rabi | Rice-wheat | CT | TPR, Saturated-Intermittent drying for rice, 3-5 Irrigations for wheat, Urea, FYM, DCD | 1.38 | Loam | 8.1 | 0.45 |
| 8 | Pathak et al.(2003) | 1999-2000 | Kharif, Rabi | Rice-wheat | CT | TPR, Saturated-Intermittent drying for rice, 3-5 Irrigations for wheat, Urea, FYM, DCD | 1.38 | Loam | 8.1 | 0.45 |
| 9 | Pathak et al.(2006) | 2002-2003 | Rabi | Wheat | CT | TPR, NPK, Straw, FYM | 1.38 | Loam | 8 | 0.42 |

**Table 8: Default values tested for soil, crop and climate parameters before calibration**

| **Before Calibration** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Soil parameters** | | | | | | | |
| **Variable data**<br>**SOC, pH and Bulk density applied as reported in the research study** | | | | | | | |
| **Default data (model generated) applied for soil textures** | | | | | | | |
| **Soil Texture** | **Field capacity (wfps)** | **Wilting point (wfps)** | **Clay fraction (0-1)** | **Conductivity (m/hr)** | **Porosity (0-1)** | **Initial $NO3^-$ (mg N/kg)** | **Initial $NH4^+$ (mg N/kg)** |
| **Loam** | 0.49 | 0.22 | 0.19 | 0.025 | 0.451 | 0.5 | 0.05 |
| **Silty clay loam** | 0.55 | 0.26 | 0.34 | 0.015 | 0.477 | 0.5 | 0.05 |
| **Sandy loam** | 0.32 | 0.15 | 0.09 | 0.124 | 0.435 | 0.5 | 0.05 |
| **Climate data (external inputs)**<br>**Variable data:** Site latitude, weather data specific to year and site | | | | | | | |
| **Default (model generated) data applied for climate parameters** | | | | | | | |
| **Atmospheric background CO2 concentration (ppm)** | 350 | | | | | | |
| **Annual increase rate of CO2 concentration (ppm/yr)** | 1 | | | | | | |
| **Crop Growth parameters** | | | | | | | |
| **Variable data** | | | | | | | |
| **Variable data (external inputs)**<br>• **Sowing and harvesting dates specific to the research study**<br>• **Crop specific to the season,**<br>• **Tillage and fertilizers and number of applications specific to the research study used for calibration** | | | | | | | |
| **Default data applied for Crop biomass** | | | | | | | |
| **Maximum biomass production** | Grain yields – 3317, Leaf - 2179.5, Stem – 2369 and Root – 1611, Biomass fraction Grain – 0.35, Leaf – 0.23, Stem – 0.25 and Root – 0.17 | | | | | | |
| **Water management** | | | | | | | |
| **Single Continuous flooding** | | | | | | | |
| **Variable data**<br>**Dates of flooding events – start date (flooding) and end dates (drain) from publications** | | | | | | | |

### *Background - Model Calibration to represent TPR/DSR Wheat crop rotation*

Model calibration was then conducted by adjusting/hand tuning of soil textural and potential crop biomass production along with water management that is specific to IGP region. These parameters were adjusted until the model matched the measured cumulative $CH_4$ and $N_2O$ flux values (Table 9).

The GHG emissions from rice-wheat systems are mainly due to the inundated conditions maintained in the conventional transplanted rice crop (5-10cm water level) establishment. Inundation causes release of methane emissions due to underlying microbial methanation processes. The two major differences between TPR and DSR crop management are (i) direct seeding of rice into the soil, instead of nursery grown transplants and (ii) the absence of inundated conditions (puddling) in the DSR crop cultivation throughout the season. Therefore, water management becomes a distinct as well as significant parameter to adjust during the model calibration process.

In the DNDC model, we began by trying continuous flooding as a parameter to represent TPR, using the initial and final water input dates from the publication to mimic field conditions. This approach aimed to accurately mirror real-world water management. However, the model produced greenhouse gas emissions nearly ten times higher than those observed in field trials, preventing us from continuing with further simulations. Additionally, continuous flooding couldn't be used to simulate emissions for second-crop wheat in the same year.

Furthermore, it's not feasible to use both flooding and irrigation in the same year in DNDC model for rice-wheat rotation. Therefore, we had to adopt a single, common water management practice for both TPR/DSR and wheat crop rotations within a year. Additionally, as we planned to use the calibrated model for quantifying field-scale data from sampled farmers later on, for both baseline (TPR) and project practice (DSR) scenarios in multi-year simulations, we explored the possibility of implementing AWD (Alternate Wetting and Drying) as a water management option.

In the publications, most of the authors reported only initial and final dates of continuous flooding sometimes also including total number of flooding events. Under the AWD option in DNDC, it is imperative to include each date of the flooding and drainage event. This necessitates hand tuning and fitting the flooding dates accurately between the initial and final flooding events in each study whilst not ignoring the reality of field conditions (draining within 24hours of flooding for example). The frequency and fitting the number of flooding events, dates and the drainage dates directly impacts $CH_4$ and $N_2O$ emission fluxes. For representing TPR conditions, flooding events were limited upto 35 and for DSR, maximum flooding events were limited to 20. Beyond 35 flooding events, DNDC interface stops/errors occur to run the simulations. The flooding and drainage events were fitted between the initial and final dates of water management until the model results obtained were comparable to the field measurement data.

***Calibration parameters***

***Variable data for Climate parameters***

Atmospheric background $CO_2$ concentration (ppm) and annual increase rate of $CO_2$ concentration (ppm/yr) were obtained for each year of the research study and applied into the simulations (Table 9).

***Fixed data applied for climatic parameters***

N concentration in rainfall (0 ppm) and atmospheric background $NH_3$ concentration (μg N/m^3) of 0.06 (default value by DNDC) were applied (Table 8).

***Variable data for soil parameters***

Soil data applied in the calibration covered three soil textures, Loam, Sandy loam and Silty clay loam that are common to IGP region. SOC, pH and Bulk density were variable parameters and were applied as per the values reported in each of the 9 studies that were used for calibration (Table 7).

***Soil textural data***

Soil texture parameters such as Field capacity (wfps), Wilting point (wfps), Clay fraction (0-1), Conductivity (m/hr), Porosity (0-1), Initial Nitrate $NO3^-$ (mg N/kg), and Initial Nitrate $NH4^+$ (mg N/kg) were calibrated (Table 9) and same values were applied for all the three soil textures as the experimental location for all the studies is same (Indian Agricultural Research Institute -IARI research site) and the values applied for calibrating the model fall in general ranges for loamy soils of IGP region (unpublished studies, Indian Agricultural Research Institute, Pathak, 2003, Pathak 2002).

Content of total soil organic carbon (SOC) includes litter residue, microbes, humads, and passive humus at surface layer (0-10 cm). After defining the total SOC content, the default SOC profile as well the SOC partitioning values for litter, humads and passive humus were automatically determined by DNDC and were applied as model defaults for all the simulations. Since these values were not reported in the publications we have applied model defaults. Microbial activity index 1 was applied (this is an index ranging from 0.0 to 1.0 for indicating impact of soil toxic materials on soil microbial activity). The default value 1.0 is for normal soils. Slope of the soil surface for a levelled soil is 0 and 0 was applied in all our simulations.

***Maximum Crop Biomass Production/Crop growth parameters***

The DNDC model includes a calibrated parameter set for a generic rice crop. This parameterization is "maximum biomass" parameter that can be manually tuned to reflect variations in yields due to local soils and climates. For calibrating "maximum biomass", crop growth parameters such as root, leaf and stem growth values (kg C/kg ha) were not reported in all the papers. Only actual grain yields (t/ha) were reported (3.0-6.04 t/ha) (Appendix- 02_Research papers used for Calibration and Validation). Therefore, we have hand tuned/calibrated the maximum potential grain yields and fixed a value of 8t/ha for all the simulations. The actual grain yields obtained from the simulations i.e., 5.14 t/ha correctly represented the grain yields obtained in farmers' fields of our project area. These yields were also compared with the measured actual grain yields from publications to evaluate model performance and accuracy.

***Water management:*** AWD Flooding was opted as the key water managementat parameter and the flooding frequency and drainage frequency were hand-tuned for simulation of GHG emissions comparable to the measured studies.

**Table 9: Calibrated/adjusted Parameters for evaluating DNDC model performance**

## Calibration Parameters

**Soil parameters**

**Variable soil parameters**

SOC, pH and Bulk density applied as reported in the research study

**Soil Textural parameters Calibrated – specific to loamy soils of Ingo Gangetic Plain region**

(fixed since all textural parameters were not reported in all studies, values below represent loamy soil characteristics and fall in the range specific to IGP region)

| Soil Texture | Field capacity (wfps) | Wilting point (wfps) | Clay fraction (0-1) | Conductivity (m/hr) | Porosity (0-1) | Initial $NO3^{-}$ (mg N/kg) | Initial $NH4^{+}$ (mg N/kg) |
|---|---|---|---|---|---|---|---|
| Loam | | | | | | 10 | 2 |
| Silty clay loam | 0.25 | 0.07 | 0.21 | 0.02 | 0.35 | 18 | 2 |
| Sandy loam | | | | | | 18 | 2 |

**Climate Parameters (external inputs)**

Applied Variable data: Site latitude, weather data specific to year and site

**Variable parameters:** Site latitude, weather data specific to year and site

| | Atmospheric background CO2 concentration (ppm) | Annual increase rate of CO2 concentration (ppm/yr) |
|---|---|---|
| **1999** | 368.54 | 1.00 |
| **2001** | 371.32 | 1.75 |
| **2004** | 377.7 | 1.50 |
| **2009** | 387.64 | 2.25 |
| **2021** | 404.41 | 3.80 |
| | | |

**Cropping Module**

Variable data (external inputs)

- **Sowing and harvesting dates specific to the research study**
- **Crop specific to the season,**
- **Tillage and fertilizers and number of applications specific to the research study used for calibration**

**Crop Growth – Maximum Biomass Production - Only Max/potential Grain Yields (set to 8 t/ha) were calibrated as root, stem and leaves growth values were not reported in all studies**

**AWD mode of Water management for Transplanted rice-wheat system**

**Adjusted Flooding Module**

| | |
|---|---|
| **Scheduled flooding option** | Alternative Wetting and Drying (-5 to 5cm) |
| **Number of Flooding events** | 15-24 |
| **Flooding frequency** | Every 2-3 days first month<br>Every 3-5 days second month -harvest date |
| **Draining frequency** | 1 day (specific to loamy soils of IGP region) (but soil remains saturated) |
| **Max. Biomass production (Potential Grain yield specific to IGP region -Fixed parameter)** | Grain yields fixed to – 3377, Leaf - 2219.5, Stem – 2412.5 and Root – 1640.5, Biomass fraction Grain – 0.35, Leaf – 0.23, Stem – 0.25 and Root – 0.17 |

### *Statistical Evaluation of DNDC Model Performance*

To confirm the reliability, DNDC model performance was evaluated using goodness of fit indicators: Relative deviation (%), $R^2$, RMSE, Mean bias error, model mean percentage error (MPE) and Nash-Sutcliffe model efficiency coefficient (NSE) (Table 10).

**Table 10: Statistical indicators used to compare the observed and simulated results for model calibration**

| Statistical Indicators | Standard Formula | Other Information |
|---|---|---|
| Bias | $\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n}$ | Where,<br>N = total no. of Observations<br>$O_i$ = Observed data<br>$\overline{O}_i$ = Mean of actual data<br>$P_i$ = Simulated data<br>$\overline{P}_i$ = Mean of Simulated data |
| Root mean square error (RMSE) | $\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$ | |
| Mean percentage error (MPE) | $\mathrm{MPE} = \frac{1}{N}\sum 100 * \frac{(O_i - P_i)}{O_i}$ | |
| Nash-Sutcliffe efficiency (NSE) | $\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O}_i)^2}$ | |
| Percentage BIAS | PBIAS = $\frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}(O_i)} * 100$ | |

**Statistical evaluation of model performance for GHG emission and actual grain yield results before calibration**

When we tested different model generated (default) climate and soil parameters along with continuous flooding option, poor statistical results were obtained (Table 11a, Figure 4). For example, Table 11a shows the effect of all three default values for soil, climate and crop on GHG fluxes and indicates that the relative deviation of these results is erratically overestimating CH4 emissions in a range of +31% to +1659% and for N2O being -49- +219%. RMSEs obtained for emissions or grain yields were also extremely poor (high values) (Table 11a) and are not acceptable for model application (in this model set-up) to estimate GHG emissions from project area.

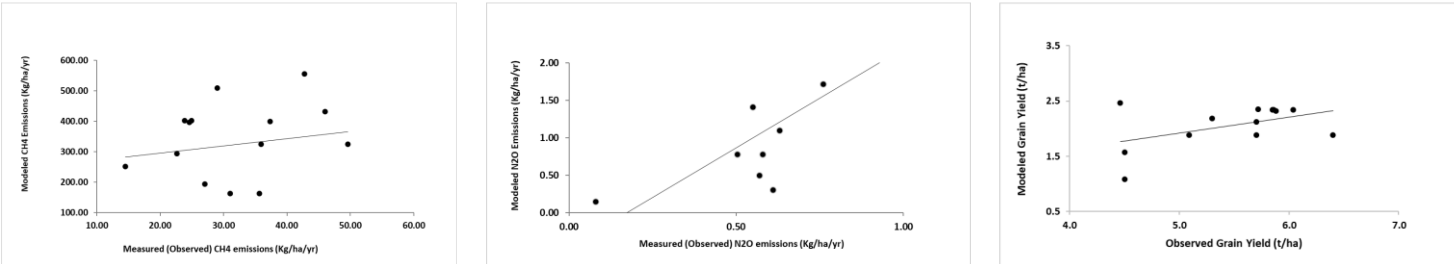
**Table 11 (a): Statistical evaluation of model performance before calibration with default soil, crop and climate parameters with continuous flooding parameter**

| | GHG Emissions | | Grain Yield |
|---|---|---|---|
| | CH4 | N2O | |
| **Observed Mean (kg/ ha/yr)** | 31.97 | 0.60 | 5.46 t/ha |
| **Simulated Mean (kg/ ha/yr)** | 324.48 | 1.13 | 2.06 t/ha |
| **RMSE** | 321.89 | 0.79 | 3.45 |
| **Bias** | 292.51 | 0.53 | -2.95 |
| **MPE** | -996.18 | -81.30 | 62.23 |
| **NSE** | -1205.41 | -12.86 | -30.56 |
| **PBIAS** | 90.15 | 46.93 | 62.33 |
| **Relative Deviation (%)** | 31.05% to 1658.62% | -49.18% to 218.53% | -44.73% to -75.93% |

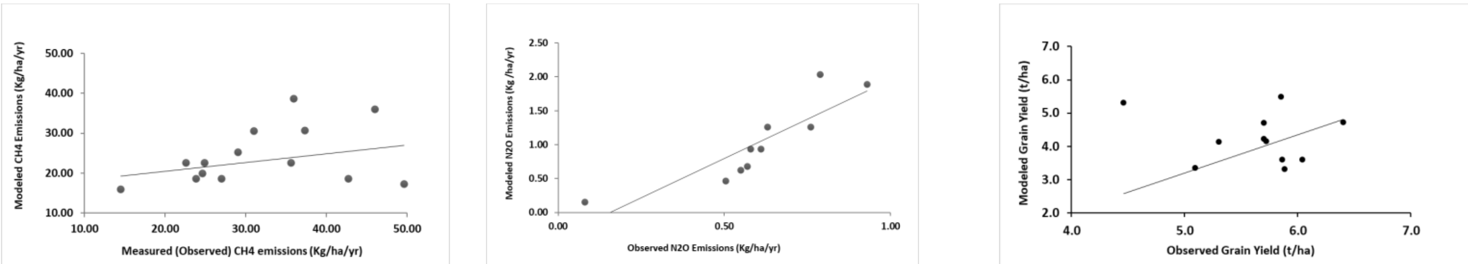
**Table 11 (b): Statistical evaluation of model performance before calibration with default soil, crop and climate parameters with AWD flooding**

| | GHG Emissions | | Grain Yield |
|---|---|---|---|
| | CH4 | N2O | |
| Observed Mean (kg/ ha/yr) | 31.97 | 0.60 | 5.46 t/ha |
| Simulated Mean (kg/ ha/yr) | 23.10 | 1.03 | 3.73 t/ha |
| RMSE | 13.70 | 0.43 | 2.09 |
| Bias | -8.87 | 0.28 | -1.73 |
| MPE | 23.35 | -67.35 | 32.31 |
| NSE | -1.18 | -6.49 | -10.55 |
| PBIAS | 27.75 | -71.27 | 31.64 |
| Relative Deviation (%) | -77.21% to 10.34% | -6.56% to 158.88% | -82.22% to 19.11% |

## Before Calibration




a) GHG emissions and grain yields when default soil textural, crop and climate parameters were applied with continous flooding.




b) GHG emissions and grain yields when default soil textural, crop and climate parameters were applied with AWD flooding (adjusted water management specific to IGP region).

**Figure 4: Statistical evaluation of DNDC model performance before calibration i.e., when default values were applied with two different water management modules. Results were compared between the field-measured and DNDC simulated GHG emissions (CH4 and N2O) and actual grain yields obtained from IGP region (project area).**

When we switched from continuous flooding to AWD mode of water management (Table 11b) in which flooding events/frequency of flooding events were adjusted, results for GHG emissions and grain yields already started to improve with lower RMSEs (13.7 for emissions and 2.09 for actual grain yields). Although these are still on a higher range to be acceptable for a good model predictive ability, adjusted water management parameter was proved to be a key parameter to be applied for representing rice-wheat system.

***Statistical evaluation of model performance for GHG emission and actual Grain yield results after Calibration***

The calibration results showed a positive linear relationship between observed and simulated CH4 (Table 12, Figure 5) and N2O emissions  indicating that the model was able to match the pattern of the observations and effectively capture the overall trend of the CH4 fluxes measured. This is an indication that the model was successfully calibrated and that the simulated data can be relied on for other purposes. Relative deviations with respect to observed CH4 emissions were variable across studies with a range of -22.04% to 37.93% and -28.10% to 42.86% for N2O emissions. Model bias for CH4 emissions was negative (-0.17) indicating that the model underestimated the CH4 emissions compared to observed emissions. For N2O emissions the bias was positive (0.05) indicating that the model slightly overestimated the emissions.

**Table 12: Statistical evaluation of model performance after calibration with calibrated parameters**

| | GHG Emissions | | Grain Yield |
|---|---|---|---|
| | CH4 | N2O | |
| Observed Mean (kg/ ha/yr) | 31.97 | 0.6 | 5.46 t/ha |
| Simulated Mean (kg/ ha/yr) | 31.81 | 0.65 | 5.14 t/ha |
| RMSE | 4.98 | 0.12 | 0.91 |
| Bias | -0.17 | 0.05 | -0.28 |
| MPE | -3.68 | -9.28 | 5.56 |
| NSE | 0.71 | 0.66 | -1.19 |
| PBIAS | -0.52 | 7.91 | 5.82 |
| Relative Deviation (%) | -22.04% to 37.93% | -28.1% to +42.86% | -39.83% to 38.17% |

**After Calibration**

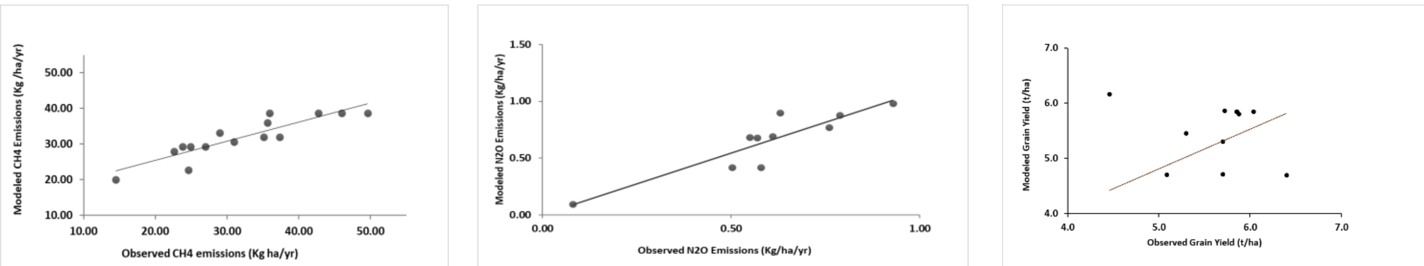



**Figure 5. Statistical evaluation of DNDC model performance after calibration. GHG emissions and Grain yields when calibrated with soil textural and crop (grain yields) parameters were applied with AWD flooding (adjusted water management specific to IGP region).**

Typically, NSE describes the predictive accuracy of a model ranging from negative infinity to 1, a perfect model; when NSE is equal to 0 the model has the same predictive ability as the mean of observations. In the current study, we observed an NSE value 0.72 for CH4 emissions and 0.66 for N2O emissions indicating acceptable level of model performance. Mean percentage error calculated for CH4 and N2O emissions indicated that the predictive capacity of the model was better for CH4 emissions with an MPE of -

3.68% than for N2O emissions with an MPE of -9.28%. Results showed that DNDC 9.5 model calibration displayed a good fit between the field observations and model-simulated data (Table 12, Figure 5).

Statistical evaluation of grain yields obtained from the model simulations also showed very good results (Table 12 and Figure 5) when model was calibrated with IGP specific soil textural values, maximum potential grain yields of 8t/ha and AWD mode of flooding with flooding/drainage events and the frequency was adjusted specific to IGP region. In the IGP region irrigated/flooded water usually drains within 24hours of the event, due to high porosity levels (40-56%, Tomar et al., 2017).

# 3. Project domain

## 3a. Land Resource Regions

***Climate zones in the project area***

The project activities took place only in some parts of the project boundary (Haryana and Punjab). The state of Punjab lies roughly 29° 30’ N latitudes, 73° E and 77° E longitudes. The state of Punjab has been classified into five agro-climatic zones based on homogeneity, rainfall pattern and distribution, temperature, soil texture and cropping pattern. Out of the five agro-climatic zones, Barnala, Sangrur and a part of Faridkot, Moga, Ferozepur district come under the Central Plain zone which is characterized by semi-arid (sub-moist) and less hot zone. Annual average temperature ranges from 23 °C to 24 °C and mean annual rainfall varies from 600 mm to 900 mm. Bathinda, Mansa and a part of Faridkot, Ferozepur and Muktsar districts fall under Western Plain zone, which is characterized by semi-arid (dry to sub-moist) zone. Annual average temperature ranges from 24 °C to 25 °C and mean annual rainfall varies from 400 mm to 600 mm. A part of Ferozepur and Muktsar districts also fall under Western zone, which is characterized by arid (dry) and hot zone. Average annual temperature ranges from 25 °C to 26 °C and mean annual rainfall varies from 200 mm to 400 mm (Chopra and Krishan, 2014, Surender Paul and OP Singh, 2014).

While the state of Haryana lies in the area bounded by 27°39’, 31°N latitudes and 74°30’ E longitudes forms the eastern part of the table land between the Sutlej and Yamuna to the South and to north of Rajasthan desert. The state has 4 topographic divisions. Bagar or Sandy plains to southwest, Alluvial plain or Yamuna Ghaggar plain, Shivalik towards northeast, and Aravalli range towards the south. Sandy soil and Alluvial soils are two major types of soils found in Haryana.

## 3b. Soils

The two states, Haryana and Punjab share similar agro-ecological conditions with similar soil textures such as Loamy, Sandy loam, Silt, Silty clay loam, and Sandy soil types. The soil map (Figure 6) indicates the physical areas of the project boundary (Haryana and Punjab) along with the agro-ecological zones and soil types shared by these two states.

The baseline information on common farmers practice in the region was documented in several publications (e.g. Jat et al., 2020). The areas included at the time of validation will be limited to those for which the baseline data on farmer practices, climatic, and soil conditions are available from Govt. reports or farmer surveys while the SOC measurements are available for farms spread across various strata in the project boundary.

### 3c. Domain covered in this validation and Emission sources

With two possible practice changes, DSR and ZT, there are three possible practice categories (PCs) in the project. PC1 = DSR-only, PC2 = ZT-only, and PC3 = DSR+ZT together. To keep the model validation and reporting fully aligned with our quantification scope and to stay conservative, we report calibration and validation parameters only for single-practice categories (PC1 and PC2). Where a field shows both practices (PC3) in a year, we reassign it to the single practice that is following our PC assignment rules described in quantification section.

We only give credit for one practice at a time (PC1 or PC2) and do not claim any extra 'stacking' benefit (PC3). This is conservative because it avoids adding interaction effects that could exaggerate results. Interaction being strongly negative is unlikely (Jat et al., 2020). And because we ignore any stacking bonus, our approach stays conservative even if small interactions exist.

***Emission Sources (ES)***

The model was validated for changes in SOC sequestration and emission reductions of CH4 and N2O.

**Table 13: Practice Change classification of enrolled farmers in the project**

| Practice categories | Baseline Practice | Improved Practice | Emission Source |
|---|---|---|---|
| **PC_1 (T→D)** | Transplanted Rice (TPR) | Direct Seeded Rice (DSR) | $CH_4$+$N_2O$ |
| **PC_2 (TC→TZ)** | Transplanted Rice-Conventional Tillage (TPR-CT) | Transplanted Rice-Reduced Tillage/Zero Tillage (TPR- ZT) | SOC |

## 4. Practice change group 1

This Practice Change (PC) group included the fields that have switched from conventional TPR system to DSR practice (abbreviated as T→D hereafter). The validation data for this PC group's is applied for all the fields that switched to DSR practice during the project period (2019-2021) in the project area (Punjab and Haryana).

The validation data are taken from a study Pathak et al., 2012, which was conducted within the project area i.e., Punjab (Table 14, 15, 16 and 17). The soil texture included in this study mainly covered loamy soils, which is a dominant type of soil texture occurring and declared in the project domain. Punjab's agro-climatic zone and soil conditions are similar to Haryana and are classified together as "trans-gangetic plains" (Subregion of the IGP, comprising the plains in northwestern India [Punjab, Haryana], straddling Ganges and Indus basin) (Singh et al., 2007).

**Table 14: Model Validation for PC 1 group (T-D) for Baseline practice corresponding to methane emissions measured/modelled in different studies (IGP region)**

| **Baseline Practice (TPR)** | | | **RICE** | |
|---|---|---|---|---|
| **Reference** | Area | Soil Texture | Observed $CH_4$ ($tCO_2$ e/ha) | Simulated $CH_4$ ($tCO_2$ e/ha) |
| **PATHAK_2012_Rozri 2_TPR_2009** | Rozri 2, Punjab | Loam | 1.18 | 1.15 |
| **PATHAK_2012_Rozri 2_TPR_2010** | Rozri 2, Punjab | Loam | 1.58 | 1.52 |
| **PATHAK_2012_Rozri 4_TPR_2010** | Rozri 4, Punjab | Loam | 1.56 | 1.56 |

**Table 15: Model Validation for PC 1 group (T-D) for project practice corresponding to methane emissions measured/modelled in different studies (IGP region)**

| **Project Practice (DSR)** | | | **RICE** | |
|---|---|---|---|---|
| **Reference** | Area | Soil Texture | Observed $CH_4$ ($tCO_2$ e/ha) | Simulated $CH_4$ ($tCO_2$ e/ha) |
| **PATHAK_2012_Rozri 1_DSR_2009** | Rozri 1, Punjab | Loam | 0.016 | 0.149 |
| **PATHAK_2012_Rozri 1_DSR_2010** | Rozri 1, Punjab | Loam | 0.114 | 0.186 |
| **PATHAK_2012_Rozri 3_DSR_2009** | Rozri 3, Punjab | Loam | 0.014 | 0.224 |
| **PATHAK_2012_Rozri 3_DSR_2010** | Rozri 3, Punjab | Loam | 0.117 | 0.149 |

**Table 16: Model Validation for PC 1 group (T-D) for Baseline practice corresponding to N2O emissions measured/modelled in different studies (IGP region)**

| **Baseline Practice TPR** | | | **RICE** | |
|---|---|---|---|---|
| **Reference** | Area | Soil Texture | Observed $N_2O$ ($tCO_2$ e/ha) | Simulated $N_2O$ ($tCO_2$ e/ha) |
| **PATHAK_2012_Rozri 2_TPR_2009** | Rozri 2, Punjab | Loam | 0.291 | 0.373 |
| **PATHAK_2012_Rozri 2_TPR_2010** | Rozri 2, Punjab | Loam | 0.424 | 0.124 |
| **PATHAK_2012_Rozri 4_TPR_2010** | Rozri 4, Punjab | Loam | 0.477 | 0.042 |

**Table 17: Model Validation for PC 1 group (T-D) for Project practice corresponding to N2O emissions measured/modelled in different studies (IGP region)**

| Project Practice | | | RICE | |
|---|---|---|---|---|
| **References** | Area | Soil Texture | Observed $N_2O$ ($tCO_2$ e/ha) | Simulated $N_2O$ ($tCO_2$ e/ha) |
| **PATHAK_2012_Rozri 1_DSR_2009** | Rozri 1, Punjab | Loam | 0.318 | 0.185 |
| **PATHAK_2012_Rozri 1_DSR_2010** | Rozri 1, Punjab | Loam | 0.583 | 0.124 |
| **PATHAK_2012_Rozri 3_DSR_2009** | Rozri 3, Punjab | Loam | 0.318 | 0.079 |
| **PATHAK_2012_Rozri 3_DSR_2010** | Rozri 3, Punjab | Loam | 0.530 | 0.082 |

## 5. Practice change group 2

This Practice Change (PC) group included the fields that have switched from conventional tillage CT - TPR system to ZT– TPR system (abbreviated as TC → TZ after). The validation data for this PC group is applied for all the fields that switched to ZT practice during the project period (2019-2021) in the project areas (Punjab and Haryana).

The validation data are taken from 6 studies (Table 18, 19), which were conducted in two different areas from project domain (Delhi and Karnal). The soil textures included in this study mainly covered sandy loams, loamy soils, sandy clay loam soils, which are commonly occurring soil textures in the project areas. Punjab's agro-climatic zone and soil conditions are similar to Haryana and are classified together as "trans gangetic plains" (Subregion of the IGP, comprising the plains in northwestern India [Punjab, Haryana], straddling Ganges and Indus basin) (Joginder Singh et al., 2007).

**Table 18: Model Validation for PC 2 group (TC-TZ) for Baseline practice corresponding to SOC measured/modelled in different studies (IGP region)**

| **Baseline Practice TC** | | | **SOC (Rice-Wheat cropping system)** | |
|---|---|---|---|---|
| **References** | **Area** | **Soil Texture** | **Observed ($tCO_2$ e/ha)** | **Simulated ($tCO_2$ e/ha)** |
| **NATH_2017** | New Delhi | Sandy loam | 11.4 | 9.88 |
| **NATH_2017*** | New Delhi | Sandy loam | 11.6 | 11.27 |
| **JAT_2019** | Karnal | Loams | 16.2 | 9.04 |
| **BHATTACHARYYA_2015** | New Delhi | Sandy clay loam | 11.33 | 10.42 |

Note: References with * indicate the field trial in which crop residues were incorporated in the soil.

**Table 19: Model Validation for PC 2 group (TC-TZ) for project practice corresponding to SOC measured/modelled in different studies (IGP region)**

| Project Practice TC → TZ | | | SOC (Rice-Wheat cropping system) | |
|---|---|---|---|---|
| **Reference** | Area | Soil Texture | Observed SOC ($tCO_2$ eq/ha) | Simulated SOC ($tCO_2$ eq/ha) |
| **NATH_2017** | New Delhi | Sandy loam | 12.20 | 9.34 |
| **NATH_2017*** | New Delhi | Sandy loam | 12.50 | 11.84 |
| **JAT_2019** | Karnal | Loams | 17.60 | 13.19 |
| **JAT_2019*** | Karnal | Loams | 22.79 | 17.15 |
| **BHATTACHARYYA_2015** | New Delhi | Sandy clay loam | 11.18 | 11.09 |
| **BHATTACHARYYA_2015** | New Delhi | Sandy clay loam | 11.30 | 10.96 |

*Note: References with * indicate the field trial in which crop residues were incorporated in the soil*

# 6. PMU and bias evaluation (Validation dataset)

## 6a. Bias calculation

In all the Practice change groups, bias was computed for each study as the mean difference between modelled and observed practice effects:

$$\mathbf{bias} = \frac{\sum_{i=1}^{n} \mathbf{modeled_i} - \mathbf{observed_i}}{\mathbf{n}}$$

where $observed_i$ is the change in SOC observed from the $i^{th}$ experimental treatment (for e.g. SOC CT– SOC ZT), $modelled_i$ is the change in SOC predicted by modelling the $i^{th}$ experimental treatment, and n is the number of treatments used from the study (per Equation 1 of the VMD0053 Model Requirements).

When a study reported observations fitting multiple categories, only the observations matching the category of interest were included in the calculation. Bias for each category was then computed as the mean of all per-study biases in that category, as per mean bias equation (pg 27, VMD0053 Model Requirements)

Bias was compared against the pooled measurement uncertainty (PMU) of the observed data (per Equation 2 of the VMD0053 Model Requirements):

$$\text{PMU} = \sqrt{\frac{\sum_{j=1}^{k} \sigma_j^2 (n_j - 1)}{\sum_{j=1}^{k} (n_j - 1)}}$$

Where k is the number of observations with uncertainty reported, $s_j$ is the standard error of the $j^{th}$ observation of differences between the treatments, and $n_j$ is the number of replicates included in the observation.

## 6b. PMU calculation

The PC x ES validation dataset contained k = six observations of practice changes that reported uncertainty for both observed treatments and therefore allow computing the standard error of the difference between treatments. Uncertainty for each baseline–practice contrast is computed from the standard deviations across replicates ($SD_1$, $SD_2$) and replicate counts ($n_1$, $n_2$) as $SE\_difference = \sqrt{(SD_1^2/n_1 + SD_2^2/n_2)}$ as per fig. 5.4 of VM0053 v1. An example PMU calculation is shown in Table 20.

## 6c. PMU coverage by category

### Practice Change Group 1

This PC group validation dataset can be applied to all the fields where farmers switched from Transplanting of rice to Direct seeding of rice practice. The GHG emission fluxes were simulated using the following datasets and a PMU was calculated (Table 21).

### Practice Change Group 2

The validation dataset for PC group can be applied to all the fields where farmers switched from conventional tillage practice to ZT practice. The SOC restored as a result of ZT practice was captured in the reference measurement datasets. These datasets were applied in the simulations to recreate the SOC effects, and a PMU was subsequently calculated (Table 22).

**Table 20: Example PMU calculation**

| | | | | Measured Practice Change [PC] Emissions (μ PC Emissions) | Emission Reductions from Practice Change (μ Baseline Emissions - μ PC Emissions ) | | | PMU |
|---|---|---|---|---|---|---|---|---|
| **Reference** | **Study Areas** | **Year** | **n** | **Combined PC ($CH_4$+$N_2O$) Emissions ± SD** | **Combined Baseline ($CH_4$+$N_2O$) Emissions ± SD** | **(μBaseline-μPractice )** | **SE_difference** | |
| Pathak_2012 | Rozri 1 | 2009 | 3 | 0.2±0.03 | 1.7 ± 0.05 | 1.50 | 0.03 | 0.02 |
| Pathak_2012 | Rozri 1 | 2010 | 3 | 0.6 ±0.02 | 1.9 ± 0.03 | 1.30 | 0.02 | |
| Pathak_2012 | Rozri 1 | 2010 | 3 | 0.5 ±0.02 | 1.8 ± 0.02 | 1.30 | 0.01 | |
| Pathak_2012 | Rozri 3 | 2009 | 3 | 0.33 ± 0.02 | 1.3 ± 0.05 | 0.97 | 0.03 | |
| Pathak_2012 | Rozri 3 | 2010 | 3 | 0.5 ±0.02 | 1.5 ± 0.03 | 1.00 | 0.02 | |
| Pathak_2012 | Rozri 3 | 2010 | 3 | 0.4 ±0.02 | 1.6 ± 0.02 | 1.20 | 0.01 | |

**Table 21: Model Validation for PC 1 group (T-D) and PMU calculation**

| Reference | Study Area Punjab | Comments | Year | Measured Practice Change [PC] Emissions (μ PC Emissions) | | Emission Reductions from Practice Change (μ Baseline Emissions - μ PC Emissions) | | | PMU |
|---|---|---|---|---|---|---|---|---|---|
| | | | | n | Combined PC ($CH_4$+$N_2O$) Emissions ± SD | Combined Baseline ($CH_4$+$N_2O$) Emissions ± SD | (μBaseline-μPractice) | SE_difference | |
| Pathak_2012 | Rozri 1 | Rozri 1 vs Rozri 2 | 2009 | 3 | 0.33 ± 0.05 | 1.48 ± 0.09 | 1.143 | 0.06 | 0.042 |
| Pathak_2012 | Rozri 1 | Rozri 1 vs Rozri 2 | 2010 | 3 | 0.7 ± 0.03 | 2.01 ± 0.06 | 1.308 | 0.04 | |
| Pathak_2012 | Rozri 1 | Rozri 1 vs Rozri 4 | 2010 | 3 | 0.7 ± 0.03 | 2.05 ± 0.04 | 1.347 | 0.03 | |
| Pathak_2012 | Rozri 3 | Rozri 3 vs Rozri 2 | 2009 | 3 | 0.33 ± 0.03 | 1.48 ± 0.09 | 1.146 | 0.05 | |
| Pathak_2012 | Rozri 3 | Rozri 3 vs Rozri 2 | 2010 | 3 | 0.65 ± 0.03 | 2.01 ± 0.06 | 1.358 | 0.04 | |
| Pathak_2012 | Rozri 3 | Rozri 3 vs Rozri 4 | 2010 | 3 | 0.65 ± 0.03 | 2.05 ± 0.04 | 1.397 | 0.03 | |

**Table 22: Model Validation for PC 2 group (TC-TZ) and PMU calculation**

| References | Comments | Year | μa_SOC_PC (t $CO_2$ eq/ha) | σa_SD (t/ha) | n | μb_SOC_Baseline (t $CO_2$ eq/ha) | σa_SD (t/ha) | Measured effect of Practice change- SOC sequestered (t $CO_2$ e/ha) | PMU |
|---|---|---|---|---|---|---|---|---|---|
| NATH_2017 | W_ZT | 2013-2015 | 12.20 | 0.73 | 3 | 11.40 | 0.71 | 0.8 ± 0.59 | 1.293 |
| NATH_2017* | W_ZT+R | 2013-2015 | 12.50 | 0.73 | 3 | 11.60 | 0.71 | 0.9 ± 0.59 | |
| JAT_2019 | R-W_ZT+R | 2009-2013 | 17.60 | 5.02 | 3 | 16.20 | 0.71 | 1.4 ± 2.93 | |
| JAT_2019* | R-W_ZT+R | 2009-2013 | 22.79 | 2.77 | 3 | 16.20 | 0.71 | 6.59 ± 1.65 | |
| BHATTACHARYYA_2015 | R-W_ZT | 2011-2013 | 11.18 | 0.73 | 3 | 11.33 | 0.71 | -0.15 ± 0.59 | |
| BHATTACHARYYA_2015 | R-W_ZT | 2011-2013 | 11.30 | 0.73 | 3 | 11.33 | 0.71 | -0.03 ± 0.59 | |
| NATH_2017 | Yr 1 PC Versus Yr 2 Baseline | 2013-2015 | 12.20 | 0.73 | 3 | 11.60 | 0.71 | 0.6 ± 0.59 | |
| NATH_2017* | Yr 2 PC Versus Yr 1 Baseline | 2013-2015 | 12.50 | 0.73 | 3 | 11.40 | 0.71 | 1.1 ± 0.59 | |

## 6d. Bias coverage by category

Bias was also calculated within the PC groups and model validity was evaluated. A model is considered valid, when Bias value is lesser than PMU, meaning that when real time measurements are simulated, model error (bias) should always be lesser than measurement uncertainties. This will ensure that real measurements are correctly represented in the model to lead to meaningful predictions. Results showed that Bias value in this validation dataset was lower than its PMU in both the practice group PC1 and PC 2. Therefore this dataset can be applied for quantifying the sampled fields as well as for larger dataset of farmers adopting this practice (Table 23 and 24).

Practice Change 1

**Table 23: Model Validation for PC 1 group (T-D) and bias calculation the project area**

| | | | Combined Baseline Emissions ($CH_4+N_2O$) | Combined PC Emissions ($CH_4+N_2O$) | Rozri 1_Modeled_Practice Change effect on emissions | Rozri 1_ Measured_Practice Change effect on emissions | Bias | Mean Bias |
|---|---|---|---|---|---|---|---|---|
| **Reference** | **Year*** | **Study area** | **($\mu_{a+b}$)** | **($\mu_{a+b}$)** | **Modeled Baseline-Modeled PC ($t\ CO_2\ eq\ /ha$)** | | **Bias = Modeled-Measured Ers** | |
| Pathak_2012 | 2009 | Rozri 1 vs Rozri 2 | 1.539 | 0.440 | 1.089 | 1.14 | -0.023 | **-0.009** |
| Pathak_2012 | 2010 | Rozri 1 vs Rozri 2 | 1.653 | 0.311 | 1.342 | 1.30 | | |
| Pathak_2012 | 2010 | Rozri 1 vs Rozri 4 | 1.610 | 0.311 | 1.299 | 1.34 | | |
| Pathak_2012 | 2009 | Rozri 3 vs Rozri 2 | 1.539 | 0.300 | 1.226 | 1.14 | 0.042 | |
| Pathak_2012 | 2010 | Rozri 3 vs Rozri 2 | 1.653 | 0.231 | 1.421 | 1.35 | | |
| Pathak_2012 | 2010 | Rozri 3 vs Rozri 4 | 1.610 | 0.231 | 1.379 | 1.39 | | |

**Bias= 0.009 < PMU =0.042**

*In 2009, only one TPR site (Rozri-2) was available, so both DSR sites (Rozri-1 and Rozri-3) were compared to Rozri-2. In 2010, a second TPR site (Rozri-4) was added, so each DSR site (Rozri-1 and Rozri-3) was compared to both TPR sites (Rozri-2 and Rozri-4), creating two independent matchupsPractice Change 2

**Table 24: Model Validation for PC 2 group (TC-TZ) and bias calculation**

| | | Modeled effect of practice change on SOC | | | Measured Practice Change effect on SOC | Bias | Mean Bias |
|---|---|---|---|---|---|---|---|
| Reference | Year | Modelled_ Baseline SOC (t $CO_2$ eq /ha) | Modelled_ PC SOC (t $CO_2$ eq /ha) | Modeled PC - Modeled Baseline (t $CO_2$ eq /ha) | Measured PC- Measured Baseline (t $CO_2$ eq /ha) | Bias = Modeled- Measured SOC | |
| **NATH_2017** | 2013-2015 | 9.88 | 9.34 | -0.540 | 0.800 | -0.835 | **0.290** |
| **NATH_2017*** | 2013-2015 | 11.27 | 11.84 | 0.570 | 0.900 | | |
| **JAT_2019** | 2009-2013 | 9.04 | 13.19 | 4.150 | 1.400 | 2.135 | |
| **JAT_2019*** | 2009-2013 | 9.04 | 17.15 | 8.110 | 6.590 | | |
| **BHATTACHARYYA_2015** | 2011-2013 | 10.42 | 11.09 | 0.670 | -0.150 | 0.695 | |
| **BHATTACHARYYA_2015** | 2011-2013 | 10.42 | 10.96 | 0.540 | -0.030 | | |
| **NATH_2017** | 2013-2015 | 11.27 | 9.34 | -1.930 | 0.600 | -0.835 | |
| **NATH_2017*** | 2013-2015 | 9.88 | 11.84 | 1.960 | 1.100 | | |

**Bias = 0.290 < PMU = 1.293**

Bias is reported once per study (first row). It is the average of the experiment-level biases within that study, per VM0053 v1.

## 6e. Scatter plots for the Model validation datasets

Practice Change 1

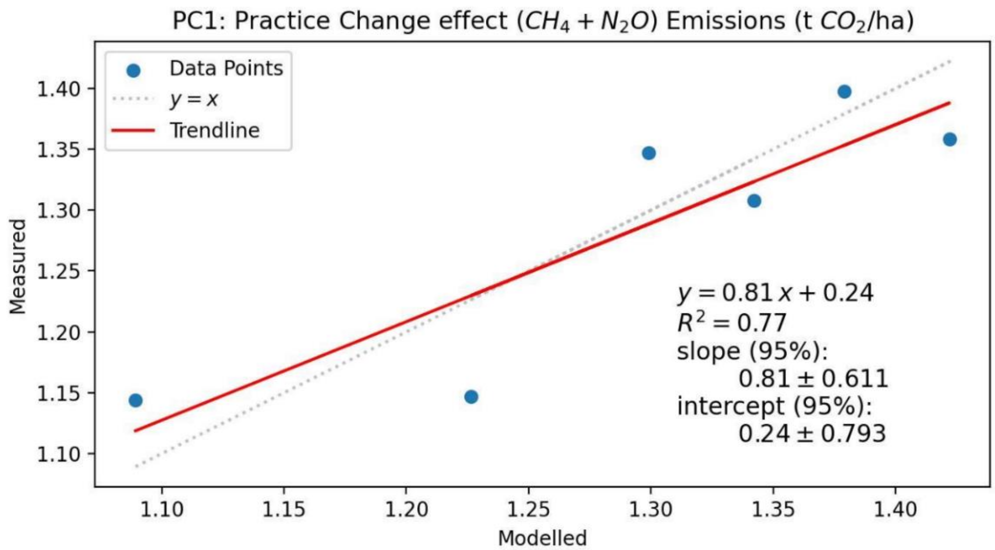



**Figure 6: Scatterplot for model predictions versus measured CH4+N2O emissions in Practice change (PC) group 1 (validation dataset)**

Practice Change 2

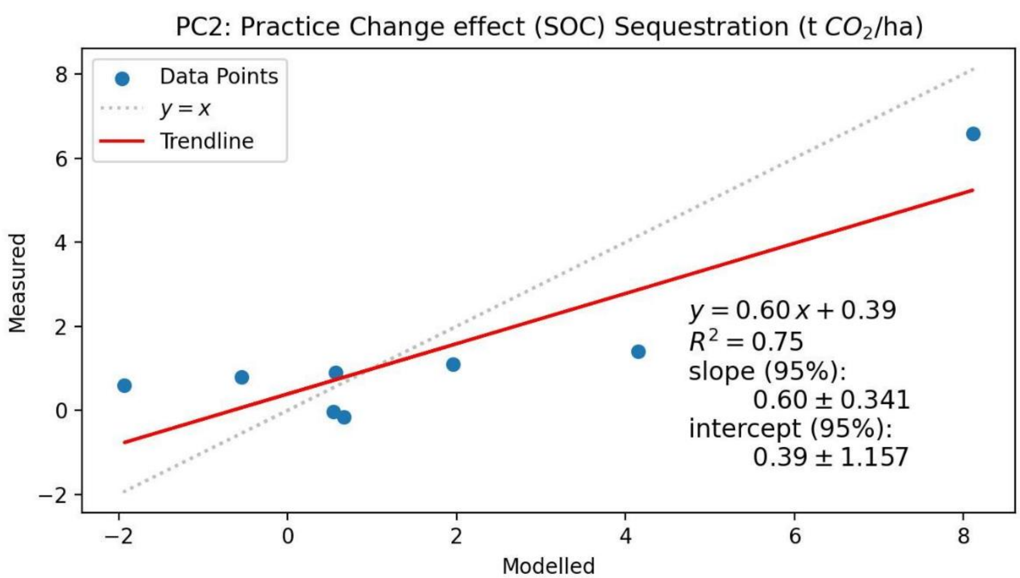



**Figure 7: Scatterplot for Model predictions versus measured SOC in Practice change (PC) group 2 (validation dataset)**

### 6f. Residuals

Histograms of the residuals for the measured and modelled data from validation dataset for each practice change group/emission source are provided in this section (Figures 8 10) as per the requirement of VMD0053 (Box 5). We have also provided additional plots (Figures 9 and 11) for illustrating the measured and modelled practice change effect (i.e., baseline – practice emissions or SOC). The plots in all the PC groups clearly indicate that the modelled emissions are in close agreement with measured emissions and thus reinforce the applicability of the model to quantify GHG emissions in this project.

We would like to highlight that the residuals for PC1 are smaller compared to PC2 by about an order of magnitude. To highlight this, we have generated histograms on free (separate) scales (Figures 8 and 10), fixed scales (Figures 12) and a combined histogram for two practice groups (). Also, please note that these histograms are being generated for less than ten available studies for each of the practice changes reported.

Practice Change Group 1

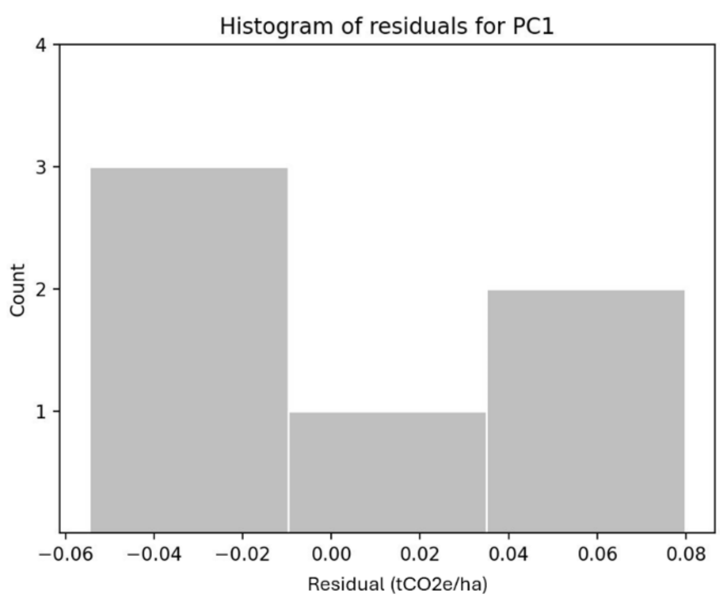



**Figure 8: Histogram of residuals for the validation dataset of PC1 group**

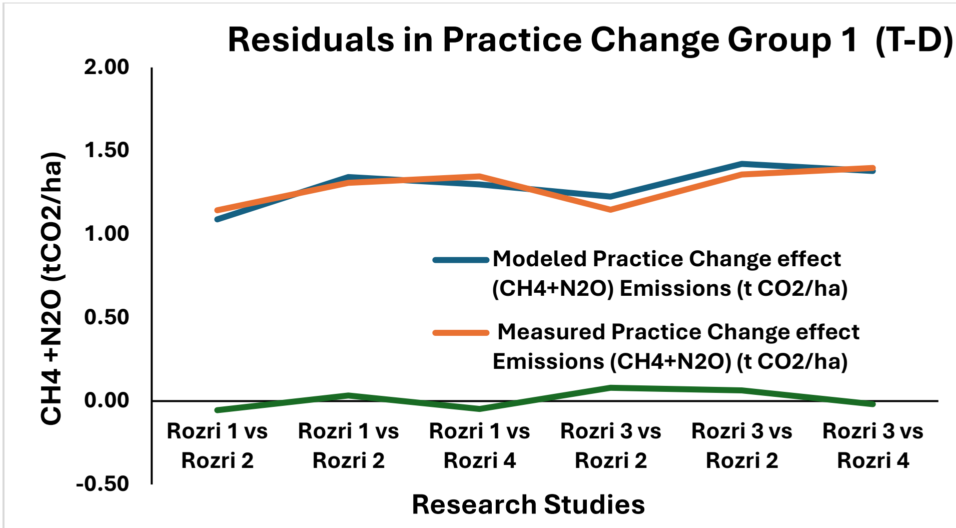



**Figure 9: Measured and Modelled practice change effect and Residuals in PC 1**

## Practice Change Group 2

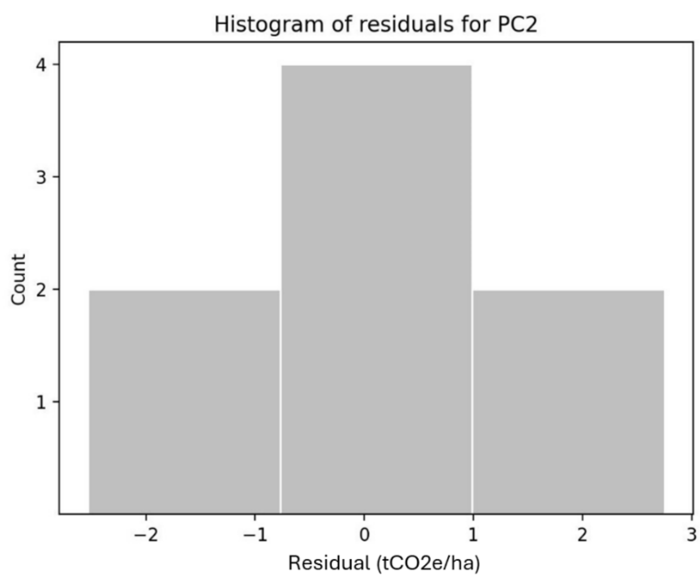



**Figure 10: Histogram of residuals for the validation dataset of PC2 group**

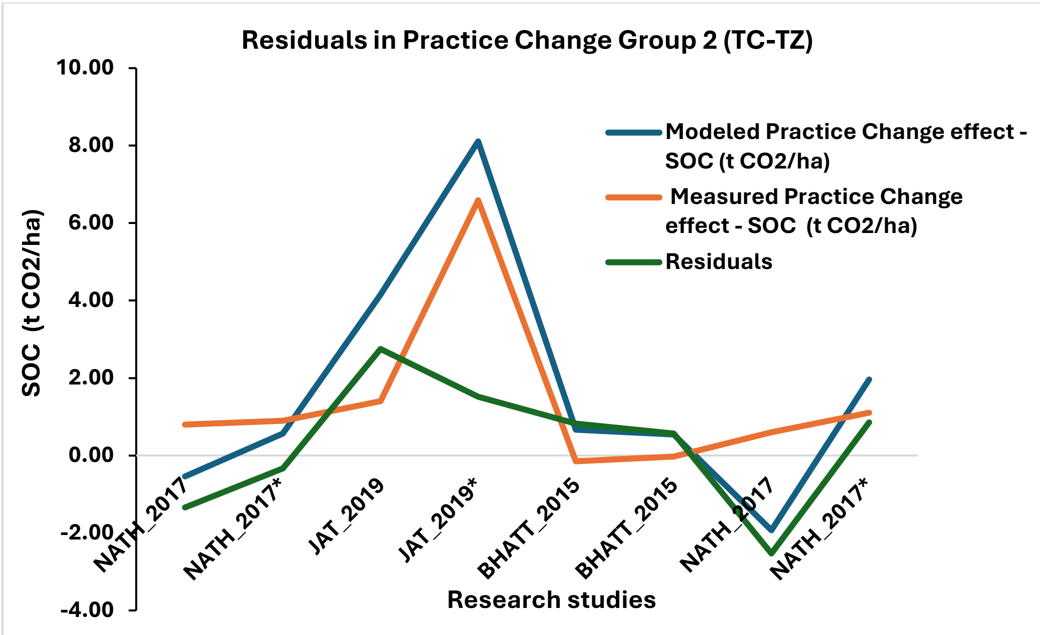



**Figure 11: Measured and Modelled practice change effect and Residuals in PC 2**

## 7. Model prediction error across PC groups (Validation dataset)

The model prediction errors are calculated as prescribed in VM0042, using equation 47 (please refer 05_Uncertainty_calculations_Including_spatial_error) (Table 25). First, a Correlation coefficient is calculated using the residuals from modelled and measured data in, both, baseline and practice change data. Subsequent values were then accounted in calculating the "standard error" in emission reduction (due to the model error). This was done for all emission sources, CH4, N2O (PC1) and SOC (PC2). The standard error generated was subsequently accounted in calculating "combined sample and model error" and then in estimating "uncertainty" in each of the PC groups. As a result, the model error and the correlation coefficient (Equation 47, VM0042) have both increased uncertainty deduction in the PC1 groups. There was an opposite effect on PC2, on account of better correlation between modelled and observed results. Revised calculations have effectively met the bias requirement and the model error requirement that 90% of measurements fell within the 90% prediction interval.

Sampling error resulting from measuring/modelling only a portion of the project area. Estimates of sampling error are contingent on the sampling design employed by the project proponent. Measurement error of model inputs including initial SOC content, bulk density, soil texture and management data, were calculated. The impact of these measurement errors on the error of emission reductions and removal (ERR) estimates is captured in model prediction error and/or sampling error) across each PC group and across project years (2019-2021).

## 7a. Combined sample and model error

To incorporate model errors, we assume that they are uncorrelated with the measurements in the sample, and we assume that model errors are independent across samples. Then by using equation no 51, VM0042, [Cochran (1977), eq. 13.39; Som (1995), eq. 25.10], the variance of $\Delta \bullet t$ incorporating sample uncertainty, lab measurement uncertainty, and model prediction uncertainty is:

**Equation 51- VM0042**

$$S^2_{\Delta=t} = S^2_{sample\ \&\ means,\Delta\bullet t} + \frac{S^2_{struct,\Delta\bullet,t}}{n \times m}$$

$$S^2_{\Delta=t} = Variance\ of\ the\ estimate\ of\ \Delta \bullet t.$$

$$(\Delta \bullet t = mean\ emission\ reductions\ from\ gas\ and\ pool \bullet at\ time\ t);\ (t\ CO2e/unit\ area)2$$

$S^2_{sample\ \&\ means,\Delta * t} =$ (Approximate) standard error in Δ• (Δ• = emission reductions in gas and pool •) due to sample error at time t; t $CO_2$e/unit area

$S^2_{struct,,\Delta * t}$ =(Approximate) standard error in Δ• (Δ• = emission reductions in gas and pool •) due to model prediction error at time t; t $CO_2$e/unit area

n = Number of primary sampling units (here, fields) selected to be sampled

m = Number of secondary sampling units (here, tiles) selected to be sampled within primary sampling units (here, fields)

**Table 25: Model errors across all practice groups in the validation dataset**

| | PC1 | PC2 |
|---|---|---|
| Model error for the validation dataset | 0.1 | 1.7 |

## 8. Prediction interval plots of measured versus modelled results (Validation dataset)

Prediction interval plots for the modelled and measured datasets are presented below. The data/plots indicated that the observed values fall inside the model's 90% prediction intervals (CH4+N2O) for the PC 1 (Table 26, Figure 13) and (SOC) PC 2 (Table 27, Figure 14) groups. Prediction interval plots were computed as per the guidelines provided in VMD0053, 5.2.5, page 29 using the following formulae.

**Table 26: PC1- Measured Vs Modelled Practice change effects on CH4 + N2O emissions**

| PC1 (T-D) Plot for PC effect on CH4 + N2O Emission Reduction (tCO2 e/ha) | | Modelled PC effect on Emission Reduction (CH4+N2O) | Measured Practice Change Effect on Emission Reduction (CH4+N2O) | | Model error |
|---|---|---|---|---|---|
| **Reference** | **Study** | **Baseline-PC** | **Baseline-PC** | **Model-Measured** | |
| **Pathak_2012** | 1 | 1.09 | 1.14 | -0.05 | 0.1 |
| **Pathak_2012** | 2 | 1.34 | 1.31 | 0.03 | |
| **Pathak_2012** | 3 | 1.30 | 1.35 | -0.05 | |
| **Pathak_2012** | 4 | 1.23 | 1.15 | 0.08 | |
| **Pathak_2012** | 5 | 1.42 | 1.36 | 0.06 | |
| **Pathak_2012** | 6 | 1.38 | 1.40 | -0.02 | |

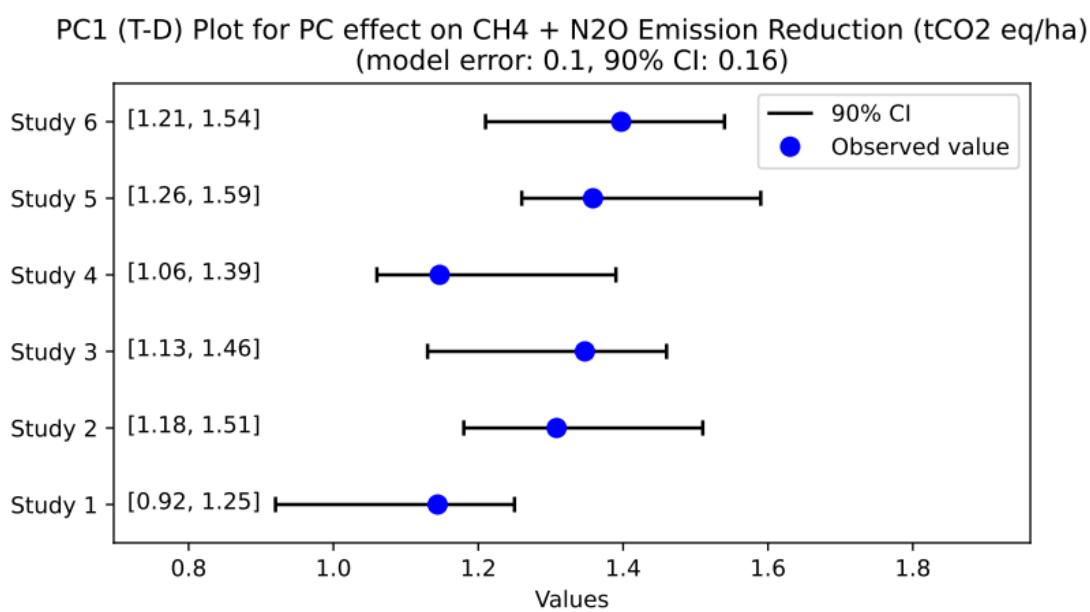



**Figure 12: Prediction interval plot for PC1 validation data**

**Table 27: PC2 - Measured Vs Modelled Practice change effects on SOC Sequestration**

| PC2 (TC-TZ) Plot for PC effect on SOC Sequestration (tCO2 e/ha) | | Modelled PC effect on SOC | Measured Practice Change Effect on SOC | | Model error |
|---|---|---|---|---|---|
| **Reference** | **Study** | **Baseline-PC** | **Baseline-PC** | **Model-Measured** | |
| **NATH_2017** | 1 | -0.54 | 0.80 | -1.34 | 1.7 |
| **NATH_2017*** | 2 | 0.57 | 0.90 | -0.33 | |
| **JAT_2019** | 3 | 4.15 | 1.40 | 2.75 | |
| **JAT_2019*** | 4 | 8.11 | 6.59 | 1.52 | |
| **BHATTACHARYYA_2015** | 5 | 0.67 | -0.15 | 0.82 | |
| **BHATTACHARYYA_2015** | 6 | 0.54 | -0.03 | 0.57 | |
| **NATH_2017** | 7 | -1.93 | 0.60 | -2.53 | |
| **NATH_2017*** | 8 | 1.96 | 1.10 | 0.86 | |

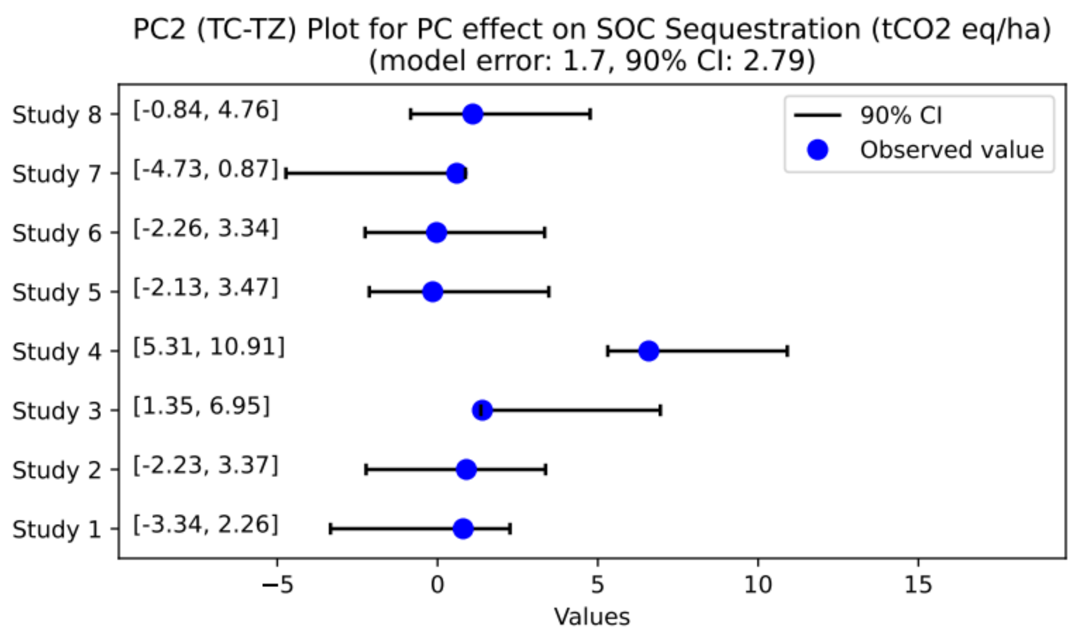



**Figure 13: Prediction interval plot for PC2 validation data**

## 9. Quantification of sampled fields from project area

*This section has been revised based on the reviews and comments by Verra to use 0-30 cm SOC stock in the model input.*

The quantification analysis was carried out using the DNDC95 biogeochemical model. The model was executed separately for each soil-sampled rice–wheat field within the project area to estimate GHG emissions and SOC sequestration. The quantification procedure followed a series of steps aligned with the model input requirements and the guidelines outlined in VM0042 v1.

Our first monitoring period spans three years. Therefore, we first assigned each field-year a provisional PC. This is the initial category inferred directly from field records/monitoring for that year (PC0, PC1, PC2, or PC3). We then converted provisional PCs to final PCs using our rules for practice continuity checks, stacked-practice (PC3) handling. Detailed PC categorization logic is provided as supplementary information (07_PC_Assignment_logic). This two-step (provisional→final) process keeps categories mutually exclusive, prevents double counting, and ensures only well-supported, conservative cases are credited.

## 9a. Soil sample collection

Soil sample collection in the project area was performed using stratified random sampling method. Within the project area (Haryana and Punjab), the Rice-Wheat-Maize cropping system is prominent with a large number of enrolled farmers geographically scattered, and thus stratified random sampling was adopted to best represent the entire project area. Soil samples collected from our project area fall into one agro-ecological zone (number Z-4.1) and agro-climatic zone (number 6) (Ahmad et al., 2017, Gajbhiye and Mandal 2000).

This zone is also called as ‘Trans Gangetic Plain’ and has been historically reported (references above) to represent homogeneity with respect to climate, crop growing periods and soil textures, which covers all features of abiotic crop environment (that can influence soil GHG emissions). Furthermore, the soil samples collected from our project geographies encompass 4 major soil types, viz, Haplic Yermosols, Calcic Xerosols, Orthic Luvisols and Cambic Arenosols (Figure 14). We have covered 3 predominant soil types since 98.01% of our enrolled farms (3819 of total 3897) are present in these three soils (Haplic Yermosols, Calcic Xerosols and Orthic Luvisols) (Figure 16).

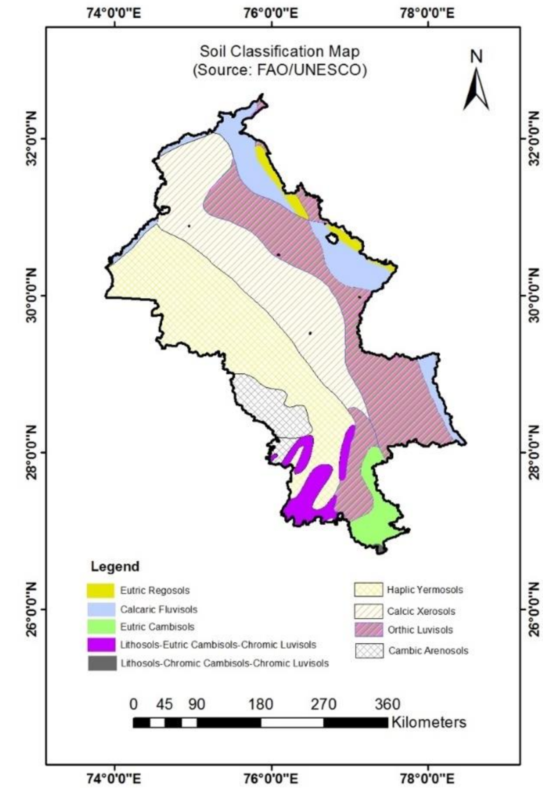



**Figure 14: Soil Map of the project boundary**

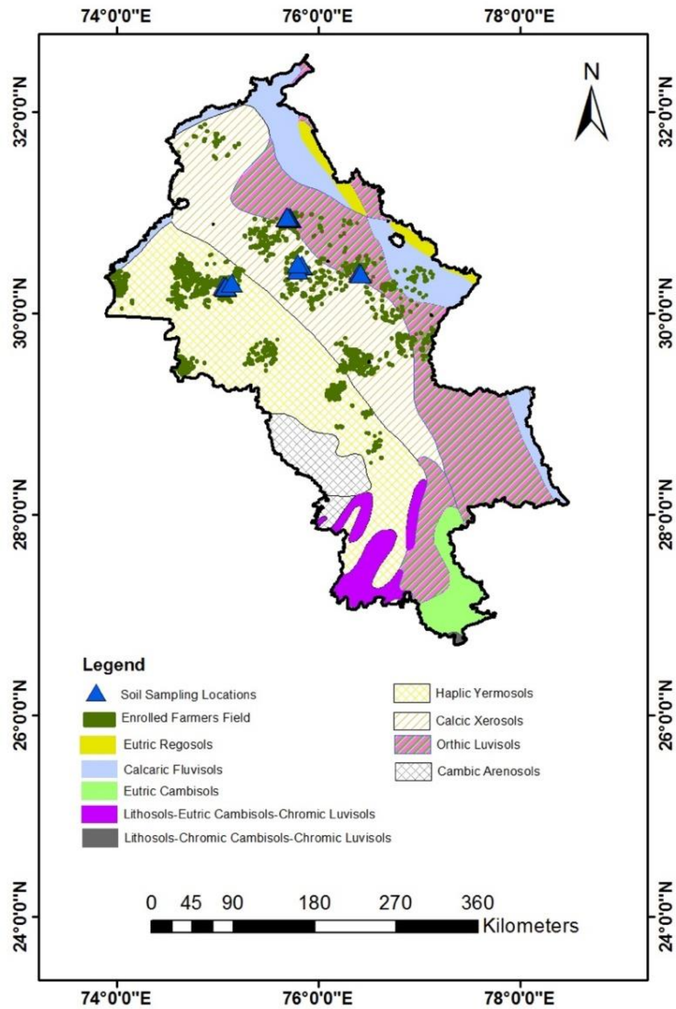



**Figure 15: Soil Map showing enrolled farmers' fields and the soil sampling area along with project boundary covering predominant soil types**

## 9b. Sample Size

We needed to estimate the desired sample size for our study. According to the VM0042, equation 46, we selected the desired confidence level as 95% and a 5% margin of error. In order to estimate the desired sample size, we also needed an estimate of the variance for emission reduction value from the practices. Equation 46 gives an allowance of 15% in the final uncertainty. We used this as the baseline value to compute the desired sample size for our soil sample collection study as follows:

*Sample size = (z * stdev / ME)^2*

*where:*

*z = 1.96 (critical score for 95% confidence level)*

*stdev = 0.15 (i.e. baseline 15% allowed in equation 46)*

*ME = 0.05 (i.e. 5% as expected in equation 46)*

*This results in:*

*Sample size = (1.96 * 0.15 / 0.05)^2 = 35 samples*

Given that sampling is a resource intensive, time sensitive and time-consuming process, we wanted to be conservative. We collected 50 samples (about 143% of desired size) during the year 2021 covering an area of 50 acres from the project area and the samples were sent for laboratory analyses for characterization of soil chemistry.

Out of 50 samples, the PC-wise and year-wise distribution of usable samples is provided in Table 28. Note that 16 samples were from fields with no practice changes, 4 fields were research sites, 1 field exited the program. Therefore, Table 28 has 29 fields in the PC-by-year matrix.

Table 28: PC-wise and year-wise distribution of soil sampled fields

| Practice Categories | 2019 | 2020 | 2021 |
|---|---|---|---|
| **PC0** | 7 | 0 | 0 |
| **PC1** | 3 | 7 | 7 |
| **PC2** | 19 | 22 | 22 |

## 9c. DNDC Model Inputs and Configuration Aligned with VM0042 Compliance

The DNDC model requires the input parameter “SOC content (0–10 cm) in kg C kg$^{-1}$ soil,” whereas VM0042 v1 specifies that SOC data must represent the 0–30 cm soil depth. In the project, soil samples were collected from two depth intervals: 0–15 cm and 15–30 cm, and SOC content along with bulk density (BD) were measured for each layer. Therefore, to ensure alignment with VM0042 v1 within the DNDC model framework, we followed the procedure outlined below.

### Soil Carbon Stock Calculation

SOC data were aggregated into a single representative 0–30 cm value using a weighted average approach, where each layer’s SOC value was weighted according to its depth interval using the following approach:

I. Individual depth interval stocks were calculated as: SOC stock = SOC% × BD × depth thickness
i. Total 0-30 cm stock was obtained by summing the stocks from both intervals

ii. Average bulk density for the 0-30 cm layer was calculated as the arithmetic mean of BD of the two depth intervals

The representative SOC concentration for the 0-30 cm layer was derived by dividing the total stock by the average bulk density and depth (30 cm)

**Soil Profile Depth Settings in DNDC**

To align DNDC with VM0042 v1, the “Depth of top-soil with uniform SOC content” was set to 30cm, ensuring SOC data reflects the actively managed layer. We set the vertical depth-decay exponent to 2 (DNDC default). This parameter only affects SOC simulated below 30 cm (e.g., 30–50 cm). Because crediting uses only 0–30 cm SOC, this choice has no impact on credited results.

**Back-Modelling for SOC analysis**

To initiate the quantification of sampled fields, a simulation file was developed comprising three years of historical data representing the baseline scenario (2016-2018), followed by three years of data reflecting the project scenario (2019-2021). This file serves as the basis for project quantification.

Since soil samples were collected in 2021 and the project commenced in 2019, a back-modelling approach was employed to establish accurate initial conditions. Back-modeling was conductedby iteratively adjusting the baseline SOC stock from 2016 under project conditions until the simulated SOC stock for 2021 aligned with the measured field values. We used manual tuning of the initial SOC using the following procedure:

i) set the initial condition (IC; input SOC in our case) to the measured 0–30 cm SOC;
ii) run DNDC, compared the model's 0–30 cm SOC output to the measured value;
iii) adjust the IC up or down using a simple difference rule (if model < measured, increase IC; if model > measured, decrease IC).
iv) Repeat this until the error (between modelled and measured SOC, 0-30cm stock) is <1%.

This method ensures the model reflects site-specific dynamics and captures the cumulative impact of management practices applied before the measurement year.

**Modeling of annual SOC Stock and GHG Emission**

For quantification, two DNDC model files were developed—one representing the baseline scenario and the other the project scenario—covering a total simulation period of seven years. Modeling was conducted at a fixed soil depth of 0–30 cm using measured SOC data.

Annual estimates of $CH_4$, $N_2O$ emissions, and SOC stock were generated year-by-year for both scenarios.

The DNDC simulation outputs provided detailed annual SOC stock and GHG emission values for each scenario. Based on these results, annual emission reduction and removal factors (expressed in $tCO_2e/ha$) were calculated using Equation [34,39,44] from the VM0042 methodology. These factors quantify the net difference in $CH_4$, $N_2O$ emissions and SOC stock between the baseline and project scenarios, enabling robust assessment of climate benefits.

# 10. Uncertainty Analyses

## 10a. Theoretical Background

Model uncertainty of the GHG emissions and SOC between the practice changes and the baseline category was estimated according to VMD0053, section 5.2.5 . Uncertainty deductions have been estimated separately for each GHG source within the project. Deductions are based on an estimate of the total error of the project's calculated GHG emission reductions or removals for that source over a given verification period.

Structural uncertainty was quantified by comparing modelled gas fluxes with empirical gas fluxes. The structural uncertainty around the size of the emission reductions of a project that combines multiple individual rice fields will decrease with increasing number of individual rice fields included. In our current project, we conducted uncertainty assessments by an initial classification of validation dataset into two practice change categories (PC1 and PC2). This classification was further applied to the sample fields data and also to the larger dataset of enrolled farmer's fields.

## 10b. Uncertainty calculations flow chart

We have calculated uncertainty deduction as per the equations guideline in VM0042. The prerequisite parameters for calculating uncertainty deduction can be obtained from equations 47, 49, 50, and 51. The flow of equations is depicted in Figure 17.

Uncertainty deduction equation 46 requires that we calculate standard error of the emission reductions including the model prediction error at time t using equation 47 to 51. Figure 17 gives a summary of these calculations, and here is a brief summary of the flow. Areal average of emission reductions can be calculated from equation 49 while standard error of sample and measurement can be calculated using equation 50. Subsequently, we calculate variance of the sample and measurement errors of emission reductions using equation 51. To compute this variance, we used Equation 47 to compute approximate standard error for emission reductions (for each emission source) due to model prediction error at time t.

Finally, we can calculate uncertainty deduction from equation 46 for all the sample fields quantified using the DNDC model.

**Equation 47**

$$s_{\text{struct},\Delta\bullet,t} = s_{\bullet}\sqrt{2(1-\rho_{\bullet})}$$

**Equation 49**

$$\overline{\Delta\bullet_t} = \frac{1}{n}\sum_{i=1}^{n}\overline{\Delta\bullet_{i,t}} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i}\sum_{k=1}^{m_i}\Delta\bullet_{i,k,t}$$

**Equation 50**

$$s^2_{\text{sample \& meas.},\Delta\bullet,t} = \frac{\sum_{i=1}^{n}\left(\overline{\Delta\bullet_{i,t}}-\overline{\Delta\bullet_t}\right)^2}{n(n-1)}$$

**Equation 51**

$$s^2_{\Delta\bullet,t} = s^2_{\text{sample \& meas.},\Delta\bullet,t} + \frac{s^2_{\text{struct},\Delta\bullet,t}}{n \times m}$$

Total uncertainty deduction, *UNC$_t$*, is quantified as:

**Equation 46**

$$UNC_t = MIN\left(100\%, MAX\left(0, \frac{T\sqrt{\sum_{\bullet} s^2_{\Delta\bullet,t}}}{\overline{\Delta CO2_t} + \overline{\Delta CH4_t} + \overline{\Delta N2O_t}} - 15\%\right)\right)$$

**Figure 16: Flow-chart of equations for calculating model uncertainty deduction for sampled fields**

In Equation 46, VM0042

$$\boldsymbol{UNC_t = MIN\left(100\%, MAX\left(0, \frac{T\sqrt{\sum\bullet\, s^2_{\Delta\bullet,t}}}{\overline{\Delta CO_{2_t}} + \overline{\Delta CH_{4_t}} + \overline{\Delta N_2O_t}} - 15\%\right)\right)}$$

| | |
|---|---|
| $UNC_t$ | Uncertainty deduction in year t (expressed as the extent to which the half width of the 95% confidence interval, as a percentage of the mean, exceeds the threshold of 15%); unitless number between 0 and 1 |
| $\sum =$ | Sum over pools and gases $CO_2$_soil, CTREE, CSHRUB, 24 $CH_4$_SOC, $CH_4$_ent, $CH_4$_md, and $N_2O$_soil, where Quantification Approaches 1 or 2 were employed. |

$S^2_{\Delta \bullet t}$ Variance of the estimate of $\Delta \bullet t$. ($\Delta \bullet t$ = mean emission reductions from gas and pool • at time t) (see); (t $CO_2$e/unit area)2

$\overline{\Delta CO_2}_t$ Areal average carbon dioxide emission reductions in year t; t $CO_2$e/unit are

$\overline{\Delta CH_4}_t$ Areal average methane emission reductions in year t; t $CO_2$e/unit area

$\Delta \overline{N_2O}_t$ Areal average nitrous oxide emission reductions in year t; t $CO_2$e/unit area

T Critical value of a student's t-distribution for significance level $\alpha$ = 0.05 (i.e., a 1 − $\alpha$ = 95% confidence interval) and the degrees of freedom $df$ appropriate for the design used (e.g., df = $n$ − 1 for a simple random sample of $n$ sample units)

15% Threshold beyond which there is an uncertainty deduction

• Gas or pool

## 10c. Correction for Spatial Autocorrelation

Physical proximity of sample locations may result in dependence among observations, as a result residuals of these sampling points are not independent. This phenomenon is known as spatial autocorrelation, and needs to be corrected for (Bivand et al, 2013). Moran's I test was used to statistically ascertain residual spatial autocorrelation (Bivand et al, 2015). We calculated the effective sample size ($n_{eff}$) using the formula (Grace, 2019):

$$n_{eff} = n \cdot \frac{1 - |Moran's\ I|}{1 + |Moran's\ I|}$$

where the n is the original sample size which is being corrected for spatial autocorrelation using the absolute value of Moran's I statistic estimate. For the analysis we used the scipy library in python. We used four nearest neighbours (k=4) to assess the spatial autocorrelation among sample sites (Grace, 2019). For PC 2019 we had only 3 samples, so we had to use two nearest neighbours (k=2) for this specific case. We used 2000 permutations for computing significance None of the six cases showed significant spatial autocorrelation. Effective sample size were computed using the approach mentioned above (Table 29).

**Table 29: PC group wise uncertainty deduction and adjustment of number of sample fields**

| PC | k | Moran_I | permutations | p_sim | n | n_adj_inter | n_adj |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **PC1 2019** | 2 | -0.500 | 2000 | 0.31 | 3 | 1 | 3 |
| **PC1 2020** | 4 | -0.064 | 2000 | 0.24 | 7 | 6 | 7 |
| **PC1 2021** | 4 | -0.064 | 2000 | 0.24 | 7 | 6 | 7 |
| **PC2 2019** | 4 | -0.004 | 2000 | 0.60 | 19 | 19 | 19 |
| **PC2 2020** | 4 | 0.010 | 2000 | 0.57 | 22 | 22 | 22 |
| **PC2 2021** | 4 | 0.010 | 2000 | 0.57 | 22 | 22 | 22 |

There is another less conservative version of this formula (Cahoon et al, 2019) which was not used:

$$n_{eff} = n \cdot \frac{1}{1 + |Moran's\ I|}$$

We used the more conservative approach as per Verra's guidelines. Another reason for taking the conservative approach is our relatively smaller sample size, which was partly out of our control, due to Covid-19 related traveling restrictions in place during this first round of sampling (2020-21).

## 11. ERR and Uncertainty deduction results across PC groups

In this section, the no. shown as uncertainty, is the uncertainty deduction (%). This is the percentage reduction applied to that year's ERR when the calculated uncertainty exceeds 15% (as per VM0042 v1). If the deduction is shown as 0, it means the uncertainty was ≤15% and no deduction applies.

In this project, uncertainty deduction penalty in each year and across each PC group is shown in Table 30. In PC1, sampling increased from 3 fields in 2019 to 7 fields in 2020 and 2021, with uncertainty deduction dropping from 26.81% to 0.00% thereafter, indicating markedly tighter estimates once coverage improved. In contrast, PC2 maintained a larger sample size of 19–22 fields but exhibited rising uncertainty deduction from 1.79% in 2019 to 12.79% in 2020 and 15.59% in 2021, suggesting greater spatial heterogeneity within that stratum despite consistent sampling intensity. Spatial autocorrelation did not necessitate any field removals, as the number of fields "adjusted after spatial error" matches the initial sampled fields for every year and PC group, and the uncertainty deduction values before and after spatial autocorrelation are identical throughout the dataset.

The analysis shows distinct trajectories for PC1 and PC2 across 2019–2021 in terms of reductions, removals, and uncertainty deduction. For PC1, total mitigation is entirely from reductions, yielding identical average ERRs in each year. For PC2, mitigation is exclusively from removals, with increasing uncertainty deduction from 1.79% to 15.59%. PC1 shows a modest decline from 2.92 to 2.79 tCO2e/ha/yr, while PC2 drops more sharply from 3.03 to 1.71 tCO2e/ha/yr in average ERRs across the same period.

**Table 30a: Baseline SOC stocks and emissions (tCO2e/ha)**

| Year | SOC stock at end of year (tCO2e/ha) | Emissions (tCO2e/ha/ year) |
|---|---|---|
| 2019-20 | 105.50 | 3.94 |
| 2020-21 | 106.47 | 4.26 |
| 2021-22 | 107.90 | 4.28 |

**Table 30b: PC1 SOC stocks and emissions (tCO2e/ha)**

| Year | SOC stock at end of year (tCO2e/ha) | Emissions (tCO2e/ha/ year) |
|---|---|---|
| 2019-20 | 105.50 | 1.02 |
| 2020-21 | 106.47 | 1.39 |
| 2021-22 | 107.90 | 1.49 |

**Table 30c: PC2 SOC stocks and emissions (tCO2e/ha)**

| Year | SOC stock at end of year (tCO2e/ha) | Emissions (tCO2e/ha/ year) |
|---|---|---|
| 2019-20 | 108.53 | 3.94 |
| 2020-21 | 108.57 | 4.26 |
| 2021-22 | 109.61 | 4.28 |

**Table 30d: Emission reductions, removals and uncertainty deductions across PC groups**

| Year | PC group | Emission reductions (tCO2e/ha) | Removals (SOC stock increase, tCO2e/ha) | Uncertainty deductions (%) after accounting for spatial error |
|---|---|---|---|---|
| **2019-20** | PC1 | 2.92 | 0 | 26.81 |
| **2020-21** | PC1 | 2.87 | 0 | 0.00 |
| **2021-22** | PC1 | 2.79 | 0 | 0.00 |
| **2019-20** | PC2 | 0 | 3.03 | 1.79 |
| **2020-21** | PC2 | 0 | 2.10 | 12.79 |
| **2021-22** | PC2 | 0 | 1.71 | 15.59 |

## 12. Procedures for missing data

For calibration and validation exercises, most of the published experiments provided sufficient detail on the experimental treatments and management including pre-experiment details. Experimental details provided in the publications, such as climate, soil, crop management data are incorporated as model inputs for carrying out the simulations. When a particular detail is missing, such as historical data on SOC, information from the literature or public sources such as National Soil Survey department (https://nbsslup.in/) was accessed and used for modelling. When no specific information was available, such as for reduced tills (number of tills considered 'reduced' by farmers) local agriculture experts/government agriculture departments were contacted for information. Documentation of validation datasets, per PC x ES combination.

During initialization process, we could not access historical measured SOC data for the years 2006-2016 consistently for the IARI site. We accessed data from publications (2005, 2012, 2013, 2016) which we further applied into the missing years. This has caused higher RMSE and lower $R^2$ with negative bias in model predictive capacity (Figure 3). In calibration section, we could not access data for maximum root, shoot and stem biomass production for all the studies in the publications. This constrained our calibration to hand-tuning of only grain yields (as grain yield data was available in all publications). Data for root, shoot and stem biomass was thus compensated by using default values generated by the model (Table 8 and Table 9).

In validation section, standard deviation values for references of Nath, 2017 and Jat 2019 were unavailable in the publications and this was highlighted in the excel sheet (20230920_PC2_PMU_Bias_ER Residual Calculations). SD values were imputed and a minimum SD value was applied for a conservative estimate of bias. As a result our model error was higher for PC2 than for PC1 (section 6, table 23). Also, we had only one or two publications for validating the regenerative (project) practice changes and the corresponding emissions/SOC changes. As a result, we had to do pairing of experiments/studies within a single publication or maximum 2-4 publications.

## 13. References

1. Aryal, JP; Bhatia, M; Jat, ML and Sidhu, HS. 2014. Impacts of Laser Land Leveling in Rice-Wheat Systems of the North-western Indo-Gangetic Plains of India. Food Security. Published online on 7th May 2015, DOI 10.1007/s12571-015-0460-y

2. Aryal, JP; Sapkota, TB; Jat, ML and Bishnoi, D. 2015. On-farm economic and environmental impact of zero-tillage wheat: a case of north-west India. Experimental Agriculture, 51: 1-16., Cambridge University Press 2014.
3. Balwinder-Singh, Shirsath, PB; Jat, ML; McDonald, AJ; Srivastava, AK; Craufurd, P; Rana, DS; Singh, AK; Chaudhari, SK; Sharma, PC; Singh, R; Jat, HS; Sidhu, HS; Gerard, B and Braun, H. 2020. Agricultural labor, COVID-19, and potential implications for food security and air quality in the breadbasket of India. Agricultural Systems, 185:102954
4. Bhattacharyya, R., Tuti, M.D., Kundu, S., Bisht, J.K., Bhatt, J.C., 2012. Conservation tillage impacts on soil aggregation and carbon pools in a sandy clay loam soil of the Indian Himalayas. Soil Sci. Soci. Am. J. 76, 617–627. https://doi.org/10.2136/ sssaj2011.0320
5. Bijarniya, D; Parihar, CM; Jat, RK; Kalvania, K; Kakraliya, SK and Jat, ML. 2020. Portfolios of Climate Smart Agriculture Practices in Smallholder Rice-Wheat System of Eastern Indo-Gangetic Plains-Crop Productivity, Resource Use Efficiency and Environmental Foot Prints. Sustainability. 10, 1561; doi:10.3390/agronomy10101561
6. Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2013). Applied Spatial Data Analysis with R.
7. Bivand, R., & Piras, G. (2015). Comparing implementations of estimation methods for spatial econometrics. *Journal of Statistical Software*, *63*, 1-36.
8. Cahoon, D. R. (2019). Hurricane Sandy impacts on coastal wetland resilience: US Geological Survey Open-File Report 2018–1142, 117 p. *Openfile report*. https://doi.org/10.3133/ofr20181142.
9. Cai, Z., T. Sawamoto, C. Li, G. Kang, J. Boonjawat, A. Mosier, R. Wassmann, and H. Tsuruta, 2003. Field validation of the DNDC model for greenhouse gas emissions in East Asian cropping systems, Global Biogeochem. Cycles, 17(4), 1107, doi:10.1029/2003GB002046. Saggar, S., R.M. Andrew, K.R. Tate, C.B. Hedley and J.A. Townsend 2003. Simulation of nitrous oxide emissions from New Zealand dairy-grazed pastures and its mitigation strategies. In Proceedings of the 3rd International Methane and Nitrous Oxide Mitigation Conference, 17-21 November, 2003 Beijing, China. pp. 461-468
10. Chakraborty, D., Ladha, JK., Rana, DS., Jat, ML., Gathala, MK; Yadav, S., Rao, AN., Ramesha, MS and Raman, A. 2017. A global analysis of alternative tillage and crop establishment practices for economically and environmentally efficient rice production. Nature Scientific Reports. 7: 9342
11. Dhyan, S., Chhonkar, P.K. and Dwivedi, B.S., 2005. Manual on soil, plant and water analysis. Westville Publishing House.
12. Fernandez-Ugalde O., Orgiazzi A., Jones A., Lugato E., Panagos P. 2018. LUCAS 2018 – Soil Component: Sampling Instructions for Surveyors. JRC Technical Reports, doi:10.2760/023673, available at https://esdac.jrc.ec.europa.eu/public_path/shared_folder/doc_pub/JRC105923_LUCAS2018_JRC TechnicalReport.pdf.
13. Grace Jim, How to Adjust for Spatial Autocorrelation (Jun 28, 2019), accessed Sep 2023 at: https://www.usgs.gov/media/files/structural-equation-modeling-how-adjust-spatial-autocorrelation

14. Hellin, H; McDonald, A; Jat, ML; Shyamsunder, P and Singh AK. 2021. Mitigating agriculture's contribution to air pollution in India. Lancet Planetary Health. Vol 5 April 2021. www.thelancet.com/planetary-health.
15. International Organization for Standardization, 2017. ISO 11272:2017 Soil quality – Determination of dry bulk density.
16. Jagadeesh Babu, Y., C. Li, S. Frolking, D.R. Nayak, and T.K. Adhya, 2006. Field validation of DNDC model for methane and nitrous oxide emissions from rice-based production systems of India. Nutrient Cycling in Agroecosystems, DOI 10.1007/s10705-005-6111-5.
17. Jat, H. S., Sharma, P. C., Datta, A., Choudhary, M., Kakraliya, S. K., Yadvinder-Singh, Sidhu, H. S., Gerard, B., and Jat, ML. 2019. Re-designing irrigated intensive cereal systems through bundling precision agronomic innovations for transitioning towards agricultural sustainability in North-West India. Nature Scientific Reports 9, 17929.
18. Jat, H.S., Datta, A., Choudhary, M., Sharma, P.C. and Jat, M.L., 2021. Conservation Agriculture: factors and drivers of adoption and scalable innovative practices in Indo-Gangetic plains of India–a review. International Journal of Agricultural Sustainability, 19(1), pp.40-55.
19. Jat, HS., Datta, A., Choudhary, M., Sharma, P. C., Yadav, A. K., Choudhary, V., Gathala, M. K., Jat, ML., & McDonald, A. 2019. Climate smart agriculture practices improve soil organic carbon pools, biological properties and crop productivity in cereal-based systems of North-west India. Catena, 181, 104059. https://doi.org/10.1016/j.catena.2019.05.005
20. Jat, HS., Datta, A., Choudhary, M., Yadav, A. K., Choudhary, V., Sharma, P. C., Gathala, M. K., Jat, ML., & McDonald, A. 2019. Effects of tillage, crop establishment and diversification on soil organic carbon, aggregation, aggregate associated carbon and productivity in cereal systems of semi-arid Northwest India. Soil and Tillage Research, 190, 128–138. https://doi.org/10.1016/j.still.2019.03.005
21. Jat, HS; Kumar, V; Datta, A; Choudhary, M; Yadvinder-Singh; Kakraliya, SK; Poonia, T; McDonald, A; Jat, ML and Sharma, PC.2020. Designing profitable, resource use efficient and environmentally sound cereal based systems for the Western Indo-Gangetic plains. Nature Scientific Reports. 10:19267, https://doi.org/10.1038/s41598-020-76035-z
22. Jat, ML., Yadvinder-Singh., Gill, G., Sidhu, HS., Aryal, JP., Stirling, C. and Gerard, B. 2015. Laser-Assisted Precision Land Leveling Impacts in Irrigated Intensive Production Systems of South Asia. Advances in Soil Science, Soil Specific Farming: Precision Agriculture, Vol: 22, eds R Lal and BA Stewart, CRC Press. Pp 323-352. doi/pdf/10.1201/b18759-14
23. Jat, ML; Chakraborty, D; Ladha, JK; Rana, DS; Gathala, MK; McDonald, A and Gerard, B. 2020. Conservation agriculture for sustainable intensification in South Asia. Nature Sustainability. 3: 336–343, www.nature.com/natsustain
24. Jha, P., Lakaria, B.L., Vishwakarma, A.K., Wanjari, R.H., Mohanty, M., Sinha, N.K., Somasundaram, J., Dheri, G.S., Dwivedi, A.K., Sharma, R.P. and Singh, M., 2021. Modelling the organic carbon dynamics in long-term fertilizer experiments of India using the Rothamsted carbon model. Ecological Modelling, 450, p.109562.
25. Kakraliya, SK; Jat, HS; Singh, I; Sapkota, TB; Singh, LK; Sutaliya, JM; Sharma, PC; Jat, RD; Choudhary, M; Ridaura, SL and Jat, ML. 2018. Performance of portfolios of climate smart

agriculture practices in a rice-wheat system of western Indo-Gangetic plains. Agricultural Water Management, 202: 122-133

26. Keil, A; Krishnapriya, PP; Mitra, A; Jat, ML; Sidhu, HS, Vijesh V. Krishna and Priya Shyamsundar. 2020. Changing agricultural stubble burning practices in the Indo-Gangetic plains: is the Happy Seeder a profitable alternative?, International Journal of Agricultural Sustainability, DOI: 10.1080/14735903.2020.1834277
27. Li, C. 2011. Mitigating greenhouse gas emissions from agroecosystems: Scientific basis and modelling approach. In Understanding Greenhouse Gas Emissions from Agricultural Management (eds. Guo, L., et al.), doi: 10.1021/bk-2011-1072.ch016 ACS Symposium Series; American Chemical Society: Washington, DC, 2011. Pp. 299-330.
28. Li, H., J. Qiu, L. Wang, H. Tang, C. Li, E.Van Ranst. 2010. Modelling impacts of alternative farming management practices on greenhouse gas emissions from a winter wheat–maize rotation system in China. Agriculture, Ecosystems and Environment, 135 (2010) 24–33
29. MoEFCC, I., 2018. Second Biennial Update Report to the United Nations Framework Convention on Climate Change. Ministry of Environment, Forest and Climate Change, Government of India, 31.
30. NAAS, 2017. Innovative Viable Solution to Rice Residue Burning in Rice-Wheat Cropping System through Concurrent Use of Super Straw Management System-fitted Combines and Turbo Happy Seeder. Policy Brief No. 2,. National Academy of Agricultural Sciences, Dev Prakash Shastry Marg, New Delhi - 110 012, New Delhi, India, 16p. https://marlo.cgiar.org/data/studies/CCAFS//CCAFS_study/Crop_Burning_Policy_Brief_-Final-24-10-2017_.pdf
31. Parihar, CM., Parihar, MD., Sapkota, TB., Nanwal, RK., Singh, AK., Jat, SL., Nayak, HS., Mahala, DM., Singh, LK., Kakraliya, SK., Stirling, CM and Jat, ML. 2018. Long-term impact of conservation agriculture and diversified maize rotations on carbon pools and stocks, mineral nitrogen fractions and nitrous oxide fluxes in inceptisol of India. Science of the Total Environment 640–641: 1382–1392
32. Paroda, RS; Jat, ML; Gautam, M; Stirling, C and Bhag Mal. 2018. Agricultural Policies and investment priorities for managing natural resources, climate change and air pollution. Policy Brief. TAAS, CIMMYT, ICAR, CCAFS and World Bank. 4 p. https://repository.cimmyt.org/handle/10883/19517
33. Pathak H., C. Li, R. Wassmann R. and J.K. Ladha, 2006. Simulation of Nitrogen Balance in the Rice-Wheat Systems of the Indo-Gangetic Plains: Upscaling Using the DNDC Model. Soil Science Society of America Journal (in press).
34. Pathak, H., Li, C. and Wassmann, R., 2005. Greenhouse gas emissions from Indian rice fields: calibration and upscaling using the DNDC model. Biogeosciences, 2(2), pp.113-123.
35. Rie Nemoto. Soil organic carbon (SOC) now and in the future. Effect of soil characteristics and agricultural management on SOC and model initialisation methods using recent SOC data. Agricultural sciences. Université Blaise Pascal - Clermont-Ferrand II, 2013. English. ffNNT : 2013CLF22430ff. fftel-00973853f
36. Sapkota, TB, Jat, ML; Rana, DS; Arun, KC; Jat, HS; Bijarniya, D; Sutaliya, JM; Kumar, M; Singh, LK; Jat, RK; Kalvaniya, K; Prasad, G; Sidhu, H; Rain, M; Satyanarana, T and

Majumdar, K. 2021. Crop nutrient management using Nutrient Expert improves yield, increases farmers' income and reduces greenhouse gas emissions. Nature Scientific Reports, 11:1564. https://doi.org/10.1038/s41598-020-79883-x

37. Sapkota, TB., Shankar, V., Rai, M., Jat, ML., Stirling, CM., Singh, LK., Jat, HS and Grewal, MS. 2017. Reducing Global Warming Potential through Sustainable Intensification of Basmati Rice-Wheat Systems in India. Sustainability. 9:1044
38. Sapkota, TB; Jat, ML; Aryal, JP; Jat, RK and Arun, KC. 2015. Climate change adaptation, greenhouse gas mitigation and economic profitability of conservation agriculture: Some examples from cereal systems of Indo-Gangetic Plains. Journal of Integrative Agriculture, 14 (8): 1524–1533
39. Sapkota, TB; Majumdar, K; Jat, ML; Kumar, A; Bishnoi, DK; McDonald, AJ and Pampolino, M. 2014. Precision nutrient management in conservation agriculture-based wheat production of Northwest India: Profitability, nutrient use efficiency and environmental footprint. Field Crops Research 155:233-244.
40. Sapkota, TB; Singh, LK; Yadav, AK; Arun KC, Jat, HS; Sharma, PC; Jat, ML and Stirling, C. 2020. Identifying optimum rates of fertilizer nitrogen application to maximize economic return and minimize nitrous oxide emission from rice–wheat systems in the Indo-Gangetic Plains of India, Archives of Agronomy and Soil Science, 66:14, 2039-2054, DOI: 10.1080/03650340.2019.1708332
41. Sapkota, TB; Vetter,SH; Jat, ML; Sirohi, S; Shirsath, PB; Singh, Rajbir; Jat, HS; Smith, P; Hillier, J and Stirling, CM. 2019. Cost-effective opportunities for climate change mitigation in Indian agriculture. Science of Total Environment. 655: 1342–1354
42. Sharma, B. D., Raj-Kumar, Manchanda, J. S., Dhaliwal, S. S., Thind, H. S., & Yadvinder-Singh. (2016). Mapping of Chemical Characteristics and Fertility Status of Intensively Cultivated Soils of Punjab, India. *Communications in Soil Science and Plant Analysis*, *47*(15), 1813–1827.
43. Shyamsundar, P., Springer, N. P., Tallis, H., Polasky, S., Jat, M. L., Sidhu, H. S., Krishnapriya, P. P., Skiba, N., Ginn, W., Ahuja, V., Cummins, J., Datta, I., Dholakia, H. H., Dixon, J., Gerard, B., Gupta, R., Hellmann, J., Jadhav, A., Jat, H. S.,...Somanathan, R. 2019. Fields on fire: Alternatives to crop residue burning in India. Science, 365(6453), 536–538. https://doi.org/10.1126/science.aaw4085
44. Sidhu, HS., Jat, M. L., Singh, T., Sidhu, R. K., Gupta, N., Singh, P., Singh, P., Jat, H. S., & Gerard, B. 2019. Sub-surface drip fertigation with conservation agriculture in a rice-wheat system: A breakthrough for addressing water and nitrogen use efficiency. Agricultural Water Management, 216, 273–283. https://doi.org/10.1016/j.agwat.2019.02.019
45. Singh J, Erenstein O, Thorpe W and Varma A. 2007. Crop–livestock interactions and livelihoods in the Gangetic Plains of Uttar Pradesh, India. Crop–livestock interactions scoping study—Report 2. Research Report 11. ILRI (International Livestock Research Institute), Nairobi, Kenya. 88 pp.
46. The Indian Express. 2021. Punjab brings 5.62 lakh hectares under DSR — its highest ever. Accessed online on Aug 31st 2021 at https://indianexpress.com/article/cities/ludhiana/punjab-brings-5-62-lakh-hectares-under-dsr-its-highest-ever-7432636/

47. The Tribune. 2021. Government: Diversification can save 954 bn litres of water in Haryana. Accessed online on Aug 31st 2021 at https://www.tribuneindia.com/news/haryana/government-diversification-can-save-954-bn-litres-of-water-in-haryana-114091
48. Tomar, Dinesh & Bhat, Mohammad & Grewal, Karambir Singh. (2017). Characterization and Classification of Soils on Different Geomorphic units of North-Eastern Haryana, India. 27. 103-116.
49. Vidhi Centre for Legal Policy. 2017. Cleaning Delhi's Air. Implementation Action Plan. Accessed March 2021 from https://vidhilegalpolicy.in/wp-content/uploads/2020/06/170407_DelhiAirPollutionImplementationActionPlan.pdf
50. Zhang, L.-M.; Zheng, Q.; Liu, Y.; Liu, S.; Yu, D.; Shi, X.; Xing, S.; Chen, H.; Fan, X. Combined Effects of Temperature and Precipitation on Soil Organic Carbon Changes in the Uplands of Eastern China. Geoderma 2019, 337, 1105–1115.

## 14. Appendices

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