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Long-term soil organic carbon and crop yield feedbacks differ between 16 soil-crop models in sub-Saharan Africa

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ABSTRACT

Food insecurity in sub-Saharan Africa is partly due to low staple crop yields, resulting from poor soil fertility and low nutrient inputs. Integrated soil fertility management (ISFM), which includes the combined use of mineral and organic fertilizers, can contribute to increasing yields and sustaining soil organic carbon (SOC) in the long term. Soil-crop simulation models can help assess the performance and trade-offs of a range of crop management practices including ISFM, under current and future climate. Yet, uncertainty in model simulations can be high, resulting from poor model calibration and/or inadequate model structure. Multi-model simulations have been shown to be more robust than those with single models and help understand and reduce modelling uncertainty. In this study, we aim to perform the first multi-model comparison for long-term simulations of crop yield and SOC and their feedbacks in SSA. We evaluated the performance of 16 soil-crop models using data from four long-term maize experiments at sites in SSA with contrasting climates and soils. Each experiment had four treatments: i) no exogenous inputs, ii) addition of mineral nitrogen (N) fertilizer, iii) use of organic amendments, and iv) combined use of mineral and organic inputs. We assessed model performance in two steps: through blind calibration involving a minimum level of experimental data provided to the modeling teams, and subsequently through full calibration, which included a more extensive set of observational data. Model ensemble accuracy was greater with full calibration than blind calibration. Improvement in model accuracy was larger for maize yields (nRMSE 48 vs 18%) than for topsoil SOC (nRMSE 22 vs 14%). Model ensemble uncertainty (defined as the coefficient of variation across the 16 models) increased over the duration of the long-term experiments. Uncertainty of SOC simulations increased when organic amendments were used, whilst uncertainty of yield predictions was largest when no inputs were applied. Our study revealed large discrepancies among the models in simulating i) crop-to-soil feedbacks due to uncertainties in simulated carbon coming from roots, and ii) soil-to-crop feedbacks due to large uncertainties in simulated crop N supply from soil organic matter decomposition. These discrepancies were largest when organic amendments were applied. The results highlight the need for long-term experiments in which root and soil N dynamics are monitored. This will provide the corresponding data to improve and calibrate soil-crop models, which will lead to more robust and reliable simulations of SOC and crop productivity, and their interactions.

1. Introduction

Food insecurity in sub-Saharan Africa (SSA) can be largely attributed to low cereal crop yields often caused by low soil fertility and low external input use (Sanchez, 2002). In fact, the large yield gaps of cereal crops in SSA can mostly be explained by soil nutrient limitations rather than climate factors (Van Ittersum et al., 2016). Soil fertility has declined in many regions of SSA as a result of the low use of mineral and organic fertilizers, the shortening of fallow periods and soil erosion (Falconnier et al., 2023; Vanlauwe et al., 2015b; Vanlauwe and Giller, 2006). Sustainable intensification schemes, such as Integrated soil fertility management (ISFM), aiming at maximizing the agronomic use efficiency of nutrients through the combined use of mineral and organic fertilizers, are promising entry points to increase both crop yield and soil organic carbon (SOC), with potential positive impacts on food security and adaptation to climate change (Gram et al., 2020; Vanlauwe et al., 2010).

Beside the short-term effects brought by the immediate crop response to mineral and organic fertilizers, the performance of ISFM depends on long-term soil-crop feedbacks. Soil-crop feedbacks describe ecological processes whereby a crop leaves biotic and/or abiotic soil legacies and vice versa, which impact the growth of subsequent crops (Bever, 1994; Pernilla Brinkman et al., 2010).

Indeed, SOC buildup through ISFM can i) increase or maintain nutrient supply in the long term through the decomposition of greater amounts of soil organic matter (SOM), and ii) enhance or maintain soil aggregation and improve soil structure which can favor root development (Adams et al., 2020). In turn, higher crop productivity with associated larger amounts of crop residues (roots and shoots) increases carbon (C) inputs into the soil. Other crop-to-soil feedbacks include nutrient cycling (e.g. direct nitrogen (N) carry over from legumes to cereals), carry-over of pests and diseases (e.g. pathogens) and mutualist biota (e.g., symbiotic N-fixing bacteria, mycorrhizal fungi) (Mariotte et al., 2018; Smith-Ramesh and Reynolds, 2017). However, mechanisms involved in soil-crop feedbacks are complex. For example, root growth is also known to stimulate SOM decomposition through the rhizosphere priming effect (Cheng and Kuzyakov, 2005; Dijkstra et al., 2021; Kuzyakov, 2002), and fertilizers do not always increase yields and C inputs into the soil, e.g. in the case of non-responsive soils (Vanlauwe et al., 2015a, 2010), but on the other hand may stimulate SOM decomposition (Feng et al., 2022; Zhou et al., 2014).

Long-term experiments on ISFM can provide valuable insights into soil-crop feedback mechanisms (Bationo et al., 2012; Cardinael et al., 2022; Laub et al., 2023b). However, such experiments are costly, and cannot capture the entire variability of soils, climatic conditions and management practices that exist in farmers' context (Körschens, 2021; Mirtl et al., 2018). Alternatively, process-based soil-crop models that simulate daily soil processes and plant growth, can help explore long-term effects of ISFM on crop growth and soil fertility for different crop genotypes, soil types, and management practices. These models extend beyond the confines of experimental settings and allow for the exploration of the interactions between these factors (G x E x M). More specifically, the coupled soil-plant models can account for some of the complex feedback mechanisms between SOC dynamics and crop growth over the long term (Basso et al., 2018; Smith et al., 2020a). In fact, the existing models incorporate crop-to-soil feedbacks primarily by considering C inputs derived from roots and/or shoots of the cultivated crops. As for the soil-to-crop feedbacks, they principally consider N supply originating from the decomposition of crop residues and SOM.

Some studies have assessed the capability of process-based soil-crop models to reproduce the effects of drought on crop yield (Kamali et al., 2022) across SSA or those of mineral and organic fertilizers on SOC content (Kamoni et al., 2007) in Kenya. However, feedbacks between SOC and crop biomass have received little scrutiny in these studies. DayCent (Del Grosso et al., 2001) and LPJ-GUESS (Smith et al., 2014), two process-based soil-plant models, simulated reasonably well average maize grain yield and SOC responses to ISFM in a long-term experiment in Kenya, but interannual variability in yield was not well captured (Ma et al., 2022; Nyawira et al., 2021). Although these studies highlighted the strengths and weaknesses of these two models, they did not capture the full diversity of existing soil-crop models and considered a limited number of climate and soil conditions that prevail in SSA.

Multi-model ensembles can help reduce the uncertainties in the simulation of soil and crop variables as a result of compensation of individual model errors and wider integration of model formalisms (Martre et al., 2015; Wallach et al., 2018). Furthermore, model intercomparisons can help understand to what extent models differ in their design and skills to accurately predict soil and crop variables, which in turn can guide the improvement of these models. Yet, model intercomparisons have mainly focused on the impact of climate change on crop yields, particularly for wheat, maize, soybean and rice (e.g. Asseng et al., 2013; Bassu et al., 2014; Kothari et al., 2022; Li et al., 2015). Few studies have focused on simulating SOC dynamics (Bruni et al., 2022; Farina et al., 2020; Smith et al., 1997, 2012), and even fewer have simulated conjointly crop yield and SOC dynamics (Basso et al., 2018; He et al., 2021; Sándor et al., 2020). In fact, multi-model comparisons regarding SOC dynamics have either been done in the absence of observations for model calibration (Basso et al., 2018), or were conducted for bare soil conditions only, i.e. without plant growth (Bruni et al., 2022; Farina et al., 2020) or for temperate climates only (He et al., 2021; Sándor et al., 2023, 2020; Smith et al., 2012). For example, Sándor et al. (2023) found that some models overestimated observed SOC contents, while others underestimated them, and that the model ensemble median outperformed individual models in 92% of cases. Inconsistencies between model simulations and observed SOC data can be caused by inaccuracies in the simulation of both soil and crop processes. Accurate model comparison is challenging due to the complexities arising from the contribution of individual components (such as the soil and crop modules) to the overall model inaccuracy (Ehrmann and Ritz, 2014).

When dealing with ISFM in SSA, two additional challenges need to be considered: i) water and N stresses need to be well accounted for in the model to accurately simulate crop yields, especially in low-input systems (Falconnier et al., 2020), and ii) organic fertilizers, that are commonly used by smallholder farmers, have to be well represented in the model and their impact on SOC dynamics and crop growth need to be accurately simulated (Cavalli et al., 2019; Levavasseur et al., 2021). Whilst Falconnier et al. (2020) showed the potential of using multi-model ensembles for accurate maize yield simulations in SSA, we are not aware of any model intercomparison that evaluates the accuracy of both crop yield and SOC simulations across a range of experimental sites over the long term (without model reinitialization each year). Indeed, most model intercomparisons use short-term field experiments for model calibration and do not account for carry-over effects of soil variables from one year to another (i.e. apply model reinitialization every year). Yet, Basso et al. (2018) and Smith et al. (2020b) found a large effect on simulated crop yields when including soil-crop feedbacks from soil C and N processes.

This study aims to assess how current soil-crop models simulate long-term crop-soil feedbacks. More specifically, we aimed to assess the performance of soil-crop models in simulating long-term trends of rainfed maize yield and SOC for contrasting environments (climate, soil texture, initial SOC level) and fertilization treatments (no input, mineral and/or organic fertilizer) in SSA. We tested five hypotheses: i) local calibration using crop yield and SOC observations is needed to improve model accuracy; ii) the median value of an ensemble of models outperforms single model results for combined yield and SOC simulations; iii) model errors of SOC and crop yield predictions accumulate over time, leading to poor predictions at the end of the long-term simulations; iv) model accuracy is lower in treatments where the number of simulated soil and crop processes and their feedbacks is higher (e.g. decomposition of organic inputs in ISFM, crop N stress when no mineral fertilizers are applied); and v) more complex soil modules, i.e. with a higher number and more types of (S)OM pools, have a higher model accuracy in simulating SOC dynamics.

2. Methods

2.1. Experimental data for model calibration

2.1.1. Experimental design

We calibrated 16 soil-crop models using data from long-term rainfed maize experiments at four sites across SSA. The sites span a range of climates (from warm to cool and from semi-arid to humid), soil textures (from sandy to clayey) and soil fertility levels (varying initial SOC contents, 0.3–3%) (Table 1). The selected long-term experiments (ranging from 9 to 18 years in duration depending on the site) were conducted on station or on farm, but managed by researchers. In three sites (Côte d'Ivoire-Gagnoa, Kenya-Embu and Kenya-Machanga), there were two crop growing seasons per year. The crop grown was maize, except in the second growing season for the site in Côte d'Ivoire where soybean was sown (in two years of the experiment), the soil was left bare (in five years of the experiment) or maize was sown (in five years of the experiment). Experiments were rainfed only, and included four treatments: i) a control without external C and N inputs (-C-N), ii) the application of mineral N fertilizer (between 100 and 160 kg N ha^{-1} per growing season depending on the site) (-C+N), iii) the application of organic fertilizer (manure, or compost from crop residues, between 3 and 4 t C ha^{-1} per year depending on site) (+C-N), and iv) the combined application of organic and mineral N fertilizer (+C+N). The experimental treatments provided proxies for water-limited (+C and +N treatments) and water plus nutrient-limited conditions (-C-N treatment) for crop growth. Weeds, diseases and pests were controlled using appropriate management to avoid biotic stresses, eliminating them as a source of uncertainty in the model predictions in this study. Crop aboveground biomass residues were all removed from the fields in each site, thus roots were the only crop residue input.

The experiments were extensively described in earlier publications, for Côte d'Ivoire-Gagnoa by Pichot et al. (1977), Guibert (1999) and Cardinael et al. (2022), for the two sites in Kenya by Chivenge et al. (2009), Gentile et al., (2009, 2011) and Laub et al. (2023a), (2023b) and for the site in Zimbabwe by Zingore et al. (2007) and Rusinamhodzi et al. (2013).

2.1.2. Meteorological data

Weather data (solar radiation, maximum and minimum air temperature, precipitation and relative humidity) over the duration of each experiment were collected from different sources depending on the site. Daily rainfall was recorded using graduated cylindrical or tipping bucket rain gauges in all sites with some missing years only in Kenya-Embu. Daily temperature (maximum and minimum) was recorded with electronic sensing thermometers in Côte d'Ivoire-Gagnoa and Kenya-Machanga in all experimental years, but with some missing years in Kenya-Embu; no records were available for Zimbabwe-Murewa. Daily incident solar radiation and relative humidity were retrieved from the NASA POWER (Prediction Of Worldwide Energy Resource) database for all years and sites (https://power.larc.nasa.gov/). Missing daily temperature and rainfall data (missing years) were gap filled with bias-corrected or original NASA-POWER data, respectively. Briefly, for correction of daily temperature, an equation for a linear regression was created using NASA data as the independent variable (x) and observed data as the dependent variable (y) at each site. The slope and intercept values obtained from the regression equation, $y = ax+b$, were utilized to generate bias-corrected estimates for the missing temperature data.

Table 1
Characteristics of the long-term experiments and the observed data available for model calibration.

		Site			
General information	Country	Côte d'Ivoire	Kenya	Kenya	Zimbabwe
	Location	Gagnoa	Embu	Machanga	Murewa
	Latitude	6.13	-0.52	-0.79	-17.81
	Longitude	-5.93	37.46	37.66	31.56
	Elevation (m)	213	1380	1022	1262
Climate	Average annual rainfall (mm)[a]	1402	1175	795	898
	Average annual temperature (°C)[a]	25.5	20.1	23.7	20.9
	FAO agro-ecological zone	warm-humid	cool sub-humid	warm semi-arid	cool-semi-arid
	Rainfall pattern	bimodal	bimodal	bimodal	unimodal
Soil	Type (FAO)	Lixisols	Humic Nitisols	Ferric Alisols	Lixisols
	Texture	sandy clay loam	clay	sandy clay loam	sandy
	Initial SOC (%) (0-20 cm)	1.1	2.9	0.3	0.5
	Initial SON (%) (0-20 cm)	0.11	0.3	0.02	0.04
Management	Experiment duration (years)	13	18	10	9
	First crop cycle	maize	maize	maize	maize
	Second crop cycle	maize or soybean or fallow	maize	maize	none
	Maize cultivar	hybrid (medium maturity, variety H507 and IRAT83)	hybrid (early maturity drought tolerant, variety H513)	hybrid (early maturity drought tolerant, variety Katumani)	hybrid (medium maturity, drought tolerant, variety SC525)
	Mineral P and K fertilization (kg/ha/cycle)	100 P + 150 K	60 P + 60 K	60 P + 60 K	/
	Treatments				
	1- No N input	0 N	0 N	0 N	0 N
	2- Mineral N fertilizer (kg/ha/cycle)	160 N	120 N	120 N	100 N + 30 P
	3- Organic fertilizer (t C/ha/year)	3 t C/ha compost of crop residues	4 t C/ha manure	4 t C/ha manure	none
	4- Mineral N fertilizer (kg/ha/cycle) + organic fertilizer (t C/ha/year)	160 N+ 3 t C/ha compost of crop residues	120 N + 4 t C/ha manure	120 N + 4 t C/ha manure	100 N + 3 t C/ha manure
	Organic fertilizer composition	29.3% C, 2.0% N, 1.0% P, 5.9% K	28.4% C, 2.4% N, 0.4% P, 3.6% K	28.4% C, 2.4% N, 0.4% P, 3.6% K	20% C, 1.1% N, 0.2% P, 0,6% K
Available data (blind calibration phase)	Emergence date	8 crop cycles	3 crop cycles	3 crop cycles	none
	Anthesis date	19 crop cycles	3 crop cycles	3 crop cycles	none
	Physiological maturity date	none	3 crop cycles	3 crop cycles	none
	Harvest date	all crop cycles	all crop cycles	all crop cycles	all crop cycles
Available data (full calibration phase)	Harvested grain yield (dry matter)	all crop cycles	all crop cycles	all crop cycles	all crop cycles
	Total aboveground biomass (dry matter)	all crop cycles	none	all crop cycles	all crop cycles
	Soil organic C and N (from 4 to 8 points depending on sites)	5 years	13 years	5 years	4 years
	Soil mineral N (one point before sowing)	3 years	none	none	none

[a] Means calculated over the length of the long-term experiment

2.1.3. *Observations and experimental data*

Data on the main soil characteristics at the start of the experiments and on crop management were collected in the experiments. Data on crop phenology were available for two sites (Côte d'Ivoire-Gagnoa and Kenya-Embu) while only general information on the maize cultivar planted was provided for Zimbabwe-Murewa and Kenya-Machanga (Table 1). Observed data of grain yield was available for all sites while data of total aboveground biomass was available for all sites except Zimbabwe-Murewa. Data from SOC measurements were available in different years over the duration of the experiments (for respectively a total of 4, 5, 8 and 13 years in Zimbabwe-Murewa, Côte d'Ivoire-Gagnoa, Kenya-Machanga and Kenya-Embu). SOC was determined from topsoil samples (0–15 cm in Kenya-Machanga and Kenya-Embu and 0–20 cm in Zimbabwe-Murewa and Côte d'Ivoire-Gagnoa). The experiment in Côte d'Ivoire contained three measurement of soil mineral N (0–20 cm) that were done before the start of the first growing season in three different years.

2.2. *Overview of the models*

An ensemble of 16 process-based soil-crop models was used in this study (Table 2). Models differed in the way they simulate soil and crop processes. The simulation of SOC dynamics is principally based on first-order decay kinetics for mass loss of SOM pools, and models differed in the number and nature of these pools. Some models have multiple SOM pools (e.g., CENTURY in DSSAT differentiate between an active, slow and passive SOM pool), while other models have a single SOM pool (e.g., CELSIUS). Ten of the 16 models include a soil microbial biomass pool that follow first-order kinetic decay. The representation of fresh OM pools (from above- and belowground crop residues, organic amendments, such as manure and compost) is the most complex in SIMPLACE (based on the SoilCN model, Corbeels et al., 2005, Molina et al., 1983), in which four pools are represented (subdivided in a metabolic, holo-cellulosic, ligno-cellulosic and woody litter pool), while half of the other models have only a single fresh OM pool. All models simulate soil N cycling coupled to the (S)OM pool(s). Multi-pool SOC models usually have pool-specific decay coefficients that govern the decomposition rate of each individual pool, leading to a non-linear behavior of the entire system (e.g. Caruso et al., 2018). The soil-crop models also differ in the representation of other soil processes (e.g., soil water dynamics, nitrate leaching) and of crop processes (e.g. leaf area development, light interception, above- and belowground biomass accumulation and grain formation) (see Table S1 for more details on the differences in the simulation of crop processes between the models).

Table 2
The 16 soil-crop process-based models used in the model intercomparison study.

Model	Abbreviation	Total C pools	Residue pools	Microbial pools	SOM pools	Soil sub-model	Crop sub-model	Model reference
APSIM v7.9	AP	3	1	1	1	SoilN	APSIM	Holzworth et al. (2014)
CELSIUS	CE	2	1	0	1	CELSIUS	CELSIUS	Ricome et al. (2017)
DayCent	DC	5	2	0	3	CENTURY	DayCent	Del Grosso et al. (2001)
DNDC v.CAN	DN	8	3	2	3	DNDC	DNDC	Smith et al. (2020b)
DSSAT v4.8.0.19 -CERES-Maize + Century	DS1	5	2	0	3	CENTURY	CERES maize	Ritchie et al. (1998); Gijsman et al. (2002); Hoogenboom et al. (2021)
DSSAT v4.8.0.19 -CERES-Maize + Ceres-SOM	DS2	2	1	0	1	CERES	CERES maize	Hoogenboom et al. (2021); Godwin and Jones (1991)
EPIC	EI	5	2	0	3	EPIC	EPIC	Izaurralde et al. (2006)
Expert-N v5.1-Gecros	EG	3	1	1	1	SoilN	similar to SUCROS	Biernath et al. (2011)
Expert-N v5.1-Spass	ES	3	1	1	1	SoilN	SPASS	Biernath et al. (2011)
Expert-N v5.1-Ceres	EC	3	1	1	1	SoilN	CERES maize	Biernath et al. (2011)
InfoCrop v2.1	IN	3	3	1	1	InfoCrop	similar to SUCROS	Aggarwal et al. (2006a,2006b)
MONICA v3.3.1	MO	6	2	2	2	DAISY	HERMES/ AGROSIM	Aiteew et al. (2023); Nendel et al. (2011)
SALUS	SA	5	2	0	3	CENTURY	SALUS	Basso et al. (2010)
SIMPLACE-Lintul + Option 1	SI1	7	4	1	2	SoilCN	Lintul	Enders et al. (2023);Gaiser et al. (2013)
SIMPLACE-Lintul + Option 2	SI2	7	4	1	2	SoilCN	Lintul	Faye et al. (2018)
STICS v10	ST	4	1	1	2	STICS	STICS	Brisson et al. (2003);Beaudoin et al. (2023)

2.3. Model calibration procedure

The models were calibrated in two phases, namely a blind and a full calibration phase, following a similar approach as other multi-model comparisons within the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013). For the blind calibration, values (measured or estimated) for a minimum set of input variables required to execute the model were provided, i.e. general soil characteristics, initial soil conditions, weather, soil and crop management, and observed dates of emergence, flowering and physiological maturity of the maize crop (Table 1). Soil depth in the model runs was set at 1.5 m for all sites. Model parameter adjustment was limited to fitting maize development stages to observed emergence, anthesis and maturity. The modelling teams could use their own method for initialization of the SOM pools (use initial SOC value, combined with spin-up runs - i.e. running the model iteratively for thousands of years to approximate the steady state solution - or with empirical functions between SOM pools and soil texture). For the full calibration, values for additional observed crop and soil variables were provided to the modelling teams, i.e. grain yield, total aboveground biomass at harvest when available, and SOC values (0- 15 cm for Kenya-Embu and Kenya-Machanga and 0–20 cm for Côte d'Ivoire-Gagnoa and Zimbabwe-Murewa) at various points in time, depending on the site (Table 1). The modeling teams were free to adjust any model parameter they found relevant to improve the match between observed data and simulations, using their usual calibration methods. The teams calibrated crop and soil-related parameters (e.g. parameters governing SOM and residue decomposition) to improve the accuracy in crop growth and SOC simulations. Simulations were performed by a single modeling team of experimented users for each model. Different options of the same model (DSSAT, Expert-N and SIMPLACE, see Table 2) were simulated by a single modelling team.

2.4. Data analysis

2.4.1. Model performance assessment

We assessed the accuracy of each individual model and the multi-model ensemble in reproducing crop yield and SOC stocks by using the root mean square error (RMSE) and normalized RMSE (nRMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - S_{i,m}\right)^2}$$

$$nRMSE = \frac{RMSE}{\bar{O}} \text{x}100,$$

where O_i and $S_{i,m}$ are the observed and simulated values (for model m) for the n^{th} measurement, n is the number of observations and $\bar{O}$ is the mean of the observed values.

The Nash–Sutcliffe modeling efficiency (EF) was also used to assess the accuracy of the multi-model ensemble in reproducing crop yield and SOC stocks as follows:

$$EF = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2},$$

where O_i is the observed value of the n^{th} measurement, $\bar{O}$ is the mean of the observed values and S_i is the simulated value corresponding to Oi.

Uncertainty in the multi-model ensemble simulations was assessed using the coefficient of variation (CV) of the 16 model simulations for yield and SOC:

$$CV_s \quad (\%) = \frac{\sigma_s}{S_s} \times 100,$$

where σ_s is the standard deviation of the simulated values among models at site s and S is the mean of the simulated values at site s.

2.4.2. Evaluation of soil-crop feedbacks

The relationships between i) maize yield or SOC versus time since the start of the experiment, ii) N mineralized and SOC, and (ii) nRMSE of SOC simulations and the number of SOM pools, were evaluated with Pearson correlation coefficients, using the cor.test function of the R Stats package (R core team, 2023). For all statistical tests, the significance level, α, was set to 0.05.

3. Results

3.1. Accuracy of multi-model ensemble: blind vs full calibration

In the blind calibration phase, the multi-model ensemble strongly overestimated average maize yields across all years and treatments of the four experiments (median ensemble nRMSE of 48%, Fig. 1. A), whilst final topsoil SOC stocks of the treatments in the four experiments were simulated with acceptable accuracy (median ensemble nRMSE of 22%, Fig. 1. B). Full calibration substantially improved the ability of the multi-model ensemble to reproduce average maize yields and final topsoil SOC stocks of the different treatments in the four sites (Fig. 1). The increase in model accuracy following full calibration was stronger for the simulations of average maize yields than for the SOC simulations, with a reduction of nRMSE by 30% and 8%, respectively (Fig. 1). The multi-model ensemble failed, however, to adequately reproduce interannual variability in maize yields (Fig. 2, Fig. S1, Fig. S2) in the blind (R^2 =0.35) and full (R^2 =0.47) calibration phases. The changes in topsoil SOC stocks over time were generally well reproduced for the experimental treatments of the four experiments in both the blind (R^2 =0.96) and full (R^2 =0.98) calibration phases (Fig. 3, Fig. S1, Fig. S3). The accuracy of the multi-model ensemble in simulating interannual yield variability was highest in Côte d'Ivoire-Gagnoa where both low and high yields were accurately reproduced for the four experimental treatments in the blind and full calibration phases (Fig. 2, Fig. S1, Fig. S2).

3.2. *Accuracy of individual models vs multi-model ensemble*

Larger differences in accuracy between individual models occurred in the blind calibration phase (nRMSE ranging from 42 to 150%) compared to the full calibration phase (nRMSE ranging from 17 to 76%) for the simulations of average maize yield across all sites and treatments (Fig. 4). Individual models also simulated final topsoil SOC stocks with larger differences in accuracy in the blind calibration phase (nRMSE ranging from 17 to 90%) compared to the full calibration phase (nRMSE ranging from 9 to 39%, with exclusion of one model whose accuracy did not change between the blind and the full calibration) (Fig. 4). Only DayCent was more accurate than the median multi-model ensemble for the simulation of average yields after full calibration (Fig. 4). Six models (ST, CE, DN, DS1, DC and EI) were more accurate than the median multi-model ensemble in simulating the final topsoil SOC stocks after full calibration (Fig. 4). Only DayCent had better accuracy than the median multi-model ensemble for both simulated average maize yields and final topsoil SOC stocks.

The ranking of the individual models differed between the blind and full calibration phases (Fig. 4). In the blind calibration phase, model ranking for average maize yield and final topsoil SOC stocks were different; some models were among the best to reproduce final SOC stocks but among the worst to reproduce average yields (e.g., EI and EC). Conversely, some models were among the best to reproduce average yields but among the worst to reproduce final SOC stocks (e.g., DS2 and DN). However, with full calibration, model ranking for averaged yield and final topsoil SOC stocks were similar. In other words, models that performed best to reproduce final SOC stocks were also performing best for average yields (e.g., ST, CE, DN).

3.3. *Multi-model ensemble drift over time*

With full calibration, the accuracy of the multi-model ensemble

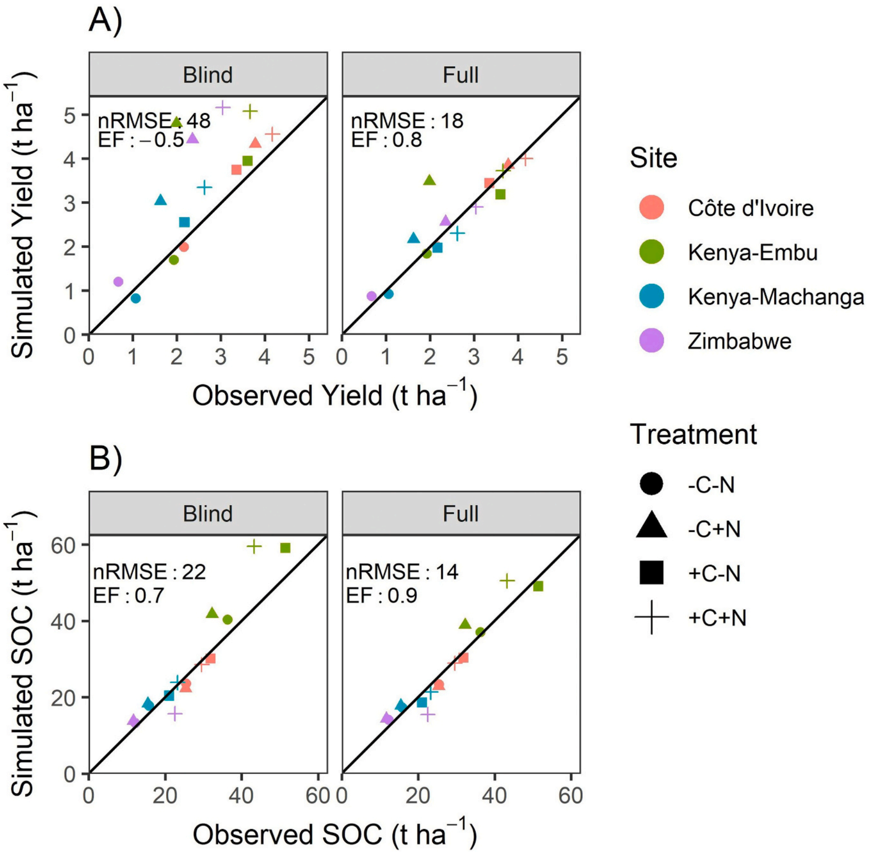

Fig. 1. Observed and simulated average maize yield (t dry matter ha^{-1}) across all years of the long-term experiments (A) and soil organic carbon (SOC, t C ha^{-1} in 0–15 cm soil depth in Kenya-Embu and Kenya-Machanga and 0–20 cm soil depth in Zimbabwe-Murewa and Côte d'Ivoire-Gagnoa) at the end of the long-term experiment (B) using blind and full model calibration, at four sites in sub-Saharan Africa, for four N fertilizer and organic amendment treatments. The simulations are the median of an ensemble of 16 soil-crop models. Treatments are without inputs (-C-N), with mineral N fertilizer inputs only (-C+N), with organic amendments only (+C-N) and with combined organic and mineral N fertilizer inputs (+C+N). nRMSE is the normalized Root Mean Square Error while EF is the Model Efficiency.

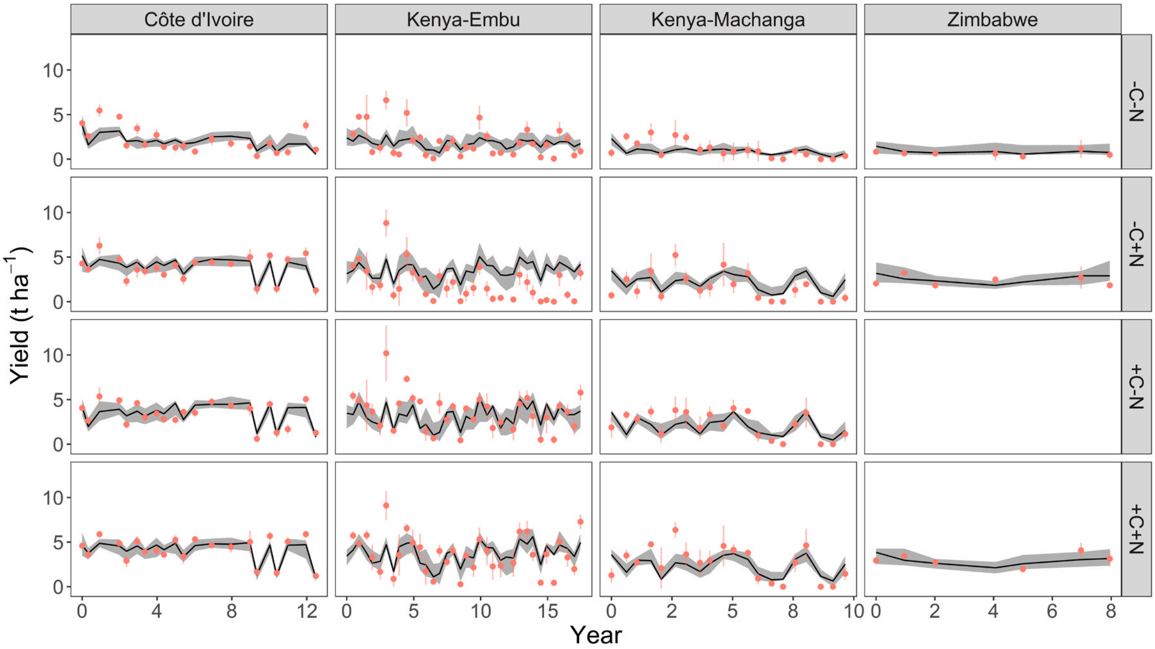

Fig. 2. Observed (red dots) and simulated maize yield (t dry matter ha^{-1}) using 16 fully calibrated models, in four sites in sub-Saharan Africa, for four N fertilizer and organic amendement treatments. Black solid lines are medians of the simulations. Dark gray areas indicate the 25th to 75th percentile range of the values simulated. Treatments are without inputs (-C-N), with mineral N fertilizer inputs only (-C+N), with organic amendments only (+C-N) and with combined organic and mineral N fertilizer inputs (+C+N).

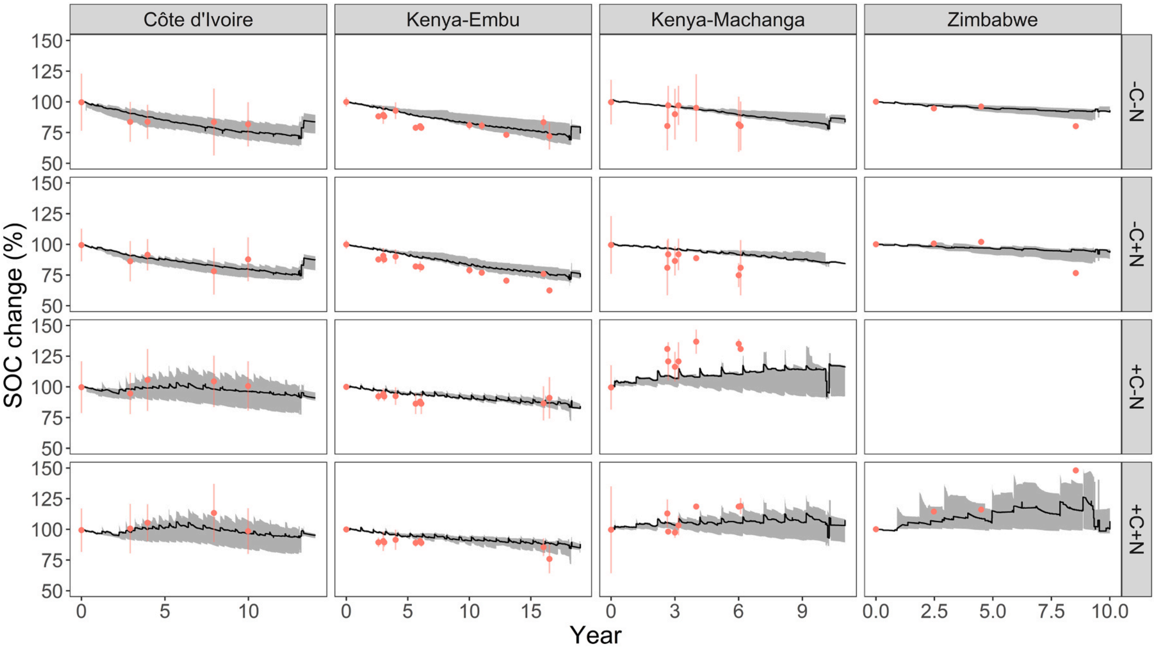

Fig. 3. Observed (red dots) and simulated relative change in soil organic carbon (SOC) (in 0–15 cm soil depth in Kenya-Embu and Kenya-Machanga and 0–20 cm soil depth in Zimbabwe-Murewa and Côte d'Ivoire-Gagnoa) using 16 fully calibrated models, in four sites in sub-Saharan Africa, for four N fertilizer and organic amendment treatments. Black solid lines are medians of the simulations. Dark gray areas indicate the 25th to 75th percentile range of the values simulated. Treatments are without inputs (-C-N), with mineral N fertilizer inputs only (-C+N), with organic amendments only (+C-N) and with combined organic and mineral N fertilizer inputs (+C+N).

(expressed as RMSE) decreased over time for the SOC simulations, and at the same time uncertainty (expressed as CV across models) increased (Fig. 5. C and 5. D). On the other hand, no clear trends could be observed for the maize yield simulations (Fig. 5. A and Fig. 5. B). In fact, the change in model accuracy over time was not treatment-specific for yield simulations, except for the -C+N treatment in Kenya-Embu where yields were increasingly overestimated towards the end of the experiment (maximum RMSE of 3.7 t/ha, Fig. 6. A). Yields were simulated with greater accuracy in the no input treatment (-C-N), but with greater uncertainty, than in any other treatments in all sites, except in Côte d'Ivoire-Gagnoa. The change in model accuracy over time was also not treatment-specific for the SOC simulations (Fig. 6. C). However, all

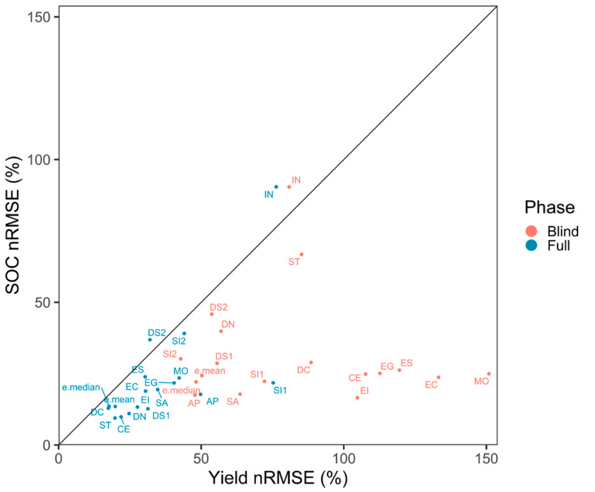

Fig. 4. Normalized root mean square error (nRMSE) for maize grain yield and soil organic carbon (SOC) simulations by individual models and model ensemble mean (e.mean) and median (e.median) for blind and full calibration. Model abbreviations: AP (APSIM), CE (CESCIUS), DS1 (DSSAT-Century), DS2 (DSSAT-Ceres), DC (DayCent), DN (DNDC), EC (Expert-N-Ceres), EG (Expert-N-Gecros), EI (EPIC), ES (Expert-N-Spass), IN (InfoCrop), MO (MONICA), SI1 (SIMPLACE-1), SI2 (SIMPLACE-2), SA (SALUS), ST (STICS).

treatments showed an increase in uncertainty of the SOC simulations over time, in all sites, and this increase was larger in treatments with addition of C inputs (Fig. 6. D).

3.4. *Causes of uncertainty in soil-crop feedbacks*

3.4.1. *SOC-yield feedbacks*

In the no input treatments (-C-N), the observed significant decline in SOC and maize yield over the experimental period in Côte d'Ivoire-Gagnoa and Kenya-Machanga, indicating significant negative soil-crop feedbacks, were reproduced by seven out of the 16 models and eight out of the 16 models, respectively (Fig. 7). On the other hand, the absence of significant conjoint SOC and maize yield decline over the experimental period in Kenya-Embu and Zimbabwe-Murewa were reproduced by 15 out of the 16 models. Some models simulated a sharp SOC decline without yield loss in Côte d'Ivoire-Gagnoa (IN, EG, EC) and Kenya-Machanga (ES, EG), while others simulated a large increase in yield without SOC increase in Kenya-Embu (SI1) and Zimbabwe-Murewa (ES, SI1). None of the models simulated a significant negative correlation between declines in SOC and yield.

3.4.2. *Soil-to-crop feedbacks (via N mineralization)*

In treatments without organic amendments (-C treatments), where N supply for crops originates from SOM decomposition, the simulated average amounts of N mineralized per year showed large differences between models in all sites, ranging from 10 to 100 kg N ha^{-1} year^{-1} in Côte d'Ivoire, from 10 to 260 kg N ha^{-1} year^{-1} in Kenya-Embu, from 10 to 80 kg N ha^{-1} year^{-1} in Kenya-Machanga, and from 5 to 70 kg N ha^{-1} year^{-1} in Zimbabwe-Murewa (Fig. 8). Consequently, models simulated largely different annual N mineralization rates, from 0.5% to 11% of soil total N in Côte d'Ivoire, 0.5% to 6% in Kenya-Embu, 0.5% to 5.5% in Kenya-Machanga, and 0.6% to 4% in Zimbabwe-Murewa (Fig. S4).

Models differed in their simulation of changes in annual N mineralization over time in response to changes in SOC (Fig. 8). Some models simulated N mineralization remaining constant with an increase in SOC (AP, MO), while others simulated an increase in N mineralization with SOC remaining constant (SI2). Among the models that simulated a significant relationship between SOC and mineralized N, large differences were found in the slope of the relationship (resulting in varying N mineralization rates). The largest N mineralization rates per ton SOC were simulated by CE (10.6 kg N t^{-1} C) and DN (8.6 kg N t^{-1} C) in all sites, compared to other models that simulated N mineralization rates of about 1.2 to 2.5 kg N t^{-1} C (ST, EG, ES, EC). Interestingly, the models that simulated SOC loss without a decrease in yield (Fig. 7) were also those that simulated a weak relationship between mineralized N and SOC (IN, EG, EC) (Fig. 8).

With addition of organic amendments (+C treatments), simulated amounts of mineralized N were higher, with much greater discrepancies between models than without added C (Fig. S5), indicating an important but highly uncertain effect of organic amendments on soil-to-crop feedbacks in the model simulations.

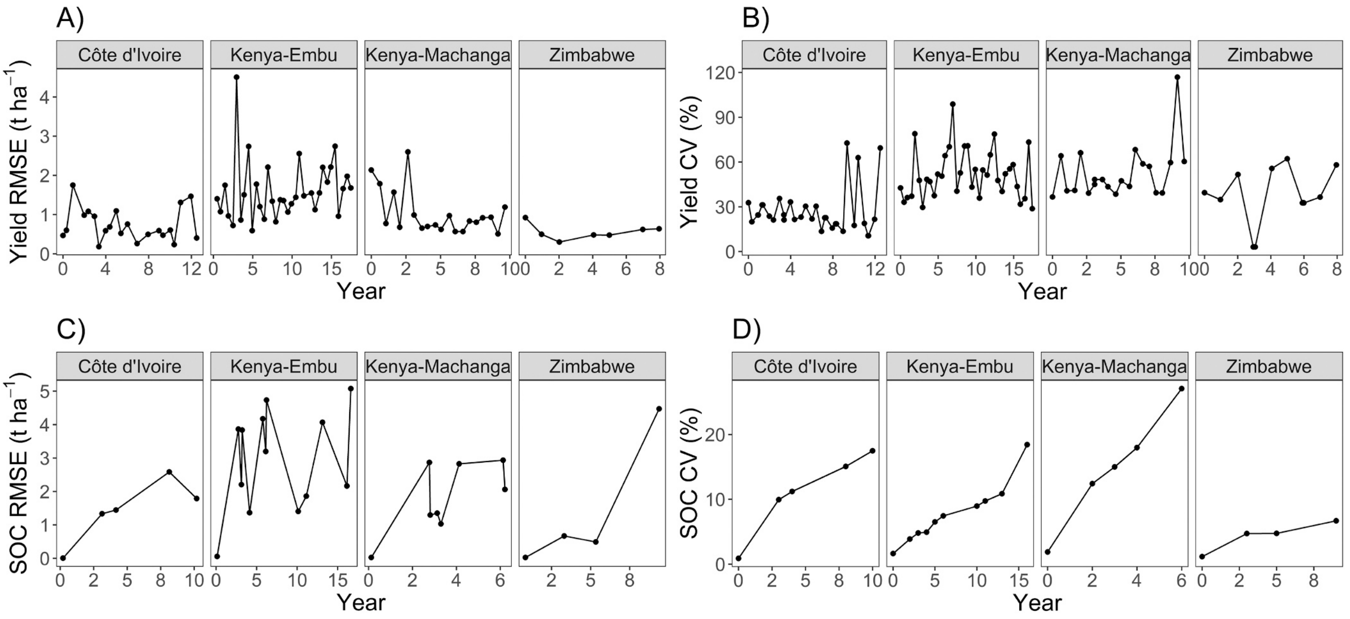

Fig. 5. Root means square error (RMSE) and coefficient of variation (CV) for maize grain yield (A, B) and soil organic carbon (SOC) (C, D) in each experimental year for fully calibrated models, in four sites in sub-Saharan Africa, across all treatments. RMSE was computed from the median of an ensemble of 16 soil-crop models while CV was based on the 16 models' simulations.

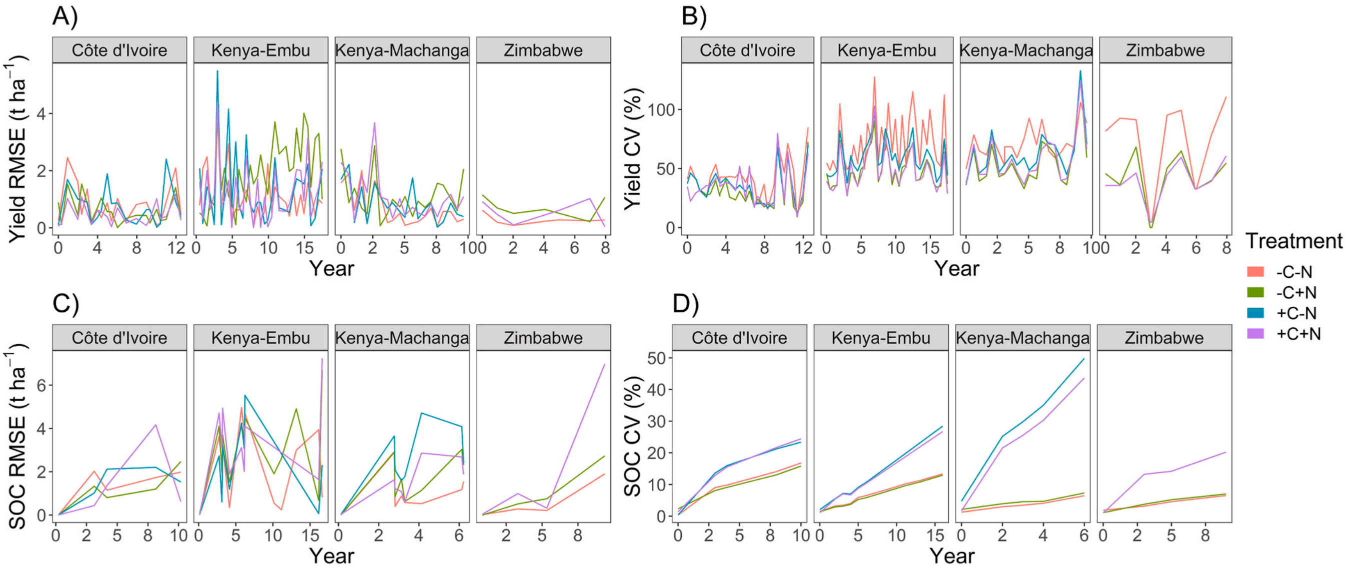

Fig. 6. Root means square error (RMSE) and coefficient of variation (CV) for maize grain yield (A, B) and soil organic carbon (SOC) (C, D) in each experimental year for fully calibrated models, in four sites in sub-Saharan Africa. Treatments are without inputs (-C-N), with mineral N fertilizer inputs only (-C+N), with organic amendments only (+C-N) and with combined organic and mineral N fertilizer inputs (+C+N).RMSE was computed from the median of an ensemble of 16 soil-crop models while coefficient of variation was computed from the 16 models individual simulations.

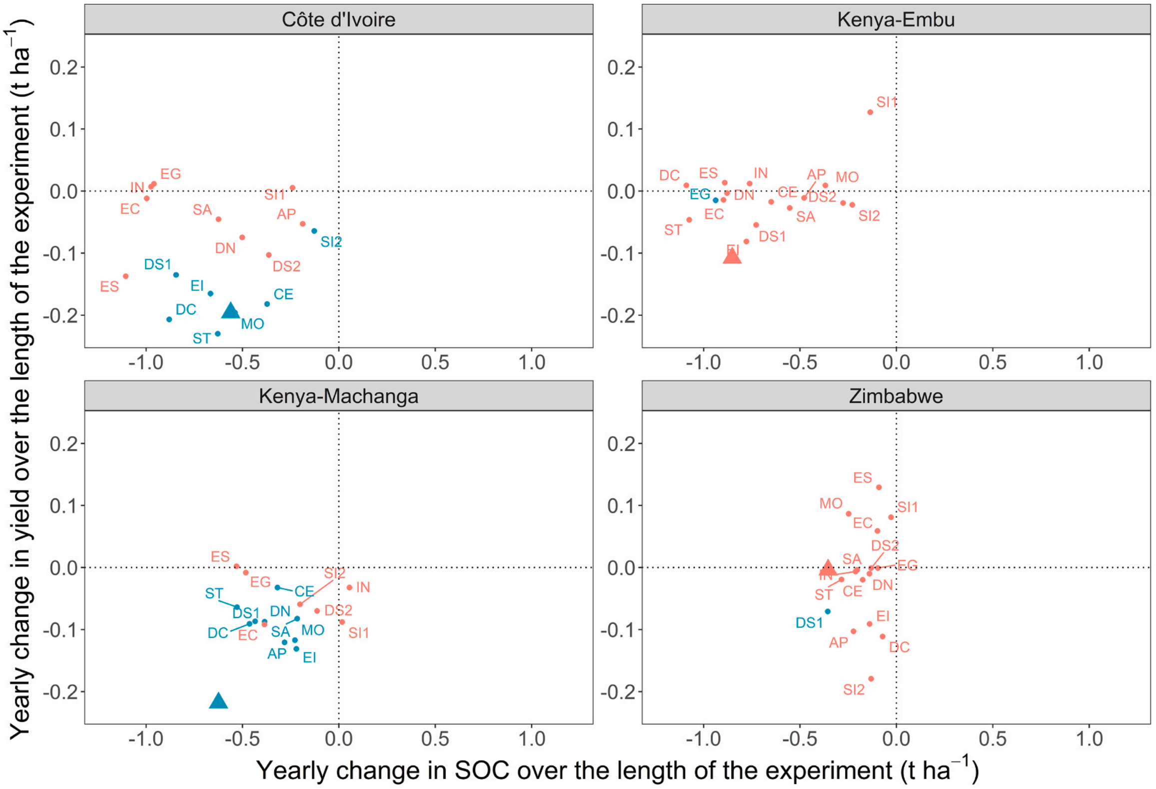

Fig. 7. Simulated (dots) and observed (triangle) yearly change in maize grain yield and soil organic carbon (SOC) over the duration of long-term experiments in four sites in sub-Saharan Africa for no input (-C-N) treatment. SOC was measured in 0–15 cm soil depth in Kenya-Embu and Kenya-Machanga and in 0–20 cm soil depth in Zimbabwe-Murewa and Côte d'Ivoire-Gagnoa. Blue symbols indicate when both changes in yield and SOC are significantly ($p \leq 0.05$) different from 0. Red symbols indicate that change in yield or change in SOC was not significantly ($P > 0.5$) different from 0. Model abbreviations: AP (APSIM), CE (CELSIUS), DS1 (DSSAT-Century), DS2 (DSSAT-Ceres), DC (DayCent), DN (DNDC), EC (Expert-N-Ceres), EG (Expert-N-Gecros), EI (EPIC), ES (Expert-N-Spass), IN (InfoCrop), MO (MONICA), SI1 (SIMPLACE-1), SI2 (SIMPLACE-2), SA (SALUS), ST (STICS).

3.4.3. Crop-to-soil feedbacks (via root inputs)

Simulated maize root biomass increased with N fertilization for most models (Fig. 9, Fig. S6). As a result, in treatments without organic amendments (C input coming only from the roots), most models simulated a decrease in SOC with a decrease in cumulative roots biomass over the duration of the experiment for all sites. Yet, some other models did

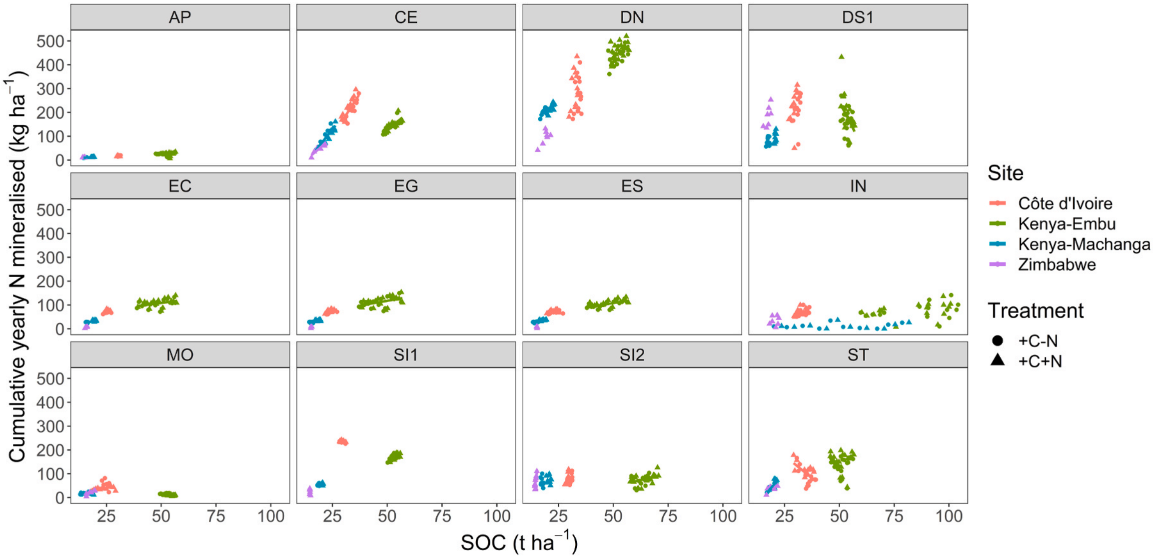

Fig. 8. Simulated soil organic carbon (SOC) and annual ammount of mineralized nitrogen (N) by individual models in four sites in sub-Saharan Africa for no input treatments only. Each point corresponds to one year of simulation. Only significant regression lines at $p < 0.05$ are displayed. Model abbreviations: AP (APSIM), CE (CELSIUS), DS1 (DSSAT-Century), DN (DNDC), EC (Expert-N-Ceres), EG (Expert-N-Gecros), ES (Expert-N-Spass), IN (InfoCrop), MO (MONICA), SI1 (SIMPLACE-1), SI2 (SIMPLACE-2), SA (SALUS), ST (STICS). 12 of the 16 models provided N mineralized.

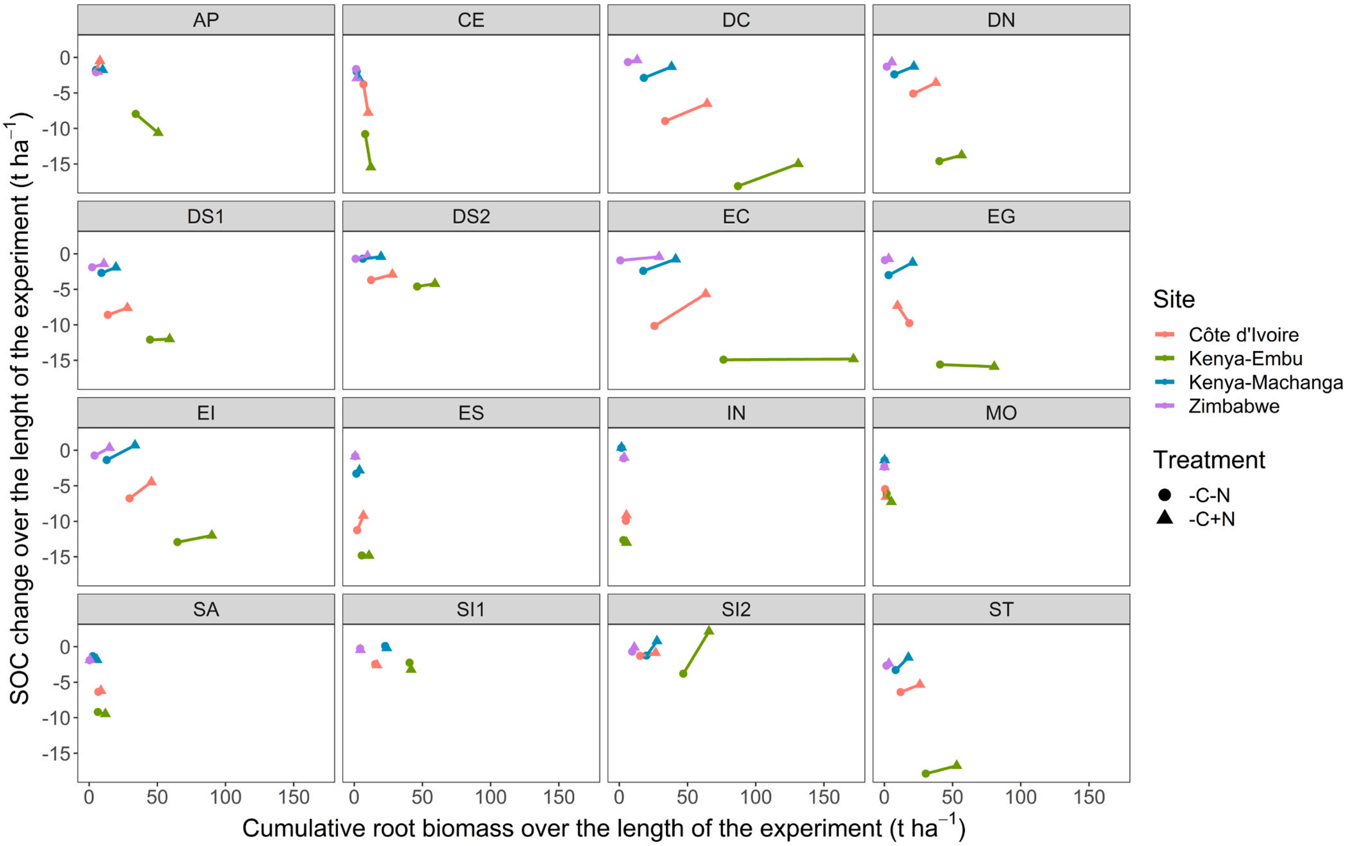

Fig. 9. Simulated change in soil organic carbon (SOC) and total maize root biomass produced during each crop cycle (t dry matter ha-1) over the length of the experiment in four sites in sub-Saharan Africa for treatments with no input (-C-N) and with mineral N fertilizer (-C+N). Model abbreviations: AP (APSIM), CE (CELSIUS), DS1 (DSSAT-Century), DS2 (DSSAT-Ceres), DC (DayCent), DN (DNDC), EC (Expert-N-Ceres), EG (Expert-N-Gecros), EI (EPIC), ES (Expert-N-Spass), IN (InfoCrop), MO (MONICA), SI1 (SIMPLACE-1), SI2 (SIMPLACE-2), SA (SALUS), ST (STICS).

not consistently reproduce this effect (AP, CE, MO, IN, SI1) (Fig. 9). Interestingly, models that simulated yield gain without SOC increase (Fig. 7) were those that did not simulate a strong relationship between cumulative root biomass and SOC (SI1, ES) (Fig. S6).

Simulated average amounts of maize root biomass per year showed large differences between models. In the no input treatment (-C-N), simulated root biomass varied from 0.2 to 1.5 t ha^{-1} per year, while in the +N + C treatments it varied from 0.2 to 3.8 t ha^{-1} per year (Fig. S6). The simulated maize root:shoot ratios differed largely between models, which explains to a large extent the uncertainty in the simulated root biomass (Fig. S7. A). Uncertainties in the simulated maize root:shoot ratios were not larger in +N and +C treatments compared to no input treatments (Fig. S7. B).

3.5. *Impact of model structure on model accuracy*

The type and the number of (S)OM pools had no significant effect on model accuracy for simulations of topsoil SOC stocks towards the end of the experiments (Fig. S8). In particular, the number of SOM pools had no significant effect on model accuracy in simulating SOC in the -C treatments, while the number of residue OM pools did not lead to improved model accuracy in simulating SOC in the +C treatments (Fig. S8). Moreover, the presence of a microbial SOM pool in the models had no significant effect on model accuracy either (Fig. S9).

4. Discussion

4.1. *Importance of local model calibration with detailed observations*

Our study revealed that full model calibration with observed crop yield and SOC data over time improves accuracy and reduces uncertainty of multi-model long-term simulations of average crop yields and final topsoil SOC stocks (Figs. 1–3). This has previously been shown in other crop modeling studies using multiple models, although for short-term model simulations (e.g. Asseng et al., 2013; Bassu et al., 2014; Falconnier et al., 2020). The multi-model ensemble failed however to reproduce the observed interannual yield variability throughout the four long-term experiments (Fig. S1), as was also reported by other studies in SSA that, however, used, a single soil-crop model (Ma et al., 2022; Nyawira et al., 2021). In contrast, in some other AgMIP crop modelling studies (Bassu et al., 2014; Falconnier et al., 2020; Li et al., 2015), multi-model ensembles simulated accurately interannual crop yield variability in short-term experiments. This was, however, possible because the full model calibration was done using more detailed data of dynamics of leaf area index (LAI), soil water, soil mineral N and plant N over the growing seasons of the experiments. In particular, observed LAI and soil moisture data is extremely valuable when calibrating models, as it enables the model to accurately reproduce yield variations resulting from changes in seasonal rainfall patterns. Therefore, in long-term experiments, model calibration based on only a few experimental years with detailed observation would help improve model accuracy, compared with calibration on many years with a low level of information. Surprisingly, complex crop models (e.g. DSSAT, STICS, APSIM) did not perform better than simpler ones in simulating average yield and interannual variability in yield (e.g. DayCent, see table S1 for a description of crop model complexity). Possibly, this was due to the lack of in-season observations of crop growth (e.g. LAI) for accurate model calibration. We did not observe any impact of model structure on model accuracy. Therefore, we could not formulate any specific recommendation for model improvement based on existing model structures for SOC simulations.

Thus, the full model calibration conducted in our study, based on a limited set of observed data (phenological stages, grain yield, aboveground biomass and SOC), does not allow for the use of the multi-model ensemble in assessing crop production risk associated with weather conditions (i.e. occurrence of low yields, crop failure). Yet, the applied model calibration proved valuable for exploring and better understanding the effect of crop management, such as ISFM, on overall crop productivity and soil fertility, including the long-term soil-crop feedbacks at play.

4.2. *The more soil and crop processes to account for, the higher the model uncertainty over time*

In our study the accuracy of the multi-model ensemble in simulating SOC decreased over time, but that of average crop yield simulations remained constant (Fig. 5). This outcome contradicts our initial hypothesis, which stated that yield simulations would become less accurate towards the end of the experiment due to accumulation of errors over time (including those associated with soil-crop feedbacks). Modelling groups performed their model calibration against observed crop yields throughout all years of the experiment (and not only using yields from e.g. year 1). This may have masked accuracy drifts over time.

The model ensemble uncertainty in simulating SOC increased over time, especially in the treatments with organic amendments (Fig. 6). This can be attributed to the uncertainties in simulating N immobilization-mineralization processes during decomposition of the organic amendments. In relation to this, we found no impact of the number of residue or SOM pools on model accuracy in our study. Cavalli et al. (2019) showed that only a few model parameters, such as those related to substrate C use efficiency, explained most of the accuracy of the models (i.e. APSIM, EPIC, FASSET and STICS) in simulating the effect of manure on soil C and N dynamics. Levavasseur et al. (2021) compared two STICS versions that included either one or two residue pools, and showed that the one-pool model simulated soil C and N dynamics as accurately as the two-pool model. Our study confirms that when detailed data on soil C and N dynamics is scarce, complex models with multiple conceptual (S)OM pools do not perform better than simple models with fewer pools and parameters (Castañeda-Vera et al., 2015). Besides, the limited availability of data for calibrating SOM pool sizes diminishes the effectiveness of using more complex models that encompass multiple SOM pools.

The uncertainty of the multi-model ensemble in simulating maize grain yield was larger for treatments without mineral and/or organic fertilizer inputs (Fig. 6). This result can be attributed to the larger influence of soil-crop feedback processes and the associated errors in simulating them, in these treatments compared to treatments with external inputs. As further discussed in the next section, model differences in simulating SOC-to-crop feedbacks in no input treatments result from large differences in simulating the amounts of N mineralized from SOM. This was especially true for the Kenya-Machanga and Zimbabwe-Murewa sites, that have the lowest initial soil fertility (SOC levels) and where N available for crop uptake that originates from SOM decomposition is limited.

Our study clearly shows that simulated impacts of experimental ISFM treatments on SOC dynamics and overall crop yield can differ depending on the model chosen for a study (Figs. 2 and 3). This raises challenges in assessing the value of ISFM for different farming contexts (soils, climate). It is therefore essential to exercise caution with crop modeling studies that aim to determine the potential impacts of sustainable intensification practices on crop productivity and soil fertility. We believe that models that correctly reproduce soil-crop feedbacks are suitable candidates to be used in model simulation studies dealing with ISFM. Methods are available to determine the optimal composition and size of the model ensemble for robust estimates of crop yields (Li et al., 2023; Rodríguez et al., 2019).

4.3. *More detailed experiments are required in SSA to reduce sources of uncertainties in soil-crop feedbacks*

Our study revealed large discrepancies in the simulated soil-crop feedbacks among models due to differences in simulating N mineralization and root C inputs (Figs. 8 and 9). These discrepancies were more pronounced in the treatments with organic amendments. The models that reproduced significant crop-to-SOC feedbacks (a decrease in SOC with a decrease in root biomass) and SOC-to-crop feedbacks (a decrease in crop N supply with a decrease in SOC) exhibited the best capability to reproduce the observed SOC and yield trends over the duration of the experiments (Figs. 4 and 7). Yet, soil C and N feedbacks on crops have often been overlooked in long-term modelling studies where soil properties were typically reinitialized in the models each year (e.g. Bassu et al., 2014; Falconnier et al., 2020).

The simulated N mineralization rates varied considerably among the models (from about 1 to 10 fold) (Fig. S4). Some models simulated annual mineralization rates that approached or exceeded the maximum value of 5% of soil total nitrogen reported in the literature (Bationo et al., 2007; Masvaya et al., 2017; Wetselaar and Ganry, 1982). The high uncertainty in simulated amounts of N mineralized leads to uncertainties in simulated soil mineral N, nitrate leaching and plant N uptake. For example, in our study most models simulated a strong accumulation of soil mineral N over the years in the fertilized treatments (data not shown). This could have masked feedbacks between SOC and yields (high soil mineral N leads to a weak influence of N mineralization on crop growth and yield). Yet, an accurate prediction of N mineralization rates and a better understanding of the reasons behind the weak correlation between changes in SOC and the amount of N mineralized in some models are a prerequisite for improved model simulations, especially in low-input cropping systems. From our study, it is evident that more soil mineral N data need to be collected in field experiments in SSA (and elsewhere) for model calibration. A thorough calibration and testing of models for soil N dynamics would be greatly beneficial for better reproducing yield responses to mineral and/or organic fertilizers and better understanding long-term soil-crop feedback mechanisms.

In low-input cropping systems, the carry-over of root residues from one cropping season to the other is important to quantify because of its critical influence on SOC and soil mineral N dynamics. The maize root biomass simulated by the models was also subject to large uncertainties (Fig. 9 and S6). Some models simulated low root biomass production resulting in very low root:shoot ratios (Fig. S7), i.e. below the likely values of 0.08 to 0.43 for maize reported in the literature (Anderson, 1988; Eghball and Maranville, 1993; Lopez et al., 2023; Ordóñez et al., 2020). Moreover, model differences in simulating maize root biomass increased with mineral and/or organic fertilizer application (Fig. S6). Yet, the effects of fertilizers on crop root biomass are complex, and probably crop- and site-specific. Experimental research found either an increase (Eghball and Maranville, 1993), no clear effects (Anderson, 1988, 1987) or a decrease (Ordóñez et al., 2021) in crop root biomass with mineral fertilization. Yet, most studies agreed that fertilization tends to cause a decline in maize root:shoot ratio (Anderson, 1988, 1987; Eghball and Maranville, 1993; Lopez et al., 2023), which was, however, not reproduced by the models (Fig. S7). This outcome calls for more experiments aimed at better understanding the effects of fertilization on root dynamics in SSA. Given the large discrepancies between models, such root biomass measurements, would prove valuable for improving model formalisms that describe the processes and factors of root development. This would in turn allow for a better assessment of root C inputs and their contribution to SOC formation (e.g Whitbread et al., 2003). Besides, more experimental research is needed to quantify the effects of roots on SOC dynamics, as roots can stabilize or destabilize SOC (Dijkstra et al., 2021).

Specific experiments in SSA are also needed to unravel the effects of organic amendment from the effects of in-situ crop residues and SOM turnover on soil-crop feedbacks. Bare soil experiments without C inputs, that measure soil C and N, are valuable for calibrating SOM turnover in models. Indeed, with bare soils, it is possible to evaluate model performance without crop C inputs and without interferences arising from crop water use and N uptake. Such experiments have for example been conducted in Australia and enabled to calibrate the SoilN module of APSIM (Dalal et al., 1995; Dimes, 1996; Probert et al., 1998). On the other hand, long-term experiments with organic inputs on bare soil can help to calibrate the residue pools associated with the organic amendment, if they are established in a way that avoids erosion. Such long-term experiments have for example been conducted in Sweden and were used to calibrate the CENTURY model (Gerzabek et al., 1997; Paustian et al., 1992). Comparisons of soil C data between bare and cropped soils, along with model simulations, can then further help to assess the effects of crops on SOC dynamics.

Besides the data needed for calibrating SOM turnover formalisms already present in models, model improvements are needed to better reproduce soil-crop feedbacks. Soil C and N fluxes remain difficult to simulate due to incomplete representation of key mechanisms in the models. Campbell and Paustian (2015) highlighted the need for advances in SOC modelling, such as the implementation of microbial pool that plays the central role in SOM stabilization, the modelling of SOM saturation kinetics, and the representation of SOM dynamics in deep soil layers. Besides, the impacts of soil structure on long-term SOC dynamics are also overlooked in current soil-crop models. Soil structure affects root development, water dynamics and SOC stabilization (e.g. inside aggregates) and decomposition while in turn, SOC also affects soil physical and hydraulic properties (Rabot et al., 2018). These complex soil structure-SOC feedbacks are now being considered in the development of new SOC models (Meurer et al., 2020a, 2020b). Other processes such as rhizosphere-SOM interactions, such as rhizodeposition and rhizosphere priming effects, are mostly not represented in models (Cavalli et al., 2019) while it has been reported that rhizosphere priming effects can offset the SOC increase caused by roots (Dijkstra et al., 2021). Moreover, soils can be unresponsive to fertilization due to other crop growth limiting factors, such as nutrient limitations other than N, P and K, or soil compaction(Vanlauwe et al., 2015a, 2010). Those processes are not represented in most models. More specifically, effects of chemical fertilizers on pH are poorly represented in models. It could, for example, explain the poor model inaccuracy in simulating the +N treatments in Embu where maize yields were adversely affected by a decrease in pH over the years (Laub et al., 2023a).

5. Conclusion

We conducted the first multi-model comparison for long-term simulations of crop (maize) yields and topsoil SOC trends, and their feedbacks, in SSA. The models differed considerably in their ability to reproduce these trends. Models that accounted for the soil-crop feedbacks showed the best accuracy. For maize yield simulations, the largest model uncertainty was observed in treatments without fertilizer inputs, while for SOC simulations uncertainty was highest when organic amendments were used. Models exhibited large differences in simulating i) soil-to-crop feedbacks as indicated by the large variations in simulated amounts of mineral N supply from SOM decomposition, and ii) crop-to-soil feedbacks as reflected in varying simulated amounts of root biomass residues for SOC formation. As a result, we advocate for an urgent need for detailed experimental data on soil N dynamics and roots in SSA. Such experimental efforts are critical to guarantee the accurate integration of soil-crop feedbacks into models, ensuring their suitability for application in SSA.

CRediT authorship contribution statement

Antoine Couëdel: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Project administration. **Gatien N. Falconnier:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft. **Myriam Adam:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft. **Rémi Cardinael:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – original draft. **Kenneth Boote:** Investigation, Methodology, Validation, Writing – review & editing, Software. **Eric Justes :** Investigation, Methodology, Validation, Writing – review & editing, Software.

Ward N. Smith: Investigation, Methodology, Validation, Writing – review & editing, Software. **Anthony M. Whitbread:** Investigation, Methodology, Validation, Writing – review & editing, Software. **François Affholder:** Software, Writing – review & editing. **Juraj Balkovic:** Software, Writing – review & editing. **Bruno Basso:** Software, Writing – review & editing. **Arti Bhatia:** Software, Writing – review & editing. **Bidisha Chakrabarti:** Software, Writing – review & editing. **Regis Chikowo:** Resources, Writing – review & editing. **Mathias Christina:** Software, Writing – review & editing. **Babacar Faye:** Software, Writing – review & editing. **Fabien Ferchaud:** Software, Writing – review & editing. **Christian Folberth:** Software, Writing – review & editing. **Folorunso M. Akinseye:** Software, Writing – review & editing. **Thomas Gaiser :** Software, Writing – review & editing. **Marcelo V. Galdos:** Software, Writing – review & editing. **Sebastian Gayler:** Software, Writing – review & editing. **Aram Gorooei:** Software, Writing – review & editing**.** **Brian Grant:** Software, Writing – review & editing. **Hervé Guibert:** Resources, Writing – review & editing. **Gerrit Hoogenboom:** Software, Writing – review & editing. **Bahareh Kamali:** Software, Writing – review & editing. **Moritz Laub:** Resources, Writing – review & editing. **Fidel Maureira:** Software, Writing – review & editing. **Fasil Mequanint:** Software, Writing – review & editing. **Claas Nendel:** Software, Writing – review & editing. **Cheryl H. Porter:** Software, Writing – review & editing. **Dominique Ripoche:** Software, Writing – review & editing. **Alex C. Ruane:** Project administration, Writing – review & editing. **Leonard Rusinamhodzi:** Resources, Writing – review & editing. **Shikha Sharma:** Software, Writing – review & editing. **Upendra Singh:** Software, Writing – review & editing. **Johan Six:** Resources, Writing – review & editing. **Amit Srivastava:** Software, Writing – review & editing. **Bernard Vanlauwe:** Resources, Writing – review & editing. **Antoine Versini:** Software, Writing – review & editing. **Murilo Vianna:** Software, Writing – review & editing. **Heidi Webber:** Software, Writing – review & editing. **Tobias Weber:** Software, Writing – review & editing. **Congmu Zhang:** Software, Writing – review & editing. **Marc Corbeels:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2024.127109.

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