A robust DayCent model calibration to assess the potential impact of integrated soil fertility management on maize yields, soil carbon stocks and greenhouse gas emissions in Kenya.

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Abstract. Sustainable intensification schemes ~~that increase crop production and soil fertility,~~ such as integrated soil fertility management (ISFM) ~~,~~ are a proposed strategy to close yield gaps, increase soil fertility, and achieve food security in sub-Saharan Africa~~while maintaining soil fertility. However, field trials are insufficient to estimate the potential impact of such technologies at the regional or national scale. Upscaling via biogeochemical models ,~~. Biogeochemical models such as DayCent ~~, from the field-scale to a larger region can be a suitable and powerful way to assess the potential of such agricultural management practices at scale~~can assess their potential at larger scales, but they need to be calibrated to new environments and ~~their reliability needs to be assured~~rigorously tested for accuracy. Here, we present a robust Bayesian calibration of DayCent to simulate maize productivity and soil organic carbon stock changes under ISFM, using data from four long-term field experiments in Kenya in a leave-one-site-out cross-evaluation approach. The experimental treatments consisted of the addition of low- to high-quality organic resources~~to the soil~~, with and without mineral N fertilizer. We ~~assess~~ assessed the potential of DayCent to accurately represent the key aspects of sustainable intensification, including 1) yield, 2) the changes in soil carbon, and 3) ~~global warming potential. The model was calibrated and cross-evaluated with the probabilistic Bayesian calibration technique~~the greenhouse gas (GHG) balance of CO_2 and N_2O combined.

The ~~standard parameters of DayCent led to poor~~ calibration with cross-evaluation improved DayCent simulations of maize yield~~(~~, evaluated across all sites, (from a Nash–Sutcliffe modeling efficiency ~~; EF0.33) and changes in SOC(EF -1.3)for different ISFM treatments. After calibration of the model, both~~ (EF) of 0.36 to 0.50) but slightly worsened those of soil organic carbon (SOC) (from EF of 0.36 to 0.34). By site, the simulation of maize yield ~~(EF 0.51) and the change in SOC (EF 0.54)improved significantly compared to the model with the standard parameter values. A leave-one-site-out~~ improved (to site-specific EF between 0.16 and 0.39) and that of SOC slightly worsened (to site-specific EF between -1.8 and 0.39). The model performance and the match between the cross-evaluation posterior credibility intervals for different sites indicated

the robustness of the ~~approach~~ model parameterization and the reliability of the Daycent model for spatial upscaling ~~(i. e., the significant improvement, described before, was achieved by calibrating with data from 3 sites and evaluating with the remaining~~ of simulations. While daily N_2O emissions were poorly reproduced by DayCent (all EF values were negative), cumulative seasonal N_2O emissions were simulated more accurately (EF ranging between 0.03 and 0.62 by site). The ~~SOC decomposition parameters were altered most severely by the calibration. They were an order of magnitude higher compared to the default parameter set. This confirms that the decomposition of SOC in tropical maize cropping systems is much faster than in temperate systems and that the DayCent temperature function is not suitable to capture this with a single parameter set. Finally, the global warming potential simulated by DayCent~~ simulated yield-scaled GHG balance was highest in control ~~-N treatments (~~treatments without N addition (between 0.5 ~~-2.5~~ and 1.5 kg CO_2 equivalent per kg grain yield ~~, depending on the site) and could be reduced by 14 to 72~~across sites) and was lower by about 10 to 60% by combined application of mineral N and manure at a ~~medium rate . In three of the four sites, the global warming potential was largely (> 75%) dominated by SOC losses. In summary~~moderate rate of 1.2t C ha^{-1} yr^{-1}. In conclusion, our results indicate that DayCent is ~~suitable for estimating~~ well-suited to estimate the impact of ISFM~~from the site to the regional level, that trade-offs between yields and global warming potential are~~ , that the trade-off between maize yield and GHG balance is stronger in low-fertility sites, and that the ~~reduction~~ control of SOC losses is a priority for the sustainable intensification of maize production in Kenya.

1 Introduction

~~Similar to many countries of~~ In Kenya, as in many other Sub-Saharan Africa (SSA) countries, maize yields have remained low, ~~the low maize yields in Kenya,~~ on average 1.7 t ha^{-1} compared to the global average of 5.6 t ha^{-1} over the last decade ~~(2011-2021) (FAO, 2023), are in part responsible for~~ (2011-2021; FAO, 2023). This contributes to the low self-sufficiency of food production~~. Consequently,~~ , with around 20% of the Kenyan population ~~lives with~~ facing severe food insecurity (World-Bank, 2021b). If yields are not improved, increased ~~demand due to~~ population growth will further deteriorate food self-sufficiency and ~~in general~~ food security in general in the coming decades (Zhai et al., 2021)~~;~~ , especially considering expected yield declines resulting from more frequent extreme weather events ~~could further exacerbate this situation~~ (Lobell et al., 2011). One of the key limitations to sustainable maize production in SSA is the ~~lack~~ insufficient use of mineral fertilizer and organic inputs (Vanlauwe et al., 2010). Integrated soil fertility management (ISFM) is a sustainable intensification practice that can alleviate these limitations by combining the use of mineral fertilizers with organic inputs (Vanlauwe et al., 2010). ~~Different studies~~ Several studies have reported that ISFM has the potential to more than double maize yields in Kenya, especially ~~in currently unfertile~~ on infertile soils, due to ~~the effects~~ its positive impact on soil fertility, including soil organic matter (SOM) content (Chivenge et al., 2009, 2011). ~~However, in addition to the amount and quality of fertilizer and organic inputs,~~ Furthermore, increasing SOM can help mitigate adverse effects of climate change, offering considerable potential in carbon-depleted soils across SSA (Corbeels et al., 2019). However, the effectiveness of ISFM in increasing yields strongly depends on local site conditions, such as soil and climate (Chivenge et al., 2011). ~~Furthermore, increasing SOM also contributes~~

~~to minimizing the negative effects of climate change, and there may be considerable potential in carbon-depleted soils in SSA (Corbeels et al., 2019).~~

~~Hence, to~~ To close yield gaps in a resource-efficient way and to assess the climate change mitigation potential of ISFM, we need to understand the ~~effects of long-term implementation of ISFM at larger scales~~long-term effects of ISFM practices at a larger scale. Ideally, this would be facilitated by implementing a large number of long-term experiments ~~(LTE)~~ across a representative range of soil and climatic conditions. However, ~~due to the high demands in terms of cost~~the significant costs, labor, and time ~~associated with maintaining LTE,~~ required to maintain long-term experiments limit the number of ~~LTE that evaluate variation in the~~ sites for evaluating the variable effects of ISFM practices ~~due to~~ under site-specific conditions~~is very limited~~. In addition, ~~using~~ relying on statistical predictive techniques to upscale results ~~obtained with a low~~ from a limited number of sites ~~could~~ may lead to low predictive power and large ~~predictive~~ errors, because it is unlikely that the effects of ~~variation in~~ soils and climate on yield and ~~the development of soil organic matter (SOM)~~ SOM would be fully captured ~~by~~ in the statistical models.

Biogeochemical process-based ecosystem models, such as DayCent (Parton et al., 1998; Del Grosso et al., 2001), ~~are able to simulate the influence of~~ simulate the effects of important driving variables ~~of~~ on crop yield and SOM formation using semi-mechanistic functions developed through decades of agronomic and soil research. Because they (partly) embed our current understanding of the complex ecosystem processes, they are more robust for ~~upscaling of~~ scaling up the yield potential (Saito et al., 2021) and the SOM building capacity (Lee et al., 2020), compared to statistical predictive techniques. However, to avoid bias in model output, it is best practice that models are calibrated and validated to local conditions (Necpálová et al., 2015)~~whenever they are applied outside the range of usual conditions, for example, in a new climate zone~~ , especially when applied in novel contexts such as different climate zones with different soils.

Although DayCent has been used to estimate ~~the development of SOM stock~~ SOM stock changes in Kenya on a national scale (Kamoni et al., 2007)~~and recently the efficiency~~ , and recently to assess the impact of conservation agriculture on SOM in Ethiopia (Lemma et al., 2021), ~~DayCent's~~ its modules of SOM and maize crop growth have never been rigorously calibrated and validated for tropical agroecosystems in SSA. A recent ~~test~~ evaluation of DayCent in Kenyan maize ~~growing~~ systems showed that SOM turnover is underpredicted by ~~DayCent~~ the model (Nyawira et al., 2021). Because SOM ~~in biogeochemical models~~ is coupled to nitrogen (N) mineralization in biogeochemical models, there is the potential that this translates into biased crop responses to N addition and biased crop ~~growth rates~~ productivity predictions in any upscaling exercise. A potential solution to this issue is the ~~joint~~ simultaneous calibration of soil and crop parameters in DayCent ~~, using long-term~~ using data from local ~~trials~~long-term experiments. Ideally, ~~it~~ this calibration would include the uncertainty in the model parameters and model outputs (Clifford et al., 2014), so a propagation of errors is possible in upscaling exercises (Stella et al., 2019). This is especially relevant ~~because~~ given a recent study ~~showed~~ showing considerable uncertainty in DayCent's SOM turnover rates, even when calibrated using a range of long-term experiments ~~for calibration~~ (Gurung et al., 2020).

In order to use DayCent to assess the potential of ISFM to ~~contribute to closing the yield gap~~ reduce yield gaps while minimizing environmental impact in Kenya and other SSA countries, ~~the aim of this study was to use~~ this study used a Bayesian calibration to derive robust DayCent parameters of SOM cycling and maize growth in Kenya. With robust, we mean that the model evaluation statistics are representative of applying the model to new sites with the same climate and soils. We used the experimental data of four long-term ISFM ~~trials~~ experiments conducted in Kenya ~~for almost two decades (Laub et al., 2022a, 2023b)~~over nearly two decades (Laub et al., 2023a, b). Of these, two sites were in humid western Kenya and two in subhumid to semi-arid central Kenya. ~~Their treatments were different additions of organic resources (1.2 and 4 t C ha^{-1} yr^{-1} including farmyard manure, high-quality *Tithonia diversifolia* and *Calliandra calothyrsus* residues as well as low-quality low quality stover of *Zea mays* and sawdust), combined with (+N) or without (-N) 120 kg mineral N fertilizer ha^{-1} season^{-1}. They thus contain a range of experimental conditions and inputs. The goal~~

The first objective of our study was to evaluate to what extent DayCent can ~~replicate~~ reproduce the differences in yields and SOM development in response to the addition of different qualities and rates of organic resources combined with different rates of N fertilizer ~~and between sites. Furthermore, because ISFM can simultaneously be a source of N_2O to the atmosphere (Leitner et al., 2020) and mitigate CO_2 emissions from the soil (Laub et al., 2022a), the~~ for a number of contrasting sites. The second objective was to evaluate the ~~total global warming potential of different~~ greenhouse gas (GHG) balance of different addition rates of organic material in ISFM to find the optimal balance between limiting ~~greenhouse gas~~ GHG emissions from the soil and optimizing ~~the~~ crop yield (that is, sustainable intensification). ISFM can be a source of N_2O to the atmosphere (Leitner et al., 2020) but at the same time mitigate CO_2 emissions due to the mineralization of SOC (Laub et al., 2023a).

~~Thus, the specific~~ The specific steps to reach the objectives of this study were (i) to test the capability of an uncalibrated version of DayCent to simulate yield and SOC development of the different ISFM practices, (ii) to calibrate DayCent to represent ISFM under Kenyan conditions using experimental data from ~~the 4 LTE~~four long-term experiments, displaying the confidence in model parameters by Bayesian calibration, and (iii) to use the calibrated model to gain ~~an understanding of possible trade-offs between yield and SOM increases under ISFM, and to understand the global warming potential~~ understanding of the GHG balance of the different ISFM treatments.

2 Material and Methods

2.1 The experimental sites

The present study used data ~~pooled from four experimental sites. The experiments tested different organic resource treatments~~ from four long-term field experiments in Kenya, in which the effect of the addition of different organic resources at different rates was tested, either alone or in combination with the application of mineral N fertilizer, in the context of ISFM. The ~~experimental setup was identical between the sites . The sites~~ sites are located in agriculturally important areas in ~~western and central Kenya.~~ central and western Kenya (Fig. A1). The Embu and Machanga sites are both located in Embu County, in the central part of Kenya. The Aludeka site is ~~located~~ situated in Busia County in western Kenya, while Sidada is located in the adjacent Siaya County, ~~just~~ south of Busia (Table A1). The experiments in Embu and Machanga ~~were initiated~~ began in early 2002~~and the experiments~~ , while those in Aludeka and Sidada ~~were initiated~~ began in early 2005. Therefore, 19 years of data were available in central Kenya and 16 years in western Kenya (2 sites x 16 years + 2 sites x 19 years = 70 ~~site years~~ site*years = 140 ~~site seasons~~site*seasons). The sites cover a range of altitudes, temperatures, and precipitations. Embu, with a mean annual temperature (MAT) of 20 °C and an annual precipitation of 1200 ~~mm annual precipitation~~ mm, is the coolest ~~of all sites~~site, while Machanga has a MAT of 24°C and ~~receives the lowest amounts of~~ the lowest annual precipitation (800 mm). Sidada (23°C, 1700 mm) and Aludeka (24°C, 1700 mm) have a high MAT and receive significantly more precipitation than the sites in central Kenya. There are two rainy seasons at each site, ~~which corresponds~~ corresponding to two maize growing seasons per year. The long rainy season ~~runs~~ occurs from March to August ~~/September,~~ or September, while the short rainy season ~~runs~~ occurs from October until January ~~/~~or February. In terms of soil texture, Machanga and Aludeka have low clay content (13% clay at both sites), while Sidada and Embu are rich in clay (56 and 60%, respectively).

All experiments were set up as a split plot design with three replicates, with different qualities and quantities of organic resources as main plots and the presence or absence of N fertilizer as subplots. Maize was grown continuously in all experiments, with two crops per year, one in the long rainy season and one in the short rainy season. The ~~design was similar in~~ experimental design was identical at all four sites and has been described in detail ~~for the Embu site (Chivenge et al., 2009; Gentile et al., 2011)~~ in earlier publications (Chivenge et al., 2009; Gentile et al., 2011; Laub et al., 2023a, b). Organic resource treatments consisted of high quality *Tithonia diversifolia* (TD) green manure and *Calliandra calothyrsus* (CC) prunings, low quality stover of *Zea mays* (MS) and sawdust from *Grevillea robusta* trees (SD), locally available farmyard manure (FYM) and a control treatment (CT) without ~~any~~ organic resource additions. Organic resources differed in quality by the contents of N, lignin and polyphenols (Table A2). Each organic resource was applied once a year at two rates, 1.2 and 4 t C ha^{-1} yr^{-1}, while ~~only one amount of applied mineral fertilizer,~~ mineral N fertilizer was applied at a fixed rate of 120 kg N ha^{-1} ($CaNH_4NO_3$) in each of the two growing seasons~~was tested. Of that~~. Of this, 40 kg N ha^{-1} were applied ~~with~~ at planting, and the remaining 80 kg N ha^{-1} about six weeks ~~after planting~~later. Organic resources were applied only once a year, prior to planting ~~for~~ in the long rainy season, i.e., in January or February. They were incorporated to a depth of 15 cm with hand hoes. Furthermore, a blanket application of 60 kg P ha^{-1} as triple superphosphate and of 60 kg K ha^{-1} as muriate potash at planting was provided to all plots ~~once~~ each season. The plots were kept weed free by hand weeding, ~~between two and~~ two to three times per season, and selective application of pesticides was used when necessary to ~~protect against~~ control armyworm, stemborer, and/or termites.

2.2 The DayCent model

~~The DayCent model (version 2020~~ DayCent (2017 version of DD_EVI) is a terrestrial ecosystem model of intermediate complexity (Del Grosso et al., 2001). It simulates daily C and N fluxes within the soil-plant-atmosphere continuum ~~on a daily basis~~ and has been parameterized for ~~many~~ several crops and ecosystems (Necpalova et al., 2018). It has submodules to simulate plant growth, organic resource and soil organic matter (SOM) decomposition ~~,~~ including mineralization of N, soil water and temperature, N gas fluxes, and CH_4 oxidation. The net primary productivity of plants is a function of their genetic potential, a simplified phenology, solar radiation, temperature, and stresses, such as reduced water or N availability. Here, we used the non-growing degree day version of the DayCent crop module, ~~which~~ that does not simulate phenology but has a seedling stage with reduced growth until a certain biomass (full canopy) is reached. SOC and soil N in the ~~upper 20 cm~~ topsoil are represented by an active, slow, and passive SOM ~~pools~~pool, while litter and organic resources are represented by a structural and metabolic litter ~~pools~~ pool (Parton et al., 1987). All ~~soil~~ SOM pools are conceptual and have no measurable counterparts, whereas the litter pools are ~~semiquantitative, that is, their~~ semi-quantitative. Their division is based on the measurable ratio of lignin to N in the organic resources and plant litter. ~~For temperate conditions, DayCent has been shown to~~ DayCent can adequately simulate crop yields, SOC and soil N dynamics, and N_2O emissions ~~(Del Grosso et al., 2005; Necpálová et al., 2015; Necpalova et al., 2018; Gurung et al., 2020, 2021). Yet, for tropical conditions the performance has not been studied in similar detail. A~~ in temperate conditions (Del Grosso et al., 2005; Necpálová et al., 2015; Necpalov but a recent paper showed ~~that the general model fit of the uncalibrated model was suboptimal~~ inadequate performance for tropical conditions (Nyawira et al., 2021).

2.3 Data used for the DayCent model ~~evaluation/~~calibration and evaluation

~~In a process that was repeated four times, a large data set was used based on~~

To provide an overall assessment of the performance of DayCent for its use in Kenya a leave-one-site-out cross-validation approach was applied. Specifically, this involved using a data sub-set from three of the four sites for ~~the model calibrationand the validation was performed based on the~~ model calibration, with validation performed using the data from the fourth site. ~~The plot-scale yield of maize grain~~ This process was repeated four times, every time with another site serving as the validation site. Different data, were used for this: Maize grain yield and the aboveground biomass, both on a dry matter basis~~(t ha^{-1})~~, were available for each cropping season between 2002 and 2020 (further details in Laub et al., 2023b). ~~In addition to that~~All this data was used with one exception - the short rainy season of 2019 at Sidada, which had unrealistically high maize grain yields of up to 16 t ha^{-1}. In addition, plot-scale SOC and total N contents in the top 15 cm ~~were available for several points over time~~ soil layer were available at several time points, and in 2021 for the 0-30 cm soil depth. In Embu and Machanga, soil samples were taken every two to three years since ~~initiation~~ the start of the experiment in 2002 until 2021, ~~but~~ while in Sidada and Aludeka, soil sampling occurred only in 2005, 2018, 2019 and 2021 ~~(further details in Laub et al., 2022a). Because bulk density~~ (further details in Laub et al., 2023a). Because soil bulk density data was not available for most ~~soil samples and in 2021~~ time points and there was no significant difference in topsoil bulk density between treatments at any site in 2021, the mean soil bulk density per site was used to calculate SOC stocks of the top 15 cm of soil depth. ~~All simulations were conducted at the site scale, so the plot-scale (i.e. replicate)measurements were aggregated to the site scale, calculating means and variances. DayCent calculates SOC to a depth of 20 cm , so we rescaled the SOC~~ We used a DayCent parameterization that was developed to simulate SOC stocks of the IPCC-recommended 0-30 cm topsoil layer (Gurung et al., 2020) (further details in section 2.3.2). Thus, the 0-15 cm SOC stocks were adjusted to 0-30 cm depth. This was done by adding the site-specific SOC stocks from the 15-30 cm layer (specifically, the 15-30 cm equivalent-soil-mass-based ones (Wendt and Hauser, 2013; Lee et al., 2009)) to the treatment-specific SOC stocks ~~for the top 15 cm to the top 20 cm , using the formula of Jobbágy and Jackson (2000):~~

$$\cancel{SOC_{20}(kg\ ha^{-1}) = \frac{1-\beta^{20}}{1-\beta^{15}} * SOC_{15}}$$

~~Here, SOC $_{20}$ and SOC$_{15}$ are SOC stocks in kg ha^{-1} in the top 20 and 15~~ from 0-15 cm. Due to limited data availability for the 15-30 cm soil depth ~~, respectively. The parameter β is the relative decrease of SOC stocks with depth, for which we took~~

~~the mean values across sites (0.9725) , calculated from the~~ (only 2021~~sampling, where samples from 0-15,~~), this approach was considered the most conservative and robust; subsoil carbon usually changes very slowly, and a statistical test revealed no differences in the equivalent soil mass based SOC stocks of the 15-30 ~~, and 30-50 cm were available for all of the sites.~~ cm layer (2.5-4.7 t soil ha^{-1}) between treatments at the same site in 2021 (with only one single exception in Aludeka; Fig. A2).

Data on N_2O emissions were used in the model evaluation phase, but not for model calibration, ~~because the data were scarce and subject to high variability~~due to their scarcity and high uncertainty. The N_2O measurements were conducted after N fertilization in 2005 (weekly measurements form March to June in Embu and Machanga and daily measurements in Machanga in November), in 2013 and 2018 (weekly measurements form March to beginning of May in Sidada and Aludeka), and in 2021 (weekly measurements form mid-March to mid-May in Sidada). ~~They were conducted with~~ The measurements applied the static chamber method (Hutchinson and Mosier, 1981) ~~. Measuring frames were permanently installed in the plots~~ with two measuring frames per plot permanently installed for a whole rainy season ~~. The~~ (one within, one between maize rows). The sampling chambers (0.27 × 0.375 × 0.11 m) ~~were made of polyvinylchloride and equipped with~~ had a vent tube and ~~a fan to homogenize gas inside them before gas sampling . The measured N_2O emissions were evaluated at two levels of aggregation. First, as site means per measurement day (from the three replicates, similar to all other data)~~ fan for to homogenize the gas sample before extraction with a 60 mL polypropylene syringe through a septum-sealed sampling port. Four gas samples were collected at 0, 15, 30 and ~~second as cumulative emissions over the whole season, for which we first~~ 45 min of chamber closure. Gas samples from within and between maize rows were combined per time point in the same syringe (Arias-Navarro et al., 2017). All analyses were conducted using a SRI 8610C gas chromatography (456-GC, Scion Instruments, Livingston, United Kingdom) equipped with an electron capture detector for N_2O analysis. Fluxes per surface area were determined using the linear slope of gas concentration over time (Pelster et al., 2017; Barthel et al., 2022). Simulated N_2O emissions were evaluated against measured daily and cumulative N_2O emissions. To determine the cumulative emissions at plot scale, we used the trapezoid method ~~at the plot scale~~ (Levy et al., 2017), specifically, the trapz function of R (Tuszynski, 2021). ~~Site-scale~~ Treatment-scale means and variances ~~were then computed for these~~ of the daily and cumulative N_2O emissions ~~, similar to all~~ were then computed in a similar way as for the other measurements.

~~Furthermore, data on soil mineral N (N_{min}), measured as NH_4^+ and NO_3^-, and measured moisture content at soil depths of 0-15 cm, were available from several measurement campaigns in the years 2012, 2013, 2018, 2019 and 2020. Finally, in the control and the 1.2 t C plots of the *Calliandra*, farmyard manure and maize stover treatments,~~ Finally, continuous soil moisture measurements ~~from~~ were conducted using sensors placed in each replicate at 10 cm soil depth (EC-5 Soil Moisture Sensor, Meter, Germany) ~~, were available for~~ in the control and the 1.2 t C plots of the *Calliandra*, farmyard manure and maize stover treatments at the Sidada and Aludeka sites (March 2018 to December 2020). These soil moisture ~~measurements~~ data were used to initially determine the optimal pedotransfer functions for soil hydraulic conductivity ~~before the actual model calibrationphase~~but not used in the model calibration.

2.3.1 Model driving variables and model assumptions

The site-specific crop management data ~~used to run the DayCent model~~ was obtained from ~~field management operation records for each season at each site. This included specific dates for the yearly application of organic resources (in all but the control plots)~~season- and site-specific records of field management operations. These included dates of organic resource application, manual plowing before planting, maize planting, split application of mineral N~~at rates of 40 kg and 80 kg N ha^{-1} per season~~, weeding and harvest~~dates. Pesticide application events~~. Dates of pesticide applications and gap filling ~~plus maize thinning~~ or maize thinning were also available, but these operations are not part of standard DayCent management and were therefore not included in ~~the DayCent schedule file. Our model runs therefore,~~ modelling. Therefore, our model runs assumed no occurrence of pests or diseases, and an optimal plant density ~~from the start, whichin practice~~ at emergence, which, in practice, was ensured by manual thinning and gap filling.

~~The climate data used to run DayCent consisted of recorded data at each of the sites. However, filling the~~ Recorded weather data existed for all sites, but filling in data gaps was necessary due to unavailability and loss of recorded data. ~~In~~ At Embu and Machanga, manual recordings of daily minimum and maximum temperature and precipitation were available from 2002 until the end of 2007, but from 2008 until 2017, only measured precipitation was available. After 2017, ~~high-quality data from~~ newly installed TAHMO stations (https://tahmo.org/climate-data/) were available ~~near the Machanga and Embu sites, with~~ for these two sites, providing daily values for temperature and precipitation. In Aludeka and Sidada, manual recordings of daily minimum and maximum temperature and precipitation were available for all years from 2005 to ~~2017, during which high-quality weather stations were installed~~ 2017. Thereafter, weather stations (Meter climate station, Meter Environment, Munich, Germany) were installed and provided the data. ~~These data~~ Data gaps were filled by using the NASA POWER product (https://power.larc.nasa.gov/docs/methodology/). A bias correction for the minimum and maximum temperature of NASA POWER data was performed, using a linear regression with measured data as dependent variable (y) and NASA POWER data as independent variable (x). Specifically, the slope and intercept of the regression equation $y = mx + b$, were used to produce a corrected estimate of these data. In our specific case, the slopes were not significantly different from 1, but intercepts (b) were significantly different from 0. The specific intercepts for maximum temperature were -0.3°C, -0.4°C, +3°C and +6°C for Embu, Machanga, Sidada and Aludeka, respectively. The intercepts for the minimum temperature were -0.25°C, -0.5°C, -3°C and +1°C for Embu, Machanga, Sidada, and Aludeka, respectively. For precipitation, no bias correction was done.

The data on the ~~hydraulic properties of the soil~~ soil hydraulic properties needed in DayCent (volumetric soil water content at field capacity, wilting point, and saturated hydraulic conductivity K_s) were calculated based on the soil texture measured at each site. ~~We tested two pedotransfer functions to see which one provided a better fit: (1) the widely applied function of Saxton and Rawls (2006) and (2) the function of Hodnett and Tomasella (2002) , which~~ The pedotransfer functions of Hodnett and Tomasella (2002) was used, because it was specifically designed for tropical soils. ~~Within the Hodnett and Tomasella (2002) equation~~Its' soil hydraulic properties also showed better agreement between the measured and simulated soil moisture contents than when soil hydraulic properties of Saxton and Rawls (2006) were used. Because the Hodnett and Tomasella (2002) equation does not provide a method to estimate K_s, K_s was calculated using the Saxton and Rawls (2006) equation, with values of the water retention curve, α and n (van Genuchten, 1982), taken ~~from Hodnett and Tomasella (2002), because their equation does not provide a way to estimate K_s. In initial test simulations, we compared the observed versus soil moisture contents in the top 15 cm, for which continuous measurements were available from Sidada and Aludeka from 2018 to 2020. In this comparison, the pedotransfer functions of Hodnett and Tomasella (2002)showed better agreement between the measured and simulated soil moisture contents than Saxton and Rawls (2006) and were consequently used in the application of the model at the four LTE sites~~calculated with the equation from Hodnett and Tomasella (2002).

2.3.2 Initial model parameterization and selection of potentially sensitive parameters for calibration

To parameterize the organic inputs, the mean lignin content and C/N ratio of the different organic materials across sites (Table A2) were used. This ~~was justified~~ approach was used because measurements were not available for all sites and years~~and because~~ , and was justified as an analysis of variance of data from the years 2002, 2003, 2004, 2005 and 2006 ~~for~~ at Embu and Machanga~~and from the year~~ , and from 2018 ~~for all sites~~at all sites, did not indicate any significant differences in lignin contents and C/N ratios between the sites or years. The C content ~~in~~ of maize grain was assumed to be 42.5% throughout the simulation period. This was the mean value of measured grain C content across sites (standard deviation 1.8%) ~~, which were available from~~ in the short rainy season 2018 and long rainy season 2019 (data not shown). Given the strong correlation between maize grain yield and aboveground biomass (r = 0.87), the aboveground biomass data was transformed to harvest index data for the model calibration process, because harvest index had a lower correlation with yield (r = 0.59) than aboveground biomass.

The DayCent simulations were conducted at the ~~site scale using averaged~~ treatment scale using average values across all three replicate plots for soil ~~texture and~~ parameters (i.e., soil texture, bulk density, pH), SOC and soil N stocks, maize grain yield and aboveground biomass~~. This~~ /harvest index. This aggregation was done to reduce the computation time of the ~~sensitivity analysis and calibration. Additionally, initial tests with the default DayCent parameterization showed that~~ simulations and because initial tests showed similar model performance as compared to applying the model to each experimental replicate individually~~did not lead to better agreement between measured and simulated values than a single simulation of the average soil parameters of the three replicates. Therefore, final model simulations were conducted with averaged values for soil parameters (i.e., texture, bulk density, soil pH) across the three replicates per site. For data used in model calibration and evaluation, the~~ . The site-specific ~~variance~~ standard deviation for each type of measurement was used as a measure of uncertainty of the measured data (~~specifically, the median variance per site and measurement type~~ computed from the three replicates ~~from~~ at each time point ~~of each treatment). Site-specific variances were used because a statistical analysis of the data in earlier work had shown that variance heterogeneity existed only between sites~~ , for each treatment at each site). This choice was based on the statistical models of Laub et al. (2023a, b), showing variance heterogeneity between sites but not between treatments~~at the same site (Laub et al., 2022a, 2023b)~~.

The standard parameter values of the DayCent 2020 version were taken as initial model parameters~~. The exceptionswere the decomposition parameters~~ , with three exceptions. First, we used the adjusted decomposition parameter values of the SOM pools ~~. For these, we used updated estimates from a recent Bayesian calibration (Gurung et al., 2020) that included data from most of the well-known long-term experiments in Europe and the US (and textures from 15-50% clay). To our~~

~~knowledge Gurung et al. (2020) provide the most up-to-date decomposition parameters, and hence, we assigned the median of reported parameter values for each SOM pool as initial parameter values in our model simulations. Furthermore~~from Gurung et al. (2020) to allow the use of DayCent for simulating SOC stocks of the 0-30 cm soil depth layer instead of the standard 0-20 cm layer. Second, we modified the parameter value representing the fraction lost as CO_2 upon structural litter and lignin turnover (ps1co(1&2)&rsplig). The default value for this parameter is 0.5 assigning a carbon use efficiency (CUE) value of 50% to structural litter, based on outdated theories that lignin-rich materials form stable SOC most efficiently (Frimmel and Christman, 1988). Newer studies have, however, clearly shown that minimal structural litter is conserved in the long term, while metabolic litter forms SOC more efficiently (Cotrufo et al., 2013; Denef et al., 2009; Puttaso et al., 2013; Kallenbach et al. . Thus, we opted for a more realistic prior value of 0.85 for ps1co(1&2)&rsplig, corresponding to a more plausible CUE value of 15% for structural litter (Mueller et al., 1997). Third, for the parameters determining the minimum and maximum proportion of nitrified N lost as N_2O, we used ~~the most~~ values that fell between the DayCent default values and recent values from Gurung et al. (2021)~~, who showed that older parameters overestimate N_2O emissions.~~ . This choice was motivated by the fact that the DayCent default parameter values led to excessively high emissions, while the Gurung et al. (2021) parameter values resulted in emissions that were too low. Finally, we assumed that the maize growth parameters of the second highest production level (C5 in DayCent) represent best the production levels observed in the experiment.

To identify which model parameters to include in the global sensitivity analysis (see section 2.4) and ~~in the~~ model calibration, we ~~screened the~~ reviewed literature for recently conducted sensitivity analyzes of the DayCent model (Necpálová et al., 2015; Gurung et al., 2020)~~and additionally used~~ . Additionally, we consulted the DayCent manual to identify and add further parameters of potential importance for the processes considered in our study (i.e., plant productivity and soil C and N ~~cycle).~~ cycling). This resulted in a selection of 66 parameters (Table 1 and Table A3). Some of these parameters ~~represented groups of the same type of parameters that can each~~ belong to the same category, but can be individually calibrated in DayCent~~, e. g.~~. For example, the "tillage multiplier" of SOM turnover can have different values for different SOM pools ~~. However, because the tillage multipliers are~~ but is usually the same for all SOM pools in the standard DayCent parameterization. Thus, we decided to have the same tillage multiplier value for ~~active, slow,~~ all SOM and litter pools. ~~In addition, some of the~~ Some parameters can have different values between the ~~SOM pools of the~~ surface and soil ~~(for example~~SOM pools (e.g., C/N ratios and turnover rates). For simplicity, we ~~decided to assign~~ assigned the same C/N ratios and a constant ratio to the turnover rates of surface and soil SOM pools ~~. Because the turnover rates of the SOM pools are typically faster on the surface than in the soil, we defined a new parameter that represents the value ratio of the surface to the soil parameters~~ (i.e., decX(2)/decX(1)). This ~~allowed us to jointly evaluate the sensitivity and calibrate parameters related~~ simplified parameter sensitivity analysis and calibration with regard to surface and soil SOM pools~~without adding too much complexity~~. Finally, the parameters ~~for~~ governing the minimum and maximum values ~~of nitrification and loss of nitrified N as N_2O, were reformulatedas maximum and the~~ were reformulated. Instead of calibrating them as a maximum and a minimum value, we considered the maximum value and the difference between the minimum and maximum ~~parameters~~ values (i.e., N2Oadjust_(max-min) and aneref(1)-anaref(2)). This ~~was done to ensure that the maximum was always higher than the minimum valuein order to avoid numerical problems~~ensured that the minimum value was smaller than the maximum value, thereby avoiding numerical problems(initial N2Oadjust_max was set to 0.015; N2Oadjust_(max-min) to 0.003).

2.3.3 ~~Spin-up and site history simulation to initialize SOC and soil N contents~~Soil organic matter pools initialization based on measured data

~~As is standard practice in DayCent, the initialization of SOM pools was conducted through a~~ Instead of relying on spin-up ~~run, which was followed by a simulation of the history of the site before experiment establishment based on~~ simulation based on uncertain historical land use and management of the simulated sites, we used measured mineral associated organic carbon (MAOC) fractions as a proxy for the initialization of the ~~knowledge of site managers. The spin-up has the aim to initialize the SOM pools to equilibrium using the typical input of biomass of the native vegetation type. The type of native vegetation for each site was determined from an available potential vegetation map (Kamoni et al., 2007) and confirmed by site managers as tropical evergreen forest in Embu, dry savanna in~~ passive SOM pool (Zimmermann et al., 2007). Replacing SOM initialization assumptions with measured proxies can enhance model performance (Laub et al., 2020; Wang et al., 2023) , and, more importantly, is less sensitive to user assumptions. It also aligns with the DayCent concepts on SOM; the manual (Hartman et al., 2020) denotes that particulate organic carbon (POC) and MAOC are related to the slow and the passive SOM pool, respectively. MAOC data for samples from the 0-30 cm soil layer was available from the year 2021 (specifically for the control -N, control +N and the farmyard manure -N and *Tithonia diversifolio* -N treatments at 4 t C ha^{-1} yr^{-1} at all sites). It was derived by density fractionation using sodium polytungstate solution (1.6 g cm^{-3} for Aludeka and 1.7 g cm^{-3} for the other sites). Aggregates were dispersed with ultrasonication at 400 J ml^{-1} (217 s at 200-240W), after which samples were centrifuged for 2h at 4700 rpm to separate the heavy and the light fraction, which were then separated, washed with deionised water, dried at 60°C for 24h and analyzed for weight and C content. A statistical analysis revealed the absence of treatments differences within the same site, so the site-specific MAOC values for the 0-30 cm soil depth across treatments (0.91, 0.88, 0.85, 0.86 g MAOC g^{-1} SOC for Aludeka, Embu, Machanga, and ~~humid savanna in Sidada and Aludeka. A 2000-year spin-up simulation was sufficient to reach a steady state of SOM pools. Site managers had a good knowledge of the type of historical cropping systems, e. g., arable vs. grasslands, types of crop rotation (e.g., maize monoculture vs. crop rotation with legumes) , manure inputs and management, but without detailed information on the duration of these systems. Therefore, the duration of cropping systems after native vegetation was adjusted at each site so that~~ Sidada in 0-30 cm, respectively) were used to initialize the SOC in the passive SOM pool in DayCent simulations. Further, 3% of initial SOC was assigned to the active SOM pool (mean value recommended in the DayCent manual) and the remainder of SOC was assigned to the slow SOM pool.

The DayCent manual further states that, although the slow SOM pool is closely related to the POC fraction, it tends to be larger (Hartman et al., 2020). Consequently, the passive SOM pool must be smaller than the MAOC fraction. Additionally, the fractionation data was from 2021, when the experiments were already 19 and 16 years old. To address these issues, two new parameters were introduced in the simulations: 1) an intercept (IC_{MAOC}) to account for the passive SOM pool being smaller than the MAOC fraction, and 2) a slope for the time since the start of the experiment (SL_t) to account for SOM changes (mostly losses) since the start of the experiments, with the passive SOM pool typically changing at the slowest rate.

Given that all sites were converted to agriculture only a few decades ago (Laub et al., 2023a), the percentage of total C in the passive SOM pool at the start of the experiment should be higher than the 30-40 %, that are common at steady state of SOM pools (Hartman et al., 2020). Considering this, it was assumed that the intercepts initial value was -0.1 g MAOC g^{-1} SOC and the slopes initial value value was -0.005 g MAOC g^{-1} SOC yr^{-1} since the ~~measured initial SOC stocks corresponded to the simulated SOC stocks at the~~ start of the experiment~~. Additionally, to achieve suitable levels of soil N stocks after the spin-up, the maximum C/N ratio of~~ , giving both terms approximately the same weight. Thus, the fraction of SOC in the passive SOM pool at the start of the experiment was

$$SOC_p(g\,g^{-1}) = MAOC_{2021} + IC_{MAOC} + SL_t * t_{dif} \tag{1}$$

Here, SOC_p represents the fraction of SOC in the ~~SOM pools had to be increased. It was increased from 14 to 20 for the active SOM pool and from 8 to 13 for the~~ passive SOM pool ~~(parameters varat12&11(1, 1)and varat3(1~~at the start of the experiment, $MAOC_{2021}$ the MAOC fraction in 2021 (g MAOC g^{-1} SOC), IC_{MAOC} the intercept, and SL_t the slope value that is multiplied by the time difference between the measurement and the start of the experiment in years (t_{dif}). With the selected standard values for IC_{MAOC} and SL_t, between 66% (Machanga) and 73% (Aludeka) of SOC were assumed to be in the passive SOM pool at the start of the experiment. The uncertainty related to this initialization approach was accounted for in the model calibration by allowing large ranges for these parameters. Finally, to initialize the soil N pools, C/N ratios of the active, slow, and passive SOM pools were set to 10, ~~1), respectively). Due to computational time constraints and to ensure a match between simulated and observed initial SOC and soil N levels, the spin-up and site history simulations were not included in the sensitivity analysis and Bayesian calibration~~17.5, and 8.5, respectively, which are the best estimates provided by the manual (Hartman et al., 2020)
.

2.4 Global sensitivity analysis

To reduce the ~~dimensionality of the calibration of the model~~number of optimised parameters during the calibration, we performed a parameter screening (van Oijen, 2020). For this purpose, a global sensitivity analysis was conducted to quantify the relative importance of different model parameters to the relevant model outputs regarding our study's focus on maize yield and ~~ISFM~~ the greenhouse gas mitigation potential ~~. The goal was to~~ of ISFM. The aim was to identify and fix less influential model parameters to their ~~default~~ initial values, reducing the computational cost for performing the consecutive Bayesian model calibration (see section 2.5). ~~Global~~ The global sensitivity analysis was performed using the Sobol method (Saltelli, 2002a, b), which allows for the estimation of the proportion of variance in the model outputs that is explained by each model parameter, while considering the interaction terms of first-order and higher-order (Gurung et al., 2020). The "sensitivity" package (function sobolSalt; Iooss et al., 2021) of R version 4.0 (R Core Team, 2020) was applied. This function implements a simultaneous Monte Carlo estimation of first-order and total-effect Sobol indices. The computational cost is $N(p+2)$ model runs, N being the dimension of the two matrices to construct the Sobol sequence, p being the number of parameters (66 in our case). Our tests indicated similar results for N = 500/1000, so we chose a dimension of 1000. The ~~preselection of~~ preselected model parameters to include ~~(~~are described above and in Tables 1 and A3~~) is described above~~. Independent uniform prior distributions were used for the global sensitivity analysis, with the upper and lower parameter boundaries centered around the ~~default~~ initial parameter value obtained as described ~~below~~above (section 2.3.2). We based the global sensitivity analysis parameter ranges on previous sensitivity analyses (e.g. Necpálová et al., 2015; Gurung et al., 2020), ~~on~~ plausible ranges reported in the DayCent manual and ~~on how the parameters varied between~~ variations observed in different maize parameterizations in the literature. The parameters were then grouped ~~by how large the ranges were. The parameters that had~~ according to the magnitude of their ranges. Parameters with very small, small and moderate ranges were varied by ± 10, 25 and 50% from the ~~default~~ initial parameter value, respectively. For parameters with large and very large ranges, the upper/lower boundaries were the ~~default~~ initial parameter values multiplied/divided by 3 and 10, respectively. ~~Additionally, we assumed that the maize parameters of the second highest production level (C5 in DayCent) would best represent the production levels in the experiment.~~ The parameter sensitivity was independently determined for the mean maize grain yield ~~,~~ and aboveground biomass, averaged over all seasons at all sites, as well as for the SOC and soil N stocks at the end of the simulation period.

2.5 ~~Combined Bayesian calibration of plant and soil model parameters~~

~~Joint Bayesian calibration of the sensitive DayCent parameters was performed using all available data on maize grain yield, aboveground biomass,and SOC stocks. The main reason for only using these data was that the yields, SOC stocks, and their trade-offs were the focus of this study. A second, technical reason, was that the creation and readout of daily simulations outputs, needed to match simulated and measured soil moisture content, mineral N content and~~

2.5 Combined Bayesian calibration of plant and soil model parameters

Bayesian calibration is a probabilistic inverse modeling ~~/~~or data assimilation technique, which is used to estimate the joint posterior distribution of model parameters (θ) given the measured data (D) and the model structure (M), expressed as $p(\theta|D,M)$. It uses the proportionality form of Bayes‘ theorem, where $p(\theta|D,M)$ is proportional to the prior belief about model parameters, $p(\theta)$ times the likelihood function ~~, $p(D,M|\theta)$:~~ of the data given the model and the parameters, $p(D|M,\theta)$:

$$p(\theta|D,M) \propto p(\theta) * p(D\cancel{,M}|M,\theta) \tag{2}$$

While the prior, $p(\theta)$, is chosen based on previous knowledge of the model parameters, the likelihood function, ~~$p(D,M|\theta)$~~$p(D|M,\theta)$, measures how well the model and the data match. In practice it is derived for a given set of ~~parameter~~ parameters sampled from the prior, by running and evaluating the model using the measured data, the simulated counterpart and the variance-covariance matrix of the ~~data. We used the median variances per site for each type of measurement (computed from the three replicates) as the diagonal elements of the variance-covariance matrix. Due to the large number of observations and the mostly balanced dataset, the off-diagonal elements were set to 0.~~ model residuals. Following Gurung et al. (2020), we applied the R software (R Core Team, 2020) to create a mixed model with restricted maximum likelihood estimation with the lme4 package

Table 1. DayCent model parameters and the coefficient of variation used in the calibration. Displayed are parameters considered for calibration due to total sensitivity index > 2.5% (top) and with a total sensitivity index > 1% (bottom). The remainder of parameters (<1%) can be found in the supplementary (Table A3).

Parameter	Description	Possible ranges of values	Units
Included in calibration (total sensitivity >2.5%)			
himax	Maximum harvest index for maize	moderate	g g^{-1} (C)
ppdf(1)	Optimum temperature for growth of maize	very small	°C
ppdf(2)	Maximum temperature for growth of maize	very small	°C
prdx(1)	Potential aboveground production of maize	large	g C m^{-2} $langley^{-1}$
clteff(1,2&4)	Tillage multiplier for SOM turnover	large	unitless
aneref(3)	Min. impact of soil anaerobiosis on SOM turnover	large	unitless
dec4	Max. turnover rate of passive SOM pool	very large	g g^{-1} yr^{-1}
dec5(2)	Max. turnover rate of slow SOM pool	large	g g^{-1} yr^{-1}
fwloss(4)	Scaling factor potential evapotranspiration	moderate	unitless
pmco2(1&2)	C lost as CO_2 with metabolic litter turnover*	large	g g^{-1} (C)
ps1co2(1&2) & rsplig	C lost as CO_2 with structural litter turnover*	large	g g^{-1} (C)
IC_{MAOC}	Intercept to derive fraction in slow pool from MAOC	very large	g g^{-1} (C)
SL_t	Slope for time difference of MAOC measurement	very large	g g^{-1} yr^{-1} (C)
Not included in calibration (total sensitivity <2.5% & > 1%)			
frtc(1)	C allocated to roots at planting, without stress	small	fraction of NPP
frtc(3)	Time after planting at which maturity is reached	small	number of days
pramn(1,2)	Min. aboveground C/N ratio at maturity	small	C/N ratio
hiwsf	Max. harvest index reduction with water stress	moderate	g g^{-1} (C)
teff(1)	Temperature inflection point (effect on SOM turnover)	moderate	unitless
varat21&22(2,1)	Min. C/N ratio for material entering slow SOM pool	small	C/N
basef	Soil water of bottom layer lost via base flow	moderate	fraction H_2~~O fluxes, slowed down the whole calibration by a fact~~
N2Oadjust_max	Proportion of nitrified N that is lost as N_2O	large	g g^{-1} (N)
MaxNitAmt	Maximum daily nitrification amount	large	g N m^{-2}

*(1 - microbial carbon use efficiency); +highest likelihood parameter set across all four sites

(Bates et al., 2015), which automatically constructed the variance covariance matrix based on the nested design of observations to account for autocorrelation of residuals. The likelihood was a function of the following form:

$$p(D|M,\theta_z) = \frac{1}{\sqrt{2\pi\Sigma}} \exp\left(-\frac{1}{2}(M(\theta_z) - D)^T \Sigma^{-1} (M(\theta_z) - D)\right) \quad (3)$$

420 Here, Σ is the variance covariance matrix, $M(\theta_z)$ is the vector of simulated values using the z-th parameter set θ_z and D the vector of observed data. In the R software, this can be constructed by setting the residual (modelled value - measured) as the dependent variable of a zero intercept model with nested random effects (i.e., sampling date within site), and assigning the

inverse of the median standard deviation (of each type of measurement at each site) as weight. The logLik() function is then used to extract the log-likelihood, which is transformed to the likelihood by raising e to the power of the log-likelihood.

The sampling importance resampling method, which was used in this study, is a direct form of Bayesian calibration, which has recently been used by Gurung et al. (2020), to calibrate the parameters of the SOM module of DayCent using a large collection of temperate long-term experiments. It samples the prior by running the model for a large sample of parameter sets of size I from the prior, computing the likelihood for each sample, and filtering the prior based on importance weights $w(\theta_z)$

$$w(\theta_z) = \frac{p(D,M|\theta_z)}{\sum_{i=1}^{I} p(D,M|\theta_i)} \frac{p(D|M,\theta_z)}{\sum_{i=1}^{I} p(D|M,\theta_z)} \tag{4}$$

where ~~$p(D,M|\theta_z)$~~ $p(D|M,\theta_z)$ is the likelihood function of the zth parameter set and $w(\theta_z)$ is the corresponding importance weight. It is consistent with the proportionality form of Bayes' theorem in that it uses the importance weights $w(\theta_z)$ as probabilities for sampling from the prior, without replacement, to derive the posterior.

Combined Bayesian calibration of the sensitive DayCent parameters was performed using all available data on maize grain yield, harvest index (calculated from aboveground biomass), and SOC stocks. A notable exception was that SOC stocks from the Machanga site were not used in the calibration process, because this site was severely affected by soil erosion (Laub et al., 2023a) that is not represented by DayCent. The main reason for only using grain yield, harvest index and SOC data was that the yields, SOC stocks, and their trade-offs were the focus of this study. Technical constraints also influenced the decision; the creation and readout of daily simulation outputs to match simulated and measured soil moisture content, mineral N content and N_2O fluxes would slow down the whole Bayesian calibration process by a factor of 5. The Bayesian calibration would have taken more than three months on the virtual machine with 64 cores. Following Gurung et al. (2020) , model parameters that had a total sensitivity index of at least 2.5% for either yield, aboveground biomass, or SOC were considered influential and thus were subjected to calibration (11 parameters). Additionally, the new parameters associated with the initialization, IC_{MAOC} and SL_t had to be calibrated, resulting in a total of 13 parameters for calibration (Table 1).

Overall, a total of 200000 simulations were performed, from which ~~, as in~~ 0.1% (200) of the parameter sets were sampled to derive the posterior distribution through resampling (Gurung et al., 2020). It was assured that this number of simulations was sufficient by splitting the simulations into two halves and visually assessing the similarity of derived posteriors for these subsets. In our experience, the sampling importance resampling algorithm is ~~ideal~~ highly suitable for DayCent, ~~which~~ that is prone to ~~model crash when using~~ crashing with inappropriate parameter combinations. ~~This method does not depend on chains, but rather on~~ Unlike chain-dependent methods such as Markov Chain Monte Carlo, this method relies on model runs that are independent of each other~~. This means~~ , ensuring that an erroneous run does not stop the algorithm~~, as would be the case in chain-dependent methods such as Markov chain Monte Carlo~~. In addition, this ~~strategy~~ method allows for an efficient cross-validation of the posterior parameter set~~.~~

~~To evaluate the model by comparing measured vs. modeled data, we conducted a~~ , such as the leave-one-site-out cross-validation ~~. This means that each of the sites is left out one by one for an independent evaluation, while the other three sites were used to compute the resampling weights and derive the posterior parameter distributions. Hence, the evaluation~~

~~is representative of up-scaling exercises of the DayCent model to other sites, because it involves evaluation of the model performance across different sites. Here, the SIR algorithm was also advantageous. We stored the model~~ employed in this study. Notably, the sampling importance resampling algorithm's advantage lies in its ability to store model results for each parameter set by site, ~~which meant that the~~ allowing for straightforward cross-evaluation ~~could be done by a simple filter by~~ by site, without the need for rerunning the model for each iteration. ~~In contrast to model~~ The posterior parameter distributions of this study are displayed for both the leave-one-site-out cross-validation ~~, the parameter posterior distributions are not displayed by site. They are displayed for all four combined sites ; hence the full dataset without leaving any site out was used to derive them. This was done to present the~~ and the combined dataset from all four sites (Fig. 2). The former shows the importance of individual sites in the calibration process, while the latter provides the most representative posterior ~~distributions and to make~~ distribution for model upscaling, making efficient use of all available data.

To ensure computational efficiency, we used informed Gaussian priors that were centered around the standard parameter values of DayCent, with coefficients of variation of 0.05, 0.1, 0.15, 0.25 and 0.3 for parameters with very small, small, moderate, large and very large ranges (Table 1). For the newly introduced parameters, we used larger coefficients of variation, namely 1 for IC_{MAOC} and 0.35 for SL_{t}.Additionally, all parameters were constrained to remain within their physically sensible limits (i.e., not <0 for all and not >1 for those representing fractions).

2.6 Model evaluation

We used the following standard model evaluation statistics (Loague and Green, 1991):

$$MSE_y = \frac{1}{n}\sum_{z=1}^{n}(O_{yz} - P_{yz})^2 \tag{5}$$

$$RMSE_y = \sqrt{MSE_y} \tag{6}$$

$$EF_y = 1 - \frac{\sum_{z=1}^{n}(O_{yz} - P_{yz})^2}{\sum_{z=1}^{n}(O_{yz} - \bar{O}_y)^2} \tag{7}$$

~~Here,~~ The MSE_y is the mean-squared-error and $RMSE$ is its root. EF_y is the Nash-Sutcliffe modeling efficiency. ~~O_{yz} is the measured value of the *z-th* measurement of the *y-th* type of measurement, $\bar{O}_y$ the mean of the *y-th* type of measurement and P_{yz} the simulated value corresponding to O_{yz}.~~ We further divided MSE_y into squared bias (*SB*), nonunity slope (*NU*) and lack of correlation (*LC*), as suggested by Gauch et al. (2003). We expressed them as a percentage of the MSE_y:

$$SB_y(\%) = \frac{(\bar{O}_y - \bar{P}_y)^2}{MSE_y} * 100 \tag{8}$$

$$NU_y(\%) = \frac{(1-b_y)^2 * (\frac{\sum_{z=1}^{n}(O_{yz}^2)}{n})}{MSE_y} * 100 \tag{9}$$

$$LC_y(\%) = \frac{(1-r_y)^2 * (\frac{\sum_{z=1}^{n}(P_{yz}^2)}{n})}{MSE_y} * 100 \tag{10}$$

Here, O_{yz} is the measured value of the *z-th* measurement of the *y-th* type of measurement, $\bar{O}_y$ the mean of the *y-th* type of measurement and P_{yz} the simulated value corresponding to O_{yz}. $\bar{P}_y$ is the mean predicted value of the *y-th* measurement type, *b* the slope of the regression of *P* on *O* and *r* the correlation coefficient between *O* and *P*. The indicators *LC*, *SB* and *NU* show the nature of model errors, that is, a high *LC* shows that it is mostly random, a high *SB* a systematic bias, while a high *NU* shows issues of model sensitivity.

2.7 ~~Net global warming potential~~Greenhouse gas balance

To compare different ISFM treatments in terms of their greenhouse gas (GHG) emissions, their net ~~global warming potential (GWP)~~ GHG balance was computed on a yearly basis (kg CO_2eq ha^{-1} yr^{-1}) ~~was derived from the outputs~~ over the whole simulation period. ~~It was calculated from~~ This calculation was based changes in the SOC content and cumulative emissions of N_2O using a 100-year time horizon of global warming potentials (Necpalova et al., 2018):

$$\cancel{GWP}GHGbalance = \frac{44}{12} * \Delta SOC + 265 * N_2O \tag{11}$$

Here, ΔSOC is the change in SOC content (kg C ha^{-1} yr^{-1}), N_2O the cumulative N_2O flux (kg N_2O ha^{-1} yr^{-1}). The CH_4 oxidation capacity was not considered, because it usually makes a very limited contribution to ~~GWP in rainfed maize cropping systems~~ GHG balance in rainfed cropping systems (Lee et al., 2020) and we did not have data to evaluate the reliability of this simulated flux. In addition to ~~GWP we calculated~~ the net annual GHG balance, we calculated the yield-scaled ~~GWP~~ GHG balance (in CO_2eq kg^{-1} maize grain yield) by dividing the cumulative ~~GWP~~ GHG balance over the entire simulation period by cumulative simulated yields (dry matter base).

3 Results

3.1 Most sensitive DayCent parameters

The results of the global sensitivity analysis showed that of the 66 model parameters ~~included~~analyzed, only 20 parameters had a Sobol total sensitivity index >1% for either maize grain yield, aboveground biomass, SOC or soil N stocks (Fig. 1). Of these, only 11 parameters had a Sobol total sensitivity index >2.5%, a threshold that captures the most influential parameters and represents a suitable selection of parameters for model calibration (Gurung et al., 2020). The parameters that turned out

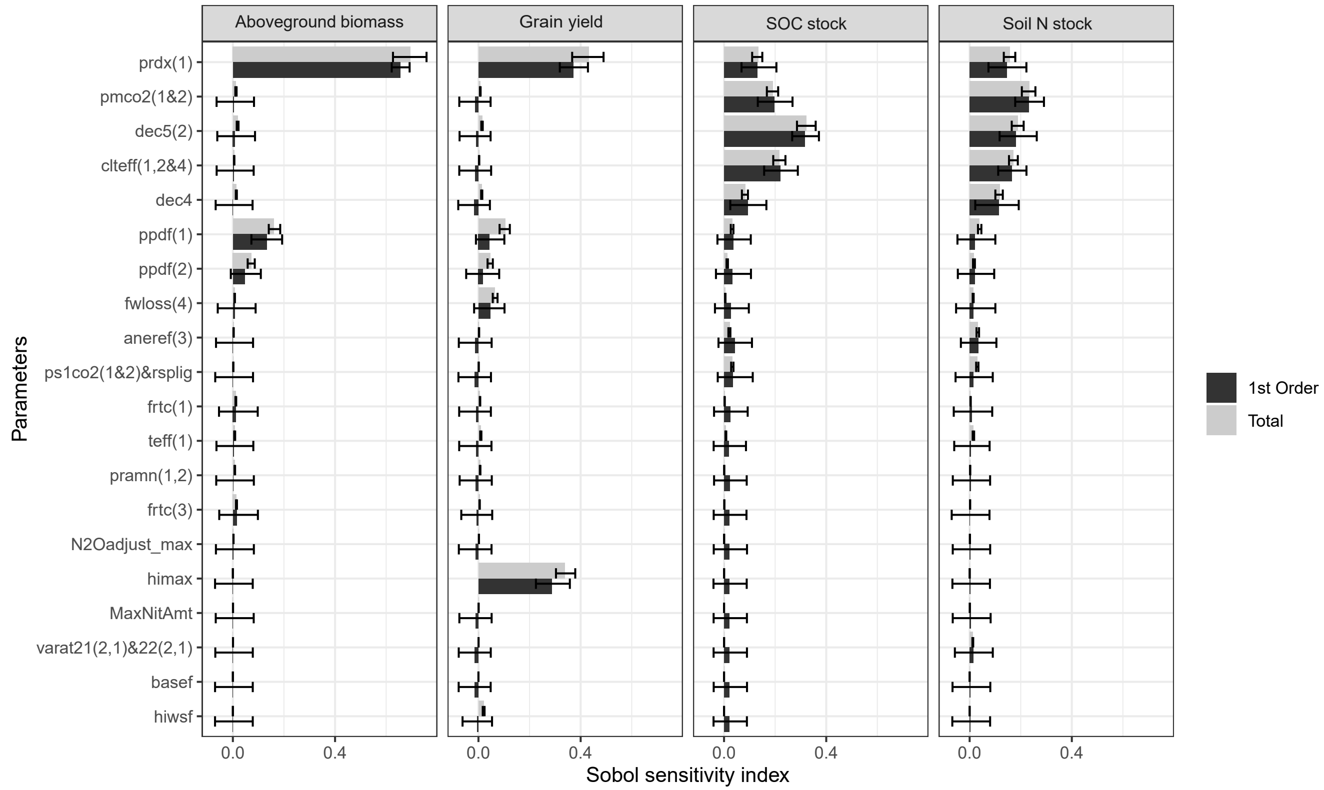

Figure 1. Results of the ~~uncertainty-based~~ global sensitivity analysis of the most relevant DayCent model parameters. Parameter sensitivity was independently determined for the mean maize aboveground biomass, grain yield, and SOC and soil N stocks at the end of the simulation period. Only parameters with a Sobol sensitivity index >1% are displayed.

to be the most sensitive, with a Sobol total sensitivity index >10% for at least one type of measurement, were radiation use efficiency (prdx(1); for all measurement types); the optimal and maximum temperature for maize growth (ppdf(1) and ppdf(2), respectively; only for grain yield ~~of maize~~ and aboveground biomass), and maximum harvest index (himax; only for ~~crop~~ grain yield). Further, the turnover rate of the slow and passive SOM pools (dec5(2) and dec4, respectively; only for SOC and soil N), the decomposition multiplier ~~after tillage events~~ for soil tillage (clteff(1,2&4); only for SOC and soil N) and the fraction lost as CO_2 ~~upon~~ of the metabolic litter pool ~~turnover~~ (pmco2(1&2), i.e., 1 - ~~microbial carbon use efficiency (~~CUE); only for SOC and soil N) belonged to the most sensitive model parameters. The parameters of further importance, with a Sobol total sensitivity index ~~<10% and~~ >2.5% and <10%, were the minimum value for the impact factor of anaerobic soil conditions (aneref(3); only for SOC and soil N), the scaling factor for potential evapotranspiration (fwloss(4); only for maize grain yield), and the fraction lost as CO_2 ~~upon~~ of the structural litter and lignin ~~turnover~~ pools (ps1co(1&2)&~~respligr~~splig, i.e., 1-CUE; only for SOC and soil N). The fact that the Sobol 1st order and total sensitivity indexes were similar for most parameters suggested only a limited number of interactions between the parameters identified by the global sensitivity analysis.

3.2 Posterior parameter distributions from the Bayesian model calibration

Following the global sensitivity analysis, ~~11 selected~~ 13 selected model parameters were calibrated using Gaussian priors centered around the initial parameter value, with standard deviations according to the uncertainty ranges (Table 1). The ranges of the ~~same ranges of possible values as defined for the sensitivity analysis. Four parameters were fully constrained by the Bayesian calibration, one was partly constrained and tended towards the upper boundary. Four showed a tendency, but values from the whole prior range were present in the posterior distribution. Finally, two showed almost no difference to the uniform prior distribution~~ prior- and the posterior distributions, using data from all four sites, were similar. Also the four different posterior distributions from the leave-one-site-out cross-validations were largely similar to each other (Fig. 2). ~~Very clearly constrained were the potential maximum maize production and the maximum maize harvest index (2.5~~ However, several parameters slightly shifted from their initial values to the best parameter values across all four sites. The strongest differences between the initial and calibrated values existed for the potential maximum maize productivity per radiation (prdx(1); from 2.25 to 1.85 g C m^{-2} langley^{-1} ~~for prdx(1)and 0.48 g g^{-1} for himax), with values slightly higher than the default values and somewhere in between the maize with the highest and second highest production levels (default DayCent maize parameters,named C6 and C5). Furthermore,the scaling factor for potential evapotranspiration was clearly constrained and slightly higher than the default value (fwloss(4~~), ~~0.9 vs 0.75). The~~ the parameter representing the increase of SOM turnover after tillage (clteff(1,2,&4); from 10 to 19.1). An increase of the turnover rate of the ~~slow SOM pool was also clearly constrained, but was centered around a value twice the default (0.2 vs 0.1~~ passive SOM pool (dec4; from 0.0035 to 0.0056 g g^{-1} yr^{-1} ~~for dec5(2)). The~~) was partly counterbalanced by a decrease in the turnover rate of the ~~passive SOM pool was clearly constrained at the lower end of possible values, it was centered around a much higher value than the default value (0.03 vs 0.0035 g g^{-1} yr^{-1} for dec4) and tended towards the upper boundary. A test with even broader ranges (up to 0.1~~ slow SOM pool (dec5(2); from 0.10 to 0.06 g g^{-1} yr^{-1})~~showed that the value around 0.03 g g^{-1} yr^{-1} was in fact the center of the posterior distribution of this parameter (Fig. **??**), but allowing the parameters to vary that much reduced the model performance to unfeasible levels (model output not shown). The optimal production temperature for maize (ppdf(1)) tended to have values lower than the default value, while the opposite was true for the maximum production temperature (ppdf(2)). Also the parameters representing CO_2 loss upon turnover of metabolic and structural litter pools~~. Furthermore the loss of carbon from the metabolic litter pool upon decomposition was significantly increased (pmco2(1&2)~~and ps1co2(1&2)&rsplig) tended towards higher values than the default values of these parameters (i. e., lower carbon use efficiencies, because the parameters represent 1-CUE), but they were not clearly constrained. Finally, the parameters representing the increase of the SOM pools turnover after tillage (clteff(1, 2,&4)) and the maximum rate limitation of soil under anaerobic conditions (aneref(3)), were poorly constrained.~~

~~Only a few strong correlations existed between the parameters of the~~ ; from 0.54 to 0.82 g g^{-1}). The two parameters that translated measured MAOC into SOC in the passive SOM pool were altered in opposite directions (IC_{MAOC}, from -0.1 to -0.21 g g^{-1}; and SL_t, from -0.005 to -0.0024 g g^{-1} yr^{-1}). Overall, the parameter correlations in the posterior parameter set ~~(Fig. A3). Namely, there was a strong positive correlation (r = 0.63) between the potential maximum production of maize (prdx(1)) and the optimal temperature for maize growth (ppdf(1)), the latter also being positively correlated with the maximum temperature~~

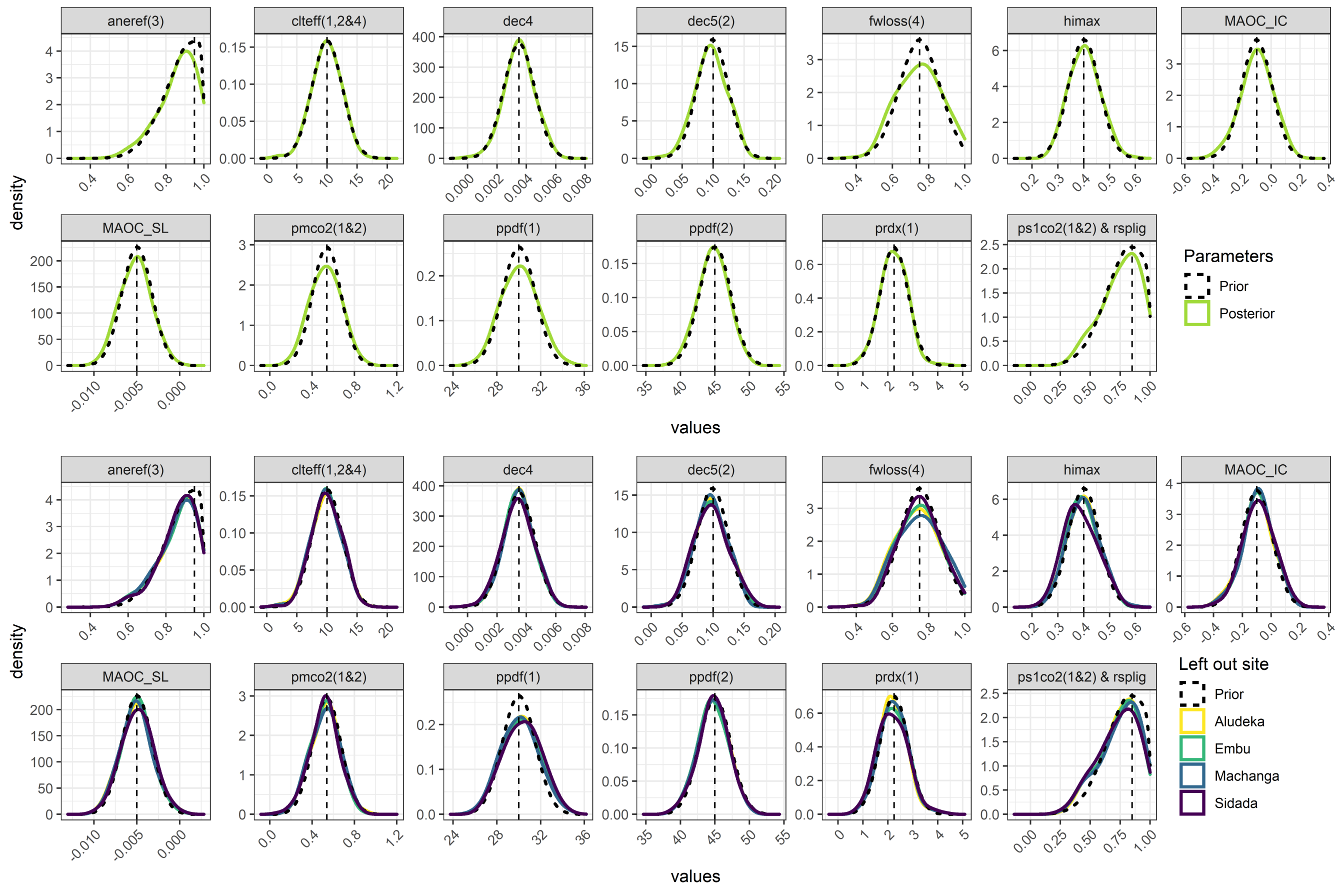

Figure 2. Prior compared to the posterior model parameter distribution resulting from the uncertainty-based Bayesian model calibration of DayCent using data from all sites combined (top) and the leave-one-site-out cross-validation (bottom). Dashed vertical lines represent the values of the ~~default~~ initially selected parameter set. The posterior distributions are based on all four study sites combined. For the description of the parameters see Table 1.

~~for maize growth (ppdf(2); r = 0.45). Furthermore, there was a negative correlation (r = -0.43) between the effect of tillage on SOM turnover and the amount of CO_2 loss upon turnover of the metabolic litter pool (pmco2(1&2)). The other correlations of the parameters were weak (i.e., below ± 0.4)and therefore were of low importance~~across the four sites were minimal, and in no case stronger than 0.2 (Fig. A3).

3.3 Simulation of maize grain yields and aboveground biomass at harvest

~~Although~~ While the overall variation of maize grain yields ~~between~~ across sites and treatments could be captured ~~with the set of default model parameters, the comparison of model results obtained with the default parameters compared to the set of parameters chosen for each site by~~ to some extent with the initial model parameter set, for two sites a negative model efficiency

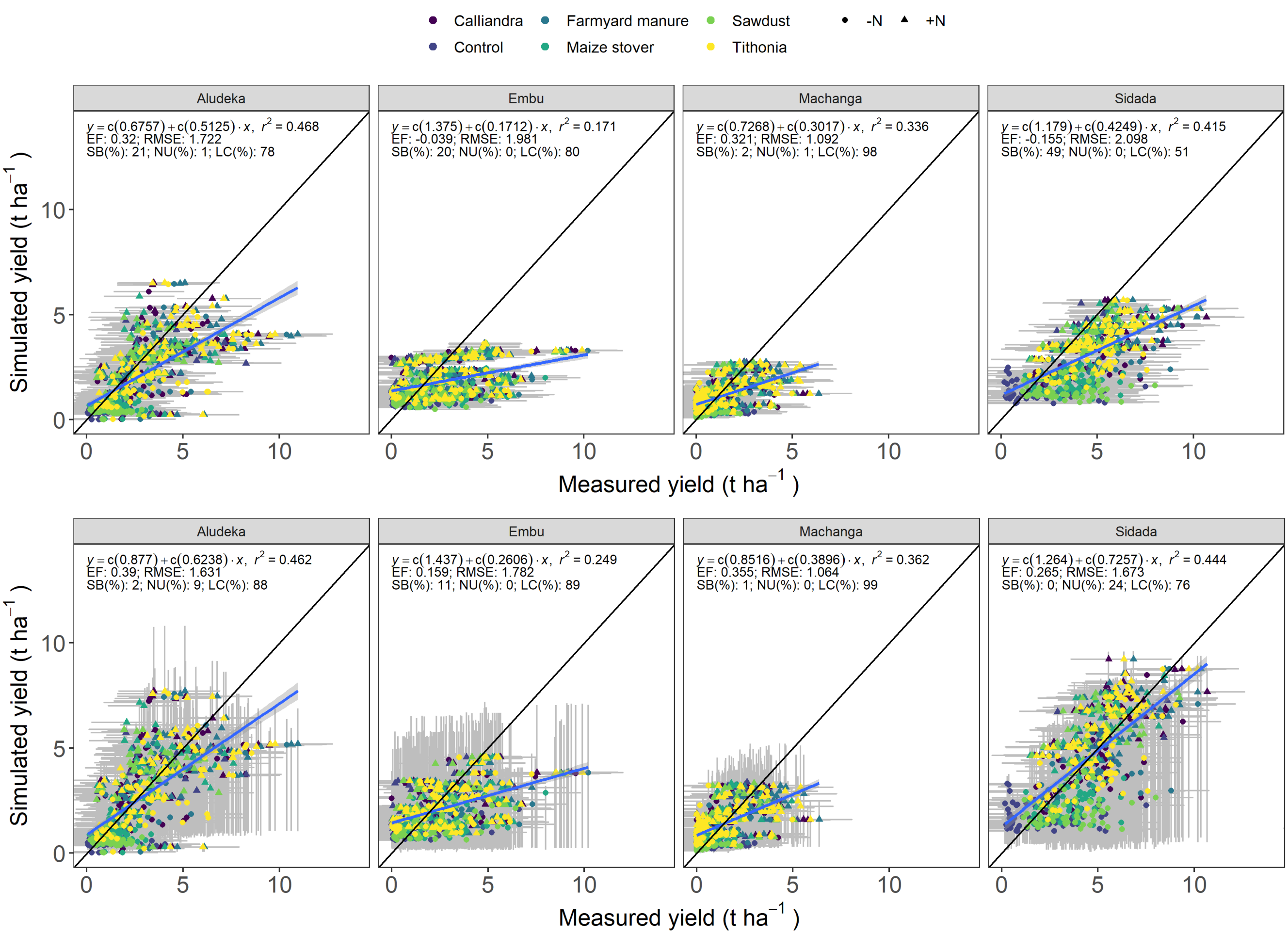

Figure 3. Simulated compared to measured maize grain yields at the four study sites for the initial DayCent parameter set (top) versus the calibrated parameter set by leave-one-site-out cross-validation (bottom). The 2985 data points correspond to the observations from the experimental treatments over 32 to 38 seasons, depending on the site. Symbols represent the different organic resource and chemical nitrogen fertilizer treatments. Grey bands show the 95% confidence intervals of measured (horizontal) values and the 95% credibility intervals of posterior distribution (vertical). Abbreviations: EF, Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics: EF, 0.358; RSME, 1.757 t ha^{-1}; SB, 21%; NU, 1%; LC, 77% before and EF, 0.495; RSME, 1.558 t ha^{-1}; SB, 2%; NU, 5%; LC, 93% after calibration, with 54% of measurements being in the 95% credibility interval of the posterior.

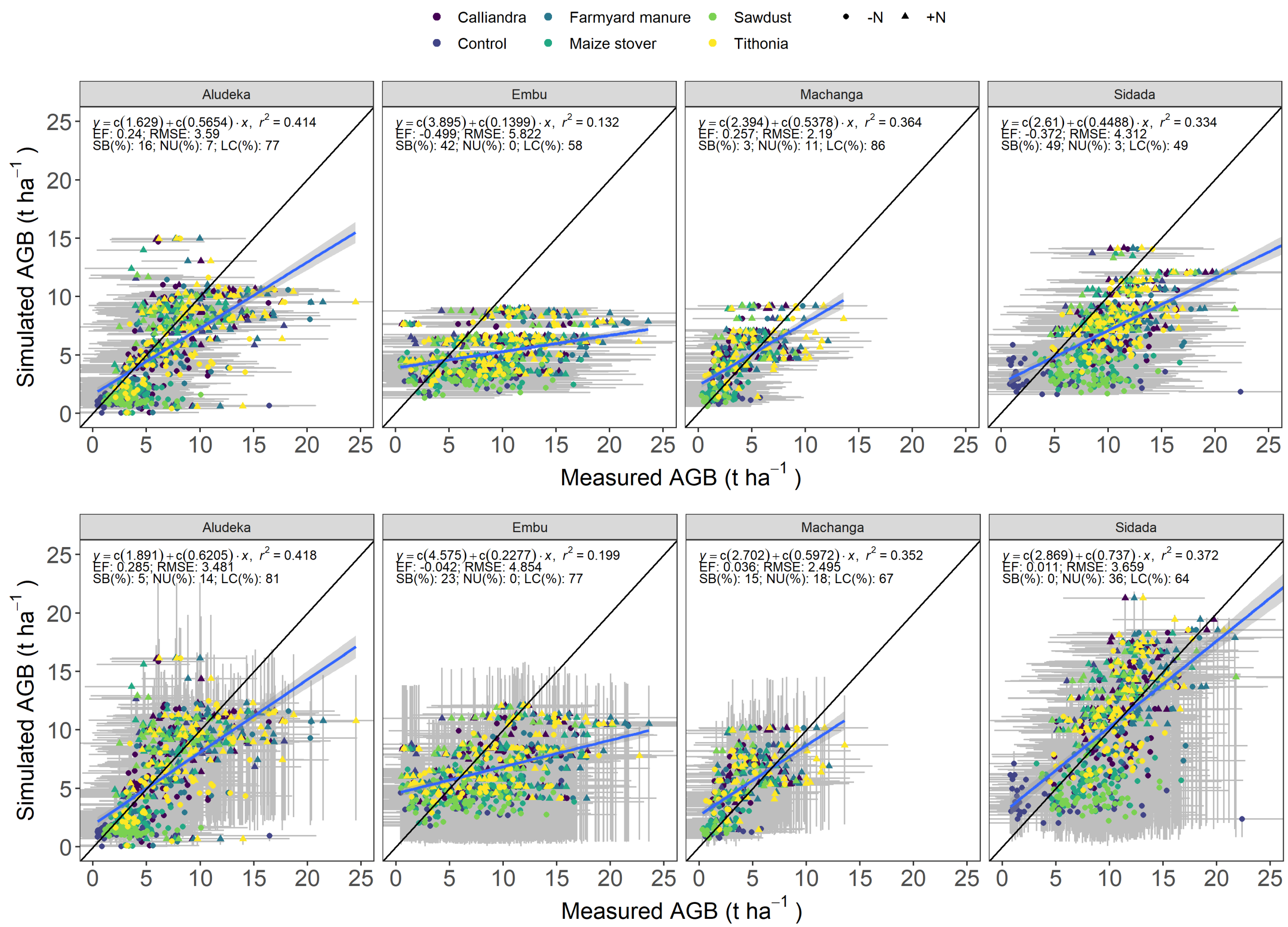

Figure 4. Simulated compared to measured maize ~~grain yields~~ aboveground biomass (AGB) at the four study sites for the ~~default~~ initial DayCent parameter set (~~top-left~~top) versus the calibrated parameter set by leave-one-site-out cross-validation (~~top-right~~bottom). The ~~same is displayed for maize aboveground biomass (AGB), showing the default DayCent parameter set (bottom-left) versus the calibrated parameter set (bottom-right). The~~ 2985 data points correspond to the observations from the experimental treatments over 32 to 38 seasons, depending on the site. Symbols represent the different organic resource and chemical nitrogen fertilizer treatments. Grey bands show the 95% confidence intervals of measured (horizontal) values and the 95% credibility intervals of posterior distribution (vertical). Abbreviations: EF, Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics: EF, 0.033; RSME, 4.392 t ha^{-1}; SB, 27%; NU, 1%; LC, 72% before and EF, 0.254; RSME, 3.856 t ha^{-1}; SB, 3%; NU, 12%; LC, 85% after calibration, with 51% of measurements being in the 95% credibility interval of the posterior.

was obtained (Fig. 3). With the leave-one-site-out cross-validation ~~showed that the Bayesian calibration significantly improved the fit of the model for both maize grain yield and aboveground biomass (Fig.3) . The calibration improved~~ approach, the model efficiency for maize grain yields at the left-out site improved ubiquitously (i.e., from 0.32 to 0.39 in Aludeka; from -0.04 to 0.16 in Embu; from 0.32 to 0.36 in Machanga, from -0.16 to 0.27 in Sidada, and from 0.36 to 0.50 across all sites) and so did RSME and bias. The same was true for the simulation of ~~grain yield for all sites and for aboveground biomass for all sites except Machanga (Fig. ??). It should be noted that despite excluding the evaluation site in the calibration step, the calibrated model was unbiased and errors mostly random for both yield (i.e., lack of correlation (LC) increased from 90% to 97%) and~~ aboveground biomass ~~(LC increased from 71%~~ (e.g., from 0.03 to ~~91%).~~ 0.25 across sites; Fig. 4), with the exception of Machanga. Overall, biases in simulated grain yields were mostly eliminated through the model calibration, and biases in simulated aboveground biomass were eliminated in Aludeka and Siadada, reduced in Embu, but increased in Machanga.

~~Furthermore, while DayCent was inclined to overestimate the lowest and underestimate the highest values of~~ The simulated posterior credibility intervals of simulated yields and aboveground biomass contained 50% and 51% of observed data, respectively, showing a that it could not capture the full uncertainty of measurements. While DayCent could not capture the full season-to-season variability of grain yields and aboveground biomass, the mean yields and aboveground biomass ~~per treatment~~ throughout the simulation period were simulated well for most treatments without the addition of mineral N (Fig. A3). The exception to this was ~~that~~ the Embu site, where there was a systematic underestimation of yields in the -N treatments. Interestingly, DayCent poorly distinguished the mean yields and aboveground biomass of treatments with high compared to very high rates of N inputs (i.e., the differences between the different organic resources and the control within the +N treatment). An additional test of the model sensitivity of mean yields to different levels of mineral N fertilizer in the control provided further insights into this (Fig. A5). In this test, the yields ~~stopped increasing~~ plateaued at mineral N rates that were lower than the maximum N rates provided in the organic resource +N treatments by mineral N and organic resources combined (up to >500 kg N per year or > 250kg N per growing season). In Machanga and Embu, simulated mean yields stopped increasing at around 100 kg N ha^{-1} per growing season, which is less the 120 kg N ha^{-1} per ~~season that~~ growing season in the control +N~~received~~. In Aludeka and Sidada, simulated mean yields stopped increasing at 200 to 250 kg N ha^{-1} per growing season, but most of the response to N was below 120 kg N ha^{-1} per growing season (Fig. A5).

Although the mean yields ~~of the high-quality inputs in the~~ in -N treatments with the high-quality inputs were well simulated, some of the low-quality input treatments in Aludeka and Sidada, namely maize stover ~~at 1.2 t C ha^{-1} yr^{-1} ,~~ and sawdust at 1.2 and 4 t C ha^{-1} yr^{-1}, had lower simulated ~~yields than the~~ than observed mean yields in their -N treatments (Fig. 5). The same was true for the control -N in Aludeka ~~, but the yields for sawdust -N at 4 t C ha^{-1} yr^{-1} in Machangawere overpredicted compared to measurements. Interestingly, the 95% credibility intervals for yield and aboveground biomass produced by the leave-one-site-out cross-validation contained only about 30% of measured data and also tended to be considerably smaller than variance-based 95% confidence intervals for the measured data.~~ and Machanga.

Figure 5. Barplots of mean simulated and mean measured maize grain yield and aboveground biomass (AGB) from cross-validation. Error bars represent standard deviation.

3.4 Simulated SOC stocks in response to integrated soil fertility management

In contrast to the simulation of maize grain yields, the simulations of change in SOC stocks following the application of organic resources at different rates (1.2 and 4 t ha^{-1} yr^{-1}) ~~was poorly simulated by DayCent with the set of default parameters. The simulated SOC losses were too low compared to~~ were not generally improved across sites by the ~~observations~~ leave-one-site-out cross-validation approach compared to using the initial model parameter set (Fig. 6). ~~The posterior parameter set obtained through Bayesian calibration with strongly increased SOM turnover rates showed a tendency for a higher loss of CO_2 from the turnover of metabolic and structural litter pools. With the posterior parameter set ,~~ Both the initial parameter set and the ~~model, in~~ calibrated parameter set resulted, however, in a better model performance compared to DayCent simulations with the default CUE value for the structural pool (these had a negative model efficiency at all four sites; Fig. A6). While Aludeka experienced improved model efficiency for simulated changes in SOC stocks with the leave-one-site-out cross-validation ~~, simulated the change in SOC much more accurately than with the default parameter set (EF of~~ (from -4.17 to -1.84), the model efficiencies for Embu and Sidada slightly worsened (from 0.54 ~~vs -1.3; LC of 88% vs 42%; Fig. 6). The 95% credibility intervals of the simulated values contained 47% of the measured data. It~~ to 0.33 in Embu and from 0.47 to 0.39 in Sidada). Even across sites, the model efficiency (computed without Machanga) slightly decreased from 0.36 to 0.34 following calibration. As expected, Machanga, for which the SOC stock data had been removed from the calibration dataset due to soil erosion at this site, exhibited poor model efficiency (-3.6 after calibration).

Despite the reduction in model performance, the Bayesian calibration effectively captured the uncertainty in SOC stock changes in Aludeka, Embu and Sidada. Overall, 84% of measurements fell within the posterior credibility intervals, though the evaluation was done with the site that was not used in calibration. While SOC changes were well captured in the control treatments across all sites, it should be noted that under- or overestimation of the change in SOC stocks ~~from the start to the last year of the experiment was rather related to site than to treatment . In Embu~~was most prominent in the treatment receiving 4 t C ha^{-1} yr^{-1} and this discrepancy varied by site. In Sidada, for example, all treatments ~~except the control +N treatment~~ that received 4 t C ha^{-1} yr^{-1} tended to have lower ~~observed than simulated~~ simulated than observed SOC losses, while in Aludeka most treatments ~~except the control -N treatment showed weaker predicted than observed SOC losses~~ that received 4 t C ha^{-1} yr^{-1} showed a stronger simulated SOC gain than what was observed (Fig. A7). ~~These tendencies are~~ The large credibility intervals of the Bayesian calibration were also evident when comparing the temporal dynamics of measured ~~versus~~ with simulated SOC stocks (Fig. 7). ~~Most of the treatments were~~ The difference between the 4 t C ha^{-1} yr^{-1} input and the control treatments were generally well simulated, but ~~it is noteworthy that there is~~ the considerable variability in the measured SOC stocks between different time points likely contributed to the large posterior intervals.

3.5 Simulated N_2O emissions and ~~global warming potential~~GHG balance

The ~~simulations and measurements of N_2O emissions on a daily basis were not well aligned. This is clear from the negative modeling~~ negative model efficiencies and the absence of ~~a clear~~ correlation between observed and ~~measured values~~ simulated N_2O values indicated that model performance for daily N_2O emissions was poor (Fig. 8). ~~Peaks~~ While treatments with higher N

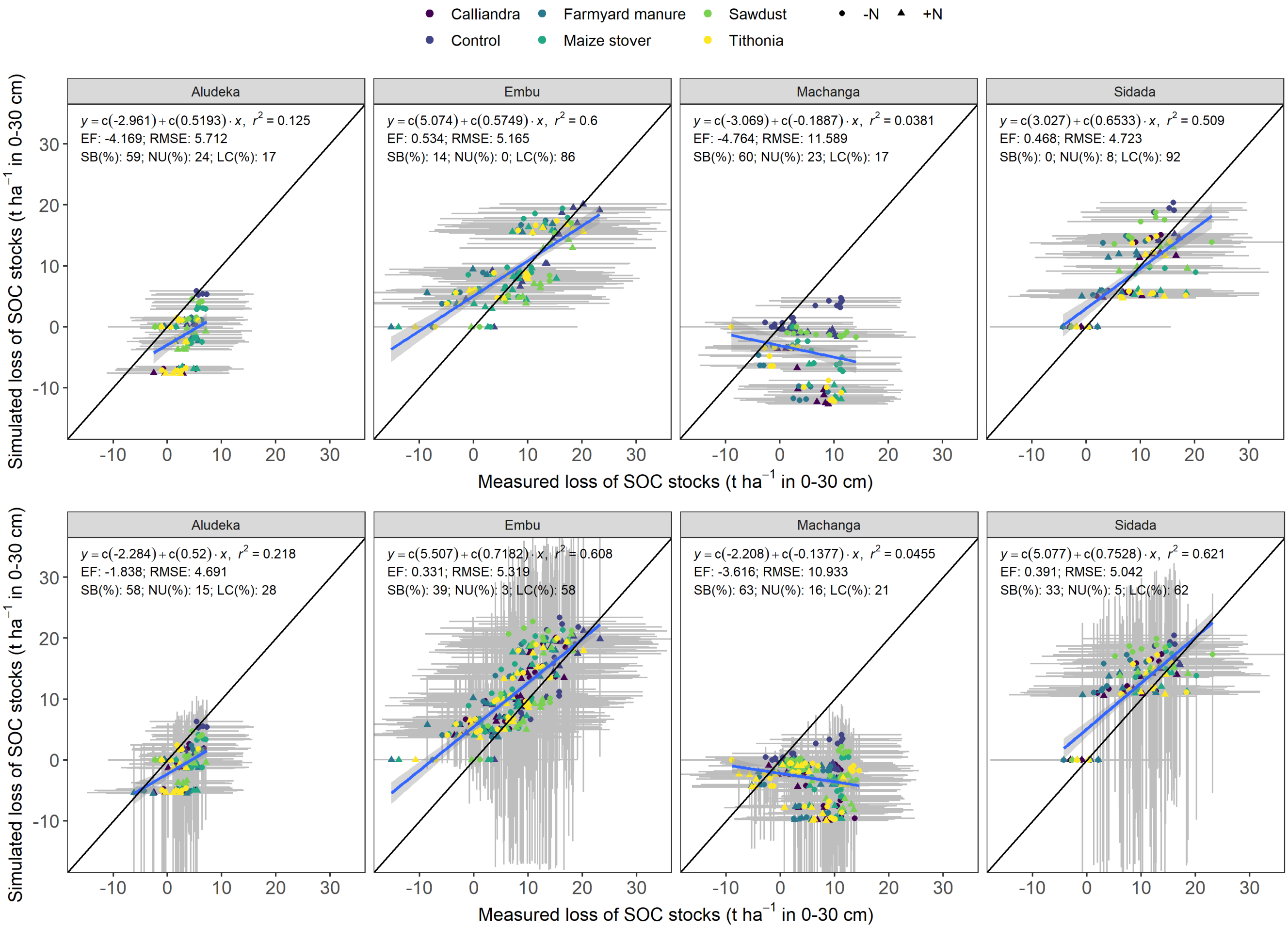

Figure 6. Simulated compared to measured changes in SOC stocks since the start of the experiment at the four study sites for the ~~default~~ initial DayCent parameter set (~~left~~top) versus the calibrated parameter set by leave-one-site-out cross-validation (~~right~~bottom). The 724 data points correspond to the observations from the experimental treatments over 32 to 38 seasons, depending on the site. Symbols represent the different organic resource and chemical nitrogen fertilizer treatments. Grey bands show the 95% confidence intervals of measured (horizontal) values and the 95% credibility intervals of posterior distribution (vertical). Abbreviations: EF, Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics without Machanga (from which SOC data was excluded in the calibration process due to strong erosion): EF, 0.364; RSME, 5.199 t ha^{-1}; SB, 1%; NU, 22%; LC, 77% before and EF, 0.339; RSME, 5.11 t C ha^{-1}; SB, 9%; NU, 29%; LC, 62% after calibration, with 84% of measurements being in the 95% credibility interval of the posterior.

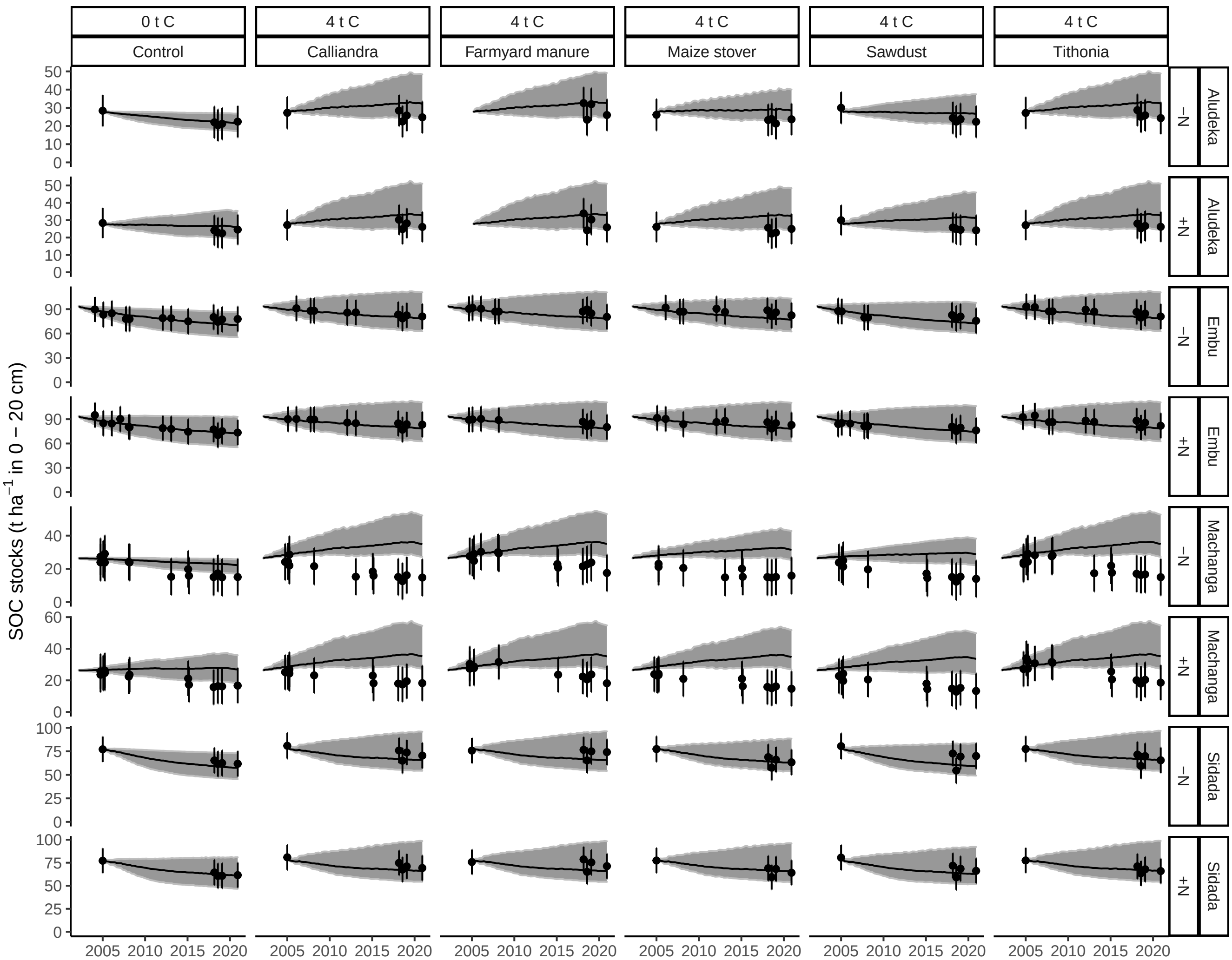

Figure 7. Measured (dots) versus simulated SOC stocks over time at the four study sites for the different organic resource and chemical nitrogen fertilizer treatments. Error bars represent 95% confidence intervals for measured data, the black solid line the simulation by the best parameter set for each site. Grey bands represent the 95% credibility intervals of the model posterior simulations, calibrated by leave-one-site-out cross-validation. Note that due to intense soil erosion, data from Machanga was not used in the calibration process.

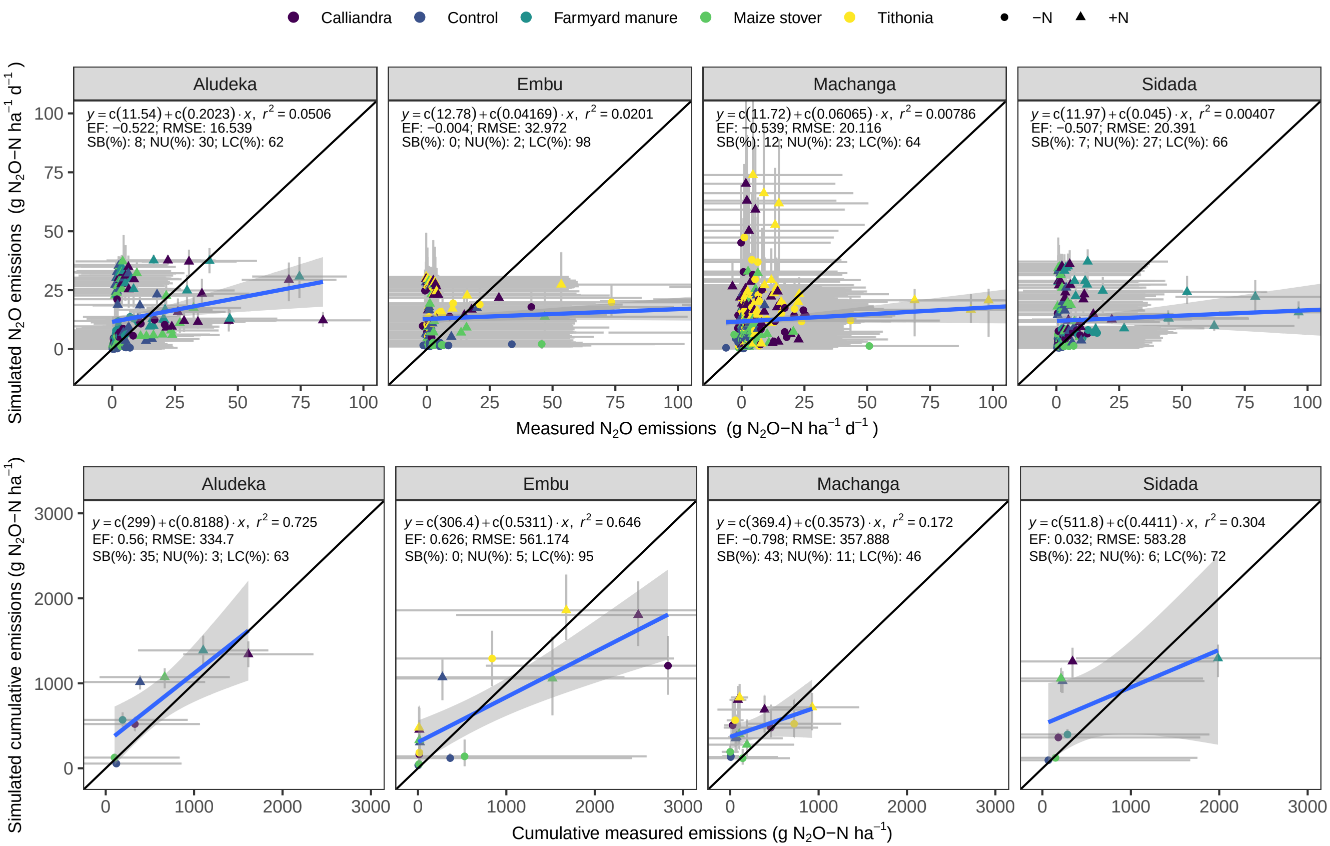

Figure 8. Simulated compared to measured N_2O emissions at the four study sites for the different organic resource and chemical nitrogen fertilizer treatments, based on the calibrated parameter set using leave-one-site-out cross-validation. Displayed are the measured versus modelled per treatment for the days where measurements were conducted (top) and for the mean of cumulative flux measurements per season using the trapeziod method (bottom). The 808 data points (top) correspond to the daily measurements from the experimental treatments over one to two seasons, depending on the site. Symbols represent the different organic resource and chemical nitrogen fertilizer treatments. Error bars represent 95% confidence intervals ~~based on BC~~ (~~simulations~~measurements) and ~~variance~~ credibility intervals (~~measurements~~simulations). Abbreviations: EF, Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation.

loads had both higher simulated and measured N_2O fluxes compared to those with lower loads, the peaks of N_2O emissions were often simulated on different dates than the measurements~~, but treatments with higher N loads tended to have higher simulated and higher measured N_2O fluxes~~. This was most noticeable in +N ~~compared to -N~~ treatments (Fig. A8). ~~For~~ Conversely, for cumulative N_2O emissions per season~~on the other hand~~, there was a ~~much better alignment~~ better agreement between the simulated and measured values. All sites~~showed positive modeling efficiency (highest EF 0.34 for Aludeka, lowest EF 0.21 for Machanga~~, except Machanga, showed positive model efficiencies (highest in Embu, 0.62; lowest in Sidada, 0.03; Fig. 8). Additionally, the correlation between ~~cumulative~~ simulated and measured N_2O emissions was ~~much higher~~ notably higher for the cumulative emission fluxes than for daily ~~emission~~ fluxes (R^2 between ~~0.26 for Sidada and 0.81 for Aludeka~~0.72 for Aludeka and 0.30 for Sidada, compared to R^2 close to 0 ~~).~~ for daily fluxes). Furthermore, despite some bias in Aludeka and Sidada, most of the error in seasonal N_2O emissions was not systematic (i.e., LC of 63 - 95%).

The simulated changes in SOC and ~~simulated cumulative~~ seasonal N_2O emissions ~~, showed positive global warming potentials (GWP)~~ revealed a positive GHG balance for all treatments at all sites (Fig. ~~??). No treatment acted as a greenhouse gas sink, but the amount~~ 9). Yet, the magnitude of emissions, as well as the ~~contribution~~ relative contributions of N_2O and CO_2, differed strongly between sites and treatments. ~~In~~ For instance, in the control -N treatment, ~~it ranged from 1.4~~ emissions ranged from 2 t CO_2 equivalent ha^{-1} yr^{-1} ~~in Aludeka to 5.1~~ at Aludeka to 6 t CO_2 equivalent ha^{-1} yr^{-1} ~~in Sidada and~~ at Embu. The relative contribution of N_2O ~~from site to site~~ also differed strongly by site. ~~In~~ At Aludeka, for example, ~~between 32 (CT+N) and 82% (FYM4+N) of the simulated GWP in the +N treatments~~ all positive GHG balance values in the 4 t C ha^{-1} yr^{-1} treatments receiving farmyard manure, *Tithonia*, and *Calliandra* came from N_2O, while ~~at all other sites, none of the treatments had more than 25% of GWP~~ SOC acted as a sink of GHG. In contrast, at Sidada and Embu, most treatments had around one-third of GHG balance associated with N_2O emissions, with the remainder attributed to SOC losses. Compared to the control -N treatment, ~~which is closest to the low-input agriculture practiced by most smallholder farmers,~~ all organic resource ~~input~~ treatments in the -N treatments were ~~projected~~ simulated to have lower emissions (Fig. ~~??). The reductions ranged from -0.2 t~~ 9). Yet, including the +N treatments, the changes ranged from an increase of CO_2 equivalent ha^{-1} yr^{-1} to ~~1~~ a reduction of 2.5 t CO_2 equivalent ha^{-1} yr^{-1}. ~~Apart from that, the only~~ Embu was the site where the addition of mineral N (+N treatment) ~~could lead to a higher simulated GWP per ha than~~ led to the strongest increase in simulated GHG balance compared to the control -N treatment~~was Embu, and this was only the case for the treatments of *Calliandra, Tithonia* and farmyard manure in both 1.2 and 4 t of C input ha^{-1} yr^{-1}. Furthermore, Embu and Machanga tended to have high~~ .

Finally, there were site- and treatment-specific differences in the yield-scaled GHG balance. The control, maize stover and sawdust treatments -N had the highest simulated emissions per kg of maize ~~yields (0.9 to 1.6 and 0.8 to 2.5~~ grain yield across sites (1 to 1.5 kg CO_2 equivalent per kg of yield~~, respectively, due to lower yield). On the contrary, the simulated emissions ranged between 0.1 and 0.7 kg CO_2 equivalent per kg of yield in Aludeka and between 0.4 and 0.9 kg CO_2 equivalent per kg of yield in Sidada. Notably, none of~~). In contrast, the farmyard manure, *Callianda* and *Tithonia* treatments at inputs of 1.2 t C ha^{-1} yr^{-1} in the +N ~~treatments in Sidada and Aludeka had higher emissions than~~ treatment and at 4 t C ha^{-1} yr^{-1} in both -N and +N treatments tended to have the lowest simulated emissions at all sites (around 0.5, 1 and 0.6 kg CO_2 equivalent per kg of yield at Aludeka, Embu, and Sidada, respectively).

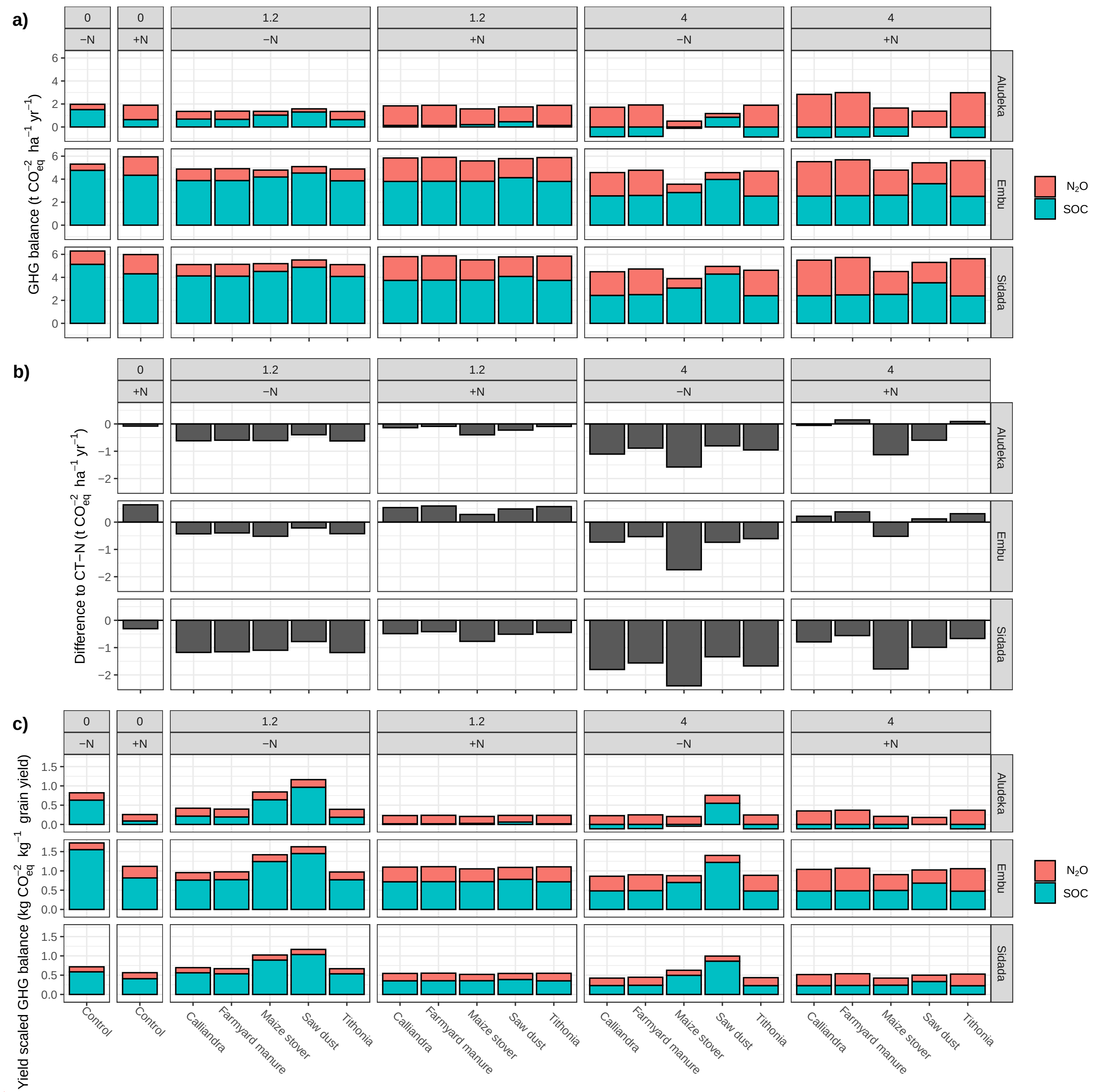

Figure 9. Cumulative simulated ~~global warming potential~~ greenhouse gas (GHG) balance of N_2O emissions and CO_2 emissions due to loss of SOC at the four study sites for different organic resource and chemical nitrogen fertilizer treatments, combined throughout the simulated period (16 years for Aludeka/Sidada; 19 years for Embu/Machanga). The ~~global warming potential~~ GHG balance is expressed in CO_2 equivalent over a 100-year horizon.

4 Discussion

4.1 Robustness of the Bayesian calibration shown by ~~cross evaluation~~cross-validation

As shown by ~~our~~ the leave-one-site-out cross-validation (Figs. 3 and ~~??~~4), the Bayesian calibration considerably improved the predictive capability of DayCent ~~to predict~~ for maize grain yield ~~, aboveground biomass and changes in SOC stocks at the four long-term ISFM experimental~~ and aboveground biomass across sites. The model evaluation statistics from this calibration ~~exercise~~ were comparable to those ~~of other~~ reported in recent publications that also combined the predictions of crop yield and SOC (Necpalova et al., 2018; Levavasseur et al., 2021; Nyawira et al., 2021). However, while these studies generally showed a better simulation of crop yield than SOC, ~~which is in contrast to our results, where crop yield and SOC were simulated equally well. Of the three types of measurements, simulated changes in SOC stocks related to different treatments were most improved after model calibration, reducing the strong bias towards simulated gains in SOC, where instead losses were measured. In general,~~ our study diverged. We found that while better yield simulations compared to SOC simulations were evident at the Aludeka and Machanga sites with soils of low clay content, the results were different at the Embu and Sidada sites with clay-rich soils. Here, SOC stock changes were more accurately simulated than maize grain yield. This, together with the fact that improved simulation of maize grain yield and aboveground biomass was coincided by a lower model performance in simulating SOC changes (Figs. 6), suggests that no single best parameter set exists for the current version of DayCent to accurately represent the conditions at all four sites. In that regard, the ~~screening of the model parameters with the global sensitivity analysis proved valuable in reducing the complexity of the calibration problem. The most sensitive parameters (Table 1)were well constrained, while the least sensitive parameters (aneref(3), ppdf(2) and ps1co2) were difficult to constrain. This suggests that a reasonable threshold for including a parameter in model calibration may even be greater than a total Sobol sensitivity index of 2.5%. This result is similar to~~ discrepancy between the sites with clay-rich and clay-poor soils could indicate that DayCent insufficiently includes soil textures effects on nutrient availability and SOC formation. Yet, drawing definitive conclusions from just four sites is probably not warranted. In the absence of data from more sites, it is preferable to apply the full range of possible parameter sets that are supported by the ~~study of Gurung et al. (2020), where the parameters with a total sensitivity index <10% were also poorly constrained. In our study, it was possible to constrain the most sensitive parameters (prdx(1), himax, dec(5)); exceptions were the two parameters pmco2(1&2) and elteff(1,2&4), but their correlation (r = -0.43) is a reasonable explanation of why they could not be well constrained despite high sensitivity. Possibly, the algorithm cannot distinguish whether organic resources are poorly stabilized due to tillage disturbance, a fast turnover rate of the slow SOM pool, or a low carbon use efficiency of metabolic and /or structural litter pools. Such a correlation between SOM stabilization and turnover parameters is common in soil models (e.g. Ahrens et al., 2014; Laub et al., 2021), especially if the SOM pools do not represent measurable fractions (Laub et al., 2020).~~ available data (Mathers et al., 2023), rather than using only the single best parameter set.

~~Robust predictions of crop yields and changes in SOC stocks, as achieved by our cross-validation, are an important basis for potential future upscaling exercises of crop yield and SOC model predictions to national scales. While many model calibration exercises often display an overly optimistic picture of the capacity of models to represent SOC dynamics, by displaying how~~

~~well the models represent absolute levels of SOC (e.g., in Nyawira et al., 2021; Ma et al., 2022; Levavasseur et al., 2021), the changes in SOC since the start of an experiment, shown in this study, are much more robust evaluation. Since models are typically parameterized to fit the observed SOC stock at the start of the experiment, absolute SOC will always closely resemble measurements, with the possible exception of experiments that run for many decades. The fallacy of this approach was shown by Necpalova et al. (2018); Gurung et al. (2020), where the absolute SOC overoptimistically masks the bias of change in SOC stocks. This is also the case for the present study, as is clear from the results of the model simulations for the absolute SOC stocks compared to the changes in the SOC stocks (Fig. ??). Since~~

Because our calibration shows a good ~~fit and is free from serious bias even for~~ model fit with observed mean yields and changes in SOC stocks ~~(that is, 88% of the errors are LCand not systematic; EF is 0.55~~across sites, with no overall major bias (positive EF and errors mostly consisting of LC), the ~~calibrated DayCent model can be used in a robust manner to estimate the change of SOC stocks under different ISFM management in Kenya. Furthermore, because the model evaluation and calibration~~ parameter set, especially the full posterior, appears suitable for upscaling of model simulations. However, on should keep in mind that the season-to-season yield variability is captured less accurately than the mean yields (lower RMSE) and that changes in SOC are better represented at sites with clay-rich soils than those with clay-poor soils. Because the model calibration and evaluation were performed at ~~different sites , it seems reasonable to use DayCentfor other~~ sites with diverse characteristics, it is reasonable to assume that DayCent, when applied to sites with similar climate and soil conditions, ~~even beyond Kenya~~will provide satisfactory results with similar model uncertainties and errors. In that respect, while the leave-one-site-out cross-validation ~~is using the data most efficiently: for evaluation, we leave one site out, but for~~ made efficient use of data for model evaluation, further model upscaling ~~exercises, ideally~~ should apply the full posterior model parameter set including all sites (Fig. 2) should be used. ~~A computationally less expensive alternative is to~~ In that case, a computationally inexpensive exercise would use only the single ~~parameter set with the highest likelihood~~ best parameter set (Table 1), while the full posterior parameter set should be used to get estimates of the posterior credibility intervals for changes in SOC stocks.

4.2 Bayesian calibration ~~suggests that SOC is lost at higher rates in tropical than in temperate soils~~shows uncertainty of model parameters

To estimate the potential yield and long-term sustainability of cropping systems without major bias using biogeochemical models, ~~regionalized~~ region-specific model calibrations are needed (Rattalino Edreira et al., 2021; Yang et al., 2021). Therefore, while previous studies have simulated crop productivity under ISFM and similar practices with ~~default parameter sets~~ the default parameter values (e.g. Nezomba et al., 2018; Nyawira et al., 2021), the results of our study ~~indicate that especially to estimate the effect on SOC, local calibration is very much needed (Fig. 6).~~ underscore the importance of a local calibration, especially when simulations are done with a single parameter set. On the other hand, the similar ranges of the prior and posterior model parameter sets indicate that including prior knowledge into model parameters substantially improves model performance compared to using default parameter values (e.g., see the poor model performance without including prior knowledge on ps1co(1&2)&rsplig; Fig. A6). In fact, the ~~turnover~~ values of the turnover rates of the slow and passive SOM pools ~~was approximately two and eight times higher than in~~ for our study sites were in alignment with those derived in a recent Bayesian calibration of DayCent for temperate ~~systems~~ conditions (Gurung et al., 2020), indicating ~~a~~ that the DayCent temperature function is well suited to handle the faster SOM turnover under tropical conditions~~, as expected~~. However, ~~since the SOM pools in DayCent do not correspond to measurable fractions and we did not have additional data (e.g., ^{14}C) , constraining the related parameters is expected to be subject to high uncertainty (e.g. Ahrens et al., 2014). Nevertheless, our results of high SOM turnover in Kenya are in line with the results of two recent studies, which also found that the default parameterizations of the DayCent (Nyawira et al., 2021) and the LPJGUESS model (Ma et al., 2022) underestimated the loss of SOC in two other long-term experiments in Kenya. In our study,~~ it is important to note that our sites were under natural vegetation (i.e. forest) or fallow until relatively shortly before the establishment of the ~~low Sobol total sensitivity indices of the maize productivity parameters for the SOC stocks suggest a limited importance of root input in the soil system for the storage of SOC. These results align with a statistical analysis of SOC stocks across depth at the same experimental sites (Laub et al., 2022a), which found limited differences between cropped and bare plots, and with another recent tropical long-term experiment (Cardinael et al., 2022), which estimated that less than 1 t of carbon input ha^{-1} per year came from maize roots.~~

~~Overall,~~ experiments (Laub et al., 2023a). Consequently, upon the start of cultivation, erosion and potentially accelerated decomposition (due to soil disturbance) occurred, and SOC has likely not yet reached a new equilibrium with C inputs from maize cultivation. Therefore, C loss is the dominant process occurring at the sites. The good simulations of these strong SOC changes using MAOC initialized SOM pools, a method not commonly used with DayCent, further supports suggestions to move away from purely conceptual SOM pools (Abramoff et al., 2018; Laub et al., 2024). Such conceptual pools require many assumptions about the initial vegetation and soil conditions (e.g., in the ~~considerably higher simulated SOM turnover rates in this study compared to those in temperate regions (Gurung et al., 2020) suggest that the lower SOM stabilization potential of highly weathered minerals in tropical soils (Doetterl et al., 2015) is not adequately accounted for in DayCent. DayCent only includes an effect of clay content. Possibly, the effect of weathered minerals is large for both slow and passive SOM pools(increased turnover by 2^1~~ the spin-up modelling or estimation of SOM pool distribution). In fact, the high uncertainty about initial vegetation, and ~~2^3 in this study, respectively) and is not adequately represented by texture alone. It was recently shown that the Millenial model, which has measurable pools , could better simulate the global SOC distribution than the CENTURY model, which has conceptual pools (Abramoff et al., 2022).Recent attempts to move DayCent in that direction have also shown some promising results (e.g. Dangal et al., 2022).Furthermore, it is possible that hand tillage twice a year and potential erosion also played a role in the high SOC losses that informed these fast turnover rates. Because DayCent does not include erosion and erosion was not measured in the experiments, the exact role of these processes is hard to determine. Therefore, the different calibrations of the DayCent model in our study and in Gurung et al. (2020), suggest that the calibration developed in this study should only be used for soils of similar mineralogy and under a similar climate and for a similar maize cropping system.~~

4.3 ~~Maize crop module is more universally applicable than soil carbon module~~

~~Although the mean yields per treatment were well represented and the provisioning of N via organic resource mineralization was well captured, as demonstrated by a good agreement between the mean simulated and measured yields in the -N treatments (Fig. 5), the improvement in the simulated maize grain yield through the joint Bayesian model calibration of SOM pools and the maize crop highlights the interconnectedness of both~~time and management since site conversion, was a major reason to move away from the model spin-up and site history run usually typically done with DayCent. Thus, ~~even if the crop parameterization is correct, as indicated by the low difference between initial and calibrated maize parameters, too low SOM pool turnover rates, by underestimating mineralization of N from soil, results in too high demand of maize for mineral N addition to produce a suitable yield. This can be seen in the poor simulation of the low input treatments of Sidada before calibration and their improvement after calibration (Fig **??**). Interestingly, in contrast to SOC turnover rates, the values of the maize crop parameters in this study were close to the set of default parameter values of DayCent, especially the maximum production capacity (prdx(1)). This~~ our study provides additional support to modify DayCent, incorporating measurable SOM pools (e.g. Dangal et al., 2022).

In that sense, the similarity of our DayCent model calibration with that of Gurung et al. (2020) and earlier studies, despite using different model initialization approaches, indicates the broad applicability of DayCent. It suggests that the ~~traits of the maize are universally represented in DayCent , whereas the turnover of the SOM is not. In this context, the changes in the values for~~ SOM turnover and maize traits in DayCent are representative for temperate to tropical conditions. The adjustments made to the values of optimal and maximum temperature for maize growth (ppdf(1) and ppdf(2)) could be attributed to the ~~adaptation of local maize species~~ local maize varieties that are adapted to the higher temperatures in Kenya. For example, Yang et al. (2021) conducted a region-specific Bayesian model calibration of the DayCent maize growing parameters and found ppdf(1) to ~~very~~ vary between 26 and 32 °C. ~~Therefore, the different optimal temperatures (33° C) and highest temperatures (40° C) for the calibration of maize to US conditions by Necpálová et al. (2015) do not contradict the range of parameters of our study.~~ However, the differences in model performance by site shows that the broad representativeness of DayCent comes at the cost of model simplification and site-specific model performance. A main reason for this may be that DayCent model formalisms do not include the latest mechanistic understandings of the role of microbes in SOM decomposition (Laub et al., 2024), and the sorption kinetics of carbon to minerals for SOM protection (Abramoff et al., 2018; Ahrens et al., 2020). Additionally, Daycent does not fully consider that a lot of stabilized SOC is formed by microbes from metabolic and not structural litter (Cotrufo et al., 2013; Kallenbach et al., 2016). For example, it was recently demonstrated that the Millenial model, which includes measurable SOM pools and improved kinetics of carbon sorption better predicts SOC stocks at the global scale than the CENTURY model, which has conceptual SOM pools (Abramoff et al., 2022). While model calibration can compensate for deficiencies in mechanistic accuracy at a single site (Laub et al., 2024), this is likely not possible across sites with different conditions.

An interesting observation is that while the model bias for the mean ~~yield of maize appears to be~~ maize yield was treatment specific (i.e., the mean yields of +N treatments of farmyard manure at 4 t C ha^{-1} yr^{-1} at all sites and of *Tithonia* at the same rate in all but Sidada, were underpredicted by DayCent), ~~while~~ the bias for SOC stocks was mostly site specific (i.e., SOC ~~loss in Aludeka was underpredicted, while overpredictedin Embu). As discussed above, the site bias of SOC is likely due to~~ formation in Aludeka at 4 t C ha^{-1} yr^{-1} was overpredicted). A potential explanation for this site-specific bias for SOC is the fact that ~~soil~~ DayCent was developed under the paradigm of SOM formation occurring mainly from recalcitrant humic compounds in the soil. Alternatively, it might indicate that soil texture alone is insufficient to explain the mineralogy-driven storage potential of SOC (e.g. Reichenbach et al., 2021; Mainka et al., 2022). ~~On the other hand, our~~ Finally, our model sensitivity test to mineral N ~~input~~ inputs suggests that the maize yield bias at high N is due to DayCent's inability to capture yield increases above 100-150 kg N per ha and season at the four sites (Fig. A5); the +N treatments of *Tithonia*, *Calliandra* and farmyard manure at 4 t C ha^{-1} yr^{-1} supplied on average >250 kg N per ha and season. ~~Another reason may be~~ Here, it should be noted that DayCent does not include other potential beneficial effects of organic resource treatments, such as increased pH from farmyard manure application (Xiao et al., 2021; Mtangadura et al., 2017)~~and higher nutrient retention and~~ , or improved water infiltration of treatments that ~~maintained~~ maintain SOC stocks compared to those that ~~showed a decline of SOC~~reduce them.

4.3 N_2O emissions and ~~global warming potential~~GHG balance

In general, the poor match between ~~daily~~ observed and measured daily N_2O emissions (Fig. A8) illustrates the difficulty of simulating the timing of microbial processes, ~~in~~ through which nitrate (NO_3^-) is converted to N_2 and N_2O gasses, with ~~intermediate complexity models~~ models of intermediate complexity such as DayCent. ~~Several recent studies show that poor simulation of N_2O emissions by process models is common (Zhang and Yu, 2021; Wang et al., 2020), which is attributed, among other factors, to a~~ One reason is the poor representation of soil ~~hydraulics. For example, Sommer et al. (2016) found mainly overestimated N_2O emissions in Kenya. Gaillard et al. (2018) reported that there is a bias in simulated N_2O emissions by most models, postulating an underestimation of strong N_2O flushes. This also seems to be the case in our study, at least for treatments with high N inputs such as farmyard manure +N. Without resorting to more intricate water flow equations, it could be difficult to make further improvements to the simulation of soil water content and N_2O emissions, particularly in terms of accurately predicting daily and hourly events. DayCent is driven by inputs that are only resolved at daily time steps and fed with pedotransfer functions that are poorly represented in the tropics (Van Looy et al., 2017).~~ moisture dynamics by the 'tipping bucket' soil water balance approach and that soil gas diffusivity is not explicitly simulated (Zhang and Yu, 2021; Wang et al., 2020) . However, the fact that cumulative N_2O emissions were better ~~captured~~ simulated than daily emissions~~and that~~ , there was no systematic under- or over-prediction of cumulative N_2O emissions, ~~does suggest that~~ and simulated N_2O emissions were ~~generally reasonably well predicted with this current DayCent calibration. This is important for the predictions of the GWP. Because the simulation of SOC change showedlow bias, we can conclude that this part of the GWP is well represented. Depending on the site and treatment,~~ within the uncertainty range of measured N_2O emissions, demonstrates the suitability of DayCent to represent average N_2O emissions with the current calibration. Given the limited bias in simulating SOC changes and cumulative N_2O emissions showed, the DayCent simulations provide a reasonable first estimate of the GHG balance. Nevertheless, the contributions of N_2O emissions ~~contributed between 80% (~~to the GHG balance of up to 100% (at Aludeka) and ~~up to 20% of the GWP (~~between 10 to 50% (at the other sites; Fig. ~~??). However, the~~ 9), are subject to high uncertainty, as evident from the measurements. The larger confidence intervals of the measured compared to the simulated cumulative N_2O emissions suggest that the DayCent model cannot fully represent the variability. ~~Although~~ Thus, although DayCent's

~~simulation~~ simulations of N_2O emissions ~~is~~ are superior to using emission ~~factors~~ factor approaches (dos Reis Martins et al., 2022), simulating N_2O emissions remains challenging and highly uncertain due to the complexity of the processes involved and the high temporal and spatial variability of N_2O emissions.

Despite this ~~uncertainty, which has not yet been resolved, our analysis of yield-scaled and area-based GWP showed the importance of the unit of reference. Our~~ unresolved uncertainty, our modeling results show that ~~ISFM with maize monocropping cannot be seen as a negative emission technology. All treatments had a positive absolute GWP, which is consistent with the reported losses of SOC in long-term maize cultivation in SSA (Sommer et al., 2018; Laub et al., 2022a). It is also consistent with~~ all ISFM options in a maize monocropping system have a net positive GHG balance, aligning with the prevalent trend of SOC losses in recently established (< 50 years) maize systems in SSA (Sommer et al., 2018; Laub et al., 2023a). The findings also support the postulate that closing ~~SSA yield gaps will boost absolute~~ yield gaps in SSA will increase N_2O emissions (Leitner et al., 2020). However, the ~~strong~~ large differences in the yield-scaled ~~GWP~~ GHG balance between treatments, such as ~~a 72, 32, 63 and 14~~ the 30 to 60% lower yield-scaled ~~GWP~~ GHG balance in the FYM 1.2+N treatment compared to the control-N treatment across the sites, indicate that ISFM has the potential to produce crops with relatively lower GHG emissions than no- or low-input input systems. Specifically, the ISFM treatments with low-emissions and high yields, ~~show that the yield-scaled GWP is highly relevant in practical terms. Low-emission and high-yield ISFM treatments ,~~ such as FYM 1.2+N, ~~producing~~ that produces between 2 and 4 t of yield per season at emissions of between 0.2 and 1 kg CO_2 equivalent per kg of yield, are a suitable mitigation practice compared to ~~standard practice, control~~ the control treatment with little or no inputs of organic and/or chemical fertilizer. ~~The difference in the yield-scaled GWP ranges of +N treatments that existed between western Kenyan sites (Aludeka and Sidada; 0.1 to 0.5 kg CO_2 equivalent per kg of yield) compared to central Kenyan sites (Embu and Machanga; 0.8 to 1.1 kg CO_2 equivalent per kg of yield), furthermore, show that N fertilizer should only be applied to responsive soils (Sileshi et al., 2022) to avoid high N_2O emissions at minimal yield.~~ Consequently, sustainable intensification and mitigation of greenhouse gases can go hand in hand.

4.4 DayCent is suitable to upscale simulations of "real" ISFM, but ~~not sensitive for very~~ limited sensitivity to high N inputs

Because mean ~~yields were represented well~~ maize yields across sites were reasonably well represented by the calibrated version of DayCent, it can be used ~~to upscale to national levels and~~ for upscaling to predict the potential ~~of ISFM to lower yield gaps~~ impact of ISFM in lowering yield gaps at national levels. However, the ~~levelling off~~ plateauing of mean yields at ~~very~~ high N loads (Fig. A5) indicates that ~~it~~ DayCent may not be suitable ~~to estimate the~~ for estimating maximum achievable yields (e.g., Ittersum et al., 2016)~~and it should~~ , and should thus be restricted to yield predictions for medium ~~input levels of N~~N input levels. Given that the historical rates of N fertilizer application in Kenya ~~were~~ are less than 50 kg of N ha^{-1} (World-Bank, 2021a), the model seems suitable to simulate the effect of ~~applying real ISFM , which aims at~~ implementing 'realistic' ISFM practices, which target maximum N use efficiency (Vanlauwe et al., 2010), with N input rates considerably below the maximum N rates ~~of the simulated field trials~~ used in the field experiments of this study (e.g., 80 kg N per season; Mutuku et al., 2020). The prediction of mean ~~yields worked well~~ maize yields was reasonably good for *Calliandra* and farmyard manure treatments at 1.2

and 4 t C ha^{-1} in the -N treatment~~and was also acceptable~~ , as well as for CT+N, i.e., all treatments that supply N at the desired rate for ISFM. Hence, at these N-levels, simulated mean maize yields are likely representative of the ~~ISFM yield potential. The poorer performance of sawdust is less relevant for upscaling, because this is a treatment for scientific understanding (testing if SOC really forms more efficient from lignin rich materials; Palm et al., 2001b).~~ achievable yield through ISFM. In summary, the ~~mean yield potential and the change in the SOC stocks were well represented, so the~~ model calibration seems suitable for assessing the long-term ~~effect~~ effects of relevant ISFM ~~treatments~~ practices on soil fertility, maize yield, and ~~greenhouse gas~~ GHG emissions as well as their trade-offs~~. Since~~ , given the good representation of mean yield potential and SOC changes by the model. Nevertheless, since year-to-year ~~variations of yield~~ yield variations were not captured ~~very well , it is questionable how well the current calibration could represent~~ well by DayCent, it remains uncertain how effectively the current model calibration can simulate scenarios of climate change, where temperature and precipitation patterns will become more erratic. In the absence of major pests (which in the ~~trials~~ experiments were controlled), the ~~yearly variation in~~ variations in seasonal precipitation and temperature ~~should be responsible for the~~ are responsible for these differences, and if these are not well represented, ~~we cannot trust that we can apply DayCent outside of~~ the applicability of DayCent beyond the climatic range that it was calibrated for is questionable.

5 Conclusions

In this study, we demonstrated the effectiveness of ~~jointly~~ simultaneously calibrating the SOM and plant modules of DayCent to simulate maize productivity and changes in SOC stocks under integrated soil fertility management (ISFM) in Kenya, using a Bayesian calibration ~~. The calibration successfully constrained the most sensitive~~ approach. Our study showed the importance of choosing correct values for model parameters, ~~which were identified by a global sensitivity analysis~~and using the full posterior parameter set is the best solution to assess the uncertainty of model outputs. Although the ~~default~~ initial DayCent maize plant parameterization represented the tropical conditions in Kenya ~~well~~ acceptably (i.e., the highest probability posterior parameter values were close to the ~~default~~ initial parameterization), the ~~highest probability posterior SOM turnover rates were two and eight times faster than the default for the passive and slow SOM pool, respectively. This indicates that there is the potential for large losses of SOC in highly weathered tropical soils. However~~overall model performance for maize grain yield and aboveground biomass was improved after calibration using local data. However, better yield simulations partially came at the cost of poorer SOC simulations at some sites. Furthermore, SOM turnover was subject to high uncertainty ~~, showing~~ and biased for clay-poor sites, indicating that the current module structure ~~suboptimally~~ inadequately captures SOM dynamics in highly weathered tropical soils. ~~Nevertheless, our~~ Our leave-one-site out cross validation showed that the calibration-derived parameter set is robust for upscaling ~~of the model~~ the model simulations to larger areas in Kenya, particularly when applying the full posterior parameter set. At the same time, while mean maize grain yields were ~~much better represented than~~ well simulated, the year-to-year ~~variability of yields, posing the question whether the~~ yield variability raised concerns about the model's ability to capture the short-term effects of climate change ~~can be adequatelycaptured by DayCent~~adequately. Finally, while no ISFM treatment was predicted to act as ~~an absolute~~ a net sink of greenhouse gases, ~~yield-scaled emissions were lowest in~~ treatments with high and intermediate yields exhibited the lowest yield-scaled emissions.

Code availability. To get the latest version of DayCent, we suggest to contact the developers directly, who in our case kindly provided the latest DayCent version.

Data availability. The data sets used for the calibration of this study are available under the IITA data repository. For SOC: https://doi.org/10.25502/wdh5-6c13/d. For yields and biomass: https://doi.org/10.25502/be9y-xh75/d.

Author contributions. JS, MN and ML designed the modeling exercise. ML summarized the data, conducted the modeling exercise and prepared the original draft. MWMM, DM, RY, SMN and WW managed and maintained the long-term experiments. ML, SMN, MN, WW, MvdB, MC and JS were involved in the various sampling campaigns. MC, MN, BV and JS acquired funding for the long-term experiments. All co-authors contributed in writing and editing of the final submitted article.

Competing interests. All authors declare that they have no conflict of interest.

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Appendix A: Appendix

A1 Site and organic resource characteristics

Table A1. Locations, soil properties and climatic conditions of the study sites. Soil properties are given for the 0 - 15 cm depth layer. Coordinates are given in the WGS 84 reference system. The table is adopted from Laub et al. (2022b) under the creative common license 4: http://creativecommons.org/licenses/by/4.0/.

Soil characteristics	Embu	Machanga	Sidada	Aludeka
Latitude	-0.517	-0.793	0.143	0.574
Longitude	37.459	37.664	34.422	34.191
Initial soil C (%)	3.1	0.8	2.6	0.7
Initial N (%)	0.3	0.05	0.21	0.06
Initail bulk density (g cm^{-3})	1.26	1.51	1.3	1.45
pH (H_2O)	5.43	5.27	5.4	5.49
Sand (%)	0	31.1	0.1	31
Clay (%)	59.8	13.2	55.7	13.4
Soil type (FAO, 1998)	Humic Nitisol	Ferric Alisol	Humic Ferralsol	Acrisol
Altitude (m)*	1380	1022	1420	1180
Annual rainfall (mm)*	1175	795	1730	1660
Mean annual temperature (°C)	20.1	23.7	22.6	24.4
Months of long rainy season	3 - 8	3 - 8	3 - 9	3 - 9
Months of short rainy season	10 - 01	10 - 01	10 - 01	10 - 01

*Means calculated based on measured data from 2005 to 2020

Table A2. Mean measured chemical characteristics (and 95% confidence intervals) of organic resources applied at all sites. Measurements were available from Embu and Machanga from 2002 to 2004, all sites from 2005 to 2007 and in 2018. Significant differences in residue properties were found between the different organic resources, but not between sites and years. Same letters within the same row indicate the absence of significant differences for that property ($p < 0.05$). Abbreviations: n.c. = not classified * according to Palm et al. (2001a). The table is adopted from Laub et al. (2023a) under the creative common license 4: http://creativecommons.org/licenses/by/4.0/.

Measured property	*Tithonia*	*Calliandra*	Maize stover	Sawdust	Farmyard manure
C (g kg^{-1})	345^{b} (333-357)	396^{c} (383-409)	397^{c} (386-408)	433^{d} (416-449)	234^{a} (213-255)
N (g kg^{-1})	33.2^{d} (28.9-38.2)	32.5^{d} (28.3-37.3)	7.2^{b} (6.5-8)	2.5^{a} (2.1-2.8)	18.1^{c} (15-21.8)
C/N ratio	12.4^{a} (10.8-14.1)	13.6^{a} (11.9-15.5)	58.7^{b} (52.8-65.2)	199.1^{c} (174.1-227.7)	12.3^{a} (9.9-15.4)
P (g kg^{-1})	2.3^{d} (1.8-2.9)	1.1^{c} (0.8-1.5)	0.4^{b} (0.3-0.6)	0.1^{a} (0-0.2)	3.1^{d} (2.3-3.9)
K (g kg^{-1})	37.2^{c} (21.2-65.2)	8.7^{b} (5-15.3)	9^{b} (6-13.5)	2.8^{a} (1.6-4.9)	19.4^{bc} (7.8-48.6)
Lignin (g kg^{-1})	90^{ab} (62-117)	105^{b} (77-133)	48^{a} (37-60)	172^{c} (144-199)	198^{c} (154-242)
Polyphenols (g kg^{-1})	19^{c} (14.9-24.3)	108.7^{d} (85.3-138.6)	11.3^{b} (9.5-13.6)	4.9^{a} (3.8-6.2)	7.8^{ab} (5.2-11.5)
Lignin/N ratio	2.6^{a} (1.8-3.7)	3.1^{ab} (2.2-4.3)	6.2^{c} (4.8-8)	58.3^{d} (41.1-82.8)	6.9^{bc} (3.9-12.3)
Quality / turnover rate*	High / fast	High / slow	Low / fast	Low / slow	n.c.
Class*	1	2	3	4	n.c.
kg N in 4.0 t C ha^{-1} yr^{-1}, -N [+N]	323 [563]	295 [535]	68 [308]	20 [260]	324 [564]
kg N in 1.2 t C ha^{-1} yr^{-1}, -N [+N]	97 [337]	88 [328]	20 [260]	6 [246]	97 [337]

Table A3. DayCent model parameters (and feasible ranges) of parameters which were not included in the Bayesian model calibration due to a Sobol total sensitivity index < 1%.

Parameter	Description	Range width	Units	Initial value	Coefficient of variation	Model file
frtc(2)	C allocated to roots at time frtc(3) without stress	small	fraction of NPP	0.20	0.1	crop.100
frtc(4)	Max. increase in C going to roots under stress	small	fraction of NPP	0.10	0.1	crop.100
frtc(5)	Max. increase in C going to roots under stress (maturity)	small	fraction of NPP	0.10	0.1	crop.100
biomax	AGB at which min.and max. C/E ratios of plant increases	small	g biomass m^{-2}	700.00	0.1	crop.100
pramx(1,2)	Max. aboveground C/N ratio with biomass > biomax	small	C/N ratio	125.00	0.1	crop.100
prbmn(1,1)	For computing min. C/N ratio for belowground matter	small	C/N ratio	45.00	0.1	crop.100
efrgrn(1)	Fraction of above ground N which goes to grain.	small	fraction	0.75	0.1	crop.100
flig(1,1)	Intercept for annual rainfall effect on lignin content	small	fraction of lignin	0.12	0.1	crop.100
ppdf(3)	Right curve shape for temperature effect on growth curve	very small	unitless	1.00	0.05	crop.100
ppdf(4)	Right curve shape for temperature effect on growth curve	very small	unitless	2.50	0.05	crop.100
favail(1)	Fraction of N available per day to plants	moderate	fraction of N	0.15	0.15	crop.100
(aneref(1)-anaref(2))	Rain/ET ratio below which, no effect of anaerobiosis	small	unitless	1.00	0.1	fix.100
aneref(2)	Rain/ET ratio with max. anaerobiosis effect	moderate	unitless	3.00	0.15	fix.100
damr(1,1)&(2,1)	Fraction of surface N and soil N absorbed by residue	large	fraction of N	0.02	0.25	fix.100
damrmn(1)	Min. C/N ratio allowed in residue after direct absorption	moderate	C/N	15.00	0.15	fix.100
dec1(2)	Max. structural litter turnover	small	g g^{-1} yr^{-1}	4.90	0.1	fix.100
dec2(2)	Max. metabolic litter turnover	small	g g^{-1} yr^{-1}	18.50	0.1	fix.100
dec3(2)	Max. active pool turnover	small	g g^{-1} yr^{-1}	7.30	0.1	fix.100
(decX(2)/decX(1))	Ratio soil to surface turnover (newly defined parameter)	small	unitless	1.25	0.1	fix.100
fwloss(1)	Scaling factor; interception & evaporation by biomass	moderate	unitless	1.00	0.15	fix.100
fwloss(2)	Scaling factor; bare soil precipitation evaporation	moderate	unitless	1.00	0.15	fix.100
fwloss(3)	Scaling factor; transpiration water loss	moderate	unitless	1.00	0.15	fix.100
pabres	Residue amount which results in max. direct N absorption	moderate	g C m^{-2}	100.00	0.15	fix.100
teff(2)	Y location of temperature inflection point (decomposition)	large	unitless	11.75	0.25	fix.100
teff(3)	Step size of temperature effect on decomposition	moderate	unitless	29.70	0.15	fix.100
teff(4)	Inflection point slope of temperature effect (decomposition)	very large	unitless	0.25	0.3	fix.100
varat11&12(1,1)	Max. C/N ratio for material entering active pool	small	C/N	20.00	0.1	fix.100
varat11&12(2,1)	Min. C/N ratio for material entering active pool	small	C/N	3.00	0.1	fix.100
varat21&22(1,1)	Max. C/N ratio for material entering slow pool	small	C/N	20.00	0.1	fix.100
varat3(1,1)	Max. C/N ratio for material entering passive pool	small	C/N	13.00	0.1	fix.100
varat3(2,1)	Min. C/N ratio for material entering passive pool	small	C/N	6.00	0.1	fix.100
drain	Fraction of excess water lost by drainage	moderate	fraction of H_2O	0.80	0.15	site.100
dmp_st	Damping factor for calculating soil temperature by layer	large	unitless	0.01	0.25	sitepar.in
N2Oadjust_(max-min)	Proportion of nitrified N that is lost as N_2O (difference)	large	fraction of N	0.003	0.25	sitepar.in
Ncoeff	Min water/temperature limitation coefficient (nitrification)	large	unitless	0.03	0.25	sitepar.in
dmpflux	The damping factor for soil water flux	large	unitless	0.00	0.25	sitepar.in
astlig_TD	lignin fraction content of organic matter	small	g g^{-1} biomass	0.09	0.1	omad.100
astrec(1)_TD	C/N ratio of added organic matter	very small	C/N ratio	12.40	0.05	omad.100
astlig_CC	lignin fraction content of organic matter	small	g g^{-1} biomass	0.10	0.1	omad.100
astrec(1)_CC	C/N ratio of added organic matter	very small	C/N ratio	13.60	0.05	omad.100
astlig_MS	lignin fraction content of organic matter	small	g g^{-1} biomass	0.05	0.1	omad.100
astrec(1)_MS	C/N ratio of added organic matter	very small	C/N ratio	58.70	0.05	omad.100
astlig_SD	lignin fraction content of organic matter	small	g g^{-1} biomass	0.17	0.1	omad.100
astrec(1)_SD	C/N ratio of added organic matter	very small	C/N ratio	199.10	0.05	omad.100
astlig_FYM	lignin fraction content of organic matter	small	g g^{-1} biomass	0.20	0.1	omad.100
astrec(1)_FYM	C/N ratio of added organic matter	small	C/N ratio	12.30	0.1	omad.100

A1 ~~Posterior, when allowing even larger ranges~~Map of the four study sites

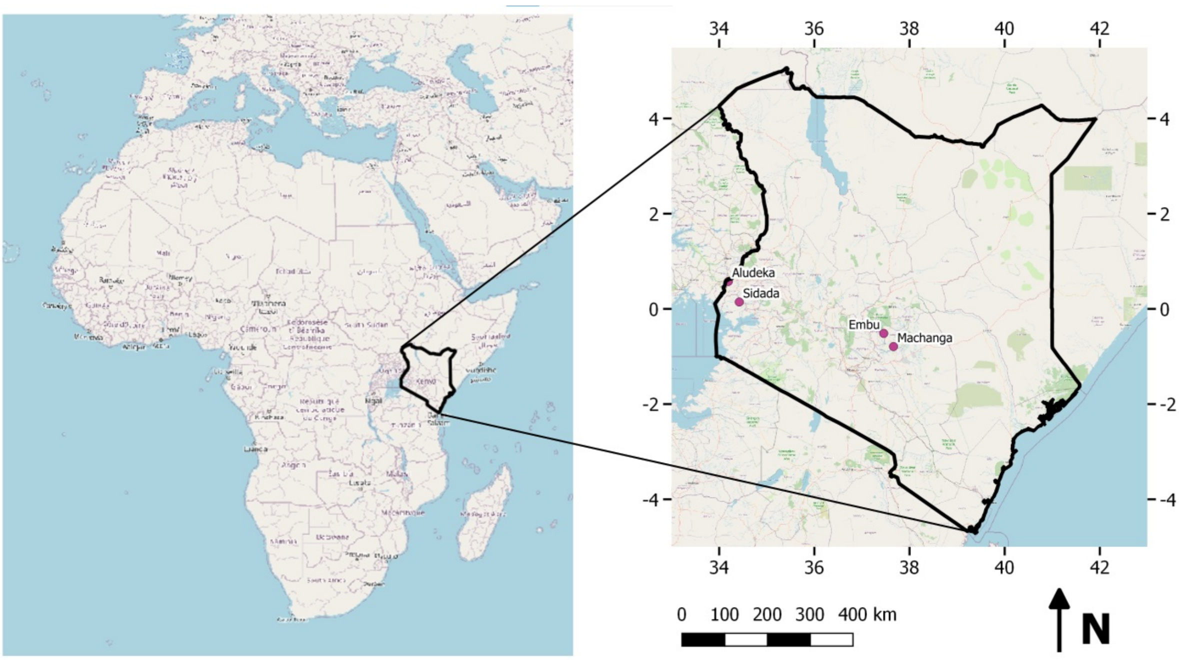


Figure A1. ~~Prior compared to posterior parameter distribution resulting from increasing~~ Map displaying the ~~ranges~~ location of the ~~uncertainty based Bayesian calibration. Dashed vertical lines represent the default parameter sets. The posterior distributions are based on all~~ four study sites~~combined~~.

~~Correlation of parameters from the posterior parameter sets. The posterior distributions are based on all four sites combined.~~

A2 Subsoil SOC stocks for scaling SOC

A3 ~~Barplots of SOC and comparing measured and simulated mean yield~~

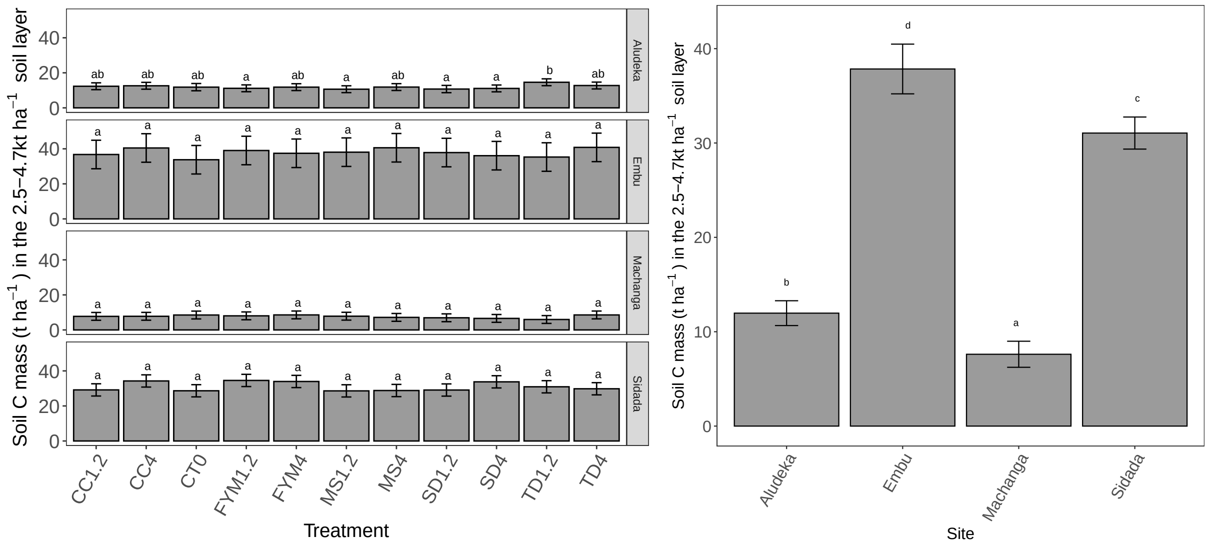


Figure A2. ~~Barplots of simulated and measured change of~~ Subsoil SOC stocks ~~until 2021 from cross-validation~~for the 2.5-4.7 kt ha^{-1} equivalent soil mass layer, ~~at~~ corresponding to an approximate soil depth of 15-30 cm. Displayed are the ~~four study sites for~~ least square means estimated by the ~~different organic resource~~ linear mixed model described in (Laub et al., 2023a) for planted plots by treatment (left) and ~~chemical nitrogen fertilizer treatments~~site (right). Error bars ~~represent~~ display the 95% confidence intervals~~based on BC~~. Same lowercase letters indicate the absence of a significant difference in SOC stocks between treatments at the same site (~~simulations~~left figure) ~~and variance~~ or between sites (~~measurements~~right figure; all $p < 0.05$). Abbreviations: CC, *Calliandra*; CT, control; FYM, farmyard manure; MS, maize stover; SD, sawdust; TD, *Tithonia Diversifolia*. 0, 1.2 and 4 correspond to C additions of 0, 1.2 and 4 t C ha^{-1} yr^{-1}.

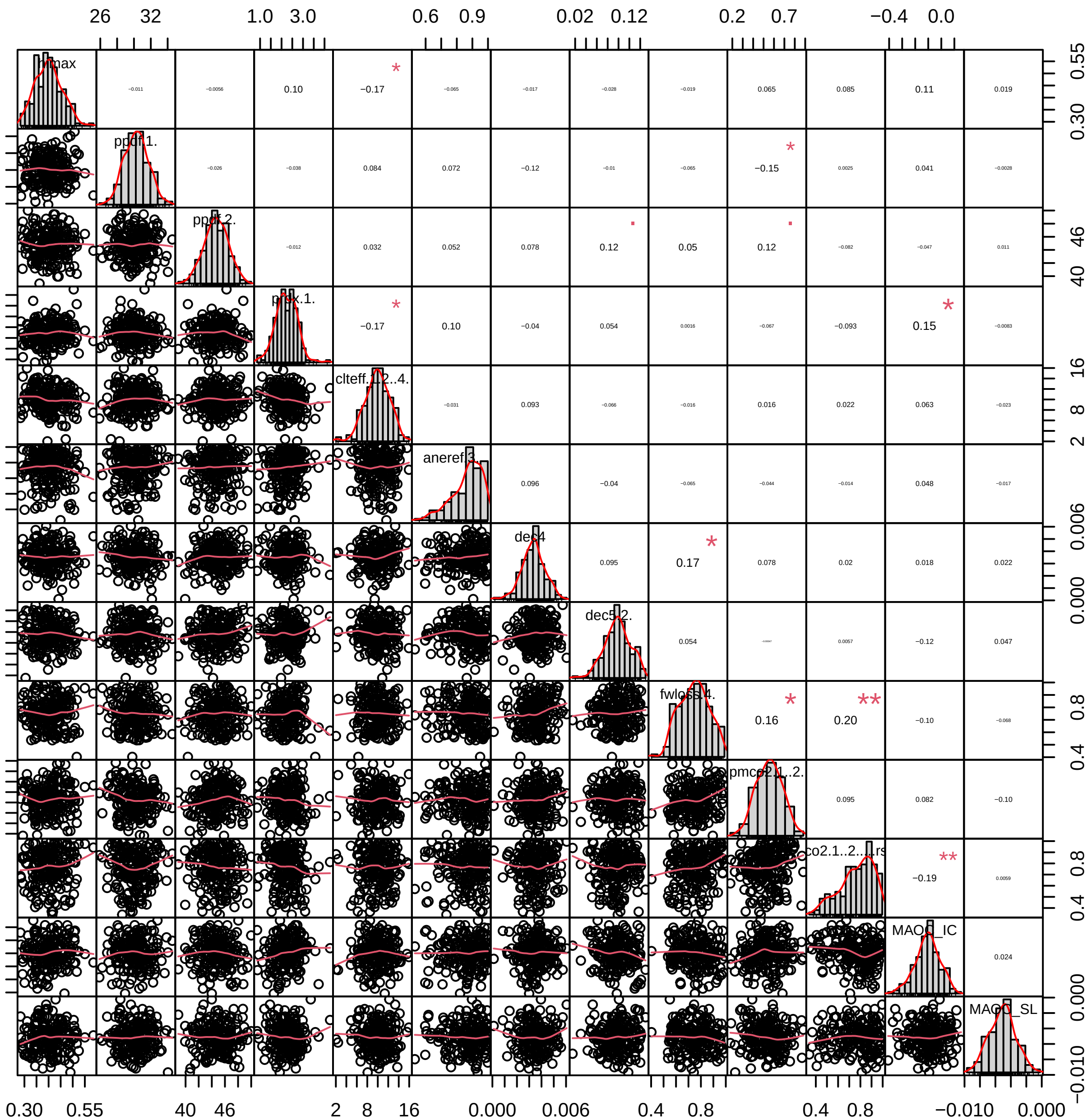
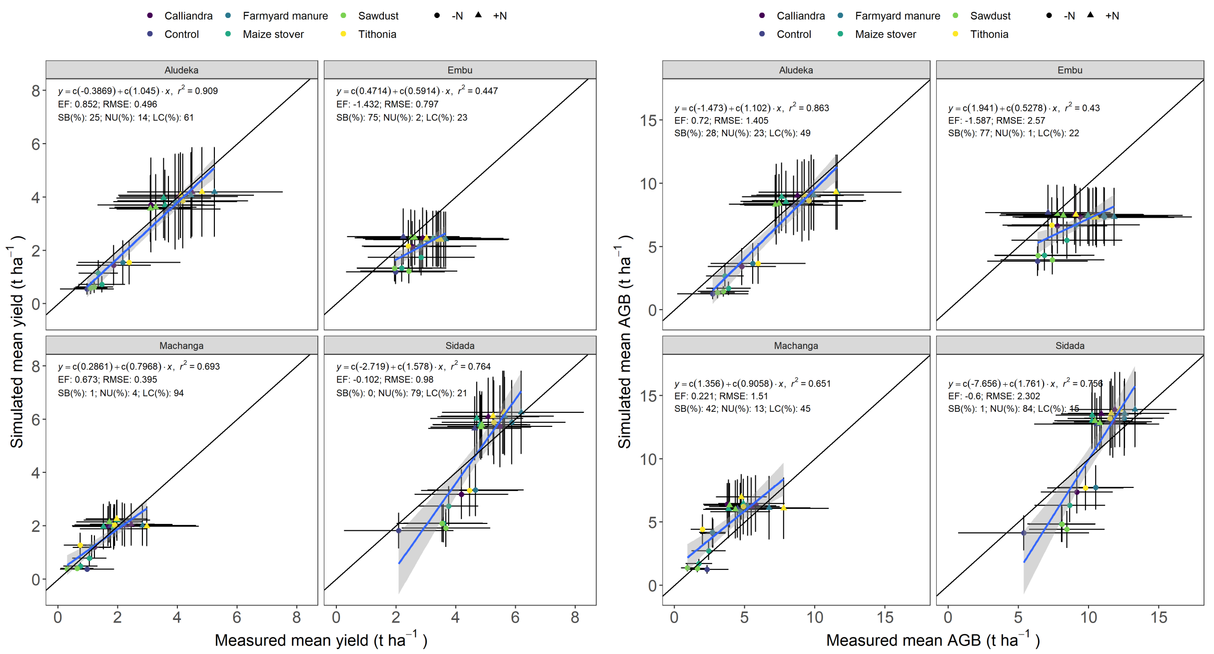


Figure A3. Correlation of parameters from the posterior parameter sets. The posterior distributions are based on all four sites combined.



~~Measured and simulated maize grain yields over time~~Abbreviations: EF, ~~at the four study~~ Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics: EF, 0.755; RSME, 0.707 t ha^{-1}; SB, 12%; NU, 25%; LC, 63% for ~~the different organic resource and chemical nitrogen fertilizer treatments~~ yield; EF, 0.583; RSME, 2.01 t ha^{-1}; SB, 5%; NU, 18%; LC, 77% for ~~the uncalibrated (top) and calibrated DayCent model (bottom)~~AGB.

~~Measured and simulated maize grain yields over time~~Abbreviations: EF, ~~at the four study~~ Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics: EF, 0.755; RSME, 0.707 t ha^{-1}; SB, 12%; NU, 25%; LC, 63% for ~~the different organic resource and chemical nitrogen fertilizer treatments~~ yield; EF, 0.583; RSME, 2.01 t ha^{-1}; SB, 5%; NU, 18%; LC, 77% for ~~the uncalibrated (top) and calibrated DayCent model (bottom)~~AGB.

Figure A4. Mean simulated versus ~~mean~~ measured yield and aboveground biomass (AGB) from the leave-one-site-out cross-validation. Error bars represent the standard deviation of measured and simulated values over all years.

~~Measured and simulated maize grain yields over time~~Abbreviations: EF, ~~at the four study~~ Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Across all sites model statistics: EF, 0.755; RSME, 0.707 t ha^{-1}; SB, 12%; NU, 25%; LC, 63% for ~~the different organic resource and chemical nitrogen fertilizer treatments~~ yield; EF, 0.583; RSME, 2.01 t ha^{-1}; SB, 5%; NU, 18%; LC, 77% for ~~the uncalibrated (top) and calibrated DayCent model (bottom)~~AGB.

A3 Comparing measured and simulated mean yield

A4 Site specific sensitivities of yield to N fertilizer

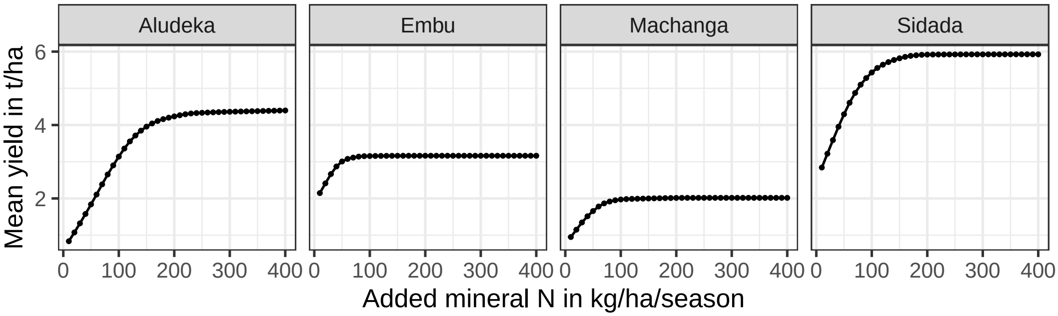


Figure A5. ~~N~~ Yield response curve ~~by site~~ of DayCent to varying levels of mineral N application (control + N treatment, without organic resources) using the calibrated DayCent parameters. ~~This was done to explain why DayCent insensitive at high N levels~~Displayed are the simulated mean yields across all simulated seasons (32 in Sidada and Aludeka, 38 seasons in Embu and Machanga). The amount of mineral N ~~was given~~ applied per season in ~~50/50~~ the simulations was evenly split ~~application, at~~ between the ~~two real~~ actual application dates of mineral N in each season at each site.

A5 ~~SOC stocks~~

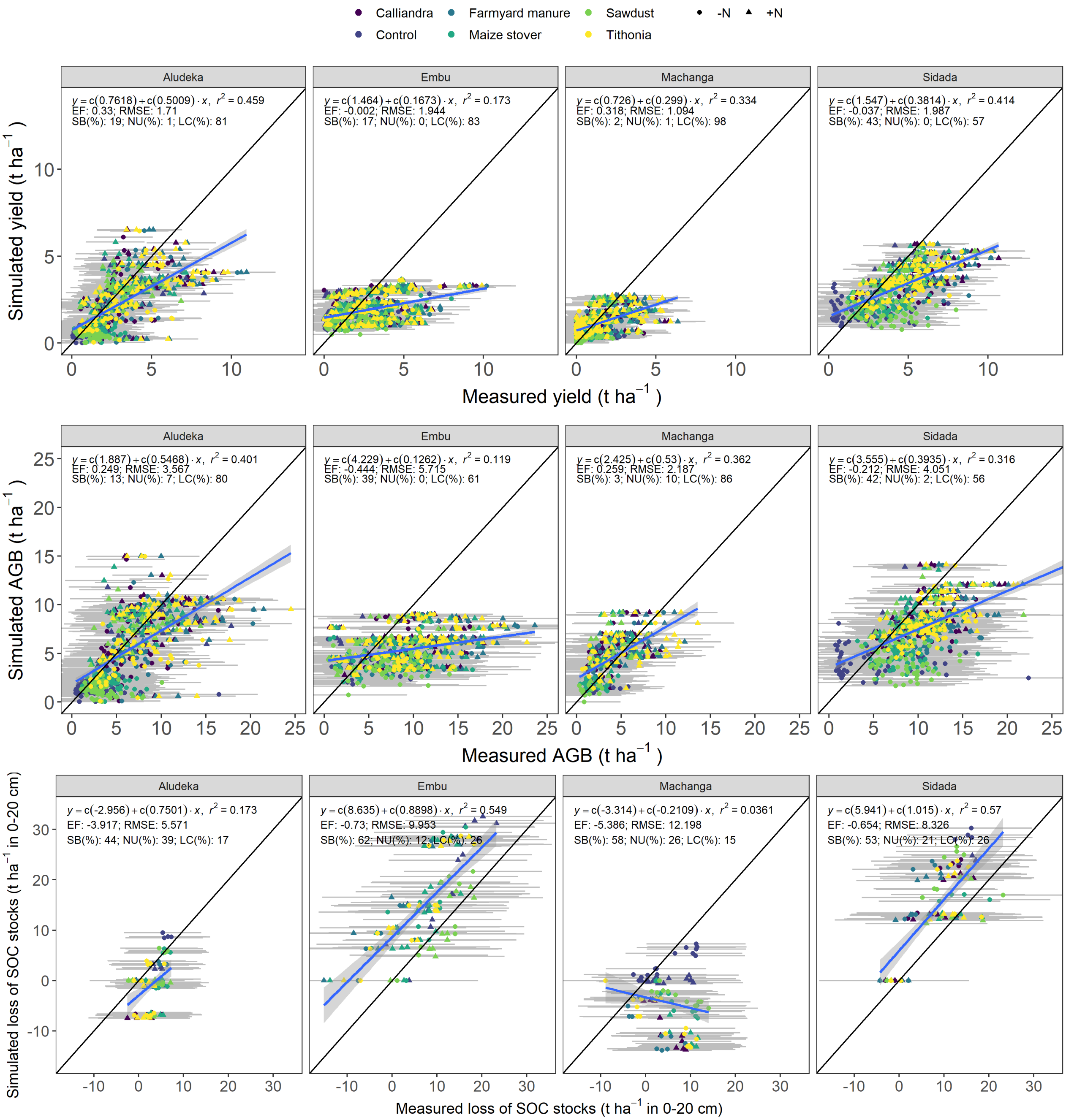


Figure A6. Simulated compared to measured maize grain yields, aboveground biomass and change in SOC ~~: 1st~~ stocks at the four study sites for the default DayCent ~~outputs initial~~ parameter set before adjusting ps1co(~~left~~1&2)~~vs calibrated by leave-one-site-out cross-validation (right)~~&rsplig from 0.5 to 0.85. Grey bands ~~denote~~ show the 95% confidence intervals of measured (horizontal) values and the 95% credibility intervals of posterior ~~simulated~~ distribution (vertical)~~values~~. Abbreviations: EF, Nash-Sutcliffe modeling efficiency; RMSE, root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation.

A5 ~~Calibration improvement by Site~~Barplots of SOC

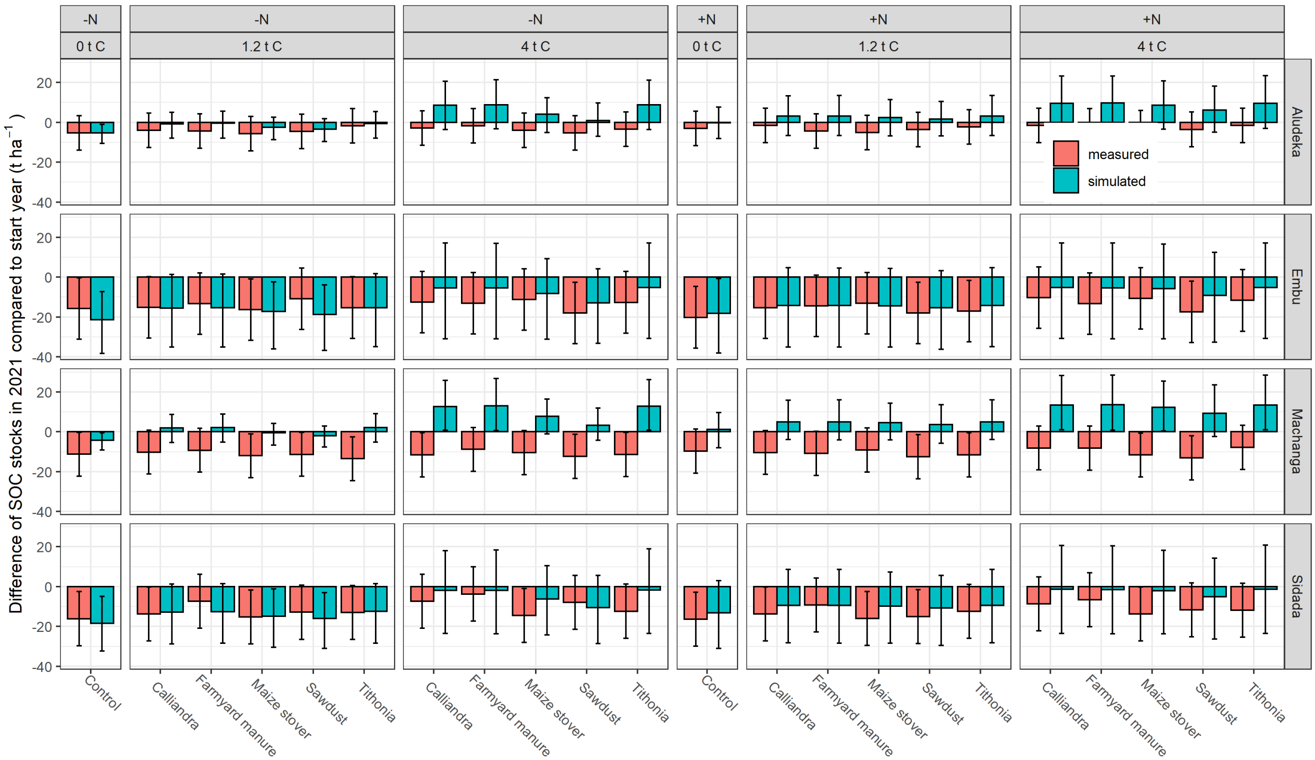


Figure A7. ~~Simulated compared to~~ Barplots of simulated and measured ~~changes in~~ change of SOC stocks ~~since experiment start for the default DayCent parameter set~~ (~~top~~0-30 cm depth) ~~vs the calibrated parameter set by leave-one-site-out~~ until 2021 from cross-validation~~(bottom). Grey bands denote~~, at the four study sites for the different organic resource and chemical nitrogen fertilizer treatments. Error bars represent 95% confidence intervals ~~of measured~~ based on BC (~~horizontal~~simulations) ~~values~~ and ~~the 95% credibility intervals of posterior distribution~~ variance (~~vertical~~measurements).

~~Simulated compared to measured yield for the default DayCent parameter set (top) vs the calibrated parameter set by leave-one-site-out cross-validation (bottom). Grey bands denote the 95% confidence intervals of measured (horizontal) values and the 95% credibility intervals of posterior distribution (vertical).~~

A6 N_2O emissions

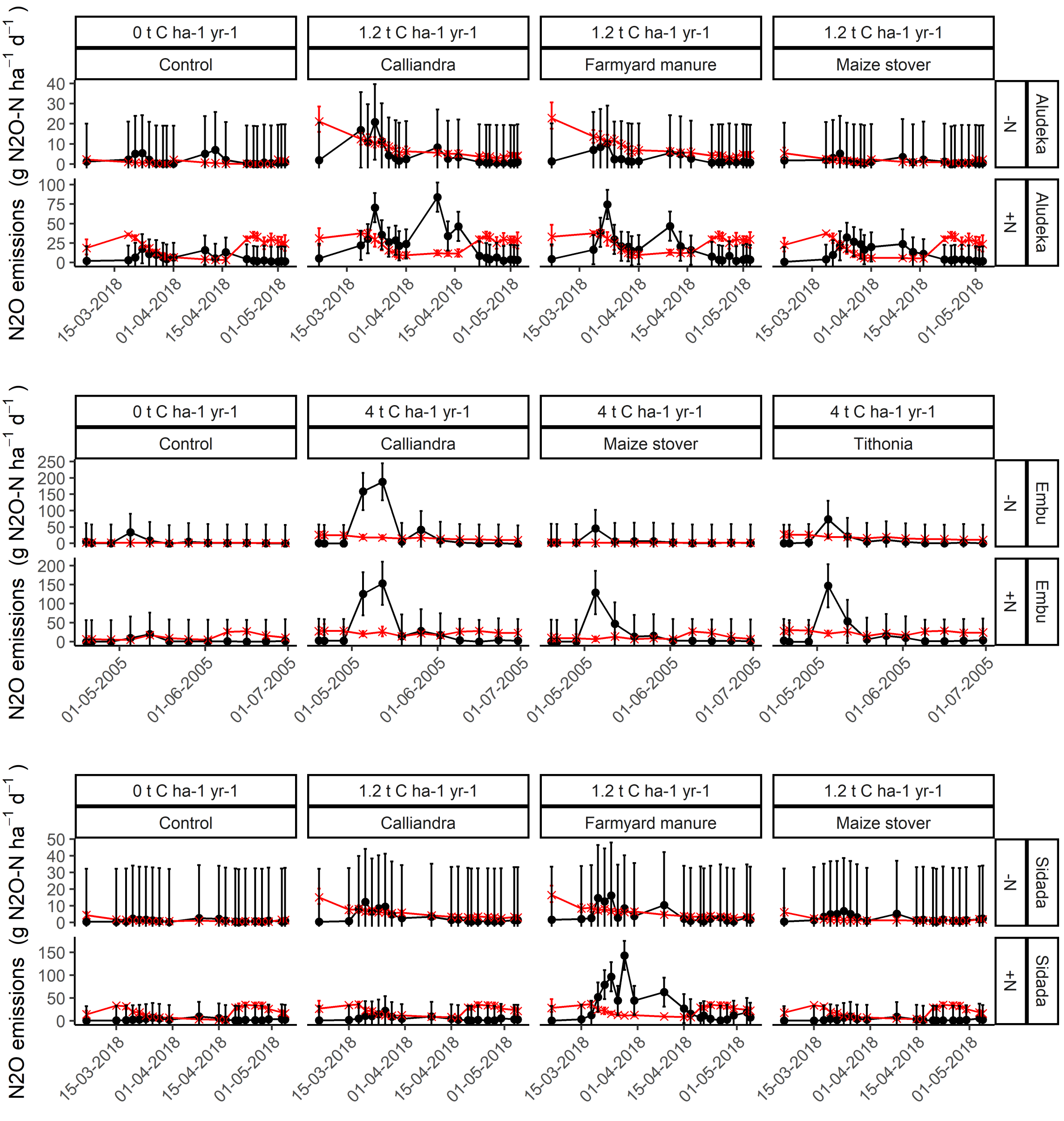


Figure A8. ~~Temporal~~ Example of the temporal development of measured (black) vs simulated (red) N_2O emissions by site. The black error bars represent the 95% confidence intervals due to spatial replication error, the red error bars represent the 95% credibility intervals of simulated N_2O emissions resulting from parameter distribution of the posterior parameter set.

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