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The ability of crop models to predict soil organic carbon changes in a maize cropping system under contrasting fertilization and residues management: Evidence from a long-term experiment

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Highlights

- *A crop model ensemble was compiled to simulate soil organic carbon and maize aboveground biomass dynamics in a long-term experiment.*
- *The performances of stand-alone models and their ensemble were assessed under contrasting fertilization and crop residue management.*
- *The multi-model ensemble using the median value of simulation was the best predictor of the variables observed in the long-term experiment.*
- *Improved performances in simulations were observed when crop residues were incorporated into the soil, regardless of the fertilization management.*
- *The uncertainty in SOC simulation increased over time for cropping systems with silage maize and organic fertilization.*

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Abstract

This study assesses the ability of an ensemble of crop models (MME) to predict the impacts of fertilization and crop residue management on soil organic carbon (SOC) and aboveground biomass (AGB) in a long-term experiment (LTE) based on continuous maize cropping systems. Data from a LTE in Northern Italy were used. Treatments included continuous grain (MG) or silage (MS) maize, fertilized with mineral, cattle slurry, and farmyard manure. The MME median resulted the best predictor of the observed values. Models performance was better when simulating MG than MS, and for crops treated with mineral compared to organic fertilizers. The ability to predict the dynamics of SOC was affected by the model used and by the year × residues management and year × fertilizer interactions. The model and the residue × fertilizer interaction affected the ability to simulate AGB dynamics. Results showed that a MME can effectively predict the long-term dynamics of SOC and maize crop production under contrasting fertilization and crop residue management, and thus their potential for climate change mitigation. The uncertainty in the simulation of SOC is related to the model routines simulating SOC partitioning and to the complexity of the interactions between management factors over time.

Introduction

The role of soil organic carbon (SOC) for the sustainability of cropping systems is central since it influences soil fertility, nutrients, and water cycles. Furthermore, adopting agricultural practices that increase SOC stocks is crucial in mitigating climate change (Follett, 2001; Chenu *et al.*, 2019; Montanarella, 2020).

Organic fertilization in maize-based agroecosystems is one of the most important practices to enhance SOC stocks (Bertora *et al.*, 2009; Cai *et al.*, 2019) while sustaining crop production. However, the impacts of organic fertilizers on SOC changes and SOC sequestration are strictly dependent on the type of organic matter supplied (Pulina *et al.*, 2018). Organic fertilizers can differ in their C/N ratio, source, and stability of the supplied organic matter (Maillard and Angers, 2014). These differences imply different impacts on soil processes and, subsequently, soil respiration (Lopez-Lopez *et al.*, 2012; Lai *et al.*, 2017; Risberg *et al.*, 2017; Pulina *et al.*, 2018), as well as different responses in terms of crop yield (Cai *et al.*, 2019), which is constrained by N availability for plant processes in the critical phenological stages for crop yield formation (Zavattaro *et al.*, 2016). Differences in soil N availability associated with different organic N sources can also impact above- and below-ground primary productivity. This may alter soil C inputs from crop residues and root systems (Pulina *et al.*, 2018) and soil metabolic activity, thus affecting C cycling in the agroecosystem (Wang *et al.*, 2015). Among N fertilizers, the best crop yields are usually obtained with the timely use of mineral fertilizers, although this can contribute to increasing SOC mineralization and N_2O emissions (Cayuela *et al.*, 2017). Nevertheless, the total or partial replacement of mineral fertilizers with organic fertilizers, as a strategy to mitigate climate change and simultaneously maintain high levels of crop productivity, is still debated (Sanz-Cobena *et al.*, 2017).

The incorporation of crop residues in maize-based cropping systems is considered among the main practices regulating biological drivers of soil C cycling (Shahbaz *et al.*, 2017; Noor *et al.*, 2021) and promoting SOC sequestration (Zhang *et al.*, 2021; Hao *et al.*, 2022), whilst maintaining adequate grain or silage maize yields (Pittelkow *et al.*, 2015). Furthermore, there is a synergy between crop residue incorporation and long-term organic fertilizers application, which can contribute to an increase in soil C pools and soil biological activities (Cui *et al.*, 2018), thus leading to an overall improvement of soil fertility and agroecosystem sustainability (Bolinder *et al.*, 2020).

Datasets from long-term experiments (LTEs) represent a valuable source of information in understanding how agricultural practices, such as fertilization and residues management, can affect long-term soil processes driving SOC changes (Smith *et al.*, 1997; West and Post, 2002; Poulton *et al.*, 2018). Although LTEs can provide information on the overall SOC dynamic over decadal scales, isolating the effects of single management practices or their interactions on the factors driving SOC changes and sequestration is challenging. The LTEs are often characterized by changes in experimental objectives and management (*e.g.* fertilization sources, crop varieties, irrigation, *etc.*), making it challenging to extrapolate information about the impacts of single agronomic techniques (Johnston and Poulton, 2018). Nevertheless, LTE datasets can represent a suitable and rich source of information to robustly calibrate and validate process-based simulation models, which are powerful tools to assess agroecosystem changes under specific management and climatic scenarios over a long time span (Smith *et al.*, 1997). To this end, LTE datasets can play a fundamental role in improving model performances hence reducing model prediction uncertainty when simulating the long-term changes of SOC (Smith *et al.*, 1997; Iocola *et al.*, 2017; Farina *et al.*, 2021).

A large share of uncertainty is attributable to the differences between model structures, which can reproduce biophysical and physiological crop and soil processes very differently. To overcome this issue, many studies agree on using multi-model ensemble (MME) outputs as more robust predictors than single-model simulations (Bassu *et al.*, 2014; Ehrhardt *et al.*, 2017; Sándor *et al.*, 2017; Farina *et al.*, 2011 and 2021). The MME approach also provides a probability distribution of results (Harris *et al.*, 2010). MMEs have been applied to simulate the long-term dynamic of SOC under a wide range of conditions, including contrasting crop residue management (Basso *et al.*, 2018; Stella *et al.*, 2019; Thiagarajan *et al.*, 2022). However, few MMEs have been used for the assessment of the impact of organic fertilization, such as those built by Riggers *et al.* (2019), which simulated SOC stock changes across German sites under different cropping systems and organic fertilization.

The need for insights into the ability of MMEs to predict the long-term impacts of both organic fertilization and crop residue management emerges from the literature. The interaction between these agronomic factors is crucial in determining the long-term viability of organic fertilization in increasing SOC, while guaranteeing high levels of primary production, which ultimately result in higher SOC sequestration and then climate change mitigation.

In this study, we hypothesized that crop models can be used effectively to simulate the complex interactions between soil, plant, climate and agronomic techniques. Specifically, the aim was to assess the ability of crop models to predict long-term SOC content dynamics, maize aboveground biomass production and grain yield dynamics, using LTE data obtained under contrasting fertilization and crop residue management systems as a 'ground-proofing' of model calibration and performance assessment. Such predictions are particularly relevant in relation to the assessment of the climate change mitigation potential of agricultural soils set by the UNFCCC COP21, in the frame of the '4 per 1000' initiative, aimed at countering anthropogenic GHG emissions with C sequestration and stock in agricultural soils. The specific hypotheses were: i) the MME of different process-based crop models ensure more accurate prediction of both SOC and maize biomass dynamics than stand-alone model simulations; ii) the different model processes simulating SOC content and the interaction between time, residue management, and fertilization strategy influence the ability of models in predicting SOC changes, and thus the uncertainty in assessing the climate change mitigation potential of maize cropping systems managed with contrasting fertilization systems.

Materials and methods

Long-term experiment description

The study was conducted using the experimental dataset built from the LTE of Tetto Frati, Turin (LTE-TO, Piedmont, IT; 44.88° N, 7.68°E), which belongs to the Italian LTE network IC-FAR (https://icfar.wordpress.com/). The climate is temperate sub-continental, the average annual rainfall is 760 mm, and the mean annual temperature is 12°C. The soil is classified as Typic Udifluvent (Soil Survey Staff, 2014), with loam texture in the upper horizon and silty in deeper horizons (Grignani *et al.*, 2007). The LTE-TO is based on continuous maize (*Zea mays* L.) irrigated cropping system. Since 1991, the LTE experimental design has assessed the impact of both mineral and organic N fertilization on grain and silage maize yield and soil traits by supplying N rates that varied over the years from 250 to 300 kg ha^{-1} of N, under different rotation schemes and cropping systems in a 3-replicates randomized complete block design (Zavattaro *et al.*, 2016). A subset of the LTE dataset was selected, including 21 years (1992-2012) of continuous grain (MG) and silage (MS) maize, both receiving the same amount of N (300 kg ha^{-1} from 1992 to 2010, 250 kg ha^{-1} in 2011-2012) from three different sources: mineral fertilizer (MIN) with urea, and two different organic fertilizers with cattle slurry (SLY) and farmyard manure (FYM). Urea fertilizer in the MIN treatment was supplied in two stages, about 2/3 of the total amount before sowing and 1/3 top-dressed and incorporated by ridging. From 1992 to 2006, SLY and FYM treatments received about 1/3 of the total N as urea during ridging, while from 2007 on, the whole N rate was supplied as organic fertilizer before sowing, followed by tillage. Mineral P was supplied as triple superphosphate and K as KCl at levels above plant requirements to prevent any interaction with N. From 1992 to 2012, nine different maize hybrids were sown, including FAO classes 500 (10 years), 600 (4 years), and 700 (7 years). After harvest, MG crop residues were incorporated into the soil. Further details on the cropping system were described by Zavattaro *et al.* (2016).

The long-term experiment dataset

The soil was sampled at each plot at a depth of 0-30 cm in the early spring in 1992, 1997, 1999, 2003, 2007, and 2012. In 1997, soil samples were taken along the whole profile (0-250 cm) to determine physical parameters (texture, wilting point, field capacity, bulk density) and pH (Table 1). The SOC content was determined in 1992, 1997, 1999, and 2003 with the Walkley-Black method and in 2007 and 2012 through an elemental analyser (NA2100 protein Carlo Erba elemental analyser). The DM maize grain yield (GRY) and aboveground biomass (AGB) production were determined annually at harvest. The AGB of MG was calculated as the sum of grain yield and aboveground crop residues. The organic fertilizers were sampled and analysed before each distribution to determine the DM content by oven-drying samples at 105°C and the actual content of N (Kjeldahl method), P and K (through nitric or perchloric acid microwave solubilization followed by ICP spectroscopy). Details on fertilizer nutrient content and cropping system productivity were described by Zavattaro *et al.* (2016).

Modelling design

The model input data on soil, weather, and crop management were extracted from the LTE dataset, which was harmonized within the common IC-FAR database (Ginaldi *et al.*, 2016).

Four crop models were used. The process-based crop models differ in their biophysical approaches and processes to simulating daily crop biomass, yield formation, and SOC dynamics (Table 2). The SOC content in these models is partitioned into different C pools based on different levels of SOC maturity and recalcitrance. To initialize soil C pools and match the SOC content at the beginning of the experimental period, a pre-run simulation over one hundred years was performed for each model, considering continuous grain maize (FAO class 700) fertilized with 100 kg ha^{-1} of N and the incorporation of residues into the soil. After the pre-run, models were calibrated on a site-specific basis for the six cropping systems reproducing the information available from the harmonized LTE dataset. The data used for the calibration purposes representing the biophysical and biological features of the different cropping systems were the SOC content (Mg ha^{-1}) in the upper layer (0-30 cm), the yearly maize GRY (Mg ha^{-1} DM), and AGB (Mg ha^{-1} DM). The model calibration was performed with the aim to achieving the best model parametrization that satisfactorily reproduced both biomass production and SOC dynamics.

Evaluation of model performances

The performances of the models were assessed following the evaluation scheme proposed by Iocola *et al*. (2017) for a MME study. The agreement of the observed data with model outputs was assessed using a set of complementary performance metrics to describe the overall ability of the models to simulate the whole system. The performance indices adopted in the study were the relative root mean square error (RRMSE), its statistical significance at 95% confidence interval (RRMSE95%), the modelling efficiency (EF), the relative bias error (E) with its statistical significance at 95% confidence interval (E95%), the coefficient of determination (R^2), and the index of agreement (dIA). The description of the indices of performance is reported in Table 3. The performance metrics were calculated for the simulations of SOC, AGB, and GRY. The performance of the MME computed as mean (MME_mean) and median (MME_median) of model outputs were also calculated. For all simulations, the single model, MME_mean, and MME_median were ranked for each performance metric. The mean values of the ranks were then re-ranked to obtain the overall ranks, first for the simulated variable and then for the comprehensive simulation.

The RRMSE between observed and simulated data was calculated for the experimental treatments for each model (excluding MME_mean and MME_median) to assess the overall ability of the single model to simulate the different cropping systems. The RRMSE for the different cropping systems was calculated for SOC, GRY, and AGB data. The sum of both RRMSEs was then calculated to assess the best-predicted cropping system.

Table 1. Soil chemical, physical, and hydrological parameters in the long-term experiment at 0-30, 30-90 cm soil depth.

Soil parameter	0-30 cm	30-90 cm
Sand (%)	48.4	26.9
Silt (%)	43.1	66.1
Clay (%)	8.5	7.0
pH	7.9	8.1
Bulk density (Mg m^{-3})	1.55	1.32
Wilting point (% volume)	11.2	11.4
Field capacity (% volume)	34.9	42.1
Saturation (% volume)	55.5	56.6

Table 2. List of crop models used in this study.

Code	Model	Reference	Biomass growth*	Yield formation°	Root distribution#	SOC dynamic
Model1	DSSAT 4.6	Hoogenboom *et al.* (2019)	RUE	Gn,B	Exp	Century
Model2	CropSyst	Stöckle *et al.* (1994); Stöckle *et al.* (2003)	RUE-TUE	HI, B	Exp	CropSyst
Model3	EPIC	Williams (1995)	RUE	HI, B	Lin	Century
Model4	SALUS	Basso and Ritchie (2015)	RUE	Gn,B	Exp	Century

*Biomass growth or light utilization: RUE, radiation use efficiency approach; TUE, transpiration use efficiency approach; °Yield formation depending on: HI, harvest index, B, total aboveground biomass, Gn, number of grains and grain-growth rate; #model of root distribution over depth: linear (Lin), exponential (Exp).

The model's deviation from observed data was calculated for each model (m) and observation (i) to assess their ability to predict the different cropping systems over time in relation to the variability of the observed data, as follows:

$$t_{m,i} = \frac{SIM_{m,i} - OBS_i}{\sqrt{s^2_{obs,i}\frac{n+1}{n}}}$$

where, for the ith observation, $t_{m,i}$ is the Student's *t* statistic with n-1 degrees of freedom, OBS_i is the observed value, $SIM_{m,i}$ is the model simulated value, and $s^2_{obs,i}$ is the sample variance of observations, n is the number of observations contributing to each OBS values (n=3). When $t_{m,i}$ value was within the interval $OBS \pm t_{(p=0.05;df=n-1)}\ s/\sqrt{n}$, the prediction is within the 95% confidence interval of the mean of the observed value. A linear mixed-effect model (lme) was fitted to test the effects of time, model, and the interaction between fertilization management and use (only for SOC and AGB) on the Student's *t* statistic, setting the sampling date as a random factor.

Data analysis, graphic representation, and mixed-effect model analysis (Lenth, 2018) were performed using the RStudio application of R software (version 4.0.5) (R Core Team, 2021). The significance of statistical computations was evaluated at $P<0.05$.

Results

Observed soil organic carbon dynamics and aboveground biomass production

Over the 21 years of the LTE-TO, the SOC significantly increased in both organic treatments of the MG and MS cropping systems. With MG_SLY ($P<0.05$), starting from an initial C content of 44.9±2.9 Mg ha^{-1}, SOC content increased by 22.0% (54.8±1.2 Mg ha^{-1}), while with MG_FYM, the SOC content increased by 38.3% (62.1±7.3 Mg ha^{-1}; $P<0.01$). The SOC content significantly increased with MS_SLY (49.1±1.1 Mg ha^{-1}; $P<0.05$), to a lesser extent (+9.4%) than with MG_SLY, while a similar SOC increase (+37.6%) was observed under MS_FYM (61.8±2.4 Mg ha^{-1}). No significant variations of the SOC content were observed with both MG_MIN and MS_MIN (Figure 1).

The average AGB production observed during the experiment (Figure 2) was 25.7 Mg ha^{-1} of DM (CV=11%), ranging from 20.1±3.0 Mg ha^{-1} (observed in MS_MIN) to 33.2±0.4 Mg ha^{-1} (under MS_SLY). Significant increasing trends in AGB production were observed with FYM treatments in MG ($P<0.05$; R^2=0.27) and MS ($P<0.001$; R^2=0.48).

The average GRY, only measured in MG (Figure 3), over the years of the LTE was 13.3 Mg ha^{-1} of DM (CV=7%), ranging from 11.3±0.6 Mg ha^{-1} to 15.6±0.5 Mg ha^{-1}, both observed in MG_SLY. No significant trends over time were observed in maize GRY.

Model performances

All models effectively simulated the SOC content dynamics across all cropping systems, while some underperformance in simulating the AGB biomass emerged from the model performance statistics (Table 4).

For all models, the RRMSE and E metrics for SOC dynamics were within the 95% confidence interval of the index, except for RRMSE calculated for Model4 (0.13), which was the lowest performing overall, considering its EF (0.03) and R^2 (0.58) values. A slight underperformance in reproducing SOC also emerged from the EF values of Model1 (0.25). Model2 was the best in predicting SOC dynamics for almost all indices (RRMSE=0.06; R^2=0.87; EF=0.77). Overall, the MME_mean (RRMSE=0.08; EF=0.67) and the MME_median (RRMSE=0.09; EF=0.57) were more effective predictors than the single models, except for Model2, as highlighted in the rank analysis (Table 4).

The overall ability to simulate AGB production was lower than that observed for SOC dynamics. The RRMSE was within its 95%

Table 3. Performance indices used in model assessment.

Performance metric	Equation	Unit	Value range and purpose	References
RRMSE, Relative root mean square error	$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}\,\frac{100}{\bar{O}}$	-	$0 \le RRMSE \le +\infty$ The best values are close to 0	Fox (1981)
E, relative BIAS error	$E = \frac{100}{n}\sum_{i=1}^{n}\frac{(O_i - P_i)}{O_i}$	%	$-\infty \le E \le +\infty$ The best values are close to 0. Negative values: overestimation; positive values: underestimation	
EF, Modelling efficiency	$\mathrm{EF} = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$	-	$-\infty < EF \le +1$ The best values are close to 1	Greenwood *et al.* (1985)
dIA, Index of Agreement	$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(\lvert P_i - \bar{O}\rvert + \lvert O_i - \bar{O}\rvert)^2}$	-	$0<d<1$ The best values are close to 1	Willmott and Wicks (1980)
R^2, coefficient of determination of the linear regression estimates *vs* measurements	$R^2 = \frac{\sum_{i=1}^{n}(P_i - O_i)\cdot(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2 \cdot \sum_{i=1}^{n}(O_i - \bar{O})^2}}$	-	$0 \le R^2 \le 1$ The best values are close to 1	

P, predicted value; O, observed value; n, number of P/O pairs; i, each of P/O pairs; $\bar{O}$, mean of observed values; $\bar{P}$, mean of predicted values.

confidence interval only for Model4 (RRMSE=0.10), which was better in the simulation of AGB, while the E index values were within their 95% confidence interval for Model1 (E= –6.77), Model3 (E= –1.69), and Model4 (E= –5.42). The E index values in Model2 showed a significant underestimation (E=20.16). As a result of these apparent limitations, the best MME predictor was the MME_median (1st in overall AGB ranking), which suitably reproduced the AGB production (RRMSE=0.10; EF=0.23).

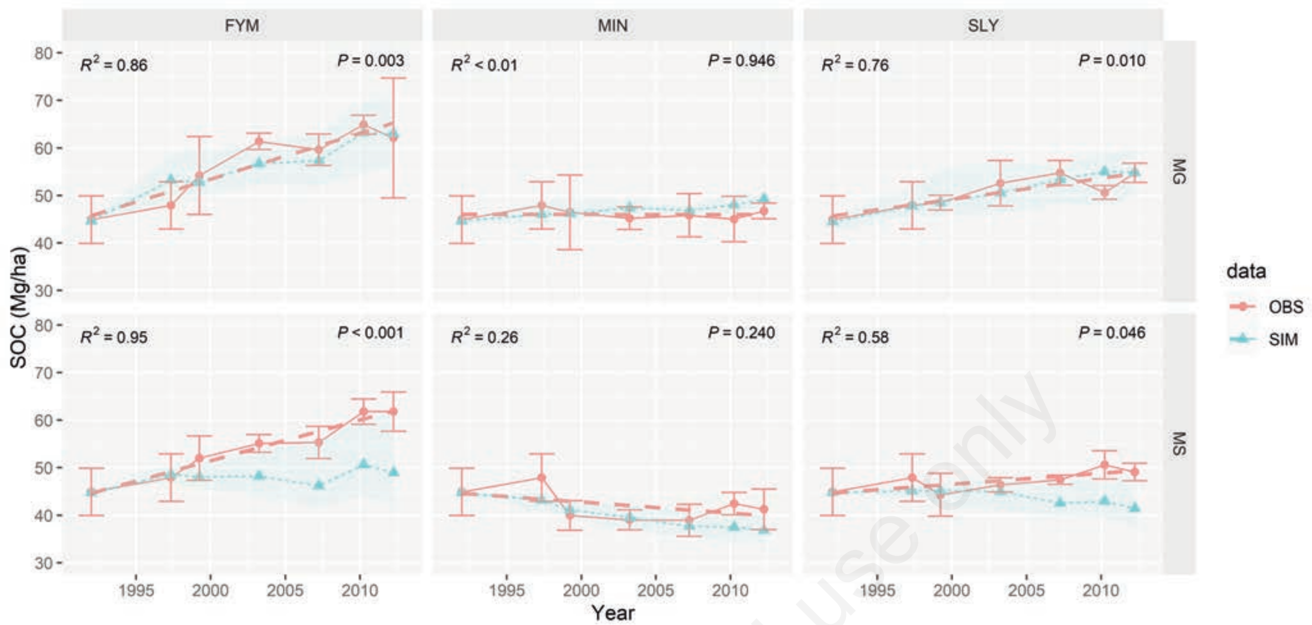

Figure 1. Observed (OBS, red dots and lines) and multi-model ensemble median (SIM, blue dots and lines) dynamics of soil organic carbon (SOC, Mg/ha) over the long-term experiment years. Red bars represent the standard deviation of the mean observed value; blue ribbons represent the interval between the mean value of the ensemble ± the standard deviation of the simulated values. The red dashed lines represent the fitted linear models (SOC~year) describing the observed SOC trends. The texts at the top report the R^2 and the P value of the fitted model. MG, grain maize; MS, silage maize; MIN, mineral; SLY, slurry; FYM, farmyard manure.

Table 4. Model assessment through the selected performance indices describing the goodness of the fit between observed and simulated data for each model, and the multi-model ensemble predictions as mean (MME_mean) and median (MME_median) values of simulated data. Numbers within parenthesis indicate the rank of the model across each index, mRANK is the mean of the ranks of the indices within each model.

	Index	Confidence interval	Model1	Model2	Model3	Model4	MME_mean	MME_median
SOC	RRMSE	0.11	0.11 (5)	0.06 (1)	0.10 (4)	0.13 (6)	0.08 (2)	0.09 (3)
	R^2		0.58 (4)	0.87 (1)	0.57 (5)	0.34 (6)	0.73 (2)	0.66 (3)
	EF		0.25 (5)	0.77 (1)	0.42 (4)	0.03 (6)	0.67 (2)	0.57 (3)
	E	±9.28	6.59 (6)	–1.73 (2)	0.04 (1)	6.39 (5)	2.82 (3)	3.41 (4)
	dIA		0.67 (5)	0.91 (1)	0.75 (4)	0.43 (6)	0.82 (2)	0.77 (3)
	mRANK		5.0	1.2	3.6	5.8	2.2	3.2
	RANK		5	1	4	6	2	3
AGB	RRMSE	0.11	0.12 (4)	0.26 (6)	0.13 (5)	0.10 (3)	0.10 (2)	0.10 (1)
	R^2		0.13 (4)	0.10 (5)	0.09 (6)	0.34 (1)	0.27 (2)	0.25 (3)
	EF		–0.23 (4)	–4.59 (6)	–0.51 (5)	0.11 (3)	0.20 (2)	0.23 (1)
	E	±9.02	–6.77 (5)	20.16 (6)	–1.69 (3)	–5.42 (4)	1.57 (2)	–1.45 (1)
	dIA		0.28 (5)	0.13 (6)	0.3 (4)	0.51 (1)	0.48 (2)	0.45 (3)
	mRANK		4.4	5.8	4.6	2.4	2.0	1.8
	RANK		4	6	5	3	2	1
GRY	RRMSE	0.10	0.12 (4)	0.19 (6)	0.13 (5)	0.08 (1)	0.09 (3)	0.09 (2)
	R^2		0.05 (5)	0.09 (4)	0.01 (6)	0.32 (1)	0.18 (2)	0.17 (3)
	EF		–2.00 (4)	–6.43 (6)	–2.47 (5)	–0.26 (1)	–0.68 (3)	–0.59 (2)
	E	±8.35	–1.24 (2)	12.30 (6)	4.73 (5)	–0.27 (1)	3.88 (4)	3.23 (3)
	dIA		0.20 (4)	0.15 (5)	0.07 (6)	0.54 (1)	0.36 (3)	0.37 (2)
	mRANK		3.8	5.4	5.4	1.0	3.0	2.4
	RANK		4	5	5	1	3	2
Overall	Mean		4.3	4.0	4.7	3.3	2.3	2.0
	RANK		5	4	6	3	2	1

SOC, soil organic carbon; AGB, aboveground biomass; GRY, grain yield.

The ability of models to simulate GRY under MG use was only slightly better than those observed for AGB. RRMSE was within the 95% confidence interval only for Model4 (RRMSE=0.10), while the E indexes were within the 95% confidence interval for Model1 (E= –1.24), Model3 (E=4.73), and Model4 (E= –0.27). A significant GRY underestimation was observed in Model2 (E=12.30). The MME_median (RRMSE=0.09; E= –3.23) was the second-best predictor of GRY after Model4.

As a result of the mean values of the single mean ranks per variable across indices (Table 4), the best predictor in reproducing the overall system was the MME_median, followed by MME_mean and Model4.

Analysis of the performances of the models in simulating the six cropping systems (Table 5) highlighted that across models, the SOC and AGB dynamics were best reproduced under MG_MIN (RRMSE=0.05). Overall, the ability of the models to simulate agroecosystem processes was higher under MG than MS cropping systems. For both maize uses, the MIN was the best-reproduced fertilization system, followed by SLY and FYM, which was the worst (mean RRMSE=0.14 and 0.16 for MG and MS, respectively). The deviations (Student's *t* statistics) of predicted data from the observations over the experimental period are illustrated in Figure 4. All SOC simulated data from Model2 were within the 95% confidence interval of observed SOC, while only one prediction of MME_median was outside the interval. Greater deviations of simulated data emerged from AGB and GRY simulations. The MME_median was outside the 95% confidence interval of observations in 6.1% and 8.8% of cases for AGB and GRY, respectively. The predictors showing the lowest number of simulations for AGB outside the 95% confidence interval of observation were Model4 and the MME_median (6.1%), while for GRY the best predictor was Model4 (5.3%).

The effects of the model and the Year × Use × Fertilizer interaction on data deviations as Student's *t* statistic (t-SOC, t-AGB, t-GRY) are illustrated in Table 6. The t-SOC was significantly affected by Model ($P<0.01$), Year × Use, and Year × Fertilizer interactions ($P<0.05$), while the t-AGB was significantly influenced by the model ($P<0.0001$) and the Use × Fertilizer interaction ($P<0.05$). Considering the deviations of GRY simulations under MG, the t-GRY was significantly affected by the Model ($P<0.0001$) and Fertilizer ($P<0.05$).

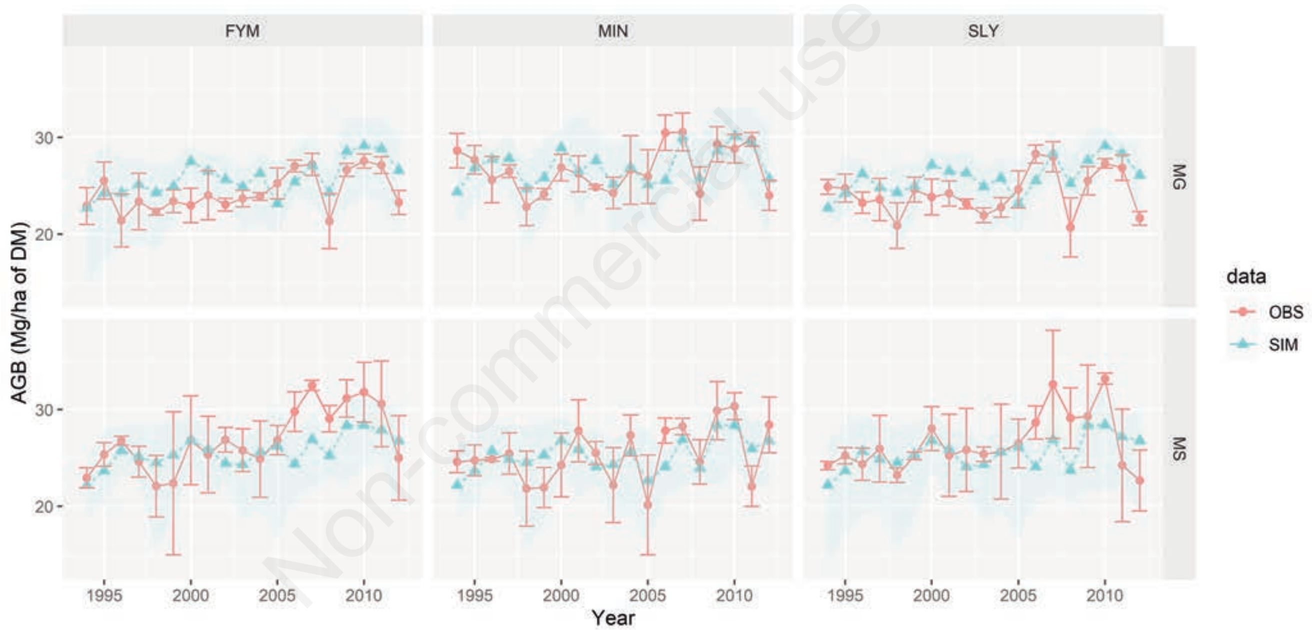

Figure 2. Observed (OBS, red dots and lines) and multi-model ensemble median (SIM, blue dots and lines) dynamics of aboveground biomass production (AGB, Mg/ha) over the long-term experiment years. Red bars represent the standard deviation of the mean observed value; blue ribbons represent the interval between the mean value of the ensemble ± the standard deviation of the simulated values. MG, grain maize; MS, silage maize; MIN, mineral; SLY, slurry; FYM, farmyard manure.

Table 5. Relative root mean square error (RRMSE) describing the goodness of the fit between observed and simulated soil organic carbon (SOC), aboveground biomass (AGB), and maize grain yield (GRY) for all experimental treatments across models.

TreatID	RRMSE_SOC	RRMSE_AGB	RRMSE_GRY	RRMSE_mean	RANK
MG_MIN	0.05	0.14	0.12	0.11	1
MG_SLY	0.08	0.14	0.13	0.12	2
MG_FYM	0.10	0.16	0.16	0.14	4
MS_MIN	0.09	0.16	-	0.13	3
MS_SLY	0.11	0.20	-	0.14	5
MS_FYM	0.15	0.17	-	0.16	6

Discussion

The observed long-term SOC dynamics of both MG and MS cropping systems clearly showed that the organic fertilization systems designed for the LTE-TO were effective in increasing SOC in the 0-30 cm layer by more than 0.4% year^{-1}, which has been a target for climate change mitigation since the UNFCCC COP21 (Lal, 2016). The FYM organic fertilization was the most effective in promoting SOC stock, with an average SOC increase of some +1.8% year^{-1} for both MS and MG, *i.e.* more than four times than that prescribed by the 4 per 1000 initiative launched at COP21. With SLY, the residue incorporation allowed MG to be compliant with the 4 per 1000 initiative target (+1.0% year^{-1}) and more effective than MS (+0.4% year^{-1}) in increasing SOC stock.

The results from the model simulations confirmed the hypothesis that the prediction of long-term SOC dynamics and biomass production of both MG and MS cropping systems based on organic or mineral N fertilization was most effective using the MME than single models. Furthermore, a significant share of uncertainty in prediction was model-dependent and affected by crop management over time.

The MME_median proved to be the best predictor of the main C dynamics of the cropping system, considering the mean ranks of all the indices. Moreover, a closer agreement between observed and simulated data was found in MG when residues were incorporated into the soil, while the performances of the model decreased in MS cropping systems, when the whole AGB was harvested. The observed and simulated SOC dynamics during the 21 years of continuous maize agree with the study of Stella *et al.* (2019), which

Table 6. Analysis of variance of the mixed-effect linear models fitted to test the effect of the model and of the interaction between year, use, and fertilizer on the deviation (Student's *t* statistic) of simulations from observed soil organic carbon (t-SOC), aboveground biomass (t-AGB), and grain yield (t-GRY).

Response variable	Factor	numDF	F-value	P-value
t-SOC	Model	3	5.02	0.002
	Year	1	22.20	0.005
	Use	1	7.13	0.008
	Fertilizer	2	9.14	<0.001
	Year: Use	1	6.42	0.012
	Year: Fertiliser	2	4.36	0.015
	Use: Fertiliser	2	0.24	0.785
	Year: Use: Fertiliser	2	1.47	0.234
t-AGB	Model	3	54.31	<0.0001
	Year	1	0.03	0.875
	Use	1	44.18	<0.0001
	Fertiliser	2	1.46	0.233
	Year:Use	1	1.94	0.165
	Year: Fertiliser	2	2.67	0.070
	Use: Fertiliser	2	3.82	0.023
	Year: Use: Fertiliser	2	0.48	0.621
t-GRY	Model	3	7.68	<0.0001
	Year	1	1.39	0.254
	Fertiliser	2	4.15	0.017
	Year: Fertiliser	2	0.87	0.423

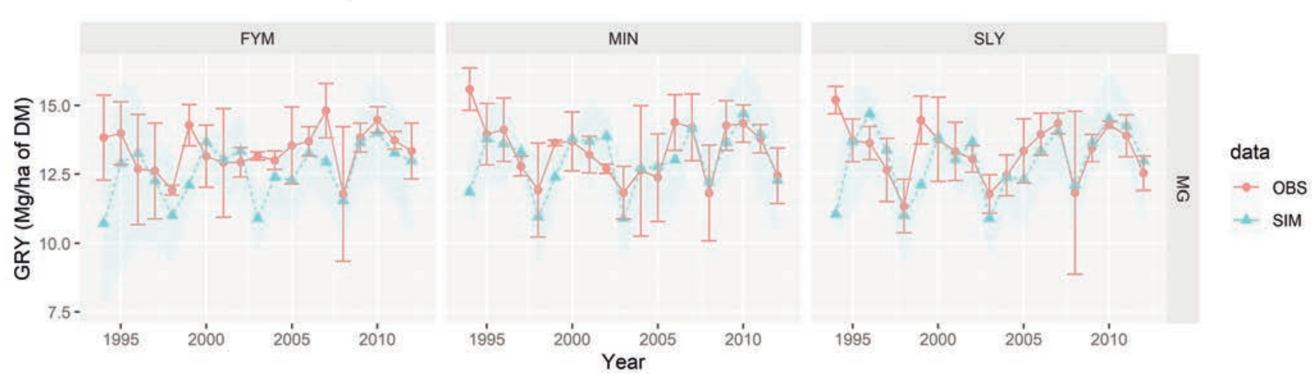

Figure 3. Observed (OBS, red dots and lines) and multi-model ensemble median (SIM, blue dots and lines) dynamics of grain yield (GRY, Mg/ha) over the long-term experiment years. Red bars represent the standard deviation of the mean observed value; blue ribbons represent the interval between the mean value of the ensemble ± the standard deviation of the simulated values. MG, grain maize; MIN, mineral; SLY, slurry; FYM, farmyard manure.

found residue management as the main driver of SOC changes in a long-term simulation study under a wide range of agronomic practices, including different crop rotations. This aspect becomes crucial when addressing cropping practices leading to SOC sequestration (Powlson *et al.*, 2011; Chowdhury *et al.*, 2021), thus assessing their potential in climate change mitigation (Álvaro-Fuentes and Paustian, 2011; Sanz-Cobena *et al.*, 2017). Nevertheless, what emerged from this study is that under continuous maize without organic fertilization, the sole incorporation of residues only guarantees SOC stability over time, as observed by other scholars (Lehtinen *et al.*, 2014; Poeplau *et al.*, 2017; Lin *et al.*, 2022). A positive effect on SOC content over the years only emerged clearly by combining crop residue incorporation into the soil with organic fertilization, particularly FYM, which was also observed by Tian *et al.* (2015).

The effect of both residue incorporation and removal was robustly reproduced by the model ensemble, confirming the findings of Saffih-Hdadi and Mary (2008), Smith *et al.* (2012), and Stella *et al.* (2019). However, when simulating the effect of FMY, all models tended to underestimate the SOC dynamics over the long term, which resulted in higher uncertainty in predicting SOC content over a longer time frame when organic fertilization was used. Conversely, no time-associated patterns of uncertainty were found in reproducing AGB and GRY, confirming the robustness of the chosen crop models in simulating the maize yield components under a wide range of management options.

The average RRMSE calculated across treatments suggested that crop residue incorporation was the highest source of uncertainty in reproducing both SOC and AGB dynamics over the experimental period. Furthermore, the amplitude of uncertainty in SOC simulations was increased by organic fertilization, particularly when residues were not incorporated. These shares of uncertainty were mainly attributed to the differences between the models' SOC routines, which differed between Model2 and the others whose SOC equations are based on the Century model. In Century-based models (Parton *et al.*, 1987; Paustian *et al.*, 1992), the organic matter contributing to soil C input is split according to the C/N ratio between structural (C/N=150) and metabolic C (C/N from 10 to 25). The structural C can contribute to the active (turnover=1.5 yr) and the slow (turnover=25 yr) soil C pools, while the metabolic C can contribute only to the active pool. The organic matter from crop residues contributing to the soil C input in Model2 is distinguished into three different fractions: fast-cycling (C/N=10), slow-cycling (variable C/N), and lignified (C/N=100) fractions (Stockle *et al.*, 2012). The first two fractions can constitute the labile (turnover rate of about 66 days) and the meta-stable (turnover rate of about three years) soil C pools, while the lignified fraction contributes only to the meta-stable pool. In the specific experimental conditions represented by the long-term observed data, the straw residues incorporated under the MG system had a C/N≈40, while the supplied organic fertilizers had a C/N 12.5 and 6.6 for FYM and SLY, respectively (Zavattaro *et al.*, 2016). These differences in the C/N imply that Model2 allocates a large fraction of SOC from organic fertilizers in meta-stable pools, while Century-based mod-

Figure 4. Deviation of simulations as Student's *t* statistic from observed data over the experimental period. Different colours represent different models, while the multi-model ensemble median (MME_Median) is represented with a bigger red dot. Horizontal dashed red lines represent the critical value of the Student's *t* statistics for a P(|t|)<0.05. MG, grain maize; MIN, mineral; SLY, slurry; FYM, farmyard manure.

els could have allocated all C derived from organic fertilizers into the active pool. This pool has a faster C turnover rate than the meta-stable pool simulated by Model2. Therefore, a smaller fraction of the total C input from organic fertilizers can contribute to the SOC stock increase, being partitioned into stable pools. Moreover, a significant share of organic C is lost as CO_2 before it is allocated into the slow and passive (stable) pools. Based on the above, the importance of the partitioning of organic inputs in the different C pools for the reliable prediction of the long-term effects of organic fertilization on SOC is clearly apparent. For Century-based models, it could be necessary to differently set the parameters regulating the impacts of organic amendment on SOC pool changes, as well as on the microbial community response in terms of mineralization. An effective advance in the ability of crop models to simulate the dynamics of SOC stocks can represent an insight into improving their ability to test and predict fertilization and strategies to mitigate climate change.

Conclusions

The results of this study confirm that a crop model ensemble can effectively predict the long-term dynamics of SOC and biomass production of maize cropping systems under contrasting fertilization and crop residue management, leading to sharp differences in long-term SOC dynamics. The performances of the model ensemble in simulating changes in SOC stocks and the related uncertainty in prediction are strictly related to the model characteristics and structures - particularly the partitioning of the organic matter input from residues and organic amendments into the soil - and to the interaction between the management factors over time.

The significant increase in SOC content observed under FYM fertilization, regardless of residue management, confirms the importance of this organic fertilizer in enhancing SOC stock while maintaining adequate levels of aboveground biomass production and yield. The incorporation of MG crop residues, combined with both FMY and SLY fertilizers, was also effective in increasing the SOC stocks at a rate far beyond the climate change mitigation target set by COP21. However, some limitations emerged in the ability of crop models to simulate the long-term effect of organic amendment without residue incorporation. The observed underestimation of the increasing SOC stocks highlighted a source of uncertainty that, under the specific conditions of continuous maize grown in loamy soils with a temperate climate, could affect the robustness of prediction of SOC changes and climate mitigation potential of the described management practices. Underestimation of SOC stocks could then also bias the predictions under climate change scenarios.

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