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Predicting soil carbon changes in switchgrass grown on marginal lands under climate change and adaptation strategies

Rafael Martinez-Feria[1] | **Bruno Basso**[1,2]

[1]Department of Earth and Environmental Sciences, Michigan State University, East Lansing, MI, USA

[2]Kellogg Biological Station, Michigan State University, Hickory Corners, MI, USA

Correspondence
Rafael Martinez-Feria, Department of Earth and Environmental Sciences, Michigan State University, East Lansing, MI, USA.
Email: mart2225@msu.edu

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Abstract

The United States Great Lakes Region (USGLR) is a critical geographic area for future bioenergy production. Switchgrass (*Panicum virgatum*) is widely considered a carbon (C)-neutral or C-negative bioenergy production system, but projected increases in air temperature and precipitation due to climate change might substantially alter soil organic C (SOC) dynamics and storage in soils. This study examined long-term SOC changes in switchgrass grown on marginal land in the USGLR under current and projected climate, predicted using a process-based model (Systems Approach to Land-Use Sustainability) extensively calibrated with a wealth of plant and soil measurements at nine experimental sites. Simulations indicate that these soils are likely a net C sink under switchgrass (average gain 0.87 Mg C ha^{-1} $year^{-1}$), although substantial variation in the rate of SOC accumulation was predicted (range: 0.2–1.3 Mg C ha^{-1} $year^{-1}$). Principal component analysis revealed that the predicted intersite variability in SOC sequestration was related in part to differences in climatic characteristics, and to a lesser extent, to heterogeneous soils. Although climate change impacts on switchgrass plant growth were predicted to be small (4%–6% decrease on average), the increased soil respiration was predicted to partially negate SOC accumulations down to 70% below historical rates in the most extreme scenarios. Increasing N fertilizer rate and decreasing harvest intensity both had modest SOC sequestration benefits under projected climate, whereas introducing genotypes better adapted to the longer growing seasons was a much more effective strategy. Best-performing adaptation scenarios were able to offset >60% of the climate change impacts, leading to SOC sequestration 0.7 Mg C ha^{-1} $year^{-1}$ under projected climate. On average, this was 0.3 Mg C ha^{-1} $year^{-1}$ more C sequestered than the no adaptation baseline. These findings provide crucial knowledge needed to guide policy and operational management for maximizing SOC sequestration of future bioenergy production on marginal lands in the USGLR.

KEYWORDS

bioenergy, climate change, crop modeling, marginal land, soil organic carbon, switchgrass

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1 | INTRODUCTION

Transitioning bioenergy systems from grain-derived sugars and lipids to lignocellulosic plant biomass is a necessary step for climate stabilization (DeCicco & Schlesinger, 2018; IPCC, 2014; Popp et al., 2011; Smith et al., 2016). Lignocellulose feedstock production and utilization are poised to become a major industry, despite potential drawbacks due to indirect land-use change, deforestation, displacement of food production, and biodiversity impacts (Fargione, Hill, Tilman, Polasky, & Hawthorne, 2008; Fletcher, Brown, Johnstone, de Ruiter, & Zyskowski, 2011; Gelfand et al., 2013). As the United States moves toward meeting goals set by the renewable fuel standards program (Schnepf & Yacobucci, 2013), the US Great Lakes region (USGLR; Figure 1a) could become a pivotal geographic location for future biomass feedstock production (Becker, Skog, Hellman, Halvorsen, & Mace, 2009). This region, which represents the northern fringe of the Corn Belt, encompasses large areas of marginal land sites that are not typically farmed and remain under perennial covers (i.e., brush, forest, hay) and that are attractive for growing bioenergy crops because of their low opportunity cost (Kells & Swinton, 2014; Swinton, Tanner, Barham, Mooney, & Skevas, 2017). Thus, assessing potential benefits and drawbacks of growing biomass crops in these marginal lands is a priority.

Many carbon (C) budgets implicitly or explicitly require lignocellulosic bioenergy systems to be C-neutral, which means that biogenic C emissions associated with its production and consumption must be offset by plant CO_2 uptake and storage in soil organic C (SOC) reservoirs (DeCicco & Schlesinger, 2018). Given this requirement, the development of bioenergy feedstocks has centered around a few high-yielding perennial species that are known to increase SOC (Agostini, Gregory, & Richter, 2015; Robertson, Hamilton, Del Grosso, & Parton, 2011; Sanchez, Nelson, Johnston, Mileva, & Kammen, 2015; Sartori, Lal, Ebinger, & Parrish, 2006), with switchgrass (*Panicum virgatum*) as the leading candidate for large-scale deployment in the United States (Mclaughlin & Kszos, 2005; Parrish & Fike, 2005). Yet, the extent to which biogenic C emissions are balanced by changes in SOC storage is specific to the pedo-climatic context, even in perennial systems (Agostini et al., 2015). Thus, predicting the SOC sequestration potential of switchgrass production systems has become a crucial step in the design of sustainable bioenergy landscapes (Field, Marx, Easter, Adler, & Paustian, 2016; Gelfand et al., 2020).

Changes in SOC in perennial systems are driven by both the amount of plant-derived C inputs to soils (root and aboveground litter) and organic C decomposition rates (Agostini et al., 2015; Fuss et al., 2014; Searchinger et al., 2008). Both of these are controlled by various site-specific factors such as climate, soil texture, and drainage (Field et al., 2018); land-use history and disturbance (Qin, Dunn, Kwon, Mueller, & Wander, 2016); and fertilizer use (Ruan, Bhardwaj, Hamilton, & Robertson, 2016). These factors dictate whether soils under perennial bioenergy feedstock production will act as net sinks or sources of C at a specific location. In switchgrass, C allocation to belowground biomass (BGB) is four to seven times that of annual crops (Anderson-Teixeira et al., 2013), producing a BGB stock in excess of 5 Mg C/ha in some cases (Sainju, Allen, Lenssen, & Mikha, 2017). It is through the turnover of this live root C pool that switchgrass has been seen able to add substantial C to soils, even when a large portion of the aboveground biomass (AGB) is harvested (Agostini et al., 2015; Robertson et al., 2011, 2017; Ruan et al., 2016; Sartori et al., 2006). With this increase in SOC storage, switchgrass bioenergy production systems have potential to partially or totally offset emissions associated with its production and conversion into biofuel or bioelectricity (Gelfand et al., 2020; Sanchez et al., 2015). Nevertheless, experimental estimates of switchgrass SOC changes vary substantially among studies, from little or no SOC gain to accrual rates upward of 2.0 Mg C ha^{-1} $year^{-1}$ (Agostini et al., 2015; Follett, Vogel, Varvel, Kimble, & Mitchell, 2012; Liebig, Schmer, Vogel, & Mitchell, 2008). This reflects the uncertainties in long-term SOC balances across heterogenous conditions.

Critically, because the development of the lignocellulosic bioenergy industry is likely to take several decades, predictions must account for how future climates might influence C sequestration in soils. Studies in annual crops suggest that projected increases in temperatures are likely to decrease plant growth mainly due to a faster accumulation of heat units and earlier maturation (Bassu et al., 2014) but also due to changes in seasonal precipitation patterns (Liu & Basso, 2020). Decreased plant growth typically means lower plant residues returning to soils. Warming also promotes greater heterotrophic soil respiration, accelerating the rate of SOC decomposition (Crowther et al., 2016; Jian, Steele, Day, & Thomas, 2018). It has been estimated that annual agricultural systems will need to increase C inputs by ~30% to maintain SOC storage under future climate projections (Wiesmeier et al., 2016). Furthermore, the bidirectional feedback between crop productivity and SOC could amplify climate change impacts on SOC storage in the long term (Basso et al., 2018). Nevertheless, these impacts have mainly been studied in annual systems, and much less are known about how perennial bioenergy production systems might respond to projected climate change, and the potential of adaptations to mitigate impacts. This is a crucial research gap that limits our ability to appropriately guide planning, implementation, and operational management of these production systems.

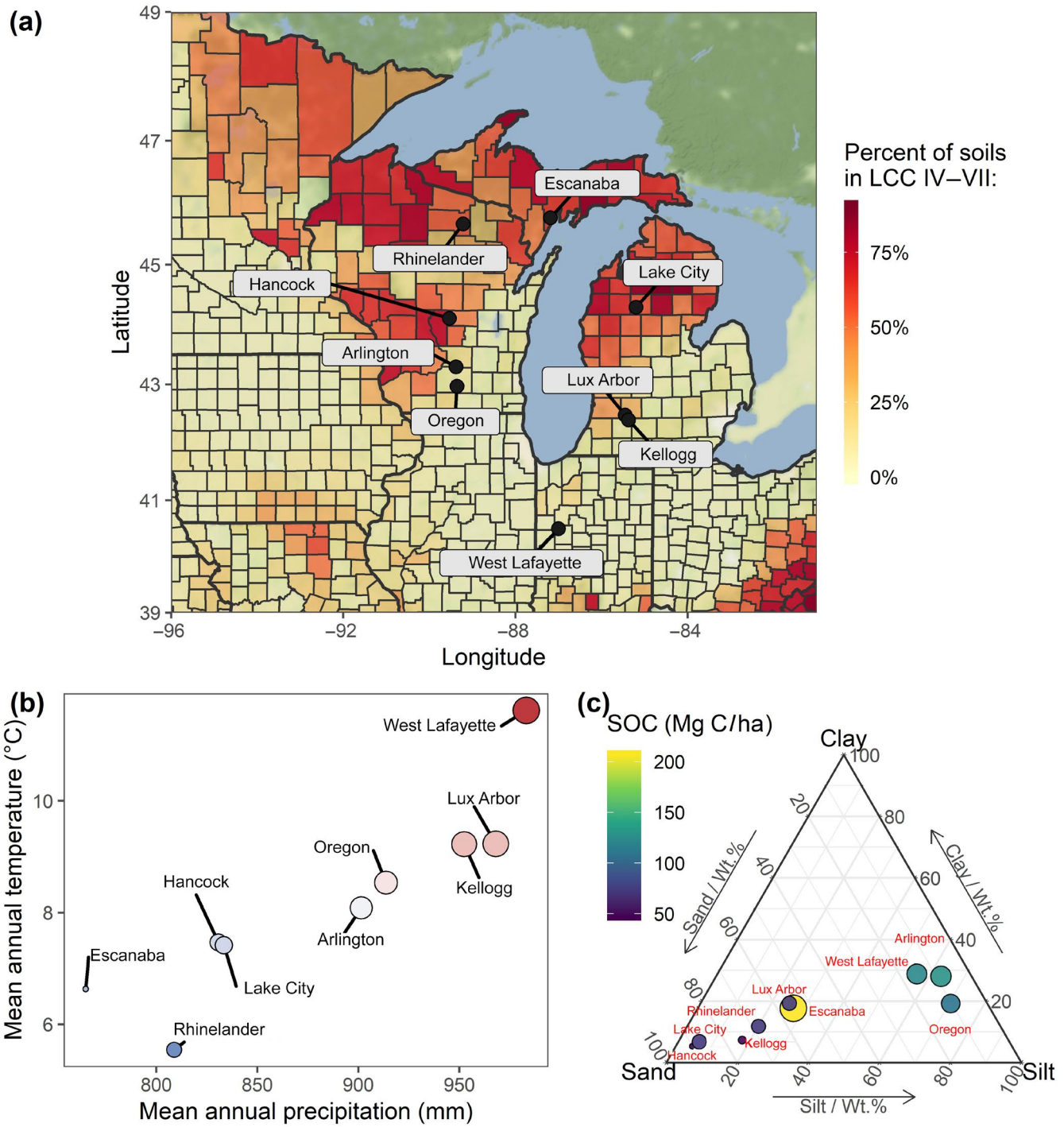

FIGURE 1 The US Great Lakes region and pedo-climatic characteristics of experimental sites. (a) Choropleth shadings for US counties indicate share of land area designated within USDA's Land Capability Classifications IV through VII (source: SSURGO [county data] and Stamen Maps [base layer]). (b) Long-term baseline climate (1980–2000). (c) Soil characteristics for the 0–100 cm profile. Size of the circle and fill color ramp indicates soil organic carbon (SOC) content. Textural classes correspond to the USDA textural classification

In this study, we hypothesize decreased C sequestration in soils by switchgrass grown on marginal lands in the USGLR under projected climate, due to concomitant decreases in soil C inputs and increases in SOC decomposition rates. Our objectives were to: (a) examine long-term SOC balances and the factors explaining variation across heterogenous sites; (b) assess how SOC changes could be affected by projected climates; and (c) explore potential adaptation strategies to mitigate climate change impacts. We based our findings on data simulated using the Systems Approach to Land-Use Sustainability (SALUS) model, which was extensively calibrated using long-term plant and soil measurements at nine experimental sites along a range of pedo-climatic conditions in the USGLR (Figure 1b,c).

2 | MATERIALS AND METHODS

2.1 | Simulation model

Systems Approach to Land-Use Sustainability is a cropping systems simulation platform that contains processed-based models derived from the well-validated CERES model, providing simulation of crop growth and development, and carbon, water, nitrogen (N), and phosphorus cycling dynamics on a daily time step. The model uses as input daily values of incoming solar radiation (MJ/m^2), maximum and minimum air temperature (°C), and rainfall (mm), as well as information on soil characteristics and management. SALUS has been tested extensively for simulating soil carbon dynamics (Basso et al., 2018; Senthilkumar, Basso, Kravchenko, & Robertson, 2009), crop yield (Basso, Bertocco, Sartori, & Martin, 2007), plant N uptake and phenology (Albarenque, Basso, Caviglia, & Melchiori, 2016; Basso, Ritchie, Cammarano, & Sartori, 2011), nitrate leaching (Basso et al., 2016; Giola, Basso, Pruneddu, Giunta, & Jones, 2012; Syswerda et al., 2012), water use efficiency (Ritchie & Basso, 2008), and transpiration efficiency (Basso & Ritchie, 2012). A general description on SALUS is provided by Basso and Ritchie (2015). Details about SOC dynamics and perennial crop simulation subroutines are included in Supporting Information S1.

2.2 | Sites and data sources

We use data from nine long-term experiments in the USGLR (Figure 1) to calibrate SALUS and test its ability to simulate switchgrass crop growth and long-term SOC change.

The experiments in Michigan and Wisconsin are part of the Great Lakes Bioenergy Research Center (GLBRC) sentinel sites network, which were established to study the feasibility of producing various bioenergy feedstocks on marginal lands in the USGLR. Experiments at Kellogg and Arlington were established in 2008. Experiments at Escanaba, Lake City, Lux Arbor, Hancock, Oregon, and Rhinelander were established in 2013. All experiments followed a completely randomized plot design ($n = 5$) with several biofuel cropping system treatments including many annual or perennial crops. Details about the GLBRC experimental sites can be found in the following studies (Jones, Oates, Philip Robertson, & Cesar Izaurralde, 2018; Ruan et al., 2016; Sprunger, Oates, Jackson, & Robertson, 2017).

Switchgrass (variety "Cave-in-rock") plots at the GLBRC sites were managed without and with N fertilizer (~56 kg N ha^{-1} year^{-1}) and harvested once a year after crop had reach maturity. Crop and soil measurements at these sites included: (a) peak AGB in late summer; (b) end of season agronomic yields (~65% of peak AGB; Figure S2.1); (c) BGB (aggregate of rhizomes, coarse roots, and fine roots) at harvest estimated using the deep core method (0–100 cm); (d) in-season leaf area index, estimated with using the AccuPAR LP-80 Ceptometer (Meter group, Inc.) or LAI-2000 Plant Canopy Analyzer (Licor Inc.); (e) daily profile volumetric soil water content (0–120 cm) using TDR100 probes (Campbell Scientific); and (f) soil texture, bulk density, total organic C and N (0–100 cm depth) measured at establishment of the plots, and in 2013 in Kellogg and Arlington.

Data for the experiment in Indiana were obtained from the database published by Ojeda, Volenec, Brouder, Caviglia, and Agnusdei (2017). This experiment was conducted in the Water Quality Field Station at Purdue University Agronomy Center for Research and Education near West Lafayette, Indiana. This dataset included in-season measurements of switchgrass (variety "Shawnee") AGB, as well as soil hydraulic properties, SOC, and bulk density. We also use BGB measurements for the same experiment collected by the pit method (0–30 cm) as reported by Burks (2013). For further details of this experimental site, we refer the reader to the original studies (Burks, 2013; Ojeda et al., 2017).

A summary of the site characteristics and measured data available at each site is provided in the Supporting Information (Tables S2.1 and S2.2). Daily weather data (1980–2018) for all of the sites were retrieved from the North American Land Data Assimilation System project phase 2 (NLDAS-2) dataset (Xia et al., 2012) using the location coordinates for each site. Management records for planting date, fertilization amount, and timing were also available (Tables S2.3–S2.5).

2.3 | Model setup and calibration

Systems Approach to Land-Use Sustainability requires several user-provided soil input parameters to adequately describe the soil hydrology and nutrient cycling dynamics of the cropping system and capture variability among different sites. We used the soil texture (sand, silt, and clay percentages), SOC content, and bulk density measured at plot establishment in pedotransfer functions (Saxton & Rawls, 2006) to derive soil fertility and hydraulic parameters for each site. The derived soils are found in the Supporting Information (Table S2.6). We configured switchgrass crop management in the model according to the management records available for each site. Briefly, switchgrass was planted the first year of the simulation typically May–June at a seeding rate 600–1,100 seeds m^{-2} and fertilized the second or third year onward with 56–75 kg N/ha. Harvesting typically occurred in mid-October or early November with 50%–75% harvesting efficiency (ratio of agronomic yield to peak AGB; Tables S2.1).

Because all the sites were planted with upland varieties ("Cave-in-rock" or "Shawnee"), we performed a single

model calibration across the nine sites. To establish a robust parameterization for all the user-defined crop and SOM parameters, we first surveyed the relevant literature to establish initial values for each model parameters (Tables S1.1 and S1.2). Next, we conducted a global sensitivity analysis (GSA) with parameter values sampled uniformly ($n = 1{,}000$) on a plus and minus 20% interval to generate random sets of parameters. ABG, BGB, and SOC changes at each model run were averaged across years and sites. Then, we followed the methodology described by Stanfill, Mielenz, Clifford, and Thorburn (2015), where univariate generalized additive model (GAM) was fit to output variable simulated by SALUS, and then, variance-based sensitivity indices were calculated using the variance terms estimated by the GAM emulator. We examined solely first-order (main effects) sensitivity indices, because we assumed that the impact of two-way and higher order interactions among parameters were small, as indicated by the high agreement between SALUS and GAM values ($R^2 > .93$; Figure S3.1). For each output variable, we ranked parameters based on their sensitivity index and selected the most sensitive parameters that together accounted for at least 70% of the total variation. This step revealed 10 most influential parameters, which we used for model optimization.

Next, we subjected the model to a multi-objective optimization routine to find values for these parameters. The objective of this optimization was to maximize the agreement between the measured and simulated values at Arlington, Kellogg, and West Lafayette sites. Agreement between observed and simulated values was assessed by using the Nash–Sutcliffe model efficiency coefficient (NSE):

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2}, \tag{1}$$

where for the ith observation, O_i and P_i are the observed and predicted values, respectively, $\overline{O}$ is the mean observed value and n is the total number of observations. The NSE measures improvement in model fit, relative to a simple mean. Negative values of NSE indicate that the model performs worse than a simple mean, whereas NSE of 1 indicates perfect fit. The optimal solution maximized average NSE across the simulated variables (AGB, BGB, LAI, soil water, and SOC change). The optimization routine was performed in R (version 3.5.2; R Core Team, 2018) via the *optim* function using the quasi-Newton method with box constraints (Byrd, Lu, Nocedal, & Zhu, 1995).

After convergence of the optimization algorithm, the calibrated model was evaluated against the agronomic yields at the remaining sites. We also used additional metrics to quantify model fit including the regression of the observed versus predicted values, and the root mean-squared error (RMSE) of the prediction (Equation 2).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{n}}. \tag{2}$$

2.4 | Future climate projections

We generated weather under future climates to reflect three shared socioeconomic pathways (SSP): a sustainability (SSP1-26), middle-of-the-road (SSP2-45), and high (SPP5-85) emission scenarios. Downscaled CMIP6 monthly climate projections for the 2081–2100 timeframe (~12 km resolution) were retrieved from the WorldClim database (Fick & Hijmans, 2017). We used the median ensemble prediction of five General Circulation Model runs: MRI-ESM2-0, MIROC6, IPSL-CM6A-LR, CNRM-CM6-1, and BCC-CSM2-MR. For each SPP scenario at each site, we calculated the delta in average monthly daily minimum and maximum temperatures and cumulative precipitation compared to the historical baseline (1981–2000; Figures S4.1–S4.3). Then, we created future weather by modifying the historical daily weather with the calculated delta factors on a month-by-month basis. Additionally, we assumed CO_2 concentrations of 385, 450, 590, and 950 ppm for the historical, SSP2-45, SSP3-70, and SSP5-85 climate scenarios, respectively (Meinshausen et al., 2019).

2.5 | Climate change and adaptation scenarios

Long-term SOC changes were simulated by configuring the model to run with 20 years of weather data at each site. Baseline management consisted on annual fertilization of 50 kg N/ha on May 30 (beginning on the third year after planting) and harvested on October 15, with a harvest efficiency of 65% (i.e., 35% of total AGB production was non-harvestable plant litter detached before harvesting and other residue), which was based on the mean observed values across the sites (Figure S2.1). This management scenario was run for the historical weather benchmark (1981–2000).

In addition, we simulated adaptation treatments which included: three doses of N fertilizer (50, 75, and 100 kg N ha^{-1} $year^{-1}$); three harvest intensities (65, 55, and 45% AGB removal); and two genotypes (baseline and adapted). To simulate the "adapted" genotype, we increased the thermal time requirement to reach maturity by 30% compared to the baseline (i.e., calibrated) genotype. Treatments were run within each site, climate scenario (historical, SSP1-26, SSP2-45, and SSP5-85), and a random ($n = 100$; ±20%) sampling for the most influential SALUS parameters

identified in the GSA, all in a full factorial grid (n = 64,800 simulations).

3 | RESULTS

3.1 | Model evaluation

Calibrated switchgrass parameter values fell well within ranges of previous studies (Table S2.1 and references within). Optimized values for the 10 most influential parameters (Figure S3.1) were determined by maximizing the fit to the observed AGB, BGB, LAI, and soil profile moisture and change in SOC concentrations at three sites (Arlington, Kellogg, and West Lafayette). The optimization routine produced a multi-objective (i.e., average) NSE of 0.69. With the optimal set of parameters, the SALUS model was able to satisfactorily capture the long-term and seasonal patterns of plant growth in both AGB (NSE = 0.74) and BGB (NSE = 0.61), with RMSE ranging 1.5–3.3 and 1.8–2.8 Mg ha for AGB and BGB, respectively (Figure 2a). Similarly, the model reproduced adequately the seasonal variation in LAI (NSE = 0.72; RMSE = 0.6 m^2/m^2 Figure 2b) and soil profile moisture measurements (NSE = 0.64; RMSE = 26 mm; Figure 2c), although these two latter measurements were only available at one site (Kellogg). Changes in SOC concentrations 5 years after establishment at the two sites

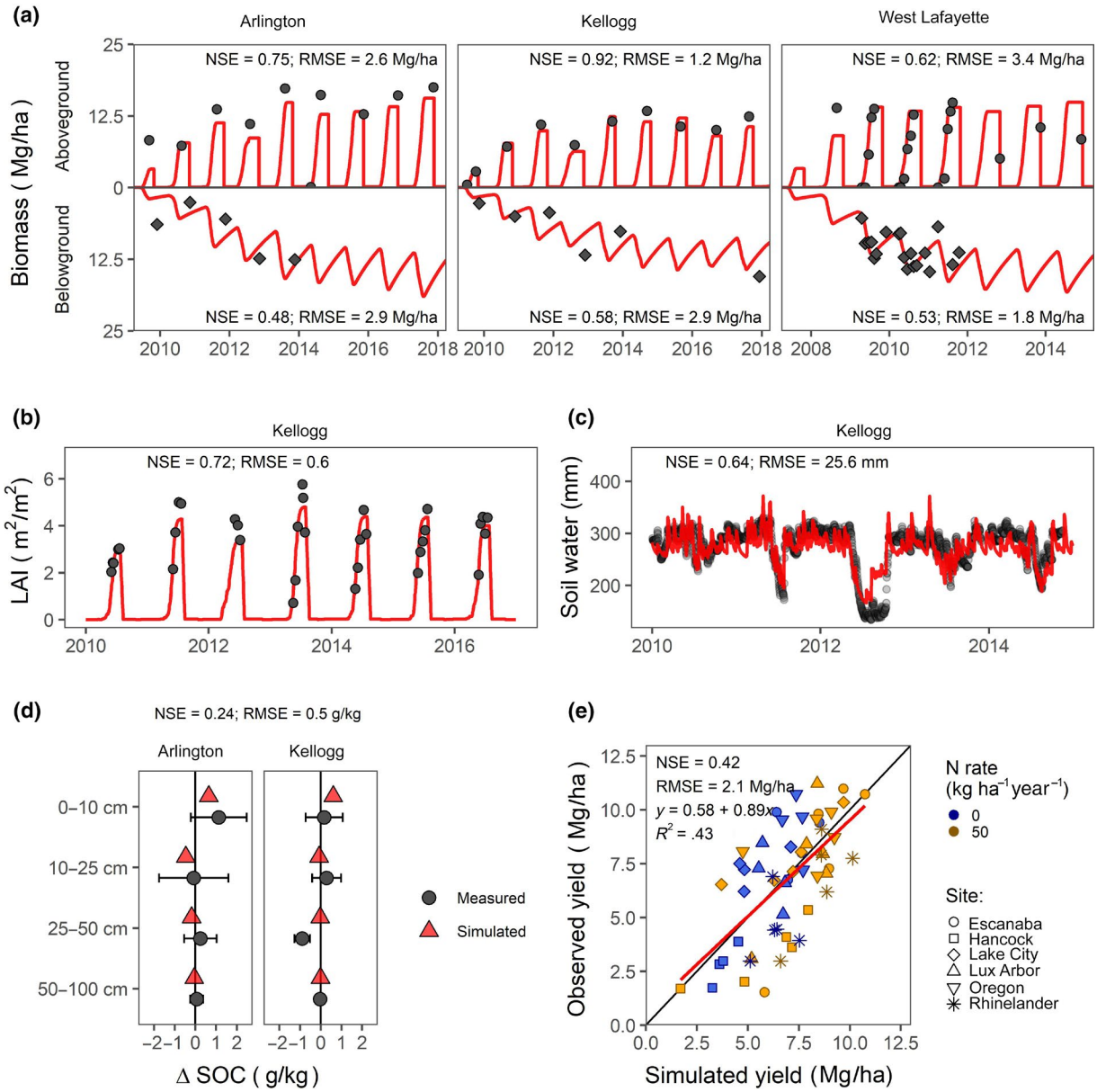

FIGURE 2 Switchgrass model calibration. Evaluation of predictions against observations of (a) aboveground and belowground biomass; (b) seasonal leaf area index (LAI); (c) total soil water content integrated to 100 cm depth; (d) change in soil C concentrations by depth; and (e) end-of-season agronomic (i.e., harvested) biomass yield; NSE, Nash–Sutcliffe modeling efficiency; RMSE, root mean squared error; SOC, soil organic carbon

were reasonably well reproduced given the large variation in the experimental measurements (NSE = 0.24, RMSE = 0.5 g/kg; Figure 2d). Finally, the model performed satisfactorily when evaluated against the end-of-season agronomic yields in plots managed with and without N fertilizer at six independent validation sites (NSE = 0.42; Figure 2e), replicating the year-to-year variation in harvested yields with an RMSE of 2.1 Mg/ha. These results indicated that the model was able to adequately capture multiple aboveground and belowground soil–plant processes, and therefore could be used to extrapolate the effects of management and weather at these sites.

3.2 | SOC changes and variability across sites

Over the 20 year historical period (1981–2000) and with baseline management (50 kg/ha N fertilizer and 65% AGB removal), mean switchgrass AGB productivity simulated with the optimized model ranged from 10.0 to 13.4 Mg dm ha^{-1} year^{-1} across sites. For the 100 cm profile, mean total (AGB + BGB) soil C inputs from plant biomass ranged between 4.1 and 5.7 Mg C/ha, with ~63% of plant C inputs to soil originating from BGB turnover (Figure 3a) and the rest from deposited AGB litter and harvest residues. Averaged across sites, simulated soil C inputs were on average 14% greater than soil CO_2-C respired (Figure 3a), resulting in a mean positive long-term gain of 0.87 Mg C ha^{-1} year^{-1} in belowground SOC pools.

Although estimates of SOC change were highly influenced by the set of parameters used for the simulation (55% of the variance), predicted changes using the optimized model also varied substantially across sites (39% of the variance; Figure 3b). Simulated SOC gain ranged from 0.2 Mg C ha^{-1} year^{-1} in West Lafayette to 1.4 Mg C ha^{-1} year^{-1} in Rhinelander. In most sites, the SOC sock was predicted to increase linearly. Only those with large initial SOC storage (Arlington, Escanaba, and West Lafayette; Figure 1) were predicted to reach a new equilibrium after 20 years of switchgrass production (Figure 3c).

Principal component analysis of six site descriptor variables revealed that 89% of the variation across the nine sites could be characterized with two principal components (PC1 and PC2; Figure 4a). Climatic variables (latitude, mean annual daily temperature, and mean annual cumulative precipitation) were mostly correlated to PC1, whereas soil variables (bulk density, sand content, and initial SOC) were mostly correlated to PC2. When regressed against SOC change, PC1 was a much better predictor (R^2 = .54) than PC2 (R^2 = .28; Figure 4b), suggesting that SOC gain in our simulations depended more on climatic parameters than soil characteristics.

3.3 | Impacts of climate change and adaptation

Running the model with projected future climate under the three SSP scenarios without adaptations marginally affected

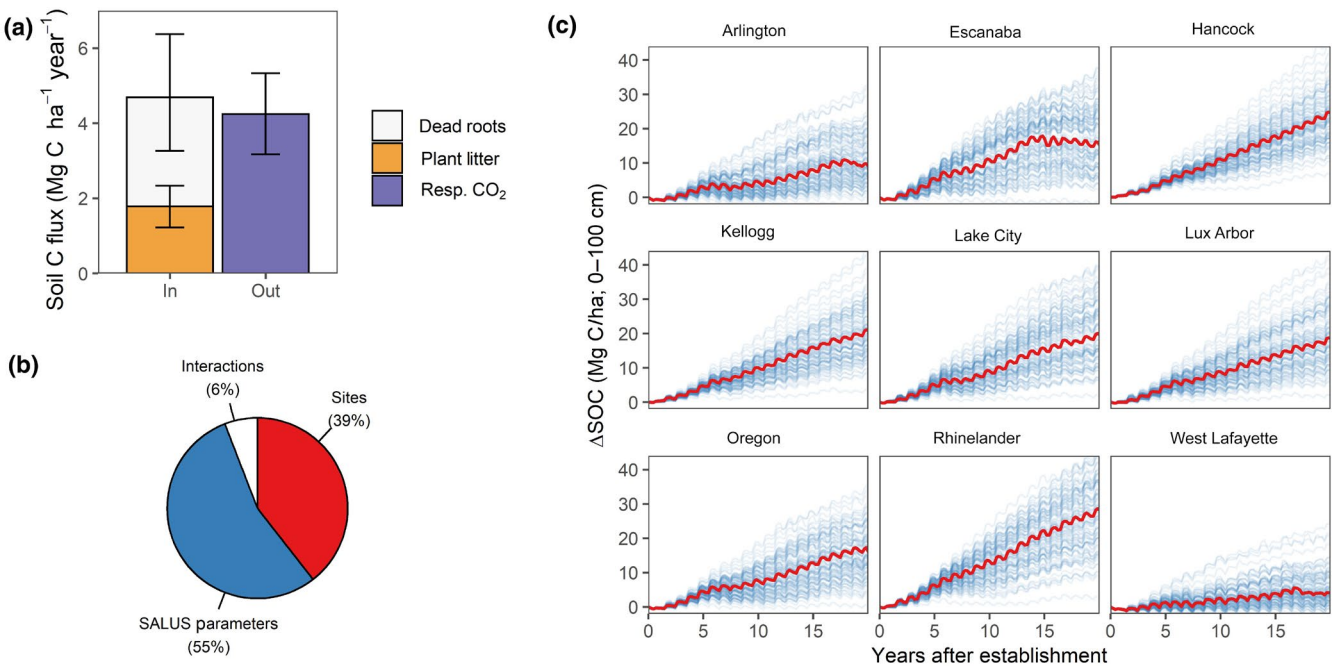

FIGURE 3 Simulated long-term C balances at the nine sites with baseline climate (1981–2000). (a) Predicted plant C inputs to soil and CO_2-C respired during decomposition of soil organic carbon (SOC). (b) Share of the variance in predicted SOC change attributable to each simulation factor. (c) Predicted change in SOC over the 20 years. Error bars in (a) and blue shadings in (c) represent ranges of simulations with randomly sampled values (n = 100, ±20%) for 10 influential SALUS model parameters (Figure S3.1). SALUS, Systems Approach to Land-Use Sustainability

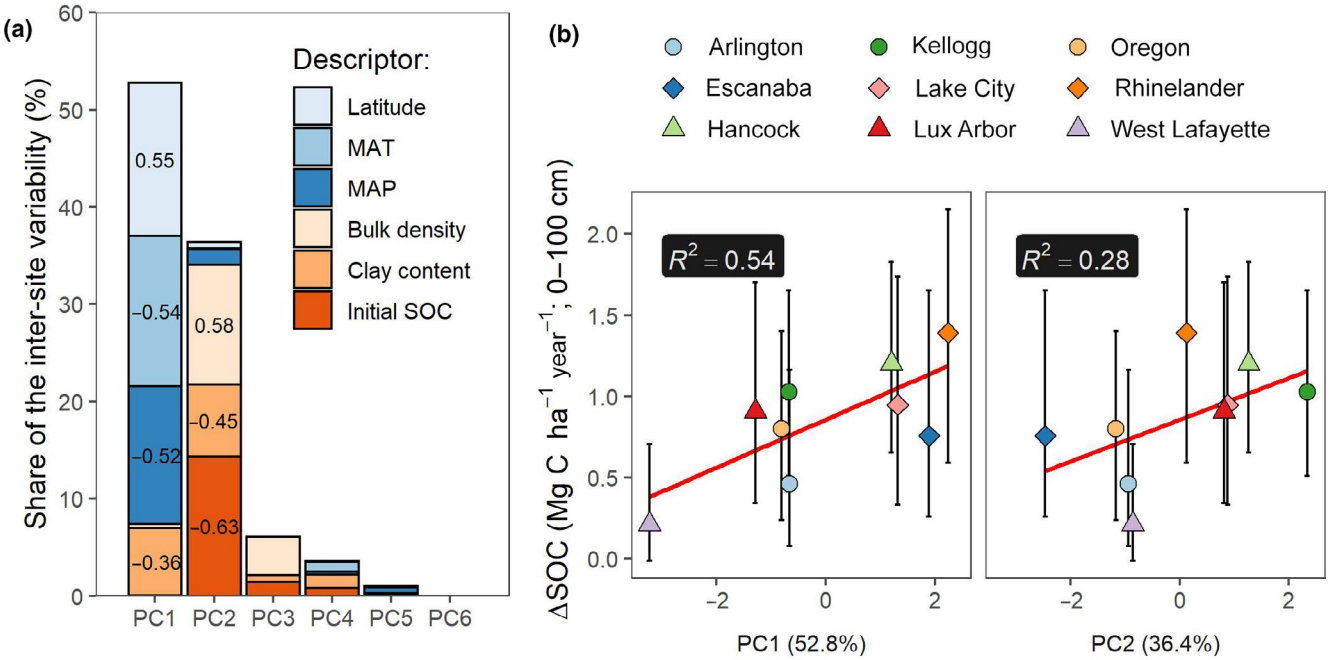

FIGURE 4 Site characteristics influencing the rate of soil organic carbon (SOC) gain. (a) Principal components for six site descriptors: latitude, mean annual daily temperature (MAT), mean annual cumulative precipitation (MAP), soil bulk density, sand content and initial SOC. Height of the var indicate the share of variance explained by each principal component, and the area within each bar represent the correlation of each variable descriptor with the principal component (i.e., loadings). (b) Correlation of the PC1 and PC2 with the rate of SOC sequestration across sites. Error bars represent ranges of simulations with randomly sampled values ($n = 100$, ±20%) for 10 influential SALUS model parameters (Figure S3.1). SALUS, Systems Approach to Land-Use Sustainability

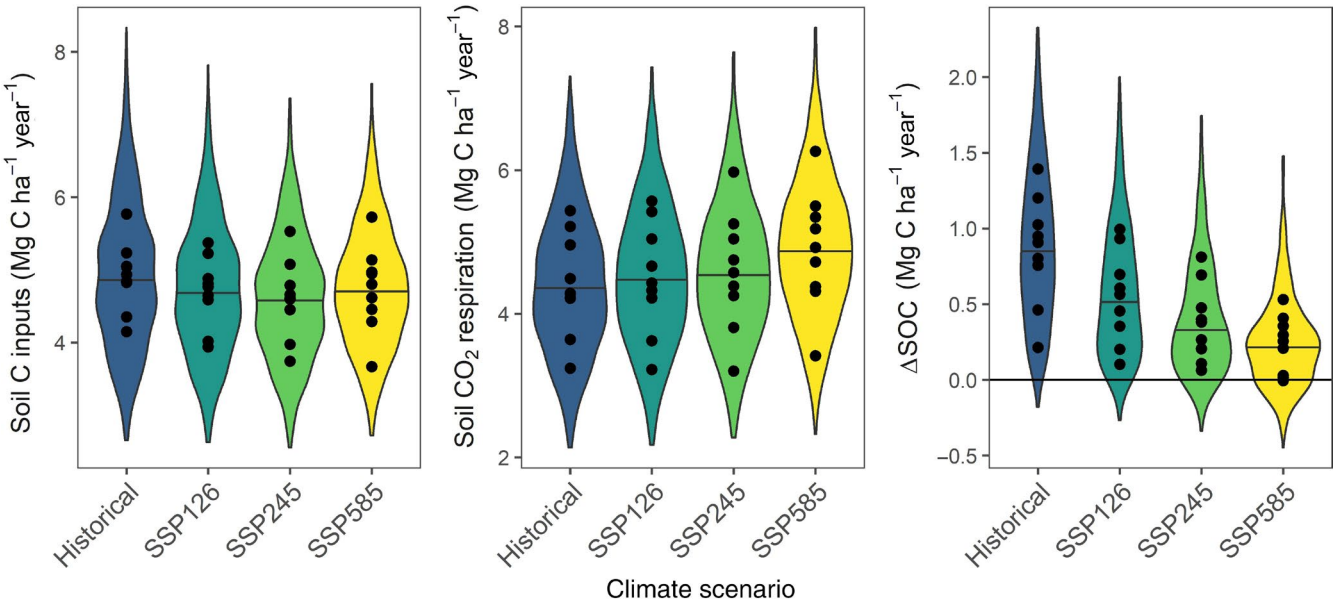

FIGURE 5 Annual rates of plant-derived soil C inputs, soil organic carbon (SOC) decomposition and SOC change under historical baseline (1981–2000) and future climate projections in the SSP1-2.6, SSP2-4.5 and SSP5-8.5 scenarios. Violins depict the distribution of the simulated values across sites and random samples ($n = 100$, ±20%) for 10 influential SALUS model parameters (Figure S3.1). Points indicate simulated values at the sites with the optimized parameter values. SALUS, Systems Approach to Land-Use Sustainability; SSP, shared socioeconomic pathway

switchgrass productivity compared to the historical climate, decreasing site average AGB by 5.7, 8.8, and 7.0% in the SSP1-26, SSP2-45, and SSP5-85 scenarios, respectively. This resulted in a reduction in mean soil C inputs of 4%–6% (Figure 5). In addition, soil respiration was predicted to increase on average by 2%, 6%, and 11% relative to the historical

baseline climate, SSP1-26, SSP2-45, and SSP5-85 scenarios, respectively. Aggregated impacts of both reduced C inputs and increased respiration resulted in a decrease in the rate of SOC gain, by 0.31, 0.48, and 0.61 Mg C ha^{-1} $year^{-1}$ in the SSP1-26, SSP2-45, and SSP5-85 scenarios, respectively (Figure 5).

Predictions of SOC change under future climate were most influenced by site and the sets of SALUS parameters used, which together they accounted for nearly two-thirds of the total variation of the simulation experiment, whereas climate scenarios and the adaptation practices examined were less influential (Figure 6a).

Increasing N fertilizer application rates and reducing the percentage of biomass removal were predicted to have minimal effects under future climate (Figure 6b). For example, doubling N fertilizer additions under projected climate produced SOC accrual rates that were greater only in the most extreme climate scenario (SSP5-85), by an average of 0.05 C ha^{-1} $year^{-1}$ compared to no adaptations. Similarly, harvesting 20% less AGB improved SOC sequestration rates relative to no adaptation across all future climate scenarios, but only by 0.05–0.1 C ha^{-1} $year^{-1}$. Combining higher fertilizer rates and lower harvest intensity was able to improve average SOC gain up to 0.16 C ha^{-1} $year^{-1}$, but only in the SSP2-45 and SSP5-85 scenarios. A greater benefit under the climate change scenarios was predicted with adapted genotypes with longer seasonal growth cycles (i.e., 30% greater thermal time required to reach maturity; Figure 5a,b). This was especially true under the SSP1-26 scenario, where average soil C sequestration rates were virtually on par with historical SOC accrual rates, achieving 0.35 Mg C ha^{-1} $year^{-1}$ SOC gain greater than with no adaptations and making this the best adaptation strategy for this climate scenario. The combination of adapted cultivar with 20% residue removal was the best

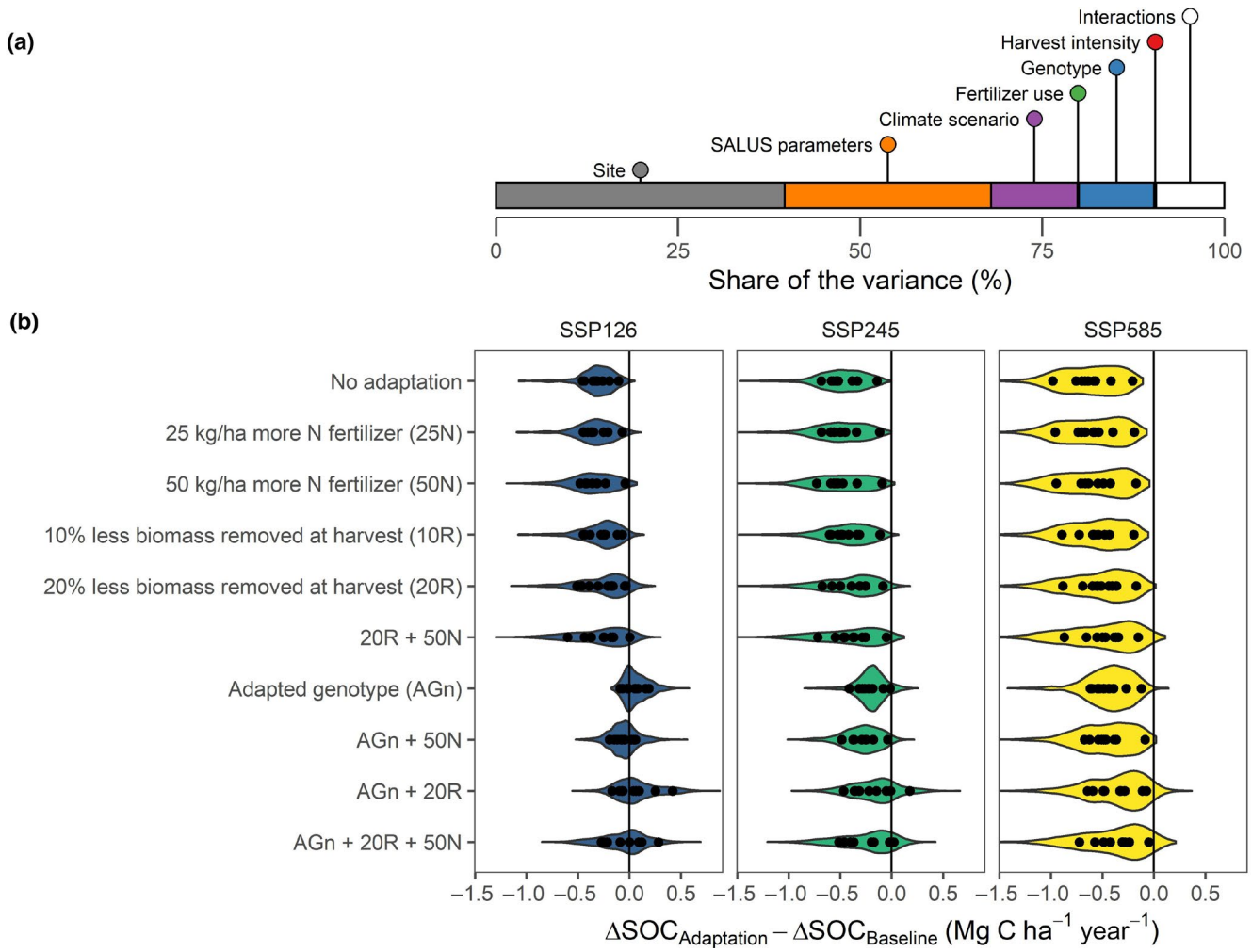

FIGURE 6 (a) Share of the variance in soil organic carbon (SOC) change attributed to each of the treatments in the long-term climate change and adaptation scenarios. (b) Rate of SOC change under different configuration of adaptation practices and climate scenarios (SSP1-26, SSP2-45, SSP5-85), compared to the rate of SOC under historical baseline climate (1981–2000) and no adaptations. Violins depict the distribution of the simulated values across sites and random samples (n = 100, ±20%) for 10 influential SALUS model parameters (Figure S3.1). Points indicate simulated values at the sites with the optimized parameter values. SALUS, Systems Approach to Land-Use Sustainability; SSP, shared socioeconomic pathway

strategy for the SSP2-45 and SSP5-85, outperforming the no adaptation baseline by 0.29 and 0.24 Mg C ha^{-1} $year^{-1}$, respectively (Figure 5b).

4 | DISCUSSION

The C neutrality of bioenergy production systems greatly depends on their ability to curtail biogenic CO_2 emissions and boost the flux of atmospheric CO_2-C into long-term SOC storage. It has been previously estimated that perennial bioenergy systems in the United States need to sequester more than 0.25 Mg C ha^{-1} $year^{-1}$ to, at a minimum, offset the CO_2 emitted by the non-renewable energy used for their cultivation and conversion into biofuel (Volk, Verwijst, Tharakan, Abrahamson, & White, 2004). Our simulations with the SALUS model, which was extensively calibrated and tested against a wealth of plant and soil measurements collected at the sites (Figure 2), indicate that current switchgrass SOC accrual rates in the USGLR could average well over this threshold (0.87 Mg C ha^{-1} $year^{-1}$) in the top 100 cm.

These simulated SOC gains are in agreement to estimates from a net ecosystem C exchange field study in Illinois (~1.0 Mg C ha^{-1} $year^{-1}$ within 3.5 years; Anderson-Teixeira et al., 2013), as well as those reported under early successional native grasslands (1.1 Mg C ha^{-1} $year^{-1}$; 0–100 cm, 12 year stand) at the Kellogg site (Gelfand et al., 2013). Similarly, a survey of 10 commercial-scale fields across the US Central Plains found that soils gained on average 1.1 Mg C ha^{-1} $year^{-1}$ in the top 30 cm within the first 5 years of switchgrass cultivation (Liebig et al., 2008). However, these estimates are much lower than observations from a field study in Nebraska (2.0 Mg C ha^{-1} $year^{-1}$ in 0–150 cm profile after 10 years; Follett et al., 2012), and higher than reports from a 3-year experiment under irrigated conditions in Washington (0.5 Mg C ha^{-1} $year^{-1}$, 0–30 cm depth) and a simulation study in Pennsylvania with the DAYCENT model (~0.42 Mg C ha^{-1} $year^{-1}$; Adler, Del Grosso, & Parton, 2007). A recent literature review has placed the global average for switchgrass SOC accrual rate around 1.5 Mg C ha^{-1} $year^{-1}$ (Agostini et al., 2015). Thus, our rates of SOC accrual can be considered lower end, conservative estimates. In addition, these predictions are made with a fair amount of uncertainty stemming from the set of model parameter values reached by the optimization phase (Figure 3). A short discussion on uncertainties in parameter values and comparison with other studies are included in Supporting Information S3.

Variation in SOC sequestration among studies may be in part attributable to methodological inconsistencies, such as sampling depth, time horizon, SOC stock calculation method (i.e., fixed depth layers vs. soil mass basis; Wendt & Hauser, 2013), or the organic matter pools included in the long-term SOC stock (Agostini et al., 2015). Nonetheless, we predict large intersite variability (range 0.2–1.3 Mg C ha^{-1} $year^{-1}$), which is in line with reports from multi-site trials (e.g., Liebig et al., 2008). According to our simulations, the variation seems to be largely driven by differences in climate and, to a lesser extent, heterogeneous soils (Figures 3 and 4). In the USGLR, northern sites with colder and dryer climates are predicted to gain more SOC than southern sites with warmer and wetter climates, mainly due to faster SOC decomposition rates in the southern sites. Within similar climates, C-depleted, coarser texture soils are predicted to have greater SOC gains than medium texture soils with already large SOC stocks (e.g., Hancock vs. Arlington; Figures 1 and 3; Senthilkumar et al., 2009). This finding suggests that, in order to maximize C sequestration in soils, policies and mechanisms to incentivize adoption should be targeted to marginal land sites based also on climatic parameters, rather than production and soil characteristics alone.

The latter is especially critical if we consider that the model predicts overall negative impacts of future climates on rates of SOC gains. The effect of climate change on the productivity of switchgrass upland cultivars used at the sites was predicted to be small. This is consistent with findings of a recent simulation study with the ALMANAC model (Kim et al., 2020) and climate envelope models for the Midwest (Tulbure, Wimberly, & Owens, 2012), though another study in Michigan found greater impacts on yields mainly associated with increased risk of water stress (Liu & Basso, 2017). In our simulations, the reductions in plant growth and soil C inputs (4%–6%) together with the increases in SOC decomposition (2%–11%) were predicted to decrease the rate of SOC gain by 70% below current rates under the most extreme climate change scenario (Figure 5). These findings support our hypothesis that, in the absence of adaptations, future climates could diminish soil C sequestration potential of switchgrass due to concomitant decreases in soil C inputs and increases in SOC decomposition rates.

Greater soil respiration under future climates, while largely driven by increases in air temperatures and precipitation, is also predicted to be a result of increased crop transpiration efficiency (i.e., decreased stomatal conductance) under elevated atmospheric CO_2 (Durand et al., 2018) and the feedback response to soil surface wetness of the transpiration fraction of total evapotranspiration (Basso & Ritchie, 2012, 2018), both of which are accounted in the SALUS model. These effects translated into lower crop water demand, greater soil moisture, and SOC decomposition (see details in Supporting Information S5). We must also point out that uncertainties surrounding SOC change diminished with increasing climate change (Figure 5), which means that variability in site characteristics and SALUS parameters becomes less important as SOC decomposition intensifies.

While, to our knowledge, this is the first study to examine and quantify climate change impacts on SOC change in

switchgrass, greater potential for SOC loss is a well-known effect of warming and it is expected to affect both cultivated and natural ecosystems alike (Basso et al., 2018; Jian et al., 2018; Liu & Basso, 2020; Senthilkumar et al., 2009; Wiesmeier et al., 2016). Yet, this fact is seldom considered in biofuel life-cycle analyses and similar assessments (DeCicco & Schlesinger, 2018; Gelfand et al., 2020). This could mean that future switchgrass soil C sequestration potential in marginal lands might be generally overestimated in these analyses, if we consider that the bioenergy supply chains may take several decades to be fully operational. It is true that perennial cropping systems might be better equipped to maintain SOC stocks under future weather relative to annual production systems (e.g., row crops; Jones et al., 2018). As such, further research is needed to elucidate relative benefits. However, from a purely C-accounting perspective, our results suggest that without C capture and storage in geological layers (Fuss et al., 2014), bioenergy production systems may not be a strong sink for atmospheric CO_2-C under future climates as originally expected. Here, we only examine production systems in the USGLR, although this finding may extrapolate to other temperate regions.

Adjusting switchgrass production practices could provide a feasible pathway to mitigate some of the impacts of future climate on C sequestration in soils, with the best-performing adaptation scenarios predicted to offset more than 60% of the climate change impact on SOC, on average leading to an additional 0.3 Mg C ha^{-1} $year^{-1}$ SOC storage compared to no adaptations (Figure 6). With about half million ha of non-forested marginal lands potentially available for bioenergy production in the USGLR (0.3 and 0.23 million ha in Michigan and Wisconsin, respectively; Gelfand et al., 2013; Liu & Basso, 2017), an SOC sequestration benefit of this magnitude would represent approximately additional atmospheric removal of 0.5 million tons of CO_2 per year. Changes in N fertilization and harvest intensity are well-known management strategies used to modulate C inputs and SOC decomposition rates (Ruan et al., 2016; Valdez, Hockaday, Masiello, Gallagher, & Philip Robertson, 2017). However, here the SOC loss mitigation potential of increasing N fertilization and reducing the amount of harvested AGB (i.e., more soil C inputs) is predicted to be modest and would come at the expense of profitability (i.e., higher inputs and lower harvested yields). Additionally, greater nitrous oxide emissions associated with higher N fertilization may offset some or all of the benefits from increased SOC gains from a greenhouse gas mitigation potential perspective (Ruan et al., 2016), as this gas has ~300 times more radiative forcing than CO_2 (Davidson & Kanter, 2014).

An introduction of genotypes adapted to longer growing seasons (e.g., lowland ecotypes) seems particularly promising as an adaptation strategy to mitigate climate change impacts on SOC, since it also means increased profitability through greater biomass yields. The more productive, longer cycle lowland ecotypes have not been historically grown in the northern United States because of poor winter survival and biomass quality issues (i.e., high moisture and N content at harvest). Both of these are related to insufficient heat units available for nutrient relocation and senescence in the fall (Casler & Vogel, 2014; Parrish & Fike, 2005). Yet, with the milder winter temperatures and longer growing seasons projected (Figures S4.1 and S4.2), areas in the USGLR could increasingly become suitable environments for lowland ecotypes in the coming decades, as shown in a previous modeling study (Tulbure et al., 2012). We must point out, however, that here genotype adaptation was simulated rather coarsely, that is, by increasing thermal time requirement for maturity by 30%, without considering other aspects of genotype adaptation such as response to daylength, winter survival, and nutrient relocation. Long-term breeding programs have shown that adaptation of southern germplasm to northern environments is possible, through two-site reciprocal transplant trails or hybridization with upland ecotypes, with promising improvements in biomass yields (Casler & Vogel, 2014). Accelerating progress in genetic adaptation to local environments is also being explored through quantitative trait loci mapping techniques (Lowry et al., 2019). Although breeding locally adapted genotypes for non-stationary climates remains a challenge, its success has large implications not only for switchgrass yield and profitability but also for the soil C sequestration and C neutrality of this bioenergy production system.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the following sources:

- Soil and management information used for model setup at the experimental sites can be found in the supplemental information and in the GLBRC data catalog at https://data.sustainability.glbrc.org/.

- NLDAS-2 dataset formatted for use with the SALUS model can be accessed with the pixel-extraction tool: https://salusmodel.ees.msu.edu/NLDAS/.
- CMIP6 monthly climate change projections can be downloaded from: https://worldclim.org/.
- Data from the simulation experiments and code to generate Figures 3–6 has been made public at the following repository: https://doi.org/10.5281/zenodo.3908645.

ORCID

Rafael Martinez-Feria https://orcid.org/0000-0002-4230-5684
Bruno Basso https://orcid.org/0000-0003-2090-4616

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SUPPORTING INFORMATION

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

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