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LETTER

Estimating the contribution of crop residues to soil organic carbon conservation

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Abstract

Crop residues contribute to the maintenance of soil organic carbon (SOC) stores, a key component of soil fertility and soil-based climate change mitigation strategies, such as the '4 per 1000' initiative. Residues are also in demand in sectors coupled to crop production, such as the supply chain of livestock and bioenergy production. Ongoing debate revolves around balancing these competing uses, but science-based assessments of the long-term sustainability of residue exploitation are rare. This work uses biophysical simulation modelling to explore the likely response of SOC to different management strategies, using the land area of North Rhine-Westphalia (Germany) as a case study. Four strategies are tested: zero, one third and 100% removal of cereal residues, plus an approach proposed by the State farm advisory service. Simulations are carried out for the period 1971–2050 and 19 crop rotations coincident with land use throughout the study area. Uncertainty associated with the modelled SOC changes is explored by sampling values of relevant parameters for SOC turnover and running an ensemble of model configurations. Simulated SOC is used to trace time-dependent response functions following a change in residue management under different soil textures, initial SOC levels and crop rotations. Results highlight a general exponential decrease in SOC, with relative changes in 2050 distributed between +10% and −40% with respect to a reference period. SOC loss can be buffered or offset by returning all crop residues to the soil. Under such management, an SOC increase can be achieved on clayey soils characterized by a low initial SOC. Under moderate crop residue removal, positive SOC trends are limited to a few crop rotations. In this context, 4 per 1000 increase rate in SOC appears largely out of reach through residue management, calling for additional measures to meet the targets of land-based mitigation of anthropogenic emissions.

1. Introduction

Soil organic carbon (SOC) is among the most important indicators of soil quality and agricultural sustainability. It enhances soil structure, biodiversity and the retention of water and nutrients while decreasing the risks of erosion and soil degradation (Lal 2009). Global SOC stocks amount to approximately three times the current atmospheric CO_2 and 240 times the annual fossil fuel emissions (Batjes 1996, Ciais *et al* 2014), often putting SOC pools in the spotlight for climate change mitigation strategies (Smith 2012, Paustian *et al* 2016). This is at the foundation of the '4 per 1000—Soils for Food Security and Climate' initiative, recently launched to increase global SOC stocks by 0.4% per year as a compensation for anthropogenic emissions of greenhouse gases (Minasny *et al* 2017). As most agricultural soils have been considerably depleted with respect to their original SOC content (Davidson and Ackerman 1993), they constitute a primary target for such initiatives.

In agricultural soils, the SOC balance is largely driven by land management (Van Wesemael *et al* 2010),

which modulates crop production, carbon inputs to the soil and the decomposition of soil organic matter (Ogle *et al* 2005, Liu *et al* 2006). Practices such as organic fertilization (Triberti *et al* 2008), inclusion of cover crops in rotations (Poeplau and Don 2015) and retention of crop residues on and in fields (Lehtinen *et al* 2014) increase *C* input and can sustain SOC. Crop residues are, however, also a primary resource for a number of competing off-farm uses (Lal 2005). They appear particularly attractive in the bioenergy sector as their use is not directly or indirectly related to land-use change (Daioglou *et al* 2016) and increases the value of agricultural output (Panwar *et al* 2011). The alternate uses of crop residues leave an open question regarding the amount of residues that can be removed from fields without jeopardizing the substantial ecosystem services that are provided by soils.

Addressing this question requires quantification of the response of SOC to different agricultural practices in a variety of soils and climate conditions. Long-term field experiments are fundamental in providing insights into the drivers of SOC changes that are inherently slow (Schmidt *et al* 2011). Experimentation is, however, impractical for the testing of multiple agricultural practices over large areas (Zhao *et al* 2013). At this scale, quantification methods based on simulation models hold promise because they embody the process-based understanding of SOC dynamics and coherently respond to a wide range of climatic and management conditions (Conant *et al* 2011). On the other hand, uncertainties stemming from model formulation and imperfect knowledge about parameters, initial values and input data may challenge the confidence placed in the results of model-based analysis (Ogle *et al* 2010). This is particularly important with regard to model parameters, known to contribute the most to overall uncertainty in the investigation of long-term SOC dynamics (Post *et al* 2008). Controlling these uncertainties is key to the improvement of decision-support tools for the design of policies promoting soil-based mitigation strategies (Paustian *et al* 2016).

This study aims at assessing, by means of simulation modelling, the response of SOC to different residue management strategies. A case study was set up in the German state of North-Rhine Westphalia, characterised by intensive agriculture in a humid temperate climate, to outline likely trajectories of future SOC across a typical spectrum of environmental and management conditions. By leveraging parameter uncertainty, the simulation outputs from the case study are translated into practical functions that represent changes in SOC resulting from changes in land management. Such functions contribute to the literature on carbon management response curves (West *et al* 2004) and can be applied to similar environments to tailor agricultural management to current land-based mitigation targets.

2. Methods

2.1. Study area

North-Rhine Westphalia (NRW), comprising about 1.3×10^6 ha of cropland in Northwestern Germany, provides a case study of pervasive and intensive agriculture in a humid, temperate climate in Europe. Annual rainfall ranges between 700 mm in the lowland and 1350 mm in the highlands, with average temperatures between 8 °C and 10 °C. Agriculture is the dominant land use (over 60% of land area), with arable land covering 73% of the utilized agricultural area. The major crops are cereals (about 60% of arable land), maize (17%, used either as silage fodder, corn cob mix or for bioenergy conversion), root crops (8%) and oilseed rape (6%; Eurostat 2016), all mainly rainfed. Prevailing soil types are Cambisols, Luvisols and Stagnosols (WRB 2014), with less fertile, sandy soils characterizing the Northwest sub-region, where highly intensive animal husbandry is responsible for considerable nitrogen loads (up to 190 kg N ha^{-1} yr^{-1}; Landwirtschaftskammer Nordrhein-Westfalen—LWK NRW 2014, figure S1 is available online at stacks.iop.org/ERL/14/094008/mmedia). The heterogeneity of NRW results in several distinct agro-ecological zones, each characterized by different pedoclimatic conditions (Roßberg *et al* 2007) and representative rotations of cash crops (figure S2, Burkhardt and Gaiser 2010). Climate (1971–2050) and soil data of NRW used in this study are presented in S3.

2.2. Cropping system modelling

2.2.1. Simulation setup and scenario assumptions
Simulations were performed with the Model for Nitrogen and Carbon dynamics in Agro-ecosystems (MONICA, Nendel *et al* 2011, S4). In this study, nine crops were ordered into 19 representative rotations distributed across NRW (figure S2). Within each agro-ecological zone, simulation units were identified as the distinct combinations ($n = 1653$) obtained by overlaying maps of representative soil profiles and estimated organic nitrogen load (S1) with climate raster cells. In these units, crop rotations were simulated continuously, without re-initialization of soil variables, over the 70 year period; permutations of each rotation were generated by shifting the initial crop to include all the crop-year (weather) combinations (Teixeira *et al* 2015). Water and nitrogen limitations to crop growth were activated to depict limited production levels (van Ittersum *et al* 2003). Typical sowing and harvest dates in the different agro-ecological zones were retrieved from state variety trials (Bundessortenamt 2000) and from the recommendation by the German Association for Technology and Construction in Agriculture (KTBL 2004) and used to set model parameters. For each agro-ecological zone and crop, sowing dates were set to the average of those recorded and harvest dates were used as a proxy for

Table 1. Summary of the factors considered in the simulation study, divided into spin-up and projection periods. Details about parameter uncertainty are presented in section 2.3.

Period	Spin-up (1971–2005)	Projection (2006–2050)
Scope	Equilibration of fast SOC pools, calibration of initial SOC (1971) to match database values at the end of the period (2001–2004)	Assessment of the impact of changes in management on SOC
Management scenarios	Baseline assumptions for residue management (33% removal) and cover crop presence (25% frequency before summer crops)	4 residue management strategies (0%, 33%, 100% removal and humus balance approach) × 3 cover crop frequencies (25%, 50% and 100% presence before summer crops)
Crop rotations	9 main crops allotted to 19 representative rotations distributed among 9 agro-ecological zones	Same rotations as spin-up. Additionally, permutations of each rotations were considered by shifting the initial crop (e.g. for rotation a–b–c, also b–c–a and c–a–b were simulated)
Simulation units	1653 combinations of soil profiles × organic N load × climate cell	Same as spin-up
Parameter uncertainty	15 parameter sets based on the posterior distribution of 7 key parameters related to SOC turnover	Same as spin-up
Distinct combinations (number of multi-year simulations)	73 005	2754 720

physiological maturity to calibrate phenology parameters accordingly.

Table 1 provides an overview of the simulation setup. Four residue management scenarios were explored: (i) the removal of 33% of the aboveground biomass left after crop harvest, assumed as the baseline scenario (LWK NRW 2014); (ii) a variable rate based on the humus balance approach (LWK NRW 2015, S5), which intends to prescribe the amount of residues that are removable from the system in a sustainable manner (Haase *et al* 2016); (iii) 100% and (iv) 0% removal of residues. These residue management scenarios were only applied to cereal crops because residues from other crops currently have limited alternative uses (Weiser *et al* 2014) and were therefore completely returned to the soil. Additional organic matter was provided with the incorporation of winter cover crops (i.e. mustard, sown the autumn before a summer crop) and the application of organic fertilizer (slurry) according to current practice. Three scenarios were generated by altering the frequency of cover crop plantings: one cover crop for every four opportunities (25%) was chosen as a baseline, with two additional scenarios increasing the rate to 50% and 100% (constant winter cover). Despite the agronomic and environmental potential of summer cover crops (e.g. during the off-season between subsequent winter cereals), only winter cover crops were considered here, as their adoption is rewarded by the European Union through greening subsidies. The amount of organic fertilizer applied each year to the main crop was retrieved from data on organic nitrogen load (LWK NRW 2014) available at the district level for the study region, and was kept constant across scenarios. Additional mineral N fertilizer was applied according to recommendations provided to farms in NRW (LWK NRW 2016).

2.2.2. Model spin-up

MONICA subdivides SOC into different pools (S4). Depending on the initial partitioning of C among these pools, SOC decomposition rates are variable (Basso *et al* 2011). In order to reduce the influence of the initial parameterization, the historical time frame (1971–2005) was used for model spin-up to allow the fast pools to approach equilibrium (Lugato *et al* 2014). Baseline management for both residue management and cover cropping was assumed for the spin-up phase, which provided the initial conditions (SOC concentrations and partitioning among the pools) for the subsequent projection period (2006–2050). For each combination of spatial unit × crop rotation × parameter set (see section 2.3), the calibration of initial (1971) SOC made it possible to obtain, by the end of spin-up, SOC concentrations (hereafter reference SOC) consistent with those reported in the soil database (S6).

2.3. Ensemble modelling via parameter perturbation

An ensemble of model configurations was created by sampling from a probability distribution of parameters (Wallach *et al* 2016) affecting the simulation of SOC dynamics. In a first step, a subset of key parameters related to soil organic matter, crop residues and organic fertilizer was identified via sensitivity analysis. For each combination of spatial simulation unit and crop rotation, the Morris method (Morris 1991) as implemented in the python library SALib (Herman and Usher 2017) was used to rank parameters. The ranking was based on their mean effect on SOC dynamics during the projection period according to the baseline scenario. Seven parameters out of 27 were identified as highly relevant based on sensitivity indices (S7), quantifying (i) the decomposition of
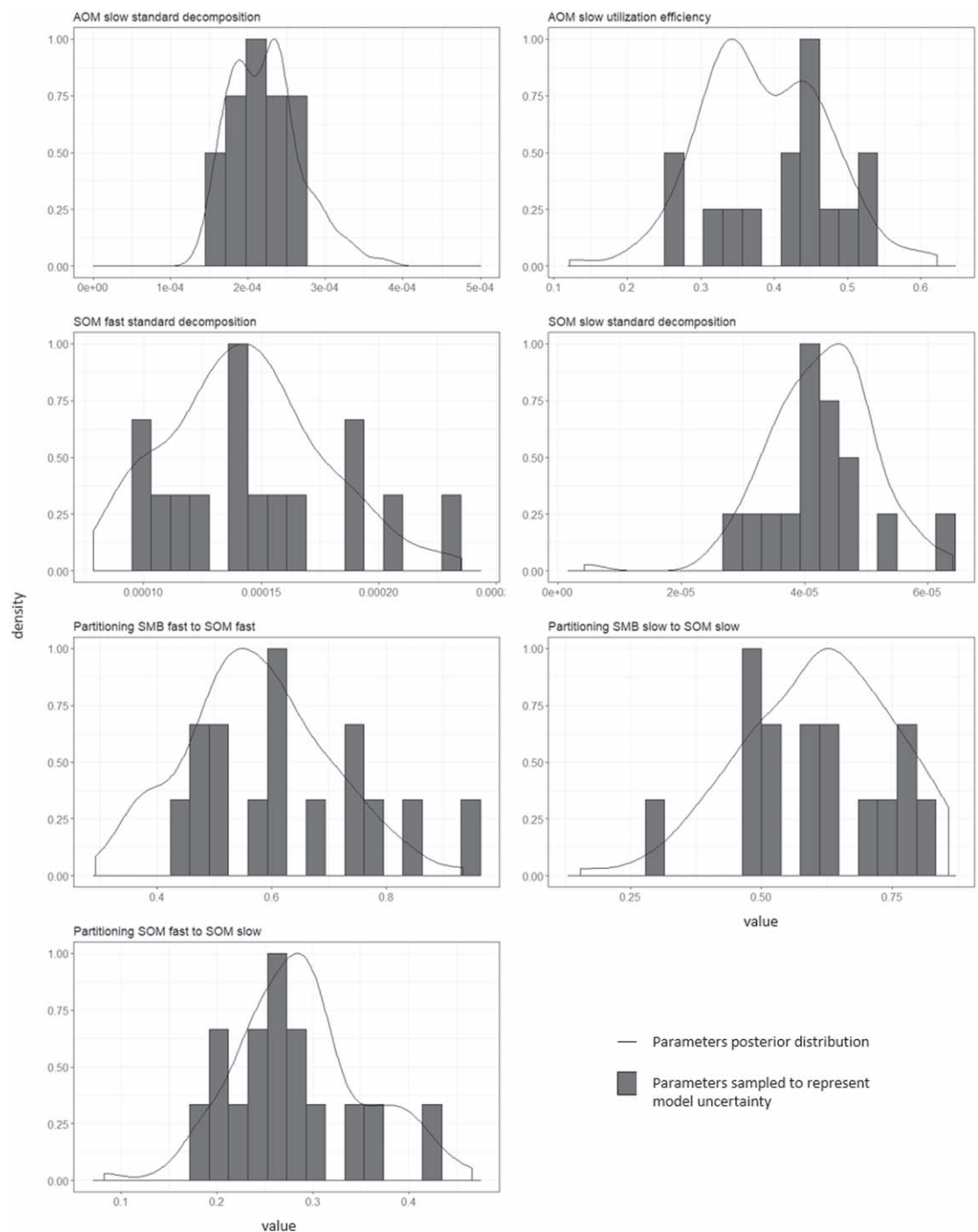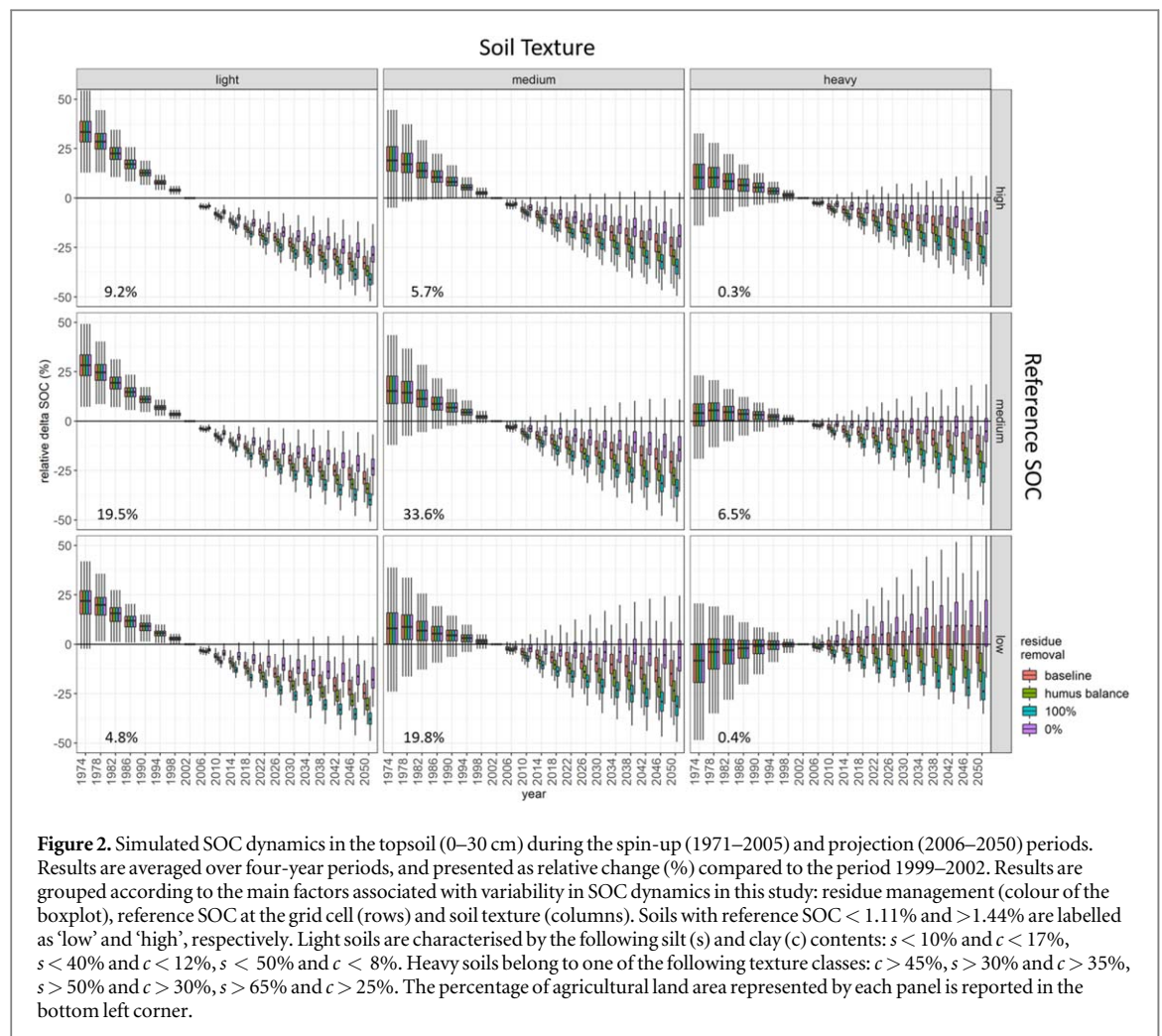
Figure 1. Parameter posterior distribution (continuous lines) and sample used in this study (bins) after uncertainty analysis of key parameters influencing SOC simulation. AOM: added organic matter; SMB: soil microbial biomass; SOM: soil native organic matter; 'fast' and 'slow' referring to the turnover rate of a subpool.

organic matter under standard conditions, (ii) the conversion efficiency of added organic matter into microbial biomass and (iii) the partitioning of C-fluxes from a decomposing pool into different pools.

The uncertainty of these parameters was explored in a second step. Prior distributions of the parameters were assumed to be normally distributed, with mean values equal to the default MONICA parameterization and standard deviations set to 25% of the mean. For each parameter, a sample of 1000 values was drawn from the prior distribution, and the DE-MC$_Z$ algorithm (Differential Evolution Markov Chain; Smith and Marshall 2008) implemented in the python SPOTPy package (Houska *et al* 2015) was used to sample sets of parameters and identify their optimal values. Posterior distributions of model parameters (figure 1) were derived by selecting the top 10%, in terms of achieving the highest likelihood in the simulation of SOC measured in the long-term field experiments (Rogasik *et al* 2004, S8). The number of parameter sets used to provide insight into model uncertainty was constrained to 15 (figure 1) due to the

Figure 2. Simulated SOC dynamics in the topsoil (0–30 cm) during the spin-up (1971–2005) and projection (2006–2050) periods. Results are averaged over four-year periods, and presented as relative change (%) compared to the period 1999–2002. Results are grouped according to the main factors associated with variability in SOC dynamics in this study: residue management (colour of the boxplot), reference SOC at the grid cell (rows) and soil texture (columns). Soils with reference SOC < 1.11% and >1.44% are labelled as 'low' and 'high', respectively. Light soils are characterised by the following silt (s) and clay (c) contents: $s < 10\%$ and $c < 17\%$, $s < 40\%$ and $c < 12\%$, $s < 50\%$ and $c < 8\%$. Heavy soils belong to one of the following texture classes: $c > 45\%$, $s > 30\%$ and $c > 35\%$, $s > 50\%$ and $c > 30\%$, $s > 65\%$ and $c > 25\%$. The percentage of agricultural land area represented by each panel is reported in the bottom left corner.

already large number of simulations required by the design of the experiment (table 1).

2.4. Analysis of temporal dynamics of SOC
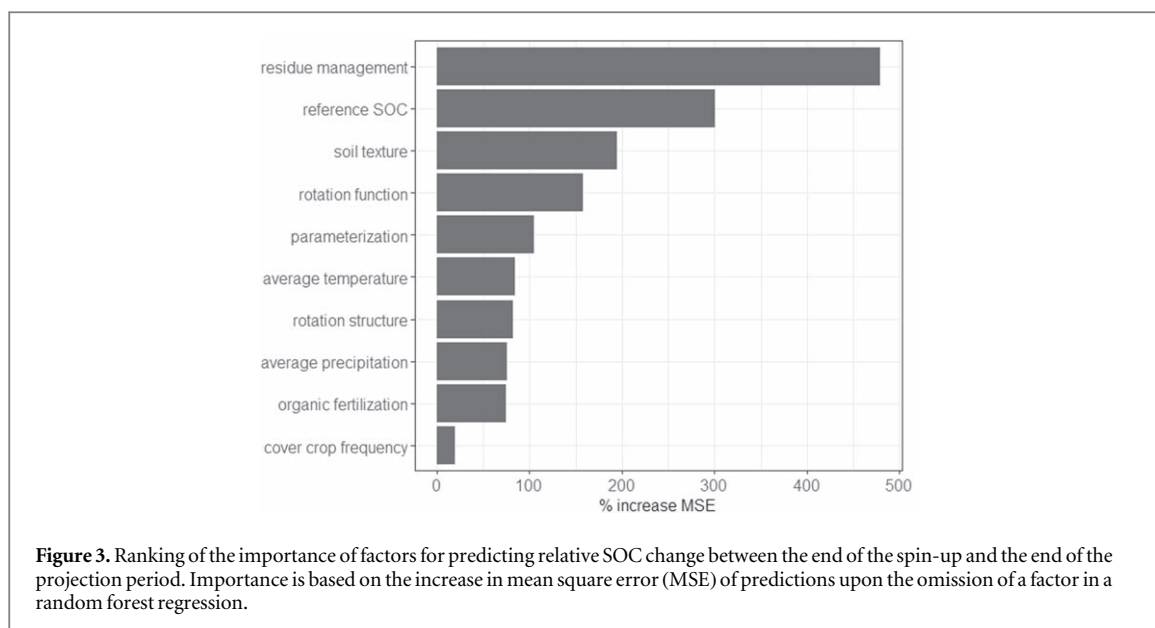
2.4.1. Random forest regression
Random forest regression (Liaw and Wiener 2002) was used to estimate the relative importance of factors associated with the change in SOC from the beginning to the end of the projection period. The importance of a factor was determined by the increase in mean squared-error of predictions resulting from the omission of that factor from the decision trees. This information was used to define regression models representing the simulation results (see 2.4.2) and as a key for their interpretation (see 3.1).

The factors considered in the analysis include (i) the aspects of the cropping system that vary across locations (crop rotation, organic fertilization) or scenarios (residue management, cover crop frequency), (ii) the input variables characterizing the pedoclimatic conditions of the simulation units (soil texture, reference SOC, average temperature and precipitation) and (iii) the model parameterization (identifier of the parameter set). Reference SOC and organic fertilization were organized according to their distributions, with the interquartile, the upper and the lower quartiles

labelled as 'medium', 'high' and 'low', respectively. The resulting range of the 'medium' categories spanned from 1.11% to 1.44% for reference SOC and from 88 to 135 kg N ha^{-1} yr^{-1} for organic fertilization. The 31 soil texture classes from the German soil-classification system (Eckelmann *et al* 2006) were aggregated into light (sandy), medium (silty and loamy) and heavy (clayey) soils. Crop rotations were typified following the approach proposed by Stein and Steinmann (2018), producing three structural classes (based on the number of distinct crops) orthogonal to four functional groups identified by the proportion of (i) broadleaf crops—in contrast with cereals—and of (ii) spring-sown (or autumn-sown) crops (S9).

2.4.2. Carbon response functions (CRFs)
CRFs are simple models to describe the change in SOC stock over time following a change in land management (West *et al* 2004) or land use (Anderson-Teixeira *et al* 2009, Poeplau *et al* 2011). Here, they are used to provide a simple and transparent overview of simulation results and to compare SOC dynamics under a variety of conditions. CRFs are developed by choosing a regression line to represent the estimated trend in SOC over time, and are usually based on relative changes in SOC with respect to a reference point. This

Figure 3. Ranking of the importance of factors for predicting relative SOC change between the end of the spin-up and the end of the projection period. Importance is based on the increase in mean square error (MSE) of predictions upon the omission of a factor in a random forest regression.

is to allow for comparisons of soils with different levels of SOC. In this study, the estimated SOC in the uppermost soil layers (0–30 cm) at the end of the spin-up phase was used as reference, and CRFs were developed to describe the relative SOC change in the projection period under alternative management scenarios. Simulation outputs from different permutations of the same rotations were averaged, and the changes in SOC were evaluated as a four-year moving average based on the duration of the longest crop rotation. A qualitative screening of these outputs led to discarding some candidate regression models (e.g. polynomial functions), and focus the analysis on linear (equation (1)) and exponential (equation (2)) models, as proposed by Poeplau *et al* (2011). For the sake of simplicity, no interactions among explanatory variables were considered:

$$\Delta SOC = (C + c_1 x_1 + \ldots + c_p x_p) \times t, \qquad (1)$$

$$\Delta SOC = (C + c_1 x_1 + \ldots + c_p x_p) \times (1 - e^{(-k \times t)}), \qquad (2)$$

where x is the explanatory variable, C is either the relative SOC variation in the linear model ($\Delta SOC\%$ yr^{-1}) or the relative SOC stock difference at the equilibrium in the exponential model ($\Delta SOC\%$), c the effect of the explanatory variable on C, t the number of years after a change in management and k a shape coefficient. Regression coefficients for linear and non-linear models were fitted using *nls* function from the R-*stats* package (R Core Team 2018). The selection of explanatory variables to be included in the CRFs was guided by the importance of factors for the prediction of SOC (see 2.4.1). Explanatory variables, ordered by decreasing importance, were sequentially added to the CRFs, with a threshold for inclusion determined by the importance achieved by model parameterization. Values falling below this threshold indicate that the contribution of a variable is shrouded in uncertainty. For each explanatory variable added to the CRFs, the

Akaike Information Criterion (AIC, Akaike 1974) was used to determine which model, either linear or exponential, was more likely to be correct. Modelling efficiency (Nash and Sutcliffe 1970; optimum and maximum = 1, minimum = $-\infty$) was used as an overall accuracy measure of the CRFs.

3. Results

3.1. Model configurations and simulated SOC changes

Simulation results show a systematic tendency toward decreasing SOC in the topsoil (0–30 cm), with relative changes during the projection period (i.e. between 2006 and 2050) roughly between +10% and −40%, depending on the conditions (figure 2). The most pronounced negative rates are associated with light soils and high SOC levels, where a substantial amount of SOC is readily available for mineralization. Conversely, the optimal conditions for SOC conservation are in heavy soils and a low initial SOC budget. In these situations, an increase in SOC is to be expected if all crop residues are left in the field.

Results indicate that the management of crop residues strongly modulates the rate of SOC change. Non-removal (0%) of residues delineates an upper limit for strategies targeting the conservation of SOC through residue management. The baseline scenario of 33% residue removal consistently outperforms the humus-balance approach, which is associated with higher removal rates across environments (S10). In all simulations and as expected, a further diminishing of SOC is associated with the ongoing and complete extraction of useful crop residues from the field.

The random forest regression indicates that the management of crop residues is the single most important factor associated with SOC changes during the projection period (figure 3). The reference SOC of

a grid cell, soil texture and crop rotation functional type follow respectively in importance ranking. All these factors appear to be more relevant than parameter uncertainty, and together explain just over 70% of the variation in simulated SOC. Including model parameterization and the other low-ranking factors such as climatic drivers, crop rotation structure, level of organic fertilization and cover-crop frequency, the explained variability increases to over 86% of total. Overall, the contribution of parameter uncertainty to the variability of model output is less than 3%. It increases, however, up to almost 25% of the residual variability not explained by factors more relevant than model parameterization (S11).

3.2. Response curves of SOC after changes in crop residue management

CRFs help to disentangle the incremental influence of each factor, and its level, on the evolution of SOC stocks through time, in conjunction with a change in field management practices. Table 2 presents the CRFs developed in this study, in order of increasing complexity, representing the number of explanatory variables considered. The simplest CRFs (M0, M1 and M2) are described in supplementary materials (S12). Regardless of the complexity, AIC and EF metrics consistently indicate that an exponential function is more suitable than a linear form for describing expected SOC dynamics in the agricultural soils of NRW.

M3 and M4 adequately capture the range of simulated values, in particular the increase of SOC occurring when specific soil conditions are combined with the most conservative residue management (0% removal). Both these models take into account the influence of soil texture type, with clay limiting organic matter decomposition in heavy soils. M4, which adds rotation functional type to the list of explanatory variables, provides the most accurate representation of the simulated SOC trends (EF up to 0.827), and indicates that rotations with a prevalence of typical winter and leaf crops are optimal for the maintenance of SOC stocks. M4 estimates that an SOC increase can be achieved in the near future adopting 0% residue removal in the following conditions: (i) heavy soils and low reference SOC (with any rotation), (ii) heavy soils and medium reference SOC (with two rotation functional types) and (iii) medium soils and low reference SOC (only with the best performing rotation type). A positive ΔSOC appears compatible with baseline residue management only when associated with two rotation types (Hleaf-Lspring and Lleaf-Lspring, table 2), heavy soils and low reference SOC. The target of 4‰ yr^{-1} increase is achieved by Hleaf-Lspring rotations on heavy soils with low reference SOC during the first ten years after the adoption of 0% residue removal.

4. Discussion

4.1. Cropping system management for carbon sequestration

Results of this study confirm the importance of crop residue management for the preservation of organic carbon stocks in agricultural soils. Despite providing a significant C input, however, crop residues alone may not be adequate to maintain SOC levels (Liu *et al* 2006): even the 0% removal strategy, exploring the lower end of the impacts of residue exploitation on SOC, does not guarantee the maintenance of SOC stocks. Notable exceptions are soils characterized by higher clay content—which tend to have a longer turnover time for organic matter (Müller and Höper 2004)—and by lower initial SOC, where even the baseline management can be sustainable.

The central role of residue removal and initial SOC content in relation to SOC stock changes is consistent with results from Zhao *et al* (2013), who found that these two factors display the strongest (negative) correlation to ΔSOC in Australian wheat systems. Also there, systematic increases of SOC were simulated only in association with low initial SOC content or 0% residue removal. In a similar study, Tang *et al* (2006) indicate the increase of residues return rate (from 15% to 50%) as the most effective management strategy to mitigate SOC decline in cropping systems across China. Long-term field experiments suggest that residue removal should be considered only when SOC can be maintained with consistent addition of organic amendments, and that the amount of residues that can be sustainably harvested vary with initial SOC, tillage practices and climate (Gollany *et al* 2011). The results of the current study further stress the role of soil in the modulation of the response of SOC to residue removal. This questions the reliability (Kolbe 2010, Lindorfer *et al* 2014) of a simplified humus balance approach—that does not account for soil properties—as a panacea solution to estimate the sustainable rate of residue removal.

This study suggests that crop residue management by itself is unlikely to produce SOC accumulation, but it can provide immediate benefits until other *C*-mitigation initiatives are implemented. In selected environments, returning all crop residues to the fields from which they originate could even be a viable option to temporarily meet the ambitious targets set for land-based remediation of anthropogenic emissions (Minasny *et al* 2017). However, the exponential response outlined by simulation output suggests that the potential for soil *C* sequestration may be finite in capacity and time (Lal 2004, West and Six 2007), and likely diminish after a few decades of best management practices as SOC stocks approach a new equilibrium (a steady-state where *C* additions and losses are balanced). Exploiting such potential for *C* mitigation may require the integration of multiple land management strategies (e.g. no-till farming, incorporation of

Table 2. Parameters and evaluation metrics of the CRFs identified through regression analysis. Exploratory variables were added in a stepwise manner, with models M1–M4 inheriting parameters from previous ones. See section 2.4.2 for the explanation of model parameters. Parameters of model M4 refer to the relative abundance of leaf and spring crops in the rotation (H: high; L: low; figure S9).

Regression model (CRF)	Added explanatory variable (x)		c	Model parameters				Evaluation			
				Linear		Exponential		Linear		Exponential	
				Estimate	Std. error	Estimate	Std. error	AIC	EF	AIC	EF
M0	—		C	−6.28E-01	1.68E-04	−3.20E + 01	4.23E-02	2.45E + 07	0.371	2.43E + 07	0.411
			k			3.25E-02	7.40E-05				
M1	Residue management	0%		2.41E-01	2.76E-04	1.23E + 01	1.32E-02	2.31E + 07	0.577	2.28E + 07	0.620
		Baseline		8.23E-02	2.76E-04	4.20E + 00	1.32E-02				
		Humus balance		−8.42E-02	2.75E-04	−4.29E + 00	1.32E-02				
		100%		−2.36E-01	2.75E-04	−1.20E + 01	1.32E-02				
M2	Reference SOC	Low		1.52E-01	2.55E-04	7.86E + 00	1.21E-02	2.26E + 07	0.641	2.21E + 07	0.685
		Medium		−1.06E-02	1.79E-04	−4.26E-01	8.49E-03				
		High		−1.29E-01	2.53E-04	−6.45E + 00	1.20E-02				
M3	Soil texture	Heavy		3.07E-01	4.17E-04	1.58E + 01	1.92E-02	2.15E + 07	0.738	2.08E + 07	0.784
		Medium		5.95E-02	1.49E-04	3.18E + 00	6.84E-03				
		Light		−1.30E-01	1.71E-04	−6.49E + 00	7.85E-03				
M4	Rotation functional type	Hleaf Lspring		1.78E-01	2.77E-04	1.03E + 01	1.25E-02	2.08E + 07	0.782	2.00E + 07	0.827
		Lleaf Lspring		1.04E-01	3.83E-04	6.75E + 00	1.73E-02				
		Hleaf Hspring		7.78E-03	1.78E-04	1.75E + 00	8.02E-03				
		Lleaf Hspring		−6.41E-02	1.40E-04	−1.83E + 00	6.31E-03				

manure and straw, agricultural extensification; Smith *et al* 2000), whose applicability may, however, be constrained by economic considerations (Smith *et al* 2007).

In this study, the effects of the combined application of organic fertilization and the increase of cover crops in rotations are limited and masked by parameter uncertainty. As a result, they do not counteract the losses associated with the reduced *C* inputs from residues. This may, however, be an inconclusive result due to the design of the case study: the application of slurry was not a controlled factor, with the highest rates occurring in areas with a prevalence of sandy soils where mineralization is fostered. Moreover, achieving *C* sequestration through organic fertilization may require higher inputs of dry matter than those generally recorded across NRW (Poulton *et al* 2018). A meta-analysis carried out by Poeplau and Don (2015) demonstrates the potential for cover crops as green manure, with expected benefits for SOC stocks extending up to 150 years from their introduction into a rotation. The apparent contrast with the limited potential of cover crops estimated in the study region can be explained by the clear prevalence of winter cash crops in the rotations analysed, constraining the presence of cover crops even in the constant winter cover scenario. Under these circumstances, untapped potential may lie in a more pervasive adoption of summer cover crops, whose effects on SOC were not evaluated here.

Results suggest that specific rotations types hold promise for buffering SOC loss while providing marketable yields, especially when they provide residues that are returned to the soil regardless of the management strategy applied to cereals (S10). In this study, winter rapeseed shows greater efficacy in SOC conservation, owing to the conspicuous production of residues. However, this advantage may diminish in the future, if alternative uses of residues (Nikvash *et al* 2010, Schlauß *et al* 2013) gain traction and thus reduce the portion of crop residue returning to agricultural soils. Structural diversity of crop rotations may play a more relevant role in SOC conservation than results of this study suggest. A meta-analysis (McDaniel *et al* 2014) revealed that adding crops in a rotation has a positive effect on SOC, associated with the increase of microbial biomass and soil biological activity. Capturing the influence of crop diversity on these factors, however, is largely beyond the capabilities of the model adopted.

4.2. Modelling SOC dynamics: signals and uncertainties

Scenarios depicted by the simulations are in line with the analysis of available datasets, showing that (i) SOC contents of the arable soils of NRW have been decreasing in the past 30 years, (ii) such decay follows an exponential trend and (iii) SOC has not yet reached

a new equilibrium (Steinmann *et al* 2016). This, in addition to the satisfactory performance of MONICA in reproducing SOC measured in long term field experiments (RMSE < 0.05%, S8), puts confidence into using modelling as a surrogate laboratory (Challinor *et al* 2009) to provide an educated guess about future SOC dynamics under a variety of management and environmental conditions.

Uncertainty in this study was leveraged to isolate factors strongly related to SOC evolution from those whose signal is indistinguishable from the noise produced by equally likely model parameterization. This approach provides a way to interpret simulation results, and allows for the translation of model mechanics into practical and transparent CRFs (West *et al* 2004) which may apply to agro-climatic conditions comparable to those of NRW. To this end, it is important to notice what appears as a dependency of results on the scale of the case study: despite the known influence of rainfall and temperature on SOC evolution (e.g. Ogle *et al* 2005), such factors are overlooked in the current analysis. On the other hand, an overestimation of parameter uncertainty may have contributed to the obfuscation of a temperature response of SOC decomposition in the study area. The analysis of additional long-term field experiments could facilitate a verification of this hypothesis while providing refined parameter distributions for follow-up studies.

The complete disentanglement of uncertainties is beyond the scope of the present work. Other studies have focused on this aspect, providing an overview and quantification of different sources of uncertainty (e.g. Post *et al* 2008, Ogle *et al* 2010). Here, the focus is solely on model parameters identified as relevant for SOC dynamics. Model structural uncertainty remains unquestioned, as well as the estimation of *C* input from crop residues, including the relative contribution of roots and above-ground organs (Kätterer *et al* 2011) to soil organic matter. Addressing such uncertainty calls for the application of multi-model ensembles (e.g. Martre *et al* 2015), ideally considering the contribution of model structure, parameters and climate projections (Tao *et al* 2018) in the assessment of future trajectories of SOC in agricultural lands. Multi-model ensembles could also establish the basis for standardized methods to determine the initial distribution of *C* among soil organic matter pools. Such distribution influences the simulation outcomes, but it can hardly be determined experimentally as the pools often do not correspond to measurable entities (Falloon and Smith 2000). Field history is determinant for the direction (Poeplau *et al* 2011) and magnitude (Franko and Ruehlmann 2018) of SOC variation after a change in land use or management. The simulation of site history therefore appears to be a rational method for model initialization, ensuring consistency across a range of models (Bruun and Jensen 2002). Currently, the representation of historic management varies considerably in the literature (e.g. Smith *et al*

2007, Zhao *et al* 2013, Lugato *et al* 2014), and hampers the comparison of modelling studies. In any case, past management practices compose an added dimension of uncertainty that propagates throughout the simulated system to eventually influence the estimation of potential *C* sequestration in agricultural soils.

5. Conclusions

SOC sequestration is seen as a major target to mitigate climate change through the compensation of anthropogenic emissions. In agriculture, crop residues are a principal component of the *C* cycle, and their removal for uses other than maintaining or enhancing soil quality contributes to the depletion of SOC pools. In the majority of the agro-environmental conditions explored here, returning all crop residues to the soil appears as a necessary but not itself a sufficient measure to achieve a land-based compensation of emissions. However, the fact that even conservative residue management may fall short of the targets set by the 4 per 1000 initiative, does not detract from its critical contribution to SOC sequestration. Retention of crop residues in fields should therefore be integral to any menu of options that aims at offsetting *C* emissions in agriculture, buying time until more effective strategies are implemented.

Conversely, as crop residue removal was shown to exacerbate the ongoing SOC loss in agricultural soils of the study region, indiscriminate residue exploitation for other purposes may result in a precarious strategy of extracting resources from within the soil. Results of this study suggest that the goal of pursuing sustainability through alternative uses of crop residues, such as the bio-economy, requires the design of removal strategies tailored to particular locations and cropping systems. With climate change potentially aggravating the figures outlined here, there is a need for further modelling studies to identify the prospects and boundaries of SOC sequestration in agricultural lands and to support informed decisions on future action.

Acknowledgments

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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