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RESEARCH ARTICLE

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Assessing long-term impacts of cover crops on soil organic carbon in the central US Midwestern agroecosystems

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Abstract

Cover crops have been reported as one of the most effective practices to increase soil organic carbon (SOC) for agroecosystems. Impacts of cover crops on SOC change vary depending on soil properties, climate, and management practices, but it remains unclear how these control factors affect SOC benefits from cover crops, as well as which management practices can maximize SOC benefits. To address these questions, we used an advanced process-based agroecosystem model, *ecosys*, to assess the impacts of winter cover cropping on SOC accumulation under different environmental and management conditions. We aimed to answer the following questions: (1) To what extent do cover crops benefit SOC accumulation, and how do SOC benefits from cover crops vary with different factors (i.e., initial soil properties, cover crop types, climate during the cover crop growth period, and cover crop planting and terminating time)? (2) How can we enhance SOC benefits from cover crops under different cover crop management options? Specifically, we first calibrated and validated the *ecosys* model at two long-term field experiment sites with SOC measurements in Illinois. We then applied the *ecosys* model to six cover crop field experiment sites spanning across Illinois to assess the impacts of different factors on SOC accumulation. Our modeling results revealed the following findings: (1) Growing cover crops can bring SOC benefits by 0.33 ± 0.06 MgC ha^{-1} $year^{-1}$ in six cover crop field experiment sites across Illinois, and the SOC benefits are species specific to legume and non-legume cover crops. (2) Initial SOC stocks and clay contents had overall small influences on SOC benefits from cover crops. During the cover crop growth period (i.e., winter and spring in the US Midwest), high temperature increased SOC benefits from cover crops, while the impacts from larger precipitation on SOC benefits varied field by field. (3) The SOC benefits from cover crops can be maximized by optimizing cover crop management practices (e.g., selecting cover crop types and controlling cover crop growth period) for the US Midwestern maize–soybean rotation system. Finally, we discussed the economic and policy implications of adopting cover crops in the US Midwest, including that current economic incentives to grow cover crops may not be sufficient to cover costs. This study systematically assessed cover crop impacts for SOC change in the US Midwest context, while also demonstrating that the *ecosys*

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model, with rigorous validation using field experiment data, can be an effective tool to guide the adaptive management of cover crops and quantify SOC benefits from cover crops. The study thus provides practical tools and insights for practitioners and policy-makers to design cover crop related government agricultural policies and incentive programs for farmers and agri-food related industries.

KEYWORDS
cover crop, *ecosys*, management practices, process-based models, soil organic carbon (SOC), US Midwest

1 | INTRODUCTION

Soil holds nearly 80% of the Earth's carbon in the terrestrial ecosystem (Ontl & Schulte, 2012), and agricultural lands have the largest carbon storage among all the land use types (Lal, 2008). Soil organic carbon (SOC), which is carbon stored as organic forms in the soil, plays a critical role in various ecosystem processes, including physical processes of maintaining soil physical structures and soil water retention, and biochemical processes of supporting soil microbe activities and soil fertility (Ontl & Schulte, 2012). Some agricultural practices have the ability to sequester atmospheric CO_2 into land and increase SOC, such as no-till, cover crop, and biochar (Bai et al., 2019; Wang & Wang, 2019), and these practices have been recently named as climate-smart farming practices due to their potential contribution in mitigating climate change (Lipper et al., 2014). Among different climate-smart farming practices, planting cover crops has been seen as one of the most effective practices to increase SOC (Guenet et al., 2021; Poeplau & Don, 2015; Zhang et al., 2022). In the US Midwest context, planting cover crop means fitting a non-harvested crop during the winter period between the two summer growing seasons, which is predominately a maize (*Zea mays* L.)–soybean (*Glycine max* L) rotation system (Behnke & Villamil, 2019). Studies have found that planting winter cover crops in the United States leads to SOC accumulation and also brings a number of co-benefits, including reducing nitrogen leaching, slowing down soil erosion, and suppressing weeds (Abdalla et al., 2019).

Reducing carbon emission and increasing soil carbon storage through climate-smart farming practices has gained more traction and momentum due to the urgent societal needs to combat climate change and increasing investments from public and private sectors (Oldfield et al., 2021, 2022; Smith et al., 2020). Targeting the global warming below 2°C goal requires drastic change to reduce a large amount of greenhouse gas (GHG) emissions, and agriculture serves as an important sector to contribute to this goal (IPCC, 2014, 2019). Both government agencies and industries need to quantify SOC benefits from climate-smart farming practices, among which planting cover crops is one of the major practices to be applied. Nevertheless, an accurate and cost-efficient SOC benefit quantification method is still largely unavailable (Guan et al., 2021). How successfully this need could be fulfilled, to a large extent, determines the future adoption of cover crops and other climate-smart farming practices.

Traditionally, researchers use soil sampling in paired field experiments (i.e., with- and without-cover-crop conditions in adjacent fields) to quantify SOC benefits from cover crops (Poeplau & Don, 2015). However, field experiments have spatial and temporal limitations in determining the magnitude of cover crop impacts on SOC. Specifically, most field studies of cover crops are site specific and generally with a short time span (e.g., <5 years), usually leading to larger uncertainties in SOC measurements compared to SOC benefits from cover crops (Maillard et al., 2017; Potash et al., 2022). As mentioned above, using soil samplings to measure SOC benefits requires both with- and without-cover-crop conditions. The without-cover-crop conditions are also called "the baseline." However, unlike research fields that have paired plots including the baseline, in most commercial cover crop fields, the baseline does not exist. To create the baseline in SOC benefit quantification, farmers have to intentionally manage the set-aside plots, which is neither practical nor convenient. Thus, it is difficult to quantify SOC benefits directly at commercial cover crop fields based on soil sampling.

To address the above issues from soil sampling, process-based models provide an alternative approach to quantify carbon-related benefits from practices, based on the following rationales (Peng et al., 2020; Smith et al., 2020). First, process-based models have the capability of simulating long-term practices in any field to quantify the SOC benefits from cover crops. Second, process-based models are readily able to quantify SOC benefits from cover crops as the difference of SOC changes between with- and without-cover-crop conditions, even if without-cover-crop conditions are counterfactual. These advancements of process-based models make them effective tools in quantifying cover crop SOC benefits. However, it is important to be aware that unconstrained or uncalibrated models with default parameters usually lead to large uncertainties in the simulated results (He et al., 2017; Peng et al., 2020). Thus, although process-based models can be effective in quantifying carbon-related benefits, they need to be carefully calibrated and validated with ground truth data before being applied for quantification (Peng et al., 2020; Smith et al., 2020).

Although cover crops could bring benefits to SOC, it is not well understood how and to what extent different factors, such as initial soil properties, cover crop types, climate during the cover crop growth period, and cover crop planting and terminating time control SOC benefits from cover crops. SOC benefits from cover crops vary among different fields, which ranges from 0.1 to 1 MgC ha^{-1} $year^{-1}$ based on earlier meta-studies and different factors lead to the variations (Abdalla et al., 2019; Blanco-Canqui et al., 2015; Jian, Du, & Stewart, 2020; Poeplau & Don, 2015). Although studies show that SOC decreases faster in soils with higher initial SOC stocks and lower clay contents, it is not clear to what extent initial soil properties (e.g., SOC stock and clay content) affect SOC changing rates and SOC benefits from cover crops (Poeplau & Don, 2015). The impacts from precipitation and temperature during the cover crop growth period on SOC benefits can be site specific and the underlying pathways remain unclear (Abdalla et al., 2019; Blanco-Canqui et al., 2015; Jian, Du, & Stewart, 2020). In addition to the above environmental factors, cover crop planting and terminating time play important roles in controlling SOC benefits from cover crops. Earlier planting and later terminating can lead to larger cover crop biomass, and thus leading to larger SOC benefits (Rosa et al., 2021). However, it remains unclear how a longer cover crop growth period increases SOC benefits quantitatively. With these issues unsolved, process-based models, with right representatives of underlying processes after calibration and validation, can be applied to address these questions. Through sensitivity analysis, process-based models that have sufficient sophistication in their processes also have the capability to reveal the impacts from different factors on SOC benefits from cover crops.

In this study, we aim to quantify the SOC benefits from cover crops under different conditions in climate and soil properties through calibrating and validating a process-based model with field-measured cover crop and SOC data. We also aim to reveal the pathways of how different controlling factors (i.e., initial soil properties, cover crop types, climate during the cover crop growth period, and cover crop planting and terminating time) affect the SOC benefits from cover crops. Specifically, we first used two sites with long-term SOC measurements to calibrate and validate the *ecosys* model. One is the Morrow plots located in Champaign County, Illinois with 100 years of SOC measurements at 0–0.15 m depth (Aref & Wander, 1997). The other is the Dixon Springs cover crop experiment site located in Pope County, Illinois with 12 years 0–0.75 m SOC measurements (Olson et al., 2010, 2014). Then, we used *ecosys* to simulate SOC benefits from cover crops at six cover crop experiment sites across Illinois, where we have previously validated the performance of *ecosys* for the maize and soybean yield as well as cover crop biomass (Qin et al., 2021). Finally, we synthesized the impacts of different factors on SOC benefits. In this study, we aim to answer two scientific questions: (1) To what extent do cover crops benefit SOC accumulation, and how do SOC benefits from cover crops vary with different controlling factors (i.e., initial soil properties, cover crop types, climate during the cover crop growth period, and cover crop planting and terminating time)? (2) How can we enhance SOC benefits from cover crops under different cover crop management options (e.g., selecting cover crop types and controlling cover crop growth period)?

2 | MATERIALS AND METHODS

2.1 | Definition of "SOC benefits from cover crops"

We define "SOC benefits from cover crops" as the difference of SOC change between with- and without-cover-crop conditions. In field experiments, "SOC benefits from cover crops" can be measured as the differences in SOC change between paired plots. Paired plots are usually neighboring plots that have similar soil properties and identical management practices except for the existence of cover crops. Thus, the differences in SOC change between two plots are induced by the implementation of cover crops. In models, two types of scenarios, including with- and without-cover-crop conditions, are set up according to the field management practices. "SOC benefits from cover crops" in models are calculated as the differences in SOC change between two scenarios.

2.2 | *Ecosys* model

The *ecosys* model is a sophisticated process-based model with comprehensive biogeochemical process representations that has been calibrated and validated at multiple sites with different conditions in climate and soil properties (Grant, 2001; Grant et al., 2001, 2020; Zhou et al., 2021). *Ecosys* is constructed from various interacting processes representing carbon, nitrogen (N), phosphorus (P), water, and energy cycles among plants, soil, and atmosphere to simulate complex ecosystem behavior (Grant, 2001; Grant et al., 2001, 2020; Zhou et al., 2021). Here we describe key processes for photosynthesis and decomposition that govern the dynamics of carbon cycle in plants and soil.

2.2.1 | Photosynthesis and autotrophic respiration

The *ecosys* model uses a multi-layer module to simulate the canopy photosynthesis, calculating the carbon assimilation for each individual leaf under different light conditions. For each leaf, the Farquhar model is used to calculate carbon assimilation for C3 crops. *Ecosys* also explicitly calculates mesophyll carbon fixation and mesophyll-bundle sheath carbon transfer for C4 crops, which is not included in the classic Farquhar model. The canopy stomatal resistance and temperature are calculated by closing the energy and water balances through the soil–root–canopy–atmosphere using plant hydraulics (Grant et al., 2006, 2009). The final leaf CO_2 fixation is calculated from coupled solutions for diffusion driven by CO_2 concentration gradients across leaf stomatal resistance and for carboxylation driven by CO_2 concentration and irradiance. Nonstructural carbon pools, which are the product of leaf CO_2 fixation, are oxidized to meet autotrophic respiration (R_A) requirements with constraints from O_2 uptake. Oxidized carbon is first used to meet requirements for maintenance respiration (R_M), then the excess oxidized carbon is used for growth respiration (R_G) to drive biosynthesis according to organ-specific growth efficiencies. Litterfall is simulated from remaining biomass subtracting removed grain carbon after harvest and from biosynthesis products which is caused by senescence when $R_A < R_M$.

2.2.2 | Decomposition and heterotrophic respiration (R_H) in *ecosys*

Ecosys simulates carbon transformations in the soil based on different SOC pools (Figure 1). Plant litterfall and animal manure represent fresh organic carbon inputs of the model. Fresh organic carbon is added to a litter pool of different complexes (i.e., carbohydrate, protein, cellulose, and lignin) and then goes through decomposition processes (Grant et al., 1993a, 1993b). Litter complexes could transfer to the particulate organic carbon (POC) pool through fragmentation (Grant et al., 2001). Dissolved organic carbon (DOC) pool in *ecosys* is produced by hydrolysis of litter pools, POC, root exudates, and mineral-associated microbial products. *Ecosys* simulates decomposition of carbon through two types of microbes (i.e., aerobic and anaerobic) by Michaelis–Menten kinetics. The decomposition rates vary with microbes and organic complexes. In *ecosys*, upon microbial mortality, some fraction of microbial carbon is recycled, some goes to microbial residue, and the remaining become mineral-associated microbial product as a function of clay content. R_H, R_M, and R_G in soils are calculated in the same way that they are calculated in plants. Soil carbon is returned to the atmosphere as CO_2 through aerobic microbes and as CH_4 through anaerobic microbes, although CH_4 emission is a very small fraction in the US Midwest maize–soybean rotation systems compared to other carbon fluxes (Omonode et al., 2007).

To assess the cover crop impacts on SOC, we consider a holistic carbon balance of the agroecosystem for a certain period (e.g., multiple years). Specifically, cover crops not only add NPP (Net Primary Production) of cover crops that leads to the increase in SOC, but also affect other carbon fluxes relating to cash crops and the soil. Therefore, to comprehensively assess the cover crop impacts on SOC, it is not only necessary but a must to holistically assess the whole carbon balance of the agroecosystem, including cover crop carbon fluxes, cash crop carbon fluxes, and soil carbon fluxes. From a long-term perspective, SOC change (ΔSOC) can be estimated by carbon input to the ecosystem less the carbon output from the ecosystem (i.e., R_H, carbon leaching and CH_4 flux). Accordingly, we quantified the impacts from cover crops on ΔSOC through each carbon flux in Equation (1):

$$\begin{aligned} \Delta \mathrm{SOC} &= \mathrm{litterfall} - R_H - CH_4 - C_{\mathrm{leaching}} + \in \\ &= (\mathrm{NPP} - \mathrm{harvest}) - R_H - CH_4 - C_{\mathrm{leaching}} + \in \\ &= (\mathrm{GPP} - R_A - \mathrm{harvest}) - R_H - CH_4 - C_{\mathrm{leaching}} + \in \end{aligned} \tag{1}$$

where litterfall represents fresh litter input to the soil (i.e., shoot and root litterfall and root exudation); litterfall can be estimated by NPP subtracting harvest; where NPP represents net primary production and harvest represents harvested carbon biomass; NPP can be calculated by GPP subtracting R_A, where GPP represents gross primary production and R_A represents autotrophic respiration; R_H represents heterotrophic respiration; CH_4 represents CH_4 emission from the soil; $C_{leaching}$ represents the leaching inorganic and organic carbon through surface runoff and subsurface discharge, ϵ represents other small carbon fluxes.

SOC change calculated from Equation (1) shall only be applied to long-term estimations. In soil science, litterfall may not be defined as SOC until the breakdown of large compounds. Therefore, ΔSOC estimated from Equation (1) has larger seasonal variations due to the inclusion of litterfall. This large variation results from the growth and termination of the plants. Considering the long-term crop rotation systems, we can assume that litterfall inputs are relatively steady for each rotation. From a long time span (>5 years), ΔSOC can be assessed by Equation (1) with confidence once each term in the equation was validated. In addition, Equation (1) can be used to assess the impacts from cover crops on each carbon flux that contributes to SOC benefits.

2.3 | Study sites

Measurements from eight field experiment sites in Illinois were used to calibrate and validate the *ecosys* model and to further

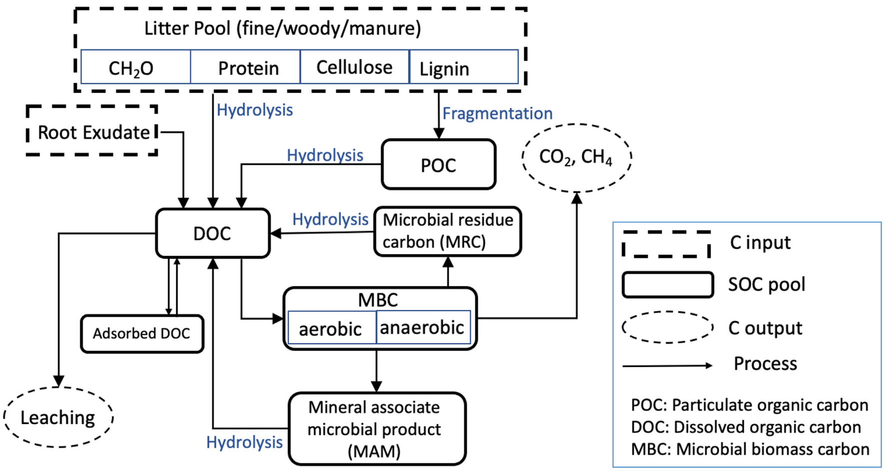

FIGURE 1 Conceptual figure of soil carbon decomposition processes in the *ecosys* model.

assess the SOC benefits from cover crops (Figure 2). The Morrow Plots (MR in Figure 2), located in central Illinois, are one of the oldest research fields with continuous measurement of SOC for the upper 0.15 m (Bergh et al., 2022). The soil in the Morrow Plots is a Flanagan silt loam (fine, smectitic, mesic Aquic Argiudoll). Long-term SOC concentration data from 1913 to 2020 of continuous maize rotations with different fertilization managements were used to calibrate *ecosys* for monitoring long-term SOC change (Aref & Wander, 1997). Two types of fertilizer management are included in our study: (1) Manure applied annually for the whole period, and (2) N fertilizer applied annually after manure annually since 1967 (Morrow Plots Data Curation Working Group, 2022; Nafziger & Dunker, 2011).

The cover crop experiment site (DS02 in Figure 2) was established from 2000 to 2012 on the Grantsburg silt loam soil (fine-silty, mixed, mesic Typic Fragiudalf). Cereal rye and hairy vetch were planted in the maize–soybean rotations with three types of tillage application (i.e., no-till, moldboard plow, and chisel plow). SOC stock was continuously measured to 0.75 m depth during the experiment period (Olson et al., 2010, 2014).

The other six cover crop sites across Illinois (i.e., MN, DK, UR, BT, CA, and DS) were established from 2013 to 2018 and have been validated with cash crop yield and cover crop biomass carbon (Qin et al., 2021). These sites were planted with different rotations of winter cover crops (Villamil & Nafziger, 2019). Specifically, there were three rotation systems, including (1) without-cover-crop (maize–soybean rotations), (2) non-legume-preceding-maize (maize–annual ryegrass–soybean–annual ryegrass rotations), and (3) legume-preceding-maize (maize–cereal rye–soybean–hairy vetch rotations). These six cover crop sites were also used in further sensitivity analysis to reveal the control factors of SOC benefits from cover crops.

2.4 | Model setup and model calibration

2.4.1 | Model setup and data inputs

The model was set up according to field management records. For the Morrow Plots, we ran the *ecosys* model for 125 years from 1897 to 2021, with 1897–1912 as the model initialization period and 1913–2020 as the analysis period. During the analysis period, different fertilization rates were applied to the continuous maize rotation systems according to the Morrow Plots records. The initial condition of soil for model input was from the Gridded Soil Survey Geographic Database (gSSURGO) database, and initial SOC (0–0.15 m) at the Morrow Plots was from field measurements (Aref & Wander, 1997). The climate data were from National Centers for Environmental Information (NCEI) at daily time step and from the North American Land Data Assimilation System 2 (NLDAS-2) at hourly time step for the period of 1913–1978 and 1978–2021, respectively (NASA, 2021; NOAA, 2022). Nitrogen deposition took up a significant portion of total nitrogen input for the system in the long-term simulations and the nitrogen deposition data were derived from the national atmospheric deposition program (NADP, 2022).

For the DS02 site, the model was set up with 1984–1999 as model initialization period and 2000–2012 as the analysis period. Field management practices in the *ecosys* model were set up with six scenarios following field records including with- and without-cover-crop rotation systems under three types of tillage applications (Table S1). For the six cover crop sites (MN, DK, UR, BT, CA, and DS), we set up the model from 1987 to 2020 with 1987 to 2012 as model initialization period and 2013–2020 as the analysis period with three different rotation systems. The climate data for these sites were from NLDAS-2 at hourly step and initial soil conditions were from

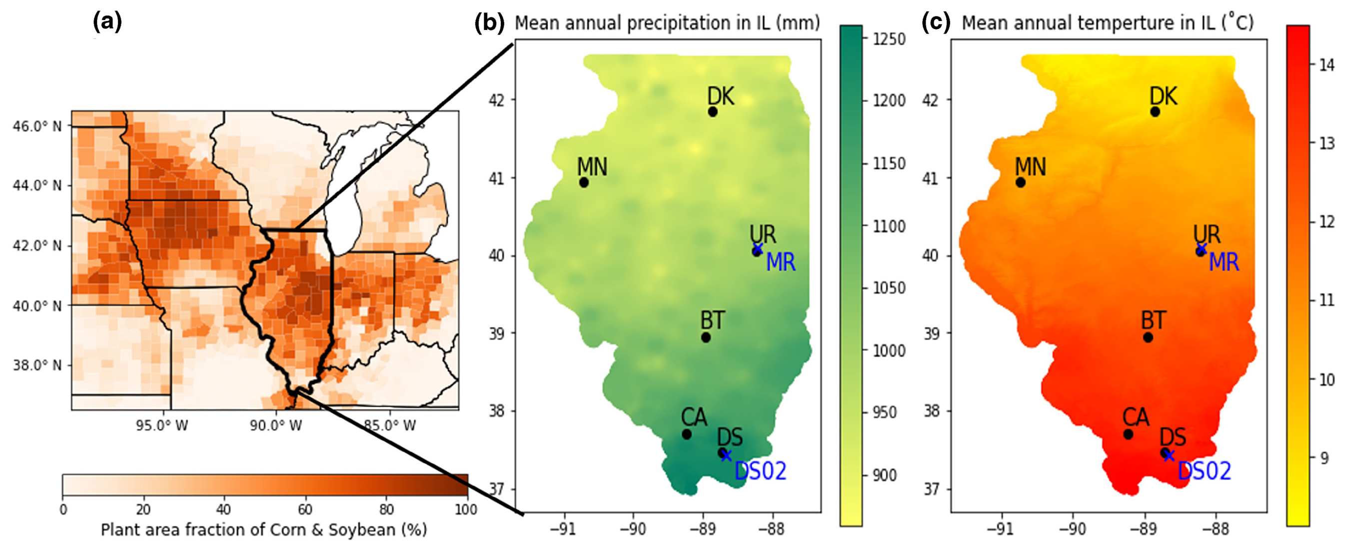

FIGURE 2 (a) Spatial distribution of plant fraction of maize and soybean in the US Midwest (USDA, NASS, 2021). (b) Mean annual precipitation in Illinois, and the selected site locations. (c) Mean annual temperature in Illinois, and the selected site locations. Sites in blue color are sites with SOC measurements and are used to calibrate and validate long-term SOC change; Sites in black color have cover crop trials and are used to assess the impacts of different factors on SOC benefits from cover crops.

gSSURGO database with initial SOC concentration data from measurements (0–0.75 m for DS02 and 0–0.9 m for six cover crop sites).

2.4.2 | Model calibration and validation

We calibrated and validated the *ecosys* model for the study sites using field measurements (Table 1). The Morrow Plots have long-term measurements of SOC concentrations for over a century, and these data were used to calibrate and validate model performance in simulating long-term SOC change. The SOC concentration measurements were separated into validation dataset and calibration dataset. We used the data from plots with manure applied annually for the whole period for calibration, and the data from plots with N fertilizer applied annually after manure annually since 1967 for validation. We calibrated two parameters, that is, "plant maturity group" and "maximum kernel number," for every 20 years; this was done to match the general increasing trend of the harvest index of maize for the past century (Sinclair, 1998). "Plant maturity group" is a parameter that refers to the total number of leaf primordia (i.e., groups of cells that develop into leaves) that differentiate into specific leaf parts after seeding for annual crops, and "maximum kernel number" is a parameter that represents the maximum number of grain kernels per fruiting site, which depends on post-anthesis growth in the *ecosys* model.

The measurements from the DS02 site were used to calibrate and validate *ecosys* simulation of SOC benefits from cover crops. We calibrated the model with multi-year averaged cash crop yield data, and then validated the model performance with SOC change data for 0–0.75 m. It is worth noting that *ecosys* does not require users to calibrate its soil parameters, including soil physical and biogeochemical processes whose parameterization has been evaluated in many previous studies and have demonstrated very consistent and good performances under various environmental conditions (Grant et al., 2011, 2020; Zhou et al., 2021). For the six cover crop sites (MN, DK, UR, BT, CA, and DS), maize and soybean yield and cover crop biomass from 2013 to 2018 had been calibrated with multi-year averaged cash crop yield and cover crop biomass data, and then the model was validated with annual crop yield and cover crop biomass data. *Ecosys* showed the capability to accurately simulate interannual variability in cover crop growth as well as cash crop productivity (Qin et al., 2021). The satisfactory validation performance of the *ecosys* model provides confidence to use it for further assessments of SOC benefits from cover crops.

It is worth noting that the soil decomposition process simulated in *ecosys* is microbial-explicit, considering interactions between heterotrophs and autotrophs regulate the soil carbon, nitrogen, and redox dynamics. For the SOC calibration and validation, we only calibrated plant-related parameters and kept the parameterization of soil biogeochemistry that has been used in past studies (Grant, 1997; Grant et al., 1993a, 1993b, 2020) involved in decomposition processes.

TABLE 1 Model calibration and validation details.

Purpose of calibration and validation	Calibration	Validation	Calibrated parameters	Sites for calibration
To calibrate model performance for simulating long-term SOC concentration	We calibrated the model with multi-year averaged yield and SOC concentration data in plots with manure applied annually for the whole period	We validated the model with SOC concentration data in plots with N fertilizer applied annually after manure annually since 1967	For maize: Plant maturity group; maximum kernel numbers (same parameters every 20 years for all scenarios)	Morrow plots (MR)
To calibrate model performance for simulating SOC benefits from cover crops	We calibrated the model with multi-year averaged cash crop yield	We validated the model with measured SOC change and SOC benefits from cover crops	For maize and soybean: Plant maturity group; maximum kernel numbers	Dixon Springs cover crop site (DS02)
To constrain the model with yield and biomass data at six cover crop sites for further assessments	We calibrated the model with multi-year averaged cash crop yield and cover crop biomass (carbon input the system)	We validated the model with annual crop yield and cover crop biomass (Qin et al., 2021)	For maize and soybean: Plant maturity group; climate zone. For cover crops: Plant maturity group; climate zone (same parameters for all the years and all scenarios for each site)	Six cover crop sites in IL (MN, DK, UR, BT, CA, and DS)

2.5 | Model sensitivity analysis to assess the impacts of climate during the cover crop growth period

We ran the *ecosys* model with different climate conditions during the cover crop growth period to test climate impacts on SOC benefits from cover crops. We applied change (i.e., −2°C, −1°C, +1°C, +2°C) to hourly temperature from September 15 to next year April 30 for the period of 2013–2020 for the six cover crop sites in Illinois. Climate data inputs to drive the model for the remaining time of year (i.e., May 1–September 14) were not changed and other management settings were based on the site-specific practices as described above. Climate change factors were applied to two rotations including with- and without-cover-crop conditions (i.e., maize–soybean rotations and maize–annual rye–soybean–annual rye rotations). SOC benefits from cover crops with each climate change factor were calculated as differences of SOC change between with- and without-cover-crop conditions accordingly. Similar to sensitivity analysis for temperature during the cover crop growth period, we applied a multiplier (i.e., 0.75, 1.5) to hourly precipitation during the cover crop growth period and used the same method to compare SOC benefits from cover crops.

2.6 | Model sensitivity analysis to assess the impacts of different planting and terminating time

We set up the *ecosys* model with different planting and termination time at the MN site from 2013 to 2020. Specifically, we set up four different cover crop planting dates (i.e., September 15, September 30, October 15, and October 30) and four different terminating dates (i.e., April 1, April 10, April 20, and April 30) in the *ecosys* model. Different planting and terminating time were applied to maize–annual ryegrass–soybean–annual ryegrass rotations. Inputs of climate and soil data and other management settings were based on the field practices at the MN site.

3 | RESULTS

3.1 | Evaluate the ecosys model performance for long-term SOC simulation

3.1.1 | Morrow plots

Ecosys performed well in simulating long-term SOC change at the Morrow Plots (Figure 3a–c). We found that the *ecosys* model has the ability to simulate long-term SOC change under different fertilization practices by comparing the simulated and measured SOC concentration. The differences in SOC change between two plots were induced by different fertilization practices. From the field measurements, we found that during 1913–1967, both plots exhibit decreasing trends in SOC concentrations, but with more rapid decreases in plots with manure applied annually for the whole period.

3.1.2 | Dixon Springs (DS02)

In addition to the centennial changes in SOC at the Morrow Plots, we also validated the *ecosys* model for its ability to simulate SOC change (multi-year averaged) for the cover crop experimental site at the DS02 site (Figure 3d). Simulation of SOC change at the DS02 site from 2000 to 2012 was validated under both with- and without-cover-crop conditions. We found that cover crops could significantly (at 95% confidence level) bring SOC benefits by 0.4 MgC ha^{-1} year^{-1} and 0.48 MgC ha^{-1} year^{-1} from *ecosys* simulations and field experiments, respectively. The consistency between the *ecosys* simulations and field-measured SOC change demonstrated that *ecosys* has the ability to accurately simulate both SOC change and SOC benefits from cover crops.

3.2 | Quantify SOC benefits at six cover crop sites (MN, DK, UR, BT, CA, and DS)

After careful calibration and validation of *ecosys* in simulating SOC change and SOC benefits, we quantified SOC benefits from cover crops at six cover crop sites (MN, DK, UR, BT, CA, and DS) in Illinois. The *ecosys* simulation results showed that during 2013–2020, planting winter cover crops could bring SOC benefits (multi-year averaged) by 0.33 ± 0.06 MgC ha^{-1} year^{-1} (Figure 4). Specifically, SOC benefits from cover crops are 0.38 ± 0.06 MgC ha^{-1} year^{-1} and 0.28 ± 0.05 MgC ha^{-1} year^{-1} under non-legume-preceding-maize and legume-preceding-maize conditions, respectively.

3.3 | Cover crop impacts on carbon budget in the central US Midwestern agroecosystems

The carbon budget of the six cover crop sites (MN, DK, UR, BT, CA, and DS) under with- and without-cover-crop conditions demonstrated that planting cover crops could benefit SOC by introducing additional net carbon input to the systems (Figure 5). On average, 4.17 ± 0.37 MgC ha^{-1} year^{-1} of grain carbon was harvested and removed from the without-cover-crop conditions in the maize years and 1.70 ± 0.16 MgC ha^{-1} year^{-1} in the soybean years, accounting for a large portion of the carbon output in the system. Cover crops could increase carbon input by bringing additional biomass of 1.51 ± 0.25 MgC ha^{-1} year^{-1} under the non-legume-preceding-maize condition, and 0.94 ± 0.27 MgC ha^{-1} year^{-1} under the legume-preceding-maize conditions.

However, SOC benefits from cover crops were much smaller than cover crop biomass. Increased carbon input in the cover crop systems was partially offset by increased carbon oxidation which

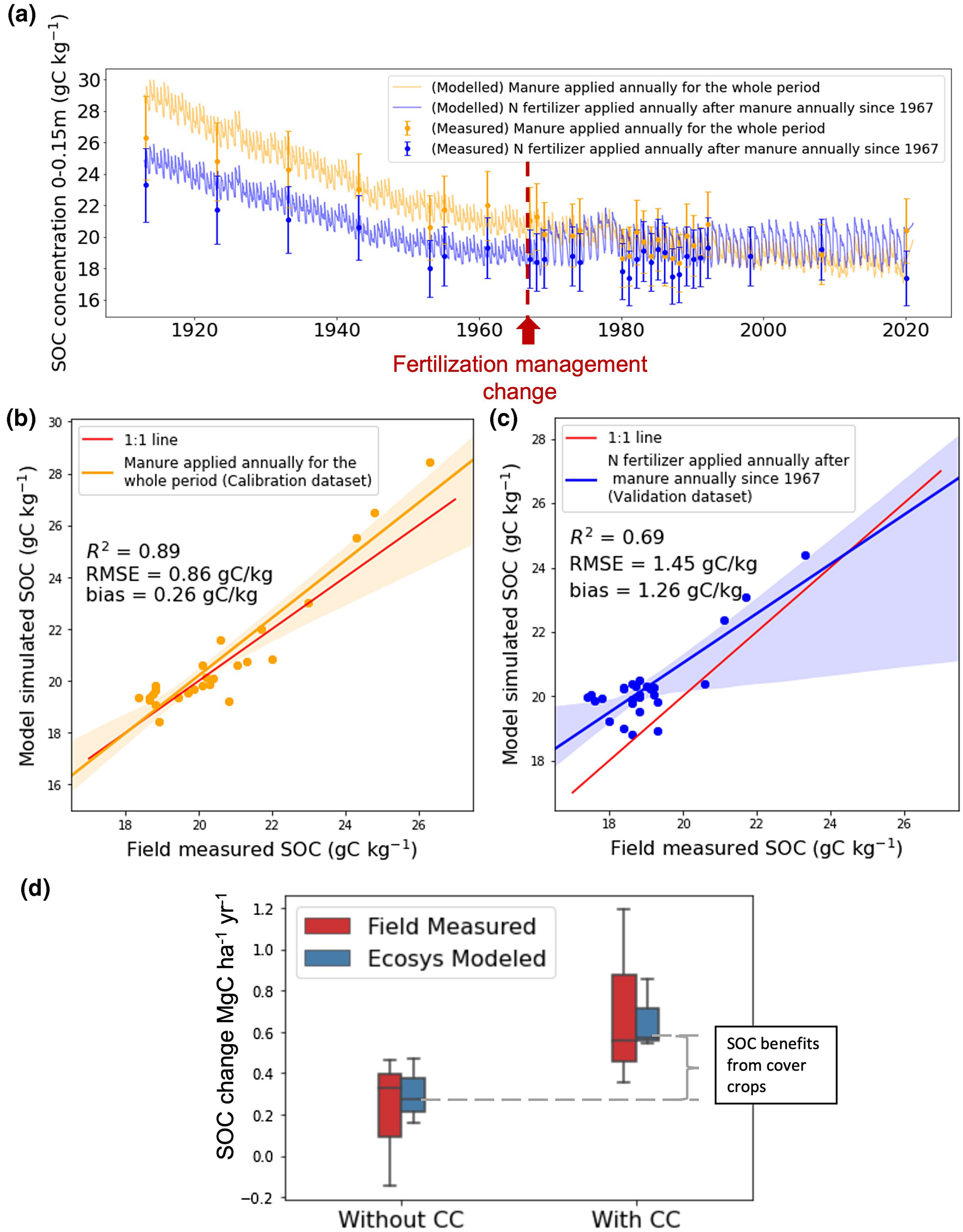

FIGURE 3 (a) *Ecosys* simulated and field-measured SOC concentration in topsoil (0–0.15 m) at the Morrow Plots in Illinois with continuous maize rotations and different fertilization practices over the last century. Manure applied annually for the whole period: 4.5 Mg ha^{-1} year^{-1} of manure (45% carbon with C:N ratio of 30) from 1913 to 2020; N fertilizer applied annually after manure annually since 1967: 4.5 Mg ha^{-1} year^{-1} of manure (45% carbon with C:N ratio of 30) from 1913 to 1967; 336 kgN ha^{-1} year^{-1} from 1968 to 1998; 224 kgN ha^{-1} year^{-1} from 1999 to 2020 (Aref & Wander, 1997). The error bars represent the assumed uncertainty level of the measurements (assumed 10% uncertainty). (b) Scatter plot of ecosys simulated and field-measured SOC concentration from 1913 to 2020 at the Morrow Plots for plots with manure applied annually for the whole period (calibration dataset). (c) Scatter plot of ecosys simulated and field-measured SOC concentration from 1913 to 2020 at the Morrow Plots for plots with N fertilizer applied annually after manure annually since 1967 (validation dataset). (d) *Ecosys* simulated and field-measured SOC change (multi-year averaged) of 0–0.75 m at the DS02 site from 2000 to 2012; The error bars represent standard deviation among plots of different tillage practices.

results in increased R_H. Meanwhile, the negative impacts of non-legume cover crops on maize yield also offset the SOC benefits from cover crops. Therefore, increased R_H and reduced maize yield after non-legume cover crops could offset the SOC benefits from cover crops. The impacts of different factors on SOC benefits are discussed in the following sections.

3.4 | Factors that affect SOC benefits from cover crops

SOC benefits from cover crops vary among different sites and different factors lead to these variations. We investigated four major factors that influence SOC change or SOC benefits from cover crops,

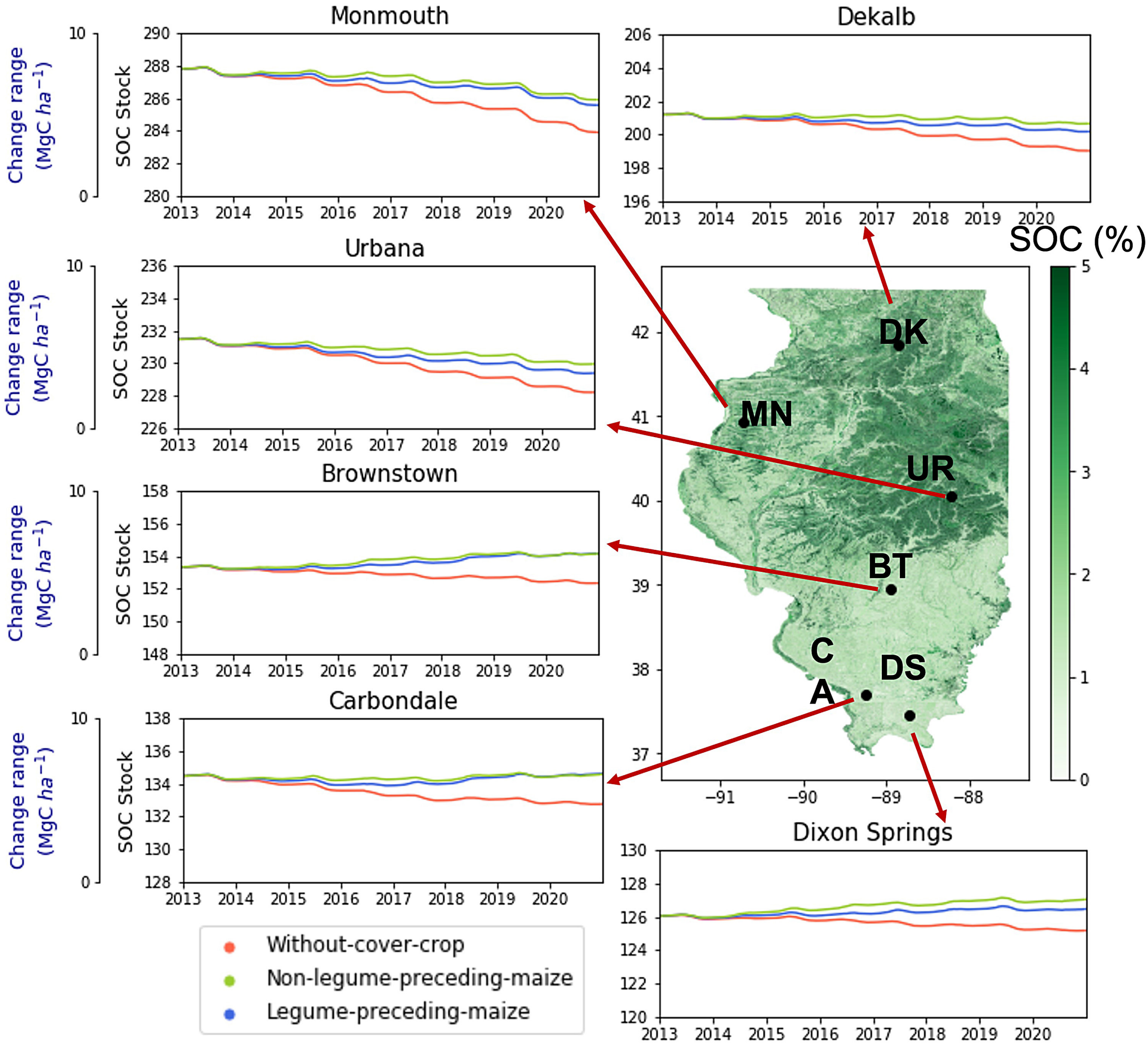

FIGURE 4 Map of SOC concentration distribution in Illinois and *ecosys* simulated SOC stock (0–2 m) at six cover crop sites (MN, DK, UR, BT, CA, and DS) in Illinois from 2013 to 2020 with three rotation systems (1) without-cover-crop (maize-soybean rotations), (2) non-legume-preceding-maize (maize-annual ryegrass–soybean-annual ryegrass rotations), and (3) legume-preceding-maize (maize-cereal rye-soybean-hairy vetch rotations). The SOC stock in this figure excludes residue carbon pool.

including (1) initial soil properties (e.g., SOC stock and clay content), (2) cover crop types, (3) climate during the cover crop growth period, and (4) cover crop planting and terminating time. Initial soil properties are important indicators for SOC change while the other three factors can affect cover crop biomass that directly controls the SOC benefits (see Section 3.4.1).

3.4.1 | Factor 1: Initial soil properties (e.g., SOC stock and clay content)

We found that initial SOC stock and clay content play important roles in quantifying SOC change. From the *ecosys* simulation, we found that SOC change is negatively correlated with initial SOC stock (Figure 6a) and positively correlated with clay content (Figure S1), indicating that the decomposition rate is faster when the SOC stock is larger, or clay content is lower. Soils with larger initial SOC normally contain larger microbe populations thereby increasing R_H. For the without-cover-crop conditions at our study sites, the fitted linear slope of the SOC benefits to cover crops with initial SOC stock (Figure 6a) is −0.0023, indicating 0.23% of the initial SOC stock (0–2 m) is lost as CO_2 annually in this system. As for soil clay contents, earlier studies have shown that decomposition rates decrease with higher clay contents, because clay mineral associations reduce the physical accessibility and chemical availability of SOC to decomposers (Epstein et al., 2002).

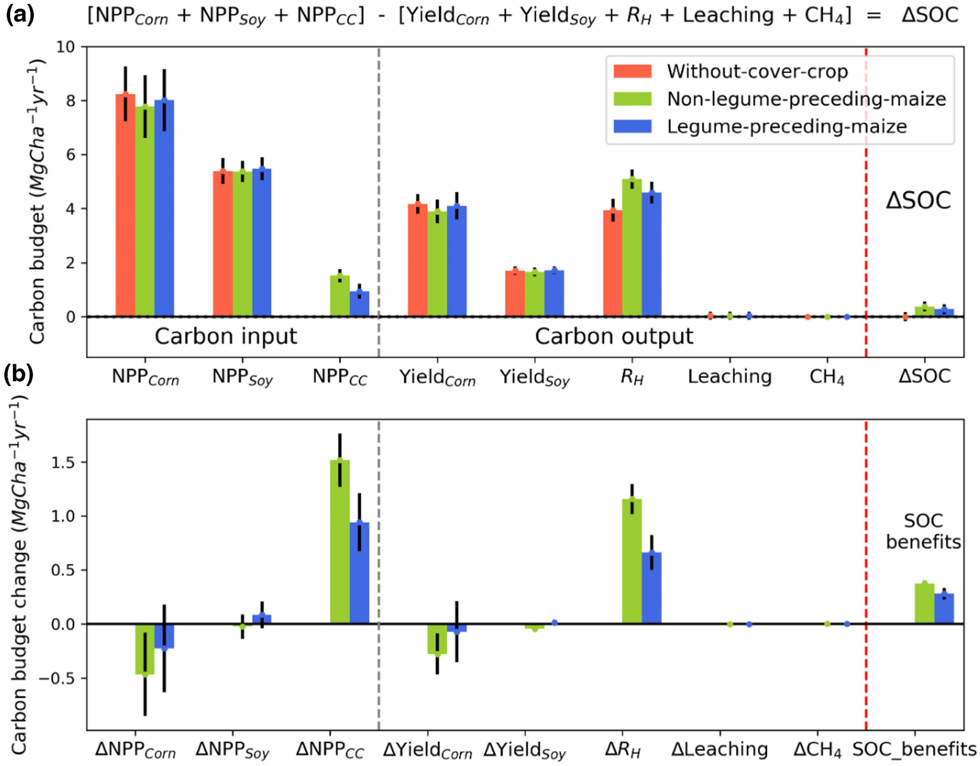

FIGURE 5 (a) *Ecosys* simulated carbon budget (upper panel) at six cover crop sites (MN, DK, UR, BT, CA, and DS) in Illinois with three rotation systems (1) without-cover-crop, (2) non-legume-preceding-maize, and (3) legume-preceding-maize. (b) Carbon budget change in non-legume-preceding-maize and legume-preceding-maize conditions compared to without-cover-crop conditions. Error bars represent standard deviation among different sites.

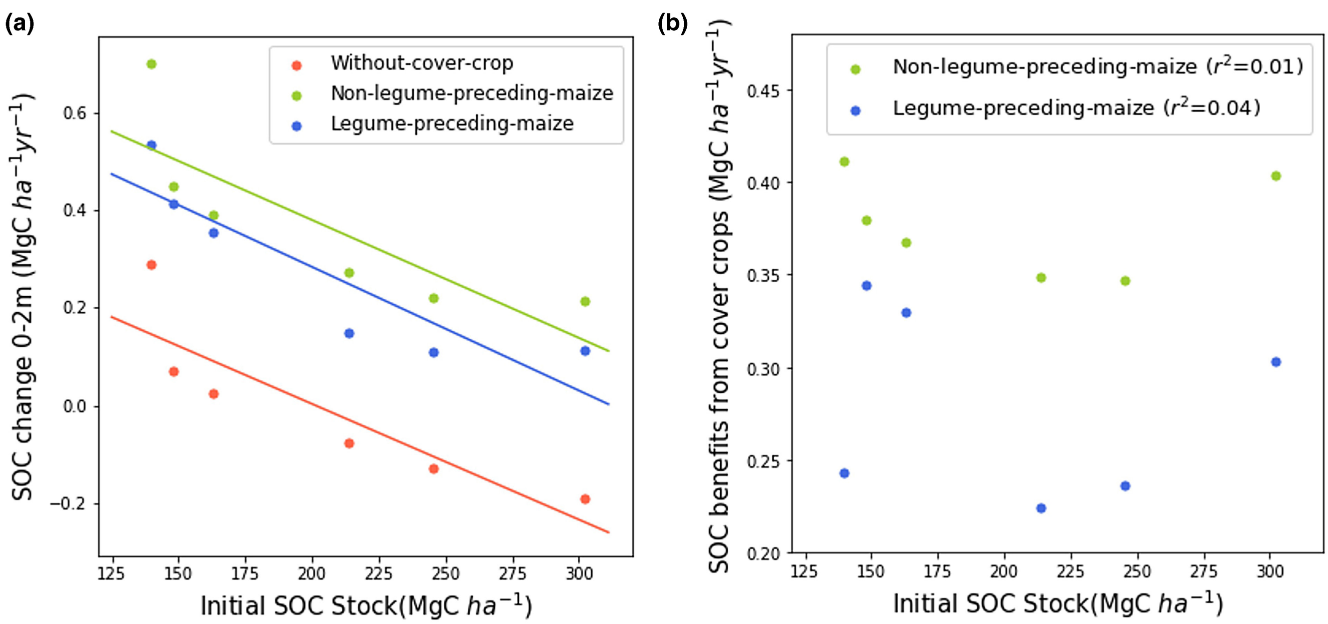

FIGURE 6 (a) Relation between *ecosys* simulated SOC change (0–2 m, multi-year averaged) and initial SOC stock (0–2 m) at six cover crop sites (MN, DK, UR, BT, CA, and DS) in Illinois from 2013 to 2020. Each point represents one rotation at one site, the points with green color represent non-legume-preceding-maize conditions, the points with blue color represent legume-preceding-maize conditions, and the points with red color represent without-cover-crop conditions. (b) Relation between *ecosys* simulated SOC benefits from cover crops (multi-year averaged) and initial SOC stock at six cover crop sites in Illinois from 2013 to 2020.

Meanwhile, we found that initial SOC stock and clay content are not closely correlated with SOC benefits from cover crops. From the simulation results (Figure 6b), we found that the impacts on SOC benefits from initial SOC stock are not significant ($r^2 < 0.05$). Although initial SOC stocks and clay content are important indicators for SOC change, they have relatively small impacts on SOC benefits from cover crops. One possible reason is that larger initial SOC stock under with- and without-cover-crop conditions both lead to faster SOC loss with a similar magnitude, leading to the similar relative difference of SOC change between conditions with different initial SOC stocks (Zhou et al., 2023). Therefore, SOC benefits from cover crops are much less sensitive than SOC change in response to initial SOC stock.

3.4.2 | Factor 2: Cover crop types

From the model simulation, we found that SOC benefits from cover crops are species specific. We found that SOC benefits are positively correlated with cover crop biomass (combined above- and belowground biomass), since cover crops bring SOC benefits by adding additional carbon to the system (Figure 7a). Our results showed that non-legume-preceding-maize conditions have larger average SOC benefits due to larger biomass of non-legume cover crops. Non-legume cover crops can develop larger biomass during winters in the US Midwest since they are more cold tolerant, leading to larger average SOC benefits than legume cover crops.

SOC benefits per unit cover crop biomass also differ among different cover crop species. For each rotation, we estimated SOC benefits per unit cover crop biomass as the linear slope of the simulated SOC benefits to cover crop biomass (assuming no intercept). The SOC benefits per unit cover crop biomass, that is, defined as "biomass-to-SOC-benefit conversion rate" is 0.22 and 0.28 for non-legume-preceding-maize and legume-preceding-maize conditions, respectively (Figure 7a). Although non-legume cover crops have larger SOC benefits, legume cover crops have larger biomass-to-SOC-benefit conversion rates. The reason is that residues of non-legume cover crops have larger C:N ratios than legume cover crops (Zhang et al., 2022), which might lead to immobilization of N (Qin et al., 2021). Insufficient N in the soil has negative impacts on maize growth, resulting in smaller maize productivity, which partially offsets the SOC benefits from cover crops. Overall, we found that non-legume cover crops contribute to larger SOC benefits in the US Midwest agroecosystems unless larger biomass of legume cover crops is achieved.

Larger root: shoot ratio of cover crops increases SOC benefits from cover crops from our simulation results. Cover crop biomass comprises a significant portion of root biomass. Our results showed that the cover crop root: shoot ratio, which is calculated as cover crop root biomass carbon divided by cover crop shoot biomass carbon, varies from 0.15 to 0.55 at six cover crop sites from 2013 to 2020 (Figure S2). We found that the biomass-to-SOC-benefit conversion rate is positively correlated with cover crop root: shoot ratio (Figure 7b), indicating that if the cover crop biomass is allocated more to belowground than aboveground, the SOC benefits could be larger. The reason could be that belowground biomass is more stable than aboveground biomass and has longer mean residence time of SOC (Berhongaray et al., 2019; Lavallee et al., 2018). Therefore, larger SOC benefits are achieved when cover crops develop more root biomass.

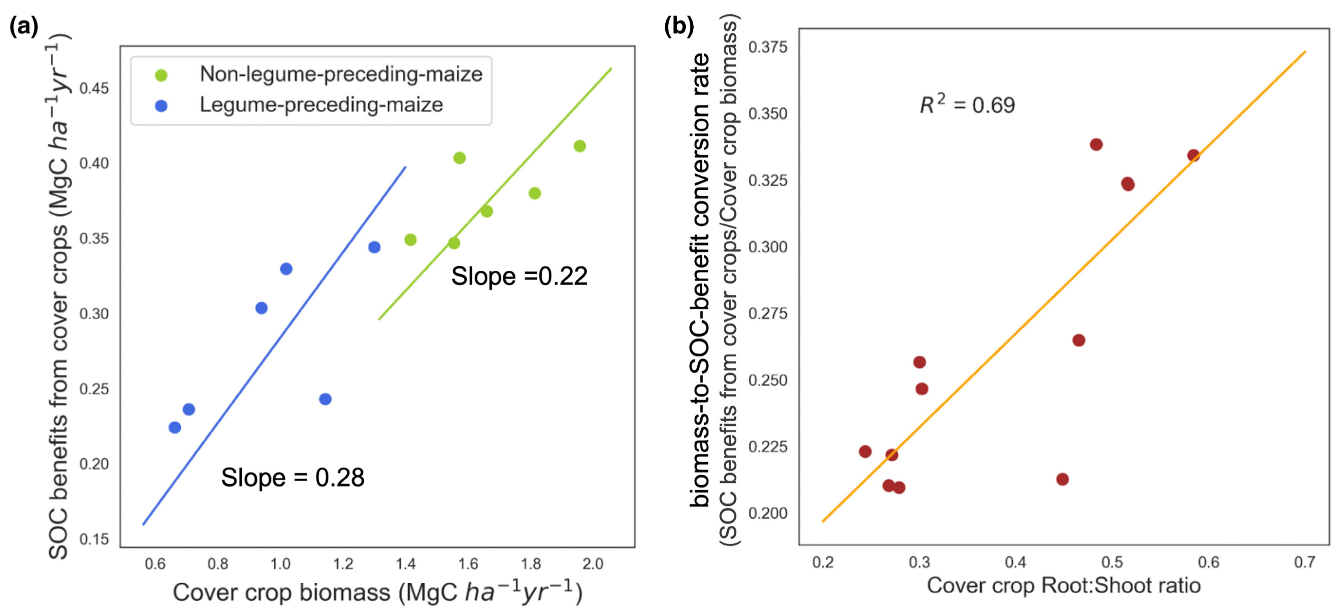

FIGURE 7 (a) Relation between *ecosys* simulated SOC benefits from cover crops (multi-year averaged) and cover crop biomass (multi-year averaged) at six cover crop sites in Illinois from 2013 to 2020. Each point represents one rotation at one site, the points with green color represent non-legume-preceding-maize conditions, and the points with blue color represent legume-preceding-maize conditions. (b) Relation between *ecosys* simulated biomass-to-SOC-benefit conversion rate (multi-year averaged) and cover crop root:shoot ratio (multi-year averaged) at six cover crop sites in Illinois from 2013 to 2020. Each point represents one rotation at one site.

3.4.3 | Factor 3: Climate during the cover crop growth period

We found that temperature and precipitation during the cover crop growth period control cover crop growth and thereby affect SOC benefits. Our sensitivity analysis using *ecosys* revealed the impacts on carbon budgets from climate during the cover crop growth period (Figure 8). Specifically, we found that warmer cover crop growth period leads to larger cover crop biomass, and thus leading to larger SOC benefits. Higher temperature during the winter and early spring resulted in larger cover crop biomass, partially offset by a larger R_H due to stimulated microbe activities during the same period (Figure 8a). Our results showed that warmer winters overall have positive impacts on SOC benefits, indicating that the increase in SOC decomposition rates (carbon output) does not exceed the increase in cover crop productivity (carbon input). Under the challenge of climate change, warmer winters could lead to larger SOC benefits from cover crops. Specifically, our results showed that SOC benefits from cover crops increase on average by 0.05 MgC ha^{-1} year^{-1} for a 2°C air temperature increase in the cover crop growth period.

The influences of precipitation during the cover crop growth period on SOC benefits from cover crops in our study sites were not significant, which have the mean annual precipitation ranging from 910 to 1320 mm/year (Figure 8b). Through the sensitivity analysis for precipitation, we found that in Illinois sites the impacts on SOC benefits from higher precipitation are not significant through a *t*-test ($p < .01$). Larger precipitation during the cover crop growth period may reduce cash crop NPP, because the larger precipitation leads to increased soil moisture, which causes oxygen stress in the early growth stage of cash crops. Higher precipitation also results in oxygen stress for microbial decomposition and thereby reducing R_H from the simulation results. In summary, combined effects from increased precipitation during the cover crop growth period are complex and site specific.

3.4.4 | Factor 4: Cover crop planting date and terminating time

Longer cover crop growth period can increase SOC benefits from cover crops. We found that earlier planting and later terminating result in larger cover crop biomass, thus leading to larger SOC benefits

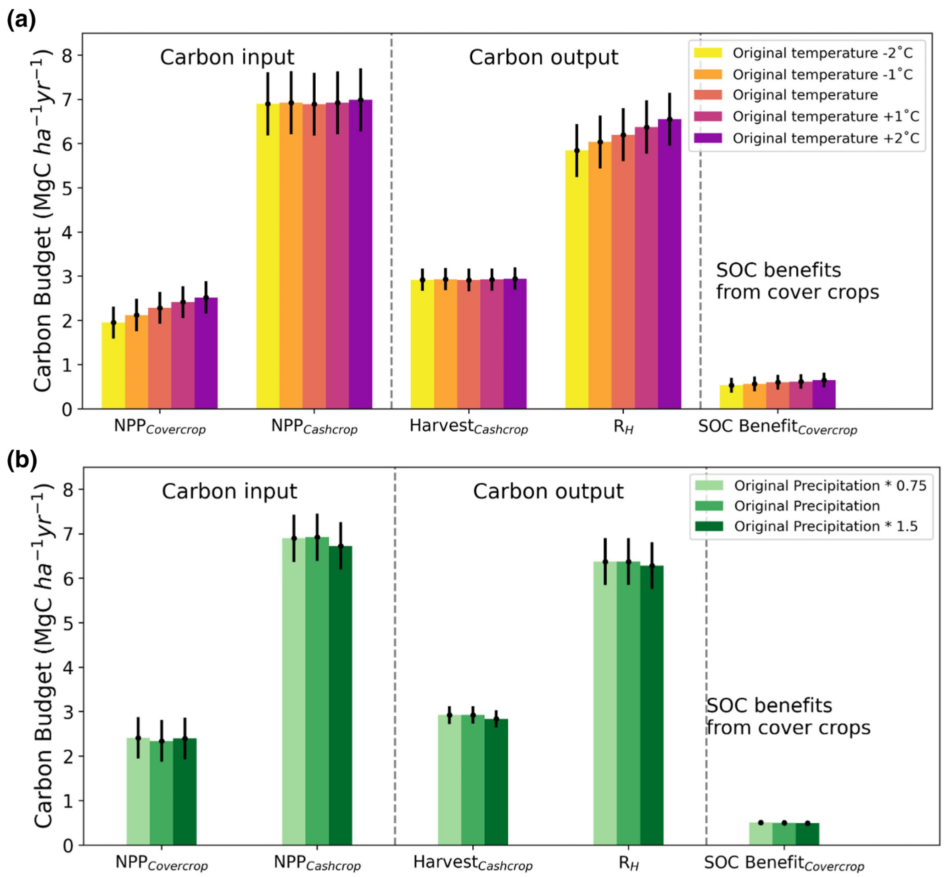

FIGURE 8 (a) *Ecosys* simulated carbon budget at six cover crop sites in Illinois under non-legume-preceding-maize conditions with changes applied to temperature during the cover crop growth period. (b) *Ecosys* simulated carbon budget at six cover crop sites in Illinois under non-legume-preceding-maize conditions with changes applied to precipitation during the cover crop growth period. SOC benefits from cover crops represent additional SOC benefits brought by cover crops compared to without-cover-crop conditions (same climate change factors applied). Error bars represent standard deviation among six cover crop sites.

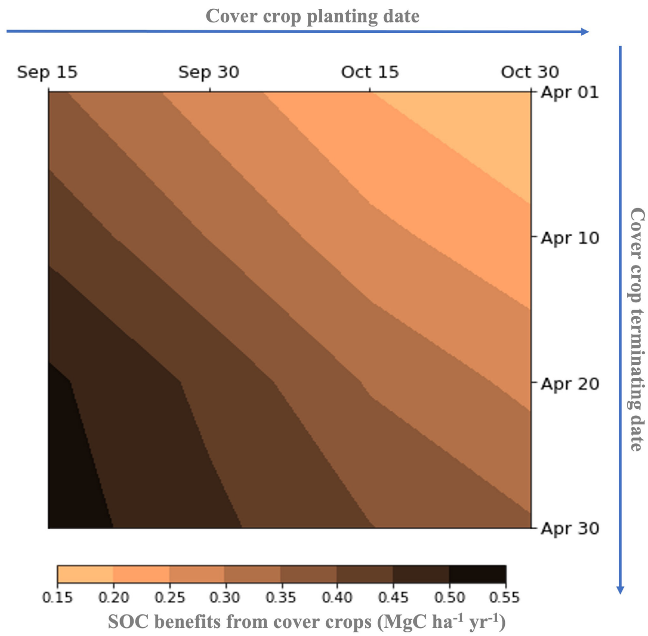

FIGURE 9 *Ecosys* simulated SOC benefits from cover crops (multi-year averaged) under non-legume-preceding-maize conditions from 2013 to 2020 with different cover crop planting and terminating time at MN site.

from cover crops. When the cover crop growth period is expanded by 50% from 5 to 7.5 months, SOC benefits from cover crops increase by 266% from 0.15 to 0.55 MgC ha^{-1} $year^{-1}$ (Figure 9). Earlier planting and later terminating allow cover crops to achieve larger biomass, which directly benefits SOC but has the risk of reducing maize yield and maize residue (Qin et al., 2021). In addition to the competition for resources (e.g., N, water, and oxygen), the allelopathy effects of winter cover crops may also negatively affect cash crop growth (Koehler-Cole et al., 2020). Allelopathy effects suggest that chemicals released by cover crops into the soil may inhibit the growth of following cash crops (Zhang et al., 2021), which could be another reason for the trade-off between cover crop biomass and cash crop yield.

4 | DISCUSSION

4.1 | Comparing the simulated SOC benefits from cover crops with prior studies

In this study, we used *ecosys* to quantify the SOC benefits from cover crops after rigorous calibration and validation with various long-term field experiment data. Validation of SOC data at the Morrow Plots demonstrates the capability of the *ecosys* model to capture long-term SOC change. *Ecosys* also performed well in modeling SOC change in winter wheat rotations over 70 years at the Breton plots in Grant et al. (2020). Accurate modeling SOC change in long-term agricultural systems builds the foundation for further assessments for SOC benefits. Then the validation of SOC change under with- and without-cover-crop conditions at the DS02 site assures the model capability in accurate quantification of SOC benefits from cover crops. We found that *ecosys* simulations not only match the SOC observations, but also reproduce the responses of SOC change to environmental factors (i.e., initial soil conditions and climate during cover crop growth period), which enables further assessment to optimize cover crop planting strategies.

We also found from the field data that SOC concentrations of surface soils decreased at the Morrow Plots over the last century, especially for the first several decades after the start of cultivation. Studies have now reached the consensus that intensive agriculture increases the carbon release from soil to the atmosphere (Lal, 2002; Miles & Brown, 2011), which stressed the need to incorporate conservative practices, such as cover crops, to slow down the SOC decreasing trends.

SOC benefits from cover crops in the model simulations are also compared with various meta-studies (Table 2). Average SOC benefits from cover crops in the *ecosys* simulations averaged 0.33 MgC ha^{-1} $year^{-1}$ and 0.40 MgC ha^{-1} $year^{-1}$ for multiple types of cover crops at six cover crop sites and for the DS02 site, respectively. Overall, our results of SOC benefits are consistent with results of meta-studies, demonstrating the *ecosys* model as an effective tool in accurately quantifying SOC benefits from cover crops at the field-scale under different conditions in climate and soil properties. Meanwhile, we found that SOC benefits from cover crops have a large variation in meta-studies: the mean SOC benefits from cover crops reported by Jian, Du, and Stewart (2020), Jian, Du, Reiter, and Stewart (2020) and Abdalla et al. (2019) are twice as much as what was reported by McClelland et al. (2021). One possible reason is the differences in the depth of measurements included in the study. Surface soils and subsurface soils have different responses after planting cover crops. Our modeling results showed that surface SOC increases in with-cover-crop conditions compared to without-cover-crop conditions (Figure S3). However, in deeper soil layers (>0.3 m), we found that the SOC stock decreases in with-cover-crop conditions compared to without-cover-crop conditions (Figure S3). This pattern is consistent with former studies (Jian, Du, Reiter, & Stewart, 2020; Jian, Du, & Stewart, 2020; Tautges et al., 2019). Due to the opposite directions of SOC benefits from cover crops in different soil layers, if measurements are only conducted in surface layers, SOC benefits from cover crops could be exaggerated. However, even taking account of differences in measurements, we could not neglect the large uncertainties in SOC benefits from cover crops in current studies. This large variation in different studies further stressed the need for accurate quantification of field-scale SOC benefits from cover crops.

In addition to the SOC benefits, cover crops could also benefit the soil environment from other perspectives. We found from the simulations that microbial biomass carbon increased with cover crops (Figure S4), which is consistent with former studies finding improvements in soil fertility (Alvarez et al., 2017; Fageria et al., 2005; McDaniel et al., 2014). Studies also reported that cover crops could reduce cash crop root disease, slow down soil erosion, and improve soil physical properties (Abdalla et al., 2019; Alvarez et al., 2017; De

TABLE 2 Comparison of *ecosys* simulated SOC sequestered by cover crops with meta-studies.

	SOC benefits from cover crops (MgC ha−1 year−1) Mean	Uncertainty	Number of studies	Number of sites	Region	Depth	Source
Meta-studies	0.32	0.08	37	139	Worldwide	A mean soil depth of 0.22 m	Poeplau and Don (2015)
	0.54	0.57	106	372	Worldwide	Normalized to 0–0.3 m	Abdalla et al. (2019)
	0.56	–	131	1195	Worldwide	Different depth	Jian, Du, Reiter, and Stewart (2020), Jian, Du, and Stewart (2020)
	0.21	–	40	181	Temperate latitude zone	Different depth	Mcclelland et al. (2021)

	SOC benefits from cover crops ($MgC\ ha^{-1}\ year^{-1}$) Mean	Uncertainty	Region	Depth	Original field study
Model simulation	0.33	0.06[a]	Six sites in IL	0–2 m	Behnke and Villamil (2019)
	0.4	0.04[b]	Dixon springs, IL	0–0.75 m	Olson et al. (2014)

[a]Uncertainty is calculated as standard deviation among different rotations in different sites.
[b]Uncertainty is calculated as standard deviation among plots with different tillage practices.

Baets et al., 2011; Wen et al., 2017), which have not yet been explored by the *ecosys* model but are worth further studies.

4.2 | Mechanistic pathways of SOC benefits from cover crops

SOC benefits from cover crops and SOC change are controlled by four major controlling factors (Figure 10), including (1) initial soil properties (e.g., SOC stock and clay content), (2) cover crop types, (3) climate during the cover crop growth period, and (4) cover crop planting and terminating time. Among these factors, initial soil properties have small influence on SOC benefits from cover crops but are important indicators for SOC change. The other three factors (i.e., cover crop types, climate during the cover crop growth period and cover crop planting and terminating time) control SOC benefits from cover crops. Growing cover crops not only adds net carbon input to the system, but also affects cash crop growth and soil microbe activities (Kim et al., 2020).

Higher temperature during cover crop growth period, selecting cold-tolerant cover crop species, earlier planting and later terminating all contribute to larger cover crop biomass, thus leading to larger SOC benefits from cover crops. We used the holistic carbon budget of the farmland to analyze the impacts on SOC benefits from different factors on their interactive controls and direct controls (i.e., carbon input and carbon output). By taking into account different carbon fluxes of the whole agroecosystem, we assessed the impacts from cover crops on carbon cycle through carbon fluxes from cover crops, cash crops, and the soil (i.e., R_H). Non-legume cover crops that are more cold tolerant directly contribute to larger cover crop biomass that increases SOC. Meanwhile, cover crops with larger root biomass that have longer mean residence time in the soil also result in larger SOC benefits due to smaller R_H. As for climate, the increase in cover crop biomass outweighs the increase in R_H in response to increased temperature during cover crop growth period. The impacts from precipitation during cover crop growth period on SOC benefits are not significant in Illinois study sites with wet springs due to combined effects on reduced crop residue and reduced R_H. It is also worth noting that larger precipitation can impact SOC benefits through two different pathways in dry sites elsewhere: (1) In contrast to wet conditions, increased precipitation in dry sites can have positive impacts on cash crop growth by alleviating water stress, thus leading to increased cash crop residue as carbon input for SOC; (2) Wetter soil could accelerate decomposition by increasing microbial activity (Kalbitz et al., 2000), thus leading to increased R_H that increases SOC loss. Finally, earlier planting and later terminating increase cover crop biomass that leads to larger SOC benefits from cover crops, although there might be a trade-off between cover crop biomass and cash crop yield (Qin et al., 2021). Overall, increasing carbon input and reducing carbon output for the cover crop systems could increase SOC benefits from cover crops and there are different pathways to achieve that.

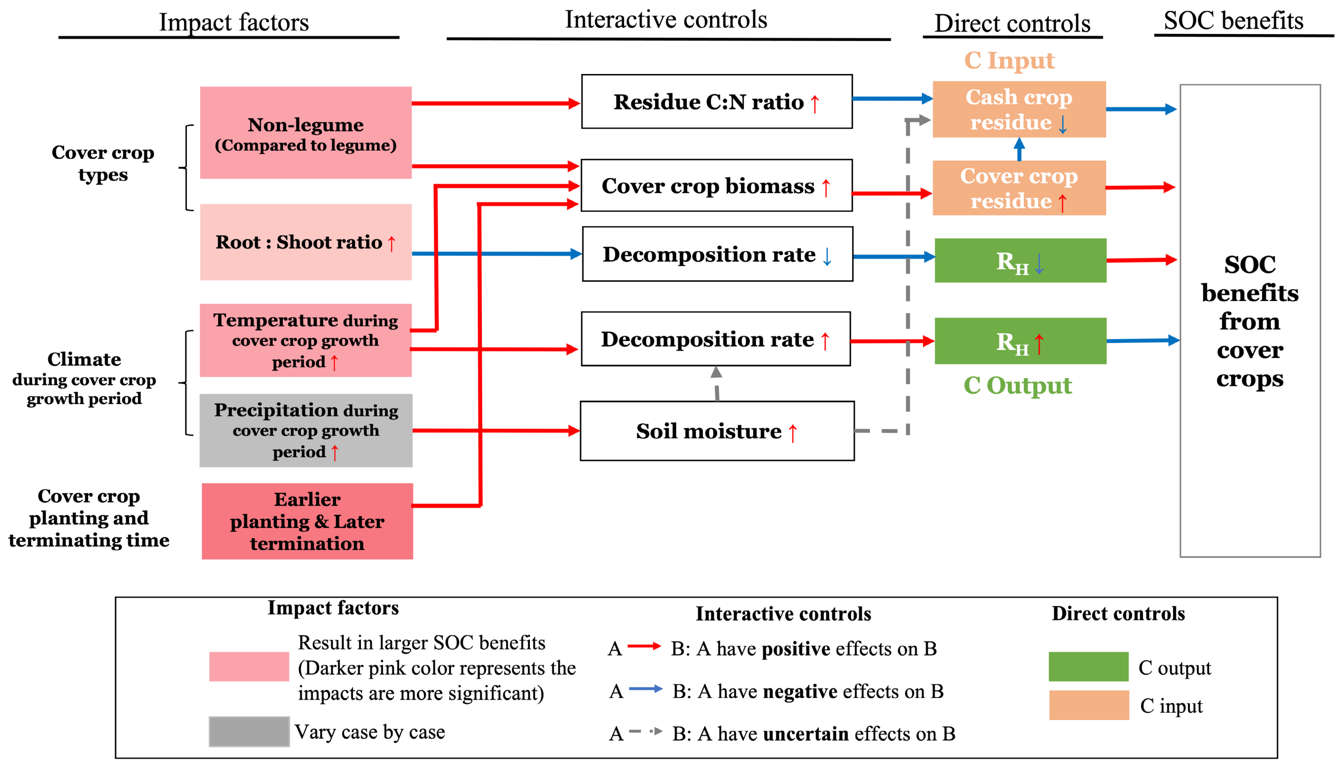

FIGURE 10 Impact factors and their interactive controls on SOC benefits from cover crops in the central US Midwest, including different cover crop types, climate during the cover crop growth period and cover crop planting and terminating time.

4.3 | Management practices to maximize SOC benefits from cover crops

We found that cover crops require proper management practices to achieve larger SOC benefits and minimize potential risks. Our results showed that management practices (e.g., selecting cover crop types and controlling cover crop growth period) are major controlling factors of SOC benefits from cover crops and cash crop production, indicating that cover crop benefits could be maximized through optimal management practices (Figure 10). Prior survey studies also showed that larger net profits of cover crops are achieved by more experienced farmers (Roesch-McNally et al., 2018), emphasizing the importance of proper management practices for cover crops.

Selecting cover crop types and managing the cover crop growth period are effective management practices, but the optimal practices at field level requires further assessment. First, proper management decisions of cover crops such as cover crop type selection are critical to maximize SOC benefits and reduce cash crop yield reduction. For instance, legume cover crops have a smaller negative impact on maize yield than non-legume cover crops (Qin et al., 2021). However, legume cover crops are more expensive to plant and less tolerant to cold climates (CTIC, 2017) and studies have found that legume cover crops can increase N_2O emission, which offsets the SOC benefits on GHG emission reductions (Basche et al., 2014). Therefore, the suitability of different types of cover crops can be site specific and requires further assessments. Second, optimizing planting and terminating dates are critical in cover crop management but there is a trade-off between cover crop biomass and maize yield. Our modeling results found that longer cover crop growth period increases SOC benefits but has larger risks of cash crop yield reduction, which is consistent with earlier studies (Alonso-Ayuso et al., 2018; Balkcom et al., 2015; Chatterjee et al., 2020), suggesting from the SOC perspective, the increase in cover crop biomass due to longer growth period exceeded the reduction in maize residue. However, due to the trade-offs between SOC benefits from cover crops and cash crop yield, single metric evaluations are not adequate to select proper cover crop type and optimize cover crop planting and terminating dates. In short, the selection of cover crop types and planting and terminating date should be determined with a comprehensive evaluation framework.

4.4 | Economic and policy implication of adopting cover crops in the central Midwest

To design the optimal management of planting cover crops, one should take full consideration of both scientific and economic factors, such as cover crop planting/seed cost, yield impacts on cash crop and cash crop price, carbon credit payments, government cost-share and other assistance payment, and co-benefits of cover crops. Such efforts require field-level assessments with the combination of economic analysis and ecosystem models. Based on recent meta-studies (Table 2), we found that compensation for carbon credits alone may not exceed cover crop costs under current carbon credit prices in voluntary markets. Average cost of planting cover crops is estimated to be around

$35–45/acre/year in the US Midwest (Plastina et al., 2018). Financial incentives for growing cover crops are from two channels at this moment: direct subsidy from the government's cost-sharing program, and carbon credit payments from voluntary markets. The former is the dominant channel and two main federal programs that subsidize cover crop adoption are Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP). However, only 27% of approved applications for EQIP received funding in fiscal year 2020 (Congressional Research Service (CRS), 2022). For most small- and middle-sized farmers who usually cannot get access to professional guidance in preparing application documents to government grants, the complicated application procedures of EQIP and CSF cause significant hurdles. The newly introduced Pandemic Cover Crop Program (PCCP) is the only federal-level cover crop supporting program that has a simple enrollment procedure. However, PCCP only offers a $5/acre/year discount on growers' crop insurance premium, which is too small compared to the cost of planting cover crops.

Consequently, adopting cover crops is not yet an economically sound move for most growers in the central Midwest. Taking Illinois as an example, a typical Illinois grower who does not enroll in EQIP or CSP, could only expect to receive a $5/acre/year discount on his crop insurance premium (Illinois Department of Agriculture, 2022) and $10-28/acre/year based on California carbon price (Worldbank, 2022) from selling carbon credits on voluntary markets assuming there is a buyer who want to purchase it (Table S2). Thus, at this stage, financial incentives in Illinois for cover crops are not large enough to cover the planting costs. The net benefits of cover crops could be even smaller if taking into account possible negative yield impacts on cash crop, cost for MRV (Monitoring, Reporting and Verification), and reserved credits by registries for potential GHG reduction reversal (Bellassen et al., 2015). Therefore, the adoption rate of cover crop is not expected to increase unless carbon credit price in voluntary markets rises significantly, or government significantly increases economic incentives and technical assistance, or environmental co-benefits of cover crops (e.g., N leaching reduction, weed suppression and soil erosion reduction) could be monetized. In other US states that succeed in promoting cover crops, such as Maryland, governments offer cost-sharing subsidies to cover crops up to $75/acre (Maryland Department of Agriculture, 2022), which is sufficient for farmers to plant cover crops in most cases. As a consequence, Maryland has a high cover crop adoption rate of 33% in 2017, much larger than the general adoption rate of 5% in the central Midwest (USDA NASS, 2019). Therefore, more interventions from the government and society are urgently needed for promoting the adoption of cover crops in the central Midwest.

4.5 | Limitation and implication of data requirements for cover crop modeling study

Accurate quantification of SOC change and SOC benefits from cover crops are the key to assess cover crop adoption and guide investment for sustainable agriculture. With more government investment on climate-smart agriculture (Lipper et al., 2014; Paustian et al., 2016; USDA Press, 2022) and increased private sector's engagement from the agricultural supply chain for low carbon farming and emerging carbon markets (Bossio et al., 2020), such a need for more accurate outcome quantification of conservation practices becomes even more urgent than ever. Rigorous calibration and validation are required for any process-based model before their use to quantify SOC benefits and reliable field data are a prerequisite for that. We highlight the importance of measuring belowground biomass in cover crop studies. However, currently there is a scarcity in high-quality field data for studying cover crop systems, as belowground biomass is seldom measured (Austin et al., 2017). Our results show that larger belowground biomass increases SOC benefits but has a large variation among site-years (Figure 7b and Figure S2). Even though we calibrated and validated cover crop aboveground biomass, the uncertainties in cover crop biomass and SOC benefits are non-negligible, stressing the need for measurements of belowground biomass. Knowing the influence of belowground–aboveground allocation helps design and select better cover crops. Models could be further improved in belowground mechanisms if additional belowground ground truth data is available.

Field measurements of soil carbon in cover crop studies should also be conducted to a deeper depth with longer time span. The SOC measurements in most cover crop studies are limited to 0.15–0.30 m depth (Jian, Du, Reiter, & Stewart, 2020; Jian, Du, & Stewart, 2020; McClelland et al., 2021). Our modeling results also showed that surface SOC and deep layer SOC have opposite responses to cover crops (Figure S3), urging the need for field experiments with SOC stock measured to at least 0.6 m. Soil sampling in paired fields with a deep depth reveals the true SOC benefits from cover crops and avoids risks of exaggerated SOC benefits. Meanwhile, long-term field experiments (>5 years) for cover crops are also of scarcity (Jian, Du, Reiter, & Stewart, 2020; Jian, Du, & Stewart, 2020). By modeling long-term cover crop growth, we found that SOC benefits from cover crops (excludes residue carbon) can accumulate if cover crops are continuously planted (Figure S5). However, if cover crop adoption terminated (i.e., followed by winter fallow), SOC benefits from cover crops may start to decay while the maximum SOC benefits are reached within 2 years after the termination of cover crops (Figure S5). We thus suggest having more long-term cover crop experiments that have soil measurements to a deep depth, and these experiment data can help us to improve the *ecosys* model in simulating cover crop SOC benefits and further guide field management.

5 | CONCLUSION

In this study, we used *ecosys* to quantify SOC benefits from cover crops in maize–soybean rotations in the central US Midwestern agroecosystems. After rigorous calibration and validation of *ecosys* in simulating SOC change with field-measured data, we assessed SOC benefits from cover crops under different conditions in climate, soil properties, and management practices. We found from the simulations that cover crops could bring SOC benefits to Illinois cropping systems of 0.38 ± 0.06 MgC ha^{-1} year^{-1}

in non-legume-preceding-maize conditions and 0.28 ± 0.05 MgC ha^{-1} year^{-1} in legume-preceding-maize conditions, respectively. Our study revealed that different factors control SOC change and SOC benefits from cover crops, including initial soil properties, cover crop types, climate during the cover crop growth period, and cover crop planting and terminating time. Specifically, large initial SOC and low clay content lead to fast SOC loss but their impacts on SOC benefits are not significant. As for cover crop types, non-legume cover crops have larger SOC benefits but smaller biomass-to-SOC-benefit conversion rates compared to legume cover crops in the central US Midwest. We also found that larger cover crop root biomass increases SOC benefits. Warmer cover crop growth period also leads to larger SOC benefits from cover crops while the impacts on SOC benefits from precipitation during the cover crop growth period are site specific. To maximize SOC benefits and minimize potential risks, cover crops need to be well managed. Selecting proper cover crop types and controlling cover crop planting and terminating time are effective ways to achieve that. Field-level cover crop suitability assessments are needed to best guide cover crop management for growers.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Illinois Data Bank at https://databank.illinois.edu/datasets/IDB-4013912.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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