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How does uncertainty of soil organic carbon stock affect the calculation of carbon budgets and soil carbon credits for croplands in the U.S. Midwest?

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ABSTRACT

Cropland carbon budget depicts the amount of carbon flowing in and out of agroecosystems and the changes in carbon stocks of soil and living biomass during the same period. Soil carbon credit is the additional change in soil carbon stock under certain farming practices compared with the business-as-usual practices. Accurately calculating cropland carbon budget and soil carbon credit is critical to assessing climate change mitigation potential in agroecosystems. The calculation of cropland carbon budget and soil carbon credit is sensitive to local soil and climatic conditions, especially initial soil organic carbon (SOC) stock, which is determined by both SOC concentration (SOC%) and bulk density (Bulk_Density). SOC stock data are either from soil sampling or gridded public survey data. In agroecosystem models, SOC stock data are a key model input for quantifying cropland carbon budget and soil carbon credit. However, various types and degrees of uncertainties exist in SOC stock datasets, which propagate to the quantification of SOC stock change. In particular, a large discrepancy is found in two widely used SOC stock datasets — Rapid Carbon Assessment dataset (RaCA) and Gridded Soil Survey Geographic Database (gSSURGO) — in the U.S. Midwest, with a relative difference (quantified using Normalized Root Mean Square Error, NRMSE) of 48.0% for 0–30 cm SOC stock between the two datasets. It remains largely unclear how uncertainty in SOC stocks affects the calculation of cropland carbon budget and soil carbon credit. To address this question, we used a well-validated process-based agroecosystem model, *ecosys*, to assess the impacts of SOC stock uncertainty on carbon budget and soil carbon credit calculation in the U.S. Midwestern corn-soybean rotation systems. Our results reveal the following findings: (1) A sizable discrepancy exists in simulated cropland carbon budget between using gSSURGO and using RaCA for their SOC% and Bulk_Density as model inputs, with a Pearson correlation coefficient (r) of only 0.4 for simulated change of SOC stock (ΔSOC) using these two different soil datasets. (2) Simulated cropland carbon budget components were more sensitive to initial SOC% than to Bulk_Density. For example, the upper and lower quartiles of multi-year averaged ΔSOC were −29.8 and 4.8 gC/m^2/year for the selected counties respectively, with an uncertainty of 13.7 and 0.7 gC/m^2/year induced by uncertainties in initial SOC% and Bulk_Density, respectively. (3) Both simulated ΔSOC and its uncertainty were negatively correlated with initial SOC%, whereas ΔSOC was negatively correlated with air temperature, and ΔSOC uncertainty was positively correlated with air temperature. (4) The uncertainty of calculated soil carbon credits was much smaller compared with the uncertainty of calculated absolute carbon budgets assuming the same SOC stock uncertainty level in the inputs. Specifically, in our assessment comparing planting cover crops vs no cover crop, the uncertainty of calculated soil carbon credits induced by initial SOC%

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uncertainty was less than 4% (relative to the quantified value of the soil carbon credits) for 90% of the cases. Our analysis highlights that high accuracy measurement of SOC% as inputs is needed for the calculation of cropland carbon budgets; however, soil carbon credit quantification is much less sensitive to the initial SOC% inputs, and the current publicly available soil datasets (e.g., gSSURGO) are largely suitable for the calculation of soil carbon credits.

1. Introduction

Terrestrial ecosystems play an important role in the global carbon cycle (Friedlingstein et al., 2020) and have been argued to have high potential for climate change mitigation by conserving and sequestering carbon (Bossio et al., 2020; Fargione et al., 2018; Minasny et al., 2017). Various natural climate solutions (e.g., conservation, restoration, and/or improved land management actions across global forests, wetlands, grasslands, and agricultural lands) have been proposed to increase carbon storage and mitigate greenhouse gas emissions in terrestrial ecosystems (Bossio et al., 2020; Fargione et al., 2018; Griscom et al., 2017). However, accurately accounting for carbon input and output flows under different interventions to assess their climate change mitigation potential remains challenging (Novick et al., 2022). Croplands, as heavily managed terrestrial ecosystems providing food, fiber, biofuel, and other ecosystem services to human society, play a critical role in regional and global carbon budgets (Zhang et al., 2015). Croplands under intensive cultivation have been losing soil carbon compared to pre-cultivation land uses such as forests or grasslands (Lal, 2002). Therefore, reversing soil carbon loss in croplands is a priority not only for climate change mitigation but also for improving soil health (Lal, 2004). Several management practices may increase soil carbon storage for croplands, such as cover cropping and reduced or no tillage (Havlin et al., 1990; Jian et al., 2020; West & Post, 2002; Xu et al., 2019). However, the effectiveness of these management practices to increase soil carbon storage and their impacts on other cropland carbon budget terms (e.g., ecosystem gross primary productivity, ecosystem respiration, and crop yield) needs to be assessed locally in order to account for soil type and climate effects (Ogle et al., 2019).

Technically, both observational and modeling approaches can be used to assess cropland carbon budgets under different management practices (Hollinger et al., 2005; Smith et al., 2010; Zhou et al., 2021a). Field observations of changes in soil organic carbon (SOC) storage and carbon fluxes like photosynthesis and respiration have significantly advanced our understanding of carbon cycling in the agroecosystems (Kucharik et al., 2001; Luo et al., 2017; Zhou et al., 2021a). However, it is often not feasible or cost-effective to collect field observations across every acre of croplands due to the high financial and labor costs. Satellite observations can provide estimations of a few carbon fluxes, such as harvested yield (Guan et al., 2016, 2017; Peng et al., 2018, Peng et al., 2020) and gross primary productivity (Jiang et al., 2021), but other carbon budget components such as heterotopic respiration are inadequately quantifiable from satellites. Moreover, it is challenging to use soil sampling to calculate soil carbon credits, because it requires comparison with a counterfactual scenario in which the intervention does not take place (Guan et al., 2022). Though we may estimate the counterfactual differences of soil carbon change using paired sites in one field, this method still has high uncertainty due to variability in soil type and topography between sites, and it is also practically difficult to implement (e.g., rarely a farmer would allow such a treatment experiment in their commercial field). Process-based models have been widely used to calculate carbon budgets for croplands (Huang et al., 2009; Li et al., 1994; Zhou et al., 2021a). However, large uncertainties exist in model-simulated cropland carbon budget mainly due to uncertainties in model structure, parameters, weather, and soil inputs (Jung et al., 2007; Mishra et al., 2017; Shi et al., 2018; Sulman et al., 2018). Among various soil input data needed by the process-based models, initial SOC stock is one of the most important input variables (Li et al., 1994; Sulman et al., 2018), and variation in initial SOC stock influences many processes including decomposition rates, soil water and oxygen dynamics, plant growth, soil microbial activity, and soil respiration (Cotrufo et al., 2013, 2015; Delogu et al., 2017; Li et al., 2021; Li et al., 2019; Liang et al., 2018; Murphy, 2015; Oldfield et al., 2019; Rajkai et al., 2004).

There are large uncertainties existing in currently available SOC stock datasets that serve as critical inputs for carbon balance models (Goidts et al., 2009; Jandl et al., 2014; Potash et al., 2022). For soil sampling data, the accuracy of measured SOC stock depends on the representativeness of sampling locations and time, and the measurement uncertainties of SOC concentration (SOC%), bulk density (Bulk_Density), and gravel content (Goidts et al., 2009; Meersmans et al., 2009). For example, using the state-of-the-art soil sampling methods, uncertainty of SOC% measurements can still be up to 16% depending upon the method adopted, while the uncertainty of Bulk_Density measurements is even larger and can lead to 10–40% uncertainty in SOC stock estimation (Goidts et al., 2009; Meersmans et al., 2009). In addition, the impact of gravel content on SOC stock estimation can be difficult to determine and is often omitted due to a lack of data (Gerzabek et al., 2005). Gridded soil datasets, primarily interpolated from soil sampling data and usually providing soil properties with representative categorical values, are widely used as model input data to support the simulation of carbon budget at regional to global scales. Those datasets not only contain uncertainties from soil sampling and interpolation methods, but also contain uncertainties from the impacts of historical land cover change and land management practices on SOC stock (Hengl et al., 2017; Ramcharan et al., 2018; Veenstra & Lee Burras, 2015). Due to these factors, SOC stocks obtained from different soil datasets have discrepancies with each other (Ramcharan et al., 2018; Zhong & Xu, 2011). It remains unclear how these uncertainties of SOC stock affect the calculation of cropland carbon budgets and soil carbon credits using process-based models.

In this study, we used an advanced agroecosystem model, *ecosys*, to quantify the impacts of uncertainty in initial SOC stock on the calculation of cropland carbon budgets and soil carbon credits over the U.S. Midwest, which is one of the most important global food baskets producing one third of global corn and soybean production. We aim to answer the following questions: (1) What are the impacts of uncertainty in the measured SOC% and Bulk_Density on the calculation of cropland carbon budgets in the U.S. Midwest? (2) How does this uncertainty manifest itself under different soil and climate conditions? (3) How large are the impacts of uncertainty in the measured SOC% and Bulk_Density on the calculation of soil carbon credits in the U.S. Midwest? To answer the first question, we first compared the cropland carbon budgets calculated based on SOC% and Bulk_Density from the Gridded Soil Survey Geographic Database (gSSURGO) and Rapid Carbon Assessment (RaCA) datasets, and quantified the impact of SOC stock inconsistency on the calculation of cropland carbon budgets over the U.S. Midwest (Section 3.1-3.2); we then conducted sensitivity analyses of quantifying cropland carbon budgets at different SOC% and Bulk_Density levels across 9 selected counties in Illinois, Iowa, and Indiana states encompassing representative climate and soil variations in this region (Section 3.3). To answer the second question, we simulated the impacts of SOC% and Bulk_Density uncertainty on cropland carbon budgets at the county scale across Illinois, Iowa, and Indiana states and also at gSSURGO soil map unit scale for Champaign County, Illinois. Based on those simulations, we investigated the spatial heterogeneity of uncertainty in cropland carbon budgets induced by SOC stock data uncertainty, and analyzed how this uncertainty varies with climate and soil conditions (Section 3.4). To answer the third question, we simulated the cropland carbon budgets at county scale assuming non-legume cover crops adopted across Illinois, Iowa, and Indiana states since 2000, and investigated the impacts of uncertainty in SOC% and Bulk_Density on the calculation of soil carbon credits due to the hypothetical cover crop adoption (Section 3.5).

2. Materials and methods

2.1. Soil datasets

We used two mainstream and publicly available soil datasets, RaCA and gSSURGO, in this study. We first compared SOC stock, SOC%, and Bulk_Density over different soil depths from these two datasets to quantify their uncertainties. We then quantified the impacts of uncertainties in SOC stock on the calculation of cropland carbon budgets and soil carbon credits in the U.S. Midwest. The detailed information about these two soil datasets and how we processed the datasets for the comparison were provided as follows.

2.1.1. Rapid Carbon Assessment dataset (RaCA)

The RaCA dataset was developed by the Natural Resource Conservation Service (NRCS), United States Department of Agriculture (USDA) (Loecke et al., 2016) to provide values of the SOC stock under different land cover types across the U.S. In the RaCA dataset, SOC% was obtained by subtracting the measured soil inorganic carbon from the total carbon, where total soil carbon was measured using the combustion method, and inorganic soil carbon was measured using the calcium carbonate calcimeter equivalence approach. The Bulk_Density above 50 cm soil depth was measured using the clod method at −33 kPa matric potential at some of the sites in this dataset. For the sites without Bulk_Density measurements or depths below 50 cm, the Bulk_Density was predicted using pedotransfer functions based on the data from the sites with bulk density measurements using the methodology of Sequeira et al (2014). The accuracies of these predictions were 0.10 to 0.15 Mg/m^3 (Sequeira et al., 2014; Loecke et al., 2016). The SOC stock within a certain soil depth was calculated using the SOC% and the coarse-fragment-adjusted Bulk_Density corresponding to that soil layer.

2.1.2. Gridded Soil Survey Geographic dataset (gSSURGO)

The gSSURGO dataset was derived from the USDA-NRCS Soil Survey Geographic (SSURGO) Database to provide statewide soil data at scales from 1:12,000 to 1:63,360. Because of its high resolution, it is the most widely used soil dataset in the U.S. for field- and subfield-scale agro-ecosystem modeling (Jin et al., 2019). Each soil map unit in gSSURGO has unique soil properties and productivity derived from the National Soil Information System (NASIS) collected by the National Cooperative Soil Survey over the past century (USDA-NRCS, 2021). The concentration of soil organic matter (SOM%) is provided in the gSSURGO dataset, expressed as the weight percentage of decomposed plant and animal residue in soil material with diameter less than 2 mm. We calculated SOC% by assuming that 58% of SOM is organic carbon (Pribyl, 2010). The Bulk_Density we used is the dry weight of soil materials (with

Table 1
Experiment design.

Experiment	Setup	Purpose
Exp 1: Comparison of calculated cropland carbon budgets between using the gSSURGO and RaCA soil datasets.	Four combinations: (1) gSSURGO SOC% + gSSURGO Bulk_Density; (2) RaCA SOC% + RaCA Bulk_Density; (3) gSSURGO SOC% + RaCA Bulk_Density; (4) RaCA SOC% + gSSURGO Bulk_Density.	To quantify the impact of SOC stock inconsistency from two different soil datasets on the calculation of cropland carbon budgets.
Exp 2: Sensitivity of cropland carbon budgets to different levels of SOC% and Bulk_Density.	Selected 9 counties across the U.S. Midwest, and (1) changed the topsoil (0–30 cm) SOC% ranges from 0.1 to 5.9% with a step of 0.2%; (2) changed the topsoil Bulk_Density ranges from 0.9 to 1.7 Mg/m^3 with a step of 0.1 Mg/m^3, respectively.	To investigate the impacts of uncertainty in SOC% and Bulk_Density on the calculation of cropland carbon budgets at different SOC% and Bulk_Density levels.
Exp 3: Simulate the impacts of uncertainties in SOC% and Bulk_Density on the calculation of **cropland carbon budgets** for the U.S. Midwest.	Simulated cropland carbon budgets at the county scale using the gSSURGO majority soil types across Illinois, Iowa, and Indiana states, and also simulated cropland carbon budget at gSSURGO soil map unit scale for Champaign County of Illinois, with the following setup: (1) changed the topsoil SOC% by adding or subtracting 0.77% (the RMSE between SOC% from gSSURGO and RaCA over top 30 cm; see Section 3.1 for more details) from the original values, and calculated the uncertainty in cropland carbon budgets induced by the SOC% uncertainty. (2) changed the topsoil Bulk_Density by adding or subtracting 0.15 Mg/m^3 (the RMSE between Bulk_Density from gSSURGO and RaCA over top 30 cm; see Section 3.1 for more details) from the original values, and calculated the uncertainty in cropland carbon budgets induced by the Bulk_Density uncertainty.	To investigate the impacts of uncertainty in SOC stock on the calculation of cropland carbon budgets, and analyze the spatial variation of such impacts with the variation of climate and soil conditions.
Exp 4: Simulate the impacts of SOC% and Bulk_Density uncertainties on the calculation of **soil carbon credits** for the U.S. Midwest.	Simulated soil carbon credits assuming non-legume cover crops adopted across Illinois, Iowa, and Indiana states during the non-growing seasons since the November of 2000 at county scale using gSSURGO majority soil types, with the following setup: (1) changed the topsoil SOC% by adding or subtracting 0.77% from the original values, and quantified the impacts of uncertainty in SOC% on the calculation of soil carbon credits (i.e., the ΔSOC difference between the scenarios with and without cover crops). (2) changed the topsoil Bulk_Density by adding or subtracting 0.15 Mg/m^3 from original values, and quantified the impacts of uncertainty in Bulk_Density on the calculation of soil carbon credits.	To investigate the impacts of uncertainty in SOC% and Bulk_Density on the calculation of soil carbon credits.

diameter less than 2 mm) per unit volume of soil at one-third bar water tension from gSSURGO (USDA-NRCS, 2022).

2.1.3. Comparison of two soil datasets

We compared values of SOC stock, SOC%, and Bulk_Density from the RaCA and gSSURGO datasets at 410 cropland sites sampled by RaCA across the U.S. Midwest. The RaCA SOC stock at 0–5 cm, 0–30 cm, and 0–100 cm depths were obtained from the RaCA SOC pedon dataset, which was calculated based on measured SOC% and Bulk_Density profiles. To determine the Bulk_Density at 0–5 cm, 0–30 cm, and 0–100 cm depth intervals, we resampled the coarse-fragment-adjusted Bulk_Density measurements using the equal-area quadratic smoothing spline method (Bishop et al., 1999). The SOC% of different soil layers was obtained by dividing the SOC stock with the resampled Bulk_Density for RaCA. For the gSSURGO dataset, we obtained the Bulk_Density and SOM % using the representative value of the majority soil type at the RaCA sampling locations. The SOC stock of gSSURGO was calculated based on the SOC% and Bulk_Density of soil profile (Eq. (1)).

$$SOC_{stock} = Depth \times Bulk\_Density \times SOC\% \tag{1}$$

where SOC_{stock}, *Bulk_Density*, *SOC%*, and *Depth* are the stock of soil organic carbon in Mg/ha, coarse-fragment-adjusted bulk density in Mg/m^3, soil organic carbon concentration at a given soil depth in %, and the thickness of the soil layer in cm, respectively.

2.2. Ecosys model

To study the impacts of SOC stock uncertainty on the calculation of cropland carbon budgets and soil carbon credits, we used an advanced agroecosystem model, *ecosys*, to simulate the cropland carbon budgets with different SOC% and Bulk_Density as model inputs in the U.S. Midwest. The *ecosys* model was developed using biophysical and biochemical principles simulating hourly carbon, water, energy, and nutrient balance in the soil–vegetation-atmosphere continuum within ecosystems (Grant, 2001). It has been applied and validated for agricultural ecosystems under different climate and soil conditions with various land management practices (e.g., tillage, fertilizer management, crop rotation, and irrigation) (Grant, 1997; Grant et al., 2001, 2007,2020; Zhang et al., 2021a, Zhang et al., 2021b). The performance of *ecosys* in simulating major carbon budget components, including gross primary productivity (GPP), net ecosystem exchange (NEE), ecosystem respiration (R_{eco}), and change in SOC stock (ΔSOC), has been validated for major types of ecosystems at both site and regional scales (Grant, 1989c; Grant et al., 2001; Grant & Flanagan, 2007; Mekonnen et al., 2017). In a previous study, we validated the model performance in simulating crop production and carbon budgets with the benchmarks from flux tower observations, USDA National Agricultural Statistics Service (NASS) county scale crop yield survey data, and a novel remotely sensed GPP dataset across the U.S. Midwestern agroecosystems (Zhou et al., 2021a).

In *ecosys*, the dynamics of SOC stock were simulated by adding carbon to soil through leaf and root senescence, root exudation, and harvest residue (both shoot and root), and losing carbon from soil via microbial respiration and leaching (Grant, 2001). At a long time scale (≥annual scale), the dynamics of SOC stock can be approximated as the difference between plant carbon fixation, harvested carbon (e.g., grain), and ecosystem respiration (Eq. (2)) (Baker & Griffis, 2005; Zhou et al., 2021a), which can be used to analyze the contribution of each individual carbon budget components to the final change in SOC stock. In the following analysis, we focused on the impacts of uncertainty in initial soil condition on the calculation of carbon budget components in Eq. (2).

$$\begin{aligned} \Delta SOC &\approx GPP - Harvest - R_{eco} \quad (\geqslant annual\ scale\ for\ a\ cropland) \\ &\approx GPP - Harvest - R_a - R_h \quad (\geqslant annual\ scale\ for\ a\ cropland) \end{aligned} \tag{2}$$

where ΔSOC is the change in soil organic carbon stock, *GPP* is the ecosystem gross primary productivity, *Harvest* is the carbon removed by harvest, R_{eco} is the ecosystem respiration, R_a is the ecosystem autotrophic respiration, and R_h is the ecosystem heterotrophic respiration, respectively.

2.2.1. Plant carbon fixation (GPP), autotrophic respiration (R_a), and crop yield

Carbon fixation (GPP) of the plant canopy in *ecosys* is calculated by summing the photosynthesis of each leaf at different canopy layers, which is simulated at hourly time intervals for each leaf under specific azimuth, leaf inclination, and light exposure conditions (Grant, 1989c; Grant et al., 1989). For C3 plants, the Farquhar model is used to calculate photosynthesis; while for C4 plants, the mesophyll-bundle sheath carbon exchange is considered explicitly. The stomatal resistance used for photosynthesis is calculated based on canopy turgor potential (ψ_t) and potential photosynthesis (V_c') using Eq. 3, considering both the water balance and energy balance for the canopy (Grant, 1995; Grant and Flanagan, 2007).

$$r_{cmin} = 0.64\left(C_b - C_i^{'}\right)/V_c^{'} \quad r_c \text{ driven by rates of carboxylation vs. diffusion} \tag{3a}$$

$$r_c = r_{cmin} + (r_{cmax} - r_{cmin})e^{-\beta\psi_t} \quad r_c \text{ constrained by water status} \tag{3b}$$

where r_c is stomatal resistance of canopy; ψ_t is the canopy turgor potential; C_b is the atmosphere CO_2 concentration in canopy; r_{cmin}, C_i' and V_c' are the minimum canopy stomatal resistance, intercellular CO_2 concentration, and potential canopy CO_2 fixation rate when canopy water potential equals 0 MPa, respectively; r_{cmax} is canopy cuticular resistance, and β is the shape parameter of stomatal resistance.

Carbon fixed by the plant is allocated to shoot and root dynamically for plant respiration and phytomass growth (Grant, 1989a, 1989b). The total autotrophic respiration (R_a) is calculated by summing the oxidation of nonstructural carbon pools in shoots and roots for growth and structural biomass maintenance, and the energy cost for nutrient uptake (Grant et al., 2003). Specifically, R_a is calculated based on the nonstructural carbon products from CO_2 fixation and on shoot and root temperatures, considering the limitation of soil O_2 concentration on root autotrophic respiration. Total respiration is first used for each plant organ's maintenance respiration, which is calculated based on the structural N biomass content, and temperature and moisture stresses for branches, roots, and mycorrhizae, respectively. If total respiration cannot meet total maintenance respiration, remobilization and senescence will occur in the plant organs. If total respiration is more than the demand from maintenance respiration, their difference will be used as growth respiration. Dry matter biomass growth of branches and roots is simulated based on the growth respiration, remobilization, and senescence in different plant organs. The dry matter formed with the growth respiration in shoot is allocated to leaf, sheath, stalk, soluble reserves, husk, cob, and grain dynamically according to the growth stages (Grant, 1989a, 1989b). The final yield is determined by the seed number and kernel mass, which are calculated during pre- and post-anthesis growth stages, respectively, considering plant biomass, nutrients status, and environmental conditions (Grant et al., 2011).

2.2.2. Heterotrophic respiration (R_h)

Ecosys simulates heterotrophic respiration (R_h) with explicit microbial community dynamics, considering the limitations from the concentration of dissolved organic carbon (DOC) produced from the solid organic carbon hydrolysis, oxygen content, microbial N and P content for each substrate-microbe complex, and microbial functional type at different soil layers (Eq. 4) (Dimitrov et al., 2010; Grant, 2014; Grant et al., 2003). There are five organic matter-microbe complexes simulated in *ecosys*, including coarse woody litter, fine non-woody litter, animal manure, particulate organic matter, and humus at different soil layers. Each substrate-microbe complex consists of five organic states, including solid organic matter, dissolved organic matter, sorbed organic matter, microbial residue, and microbial decomposers (Grant, 2014). *Ecosys* considers the heterotrophic, autotrophic, facultative anaerobes, obligate anaerobes, diazotrophic, and obligate aerobe microbial functional types. Heterotrophic respiration is computed as follows,

$$R_h = \Sigma_i \Sigma_n \Sigma_l R_{hi,n,l} \quad \text{Total heterotrophic respiration} \tag{4a}$$

$$R_{hi,n,l} = R'_{h\,i,n,l}\left(U_{O2i,n,l} \Big/ U'_{O2i,n,l}\right) \quad R_h \text{ limited by } O_2 \tag{4b}$$

$$R'_{h\,i,n,l} = M_{i,n,a,l,C}\left\{\boldsymbol{R_{hi,n,l}}\left[Q_{i,l,C}\right]\right\} \Big/ \left\{\left(K_{mQC} + \left[Q_{i,l,C}\right]\right)\right\} f_{tgl} f_{\psi gl} \quad R_h \text{ limited by substrate DOC} \tag{4c}$$

$$\boldsymbol{R_{hi,n,l}} = R'_{hn} min\left\{C_{Ni,n,l,a} \big/ C_{Nj}, C_{Pi,n,l,a} \big/ C_{Pj}\right\} \quad R_h \text{ limited by microbial N and P} \tag{4d}$$

where R_h is the total heterotrophic respiration; $R_{hi,n,l}$ is the heterotrophic respiration of substrate-microbe complex *i* and microbial functional type *n* in soil layer *l*; R'_{hn} is the specific heterotrophic respiration of $M_{i,n,a,l}$ without limitations from DOC, O_2, soil moisture, and nutrients at 25 °C; $U_{O2i,n,l}$ and $U'_{O2i,n,l}$ are active O_2 uptake coupled with radial diffusion of O_2, assuming O_2 demand driven by potential R_h (corresponding to the oxidation of glucose), respectively; $M_{i,n,a,l,C}$ is the active microbial C of microbial functional type *n*; $[Q_{i,l,C}]$ is the concentration of DOC produced from the solid soil organic carbon hydrolysis; K_{mQC} is the Michaelis–Menten constant for $R_h{'}_{i,n}$ on $[Q_{i,C}]$; f_{tgl} and $f_{\psi gl}$ are the responses of microbial growth to soil temperature and soil moisture, respectively; C_{Nj} and C_{Pj} are the maximum ratio of microbial N and P to microbial C, respectively; $C_{Ni,n,l,a}$ and $C_{Pi,n,l,a}$ are the ratio of microbial N and P to microbial C, respectively. More details on soil biogeochemistry processes and parameters of *ecosys* can be found in the supplementary materials of Grant et al. (2019).

2.3. Simulation experiment design

We conducted four different types of simulations (Exp 1 to 4 in Table 1) using *ecosys* to evaluate the impacts of uncertainty in SOC stock on the calculation of cropland carbon budgets and soil carbon credits. In these simulations, we used climate data from North American Land Data Assimilation System (NLDAS-2) (Xia et al., 2012) as model inputs, and ran the model with corn-soybean rotation without irrigation, which reflects typical crop rotations and management practices in the rainfed U.S. Midwest (Zhou et al., 2021b). The crop-specific state-wise fertilizer information from USDA (USDA, 2019) was applied before planting for the simulations over Illinois, Iowa, and Indiana states. The model was run from 1979 to 2018 (1979–2000 was treated as the spin-up period to get the reasonable initial conditions, e.g., soil moisture content, microbial community, and nitrogen content), and the simulated carbon budgets during 2001 and 2018 and the simulated soil carbon credits assuming non-legume cover crops adoption during the non-growing seasons since November of 2000 were used for the following analysis. More detailed information about the model setup for the simulations across Illinois, Iowa, and Indiana can be found in Zhou et al. (2021a).

2.3.1. Definitions of SOC change and soil carbon credits

We defined SOC change (ΔSOC) as the absolute change in SOC stock, which is calculated based on the difference of SOC stock between the end and beginning of the targeted period under a specific crop management, soil, and climate condition (A_0 in Fig. 1). Soil carbon credits are the additional change of SOC under intervention practices compared with the business-as-usual practices. In other words, soil carbon credits are the difference of ΔSOC between the scenarios with and without an intervention practice (Eq. (5), C_0 in Fig. 1).

$$Soil\ carbon\ credits = \Delta SOC_{intervention} - \Delta SOC_{business-as-usual} \tag{5}$$

where $\Delta SOC_{intervention}$ is the SOC stock change of the scenario with an intervention practice, $\Delta SOC_{business\text{-}as\text{-}usual}$ is the SOC stock change of the scenario with business-as-usual practices.

2.3.2. Exp 1: Comparison of calculated cropland carbon budgets between using the gSSURGO and RaCA soil datasets

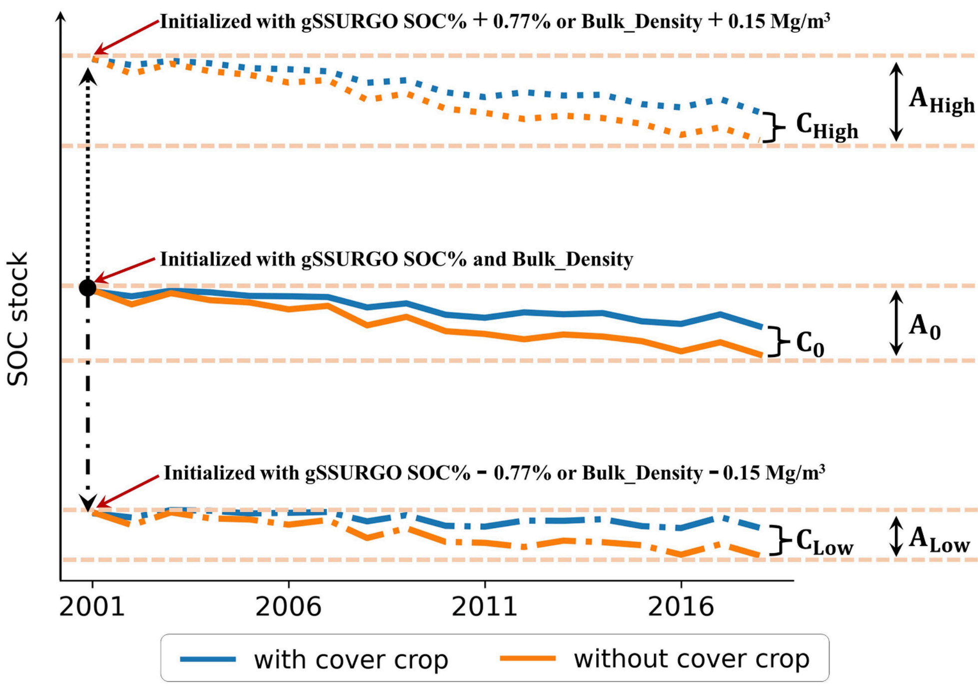
To investigate how the uncertainty of SOC stock from publicly available soil datasets affects the calculation of cropland carbon budgets (GPP, R_a, R_h, Harvest, rate of SOC stock change), we compared the simulated carbon budgets based on gSSURGO and RaCA datasets at the RaCA cropland sites in the U.S. Midwest. Specifically, we designed four different simulations to investigate the impacts of SOC% and Bulk_Density on calculated cropland carbon budgets: (1) using both SOC% and Bulk_Density from gSSURGO; (2) using SOC% from gSSURGO and Bulk_Density from RaCA; (3) using SOC% from RaCA and Bulk_Density from gSSURGO; and (4) using both SOC% and Bulk_Density from RaCA. We did the simulations with 18 gN/m^2 fertilizer, a regionally moderate rate (Cao et al., 2018), before corn planting and no fertilizer before soybean planting, and all other soil properties were from gSSURGO except SOC% and Bulk_Density.

2.3.3. Exp 2: Sensitivity of cropland carbon budgets to different SOC% and Bulk_Density levels

We selected 9 counties in the U.S. Midwest, which cover representative soil and climate variation in this region (Fig. 2a), to investigate the sensitivity of cropland carbon budgets to different levels of SOC% and Bulk_Density. In the simulations, soil properties of the major soil types over croplands in each county from gSSURGO were used as initial soil inputs. To simulate the sensitivity of cropland carbon budgets to different SOC% levels, we used the topsoil (0–30 cm) SOC% scenarios from 0.1% to 5.9% with an interval of 0.2%, which encompasses most SOC% levels in the U.S. Midwest, and using Bulk_Density of major soil types over croplands in each county from gSSURGO. To simulate the sensitivity of cropland carbon budgets to different Bulk_Density levels, we used the topsoil Bulk_Density scenarios from 0.9 to 1.7 Mg/m^3 with an interval of 0.1 Mg/m^3 to cover the range of Bulk_Density in this region, and using SOC% of major soil types over croplands in each county from gSSURGO.

2.3.4. Exp 3: Simulate the impacts of uncertainties in SOC% and Bul_Density on the calculation of cropland carbon budgets for the U.S. Midwest

We also simulated the cropland carbon budgets for 293 counties in Illinois, Iowa, and Indiana states with soil properties of major soil types over croplands in each county from gSSURGO. In these simulations, we perturbed the topsoil SOC% and Bulk_Density to quantify the impacts of uncertainties in SOC% and Bulk_Density on the calculation of cropland carbon budgets at given uncertainty levels. We further analyzed the impacts of climate and soil conditions on the uncertainty of calculated cropland carbon budgets. The uncertainty levels of SOC% and Bulk_Density used were 0.77% and 0.15 Mg/m^3, which were the RMSE



$$\mathbf{\Delta SOC\ uncertainty} = \frac{\mathrm{abs}(\mathbf{A_{High}} - \mathbf{A_{Low}})}{\mathbf{2}}$$

$\mathbf{A_0}$ is the simulated ΔSOC with gSSURGO SOC% and Bulk_Density;
$\mathbf{A_{Low}}$ is the simulated ΔSOC with gSSURGO SOC% - 0.77% or Bulk_Density - 0.15 Mg/m^3;
$\mathbf{A_{High}}$ is the simulated ΔSOC with gSSURGO SOC% + 0.77% or Bulk_Density + 0.15 Mg/m^3.

$$\mathbf{Soil\ carbon\ credits\ uncertainty} = \frac{\mathrm{abs}(\mathbf{C_{High}} - \mathbf{C_{Low}})}{\mathbf{2C_0}} \times \mathbf{100\%}$$

$\mathbf{C_0}$ is the simulated soil carbon credits with gSSURGO SOC% and Bulk_Density;
$\mathbf{C_{Low}}$ is the simulated soil carbon credits with gSSURGO SOC% - 0.77% or Bulk_Density - 0.15 Mg/m^3;
$\mathbf{C_{High}}$ is the simulated soil carbon credits with gSSURGO SOC% + 0.77% or Bulk_Density + 0.15 Mg/m^3.

Fig. 1. Illustration of soil carbon change (ΔSOC), soil carbon credits, and their uncertainty assuming cover crop adopted since the winter of 2000. The solid lines are the changes in model simulated SOC stock initialized with gSSURGO SOC% and Bulk_Density, the dotted lines are the changes in model simulated SOC stock initialized with gSSURGO SOC% + 0.77% or Bulk_Density + 0.15 Mg/m^3, and the dashdot lines are the changes in model simulated SOC stock initialized with gSSURGO SOC% − 0.77% or Bulk_Density − 0.15 Mg/m^3. We use ΔSOC as an example component of the cropland carbon budgets here, but the uncertainty quantification method also applies to other carbon budget components in Eq. (2).

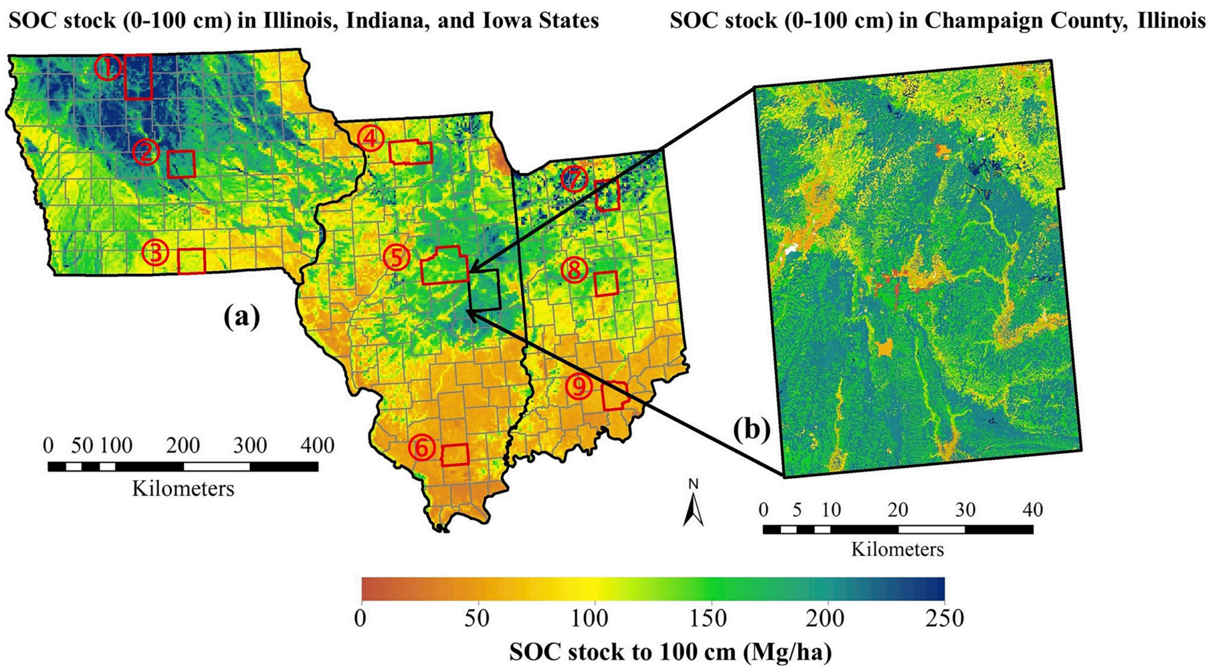


Fig. 2. (a) Soil organic carbon (SOC) stock of Illinois, Indiana, and Iowa integrated over 0–100 cm using data from gSSURGO, and the location of Champaign County, Illinois; (b) The distribution of 0–100 cm SOC stock in Champaign County, Illinois. The counties with red boundaries and numbers in (a) were selected for the sensitivity analysis in Fig. 5.

between the top 30 cm SOC stock data from gSSURGO and RaCA (see Section 3.1 and Fig. 3f and g for more details). We either (1) changed the topsoil SOC% by adding or subtracting 0.77% from the original gSSURGO values, or (2) changed the topsoil Bulk_Density by adding or subtracting 0.15 Mg/m^3 from the original gSSURGO values. Similar analysis was also conducted at gSSURGO soil map unit scale but only in Champaign County, Illinois.

The uncertainties of cropland carbon budgets induced by uncertainties in SOC% or Bulk_Density were quantified using half of the absolute difference between the simulated cropland carbon budgets with high and low SOC% (gSSURGO SOC% ± 0.77%) inputs, or/and with high and low Bulk_Density (gSSURGO Bulk_Density ± 0.15 Mg/m^3) inputs, respectively (Fig. 1).

2.3.5. Exp 4: Simulate the impacts of uncertainties in SOC% and Bulk_Density on the calculation of soil carbon credits for the U.S. Midwest

Similar simulations were conducted as in Section 2.3.4 but with the addition of winter cover crops to quantify the uncertainty of soil carbon credits induced by the uncertainty of SOC% and Bulk_Density across the same 293 counties. For this analysis, in *ecosys* we hypothetically planted the non-legume annual ryegrass (Qin et al., 2021) on November 5 for each year since 2000, and terminated 7 days before cash crop planting in those simulations. The soil carbon credits were calculated as the difference in simulated ΔSOC between Exp 4 (with cover crops) and Exp 3 (without cover crops) with the same soil inputs (i.e., C_0, C_{High}, C_{Low} in Fig. 1).

To quantify the relative uncertainties of calculated soil carbon credits induced by uncertainties in SOC% or Bulk_Density, we first calculated the absolute difference between the simulated soil carbon credits with high and low SOC% (gSSURGO SOC% ± 0.77%, C_{High} and C_{Low} in Fig. 1) as inputs, or with high and low Bulk_Density (gSSURGO Bulk_Density ± 0.15 Mg/m^3, C_{High} and C_{Low} in Fig. 1) as inputs. We then calculated the ratio between half of the before-mentioned absolute difference (i.e., abs(C_{High} - C_{Low})/2) and the simulated soil carbon credits with gSSURGO SOC% and Bulk_Density (i.e., C_0 in Fig. 1), and use this ratio as a metric to indicate the relative uncertainty in the calculated soil carbon credits (Fig. 1).

3. Results

3.1. Comparison of gSSURGO and RaCA soil datasets at the U.S. Midwestern croplands

Significant differences exist between the gSSURGO and RaCA datasets in terms of SOC stock, SOC%, and Bulk_Density at different soil depths, with p-value < 0.1 based on paired t-test except for topsoil (0–30 cm) SOC stock (Fig. 3). Compared with RaCA, gSSURGO has higher Bulk_Density and lower SOC% in the topsoil at the cropland sites. Correlations between these two datasets are low for both Bulk_Density and SOC%, with Pearson correlation coefficients (r) ranging from 0.18 to 0.50 (Fig. 3). The relative differences between these two datasets quantified by Normalized Root Mean Square Error (NRMSE) were 48.0%, 53.2%, and 11.3% for topsoil SOC stock, SOC% and Bulk_Density, respectively. For surface layer (0–5 cm), gSSURGO has lower SOC% and higher Bulk_Density compared with RaCA; for subsurface layer (0–30 cm) and more deeper soil layer (0–100 cm), the bias between gSSURGO and RaCA is smaller for both SOC% and Bulk_Density compared with surface layer, but large discrepancy still exists between these two soil datasets.

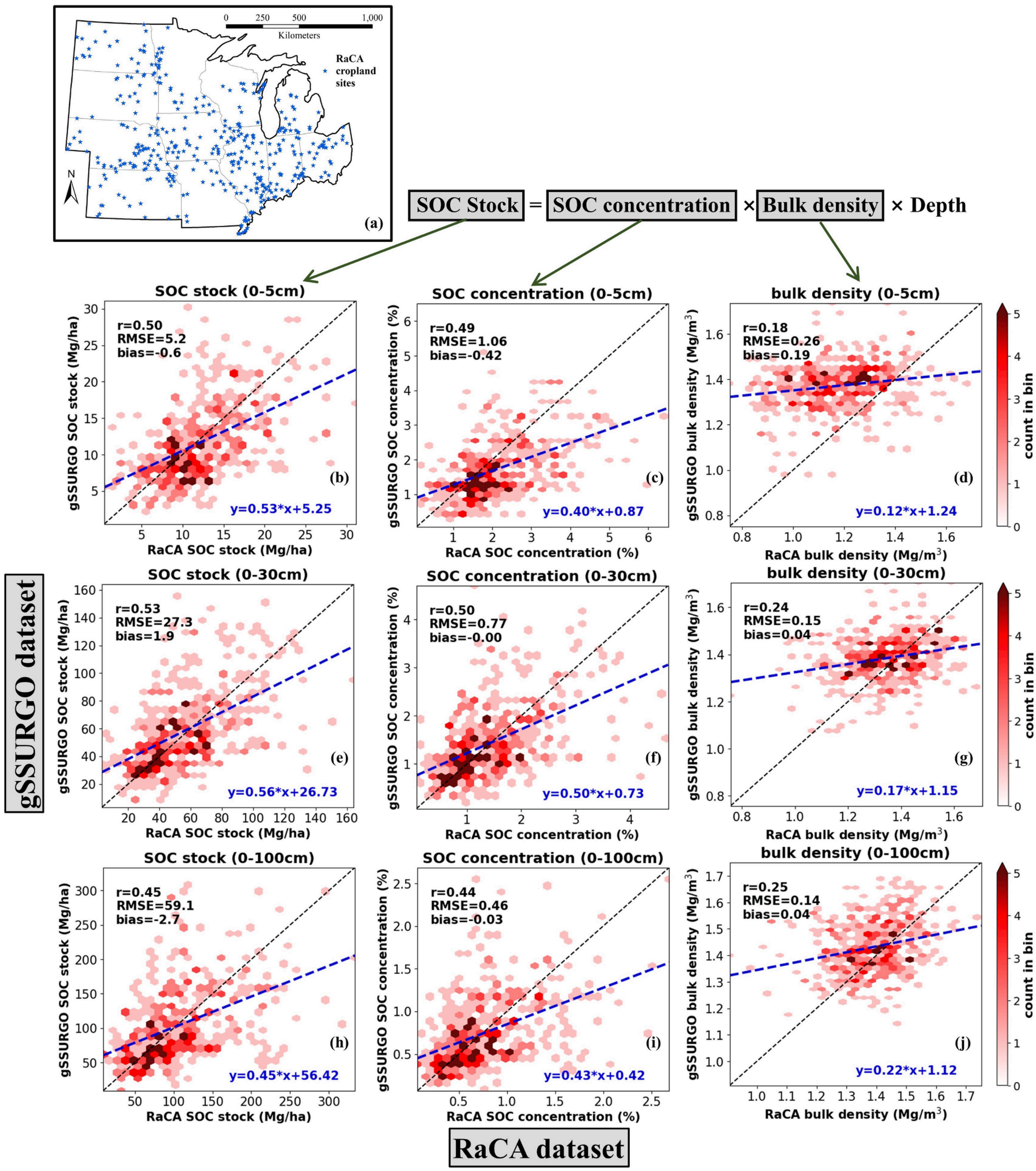


Fig. 3. Comparison of SOC stock, SOC concentration (SOC%), and coarse-fragment-adjusted bulk density (Bulk_Density) between the RaCA measurements and gSSURGO dataset at different soil depths for 410 cropland sites sampled by the RaCA across the U.S. Midwest.

3.2. Comparison of calculated cropland carbon budgets based on gSSURGO and RaCA soil datasets in the U.S. Midwest

To compare the cropland carbon budgets calculated based on different soil datasets and investigate which soil properties induced such differences, we simulated carbon budgets with different combinations of SOC% and Bulk_Density from gSSURGO and RaCA as model inputs at the RaCA cropland sites (Fig. 4 and Fig. S1). We found that large discrepancies exist in the simulated cropland carbon budgets (i.e., ΔSOC) when using SOC% and Bulk_Density from gSSURGO as the model inputs versus using data from RaCA (Fig. 4a). The correlation coefficient between RaCA-based and gSSURGO-based ΔSOC was only 0.4, and the gSSURGO-based ΔSOC was larger than RaCA-based ΔSOC at the sites with smaller ΔSOC (Fig. 4a), which was caused by the inconsistency of SOC% in these two datasets (Fig. 4b). The mean and standard deviation of the difference between RaCA-based and gSSURGO-based ΔSOC across all the selected sites were −2.7 and 25.7 gC/m^2/year, respectively. From both the RaCA-based and gSSURGO-based ΔSOC, we found that the long-term (i.e., 2001 to 2018) SOC stock change was correlated with both the local specific soil and climate conditions for the corn-soybean rotation system, in particular correlated with initial SOC% and air temperature (Fig. S2).

We treated the carbon budgets simulated with RaCA SOC% and Bulk_Density as the baseline, and calculated the difference between the carbon budgets simulated with other SOC% and Bulk_Density combinations and the baseline (SOC%$_{RaCA}$ + Bulk_Density$_{RaCA}$, Fig. 4b and

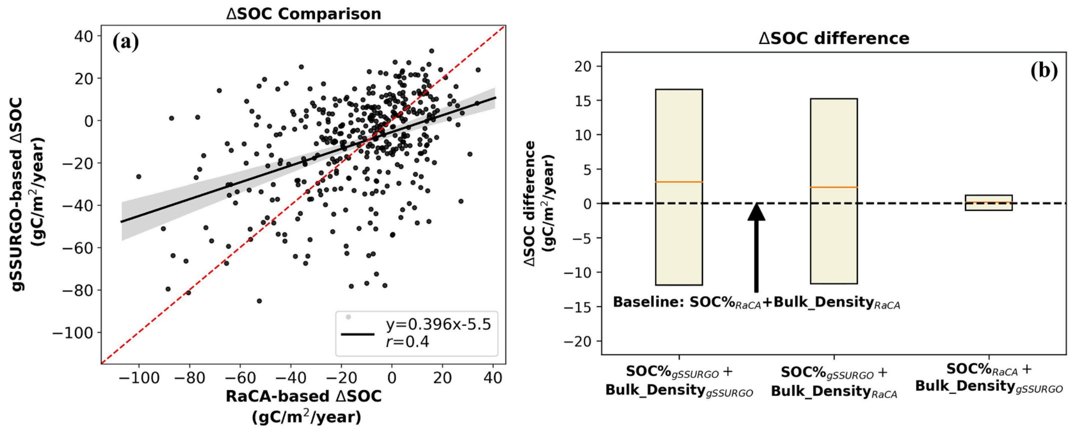


Fig. 4. (a) Comparison of ΔSOC simulated with gSSURGO and RaCA soil datasets; and (b) the difference of ΔSOC simulated using different combinations of gSSURGO and RaCA SOC% and Bulk_Density data, compared with the baseline simulations with SOC% and Bulk_Density from RaCA at the RaCA cropland sites in the U.S. Midwest. In the boxplots of (b), the center marks the medians, and the edges mark the 25th and 75th percentiles of the ΔSOC difference between the simulations with different SOC% and Bulk_Density combinations and the baseline among all the simulated sites, respectively.

Fig. S1). We found that (1) the distributions of differences in plant-related carbon budget components (i.e., GPP, R_a, Harvest) were similar for the combinations with different SOC% sources but same Bulk_Density sources (i.e., Fig. S1b, d, and e), which means the difference in SOC% was not the major cause of differences in the plant-related carbon budget components. Bulk_Density had larger impacts on the calculation of plant-related cropland carbon budgets compared with SOC%. The median of GPP difference caused by Bulk_Density difference was about 6.6 gC/m^2/year, with ranges (i.e., 25th and 75th percentiles) from −4.2 to 18.4 gC/m^2/year; while the median of GPP difference caused by SOC% difference was about −0.5 gC/m^2/year, with ranges from −7.5 to 6.4 gC/m^2/year across all the RaCA cropland sites (Fig. S1b). (2) The different sources of SOC% had larger impacts on the calculated R_h and ΔSOC than those of Bulk_Density (Fig. 4b, Fig. S1a and f). The median and ranges of R_h and ΔSOC difference between the combinations using gSSURGO SOC% (i.e., SOC%$_{\text{gSSURGO}}$ + Bulk_Density$_{\text{gSSURGO}}$ and SOC%$_{\text{gSSURGO}}$ + Bulk_Density$_{\text{RaCA}}$) and the baseline were greater than that between combinations with RaCA SOC% (SOC%$_{\text{RaCA}}$ + Bulk_Density$_{\text{gSSURGO}}$) and the baseline. The median of ΔSOC difference caused by SOC% difference was about 3.1 gC/m^2/year, with ranges from −11.9 to 16.6 gC/m^2/year; while the median of ΔSOC difference caused by Bulk_Density difference was about 0.2 gC/m^2/year, with ranges from −1.0 to 1.2 gC/m^2/year across all the RaCA cropland sites in the Midwest (Fig. 4b). This result means that SOC% had larger impacts on the calculation of cropland carbon budgets compared with Bulk_Density.

3.3. Sensitivity of cropland carbon budgets to SOC% and Bulk_Density

To analyze the sensitivity of cropland carbon budgets to different SOC% and Bulk_Density levels, we selected 9 counties over Illinois, Iowa, and Indiana (Fig. 2a), and simulated carbon budgets in these counties using *ecosys* by changing topsoil SOC% and Bulk_Density systematically (Fig. 5). Overall, almost all carbon budget components showed higher sensitivity to changes in SOC% than to changes in Bulk_Density, especially for ΔSOC. For example, the magnitude of simulated ΔSOC increased quickly with the increase of SOC% throughout all the selected counties (Fig. 5a), while the simulated ΔSOC had changed slightly with respect to the change of Bulk_Density (Fig. 5g).

The response of different carbon budget components to variation in SOC% showed similar patterns for all the selected counties (Fig. 5a-f). The plant-related components of carbon budgets (i.e., GPP, R_a, and Harvest) increased markedly with the increase of SOC% when SOC% is smaller than 2.0%, and increased more slowly when SOC% is above 2.0% (Fig. 5b, d, e). However, ecosystem respiration, R_{eco}, showed higher sensitivity to the change of SOC% even in the high SOC% region (i.e., SOC% > 2.0%) compared with other plant-related components. In R_{eco}, R_h was more sensitive to the change of SOC% than R_a at high SOC%, and R_h dominated the increases of R_{eco} with the increases of SOC% at high SOC%. Thus, among other cropland carbon budget components, the changes in R_h primarily drove ΔSOC changes at different SOC% levels.

Compared with the sensitivity of carbon budgets to different SOC% levels, there was less sensitivity of carbon budgets to the changes in Bulk_Density, especially within low Bulk_Density regions (Fig. 5g-l). GPP, R_{eco}, Harvest, R_a, and R_h showed little sensitivity to changes in Bulk_Density in regions where Bulk_Density was lower than 1.5 Mg/m^3, but showed greater sensitivity to the change of Bulk_Density in the high Bulk_Density region (Fig. 5h-l). This is due to the soil porosity being smaller at higher Bulk_Density, which results in smaller soil water and oxygen storage/exchange capacities, and limits crop water and N uptake as well as the microbial activity.

3.4. Quantifying the uncertainties in cropland carbon budgets induced by uncertainties in SOC% and Bulk_Density in the U.S. Midwest

To quantify the impacts of uncertainty from SOC% and Bulk_Density on the calculation of cropland carbon budgets in the U.S. Midwest, we ran *ecosys* at the county scale for Illinois, Iowa, and Indiana states and at the soil map unit scale for Champaign County of Illinois, and perturbed the topsoil SOC% and Bulk_Density based on the uncertainties obtained from the comparison of RaCA and gSSURGO datasets (Fig. 3).

Overall, the uncertainty of cropland carbon budgets induced by SOC % uncertainty was larger than that induced by Bulk_Density uncertainty, especially for ΔSOC, R_{eco} and R_h (Fig. 6), which was consistent with the sensitivity analysis results in Section 3.3 (Fig. 5). This finding was consistent with the county-level simulations for the three states and also with the soil map unit scale simulations for Champaign County of Illinois (Fig. 6). Specifically, for Illinois, Iowa, and Indiana states, the uncertainties of ΔSOC, R_{eco} and R_h induced by SOC% uncertainty were higher than that induced by Bulk_Density uncertainty for most counties (Fig. 7). The relative uncertainties in calculated carbon budget components induced by initial SOC% uncertainty were 1.1%, 2.4%, 2.1%, 1.1% and 3.6% for GPP, Harvest, R_{eco}, R_a, and R_h, respectively. In contrast, the relative uncertainties in calculated carbon budget components induced by initial Bulk_Density uncertainty were 0.3%, 0.4%, 0.3%, 0.3% and 0.3% for GPP, Harvest, R_{eco}, R_a, and R_h, respectively from the simulations for Illinois, Iowa, and Indiana states (Fig. 6). As the residual of the major carbon budget components (ΔSOC ≈ GPP - Harvest - R_{eco}), the 25th and 75th percentiles of multi-year averaged ΔSOC were −29.8 and

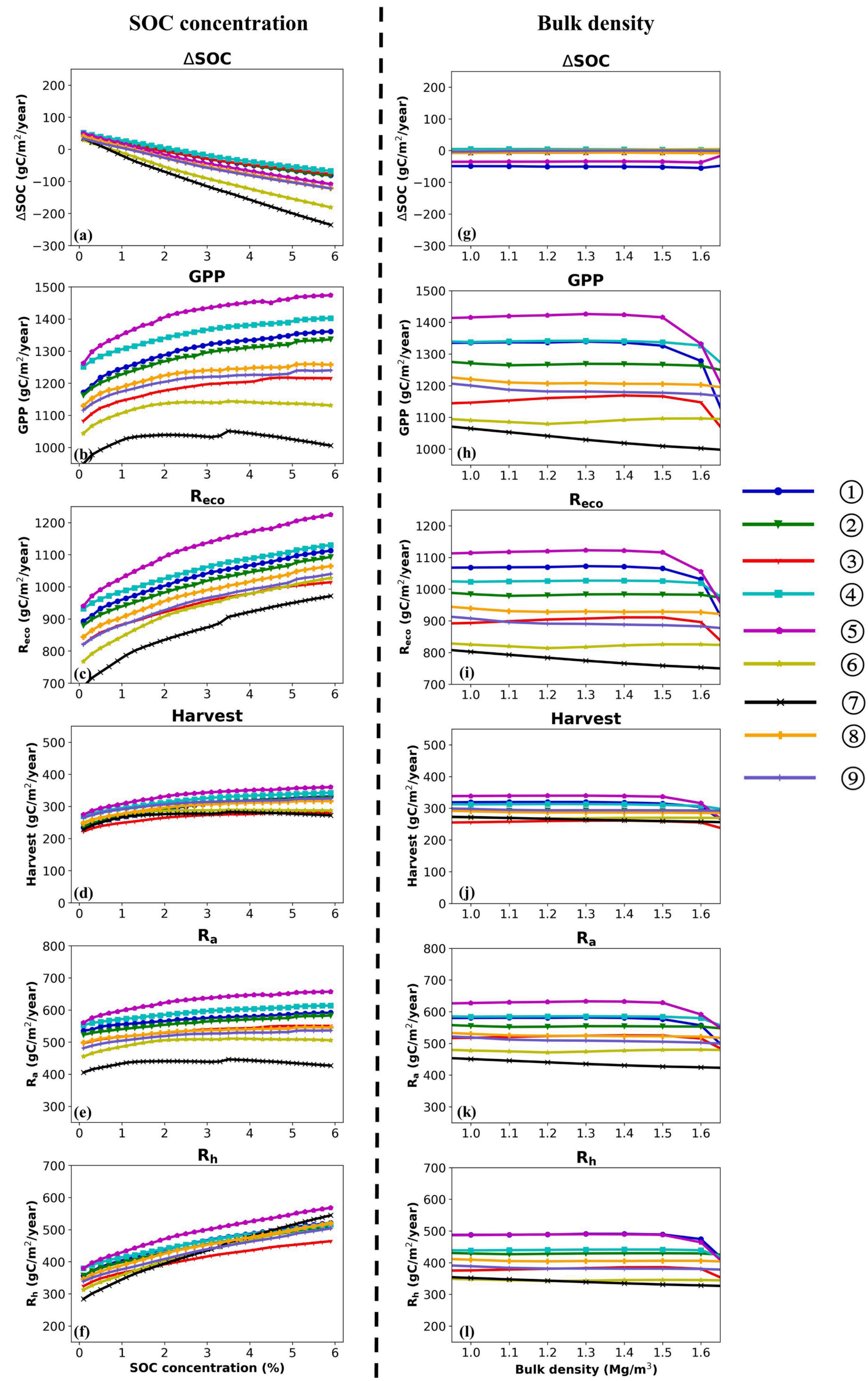


Fig. 5. The sensitivity of cropland carbon budgets to the change of SOC% and Bulk_Density at selected counties (labeled from 1 to 9) highlighted in Fig. 2a.

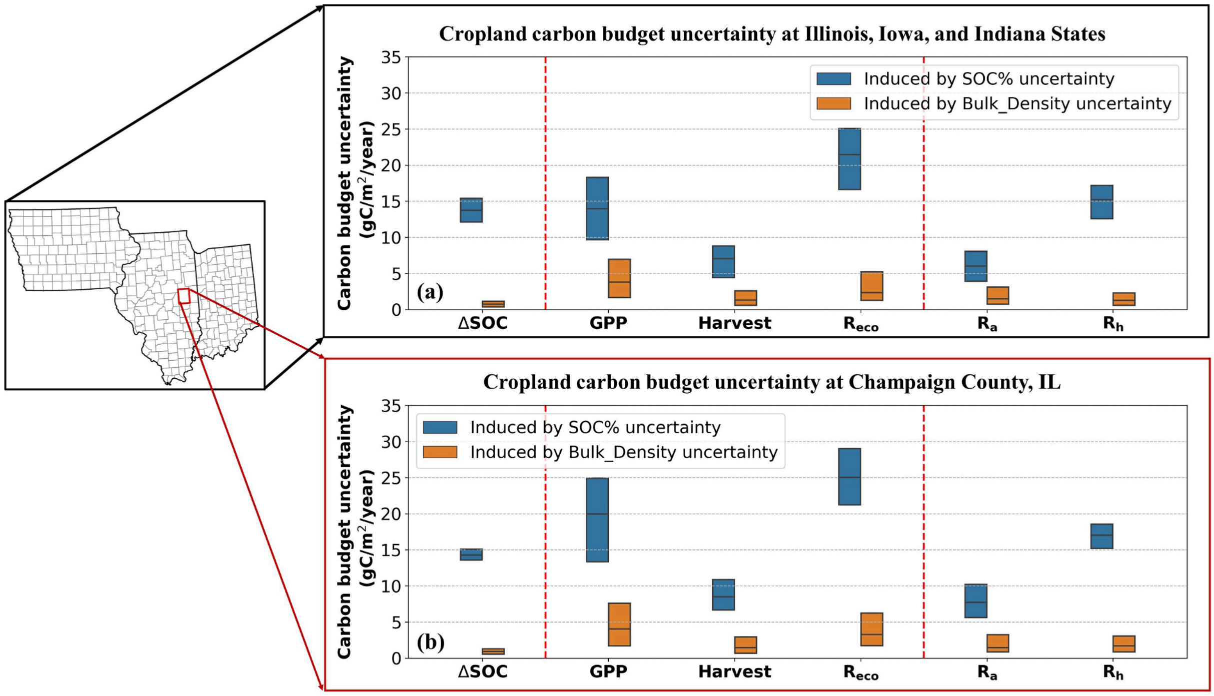


Fig. 6. The uncertainty of carbon budget components induced by the uncertainties of SOC% and Bulk_Density in (a) Illinois, Iowa, and Indiana states and (b) Champaign County of Illinois. In the boxplots of (a) and (b), the central marks the medians, and the edges mark the 25th and 75th percentiles of the carbon budget components uncertainties, respectively. For (a), the boxplots were based on the county scale simulations of carbon budgets over Illinois, Iowa, and Indiana states. For (b), the boxplots were based on the soil map unit scale simulations of carbon budgets over Champaign County, Illinois.

4.8 gC/m^2/year across the selected counties with an uncertainty of 13.7 gC/m^2/year and 0.7 gC/m^2/year induced by uncertainties in initial SOC % and Bulk_Density, respectively (Fig. 6). In the southern part of Illinois, Iowa, and Indiana states, the uncertainties of ΔSOC, R_{eco} and R_h induced by SOC% uncertainty were higher than that in the northern part (Fig. 7g, j, l), which was opposite to the distribution of SOC% (Fig. S3). This spatial contrast was caused by the larger sensitivity of ΔSOC and R_h to SOC% at low SOC% conditions, as shown in Fig. 5. For the simulations for Champaign County of Illinois, the uncertainty of all carbon budget components induced by SOC% uncertainty was greater than that induced by Bulk_Density uncertainty, especially for ΔSOC, R_{eco}, and R_h across almost all the soil map units (Fig. 8). These results were consistent with the county scale simulations at Illinois, Iowa, and Indiana states (Fig. 7), but the spatial heterogeneity of uncertainties in simulated carbon budgets induced by both SOC% and Bulk_Density uncertainties at Champaign County of Illinois (Fig. 8) was much smaller than that at Illinois, Iowa, and Indiana states (Fig. 7), because the spatial variations of soil and climate conditions in Champaign County of Illinois were much smaller than those at regional scale of Illinois, Iowa, and Indiana states (Fig. S3 and S4).

We further investigated the variation of ΔSOC and its uncertainty across a range of different soil and climate conditions. Both ΔSOC and its uncertainty showed negative correlation with initial SOC% at the county scale in Illinois, Iowa, and Indiana (Fig. 9a and b) and at the soil map unit scale in Champaign County of Illinois (Fig. 9e and f); this means that the uncertainty in calculated ΔSOC was larger at low SOC% regions than in high SOC% regions under the same SOC% uncertainty level. In Illinois, Iowa, and Indiana, ΔSOC and its uncertainty were also influenced by air temperature (Fig. 9c and d). The response of ΔSOC to SOC% and air temperature in Illinois, Iowa, and Indiana was consistent with the simulated response in RaCA cropland sites (Fig. S2). For counties with the same level of SOC%, larger ΔSOC uncertainty existed in the counties with higher air temperature under the same SOC% uncertainty level (Fig. 9d). This may be due to enhanced microbial activity and soil respiration under higher temperature conditions, thus R_h and its uncertainty are larger when air temperature is higher under the same SOC % and SOC% uncertainty levels.

3.5. Uncertainty of calculated soil carbon credits induced by SOC stock uncertainty

To quantify the impacts of uncertainty from SOC% and Bulk_Density on the calculation of soil carbon credits, we used the hypothetical addition of cover crops in the corn-soybean rotation system as an example. We ran *ecosys* at the county scale for Illinois, Iowa, and Indiana under the scenarios with and without cover crops, and perturbed the topsoil SOC% and Bulk_Density based on the uncertainty obtained from comparison of the RaCA and gSSURGO datasets (Fig. 3). The uncertainties of soil carbon credits induced by uncertainties in SOC% and Bulk_Density were smaller than the uncertainties of carbon budgets under the same SOC% and Bulk_Density uncertainty levels (Fig. 10c-d vs Fig. 6). The soil carbon credits generated from adopting winter cover crops ranged from 11.7 to 18.7 gC/m^2/year (25% to 75% of the counties) with a median value of 15.7 gC/m^2/year across Illinois, Iowa, and Indiana. The relative uncertainty in soil carbon credits induced by initial SOC% uncertainty was less than 3.6% for 90% of counties, and less than 2.4% for 75% of counties, and the relative uncertainty in soil carbon credits induced by initial Bulk_Density uncertainty was less than 5.6% and less than 2.6% for 90% and 75% of the selected counties, respectively (Fig. 10).

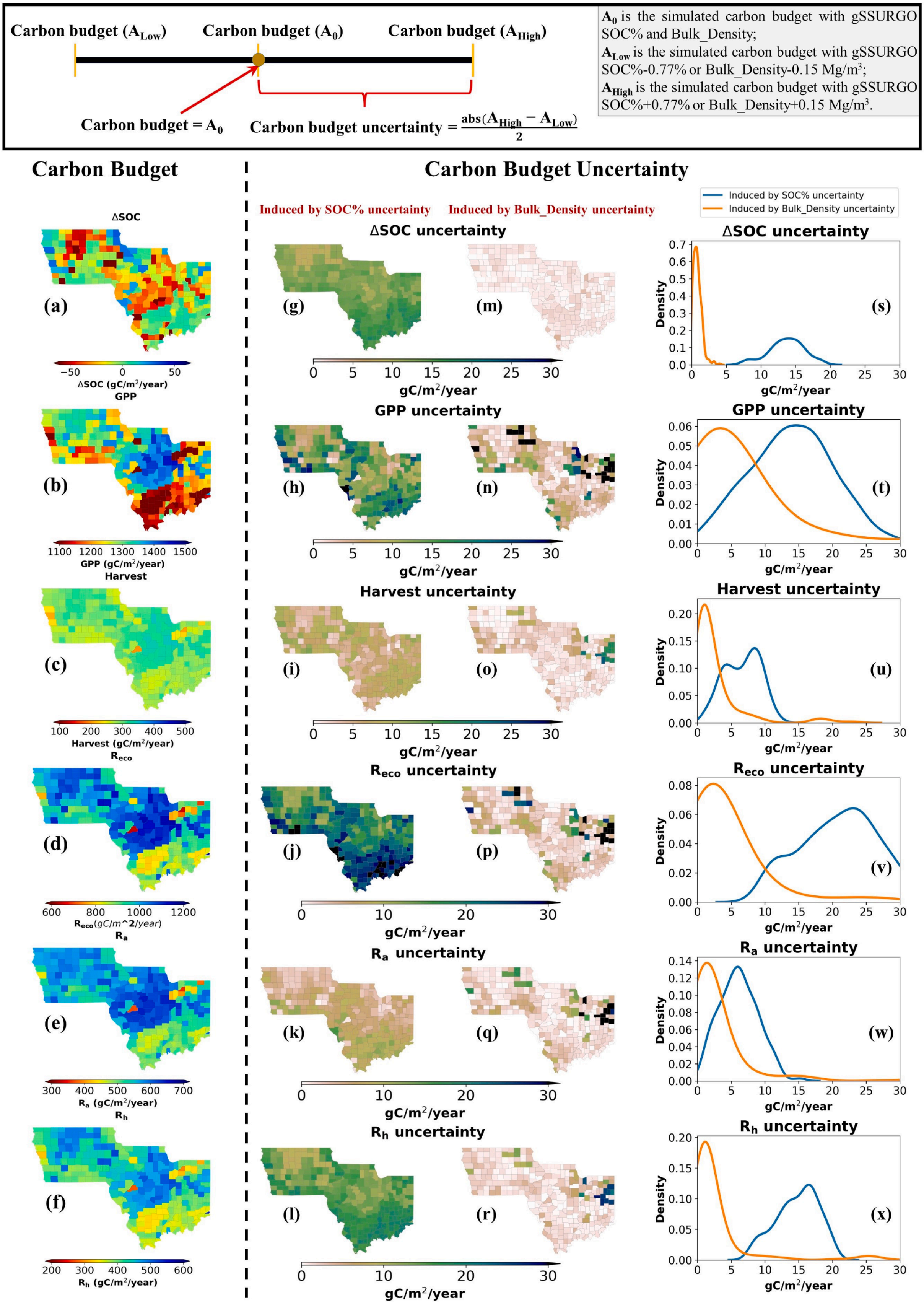


Fig. 7. Simulated carbon budgets and their uncertainties induced by SOC% or Bulk_Density uncertainty for Illinois, Iowa, and Indiana states.

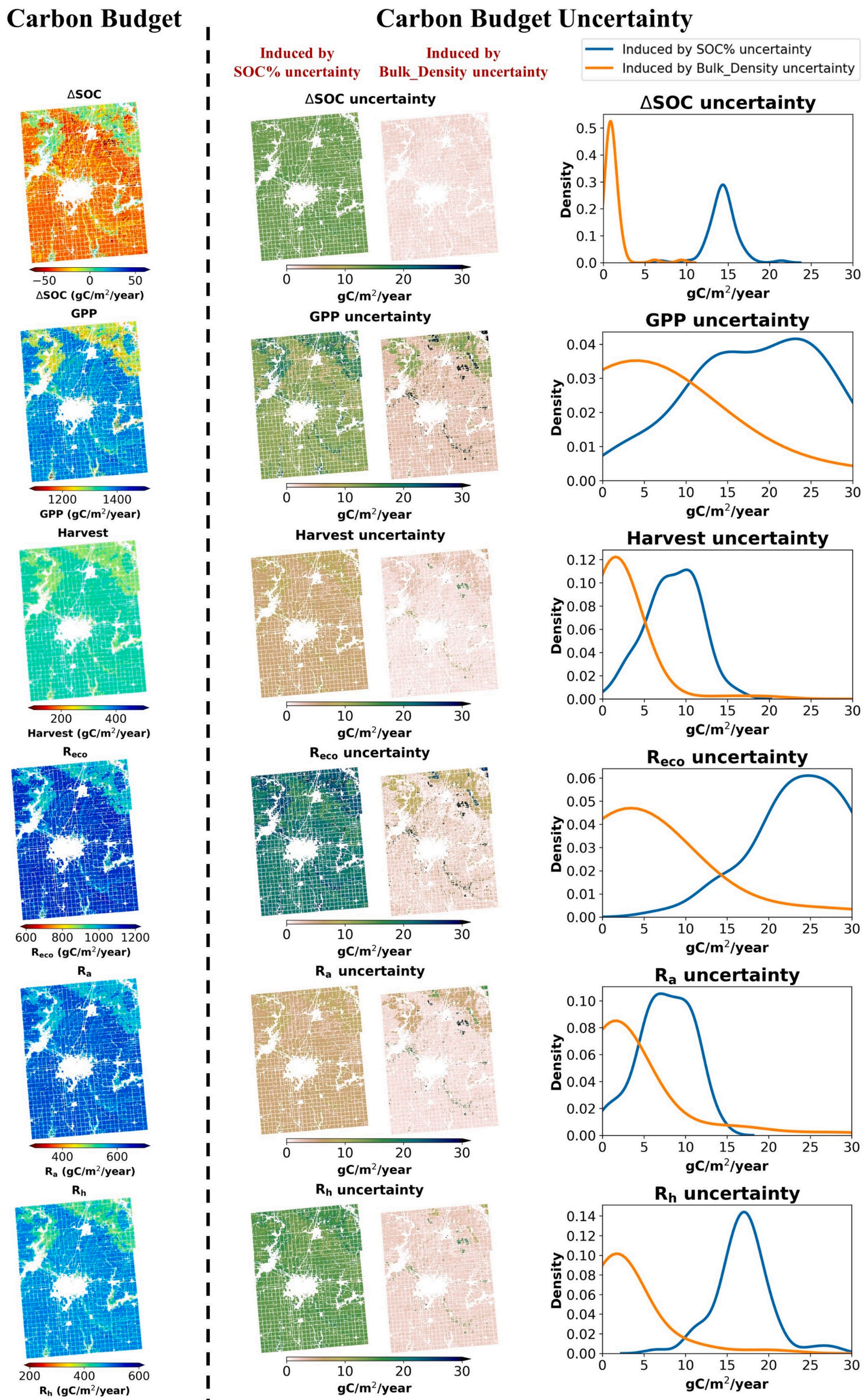


Fig. 8. Simulated carbon budgets and their uncertainties induced by SOC% or Bulk_Density uncertainty in cropland for Champaign County of Illinois.

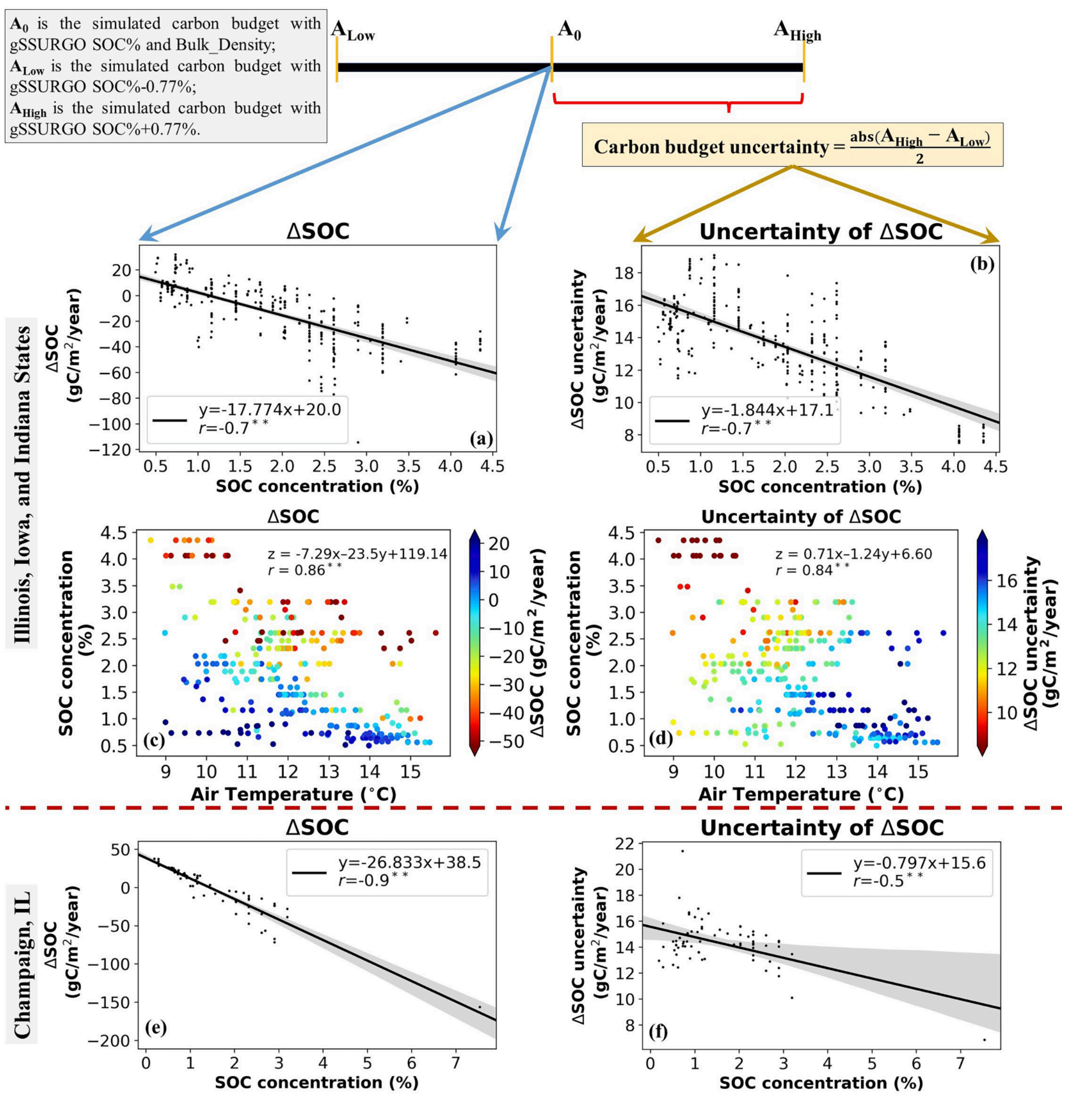


Fig. 9. Relationship of ΔSOC (left column) and its uncertainty (right column) with initial SOC% and air temperature under the same SOC% uncertainty level at the county scale for Illinois, Iowa, and Indiana states and at the soil map unit scale for Champaign County of Illinois.

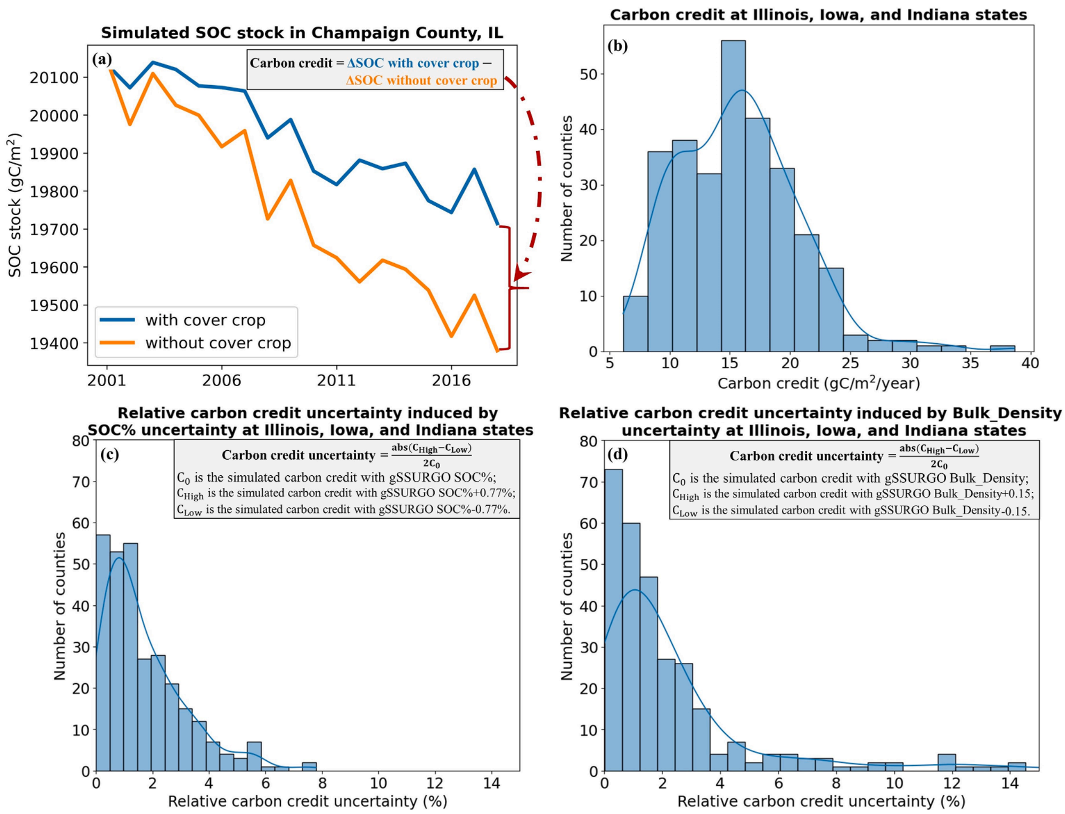


Fig. 10. The impacts of initial SOC stock uncertainty on the calculation of soil carbon credits. (a) An example illustrating the calculation of soil carbon credits for the corn-soybean rotation system assuming hypothetical adoption of winter cover crop since the winter of 2000 in Champaign County of Illinois; (b)-(d) refer to: (b) simulated soil carbon credits, (c) uncertainty of soil carbon credits induced by SOC% uncertainty, and (d) uncertainty of soil carbon credits induced by Bulk_Density uncertainty, assuming hypothetical adoption of winter cover crop since the winter of 2000 in the states of Illinois, Iowa, and Indiana.

4. Discussion

In this study, we analyzed the impacts of SOC% and Bulk_Density uncertainty on the calculation of cropland carbon budgets and soil carbon credits in the U.S. Midwestern corn-soybean rotation system using the advanced agroecosystem model, *ecosys*. Specifically, we conducted the following analyses: (1) Compared the simulated carbon budgets using the RaCA-based and gSSURGO-based soil properties at RaCA cropland sampling sites in the U.S. Midwest. (2) Analyzed the sensitivity of cropland carbon budgets to SOC% and Bulk_Density levels for Illinois, Iowa, and Indiana states. (3) Quantified the uncertainties of cropland carbon budgets induced by uncertainties in initial SOC% and Bulk_Density, and investigated their variation across a range of soil and climate conditions. (4) Analyzed the impacts of SOC% and Bulk_Density uncertainty on the calculation of soil carbon credits for Illinois, Iowa, and Indiana states. In the following, we will first address the potential limitations of this research, including the comparison of RaCA and gSSURGO soil datasets and the use of the *ecosys* model, and then synthesize the results to answer the questions proposed in the Introduction Section 1.

4.1. *Limitations of comparison between RaCA and gSSURGO soil datasets and use of the ecosys model*

The comparison of gSSURGO and RaCA datasets reveals that significant inconsistency exists in these two datasets for both SOC% and Bulk_Density. These inconsistencies may come from several aspects. First, there is scale mismatch between gSSURGO and RaCA, as gSSURGO is a gridded dataset derived by upscaling the point-based samples to soil map units, while RaCA is a point-based-only sampling dataset. Second, the measurement methods of both SOC% and Bulk_Density in gSSURGO and RaCA are different. Third, there is a temporal shift between gSSURGO and RaCA field sampling, and changes in land management during that period may change the SOC% and Bulk_Density. Finally, we calculated the SOC% of gSSURGO from SOM by treating 58% of SOM as SOC, and this conversion factor may introduce some uncertainty to the comparison (Pribyl, 2010).

Though there are some limitations in the direct comparison of RaCA and gSSURGO soil datasets (i.e., gSSURGO is at soil map unit scale, while RaCA is at point scale), these are the best and also the most widely used soil datasets we could use to address the current research goals related to uncertainty of SOC stock data and its impact on the quantified carbon budget. As stated before, quantification of carbon budget and soil carbon credits currently needs to rely on process-based models, and SOC stock data are among the most important input data for models. Although the RaCA dataset is based on soil samples collected more recently than the gSSURGO dataset, it only provides soil information at some sampling sites, and the sparse distribution of RaCA sampling sites limits its application. The gSSURGO SOC stock dataset has its uncertainties from soil sampling methodology, the interpolation methods based on soil map unit, and majority of gSSURGO raw data were collected 40 years ago and thus it may not be fully representative of the current situation (though SOC change is relatively slow). However, gSSURGO is the only dataset currently available for quantifying cropland carbon budgets at field scale across the Midwest or for the contiguous U.S.

The results presented in this study were obtained from the *ecosys* model, which explicitly and mechanistically simulates the biophysical and biogeochemical processes and their impacts on carbon budgets of the ecosystem. Besides complicated aboveground processes (crop growth, canopy energy balance, hydraulic and stomatal controls on water use and carbon uptake), *ecosys* also simulates dynamics of water, carbon, oxygen and nutrient content, and microbial activities in soil. Specifically related to SOC dynamics, *ecosys* explicitly simulates the dynamics of five organic matter-microbe complexes in soil (Grant et al., 1993; Grant, 2013), which can easily be mapped to the measurable particulate organic carbon (POC) and mineral-associated organic carbon (MAOC) pools (Cotrufo et al., 2019). We previously had validated the model performance in simulating the major carbon budget components (i.e., GPP, R_{eco}, NEE, and yield) and their responses to environmental conditions at both site scale and regional scale, benchmarked with flux tower observations, remotely sensed GPP dataset and county scale NASS crop yield data (Zhou et al., 2021a). Thus based on the comprehensive processes included by *ecosys* and the prior validations of the *ecosys* performance, we are confident about the reliability of using the *ecosys* model to simulate the impacts of SOC stock uncertainty on the calculation of carbon budgets. Although the results presented in this study are based on *ecosys* simulations, the proposed methodology to quantify the impacts of SOC stock uncertainty on the calculation of carbon budgets and soil carbon credits should also be applicable to other soil biogeochemistry models like CENTURY, Daycent, DNDC, and MEMS (Parton et al., 1988; Li et al., 1994; Zhang et al., 2021c; Cotrufo et al., 2022).

4.2. What are the impacts of SOC stock uncertainty on the calculation of cropland carbon budgets in the U.S. Midwest?

To analyze the impacts of SOC stock uncertainty on model-based calculation of cropland carbon budgets, we separated uncertainty in SOC stock into those caused by SOC% or Bulk_Density. Our results revealed that the uncertainty in SOC% has larger impacts on the calculation of cropland carbon budgets compared with that in Bulk_Density (Figs. 4-8).

The calculated cropland carbon budget is sensitive to the SOC% level, especially at low SOC% regions, and the soil carbon sequestration potential (i.e., ΔSOC) is higher in lower SOC% regions (Fig. 5a-f). Based on the *ecosys* simulations, we found that the simulated carbon budget components show large sensitivity to SOC% at the county scale in Illinois, Iowa, and Indiana and at the soil map unit scale in Champaign County of Illinois (Figs. 6-8), but the impacts of SOC% are different for plant-related (i.e., GPP, R_a, and Harvest) and soil-related (i.e., R_h and ΔSOC) carbon budget components. Plant-related carbon budget components show larger sensitivity to SOC% levels in regions with SOC concentration less than 2%, and less sensitivity to SOC% levels in regions with larger SOC concentration (> 2%). In contrast, soil-related carbon budget components show higher sensitivity to SOC% levels under both low and high SOC% conditions compared with plant-related carbon budget components. Under high SOC% conditions, heterotrophic microbial populations are larger than those under low SOC% conditions as long as there are no limitations from soil moisture, temperature, and oxygen. The above results can be largely explained by the processes included in the *ecosys* model. Heterotrophic respiration and soil mineralization are more accelerated under high SOC% conditions. With higher mineralization rates in higher SOC% soils, the soil can provide more N, P and S to support plant growth. However, the amount of nutrients that can be uptaken by plants is limited by the plant nutrient uptake ability, which is determined by root length and root distribution, soil oxygen concentration, soil water content, soil temperature, and inorganic N/P availability. Thus, the plant-related carbon budget components are more sensitive to SOC% levels for low SOC% regions, and less sensitive to SOC% levels for high SOC% regions.

Our simulation shows that Bulk_Density has less impact on the calculation of carbon budgets than that of SOC% (Fig. 5). The simulated carbon budgets show smaller sensitivity to Bulk_Density under normal Bulk_Density regions (i.e., <1.5 Mg/m^3), but show larger sensitivity to Bulk_Density at higher Bulk_Density regions for both plant and soil-related carbon budget components (Fig. 5). With the increase of Bulk_Density, the soil porosity decreases, which reduces soil water holding capacity and oxygen transfer capacity. At high Bulk_Density region, such impacts may become large because water and oxygen become the limiting factors for plants and microbial growth under low soil porosity conditions, particularly in high rainfall regions, which may result in large impacts on both plant and soil related carbon budget components.

4.3. How do local soil and climate conditions regulate the impacts of SOC stock uncertainty on the calculation of cropland carbon budgets?

The uncertainty of calculated cropland carbon budgets (i.e., ΔSOC) caused by initial SOC stock uncertainty is mainly induced by the uncertainty in SOC%, such impact is modulated by local climate and soil conditions. Our simulated results show that regions with lower SOC% have larger uncertainty in calculated carbon budget components than that for higher SOC% regions under the same SOC% uncertainty level and climate conditions. Regions with higher temperature also have larger uncertainty in calculated carbon budget components, ceteris paribus. Thus, locations with lower SOC% and higher temperature have larger uncertainty in calculated carbon budgets compared with locations with higher SOC% and lower temperature under the same SOC% uncertainty level (Fig. 9d and f). At low SOC% regions, both plant and soil related carbon budget components show larger sensitivity to SOC% levels compared with that at high SOC% regions (Fig. 5a-f), which may result in the pattern that the uncertainty of ΔSOC induced by SOC% uncertainty is larger at lower SOC% regions. For higher temperature regions, the microbial activity and heterotrophic respiration is higher when soil temperature is below the optimal temperature for microbial growth (Yvon-Durocher et al., 2012). Thus, in higher temperature regions, the uncertainty of ΔSOC induced by SOC% uncertainty is larger than that in lower temperature regions under the same SOC% and SOC% uncertainty level due to the increase of heterotrophic respiration.

4.4. How large are the impacts of uncertainty in SOC% and Bulk_Density on calculated soil carbon credits in the U.S. Midwest?

The impacts of SOC% and Bulk_Density uncertainties on the calculation of soil carbon credits are much smaller compared to its impacts on the calculation of carbon budgets. The relative uncertainties of calculated soil carbon credits induced by SOC% or Bulk_Density uncertainty are less than 3.6% or 5.6%, respectively, for 90% of selected counties across the U.S. Midwest assuming planting cover crops (Fig. 10). The uncertainty of calculated ΔSOC induced by SOC% uncertainty is about 13 gC/m^2/year across the U.S. Midwest, and the ratio of soil carbon credits uncertainty to ΔSOC uncertainty is about 4%. The much smaller impact of soil stock uncertainty on the calculation of soil carbon credits is mostly due to the unique definition of soil carbon credits. Soil carbon credits quantify the relative difference of soil carbon changes between two counterfactual scenarios, i.e., the scenario with intervention management practices and the business-as-usual scenario. Since the impacts of SOC stock uncertainty on ΔSOC under these two counterfactual scenarios tend to be in the same direction with a similar magnitude, the uncertainty of calculated soil carbon credits (ΔSOC difference between these two scenarios) induced by SOC stock uncertainty has been significantly mitigated. Our results demonstrate that the uncertainty of the public soil data only has a relatively small impact on the calculation of soil carbon credits, which means that current publicly-available soil datasets like gSSURGO and RaCA can be used for calculating soil carbon credits with high accuracy.

4.5. Practical implications of our finding

Uncertainties in SOC stock exist in both *in-situ* soil sampling measurement and gridded SOC datasets, arising from measurement uncertainties of SOC% and Bulk_Density, as well as the interpolation method used for generating the gridded data. We found that the uncertainty in SOC% has a larger impact on the calculation of cropland carbon budgets than that in Bulk_Density. We thus recommend efforts to further reduce uncertainty of SOC% measurements. Novel approaches, such as remote sensing (Wang et al., 2022; Gholizadeh et al., 2021; Sanderman et al., 2021), can be used to estimate topsoil SOC% at large scale to reduce the topsoil SOC% uncertainty. Although the uncertainty in Bulk_Density has less impact on the calculation of cropland carbon budgets compared with that in SOC%, we still recommend to have accurate Bulk_Density measurements especially at high Bulk_Density regions, because both plant-related and soil-related carbon budget components are sensitive to Bulk_Density levels at high Bulk_Density regions.

To enhance soil carbon sequestration, several farming practices have been suggested, such as planting cover crops and reduced tillage, but their potential in enhancing SOC stock needs to be assessed locally. Process-based models are used to quantify cropland carbon budget and soil carbon credits of these farming practices with the inputs of local soil and climatic information (Basche et al., 2016; Huang et al., 2020). Errors in initial SOC stock data will be propagated to the calculations of cropland carbon budgets and soil carbon credits (Guan et al., 2022). From our results, the uncertainty of SOC% appears to have large impacts on the calculated cropland carbon budgets, but only a slight impact on the calculated soil carbon credits (Fig. 10). These results suggest that quantifying soil carbon credits from intervention practices may not require in-field soil sampling for the baseline, and the current public soil data such as gSSURGO can largely fulfill the needs. This finding has important implications for the agricultural carbon credit market, considering the high cost and low scalability of soil sampling.

As initial SOC stock (or reference SOC stock) is one of the basic inputs to generate greenhouse gas (GHG) inventories using process-model-based approaches at regional scale, based on our results, we recommend to explicitly consider the uncertainty of GHG emissions induced by initial SOC stock uncertainty in the GHG inventories. Therefore, the proposed approach to quantify the impacts of SOC stock uncertainty in this study built a foundation that can be applied to other process-based modeling approaches or industry protocols to assess the uncertainties of soil carbon credits.

5. Conclusion

In conclusion, by simulating the U.S. Midwestern cropland carbon budgets, we assessed the impacts of SOC stock uncertainty on the calculation of cropland carbon budgets and soil carbon credits under corn-soybean rotations. Our results reveal the following important findings. (1) The gSSURGO-based calculation of cropland carbon budgets shows a large discrepancy with the RaCA-based calculation of cropland carbon budgets. (2) The SOC% uncertainty has larger impacts on the calculation of cropland carbon budgets for most of the carbon budget components compared to Bulk_Density, especially for ΔSOC and R_{eco}. (3) The uncertainty of ecosystem respiration, especially heterotrophic respiration, is the major contributor of uncertainty in calculated cropland carbon budgets induced by SOC% uncertainty. (4) Both ΔSOC and its uncertainty show negative correlation with initial SOC%; while ΔSOC shows negative correlation with air temperature, and uncertainty of ΔSOC shows positive correlation with air temperature. (5) The uncertainty of SOC% and Bulk_Density has a much smaller impact on the calculation of soil carbon credits. These analyses provided insights on how uncertainties in initial SOC stock affect the quantification of cropland carbon budgets and soil carbon credits, and highlighted that (i) high-accuracy SOC% measurement is needed to quantify the cropland carbon budgets; and (ii) current publicly-available soil datasets can be used for quantifying soil carbon credits with a relatively small uncertainty. The approach to quantify the impacts of SOC stock uncertainty on cropland carbon budgets and soil carbon credits used in this study can be applied to other models and used to assess uncertainties of carbon sequestration potential of various farming practices.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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