ANL/ESD-21/12

FEEDSTOCK CARBON INTENSITY CALCULATOR (FD-CIC)

Users' Manual and Technical Documentation

Energy Systems Division

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FEE**D**STOCK **C**ARBON **I**NTENSITY **C**ALCULATOR **(FD-CIC)**

Users' Manual and Technical Documentation

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October 2021

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1. Introduction

The carbon intensities (CIs) of biofuels are determined with the life cycle analysis (LCA) technique, which accounts for the energy/material uses and emissions during the complete supply chain of a biofuel including feedstock production and fuel conversion stages.

Regulatory agencies such as California Air Resources Board (CARB) adopts LCA to calculate biofuel CIs. The Low Carbon Fuel Standard (LCFS) program developed by CARB allows individual biofuel conversion facilities to submit their own biofuel CIs with their facility input data and incentivizes the reduction in the CI specific to that particular facility compared to a reference fuel's CI (Liu, Kwon, et al., 2020). Such an incentive program has driven innovations in biorefineries to reduce their greenhouse gas (GHG) emissions by linking the plant's revenue directly to its CI score through LCFS credit trading.

Besides biofuel conversion stage, different farming practices for feedstock growth can result in significant CI variations for feedstocks, thus for biofuels. To provide evidence-based research findings, the U.S. Department of Energy's Advanced Research Projects Agency–Energy (ARPA-E) has supported the Systems Assessment Center of the Energy Systems Division at Argonne National Laboratory to examine CI variations of different farming practices to grow agricultural crops for biofuel production. Meanwhile, the ARPA-E has launched the Systems for Monitoring and Analytics for Renewable Transportation Fuels from Agricultural Resources and Management (SMARTFARM) program to develop technologies and data platforms that enable an accurate measurement of key farming parameters that can help robust accounting of the GHG benefits of sustainable, low-carbon agronomic practices at farm level.

A transparent and easy-to-use tool for feedstock-specific, farm-level CI calculation of feedstocks is especially helpful. With the ARPA-E support, we have developed a tool - the Feedstock Carbon Intensity Calculator (FD-CIC). The first version of FD-CIC was released with the GREET® model in 2020 (Wang et al., 2020) so that corn feedstock producers can use this publicly available tool (https://greet.es.anl.gov/tool_fd_cic) to quantify corn grain CIs with farm-level input data and management practices. In the 2021 version, we expand the tool's capabilities by including additional feedstocks such as soybeans, sorghum, and rice. Similar to corn, it calculates the farm-level CI for these feedstocks by allowing user-defined farm-level farming inputs and incorporating the GHG emission intensities of these inputs from GREET (in particular, GREET1, the fuel cycle model of GREET).

Currently, dynamic and standalone versions of FD-CIC are available. The dynamic version interacts with the GREET model by directly reading the life-cycle inventory (LCI) data of key farming inputs from it. This version suits well when users want to change the GREET default settings that affect the GHG emission intensities of farming inputs. For example, if the users want to assess the impact of using regional electricity grid mix to produce key farming inputs, instead of the U.S. average grid mix, they can modify the grid mix in the GREET model and utilize the interacting feature in the FD-CIC to re-read the updated CI values for those key farming inputs. The interacting feature also enables the CI values to be updated with annual GREET release. The standalone version is built for users who are not familiar with the GREET model and contains the GREET default LCI data for key farming inputs.

2. Description of the FD-CIC

2.1 System boundary and key parameters

The system boundary of FD-CIC covers the cradle-to-farm-gate activities, including upstream emissions related to farming input manufacturing and feedstock production (Fig. 1).

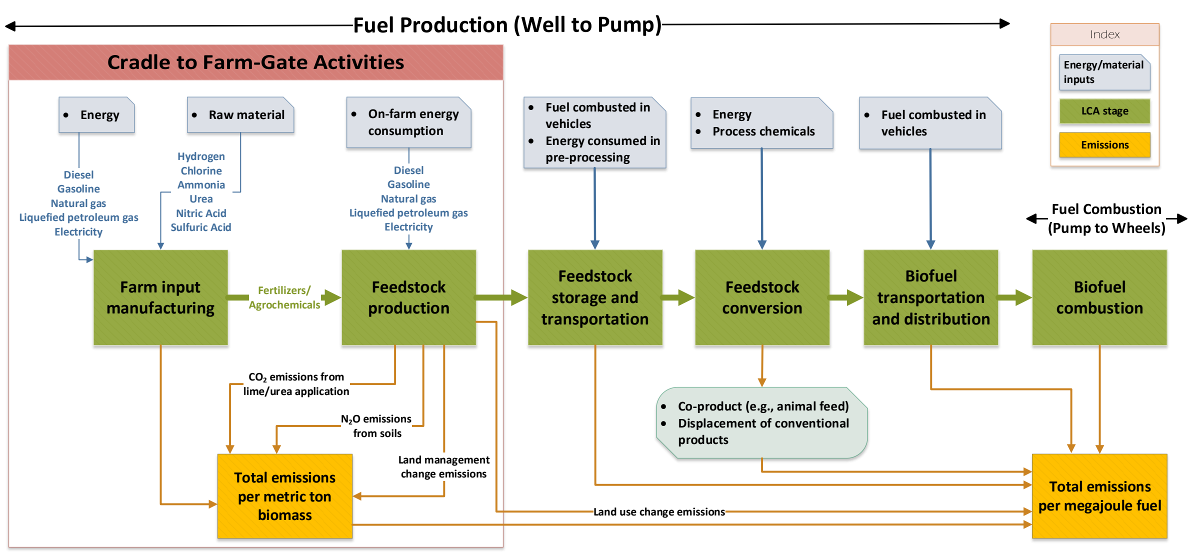

Figure 1: The system boundary of FD-CIC (i.e. cradle-to-farm-gate activities) compared to a complete supply chain of a biofuel (Modified from Liu *et al* 2021).

The FD-CIC helps stakeholders to assess effects of changing farm-level input parameters on feedstock CI scores in the biofuel LCA context. Three key sources of GHG emissions from feedstock production are accounted for in FD-CIC, as detailed in the following three subsections.

2.2 Emissions from farming inputs and on-farm energy consumption

Farming inputs and on-farm energy consumption are the main LCI data required to estimate the GHG emissions associated with their upstream manufacturing and on-farm use. In FD-CIC, the users need to enter the usage amount per acre for fertilizer/chemical inputs and common energy carriers – diesel, gasoline, natural gas, liquefied petroleum gas, and electricity. If farms have not used a specific energy/fertilizer type, as defined in FD-CIC, the value for the specific type should be set to zero. The GREET default farming input data are also provided as the reference, which are based on results from U.S. Department of Agriculture (USDA)'s major survey programs, such as the National Agricultural Statistics Service (NASS), the Economic Research Service (ERS), and the Office of the Chief Economist (OCE) reports. The collected data are mostly accessible through the Quick Stats database (https://quickstats.nass.usda.gov/). Through personal communications with USDA ERS staffs, we received the on-farm energy consumption data that are based on Agricultural Resource Management Survey (ARMS) costs and returns survey for three feedstocks, namely, corn in 2016, soybean in 2018, and rice in 2013, which are not publicly available yet. USDA ERS has approved Argonne's public release of the data through the GREET® Open-Source Database (https://greet.es.anl.gov/databases). We also compiled the energy use in sorghum farming from National Sorghum Grower (NSP)'s report and tool (https://sorghumgrowers.com/sustainability/).

2.3 Soil nitrous oxide emissions from nitrogen inputs

Two sources of nitrogen inputs to soil are considered in GREET and FD-CIC, namely, nitrogen from fertilizer application and nitrogen in crop residues left in the field after harvest. The content of nitrogen in crop residues is estimated using the harvest index and nitrogen contents of above- and below-ground biomass (Wang, 2007).

On-field N_2O emissions from fertilizer and biomass nitrogen inputs to soil have the largest contribution to the cradle-to-farm-gate GHG emissions of corn (Liu, Kwon, et al., 2020) due to the high global-warming potential of N_2O (265 g CO_2e/g N_2O base on IPCC's AR5 100-year global warming potential) as compared to CO_2. As with GREET, FD-CIC calculates soil N_2O emissions associated with feedstock production using the empirically derived emission factors (EFs), which assume a linear relationship between soil N_2O emissions and nitrogen inputs. FD-CIC 2021 adopts the direct soil N_2O EFs disaggregated by climate zones (i.e. wet or dry), according to a meta-analysis of field experiment data collected from nine major corn producing states (Xu et al., 2019), as shown in Fig. 2 and Table 1.

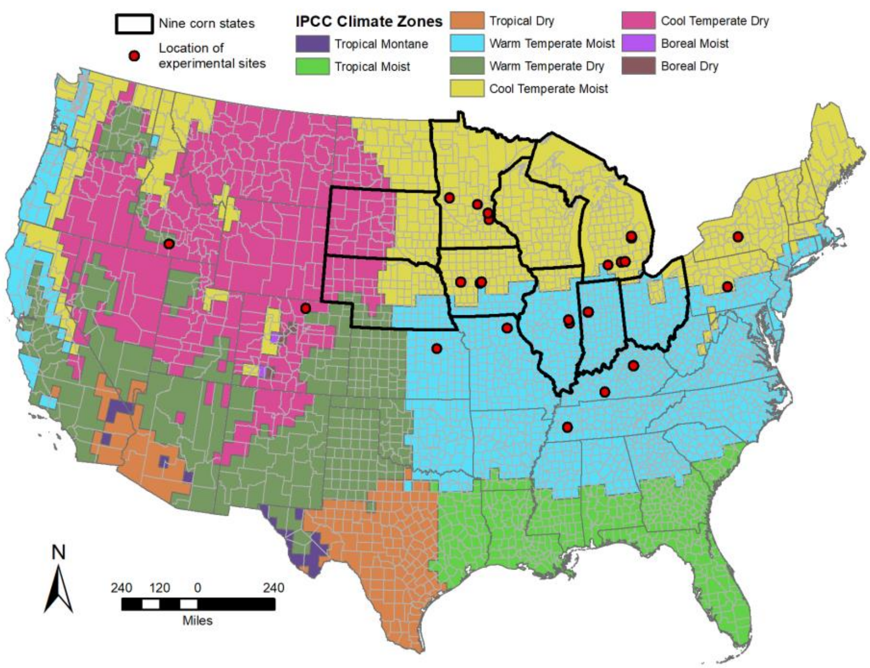

Figure 2. IPCC climate zone for the conterminous U.S and location of field experiments included in the expanded database of Xu *et al* (2019).

Table 1 The direct EFs (kg N_2O-N per kg N) disaggregated from (Xu et al., 2019) **for corn farming**

By climate	Mean[1]	Standard deviation	Sample size	Standard error	95% Confidence interval
Wet	**0.01**	0.012	200	0.0008	0.002
Dry	**0.005**	0.0039	94	0.0004	0.0008

[1] The values in bold is adopted in FD-CIC.

[2] The EFs are calculated as arithmetic averages of measurements from each experimental site to represent the entire climate zone, instead of weighted averages using crop production capacity as the weighting factor

Note that the IPCC recently published the report of 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2019) where direct N_2O EFs are disaggregated by climate. However, we did not choose to employ the IPCC 2019 direct N_2O EFs since they are not crop specific and thus may not represent direct N_2O emissions from corn farming in U.S. Midwest where corn-soybean rotation is a representative agricultural rotation. By default, FD-CIC employs a 1% N_2O EF to estimate the direct N_2O emissions from soil (Table 1). Due to the lack of crop-specific N_2O EF, we apply the corn-based N_2O EF to other U.S. feedstock production (i.e., soybean and sorghum) while employing the IPCC 2019 direct N_2O EF for flooded rice production (0.004 kg N_2O-N per kg N).

In addition to the direct N_2O emissions, N_2O can also be produced through indirect processes, which include the volatilization of nitrogen fertilizers, and the leaching and runoff of nitrate from the fertilizers. Instead of the indirect N_2O EFs from the IPCC 2006 used in previous GREET versions and FD-CIC 2020, GREET 2021 and FD-CIC 2021 adopt the new EFs updated in IPCC 2019 refinements (Table 2). The decision on whether to use aggregated or disaggregated EFs was made based on the uncertainty range. One noticeable difference is that the indirect EF for leaching/runoff is now disaggregated into dry and wet climate zones.

Table 2. Indirect EFs (kg N_2O-N per kg N) in IPCC 2019 refinement

	Aggregated[1]		**Disaggregate**[1]		
Emission factor	**Default value**	**Uncertainty range**	**Climate zone**	**Default value**	**Uncertainty range**
$\mathbf{EF_{leach}}$ (leaching/runoff)	**0.011**	0 - 0.02			
$\boldsymbol{Frac_{leach}}$	**0.24**		Wet	**0.24**	0.01 - 0.73
			Dry	**0**	
$\mathbf{EF_{vol}}$ (Volatilization)	**0.010**	0.002 – 0.018	Wet	**0.014**	0.011 – 0.017
			Dry	**0.005**	0.000 – 0.011
$\boldsymbol{Frac_{vol}}$ ***from synthetic fertilizer***	**0.11**	0.02 – 0.33			
$\boldsymbol{Frac_{vol}}$ ***from all organic N fertilizers applied, and dung and urine deposited by grazing animals***	**0.21**	0.00 – 0.31			

[1] The values in bold is adopted in FD-CIC.

In summary, the updated EFs without consideration of climate zones are revised from 0.01325 to 0.01374 kg N_2O-N per kg N (Table 3).

Table 3. Updated EFs (kg N_2O-N per kg N) based on IPCC 2019 refinement

	Direct EF	Indirect EF (nitrogen source[1])
Aggregated	0.01	0.00264 (crop residue), 0.00374 (synthetic fertilizer), and 0.00474 (manure)
Disaggregated		
Wet	0.01	0.00264 (crop residue), 0.00418 (synthetic fertilizer), and 0.00558 (manure)
Dry	0.005	0 (crop residue), 0.00055 (synthetic fertilizer), and 0.00105 (manure)

[1] No volatilization from crop residue.

2.4 Soil organic carbon sequestration

Feedstock production can be managed to enhance soil organic carbon (SOC) sequestration with conservation land management practices, by either increasing carbon inputs to soils (via crop residues) and/or reducing carbon losses from soils (Paustian et al., 2019). However, shifting farming practices to increase SOC stock has not been incentivized by biofuel regulatory programs yet, due to the lack of protocols for monitoring this variable and the permanency issue associated with SOC (Liu et al., 2021). Without properly accounting for the impacts of SOC change, the benefits introduced by the adoption of conservation practices tied to carbon sequestration and abatement may not be adequately quantified and incentivized. Therefore, it is an emerging area attracting increasing attentions from stakeholders in the bioeconomy, including feedstock producers, government agencies, and fuel regulatory programs.

To address this need from stakeholders, the FD-CIC accounts for the potential impacts of SOC changes associated with changes in farming practices on the feedstock CI accounting. The SOC impacts on corn and soybean CI are evaluated by modeling the county-level SOC changes under corn-soybean rotation prevalent in most of U.S. Midwest (Liu, Kwon, et al., 2020).

As an important component in biofuel LCA, land use change (LUC) -induced emissions have been incorporated into biofuel CI calculation to account for SOC sequestration/GHG emissions associated with the shift in land-use and land-cover for large-scale biofuel feedstock production. However, since the FD-CIC focuses on the cradle-to-farm-gate activities, it does not include LUC emissions in CI calculation but has a lookup table for SOC sequestration potentials of diverse farming practices to address great opportunities for CI reductions. LUC-induced direct and indirect emissions are included in the Carbon Calculator for Land Use and Land Management Change from Biofuels Production (CCLUB) module of the GREET model (Kwon et al., 2020).

3. Use of FD-CIC

The structure of the FD-CIC tool is presented in the "Overview" worksheet (Fig. 3) that defines the color schemes of cells for different types of parameters used in the FD-CIC and provides the key references that support the development of the FD-CIC. For each feedstock considered by FD-CIC, we include separate worksheets - "Inputs", "Intensities of Inputs", and "Results". This design is to facilitate users who are interested in a particular feedstock. We incorporate separate "Intensities of Inputs" tab for each feedstock so that users can independently evaluate the impacts of CI changes in farming inputs on the CI of feedstock produced. The dynamic version has a control button named "Read from GREET" while the standalone version does not. This function enables the interaction between the FD-CIC and the GREET model. This "Read from GREET" button will only work if users have GREET version 2020 or later. Moreover, the GREET1 excel file should be in the same folder of one's computer as with the FD-CIC tool to make this function work.

3.1 Overview worksheet

This worksheet contains a section for the users to select the crop of interest. For example, the user can click the "Corn" button to jump to the "Corn Inputs" sheet.

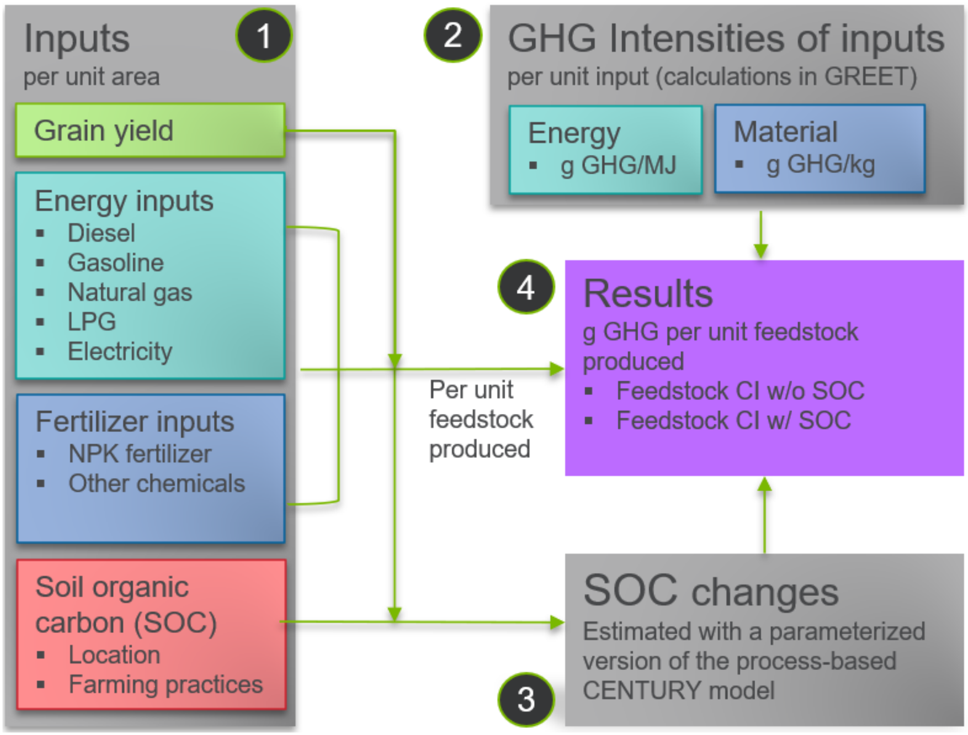

Figure 3. Structure of FD-CIC

The users can activate/deactivate the stochastic simulation function by clicking the "Load Stochastic Toolkit"/ "Unload Stochastic Toolkit" button. In FD-CIC 2021, we incorporated stochastic simulation capability to perform uncertainty analysis on feedstock CI estimates, leveraging the stochastic simulation capability of the GREET model (Subramanyan & Diwekar, 2005). More details will be discussed below in Section 3.5.

The FD-CIC tool uses U.S. customary units by default (e.g., pound per acre, short ton), followed by intermediate calculations to translate them into the GREET customary units for CI calculation (i.e., grams of GHG emitted per short ton of fertilizer or per British Thermal Unit of energy), so that the CI coefficients obtained from the GREET model can be utilized. It is noteworthy that herbicide and insecticide types are not differentiated because of their small contribution to the overall feedstock CI (< 2%).

3.2 Inputs worksheet

3.2.1 Farming input parameters

3.2.1.1 Corn specific inputs

Key parameters affecting corn feedstock CI include corn yield, fertilizers/chemicals application rates, and agronomic practices. GREET default values reflecting US average corn farming are provided as the baseline scenario (Fig. 4). Users can modify the blue cells to build their specific case and compare the results with the GREET default scenario. Note that in FD-CIC, the units for fertilizer are in actual nutrient contents/acre, instead of actual products/acre.

1) Annualized farming input parameters			
1.0) Farm size	User Specific Value	GREET Default Value	Unit
1.0.1) Farm size	1000	1000	acre
1.1) Yield	User Specific Value	GREET Default Value	Unit
1.1.1) Corn yield	166	166	Bushels/acre
1.2) Energy	User Specific Value	GREET Default Value	Unit
1.2.1) Diesel	4.4	4.4	Gallons/acre
1.2.2) Gasoline	1.5	1.5	Gallons/acre
1.2.3) Natural gas	158.4	158.4	ft3/acre
1.2.4) Liquefied petroleum gas	2.4	2.4	Gallons/acre
1.2.5) Electricity	15.5	15.5	kWh/acre
1.3) Nitrogen Fertilizer	User Specific Value	GREET Default Value	Unit
1.3.1) Ammonia	43.4	43.4	lbs N/acre
1.3.2) Urea	32.2	32.2	lbs N/acre
1.3.3) Ammonium Nitrate	2.8	2.8	lbs N/acre
1.3.4) Ammonium Sulfate	2.8	2.8	lbs N/acre
1.3.5) Urea-ammonium nitrate solution	44.8	44.8	lbs N/acre
1.3.6) Monoammonium Phosphate	5.6	5.6	lbs N/acre
1.3.7) Diammonium Phosphate	8.4	8.4	lbs N/acre
1.4) Phosphorus Fertilizer	User Specific Value	GREET Default Value	Unit
1.4.1) Monoammonium Phosphate	24.5	24.5	lbs P2O5/acre
1.4.2) Diammonium Phosphate	25.2	25.2	lbs P2O5/acre
1.5) Potash Fertilizer	User Specific Value	GREET Default Value	Unit
1.5.1) K2O	53.6	53.6	lbs K2O/acre
1.6) Lime	User Specific Value	GREET Default Value	Unit
1.6.1) CaCO3	472.2	472.2	lbs/acre
1.7) Herbicide	User Specific Value	GREET Default Value	Unit
1.7.1) Herbicide	971.6	971.6	g/acre
1.8) Insecticide	User Specific Value	GREET Default Value	Unit
1.8.1) Insecticide	2.1	2.1	g/acre

Figure 4: Farm-level inventory required by FD-CIC

FD-CIC provides several regional/technological options for users to choose from and explore their impacts on the cradle-to-farm gate GHG emissions for corn farming (Fig. 5):

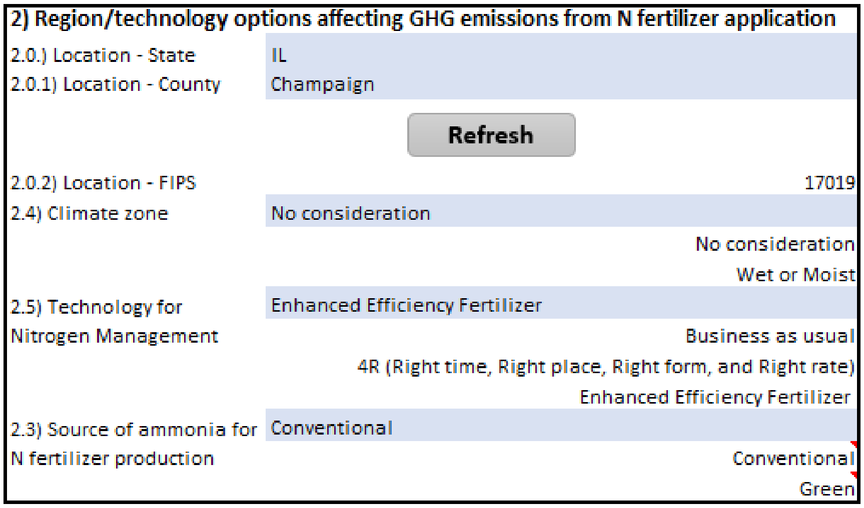

Figure 5: Region/technology options affecting GHG emissions from N fertilizer application for corn feedstock production.

Disaggregated N_2O EFs based on climate zone information — These EFs allow users to choose the county in which their farm-of-interest is located. The users then need to press the "Refresh" button to fetch the climate zone information and decide whether they want to use the climate zone-specific N_2O EF or the default one, as detailed in Section 2.3.

Applying Enhanced Efficiency Fertilizer (EEF) — EEF reduces fertilizer-induced N_2O emissions but incurs additional GHG emissions in its upstream production. Nitrification inhibitor (NI) is a type of EEF, which slows down the nitrification process in which fertilizers are broken down to nitrates and N_2O. According to Thapa et al. (2016), NI reduces N_2O emissions compared to conventional nitrogen fertilizer by 30%. This empirical value is adopted by FD-CIC. Nevertheless, FD-CIC has not accounted for the GHG emissions associated with the production and transportation of NI since it contributes only a minor proportion of the cradle-to-farm-gate emissions for corn farming.

Using 4R (Right time, Right place, Right form, and Right rate) nitrogen fertilizer management — This management practice enhances nitrogen use efficiency while reducing direct

N_2O emissions. The current GREET model adopts a single nitrogen to N_2O conversion factor for nitrogen-based fertilizer. While this approach has been well accepted in LCA models, there is a growing interest in evaluating the impact of 4R nitrogen fertilizer management on N_2O emission reduction. Evidence suggested that the right fertilizer rate is the most important factor among 4R management (Millar et al., 2010). In reality, many corn farmers have already implemented 4R practice to some extent by determining the right rate. This process requires the estimation of "nitrogen need" from historical corn yields, crop rotations, and soil characteristics so that economic optimum nitrogen rate for each field is determined and applied to soils without the surplus nitrogen, which is vulnerable to environmental losses.

In FD-CIC 2021, we incorporated a technological option "Whether nitrogen is managed by 4R practice" for corn farming to let the users approximately estimate the direct N_2O emission reduction potential if 4R nitrogen fertilizer management practice is implemented on farm. Due to the significant spatial variations in soil and climate conditions, the optimal nitrogen application rate, form, place, and timing would vary between farms. Therefore, we employed a simplified nitrogen balance approach, as detailed in Eagle et al. (2020). This study indicated that the soil surface nitrogen balance, which is the difference between nitrogen inputs to and outputs from a farm field, is a robust indicator of direct N_2O emissions from fields with corn and other major rainfed temperate-region crops (Eq 1).

$$N_2O - N = exp(0.339 + 0.0047 \times NBal) \qquad \text{(Eq.1)}$$

where N_2O-N is the annual cumulative N_2O emissions in the unit of kg N_2O-N ha^{-1}; the nitrogen balance or NBal is the annual nitrogen balance in the unit of kg N ha^{-1}, which is calculated as the difference between total N applied (i.e. N from synthetic fertilizer, organic amendment, N-fixing cash or cover crops, and irrigation water) and total N harvested (i.e. N in crop and crop residue removed). Inserting the national estimate of NBal, 60 kg N ha^{-1} from Xia et al. (2021), into Eq.1 renders a direct N_2O EF of 1.86 kg N_2O-N ha^{-1}, which coincides with the 1.81 kg N_2O-N ha^{-1} value calculated via the empirically-derived EFs approach using the GREET model (Section 2.3). This indicates that the simplified nitrogen balance approach in Eagle et al. (2020) can be utilized to estimate the direct N_2O emissions if NBal is available. We assume that whenever nitrogen inputs are managed by 4R practices, the NBal should be close to zero, meaning that nitrogen has only been applied in the right rate and form when and where needed with minimized surplus. While this assumption may be simplistic, it provides a rough estimation of the maximum direct N_2O emission reduction potential. Under this assumption, the direct N_2O emission would be 1.4 kg N_2O-N ha^{-1}, regardless of nitrogen input rates applied to soils. Considering a national average corn yield of 166 bushel ac^{-1}, the direct N_2O emission is 5.4 grams N_2O (1,421 g CO_2e) per bushel of corn produced. Adding the indirect N_2O emission renders a total N_2O emission of 1,642 g CO_2e $bushel^{-1}$, which is a 35% reduction compared to the default FD-CIC value of 2,535 g CO_2e $bushel^{-1}$.

Application of low-carbon nitrogen fertilizer — This provides an option for users to choose whether to use grey or green ammonia as the nitrogen fertilizer building block. Grey ammonia is the ammonia produced from conventional steam methane reforming of natural gas, which is a GHG intensive process and the GREET default ammonia production option. On the other hand, green ammonia is the ammonia produced by obtaining N_2 from cryogenic distillation and H_2 from low-temperature electrolysis using renewable electricity. More information on other alternative pathways to produce low-carbon ammonia can be found in (Liu, Elgowainy, et al., 2020). This option is provided in the Inputs sheet for other feedstocks as well.

3.2.1.2 Rice specific inputs

Methane (CH_4) emission is a particular concern for rice cultivation. In FD-CIC, annual CH_4 emissions (per area) from rice fields are calculated by multiplying daily EFs by cultivation period of rice, with Eq 2 adopted from the IPCC 2019 Chapter 5, Eq 5.1 (IPCC, 2019):

$$CH_4 = EF_i \times d_i$$
$$EF_i = EF_c \times SF_w \times SF_p \times SF_o$$
$$SF_o = (1 + \textstyle\sum_i ROA_i \times CFOA_i)^{0.59} \qquad \text{(Eq.2)}$$

Where CH_4 is the annual methane emission (kg CH_4 ha^{-1}); EF_i is the daily emission factor for a specific condition *i* (kg CH_4 ha^{-1} d^{-1}) and d_i is the cultivation days of rice for a specific condition *i*. EF_c is the baseline EF for continuously flooded fields without organic amendments. SFw is the scaling factor to account for the differences in water regime during the cultivation period. SF_p is the scaling factor to account for the differences in water regime in the pre-season before the cultivation period. SF_o is the scaling factor that varies with both the type and amount of organic amendment applied. ROA_i is the application rate of organic amendment *i*, in dry weight for straw and fresh weight for others (Mg ha^{-1}). $CFOA_i$ is the conversion factor for organic amendment *i* in terms of its relative effect with respect to straw applied shortly before cultivation. The values for the above-mentioned parameters can be found in Table 4.

Table 4. The EF (kg CH_4 ha^{-1} d^{-1}) and coefficients to calculate annual CH_4 emissions from U.S. rice farming

	Disaggregate		
Emission factor	**Application domain**	**Default value[1]**	**Uncertainty range**
EF_c[2]	North America	**0.65**	0.44 – 0.96
d (days)	North America	**139**	110 – 165
SF_w	Continuously flooded	**1.00**	0.73 – 1.27
	Single drainage period	**0.71**	0.53 – 0.94
	Multiple drainage periods	**0.55**	0.41 – 0.72
	Regular rainfed	**0.54**	0.39 – 0.74
	drought prone	**0.16**	0.11 – 0.24
	Deep water	**0.06**	0.03 – 0.12
SFp	Non flooded pre-season <180 d	**1.00**	0.88 – 1.12
	Non flooded pre-season >180 d	**0.89**	0.80 – 0.99
	Flooded pre-season (>30 d)	**2.41**	2.13 – 2.73
	Non-flooded pre-season >365 d	**0.59**	0.41 – 0.84
CFOA	Straw incorporated shortly (<30 days) before cultivation	**1.00**	0.85 – 1.17
	Straw incorporated long (>30 days) before cultivation	**0.19**	0.11 – 0.28
	Compost	**0.17**	0.09 – 0.29
	Farm yard manure	**0.21**	0.15 – 0.28
	Green manure	**0.45**	0.36 – 0.57

[1] The values in bold is adopted in FD-CIC.

[2] CH_4 emission is not CH_4-C kg emission.

It should be noted that SFp, however, is only used to estimate CH_4 emission during the rice growing period and cannot be used to quantify CH_4 emissions that occurred before the cultivation period or after harvest (i.e., outside of rice growing season, such as CH_4 emission during winter flooding period).

3.2.2 Soil organic carbon lookup for corn and soybean

The FD-CIC provides a lookup table for the SOC sequestration potentials corresponding to different farming practices based on default simulation results using county-level information (i.e., corn/soybean yield record, soil, and climate information) under a 2-year corn-soybean rotation (Liu, Kwon, et al., 2020). The following practices are of particular interest, namely whether to adopt conservation tillage, whether to apply manure, and whether to plant cover crops. The users need to choose from the drop-down list, press the "Refresh" button, and look up the corresponding SOC change results (Fig. 6). It should be noted that positive SOC values represent CO_2 emissions while negative values represent SOC sequestration. Furthermore, the farm-level yields of cover crop and main crops (e.g., corn and soybean) provided by users would not affect the SOC change per hectare, but the SOC change per bushel of feedstock produced. That is, SOC estimates in the FD-CIC are developed at the U.S. County level, not at the farm level.

In addition, since SOC modeling results are summarized for annualized SOC changes regardless of crops grown, the SOC lookup table in FD-CIC 2020 did not provide land management induced SOC change for a specific feedstock (e.g., corn). To improve the SOC lookup table for feedstock-specific results, the total SOC changes estimated from corn-soybean rotation were attributed into corn and soybean, separately. It should be noted that the total changes in SOC were driven by the changes in both crop yield and farming practices from 2016 through 2045. We first assumed that crop yields are constant over the next 30 years (2016 - 2045) based on the yield average from 2006 to 2015 and then simulated the effects of crop yield on SOC for both corn and soybean. Similarly, the effect of diverse farming practices on SOC were simulated with the same assumption on the yield. Then, for both cases, we allocated the simulated SOC changes from corn-soybean rotation to corn and soybean separately by using the total biomass input rates to the soil from individual crops (either corn or soybean). This rendered the feedstock-specific SOC sequestration potentials due to the changes in farming practices. Finally, we updated the lookup tables with this new information in the FD-CIC 2021.

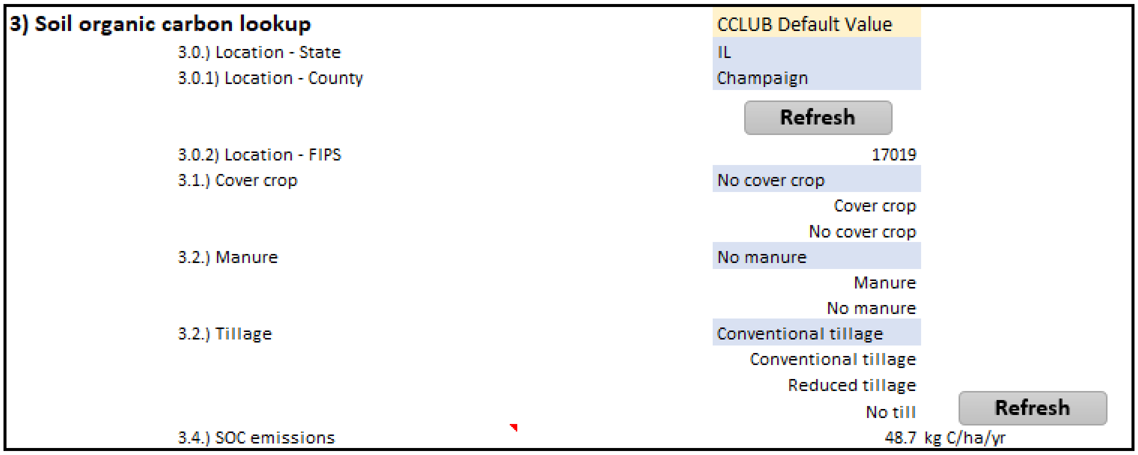

Figure 6: Soil organic carbon look-up table

3.3 Intensities of Inputs worksheet

In the Intensities of Inputs worksheets, the GHG emissions related to farming inputs manufacturing (e.g., fertilizers and energy sources) are all based on the LCI emission results from the GREET model to maintain the transparency of CI calculation in FD-CIC.

3.4 Results worksheets

FD-CIC estimates the GHG emissions in the unit of carbon dioxide equivalent (CO_2e) by combining the amount of CO_2, biogenic CH_4, fossil CH_4, and N_2O with their 100-year global warming potentials of 1, 28, 30, and 265, respectively (Myhre et al., 2013). It reports both GREET default and user-specific CI for comparison purpose. The tool provides figures for comparison as well. The contribution from each emission source is also calculated and depicted in a pie chart.

3.5 Stochastic simulation function

This function requires users to assign probability density functions for key farming inputs parameters, specify the number of samples required and the sampling technique to be used, and define the forecast variables based on which the stochastic simulations are performed.

To load the Stochastic Toolkit or unload, the users can click “Load Stochastic Toolkit” or “Unload Stochastic Toolkit” on the Overview worksheet. After loading the stochastic toolkit, it will be loaded to the “Add-ins” section in the excel Ribbon.

3.5.1 Assign probability distribution functions to the input variables

To assign a probability distribution function, the users need to select an input variable with numeric value in excel, click “Cell Input” tab in the stochastic toolkit, select a probability distribution function for the input variable (Fig. 7) and parameterize the selected distribution (Fig. 8). The users would then be asked to set a name for the variable or click “Cancel” to use location instead of name. It is recommended, however, to use the defined name approach. After successfully assigning a probability distribution function to the input variable, the cell turns green and the variable is automatically added to the “Dist_Spec” sheet. The users need to repeat the process until all the input variables participating in the stochastic simulations are defined. To delete the distribution from a cell, users can select that cell and click “Delete Distribution” tab in the stochastic toolkit.

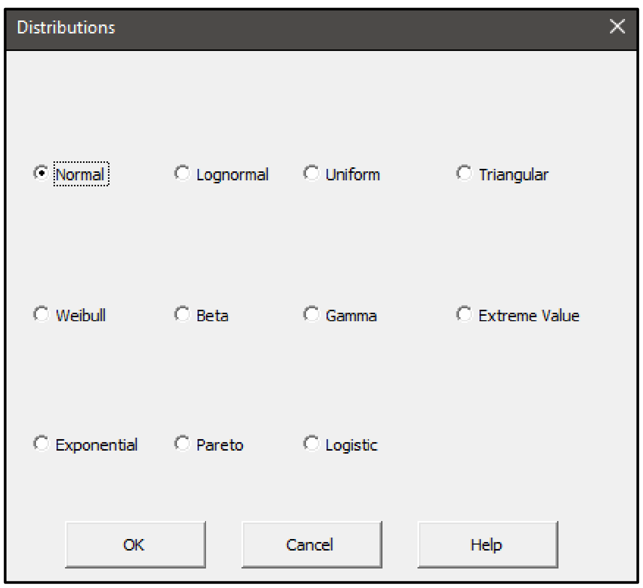

Figure 7: A list of probability distribution function for users to choose from

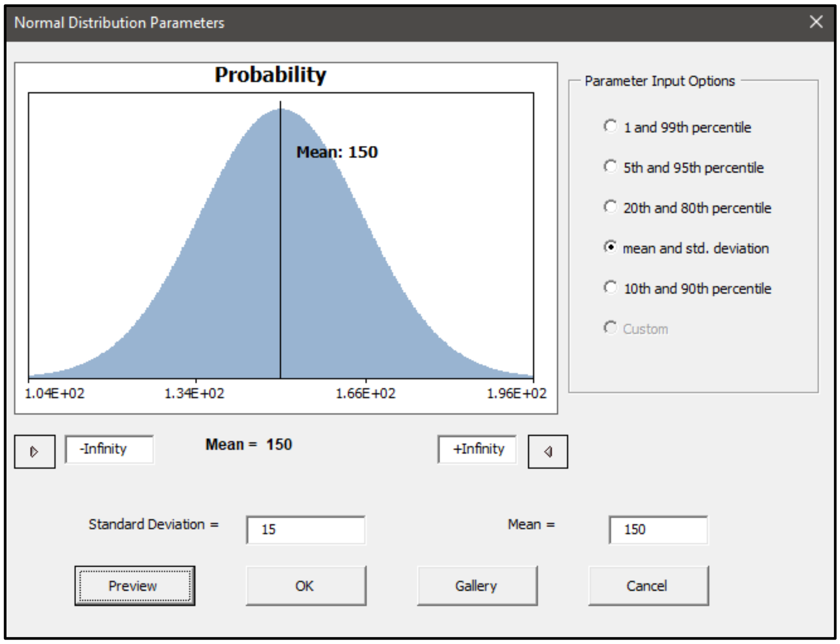

Figure 8: Parameters for a normal distribution. Note that parameters depicted in this panel would be different when users choose different probability distribution functions in the previous step.

3.5.2 Specify the number of samples and the sampling technique

To specify the number of samples and the sampling technique, the users need to click "Sampling" tab in the stochastic toolkit. The users can choose between four different sampling techniques and enter the number of samples (Fig. 9). An overview of the four sampling techniques is provided by (Subramanyan & Diwekar, 2005).

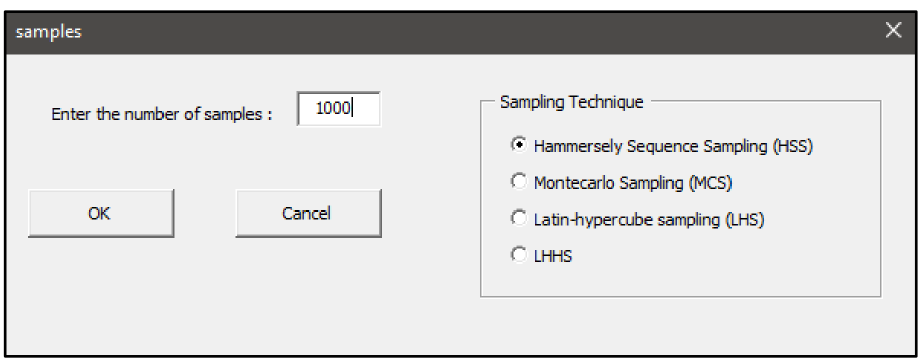

Figure 9: Specification of the number of samples and the sampling technique

3.5.3 Define the forecast variables

To define forecast variables, the users need to go to the "Forecast_Specs" sheet, type in the sheet and cell addresses of the forecast variables, and the names defined for the forecast variables (if applicable).

3.5.4 Run stochastic simulation

To run the stochastic simulation, the users need to click "Run Simulation" tab in the stochastic toolkit and set seed automatically or manually. After completing the simulation run, an Excel workbook will be generated to display the results from the stochastic simulation. Statistical values such as the mean, standard deviation, and 0th to 100th percentile are calculated automatically for each forecast variable. The users can save the output Excel file to the directory of their choice.

4. Acknowledgement

The development of the FD-CIC was supported by the Systems for Monitoring and Analytics for Renewable Transportation Fuels from Agricultural Resources and Management (SMARTFARM) program of the Advanced Research Projects Agency – Energy (APRA-E) of the U.S. Department of Energy under Contract No.18/CJ000/01/01.

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