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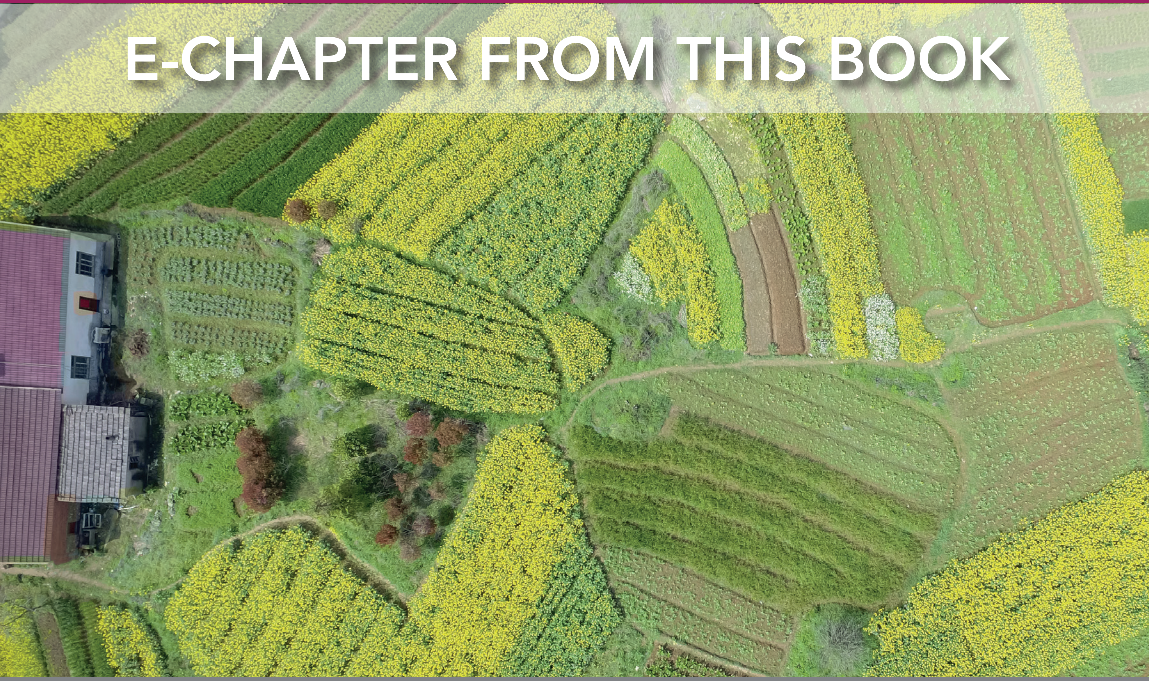

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Modeling crop rotations: capturing short- and long-term feedbacks for sustainability and soil health

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1 Introduction

Crop rotations are cyclic sequences of crop-plant species grown on the same parcel of land. This contrasts with intercropping (multiple species grown simultaneously), or monocropping (growing a single species continuously). Throughout most of human history, rotating crops was one of the few tools farmers had at their disposal to sustain soil fertility, combat pests, and improve yields (Bullock, 1992; Karlen et al., 1994; Leighty, 1938). Since the 1950s, the use of synthetic fertilizers and biocides to manage fertility and pests has allowed monocropping on a more prominent scale. However, crop rotations are still used extensively worldwide (Alhameid et al., 2017). The reasons for the current widespread adoption are very much the same benefits that early farmers identified. Well-designed rotations can (1) effectively break growth cycles of weeds (Liebman and Dyck, 1993; Stevenson and van Kessel, 1996), insects (Miller et al., 2006), and diseases (Curl, 1963; Médiène et al., 2011); (2) improve soil fertility and health by alternating plant nutrient requirements, as well as the quality and quantity of crop residue inputs into the soil (Bennett et al., 2012; Kay, 1990; Reeves, 1994); (3) allow for more flexibility in logistics, as distinct crop growth cycles spread out the allocation of labor (Zentner et al., 2002); and (4) manage risks related to market fluctuations (Zentner et al., 2001).

http://dx.doi.org/10.19103/AS.2019.0061.11

Chapter taken from: Boote, K. (ed.), *Advances in crop modelling for a sustainable agriculture*, Burleigh Dodds Science Publishing, Cambridge, UK, 2019, (ISBN: 978 1 78676 240 5; www.bdspublishing.com)

Given their large footprint and important role in crop production, examining the biophysical dynamics resulting from growing diverse crops in sequence has been a common topic of research in the agronomy and agroecology fields. Alternating among crop species fundamentally changes the cycling of water and nutrients and their distribution in the soil profile (Fletcher et al., 2011; Hirsh and Weil, 2019; Ryan et al., 2009). Additionally, differing quantities and qualities of aboveground and belowground crop residues influence the amount and timing of plant nutrient availability, water infiltration and runoff, soil temperature and long-term soil carbon storage, and potential risk of nutrient leaching (Blanco-Canqui and Lal, 2009; Poffenbarger et al., 2017; Puntel et al., 2016). These 'legacy', 'carry-over', or 'rotation' effects are often observed as increased crop yields or greater resilience to environmental stress (Reeves, 1994; Ryan et al., 2008). Because of these complex feedbacks, legacy effects and their interactions with weather are generally not well understood, and their ultimate influence on yields and environmental quality is difficult to predict.

Crop simulation models offer a way of parsing through this complexity. Their explicit representation of the fundamental processes driving crop growth and development, as well as water, carbon, and nutrient cycles, have made them popular tools for evaluating many aspects of cropping systems. These models use information on soils, weather, crop cultivars, and management as inputs in mathematical algorithms to calculate changes in the system state across various temporal scales (Wallach et al., 2014). Many of these have the capability to simulate crop rotations, and their implementation in this context has been useful to examine differences in water and nutrient flows among crop sequences and phases (Dietzel et al., 2016; Martinez-Feria et al., 2018; Post et al., 2007; Salado-Navarro and Sinclair, 2009), estimate environmental nitrogen (N) losses over long periods (Basso et al., 2016; Gillette et al., 2018; Kovács et al., 1995; Martinez-Feria et al., 2016), predict changes in soil carbon storage (Basso et al., 2015, 2018; Berntsen et al., 2007; Hlavinka et al., 2014; Jarecki et al., 2018), and assess the economic impacts of management (Puntel et al., 2016; Araya et al., 2017; Nielsen et al., 2009).

Methodologically speaking, two general approaches exist when simulating crop growth cycles and, by extension, crop rotations (Basso et al., 2015). The first and most widely used approach is to simulate single crop phases independently using the same initial soil state conditions (e.g. water, organic carbon, or nutrient levels) for every simulation cycle. This approach, often referred to as the seasonal 'reset' mode, is a holdover from when crop models were only capable of simulating single crop growing seasons. There are obvious limitations with this approach, namely that the legacy effects on soils, such as the ones discussed above, are ignored (Ewert et al., 2015; Teixeira et al., 2015). Despite this, running models under reset mode has been standard practice in impact assessments such as those for climate change (Kollas et al., 2015; White et al., 2011). Most models today are now capable of running continuous simulations over multiple crop rotation phases in what is known as 'sequential' mode, and several studies have discussed its advantages, both in terms of predicting yield (Kollas et al., 2015; Teixeira et al., 2015, 2018) and soil carbon storage (Basso et al., 2015, 2018). Under this approach, the legacy effects from one phase of the rotation to the next emerge from the simulation process itself; thus the user is only required to provide initial conditions for the first year of the simulation.

Although running crop models under either reset or sequential mode each have their limitations and advantages, they also provide distinct insights on the behavior of the system. To illustrate and discuss this point, in this chapter we focus on two case studies that evaluate short- and long-term outcomes of distinct crop rotations. In the first case study, we use APSIM (Agricultural Production Systems sIMulator; Holzworth et al., 2014) run with reset mode to examine short-term weather and legacy impacts on hydrological nitrate (NO_3) losses and evaluate mitigation strategies in distinct crop rotation phases. The second case study uses system approach to land use sustainability (SALUS) (Basso and Ritchie, 2015) run on sequential mode to identify adaptations to crop rotations for maintaining long-term productivity and soil health under climate change.

2 Reset mode crop models: the example of mitigating nitrate loss from corn-based crop rotations

Loss of NO_3 from corn (*Zea mays* L.) and soybean (*Glicyne max* L [Merr.]) cropland into surface waters is one of the major environmental impacts of crop production in the Midwest US (David et al., 2010; Robertson and Vitousek, 2009). While many studies attribute the loss of NO_3 to the overuse of nitrogen (N) fertilizer (Cassman et al., 2002; Zhang et al., 2015), the release of native soil N can also contribute substantially to NO_3 loss (Bowles et al., 2018; Martinez-Feria et al., 2018). Without a strong sink (e.g. plant growth) to retain N during the extensive fallow periods (October to May), NO_3 from fertilizer or organic matter mineralization sources builds up in soils and is transported into subsurface drainage systems during heavy rains (Randall and Mulla, 2001). With spring rainfall increasing in many areas of the Midwest (Melillo et al., 2014), the NO_3 loss problem will continue to worsen (Bowles et al., 2018).

From a crop management perspective, two strategies are often cited as having great potential to mitigate NO_3 losses into subsurface drainage (Christianson et al., 2018): (1) applying N fertilizer in season rather than before planting and (2) growing cover crops during the fallow period. In this case study, we use APSIM to evaluate the NO_3 loss reduction effectiveness of these practices across ranges of weather and legacy conditions, aiming to identify scenarios where these practices may be the most effective.

2.1 Sites and data sources

Soil and weather data from four long-term experimental field sites located in Iowa were used to configure and drive the simulation model (Table 1). The Ames and Nashua sites have been described in detail in previous studies (Dietzel et al., 2016; Martinez-Feria et al., 2018), while the information for Gilmore and Crawfordsville were extracted from the Sustainable Corn CAP Research Database (Abendroth et al., 2017). Soil information for each site was obtained from the SSURGO database (Soil Survey Staff). The soils in these sites are deep, fertile, and artificially drained using subsurface drain tubes. Daily weather (1987–2016) for all sites was retrieved from the Daymet dataset (Thornton et al., 2018) using the single pixel extraction tool (downscaled to 1 km × 1 km resolution).

2.2 The APSIM model

APSIM is an open-source cropping systems simulation platform with interconnected crop, hydrological and nitrogen cycling process-based models. Using daily weather and user-defined soil and management information, the model calculates many soil-plant-atmosphere variables, including crop growth processes, soil water, soil temperature, and N and C cycling. For in-depth descriptions of APSIM, we refer the reader to Holzworth et al. (2014).

2.3 Model configuration

APSIM (version 7.8) was configured using the information on soil, drainage specifications, and management available for each site (Table 1). When configuring the simulations, we used the following APSIM modules: *maize* (corn), *soybean, wheat* (for rye cover crop), *SWIM3* (soil hydrology), and *soilN* (C and N cycling). The corn and soybean APSIM cultivars used have been calibrated to broadly characterize locally adapted commercial genotypes in the region (Archontoulis et al., 2014a,b). We selected maturity groups appropriate for each site based on the management records available. The *wheat* module was calibrated following Dietzel et al. (2016) and Martinez-Feria et al. (2016) and was used to simulate the rye cover crop.

Before conducting simulation experiments, we ran the model for a 'spin-up' period. This was to remove the confounding effects of buildup or decline in soil organic carbon (SOC) humic or microbial pools (Puntel et al., 2016). In this case, a maize-soybean rotation was simulated sequentially for 15 years at each

Table 1 Summary of the sites used for simulation modeling

	Location		Soil			N fertilizer rate[d] (kg N ha^{-1})		Subsurface drainage	
Site	Lat.	Long.	Texture	OC (%)	PAWC (mm)	Corn after corn	Corn after soybean	Depth (cm)	Spacing (m)
Ames[a,b]	41.92	−93.75	Silty clay loam	2.0	132	211	175	110	13.5
Gilmore[c]	42.75	−94.50	Silty clay loam	2.2	123	211	157	110	7.6
Nashua[a]	42.93	−92.57	Loam	1.3	124	211	157	120	28.5
Crawfordsville[c]	41.19	−91.48	Silty clay loam	1.6	110	228	171	122	18.3

Source: [a] Martinez-Feria et al. (2018); [b] Dietzel et al. (2016); [c] Abendroth et al. (2017); [d] Based on university recommendations (N rate calculator: http://cnrc.agron.iastate.edu/) and Sawyer et al. (2006).

OC = organic carbon; PAWC = plant available water content (0–1 m).

site. Initial values for soil nitrate and moisture, and above- and below-ground residue amount and C:N were also derived from this step. To avoid introducing bias from a given set of conditions experienced during the last year of the spin-up, we used the average value of these variables at harvest for the last five simulated years for each crop. The values for initial conditions, as well as further details on model configuration, testing, and performance against measured data, are provided by Martinez-Feria (2018).

2.4 Simulation experiments

The simulation experiments were designed to quantify the impact of weather and management factors on cumulative annual NO_3 loads (kg N ha^{-1}) in subsurface drains for cropland under a corn-corn-soybean rotation at the long-term sites. Each of the phases of the rotation was simulated with 30 years of historical weather (1987–2016). To decouple the effect of weather-year from the legacy rotation effects, the soil states (i.e. moisture and N levels) were reset every year on 20 October. This means that simulation accounted for the period from 20 October to 19 October of the following year, roughly representing a harvest-to-harvest cycle.

As default initial values of soil N, we use the average soil NO_3 content on 19 October in spin-up runs. This was then increased and decreased by a factor of 0.5, which provided a low, average, and high value. Similarly, the initial water content in the profile was altered by initializing the water table 12 cm above, 12 cm below, and at the depth of subsurface drains, providing a shallow, deep, and average water table level, respectively.

In addition to these legacy initialization factors, we evaluated the impact of two management practices in each of the rotation phases. In the corn phases, we simulated two N fertilizer application timing treatments: at planting and in-season split (with 50% applied at planting and 50% applied 40 days later). N fertilizer rates followed university recommendations (http://cnrc.agron.iastate.edu/; Sawyer et al., 2006; Table 1). In the soybean phase, we also evaluated the impact of planting time, with early (late April) and late (late May) planting treatments. Finally, we also evaluated the inclusion of winter rye cover crop in all crop phases. Cover crops in each simulation cycle were planted every year on 1 November and terminated in the spring 7 days before planting of the main crop. The combination of 4 sites, 3 rotation phases, 9 sets of initial conditions, 4 management treatments, and 30 weather years produced 12,960 individual simulations.

2.5 Findings

Table 2 shows the percent of the total variance (i.e. proportion of the sums of squares) explained by each factor in the simulation experiment. In all sites,

Table 2 Share of the total variance in simulated NO_3 loss attributed to simulation factors

	Site				
Simulation factor	Ames (%)	Gilmore (%)	Nashua (%)	Crawfordsville (%)	All (%)
Corn after corn					
Initial conditions	17	21	30	17	19
Weather-year	69	63	56	71	67
Management treatments	4	3	2	2	3
Interactions	11	13	13	10	11
Corn after soybean					
Initial conditions	6	12	20	6	8
Weather-year	85	75	65	86	83
Management treatments	1	1	1	1	1
Interactions	8	12	15	7	8
Soybean after corn					
Initial conditions	24	23	29	24	24
Weather-year	53	58	54	57	56
Management treatments	7	5	3	4	5
Interactions	16	15	14	15	15

weather-year was the factor that had the most impact on annual NO_3 loads (53–86% of the variation) followed by the soil initial conditions (6–30%), and then by management factors (2–7%). All interactive effects explained 7–16% of the total variation in simulated annual NO_3 loads.

Across all sites, annual NO_3 loads responded positively to the amount of spring rainfall and legacy soil NO_3, although the response differed substantially among crop phases (Fig. 1). Very few differences were noticeable between N fertilizer timing treatments (corn phases) or planting date (soybean phase) treatments, whereas these were greater between cover crop treatments. The corn-after-corn and the soybean-after-corn phases of the rotation had

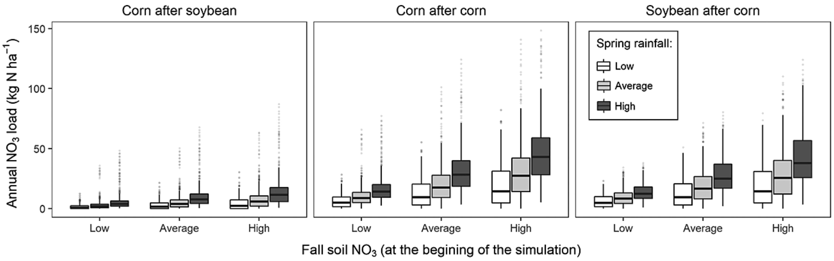

Figure 1 Simulated response of annual NO_3 loads to increasing spring rainfall and initial soil NO_3 content across all the sites and management treatments.

generally higher NO_3 losses than the corn-after-soybean phase (Fig. 1). This suggests that prior corn crop fertilization (e.g. legacy soil N from the previous crop) is an important contributor to the NO_3 losses, and that corn-soybean crop rotations have overall lower potential of annual NO_3 losses than continuous corn monocrops. This is consistent with experimental evidence (Christianson and Harmel, 2015) and other simulation studies (Martinez-Feria et al., 2018).

The scenarios with no cover crop, N fertilizer applied to corn at planting, and soybean with late planting (late May) averaged 7.2, 27, and 24 kg N ha^{-1} yr^{-1} annual NO_3 loads, in the corn after soybean, corn after corn, and soybean after corn phases, respectively. Using these as management baselines (Table 3), we see that improved practices reduced annual NO_3 loads more in wet springs. Likewise, reductions were greater in the soybean phase of the rotation. Few differences in the relative reduction were detected across levels of initial soil NO_3 content.

Even though management overall explained a small percent of the variation (Table 2), combining the establishment of a cover crop with other improved practices can still significantly reduce NO_3 losses when compared to a baseline management scenario, especially in wet years (Table 3).

Interestingly, the NO_3 loss mitigation potential of the cover crop was greater after corn than after soybean, perhaps due to the greater amount of residual NO_3 in the soil following corn. Based on these findings, we conclude that a corn-soybean rotation with cover crops, paired with early planting in soybeans and in-season N applications in corn is the best performing cropping system among the options examined in this case study.

Table 3 Reduction in annual NO_3 loads relative to baseline management

	Spring rainfall			Fall soil NO_3		
Treatment	Low (%)	Average (%)	High (%)	Low (%)	Average (%)	High (%)
Corn after corn						
Baseline (BL) + Split N	0	1	3	2	1	1
BL + Cover crop	21	26	30	25	27	26
BL + Split N + Cover crop	21	28	34	28	29	27
Corn after soybean						
BL + Split N	1	2	4	3	2	2
BL + Cover crop	9	7	21	16	12	12
BL + Split N + Cover crop	9	11	27	20	15	15
Soybean after corn						
BL + Early planting	8	4	2	4	5	5
BL + Cover crop	25	32	38	31	34	36
BL + Early planting + Cover crop	26	35	40	31	33	32

3 Sequential crop models: the example of adapting crop rotations to sustain yields and soil health under climate change

Changing climatic conditions will likely reshape the nature of future food production. In many regions of the world, the negative impacts of climate change on crop yields are already visible (Lobell et al., 2011; Porter et al., 2014). Yields are projected to decrease by the second half of the twenty-first century in many temperate and tropical areas (Challinor et al., 2014; Porter et al., 2014; UNFAO, 2016). Increasing microbial activity due to higher soil temperatures and decreasing crop residues due to low yields will also affect the ability of agricultural soils to store carbon (Powlson et al., 2014), and impoverish their fertility (Jarecki et al., 2018). While management practices can help farmers adapt, the interactions between management, soils, and climate remain poorly understood (Basso et al., 2018). The objective of this case study was to evaluate the performance of corn-based cropping systems under projected climate changes across a range of Midwestern soils. We aim to identify a system that could be best adapted to maintain crop yields and soil health in future climates.

3.1 Sites and soils

We used data from experimental sites located in eight states across the Midwest US: Iowa, Illinois, Indiana, Michigan, Minnesota, Missouri, Ohio, and Wisconsin (Table 4). Each site has dedicated field trials with site-specific treatments to study corn-based cropping systems in terms of productivity and environmental impacts. Soils in these sites range from low (MI and IN) to very high (MN) organic carbon content (Table 4). Measured soil texture, bulk density, and organic carbon content were available for the top 0–60 cm at most sites, and information below 60 cm was obtained from the SSURGO database. These data were used to calculate soil hydraulic properties with pedotransfer functions (Ritchie et al., 1999; Suleiman and Ritchie, 2001). Further details about the sites and experimental treatments are available in Necpalova et al. (2014).

3.2 Historic and future weather

Historical weather data (1979–2013) downscaled to the location of the experimental sites were obtained from the National Centers for Environmental Prediction North American Regional Reanalysis (NCEP-NARR) model (Mesinger et al., 2006). We generated time-series climate change weather for the 2070–2100 time frame under the representative concentration pathway (RCP) 2.6 and 6.0 emissions scenarios by simple transformations of historical NARR dataset (i.e., delta method; Table 5). The RCP 2.6 represents a 'best-case' climate

Table 4 Summary of location and soil characteristics at the sentinel sites

		Location			
State	Site	Lat.	Long.	Soil type	Soil organic carbon (Mg C ha^{-1}; 0–60 cm)
IA	ISUAG	42.00	−93.78	Loam and clay loam	137
IL	NWREC	40.93	−90.72	Silt loam and silty clay loam	153
IN	SEPAC	39.02	−85.54	Silt loam	47
MI	KBS	42.41	−85.37	Loam and sandy loam	48
MN	SWROC.B	44.35	−95.53	Silty clay loam	215
MO	Bradford	38.90	−92.20	Silty clay loam	76
OH	Hoytville	41.21	−83.76	Clay loam	99
WI	Marshfield	44.76	−90.09	Silt loam	173

change scenario, where global annual GHG emissions peak between 2010 and 2020 and decline thereafter, whereas the RCP 6.0 is a scenario where emissions peak around 2080, then stabilize (Meinshausen et al., 2011). The magnitude of the changes, at the annual level or as a seasonal pattern, was derived from the IPPC 5th assessment report (IPCC, 2014) and its actual translation at the US level, as reported in the National Climate Assessment of the US Global Change Research Program (Melillo et al., 2014). The three main changes applied to the historical records are shown in Table 5.

3.3 The system approach to land use sustainability (SALUS) model

The system approach to land use sustainability (SALUS) model is a process-based modeling system that simulates plant growth and development responses to environmental conditions (soil and weather), genetics, and management strategies in a sequential mode (Basso and Ritchie, 2015). The model uses daily values of incoming solar radiation (MJ m^{-2}), maximum and minimum air temperature (°C), and rainfall (mm), as well as soil and management information to simulate crop yields, and water, N and C cycling. More information about SALUS and its performance against measured data is available in the following studies: Albarenque et al., 2016; Basso et al., 2016, 2018; Basso and Ritchie, 2015.

3.4 Crop rotation scenarios

Four corn-based cropping systems were designed for evaluation (Table 6): (i) continuous corn (SC1-2); (ii) corn-soybean rotation with rye cover crop (Corn-cc-SB-cc; SC3); and (iii) corn-soybean-wheat rotation with rye cover crop

Table 5 Operations used to generate future weather (2070–2100) from historic weather (1979–2013)

Scenario	Variable	Period DJF	MAM	JJA	SON	Operation
Baseline (BL)	–	NCEP-NARR (1979–2013)				–
RCP 2.6	Precipitation	1.1	1.1	0.95	1	Multiplying BL by coef.
	Temperature	-----------+3°C-----------				Adding fixed value to BL
	$[CO_2]$	-----------400 ppm-----------				Replacing BL value
RCP 6.0	Precipitation	1.2	1.2	0.9	1	Multiplying BL by coef.
	Temperature	-----------+6°C-----------				Adding fixed value
	$[CO_2]$	-----------540 ppm-----------				Replacing value

Table 6 Synthesis of corn-based system evaluated with the SALUS model

Scenario	Rotation[a]	Manure	Timing of N fertilization to corn[b]	Tillage
SC1	Corn	Fall manure	100% at planting	Conv. Till.
SC2	Corn	No manure	25% at planting and 75% at V6	No Till.
SC3	Corn-cc-SB-cc	Fall manure	25% at planting and 75% at V6	Minimum Till
SC4	Corn-cc-SB-WW-cc	Fall manure	25% at planting and 75% at V6	Minimum Till

[a] SB = Soybean, WW = winter wheat, cc = rye cover crop.

[b] Corn received 200 kg N ha^{-1} in all scenarios.

following corn and wheat (Corn-cc-SB-WW-cc; SC4). In addition, we evaluated two N management strategies common in the Midwest: (i) 200 kg N ha^{-1} applied to corn at planting and (ii) 50 kg N ha^{-1} at corn planting and 150 kg N ha^{-1} applied at corn V6 growing stage. In addition, scenarios 1, 3, and 4 also included fall manure applications prior to corn (e.g. 500 kg C ha^{-1} and 50 kg N ha^{-1}). Three tillage regimes were also evaluated: (i) conventional tillage in the 0–30 cm soil profile (SC1); (ii) no tillage in which fresh organic carbon and residues remained on the soil surface; and (iii) minimum tillage regime with shallow tillage (22 cm) once every rotation cycle to incorporate crop residues and manure when applied to corn.

3.5 Findings

Simulated grain yields at most of the sites were impacted negatively by climate change. For instance, yields under SC1 crop rotation over the 35-year period decreased on average by 5% and 20% under the RCP 2.6 and 6.0 climate scenarios, respectively. Yield losses due to climate change were more extreme in Ohio, Illinois, and Iowa, ranging from 22% to 46%. Only two sites, Michigan and Wisconsin, saw slight yield gains under the climate change scenarios, probably due to increased precipitation and the low soil water holding capacity at those sites (Table 4), where water and temperature stress limitations were not enough to overcome the positive effects of increased CO_2 (Table 5). However, these gains were partially or totally offset under RPC 6.0.

On average, corn yield losses under climate change were the greatest with rotation SC4 (13% and 32% under RPC 2.6 and 6.0, respectively). We should note that SC4, the most complex rotation that included cover crops and winter crops (Table 4), also was the one with the greatest yield under baseline conditions in most states. On the other hand, SC2 seems to be the least impacted (2% and 10% yield loss under RPC 2.6 and 6.0, respectively), although this cropping system had generally low yields even with the historical weather baseline (7% lower than SC1; Table 7).

As expected, climatic change had a negative impact on the amount of SOC storage. Table 8 shows the change in SOC over the 35 years of the simulation for four of the simulated crop rotations. On average, soils lost 20 and 26 Mg C ha^{-1} under RPC 2.6 and 6.0, respectively, in the SC1 scenario. This is more than double of that lost with the historical baseline climate. This trend was similar across all the crop rotation scenarios. The no-till scenario (SC2) was the only condition that resulted in SOC gains under the baseline, although these gains were partially or totally offset by climate change. Where no-tillage techniques were applied, and cover crops were part of more complex rotations, the SOC losses remained limited (Table 8).

All of this suggests that maximizing the amount of residues returned to the soil and minimizing tillage are broadly the most effective strategies for

Table 7 Comparison of corn grain yields of simulated crop rotations under different climate scenarios

Scenario		Mean change in corn yield relative to SC1 over 35-yr (%)		
Climate	Rotation	Min	Mean	Max
BL	SC2	−17.5(MI) and −14.2(IA)	−7.10	+4.9(MO) and +3.2(OH)
	SC3	−20.8(IA) and −8.5(MI)	−5.00	+2.1(OH) and +1.9(MO)
	SC4	−38.8(IL) and −5.7(IA)	−4.70	+6.24(MI) and +4.9(OH)
RCP 2.6	SC2	−16.6(MI) and −12.5(IA)	−1.10	+18.6(WI) and +8.0(IL)
	SC3	−20.7(MO) and −15.1(IA)	−1.50	+14.1(OH,WI) and +9.8(IL)
	SC4	−40.0(IL) and −32.5(IA)	−12.7	+10.0(OH) and +5.7(WI)
RCP 6.0	SC2	−12.1(MI) and −8.8(IA)	+3.5	+37.3(IL) and +13.1(WI)
	SC3	−43.4(IL) and −25.0(MO)	−11.6	+11.1(WI) and −0.4(OH)
	SC4	−41.7(IA) and −28.1(IL)	−17.0	+0.1(OH) and −1.7(IN)

Table 8 Effect of rotation and climate scenarios on the change in soil organic carbon (SOC) as simulated by SALUS

Scenario		35-yr change in SOC (Mg C ha^{-1})		
Rotation	Climate	Min	Mean	Max
SC1	BL	−44.9(IL) and −35.9(IA)	−10.7	+15.9(MN) and +12.7(IN)
	RCP 2.6	−54.4(IL) and −47.6(IA)	−20.4	+8.3(MN) and +4.7(IN)
	RCP 6.0	−60.4(IL) and −55.4(IA)	−26.6	+3.9(MN) and −0.3(IN)
SC2	BL	−4.2(IL) and +1.9(IA)	8.7	+18.3(MN) and +15.7(IN)
	RCP 2.6	−13.6(IL) and −8.0(IA)	4.2	+19.3(MN) and +16.3(IN)
	RCP 6.0	−19.7(IL) and −14.8(IA)	−0.7	+15.9(MN) and +11.6(IN)
SC3	BL	−30.4(IL, OH) and −28.9(IA)	−7.2	+19.6(IN) and +13.8(MN)
	RCP 2.6	−40.6(OH) and −38.8(IL, IA)	−14.8	+13.2(IN) and +7.6(MN)
	RCP 6.0	−47.4(OH) and −46.4(IL)	−19.9	+8.7(IN) and +5.4(MN)
SC4	BL	−39.2(IA) and −34.7(IL)	−11.8	+14.8(IN) and +8.8(MN)
	RCP 2.6	−40.7(OH) and −40.0(IA, IL)	−16.1	+10.4(IN) and +5.4(MN)
	RCP 6.0	−45.3(IA, OH) and −43 (IL)	−20.2	+4.9(IN) and +2.2(MN)

mitigating SOC changes under climate change, which agrees with literature (Basso et al., 2018; Poffenbarger et al., 2017). The 2- and 3-year rotations (SC3 and SC4) included low-residue crops, and it appears that manure applications and minimum tillage would not be able to offset the SOC losses. The decline of SOC over the long term introduced negative feedbacks (e.g. more evaporation, less soil N mineralization), which contributed to the lower corn yields under the SC4. Based on these findings, we conclude that among the evaluated systems, the no-till continuous corn system (SC2) had the highest potential to mitigate the negative yield and SOC impacts of climate change.

4 Conclusion: improving crop rotations through modeling

Crop rotations have been identified in many studies as a means to improve the agronomic and societal outcomes from crop production (Bennett et al., 2012; Davis et al., 2012; Karlen et al., 1994; Zentner et al., 2001) and as possible adaptation strategies to changing climates (Farina et al., 2018; Nendel et al., 2014; Reidsma et al., 2010; Teixeira et al., 2018). The case studies presented here examined simulations from various hypothetical crop rotations to explore pathways to increase the future sustainability and resilience of Midwestern corn production.

Here we show that crop rotation coupled with improved management is an effective way to mitigate NO_3 losses under wet springs (Table 3), which are expected to be more common (Bowles et al., 2018). Over the long term, increasing temperatures will more likely be detrimental for both corn yields and

SOC storage (Basso et al., 2018), and only a few of the crop sequence scenarios examined here seem to have the potential to reverse this trend. Critically, while the extended crop rotation that included corn, soybean, winter grains, and cover crops seemed to have overall corn yield benefits (compared to continuous corn monoculture) under historical weather (Table 7), these benefits seem to be negated under climate change because of lower amounts of crop residue input to the soil (greater SOC depletion) in these systems, compared to continuous corn (Table 8). It should be noted that these analyses cover only biophysical and geochemical aspects of crop rotations and not biotic benefits such as reduced pest and diseases or increased habitat for beneficial organisms, which can account for a significant share of the rotation effect (Bennett et al., 2012).

These results highlight the importance of considering crop rotation legacies when assessing the impact of drivers such as weather and soils, and of the value of simulation approaches in this respect. Experimental evidence for the frequently observed productivity and environmental advantages of crop sequences is difficult to discern, because the legacy effects are often not the result of one single factor, but of many. Moreover, these legacies are often simultaneously at play; thus the ultimate result depends on the magnitude of each individual effect and its interaction with weather conditions (Martinez-Feria et al., 2016). Accounting for such legacy effects is not only needed for accurately predicting short-term outcomes (e.g. crop yield responses to N fertilizer; Puntel et al., 2018), but has also shown to be very important for estimating long-term impacts, such as nutrient balances (Martinez-Feria et al., 2018) or soil carbon storage (Basso et al., 2018). The case studies presented here focus on a few rotation effects important in rainfed temperate regions (i.e. NO_3 loss, yield, and SOC change). In semi-arid regions where soil profile moisture is typically depleted by the end of each season, examining how crop rotations affect the carry-over soil moisture can help assess the probability of obtaining a given yield the next growing season (Nielsen et al., 2009). It also provides insight into possible adjustments to management (e.g. sowing date, sowing density, N fertilization, choice of cultivar or crop) or to irrigation strategies where irrigation water is available (Araya et al., 2017).

While the legacy effects (e.g. soil N and water content, or quantity and quality of crop residues) are not inherently accounted for when models are run with reset mode, these may be approximated by altering the soil initial conditions as part of the scenario analysis. This decoupling of the weather effects from the legacy factors allows for easier interpretation of modeling results, especially when the examination of the effect of year-to-year differences in weather patterns are the focus of study. Consider the example of the year 2013 in our reset mode case study. Iowa experienced a drought in 2012, which resulted in reduced yields and large amounts of residual soil NO_3 at harvest. Because of this, NO_3 losses in 2013 are heavily influenced by the previous year when running the model in sequential mode (as it does in reality). Thus, separating the effect of 2013 weather and management from the 2012 drought is rather difficult. If our interest is to find best management options within a crop rotation for different weather patterns (e.g. Table 3), the reset mode allows us to examine this independently from important rotation legacy factors, such as soil NO_3 left over by the previous crop (i.e. the initial soil NO_3 in the simulation). In this case, initial conditions should be representative and preferably explore a range of potential values, such as we do in this case study.

Predefining initial conditions every season, however, runs the risk of introducing uncertainty and biases. These have been seen to affect the ability of models to accurately predict yield, especially under extremely dry weather conditions (Teixeira et al., 2015). If there is confidence in the representation of the processes being simulated, then legacies should be sufficiently well captured by the sequential simulation mode. A recent study showed that yield simulation error decreased as the number of successive crops modeled increased, which was interpreted as evidence that the inadequacy of initial conditions becomes less important with each passing crop as the system reaches equilibrium (Gaydon et al., 2017). However, another study was not able to establish a clear advantage of sequential simulations over seasonal reset mode (Yin et al., 2017), which was attributed to uncertainty regarding how well the process was simulated.

In the context of long-term impacts, biases in the simulation of crop yields within decadal time frames lead to long-term biases in soil residue inputs, obscuring the potential for management to mitigate the negative climate change impacts on SOC (Basso et al., 2015). This could have been the case in our seasonal reset mode study if, for example, we had only considered initializing the model with low soil NO_3. In the corn-following-soybean phase of the rotation, this led to a higher NO_3 loss reduction effectiveness with cover crops, when compared to average and high levels (Table 3). Here the initial soil conditions were varied within reasonable ranges (i.e. 50% more or less initial soil N; soil water saturation 12 cm above or below the subsurface drain), which reflect variations observed in field data (Hirsh and Weil, 2019). Still, varying these legacy conditions contributed up to 30% of the variation in NO_3 losses, a much greater influence than the management treatments simulated (Table 2). To mitigate the introduction of potential biases, the model can be run for a 'spin-up' period (typically 10–20 years) to derive robust initial conditions. This is a common technique often used to define stable SOC pool fractions, which has been seen to improve SOC simulation (O'Leary et al., 2016). A benchmark for defining reasonable initial conditions could be an average of the last 5–10 years of the spin-up or by other approaches (Teixeira et al., 2015).

Though some progress has been made in recent years (Donatelli et al., 2017), most crop-soil models currently do not account for other important benefits of crop rotations such as breaking weeds and pests lifecycles, or the positive impacts to the diversity and function of microbial and beneficial insect communities. Yet these results highlight the value of simulation approaches to assess the impact of drivers such as weather and soils, and their feedbacks on crops grown within a rotation. As evaluation of cropping patterns extends to include the spatial configuration of the crop in the landscape (e.g. economic and environmental benefits of allocating low-productivity areas to native vegetation; Basso et al., 2019), crop models linked with geospatial technologies will continue to play a critical role in capturing interactions between soil processes, crop growth, management, climate variability, and spatial and temporal variation under future climate projections.

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