Soil organic carbon stocks potentially at risk of decline in organically farmed croplands

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Increasing soil organic carbon (SOC) stocks in agricultural lands is key to mitigate climate change and organic farming shows promising results. Evidence of higher SOC stocks in organic farms compared to conventional farms reflects current situations where organic farming occupies small fractions of agricultural areas, with access to ample amounts of resources for organic fertilisation. Using a modelling approach, we estimated global SOC stocks following a 100% conversion to organic farming of global croplands under a normative and an optimal organic scenario. We found that global soil carbon inputs would be reduced by 39% and 29% for both scenarios respectively, leading to a 9% and a conservation of global SOC stocks reduction (with spatial variations) after 20 years in the normative and optimal organic scenario, respectively. These results suggest that an expansion of organic farming might reduce its potential to mitigate climate change through soil carbon sequestration unless appropriate practices – such as widespread cover cropping and enhanced residue recycling – are implemented.

The agricultural sector is responsible for 23% of global anthropogenic greenhouse gas (GHG) emissions worldwide[1,2], but there is an opportunity for mitigation of climate change through carbon sequestration in agricultural soils. While arable lands have lost up to half of their organic carbon stocks since the industrial revolution[5], agricultural practices could help increase soil organic carbon stocks, by increasing carbon inputs to soils or by reducing soil carbon mineralisation[6].

Organic farming is proposed as a way to increase soil organic carbon (SOC) stocks[7]. Meta-analyses of field experiments have shown that organically managed cropland soils have, on average, higher SOC stocks (+3.5 $tC.ha^{-1}$) and soil carbon sequestration rate (+0.45 $tC.ha^{-1}.yr^{-1}$) than conventional (i.e. non-organic) ones[8,9]. These results are largely explained by higher soil carbon inputs in organic systems through both enhanced manure application rates and the use of more complex crop rotations with higher frequency of temporary pastures and cover crops[10], resulting in higher organic carbon inputs to soils. However, concerns have been raised that these positive effects of organic farming may result from carbon transfers from other ecosystems through manure and compost inputs, so that there may be no net change in carbon stocks over the whole land area[11]. Accounting for these lateral carbon transfers and capturing their effects is therefore essential for obtaining accurate estimates of the potential of organic farming to sustain global SOC stocks.

Organic farming occupies less than 2% of the global utilized agricultural area (UAA)[12]. Evidence provided by meta-analyses reflect situations where organic materials, such as animal manure or compost are readily available for fertilisation of organically managed soils[13]. In contrast, the expansion of organic farming might trigger competition for fertilising resources, possibly resulting in a reduction of potential for soil carbon inputs and soil carbon sequestration. A recent study has shown that organic farming upscaling to 100% of the UAA would lead to a 56% crop yield reduction due to severe nitrogen (N) limitation[14] – a significant drop compared to the 20-30% yield reduction previously reported by field-based meta-analyses[15,16]. This drop is mostly due to the ban of synthetic N fertilizers in organic guidelines that reduces both the range of N fertilization resources (e.g., crop residues, livestock manure) and their global availability, with large consequences for soil fertilisation – a result confirmed by recent studies highlighting N fertilisation limitation when organic farming is upscaling[17–19]. Expansion of organic farming is thus likely to have major consequences for soil carbon inputs from crop residues and fertilising materials, potentially resulting in large changes in SOC stocks.

Capturing these systemic feedbacks is key to accurately estimating soil carbon inputs in scenarios of large-scale organic farming. We addressed these knowledge gaps by combining (i) GOANIM, a spatially explicit model simulating cropland N cycle, crop productivity and livestock populations under scenarios of large organic farming expansion[14] with (ii) RothC, a dynamic, first order kinetic model simulating carbon dynamics in soils [20,21]. We used GOANIM outputs about livestock manure and crop residue production to estimate carbon fluxes between croplands, grasslands and livestock, and to estimate soil carbon inputs (SCI) in scenarios of large organic farming expansion for croplands. We then used the estimated SCI as an input to RothC to simulate the changes in SOC stocks under different time horizons. We assessed different scenarios combining (i) variations in organic farming practices (e.g., cover cropping, use of conventional manure on organic croplands, residue recycling) and (ii) variations in the level of organic farming expansion globally, each compared with a baseline scenario of no changes in current agricultural practices.

Although all organic regulations are gathered under the ban of synthetic fertilisers[22], organic farming encompasses a diverse set of farming practices, depending on regional regulations, farming contexts and markets[16,23,24]. In particular, organic farmers may adopt cropping practices that are known to improve soil carbon sequestration (e.g. cover cropping, extensive crop residues recycling, diversified crop rotations including pasture). We captured this variability in cropping practices by considering both (i) a normative organic scenario in which organic farming is restricted to the ban of synthetic fertilizers, some differences in crop rotations, no cover-crops and a redistribution of livestock population compared to conventional farming and (ii) an optimal organic scenario that may favour carbon inputs to cropland soils mostly through extensive cover-cropping and enhanced residue recycling. Note that the assumptions related to the normative scenario were well aligned with those of a previous study about organic farming expansion that resulted in drastic reduction of global cropland production and livestock population reduction in a fully organically managed world, with a large shift towards ruminant animal species[14]. In contrast, the optimal scenario was well aligned with observational data that show that covering soils by catch and cover-crops is a common practice that many organic farmers implement[10,11]. We hypothesized that, in the normative organic scenario, both soil carbon inputs and SOC stocks would be negatively affected by a global transition to organic farming whereas those negative effects can be partly ameliorated when additional cropping practices are considered, as in the optimal organic scenario. Hereafter, we first focus on results from a hypothetical 100% conversion of cropland areas to organic farming before analysing scenarios with an intermediate level of organic farming expansion. The scenarios are not intended to be prescriptive; rather they are exploratory, offering a framework for analysis. Thus, the primary goal of our modelling exercise is not to assess if organic farming will change SOC stocks, but rather to explore if, how and where SOC stocks could be at risk of decline under organic farming expansion.

Results

Carbon flows and stocks in an organic world

SCI reduction in an organic world

Table 1. Global soil carbon inputs (PgC.yr^{-1}) for croplands under both 100% organic scenarios and the baseline.

		Plant-based residues	Manure	Total
Baseline		2.50	0.22	2.72
100% organic scenario	Normative	1.51	0.11	1.62
	Optimal	1.77	0.11	1.87
Ratio organic / baseline	Normative	0.61	0.48	0.60
	Optimal	0.71	0.48	0.69

Globally, we found a 40 and 31% reduction in the total SCI to croplands for the normative and optimal organic scenarios, respectively (**Table 1**). Such massive drop of SCI is primarily due to (i) 39% and 29% reduction in plant-based residues returned to the soil (-1 PgC.yr^{-1} and -0.7 PgC.yr^{-1}), followed by (ii) a 68% reduction in farmyard manure application rate (-0.11 PgC.yr^{-1}) in both 100% organic scenarios compared to the baseline. In the normative organic scenario, the reduction in plant-based residues returns is mainly due to a 51% reduction of annual crop dry matter production, partially attenuated by increased frequency of temporary rotational pastures, resulting in an overall 47% reduction of cropland biomass production **(Supplementary Table 1)**. The reduction in manure application rate is mainly due to a 66% reduction in the global livestock population, as well as changes in animal types and in the regional distribution of livestock populations. In the optimal organic scenario, the additional 0.25 PgC.yr^{-1} carbon inputs compared to the normative organic scenario is explained by 83% of additional SCI from the use of cover crops on 50% of organically managed croplands (+0.21 PgC.yr^{-1} , +0.07 tC.ha^{-1}.yr^{-1} on average).

These global changes in soil carbon inputs mask large variations among world regions **(Figure 1)**. In some specific regions – such as Central Africa or Russia – soil carbon inputs are increased in the normative 100% organic scenario compared to the baseline. This is explained by higher inputs as plant-based residues **(Supplementary Figure 1)** due to (i) high manure application rates that help to sustain high crop yields in organic farming **(Supplementary Figure 1)** and (ii) high share of carbon fixing crops – such as temporary pastures – in organic rotations[10,25]. Note, that in other regions – such as Northern Brazil – the increase in plant-based residues resulting from more frequent carbon fixing crops in organic rotations is offset by a drop in farmyard manure application, resulting in reduced soil carbon inputs to cropland soils. In the optimal 100% organic scenario, we found that regions such as Central Canada, Eastern Europe or Southern Russia have a higher soil carbon inputs compared to the baseline (**Figure 1b**). In those regions, additional soil carbon inputs from cover crops are sufficient to compensate the reduction of soil carbon inputs due to drop in crop production resulting from the ban of synthetic fertilizers (**Supplementary Figure 1**).

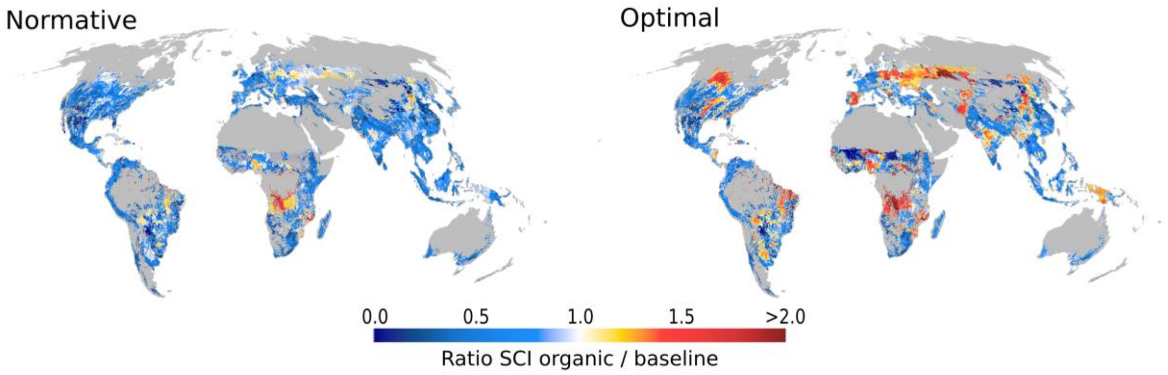

Figure 1. Maps of annual organic-to-baseline ratios of soil total carbon inputs for the normative (left) and optimal (right) 100% organic scenario.

SOC stocks

In the normative scenario, the transition to 100% organic farming would result in a 9, 13 and 18% SOC stock reduction in croplands after 20, 50 and 100 years, respectively, compared to the baseline (**Table 2**). This reduction would represent an overall loss of -6.8 PgC from croplands in the first 20 years after that transition and a mean loss of 0.23 tC.ha^{-1}.yr^{-1}. However, a transition to 100% organic farming in the optimal scenario would result in the conservation or slight increase in croplands SOC stock. In particular, cropland SOC stocks would slightly increase, by 0.3 PgC 20 years after the transition to organic farming, leading to an average storage of 0.01 tC.ha^{-1}.yr^{-1}.

Table 2. Global changes in SOC stocks (PgC) in croplands after 20, 50, and 100 years following conversion to organic farming. Ratios and differences between the organic and the baseline are indicated.

		Global soil organic carbon stocks [PgC]		
		20 years	**50 years**	**100 years**
Baseline			75.7	
100% organic scenario	Normative	68.9	65.5	62.3
	Optimal	76.1	77.1	78.5
Ratio org / baseline	Normative	0.91	0.87	0.82
	Optimal	1.00	1.02	1.04
Difference org - baseline [tC.ha^{-1}.yr^{-1}]	Normative	-0.23	-0.23	-0.18
	Optimal	0.01	0.03	0.04

Again, these global results mask spatial variations among world regions (**Figure 2**). In the normative scenario, cropland SOC stocks increase in some regions (such as central Africa) while others they decrease in others (such as India and Mexico) (**Figure 2b**) – a result largely explained by regional variations in soil carbon inputs (**Figure 1a**). In the optimal scenario, some of those latter regions (such as India) would experience an increase in cropland SOC stocks. Those regions are marked by high potential of additional SOC stocks per hectare due to cover cropping (**Figure 3**). This positive effect of cover crops in the optimal scenario is due to (i) an additional soil carbon input of +0.07 tC.ha^{-1}.yr^{-1} on average on global cropland soils and (ii) a ground covering effect that reduces soil carbon mineralisation. Both effects result in an additional global mean increase in cropland SOC of +0.47 tC.ha^{-1}.yr^{-1} over the 20 first years following conversion to organic farming.

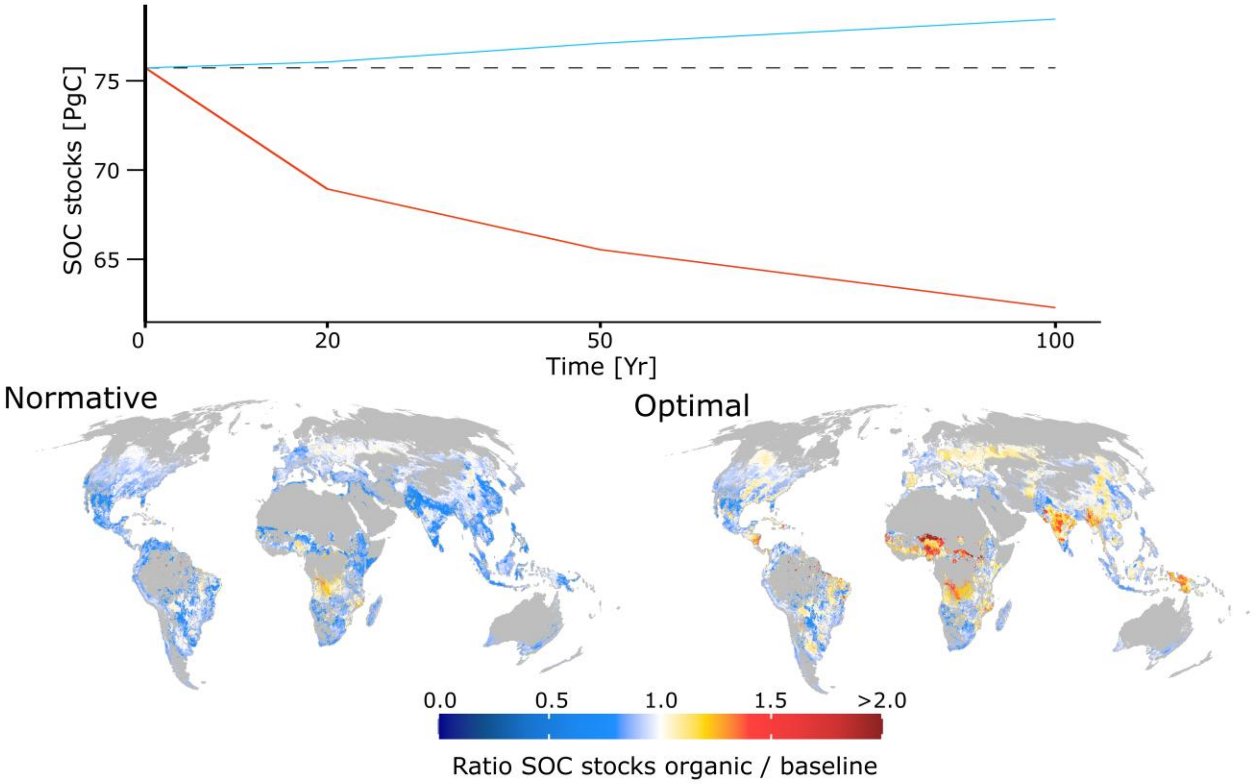

Figure 2. Global changes in soil organic carbon (SOC) stocks (PgC) in croplands over time, and maps of the SOC stock ratios between the 100% organic scenarios (either normative or optimal) and the baseline at 20 years. Changes in global SOC stocks in croplands and spatial distribution are reported for the normative (red line) and optimal (blue line) 100% organic scenarios. The black dashed line represents the global SOC stocks for croplands in the baseline.

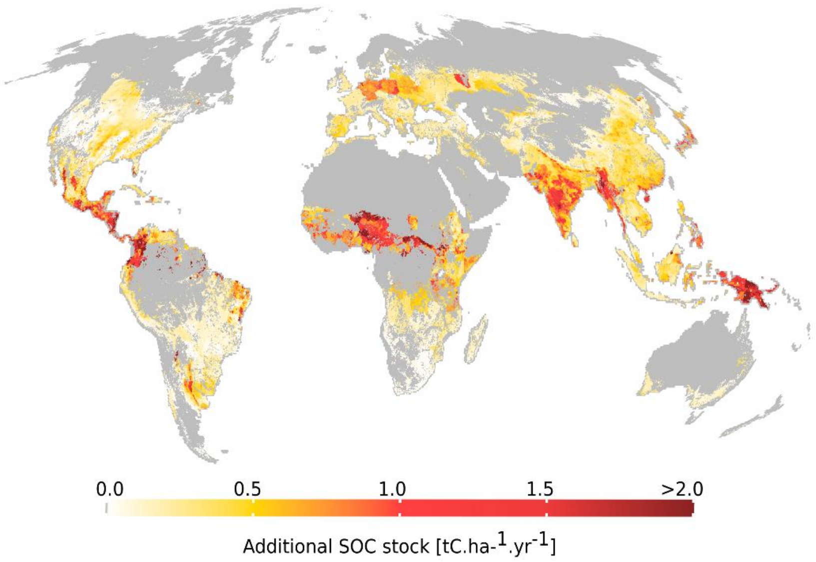

Figure 3. Additional SOC stocks per ha [tC.ha^{-1}.yr^{-1}] due to cover cropping in the optimal organic scenario compared to the normative organic scenario.

In the normative scenario, SOC stocks reduced drastically in the first 20 years after transitioning to organic farming (-0.5 % per ha and per year on average), whereas the SOC reduction would slow down thereafter (-0.2 % per ha and per year on average) **(Supplementary Figure 2)**. This rapid decline in the first 20 years followed by slower loss after 20 years is frequently observed in field studies[26,27].

Intermediate scenarios of organic farming expansion

Because converting the entire agricultural area to organic farming is a drastic thought experiment, we also explored more realistic scenarios of intermediate conversion to organic farming. In those intermediate scenarios, manure surplus from conventional farming systems – i.e. conventional manure that is in excess compared with conventional cropland N requirements – may be applied on organically farmed lands. Therefore, we introduced two variants of our normative and optimal organic scenarios by considering (i) the application or (ii) the ban of conventional manure surplus on organically managed lands.

We found that, in situations without conventional manure application, changes in global SOC stocks in croplands was linearly correlated with increasing share of the UAA under organic farming. This linear relationship would be strongly negative in the normative organic scenarios, reflecting that expanding normative organic systems would put SOC stocks in global croplands at risk. In contrast, the slightly positive relationship between global SOC stocks and share of UAA under organic farming in the optimal organic scenarios suggests that sustaining expansion of diversified organic systems would help to protect SOC stocks **(Figure 4a)**.

Using conventional manure surplus as an additional, external source of organic fertilising material on organically managed croplands – a practice often implemented by organic farmers[13,28] – would make SOC stocks non-linearly correlated with the share of the global UAA under organic farming **(Figure 4a)**. In both the normative and optimal organic scenarios, applying conventional manure would help to increase global SOC stocks as well as SOC sequestration rates **(Figure 4a and b)**. For instance, in the normative scenario, when 20% of the global UAA is converted to organic farming, agricultural SOC stocks would be close to those reported in the baseline 20 years after the conversion. Transferring animal manure from conventional to organic systems increases SOC stocks in organically managed lands through both direct effects (through the application of additional soil carbon input to organic soils) and indirect effects (by alleviating at least partly their often reported N deficiency[14–16] thereby boosting organic crop yields with positive feedback on crop residues returns to soils).

Some regions – such as the UK, Northern India and Northern China – would see their cropland SOC stocks increasing compared to the baseline in both the normative and optimal scenarios (**Figure 4c**). In those same regions, SOC stock would decrease in a scenario with 20% of the UAA under organic farming without conventional manure application compared to the baseline. This regional effect is explained by the uneven geographic distribution of conventional manure surpluses at the global scale **(Supplementary Figure 3)**, with major consequences for soil carbon inputs. Interestingly, our results also show that SOC stocks in conventionally managed lands would remain constant with or without the use of conventional manure surplus on organically managed lands (**Supplementary table 2**). This absence of an effect of transferring carbon from conventionally to organically managed lands is explained by the small share (less than 1%) that conventional manure surplus represents over the total soil carbon inputs in conventionally managed lands.

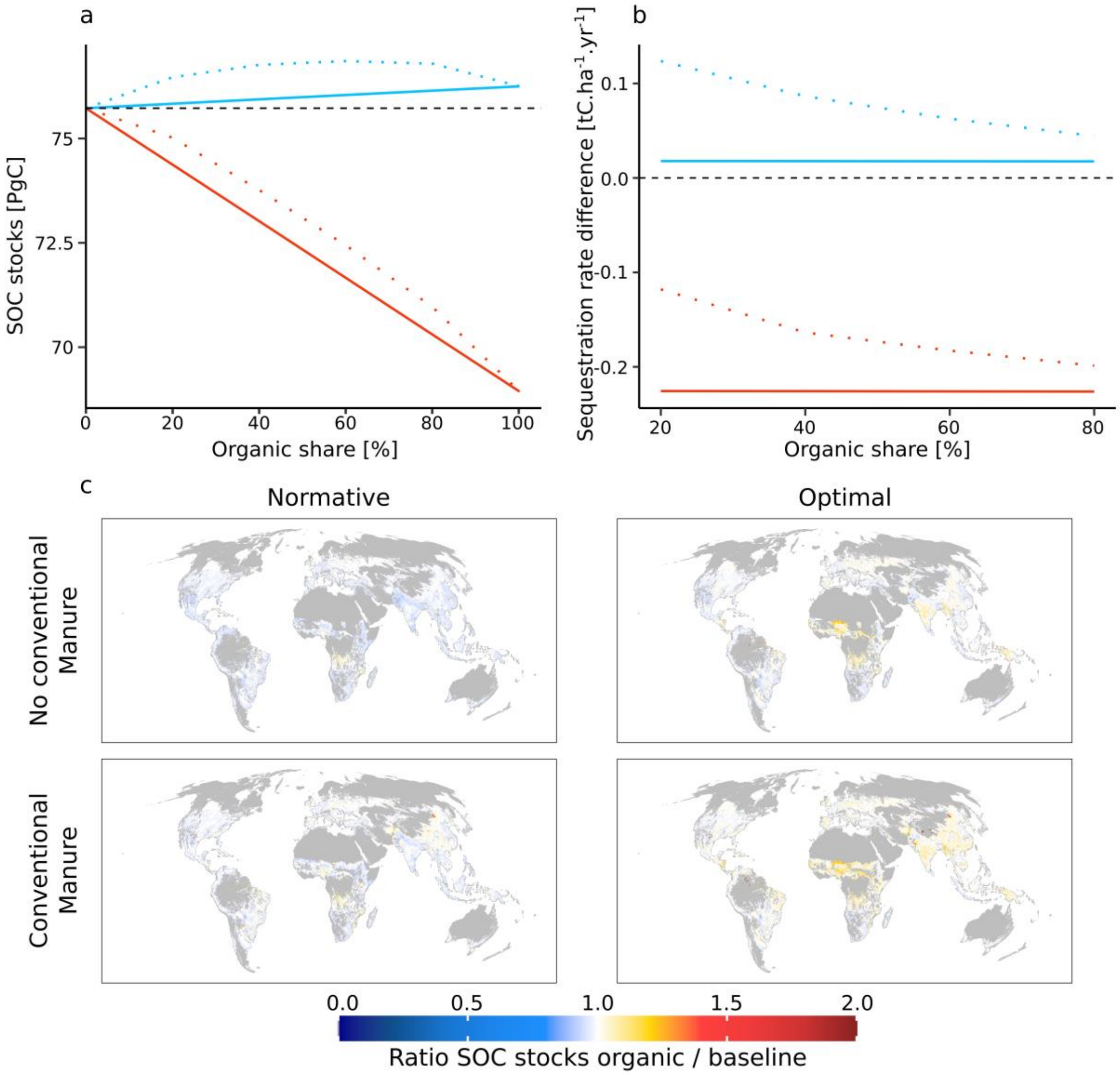

Figure 4. Evolution of global SOC stocks (PgC) at 20 years (a) and mean difference (organic minus baseline) of SOC sequestration rate (tC.ha^{-1}.yr^{-1}) over the first 20 years (b) with maps of SOC stock ratio at 20 years and with 20% of the global UAA under organic farming (c). In both upper panels, the red lines represent the normative organic scenario and the blue line the optimal organic scenario. The dashed lines represent situations where conventional manure surplus are applied on organically managed croplands whereas the solid lines represent situations without conventional manure application.

Achieving 20% of the global UAA under organic farming – although being far above the current 1.5% share of organic farming – is the most realistic of the situations we simulated. In this situation, we found that global SOC stocks would decrease by -2% to -1% in the normative organic scenario (without and with conventional manure, respectively) whereas they would increase by +0.1% to +1% in the optimal organic scenario (without and with conventional manure, respectively). This would translate into a -0.118 tC.ha^{-1}.yr^{-1} difference in SOC sequestration rate between organic and conventional farming (with conventional manure) in the normative organic scenario, whereas this difference would increase to +0.124 tC.ha^{-1}.yr^{-1} in the optimal organic scenario (**Figure 4b**, **Supplementary table 2**).

Discussion and conclusion

Contrary to what is sometimes claimed[29,30], our results suggest that global SOC stocks may be at risk of decline if organic farming expands, especially if the expansion occurs through normative organic farming systems. This would result from a drastic reduction in global soil carbon inputs (SCI), mostly as crop residues and animal manure due to large N deficiency, resulting in severe decline in crop production, as well as a reduction in livestock populations[14]. In addition, our results show that SOC stocks could be conserved under the optimal organic scenarios, thanks to extensive cover-cropping and enhanced residue recycling. Our findings are in contrast to previous studies reporting strong carbon sequestration potential of organic farming based on field observations at the local scale[8]. These results highlight that soil carbon impacts of organic farming cannot be assessed simply from extrapolation of local field observations without considering whole-system effects. The assessment of the impacts of expansion of organic farming systems needs to consider the systemic feedbacks that go along with organic farming expansion itself[31], in particular the availability of fertilising resources and related effects on crop production[14,32].

Our results are, however, fairly well aligned with local reports on organic farming expansion. For instance, the N deficiency – and its resulting effects on crop biomass production –simulated by the GOANIM model here is consistent with local observations that N fertilising resources may become scarce if organic farming expands widely, as recently highlighted in France[33], India[34] or Bhutan[35]. In addition, our results on limited SOC benefits from organic farming are consistent with findings from a recent meta-analysis that organic farming may not increase SOC stocks compared to conventional farming if there is no lateral carbon transfer from other agroecosystems[11]. Finally, our global estimates of 0.124 $tC.ha^{-1}.yr^{-1}$ SOC sequestration rates in the optimal organic scenario and under 20% of the global UAA under organic farming are close to the 0.07-0.14 $tC.ha^{-1}.yr^{-1}$ values reported from an extensive meta-analysis on SOC sequestration potential of organic farming when lateral carbon transfers are controlled[8].

Besides those global estimates, our results also show that a range of additional cropping practices could sustain or increase SOC stocks in organically managed croplands. In particular, we found that the extensive use of cover crops is key to increase SOC stocks through both increasing SCI and reducing SOC mineralisation[36–39]. Estimating the real benefits that extensive use of cover-crops could bring for SOC stocks in organic farming at the global scale is subject to many uncertainties given the lack of precise information on (i) potential areas available for cover cropping, (ii) spatially explicit species composition of the cover crops and (iii) cover crops biomass potential production. However, the potential additional SOC stocks offered by cover crops that we found in our study (0.29 $tC.ha^{-1}.yr^{-1}$) is very similar to the 0.32 $tC.ha^{-1}.yr^{-1}$ value reported in a recent meta-analysis[40].

Other practices – such as agroforestry[41,42], enhanced circularity[38,43] and increased frequency of temporary N-fixing leys or cover-crops in organic rotations[15,16] – may have positive impacts on N resource conservation (by avoiding nitrate leaching[45]), N supply to plants[38,44] and SOC stocks. External fertilising organic materials – such as urban compost, green wastes, food industry by-products or eventually sewage sludge – could also provide N to soils as well as providing additional soil carbon inputs[46]. Modelling the benefits brought by this extensive set of additional cropping practices was beyond the scope of this study but our results suggest that making organic farming more climate beneficial will require some of these additional practices.

Modelling variations in soil organic carbon stocks in different farming scenarios at the global scale has some limitations. In particular, SOC stocks were modelled using RothC, a model that has proved its potential to accurately simulate SOC changes at the local[47] and large[48] scales, but that requires some specific modelling assumptions. Among them, we had to assume that carbon stocks in the baseline are at the equilibrium[48]. It is likely that this assumption does not always reflect the reality[49,50] which may have implications for our findings. However, we found evidence that the error brought by this assumption was negligible with only 1% reduction of global croplands SOC stocks after 100 years compared to the initial situation when SOC stocks were not considered at the equilibrium in the baseline (see Supplementary Information). Another limitation may be related to the fact that the soil organic carbon mineralisation tracks nitrogen mineralisation[51] which may sustain plant growth, a factor we did not consider in our study. This may lead to a slight over-estimation of SOC stock reduction due to over-estimating the reduction in soil carbon inputs compared to the baseline, an effect that should be addressed in further analyses.

The estimates of global changes in SOC stocks in croplands provided by this study should be complemented by similar estimates for grasslands. Indeed, carbon transfers between grasslands and croplands through livestock grazing and manure collection and disposal on croplands – although probably minimal at the global scale – may affect local SOC stocks under grasslands, especially when livestock species and spatial distribution are modified in organic farming. However, we found that converting global agriculture to organic farming would result in small changes in grassland SOC stocks (see Supplementary Information). Additionally, the region with the biggest effects is India, where information on grasslands management is highly uncertain[52–55], calling for caution in interpreting the estimates of grassland SOC stocks.

Simulations were performed considering recent past climate. However, ongoing climate change is likely to affect (i) crop yields and livestock farming, with major consequences on soil carbon inputs to agricultural soils and (ii) SOC mineralisation through a series of processes that are soil temperature and moisture dependent. Accounting for those climate change effects would make sense to allow mitigation and adaptation the be explored together. However, modelling climate change effects on SOC stocks in organic farming would require a series of additional and disputable assumptions (about climate change effects on crop yields, cropping area spatial distribution, livestock farming and animal production[57]), and would likely result in increased uncertainties. . More importantly, the literature critically lacks of data about how climate change effects would differ in organic vs. conventional farming[9]. Addressing these issues is necessary to derive accurate estimates of SOC stocks in organic farming under future climate.

This study provides important information to estimate the potential of organic farming to reduce GHG emissions from agriculture. Our results provide an alternative estimate of changes in SOC stocks following conversion to organic farming, to those which upscale SOC stock differences based on field observations[17,59]. Because organic farming expansion is also likely to affect CH_4 and N_2O emissions through a series of processes related to rice cultivation, animal husbandry, manure management, and N fertilisation, deriving accurate estimates for those emissions is much needed in order to complement our SOC stock change estimates provided in this study.

Methods

The objective of this study was to estimate the potential impact of global organic farming expansion on soil organic carbon (SOC) stocks. To do so, we used a modelling approach to estimate the SOC stock changes in scenarios of global organic farming expansion compared to the currently observed SOC stocks. Currently, organic farming occupies less than 2% of the global agricultural lands. Therefore, we consider that the currently observed SOC stocks are those observed under conventional farming, hereafter called the baseline. The modelling approach was based on two separate steps, as explained below.

First, we estimated the soil carbon inputs (SCI) in scenarios of large organic farming expansion and in the baseline for croplands in a spatially explicit way (5 arc-min resolution, i.e. ~10x10km at the equator). In both the organic scenarios and the baseline, we estimated the SCI as a sum of (i) the amount of carbon that is returned to agricultural lands as plant residues (crop-based and grass-based residues) and (ii) the amount of carbon excreted by animals as farmyard manure (FYM) applied to lands after accounting for C losses during manure storage. The SCI estimates for organic farming scenarios were computed using outputs from the GOANIM model[14]. GOANIM is a spatially explicit (5 arc-min resolution) linear optimisation model that simulates nitrogen flows to and from croplands and grasslands under scenarios of organic farming upscaling. GOANIM calculates cropland N budget and its effects on crop yield for 61 crop species. The optimising module of GOANIM is designed to maximise food availability at the global scale (from both crop-based and animal-based products) by spatially optimising the global livestock population and the N allocation from animal manure to the different considered crops. We used the latest version of GOANIM, accounting for (i) differences in feed rations and feed use efficiency between organic farming and conventional farming[60], (ii) the 2019 refinement of the IPCC guidelines values on manure management and nitrogen losses (as direct N_2O emissions, nitrate leaching and ammonia volatilisation) and (iii) representation of non-productive, young animals. Further details about the GOANIM model can be found in Barbieri et al. 2021[14], especially about the case of Sub-Saharan Africa where drops in yields following the conversion to organic farming due to factors other than N limitation (e.g., poor pest and weed control) were negligible. In addition, two organic farming scenarios were considered in this study: (i) a normative organic scenario in which organic farming is restricted to the ban of synthetic fertilizers, differences in the type of crop grown in crop rotations as reported by Barbieri et al. 2019[25], no cover-crops and redesign of the global livestock population as reported by Barbieri et al. 2021[14], and (ii) an optimal organic scenario that draw upon the normative scenario but with cover cropping implemented on 50% of the bare soil periods between two cash crops (in organically managed lands), increased root-shoot ratio and enhanced plant-based residues recycling on croplands (see below for additional details on this optimal scenario).

Second, we used the estimated SCI from both organic scenarios as inputs to the RothC[20,21] model to estimate changes in SOC stocks over the 0-30 cm soil depth, in context of large organic farming upscaling, considering only annual crops (which represents 45 of the 61 crops in GOANIM, thereby assuming no changes in carbon inputs to soils for perennial crops). RothC is a model that estimates soil organic carbon turnover in both croplands and grasslands according to SCI, soil covering, climate and soil properties. RothC considers four active soil organic carbon compartments: the resistant plant pool (RPM), the decomposable plant pool (DPM), the microbial pool (BIO) and the humic pool (HUM). An additional inert organic matter (IOM) pool is considered but the latter is supposed to be constant over time in RothC; it is thus assumed unchanged in the organic scenarios vs. in the baseline, and is not included in the equations below. RothC estimates the carbon flows among the four active compartments as well as the amount of carbon mineralised from each compartment, with a monthly time step and through first order kinetic equations. In this study, we used the continuous formulation of RothC[21] summarized in equation (1).

$$(1): SOC'(t) = \rho(t) * A * SOC(t) + B(t)$$

Where *SOC'(t)* represent the derivative of *SOC* with respect of time, *SOC(t)* represent the SOC stocks at time *t*. *A* is a 4x4 matrix representing the mineralisation and carbon flows among the four active soil organic carbon pools. *ρ(t)* is the decomposition rate modifier and depends on the climatic, edaphic and soil covering conditions. Note that soil covering affects SOC dynamics by reducing its mineralisation rate in RothC. We assumed similar rates of soil organic carbon stabilisation and mineralisation in both the organic scenarios and the baseline – a rather conservative estimate due to lack of consistent data, despite preliminary evidence of more active carbon cycling in organically managed soils[61]. Spatially explicit climatic data were retrieved from the AgMERRA dataset[62] combined with the Penman equation to estimate potential evapotranspiration. Spatially explicit data on soil clay content were retrieved from the harmonized world soil database[63]. Finally, spatially explicit soil covering data for all crops considered where extracted from Sacks et al. 2010[64]. *B(t)* represents the soil carbon inputs at time *t* and was estimated using equation (2):

$$(2): B(t) = \Big[(a_{dpm} \quad a_{rpm} \quad a_{bio} \quad a_{hum})^T_{cropresidues} * (1 - \%FYM) + \\ (a_{dpm} \quad a_{rpm} \quad a_{bio} \quad a_{hum})^T_{farmyardmanure} * \%FYM\Big] * b_t$$

Where a_{dpm}, a_{rpm}, a_{bio} and a_{hum} are four coefficients that define the proportions of the carbon inputs to soils attached to the four active soil organic carbon pools for both crop residues and farmyard manure. Here, a_{dpm}, a_{rpm}, a_{bio} and a_{hum} were parametrised as follows: (0.6,0.4,0,0) for crop-based residues, (0.4,0.6,0,0) for grass residues and (0.49,0.49,0,0.02) for farmyard manure. *%FYM* represents the share of farmyard manure in total soil carbon inputs and b_t represents the total soil carbon inputs at time *t* (in t $C.ha^{-1}$).

Soil carbon input (SCI) estimation

For both the organic scenarios and the baseline, we estimated the annual SCI using equation (3):

$$(3): SCI = AgC * \%Recycled + BgC + FYM_{applied}$$

Where SCI represents the inputs of organic carbon to either cropland or grassland soils (in t $C.ha^{-1}.yr^{-1}$). *AgC* and *BgC* (in t $C.ha^{-1}.yr^{-1}$) are respectively the above and belowground plant carbon biomass (the latter being estimated over the 0-30 cm soil depth). *%Recycled* (in %) represents the percentage of the *AgC* that remains on field. In croplands the *%Recycled* data were extracted from the GOANIM model[14]. In grasslands, *%Recycled* represents the non-grazed carbon share of the entire grassland biomass production. Finally, $FYM_{applied}$ (in t $C.ha^{-1}$) is the carbon from farmyard manure applied to the cropland or grassland soils. We assumed that biomass quality and its related carbon stabilisation and mineralisation properties were similar in both the organic scenarios and the baseline due to inconsistent data in the literature[65]. We estimated AgC and BgC using equation (4) and (5):

$$(4): AgC = Yield * 0.5/HI$$

$$(5): BgC = AgC * RS$$

Where *HI* and *RS* represent the crop-specific harvest index (unit-less) and the root-shoot ratio (unit-less), respectively, for each of the considered 45 crop species. Both *HI* and *RS* values were retrieved from Monfreda et al. 2008[66] and Smil et al. 1999[67]. *Yield* refers to the crop yields (in tons DM.ha^{-1}) as retrieved from Monfreda et al. 2008[66](for the baseline) or from the GOANIM model (for the organic scenarios)[10]. To convert the estimated dry matter production in C, we used a 0.5 coefficient value (in t C.t DM^{-1}).

FYM$_{\text{applied}}$ was estimated using equation (6) and (7)

$$\text{(6): } FYM_{applied} = \frac{C_{ex}*(1-\beta)}{HA}$$

$$\text{(7): } C_{ex} = \sum_{a} VS_a * Pop_a$$

Where C_{ex} (in tC.yr^{-1}) is the total amount of carbon excreted by the livestock population as farmyard manure and *HA* is the total harvested area (ha). β represents the share of C_{ex} that is not applied to the agricultural lands. In croplands, β represents the share of C_{ex} that is left on pasture during animal grazing, used for non-agricultural purposes (e.g., as fuel) and is lost during the manure management process. In grasslands, β the share of C_{ex} that is not left on pasture during animal grazing. β was estimated following the 2019 IPCC guidelines refinement[68]. The amount of carbon lost in the manure management process was estimated according to Bareha et al. 2021[69]. In equation (7), Pop_a is the livestock population (in heads) for each of the nine considered animal species a. *VS* (in tC.head^{-1}.yr^{-1}) is the amount of volatile solid carbon excreted per animal and per year and was estimated using equation 10.24 of the 2019 refinement of IPCC guidelines represented in equation (8).

$$\text{Equation 8: } VS = \left[GrE * \left(1 - \frac{DE}{100}\right) + (UE * GrE)\right] * \left[\left(\frac{1-ASH}{18.45}\right)\right]$$

Where, *GrE* is the gross energy intake (MJ.day^{-1}), *DE* is the feed digestibility (%), *UE* is the urinary energy (% of *GrE*) and ASH is the ash content of the feed (% of DM). *UE* had a value of 0.02 for pigs and 0.04 for all other animals. In the organic scenario, the estimation of *GrE*, *DE* and *ASH* where made using the feed nutritional composition from feedipedia (feedipedia.org). In the baseline, we used data from Herrero et al. 2013[70] to estimate *DE* and *ASH* and used equation (9)[71] to estimate *GrE*.

$$\text{Equation 9: } GrE = CP * 0.056 + Fat * 0.096 + (100 - CP - Fat - ASH) * 0.042$$

Where, *CP* is the crude protein content of the ration (%), *Fat* is the fat content of the ration (%) and *ASH* is the mean ash content of the ration (%). *CP, Fat* and *Ash* were retrieved from Herrero et al. 2013[70].

We made sure that the *VS* excretion would remain in a range of 10 to 50% of the total C ingested by livestock animals[72]. This helped to close the carbon cycle within both the organic scenarios and the baseline, thereby avoiding any overestimation of soil carbon inputs.

SCI for the optimal organic scenario

We designed the optimal organic scenario to estimate the benefits brought by a more carbon-oriented farming and to capture the potential effect of additional cropping practices on SOC stocks. Based on a preliminary sensitivity analysis of SCI and SOC stocks to various cropping parameters (see **Supplementary table 3**), we built the optimal organic scenario on the assumption that the fraction of crop residues recycled on croplands (*%Recycled*) and *RS* would be increased. More precisely, we used equation (3) using modified *%Recycled*, AgC and BgC (hereafter called AgC_{opt} and BgC_{opt}) values, with *%Recycled* being increased by 10% and AgC_{opt} and BgC_{opt} being estimated using equations (10), (11) and (12).

$$(10): Total = Yield * 0.5 * (1 + RS)/HI$$

$$(11): AgC_{opt} = \frac{Total}{(1+RS\prime)}$$

$$(12): BgC_{opt} = Total - AgC_{opt}$$

Where *Total* is the total carbon biomass produced. AgC_{opt} and BgC_{opt} are the total carbon in the above-ground and below-ground biomass in the optimal organic scenarios, respectively. Evidences show that *RS* is up to twice higher for crops in conditions of low N availability compared to conditions of high N availability[73]. We estimated a modified *RS'* root-shoot ratio for situations of N availability in the optimal organic croplands using equation (13):

$$(13): \begin{cases} if Yield < Yield_{max} then RS' = \left(2 - \frac{Yield}{Yield_{max}}\right) * RS \\ if Yield = Yield_{max} then RS' = RS \end{cases}$$

Where $Yield_{max}$ is the crop specific maximum attainable yield for organic farming (in tons $C.ha^{-1}$) as defined in the GOANIM model[14].

In addition, we also simulated extensive use of cover-crops in the optimal organic scenario based on the observed higher share of cover-crops in organic crop rotations compared to conventional ones[10]. The use of cover crops is limited by agronomic and pedo-climatic conditions. Based on a previous meta-analysis on the extent of cover-crops, we considered that cover cropping could be potentially applied on 50% of global croplands[40] where bare-soil periods exist between main cash crops. We estimated the additional SCI from cover crops using equation (14). Meanwhile, we assumed that there were no cover crops in the baseline.

$$(14): SCI_{cc,i,month} = \frac{\frac{1.87}{GMBSP} * Yield_{plant,i}}{Yield_{plant,world}}$$

Where $SCI_{cc,i,month}$ (in t $C.ha^{-1}.month^{-1}$) is the soil carbon input from cover crops in country *i* per month of cover cropping. The 1.87 value (in t $C.ha^{-1}.yr^{-1}$) is the global annual mean of soil carbon input from cover crops estimated by Poeplau et al. 2015[40]. We divided this 1.87 value by the estimated global mean duration of the bare soil period in the baseline (*GMBSP*, expressed in month). To account for the variability of cover cropping productivity among countries – that is driven by climatic and farming factors[74] – we multiplied this global mean cover-cropping biomass production by the ratio of the country specific mean yield ($Yield_{plant,i}$) to the global mean yield ($Yield_{plant,world}$) for the most productive crop species between wheat and maize in the country. Finally, for each of the considered grid-cells, this monthly $SCI_{cc,i,month}$ was multiplied by the average bare-soil period (in months) between main cash crops, based on sowing and harvesting dates retrieved from Sacks et al. 2010[64].

Note that sharp differences in SCI for this optimal scenario may appear among countries in Figure 1, such as between Spain and France. Those differences are likely due to differences in climate. Because crop productivity is significantly lower in Spain compared to France due to its more arid conditions, even small additional carbon inputs to soils from cover crops are likely to raise the SCI ratio above 1 in Spain. On contrast, because of higher crop productivity in France, much higher carbon provisioning is needed from cover-crops to raise the SCI ratio above 1 in that country. The same holds true for several Sub-Saharan African countries. Another explanations lie in the data and model parametrisation we used in our simulations. Several parameters – such as the biomass productivity of cover crops – were in fact defined by country or climatic region. These effects are in fact quite common in global databases, and they are in most cases an artefact from the interpolation of climate data.

RothC parametrisation

We used RothC assuming carbon pools to be at steady state in the baseline. This necessary assumption translates into a steady state assumption for climatic conditions and soil carbon inputs over the years for both the organic farming scenarios and the baseline. Although partly unrealistic, this assumption is consistent with the thought experiment of large organic farming expansion that we report in this study. To remain in line with this steady state assumption in the baseline, we first estimated the SCI that are required to keep baseline SOC stocks at their current level (SCI_0) by using the method developed by Martin et al. 2007[21] and summarized in equation (15).

$$(15): SCI_0 = (I_4 - F) * SOC^*$$

Where SCI_0 is the carbon inputs (in t $C.ha^{-1}.yr^{-1}$) required to maintain SOC stocks at their current level. F is a 4x4 matrix representing the mineralisation and carbon flows among the four active soil organic carbon pools. F values depend on the climatic, edaphic and soil covering conditions. SOC^* is the current active (i.e. not comprised in the IOM pool) SOC stocks that is assumed to be at the equilibrium (in either croplands or grasslands). Total SOC stocks were retrieved from the AEZEF dataset[75] that provides estimates of soil organic carbon stocks for croplands on the first 30 cm of topsoils per country and for 18 agroecological zones. SOC^* was estimated after subtracting the IOM content which was estimated using the Falloon's et al. (1998) equation[47].

To estimate the SCI in the organic farming scenarios (SCI_1), we corrected SCI_0 by the ratio of SCI_{org} to $SCI_{baseline}$ (RCI) as detailed in equation (16).

$$(16): SCI_1 = SCI_0 * RCI = \frac{SCI_0 * SCI_{org}}{SCI_{baseline}}$$

Where SCI_{org} and $SCI_{baseline}$ are the soil carbon inputs for the organic farming scenarios and the baseline, respectively, estimated using the methods presented in the previous sections. We used SCI_1 as input in the RothC model to estimate the changes in SOC stocks in the organic farming scenarios – 20, 50 and 100 years after a global conversion to this farming system – using equation (1). We assumed constant climate data over the simulation periods. This assumption is disputable given current and future climate change, but it remains consistent with our thought experiment that consists in exploring situations of drastic expansion of organic farming. Further studies that are beyond the scope of this article would be needed to account for future climate scenarios. The estimated SCI_1 is expressed in $tC.ha^{-1}.yr^{-1}$, though RothC requires monthly data. We assumed that the annual soil carbon inputs were equally distributed between the twelve months of the year.

In order to account for the observed differences in crop rotations between organic and conventional farming[10], we ran RothC in the organic farming scenarios for each of the 45 considered crop species separately, and then, estimated a weighted mean of SOC stocks according to crop species harvested areas, as detailed in equation (17).

$$(17): SOC_{t,mean} = \frac{\sum_i SOC_{t,i} * HA_i}{HA_{total}}$$

Where $SOC_{t,mean}$ is the weighted mean of SOC stocks at time t and $SOC_{t,i}$ is the SOC stock estimated by the run of RothC for each specific crop i, HA_i represents the harvested area of crop i in the organic farming scenarios and HA_{total} is the total harvested area (all crop considered). HA_i and HA_{total} were retrieved from Barbieri et al. 2019[25].

Limitations and uncertainties

Although the modelling foundations of our work are solid, its global extent requires a large set of input data that may come with some limitations. In particular, both the baseline and the organic scenarios required detailed, spatially explicit distribution of cropland areas, types of crops grown and crop yields. These data were derived from Ref[66] and Earthstat, and were centred circa year 2000. Many changes have occurred in agriculture during these last 20 years (including about expanding irrigation and changes in varieties) that may affect our simulations. However, to the best of our knowledge, these databases remain the most appropriate given their global extent, higher number of crop species considered, and data quality and cross-validation. Note that uncertainties and possibly caveats may remain in those databases, e.g. about cropland areas in the island of Guinea or about grassland areas in India, as already mentioned.

Finally, several of our input data may be affected by some uncertainties. The complexity of the GOANIM and RothC models and limited knowledge about several aspects of input data makes the quantification of these uncertainties very difficult. However, the SOC stocks we estimated were determined over long periods (20, 50 and 100 years). Long term averages show reduced errors on estimated variables due to reduced aggregation effects by the input data – especially the climate data[58]. In addition, this study is based on the comparison of organic farming to a baseline, that are both affected by the same errors and uncertainties. Therefore, concentrating the analysis on the ratios (or differences) of organic to conventional estimation helps to reduce errors and uncertainties.

Data treatment & code availability

All analyses were made using R x64 3.5.3. GOANIM was used in its most recent version deposited in a public repository (**https://github.com/Pie90/GOANIM_public**). For RothC we used the *cin_month* and *runExplicitSol* functions from the RothC package[76] to respectively estimate SCI_0, and SOC stock evolution across time.

Conflicts of interest

The authors declare no competing interests.

Further correspondence

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Acknowledgments

We would like to thank Romain Girault and Younes Behara for their help regarding carbon losses in manure management process. We would also thank Denis Angers, Eric Ceschia and Christopher Poeplau for their inputs on how to consider cover crops. This work was funded by ADEME, Bordeaux Sciences Agro (Univ. Bordeaux), INRAE's intern committee on organic farming (MP Métabio) and Aberdeen's university. Matthias Kuhnert and Pete Smith acknowledge support from the CIRCASA project which received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement no 774378.

Authors' contributions

U.G., M.K., S.P. and T.N. designed the study; U.G. performed the modelling work, with the help of P.B. for the GOANIM model and M.K, and M.M. for the RothC model. All authors were involved in the interpretation of results and contributed actively to writing and revising the manuscript.

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