

The carbon and nitrogen cycle impacts of reverting perennial bioenergy switchgrass to an annual maize crop rotation

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Abstract

In the age of biofuel innovation, bioenergy crop sustainability assessment has determined how candidate systems alter the carbon (C) and nitrogen (N) cycle. These research efforts revealed how perennial crops, such as switchgrass, increase below-ground soil organic carbon (SOC) and lose less N than annual crops, like maize. As demand for bioenergy increases, land managers will need to choose whether to invest in food or fuel cropping systems. However, little research has focused on the C and N cycle impacts of reverting purpose-grown perennial bioenergy crops back to annual cropping systems. We investigated this knowledge gap by measuring C and N pools and fluxes over 2 years following reversion of a mature switchgrass stand to an annual maize rotation. The most striking treatment difference was in ecosystem respiration (ER), with the maize-converted treatment showing the highest respiration flux of 2,073.63 (\pm 367.20) g C m⁻² year⁻¹ compared to the switchgrass 1,412.70 (\pm 28.72) g C m⁻² year⁻¹ and maize-control treatments 1,699.16 (\pm 234.79) g C m⁻² year⁻¹. This difference was likely driven by increased heterotrophic respiration of belowground

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switchgrass necromass in the maize-converted treatment. Predictions from the DayCent model showed it would take approximately 5 years for SOC dynamics in the converted treatment to return to conditions of the maize-control treatment. N losses were highest from the maize-converted treatment when compared to undisturbed switchgrass and maize-control, particularly during the first conversion year. These results show substantial C and N losses occur within the first 2 years after reversion of switchgrass to maize. Given farmers are likely to rotate between perennial and annual crops in the future to meet market demands, our results indicate that improvements to the land conversion approach are needed to preserve SOC built up by perennial crops to maintain the long-term ecological sustainability of bioenergy cropping systems.

KEYWORDS

bioenergy, eddy covariance, land use change, soil biogeochemical cycles

1 | INTRODUCTION

Bioenergy crops offer a renewable fuel source that can be more environmentally sustainable than fossil petroleum fuel if managed appropriately (Robertson et al., 2017; Whitaker et al., 2018). The Intergovernmental Panel on Climate Change (IPCC) identifies bioenergy crops as crucial for capping atmospheric carbon dioxide (CO₂) concentration at 450 ppm by 2100 (IPCC, 2014). These benefits are provisional to bioenergy crops avoiding petroleum use and increasing C sequestration through soil C inputs (Anderson-Teixeira et al., 2013; Robertson et al., 2017). However, such emission reduction benefits are partly contingent on the C costs of land conversion, which can result in large losses of C stored as soil organic carbon (SOC), and can take many years to repay once lost (Elshout et al., 2015; Fajardy, Dowell, & Fajardy, 2017; Khanna, Crago, & Black, 2011). The N fertilization requirements and N losses from cropping systems also needs consideration when accounting for the long-term sustainability of bioenergy fuel sources, as excess N can have large-scale impacts on greenhouse gas emissions, farming costs and environmental costs from dissolved inorganic N in surface runoff (Davis et al., 2010; Ruan, Bhardwaj, Hamilton, & Robertson, 2016; VanLooke, Twine, Kucharik, & Bernacchi, 2017). Therefore, a pressing need exists to quantify the C and N losses caused by land conversion, including the payback time for any losses, if bioenergy crops are to be managed sustainably in the future.

Annual crops, such as maize (*Zea mays* L.), are high-yielding crops that provide large quantities of carbohydrate for bioenergy production. However, land cover assessment studies show it can take several decades to repay ecosystem C lost from land conversion for maize bioenergy production (Elshout et al., 2015; Khanna et al., 2011). The longer payback times reported for US systems (i.e., 98–380 years) result from conversion of native ecosystems, such

as conservation reserve program (CRP) grasslands (Abraha, Gelfand, Hamilton, Chen, & Robertson, 2019; Fargione, Hill, Tilman, Polasky, & Hawthorne, 2008; Gelfand et al., 2011), while conversion of degraded and marginal lands report less payback time (i.e., 15 years) for maize (Yang & Suh, 2015). Additionally, maize requires a large amount of N to reach its yield potential, which leads to high N fertilization rates that often result in high N leaching and emission of nitrous oxide (N₂O), depending on the land management approach (Davis et al., 2013; Donner & Kucharik, 2008). The high nutrient demand and annual phenology of maize results in a large amount of C leaving the agro-ecosystem annually via yield removal (Zeri et al., 2011) and soil C turnover from tillage (Anderson-Teixeira et al., 2013; Paustian, Six, Elliott, & Hunt, 2000). While maize has value in its dual use as a food or fuel crop, there remains large uncertainty surrounding the long-term ecological sustainability of maize as a bioenergy crop source.

Conversely, perennial bioenergy crops, such as switchgrass (*Panicum virgatum* L.), can repay their land conversion debts much faster (0–10 years) than maize (Abraha et al., 2019; Gelfand et al., 2011; Zeri et al., 2011). The key advantage of perennial crops, from a fuel sustainability and emissions reduction perspective, is they invest more C resources into development of belowground biomass that contribute more to soil C storage, and they require much less soil disturbance than their annual maize counterparts (Anderson-Teixeira et al., 2013; Hudiburg, Davis, Parton, & Delucia, 2015). Perennial crops also require less N for biomass production (Heaton, Dohleman, & Long, 2009; Ruan et al., 2016) and translocate N belowground prior to harvest (Masters et al., 2016), thus reducing the amount of N lost from these systems (Smith et al., 2013). When compared to maize, perennial bioenergy crops are usually considered superior in their ecological sustainability (Robertson et al., 2017; Whitaker et al., 2018).

With an expanding bioenergy economy, land managers will be faced with the challenge of whether to invest in food or fuel crops. Considering the likelihood that bioethanol prices will fluctuate in accordance with the petroleum market (Bocquého & Jacquet, 2010; Song, Zhao, & Swinton, 2011; Tyner, 2008), land managers who invest in perennial crops may face financial pressure to revert to annual food agriculture. Song et al. (2011) examined investment uncertainty for perennial (i.e., switchgrass) and annual (i.e., maize) bioenergy crops and concluded a land manager would be more likely to invest in perennials knowing they could easily convert back to annual crops if markets changed. However, Song et al. (2011) did not account for C lost from land conversion, which could incur a significant cost to farmers if C credits are included in future markets (Khanna et al., 2011). Findings from the conversion of CRP grasslands to maize or perennial systems showed the largest C and N losses occurred during and immediately after land conversion (Abraha et al., 2019; Gelfand et al., 2011), as did reversion of miscanthus and willow to perennial ryegrass (McCalmont et al., 2018). Yet, empirical assessment of the magnitude of such losses from reverting a perennial bioenergy system back to an annual maize rotation is lacking and is needed for economic forecasting models to account for these costs.

We closed this understanding gap by reverting a mature perennial switchgrass cropping system back to an annual maize rotation and measured the effects on ecosystem C and N cycling over 2 years. We hypothesized that reversion from switchgrass to maize as a feedstock for bioenergy production would (a) cause large initial losses of soil C from the ecosystem driven by field disturbance (Gelfand et al., 2011; Zeri et al., 2011), and (b) N losses would increase as a result of increased fertilizer application and soil disturbance (Abraha, Gelfand, Hamilton, Chen, & Robertson, 2018; Davis et al., 2010). Using the DayCent model (Hartman et al., 2011; Parton, Hartman, Ojima, & Schimel, 1998), we estimated how long it would take for SOC dynamics and greenhouse gas (GHG) emissions in the converted system to resemble a reference maize system.

2 | MATERIALS AND METHODS

2.1 | Site description and experimental design

This research occurred at the University of Illinois Urbana-Champaign (UIUC) Energy Farm located in the Midwest region of the United States (Figure S1). The region experiences a humid continental climate characterized by severe cold winters, no dry season, and a hot summer. Mean annual temperature (1981–2010) is 10.9°C and mean annual rainfall is 1,051 mm (Illinois State Water Survey, 2020). The UIUC

Energy Farm is a 130 ha farm established in 2008 for bioenergy research. Soils at the Energy Farm are Drummer silty clay loam that are deep and poorly drained (Soil Survey Staff, 2015). In 2008, a 4 ha perennial switchgrass plot and a 4 ha maize–maize–soybean annual rotation plot were established. The two fields were instrumented with eddy covariance flux towers to provide high temporal resolution measurements of C, water, and energy flux from the two cropping systems (Zeri et al., 2011). The flux towers were located in the center of these fields as wind conditions were largely omnidirectional at the Energy Farm (Figure S1). Both sites were registered as Ameriflux sites in 2019 (US-UiA for Switchgrass and US-UiC for Maize). In addition to the 4 ha eddy covariance plots, 1 ha maize and switchgrass plots ($n = 4$ per crop system) were established in 2008 to permit spatial replication of other aboveground and belowground biogeochemical pools and fluxes (Anderson-Teixeira et al., 2013; Smith et al., 2013).

The switchgrass plots reached maturity in 2011, then experienced steady yield declines from 2013 onward, so in 2016, the decision was made to convert the switchgrass plots back to an annual maize rotation, beginning in 2017. The existing 1 ha ($n = 4$) maize plots remained intact and are hereafter referred to as “maize-control,” while the 4 ha ($n = 1$) maize-control plot was relocated in 2016 to accommodate another study (Figure S1). For the switchgrass plots, half of each 1 ha plot was converted to maize ($n = 4$), hereafter referred to as “maize-converted,” and the remaining half of the 1 ha plots were left as switchgrass to act as the unmodified control. In 2018, the maize-control plots were also split in half to accommodate another experiment, but management practices within the maize-control half of the plot remained intact (Table S1). The whole 4 ha switchgrass plot was reverted to maize. In February 2017, a moldboard plow was used to prepare the fields for planting in an effort to prevent re-sprouting of switchgrass during maize establishment. Annual crops at the UIUC Energy Farm were chisel plowed and local pest and weed management practices were applied to all fields (Table S1).

2.2 | Eddy covariance instrumentation and data analysis

Ecosystem scale C dynamics were determined by the eddy covariance technique using scaffold flux towers. Each tower was instrumented as in Table S2 and as outlined by Zeri et al. (2011). CO₂, water, and energy fluxes were recorded along with U, V, and W wind vector components at 10 Hz, with instrument height ranging from 2.5 to 4 m to maintain instruments >1 m above the canopy. Cospectra analysis showed this height was sufficient to capture vertical turbulent transport (Figure S2). All other meteorological measurements

were averaged every 30 min. Precipitation was obtained from the Illinois Water Survey (Illinois State Water Survey, 2020). Given advances made in eddy covariance data processing since Zeri et al. (2011) published these data, we chose to reprocess the data for this study using updated tools. The 10 Hz flux data were processed to 30 min averages using Eddy Pro (v6.2.0; LICOR Biosciences), where standard flux corrections were applied including a double rotation tilt correction, Webb–Pearman–Leuning (WPL) density correction (Webb, Pearman, & Leuning, 1980), block average flux de-trending, covariance maximization time lag compensations, and identification and removal of spikes using the approach of Vickers and Mahrt (1997). The flux footprint was calculated through EddyPro using the Hsieh, Katul, and Chi (2000) method. The 30 min data were post-processed using PyFluxPro (v1.1.0), developed by Isaac et al. (2017) and are available on GitHub (<https://github.com/OzFlux/PyFluxPro>). First, data were quality assured and quality checked (QA/QC) to remove spikes and erroneous data. Footprint exclusions were applied by PyFluxPro to remove data when more than 50% occurred outside of the field of interest to avoid excessive nighttime data loss (Figure S3).

The percentage of missing (i.e., from power failure and sensor malfunction) and removed (i.e., from QA/QC) data for sites varied from 4% to 60%, with C and water fluxes at the higher end of this range and most loss occurring outside of the growing season (Figure S3). To provide a complete data set for inter-annual comparison, meteorological data were gap filled by PyFluxPro using external data sourced from a weather station 7.4 km away at the University of Illinois Willard Airport (station ID: 725315-94870), and gridded ERA-Interim data (Dee et al., 2011). A site-specific climatology file was generated by PyFluxPro using simple linear interpolation to use for filling meteorological gaps of less than 2 hr. For all other gaps, a 90 day window was used to reduce the effect of bias from external data on site-based meteorological data (Isaac et al., 2017). A friction velocity (u^*) threshold was calculated by PyFluxPro for each year using the moving point test (Papale et al., 2006) and was applied before gap filling to exclude fluxes when atmospheric turbulence was too low to satisfy the vertical transport assumption of eddy covariance (Table S3).

The remaining fluxes of sensible heat, latent heat, and CO_2 after application of the u^* threshold were gap filled using a self-organizing linear output (SOLO) artificial neural network model run within PyFluxPro, with the meteorological variables of net radiation (W/m^2), ground heat flux (W/m^2), specific humidity deficit (kg/kg), air temperature ($^\circ\text{C}$), and soil temperature ($^\circ\text{C}$) used as model drivers (Figure S4). Assessment of energy balance closure at our sites showed our sites fell within typical range of 0.70–0.78 for crop flux tower sites (Figure S5; Stoy et al., 2013), particularly when integrated over the diurnal timescale (Leuning, van Gorsel, Massman, & Isaac, 2012). Lastly, net ecosystem CO_2

exchange (NEE) was partitioned into ecosystem respiration (ER) and gross primary productivity (GPP) using two methods available in PyFluxPro to account for the uncertainty in each (Isaac et al., 2017). One method was the Lloyd and Taylor (1994) nocturnal approach, where an Arrhenius function with air temperature was applied to nighttime u^* filtered NEE to estimate ER. The other method used SOLO to estimate ER, which also applied a u^* filter to nighttime NEE to estimate ER with air temperature, soil temperature, and soil moisture as model drivers (Isaac et al., 2017). Lastly, GPP was calculated as the difference between NEE and ER. Given each method has its own limitations, assumptions, and uncertainty, ER (and thus GPP) slightly differed between the two techniques. Therefore, the NEE, GPP, and ER data presented are an average of the two outputs, which were used to calculate cumulative annual totals for each year and then the cumulative annual mean (\pm mean error) for each treatment. Flux data presented for the maize-control site from 2008 to 2018 include only maize years (i.e., soybean years removed). To reduce inter-annual bias, the switchgrass years that also occurred during soybean years were removed from the analysis (i.e., 2010, 2013 and 2016). Carbon flux acronyms are based off Chapin et al. (2006).

2.3 | Soil respiration measurement and analysis

Soil autotrophic and heterotrophic respiration were estimated by applying the root exclusion approach to survey soil respiration measurements (Vogel & Valentine, 2005). Shallow 20 cm diameter polyvinyl chloride (PVC) soil collars (5 cm below the surface) were installed to assess total soil respiration (RS) and deep collars (50 cm below the surface) were used to exclude plant roots, providing the heterotrophic soil respiration (RH) contribution. The difference between the two collar measurements was autotrophic respiration (RA). Shallow collars were installed after moldboard plowing as soils warmed, and deep collars were installed in the days following tillage and planting, with measurements commencing at least 7 days after installation to allow disturbance effects to settle. In maize, all collars were removed prior to fall tillage and were reinstalled the following spring after planting. Survey measurements for each treatment were made on a weekly to monthly basis during the growing seasons of 2017 and 2018 using an LI-8100 portable gas analyzer with an LI8100-103 survey chamber (LICOR Biosciences). The measurements were made in four subplots within each of the 4 ha plots and in two subplots within each of the 1 ha plots. For each measurement date, the subplot measurements were averaged by plot, resulting in an overall sample size of $n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted.

Soil respiration measurement campaigns were centered near midday to encompass the time when soil temperature changes were minimal. Linear interpolation between survey points was used to estimate daily fluxes and calculate cumulative growing season respiration totals. Soil flux acronyms are based off Chapin et al. (2006).

2.4 | Biomass collection and tissue analysis

Aboveground and belowground biomass in 2017 and 2018 was measured to determine how biomass C pools changed due to crop conversion. Peak aboveground biomass was quantified when leaf area index (LAI) reached its maximum (i.e., July) for maize ($5.36 \pm 0.06 \text{ m}^2/\text{m}^2$) and switchgrass ($5.68 \pm 0.79 \text{ m}^2/\text{m}^2$). LAI was measured using an LAI-2200C plant canopy analyzer with its associated processing software (LICOR Biosciences). Quadrats of $0.45 \times 0.45 \text{ m}$ for switchgrass and $0.75 \times 0.75 \text{ m}$ for maize were used to harvest all aboveground biomass in randomly selected areas of each plot. Two quadrats were harvested in each 1 ha plot and four quadrats were harvested from the 4 ha plots ($n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted). Samples were dried at 60°C for at least 48 hr until weight was constant, then were weighed for dry weight (g).

At the time of aboveground biomass sampling, three 5.08 cm soil cores from each quadrat were randomly collected to 30 cm using an AMS split core sampler, separated into 0–10 and 10–30 cm depths, and compiled by depth. Root and rhizome material were elutriated from each core and then oven dried as with aboveground material. Large belowground biomass samples were first homogenized using knife mills (Retsch cross beater mill SK 300, Retsch) and all biomass was ground to a powder using a bead beater (Geno Grinder 2010, BT&C). Ground material was weighed into tin capsules and combusted with an elemental analyzer (Costech 4010 CHNSO Analyzer; Costech Analytical Technologies Inc.), using acetanilide and apple leaves (National Institute of Science and Technology, Gaithersburg Maryland, USA) as standards to obtain percent N and C. Biomass data are presented in units of $\text{g C}/\text{m}^2$.

2.5 | Nitrogen fluxes

Gaseous N losses via net soil–atmosphere N_2O fluxes were measured on a weekly to monthly basis in all plots in the 2 years following conversion in 2017, with more frequent sampling in the early to mid-growing season when N_2O peaks associated with fertilization and rain events were expected. The gas fluxes were measured using 26 cm diameter PVC collars and a vented acrylonitrile-butadiene-styrene plastic

chamber top as described by Krichels, DeLucia, Sanford, Chee-Sanford, and Yang (2019). The chamber headspace was sampled with a polypropylene syringe at 0, 10, 20, and 30 min after chamber closure, with 20 ml samples stored in 10 ml pre-evacuated glass vials. Each 4 ha plot was sampled with four subplot replicates and each of the four replicate 1 ha plots was sampled with two subplot replicates per sampling campaign; fluxes from the subplot replicates were averaged to obtain plot-level fluxes, resulting in $n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted. Gas samples were analyzed for N_2O concentrations using a Shimadzu GC-2014 gas chromatograph (Shimadzu Scientific Instruments) equipped with an electron capture detector. Net N_2O fluxes were calculated from the change in N_2O concentration over time by fitting an exponential curve to the data using an iterative model, assuming zero net flux when no significant ($p > .05$) relationship between gas concentration and time could be found (Matthias, Yarger, & Weinbeck, 1978).

To characterize soil N dynamics, inorganic N pools and gross mineralization rates in surface soils (0–10 cm depth) were measured in all plots at two points during the 2017 growing season (June 6 and June 16). These dates were chosen to represent an appropriate time after conversion to understand how management impacts soil N dynamics. Soil ammonium (NH_4^+) and nitrate (NO_3^-) concentrations in 2 M KCl soil extracts were determined colorimetrically on a Lachat Quikchem flow injection auto-analyzer (Lachat Instruments). Gross N mineralization rates were measured using the stable isotope pool dilution method (Hart, Stark, Davidson, & Firestone, 1994). The NH_4^+ pool was enriched by adding 1 ml of $21.96 \mu\text{g } ^{15}\text{N-NH}_4^+/\text{ml}$ solution in deionized water to un-sieved soil samples and mixing by hand to ensure homogenous distribution of the ^{15}N label. The initial ^{15}N enrichment of the NH_4^+ pool was determined using 2 M KCl soil extraction at 15 min following addition of the ^{15}N label (Davidson, Hart, Shanks, & Firestone, 1991). Initial enrichment averaged 9.7 atom % ^{15}N and ranged 1.8–30.0 atom % ^{15}N . The ^{15}N -labeled soils were incubated in canning jars under ambient atmosphere and temperature for 4 hr before determination of the final ^{15}N enrichment of the NH_4^+ pool. The isotopic composition of NH_4^+ in the 2 M KCl soil extracts was determined via acid-trap diffusion (Herman, Brooks, Ashraf, Azam, & Mulvaney, 1995) and analysis on an Elementar Vario Micro Cube elemental analyzer interfaced with an IsoPrime 100 isotope ratio mass spectrometer (Isoprime Ltd.; Elementar). Gross N mineralization rates were calculated from the change in ^{15}N enrichment of the NH_4^+ pool following Kirkham and Bartholomew (1954).

Lastly, 5 cm diameter resin lysimeters were used to quantify annual NH_4^+ and NO_3^- leaching from all treatments. The lysimeters were made of the ion exchange resin Rexyn/Lewatit (NM 60; Fisher Chemical) housed between two layers of nylon mesh in PVC cylinders. This technique allowed us to

quantify N leaching from all treatments. In November 2016 and 2017, eight lysimeters were installed in the 4 ha plots and four were installed in the 1 ha plots at a depth of 50 cm before the start of the growing season and were removed for analysis after 1 year. New lysimeters were installed when the old ones were removed, into an undisturbed soil profile. Each lysimeter contained 25 g of fresh resin (10 g dry), giving it a trapping capacity of $42.5 \text{ mEq N g}^{-1} \text{ min}^{-1}$ as NH_4^+ and NO_3^- (Smith et al., 2013; Susfalk & Johnson, 2002). After removal, the resin was extracted using a 1 M KCl solution followed by colorimetric flow injection analysis (Lachat QuikChem 8000).

2.6 | Biogeochemical modeling

The DayCent biogeochemical model (Parton et al., 1998) was used to predict how long it would take, beyond the 2 years scope of the conversion measurements, for SOC dynamics and GHG emissions in the converted 8 year old switchgrass treatment to approach those found in the reference maize treatment. We used a new version of DayCent that was developed by the Center for Advanced Bioenergy and Bioproducts Innovation (DayCent-CABBI) based on the DayCent-Photo model version (Straube et al., 2018), with modifications to perennial plant parameterizations that were necessary for a more process-based representation of large perennial biofuel grasses such as switchgrass (Berardi et al., 2020). DayCent has been used to evaluate the effects of climate, land use change, and management practices on soil C, greenhouse gas emissions, and nutrient cycling in agricultural and natural terrestrial ecosystems (Del Grosso et al., 2001; Hartman et al., 2011; Hudiburg et al., 2015, 2016).

DayCent-CABBI perennial plant parameterizations allow for temporally dynamic variation of aboveground plant biomass structure (leaves and stems) and chemical composition (lignin and C:N ratios) of plant parts. The new perennial plant parameterizations differ from traditional crop/grass plant types in DayCent by differentiating between leaves and stems rather than just shoots. We were able to specify C:N ratios for both leaves and stems derived from empirical UIUC Energy Farm data resulting in more realistic C and N allocation through time. Similarly, belowground plant material in the new version includes representation of both fine roots and rhizomes, instead of a single belowground biomass pool. In order to represent legacy effects from one growing season to the next, perennial plants increase carbohydrate storage toward the end of the growing season, which will be available for growth in the subsequent season. Similarly, during senescence large perennial grasses translocate N from leaves to belowground biomass, which will then be available for growth in the subsequent growing season. The use of this more dynamic and process-based

parameterization for switchgrass increases our confidence in the ability of DayCent to simulate establishment and legacy effects in future scenarios.

Daily minimum temperature, maximum temperature, and precipitation from 1980 to 2018 used for historical and current day simulations were downloaded from the Daymet database (Thornton et al., 2012). The weather data were randomized for future simulations. We used agricultural history and site management described by Hudiburg et al. (2015) for the Energy Farm prior to the 2008 growing season. Management during the growing season of 2008–2018 for maize, soybean, and switchgrass (Table S1) was implemented in model simulations. DayCent-CABBI was calibrated to measurements of above- and belowground measured peak biomass (2008–2018), average site soil C measured at field establishment (i.e., 2008), and N_2O emissions measured from 2008 to 2012. We then validated the model against monthly above- and belowground net primary productivity (NPP) using monthly biometric estimates collected from 2008 to 2012 (Anderson-Teixeira et al., 2013) and annual NPP from 2013 to 2018. We also validated model estimates against measured cumulative N_2O emissions in 2017 and 2018 (Figure S6). Extensive DayCent model validations for both soil C and NPP estimates for the UIUC Energy Farm were completed in previous studies (Hudiburg et al., 2015, 2016).

Future simulations from 2019 to 2050 were conducted for maize-control, maize-converted, and a scenario where switchgrass was not converted back to maize. For the switchgrass scenario, we did not simulate replanting following some number of years, as some other modeling studies have in the past (Hudiburg et al., 2015), because replanting is debated and based on assumptions rather than a documented decline in yield. Small declines in switchgrass yield have been found in one of the few existing long-term studies (Alexopoulou et al., 2015); however, to our knowledge, there is not enough data-driven evidence to support modeling replanting assumptions.

Model output was used to estimate the net GHG emissions from N_2O and sequestered soil C using methods described in the IPCC AR5 report (IPCC, 2013). GHG emissions from N_2O were estimated using modeled direct N_2O efflux from the soil and indirect emissions were calculated from modeled volatilization and leached N estimates using IPCC emission factors of 0.01 and 0.0075, respectively. We calculated the GHG contribution in CO_2 equivalents of N_2O assuming 298 times the 100-year horizon of global warming potential of CO_2 (Myhre et al., 2013).

2.7 | Statistical analyses

Differences in above- and belowground biomass, total cumulative RS, RH, RA, and N_2O fluxes, N pool sizes, N

mineralization rates, and N leaching between treatments (switchgrass, maize-control, and maize-converted) during the two conversion years (i.e., 2017 and 2018) were compared using an analysis of variance (ANOVA) with treatment and year (or day of year), and a treatment-by-year interaction term. All statistical tests were performed in R, version 3.6.3 (R Core & Team, 2020) with a significance level of $\alpha = 0.05$. Data were square-root or log transformed where appropriate to meet assumptions of normality and equal variance in residuals. Post hoc Tukey HSD tests were used to make pairwise comparisons between treatments using the multcomp package in R (Hothorn, Bretz, & Westfall, 2008).

3 | RESULTS

Comparison of flux tower measurements between maize-converted, maize-control, and switchgrass revealed an immediate effect of land use change in the converted switchgrass treatment (Figure 1a). The conversion event led to higher net positive NEE, particularly in the period pre-planting (day of year [DOY] 0–150). This resulted in a mean annual cumulative NEE of $100.85 \pm 74.26 \text{ g C m}^{-2} \text{ year}^{-1}$ from the maize-converted treatment, followed by $-34.26 \pm 127.32 \text{ g C m}^{-2} \text{ year}^{-1}$ from maize-control and $-417.63 \pm 56.66 \text{ g C m}^{-2} \text{ year}^{-1}$ from switchgrass. Partitioning of NEE into its component fluxes showed ER was highest from the maize-converted treatment ($2,073.63 \pm 367.20 \text{ g C m}^{-2} \text{ year}^{-1}$) compared to switchgrass ($1,412.70 \pm 28.73 \text{ g C m}^{-2} \text{ year}^{-1}$) or maize-control ($1,699.16 \pm 234.79 \text{ g C m}^{-2} \text{ year}^{-1}$, Figure 1b). In contrast, GPP did not differ greatly between the three treatments (Figure 1c), with maize-converted ($1,972.78 \pm 292.95 \text{ g C m}^{-2} \text{ year}^{-1}$) having slightly higher cumulative mean annual GPP than switchgrass ($1,830.32 \pm 52.87 \text{ g C m}^{-2} \text{ year}^{-1}$) and maize-control ($1,733.42 \pm 175.61 \text{ g C m}^{-2} \text{ year}^{-1}$). Therefore, at the field scale, the increased C loss from the maize-converted treatment shown

by NEE (Figure 1a) was driven primarily by increased ER (Figure 1b) as opposed to GPP (Figure 1c) compared to the other treatments.

Closer inspection of the RS component of ER during the June–August growing seasons revealed differences between treatments, with maize-converted significantly higher than maize-control in both 2017 and 2018 ($t = 3.15$, $p = .01$, Figure 2a). Likewise, RH was significantly higher for maize-converted than for maize-control over the 2 years ($t = 3.43$, $p = .006$, Figure 2b). Switchgrass showed no significant differences with maize-converted or maize-control (Figure 2). Likewise, RA did not significantly differ between treatments ($p = .33$, Figure 2), indicating that RH was a key driver of differences in RS, and thus in ER.

The quantity of C in peak belowground biomass (i.e., alive and dead) differed between the three treatments over two depths. In the surface layer (0–10 cm) across both years (2017–2018), switchgrass had the highest belowground C followed by maize-converted then maize-control, all of which were significantly different to each other ($p < .01$, Figure 3b). In the deeper 10–30 cm layer, belowground C was significantly different between treatments only for maize-control (Figure 3b), with switchgrass and maize-converted showing no significant difference across the 2 years ($p = .66$, Figure 3b). The difference in belowground C between maize-control and maize-converted is in contrast to aboveground C differences, which saw no significant change across years for the two treatments ($p = .83$, Figure 3a).

Along with differences in the C fluxes and pools, treatment differences in N fluxes and pools occurred following conversion (Figure 4). In the 2017 growing season, maize-converted exhibited higher instantaneous N_2O fluxes than maize-control and switchgrass on most sampling dates (Figure S7), resulting in the highest cumulative N_2O flux from maize-converted compared to maize-control ($t = 3.61$, $p < .01$) and switchgrass ($t = 4.04$, $p < .01$, Figure 4a). However, in 2018, N_2O flux from the two

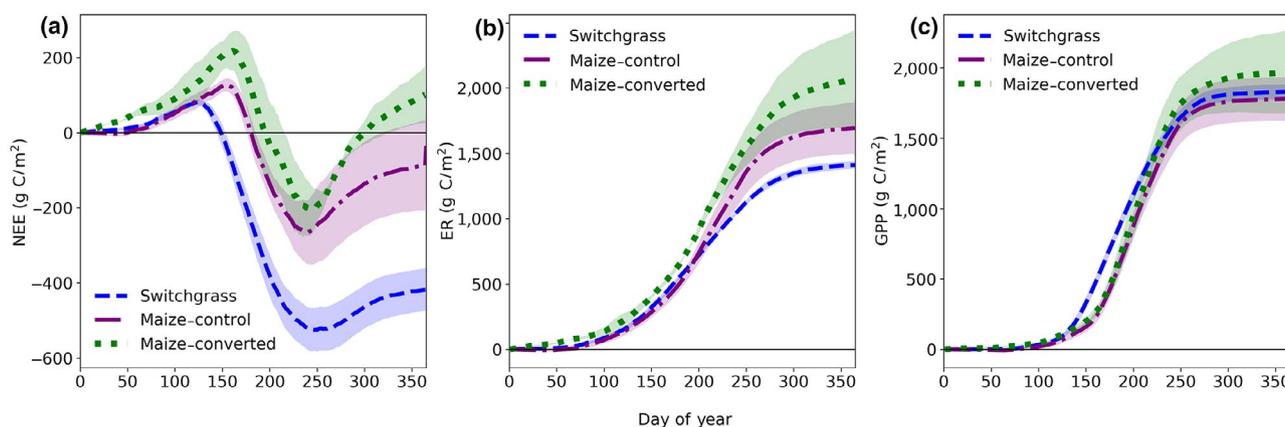


FIGURE 1 Mean annual cumulative (a) net ecosystem exchange (NEE), (b) ecosystem respiration (ER), and (c) gross primary productivity (GPP) for maize-control (2008–2018), switchgrass (2008–2016) and maize-converted (2017–2018) at the University of Illinois Energy Farm, Illinois, United States. The shading around the mean represents the standard error of the mean, also indicating inter-annual variability for each flux variable

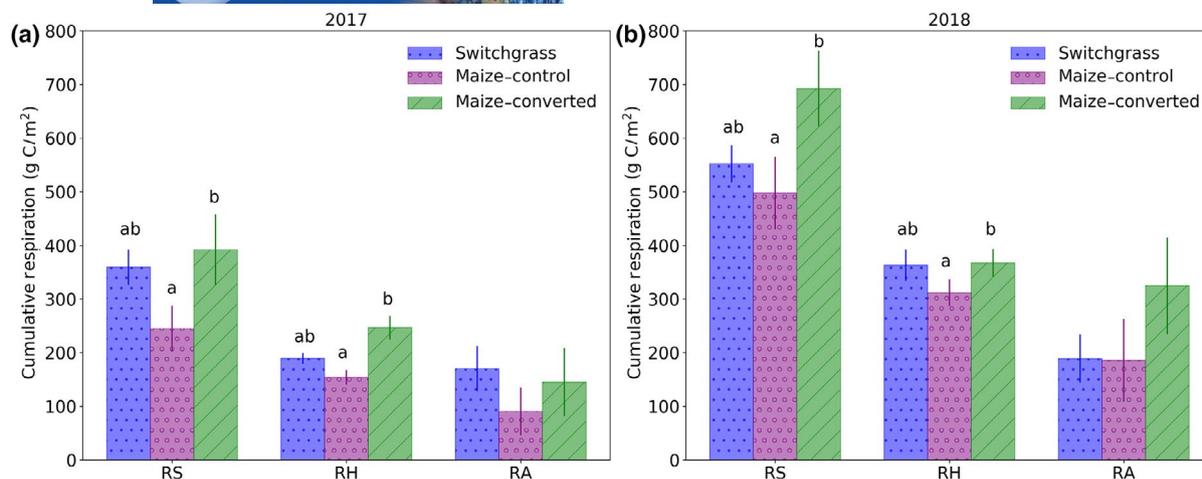


FIGURE 2 Mean cumulative total soil respiration (RS), soil heterotrophic respiration (RH), and soil autotrophic respiration (RA) of switchgrass, maize-control, and maize-converted during the (a) 2017 and (b) 2018 growing season (June–August) at the University of Illinois Energy Farm, Illinois, United States. Error bars represent the standard error of the mean for each crop treatment ($n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted). Letters above the bars represent significant differences from pairwise comparisons of the treatments within each respiration category using a repeated measures ANOVA

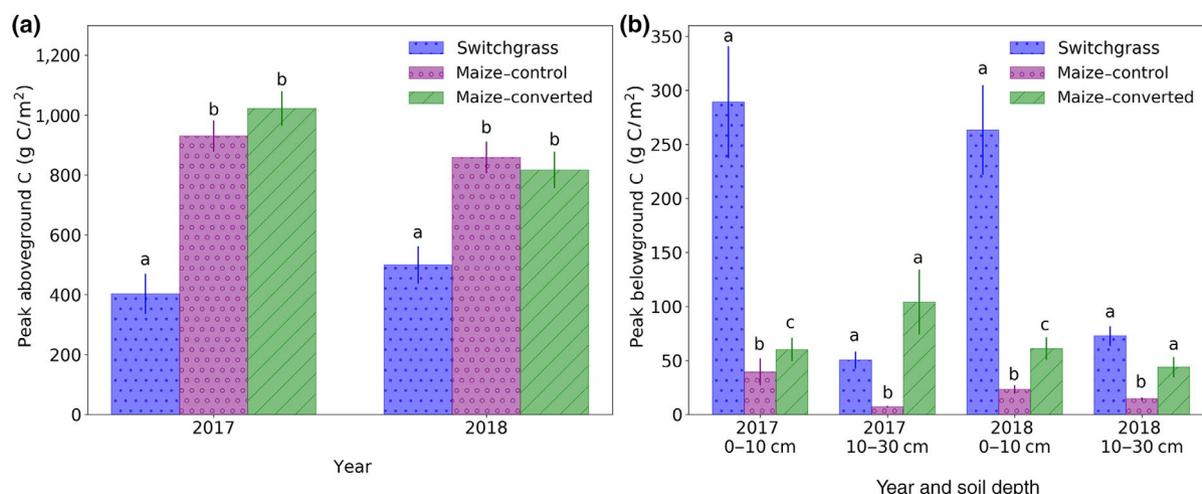


FIGURE 3 Two years of (a) aboveground and (b) belowground peak biomass C content from 0 to 10 and 10–30 cm for switchgrass, maize-control and maize-converted during the 2017 and 2018 growing season at the University of Illinois Energy Farm, Illinois, United States. Error bars represent the standard error of the mean for each crop type ($n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted). Letters above the bars represent pairwise comparisons of the sites within each category listed on the x-axis of each figure

maize treatments was not statistically different from each other ($p = .87$, Figure 4b), yet switchgrass N_2O flux remained significantly lower than both maize-converted ($t = 3.02$, $p = .02$) and maize-control ($t = 3.50$, $p = .01$, Figure 4b). Gross N mineralization rates were significantly higher for maize-converted than for switchgrass ($t = 6.19$, $p < .001$) or maize-control ($t = 4.99$, $p < .001$, Figure 4e). Likewise, soil NH_4^+ concentrations were significantly higher in maize-converted than in switchgrass ($t = 8.34$, $p < .001$) or maize-control ($t = 4.54$, $p < .001$, Figure 4c), but leaching of NH_4^+ was not significantly different between treatments (Figure 4f). Interestingly, soil NO_3^- did not statistically differ between the two maize treatments ($p = .43$), but both maize-converted ($t = 21.34$, $p < .001$) and maize-control ($t = 22.60$, $p < .001$) were significantly higher

than switchgrass (Figure 4d). Leaching of NO_3^- was significantly higher from maize-converted than from switchgrass in 2017 ($t = 2.65$, $p = .04$) and 2018 ($t = 4.86$, $p < .001$), but was only different from maize-control in 2017 ($t = 2.69$, $p = .04$, Figure 4g).

Model-data comparisons showed the DayCent-CABBI model performed well at capturing both aboveground and belowground NPP and N_2O fluxes measured across the three treatments (Figure S6; Table S4). The model results indicated that SOC stocks in the maize-converted treatment were expected to increase to levels above those found in the reference switchgrass and maize-control treatments after conversion due to the large input from the belowground switchgrass necromass (Figure 5a). However, the increase

FIGURE 4 Mean cumulative nitrous oxide (N_2O) fluxes during the (a) 2017 and (b) 2018 growing season, (c) soil ammonium (NH_4^+) and (d) nitrate (NO_3^-) concentrations, (e) gross N mineralization rate, and (f) NH_4^+ and (g) NO_3^- leaching for switchgrass, maize-control, and maize-converted treatments at the University of Illinois Energy Farm, Illinois, United States. Error bars represent the standard error of the mean for each treatment ($n = 4$ for switchgrass and $n = 5$ for maize-control and maize-converted). Note differences in scale. Letters beside the points represent pairwise comparisons of the treatments within each year. (c–e) Data are from 2017 only

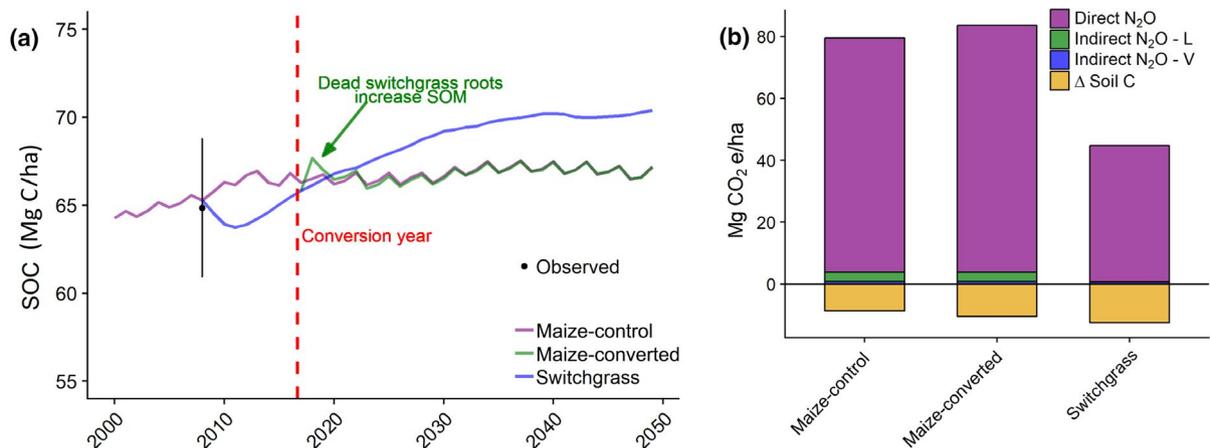
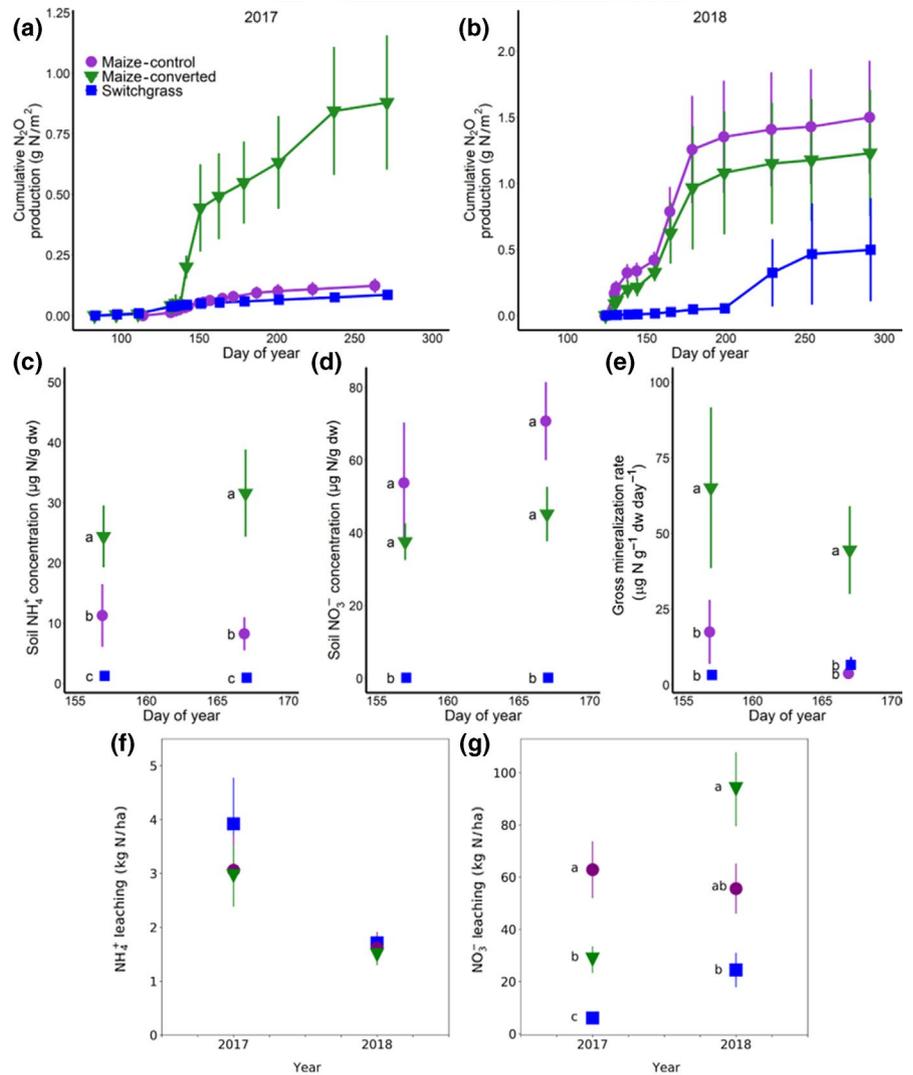


FIGURE 5 DayCent-CABBI model predictions of (a) soil organic C (SOC) change and (b) direct and indirect nitrous oxide (N_2O) and soil C change for switchgrass, maize-converted and maize-control. The observed data (black line) in (a) represent mean (\pm SE) SOC measured in 2008 and 2009 from the switchgrass plots ($n = 4$) and for (b) Cumulative greenhouse gas emissions in CO_2 equivalents from the time of conversion (2017) to 2050. Indirect emissions in (a) were estimated from model volatilization (V) and leaching (L)

in SOC stocks within the maize-converted treatment was short-lived, with the system returning to the temporal dynamics of the maize-control treatment approximately 5 years

after conversion (Figure 5a). DayCent-CABBI simulates an initial decrease in SOC from switchgrass due to the lower NPP of switchgrass during its establishment, compared to

maize (i.e., $<250 \text{ g C/m}^2$ in year 1 and $<400 \text{ g C/m}^2$ in year 2 from switchgrass and $>800 \text{ g C m}^{-2} \text{ year}^{-1}$ from maize). Cumulative GHG emissions from 2017 to 2030, expressed as CO_2 equivalents, were highest in the maize-converted scenario, while emissions from switchgrass were approximately half that of the two maize treatments (Figure 5b).

4 | DISCUSSION

The immediate loss of belowground biomass C (Figure 3), increased respiration (Figures 1 and 2), and N losses (Figure 4) from reversion of switchgrass to maize is reflective of the consequences of land use change on the sustainability of bioenergy crops as a viable fuel alternative (Abraha et al., 2019; Gelfand et al., 2011; Robertson et al., 2017; Zeri et al., 2011). The primary pathway of C loss from the reverted system, once plowing occurred, was through increased RH (Figure 2). This response would have been fueled by the large dead switchgrass biomass C pool that became available, which is evident in Figure 3b. The rapid temporal decline in belowground biomass within the maize-converted treatment represents C from the dead switchgrass biomass that was being utilized by soil microbes and other fauna, which is expected to cause temporary increases in RH and SOC stocks. In addition to this C stock, there was greater N availability from fertilizer applied to the field for maize production (Table S1). In particular, the availability of C in combination with available N would provide the substrate needed for enhanced denitrification by the microbial community (Abraha et al., 2018; Grandy & Robertson, 2006), as the same increases were not seen in the maize-control plot (Figure 2) despite it receiving the same amount of N fertilization (Table S1). While total RS, soil RH, and soil RA results are from the growing season months only (June–August, Figure 2), these months represent the periods where soil moisture and soil temperature are at their optimum for RH in temperate agricultural systems (Anderson et al., 2013; von Haden, Marín-Spiotta, Jackson, & Kucharik, 2019). For periods outside the growing season, the partitioned ecosystem scale NEE showed how ER was immediately increased by the conversion (Figure 1), so the differences in growing season respiration should be reflective of the maximum differences in soil respiration processes between the three treatments.

Past research efforts have shown how converting unmanaged grassland ecosystems (i.e., CRP) to perennial or annual crop agriculture causes significant soil C turnover and N_2O emissions, resulting in a large C debt repayment time for the bioenergy product (Abraha et al., 2019; Gelfand et al., 2011). Abraha et al. (2019) attribute this debt to the time it takes for the system to reach C stabilization after conversion, applying the C debt to the new

crop to recover. A single tillage event causes significant structural changes to soil aggregates and C distribution in soils (Grandy & Robertson, 2006), which can take years to recover once disturbed (von Haden, Kucharik, Jackson, & Marín-Spiotta, 2019). The reversion of switchgrass to maize in this study is similar to the scenario of converting CRP grassland to maize in that the switchgrass plot was 8 years old at the time of conversion, which was calculated by Abraha et al. (2019) as the maximum time needed for switchgrass to repay its C debt from land conversion. The DayCent-CABBI model projected that SOC equilibrium would not be reached for the switchgrass treatment until approximately 30 years after establishment, but that it recovered to pre-conversion levels within approximately 10 years (Figure 5). For the same switchgrass field as used in this study, Zeri et al. (2011) showed the ecosystem had a net uptake of C within 1–2 years of planting, which was likely due to the accrual of C stored in live roots that the DayCent-CABBI and Abraha et al. (2019) models did not account for in their long-term projections.

Similar to the response of the ecosystem C balance, the N balance was disrupted by converting switchgrass to maize. Higher rates of N_2O flux were observed along with increases in NH_4^+ concentrations and gross N mineralization rates (Figure 4), suggesting that tillage increased the availability of N for soil N cycling processes. These findings are consistent with N responses seen under CRP grassland conversion to maize (Abraha et al., 2018). Interestingly, NO_3^- concentration was higher in the maize-control treatment, which was likely either a result of higher background NO_3^- concentrations from prior years of fertilization in the maize-control treatment, greater NO_3^- leaching from the disturbed soil in the maize-converted plot, or a C subsidy from the switchgrass root necromass supporting higher rates of denitrification consuming NO_3^- in the maize-converted treatment. While our N flux and pool measurements did not capture the N losses that occurred immediately after plowing, the effect of this disturbance on soil N cycling was still clear during the first growing season after conversion. The increased N loss from the converted field shows that careful fertilizer management is required to minimize the impacts this excess N would have on ecosystems affected by agricultural runoff (VanLoocke et al., 2017).

The moldboard plow used for field preparation in this experiment is a destructive method of land conversion and is not typically used in annual agricultural systems in the United States (Lal, Reicosky, & Hanson, 2007). However, this method was chosen to represent an approach a land manager might take to quickly convert a field from a perennial to annual crop with little perennial re-sprouting, as the plow would break apart root and rhizome material to prevent switchgrass re-sprouting before the maize could establish. A consequence of this approach is the enhanced soil C turnover caused by the deeper soil disturbance from the plow (Lal et al., 2007).

Therefore, the findings from this experiment likely reflect the upper limit of C and N loss due to land use change at our site. If a less destructive land conversion technique was applied, the immediate loss of C from the system would likely be reduced (Al-Kaisi & Yin, 2005; Reicosky & Archer, 2007).

The time estimated for the maize-converted field to reach SOC re-equilibration (~5 years from land conversion, Figure 5) and the resulting higher GHG emissions reflects how quickly the C and N cycle benefits of perennial bioenergy systems can be overturned by converting land back to annual row crop agriculture. In the case of this study, SOC in the switchgrass system had not yet reached steady-state before it was converted back to maize. The lifespan of the switchgrass plot in this study was cut shorter than would typically be expected for a switchgrass crop (Alexopoulou et al., 2015; Hudiburg et al., 2015) due to a disease that reduced yields. If the crop was unaffected by disease and continued to deliver high yields, SOC would have continued to accumulate for another 10+ years (Figure 5).

There is a need to balance the benefits of C sequestration through increased SOC with the ability of a bioenergy crop to deliver the highest yields possible for fuel production. This study highlights the need for incentives, such as carbon credits (Khanna et al., 2011), to encourage land managers who invest in bioenergy crops to maintain these crops over the long term. The act of switching from perennial to annual crops as market prices fluctuate for different food and fuel crops will be detrimental to the C sequestration potential of bioenergy cropping systems if not properly managed. Avoiding conversion from perennial to annual crops altogether would be the best way to ensure the C stored by these systems remains intact. However, given the potential need to re-plant switchgrass to maintain yields, this approach may be infeasible in the long term. Improvements are needed in land cultivation and conversion techniques, so large disturbances to the soil can be minimized to keep CO₂ emissions and N losses to a minimum. Scaling of the findings from this study across a larger regional area would be a useful next step in assessing the broader GHG implications at the landscape scale of switching between annual and perennial cropping systems for bioenergy production.

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AUTHOR CONTRIBUTIONS

All authors contributed to the experimental design. Manuscript preparation was led by Moore with input from all co-authors. Data contributions are as follows: Moore, Dracup, Gomez-Casanovas, and Bernacchi provided eddy covariance data collection and processing. Kantola, Masters, von Haden, and DeLucia collected above- and belowground biomass measurements, soil respiration sampling, and the lysimeters. Van Allen, Egenriether, and Yang characterized nitrogen fluxes and pools. Berardi, Blanc-Betes, Hartman, Parton, and Hudiburg provided all DayCent model work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from either the supplemental material of this article, from the Ameriflux network (site US-UiA for Switchgrass flux data and site US-UiC for Maize flux data), or from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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