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ABSTRACT

It is critical to evaluate conservation practices that protect soil and water resources from climate change in the Midwestern United States, a region that produces one-quarter of the world's soybeans and one-third of the world's maize. An over-winter cover crop in a maize–soybean rotation offers multiple potential benefits that can reduce the impacts of higher temperatures and more variable rainfall; some of the anticipated changes for the Midwest. In this experiment we used the Agricultural Production Systems sIMulator (APSIM) to understand how winter rye cover crops impact crop production and environmental outcomes, given future climate change. We first tested APSIM with data from a long-term maize–soybean rotation with and without winter rye cover crop field site. Our modeling work predicted that the winter rye cover crop has a neutral effect on maize and soybean yields over the 45 year simulation period but increases in minimum and maximum temperatures were associated with reduced yields of 1.6–2.7% by decade. Soil carbon decreased in both the cover crop and no cover crop simulations, although the cover crop is able to significantly offset (3% less loss over 45 years) this decline compared to the no cover crop simulation. Our predictions showed that the cover crop led to an 11–29% reduction in erosion and up to a 34% decrease in nitrous oxide emissions (N_2O). However, the cover crop is unable to offset future predicted yield declines and does not increase the overall carbon balance relative to current soil conditions.

1. Introduction

The Midwestern United States is known for its high agricultural productivity, as the region is a national leader in commodity crop production, specifically maize and soybeans (USDA-NASS, 2015). The Midwest "Corn Belt" region accounts for >80% of national productivity for these two commodities which represents approximately one-quarter to one-third of global output (FAOSTAT, 2015; USDA-NASS, 2015). Therefore, potential climate change impacts to agriculture in this region have global implications. Climate change is already known to threaten the built-in adaptive capabilities of the Earth System's ecology (Steffen et al., 2015). In agro-ecological managed systems, human decision-making is required to develop adaptive management capabilities for climate risks that directly threaten the soil and water resources and agricultural productivity (FAO, 2011; Walthall et al., 2013; Hatfield et al., 2014; Porter et al., 2014; Amundson et al., 2015; Ray et al., 2015).

In general, analyses performed using historical data for the Midwest over the last several decades indicate an increase in the frequency of heavy rainfall (Groisman et al., 2012) and flood events (Mallakpour and Villarini, 2015). Further, global climate model analyses agree that trends of increased rainfall variability will continue and potentially increase in the region (Winkler et al., 2012; Daniel, 2015). Increases in rainfall variability can have many impacts on agriculture, and range from waterlogged soils delaying spring planting and decreasing crop productivity to drought-driven crop failure as was experienced across the region in 2012 (ICCIC, 2010; Al-Kaisi et al., 2013). In light of these climate-driven risks to production and natural resources, advancing our understanding of soil and water conservation management practices as well as increasing their levels of adoption are urgent priorities (SWCS, 2003; ICCIC, 2010; Lal et al., 2011; Al-Kaisi et al., 2013; VanLiew et al., 2013).

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To mitigate risks from both excess rainfall and drought events, management practices that improve water infiltration, store soil water, and reduce runoff and erosion should be employed (Stewart and Peterson, 2015). The addition of an over-winter cover crop in an annual cropping system, such as maize and soybeans where the soil is left bare without living plants for about half of the year, is one approach that could help meet all of these goals (Kaspar and Singer, 2011). Improved water infiltration may be achieved both by structural soil changes as well as by the addition of soil organic matter (Hudson, 1994; Hati et al., 2007; Bhogal et al., 2009). Several studies highlight the soil water or soil structural improvements (i.e. decreasing bulk density, increased water-aggregate stability; increased macroporosity) of utilizing a cover crop for several years in maize-based systems (Kaspar and Singer, 2011). Cover crops are also known to increase soil organic matter between 9% and 85% depending upon biomass accumulation and region-specific soil and climate conditions (Kaspar and Singer, 2011). More recent research in Iowa found a 15% higher soil organic matter content (at 0–5-cm depth) nine years after a winter rye cover crop was added to a maize silage rotation (Moore et al., 2014). Further, in a global meta-analysis, Poeplau and Don (2015) calculated that cover crops increased soil carbon in the 0–22-cm depth by 0.32 Mg ha^{-1} over several decades. Cover crops have reduced erosion from rainfall events by up to 95% (Kaspar et al., 2001) and cropping systems with full cover compared to bare soil are found to decrease erosive soil losses by at least 50% (Labrière et al., 2015).

Given that most field experiments are conducted in the short-term (<5 years) and even longer-term experiments (>10 years) cannot take into account future weather trends, one way to extrapolate short-term results in time is by using process-based simulation models. The APSIM platform, the Agricultural Production Systems sIMulator, is an advanced simulator of cropping systems capable of simulating growth of several crop species, water balance, carbon and nitrogen transformations, and soil erosion (Keating, 2003; Holzworth et al., 2014). It was developed to predict the long-term impacts of cropping systems such as crop rotations in relation to greenhouse gas emissions and climate change (Huth et al., 2010; Thorburn et al., 2010; Biggs et al., 2013). As one example, modeling platforms, like APSIM, can be used to understand how climatic change will impact soil carbon given that the long-term balance is a result of the interactions of climate, crop, soil and management conditions. In Iowa's naturally carbon-rich soils, field data confirms that it can be difficult to detect how alternative management affects soil carbon (Karlen et al., 1999; Kaspar et al., 2006; Guzman and Al-Kaisi, 2010).

There are several model-based evaluations of the impact of cover crops (Feyereisen et al., 2006b; Malone et al., 2007; Farahbakhshazad et al., 2008; Li et al., 2008; Qi et al., 2011; Malone et al., 2014). Much of this work, however, was focused on simulating cover crop reductions of nitrate leaching losses (Feyereisen et al., 2006b; Malone et al., 2007; Malone et al., 2014) while others were theoretical studies without measures of cover crop growth (Farahbakhshazad et al., 2008; Schipanski et al., 2014). While it is important to predict the impact of cover crops on nitrate leaching losses given the emphasis on cover crops as a water quality improvement tool (EPA, 2008; INRS, 2012), there are other in-field soil benefits to utilizing cover crops, such as erosion prevention and organic matter accumulation, which have not been measured or simulated for long-term cover crop use in this region.

We hypothesize that the addition of a cover crop will lead to an improvement in environmental variables and crop production in the context of climate change. We had two major objectives in this study. The first was to use APSIM to assess predicted long-term impacts of cover crops on maize and soybean production. Our second objective was to assess the predicted improvements that cover crops offer to several environmental variables, including soil carbon, soil erosion and nitrous oxide (N_2O) emissions. We utilized both future climate scenarios as well as long term weather data with no greenhouse gas forcing to meet both of these objectives. Using the two sets of weather scenarios should demonstrate the relative impact of climate change on both crop production and environmental goals. Given the predominance of maize production globally, enhancing our understanding of conservation practices within the Midwest can serve as a model for other maize growing regions.

2. Materials and methods

2.1. Overview

In this study we simulated maize and soybean production as well as environmental variables using APSIM (version 7.5). We based our model performance testing and simulations on data from a long-term field site in Central Iowa. The cropping systems model APSIM was chosen because of its flexible modules, particularly in management and cropping sequences (Holzworth et al., 2014). Recently Archontoulis et al. (2014a) tested several APSIM modules for Central Iowa and found acceptable model predictions. In this study the following APSIM modules were configured into the simulation platform: maize, soybean, soilN (organic matter and N), surfaceOM (residue), SWIM (Soil Water Infiltration and Movement), soil temperature, erosion and a modified wheat module to represent the winter rye cover crop.

The Kelly Tile Experiment was established in 1999 in Boone County, Iowa (42.05N, 93.71W) on a 3.7-ha field. The site includes six experimental treatments in a maize–soybean rotation with four

Table 1
Management dates and operations.

Year	Cash crop	Cover crop termination date	Cash crop planting date	Harvest date	Cover crop planting	Total N applied kg ha^{-1}	Cover crop seeding method
2001					20-Aug		Aerial seeding
2002	Maize	17-Apr	25-Apr	30-Sep	10-Sep	235	Aerial seeding
2003	Soybeans	6-May	12-May	30-Sep	2-Oct		Drilled after harvest
2004	Maize	16-Apr	28-Apr	4-Oct	6-Oct	246	Drilled after harvest
2005	Soybeans	25-Apr	6-May	30-Sep	30-Sep		Drilled after harvest
2006	Maize	21-Apr	4-May	20-Oct	24-Oct	225	Drilled after harvest
2007	Soybeans	10-May	22-May	26-Sep	28-Sep		Drilled after harvest
2008	Maize	29-Apr	14-May	28-Oct	29-Oct	198	Drilled after harvest
2009	Soybeans	21-May	22-May	28-Sep	28-Sep		Drilled after harvest
2010	Maize	19-Apr	29-Apr	16-Sep	17-Sep	198	Drilled after harvest
2011	Soybeans	5-May	18-May	29-Sep	30-Sep		Drilled after harvest
2012	Maize	23-Apr	4-May	19-Sep	4-Sep	175	Aerial seeding
2013	Soybeans	13-May	23-May	20-Oct	4-Sep		Aerial seeding
2014	Maize	10-Apr	6-May	17-Oct	9-Sep	196	Aerial seeding

replicates (30.5-m wide and 42.7-m long). For the purposes of this modeling study we utilized data from two treatments: the no-till maize/soybean rotation and the no-till maize/soybean rotation with a winter rye cover crop grown every year. These treatments represent a long-term record of cover crop impacts within maize–soybean cropping systems, the predominant land use pattern across the Midwest Corn Belt.

Maize was planted between mid-April and early May in even-numbered years and soybeans in early to mid-May in the odd-numbered years. In maize years, nitrogen fertilizer was applied at planting and post planting as a side-dress in mid-June at rates varying from 246 kg ha^{-1} in the early years to 175 kg ha^{-1} in the latter years. Higher N rates were used in the early years because of the transition to no-till and to provide non-limiting N supplies. The winter rye cover crop was drilled following maize and soybean harvests every year except for the fall of 2001, 2002, 2012 and 2013 when it was overseeded into the standing crops in the late summer. The winter rye cover crop was terminated with glyphosate prior to maize and soybean planting where timing depended upon the following crop and weather conditions. The major management dates including cover crop planting and termination dates are outlined in Table 1. For more details related to field site management, see Kaspar et al. (2007) and Kaspar et al. (2012).

Subsurface drainage tiles consisting of 7.62-cm diameter perforated plastic were installed at the onset of the experiment lengthwise down the center of each plot at a depth of 1.2-m in 1999. Soil moisture sensors were installed in 2008 in three of the four experimental replications to measure volumetric water content. Two *Theta Probe* soil moisture sensors (Parkin and Kaspar, 2004; Kaleita et al., 2005; Unidata Manual, 2007) were present in each replication to capture within plot variability. From 2008–2011 continuous hourly measurements were reported at 5, 10 and 15-cm depths and from 2012–2014 at 5, 15 and 30-cm depths.

2.2. Statistical analysis

Model performance was evaluated with root mean square error (RMSE) and relative root mean square error (RRMSE) providing indicators of the goodness of fit between the model predictions and field observed values. Model efficiency (perfect fit between predictions and observations equals 1) was also calculated to interpret the predictive ability of the model. These indices were calculated with the equations found in Makowski et al. (2007). Model application analyses comparing treatment effects (no cover crop versus with cover crop) and effects of weather (future climate change scenarios versus randomly generated weather scenarios) were performed using the MIXED procedures in SAS with each climate scenario as a random effect and weather and treatment as fixed effects. The interactions between treatment, climate scenario and GCM-generated or randomly-generated weather scenario were also included. The effect of time, in this case year into the future (2015–2060) was included as a repeated measure and the variance-covariance matrix of the residuals was modeled using an autoregressive structure (SAS Institute 2010).

2.3. Calibration protocol

For model calibration and validation, we utilized available data for grain yields, maize and soybean biomass, cover crop biomass, soil moisture, soil temperature and soil carbon as outlined in Table S1. We utilized climate data from the Iowa Environmental Mesonet (IEM, 2015). We incorporated the calibration dataset into APSIM to visualize model performance with field measurements (data from Table S1). We then followed an iterative process in which we assessed how well the measured data fit to model simulations, following the order of crop phenology, soil temperature, soil water, soil N, plant biomass, maize and soybean carbon and nitrogen partitioning and yield. This same calibration protocol was followed by Archontoulis et al. (2014a). Maize and soybean genotypes changed over time in the field but in the model we considered the same cultivars over time due to the lack of cultivar specific information. This introduces some uncertainty and unexplained variation in model predictions as compared to measurements (Section 2.3.4). Given the extensive data available from the experimental site we utilized the field site measurements from 2003 to 2008 for model calibration and data from 2009 to 2014 for model evaluation. We ran APSIM sequentially and we ran the model beginning 10 years before the anticipated start day by simulating a maize–soybean rotation to minimize the uncertainty associated with the initial model input parameters (Bryan et al., 2014). The main highlights and statistics from our model testing are detailed in Section 2 (within relevant content areas) and results of model application for future climate change appear in the results, Section 3.

2.3.1. Soil profile chemical and physical properties

The parameter values to run the model (Table 2) are based on site-specific measurements supplemented with information from the Web Soil Survey (Soil Survey Staff, 2013) when necessary (depths >1.2 m). These values are reasonable for our chosen field site as they are within the range of those used by Archontoulis et al. (2014a) and Malone et al. (2007) for Central Iowa APSIM studies. The partitioning of carbon into the more active and passive organic pools also followed the parameters utilized by Archontoulis et al. (2014a) and Malone et al. (2007).

2.3.2. Soil water

The SWIM module in APSIM simulates water balance using Richard's equation and was selected over the default soil water module in APSIM (SOILWAT) because of its capability to simulate water flow in tiles (Malone et al., 2007). For a detailed description of the SWIM model see Verburg et al. (1996) and Huth et al. (2012). Soil water dynamics were manually calibrated using the available field dataset from 2008 to 2014 (Table S1). The main parameters we focused on were the drainage upper limit, lower limit, saturation

Table 2
Soil module input parameters.

Depth (cm)	Bulk density g cm^{-3}	Air dry mm^3 mm^{-3}	Lower limit mm^3 mm^{-3}	Drainage upper limit mm^3 mm^{-3}	Saturation mm^3 mm^{-3}	Organic carbon (%)	pH	Fraction biom carbon (0–1)	Fraction inert carbon (0–1)
0–15	1.30	0.115	0.161	0.300	0.430	2.986	6.6	0.035	0.40
15–30	1.270	0.125	0.173	0.310	0.479	2.340	6.6	0.019	0.500
30–60	1.30	0.125	0.173	0.310	0.459	1.200	6.6	0.014	0.640
60–90	1.350	0.135	0.173	0.310	0.459	0.940	6.6	0.010	0.800
90–120	1.420	0.155	0.173	0.310	0.453	0.940	6.7	0.010	0.800
120–150	1.830	0.152	0.173	0.310	0.403	0.500	7.8	0.010	0.816
150–180	1.830	0.152	0.173	0.310	0.403	0.350	7.8	0.010	0.816

and hydraulic conductivity, which were manually calibrated. The model simulated 5-cm depth volumetric water content with a RRMSE error of 14% and RMSE of 0.05 $mm^3\,mm^{-3}$ during model calibration and RRMSE of 27% and RMSE of 0.06 $mm^3\,mm^{-3}$ during model validation. At the 15-cm depth, the model simulated volumetric water content with a RRMSE error of 12% and RMSE of 0.04 $mm^3\,mm^{-3}$ during the calibration period and with a RRMSE error of 19% and RMSE of 0.06 $mm^3\,mm^{-3}$ during the validation period (Figs. S2a, S2b). Overall the calculated statistical values fell within the range reported for soil moisture simulations (Archontoulis et al., 2014a; Dietzel, 2014).

2.3.3. Soil temperature

An alternative soil temperature model available in APSIM was utilized in this study as it performed better compared to the default model. Archontoulis et al. (2014a) found that both available soil temperature models in APSIM performed well in Iowa during the growing season, but the one based on Campbell (1985) and described and utilized by Chauhan et al. (2007) was superior to the default. The optional soil temp module requires additional inputs of boundary layer conductance (set to 20 $J\,s^{-1}\,m^{-1}\,K^{-1}$) and clay content (25%) for the soil.

Model predictions at the 5-cm depth had a RRMSE of 11.8% and RMSE of 2.2 °C during the calibration period and RRMSE 12.2% and RMSE of 2.2 °C during the validation period. At 15-cm, APSIM predicted a RRMSE of 7.9% and RMSE of 1.4 °C for the calibration period and a RRMSE of 10.4% and RMSE of 1.8 °C for the validation period (Figs. S3a, S3b). The optional soil temperature module compared to the default module decreased RMSE from 5.7 °C to 2.2 °C at 5-cm and 5.0 °C to 1.4 °C (during the validation period). Model efficiency values for soil temperature were 0.81 for the 5-cm depth calibration period, 0.86 for the validation period and 0.91 for the 15-cm depth calibration period and 0.89 during the validation period. In general, APSIM predicted lower soil temperatures in the month of April in the cover crop plots (pre-termination) by about 1–2 °C (0–30-cm depths).

2.3.4. Grain crop yields

Cultivar specific parameters for maize and soybean were used based on the work of Archontoulis et al. (2014a,b). A typical 110-day maturity maize hybrid and group 2.5 maturity soybean cultivar were used. The model simulated maize yields for both treatments with a RRMSE of 12% and RMSE of 1547 $kg\,ha^{-1}$ and soybean yields for both treatments with a RRMSE of 25% and RMSE of 775 $kg\,ha^{-1}$. For the maize and soybean yields there is a slight trend toward over prediction (Figs. S4a, S4b). This is most likely attributed to biotic factors that are not represented in the current APSIM version. APSIM does not at this time represent all of the processes that might occur over a growing season, such as disease, weed, or pest pressure or allelopathic effects of rye before maize (Barnes and Putnam, 1986; Raimbault et al., 1990, 1991; Tollenaar et al., 1993; Kessavalou and Walters, 1997) which might also lead to yield declines. This could also be a result of maintaining the same cultivar from year to year in the simulation.

2.3.5. Winter rye cover crop

Cereal rye is not listed as a crop model in APSIM version 7.5 so we chose to work with the APSIM-wheat crop module as it represented the most similar available plant. When cereal rye is grown as a winter cover crop in the Midwest, it generally does not reach the heading stage of development. Therefore we chose to focus model changes on the known differences between wheat and cereal rye impacting vegetative growth stages to try to improve its performance as a cover crop in Iowa, beginning with an American wheat cultivar (*yecora*) (Table S2). In the wheat model, we changed the optimal temperature from 26 to 18 °C and maximum temperature from 34 to 30 °C (Nuttonson, 1958; Nalborczyk and Sowa, 2001) and left the base temperature at its default of 0 °C. To improve model predictions we increased vernalization to a value of 5 units, the value used by Malone et al. (2007). More detail on specific modifications related to the cover crop aspects of the simulation can be found in the supplemental material.

The average predicted biomass values over the calibration and validation period were reasonable (Fig. S5a), with an RRMSE of 56% and RMSE of 895 $kg\,ha^{-1}$. The default (uncalibrated) APSIM wheat crop module parameters results in an RRMSE of 91% and an RMSE of 1457 kg ha−1. Average winter rye biomass predicted by APSIM during this period was 1411 $kg\,ha^{-1}$ compared to average observed field values of 1596 $kg\,ha^{-1}$. On average, APSIM predicted cover crop biomass well but did not always capture year to year variability especially in 2003, 2005, and 2011. The simulated N uptake values had an RMSE is 19 $kg\,ha^{-1}$ and RRMSE is 42% (Fig. S5b) which is higher than the range reported by Feyereisen et al. (2006a). We evaluated the statistics for the yields of the two cash crops combined with aboveground biomass for the cover crop in the rotation and these values had a predicted RRMSE of 19% and model efficiency of 0.94. This indicates very acceptable model performance for plant growth observations.

2.3.6. Erosion module

The erosion model was coupled to the simulation for the model application phase of this study. We utilized the Freebairn erosion module in APSIM which is built from a modified USLE equation (Freebairn and Wockner, 1986a,b; Littleboy et al., 1989). It was revised to include a greater effect of surface cover and runoff, the main factors that can be affected by management within the APSIM framework. The calculation of erosion is based on cover and runoff volume and uses slope-length, erodibility, and supporting practice factors. The surface cover value is derived from the surface organic matter module and accounts for combined crop and residue covers on the soil surface. The runoff value is derived from SWIM. We assumed a soil erodibility factor of 0.29 based on a loam soil with >2% organic matter (Stewart et al., 1975) and a slope of 1% for the experimental site. To estimate a range of values of erosion prevention for our region, we also investigated slopes of 2% and 5% in our model application. Further, we explored how changes in the USLE supporting practice factor (P) would change erosion predictions, as this is an explicit input in the erosion module while crop management (C) is not explicitly included as described above. We used a supporting practice factor for the cover crop of 0.9, which we consider to be conservative. Arabi et al. (2008) used a supporting practice factor (P factor in RUSLE) of 0.55 in SWAT where residue cover equaled 500 $kg\,ha^{-1}$ which would be a low total for cover crop residue at our research site. For assessment of future erosion impacts related to slope or support practice factor changes, we selected a subset of four global climate model scenarios. (Sections 2.4 and 3.2.2).

2.4. Model application

We generated future weather predictions using the methodology of the AgMIP Guide For Running Climate Scenario Generation Tools with R (AgMIP, 2013). We utilized 20 different Coupled Model Intercomparison Project 5 (CMIP5) global climate model (GCM) outputs and ran simulations through 2060. We utilized GCM outputs with representative carbon pathway (RCP) 4.5, which represents a "stabilization" scenario where radiative forcing stabilizes by 2100 and an average global temperature increase of 1.8 °C by 2100 relative to pre-industrial levels (IPCC, 2013). We also utilized several randomly generated meteorological files based on current trends to look for differences between the long-term climate record compared to a future weather accounting for changes due to greenhouse gas forcings (referred to as GCM-generated scenarios and randomly-generated weather scenarios) (Figs. S6a–S6d).

For these simulations, we set soybean to be planted every odd numbered year on May 15 and maize every even numbered year on May 1. We set maize to be fertilized on June 1 with a rate of 198 kg ha^{-1} of liquid urea-nitrate representing an average value for the field site. For the cover crop, we utilized model set up to represent direct drilled planting after maize on October 20 and after soybean harvest on October 1. The cover crop was terminated before the maize growing season on April 15 and soybean years on May 1. Attempts to represent the cover crop management with the aerial seeding set up showed a bias toward over prediction that was not reflective of actual field growth. Therefore, we chose a more conservative cover crop planting window that would better represent cover crop planting and termination dates between typical harvest and planting for a maize–soybean rotation in our region.

3. Results

3.1. Crop production impacts of climate change and cover crops

3.1.1. Cover crop impacts on maize and soybean yields

Yield predictions resulted in non-significant differences for both maize ($p = 0.92$) and soybean ($p = 0.94$) between the cover crop and no cover treatments over the simulation period (2015–2060). Over the period of model calibration (2003–2008) and validation (2009–2014), there were also not any years at the research site where there were statistically different crop yields

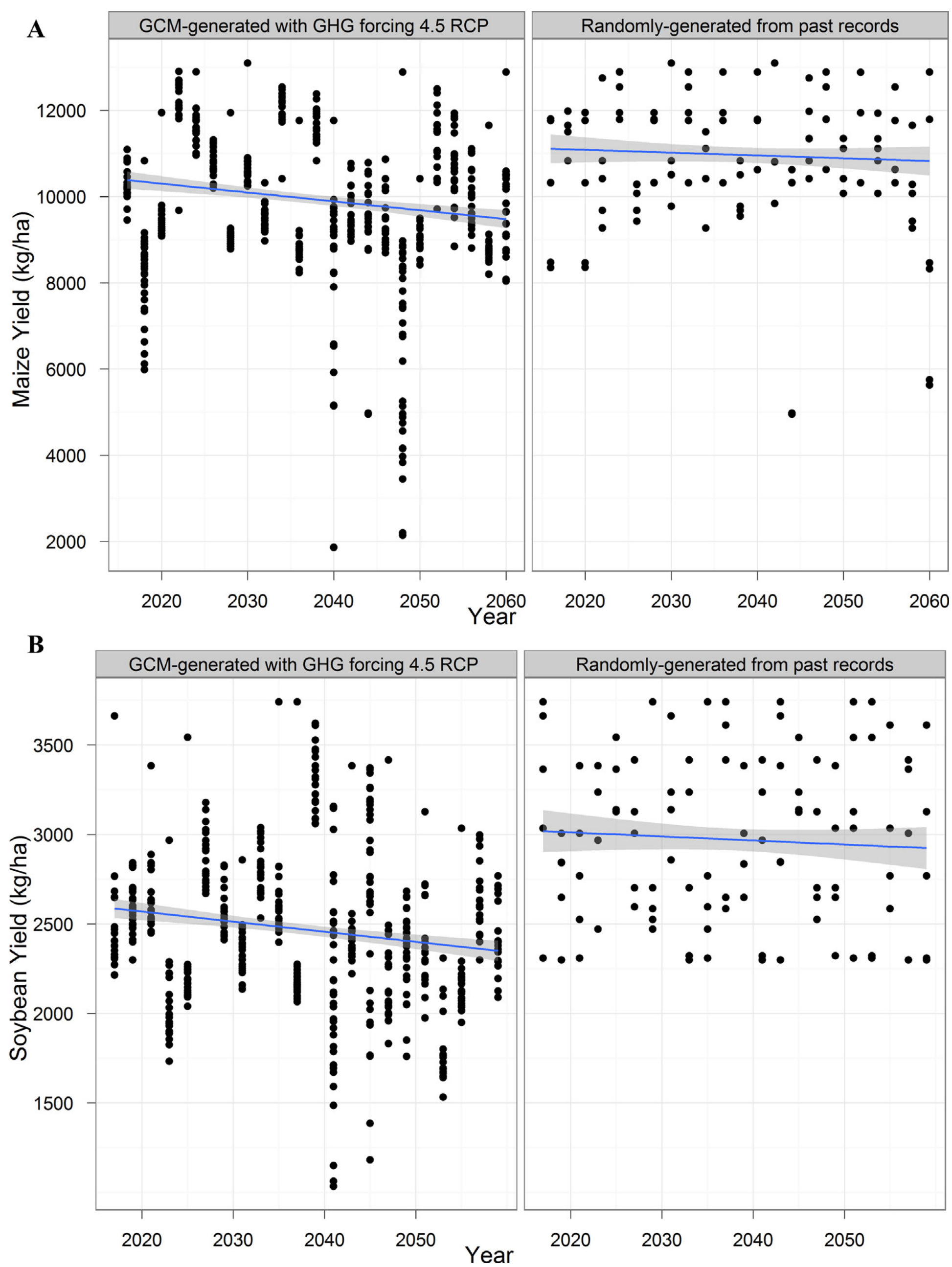

Fig. 1. (A) Maize yields predicted by APSIM through 2060 for the cover crop and no cover crop treatments for each of the 20 global climate model (future) generated future weather scenarios and the five randomly generated weather scenarios (random), beginning in 2015. Trend line in gray. The global climate model driven weather scenarios show a decrease in yield not observed in the randomly generated weather scenarios. (B) Soybean yields predicted by APSIM.

between the cover and no cover crop treatment (Kaspar et al., 2007, 2012; Basche, 2015). This level of agreement with the field data gives us confidence in our predictions for yield differences between the two treatments.

3.1.2. Climate change impacts on maize and soybean yields

Throughout the duration of the simulation period (through 2060), both maize and soybean (in the cover and no cover treatments) show a trend toward a decrease in yield (Fig. 1a,b) with an average decline of 1.6% by decade in maize and 2.7% by decade in soybeans for the GCM-generated weather scenarios. We found that the GCM-generated scenarios predict several mechanisms that could lead to crop yield declines that are different than the randomly-generated scenarios, including more years with significant crop water stress as well as greater soil water demand and evapotranspiration (results not shown). The greenhouse gas forcing in the GCM-generated weather files and increased temperature trends (Figs. S6a, S6b) appear to be responsible for driving the increased water demands and stressors. We further found that the GCM-generated weather scenarios with a lower increased temperature trend lead to smaller rates of yield decline (results not shown). It should be noted that there was a greater declining trend in soybean compared to maize, particularly for the later years of the simulation (2040–2060) which may indicate greater stress on soybean physiology by anticipated temperature increases as a result of its lower optimum temperature for growth in APSIM as compared to maize.

3.1.3. Winter rye cover crop biomass

During this 45-year simulation period, the average predicted cover crop biomass is 1300 kg ha^{-1} (standard error of 800 kg ha^{-1}) over all of the weather scenarios (Fig. 2). We further observed a slight increase in cover crop growth in the GCM-generated weather scenarios that is not present in the randomly generated weather scenarios. This is further evidence that the predictions of a decrease in crop yields and an increase in over winter cover crop growth result from the increasing temperature trend. However, there are years after 2040 where predictions of rye cover crop biomass are both very high (>4000 kg ha^{-1}) and very low (<500 kg ha^{-1}), which demonstrates that even with a warming trend, not every year will experience very high cover crop biomass. One adaptation strategy for farmers not accounted for in our analysis is the lengthening of the growing season for maize and soybeans. However, the planting window utilized in our model application is conservative enough not to overestimate potential growing degree units available for cover crop growth into the future. The conservative planting window, even more so than utilized at our research site, is likely the reason that the randomly-generated weather scenarios predict lower than observed cover crop biomass

3.1.4. Wet and dry year analysis

As addressed previously, APSIM predicted only minor, non-significant maize and soybean yield differences between the cover and no cover crop treatments over the period of the 45-year simulation (Section 3.1.1). However, the predicted yield declines that did occur in both maize and soybean in the cover crop treatments were predicted in years with lower rainfall totals. In general, declines ranged from 1–10% in maize and 1–30% in soybean in a limited number of years where rainfall was more than 25% below average (Figs. S8a, S8b) or less than 690 mm. We found that the model tended to predict more water stress in these years in the cover crop simulation in the mid-summer period (results not shown) which could account for the reduced crop yield. The predictions demonstrate that the cover crop could compete with the cash crop for water in abnormally dry years. Whish et al. (2009) similarly found that a millet cover crop before wheat in a semi-arid region of Australia only impacted wheat years in 2% of years when properly managed. This trend of water stress in mid-summer is not something we observed in the field in 2012, the single year on record at our site with close to this abnormally low amount of rainfall (637 mm). Although there was a non-significant maize yield reduction in the cover crop treatment, our analysis of the soil water record indicated higher moisture levels at 5-cm, 15-cm and 30-cm depths during the grain fill period for maize (Basche, 2015). Even with the competition for soil water predicted by APSIM in the very dry seasons, yield reductions predicted in the cover crop treatment are relatively small in these years.

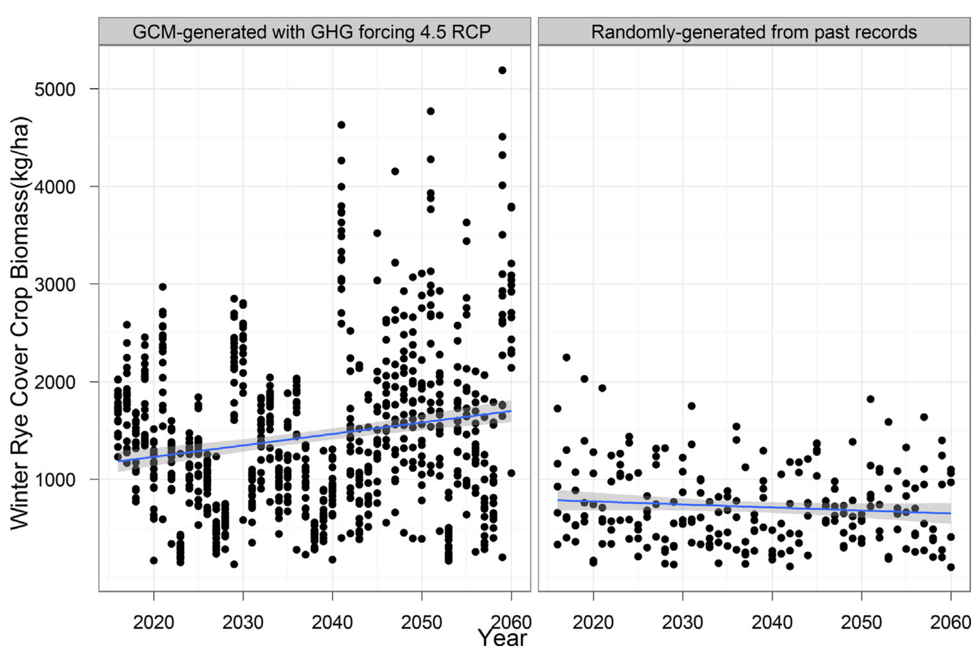

Fig. 2. Biomass predictions for the winter rye cover crop for each of the 20 global climate model (future) generated future weather scenarios and the five randomly generated weather scenarios (random), beginning in 2015. Trend line in gray.

3.2. Environmental impacts of cover crops and climate change

3.2.1. Soil carbon

APSIM predicted carbon declines at the 0–30-cm depth in both treatments and weather scenarios, although the declines were not uniform (Fig. 3). In the GCM-generated weather scenarios, predictions for the total mass of carbon over the 0–30 cm depth show significant differences between the treatments ($p < 0.0001$), with the no cover crop treatment losing an average of 5000 kg ha^{-1} more than the cover crop plots over the simulation period (annual loss of 110 kg ha^{-1} y^{-1}). This represents a decline in carbon mass of 6% in the no cover crop treatment and 3% in the cover crop treatment over the 2015–2060 period. The randomly generated weather scenarios show significant differences between treatments as well ($p=0.01$), with the no cover crop treatment losing an average of 71 kg ha^{-1} yr^{-1} (3% decline) more than the cover crop plots (2% decline). We also compared the relative contribution of weather scenario (GCM-generated versus randomly-generated) and treatment (cover or no cover crop) to this soil carbon decline. We found very similar effects of treatment ($p = 0.008$) to the impact of future climate change ($p = 0.017$) at the 0–30-cm depth. Our results seem to indicate that even without a warmer climate change scenario, soil carbon would decline over several decades at our research site. The cover crop, however, is able to offset some of that declining trend.

3.2.2. Soil erosion

Soil loss prevented in the cover crop treatment ranged from an 11–29% reduction in erosion (1% slope) compared to the no cover treatment (Table S3). These percentages were basically unchanged when we increased field slope to 2% and 5%. We also explored the impacts of changing the supporting practice factor in the erosion module which resulted in predictions of erosion prevention from a cover crop increasing to 20– 36% (Table S3). This range in erosion prevention resulted from the different future weather scenarios utilized. We would expect this given that the APSIM erosion module predicts erosion in part based on runoff (Section 2.3.6) resulting from rainfall projections.

3.2.3. Nitrous oxide emissions

Predictions for soil nitrous oxide (N_2O) emissions varied by future weather scenario utilized, where the range was from an increase in N_2O with the cover crop of 0.2% and a decrease of 33.5% (Fig. 4). Of the factors that a cover crop might influence – soil nitrate, reactive carbon, soil moisture and soil temperature – our analysis of selected weather scenarios found that the reduction in soil nitrate was most responsible for the cover crop's reduction in soil N_2O emissions (results not shown). In many years and weather scenarios there were large decreases in soil nitrate in the cover crop simulation and therefore we infer that this is the reason for the decreased N_2O predictions. Further, the GCM-generated future scenarios with higher temperature projections tended to predict

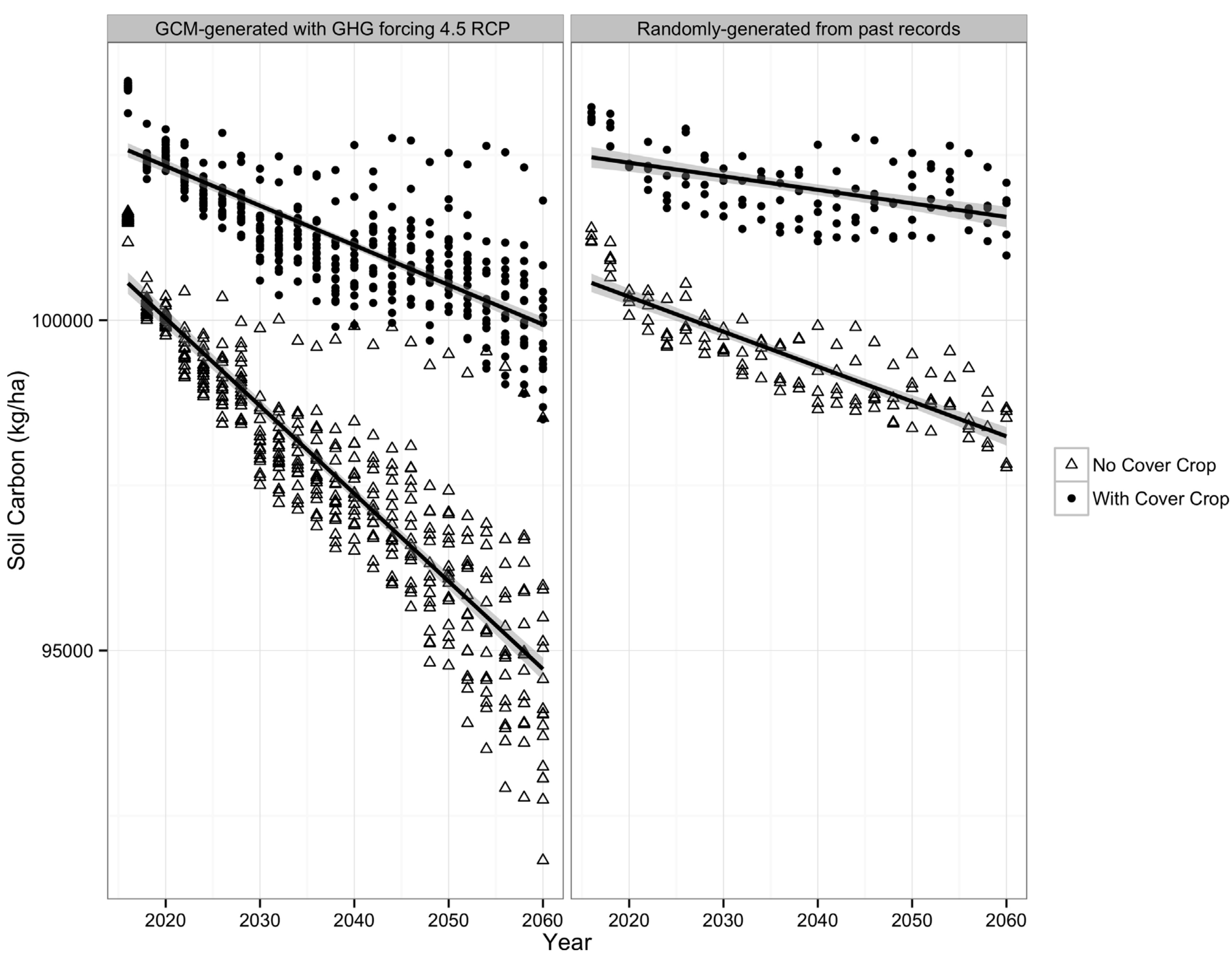

Fig. 3. Predicted soil carbon changes from 2015–2060 at the 0–30 cm depth for the cover (circles) and no cover crop (triangles) simulations.

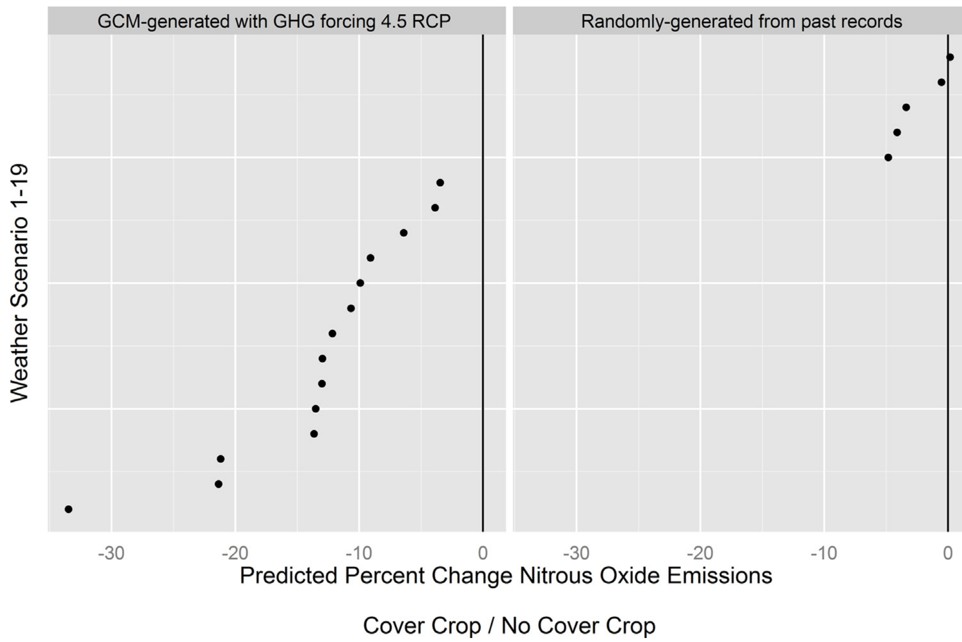

Fig. 4. Predictions of the nitrous oxide response ratio (with cover crop/no cover crop) from a subset of nineteen weather scenarios. Across a series of varied weather conditions, APSIM predicts that for our location and management, the cover crop generally reduces nitrous oxide emissions.

the greatest N_2O emission reduction from the cover crop treatments, where those that project no temperature increases predicted smaller decreases in N_2O emissions (as well as the one weather scenario predicting a minor N_2O increase) from the cover crop (Fig. 4). This indicates that in a warmer climate, the cover crop could act as a potential mitigation strategy.

4. Discussion

4.1. Crop production impacts

We analyzed the movement of carbon, nitrogen and water in the model to better understand the mechanisms behind the predicted differences between the treatments. Model predictions indicated that in the cover crop treatment the carbon levels in the two rapidly cycling carbon pools (the microbial and fresh organic matter pools) were higher compared to no cover crop treatment as a result of additional C input from the cover crop. We found greater N immobilization in the cover crop treatments most years from April until July (average increase between the two simulations of 13 $kg\,ha^{-1}\,yr^{-1}$), as well as higher gross mineralization rates for the cover crop treatment (average increase between the two simulations of 17 $kg\,ha^{-1}\,yr^{-1}$). The resulting net mineralization rate was only slightly higher in the cover crop simulation and this might be one of the reasons why the simulated rye cover crop had minor impacts on following crop yields (results not shown). We believe that the greater gross mineralization rate was the result of the low C/N ratio of the rye above ground biomass ($\sim$16) that contributes to higher N availability and the greater immobilization imposed by the high below ground root C/N ratio ($\sim$40). The amount of above and below ground rye biomass was variable from year-to-year, which generated variability in N cycling.

In our analysis of water dynamics, APSIM predicted higher soil water levels in the cover crop simulation before and after cover crop termination at both 5-cm and 15-cm, with a more noticeable increase at 5-cm, due to lower soil evaporation predictions during this period. The cover crop treatment was predicted to reduce soil evaporation between 2-18% with the greater reductions coming in drier seasons. APSIM predicted reduced soil evaporation and small increases in soil water in spite of cover crop transpiration, which on average reached values of 10-mm in the fall and 50-mm, depending on biomass levels. In the field, we observed greater evidence of soil water depletion (as compared to APSIM predictions) as the winter rye cover crop grows, but in the simulations as well as in the field observations spring rainfall in Iowa restores soil moisture to the same level in both treatments (Basche, 2015). Further, as cash crop growth proceeded, soil water predictions tended to be the same in the cover crop and no cover crop simulations (Figs. S7a, S7b). APSIM predicted nearly identical maize and soybean crop water use in the two treatments (results not shown) and field observations of maize and soybean biomass did not indicate growth differences between the cover and no cover crop treatments during two growing seasons (Basche, 2015). The predicted changes suggest that APSIM is representing the dynamics of reduced evaporation, improved infiltration and cover crop water use, but perhaps not to the extent that is observed in the field, where we saw greater evidence of crop water use or reduced soil evaporation. The small predicted differences in water and nitrogen could be the reason that the model predicts no major yield effects. If the model was able to capture the full extent of cover crop impacts, there might be potential to yield improvements over time, as is often reported by farmers (SARE-CTIC, 2013, 2014, 2015). However, Miguez and Bollero (2005) show no increase in yield on average by using a cereal winter cover crops, which is in agreement with the results from the field study and the simulations.

Planting dates and cultivars were not changed for both the cash crops as well as for the cover crop. Therefore our results may not fully reflect adaptation in management for earlier cash crop planting dates and later cash crop maturities that farmers may utilize in the future (Sacks and Kucharik, 2011) which could lead to an advantageously longer growing season for maize and soybeans. This might in part account for the small yield decline in the randomly-generated weather scenarios. It should also be noted that our analysis does not include effects of increasing carbon dioxide atmospheric concentration, which has the potential to offset some, but not all, of the other future climate change impacts (Long et al., 2004, 2006). Further, Hatfield et al. (2011) note that the potential impacts on water use efficiency from carbon dioxide increases will be offset by crop loss associated with heat stress, increases in evaporative demand and or decreases in water availability. The yield declines predicted by APSIM in our experiment are within the range predicted by other reported studies evaluating climate change scenarios. A summary of crop and climate change modeling studies, Porter et al. (2014) found that for the major cereal crops in temperature regions, average predicted declines were from 0 to 2% by decade into the future. The IPCC's summary also points to an increase in the number of studies reporting yield declines as well as an increase in the magnitude of crop yield decline by decade as 2100 is approached.

4.2. Environmental effects

Predicted results for soil carbon are substantiated by long-term field trials as well as other modeling efforts. Over sixty years of cultivation, wheat–fallow rotations in Oregon lost carbon at the 0–30-cm and 30–60-cm depth (Rasmussen et al., 1998). Rasmussen et al. (1998) note that few long-term experiments measure data below 30-cm, resulting in further uncertainty in soil carbon changes. Sainju et al. (2015) similarly found carbon declines at the 0–7.5-cm depth in all crop rotations studied over a 30-year period in Montana, where lower rates of decline were observed in treatments with less tillage intensity and greater annual carbon input. In Illinois, the Morrow Plots measured carbon declines in the 0–20-cm depth over ninety years in multiple crop rotations even with adequate fertilizer (continuous maize, maize-oats, maize-oats-hay) (Odell et al., 1984; Huggins et al., 1998). Prior APSIM modeling results predict soil carbon declines into the 21st century in Iowa, where the incorporation of a winter rye cover crop can help to slow the rate of carbon loss (Dietzel, 2014). Luo et al. (2011) predicted temperature driven carbon declines at a particular site in Australia with similar levels of recalcitrant and decomposable carbon (Section 2.3) as found at our research site. Prior modeling suggests that management can have a greater influence on soil carbon sequestration than future climate change (Thomson et al., 2006; Lugato and Berti, 2008). However, the relative contribution of these factors likely varies in different locations and cropping systems and even with the use of a biophysical model like APSIM can be difficult to discern.

APSIM predicts that carbon decomposition rates are based on soil temperature, soil water and the C:N ratio of the soil organic matter pools (Probert et al., 1998). Given the performance of carbon, water and temperature in model testing (Section 2.3, Fig. S1–S3), we also believe the long-term carbon predictions to be plausible. The overall decline in carbon in the future weather scenarios could be a result of the projected soil temperature increases (Fig. S6d) driving carbon decomposition to a declining level that the addition of a cover crop cannot completely reverse. It could also be a result of the future weather scenarios predicting yield declines which resulted in lower overall carbon residue inputs. These simulations, however, do not take into account the effect of increasing atmospheric CO_2 levels on cash crop or cover crop growth. We conclude that the cover crop has the potential to serve as an adaptation strategy to slow some of the soil carbon loss. However, the cover crop may not be able to completely overcome future climate change effects on soil carbon declines as the maize–soybean rotation results in soil carbon loss under the current climate.

There are several limitations to our current erosion reduction estimates. Model calculations rely heavily on ground cover and may not account for all of the physical forces by which a plant's roots would prevent residue, soil, and water movement, which might explain in part why percentages showed only minor changes when slope was increased. Further, surface roughness factors and peak runoff rates are not included in erosion calculations. Finally there are limitations to the current downscaling capabilities of global climate models to accurately reflect daily precipitation changes into the future which might have the greatest impact on erosion. Nearing et al. (2004) estimate that erosion increases will be 1.7 times greater than annual rainfall increases in the future. If the increase in rainfall intensity is not well estimated by current downscaling techniques of global climate models then this could lead to an underestimation of erosion impacts in general.

In spite of these limitations, the erosion estimates are reasonable considering that these are cumulative values (over wetter and drier years) and the direction of the model is consistent with our understanding of crop and soil processes. At a field site closely located to the one used in this study for calibration of the model, Kaspar et al. (2001) measured significant reductions in inter-rill erosion rates before cover crop termination in late April in three consecutive years (48–62%) and even larger reductions in rill erosion rates (86–93%) when a rye cover crop was grown over winter following no-till soybeans on a 4.5% slope. Thus, we believe for long term averages the APSIM predictions for cover crop reductions are reasonable and demonstrate that the cover crop, even in a no-till system, can have a significant effect on erosion reduction in the context of climate change.

Prior work indicates that cover crops do not consistently reduce nitrous oxide emissions from the soil surface (Basche et al., 2014), given their ability to reduce soil nitrogen, increase surface residue, increase or decrease soil water, and increase soil carbon, all of which could increase or decrease nitrous oxide losses. Basche et al. (2014) also found that the traditional management of a cover crop in a maize–soybean system in the Midwest (non-legume plant species that is chemically terminated) is less likely to lead to a net increase in N_2O oxide emissions (compared to legume plant species and mechanical termination methods). Given these complex interactions, we utilized our calibrated model to explore the impact of the cover crop on N_2O emissions with climate change scenarios. APSIM calculates N_2O emissions based upon soil carbon, soil water, soil temperature, and soil pH and soil NO_3–N (Thorburn et al., 2010). Field trials in Iowa maize–soybean rotations testing the effect of cover crops on N_2O emissions are mixed. Parkin and Kaspar (2006) found small insignificant emissions increases in three of four site-experiment years, while Jarecki et al. (2009) and Mitchell et al. (2013) measured increases with a cover crop in some of their site-experiment years. A controlled environment study found more consistent declines in N_2O emissions after manure applications when a winter rye cover crop was alive and taking up nitrate (Parkin et al., 2006) after soybean harvest. In the aggregate, research in Iowa demonstrates a net neutral effect of cover crops on N_2O emissions and whereas this modeling simulation predicts that under projected future climate conditions, a winter rye cover crop in a maize–soybean rotation can lead to declines in N_2O emissions compared to a bare soil control.

5. Conclusion

From this study, we conclude that in the long-term a winter rye cover crop had neutral effects on maize and soybean yields. However, climate change scenarios predict yield declines in both of the treatments. An average cover crop biomass of 1300 kg ha^{-1} yr^{-1} results in significant improvements to environmental impacts, including an average erosion reduction of 11–29%. Although soil carbon declines at lower depths in the soil profile (>15 cm) in both treatments and weather scenarios, the cover crop simulation is able to offset that loss by 3%. In the GCM-generated climate change scenarios, carbon decline results from declining crop yields and increasing soil temperatures. Most weather scenarios predict soil N_2O emissions reductions with the winter rye cover crop. Our results show that with future climate change, a winter rye cover crop does not lead to soil carbon increases and cannot offset future projected yield declines, however soil N_2O emissions are decreased and erosion prevention is increased. Thus, there is evidence that the cover crop improves outcomes with future climate but perhaps not enough to offset all potential future changes that the region may experience. Additionally, we understand that the model simulations do not fully reflect changes in soil structure, pest, diseases, and nutrient cycling that the cover crop might cause over time. Given the current understanding of regional climate changes, this research demonstrates that it will continue to be a challenge to design cropping systems that enhance future soil and water resources. Future modeling efforts could investigate the potential benefit of carbon dioxide increases, longer growing seasons, and improved cover crop cultivars or species mixes to offset more of the anticipated climatic change in the Midwestern United States.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agee.2015.11.011.

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