Soil Organic Carbon Accumulation Due to On-Farm Practices

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More information about the Consortium and its resources is available at: https://www.soilcarbonsolutionscenter.com/consortium.

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1. Introduction

Growing application of sustainable land management practices, driven by policy incentives and climate targets, has spurred interest in soil organic carbon (SOC) sequestration, including within broader energy and climate policy regimes. Key policies such as the Section 45Z Clean Fuel Production tax credit under the Inflation Reduction Act (IRA) include significant funding and incentives for SOC sequestration through soil conservation practices. In the future, potential revisions to state-level Low Carbon Fuel Standards as well as a proposed national-scale Clean Fuel Standard could include further incentives for these practices. Since these policies guide land management decisions, and can act as a form of carbon offset, it is imperative that SOC accumulation estimates are accurate and robust. These policies rely on modeling, which makes the accuracy of the dynamic soil process models underpinning their SOC accounting particularly important. We investigate modeled SOC accumulation as a function of target conservation strategies: cover cropping and conservation tillage. We also test the robustness of modeled results, through the sensitivity of this modeling to key farm practices and methodological accounting choices and compare the results with empirical measurements of SOC accumulation.

1.1 Policy context

The U.S. Inflation Reduction Act offers valuable production tax credits to producers of low-carbon transportation fuels among other renewable energy systems. The federal Section 45Z Clean Fuel Production Credit for aviation fuel, for example, offers a direct subsidy for as much as \$156 per T CO_2e abated, though it will be reduced to a maximum of about \$89 per T CO_2e in 2026 (The Section 45Z Clean Fuel Production Credit, 2025)[1]. By incorporating soil carbon accumulation directly into these life cycle assessment (LCA) calculations, the Treasury Department is offering a significant market value for what are, in effect, uncertain, unregulated, and potentially non-additional carbon offsets.

Soil carbon crediting has not been introduced in regulatory schemes such as California's Low Carbon Fuel Standard (LCFS) or the federal Renewable Fuel Standard (RFS), though there have been efforts to explore it (Gradable, 2020). A limited soil carbon crediting method was introduced for the federal 40B sustainable aviation fuel (SAF) tax credit, known as the climate smart agricultural (CSA) practices pilot program (IRS, 2024), which allows corn and soy producers to attribute changes in soil carbon to their biofuels on a g CO_2e per MJ basis. For corn production, farmers must simultaneously implement three practices on the same acreage: no-till farming, cover crops, and enhanced efficiency nitrogen fertilizers.

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[1] *The production tax credit offers \$1.75/gallon (reduced to \$1.00 in 2026) for production of aviation fuels with calculated carbon intensity of 0 kg CO2e/MMBtu. The credit value decreases linearly with the emission factor of the sustainable aviation fuel, with the emission factor being the amount the CI is lower than a baseline of 50kg/MMBtu as a fraction of the baseline. Assuming the SAF has a lower heating value energy density of 126.37 MJ/gal (U.S. Department of Energy, 2024), and that the fossil fuel alternative is assumed to have a carbon intensity is 89 g CO_2e/MJ (ICAO, 2020), the current maximum subsidy rate for a SAF with a calculated CI of 0 kg CO2/MMBtu would be \$156 and reduced to \$89 starting in 2026.*

The CSA pilot program incorporates several elements drawn from offset programs to attribute changes in soil carbon to agricultural practices but falls short of ensuring additionality, durability or validation through measuring soil carbon change. The program requires documentation of the practices, along with a letter of intent to practice no-till and cover crops continuously on the same acreage except for periodic tillage (no more than once every five or ten years). The program credits a reduction of net corn ethanol carbon intensity by 10 gCO_2e/MJ. This carbon intensity reduction estimate includes GHG emission reductions and carbon sequestration in the soil from the practices. The program does not require a set timeframe over which the practices are implemented, offering the same intensity reduction credit to a first-year farm as one that has maintained the practices over a longer period.

The U.S. Department of Agriculture's recently proposed Technical Guidelines for Climate-Smart Biofuel Feedstocks also provide some insight on how soil carbon crediting may work in future biofuels policies. In this program, reduced-till, no-till, and cover cropping can be implemented individually or together for corn, soy, or sorghum cropping systems, and their impact on soil carbon over 30 years of continuous implementation can be assessed on a per-bushel basis using the provided Feedstock Carbon Intensity Calculator (FD-CIC). GHG estimates are calculated using a parameterized set of DayCent model results for the combined set of crops and management practices, which are estimated based on the county selected. Notably, this approach only requires record-keeping that the practices are occurring consistently with the technical standards established for each practice but does not require any measurement or guarantee of a long-term change in practice.

1.2 SOC modeling is highly sensitive and uncertain

Globally, the conversion of natural ecosystems to agricultural production has depleted stocks of soil organic carbon (SOC) in the soil. This soil C has largely been released to the atmosphere, increasing the atmospheric C pool by an estimated 78 Pg (Lal, 2004). Depleted soils have the potential to store additional carbon (Paustian et al., 2000; Stockmann et al., 2013). Restoring C to the soil provides a variety of benefits, including climate change mitigation, improved soil fertility, increased soil water retention, and augmented productivity (Alvaro-Fuentes et al., 2009).

A variety of land management practices have been identified that may increase SOC and create a positive C budget in soils used for agricultural production, including the addition of soil amendments (e.g., manure, compost), reduced or eliminated tillage of soil, and the use of cover crops (Stockmann et al. 2013). However, the magnitude and persistence of SOC is influenced by land use and farming practices. Moreover, SOC is highly dynamic, varying over time and space, as the carbon is a source of energy for soil biota (Lal et al., 2015).

The possibility of enhanced soil carbon storage is promising, from a climate change mitigation perspective – a proposal to increase SOC stocks by 0.4% is estimated to be able to offset 20-35% of global GHG emissions (Minasny et al., 2017). However, estimates of soil C storage under different on-farm practices and in different contexts are not well-established, and there is considerable uncertainty and variability in how much additional carbon these practices can add to the soil.

Empirical estimates of SOC accumulation under differing on-farm practices are highly variable and difficult to measure (Popkin, 2023). In general, “conversion from nearly all other land uses to cropping or monocultures results in losses of SOC” (Stockmann et al., 2016, p. 82). Moisture and temperature are strong controls on rates of organic matter decomposition, which in turn influence the rate of SOC accumulation. In general, intensive tillage accelerates decomposition of organic matter, while conservation tillage (no-till or reduced-till) can enhance soil C storage, though soil type, study duration and historic tillage practices all contribute to variability in the results (Al-Shammary, 2024). Cover cropping -- the practice of rotating what is planted in a field between plants for harvesting and plants that provide benefits to the soil, including nutrient availability, erosion prevention, pest control, improved water availability – has variable impacts to SOC. A recent meta-analysis of the literature found 4.0-5.9% increases in SOC accumulation from cover cropping (He et al., 2025), though most of the data points were from short term experiments. The SOC dynamics in cover cropping systems are impacted by soil properties, crop species, duration and climate (He et al., 2025, Hu et al., 2023). Questions remain regarding the conditions under which an on-farm practice can enhance long-term soil C sequestration.

Modeled estimates of SOC accumulation due to on-farm practices are sensitive to model assumptions, and the uncertainty of model predictions are hard to quantify. Process-based models, such as DayCent and Century, are commonly used to estimate changes in SOC due to on-farm practices, climate, or other effects. Uncertainty in model estimates is not commonly evaluated; however, Ogle et al. (2010) estimated that model uncertainties varied inversely with regional scale and varied with the magnitude of the SOC stock change, with larger changes associated with lower uncertainties. The magnitude of these uncertainties often exceeded 100% (Ogle et al., 2010). The model selected, as well as the parameterization of the model, are key factors affecting the overall uncertainty of the modeled result.

1.3 Investigating the magnitude and uncertainty of SOC accumulation in corn farming

This report aims to provide insights that will be useful to policymakers in considering whether and how to incorporate SOC accumulation in policies providing direct support for agricultural products based on their life-cycle climate performance. However, rigorously crediting increases in carbon storage to an agricultural practice poses many important challenges. The following are three key challenges associated with directly crediting changes in SOC and the approach taken to address each in this report.

1. **Effectiveness:** In order to credit SOC accumulation to a particular cultivation method, the effectiveness of that method in stimulating an increase in SOC compared to a business-as-usual baseline must be rigorously estimated. We use a leading SOC model, DayCent (Parton et al., 1998), to estimate the SOC accumulation associated with cover cropping and two conservation tillage strategies over 30 years. DayCent is a state-of-the-art research tool, already being put to use by the federal government for agriculture sector emissions accounting (EPA, 2024) and for incentivizing agricultural practices

within biofuel supply chains. See, for example, USDA's Technical Guidelines for Climate-Smart Agriculture Crops Used as Biofuel Feedstocks (USDA, 2025).

2. **Accuracy:** Model results alone are insufficient to formulate effective incentive structures. In order to assess the accuracy of the estimates emerging from DayCent, we compared them to the empirical record provided by published field trials that applied conservation tillage or cover crops on lands cultivated with corn. We compare a meta-analysis of this empirical record to DayCent results for SOC accumulation under these practices.
3. **Consistency:** Soil carbon accumulation rate is highly sensitive to the specific characteristics of the cultivation system. Details such as soil type, climatic characteristics, fertilization rates, historical land use, and the consistency with which practices are applied have significant impact on the efficacy of SOC accumulation. Results are also impacted by subjective methodological accounting choices, such as assumed baseline farming practices, which carbon pools are included in the analysis and the length of time that the practice is assumed to be implemented. We explored the sensitivity of SOC accumulation estimates to these real-world variations and methodological choices and report our results in section 3.3 below.

1.4. Unaddressed Considerations: Economics, Durability, Indirect Effects

Systems that quantify total emissions and compensate or charge operators on the basis of these emissions effectively function as carbon markets. In practice, awarding a soil C sequestration credit to a land management practice within a system (e.g., IRA tax credits) functions as though it were issued as a C offset by reducing the calculated net emission of the fuel in question. As described in footnote[1] above, operators are in effect being compensated at up to $156 for this estimated carbon sequestration – a rate much higher than they could receive from any formal carbon market instrument at present.

However, this offset is only truly equivalent to an emission abatement if the soil C remains in long-term storage, and if that carbon would not have been stored anyway had the relevant incentive not been applied. Even where formal carbon offsets are issued for SOC accumulation, quantification, permanence, and additionality can be uncertain (Popkin, 2023). Also, awarding C sequestration to a tax incentive would be complicated by a lack of oversight or additionality requirement that would apply on the formal offset market. The *additionality* of this carbon storage – the extent to which any carbon storage or depletion would have occurred in the absence of the policy or economic intervention to which it's being attributed – is uncertain.

This report does not directly assess the financial additionality of the soil carbon accumulation strategies being investigated. Instead, we estimate the SOC accumulation impact of implementing a conservation management practice *assuming* that the farm would have otherwise practiced conventional corn cultivation. To shed light on the impact of this assumption, we use modeling to explore the sensitivity of SOC accumulation to the baseline cultivation practice, which allows us to assess the extent to which the assumption about the avoided cultivation practice influences the calculated sequestration.

Our primary results do not include explicit accounting for the *durability* of SOC gains. Unlike some other forms of carbon sequestration, SOC gains are reversible and can be lost due to changes in land management, climate, or other factors. While our sensitivity analysis touches on this uncertainty, we do not model potential future emissions resulting from carbon reversals under changing conditions. As such, the carbon benefits reported in our main results represent modeled accumulation assuming stable conditions and should not be interpreted as permanent carbon removals. This omission is important to consider, especially in policy contexts where long-term climate benefits are assumed or required.

In addition, our analysis does not account for *indirect effects* that may arise from adopting conservation management practices. These effects refer to broader system-level consequences that occur outside the model boundary, often as a result of changes in productivity, land use, or resource availability. For example, adopting a conservation practice that reduces yields could incentivize expansion of crop production elsewhere to meet demand—potentially resulting in land conversion, increased emissions, or biodiversity loss. Alternatively, practices that increase productivity might reduce land pressure but lead to changes in irrigation or fertilizer demand, which may lead to climate impacts. These indirect impacts were not captured in our analysis.

2. Methods

2.1 Modeling

2.1.1 DayCent model

The DayCent model is a process-based ecosystem model that uses a daily time step to estimate trace gas fluxes between the atmosphere, vegetation, and soil (Parton et al., 1998, Del Grosso et al., 2005). Key inputs to the model include daily maximum and minimum temperature, the timing and description of land management practices (e.g., tillage, crop rotation, fertilization, irrigation), historical land use, and soil properties (Del Grosso et al., 2005). The model is broadly used at the global (e.g., Henderson et al., 2015), regional (e.g., Del Grosso et al., 2005), and field scales (Ryals et al., 2015), in the fields of ecology, biogeochemistry, life cycle assessment, and environmental science to estimate ecosystem response to land use changes (e.g., Henderson et al., 2015).

DayCent models farm activities based on ‘schedule files’, which describe the timing of farming practices (e.g., planting on day x, fertilizing at rate y on day z). Each practice is described using a key word which corresponds to a group of parameters defined in ‘.100’ files. The model output includes hundreds of variables detailing information about crop growth, nutrient stocks in soil and crop pools, details about decomposition rates, trace gas emissions and more. Daily estimates are available for biomass growth, soil respiration and hydrological dynamics. The main output variables we used in our analysis are the SOC stocks (in active, slow, and passive pools), surface carbon stock changes and mass carbon harvested in corn.

Of the many versions of the DayCent model, we chose to use a version that was developed for the Center of Advanced Bioenergy and Bioproducts Innovation (DayCent-CABBI) to advance the biofuel-plant (‘grasstree’) modeling capabilities. This model version was selected because of its availability (a complete set of model files was distributed in supplementary material published by Hartman et al. (2022)). We used the complete model package associated with the study, including the DayCent executable, as well as weather and soil data, site characteristics, historical land use schedule files, and specific crop, fertilization, harvest, irrigation ‘.100’ parameter files. The model was built by Hartman et al. (2022) to evaluate nitrogen cycling dynamics associated with sorghum production at a research plot located at the Energy Farm associated with University of Illinois. Certain model variables were calibrated and validated for the research site located in Urbana-Champaign, Illinois. The soil at the location is “very deep, poorly drained Drummer silty clay loam (fine-silty, mixed, superactive, mesic Typic Endoaquolls)” (Hartman et al., 2022), with mean growing season temperature of 17° Celsius and growing season precipitation of 598 mm.

The DayCent-CABBI model with parameterizations supplied by Hartman et al. (2022) was used to simulate the Energy Farm site up until 2020. This included a model ‘spin-up’ period from year 0 to 1847, in which land use was modeled as native grasslands with rotational grazing and occasional fires, attempting to converge on an equilibrium of pre-industrial agricultural soil properties. The ‘spin-up’ was followed by modeled approximation of historical land use through 2019, including beginning corn farming in 1848 with (assumed) conventional practices involving rotations with other crops, grazing, increasing fertilization, crop genetic improvements, and various equipment changes over time until 2011. From 2011-2019, the Energy Farm’s land use deviated from conventional practices in the area when sorghum trials were modeled and the model was calibrated and validated to field measurements of nitrous oxide emissions, sorghum production and other variables in 2019. From 2020 onward, we modeled various alternative land management practices (detailed in the next section) to analyze SOC dynamics for the purpose of this report. For the contemporary modeling, we supplemented the DayCent-CABBI files with parameterization files from the DayCent® version 491 release (copyright Colorado State University 2024), obtained through the Soil Carbon Consortium (*Consortium*, 2024). Figure 1 shows modeled SOC levels over the full model run, including the model periods defined by Hartman et al., 2022 (prior to 2020) and conventional corn modeling 2020-2050 built for the purpose of this study.

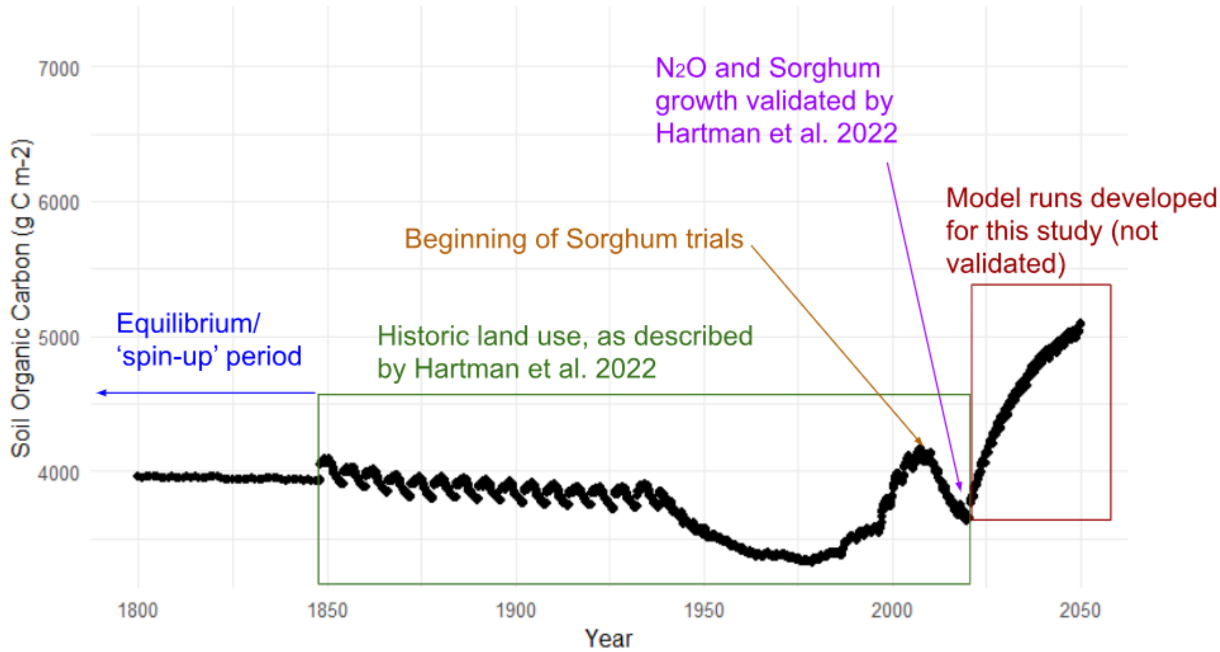

Figure 1: Modeled SOC over full model period. Years 0-2019 were modeled using Hartman et al., 2022 files. The reference continuous corn production was modeled from 2020-2050, which was not validated or calibrated to empirical data.

2.1.2 Main model runs: comparing various land management practices in contemporary timeframe

In order to investigate the modeled SOC impacts associated with conservation tillage and cover cropping we modeled these practices and compared the results to a counterfactual case of continuous corn production using assumed conventional practices. Given that DayCent is a process-based model, and that our study question concerns the impacts of processes rather than modeling outcomes at a specific site, we looked at the *difference* in carbon accumulation between the modeled conservation practices and a modeled baseline conventional corn production system. This strategy was chosen to avoid conclusions that are site-specific but to capture results from general process changes. For example, if the individual model site was abnormal compared to other Midwest sites, the abnormality would be present and impact both the test management and reference management, with only the relative difference between the practices representing the management change. The schedule file representing conventional corn production was developed by compiling data from literature and various university Agricultural Extension Offices. In general, the reference conventional corn production model represents an annual cycle of spring field cultivation, fertilizer application at rate of 200 kg N/ha, corn harvest with no residue (stover) removal and fall chisel plowing. The specific parameter values and their sources are outlined in Appendix A.

In the DayCent model, nutrients are tracked as they move through different conceptual pools in the ecosystem. For our modeling, we analyzed the changes to carbon in the active, slow, and passive organic matter pools of the soil and surface organic matter, while excluding litter due to its short residence times. Hereafter, we refer to this set of conceptual carbon pools as 'Soil Organic Carbon' or SOC. All results are reported as a difference between SOC concentration in the management practice of interest and the reference management practice, never as the difference between two times in a single modeled management practice.

We developed schedule files for the three conservation management practices (cover cropping, reduced-till, and no-till), to determine their impact on SOC accumulation. The cultivation, soil preparation, harvest, and fertilization details were selected based on literature values and available parameterized farming practices model files. We kept other variables consistent between the conservation and reference scenarios, as long as they did not conflict with literature descriptions of the practices. For example, we maintained the fertilization rate from the reference system to the cover crop and no-till model runs. Planting and harvesting days were kept consistent between all modeled scenarios. The complete schedule information for each model run is presented in Appendix A. Each model was simulated for 30 years, with a model timeframe between 2020-2050. These years were selected because we used a model that was validated in 2019, and because the real model years is irrelevant since the result we are modeling is the difference of SOC over time, not the actual SOC at any specific point in time. For each of the model runs, the SOC in all pools (active, slow, and passive) in the top 20 cm of the soil profile and organic carbon in surface biomass was output, along with the carbon removed in the corn harvested per year. The model was used to simulate only the top 20 cm of soil because the DayCent soil organic matter dynamics are parameterized for this depth (Hartman et al., n.d.).

2.1.3 Units

We present the SOC changes as mass of C per time per surface area, compared to conventional SOC changes over the same period. We also standardized results by the carbon removed from the landscape through corn harvest over the same timeframe, and by ethanol that could be produced from the corn grain harvested. To make these conversions, the carbon removed in corn was converted to energy content in ethanol, assuming 43.5% of corn grain by mass is carbon (Gescha et al., 2010), 2.86 gallons of ethanol can be produced from a bushel of corn[2], and an energy content of ethanol of 76,330 Btu / US gallon[3]. The unit conversion is shown below in Equation 1.

$$\frac{kg\ corn}{0.435\ kg\ C_{grain}} * \frac{bushel\ corn}{25.4\ kg\ (56\ lbs) corn} * \frac{2.86\ gal\ EtOH}{bushel\ corn} * \frac{76{,}330\ Btu}{gal\ EtOH} * \frac{MJ}{947.817\ Btu} = 20.85 \frac{MJ}{kg\ C_{grain}} \quad \text{(Eq. 1)}$$

2.1.4 Sensitivity analysis

2 Argonne National Laboratory's Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) model value for 'Dry milling with corn oil extraction'

3 Lower Heating Value (LHV) for E100 (DOE, 2025)

To test the influence of some key assumptions on the modeled results, we conducted a sensitivity analysis by varying four key aspects: counterfactual farm practices (what would have otherwise happened in the baseline case), historical land use (initial soil properties), nitrogen fertilization rates, carbon pools included, the time horizon of the analysis and inconsistencies in practice implementation.

Counterfactual conventional

The baseline analysis assumed that the counterfactual management ("conventional") consisted of spring field cultivation, fixed annual nitrogen fertilization, harvesting with 0% residue removal and fall chisel plowing. To test the impact of these assumptions, we modeled several alternative tillage equipment and intensities, while keeping the fertilization and residue removal rate constant. The 30-year SOC concentrations were compared to the assumed baseline conventional SOC concentrations and the net sequestration between no-till and the various conventional reference runs was calculated.

Historical Land Use

Our modeling began with the pre-built Energy Farm model, which included a well-documented, though atypical, land use history (including sorghum trials), which resulted in a set of soil properties at the beginning of our modeling including depleted SOC levels. To test the sensitivity of land use history and corresponding initial soil properties, we paired our management schedules (2020-2050) with two alternative hypothetical land use histories. The alternative land use histories modeled was continuous corn cropping from 2011-2020, with and without tillage, instead of the sorghum cultivation trials.

Fertilization Rate

Nitrogen fertilization rates were identified as a high-impact variable on plant productivity and therefore carbon inputs from residues. Nitrogen fertilization rates were varied to evaluate the influence. We modeled alternative N application rates for both conventional and conservation practices to determine how changes in fertilization influence net SOC outcomes of conservation practices.

Carbon Pools included as carbon sequestration

In nutrient cycling modeling and soil studies, carbon is often characterized by its rate of decomposition (active, passive, slow), and its location in the soil profile. In the primary analysis on SOC accumulation, all active passive and slow pool soil and surface carbon is included, while litter and microbial pools were excluded. To investigate the impact of this methodological choice, we compare our preliminary results with alternative results from including different subset of carbon pools (e.g. all carbon pools or only slow and passive pools).

Length of time

While a 30-year period was selected for the baseline analysis, we also considered shorter timeframes relevant to near-term climate goals. SOC changes were analyzed over multiple time horizons (5, 10, 20, 30 years) to assess the influence on analysis duration.

Inconsistent Conservation Implementation

In our primary analysis, we assumed that the conservation practice would be implemented every year for the whole period of study (30 years). To evaluate the effect of the practice being implemented less consistently, we modeled several hypothetical implementation schedules. First, we modeled a scenario where the conservation practice was implemented for 2 years, then reverted to conventional tillage for the remaining 28 years of the study period. Second, we looked at the scenario where a conservation practice is implemented for the study period, but every 5 years is reverted to conventional practices for one year (4 years alternative management, 1 year conventional, repeated for six 5-year cycles).

2.2 Meta Analysis

We compared our model results with empirical data on SOC accumulation due to conservational on-farm practices. We used a dataset called the 'Global Soil Carbon Fractions: Regenerative + Conventional Croplands' (Prairie et al., 2023) that was provided by the Soil Carbon Solutions Center's Ecosystem Modeling and Data Consortium (*Consortium*, 2024). This is a dataset of peer-reviewed primary literature that reports SOC changes associated with changes to management practices, including changes to tillage and cover cropping.

We filtered this dataset to only include studies involving corn production and those that included measurements of SOC stock (Mg C/ha) to a soil depth of 20 cm or more. Observations at various depths (at the same observation site and time) were compiled into a single estimation of SOC stock in the top 20 cm of the soil profile. This was done by adding SOC stocks in horizons between 0 and 20 cm depth. In cases where the SOC stocks were measured for a soil horizon that exceeded 20 cm, the measured stock was standardized per centimeter of soil depth and then prorated to 20 cm. The proration method relied on an assumption that SOC stock was constant across the depth in the horizon being prorated, which has been shown to underestimate SOC stock (Fowler et al., 2023), though small horizon increments reduced the uncertainty induced by this method.

In each experiment, we selected a single observation to represent 'conventional' corn production, to serve as the reference SOC measurement. Occasionally we selected multiple reference conditions with which to compare multiple observations. For example, if multiple crop-rotations were tested with different tillage treatments, we selected a conventional tillage reference measurement for each crop rotation to be paired with, in an attempt to isolate the impacts of the tillage. Some data were excluded if there was no observation of a reasonable representative of conventional corn (for example, some compared different cropping rotation within regenerative practices but did not include any measurements from conventional cropping at the same location). Additionally, only data that included variable tillage or cover crop were included; trials that only experimented with crop rotation were excluded. Trials that included multiple changes were included. Several trials incorporated both regenerative tillage practices and cover cropping; these were included in both the tillage and cover crop results. The filtered database contained 43 reference conventional observations and 60 regenerative practice SOC observations.

3. Results

We estimated SOC accumulation that could be attributed to cover cropping or limiting tillage by modeling corn production using the conservation practices and comparing the SOC stock to a baseline model of conventional corn. The model results were then compared to empirical data to assess their accuracy. Sensitivities of model assumptions were investigated in subsequent model runs.

3.1 Effectiveness: Modeling SOC accumulation due to alternative farm practices relative to a baseline

We use DayCent to model SOC changes due to implementation of conservational farm practices, with the goal of comparing SOC changes from conservational farm practices to the baseline case of conventional corn farming. The modeled soil carbon stock changes for the three conservation management scenarios relative to the baseline conventional case are shown in Figure 2. All three conservation farm practices resulted in higher modeled SOC than the baseline conventional scenario over the long-term (net positive). The conservation practices followed different rates of net SOC accumulation over the simulation period, with reduced-till and no-till management closely paired in the first decade but diverging after. By year 30, no-till and cover crop resulted in tightly paired net SOC accumulation, which was greater than the accumulation attributable to reduced-till. The positive and increasing net SOC accumulation indicate SOC gains due to these three conservation practices are additional to the assumed conventional corn status quo and increase with implementation duration.

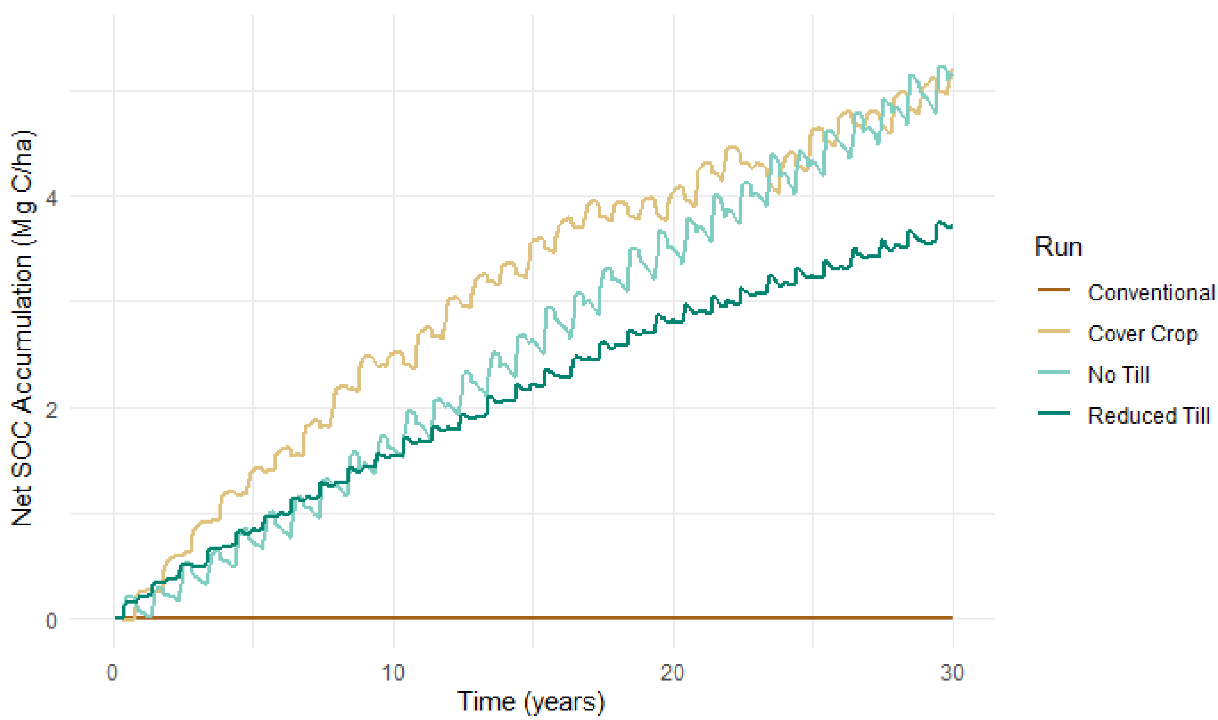

Figure 2: Modeled change in soil organic carbon stock (including carbon in the active, slow, and passive pools in the soil and on the surface) in the top 20 cm for conservation practices relative to the reference conventional corn scenario ("net" SOC accumulation). All conservation practices showed positive net sequestration, with no-till and cover crop practices exceeding reduced-till practices in the second half of the study period.

The difference between the modeled SOC stock after 30 years of implemented conservation practices versus 30 years of conventional corn production is presented in Table 1. The average rate of net accumulation over that timeframe, as well as the net SOC accumulation standardized to the corn harvested and ethanol produced are also presented in Table 1. Modeled corn productivity over the 30-year period was greatest in no-till management (143 Mg C/ha), followed by conventional (140 Mg C/ha), then reduced-till (134 Mg C/ha) and was lowest in the cover-crop scenario (114 Mg C/ha).

Table 1. Modeled SOC changes in the top 20 cm of soil over 30 years as the difference between conservation management and the reference conventional corn production.

Conservation Practice	SOC accumulation	Average Annual SOC Accumulation	SOC accumulation per grain C harvested	SOC accumulation per bushel corn	SOC accumulation per MJ ethanol
	(Mg C/ ha)	(Mg C/ ha/ yr)	(kg C/ Mg Corn-C)	(kg C/ bushel)	(g CO_2e/ MJ Corn Ethanol)
No-Till	5.13	0.171	36.0	0.397	6.32
Reduced-Till	3.71	0.124	27.8	0.307	4.88
Cover Crop	5.21	0.174	45.9	0.507	8.07

The values for SOC accumulation for each conservation practice (Figure 1 and Table 1) are positive, meaning that all conservation practices resulted in additional SOC relative to conventional corn cultivation. No-till and cover cropping yielded higher SOC accumulation than reduced-till (5.13 Mg C/ha and 5.21 Mg C/ha, versus 3.71 Mg C/ha, respectively).

3.2 Accuracy: Meta-analysis of empirical measurements of SOC accumulation

We compared the modeled SOC accumulation results to empirical data to assess the accuracy of the modeled results. We standardized the duration of carbon accumulation by dividing the total accumulation by the study duration or 30-year model duration (shown in the third column of Table 1). Based on 42 data points from 28 empirical studies, both no-till (NT) and reduced-till (RT) experiments showed mostly increased SOC levels compared with conventional cultivation (i.e., the "Delta SOC" is greater than zero; see Figure 3). The 33 no-till data points were extracted from 21 unique studies and encompassed experiments ranging in duration from 3 to 30 years, with an average duration of 13 years. The nine reduced-till data points were derived from seven studies, with experiments ranging in duration from 3 to 25 years (with an average experiment duration of 9 years). For all conservation treatments, the empirical record average showed a greater rate of SOC accumulation in shorter (less than 10 year) studies, and lower accumulation rate in 10-20- and 20-30-year duration studies. Our modeled SOC accumulation for no-till (0.171 Mg C/ha/yr) was consistent with long-term empirical rates (mean of 20–30-year studies: 0.18 Mg C/ha/yr). Though limited long-term reduced-till studies were included, our modeled SOC accumulation rate from reduced-till (0.124 Mg C/ha/yr) was lower than all reduced-till empirical results (mean across all study durations: 0.65 Mg C/ha/yr) (see Figure 3).

Empirical data for the impact of cover cropping on SOC accumulation ranged from negative to positive values (see Figure 3, left panel). For cover cropping, 12 data points were extracted from six studies, with experimental durations ranging from 5 to 21 years (14 years on average). These data showed variable net SOC from cover cropping, with an interquartile range spanning 0 (-0.15 to 0.22 Mg C/ha/yr), suggesting no net change relative to conventional. The mean SOC accumulation from cover cropping across all duration empirical studies was slightly positive (0.037 Mg C/ha/yr) and the median slightly negative (-0.085 Mg C/ha/yr). The mean value for studies greater than 20-years duration was slightly negative (-0.12 Mg C/ha/yr). Comparatively, our model results (0.174 Mg C/ha/yr) were moderately higher than the mean empirical value (0.037 Mg C/ha/yr) and directionally different from the long-term empirical results (which were negative).

Based on these comparisons and assuming the long-term (20-30 year) empirical dataset represents reality, our model overpredicted long-term SOC accumulation from cover cropping, underpredicted for reduced tillage, and approximated the mean value for no-till (Figure 3).

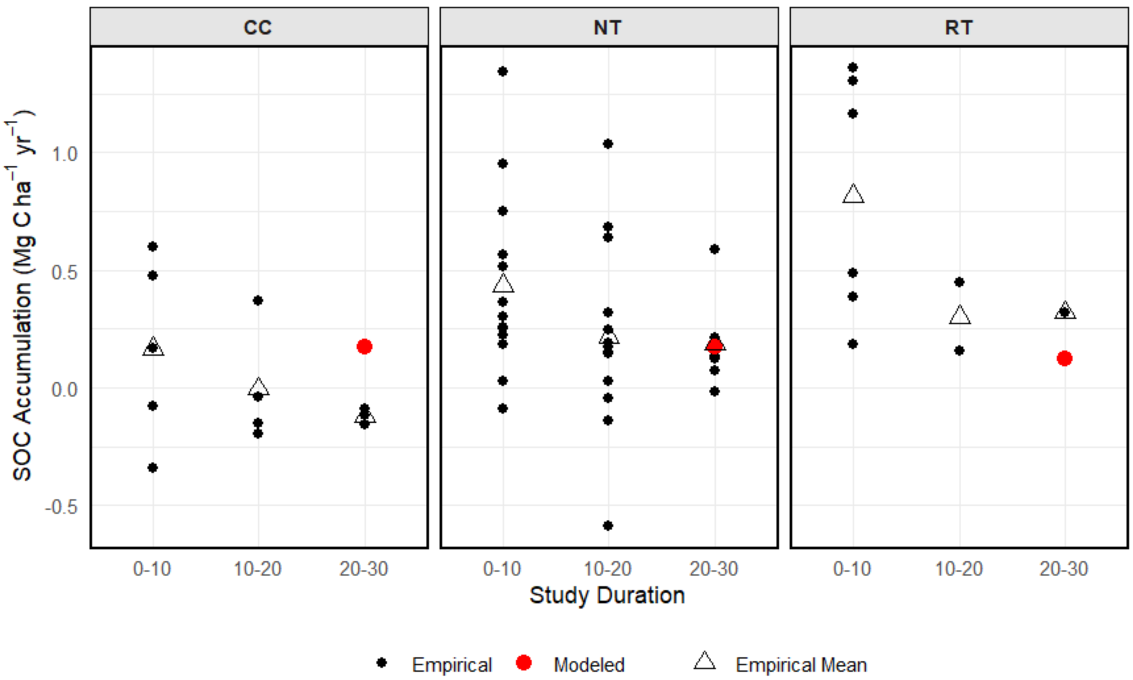

Figure 3: Meta-analysis of published values on SOC accumulation due to conservation practices relative to conventional, compared with modeled results. SOC accumulation is shown on the y-axis and study duration on the x-axis. Data are separated by farm practice, with CC = cover crop, NT= no-till, and RT = reduced-till. Empirical data is shown as black dots with the mean for each duration bin shown in empty black triangles. Modeled values from this study are shown in red circles.

Table 2: Empirical SOC accumulation rates across all study durations and limited to studies at least 20 years long. Model predicted SOC accumulation was based on 30 years of modeled implementation. All results are the net difference between SOC stock in the top 20 cm under conservation practice implementation and under conventional management.

	Measured SOC accumulation rate from all empirical records (Mg C/ha/yr)	Measured SOC accumulation rate from long-term (>20 year) empirical records (Mg C/ha/yr)	Model predicted 30-year average SOC accumulation rate (Mg C/ha/yr)
No-till	0.30	0.18	0.171
Reduced-till	0.65	0.16	0.124
Cover crop	0.037	-0.12	0.174

3.3. Consistency: evaluating sensitivity to key parameters

In this section, we assess how key methodological decisions, farming practice assumptions, and model uncertainties affect modeled SOC accumulation results. This analysis looks at both uncertainties in agricultural systems (e.g., what the baseline avoided practices would have been if the conservation practice were not implemented) and those arising from model limitations (e.g., whether tillage parameters reflect real world conditions) without differentiation. We evaluate the overall uncertainty in crediting soil carbon impacts to conservation practice implementation by analyzing the magnitude of change between our primary modeled estimates of the effectiveness of the practices and the result with various isolated changes in the analysis (methodological decision, farming practice assumption or model input). Specifically, we examine the variation in results from altering assumptions about baseline conventional agricultural practices, varying historic land use, altering nitrogen fertilization rate, inclusion of alternative carbon pools, analyzing over different timescales (5-20 years), and inconsistencies in conservation practice implementation.

3.3.1 Baseline "Conventional" production methods

Crediting carbon sequestration from land management practices requires evaluating both the management changes implemented and the practices that would have occurred otherwise, to ensure additionality of any SOC changes. In our primary analysis, we assumed a conventional corn production system characterized by spring disking, application of fixed annual nitrogen fertilization, harvesting with 0% residue removal, and fall chisel plowing (detailed in Appendix A). To test the sensitivity of our results to these assumptions of conventional corn production, we evaluated several alternative plausible conventional corn production systems and compared the SOC accumulation under no-till management against SOC accumulation modeled for these alternative counterfactuals.

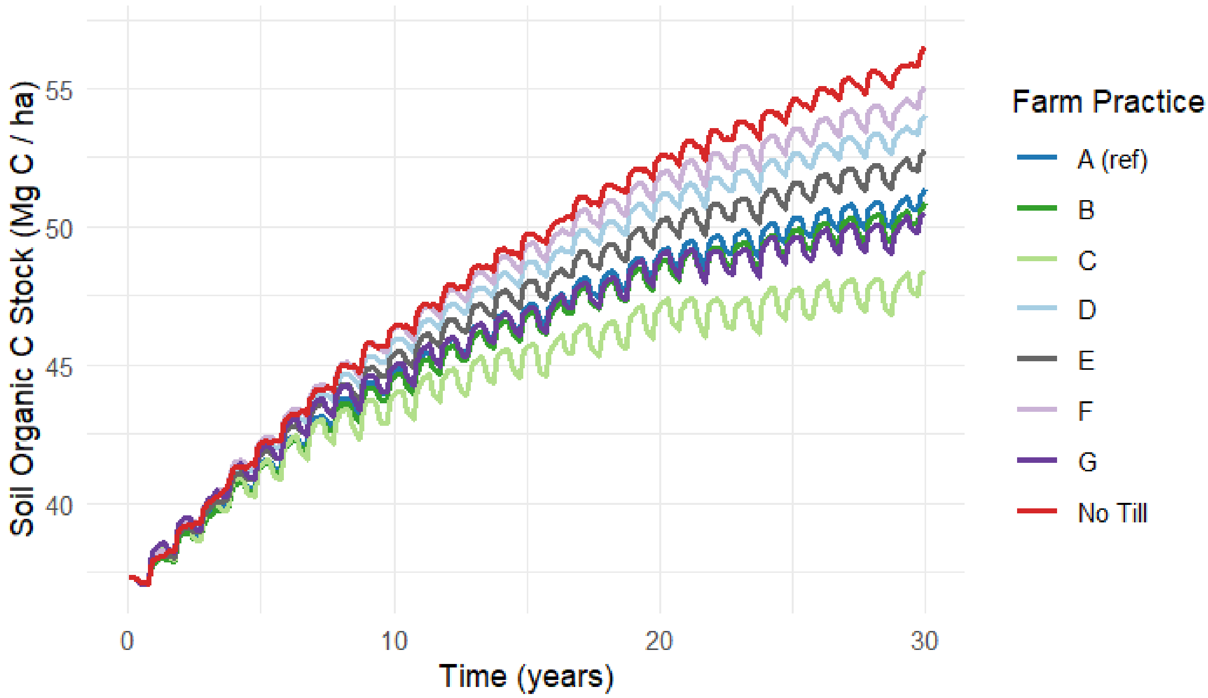

Figure 4: SOC concentration levels in alternative reference baseline (counterfactual) corn production systems and under no-till. A = reference conventional cultivation used in primary results, field cultivator in spring, chisel plow in fall. B = spring sweep or tandem disk, fall chisel plow. C = Spring field cultivator, 'generic' fall plowing (from DayCent v.491 parameterizations). D = Spring row cultivator, fall chisel plow. E = Spring field cultivator, fall tandem disk. F = Spring row cultivator, fall tandem disk plow (also used as 'reduced till' in primary results). G = Spring harrow, fall disk chisel (mulch tiller).

Table 3. SOC accumulation across alternative reference corn production systems, expressed as a deviation from the original reference conventional corn system (in the middle column). The net SOC accumulation attributed to no-till management (calculated as the difference between no-till management and each reference management) is shown to illustrate the impact of varying reference assumptions on conservation practice outcome. The percent change from the primary no-till result (no-till SOC accumulation relative to primary reference conventional) is shown as a percentage in parentheses. All results represent modeled SOC changes in the top 20 cm of soil over 30 years.

Reference Management Tillage Description *(all options include 200 kg N/ha fertilization, 0% residue removal and consistent planting and harvesting days, only tillage type/intensity are varied)*	SOC difference between baseline conventional and alternative conventional (Mg C/ha)	Net SOC sequestration result between No-Till and Reference management (Mg C/ ha) **(relative difference from primary result)**
Spring field cultivator, fall moldboard plow	-2.94	8.07 **(+57%)**
Spring harrow, fall disk chisel (mulch tiller)	-0.86	5.99 **(+17%)**
Spring sweeps or tandem disks, fall chisel plow	-0.50	5.63 **(+10%)**
Spring field cultivator, fall chisel plow (baseline)	-	5.13 **(-)**
Spring field cultivator, fall tandem disk	1.4	3.71 **(-28%)**
Spring Row Cultivator, Fall Chisel	2.65	2.48 **(-52%)**
Spring row cultivator, fall tandem disk plow (‘reduced-till’ in primary analysis)	3.71	1.42 **(-72%)**

Table 3 shows substantial variability – ranging from +57% to -72% – in the SOC accumulation credited to No-Till management implementation depending on the assumptions of the “reference” conventional corn cultivation system. Figure 4 shows SOC accumulation over time for alternative reference conventional corn cultivation systems, relative to no-till.

3.3.2 Historic land use (initial conditions)

For this study, we used a pre-built model of the Energy Farm with a well-documented, albeit atypical, land use history (e.g., sorghum trials from 2011 to 2019), which may not reflect the broader Corn Belt’s agricultural practices. In the absence of site-specific SOC measurements, initial SOC levels at the time of the management change were approximated by modeling prior land use history. To explore the sensitivity of our model results on the initial conditions, we paired our corn production scenarios with an alternative, hypothetical land use history to represent potential variability in starting SOC conditions (and other soil properties resulting from the historic land use). For this analysis, we tested cases where, instead of the sorghum trials from 2011-2019, the site was under continuous corn production with variable tillage (using consistent parameters to historical corn at the site, except that no residue was harvested). The alternative historical management during this period resulted in higher initial SOC levels at the beginning of our modeling (49.3 Mg C/ha conventional corn, 50.5 for no-till corn) compared to the model of the real historic management (37.3 Mg C/ha) (see Figure 5). The differing initial (2020) conditions resulted in variable impacts from conventional management compared to conventional (shown as the difference between the green and blue lines for no-till in Figure 5).

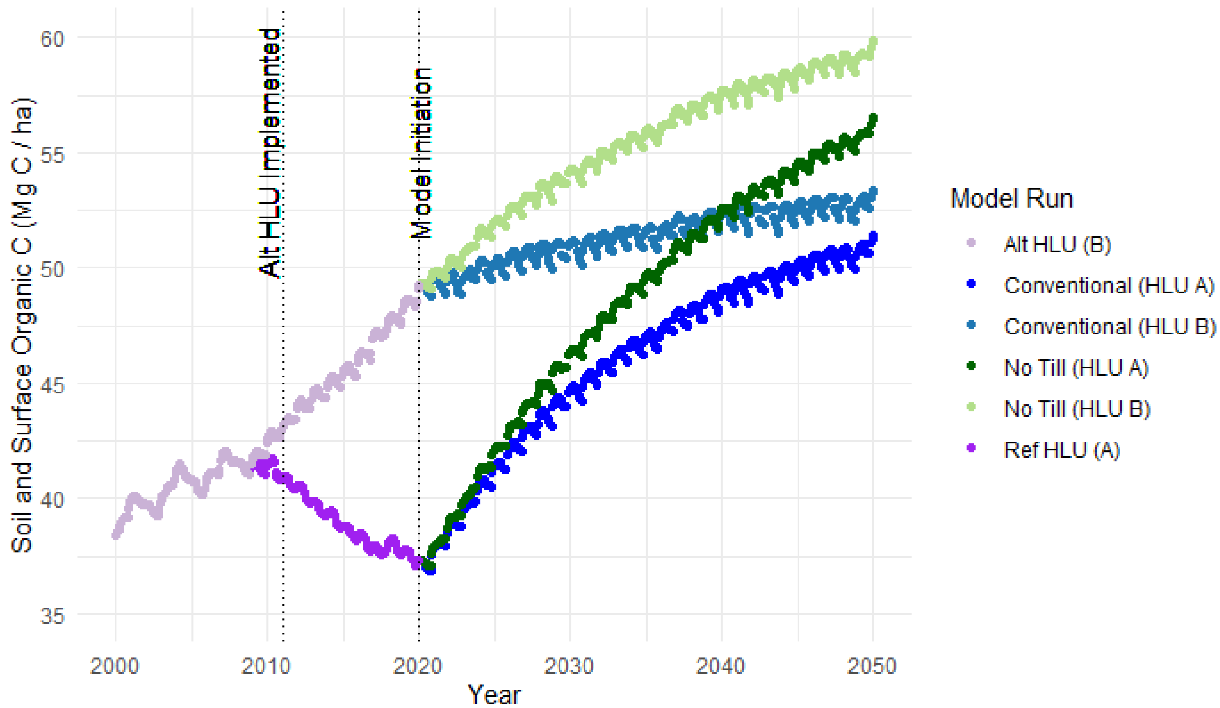

Figure 5: Modeled SOC concentrations resulting from alternate historical land use (HLU) between 2010-2020 (A = approximate true historic land use including sorghum trials, used in primary analysis, B = hypothetical continuous corn with 0% residue removal) and impact on modeled future management (no-till in shades of green and conventional in shades of blue). Each of the contemporary management scenarios are paired with an initial state resulting from the HLU (historical land use). The net accumulation attributable to no-till is the difference between the SOC in the no-till management and the conventional management (green minus blue).

Table 4 summarizes the 30-year SOC accumulation result from conservation management practices with varied historical land use prior to the trials. The net SOC accumulation for all three conservation practices, under the alternative historical land use practices, is positive. With an alternative historical land use of continuous corn production (rather than the sorghum), more SOC would be accumulated under all three conservation practices, relative to the real historical land use of the site that was initially modeled. This was true whether the hypothetical historic corn management was using conventional methods or had already been practicing no-till management for 5 years prior to the contemporary model period. For both of the modeled alternative historical land uses, the differences in SOC accumulation are largest for no-till, followed by reduced-till, and only minor increases for cover crop.

Table 4. Sensitivity of modeled carbon sequestration with alternative historical land uses. All model results present the net sequestration from implementation of the conservation management practice and assumed reference conventional over 30 years in the top 20 cm. The percent difference from the baseline results (column 1) are shown in parentheses.

Management	SOC accumulation over 30 years (deviation from reference conventional) using baseline (actual) HLU (Mg SOC/ha)	SOC accumulation modeled with hypothetical corn HLU (Mg SOC/ha)	SOC accumulation modeled with hypothetical no-till corn HLU (Mg SOC/ha)
No-Till	5.13	6.52 **(+27%)**	6.68 **(+30%)**
Reduced-Till	3.71	4.37 **(+18%)**	4.44 **(+20%)**
Cover Crop	5.21	5.25 **(+0.9%)**	5.26 **(+1%)**

3.3.3 Fertilization rate

Nitrogen (N) application rates emerged as a key driver of SOC dynamics, significantly affecting modeled SOC and corn production outcomes. To assess the sensitivity of conservation practice impacts to fertilization, we evaluated scenarios with alternative N application rates for both conventional and conservation practices. The baseline assumed N application rate was 202 kg N per hectare, described as typical corn grower's rate of nitrogen fertilizer by Bryan (2024) and consistent with the range of rates which maximize economic return to N application for the simulation site (CNRC, n.d.). The simulated reduced N application rate was 91 kg N/ha, which was the average annual N fertilization rate in Illinois corn production in 2021, based on survey results compiled by the National Agricultural Statistics Service (USDA, 2021). Table 5 shows that lower N inputs were associated with lower SOC accumulation relative to the baseline for all three conservation practices.

Table 5. Changes in SOC accumulation relative to the reference conventional case. (Mg SOC/ha) when practices are modeled with low N input. In each simulation, both conservation and paired conventional corn production used the same N input rate.

Management	SOC accumulation over 30 years (deviation from reference conventional) using baseline N input rate (Mg SOC/ha)	SOC accumulation over 30 years (deviation from reference conventional) modeled with low N input rate (Mg SOC/ha)
No-Till	5.13	3.90 **(-24%)**
Reduced-Till	3.71	2.07 **(-44%)**
Cover Crop	5.21	3.17 **(-39%)**

3.3.4 Carbon pools included

Carbon cycling in agricultural ecosystems is complex, involving C storage and migration through multiple carbon pools, including living plant biomass, dead organic matter, organic carbon in the soil or on the soil surface, inorganic soil carbon, harvested crops and the atmosphere. Among these, soil organic carbon is generally considered more stable and longer-lived than carbon stored in crop biomass or residues and is impacted by management practices. Due to these factors, SOC is widely used to as a metric for carbon sequestration in agricultural systems (Olson et al., 2014). However, the boundary between SOC and other carbon pools is not always clear, especially within the modeling framework, where carbon is disaggregated into various dynamic pools. Our baseline approach defined SOC to include both surface and soil organic matter in the active, passive and slow pools. In this sensitivity analysis, we explored how alternative interpretations of SOC influence modeled carbon accumulation results.

For example, while the model distinguishes between surface and soil organic matter, empirical measurements of SOC typically begin at the soil surface and extend to a defined depth. This is why our primary analysis includes both surface and subsurface carbon pools under the umbrella of SOC. When we excluded the surface organic matter pools (both active and passive), the impact on modeled carbon accumulation over 30 years was substantial for no-till, reducing accumulation by 34%, while more modest for cover crop and reduced-till results (-5% and +5%). The surface organic matter pools include active and passive pools (correlating to annual and decadal turnover rates). If instead, we included surface and soil pools but only those which contribute to long term carbon storage (10+ years in passive and slow pools), our results would have been reduced by 10, 17 and 44% for reduced-till, cover crop and no-till respectively. Another approach might be to include all organic carbon in the soil pools (including litter and microbial biomass) but to exclude all pools labeled as ‘surface’ – this would also cause minor changes to the reduced-till and cover crop results (-0.5% and +13%) but major impacts to the no-till result (-36%). Another possible scenario would be to compare all nonliving carbon on the landscape. This method had relatively minor impacts to our primary results (-0.2 to 11%). The methodological decision of which C pools to include showed substantial impacts to the modeled 30-year carbon accumulation for no-till management with less impact for reduced-till and cover crop (see Table 6).

Table 6. Carbon accumulation (Mg C/ha) over 30 years of the conservation practices relative to the reference conventional baseline with different carbon pools included. The bold percent difference is the deviation of the result to the primary model result (first column) using active, slow and passive SOC pools.

Management	Net C accumulation (including soil and surface organic matter pools; baseline) (Mg C/ha)	Net C accumulation (*soil* organic matter, excluding *surface* organic matter) (Mg C/ha)	Net C accumulation (surface and soil organic matter, excluding active C pools) (Mg C/ ha)	Net C accumulation (all *soil* C pools including litter, excluding *surface* pools (Mg C/ ha)	Net C accumulation if including all non-living system C pools (Mg C/ ha)
No-Till	5.13	3.40 **(-34%)**	2.89 **(-44%)**	3.3 **(-36%)**	5.69 **(+11%)**
Reduced-Till	3.71	3.91 **(+5%)**	3.32 (**-10%)**	4.19 **(+13%)**	3.71* **(-0.2%)**
Cover Crop	5.21	4.94 **(-5%)**	4.34 **(-17%)**	5.18 **(-0.5%)**	5.26 **(+1%)**

* *These values are smaller than the baseline soil carbon value, which is possible because the conservation C sequestration is being compared with the C sequestration of reference conventional (despite including additional C pools).*

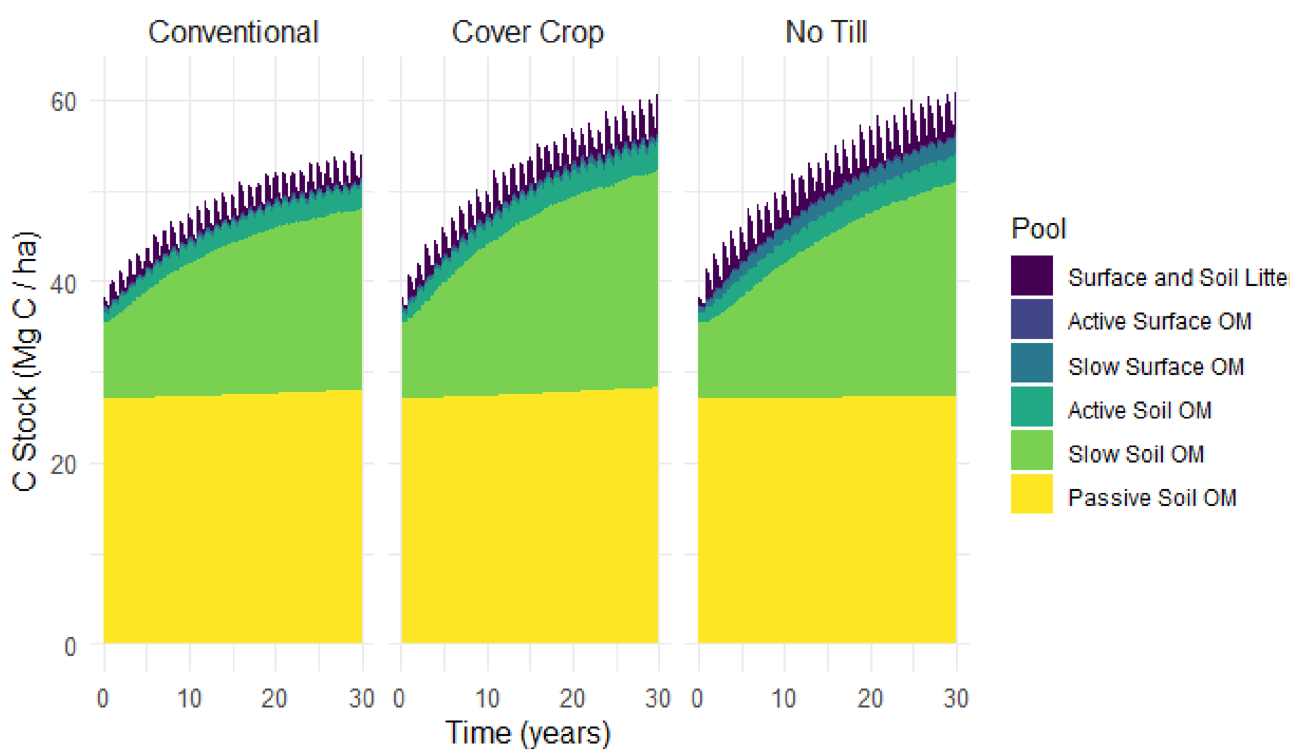

Figure 6: Stacked area chart of carbon stock changes by carbon pool over time in distinct conceptual carbon pools under modeled conventional, cover crop and no-till management. In our primary results, the surface and soil litter pool is excluded from the total SOC estimates.

Figure 6 shows the modeled C accumulation in different carbon pools over time for no-till and conventional management. The passive organic matter in the soil makes up the majority of carbon stock in both management systems and remains largely unchanged over time, with very slightly more accumulation in this pool in conventional than no-till. The slow soil organic matter pool shows deviation between the two practices, with conventional management having less carbon accumulation here. The passive and slow soil organic matter pools are consistent across all carbon pool combinations selected for analysis in Table 6.

3.3.5 Length of time

In our primary analysis, we selected a 30-year timeframe for reporting SOC changes, consistent with past and proposed future biofuel modeling frameworks like the Carbon Calculator for Land Use and Land Management Change from Biofuels Production (CCLUB) module of the Greenhouse Gases, Regulated Emissions, and Energy use in Technologies (GREET) model (Dunn et al., 2017) and the USDA's Feedstock Carbon Intensity Calculator (FD-CIC) (ICF International, 2025). However, near-term climate goals and the urgency to avoid tipping points might justify placing greater value on near-term carbon storage. Results for 5-, 10-, 20-, and 30-year timeframes are presented in Table 7, demonstrating the influence of timescale on the modeled results. For no-till practices, the 5- and 10-year net SOC accumulation rate was lower than the 30-year average, while the rest of the management-duration pairs were greater than the 30-year average SOC accumulation rates. For reduced-till and cover crop scenarios, the rate of accumulation was elevated at the beginning of the implementation period and slowed over time (36 and 62% higher rate of accumulation in the first 5 years than the 30-year-average for reduced-till and cover crop respectively).

Table 7: Modeled SOC accumulation rate from modeled conservation practices reported as deviation from conventional SOC accumulation rate at various timeframes (all in top 20 cm of soil). The percent difference between the result and the 30-year result is shown in bold.

Modeled Conservation Practice	5-year SOC Accumulation Rate (Mg C/ha/yr)	10-year SOC Accumulation Rate (Mg C/ha/yr)	20-year SOC Accumulation Rate (Mg C/ha/yr)	30-year SOC Accumulation Rate (Mg C/ha/yr)
No-Till	0.148 **(-14%)**	0.161 **(-6%)**	0.175 **(+2%)**	0.171
Reduced-Till	0.169 **(+36%)**	0.154 **(+25%)**	0.141 **(+14%)**	0.124
Cover Crop	0.282 **(+62%)**	0.251 **(+45%)**	0.203 **(+17%)**	0.174

3.3.6 Inconsistent Conservation Practice Implementation

In order for SOC accumulation to provide a meaningful contribution to climate mitigation, the carbon must not only be added to the soil, but must remain there for an ecologically-significant period of time. The longevity of sequestration in various soil carbon pools is both uncertain and sensitive to ecological and anthropogenic disturbances (Matthews et al., 2023). Rigorously establishing it for a given site would require a careful experimental setup with long-term measurement of soil C as well as greenhouse gas emissions (Popkin, 2023). Importantly, SOC accumulation and subsequent degradation are influenced by the extent to which these practices are maintained over time. If a practice such as reduced tillage is adopted temporarily to qualify for a tax credit or other incentive only to return to conventional tillage thereafter, accumulated SOC may be lost.

In our primary analysis, we assumed that the conservation practice would be implemented continuously over the 30-year study period. However, in reality, implementation may be inconsistent. To assess the impact of temporary and inconsistent adoption, we modeled two alternative scenarios: (1) implementing the practice for 2 years before reverting to conventional management for the remaining 28 years, and (2) maintaining the conservation practice for 30 years but reverting to conventional management every 5th year. Both scenarios are compared to conventional management over 30 years, with net results shown in Table 8.

The short-term implementation of conservation practices showed lower net sequestration over the 30-year period compared to modeled conventional management, implying that implementing these practices for a short period of time was worse than never implementing them at all, in terms of SOC accumulation. The cycling of conservation practices with conventional management every 5 years showed lower SOC accumulation for all practices over the 30 years, ranging in impact from 20-29% reduction. (see Table 8).

Table 8. Sensitivity of modeled carbon sequestration with inconsistent conservation practice implementation. All model results show the net sequestration between the management practice and assumed reference conventional over 30 years in the top 20 cm. The percent difference from the baseline results (column 1) are shown in parentheses.

Management	SOC accumulation over 30 years (deviation from reference conventional) (Mg SOC/ha)	SOC accumulation from conservation practice modeled for 2 years, followed by 28 years of conventional (Mg SOC/ha)	SOC accumulation from cycling of conservation practice for 4 years followed by conventional 1 year (Mg SOC/ha)
No-Till	5.13	-0.43 **(-108%)**	4.13 **(-20%)**
Reduced-Till	3.71	-0.40 **(-111%)**	2.65 **(-29%)**
Cover Crop	5.21	-0.31 **(-106%)**	4.11 **(-21%)**

3.4 Comparison to policy values:

Values from USDA's proposed FD-CIC tool were extracted to compare with our modeling and meta-analysis results. The FD-CIC results were developed using DayCent and another process-based crop model called SALUS (System Approach to Land Use Sustainability; Basso & Ritchie, 2015) to simulate SOC in the top 30 cm of the soil profile over 30 years. The SOC sequestration estimates were extracted from the FD-CIC tool for a continuous corn system in Champaign County, Illinois using the generalized no-till, reduced-till and cover crop practices. The 'per-bushel' SOC sequestration values were converted from g CO_2e per bushel to Mg C per hectare assuming our model output corn production for the same practices (4.76, 4.46, and 3.79 Mg corn C per hectare respectively), and assuming 43% of corn bushel mass is carbon, and unit conversions. The resulting SOC accumulation rates resulting from the FD-CIC tool are 0.184, 0.0294 and 0.112 Mg C per hectare per year for no-till, reduced-till and cover crop, respectively. Compared to our model results, the FD-CIC estimates for no-till, reduced-till and cover crop were 8% greater, 76% lower and 36% lower, respectively. Note that these modeled FD-CIC results include a deeper soil profile than the modeled and empirical data reported in the previous sections. Our primary model results, the empirical data and the FD-CIC result are compared in Figure 7. It should be noted that the empirical SOC accumulation rates shown in Figure 7 boxplots include variable study durations (standardized to annual accumulation rates).

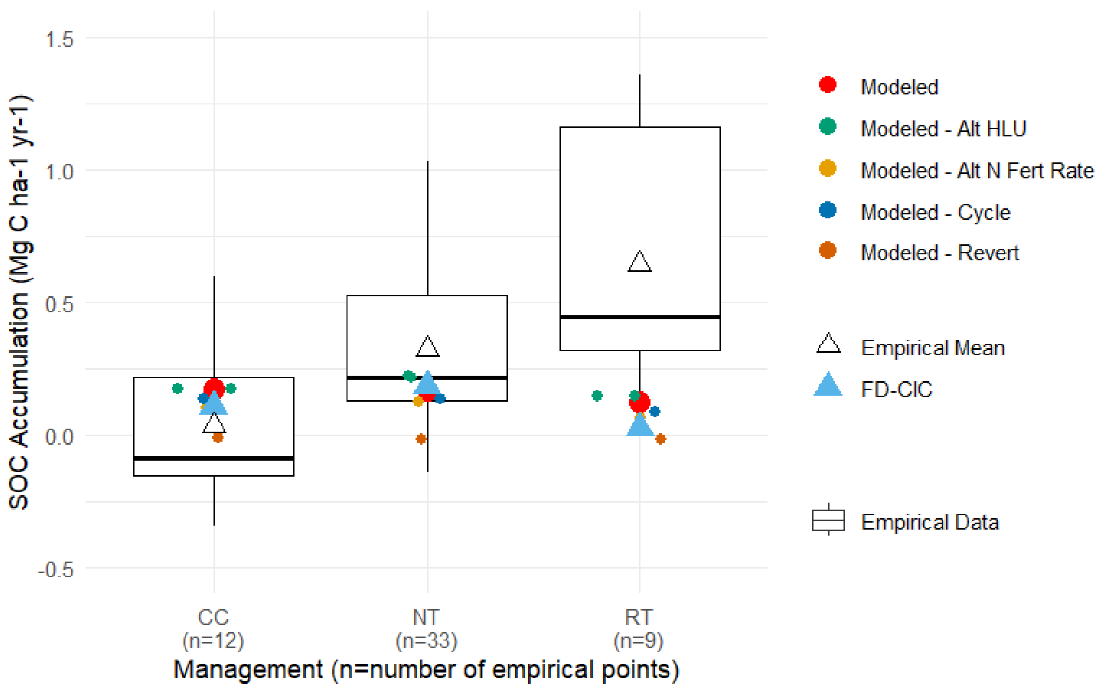

Figure 7: Soil Organic Carbon accumulation (Mg C / ha-yr) for three conservation practices (CC=cover crop, NT= No-Till, RT= Reduced Till) relative to reference conventional corn. Empirical data shown here as boxplots, with the median shown as a solid black line and the mean is shown as a black-outlined triangle. Modeled results from this study are shown as dots

(red represents the baseline modeling for each management scenario and other colors showing some of the sensitivity analyses). As reference, the FD-CIC tool SOC sequestration estimates for the conservation practices in Champaign IL is shown as blue triangles.

4. Discussion

4.1 Effectiveness

Corn production under both conventional and conservation practices was modeled using DayCent, and all three conservation practices – cover cropping, reduced tillage and no tillage – resulted in net SOC accumulation compared to conventional corn cultivation over the 30-year simulation period. Specifically, no-till, reduced-till and cover cropping led to SOC gains of 5.13, 3.71 and 5.21 Mg SOC per hectare over a 30-year period, respectively, relative to conventional management. Cover cropping and no-till increased soil organic carbon more than did reduced-till management.

The practice of tilling breaks up soil agglomerates that increase soil stability, protects soil C from mineralization and reduces C losses via erosion; the absence (or reduction) of tilling protects these soil agglomerates (Weidhuner et al 2021). Tillage intensity also impacts the degree and speed of integration of surface material (such as surface litter and dead plant material) into the soil column. The impacts to carbon cycling from tillage intensity are represented in the model through conceptual pool allocations and decomposition parameters. The conservation tillage parameters included lower decomposition multipliers for soil carbon pools compared to conventional tillage. The slower decomposition of the soil carbon pools likely reduced C losses and therefore increased net SOC accumulation relative to conventional tillage. No-till management resulted in greater productivity in corn than reduced-till or conventional management. The increased corn productivity under no-till management directly leads to more carbon on the landscape and as all corn residue was assumed to remain onsite, likely led to higher SOC stock as the residues decompose into soil organic matter. We see – and would expect – more C sequestration from the absence of tillage than from reduced tillage.

Cover cropping likely enhanced SOC levels by introducing an additional carbon source through winter cover crop photosynthesis, whereas the other modeled practices assumed no plant growth (and thus no biomass carbon input) between November and May. Cover cropping also reduces C losses from erosion (Peng et al 2023).

4.2 Accuracy

To relate our results to relevant policy, we compared both the modeled and empirical SOC accumulation values to the USDA's proposed FD-CIC calculator values. Our model results (including our sensitivity analyses) and the FD-CIC SOC accumulation were similar in magnitude, as would be expected, since they followed similar model methodology. Figure 7 above shows that our baseline model results closely replicated the FD-CIC values for cover cropping and no-till. Our baseline estimate for the SOC effect of reduced tillage was significantly higher than the FD-CIC value, perhaps due to different assumptions about the tillage practices under ‘reduced-till’ as well as how the reference conventional production was characterized and modeled. Though the FD-CIC methods were similar to our modeling methods, FD-CIC used different values from different sources to determine variables such as soil characteristics, fertilization rates, planting timing, reference (baseline) management practices, tillage assumptions, and cover crop species. For example, in the FD-CIC modeling no-till management included one year of conventional tillage every five years, whereas in our primary no-till result we assumed no tillage occurred over the 30-year simulation period. Another important difference between the two models is that the FD-CIC values represent C accumulation over 30 years in the top 30 cm of soil, whereas the results of our modeling and the collection of empirical values represent C accumulation in the top 20 cm.

We found the SOC accumulation estimates modeled with DayCent - both ours and those of the USDA - to have a more mixed record of accurately reflecting the empirical measurements of SOC in the field. Measured SOC accumulation showed substantially more variability than we were able to replicate with our model runs. This is not entirely surprising, as there are many factors that may have contributed to the large variability seen in the empirical results. These results were extracted from studies across the world, with variable site conditions, historic land uses, and management implementation. The baselines (‘conventional management’) against which these studies compared their soil conservation practices were themselves variable, differing in crop rotations, tillage equipment, and other management choices. These variations demonstrate the real-world variability in SOC accumulation under broadly defined practices.

Other methodological factors - such as study duration and sampling method (including soil depth increments) - also varied between studies. Ideally, these variables would have been held constant, as they likely introduced some additional variation in SOC results. The empirical values were derived from studies that varied in length of time that the practice was implemented (where model simulations represent 30 years, in our study and in the FD-CIC values). To make relevant comparisons, we normalized the accumulation by the length of practice implementation. However, given that the accumulation may not be constant, the study length likely caused additional variability in the empirical results that did not result from the implementation of the conservation management alone.

One notable deviation between our modeling results and the empirical record is the long-term SOC accumulation resulting from cover-cropping (Figure 3). Our model prediction of the 30-year average rate of accumulation was 0.174 Mg C/ha/yr, while the average accumulation from empirical studies 20 years or longer in duration was -0.12 Mg/ha/yr – lower SOC accumulation than the reference conventional practice. Another large difference is observable between our modeled result and empirical values for reduced tillage, shown in Figure 7. Our modeled SOC accumulation (0.124 Mg C/ha/yr) is lower than all empirical data points. However, the empirical data shown in Figure 7 are from studies of variable duration, and there were very few long-term data points in the dataset. For the sole data point from a study that was longer than 20 years in duration (25 years), the SOC accumulation rate (0.32 Mg C/ha/yr) was closer to our 30-year average modeled SOC accumulation (0.124 Mg C/ha/yr) than was the shorter-term study average. This difference in SOC accumulation by timescale of study suggests that the rate of accumulation is likely not linear, with higher accumulation rates early-on in conservation practice implementation and leveling off over time, at least for conservation tillage.

4.3 Model Sensitivities

The variability in SOC accumulation due to modeled sensitivities was minor compared to the empirical variation among conservation practices (Figure 7). However, relative to the initial modeled SOC accumulation for each conservation practice, the variables tested in the sensitivity analyses had major impacts on the results, in some cases changing the carbon accumulation result by over 100%. Our primary findings depend on assumptions about counterfactual farm practices, historical land use, fertilization rates, and consistent practice implementation. Some assumptions were site-specific, while others relied on regional averages or available parameterizations. To assess their influence, we adjusted key variables and compared the results. Both uncertainties in these inputs and methodological choices—such as which carbon pools to include and how sequestration is credited over time—significantly affected the resulting modeled SOC accumulation.

Since conservation practice SOC accumulation is measured relative to an assumed conventional baseline, the choice of that baseline strongly influences results. Varying the cultivation equipment and the parameters that represent the cultivation activities resulted in substantial deviation from the assumed baseline conventional practices. For example, if conventional management had used a row cultivator instead of a field cultivator in spring, conventional SOC sequestration would have been credited an additional 2.65 Mg C/ha over 30 years, overestimating conservation practices SOC benefit by 51-71%. Across all alternative conventional management scenarios modeled, the carbon sequestration benefit of adopting no-till management varied by -72% to +57%, underscoring the importance of accurately and transparently defining baseline practices. The magnitude of variation in SOC accumulation results from variable reference tillage equipment also highlight the sensitivity of the modeled SOC accumulation to individual variables.

The initial conditions of the model also substantially influenced the SOC accumulation results. Each simulation began with a spin-up to the beginning of American commercial corn production followed by historical land use from the mid-19th century to 2020, based on Hartman et al. (2022). To test the sensitivity of SOC accumulation to land use history, we simulated two alternative recent land use history scenarios: (1) replacing 2010–2020 land use with continuous corn cultivation, instead of sorghum soy rotations and (2) the same as (1) but assuming corn was produced under no-till practices. Both scenarios resulted in higher SOC levels among other changes to soil properties at the start of the contemporary model (2020). These differences in historic land use (and associated changes to initial conditions of the contemporary modeling) increased SOC accumulation credited to no-till over the 30-year model period by 27–30% and for reduced-till by 17–20%, while cover cropping remained largely unaffected (Table 4).

The larger differences in SOC accumulation between conventional and reduced- or no-till practices (i.e., net SOC accumulation) were observed in model runs that began with higher initial SOC concentrations, as seen in the alternative historic land use scenarios. This result was somewhat counterintuitive. One might expect that lower initial SOC—being farther from equilibrium—would allow for greater accumulation in both conventional and conservation systems, potentially widening the gap between them. However, the modeled divergence between conservation and conventional SOC outcomes was actually smaller in the lower-initial-SOC runs, at least for the no-till and reduced-till cases. One possible explanation is that higher initial SOC levels, closer to equilibrium for the both the conventional and conservation systems, but greater difference relative to the initial conditions, may cause greater differences in the rate of accumulation. As a result, conservation practices might continue to accumulate SOC more rapidly, while conventional practices plateau, widening the gap between them over time. This pattern did not hold for the cover-crop scenarios, suggesting that different mechanisms and saturation levels may be at play for different conservation strategies. While a simple first-order decay model—often used to describe SOC accumulation across a single soil carbon pool—might not predict this outcome, the results are consistent with the more nuanced structure of the DayCent model. DayCent simulates multiple interacting carbon pools and dynamically adjusts SOC processes on a daily basis in response to environmental conditions, nutrient cycling, and soil properties. For example, soils with higher initial SOC are likely to be more nutrient-rich, potentially supporting greater plant productivity and therefore higher carbon inputs. These dynamics could amplify differences between management systems, contributing to the larger net SOC gains observed in high-SOC scenarios. Of course, there is also the possibility that this somewhat counterintuitive pattern is not, in fact, reflective of an unexpected dynamic at play in these systems, but instead stems from an inconsistency in the DayCENT model itself as it reflects these subtle dynamics.

While our analysis focuses on differences between conservation practices and the conventional baseline, all modeled corn production scenarios—including conventional—led to significant SOC gains over 30 years (see SOC accumulation for each practice in Appendix B, Figure 1). This is likely due to increased net primary productivity from nitrogen fertilization, and as our baseline assumption is that none of the residue is removed, this extra biomass becomes a significant carbon input to the system. The trend of increased SOC started around 1975 (shown in Fig 1), when increasing levels of nitrogen fertilization followed a century of SOC depletion. Our baseline assumption for 2020-2050 corn production is that about 200 kg N/ha (~180 lbs/ac) are applied annually, based on various descriptions of corn production in the US (Morrow Plots Data Curation Working Group, 2022; O'Brien et al., 2020). However, fertilization rates are variable and likely to depend on site-specific factors. To check the impact of varying the fertilization rate, we ran both the conservation and conventional management scenarios with a lower nitrogen application rate (91 kg N/ha), which was the average annual N fertilization rate in Illinois corn production in 2021, based on survey results (USDA, 2021). Lower nitrogen application significantly reduced SOC accumulation relative to conventional for all conservation practices, with the largest impact on reduced-till, lowering its SOC sequestration by 44%. Fertilization assumptions strongly influence modeled sequestration benefits, potentially altering conclusions about the effectiveness of conservation practices.

4.4 Methodological Impacts

Our results were also influenced by methodological choices, particularly the timeframe of analysis and the selection of carbon pools. In our primary analysis, we analyzed the total organic carbon sequestered in the soil and surface layers over a 30-year period, comparing conservation practices to a conventional corn reference case.

The 30 year timeframe aligns with other bioenergy soil carbon analyses (Basso, 2024; Dunn et al., 2017; ICF International, 2025; Kwon & Hudson, 2010) and literature (Hudiburg et al., 2015). However, shorter time horizons may be relevant given near-term climate goals, tipping points, and uncertainties in future land management. The chosen timeframe for analysis strongly influenced the modeled SOC accumulation, as shorter time horizons yielded different conclusions about the efficacy of conservation practices. For example, relative to the 30-year SOC accumulation rate, modeling over five years resulted in up to 62% increase in estimated SOC rate gains from cover cropping. Even modeling over a 20-year timeframe led to cover cropping SOC accumulation rate outcomes that were 17% higher than the 30-year result. These findings highlight the need to carefully consider timescales when assessing the climate benefits of land management, particularly given the challenges of committing farmers to multi-decade practices.

In agricultural systems, carbon exists in multiple forms, and the DayCent model categorizes carbon into conceptual pools. The decision of which pools to include in carbon accumulation calculations significantly affects modeled outcomes. For our primary analysis, we included carbon in the active, slow, and passive organic matter pools, both in soil and surface organic matter, while excluding litter due to its short residence times. Alternative carbon pool selection produced vastly different results.

Expanding the included pools to encompass all non-living carbon - such as dead plant litter on the soil surface and within the soil profile - led to an 11% increase in carbon accumulation under modeled no-till, with little impact on the reduced-till and cover crop results. These additional pools have shorter residence time, increasing intra-annual variation (Appendix B, Figure 3). Conversely, excluding short-lived pools that are more susceptible to loss, significantly reduced modeled sequestration. Omitting surface organic matter lowered no-till carbon accumulation by 34%, while excluding active carbon pools (residence time <1 year) reduced it by 44% (Table 6). In both cases, restricting carbon accounting to more durable pools made no-till appear less effective in carbon accumulation than reduce-till and cover crop (Table 6, Figure 2 and 4 in Appendix B). These findings suggest that much of no-till's SOC gains occur in surface and active pools, raising concerns about their permanence and how carbon with different residence times should be valued in sequestration policies.

Defining which carbon pools should count toward carbon sequestration remains complex. While it is logical to prioritize carbon pools with longer residence times and greater stability, the threshold for durability remains subjective. This distinction has significant implications for both the total sequestration estimated and the relative effectiveness of different management practices. The challenge is further compounded by the fact that DayCent's carbon pools are conceptual rather than physically distinct, making them difficult to parameterize and interpret. Some researchers have emphasized the need to align these modeled pools with measurable carbon fractions to improve calibration and validation with empirical data (Dangal et al., 2022).

Another methodological decision is whether C accumulation is standardized to area or corn production. Different cultivation practices yield differences in productivity. By analyzing carbon accumulation on a ‘per-acre’ basis, this impact to corn production is ignored. As shown in Table 1, when C accumulation is standardized to corn (or ethanol) production, cover crop shows more SOC accumulation than no-till (8.07 compared to 6.32 g CO2e/ MJ corn ethanol), whereas if it is standardized per acreage, the SOC accumulation from the two conservation practices are more similar in magnitude. Ignoring the change in productivity may lead to over-crediting the ethanol product in cases where productivity increased with conservation practice implementation. Though, standardizing ethanol production would more heavily weight the SOC gains in systems with low productivity, perhaps leading to a perverse outcome in which lowering productivity could be directly incentivized.

4.5 Consistency and Additionality

Even if incentives for agricultural SOC accumulation strategies are based on models that accurately characterize the SOC impact of those practices, they may still lead to distortionary outcomes if the practices are inconsistently applied and/or would have happened without the incentive being applied.

For example, if the conservation management is interrupted with conventional practices every 5 years, the modeled net SOC accumulation over 30 years is reduced substantially (by 19%, 29% and 21% for no-till, reduced-till and cover cropping respectively), compared to consistent implementation. Even more concerning, a scenario in which conservation practices are adopted for only two years before reverting to conventional management for the remaining 28 years leads to a net *loss* in SOC. In this case, modeled SOC accumulation levels were not only lower than in consistent conservation scenarios (by more than 100%), but also lower than consistent conventional management! These findings highlight the need for safeguards to ensure long-term commitment to conservation management in order to access incentives. One potential approach would be to require a minimum implementation period or to establish a payback mechanism that reclaims incentives if conservation practices are not maintained.

Another potential case that may lead to inaccurate carbon accounting is awarding credits for practices that were adopted before the start of the crediting period. In a modeled scenario where no-till was implemented several years before year 0 of the modeled credit period, SOC accumulation over the subsequent 30 years was 30% higher than in our primary no-till scenario (Table 4). This suggests that early adopters continue to provide climate benefits, and that crediting them under the same mechanism as new adopters might not lead to over-crediting. This scenario was only tested with the no-till conservation practice and this trend might be different for reduced-till and cover cropping.

However, this raises the broader issue of additionality. For incentives to be effective, they must drive behavior that would not occur otherwise. If a landowner adopted no-till management prior to any incentive, that conservation practice is not additional – it is not caused by the incentive. Awarding a valuable incentive therefore does not lead to *additional* carbon benefits, unless there is evidence that the practice would have been discontinued in the absence of the credit.

Incentives must be structured in a way that at least acknowledges that these reductions are non-additional and should not, for example, be used as an offset for new or existing emissions.

4.6 Limitations and Future Work

This analysis is focused solely on carbon accumulation and does not account for other greenhouse gas fluxes, most notably nitrous oxide (N_2O) emissions. Given nitrous oxide's high global warming potential, any change in N_2O emissions may substantially alter the net climate impact of different management practices. We also chose to analyze a system where the corn *grain* was assumed to be used for ethanol production rather than the corn stover. Leaving the corn residues onsite acts as a carbon input to the system (as carbon accumulates in the corn plant through photosynthesis, some of which is integrated into the soil as the residue decomposes (Blanco-Canqui & Lal, 2015)). Removing this carbon input via residue removal would likely lower the modeled SOC accumulation in both conservation and conventional management, with unknown impacts to the net accumulation of conservation practices. In addition, we have not sought to capture any market-mediated effects from changes in productivity owing to the changes in cultivation practices modeled here. A full life cycle assessment would be recommended in evaluating the management changes. This LCA should include all greenhouse gas fluxes as well as potential changes in equipment-related GHG emissions, and effects from altered herbicide or fertilizer applications that may accompany some management scenarios. It could also address any indirect land-use or other market-mediated effects attributable to the cultivation changes being investigated.

We modeled a single site but aimed to capture generalized impacts of management practices applicable across the Corn Belt by analyzing the *process-based* carbon accumulation (through looking at carbon sequestration of conservation *relative* to conventional management rather than accumulation over time for a conservation practice). However, SOC dynamics are influenced by site-specific factors such as soil properties and climate, which were held constant, as we modeled only one site. Further analysis should be completed to evaluate the sensitivity of these site-specific variables. This could be done by applying our contemporary modeling simulations to a model that is parameterized to a different site.

DayCent modeling relies on over a thousand parameters (Hartman et al., n.d.), some site-specific and others generalized. While we used site-specific parameters from Hartman et al. (2022), we primarily used default parameters for processes such as tillage impacts on decomposition, crop specific growth factors and specific rates of re-distribution of plant parts during harvest or cultivation. The DayCent manual cautions that generalized parameters may reduce accuracy for certain site-treatment combinations and it is recommended that after building a DayCent model, the SOC levels be validated since "SOC integrates many processes in the model" (Hartman et al., n.d.). Additional calibration with empirical data, especially SOC, could greatly improve model fidelity.

This study would benefit from including more empirical results from other studies. Additionally, further refinement of methodology for converting measured variables to comparable SOC accumulation results should be investigated. For example, many of the empirical SOC stock changes were derived from multiplying measurements of soil bulk density and carbon concentration in the top 20 cm soil profile. This may cause some error, as changes to soil carbon stock should be weighted to equivalent soil mass, rather than to constant depth (Ellert & Bettany, 1995; Jarecki et al., 2005). When comparing practices that may have significantly different impacts on soil bulk density (such as variable intensity tillage), this error may be compounded.

Another methodological decision that we did not evaluate, but warrants thought, is the depth of soil that C is accounted for. We chose to model to 20 cm of soil depth because it is the depth at which the DayCent model was parameterized to simulate soil organic matter dynamics (Hartman et al., n.d.). Modeling deeper soils may yield different results, considering that deeper soils tend to exhibit lower decomposition rates.

Our sensitivity analysis involved systematically isolating individual methodological choices and substituting plausible alternatives. However, many of these variables interact in complex ways, and their combined effects should be explored further. Additionally, we assessed sensitivity based on deviations from the baseline scenario, but because alternative values were chosen for plausibility rather than consistent directional differences, their impacts are not always directly comparable. Future work could refine these analyses by explicitly evaluating interactions and trade-offs between methodological choices.

5. Conclusion and policy implications

A thorough body of research has shown wide-ranging C benefits from implementing conservation management practices in corn agriculture. Our modeling confirmed positive net C sequestration benefits from conservation tillage and the use of cover crops. However, the amount of carbon sequestered is highly variable and uncertain. This analysis found substantial sensitivity of SOC accumulation to site-specific characteristics and cultivation practices. This sensitivity highlights the limitations of any generalized estimate of the efficacy of soil conservation practices. Policy tools aiming to encourage the use of cultivation practices believed to stimulate soil carbon accumulation could be effective, but any attempt to directly quantify that effect and to compensate farmers for a specific SOC accumulation based on modeled projections may well lead to inaccurate or adverse outcomes. Additionally, incentives for outcomes from long-term continuous management require safeguards in terms of permanence and additionality. In particular, we highlight the following key findings that should be considered when evaluating incentive policies for SOC accumulation:

1. *When cultivation practices are being credited for SOC accumulation based on model results, ground-truthing with empirical data is critically necessary.* Modeling results don't adequately represent the variability that is seen across the landscape of real corn production.
2. *Modeling results are very sensitive to assumptions of:* historic land use/initial conditions, fertilizer application rates, consistency of practice implementation and avoided cultivation management practices.
3. *Subjective methodological decisions have significant impacts on the modeled net carbon sequestration outcome*. These include the timeframe of analysis, carbon pools

considered, consistency of practice implementation, and whether carbon sequestration results are normalized to corn production or area of cropland. Modeling methods and incentive guidelines must be aligned to ensure modeled C sequestration benefits are actualized.

In addition to the above sensitivities, we find that soil carbon modeling should not be treated in isolation, because it is only one factor in a more complex life cycle. The changes modeled here may alter the emissions of other greenhouse gases as well as the emissions associated with cultivation. They may also lead to changes in crop productivity, with attendant indirect, market-mediated effects on emissions. Also, this study does not address financial additionality – we model the SOC impact of changes in cultivation practice, but cannot ascertain whether those changes are being stimulated by a given policy support.

The subsidies for low-carbon fuels created by LCA-driven policy frameworks can be very significant. Counting SOC accumulation directly in pathway carbon intensity calculations in frameworks such as the IRA section 45Z tax credits for aviation fuel in effect creates a new class of carbon offsets. Compared to conventional carbon credits, however – especially those used for compliance with regulatory obligations – these offsets face little oversight or verification. Critically, if these avoided tons of emissions were to be counted as an offset, operators would need to prove that they are legitimately "additional" – i.e., that the farm would have been using intensive tillage with no cover crop were it not for the payment in question. In fact, there is evidence to suggest that some conservation practices modeled here may already be standard practice for some farmers; Rosenberg & Wallander, 2022 report that 76% of corn farmers in the US were using conservation tillage practices by 2021. The widespread adoption of conservation practices raises questions about whether these practices warrant carbon credits and tax incentives. While our modeling suggests that crediting existing no-till management with SOC accumulation from new no-till implementation would *under*estimate real SOC accumulation, the fact that this practice is not additional could undermine any claimed climate outcomes.

Since the IRA tax credits are structured around calculated fuel carbon intensity and are applied when a facility is built, the SOC calculation assumptions can prove very important. As we have shown in this report, while SOC estimates from DayCent may be accurate in some circumstances, they vary with and are contingent on modeler assumptions. Our findings highlight the importance of case-specific modeling as well as policy guardrails to verify feedstock sourcing, and to ensure that conservation practices continue to be implemented.

As discussed above, soil carbon savings from these conservation practices may not be additional, and conservation tillage and cover cropping are not the only ways to increase carbon uptake on the landscape. Offering incentives to use conservation practices with corn cultivation may also increase demand for corn overall by creating new renewable fuel manufacturing infrastructure. There may be opportunities for greater GHG reductions through alternative land management. By comparing SOC accumulation in continuous corn production under conservation and conventional management, our approach credits carbon sequestration to conservation practices, even if total system emissions remain positive. This highlights the need to explore other management strategies that are truly net-negative, such as reversion to grasslands or integration of perennials, which could offer more durable carbon storage.

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Appendix A: Modeled Corn Production System Parameters

A.1 Conventional:

The Daycent schedule file representing conventional corn production served as the baseline, reference or counterfactual condition for our modeling. It played an important role in simulating baseline biogeochemical processes against which modeled alternative management practices were compared to estimate their potential SOC 'savings'. This schedule file served as a template for constructing conservation practice scenarios, maintaining as much consistency as possible to isolate the effects of those practices.

In general, the schedule simulates continuous corn production from 2020-2050. This timeframe was selected because the historic land use up to 2020 was simulated using Hartman (2022) model and we wanted to use a 30-year study period. Crop production and genetic parameters were based on the Hartman et al. (2022) model, while cultivation equipment parameters were derived from DayCent release version 491 (Hartman et al., n.d.). The schedule management sequence includes cultivation with a cultivator, fertilization and corn planting on May 8 (day 128). The May 8 planting date was selected based on historic corn production (1996-2007) from the Energy Farm, as reflected in the historic land use schedules developed by Hartman et al. (2022). This date also aligns with research showing that corn yields in Illinois tend to be highest when planting occurs at the end of the first week of May (Nafziger, 2023). Fertilization was applied at a rate of 202 kg N per hectare in the form of UAN (urea ammonium nitrate). This rate and fertilizer type reflect historic corn production at the site, reflected in the historic land use schedule files (Hartman et al. 2022). The fertilization rate was consistent with the level suggested to optimize

The date of harvest was estimated to be October 8 (day 282). We assumed that only the grain was harvested and all stover residue was left onsite. This was based on data from the National Agricultural Statistics Service (USDA, 2025) which showed that in 2022, only about 7% of acres where corn cultivation acres in the US had silage harvested, others estimated that 0-5% of corn production in Illinois included residue harvest (Schmer et al., 2017).

Corn harvest was followed by chisel plowing on day 297 (parameterized by cult.100 file from the version 491 Daycent release).

Schedule file: cnt2_corn_sDfF.sch

```
2020        Starting year
2050        Last year
cnt_enfarm.100    Site file name
0           Labeling type
-1          Labeling year
-1          Microcosm
-1          CO2 Systems
-1          pH effect
-1          Soil warming
-1          N input scalar option
```

-1 OMAD scalar option
-1 Climate scalar option
1 Initial system
C10 Initial crop
Initial tree

Year Month Option
1 Block # @enfarm
2050 Last year
1 Repeats # years
2020 Output starting year
1 Output month
0.0833 Output interval
F Weather choice
enfarm_2008-2020.wth
1 128 CULT D491 #cultivator (description from Moore et al. 2021: pre-plant using sunflower cultivator)
1 128 CROP C10 #corn-c10 (parameterized from Hartman...)
1 128 PLTM
1 128 FERT UAN20 #202_kg_N_ha
1 282 HARV G #Grain_with_0%_straw_removal--GRAL
1 297 CULT F491 #Chisel Plow, 491 parameterizations
1 297 LAST
-999 -999 X

A.2 No-Till

No-till management was estimated by simply removing the tillage events from the conventional schedule file and adding no-till drill cultivation for planting (parameterized in the cult.100 file from the version 491 Daycent release). Date of planting, fertilization amount and timing and harvest rate and timing were kept consistent with the other schedules

Schedule File: cnt2_corn_notill0Rv2.sch
2020 Starting year
2050 Last year
cnt_enfarm.100 Site file name
0 Labeling type
-1 Labeling year
-1 Microcosm
-1 CO2 Systems
-1 pH effect
-1 Soil warming
-1 N input scalar option
-1 OMAD scalar option
-1 Climate scalar option
1 Initial system
C10 Initial crop
Initial tree

Year Month Option
1 Block # @enfarm
2050 Last year
1 Repeats # years
2020 Output starting year
1 Output month
0.0833 Output interval
F Weather choice
enfarm_2008-2020.wth
1 128 CULT N #NO-TILL-DRILL
1 128 CROP C10 #corn-c10 (parameterized from Hartman...)
1 128 PLTM
1 128 FERT UAN20 #202_kg_N_ha
1 282 HARV G #Grain_with_0%_straw_removal--GRAL
1 283 CULT CNT
1 297 LAST
-999 -999 X

A.3 Reduced-Till

Corn production using reduced-till included less intensive cultivation events than the conventional schedule. For this, the cultivation events were replaced with row cultivator in the spring and tandem disk plow in the fall (both parameterized in the cult.100 file distributed in the version 491 DayCent files) on the same date as the conventional cultivation activities. Fertilization amount, date and harvest rate and date were kept consistent with the other schedules.

Schedule File: cnt2_corn_sBfE.sch
2020 Starting year
2050 Last year
cnt_enfarm.100 Site file name
0 Labeling type
-1 Labeling year
-1 Microcosm
-1 CO2 Systems
-1 pH effect
-1 Soil warming
-1 N input scalar option
-1 OMAD scalar option
-1 Climate scalar option
1 Initial system
C10 Initial crop
Initial tree

Year Month Option
1 Block # @enfarm
2050 Last year

```
1          Repeats # years
2020         Output starting year
1          Output month
0.0833       Output interval
F          Weather choice
enfarm_2008-2020.wth
  1  128 CULT B491     #row cultivator, 491 parameterizations
  1  128 CROP C10       #corn-c10 (parameterized from Hartman...)
  1  128 PLTM
  1  128 FERT UAN20     #202_kg_N_ha
  1  282 HARV G    #Grain_with_0%_straw_removal--GRAL
  1  297 CULT E491     #Chisel Plow, 491 parameterizations
  1  297 LAST
-999 -999 X
```

A.4 Cover Crop

Corn production using a cover crop was estimated by adding a barley cover crop over the winter to the conventional management schedule. To simulate this, a barley crop was added to be planted the day after corn harvest and the barley was harvested (at a rate of 85% of the plant material) the day before cultivation for corn. No additional barley harvest was simulated. Fertilization amount, date and harvest rate and date were kept consistent with the other schedules.

Schedule File: cnt2_corn_sDfFcovercrop.sch

```
2020         Starting year
2050         Last year
cnt_enfarm.100     Site file name
0           Labeling type
-1           Labeling year
-1           Microcosm
-1           CO2 Systems
-1           pH effect
-1           Soil warming
-1           N input scalar option
-1           OMAD scalar option
-1           Climate scalar option
1           Initial system
C10          Initial crop
           Initial tree

Year Month Option
1          Block #   @enfarm
2050         Last year
1          Repeats # years
2020         Output starting year
1          Output month
0.0833       Output interval
F          Weather choice
```

```
enfarm_2008-2020.wth
   1   127 CULT CSG      #85% aboveground biomass harvested 5% remains as stdedc SG stubble 10% goes to clittr(1,1) as surface litter
   1   128 CULT D491      #cultivator (description from Moore et al. 2021: pre-plant using sunflower cultivator)
   1   128 CROP C10        #corn-c10 (parameterized from Hartman et al. 2022)
   1   128 PLTM
   1   128 FERT UAN20      #202_kg_N_ha
   1   282 HARV G    #Grain_with_0%_straw_removal--GRAL
   1   282 CULT F491     #Chisel Plow, 491 parameterizations
   1   283 CROP BAR    #barley_cover_crop
   1   283 PLTM
   1   365 LAST
-999 -999 X
```

Appendix B: Supplementary Figures

Shown below are graphs of various carbon pools over time under the simulated management practices.

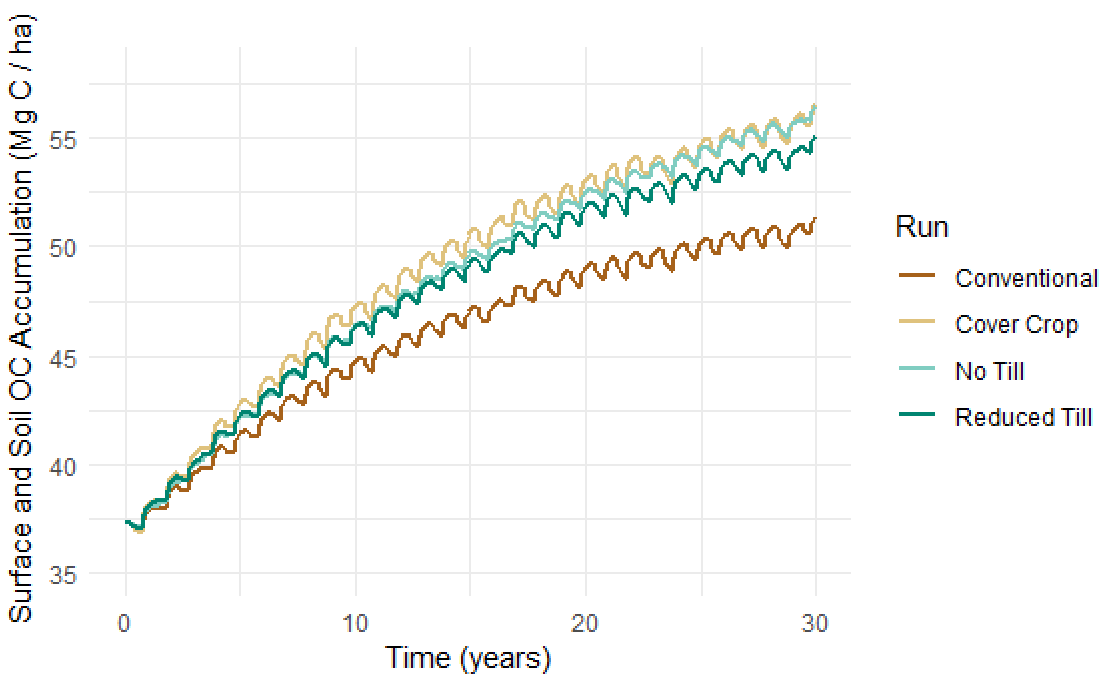

Figure 1: Modeled surface and soil organic carbon stock (including carbon in the active, slow, and passive pools) in the top 20 cm for reference conventional and conservation treatments. By 30-years, cover crop resulted in the highest SOC accumulation, followed by no-till then reduced-till.

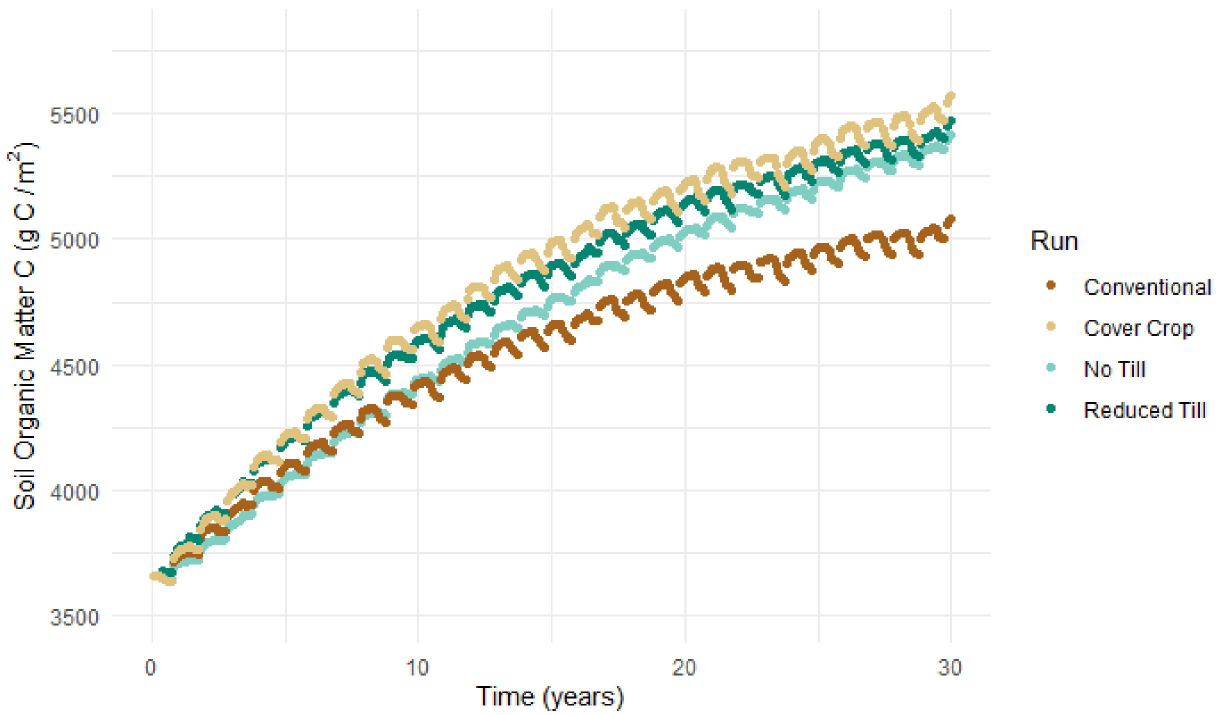

Figure 2: Modeled soil organic carbon stock (including carbon in the active, slow, and passive pools) in the top 20 cm for reference conventional and conservation treatments. Note, that compared to our primary results, this is excluding surface organic carbon pools. Cover crop and manure addition resulted in the highest SOC accumulation and reduced-till and no-till scenarios showed modestly higher SOC levels compared to the reference conventional.

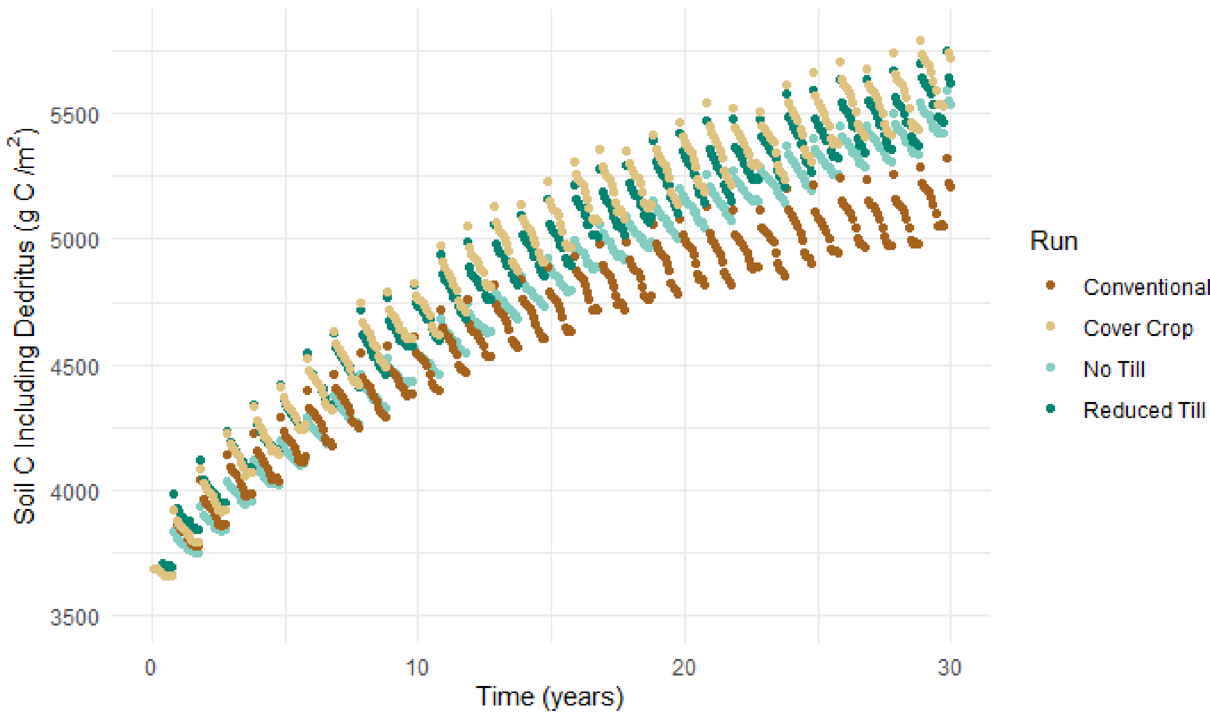

Figure 3: Modeled soil organic carbon stock (including carbon in the active, slow, passive and detritus pools) in the top 20 cm for reference conventional and conservation treatments. Note, that compared to our primary results, this is excluding surface organic carbon pools and including soil detritus. By 30 years, cover crop and no-till incurred the greatest C accumulation in these pools, followed by reduced-till. All conservational practices resulted in greater C accumulation compared to the reference conventional.

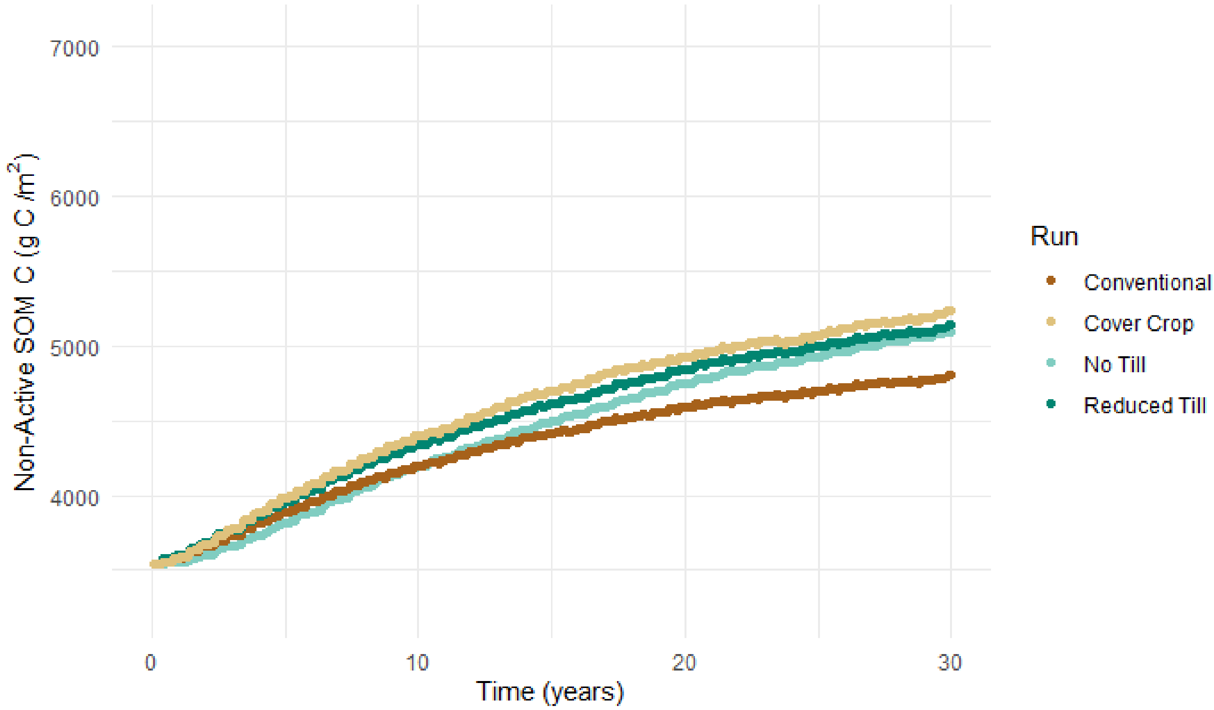

Figure 4: Modeled soil organic carbon stock (including carbon in the slow and passive pools) in the top 20 cm for reference conventional and conservation treatments. Note, that compared to our primary results, this is excluding surface organic carbon pools and the active soil organic matter pool. By 30 years, cover crop incurred the greatest C accumulation in these pools, followed by no-till and reduced-till. All conservational practices resulted in greater C accumulation in these pools compared to the reference conventional.

The results from runs with alternative historic land use were shown only for no-till in the main report. Here we show the same graph but for the cover crop scenario. The shapes of carbon accumulation curves over time looks consistent with the no-till result but the difference between the conventional and conservation practice show different trends. The 'net' SOC accumulation (difference between conventional and conservation) was greater for the alternative land use scenario in the no-till result, whereas it was relatively unchanged in the cover-crop result.

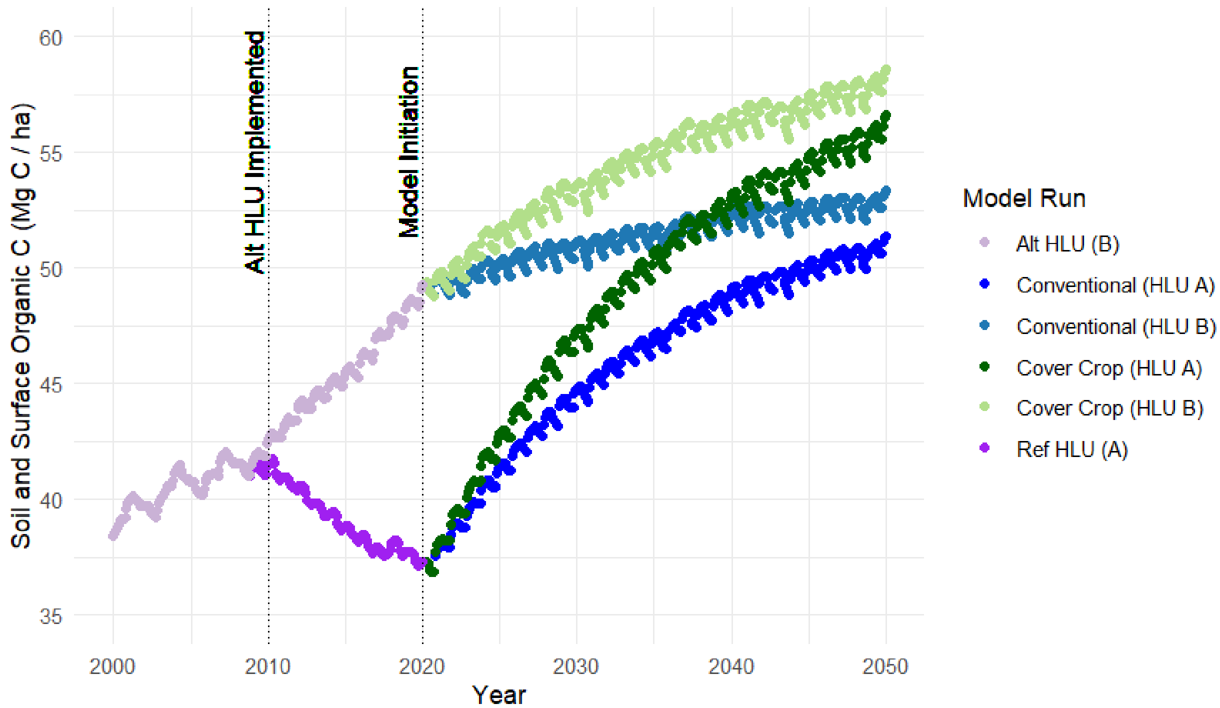

Figure 5: Modeled SOC concentrations resulting from alternate historical land uses (HLU) between 2010-2020 (A = approximate true historic land use including sorghum trials, used in primary analysis, B = hypothetical continuous corn with 0% residue removal) and impact on modeled future management (cover crop in shades of green and conventional in shades of blue). The net accumulation attributable to cover cropping is the difference between the SOC in the no-till management and the conventional management.