DNDC Validation Report

Prepared for: CAR

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1 Report type

1.1 Report type

Type 2 validation: A generalized validation to demonstrate overall performance of the model without specific project.

1.2 CAR SEP version

SEP version 1.1 May 31, 2022

1.3 CAR SEP model requirements version

Requirements and Guidance for Model Calibration, Validation, Uncertainty, and Verification For Soil Enrichment Projects; Version 1.1a; April 2022 (referenced as CAR's Guidance or the guidance).

1.4 Changes from previous validation report

DNDC v10.3 was previously validated in a generalized report submitted to CAR on August 4 2022. This report updates the original report with the following changes:

1. DNDC v10.3 replaced by DNDC v11.0.0 (see section 3.1 Model version for a detailed description).
2. In the first draft (DNDC v10.3, from August 2022), standard error values were mistakenly treated as standard deviation values in the PMU calculations. The final PMU calculations included an extra division of the square-rooted replicate counts from studies making the PMU values smaller than they should have been. Since this error resulted in more conservative values, the original report (DNDC v10.3, from August 2022) was not retracted. The calculation has been corrected in this current version to reflect the correct standard error values, thus why some variation may be seen in PMU values (equations 5 and 6 are updated see section 4.4 Assessment of bias for more details).
3. The first report included a mix of studies with data at treatment and replicate levels. The separation was not clear because replicates had been coded as different treatments. This results in additional variance at the treatment pair level, which is conservative. The coding of treatment

has been updated to exclude tags of sub treatment differences for most studies and this report is only valid at the treatment level (i.e. when replicate level data are available they are averaged). This change also made available additional studies for PMU calculations. (see appendix B for study specific changes and section 4.4.1 - 4.4.3 for PMU changes)

4. Some validation points of the difference in treatment pair annual changes in SOC (dSOC) were removed from the original set. Specifically points where the first time point was different from the t = 0. Previously if for example a study-site-treatment-pair had SOC measurements as time t=0, t=5, and t=10. Annual differences were calculated based on t1=0 & t2=5, t1=5 & t2=10, t1=0 & t2=10. For this report only annual differences based on t1=0 & t2=5 and t1=0 & t2=10 are included. (see appendix B for study specific changes in number of treatment pairs)

5. The prediction interval coverage method was updated to make use of an approximate leave-one-out cross-validation based on Pareto-smoothed importance sampling (LOO-PSIS) (Vehtari et al., 2017). (see section 4.5)

6. Gap-filling method for N2O time series in the calculation of measured seasonal/annual N2O emissions was updated from linear to exponential (see section 4.3.1)

7. Validation domain was expanded to include a new crop (rice) and practice category (irrigation); see sections 4.1 and 4.2.

8. CH4 uncertainty quantification was added specific for flooded rice (see section 4.4 and 4.5)

2 Introduction

DNDC is a process-based, soil biogeochemical model designed to assess the impact of agricultural management practices on soil carbon and nitrogen dynamics (Li et al. 1992; Li et al. 1994, Li 2000). The model runs on a daily time step and is capable of simulating both aerobic and anaerobic soil conditions. The DNDC model has been applied across a wide range of agro-ecosystems globally, extensively validated and peer reviewed in over 200 peer-reviewed publications (Giltrap et al. 2010; Gilhespy et al. 2014; Yeluripati et al. 2015).

DNDC conducts a full accounting of carbon and nitrogen cycling by simulating the impacts of major ecological drivers (climate, soil, vegetation, management) on soil climate conditions, plant growth, and decomposition (Figure 1). The model is built using classical laws of physics, chemistry, and biology, as well as empirical equations generated from laboratory studies to parameterize specific biogeochemical processes.

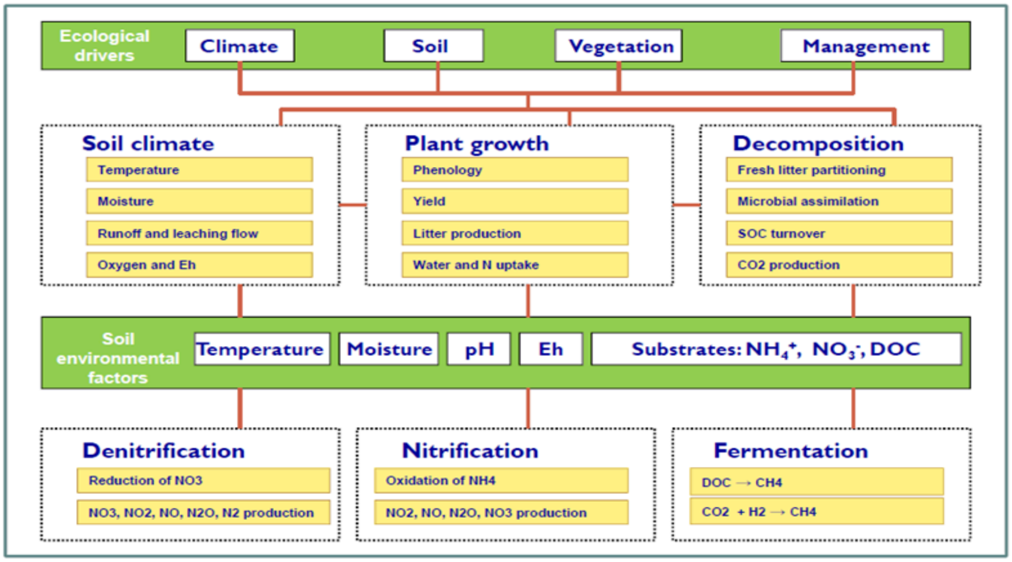

Figure 1. DNDC drivers (green boxes) and process based sub-modules (dashed boxes). Agricultural management practices directly modify the soil climate and plant growth sub-modules and indirectly alter organic matter decomposition and nutrient cycling (denitrification, nitrification, fermentation).

3 Model Calibration

3.1 Model Version

Multiple versions of DNDC have been created for research, education, and marketing purposes since the model's initial development. Customized versions of DNDC have been developed for the California Air Resources Board to support their Greenhouse Gas Emission Inventory Program (Deng et al. 2017) and the Canadian government to support estimates of crop yield, GHG emissions and water quality (Smith et al. 2013). Version 9.5 of DNDC is publicly available and infrequently maintained by the University of New Hampshire. Regrow has developed the most recent version (v11.0.0) of DNDC under an exclusive commercial license to support the scaling of ecosystem services markets. Progressing from v10.3.0, v11.0.0 eliminates more bugs, improves fertigation modeling, adds support for new features (precision fertilizer, auto-fertilizer, biomass and residue burning, biochar, event-based tile drainage, dynamic erosion), and creates more computationally efficient and well-engineered code (level 1 optimization, clearer and more consistent documentation, more testing and patterned and well-organized code to facilitate identification and prevention of bugs). Additionally, limited calibration was conducted with the updated DNDC model to improve simulation of crop yield and methane emissions. These procedures are described in the subsequent sections.

3.2 Calibration Method Description

SEP Model Requirements and Guidance define model calibration as "any process involving the adjustment of parameters and constants within a model so that the model more accurately simulates measured values." The Guidance defines parameter sets as "all values internal to a model that determine how input data drive model performance and behavior, and that are changed using processes independent of model-driving input datasets." DNDC has multiple types of input parameters that drive internal model processes. These types of input parameters include the following:

- Weather parameters
- Soil parameters
- Crop parameters
- Tillage parameters
- Fertilizer parameters
- Manure parameters
- Cutting parameters
- Grazing parameters
- Flooding parameters
- Irrigation parameters
- Plastic mulch parameters

Some model input parameters are rarely if ever measured and instead determined as a function of other, more easily measured input parameters. In addition, there are parameters that are fixed by default but can be improved via calibration to align model behavior following structural changes, better reflect regional variation, or otherwise improve model skill. Appendix A lists all DNDC input parameters and their dependencies for the model version covered by this report.

In this validation report, we maintain the default parameter set from version 10.3 for DSOC and N2O, and calibrate the internal parameter called the maximum CH4 production rate factor (see Appendix A) to improve the simulation of CH4 emissions of flooded systems.

A model sensitivity analysis was performed under different conditions and in different LRRs prior to this calibration and validation process. Considering the large number of input parameters used in the DNDC model, a method based on Morris Screening was selected to reduce the number of parameters considered influential on model outputs. The derivative-based global sensitivity measures (DGSM) combined with Latin Hypercube sampling (LHS) were selected to perform global sensitivity analysis (GSA) on the DNDC model (Kiparissides et al. 2009, Sobol et al. 2010) for the following goals.

1. To identify and document sensitivity of results with respect to input and internal model parameters
2. To screen, select and evaluate input and internal parameters with respect to required model refinements.

With respect to CH_4 emission, the sensitivity analysis revealed that three of the internal DNDC parameters (microbial index, factor_ch4_P1, and factor_ch4_fPGI) were among the highest ranking parameters to influence CH_4 emission simulations. These parameters are listed in Appendix A. The Morris indices from the sensitivity analysis process showed that factor_ch4_P1 (maximum CH_4 production rate factor) was consistently the highest ranking parameter in respect to the CH_4 emission.

Following the sensitivity analysis, a calibration procedure was conducted. The calibration method is based on the frequentist approach as described in Wong et al. 2017. To begin, the calibration studies were divided into training and evaluation sets. Using the Latin Hypercube Sampling (LHS) approach, a uniformly distributed joint probability space was generated. The results of the simulations were compared against the calibration studies' empirical data to compute an absolute error for each result. This data was used to select parameter values that would minimize the mean absolute error over the evaluation set.

Given the fairly limited number of studies that were available for the calibration process, the calibration process was restrained to target only the factor_ch4_P1 parameter while the factor_ch4_fPGI parameter (growth stage root exudation factor) and microbial index parameter were maintained at their default values. Through the calibration procedure, CH_4 emission demonstrated disparate simulated bias in accordance with the Alternate Wetting and Drying (AWD) management regime. As such, factor_ch4_P1 under flooded conditions was adjusted from the default of 0.5 to 0.9 under AWD and 0.2 under conventional flooding.

3.3 Documentation of Model Parameters

All model input parameters, along with their dependencies when measurements are not available, are listed in Appendix A. A single parameter set is used throughout the entire domain validated by this report and can be shared upon request.

The observational database and computational code (model base code, processing scripts, uncertainty model code) necessary to fully reproduce the entirety of this work is permanently archived and versioned for posterity. We have demonstrated that such an archiving procedure is the best method to ensure reproducibility of prior simulations. Documenting a list of model parameters that are influenced by (or in some way derivative to) a set of user inputs does not, in itself, ensure reproducibility because there may be various updates to the model base. Regular updates of the model code base are intended to improve performance, to update process-representation (e.g., a new N_2O emission pathway), add simulated events (e.g., fire, erosion), or provide bug fixes. For these reasons, we regularly version and archive to ensure reproducible results and transparency of the model code base. Archived versions associated with Validation Reports or Projects are available upon request.

3.4 Data Split Process and Justification

Regrow maintains a large database (CALVIN) of experimental studies used for regular calibration and validation of DNDC. This database is populated through literature review of peer-reviewed studies and datasets that report changes in emission sources of interest within targeted validation domains. Studies must report sufficient data to enable DNDC simulations to be included in the database.

The database is used to build and run DNDC simulations for relevant experimental **treatments**. Each treatment is defined by longitudinal measurements of a target emissions source (i.e. SOC stock change, N2O emissions flux, CH4 emissions flux) under specific management, soil, and climate conditions. Each treatment is linked to a **study** in the CALVIN database. A study represents a unique experimental design from which data is collected. Multiple publications can refer to a single study, for example the Morrow plots, established in 1876 in Urbana, Illinois, contain the oldest experimental plots in the US including the longest continuous corn plot in the world (Odell, 2015). Over time the field has been divided into sub plots studying the impact of changing fertilizer rates and forms as well as crop rotations. Multiple publications in the Regrow database report outcomes of different treatments on multiple emission sources from this single study. Each treatment is also linked to a **site** that represents a unique set of experimental fields with shared climate and soils data. One study can therefore span multiple sites (i.e. when geography or soil type is a factor of interest) but does not have to. Each treatment is therefore linked to a unique **study-site** combination.

Treatments are paired within study-sites to evaluate DNDC's ability to predict changes in emissions between treatments. This scale of model evaluation mimics the subsequent credit quantification in CAR SEP where the credit is the difference in GHG outcomes between two paired management scenarios (baseline and project). A given **treatment-pair** in Regrow's validation database may have multiple sets of measurements over the duration of the treatments (i.e. measurements at *t = 0, 5,* and *10*). In this case, all time comparisons between the starting date and dates 5 or more years apart are used for model validation (2 paired measurements in the previous example, 5-0 and 10-0) (Section 3 of this report).

When both calibration and validation are needed, each study-site within the database is assigned to either the calibration or validation pool. This split is not done at random and is intended to result in complete coverage of the target validation domain by both the calibration and validation pools. The split also aims to evenly represent GHG-relevant elements of study design (i.e. length of study, depth of soil sampling) between calibration and validation pools. While study-sites are not assigned randomly to either calibration or validation pools, assignment is done prior to any model calibration and assessment to avoid biasing study-site allocation to improve model performance. Only data from the calibration pool was utilized for calibration and model improvement purposes. The study-sites in the validation pool (Appendix B) were used exclusively for model validation .

4 Validating and Reporting Model Performance and Uncertainty

Validation of DNDC is demonstrated through the description of an uncertainty model, allowing for the propagation of the uncertainty quantified through the validation data to new modeling units included in the validation domain.

4.0 Description of Uncertainty Model

Regrow's uncertainty model is an empirical model that estimates the lack of fit between model estimates and measured values of differences in a given Emissions Source (ES) between two paired scenarios. A separate uncertainty model exists for each Emissions Source. In this report Regrow presents uncertainty models for both soil organic carbon (SOC) sequestration and Direct N2O emissions.

This report validates the following simple statistical model:

$$y_i = \eta_i + \delta_i + \epsilon_i$$

where y_i are the measurements of treatment-pair level differences (offsets) from the validation dataset, n_i are the DNDC model estimates of these treatment-pair level differences (offsets), δ_i is a single bias/model discrepancy estimate, and the ϵ_i's are independent random normals centered at 0 with the same single variance parameter σ, which captures the observational error and other random variability such as within field variability.

Regrow estimates the uncertainty model using a Bayesian framework to simplify the model's parameter uncertainties along with its prediction uncertainty to new modeling units. A half-Cauchy distribution with location parameter 0 and scale parameter 1 is used for the non-informative prior distribution of σ following a recommendation by Gelman (2006), while a Normal distribution centered at 0 with a large standard deviation of 100 is used as the prior distribution for □. Posterior probability distributions for both parameters are sampled using Markov Chain Monte Carlo (MCMC) methods, a standard Bayesian sampling method that iteratively draws samples from approximate distributions called transition distributions, which through the use of a Markov Chain are improved with each iteration until the chain converges to the target posterior distribution (Gelman et al., 2013). Sampling is done in Stan software (Carpenter et al., 2017) using the No-U-Turn Sampler developed by Hoffman and Gelman (2014). Initial warm-up samples from each MCMC run (the so-called "burn-in") are discarded yielding a final distribution of 1000 samples. Convergence is evaluated using the Gelman-Rubin statistic, which approaches 1 as the model converges (Gelman & Rubin, 1992). Once sampled, the posterior distributions of δ and σ are used to propagate the structural uncertainty in the validation dataset to DNDC offset estimates of new fields via Monte Carlo integration.

4.1 Declare Practice Categories Requiring Evaluation

This validation report declares the practice categories listed in Table 1 valid for the specified emissions sources (ES) within the domain described in Section 4.2. All Practice Category and Emission Source combinations are based on at least one treatment pair with an unstacked practice category.

Table 1. Practice categories validated by Emissions Source within the domain described in this report. Study-sites listed in **bold font** for Direct N2O report annual emissions over a >310 day period (see also Table 10 and Appendix D of this report). International studies include the country name in parenthesis.

Practice Category	PC Code	emission source	LRR Key	IPCC Zone Id	study-site	count unstacked pairs
Soil disturbance and/or residue management	TR	SOC	C	6	mitchell_2015_2017-wsrec	8
			F	8	MTSINVND-NVND	4
					sainju_2014a-SID_MT	0
			G		COFOARD1_GHG_123_SOC-ARDEC	2
			K	7	clapp_2000-UMROC	102
			M	5	al-kaisi_2005a-SRDF	1
				7	al-kaisi_2005a-NRDM	1
			N	5	sainju_2008-AAES	7
			O		locke_2013-CPSRUF	1
			P	3	balkcom_2013-PARU	6
		Direct N2O	F	8	MTSINVND-NVND	16
					sainju_2014a-SID_MT	0
			G		**COFOARD1_GHG_123_SOC-ARDEC**	10
					COFOARD2_GHG-ARDEC	6
					COFOARD3_GHG-ARDEC	14
			M	5	nash_2012-GMRC	2
				7	**parkin_and_kaspar_2006-AEARRF**	4
					SDBRREAP-SDBRREAP	0
					wegner_2018-NCARL	3
			N	5	smith_2012-SAREC	1

Cropping practices, planting and harvesting (e.g., crop rotations, cover crops)	**Crop**	**SOC**	C	6	mitchell_2015_2017-wsrec	8
			F	8	MTSINVND-NVND	6
					sainju_2014a-SID_MT	2
			H	5	varvel_2008-UNE_Shelton	15
			K	7	WICST-WIARS	6
			M	5	sanborn_field-SF	3
				7	pikul_2008-ESDSWRF	9
					poffenbarger_2017-central	5
			N	5	sainju_2008-AAES	0
			O		locke_2013-CPSRUF	3
			P	3	balkcom_2013-PARU	3
				5	sainju_2002-ARS	6
		Direct N2O	C	6	burger_and_horwath_2012_alfalfa-winters	2
			F	8	MTSINVND-NVND	24
				8	sainju_2014a-SID_MT	28
			G	8	COFOARD2_GHG-ARDEC	10
			H	5	**mcgowan_2018-KSU_ARF**	36
			M	5	hernandez-ramirez_2009-ACRE	6
				7	**parkin_and_kaspar_2006-AEARRF**	14
				7	SDBRREAP-SDBRREAP	0
				7	wegner_2018-NCARL	3
			O	5	karki_2021-Burdette	0
		CH4	O	5	brye_2017-RREC	14
					karki_2021-Burdette	0
					smartt_2016a-NREC	10
					smartt_2016b-NEREC	0
Inorganic nitrogen fertilizer application	**InN**	**SOC**		3	zhang_2023-CQ (China)	1
					zhang_2023-JX (China)	1
					zhang_2023-NC (China)	1
					zhang_2023-QY (China)	1
				5	zhang_2023-SN (China)	1

Inorganic nitrogen fertilizer application					zhang_2023-SZ (China)	1
					zhang_2023-WH (China)	1
				5	rob_2022-DIV2 (Germany)	28
			F	8	MTSINVND-NVND	4
					sainju_2014a-SID_MT	3
			G		COFOARD1_GHG_123_SOC-ARDEC	36
			H	5	varvel_2008-UNE_Shelton	30
			K	7	clapp_2000-UMROC	22
			M	5	sanborn_field-SF	18
				7	pikul_2008-ESDSWRF	9
					poffenbarger_2017-central	20
			N	5	sainju_2008-AAES	2
			P		sainju_2002-ARS	3
		Direct N2O	C	6	adviento-borbe_2013-CA1_Nrate	10
					adviento-borbe_2013-CA2_Nrate	10
			E	8	engel_2010-APF	30
			F		MTSINVND-NVND	16
			G		**COFOARD1_GHG_123_SOC-ARDEC**	54
					COFOARD2_GHG-ARDEC	24
					COFOARD3_GHG-ARDEC	114
					COFOARD4-ARDEC	12
			L	7	hoben_2011-Mason	15
			M	5	fernandez_2015-CSREC	18
					hernandez-ramirez_2009-ACRE	0
					nash_2012-GMRC	6
					nash_2015-GMRC	12
					omonode_and_vyn_2013-Haubstadt	2
				7	**parkin_and_hatfield_2010-ISURF**	2
			N	5	KYBGGHG-KYBGGHG	63
					smith_2012-SAREC	6
			O		adviento-borbe_2013-AR_RREC_Nrate	3

Inorganic nitrogen fertilizer application			O		karki_2021-Burdette	0
		CH4	C	6	adviento-borbe_2013-CA1_Nrate	10
					adviento-borbe_2013-CA2_Nrate	10
			O	5	adviento-borbe_2013-AR_RREC_Nrate	6
					brye_2017-RREC	0
					karki_2021-Burdette	0
					smartt_2016b-NEREC	1
Organic amendments application	**OrN**	**SOC**		3	zhang_2023-CQ(China)	0
					zhang_2023-JX(China)	0
					zhang_2023-NC(China)	0
					zhang_2023-QY(China)	0
				5	zhang_2023-SN(China)	0
					zhang_2023-SZ(China)	0
					zhang_2023-WH (China)	0
				5	rob_2022-DIV2 (Germany)	7
			M	5	sanborn_field-SF	3
			N	5	sainju_2008-AAES	2
		Direct N2O	G	8	**COFOARD4-ARDEC**	4
			K	7	sherman_2021-MARS	9
			M	5	hernandez-ramirez_2009-ACRE	2
			N		KYBGGHG-KYBGGHG	3
					smith_2012-SAREC	3
Water management /irrigation	**Water**	**SOC**	F	8	MTSINVND-NVND	2
				3	zhang_2023-CQ(China)*	0
					zhang_2023-JX(China)*	0
					zhang_2023-NC(China)*	0
					zhang_2023-QY(China)*	0
				5	zhang_2023-SN(China)*	0
					zhang_2023-SZ(China)*	0
					zhang_2023-WH (China)*	0
				5	lagomarsino_2016-SIS (Italy)	2

Water management /irrigation	Water	Direct N2O	F	8	MTSINVND-NVND	8
			O	5	karki_2021-Burdette	0
		CH4	O	5	lagomarsino_2016-SIS (Italy)	2
					karki_2021-Burdette	0
			T	3	sigren_1997-TX_AREC_AWD	1
					sigren_1997-TX_Richmond_AWD	1

* Zhang et al (2023) includes measurements of SOC change for flooded rice, but the practice changes of this study compare fertilizer amounts and not water management. Included for support of quantifying SOC for flooded rice systems

Table 2. LRR Lookup Table. For maps of each LRR see this NRCS website.

Land Resource Region (LRR)	**LRR Key**
California Subtropical Fruit, Truck, and Specialty Crop Region	C
Rocky Mountain Range and Forest Region	E
Northern Great Plains Spring Wheat Region	F
Western Great Plains Range and Irrigated Region	G
Central Great Plains Winter Wheat and Range Region	H
Northern Lake States Forest and Forage Region	K
Lake State Fruit, Truck Crop, and Dairy Region	L
Central Feed Grains and Livestock Region	M
East and Central Farming and Forest Region	N
Mississippi Delta Cotton and Feed Grains Region	O
South Atlantic and Gulf Slope Cash Crops, Forest, and Livestock Region	P
Atlantic and Gulf Coast Lowland Forest and Crop Region	T

Table 3. IPCC Climate Zone Lookup Table

Zone ID	**IPCC Climate Zone Name**
3	Tropical Moist

5	Warm Temperate Moist
6	Warm Temperate Dry
7	Cool Temperate Moist
8	Cool Temperate Dry

4.2 Definition of the Model Validation Domain

Regrow's approach to validating model performance within a validation domain deviates from CAR's Guidance. In accordance with the guidance, Regrow's approach still defines a validation domain as the multidimensional space of biophysical attributes within which a model has been confronted with data. For a given emissions source (ES), these biophysical attributes include land resource regions (LRRs), crop functional groups (CFGs) and soil texture classes. However, this report does not evaluate model performance for each unique combination of attributes. Such a granular requirement for model validation greatly reduces the data available for validation and is untenable for many combinations. Instead, this report considers a single evaluation of model performance for a given emissions source (ES) across the entirety of a validation domain sufficient to validate the model. Model performance across the entire domain is described by a general uncertainty model (another deviation from the CAR Guidance, Sections 4.4 and 4.5) that allows for the propagation of any bias and error in the validation dataset to crediting simulations. This deviation has previously been presented to and approved by CAR (Appendix C).

The extent of a validation domain is defined by the dimensions of the biophysical attributes covered by the studies used to generate the validation dataset. For example, consider the domain represented by the two following hypothetical studies in Table 4.

Table 4. Hypothetical validation domain created by two studies

	Study 1	**Study 2**	**Domain for SOC (Studies 1 + 2)**	**Domain for Direct N2O (Study 2 only)**
Emissions Sources (ES)	SOC	SOC, Direct N2O	-	-
Practice Categories (PC)	soil disturbance	soil disturbance	soil disturbance	soil disturbance
Land Resource	Central Feed	Lake States	Central Feed Grains,	Lake States

Regions (LRR)	Grains		Lake States	
Crop Functional Groups (CFG)	C4 annual, C3 N-fixing	C3 annual	C4 annual, C3 N-fixing, C3 annual	C3 annual
Soil Texture Class	loam	clay loam	loam, clay loam	clay loam

4.2.1 Model validated Practice Categories and Crop Functional Groups by Emission Source

This validation report declares the crop functional groups (CFGs) listed in Table 5 valid for the specified emissions sources (ES).

Table 5. Crop functional groups validated by Emissions Source within the domain described in this report

Crop Functional Group	CFG Code	SOC Study-site Key	Direct N2O Study-site Key	CH4 Study-site Key
C4, annual, non-N-fixing, herbaceous, non-flooded	C4A	al-kaisi_2005a, NRDM al-kaisi_2005a, SRDF balkcom_2013, PARU clapp_2000, UMROC COFOARD1_GHG_123_SOC, ARDEC pikul_2008, ESDSWRF poffenbarger_2017, central sainju_2008, AAES sanborn_field, SF varvel_2008, UNE_Shelton WICST, WIARS	COFOARD1_GHG_123_SOC, ARDEC sainju_2014a, SID_MT COFOARD2_GHG, ARDEC COFOARD3_GHG, ARDEC COFOARD4, ARDEC fernandez_2015, CSREC hernandez-ramirez_2009, ACRE hoben_2011, Mason KYBGGHG, KYBGGHG mcgowan_2018, KSU_ARF nash_2012, GMRC nash_2015, GMRC omonode_and_vyn_2013, Haubstadt parkin_and_hatfield_2010, ISURF parkin_and_kaspar_2006, AEARRF SDBRREAP, SDBRREAP smith_2012, SAREC	None
C3, annual, non-N-fixing,	C3A	balkcom_2013, PARU locke_2013, CPSRUF mitchell_2015_2017, wsrec MTSINVND, NVND	COFOARD2_GHG, ARDEC engel_2010, APF MTSINVND, NVND	None

herbaceous, non-flooded		pikul_2008, ESDSWRF rob_2022, DIV2 sainju_2002, ARS sainju_2008, AAES sainju_2014a, SID_MT sanborn_field, SF WICST, WIARS zhang_2023, CQ (China) zhang_2023, SN (China) zhang_2023, SZ (China) zhang_2023, WH (China)	parkin_and_kaspar_2006 , AEARRF sainju_2014a, SID_MT wegner_2018, NCARL	
C3, annual, N-fixing, herbaceous, non-flooded	C3A N	al-kaisi_2005a, NRDM al-kaisi_2005a, SRDF locke_2013, CPSRUF mitchell_2015_2017, wsrec MTSINVND, NVND pikul_2008, ESDSWRF poffenbarger_2017, central sainju_2002, ARS sainju_2014a, SID_MT sanborn_field, SF varvel_2008, UNE_Shelton WICST, WIARS	COFOARD2_GHG, ARDEC hernandez-ramirez_2009, ACRE mcgowan_2018, KSU_ARF MTSINVND, NVND parkin_and_kaspar_2006 , AEARRF sainju_2014a, SID_MT SDBRREAP, SDBRREAP wegner_2018, NCARL	None
C3, annual, non-N-fixing, shrub, not-flooded	C3AS	balkcom_2013, PARU locke_2013, CPSRUF mitchell_2015_2017, wsrec sainju_2008, AAES	None	None
C4, perennial, non-N-fixing,herbaceous, not-flooded	C4P	None	mcgowan_2018, KSU_ARF	None
C3, perennial, non-N-fixing, herbaceous, not-flooded	C3P	sanborn_field, SF	None	None
C3, perennial, N-fixing, herbaceous, not-flooded	C3P N	pikul_2008, ESDSWRF WICST, WIARS	burger_and_horwath_20 12, winteres sherman_2021, MARS	None

C3, annual, herbaceous, non-N-fixing, flooded	C3AF	zhang_2023, CQ (China) zhang_2023, JX (China) zhang_2023, NC (China) zhang_2023, QY (China) zhang_2023, SN (China) zhang_2023, SZ (China) zhang_2023, WH (China)	adviento-borbe_2013, CA1 adviento-borbe_2013, CA2 adviento-borbe_2013, AR_RREC karki_2021, Burdette lagomarsino_2016, SIS	adviento-borbe_2013, CA1 adviento-borbe_2013, CA2 adviento-borbe_2013, AR_RREC Brye_2017, RREC karki_2021, Burdette lagomarsino_2016, SIS Smartt_2016a, NEREC Smartt_2016b, NEREC sigren_1997, TX_AREC sigren_1997, TX_Richmond

4.2.2 Validated Land Resource Regions by Emission Source

See Section 4.1 (Tables 1a and 1b) for a list of all LRRs validated for the specified emissions sources by this report.

4.2.3 Validated Soils by Emission Source

This validation report declares the soil texture classes listed in Table 6 valid for the specified emissions sources (ES). Representative clay fractions come from Li et al. 1992 and Li et al. 2014.

Table 6. Soil texture classes validated by Emissions Source within the domain described in this report

Soil Texture Class	**Representative Clay Fraction**	**Validated GHG Pools/Gasses**
Clay	0.63	Direct N2O, CH4
Sandy Clay	0.49	None
Silty Clay	0.43	CH4
Clay Loam	0.41	SOC, Direct N2O, CH4
Silty Clay Loam	0.34	SOC, Direct N2O, CH4

Sandy Clay Loam	0.27	SOC, Direct N2O
Loam	0.19	SOC, Direct N2O, CH4
Silt Loam	0.14	SOC, Direct N2O, CH4
Silt	N/A	None
Sandy Loam	0.09	SOC, Direct N2O
Loamy Sand	0.06	None
Sand	0.03	None

Clay range in model simulations:

- SOC: min = 5% (Rob 2022 - DIV2 Germany), max = 33% (COFOARD1_GHG_123_SOC ARDEC), range = 28%
- N2O: min = 11.9% (Smith 2012 SAREC), max = 59% (Adviento-borbe 2013 CA1), range = 47.1%
- CH4: min = 18% (Adviento-borbe 2013 AR_RREC), max = 59% (Adviento-borbe_2013 CA1), range = 41%

4.3 Data to Validate Model Performance and Uncertainty

4.3.1 Generalized Dataset Attributes

The validation dataset for each emissions source (ES) consists of studies reporting measurements of the emissions source of interest. Requirements for studies to be included in the validation dataset are listed in Table 7. Additional details of each emission source validation data are discussed following this table.

Table 7. Management data requirements for inclusion in validation datasets for two emissions sources (SOC and Direct N2O).

category	parameter	SOC	Direct N2O	Direct CH4
crop	plant_date	can be estimated	required	required
crop	harvest_date	can be estimated	required *...if post-season emissions measured*	required *...if post-season emissions measured*

crop	residue_fraction	required	required *...for multi-year measurements*	required *...for multi-year measurements*
tillage	till_date	can be estimated	required *...for events during measurement timeframe*	required *...for events during measurement timeframe*
tillage	till_depth	can be estimated*	can be estimated	can be estimated
fertilizer	fert_date	can be estimated	required	required
fertilizer	fert_type	can be estimated	required	required
fertilizer	fert_rate	can be estimated	required	required
fertilizer	fert_depth	can be estimated	required	required
manure	manure_date	can be estimated	required	required
manure	manure_amount	required	required	required
manure	manure_cn	required	required	required
manure	manure_method	required	required	required
irrigation	irrig_date	can be estimated	required	required
irrigation	irrig_amount	can be estimated	required	required
flooding	start_date	can be estimated	required	required
flooding	end_date	can be estimated	required	required

* tillage depth can be estimated when information on the tillage implement is provided

For SOC, studies needed to report measurements over at least a five-year period. Measurements of bulk density were required for the initial SOC stock measurement but not for subsequent measurements. Methods of collection and analysis had to be described and consistent between treatments. All studies were focused on SOC measurements and thus removed surface litter, tree branch, wood chips, as well as larger particles before analyzing for SOC. For soils where no inorganic carbon forms are present (non-calcareous soils and soils not recently limed) the total carbon can be considered to be organic carbon. With calcareous soils, recently limed soils, or in geographic areas where parent material/geology is limestone, dolomite, or other carbonate-bearing mineral, organic carbon may be estimated as the difference between total carbon and inorganic carbon concentrations (Schumacher, 2002). The most common methods for deriving SOC within our studies were were: (1) dry combustion at high temperatures for total carbon determination on the sample (2) analysis of a soil for total carbon and inorganic carbon and subtraction of the inorganic carbon concentration for the total C content and (3) dichromate oxidation procedures, which involves oxidation of organic carbon compounds by Cr2O72- and subsequent determination of unreduced Cr2O72- by oxidation-reduction titration with Fe+2 or by colorimetric methods (Sparks et al. 2020). Depth of soil sampling within the final dataset ranged from 10 to 30 cm. The units of interest used in uncertainty quantification were annual changes in time and differences between treatments (Equation 1) in tCOe per acre per year. Treatment-pairs were required to share a common soil sampling depth and length between sampling dates.

Equation 1: Difference in treatment pair annual changes in SOC

$$dsoc_j = \frac{soc_{t_1,d_2,j} - soc_{t_1,d_1,j} - (soc_{t_2,d_2,j} - soc_{t_2,d_1,j})}{y_j}$$

where

j : treatment pair case (row id)

t_1 : treatment 1

t_2 : treatment 2

d_1 : date 1

d_2 : date 2

y : length of time in years between date 1 and date 2

For Direct N2O, studies needed to report measurements of Direct N2O emissions at a daily temporal scale over at least a full growing season (please see Appendix D for list of studies and coverage with sampling > 310 days). All n2o measurements in this validation were from either manual or automatic static chambers. Best efforts were made to eliminate studies from entering our database with infrequent sampling greater than ~1-2 weeks, especially if the sampling was on a regular interval (as opposed to event-based). However, some older studies with sparser data were maintained as completely eliminating older studies that may have followed older best practice protocols (Parkin et al., 2003 vs. 2010) would have eliminated some very valuable information. Further, since the main purpose was to compare differences between treatments and not just calculate or present annual emissions, comparison between treatments with the same sampling methods allows measurement of impact of treatments even when sampling was not as high density as would be desired. Treatment-pairs were required to share a common season/year. Units of interest for uncertainty quantification were differences between treatment pairs of total (seasonal/annual) direct N2O emissions in tCO2e per acre (Equation 2).

Where gaps in daily data were present, exponential interpolation was used to calculate seasonal Direct N2O emissions. Nitrous oxide emissions are highly variable, both temporally and spatially where pulse events can make up a majority of n2o emissions (Shcherbak et al., 2014; Barton et al., 2016; Wagner-Riddle et al., 2017). Continuous sampling is still uncommon, with most data sets sampling periodically, with meta-analysis suggesting ~75% of N2O data sets are based on less than 50 samples in a year (Dorich et al., 2020a, Dorich et al., 2020b; Shang et al., 2020). Thus gaps within n2o datasets is the norm, and gap-filling is thus a requirement for deriving cumulative or annual emissions. It should be no surprise then that sampling method (e.g., strategy, frequency, gap-filling method and other methodological choices) have been shown to impact resulting N2O results and emission factor (EF) calculations (Parkin 2008; Mishurov and Kiely, 2011; Savage, Phillips, & Davidson, 2014; Reeves and Wang, 2015; Barton et al., 2015; Shang et al., 2020).

Linear interpolation has commonly been used, but is more used out of default rather than scientific evidence pointing to accurate gap-filling (Mishurov and Kiely, 2011; Dorich et al, 2020b). Due to the episodic nature of N2O emissions, driven by soil conditions, microbial communities and arrhenius dynamics, and the resulting nitrogen reactions, an exponential relationship around peak emission periods is in line with expected flux and microbial patterns seen in measurement data and is likely an improvement over linear interpolation (Grant and Pattey, 2008). As the exponential method does not utilize other covariates, like novel neural network methods, it will also not introduce high unexpected peaks during lower N2O measurement periods (Dorich et al., 2020b; Bigaignon et al., 2020). Given this episodic nature of N2O emissions, the use of linear gap-filling in studies that sample with peak "chasing" methods, or specific sampling around timing of expected events, can lead to overestimation or increased uncertainty of N2O estimates as linear interpolation amplifies these high and uncommon emission events.

While more advanced methods for gap-filling are being explored, they often require further associated covariates that may be uncommon in n2o studies (e.g., continuous soil temperature or moisture, soil inorganic nitrogen, etc) (Bigaignon et al., 2020, Cowan et al., 2019; De Rosa et al., 2018; Taki et al., 2018). While these advanced methods have been shown to be improvements for estimating peak N2O emission periods, they have also been prone to overestimating N2O emissions during periods of time with lower N2O emissions and thus more research is needed before these methods are utilized (Bigaignon et al., 2020; Dorich et al., 2020b). Thus exponential interpolation allows for improved interpolation compared to that of linear interpolation as it better represents the episodic events and underlying characteristics driving n2o fluxes while not overestimating lower periods like the novel methods still under development. The exponential interpolation used in this methodology is that used in the California Air Resources Board (CARB) methodology (Li et al., 2013 -CARB Contract 10-309)

Equation 2: Difference in treatment pair changes in seasonal/annual Direct N2O emissions

$$\sum_{d=1}^{N} e_{dt_1} - e_{dt_2}$$

where

e : direct N2O at daily temporal scale

t_1 : treatment 1

t_2 : treatment 2

d : day number since start of measurement period within a given crop year

N : total number of days between the start and end dates of the common crop season/year of treatments 1 and 2

All CH4 measurements are from chambers. To be included, studies needed to report measurements of CH4 emissions at a daily temporal scale over at least a full growing season (please see Appendix D for list of studies and coverage with sampling > 310 days). Linear interpolation (Smartt et al., 2016a; Linquist et al., 2015; Rogers et al., 2017; Simmonds et al., 2015a) was used to gapfill daily observations in the calculation of seasonal CH4 emissions. Treatment-pairs were required to share a common season/year. Units of interest for uncertainty quantification were differences between treatment pairs of total (seasonal/annual) CH4 emissions in tCO2e per acre (Equation 3).

Equation 3: Difference in treatment pair changes in seasonal/annual CH4 emissions

$$\sum_{d=1}^{N} e_{dt_1} - e_{dt_2}$$

where

e : direct CH4 at daily temporal scale
t_1 : treatment 1
t_2 : treatment 2
d : day number since start of measurement period within a given crop year
N : total number of days between the start and end dates of the common crop season/year of treatments 1 and 2

The number of LRRs/IPCC climate zones declared valid by this report is the same as the number of LRRs/IPCC climate zones covered by the validation dataset (Section 4.2.2).

The extent of the single validation domain specified for each Emissions Source includes all soil texture classes covered by study-sites in the validation dataset (Section 4.2.3). The range of clay content represented within these two validation domains is roughly 5-33% clay for SOC, 12-59% for Direct N2O and 18-59% for CH4 (Section 4.2.3).

4.3.3 Special Rules for Practice Categories

There are no special rules for practice categories to consider under this report. Regrow's requested deviation results in the dissolution of CFG x PC x ES unit to only ES units. Per this request, any crop rotation of crops covered by the declared crop functional groups (Section 3.2.1) would be valid.

4.3.4 Model Initialization and Gap-filling Methods

DNDC simulations are built and run for each treatment in the validation dataset. Each simulation is initialized over a spin-up period consisting of the five years prior to the first measurement date of the Emissions Source of interest. Where the data presented in the study does not provide all necessary DNDC input parameters, simulations are gap-filled using the methods in Appendix A.

4.3.5 Studies in the Validation Dataset

All studies in the validation dataset are summarized by Emissions Source, Land Resource Region, Crop Functional Group, Practice Category, and Soil Texture Class in Appendix B.

4.4 Assessment of Bias for Each PC/CFG/ES Combination

Regrow's approach to evaluating model bias results in the following deviations from the CAR Guidance (see also Appendix C):

- Regrow estimates model bias once for each Emissions Source across the entire validation domain and not at the PC x CFG x ES level specified in the Guidance.
- The measured and modeled units of interest for Regrow's calculation of model bias are the differences in emissions for a given Emissions Source (annual dSOC or total (seasonal/annual) N2O and CH4) *between paired treatment measurements.* This is implicitly assumed but not explicitly stated in Equation 3.1 of the Guidance.
- Regrow's uncertainty model includes a model discrepancy term (Section 4.0 & Figure 2) that allows for the correction of any bias and propagation of this estimate's uncertainty to model simulations of credited fields, while the Guidance calculates bias using the empirical Equation 3.1 but does not account for it in novel crediting simulations. The model discrepancy term (delta) is similar to the bias calculation (equation 3.1) in that the posterior mean of delta is approximately the average of measured and modeled differences. Unlike in equation 3.1, it is the measured minus modeled, thus a negative value indicates that the model overestimates measured emission differences between treatment-pairs while a positive value indicates an underestimate. Furthermore, the delta parameter has no weighting by study. Tables of specific study bias using equation 3.1 are available in appendix G.
- Regrow reports a single value of pooled measurement uncertainty (PMU) by emission source based on all available treatment pairs from studies in the validation database reporting replicated variability. We compare the posterior distribution of the delta parameter for each emission source to the corresponding PMU estimate. For CH4 we include calibration and validation datasets in the PMU calculation. Studies comprising the calibration dataset are specified in table 12, with associated references listed in section 7.

Histograms showing the model discrepancy parameter's posterior distribution for SOC, Direct N2O emissions and CH4 emissions are shown in Figure 2.

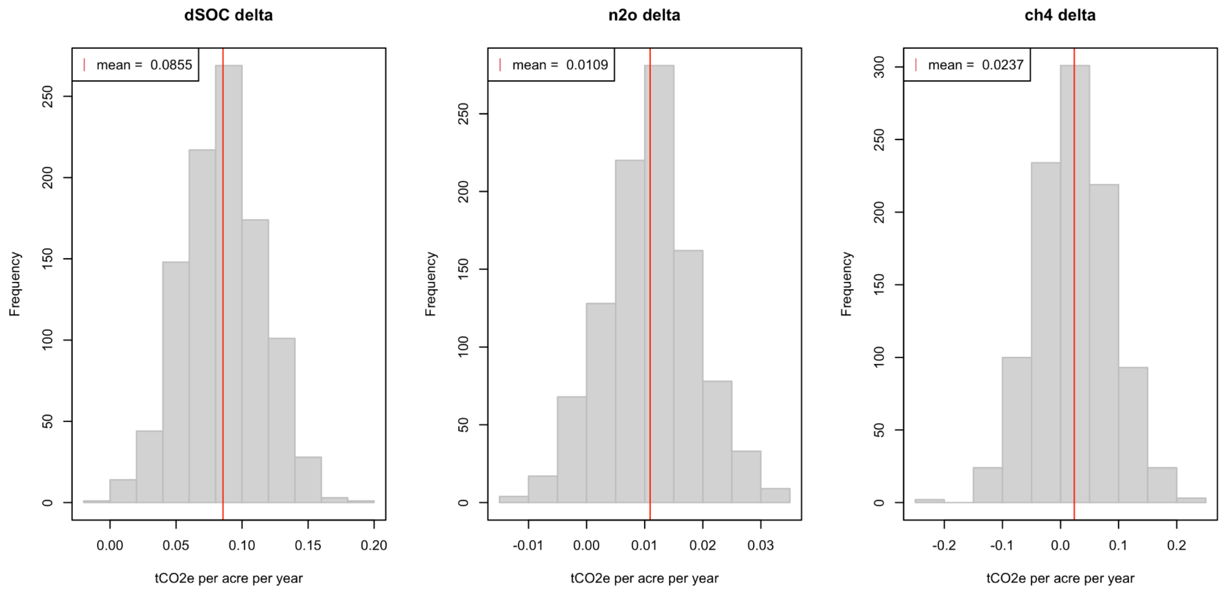

Figure 2. Posterior distributions of the model discrepancy/bias parameter of the uncertainty model by emission type based on the validation set.

4.4.1 PMU calculations dSOC

Table 8 lists the studies used in the PMU calculation for dsoc. These studies report the SOC measurement error and the number of replicates used in the calculations, but not information about correlations between measurements at different times and treatments.

Table 8: Counts of dSOC treatment pairs with 5 or more years between SOC measurement from studies used for PMU calculation for dsoc by study and by those reporting standard error.

Study-site Key	**Treatment paired measurements**	**Treatment paired reporting standard error**	**Depth of measurements (cm)**
balkcom_2013-PARU	21	21	15
poffenbarger_2017-central	45	45	15
mitchell_2015_2017-wsrec	34	6	30
MTSINVND - NVND	66	66	20
rob_2022-DIV (Germany)	70	70	20
Sum Total	**236**	**208**	

We calculate approximate measurement errors of SOC changes based on the available information (Equation 4). We note that the example calculation of measurement errors due to practice changes (general for any emission) in Figure 3.1 of the SEP Model Guidance uses the same approximation (i.e. the variance of the difference is the sum of the variances). This approximation is exact if the two differenced quantities are uncorrelated, otherwise it overestimates.

Equation 4. Measurement error for changes in SOC tCOe2 per acre per year due to practice change

$$\sigma_j = \frac{\sqrt{se^2_{t_1,d_1,j} + se^2_{t_1,d_2,j} + se^2_{t_2,d_1,j} + se^2_{t_2,d_2,j}}}{y_j}$$

where

j : treatment pair case (row id)

se^2 : SOC replicate mean standard error squared (includes t, d and j subscripts)

t_1 : treatment 1

t_2 : treatment 2

d_1 : date 1

d_2 : date 2

y : length of time in years between date 1 and date 2

The total number of treatment pair measurements used in the calculation was 208 of which 12 had an unbalanced number of replicates between treatments. We thus apply an additional modification to equation 3.2 of the Model Guidance where we used the largest replicate count for n_j. This results in the smallest estimate of PMU given the available information which is the most conservative threshold. Equation 5 shows the complete calculation for PMU using all 208 treatment pairs, which Table 9 gives a partial calculation for demonstration purposes. The study in table 9 (Mitchell_2015_2017, site=wsrec) measures total C and total N by combustion using a combustion C analyzer (CE Elantech, Inc., Lakewood, NJ).

Equation 5. PMU of changes in SOC tCOe2 per acre per year due to practice change

$$PMU = \sqrt{\frac{\sum_{j=1}^{208} \sigma_j^2 (n_j - 1)}{\sum_{j=1}^{208} (n_j - 1)}}$$ = 0.425 tCO2e per acre per year

where $n_j = max(n_{t_1,d_2}, n_{t_1,d_1}, n_{t_2,d_2}, n_{t_2,d_1})$.

Table 9: Example dSOC PMU Calculation (all units are tCO2e/acre/year)

study, site	***date1***	***date2***	***y***	***se^2_t1_d1***	***se^2_t1_d2***	***n_t1_d1***	***n_t1_d2***
mitchell_2015_2017, wsrec	1999-10-17	2007-10-17	8	2.5124	1.1164	8	8
	1999-10-17	2007-10-17	8	2.5124	1.1164	8	8

	1999-10-17	2007-10-17	8	2.5124	1.1164	8	8
	1999-10-17	2007-10-17	8	0.8076	0.2913	8	8
	1999-10-17	2007-10-17	8	0.8076	0.2913	8	8
	1999-10-17	2007-10-17	8	0.2697	1.4661	8	8

study_site	***se^2_t2_d1***	***se^2_t2_d2***	***n_t2_d1***	***n_t2_d2***
mitchell_2015_2017, wsrec	0.8076	0.2913	8	8
	0.2697	1.4661	8	8
	3.0856	1.0395	8	8
	0.2697	1.4661	8	8
	3.0856	1.0395	8	8
	3.0856	1.0395	8	8

study_site	***sigma_j***	***sigma_j^2***	***nj-1***	***sigma_j^2(nj-1)***
mitchell_2015_2017, wsrec	0.2716	0.0738	7	0.5164
	0.2893	0.0837	7	0.5860
	0.3478	0.1210	7	0.8469
	0.2103	0.0442	7	0.3096
	0.2855	0.0815	7	0.5706
	0.3024	0.0915	7	0.6402
			total	**total**
			42	3.4697
			PMU =	0.2874

The range of the Monte Carlo samples approximating the posterior distribution of the dSOC delta parameter from the uncertainty model is -0.0176 to 0.1847 (tCO2e/acre/yr) with a mean value at 0.0855 (tCO2e/acre/yr). In absolute value the posterior mean for delta (0.0855 tCO2e/acre/yr) is not more extreme than the PMU (0.425 tCO2e/acre/yr). Additionally per equation 3.1 of CAR SEP model guidance the unweighted study average bias of 0.1698 tCO2e/acre/yr (see Appendix G) is not more extreme in absolute value than the PMU (0.425 tCO2e/acre/yr).

4.4.2 PMU calculations N2O

For N2O, the PMU for differences in treatments for seasonal/annual estimates of N2O are based on 1015 treatment pairs, 67 of which span a period greater than 310 days. These come from the studies reported in table 10.

Table 10: Treatment Pair count by study and length greater than 310 days used for PMU calculation of paired treatment differences in annual/seasonal N2O total emissions.

Study-Site Key	Treatment paired measurements	Treatment paired measurements used	Treatment paired measurements used with > 310 days
adviento-borbe_2013, CA1	10	10	0
adviento-borbe_2013, CA2	10	10	10
burger_and_horwath_2012, Winters	2	2	0
COFOARD1_GHG_123_SOC, ARDEC	127	127	15
COFOARD2_GHG, ARDEC	132	132	0
COFOARD3_GHG, ARDEC	240	240	21
COFOARD4, ARDEC	40	40	20
engel_2010, APF	30	25	0
hoben_2011, Mason	15	15	0
karki_2021, Burdette	3	3	0
KYBGGHG, KYBGGHG	108	108	0
lagomarsino_2016, SIS (Italy)	2	1	0
mcgowan_2018, KSU_ARF	36	36	1
MTSINVND, NVND	264	264	0

omonode_and_vyn_2013, Haubstadt	2	2	0
Sum Total		**1015**	**67**

The seasonal/annual N2O measurement standard errors are based on exponential interpolations of the upper bound of reported error on daily n2o measurements. The paired difference variances are calculated using the seasonal/annual total emissions measurement errors (Equation 6). This is the same calculation used in the example of CAR SEP Model Guidance Figure 3.1. However, it is an approximation that overestimates the variance when treatments (baseline and practice) are correlated.

Equation 6: Measurement variance for total annual/seasonal N2O emissions due to practice change

$$\sigma_j^2 = se_{t_1,j}^2 + se_{t_2,j}^2$$

where

j : treatment pair case (row id)

se^2 : seasonal/annual N2O replicate standard error of mean squared (includes t and j subscripts)

t_1 : treatment 1

t_2 : treatment 2

Equation 7 shows the complete calculation for PMU using all 1015 treatment pairs, which Table 11 gives a partial calculation for demonstration purposes. The study in table 11 (omonode_and_vyn_2013) measures soil N2O fluxes by the vented chamber procedure (Mosier et al., 2006). Equation 7 is exactly the Model Guidance equation 3.2 since for N2O all N2O treatment pairs the replicates are balanced (i.e. $n_{t_1,j} = n_{t_2,j}$).

Equation 7: PMU of treatment pair differences between annual/seasonal N2O total emissions

$$PMU = \sqrt{\frac{\sum_{j=1}^{1015} \sigma_j^2 (n_j - 1)}{\sum_{j=1}^{1015} (n_j - 1)}}$$ = 0.0729 tCO2e per acre per year

where:

n_j : number of replicates

Table 11: Example N2O PMU Calculation (all units are tCO2e/acre/year)

study	se^2_t1	se^2_t2	n_t1	n_t2	sigma_j^2	nj-1	sigma_j^2(nj-1)
omonode_and_vyn_2013	0.00804	0.00403	3	3	0.01207	2	0.02414
omonode_and_vyn_2013	0.00004	0.00002	3	3	0.00006	2	0.00011

study	se^2_t1	se^2_t2	n_t1	n_t2	sigma_j^2	nj-1	sigma_j^2(nj-1)
						total	total
						4	0.02425
						PMU =	0.0779

The range of the Monte Carlo samples approximating the posterior distribution of the N2O delta parameter from the uncertainty model is -0.0131 to 0.035 with a mean value at 0.0109 tCO2e/acre/year. In absolute value the posterior mean for delta (0.0109 tCO2e/acre/year) is not more extreme than the PMU (0.0729 tCO2e/acre/year). Additionally per equation 3.1 of CAR SEP model guidance the unweighted study average bias of 0.0137 tCO2e/acre/yr (see Appendix G) is not more extreme in absolute value than the PMU (0.0729 tCO2e/acre/yr).

4.4.3 PMU calculations CH4

For CH4, the PMU for differences in treatments for seasonal/annual estimates of CH4 are based on 40 treatment pairs. Since there were limited CH4 standard error measurements in the validation dataset, the PMU is based on standard error measurements from the validation dataset (n=26 pairs) and the calibration dataset (n=14 pairs). Of the 40, 10 (all from the validation dataset) span a period greater than 310 days. Table 12 gives a summary of the studies used in the PMU calculation for CH4.

Table 12: Treatment Pair count by study and length greater than 310 days used for PMU calculation of paired treatment differences in annual/seasonal CH4 total emissions.

Study-Site Key	**dataset**	**Treatment paired measurements used**	**Treatment paired measurements used with > 310 days**
adviento-borbe_2013, AR_RREC	validation	6	0
adviento-borbe_2013, CA1	validation	10	0
adviento-borbe_2013, CA2	validation	10	10
linquist_2015, AR_RREC	calibration	6	0
simmonds_2015a, AR2_RREC	calibration	6	0
rogers_2017, AR_RREC_AS	calibration	1	0

rogers_2017, AR_NEREC_AS	calibration	1	0
Sum Total		**40**	**10**

The seasonal/annual CH4 measurement standard errors are based on linear interpolations of the upper bound of reported error on daily ch4 measurements. The paired difference variances are calculated using the seasonal/annual total emissions measurement errors (Equation 8). This is the same calculation as Equation 6 but for CH4.

Equation 8: Measurement variance for total annual/seasonal CH4 emissions due to practice change

$$\sigma_j^2 = se_{t_1,j}^2 + se_{t_2,j}^2$$

where

j : treatment pair case (row id)

se^2 : seasonal/annual CH4 replicate standard error of mean squared (includes t and j subscripts)

t_1 : treatment 1

t_2 : treatment 2

Equation 9 shows the complete calculation for PMU using the 40 treatment pairs, which Table 13 gives a partial calculation for demonstration purposes. The study in table 13 (adviento-borbe_2013, site = AR_RREC) measures soil ch4 fluxes using a static vented chamber technique (Hutchinson and Livingston, 1993).

Equation 9: PMU of treatment pair differences between annual/seasonal CH4 total emissions

$$PMU = \sqrt{\frac{\sum_{j=1}^{40} \sigma_j^2 (n_j - 1)}{\sum_{j=1}^{40} (n_j - 1)}}$$ = 0.4999 tCO2e per acre per year

where:

n_j : number of replicates

Table 13: Example CH4 PMU Calculation (all units are tCO2e/acre/year)

study, site	se^2_t1	se^2_t2	n_t1	n_t2	sigma_j^2	nj-1	sigma_j^2(nj-1)
adviento-borbe_2013, AR_RREC	0.01150	0.02001	3	3	0.03151	2	0.06302
	0.01150	0.05950	3	3	0.07100	2	0.14199
	0.01150	0.05950	3	3	0.07100	2	0.14199
	0.02001	0.05950	3	3	0.07951	2	0.15903

	0.02001	0.05950	3	3	0.07951	2	0.15903
	0.05950	0.05950	3	3	0.11900	2	0.23799
						total	**total**
						12	0.90305
						PMU =	0.2743

The range of the Monte Carlo samples approximating the posterior distribution of the CH4 delta parameter from the uncertainty model is -0.2150 to 0.2276 with a mean value at 0.0237 tCO2e/acre/year. In absolute value the posterior mean for delta (0.0237 tCO2e/acre/year) is not more extreme than the PMU (0.4999 tCO2e/acre/year). Additionally per equation 3.1 of CAR SEP model guidance the unweighted study average bias of -0.0811 tCO2e/acre/yr (see Appendix G) is not more extreme in absolute value than the PMU (0.4999 tCO2e/acre/yr).

4.5 Evaluate Model Prediction Error

Regrow's approach to evaluating model prediction error results in the following deviations from the CAR Guidance (see also Appendix C):

- Regrow provides the data summary of measured versus modeled scatterplots, histograms of residuals and mean square error statistics, and 90% prediction interval coverage probabilities over the entire validation domain by Emissions Source but not at the PC x CFG x ES level specified in the Guidance. Practice category and crop functional group are not parameters in the uncertainty model and thus the summaries by these categories would not propagate to new modeling units.
- The measured and modeled units of interest for Regrow's calculation of model prediction error are the differences in emissions for a given Emissions Source over time and *between paired treatments.* This is implicitly assumed but not explicitly stated in Section 3.5 of the Guidance.

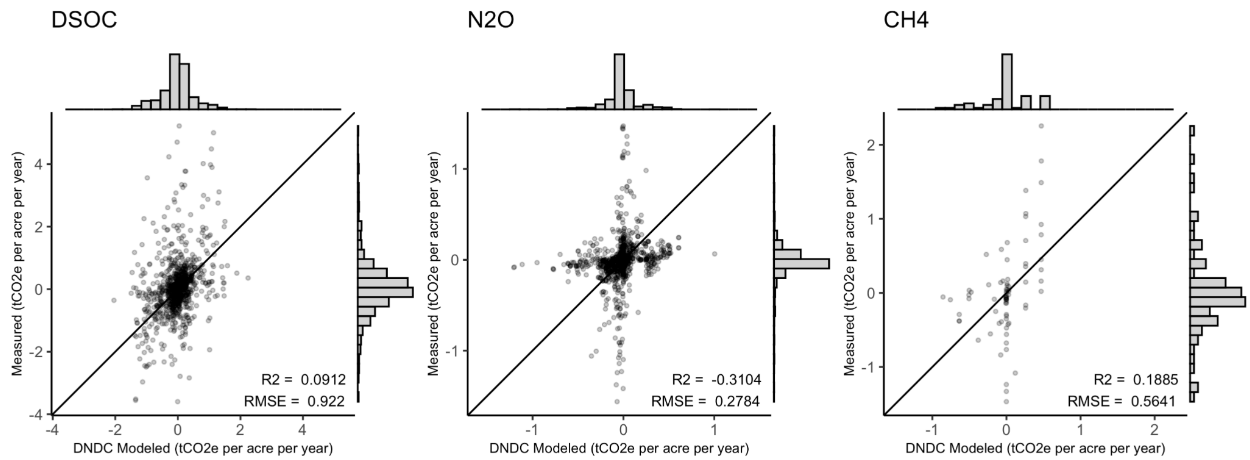

Figure 3. Scatterplots of Measured versus DNDC modeled by Emission Source for the entire validation set. Left: dSOC treatment differences (equation 1), Middle: N2O treatment differences (equation 2), Right: CH4 treatment differences (equation 3)

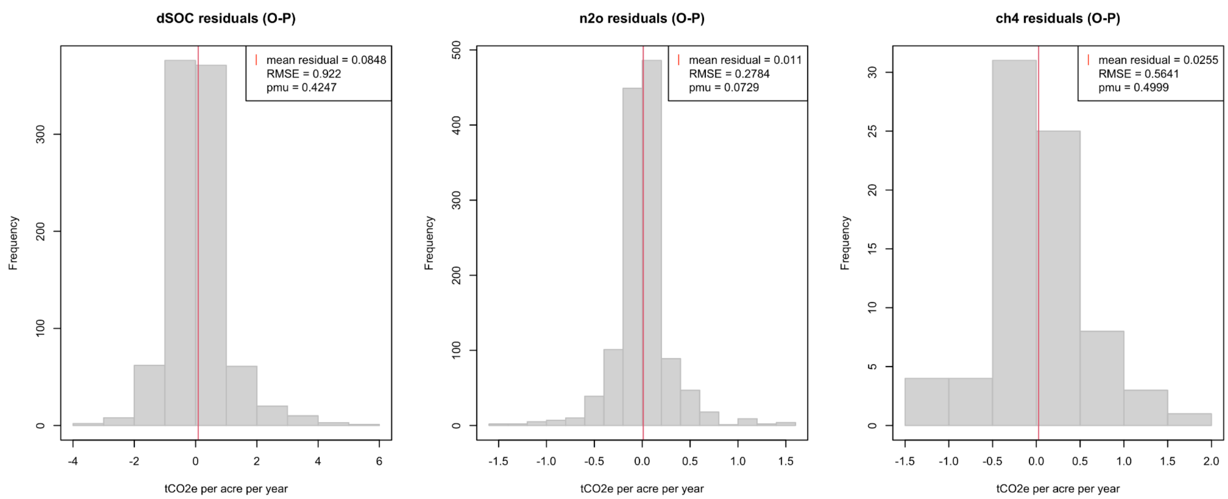

Figure 4. Histograms of residuals (measured - modeled) by Emission Source for the entire validation set.

Note in the histograms above (Figure 4) the mean residual for each emission source is approximately equal to the mean of posterior distribution of delta (Section 4.4, Figure 2) while the root mean squared error (RMSE) is approximately equal to the mean of the posterior distribution of sigma shown below (Figure 5).

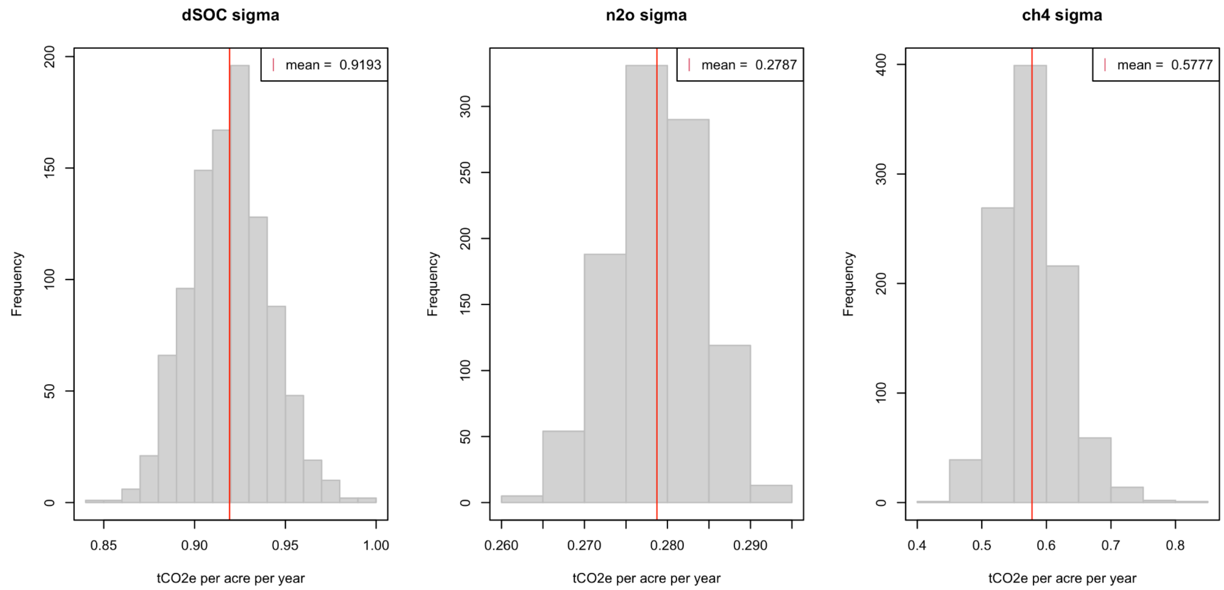

Figure 5. Posterior distributions of the sigma parameter of the uncertainty model by emission type based on the validation set.

Model prediction error is defined as the standard error of the posterior predictive distribution based on the uncertainty model. The posterior predictive distribution is the distribution of offsets at a new modeling unit not in the validation data conditional on the uncertainty model. 1000 samples are obtained from this distribution using Monte Carlo (MC) integration. To demonstrate the coverage probability of the 90% prediction intervals derived from these distributions, we generate 90% prediction intervals based on an approximate leave-one out (LOO) cross-validation procedure (Vehtari et al., 2017) for the modeled values in the validation dataset. The number of corresponding measured validation values that fall within the 90% prediction intervals is reported. For dSOC, 826 of the total 914 measured validation values were contained in the 90% prediction intervals (for a 90.37% coverage probability), for N2O 1159 of the total 1271 measured validation values were contained in the 90% prediction intervals (for a 91.19% coverage probability) and for CH4 68 of the total 76 measured validation values were contained in the 90% prediction intervals (for a 89.47% coverage probability) (Figure 6). The coverage probability for CH4 is slightly under the required 90% coverage, however this is within the precision of the coverage probability estimate given the smaller number of pairs. One more pair included in the coverage, i.e. 69/76 results in a coverage probability of 90.78% larger than 90%.

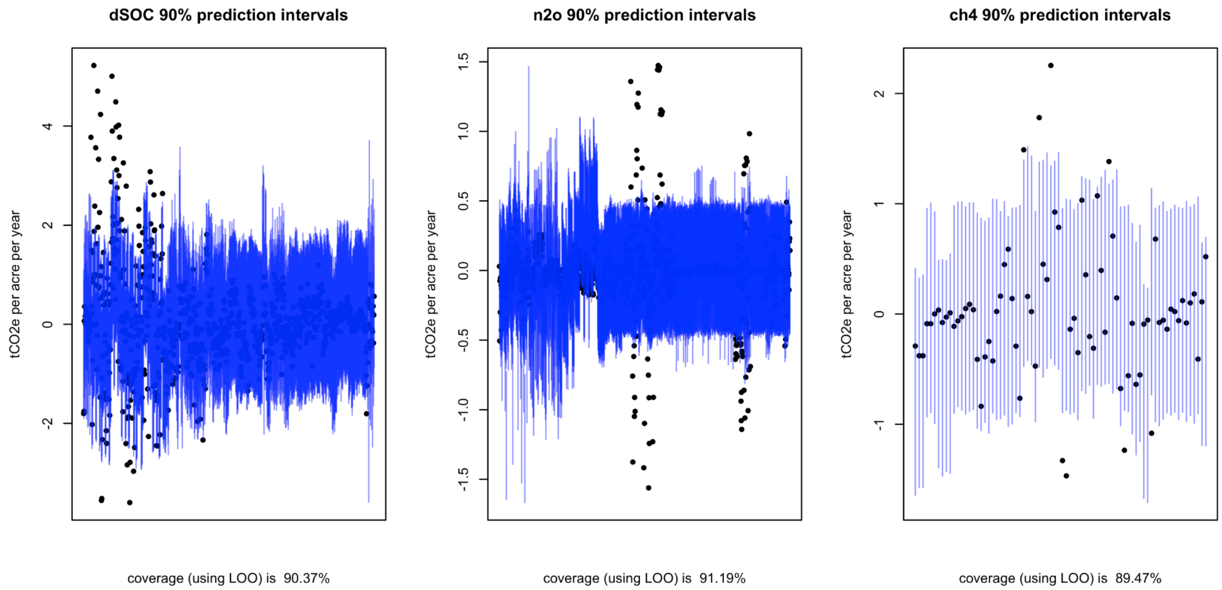

Figure 6. Measured validation values (dots) compared with 90% prediction interval (blue).

We also present model prediction error for dSOC as a function of both study-site and depth of soil measurements (Figure 7). This figure shows that model prediction error is more so a function of study-site than measurement depth across the domain, justifying the inclusion of soil measurements to <30 cm depth in the validation pool. Furthermore, there is no evidence that dSOC measurements at shallow depths (<30 cm) overestimate change in SOC relative to measurements at deeper depths (30 cm) (Appendix E).

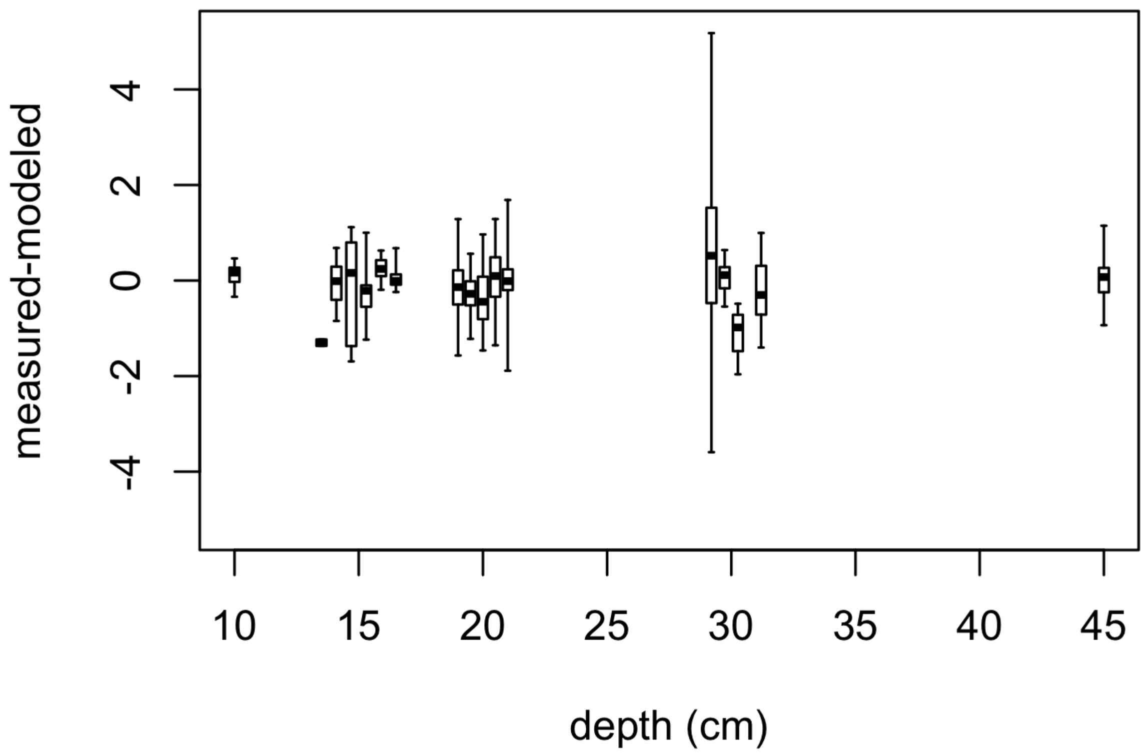

Figure 7. Model prediction error (measured - modeled) for dSOC between treatment pairs as a function of study-site (boxes) and measurement depth.

Table 15. Count of observations and study-site by depth

SOC depth (cm)	count observations	count of study-sites
10	15	1
15	219	7
20	227	11
30	266	3
30.4	52	1
45	135	1

4.6 Extension of Uncertainty Model to Soil Enrichment Protocol

Regrow's deviation from the CAR SEP Guidance necessitates an additional deviation from the CAR SEP with regards to methods used to propagate model structural uncertainty from validation data to novel simulations of project fields. In particular, SEP Appendix D specifies (page 116) that “the estimate of total emissions reduction is made using measurements and model predictions on a subset of the project selected through a random sample,” and thus that the sampling error is included in the quantification.

Regrow’s deviation requires that model predictions be done at a sampling unit defined as a field (a contiguous area in which management practices are homogenous) and that model predictions will be made for all sampling units (fields) included in the project. This definition of the sample unit as a field is allowed by the protocol (given as an example on page 31 section 5), so when model predictions are obtained for all sample units there is no additional sampling error.

Under this deviation, Regrow will still take model input measurements of soil parameters such as initial soil organic carbon at each sample unit (field), and the average value will be used as model input. This follows the methods used in the construction of the validation data from literature studies to develop the model prediction errors, as studies commonly only report field level averages of initial soil parameters.

Quantification of field and project-level assets and uncertainty would proceed using the following process:

1. A deterministic credit value for the ES is calculated as the difference between outputs from two DNDC simulations (project - baseline for SOC, baseline - project for Direct N2O).
2. For each value of δ and σ, a single credit value is sampled from a normal distribution with **mean =** deterministic credit value + δ and **standard deviation =** σ. This is Monte Carlo integration that obtains 1000 values (one for each value of δ and σ) samples from a field-level posterior predictive distribution.
3. The samples for each field are added together across all fields in a project, resulting in a final sample of 1000 credit values that represent the project-level uncertainty distribution for the given ES.

The uncertainty deduction calculated in Equation 5.1 of the CAR SEP can be calculated using the project-level uncertainty distribution. Because this report describes an uncertainty model for Direct N2O as well as SOC, uncertainty deductions for N2O emissions reductions can be calculated along with deductions for SOC removals. In order to calculate the emissions reduction from soil organic carbon across a project in a given year, this approach necessitates a modification to CAR SEP Equation 5.3:

$$\Delta CO2\_soil_t = \Delta SOC_\mu \times (1 - UNC_t)$$

Where:

$\Delta CO2\_soil_t$ = Carbon dioxide emission reductions from the soil organic carbon pool across the project during cultivation cycle *t* (tCO2e)

ΔSOC_μ = Average change in carbon stocks in the soil organic carbon pool *between project and baseline scenarios* across the project during cultivation cycle *t* (tCO2e)

UNC_t = Uncertainty in cultivation cycle *t* (Equation 5.1)

5 Substitution for Missing Crops

No crop parameters were substituted with alternative crop parameters for this validation.

6 Verification of Model Usage

Not applicable.

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8 Appendices

Appendix A: DNDC Parameterization for Default Calibration

Category	Parameter	Description	Units	Dependency for Default Calibration	Gap-filling Data Source	Gap-filling Method
Weather	Min_temp	Minimum daily air temperature	Celsius	User provided	PRISM	Download for years of interest
Weather	Max_temp	Maximum daily air temperature	Celsius	User provided	PRISM	Download for years of interest
Weather	Precip	Daily precipitation	mm	User provided	PRISM	Download for years of interest
Soil	Texture_id	Soil texture ID	string	User provided	SSURGO	Download for geography of interest
Soil	Bulk_density	Bulk density	g/cm3	User provided	SSURGO	Download for geography of interest
Soil	ph	pH	pH	User provided	SSURGO	Download for geography of interest
Soil	Clay_fraction	Clay_fraction	Fraction	User provided or function of texture_id	SSURGO	Download for geography of interest
Soil	Porosity	Fraction of void space	Fraction	Function of Texture_id	N/A	

Soil	Field_capacity	Field capacity	WFPS	Function of texture_id	N/A	
Soil	Wilting_poitn	Wilting point	WFPS	Function of texture_id	N/A	
Soil	Hydro_conductivity	Hydraulic conductivity	m/h	Function of texture_id	N/A	
Soil	Top_layer_soc	Initial SOC fraction	Fraction	User provided	SSURGO	Download for geography of interest
Soil	Frac_litter	SOC litter fraction	Fraction	Function of texture_id	N/A	
Soil	Frac_humads	SOC humads fraction	Fraction	Function of texture_id	N/A	
Soil	Frac_humus	SOC humus fraction	Fraction	Function of texture_id	N/A	
Soil	Adjusted_litter_factor	Litter decomposition rate adjusting factor	Fraction	Function of texture_id	N/A	
Soil	Adjusted_humads_factor	Humads decomposition rate adjusting factor	Fraction	Function of texture_id	N/A	
Soil	Adjusted_humus_factor	Humus decomposition rate adjusting factor	Fraction	Function of texture_id	N/A	
Soil	cn_humads	Humads C:N	Ratio	Function of texture_id	N/A	

Soil	cn_humus	Humus C:N	Ratio	Function of texture_id	N/A	
Soil	Frac_passive_c	Passive C fraction	Fraction	Function of texture_id	N/A	
Soil	cn_passive_c	Passive C C:N	Ratio	Function of texture_id	N/A	
Soil	soc_profile_a	Depth of uniform SOC	cm	User provided	SSURGO	Download for geography of interest
Soil	soc_profile_b	SOC decrease rate	Numeric	Derived from validation data where multiple soil profiles reported. Otherwise, defaulted to 1.5.	N/A	
Soil	Initial_nitrate_ppm	Initial soil nitrate	ppm	Function of texture_id	N/A	
Soil	initial_ammonium_ppm	Initial soil ammonium	ppm	Function of texture_id	N/A	
Soil	microbial_index	Microbial activity index	fraction	Function of texture_id	N/A	
Soil	watertable_depth	Depth to water table	m	2 m	N/A	
Soil	factor_ch4_P1	maximum CH4 production rate factor	fraction	user provided or function of water management, otherwise defaulted to 0.5	N/A	

Soil	factor_ch4_fPGI	growth stage root exudation factor	fraction	defaulted to 0.625	N/A	
Crop	name	DNDC crop name	NA	user provided	N/A	
Crop	crop_id	DNDC crop id	index	user provided	CDL	Downloaded for geography of interest
Crop	plant_date	planting date	date	user provided	NASS	Downloaded for state x crop of interest
Crop	end_date	crop termination date (if not harvested)	date	user provided	NASS	Downloaded for state x crop of interest
Crop	harvest_date	harvest date	date	user provided	NASS	Downloaded for state x crop of interest
Crop	residue_fraction	fraction of plant remaining on soil surface after harvest	fraction	user provided	NASS	Downloaded for state x crop of interest
Crop	max_biomass	Potential maximum biomass	kgC/ha	Function of crop_id	N/A	
Crop	frac_leaf	Leaf fraction	fraction	Function of crop_id	N/A	
Crop	frac_shoot	Stem fraction	fraction	Function of crop_id	N/A	

Crop	frac_root	Root fraction	fraction	Function of crop_id	N/A	
Crop	frac_grain	Grain fraction	fraction	Function of crop_id	N/A	
Crop	cn_leaf	Leaf C:N	ratio	Function of crop_id	N/A	
Crop	cn_stem	Stem C:N	ratio	Function of crop_id	N/A	
Crop	cn_root	Root C:N	ratio	Function of crop_id	N/A	
Crop	cn_grain	Grain C:N	ratio	Function of crop_id	N/A	
Crop	tdd	Temperature degree days maturity	Degree-days	Function of crop_id	N/A	
Crop	optimum_temperature	Optimal temperature	Degrees Celsius	Function of crop_id	N/A	
Crop	water_demand	Water use efficiency	g H2O / g DM	Function of crop_id	N/A	
Crop	n_fixation_index	N fixation index (plant N / N from soil)	ratio	Function of crop_id	N/A	
Crop	vascularity_index	Vascularity index	index	Function of crop_id	N/A	
Crop	is_cover_crop	Cover crop flag	boolean	Function of crop_id	N/A	
Crop	is_perennial_crop	Perennial crop flag	boolean	Function of crop_id	N/A	

Tillage	till_date	Tillage date	date	User provided	OpTIS + internal logic	Available upon request
Tillage	till_depth	Tillage depth	cm	User provided	Regrow lit review	Available upon request
Tillage	invert	Tillage inversion	boolean	User provided	Regrow lit review	Available upon request
Fertilizer	fert_date	Date of fertilizer application	date	User provided	ERS ARMS	Downloaded for state x crop of interest
Fertilizer	fert_id	DNDC fertilizer ID	string	User provided	ERS ARMS	Downloaded for state x crop of interest
Fertilizer	fert_rate	Rate of fertilizer application	kg / ha	User provided	ERS ARMS	Downloaded for state x crop of interest
Fertilizer	fert_method	Fertilizer application method (surface/injected)	string	User provided	ERS ARMS	Downloaded for state x crop of interest
Fertilizer	fert_depth	Depth of fertilizer injection	cm	User provided	ERS ARMS	Downloaded for state x crop of interest
Fertilizer	nitrate	Fertilizer nitrate content	fraction	Function of fert_id	N/A	

Fertilizer	ammonia	Fertilizer ammonia content	fraction	Function of fert_id	N/A	
Fertilizer	ammonium_bicarbonate	Fertilizer ammonium bicarbonate content	fraction	Function of fert_id	N/A	
Fertilizer	urea	Fertilizer urea content	fraction	Function of fert_id	N/A	
Fertilizer	anh	Fertilizer anhydrous ammonia content	fraction	Function of fert_id	N/A	
Fertilizer	ammonium	Fertilizer ammonium content	fraction	Function of fert_id	N/A	
Fertilizer	sulfate	Fertilizer sulfate content	fraction	Function of fert_id	N/A	
Fertilizer	cr	Controlled release fertilizer	boolean	Function of fert_id	N/A	
Fertilizer	cr_duration	Number of days for uniform release of cr fertilizer	days	Function of fert_id	N/A	
Fertilizer	ni	Nitrification inhibitor fertilizer	boolean	Function of fert_id	N/A	
Fertilizer	ni_duration	Number of days for reduced	days	Function of fert_id	N/A	

		nitrifying activity by ni fertilizer				
Fertilizer	ni_efficiency	Fraction of nitrifying activity inhibited by ni fertilizer	fraction	Function of fert_id	N/A	
Fertilizer	ui	Urease inhibitor fertilizer	boolean	Function of fert_id	N/A	
Fertilizer	ui_duration	Number of days for reduced urease activity by ui fertilizer	days	Function of fert_id	N/A	
Fertilizer	ui_efficiency	Fraction of urease activity inhibited by ui fertilizer	fraction	Function of fert_id	N/A	
Manure	manure_date	Date of manure application	date	User provided	Regrow lit review	Available upon request
Manure	manure_id	DNDC manure ID	string	User provided	Regrow lit review	Available upon request
Manure	manure_rate	Rate of manure application	kg / ha	User provided	Regrow lit review	Available upon request
Manure	manure_method	Method of manure application (broadcast, injected, incorporated)	string	User provided	Regrow lit review	Available upon request

Manure	manure_depth	Depth of manure application (if injected or incorporated)	cm	User provided	Regrow lit review	Available upon request
Manure	manure_cn	Manure C:N ratio	ratio	Function of manure_id	N/A	
Manure	manure_org_n	Manure organic N content	fraction	Function of manure_id	N/A	
Manure	manure_nh4	Manure ammonium content	fraction	Function of manure_id	N/A	
Manure	manure_no3	Manure nitrate content	fraction	Function of manure_id	N/A	
Cutting	cut_date	Date of cutting	date	User provided	Regrow lit review	Available upon request
Cutting	cut_fraction	Fraction of aboveground biomass cut	fraction	User provided	Regrow lit review	Available upon request
Grazing	start_date	Start date of grazing event	date	User provided	No grazing data in this report	
Grazing	end_date	End date of grazing event	date	User provided	No grazing data in this report	
Grazing	grazer_id	DNDC grazing animal ID	string	User provided	No grazing data in this report	

Grazing	heads	Number of grazing animals during event	integer	User provided	No grazing data in this report	
Grazing	hours	Hours per day spent grazing	integer	User provided	No grazing data in this report	
Grazing	additional_feed_per_head	Supplemental feed per head	kg C / head	User provided	No grazing data in this report	
Grazing	feed_cn	Feed C:N ratio	ratio	User provided	No grazing data in this report	
Grazing	excreta_removal	Was manure removed	boolean	User provided	No grazing data in this report	
Flooding	start_date	Start date of flooding event	date	User provided	Internal logic	Plant date + 30 days
Flooding	end_date	End date of flooding event	date	User provided	Internal logic	Harvest date - 21 days
Flooding	flood_water_n	Flood water N rate	kg N / ha	User provided	Regrow lit review	Available upon request
Flooding	water_leak_rate	Field water loss rate	mm / day	User provided	Regrow lit review	Available upon request
Flooding	water_gether_index	Field watershed area	hectares	User provided	Regrow lit review	Available upon request
Irrigation	irrig_date	Irrigation date	date	User provided	MIRAD	Downloaded for geography of interest

Irrigation	irrig_method	Irrigation method (flood, sprinkler, drip)	string	User provided	Internal logic	Sprinkler method
Irrigation	irrigation_index	Water deficit met by automatic irrigation	fraction	Function of irrig_date	N/A	
Plastic Mulch	start_date	Plastic mulch event start date	date	User provided	No plastic mulch gap-filling needed	
Plastic Mulch	end_date	Plastic mulch event end date	date	User provided	No plastic mulch gap-filling needed	
Plastic Mulch	cover_fraction	Fraction of field covered by plastic mulch	fraction	User provided	No plastic mulch gap-filling needed	

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Appendix B: Studies in the Validation Dataset

Study-site Key	DOIs	Emissions Sources	Land Resource Region	IPCC climate Zone ID	Crop Functional Groups	Practice Categories (changes)	Soil Texture Classes	# of Treatment Pairs
al-kaisi_2005a -NRDM	10.1016/j.agee.2004.08.0 02 10.1016/j.apsoil.2005.02. 014 10.2134/jeq2005.0437	SOC	M	7	C4A, C3AN	TR (tillage)	loam	1 (at 15cm)
al-kaisi_2005a -SRDF	10.1016/j.agee.2004.08.0 02 10.1016/j.apsoil.2005.02. 014 10.2134/jeq2005.0437	SOC	M	5	C4A, C3AN	TR (tillage)	silty clay loam	1 (at 15cm)
balkcom_2013 -PARU	ISBN 978-1-888626-12-4 10.2136/sssaj2013.01.00 34 ISBN 978-1-888626-18-6	SOC	P	3	C3A, C4A, C3AS	TR, Crop (cover crop and tillage)	sandy loam	21 (at 15cm)
clapp_2000-U MROC	10.2136/sssaj2004.1366 10.1016/S0167-1987(00) 00110-0 10.1016/S0167-1987(00) 00139-2	SOC	K	7	C4A	InN, TR (N-rate, residue removal, tillage	silt loam	226 (at 30cm)
COFOARD1_G HG_123_SOC-ARDEC	doi.org/10.2134/jeq2008. 0517 10.2136/sssaj2012.0413 10.2134/agronj2011.0102 10.2134/jeq2007.0268 10.2134/jeq2011.0194 10.2134/agronj2010.0455 10.2134/jeq2005.0232 https://doi.org/10.15482 /USDA.ADC/1503969 https://doi.org/10.15482 /USDA.ADC/1503997 https://doi.org/10.15482 /USDA.ADC/1503998	SOC, Direct N2O	G	8	C4A	InN, TR (N-rate, N-form, tillage)	clay loam	52 - SOC (at 30.4cm) 127 - N2O
locke_2013-CP SRUF	10.2136/sssaj2012.0325	SOC	O	5	C3A, C3AN, C3AS	TR, Crop (cover crop, tillage)	silt loam	10 (at 15cm)
mitchell_2015	10.2134/agronj14.0415	SOC	C	6	C3A, C3AN,	TR, Crop	sandy	34 (at 30cm)

_2017-wsrec	10.1016/j.still.2016.09.001 https://anrcatalog.ucanr.edu/pdf/8208.pdf - publication 8208 10.3733/ca.v060n03p146				C3AS	(cover crop, tillage)	clay loam	
MTSINVND-NVND	10.1016/j.jenvman.2007.07.012 10.1016/j.still.2011.10.020 Sainju_2006 workshop/AgAirQuality2006.1086 10.2134/jeq2006.0392 10.2136/sssaj2013.12.0514 10.2136/sssaj2009.0447 10.2134/jeq2012.0176 10.2134/jeq2013.10.0405 Sainju (2020) MTSINVND USDA dataset	SOC, Direct N2O	F	8	C3A, C3AN	InN, TR, Crop, Water (N-rate, tillage, overhead sprinkler, crop)	sandy loam	66 - SOC (at 20cm) 264 - N2O
pikul_2008-ESDSWRF	10.1016/S0167-1987(01)00174-X 10.2134/agronj2004.0263 10.2136/sssaj2005.0334 10.2136/sssaj2008.0020	SOC	M	7	C3A, C4A, C3AN, C3PN	InN, Crop (crop rotation, N-rate)	sandy clay loam	36 (at 15cm)
poffenbarger_2017-central	10.1371/journal.pone.0172293	SOC	M	7	C4A, C3AN	InN, Crop (crop rotation, N-rate)	loam	45 (at 15cm)
rob_2022-DIV2 (Germany)	10.3390/agriculture12020170	SOC	none	5	C3A	InN, OrN (N-rate, N-form, organic amendment(form,rate))	sandy loam	70 (at 20cm)
sainju_2002-ARS	10.1016/S0167-1987(01)00244-6	SOC	P	5	C3A, C3AN	InN, Crop (cover crop, N-rate)	sandy loam	15 (at 20cm)
sainju_2008-AAES	10.2134/agronj2000.925992x 10.2134/agronj2000.9251000x 10.2134/agronj2004.1641 10.1016/j.agee.2008.04.0	SOC	N	5	C3A, C4A, C3AS	InN, OrN, TR, Crop (cover crop, crop rotation, N form, N-rate, tillage, organic amendment(fo	silt loam	55 (at 20cm)

	06					rm,rate))		
sainju_2014a-SID_MT	10.2134/agronj14.0026 10.2136/5ssaj2012.0076 10.2136/sssaj2013.08.0325	SOC, Direct N2O	F	8	C3A, C3AN	InN, TR, Crop (crop rotation, N-rate, tillage) - SOC TR, Crop (crop rotation, tillage)- N2O	loam	15 - SOC (at 10cm) 60 - N2O
sanborn_field-SF	10.1201/9780367811693 10.1081/CSS-120024062 10.22004/ag.econ.257842 10.2134/agronj2010.0221s 10.1007/s00374-002-0500-6 [Motavalli and Miles (2002) Better Crops, 86(3), pp.20-23.]() 10.1007/s10533-013-9868-7	SOC	M	5	C3A, C4A, C3AN, C3P	InN, OrN, TR, Crop (crop rotation, N source, organic amendment(form,rate))	silt loam + clay loam	135 (at 45cm)
varvel_2008-UNE_Shelton	10.2134/agronj2007.0383 10.2134/agronj2003.1220	SOC	H	5	C4A, C3AN	InN, Crop (crop, crop rotation, N rate)	silt loam	105 (at 15cm)
WICST-WIARS	10.2134/agronj2007.0058 10.1017/S0889189300006238 10.1016/j.agee.2012.08.011	SOC	K	7	C4A, C3AN, C3A, C3PN	Crop (crop rotation)	silt loam	6 (at 30cm)
COFOARD2_GHG-ARDEC	10.2136/sssaj2009.0072	Direct N2O	G	8	C3A, C4A, C3AN	InN (EEF, N form, N rate), TR (tillage), Crop(crop rotation)	clay loam	132
COFOARD3_GHG-ARDEC	10.2134/jeq2012.0129	Direct N2O	G	8	C4A	InN(EEF, N depth, N form, N rate), TR(tillage)	clay loam	240
COFOARD4-ARDEC	10.2134/jeq2015.08.0426 10.2134/agronj2015.0402 https://doi.org/10.15482/USDA.ADC/1503970	Direct N2O	G	8	C4A	InN(EEF, N form, N rate), OrN(EEF, N form, N rate)	clay loam	40

burger_and_horwath_2012-winters	10.1029/2017JG004260	Direct N2O	C	6	C3PN	Crop(crop)	clay	2
engel_2010-APF	10.2134/jeq2009.0130	Direct N2O	E	8	C3A	InN (N depth, N rate)	silt loam	30
fernandez_2015-CSREC	10.2134/jeq2013.12.0496	Direct N2O	M	5	C4A	InN (N form)	silt loam + sandy clay loam	18
hernandez-ramirez_2009-ACRE	10.2134/jeq2007.0565	Direct N2O	M	5	C4A, C3AN	OrN(timing, form), Crop(crop rotation), InN(N form)	sandy clay loam	20
hoben_2011-Mason	10.1111/j.1365-2486.2010.02349.x	Direct N2O	L	7	C4A	InN(N rate)	sandy loam	15
KYBGGHG-KYBGGHG	10.2134/jeq2011.0197 10.2134/agronj2013.0087 https://doi.org/10.15482/USDA.ADC/1503968	Direct N2O	N	5	C4A	InN(EEF, N form), OrN(EEF, N form, rate)	silty clay loam	108
mcgowan_2018-KSU_ARF	10.2134/agronj2018.03.0187 10.2134/agronj2018.03.0172 10.2134/agronj2009.0462	Direct N2O	H	5	C4A, C3AN, C4P	Crop (crop rotation)	silt loam	36
nash_2012-GMRC	10.2136/sssaj2011.0296 10.1007/s10457-010-9362-3	Direct N2O	M	5	C4A	InN(N form), TR (tillage)	silt loam	20
nash_2015-GMRC	10.2489/jswc.70.4.267	Direct N2O	M	5	C4A	InN(N form)	silt loam	12
omonode_and_vyn_2013-Haubstadt	10.2134/agronj2013.0184	Direct N2O	M	5	C4A	InN (N form)	silt loam	2
parkin_and_hatfield_2010-ISURF	10.1016/j.agee.2009.11.014	Direct N2O	M	7	C4A	InN(EFF)	silty clay loam	2
parkin_and_kaspar_2006-AEARRF	10.2134/jeq2005.0183	Direct N2O	M	7	C3A, C4A, C3AN	TR (tillage), Crop (crop, cover crop)	clay loam	30
SDBRREAP-SD	doi:10.2136/sssaj2011.04	Direct	M	7	C4A ,C3AN	TR (residue	silty clay	30

BRREAP	21 10.1007/s12155-014-9413-0 10.2136/sssaj2011.0420 10.1007/s12155-016-9754-y Lehman(2020) USDA SDBRREAP Dataset	N2O				mgt.), Crop (cover crop)	loam	
sherman_2021-MARS	10.3390/agriculture11080750	Direct N2O	K	7	C3PN	OrN (depth, rate)	silt loam	9
smith_2012-SAREC	10.1016/S1002-0160(12)60045-9	Direct N2O	N	5	C4A	InN(N depth, N form), OrN(depth,rate), TR (tillage)	sandy loam	28
wegner_2018-NCARL	10.2134/jeq2018.03.0093	Direct N2O	M	7	C3A, C3AN	TR(cover crop), Crop(residue mgt.)	silty clay loam	18
adviento-borbe_2013-AR_RREC	10.2134/jeq2013.05.0167	Direct N2O, CH4	O	5	C3AF	InN (N-rate)	silt loam	3 - N2O 6 - CH4
adviento-borbe_2013-CA1	10.2134/jeq2013.05.0167	Direct N2O, CH4	C	6	C3AF	InN (N-rate)	clay	10 - N2O 10 - CH4
adviento-borbe_2013-CA2	10.2134/jeq2013.05.0167	Direct N2O, CH4	C	6	C3AF	InN (N-rate)	clay loam	10 - N2O 10 - CH4
brye_2017-RREC	10.1016/j.geodrs.2017.08.004 10.1097/SS.0000000000000039	CH4	O	5	C3AF	Crop, InN (crop N-rate, N timing)	silt loam	30
karki_2021-Burdette	10.3390/agriculture11030261	Direct N2O, CH4	O	5	C3AF	Crop (cover crop), InN(N rate, N timing), Water(miri_furrow)	clay loam + loam + clay	3 - N2O 3 - CH4
lagomarsino_2016-SIS (Italy)	10.1016/S1002-0160(15)60063-7	Direct N2O, CH4	none	5	C3AF	Water (AWD)	silty clay loam	2 - N2O 2 - CH4
smartt_2016b-NEREC	10.1097/SS.0000000000000139	CH4	O	5	C3AF	Crop(fallow), InN(N rate)	clay	3
sigren_1997-TX_AREC	10.1029/97GB00627	CH4	T	3	C3AF	Water (AWD)	clay loam	1

sigren_1997-TX_Richmond	10.1029/97GB00627	CH4	T	3	C3AF	Water (AWD)	loam	1
smartt_2016a-NREC	10.1155/2016/9542361	CH4	O	5	C3AF	Crop(crop)	silty clay	10
zhang_2023-CQ (China)	10.3389/fenvs.2023.1152439	SOC	none	3	C3A,C3AF	InN(N rate, N form), OrN(manure application)	loam	3 (at 20cm)
zhang_2023-JX (China)	10.3389/fenvs.2023.1152439	SOC	none	3	C3AF	InN(N rate, N form), OrN(manure application)	silty clay loam	3 (at 20cm)
zhang_2023-NC (China)	10.3389/fenvs.2023.1152439	SOC	none	3	C3AF	InN(N rate, N form), OrN(manure application)	loam	3 (at 20cm)
zhang_2023-QY (China)	10.3389/fenvs.2023.1152439	SOC	none	3	C3AF	InN(N rate, N form), OrN(manure application)	clay loam	3 (at 20cm)
zhang_2023-SN (China)	10.3389/fenvs.2023.1152439	SOC	none	5	C3A,C3AF	InN(N rate, N form), OrN(manure application)	clay loam	3 (at 20cm)
zhang_2023-SZ (China)	10.3389/fenvs.2023.1152439	SOC	none	5	C3A,C3AF	InN(N rate, N form), OrN(manure application)	silty clay loam	3 (at 20cm)
zhang_2023-WH (China)	10.3389/fenvs.2023.1152439	SOC	none	5	C3A,C3AF	InN(N rate, N form), OrN(manure application)	loam	3 (at 20cm)

Appendix C: Deviation Requests Email correspondences with CAR

On Tue, Jul 25, 2023 at 10:23 AM Lucia Von Reusner <lucia.vonreusner@regrow.ag> wrote:

Hi Mckenzie,

I'm reaching out to introduce myself as the new head of Carbon Protocol Products with Regrow, and to support advancing Regrow's DNDC Validation Report for approval under CAR SEP, which we are in the process of finalizing.

I'm reaching out to request CAR approval on the following two issues. Please advise if additional information is required on your side to make a decision on these matters. I am also cc'ing our reviewer Brian McConkey. Requests for CAR Approval:

1. Per model guidance on page 17 that "Because not all studies will report measurement standard error, PMU may be computed using all studies used in a Validation Report using the same measurement technique. When PMU cannot be reasonably obtained, a default replacement value may be used for PMU that is based on typical measurement error for a given measurement technique, per approval of the Registry"We are requesting that the Registry approve of a default replacement value of CH_4 PMU that is calculated using the measurement data from a mixture of calibration and validation studies, because there is insufficient data from the validation studies alone.

2. Per model guidance on page 14, "If the available data fail to meet one of these minimums… (3 or more, the validation dataset for that combination must include at least 3 (declared) LRRs.) but exceeds the others in a way that supports a demonstrable test of generalized model performance, a case may be made for a valid exception to Requirement 2(Specific Dataset Requirements to Validate Model). This should be addressed explicitly in the Validation Report and will need to be approved by the Registry and by the external reviewer."We have validation datasets from only 2 LRR for the SOC/Organic Amendment, Water/CH_4 and Water/N_2O PC/ES combinations. However, on page 13 the guidance states that "Datasets may be used from studies outside of the US." We ask the Registry to approve the use of studies from outside the US to meet the minimum requirement of 3 unique regions (2 LRR + IPPC zone).

We would appreciate your input on these topics, and are happy to schedule a call to discuss if needed.

Best,
Lucia

Lucia von Reusner
Senior Manager, Carbon Protocol Products
Regrow | http://regrow.ag/
Climate Action through Agriculture
Regrow is hiring! Explore our open positions here.

On Tue, Jul 25, 2023 at 4:51 PM Brian McConkey <brianmcc.soils22@gmail.com> wrote:

Dear McKenzie:

As reviewer of this DNDC Model Validation Report from Regrow, I believe these requests for minor variances from the Requirements and Guidance for Model Calibration, Validation, Uncertainty, and Verification For Soil Enrichment Projects, Version 1.1a are scientifically sound and and do not contravene any principles of the Requirements and Guidance.

Best regards,

Brian McConkey, PhD

From: Lucia Von Reusner <lucia.vonreusner@regrow.ag>
Sent: Aug 4, 2023, 12:54 PM
Hi McKenzie,

Great. We are in the process of working with Brian to complete our updated model validation report.

Best,

Lucia

On Wed, Aug 2, 2023 at 8:07 AM McKenzie Smith <msmith@climateactionreserve.org> wrote:

Good morning,

I can confirm these exceptions are in line with our Model Validation and Calibration guidance and can be incorporated in your validation report for final review. To confirm, you are currently working with Brian to complete an updated model validation report?

Thank you,

McKenzie

McKenzie Smith, M.Sc.

Associate Director
msmith@climateactionreserve.org
Climate Action Reserve, the most trusted global offset registry.
(she/her) | California | office: (213) 542-0282 | mobile: 408-759-3125

From: SamiOsman <sosman@climateactionreserve.org>
Sent: Friday, October 22, 2021 4:17 PM
To: bill@regrow.ag
Cc: Beatriz Zavariz <bzavariz@climateactionreserve.org>
Subject: RE: DNDC model validation report

Hi Bill,

I hope you're well.

My sincere apologies for taking so long to get back to you. Bety and I have been carefully considering the issues raised in your email and would like to provide the following guidance:

We are writing to update you on Regrow's progress validating the DNDC model under the Reserve's Soil Enrichment Protocol. Attached you will find two versions (short and long) of Regrow's recent model validation report. The report is intended to meet SEP requirements for model calibration, validation, and uncertainty when feasible and document Regrow's alternative approach when SEP requirements are not feasible. Our report differs from SEP requirements in the following ways:

- We have validated DNDC and evaluated its bias and uncertainty for both soil organic carbon (SOC) and nitrous oxide (N2O) over a single validation domain comprising multiple Land Resource Regions, Practice Categories, and Crop Functional Groups. We do not evaluate model bias and pooled measurement uncertainty for specific combinations of LRRs, PCs, and CFGs as there is insufficient data at this fine resolution. SO: The Reserve approves this approach to evaluating bias and pooling measurement uncertainty, provided the methodology is outlined clearly in the validation report, and it's use in this manner is approved by the independent expert reviewing the validation report.

- We use an Uncertainty Quantification methodology that leverages Monte Carlo methods to propagate model structural uncertainty from validation data to novel simulations of project fields. This approach follows the deviation request to Verra's VM0042 methodology that is currently under review. SO: The Reserve approves the use of this uncertainty quantification methodology, leveraging Monte Carlo methods, provided the methodology is outlined clearly in the validation report, and it's use in this manner is approved by the independent expert reviewing the validation report.

We have the following questions about the process for the Reserve reviewing and hopefully approving our report. Specifically:

● Regrow is not a project developer and instead aims to provide our technical expertise in biogeochemical modeling as a service to project developers. How can we therefore find a way to work directly with CAR and your science advisors to adopt/approve our approach to modeling projects under SEP? SO: Continue to engage directly with Reserve staff via email (direct all enquiries to Bety Zavariz). Reserve staff will provide direction accordingly.

● Our report is a generalized report of model performance not tied to any specific project (Option 2 in Section 3.6 of the SEP Model Requirements and Guidance document). What steps are necessary for CAR to approve such a report without tying it to a specific project? SO: The report will need to undergo review and approval by the independent expert chosen by REGROW and approved by the Reserve following a Conflict Of Interest review. The report will then come to the Reserve for final review.

● Our methods are under active development to improve overall accuracy and to provide more targeted evaluation of our ability to simulate the carbon/GHG effects of specific agricultural practices. How would CAR approval proceed in the future when (i) model developments occur (such as a new ability to simulate tile drainage practices, or changes are made to how tillage is modeled), or (ii) when the calibration/uncertainty algorithm is updated for improvement, or (iii) when new observational data are added to the validation dataset? SO: Continue to engage directly with Reserve staff via email (direct all enquiries to Bety Zavariz). Reserve staff will provide direction accordingly. It may be the certain of these changes necessitates a further review and approval by an independent expert approved by the Reserve.

Please note that the Reserve is in the midst of scoping an update to the SEP, which will likely include updates with respect to calculating uncertainty. Going forward you will be in very good hands with Bety. Bety was instrumental in developing some of the most complex aspects of this protocol and many of our protocols. Please do feel free to reach out anytime to Bety to talk through the above.

Thanks again for all your assistance with this work to date Bill. I wish you all the best.

Cheers.

Sami Osman

Policy Director |

Climate Action Reserve, a California Offset Project Registry

818 West 7th Street, Suite 710

Los Angeles, CA 90017

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Main: (213) 891-1444

Appendix D: Domain coverage for near full year N20 & CH4 Studies

The aim of study selection was to ensure inclusion of studies with measurements covering and exceeding the growing season. The below table shows the required coverage of texture (clay), LRR, IPCC climate zone ID as well as all PCs and CFGs using a requirement of 310 day coverage.

Study-sites > 310 days of coverage		**LRR**	**IPCC ID**	**Texture**	**PC**	**CFG**	**EC**
COFOARD1_GHG_123_SOC	ARDEC	G	8	clay loam	InN, TR	C4A	n2o
COFOARD3_GHG	ARDEC	G	8	clay loam	InN	C4A	n2o
COFOARD4	ARDEC	G	8	clay loam	InN, OrN	C4A	n2o
mcgowan_2018	KSU_ARF	H	5	silt loam	Crop	C4P	n2o
parkin_and_hatfield_2010	ISURF	M	7	silty clay loam	InN	C4A	n2o
parkin_and_kaspar_2006	AEARRF	M	7	clay loam	TR, Crop	C3A, C4A, C3AN	n2o
adviento-borbe_2013	CA2	C	6	clay loam	InN	C3AF	n2o, ch4

Additionally we highlight that our database includes more studies in our database that covered periods outside of just the growing season but were less than the ~10 month filter we imposed above. For example the Brookings, SD study site SDBBREAP had ~8 months of coverage that clearly showed measurements beyond the typical planting and harvest period which was ~5-6mo of the year. In this study " Sampling was discontinued during periods where installation of the chambers on the collars would have necessitated disturbance of snow cover causing a non representative sampling location".

Appendix E: Measured Treatment Effects on SOC vs Measurement Depth

Some literature suggests that positive changes in SOC at shallow depths (<30 cm) can be offset by losses at deeper depths (30 cm and deeper) (Chenu et al. 2019). Inclusion of studies measuring SOC only at shallow depths may therefore overestimate changes in SOC to the 30 cm depth required by CAR SEP. However, studies sampling at shallow depths may provide data necessary to extend a model's validation domain. Regrow's validation database was analyzed to determine the impact of measurement depth on treatment-paired differences in dSOC (Figure 1). A negative relationship between depth and treatment-paired difference would indicate overestimates at shallow depths necessitating removal of those studies from the validation dataset.

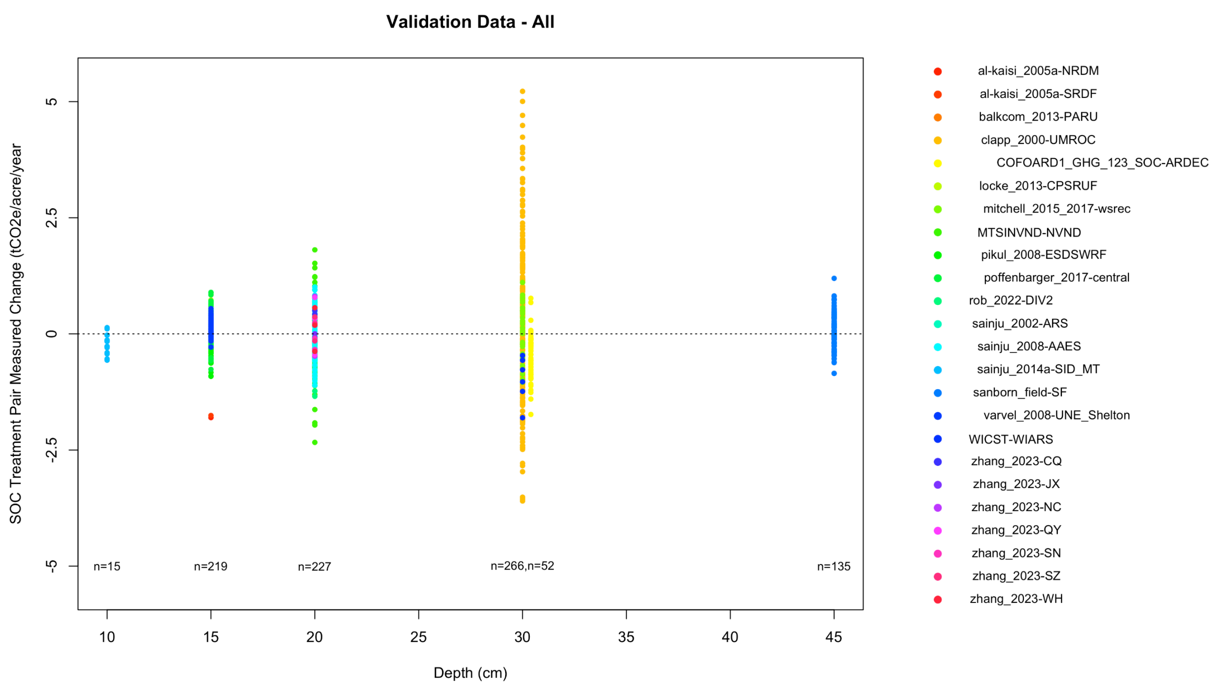

Figure 1. Measured change in SOC treatment-pairs by depth and study_site. The dashed line shows 0. The total number of measurements at each depth is shown at the bottom of the plot (n = 266 at 30 cm and n = 52 at 30.4 cm).

A mixed-effects model was used to analyze the effect of measurement depth while controlling for the random effect of study_site. The model showed no significant effect of depth on dSOC (Table 1).

Table 1

Random Effects		Intercept	Residual	
	study_site (StdDev)	0.24	0.94	
Fixed Effects		Value	Std Error	t-value

	Intercept	-0.0674	0.1913	-0.353
	Depth	0.0014	0.0079	0.177

The validation dataset was then filtered to consider only the treatment pairs corresponding to only tillage (i.e. no consideration of tillage + cover crops or tillage + nutrient management). This analysis showed a similar trend (Figure 2) with no evidence for a negative relationship between depth of measurement and treatment-pair outcomes (Table 2).

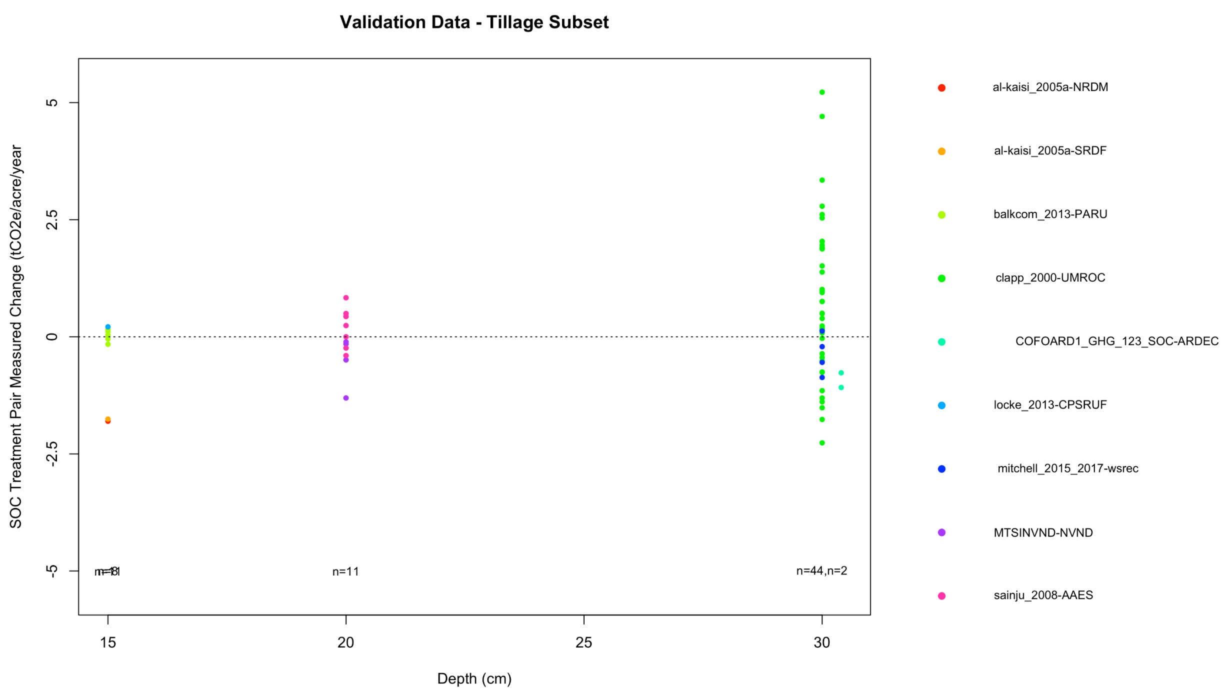

Figure 2. Measured change in SOC treatment-pairs by depth and study_site for tillage pairs only. The dashed line shows 0. The total number of measurements at each depth is shown at the bottom of the plot (n = 44 at 30 cm and n = 2 at 30.4 cm).

Table 2.

Random Effects		Intercept	Residual	
	study_site (StdDev)	0.41	1.39	
Fixed Effects		Value	Std Error	t-value
	Intercept	-1.13	1.025	-1.103
	Depth	0.048	0.041	1.158

Neither analysis provided evidence that Regrow's validation database overestimates treatment-paired effects on SOC changes at shallow depths. Therefore, shallow measurements remain in the database for this report.

Appendix F: Measured annual SOC changes vs duration between measurements

The temporal change in SOC is defined on an annual unit (for both measured and modeled values) in order to facilitate the required reporting of uncertainty of SOC change annually. Measurements of annual changes have higher variances for shorter durations (Figure 1). However variance due to duration is mostly stable when there are 5 or more years between measurements (Figure 2).

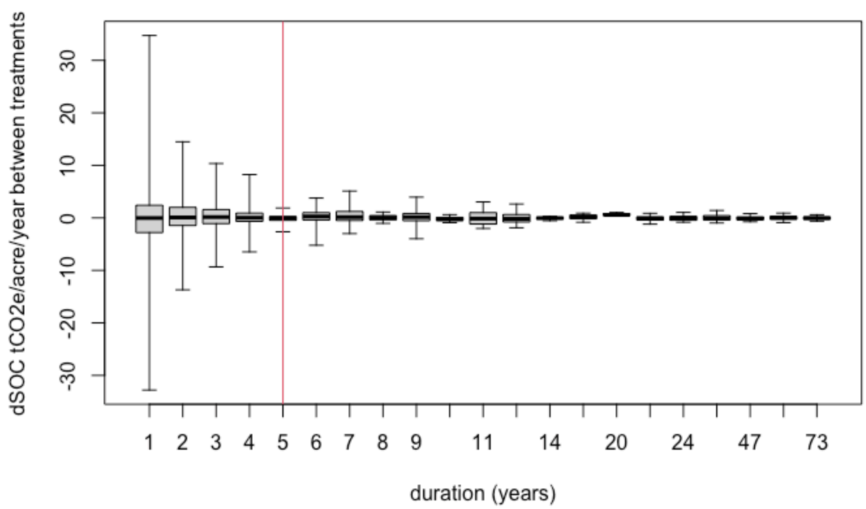

Figure 1. Annual changes of SOC in tCOe/acre/year between changes by time duration between measurements. All time durations are included.

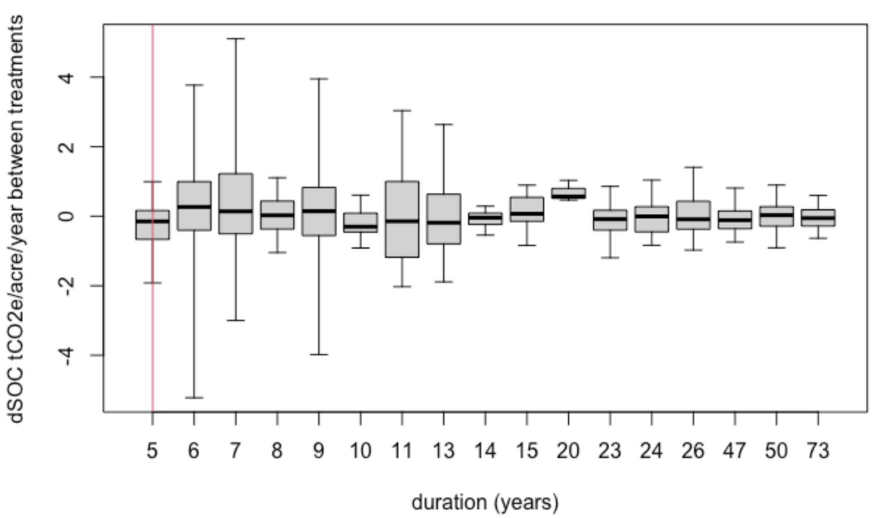

Figure 2. Annual changes of SOC in tCOe/acre/year between changes by time duration between measurements. Only time durations of 5 or more years are included.

Appendix G: Study specific bias

Table 1. Study specific bias for dSOC using equation 3.1 of Model Guidance

study	mean measured difference (tCO2e per acre per year)	mean modeled difference (tCO2e per acre per year)	bias (equation 3.1) (tCO2e per acre per year)	number of pairs
al-kaisi_2005a	-1.7795	-0.4792	1.3003	2
balkcom_2013	0.0273	0.1264	0.0991	21
clapp_2000	0.3954	-0.1084	-0.5038	226
COFOARD1_GHG_123_SOC	-0.4781	-0.2520	0.2261	52
locke_2013	0.2335	0.3994	0.1659	10
mitchell_2015_2017	0.0404	-0.0384	-0.0788	34
MTSINVND	-0.1960	-0.0882	0.1077	66
pikul_2008	-0.2849	0.0040	0.2888	36
poffenbarger_2017	0.2297	-0.0187	-0.2483	45
rob_2022 (Germany)	-0.2827	-0.0184	0.2643	70
sainju_2002	0.1988	0.6062	0.4074	15
sainju_2008	0.0449	-0.0196	-0.0645	55
sainju_2014a	-0.2121	-0.3295	-0.1174	15
sanborn_field	0.0765	0.0309	-0.0456	135
varvel_2008	0.1288	0.0714	-0.0574	105
WICST	-0.9799	0.1210	1.1009	6
zhang_2023 (China)	0.1323	0.1742	0.0419	21
	unweighted overall average study bias		0.1698	17 studies

Table 2. Study specific bias for N2O using equation 3.1 of Model Guidance

study	mean measured difference (tCO2e per acre per year)	mean modeled difference (tCO2e per acre per year)	bias (equation 3.1) (tCO2e per acre per year)	number of pairs
burger_and_horwath_2012	-0.2380	-0.0005	0.2375	2
COFOARD1_GHG_123_SOC	-0.0086	-0.0716	-0.0630	127
COFOARD2_GHG	0.0243	-0.1414	-0.1657	132
COFOARD3_GHG	-0.0203	0.0497	0.0700	240
COFOARD4	-0.0185	-0.0539	-0.0354	40
engel_2010	0.0041	-0.0006	-0.0048	30
fernandez_2015	-0.0053	-0.0219	-0.0166	18
hernandez-ramirez_2009	0.1205	0.0001	-0.1204	20
hoben_2011	-0.0009	-0.0086	-0.0077	15
KYBGGHG	0.0476	-0.0180	-0.0655	108
mcgowan_2018	-0.0252	0.0094	0.0346	36
MTSINVND	0.0008	0.0012	0.0004	264
nash_2012	-0.2086	-0.0255	0.1830	20
nash_2015	-0.6725	-0.0243	0.6482	12
omonode_and_vyn_2013	0.0822	0.0000	-0.0822	2
parkin_and_hatfield_2010	-0.0363	0.0000	0.0363	2
parkin_and_kaspar_2006	0.0187	-0.0645	-0.0832	30
sainju_2014a	-0.0003	0.0006	0.0009	60
SDBRREAP	-0.0040	-0.0277	-0.0238	30
sherman_2021	-0.1078	-0.0057	0.1021	9
smith_2012	0.0144	-0.0001	-0.0146	28
wegner_2018	-0.0003	-0.0011	-0.0008	18
adviento-borbe_2013	-0.0618	-0.0273	0.0345	23
karki_2021	0.1394	0.0013	-0.1381	3
lagomarsino_2016 (Italy)	0.1874	0.0039	-0.1834	2
unweighted overall average study bias			0.0137	25 studies

Table 3. Study specific bias for CH_4 using equation 3.1 of Model Guidance

study	mean measured difference (tCO2e per acre per year)	mean modeled difference (tCO2e per acre per year)	bias (equation 3.1) (tCO2e per acre per year)	number of pairs
adviento-borbe_2013	-0.0873	-0.1671	-0.0798	26
brye_2017	0.1751	0.2181	0.0430	30
karki_2021	-0.4257	-0.2540	0.1717	3
lagomarsino_2016 (Italy)	-0.0739	-0.8065	-0.7327	2
sigren_1997	-0.2014	0.0651	0.2665	2
smartt_2016a	0.0053	0.0017	-0.0036	10
smartt_2016b	0.0733	-0.1596	-0.2328	3
unweighted overall average study bias			-0.0811	7 studies

Appendix H: Specific bias by Practice Category and by Crop Functional Group

The following tables provide a bias analysis specific to each emission (dSOC, N2O and CH4) and practice category combinations and bias specific to each emission and crop functional group combination for which we are validating in this report.

We provide two metrics of bias. The average study bias is the unweighted mean of study mean differences between modeled and measured (e.g. Equation 3.1 of the model guidance). The mean residual is the mean difference between modeled and measured irrespective of study. We believe this second is also useful as the uncertainty model does not include a study specific effect.

Model guidance requires that bias be no greater in absolute value than the pooled measurement uncertainty (PMU).

For dSOC (table 1 and table 2), only the average study bias metric for the perennial crop functional group has a bias larger than the estimated PMU, 0.51>0.425. The mean residual (bias uncorrected by study) is less than the estimated PMU.

For N2O (tables 3 and 4), the water practice category has average study bias greater than PMU but not the mean residual. The c3-a-h-nfix0-flood1 and c3-a-h-nfix1-flood0 crop functional groups have average study bias greater in absolute value than PMU but not the mean residual. The perennial crop functional group has both average study bias and mean residual larger than PMU. While the observations from studies with the c3-a-h-nfix0-flood1 and perennial crop functional groups were included in the PMU calculations, the sample sizes are very small.

For CH4 (tables 5 and 6), none of the biases are larger than PMU.

Table 1. dSOC Practice Category Bias:

practice category	average study bias	N studies	mean residual	N	90% CI coverage count	Count of cases with the single practice only
TR	0.146	9	-0.281	351	272	132
Crop	0.11	12	0.01	336	330	66
InN	0.037	12	-0.06	643	605	182
OrN	0.056	4	0.043	192	190	12
Water	0.098	1	0.098	36	35	2

Bold = absolute value of mean residual is greater than PMU (PMU = 0.425)

Table 2. dSOC Crop Functional Group Bias:

Crop Functional Group(cfg)	average study bias	N studies	mean residual	N	90% CI coverage	Count of cases with

					count	the single cfg only
c3-a-h-nfix1-flood0	0.249	11	-0.001	396	390	10
c4-a-h-nfix0-flood0	0.209	10	-0.16	673	591	304
c3-a-h-nfix0-flood0	0.21	12	0.079	450	444	110
c3-a-s-nfix0-flood0	0.03	4	-0.021	120	118	0
c3-a-h-nfix0-flood1	0.042	1	0.042	21	19	9
c3-p-h-nfix1-flood0 (n=26), c3-p-h-nfix0-flood0 (n=72)	**0.514**	3	0.099	98	96	0

Bold = absolute value of mean residual is greater than PMU (PMU = 0.425)

Table 3. N2O Practice Category Bias:

Practice category	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single practice only
Crop	-0.031	10	-0.039	419	388	123
InN	0.020	17	-0.009	945	857	397
TR	-0.024	10	0.007	501	464	56
OrN	-0.004	5	-0.045	117	86	21
Water	**-0.106**	3	-0.002	149	149	10

Bold = absolute value of mean residual is greater than PMU (PMU = 0.0729)

Table 4. N2O Crop Functional Group Bias:

Crop Functional Group (cfg)	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single cfg only
c4-a-h-nfix0-flood0	0.0157	16	-0.0190	823	712	705
c3-a-h-nfix0-flood0	-0.0336	6	-0.0126	406	397	253
c3-a-h-nfix1-flood0	**-0.0862**	8	-0.0347	232	215	24
c3-a-h-nfix0-flood1	**-0.0957**	3	0.0005	28	28	28
c4-p-h-nfix0-flood0 (n=18), c3-p-h-nfix1-flood0 (n=11)	**0.1336**	3	**0.0861**	29	28	13

Bold = absolute value of mean residual is greater than PMU (PMU = 0.0729)

Table 5. CH4 Practice Category Bias:

practice category	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single practice only	90% CI coverage count for single practice only
Water	-0.09816	3	-0.05962	7	6	4	3
InN	-0.0002	4	-0.00034	48	42	27	27
Crop	-0.11039	4	0.00666	44	37	24	23

Bold = absolute value of mean residual is greater than PMU (PMU = 0.4999)

Table 6. CH4 Crop Functional Group Bias:

Crop Functional Group (cfg)	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single cfg only
c3-a-h-nfix0-flood1	-0.0811	7	-0.02548	76	68	76

Bold = absolute value of mean residual is greater than PMU (PMU = 0.4999)

CAR DNDC Validation Report – addendum for N2O C3AS

Date: December 18, 2023
Prepared by: Regrow

Contents

1. Summary

C3AS is an abbreviation for the crop functional group code c3-a-s-nfix0-flood0. This CFG represents annual, non-N-fixing, unflooded shrubs with a C3 photosynthetic pathway. Cotton is the primary crop with this classification. In the CAR SEP validation for DNDC version 11, no studies were included that contained N2O measurements in fields growing C3AS crops (cotton).

In this addendum, we evaluate the applicability of the uncertainty quantification described in the September 1 2023 validation report, to the quantification of DNDC uncertainty for direct N2O of the crop functional group, C3AS (cotton). This was done by generating DNDC N2O seasonal outputs for C3AS studies having measured N2O emissions and applying the uncertainty modeled from the September 1 2023 report as it would be applied in a project. We found the uncertainty parameters (delta and sigma) sufficient (conservative) for the uncertainty in these new studies. Thus we present this as evidence that the September 1 2023 DNDC version and uncertainty should be conservative for direct N2O quantification for projects including the C3AS crop functional group.

2. Model and Database Version

This report uses DNDC version 11.0.0 and the uncertainty parameters described in the September 1, 2023 validation report. Histograms of the delta and sigma parameters for N2O are reproduced in figure 1. There was no adjustment to the distributions of delta and sigma in this addendum.

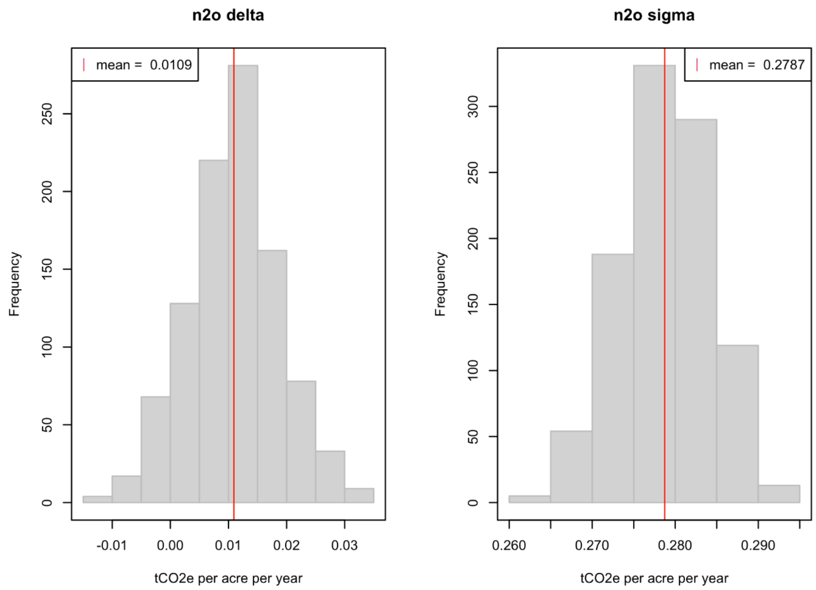

Figure 1. Uncertainty parameter histograms for N2O. Left: Delta distribution reproduced from figure 2 on page 23 of the September 1 2023 report. Right: Sigma distribution reproduced from figure 5 on page 32 of the September 1 2023 report.

3. Study selection or comments about no calibration

Two studies were identified through literature review for N2O studies of cotton in the USA as having sufficient information for DNDC simulation (the sufficient information requirements are given in table 7 page 16-17 of the September 1, 2023 validation report). These studies were not used to calibrate DNDC 11.0.0.

Prediction intervals for N2O cotton studies are calculated using the following process:

1. The modeled N2O value is obtained based on equation 2 of the main report (see page 20 of Sept 1, 2023 validation report) after any gap-filling using exponential interpolation. This is the same process as for all other observations in the N2O validation set.
2. For each value of posterior distributions of δ (figure 1) and σ (figure 1), a single value is sampled from a normal distribution with **mean =** modeled + δ and **standard deviation =** σ. This Monte Carlo integration obtains 1000 values (one for each value of δ and σ) sampled from a posterior predictive distribution.
3. The 5th and 95th percentiles of this posterior predictive distribution are calculated and compared to the measured value for determining coverage for the N2O cotton studies.

4. Summary of updates to Model validation Domain for N2O

Table 1. Updated summaries of the direct N2O practice categories of Inorganic fertilizers and Organic amendments. (table 1 in Sept 1 2023 report). Study-sites listed in **bold font** for Direct N2O report annual emissions over a >310 day period.

Practice Category	PC Code	emission source	LRR Key	IPCC Zone Id	study-site	count unstacked pairs
Inorganic nitrogen fertilizer application	InN	Direct N2O	C	6	adviento-borbe_2013-CA1_Nrate	10
					adviento-borbe_2013-CA2_Nrate	10
			E	8	engel_2010-APF	30
			F		MTSINVND-NVND	16
			G		**COFOARD1_GHG_123_SOC-ARDEC**	54
					COFOARD2_GHG-ARDEC	24
					COFOARD3_GHG-ARDEC	114
					COFOARD4-ARDEC	12
			L	7	hoben_2011-Mason	15
			M	5	fernandez_2015-CSREC	18
					hernandez-ramirez_2009-ACRE	0
					nash_2012-GMRC	6
					nash_2015-GMRC	12
					omonode_and_vyn_2013-Haubstadt	2
				7	**parkin_and_hatfield_2010-ISURF**	2
			N	5	KYBGGHG-KYBGGHG	63
					smith_2012-SAREC	6
			O		adviento-borbe_2013-AR_RREC_Nrate	3
					karki_2021-Burdette	0
				3	tian_2015-CRS	20
			P	3	watts_2015-AAESSRC	45
Organic amendments application	OrN	Direct N2O	G	8	**COFOARD4-ARDEC**	4
			K	7	sherman_2021-MARS	9
			M	5	hernandez-ramirez_2009-ACRE	2
			N		KYBGGHG-KYBGGHG	3
					smith_2012-SAREC	3
			P	3	watts_2015-AAESSRC	3

Table 2. Updated summaries of the direct N2O Crop Functional Group C3AS. (table 5 in Sept 1 2023 report)

Crop Functional Group	CFG Code	SOC Study-site Key	Direct N2O Study-site Key	CH4 Study-site Key
C3, annual, non-N-fixing, shrub, not-flooded	C3AS	balkcom_2013, PARU locke_2013, CPSRUF mitchell_2015_2017, wsrec sainju_2008, AAES	Tian_2015, CRS Watts_2015, AAESSRC	None

Table 3. Updated summaries of the direct N2O Soil texture classes (table 6 in Sept 1 2023 report)

Soil Texture Class	Representative Clay Fraction	Validated GHG Pools/Gasses
Clay	0.63	Direct N2O, CH4
Sandy Clay	0.49	None
Silty Clay	0.43	CH4
Clay Loam	0.41	SOC, Direct N2O, CH4
Silty Clay Loam	0.34	SOC, Direct N2O, CH4
Sandy Clay Loam	0.27	SOC, Direct N2O
Loam	0.19	SOC, Direct N2O, CH4
Silt Loam	0.14	SOC, Direct N2O, CH4
Silt	N/A	None
Sandy Loam	0.09	SOC, Direct N2O
Loamy Sand	0.06	Direct N2O

Sand	0.03	None

Update Clay percent range for Direct N2O:

- N2O: min = 6% (Watts 2015 AAESSRC), max = 59% (Adviento-borbe 2013 CA1), range = 53%

5. Bias Assessment

The addition of studies tian_2015 and watts_2015 does not change the PMU calculation of N2O as measurement error information was not available for these studies.

The unweighted overall average study bias for N2O studies after including these two studies is 0.0154 tCO2e/acre/year and is less than the PMU of 0.0729 (shown in the Sept 1 2023 validation).

5. Model Prediction Error

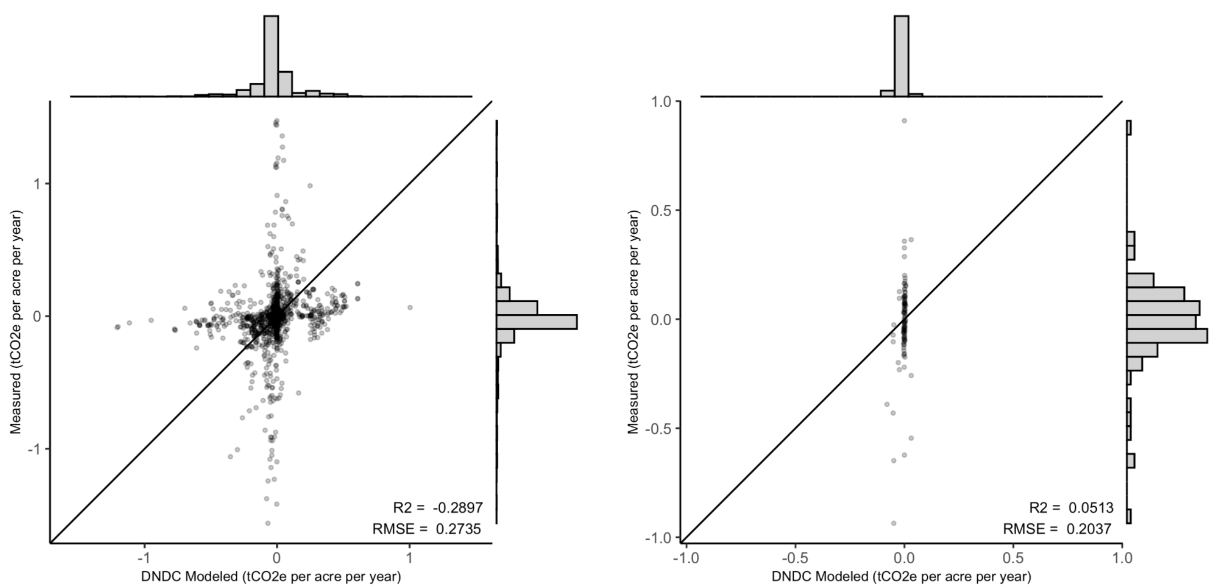

Figure 2. Scatterplot of measured versus modeled. On the left is annual/season N2O emissions in tCO2e/acre/year for all studies and on the right is annual/season N2O emissions in tCO2e/acre/year for only the cotton studies. The gray line denotes the 1:1 relationship. (compare with figure 3 in Sept 1 2023 validation report)

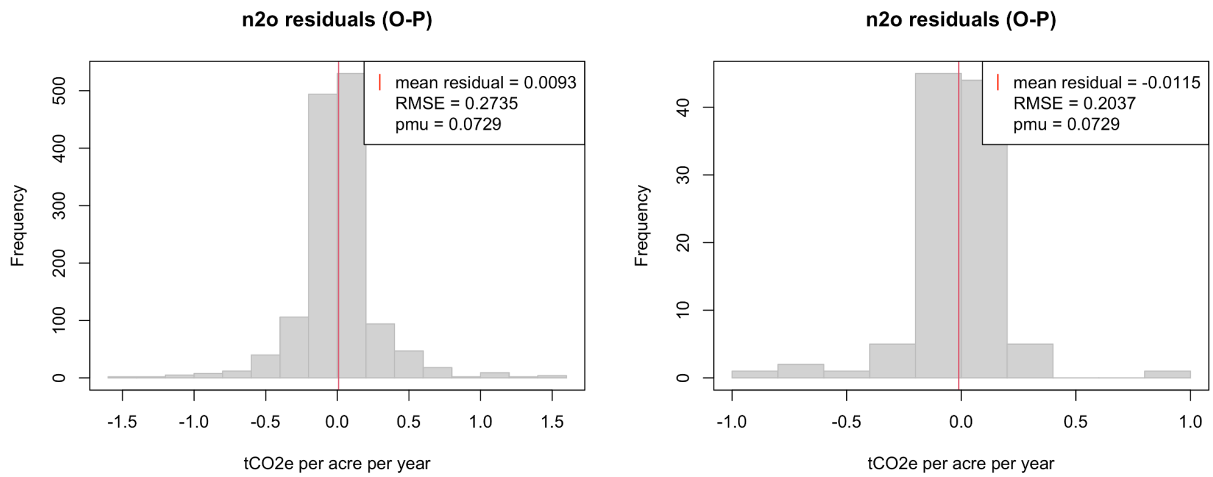

Figure 3. Histogram of residuals (measured - modeled) in tCO2e per acre per year. The left plot shows results for all N2O studies and the right plot only the newly added cotton N2O studies. (compare with figure 4 in Sept 1 2023 validation report)

Coverage probabilities for all N2O (1258/1375 = 91.49%) and N2O only for cotton studies (99/104 = 95.19%) are both over 90%. Thus based on this analysis, using the N2O uncertainty as quantified in the CAR SEP report is conservative for fields growing cotton.

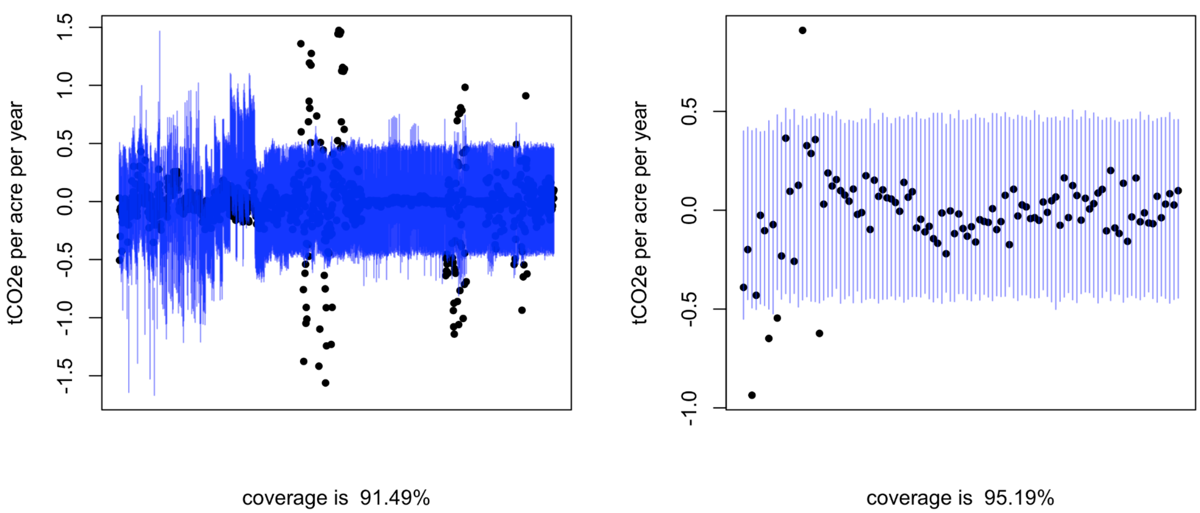

Figure 4. Measured validation values (dots) compared with 90% prediction interval (blue). The right plot is the coverage for all N2O studies while the left plot is coverage for only the cotton N2O studies. (compare with figure 6 in the Sept 1 2023 validation report).

6. Updates to tables in the Appendices

Additions to Appendix B table:

Study-site Key	DOIs	Emissions Sources	Land Resource Region	IPCC climate Zone ID	Crop Functional Groups	Practice Categories (changes)	Soil Texture Classes	# of Treatment Pairs
tian_2015-CRS	10.1016/j.scitotenv.2015.06.147	Direct N2O	O	3	C3AS	InN(EEF, N form) *TR, CROP**	silt loam	20
watts_2015-AAESSRC	10.2134/jeq2015.01.0036	Direct N2O	P	3	C3AS	InN, OrN (varying N form of fertilizer including chicken litter) *TR, CROP**	loamy sand	84

*Here we highlight that the two cotton studies covered a range in base management practices for the Practice Categories TR and CROP. While not changed *within* studies, watts_2015-AAESSRC grew cotton with No Till and a rye winter cover crop, tian_2015-CRS treatments grew continuous cotton with no cover crop and disc tillage.

Appendix G – Study specific bias N2O table (table 2 in appendix G from Sept 1 2023 validation report)

Table 2. Study specific bias for N2O using equation 3.1 of Model Guidance

study	mean measured difference (tCO2e per acre per year)	mean modeled difference (tCO2e per acre per year)	bias (equation 3.1) (tCO2e per acre per year)	number of pairs
burger_and_horwath_2012	-0.2380	-0.0005	0.2375	2
COFOARD1_GHG_123_SOC	-0.0086	-0.0716	-0.0630	127
COFOARD2_GHG	0.0243	-0.1414	-0.1657	132
COFOARD3_GHG	-0.0203	0.0497	0.0700	240
COFOARD4	-0.0185	-0.0539	-0.0354	40
engel_2010	0.0041	-0.0006	-0.0048	30
fernandez_2015	-0.0053	-0.0219	-0.0166	18
hernandez-ramirez_2009	0.1205	0.0001	-0.1204	20
hoben_2011	-0.0009	-0.0086	-0.0077	15
KYBGGHG	0.0476	-0.0180	-0.0655	108
mcgowan_2018	-0.0252	0.0094	0.0346	36
MTSINVND	0.0008	0.0012	0.0004	264
nash_2012	-0.2086	-0.0255	0.1830	20
nash_2015	-0.6725	-0.0243	0.6482	12
omonode_and_vyn_2013	0.0822	0.0000	-0.0822	2
parkin_and_hatfield_2010	-0.0363	0.0000	0.0363	2
parkin_and_kaspar_2006	0.0187	-0.0645	-0.0832	30
sainju_2014a	-0.0003	0.0006	0.0009	60
SDBRREAP	-0.0040	-0.0277	-0.0238	30
sherman_2021	-0.1078	-0.0057	0.1021	9
smith_2012	0.0144	-0.0001	-0.0146	28
wegner_2018	-0.0003	-0.0011	-0.0008	18
adviento-borbe_2013	-0.0618	-0.0273	0.0345	23
karki_2021	0.1394	0.0013	-0.1381	3
lagomarsino_2016 (Italy)	0.1874	0.0039	-0.1834	2
tian_2015	-0.0982	-0.0192	0.0790	20
watts_2015	0.0051	0.0005	-0.0046	84

unweighted overall average study bias	0.0154	27 studies

Appendix H N2O Practice category and crop functional group specific biases (tables 3 and 4 from Sept 1 2023 validation report)

Updates occur for Practice categories InN and OrN, but these do not result in any different conclusions. Both still have biases less in absolute value than PMU. The only update to crop functional groups is the addition of the category c3-a-s-nfix0-flood0 for cotton, which demonstrated a lower absolute bias than PMU.

Table 3. N2O Practice Category Bias:

Practice category	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single practice only
Crop	-0.031	10	-0.039	419	388	123
InN	0.022	19	-0.008	1046	953	462
TR	-0.024	10	0.007	501	464	56
OrN	-0.004	6	-0.034	156	125	24
Water	**-0.106**	3	-0.002	149	149	10

Bold = absolute value of mean residual is greater than PMU (PMU = 0.0729)

Table 4. N2O Crop Functional Group Bias:

Crop Functional Group (cfg)	average study bias	N studies	Mean residual	N	90% CI coverage count	Count of cases with the single cfg only
c4-a-h-nfix0-flood0	0.0157	16	-0.0190	823	712	705
c3-a-h-nfix0-flood0	-0.0336	6	-0.0126	406	397	253
c3-a-h-nfix1-flood0	**-0.0862**	8	-0.0347	232	215	24
c3-a-h-nfix0-flood1	**-0.0957**	3	0.0005	28	28	28
c3-a-s-nfix0-flood0	0.0372	2	0.0115	104	99	104
c4-p-h-nfix0-flood0 (n=18), c3-p-h-nfix1-flood0 (n=11)	**0.1336**	3	**0.0861**	29	28	13

Bold = absolute value of mean residual is greater than PMU (PMU = 0.0729)