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PREDICTING SOIL ORGANIC CARBON IN AGROECOSYSTEMS UNDER CLIMATE CHANGE

Perennialization and Cover Cropping Mitigate Soil Carbon Loss from Residue Harvesting

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Abstract

While the US Midwest is expected to serve as a primary feedstock source for cellulosic biofuel production, the impacts of residue harvesting on soil organic carbon (SOC) may greatly limit sustainable production capacity. However, viable feedstock production could be realized through adoption of management practices and cropping systems that offset residue-harvest-induced SOC losses. Sequestration of SOC can be enhanced by increasing the duration of crop soil cover through cover or double cropping or cultivation of dedicated perennials. However, assessing the efficacy of such options across sites and over long periods is experimentally challenging. Hence, we use the Environmental Productivity Integrated Climate (EPIC) model to provide such an assessment. Model-data integration was used to calibrate and evaluate model suitability, which exhibited reasonable effectiveness through R^2 of 0.97 and 0.63 for SOC stock and yield, respectively. Long-term simulations indicate considerable capacity for offsetting SOC loss. Incorporating rye (*Secale cereal* L.) into continuous corn (*Zea mays* L.) and corn–soybean [*Glycine max* (L.) Merr.] systems offset the SOC losses induced by harvesting 21.2 and 38.3% of available stover, respectively. Similarly, converting 20.4% of corn–soybean land to miscanthus (*Miscanthus* ×*giganteus* J.M. Greef & Deuter ex Hodkinson & Renvoize) or 27.5% of land to switchgrass (*Panicum virgatum* L.) offset the SOC impacts of harvesting 60% of stover from the remaining corn–soybean lands. These responses indicate that adoption of such measures would sizably affect the life cycle consequences of residue-derived biofuels and expand estimates of sustainable cellulosic feedstock production capacity from the US Midwest.

Core Ideas

- EPIC suitably assessed SOC under annual, cover, double, and perennial crops.
- Perennial cultivation offset the SOC losses of considerable residue harvesting.
- Rye double crops offset sizable residue-induced SOC losses.
- Adoption could greatly expand Midwestern sustainable biofuel production capacity.

Cellulosic biofuels have shown potential to serve as a productive and environmentally sustainable source of fuel, with the capacity to contribute broadly to ecosystem services such as greenhouse gas mitigation, increased soil carbon stocks, improved soil fertility, pollination services, and pest suppression (Robertson et al., 2017). However, site-specific responses are complex, and the magnitude and directionality of these responses can vary greatly through vegetation–soil–climate–management interactions (Carroll and Somerville, 2009; van der Weijde et al., 2013; Robertson et al., 2017). Accordingly, the capacity for sustainable biofuel production from feedstocks derived through harvesting of agricultural residues or cultivation of dedicated perennials can vary widely by location, topography, management, and plant genetics (Wilhelm et al., 2007; Wullschleger et al., 2010; Gollany et al., 2011; Mbonimpa et al., 2016).

One pathway toward sustainable bioenergy systems is through soil carbon sequestration, which has been identified as a cost-effective climate mitigation option from agricultural systems (Lal, 2011), yet its positive influence on soil organic carbon (SOC) stocks is not an inevitability. Research has demonstrated the potential for residue-derived cellulosic biofuels to deplete soil carbon stocks (Blanco-Canqui and Lal, 2007; Lal and Pimentel, 2007; LeDuc et al., 2017). However, studies have also demonstrated the ability to increase SOC stocks through greater cropping frequency such as double cropping or cover cropping (Luo et al., 2010; Lal, 2011; Moore et al., 2014; Olson et al., 2014; Austin et al., 2017). Such measures may offset some or all of the SOC impacts of residue harvesting. Reduced soil disturbance through the adoption of no-till or reduced tillage management is often believed to slow respiration and enhance carbon sequestration (West and Post, 2002; Lal, 2004; Baker et al., 2007). However, studies have demonstrated that tillage reductions may fail to positively influence carbon sequestration, with the impacts altering the distribution of SOC toward greater concentrations near the soil surface but reducing concentrations at greater depths such that whole profile SOC stocks are generally unaltered (Baker et al., 2007;

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Abbreviations: DREAM, Differential Evolution Adaptive Metropolis; EPIC, Environmental Productivity Integrated Climate; NSE, Nash–Sutcliffe coefficient of efficiency; SOC, soil organic carbon.

Angers and Eriksen-Hamel, 2008; Luo et al., 2010; Powlson et al., 2011, 2014). Conversely, cultivation of perennial species such as switchgrass (*Panicum virgatum* L.) and miscanthus (*Miscanthus ×giganteus* J.M. Greef & Deuter ex Hodkinson & Renvoize) have been generally shown to increase SOC stocks in addition to other environmental benefits (West and Post, 2002; Gelfand et al., 2013; Mbonimpa et al., 2016; LeDuc et al., 2017).

Numerous field experiments have assessed the response of SOC levels under different cropping systems and harvesting rates, including harvesting of residue from corn (*Zea mays* L.)-based systems, from corn-based systems with the inclusion of cover crops or double crops, and from dedicated perennial crops (Blanco-Canqui and Lal, 2007; Olson et al., 2014; Poeplau and Don, 2014; Stewart et al., 2015; Austin et al., 2017). However, experiments assessing all of these scenarios are very limited, and most have not persisted for a sufficient duration to assess changes in SOC stocks. A need for modeling efforts has been identified for considering site- and system-specific responses (Qin et al., 2016). Modeling can serve as a useful tool for translating fundamental experimental understanding into assessment scenarios or at scales unfeasible for experimental assessment.

One such model that is well suited for such system interactions is the Environmental Policy Integrated Climate (EPIC; Williams et al., 1989; Zhang et al., 2010) terrestrial ecosystem model. The EPIC model considers detailed agroecosystem processes including plant growth; cycling of water, carbon, nitrogen, and phosphorus; tillage; and wind and water erosion. The model has been widely used for simulating cropping system responses under many species including biofuel crops (Zhang et al., 2010; Bandaru et al., 2013; Gelfand et al., 2013; Jones et al., 2017; LeDuc et al., 2017). However, although it includes well-developed and tested methods for simulating SOC dynamics (Izaurralde et al., 2006; Causarano et al., 2007; Wang et al., 2012; Jones et al., 2017), these SOC simulations have not been tested thoroughly under many cover cropping, double cropping, and dedicated perennial systems. Here, we conduct a modeling study using experimental datasets to prepare the EPIC model for simulating long-term SOC responses across a range of cropping systems and management options, focusing on implications on the sustainability of residue-derived cellulosic biofuel feedstocks.

Materials and Methods

In an effort to assess the impact of residue harvesting under annual, cover, double, and perennial cropping on SOC stocks in the US Midwest, we focused on continuous corn and corn–soybean [*Glycine max* (L.) Merr.] cropping systems, the inclusion of rye (*Secale cereale* L.) cover crops and double crops into these traditional systems, and dedicated perennial systems of switchgrass and miscanthus. The traditional continuous corn and corn–soybean systems constitute the predominant cropping systems in the US Midwest and a massive existing potential feedstock supply (Langholtz et al., 2016), whereas switchgrass and miscanthus represent two of the more promising perennial biofuel crops (Robertson et al., 2017). We also focus on rye cover and double crops due to their promise for increasing SOC levels (Luo et al., 2010), as well as the suitability and widespread use of rye as an overwintering crop (Singer, 2008; Moore et al., 2014; Koch et al., 2015).

To inform and evaluate the EPIC modeling efforts, nine previously published experiments from the US Midwest were identified that monitored crop growth and SOC stocks under residue harvesting from corn-based cropping systems, corn-based systems with inclusion of cover crops or double crops, or the dedicated perennials switchgrass or miscanthus (Table 1). Experiments were selected within the US Midwest due to the region's importance to US agricultural production and potential for biofuel production. Although this tailors the analysis for assessments in the US Midwest and similar regions, the limited geographic range of experiments at locations with generally plentiful precipitation indicates that system responses may not reflect behavior in disparate regions. Collected data were split into two subsets, with roughly two-thirds of treatments used for model calibration and one-third of treatments used for model evaluation. To ensure balanced allocation of treatments between calibration and evaluation datasets, treatments from each unique site–crop combination were randomly assigned to a calibration or evaluation subset such that no more than two-thirds of the treatments within that site–crop combination were assigned to the calibration dataset. In cases where a single treatment with a particular crop type was available at a particular site, if that crop type was also only available as a single treatment at multiple sites, treatments were randomly allocated to calibration or evaluation subsets such that no more than two-thirds of treatments were allocated to the calibration subset. This resulted in 30 unique site-treatments and 291 unique measurements of yield for calibration, and 17 unique site-treatments and 170 unique measurements of yield for evaluation. Similarly, it resulted in 25 unique site-treatments and 644 unique measurements of SOC for calibration, and 16 unique site-treatments and 436 unique measurements of SOC for evaluation.

The files required for EPIC simulations were created to represent the site and treatment-specific conditions within each experiment. Soil characteristics were estimated using the Soil Survey Geographic (SSURGO; Soil Survey Staff, 2017) database, with treatment-specific soil measurements used to supplement characteristics as available. Some detailed soil information was available at each of the five core experimental sites where SOC was measured, including texture, bulk density, pH, and cation exchange capacity. Soil carbon levels were initialized to align with the first available SOC measurements, and as such, these initial data points were eliminated from model performance estimates to ensure fair and independent assessment. The initial SOC pools were split between passive, slow, and biomass pools on the basis of the years the site had been under cultivation according to Izaurralde et al. (2012), with organic nitrogen stocks initialized assuming a 10:1 carbon-to-nitrogen ratio. To improve the initialization of other soil variables such as mineral nitrogen and water to appropriate levels, a 10-yr spin-up period was simulated under common regional cropping practices. Daily weather data including precipitation, maximum and minimum temperature, wind speed, and relative humidity were derived from onsite or nearby weather stations when available, and from the reanalysis North American Land Data Assimilation System 2 (NLDAS-2; NASA, 2017) when missing or unavailable. Management information was derived from experimental records and reporting as available and from regionally appropriate practices when unavailable. As necessary, average planting and harvesting dates for corn and soybean were estimated using state-level dates derived from USDA National Agricultural Statistics Service crop progress surveys (USDA-NASS, 2017). Default rye planting and termination dates assumed planting to occur 2 d after harvesting of the summer crop and termination to occur 14 d prior to planting of the subsequent summer crop according to Feyereisen et al. (2013). Default fertilizer rates were estimated based on USDA Economic Research Service state-level crop-specific rates (USDA-ERS, 2013).

Prior to conducting the model calibration, a sensitivity analysis was performed to identify the most influential parameters. First, an initial group of parameters were chosen with potential for considerable impact on SOC cycling. Uniform distributions were assumed for all parameters with ranges determined from literature values (Zhang et al., 2011; Wang et al., 2012), model documentation, and expert knowledge (Table 2). Using these parameter distributions, Morris' elementary screening method (Morris, 1991; Campolongo et al., 2007) was implemented to estimate relative parameter importance. The method efficiently provides a general assessment of global parameter sensitivity, on which selection of parameters of high importance and elimination of parameters of low importance can be made for subsequent calibration. The selected group of parameters was calibrated using the Differential Evolution Adaptive Metropolis (DREAM) algorithm (Vrugt et al., 2008). To assess model fit, the Nash–Sutcliffe coefficient of efficiency (NSE; Nash and Sutcliffe, 1970) was calculated for the SOC stock and the crop yield. The average of these two NSE values was used as the objective function for the DREAM procedure. To more completely characterize model performance, the R^2, RMSE, and percent bias (bias) metrics were calculated. The calibration procedure was conducted using roughly two-thirds of the treatments, whereas the evaluation was conducted using at least one-third of the remaining treatments.

Table 1. Description of experiments used for data-model integration. Rotations include corn (C), soybean (S), switchgrass (SW), and miscanthus (M) crops. Tillage includes no-till (NT), chisel plow (CP), moldboard plow (MP), and disk tillage (DT).

Site†	Reference	State	Measures SOC‡	Rotations	Cover or double crops	Stover removal rates	Tillage	Soil subgroup
						%		
Simpson	Olson et al. (2014)	IL	Yes	C–S	Yes	0	NT, CP, MP	Typic Fragiudalf
NEMERREM	Stewart et al. (2015)	NE	Yes	C, SW	No	0, 50	NT	Pachic Argiudoll
IAAM7071	Del Grosso et al. (2013)	IA	Yes	C	Yes	0, 50, 100	NT	Typic Hapludolls
KBS	Oates et al. (2016)	MI	Yes	C, C–S, SW, M	Yes	50	NT	Typic Hapludalfs
Arlington	Oates et al. (2016)	WI	Yes	C, C–S, SW, M	Yes	65	NT	Typic Argiudolls
Lamberton	Strock et al. (2004)	MN	No	C-S	Yes	0	DT	Aquic Hapludolls
Ames	Singer et al. (2007)	IA	No	C-S	Yes	0	NT	Cumulic Hapludolls
Champagne	Miguez and Bollero (2006)	IL	No	C	Yes	0	NT	Typic Endoaquoll
Boone	Kaspar et al. (2007)	IA	No	C-S	Yes	0	NT	Typic Hapludolls

† IAAM7071, Ames, IA, Field 7071; KBS, Kellogg Biological Station.

‡ SOC, soil organic carbon.

Table 2. Parameters considered in the sensitivity and calibration procedures, calibrated values, default values, and value limits. Note that calibrated values are not reported for parameters excluded from the calibration procedure.

Parameter	Calibrated	Min.	Max.	Default	Definition
PARM1	1.19	1.00	2.00	2.00	Crop canopy resistance factor
PARM2	1.18	1.10	1.50	1.50	Root growth soil strength constraint factor
PARM24	0.14	0.10	0.50	0.30	Maximum biological mixing depth
PARM25	0.20	0.10	0.50	0.30	Biological mixing efficiency
PARM47	6.40×10^{-4}	4.10×10^{-4}	6.80×10^{-4}	5.48×10^{-4}	Slow humus transformation rate
PARM48	1.06×10^{-5}	8.20×10^{-5}	1.50×10^{-5}	1.20×10^{-5}	Passive humus transformation rate
PARM51	0.65	0.50	1.00	0.90	Microbial activity coefficient
PARM52	–	5.0	15.0	10.0	Tillage effect on residue decay rate
PARM53	–	0.50	1.00	0.90	Microbial activity with depth coefficient
OPV1.CANA	0.55	0.50	1.50	1.00	Canola relative heat units to maturity
OPV1.MISC	0.73	0.50	1.50	1.00	Miscanthus relative heat units to maturity
OPV1.RYE	0.52	0.50	1.50	1.00	Rye relative heat units to maturity
OPV1.CORN	–	0.50	1.50	1.00	Corn relative heat units to maturity
OPV1.SOYB	1.50	0.50	1.50	1.00	Soybean relative heat units to maturity
OPV1.SWCH	0.91	0.50	1.50	1.00	Switchgrass relative heat units to maturity
RWPC1.MISC	0.46	0.45	0.90	0.45	Miscanthus root weight fraction at emergence
RWPC1.SWCH	0.74	0.45	0.90	0.45	Switchgrass root weight fraction at emergence
RWPC2.MISC	0.11	0.10	0.45	0.20	Miscanthus root weight fraction at maturity
RWPC2.SWCH	0.16	0.10	0.45	0.20	Switchgrass root weight fraction at maturity
WA.MISC	61.6	35.0	75.0	39.0	Miscanthus radiation use efficiency
WA.SWCH	48.8	30.0	50.0	31.0	Switchgrass radiation use efficiency

To assess the long-term SOC impacts of various biofuel production systems, the calibrated EPIC model was applied to simulate the impact of cropping system (corn, corn–soybean, switchgrass, and miscanthus) under no-till management, incorporation of rye double crops into corn-based systems (with and without double crop), and stover harvest rate (0–60%) on whole-profile SOC stocks at the five core experimental sites. The soil profile was initialized in the same manner as for the calibration and evaluation; however, initial levels of measured characteristics were set to the average of the treatments at each particular site. Simulations were conducted for 30 yr using historical weather, and model treatments were assessed in terms of final SOC stock, as well as change in final SOC stock relative to corn–soybean rotations without double cropping or residue removal, which was considered the reference treatment most representative of agricultural lands in the US Midwest. The SOC response of different corn-based systems to rate of residue removal was assessed using linear regression, with particular interest in estimating the amount of residue-removal-induced SOC loss that could be offset by incorporation of double cropping into corn and corn–soybean rotations.

Results and Discussion

The sensitivity analysis indicated fairly uniform sensitivity of SOC level and yield to the parameters and parameter ranges considered (Fig. 1). The ranking factors ranged from 4.74 to 5.35, whereas higher order effects ranged from 2.75 to 5.60. The range of higher order effects narrows considerably to 4.65 to 5.60 when PARM48 is ignored, with PARM48 standing out as having direct influence independent of other parameter effects. Since the Morris method provides rough estimates of parameter sensitivity, it is recommended for use as a filtering method. Due to the lack of large separation in model sensitivities, parameters were filtered conservatively. Hence only the OPV1.CORN, PARM52, and PARM53 parameters were excluded from calibration.

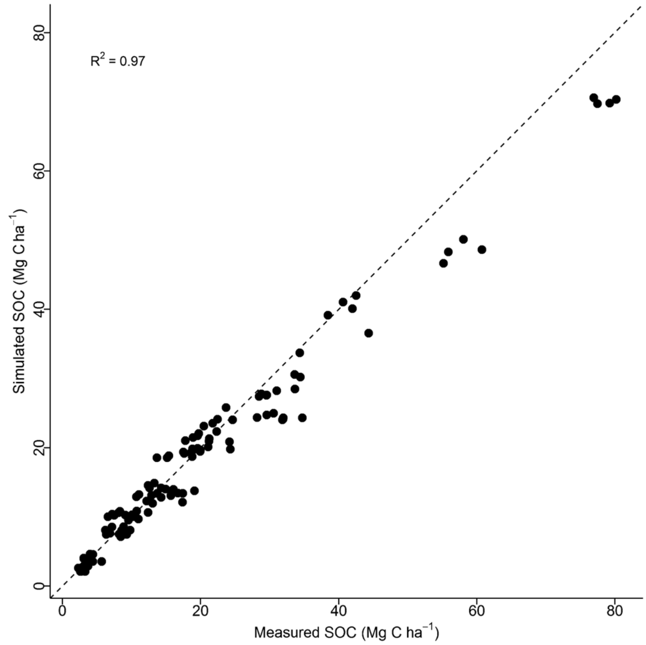

Fig. 2. Simulated versus measured soil organic carbon (SOC) values from the validation dataset.

The model calibration procedure resulted in a best set of parameters using the calibration dataset (Table 2). Using this set of parameters, the simulations were evaluated by comparing simulations against the validation dataset. Model performance indicated good prediction of SOC (R^2 = 0.97, NSE = 0.96, RMSE = 3.51 Mg C ha^{-1}, bias = −5.6%; Fig. 2) and adequate prediction of yield (R^2 = 0.63, NSE = 0.60, RMSE = 2.87 Mg, bias = −10.6%; Fig. 3). The NSE values were similar to the R^2 values for both SOC and yield simulations, indicating fairly unbiased estimates, although each demonstrated a tendency for underprediction. Such model fits compare favorably with other modeling studies in terms of SOC (Izaurralde et al., 2006; Cheng et al., 2014; Li

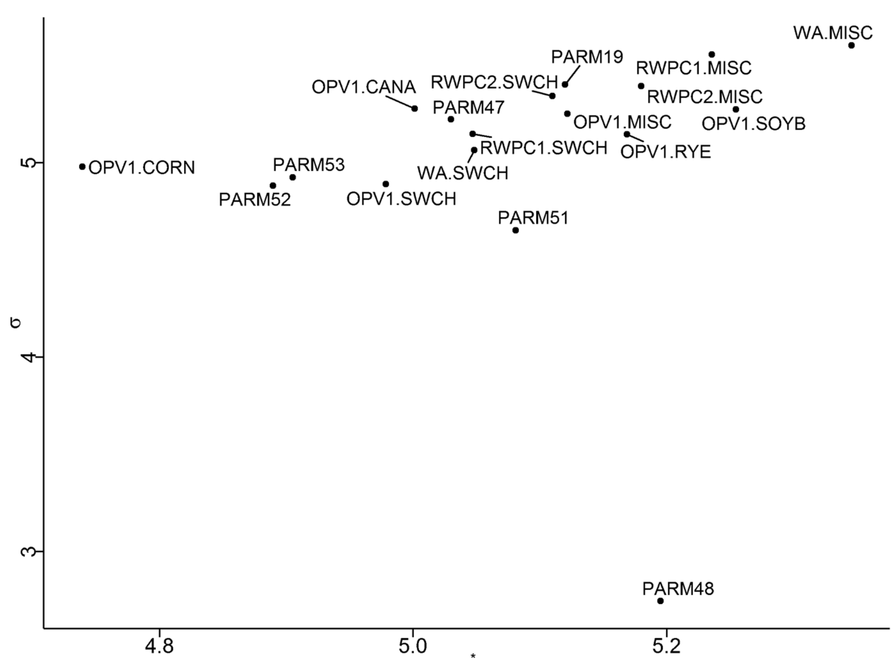

Fig. 1. Parameter sensitivities in terms of main effect (μ*) and interactive effect (σ). See Table 2 for parameter definitions.

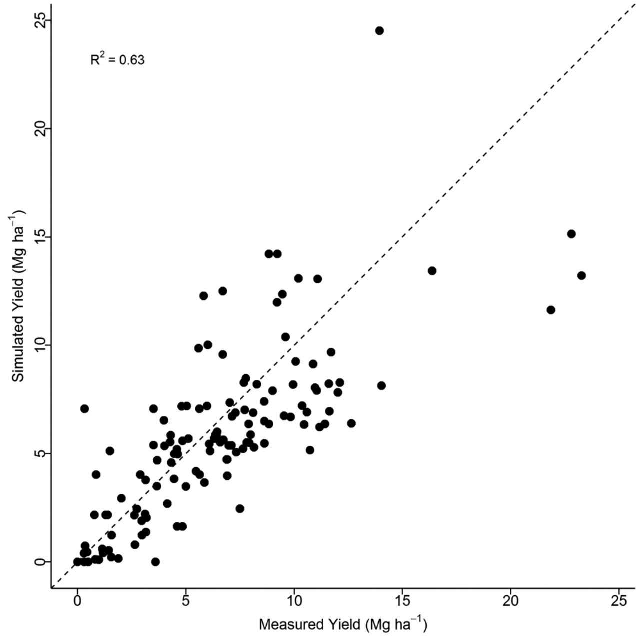

Fig. 3. Simulated vs. measured yield values from the evaluation dataset.

et al., 2015; Jones et al., 2017) and yield (Izaurralde et al., 2006; Cheng et al., 2014; Li et al., 2015; Jones et al., 2017).

Applying the calibrated model for the treatment scenarios to assess the long-term responses of SOC to rotation, rye double cropping, and rate of residue harvest indicated substantial differences in SOC stocks among treatments. The average SOC responses across the five sites (Fig. 4) demonstrate noticeably greater SOC levels under perennial compared with annual cropping. Miscanthus and switchgrass systems resulted in average final SOC stocks of 144 and 138 Mg C ha^{-1}, respectively, compared with 132 Mg C ha^{-1} under continuous corn with double cropping and zero residue removal, which was the best performing annual system. Double cropping increased SOC stocks, with average final stocks of 128 and 125 Mg C ha^{-1} for double-cropped and non-double-cropped annual systems, respectively. Double cropping was more effective for corn–soybean rotations than for continuous corn, with double crops increasing SOC levels 2.3 vs. 1.8% relative to non-double-cropped systems for corn–soybean and continuous corn systems, respectively. Harvesting of corn stover from annual systems reduced SOC levels, with 60% residue rates resulting in 4.7% less SOC than with 0% removal. Harvesting of corn stover had greater impacts on continuous corn systems than corn–soybean systems, with

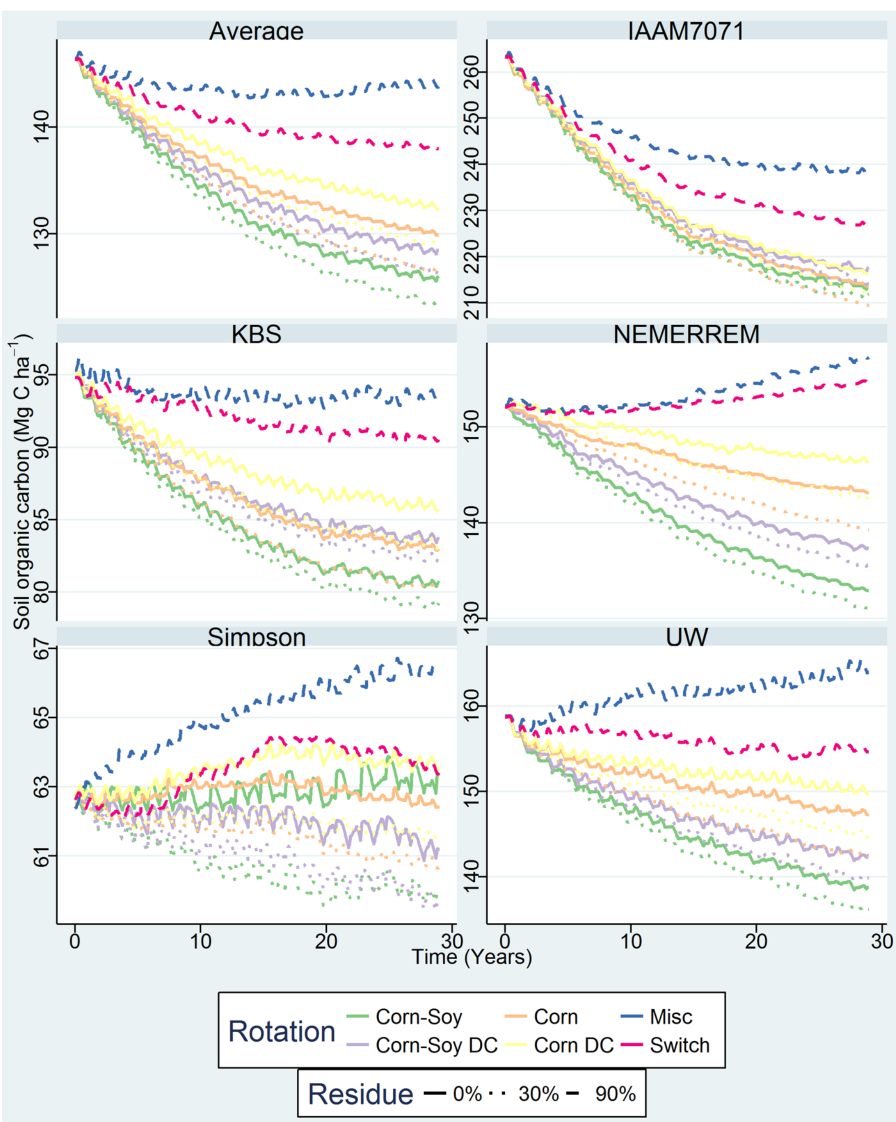

Fig. 4. The soil organic carbon (SOC) stock responses of scenarios on average and at each of five core study sites. Note that "DC" indicates inclusion of rye double crop. See Table 1 for descriptions of the study sites. Soy, soybean; Misc, miscanthus; Switch, switchgrass.

60% stover harvest rates resulting in 5.2% lower SOC levels than with 0% stover harvesting for continuous corn systems, compared with a 3.3% difference for corn–soybean systems. In addition to the SOC impacts, residue harvesting negatively affected grain yields. Linear fitting of the yield responses indicated that average corn grain yields were reduced 6.2 kg DM ha^{-1} for each percentage of residue removed, with average yields of 7.72 kg DM ha^{-1} under 0% residue removal dropping to 7.35 kg DM ha^{-1} at 60% residue removal. In terms of the average impacts on final SOC levels, conversion of 20.4% of corn–soybean land to miscanthus or 27.5% of corn–soybean land to switchgrass offset the SOC impacts of harvesting 60% of stover from the remaining corn–soybean lands.

To consider the variability of treatment responses across sites, treatment impacts were also assessed in terms of SOC change relative to the corn–soybean rotation without double cropping or stover harvesting to normalize SOC stock differences across sites driven by soil type. These responses are demonstrated in Fig. 5, with a subset of residue harvesting rates (0, 30, 60, and 90%) presented to facilitate visual interpretation of responses. Despite demonstrating greater variability than the annual systems, the perennial systems consistently resulted in greater SOC gains, with the exception of the Simpson site in Illinois, where SOC responses were similar for switchgrass systems and continuous corn systems without double cropping or residue harvesting. Although each perennial system demonstrated considerable variability, the miscanthus system resulted in greater SOC levels than the switchgrass system at all sites. Although continuous corn tended to result in greater SOC gains than corn–soybean systems, the responses were site specific, with similar or greater gains under corn–soybean at the IAAM7071 and Simpson sites. The differences in SOC levels between continuous corn and corn–soybean systems attenuated with increased residue harvesting and double cropping as the carbon contributions of the additional biomass production under corn compared with soybean was offset by its harvest and dilution from double crop residue contributions. Comparing the SOC impacts of residue removal and double cropping, it is notable that SOC levels are generally higher with double cropping and an additional 30% residue harvesting than without double cropping under corn–soybean systems, which demonstrates that double cropping offsets the SOC losses associated with the harvesting of >30% of available corn stover. Under continuous corn systems, the SOC benefits of double cropping were not sufficient to offset harvesting of 30% of stover.

To better estimate the SOC benefits of double cropping in terms of offsetting stover-harvest-associated losses, SOC responses of the four annual rotations were fit to linear regression models. The results of these fittings demonstrate higher SOC levels under continuous corn systems and under double cropping, with steeper SOC losses as a function of residue harvest under continuous corn (Fig. 6, Table 3). The increase in SOC from double cropping for continuous corn and corn–soybean systems are comparable with zero residue harvest at 2.53 and 2.47 Mg C ha^{-1}, respectively. However, the benefits of double cropping under residue removal are greater under corn–soybean systems, with the slope reduced 14.5% vs. being increased 7.2% under continuous corn. Relative to a 0% stover harvest baseline, this indicates that double cropping offsets the SOC losses associated with the removal of 38.3% of available corn stover under corn–soybean rotations. Similarly, double cropping offsets the SOC losses associated with the removal of 21.2% of stover from continuous corn systems, whereas converting from corn–soybean to continuous corn systems offsets the SOC losses associated with the removal of 34.3% of residue. Finally, converting from a corn–soybean system to a continuous corn system with double cropping offsets the SOC impacts of harvesting 53.1% of available residue. Although these SOC impacts of double cropping are sizeable, they may in fact be conservative, as Austin et al. (2017) estimated that rye cover cropping could offset as much as 80% of corn stover removed from continuous corn systems. Their study showed that roughly 45% of SOC contributions from the rye crop were derived from shoots. Hence, with rye residues being harvested, the comparable potential amount of corn stover replaced by a rye double crop would be roughly 44%.

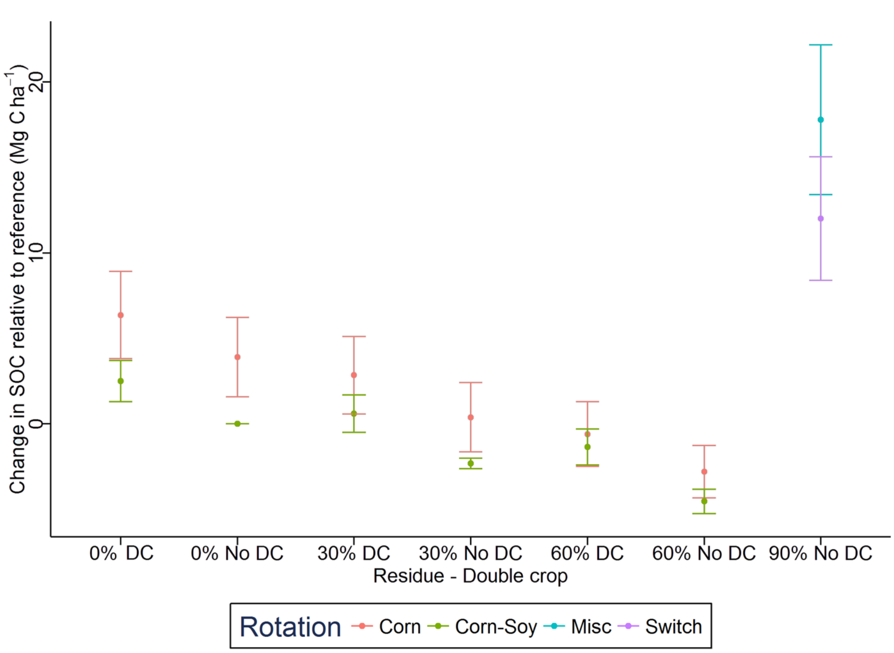

Fig. 5. The soil organic carbon (SOC) change relative to baseline corn–soybean (soy) rotation with no residue harvest and no double crop. Error bars represent ± 1 SE. Note that "DC" indicates inclusion of rye double crop. Misc, miscanthus; Switch, switchgrass.

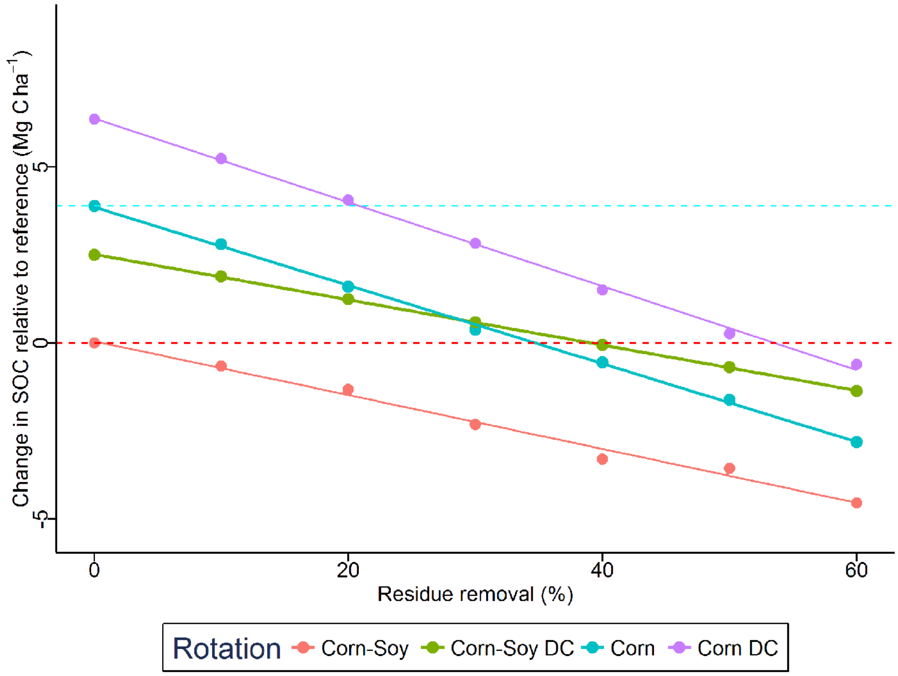

Fig. 6. The soil organic carbon (SOC) response to residue removal in corn-based systems with and without double cropping. Soy, soybean; DC, rye double crop.

Overall, these results indicate that viable options exist for sustainable production of cellulosic biofuels in the US Midwest. Numerous studies have demonstrated the capacity for environmental benefits from dedicated perennial bioenergy crops such as switchgrass and miscanthus (Gelfand et al., 2013; Poeplau and Don, 2014; Qin et al., 2016). The results here affirm such findings while further contextualizing the responses to a diversity of cropping system and management options. Further, these efforts fill an identified need (Qin et al., 2016) for modeling efforts to integrate experimental knowledge of SOC responses to cropping system and management into ecosystem models and apply these tools for assessing long-term responses under a range of treatments. This is particularly impactful for EPIC modeling applications, as the model has been widely used for simulating the sustainability of biofuel cropping systems but has not been thoroughly tested for simulating SOC responses under cover, double, switchgrass, and miscanthus cropping. Ultimately, this assessment indicates that the SOC benefits of double cropping demonstrated here could have considerable implications on the viability of the use of corn residues as cellulosic feedstocks. Liska et al. (2014) called into question the ability of corn-stover-derived biofuels from the US Midwest to meet US standards for cellulosic biofuels, mainly due to large SOC losses induced by stover removal. A subsequent analysis by Jones et al. (2017) estimated that while such feedstocks could meet a small portion of US targets under current cropping management, small mitigation of SOC losses would allow large expansion of suitable production. Although the results here are based on a small subset of sites within the US Midwest, if these responses are regionally representative, inclusion of double crops or cover crops into corn-based systems would result in a magnitude of SOC mitigation that would allow such an expansion of viable cellulosic feedstock sources without alteration to existing crop rotations.

Table 3. Linear models for estimating the soil organic carbon (SOC) response to residue removal in annual systems.

System	Equation
Corn–soybean	$\Delta SOC = 0.05 - 0.076(\text{Residue})$
Corn–soy double cropped	$\Delta SOC = 2.52 - 0.065(\text{Residue})$
Corn	$\Delta SOC = 3.86 - 0.111(\text{Residue})$
Corn double cropped	$\Delta SOC = 6.39 - 0.119(\text{Residue})$

Conclusions

Evaluation of EPIC simulations against site-level experimental measurements indicated that the model performed suitably for assessing SOC responses under corn-based annual rotations with and without cover crops or double crops and at a range of residue removal rates, as well as under the dedicated perennials switchgrass and miscanthus. Long-term simulations indicated that the positive impacts of dedicated perennial cultivation on SOC stocks relative to traditional annual systems could offset the SOC losses induced by residue harvesting on a considerable area of land. Additionally, these simulations demonstrated the capacity for offsetting a sizable amount of residue-induced SOC losses through incorporation of rye double crops into corn-based rotations. Such measures are expected to have sizeable impacts on the carbon sequestration consequences of residue-derived biofuels. Incorporation of such measures into regional modeling and life cycle analyses is expected to considerably expand estimates of the capacity for sustainable cellulosic feedstock production from the US Midwest.

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