

Simulating soil organic carbon in maize-based systems under improved agronomic management in Western Kenya

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ABSTRACT

Improved management practices should be implemented in croplands in sub-Saharan Africa to enhance soil organic carbon (SOC) storage and/or reduce losses associated with land-use change, thereby addressing the challenge of ongoing soil degradation. DayCent, a process-based biogeochemical model, provides a useful tool for evaluating which management practices are most effective for SOC sequestration. Here, we used the DayCent model to simulate SOC using experimental data from two long-term field sites in western Kenya comprising of two widely promoted sustainable agricultural management practices: integrated nutrient management (i.e. mineral fertilizer and crop residues/farmyard manure incorporation) and conservation agriculture (i.e. minimum tillage and crop residue retention). At both sites, correlations between measured and simulated SOC were low to moderate (R^2 of 0.25–0.55), and in most cases, the model produced fairly accurate prediction of the SOC trends with a low relative root mean squared error (RRMSE < 7%). Consistent with field measurements, simulated SOC declined under all improved management practices. The model projected annual SOC loss rates of between 0.32 to 0.35 Mg C ha⁻¹ yr⁻¹ in continuously tilled maize (*Zea mays*) systems without fertilizer or organic matter application over the period 2003–2050. The most effective practices in reducing the losses were the combined application of 4 Mg ha⁻¹ of farmyard manure and 2 Mg ha⁻¹ of maize residue retention (reducing losses up to 0.22 Mg C ha⁻¹ yr⁻¹), minimum tillage in combination with maize residue retention (0.21 Mg C ha⁻¹ yr⁻¹), and rotation of maize with soybean (*Glycine max*) under minimum tillage (0.17 Mg C ha⁻¹ yr⁻¹). Model results suggest that response of the passive SOC pool to the different management practices is a key driver of the long-term SOC trends at the two study sites. This study demonstrates the strength of the DayCent model in simulating SOC in maize systems under different agronomic management practices that are typical for western Kenya.

1. Introduction

Over the last decades, substantial soil organic carbon (SOC) losses have occurred due to continuous cultivation of areas that were historically covered by natural vegetation. Cumulatively, one-half to two-thirds (30–40 Mg C ha⁻¹) of the original SOC pool has been lost in agro-ecosystems across the globe (Lal, 2004), corresponding to an agriculturally-induced SOC debt of 133 Pg C that continues to deepen (Sanderman et al., 2017). Since soils are not only a source but also a sink of carbon, increasing SOC storage in agricultural landscapes can

contribute to climate change mitigation. With the launch of the 4per1000 initiative at the United Nations Framework Convention for Climate Change Conference of the Parties (UNFCCC COP 21) in Paris (<https://www.4p1000.org/>), many countries now recognize the potential of SOC sequestration in agricultural lands to mitigate climate change. To assess the feasibility of achieving the ambitious 3.5 Gt C annual sequestration rate target set in this initiative, extensive research and robust tools such as predictive models are needed to analyse the response of SOC to improved agronomic management practices in different areas.

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Adoption of improved agricultural management practices such as manure application, residue retention, conservation tillage and fertilization has the potential to enhance SOC sequestration or reduce the losses associated with historical land use change, with co-benefits for soil quality (Paustian et al., 2016; Smith et al., 2008). However, the response of SOC to management practices is complex and depends on many factors, notably soil and climate conditions, which affect both the turnover and litter-input controls of SOC (Nyawira et al., 2017). Process-based soil organic matter models, such as DayCent (Parton et al., 1998), Century (Parton et al., 1993), RothC (Coleman and Jenkinson, 1996), and DNDC (Li et al., 1994) include mathematical representations of the interactions between carbon inputs and decomposition; thus they can capture the fine-scale influence of site-specific factors on long-term SOC dynamics (Nguyen et al., 2017). These models have been successfully used to predict SOC trends for different agricultural systems (e.g., Lugato et al., 2014; Smith et al., 1997; Yu et al., 2012). One major advantage of the modelling approach is that once a model has been thoroughly evaluated against field-based data, it can be used to quantify the impacts of various management options on long-term SOC dynamics and sequestration. Such quantifications are impractical to achieve with field experiments as they are often limited, incomplete and/or expensive to maintain.

Despite the usefulness of process-based SOC models, applying these to novel agroecosystem contexts can be challenging. First, site-specific inputs such as soil, weather, and management data need to be acquired and formatted according to the model's requirements. Second, the model needs to be parameterized for the crop species, cultivars, or the management options of interest. Finally, and often most challenging, a thorough evaluation of the parametrized model against long-term experimental data that are specific to the agroecosystem is needed to alleviate the intrinsic model structural uncertainties. These challenges related to model development, calibration, and implementation limit the use of process-based SOC models in assessing the impacts of management practices on SOC dynamics in tropical agroecosystems in sub-Saharan Africa.

Compared to temperate agroecosystems, particularly in heavily studied north America, western Europe and east Asia, there are limited modelling studies in tropical agroecosystems and particularly on weathered soils. This may in part reflect the relatively fewer long-term evaluations of SOC dynamics in this agroecosystem type (Powlson et al., 2016). In one rare example, Kamoni et al., 2007 evaluated the ability of two monthly resolved models, namely Century and RothC, to estimate changes in SOC resulting from varying management practices for cropping systems in eastern and central Kenya. Although the models showed a fairly good fit to measured data, the authors concluded that future model validation for different climate and soil conditions would be needed for broader applications. To date no studies have evaluated the potential of processed-based SOC models to simulate both SOC dynamics and crop yields under different agronomic management practices in western Kenya, a region that is witnessing accelerating pressure on agricultural soils due to population growth (Mugizi and Matsumoto, 2020). Forecasting the response of SOC in this region to a diversity of management practices therefore stands to integrate the role of tropical smallholder agriculture in regional to global SOC initiatives.

Utilizing two long-term experiments in western Kenya, the objectives of the current study are to: (i) evaluate the effectiveness of the DayCent model in estimating SOC dynamics and yields, and (ii) project the future changes in SOC associated with the adoption of integrated soil fertility management and conservation agriculture practices.

2. Materials and methods

2.1. Long-term trial and data description

We used data from two on-farm long-term trials (INM3 and CT1) that have been maintained by the International Center for Tropical

Agriculture (CIAT) since 2003. The INM3 trial evaluates integrated soil fertility management practices comprising of manure and/or maize residue application in systems under conventional tillage, whereas the CT1 trial is designed to test soil fertility and agronomic outcomes of conservation and conventional agriculture. Both experiments are located in western Kenya at an altitude of 1330 m above sea level, 50 km northwest of the city of Kisumu (Sommer et al., 2018). INM3 is located at 0.14 °N, 34.40 °E and CT1 at 0.13 °N, 34.41 °E. The climate in the study area is mainly sub-humid with a mean annual temperature of 22.5 °C and an annual rainfall between 1,200 and 2,206 mm. The dominant staple crop in western Kenya is maize (*Zea mays*) and it is often intercropped with common bean (*Phaseolus vulgaris*) and most recently soybean (*Glycine max*). The soils at the two sites have been classified as an Acric Ferralsol, with a clay content of 55 % in the topsoil (0–20 cm) and 85 % in the subsoil (20–190 cm) (Table S1), low cation exchange capacity, high aluminium saturation and severe phosphorus (P) deficiency, particularly at CT1 (Margenot et al., 2017a). The major crop growth limiting nutrients at these sites, in order of importance, are P, nitrogen (N) and potassium (K) (Kihara and Njoroge, 2013). The INM3 site was previously under a grass-shrub fallow system for unknown length of time until 2002, while CT1 had been under unfertilized maize from 1992 to 1994, then fallowed for 6 years and later cultivated with maize until 2002 with seasonal fertilizer inputs (Sommer et al., 2018). Since 1997, daily maximum and minimum temperature and daily precipitation were recorded manually until 2007 when an automatic weather station was installed at the INM3 site.

Both the INM3 and CT1 experiments have a split-split-split plot design with four replicates, 48 treatments and 192 plots with each plot measuring 4.5 m by 6 m (INM3) and 4.5 m by 7 m (CT1). The first split in INM3 includes (FYM+) or excludes (FYM-) 4 Mg ha⁻¹ of (air-dried) farmyard manure application every season and the second split factor addresses residue retention with 2 Mg ha⁻¹ of maize residue retained (R+) or removed (R-) every season. The third split factor comprises of three crop rotations continuous maize (M-M), maize-tephrosia (M-T) and tephrosia-maize (T-M) rotation (M-, where M-T indicates the rotation where maize is grown in the long rainy season followed by tephrosia in the short rainy season, and T-M denotes the reverse. Tephrosia (family *Fabaceae*) is a legume genus that comprises of more than 20 different perennial species. *Tephrosia candida* is used at the INM3 site. CT1 has two tillage systems – minimum and conventional tillage – as main plots, and two residues levels: one on which 2 Mg ha⁻¹ of maize stover is retained (R+) and the second where all the residues are removed (R-). The sub-sub plots consist of three cropping rotations, namely continuous maize (M-M), soybean-maize and maize-soybean rotation (M-S or S-M; notation analogous to M-T/T-M in INM3). Tephrosia and soybean residues were chopped and left in the field while maize stovers were removed after harvest, air-dried, and then re-applied a few days before planting by broadcasting on the soil surface in the treatments with maize residue application. The continuous maize sub-sub-sub plots in both experiments received 0, 30, 60 and 90 kg N ha⁻¹ per season (N0, N30, N60, and N90) while soybean rotation plots received 0 or 60 K C ha⁻¹ yr⁻¹ kg N ha⁻¹ per season (N0 and N60) in the form of urea. Tillage was done by hand hoeing to maximum 20 cm, with soil disturbance and mixing diminishing with depth. For the treatments with minimum tillage, tillage was restricted to opening of planting holes with a hoe and light surface-scratching with a manual weeder (about 2–3 cm deep) to remove weeds (Sommer et al., 2018, 2016).

SOC in the top soil (0–15 cm) was measured biennially from 2005 to 2015 in the INM3 experiment and every third year from 2006 to 2012 in the CT1 experiment. The yields were measured each year from 2003 to 2016. A detailed description of the methods used in analysing the soil samples to obtain SOC content can be found in Sommer et al., 2018. Soil texture and bulk density were measured at 0–195 cm at one location point in the INM3 and CT1 trial with different incremental depths (Table S1).

In the present study, we used only continuous maize (M-M), maize-

soybean (M-S) and soybean-maize (S-M) rotation treatments (40 in total) and excluded the tephrosia ones, because the temperature, nutrient and growth parameters for tephrosia were not available in the crop parameter library for the DayCent model, and had not been collected for our experiments. The names used to represent the different treatments in the results section indicate whether manure and/or maize residues were applied, rotation type and N application rate. For instance, in the INM3 trial a treatment under continuous maize, no manure and residues application, and with 30 kg N ha⁻¹ fertilizer application is denoted as FYM-R-M-M_N30, whereas a treatment with the same amounts of N and both manure and residues application is denoted as FYM+R+M-M_N30. All CT1 trials have no manure application and are denoted with FYM-. Therefore, FYM-R+M-M_N30 represents a continuous maize treatment with maize residues and 30 kg N ha⁻¹ application, while FYM-R+M-S_N60 denotes a maize-soybean rotation with maize residue and 60 kg N ha⁻¹ application. Table S2 and S3 provide a detailed summary of all the treatments used in the present study.

2.2. DayCent modelling procedures

2.2.1. DayCent model

DayCent (version DD17centEVI) is a daily time step version of the CENTURY model, which simulates fluxes of carbon and nitrogen among the vegetation, soil and the atmosphere (Del Grosso et al., 2001; Parton et al., 2001, 1998). The model has various routines representing plant growth and productivity, movement of water and nutrients through soil layers, decomposition of residues, and other ecosystem processes (Del Grosso et al., 2008). Each vegetation type has a set of parameters that describe the growth, temperature and sensitivity of plants to water and nutrient availability. Soil organic matter (SOM) dynamics are simulated for two types of plant litter pools (metabolic and structural) and three types of SOM pools (active, slow, and passive). All litter and SOM pools have above- and below- ground components except for the passive pool. The metabolic pool contains easily decomposable litter material, while the structural pool contains lignin plant material that is resistant to decomposition. SOM pools are defined by their intrinsic turnover rates. The actual rate of litter and SOM decomposition varies depending on soil texture, temperature, water content, tillage intensity and the substrate quality (lignin content, C/N ratio). SOC is a function of carbon inputs minus the loss from turnover and the equations governing the decomposition of SOM in DayCent are similar to the Century model (Parton et al., 1993).

The inputs required for running DayCent include daily and maximum/minimum temperature, soil properties of texture, bulk density and hydraulic conductivity, and timing and description of the management events (e.g. tillage, fertilization, manure application and irrigation), which are summarized using a schedule file. The model has been widely applied to simulate a range of agricultural management practices, including manure and fertilizer application, crop residue retention, tillage operations, irrigation and grazing (e.g., Bista et al., 2016; Chang et al., 2013; Congreves et al., 2015; Del Grosso et al., 2008; Hartman et al., 2011).

2.2.2. Simulation of the baseline conditions

Before conducting experimental simulations with DayCent, the model was initialized using pre-settlement and historical land use conditions. The model initialization included two steps: an initialization spin-up run followed by a simulation of the historical land use. The spin up simulation is usually conducted to estimate the equilibrium SOC stocks assuming little or no disturbance from human activities prior to the conversion to agriculture. We chose grassland as the native vegetation in both the INM3 and CT1 sites and performed a 4000-year spin-up. In this run, the site-specific soil texture data and bulk density for the top soil (Table S1) were used to initialize the model, and the soil hydraulic properties (i.e. wilting point, field capacity and saturated hydraulic conductivity) were estimated from the texture using the

equations provided in Saxton et al. (1986). The recorded weather data (i.e. precipitation and maximum and minimum temperature) for the period 1997–2016 was repeated over the spin up simulation years. The model run was extended from the achieved equilibrium condition using the documented land use history at the two sites. For the INM3 site a grass-shrub fallow system was simulated for 102 years (1901–2002), whereas in the CT1 experiment a grass-shrub fallow system was simulated for 90 years (1901–1991) followed by continuous maize (unfertilized) from 1992 to 1994, fallow from 1995 to 2000 and continuous maize to 2002 with seasonal inputs of 18 kg N ha⁻¹ (Sommer et al., 2018). We assumed that prior to the field experiments, the sites were under grass-fallow system, as this information was not available from the land owners.

2.2.3. Model calibration and evaluation

Model simulations were extended from the baseline conditions using the experimental setup described in section 2.1 for the period from 2003 to 2016. In total, 40 of the treatments in the INM3 and CT1 experiments were simulated in the present study, half for model calibration and the other half for evaluation (Table S2 & S3). To parameterize the manure and maize residues application events in DayCent, the carbon to nitrogen (C:N) ratio and lignin fraction content were defined based on the peer-reviewed literature values for smallholder farming systems in Kenya, as this data was not available for the two experiments. Farmyard manure was assumed to contain 1.75 % N with a C:N ratio of 15.5, while the maize residues were assumed to contain 0.74 % N with a C:N ratio of 49 (Gichangi et al., 2006). The manure and maize residue lignin contents were calculated using the C%, N% and lignin/N ratios in Gichangi et al., 2006 and set to 0.14 and 0.07, respectively. Land preparation in the treatments under conventional tillage was characterized using the mouldboard plow cultivation type, which transfers all the shoots, roots, standing dead and surface litter into the soil litter pools and has high multipliers for increasing the decomposition rates in the active, slow and passive pools. For the treatments under minimum tillage, we selected a cultivation type with low decomposition multipliers to mimic a light surface-scratching with a manual weeder to remove weeds. In both the conventional and minimum tillage treatments, weed control was defined using a hand hoeing cultivation type that only influenced decomposition without transferring the above ground biomass into litter pools. Harvest consisted of 95 % removal of the maize residues, with the soybean residues left in the field at the end of the growing season.

For our simulations, we used the default parameters for corn and soybean crops in DayCent and repeatedly adjusted a subset of parameters to calibrate the simulated yields, including parameters that influence the potential the radiation use efficiency, the N demand per unit of sequestered carbon and the harvest index (Table S4). For SOC, we adjusted the decomposition parameters for the structural and metabolic litter pools in order to account for the high termite activity in the tropics that has been shown in previous studies (Ayuke et al., 2011; Kihara et al., 2015). In addition, the tillage decomposition multipliers were also adjusted to match the observed trend of SOC and to minimize the error between the simulated and observed values. Only one optimal parameter set was used for both the INM3 and CT1 treatments to avoid over-fitting. The evaluation treatments were simulated using the calibrated model parameters.

2.3. Data analysis

DayCent performance was assessed comparing simulated and the measured yields and SOC data (0–20 cm). The simulated grain yield values were converted from biomass carbon to dry matter using a ratio of 0.45 (Monje and Bugbee, 1998) and the measured moisture content of 13 % at harvest. We calculated SOC stocks at 0–15 cm depth using SOC concentration, the bulk density for the top soil in the two experiments and the depth using the Eq. 1.

$$SOC \left(\frac{Mg}{ha} \right) = SOC \left(\frac{g}{C} \right) \times Bulk\ density \left(\frac{kg}{m^3} \right) \times depth(m) \times 10000\ m^2 \times 10^{-6} \quad (1)$$

$$Y = 1 - \beta^d \quad (2)$$

$$SOC_{20} = \frac{1 - \beta^{20}}{1 - \beta^{15}} \times SOC_{15} \quad (3)$$

For SOC comparability, the measured SOC stocks at 0–15 cm were scaled to 0–20 cm using the depths functions developed by Jobbágy and Jackson, 2000 according to the Eqs. 2 and 3; where, Y represents the cumulative proportion of SOC stock from the surface to depth d (cm), β is the relative decrease of SOC stocks with depth, SOC_{20} is the cumulative SOC stock at the top 20 cm, SOC_{15} is the cumulative SOC stock at 0–15 cm. β was estimated for each site based on the measured SOC content along the soil profile at the INM3 and CT1 sites (Table S1), and was assumed to stay constant among all the treatments. The estimated β values for INM3 and CT1 sites were 0.971 and 0.974, respectively.

The accuracy of the model in simulating SOC and yields was evaluated using the coefficient of determination (adjusted R^2), root mean squared error (RMSE) (Eq. 4), relative root mean squared error (RRMSE) (Eq. 5), and model efficiency (E) (Eq. 6): where, O_i and S_i indicate the observed and simulated values, \bar{O} is mean value of observed data and n is the number of measurements. E shows the efficiency of the model in describing the observed data relative to the mean of the observations. The E values can be positive or negative with a maximum value of 1. A positive value indicates that the simulated values describes the trend in the measured data better than the mean of the observations, and the negative value indicates that the simulated values describe the data less well than a mean of the observations (Nash and Sutcliffe, 1970).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - S_i)^2}{n}} \quad (4)$$

$$RRMSE = \frac{RMSE}{\bar{O}} * 100 \quad (5)$$

$$E = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (6)$$

2.4. Projected SOC changes

To project the long-term impacts of improved management on SOC, we extended the model simulations for some of the treatments from 2016 to 2050. In the projection simulations, the observed weather data was repeated until 2050, and the soil conditions and management were the same as that of the experimental period. The future period was conceptualized assuming no changes in the maize and soybean cultivars. We assessed the trend of the total SOC as well as the SOC in the active, slow and passive pools. Only 8 of the total 40 treatments most representative of different management options that are typical for western Kenya cropping systems were selected for the forecast analysis:

- “residues only”: FYM-R+_M-M_N90
- “manure only”: FYM+_R-_M-M_N90
- “integrated nutrient management (manure and residues)”: FYM+_R+_M-M_N90
- “minimum tillage and residues”: FYM-R+_M-M_N90
- “rotation only”: FYM-R-_M-S_N60
- “conservation agriculture (minimum tillage, residues, and rotation)”: FYM-R+_M-S_N60

- “worst case management”: FYM-R-_M-M_N0 for both the CT1 and INM3 experiments

3. Results

3.1. Model performance

In most cases, the simulated annual maize and soybean grain yields were significantly correlated albeit with low R^2 values ranging 0.06 to 0.23 at the two experimental sites (Fig. 1). However, the correlation between the simulated and measured soybean yields was insignificant for the CT1 treatments under minimum tillage (Fig. 1e). The DayCent model did not well predict the inter-annual variations of the yields across all the considered treatments, yielding a negative model efficiency (E), and a high RMSE and RRMSE (Table 1). Even though the model was not able to capture the observed inter-annual variability in the yields (see example for maize in Fig. S1), the average simulated and measured yields for the entire period (2004–2015) for both maize and soybean compared well across all the treatments, with the simulated values falling within the measured standard deviation range (Fig. S2). The measured and simulated estimates showed slightly higher average yields in the treatments under continuous application of manure and/or residues compared to the control treatments.

The simulated SOC followed the trend of the measurements reasonably well with all the treatments in the INM3 and CT1 experiments exhibiting a decline in SOC (Figs. 2 and 3). Linear regression analyses showed a significant correlation between the measured and simulated SOC stocks (Fig. 4), with the model explaining 50 %, 55 % and 25 % of the variation in SOC in the INM3, CT1 under conventional tillage and the CT1 under minimum tillage treatments, respectively. The RMSE ranged between 1.28–2.64 Mg C ha⁻¹ for the INM3 treatments, 0.59 and 2.00 Mg C ha⁻¹ for CT1 treatments under conventional tillage and 1.19–2.00 Mg C ha⁻¹ for the minimum tillage treatments (Table 2). The RRMSE across all the treatments was low (less than 7%). E values were positive in 12 out of the 20 treatments used for model validation, indicating that the model was able to capture the temporal changes in SOC. These results show that DayCent is suitable for predicting SOC trends in maize systems on highly weathered soils under manure and residue application, and under different tillage regimes (conventional versus minimum).

3.2. Simulated SOC changes

Compared to observations, the model generally underestimated SOC loss rates across all the treatments in the INM3 experiment. As expected, the model simulated the highest losses in the treatments with no farm-yard manure application and maize residues retention in the INM3 experiment, with this SOC loss mitigated by higher fertilizer rates (Table 2). For the treatments under 90 and 30 kg N ha⁻¹ application, the model simulated a loss of 3.61 and 4.90 Mg C ha⁻¹ (0.33 and 0.45 Mg C ha⁻¹yr⁻¹) with maize residues only, 2.82 and 3.31 Mg C ha⁻¹ (0.26 and 0.30 Mg C ha⁻¹ yr⁻¹) with manure application only, while the application of both manure and residues resulted in a loss of 2.05 and 2.36 Mg C ha⁻¹ (0.19 and 0.21 Mg C ha⁻¹ yr⁻¹) (Table 2). The average annual loss rates for the treatment with no fertilizer and organic matter inputs (FYM-R-_M-M_N0) was 0.65 Mg C ha⁻¹ yr⁻¹. Thus, the combination of manure and residue applications reduced SOC loss by 71 % when combined with 90 kg N ha⁻¹.

The model slightly overestimated the loss rates in the treatments at the CT1 trial. Similar to INM3, the model simulated the highest SOC losses in the continuous maize systems with no residue retention in the CT1 experiment (Table 2). Under conventional tillage, the model simulated a loss of 2.48 and 3.32 Mg C ha⁻¹ (0.35 and 0.47 Mg C ha⁻¹ yr⁻¹) in the continuous maize treatments with maize residue and fertilizer application (FYM-R+_M-M_N90 and FYM-R+_M-M_N30), and a loss of 2.94 and 3.04 Mg C ha⁻¹ (0.42 and 0.43 Mg C ha⁻¹ yr⁻¹) in the rotation treatments with application of maize residues and 60 kg N ha⁻¹, and

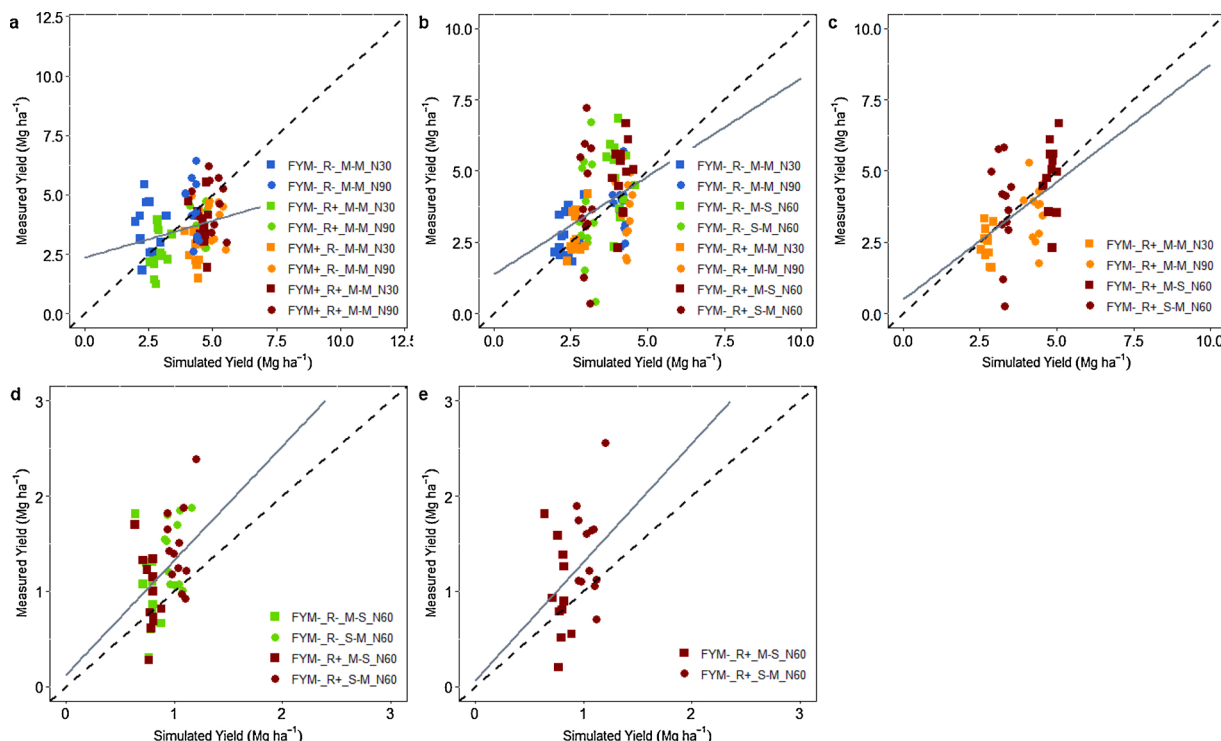


Fig. 1. Measured versus simulated maize and soybean grain yields for the model evaluation treatments for 11 years (2004 to 2015). (a) Maize yields in the INM3 treatments, Adjusted $R^2 = 0.06$, slope = 0.21, $p = 0.01$; (b) maize yields in the CT1 treatments under conventional tillage, Adjusted $R^2 = 0.12$, slope = 0.18, $p < 0.001$; (c) maize yields in the CT1 treatments under minimum tillage, Adjusted $R^2 = 0.23$, slope = 0.30, $p < 0.001$; (d) soybean yields in the CT1 treatments under conventional tillage, Adjusted $R^2 = 0.13$, slope = 0.12, $p < 0.01$; and (e) soybean yields in the CT1 treatments under minimum tillage, Adjusted $R^2 = 0.09$, slope = 0.10, non-significant. For the continuous maize treatments, the yield represents an annual mean over the long and short rainy seasons. The dashed line is the 1:1 line and the grey line is the regression line.

Table 1

Evaluation of the model performance to simulate yields ($n = 11$) and SOC ($n = 6$ and $n = 4$ in INM3 and CT1 treatments) using root mean square error (RMSE), relative RMSE (RRMSE) and model efficiency (E).

Treatment ¹	Maize/soybean yield ²			SOC		
	RMSE (Mg ha ⁻¹)	RRMSE (%)	EF	RMSE (Mg C ha ⁻¹)	RRMSE (%)	EF
INM3						
FYM-R-M-M_N30	1.57	44	-1.41	2.50	6.60	0.47
FYM-R-M-M_N90	1.22	28	-0.13	1.56	4.14	0.70
FYM-R+_M-M_N30	0.83	32	-0.04	1.28	3.46	0.80
FYM-R+_M-M_N90	1.20	34	-2.28	1.80	4.74	0.62
FYM+_R-M-M_N30	1.78	65	-4.39	1.95	5.14	0.34
FYM+_R-M-M_N90	1.36	35	-2.03	1.92	4.91	0.40
FYM+_R+_M-M_N30	1.25	33	-1.02	2.64	6.89	-0.30
FYM+_R+_M-M_N90	1.16	28	-0.31	1.92	4.83	0.36
CT1 conventional tillage						
FYM-R-M-M_N30	0.81	29	-0.18	1.86	4.88	-3.13
FYM-R-M-M_N90	0.99	27	-0.30	0.59	1.52	0.86
FYM-R-M-S_N60	1.50/0.49	31/48	-0.50/-0.48	1.30	3.39	-0.20
FYM-R-S-M_N60	1.82/0.52	51/37	-0.13/-1.29	2.00	5.25	-0.75
FYM-R+_M-M_N30	0.66	24	0.13	1.07	2.78	-0.91
FYM-R+_M-M_N90	1.31	36	-0.41	0.93	2.41	0.36
FYM-R-M-S_N60	1.30/0.45	27/48	-0.25/-0.45	1.03	2.68	-0.05
FYM-R+_M-S_N60	2.17/0.58	54/40	-0.29/-1.12	0.85	2.21	-0.14
CT1 minimum tillage						
FYM-R+_M-M_N30	0.62	24	-0.36	1.36	3.40	-0.28
FYM-R+_M-M_N90	1.25	35	-0.76	2.00	5.05	-1.00
FYM-R-M-S_N60	1.14/0.51	24/53	0.04/-0.32	1.19	3.00	0.20
FYM-R-S-M_N60	1.69/0.62	47/43	-0.13/-0.68	1.54	3.84	0.44

¹ The treatment names show the inclusion (+) or exclusion (-) of farmyard manure (FYM), and/or maize residues (R+). M-M represents continuous maize, M-S is a maize-soybean rotation where maize is grown in the long rain season and soybean in the short rain season and S-M represents the vice versa. N30, N60 or N90 indicates that 30 kg ha⁻¹, 60 kg ha⁻¹ or 90 kg ha⁻¹ of mineral nitrogen fertilizer was applied every season.

² For the rotation treatments the first value is for maize yields and the second is for the soybean yields.

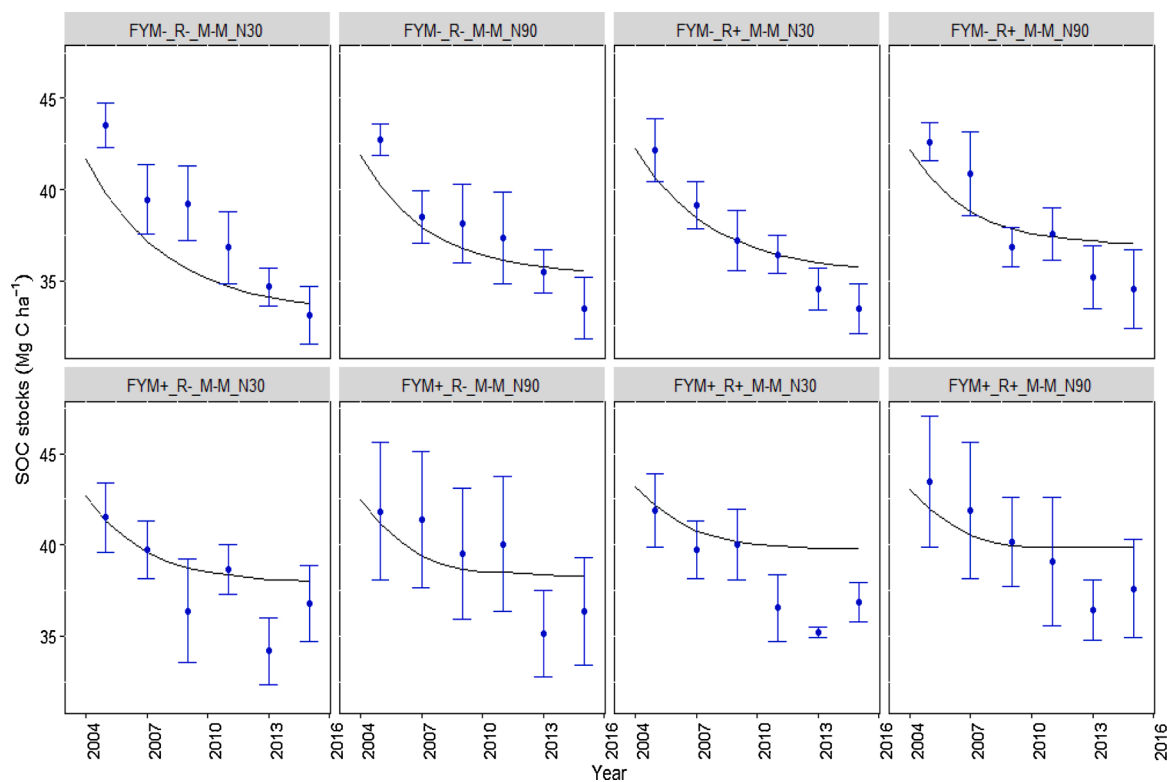


Fig. 2. The simulated and measured SOC stocks in the top soil (0 to 20 cm) for the evaluation treatments in the INM3 experiment. The black line is the simulated soil carbon, the blue dot is the measured mean over the four replicates in the treatment and the bar represents the standard deviation. See Fig. S3 for the calibration treatments results.

soybean residues retained (FYM-R+_S-M_N60 and FYM-R+_M-S_N60). As expected, the total loss of SOC in treatments under minimum tillage was lower than in the conventional ones, with the continuous maize treatments under maize residues application having a loss of 2.18 and 3.21 Mg C ha⁻¹ (0.31 and 0.46 Mg C ha⁻¹ yr⁻¹), and the rotation treatments having a loss of 2.69 and 2.77 Mg C ha⁻¹ (0.38 and 0.40 Mg C ha⁻¹ yr⁻¹). Compared to the continuously tilled maize control plot with zero fertilizer and no residues application (FYM-R_M-M_N0), which had a loss rate of 0.67 Mg C ha⁻¹ yr⁻¹, the application of maize residues and 90 kg ha⁻¹ nitrogen fertilizer reduced the loss by 47 %, while the adoption minimum tillage in this treatment further reduced the loss by 54 %. The simulated loss in the rotation treatments (FYM-R+_M-S_N60 and FYM-R+_S-M_N60) with residue retention and minimum tillage was 40 % and 43 % lower than in the control plot.

3.3. Projected SOC changes

Model projections showed that the SOC would continue declining in the treatments with no manure and maize residues retention, including the maize-soybean rotation (Fig. 5). By 2050, the SOC for the worst case management scenario (FYM-R_M-M_N0) had reached 28.48 and 28.87 Mg C ha⁻¹ at the INM3 and CT1 sites, respectively, with a loss of 37 and 41 % since the onset of the trial. This loss is in line with past estimates of observed relative SOC changes associated with the conversion of grassland to croplands (e.g., Don et al., 2011). The projections showed that SOC in the treatment where both manure and maize residues were applied would start to stabilize after 10 years of adopting improved management practices (Fig. 5). The SOC in the treatments with either residue application or minimum tillage stabilized 20–25 years after adopting improved management.

Expressed as annual averages, the worst case management scenarios triggered annual loss rates of 0.32 and 0.35 Mg C ha⁻¹ yr⁻¹ by mid-century. Residue retention and farmyard manure application in

continuous maize with 90 kg N ha⁻¹ fertilizer reduced the loss to 0.10 Mg C ha⁻¹ yr⁻¹ (Table 3). Minimum tillage and residue retention reduced the loss to 0.14 Mg C ha⁻¹ yr⁻¹ in continuous maize with 90 kg N ha⁻¹ fertilizer, while residue retention in maize-soybean rotation with 60 kg N ha⁻¹ reduced the loss to 0.17 Mg C ha⁻¹ yr⁻¹. Overall, carbon emissions of approximately 0.22, 0.21 and 0.17 Mg C ha⁻¹ yr⁻¹ could be avoided by adopting these improved management practices.

Further analysis of the DayCent carbon pools revealed that the slow SOC pool declined throughout the experiment period to stabilize by 2025 (Fig. S5). Except for the treatment with manure and residue retention, where SOC in the passive pool increased at the start of the experiment, the other treatments exhibited losses in this pool that continued beyond 2050. These results suggest that increased manure application and residue retention are likely to have different effects on the pools that govern SOC dynamics.

4. Discussion

4.1. Data limitations and uncertainties in model simulations

The model results suggest that the DayCent model can reasonably simulate the average maize and soybean yields for the different treatments for the considered 12 years (2004–2016). However, the observed inter-annual variability in the maize and soybean yields among treatments was not captured by the DayCent model. This issue is not unique for our study site, and has also been found for maize in temperate systems in the USA (Campbell et al., 2014). The poor simulations of yield variability are likely due to the model not accounting for the interactions between temperature, moisture and grain yields, e.g. the high or low precipitation events that affect flowering or grain filling (Campbell et al., 2014). Even though these biases may not be so evident in the simulated SOC, because of the fixed amount of maize residues returned to the soil, below ground carbon inputs via the roots can have significant

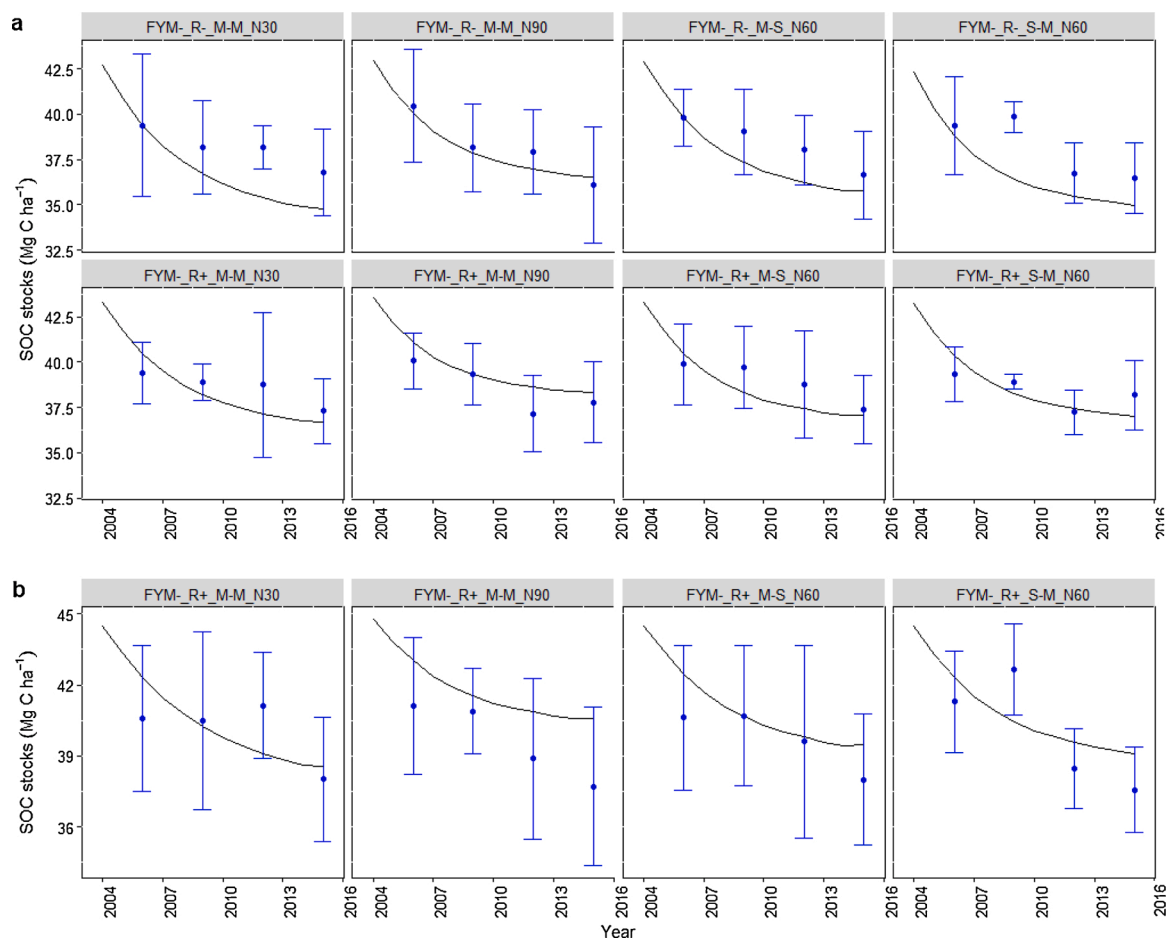


Fig. 3. (a) The simulated and measured SOC stocks in the top soil (0 to 20 cm) for the evaluation treatments under conventional tillage in the CT1 experiment, and (b) the simulated and measured SOC stocks in the top soil (0 to 20 cm) for the evaluation treatments under minimum tillage in the CT1 experiment. The black line is the simulated soil carbon, the blue dot is the measured mean over the four replicates in the treatment and the bar represents the standard deviation. See Fig. S4 for the calibration treatment results.

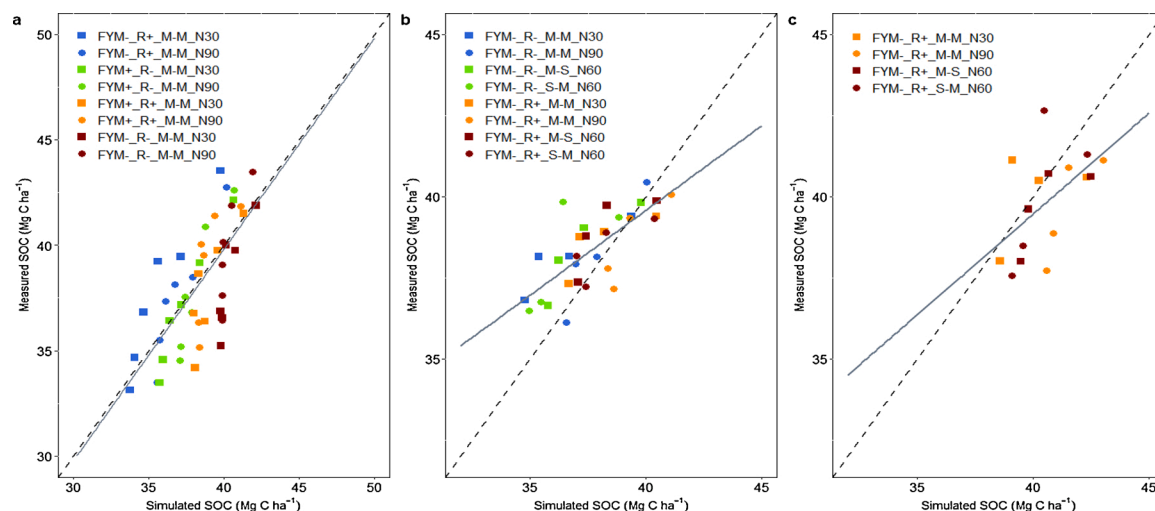


Fig. 4. (a) Measured versus simulated SOC stocks for the model evaluation treatments in the INM3 experiment for the six sampled years. Adjusted $R^2 = 0.50$, slope = 0.51, $p < 0.001$; (b) Measured versus simulated SOC stocks for the model evaluation treatments in the CT1 experiment under conventional tillage for the four sampled years. Adjusted $R^2 = 0.55$, slope = 1.09, $p < 0.001$; (c) Measured versus simulated SOC stocks for the model evaluation treatments in the CT1 experiment under minimum tillage for the four sampled years. Adjusted $R^2 = 0.25$, slope = 0.49, $p < 0.05$. The dashed line is the 1:1 line and the grey line is the regression line.

Table 2

The observed and simulated absolute SOC loss and loss rates for the evaluation treatments for the period 2005–2015 in the INM3 experiment and 2006–2012 in the CT1 experiment. The annual loss rates were obtained by dividing the absolute loss by the number of years between the first and last sampling year in the respective experiment (11 in INM3 and 7 in CT1).

Treatment ¹	Absolute SOC loss (Mg C ha ⁻¹)		SOC loss rate (Mg C ha ⁻¹ yr ⁻¹)	
	Observed	Simulated	Observed	Simulated
INM3				
FYM-R-M-M_N30	-10.41	-6.03	-0.95	-0.55
FYM-R-M-M_N90	-9.25	-4.64	-0.84	-0.42
FYM-R+M-M_N30	-8.68	-4.90	-0.79	-0.45
FYM-R+M-M_N90	-8.06	-3.61	-0.73	-0.33
FYM+R-M-M_N30	-4.71	-3.31	-0.43	-0.30
FYM+R-M-M_N90	-5.50	-2.82	-0.50	-0.26
FYM+R+M-M_N30	-5.02	-2.36	-0.46	-0.21
FYM+R+M-M_N90	-5.87	-2.05	-0.53	-0.19
CT1 conventional tillage				
FYM-R-M-M_N30	-1.25	-4.00	-0.18	-0.57
FYM-R-M-M_N90	-2.52	-3.09	-0.36	-0.44
FYM-R-M-S_N60	-1.78	-3.56	-0.25	-0.51
FYM-R-S-M_N60	-2.62	-3.34	-0.37	-0.48
FYM-R+M-M_N30	-0.64	-3.32	-0.09	-0.47
FYM-R+M-M_N90	-2.91	-2.48	-0.42	-0.35
FYM-R-M-S_N60	-1.09	-3.04	-0.16	-0.43
FYM-R+M-S_N60	-2.09	-2.94	-0.30	-0.42
CT1 minimum tillage				
FYM-R+M-M_N30	0.53	-3.21	0.08	-0.46
FYM-R+M-M_N90	-2.24	-2.18	-0.32	-0.31
FYM-R-M-S_N60	-1.00	-2.69	-0.14	-0.38
FYM-R+M-S_N60	-2.81	-2.77	-0.40	-0.40

¹ The description of treatment names can be found in Table 1.

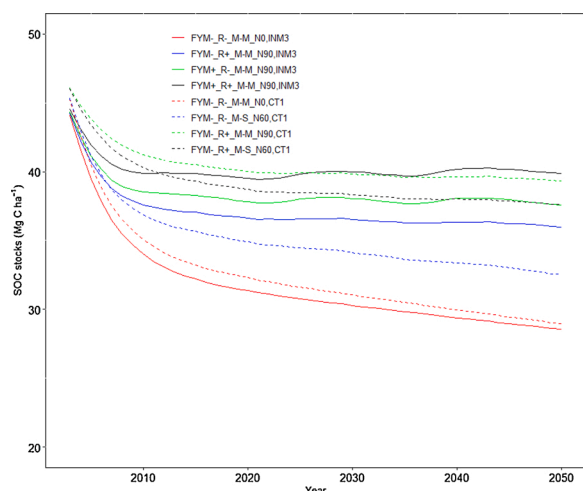


Fig. 5. Projected SOC trends for a few selected treatments representing different improved management practices at the INM3 and CT1 sites. See section 2.1 and 2.2.5 for a detailed description of the treatments.

effects on SOC. This may partially explain the differences in the rates of SOC loss between the observed and simulated values (Table 2).

While the model captured the observed trend of SOC loss across all the considered treatments, the simulated loss rates were lower than the observed for the INM3 treatments and higher for the CT1 ones. The SOC content at the two experiment sites was only measured to a depth of 15 cm, while the DayCent model simulates SOC to a depth of 20 cm. Past studies show that in cropland areas tillage intensity can have an effect on SOC up to deeper depths (Baker et al., 2007; Haddaway et al., 2017). In our analysis, we applied a simple extrapolation for scaling SOC content

Table 3

Predicted losses of SOC stocks, average annual loss rates, and the avoided losses resulting from the adoption of improved management in the top 20 cm at the INM3 and the CT1 sites for the period between 2003 and 2050. The avoided loss is calculated by subtracting the loss under the improved management from the loss of the worst case management scenario.

Treatment	Description	SOC difference 2003–2050 (Mg C ha ⁻¹)	Average annual loss of SOC (Mg C ha ⁻¹ yr ⁻¹)
FYM-R-M-M NO	Worst case management, INM3	-15.57	-0.32
FYM-R+M-M N90	Residues only	-8.21	-0.17
FYM+R-M-M N90	Manure only	-6.70	-0.14
FYM+R+M-M N90	Integrated nutrient management (manure and residues)	-4.61	-0.10
FYM-R-M-M NO	Worst case management, CT1	-16.35	-0.35
FYM-R-M-S_N60	Rotation only	-12.80	-0.27
FYM-R+M-M N90	Minimum tillage and residue retention.	-6.69	-0.14
FYM-R+M-S_N60	conservation agriculture (residues, rotation and minimum tillage)	-8.46	-0.18
Avoided losses			0.08–0.22

with depth. However, the extrapolated SOC values for the top 20 cm are likely to differ from observed values due to the varying management effects on SOC changes with depth. Absence of baseline soil samples at the onset of the trial challenge the comparison of simulated absolute SOC losses to the observed and for quantifying the effectiveness of different management options. The simulated SOC trends suggest that for some of the treatments the simulated SOC stocks in 2003 may have been different from observed (Figs. 2 and 3). Adjusting the initial SOC content for these treatments is likely to change the final simulated SOC values in 2015, and consequently affect the simulated loss rates. However, the simulated trend of SOC loss would remain the same since the decomposition rates would be unchanged.

The amount of carbon added via manure application events is another factor that would affect the simulated trends of SOC. Variations in C:N ratio of FYM can be expected from the different sources of plant species consumed by the livestock. However, in our simulations we assumed a constant C:N ratio for FYM for all the simulated years based on literature values (Gichangi et al., 2006). The observed variability in the measured SOC in the treatments with FYM at the INM3 site is likely due to the changes in the carbon content of the applied manure (Sommer et al., 2018). Thus, annual characterization of manure composition used at the two sites can improve the applicability of the considered data in evaluating process-based models. Furthermore, the possible changes in the bulk density associated with manure and residue application, and minimum tillage, were not considered in calculating the observed SOC stocks. Although increases or decreases in bulk density would change the total observed SOC stocks, the simulated results are not likely to substantially differ given that previous studies have shown that SOC in the DayCent model is not highly sensitive to changes in bulk density (Begum et al., 2017).

4.2. Impact of cropping systems and integrated management on SOC changes

Application of farmyard manure and residues increase SOC through providing additional carbon inputs to the soils while minimum tillage slows decomposition. Although SOC sequestration was not achieved at the two long-term experiments (Fig. 2 and 3), the results in this study

show a reduction in the SOC losses following the adoption of integrated nutrient management and conservation agriculture in continuous maize systems (Table 4), which is line with observations. Our results corroborate previously observed SOC losses in maize systems under manure and residue application in the central highlands of Kenya (Kamoni et al., 2007; Kapkiyai et al., 1999), with overall similar soil and climatic conditions as our study site.

In the treatments under integrated nutrient management practices (INM3), model results showed that the application of 4 Mg ha⁻¹ had a stronger effect in reducing SOC losses than the addition of 2 Mg ha⁻¹ of maize residues, with this loss further reducing with increased amounts of N fertilizer. This is expected as more carbon is added via manure application. Applying both manure and residues reduced the losses further. Despite the model uncertainty in simulating yields, the results suggest that the reduced SOC losses would translate to higher maize yields compared to continuous maize systems without organic matter inputs. Although differences in the amounts of applied N fertilizers across treatments prevents an exact comparison of SOC response in continuous maize versus the maize-soybean rotation systems under conservation agriculture, the simulated results have value in identifying that systems in which maize residues are retained would have a stronger effect in reducing SOC losses in continuous maize compared to the retention of soybean residues in rotated systems. This is because the carbon inputs associated with the 2 Mg ha⁻¹ maize residue application in each season is higher than for soybean residues. Mixed-crop livestock farmers in western Kenya in most case use the maize Stover's for livestock feeding. Furthermore, the high quantities of residues applied at the sites may not be achievable in most smallholder farms where maize production is quite low (Sommer et al., 2018). Both the simulated and observed results show that the average maize yields (3.00 to 4.82 Mg ha⁻¹) are higher than the soybean yields (0.77 and 1.03 Mg ha⁻¹) in rotated in systems (Fig. S2). While this may translate into higher maize returns for the farmers, continuous maize planting is likely to deplete the N in the soils; hence integrating legumes such as soybean into maize systems, which also provides additional N to the soil (Franke et al., 2018), is likely to be a much more viable strategy for reducing SOC and increasing maize yields.

The initial SOC content at the onset of a long-term trial can significantly influence the long-term of dynamics of SOC (Sanderman and Baldock, 2010). In agroecosystems where SOC is decreasing due to the land use history, sequestration is not guaranteed with increased organic matter inputs and minimum tillage, while a net sequestration is likely to be achieved in systems with a new equilibrium after prolonged continuous cultivation. The INM3 site was under natural grassland prior to the onset of the experiment, hence the observed decline in SOC is likely due to increased decomposition associated with tillage and outstripping inputs of carbon (e.g., residue, manure). Despite a decade of cultivation at the relatively proximate CT1 site and similarity of soil type, it appears that a new equilibrium level had not been achieved in most of the sites and hence the adoption of the improved agronomic management practices only resulted in SOC losses. This result is in line with a long-term chronosequence study in western Kenya which reported continued SOC losses even after more than 50 years of conversion of natural forest to maize (Moebius-Clune et al., 2011). These results suggest that the targets set in initiatives such as 4p1000 may not be achievable in continuously cultivated soils where the SOC is on a declining trend, and where large carbon deficits exists with agriculture (Sanderman et al., 2017).

The dominant future loss of simulated SOC in the passive pool for most treatments in our results is contrary to previous studies in temperate agroecosystems, which found the slow pool to be the main driver of SOC changes (e.g., Begum et al., 2017; Cong et al., 2014). This loss stems from the increase in the multiplier parameters that govern tillage effects on decomposition, which were adjusted in the calibration phase to match the observed trend of SOC losses. The simulated percentage of SOC in the passive pool prior to the start of the two

experiments (2003) was on average $\approx 70\%$; hence the response of total SOC to management is highly dependent on the response of this pool. At CT1, a previous study found that permanganate-oxidizable carbon (POXC), thought to represent biologically processed carbon (Culman et al., 2012; Hurisso et al., 2016), was $\approx 2\text{--}3\%$ of the total SOC (Margenot et al., 2017b). This is consistent with generally lower proportions of POXC in less weathered soils of 4–6 % (Pulleman et al., 2021), perhaps mediated by high clay and iron oxide content in those soils. For the treatment with both manure and residue application, the model shows a gain in SOC in the passive pools after few years of adoption, suggesting that the carbon inputs may overtime exceed the decomposition losses. Although one may expect an increase in recalcitrant SOC from increased organic matter inputs in the fine-textured soils at the two sites (Table S1), this is likely hindered by the 1:1 phyllosilicate (kaolinitic) mineralogy that dominates western Kenya (Kihara et al., 2012). Moreover, past studies show a lack of SOC protection in soil aggregates despite increased aggregate stability with the adoption of conservation agriculture (Kihara et al., 2012; Paul et al., 2013). Thus, the results in this study suggest the turn-over driven carbon losses associated with fast decomposition at the site exceed the gains resulting from increased carbon inputs from manure and residue application; therefore, the current carbon inputs in these systems need to be greater and the decomposition losses ameliorated by reduced tillage.

The model projected that the observed SOC losses would continue under most improved management practices. Model results suggest that this loss may decrease or cease depending on how the recalcitrant carbon responds to tillage. The 4p1000 sets a target of 3.5 Gt C yr⁻¹ SOC sequestration in cropland areas in order to mitigate global climate change. A recent study showed that only about 26–53% of this target would be achievable in the top 30 cm of global croplands (Zomer et al., 2017). Our results further suggest that croplands situated on highly weathered soils in tropical climates may not achieve these targets: across the diversity of treatments evaluated, only SOC losses were observed. Despite SOC sequestration not being achieved at these sites, practices that mitigate the decline in SOC can still offer benefits to crop productivity in this and similar agroecosystems (Kihara et al., 2020).

5. Conclusion

Our study shows that the DayCent model performs reasonably well in simulating SOC in continuous maize and maize-soybean cropping systems under a range of management practices in western Kenya. Hence, DayCent appears suitable to quantify the impacts of improved management practices on SOC in maize systems at a large-scale, and for quantifying the hypothesized impacts of conservation agriculture and integrated nutrient management. Both simulations and measurements confirm that SOC continues to decline despite the continuous application of manure, residues and fertilizer and the adoption of minimum tillage in the considered cropping systems. Although our simulated results illustrate how these practices can minimize SOC losses, the model projects that in most of the cases the loss would continue under present-day climate conditions. Model results suggest that the SOC losses are likely due to the high turnover of the carbon in the passive pool, which surpasses the gains from increased organic matter inputs in most of the considered treatments. More field measurements on the response of the labile recalcitrant SOC pools to increased organic matter inputs and under different tillage regimes would be useful to confirm this finding. Moreover, future modelling studies should assess the effectiveness of other management practices such as cover crops, agroforestry and perennial forage grasses in reducing losses or sequestering SOC in order to support the recommendation of sustainable agricultural practices in these systems.

Declaration of Competing Interest

This work was conducted as part of the Federal Ministry for

Economic Cooperation and Development, Germany (BMZ) funded project on “Scaling up soil carbon enhancement interventions for food security and climate across complex landscapes in Kenya and Ethiopia” (contract: 81206681). The authors declare no competing and conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.still.2021.105000>.

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