

Soil organic carbon modeling: estimating carbon input changes required to reach policy objectives aimed at increasing soil organic carbon stocks

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Soil organic carbon modeling: estimating carbon input changes required to reach policy objectives aimed at increasing soil organic carbon stocks

Thèse de doctorat de l'université Paris-Saclay

École doctorale n°581 : agriculture, alimentation, biologie, environnement, santé (ABIES) Spécialité de doctorat : Sciences de l'environnement Graduate School : Biosphera. Référent : AgroParisTech

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HESE DE DOCTORAT

NNT: 2022UPASB012

ÉCOLE DOCTORALE



Agriculture, alimentation, biologie, environnement, santé (ABIES)

Titre : Modélisation du carbone organique du sol : estimation des changements d'apport de carbone nécessaires pour atteindre des objectifs politiques d'augmentation des stocks de carbone organique du sol

Mots clés : Stockage du carbone organique du sol, Modélisation du sol, Changements climatiques, 4 pour 1000

Résumé : Pour compenser partiellement les émissions de CO₂, l'initiative 4 pour 1000 a proposé un objectif d'augmentation annuelle de 4‰ des stocks de carbone organique du sol (COS). Pourtant, la faisabilité d'une telle augmentation fait l'objet de débats. Le moyen le plus efficace pour accroître les stocks de COS est d'augmenter l'apport de C dans le sol. L'objectif de cette thèse est d'estimer l'apport de C nécessaire pour augmenter annuellement les stocks de COS de 4‰ dans les terres cultivées européennes. Pour cela, nous avons construit une modélisation inverse et nous l'avons testée sur un modèle de COS, en estimant les entrées nécessaires à atteindre un objectif de 4‰ sur plusieurs expériences agricoles européennes de longue durée. Ensuite, nous avons appliqué cette approche à un ensemble multi-modèle et nous avons ainsi évalué les incertitudes dans les estimations des entrées de C selon différentes représentations de la dynamique du COS.

Afin de fournir un premier aperçu aux décideurs politiques sur la faisabilité de l'objectif 4‰ en Europe, nous avons appliqué un ensemble multimodèle sur l'ensemble des terres cultivées européennes et nous avons généré des cartes d'apport de C pour deux scénarios de changement climatique. Pour améliorer la simulation des stocks de COS à l'échelle Européenne, nous avons testé une nouvelle paramétrisation issue de dérivée statistiques.

Notre étude a démontré qu'il existe des incertitudes substantielles autour de l'apport de C nécessaire pour atteindre un objectif de 4‰. Cependant, un profil général émerge, où atteindre un objectif d'augmentation de 4‰ du stock de COS à l'échelle des terres cultivées européennes semble réalisable pour les scénarios futurs de changement climatique, uniquement via des augmentations drastiques d'apports de C au sol.

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Keywords: Soil organic carbon stock, Soil modeling, Climate change, 4 per 1000

Abstract: To partially compensate for CO₂ emissions, the 4 per 1000 initiative proposed an annual 4‰ soil organic carbon (SOC) stock increase. Yet, the feasibility of such an ambitious target is still under debate. The most efficient way to increase the SOC stocks is to increase the C input to the soil. The objective of this thesis was to estimate the C input required to yearly increase the SOC stocks by 4‰ in European croplands. To solve this problem, we built an inverse modeling approach and tested it on a SOC model, by estimating the C input required to reach the 4‰ objective at multiple long-term agricultural experiments in Europe. Then, we applied this approach to a multi-model ensemble, to assess the uncertainties of the estimations according to different representations of the SOC dynamics.

As a first attempt to provide insights for policymakers on the feasibility of a 4‰ target in Europe, we applied a multi-model ensemble over the whole European cropland area and we generated maps of the required C input under two scenarios of climate change. To improve the simulation of SOC stocks at the European scale, we tested a new, statistically derived, parametrization technique.

Our study demonstrates that there are substantial uncertainties around the C input required to reach a 4‰ target. However, a general pattern emerges at the European cropland scale, where the 4‰ target seems feasible under future scenarios of climate change, only assuming drastic increases of C input to the soil.

RESUME

Les émissions anthropiques de gaz à effet de serre (GES) provoquent un changement climatique irréversible et l'Union Européenne (UE) s'est engagée à diminuer fortement ses émissions de GES. Cependant, pour atteindre la neutralité carbone (C) d'ici 2050, il sera également nécessaire de séguestrer du C atmosphérique dans des puits naturels, tels que les sols. Pour compenser partiellement les émissions de CO₂, l'initiative 4 pour 1000 a proposé en 2015 un objectif d'augmentation annuelle de 4‰ des stocks de carbone organique du sol (COS) dans les 30-40 premiers cm de profondeur du sol. Pourtant, la faisabilité d'une telle augmentation fait encore l'objet de débats car elle pourrait nécessiter des changements substantiels et rapides dans les pratiques agricoles qui seraient difficiles à mettre en œuvre. Le moyen le plus efficace pour accroître les stocks de COS est d'augmenter l'apport de C dans le sol. Les modèles basés sur les processus biogéochimiques peuvent simuler la dynamique du COS et sont de plus en plus utilisés pour aider les décideurs dans leurs politiques d'atténuation du COS. Cependant, malgré les nombreux modèles disponibles pour décrire la dynamique du COS, les simulations sont encore peu fiables. En effet, les incertitudes ne proviennent pas seulement de la structure mécaniste des modèles et des processus qu'ils prennent en compte, mais aussi des données utilisées en entrée et des valeurs des paramètres.

L'objectif de cette thèse est d'estimer l'apport de C nécessaire pour augmenter annuellement les stocks de COS de 4‰ dans les terres cultivées européennes. Pour cela, nous avons construit une modélisation inverse et nous l'avons testée sur un modèle de COS, en estimant les entrées nécessaires à atteindre un objectif de 4‰ sur plusieurs expériences agricoles Européennes de longue durée. Ensuite, nous avons appliqué cette approche à un ensemble multi-modèle et nous avons ainsi évalué les incertitudes dans les estimations des entrées de C selon différentes représentations de la dynamique du COS. Afin de fournir un premier aperçu aux décideurs politiques sur la faisabilité de l'objectif 4‰ en Europe, nous avons appliqué un ensemble multimodèle sur l'ensemble des terres cultivées européennes et nous avons généré des cartes d'apports de C pour deux scénarios de changement climatique. Pour améliorer la simulation des stocks de COS à l'échelle Européenne, nous avons testé une nouvelle paramétrisation issue de dérivée statistiques.

Notre étude a démontré qu'il existe des incertitudes substantielles autour de l'apport de C nécessaire pour atteindre un objectif de 4‰. Cependant, un profil général émerge, où atteindre un objectif d'augmentation de 4‰ du stock de COS à l'échelle des terres cultivées européennes semble réalisable pour les scénarios futurs de changement climatique, uniquement via des augmentations drastiques d'apports de C au sol. En particulier, un apport de C plus élevé est nécessaire en Europe du Nord, tandis qu'en Europe du Sud les incertitudes sont plus élevées. La grande variabilité dans les simulations d'apport de C nécessaires à l'objectif 4‰ souligne l'avantage d'utiliser des ensembles multi-modèles, afin de prendre en compte la gamme d'incertitudes liées à leurs différentes structures mécanistiques. Cependant, les ensembles multi-modèles ont encore tendance à sous-estimer l'apport de C nécessaire pour augmenter les stocks de COS. Des progrès importants doivent donc encore être faits pour améliorer les simulations des modèles, en particulier pour saisir l'effet d'un apport supplémentaire de C sur l'accumulation de COS. A l'échelle locale, la calibration des paramètres des modèles a été nécessaire pour simuler les variations observées des stocks de COS. Lorsqu'un suivi à long terme du stock de COS n'est pas disponible, il est nécessaire d'améliorer les techniques de paramétrisation. La calibration que nous avons proposée à l'échelle européenne a amélioré la simulation des stocks de COS de la première année, mais a augmenté la divergence des stocks de COS prédits par les modèles. De futurs travaux se concentrant sur la réduction des incertitudes des modèles sont donc essentiels, afin de fournir des prédictions fiables des futures variations des stocks de COS et des processus associés.

Les chapitres de cette thèse peuvent être résumés comme suit :

 Le Chapitre 2 développe une approche de modélisation inverse utilisant le modèle de COS Century (Parton et al., 1988b) pour estimer l'apport de C nécessaire à augmenter les stocks de COS de 4‰ par an dans plusieurs

expériences de long-terme en Europe, où différents types de matières organiques ont été ajoutés au sol. Nous évaluons la performance du modèle sur ces expériences et nous calibrons ses paramètres pour faire correspondre l'évolution des stocks de COS aux différents traitements de contrôle. Enfin, nous estimons la sensibilité du modèle à différents scénarios d'augmentation de la température ;

- Le Chapitre 3 applique l'outil de modélisation inverse à un ensemble multimodèle (AMG, Century, ICBM, Roth-C, Millennial et MIMICS) pour évaluer l'incertitude de l'apport de C simulé pour atteindre l'objectif de 4‰, relatif aux différentes représentations des processus de COS dans les modèles sélectionnés;
- Le Chapitre 4 étend l'analyse à l'ensemble des terres cultivés européennes avec un sous-ensemble du multi-modèle, dans une première tentative d'étudier la faisabilité de l'objectif de 4‰ à l'échelle de l'Europe. Nous proposons une technique de calibration pour améliorer les simulations des modèles et fournissons des cartes montrant l'apport en C nécessaire pour atteindre l'objectif de 4‰, selon deux scénarios de changement climatique ;
- Le Chapitre 5 discute des différentes manières de calculer les objectifs quantitatifs de stockage de COS, et montre leurs implications en termes d'apport supplémentaire de C, à travers une étude de cas basée sur des expériences agricoles de long-terme avec des traitements de matière organique exogène ;
- Le Chapitre 6 résume les résultats les plus saillants et discute d'autres implications pour les recherches futures.

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COMMUNICATIONS

2021 **Youg Soil Researchers Forum** - Assessing the feasibility of soil organic carbon stock increase in Europe with a multi-modelling ensemble

2021 Workshop on soil organic carbon modelling approaches - Estimating the amount of C input to reach a 4 per 1000 increase of SOC stocks with a multi-modeling approach: what categories of models emerge?

2021 **Eurosoil** - Increasing soil organic carbon storage: the 4 per 1000 objective through a modelling based approach

2021 International Soil Modeling Consortium - Increasing soil organic carbon stocks in agricultural fields: a multi-modelling analysis evaluating the carbon inputs required to maintain and increase soil organic carbon stocks in Europe

2021 **EGU** - How much should we increase carbon inputs to the soil to reach a 4per1000 objective of soil organic carbon storage in European agricultural sites: a multi-modelling approach

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1 CHAPTER 1 GENERAL INTRODUCTION

Increasing soil organic carbon (SOC) stocks is a promising option to reduce atmospheric carbon dioxide (CO₂) concentration and mitigate climate change (Lal, 2016; Minasny et al., 2017; Martin et al., 2021). By improving soil fertility and other soil conditions that are essential for crop growth, increased SOC stocks also promote food security (Lal, 2016). SOC stock variations at the field scale derive from imbalances between carbon (C) input to the soil, such as crop residues, litterfall, roots, and organic amendments, and C output from the soil, e.g., from mineralization, leaching, and soil erosion. Some agricultural practices, such as reduced tillage, may decrease SOC mineralization rates (Haddaway et al., 2016). Nevertheless, there is a consensus that the most efficient way to increase SOC stocks is to increase the C input to the soil (Virto et al., 2012; Autret et al., 2016; Fujisaki et al., 2018). When compared to conventional agricultural practices, examples of practices for croplands that produce and return additional C input to the soil are: agroforestry systems, cover cropping, lengthening leys in temporary grasslands, and effective restitution of crop residues and organic amendments to the soil (Chenu et al., 2019). Recently, several international efforts have been made to promote the increase of SOC stocks at the global scale. For example, in 2015 the "4 per 1000" initiative was launched to promote SOC storage increases through recommended land management practices (www.4p1000.org). Another example is the aspirational target that the Mission Board for Soil Health and Food has proposed for 2030, which is to reverse current SOC content decreases in European croplands to an annual increase of 1‰ to 4‰ (Veerman et al., 2020). The feasibility of such quantitative targets is still under debate (e.g., Chabbi et al., 2017; van Groenigen et al., 2017; Soussana et al., 2019; Rumpel et al., 2020).

In this thesis, we formulated the following question: "What is the amount of C input required to annually increase SOC stocks by a certain fixed target, like 4‰ per year?" The next chapters tackle this question using process-based models at the European cropland scale.

1.1 FUTURE CHALLENGES FOR SOILS IN A WARMER CLIMATE

The assessment reports of the Intergovernmental Panel on Climate Change address the most up-to-date physical understanding of the climate system and climate change. The sixth and latest report announced that human-induced climate change is already affecting every region across the world (IPCC, 2021). Many of the observed changes in the climate system are irreversible over hundreds to thousands of years and continued global warming is projected to further intensify extreme events of the climate system (IPCC, 2021). Limiting humaninduced global warming requires reducing cumulative CO₂ emissions and other greenhouse gases (GHGs) until a net-zero emissions target is reached. Despite the Paris Agreement's objective to limit global warming "well below 2°C" relative to the pre-industrial period, global average CO₂ emissions are still rising (Le Quéré et al., 2018). The Europe 2020 Strategy goal, which set a 20% GHGs emission reduction relative to 1990, was not reached by any Member State (Becker et al., 2020). Yet, with the "European Climate Law", the European Commission has set even more ambitious targets (European Commission, 2021). Compared to 1990 levels, by 2030 the EU aims to decrease net GHGs emission by at least 55%, in order to reach C neutrality by 2050. To achieve C neutrality it will be necessary to implement land-based mitigation solutions that sequester large amounts of CO₂ from the atmosphere (Krause et al., 2020). For instance, this can be done: by enhancing the natural sink of C via avoided deforestation and reforestation, through bioenergy cultivation with C capture and storage, and via the sequestration of C in agricultural soils through improved management practices (Fuglestvedt et al., 2018). This latter land-based solution will be particularly critical, considering that the human population is predicted to reach 9.7 billion in 2050 and to increase further to 10.9 billion by the end of the century (Gu et al., 2021). With this population growth, agricultural soils will have to maintain and improve their productivity in order to ensure food security (Molotoks et al., 2021). Increasing SOC has positive consequences on the soil structure and soil quality. This latter can be defined as the capacity of the soil to produce economic goods and provide ecosystem services (Lal, 2010). The combined capacity of soils to provide food and sequester atmospheric CO₂ highlights their central role in tackling today and future challenges of the human society. Based on these ideas, the "4 per 1000" initiative was proposed in 2015 to promote agricultural practices that maintain and increase global SOC stocks.

1.2 THE 4 PER 1000 INITIATIVE AND THE EUROPEAN TARGETS OF SOC STOCK INCREASE

Globally, soils store two to three times more C than the atmosphere (Le Quéré et al., 2018) (Figure 1-1). The annual GHG emissions from fossil fuels are estimated at 9.4 Gt C (i.e., 1015

g C), while global SOC stocks up to 2 m depth are estimated at around 2400 Gt C (Le Quéré et al., 2018). Taking the ratio between these two values gives approximately 0.4% (or 4‰, i.e., 4 per 1000), which is the annual increase of global SOC stocks theoretically required to compensate for GHG emissions from fossil fuels burning (Balesdent and Arrouays, 1999). The "4 per 1000" proposal calls for a voluntary action plan to protect existing SOC stock, and to enhance SOC stocks of world soils to a 30-40 cm depth at the rate of 4‰ per year (Lal, 2016). A 4‰ increase target cannot be implemented everywhere because soils vary widely in terms of C storage (e.g., deserts, peatlands, and mountains) (Minasny et al., 2017). The strategy of the initiative is instead to focus on agricultural soils. The two main reasons are that agricultural soils are markedly SOC-depleted and agricultural management practices can be modified within a relatively short period of time. In addition to that, the agricultural sector emits 6.2 \pm 1.4 Gt carbon dioxide equivalents (CO₂eq) each year (IPCC, 2019). To avoid GHGs emissions and additionally exploit the potential of soils to store C, it is crucial to improve the management of this sector. Further benefits will derive in terms of soil health and food security. It is worth noting that reducing GHGs emissions remains the first-order solution to reach a net-zero emission target. In fact, when considering global agricultural soils, a 4‰ target would only partially offset anthropogenic emissions from fossil fuel burning (Lal, 2016; Minasny et al., 2017).

The Mission Board for Soil Health and Food of the European Union (EU) proposed a series of quantitative targets to improve the health of European soils (Veerman et al., 2020). One of the objectives for 2030 is to reverse current C concentration losses in European croplands, which were estimated at 5‰ yr⁻¹ on average, to an increase of 1‰ to 4‰ yr⁻¹ (Veerman et al., 2020). Increasing SOC stocks also supports the Sustainable Development Goals (SDGs) of the United Nations (UN). In particular, it promotes Target 2.4 for land and soil quality, and Target 15.3 for land degradation neutrality (Rosa, 2017).



Figure 1-1 Global carbon cycle between the land and the atmosphere. Average values for 2008-2017 (see the legend for the corresponding arrows and units) were taken from Ciais et al. (2013). Uncertainty in the atmospheric CO₂ growth rate is \pm 0.02 Gt C yr⁻¹. Figure adapted from Le Quéré et al. (2018). Icons made by Freepik from www.flaticon.com.

1.3 INCREASING SOC STOCKS IN AGRICULTURAL SOILS

Soils contain C in both organic (SOC) and inorganic forms (e.g., carbonates and lime) (Abbas et al., 2020). Through photosynthesis, plants sequester atmospheric CO₂ and form OC compounds, which are partly transferred to the soil via rhizodeposition (Figure 1-1). When they die, plants and other biological materials are also degraded by soil organisms into OC compounds. During the mineralization processes, some CO₂ is released back to the atmosphere. Meanwhile, the entrapment of organic compounds into microsites inaccessible to microorganisms and the adsorption of organic compounds (e.g., char) intrinsically decompose very slowly. The storage of SOC under forms that are not accessible to microorganisms and long turnover times of organic compounds result in the accumulation of SOC (Abbas et al., 2020). In natural conditions, SOC is in a state of dynamic equilibrium where continuous losses are counterbalanced by continuous gains (Janzen, 2006). If either the input or loss rate is altered due to some disturbance, such as a change in the land use or land

management, the SOC stock will evolve out of steady-state for a certain period, to eventually reach a new equilibrium value (Chenu et al., 2019). In recent centuries, SOC stocks in agricultural soils have often declined as a consequence of cultivation (Janzen, 2006). Compared to less intensively managed ecosystems, the continuous harvesting of plants reduces the amount of plant litter that is returned to the soil. Under agricultural management, soil aggregates are also disrupted and SOC is made more accessible to biological decay (Janzen, 2006). Cumulative C losses from cultivated soils exceed 50 Pg C, with average losses per hectare of cultivated land of approximately 30 Mg C (Janzen, 2006). Past losses of SOC constitute nowadays the opportunity for future SOC sinks (Janzen, 2006).

An increase in SOC stocks can be achieved either by increasing the amount of C entering the soil or by decreasing the C output from the soil. The C input depends on the rate of photosynthesis and on the proportion of net primary production (NPP, i.e., the product of photosynthesis) that is returned to the soil. The C output can be reduced by decreasing the mineralization rate of C or, at least locally, by limiting soil erosion. Compared to decreasing mineralization (e.g., through no tillage), several studies suggested that the addition of C input is the best option to increase SOC stocks in agricultural soils (Chenu et al., 2019). For croplands, some examples of recommended management practices (RMPs) that increase the C input to the soil are the use of crop species and varieties that have a greater root mass, the use of cover crops during fallow periods, increased residue retention and addition of amendments such as compost and biochar, and the mixture of crops with trees in agroforestry systems (Soussana et al., 2019b; Chenu et al., 2019).

While the capacity of these practices to increase SOC stocks gathers consensus among soil researchers, there is still debate on their potential to achieve the aspirational 4‰ target, due to both biophysical and socio-economic limitations (Chabbi et al., 2017; van Groenigen et al., 2017; Soussana et al., 2019a; Rumpel et al., 2020; Poulton et al., 2018).

1.4 FEASIBILITY OF A 4 PER 1000 TARGET

Despite socio-economic limitations represent important barriers for the implementation of RMPs (Poulton et al., 2018), this thesis focuses on the biophysical aspect of the 4‰ feasibility. Criticisms of the "4 per 1000" initiative have mainly emphasized the limitation of soils to sequester SOC indefinitely and permanently, as well as the large amount of nutrients it requires (Baveye et al., 2018; Minasny et al., 2017; VandenBygaart, 2018; Lal, 2016). While

SOC sequestration rates may be high when a new sequestration practice is implemented, they slow down over time until SOC stocks reach a new steady-state (Smith, 2012). Furthermore, if soils are poorly managed, C sinks can be reversed at any stage (Smith, 2012). To conserve the attained level of SOC stocks, improved management practices must be maintained indefinitely, but with no additional benefits in terms of C sink. Noulèkoun et al. (2021) observed this effect while studying the potential of grazing exclosures in Northern Ethiopia. Following the conversion of degraded grazing lands to exclosures, they found that the rates of increase of SOC stocks across the different sites were initially as high as 7% to 19% yr⁻¹. After 8 years, the SOC stocks declined to eventually reach a new steady-state.

Another biophysical limitation to the 4‰ is linked to soil nutrients, and particularly to nitrogen (N). Because the C and N cycles are tightly coupled, the increase of C input also increases the demand for N. To preserve N availability, large amounts of mineral fertilizers have to be applied to the soil. However, the use of mineral fertilizers produces N₂O emissions and nitrate leaching, with negative consequences for climate and groundwater pollution. Additionally, in order to be produced, mineral fertilizers create further GHGs emissions. As a whole, the net storage potential of the implemented practice may be limited. Details on the C and N cycle and tradeoffs between C storage and N₂O emissions are elaborated in Appendix I.

A growing number of works has focused on the feasibility of the 4‰ target, both from empirical evidence and from a modelling perspective. Wiesmeier et al. (2020) studied the potential of different agricultural practices to sequester C in Bavaria. They found that the 4‰ target was not achievable in this region. Among the selected practices, they identified cover cropping and agroforestry as having the highest potential to increase SOC stocks in agricultural soils. In a systematic review of SOC storage under agroforestry and conservation agriculture in sub-Saharan Africa, Corbeels et al. (2019) showed that some agro-systems reached the 4‰ target, while others did not. In particular, SOC storage rates in fallows and multitstrata agroforestry systems were significantly higher than 4‰ yr⁻¹. Systems under conservation agriculture, i.e. under no or minimum tillage, permanent soil coverage, crop residue retention, and intercropping or crop rotation, also had similar outcomes. Poulton et al. (2018) evaluated the feasibility of the 4‰ target in 16 agricultural long-term experiments (LTEs) in the United Kingdom. The experiments consisted in adding organic amendments or N fertilizers to the soil, introducing pasture leys into continuous arable systems, and the

converting arable land to woodland. The authors found that the 4‰ target was achieved or exceeded in the majority of the experiments. Even so, due to the high resources required for farmers (i.e., animal manure) and because the majority of the practices they studied was already widely adopted (e.g., the use of organic amendments and N fertilizers), they suggested a limited applicability of the 4‰ target, and pointed out the socio-economic barriers to the *4 per 1000*.

From a modelling perspective, Martin et al. (2021) assessed the feasibility of the 4‰ target in mainland France using an inverse Roth-C modelling approach. They estimated that a 30 to 40% increase of C input will be necessary to obtain a 4‰ annual increase of SOC stocks over 30 years. They found that cropland soils were mainly unsaturated. That is to say, additional SOC could potentially be stabilized in the fine fractions of these soils. For this reason, they suggested that increases in NPP returns to cropland soils should be prioritized. For German croplands, a study with different SOC models from Riggers et al. (2021) estimated that an increase of C input of 213 to 283% will be required to increase SOC stocks by 4‰ yr⁻¹ between 2090 and 2099, relative to 2014, according to different climate change scenarios. Although these studies provide an estimate of the amount of C input required to reach the 4‰ target in France and Germany, a lack of knowledge arises at the European scale.

1.5. SIMULATING SOC STOCKS WITH PROCESS-BASED MODELS

Since the 1930s, several SOC models have been developed to mathematically describe biogeochemical processes in the soil (Manzoni and Porporato, 2009). Although there is a large number of models with different levels of complexity (see Manzoni and Porporato, 2009 and Campbell and Paustian, 2015), the predominant formalism since its first appearance in 1945 is the system of ordinary differential equations (ODEs). In this formalism, each ODE describes the mass balance of SOC in continuous time within a soil compartment, and each compartment is characterized by a specific rate of decomposition of SOC (Manzoni and Porporato, 2009). While the number of equations (i.e., compartments) and the degree of nonlinearity vary from model to model, they all can be described by the following system of equations:

$$\frac{dC_i(t)}{dt} = I(t) - K_i(t) \cdot C_i(t)$$
Eq. 1

Where $\frac{dC_i(t)}{dt}$ is the variation of SOC with time within a soil compartment (i = 1, ..., n denoting the soil compartment); I(t) is the amount of C that enters the system; and the term $K_i(t)$. $C_i(t)$ represents the fraction of C that is lost by the system through decomposition. The rate at which C is decomposed may be described through different kinetic reaction forms (e.g., linear, multiplicative Michaelis-Menten and inverse Michaelis-Menten kinetics). SOC models use temperature and water response functions to link the rate of SOC decomposition to climatic factors, such as soil or air temperature, soil humidity, precipitation, and evapotranspiration. The rate of SOC decomposition may also depend on soil characteristics, such as the clay and carbonate (CaCO₃) contents in the soil (Andriulo et al., 1999). Climate and soil variables are then input to the models to simulate the variation of SOC stocks with time. If they do not explicitly simulate plant-growth, models also need data on the amount of C input to the soil, I(t). That is, C input from plants (e.g., crop residues, litterfall, roots and roots exudates) and other organic material (e.g., organic amendments). Linear systems of equations with constant coefficients can be solved analytically (e.g., Andrén and Kätterer, 1997; Bolker et al., 1998; Saffih-Hdadi and Mary, 2008), while nonlinear models need to be solved numerically (Manzoni and Porporato, 2009). Despite the presence of nonlinearities, some models can be solved analytically at steady-state (by setting Eq. 1 to zero) and numerically afterwards (e.g., Xia et al., 2012; Huang et al., 2018).

Models can be applied at different scales (e.g., microbial, ecosystem or global scale). They can be used to understand the processes that drive SOC decomposition and accumulation, study their sensitivity to changes in climate or land-use, and predict the evolution of SOC stocks with time. Models may have more or less explicit processes. For example, some models have microbial explicit pools that mediate SOC decomposition (e.g., Wieder et al., 2015; Abramoff et al., 2018), while other simpler models do not account for microbial activity and will only represent the effect of microorganisms through an active pool, where SOC is rapidly decomposed (e.g., Parton et al., 1988; Coleman and Jenkinson, 1996; Andriulo et al., 1999). Because the soil system is highly complex, it remains fundamentally impossible to describe all of its processes in a model. Furthermore, models are a simplified representation of reality, thus choices have to be made on what processes to include, how to parametrize them and what parts to neglect. This wide range of possible representations of the SOC dynamics constitute an asset for soil modelers who want to predict the evolution of SOC stocks over time, while accounting for the existing uncertainty around SOC processes. In climate modelling, the use of multi-model ensembles is a consolidated practice (Tebaldi and Knutti, 2007; Parker, 2010; Jebeile and Crucifix, 2020). It capitalizes on the numerous mathematical formalisms available in the literature to provide uncertainty ranges for climate change predictions. The soil modelling community still rarely relies on multi-model ensembles for SOC stock predictions. Compared to singular model simulations, multi-model ensemble means are expected to provide improved estimates, due to the relative independence of SOC model simulations' errors (IPCC, 2007). Increasing the reliability of SOC model predictions by accounting for their uncertainty is particularly relevant to improve future climate change projections, due to the potentially significant feedbacks between the climate system and the C cycle. The more so, because model simulations serve as basis for policy makers who may have to provide financial support for the implementation of practices that increase SOC stocks.

1.6 FIXING QUANTITATIVE TARGETS OF SOC STOCK INCREASE

The adoption of practices that increase SOC stocks may be incentivized by policy makers through farm-level payments. To promote and monitor the implementation of RMPs, it is convenient to fix quantitative targets for SOC stock increase (European Commission, 2021). For this reason, it must be defined a reference against which the SOC stock increase is calculated. In a set of theoretical examples, Pellerin et al. (2019) and Soussana et al. (2019) illustrated the potential impact of a 4‰ increase calculated against a baseline, or independently of it. A baseline is a reference practice where SOC stocks are monitored over time and to which the RMP is compared. If the SOC stock increase target is calculated against a baseline, the increase rate required to reach the target will be independent of the former SOC stock trend. A second possibility is to consider a single SOC measurement against which to calculate the SOC stock increase. In this case, if SOC stocks are not at equilibrium, the rate of increase required to reach the target will depend on the SOC stock trend previous to the implementation of the practice (Soussana et al., 2019). Calculating the increase independently of the baseline will put the pressure on soils with degrading SOC stocks, because the rate at which they will have to increase will be higher than soils with stabilized or increasing stocks (Soussana et al., 2019). This has been advocated as the most relevant option because it is in line with the Land Degradation Neutrality target of the UNCCD

(Soussana et al., 2019). However, increasing SOC stocks by 4‰ independently of the baseline may require high amounts of C input in soils with negative SOC stock trends. It is important to assess the feasibility of quantitative SOC stock increase targets calculated independently of the baseline, such as those proposed by the Mission Board for Soil Health and Food (Veerman et al., 2020) and discuss the implications in terms of additional C input required. The fifth Chapter of this thesis is dedicated to the estimation of the additional C input required to reach a 1‰-4‰ SOC increase target in a set of agricultural LTEs with additional EOM inputs, calculated with the two different approaches described above. This will help understanding how the calculation of a quantitative target may have different implications in terms of additional C input required.

1.7 OVERVIEW OF THE THESIS

The primary objectives of this research can be summarized as follows:

- Chapter 2 develops an inverse modelling approach using the SOC model Century (Parton et al., 1988a) to estimate the C input required to increase SOC stocks by 4‰ yr⁻¹ in several LTEs around Europe, where different types of OM were added to the soil. We evaluate the performance of the model on the LTEs and we calibrate its parameters to fit the evolution of SOC stocks in the different control treatments. Finally, we estimate the sensitivity of the model to different scenarios of temperature increase;
- Chapter 3 applies the inverse modelling tool to a multi-model ensemble (AMG, Century, ICBM, Roth-C, Millennial and MIMICS) to assess the uncertainty of the simulated C input required to reach the 4‰ target, relative to different representations of the SOC processes in the selected models;
- Chapter 4 upscales a subset of the multi-model ensemble to the European cropland area, in a first attempt to study the feasibility of the 4‰ target at the European scale.
 We propose a calibration technique to improve model simulations and provide maps of C input required to reach the 4‰ target under two scenarios of climate change;
- Chapter 5 discusses different ways to calculate quantitative targets, and shows their implications in terms of additional C input, through a case study based on long-term agricultural experiments with EOM treatments;

• Chapter 6 summarizes the most salient results and discusses further implications for future reasearch.

2 CHAPTER 2 ADDITIONAL CARBON INPUTS TO REACH A 4 PER 1000 OBJECTIVE IN EUROPE : FEASIBILITY AND PROJECTED IMPACTS OF CLIMATE CHANGE BASED ON CENTURY SIMULATIONS OF LONG-TERM ARABLE EXPERIMENTS

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Abstract. The 4 per 1000 initiative aims to maintain and increase soil organic carbon (SOC) stocks for soil fertility, food security and climate change adaptation and mitigation. One way to enhance SOC stocks is to increase carbon (C) inputs to the soil.

In this study, we assessed the amount of organic C inputs that are necessary to reach a target of SOC stocks increase by 4‰ per year on average, for 30 years, in 14 long-term agricultural sites in Europe. We used the Century model to simulate SOC stocks and assessed the required level of additional C inputs to reach the 4 per 1000 target at these sites. Then, we analyzed how this would change under future scenarios of temperature increase. Initial stocks were simulated assuming steady state. We compared modelled C inputs to different treatments of additional C used on the experimental sites (exogenous organic matter addition and one treatment with different crop rotations). The model was calibrated to fit the control plots, i.e. conventional management without additional C inputs from exogenous organic matter or changes in crop rotations, and was able to reproduce the SOC stocks dynamics.

We found that, on average among the selected experimental sites, annual C inputs will have to increase by 43.15 \pm 5.05 %, which is 0.66 \pm 0.23 MgC ha⁻¹ per year (mean \pm standard error), with respect to the initial C inputs in the control treatment. The simulated amount of C inputs required to reach the 4‰ SOC increase was lower or similar to the amount of C inputs actually used in the majority of the additional C input treatments of the long-term experiments. However, Century might be overestimating the effect of additional C inputs were increasing by 0.25% on average. This means that the C inputs required to reach the 4 per 1000 target might actually be much higher. Furthermore, we estimated that annual C inputs will have to increase even more due to climate warming, that is 54% more and 120% more, for a 1°C and 5°C warming, respectively. We showed that modelled C inputs required to reach the target depended linearly on the initial SOC stocks, raising concern on the feasibility of the 4 per 1000 objective in soils with a higher potential contribution on C sequestration, that is soils with high SOC stocks. Our work highlights the challenge of increasing SOC stocks at large scale and in a future with warmer climate.

2.1 INTRODUCTION

Increasing organic carbon (C) stocks in agricultural soils is beneficial for soil fertility and crop production and for climate change adaptation and mitigation. This consideration was at the

basis of the 4 per 1000 (4p1000) initiative, proposed by the French Government during the 21st Conference of the Parties (COP21) on climate change. The 4p1000 initiative aims to promote agricultural practices that enable the conservation of organic carbon in the soil (www.4p1000.org). Because soil organic carbon (SOC) stocks are two to three times higher than those in the atmosphere, even a small increase of the SOC pool can translate into significant changes in the atmospheric pool (Minasny et al., 2017). To demonstrate the importance of SOC, the initiative took as an example the fact that increasing global SOC stocks up to 0.4 m depth by 4p1000 (0.4%) per year of their initial value could offset the net annual carbon dioxide (CO₂) anthropogenic emissions to the atmosphere (Soussana, 2017). While increasing SOC stocks by 4p1000 annually is not a normative target of the initiative, this value can be taken as a reference to which current situations and alternative strategies are compared (e.g. Pellerin et al., 2017).

Strategies of conservation and expansion of existing SOC pools may be necessary but are not sufficient to mitigate climate change (Paustian et al., 2016). In this sense, increasing SOC stocks cannot be regarded as a dispensation to continue business as usual, but rather as a wedge of negative greenhouse gases (GHG) emissions (Wollenberg et al., 2016), as well as a strategy for improving most soils' resilience to changes in the climate.

The potential to increase SOC stocks is particularly relevant in cropped soils, where the depletion of organic matter with respect to the original non-cultivated situation has been demonstrated (Clivot et al., 2019; Goidts and van Wesemael, 2007; Meersmans et al., 2011; Saffih-Hdadi and Mary, 2008; Sanderman et al., 2017; Zinn et al., 2005) and where straightforward management practices can be implemented to promote the conservation or increment of SOC (Chenu et al., 2019; Guenet et al., 2020; Paustian et al., 2016). Moreover, increasing the organic C content in agricultural soils is known to improve their fertility and water retention capacity (Lal 2008), indirectly enhancing agricultural productivity and food security.

SOC stocks are a function of C inputs and C outputs. To increase SOC stocks one can either increase C inputs to the soil (i.e. adding plant material or organic fertilizers) or reduce C outputs resulting from mineralization and, in some cases, soil erosion. Increasing SOC stocks can be achieved via agricultural practices such as retention of crop residues and organic amendments to the soil, cover cropping, diversified rotations and agroforestry systems (Chenu et al., 2019; Powlson et al., 2011). However, some of these practices only lead to local

carbon storage at field scale, rather than a net *carbon sequestration* from the atmosphere at larger scales (Chenu et al., 2019).

Assessing the evolution of SOC stocks over time is important to estimate correctly the potential of SOC storage in agricultural soils and evaluate management practices in terms of both SOC stocks increase and sequestration potential. The dynamics of SOC stocks can be either measured in agricultural soils through long-term experiments (LTEs) and soil monitoring networks or estimated via biogeochemical models (Campbell and Paustian, 2015; Manzoni and Porporato, 2009). Combining measurements of SOC with models provides a wider applicability of the information collected in field trials, as it allows SOC stocks and their future trends to be estimated. However, validity of models in the studied areas has to be assessed and models need to be initialized. This means that the initial status of SOC has to be set, either for lack of data on total initial stocks, or to determine the allocation of C among model's compartments that cannot be measured. This is commonly accomplished by assuming that SOC is at equilibrium at the beginning of the experiment (Luo et al., 2017; Xia et al., 2012).

The feasibility and applicability of a 4‰ increase target depend on biotechnical and socioeconomic factors. As we mentioned earlier, a number of practices are known to increase SOC stocks in agricultural systems. However, it is still debated whether they will be sufficient to reach the 4p1000 objective. Minasny et al. (2017) described opportunities and limitations of a 4‰ SOC increase in 20 regions across the world. Several authors (e.g. Baveye et al., 2018; van Groenigen et al., 2017; VandenBygaart, 2018) argued that some of the examples described in Minasny et al. (2017) were not representative of wide-scale agriculture and suggested that a 4‰ rate is not attainable in many practical situations (Poulton et al., 2018). Implementing new agricultural practices that allow the maintenance and increase of SOC stocks might require structural land management changes that not all farmers will be willing to adopt. Incentivizing and sustaining virtuous practices to increase SOC stocks should be a strategy for policymakers to overcome socio-economic barriers (e.g. Lal, 2018; Soussana, 2017) and in order to do that, they need to be correctly informed. Recent works have assessed the biotechnical limitations of a SOC increase, studying the required and available biomass to reach a 4p1000 target in European soils (Wiesmeier et al., 2016; Martin et al., 2021; Riggers et al., 2021).

Our work was set up in this context with the objectives to: 1) estimate the amount of C inputs needed to increase SOC stocks by 4‰ per year; 2) investigate if this amount is attainable with currently implemented soil practices (i.e. organic amendments and different crop rotations) and 3) study how the required C inputs are going to evolve in a future driven by climate change. We used the biogeochemistry SOC model Century, which is one of the most widely used and validated models (Smith et al., 1997), to simulate SOC stocks in 14 different agricultural LTEs around Europe. We set the target of SOC stocks increase to 4‰ per year for 30 years, relative to the initial stocks in the reference treatments. With an inverse modeling approach, we estimated the amount of additional C inputs required to reach a 4p1000 target at these sites. Finally, we evaluated the dependency of the required additional C inputs to different scenarios of increased temperature.

2.2 MATERIALS AND METHODS

2.2.1 Experimental sites

We compiled data from 14 LTEs in arable cropping systems across Europe (Figure 2-1), where a total of 46 treatments with increased C inputs to the soil were performed and one control plot in each experiment was implemented (Table 2-1). The experiments lasted between 11 and 53 years (median value of 16 years) in the period from 1956 to 2018. Most of the experiments had at least 3 replicates, except for the Italian site *Foggia*, the French site *Champ Noël 3* and the British site *Broadbalk*, where no replicates were available. We selected experiments where dry matter (DM) yields and SOC had been measured at several dates. C inputs in all sites, except for control plots and all plots in *Foggia*, included exogenous organic matter (EOM) addition, e.g. animal manure, household waste, sewage sludge or compost additions. In *Foggia*, different rotations without organic matter addition were studied and compared to a wheat-only treatment, considered as the control plot. The annual C inputs to the soil were substantially higher in the rotations compared to the control. More information on crop rotations and C inputs for each treatment can be found in Table 2-1.

Cropping systems in the 60 treatments (14 control plots and 46 additional C input treatments) were mainly cereal-dominated rotations (wheat, maize, barley and oat). In particular, four were cereal monocultures (silage maize in *Champ Noël 3, Le Rheu 1* and *Le Rheu 2* and winter wheat in *Broadbalk*) and four sites had rotations of different cereals (winter wheat and silage

or grain maize in Crécom 3 PRO, Feucherolles, La Jaillière 2 PRO and Avrillé). The other sites rotated cereal crops with legumes (chickpea, pea) and/or root crops (fodder beet, fodder rape and Swedish turnip), oilseed crops (sunflower and oilseed rape), cover crops (mustard and rapeseed) and one rotation included tomatoes. Straw residues were systematically exported except in French sites, where residues were sometimes incorporated into the soil as accounted for in the C input calculations. All LTEs were under conventional tillage, which was performed with a tractor, except in the case of Ultuna, where it was performed manually. All experiments were rainfed, except for Foggia, where tomatoes were irrigated in summer. The French sites Champ Noël 3, Crécom 3 PRO, La Jaillière 2 PRO, Le Rheu 1 and Trévarez received optimal amounts of mineral fertilizers both in the control plot and in the different organic matter treatments. All other experiments did not receive any mineral fertilization. All control plots, apart from Arazuri, had decreasing SOC stock trends (SOC approximated with a linear regression: $SOC = m \cdot t + SOC_0$, with average relative change: $\frac{m}{SOC_0} \cdot 100 = -0.76$ %, R² = 0.58). Over the 46 treatments of additional C input, 18 exhibited increasing SOC stocks at a higher rate than 4‰ per year on average over the experiment length (Table 2-1.). Six treatments had increasing SOC stocks, but at a lower ratio than 4p1000. The other 22 treatments with additional C inputs had decreasing SOC stocks (MgC ha⁻¹). However, the decreasing trend was, in these cases, lower than the decreasing trend in the respective control plot, on the majority of the treatments.

2.2.2 Climate forcing

Mean temperature of the sites ranged from a minimum of 5.7 °C to a maximum of 15.5 °C, while mean soil humidity to approximately 20 cm depth ranged between 20.2 and 24.6 kg_{H2O} m⁻²_{soil} in the dataset (Table 2-2). When available, observed daily air temperature was used as an approximation of soil temperature. Otherwise, land-atmosphere model ORCHIDEE was used to simulate soil surface temperature and soil humidity at site-scale (Krinner et al., 2005). ORCHIDEE simulations were run over each site using a 3-hourly global climate dataset at 0.5° (GSWP3 http://hydro.iis.u-tokyo.ac.jp/GSWP3/). Plant cover was set to C3 plant functional type (PFT) for agriculture.

2.2.3 Soil characteristics

The sampling depth of the experiments varied between 20 and 30 cm. SOC stocks were measured in 3 – 4 replicates, apart from *Foggia* and *Champ Noël 3* experiments, where no replicates were available, and *Broadbalk*. In this experiment, SOC was measured in each plot using a semi-cylindrical auger where 10-20 cores were taken from across the plot and bulked together (more details can be found on the e-RA website¹). The clay content ranged from 10% (*Jeu-les-Bois*) to 41% (*Foggia*). Soil pH varied from a minimum of 5.85 in *Le Rheu 1* to a maximum of 8.33 in *Colmar*. The average bulk density (BD) in the control plots was 1.38 g cm⁻³. SOC stocks (MgC ha⁻¹) were calculated at each site using the following equation:

$$SOC (MgC ha^{-1}) = SOC(\%) \cdot BD(g \ cm^{-3}) \cdot sampling \ depth \ (cm), \tag{1}$$

where SOC (%) is the concentration of organic C in the soil, BD is the average bulk density of the experimental plot. It should be noted that the application of EOMs might induce differences in BD with time, which in turn affects the calculations of SOC stocks. No adjustment was made in this sense, since data on the evolution of BD was available only for a few sites. This might explain differences between the SOC stocks calculated for *Broadbalk* in this paper and those found by Powlson et al. (2012) in the same site, by adjusting soil weights to observed decreases in top soil BD due to accumulating farmyard manure (FYM). Initial SOC stocks values in the control plot and mean climate variables for each site are reported in (Table 2-2).

Table 2-1: Summary of the agricultural experiments included in the study: crop rotations grown at site, amount of carbon inputs (MgC ha-1 per year) estimated from crop yields as in (Bolinder et al., 2007), type of treatments, amount of additional organic carbon from organic treatments (MgC ha-1 per year) and mean annual SOC stocks variation (%).

Site	ID Treatment	Rotations*	Carbon inputs Treatment		Additional	SOC annual
			from crop	type	carbon inputs	variation
			rotations		from organic	
					treatments	
			MgC ha-1		MgC ha-1	%
			year ⁻¹		year-1	
Champ Noël 3	Min**	sM	1.29	Reference+N*	0	-0.92
				*		
(CHNO3)	LP	Silage maize	1.49	Pig manure	0.79	-0.89
Colmar	то	wW/Mg/sB/S	2.79	Reference	0	-0.78

¹ www.era.rothamsted.ac.uk

(COL)	BIO1	wW/Mg/sB/S	3.93	Biowaste	1.01	0.15	
	BOUE1	wW/Mg/sB/S	3.96	Sewage	0.49	-0.61	
				sludge			
	CFB1	wW/Mg/sB/S	4.04	Cow manure	1.07	-0.01	
	DVB1	wW/Mg/sB/S	4.00	Green	1.08	0.18	
				manure+Sewa			
				ge sludge			
	FB1	wW/Mg/sB/S	3.93	Cow manure	1.36	-0.01	
Crécom 3 PRO	Min	wW/sM	1.84	Reference+N	0	-0.06	
(CREC3)	FB2	wW/sM	1.92	Cow manure	1.82	0.49	
	FV	wW/sM	1.96	Poultry	0.47	-1.46	
				manure			
Feucherolles	ТО	wW/ Mg	2.22	Reference	0	-0.66	
(FEU)	BIO1	wW/Mg	3.44	Biowaste	2.21	3.60	
	DVB1	wW/Mg	3.45	Green	2.45	3.69	
				manure+Sewa			
				ge sludge			
	FB1	wW/Mg	3.55	Cow manure	2.28	1.36	
	OMR1	wW/Mg	3.45	Household	2.11	1.72	
				waste			
Jeu-les-Bois	M0	wB/R/wW	2.99	Reference	0	-1.33	
(JEU)	CFB1	wB/R/wW	2.89	Cow manure	1.1	1.61	
	CFB2	wB/R/wW	3.06	Poultry	1.94	1.52	
				manure			
	FB2	wB/R/wW	3.11	Cow manure	2.43	0.99	
La Jaillière 2	Min	sM/wW	1.59	Reference+N	0	-1.43	
PRO							
(LAJA2)	CFB	sM/wW	1.25	Cow manure	1.14	-0.88	
	CFP	sM/wW	1.21	Pig manure	1	-1.09	
	CFV	sM/wW	1.31	Poultry	0.94	-1.60	
				manure			
	FB	sM/wW	1.29	Cow manure	1.44	-0.64	
	FP	sM/wW	1.27	Pig manure	1.07	-1.03	
	FV	sM/wW	1.40	Poultry	0.93	-1.59	
				manure			
Le Rheu 1	Min	sM	1.31	Reference+N	0	-1.51	
(RHEU1)	CFB1	sM	1.31	Cow manure	1.06	-1.21	
Le Rheu 2	ТО	sM	1.03	Reference	0	-1.72	
(RHEU2)	CFP1	sM	1.20	Pig manure	0.78	-1.28	
	FP	sM	1.30	Pig manure	1.62	-0.74	
Arazuri	DO_N0	B/P/W/Sf/O	0.98	Reference	0	1.00	
(ARAZ)	D1_F1	B/P/W/Sf/O	1.40	Sewage	2.82	0.40	
				sludge			

	D1_F2	B/P/W/Sf/O	1.41 Sewage		1.4	1.22
				sludge		
	D1_F3	B/P/W/Sf/O	1.44	Sewage	0.78	1.22
				sludge		
	D2_F1	B/P/W/Sf/O	1.30	Sewage	5.64	0.22
				sludge		
	D2_F2	B/P/W/Sf/O	1.40	Sewage	2.8	2.32
				sludge		
	D2_F3	B/P/W/Sf/O	1.49	Sewage	1.56	0.93
				sludge		
Ultuna	РО_В	O/sT/Mu/sB/FB/OsR/W/F R/M	1.03	Reference	0	-0.52
(ULTU)	S_F	O/sT/Mu/sB/FB/OsR/W/F R/M	1.10	Straw	1.77	-0.09
	GM_H	O/sT/Mu/sB/FB/OsR/W/F R/M	1.82	Green manure	1.76	0.11
	PEAT_I	O/sT/Mu/sB/FB/OsR/W/F R/M	1.14	Peat	1.97	2.17
	FYM_J	O/sT/Mu/sB/FB/OsR/W/F R/M	1.76	Farmyard	1.91	0.69
	SD_L	O/sT/Mu/sB/FB/OsR/W/F	0.82	Sawdust	1.84	0.56
	SS_O	O/sT/Mu/sB/FB/OsR/W/F	2.59	Sewage	1.84	1.36
Dece allocal	2 111	R/IVI	0.00	Sludge		0.00
Broadbalk	3_INIII	ww	0.36	Reference	0	-0.09
(BROAD)	19_Cast	wW	0.65	Castor meal	0.43	0.42
	22_FYM	wW	2.07	Farmyard Manure	3	0.38
Foggia***	Т0	W	1.56	Reference	0	-0.86
	Dw-Dw-Fall	W/W/F	2.13	Rotation	0.57	0.01
	Dw-Fall	W/F	1.95	Rotation	0.39	-0.33
	Dw-Oa-Fall	W/O/F	2.20	Rotation	0.64	-0.33
	Dw-Dw-Cp	W/W/C	2.53	Rotation	0.97	-0.15
	Dw-Dw-To	W/W/T	2.57	Rotation	1.01	-0.59
Trévarez	Min	RG/Mg/wW/sM	1.94	Reference+N	0	-0.66
(TREV)	FB	RG/Mg/wW/sM	2.04	Cow manure	1.52	-0.39
	FP	RG/Mg/wW/sM	2.02	Pig manure	1.18	-0.18
Avrillé	T12TR	wW/sM	2.25	Reference	0	-1.18
(AVRI)	T2TR	wW/sM	2.36	Cow manure	1.68	-0.76

*Crops: sM = silage Maize, Mg= Maize grain, wW = winter Wheat, W = Wheat, sB

= spring Barley, wB = winter Barley, B = barley, S = sugarbeet,

R = Rapeseed, Sf = Sunflower, O = Oats, P = Pea, sT = Swedish Turlip, Mu =

Mustard, DF = Fodder Beet, OsR = Oilseed Rape, FR = fodder Rape,

F = green Fallow, C = Chickpeas, T = Tomato, RG = Ray Grass

**Optimal amounts of mineral fertilizers added to the control plot and to all other treatments in the experiment

*** In Foggia, additional carbon inputs from organic treatments were calculated for each rotation as the difference between C inputs in the rotation and the reference wheat-only rotation.



Figure 2-1. Location of the 60 field trials distributed among the 14 cropland experiments around Europe.

Table 2-2: Information about experimental sites, including: mean annual values of temperature (C°) and soil humidity to approximately 20 cm depth (kgH2O m-2soil) simulated with the ORCHIDEE model at each experimental site, measured pH, bulk density (g cm-3), clay (%) and initial SOC stocks in the control plots (MgC ha-1) at the experimental sites. Reference papers for each site are indicated. 1For Arazuri, data were directly provided by the Spanish Mancomunidad de la Comarca de Pamplona.

Sites	Reference paper	Coordinates	Years	Mean annual Temperature	Mean annual soil humidity	рН	Bulk density	Clay	Initial SOC stocks
				°C	$kgH_2Om^2_{soil}$		g cm ⁻³	%	MgC ha ⁻¹
Champ Noël	(Clivot et al.,	48.09° N,	1990 - 2008	12.1	21.6	6.3	1.35	15.1	40.57
3*	2019)	1.78 ° W							
Colmar	(Levavasseur	48.11 °N,	2000 - 2013	9.6	24.6	8.33	1.3	23.1	54.33
	et al., 2020)	7.38 ° E							
Crécom 3	(Clivot et al.,	48.32 °N,	1986 - 2008	11.8	22.9	6.15	1.36	14.6	62
PRO	2019)	3.16 ° W							
Feucherolles	(Levavasseur	48.88° N,	1998 - 2013	11.9	21.2	6.73	1.32	15.6	39.78
	et al., 2020)	1.96° E							
Jeu-les-Bois	(Clivot et al.,	46.68° N,	1998 - 2008	12.2	22.1	6.27	1.52	10	48.53
	2019)	1.79° E							
La Jaillière 2	(Levavasseur	47.44° N,	1995 - 2009	12.7	20.5	6.8	1.37	20.8	32.42
PRO	et al., 2020)	0.98° W							
Le Rheu 1*	(Clivot et al.,	48.09°N,	1994 - 2009	12.2	21.8	5.85	1.27	16.4	36.23
	2019)	1.78° W							
Le Rheu 2*	(Clivot et al.,	48.09 N,	1994 - 2009	12.2	21.8	6.05	1.28	13.9	36.53
	2019)	1.78 W							
Arazuri ¹	-	42.81° N,	1993 - 2018	12.7	20.4	8.6	1.67	27.9	55.39
		1.72° W							
Ultuna	(Kätterer et	59.82°N,	1956 - 2008	5.7	22.6	6.23	1.4	36.5	41.72
	al., 2011)	17.65° E							
Broadbalk	(Powlson et	51.81° N,	1968 - 2015	10.2	21.5	7.8	1.25	25	24.84
	al. 2012)	0.37° W							
Foggia	(Farina et al.,	41.49° N,	1992 - 2008	15.5 11.8	22.4 23.4	8.1 6.01	1.32	41	63.22 115.33
	2017)	15.48° E							
Trévarez	(Clivot et al.,	48.15° N,	1986 - 2008				1.48	19.2	
	2019)	3.76° W							
Avrillé*	(Clivot et al.,	47.50°N,	1983 - 1991	12.0	20.2	6.59	1.4	17.6	54.46
	2019)	0.60° W						-	
*These experiments were part of the initial French database (AIAL) described in Clivot et al. (2019), but they were not selected for the									

final modelling work of this latter study. For more information, see also Bouthier et al. (2014).

2.2.4 Carbon inputs

The allocation of C in the aboveground and belowground parts of the plant was estimated with the approach first described by Bolinder et al. (2007) for Canadian experiments and then adapted by Clivot et al. (2019) to the same French sites we use in this study. This methodology allows splitting C inputs from crop residues after harvest into aboveground and belowground C inputs, using measured dry matter yields and estimations of the shoot-to-root ratio (S:R) and harvest indexes (HI) of the crops (see Figure 2-2). The aboveground plant material is estimated as the harvested part of the plant (C_P), which is exported from the soil, plus the straw and stubble that are left in the soil after harvest (Cs). The harvested part consists of the measurements of DM yields (Y_P), while the straw and stubble are estimated using the HI coefficient of the different crops in the rotation (Bolinder et al., 2007). We assumed that the values used in Clivot et al. (2019) for the HI compiled from French experimental sites were applicable to all the sites in our dataset, which mainly include temperate sites over Europe. When these values were not available for some crops, they have been directly derived from Bolinder et al. (2007) or other sources in the literature (S:R ratio for fallow from Mekonnen, Buresh, and Jama (1997) and tomato from Lovelli et al. (2012)). When straw was exported from the field, we considered that only a fraction of C_s was left on the soil. This fraction was set to 0.4 for all sites and to 0.2 in Ultuna, where almost no stubble was left on the soil, since plots were harvested by hand and crops were cut at the soil surface. We considered a C content of 0.44 gC gDM⁻¹ in the aboveground plant material (Redin et al., 2014) and 0.4 gC gDM⁻¹ in the belowground part material (Bolinder et al., 2007). We used the asymptotic equation of Gale and Grigal (1987) to determine the cumulative BG input fraction from the soil surface to a considered depth:

$$BG_{F\,depth} = 1 - \beta^{depth},\tag{2}$$

where β is a crop-specific parameter determined using the root distributions for temperate agricultural crops, reported in Fan et al. (2016) and Clivot et al. (2019). The depth was set to 30 cm, since it was the depth at which soil samples were taken in the majority of the sites. For more details on the C inputs allocation method and the allometric functions involved, see Bolinder et al. (2007) and Clivot et al. (2019).



Figure 2-2 Adapted from (Bolinder et al., 2007). Representation of the distribution of carbon in the different parts of the plant: CP represents the carbon in the harvested product (grain, forage, tuber); CS is the carbon in the aboveground residues (straw, stover, chaff); CR is the carbon present in roots and CE represents all the extra-root carbon (including all root-derived materials not usually recovered in the root fraction).

2.2.5 Century model

2.2.5.1 Model description

For this study, we selected the Century model, which has proved to be well suited to simulate accurately the soil C dynamics in a range of pedoclimatic areas and cropping systems (Bortolon et al., 2011; Cong et al., 2014; Parton et al., 1993), and because we had the full command of the model for fine tuning of parameters. Soil C dynamics in a soil organic matter (SOM) model with first-order kinetics can be mathematically described by the following first-order differential matrix equation:

$$\frac{\mathrm{d}\boldsymbol{SOC}(t)}{\mathrm{d}t} = \boldsymbol{I} + \mathbf{A} \cdot \boldsymbol{\xi}_{\mathrm{TWLCI}}(t) \cdot \mathbf{K} \cdot \boldsymbol{SOC}(t), \tag{3}$$

where *I* is the vector of the external C inputs to the soil system, with four nonzero elements (Figure 2-3). The second term $\mathbf{A} \cdot \boldsymbol{\xi}_{\mathsf{TWLCI}}(t) \cdot \mathbf{K} \cdot SOC(t)$ of the equation represents organic matter decomposition rates (diagonal matrix **K**), losses through respiration ($\boldsymbol{\xi}_{\mathsf{TWLCI}}(t)$), transfers of C among different SOC pools (**A**) and SOC evolution with time (SOC(t)) (see Appendix A). We used the daily time-step version of the SOM model Century (Parton et al., 1988) to simulate the amount of C inputs required to reach a 4‰ annual increase of SOC storage over 30 years. In the version used, only SOC is modelled and plant growth is directly accounted as variations of C inputs. The original version of Century simulates the fluxes of SOC depending on soil relative humidity, temperature and texture (as a percentage of clay). As shown in Figure 2-3, the model is discretized into 7 compartments that exchange C with each other: 4 pools of litter (aboveground metabolic, belowground metabolic, aboveground

structural and belowground structural) and 3 pools of SOC (active, slow and passive). The litter C is partially released to the atmosphere as respired CO₂ and partially converted to SOM in the active, slow and passive pools (see Table S1 in the supporting information for default Century parameters). The decomposition rate of C in the *i*th pool depends on climatic conditions, litter and soil characteristics and is calculated using environmental response functions, as follows:

$$\xi_{TWLCl}(t)_i \cdot K_i = k_i \cdot f_T(t) \cdot f_W(t) \cdot f_{L\,i} \cdot f_{Clav\,i},\tag{4}$$

where i = 1, ..., 7 is one of the aboveground (AG) and belowground (BG) metabolic and structural litter pools, and the active, slow and passive SOC pools; K_i is the $(K)_{ii}$ element of the diagonal matrix **K** in Eq. (3); k_i is the specific mineralization rate of pool i, $f_T(t)$ is a function of daily soil temperature, $f_W(t)$ is a function used as a proxy to describe the effects of soil moisture, $f_{L\,i}$ is a reduction rate parameter acting on the AG and BG structural pools only, depending on the lignin concentration in the litter and $f_{Clay\,i}$ is a reduction rate function of clay on SOC mineralization in the active pool. The temperature function $f_T(t)$ describes the exponential dependence of soil decomposition on surface temperature, through the Q₁₀ relationship that was first presented by M. J. H. van't Hoff in 1884:

$$f_{\rm T}(t) = Q_{10} \frac{\frac{(I(t) - I_{ref})}{10}}{10},$$
(5)

where Q_{10} is the temperature coefficient, usually set to 2 and T_{ref} is the reference temperature of 30 °C. The Q_{10} factor is a measure of the soil respiration change rate as a consequence of increasing temperature by 10°. The other environmental response functions are described in Appendix A.



Figure 2-3 Representation of litter and soil organic carbon (SOC) pools in Century. The model takes as inputs litter carbon from plants (aboveground metabolic (I1), belowground metabolic (I2), aboveground structural (I3) and belowground structural (I4)). A certain fraction of carbon can be transferred from one pool to another and each time a transfer occurs,
part of this carbon is respired and leaves the system to the atmosphere as CO2. The SOC active pool receives carbon from each litter pool, while only the structural material is transferred to the SOC slow pool. Litter material never goes directly to the SOC passive pool while the three SOC pools exchange C within each other.

2.2.5.2 Model initialization

The initialization of the model consists of specifying the sizes of the SOC pools at the beginning of the experiment. Here, we assumed initial pools are in equilibrium with C inputs before the experiments begin, in absence of knowledge about past land use and climate making initial pools different from steady state (Sanderman et al., 2017). Then, initialization can be done either by running the model iteratively for thousands of years to approximate the steady state solution (numerical spin-up), or semi-analytically by solving the set of differential equations that describes the C transfers within model compartments (Xia et al., 2012). We solved the matrix equation by inverse calculations for determining pools sizes at steady state, as in Xia et al. (2012) and Huang et al. (2018). These authors demonstrated that the matrix inversion approach exactly reproduces the steady state and SOC dynamics of the model. By speeding up the performance of the simulations, this technique allowed us to perform the optimization of model parameters, the sensitivity analysis of SOC to climatic variables and the quantification of model outputs uncertainties through Monte-Carlo (MC) iterative procedures. We solved the matrix equation by using its semi-analytical solution and the following algorithm: 1) calculating annual averages of matrix items obtained by Century simulations, driven by 30 years of climatic forcing; 2) setting Eq. (3) to zero to solve the state vector **SOC**. For each agricultural site, the 30 years of climate forcing were set as the 30 years preceding the beginning of the experiment, and the litter input estimated from observed vegetation was set to be the average litter input in the control plot over the experiment duration.

2.2.5.3 Model calibration: optimization of the metabolic:structural fractions of the litter inputs

In the Century model, AG and BG carbon inputs are further separated into metabolic and structural fractions, according to the lignin to nitrogen (L:N) ratio. Because the L:N ratio was not available for all the crops in the database, we fitted model simulations to observed SOC dynamics for the control plot of each site, i.e. the reference plot without additional C inputs, in order to get the metabolic:structural (M:S) fraction of the AG and BG carbon inputs. We used the sequential least-squares quadratic programming function in Python (SciPy v1.5.1,

scipy.optimize package with method='SLSQP'), a nonlinear constrained, gradient-based optimization algorithm (Fu et al., 2019). We successfully performed the optimization on 13 sites, where at least three measures of SOC stocks were available. For *Jeu-les-Bois*, which includes two SOC measurements only, we decided to use the same optimized values as for *Feucherolles*, which has similar pedoclimatic conditions and crop rotations. The optimization consisted in minimizing the following function:

$$J_{fit} = \sum_{i=1}^{n} \frac{\left(SOC_i^{model} - SOC_i^{obs}\right)^2}{\sigma_i^{2} SOC_{obs}},$$
(6)

where i=1,...,n is the year of the experiment, SOC_i^{model} (MgC ha⁻¹) is the SOC simulated with Century for year i, SOC_i^{obs} (MgC ha⁻¹) is the observed SOC for year i in the control plot and $\sigma_i^{2SOC_{obs}}$ is the variance of the SOC_i^{obs} estimated from the different replicates. When replicates were not available, we recalculated $\sigma_i^{2SOC_{obs}}$ as the variance amongst SOC_{obs} samples of the whole experiment. The optimized M:S values are reported in Table 3-3 and represent the average quality of litter C in the rotating crops along the duration of the experiments that match control SOC data at each site.

Table 2-3 Optimized values of the aboveground metabolic (AM), aboveground structural (AS), belowground metabolic (BM) and belowground structural (BS) fractions of the litter inputs and the Q10 and reference temperature (°C) parameters.

Site	AM	AS	BM	BS	Q ₁₀	Reference temperature	
						°C	
CHNO3	0.85	0.15	0.26	0.74	5.0	21.2	
COL	0.85	0.15	0.57	0.43	2.0	30.0	
CREC3	0.15	0.85	0.29	0.71	2.0	30.0	
FEU	0.85	0.15	0.52	0.48	5.0	21.6	
JEU*	0.85	0.15	0.52	0.48	5.0	21.6	
LAJA2	0.85	0.15	0.72	0.28	5.0	21.5	
RHEU1	0.85	0.15	0.49	0.51	5.0	21.3	
RHEU2	0.85	0.15	0.32	0.68	5.0	21.3	
ARAZ	0.53	0.47	0.53	0.47	3.0	30.0	
ULTU	0.85	0.15	0.85	0.15	2.2	30.0	
BROAD	0.42	0.58	0.15	0.85	2.9	30.0	
FOGGIA	0.15	0.85	0.15	0.85	5.0	27.1	
TREV1	0.15	0.85	0.15	0.85	5.0	23.0	
AVRI	0.85	0.15	0.76	0.24	2.0	30.0	

2.2.5.4 Model calibration: optimization of temperature dependency parameters

We optimized the Q_{10} and daily soil reference temperature parameters, which affect SOC decomposition. The Q_{10} factor is fixed to 2 in Century. However, many authors have shown that Q_{10} measurements vary with pedoclimatic conditions and vegetation activity (Craine et al., 2010; Lefèvre et al., 2014; Meyer et al., 2018; Wang et al., 2010). For this reason, and to reproduce correctly interregional variations among the sites in the dataset, we optimized both the Q_{10} and reference temperature parameters to better fit the SOC dynamics (MgC ha⁻¹) of each agricultural site at control plot. We decided to bind the Q_{10} between 1 and 5, following the variation of Q_{10} found by Wang et al. (2010) over 384 samples collected in the Northern Hemisphere. The reference temperature ranged between 10 and 30°C. We used the SLSQP optimization algorithm and the cost function of Eq. (6) to perform the optimization, which was successful in 13 sites and we assigned the values obtained from the optimization of *Feucherolles* to *Jeu-les-Bois*, where SOC measurements were too sparse to perform a two-dimensional optimization. Optimized values of Q_{10} and reference temperature are reported in Table 3-3.

Model performance in the control plot was evaluated using two residual-based metrics. The first one is the Mean Squared Deviation (MSD), decomposed into its three components to help locating the source of error of model simulations: the Squared Bias (SB), the Non-Unity slope (NU) and the Lack of Correlation (LC). The second metrics used is the Normalized Root Mean Squared Deviation (NRMSD) (see Appendix B).

2.2.6 4p1000 analysis

2.2.6.1 Optimization of C inputs to reach the 4p1000 target

After the spin-up to steady state, the model was set to calculate the SOC stocks dynamics of the control plot and the C inputs for virtual treatments, assuming an average increase of SOC stocks by 4‰ per year over 30 years. 30 years is considered as a period of time over which the variation of SOC can be detected correctly. During this period length, we supposed the soil was fed with constant amounts of C inputs from plant material. For the control, we derived C inputs from measurements of DM yields and calculated the annual mean over the whole experiment length. For the virtual treatments, we used an optimization algorithm to calculate the required amount of C inputs to reach a linear increase of SOC storage by 4‰ per

year above the SOC stock at the start of the simulation. Mathematically, we minimized the following function:

$$J_{4p1000} = |SOC_0 \cdot (1 + 0.004 \cdot 30) - SOC_{30}^{model}(I)|,$$
(7)

where I is the 1x4 vector of C inputs to minimize over, SOC_0 is the initial SOC stock and $SOC_{30}^{model}(I)$ is the SOC stock after 30 years of simulation. During the optimization, the M:S fractions were allowed to vary to estimate the quality of the optimal C inputs. Instead, we kept the aboveground:belowground ratio of the C inputs fixed to its initial value, to bind the model in order to represent agronomically plausible C inputs. In fact, if not bound, the model tends to increase the belowground C fraction to unrealistic values (assuming the same crop rotations persisted on site). On the other hand, keeping the aboveground:belowground ratio fixed implies that the simulated additional C inputs will be spread equally on surface and belowground. As for the previous optimizations, we used the Python function SLSQP to solve the minimization problem. The outcome of the optimization is a 4x1 vector (I_{opt}) representing the amount of C in the four litter input pools that matches the 4p1000 rate target.

2.2.6.2 Uncertainties quantification

Uncertainties of model outcomes were quantified using a Monte-Carlo approach. We initially calculated the standard error (SE) of the mean C inputs derived from yield measurements for each experimental site:

$$SE = \sqrt{\frac{\sigma^2_I}{s}},\tag{8}$$

where σ_{I}^{2} is the variance of the estimated C input from yield measurements and s is the length of the experiment. If not available, we calculated σ_{I}^{2} as the average relative variance of C inputs among the control plots. We therefore randomly generated N vectors of C inputs (*I*) around the calculated standard error and performed the 4p1000 optimization N times, each time using one of the generated vectors *I* as a prior for the optimization. To correctly assess the uncertainty over the required C inputs we set N to 50 (Anderson, 1976). The standard error of model outputs was calculated with Eq. (8), where the variance was set as the variance of the modelled carbon outputs and the experiment size (s) to 50.

2.2.6.3 Sensitivity analysis to temperature

We tested the sensitivity of model outputs to temperature, running two simulations with increased temperatures. We considered two representative concentration pathways (RCPs) of global average surface temperature change projections (IPCC, 2015). The first scenario (RCP2.6) is the one that contemplates stringent mitigation policies and predicts that average global land temperature will increase by 1°C during the period 2081-2100, compared to the mean temperature of 1986-2005. The second scenario (RCP8.5) estimates an average temperature increase of +4.8°C, compared to the same period of time. We ran two simulations of increasing temperature scenarios with Century. We considered the same initial conditions as the standard simulations, hence running the spin-up with the average soil temperature and relative humidity of the 30 years preceding the experiments. Then, we increased daily temperature by 1°C (AS1) and 5°C (AS5) for the entire simulation length, to assess the sensitivity of modelled C inputs to increasing temperatures. Nevertheless, it must be noted that our simulations are running over a 30 years period, not the entire 21st Century. Thus, the temperature sensitivity analysis should not be considered as a test of climatic scenarios but as a classical sensitivity analysis where the boundaries were defined following RCP2.6 and RCP8.5 predictions of increased temperatures.

2.3 RESULTS

2.3.1 Fit of calibrated model to control SOC values

Modelled and measured SOC stocks in the control plot were compared to evaluate the capability of the calibrated version of Century to reproduce the dynamics of SOC stocks in the selected sites (Figure 2-4.c). As shown in Figure 2-4.b, the NRMSD of the control plot SOC stocks is lower than 15% for all the treatments, indicating that overall model simulations fitted the observed SOC stocks well (observed SOC stocks variance was 16.3% on average in the control plots). The correlation coefficient between modelled and observed SOC stocks in the control plots was 0.96 (Figure 2-4.c). Figure 2-4.a provides the values of the three components of the MSD indicator for each site. It can be noticed that the LC and NU components are the highest contributors to MSD. This means that the major sources of error are the representation of the data shape and magnitude of fluctuation among the measurements. The highest NRMSD can be found in *Le Rheu 1* and *Le Rheu 2* (around 12% and 14%

respectively). In these sites the model seems to better capture the shape of the data (low LC compared to the other sites), but it misses the representation of mean SOC stock (high SB) and data scattering (high NU) of the experimental profiles. We tested the capability of Century to reproduce SOC stocks increase in the additional C input treatments (Figure 2-5). Figure 2-5 shows the correlation between additional C inputs and SOC stock increase in the C input treatments ($R^2 = 0.23$). In the same graph, we can appreciate additional C inputs simulated by Century to reach the 4p1000 target being 0.66 \pm 0.23 MgC ha⁻¹ per year (mean \pm standard deviation from the mean). This shows that Century is generally overestimating the effect of additional C inputs on SOC stocks increase. However, the effect of additional C inputs on observed SOC stock increase varies largely across different treatments.



Figure 2-4 a) Decomposed mean squared deviation (MgC ha⁻¹)² in control plots for all sites. LC = Lack of

Correlation, NU = Non-Unity slope and SB = Squared Bias. b) Normalized root squared deviation (%) in control plots for all sites c) Fit of predicted versus observed SOC stocks (MgC ha⁻¹) in control plots for all sites ($R^2 = 0.96$).



Figure 2-5 Correlation between additional carbon inputs (MgC ha⁻¹ per year) and annual SOC stock increase (%) in the carbon inputs treatments and mean \pm standard deviation of the additional carbon inputs to reach the 0.4% target in Century.

2.3.2 Estimates of additional carbon inputs and SOC changes

2.3.2.1 Virtual C inputs to reach the 4p1000

Figure 2-6 represents the average percentage change of C inputs required to reach the 4‰ annual increase of SOC stocks, among the whole sites. The increase of C inputs is given for each litter pool. On average, a 43.15 \pm 5.05 % (mean \pm SE across sites) increase of total annual C inputs compared to the current situation in the control plot, is required to meet the 4p1000 target. In terms of absolute values, this represents an additional 0.66 \pm 0.23 MgC ha⁻¹ inputs per year, i.e. 2.35 \pm 0.21 MgC ha⁻¹ total inputs per year (equivalent approximately to 4.05 \pm 0.36 MgDM ha⁻¹ per year). What stands out in the graph is that, on average among the studied sites, the AG structural litter pool should be more than doubled, while the other pools need only to increase by about half of their initial value. In terms of absolute values, the structural AG biomass (which was initially 0.29 MgC ha⁻¹ per year on average in the control treatments) would need an additional 0.18 MgC ha⁻¹ per year to reach the 4p1000; the metabolic AG (initially 0.70 MgC ha⁻¹ per year on average) needs an additional 0.14 MgC ha⁻¹

per year; structural and metabolic BG biomass (initially 0.65 and 0.52 MgC ha⁻¹ per year) require an additional C input corresponding to 0.21 and 0.13 MgC ha⁻¹ per year respectively. Analysis of the SOC pools evolution in the runs with optimized C inputs to match the 4p1000 increase rate, indicates that the active and slow pools increased by 0.58% and 0.61% per year respectively, while the passive pool increased annually by 0.01% (Figure 2-7). In absolute values, the slow compartment contributed the most to the increase of SOC during the 30 years runs, as it increased by 2.7 MgC ha⁻¹ on average among the sites (against an increase of 0.1 and 0.06 MgC ha⁻¹ in the active and passive compartments respectively). This corresponds to a storage efficiency for the 30 years of simulation of approximately 13.7 % in the slow pool, compared to a storage efficiency of 0.5% and 0.34% in the active and in the passive pools respectively.

We found a high linear correlation (R²=0.80) between observed initial SOC stocks and optimized C inputs (Figure 2-8). It is logical and expected that for low initial SOC stocks in steady state, a small increase of C inputs is sufficient to reach the 4p1000 target. Conversely, when SOC is high at the beginning of the experiment (e.g. *Trévarez*) much higher C inputs must be employed since our target increase rate is a relative target. The regression line that emerges from the cross sites' relationship can be written as:

 $I^{4p1000} = 0.013 \cdot SOC_0^{obs} + 0.001, \tag{9}$

where I^{4p1000} are the simulated C inputs needed to reach the 4p1000 target ($MgC ha^{-1}$ per year) and SOC_0^{obs} ($MgC ha^{-1}$) is the observed initial SOC stock.



Figure 2-6 Sites average percentage change of carbon inputs needed to reach the 4p1000 (TOT), separated into the four litter input pools. AM = aboveground metabolic, BM = belowground metabolic, AS = aboveground structural, BS = belowground structural and TOT = total litter inputs. Error bars indicate the standard error. N.B: Total change of carbon inputs (TOT) was calculated as the percentage change between the total amount of carbon inputs before and after the 4p1000 optimization, averaged across all sites.

2.3.2.2 Virtual versus actual C inputs in the experimental carbon treatments

In Figure 2-9 we compare the C inputs required to reach the 4p1000 target to the actual inputs used across the 46 treatments of additional C. The additional C (MgC ha⁻¹ per year) shown in the graph for all experimental treatments refers to exogenous organic amendments, plus additional C due to increased crop yields, relatively to the control plot. The most striking result emerging from the data is that modelled additional C inputs are systematically lower or similar to at least one treatment of additional C in all sites, except for *Foggia*. In *Foggia* experiment, different crop rotations were compared and no additional EOM was incorporated to the soil. Here, none of the rotations had sufficient additional C content (compared to the control wheat-only treatment), to meet the required C input level predicted by Century for a 4p1000 increase rate. Overall, 86.91% of the experimental treatments used higher amounts of C inputs compared to the modelled need of additional C inputs in the same site. For the other treatments, the difference between simulated and observed additional C input was not significant. In the experimental treatments were applied 1.52 MgC ha⁻¹ per year on average and SOC stocks were found to be increasing by 0.25% per year relative to initial stocks.

Modelled additional C input to reach a 0.4% increase was 0.66 MgC ha⁻¹ per year, on average among the sites.



Figure 2-7 Sites average soil organic carbon pools (ACT = active, SLOW = slow and PASS= passive) evolution (MgC ha⁻¹) over the 30 years of simulation to reach the 4p1000 target. In the graph the mean percentage increase is given for each SOC pool.



Figure 2-8 Correlation between initial observed SOC stocks (MgC ha⁻¹) and modelled carbon inputs needed to reach the 4p1000 target (MgC ha⁻¹ year⁻¹). The correlation coefficient (R²) is 0.80 and the regression line is $y = 0.013 \cdot x + 0.001$.

2.3.3 Carbon input requirements with temperature increase

The temperature sensitivity analysis of the Century model for the 4p1000 target framework is plotted in Figure 2-10. The required amount of C inputs to reach the 4p1000 target is likely

to increase with increasing temperature scenarios. In particular, C inputs will have to increase on average by 54% in the AS1 scenario of $+1^{\circ}$ C and 120% in the AS5 scenario of $+5^{\circ}$ C temperature change, relative to current C inputs in the control plots. This represents an additional C inputs increase of 11% and 77% respectively, compared to the business as usual scenario with current temperature setup (CURR). What can be clearly seen in the graph is the increased amount of C inputs required in *Trévarez*, where C inputs should more than quadruplicate to reach the 4p1000 objective.

2.4 DISCUSSION

2.4.1 Reliability of the Century model

The Century model has been widely used to simulate SOC stocks dynamics in arable cropping systems (Bortolon et al., 2011; Cong et al., 2014; Kelly et al., 1997; Xu et al., 2011). Optimizing the metabolic:structural ratio in the reference plots allowed us to initialize the C inputs compartments, since no measurement of the L:N ratio was available. This allowed us to: 1) take into account the average C quality of the litter pools in the different crops rotations and 2) estimate correctly the initial values of SOC stocks on the majority of the sites. On the other hand, this could have influenced the predicted redistribution of C in the additional C inputs required to reach the 4p1000 (Figure 2-6). We suggest that taking into account the historical site-specific land use could help initialize SOC stocks without requiring any assumption regarding the M:S ratio (e.g. with historically based equilibrium scenarios as in Lugato et al. (2014)). To further improve SOC stock simulations, we optimized the Q₁₀ and reference temperature parameters on the control plots, to account for the different pedo-climatic conditions of the experimental sites and enhance model predictions of SOC stocks dynamics (Craine et al., 2010; Lefèvre et al., 2014; Meyer et al., 2018; Wang et al., 2010). Although the dispersion of SOC stocks over time is not perfectly captured in the majority of the control plots (see the high LC component of the MSD in Figure 2-4), the simulations of SOC dynamics were improved by the optimization of temperature related parameters and the NRMSD was found to be lower than 15% on all sites. Figure C2 shows that the optimization of temperature sensitive parameters did not affect significantly the required C input estimation for the current temperature scenario. This means that, although parameters optimization improved the simulation of SOC stocks in the control plots, the final results are not affected by it. The

capability of Century to simulate SOC stocks in the simulations of additional C treatments might be a major shortcoming of modeling results. In fact, although SOC stocks were found to be increasing on average in the additional C treatments (0.25% per year with 1.52 MgC ha⁻¹ yearly additional C inputs), this increase rate is lower than the 0.4% increase of SOC stocks predicted by Century with lower amounts of virtual C inputs (0.66 MgC ha⁻¹ per year). This is pointed out in Figure 2-5, where we can see that predicted additional C inputs to reach the 4‰ are lower than the correlation line between additional C inputs and SOC stocks increase in field treatments. The overestimation of the C input effect on SOC stocks in Century might be related to the assumption that SOC stocks are in equilibrium with C inputs at the onset of the experiment and on the high sensitivity of the model to C inputs.



Figure 2-9 Additional modelled carbon inputs (MgC ha⁻¹ year⁻¹) to reach the 4p1000 (grey bars) compared to additional carbon input treatments (colored bars) on each experimental site. Additional carbon inputs for field trials are calculated as the sum of organic fertilizers and the delta carbon inputs from crop yields (compared to the control plot). Additional carbon treatments are separated into different categories: BIO waste = biowaste compost, green manure, green manure + sewage sludge and household waste, Cow Manure = cow manure and farmyard manure (in Broadbalk and Ultuna), Pig Manure, Poultry Manure, Sewage Sludge, Rotations = different crop rotations, Other organic amendments (OA) = straw, sawdust and peat (in Ultuna) and Castor Meal (in Broadbalk). The error bars shown are the standard errors computed with the Monte Carlo method.



Figure 2-10 Temperature sensitivity analysis of carbon inputs increase (%) to reach the 4p1000 objective. CURR=business as usual simulation, AS1=RCP2.6 scenario of +1°C temperature increase, AS5=RCP8.5 scenario of +5°C temperature change.

2.4.2 Increasing annual SOC stocks by 4p1000

2.4.2.1 Modelled carbon inputs to reach the 4p1000

Century simulations estimated that annual C inputs should increase by $43\pm5\%$ (SE) on average to reach the 4p1000 target on the selected experimental sites, under the condition that the additional C inputs are equally distributed among the surface and belowground, in order to maintain the same aboveground:belowground ratio as at the beginning of the experiment. Martin et al. (2021) found similar values of required additional C inputs to reach a 4p1000 target in France croplands (i.e. 42%, that is 0.88 MgC ha⁻¹ per year). This is higher than the values found by Chenu et al. (2019) using default RothC 26.3 parameters, who estimated a relative increase of C inputs in temperate sandy soils by 24% and in temperate clayey soils by 29%. Riggers et al. (2021) found that in 2095, a minimum increase of C inputs by 45% will be required to maintain SOC stocks of German croplands at the level of 2014. However, they found that to increase SOC stocks by 4‰ per year, a much higher effort will be required. That is, C inputs in 2095 will have to increase by 213% relative to current levels.

In our study, not only the quantity of C but also the quality will need to change according to Century predictions. In fact, the predicted aboveground structural litter change was threefold higher than all other pools on average, representing an additional 0.18 MgC ha⁻¹ each year. A way for the farmer to increase the structural fraction of the C inputs is to compost the organic amendments that will be spread on soil surface. Increasing EOM in large quantities may not be possible everywhere. First of all, the amount of organic fertilizers is limited at regional scale. If farmers source additional EOMs elsewhere, only those EOMs that otherwise would be mineralized (e.g. burnt) and not applied to land account as sequestration. Second, farmers may be prevented from applying high amounts of EOM because of the risk of nitrate and phosphate pollution (Li et al., 2017; Piovesan et al., 2009). Moreover, producing additional animal manure implies larger GHG emissions through animal digestion and manure decomposition. Consequently, even if more manure is returned to the soil, it will not necessarily result in climate change mitigation.

2.4.2.2 Stability of the additional carbon stored

Another important aspect to take into consideration is the stability of the additional C. In fact, the duration and persistence of C in the soil might be very different depending on whether or not the proportion of stable C is important. In the Century model, this translates into questioning whether the fractions of the long turnover rate pools (the slow and passive SOC pools) have increased. In our simulations, a general pattern can be detected (Figure 2-6) where both passive and slow pools increased, but at very different rates (0.1‰ and 6.1‰ per year respectively). The active pool increased by 5.8‰ annually, with benefits for soil fertility and hence food security. The additional C is mainly stored in the slow pool (2.7 MgC ha⁻¹ in 30 years of simulations), meaning that it will be stored in the soil for around 20 to 30 years. The increase in C inputs must be sustained to increase SOC stocks at the desired rate, until a new equilibrium will be reached. To further increase SOC stocks after the new equilibrium, new strategies of additional C could be implemented later on. For instance, this could be achieved

through the implementation of complementary management options to those considered in the long-term experiments described here, such as residue management, cover crops, conservation agriculture and agroforestry systems (Chenu et al., 2019; Lal, 1997; Smith et al., 1997).

2.4.2.3 Simulated carbon inputs and experimental carbon addition treatments

Different types of organic C treatments were considered in this study and compared to Century simulations of C inputs required to reach the 4p1000. In all experimental sites with additional EOM inputs, at least one treatment employed higher amounts of C inputs compared to the simulated C inputs required for a 4‰ annual target. In *Foggia*, C inputs from different crop rotations were studied, but none employed sufficient amounts of additional C to reach the 4p1000, as predicted by Century. Model results in *Foggia* had a high standard error, mainly due to the fact that the variability of crop yields for this site was not available. Thus, for this site, we calculated model uncertainty using the average relative variability across the whole dataset, which could have increased the uncertainty of model outputs.

It is important to note that the amount of C inputs simulated by Century was constrained to have the same AG:BG ratio as at the beginning of the experiment. This means that the additional C inputs should be distributed equally on soil surface and belowground, not to change the initial allocation of C in the litter pools. Since all field treatments were performed under conventional tillage, the comparison between modelled and observed additional C inputs under this constraint holds well.

The annual SOC stocks variation (0.25%) estimated in the experimental C treatments across the 14 sites, indicates that Century might be overestimating the effect of additional C inputs on SOC stocks. In particular, only 18 out of 46 field treatments (with average additional C inputs of 1.93 MgC ha⁻¹ per year) were found to be actually increasing SOC stocks at a higher rate than 4‰ per year, relatively to their initial SOC stocks. This is similar to the values found by Poulton et al. (2018), who estimated that adding similar high amounts of C inputs increased SOC stocks at an annual rate higher than 4‰ in 16 long-term agricultural experiments. Thus, Century seems to be over-predicting the effect of adding C inputs in the virtual simulations. The overestimation of the Century model might be due to several factors. First of all, the C inputs prescribed to model simulations were constant through time, while C inputs from plant material actually vary annually and over the years because of agronomical and climatic

factors. Historical land use and management practices such as tillage were not taken into account, although they affect SOC stocks (Pellerin et al. 2017). Another factor that the model is not taking into account is N and other nutrients availability, which might affect the SOC stocks dynamics. This is especially true for treatments with different frequencies of application (e.g. *Arazuri*), where nutrients depletion is likely to be more evident when the application is sparser. The method used to estimate C inputs (i.e. the allometric functions from Bolinder et al. (2007) in our case) also influences the simulation of SOC stocks (Clivot et al., 2019). However, estimating the increase of C inputs relative to their initial value has likely cancelled out uncertainties related to the C inputs estimation method in our analysis.

2.4.2.4 Organic carbon inputs use in Europe

Zhang et al. (2017) estimated that the amount of N inputs from livestock manure applied to European croplands was 3.9 Tg N in 2014, for a cropland area of 127 Mha in 2015 (Goldewijk et al. 2017). Cattle manure, which represents the highest proportion of manure produced and applied to croplands, has average C:N ratio ranging between 10 and 30 (multiple sources from Fuchs et al. (2014) and Pellerin et al. (2017)). With these data, we can roughly estimate the application of C manure from livestock in European agricultural soils as ranging between 0.30 and 0.92 MgC ha⁻¹ each year. Most of the experiments used in this study used higher amounts of C input (1.52 MgC ha⁻¹ per year on average). However, the C inputs requirement predicted by Century, which ranged between 0.24 ± 0.02 and 1.20 ± 1.00 MgC ha⁻¹ per year, plus one site with 1.45 ± 0.16 MgC ha⁻¹ per year, is in line with the average use of livestock manure in Europe. In terms of C sequestration, organic fertilizers coming from animal manure are usually being applied to the soil at some location, hence they cannot account for additional climate mitigation potential (Poulton et al., 2018). Rather, they are considered as a business as usual situation that can unlikely be significantly expanded. However, according to Zhang et al. (2017) estimation, there is room for improvement since the fraction of livestock manure applied to cropland in the 2010s was approximately 26% of total livestock production in Europe. The estimates from Zhang et al. (2017) refer to livestock manure only. In our study, we also considered treatments with other types of EOM addition, such as sewage sludge and household waste. In many countries, a significant proportion of food and urban waste is currently left on disposal areas, where C is lost to the atmosphere as CO_2 or methane (CH₄) emissions (Bijaya et al. 2006). Pellegrini et al. (2016) reported the amounts of sewage sludge

disposed on landfill in Europe (EU26) from Eurostat (2014b). In 2010, this was 0.914 TgDM. Using the Van Bemmelen factor (1.724) to convert OM to OC (McBratney and Minasny, 2010; Rovira et al., 2015), we estimated that the sewage sludge disposed on landfill in Europe was around 0.004 MgC ha⁻¹ per year in 2010. If applied to cropland, this could potentially increase C inputs to the soil and decrease GHG emissions associated to landfilled waste. However, in some countries social acceptability of spreading EOM such as sewage sludge is very low, limiting its actual potential. In Europe, landfilled municipal waste was 0.3 MgC ha⁻¹ in 2019 (estimated from Eurostat (2020) considering a C content in household waste of 71% (Larsen et al., 2013)). This is higher than the amount of municipal waste currently composted in Europe (i.e. 0.22 MgC ha⁻¹ in 2019, according to Eurostat (2020)), showing that additional efforts to improve the reutilization of municipal waste could help to increase C inputs in agriculture. A contribution to the sequestration of C from the atmosphere could also come from changing the treatment methods which affect the quality of C in crop residues and manure, so that their turnover time decreases, e.g. through fermentation or biochar. However, a full C cycle assessment should be considered to make sure that GHG emissions associated to such treatments do not exceed additional C storage (Guenet et al., 2020). In general, improving the use efficiency of EOM to the soil by managing it differently could contribute to some extent to climate change mitigation, increase soil quality, and reduce mineral fertilizers use (Chadwick et al. 2015). In this study, we did not include other potentially beneficial management practices, such as cover crops, reduced tillage, biochar application, improved soil pH, landscape differentiation and mineral amendments. Further research should investigate if long-term experiments with these management practices would be able to increase SOC stocks by 4p1000, following Century predictions.

2.4.2.5 Reaching a 4p1000 target: only a matter of initial SOC stocks?

As we expected, the estimated amount of C inputs to reach the 4p1000 target was linearly correlated to the initial observed level of SOC stocks (Figure 2-7). This result means that site differences in Q₁₀ and decomposition rates are less influential than initial SOC in determining the optimal input increase to reach the 4‰ per year target. The linearity between C inputs and initial SOC stocks is primarily due to the linear structure of the Century model. In fact, if we consider the stationary solution for which Eq. (2) is equal to 0, SOC depends linearly on the carbon inputs. Therefore, the opposite is also true (i.e. carbon inputs are linearly

dependent to the initial amount of SOC stocks). Moreover, the 4p1000 target itself is defined as the increase of SOC by 0.4% per year, relatively to its initial value (Minasny et al., 2017). Hence, it implies a proportional contribution that depends on the initial SOC stocks. Wiesmeier et al. (2016) also observed a linear relationship between SOC increase and C inputs. This linear relationship means that soils with high SOC stocks will have to increase their carbon stocks more in absolute terms to meet this quantitative target. On the other side, smaller amounts of C will have to be employed in sites with low levels of SOC stocks, to reach a 4p1000 target. However, increasing C inputs where SOC stocks are low might require substantial changes in the agricultural systems and such quantity of additional OM might not be available at a large scale. A counterpoint is also that the largest contribution of C sequestration will come from soils with medium or high SOC stocks (i.e. higher than 50 MgC ha⁻¹, such as grasslands and forests). In these soils, the required additional C inputs will have to be higher according to Century, raising concern on a compensation of CO₂ emissions through improved SOC stocks at a global scale. This result depends on the quality of the simulated carbon inputs (i.e. the predicted metabolic:structural ratio) and does not take into account any notion of soil saturation. Before applying this trend to calculate the required C inputs from current SOC stocks, we should extend the database to cover different pedoclimatic regions and different ecosystems of the world. Moreover, inaccuracies in simulations outcomes, such as those found in this study, need to be reduced. As discussed in subsection 4.2.3, a better representation of C inputs dynamics and management practices could improve the simulation of SOC stocks.

We suggest to consider multi-model analysis for this type of work in the future (Farina et al., 2021), to acknowledge different representations of SOC and reduce the effect of single models' uncertainties. Furthermore, the likely increase of SOC mineralization due to future climate change (Wiesmeier et al., 2016) needs to be taken into account.

2.4.3 Sensitivity analysis

The predicted need of additional C inputs to reach the 4p1000 target is likely to be higher with future global warming, as a consequence of modified SOC decomposition rates. Considering the crucial role of soil as a land-use based option for mitigating climate change, recent studies have shown a growing interest in temperature sensitivity of SOC stocks decomposition (Dash et al., 2019; Koven et al., 2011; Parihar et al., 2019; Wiesmeier et al., 2016). We know that

the decomposition rate of SOM is affected – generally increased – with increasing temperatures. However, the magnitude of expected feedbacks is still surrounded by controversy. In particular, this is mainly due to the diversity of organic compounds in the soil that are known to have inherent sensitivities to temperature (Davidson and Janssens, 2006). In fact, a diversity of responses of decomposition rates to future climates can be expected, including increases due to higher temperature as well as decreases due to water limitation. In this context, the study of the Century model response to predicted scenarios of temperature increase is of primary importance. We mimicked the most optimistic (+1°C) and pessimistic (+5°C) RCPs scenarios of the 5th IPCC assessment report. Although these scenarios are calculated over ~100 years, we used these values over a 30 years simulation to assess the sensitivity of Century to temperature increase. What is striking from our results is that with increasing temperatures all sites will have to provide considerably higher amounts of C inputs to reach the 4p1000 target (Figure 2-9). In particular, the C inputs change needs to more than double in all sites, according to the worst-case scenario of +5°C. It is important to point out that the optimization of the Q₁₀ and reference temperature parameters are likely to influence the outcomes of the simulated SOC stocks and therefore the C inputs need. Nevertheless, comparing the carbon input change simulated with the optimized version of Century (Figure 2-9) to that simulated with the default parameters setting (Fig. C1), shows that the predicted C inputs change follows the same pattern, even though the intensity of the increase is considerably higher in the optimized version. These results can be understood in two ways. Either the optimized version of Century is overestimating the effect of temperature on SOC stocks decomposition, or SOC stocks decomposition patterns are likely to increase even more intensively when considering the entire range of possible Q_{10} values. In either case, further research is needed to reduce the uncertainty around the impact of climate change on SOC decomposition. Studies should also examine moisture change, which we did not take into account here. This is likely to be impacted as a consequence of modified precipitations and temperature (IPCC, 2015), with consequences on root respiration and microbial decomposition (Davidson and Janssens, 2006). Additionally, increased temperature and CO_2 concentration in the atmosphere, as well as changes in precipitations are likely to influence net primary production and therefore C inputs to the soil. All these feedbacks are important and must be taken into account for a comprehensive evaluation of C cycle effects on climate change.

2.5 CONCLUSION

The Century model predicted an average increase of annual C inputs by $43\pm5\%$ to reach a 4p1000 target over a range of 14 agricultural sites across Europe, with diverse soil types, climates, crop rotations and practices. The required simulated amount of additional C inputs was found to be systematically lower or similar to the 46 treatments of C inputs carried out in these sites. However, Century might have overestimated the predicted effect of additional C inputs on the SOC stocks variation rate, as the only field treatments that were found increasing SOC stocks by at least 4‰ annually were those using very high amounts of C inputs (~1.93 MgC ha⁻¹ per year). The predicted amount of additional C inputs depended linearly on the initial amount of observed SOC stocks in the control experiments, indicating that lower amounts of C inputs might be sufficient to reach the 4p1000 target where SOC stocks are low. However, increasing C inputs might require substantial changes in the agricultural systems and high quantities of additional organic matter might not be available at a large scale. Furthermore, the required amount of additional C inputs was found to increase substantially with future scenarios of changes in temperature, raising concern about the feasibility of a 4p1000 target under climate change and beyond that, the feasibility of SOC stock preservation. The magnitude of SOC storage potential in agricultural soils depends largely on site-specific conditions, such as climate, soil type and land use. In this study, we did not take into account the whole life cycle of C at the farm. However, compensating CO₂ emissions from human activities through SOC sequestration should also comprehend GHG emissions related to the management of additional EOM. In this study, we considered only temperate, subhumid and Mediterranean climates. A broader evaluation of the required C inputs and associated agricultural practices to increase SOC stocks should be carried out at larger scales. Causes of biases in model simulations should be addressed in future studies and the representation of C inputs should be improved. We also suggest that future research should include multiple models, to reduce the influence of extreme model outcomes on the representation of SOC stocks.

Authors contribution

YH provided the initial model code. EB edited and developed the model code, performed the simulations and prepared the manuscript with contributions from all co-authors. EB, CC, PC and BG designed the study. HC, IV, RF, TK and MM provided the data. All co-authors participated to the results analysis and the writing.

Competing interests

The authors declare that they have no conflict of interest.

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2.6 APPENDIX A – CENTURY MODEL DESCRIPTION AND ENVIRONMENTAL FUNCTIONS USED

The temporal evolution of soil organic carbon is described in the Century model as a first order differential matrix equation:

$$\frac{dSOC(t)}{dt} = I + \mathbf{A} \cdot \boldsymbol{\xi}_{\text{TWLCI}}(t) \cdot \mathbf{K} \cdot SOC(t),$$
(2)

where SOC(t) is the vector describing the SOC state variables. The first term on the right side of the equation represents carbon inputs to the soil coming from plant residues and organic material. Carbon inputs are allocated into four different litter pools. Hence, *I* is a 1x7 matrix with four nonzero elements. The second term of the equation represents carbon outputs from the soil, following a first order decay kinetics. **A** is a 7x7 carbon transfer matrix that quantifies the transfers of carbon among the different pools. The diagonal entries of **A** are equal to -1, denoting the entire decomposition flux that leaves each carbon pool. The nondiagonal elements represent the fraction of carbon that is transferred from one pool to another. **K** is a 7x7 diagonal matrix with the diagonal elements representing the potential decomposition rate of each carbon pool. $\xi_{TWLCI}(t)$ is the environmental scalar matrix, a 7x7 diagonal matrix with each diagonal element denoting temperature $(f_T(t))$, water $(f_W(t))$ lignin $(f_{L\,i})$ and clay $(f_{Clay\,i})$ scalars, which modify the potential decomposition rate. Temperature response function $f_T(t)$ is described by Eq. (4), the others are expressed as follows. The moisture function $f_W(t)$ is a polynomial function ranging from 0.25 and 1 and taking the form of:

$$f_{W}(t) = -1.1 \cdot w^{2} + 2.4 \cdot w - 0.29, \tag{A1}$$

where w is the daily relative humidity coefficient, which varies between 0 and 1 and was calculated from soil moisture $(m^3_{water} m^{-3}_{soil})$, using the following function from (Krinner et al., 2005):

 $w = \sum_{texture} \frac{conc_{texture} \cdot moisture - WP_{texture}}{FC_{texture} - WP_{texture}},$

where *w* is the estimated relative humidity, ranging between 0 and 1; *texture* = sand, silt and clay; *conc*_{texture} is the concentration of the different textures; *moisture* is soil moisture $(m^3_{water} m^{-3}_{soil})$, $WP_{texture}$ is the wilting point of the different textures (equivalent to 0.0657, 0.0884, 0.1496 for sand, silt and clay respectively) and $FC_{texture}$ is the field capacity of texture (equivalent to 0.1218, 0.1654, 0.2697 for sand, silt and clay respectively). The decomposition rate of structural litter pools is affected by their lignin content: $f_{Li} = e^{-lgc \cdot L}$, (A2)

where lgc is the coefficient that regulates the lignin effect, while L is the lignin structural fraction of the aboveground and the belowground litter pools.

Finally, the fraction of clay in the soil ($g \ clay \ g^{-1} soil$) influences the decomposition rate of the active pool:

$$f_{Clay i} = 1 - 0.75 \cdot clay.$$
 (A3)

2.7 APPENDIX B – MODEL EVALUATION

Two residual-based metrics were used to evaluate the goodness-of-fit of modelled and observed SOC stocks for each site: the Mean Squared Deviation (MSD) and the Normalized Root Mean Squared Deviation (NRMSD). The MSD for each site is defined as:

$$MSD = \frac{\sum_{i=1}^{n} (m_i - o_i)^2}{s},$$
 (B1)

where i = 1,...,n is the year of the experiment, m_i and o_i are respectively modelled and observed values of SOC stocks and s is the number of observations in the experiment. Following Gauch et al. (2003), the MSD can be decomposed into three components: the Squared Bias (SB), the Non-Unity slope (NU) and the Lack of Correlation (LC). SB is calculated as:

$$SB = (\bar{m} - \bar{o})^2, \tag{B2}$$

where \overline{m} and \overline{o} are the mean values of modelled and observed SOC stocks respectively. Calling $\Delta M_i = (\overline{m} - m_i)$ and $\Delta O_i = (\overline{o} - o_i)$ we have:

$$NU = \left(1 - \frac{\sum_{i=1}^{n} \Delta M_i \cdot \Delta O_i}{\sum_{i=1}^{n} \Delta M_i^2}\right)^2 \cdot \frac{\sum_{i=1}^{n} \Delta M_i^2}{s},\tag{B3}$$

$$LC = \left(1 - \frac{\sum_{i=1}^{n} (\Delta M_i \cdot \Delta O_i)^2}{\sum_{i=1}^{n} \Delta O_i^2 \cdot \sum_{i=1}^{n} \Delta M_i^2}\right) \cdot \frac{\sum_{i=1}^{n} \Delta O_i^2}{s}.$$
(B4)

These three components add up to MSD and help locating the causes of error of model predictions, determining areas in the model that require further improvement (Bellocchi et al., 2010). In particular, SB provides information about the mean bias of the simulation from measurements, NU indicates the capacity of the model to correctly reproduce the magnitude of the fluctuation among the measurements and LC is an indication of the dispersion of the points over a scatterplot, i.e. the capacity of the model to reproduce the shape of the data (Kobayashi and Salam, 2000).

The second statistical measure we used was computed as the squared root of the MSD, normalized by the mean observed SOC stocks:

$$NRMSD = \frac{\sqrt{MSD}}{\bar{o}} \cdot 100. \tag{B5}$$

This indicator is expressed as a percentage and allows to evaluate the model performance independently to the units of SOC stocks.



2.8 APPENDIX C – SENSITIVITY ANALYSIS WITH DEFAULT CENTURY PARAMETERS

Figure C1: Temperature sensitivity analysis of carbon inputs change (%) to reach the 4p1000 objective, using Century default Q10 and reference temperature parameters. CURR=business as usual simulation, AS1=RCP2.6 scenario of +1°C temperature increase, AS5=RCP8.5 scenario of +5°C temperature change.



Figure C2: Effect of the optimization of the Q_{10} and reference temperature (T_{ref}) parameters on the additional carbon inputs to reach the 4p1000 predicted by Century (mean \pm standard deviation).

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2.10 SUPPLEMENTARY MATERIAL

Table S1: Default parameters of the Century model affecting litter and SOC dynamics (Parton et al., 1988).

Parameter	Matrix source	Description	Value	Range	Units
fam2a	Α	Transfer fraction, aboveground metabolic litter to active SOC	0.45	[0:1]	
fbm2a	Α	Transfer fraction, belowground metabolic litter to active SOC	0.45	[0:1]	
fas2a	Α	Transfer fraction, aboveground structural litter to active SOC	0.55	[0:1]	
fbs2a	Α	Transfer fraction, belowground structural litter to active SOC	0.45	[0:1]	
fas2s	Α	Transfer fraction, aboveground structural litter to slow SOC	0.7	[0:1]	
fbs2s	Α	Transfer fraction, belowground structural litter to slow SOC	0.7	[0:1]	
fa2p	Α	Transfer fraction, active to passive SOC	0.004	[0:1]	
fs2a	Α	Transfer fraction, slow to active SOC	0.42	[0:1]	
fs2p	Α	Transfer fraction, slow to passive SOC	0.03	[0:1]	
fp2a	Α	Transfer fraction, passive to active SOC	0.45	[0:1]	
clay	A , f_{Clay}	Clay content		[0:1]	
lgc	A , <i>f</i> _{<i>L</i>}	Lignin coefficient of structural litters	3	[0:10]	
lga	A , <i>f</i> _{<i>L</i>}	Belowground lignin content	0.76	[0:1]	
lgb	A , <i>f</i> _{<i>L</i>}	Aboveground lignin content	0.72	[0:1]	
tau4ml	К	Turnover time, metabolic litter	0.066	[0:0.066]	year
tau4sl	К	Turnover time, structural litter	0.245	[0:0.245]	year
tau4a	К	Turnover time, active SOC	0.149	[0:0.149]	year
tau4s	К	Turnover time, slow SOC	5.48	[0:5.48]	year
tau4p	К	Turnover time, passive SOC	241	[0:241]	year

3 CHAPTER **3** MULTI-MODEL PREDICTIONS SHOW HIGH UNCERTAINTY OF CARBON INPUT CHANGES TO REACH A **4** PER **1000** ANNUAL INCREASE OF SOIL ORGANIC CARBON STOCKS

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Abstract

Increasing soil organic carbon (SOC) stocks by 4‰ per year in agriculture is one of the landbased mitigation solutions which is expected to limit future global warming. The main objective of this study was to estimate the feasibility and required C input changes of a 4‰ SOC stock increase. We used an ensemble of six SOC models to estimate the C input changes required to increase SOC stocks by 4‰ per year in 17 long-term agricultural experiments around Europe. We ran the models in two configurations: 1) with default parametrization and 2) with parameters calibrated site-by-site to fit the evolution of SOC stocks in the control treatments of the experiments (i.e. treatments without exogenous organic matter addition). We compared model simulations and analyzed the factors generating variability across models.

The calibrated ensemble was able to reproduce the SOC stock evolution in the control treatments. We found that, on average, the experimental sites needed additional 1.5 ± 1.2 Mg C ha⁻¹ yr⁻¹ to increase SOC stocks by 4‰ per year compared to initial conditions (multi-model median \pm median standard deviation across sites). That is, a 107% increase compared to initial conditions. While different variables related to climate and soil conditions explained the variability of the models in the default configuration (i.e., their relative standard deviation from the mean), only the structural differences among models could explain their diverging behavior when they were calibrated. Our work highlights the challenge of increasing SOC stocks in agriculture and accentuates the need to increasingly lean on multi-model ensembles when predicting SOC stock trends and related processes. To increase the reliability of SOC models under future climate changes, we suggest model developers to pay particular attention to the effect of additional C input on the variation of SOC stocks.

3.1 INTRODUCTION

The latest report of the Intergovernmental Panel on Climate Change (IPCC, 2021) announced observed changes in the whole climate system in every region across the world. Although many of the changes already set in motion are irreversible over hundreds to thousands of years, strong and sustained reduction of greenhouse gas emissions (GHGs) could still limit climate change (IPCC, 2021). Additional efforts to decrease the level of carbon dioxide (CO₂) and other GHGs in the atmosphere are expected from land-based mitigation solutions.
The European Commission has recently released a set of targets for European soils to become healthy, which include their contribution to climate change mitigation via increased atmospheric carbon (C) sequestration. The current average decline of SOC in European croplands (i.e. 5% yr⁻¹) is aimed to be reversed to a 1%-4‰ annual increase (Veerman et al., 2020). With the same perspective, the 4 per 1000 (4p1000) initiative has gathered contributions from hundreds of partners across the world since 2015, to promote agricultural practices that help to maintain or enrich cultivated soils in organic carbon (SOC), including those which restrict mineralization of SOC and increase its content in soil (Minasny et al., 2017). This will have the combined effect of improving soil quality (e.g., soil fertility and water retention (Lal, 2008)) while mitigating climate change through increased C sequestration in the soil. Despite the multiple benefits provided by increasing SOC stocks, the feasibility of a 4‰ objective with current agricultural management practices is still under debate (e.g. Chabbi et al., 2017; van Groenigen et al., 2017; Soussana et al., 2019; Rumpel et al., 2020). Recently, some studies using process-based modelling approaches focused on the biotechnical feasibility of SOC stock increase targets, such as a the 4‰ objective (e.g. Bruni et al., 2021; Martin et al., 2021; Riggers et al., 2021). Individual model's predictions of a 4‰ increase target in Europe are relatively optimistic. That is, a required 30 to 40% C input increase in France according to Martin et al. (2021) and a 43% increase in European long-term experiments (LTEs) according to Bruni et al. (2021) under constant climate conditions. A multimodelling exercise from Riggers et al. (2021) predicted a much larger increase, that is a 213-283% increase of C input required between 2090 and 2099, compared to 2014, under different climate change scenarios. Multi-model ensemble means are expected to provide improved estimates compared to singular model's simulations, due to the relative independence of different SOC models' simulation errors (IPCC, 2007). Furthermore, simulations designed with multiple models that have underlying structural differences provide an uncertainty range of SOC projections that reflects our current understanding of SOC processes and their possible representations. The use of multi-model ensembles to predict the evolution of complex systems is a widespread practice in other disciplines, such as climate modelling (Tebaldi and Knutti, 2007; Parker, 2010; Jebeile and Crucifix, 2020). Although some efforts have been made in the soil modelling community to embrace this practice (e.g., Palosuo et al., 2012; Sulman et al., 2018; Farina et al., 2021; Riggers et al., 2021), its use is not consolidated yet.

In the present paper, we aim to: 1) use multi-model ensembles to simulate the SOC stock evolution in long-term cropland experiments and evaluate two multi-model ensemble configurations, one with default model parameters and the other with parameters calibrated site-by-site, 2) provide an estimate of the C input required to annually increase SOC stocks by 4‰ in 17 long-term experiments (LTEs) across Europe, and 3) identify potential factors creating uncertainty across models. With this work, we want to contribute to the understanding of the feasibility of a 4‰ SOC stock increase target in Europe and to add a piece to the ongoing discussion about the use of multi-model ensembles in soil science.

3.2 MATERIALS AND METHODS

3.2.1 Experimental sites

The dataset used in this study compiles 17 long-term cropland experiments located in Europe (10 in France and 1 each in Spain, Great Britain, Sweden, Italy, Germany, Poland and Austria). Each experiment includes a control treatment and one or several treatments of additional exogenous organic material (EOM), for a total of 46 EOM treatments. The data consists of several measurements of SOC content and its variance across replicates, yearly crop yields and different soil characteristics (Table A1). The experiments lasted on average 25 years (median of 19 years), in the period between 1956 and 2018. EOM inputs were applied to the soil at different rates and frequencies and varied from animal manure (swine, bovine and poultry) to sewage sludge, peats, castor meal, sawdust, biowaste, green manure and household waste (i.e., residual organic material generated from residential waste). Data for Bologna's experiment were directly extracted from Triberti et al. (2008) and consist of the average SOC stock evolution in different inorganic nitrogen (N) experiments (i.e., one treatment without any inorganic fertilizer and 3 treatments with different levels of N input). Cropping systems (Table A2) were cereal-dominated rotations (wheat, maize, barley and oat). In particular, four were monocultures of forage crops or cereals (silage maize in Champ Noël 3, Le Rheu 1 and Le Rheu 2 and winter wheat in Broadbalk) and five sites had rotations of different cereals (winter wheat and silage or grain maize in Crécom 3 PRO, Feucherolles, La Jaillière 2 PRO, Avrillé and Bologna). The other experiments rotated cereal crops with legumes (chickpea, pea) and/or root crops (potatoes, fodder beet, fodder rape and Swedish turnip),

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oilseed crops (oilseed flax, sunflower, oilseed rape, mustard and rapeseed), and cover crops (rye grass).

Except for Müncheberg that was irrigated in 4 out of 8 replicates between 1974 and 1981, all experiments were rainfed and managed under conventional tillage (the Ultuna trial was tilled by hand with a spade to mimic conventional tillage). Straw residues were exported from the field, except in the French, Austrian and German sites, where residues were partly or totally incorporated to the soil. The French experiments Champ Noël 3, Crécom 3 PRO, La Jaillière 2 PRO, Le Rheu1 and Trévarez received optimal amounts of mineral nitrogen (N) fertilizers both in the control and in the treatments. In the Polish experiment in Grabów, N was applied as ammonium nitrate (34% N), phosphorus (P) as triple superphosphate (45% P₂O₅) and potassium (K) as potassium chloride (60% K₂O).

3.2.2 Climate forcing

Daily soil surface temperature, moisture and potential evapotranspiration were simulated for each site using the land-surface model ORCHIDEE (Krinner et al., 2005). Simulations were run using a 3-hourly global climate dataset at 0.5° (GSWP3 http://hydro.iis.utokyo.ac.jp/GSWP3/), from which we also derived daily precipitation data. Mean annual surface temperature (MAST) during the experiments ranged between 5.7 °C and 12.8 °C across the sites, while mean annual precipitation (MAP) was 851 mm, with a minimum of 613 mm and a maximum of 1314 mm (Table A3). The virtual amount of C input required to increase SOC stocks was analyzed over the period 1980-2010, which was the 30-yearlong interval covering the majority of the experiments.

3.2.3 Soil sampling

Soil samples were collected between 20 and 40 cm depth, in 3 to 8 replicates. In Champ Noël 3 replicates were not available and in Broadbalk, SOC was measured using a semi-cylindrical auger, bulking together 10-20 cores from across the plot. SOC stocks were calculated using the standard formula:

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

where SOC (%) is the concentration of organic C in the soil and BD is the average bulk density of the experimental plot. BD across the sites ranged between 1.1 and 1.7 $g \cdot \text{cm}^{-3}$. Its

evolution over time in the EOM treatments was not taken into account due to lack of data for all experiments. In Ritzlhof, BD measurements were not available. Hence, we estimated BD using the pedotransfer function developed by Kaur et al. (2002), using clay and silt content in the soil. We found a similar value as Kaur et al. (2002) in LUCAS soil maps (Ballabio et al., 2016). Clay content ranged from 5% to 36%, while soil pH varied from 5.8 to 8.6 across the sites. Calcium carbonate (CaCO₃) content was particularly important in Arazuri, Colmar, Grabów and Broadbalk soils (160, 130, 77 and 20 $g_{CaCO_3} \cdot kg^{-1}_{soil}$ respectively), while the rest of the sites had none or negligible quantities of CaCO₃.

3.2.4 Multi-model ensemble

Six SOC models were used for the multi-model ensemble analysis: Century (Parton et al., 1988), Roth-C (Jenkinson, 1990), ICBM (Andrén and Kätterer, 1997), AMG (Andriulo et al., 1999), MIMICS (Wieder et al., 2015) and Millennial (v2) (Abramoff et al., 2022). All six models take as inputs C from plant litter and other organic material and focus on the dynamics of C within a single soil layer (0 - 30 cm). Four of the models (i.e., Century, Roth-C, ICBM and AMG) represent soil C dynamics using a conventional multi-compartmental structure, where C is decomposed following first order decay rates. The number of equations (and compartments) differs from model to model. The remaining two more recent models (i.e., MIMICS and Millennial) have microbial explicit C pools, where the turnover of litter and SOC pools is governed by temperature-sensitive Michaelis-Menten kinetics. Each model was initialized with the standard modelling practice which is commonly used for the model and using methods that reduced the running time of the spin-up (e.g., the semi-analytical spin-up for Century and Roth-C).

ICBM is run at an annual time step and can be solved analytically due to the linearity of its system of equations. The model consists of two compartments: a young and an old SOC pool. Environmental factors are summarized into one coefficient that affects the decomposition rates of both soil compartments equally (r). The response functions to the temperature and moisture used to calculate the parameter r, which has to be normalized against the Ultuna experiment, were derived from Fortin et al. (2011) and Karlsson et al. (2011). Following its standard initialization method (Saffih-Hdadi and Mary, 2008), AMG was initialized using the value of SOC during the first year of the experiments and run numerically afterwards. The model contains one fresh organic matter pool and two SOC pools (active and stable). The

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stable pool is considered constant throughout the simulation length, while the other pools are decayed at an annual rate. Both Roth-C and Century models were solved semi-analytically, following the method described in Huang et al. (2018) and Xia et al. (2012). The method consists of: 1) solving the set of differential equations by inverse calculations to determine pools sizes at steady state 2) running the model numerically for the rest of the simulation. Century has four litter pools (structural and metabolic aboveground litter C and structural and metabolic belowground litter C) and three SOC pools (active, slow and passive), which differ for their decomposition rates. It was run at a daily time step. Roth-C simulates the SOC evolution on a monthly time step and was converted into its matrix continuous form following Parshotam (1996). The model has five pools: decomposable and resistant plant material (DPM and RPM), microbial biomass, humified organic matter (HUM) and inert organic C. This latter pool is constant through time and is calculated from the level of SOC at the beginning of the experiment. Both MIMICS and Millennial models were initialized using a Newton-Raphson approach that calculates the steady-state of the C pools analytically (stode function of the rootSolve package in R (Soetaert and Herman, 2009)). They were run numerically afterwards. MIMICS has seven SOC pools: two litter C pools that correspond to metabolic and structural litter, two microbial pools and three soil organic matter (SOM) pools (a physically protected, a bio-chemically recalcitrant and an available SOM pool). It is usually run at an hourly time step, but it was run at a daily time step instead, to decrease the running time of the simulations. The Millennial model has five measurable pools of C: particulate organic matter (POM), low molecular weight C (LMWC), aggregate C, mineral-associated organic matter and microbial biomass C (MIC). It was run at a daily time step.

3.2.5 Calibration of model parameters

All models were run with two configurations: 1) using default parameters and 2) using calibrated parameters that were optimized site by site in order to fit the evolution of observed SOC stocks in the control treatments. In Century, Roth-C, ICBM and AMG, the calibration of the parameters was performed using the sequential least-squares quadratic programming function in Python (SciPy v1.5.1, scipy.optimize package with method='SLSQP'), a nonlinear constrained, gradient-based optimization algorithm (Fu et al., 2019). For MIMICS and Millennial, we used the limited-memory quasi-Newton method (optim function in the stats package in R, with method= "L-BFGS-B", Byrd et al., 1995). We applied a different algorithm

to these two models because the SLSQP function was not available in R. The use of R for MIMICS and Millennial was imposed by the fact that they needed to be spun-up each time a new set of parameters was generated for calibration using the stode function in R.

To standardize the optimizations, we selected parameters that affect C decomposition (see Table 3-1 and Appendix B). In ICBM, the young pool is multiplied by a decomposition rate (k_1) and the old pool is altered by two decomposition rates (k_1 and k_2). Both pools are also altered by the environmental factor r. These three parameters were optimized, following Andrén and Kätterer (1997). The active pool in AMG is decayed at a rate k, which depends on environmental factors and on a potential mineralization rate (k₀). k₀ is usually optimized to fit SOC stocks (Andriulo et al., 1999 and Clivot et al., 2019). In Century, C decomposition is mostly influenced by the temperature response function, which follows the van't Hoff relationship, based on the Q₁₀ factor (M. J. H. van't Hoff, 1884). Following Bruni et al. (2021), we calibrated the Q₁₀ and reference temperature factors (T_{ref}), after calibrating the metabolic:structural litter ratio of the aboveground (M:S_{AG}) and belowground (M:S_{BG}) litter pools. These latter parameters are used to partition the C input into the different litter pools, and are a function of the nitrogen: lignin (N:L) ratio of the plants. They were optimized since no data was available on the N:L ratio of the different crops. SOC decomposition in Roth-C is also sensitive to the temperature response function, which is an empirical function initially built for the Rothamsted experiment (Jenkinson, 1990). We calibrated the temperature function parameter (T_{param}) for each experimental site. In MIMICS, we calibrated the tuning coefficients $(a_v \text{ and } a_k)$ of the temperature-sensitive kinetic parameters, on which the rates of C decomposition depend. As in Century, we also calibrated the parameter that is used to partition litter inputs into their metabolic and structural fraction (f_{met}). In Millennial, we optimized 1) the activation energy (Ea_{pl}) and 2) the half-saturation constant (K_{pl}) of the maximum rate of POM decomposition, and 3) the activation energy (Ea_{lb}) of the maximum uptake rate of the LMWC pool. Both activation energies are modified by an Arrhenius temperature relationship and are linked to the decomposition of POM into LMWC and to the microbial uptake of LMWC (Abramoff et al., 2022).

Carbon input from plant material was calculated from annual crop yield measurements, following the method developed by Bolinder et al. (2007) for Canadian experiments and adapted by Clivot et al. (2019) to the same French experiments used in this study. The allometric functions used to estimate the C input and its allocation to the aboveground and

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belowground part of the plant can be found in the paper from Clivot et al. (2019) and have already been applied to other agricultural experiments in European temperate climates such as those in our study (Bruni et al., 2021).

Model	Decomposition-	Description	Unit	Reference
	related optimized			paper
	parameters			
Century	M:S _{AG}	Metabolic:structural ratio		Parton et al.
		of the aboveground litter		(1988)
		pools		
	M:S _{BG}	Metabolic:structural ratio		
		of the belowground litter		
		pools		
	Q ₁₀	Q_{10} coefficient of the		-
		temperature response		
		function		
	T _{ref}	Reference temperature of	°C	
		the temperature response		
		function		
Roth-C	T _{param}	Parameter of the rate		Coleman and
		modifying factor for		Jenkinson
		temperature		(1996)
ICBM	k ₁	Potential mineralization	yr ⁻¹	Andrén and
		rate affecting the young		Kätterer
		and old SOC pools		(1997)
	k ₂	Potential mineralization	yr ⁻¹	
		rate affecting the old SOC		
		pool		

Table 3-1 Description of the calibrated parameters related to the decomposition of SOC in the different models.Functions where they appear are described in detail in Appendix B.

	r	Temperature and moisture	
		response function	
		parameter	
AMG	k ₀	Potential mineralization yr ⁻¹	Andriulo et al.
		rate of the active SOC pool	(1999)
MIMICS	f _{met}	Metabolic:structural ratio	Wieder et al.
		of the litter inputs	(2015)
	a _v	Tuning coefficient of the	
		maximum reaction velocity	
		of the Michaelis-Menten	
		kinetics	
	a _k	Tuning coefficient of the	
		half saturation constant of	
		the Michaelis-Menten	
		kinetics	
Millennial	Ea _{pl}	Activation energy for the J mol ⁻¹	Abramoff et
		maximum rate of POM	al. (2022)
		decomposition	
	K _{pl}	Half-saturation constant of $$ g C m ⁻²	
		POM decomposition to	
		LMWC	
	Ea _{lb}	Activation energy for the J mol ⁻¹	
		potential LMWC uptake	
		rate	

3.2.6 Required C input to increase SOC stocks by 4‰ per year

SOC stocks were simulated for each control treatment over the experiments' duration, to evaluate the capability of the models to reproduce observed SOC stocks. The period 1980-2010 was selected to analyze the virtual amount of additional C input required to increase

SOC stocks. We simulated one scenario of SOC stock evolution, where SOC stocks increased on average by 4‰ yr⁻¹ for 30 years, relative to the initial SOC stocks in the control treatments. The amount of C input required to increase SOC stocks by the defined target, was calculated using an inverse modelling approach that consisted in minimizing the following equation:

$$J = |SOC_0 \cdot target - SOC_{30}^{model}(I)|,$$

Where target = 1.12 (i.e., $1 + 0.004 \cdot 30$) since the objective was to reach an average SOC stock increase of 4‰ yr⁻¹ for 30 years. We used the Python function SLSQP to solve the optimization problem. C input quality is accounted differently in the different models. In Millennial, regardless of its quality 1/3 of the C input is allocated to POM and the rest 2/3 to LMWC (Abramoff et al., 2022). In Century and MIMICS, the allocation of the C input to the metabolic and structural litter pools depends on the L:N ratio of the C input material. Hence, the C input quality can be inferred by the M:S ratio of the C input. For these models, during the optimization process we did not prescribe the quality of the C input since the optimization directly simulated the optimal allocation of C in the different litter pools to reach the 4‰ target. However, for Century, we constrained the virtual C input to have the same aboveground:belowground ratio as the initial litter inputs, assuming that crops would not change with the 4‰ implementation and that the EOM would be equally split above and below the soil surface (see Bruni et al., 2021).

In AMG and ICBM, the humification coefficient h varies according to the quality of the C input. For instance, in AMG h = 0.217 for aboveground winter wheat and h = 0.52 for cow manure (Bouthier et al., 2014). In ICBM, h = 0.125 for straw and crop residues and h = 0.31 for farmyard manure (FYM) (Andrén and Kätterer, 1997). In Roth-C, when entering the soil, 59% of litter inputs from crop plant material are allocated to DPM and 41% to the RPM compartment, while FYM is assumed to be more decomposed and is split in the following way: 49% DPM, 49% RPM and 2% HUM (Coleman and Jenkinson, 1996). For these three models, a fraction *f* of the estimated C input was set to have the same quality as the litter input in the control treatment (i.e., its parametrization or its allocation to the different pools). The remaining (1 - f) fraction of C input was set to have the average quality of the EOM in the different treatments at the experimental site. For example, for AMG a site with initial litter input from winter wheat equal to 2 Mg C ha⁻¹ yr⁻¹ in the control treatment, and with a cow manure treatment only, a fraction f = 2/I was set to have aboveground h = 0.217 and

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the remaining fraction (1 - f) was set to have above ground h = 0.52, where *I* is the estimated C input and where the maximum value of *f* was set to be 1.

Both non-calibrated and calibrated models were run independently to estimate the amount of C input to reach the 4‰ target at the 17 experimental sites.

3.2.7 Comparison of models' outputs

Models' outputs were compared using different techniques. First, we tested the effect of the models and of the calibration on the simulated C input needed to reach the 4‰ target. This was done using a linear mixed-effect (LME) model, with fixed effects for the explanatory variables: "model", "calibration" and the interaction between the two, and including a random effect for "sites". The model was fit by maximizing the log-likelihood and an analysis of variance (ANOVA) was applied to test the effect of the different explanatory variables on the simulated C input. Second, we looked for groups of models that behaved similarly. We created clusters based on the minimum correlation distance between models' outputs (i.e. the additional C input to reach the 4‰ target). The distance was calculated with an optimization algorithm based on minimum spanning tree (Müller et al., 2012). To estimate which measured variables better explained the differences between the models' outputs, we used a linear model. The explanatory variables of the linear model were: MAST, MAP, PET, initial C input (C_0^{in}) , clay and CaCO₃ content, soil C:N and pH, initial SOC stocks and N input (Nin). This latter was considered as a categorical variable, equal to 1 if N inputs were applied at any dose and 0 otherwise. The response variable was the relative standard deviation (RSD) among models' outputs. To select the more parsimonious model, we performed a step wise regression by Akaike Information Criteria (AIC). The results for the multi-model ensembles are provided as their multi-model median (MMM) and mean.

3.3 RESULTS

3.3.1 Evaluation of the multi-model ensemble configurations: prediction of the SOC stocks in the control treatments

In Figure 3-1 we show the regression of the predicted and observed SOC stocks in the control treatments. The MMM of the non-calibrated models (Figure 3-1.a) shows a coefficient of determination (R^2) of 0.18. The calibration of model parameters improved the simulation of SOC stocks in the control treatments ($R^2 = 0.98$) (Figure 3-1.b). A summarized description of

models' performances is presented in the Taylor diagram of Figure 3-2. The similarity between simulated and observed SOC stocks in the control treatments is quantified in terms of: 1) their correlation (R), 2) their SD, which is normalized against the observations, and 3) their centered root-mean squared error (NRMSE). Apart from Century (normalized SD of 1.04), the noncalibrated models overestimated (i.e., Roth-C) or underestimated (i.e., AMG, ICBM, Millennial and MIMICS) the variation of SOC stocks from their mean. The calibration of model parameters reduced this error, since the normalized SD is closer to 1 in all calibrated models. The non-calibrated AMG outperformed the other non-calibrated models both in terms of correlation (R = 0.96) and NRMSE (0.28). It also outperformed the calibrated version of Millennial (R = 0.81 and NRMSE = 0.62) and performed similarly to the calibrated version of MIMICS (R = 0.96 and NRMSE = 0.28). Table 3-2 presents the R^2 and the RMSE for all models and for the MMM. In the calibrated configuration, ICBM outperformed the other models with the highest R² (0.98 as in AMG and in the MMM) and the lowest RMSE (1.92). Except for AMG, the MMM performs better than all single models in the non-calibrated configuration. In the calibrated configuration, the MMM ($R^2 = 0.98$ and RMSE = 2.34) outperforms all single models, except for ICBM and AMG which have the same R² and a slightly lower RMSE.



Figure 3-1 Predicted and observed SOC stocks (Mg C ha⁻¹) in the control treatments, for the six models with: (a) non-calibrated and (b) calibrated parameters. The purple lines represent the multi-model median (MMM).



Figure 3-2 Taylor diagrams showing the non-calibrated (full spots) and calibrated (crossed spots) model performances. X-axis and Y-axis show the standard deviation of SOC stocks' simulations for each model, normalized against the observations. The circumference of the quarter circle shows the correlation coefficient (R) of the different models between simulated and observed SOC stocks in the control treatments and the grey arcs represent the centered normalized root-mean squared error.

	P ² non-calibrated	P ² calibrated	RMSE	RMSE calibrated	
	K Hon-calibrated	K Calibrated	non-calibrated		
CENTURY	0.02	0.96	20.05	2.89	
ROTHC	0.05	0.96	28.79	2.87	
ICBM	0.02	0.98	21.09	1.92	
AMG	0.92	0.98	4.26	2.28	
Millennial	0.06	0.66	20.08	9.42	

Table 3-2 Statistics of models and MMM performances.

MIMICS	0.10	0.93	17.08	4.26
MMM	0.18	0.98	15.36	2.34

3.3.2 Evaluation of the multi-model ensemble configurations: effect of additional C input on the SOC stock increase

The capability of the multi-model ensemble to predict the effect of additional C input on SOC stock changes is illustrated in Figure 3-3. The graph shows the correlation between additional C input and SOC stock increase in the EOM treatments (R² = 0.55). For the treatments, additional C input was calculated as the yearly average amount of EOM added to the soil, plus the increased crop productivity relative to the control treatment. The correlation line and its confidence interval (CI) at 95% can be compared to the simulated non-calibrated and calibrated MMMs of the additional C input to reach a 4‰ increase of SOC stocks. The MMMs are shown together with their CI across sites (blue and orange crosses, respectively). The non-calibrated configuration is significantly different from the correlation line in the EOM treatments. In particular, the effect of additional C input on the SOC stocks is overestimated by the non-calibrated MMM. On the contrary, the calibrated MMM is not significantly different from the calibrated multi-model ensemble configuration is able to predict correctly the effect of additional C input on SOC stocks, when compared to the 46 EOM treatments of the 17 experimental sites in our database.



Figure 3-3 SOC stock increase (%) for different levels of additional C input in the organic amendment treatments experiments (black spots) and additional C input required to reach the 4‰ SOC increase according to the 1) non-calibrated multi-model median, MMM (blue cross) and the 2) calibrated multi-model median (orange cross). Errors are shown as confidence intervals (CI) The regression line between additional C input and SOC stock increase in the EOM treatments is indicated in the figure ($y = m \pm SD \cdot x + b \pm SD$).

3.3.3 Required C input to reach a 4‰ target

Both non-calibrated and calibrated model configurations were run inversely to estimate the amount of C input required to increase SOC stocks by 4‰ yr⁻¹ on average, for 30 years. Table 3-3 shows the percentage change of C input required to reach the target, relative to the initial level of C input in the control treatment. In the non-calibrated configuration, the median C input change is 59.4% (MMM), with a multi-model mean (\pm SD) of 84.5% (\pm 77.5%). The calibrated configuration predicts a median increase of 107.4% (MMM) to reach the target and a multi-model mean of 107.4% (\pm 54.8%). We can see that there is a high variability across models for both configurations (Table 3-3). However, when comparing the relative standard deviation (RSD = SD/mean \cdot 100) of the non-calibrated (91.6%) and calibrated (51%) configurations, we can see that the calibration reduces the variability among models (Table 3-3).

Figure 3-4 shows the mean additional C input across sites predicted by each model, and the MMM for both ensemble configurations. The calibrated MMM (1.49 \pm 1.19 Mg C ha⁻¹ yr⁻¹, median of the average C input across sites \pm median SD across sites) is higher than the non-calibrated MMM (0.87 \pm 0.34 Mg C ha⁻¹ yr⁻¹). As shown in Figure 3-3, the calibrated MMM is lower but not significantly different from the C input needed to increase SOC stocks by 4‰ inferred from the EOM treatments (regression line at x = 0.4 in Figure 3-3), i.e., 1.98 \pm 0.15 Mg C ha⁻¹ yr⁻¹.

The increased median variability across sites of the calibrated ensemble (RSD = 40% in the non-calibrated and 80% in the calibrated configuration) is mainly an effect of the ICBM, Millennial and MIMICS models. Indeed, the calibrated versions of these models have a higher RSD relative to their non-calibrated versions. Compared to the other models, both Century and Roth-C seem less sensitive to the calibration of the parameters. In these models, the mean additional C input and its RSD from the mean virtually do not change from one configuration to the other. AMG is the only model where the calibration decreases the variability of the estimated C input across sites (RSD = 77%), compared to its non-calibrated version (RSD = 94%). Table 3-4 shows the results of the ANOVA of the LME model. We found that the explanatory variable "model" had a significant effect on the simulated C input (p < 0.05), i.e., the difference between simulated C input in the various models was statistically significant. Furthermore, we observed a significant interaction effect between models and calibration. This means that the effect of the calibration on the simulated C input depended on the model (Table 3-4).



Figure 3-4 Required additional C input to reach a mean annual 4‰ SOC stock increase for 30 years according to the different models, and MMM for the 1) non-calibrated (blue) and 2) calibrated (orange) models' versions.

Table 3-3 Required percentage change of C input to increase SOC stocks by 4‰ per year on average over the period 1980 – 2010 for the non-calibrated and calibrated models' configurations. In the table are specified the multi-model median (MMM), the multi-model mean, the standard deviation (SD) from the mean and the relative standards deviation (RSD).

	C input change (%) required to increase SOC stocks by						
	4‰ yr ⁻¹ on average for 30 yea	rs					
	Non-calibrated	Calibrated					
AMG	216.1	142.9					
CENTURY	27.1	40.5					
ICBM	21.1	101.5					
MILLENNIAL	149.3	189.2					
MIMICS	57.5	113.2					
ROTHC	61.3	57.4					
MMM	59.4	107.4					
Mean	84.5	107.4					
SD	77.5	54.8					
RSD	91.6	51.0					

Table 3-4 Effect of "model" and "calibration" on the estimated C input to reach the 4p1000 target. Results fromthe ANOVA of the LME model, with random effect of the sites.

	p-value
Intercept	< 0.0001
Model	< 0.0001
Calibration	0.0404
Model · Calibration	0.0021

3.3.4 Clusters and variability among models

The heatmap of Figure 3-5 shows the level of the additional simulated C input to reach the 4‰ for each site and each calibrated model. On the above part of the figure are drawn the relationships of similarity among models. The clusters are based on the minimal correlation distance among simulated C input. What can be appreciated from the graph is that there are two main groups of models that behave similarly, when calibrated. The first cluster is formed between the AMG and ICBM models. The second cluster incorporates Century, Roth-C, Millennial and MIMICS (the first two models being more correlated to each other than the other two). The results of the stepwise AIC algorithm (**Table 3-5**) show that no variable has a significant effect (p < 0.05) on the RSD of the simulated C input among calibrated models. In the non-calibrated configuration, the RSD is explained by different variables (i.e., initial SOC stocks, MAP, initial C input and soil pH, **Table 3-5**)



Figure 3-5 Heatmap of the simulated additional C input to reach the 4‰, for each calibrated model and each site. Darker cells show lower C input and light cells represent higher C input. Dendograms above the heatmap represent the relationship of similarity among groups of models, calculated as the minimal correlation distance.

Table 3-5 Results of the stepwise AIC model for the non-calibrated (left) and calibrated (right) configurations. The linear model was originally built with the following variables: initial SOC stocks, mean annual surface temperature (MAST) and precipitation (MAP), potential evapotranspiration (PET), initial C input (C_0^{in}), clay and CaCO₃ content, soil C:N ratio, soil pH and N input (N_{in}). This latter was provided as a categorical variable, equal to 1 if the experiment was fed with some N input, and 0 otherwise. In the table are shown the variables selected by the stepwise algorithm as being the most significant to explain the RSD of the simulated C input among models. At the bottom are specified: the residual standard error, the multiple and adjusted R², the F-statistic and *the p-value of the selected AIC model*.

Non-calibrate	Non-calibrated					Calibrated				
		Std.						Std.		
	Estimate	Error	t value	Pr(> t)			Estimate	Error	t value	Pr(> t)
(Intercept)	1.017	0.259	3.933	0.0043	**	(Intercept)	3.290	2.522	1.305	0.2330
Initial SOC						Initial SOC				
stocks	0.005	0.002	2.527	0.0354	*	stocks	-0.015	0.007	-2.054	0.0790
MAST	0.036	0.024	1.524	0.1661		MAST	0.254	0.178	1.421	0.1980
MAP	0.001	0.000	4.060	0.0036	**	MAP	0.001	0.001	1.349	0.2190
PET	0.000	0.000	-1.080	0.3116		PET	-0.002	0.001	-1.644	0.1440
C_0^{in}	-3.790	0.521	-7.276	0.0001	***	C_0^{in}	5.285	3.491	1.514	0.1740
Clay	0.684	0.452	1.513	0.1687		Clay	6.538	4.014	1.629	0.1470
рН	-0.117	0.048	-2.461	0.0392	*	CaCO ₃	0.008	0.006	1.413	0.2010
c(N _{in})	-0.111	0.071	-1.567	0.1559		рН	-0.604	0.511	-1.181	0.2760
						Soil C:N	-0.149	0.082	-1.820	0.1120
Significative codes: 0 '***' 0.001 '**' 0.01					•					
Residual standard error: 0.1 on 8 degrees of freedom				Residual standard error: 0.4 on 7 degrees of freedom						
Multiple R-squared: 0.95,				Multiple R-squared: 0.62, Adjusted R-squared: 0.14						
F-statistic: 17.	15 on 8 and 8	DF, p-val	ue: 0.0002			F-statistic: 1.291 on 9 and 7 DF. p-value: 0.3764				

3.4 DISCUSSION

3.4.1 Evaluation of the multi-model ensemble configurations

The calibration of model parameters improved the simulation of SOC stocks in the control treatments of the 17 LTEs used in this study (Figure 3-1). In a multi-modelling exercise, Farina et al. (2021) showed that site-specific calibration improved the simulation of SOC stocks in 7 barefallow LTEs in Europe. This was true both compared to a non-calibrated and to a multi-site calibration configuration (i.e., where generic parameters are optimized for all sites together). Site-specific calibration accounts for the spatial variability of model parameters across sites. However, in order to have a unique solution to the parameters' calibration, site-specific calibration of a chrono-sequence requires a high number of SOC measurements in time at each site (since the number of parameters to calibrate must be lower than the number of data points). In our study, the calibration was also validated against the effect of C input on SOC stocks. In fact, the calibrated multi-model ensemble better reproduced the effect of C input on SOC stocks in the 46 EOM treatments, compared to the non-calibrated configuration (Figure 3-3). However, we found that the MMM of the additional C input to reach the 4‰, simulated by the non-calibrated and calibrated ensembles were not different from each other at a statistically significant level of p = 0.05 (Figure 3-3). This was partly because the variability across sites was high in both configurations (i.e., RSD across sites was 40% and 80% in the non-calibrated and calibrated ensembles, respectively) and that the variability across models was also high in both configurations (i.e., RSD across models was 91.6% and 51%, respectively).

The higher variability across sites in the calibrated configuration, compared to the non-calibrated ensemble was expected. In fact, the parameters were calibrated independently at each site, while in the default configuration models' parameters are constant for all sites.

3.4.2 Single model performances and MMM

Figure 3-2 helps to visualize models' performances. Although both ICBM and AMG outperformed the other models in the calibrated configuration ($R^2 = 0.98$), AMG performed better than any other model in its non-calibrated version ($R^2 = 0.92$ against a MMM $R^2 = 0.18$, Table 3-2).

However, AMG's comparison with the other models might be partly biased. Indeed, AMG is a French model that was initially calibrated on several LTEs across France, which include many of the experiments in our database. Hence, we cannot ascertain that its application to other sites outside the European temperate zone would be as straightforward, although the model has already been evaluated on a few sites outside Europe (Andriulo et al., 1999; Saffih-Hdadi and Mary, 2008). Furthermore, AMG was the only model initialized with observed initial SOC stocks, while the other models were spun-up either analytically or semi-analytically. In fact, AMG prescribes the initial fraction of total SOC that is considered stable, allowing to initialize the model with observed initial SOC stocks (Saffih-Hdadi and Mary, 2008). Most pool-based models do not prescribe default partitioning in the different SOC pools at the beginning of the experiment. Hence, initialization to allocate the C in their different pools is typically done by running the models with constant or repeating inputs until the C pools reach an equilibrium (i.e., spin-up). The amount of C allocated to each pool at equilibrium is a function of the inputs to the model and the parameters. Spin-up assumes that soils are at equilibrium (Luo et al., 2017; Xia et al., 2012), which is often not the case, especially for the agricultural soils with changing management practices considered in this study. Hence, simulations might be started at wrong initial values (e.g., Wutzler and Reichstein, 2007). An alternative initialization method that could be tested to compare models' performances using observed initial total SOC stocks would be to prescribe the initial partitioning of SOC in the different pools of those models that are usually initialized with spin-up. An attempt was made for instance with Roth-C in an Australian catchment (Karunaratne et al., 2014).

Although the calibration partly reduced the simulation's errors of models initialized with spin-up, not all calibrated models were able to start from the correct initial level of SOC stocks (FigS1). In particular, Millennial showed the lowest R² (0.66) among the calibrated models. The difficulty to fit Millennial's simulations to observed SOC stocks is likely due to the more complex processes described in the model (e.g., explicit Langmuir sorption to mineral aggregation, density-dependent microbial turnover, etc.), which cause the model to be less sensitive to the calibration of a few parameters. Limitations other than parametrization might also explain errors in modelling predictions. For example, previous land-use or current management practices, which

are likely to influence the level of SOC stocks at the onset of the experiment, were not prescribed to the models. In AMG, previous land-use is somehow accounted for, by setting a different fraction of SOC that is considered stable according to the historical use of the land (Clivot et al., 2019). While AMG has the clear advantage of starting its simulations at the observed SOC level, it also requires supplementary information which constrains its use to sites where SOC stock measurements are available at the onset of the experiment and previous land-use is known. Not only AMG outperformed all other models in the non-calibrated configuration, it also performed better than the MMM in both configurations (Table 3-2). However, the R^2 of the MMM fit was substantially higher than all other single models in the non-calibrated configuration and higher or similar to other single models in the calibrated configuration (Table 3-2). Tebaldi and Knutti (2007) pointed out that, while for a single given simulation the multi-model performance might not be significantly better than the single best model, improvements are more substantial when aggregated performances over many simulations are considered. In fact, not knowing a priori which one is the best model, it would still be more likely to get better results with the multi-model ensemble than with any of the models individually. Of course, as the multimodel ensemble gets larger, the estimates will be more reliable. Farina et al. (2021) suggested that the minimum number of models to obtain reliable results in SOC modelling would be ~ 10 models for non-calibrated multi-model ensembles, and 3 to 4 models if site-specific calibration is realizable. However, this likely depends on how much the mechanical structure varies among the multi-model ensemble.

3.4.3 Reaching a 4‰ target

Many recent works have studied the feasibility of the 4‰ target through a modelling perspective. Martin et al. (2021) estimated that a 30% to 40% increase in C input would be needed to reach a 4‰ objective in France, using an inverse Roth-C modelling approach. Bruni et al. (2021) used a similar inverse modelling approach with the Century model and applied it to 14 LTEs across Europe. They estimated that C input should increase by 43% on average, compared to the initial value of the experimental control treatments. These results are similar to our outputs from the Roth-C and Century model (Table 3-3). However, they are by far the most optimistic ones when compared to other models (Table 3-3). Furthermore, Bruni et al. (2021) showed that this prediction was largely affected by soil temperature changes. Riggers et al. (2021) used a multimodel ensemble to predict SOC stock increase scenarios under future climate change in German croplands. They estimated an average increase of C input of 213-283% to reach an average 4‰ increase between 2090 and 2099, compared to 2014. Our results seem to be in the middle of the range of existing estimates (i.e., a median increase of 107% according to the calibrated ensemble), which refer to the period 1980-2010 under current climate. Indeed, although the estimate of Riggers et al. (2021) is higher than ours, they estimated this change over a longer period (and under future changes in climate), when SOC stocks in German croplands are expected to decrease at a strong rate because of forecasted increased temperatures (Wiesmeier et al., 2016; Riggers et al., 2021).

Our findings show that the use of one single model to predict the evolution of SOC stocks and its related variables (e.g., the C input) is likely to bias the outputs of the modelling exercise. The present study raises the attention of the soil modelling community to the importance and utility of multi-modelling approaches. Multi-modeling approaches are especially necessary when models are used at new sites without previous validation. Besides, multi-modelling has been an established practice in climate projections for decades (Tebaldi and Knutti, 2007; Parker, 2010; Jebeile and Crucifix, 2020), one example being the Coupled Model Intercomparison Project (CMIP), which was created in 1995 and is nowadays the reference framework in which climate models are aggregated to predict future scenarios of climate change (Jebeile and Crucifix, 2020). These ensembles are currently used in the IPCC reports, considered to be the most reliable source of knowledge about climate change.

As for the feasibility of a 107% increase of C input, this likely depends on the reference practice against which it is compared. In fact, minerally fertilized crops might already have higher C input compared to unfertilized crops, due to higher nutrient availability that enhances net primary production (Gross and Glaser, 2021), making it harder to increase C input by ~107% in minerally fertilized crops. Doubling the C input where mineral fertilizers and EOM inputs are already applied will likely require the implementation of other agricultural practices (e.g., agroforestry systems, cover cropping, or crops with a high belowground biomass). This is the case for Europe, for example, where croplands are usually minerally fertilized (Eurostat, 2021) and where EOM

inputs are already widely applied (Zhang et al., 2017; Foged et al., 2011; Soussana et al., 2019). Furthermore, it is worth to note that the use of EOM does not result in additional C sequestration but rather to locally increased SOC stocks. For example, extracting peats from former peatlands is not itself a climate-relevant C sequestration practice. In our work, EOM treatments were used for methodological investigation purposes only. That is, to evaluate the multi-modeling tool with available agricultural LTEs where SOC stocks were measured after increasing C inputs to the soil.

3.4.4 Variability between calibrated models is due to structural model differences

The LME model showed that the models significantly affected the prediction of C input to reach the 4‰. That is, the prediction of each model was significantly different from the others. Furthermore, the effect of the calibration on the simulated C input was model-dependent. This can also be observed in Figure S2, where the relationship between C input and SOC stocks is plotted for each model in both configurations. We can see that the models have different sensitivities to the calibration when we look at the relationship between C input and SOC stocks (Figure S2). A part from Millennial, all models have a strong linear relationship between C input and SOC stocks in their non-calibrated configuration. However, both AMG and ICBM become less linear with calibration.

Figure 3-5 shows the creation of clusters between models that behaved similarly when calibrated to fit the SOC stocks. Although the ensembles' prediction of additional C input was highly variable in both configurations (Figure 3-4), some models' outputs were correlated to each other once calibrated to fit the stocks (while they were not in the default configuration, see Figure S3). Many factors could be responsible for the creation of such clusters. First of all, similarities in the mathematical structure of the models, such as the number of C pools, the linearity of the system of equations, or the type of kinetics reactions. Other computational differences could have introduced this clustering behavior. For instance, the spin-up method or the number and choice of parameters calibrated. Finally, the inherent representation of soil processes, i.e., the different characterization of pedo-climatic variables in the models' functions, which is also known as structural uncertainty in ensemble modelling (Tebaldi and Knutti, 2007).

Disregarding analogies in the mathematical structures of the models and their technical resolution, we investigated the effect of field variables on the variability of model outputs. We

found that, while in the non-calibrated configuration MAP, initial SOC stocks, initial C input and soil pH explained the divergence between models' outputs (i.e., their RSD), no field variable had a significant linear effect when models were calibrated (Table 3-5). This means that the calibration realigned the effect of all those variables that were causing models' outputs to diverge. These results suggest that the high variability across calibrated models was mainly due to their structural differences and/or to the technical resolution used. In particular, simpler models like AMG and ICBM seemed to behave similarly when calibrated (see Figure 3-5). Models with a higher number of pools clustered together, and among them models with similar types of kinetics were more correlated to each other (i.e., Century and Roth-C, which have first order kinetic reactions, and Millennial and MIMICS, which have Michaelis-Menten kinetics). It is likely that the way models account for C inputs (e.g., their humification rates, their partitioning within different litter pools, and the number of litter pools itself) also affected the variability among models' outputs and created the "structural clusters" of Figure 3-5. If models are correctly parametrized and simulate well the evolution of SOC stocks with time, we would expect them to converge regardless of their different mechanistic structures. However, our results suggest that the choice of the mathematical formalism with which SOC processes are represented affected significantly model predictions. This is particularly true for inverse modelling predictions of C input changes, where supplementary choices on the litter pools optimization have to be made. Our results show that, while improved parametrization reduces part of the uncertainty in the predictions, structural differences among models are a major factor producing diverging results. Because of the feedbacks between the climate system and the C cycle (e.g., changes in net primary productivity due to increased temperatures and CO₂ accumulation), the uncertainty of the effect of increased C input on SOC stocks is particularly relevant since it is likely to affect climate change projections. This underlines the importance of multi-model ensembles, both to account for and to potentially reduce the uncertainty among SOC models' predictions.

3.5 CONCLUSION

We found that the calibrated multi-model ensemble was able to correctly reproduce the SOC stocks changes at the 17 long-term European cropland experiments. We estimated that C input will have to increase by 107% (MMM) compared to the unamended controls to reach a 4%

objective at the experimental sites. Although still very high, we observed that the uncertainty among the different models was reduced when parameters were calibrated. The uncertainty among calibrated models was not explained by any field variable, indicating that the divergence in models' estimation of additional C input depended on their mechanistic structures.

We suggest that the soil modelling community increasingly rely on multi-modeling ensembles to account for such uncertainty. This is particularly important since uncertainties on the relationship between C input and SOC stocks will likely affect climate change projections, due to SOC-related feedbacks on the climate system.

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3.6 APPENDIX A

 Table A1 Information about the soil at the experimental sites in the control treatments at the onset of the experiments.

Site name	Sampling depth	Bulk density	Carbonate	Clay	Initial SOC stock	Soil C:N	рН	Reference paper
	cm	g cm ⁻³	g _{CaCO3} kg ⁻¹	%	Mg C ha ⁻¹			
Champ Noël 3 (CHNO3)	0-30	1.35	0	15	40.57	8.96	6.3	Clivot et al. (2019)
Colmar (COL)	0-28	1.3	129.57	23	54.33	10.52	8.33	Levavasse ur et al. (2020)
Crécom 3 PRO (CREC3)	0-30	1.36	0	15	62	10.17	6.15	Clivot et al. (2019)
Feucherolles (FEU)	0-29	1.32	0	16	39.78	9.89	6.73	Levavasse ur et al. (2020)
Jeu-les-Bois (JEU)	0-30	1.52	0	10	48.53	9.66	6.27	Clivot et al. (2019)
La Jaillière 2 PRO (LAJA2)	0-25	1.37	0	21	32.42	9.01	6.8	Levavasse ur et al. (2020)
Le Rheu 1 (RHEU1)	0-30	1.27	0	16	36.23	10.05	5.85	Clivot et al. (2019)
Le Rheu 2 (RHEU2)	0-30	1.28	0	14	36.53	8.22	6.05	Clivot et al. (2019)
Arazuri (ARAZ)	0-30	1.67	160	28	55.39	6.44	8.6	Simoes- Mota et al. (2021)
Ultuna (ULTU)	0-20	1.4	0	36	41.72	8.82	6.23	Kätterer et al. (2011)

Indefinition 0-23 1.25 20 25 24.84 8.95 7.25 et al. (2012) Trévarez (TREV) 0-30 1.48 0 19 115.33 9.49 6.01 (2012) Avrillé (AVRI) 0-30 1.48 0 19 115.33 9.49 6.01 (2012) Bologna 0-30 1.4 0 18 46.2 8.91 6.59 (2019) Bologna 0-40 1.16 0 28 25.41 7 6.9 Triberti et (BOLO) 0-40 1.16 0 28 25.41 7 6.9 Martyniuk (GRAB) 0-25 1.4 76.66 5 31.08 10.76 5.87 et al. (MÜNCHE) 0-25 1.47 0 5 19.66 10 5.95 et al. (RITZ) 0.25 1.47 0.03 23 28.88 9.42 6.88 n et al. (RITZ) 0-25 1.1 0.03 23.72 18.65	Draadhall								Powlso	on
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Arring (AVR) 0-30 1.4 0 18 46.2 8.91 6.39 $al. (2019)$ Bologna (BOLO) 0-40 1.16 0 28 25.41 7 6.9 Triberti et al. (2008) Grabów (GRAB) 0-25 1.4 76.66 5 31.08 10.76 5.87 et et al. al. Müncheberg (MUNCHE) 0-25 1.47 0 5 19.66 10 5.95 et et al. al. Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. n (2007) Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85		0.20	1 4	0	10	46.2	0.01	6 50	Clivot	et
Bologna (BOLO) $0 - 40$ 1.16 0 28 25.41 7 6.9 $Triberti et al. (2008)$ Grabów (GRAB) $0 - 25$ 1.4 76.66 5 31.08 10.76 5.87 et $al. (2008)$ Müncheberg (MUNCHE) $0 - 25$ 1.47 0 5 19.66 10 5.95 et $al. (2019)$ Ritzlhof (RITZ) $0 - 25$ 1.47 0 5 19.66 10 5.95 et $al. (2007)$ Mean 1.36 0.03 23 28.88 9.42 6.88 n et $al. (2007)$ Mean 1.36 22.72 18.65 43.46 8.61 6.63 (2020) Mean 1.36 0 18.32 40.17 8.98 6.44 (2020) Marinum 1.67 160 36 15.33 10.76 8.6 (200)	Avrille (AVRI)	0-30	1.4	0	18	46.2	8.91	6.59	al. (20	19)
(BOLO) 0-40 1.16 0 28 25.41 7 6.9 al. (2008) Grabów 0-25 1.4 76.66 5 31.08 10.76 5.87 et al. (2019) Müncheberg 0-25 1.47 0 5 19.66 10 5.95 et al. (2007) Mürschel 0-25 1.47 0 5 19.66 10 5.95 et al. (2007) Ritzlhof 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.67 160 36 115.33 10.76 8.6	Bologna	0.40	4.4.5	0	20	25.44	-	6.0	Tribert	ti et
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	(BOLO)	0-40	1.10	0	28	25.41	/	6.9	al. (20	08)
Grabow 0-25 1.4 76.66 5 31.08 10.76 5.87 et al. (GRAB) 0-25 1.47 0 5 19.66 10 5.95 et al. (MUNCHE) 0-25 1.47 0 5 19.66 10 5.95 et al. Ritzlhof 0-25 1.17 0.03 23 28.88 9.42 6.88 n et al. (RITZ) 0-25 1.16 0.03 23 28.88 9.42 6.63 Mean 1.36 0 18.32 40.17 8.98 6.44									Marty	niuk
(GRAB) (2019) Müncheberg (MUNCHE) 0-25 1.47 0 5 19.66 10 5.95 et al. (2007) Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6	Grabow	0-25	1.4	76.66	5	31.08	10.76	5.87	et	al.
Müncheberg (MUNCHE) 0-25 1.47 0 5 19.66 10 5.95 et al. (2007) Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6	(GRAB)								(2019)	
Muncheberg (MUNCHE) 0-25 1.47 0 5 19.66 10 5.95 et al. (2007) Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63									Mirsch	el
(MUNCHE) (2007) Ritzlhof 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6	Muncheberg	0-25	1.47	0	5	19.66	10	5.95	et	al.
Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6	(MUNCHE)								(2007)	
Ritzlhof (RITZ) 0-25 1.1 0.03 23 28.88 9.42 6.88 n et al. (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6									Kurzer	nan
(R12) (2020) Mean 1.36 22.72 18.65 43.46 8.61 6.63 Median 1.36 0 18.32 40.17 8.98 6.44 Minimum 1.1 0 5 19.66 0.09 5.85 Maximum 1.67 160 36 115.33 10.76 8.6	Ritzlhof	0-25	1.1	0.03	23	28.88	9.42	6.88	n et	al.
Mean1.3622.7218.6543.468.616.63Median1.36018.3240.178.986.44Minimum1.10519.660.095.85Maximum1.6716036115.3310.768.6	(RITZ)								(2020)	
Median1.36018.3240.178.986.44Minimum1.10519.660.095.85Maximum1.6716036115.3310.768.6	Mean		1.36	22.72	18.65	43.46	8.61	6.63		
Minimum1.10519.660.095.85Maximum1.6716036115.3310.768.6	Median		1.36	0	18.32	40.17	8.98	6.44		
Maximum 1.67 160 36 115.33 10.76 8.6	Minimum		1.1	0	5	19.66	0.09	5.85		
	Maximum		1.67	160	36	115.33	10.76	8.6		

Table A2 Agronomic information on the experimental sites.

Site	Experime	Treatment	Rotations *	C input from	C input from	Treatment	Initial	SOC
name	nt length	name		plants	EOM	type	SOC	stock
							stocks	increase
								**
				Mg ha ⁻¹ yr ⁻¹	Mg ha ⁻¹ yr ⁻¹		Mg ha⁻¹	%
CHNO3	19	Min	sM	1.29	0.00	Reference	40.57	-0.92
						+ N ***		
		LP	sM	1.49	0.79	Pig	43.30	-0.89
						Manure		
COL	14	Т0	wW/Mg/sB/S	2.79	0.00	Reference	54.33	-0.78

BOUE1 wW/Mg/sB/S 3.96 0.49 Sewage 54.33 -0.61 sludge			BIO1	wW/Mg/sB/S	3.93	1.01	Biowaste	54.78	0.15
IndexSinderSinderCFB1wW/Mg/sB/S4.041.07Cow51.420.01manurewW/Mg/sB/S4.001.08Green53.690.18manure +sewagesewagesewagesewagesewageFB1wW/Mg/sB/S3.931.36Cow53.690.01manure +sewagesewagesewagesewagesewageCREC323MinwW/sM1.840.00Reference62.000.06FB2wW/sM1.921.82Cow61.270.49manuresewagesewagesewagesewagesewageFEU16T0wW/Mg3.442.21Biowaste41.233.60DVB1wW/Mg3.452.45Green40.523.693.69DVB1wW/Mg3.452.11Househol39.681.72JEU11M0wB/R/wW2.990.00Reference46.531.33JEU11M0wB/R/WW2.990.00Reference46.531.33GFB2wB/R/WW3.061.94Cow40.511.52HEUFB2wB/R/WW3.112.43Cow40.980.99ManuresewagesewagesewagesewagesewagesewageFEUFB1wB/R/wW2.990.00Reference46.531.33GRECFB1wB/R/wW2.990.00<			BOUE1	wW/Mg/sB/S	3.96	0.49	Sewage	54.33	-0.61
CFB1 wW/Mg/sB/S 4.04 1.07 Cow 51.42 -0.01 manure manure manure manure							sludge		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			CFB1	wW/Mg/sB/S	4.04	1.07	Cow	51.42	-0.01
DVB1 wW/Mg/sB/S 4.00 1.08 Green 53.69 0.18 manure + sewage sludge -							manure		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			DVB1	wW/Mg/sB/S	4.00	1.08	Green	53.69	0.18
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$							manure +		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$							sewage		
$\begin{tabular}{ c c c c c c } FB1 & WW/Mg/sB/S & 3,93 & 1.36 & Cow & 53.69 & -0.01 \\ manure & & & & & & & & & & & & & & & & & & &$							sludge		
CREC3 23 Min wW/SM 1.84 0.00 Reference 62.00 -0.06 $+ N$ + + + + -			FB1	wW/Mg/sB/S	3.93	1.36	Cow	53.69	-0.01
CREC3 23 Min wW/sM 1.84 0.00 Reference 62.00 -0.06 FB2 wW/sM 1.92 1.82 Cow 61.27 0.49 FB2 wW/sM 1.92 1.82 Cow 61.27 0.49 FV wW/sM 1.96 0.47 Poultry 64.07 -1.46 manure FV wW/Mg 2.22 0.00 Reference 39.78 -0.66 BIO1 wW/Mg 3.44 2.21 Biowaste 41.23 3.60 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage sludge							manure		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	CREC3	23	Min	wW/sM	1.84	0.00	Reference	62.00	-0.06
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$							+ N		
FU FV wW/sM 1.96 0.47 Poulty nanure 64.07 -1.46 manure FEU 16 T0 wW/Mg 2.22 0.00 Reference 39.78 -0.66 BIO1 wW/Mg 3.44 2.21 Biowaste 41.23 3.60 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage sewage sludge - - 1.61 - - - - - - 1.61 -			FB2	wW/sM	1.92	1.82	Cow	61.27	0.49
FV wW/sM 1.96 0.47 Poultry nanure 64.07 -1.46 manure FEU 16 T0 wW/Mg 2.22 0.00 Reference 39.78 -0.66 BI01 wW/Mg 3.44 2.21 Biowaste 41.23 3.60 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage							manure		
FEU 16 T0 wW/Mg 2.22 0.00 Reference 39.78 -0.66 BIO1 wW/Mg 3.44 2.21 Biowaste 41.23 3.60 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage sludge sewage sludge 1.12 1.36 Manure PB1 wW/Mg 3.55 2.28 Cow 42.99 1.36 Manure 0MR1 wW/Mg 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 40.71 1.52 manure FB2 wB/R/wW 3.06 1.94 Cow 40.98 0.99 manure FB2 wB/R/wW 3.11 <t< td=""><td></td><td></td><td>FV</td><td>wW/sM</td><td>1.96</td><td>0.47</td><td>Poultry</td><td>64.07</td><td>-1.46</td></t<>			FV	wW/sM	1.96	0.47	Poultry	64.07	-1.46
FEU 16 T0 wW/Mg 2.22 0.00 Reference 39.78 -0.66 BIO1 wW/Mg 3.44 2.21 Biowaste 41.23 3.60 DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage sludge sludge							manure		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	FEU	16	Т0	wW/Mg	2.22	0.00	Reference	39.78	-0.66
DVB1 wW/Mg 3.45 2.45 Green 40.52 3.69 manure + sewage sludge slu			BIO1	wW/Mg	3.44	2.21	Biowaste	41.23	3.60
Imanure + sewage sewage sludge FB1 wW/Mg 3.55 2.28 Cow 42.99 1.36 Manure 0MR1 wW/Mg 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure 6 1.52 manure FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure 5.11 2.43 Cow 40.98 0.99			DVB1	wW/Mg	3.45	2.45	Green	40.52	3.69
sewage sludge FB1 wW/Mg 3.55 2.28 Cow 42.99 1.36 Manure NM 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure S.66 1.94 Cow 40.71 1.52 FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure S.11 2.43 Cow 40.98 0.99							manure +		
sludge FB1 wW/Mg 3.55 2.28 Cow 42.99 1.36 Manure Manure Manure 1.72 d waste 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure E FB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99							sewage		
FB1 wW/Mg 3.55 2.28 Cow 42.99 1.36 Manure OMR1 wW/Mg 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure CFB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure Cow 40.98 0.99 0.99 manure 100 100 100 100 100 100 100 1.52 M0 MB/R/wW 3.06 1.94 Cow 40.98 0.99 1.52 M0 MB/R/wW 3.11 2.43 Cow 40.98 0.99 M0 MB/R/wW 1.10 MB/R/wW 3.11 1.43 MB/R/wW 1.52							sludge		
Manure Manure OMR1 wW/Mg 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure CFB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99			FB1	wW/Mg	3.55	2.28	Cow	42.99	1.36
OMR1 wW/Mg 3.45 2.11 Househol 39.68 1.72 JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure E K K K K K K FB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure K K K K K K K FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure K K K K K K K K							Manure		
JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure KB/R/wW 3.06 1.94 Cow 40.71 1.52 FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure 5.11 2.43 Cow 40.98 0.99			OMR1	wW/Mg	3.45	2.11	Househol	39.68	1.72
JEU 11 M0 wB/R/wW 2.99 0.00 Reference 48.53 -1.33 CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure manure FB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure							d waste		
CFB1 wB/R/wW 2.89 1.10 Cow 42.78 1.61 manure	JEU	11	M0	wB/R/wW	2.99	0.00	Reference	48.53	-1.33
CFB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure			CFB1	wB/R/wW	2.89	1.10	Cow	42.78	1.61
CFB2 wB/R/wW 3.06 1.94 Cow 40.71 1.52 manure							manure		
manure FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure			CFB2	wB/R/wW	3.06	1.94	Cow	40.71	1.52
FB2 wB/R/wW 3.11 2.43 Cow 40.98 0.99 manure							manure		
manure			FB2	wB/R/wW	3.11	2.43	Cow	40.98	0.99
							manure		

LAJA2	15	Min	sM/wW	1.59	0.00	Reference	32.42	-1.43
						+ N		
		CFB	sM/wW	1.25	1.14	Cow	31.79	-0.88
						manure		
		CFP	sM/wW	1.21	1.00	Pig	31.36	-1.09
						manure		
		CFV	sM/wW	1.31	0.94	Poultry	31.36	-1.60
						manure		
		FB	sM/wW	1.29	1.44	Cow	31.01	-0.64
						manure		
		FP	sM/wW	1.27	1.07	Pig	33.05	-1.03
						manure		
		FV	sM/wW	1.40	0.93	Poultry	33.40	-1.59
						manure		
RHEU1	16	Min	sM	1.31	0.00	Reference	36.23	-1.51
						+ N		
		CFB1	sM	1.31	1.06	Cow	36.23	-1.21
						manure		
RHEU2	16	Т0	sM	1.03	0.00	Reference	36.53	-1.72
		CFP1	sM	1.20	0.78	Pig	36.53	-1.28
						manure		
		FP	sM	1.30	1.63	Pig	36.53	-0.74
						manure		
ARAZ	17	D0_N0	W/B/Sf/O	1.34	0.00	Reference	55.39	1.00
		D1_F1	W/B/Sf/O	1.92	2.79	Sewage	62.17	0.40
						sludge		
		D1_F2	W/B/Sf/O	1.87	1.30	Sewage	63.19	1.22
						sludge		
		D1_F3	W/B/Sf/O	1.95	0.68	Sewage	63.19	1.22
						sludge		
		D2_F1	W/B/Sf/O	1.75	5.56	Sewage	74.02	0.22
						sludge		
		D2_F2	W/B/Sf/O	1.84	2.60	Sewage	57.53	2.32
						sludge		

		D2_F3	W/B/Sf/O	1.98	1.32	Sewage	63.18	0.93
						sludge		
ULTU	53	P0_B	O/sT/Mu/sB/	1.03	0.00	Reference	41.72	-0.52
			Fb/OsR/FR/M					
		S_F	O/sT/Mu/sB/	1.10	1.77	Straw	42.28	-0.09
			Fb/OsR/FR/M					
		GM_H	O/sT/Mu/sB/	1.82	1.76	Green	40.6	0.11
			Fb/OsR/FR/M			manure		
		PEAT_I	O/sT/Mu/sB/	1.14	1.97	Peat	41.16	2.17
			Fb/OsR/FR/M					
		FYM_J	O/sT/Mu/sB/	1.76	1.91	Farmyard	41.72	0.69
			Fb/OsR/FR/M			manure		
		SD_L	O/sT/Mu/sB/	0.82	1.84	Sawdust	40.88	0.56
			Fb/OsR/FR/M					
		SS_O	O/sT/Mu/sB/	2.59	1.84	Sewage	43.12	1.36
			Fb/OsR/FR/M			sludge		
BROAD	48	3_Nill	wW	0.36	0.00	Reference	24.84	-0.09
		19_Cast	wW	0.95	0.43	Castor	32.74	0.42
						meal		
		22_FYM	wW	2.07	2.99	Farmyard	61.49	0.38
						manure		
TREV1	23	Min	RG/Mg/wW/s	1.94	0.00	Reference	115.33	-0.66
			Μ			+ N		
		FB	RG/Mg/wW/s	2.04	1.52	Cow	110.67	-0.39
			Μ			manure		
		FP	RG/Mg/wW/s	2.02	1.18	Pig	109.50	-0.18
			Μ			manure		
AVRI	8	T1TR	wW/sM	1.62	0.00	Reference	46.20	-1.18
		T2TR	wW/sM	1.71	1.58	Cow	47.13	-0.76
						manure		
BOLO	29	Т0	M/wW	1.96	0.00	Reference	25.41	0.41
						+ N *** (b)		
		CM	M/wW	2.21	2.24	Cow	28.63	1.18
						manure		
		CS	M/wW	2.15	2.64	Cow slurry	26.70	0.93

-	CRARÓW	22	CD		2 10	0.00	Poforonco	21.09	0 00
	GRADOW	33	Cr	F/D/WW/W/WW	2.10	0.00	Reference	51.00	-0.00
				sM			+ N *** (c)		
			T1	P/B/wW/Mu/	2.39	0.98	Farmyard	33.18	-0.54
				sM			manure		
	MUNCHE	54	СР	gM/wR/P/sW	0.47	0.00	Reference	19.66	-0.29
				/S/sB/wW/Of			***		
				lax/fPea/sM/					
			FYM2	gM/wR/P/sW	0.50	1.40	Farmyard	20.48	0.18
				/S/sB/wW/Of			manure		
				lax/fPea/sM/					
-	RITZ	28	СР	M/sW/wB/Pe	1.52	0.00	Reference	28.88	0.59
				a/wW/wB					
			BW	M/sW/wB/Pe	1.88	1.73	Biowaste	28.88	1.39
				a/wW/wB					

*Rotations legend: M = maize / wM = winter maize / sM = silage maize / Mg = maize grain / gM = green maize / W = wheat / wW = winter wheat / sW = spring wheat / B = barley / wB = winter barley / sB = spring barley / O = Oats / P = potato / S = sugar beet / R = rapeseed / Sf = sunflower / sT = Swedish turnip / Mu = mustard / Fb = fodder beet / OsR = oilseed rape / FR = fodder rape / RG = ray grass / wR = winter rye / Oflax = oil flax / fPea = fodder peas / Pea = peas

** Calculated by approximating the SOC stock evolution with a linear regression of the form: SOC = mt+b, where t = the number of the year, m is the slope and b is the intercept

*** (a) Optimal amount of N inputs in both the reference and the treatments; (b) in Bologna, data represents the mean of several treatments with different inorganic fertilization rates (see Triberti et al. (2008)); (c) in Grabów N was applied as ammonium nitrate (34% N), phosphorus (P) as triple superphosphate (45% P2O5) and potassium (K) as potassium chloride (60% K2O)

Table A1-1 Mean annual climate variables extracted from the GSWP3 climate dataset (i.e., mean annual precipitation (MAP)) or simulated by the ORCHIDEE model at each site (i.e., mean annual potential evapotranspiration (PET), mean annual surface temperature (MAST), and mean annual soil water content (SWC)). In the table are also specified the geographical coordinates of the experiments and the years of the simulations.

	Coordinates	Years	PET	MAP	MAST	SWC
			mm		°C	kg _{H2O}
					C	m² _{soil}
CHNO3	48.09 °N, 1.78 °W	1990-2008	1107.5	818.1	12.2	21.6
COL	48.11 °N, 7.38 °E	2000-2013	866.6	1126.7	9.7	24.6
CREC3	48.32 °N, 3.16 °W	1986-2008	1131.3	1150.1	11.8	22.9
FEU	48.88 °N, 1.96 °E	1998-2013	1049.9	707.3	11.9	21.2
JEU1	46.68 °N, 1.79 °E	1998-2008	1205.4	869.1	12.2	22.1
LAJA2	47.44 °N, 0.98 °W	1995-2009	1314.7	794.7	12.8	20.5
RHEU1	48.09 °N, 1.78 °W	1994-2009	1106.6	841.2	12.3	21.8
RHEU2	48.09 °N, 1.78 °W	1994-2009	1106.6	841.2	12.3	21.8
ARAZ	42.81 °N, 1.72 °W	2002-2018	1416.4	866.0	12.6	20.3
ULTU	59.82 °N, 17.65 °E	1956-2008	824.5	613.4	5.7	22.6
BROAD	51.81 °N, 0.37 °W	1968-2015	872.0	665.6	10.3	21.5
TREV1	48.15 °N, 3.76 °W	1986-2008	1139.5	1314.5	11.9	23.4
AVRI	47.50 °N, 0.60 °W	1984-1991	1170.1	680.7	12.0	20.0
BOLO	44.55 °N, 11.35 °E	1972-2000	1474.3	890.9	11.3	19.4
GRABÓW	51.35 °N, 21.66 °E	1980-2012	974.8	638.1	8.5	13.5
MUNCHE	14.11 °N, 52.51 °E	1963-2016	938.3	639.9	9.2	20.9
RITZ	48.18 °N, 14.25 °E	1991-2018	675.5	1010.5	9.1	25.4
Mean			1080.8	851.0	10.9	21.4
Median			1106.6	841.2	11.9	21.6
Minimum			675.5	613.4	5.7	13.5
Maximum			1474.3	1314.5	12.8	25.4

3.7 APPENDIX B

The parameters calibrated in the models are linked to SOC decomposition (Table 3-1). Below, we detail the different functions in which they appear.

Century

In Century, the C input is partitioned into the metabolic and structural litters according to the $M: S_{ratio}$:

$$\frac{dLIT_{SAG,BG}}{dt} = f_{SAG,BG} \cdot I_{AG,BG} - F_{LSAG,BG} \text{ (Eq. B1)}$$
$$\frac{dLIT_{MAG,BG}}{dt} = f_{MAG,BG} \cdot I_{AG,BG} - F_{LMAG,BG} \text{ (Eq. B2)}$$

Where AG = aboveground and BG = belowground, $\frac{f_{MAG,BG}}{f_{SAG,BG}} = M: S_{ratio}$ is the metabolic:structural ratio of the litter inputs, $LIT_S(t)$ and $LIT_M(t)$ are the state variables of the structural and metabolic litter pools, respectively (g C m⁻²), *I* is the C input (g C m⁻² d⁻¹), F_{LS} is the outflux from the structural litter pool (g C m⁻² d⁻¹), and F_{LM} is the outflux from the metabolic litter pool (g C m⁻² d⁻¹).

$$F_{LS AG,BG} = LIT_{S AG,BG}(t) \cdot k_{LS} \cdot f(T) \cdot f(W) \cdot e^{-3 \cdot lignin_{S AG,BG}}$$
(Eq. B3)
$$F_{LM AG,BG} = LIT_{M AG,BG}(t) \cdot k_{LM} \cdot f(T) \cdot f(W)$$
(Eq. B4)

Where $k_{LS} = 0.01$ and $k_{LM} = 0.041$ (d⁻¹) are the turnover rates of the structural and metabolic litter pools, respectively, f(T) and f(W) are the temperature and moisture response functions, $lignin_{SAG} = 0.76$ and $lignin_{SBG} = 0.72$ are the lignin fractions in the aboveground and belowground structural litter pools, respectively.

And where the temperature response function is defined as:

$$f(T) = Q_{10}^{\frac{(T(t) - T_{ref})}{10}}$$
 (Eq. B5)

Where Q_{10} is the temperature coefficient of the Van't Hoff equation (M. J. H. van't Hoff, 1884), T_{ref} is the reference temperature (°C), and T(t) is temperature (°C).

Roth-C

In Roth-C, the temperature response function takes the form:

$$f(T) = \frac{47.91}{1 + e^{(\frac{106.06}{T(t) + Tparam})}}$$
(Eq. B6)

Where T(t) is temperature (°C) and T_{param} is a parameter.

ICBM

In ICBM, the ordinary differential equations of the young and old SOC pools are:

$$\frac{dY}{dt} = i - k_1 \cdot r \cdot Y(t) \text{ (Eq. B7)}$$
$$\frac{dO}{dt} = h \cdot k_1 \cdot r \cdot Y(t) - k_2 \cdot r \cdot O(t) \text{ (Eq. B8)}$$

Where Y(t) is the state variable of the young SOC pool (kg C m⁻²), O(t) is the state variable of the old SOC pool (kg C m⁻²), *i* is the C input (kg C m⁻² yr⁻¹), k_1 is the potential mineralization rate affecting both the young and the old SOC pools (yr⁻¹), k_2 is the potential mineralization rate affecting the old SOC pool (yr⁻¹), *r* is the environmental parameter, and h is the "humification coefficient", i.e., the fraction of the annual outflux from the young to the old pool. The environmental parameter *r* was calculated using the temperature and moisture response functions described in Fortin et al. (2011) and Karlsson et al. (2011) and normalized against the Ultuna experiment.

AMG

In AMG, the mineralization rate constant k of the active pool (yr⁻¹) depends on:

 $k = k_0 \cdot f(T) \cdot f(W) \cdot f(A) \cdot f(CaCO_3) \text{ (Eq. B9)}$

Where k_0 is the potential mineralization rate of the active SOC pool (yr⁻¹), f(T) is the temperature response function, f(W) is the water response function, and f(A) and $f(CaCO_3)$ are functions describing the effect of clay and $CaCO_3$ soil content on SOC mineralization.

MIMICS

$$\begin{aligned} \frac{dLIT_S}{dt} &= (1 - f_{MET}) \cdot I - F_{LS} \text{ (Eq. B11)} \\ \frac{dLIT_M}{dt} &= f_{MET} \cdot I - F_{LM} \text{ (Eq. B12)} \\ F_{LS} &= MIC_r(t) \cdot V_{max} \cdot \frac{LIT_S(t)}{K_m + LIT_S(t)} + MIC_k(t) \cdot V_{max} \cdot \frac{LIT_S(t)}{K_m + LIT_S(t)} \text{ (Eq. B13)} \\ F_{LM} &= MIC_r(t) \cdot V_{max} \cdot \frac{LIT_M(t)}{K_m + LIT_M(t)} + MIC_k(t) \cdot V_{max} \cdot \frac{LIT_M(t)}{K_m + LIT_M(t)} \text{ (Eq. B14)} \end{aligned}$$

Where $LIT_s(t)$ and $LIT_M(t)$ are the state variables of the structural and metabolic litter pools, respectively (mg C cm⁻³), $MIC_r(t)$ and $MIC_k(t)$ are the state variables of the copiotrophic and oligotrophic microbial biomass pools, respectively (mg C cm⁻³), I is the C input (mg C cm⁻³ d⁻¹), f_{MET} is the fraction of the C input that goes to the metabolic litter pool, and F_{LS} and F_{LM} are the outfluxes from the two litter pools (mg C cm⁻³ d⁻¹), and with temperature sensitive maximum reaction velocities V_{max} (mg C (mg MIC)⁻¹ d⁻¹) and half-saturation constants K_m (mg C cm⁻³) of the Michaelis-Menten kinetics:

$$V_{max} = e^{V_{slope} \cdot T(t) + V_{int}} \cdot a_v \cdot V_{mod} \text{ (Eq. B15)}$$

$$K_m = e^{K_{slope} \cdot T(t) + K_{int}} \cdot a_k \cdot K_{mod} \text{ (Eq. B16)}$$

Where V_{slope} (ln(mg C (mg MIC)⁻¹ d-1)°C⁻¹) and K_{slope} (ln(mg C cm⁻³)°C-1) are regression coefficients (ln(mg C (mg MIC)⁻¹ d⁻¹)°C⁻¹), V_{int} (ln(mg C (mg MIC)⁻¹ d⁻¹)) and K_{int} (ln(mg C cm⁻³)) are regression intercepts, a_v and a_k are tuning coefficients, V_{mod} and K_{mod} are coefficients modifying V_{max} and K_m for fluxes into the microbial pools, and T(t) is temperature.

Millennial

$$F_{pl} = V_{pl}S_{w,D}P \frac{B}{K_{pl}+B} \text{ (Eq. B17)}$$

$$V_{pl} = \alpha_{pl}e^{-Ea_{pl}/(R(T(t)+273.15))} \text{ (Eq. B18)}$$

$$V_{lb} = \alpha_{lb}e^{-Ea_{lb}/(R(T(t)+273.15))} \text{ (Eq. B19)}$$

Where V_{pl} is the maximum rate of POM decomposition to LMWC (d⁻¹) and V_{lb} is the maximum uptake rate of LMWC (d⁻¹), $S_{w,D}$ is the diffusion limitation of substrates, P is the POM pool, B is the microbial biomass pool, K_{pl} is the half-saturation constant of POM decomposition to LMWC (g C m⁻²), α_{pl} (g C m⁻² (g C m⁻²)⁻¹ d⁻¹) and α_{lb} (g C m⁻² (g C m⁻²)⁻¹ d⁻¹) are the pre-exponential constants of V_{pl} and V_{lb} , respectively, Ea_{pl} (J mol⁻¹) and Ea_{lb} (J mol⁻¹) are the activation energies of V_{pl} and V_{lb} , respectively, R is the gas constant (J K⁻¹ mol⁻¹), T(t) is temperature (°C).

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3.9 SUPPLEMENTARY MATERIAL

Figure S1 SOC stock simulations in the control plots of the 17 LTEs. The blue lines represent the multi-model median (MMM) simulations and the uncertainty range (SD) among the different models. Observed SOC stocks are represented by the orange dashed line.



Figure S2 Relationship between simulated additional C input to reach the 4‰ and initial SOC stocks in the control treatments. Left-side panel shows the non-calibrated models and right-side panel shows the calibrated models.



Figure S3 Heatmap of the simulated additional C input to reach the 4‰, for the non-calibrated models at each site. Darker cells show lower C input and lighter cells represent higher C input. Dendrograms above the heatmap represent the relationship of similarity among groups of models, calculated as the minimal correlation distance

4 CHAPTER 4 EUROPEAN CROPLANDS UNDER CLIMATE CHANGE : CARBON INPUT CHANGES REQUIRED TO INCREASE PROJECTED SOIL ORGANIC CARBON STOCKS

Abstract

The European Union (EU) aims to increase soil organic carbon (SOC) stocks in croplands by 1‰-4‰ yr⁻¹ by 2030, to limit future global warming and improve food security. The feasibility of such objective is under debate, since even a relatively low increase of SOC stocks could potentially require significant amounts of carbon (C) input to the soil. The required changes of C input can be estimated with process-based models, which simulate the dynamics of OC in the soil. In particular, the use of multi-model ensembles provides the level of uncertainty of such estimates, based on different representations of SOC processes. However, without a proper evaluation of their ability to reproduce SOC stock variations, model simulations remain somewhat unreliable. In this study, we used three SOC models (AMG, ICBM, and Roth-C) to predict the evolution of

SOC stocks during the next century in European croplands, under two scenarios of climate change. For our simulations, we used the European database of topsoil OC (LUCAS) and climate forcing from the ISIMP project. With an inverse modelling approach, we estimated the amount of C input required to increase SOC stocks by 4‰ yr⁻¹ in European croplands, considering constant C input throughout the simulation length. To improve model simulations, we tested a new calibration technique, where SOC model parameters were estimated for each cropland location of the LUCAS database, using statistical relationships between the model parameters and the pedo-climatic conditions of the sites.

This approach improved the simulations of first-year SOC stocks for models that were initialized with spin-up and had initially high relative errors. However, it increased the divergence between SOC stock predictions across models. Our multi-model simulations showed that reaching a 4‰ SOC stock increase target in European croplands might be feasible under future scenarios of climate change, only assuming drastic increases of C input to the soils, especially in Northern Europe. However, model predictions of SOC stocks remain highly uncertain. Future works should

focus on the reduction of model uncertainties to provide reliable predictions of future SOC stocks, and improve the estimates of related C input needs.

4.1 INTRODUCTION

The European Union (EU) has set ambitious targets to tackle climate change. In comparison to the levels of 1990, by 2050 one aim is to reach net zero greenhouse gas (GHG) emissions (European Commission, 2021). In addition, by 2030 the EU has also introduced an overall target for carbon (C) removals by natural sinks equivalent to 310 Tg of CO₂ emissions (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 stocks (Lal, 2008). Policy frameworks addressing land use and land use changes at the European level could generate significant changes in SOC stock levels. In this context, the Mission Board for Soil Health and Food (Veerman et al., 2020) has recently proposed a series of quantitative targets that by 2030 should improve soil health in the EU. In particular, the mission aims to restore 50% of degraded land, and to reverse current C concentration losses on cultivated land (0.5% yr⁻¹ at 20 cm depth) to an increase of 0.1 - 0.4% yr⁻¹ (Veerman et al., 2020). An annual target of 0.4% (i.e., 4‰) SOC stock increase had already been proposed in 2015 by the "4 per 1000" initiative (https://www.4p1000.org/, last access: 29 December 2021). It suggested a voluntary action plan to maintain and increase existing SOC stocks by 4‰ yr⁻¹ to a 30-40 cm depth at the global scale, in order to mitigate climate change and improve food security (Lal, 2016). Since the "4 per 1000" initiative was launched, a number of studies have investigated the feasibility of a 4‰ annual SOC stock increase (e.g. Poulton et al., 2018; Wiesmeier et al., 2020; Noulèkoun et al., 2021; Riggers et al., 2021; Martin et al., 2021). However, a global assessment at the European level is still missing.

To increase SOC stocks one could either increase C input into the soil (e.g., adding organic matter (OM) inputs or increasing atmospheric CO₂ fixation through plant growth) or decrease C output from the soil (e.g., decreasing SOC mineralization or soil erosion). 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). When compared to conventional practices, examples of practices for croplands that produce and return additional C inputs to the soil include:

agroforestry systems, cover cropping, lengthening leys in temporary grasslands, and effective restitution of crop residues and organic amendments to the soil (Chenu et al., 2019).

Process-based models are used to simulate and predict the dynamics of SOC stocks. They can be run inversely to simulate the amount of C input required to reach a pre-fixed SOC stock increase target. However, if not properly tested and calibrated, SOC models may predict false SOC stock variations. To avoid reliance on one single model simulation, multi-model ensembles can be run that provide a range of uncertainty around simulated SOC stock variations, according to different representations of SOC processes (Farina et al., 2021; Bruni et al., in prep). Model parametrization is also a key aspect that should be considered to improve the reliability of model simulations. When the default parametrization is used, parameters are kept constant and their values usually rely on empirical functions that were derived from one or few experiments in the same pedo-climatic conditions (e.g. Coleman and Jenkinson, 1996). And yet, it is well known that parameter values should vary depending on soil and climatic conditions. SOC models are sometimes evaluated on their ability to simulate SOC changes at different locations (e.g., Smith et al., 1997), and model parameters can be tuned to improve the representation of observed SOC changes. For instance, to increase the reliability of model simulations, long-term experiments (LTEs) where SOC stocks are monitored over time can be used to calibrate model parameters and fit the observed SOC stock variations.

To estimate the spatial variability of the C input change requirements to reach an annual 4‰ SOC stock increase target in European croplands, we ran a multi-model ensemble of SOC processbased models (AMG, Andriulo et al., 1999; ICBM, Andrén and Kätterer, 1997; and Roth-C, Jenkinson, 1990). The ensemble was run over 5785 arable locations derived from the most extensive harmonized land use and soil inventory network available for the EU (Land Use and Coverage Area frame Survey, LUCAS) (Ballabio et al., 2016). The evolution of SOC stocks from 2015 to 2100 could then be simulated according to two climate change scenarios, derived from the representative concentration pathways (RCPs) 2.6 and 6.0 (IPCC, 2015). Relative carbon input changes needed to increase SOC stocks by 4‰ yr⁻¹ between 2015 and 2100, compared to average levels of C input between 2000 and 2009, were estimated by running each model inversely, considering no land use changes over the simulated period. In a previous work, selected model

parameters were calibrated to fit the evolution of SOC stocks at 16 LTEs in European croplands (Bruni et al., in prep). In this paper, we proposed a new parametrization configuration for the SOC models, where the calibrated parameters from Bruni et al. (in prep) were linked to the pedoclimatic conditions of the LTEs through multiple linear statistical regressions. The parameter values were then estimated for all 5785 cropland sites of the LUCAS database by applying these statistical relationships. The present paper aims to provide insightful maps of required C input changes to increase SOC stocks by 4‰ yr⁻¹ under future climate change in European croplands, and to test a calibration technique for SOC models based on statistical relationships between calibrated model parameters and pedo-climatic conditions at different sites.

4.2 MATERIALS AND METHODS

4.2.1 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 20000 sampling locations over all land use and land cover types. The survey was repeated in 2015 over most of the same sampling points (Jones et al., 2020). For the purpose of this study, we included only sites under agricultural land use classified as arable under rotational crops, both in 2009/2012 and 2015 sampling campaigns (Figure 4-1). The properties considered for the topsoil layer included: soil texture (i.e., clay content), pH (in CaCl₂), coarse fragments, carbonate (CaCO₃) content, total nitrogen (N) content, SOC content in 2009/2012 and in 2015. Bulk density was derived from a pedotransfer function using soil texture and SOC as inputs (Panagos et al., 2020), to calculate SOC stocks with Equation 1:

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



Figure 4-1 Soil organic carbon stocks (Mg C ha⁻¹) in European croplands, calculated with Eq. 1 for (a) 2009/2012 and (b) 2015

4.2.2 Climatic data

Climatic forcing data (i.e., daily surface temperature and daily precipitation from water and snowfall) were derived from the IPSL-CM5A-LR model in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) framework (Figure 4-2) (Frieler et al., 2017). For potential evapotranspiration and soil moisture (up to 24.8 cm depth), we derived the monthly output from the ORCHIDEE model, coupled with the IPSL-CM5A-LR model in the ISIMIP framework (Figure 4-2). We used two climatic scenarios of global climate change projections: the RCP 2.6 and RCP 6.0. The RCP 2.6 scenario contemplates stringent mitigation policies and predicts an average global land temperature increase of 1°C during the period 2081-2100, compared to mean temperatures in 1986-2005. The RCP 6.0 estimates an average temperature increase of 2.2°C, compared to the same period of time. To estimate initial conditions for models that had to be initialized through analytical or semi-analytical spin-up, the assumption that SOC stocks were at steady-state at the onset of the simulations (i.e., in 2015) was made. For spin-up, average climatic forcing between 2006 and 2014 under RCP 2.6 and 6.0.



Figure 4-2 Average climatic forcing between 2006 and 2100 across the 5785 sites of the study area, according to the representative concentration pathways (RCPs) 2.6 and 6.0 (the blue and the red lines correspond to the average across sites for RCP 2.6 and RCP 6.0, respectively, and the colored areas correspond to their standard deviation). Data were derived and annually averaged from the IPSL-CM5A-LR model in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) framework ((a) mean annual surface temperature, and (b) mean annual precipitation) and from the coupled ORCHIDEE and IPSL-CM5A-LR models ((c) mean annual potential evapotranspiration, and (d) mean annual soil moisture at 24.8 cm depth).

4.2.3 Carbon input

Carbon input levels were derived from the net primary production (NPP) product of the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data (average NPP between 2000 and 2009) (Zhao et al., 2005), corrected by removing the fraction of NPP that was harvested with values from Plutzar et al. (2016). Both MODIS annual NPP estimates and human

appropriated NPP fraction (HANPPf) values were provided at 1 km spatial resolution and were derived for each cropland location of the LUCAS database. The HANPPf from Plutzar et al. (2016) includes the human-induced alteration of NPP due to land use and harvest. The C input was calculated by multiplying the total annual NPP by HANPPf, and adding the C input from organic fertilizers. Organic fertilization from animal manures was derived from the 'Gridded Livestock of the World' FAO dataset (Robinson et al., 2014) (see Lugato et al., 2014). Model simulations were run with constant land-use and C input between 2015 and 2100. That is, land-use was supposed not to change, and C input variations over time were not considered.

4.2.4 Models

We used three mechanistic SOC models that were initially built to simulate the SOC stock dynamics in agro-ecosystems and were largely evaluated in temperate cropland sites: AMG (Andriulo et al., 1999), ICBM (Andrén and Kätterer, 1997) and Roth-C (Jenkinson, 1990). All three models simulate SOC stocks within a single soil layer (0-30 cm), using a conventional multi-compartmental structure. C inputs enter the different SOC pools and are partly decomposed, following first order decay rates. The only C outputs considered are those from respired CO₂. A detailed description of each model is provided in Appendix A. Mathematical equations of the models can be found in: Clivot et al. (2019) for AMG, Andrén and Kätterer (1997) for ICBM, Coleman and Jenkinson (1996) for Roth-C, and Parshotam (1996) for Roth-C's continuous version. To provide average SOC stocks were averaged over the entire database, and the mean of the multi-model ensemble (\overline{x}) and its standard deviation ($SD_{\overline{x}}$) were calculated as Equations 2 and 3:

$$\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n};$$
(2)

$$SD_{\overline{x}} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}};$$
(3)

Where: x_i is the average SOC stock across all locations, predicted by individual model i (with i = AMG, ICBM and Roth-C). In the text, we will refer to \overline{x} and $SD_{\overline{x}}$ as the multi-model mean of the averages and multi-model standard deviation (SD) of the averages, indicating that they were calculated from the average model predictions of SOC stocks over Europe. In contrast, when the

multi-model means and SDs are calculated for each location, they will simply be called multimodel means and multi-model SDs. Finally, when referring to the spatial variation of the data over the study area, (i.e., the SD of the data distribution), we will call it spatial SD.

4.2.5 Models' parametrization

Models were run in two configurations: 1) with default parametrization and 2) with one or several "statistically calibrated" parameters. The parameters that were selected to be calibrated (Table 4-1) were linked to the decomposition rate of C or to the temperature control function, which is indirectly linked to the SOC decomposition. In the default configuration, those parameters were constant across sites. The approach used to statistically calibrate the parameters is described hereafter. First, we calibrated the selected parameters by fitting the evolution of SOC stocks with time at 16 LTEs carried out in European croplands (Bruni et al., in prep). The fit consisted in minimizing the difference between simulated and measured SOC stocks, weighted by the errors between SOC stock measurements' repetitions. Second, we estimated a statistical relationship between the calibrated parameters and the pedo-climatic conditions of the 16 sites. 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 CaCO₃ content, soil C:N and pH, initial SOC stocks and N input at the LTEs. N input was considered as a dummy variable, equal to 1 if N inputs were applied at any dose and 0 otherwise. Climatic 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. To select the more parsimonious model, we performed a step wise regression by Akaike Information Criteria (AIC). The pedo-climatic functions estimated to derive the calibrated parameters are described in Table 4-1. As a final step, we derived the statistically calibrated parameters values for all 5785 locations using: the estimated statistical pedo-climatic functions for each parameter, the soil variables from the LUCAS survey and the climatic variables from the ISIMIP framework (RCPs 2.6 and 6.0). The statistically calibrated parameters were bound to assure physical realistic values. The AMG decomposition rate parameter (k₀) was bounded

between 0 and 1. The Roth-C reference temperature parameter (T_{param}) was bounded 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 that SOC was completely decomposed when the calibrated T_{param} took values toward the upper bound (see Coleman and Jenkinson, 1996). The ICBM decomposition rate parameter of the young pool (k_1) was bounded between 0.1 and 30, the decomposition rate parameter of the old pool (k_2) was bounded between 0.001 and 1, and the environmental factor parameter (r) was bounded between 0.001 and 10. Additionally, k_1 was constrained to be higher than k₂, to assure 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 statistically calibrated model using different combinations of statistically calibrated parameters (i.e., all three parameters statistically calibrated, both k₁ and k₂ statistically calibrated, k₁ and k₂ individually statistically calibrated, both k_1 and r statistically calibrated, and both k_2 and r statistically calibrated). Then, we selected the combination of statistically calibrated parameters that minimized the average absolute relative error (RE) between simulated and observed SOC stocks in 2015 (see Eq. 4). That is to say, the configuration where only k_1 was statistically calibrated.

4.2.6 Performance evaluation of the statistical parameter calibration

To evaluate our approach, we performed a leave-one-out cross validation (LOOCV) test (Table 4-2), where the multiple linear regressions by stepwise AIC were 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, i.e., in our case n = 16 and the training set has 15 samples). This is 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^2), and the mean absolute error (MAE) of the statistical models built for each calibrated parameter (Table 4-2).

Model simulations of first-year SOC stocks were compared to measured SOC stocks in 2015 for all 5785 locations, for both non-calibrated and calibrated configurations of the ICBM and Roth-C

models. Since AMG uses first-year SOC stock measurements to initialize the simulations, we could not use this model for evaluation. Percentage relative error between simulated and measured SOC stocks in 2015 were calculated as Equation 4:

RE (%) =
$$\frac{(SOC_{2015}^{model} - SOC_{2015}^{measure})}{SOC_{2015}^{measure}} \cdot 100$$
 (4)

Where RE (%) is the relative error, SOC_{2015}^{model} is the SOC stock in 2015 simulated by either ICBM or Roth-C models, and $SOC_{2015}^{measure}$ is the measured SOC stock in 2015. Negative values of RE denote that the model is underestimating the measured SOC stock in 2015, while positive values indicate that the model is overestimating the measured SOC stock in 2015. Average absolute relative error across the dataset was calculated for each model as the average of the absolute value of RE.

 Table 4-1 Coefficients of the multiple linear regressions.

	Response		Coefficients										
	variable		of multiple										
			linear										
			regression										
Model	Parameter		Intercept	Mean	Mean	Mean annual	Initial	Initial	Clay	CaCO₃	рН	Soil C:N	N input
				annual	annual	potential	SOC	carbon					
				surface	precipitation	evapotranspiration	stock	input					
				temperature									
		Units		°C	mm	mm	Mg C	Mg C ha ⁻¹	g g-1	g kg-1			0-1
							ha-1	yr-1					dummy
													variable
AMG	k ₀	yr-1	0.75	-0.02	-1 · 10 ⁻⁴	2.10-4	-12.10-4	0.08		7·10 ⁻⁴	-0.08		
	k ₁	yr-1	74.69	1.82		-0.02				0.05	-6.60	-3.08	
ICBM	k ₂	yr-1	-0.06	-0.01	7.36	1.10-4	-7·10 ⁻⁴						
	r		7.81	0.75							-1.83		-1.97
Roth-	T _{param}	°C	34.3	-1.30	-43· 10 ⁻⁴	0.01	-0.12	6.20	6.15		-1.94		
С													

4.2.7 Inverse modelling

The amount of C input required to increase SOC stocks by 4‰ yr⁻¹ over the period 2015-2100 was calculated using an inverse modelling approach that consisted in minimizing Equation 4:

$$J = |SOC_{2015}^{model} \cdot (1 + 0.004 \cdot 85) - SOC_{2100}^{model}(I)|, \qquad (4)$$

Where SOC_{2015}^{model} and SOC_{2100}^{model} are the simulated SOC stock levels in 2015 and 2100, respectively, and I is the C input.

The amount of C input from livestock manure was supposed 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 supposed to be 0 and the estimated C input considered as plant material only.

4.3 RESULTS

4.3.1 Evaluation of the statistical models for statistical parameter calibration

Figure 4-3 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 over the 16 LTEs. The reference temperature parameter (T_{param}) of the Roth-C model showed the highest R² (0.96) between predicted and calibrated parameters, followed by the decomposition rate parameter k_0 of AMG (0.77), the decomposition rate parameters k_2 (0.72) and k_1 (0.45) of ICBM, and the environmental parameter r of ICBM (0.43) (Figure 4-3). shows the results of the LOOCV test. The statistical model built for T_{param} had the highest R² (0.68)

and lowest r-RMSE (0.14), compared to the other models, and a MAE of 2.48 °C. All the other statistical models had a R^2 lower than 0.1 and a r-RMSE between 1.03 (k_0) and 3.53 (k_1) (Table 4-2).

		-		
Model	Parameter	R ²	MAE	r-RMSE
AMG	k ₀	0.01	0.13	1.03
ICBM	k ₁	0.05	12.22	3.53
	k ₂	0.00	0.03	3.2
	r	0.07	4.11	1.84
Roth-C	T _{param}	0.68	2.48	0.14

 Table 4-2 Results of the leave-one-out cross correlation test of the multiple linear regression for the soil organic

 carbon models' parameters.



Figure 4-3 Correlation between the predicted soil organic carbon (SOC) model parameters estimated with the multiple linear regression (see Table 4-1), and the calibrated parameters estimated by fitting the SOC models to the measured SOC stock evolution in 16 cropland long-term experiments. (a) T_{param} (°C) is the reference temperature parameter of the temperature response function in the Roth-C model, (b) k_1 (yr⁻¹) and (c) k_2 (yr⁻¹) are the decomposition rate parameters of the young and the old pool in the ICBM model, respectively, (d) r is the environmental factor parameter in the ICBM model, and (e) k_0 (yr⁻¹) is the decomposition rate parameter of the active pool in the AMG model.

4.3.2 Relative error of simulated soil organic carbon stocks in 2015

Figure 4-4 shows the relative errors between simulated and measured SOC stocks in 2015, over the study area, for the non-calibrated and calibrated ICBM (with only k₁ statistically calibrated) and Roth-C models. AMG is not presented here since it was initialized using observed SOC stock values. The non-calibrated models both underestimated and overestimated first-year SOC stocks, at different locations (Figure 4-4.a and Figure 4-4.c). However, as can be seen from Figure 4-5, while non-calibrated Roth-C mainly tended to overestimate the observed SOC stocks, non-calibrated ICBM tended to underestimate them. For non-calibrated ICBM, the mean absolute RE of first-year SOC stocks over Europe was 60 ± 378 % (mean \pm spatial SD) (Table 4-3). For non-calibrated Roth-C, mean absolute RE was 99 ± 595 % (Table 4-3). Overall, the non-calibrated multi-model ensemble had a mean absolute RE of 48 \pm 320 % on first-year SOC stocks (Table 4-3).

Overall, the statistical calibration of model parameters decreased the mean absolute RE by approximately 40% (Table 4-3). However, the statistical calibration was in reality capable to reduce the mean absolute RE only for one out of two models (AMG could not be tested since it was initialized with first-year SOC stocks). In fact, while the calibration of Roth-C's T_{param} improved the simulation of first-year SOC stocks by 63%, compared to non-calibrated Roth-C (i.e., mean absolute RE decreased to 36 ± 283 %), the improvement of ICBM's simulations with calibrated k₁ was negligeable (i.e., mean absolute RE was 59 ± 359 %) (Table 4-3).

Table 4-3 Mean percentage relative error (RE) \pm spatial standard deviation (SD) between measured and predicted
soil organic carbon stocks in 2015, for the non-calibrated and calibrated ICBM, Roth-C and multi-model ensemble.

	Relative error (mean \pm SD %)				
	Non-calibrated	Calibrated			
ICBM	59.6 <u>+</u> 378.0	59.0 <u>+</u> 358.8			
Roth-C	99.0 ± 595.8	36.5 <u>+</u> 282.6			
Multi-model mean	47.8 <u>+</u> 320.1	28.5 <u>+</u> 212.7			

RCP 2.6



Figure 4-4 Relative error (%) of predicted soil organic carbon (SOC) stocks in 2015 (Eq. 3) under representative concentration pathway (RCP) 2.6 for the: (a) non-calibrated ICBM, (b) calibrated ICBM (k₁), (c) non-calibrated Roth-C, and (d) calibrated Roth-C models.



Figure 4-5 Predicted versus observed soil organic carbon (SOC) stocks (Mg C ha⁻¹) in 2015 for the (a) ICBM and (b) Roth-C models.

4.3.3 Projected soil organic carbon stocks under RCPs 2.6 and 6.0

Future SOC stock projections between 2015 and 2100 were performed with each model, considering two scenarios of climate change (RCPs 2.6 and 6.0), and considering constant C inputs throughout the simulations. Thus, only the effect of climate change on soil decomposition was considered here and not that of elevated CO₂ concentration in the atmosphere. The average SOC

stock evolution over Europe was calculated for each model (Figure 4-6), and the multi-model mean and SD of the averages (calculated with Eqs. 2 and 3) were plotted in Figure 4-6. We can see that, under both non-calibrated and calibrated multi-model configurations, the evolution of average SOC stocks over Europe was approximately stable or slightly increasing (Table 4-4). This was mainly due to a compensation between models, since the SOC stock trends predicted by the models strongly diverged from each other, under both configurations and climate change scenarios. In fact, AMG predicted a strong increase in average SOC stocks (i.e., from a 0.08% under non-calibrated RCP 2.6 to a 0.15% under calibrated RCP 6.0, Table 4-4). ICBM predicted slightly increasing average SOC stocks (i.e., from 0.03% under non-calibrated RCP 2.6 to a 0.06% under calibrated RCP 6.0, Table 4-4). Contrastingly, Roth-C predicted decreasing average SOC stock trends (i.e., from a -0.04% under non-calibrated RCP 6.0 to a -0.07% under calibrated RCP 2.6, Table 4-4). The calibration effect on the different models was manyfold. The calibration of Roth-C decreased predicted first-year average SOC stocks, compared to the non-calibrated configuration (Figure 4-6). Furthermore, in the calibrated configuration of Roth-C average SOC stocks were decreasing at a higher rate, compared to non-calibrated Roth-C, especially under RCP 2.6 (Table 4-4). In contrast, the calibration of ICBM had almost no effect on the initial average SOC stocks, while it amplified the increasing rate of the average SOC stock trend (Table 4-4). Similarly, the rate of increase of average SOC stocks in the AMG model increased with the calibration. In both ICBM and AMG models, the average rate of increase under RCP 6.0 was higher than under RCP 2.6. Furthermore, while in ICBM the average SOC stock increase was constant with time, average SOC stocks in the AMG model increased more intensively in the second half of the century (Figure 4-6). What stands out from Figure 4-6 is that the multi-model SD of the averages is lower in the calibrated ensemble, compared to the non-calibrated ensemble. However, in the non-calibrated configuration the multi-model SD of the averages decreases with time, since model predictions start from very different points and tend to converge with time. In contrast, in the calibrated configuration the multi-model SD of the averages increases with time, as the models tend to diverge more intensively.



Figure 4-6 Projected soil organic carbon (SOC) stocks between 2015 and 2100. Means between SOC models and standard deviation from the means (calculated with Eqs. 2 and 3) are shown in blue for the representative concentration pathway (RCP) 2.6 and in red for RCP 6.0, for both non-calibrated (left side figures) and calibrated (right side figures) configurations. Colored lines show the SOC stocks predicted by the AMG, ICBM and Roth-C models.

	Non-		Non-		
	calibrated	Calibrated	calibrated	Calibrated	
	RCP 2.6	RCP 2.6	RCP 6.0	RCP 6.0	
AMG	0.075	0.087	0.127	0.148	
ICBM	0.035	0.039	0.055	0.063	
ROTHC	-0.050	-0.044	-0.074	-0.058	
Multi-model mean	0.010	0.028	0.021	0.052	

Table 4-4 Average annual soil organic carbon (SOC) stock changes (%) in European croplands between 2015 and2100, under representative concentration pathways (RCPs) 2.6 and 6.0, considering constant carbon inputs.

4.3.4 Required carbon input changes to reach a 4‰ soil organic carbon stock increase

Figure 4-7 shows the relative change of C input required to reach an average annual 4‰ increase of SOC stocks between 2015 and 2100, relative to average C input levels between 2000 and 2009. Carbon input change patterns were similar for both non-calibrated and calibrated configurations, and for both climate change scenarios (RCPs 2.6 and 6.0), with the level of increase of the required C input generally decreasing with the latitude. However, we found also that the multimodel SD relative to the multi-model mean (i.e., the multi-model RSD) was increasing with decreasing latitudes in both configurations (Figure 4-7). This means that, required relative C input change predictions tended to diverge more across models at low latitudes (see Supplementary Figure 1). On average, the multi-model RSD of required C input change was similar between the non-calibrated and calibrated configurations under RCP 2.6 (i.e., multi-model RSD was 135% and 133% in the non-calibrated and calibrated configurations, respectively), but it was much higher in the calibrated configuration under RCP 6.0 (i.e., multi-model RSD was 111% and 2945% in the non-calibrated and calibrated configurations, respectively). This means that, the required relative C input change predictions in the calibrated configuration diverged more strongly across models under amplified climate change. Furthermore, we found that the calibration of model parameters tended to decrease the dispersion of the predicted relative C input change relative to the mean (i.e., their spatial RSD), across the different locations (Table 4-5). This was not the case for the required mean additional C input predicted by the calibrated models (i.e., the absolute difference in Mg C ha⁻¹ yr⁻¹), for which the calibrated configuration showed a higher spatial RSD, compared to the non-calibrated configuration (Table 4-5).

Table 4-5 Simulated average carbon input changes required to increase soil organic carbon stocks by 4‰ yr⁻¹, on average between 2015 and 2100, relative to average annual C input levels in 2000-2009 (mean \pm standard deviation (SD) and relative standard deviation (RSD)).

Configuration	Climate	Required relative char	nge of C input to	Required additional C input to reach		
	scenario	reach the 4‰ target		the 4‰ target		
		Mean of multi-model Multi-model		Mean of multi-	Multi-model	
		means \pm multi-model	spatial RSD	model means \pm	spatial RSD	
		spatial SD		multi-model		
				spatial SD		
		%	%	Mg C ha ⁻¹	%	
Non-calibrated	RCP 2.6	128.7 ± 345.7	268.5	2.5 ± 1.6	63.1	
	RCP 6.0	129.4 ± 328.9	254.2	2.5 ± 1.8	69.7	
Calibrated	RCP 2.6	108.2 ± 221.8	205.0	2.7 ± 2.3	85.2	
	RCP 6.0	106.2 ± 217.8	205.2	2.7 ± 2.5	93.3	



Figure 4-7 Predicted carbon input increase (%), relative to average carbon input levels in 2000-2009, required to increase SOC stocks on average by 4‰ yr⁻¹ from 2015 to 2100. Multi-model means (MMM) and relative standard deviations (RSD) are shown for the non-calibrated and calibrated representative concentration pathways (RCPs) 2.6 and 6.0 scenarios.

4.4 DISCUSSION

4.4.1 Ensemble modelling

For the non-calibrated multi-model ensemble, the difference between simulated and observed first-year average SOC stocks over Europe was very small (Figure 4-6). This indicates that the noncalibrated multi-model ensemble was able to correctly assess average SOC stocks in 2015, at the European cropland level. However, as can be seen in Figure 4-6, this was mainly due to a bias compensation between the Roth-C and ICBM models, which were both initialized with spin-up techniques (the first one semi-analytically and the second one analytically). Roth-C and ICBM respectively severely overestimated and underestimated first-year average SOC stocks. As a result, the multi-model mean of average SOC stocks was closer to observed values. On the one side, this highlights that multi-model ensembles may improve the simulations of average SOC stocks. In fact, despite the low number of models in the ensemble, the chance to mispredict firstyear SOC stocks in Europe would have been higher, whether a single SOC model had been chosen. On the other side, our results show that multi-model means may predict initial average SOC stock levels that are closer to observations, albeit for the wrong reasons. Incorrect initial SOC stock predictions and uncertainties within different models may be the result of defective estimations of the initial conditions, different model structures, and parameter values (Shi et al., 2018). In our exercise, a necessary assumption to perform the inverse modelling was for the models to be at steady-state before starting the simulations. This implies that first-year SOC stocks (2015 in our case) were at equilibrium, whereas this is unlikely (Sanderman et al., 2018). Indeed, it is suggested that on average SOC stocks in European arable soils are currently decreasing by 0.5% (Veerman et al., 2020). Errors in the initial conditions then propagate through the projection of future SOC stocks (e.g. Shi et al., 2018). In addition to incorrect initial conditions, Shi et al. (2018) also found that increasing complexity in model structures amplified the uncertainty in predicted responses to climate change. That is, vertically resolved and microbial explicit SOC models projected higher uncertainties to climate change than a conventional one-layer SOC model. In our work, we used three different SOC models, all based on the conventional framework of onelayer SOC pools. However, we found that even models with similar structures predicted highly

divergent SOC stock evolutions under future climate change. One way to improve model predictions is through the calibration of model parameters, in order to reduce the difference between simulated and observed SOC stock changes. If chronosequences of SOC stock measurements are available, the calibration can be performed *via* optimization techniques that estimate the best parameters values to minimize the difference between observed and predicted SOC stocks (see for instance Bruni et al., 2021). At a large scale, SOC stock change measurements are very rare. In this work, we proposed a calibration technique where pedo-climatic data from several LTEs was used to derive statistical relationships between model parameters and pedo-climatic conditions, which could be used to re-parameterize SOC models at a larger scale.

4.4.2 Calibration of model parameters using statistical regressions

Model parameters are usually constant in default SOC model configurations. However, it is commonly known that parameter values vary with soil and climatic conditions. For example, the temperature sensitivity of soil respiration (i.e., the increase in soil respiration due to temperature changes) is known to depend on other environmental factors that influence the quantity and degradability of SOC, such as soil moisture, texture, pH, and land use (Meyer et al., 2018; Wang et al., 2010). Our results show that it is possible to link calibrated model parameters to pedoclimatic factors via statistical regressions (Figure 4-3), and then use these regressions to predict calibrated parameter values at other sites. The statistical calibration of model parameters was able to reduce the bias compensation between the different models, as well as the uncertainty of SOC stock predictions (see lower multi-model SD of the averages in Figure 4-6). Furthermore, the statistical calibration reduced the mean absolute RE of the first-year SOC stocks predicted by the multi-model ensemble by 40% (Table 4-3). In particular, the statistical calibration of the reference temperature parameter (T_{param}) of the Roth-C model (Coleman and Jenkinson, 1996) reduced the mean absolute RE between simulated and observed first-year SOC stocks by 63% (Table 4-3). In contrast, ICBM simulations were less sensitive to the statistical calibration, when the decomposition rate parameter of the young pool (k_1) was used. Simulations of first-year SOC stocks were even worse compared the non-calibrated configuration, when all three ICBM parameters (k_1 , k_2 and r) were simultaneously statistically calibrated (see Supplementary Figure 2). One possible reason why the statistical calibration of ICBM over the 5785 locations

underperformed, compared to Roth-C, is that the fit of ICBM at the 16 LTEs was done by simultaneously calibrating three parameters. This may have introduced correlations between parameters and induced data overfitting, which as a consequence decreased the capability of the derived statistical relationships to correctly predict the best parameter values (Table 4-2).

Another possible explanation is that ICBM parameters may be intrinsically less linked to pedoclimatic factors. Furthermore, the relatively small number of LTEs available for our analysis to derive calibrated model parameters, limited the consistency of the statistical regressions built (Table 4-1). The only regression model that showed a good performance at the LOOCV test (i.e., $R^2 > 0.6$ and r-RMSE < 0.15, Table 4-2) was indeed the one built for T_{param}.

These results suggest that, if correctly constrained by pedo-climatic factors, statistical relationships between SOC model parameters and pedo-climatic variables allow estimating site-specific parameter values that may reduce the error of SOC model predictions (Table 4-3), and the uncertainty across models (Figure 4-6). However, the capability to predict the calibrated parameters *via* the statistical regressions should be evaluated before applying it to the SOC models. Increasing the number of experiments on which the statistical relationships are derived may enhance the consistency of the statistical regressions and increase the reliability of the statistical calibration. In this work, we evaluated the calibration only against 2015's SOC stock measurements, because the temporal trend of SOC stock between 2009/2012 and 2015 was not detectable (Panagos et al., 2020). However, oncoming sampling campaigns of the LUCAS survey (European Commission, 2021) may allow testing the validity of our calibration technique on SOC stock changes.

4.4.3 Uncertainty of projected soil organic carbon stocks under future climate change

Multi-model ensembles predicted approximately stable average SOC stocks in Europe under both RCP 2.6 and 6.0. However, this was mainly due to a compensation between different SOC stock trends across models (Figure 4-6). The statistical calibration was able to reduce the uncertainty between predicted average SOC stocks across models. However, this was mainly due to decreased uncertainty across models around initial SOC stock. In fact, the SOC stock trends in the models were different from each other, and diverged even more intensively under statistical calibration (Table 4-5). As a consequence, in the calibrated configuration, the multimodel SD of the average SOC stocks increased with time (Figure 4-6).

Other works have predicted future SOC stocks in Europe. Yigini and Panagos (2016) predicted an increase of SOC stocks by 2050 in Europe (EU26) under different climate change and land cover scenarios. Shi et al. (2018) predicted SOC stock evolutions by 2100 under RCP 8.5 with different SOC models and parametrizations. At the European scale, they found stable SOC stocks when using a microbial explicit SOC model, slightly increasing SOC stocks when using a vertically resolved model, and strongly increasing SOC stocks when using a conventional one-layer model. Our projections of SOC stock changes between 2015 and 2100 only took into account the direct effect of climate variations. In fact, while climate variables changed over time, C input and land use were considered constant. The hypothesis of a constant C input over time is unlikely for multiple reasons. First, changes in climatic conditions, atmospheric CO₂ concentration and technology development affect the C inputs due to changes in plants productivity (Ewert et al., 2005). These factors also affect SOC stocks, inducing a feedback loop from the soil to the plant, since plant growth depends on SOC changes through soil fertility. Second, it is likely that the land use will change and evolve over a period of 75 year. However, the hypothesis of a constant C input was necessary to solve the inverse modelling exercise and, it gives a first estimate of the different responses of the models to the direct effect of climate on SOC stock changes. AMG's predictions of an amplified SOC stock increase under RCP 6.0 (Figure 4-6) were likely due to the predicted increase in mean annual potential evapotranspiration, which was not counterbalanced by an increase in mean annual precipitations (Figure 4-2). In fact, soil moisture decreased as a consequence of increased potential evapotranspiration. Thus, SOC decomposition decreased as well (Supplementary Figure 3). However, soil moisture response functions in SOC models are often not realistic (Moyano et al. 2012), and this may partly explain the different predicted effects of climate change on the SOC models.

4.4.4 Feasibility of the 4‰ soil organic carbon stock increase target

Our maps show that C input change requirements will be higher in Central and Northern Europe, compared to Southern Europe (Figure 4-7). This was true for both non-calibrated and calibrated multi-model configurations. However, the multi-model RSD was higher at lower latitudes,

indicating that the C input change requirements in the European South are highly uncertain. The higher uncertainty across models in the calibrated configuration under RCP 6.0 was likely due to the effect of the statistical calibration on the SOC stock trends, which amplified the divergence across models with time. Other works have recently estimated the required C input change to reach a 4‰ target at a country or site-specific level. Riggers et al. (2021) found that, in German croplands, the required C input increase in 2099 compared to the C input levels in 2014 under the RCP 2.6 scenario was 221%, in order to reach an average 4‰ SOC stock increase between 2090 and 2099. This is higher than our estimate of a 129 \pm 346% and 108 \pm 222% (mean \pm spatial SD) C input increase in European croplands under RCP 2.6, in the non-calibrated and calibrated configurations, respectively. In addition to differences in SOC stocks levels between countries, which might explain part of the differences in our projections compared to Riggers et al. (2021), they also predicted high SOC stock losses under climate change, while our projections were rather stable or even increasing in the non-calibrated configuration. In a modelling exercise with the Century model over a set of European cropland LTEs, Bruni et al. (2021) found that C input had to increase by 43% to reach a 4‰ SOC stock increase over a 30-year period, compared to initial conditions. This was similar to Martin et al. (2021), who found with Roth-C that a 30-40% increase of C input to the soil would be needed to obtain a 4‰ SOC stock increase over 30 years, in mainland France. These studies show that there is still high uncertainty around the required C input level to reach a 4‰ target increase of SOC in European croplands. The statistical calibration that we proposed here was able to reduce the uncertainty of the multi-model ensemble around the predicted average SOC stocks. However, when calibrated, average trends of SOC stocks had steeper slopes, which resulted in a high uncertainty around the required C input changes, especially under RCP 6.0. To increase the reliability of projected SOC stocks, future works should focus on the improvement of the initial conditions of the models, on the calibration of model parameters based on large data samples, and on the improvement of model representations of soil responses to climatic variables (Moyano et al., 2012).

4.5 CONCLUSION

The EU climatic commitments require strong decreases in GHGs emissions, along with C removals by natural sinks, such as soils. Modelling exercises are needed to evaluate the potential of

cropland soils to store C. Our multi-model simulation showed that reaching a 4‰ SOC stock increase target in European croplands might be feasible under future scenarios of climate change, only assuming drastic increases of C input to the soils, especially in Northern Europe. However, model predictions of SOC stocks under climate change are still highly uncertain. Future works should focus on the reduction of model uncertainties to provide reliable predictions of future SOC stocks, and improve the estimates of related C input needs.

4.6 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 (Levavasseur et al., 2020). In the active pool, the C is decomposed following temperature and water dependent functions (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.

For livestock manures, since the animal source was unknown, we used the average optimized humification coefficients for different types of animal manures from Levavasseur 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 (Andrén and Kätterer, 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, and environmental factors. The environmental factors are summarized into one parameter, which is calculated 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 CO₂ 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 CO₂, HUM and BIO. SOC decomposition is dependent on temperature and moisture control functions (a and b, respectively), this latter being a function of mean monthly precipitation, mean monthly potential evapotranspiration, clay, and soil cover coefficient (0.6 for vegetated soil). 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 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.

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4.8 SUPPLEMENTARY MATERIAL



Supplementary Figure 1 Boxplots showing the distribution of the non-calibrated (blue) and calibrated (orange) multi-model relative standard deviations (RSD) between observed and measured first-year soil organic carbon stocks for each 5° bin of latitude.

RCP 2.6



Supplementary Figure 2 Relative error (%) of predicted soil organic carbon (SOC) stocks in 2015 (Eq. 3) under representative concentration pathway (RCP) 2.6 for the: (a) non-calibrated ICBM, (b) calibrated ICBM (k₁, k₂ and r), (c) non-calibrated Roth-C, and (d) calibrated Roth-C models.



Supplementary Figure 3 Evolution of the moisture control function of the AMG model (see Clivot et al., 2019) between 2006 and 2100, under representative concentration pathways (RCPs) 2.6 and 6.0.

5 CHAPTER 5 DEFINING QUANTITATIVE TARGETS FOR TOPSOIL ORGANIC CARBON STOCK INCREASE IN EUROPEAN CROPLANDS : CASE STUDIES WITH EXOGENOUS ORGANIC MATTER INPUTS

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Abstract

The Mission Board for Soil Health and Food proposed a series of quantitative targets for European soils to become healthier. Among them, current soil organic carbon (SOC) concentration losses in croplands (0.5% yr⁻¹ on average at 20 cm depth) should be reversed to an increase of 0.1-0.4% yr⁻¹ by 2030. Quantitative targets are used by policy makers to incentivize the implementation of agricultural practices that increase SOC stocks. However, there are different approaches to calculate them.

In this paper, we analyzed the effect of exogenous organic matter (EOM) inputs on the evolution of SOC stocks, with a particular focus on the new European targets and the different

approaches to calculate them. First, we illustrated through two case-study experiments the different targets set when SOC stock increase is calculated considering as reference: 1) the SOC stock level at the onset of the experiment and 2) the SOC stock trend in a baseline, i.e. a control treatment without EOM addition. Then, we used 11 LTEs with EOM addition in European croplands to estimate the amount of C input needed to reach the 0.1% and 0.4% SOC stock increase targets proposed by the Mission Board for Soil Health and Food, calculated with two different approaches. We found that, to reach a 0.1% and 0.4% increase target relative to the onset of the experiment, 2.51 and 2.71 Mg C ha⁻¹ yr⁻¹ of additional C input were necessary, respectively. Reaching a 0.1% and 0.4% increase target relative to the baseline required 1.38 and 1.65 Mg C ha⁻¹ yr⁻¹ of additional input, respectively. Depending on the calculation method used, the estimated amounts of additional C input required to reach each quantitative target were significantly different from each other. Furthermore, the quality of C input as represented by the C retention rate of the additional organic material (EOM and crop residue), had a significant effect on the variation of SOC stocks. Our work highlights the necessity to take into consideration the additional C input required to increase SOC stocks, especially for soils with decreasing SOC stocks, when the target is set independently of the baseline.

5.1 INTRODUCTION

Land based agricultural activities contribute globally to greenhouse gases (GHG) emissions with approximately 6.2 Gt carbon dioxide equivalents (CO₂eq) each year (including non-food use of agricultural products and excluding emissions associated to land use change) (IPCC, 2019). Improved management practices have the potential to reduce the impact of agriculture on GHG emissions (Smith et al., 1997), and additionally to sequester carbon (C) from the atmosphere through increased soil organic carbon (SOC) stocks (Lal, 2008; Minasny et al., 2017). The potential of agricultural soils to both mitigate climate change and increase food security through improved soil quality (e.g. increased soil fertility and water retention (Lal, 2008)), has been an issue in numerous political agendas for years. It finally gained an international breakthrough in 2015, with the *4 per 1000* initiative proposed at the COP21 (Minasny et al., 2017). The name of the initiative comes from the idea that an increase of SOC stocks of 0.4% (i.e. 4‰) yr⁻¹ in the first 30-40 cm of the soil could, at least partially, compensate for the CO₂ emissions from fossil fuel burning. More recently, the Mission Board for Soil Health and Food of the European Union (EU) proposed a series of quantitative targets for European soils to become healthier. Among them, current SOC concentration losses in croplands (calculated in the first 20 cm of the soil from the LUCAS survey as being 0.5% yr⁻¹ on average) should be reversed to an increase of 0.1 to 0.4% yr⁻¹ by 2030 (Veerman et al., 2020). It is important to note that SOC concentration losses can result in no changes or even increases in SOC stocks when soil bulk density (BD) increases. Veerman et al (2020) refer to SOC concentration losses. However, to avoid confusion, we point out that the aimed target in order to have a climate mitigation benefit, should refer to SOC stock increases.

Management practices that potentially increase SOC stocks include, among others, cover cropping, improved crop rotations, agroforestry systems, converting cropland to grassland, and adding fertilizers and organic amendments to the soil (Soussana et al., 2019; Chenu et al., 2019; Bolinder et al., 2020). Although this latter does not contribute to sequester CO₂ from the atmosphere, adding exogenous organic matter (EOM) can improve soil quality. For instance, through increased water retention and soil fertility (Reeves, 1997; Robertson et al., 2014), EOM may reduce soil erosion and increase crop productivity, indirectly enhancing a virtuous C cycle. That is, by increasing crop productivity, plants' CO₂ fixation is enhanced and higher amounts of crop residue might be left on the soil, increasing the C input and hence the SOC stocks.

Farm-level payments can be used to incentivize the adoption of practices that increase SOC stocks. Payments can be action-based or result-based. Action-based schemes reward farmers for implementing agricultural practices that potentially increase SOC stocks. In contrast, the payment of result-based schemes is contingent upon the achievement of a certain measurable result (European Commission, 2021). Policy makers tend to prefer result-based incentives because the use of funds is more directly linked to the benefit they provide. In this context, it is necessary to set quantitative SOC stock increase targets in order to measure, report and verify the achieved results, and to define a reference against which the SOC stock increase is calculated.

Pellerin et al. (2019) and Soussana et al. (2019) illustrated a 0.4% SOC stock increase target, calculated against a baseline of reference or independently of it, in a set of theoretical examples. On the one hand, setting the target of SOC stocks independently of a baseline, i.e. considering the SOC stocks at the onset of the implementation of an improved practice (that is, at time t₀) as the reference, requires the measurement of SOC stocks only at t₀. However,

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if SOC stocks are not at steady-state, the rate of increase required to reach the target will depend on the SOC stock trend previous to the implementation of the improved practice (Soussana et al., 2019). In this case, the pressure will be set on soils with degrading SOC stocks, because the rate at which they will have to increase will be higher than soils with stable or increasing stocks (Soussana et al., 2019). On the other hand, increasing SOC stocks relative to a baseline means that the rate of increase to reach the target will be fixed, i.e. independent of the previous SOC stock trend. However, to fix the target it is necessary to collect data on the previous SOC stock trend for at least 5 to 10 years, which is considered the minimum duration to derive a trend in SOC stocks (Pellerin et al., 2019). For this reason, a large-scale deployment of this latter approach is not straightforward since each SOC storing practice must be associated with a control treatment and this adds complexity to land management. Topsoil OC stocks are often decreasing in cropland soils in Europe (Clivot et al., 2019; Goidts and van Wesemael, 2007; Meersmans et al., 2011; Saffih-Hdadi and Mary, 2008; Sanderman et al., 2017; Fernández-Ugalde et al., 2011, Veerman et al., 2020). However, opposite examples exist. For instance, SOC stocks (at 15-20 cm depth) are increasing in Swedish cropland due to the presence of more perennial forage crops (Poeplau et al., 2015). In this context, calculating a quantitative target of SOC stocks' increase independently of the baseline seems more appropriate, since it puts the priority on the restoration of degraded soils (Soussana et al., 2019). This is particularly relevant considering the land degradation neutrality (LDN) target of the United Nation Convention to Combat Desertification (UNCCD) (Soussana et al., 2019) and the recently adopted European Green New Deal, which aims to bring the EU (27 countries) to climate-neutrality by 2050.

Although some agricultural practices such as reduced tillage may decrease C outputs from the soil through decreased SOC mineralization rates (Haddaway et al., 2016), there is a general consensus that the most efficient way to increase SOC stocks is to increase C inputs to the soil (Virto et al., 2012; Autret et al., 2016; Fujisaki et al., 2018). Increasing SOC stocks independently of the baseline means that additional efforts to increase C inputs will be necessary in soils with decreasing trends. The amount of additional C input required to increase SOC stocks by 0.1% and 0.4% yr⁻¹ (as targeted by the Mission Board for Soil Health and Food, Veerman et al., 2020), relative to the baseline or independently from it, has not been quantified yet.

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In this study, we estimated the amount of C input required to reach the 0.1% and 0.4% SOC stock increase targets to 20-30 cm depth, calculated with two different approaches, for 11 cropland long-term experiments (LTEs) of additional EOM inputs located in France and Sweden. We hypothesized that reaching the quantitative target calculated independently of the baseline would require higher C inputs relative to the same target calculated against a baseline with decreasing SOC stocks. We also hypothesized that the quality of the EOM would have an impact on the SOC stock change. We used the largely available data on LTEs with EOM treatments as an example that can be expanded to other practices. For other practices such as agroforestry systems or cover cropping, however, one should correct the statistical relationship between C input and SOC stocks, since the C input quality is not the same as for EOM.

Site	Coordinates	Years of	Initial	Carbon input	Mean	Mean
		experiments	SOC	from crops	annual	annual
			stocks		precipiration	surface
						temperature
			Mg C	Mg C ha⁻¹	mm yr⁻¹	°C
			ha⁻¹	yr ⁻¹		
Champ Noël	48.09	1990–2008	40.6	1.29	818.1	12.2
3	°N,					
	1.78					
	°W					
Colmar	48.11	2000–2013	54.3	2.79	1126.7	9.7
	°N,					
	7.38 °E					
Crécom 3	48.32	1986–2008	62	1.84	1150.1	11.8
	°N,					
	3.16					
	°W					
Feucherolles	48.88	1998–2013	39.8	2.22	707.3	11.9
	°N,					
	1.96 °E					
Jeu-les-Bois	46.68	1998–2008	48.5	2.99	869.1	12.2

Table 5-1 Characterization of the control treatments at the long-term experiments (LTEs). Mean annual surface temperature and precipitation were derived from an hourly global climate dataset at 0.5° (GSWP3 http://hydro.iis.u-tokyo.ac.jp/GSWP3/).

	°N,					
	1.79 °E					
La Jaillière 2	47.44	1995–2009	32.4	1.59	794.7	12.8
	°N,					
	0.98					
	°W					
Le Rheu 1	48.09	1994–2009	36.2	1.31	841.2	12.3
	°N,					
	1.78					
	°W					
Le Rheu 2	48.09	1994–2009	36.5	1.03	841.2	12.3
	°N,					
	1.78					
	۰VV	1056 2000				
Ultuna	59.82	1956-2008	41.7	1.03	541.9*	5.7
	°N,					
	17.65 °⊏					
- /		1986-2008	445.2	1.04	42445	11.0
Trevarez	48.15 °N	1980 2008	115.3	1.94	1314.5	11.9
	N, 2 76					
	°W					
Avrilló	47 50	1983–1991	16.2	2 25	603.8	12
Avrille	۹۷.50 N		40.2	2.25	095.8	12
	0.60					
	°W					
Mean			50.3	1.84	881.7	11.3
Median			41.7	1.84	841.2	12
Minimum			32.4	1.03	541.9	5.7
Maximum			115.3	2.99	1314.5	12.8

*From onsite measurements.

5.2 MATERIALS AND METHODS

5.2.1 Experimental sites

We analyzed SOC stock data from 11 long-term cropland experiments in France and Sweden. Each experiment consisted of one control treatment (with or without nitrogen (N) inputs), and one or several treatments of EOM addition (i.e. different types of animal manure, green compost, sewage sludge, peat and sawdust). The total number of treatments with additional EOM was 33, with an average C input from additional organic material of 1.86 Mg C ha⁻¹ yr⁻¹ (1.46 Mg C ha⁻¹ yr⁻¹ from EOM inputs and 0.40 Mg C ha⁻¹ yr⁻¹ from additional crop residue input due to increased crop growth, relative to the control treatment) and a median of 1.84 Mg C ha⁻¹ yr⁻¹. The duration of the experiments varied between 9 and 53 years, with an average of 19 years and a median of 16 years (Table 5-1). The experiments were established in the period between 1956 to 2013. EOM inputs were applied at different frequencies and quantities and the evolution of SOC stocks (at 20-30 cm depth) over time relative to a control treatment without any EOM addition was monitored. Plant inputs to the soil were transformed to C input via allometric functions, following the Bolinder method (Bolinder et al., 2007) and its adaptation to French cropland experiments from Clivot et al. (2019) (see also its application to European cropland experiments in <u>Bruni et al., 2021</u>). The Bolinder method uses yields' measurements and crop-specific coefficients (i.e. the harvest index and the shootto-root ratio), to allocate the C to the aboveground and belowground part of the plant (Bolinder et al., 2007). If not specified otherwise, mean annual surface temperature and precipitation were derived from an hourly global climate dataset at 0.5° (GSWP3 http://hydro.iis.u-tokyo.ac.jp/GSWP3/). Average annual surface temperature of the experiments ranged from 5.7° C (in Ultuna) to 12.8°C (in La Jaillière 2), with an average 11.3° C surface temperature across the sites (Table 5-1). Mean annual rainfall was 881.7 mm across the experiments, with a minimum of 541.9 mm per year in Ultuna and a maximum of 1314.5 mm per year in Trévarez. The experiments were all under arable use during the study period and, most of them, had a long-term arable history (Levavasseur et al. (2020); Clivot et al. (2019); Kätterer et al. 2011). All treatments were rainfed. French sites underwent conventional tillage, with deep ploughing performed almost every year, in addition to some superficial tillage operations (Table S1). At Ultuna, tillage was performed with a spade at 20 cm depth. Cropping systems were cereal-dominated rotations (Triticum aestivum, Zea mays, Hordeum vulgare and Avena sativa) (Table S1). In particular, three were cereal monocultures of silage Zea mays (Champ Noël 3, Le Rheu 1 and Le Rheu 2); four sites had rotations of different cereals (Triticum aestivum and silage or grain Zea mays in Crécom 3, Feucherolles, La Jaillière 2 and Avrillé); and the other sites rotated cereal crops with root crops (Beta vulgaris fodder beet, Brassica napus fodder rape and Brassica napus Swedish turnip), oilseed crops (Brassica napus) and silage Zea mays. Straw residue was partially or totally incorporated into the soil (Table S1), except in Ultuna, where all aboveground residues were removed. Champ Noël 3, Crécom 3, La Jaillière 2, Le Rheu 1 and Trévarez received optimal amounts of mineral N fertilizers both in the control and in the EOM treatments, while the other experiments did not receive any N inputs. EOM treatments included: cow manure (12 treatments); 1 treatment where different types of farmyard manure were mixed together; compost (6 treatments, including 2 treatments of biowaste compost, 2 treatments of green manure mixed with sewage sludge, 1 treatment of household waste and 1 treatment of green manure); pig manure (6 treatments, including 2 treatments of composted pig manure and 1 treatment of pig slurry); poultry manure (3 treatments, including one treatment of composted poultry manure); sewage sludge (2 treatments); 1 treatment of straw residue incorporation; 1 peat treatment; and 1 sawdust treatment. Sources of green manure and straw residue, and animal species are specified in Table S1.

	Sampling depth	Bulk density Clay		Soil C:N	рΗ
	cm	g cm ⁻³	%		
Champ Noël 3*	0–30	1.4	15	9	6.3
Colmar	0–28	1.3	23	10.5	8.3
Crécom 3*	0–30	1.4	15	10.2	6.2
Feucherolles	0–29	1.3	16	9.9	6.7
Jeu-les-Bois	0–30	1.5	10	9.7	6.3
La Jaillière 2*	0–30	1.4	21	9	6.8
Le Rheu 1*	0–30	1.3	16	10	5.8

Table 5-2 Soil properties for the minerally unfertilized and fertilized* control treatments at the beginning of the experiment. More information on the experiments can be found in Clivot et al. (2019), Kätterer et al. (2011), Levavasseur et al. (2020) and Bruni et al. (2021).

Le Rheu 2	0–30	1.3	14	8.2	6
Ultuna	0–20	1.4	36	8.8	6.2
Trévarez*	0–30	1.5	19	9.5	6
Avrillé	0–30	1.4	18	8.9	6.6

5.2.2 Soil samples

Soils were sampled between 0-20 and 0-30 cm depth (Table 5-2) in 3 to 4 replicated plots (plot sizes for each treatment are listed in Table S1). The SOC stocks were calculated using Equation 1 (Poeplau et al., 2017):

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

where SOC (%) is soil organic carbon content and BD is the bulk density (Table 5-2). Multiple BD measurements were performed over time at Ultuna, Colmar and Feucherolles. Significant changes of BD with time were found for Ultuna and Feucherolles, while BD remained constant in Colmar and was assumed to be constant for all other sites (i.e. only one measurement of BD was performed). SOC stocks were thus calculated at a fixed soil depth for these sites. Clay content varied between 10% and 36%. Soil pH ranged from 5.8 to 8.3 (Table 5-2).

5.2.3 Statistical analysis

It is well established that SOC does not accumulate indefinitely but eventually reaches a steady-state (i.e. under constant conditions, C inputs and C outputs eventually outbalance each other and SOC is approximately stable). Hence, SOC accumulation can be represented by an asymptotic curve (Poulton et al., 2018). However, a linear approximation holds well for short periods of time (Arrouays et al., 2002). Since we were studying a relatively short-term period (i.e. 30 years), we analyzed the simulation of SOC stocks' evolution in each treatment with a linear regression (see Fig. S1) and obtained a coefficient of determination (R²) of 0.59. This can be written as Equation 2:

$$SOC = m \cdot t + b, \tag{2}$$

Where SOC is the soil organic carbon stock in Mg C ha⁻¹, m is the slope coefficient, b the intercept, t is time (i.e. the number of years since the beginning of the experiment).

We evaluated the effect of total C input on the evolution of SOC stocks, calculated with two approaches (T₀ and B, see Eqs. 4 and 5). We used a linear mixed effect model, with an interaction effect between the quantity and the quality of the total C input. The quality was expressed through the C retention coefficient of the exogenous C input, which represents the proportion of exogenous C that is incorporated into SOC and is not mineralized within 1 year. Values for the C retention coefficient were taken from Levavasseur et al. (2020) and Clivot et al. (2019) for each EOM and crop type (Table S1). The authors derived this coefficient by optimizing the "h" parameter of the AMG model (Andriulo et al., 1999) in order to fit time series of differences in SOC stocks between EOM treatments and controls (Levavasseur et al., <u>2020</u>]. Thus, the C input quality factor (i.e. the C retention coefficient) expresses numerically the quality of the crop species and EOM input of the treatment. Since C input in each treatment came from multiple sources with different C retention coefficients (i.e. aboveground plant material, belowground plant material and EOM inputs), C_{quality} was calculated as the weighted average between the different sources of C input in the treatment. We assumed that the explanatory variables, i.e. C input quantity and C retention coefficient had fixed effects, while the experimental site was set to have a random effect. This eliminates the spatial correlation among treatments carried out at the same site. Model parameters were estimated by maximizing an approximation to the likelihood integrated over the random effect, as in Equation 3:

SOC increase_i (%) =
$$a_0^{site} + a_1 \cdot C_{quantity} + a_2 \cdot C_{quality} + a_3 \cdot C_{quantity} \cdot C_{quality} + \varepsilon$$
, (3)

With $i = T_0$ or *B* (i.e. SOC stock increase calculated with T_0 or B approaches, see subsection 2.4). And where: a_0^{site} is the site-dependent intercept of the regression; a_1 and a_2 are the coefficients of the main factors, i.e. the quantity of total C input ($C_{quantity}$) and the C retention coefficient ($C_{quality}$), respectively; a_3 is the coefficient of the interaction effect between $C_{quantity}$ and $C_{quality}$; and ε is the error term of the linear mixed effect model ($\varepsilon \sim (0, \sigma^2)$).

To test the significance of differences between C input quantities to reach the 0.1% and 0.4% targets (calculated with T_0 or B approaches) at the experimental sites, one-way ANOVA combined with post-hoc tests (Bonferroni) and Student's t tests were applied. Normal distribution of the data was tested with a Shapiro-Wilks normality test.

5.2.4 Calculating a 0.1% and 0.4% SOC stock increase target

The increase of SOC stocks can be calculated 1) relative to the value of the SOC stocks at the onset of the study period (i.e. at t_0) or 2) relative to a baseline, i.e. the SOC stock trend of a control treatment. Assuming that we want to increase SOC stocks by 0.1% or 0.4% each year, the first approach (T_0) can be written as Equation 4:

$$SOC_{T_0} = SOC_0^{control} \cdot (1 + \text{target} \cdot n),$$
 (4)

Where SOC_{T_0} is the amount of SOC stock targeted by the T₀ control approach, $SOC_0^{control}$ is the SOC stock in the control treatment at t₀, target = 0.001 or 0.004, for a 0.1% and 0.4% SOC stock increase, respectively, and *n* is the number of years for which the SOC increase is estimated. Assuming SOC stocks evolve linearly with time, the second approach (B) to calculate a 0.1% or 0.4% SOC stock increase target is equal to Equation 5.

$$SOC_B = SOC_0^{control} \cdot (1 + (relative_slope^{control} + target) \cdot n),$$
(5)

Where SOC_B is the target set by the baseline approach, $relative_slope^{control} = \frac{m}{SOC_0^{control}}$, with m being the slope coefficient of the regression line of the SOC stocks in the control treatment (see Eq. 2), For the rest of the study, the predicted SOC stocks will be evaluated over 30 years, i.e. n = 30.

5.3 RESULTS

5.3.1 Effect of the target calculation approach: two case studies

We applied the two approaches described above (i.e. Eq. 4 for T₀ and Eq. 5 for B) to two case study LTEs with very different SOC stock dynamics in their control treatment, to illustrate how different SOC stock increase targets are set. The first case study was the 23 years old experiment Crécom 3, where SOC stocks in the first 30 cm are approximately at steady-state (Figure 5-1.A) (i.e. over time, fresh C inputs to the soil compensate SOC losses by decomposition and SOC stocks can be approximated with a constant line). This site, located in northwestern France, has a control treatment with an annual SOC stock change of -0.06 % (correlation coefficient of the regression line between SOC stocks and time, R² = 0.04). The slope coefficient of the correlation between SOC stocks and time in the control treatment was -0.038 \pm 0.125 (mean \pm standard error, SE) (Table 5-3). The second site Feucherolles was a 16 years old northcentral French experiment. At the control treatment, SOC stocks at 20 cm depth were decreasing with a strong relative annual change of -0.65 % ($R^2 = 0.65$) (Figure 5-1.B).

5.3.2 The importance of considering the baseline

In Figure 5-1, we illustrate the theoretical SOC stock increase imposed by a 0.4% target calculated with T_0 (Eq. 4) (blue colored area) and B (Eq. 5) (orange colored area). Outcomes are different whether the control treatment's trend is at steady-state (Figure 5-1.A) or not (Figure 5-1.B). If SOC stocks in the control treatment are approximately stable (e.g. Crécom 3), calculating the 0.4% increase with Eqs. 4 or 5 sets similar targets of SOC stock increases. In both cases, the SOC stocks after 30 years of implementation of the storing practice has to be higher than their initial SOC stock level. If SOC stocks in the control treatment are not at steady-state (Figure 5-1.B), the two approaches result in different SOC stock increase targets. If SOC stocks are decreasing, we can see from Figure 5-1.B that the target based on B allows increasing SOC stocks relative to the control treatment. However, SOC stocks are still decreasing (though at a weaker rate than the baseline, since the SOC stock target increase was set against the baseline).

To summarize, B (relative to the baseline) sets fixed targets for soils with decreasing, stable or increasing SOC stocks, but does not guarantee to have a net increase of SOC stocks after *n* years. On the contrary, T₀ (relative to SOC stocks at t₀) imposes both stable and decreasing SOC stocks to increase (accruing SOC stocks have to increase only if their rate of increase is lower than the target rate). However, in this case, soils with decreasing SOC stocks have to increase at a much higher rate. Note that we showed the theoretical results for two case studies for illustrative purposes. However, these results are generalizable for any soil with stable or decreasing SOC stocks that can be approximated with a linear regression (Appendix A).

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Figure 5-1 Theoretical SOC stock evolution needed to reach an average annual 0.4% SOC stock increase for 30 years, based on two calculation methods (T_0 and B, calculated with Eq. 4 and Eq. 5, respectively) for (1) Crécom 3 and (2) Feucherolles (detailed demonstration available in Supplementary Material). Observed SOC stocks (at 0-30 cm depth) and predicted SOC stocks (with a linear regression) for the control treatments are normalized against initial SOC stocks.

Table 5-3 Predicted coefficients of the linear regression of soil organic carbon (SOC) stock change in 30 cm depth with time for the Crécom 3 and Feucherolles control treatments.

		Predicted	Standard		Confic		dence
		coefficients	Error	t statistics	p value	interva	l (95%)
Crécom 3	Intercept	60.3944	1.897	31.831	0.001	52.231	68.558
	slope	-0.0385	0.125	-0.308	0.787	-0.577	0.5
Feucherolles	Intercept	38.7868	0.658	58.991	0	37.178	40.396
	slope	-0.2553	0.076	-3.349	0.015	-0.442	-0.069

5.3.3 Temporal changes in topsoil organic carbon stocks at the long-term experiments

Concerning all the 11 LTEs, in the control treatments SOC stocks were decreasing by 0.98 \pm 0.47 % yr⁻¹ (mean \pm standard deviation, SD) on average (i.e. -0.44 \pm 0.20 Mg C ha⁻¹ yr⁻¹, mean \pm SD). The average R² of the linear regressions between SOC stocks and time in the control treatments was 0.64. The SOC stocks in the additional C input treatments were increasing by 0.17 \pm 1.35 % yr⁻¹ on average (i.e. 0.07 \pm 0.56 Mg C ha⁻¹ yr⁻¹, R² = 0.57). Predicted SOC stocks after 30 years are shown in Table 5-4, together with the 0.1% and 0.4% SOC stock targets

calculated with Eq. 4 (T₀) and Eq. 5 (B). Overall, almost 50% of treatments increased SOC stocks by at least 0.1%, compared to the initial level of SOC stock (T₀) and more than 90% of treatments increased SOC stocks by at least 0.1% compared to the baseline (B) (Table 5-4). 33% of C input treatments increased SOC stocks by at least 0.4% yr⁻¹ (T₀) and 76% of treatments increased SOC stocks by at least 0.4% yr⁻¹ (B) (Table 5-4). Since SOC stocks in all control treatments were decreasing or approximately stable, treatments that met the T₀ target also reached target B. Overall, almost 10% of EOM treatments did not reach any increase target.

Table 5-4 Predicted soil organic carbon (SOC) stocks (Mg C ha⁻¹) of the experimental sites. t_0 and t_{30} indicate the 1st and the 30th year of the prediction, respectively. T1, T2, ..., T6 indicate the EOM treatments' identification code for each site (detailed description of the EOM treatments are provided in Table S1). The target SOC stock level was calculated for a 0.1% and 0.4% average annual increase over 30 years, based on approach T₀ and B.

	SOC	SOC	SOC	SOC	SOC	SOC	SOC	SOC	SOC	SOC	SOC	SOC
	stock t_0	stock t ₃₀	stock	stock	stock	stock						
Sites	control	control	t ₃₀ at	0.1%T ₀	0.1% B	0.4%T ₀	0.4% B					
	treatmen	treatmen	T1	T2	Т3	T4	T5	Т6	target	target	target	target
	t	t										_
Champ Noël 3	39.2	28.7	30.5						40.4	29.5	43.9	33.0
Colmar	53.4	41.3	56.4	44.2	51.2	55.9	53.2		55.0	42.5	59.8	47.3
Crécom 3	60.4	59.3	69.7	37.0					62.2	61.1	67.6	66.5
Feucherolles	38.8	31.4	81.1	81.2	62.8	59.7			40.0	32.3	43.4	35.8
Jeu-les-Bois	48.5	29.8	62.7	58.7	52.7				50.0	30.6	54.4	34.9
La Jaillière 2	33.1	19.4	25.3	22.8	17.5	26.8	24.4	18.4	34.1	19.9	37.1	22.9

Le Rheu 1	38.2	21.5	25.2						39.4	22.1	42.8	25.5
Le Rheu 2	37.4	18.7	23.7	30.2					38.5	19.2	41.9	22.5
Ultuna	40.9	34.8	43.0	43.4	56.4	47.6	44.7	50.3	42.2	35.8	45.8	39.5
Trévarez	108.2	87.6	95.1	100.3					111.4	90.1	121.2	99.8



Figure 5-2 Correlation between annual soil organic carbon (SOC) stock increase (%) (at 20-30 cm depth) and additional C input in the EOM treatments (Mg C ha⁻¹ yr⁻¹). Different colors indicate whether the 0.4% SOC stock increase target was reached, based on the different approaches used to calculate the target (blue indicates that both 0.4% T₀ and 0.4% B targets were reached, orange indicates that 0.4% B was reached and green indicates that no 0.4% target was reached). Different symbols indicate whether the 0.1% SOC stock increase target was reached, based on the different approaches used (squares indicate that both 0.1% T₀ and 0.1% B targets were reached, inverse triangles indicate that 0.1% Bwas reached and crosses indicate that no target was reached). SOC stock increase was calculated relative to the first year of experiment in the control treatment. Additional C input consisted of EOM inputs and additional C from increased crop growth, relative to the control treatment.

Table 5-5 Amount of additional carbon (C) input (Mg C ha⁻¹ yr⁻¹) (relative to the C input in the control treatment) that increased soil organic carbon (SOC) stocks by 0.1% and 0.4% yr⁻¹ on average for 30 years, according to T_0 and B. Additional C input refers to exogenous organic matter (EOM) inputs plus C input from increased crop growth relative to the control treatment.

Statistics	Additional C input	Target							
			0.2	1%	0.4%				
		To	В	Not reached	T ₀	В	Not reached		
Min	Mg C ha ⁻¹ yr ⁻¹	1.0	0.62	0.60	1.0	0.75	0.6		
Max	Mg C ha ⁻¹ yr ⁻¹	3.68	2.49	0.74	3.68	2.55	1.66		
Mean	Mg C ha ⁻¹ yr ⁻¹	2.51	1.38	0.66	2.61	1.77	0.99		
SD	Mg C ha ⁻¹ yr ⁻¹	0.19	0.15	0.03	0.27	0.17	0.14		



Figure 5-3 Additional C input (Mg C ha⁻¹ yr⁻¹) relative to the control treatment for groups of treatments where: (1) 0.1% T₀ and B targets were reached or not, (2) 0.4% T₀ and B targets were reached or not. Boxes extend from the lower to the upper quartile values of the data, with a line at the median and a spot at the mean. Whiskers show the range of the data and points past the end of the whiskers are flier points. Groups within the same panel with different lowercase letters are significantly different ($p \le 0.05$) from each other.

5.3.4 Amount of additional carbon input needed to reach the 0.1% and 0.4% soil organic carbon stocks increase targets

The increase in SOC stocks at 20-30 cm depth was positively correlated to the additional C input from EOM and increased crop growth ($R^2 = 0.71$) (Figure 5-2). Figure 5-2 shows the relationship between additional C input and SOC stock increase, highlighting the levels of C input in the treatments where the 0.1% and 0.4% targets were reached, according to T₀ and B. Table 5-5 shows the additional C input in the treatments where both the 0.1% and 0.4% increase target were reached, or not. We found that the amount of additional C in the group of treatments that reached a 0.1% T₀ target was significantly different ($p \le 0.05$) from the group that reached a 0.1% B target (Figure 5-3). However, the average amount of additional C input in the group of treatments that reached a 0.1% B target was not significantly different from the average amount of additional C in the group of treatments where no 0.1% target was reached. Concerning the 0.4% increase target, all groups of treatments were different from each other at a significant level of 0.05 (Figure 5-3.B). Treatments where the 0.4% T₀ target was reached, had between 1.0 and 3.68 Mg C ha⁻¹yr⁻¹ inputs (EOM plus additional inputs due to enhanced crop growth relative to the control treatment), with an average of 2.61 ± 0.27 Mg C ha⁻¹yr⁻¹ (mean \pm SE) (Table 5-5). To reach a 0.1% T₀ target, 2.51 \pm 0.19 Mg C ha⁻¹yr⁻¹ were sufficient. Treatments that reached the 0.4% B target had 1.77 \pm 0.17 Mg C ha⁻¹yr⁻¹ inputs on average, while treatments that reached the 0.1% B target had 1.38 \pm 0.15 Mg C ha⁻¹yr⁻¹ inputs. Treatments that reached the B target had a high variability of C input, i.e. between 0.75 and 2.55 Mg C ha⁻¹yr⁻¹ for a 0.4% B target and between 0.62 and 2.49 Mg C ha⁻¹yr⁻¹ for a 0.1% B target (Table 5-5). Treatments where no target was reached had 0.66 \pm 0.03 Mg C ha⁻¹yr⁻¹ inputs on average. C input in these treatments ranged between 0.60 and 0.74 Mg C ha⁻¹ annually (Table 5-5). Considering EOM only, the necessary average C input was: 1.95 ± 0.10 Mg C ha⁻¹yr⁻¹ to reach a 0.4% T₀ target, 1.84 ± 0.11 Mg C ha⁻¹yr⁻¹ to reach a 0.1% T_0 target, 1.38 \pm 0.11 to reach a 0.4% B target, and 1.16 \pm 0.09 to reach a 0.1% B target.

	SOC stoo	ck variation (То)	SOC sto	ock variation (I	3)
	Predicted	Standard		Predicted	Standard	
	coefficients	error	p value	coefficients	error	p value
Intercept	3.51	1.79	0.059	2.57	1.84	0.1726
$C_{quality}$	-14.64	4.65	0.0037	-9.03	4.80	0.0697
$C_{quantity}$	-1.82	0.58	0.0039	-1.24	0.60	0.0484
Interaction effect	6.19	1.48	0.0002	4.49	1.53	0.0064

Table 5-6 Results of the linear mixed effect model of Eq. 3.



Figure 5-4 Relationship between soil organic carbon (SOC) stock annual variation (%) and 1) total carbon (C) input (Mg C ha⁻¹ yr⁻¹) (panel (1) and (3)); 2) retained C input (Mg C ha⁻¹ yr⁻¹) panel (2) and (4)). Retained C inputs were calculated as the total C input, multiplied by the C retention coeffcient for each C input quality (Table S1). The SOC stock annual variation was calculated with T₀ (panel (1) and (2)) and with B (panel (3) and (4)).

5.3.5 Effect of the quality of carbon input on the variation of soil organic carbon stocks

We found that the quantity of C input and the quality of C input (i.e. the C retention coefficient) both had an effect on the increase of SOC stocks ($p \le 0.05$), when this was calculated relative to t₀(T₀) (Table 5-6). We also found that there was a significant interaction effect between $C_{quantity}$ and $C_{quality}$, meaning that the effect of $C_{quantity}$ depended on the value of the $C_{quality}$ and vice versa (Table 5-6). This interaction was also significant when the SOC stock increase was calculated relative to the baseline in the control treatment (B). But in this case, while the C input quantity had a significant effect, no main significant effect of the C retention coefficient was found (Table 5-6). Figure 5-4 shows the relationship between annual SOC stock variation and: 1) total C input in all treatments (Figure 5-4.A and Figure 5-4.C) and 2) total C input multiplied by the C retention coefficient in all treatments (Figure 5-4.B and Figure 5-4.D). The annual SOC stock variation was calculated against the initial SOC stock in the control treatment or against the baseline. We can see that, when the C retention coefficient is taken into account, the R² between annual SOC stocks is calculated with T₀ and from 0.51 to 0.67 when the variation of SOC stocks is calculated with B).

5.4 DISCUSSION

5.4.1 Reaching targets of soil organic carbon stock increase to 20-30 cm depth

We compared two approaches to calculate the increase of SOC stocks. One where the control was the SOC stock at the onset of the experiment (Eq. 4) and one where the control was the trend of the SOC stocks in the control treatment (Eq. 5). Both can be used to set quantitative targets for the implementation of SOC stock increasing practices, in the context of result-based incentives. The two case studies of Crécom 3 and Feucherolles illustrated that the two approaches set different targets, depending on the initial state of SOC stocks due to previous practices. In particular, if SOC stocks are declining in the control treatment, a target calculated against a baseline (B), might not be sufficient to induce a net positive SOC storage after implementation of the improved practice. In contrast, the T₀ target will guarantee decreasing SOC stocks to reverse their trend. However, reaching such target requires the implementation of practices that supply sufficient levels of additional C input (e.g. from EOM and crop residue inputs).

Many authors have shown that adding EOM inputs to the soil increases SOC stocks (e.g. Maillard and Angers, 2014; Li et al., 2021). In the 11 LTEs studied, the majority of EOM input treatments increased SOC stocks by 0.1% and 0.4% yr⁻¹ on average for 30 years, relative to the baseline situation where no additional EOM was added to the soil (target B). However, we found that the increase of SOC stocks from additional EOM treatments was not sufficient to reach a 0.1% or 0.4% SOC stock target relative to the initial SOC stocks after 30 years (target T₀), unless very high amounts of C input were added to the soil. That is, 2.51 Mg C ha⁻¹ yr⁻¹ for a 0.1% T₀ target and 2.61 Mg C ha⁻¹ yr⁻¹ for a 0.4% T₀ target over 30 years, considering total additional C input, and 1.84 and 1.95 \pm 0.11 Mg C ha⁻¹ yr⁻¹, respectively, considering EOM inputs only. This is in line with Poulton et al. (2018), who found that with similar high amounts of additional C input, SOC stocks increased more than 0.4% yr⁻¹ relative to their value at t₀ at several LTEs in the UK.

Additionally, we found that the quality of the C input, as expressed by its C retention coefficient, had a main significant effect on the SOC stocks' increase only when this was calculated against t₀. This is probably due to the lower target set by B, and because almost all EOM input treatments increased SOC stocks compared to a reference situation where SOC stocks were decreasing (Table 5-4). However, we found that the interaction effect between C input quantity and quality was significant for both calculation approaches. This means that not only the quantity but also the quality of the C input has a significant effect on the SOC stock increase. The relevance of adequately determining the mineralization and C retention coefficients of EOMs for accurate estimations of their long-term effects on soil fertility and SOC stocks is well known, as recently summarized by Levavasseur et al. (2021). The work from Levavasseur et al. (2021) provides evidence from controlled laboratory experiments that some sources of EOM after application remain in soils in higher proportions over time. For example, they found that composts generally had a lower C mineralization rate compared to other EOMs, such as sewage sludges and animal residues (e.g. animal manures and anaerobic digestates) (Levavasseur et al., 2021). This can be expected since the composting process converts biodegradable organic matter into more stable organic materials.

The evolution of the retained C input with time (i.e. the amount of C input multiplied by its associated C retention coefficient over time), together with the evolution of the measured and predicted SOC stocks over the experiments' length can be found in Fig. S2 for each treatment. Because the number of SOC stock measures in time was small in the majority of

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the treatments, it was not possible to assess correctly the cross-correlation between retained C input and measured SOC stocks with time. Using the predicted SOC stocks (see Eq. 2) instead of measured SOC stocks, we found that the average R² between retained C input and predicted SOC stocks was 0.17. While our results suggested that the average SOC stock change rates depended on the quality of the C input, more experiments with frequent SOC stocks. More frequent SOC stock measures would also allow to predict SOC stock trends with more reliability and avoid overfitting the data. This was the case in Crécom 3 T2 and Jeules-Bois treatments, where only two measures of SOC stocks with time were available. Furthermore, a higher number of treatments with similar qualities of C input would be necessary to assess the effect of "categories" of C inputs (e.g. cow manures, composted cow manures, sewage sludges, etc.) on SOC stocks.

5.4.2 Reaching the 0.1% and 0.4% targets in European croplands

The Mission Board for Soil Health and Food (Veerman et al., 2020) reported that 23% of European soils have low SOC concentration and declining SOC stocks in the top 20 cm, almost all being under agricultural use. Panagos et al. (2020) estimated that arable land has experienced a loss of SOC stocks, at the same depth, of about 0.06% between 2009/2012 and 2015 (LUCAS JRC). This loss amounts to 0.5% yr⁻¹ in soils that were under cropland at both survey dates (i.e. 2009/2012 and 2015), with a large variability of the SOC stock variation across the database (Veerman et al., 2020; Hiederer, 2018). In the LTEs analyzed here, SOC stocks in the control treatments (including both fertilized and unfertilized controls) were decreasing on average by 0.98 \pm 0.47 % yr⁻¹, which is similar to the average situation of SOC stocks in European cropland soils. The Mission Board for Soil Health and Food aims to improve the health of 75% European soils by 2030. In particular, the current SOC losses in cropland soils are expected by the Mission Board for Soil Health and Food to be reversed to an increase of 0.1 to 0.4% yr⁻¹ by 2030, compared to current SOC levels. This is equivalent to setting an increase target calculated against t_0 (T₀). Here, we showed that at the plot scale, the necessary increase of C input depends both on the objectives and calculation method used, and on the quality of the C input. Although the control treatments in the 11 LTEs analyzed have similar SOC stock trends as the average cropland soils in Europe, observations from two European countries cannot be extrapolated to entire Europe. However, our analyses show that, even considering relatively similar pedo-climatic conditions, the amounts of C input required to reach quantitative targets of SOC stock increase were significantly different from each other, depending on the approach used to calculate these targets. These results are important for policy makers who may want to implement adequate subsidies, depending on specific soil conditions and targets aimed.

It is important to note that we used EOM treatments as a study case since we had access to data from 11 LTEs where SOC stocks (at 20-30 cm depth) and C input were monitored over 9 to 53 years. However, large scale additional increases in SOC stocks through EOM management in Europe are unlikely because EOM are already applied to soils (Zhang et al., 2017; Foged et al., 2011; Soussana et al., 2019). Moreover, although EOM inputs improve soil fertility and soil health, they are not *per se* a climate mitigation measure. In fact, adding EOM inputs to the soil does not sequester additional CO₂ from the atmosphere but it redistributes spatially C that is already fixed.

In the experiments analyzed, EOM inputs were spread on the soil surface. Hence, the major effects on SOC stocks can be expected in topsoil layers. Although there might be an impact of the addition of EOM inputs at deeper soil layers because of advection or bioturbation processes, deeper soil layers were not considered because data on the biological activity or on deeper SOC were not available.

Our results, together with the recent work from Levavasseur et al. (2021), show that the quality of the additional C input is critical to increase SOC stocks. Strategies to enhance SOC stocks should increase the quality of the EOM brought to soils, as well as redistributing EOMs from lands with high EOM inputs to croplands that do not have sufficient EOMs (Aillery et al., 2018; Asai et al., 2014). The cost associated to the transportation of EOMs is often a limit to the distance at which they are commuted. A study from Asai et al. (2014) reported that the maximum distance covered from the majority of farmers involved in manure exchange in Denmark ranged between 1 and 5 km. Although the distance was higher for organic farmers, the majority of them still hauled less than 10 km. Also, transporting EOM induces GHG emissions that might offset the benefits of increased SOC stocks.

Our results show that SOC stock increase in cropland soils might be feasible using sufficient amounts of C input (i.e. between 1.38 Mg C ha⁻¹ yr⁻¹ and 2.71 Mg C ha⁻¹ yr⁻¹ according to the 11 LTEs analyzed, depending on the SOC stock increase target) and supposing that SOC variations are linearly controlled by C input. Such linear relationships remain to be established

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for other agricultural practices that provide additional C input to the soil, such as cover crops, improved crop rotations, temporary leys and agroforestry (Soussana et al. 2019). For instance, Cardinael et al. (2018) estimated that, in an agroforestry system in Southern France, 2.73 additional Mg C ha⁻¹ yr⁻¹ from vegetation, litterfall, and crop residues increased SOC stocks by 0.45% yr⁻¹ for 18 years up to 30 cm depth, compared to an agricultural control treatment. This is similar to our results with EOM treatments in the first 20-30 cm depth, suggesting that a 0.4% target might be feasible with the implementation of other practices, such as agroforestry systems. To predict with more confidence the potential of different qualities of C input to increase SOC stocks, other LTEs with such practices should be considered. For example, Wiesmeier et al. (2020) identified cover cropping and agroforestry systems as the practices with the highest potential to increase SOC stocks up to 40 cm depth in Bavaria, compared to current land management. However, they estimated that a 0.4% SOC stock increase target was not possible.

5.5 CONCLUSION

In the 11 cropland LTEs analyzed, reaching quantitative targets of SOC stock increase required significantly different amounts of additional C input, whether the targets were calculated against the initial level of SOC stocks or against a baseline practice (i.e. a control treatment with or without mineral fertilizer inputs and without any EOM, where SOC stocks were mainly decreasing). Incentives to implement agricultural practices that increase SOC stocks should take into consideration that higher C input are required for soils with decreasing SOC stock, if quantitative targets of SOC stock increase are calculated regardless of the current SOC stock trends. Since EOM inputs are already widely applied in European croplands, future works should analyze the effect of C input on SOC stocks in LTEs, considering the implementation of other practices, such as agroforestry systems and cover cropping. Strategies to implement a portfolio of agricultural practices that allow increasing SOC stocks should be considered to reach the Mission Board for Soil Health and Food's targets by 2030.

5.6 APPENDIX A: GENERALIZATION OF THE TARGETS' COMPARISON

<u>Demonstration that T₀ target is always higher than B target if SOC stocks in a control</u> <u>treatment are decreasing and approximated with a linear regression</u> Imagine that a control treatment can be approximated by a linear regression. Then, it can be written as Equation A1:

$$SOC^{control} = m * t + SOC_{o}^{control}$$
(A1)

Where: $SOC^{control}$ are the soil organic carbon stocks in the control treatment, t is time (i.e. the number of years since the beginning of the experiment), m is the slope of the regression line and $SOC_0^{control}$ are the SOC stocks at t = 0.

The relative slope (i.e. the slope of the SOC stocks, relative to the first year of SOC stocks in the control treatment) can be written as Equation A2:

$$relative_slope^{control} = \frac{m}{SOC_0^{control}}$$
(A2)

If we suppose that the control treatment has a decreasing SOC stock trend, this means that the slope (m) is negative, hence the *relative_slope*^{control} is negative too.

From Eqs. 4 and 5 we derive the targets set, based on T_0 (i.e. SOC_{T_0}) and B (i.e. SOC_B), respectively. We calculate the difference between SOC_{T_0} and SOC_B (SOC_{T_0} - SOC_B). That is, the difference between Eq. 4 and Eq. 5. With a few simple computations, we derive Equation A3:

$$SOC_{T_0} - SOC_B = -SOC_0^{control} \cdot n \cdot relative_slope^{control}$$
 (A3)
Since $SOC_0^{control} > 0$, $n > 0$ and $relative_slope^{control} < 0$, $SOC_{T_0} - SOC_B > 0$. Hence,

$$SOC_{T_0} > SOC_B.$$

Similarly, we can demonstrate that T_0 target is equal to B target if SOC stocks in the control treatment are at steady-state and approximated with a linear regression.

If SOC stocks are at steady-state, m = 0. Hence, $SOC_{T_0} = SOC_B$.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or

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Author Contributions

EB performed the calculations and prepared the manuscript with contributions from all co-

authors. HC, TK, IV and MM provided the data.

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Data Availability

The datasets analyzed for this study were provided by the data owners of the different longterm experiments. Please, contact them to get access to the data.

5.8 SUPPLEMENTARY MATERIAL



Supplementary Figure 1 Linear regression of the exogenous organic matter (T1 to T6) and control treatments (T0) of the long-term experimental sites. Black spots indicate measured SOC stocks and red solid lines indicate the predicted linear regression.



Supplementary Figure 2 Measured and predicted SOC stocks with time for each treatment over the experiment length and retained C input over time. Retained C inputs (from crop residues and EOM) were calculated as the amount of C input, multiplied by its C retention coefficient (Table S1)

Supplementary Table 1 Agronomic information on the experiments.

							Percentage				
							of				
							experiments'		Carbon	Carbon	Carbon
							length for		retention	retention	retention
			Control		Crop	Crops	which straw	Maximal	coefficient	coefficient	coefficient
	Treatment	Plot	/EOM	Species	rotations	botanical	residue was	tillage	abovegroun	belowgrou	EOM
Site	name	size	type	name	1	names	exported	depth ²	d crop	nd crop	inputs
		m2					%	cm			
Champ											
Noel 3											
(CHNO3)	то	150	Control		sM	Zea mays	100	25	0.23	0.40	
				Sus							
			Pig	domesti							
	T1	150	slurry	cus	sM	Zea mays	100	25	0.23	0.40	0.15
						Triticum					
						aestivum,					
						Zea mays,					
						Hordeum					
						vulgare,					
Colmar					wW/Mg/	Beta					
(COL)	то	90	Control		sB/S	vulgaris	0	28	0.24	0.40	
			Green		wW/Mg/	Triticum					
	T1	90	waste		sB/S	aestivum,	0	28	0.24	0.40	0.83

		and			Zog mays					
		anu			zeu muys,					
		biowast			Hordeum					
		е			vulgare,					
		compos			Beta					
		t			vulgaris					
					Triticum					
					aestivum,					
					Zea mays,					
					Hordeum					
					vulgare,					
		Urban		wW/Mg/	Beta					
Т2	90	sludges		sB/S	vulgaris	0	28	0.24	0.40	0.54
					Triticum					
					aestivum,					
					Zea mays,					
		Compos			Hordeum					
		ted			vulgare,					
		Cattle	Bos	wW/Mg/	Beta					
Т3	90	manure	taurus	sB/S	vulgaris	0	28	0.24	0.40	0.61
					Triticum					
		Green			aestivum,					
		waste			Zea mays,					
		compos		wW/Mg/	Hordeum					
T4	90	t		sB/S	vulgare,	0	28	0.24	0.40	0.65

						Beta					
						vulgaris					
						Triticum					
						aestivum,					
						Zea mays,					
						Hordeum					
						vulgare,					
			Cattle	Bos	wW/Mg/	Beta					
	T5	90	manure	taurus	sB/S	vulgaris	0	28	0.24	0.40	0.65
						Triticum					
Crécom						aestivum,					
(CREC3)	т0	130	Control		wW/sM	Zea mays	100	30	0.22	0.40	
						Triticum					
			Cattle	Bos		aestivum,					
	T1	130	manure	taurus	wW/sM	Zea mays	100	30	0.22	0.40	0.52
				Gallus							
				gallus		Triticum					
			Poultry	domesti		aestivum,					
	Т2	130	manure	cus	wW/sM	Zea mays	100	30	0.22	0.40	0.40
						Triticum					
						aestivum,					
						Zea mays,					
Feucheroll					wW/Mg/	Hordeum					
es (FEU)	Т0	450	Control		wB	vulgare ³	56	29	0.22	0.40	

			Biowast								
			e and			Triticum					
			green			aestivum,					
			waste			Zea mays,					
			compos		wW/Mg/	Hordeum					
	T1	450	t		wB	vulgare ³	56	29	0.22	0.40	0.83
						Triticum					
			Green			aestivum,					
			waste			Zea mays,					
			compos		wW/Mg/	Hordeum					
	Т2	450	t		wB	vulgare ³	56	29	0.22	0.40	0.65
						Triticum					
						aestivum,					
						Zea mays,					
			Cattle	Bos	wW/Mg/	Hordeum					
	Т3	450	manure	taurus	wB	vulgare ³	56	29	0.22	0.40	0.65
			Municip			Triticum					
			al solid			aestivum,					
			waste			Zea mays,					
			compos		wW/Mg/	Hordeum					
	Т4	450	t		wB	vulgare ³	56	29	0.22	0.40	0.53
Jeu-les-						Triticum					
Bois					wB/R/w	aestivum,					
(JEU1)	т0	72	Control		W	Brassica	55	30	0.22	0.40	

						napus L.,					
						Hordeum					
						vulgare					
						Triticum					
						aestivum,					
			Compos			Brassica					
			ted			napus L.,					
			Cattle	Bos	wB/R/w	Hordeum					
	T1	144	manure	taurus	W	vulgare	55	30	0.22	0.40	0.61
						Triticum					
						aestivum,					
			Compos			Brassica					
			ted			napus L.,					
			Cattle	Bos	wB/R/w	Hordeum					
	Т2	144	manure	taurus	W	vulgare	55	30	0.22	0.40	0.61
						Triticum					
						aestivum,					
						Brassica					
						napus L.,					
			Cattle	Bos	wB/R/w	Hordeum					
	Т3	144	manure	taurus	W	vulgare	55	30	0.22	0.40	0.52
						Triticum					
La Jaillère						aestivum,					
2 (LAJA2)	Т0	70	Control		sM/wW	Zea mays,	93	22	0.23	0.40	

					Brassica					
					napus L.					
					Triticum					
		Compos			aestivum,					
		ted			Zea mays,					
		Cattle	Bos		Brassica					
T1	70	manure	taurus	sM/wW	napus L.	93	22	0.23	0.40	0.61
					Triticum					
					aestivum,					
		Compos	Sus		Zea mays,					
		ted Pig	domesti		Brassica					
Т2	70	manure	cus	sM/wW	napus L.	93	22	0.23	0.40	0.61
					Triticum					
		Compos	Gallus		aestivum,					
		ted	gallus		Zea mays,					
		Poultry	domesti		Brassica					
Т3	70	manure	cus	sM/wW	napus L.	93	22	0.23	0.40	0.61
					Triticum					
					aestivum,					
					Zea mays,					
		Cattle	Bos		Brassica					
T4	70	manure	taurus	sM/wW	napus L.	93	22	0.23	0.40	0.52

						Triticum					
						aestivum,					
				Sus		Zea mays,					
			Pig	domesti		Brassica					
	Т5	70	manure	cus	sM/wW	napus L.	93	22	0.23	0.40	0.53
						Triticum					
				Gallus		aestivum,					
				gallus		Zea mays,					
			Poultry	domesti		Brassica					
	Т6	70	manure	cus	sM/wW	napus L.	93	22	0.23	0.40	0.40
Le Rheu 1											
(RHEU1)	т0	60	Control		sM	Zea mays	100	30	0.23	0.40	
			Compos								
			ted								
			Cattle	Bos							
	T1	60	manure	taurus	sM	Zea mays	100	30	0.23	0.40	0.61
Le Rheu 2											
(RHEU2)	то	60	control		sM	Zea mays	100	30	0.23	0.40	
			Compos	Sus							
			ted Pig	domesti							
	T1	60	manure	cus	sM	Zea mays	100	30	0.23	0.40	0.61
				Sus							
			Pig	domesti							
	Т2	60	manure	cus	sM	Zea mays	100	30	0.23	0.40	0.40

						Avena					
						sativa,					
						Brassica					
						napus,					
						Sinapis					
						alba and					
						Brassica					
						nigra					
						mixture⁴,					
						Triticum					
						aestivum,					
						Hordeum					
					O/sT/Mu	vulgare,					
					/sW/sB/F	Beta					
Ultuna					b/OsR/F	vulgaris,					
(ULTU)	Т0	4	Control		R/M	Zea Mays ⁵	100	20	0.23	0.40	
						Avena					
						sativa,					
						Brassica					
						napus,					
					O/sT/Mu	Sinapis					
					/sW/sB/F	alba and					
			Straw	Cereal	b/OsR/F	Brassica					
	T1	4	residue	straw	R/M	nigra	100	20	0.23	0.40	0.23

					mixture⁴,					
					Triticum					
					aestivum,					
					Hordeum					
					vulgare,					
					Beta					
					vulgaris,					
					Zea Mays⁵					
					Avena					
					sativa,					
					Brassica					
					napus,					
					Sinapis					
					alba and					
					Brassica					
					nigra					
					mixture⁴,					
					Triticum					
					aestivum,					
			Grass		Hordeum					
			hay	O/sT/Mu	vulgare,					
			(differe	/sW/sB/F	Beta					
		Green	nt	b/OsR/F	vulgaris,					
Т2	4	manure	species)	R/M	Zea Mays⁵	100	20	0.23	0.40	0.76

					Avena					
					sativa,					
					Brassica					
					napus,					
					Sinapis					
					alba and					
					Brassica					
					nigra					
					mixture⁴,					
					Triticum					
					aestivum,					
					Hordeum					
				O/sT/Mu	vulgare,					
				/sW/sB/F	Beta					
				b/OsR/F	vulgaris,					
Т3	4	Peat		R/M	Zea Mays⁵	100	20	0.23	0.40	0.93
					Avena					
					sativa,					
					Brassica					
			Bos		napus,					
			taurus	O/sT/Mu	Sinapis					
		Farmyar	and	/sW/sB/F	alba and					
		d	straw	b/OsR/F	Brassica					
Τ4	4	manure	residue	R/M	nigra	100	20	0.23	0.40	0.52

					mixture⁴,					
					Triticum					
					aestivum,					
					Hordeum					
					vulgare,					
					Beta					
					vulgaris,					
					Zea Mays⁵					
					Avena					
					sativa,					
					Brassica					
					napus,					
					Sinapis					
					alba and					
					Brassica					
					nigra					
					mixture⁴,					
					Triticum					
					aestivum,					
			Tree		Hordeum					
			secies	O/sT/Mu	vulgare,					
			(not	/sW/sB/F	Beta					
		Sawdus	specifie	b/OsR/F	vulgaris,					
T5	4	t	d)	R/M	Zea Mays⁵	100	20	0.23	0.40	0.45

						Avena					
						sativa,					
						Brassica					
						napus,					
						Sinapis					
						alba and					
						Brassica					
						nigra					
						mixture⁴,					
						Triticum					
						aestivum,					
						Hordeum					
					O/sT/Mu	vulgare,					
					/sW/sB/F	Beta					
			Sewage		b/OsR/F	vulgaris,					
	Т6	4	sludge		R/M	Zea Mays⁵	100	20	0.23	0.40	0.54
						Triticum					
						aestivum,					
						Zea mays,					
Trévarez					RG/Mg/	Lolium					
(TREV1)	т0	156	Control		wW/sM	perenne L.	100	30	0.23	0.40	
						Triticum					
			Cattle	Bos	RG/Mg/	aestivum,					
	T1	156	manure	taurus	wW/sM	Zea mays,	100	30	0.23	0.40	0.52

						Lolium					
						perenne L.					
						Triticum					
						aestivum,					
				Sus		Zea mays,					
			Pig	domesti	RG/Mg/	Lolium					
	T2	156	manure	cus	wW/sM	perenne L.	100	30	0.23	0.40	0.53
						Triticum					
						aestivum,					
						Zea mays,					
Avrillé						Lolium					
(AVRI)	т0	360	Control		wW/sM	perenne L.	78	30	0.23	0.40	
						Triticum					
			Cattle	Bos		aestivum,					
	T1	360	manure	taurus	wW/sM	Zea mays	78	25	0.23	0.40	0.52
¹ Rotations legend: M = maize / wM = winter maize / sM = silage maize / Mg = maize grain / gM = green maize / W = wheat / wW = winter wheat / sW = spring											
wheat / B = barley / wB = winter barley / sB = spring barley / O = Oats / P = potato / S = sugar beet / R = rapeseed / Sf = sunflower / sT = Swedish turnip / Mu											
= mustard / Fb = fodder beet / OsR = oilseed rape / FR = fodder rape / RG = ray grass / wR = winter rye / Oflax = oil flax / fPea = fodder peas / Pea = peas											
² For Ultuna, tillage depth (cm)											
³ Winter Barley (<i>Hordeum vulgare</i>) only in 2007											
⁴ Most likely	hypothesis on	the crop	species for	mustard							
⁵ Zea mays grown every year since 2000 to get a 13C signal in SOM											

Supplementary Table 2 Annual average CO_2 fluxes (Mg CO_2 eq ha⁻¹ yr⁻¹), calculated from the annual average SOC stock variation in the control treatments, and potential annual average CO_2 fluxes if the SOC stock increase targets (0.1% T₀, 0.1% B, 0.4% T₀, and 0.4% B) are reached implementing CO_2 storing practices. Negative values represent net CO_2 emissions from the soil to the atmosphere, while positive values represent potential CO_2 storage.

	Annual average CO ₂ fluxes										
	Mg CO ₂ eq ha ⁻¹ yr ⁻¹										
	Control	Target T ₀	Target B	Target T ₀	Target B						
	treatment	0.1%	0.1%	0.4%	0.4%						
CHNO3	-1.33	0.14	-1.18	0.57	-0.75						
COL	-1.53	0.20	-1.33	0.78	-0.75						
CREC3	-0.14	0.22	0.08	0.89	0.74						
FEU	-0.94	0.14	-0.79	0.57	-0.37						
JEU1	-2.37	0.18	-2.19	0.71	-1.66						
LAJA2	-1.73	0.12	-1.61	0.49	-1.25						
RHEU1	-2.11	0.14	-1.97	0.56	-1.55						
RHEU2	-2.36	0.14	-2.23	0.55	-1.81						
ULTU	-0.80	0.15	-0.65	0.62	-0.18						
TREV1	-2.61	0.40	-2.21	1.59	-1.02						
AVRI	-2.01	0.17	-1.84	0.69	-1.33						
Mean <u>+</u>	-1 63 + 0 73	0 18 + 0 07	-1 45 + 0 72	0 73 + 0 29	-0 90 + 0 72						
SD	1.00 - 0.75	0.10 - 0.07	1.75 <u>-</u> 0.72	<u> </u>	0.50 <u>-</u> 0.72						

6 CHAPTER 6 GENERAL DISCUSSION, CONCLUSIONS AND FUTURE DIRECTIONS

One of the land-based solutions that are expected to reduce atmospheric CO₂, while increasing soil fertility and enhancing food security, is the increase of SOC stocks (Lal, 2016; Minasny et al., 2017; Martin et al., 2021). At the European scale, the possibility to reach an annual 4‰ SOC stock increase, as targeted by the Mission Board for Soil Health and Food, is still under debate. Recent works focused on the estimation of the amount of C input required to reach the 4‰ target at national or regional levels (Poulton et al., 2018; Riggers et al., 2021; Martin et al., 2021). As of today, a global assessment of the 4‰ target at the European scale is missing.

In this thesis, we built an inverse modelling tool to assess the amount of C input required to reach a quantitative target of SOC stock increase, according to the simulation of SOC models. After testing it on LTEs at local scale, we applied it at the European level to provide a first estimate of the spatial variability of the C input required to reach a 4‰ target under future scenarios of climate change.

6.1 SETTING QUANTITATIVE TARGETS FOR SOC STOCK INCREASES IN EUROPEAN CROPLANDS

In the 5th Chapter, we have shown that there are different approaches to calculate quantitative targets of SOC stock increase. For example, we could use one measurement of SOC stocks at the onset of the experiment to calculate the desired increase (T₀), or we could calculate the increase relative to the baseline SOC stocks in a reference practice (B) (Figure 5.1). Although both approaches are valuable for different purposes, they might set very different targets if SOC stocks are not close to steady-state (Figure 5.1). This was discussed by Soussana et al. (2019) and Pellerin et al. (2017), who showed the different targets set with the two approaches mentioned above in a few theoretical examples. As pointed out by Soussana et al. (2019), setting the increase target relative to the level of SOC stocks at the onset of the experiment is particularly relevant because it puts the pressure on soils with decreasing SOC stocks. This is in line with the objective of the UNCCD to reach land degradation neutrality by 2030 (Soussana et al., 2019), as well as the recently adopted

European Green New Deal, which aims to bring the EU to climate-neutrality by 2050. Furthermore, topsoil OC stocks are often decreasing in European croplands (Clivot et al., 2019; Goidts and van Wesemael, 2007; Meersmans et al., 2011; Saffih-Hdadi and Mary, 2008; Sanderman et al., 2017; Fernández-Ugalde et al., 2011, Veerman et al., 2020). In the 5th Chapter, we analyzed a set of cropland LTEs where EOM inputs were added to the soil and SOC stocks were monitored over time. We showed that the amount of C input required to reach quantitative targets calculated relative to the SOC stock at the onset of the experiment were significantly higher ($p \le 0.05$) than the C input required to reach the targets calculated against a baseline treatment, where SOC stocks were mainly decreasing. Policy makers who may want to incentivize the implementation of agricultural practices that increase SOC stocks should take into consideration that significantly higher C input are likely to be required for soils with decreasing SOC stocks, if quantitative increase targets are calculated regardless of current SOC stock trends. Lands where SOC stocks are decreasing may require substantial management changes to provide sufficient C inputs to the soil (e.g., transformation from mono to rotational cultures, adoption of agroforestry systems, and use of cover crops) (Wiesmeier et al., 2020; Corbeels et al., 2019)

In order to be in line with the European targets of SOC stock increase and the land degradation neutrality objective of the UNCCD, in our modelling exercise we set the 4‰ target relative to the SOC stocks at the onset of experiment.

6.2 UNCERTAINTY QUANTIFICATION IN PROCESS-BASED MODELLING

Process-based models are increasingly used to explore the impact of climate change and land use management on SOC stocks, and to evaluate the potential feedbacks of SOC decomposition rate changes on the climate system (e.g., Wieder et al., 2015b; Wiesmeier et al., 2016; Shi et al., 2018). Large uncertainties associated with input data and parameter values, as well as lacking knowledge about SOC processes, limit the predictive abilities of the SOC models (Luo and Schuur, 2020). To improve the reliability of SOC stock projections, it is of primary importance to assess and eventually reduce the uncertainties of model simulations.

In this thesis, we addressed the issue of uncertainty quantification in manifold ways. In the 2nd Chapter, we used a Monte Carlo approach to assess the uncertainty of the C input required to reach the 4‰ target, simulated by the Century model. In the 3rd Chapter, we used a multi-model ensemble to estimate the uncertainty of the required C input, according to different representations of the SOC dynamics. Finally, in the 4th Chapter we developed and evaluated a calibration technique to improve model simulations of SOC stock and assessed the uncertainty of the required C input change, relative to different configurations of parameters.

6.3 ESTIMATION OF THE CARBON INPUT

One important input data of SOC models is the C input deriving from plants and EOMs (e.g., organic amendments and fertilizers) to the soil (Eq. 1). In agricultural experiments, EOM inputs are usually measured. In contrast, direct measurements of C input from crops are rare because they include both aboveground and belowground crop residues, and these latter are especially difficult to sample. Instead of total crop C input measurements, crop yields can be measured and linked to the total C in the plant via allometric equations (Keel et al., 2017). In the literature, there are different allometric approaches to estimate the C input from crop yields (e.g. Bolinder et al., 2007; Franko et al., 2011; Jacobs et al., 2018). In Chapter 2 and 3, the C input from crop material was calculated using allometric equations, following the Bolinder approach (Bolinder et al., 2007), and its adaptation to European cropland experiments from Clivot et al. (2019). Keel et al. (2017) tested several allometric equations for the estimation of the C input to the C-TOOL model on a Swiss experiment and found that the choice strongly affected the simulations of SOC stocks. Since we worked with relative changes of C inputs (i.e., the relative C input change required to increase SOC stocks by 4‰ yr⁻¹, compared to initial C input), our exercise remains relatively less sensitive to the C input estimation. However, future works should assess the uncertainty related to the calculation method used to estimate the C input from crops, such as in Riggers et al. (2021) and Clivot et al. (2019).

In addition, we considered that the C input to the soil was constant over time. This may have introduced an additional error to the simulations, because C input actually vary over time, at

a monthly or daily time-scale. However, the hypothesis of constant C input was necessary to solve the inverse problem of optimal C input calculation. In the 2nd Chapter, we used a Monte-Carlo approach to quantify the uncertainty of the C input change requirement introduced by this hypothesis, considering the variability of the interannual C input at each site (see Figure 2.9). This provided an estimate of the variability of the C input required to reach the 4‰ target, considering a larger range of potential C input at the experimental sites. However, the variation of the C input with time was still not considered and this could have introduced simulation errors that should be further investigated, by considering intra-annual and interannual C input variations.

In the 4th Chapter, we approximated the C input in European croplands with the average NPP between 2000 and 2009 from MODIS satellite data, adjusted with the fractions of harvested NPP from Plutzar et al. (2016). Other global databases of annual NPP are available from model simulations (e.g. from ISIMIP, Grieser et al., 2006; Rosenzweig et al., 2014; Zhang et al., 2020; Del Grosso et al., 2008) that could be used to estimate the variability of projected SOC stocks according to different NPP data sources. Furthermore, the estimated proportion of NPP removed from the soil through harvest was also dependent on the approach used (Plutzar et al., 2016). In the analyzed cropland sites, the average proportion of NPP removed was 38% \pm 23% (mean \pm SD), according to the Plutzar et al. (2016) approach. This is similar to Wolf et al. (2015), who estimated a crop-specific proportion of harvested NPP, and found that in Western Europe around 39% of NPP biomass was harvested (mean across 2005-2011). However, local differences might arise from the different estimation method used.

Further improvements to the simulations could also be achieved by considering a crop growth module. This would allow simulating the interactions between increased SOC stocks and plant growth, which could potentially trigger positive feedbacks to the SOC storage. However, it is worth to consider that such positive feedbacks may be limited by the availability of the plants to the nutrients (see Annex I). Also, one thing that most models do not consider, although it has been widely observed, is that root C – especially from rhizodeposits – tends to have a longer residence time in soil, compared to aboveground C input (Rasse et al., 2005; Sokol et al., 2019).

6.4 THE IMPORTANCE OF CONSIDERING MULTI-MODEL ENSEMBLES

In addition to uncertainties in the input data, models also lack to explicitly incorporate all the mechanisms and factors involved in the SOC dynamics. In fact, models are just an abstraction of real-world processes, and rely on the limited knowledge that is available about SOC dynamics. One way to consider different mechanisms and factors involved, and to include a larger range of possible representations of SOC processes, is to use multi-model ensembles (Tebaldi and Knutti, 2007).

In the 3rd Chapter, we used a multi-model ensemble to estimate the uncertainty of the C input required to reach the 4‰ target, according to different representations of the SOC dynamics. We found that the simulated C input required to reach an annual 4‰ SOC stock increase at 17 LTEs in European croplands was strongly uncertain, according to the multi-model ensemble. Under default parametrization, SOC stock simulations diverged strongly within the six different models (Figure 3.1). The differences in the simulated SOC stock could partly explain the different C input requirements predicted by the models (Figure 3.4). However, when models when calibrated to fit the evolution of SOC stocks at the LTEs, C input requirements were still highly variable across models (Figure 3.4). Possible explanations to these differences are: the initialization technique used for the different models, the choice of the calibrated parameters, the mechanistic structure of the models, and the mathematical formalism used to describe them. On the one side, including more recent models likely updates model assumptions to contemporary understanding of soil microbial activity and metabolic traits (Wieder et al., 2015b; Abramoff et al., 2018). However, the use of older but highly evaluated models allows to capture many essential features of ecosystem dynamics, which these models have proven to correctly simulate (e.g. Parton et al., 1983, 1988, 1989a, b).

The use of multi-model ensembles has been a consolidated practice in climate modelling for decades (Tebaldi and Knutti, 2007; Parker, 2010; Jebeile and Crucifix, 2020). In soil modelling, increasingly more papers have been using multi-model ensembles to simulate long-term SOC evolution and assess the associated uncertainty (e.g., Palosuo et al., 2012; Sulman et al., 2018;

Farina et al., 2021; Riggers et al., 2021). Our findings contribute to highlighting the importance of multi-model ensembles, to assess the uncertainty of SOC stock predictions and related processes.

Our work could be improved by uniformizing the optimization and resolution techniques used for the different models, in order to isolate the mechanistic structure effect of the models on the simulated outputs.

6.5 MODEL PARAMETRIZATION

Multi-model ensembles allow to estimate the uncertainty of SOC simulations by considering different types of processes involved in SOC dynamics. However, there are always processes that the models do not explicitly include. These processes are called "processes at unresolved scales" (Luo and Schuur, 2020). In an attempt to deal with processes at unresolved scales, the soil community has made major efforts to explicitly represent microbes in SOC models (Allison et al., 2010; Wieder et al., 2015b, a; Georgiou et al., 2017; Abramoff et al., 2018, 2022). However, even extremely complex models could not represent all SOC processes explicitly. Hence, interactions between processes at unresolved scales with those at resolved scales should be reflected in model parameters (Luo and Schuur, 2020). Parameters are commonly considered constant in SOC models. For example, the decomposition rate parameters of SOC are usually kept constant over time and space (e.g., Parton et al., 1988a; Coleman and Jenkinson, 1996; Andriulo et al., 1999). Nevertheless, ecosystem properties have been frequently shown to change over time, space and pedo-climatic conditions. Thus, parameters should also vary to capture the changing properties of the ecosystem processes that they represent.

In the 4th Chapter, we proposed a calibration technique for large scale simulations of SOC models, where parameter values were allowed to vary over space. In an attempt to capture changes in ecosystem properties through changes in parameter values, we estimated the statistical relationships between on-site calibrated parameters and observed pedo-climatic conditions, and applied them at larger scale to test the validity of the approach on independent sites.

Our simulations proved to better represent the spatial distribution of first-year SOC stocks, compared to default parametrization (Figure 5.4). However, there was still a high uncertainty in the projected SOC stocks across models (Figure 5.6). In fact, the three SOC models used for the analysis predicted divergent SOC stock trends under future climate change, and these trends were even steeper when the models were statistically calibrated (Table 5.4). As a consequence, the uncertainty around projected SOC stocks were propagated to the inverse modelling calculations, and estimated C input changes required to reach the 4‰ target in European croplands varied largely across models (Figure 5.7). Our results show that model parameters may be largely responsible for uncertainties in SOC model predictions, as it has been previously demonstrated (e.g., Post et al., 2008; Shi et al., 2018; Luo and Schuur, 2020). Furthermore, higher uncertainties across model predictions may be expected if parameters are allowed to vary over space following spatial variations of pedo-climatic factors.

What we did in this chapter should be considered as a of 'proof of concept' showing the feasibility of optimizing model parameters at large scale. However, since the proposed technique is based on statistical relationships, we are confident that these results could be improved by using a higher number of LTEs to link parameter values to specific environmental conditions. Furthermore, improving initial conditions of models initialized with spin-up, and systematically selecting the parameters to calibrate though sensitivity analysis, may also reduce the uncertainty of SOC model simulations.

6.6 FEASIBILITY OF THE 4‰ TARGET IN EUROPEAN CROPLANDS UNDER FUTURE CLIMATE CHANGE

The uncertainties of SOC stock predictions across different models partly derived from their representation of the C input - SOC stocks relationship. In fact, the estimated C inputs required to reach the 4‰ target were highly variable across models, and under both default and calibrated configurations.

In the 1st Chapter, we used the Century model to estimate at 14 cropland sites the amount of C input required to increase SOC stocks by 4‰ yr⁻¹ over 30 years, compared to initial SOC stocks. We found that C inputs had to increase by 43%, compared to initial C inputs. In

comparison, the additional C input actually used in the 14 LTEs (i.e., from additional EOM inputs and crop growth, or from improved crop rotations) was approximately 160% higher than the C input in the control treatments. However, the model was likely overestimating the effect of the additional C input on the SOC stocks (Figure 2.5). This means that the C input required to reach the 4‰ target could have been much higher. In the 2nd Chapter, we ran a similar analysis using six different SOC models over 17 LTEs in European croplands. We found that Century was indeed underestimating the C input required to reach the 4‰ target, compared to the other models (Figure 3.4). Furthermore, there was a high uncertainty across all models in both their non-calibrated and calibrated configurations. The multi-model ensemble predicted that the C input would have to more than double in order to reach the 4‰ target over 30 years. That is, C input had to increase by 107% on average, compared to initial conditions (Table 3.3). This result is similar to the predictions at the European cropland level, over the period 2015-2100. We found that the C input had to increase by 129% and 108% on average under RCP 2.6, according to the non-calibrated and calibrated multi-model ensembles, respectively (Table 4.5). Results were similar under RCP 6.0 (i.e. C input had to increase by 129% in the non-calibrated configuration, and by 106% in the calibrated configuration). The C input increase requirements were higher in Northern Europe, compared to lower latitudes (Figure 4.7). In the European South, we found larger uncertainties around model simulations. This suggests that model simulations may actually be underestimating the amount of C input required in those regions. In the 5th Chapter, we used EOM treatments to discuss how the quantitative definition of SOC stock increase targets affected the C input change requirement. We found that, the average C input required to reach the 4‰ target calculated against initial SOC stocks, was significantly different to the average C input to reach the 4‰ target, when it was calculated against the SOC stock trend in a control plot without any EOM addition (Figure 5.3). That is, an average 142% and 136% increase of C input was required, respectively (i.e., average C input required/ average C input in the control treatment *100). This suggests that the multi-model ensemble may be still underestimating the amount of C input required (see also Figure 4.3).

We used data from the long-term experimental sites to compare model requirements to the EOM input used in the treatments (Figure 2.9). However, the amount of C input used in the LTEs was much higher than the average C input used in European croplands from livestock manures (Zhang et al., 2017). Furthermore, EOM inputs are currently already added to the soil in European croplands, thus they cannot be considered as *additional* C input (Foged et al., 2011). Also, since EOM inputs are only lateral transfers of C that was already sequestered from the atmosphere, they do not account as an additional climate mitigation potential (Poulton et al., 2018).

In this context, increasing the C input by more than 100% will likely demand for drastic changes in the agricultural practices at the European scale. Increasing the quantity and the stability of the C input to the soil will require the adoption of diverse agronomic practices that have proven to increase SOC stocks. For instance, crop species and varieties with greater root mass and deeper roots, crop rotations providing greater C input, N-fixing legumes where soils have limited available N, use of cover crops during fallow periods, and adoption of agroforestry systems (Soussana et al., 2019; Chenu et al., 2019). Not only it will be necessary to adopt new practices, but it will also be crucial to ameliorate the current management of agricultural soils, through improved crop residues retention and organic amendment addition (Soussana et al., 2019).

6.7 PERSPECTIVES

Although model simulations are still highly uncertain, there is compelling evidence that a radical change in agricultural management will be required to cope with climate change and food security in the near future. The European Commission has been suggested to set ambitious targets to increase SOC stocks and improve the health of European soils (Veerman et al., 2020). Yet, we are far from being optimistic. The last fifty years of international agreements about the response of world nations to climate change have proven that, no matter how compelling evidence the scientific community provides, indicators of adverse change are still on a rise (Glavovic et al., 2021). Thus, governments have to take action before it is too late.

In the last decades, thousands of works have been published on the effects of land management, land-use change and climate change on SOC (Beillouin et al., 2022). However, studies are narrowed to a selected number of specific drivers and geographical regions (Beillouin et al., 2022). In fact, studies on agricultural management practices mostly focused on mineral fertilization, organic amendments, and tillage. Furthermore, drivers of SOC changes have only occasionally been studied in North and Central Africa, and in the Middle East and Central Asia (Beillouin et al., 2022). Future research should focus on more local and diversified knowledge on how to preserve and restore SOC stocks, while covering understudied geographical regions. Besides, increased knowledge on the effects of diversified practices on SOC stock changes, under different pedo-climatic conditions, will help to improve model simulations and provide reliable SOC stock projections under future climate change.

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7 ANNEX I CAN N₂O EMISSIONS OFFSET THE BENEFITS FROM SOIL ORGANIC CARBON STORAGE **?**

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Abstract

To respect the Paris agreement targeting a limitation of global warming below 2°C by 2100, and possibly below 1.5°C, drastic reductions of greenhouse gas emissions are mandatory but not sufficient. Large-scale deployment of other climate mitigation strategies is also necessary. Among these, increasing soil organic carbon (SOC) stocks is an important lever because carbon in soils can be stored for long periods and land management options to achieve this already exist and have been widely tested. However, agricultural soils are also an important source of nitrous oxide (N₂O), a powerful greenhouse gas, and increasing SOC may influence N₂O emissions, likely causing an increase in many cases, thus tending to offset the climate change benefit from increased SOC storage. Here we review the main agricultural management options for increasing SOC stocks. We evaluate the amount of SOC that can be stored as well as resulting changes in N₂O emissions to better estimate the climate benefits of these management options. Based on quantitative data obtained from published metaanalyses and from our current level of understanding, we conclude that the climate mitigation induced by increased SOC storage is generally overestimated if associated N₂O emissions are not considered but, with the exception of reduced tillage, is never fully offset.

Some options (e.g. biochar or non-pyrogenic C amendment application) may even decrease N₂O emissions.

7.1 INTRODUCTION

The United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement adopted in 2015 aimed at keeping global warming below 2°C by 2100, and at possibly further limiting the temperature increase to 1.5°C. This requires not only drastic reductions in GHG emissions in the near future, but also net negative emission technologies because not all emissions will be reducible to zero within this time scale (Rogelj et al., 2015; Seneviratne et al., 2018). To a large extent, these negative emissions imply land-based mitigation strategies (IPCC, 2018), mostly involving the production of organic matter by plant photosynthesis coupled with carbon storage in living biomass and/or soil organic matter (SOM; Paustian et al., 2016).

A pathway frequently discussed known as bioenergy with carbon capture and storage (BECCS) comprises generating energy using biomass, capturing the CO₂ evolved from this process and storing it in geological reservoirs. The deployment of BECCS faces both technical challenges and most likely limitations due to high costs and adverse environmental impacts such as increased pressure on land and water resources (Obersteiner et al., 2018; Smith et al., 2016). On the other hand, the net removal of atmospheric CO₂ taken up by plants in agricultural soils (i.e. carbon sequestration) has recently come under sharp focus as a more affordable and practical alternative, potentially associated with positive economic outcomes and possibly applicable at large scale in managed lands (Hepburn et al., 2019; Minasny et al., 2017).

The role of soils as a key component of the global carbon cycle is now recognized by the scientific community and also by policy-makers (Obersteiner et al., 2018; Smith et al., 2016). Soils have never been harnessed at large scale for the purpose of sequestering carbon, although they currently make up the largest reservoir of organic carbon in the terrestrial biosphere, with a size of 1,500–2,400 Pg C to a depth of 1 m (Ciais et al., 2013). However, the ecosystems which contain the largest stocks of soil organic carbon (SOC) are unmanaged

(comprising boreal forests, permafrost soils and wetlands), whereas only soils from managed ecosystems, in particular agricultural soils, may be managed to increase SOC stocks (i.e. carbon sequestration). Agriculture is also a key target sector for the reduction of methane (CH₄) and nitrous oxide (N₂O) emissions (IPCC, 2019; Tian et al., 2016; Wollenberg et al., 2016). Yet, few countries have included agriculture in their nationally determined contributions—a roadmap volunteered by national governments as part of the Paris Agreement to express their efforts to reduce GHG emissions— because of potential trade-offs with food production and uncertainties on achievable potentials (Frank et al., 2017).

Recent emphasis on promoting SOC storage has resulted in international initiatives such as the '4 per mil' initiative launched by France during the UNFCCC conference of the parties (COP) 21 (Minasny et al., 2017; Soussana et al., 2019). It relies on the concept that even a very small relative increase in SOC pools worldwide could offset a significant fraction of CO_2 emissions. Preliminary evaluation indicated that increasing global agricultural SOC stocks at an annual rate of 4‰ would result in a C sequestration potential of 2–3 Pg C/year (Minasny et al., 2017). This may contribute significantly to the objectives of the land sector to achieve the Paris agreement target (Roe et al., 2019). Moreover, even if it would not be sufficient to totally offset anthropogenic emissions, SOC increase is generally associated with several positive feed backs on biodiversity, crop yields, soil water retention, etc. (Mäder et al., 2002; Soussana et al., 2019). Nevertheless, several stud ies have discussed and criticized the feasibility of enriching soils at a rate of 4‰ over a sustained period of years (Chabbi et al., 2017; Poulton et al., 2018; Van Groenigen et al., 2017) because: (a) it requires large amounts of new organic matter inputs, (b) it requires large amounts of nutrients, (c) it is difficult to achieve this target rate in all agricultural systems, and (d) it may be hampered by the climate change-induced enhancement of SOC decomposition. Moreover, altered management practices may impact farm ers' income and imply trade-offs with food production (Poulton et al., 2018). Data from long-term experiments show that it is very difficult to achieve the 4 per mil rate in temperate arable systems without drastic changes in management (Batjes, 2019; Poulton et al., 2018). Finally, the annual rate of SOC increase generally levels off over time as the SOC pool increases and approaches a new equilibrium level (Stewart et al., 2007).

Nevertheless, concrete management options exist to increase SOC stocks such as cover crops, tillage management, crop rotations, organic amendments, agroforestry and biochar amendments with effects depending on local conditions (Chenu et al., 2019; Corbeels et al., 2019; Dignac et al., 2017). These options have socio-economic impacts on farmers and land managers and indirect effects on ecosystem services, through changes in crop yields, water consumption, nitrate leaching and CH₄ and N₂O emissions which have to be considered when evaluating the feasibility and the relevance of implementing SOC storage options. For instance, maintaining SOC storing practices may incur costs, thus affecting farmers' profitability and implying a need for governmental payments, depending on CO₂ price. Smith et al. (2008) estimated that 47%, 65% and 86% of the technical potential SOC storage in agricultural lands could be reached at costs of 20, 50 and 100 USD per ton of CO₂ respectively. The SOC storage potential of the various practices has been extensively assessed in the recent scientific literature (Cardinael, et al., 2018; Chenu et al., 2019; Fujisaki et al., 2018; Ogle et al., 2019; Paustian et al., 2016; Poulton et al., 2018), and recently revised by IPCC in its 2019 report on climate change and land (IPCC, 2019). However, implications for the N cycle (in particular N₂O emissions), and other biogeochemical cycles or crop yields have not been thoroughly documented so far (Bossio et al., 2020; Lugato et al., 2018; Oldfield et al., 2019). Neither have been the consequences of large-scale deployment of these measures, and constraints related to the nitrogen (N), phosphorous (P) and potassium (K) cycles. These aspects are important because they determine the overall GHG abatement efficiency of mitigation measures and set limits on their potential deployment. C and N cycles are strongly interlinked (Figure 1) in particular in soils and, we assume that the deployment of land-based mitigation options to increase SOC may impact the N cycle and the associated N_2O emissions. A recent modelling study suggests that measure to increase SOC sequestration might be offset by increased N_2O , depending on the crop rotation and on the duration of the land management practices (Lugato, et al., 2018). Recent progress in modelling SOC may help to better understand SOC dynamics and how we can enhance SOC storage (Abramoff et al., 2018; Cotrufo et al., 2013; Zhang et al., 2018, 2020), but so far the interaction between C and N cycles is still poorly represented in models. A better understanding of such interactions is

necessary to evaluate the benefits of different management practices aimed at increasing SOC storage and to predict the full GHG balance of each practice. Nevertheless, measuring N₂O fluxes is challenging and large uncertainties exist due to difficult methodology (Chapuislardy et al., 2007). Indeed, most of the existing data are measured using chamber systems and several authors considered that a net N₂O uptake by the soils was due to technical limitation, in partic- ular when measurements had been carried out close to detection limits (Chapuis-lardy et al., 2007). Recent publications using other methods clearly showed that a net N₂O uptake is possible mainly during daytime (Keane et al., 2019; Shurpali et al., 2016). Despite such large uncertainties in the raw measurements of N₂O fluxes, when comparing a given management option against a control we may assume that the methodological bias are similar and the relative effect is still valid.

Here we focus on the interactions between soil C and nutrient dynamics, and in particular on N dynamics and N₂O emissions. The aims of the paper are to (a) describe the mechanisms linking the C and N cycles in soils, (b) assess how N₂O emissions may be affected by increased SOC pools as a land-based mitigation option, (c) review our knowledge on the other impacts of these practices.



Figure 1 A schematic representation of C–N interactions in the terrestrial ecosystem. Note that biological nitrogen fixation and denitrification are process performed by microorganisms that also need C as substrate and that the schematic is more representative of agroecosystems.

7.2 INTERTWINED SOIL CARBON AND NITROGEN CYCLES

Because C and N cycles are tightly coupled in soils, and altering one will affect the other as shown in Figure 1. In soils the C and the N cycles are sometimes totally interdependent, in particular when both are in organic forms but are sometimes uncoupled when C or N are present as minerals. This section summarizes the main mechanisms explaining how changes in the soil C cycle and SOC sequestration interact with N cycle processes, and in particular N₂O emissions (Figure 1). The first reason why soil C and N dynamics are interdependent is that both elements are stored predominantly as organic forms in the soil, sometimes within the same compounds (amino acids, proteins, etc.), thus mineralization generally affects both. Moreover, the availability of mineral N in the soil controls a number of processes in both cycles and vice versa. For instance, mineral N transformations depend on carbon availability and plant dry matter production is limited by N availability. Nitrogen is needed to sustain photosynthesis and other physiological processes (Engels et al., 2012); therefore higher N availability would likely lead to greater primary productivity and inputs of plant-derived organic matter to the soil (Glendining et al., 1996). On the other hand, higher N availability also tends to lower the allocation of photosynthates to the root system (Pausch & Kuzyakov, 2018). As root-derived C inputs contribute at least 2–3 times more than shoot-derived C inputs to SOC storage (Kätterer et al., 2011; Rasse et al., 2005), a high soil N availability could theoretically increase the plant biomass but the plant biomass produced might not be transformed into SOC as efficiently because of a reduced amount of root-derived C entering the soil (Han et al., 2016).

Soil organic matter turnover (i.e. rate of mineralization and transformation of SOM) also depends on the availability of N to microorganisms. While a low mineral N availability may limit the mineralization rate of plant residues and amendments (Fang et al., 2018; Recous et al., 1995), the combination of regular inputs of fresh organic C with a low soil N availability can lead to positive priming effect, that is, a higher rate of SOM mineralization, and a lower SOC storage potential (Chen et al., 2014; Fontaine et al., 2004). Moreover, because of the relatively narrow range of C:N ratios of SOM in mineral layers (Van Groenigen et al., 2017)

and because of the importance of soil microbial processing for building up stable SOM (Cotrufo et al., 2013) in some ecosystems, large amounts of N are inevitably required to stabilize large amounts of SOC (Bertrand et al., 2019; Cotrufo et al., 2019). Because of this stoichiometric requirement, it might seem acceptable to maintain a high availability of N in the soil by applying large amounts of mineral fertilizers. Such a strategy would, however, lead to potential N losses, for example, as N₂O emissions or nitrate leaching from soil, and further increase GHG emissions during fertilizer production. Thus the modest increases in SOC resulting from N fertilizer applications up to sensible agronomic rates are welcome in the context of C sequestration, but it would be counterproductive and inappropriate to recommend higher rates of N application aimed at promoting an additional increase in soil C.

Input of N to terrestrial ecosystems by biological N_2 fixation is another example of a close link between C and N resources. Root-associated or free-living N₂-fixing bacteria depend on the availability of organic C resources for sustaining their heterotrophic needs, which may explain why N₂ fixation is only triggered when the amount of soil mineral N is low. In particular, the en ergy cost of N₂ fixation represents between 5% and 23% of daily photo-assimilated C (Lambers, 1987). The associated CO_2 losses by respiration may therefore decrease the amount of plant C entering the soil. However, the consequence of this on the potential of SOC storage remains unclear. For example, the presence of leguminous plants can result in lower belowground C inputs compared to gramineous plants, leading to lower SOC concentrations (Bessler et al., 2009; Lange et al., 2015). However, the net inputs of N to soils by leguminous plants have been shown to correlate with a net accumulation of SOC, by providing the organic N required to stabilize an additional amount of SOC in soils (Jensen et al., 2012). Similarly, crop rotations that include leguminous plants appear to store more SOC than conventional monocultures (Drinkwater et al., 1998), although this effect may be mainly due to longer periods of plant cover, and to the presence of deeper root systems than to biological N₂ fixation itself (Jensen et al., 2012). These feedbacks also depend on which non-leguminous plants are associated (King & Blesh, 2018) to the N₂-fixing plant, and may lead to contrasting results in terms of SOC storage (Pellerin et al., 2019). Of course, obtaining N from legumes,

where this is practicable, rather than from N fertilizer does eliminate the GHG emissions associated with N fertilizer manufacture.

N₂O emissions represent a particular case that illustrates how the soil N cycle may be influenced by the C cycle. First, as N₂O mainly originates from the nitrification of ammonium (NH_4^+) or the denitrification of (NO_3^-) by specific groups of microorganisms, any process that can affect the total amount of mineral N in soils, such as N uptake by plants or plant residue mineralization, is likely to affect N₂O emissions. Moreover, fresh C inputs to the soil through root exudates or amendments may temporarily decrease or increase soil pH, affecting the magnitude of N_2O emissions. Consumption of these organic products by microorganisms may also decrease the local concentration of oxygen, leading to anaerobic conditions which are favourable to denitrification and N₂O emissions (Chen et al., 2013). Furthermore, because organic materials generally act as electron donors in the denitrification process and because SOM content may lower the redox potential of the soil (Quin et al., 2015), increasing the amount of SOM may also increase the activity of denitrifiers and therefore increase N₂O emissions (Brettar et al., 2002; Li et al., 2005). These mechanisms likely explain why higher SOC contents in soils have indeed been shown to correlate with larger N₂O emissions (Hénault et al., 2012; Stehfest & Bouwman, 2006). As a rule, net N₂O emissions from the soil at a given soil water-filled pore space (WFPS) will usually be lower when the soil mineral N content is low and when soil pH is alka-line or when C availability is reduced. Furthermore, because a low soil redox potential (<400 mV; Brettar et al., 2002) is required for denitrification, N₂O emissions have been suggested to have their optimum at 70%-80% WFPS, while prolonged waterlogging conditions may result in complete nitrate reduction to N_2 instead of N_2O (Butterbach-Bahl et al., 2013). This view is consistent with the classical model proposed by Firestone and Davidson (1989) but, recent results suggest that N_2O can be reduced to N₂ by non-denitrifier bacteria (Hallin et al., 2018). Thus, N₂O reduction rate might be higher than previously assumed explaining some net uptakes sometimes observed but generally considered as methodological artefacts (Chapuis-lardy et al., 2007). N₂O uptake is also controlled by environmental factors including pH or SOC (Assémien et al., 2019). Therefore, any modifications of soil conditions (e.g. redox potential, soil moisture, etc.) due

to land management practices may affect N₂O uptake.

Several mechanisms can therefore explain why attempts to modify the soil C cycle may also affect N₂O emissions. On a longer timescale, the build-up of SOC by various strategies may be expected to increase the retention of water and fertilizer-N in the rooting zone through improved soil properties (e.g. water holding capacity, porosity, hydrophilicity). This might trigger a higher primary production and enhance further SOC storage, but also increase the risk of N₂O emissions because of the increase in N sources and the shift to soil environmental conditions more favourable to N₂O emissions. In the remainder of this paper, we consider possible interactions between increased SOC and changes in N₂O emission for a range of management practices designed to increase SOC (Table 1). Table 1 Summary of the effects of management practices on soil organic carbon (SOC) storage and N_2O emissions

Management practice	Effect on soil C stocks	Effect on N ₂ O emissions
Reduced tillage/zero tillage	Reduced C loss/increased C inputs to soils when associated with a reduced weed management (Angers & Eriksen-Hamel, 2008; Virto et al., 2011)	Promote denitrification (anaerobiosis; Mei et al., 2018)
Erosion control (contour plowing, terracing)	Reduced C loss (Moraru & Rusu, 2010)	Unclear
Additionofnon-pyrogenicorganicamendments(compost,manure,crop residues)	Increased C input but in some cases (e.g. manure) rather a transfer from one terrestrial location to another than a transfer of C from atmosphere to soil (Diacono & Montemurro, 2011)	Enhanced denitrification rate (via anaerobiosis and the supply of electron donors), and soil N availability (Charles et al., 2017)
Use of cover crops	Reduced C loss/increased C input (Poeplau & Don, 2015)	Decreased denitrification because of N uptake by plants; may be compensated for by N inputs from biological nitrogen fixation (Lugato, et al., 2018; Thapa et al., 2018)
Biochar	Increased C input (Lehmann et al., 2006)	Decreased nitrification due to adsorption of mineral N with biochar (Borchard et al., 2019)
Agroforestry	Increased C input, reduced C loss, increased aggregate stability (Feliciano et al., 2018)	Decreased denitrification (lower soil moisture, increased soil porosity, increased nitrogen uptake), except for N ₂ -fixing trees (increasing soil available N; Kim et al.,
		2016)

7.3 How SOC storing practices affect N_2O emissions

7.3.1 Balancing the nitrogen inputs

Since mineral N availability drives N₂O emissions as well as crop productivity and C inputs into the soil (Ladha et al., 2011; Wang et al., 2019), N fertilization should be carefully managed. A balance should be obtained between N inputs (including fertilizers, manures and biological nitrogen fixation through symbiosis between N₂-fixing bacteria and some plant species) and N exported in harvested products in order to reduce a N surplus that can be source of N_2O_1 , but without a major negative effect on crop productivity. This N surplus should ideally be zero, but it is actually large and positive in many regions of the world, that have intensive agriculture (e.g. parts of China, India, Europe, North America), and negative in other regions (e.g. Africa; Gruber & Galloway, 2008). Excess N associated with a positive surplus is a major cause of N₂O emissions on farms, but also of nitrate leaching losses, part of which contributes to indirect N₂O emissions if nitrate is denitrified within surface waters. Overall, N surplus is a strong driver of N₂O emissions, especially when considering that the rate of emission is no longer linear for high N input (Shcherbak et al., 2014). The relatively low cost of mineral N fertilizers in developed countries compared to the price of agricultural products incentivizes farmers to apply more N than recommended by good practices, as an 'insurance' against unforeseen N losses due to climate variability. In some regions of the world, but not all, there is considerable potential to lower agricultural N₂O fluxes in inten- sive farming by reducing the N surplus without affecting farmers' incomes (Hoben et al., 2011). Therefore, the use of mineral N to increase crop productivity may induce an increase of C input into the soil but a complex balance must be found to avoid excessive N₂O emissions and N leaching.

7.3.2 Reduced tillage/non tillage

The effect of reduced tillage has attracted attention as a practice leading to increased SOC storage. However, recent metaanalyses demonstrate only a small positive effect of no-tillage on SOC stocks in the topsoil (0–30 cm layer) compared to conventional tillage, while it may vary widely across pedoclimatic situations (Angers & Eriksen-Hamel, 2008; Luo et al., 2010; Meurer et al., 2018; Powlson et al., 2016; Virto et al., 2011). Moreover, it must be recognized that the largest impact of reducing tillage is a redistribution of SOC towards the soil surface

(Angers & Eriksen-Hamel, 2008; Baker et al., 2007; Meurer et al., 2018; Ogle et al., 2019; Powlson et al., 2016). As a consequence, data from field trials must be carefully examined to distinguish between a genuine increase in SOC stocks in the surface soil layers from a simple change in the vertical distribution of SOC concentration. There has been considerable discussion as to whether the increased SOC in soil under zero tillage, especially near the surface, might increase N₂O emissions, because: (a) increased organic matter content can increase N₂O release (Mei et al., 2018), either because of increased energy supply to denitrifying organisms or because increased biological activity utilizes oxygen in soil, thus possibly leading to anoxic conditions at some microsites and (b) reducing tillage can be associated in the short term with a less porous soil structure, conducive of anoxy (Linn & Doran, 1984; Table 1). However, increased anoxia may have the opposite effect on N₂O emissions by accelerating N₂O reduction to N₂ as recently shown. This is due to the complex soil physical structure creating anoxic microsites that may simultaneously produce more N₂O but also accelerate N₂O reduction to N₂ (Buchen et al., 2019; Parkin, 1987). The different meta-analysis we compiled here (Figure 2) suggest that N₂O emissions may offset the C storage in no-till system when both fluxes are compared in CO_2 equivalents. However, there is conflicting evidence on whether or not this risk is actually realized (Mei et al., 2018; van Kessel et al., 2013). Recent meta-analyses suggest that, in the majority of situations, N₂O emissions are either unchanged or slightly decreased under zero or reduced tillage; the result will certainly be influenced by soil type and local climate and weather conditions so it may not be possible to draw a conclusion that is universally valid (Mangalassery et al., 2014; van Kessel et al., 2013). Furthermore, in some studies, N₂O emissions were expressed on both an area basis and a yield-scaled basis (van Kessel et al., 2013); because crop yields were slightly decreased under reduced tillage in some environments, N₂O emissions per unit of grain (or other product) were sometimes increased compared to conventional tillage.

7.3.3 Erosion control—Terracing

Erosion control practices are able to maintain or increase SOC content at the plot scale (Moraru & Rusu, 2010), although on a larger scale whether erosion is net C sink or a net source is still debated (Berhe et al., 2018; Lugato, et al., 2018; Van Oost et al., 2007). Erosion control encompasses a wide range of practices such as protecting the soil surface with cover crops or unharvested biomass (pruned fronds and other plant residues),

agroforestry, crop rotations, conservation tillage, or terracing on steep slopes. Some of these practices are already addressed in other sections of this paper (3.2, 3.4 and 3.5), and the following focuses on terracing.

Terracing is an ancient form of erosion control and a soil conservation method performed for thousands of years in steep landscape regions (Dotterweich, 2013; Tarolli et al., 2014). Despite its importance, studies focusing on quantifying soil erosion rates and the resulting C fluxes and SOC stocks in terraced areas are limited, especially at regional scales. Generally, terracing reduces soil erosion by reducing the slope gradient and length, and can decrease soil erosion rates by up to 95% (Fu, 1989; Upadhyay et al., 2005). It accordingly preserves SOC and nutrients. A meta-analysis on the ecosystem benefits of terracing shows that, compared to unterraced slopes, soil in terraced slopes contains 28.1% and 41.7% more N and C, respectively (Wei et al., 2016). However, the overall net effect of terracing on erosion depends on the terrace structure and maintenance, crop type, soil conditions, crop management practices or agricultural machinery. To maximize its positive effects, terracing needs to be combined with other soil conservation measures such as cover crops, agroforestry, organic amendments or no-till (Chen et al., 2017; McLauchlan, 2006). Furthermore, terraces need to be sustained, otherwise abandoned terraces can become sources of substantial land degradation due to gully formation. This is the case in the Mediterranean region where over 50% of the terraces have been abandoned (Tarolli et al., 2014; Wei et al., 2016).

The N₂O emissions associated with terracing are still poorly known. Terracing decreases the aggregate breakdown and transport of soil by erosion, which would lead to reduced N₂O emissions. However, as stated previously, N₂O emissions may increase with increased SOC. In addition, terracing tends to change the soil C:N ratio (Wei et al., 2016) and this may change the N availability for nitrifying/denitrifying bacteria and thus affect N₂O emissions. Finally, to fully estimate the effect of erosion control on N₂O budgets, it is important to measure emissions at the catchment scale not only at the field scale. Since erosion control aims to avoid lateral losses of soil material (containing various forms of N) ending up in rivers or in floodplains, it is necessary to combine measurements in the terraced or unterraced fields with measurements and modelling on the fate of erosed N in floodplains and rivers.



Figure 2 Estimation of the soil organic carbon storage and N_2O emissions of land-based mitigation options expressed in CO₂ equivalents. Negative values indicate a net reduction in GHG emissions in terms of CO₂ equivalents, while positive values show a net increase of CO₂ equivalent emissions. All values refer to the difference between the land-based mitigation option in question and a 'control' land (e.g. no-tillage vs. conventional tillage). For agroforestry, the control land is cropland and different types of agroforestry systems were considered. NB: In Kim et al. (2016) the majority of soil C storage data comes from intercropping, improved fallows and rotational woodlots, which are systems with high tree density. This could partially explain the very high estimation of soil C storage found in Kim et al. (2016) compared to other papers. Organic amendments do not include biochar. The control used for comparison with organic amendments is an experiment managed with inorganic fertilizers. For cover crops meta-analysis, Vicente-Vicente et al. (2016) only consider Mediterranean woody crops (olive, almond and vineyards), which could also explain the large soil C rates estimated. Uncertainty is given as standard error (SE) for every paper. If it was provided as a confidence interval (CI) or standard deviation (SD) it has been adequately transformed to unify the units. (*Reviews; **For these meta-analysis the values reported in the graph have been recalculated as the weighted mean across all experiments, from the database provided by the authors, because the values coming from the papers could not be used as they were reported as a percentage only) (Abdalla et al., 2019; Du et al., 2017; Skinner et al., 2014; Vicente-Vicente et al., 2016)

7.3.4 Cover crops

Planting cover crops is an effective management practice to increase SOC content. According to a recent meta-analysis, it leads to SOC accumulation rates in the order of 1.18 t CO₂-eq. ha⁻¹ year⁻¹ over 50 years (Poeplau & Don, 2015) in the topsoil, with a positive ef fect independent of tillage method, climatic zone or plant type (leguminous vs. nonleguminous). The impact of cover crops on SOC will depend on their duration and the frequency with which they are included in a crop rotation, and this information is sometimes unclear in published reports of field trials (Poeplau & Don, 2015). It is also necessary to interpret reviews of SOC data from cover crop experiments with caution because annual rates of increase are greatest in the early years following their introduction, so it is incorrect to assume that these rates can be sustained over long periods. As the majority of experiments reported in Figure 2 are short term (e.g. often only 2 years in Abdalla et al., 2019), all the average values shown for SOC increases from cover crops are likely to be overestimates. In addition the large rates shown by Vicente-Vicente et al. (2016) are for situations where cover crops were grown between rows of woody perennial crops; in this situation cover crops cover a larger area than in arable agriculture with annual crops and may be present permanently. The main driver of SOC storage seems to be the extra C input, as suggested by the high correlation between rates of SOC stock change and the amounts of C returned to the soil by cover crop biomass (Soane et al., 2012). However, there are limitations to the use of cover crops depending on cropping systems and climate conditions. For example, in temperate regions they can be readily utilized during the winter period prior to sowing a spring- sown crop, when the soil would otherwise be bare. But if only autumnsown crops are grown, there is very limited time between harvesting and the sowing of the subsequent crop. The effects of cover crops on N₂O emissions are more variable and contrasted than those on SOC changes (Table 1). Many factors influence the magnitude of N₂O emissions, such as the C:N ratio of cover crop residues, their rate of decomposition, the extra inputs of fertilizer N sometimes applied to cover crops, whether the residues are ploughed or left to decay on the soil surface. Current evidence points to a negative relationship between N₂O emissions and the C:N ratio of residues (Chen et al., 2013). A low C:N ratio will increase the availability of soil N for microbial transformations (e.g. nitrification and denitrification), whereas larger ratios will result in N immobilization and deplete the soil inorganic N pool (Gentile et al., 2008). Additional C inputs from cover crops may stimulate the activity of denitrifier bacteria, which use these organic compounds as a source of energy (Mitchell et al., 2013). A meta-analysis (Basche et al., 2014) reported a significant increase in N₂O emission when leguminous cover crops were introduced. However, another review

(Han et al., 2017) found out that the incorporation of either legume and non-legume cover crops tended to increase N₂O emissions but the magnitude of the effect was not significant due to the high variability of data. The small average increase in N₂O emission shown by Abdalla et al. (2019) in figure 2 is somewhat misleading as there was a considerable range in emissions in the data they summariszd, including both increases and decreases. The effect of cover crops on N₂O emissions is therefore not yet fully understood and may well be highly site specific. One of the key points controlling cover crop effect on N₂O emissions is how often leguminous crops are integrated within the crop rotation. Leguminous cover crops generally have a lower C:N ratio than non-leguminous crops, and can fix substantial amounts of atmospheric N, reaching up to 0.1–0.2 t N ha⁻¹ year⁻¹ (Anglade et al., 2015). These rates may lead to an N surplus if all the leguminous cover crop biomass is incorporated. A recent study, using a biogeochemistry model framework at European scale, estimated that systematic planting of N-fixing cover crops may lead to a N surplus of about 0.04 t N ha⁻¹ year⁻¹, compared to the use of non-legumes as cover crop (Lugato, et al., 2018). In this scenario, the cumulative climate change mitigation effect of SOC sequestration was, on average, totally offset after 50 years since the adoption of cover crops, due to enhanced N₂O emissions. While cover crops may induce higher N₂O emissions, in particular if leguminous crops are extensively used, they can also reduce nitrate leaching, by about 56% on average (Thapa et al., 2018). This is beneficial for water quality and would be expected to lead to decreased indirect N₂O emission through denitrification of nitrate entering surface water. Finally, another indirect effect of leguminous cover crops on N₂O emissions will strongly depend on whether or not mineral N fertilization rates are reduced to take account of N provided by biological fixation. The meta-analyses we compiled here indicate that, on average, additional N₂O emissions decrease the SOC storage benefit of cover crops, but do not fully offset it (Figure 2). But, as discussed above, the overall effects may be highly site specific.

7.3.5 Agroforestry

Agroforestry systems include a diversity of practices ranging from complex associations found in homegardens, multistrata systems or agroforests to simpler systems such as alley crops, silvopastoral systems, riparian plantings, shelterbelts, windbreaks or hedgerows (Nair, 1985). Despite this broad diversity, recent reviews and meta-analyses consistently

suggest that the conver sion of arable land to agroforestry systems increases SOC stocks (Feliciano et al., 2018; Kim et al., 2016; Lorenz & Lal, 2014). In temperate regions, SOC accumulation rates are usually around 0.92 t CO₂-eq. ha⁻¹ year⁻¹ in the topsoil (0–30 cm; Cardinael, et al., 2015; Cardinael et al., 2017). They are highly dependent on local pedoclimatic conditions and on the type and design of agroforestry systems (tree density, tree species, pruning management, etc), but rarely exceed 3.67 t CO2-eq. ha⁻¹ year⁻¹ (Cardinael, et al., 2018; Corbeels et al., 2019). However, the spatial distribution of SOC stocks in agroforestry systems is usually very heterogeneous, with higher stocks under the tree canopy or along tree rows (Bambrick et al., 2010; Cardinael, et al., 2015). Several mechanisms contribute to explain SOC sequestration in agroforestry systems. The main one is probably being linked to higher organic inputs to the soil compared to treeless agricultural land (Cardinael, et al., 2018), including litterfall, pruning residues and root inputs (Germon et al., 2016). A recent synthesis of N₂O emissions under agroforestry compared to adjacent agricultural lands only found minor differences in net emissions, with no clear overall direction of change (Kim et al., 2016). However, several authors found increased N₂O emissions in agroforestry, related to a greater N supply through N_2 - fixing trees (Chikowo et al., 2004; Dick et al., 2006; Hall et al., 2006; Hergoualc'h et al., 2008) or to the incorporation of tree residues (Baggs et al., 2006; Millar & Baggs, 2004). By contrast, N₂O emissions are often reduced in silvoarable systems and in riparian buffers (Kim et al., 2016). Some authors suggest that concerns over N₂O emissions from N₂-fixing trees are unwarranted since fluxes from soils planted with N2-fixing trees are similar to those fertilized with mineral N (Rosenstock et al., 2014). Furthermore, the yield of crops in tropical agroforestry systems may be boosted as a result of higher N inputs from trees. In temperate regions where agroforestry systems are generally planted with non-legume trees, N₂O emissions are often reduced (Kim et al., 2016), with several processes contributing to the trend. Increased nitrogen utilization at the plot scale may be due to the presence of deep-rooted trees (Cardinael, et al., 2015), which are capable of taking up nitrate-N that has leached below crop rooting depth (Andrianarisoa et al., 2016; Bergeron et al., 2011; Tully et al., 2012). This process can potentially reduce the amount of N available for nitrification and denitrification, and thus reduce indirect N₂O emissions. Soil water content is often lower in agroforestry than in treeless plots (Zhu et al., 2019), due to a higher daily water consumption by trees

and crops (Sarmiento-Soler et al., 2019). A drier soil profile in agroforestry systems could therefore lower N₂O emissions. In temperate silvoarable systems, tree rows are usually uncropped and unfertilized. This reduction in the fertilized cropping area indirectly leads to lower N₂O emissions per hectare. An obvious consequence of agroforestry, especially as tends to be practiced in temperate regions, is that a smaller area of land is devoted to the agricultural crop being grown. So the impact of decreased N₂O emissions may be different if expressed on an area basis compared to per unit of production.

7.3.6 Non-pyrogenic organic amendments

A literature review (Diacono & Montemurro, 2011) reported increases in SOC (sometimes expressed as stocks and sometimes as concentration) after prolonged large applications of organic amendments under several different agroclimatic conditions. These increases ranged from 20% to 90% of the initial total SOC after few years (3–60 years), compared to unfertilized controls or treatments receiving only synthetic mineral N fertilizers, with most being in the range of 20%–45%. A meta-analysis (Maillard & Angers, 2014) based on 130 observations worldwide quantified the response of SOC stocks to manure application over periods ranging from 3 to 82 years. The mean manure-C retention coefficient defined as the average proportion of manure-C remaining in the soil was estimated at 12% for an average study duration of 18 years. The authors finally estimated a relative SOC stock change factor of 26% which was also related to cumulative manure inputs. Concerning Mediterranean cropping systems, and shorter durations, a meta-analysis (Aguilera et al., 2013) reported that the application of organic amendments increased SOC stocks by 23.5% with an average SOC storage rate of 4.81 t CO₂-eq. ha⁻¹ year⁻¹ calculated for an average duration of 7.9 years. From these meta-analyses, it seems that there is a consensus that organic amendments lead, on average, to a relative increase of SOC stocks in the top soils (roughly 20–30 cm) of about 25% on a 20 year time frame (or three times the '4 per mil' target). In one example (Poulton et al., 2018) where manure was applied an nually at a high rate compared to what is usual in agrosystems, the annual rate of SOC accumulation averaged 18‰ per year in the first 20 years, then declined to 6‰ per year after 40–60 years, and to only 2‰ per year after 80–100 years. However, from the perspective of mitigating climate change, it is arguable whether any increase in SOC stocks resulting from applications of manure or similar mate rials can be considered as C mitigation in the sense of either a trans-fer of C from atmosphere to land or

an avoided emission. Manure is generated in agricultural systems and is almost always used in some way by application to soils, though often quite inefficiently. Thus, an increase in SOC stocks at a given location mainly represents a transfer of C from one site to another as opposed to a net removal of atmospheric carbon (Poulton et al., 2018). Local additional SOC storage may not represent a CO₂ sink, that is, a net transfer of carbon from the atmosphere to the soil at the landscape scale. Because organic amendments such as manures contain readily decomposable N-rich compounds, there is a significant risk that they may enhance N₂O emissions (Cayuela et al., 2010; Laville et al., 2014; Obriot et al., 2016). Conversely, their use permits decreased use of mineral N fertilizers, thereby saving N₂O emission from this source and fossil energy and the associated GHG emissions from fertilizer manufacture. A further complicating factor in assessing the overall impact of manure use is that indirect emissions due to storage or management are not negligible (Venterea et al., 2011). There are few reports in the literature of long-term monitoring of N₂O emissions compared to data on SOC stock changes, primarily because the former are much more difficult to measure. However, the effects of multiple types of organic amendments on SOC storage and N₂O emissions have been evaluated in short-term experiments for various soil types, climates, soil incorporation practices and amendments types including crop residues, manure, composts of various origin and maturation stages and sewage sludge. A meta-analysis (Charles et al., 2017) concluded that the N₂O emission factors (EFs) related to N inputs were mainly controlled by the C:N ratios of the added material, but that many other factors influenced emission, such as soil properties (texture, drainage, SOC and N content), and climatic factors. For instance, the authors observed that the EFs were on average 2.8 times greater in finetextured soils compared to coarse-textured, consistent with a previous meta-analysis (Chen et al., 2013). However, we should mention that the value of meta-analyses is often limited due to numerous controlling factors that are not always correctly reported in the papers reviewed, and the general paucity of organic amendments' characterization in the literature. For instance, the two meta-analyses mentioned in this paragraph only involved 28–38 individual journal articles (Charles et al., 2017; Chen et al., 2013). Another approach is to compare organically managed soils with those managed without organic amendments (Skinner et al., 2014). Results from such a comparison seem to indicate reduced N_2O emissions compared to situations relying totally on mineral fertilizers, as shown in Figure 2. It should be noted that there is limited data from long-term studies on N₂O emissions

associated with additions of organic amendments; the data cover only a limited diversity of pedoclimatic conditions, and especially the range of soil water filled pore space values explored.

7.3.7 Biochar amendments

Biochar (pyrolyzed organic matter amended to the soil) technology is considered by some authors to be one of the methods with the highest potential to sequester carbon in soils compared to natural C cycle without biochar production step (Paustian et al., 2016). The aim of biochar production from biomass pyrolysis is to produce recalcitrant organic matter (i.e. charcoal and biomass-derived black C) which is then added to the soil. For this reason, biochar can be considered as a negative emission technology different from other soil C sequestration methods (Smith et al., 2016). Biochar properties and effects on SOC stabilization strongly depend on the feedstock material and pyrolysis conditions (e.g.. maximum temperature, heating rates; Baveye, 2014; Fang et al., 2014; Singh et al., 2012; Weldon et al., 2019; Zimmerman et al., 2011), as well as biochar ageing and soil properties (Luo et al., 2011; Paetsch et al., 2018). The efficiency of biochar for C sequestration is twofold as compared to simply relying on soil stabilization processes. First, slow pyrolysis for biochar production results in a much higher proportion of the feedstock C bound in persistent molecular structures than through in situ stabilization by addition of unprocessed organic matter to soil (Lehmann et al., 2006). With a slow pyrolysis at about 500°C, approximately 50% of the carbon contained in a feedstock of Miscanthus or maize cobs ended up within the biochar and can therefore be assumed to be more stable than carbon in the raw bio mass (Budai et al., 2014). This compares with only 8%-12% of straw residue returned to the field being transformed into longer-lived SOM forms (Bolinder et al., 1999; Fujisaki et al., 2018). Thus, pyrolysis is about four times more efficient than SOM-formation processes to produce persistent C in soils. Second, field studies show that biochar has a longer mean residence time in soils than SOM, that is, >100 years (Rasse et al., 2017) versus about 50 years for the latter (Schmidt et al., 2011). Combining effects of the higher persistent C yield with that of the longer mean residence time, biochar appears at least eight times more efficient at storing SOC than the return of non-pyrolysed residues. In meta-analyses, biochar amend-ment tends to increase the SOC stocks by 40% but the studies used were generally short term (no more than 4 years; Liu et al., 2016). Nevertheless, this result must be considered with due care

since it is not straightforward to measure the effect of biochar, which is mainly C, on native SOC but one published study suggests that biochar amendment increases total SOC including non-biochar C (Liang et al., 2010).

In addition to the direct inputs of pyrolyzed biomass to the soil, recent studies showed that biochar amendments could increase (positive priming), decrease (negative priming) or have no effect on the mineralization of native SOM. The biochar effect on the magnitude and direction of priming is influenced by the incubation period and pyrolysis temperature (Fang et al., 2014; Kerré et al., 2016; Zimmerman et al., 2011). Positive priming, which would cause destabilization of SOM, thus offseting part of the increased SOC storage, could result from the biochar affecting microbial biomass activity and enzyme production (Lehmann et al., 2011) through changes in availability of organic substrates and nutrients, and modification of microorganism habitat associated with the great porosity and large specific surface area of charcoal particles (Lehmann et al., 2011). Conversely, some studies showed that biocharinduced negative priming, leading to further SOC storage in addition to direct biochar-C inputs, resulted from the enhancement of organo-mineral interactions and soil aggregation with biochar (Pituello et al., 2018; Singh & Cowie, 2014), and a greater adsorption of dissolved organic carbon onto biochar particles (Hernandez-Soriano et al., 2016). In addition, biochar amendments have been shown to increase soil water holding capacity, the availability of some nutrients (Ca²⁺, Mg²⁺ in particular) and to increase soil pH. All of these mechanisms could further enhance crop productivity and biomass inputs into soil (Atkinson et al., 2010; Biederman & Harpole, 2013; Hardy et al., 2017; Jeffery et al., 2011), with clearer effects on crop yields in highly weathered tropical soils (Crane-Droesch et al., 2013). Nevertheless, to process biomass into biochar, transport it and incorporate it to the soil, some energy is needed (possibly produced by pyrolysis) and the related GHG emissions associated with this process must be accounted for to calculate a full GHG balance for biochar. Life cycle assessments (LCA) have shown that a positive balance can be obtained, illustrated by GHG reductions up to 2.74 t CO₂ equivalent per ton of biochar amended on volcanic soils from Southern Chile (Muñoz et al., 2017). The balance can also significantly increase when plant biomass production is accompanied by an efficient use of the bioenergy produced during the pyrolysis process in order to maximize climate benefits from biochar production followed by addition to soil, as shown by an LCA performed in Spain (Peters et al., 2015); implementation

costs were also decreased. One simulation study suggests that the maximum sustainable technical potential of biochar to mitigate climate change, involving the widespread use of biochars, without threatening food security and landscapes, could be a mitigation of 12% of current anthropogenic CO_2 emissions (1.8 Pg CO_2 -C equivalent per year; Woolf et al., 2010). The C:N ratio of SOM approximates 14 (Cleveland & Liptzin, 2007) while that of biochar is generally higher than that of its feedstock, that is, generally >50 for straw biochar and >100 for wood biochar. It takes therefore at least five times less N to stabilize organic C in the form of biochar than in the form of SOM. Beyond this critical observation, biochar has other important interactions with the N cycle, notably: (a) volatilization and immobilization of N during the pyrolysis process (Mandal et al., 2016), (b) reduction of N_2O emissions after application to arable fields (Borchard et al., 2019), (c) reduction of NO₃ and NH₄ leaching (Lehmann et al., 2003). Emissions of N₂O fromsoils are in most cases substantially reduced by biochar addition: a recent meta-analysis reported an average decrease of 38% across studies (Borchard et al., 2019). However, most measurements are short term, the majority in this meta-analysis being <30 days; the impact over an entire growing season under field conditions has rarely been measured. This effect appears consistent when bio-char is produced at over ~450°C, so that the product has both a high pH and a high surface area while containing very little labile C (Weldon et al., 2019). The contribution of N₂O emissions attenuation with biochar was shown to be negligible in the LCA performed in Southern Chile, compared to the climate change mitigation associated to C storage (Muñoz et al., 2017). Furthermore, reductions in N₂O emission with biochar appears only significant for the first year after application, which suggests that frequent applications are necessary to maintain such an effect. In view of the large quantities of biochar usually applied in such studies, this may greatly limit the practical and/or economical potential for using biochar as a method for decreasing N₂O emissions. One approach to capitalizing on the positive interactions between biochar properties and the N cycle is through the development of biochar-based fertilizers made by mixing biochar with mineral or organic sources of nutrients (Hagemann et al., 2017). This method aims at reducing nitrate losses and N₂O emissions, and at in creasing N use efficiency. Moreover, biochar tends to adsorb mineral N and the mixing with a nutrient-rich material prevents potential N deficiency created by field application of large amounts of raw biochar. Some biochar structures have been successfully loaded with ni-trate ions through co-composting, which could greatly increases the fertilization value of the product (Kammann

et al., 2015). Producing biochar fertilizers requires the development of appropriate technologies. For example, mixing raw biochar—a high pH product—with manure and slurries can result in large amounts of NH₃ being volatilized. Therefore, biochar acidification is generally required when making biochar fertilizers from organic feedstocks. However, biochar is also a strong sorbent for NH₃ (Taghizadeh-Toosi et al., 2012), which may be captured from the atmosphere during the pyrolysis process and made available to plants later. This is a promising tech- nology to abate anthropogenic emissions of NH₃ (Taghizadeh-Toosi et al., 2012) as well as directly reduce NH₃ volatilization from soils (Mandal et al., 2016). In conclusion, pending proper technology, bio-char may be intimately mixed with N sources and applied each year as a fertilizer to maximize reductions in both N₂O emissions and nitrate leaching, while sequestering C in a structure requiring little N. However, further studies are needed to validate the scant results currently available.

7.3.8 Overview of the current evidence

Figure 2 summarizes published data on rates of change in SOC and rates of emission of N₂O resulting from four prominent sets of practices designed to increase SOC, namely agroforestry, cover crops, no-tillage and organic amendment. All fluxes are expressed in CO₂ equivalents, using a global warming potential value inte- grated over 100 years and including global warming potential (GWP) of 298 for N₂O as recommend by last IPCC report (Myhre et al., 2013). GWP is the time-integrated radiative forcing induced by a pulse emission of a given component (here N_2O), relative to a pulse emission of an equal mass of CO_2 (Myhre et al., 2013). The data in Figure 2 were taken from several meta-analyses and re view papers. Here we did not re-analyse the data gathered by such meta-analysis, but rather presented the mean effect size from each study converted in CO_2 equivalents. When results were given for the whole experiment duration, we divided by the duration of the experiment to obtain the mean annual SOC storage/N₂O emissions (see Supporting Information for detailed methods). The data in Figure 2 are based on over 700 measurements of SOC change and 200 measurements of N_2O . Even allowing for some papers being cited in more than one metaanalysis, this is a large body of data and, to our knowledge, has not previously been assembled in this way. At first sight it appears that SOC increases produced by the four sets of treatments varied widely from -0.52 ± 0.46 to -6.74 ± 1.21 t CO₂-eq. ha⁻¹ year⁻¹, the negative sign representing accumulation of SOC that is; transfer of C from atmosphere to soil.

However, this wide range is somewhat deceptive as the two largest values are from very specific situations. The value of $-6.74 \pm 1.21 \text{ t CO}_2$ -eq. ha⁻¹ year⁻¹ for agroforestry (Kim et al., 2016) is from 34 sets of data for systems with a particularly high tree density (see legend to Figure 2); the other two meta-analyses for agroforestry, based on >200 data sets, give values of less than half this at around $-3 \text{ t } \text{CO}_2$ -eq. ha⁻¹ year⁻¹. For cover crops the majority of data, based on 186 data sets, lead to mean rates of C accumulation in the range of -1.2 to -2.0 t CO₂-eq. ha⁻¹ year⁻¹. The highest value observed for cover crop was 3.67 t CO₂-eq. ha⁻¹ year⁻¹ but it specifically refers to cover crops included between the wide rows of Mediterranean woody crops (olive, almond and vineyards) where the soil would otherwise be bare (Vicente-Vicente et al., 2016). This is clearly an important management change within this environment but represents a much greater input of plant material than, say, cover crops grown during winter within temperate arable cropping systems. For both agroforestry and cover crops, and even ignoring the two sets of data for SOC increases that are especially large, it appears from the summarized data in Figure 2 that SOC increases resulting from these two changes in management considerably outweigh increased N₂O emissions when both are expressed on a CO₂-eq basis and these management changes can be expected to beneficial for climate change mitigation. However, the annual rates of SOC increase shown in Figure 2, especially for cover crops, are probably overestimates because they are based on short-term measurements, in some cases only 2 years; over longer periods the annual rate will decline as SOC moves towards a new equilibrium value. For no-tillage the situation is different: the relatively small rates of SOC accumulation are approximately equal to the increases in N₂O emission when both are expressed on a CO_2 -eq basis, so there appears to be no overall climate change benefit. For organic amendments the results indicate that N₂O emissions are decreased and thus reinforce the SOC benefit, though this is based on a very limited amount of data and also, as discussed earlier, it is questionable whether SOC increases from addition of organic amendments can be fully regarded as climate change mitigation. It should be noted that most of the studies are performed over a few years and assessment of GHG balance in the long term, especially for N₂O, are still missing (Lugato, et al., 2018). Some practices were too little documented or with not enough information to be compared with the others (e.g. biochar or erosion control).

7.4 DISCUSSION AND OUTLOOK

Overall, the meta-analysis we gathered here (Figure 2) suggest that, with the exception of reduced tillage practices, increased N₂O emissions are not sufficient to invalidate the GHG abatement potential achieved by SOC sequestration strategies. Some sequestration strategies (e.g. biochar or non-pyrogenic organic amendment application) may even generate win-win situations through a decrease in N₂O emissions, although the experimental evidences are still scant. This N₂O emissions reduction is more and more scrutinized (Assémien et al., 2019; Buchen et al., 2019; Conthe et al., 2019; Shurpali et al., 2016) and some win-win practices may emerge in the near future from increasing SOC to reduce N₂O emissions. For instance, biochar application known to im- prove SOC storage (Lehmann et al., 2006) may also be associated with an N_2O emissions reduction by decreasing labile N availability, N-cycling enzymatic activity and nitrification/denitrification rates (Song et al., 2019). In addition, the economic impacts and large-scale effects of the options examined here warrant further assessment. Some practices may affect crop yields or farmers' income, depending on pedoclimatic conditions and the details and practicalities of the cropping systems. For instance, conservation practices, and especially no-till may slightly decrease crop yields under temperate climates but be beneficial in drier conditions (Pittelkow et al., 2015). Similarly, the yield of arable crops is usu ally reduced in agroforestry systems in temperate regions (Pardon et al., 2018) but in more arid climates, crops perform better (Bright et al., 2017). Nevertheless, for agroforestry, trees produce timber, firewood, honey, fruits, etc. that are also a source of incomes for the farmers and may lead to greater overall sustainability. Beyond yield impacts, some socio-cultural or economic factors come into play that may hinder the adoption of carbon sequestration practices. For example, in the United States, the cost of carbon capture through Natural Resources Conservation Service programs is estimated at US 32-442 per tonne of CO₂, with an average of US 183 (Biardeau et al., 2016). A carbon price much higher than the present value (around US \$10 as a global average; Ramstein et al., 2019) would be necessary to promote carbon sequestration practices, as well as a regulation to direct the financial flow of in dustrial and energy emitters to the agricultural sector. For biochar, there are still questions about whether a sufficient quantity could be produced in order to make the approach realistic at large scale, in addition to the ongoing debate regarding the actual impacts of biochar on soils and crops and the mechanisms

involved. To be deployed at large scale and to enter emission trading systems, the GHG fluxes of each change in agricultural practices should be estimated precisely. Various models may be used to account for scale or leakage effects such as indirect land-use changes (Qin et al., 2016). The methods currently available include data-driven approaches based on worldwide measurement networks (Shang et al., 2019), statistical or empirical flux-upscaling models (Shang et al., 2019; Wang et al., 2019), process-based models and, lastly, integrated assessment models (IAM; Zomer et al., 2016). Process-based models include a representation of N cycling processes, which are an essential tool in assessing and predicting the terrestrial N cycle and N_2O fluxes in response to multi-factor global changes. Such models have been used to estimate N₂O emissions from natural and agricultural soils at various scales, from field to global level via the integration of a prognostic N cycle into different land surface models (Tian, et al., 2018). As an example, Figure 3 shows the results of simulations by various models at global scale. Most of N₂O emissions from cropland are due to the use of min-eral fertilizers (Figure 3a) and are mainly located in United States, Europe, India and China. They may be used to quantify carbon sequestration in soil minus the N₂O emission trade-off at global scale, based on ensemble runs as was initiated in the global N₂O Model Inter-Comparison Project (Tian, et al., 2018). Integrated assessment models focus on the interactions between the economic activities and earth system responses and are vital for estimating what socio-economic changes would be needed to reduce GHG emissions across sectors and increase biospheric C sinks (IPCC, 2014). Until recently, most IAMs did not explicitly take into account SOC restoration practices (Smith et al., 2016). A recent study that did include them found that soils could be a sink of 3.5 Gt CO₂-eq/year by 2050 under a carbon price of 190 USD/tCO₂ (Frank et al., 2017). This carbon mitiga tion option, if achievable in practice, would reduce the burden of climate stabilization for all sectors of the economy, including agriculture. In addition, SOC increases are often correlated with higher crop yields and contribute to a range of other environ mental benefits and increased sustainability of agricultural systems. Practices designed to increase SOC can offer a win-win solution vis a vis food security, by mitigating food calorie losses resulting from the application of emission reduction targets (e.g. through decreased applications of mineral fertilizers) and reducing undernourishment. Finally, many of the practices reviewed (Table 1) here may be combined on a given field: for example, no-till can be combined with cover crops, organic amendments or agroforestry. Such combinations have been little tested in practice and in particular

synergetic effects between them have not been evaluated in depth (Autret et al., 2016, 2019). Conversely, they may come with trade-off, antagonistic or synergistic effects regarding SOC storage rates, as well as N₂O emissions or other impacts and these needs to be identified and quantified. Furthermore, proper assessment of carbon sequestration measures raises classical GHG accounting issues, such as double counting, improper setting of system boundaries and counterfactual scenarios (Smith et al., 2016). Although further research is still needed to quantify the potential of SOC sequestration options on a local to regional basis, it appears that their potential to mitigate climate change, even when factoring in N₂O emissions is still significant and that they deserve further consideration in climate stabilization scenarios. Including the state-of-the-art knowledge re- viewed here on the effectiveness of such measures in land system or integrated assessment models could be a prime target to assess their impacts at global scale.



Figure 3 Spatial and latitudinal patterns of contributions of fertilizer (a) and manure (b) on cropland soil N_2O emissions obtained during the global N_2O Model Intercomparison Project (Tian, et al., 2018). Average over the 2006–2015 period

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7.7 SUPPORTING INFORMATION

Additional methods

It was necessary that the meta-analyses selected in this study must provide information on SOC storage and/or N₂O emissions for one of the land management practices we presented. We therefore excluded some studies that focused on C or N cycles for a given practices but which may not directly measure SOC storage or N₂O emissions (Abdalla et al., 2016). For each of the practices, when directly given in the main text or in the supplementary materials, we evaluated the effect on SOC storage and/or N₂O emissions by comparing with a control corresponding to conventional practice. For C, in every study, only SOC storage (excluding belowground and aboveground biomass) was considered. If the results were already presented in in t CO₂eq ha⁻¹ y⁻¹, the results we presented are directly taken from the metaanalysis. If not, all the fluxes are converted in t CO₂eq ha⁻¹ y⁻¹ with a 3.67 mass conversion coefficient for SOC and using a global warming potential value integrated over 100 years and including climate carbon feedbacks of 298 for N₂O as recommend in the last IPCC report (Myhre *et al.*, 2013). We use negative values to represent a net removal of GHG gases from the atmosphere and positive vales for net emissions. When the values were not given per year by the meta-analysis considered we converted them using the average duration of the study. The error is expressed as the standard error (SE) for all meta-analysis. It was appropriately converted from the standard deviations (SD) or confidence intervals at 95% (CI 95%) provided by the authors with, respectively, the following equations:

$$SE = \frac{SD}{\sqrt{n}}$$
(1)

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$$SE = \frac{CI(95\%)_{uppper \, limit} - CI(95\%)_{lower \, limit}}{3.92}$$

Where n is the number of experiments in the meta-analysis.

For instance, mean absolute change in SOC storage under agroforestery was calculated from the supplementary materials provided by the authors(Feliciano et al., 2018) as the weighted mean between all experiments (n=73). We estimated Δ SOC as -2.39 ± 1.48 t CO₂eq ha⁻¹ y⁻¹, where Δ SOC is the difference between the control land management (cropland) and any agroforestry system. The same procedure was applied for another study (Kim *et al.*, 2016) to calculate the mean absolute change in SOC storage and we obtained a Δ SOC =-1.83 tC ha⁻¹ yr⁻ ¹ *3.67 = -6.74 t CO₂eq ha⁻¹ y⁻¹ \pm 1.21 (n = 34). Finally, we also considered a greatly extended database (Cardinael et al., 2018) of Feliciano et al. (2017) (n=141) and obtained a value of -2.75 ± 0.36 t CO₂eq ha⁻¹ y⁻¹. Increased SOC sequestration was found in all cover crops metaanalysis with different values observed (0.32 tC ha⁻¹ y⁻¹, (n=139) (Poeplau & Don, 2015) and 1.03 tC ha⁻¹ y⁻¹, (n=61, with only Mediterranean woody crops (olive, almond and vineyards)) (Vicente-Vicente et al., 2016)) all converted in in t CO₂eq ha⁻¹ y⁻¹ as explained above. For notillage, a mean absolute change in SOC storage over the experiments duration of -3.40 tC ha-¹ was estimated by some authors (Virto *et al.*, 2011). Dividing this value by the mean duration (15 years) of the experiments we estimated a \triangle SOC of -0.83 ± 0.01 t CO₂eq ha⁻¹ y⁻¹ (n=92). Two different approaches (based on depth or on soil mass) to calculate the mean SOC storage absolute changes between tilled and no-tilled plots, over 95 experiments were also used (Du et al., 2017). In that case, the fixed-depth approach provided a \triangle SOC of -0.30 tC ha⁻¹ yr⁻¹ that is equivalent to -1.01 \pm 0.46 t CO₂eq ha⁻¹ y⁻¹. The equivalent soil mass approach gave a lower value (Δ SOC = -0.52 ± 0.45 t CO₂eq ha⁻¹ y⁻¹). We selected the equivalent mass method since it is more accurate (Angers & Eriksen-Hamel, 2008). A mean absolute change in SOC storage of -0.23 tC ha⁻¹ yr⁻¹ was observed when shifting from high intensity to no-tillage(Meurer et al., 2018). We converted this value to CO₂ equivalents and obtained -0.84 \pm 0.40 t CO₂eq ha⁻¹ y⁻¹ (n=43). For organic amendments, we only considered in the meta-analysis experiments where control plot was amended with inorganic fertilizers (Maillard & Angers, 2014). The authors found an absolute change of SOC storage of -5.6 tC ha⁻¹ over the entire experiments duration. Dividing this value by the average experiments duration (21.7 years) and converting it to CO₂ equivalents, we obtained an annual SOC storage change of $-0.26 \pm 0.15 \pm 0.02$ eq ha⁻¹ y⁻¹ (n=42).

For N₂O emissions, much less meta-analysis data was available. In agroforestry, a net change of 0.80 \pm 1.63 t CO₂eq ha⁻¹ y⁻¹ was calculated when shifting from agriculture to agroforestry (n=22) (Kim *et al.*, 2016). For cover crops, a non-significant increase in net N₂O emissions was observed when considering direct emissions (Abdalla et al., 2019). Indeed, direct emissions were -0.08 t CO₂eq ha⁻¹ y⁻¹, meaning there has been a small positive gain of CO₂ equivalents by the soil, while indirect emissions were found to be 0.16 t CO_2 eq ha⁻¹ y⁻¹ (i.e. positive emissions from the soil). Considering both direct and indirect emissions, we calculated a net increase of N₂O emissions of 0.08 \pm 0.06 t CO₂eq ha⁻¹ y⁻¹. For reduced or no till treatments, we calculated the absolute change in N₂O emissions from a database provided in supplementary materials (Mei *et al.*, 2018). The authors stated that no-tillage increased N_2O emissions by 19.2% compared to conventional tillage. Hence we calculated the annual mean of N emissions from no-tillage only experiments (n=61) and divided this value by 1.192 to calculate the associated conventional tillage departure value. The difference in emissions was estimated by subtracting the emissions from conventional tillage to no-tillage emissions and we came up with a value of 0.17 kgN ha⁻¹ y⁻¹. This is equal to 0.167 t CO₂eq ha⁻¹ y⁻¹. Since experimental errors were not provided in this meta analysis, we estimated the mean SE as follows. First, we calculated the SD as a percentage of the mean from another meta-analysis on N₂O emissions under reduced or no till (van Kessel et al., 2013). Then we multiplied this SD by the mean N₂O emissions previously estimated for Mei et al. (2018). We finally converted the SD to the SE by dividing SD by the square root of the number of studies considered in Mei et al. (2018). Kessel et al. (2013) provided us with the entire dataset of N₂O emissions from tilled and no-tilled experiments. We calculated the net change of N₂O emissions as 2.35 kg N₂O ha⁻¹ y⁻¹, which duly converted to tons of CO₂ equivalents (0.7 \pm 0.13 tCO₂eq ha⁻¹ y⁻¹). For organic amendments, it was found that N₂O emissions were reduced by 492 kg CO₂eq ha⁻¹ y⁻ ¹ when shifting from a mineralized to an organically managed plot (Skinner *et al.*, 2014). This corresponds to -0.492 \pm 0.16 t CO₂eq ha⁻¹ y⁻¹ (negative sign to express a positive uptake of CO_2 equivalents from the soil).

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