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# European croplands under climate change: Carbon input changes required to increase projected soil organic carbon stocks

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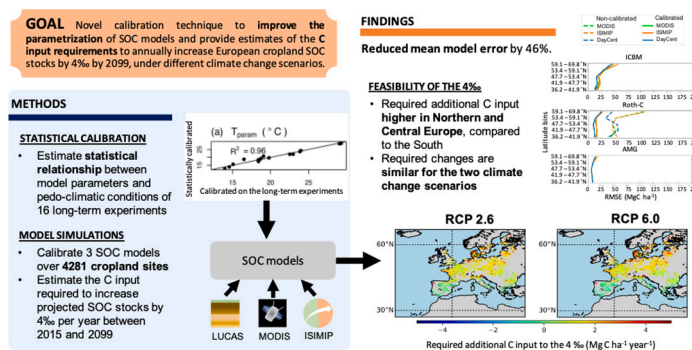
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## HIGHLIGHTS

- A novel calibration approach enhances soil organic carbon stock simulations.
- Northern Europe requires higher C input additions to reach the 4‰ target.
- Similar C input requirements under RCP 2.6 and RCP 6.0.
- C input change requirements exceed predicted changes in net primary productivity.

## GRAPHICAL ABSTRACT



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## ABSTRACT

Increasing soil organic carbon (SOC) stocks in agricultural systems is a pivotal strategy for promoting soil health and mitigating climate change. Global initiatives have set ambitious targets, aspiring to achieve an annual SOC stock increase of 4‰. In the European Union, the recently approved Nature Restoration Law aims to increase SOC stock trends in the top 30 cm of cropland mineral soils. However, current monitoring and reporting practices in some countries rely on simplistic SOC models with default parameters, which may not provide reliable predictions.

In this paper, we study the feasibility of a 4‰ target in European croplands (i.e., an aspirational target proposed by The international “4 per 1000” Initiative), through estimations of required C input changes. To ensure robust predictions, we propose a novel calibration approach that links model parameters to pedo-climatic variables via statistical relationships from 16 long-term experiments. The effectiveness of the method is evaluated for three SOC models across 4281 sites from the European LUCAS soil survey.

Our findings demonstrate that the statistical calibration of the multi-model ensemble improves the accuracy of 2015 and 2018 SOC stock predictions, compared to default parameterization. This improvement was however mainly due to the substantial enhancement of one of the models. According to the weighted multi-model mean, median C input changes to reach a 4‰ target for Northern, Central, and Southern Europe stand at 1.85, 1.20, and 0.13 Mg C ha<sup>-1</sup> yr<sup>-1</sup> under RCP 2.6, and 2.21, 1.26, and -0.10 Mg C ha<sup>-1</sup> yr<sup>-1</sup> under RCP 6.0, respectively.

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To achieve the aspirational 4 % target, estimated C input change requirements exceed the predicted changes in net primary productivity under RCP 2.6 and RCP 6.0. This emphasizes the importance of strategic land-use and land-management interventions to enhance SOC stocks.

## 1. Introduction

The European Union (EU) has set ambitious targets to tackle climate change. In comparison to the levels of 1990, one aim is to reach net zero greenhouse gas (GHG) emissions by 2050 (European Commission, 2021). In addition, by 2030 the EU has also introduced an overall target for land carbon (C) removals by natural sinks of 310 Tg of CO<sub>2</sub> equivalent (European Commission, 2021). Soil is recognized as the second largest C sink after oceans, and among terrestrial ecosystems soil organic carbon (SOC) stocks are the largest C pool (Lal, 2008). Policy frameworks addressing land-use and land-use changes in Europe could generate significant changes in SOC stock levels. For example, the recently approved Nature Restoration Law of the EU sets binding restoration targets to recover degraded ecosystems by 2050 (European Commission, 2022a). Among these targets, one is to increase SOC stock trends in the top 30 cm of cropland mineral soils (European Commission, 2022a) via carbon farming activities (European Commission, 2022b).

An aspiring target of an annual 0.4 % (i.e., 4 ‰) SOC stock increase had been proposed in 2015 by The international “4 per 1000” Initiative (<https://www.4p1000.org/>, last access: 25 June 2024). It suggested a voluntary action plan to maintain and increase existing SOC stocks by 4 ‰ yr<sup>-1</sup> to a 0 to 30–40 cm depth at the global scale, in order to mitigate climate change and improve food security (Lal, 2016). The underlying principle of the initiative is that, improving agricultural practices to protect existing SOC stocks and, whenever possible, increase SOC stocks by a relatively low annual rate can create a win-win scenario, by offsetting some GHG emissions from human activities while sustaining soil health for food productivity (Minasny et al., 2017). This approach aligns with European climate targets to achieve C neutrality and combat soil degradation. Since the “4 per 1000” initiative and the carbon voluntary market were launched, a number of studies have investigated the feasibility of a 4 ‰ annual SOC stock increase (Poulton et al., 2018; Noulékoun et al., 2021; Martin et al., 2021; Riggers et al., 2021; Bruni et al., 2021, 2022a, 2022b; Bamière et al., 2023). However, a global assessment at the European level is still missing.

There is a general consensus that the most efficient way to increase SOC stocks is through increased C input (Virto et al., 2012; Autret et al., 2016; Fujisaki et al., 2018), for example, via additional organic matter inputs or increased atmospheric CO<sub>2</sub> fixation through extended plant growth. Examples of cropland practices that return additional C inputs to the soil compared to conventional practices, include: agroforestry systems, hedges, cover cropping, lengthening leys in temporary grasslands, and effective restitution of crop residues and organic amendments to the soil (Chenu et al., 2019). In an effort to monitor and increment SOC stocks, several organizations are supporting countries to report their national C budgets using simple process-based models (e.g., FAO, 2018; Lesschen et al., 2021; Peralta et al., 2022). This is important and effective to standardize SOC stock estimates across countries. It also improves the level of methodological complexity of the estimation, compared to a Tier 1 or Tier 2 approach (IPCC, 2006). These methods use simpler, more generalized approaches to estimate SOC sequestration, requiring less data but resulting in lower accuracy. In contrast, model-based Tier 3 methods employ high-quality, site-specific data and complex models, making them the cutting-edge approach in SOC sequestration estimation (IPCC, 2006). However, simulations based on a single model with default constant parameters may not provide reliable predictions, as they often fail to capture the dynamics and site-specific variations in SOC (Luo and Schuur, 2020; Farina et al., 2021).

To increase reliability, models typically need to be calibrated and validated against observed data (Garsia et al., 2023). Calibrated model

parameters integrate those processes that are not explicitly represented in the models (i.e., processes at unresolved scales) (Luo and Schuur, 2020), which typically vary spatially with pedo-climatic conditions and land-use. For example, the temperature sensitivity of soil respiration (i.e., the increase of soil respiration due to temperature changes) is usually represented by the fixed Q<sub>10</sub> parameter (Davidson and Janssens, 2006), although Q<sub>10</sub> is known to vary with other environmental factors, such as soil moisture, texture, pH, and land-use (Meyer et al., 2018; Wang et al., 2010). Thus, it is important that parameters vary according to local conditions. For future projections, it is also important to perform the calibration on data that inform on the temporal dynamics of the system, such as those obtained from long-term experiments (LTEs) (Le Noë et al., 2023). The challenge lies in the scarcity of such experiments, the lack of harmonization among soil surveys, and the difficulty of generalizing findings from few experiments to entire countries or continents (Jandl et al., 2014). Efforts to facilitate the parametrization of process-based models should be undertaken to allow for a larger applicability. In addition, multi-model ensembles should also be considered in order to estimate and possibly reduce the uncertainties linked to the structure of the models (Riggers et al., 2019; Bruni et al., 2022b).

Based on these considerations, we developed a parametrization method that relies on statistical relationships between model parameters and observational data from LTEs. The statistical relationships were established by linking model parameters associated to C decomposition rates with the pedo-climatic conditions of the sites, through multiple linear regression models. The method allows for the estimation of site-specific parameter values, based on the application of simple mathematical functions calculated with local pedo-climatic conditions. The data used to estimate the statistical relationships spanned across 16 European sites and covered the major pedo-climatic gradients of the continent, enabling the applicability of the methodology at the European scale. The choice of multiple linear regressions was based on the need of a simple and interpretable model that could be trained on a relatively small amount of data. We tested the performance of the statistical parametrization on three SOC models (AMG, Andriulo et al., 1999; ICBM, André and Kätterer, 1997; and Roth-C, Jenkinson, 1990) over 4281 locations derived from the most extensive harmonized land-use and soil survey available for the EU (Land Use and Coverage Area frame Survey, LUCAS) (Orgiazzi et al., 2018). Then, we estimated the C input change requirements to reach an annual 4 ‰ SOC stock increase between 2015 and 2099 in European croplands. The proposed method allows to employ simple multi-linear functions for parametrizing SOC models. This has the potential to improve the reliability of large-scale SOC simulations, particularly in situations where parameter calibration is not possible due to a lack of observational data.

## 2. Materials and methods

### 2.1. Soil data

The LUCAS database gathers harmonized data on land-use and land cover across the EU, combining remote sensing and direct field observations (Ballabio et al., 2016). It provides topsoil data (0–20 cm) for 2009 (2012 for Romania and Bulgaria) on approximately 20,000 sampling locations over all land-use and land cover types. The survey was repeated in 2015 (Jones et al., 2020) and in 2018 (Fernandez-Ugalde et al., 2022) over most of the same sampling points. For the purpose of this study, we included only sites under agricultural land-use classified as arable under rotational crops in all three sampling campaigns (i.e., 2009/2012, 2015, and 2018). That is, 4281 points (Fig. S1). The

properties considered for the topsoil layer include soil texture (i.e., clay content), pH (in  $\text{CaCl}_2$ ), coarse fragments, carbonate ( $\text{CaCO}_3$ ) content, total nitrogen (N) content, and SOC content in 2009/2012, 2015, and 2018. Bulk density (BD) was not directly measured in the initial campaigns of the LUCAS framework, but was derived from a pedotransfer function that uses soil texture and SOC concentration as inputs (Hollis et al., 2012). Based on LUCAS data, SOC stocks were then calculated with Eq. (1):

$$\text{SOC} (\text{MgC ha}^{-1}) = \text{SOC}(\%) \bullet \text{BD} (\text{g cm}^{-3}) \bullet \text{sampling depth} (\text{cm}) \bullet (1 - \text{rock fragments fraction} (\text{vol.}\%/100)), \quad (1)$$

A recent study indicated that the BD estimated using the Hollis et al. (2012) approach for the 2018 LUCAS survey in agricultural lands was, on average, 8 % higher than measured values (Panagos et al., 2024), potentially introducing some uncertainties in SOC stock estimations. However, the authors demonstrated a strong alignment with measured soil BD for agricultural soils, reinforcing its suitability for such estimations (Panagos et al., 2024).

## 2.2. Climate data

Climate forcing data were derived from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) repository, protocol 2b (Frieler et al., 2017). Climate data at this relatively large spatial scale ( $0.5^\circ$ ) is still highly correlated to meteorological station observations (Karger et al., 2023). Data input values were extracted at the 4281 cropland locations based on the geographic coordinates of the LUCAS database, such that the spatial resolution of the data input was harmonized. Uncertainty in the climate data was considered by averaging an ensemble of different models. In particular, daily surface temperature and daily precipitation from water and snowfall were derived and averaged from the IPSL-CM5A-LR and MIROC5 models (Fig. S2). For potential evapotranspiration and soil moisture down to 18 cm depth, we derived and averaged the monthly output from the ORCHIDEE model, coupled with IPSL-CM5A-LR and MIROC5 climate models (Fig. S2). We used two scenarios of global climate change projections: the Representative Concentration Pathway (RCP) 2.6 and RCP 6.0. Recall that the RCP 2.6 scenario considers stringent mitigation policies and predicts an average global land temperature increase of  $1^\circ\text{C}$  during the period 2081–2100, compared to mean temperatures in 1986–2005, while the RCP 6.0 estimates an average temperature increase of  $2.2^\circ\text{C}$ , for the same time period (Field et al., 2014). Both scenarios were run assuming a fixed year-2005 land-use, nitrogen deposition and fertilizer input (Frieler et al., 2017). The choice of using climate forcing generated with fixed land-use from 2005 allowed us to estimate the additional C inputs to reach the 4 % target, relative to a business-as-usual scenario. To compare simulated C input change requirements with predicted changes in NPP due to shifts in land-use, we used ISIMIP simulations of NPP between 2015 and 2099 (multi-model average between DLEM and LPJ-GUESS, coupled with IPSL-CM5A-LR and MIROC5). The land-use scenario consisted in varying land-use, water abstraction, nitrogen deposition and fertilizer input according to the “Middle of the Road” shared socio-economic pathway (SSP2), defined in the IPCC Sixth Assessment Report (AR6) (Masson-Delmotte et al., 2021).

## 2.3. Carbon input

Carbon input levels were derived from three sources. The first is the net primary productivity (NPP) product from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data, covering the average NPP between 2000 and 2009 (Zhao et al., 2005). The second source is the multi-model average NPP between 2006 and 2015, calculated from a combination of earth system models (DLEM and LPJ-GUESS) and climate models (IPSL-CM5A-LR and MIROC5) derived from ISIMIP (protocol 2b) (Frieler et al., 2017). The third source is the average C

input between 2015 and 2019 simulated by the DayCent model, which includes both plant-derived and organic manure inputs (Lugato et al., 2017). For MODIS and ISIMIP forcings, the C input was calculated by multiplying the total annual NPP by the human appropriated NPP fraction (HANPPf) from Plutzer et al. (2016), and adding the C input from organic fertilizers. The HANPPf from Plutzer et al. (2016) includes the human-induced alteration of NPP due to land-use and harvest. The spatial resolution of MODIS NPP, human appropriated NPP fraction (HANPPf), and C input from DayCent was 1 km, while for ISIMIP NPP, it was  $55 \text{ km}^2$ . Organic fertilization from animal manures was derived from the ‘Gridded Livestock of the World’ FAO dataset (Robinson et al., 2014; Lugato et al., 2014). For all datasets, the values were derived for each cropland location of the LUCAS database. Running the models with different C input sources (Fig. S3) enabled the consideration of potential uncertainties associated with varying spatial resolutions. The temporal scale of the initial C input data was harmonized by averaging the data across different time periods (i.e., 2006–2009/2006–2015/2015–2019).

## 2.4. Models

We used three SOC models that were built to simulate the SOC stock dynamics in agro-ecosystems and were largely evaluated in temperate cropland sites: AMG (Andriulo et al., 1999), ICBM (Andr n and K tterer, 1997) and Roth-C (Jenkinson, 1990). The choice of models was driven by their structural simplicity, with the goal to select models that are either currently used or have the potential to be used for national C inventories at the European scale (Bouthier et al., 2014; Lesschen et al., 2021; Peralta et al., 2022; Swedish Environmental Protection Agency, 2023). Improving the parametrization of these models could thus impact the reporting of GHG inventories, which currently suffers from technical and comparability flaws (Chevallier, 2021). All three models simulate SOC stocks within a single topsoil layer (0–20 cm), using a conventional multi-compartmental structure. Each model has a different number of compartments, enabling different levels of flexibility in reproducing the SOC dynamics (Bruni et al., 2022b). Carbon inputs enter the soil and are transferred within the different SOC compartments. During the transfer, the C is partially decomposed, following first order decay rates. The decomposition rates depend on climate conditions with functions specific to each model. For example, ICBM uses soil moisture and temperature as forcing variables, while AMG and Roth-C use precipitation and potential evapotranspiration in addition to temperature. The only C outputs considered are those from respired  $\text{CO}_2$ . A detailed description of modeling assumptions is provided in Appendix A. Mathematical equations of the models can be found in: Clivot et al. (2019) for AMG; Andr n and K tterer (1997) for ICBM; Coleman and Jenkinson (1996) for Roth-C; and Parshotam (1996) for Roth-C's continuous version. Contrary to the other models, the initial conditions in AMG are pre-defined based on total initial SOC stocks (i.e., in 2015) and the previous land-use history of the site (Appendix A). This avoids the need of steady-state assumption for initialization. For the other models (i.e., ICBM and Roth-C), the assumption that SOC stocks were at steady-state at the onset of the simulations was made, in order to estimate the initial conditions of the SOC pools through analytical or semi-analytical spin-up. For spin-up, average climate forcing between 2006 and 2014 under RCP 2.6 was used. It is important to note that for past periods both RCPs are similar. We used 2015 SOC stocks as the initial date in order to have sufficient data for the spin-up forcing (i.e., 2006–2014). Forward simulations were run from 2015 to 2099, with climate forcings from RCPs 2.6 and 6.0.

## 2.5. Parametrization of the models

Models were run in two configurations: 1) with default parametrization and 2) with one or several statistically calibrated parameters. In the default configuration, all parameters were constant across sites, while statistically calibrated parameters varied spatially (Table 1). In

**Table 1**  
Coefficients of the multiple linear regressions. Pedo-climatic variables refer to their mean values over the duration of the experiments.

Model	Response variable	Adjusted R <sup>2</sup>	Coefficients of multi-linear regression																
			Intercept	Mean annual surface temperature	Mean annual precipitation	Mean annual potential evapotranspiration	Initial SOC stock	Initial carbon input	Clay	CaCO <sub>3</sub>	pH	Soil C:N	Wetness index						
	Parameter <sup>a</sup>		°C	mm	mm	mm	Mg C ha <sup>-1</sup>	Mg C ha <sup>-1</sup>	g g <sup>-1</sup>	g kg <sup>-1</sup>									
AMG	k <sub>0</sub>	0.77	<b>-4.37•10<sup>-1</sup>*</b>	<b>-1.43•10<sup>-2</sup></b>		<b>3.24•10<sup>-4</sup>*</b>	<b>3.48•10<sup>-2</sup></b>	<b>-1.50•10<sup>-3</sup>*</b>	<b>3.48•10<sup>-2</sup></b>										
ICBM	k <sub>1</sub>	0.60	<b>-1.20E•10<sup>1</sup></b>	1.53		<b>-9.58•10<sup>-3</sup></b>	<b>1.05•10<sup>-1</sup></b>	<b>1.05•10<sup>-1</sup></b>	<b>-3.52•10<sup>1</sup></b>										
	k <sub>2</sub>	0.63	<b>1.65•10<sup>-1</sup></b>	<b>-7.91•10<sup>3</sup>*</b>	<b>4.65•10<sup>-5</sup></b>	<b>6.98•10<sup>-5</sup></b>	<b>-6.65•10<sup>-4</sup>*</b>	<b>1.55•10<sup>-2</sup></b>											
Roth-C	r	0.55	<b>-2.33•10<sup>1</sup></b>	<b>7.83•10<sup>-1</sup>*</b>			<b>3.50•10<sup>-2</sup></b>	<b>3.50•10<sup>-2</sup></b>	<b>-1.43•10<sup>1</sup></b>										
	T <sub>param</sub>	0.93	<b>3.43•10<sup>1</sup>*</b>	<b>-1.30*</b>	<b>-4.34•10<sup>-3</sup></b>		<b>1.04•10<sup>-2</sup>*</b>	<b>-1.19•10<sup>-1</sup>*</b>	<b>6.20*</b>	<b>6.15</b>									

\* Bold values indicate significant coefficients (p-value < 0.05).

<sup>a</sup> k<sub>0</sub> is AMG decomposition rate coefficient of the active pool, k<sub>1</sub> and k<sub>2</sub> are ICBM decomposition rate coefficients of the young and old pools, respectively, r is ICBM environmental scalar, and T<sub>param</sub> is the reference temperature parameter of Roth-C temperature control function.

the following paragraphs we describe the approach used to statistically calibrate the parameters.

The first step was to derive from Bruni et al. (2022b) the values of model parameters calibrated site-by-site to fit observed SOC stock evolutions at 16 LTEs carried out in European croplands. The experiments had an average duration of 26 years and spanned from approximately 42.81°N to 59.82°N in latitude and 3.76°W to 21.66°E in longitude (9 were located in France and 1 each in Spain, Great Britain, Sweden, Italy, Germany, Poland and Austria) (Bruni et al., 2022b). Mean annual surface temperatures ranged between 5.7 °C and 12.8 °C, and mean annual precipitations between 613 mm and 1314 mm (Bruni et al., 2022b). Soils were quite diversified, encompassing both highly calcareous (160 gCaCO<sub>3</sub> kg<sup>-1</sup>) and non-calcareous soils, with clay concentrations ranging from 5 % to 36 %, and pH levels between 5.85 and 8.60 (Bruni et al., 2022b). The parameters selected in Bruni et al. (2022b) for the calibration affected the C decomposition rates, being either decomposition rate coefficients of the model compartments, or parameters of the environmental control functions modifying the decomposition rates. That is, the k<sub>0</sub> coefficient of the active pool in AMG, the k<sub>1</sub> and k<sub>2</sub> coefficients of the young and old pools in ICBM, respectively, the r environmental factor altering both decomposition rates in ICBM, and the reference temperature parameter (T<sub>param</sub>) of the temperature control function in Roth-C (Appendix A).

The second step consisted in estimating a statistical relationship between the calibrated parameters and the pedo-climatic conditions of the 16 sites (mean values over the experiment duration). For that, we used a multiple linear regression model where the response variable was the calibrated parameter and the explanatory variables were: mean annual surface temperature, mean annual precipitation, mean annual potential evapotranspiration, mean C input, clay and CaCO<sub>3</sub> content, soil C:N and pH, initial SOC stocks and wetness index at the LTEs. Climate variables used for SOC model simulations at the 16 LTEs, and for statistical regressions (i.e., daily mean surface temperature, precipitations and potential evapotranspiration) were derived from an hourly global climate dataset at 0.5° (GSWP3 <http://hydro.iis.u-tokyo.ac.jp/GSWP3/>), and annually averaged. The wetness index was derived from the 2015 Copernicus Land Monitoring Service products (Langanke et al., 2018). To select the most parsimonious model and reduce the risk of overfitting, we performed a step wise regression by Akaike Information Criteria (AIC). The developed pedo-climatic statistical functions estimated to derive the calibrated parameters are described in Table 1. As a final step, we derived the statistically calibrated parameters values for all 4281 locations using the estimated statistical functions for each parameter, the soil variables from the LUCAS survey, the wetness index from Copernicus, and the climate variables from the ISIMIP multi-model average (RCPs 2.6 and 6.0) (Fig. 1 shows the latitudinal distribution of the statistically calibrated parameters for RCP 2.6). See Appendix A for details on the parameter bounds.

## 2.6. Performance evaluation of the statistical parameter calibration

To evaluate the performance of the multiple linear regressions by stepwise AIC, we performed a leave-one-out cross validation (LOOCV) test (Table S1), where the regressions were iteratively trained over a subset of the database and tested on the left-out samples. LOOCV is a particular type of cross-validation, where the number of samples in the training set is n-1 and the number of test samples is 1, with n being the total number of samples. In our case, n = 16 and the training set had 15 samples. This was repeated iteratively for all samples in the dataset, with a total of n models being trained and tested. The LOOCV test results are provided as the relative root-mean-squared-error (r-RMSE), calculated as the RMSE divided by the mean of the parameter's values, the coefficient of determination (R<sup>2</sup>), and the mean absolute error (MAE) of the statistical models built for each statistically calibrated parameter (Table S1).

For both default and statistically calibrated configurations, model simulations of SOC stocks under RCP 2.6 were compared to LUCAS measurements by estimating the RMSE at each site. For ICBM and Roth-C models, both 2015 and 2018 measurements were considered. For AMG, only 2018 measurements were used because 2015 SOC stock measurements were prescribed to the model for initialization (Appendix A). The performance of the models to simulate SOC stocks in 2018 and/or 2015, i.e., their RMSE, was calculated as Eq. (2):

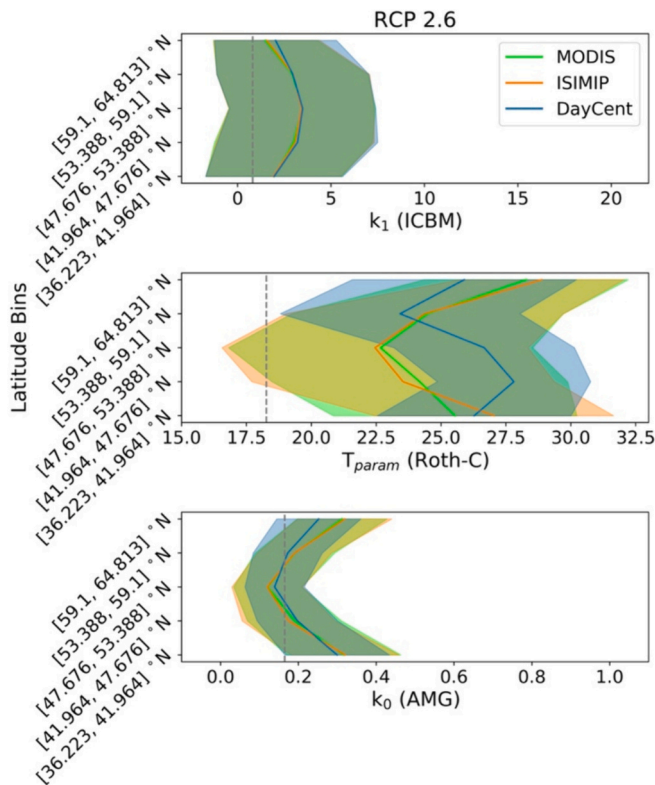
$$RMSE_i = \sqrt{\frac{\sum_{j=1}^N \sum_{z=1}^M (SOC_{i,j,z} - SOC_{j,z}^{obs})^2}{N \bullet M}}, \text{ for } i = 1, \dots, 18, \quad (2)$$

where,  $i = 1, \dots, 18$  are the model configurations (i.e., 3 models  $\times$  3

$$Y_{ij} = |SOC_{ij}^{2015} \bullet (1 + 0.004 \bullet 85) - SOC_{ij}^{2099}(I)|, \text{ for } i = 1, \dots, 18 \text{ and } j = 1, \dots, N, \quad (3)$$

input forcing  $\times$  2 calibrations);  $j = 1, \dots, N$  are the cropland locations of the LUCAS database for which the forcing input was available;  $N$  being equal to 4281 for MODIS forcing, 4233 for ISIMIP, and 3910 for DayCent;  $z = 1, \dots, M$  are the number of years for which the models were evaluated (i.e., 1 for AMG, and 2 for ICBM and Roth-C);  $SOC_{i,j,z}$  is the modeled SOC stock for model configuration  $i$ , location  $j$ , and number of years  $z$ ; and  $SOC_{j,z}^{obs}$  is the observed SOC stock for location  $j$  and number of years  $z$ .

The effect of the models and parametrizations (i.e., with or without statistically calibrated parameters) on the RMSE was estimated with a



**Fig. 1.** Latitudinal distribution of the statistically calibrated parameters. The average value of the statistically calibrated parameters for each latitude bin is shown with different colored lines according to the different forcings, and the standard deviation of the parameters across sites is represented by the colored shades. Default parameter values in the non-calibrated configurations are shown with the grey dashed vertical line.

linear mixed-effect (LME) model, where we assumed fixed effects for the explanatory variables: “model”, “parametrization”, and the interaction between the two, and a random effect for the “forcing” variable. After testing for normality of the residuals with a Shapiro-Wilk test, we assessed the significance of fixed effect terms with an analysis of variance (ANOVA). The effect of the coefficients was considered significant for  $p$ -values  $< 0.05$ .

## 2.7. Inverse modeling

The amount of C input required to increase SOC stocks by 4 ‰ yr<sup>-1</sup> over the period of 2015–2099 was calculated using an inverse modeling approach that consisted of minimizing Eq. (3):

where  $SOC_{ij}^{2015}$  and  $SOC_{ij}^{2099}$  are the 2015 and 2099 SOC stock levels simulated by model configuration  $i$  at location  $j$ , respectively, and  $SOC_{ij}^{2099}$  is a function of the C input to be optimized ( $I$ ).

The amount of C input from livestock manure was assumed to be maintained at current levels, unless the estimated C input to reach the 4 ‰ target was lower than the amount of C input from livestock manure. In that case, the amount of livestock manure was assumed to be 0 and the estimated C input considered as plant material only. This allowed to estimate the relative change of C input required to reach the 4 ‰ target from plant material only. For each model configuration and at each location, the additional C input required to reach the 4 ‰ target was then estimated as Eq. (4):

$$\Delta I_{ij}^* = I_{ij}^* - I_{ij}^{2015}, \text{ for } i = 1, \dots, 18, \text{ and } j = 1, \dots, N, \quad (4)$$

where  $I_{ij}^*$  is the required C input to reach the 4 ‰ target over the period of 2015–2099, and  $I_{ij}^{2015}$  is the amount of C input in 2015 for model configuration  $i$  and location  $j$ . The change of C input required to reach the 4 ‰ target, relative to 2015, was calculated as Eq. (5):

$$I_{ij}^* \text{ relative change } (\%) = \frac{\Delta I_{ij}^*}{I_{ij}^{2015}} \bullet 100. \quad (5)$$

At each location, we calculated the weighted multi-model mean of the required additional C input, using as weights the inverse of the RMSE:

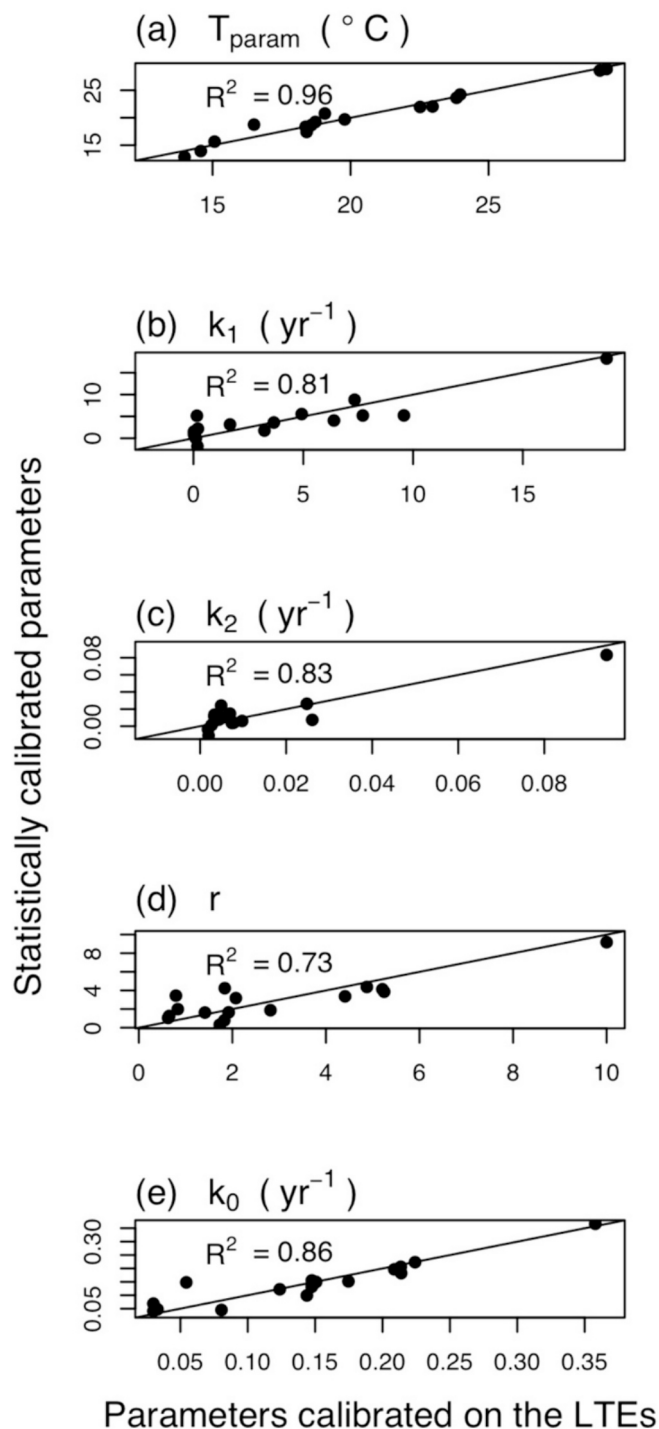
$$\overline{\Delta I_j^*} = \frac{\sum_{i=1}^{18} \frac{1}{RMSE_i} \bullet \Delta I_{ij}^*}{\sum_{i=1}^{18} \frac{1}{RMSE_i}}, \text{ for } j = 1, \dots, N. \quad (6)$$

The weighted standard deviation was then calculated with Eq. (7):

$$\sigma_{\Delta I_j^*} = \sqrt{\frac{\sum_{i=1}^{18} \frac{1}{RMSE_i} (\Delta I_{ij}^* - \overline{\Delta I_j^*})^2}{(18-1) \sum_{i=1}^{18} \frac{1}{RMSE_i}}}. \quad (7)$$

To assess the deviation of the models around the multi-model weighted mean, the weighted relative standard deviation ( $wRSD_j$ ) was computed as the absolute value of the coefficient of variation (note that this measure is dimensionless and not expressed as a percentage):

$$wRSD_j = \left| \frac{\sigma_{\Delta I_j^*}}{\overline{\Delta I_j^*}} \right|. \quad (8)$$



**Fig. 2.** Correlation between the predicted SOC model parameters estimated with the multiple linear regression (see Table 1), and the calibrated parameters estimated by fitting the SOC models to the measured SOC stock evolution in the 16 LTEs. (a)  $T_{\text{param}}$  ( $^{\circ}\text{C}$ ) is the reference temperature parameter of the temperature control function in the Roth-C model, (b)  $k_1$  ( $\text{yr}^{-1}$ ) and (c)  $k_2$  ( $\text{yr}^{-1}$ ) are the decomposition rate parameters of the young and the old pool in the ICBM model, respectively, (d)  $r$  is the environmental modifier in the ICBM model, and (e)  $k_0$  ( $\text{yr}^{-1}$ ) is the decomposition rate parameter of the active pool in the AMG model.

### 3. Results

#### 3.1. Evaluation of the multiple linear regressions for statistical parameter calibration

Fig. 2 shows the correlation between the parameters predicted with the multiple linear regressions (i.e., the statistically calibrated parameters) and the values of the parameters calibrated on the 16 LTEs. The reference temperature parameter ( $T_{\text{param}}$ ) of the Roth-C model showed the highest  $R^2$  (0.96) between predicted and calibrated parameters, followed by the decomposition rate parameter  $k_0$  of AMG (0.86), the decomposition rate parameters  $k_2$  (0.83) and  $k_1$  (0.81) of ICBM, and the environmental parameter  $r$  of ICBM (0.73) (Fig. 2). Despite the relatively high portion of variance explained by the environmental variables in the multiple linear regression models (adjusted  $R^2 \geq 0.55$ , Table 1), only the statistical model built for the Roth-C parameter ( $T_{\text{param}}$ ) had good indexes of performance when tested with the LOOCV test (Table S1). In fact, the multiple linear regression model built for  $T_{\text{param}}$  had the highest average  $R^2$  (0.69) across the LOOCV test iterations, and lowest r-RMSE (0.14), compared to the other models, and a MAE of 2.30  $^{\circ}\text{C}$ . All other statistical models had an average  $R^2$  lower than 0.2 and a r-RMSE between 0.75 ( $k_0$ ) and 3.43 ( $k_1$ ) across the LOOCV test iterations (Table S1).

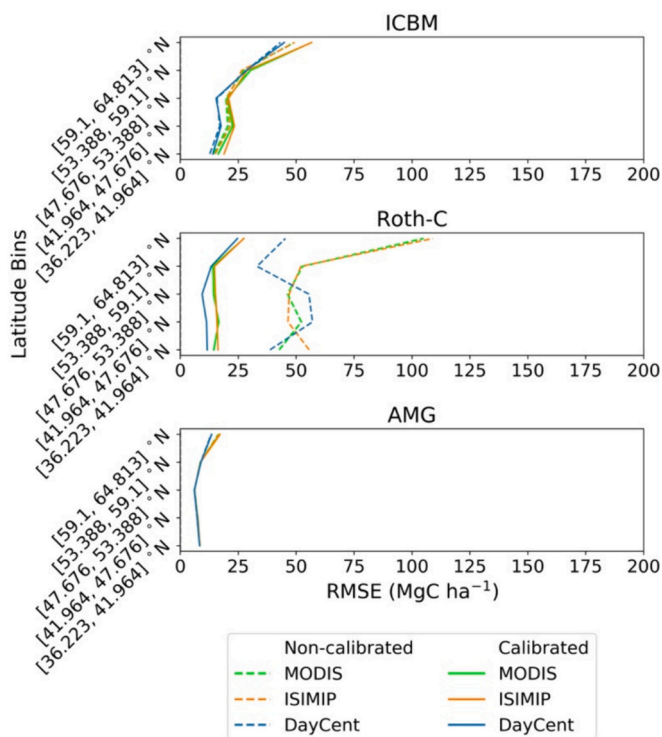
#### 3.2. Effect of the statistical calibration on the SOC stock predictions

Considering all models and forcings, compared to the default parametrization, the statistical calibration reduced by almost half the RMSE of the simulated SOC stocks, from 45.29  $\text{Mg C ha}^{-1}$  to 24.69  $\text{Mg C ha}^{-1}$  (Table 2). However, this was mainly due to the improved performance of the Roth-C model under statistical calibration. Instead, the RMSE of ICBM and AMG were not reduced by the statistical calibration (Table 2). In Fig. 3, the latitudinal distribution of the RMSE across model configurations shows that all the models tend to have higher RMSEs at high latitudes, especially under ISIMIP and MODIS forcings, which generally appear to be more closely aligned. In Roth-C under statistical calibration, this bias is significantly reduced (Fig. 3). From the statistical analysis of the LME model (conditional  $R^2 = 0.99$ ), we found that the models and parametrizations had a significant effect on the RMSE (Table S2). There was also a significant interaction between models and

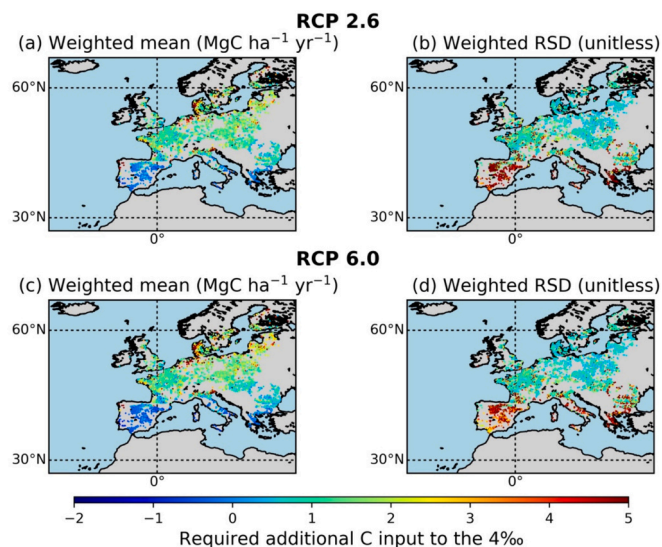
**Table 2**

RMSE of the different model configurations (Eq. (2)), where N•M is the number points for which the RMSE was calculated, N being the number of cropland points and M the number of years.

Model × Forcing	N•M	RMSE	
		Non-calibrated	Statistically calibrated
		$\text{Mg C ha}^{-1}$	
ICBM × MODIS	4281•2	29.34	32.63
Roth-C × MODIS	4281•2	67.45	22.93
AMG × MODIS	4281	15.39	15.55
ICBM × ISIMIP	4233•2	29.19	32.32
Roth-C × ISIMIP	4233•2	67.30	23.69
AMG × ISIMIP	4233	15.44	15.60
ICBM × DayCent	3910•2	26.00	26.55
Roth-C × DayCent	3910•2	59.13	16.56
AMG × DayCent	3910	15.23	15.42
All models			
MODIS	4281•(2 + 2 + 1)	47.03	26.16
ISIMIP	4233•(2 + 2 + 1)	46.90	26.29
DayCent	3910•(2 + 2 + 1)	41.42	20.96
All models and forcings			
Total	(4233 + 4281 + 3910)•5	45.29	24.69



**Fig. 3.** Latitudinal distribution of the RMSE for the different model configurations.



**Fig. 4.** Map of the required additional C input ( $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ ) to reach an annual 4 % SOC stock increase between 2015 and 2099, relative to 2015, in European croplands. Panel (a) and (c) show the weighted multi-model means under RCP 2.6 and RCP 6.0, respectively, while panels (b) and (d) show the weighted relative standard deviations (RSD) for the same climate change scenarios. Note that negative values indicate a required C input level lower than the C input in 2015 (Eqs. (4), (6)).

parametrizations, indicating that the effect of the parametrization on the RMSE depended on the model considered (Table S2).

### 3.3. Carbon input changes required to reach a 4 % SOC stock increase

Under both RCP 2.6 and RCP 6.0, the required additional C input to

reach a 4 % SOC stock increase between 2015 and 2099 was higher in Northern and Central Europe, compared to Southern Europe (Fig. 4). In particular, the median additional C input was 1.85, 1.20, and 0.13  $\text{Mg C ha}^{-1} \text{ yr}^{-1}$  under RCP 2.6, and 2.21, 1.26, and  $-0.10 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  under RCP 6.0, for Northern, Central, and Southern Europe, respectively (Table 3). Negative values indicate that less C input than what was applied in 2015 would be sufficient to reach the 4 % target. The predicted average requirements were found to be similar under the two climate change scenarios (i.e., median of 41.8 and 41.4 % under RCP 2.6 and RCP 6.0, respectively), with differences of the required relative changes in the range of  $-6.2 \%$  (Q1) and  $6.3 \%$  (Q3) (Table 3). Although similar on average, the effect of the climate change scenarios differed across regions. In particular, differences of the medians between the two climate change scenarios were higher in Northern (16.0 %) and Southern Europe ( $-7.1 \%$ ), compared to Central Europe (3.4 %). However, while in Northern and Central sites the C input change requirements were higher under RCP 6.0 (i.e., positive sign), Southern sites required higher C input changes under RCP 2.6 (Table 3). In absolute values, the predicted C input requirements within each region showed similar variability. The distance from the median to the lower and upper quartiles ranged between  $0.31 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  and  $0.92 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$  across regions (Table 3). The weighted relative standard deviation was higher in the Southern region, compared to the rest of Europe (Fig. 4b, d), indicating a larger discrepancy across model predictions in the South.

We compared the 4 % C input change requirements to the NPP changes between 2015 and 2099, predicted by the ISIMIP multi-model average under the varying land-use scenario (Fig. 5). We found a statistically significant difference between C input change requirements and NPP changes under both RCPs (ANOVA  $p$ -value  $< 0.05$ ). In particular, the median C input change requirements to reach the 4 % target were higher than the predicted NPP changes with varying land-use (Fig. 5).

## 4. Discussion

### 4.1. An innovative method to improve the parametrization of process-based models

The method that we propose defines generic mathematical functions to parametrize simple process-based models. The idea is to link parameter values to those processes that are not explicitly represented in the models, and to find emerging statistical relationships with pedoclimatic variables that affect these processes. By leveraging the data from 16 LTEs, this allows to account for both the spatial variability of the parameters and the temporal dynamics of SOC stocks. To our knowledge, the method that we propose in this study is unique in that it allows for the direct implementation of a spatialized parametrization into simple SOC models, based on local pedo-climatic conditions.

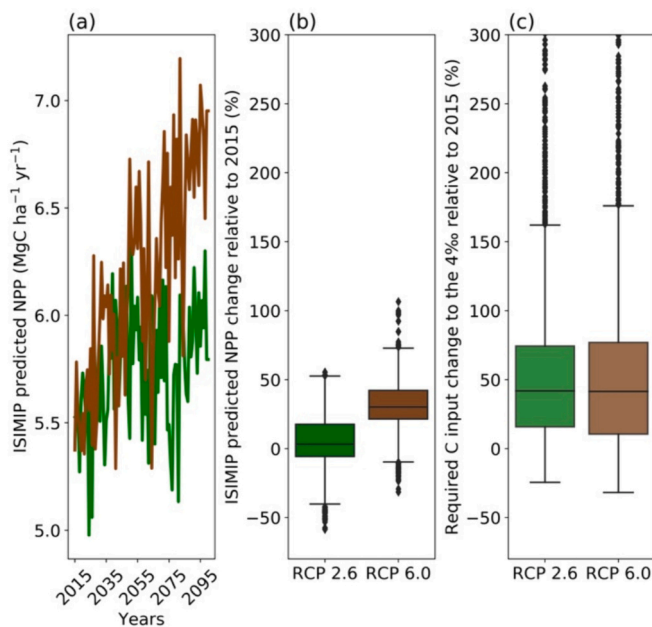
This approach also allows for a more refined understanding of the connections between model parameters and their environmental drivers. For example, Fig. 1 shows that the decomposition rate of the active pool in AMG increases at higher and lower latitudes, compared to central Europe, and it is significantly correlated to water and soil variables (i.e., mean annual potential evapotranspiration, wetness index, initial SOC stocks, and C:N ratio, Table 1). Also, the reference temperature parameter in Roth-C significantly correlated to the amount of C input in the LTEs (Table 1), which could partly explain why the RMSE in Roth-C predictions had a different latitudinal distribution when forced with DayCent inputs (Fig. 3). In fact, the DayCent forcing was derived from direct model simulations of plant C inputs, whereas the other forcings consisted in the correction of NPP data with values of human appropriation from Plutzer et al. (2016). The lower spatial resolution of ISIMIP data partly explains the generally lower performance of the models when using ISIMIP forcing (Table 2, Fig. 3). This parametrization approach also offers the advantage of being straightforward to implement since it consists in the application of mathematical functions to



**Table 3**

Required C input change to reach the 4‰ target between 2015 and 2099, under RCP 2.6 and RCP 6.0 scenarios. The 1<sup>st</sup>, 2<sup>nd</sup>, and 3<sup>rd</sup> quartiles (Q1, Q2, and Q3, respectively) of the multi-model simulations (weighted mean) are specified for North ( $\geq 55.5^\circ\text{N}$ ), Center ( $< 55.5^\circ\text{N}$  and  $> 45.5^\circ\text{N}$ ), and South ( $\leq 45.5^\circ\text{N}$ ) Europe, as well as for the whole 4281 sites (Total).

European region	RCP 2.6			RCP 6.0			Difference RCP 6.0 – RCP2.6		
	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
<b>Required additional C input (Mg C ha<sup>-1</sup> yr<sup>-1</sup>)</b>									
North	1.37	1.85	2.67	1.63	2.21	3.13	0.24	0.34	0.51
Center	0.85	1.20	1.69	0.87	1.26	1.79	-0.01	0.08	0.17
South	-0.23	0.13	0.76	-0.41	-0.10	0.45	-0.35	-0.19	-0.12
Total	0.41	1.02	1.60	0.26	1.00	1.69	-0.16	0.02	0.16
<b>Required C input change (%)</b>									
North	58.36	89.42	132.25	68.51	106.14	154.86	10.15	16.04	23.22
Center	33.56	53.09	80.88	35.11	55.68	84.54	-0.05	3.37	7.35
South	-7.41	7.43	28.93	-13.51	-2.4	18.21	-12.51	-7.14	-4.31
Total	15.72	41.85	74.30	10.50	41.37	76.90	-6.24	0.86	6.35



**Fig. 5.** Comparison between ISIMIP predictions of NPP changes between 2099 and 2015 under RCP 2.6 and RCP 6.0 and required C input changes in the same period according to the weighted multi-model mean. In panels (b) and (c), the black horizontal bars indicate the median.

determine the parameter values at different locations, and only requires data on the pedo-climatic conditions of the sites (that are in any case needed to run the simulations).

Recently, the synergy between statistical methods and process-based models has been gaining attention (Karpatne et al., 2017; Reichstein et al., 2019; Daw et al., 2021). A few studies have applied machine learning techniques to improve the parametrization of process-based models. For example, Gentile et al. (2018) used a deep learning approach to spatially parametrize moist convection in a global atmospheric model. Also, Tao et al. (2020) have used a neural network method combined with data assimilation to improve the representation of SOC in a land C model.

These works are showing the potential of artificial intelligence to reduce model biases and improve their ability to reproduce the spatial patterns of physical variables. The primary strength of these approaches lies in the substantial amount of data used to train and validate the

models. Deep learning techniques require large datasets to avoid overfitting and ensure robust performance. Our dataset, while extensive, was not sufficiently large for such applications. Given the limitations of the dataset, we opted for a simpler yet more interpretable multiple linear regression model. This allowed to understand the relationships between variables and gain insights into the factors influencing C dynamics. Our work builds upon previous efforts to merge data-driven approaches with process-based models, and it offers the added advantage of being readily applicable. As more comprehensive datasets become available, advanced modeling techniques should be employed to explore non-linear relationships in the SOC system.

#### 4.2. Feasibility of the 4‰ in Europe and comparison to other studies

Our maps show that C input change requirements will be higher in Northern and Central Europe, compared to Southern Europe (Fig. 4). This may be partly explained by the typically higher SOC stocks in those cropland regions, as shown by Lugato et al. (2021) and De Rosa et al. (2023), and by the sensitivity of SOC models to temperature and water-related variables (Bruni et al., 2022b). However, model errors were also higher at Northern latitudes (Fig. 3), which indicates that predictions in those regions are also less robust.

Other works have recently estimated the required C input change to reach a 4‰ target at a country or site-specific level. Those estimates range widely between a 30–40 % increase over a 30-year period estimated by Martin et al. (2021) for continental France, and a similar 43 % increase for European cropland sites (Bruni et al., 2021), up to a 119 % increase estimated with a multi-model ensemble over several European cropland sites (Bruni et al., 2022b), and a 221 % increase in German croplands for the period 2014–2099, under RCP 2.6 (Riggers et al., 2021). Although highly variable across sites, the estimates provided in our study fall in the lower range (Table 3). That is, a median 41.8 and 41.4 % C input increase over the whole European cropland area, under RCP 2.6 and RCP 6.0, respectively. Different estimates across these studies are mainly due to differences in modeling assumptions, such as the parametrization used, the models considered, and the variables used to force the models.

NPP changes due to projected land-use and climate were found to be insufficient to meet the 4‰ target (Fig. 5). This implies that relying solely on predicted NPP changes due to future land-use and climate will not be sufficient to reach the 4‰ target, especially in Northern European sites, where the additional C input required was very high (Q3 = 132.2 % and 154.9 % under RCP 2.6 and 6.0, respectively, Table 3). As it has already been extensively articulated in previous studies (Soussana et al., 2019; Chenu et al., 2019; Wiesmeier et al., 2020; Martin et al.,

2021; Bruni et al., 2022b), our findings highlight the necessity for strategic land-management interventions in the coming decades to increase SOC stocks in European croplands. Various practices to increase total NPP of agro-ecosystems exist (Chenu et al., 2019; Soussana et al., 2019). Among them, the adoption of continuous cover cropping has been shown to increase SOC stocks due to higher C inputs, relative to its non-adoption (Poeplau and Don, 2015). Similar effects have been found with the implementation of agroforestry systems and hedges (Cardinael et al., 2018). These practices are also associated to higher belowground C inputs, which contribute more to relatively stable SOC (Kätterer et al., 2011). Diversification of crop rotations has also been identified as a potential strategy to increase SOC storage (Chenu et al., 2019). In fact, greater crop diversity is associated to higher C input quality, quantity, and chemical diversity, which fosters the growth and diversity of soil microbial communities, thereby enhancing the formation and storage of SOC (Zhang et al., 2021). Reduction of yield gaps could also contribute to higher C inputs in some regions (Soussana et al., 2019). In particular, by reducing the cereal yield gap from 42 % to 20 % of the yield potential in Eastern Europe, it has been shown that there is the potential to boost the production by almost 40 % (Schils et al., 2018), thus partially fulfilling the additional C input needs in those regions.

It is important to note that the “4 per 1000” initiative's goals are aspirational, with the 4 ‰ increase rate serving as a quantitative target to explore the general feasibility of enhancing SOC stocks through improved land management practices. As Minasny et al. (2017) highlighted, not all soils have the potential to store additional SOC. Soils with inherently high SOC content may have already reached equilibrium under current management practices, while soils with low SOC content may struggle to increase SOC levels due for example to higher temperatures that accelerate decomposition (Minasny et al., 2017). In peat soils, it is very unlikely to increase the SOC stocks by 4 ‰ even under natural conditions (Minasny et al., 2017). Hence, in these regions the main challenge is to ensure C neutrality by avoiding SOC losses. In addition to the technical potential of management practices, adoption constraints and socio-economic barriers that limit the feasibility of the 4 ‰ target have seldom been accounted for, but should also be considered (Soussana et al., 2019; Bamière et al., 2023).

#### 4.3. Limits of our study

Despite the abovementioned benefits of our approach, important limitations and potential improvements must be pointed out. First, the number of sites that we used for the parameter calibration (i.e., 16 LTEs) is quite low for an extrapolation at the continental scale. Nevertheless, we expect that the major pedo-climatic gradients are well captured by the ensemble of sites. Also, default parameters in SOC models are usually estimated with empirical functions derived from one or few experiments in the same pedo-climatic conditions (e.g., the Rothamsted experiment in UK for Roth-C (Coleman and Jenkinson, 1996); the Boigneville experiment in France for AMG (Saffih-Hdadi and Mary, 2008); and the Ultuna experiment in Sweden for ICBM (Andrén and Kätterer, 1997)). Default parameters are generally used to forecast SOC dynamics without considering their variability across sites (Martin et al., 2021). This means that our approach necessarily improves the value of default parameters by including additional information from experiments in different pedo-climatic conditions and considering processes at unresolved scales. Adding more LTEs to the statistical analysis is expected to improve the performance of the approach and further reduce model biases. In particular, increasing the number of sites from Northern latitudes may help to better represent SOC stocks in those regions, where models have the highest errors (Fig. 3).

Second, the statistical parametrization did not improve ICBM and AMG simulations. For AMG, this may be due to the fact that the model was initialized with observed 2015 SOC and, after three years, the difference of errors between default and statistically calibrated parameters is expected to be quite low. It would be interesting to evaluate the

parametrization in the longer term to see whether the SOC stock dynamics is better captured with spatially variable parameters. For ICBM, parameter calibration in the LTEs may be compensating for structural lacks of the model. This means that the model may be omitting some important processes that should be integrated to improve its validity. Table 1 shows in fact that the majority of pedo-climatic variables were not significantly correlated to ICBM parameters, indicating that the empirical functions built for this model did not correctly capture missing processes at unresolved scales. In general, simple model structures increase parameter identifiability through observations, but oversimplification of model structure can lead to a decline in model accuracy (Her and Chaubey, 2015). Fig. 3 also shows that ICBM performance was not particularly sensitive to the statistical calibration of  $k_1$ . In general, an effort should be made to link parameters to physical factors that can be empirically estimated. On the contrary, the improved accuracy of Roth-C was due to the good performance of the statistical model in predicting its reference temperature parameter with pedo-climatic data (Table S1, Fig. 2). With an increased number of data, it would also be possible to employ deep learning techniques for the statistical analyses, which are likely more powerful for finding relevant relationships between model parameters and pedo-climatic data (Tao et al., 2020). Efforts from projects sharing data through open-source platforms (Ballabio et al., 2016; Poggio et al., 2021) and compilations of existing LTEs (Grosse et al., 2021; Donmez et al., 2022; Marazza et al., 2023) align with the requirements of our work and are expected to enhance the performance of the parametrization method that we propose.

Another important limitation of this study is that ensemble estimates had higher weights on AMG, which was not changed much from the default by the proposed calibration approach. Thus, the calibration did not contribute considerably to refining the maps of required additional C inputs (Fig. 4). High weights on AMG predictions also dragged down estimates of C input requirements in Southern Europe (Table S3). Differences in the levels of C input requirements among models were likely due to differences in the initialization method used. In fact, the assumption of steady-state for ICBM and Roth-C tended to stabilize SOC stock trends also in the forward run, whereas in AMG initial SOC stocks were prescribed and the model predicted overall increasing SOC stock trends, particularly high in Southern regions (Table S4). These differences are important to have in mind, especially because estimations of required C input additions to reach the 4 ‰ can be largely influenced by the current trend of the SOC stocks (Bruni et al., 2022a). Other works have predicted that SOC stocks will increase in Europe by 2050 and 2100 under current and projected land-use and different climate scenarios, but indicated SOC losses in Southern Europe (Lugato et al., 2014; Yigini and Panagos, 2016). This suggests that our results may be underestimating the level of C input required to increase the SOC stocks in Southern regions.

Model simulations are still highly uncertain due to the complexity of the processes represented, but also the parametrization and the data used to constrain the models (such as climate forcing, C inputs and initial SOC pools). To increase the reliability of projected SOC stocks, future works should prioritize accurate determination of initial SOC conditions (Kanari et al., 2022), independent and diachronic calibration of model parameters using extensive datasets (Le Noë et al., 2023; Garsia et al., 2023), and refinement of model representations of soil responses to climate variables (Moyano et al., 2012; Todd-Brown et al., 2012). The integration of different modeling approaches via multi-model ensemble simulations offers a more robust and complete representation of SOC processes (Farina et al., 2021; Bruni et al., 2022b; Le Noë et al., 2023). Structural uncertainties can be reduced by selecting the best performance models (Riggers et al., 2019) and identifying processes associated with high prediction errors (Bruni et al., 2022b).

## 5. Conclusion

The EU climatic commitments require strong decreases in GHGs

emissions, along with C removals by natural land sinks, such as soils. Modeling exercises are needed to evaluate the potential of cropland soils to store C. However, single model simulations with default parametrization are not robust for predicting SOC stock changes.

We proposed a method to calibrate SOC models via simple multi-linear functions linking model parameters to various pedo-climatic variables. On average, the method improved the accuracy of first years SOC stock predictions. Our multi-model simulations showed that reaching a 4 % SOC stock increase target in European croplands may require large increases of C input to the soils and land-management interventions to augment SOC stocks, especially in Northern Europe.

Our work builds upon previous efforts to integrate data-driven approaches with process-based models and has the advantage to be easy to apply. The effectiveness of the method we proposed can be further enhanced by incorporating additional LTEs into the statistical analysis.

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### CRedit authorship contribution statement

**Elisa Bruni:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Emanuele Lugato:** Writing – review

### Appendix A. Models

#### AMG

AMG is a three compartmental model that simulates SOC dynamics at an annual time step (Andriulo et al., 1999). It has one fresh organic matter pool, separated into aboveground and belowground material, and two SOC pools (active and stable). The C in the fresh organic matter pool is partly respired and partly transferred to the active SOC pool, according to C input-specific humification coefficients (Levassasseur et al., 2020). In the active pool, the C is decomposed following temperature, water, clay, and CaCO<sub>3</sub> dependent functions, and a decomposition rate coefficient ( $k_0$ ) (Clivot et al., 2019). The stable pool is considered constant throughout the simulation length. The model is initialized using the SOC stock value at the onset of the simulation (Saffih-Hdadi and Mary, 2008). For the initialization, total SOC is split among the active and stable pool according to the historical land-use of the simulated site. Lacking information on historical land use, all sites were considered as having a long-term arable history (i.e., 65 % of initial SOC stock was considered stable). For our simulations, each crop species from the LUCAS database was associated to its shoot:root ratio (Clivot et al., 2019), in order to determine the repartition of the C input into its aboveground and belowground pools. Furthermore, each crop species was associated to an aboveground crop humification rate, while the belowground crop humification rate was 0.4 for all species (Clivot et al., 2019). Since the crop rotation at the different sites was unknown, we simulated the SOC dynamics using the weighted average shoot:root ratio and humification coefficients for all sites. Test simulations showed that using values specific to the current crop did not affect the results.

For livestock manures, since the animal source was unknown, we used the average optimized humification coefficients for different types of animal manures from Levassasseur et al. (2020) (i.e.  $h = 0.548$  for all sites). Animal manures were supposed to be spread mainly on the soil surface (i.e. 90 % of total animal manure was spread aboveground and the rest 10 % belowground).

#### ICBM

ICBM is a two compartmental SOC model that is run at an annual time step and can be solved analytically (Andr n and K tterer, 1997). C input is directly transferred to the young and the old SOC pools, where the C is decomposed according to: a C input type-dependent humification coefficient, decomposition constants ( $k_1$  and  $k_2$  for the young and the old pool, respectively), and environmental factors. The environmental factors are summarized into one parameter ( $r$ ), which is calibrated from temperature and soil moisture response functions (Fortin et al., 2011; Karlsson et al., 2011) and normalized against a Swedish north-temperate site. For our simulations, we normalized the environmental parameter against a site situated at 59.82°N–17.28°E.

#### Roth-C

Roth-C is a five SOC pools model that is run at a monthly time step (Jenkinson, 1990). It was converted to its matrix continuous form following Parshotam (1996). The C input is split into the decomposable and resistant plant material (DPM and RPM) pools. For agricultural crops, a DPM/RPM ratio of 1.44 is used. Carbon from both DPM and RPM are partly respired as CO<sub>2</sub> and partly split into the humified organic matter (HUM) and microbial biomass (MIC) pools, depending on the clay content of the soil. Afterwards, the BIO and HUM pools decompose to form more CO<sub>2</sub>, HUM and BIO. SOC decomposition is dependent on temperature and moisture control functions, the first one being a logistic function that depends on mean monthly temperature and a temperature reference parameter ( $T_{param}$ ), and the latter being a piecewise function depending on mean monthly precipitation, mean monthly potential evapotranspiration, clay, and a soil cover coefficient (0.6 for vegetated soil) (Coleman and Jenkinson, 1996). A small amount of total initial SOC is considered inert (IOM) and is constant through time. Roth-C was solved semi-analytically, following the method described in

& editing, Resources, Methodology. **Claire Chenu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Bertrand Guenet:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

### 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

The model codes, scripts and small dataset used are available on GitHub at [https://github.com/elisabruni/Europe\\_4p1000/](https://github.com/elisabruni/Europe_4p1000/). Large input datasets are available upon request to the corresponding author.

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Huang et al. (2018) and Xia et al. (2012). That is to say: 1) the set of differential equations were solved by inverse calculations to determine pools sizes at steady state 2) the model was run numerically for the rest of the simulations.

#### Parameter bounds

The statistically calibrated parameters were bound to ensure physical, realistic values. The AMG decomposition rate parameter ( $k_0$ ) was bound between 0 and 1 (Clivot et al., 2019). The Roth-C reference temperature parameter ( $T_{\text{param}}$ ) was bound between 15 °C and 30 °C. The temperature response function (a) of Roth-C was additionally constrained to be lower than 4.5, to avoid completely decomposed SOC when the values of the calibrated  $T_{\text{param}}$  were close to the upper bound (see Coleman and Jenkinson, 1996). The ICBM decomposition rate parameter of the young pool ( $k_1$ ) was bound between  $1 \bullet 10^{-1}$  and 15, the decomposition rate parameter of the old pool ( $k_2$ ) was bound between  $1 \bullet 10^{-3}$  and 1, and the environmental factor parameter ( $r$ ) was bound between  $1 \bullet 10^{-3}$  and 10 (Andr n and K tterer, 1997). Additionally,  $k_1$  was constrained to be higher than  $k_2$ , to ensure that the turnover rate of the young pool was faster than the old pool. Since ICBM was calibrated on the 16 LTEs with multiple parameters, we tested the performance of the model using different combinations of statistically calibrated parameters: (i.e.,  $k_1$ ,  $k_2$  and  $r$ ;  $k_1$  and  $k_2$ ;  $k_1$  and  $r$ ;  $k_1$ ; and  $k_2$ ). Then, we selected the combination of statistically calibrated parameters that minimized the root mean squared error (RMSE) between simulated and observed SOC stocks in 2015 and 2018 (Eq. (2)). That is to say, the configuration where only  $k_1$  was statistically calibrated.

## Appendix B. Supplementary data

Supplemental data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2024.176525>.

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