

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof. Reference herein to any social initiative (including but not limited to Diversity, Equity, and Inclusion (DEI); Community Benefits Plans (CBP); Justice 40; etc.) is made by the Author independent of any current requirement by the United States Government and does not constitute or imply endorsement, recommendation, or support by the United States Government or any agency thereof.

Expansion and Update of the R&D Feedstock Carbon Intensity Calculator (FD-CIC) for R&D GREET 2025

**Life Cycle Analysis and Technology Assessment Department
Energy Systems and Infrastructure Assessment Division**

About Argonne National Laboratory

Argonne is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC under contract DE-AC02-06CH11357. The Laboratory's main facility is outside Chicago, at 9700 South Cass Avenue, Lemont, Illinois 60439. For information about Argonne and its pioneering science and technology programs, see www.anl.gov.

DOCUMENT AVAILABILITY

Online Access: U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free at OSTI.GOV (<http://www.osti.gov/>), a service of the US Dept. of Energy's Office of Scientific and Technical Information.

Reports not in digital format may be purchased by the public from the National Technical Information Service (NTIS):

U.S. Department of Commerce
National Technical Information Service
5301 Shawnee Rd
Alexandria, VA 22312
www.ntis.gov
Phone: (800) 553-NTIS (6847) or (703) 605-6000
Fax: (703) 605-6900
Email: **orders@ntis.gov**

Reports not in digital format are available to DOE and DOE contractors from the Office of Scientific and Technical Information (OSTI):

U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
www.osti.gov
Phone: (865) 576-8401
Fax: (865) 576-5728
Email: **reports@osti.gov**

Disclaimer

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor UChicago Argonne, LLC, nor any of their employees or officers, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of document authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, Argonne National Laboratory, or UChicago Argonne, LLC.

Expansion and Update of the R&D Feedstock Carbon Intensity Calculator (FD-CIC) for R&D GREET 2025

prepared by

Hoyoung Kwon, Xinyu Liu, Thomas Sykora, Hao Cai, and Michael Wang
LCA and Technology Assessment Department,
Energy Systems and Infrastructure Assessment Division,
Argonne National Laboratory

December 2025

CONTENTS

Acknowledgments.....	iv
1 Introduction	6
2 Feedstock Additions and Data Updates.....	7
2.1 Winter and Spring Wheat.....	7
2.2 Spring Canola.....	8
3 Soil Organic Carbon Modeling for Farming Practices.....	9
4 Manure Application Updates.....	11
5 Emissions Results Comparison	11
6 References	13
Appendix A: DayCent Management Practice Analysis.....	14
Appendix B: Methodology for Estimating Feedstock-Specific Soil Organic Carbon Changes from Farming Practice Adoption	23
Appendix C: Outlier Analysis and Proxy Development.....	29

TABLES

Table 1: National average of yields and application rates of fertilizers/chemicals for winter and spring wheat production.....	7
Table 2: National average of herbicide mix for winter and spring wheat production.	7
Table 3: Energy consumption in winter and spring wheat farming in 2017.....	8
Table 4: Input data for spring canola farming (unit: per metric ton canola, as received).....	9
Table 5: Spring canola farming nitrogen fertilizer shares	9
Table 6: Manure types and corresponding chemical characteristics and modeled SOC contribution factor.....	11
Table 7: Comparison of feedstock production emissions between the 2023 and 2025 versions..	12

Acknowledgments

This effort was supported by the Bioenergy Technologies Office of the Office of Critical Minerals and Energy Innovation, U.S. Department of Energy under Contract Number DE-AC02-06CH11357. We thank John Cabaniss and Brandon McMurtry of Department of Energy for their guidance and support. We are grateful to Stephen Ogle, Ames Fowler, and Alisa Keyser of Colorado State University for providing us DayCent modeling results; Deanna Lizas, Hazelle Tomlin, Kelly Summers, and Kirsten Jaglo of ICF for processing DayCent results and for providing other data; and Corinne Scown of Lawrence Berkeley National Laboratory for providing technical comments. The authors of this report are solely responsible for the contents and conclusions of the report.

Argonne does not warrant that the results presented in this report are consistent with the requirements of any particular regulatory or incentive program. Users interested in specific programs are encouraged to review guidance specific to those programs.

This page is intentionally left blank.

1 Introduction

The R&D Feedstock Carbon Intensity Calculator (R&D FD-CIC) is a transparent and easy-to-use tool to estimate feedstock-specific carbon intensity (CI) of biofuel feedstocks, and to examine potential CI variations of different farming practices to grow agricultural feedstocks for biofuel production. The objective of the tool is to assess potential effects of different farming practices with underlined factors to reduce uncertainties in such assessment and help R&D activities. The original work and early versions of R&D FD-CIC were supported by Advanced Research Projects Agency–Energy (ARPA-E) of the Department of Energy, with recent support by the Bioenergy Technologies Office of the Department of Energy.

The tool uses life cycle inventory (LCI) data of key farming inputs from the R&D Greenhouse gases, Regulated Emissions, and Energy use in Technologies (R&D GREET) model. The system boundary of R&D FD-CIC covers the cradle-to-farm-gate activities, including upstream emissions related to farming input manufacturing and feedstock production.

Since its launch in 2020, R&D FD-CIC has undergone continuous expansion to incorporate LCI data for key domestic biofuel feedstocks, such as corn, soybeans, grain sorghum, and rice, as well as significant international biofuel feedstocks, including Canadian corn and Brazilian sugarcane.

R&D FD-CIC details the greenhouse gas (GHG) emissions by breaking them down into different sources such as energy use for on-farm operations, manufacturing and consumption of nitrogen fertilizer and fuels, production of other agricultural chemicals, and in-field emissions of N₂O (from synthetic nitrogen fertilizer and biomass residue) and CO₂ (from urea fertilizer and lime application).

Previous versions of R&D FD-CIC accounted for potential soil organic carbon (SOC) changes associated with changes in farming practices, which were modeled using a parameterized version of the process-based CENTURY model at the U.S. County level. In-field N₂O emissions were also accounted for by employing an empirical emission factor-based approach, which was consistent with Intergovernmental Panel on Climate Change (IPCC) Tier 1 approach. More detailed information on previous versions of R&D FD-CIC can be found in Liu et al. (2023).

In 2025, we expanded R&D FD-CIC to include two primary wheat types - winter and spring wheat-distinguished by growing season, as well as spring canola, the dominant canola type by U.S. acreage. Separately, we updated the R&D GREET farming inputs for soybeans, grain sorghum, and Brazilian sugarcane feedstocks. More details on these updates were documented in Wang et al. (2024). These R&D GREET inputs were included in this version of R&D FD-CIC. Furthermore, we updated the potential impacts of various farming practices on SOC stock changes for four biofuel feedstocks (i.e., corn, soybeans, grain sorghum, and spring canola) using a process-based simulation model – DayCent model (which replaces the CENTURY model as in the previous R&D FD-CIC) – by Colorado State University (CSU). Potential impacts of these farming practices on in-field N₂O emissions were accounted for by employing the IPCC Tier 1 approach.

2 Feedstock Additions and Data Updates

2.1 Winter and Spring Wheat

The United States Department of Agriculture (USDA) classifies wheat by seeding season. Winter wheat is seeded in the fall of the previous calendar year), overwinters, resumes growth in spring, and is harvested the following year; spring wheat is seeded in the spring of the current calendar year and harvested later that same year. We collected the following data from USDA National Agricultural Statistics Service (NASS):

- State-level production for winter and spring wheat (presented in bushels)
- State-level planted and harvested acres for winter and spring wheat
- State-level total applications for winter and spring wheat of:
 - Herbicides broken down by active ingredient, presented in pounds.
 - Insecticides broken down by active ingredient, presented in pounds.
 - Aggregated fertilizer rates for N, P₂O₅, and K₂O, presented in pounds.

The state-level application rates of chemicals for winter and spring wheat farming are calculated by dividing the total applications by the harvested bushels. This result is then weighted by the production volume of each state to determine the national averages (Table 1 and Table 2). Values in these tables represent the 3-year production-weighted averages among 2017, 2019, and 2022. More detailed information on state-level yields and application rates is available in (Liu et al., 2024).

Table 1: National average of yields and application rates of fertilizers/chemicals for winter and spring wheat production

	Winter wheat	Spring wheat
Yield (bushel/harvested acre)	49.2	45.2
Nitrogen (N) (g/bushel)	734.5	973.0
Phosphate (g/bushel)	230.4	350.5
Potash (g/bushel)	130.2	65.1
Herbicide (g/bushel)	7.76	9.1
Insecticide (g/bushel)	0.25	0.06

Table 2: National average of herbicide mix for winter and spring wheat production

	Winter wheat	Spring wheat
Glyphosate	55.5%	56.9%
2,4-D	24.4%	12.8%
Dicamba	5.7%	1.4%
MCPA	4.0%	7.9%
Paraquat	3.2%	0.0%
Atrazine	1.5%	0.0%
Others	5.9%	21.0%

To derive energy use in wheat farming, we utilized data from the 2017 Agricultural Resource Management Survey (ARMS) for wheat, as it is the most recent survey conducted by USDA on wheat farming energy use. However, it is noteworthy that the survey did not differentiate between winter, spring, and durum wheat. Therefore, we employed a disaggregation approach, which is described with further details in (Liu et al., 2024). The results on energy consumption for winter and spring wheat farming, broken down by fuel types, are summarized in Table 3.

Table 3: Energy consumption in winter and spring wheat farming in 2017

	Winter wheat	Spring wheat
Energy (Btu [low-heating value]/bushel)	15,254	12,045
Diesel (%)	63.6	77.0
Gasoline (%)	15.0	15.1
LPG (%)	1.7	4.0
NG (%)	0.8	0.7
Electricity (%)	18.9	3.3

2.2 Spring Canola

The life-cycle inventory (LCI) data for U.S. canola in R&D GREET has been derived from national survey data and an LCA report by (S&T)² Consultants Inc. on Canadian spring canola farming, given the agroecological and management similarities with northern U.S. spring canola systems. Since winter canola accounts for less than 5% of total U.S. canola acreage (U.S. Canola Association, 2024), this dataset can be considered representative of the national average.

In addition to distinctions based on growing season, canola can also be classified by production system into main and intermediate types for biofuel feedstock production. Intermediate winter canola is an emerging option typically cultivated in double- or relay-cropping systems between the growing seasons of primary crops. In contrast, main canola—which includes primarily spring canola, as well as winter canola planted and harvested within a single growing season—is produced as a standalone crop.

We compiled the updated data for spring canola as a primary or main canola, based on a report from (S&T)² Consultants Inc (2022). Table 4 provide a summary of the updated data (which are used in R&D GREET 2023 Rev1), highlighting changes in comparison to the previous version of the R&D GREET model. More details regarding the compilation of the data can be found in Wang et al. (2025).

Also in early versions of R&D FD-CIC and R&D GREET 2023 Rev.1, the nitrogen fertilizer to N₂O emission factors (EFs) from synthetic nitrogen fertilizer application and nitrogen in canola biomass were 1.04% and 0.94%, respectively, which were taken from (S&T)² Consultants Inc (2017). To ensure consistency across all feedstocks, we updated the N₂O EFs for canola (and other crops and biomass) based on IPCC 2019 Tier 1 values: 1.374% for synthetic nitrogen and 1.264% for nitrogen in canola biomass residue in both R&D GREET 2025 and R&D FD-CIC 2025.

Table 4: Input data for spring canola farming (unit: per metric ton canola, as received)

	R&D GREET 2023 Rev1	Updated in R&D GREET 2025 and R&D FD-CIC 2025 ¹
Farming Energy Use (Btu)	528,667	438,891
Diesel (%)	96.6%	96.2%
Natural gas (%)	1.7%	1.1%
Electricity (%)	1.6%	2.8%
Fertilizer Use		
Nitrogen (g)	51,648	51,638
P ₂ O ₅ (g)	15,919	15,994
K ₂ O (g)	4,163	5,747
Pesticide Use		
Herbicide (g)	417.0	589.5
Insecticide (g)	39.0	13.6
Total N in above and below ground biomass (g)	22,216	22,216
N ₂ O emissions: N in N ₂ O as % of N in N fertilizer	1.040% ²	1.374%
N ₂ O emissions: N in N ₂ O as % of N in biomass	0.940% ²	1.264%

¹ ((S&T)² Consultants Inc, 2022); ² ((S&T)² Consultants Inc, 2017).

Table 5: Spring canola farming nitrogen fertilizer shares

	R&D GREET 2023 Rev1	Updated in R&D GREET 2025 and R&D FD-CIC 2025 ¹
Ammonia	31.0%	25.8%
Urea	23.0%	55.9%
Ammonium Nitrate	2.0%	1.0%
Monoammonium Phosphate	4.0%	1.3%
Diammonium Phosphate	6.0%	0.0%
UAN Solution (per ton N product)	32.0%	9.2%
Ammonium Sulfate	2.0%	6.8%

¹ ((S&T)² Consultants Inc, 2022).

3 Soil Organic Carbon Modeling for Farming Practices

The early development of R&D FD-CIC through the 2023 versions relied on simulated SOC changes from a parameterized version of CENTURY to populate the domestic crop SOC lookup table in the “Inputs_DomesticCrops” worksheet. That table provides county-level SOC changes attributable to various farming practices relative to baseline practices (i.e., no cover crops and no manure). We have now updated the lookup table for single-year CI calculations using DayCent

modeling results generated by CSU and expanded coverage to four feedstocks: corn, soybeans, grain sorghum, and spring canola.

CSU ran DayCent (A daily time-step version of CENTURY) to simulate 30-year, annualized SOC stock change estimates for combinations of crop rotations and management practices, including cover cropping, conservation tillage, and manure application (Appendix A). DayCent employed the U.S. national GHG inventory baseline used in the Environmental Protection Agency’s annual U.S. GHG inventory report, incorporating cropping histories from the National Resources Inventory (NRI) to reflect actual farming practices. Projection simulations were initiated at the end of the current inventory (2020) and run forward for 30 years. Using the inventory baseline for forward projections ensures the prevailing mix of conventional and conservation practices is represented, avoiding overstated SOC gains that could arise if conservation practices were excluded from the baseline. This baseline thus provides a representative sample of adopters and management histories relative to idealized rotations.

For scenarios involving cover crops and conservation tillage, DayCent preserved the baseline crop sequences, management events, and timing; only the practices under evaluation were varied. Model outputs at NRI survey locations were aggregated by Major Land Resource Areas (MLRAs), geographically defined regions delineated by the Natural Resources Conservation Service (NRCS) based on shared soils, climate, vegetation, and land use. This MLRA-level aggregation, applied during post-processing, was used to compute annualized SOC stock change rates (Appendix B) and to mitigate the influence of outliers at individual NRI points. The resulting DayCent outputs were then screened through an outlier analysis to remove or replace MLRA-level values that were significantly different from the national average. Finally, feedstock-specific SOC stock change rates were calculated and expressed in grams of CO₂-equivalent (CO₂e) per bushel for each MLRA and farming practice scenario, with county-level SOC estimates generated via MLRA-to-county mapping (Appendix C).

Manure application scenarios required a different approach because many NRI survey points in the baseline already included manure. To isolate the incremental SOC effect of manure additions, CSU estimated carbon contribution factors—defined as additional SOC per unit of carbon in the applied manure—using DayCent simulations. For corn NRI points within each MLRA, DayCent was run with a post 2020 “no manure” baseline and four manure application scenarios in which manure N replaced with 25, 50, 75, and 100% of synthetic N over the subsequent 30-year period. For each scenario, CSU computed the 30-year annualized dSOC relative to the “no manure” baseline, estimated the average annual manure C applied, and calculated the resulting manure SOC contribution factors. These factors were then aggregated to the MLRA level using weighted averages based on NRI acreage weights (the acreage expansion factor for each NRI point), stratified by manure type (Appendix A). MLRA-level soil carbon contribution factors, by manure type, were used to compute acreage-weighted national averages, based on the distribution of that corn area across MLRAs. These factors were applied to other three feedstocks and used to update emissions associated with manure applications.

4 Manure Application Updates

To incorporate soil carbon contribution factors from manure application, along with related N₂O emissions, we expanded the manure application section in the “Inputs_DomesticCrops” worksheet to handle both solid and liquid forms of four manure types: swine, dairy cow, beef cattle, and poultry. Correspondingly, we updated relevant parameters in the “Parameters” worksheet, including C:N ratios and nitrogen concentration for each manure type. These updates enable more accurate estimates of SOC and N₂O emissions associated with manure application (Table 6).

Table 6: Manure types and corresponding chemical characteristics and modeled SOC contribution factor

Manure type	C:N ratio	N concentration (g N/ton or 1,000 gallons) ¹	National average SOC factor
Solid			
Swine	11.3	5,897	0.132
Dairy Cow	16.8	4,536	0.136
Beef Cattle	15.0	4,536	0.136
Poultry	17.7	18,144	0.139
Liquid			
Swine	10.8	11,340	0.132
Dairy Cow	8.4	14,062	0.136
Beef Cattle	11.0	11,340	0.136
Poultry	2.5	27,216	0.139

¹ Minnesota Department of Agriculture. Nutrient Management Tables (<https://www.mda.state.mn.us/sites/default/files/2018-05/nutmantables.pdf>).

5 Emissions Results Comparison

This section summarizes key emissions updates in FD-CIC 2025 relative to the 2023 version (Table 7). Emissions are reported as grams of CO₂-equivalent per unit of crop yield, using 100-year Global Warming Potentials (GWP100) for CO₂, CH₄, and N₂O from the IPCC Sixth Assessment Report (Arias et al., 2021).

Overall, the 2025 updates lead to modest changes in total feedstock-production emissions relative to 2023: soybeans, grain sorghum, and Brazilian sugarcane decline by 0.4%, 0.3%, and 2.0%, respectively, while spring canola increases by 2.9%. The canola increase reflects adoption of IPCC (2019) Tier 1 N₂O EFs, which are higher than the previously used Canadian EFs.

Table 7: Comparison of feedstock production emissions between the 2023 and 2025 versions

	Soybeans (per bushel)		Grain sorghum (per bushel)		Brazilian sugarcane (per metric tonne)		Spring Canola (per lb)	
	2023	2025	2023	2025	2023	2025	2023 ⁵	2025
Energy	1,329	1272	691	686	15,008	12428	18	19
Fertilizer/Chemical								
Nitrogen	181	170	1,597	1577	3,747	4104	65	62
All others ¹	1,139	1061	672	649	2,154	1795	22	21
In-Field Emissions								
N ₂ O emissions ²	5,324	5309	3,552	3552	15,590	11493	182	193
CO ₂ emissions ³	33	31	287	287	3,491	3174	22	22
Sugarcane-specific ⁴	NA	NA	NA	NA	-1,840	4259	NA	NA
Total (g CO₂e)	8,005	7843	6,801	6752	38,150	37251	309	317

¹ Include phosphate, potash, herbicide and insecticide uses.

² N₂O emissions are attributed to nitrogen fertilizer, biomass residue, and nitrogen fixation (only for soybeans).

³ CO₂ emissions result from the use of urea and lime.

⁴ GHG emissions from soil amendment application (vinasse and filtered cake) and open field burning of sugarcane straw.

⁵ Spring canola in 2023 was estimated from R&D GREET 2023 Rev1.

Estimating the CI impacts of different farming practices is inherently limited by data availability and uncertainties in model simulation outputs that R&D FD-CIC relies on. Farming activities are distributed across millions of U.S. farms, creating significant challenges in collecting the data required for CI and SOC simulations. These challenges are even greater for less prevalent crops, such as canola and sorghum. Indeed, improving data collection technologies and methodologies was one of the motivations behind the ARPA-E SMARTFARM program. Annual variations in climatic conditions can substantially affect yields and other performance indicators, making year-to-year estimation of feedstock CI difficult—if not impossible. SOC modeling of farming practices in process models such as DayCent relies on historically limited SOC measurements, particularly for less common crops and practices. Additionally, the permanence of SOC gains associated with certain farming practices remains an active area of debate. Collectively, these factors contribute to the uncertainty in simulated CI effects of various farming practices. A key objective of R&D FD-CIC is to highlight the sensitivity of results to critical farming-practice parameters and provide insights that guide future R&D efforts aimed at reducing these uncertainties.

6 References

- Arias, P., Bellouin, N., Coppola, E., Jones, R., Krinner, G., Marotzke, J., Naik, V., Palmer, M., Plattner, G.-K., & Rogelj, J. (2021). *Climate Change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; technical summary.*
- Liu, X., Cai, H., Kwon, H., & Wang, M. (2023). *Feedstock Carbon Intensity Calculator (FD-CIC): Users' Manual and Technical Documentation.* <https://doi.org/10.2172/2205308>
- Liu, X., H., K., Cai, H., Lee, K., Vyawahare, P., Sun, P., Elgowainy, A., Li, Y., Xu, H., & Wang, M. (2024). *GREET® Analysis for TERRA/ROOTS Success Scenarios Program Closing Final Report.*
- (S&T)2 Consultants Inc. (2017). *Carbon footprint for Canola Biofuel.*
- (S&T)2 Consultants Inc. (2022). *Carbon Footprint for Canadian Canola.*
- U.S. Canola Association. (2024). *Canola Quick Bytes – February 2024.*
<https://www.uscanola.com/newsletter/canola-quick-bytes-february-2024/>
- Wang, M., Cai, H., Liu, X., Kwon, H., Gracida-Alvarez, U., Kar, S., Do, T. N., Ou, L., & Sykora, T. (2024). *Life Cycle Analysis of Greenhouse Gas Emissions of Clean Fuels with the R&D GREET 2024 Model.*

Appendix A: DayCent Management Practice Analysis

Stephen M. Ogle, Ames F. Fowler and Alisa Keyser

Natural Resource Ecology Laboratory, Colorado State University (CSU)

December 2025

1. Introduction

The DayCent ecosystem model (Parton et al. 1998, 2001; Del Grosso et al. 2001, 2011, 2022) has been used in this analysis. DayCent simulates biogeochemical carbon (C) and nitrogen (N) cycles between the atmosphere, vegetation, and soil, using a broad suite of environmental drivers. These drivers include soil characteristics, weather patterns, crop and forage characteristics, and management practices.

DayCent utilizes the soil C modeling framework developed in the Century model (Parton et al. 1987, 1988, 1994) but has been refined to simulate dynamics at a daily time-step. C and N dynamics are linked in plant-soil systems through biogeochemical processes of microbial decomposition and plant production. Nutrient supply is a function of external nutrient additions as well as litter and soil organic matter (SOM) decomposition rates. Increasing decomposition can lead to a reduction in soil organic carbon (SOC) stocks due to microbial decomposition, and greater nitrous oxide (N₂O) emissions by enhancing mineral N availability in soils. DayCent has been tested and applied in many studies, but the most recent calibration associated with this version utilized Bayesian methods for SOC and N₂O emissions (US-EPA 2024; Gurung et al. 2020, 2021).

2. Modeling Frameworks

DayCent was used to approximate initial values of C and N in the plant and soil system for this analysis using the national resource inventory (NRI) framework and NRI survey data. First, the DayCent model was used to establish the initial conditions and SOC stocks for 1979, which is the first year of the NRI survey. Second, DayCent was used to simulate land-use and management histories recorded in the 2017 NRI histories (USDA-NRCS 2020) extended through 2020 using USDA-NASS Crop Data Layer (CDL) (USDA-NASS 2021).

Using these histories to establish initial conditions ensures that forward projection for this analysis is consistent with the US National Greenhouse Gas Emissions Inventory for agricultural lands (US-EPA 2024). The forward simulations for the 30-year projection are described in sections below using the last 5 years of the NRI histories, which are replicated 6 times in this analysis.

2.1 Baseline

We simulated every NRI survey location at least one of the biofuel crops (corn, soybeans, grain sorghum, and canola) in the most recent five years of crop history (i.e., 2016-2020) (Figure 1).

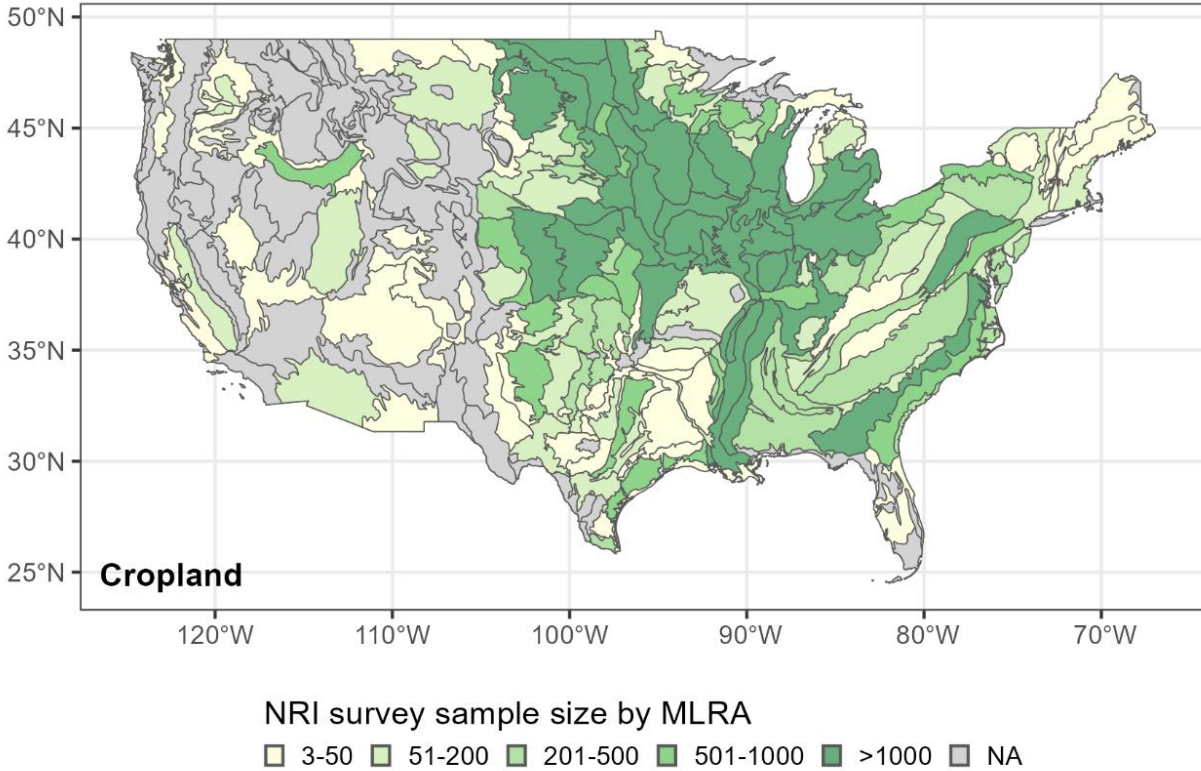


Figure 1: The NRI survey sample size by MLRA that was used in the analysis

The histories provide a statistical representation of cropland producing biofuel crops and were used to assess the impact of practice changes. Some survey locations informed impacts for multiple crops when histories included more than one biofuel crop. The baseline projection repeated this five-year rotation over 30 years.

We excluded NRI survey locations with recent land use conversions to cropland (i.e., grassland to cropland, forestland to cropland, wetland to cropland, and settlements to cropland) because land use changes have much larger effects on trends in SOC stocks and, to a lesser extent, N₂O emissions, compared to changes in management practices (Figure 2). Our objective was to focus on management effects rather than land use change as a driver of GHG emissions.

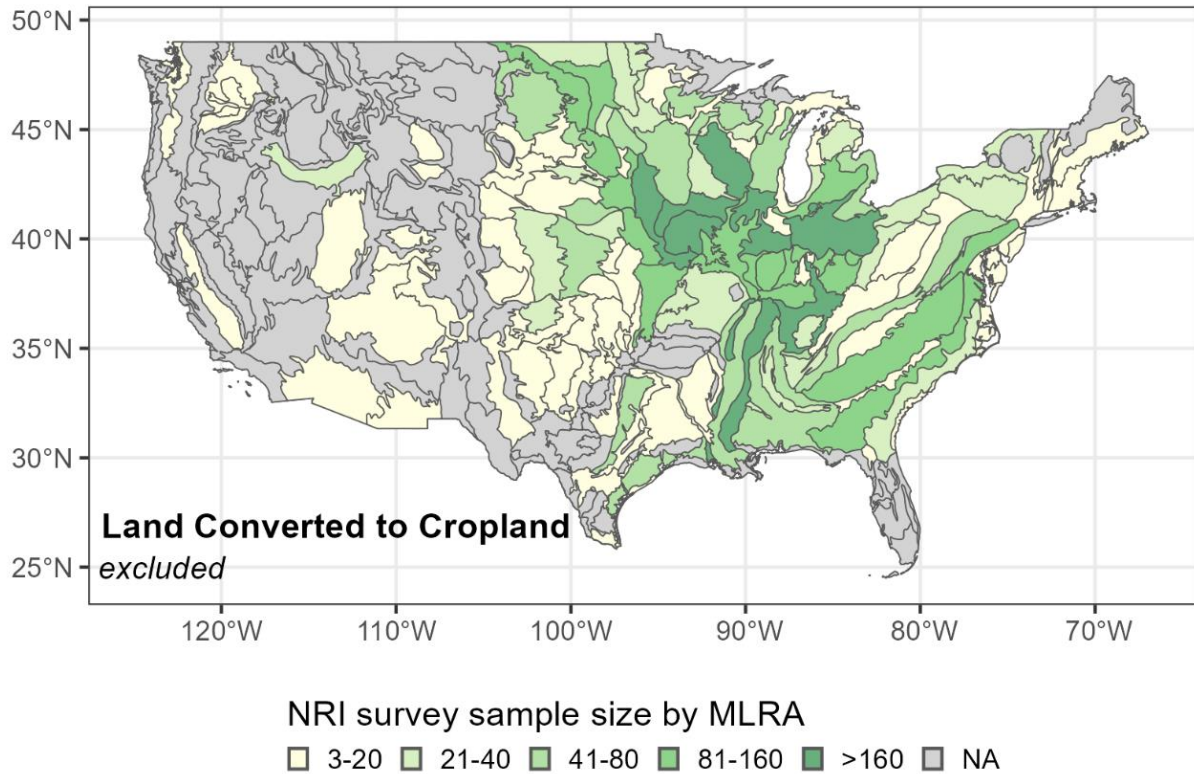


Figure 2: The NRI survey sample size by MLRA that was excluded in the analysis due to recent land use conversion.

The baseline captured the current management practices in U.S. farmland, which included a combination of conventional and conservation practices. Management activity data from several sources supplemented the activity data from the NRI. The USDA-NRCS Conservation Effects and Assessment Project (CEAP) provided data on mineral fertilization, manure amendments, cover crop usage, as well as planting and harvest dates (USDA-NRCS 2022; USDA-NRCS 2018; USDA-NRCS 2012). Fertilization data were also used from Agricultural Resource Management Surveys (ARMS) (USDA-ERS 2020). Tillage and cover crop data were also informed by the OpTIS Data Product¹ (Hagen et al. 2020). Cover crop data are also utilized from the USDA Census of Agriculture (USDA-NASS 2012, 2017). See the US National Greenhouse Gas Emissions Inventory report (US-EPA 2024) for more information about the historical management data that was used to create the baseline.

We made several assumptions in the baseline that are listed below.

- Cover crops were not planted before or after hay or pasture crops except when present on the first year of the baseline sequence where they were carried through the 30-year projection, and the fifth year could have been hay or pasture.

¹ OpTIS data on tillage practices provided by Regrow Agriculture, Inc.

- Tillage was classified at NRI survey locations as a management system based on the national GHG inventory data (US-EPA 2024). All crops in a rotation received the same tillage practice (i.e., no-till system had no-till in each year). Consequently, there is no intermittent tillage in the baseline. The exception was hay and pasture in crop histories with annual crops, also referred to as rotations, in which hay and pasture were not tilled in years following establishment.
- Fertilizer rates were based on CEAP and ARMS data as statistically imputed for 2016-2020 in the national GHG inventory (US-EPA 2024). All fertilizer was assumed to be 80%/20% ammonium/nitrate. There were insufficient data to inform the timing when the last national GHG inventory was compiled (US-EPA 2024). All fertilizer was applied at the time of planting except for corn and grass hay which received split applications. Corn received 25% at planting and 75% 40 days after planting, while grass hay received 50% at planting and 50% in June.

Using the inventory baseline for the forward projection captured the current mixture of conventional and conservation practices. This approach limited over-estimation of SOC gains in the management scenarios, which could occur if we assumed that all lands were under conventional management practices.

Due to differences in data availability, the fertilizer rates of baseline for spring canola was developed using a different method than that used for the other three crops. We combined expert judgement with the best available data to define baseline management. Fertilizer inputs were determined using a yield-to-fertilizer ratio derived from Montana field trials that reported both yield and fertilizer rates. Spring canola yield data from Washington, Montana, Idaho, and North Dakota were used to develop a linear mixed-effects model predicting yield as a function of mean annual precipitation by state. We applied this model to NRI points to estimate yields, then determined fertilizer application rates based on the yield-to-fertilizer ratio described above.

We categorized the five-year crop rotation sequences into ten rotation types to differentiate generalized rotation effects on SOC and N₂O emissions as requested by USDA. Here is a summary of rules for rotation types:

- Continuous corn (CC) with corn in the last five years of the NRI history
- Continuous soybeans (SS) with soybeans in the last five years of the NRI history
- Corn and soybeans (CS) with any combination of corn and soybeans in the last five years of the NRI history
- Corn and hay/pasture (CHP) with at least one year of corn and two years of hay or pasture (grass, alfalfa, etc.) in the last five years of the NRI history
- Soybeans and hay/pasture (SHP) with at least one year of soybeans and two years of hay or pasture (grass hay, alfalfa, etc.) in the last five years of the NRI history
- Corn, soybeans and hay/pasture (CSHP) with at least one year of soybeans, one year of corn, and two years of hay or pasture (grass hay, alfalfa, etc.) in the last five years of the NRI history
- Corn and other crops in rotation (CO) with a year or more of corn in the last five years of the NRI history

- Soybeans and other crops in rotation (SO) with a year or more of soybeans in the last five years of the NRI history
- Continuous Sorghum (SGSG) with sorghum in the last five years of the NRI history
- Sorghum and other crops in rotation (SGO) with sorghum in at least one of the last five years of the NRI history
- Spring canola and other crops in rotation (CaO) with canola in at least one of the last five years of the cropping history

Some rotations are non-exclusive, so the same NRI survey point may be evaluated for multiple crop rotation types. For example, points with both soybeans and grain sorghum in rotation are defined as both Soybean Other and Sorghum Other, and that NRI survey point would be used for assessing scenario effects for both rotation types.

We replicated the most recent eight years of weather data from PRISM (PRISM Climate Group 2022); this accounts for the timing of leap years and provides an offset with the crop rotation length to reduce crop year interactions that could produce artifacts in the projection. We did not simulate future climate effects in this stage of the analysis. We used the soils data from the national GHG inventory. Soil profiles and associated edaphic characteristics are from the NRCS gSSURGO database (Soil Survey Staff 2020).

2.2 Practice Scenarios

All scenarios have the same crop sequences, management events, and timing as the baseline, except for specific management interventions detailed below.

Cover crop scenario:

We simulated one cover crop scenario, winter rye (ccR), in this analysis.

- ccR:
- We simulated cover crops every year except in years that have small winter grains (e.g., winter wheat) or perennial hay or pasture.
 - We simulated cover crop termination as a chemical/herbicide termination without biomass removal and soil disturbance. Tillage termination was evaluated in a previous study and resulted in decreases or no change in SOC stocks (Ogle et al., 2023). Regardless, other termination methods could be evaluated in the future.
 - Planting and harvest dates were based on national GHG inventory data for cover crops (US-EPA 2024). Cover crops did not receive any fertilizer (US-EPA 2024).

Tillage scenarios:

We simulated scenarios with conversion to continuous reduced tillage (RT), continuous no-till (NT), and NT with intermittent intensive tillage (IT) and reduced tillage (RT), as noted below.

- RT: All NRI survey points with IT in the baseline are converted to RT.

- NT: All NRI survey points under IT and RT in the baseline are converted to NT.
- NTRT: All NRI points in the baseline are converted to NT with one year of RT in the fifth year. If the fifth year falls on a hay/pasture crop, the tillage is moved to the next non-perennial crop in the rotation.
- NTIT: All NRI points in the baseline are converted to NT with one year of IT in the fifth year. If the fifth year falls on a hay/pasture crop, the tillage is moved to the next non-perennial crop in the rotation.

Manure management scenarios:

We simulated manure management scenarios on corn production points within each MLRA using four manure replacement scenarios for synthetic nitrogen: 25%, 50%, 75%, and 100%. These scenarios were not modeled as stacked practices. Their purpose was to isolate the SOC impacts of manure applications and derive SOC manure factors. The impacts of manure on SOC were calculated using carbon contribution factors (additional SOC per unit of manure C) generated through DayCent simulations.

DayCent simulations for corn points within each MLRA used the four manure replacement levels. For each scenario, we computed:

- The 30-year annualized dSOC relative to the baseline (no manure)
- Average annual manure C applied per point
- dSOC per unit of manure C (tons additional SOC per tons added manure)

Carbon contribution factors were then aggregated up to MLRA using weighted averages based on NRI acreage weights (the acreage expansion factor associated with each NRI point) and then averaged across the four replacement levels for each MLRA and manure type. MLRA-level carbon contribution factors for corn, by manure type, were then applied to all other crops.

2.3 Aggregation and Outputs

For each rotation type and scenario, simulated values and supporting scenario data are aggregated to the MLRA level using NRI survey area weights. Outputs are aggregated by rotation (across all years) or by rotation and crop type (across years with the crop of interest) for each scenario. The reported outputs include:

1) Across all rotations by MLRA:

- Percentage of the area each crop rotation relative to the total simulated area in each MLRA

2) Within each rotation by MLRA and scenario:

- Average annual area proportion of the crop and any "Other" crop/silage
- Average annual area proportion (0:1) with a cover crop by year

- Average annual area proportion with a cover crop in any year
- Average number of years with a cover crop
- Average annual delta SOC
- Average annual area proportion of full tillage (IT)
- Average annual area proportion of reduced tillage (RT)
- Average annual area proportion of no-tillage (NT)
- Average annual area proportion receiving manure
- Average annual area proportion receiving manure in any year
- Average number of years receiving manure

3) Within each rotation and crop by MLRA and scenario:

- Average annual direct N₂O flux in kg/ha
- Average annual indirect N₂O flux in kg/ha
- Average annual C in grain (yield) in gC/m²
- Average annual aboveground biomass in gC/m²
- Average annual belowground biomass in gC/m²
- Average annual total biomass in gC/m²
- The proportion of the total nitrogen available applied as fertilizer
- The proportion of the crop's total biomass to the rotation's total biomass
- Average annual total nitrogen sources in g N/m²
- Average annual total N fertilizer in gN/m²
- Average annual litter N in gN/m²
- Average annual total N in manure for NRI survey points receiving manure in gN/m²
- Average annual total C in manure for NRI survey points receiving manure in gC/m²
- Average annual total N in manure across all NRI survey points in gN/m²
- Average annual total C in manure across all NRI survey points in gC/m²

3. References

Del Grosso, S.J., W.J. Parton, A.R. Mosier, M.D. Hartman, J. Brenner, D.S. Ojima, and D.S. Schimel (2001) "Simulated Interaction of Carbon Dynamics and Nitrogen Trace Gas Fluxes Using the DayCent Model." In Schaffer, M., L. Ma, S. Hansen, (eds.); Modeling Carbon and Nitrogen Dynamics for Soil Management. CRC Press. Boca Raton, Florida. 303-332.

Del Grosso, S.J., S.M. Ogle, W.J. Parton, and F.J. Breidt (2010) "Estimating Uncertainty in N₂O Emissions from U.S. Cropland Soils." *Global Biogeochemical Cycles*, 24, GB1009, doi:10.1029/2009GB003544.

Del Grosso, S.J., W.J. Parton, C.A. Keough, and M. Reyes-Fox. (2011) Special features of the DayCent modeling package and additional procedures for parameterization, calibration, validation, and applications, in *Methods of Introducing System Models into Agricultural Research*, L.R. Ahuja and Liwang Ma, editors, p. 155-176, American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, WI. USA.

Del Grosso, S. J., S. M. Ogle, C. Nevison, R. Gurung, W. J. Parton, C. Wagner-Riddle, W. Smith, W. Winiwarter, B. Grant, M. Tenuta, E. Marx, S. Spencer, and S. Williams. 2022. A gap in nitrous oxide emission reporting complicates long-term climate mitigation. *Proceedings of the National Academy of Sciences* 119:e2200354119.

Gurung, R. B., Ogle, S.M., Breidt, F.J., Williams, S.A., Parton, W.J. (2020) Bayesian calibration of the DayCent ecosystem model to simulate soil organic carbon dynamics and reduce model uncertainty. *Geoderma* 376: 114529.

Gurung RB, Ogle SM, Breidt FJ, et al. (2021) Modeling nitrous oxide mitigation potential of enhanced efficiency nitrogen fertilizers from agricultural systems. *Science of The Total Environment*. 2021/12/20/;801:149342.

Hagen, S. C., G. Delgado, P. Ingraham, I. Cooke, R. Emery, J. P. Fisk, L. Melendy, T. Olson, S. Patti, N. Rubin, B. Ziniti, H. Chen, W. Salas, P. Elias, and D. Gustafson. 2020. Mapping Conservation Management Practices and Outcomes in the Corn Belt Using the Operational Tillage Information System (OpTIS) and the Denitrification–Decomposition (DNDC) Model. *Land* 9:408.

Ogle, S.M., F.J. Breidt, M. Easter, S. Williams and K. Paustian. (2007) “Empirically-Based Uncertainty Associated with Modeling Carbon Sequestration Rates in Soils.” *Ecological Modeling* 205:453-463.

Ogle, S.M., F.J. Breidt, M. Easter, S. Williams, K. Killian, and K. Paustian (2010) “Scale and uncertainty in modeled soil organic carbon stock changes for U.S. croplands using a process-based model.” *Global Change Biology* 16:810-822.

Ogle, S.M., Breidt, F.J., Del Grosso, S., Gurung, R., Marx, E., Spencer, S., Williams, S., Manning, D. (2023) “Counterfactual scenarios reveal historical impact of cropland management on soil organic carbon stocks in the United States.” *Scientific Reports* 13(1):14564.

Parton, W.J., M.D. Hartman, D.S. Ojima, and D.S. Schimel (1998) “DayCent: Its Land Surface Submodel: Description and Testing”. *Glob. Planet. Chang.* 19: 35-48.

Parton, W.J., E.A. Holland, S.J. Del Grosso, M.D. Hartman, R.E. Martin, A.R. Mosier, D.S. Ojima, and D.S. Schimel (2001) Generalized model for NO_x and N₂O emissions from soils. *Journal of Geophysical Research*. 106 (D15):17403-17420.

PRISM Climate Group (2022) PRISM Climate Data, Oregon State University, <http://prism.oregonstate.edu>, downloaded January 2022.

Soil Survey Staff (2020) Gridded Soil Survey Geographic (gSSURGO) Database for the Conterminous United States. United States Department of Agriculture, Natural Resources Conservation Service, Accessed February 2020 (FY2020 official release), Available online at <https://gdg.sc.egov.usda.gov/>.

USDA-NASS (2012) 2012 Census of Agriculture. USDA National Agricultural Statistics Service, Complete data available at <http://www.nass.usda.gov/AgCensus>.

USDA-NASS (2017) 2017 Census of Agriculture. USDA National Agricultural Statistics Service, Complete data available at <http://www.nass.usda.gov/AgCensus>.

USDA-NASS (2021) Published crop data layer. Available at <https://nassgeodata.gmu.edu/CropScape/>, Accessed July 2021, USDA-NASS, Washington, DC.

USDA-NRCS (2012) Assessment of the Effects of Conservation Practices on Cultivated Cropland in the Upper Mississippi River Basin. US Department of Agriculture, Natural Resources Conservation Service, https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1042093.pdf.

USDA-NRCS (2018) CEAP Cropland Farmer Surveys. USDA Natural Resources Conservation Service. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/technical/nra/ceap/na/?cid=nrcs143_014163.

USDA-NRCS (2020) Summary Report: 2017 National Resources *Inventory*. Natural Resources Conservation Service, Washington, DC, and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa. <https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/technical/nra/nri/results/>.

USDA-NRCS (2022) Conservation practice on cultivated croplands: A comparison of CEAP I and CEAP II survey data and modeling. United States Department of Agriculture, Natural Resources Conservation Service, <https://www.nrcs.usda.gov/sites/default/files/2022-09/CEAP-Croplands-ConservationPracticesonCultivatedCroplands-Report-March2022.pdf>.

US-EPA (2024) Inventory of U.S. Greenhouse gas emission and sinks: 1990-2022. United States Environmental Protection Agency, EPA 430-R-24-004.

Appendix B: Methodology for Estimating Feedstock-Specific Soil Organic Carbon Changes from Farming Practice Adoption

ICF

December 2025

1. Background

This appendix details the methodology for quantifying changes in soil organic carbon (SOC) associated with adopting various farming practices in the production of biofuel feedstocks. Results used are from simulations that were conducted with DayCent at the scale of USDA/NRCS Major Land Resource Areas (MLRAs), agroecological regions delineated by shared soils, climate, and vegetation (i.e., local growing conditions) (see Appendix A above).

DayCent simulations produced MLRA-level SOC stock change estimates for four crops—corn, soybeans, grain sorghum, and spring canola— within 11 different crop rotations under a business-as-usual (BAU) baseline and various practice scenarios (Appendix A). The BAU baseline was developed based on historical practice data from the Natural Resources Inventory (NRI), USDA-NRCS Conservation Effects and Assessment Project (CEAP), Agricultural Resource Management Surveys (ARMS) and OpTIS. ICF then post-processed the simulation outputs to compute SOC stock changes that are incorporated in R&D FD-CIC.

2. SOC Allocation and Aggregation by MLRA and Crop

Results from DayCent are reported as the annualized change in SOC (dSOC) to 30 cm soil depth for each 5-year crop rotation modeled for 30 years. To apportion the dSOC from feedstock crop production, a biomass-based allocation method was used where dSOC is allocated based on both (a) the biomass of the feedstock crop as a percentage of the total biomass of the rotation and (b) the amount of time any given feedstock crop is planted in the 5-year rotation. The rotation frequency modelled was based on historical data from NRI survey data. The SOC methodology described in this section applies to all modeled crop rotations.

By allocating dSOC based on crop-specific biomass, it is assumed that feedstock crops which produce more biomass will result in greater dSOC due to the conversion of decayed feedstock crop residue into SOC. This method was adopted to ensure consistency with SOC methodologies previously established by Argonne National Laboratory (ANL) and by expert recommendation.

A different approach was used for rotations that included rye cover crop production, as dSOC from cover crop production is due to the biomass of the cover crop (and not the feedstock crop). The change in SOC from cover crop adoption is assumed to be equal to the difference between cover crop scenarios dSOC and non-cover crop scenarios dSOC. Therefore, cover crop adoption should result in similar changes in dSOC/acre for all crops in the rotation. This SOC benefit from

cover crops is then added to the crop-specific allocated dSOC from the non-cover crop scenarios. See below for the detailed formulas used.

2.1 Allocation of dSOC for Scenarios without Additional Cover Crop Adoption

Equation 1 uses the ratio of biomass from each crop among all crops in the rotation and the frequency of the crop in the rotation to return an annualized dSOC value that is allocated to the feedstock crop of interest.

Equation 1. SOC allocation method for scenarios without additional cover crops

$$dSOC_{crop,rotation,MLRA,no\ ccR} = \frac{(dSOC_{rotation,MLRA,no\ ccR}) \times (M_{crop,rotation,MLRA})}{CP_{crop,rotation,MLRA}}$$

Where:

<i>no ccR</i>	BAU cover crop adoption
<i>ccR</i>	High adoption of rye cover crop
$dSOC_{crop,rotation,MLRA,no\ ccR}$	The annualized change in SOC [Mg C/ha] for non-cover crop scenarios allocated by crop for each rotation and MLRA.
$dSOC_{rotation,MLRA,no\ ccR}$	The annualized change in SOC [Mg C/ha] for non-cover crop scenarios by rotation and MLRA.
$M_{crop,rotation,MLRA}$	The proportion of the crop's total biomass relative to the rotation's total biomass over the 30-year period. Total biomass includes above and belowground biomass. This value is provided by DayCent.
$CP_{crop,rotation,MLRA}$	The average proportion of annual area of the feedstock crop and any "Other" crop/silage in the rotation. This value is provided by DayCent.

2.2 Allocation of dSOC for Scenarios with Additional Cover Crop Adoption

The dSOC associated with cover crop adoption is allocated to feedstock crops in the rotation based on the frequency in the rotation. The change in SOC from cover crop adoption is assumed to be equal to the difference between cover crop scenarios (ccR) and non-cover crop scenarios (no ccR). Therefore, cover crop adoption should result in similar changes in dSOC/acre for all crops in the rotation.

Equation 2. SOC allocation method for scenarios with additional cover crops

$$dSOC_{crop,rotation,MLRA,ccR} = [(dSOC_{rotation,MLRA,ccR} - dSOC_{rotation,MLRA,no\ ccR}) + dSOC_{crop,rotation,MLRA,no\ ccR}]$$

Where:

<i>no ccR</i>	BAU cover crop adoption
<i>ccR</i>	High adoption of rye cover crop
$dSOC_{crop,rotation,MLRA,ccR}$	The annualized change in SOC [Mg C/ha] for cover crop scenarios allocated by crop for each rotation, and MLRA.

$dSOC_{rotation,MLRA,ccR}$	The annualized change in SOC [Mg C/ha] for cover crop scenarios by rotation, and MLRA. This value is provided by DayCent.
$dSOC_{rotation,MLRA,no\ ccR}$	The annualized change in SOC [Mg C/ha] for BAU cover crop scenarios by rotation, and MLRA. This value is provided by DayCent.
$dSOC_{crop,rotation,MLRA,no\ ccR}$	The annualized change in SOC [Mg C/ha] for non-cover crop scenarios allocated by crop for each rotation, and MLRA. This value is calculated in Equation 1.

2.3 Aggregating dSOC Estimates Across Rotations to Create a Crop-Specific Value for the MLRA

The crop-specific value for dSOC is constructed as a crop-specific weighted average of the rotation-specific values based on the acreage of each rotation within the MLRA. These values are then used to develop CI factors by MLRA, crop, and conservation practice.

DayCent modeled the rotation area proportion (RP) of the total MLRA area that is cropped in each of the eleven representative crop rotations. Additionally, DayCent also outputs the frequency of the feedstock crop versus any “other crop” within each rotation for each MLRA ($CP_{crop,rotation,MLRA}$). These two variables can determine how much of an MLRA’s crop production is attributed to one rotation versus another.

Equation 3. The portion of the MLRA's crop production from each rotation

$$CRP_{crop,rotation,MLRA} = \frac{RP_{rotation,MLRA} \times CP_{crop,rotation,MLRA}}{\sum_0^i (RP_{rotation,MLRA} \times CP_{crop,rotation,MLRA})}$$

Where:

i	The number of rotations in the MLRA that include the feedstock crop
$CRP_{crop,rotation,MLRA}$	The proportion of an MLRA’s crop production that is attributable to a specific rotation.
$RP_{rotation,MLRA}$	The proportion of the area each crop rotation relative to the total simulated area in each MLRA. This value is provided by CSU.
$CP_{crop,rotation,MLRA}$	The average proportion of annual area of the feedstock crop and any "Other" crop/silage in the rotation. This value is provided by DayCent.

Once this is calculated, the crop-rotation proportion can be applied to each rotation’s dSOC value to develop a weighted average dSOC value for each crop, MLRA, and farming practice scenario.

Equation 4. Aggregate rotation dSOC by MLRA

$$dSOC_{crop,MLRA,practice} = \sum_0^i (dSOC_{crop,rotation,MLRA,practice} \times CRP_{crop,rotation,MLRA})$$

Where:

i	The number of rotations in the MLRA that include the feedstock crop
$dSOC_{crop,MLRA,practice}$	The annualized change in SOC [Mg C/ha] allocated by crop for each MLRA and practice.
$dSOC_{crop,rotation,MLRA,practice}$	The annualized change in SOC [Mg C/ha] allocated by crop for each rotation, MLRA and practice. This value is calculated in either Equation 1 or Equation 2.
$CRP_{crop,rotation,MLRA}$	The proportion of a MLRA's crop production that is attributable to a specific rotation. This value is calculated in Equation 3.

2.4 Accounting for Yield Changes from Farming Practices

In addition to affecting SOC accumulation, various farming practice adoption can also affect crop yields. Crop, rotation, and MLRA-specific yields were estimated based on DayCent-modeled crop yield reported in g C/m². The following equation was used to convert crop yields from g C/m² to bu/ha.

Equation 5. DayCent Yield Conversion

$$Yield_{crop,rotation,MLRA,practice} = \left(\frac{CY_{crop,rotation,MLRA,practice}/BC}{(1 - Moisture_{crop})} \right) \div (g_to_lb \times m^2_to_ha) \div Lb_to_Bu_{crop}$$

Where:

$Yield_{crop,rotation,MLRA,practice}$	The crop grain yield [bu/ha] for the rotation, MLRA and conservation scenario.
$CY_{crop,rotation,MLRA,practice}$	The crop, rotation and MLRA-specific grain yield [g C/m ²] for the conservation scenario. This value is provided by DayCent.
BC	The assumed biomass carbon percentage (45%) of total crop dry matter (Kwon 5/29/2025).
$Moisture_{crop}$	The assumed moisture content for each modeled feedstock crop, provided by ANL (Kwon 5/29/2025). The moisture content assumptions are as follows: canola (8.5%), corn (15.5%), sorghum (14%), soybean (13%).
g_to_lb	Conversion factor from grams to pounds. 1 lb = 453.59 g.
$m^2_to_ha$	Conversion factor from m ² to hectare. 1 hectare = 10,000 m ² .
$Lb_to_Bu_{crop}$	Crop-specific factor from pounds to bushel. 1 bushel of corn or sorghum = 56 lbs; 1 bushel of soybeans = 60 lbs; 1 bushel of canola = 50 lbs.

Because the crop yields are modeled to be specific to a crop rotation, they need to be aggregated for each MLRA following a similar process as Equation 6.

Equation 6. Aggregate rotation change in crop yield by MLRA

$$Yield_{crop,MLRA,practice} = \sum_0^i (Yield_{crop,rotation,MLRA,practice} \times CRP_{crop,rotation,MLRA})$$

Where:

i	The number of rotations in the MLRA that includes the feedstock crop.
$CRP_{crop,rotation,MLRA}$	The proportion of an MLRA's total crop production attributable to a specific rotation. This value is calculated in Equation 3.
$Yield_{crop,rotation,MLRA,practice}$	The crop grain yield [bu/ha] for the rotation, MLRA and conservation scenario. This value is calculated in Equation 5.
$Yield_{crop,MLRA,practice}$	The aggregated MLRA crop grain yield [bu/ha] for the conservation scenario.

2.5 Calculate Change in SOC per Bushel from Farming Practices

To estimate the crop and MLRA-specific change in SOC resulting from farming practice adoption, the dSOC per bushel under the baseline scenario is subtracted from dSOC per bushel of the farming practice scenario. The MLRA-specific conservation and baseline scenario dSOC/hectare values can be converted to dSOC/bushel values by dividing MLRA-specific dSOC/ha values by the MLRA-specific yield/hectare values (derived from the DayCent yield values in g/m²).

Equation 7. Calculating the change in dSOC/bu from farming practices

$$dSOC/bu_{crop,MLRA,practice} = dSOC_{crop,MLRA,practice}/Yield_{crop,MLRA,practice} - dSOC_{crop,MLRA,base}/Yield_{crop,MLRA,base}$$

Where:

$dSOC/bu_{crop,MLRA,practice}$	The annualized crop and MLRA-specific change in SOC [Mg C/bu] for the farming practice scenario.
$dSOC_{crop,MLRA,practice}$	The crop and MLRA annualized change in SOC [Mg C/ha] for the farming practice scenario. This value is calculated in Equation 4. Equation 4
$Yield_{crop,MLRA,practice}$	The average MLRA-specific crop yield [bu/ha] for the MLRA for the farming practice scenario. This value is calculated in Equation 6.
$dSOC_{crop,MLRA,base}$	The crop and MLRA annualized change in SOC [Mg C/ha] for the baseline scenario. This value is calculated in Equation 4.
$Yield_{crop,MLRA,base}$	The average MLRA-specific crop yield [bu/ha] for the baseline scenario. This value is calculated in Equation 6.

The dSOC value in grams C per bushel can be converted to grams of CO₂e per bushel by multiplying by conversion factors for carbon to carbon dioxide and megagrams to grams.

Equation 8. Calculating the change in dSOC/bu from practice adoption in g CO₂ per bu

$$dSOC/bu_{crop,MLRA,practice} [CO_2e/bu] = dSOC/bu_{crop,MLRA,practice} * \frac{1e^6 g}{1Mg} * \frac{3.67 g CO_2e}{1 g C}$$

Where:

$dSOC/bu_{crop,MLRA,practice}$ [CO_2e/bu]

The final change in SOC per bushel from practice adoption for the crop and MLRA converted to carbon intensity of potential grams of CO_2 per bushel.

$dSOC/bu_{crop,MLRA,practice}$

The annualized crop and MLRA-specific change in SOC [Mg C/bu] for the conservation scenario. This is calculated in Equation 7.

Appendix C: Outlier Analysis and Proxy Development

Argonne National Laboratory and ICF

December 2025

A multi-step approach was employed to identify and remove outlier results from DayCent model outputs and to develop proxy values for MLRAs lacking data. The methodology is detailed below.

1. Outlier Identification and Removal

Outlier values were primarily associated with MLRAs exhibiting poorly calibrated baseline crop biomass yields. Based on that observation, the following steps were taken:

- MLRAs were removed if their baseline dSOC per bushel (kg CO₂e/bu) fell outside two standard deviations of the mean. Table 1 and Figure 1 summarize the number and identifiers of MLRAs removed for each feedstock.

Table 1. Summary of Removed MLRAs

Crop	Count of MLRAs
Corn	7
Soybeans	8
Grain sorghum	4
Canola	1

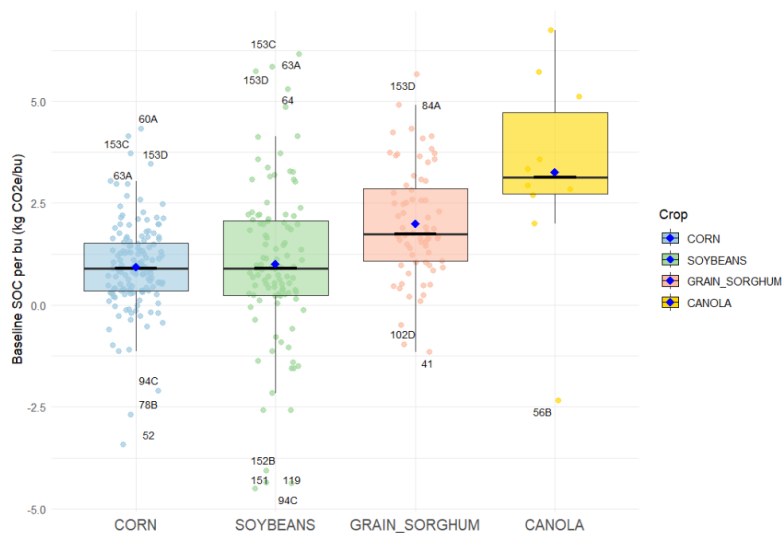


Figure 1: Distribution of baseline SOC per bushel (kg CO₂e/bu) by crop at the MLRA level. Boxplots depict the Interquartile Range (IQR); MLRAs with values beyond ± 2 standard deviations from the mean are labeled; the mean is shown as a blue diamond, and the median as a black line.

- For MLRAs within two standard deviations of the mean, the mean and standard deviation for each crop and practice were calculated. Any MLRA values outside two standard deviations of the mean for a given crop, practice, and CI attribute were capped at the corresponding two-standard-deviation limit.
- Values for MLRAs removed in Step 1 were later proxied using the methodology described below.

2. Development of SOC Proxy Values

After removing outliers, proxy values were developed for MLRAs lacking data, focusing on those with NASS production data reported within the past five years (2019-2023). The assignment of these values followed three cases:

- Case 1: MLRA with both NASS production data and DayCent-modeled SOC values: Existing values were retained. If values were removed as outliers, proxies were calculated using the method described below.
- Case 2: MLRA with modeled SOC but no NASS production data: These MLRAs were excluded from the analysis.
- Case 3: MLRA with NASS production data but no modeled SOC: Missing values were typically due to insufficient NRI points in an MLRA. Proxy values were generated using Land Resource Region (LRR) averages.

For each missing MLRA - including outlier-removed MLRAs (Case 1) and MLRAs with NASS production but no modeled SOC (Case 3) - average values for dSOC/bu were applied based on the LRR containing the MLRA. MLRAs were mapped to 28 unique LRRs, which provide more robust averages due to their larger geographic coverage. If the LRR contains only a single MLRA and that MLRA is either a Case 1 outlier or falls under Case 3—that LRR was excluded. In total, proxy values were developed for 73 unique MLRAs, plus 20 additional MLRAs removed during outlier analysis (Figure 2).

3. County-Level Mapping

After proxy values were established, CSU provided a county-to-MLRA crosswalk mapping each U.S. county to a MLRA. For each county, the MLRA occupying the largest share of its area was designated as the representative. This mapping supports the generation of county-level SOC estimates.

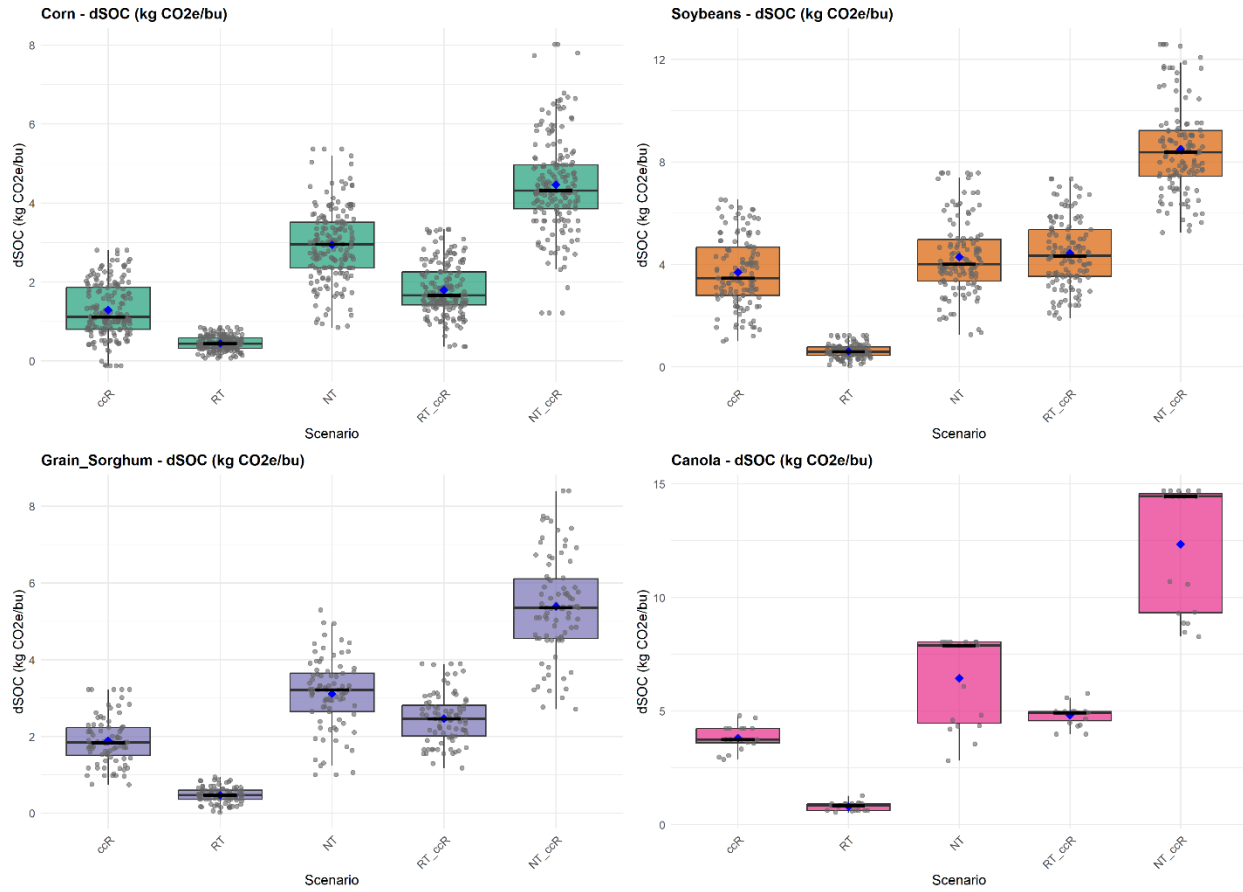


Figure 2: Distribution of dSOC per bushel by crop at the MLRA level under selected farming practices. ccR, RT, NT denote cover crop, reduced tillage and no-till practices, respectively. Boxplots depict the Interquartile Range (IQR); the mean is shown as a blue diamond, and the median as a black line.



Energy Systems and Infrastructure Analysis Division

Argonne National Laboratory
9700 South Cass Avenue
Lemont, IL 60439

www.anl.gov



Argonne National Laboratory is a U.S. Department of Energy
laboratory managed by UChicago Argonne, LLC