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Feasibility of the 4 per 1000 aspirational target for soil carbon: A case study for France

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Abstract

Increasing soil organic carbon (SOC) stocks is a promising way to mitigate the increase in atmospheric CO_2 concentration. Based on a simple ratio between CO_2 anthropogenic emissions and SOC stocks worldwide, it has been suggested that a 0.4% (4 per 1000) yearly increase in SOC stocks could compensate for current anthropogenic CO_2 emissions. Here, we used a reverse RothC modelling approach to estimate the amount of C inputs to soils required to sustain current SOC stocks and to increase them by 4‰ per year over a period of 30 years. We assessed the feasibility of this aspirational target first by comparing the required C input with net primary productivity (NPP) flowing to the soil, and second by considering the SOC saturation concept. Calculations were performed for mainland France, at a 1 km grid cell resolution. Results showed that a 30%–40% increase in C inputs to soil would be needed to obtain a 4‰ increase per year over a 30-year period. 88.4% of cropland areas were considered unsaturated in terms of mineral-associated SOC, but characterized by a below target C balance, that is, less NPP available than required to reach the 4‰ aspirational target. Conversely, 90.4% of unimproved grasslands were characterized by an above target C balance, that is, enough NPP to reach the 4‰ objective, but 59.1% were also saturated. The situation of improved grasslands and forests was more evenly distributed among the four categories (saturated vs. unsaturated and above vs below target C balance). Future data from soil monitoring networks should enable to validate these results. Overall, our results suggest that, for mainland France, priorities should be (1) to increase NPP returns in cropland soils that are unsaturated and have a below target carbon balance and (2) to preserve SOC stocks in other land uses.

KEYWORDS
4 per 1000, climate change mitigation, net primary productivity, RothC, SOC saturation, soil organic carbon

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1 | INTRODUCTION

Increasing soil organic carbon (SOC) stock is a promising option to mitigate the increase in atmospheric CO_2 concentration (Minasny et al., 2017; Zomer et al., 2017). Worldwide, the SOC stock in soils reaches 2400 Pg C, which is three times more than the amount of C contained as CO_2 in the atmosphere (860 Pg C; Le Quere et al., 2018). The ratio between annual anthropogenic emissions due to fossil fuel combustion (9.4 Pg C) and SOC stocks (2400 Pg C) over total soil depth results in a value of approximately 4‰, suggesting that a 4‰ yearly increase in soil C stocks could theoretically compensate all anthropogenic CO_2 emissions (Balesdent & Arrouays, 1999). A more realistic calculation of the 4 per 1000 aspirational target for the topsoil (0–30 cm) leads to a lower global potential (2.8 Pg C year^{-1}) which is in the range of current estimates (Lal, 2010; Smith et al., 2013) of the total technical soil carbon sequestration potential (Soussana et al., 2019). Based on these calculations, and on the potential of soil carbon sequestration for climate change adaptation and food security (Soussana et al., 2019), the '4 per 1000 Initiative: soils for food security and climate' was launched in 2015.

Meanwhile, some authors have highlighted the limits of this aspirational target: (1) additional C storage in soils is only possible during a finite period of time and on a limited space, mainly the areas already managed by humans (i.e. excluding permafrost and natural peatlands), (2) it is a reversible process, (3) increasing SOC requires additional N inputs because of stoichiometric constraints (Groenigen et al., 2017; Poulton et al., 2018) and (4) it may be hampered by climate change itself which is likely to foster SOC losses by mineralization (Meersmans et al., 2016). Moreover, agronomic, economic and social barriers are likely to delay the adoption of farming practices fostering C storage or limit the achievable SOC stock increase (e.g. Amundson & Biardeau, 2018; Corbeels et al., 2018; Lal et al., 2018; Soussana et al., 2019). Despite these limits, there is a growing interest in the role of increasing soil C stocks for climate change mitigation and large co-benefits of this option for climate change adaptation, reversing land degradation and desertification, and enhancing food security, have been identified by the Intergovernmental Panel on Climate Change (Smith et al., 2019).

At the field scale, changes in SOC stocks result from an imbalance between C inputs (crop residues, litterfall, root exudates, manure application, etc.) and C outputs due to harvests, mineralization of organic C, leaching or erosion (e.g. Lal, 2018). Although some farming practices may reduce mineralization rates (e.g. reduced tillage, see a recent review by, Haddaway et al., 2017), it is generally agreed that the most efficient way to increase SOC stocks is to increase C inputs (e.g. Virto et al., 2012; Autret et al., 2016; Fujisaki et al., 2018). This can be achieved by increasing on-field biomass production and residue return (e.g. cover crops, Poeplau & Don, 2015), or by mobilizing and spreading external C resources such as manures or composts. Indeed, high C stock increases are often observed in experiments with high rates of organic fertilization (Maillard & Angers, 2014; Poulton et al., 2018). However, as manures are often already applied to soils, they do not necessarily represent a potential source of additional soil C gain at global scale. In a context of increasing competition for C resources (e.g. for food, feed, fibre or energy production), the question arises of how much additional C is needed to reach the aspirational target of 4‰.

Another question is how efficient will these additional C inputs be in terms of accumulating stable SOC. Some SOC models used to characterize SOC mineralization with first-order kinetics processes imply that steady-state SOC stocks are proportional to C inputs (Paustian et al., 1997; Stewart et al., 2007). Hence, simulated steady-state SOC can increase unlimitedly with an increase in C inputs (Stewart et al., 2007). However, it has been proposed that there can be an upper limit to the capacity of soil to stabilize SOC as organo-mineral complexes (Cotrufo et al., 2019; Hassink, 1997; Six et al., 2002). Indeed, interactions with mineral surfaces are considered to be one of the principal stabilization mechanisms of organic C in soils (von Lutzow et al., 2006; Schmidt et al., 2011). This upper limit of mineral-associated SOC was found to be related to the proportion of fine fractions for world soils (Hassink, 1997) and European soils (Cotrufo et al., 2019) but also to mineral surface area for New Zealand soils (McNally et al., 2017). Carbon storage beyond this upper limit is still possible, but in coarser and presumably more labile forms. This concept has been shown to be useful for estimating the SOC sequestration potential of a region under projected land use and land management changes (Chen et al., 2018; Wiesmeier et al., 2020).

The objectives of this paper are to (i) investigate the amount of additional C that is necessary for increasing the SOC stock by 4 ‰ per year during 30 years, (ii) assess the feasibility of the 4‰ target (increase the SOC stocks by 4‰) in terms of available net primary productivity (NPP) and (iii) discuss the feasibility when considering the SOC saturation concept (i.e. maximum SOC stabilization capacity by the fine silt + clay fraction). The study was performed at the country scale, and France was chosen as a case study as it is characterized by a wide diversity of soils, land uses and initial SOC stocks (Mulder et al., 2016). We used a reverse modelling approach based on RothC, a widely used soil C turnover model that has been evaluated in many climate and soil contexts relevant for mainland France (see for instance Dib et al., 2014; Jenkinson & Coleman, 2008; Palosuo et al., 2015; Smith et al., 1997). The carbon input levels needed to maintain current C stocks, and then to reach the 4‰ target were compared to the NPP of ecosystems minus anthropogenic biomass removals. Finally, soils were characterized in terms of SOC saturation to assess the efficiency of strategies aimed at reaching the 4‰ target.

2 | MATERIALS AND METHODS

2.1 | Modelling the required carbon input to the soil

The RothC model (Jenkinson et al., 1992) was originally developed to simulate changes in SOC stock in arable topsoils in the long-term field experiments at Rothamsted Research in the UK. It was then extended to model SOC turnover in grasslands and forests and evaluated in a variety of ecosystems in different climatic regions (Smith et al., 1997). The RothC model can be written as follows:

$$\frac{dSOC(t)}{dt} = F \cdot SOC(t) + C_{in}(t), \tag{1}$$

where SOC is a dimension 4 vector with four components, each component referring to the organic carbon content in one of the four dynamic compartments of the RothC model: the resistant plant pool (RPM), the decomposable plant pool (DPM), the microbial pool (BIO) and the humic pool (HUM). C_{in} is a dimension 4 vector that represents the C amounts incorporated in the four dynamic pools, and F is a 4 × 4 matrix representing SOC mineralization and carbon flows between pools. The type of vegetation influences the distribution of C inputs into the RPM and DPM pools; hence, the DPM:RPM ratio typically depends on the vegetation type. In RothC, four vegetation types are considered: croplands, improved grasslands, unimproved grasslands and forests with a DPM:RPM ratio of 1.44, 1.44, 0.67 and 0.25, respectively. For a given total carbon input and mineralization rate, land use with lower values of the DPM:RPM ratio will exhibit higher total SOC stocks.

The RothC model, like many other first-order kinetic SOC dynamic models, results in equilibrium SOC stocks on the long term, assuming that both SOC inputs and mineralization factors are constant or at least exhibit periodicity (Cordier et al., 2012; Martin et al., 2007):

$$\lim_{t \to \infty} SOC(t) = SOC^*,$$

where SOC^*, hereafter called the equilibrium or steady state, can then be easily calculated and depends on organic carbon (OC) input rates and the F matrix:

$$SOC^* = (I_4 - F)^{-1} C_{in}^0, \tag{2}$$

where I_4 is the identity matrix of dimension 4 × 4 and C_{in}^0 is the vector of constant carbon inputs. Conversely, if estimates of SOC^* and F exist, C_{in}^0 can, in turn, be estimated, assuming that the soil has reached equilibrium and that climatic conditions are constant. Note that SOC refers to SOC that is subject to SOC dynamics. For the RothC model, this dynamic SOC is a fraction of the total SOC.

$$SOC_{total} = SOC + IOM,$$

where SOC_{total} is the total SOC, which can be measured, and IOM the inert SOC, which is, according to RothC, constant over time. IOM is usually estimated using the Falloon et al. (1998) equation. Equation (2) gives:

$$C_{in}^0 = (I_4 - F)\, SOC^*. \tag{3}$$

Like in Equation (1), C_{in}^0 is a dimension 4 vector. For the purpose of simplicity, C_{in}^0 (and later on C_{in}^{4p1000}) hereafter refers to total carbon inputs into the soil, that is, the sum of the four components of this vector.

In the present study, we used the RothC model to estimate (i) the inputs of SOC that would be needed to maintain current SOC stocks, hypothesizing that these are at steady state and (ii) the increase in SOC inputs needed to reach SOC stocks in 30 years from now, assuming a constant yearly 4‰ rate of increase in SOC. Note that the steady-state hypothesis is not supported by any data since a robust dataset is not yet available for mainland France. It was tested at a later stage of our work when we compared carbon input levels estimated by RothC under this hypothesis and NPP levels obtained independently from RothC (see Section 2.3).

This procedure involving RothC was applied at every location in France using a 1 km × 1 km raster representation. More specifically, at each location, we performed the following algorithm, again hypothesizing that SOC stocks obtained from the 1 km × 1 km SOC map of soils of mainland France (see below in Section 2.2.1), hereafter named SOC_{total}^0, were currently at equilibrium in each location:

1. Compute SOC^0 as $SOC_{total}^0 - IOM = SOC_{total}^0 - 0.049(SOC_{total}^0)^{1.139}$ (Falloon et al., 1998)
2. Using Equations (2) and (3)
   a. Split SOC among RPM, DPM, BIO and HUM
   b. Calculate C_{in}^0 needed to have the observed SOC^0
3. Compute SOC^{4p1000} as $SOC_{total}^0 \cdot (1.004)^{30}$ (4‰ increase in a 30-year period)
4. Estimate C_{in}^{4p1000} needed to reach SOC^{4p1000}

Step 4 was done using a differential evolution optimization algorithm (Ardia et al., 2016). From the C_{in}^{4p1000} estimate, the increase in SOC input was calculated as

$$\Delta C_{in} = C_{in}^{4p1000} - C_{in}^0. \tag{4}$$

Additionally, to assess the effect of climate change on SOC inputs needed to maintain or increase SOC stocks, RothC was run with two climatic datasets: observed data (1980–2010) and simulated data taking into account climate change (RCP 8.5). This scenario was selected because it predicts the highest increase in temperature and cumulative CO_2 emissions, with potentially important consequences on SOC dynamic which is affected by both the increase in temperature and the increase in C inputs due to the CO_2 fertilization effect (Meinshausen et al., 2011; Wieder et al., 2015). Furthermore, Schwalm et al. (2020) showed that, looking at mid-century and sooner, RCP 8.5 is clearly the most useful choice: it is consistent with historical total cumulative emissions for the present period, and given current and stated policies, it gives the most plausible cumulative emissions for the 2030–2050 period. Results for the observed 1980–2010 climatic conditions are presented first, and those for the 8.5 RCP scenario (1980–2010 and 2020–2050) are further used to discuss the effect of climate change.

The RothC model was implemented within the RothC R package (Martin, 2018), GIS operations using GRASS GIS software (GRASS Development Team, 2018) and statistical analysis using R software (R Core Team, 2015).

2.2 | Data for estimation of C_{in} with RothC

RothC needs several input variables to simulate carbon dynamics and SOC mineralization. SOC mineralization is a function of soil clay content (which drives SOC stabilization in different pools and soil moisture), temperature, precipitation, potential evapotranspiration and soil cover (bare or covered). Soil cover drives mineralization both directly and indirectly through soil moisture content. Temperature drives mineralization directly, and precipitation and potential evapotranspiration drive mineralization indirectly through soil moisture content. Additionally, in our framework, we needed maps of SOC in the top 23 cm of soil (as RothC is parameterized to model SOC stocks in the 0–23 cm soil layer) as inputs for Equation (3), and the share of total C inputs between plant residues and organic fertilization since these two categories of C inputs is characterized by specific parameters.

2.2.1 | Soil data

We used the data from the recently produced GlobalSoilMap products for France (Mulder et al., 2016), for both clay and SOC. GlobalSoilMap products provide estimates for, among others, the 0–5, 5–15, 15–30 cm depth layers at 90 m resolution for France. Clay and SOC datasets were aggregated to the 0–23 cm layer using weighted averages of estimates for GlobalSoilMap layers. SOC stocks were calculated assuming a constant rock fragments content (2%) and estimating bulk density with a pedotransfer function (see Meersmans et al., 2012 for details). For French soils, GSM estimates of bulk density are not yet available mainly because of data scarcity and issues related to measurement methods. The same applies for rock fragments content. Soil depth estimates (Lacoste et al., 2016) were used to truncate soil profiles on pixels. For instance, where soil depth *d* is less than 23 cm, stocks are computed on 0-*d* cm instead of on 0–23 cm. All calculations were first performed on a 90 m resolution grid, and later aggregated to a 1 km resolution grid. All subsequent work was done on this 1 km resolution grid to reduce computation time. A finer resolution was not required for our study, as the maps produced were only used to analyse regional and national patterns.

2.2.2 | Climate data

Monthly rainfall (mm month^{-1}), reference evapotranspiration (PET, mm month^{-1}) and temperature (monthly averages, in degrees Celsius) were averaged over the 1980–2010 period from the French SAFRAN reanalysis in order to yield a reference year representing current climate in France on 8 × 8 km^2 pixels (Quintana-Segui et al., 2008). PET was calculated using the FAO Penman–Monteith method (Allen et al., 1998). Climate projections data are from the French climate model ALADIN (CNRM-CM5/CNRM-ALADIN53) for the CO_2 concentration scenario RCP 8.5. Climate projections have been debiased with the SAFRAN reanalysis on each pixel using a Statistical Downscaling Method based on a Quantile Mapping approach. PET was again calculated with downscaled climate data (temperature, relative humidity, solar radiation and wind speed).

2.2.3 | Landcover

Landcover was estimated using ecoclimap data (Faroux et al., 2013), at 1 km resolution (see Figure 1; Supporting Information S1). Ecoclimap predictions were grouped into four main categories (i.e. croplands, grasslands, forests and others). Simulations were only performed on croplands, permanent grasslands and forests. We distinguished improved permanent grasslands from unimproved permanent grasslands using data on grassland types from a previous study (Tibi & Therond, 2018), which relied on a classification proposed by Devun and Legarto (2011).

2.2.4 | Management and input data scenario for RothC

When run in inverse mode, that is in order to estimate required carbon input levels to reach a given SOC level, RothC solely needs two input data related to management. The first one is the number of months where soils are left bare. This input variable, only applicable for croplands, was set to 4 months except when soils belonged to nitrate vulnerable zones where it was set to 2 months since cover crops are mandatory in these zones. The second input variable is the proportion of carbon inputs to the soil that consists of organic amendments. OC inputs to the soil are mainly the result of plant residues and of additions of animal manure and other organic products (hereafter referred to as organic amendments). In RothC, the fate of carbon provided by plant residues and organic amendments is specific, reflecting their difference in terms of decomposability. Therefore, in order to use RothC with the framework presented above, to estimate the amount of C input needed to sustain a given carbon stock, or to increase it, one needs to decide the share between plant residues and organic amendments in C inputs. This proportion was thus prescribed, based on previous studies having estimated it at the regional scale for France (Tibi & Therond, 2018). Furthermore, we considered that the only type of organic amendment was farmyard manure, for which RothC provides a default composition and which represents about 60% of organic amendments spread on agricultural soils in France (Houot et al., 2014). In RothC, the OC in this organic material is split into the RPM, DPM and HUM pools in the following proportions: 49%, 49% and 2%. Although another parameterization has been proposed for RothC (Peltre et al., 2012), with higher HUM fraction

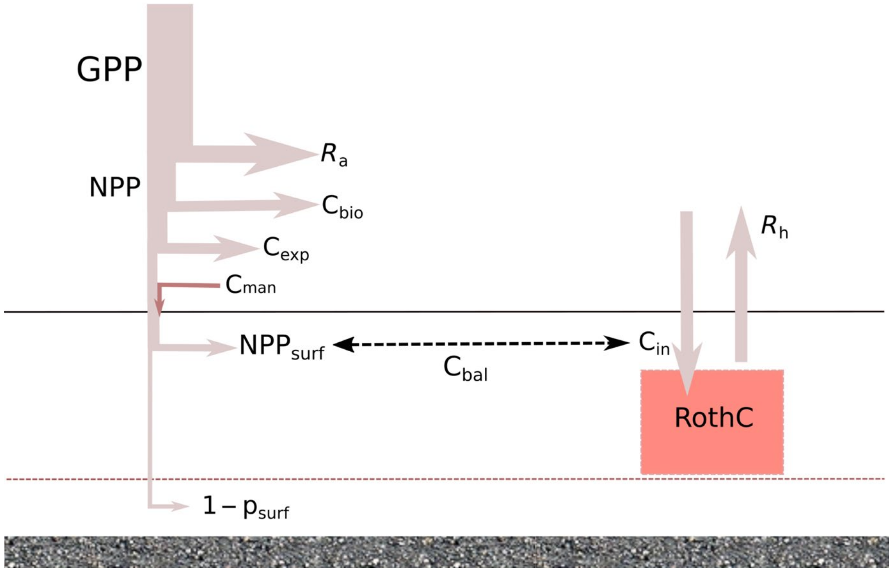

FIGURE 1 Estimating the fraction of net primary productivity (NPP) flowing to the soil layer under consideration and comparing it with C_{in}, the amount of carbon entering the soil needed to sustain existing levels or to reach a given level of soil organic carbon (SOC stocks). C_{in} is estimated by the RothC model, in inverse mode. The balance (C_{bal}) was evaluated as the difference between NPP_{surf} and C_{in}. C_{bio}, increase in plant biomass carbon; C_{exp}, carbon exported (e.g. harvests) through human activities, including livestock breeding; C_{man}, carbon return through manure and excreta at grazing; GPP, gross primary productivity; NPP_{surf}, remaining NPP flowing into the surface soil layer considered here, with a proportion of (1-p_{surf}) flowing to the soil layer below; R_a, vegetation autotrophic respiration; R_h, soil heterotrophic respiration

for organic amendments, taking it into account was not possible because spatial data on the nature of organic amendments were not available for our study. Organic amendments were only allowed on croplands and grasslands, not on forests. We also considered that an increase in total OC inputs during the 4‰ carbon storage period (i.e. between *t*0 and *t*0 + 30 years) was only possible through an increase in inputs of plant residues, and not through increments of organic amendments. In mainland France, all animal manures are already spread on agricultural soils so that it is not possible to increase the availability of this resource (Houot et al., 2014). Moreover, because of the low social acceptability of spreading urban and industrial organic products, increasing the amount spread on agricultural soils is unlikely. Note that other information about management practices in croplands, grasslands and forests were used in this study, but at a later step in the process, that is, for estimating independently from RothC the available NPP flowing to the soil (see also Figure 1), which is presented in the next section.

2.3 | Available NPP and ecosystems' carbon balance

To evaluate an ecosystem's ability to provide the estimated quantity of C inputs needed to maintain current SOC stocks and those needed to reach the 4‰ target, we estimated the ecosystem's available NPP (NPP_{surf}) as (see also Figure 1):

$$NPP_{surf} = \left[NPP - C_{bio} - C_{exp} + C_{man}\right] \cdot p_{surf}, \tag{5}$$

where NPP is the net primary productivity, C_{bio} is the amount of NPP allocated to increase plant biomass, C_{exp} are exports due to human activity, C_{man} the carbon returned through animal faeces and manure application, and p_{surf} is the proportion of total C inputs into the soils allocated to the 0–23 cm soil layer only (which is the layer considered by the RothC model, and which matches, for France, the average depth of the plough layer; Arrouays et al., 2001). p_{surf} was derived from recently published estimates of belowground NPP flows (Balesdent et al., 2018), depending on land use, clay content, mean annual temperature and the mean ratio of annual precipitation to potential evapotranspiration. For grasslands and croplands, C_{bio} was assumed to be equal to 0 considering that, based on a yearly average, the amount of carbon in aboveground and belowground plant biomass remains constant in the long term, contrary to non-mature forest systems.

We defined the carbon balance of a given soil as the difference between available NPP flowing to the considered soil layer (NPP_{surf}) and the soil carbon input (C_{in}), as estimated with the RothC model, needed to maintain current SOC levels or to reach the 4‰ target SOC stocks.

$$C_{bal} = NPP_{surf} - C_{in}, \tag{6}$$

with C_{in} equal to C_{in}^{0} or C_{in}^{4p1000} (see Section 2.1 about the modelling framework), yielding, respectively, C_{bal}^{0} and C_{bal}^{4p1000}.

NPP_{surf} and C_{in} were evaluated with separate methods and data sources, and computing the balance between them addressed the following question: is the carbon input to the soils required to sustain current stocks or to reach the 4‰ target available? Figure 2

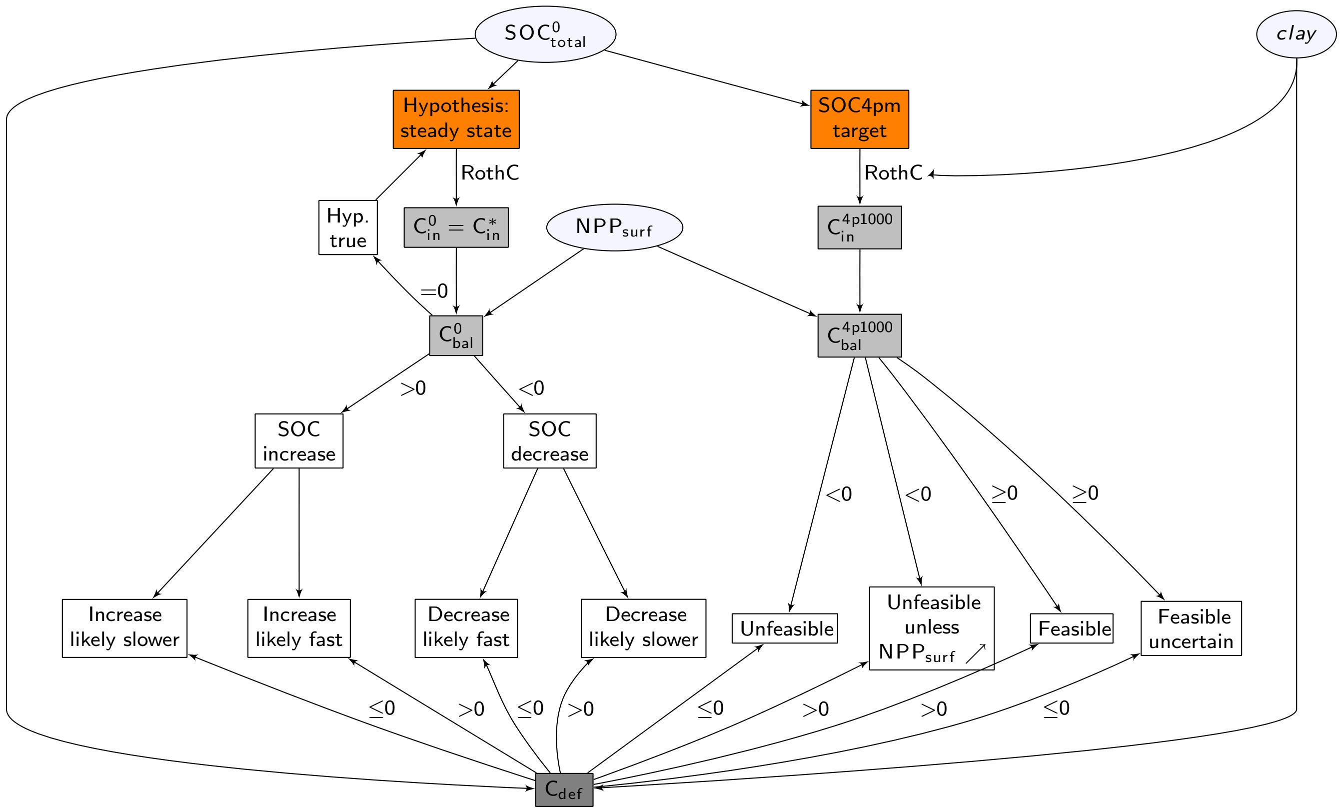

FIGURE 2 Diagram of the proposed approach. Main input variables are current soil organic carbon stocks (SOC^{0}_{total}), available net primary productivity (NPP_{surf}) and clay content. Two cases are considered. The first one deals with current SOC stocks and the second one with the 4‰ target. Both the carbon balances (C_{bal}, Equation 6) and the carbon saturation deficit (C_{def}, Equation 7) are used to assess the status of current SOC stocks and the feasibility of the 4‰ target. Note that the clay soil input variable is used for RothC computations for both C^{0}_{in} and C^{4p1000}_{in}. The steady-state hypothesis enables to estimate C^{0}_{in} using Equation (3), the right-hand side of which is called here C^{*}_{in} for the sake of conciseness. The expected trends of current stocks and the feasibility of the 4 do not account for possible future changes in SOC mineralization rates

summarizes this approach based on a comparison between the required carbon input, represented by the C_{in} variable, and the available carbon input is represented by the NPP_{surf} variable, estimated here using data about plant productivity and human activities. Studying the sign of C^{0}_{bal} may lead to different conclusions depending on the hypothesis on the stationarity of SOC stocks. If C^{0}_{bal} differs from zero, the steady-state hypothesis is currently not valid. $C^{0}_{bal} < 0$ indicates that C_{in} is not sufficient to sustain existing SOC stocks which are on a declining trend. If $C^{0}_{bal} > 0$, SOC stocks might be on an increasing trend. Alternatively, when RothC is used to compute C^{4p1000}_{in}, that is, carbon required to reach the 4 target after 30 years, negative C_{bal} values indicate that, given NPP levels and human activity, there is indeed insufficient carbon to reach this target. Positive values indicate that higher targets could, indeed, be reached. Note that C_{bal} calculations were performed using a current database, thus based on current plant productivity and existing agricultural and forestry systems. Moreover, the proposed framework ignores some of the relatively minor fluxes that result in C inputs and outputs. These include erosion, fires, dissolved organic carbon leaching, methane emissions and volatile organic carbon emissions (see Soussana et al., 2019 for a full accounting of these components). This choice was made because of available data and for the sake of simplicity. However, as all these fluxes result in SOC losses, it might induce a global overestimation of the carbon balances proposed here. RothC itself does not represent some output fluxes including vertical transport in the deep layer due to bioturbation or advection or lateral transport due to erosion. This may also contribute to carbon balance overestimation but these non-represented fluxes are considered to be of second order compared to heterotrophic respiration (Jagercikova et al., 2014; Naipal et al., 2018; Warner et al., 2019) and are particularly difficult to model at regional scales.

Several datasets were combined to yield spatial estimates of NPP, C_{bio}, C_{exp} and C_{man} on our 1 km × 1 km grid, depending on land use of the grid cells. Comparison of the results yielded by the different sources of input data was then used to discuss the uncertainty of our results. These datasets included NPP estimates derived from MODIS for the 2001–2012 period (Zhao et al., 2005), NPP and its human appropriation for the year 2006 (Plutzar et al., 2016, using the LPJml model for forests and grasslands and a model based on regional yield statistics for croplands). LPJml is a global model (GM), meaning that although it accounts for plant productivity variations, in managed and unmanaged areas, it does so less specifically than do domain models (DM), for example, models dedicated to grasslands and croplands. French inventory data were used to estimate human appropriation in forests (IGN, 2018). NPP and human appropriation data yielded by previous simulations (Tibi & Therond, 2018) with the STICS (a crop model, Brisson et al., 1998, 2003) and PASIM (a pasture simulation model, Riedo et al., 1998) domain models were also used. Lastly, for the C_{man} variable, we used data assembled from national inventories to estimate organic fertilization (Tibi & Therond, 2018). How the different data sources were combined depending on the land use is detailed in Table 1 of Supporting Information S1.

2.4 | Estimates of SOC saturation levels and saturation deficit

Several studies have assessed C sequestration potential or C saturation deficit (i.e. additional SOC that can be stabilized in the fine fraction) across different land uses (croplands, grasslands, forests) at large extent (Angers et al., 2011; Chen et al., 2018; Wiesmeier, Hübner, Spörlein, et al., 2014). We estimated the SOC saturation level (C_{sat}) based on concentrations of mineral fine fractions and applied the equation proposed by Hassink (1997). Fine fraction content comprises the particle of size <20 µm (%). To estimate fine silt (2–20 µm) fractions for each of our 1 km × 1 km grid cells, we combined GlobalSoilMap predictions of clay (<2 µm) with estimates of clay:fine silt ratio based on the French soil monitoring network data (Réseau de Mesures de la Qualité des Sols: RMQS, Jolivet et al., 2006). The sum of clay and fine silt fractions was then used in Hassink's equation to estimate SOC saturation levels. From the SOC content at saturation, SOC stock at saturation was estimated using the same method as previously explained for predictions based on the GobalSoilMap SOC content. The SOC saturation deficit was then estimated as

$$C_{def} = C_{sat} - (C_{HUM} + C_{IOM}), \tag{7}$$

where C_{sat} (Mg ha^{-1}) is the SOC stock at saturation and C_{HUM} and C_{IOM} are the SOC stock in the HUM and IOM pools as predicted by RothC for the current SOC stock. In so doing, we assumed that RothC's RPM and DPM pools are the same as particulate organic matter, by definition not included in soil organic matter bound to the fine fraction (Stewart et al., 2007), and further, we assumed that carbon in the BIO pool was negligible compared to that in the HUM and IOM pools.

2.5 | Uncertainty analysis

Our uncertainty analysis consisted in estimating the variance of the 4 carbon balance (C_{bal}^{4p1000}) and of the saturation deficit (C_{sat}). We included all variables and parameters used in their calculation and for which information about variance was available. We used the uncertainty estimates of the clay and SOC estimates attached to the GlobalSoilMap data. Although uncertainty attached to the NPP products was not available, we explicitly included in the analysis the variance resulting from using different sources of NPP data. This variance was considered to be representative of the uncertainty associated with the current knowledge of NPP levels. We also included parameter-related uncertainty when it was available, that is, for parameters of the p_{surf} function (Balesdent et al., 2018), for the parameters of the function used to estimate the amount of inert organic carbon (Falloon et al., 1998) and for the parameters of the equation used to estimate the carbon saturation deficit (Hassink, 1997). The propagation of the uncertainty attached to these input variables and parameters was based on an analytical formulation of C_{bal} and C_{sat}, taking advantage, among others, of the simplicity of the RothC model and the availability of explicit solutions of Equation (1) (see Supporting Information S3). We applied a first-order Taylor analysis to calculate the variance of intermediate functions of C_{bal} and C_{sat}, an approach which was previously applied in soil sciences (Heuvelink et al., 1989; Román Dobarco et al., 2019). Using the Taylor analysis enables one to approximate the variance of any continuously differentiable function of a set of variables or parameters. This approach has the major advantage to reduce computation time (compared to Monte-Carlo approaches) and to facilitate the identification of the various sources of uncertainty. Details of our procedure are presented in Supporting Information S2.

3 | RESULTS

3.1 | Carbon input levels needed to maintain current SOC stocks

Overall, carbon inputs needed to maintain SOC stocks levels (C_{in}^{0}) were clearly correlated with current SOC stocks (Figure 3), as expected from Equation (3). Distributions differed among land uses although covering approximately the same ranges. Differences among means were significant for all pairwise comparisons (with Bonferroni correction) with mean C_{in}^{0} values of 2.142 ± 0.004, 2.596 ± 0.004, 2.452 ± 0.012 and 2.773 ± 0.005 Mg ha^{-1} year^{-1} for croplands, improved grasslands, unimproved grasslands and forests, respectively.

Forests needed, on average, higher C_{in} values than croplands to sustain current SOC stocks. They exhibited greater variability than croplands (Figure 4). Improved grasslands and forests with high C_{in}^{0} values were found in plains of western France and low mountains of eastern France, with average to high mineralization coefficients and nevertheless high SOC stocks (Figure 5a–c). Some of the highest carbon input needs were found in western Brittany, where high SOC stocks are found in improved grasslands, associated with high mineralization coefficients related to the mild moist conditions, and the Landes de Gascogne forests (in south-western France) with high SOC stocks and sandy soils. On the opposite, other areas exhibited low carbon input levels, below 1.5 Mg ha^{-1} year^{-1}, because of low SOC stocks and moderate to low mineralization levels. Such areas are found in improved and unimproved grasslands of south-eastern France and cropland areas of the Paris Basin and central parts of south-western France.

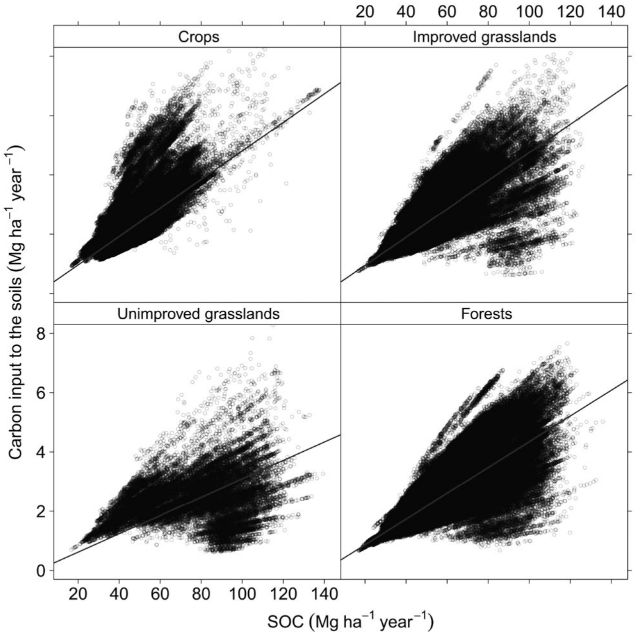

FIGURE 3 The amount of carbon inputs (C_{in}, the sum of added biomass and organic amendments) needed, as estimated by RothC, to sustain current SOC stocks as a function of initial soil organic carbon (SOC) stocks. Each plot gives the relationship for a specific land use. Carbon inputs were calculated for current climatic conditions (1980–2010)

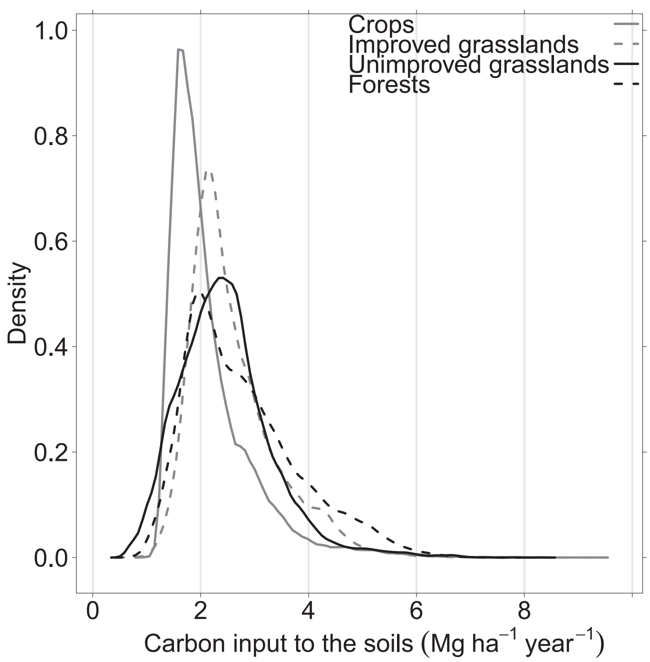

FIGURE 4 The amount of carbon inputs into the soil (C_{in}), resulting from biomass and organic amendments, needed to sustain current soil organic carbon (SOC) stocks, depending on the land use. The C_{in} values are yielded by the RothC model run in inverse mode under current climatic conditions (1980–2010), based among others on the SOC map for the French territory

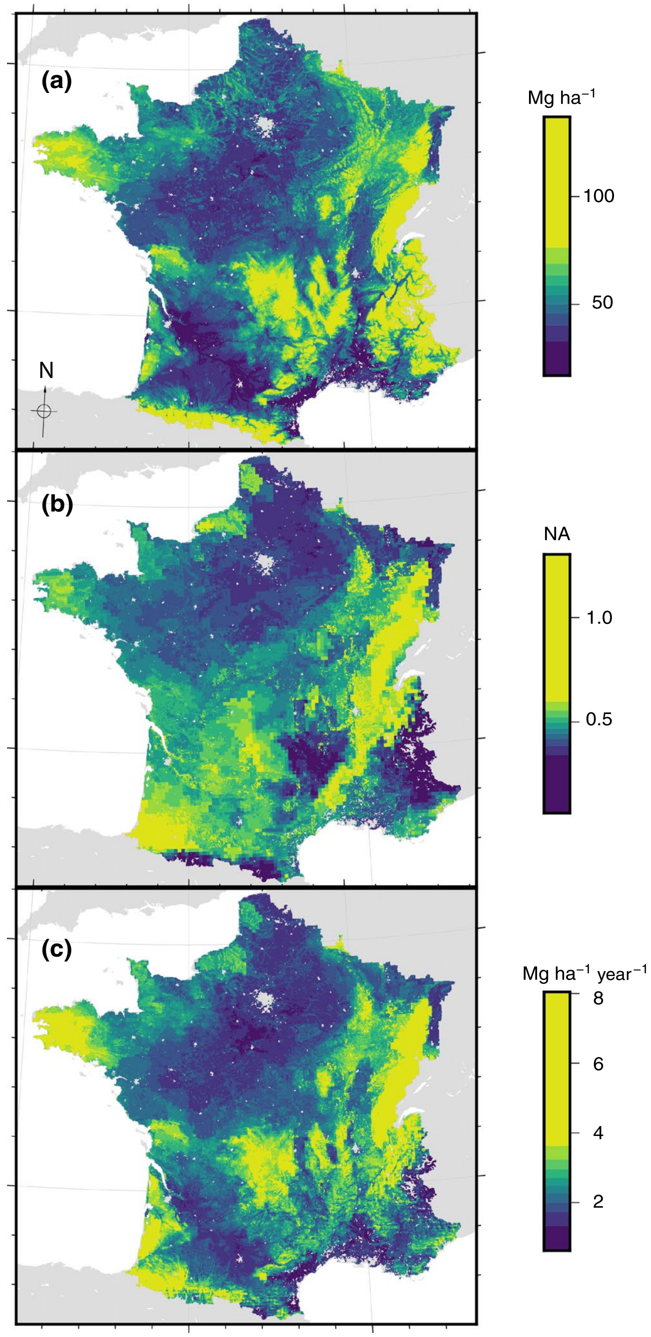

FIGURE 5 (a) soil organic carbon (SOC) stocks in the top 23 cm layer, (b) RothC mineralization modifiers, including the effect of soil moisture and temperature under current climatic conditions (1980–2010). Low values indicate that SOC mineralization rate is low. (c) represents the yearly carbon inputs needed to sustain current SOC stocks (C^0_{in})

3.2 | Carbon input levels needed to reach the 4‰ target

Additional carbon inputs needed to reach the 4‰ target (ΔC_{in}, Equation 4) were, on average, 0.880 ± 0.001, 1.070 ± 0.001, 1.049 ± 0.004 and 0.93 ± 0.00 Mg ha^{-1} year^{-1} for crops, improved and unimproved grasslands and forests, respectively (representing 42%, 42%, 45% and 34% of increase, respectively).

In our framework, the SOC stock increment needed to reach the 4‰ target is strictly proportional to SOC^0 (i.e. the current SOC stocks) and all locations share the same increment factor. Proportionality to SOC^0 implied that the ranking of ΔC_{in} values among pixels was the same as the ranking of C_{in}^0 values and the spatial structure of these two variables within mainland France was the same. Put differently, a location exhibiting a high C_{in}^0 value because of high SOC^0 and high mineralization rates will also exhibit a high ΔC_{in} value. However, some additional differences were found for croplands and grasslands. Some cropland and grassland areas had to increase C_{in} by up to 65% and 136%, respectively, to reach the 4‰ target. These areas with the highest % increase in C_{in} also had the highest proportion of organic manure in initial carbon inputs. This was a logical consequence of our simulation setup, where the amount of organic amendments was not allowed to increase when trying to reach the 4‰ target.

Nevertheless, in most cases, for all land use types, the required % increase in carbon input to the soil associated with plant residues was less than 50% (Figure 6, right panel). Overall, reaching the 4‰ target needed a minimum 24% increase in C_{in} from plant material returned to the field.

3.3 | Carbon balance

In our framework, C_{in}^0 estimates are those needed to maintain current SOC stocks at steady state (and C_{in}^{4p1000} those needed to reach the 4‰ target after 30 years). We compared the NPP_{surf} (Mg ha^{-1} year^{-1}) to both C_{in}^0 and C_{in}^{4p1000} and the difference was termed the carbon balance (Equation 6). The current balance C_{bal}^0 may be used to assess whether current SOC stocks are increasing or decreasing, and the 4‰ balance C_{bal}^{4p1000} indicates whether French ecosystems could provide enough organic matter to reach the 4‰ target. C_{bal}^0 and C_{bal}^{4p1000} are given for each land use and each NPP data source on Figure 7, left and right panels, respectively. Because of the high number of pixels used for estimating the C_{in}^0 and C_{in}^{4p1000} variables, mean values for each land use and each NPP estimate were all significantly different from 0, although absolute values of the mean were in some cases very small.

C_{bal}^0 was, for croplands, consistently negative across the different NPP estimates with a mean value of −0.5 ± 0.006, −0.8 ± 0.004 and −0.8 ± 0.007 Mg ha^{-1} year^{-1} for STICS DM, the GM/Stat. estimate (Plutzar et al., 2016, see Section 2 and the Supporting Information S1) and MODIS estimates, respectively (Figure 7, left). It indicated that available NPP was less than the estimated carbon input levels needed to sustain current SOC stocks and consequently was not sufficient to maintain stocks at steady state. Current cropland stocks are hence, on average, likely to be decreasing. Improved grasslands had a positive balance, and a greater variability both within each NPP estimate (with greater interquartile values as shown on Figure 7, left) and among NPP estimates, with a mean C_{bal}^0 of 2.2 ± 0.010, 0.1 ± 0.005 and 1.2 ± 0.010 Mg ha^{-1} year^{-1} for the PASIM DM, the GM/Stat. and MODIS estimates, respectively. Unimproved grasslands were consistently estimated to have positive C_{bal}^0, hence indicating increasing SOC stocks, faster with the PASIM estimate which gave a positive C_{bal}^0 values of 4.4 ± 0.032 Mg ha^{-1} year^{-1}. Forest soils showed a close to neutral balance with a mean slightly positive balance of 0.2 ± 0.007 and a more systematically positive one of 1.5 ± 0.013 Mg ha^{-1} year^{-1} for the GM/Stat. and MODIS estimates, respectively.

The right panel in Figure 7 gives the balance between available NPP and estimated C_{in}^{4p1000} values, represented by the C_{bal}^{4p1000} variable. By definition, the carbon inputs needed for the 4‰ target are greater than those for the maintenance target ($C_{in}^{4p1000} > C_{in}^0$). As a logical consequence (see Equation 6), the carbon balance for the 4‰ target is smaller than for the maintenance target ($C_{bal}^{4p1000} < C_{bal}^0$) because available NPP is, in our framework, kept constant between the 4‰ and the maintenance targets. in Figure 7, logically, situations where C_{bal}^0 (left panel) was negative, again had a negative balance with respect to the 4‰ objective (C_{bal}^{4p1000}, right panel). For croplands, the C budget in the context of the 4‰ target is clearly negative, meaning that this target may not be reached given current NPP_{surf} levels. For this land use, it would take, on average, 1.4 ± 0.007, 1.7 ± 0.005 and 1.6 ± 0.008 Mg ha^{-1} year^{-1} additional carbon input to reach the target, for the STICS DM, the GM/Stat. and the MODIS estimates, respectively. For improved grasslands and forests, the 4‰ target might or might not be achievable depending on the NPP estimate used. The GM/Stat. estimate yielded a negative mean C_{bal}^{4p1000} for both improved grasslands and forests (−1.0 ± 0.006 and −0.7 ± 0.008, respectively) and the MODIS estimate yielded close to neutral C_{bal}^{4p1000} for both

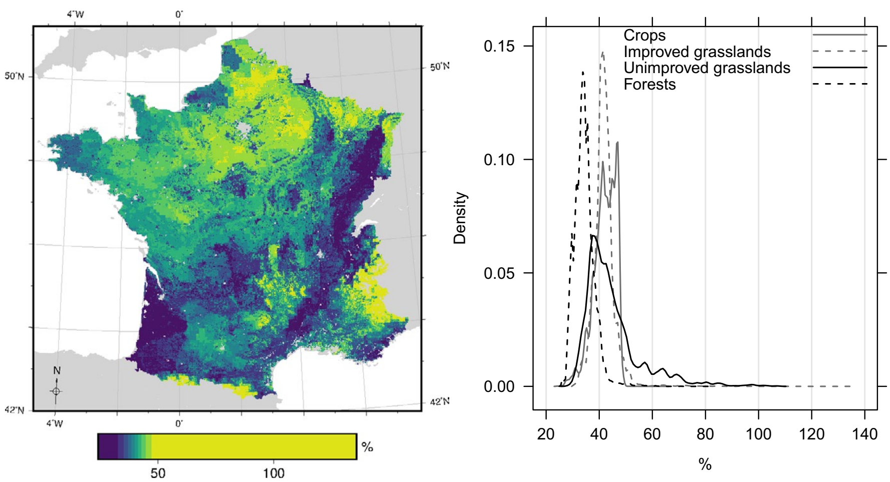

FIGURE 6 Percentage increase in the carbon input to the soil (C_{in}) associated with plant residues (hence excluding organic amendments), needed to reach the 4‰ target, at the end of a 30-year period under current climatic conditions. Left panel presents the value of this variable on mainland France. Right panel gives the distribution of the variable, depending on the land use

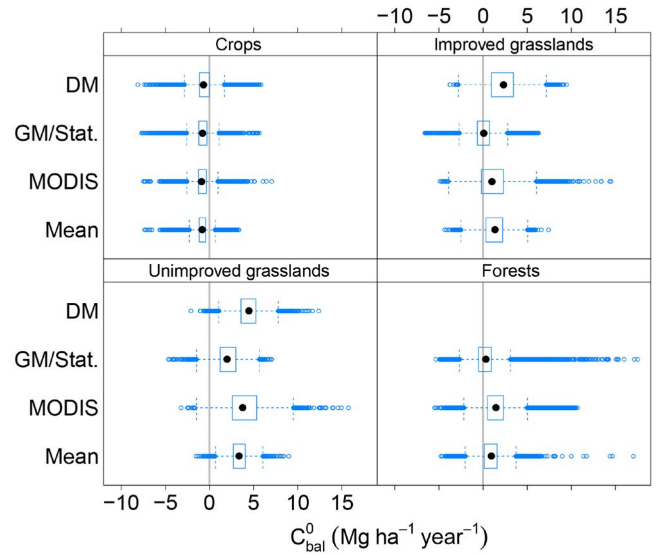

FIGURE 7 Carbon balance for the four land uses considered in this study and for the different estimates of net primary productivity (NPP), represented with box and whisker plots. The box gives the upper and lower quartiles and the median. Dashed bars give the upper and lower extremes and dots may be considered as outliers. The carbon balance (Mg ha^{-1} year^{-1}) is computed like in Equation (6), with the C_{in} needed to maintain current SOC stocks on the left panel and to reach the 4‰ target on the right panel. Mean distributions are computed from pixels where all relevant NPP estimates are available, to grant equal weight to the various NPP estimates. Negative values indicate that current stocks cannot be maintained, or that the 4‰ target cannot be reached with current land management. Carbon balances were calculated under current climatic conditions. DM, domain models, that is, the STICS model for croplands and the PASIM model for grasslands; GM/Stat., NPP estimates provided by Plutzar et al. (2016), either the LPJmL global model or the model based on yield statistics, depending on the land use; MODIS, NPP directly derived from this product

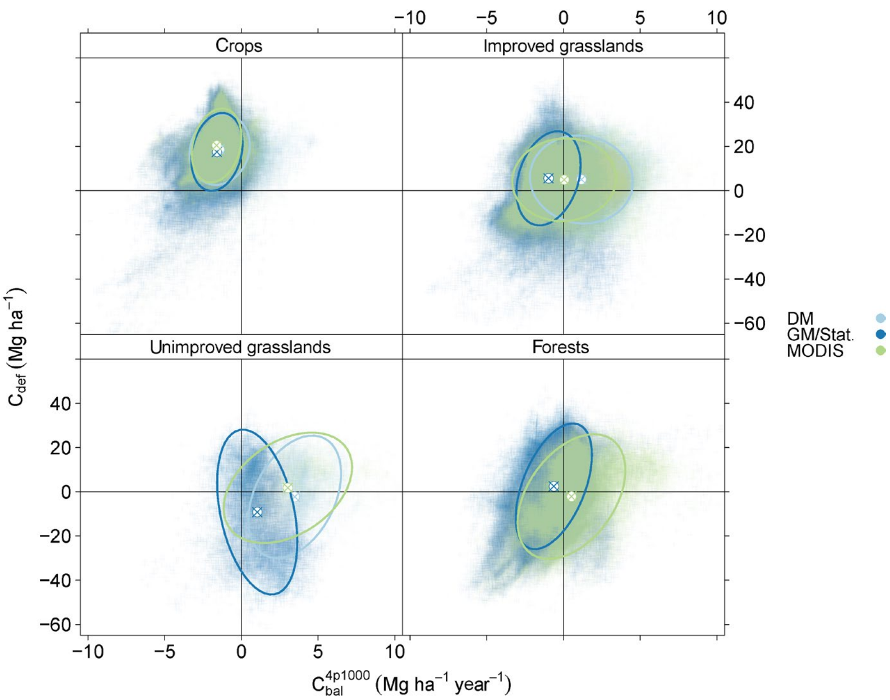

FIGURE 8 Carbon saturation deficit for the current state (C_{def}) as a function of the carbon balance according to the 4‰ objective (C_{bal}^{4p1000}), one panel for each land use and one colour for each net primary productivity (NPP) estimate. A positive carbon balance means that the availability of carbon inputs makes the 4‰ target achievable. A positive carbon saturation deficit means that the soil is unsaturated, which means that a soil C stock increase is unlikely to be constrained by saturation and that carbon can be accumulated in a less labile form. For each land use and NPP estimates, bi-dimensional ellipsoids with a 90% confidence level are given. DM, domain models, that is, the STICS model for croplands and the PASIM model for grasslands; GM/Stat., NPP estimates provided by Plutzar *et al.* (2016); MODIS, NPP directly derived from this product

improved grasslands and forests (0.1 ± 0.011 and 0.5 ± 0.014, respectively). The PASIM DM yielded a positive mean C_{bal}^{4p1000} for improved grasslands (1.1 ± 0.010). Conversely, unimproved grasslands, which are characterized by a rather large positive mean C_{bal}^{0} values, are likely to continue to display such a positive trend in the perspective of reaching the 4‰ target.

3.4 | Taking soil organic carbon saturation into account

Figure 8 plots the simulated points both in terms of carbon balance calculated under the 4‰ objective (C_{bal}^{4p1000}, *X*-axis) and the carbon saturation deficit for the current state (C_{def}, Equation 7, *Y*-axis).

These two variables were chosen as they reflect the capacity for additional C storage under stabilized forms at the beginning of the 4‰ scenario and the ability of the ecosystems to provide enough C for this scenario (see also Figure 2). The combination of both defines four crossed categories (unsaturated, positive *Y*-axis values, and positive C_{bal}^{4p1000}, positive *X*-axis values; unsaturated and negative C_{bal}^{4p1000}; saturated and positive C_{bal}^{4p1000}; saturated and negative C_{bal}^{4p1000}). Contrary to the other data sources, Plutzar et al. (2016) provided estimates for the four land use classes considered in the present study on every single pixel. Thus, the number of pixels for which C_{bal} was estimated using this data source was the highest. This can be seen in Figure 8 where the greatest spread of dots is for the GM/Stat. category. Croplands are mainly characterized by negative C_{bal}^{4p1000} and positive C_{sat}, hence unsaturated soils. Forests and improved grasslands were characterized by diverse situations. Unimproved grasslands were characterized mainly by positive C_{bal}^{4p1000}. Overall, saturated zones are found in western Brittany, in the Landes de Gascogne (sandy soils under forest) and mountainous areas covered by unimproved grasslands or forests (Alps, Pyrenees, Massif Central, Vosges, see Figure 9). Soils of intensive cropland plains were mostly unsaturated (e.g. Great Paris Basin). For each land use, the percentage of the area under each category is given in Table 1. For croplands, 88.4% of the area were unsaturated in the 0–23 cm layer, but with a negative C_{bal}^{4p1000}. This percentage was lower but still high for improved grasslands (37.5%). Conversely, 65.2% of unimproved grasslands fell into saturated categories (6.1% and 59.1% with a negative and positive C_{bal}^{4p1000}, respectively). For forests, 56.5% of the area are unsaturated, among which 25.5% with a negative C balance.

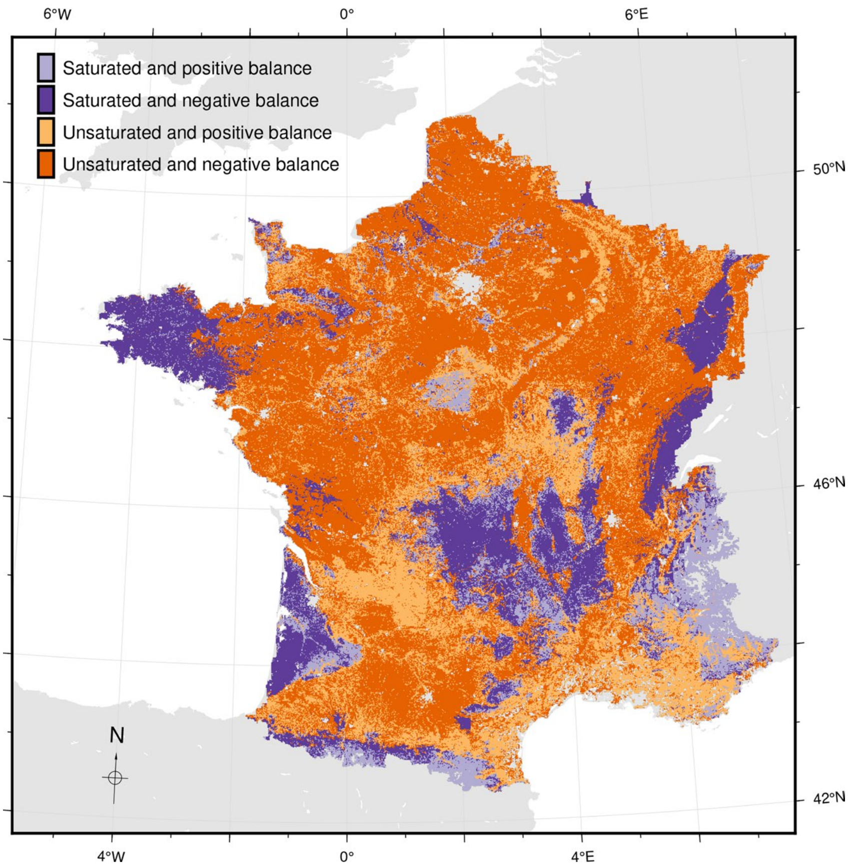

FIGURE 9 Map of the carbon storage potential in France up to the 4‰ target. The potential was assessed by combining the carbon balance (C_{bal}^{4p1000}, Equation 6) and the soil SOC saturation deficit (C_{def}, Equation 7). Unsaturated (vs. saturated) refers to soils where $C_{def} > 0$ (vs. $C_{def} < 0$). The C_{bal} is computed using average (of the GM/Stat., the MODIS and the domain model estimates) NPP_{surf} estimates

TABLE 1 Percentage of the area per category for each land use. Saturation was considered in the current situation and the C_{bal} was calculated under the 4‰ scenario. The value in bold gives the average over all the NPP estimates available at each pixel. The two values in parenthesis give the minimum and maximum values over all the NPP estimates available at each pixel

	Crops	Improved grasslands	Unimproved grasslands	Forests
Saturated and negative balance	**5.0** (2.5, 5.1)	**16.9** (7.1, 25.6)	**6.1** (5.2, 12.8)	**31.7** (26.5, 36.0)
Saturated and positive balance	**0.2** (0.1, 0.3)	**13.0** (4.3, 21.9)	**59.1** (36.0, 52.4)[a]	**11.8** (7.5, 27.2)
Unsaturated and negative balance	**88.4** (86.5, 91.4)	**37.5** (20.2, 56.1)	**3.5** (0.5, 8.9)	**25.5** (9.1, 31.4)
Unsaturated and positive balance	**6.4** (3.5, 10.6)	**32.6** (14.0, 50.8)	**31.3** (25.8, 56.2)	**31.0** (25.2, 37.2)

[a] The average here is outside the minimum and maximum value interval. This comes from the fact that each estimate is not available on the same set of pixels.

4 | DISCUSSION

Accurate estimates of the organic carbon inputs into the soils are crucial to properly forecast SOC changes. We will first discuss how our two independent estimates of carbon input into the soils, the first one based on available NPP and the second one representing the carbon input required to reach a given SOC level, compare to previously published values. The current status of mainland France SOC stocks will then be examined in light of the carbon balance of soils as influenced by the two carbon input estimates. The weight in the uncertainty of the carbon balance of several input variables, including NPP-based carbon input, and of several functions' parameters will then be discussed. Finally, we will present how climate change and the increase in atmospheric CO_2 concentrations might impact the future carbon balance and, following, what is the feasibility of the 4 target.

4.1 | Estimating carbon input into the soils

Different methods have been used to estimate carbon input to the soil for modelling purposes. They range from inverse modelling

TABLE 2 Estimated carbon input (Mg ha^{-1} year^{-1}) for a range of crops and systems in different countries, adapted from Wiesmeier, Hübner, Dechow, et al. (2014). Results concerning our study are of two kinds (1 and 2, see below) but three other kinds may be found in the literature.

Agricultural system	Plant	Country	Carbon input	Source
Croplands		France	2.0–2.3	This study[1]
Croplands		France	2.07 ± 1.43	This study[2]
Croplands		Germany	3.8–6.7	Wiesmeier, Hübner, Dechow, et al. (2014)[3]
	Wheat	France	2.5	Meersmans et al. (2013)[2]
		Global	2.9 ± 1.3	Wang et al. (2016)[2]
		Germany	2.4	Ludwig et al. (2007)[4]
		USA	2.9	Johnson et al. (2006)[3]
		Japan	3.3	Koga et al. (2011)[3]
	Barley	France	4.5	Meersmans et al. (2013)[2]
		Germany	1.2	Ludwig et al. (2007)[4]
		USA	3.4	Johnson et al. (2006)[3]
	Grain-corn	France	3.7	Meersmans et al. (2013)[2]
		Belgium	3.6	Wesemael et al. (2010)[3]
		USA	6.8	Johnson et al. (2006)[3]
		Japan	1.8	Koga et al. (2011)[3]
	Oats	USA	2.3	Johnson et al. (2006)[3]
		Japan	2.6	Koga et al. (2011)[3]
	Cereals	Belgium	2.4	Wesemael et al. (2010)[3]
Grassland	Improved	France	3.3–6.0	This study[1]
		France	2.52 ± 1.54	This study[2]
	Unimproved	France	5.5–8.7	This study[1]
		France	2.40 ± 1.66	This study[2]
Grasslands		Germany	2.4	Wiesmeier, Hübner, Dechow, et al. (2014)[3]
		France	5.2	Meersmans et al. (2013)[2]
		Ireland	1.18–3.52	Xu et al. (2011)[2]
		Australia	2.4	Coleman et al. (1997)[5]
		U.K.	3.24, 3.0	Coleman et al. (1997)[5]

[1]NPP – C_{exp} amount (see Equation 5), that is, carbon input to the soils related to the grown plants. Note that NPP – C_{exp} represents carbon inputs to the soils for the whole soil profile when C_{in}^{0} represents carbon input to the soil for the 0–23 cm layer only.

[2]C_{in} variable which is estimated by the RothC inverse modelling procedure or for the studies other than ours based on a similar approach.

[3]Use of allometric equations usually taking yield data as input variables.

[4]Direct measurements.

[5]Expert opinion or unexplained estimates.

(Meersmans et al., 2013; Wang et al., 2016), allocation functions (Wiesmeier, Hübner, Dechow, et al., 2014), to expert opinion (Coleman et al., 1997). The diversity of methods and contexts results in a great variety of estimates, as shown in Table 2. In our work, we used two different methods based on a rationale of using the relevant data and of characterizing the two sides of the SOC dynamics coin (i.e. the carbon input needed maintain or reach given SOC levels and SOM mineralization rates and the carbon input actually provided by plant productivity given its human appropriation). Overall, estimated carbon inputs presented here were in line with other estimates found in the literature (Table 2). Carbon input levels in the literature ranged between 1.8 (Koga et al., 2011) and 6.8 Mg ha^{-1} year^{-1} (Johnson et al., 2006) for croplands, and between 1.18 (Xu et al., 2011) and 5.2 Mg ha^{-1} year^{-1} (Meersmans et al., 2013) for grasslands.

When estimated using an inverse modelling approach, the calculation of these carbon input levels results from the interplay between observed SOC stocks, the SOC mineralization rates and the quality of the incoming organic matter (plant residues and organic amendments). Detailed observation revealed a few unexpected results. For instance, SOC stocks were higher in unimproved (74.95 ± 0.31 Mg ha^{-1}) than in improved grasslands (54.33 ± 0.07 Mg ha^{-1}), but surprisingly, unimproved grasslands needed slightly less carbon inputs to maintain current stocks. This might be explained by the fact that unimproved grasslands are mainly located in high altitude regions, with lower SOM mineralization rates due to lower temperatures compared to other warmer areas (see areas in Figure 5) and also by the quality of incoming plant material which has to be specified in inverse modelling approaches.

When estimated using plant productivity and human appropriation data, the variability of carbon input estimates depends on methodological aspects, such as the crop model or remote sensing processing function design and parameterization (see for instance Hashimoto et al., 2011 using the MODIS product) or the choice of input data. Comparison of our several estimates illustrates the variability that might be expected from this method (Table 3).

To conclude, one of the outcomes of our study is a quantification of the possible gaps between estimates based on inverse modelling and those based on data on plant productivity and human appropriation. All estimates based on inverse modelling and steady-state hypothesis (this study, C_{in}^{0} estimate, Meersmans et al., 2013; Wang et al., 2016) might lead to biased estimates of carbon inputs for soil when SOC is not at steady state. French croplands exemplify this with a large discrepancy between carbon input estimated using available plant productivity and carbon input to the soils estimated using the RothC inverse approach.

4.2 | What is the status of current SOC stocks?

Indeed, the C_{bal}^{0} calculations (available NPP minus C inputs needed to maintain current soil C stocks, Equation 6) show that soils under croplands are characterized by negative carbon balances (Figure 6). SOC in these soils could hence be on a decreasing trend. In some areas where organic amendments were high, C_{in}^{0} might be overestimated because of the aforementioned mis-parameterization for organic amendments. Hence, for these areas, the carbon budget might be closer to neutral than presented here. Only a few estimates based on comprehensive data are available for French croplands, but although spatially contrasted, SOC stocks could have slightly decreased in the 1990's, and could have slightly increased since then. Modelling studies at the European scale (Ciais et al., 2010) or for France (Clivot et al., 2019; De Cara & Thomas, 2008) tend to confirm this slightly negative trend, although there is still considerable uncertainty depending on how the effect of agricultural practices on SOC levels is represented in models (Ciais et al., 2011).

Improved grasslands SOC stocks were, on average, closer to equilibrium, whereas unimproved grasslands consistently exhibited large positive C_{bal}^{0} values. The latter result might be surprising as most French unimproved grasslands have been established for decades and would thus be expected to have reached equilibrium. Soussana et al. (2010), compiled a dataset for temperate grasslands in which grasslands stored on average 0.05 ± 0.30 Mg ha^{-1} year^{-1} based on inventories of SOC stocks and 0.22 ± 0.56 Mg ha^{-1} year^{-1} according to measurements of the C flux balance. However, the evidence for unimproved grasslands being a strong sink is weak and further studies for confirming this should be a priority. No specific measurements for France are currently available and it is worth mentioning that the diversity of situations, in terms of climate, soils and agricultural practices (improved vs unimproved), might even be greater than for croplands, as represented by the dispersion of C_{in} values in both types of grasslands (Figure 4).

Forest soils showed a consistently close to neutral or positive balance. Jonard et al. (2017) estimated that French forests were C sinks for the period 1993–2012. The sequestration rate was 0.35 Mg ha^{-1} year^{-1} for the forest floor and 0–40 cm layer of mineral

TABLE 3 Mean (±the distance to the 2.5% and 97.5% quantiles) of net primary productivity (Mg ha^{-1} year^{-1}) per land use class estimated by LPJmL and MODIS and the STICS and PASIM models. In parenthesis, the amount of carbon exported at harvest (mean ± the distance to the 2.5% and 97.5% quantiles, Mg ha^{-1} year^{-1})

Land use	LPJmL/Stat. (2006)	MODIS (2001–2012)	STICS/PASIM (1980–2010)
Crops	6.4 ± 4.4 (4.3 ± 5.0)	6.0 ± 1.5 (4.0 ± 2.4)	7.5 ± 3.3 (5.1 ± 3.9)
Improved grasslands	6.3 ± 3.0 (3.0 ± 3.8)	9.1 ± 4.4 (4.4 ± 3.9)	10.9 ± 3.1 (4.9 ± 4.4)
Unimproved grasslands	5.9 ± 2.0 (0.5 ± 1.0)	9.4 ± 5.1 (1.1 ± 2.1)	9.7 ± 4.2 (1.0 ± 2.2)
Forests	6.2 ± 2.3 (1.8 ± 2.9)	8.0 ± 2.6 (2.1 ± 3.2)	

soil. Their approach was based on consecutive soil monitoring surveys but did not include sites in Mediterranean forests. Although Jonard et al. (2017) did not observe an increase in litterfall or in belowground litter production, they estimated a decrease in the decomposition rates for litterfall and fine roots related to a decrease in litter nitrogen concentration and climate conditions during the study period. The average SOC stock of the 0–20 cm layer of mineral forest soils was around 50 Mg ha^{-1}, which is in the lower range limit of the SOC we estimated for most forested areas in the present study. The fact that forests soils exhibited higher SOC stocks in our study and are hence likely to require higher C_{in} levels might explain why we did not observe a greater positive C_{bal} for these soils.

4.3 | Sources of uncertainty

Our analysis showed a major contribution (58%) of the uncertainty related to the NPP flowing into the top 0–23 cm layer of the soils, to the carbon balance (C_{bal}), for the 4 target. The main reason for this relates to the substantial differences in the data source used for estimating NPP within each land use class (Table 3). MODIS NPP estimates were higher than LPJmL NPP for grasslands and forests, whereas for croplands, the harvest statistics-based (Plutzar et al., 2016) NPP was slightly higher than MODIS NPP. The comparatively high values of MODIS estimates for forests confirm previous findings regarding this data source (Neumann et al., 2015). LPJmL estimated a slightly higher NPP for improved grasslands than for unimproved grasslands, but the opposite trend was observed with MODIS. MODIS and the harvest statistics-based NPP estimates were lower than STICS NPP estimates for croplands. A comparison of several NPP estimates found in the literature is provided in the Supporting Information S1. In addition to intrinsic methodological differences among the various NPP products, the limited temporal and thematic (i.e. the land use classes definition and spatial distribution used in these products) overlap between them contributes to explain the large contribution to the total uncertainty. Being able to distribute carbon inputs from NPP vertically into the soil is also of uttermost importance. This component, embodied in our case by the p_{surf} function, represented 18% of the total variance of the C_{bal}^{4p1000}. More generally, the ability to estimate carbon inputs to the soil accurately is crucial to the understanding of the terrestrial carbon cycle (Hashimoto et al., 2011) and can be, as we showed here, a major source of uncertainty.

Maps of soil properties are also known to carry a significant uncertainty due to the limited soil data available to calibrate the statistical models used to derive maps (Arrouays et al., 2020; Somarathna et al., 2017). Although for mainland France, maps of clay content usually exhibit higher local inaccuracy compared to SOC maps (Mulder et al., 2016), variance attached to clay content had a negligible impact to the overall C_{bal}^{4p1000} uncertainty compared to the variance attached to the SOC maps (0.2% vs. 7.3%) and noticeably, the covariance between these two variables significantly contributed to reduce the C_{bal}^{4p1000} variance, by 13%. Finally, the uncertainty attached to the parameters used to distinguish the inert SOC from the active SOC, as represented by RothC, reached on average 25% of the C_{bal} uncertainty. This result confirms the sensitivity of RothC simulations to this specific point (Janik et al., 2002).

Locally, the uncertainty of the carbon balance was important with an average standard error of C_{bal}^{4p1000}, at the pixel level, of 1.16 Mg ha^{-1} $year^{-1}$ (see also Figure 3 in Supporting Information S2). However, it resulted in a small uncertainty of the average carbon balance at the country level and by land use (with standard error on the average C_{bal}^{4p1000} ranging between 3×10^{-5} and 2.6×10^{-4} Mg ha^{-1} $year^{-1}$, depending on the land use). The uncertainty on the mean carbon saturation was more noticeable and significantly influenced by the uncertainty of the soil input variables, and of the Hassink's and Faloon's equation parameters. At the country scale, 22% of the area had uncertain status (i.e. could not be classified as saturated or unsaturated because of the uncertainty attached to the carbon saturation deficit computation). However, despite this uncertainty, the general trends and differences among land uses remained robust.

4.4 | Effect of climate change on the carbon balance

We evaluated the additional carbon inputs into the soils needed to reach the 4‰ objective (ΔC_{in}, Equation 4) with the climate data from projections based on the 8.5 RCP scenario, for the 2020–2050 period. Climate change resulted in an overall increase in carbon input levels required to maintain current stocks or to reach the 4 target, mainly because of the effect of temperature on SOC mineralization. ΔC_{in} values were, on average, 0.369 ± 0.001 Mg ha^{-1} $year^{-1}$ higher compared to ΔC_{in} assuming current climate conditions. This represents an increase in additional carbon input of 36%, caused by climate change, to reach the 4‰ target. This additional carbon input also equaled on average 14% of C_{in}^{0} amounts (17%, 13%, 15% and 12% for unimproved grasslands, improved grasslands, crops and forests, respectively). This increase in ΔC_{in} was not negligible when compared to the C_{bal}^{4p1000} values obtained in our work, and may limit the ability of many soils to reach the 4‰ target. On the other hand, the increase in CO_2 concentrations might also result in an increase in plant productivity. For instance, Guenet et al. (2018) showed that a large increase in plant productivity (+20%) could result, at the global level and by 2050, from the increase in atmospheric CO_2 concentrations. Wieder et al. (2015) concluded that an increase in plant productivity between +10% and +20% depends on whether nutrient availability was considered or not. In our work, C_{in}^{0} values, representing carbon input needed to sustain current stocks, were on average 11% higher when considering climate change. Hence, NPP increases related to CO_2 concentration increase could compensate for additional SOC mineralization related to temperature increases and enable maintaining current stocks. However, the effect of temperature increase is likely to overrule the NPP increase in the perspective of a 4‰ target, as our results regarding the increase in ΔC_{in} suggest.

These figures are nevertheless hypothetical, as it is currently difficult to assess the future trend in plant productivity on large areas such as France. They are expected to vary considerably spatially (Wang et al., 2019), resulting from spatial and temporal interactions between temperature, water and nutrients availability, and atmospheric CO_2 concentrations (Ainsworth et al., 2020). Our result based on a single projected climate time series should of course be tested using other climate projections for the same RCP scenario (as in Wiesmeier et al., 2016) and possibly on other RCPs. In addition to the choice of the specific RCP, the choice of a climate model for representing RCP effects at a global scale and regional models for downscaling climatic variables and, in turn, estimates of RothC input variables (temperature, precipitation and PET) is particularly critical given the sensitivity of the model to these factors.

4.5 | Feasibility of the 4‰ target

As shown in Table 1, 94.8% of the cropland area were considered unsaturated (in terms of mineral-associated SOC), in agreement with the results obtained by other authors (Angers et al., 2011; Chen et al., 2018), but mostly with a negative C_{bal}. With grasslands, this percentage was lower than for croplands but remained high for improved grasslands (70.1%). The majority of soils under improved grasslands also showed negative C_{bal}^{4p1000} values. These numbers suggest that for croplands and improved grasslands additional C storage is possible but C inputs to the soil are likely to be the limiting factor. Because of the high proportion of unsaturated soils in these two land use classes, storage would likely be in the fine fraction, and hence would lead to stabilized SOC stocks. This result is in line with several authors who claimed that restrictions due to available biomass production and associated removals by human appropriation is one of the most severe limitations for the 4‰ objective (Poulton et al., 2018; Zomer et al., 2017). In unimproved grasslands, most soils had positive C_{bal}^{4p1000} values (90.4%), but 59.1% were saturated. There, C storage occurs thanks to a positive C balance but SOC stocks are likely to be less stabilized, because the fine fraction is often already saturated. The situation is more contrasted for forests, with 56.5% of the area unsaturated, among which 25.5% have a negative C budget. Saturation of areas like the pine forests in Landes de Gascogne (southwest France) on the sandy soils and forest in the Massif Central and Vosges areas was in line with the recent estimate made by Chen et al. (2018), although the total area was smaller in our study. The proportion of saturated sites in forests increased from 43.5% to 56.9% when considering not only the current SOC stocks but also the 4‰ target.

This combination of two indicators (carbon balance and SOC saturation) makes it possible to qualify the different regions of mainland France in terms of their suitability to achieve the 4‰ objective as well as identifying best management strategies. In croplands, the main limiting factor is the availability of C resources, thus highlighting the interest of farming practices that produce and return additional biomass to the soils, such as cover crops (Poeplau & Don, 2015), straw management (Liu et al., 2014), increasing the duration of sown grasslands and agroforestry systems (Cardinael et al., 2017; Lorenz & Lal, 2014). From a long-term perspective, plant breeding and technological developments increasing plant productivity, especially those taking advantage of future higher atmospheric CO_2 concentrations, or altering C management within the plant (e.g. higher root:shoot ratio; root exudation) may also contribute to increase C inputs in cropland soils (Bailey-Serres et al., 2019). Incorporating more organic wastes from urban or industrial sources would be another way to increase soil C stocks in cropland areas. In mainland France, urban and industrial wastes represent 4.6 Tg C $year^{-1}$, from which only 24% are already spread on agricultural soils. Compared to the amount of animal manure (10 Tg C $year^{-1}$), these figures show that urban and industrial wastes represent a significant source of C (ADEME, 2007; Marsac et al., 2018). However, using this resource is restricted based on soil contamination concerns and social 'acceptability'.

For unimproved grasslands, and to a lesser extent for forests, one key limitation is that many soils are already saturated. A negative saturation deficit does not necessarily indicate that soil cannot store additional SOC. It merely indicates locations where an increase in C_{in} will be less likely to be associated with fine mineral particles. Cotrufo et al. (2019) clearly showed that the fine fraction of European grasslands and forest soils does reach a saturation level but not the coarse fraction. Once the mineral-associated SOC is saturated, any increase in SOC is likely to require higher increase in carbon input, compared to the unsaturated case, because the increase in SOC will be made of uncomplexed SOC, with presumably higher turnover. RothC does not represent this process, and any increase in SOC requires the same increase in organic carbon input into the soil whatever the SOC level. Hence, in saturated conditions, the required carbon input levels, as estimated by RothC, might be underestimated.

Moreover, SOC stocks in saturated zones with a negative carbon balance may currently be particularly at risk of losing C (Meyer et al., 2017). There, C_{in} is not high enough to maintain current stocks and a significant proportion of SOC is found in the uncomplexed fraction. These soils are found, for instance, in western Brittany where the grassland-based livestock production is concentrated and where SOC mineralization is potentially high due to climatic conditions and relatively low soil clay content.

5 | CONCLUSION

Taken together, our results show that there is a room for additional C storage in some mainland French soils. The aspirational target of 4‰ may however not be achievable in large parts of mainland France, both because of limited C availability in some areas (especially under croplands, unless land management practices are modified) and because of soil organic carbon saturation (i.e. physicochemical limitations to SOC storage in the fine mineral fractions) in others. In unimproved grasslands, with 65.2% of SOC saturation in topsoils, there is, on average, high enough NPP returns to the soil to reach the target, but the additional carbon would be largely stored in relatively labile fractions. In other land use types, additional organic carbon returns to soils would be needed to reach the target. For instance, in croplands, where topsoils are mostly unsaturated, reaching the target requires additional annual biomass production and return to the soil (e.g. through cover crops). In forests, 43.5% of the topsoils are already saturated which implies that the increase in carbon returns to soils could be less efficient for stabilized SOC accumulation. This approach makes it possible to identify vulnerable SOC stocks, particularly those characterized by a negative balance in saturated soils. The main recommendation for mainland France would be to prioritize NPP returns in cropland soils that are unsaturated and have a negative carbon balance and to protect SOC in forests and unimproved grasslands given their high stocks and relatively high saturation levels.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in https://data.inrae.fr/ at http://doi.org/10.15454/OGJNIC.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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