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Model for Multifunctional Agriculture Land Optimization (MMALO-V1) for soil carbon stocks and agricultural production

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Abstract. We present MMALO (Model for Multifunctional Agriculture Land Optimization), a multi-objective optimization model to find land use strategies that increase soil carbon stocks in agricultural lands while maintaining high and stable crop production. The model optimizes the composition of agricultural lands and the fraction of residual biomass left on fields in order to balance three potentially competing objectives: (i) enhance soil carbon stocks in agricultural topsoils, (ii) maximize crop-based food energy production, and (iii) minimize the interannual variance of agricultural production.
Here, we present the model equations and the calibration for France at the NUTS3 resolution. Results show that soil carbon accrual could be achieved without compromising food production or stability at the national level, up to an annual increase target of 6 Mt C over a period of 30 years, close to the aspirational rate of the 4per1000 initiative. The highest simulated target of 8 Mt C per year over the same period would result in a trade-off, with food production decreasing by 8% compared to the current state. Uncertainty in soil carbon turnover time, an uncertain input variable in the one pool carbon model implemented in MMALO, translated into coefficients of variation of up to 9% for projected food production and up to 3% for production stability. Overall, MMALO provides a flexible framework for supporting land use planning able to increase soil carbon stocks and ensure sustainable food production.

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1 Introduction

Agricultural expansion on natural ecosystems has historically led to substantial losses of soil organic carbon (Sanderman et al., 2017), framing food production and carbon storage as competing land use objectives (West et al., 2010; Johnson et al., 2014). This issue has motivated the development of multi-objective land use optimization frameworks balancing this trade-off and informing policy makers (Heck et al., 2018; Strassburg et al., 2020; Shi et al., 2021; Bayer et al., 2023; Chen et al., 2023, Ekholm et al., 2024).

However, most existing frameworks do not represent the diversity of crop types, but instead optimize the spatial allocation of broader land use classes such as croplands, pastures, and forests to balance carbon storage and food production objectives. Consequently, little attention has been given to how current agricultural lands can be optimally re-allocated among crop and grassland types at a large spatial scale to jointly enhance soil carbon storage and food production. Yet, the dynamics and storage of soil organic carbon (hereafter abbreviated to soil carbon) are jointly influenced by the spatial variability of (i) crops and grasslands yields, which drives carbon inputs to soils from plant residues (Monfreda et al., 2008; Sun et al., 2021) and (ii) soil and climate properties, controlling the turnover and stabilisation of organic matter (Chen et al., 2019; Zomer et al., 2017). In turn, the coupling between productivity, land use type, and soil carbon suggests that targeted spatial re-allocation of crops and grasslands could enhance soil carbon stocks within existing agricultural lands.

Moreover, so far, optimization of land use for agricultural production has largely focused on average production levels while overlooking the temporal stability of production. Crop yields and soil carbon inputs can strongly vary year to year, for instance due to climate variations, which warrants consideration of temporal variability in land use optimization frameworks. Notably, previous studies have shown that reaching a higher mean production is often associated with increased year to year yield variability, highlighting a trade-off between productivity and stability (Ben-Ari & Makowski, 2016).

To our knowledge, there is no optimization model for agricultural land use able to consider the triple objective of: (1) achieving a high average production of calories while keeping a reasonable diversity of crop types; (2) minimizing the year to year variation of production, to avoid adverse yield shocks for producers and consumers, and (3) increasing soil carbon storage. We address this research gap by introducing the MMALO model (Model for Multifunctional Agriculture Land Optimization). MMALO was designed to identify agricultural land use strategies at large spatial scales (national or even larger) that increase soil carbon stocks above present levels while maintaining high and stable production. To this end, the model optimizes the allocation of agricultural land to different types of crop and grassland. The fraction of residual biomass left on fields can also be optimized or fixed to reflect current farming practices. The model's objectives are to maximize mean annual food production, minimize interannual production variability, and achieve a predefined soil carbon accrual

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target over 30 years. The evolution of soil carbon stocks is simulated using a one-pool, first order decay model. Soil carbon dynamics are controlled by a data-driven mean turnover time of soil carbon, which represents the apparent average time that carbon remains in the soil.

The proposed model is applied to France, at the NUTS3 resolution, for the period 2000-2020. France was chosen as a case study because it has the largest agricultural area in the European Union (Eurostat 2025) and is a major European producer of food and feed. The country contains a large diversity of crop types (e.g. wheat, maize, rapeseed, pea), grasslands and carbon contents, providing a broad range of land use options for optimization. Finally, France initiated the '4 per 1000' initiative, which set an aspirational goal of increasing global soil carbon stocks by an annual rate of 4‰ (Soussana et al., 2019). Consequently, strategies for increasing soil carbon stocks have been investigated in detail in this country (Chen et al., 2018; Pellerin et al., 2020; Martin et al., 2021). Most French agricultural topsoils are considered to be unsaturated, with soil carbon accrual being limited by carbon inputs (Martin et al., 2021), making France well suited for investigating the potential of land use re-allocation to enhance soil carbon sequestration.

Here, we present optimization results for France under four increasing soil carbon accrual targets and quantify the trade-off between increasing soil carbon stocks and maintaining high food production and stability at the national scale. In addition, we assess the sensitivity of the model outputs to uncertainties in soil carbon turnover time, given that the latter is a dominant source of uncertainty in global land surface models (Ito et al., 2020)..

The remaining sections are structured as follows : we describe the model structure and equations in Sect. 2. In Sect. 3, we present the results of the model calibration for France. In Sect. 4, we present the sensitivity analysis to soil carbon turnover time. In Sect. 5, we present the results of our analyses and discuss them along with the strengths and limitations of MMALO.

2 Description of the model

2.1 Overview of the model

The model starts from an initial state representing current agricultural land use conditions, defined using local observations of harvested areas, yields, yield variability, and soil carbon stocks over a number of spatial units in the study region (here France, at a NUTS3 resolution). From this initial condition, the model re-allocates agricultural land within each spatial unit to different crop and grassland types and determines the fraction of residual biomass that is left on fields in order to reach three objectives: (1) maximizing mean annual food crops production; (2) minimizing interannual variability in plant production; (3) achieving a predefined soil carbon stock accrual target over a 30 years time horizon. The optimization is also subject to a set of constraints that preserves key characteristics of agricultural systems, including satisfying livestock feed requirements and harvested crop residues demand, as well as limiting deviations from the current composition of food production.

The mean annual plant production is computed at the national scale from mean yield multiplied by the areas allocated to the different types of crops and grasslands considered in the NUTS3 units. The model partitions the aboveground plant

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production between harvested biomass (e.g. for food or feed) and residual biomass left on fields. This allocation can be either fixed to represent current farm management practices or optimized to explore alternative management strategies. The inter-annual variability of plant production is computed at the national scale from the yield variances and covariances in NUTS3 units. Soil organic carbon stocks are simulated with a one-pool, first order decay model, from a balance between carbon inputs and outputs such as respiration and erosion. Soil carbon inputs include residual biomass left on fields and animal manure. Carbon outputs are governed by a data-driven mean apparent turnover time (hereafter turnover time τ), which derives total soil carbon losses over time from substrate availability. In the current version of MMALO, livestock numbers and their spatial distribution are assumed constant as well as their requirements for feed (i.e. crop grains and fodders) and animal bedding (i.e. crop residues).

The main input data required to run the model are yearly harvested areas and annual yields over 2000-2020, initial soil carbon stocks, turnover time, as well as livestock feed requirements and manure inputs to soils. The main outputs are the optimal land re-allocation among crop and grassland types within each NUTS3 unit, together with the associated food production, variability, soil carbon inputs and projected stocks. Each component of the model is described in the following sections. In addition, all variables are summarized in Table A1 and A2.

The dimensions of the model are spatial units ($i=1, \ldots, n$) and crop and grassland types ($j=1, \ldots, m$).

The spatial units are the NUTS3 statistical units in France ($n= 90$). Because some data are only accessible at a coarser resolution, namely annual statistics on the number of poultry heads used to compile carbon flows from livestock manure, we also consider a coarser resolution corresponding to the NUTS1 level. Each NUTS1 unit is denoted r.

We consider 18 annual crop types and 2 grassland types in France ($m = 20$), classified according to two complementary schemes (Table 1). First, they are grouped according to their agricultural uses to define production and feed constraints. Here, G is the subset of grassland types, including both temporary and permanent grasslands. F is the subset of annual fodders grown for animal consumption. O is the subset of other annual crops (e.g. arable crops including cereals, oilseeds, root crops and protein crops) that can be used as food for humans or feed for livestock. Other crops are not included in the analysis (e.g. fibre crops, fruits and vegetables). Second, all crop and grassland types are grouped into two aggregated land use classes for projecting soil carbon stocks, with $k \in \{1, 2\}$, where k=*1* represents croplands (including annual crops and temporary grassland) and k=*2* corresponds to permanent grasslands, specifically. Soil carbon modelling is done at the aggregated land use class level for two reasons : (i) croplands and permanent grasslands typically display distinct soil carbon turnover times (Zhang et al., 2025) and (ii) land re-allocation represents the long term average composition of agricultural lands, whereas annual crops are expected to rotate spatially through time at the field level. Consequently, the individual crop level would not be a meaningful level of representation. Here note that temporary and permanent grasslands both belong to set G when considering production constraints, but are assigned to different land use classes for soil carbon modelling because temporary grasslands are typically part of crop rotations.

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Last, the temporal dimension is not explicitly incorporated in MMALO. In the model, average soil carbon stocks are estimated for a predefined time horizon.

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Table 1. Crop and grassland types considered in MMALO for land use optimization in France, their corresponding land use class and subsets.

j	Land use class	Subset for constraints on plant production
Soft wheat	Cropland	Non fodder annual crops (*O*)
Durum wheat	Cropland	Non fodder annual crops (*O*)
Barley	Cropland	Non fodder annual crops (*O*)
Oats	Cropland	Non fodder annual crops (*O*)
Triticale	Cropland	Non fodder annual crops (*O*)
Maize (grain)	Cropland	Non fodder annual crops (*O*)
Sorghum (grain)	Cropland	Non fodder annual crops (*O*)
Other cereals	Cropland	Non fodder annual crops (*O*)
Rapeseed	Cropland	Non fodder annual crops (*O*)
Sunflower seed	Cropland	Non fodder annual crops (*O*)
Soybean	Cropland	Non fodder annual crops (*O*)
Pea	Cropland	Non fodder annual crops (*O*)
Bean	Cropland	Non fodder annual crops (*O*)
Green bean	Cropland	Non fodder annual crops (*O*)
Sugar beet	Cropland	Non fodder annual crops (*O*)
Potato	Cropland	Non fodder annual crops (*O*)
Maize (fodder)	Cropland	Fodder annual crops (*F*)
Other fodders	Cropland	Fodder annual crops (*F*)
Temporary grassland	Cropland	Grassland (*G*)
Permanent grassland	Permanent grassland	Grassland (*G*)

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2.2 Optimization procedure

The three objectives defined at the national scale are (1) maximizing the interannual mean crop-based caloric food production, noted $P_{food}(S)$, (2) minimizing interannual variance of plant production, noted $V(S)$ and (3) achieving a target soil carbon stock accrual in topsoils after a specified duration of 30 years, $C(S, P_{left})$. To this end, we define a land allocation solution S as a vector of size $p = n \times m$ where each value $S_{i,j}$ contains the share (in the range 0-1) of the agricultural area in the spatial unit i ($i=1, \ldots, n$) allocated to crop or grassland type j ($j=1, \ldots, m$). We further define $P_{left\ i,j}$ as the annual amount of above-ground plant biomass left on fields [in MtDM yr^{-1}]. For clarity, $P_{left\ i,j}$ is denoted $P_{crop\ res\ left\ i,j}$ for crop residues left on fields, and $P_{grass\ left\ i,j}$ for grassland residual biomass (Fig. 1).

Given a land use defined by S, the mean annual crop-based food production $P_{food}(S)$ [in Exajoules per year EJ yr^{-1}] is calculated as the total production of non-fodder crops (noted O, Table 1.) minus the production of crop-based animal feed :

$$P_{food}(S) = \sum_{i}^{n} \sum_{j \in O} (S_{i,j} \cdot A_i \cdot p_{i,j} \cdot e_j) - P_{feed\ tot} \quad (1)$$

where A_i is the total agricultural area in the spatial unit i [in million ha Mha], $p_{i,j}$ is the average yield of crop type j, in unit i over the period considered, here 2000-2020, in dry matter equivalent [tDM ha^{-1} yr^{-1}] and e_j a crop-specific gross energy content to dry matter conversion factor [in TJ tDM^{-1}]. $P_{feed\ tot}$ is a prescribed variable defining the total energy production from food crops used as animal feed, including processed feed crops e.g. cakes from oil seeds.

The interannual variance of the national agricultural production $V(S)$ [EJ^2 yr^{-2}] is computed as a quadratic form with :

$$V(S) = A(S)^T \Gamma A(S) \quad (2)$$

where $A(S)$ is a vector of size $p = n \times m$ containing the area [in Mha] of crop j in each unit i, that is $A_{i,j}(S_{i,j}) = S_{i,j} \cdot A_i$. $A(S)$ is obtained by stacking these values following a consistent i,j ordering. Γ is a symmetric positive semi-definite variance-covariance matrix of annual yields in gross energy equivalent [in TJ ha^{-1}], with size $p \times p$. It describes the variability of annual yields for each i,j pair during the period 2000-2020 (diagonal terms) and the co-variability of annual yields between different i,j pairs (off-diagonal terms). The value of $V(S)$ increases when area is allocated to pairs with higher variance or to combinations of i,j pairs with higher covariances.

Last, the land allocation S drives the soil carbon $C(S, P_{left})$ through a series of intermediate variables shown in Figure 1. Specifically, different land allocations result in different levels of plant production and crop residues production. The fraction of biomass that is left on fields (P_{left}) determines soil carbon inputs. It represents a management variable whose value is either fixed to represent current management practices or optimized. The partitioning of plant production is detailed separately in

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Sect. 2.3. $C(S, P_{left})$ is obtained from a one pool model following a first order decay differential equation detailed separately in Sect. 2.5.

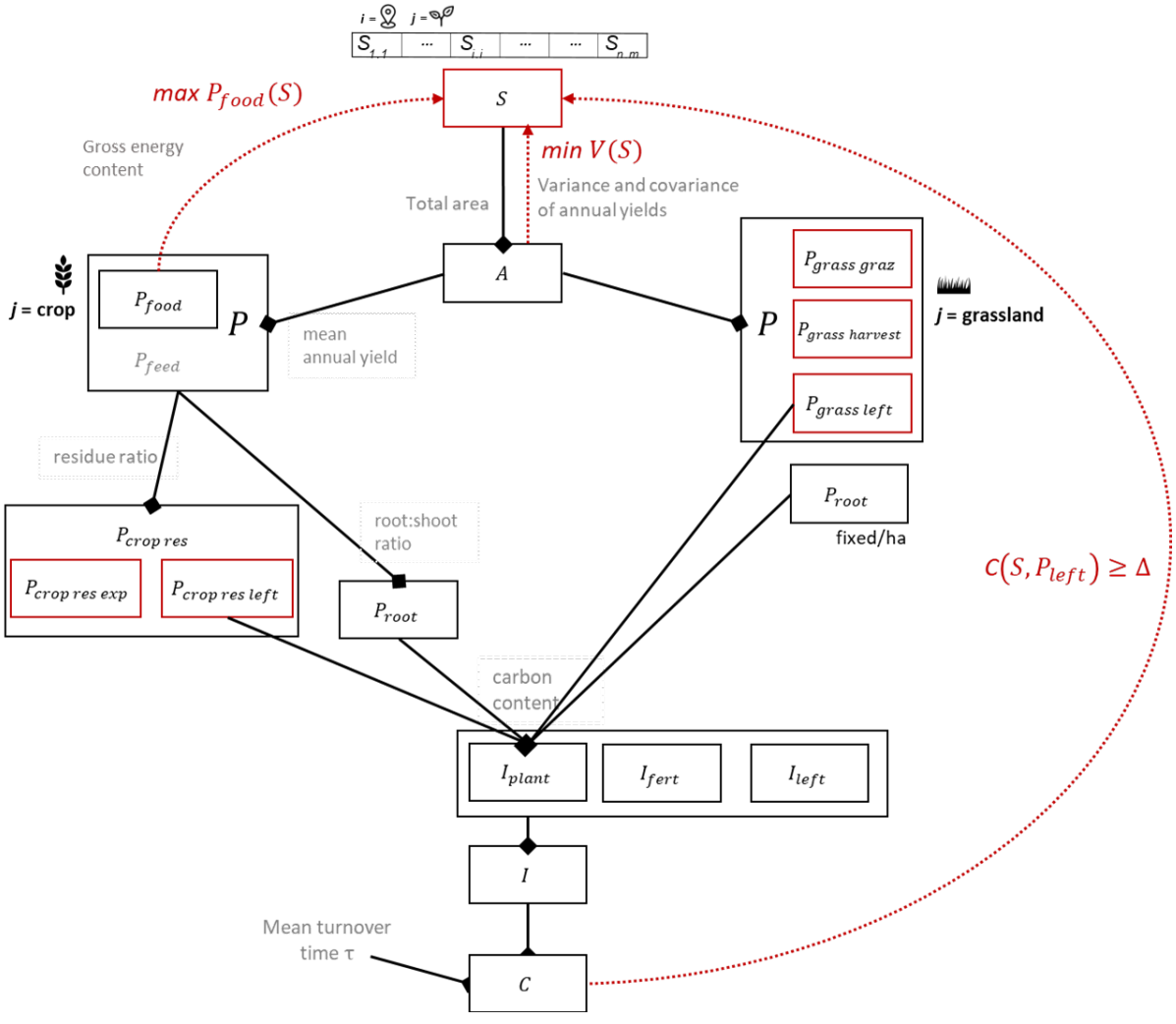

Figure 1. Conceptual framework of MMALO showing the main relationships among model variables. Variables enclosed in red : the optimized variable S, which is the share of the agricultural area in each spatial unit *i* allocated to each crop or grassland type *j* and the optimized partitioning of crop residues production and grasslands production that determines, together with *S*, the amount of residual biomass input to the soils. Note that the partitioning can be optimized or constrained to reflect current practices. Variables enclosed in black : other endogenous variables. Red arrows : the three objectives of the model. Fixed inputs variables are in grey and not enclosed. A: area; P: production; I: soil carbon inputs; C: soil carbon stocks.The description of the variables is provided in tables A1 and A2 .

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The optimization problem consists of maximizing Eq. (3) while ensuring that the projected soil carbon stocks meet a prescribed target. It is formulated as :

$$Arg \max_{S} P_{food}(S) - \lambda V(S) \quad \text{s.t.} \quad C(S, P_{left}) \geq \Delta \tag{3}$$

where λ is a weighting coefficient between the two objectives $P_{food}(S)$ and $V(S)$. As the value of λ increases, greater emphasis is placed on minimizing interannual variability relative to maximizing mean production. Δ is the user-defined national target of soil carbon accrual [Mt C] over a defined time horizon of 30 years. We employ quadratic optimization with the Python library CVXPY (Diamond and Boyd 2016; Agrawal et al., 2018).

The optimization is performed considering two additional constraints on land use allocation. First, the model assumes a constant total agricultural land within each spatial unit *i*, equivalent to assuming that:

$$\forall i, \sum_{j}^{m} S_{i,j} = 1 \tag{4}$$

Second, although *S* ranges from 0 to 1, we constrained each $S_{i,j}$ to be lower than an upper bound such as :

$$S_{i,j} \leq S_{max,j} \tag{5}$$

where $S_{max,j}$ is set to the 95th percentile of the observed mean shares of *j* across all spatial units *i* over the period 2000-2020. The constraint (5) is used to avoid unrealistic land use change, totally different from the historical land use.

2.3 Plant production and allocation of biomass flows

The land allocation optimization determines *S*, from which the mean annual aboveground plant production for each *i,j* pair, noted $P_{i,j}$ [MtDM. yr^{-1}] is calculated as the product of the allocated areas to the corresponding yields $p_{i,j}$:

$$P_{i,j} = S_{i,j} \cdot A_i \cdot p_{i,j} \tag{6}$$

Subsequently, MMALO allocates aboveground production into different biomass fluxes (Fig 1.). The allocation differs for annual crops (*F* and *O*, Table 1.) and grasslands (*G,* with *G = 2* for temporary and permanent grasslands) to account for different management practices influencing the fraction of aboveground biomass left on fields, namely crop residue management for annual crops and grassland use intensity for grasslands. MMALO can reproduce current practices or explore alternative strategies through optimizing the allocation of plant production. The two formulations are explained below.

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2.3.1 Crop residues production and management

The production of above-ground crop residues $P_{crop\ res\ i,j}$ [Mt DM yr^{-1}] is calculated by multiplying the total crop production by a crop-specific ratio rpr_j.

$$P_{crop\ res\ i,j} = P_{i,j} . rpr_j \quad \forall j \in O, F \tag{7}$$

where F denotes annual fodder crops and O non fodder annual crops.

$P_{crop\ res\ i,j}$ is partitioned by the model between a flux exported for human activities such as animal bedding ($P_{crop\ res\ exp\ i,j}$) and a flux left on fields ($P_{crop\ res\ left\ i,j}$). Mass conservation is ensured by Eq. (8), as :

$$P_{crop\ res\ i,j} = P_{crop\ res\ exp\ i,j} + P_{crop\ res\ left\ i,j} \tag{8}$$

The value of $P_{crop\ res\ left\ i,j}$ depends on the fraction of crop residues left on fields. When management practices are prescribed, the fraction of crop residues left on fields is fixed. This is given by :

$$P_{crop\ res\ left,\ i,j} = P_{crop\ res,\ i,j} \cdot L_{i,j} \tag{9}$$

where $L_{i,j}$ is the current observed fraction of residues left on fields [unitless]. When management practices are optimized , the fraction of crop residues left on fields is bounded by :

$$P_{crop\ res,\ i,j} \cdot L_{max\ i,j} \geq P_{crop\ res\ left,\ i,j} \tag{10}$$

where $L_{max\ i,j}$ represents the maximum residues retention fraction [unitless]. Last, the total amount of crop residues exported is constrained to match a prescribed national requirement REQ_{res} [Mt DM yr^{-1}] of residue use by human activities:

$$\sum_i \sum_j P_{crop\ res\ exp\ i,j} \geq REQ_{res} \tag{11}$$

2.3.2 Grasslands production and management

The aboveground production of grasslands [Mt DM yr^{-1}] determined by Eq. (6) is allocated by the model between a flux $P_{grass\ graz\ i,j}$ that feeds grazing livestock, a flux $P_{grass\ harvest}$ of harvested forage grass and a flux $P_{grass\ left}$ left on fields, with mass conservation ensured by :

$$P_{i,j} = P_{grass\ graz\ i,j} + P_{grass\ harvest\ i,j} + P_{grass\ left\ i,j} \quad \forall j \in G \tag{12}$$

The value of $P_{grass\ left\ i,j}$ depend on farmers management practices through grassland use intensity. We define grassland use intensity as the ratio of grass exported (harvested or grazed) to the total aboveground production. When management is prescribed, grassland use intensity is fixed to its initial value with :

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$$P_{i,j} \cdot gui_{i,j} = P_{grass\ graz\ i,j} + P_{grass\ harvest,\ i,j} \quad (13)$$

where $gui_{i,j}$ is the grassland use intensity in the initial state. When the management is optimized, the intensity of use is bounded by two parameters depending on management types (grazing vs harvesting). We consider that a maximum of 80% of the aboveground biomass can removed by grazing livestock while up to 95% of the aboveground production can be exported through harvest, which corresponds to grasslands harvest index in Wolf et al. (2015), as :

$$P_{i,j} \geq \frac{P_{grass\ graz\ i,j}}{0.8} + \frac{P_{grass\ harvest,\ i,j}}{0.95} \quad (14)$$

2.3.3 Other constraints on plant production

Additional constraints are implemented on the production terms to ensure that optimized land allocation provide sufficient amounts of feed for livestock for four feed categories: (i) grazed grass, (ii) harvested grass, (iii) fodder crops and (iv) concentrate feeds, including grain crops and processed grain by-products e.g. oil seed cakes. A grazing grass requirement $REQ_{g\ graz\ i}$ must be fulfilled locally in each spatial unit *i*, which is given by:

$$\sum_{j \in G} P_{grass\ graz\ i,j} - REQ_{g\ graz\ i} = 0 \quad (15)$$

The harvested grass production is constrained to satisfy the annual requirement $REQ_{g\ harvest\ i}$ in each unit *i* that belongs to NUTS1 region *r*, under the assumption that harvested fodder resources can be transported but remain used in the same region, which is given by:

$$\sum_{i \in r} \sum_{j \in G} P_{grass\ harvest\ i,j} \geq \sum_{i \in r} REQ_{g\ harvest\ i} \quad (16)$$

Similarly, the fodder crop production is constrained to satisfy the annual requirement $REQ_{f\ i}$ in each unit *i* that belongs to a NUTS1 region *r* :

$$\sum_{i \in r} \sum_{j \in F} P_{i,j} \geq \sum_{i \in r} REQ_{f\ i} \quad (17)$$

Feed production from other non-fodder crops is constrained to satisfy the requirement $REQ_{o\ j}$ at the national scale:

$$\sum_{i} P_{i,j} \geq REQ_{o\ j} \quad \forall j \in O \quad (18)$$

Where *O* is the total number of other non fodder crop types that can be used for concentrate feed production. We note that the imports of feed products from other countries are implicitly considered, as our feed requirements are the quantities that must be produced domestically, i.e. total feed requirements minus imports. Therefore, unlike the other feed resources, the

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concentrate feed production requirements $REQ_{o\,j}$ is obtained at the national scale because imports can only be estimated at this level. We assumed no imports of fodder crops from foreign countries, consistently with annual national commodity balance sheets (Agreste, 2025a).

Last, the model is designed to explore land use reallocation possibilities while avoiding abrupt changes in the structure of food supply. We therefore impose a constraint on the composition of total food calorie production to ensure that the optimized production patterns remain consistent with the initial situation. Let f_j denote the fraction of food crop j in the total food calorie production, which is maximized at the national scale in Eq.(3). In the initial situation, this fraction is noted $f_{0\,j}$. To limit drastic changes from the initial structure of food supply, we constrain the share of each crop type to the total food calories as:

$$0.5 f_{0\,j} \leq f_j \leq 1.5 f_{0\,j} \quad \forall j \in O \tag{19}$$

With :

$$f_j = \frac{\sum_i \left(P_{i,j} \cdot e_j\right) - P_{feed\,j}}{\sum_i \sum_j \left(P_{i,j} \cdot e_j\right)} \quad \forall j \in O \tag{20}$$

where f_j and $f_{0\,j}$ are unitless and $P_{feed\,j}$ is the feed production of crop type j [EJ yr^{-1}] across the O crop types that can be used for feed.

2.4 Carbon inputs to soils

The optimization under the constraint to store additional carbon in soils links the production terms as detailed above to the annual carbon inputs to soils $I_{i,j}$ [MtC yr^{-1}]. We consider three categories of soil carbon inputs: (1) aboveground and belowground plant residues $I_{plant\,i,j}$, (2) livestock manure left on grasslands during grazing $I_{man\,graz\,i,j}$, and (3) livestock manure collected at farm level and applied to crops or grasslands as a fertilizer, $I_{man\,crop+grass\,i,j}$. The total annual carbon inputs for each unit i and agricultural land use type j is given by:

$$I_{i,j} = I_{plant\,i,j} + I_{man\,graz\,,i,j} + I_{man\,crop+grass\,i,j} \tag{21}$$

The input flux $I_{plant\,i,j}$ is calculated as the sum of the above-ground biomass left on fields, $P_{res\,left}$ determined with Eqs. (7-14) and of the below-ground biomass $P_{root,\,i,j}$ multiplied by their respective carbon contents $c_{res\,j}$ and $c_{root\,j}$ [tC tDM^{-1}], as given by:

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$$I_{plant\ i,j} = P_{res\ left\ i,j} \cdot c_{res\ j} + P_{root\ i,j} \cdot c_{root\ j} \quad (22)$$

For non-root crops, $P_{root\ i,j}$ is computed using crop specific root:shoot ratios obtained from Wolf et al. (2015). For root crops such as sugar beet and potatoes, only the above-ground residues are included with residues ratio taken from Bolinder et al. 2015, and $P_{root\ i,j}$= 0. For grasslands, we used a fixed root derived carbon input of 2.22 tC ha^{-1} yr^{-1} after Poeplau et al., (2021). Since we consider the topsoils, we adjusted the total root biomass by a factor of 0.7 for crops and 0.8 for grasslands to only account for the proportion of root biomass in the 0-30 cm soil layer, following Poeplau et al (2021).

The total input flux from livestock manure is a non neglectable component of soil carbon inputs, amounting to 18.3 Mt C yr^{-1} compared to plant residue inputs amounting to 66.5 Mt C.yr^{-1} (Table 2) . We assumed that the number of livestock animals remains constant throughout the optimization period, at the value of its initial state. Therefore, the total amount of available livestock manure inputs is fixed from current statistics. We nevertheless distinguish between manure left on grasslands during grazing, $I_{man\ graz\ i,j}$, and manure collected by farmers in buildings and applied as a fertilizer on both crops and grasslands, $I_{man\ crop+grass\ i,j}$. First, $I_{man\ graz\ i,j}$ is obtained by distributing the total manure left during grazing $M_{graz\ i}$ [Mt C yr^{-1}] to temporary and permanent grasslands proportionally to the fraction of grazing requirements that they respectively cover, as given by:

$$I_{man\ graz\ i,j} = M_{graz\ i} \cdot \frac{P_{grass\ graz,\ i,j}}{REQ_{g\ graz\ i}} \quad \forall j \in G \quad (23)$$

where $M_{graz\ i}$ is calculated by multiplying the carbon excretion rates of grazing animals, including cattle, sheep, and goats by their mean annual number of heads between 2000-2020, and by the fraction of manure excreted during grazing (Supplement S1.1). Secondly, $I_{man\ crop+grass\ i,j}$ is obtained from multiplying the area of each *i,j* pair with manure application rates noted $m_{farm\ i}$ [tC ha^{-1} yr^{-1}]. $m_{farm\ i}$ was obtained by dividing the total amounts of manure collected in livestock buildings at the regional (NUTS1) level by the total regional agricultural area. This approach was chosen because poultry statistics are only publicly reported at this coarser resolution. It is therefore assumed that all crop and grassland types *j* receive manure proportionally to their areas in each NUTS1 region.

$$I_{man\ crop+grass\ i,j} = m_{farm\ i} \cdot S_{i,j} \cdot A_i \quad (24)$$

2.5 Soil organic carbon stocks

Below, we describe the soil carbon module of MMALO. The calculation of soil organic carbon stocks *C* [Mt C] considers only the topsoils typically between 0 and 30 cm. *C* represents the 'active' fraction of the total topsoils stocks, which responds

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to changes in carbon inputs over the optimization time frame, estimated at 89% of the total topsoils stocks (Copard et al., 2025). The remaining stable fraction is supposed to stay constant.

Within each unit *i*, *C* is calculated in croplands and permanent grasslands land use classes denoted by index *k*, with *k = 1* for croplands and *k = 2* for permanent grasslands (Sect. 2.1; Table 1). Accordingly, soil carbon turnover is defined at the land use class level rather than for individual *j* types. This aggregation is justified by the fact that crop types within croplands vary annually through crop rotations and may change over a few years, whereas our optimized land allocation represents a long term average composition of agricultural lands at the NUTS3 level which meets some large-scale constraints. The dynamics of *C* is simulated with a one pool model following a first order decay differential equation. This formulation is a simplified version of the equations used in most soil carbon models like CENTURY and ROTHC which have multiple pools, here simplified to a single active pool. The integral form of the soil carbon equation is given by Eq. (25), where the first term represents the decay of the initial inherited stock over time and the second term accounts for the accumulation and decay of 'new' organic carbon with changing inputs over time from the optimization:

$$C(t) = \sum_{i=1}^{n} \sum_{k=1}^{2} C(0)_{i,k} \cdot e^{\frac{-t}{\tau_{i,k}}} + I_{i,k} \cdot \tau_{i,k} \cdot \left(1 - e^{\frac{-t}{\tau_{i,k}}}\right) \quad (25)$$

where $C(0)_{i,k}$ is the initial inherited stock for a given unit *i* and land use class *k* [Mt C], *t* is the time horizon for projecting future stocks, here set to 30 years. $\tau_{i,k}$ is the turnover time of organic carbon entering the soil [years]. It varies spatially across units and land use categories *k* (Fig. 2). Because of important uncertainties regarding soil carbon turnover time, we derived two alternative parameterizations and evaluated their influence on the optimization outcomes in Sect. 4. $I_{i,k}$ *is* the mean annual carbon inputs to the soil [Mt C yr^{-1}], here with a *k* index but we keep track of separate inputs for each *j* land use type belonging to each land use class. Soil carbon inputs given by equations listed in Sect. 2.3 are aggregated for croplands according to Eq. (26) while $I_{i,2}$ is equal to soil carbon inputs estimated in Sect 2.3 for *j*=permanent grasslands (Table 1).

$$I_{i,1} = \sum_{j \in Cropland} I_{i,j} \quad (26)$$

Our framework represents land use transitions between croplands (*k=1*) and permanent grasslands (*k=2*). To simulate the decay of inherited initial stocks $C(0)$, we assumed that the turnover time of inherited soil carbon is equal to that of the new land use class, following land use transitions. This assumption was adopted because it improves the agreement between simulated and observed stock changes following land use change (Fig. 3). Therefore, MMALO calculates the distribution of inherited soil carbon between land use classes, after transitions. Land use changes between croplands and permanent grasslands are represented by changes in the control variables $\Delta A_i^{1\to2}$ and $\Delta A_i^{2\to1}$ [Mha] which are linked to land allocation optimization through:

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$$A_{i,1} = \sum_{j \in Cropland} A_{i,j} = A_{0\,i,1} - \Delta A_i^{1\to2} + \Delta A_i^{2\to1} \quad (27)$$

Where $A_{i,1}$ is the optimized cropland area in unit i and $A_{0\,i,1}$ is the initial cropland area. An equivalent equation applies to permanent grasslands. To ensure that conversion from croplands to permanent grasslands cannot exceed the total initial cropland area in each unit, we impose that:

$$\Delta A_i^{1\to2} \leq A_{0\,i,1} \quad (28)$$

A similar constraint is applied to limit the conversion from permanent grasslands to croplands.
Inherited soil carbon stocks are distributed between cropland and permanent grasslands after land use transitions. For croplands, this is given by:

$$C(0)_{i,1} = c(0)_{i,1} \cdot \left(A_{0\,i,1} - \Delta A_i^{1\to2}\right) + c(0)_{i,2} \cdot \Delta A_i^{2\to1} \quad (29)$$

where $C(0)_{i,1}$ is the initial croplands' soil carbon stocks after land allocation optimization [Mt C] calculated with the new areas and the soil carbon densities $c(0)_{i,1}$ and $c(0)_{i,2}$ of croplands and permanent grasslands in their initial state [tC ha^{-1}]. The same approach is applied to permanent grasslands. Last, we conserve to total inherited soil carbon stocks, ensuring that no carbon is created or lost after land use change optimization, which is given by :

$$C(0)_{i,1} + C(0)_{i,2} = c(0)_{i,1} \cdot A_{0\,i,1} + c(0)_{i,2} \cdot A_{0\,i,2} \quad (30)$$

3. Calibration of the model

Table 2 provides aggregated national scale values describing the initial state of the French agricultural system (e.g. agricultural area and production, soil carbon stocks, and carbon fluxes). The model is calibrated at the subnational level, with specific values assigned to each land use type and spatial unit. The data sources and methods are described below and summarized in Table A2.
In the initial state, the average annual plant production in France was 2.85 EJ, with the interannual standard deviation of plant production equal to 0.227 EJ (8.1%) (Table 2). The fraction of plant production available for human consumption was 0.96 EJ (ca 2.3×10^{14} kcal). The remaining 1.89 EJ consisted of fodders and grass (1.53 EJ) and grain crops used as livestock feed (0.36 EJ), highlighting the importance of feed production in France.

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Table 2. National scale values describing the initial state of the French agricultural system, including areas, production, soil organic carbon stocks and carbon fluxes. These aggregated values are reported to summarize the initialization dataset and provide context. Model initialization is performed at the sub national level, where each spatial unit and land use type is assigned its own initial values. RMQS : French soil monitoring network

Variable	Unit	Values	Source
Total agricultural area (*A*)	Mha	26.4	Agreste, 2025b
croplands		17.1	Agreste, 2025b
permanent grasslands		9.3	Agreste, 2025b
Soil carbon stocks in the active pool of agricultural topsoils *C(0)*	MtC	1626	Data from RMQS (INRA et al., 2021; INRA et al., 2024). Active fraction from Copard et al., (2025), Sect. 3.4
Agricultural production for food P_{food}	EJ	0.96	This study Eq (1)
Agricultural production from non fodder crops used as feed P_{feed}	EJ	0.36	This study Sect. 3.2
Agricultural production from fodders and grass	EJ	1.53	This study Sect. 3.2
Interannual variability of agricultural production *V* (std)	EJ	0.227	This study Eq (2)
Annual inputs from plant materials I_{plant}	MtC yr^{-1}	66.5	This study Eq. (22)
Annual inputs from manure left on pasture I_{left}	MtC yr^{-1}	6.3	This study, Sect. 3.3
Annual inputs from manure collected in buildings I_{man} $_{crop + grass}$	MtC yr^{-1}	12.0	This study, Sect. 3.3

3.1 Crop and grassland areas and yields

We retrieved harvested areas (A_i) and yields ($p_{i,j}$) for 18 annual crops and 2 grasslands types (Table 1) from the agricultural annual statistics from the Statistics and Foresight Service (SSP) of the French Ministry of Agriculture for the time period 2000-2020 (Agreste, 2025b). Yields were converted into dry matter equivalent using DM content retrieved from Wolf et al. (2015).

The carbon content of residues and roots ($c_{res\,j}$ and $c_{root\,j}$), Energy content (e_j), and the fraction of crop residues left on fields ($L_{i,j}$) were compiled from various sources presented in Table A2. The intensity use of temporary and permanent grasslands ($gui_{i,j}$) was computed in each unit *i* by combining production statistics, estimates of livestock requirements for grazed grass and harvested fodders, and data on grassland management, namely the share of grassland areas being grazed, harvested, or both. These data are available for the year 2017 at the NUTS1 level (Agreste, 2020). The procedure for reconciling the different datasets is described in more details in Supplements S1.1.

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3.2 Livestock numbers and feed requirements

The numbers of livestock heads for seven livestock categories, dairy and meat cattle, dairy and meat sheep, goats, pigs and poultry, per age class, was retrieved from agricultural annual statistics and averaged over 2000-2020 (Agreste, 2025b). We characterized grass and fodders requirements ($REQ_{g\ graz\ i}$, $REQ_{g\ harvest\ i}$ and $REQ_{f\ i}$) on the basis of technical reports from Devun et al. (2012), Jousseins et al. (2014) and Bossis et al. (2015) for cattle, sheep, and goats, respectively. Our estimate for the annual fodder consumption at the national scale over 2000-2020 is 70.35 Mt DM, with 46% of grazed grass and 54% harvested grass and fodders, consistent with values reported by Sailley et al. (2021). For concentrate feeds ($REQ_{o\ j}$), we retrieved the national production used as feed for each crop product that contributed more than 1% of the national feed production from annual national commodity balance sheets (Agreste, 2025a). Transformed feed products (e.g., oil cakes) were converted to "raw grain equivalent" to estimate the amount of grain dedicated to their production in the initial state, using the technical transformation coefficients for agricultural commodities from the Food and Agriculture Organization (FAO, 2000). Our estimated energy production from fodders and feed is consistent with Harchaoui and Chatzimpiros (2018).

3.3 Livestock manure

Carbon in livestock manure was estimated by multiplying the number of heads by individual excretion rates for each livestock category. Annual excretion rates were estimated from volatile solids (VS) excretion rates [kg DM head^{-1} yr^{-1}] following the IPCC Tier 1 approach (IPCC, 2019) and assuming a 50% carbon content. The total amount of excreta was partitioned between the fraction deposited directly on pasture during grazing ($M_{graz\ i}$) and the fraction collected in buildings (divided by regional areas to derive $m_{farm\ i}$) using data from the National inventory of emissions and removal from the agriculture and forestry sectors (CITEPA, 2023). Bedding litter was included in the calculation of carbon inputs from manure collected in buildings, using data from the National observatory of agricultural biomass Database (FranceAgriMer, 2025) (Supplements S1.2). We corrected manure data for decomposition losses during storage and management to obtain the amount delivered as soil carbon inputs (Supplements S1.2).

3.4 Initial soil organic carbon stocks

We collected 'initial' carbon concentration measurements as well as soil bulk density and thickness from the RMQS soil monitoring network (INRA et al., 2021; INRA et al., 2024), including 886 samples from croplands and 537 from permanent grasslands. Crop types were not distinguished in the sampled sites, as they vary over time following crop rotations. We averaged the values within each unit *i* and converted them from carbon concentration $c_{\%}$ [gC. kg^{-1}] to soil carbon density *c(0)* [tC.ha^{-1}] using:

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$$c(0)_{i,k} = c_{\%\,i,k} \cdot BD_{i,k} \cdot h_{i,k} \cdot 0.89 \quad (31)$$

where $c_{\%}$ is the average carbon concentration in topsoils obtained from the RMQS sites, BD the soil bulk density [g cm^{-3}] and $h_{i,k}$ the thickness of the top soil horizon [cm] measured for each sample and averaged within each unit i and land use category k (cropland, permanent grasslands). The coefficient 0.89 is applied to reduce soil carbon densities to the active fraction, the rest being considered to be inert old soil carbon, following radiocarbon soil profiles data collected and analyzed by Copard et al. (2025).

4. Sensitivity analysis

Among the model inputs, the soil carbon turnover time (τ) is expected to be the dominant source of uncertainty because it must be inferred from simplifying assumptions. Indeed, τ is challenging to estimate from observations, as it is spatially variable and depends on climate, soil properties controlling the stabilization of organic matter, and vegetation drivers (Chen et al., 2020), as well as on land use and management characteristics (Poeplau et al., 2021). In addition, τ is a dominant source of uncertainty in global Earth System models (Ito et al., 2020). Hereafter, we therefore focus the sensitivity analysis on τ.

4.1 Uncertainty in soil carbon turnover times

Turnover time is typically computed as the ratio of soil carbon stocks to annual organic carbon outputs or inputs (Sierra et al., 2017). Deriving τ from the ratio of stocks to inputs assumes that soil carbon is at equilibrium in the initial state, such that inputs equal outputs, which is a common simplification (Ge et al., 2019). We tested this approach because it is the most parsimonious in terms of required data and the most generic method applicable to all regions. However, carbon stocks in agricultural soils are usually not in equilibrium and are likely decreasing in many croplands (De Rosa et al., 2024; Emde et al., 2024; Harbo et al., 2026; Poeplau and Dechow, 2023). To address uncertainties associated with this equilibrium assumption, we computed τ in croplands and permanent grasslands at the NUTS3 resolution with two approaches which differ in their equilibrium vs. non-equilibrium assumptions, and propagated the uncertainty associated with each estimate.
The first approach assumes that initial stocks are at equilibrium. In this approach, the turnover times $\tau_{eq\,i,k}$ are calculated as the ratio of carbon stocks to carbon inputs :

$$\tau_{eq\,i,k} = \frac{c(0)_{i,k} \cdot A_{0\,i,k}}{I_{i,k}} \quad (32)$$

where $A_{0\,i,k}$ is the mean area of cropland or permanent grassland in each unit i during 2000-2020, initial densities $c(0)$ [tC ha^{-1}] are from Eq. (31) and $I_{i,k}$ is the mean annual 'initial' soil carbon inputs during 2000-2020 computed from equations

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listed in section 2.4, except that here the areas correspond to the mean observed initial values over 2000-2020 rather than the optimized areas.

The second approach estimates τ as a non steady state parameter defined by the ratio of stocks to outputs, where outputs are not in steady state and are obtained from the difference between inputs and annual soil carbon change, according to:

$$\tau_{non\ eq\ i,k} = \frac{c(0)_{i,k} \cdot A_{0\ i,k}}{I_{i,k} - \Delta C_{i,k}} \quad (33)$$

where $\Delta C_{i,lu}$ [tC ha^{-1} yr^{-1}] is the annual change in soil carbon stocks retrieved from de Rosa et al. (2024). The authors fitted a soil carbon model using data from 4,482 sample sites across the EU that were visited during successive LUCAS campaigns in 2009, 2015, and 2018. Then, they upscaled predictions of annual changes to a 500 by 500 m grid using the Corine Land Cover dataset. We aggregated French data from their original grid to each unit *i*.

We calculated an uncertainty range on τ_{eq} and $\tau_{non\ eq}$ based on the standard errors of $c(0)_{i,k}$ and $I_{i,k}$, following the approach proposed by Varney et al. (2022). The lower and upper bounds of $\tau_{eq\ i,k}$, respectively $\tau^{+}_{eq\ i,k}$ and $\tau^{-}_{eq\ i,k}$, are given by:

$$\tau^{-}_{eq\ i,k} = \frac{c(0)^{-}_{i,k} \cdot A_{0\ i,k}}{I^{+}_{i,k}} \quad (34)$$

$$\tau^{+}_{eq\ i,lu} = \frac{c(0)^{+}_{i,k} \cdot A_{0\ i,k}}{I^{-}_{i,k}} \quad (35)$$

where $c(0)^{-}$ is the mean soil carbon density minus its standard error (the standard deviation of soil carbon density measurements divided by the square root of the number of samples for each unit *i* and land use category *k*), and I^{+} is the upper bound of soil carbon inputs derived from the mean annual yields plus their standard error (the standard deviation of annual yields divided by the square root of the number of years, n = 21). Similarly, the lower and upper bounds of $\tau_{non\ eq}$, respectively $\tau^{+}_{non\ eq\ i,k}$ and $\tau^{-}_{non\ eq\ i,k}$, are given by:

$$\tau^{-}_{non\ eq\ i,k} = \frac{c(0)^{-}_{i,k} \cdot A_{0\ i,k}}{I^{+}_{i,k} - \Delta C_{i,k}} \quad (36)$$

$$\tau^{+}_{non\ eq\ i,k} = \frac{c(0)^{+}_{i,k} \cdot A_{0\ i,k}}{I^{-}_{i,k} - \Delta C_{i,k}} \quad (37)$$

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4.2 Simulations

The model was run for a series of distinct national soil carbon accrual target Δ over 30 years, defined as S_{+2}, S_{+4}, S_{+6} and S_{+8} where the subscript indicates the mean national accrual rate [MtC yr^{-1}], corresponding to total increases of +60, +120, +180, and +240 MtC, respectively, over 30 years. For each target, simulations were performed using values of τ_{eq} and $\tau_{non\ eq}$, successively, to study the effects of the assumption used to derive τ. Then, we propagated uncertainties on the model outputs by running 4000 simulations for each value of Δ, based on 2000 values of τ_{eq} and on 2000 values of $\tau_{non\ eq}$ randomly drawn from their uncertainty ranges given by Eqs. (34-37) using uniform distributions, for each spatial unit and land use class.
The parameter λ defining the weight given to minimizing production variability was set to 10 in all experiments. This value was chosen as it yields a balanced compromise between maximizing production and minimizing variability. Using a common value of λ ensures that differences between simulations reflect the tested turnover time assumptions rather than changes in optimization preferences. All simulations included the optimization of the management of crops residues and grasslands intensity use described in Sect 2.3.

5. Results and discussions

5.1 Soil carbon turnover time variations and uncertainties

The distributions of turnover times are shown in Fig. 2. The average values obtained with the steady state assumption τ_{eq} were 15.9 years (std = 5.9 years) in croplands and 29.1 years in permanent grasslands (std =12.3). We found shortest values in spatial units exhibiting low initial soil carbon stocks and high annual inputs, and longest ones in spatial units with high initial stocks and low inputs (Supplements S2.1). The non-equilibrium assumption gave shorter τ values in most croplands (average of 14.7 years, std = 4.6) and longer values in most permanent grasslands (40 years, std = 13.2). These differences stem from the fact that $\tau_{non\ eq}$ accounts for decreasing soil carbon stock in most croplands and increasing stocks in most grasslands (De Rosa et al., 2024). Under both approaches, τ was consistently longer in permanent grasslands compared with croplands (in 86 and 89 spatial units out of 90 for τ_{eq} and $\tau_{non\ eq}$ respectively), yet the absolute differences were amplified for $\tau_{non\ eq}$. The average difference between permanent grasslands and croplands was 13.1 years for τ_{eq} and 19.2 years for $\tau_{non\ eq}$.
The distributions of the lower and upper bounds of the uncertainty ranges are shown in Fig. 2, in dashed and solid lines, respectively. In croplands, uncertainties corresponded to a variation in τ of ±2 years on average across spatial units (-2.0/-1.9 and +2.17/+2.0 years for τ_{eq} and $\tau_{non\ eq}$). The variation was greater for permanent grasslands. On average, the lower bounds corresponded to τ values that were -4.0 and -4.8 years shorter for τ_{eq} and $\tau_{non\ eq}$, respectively, whereas the upper bounds corresponded to τ values that were +4.2 and +5.1 years longer.

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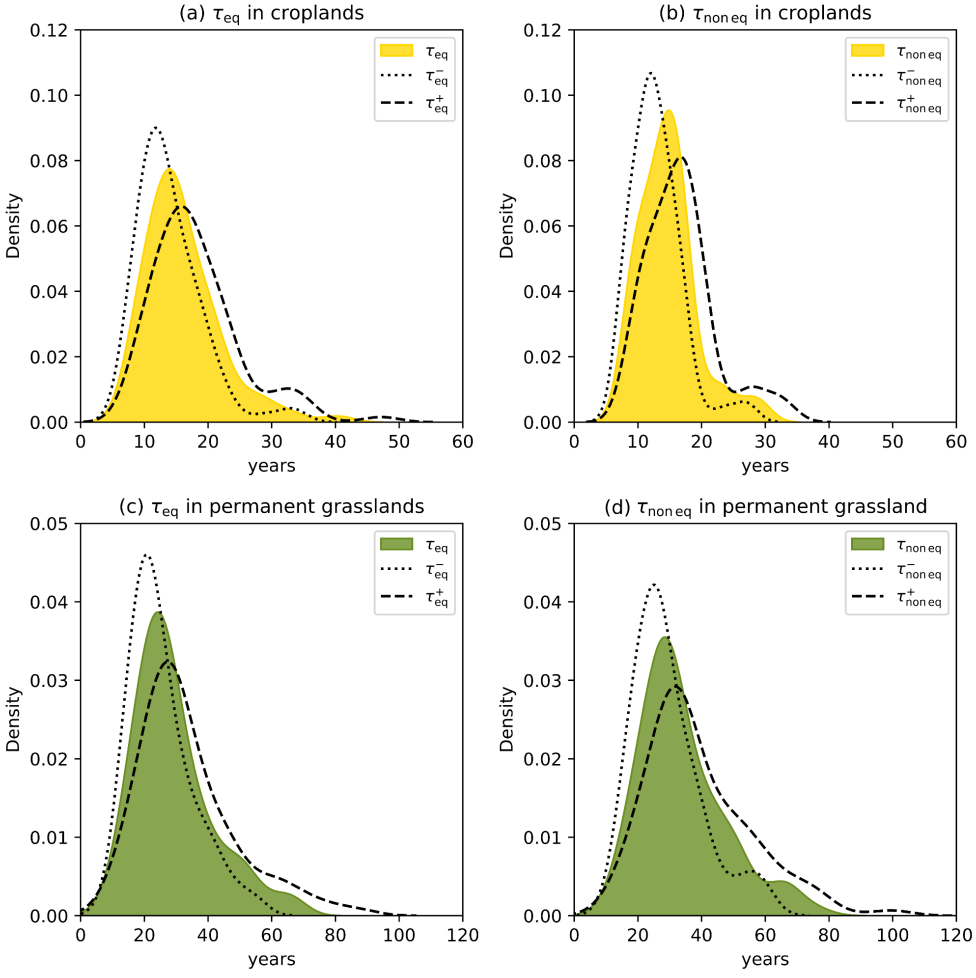

Figure 2. Density plots of soil carbon turnover time (τ) estimates across the 90 spatial units *i* in croplands (a and b) and permanent grasslands (c and d), obtained from the two assumptions τ_{eq} (a and c) and $\tau_{non\ eq}$ (b and d). τ_{eq} assumes that carbon stocks are at equilibrium in the initial state and derives τ as the ratio of stocks to annual mean inputs. $\tau_{non\ eq}$ derives τ as the ratio of stocks to annual mean outputs. In each panel, the estimated values are shown in filled solid lines, with the dotted line representing the distribution of the lower bounds and the dashed line representing the distribution of upper bounds used for the sensitivity analysis.

5.2 Evaluation of soil carbon turnover times against independent sources

We evaluated our estimated turnover times against independent published values. First, our τ_{eq} estimates were consistent with steady state turnover times reported by Poeplau et al. (2021), who derived values from 2,100 soil samples collected in Germany. In particular, τ_{eq} were very similar for permanent grasslands (29.0 years, std = 11.9), whereas our average estimate for croplands was approximately 20% lower (19.4 years, std = 10.7 compared with 15.9 years in our study). Secondly, we

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simulated soil carbon changes following land use change between croplands and permanent grasslands in each unit *i* after 5 or 20 years based on our estimated τ values. We compared our results with observational chronosequence data from Europe from the meta-analysis of Li et al. (2018), distinguishing between observations spanning 0-10 and 10-30 years after land use change. The magnitude and variability of soil carbon changes estimated with both τ_{eq} and $\tau_{non\ eq}$ compared reasonably well with observations, as shown in Fig. 3a and b. For cropland to grassland conversion, the interquartile range [Q1, Q3] was [0.42, 0.96] tC ha^{-1} yr^{-1} for observations spanning 10-30 years since conversion vs. [0.56, 1.09] and [0.79, 1.31] tC ha^{-1} yr^{-1} for simulations at 20 years using τ_{eq} and $\tau_{non\ eq}$, respectively. For grassland to cropland conversion, the corresponding ranges were [-2.17, -1.43] , [-1.68, -0.67] and [-1.79, -0.79] tC ha^{-1} yr^{-1} , for observations, τ_{eq} and $\tau_{non\ eq}$, respectively.

Thirdly, we estimated the soil carbon storage 'efficiency' as the fraction of carbon inputs remaining in cropland soils after 30 years, calculated as $e^{-30/\tau}$ (Fig. 3c). The national mean storage efficiency was 15% with τ_{eq} with important variations across units (std = 9%), and 13% with $\tau_{non\ eq}$ (std = 7%). These efficiency values are consistent with results reported in Bruni et al. (2021) for 14 cropland sites in Europe. The authors found an average storage efficiency of 13.7% over 20-30 years, using a widely used 3 pool SOC (CENTURY) model, and also noted important spatial variability.

Fourthly, we predicted soil carbon changes over 30 years following Eq. (24) without optimizing areas or management (Fig 3.d). By construction, there were no changes in soil carbon stocks with τ_{eq}. With $\tau_{non\ eq}$ the national average soil carbon changes were a loss of -0.05 tC ha^{-1} yr^{-1} in croplands and a gain of +0.23 tC $ha^{-1}yr^{-1}$ in permanent grasslands. The values obtained with $\tau_{non\ eq}$ are comparable with the ranges provided in Pellerin et al. (2020), who combined literature-based estimates from empirical studies with modelling results from the STICS and PaSim models. The authors reported changes ranging from -0.17 to +0.04 tC ha^{-1} yr^{-1} in croplands and +0.11 to +0.21 tC ha^{-1} yr^{-1} in permanent grasslands over 30 years on a national average. Their lower and upper bounds corresponded to the literature based and modelling estimates, respectively, with the authors attributing part of this difference to the lack of accounting for previous land use in the modelling approach. Propagating uncertainties in τ resulted in strong uncertainties to soil carbon changes over 30 years (Fig 3.d.). Under the lower and upper bounds of τ_{eq} , the estimated uncertainty ranged from -0.16 to +0.15 tC ha^{-1} yr^{-1} in croplands (-0.34 to +0.33% per year) and -0.26 to 0.23 tC ha^{-1} yr^{-1} in permanent grasslands (-0.30 to +0.26% per year). The values obtained with $\tau_{non\ eq}$ ranged from -0.21 to +0.09 tC ha^{-1} yr^{-1} for croplands (-0.45% to +0.21% per year) and -0.03 to +0.47 tC .ha^{-1} yr^{-1} for permanent grasslands (-0.04% to +0.52% per year). For croplands, our uncertainty range obtained from $\tau_{non\ eq}$ is comparable to the range reported in Pellerin et al. presented above. Conversely, our uncertainty range for permanent grasslands is considerably higher, which likely results from important variability in initial soil carbon density measurements within spatial units. Taken together, this comparison suggests that the equilibrium assumption may underestimate soil carbon changes in the baseline, although both approaches are subject to substantial uncertainty

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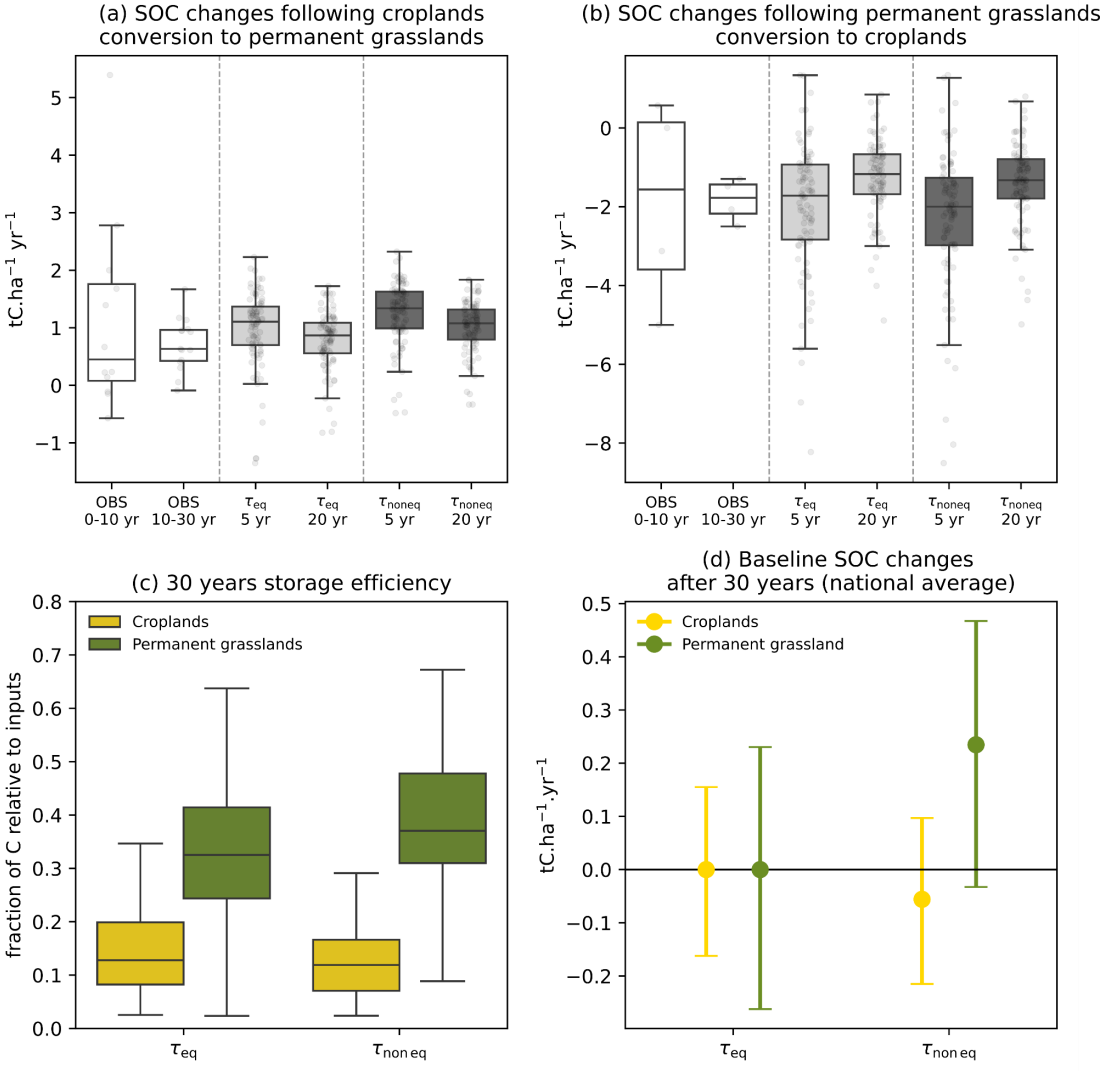

Figure 3. Soil carbon changes indicators derived from the two assumptions τ_{eq} and $\tau_{non\ eq}$ used to estimate soil carbon turnover time. Panel (a) and (b) present the distribution of simulated soil carbon changes across the 90 spatial units following land use changes between croplands and permanent grasslands, with the year labels indicating the time since land use change. The white plots represent observation values retrieved from Li et al. (2018) meta-analysis. We distinguished observations spanning 0-10 and 10-30 years after land use change and compared them with simulated changes 5 and 20 years after conversion, respectively. Panel (c) presents the 30 year carbon storage efficiency, defined as the fraction of C inputs at year 0 that remains stored in the soils after 30 years**.** Last, panel (d) presents simulated soil carbon changes after 30 years assuming that areas and annual inputs remain as in the initial situation. These values are national averages, obtained as total soil carbon changes in each land use class divided by their respective total area. Dots indicate values obtained from the two assumptions τ_{eq} and $\tau_{non\ eq}$ whereas the bars represent the ranges derived from the lower and upper bounds calculated for the two datasets.

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5.3 Results of optimization over France

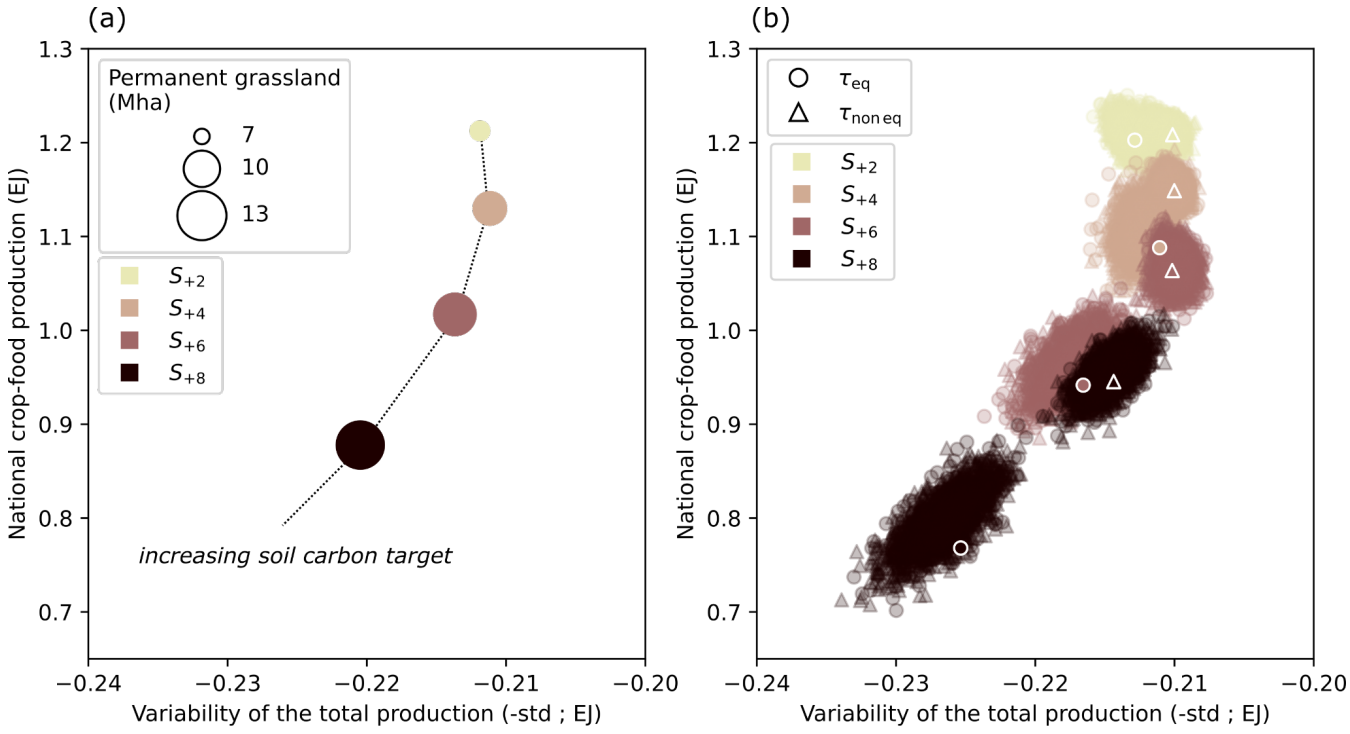

Figure 4. Interannual mean food production (y-axis) and standard deviation of the agricultural production (x-axis) obtained with the optimization model for different soil carbon accrual targets. The panel (a) represents the mean values across simulations (4000 simulations with τ values randomly drawn from the uncertainty ranges of τ_{eq} and $\tau_{non\ eq}$). The size of the circles indicating the optimized area of permanent grasslands at the national level. The panel (b) shows the variability across simulations. Circles with white edges correspond to the solutions obtained with τ_{eq}, where turnover times are obtained as the ratios of stocks to inputs in the initial state. Triangles with white edges correspond to the solutions obtained with $\tau_{non\ eq}$, where turnover times are obtained as the ratios of stocks to outputs in the initial state. The other points correspond to solutions obtained with values of τ randomly sampled within the uncertainty ranges.

Fig. 4 presents the optimization results for average crop-food production and the standard deviation of total production, when considering four soil carbon accrual targets (S_{+2} to S_{+8}). For the two lowest soil carbon targets (S_{+2} and S_{+4}), the optimized allocation of agricultural land and residual biomass flows increased both soil carbon stocks and food production while decreasing the interannual standard deviation of agricultural production, compared to the current state (Table 2.). However, scaling up the soil organic carbon target was associated with lower food production and greater variability across simulations from propagating uncertainty in turnover times. Across simulations, the average food production was 1.2 EJ for S_{+2} (CV = 1%) and 1.1 EJ for S_{+4} (CV = 3%), corresponding to +25% and +14% increases relative to the initial value of 0.96 EJ (Table 2). The S_{+6} scenario corresponds to a soil carbon accrual of approximately 3.7‰ per year for 30 years, close to the 4‰ benchmark. Under this scenario, food production was, on average, slightly increased relative to the initial level (1.0 vs. 0.96 EJ), although with a lower level of confidence due to greater variability across simulations (CV = 6%). The S_{+8} scenario involved a trade-off between food production and soil carbon accrual, with an average food production of 0.88 EJ (-8%), and

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the highest uncertainty in food production outcomes (CV = 9%). Relative to the initial state, the interannual standard deviation decreased across all scenarios. As for food production, its variability across simulations increased with higher soil carbon targets. Specifically, the interannual standard deviation was, on average, 0.212 EJ in S_{+2} (CV = 1%), 0.211 EJ in S_{+4} (CV = 1%), 0.214 EJ in S_{+6} (CV = 2%), and 0.220 EJ in S_{+8} (CV = 3%), compared with 0.227 in the initial state (Table 2).

In MMALO, the targeted increase in soil carbon can be achieved through increasing inputs or through land use changes, namely the conversion of croplands to permanent grasslands (Fig. 3). Across scenarios, the optimization consistently increased plant carbon inputs per ha, whereas the extent of cropland to permanent grassland conversion increased with the soil carbon target. Specifically, the percentage of spatial units with increased inputs per ha ranged from 73% to 76% in croplands, and from 63% to 69% in permanent grasslands (Table A3). Higher inputs resulted from higher crop residue production permitted by crop switching in croplands and from lower intensity use in permanent grasslands (Fig. 6). As a result, optimized land use strategies increased soil carbon accumulation by +0.12 to +0.17 tC ha^{-1} yr^{-1} in croplands and +0.08 to +0.14 tC ha^{-1} yr^{-1} in permanent grasslands at the national scale compared with projections without optimizing land allocation or management (Fig. 5b). In contrast, the percentage of spatial units experiencing a transition from croplands to permanent grasslands increased with the soil carbon target, from 28% for S_{+2} to 40% for S_{+4} , 52% for S_{+6} and 60% for $S_{+8.}$ (Table A3). These shifts enable additional soil carbon gains because the transition from cropland to permanent grassland has a much higher sequestration rate than croplands remaining croplands. Nonetheless, it reduces the area available for cultivating food crops. The trade-off between food production and high soil carbon accrual therefore results from a greater proportion of agricultural land allocated to permanent grasslands in these scenarios (Fig. 5a).

The model outcomes were sensitive to the choice of turnover time. The solutions obtained with $\tau_{non\ eq}$ were more effective in maximizing crop-food production than those obtained with τ_{eq} (Fig. 4b) because longer turnover times in permanent grasslands with $\tau_{non\ eq}$ allow more carbon accumulation in existing grasslands. The differences between the two assumptions were more pronounced at higher soil carbon targets (S_{+6} and S_{+8}), reaching up to 19% in optimized food production in S_{+8}. This could suggest that the equilibrium assumption overestimates the trade-off between soil carbon accrual and food production. However, these results are derived from the French case study and may not hold in other regions with different land use history, climate, and soil carbon dynamics (de Rosa et al., 2024). Propagating uncertainty in τ led to substantial uncertainty in the magnitude of soil carbon sequestration rates across spatial units (Fig. A1), which translated into variability in food production and interannual standard deviation, particularly for S_{+6} and S_{+8} (Fig. 4b). Nonetheless, we found that the model exhibited consistent behavior in terms of land use allocation. Specifically, spatial units in which the optimization resulted in an increase or a decrease in the area allocated to a given crop or grassland type tended to exhibit the same pattern, regardless of the sampled value of τ within its uncertainty bounds (Supplement S2.1). Thus, while uncertainty in τ affected

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583 the magnitude of the optimized outcomes, the direction of relative changes in land allocation and performance outcomes
584 remained consistent. This suggests that these relative changes can be interpreted in relation to the defined soil carbon target.

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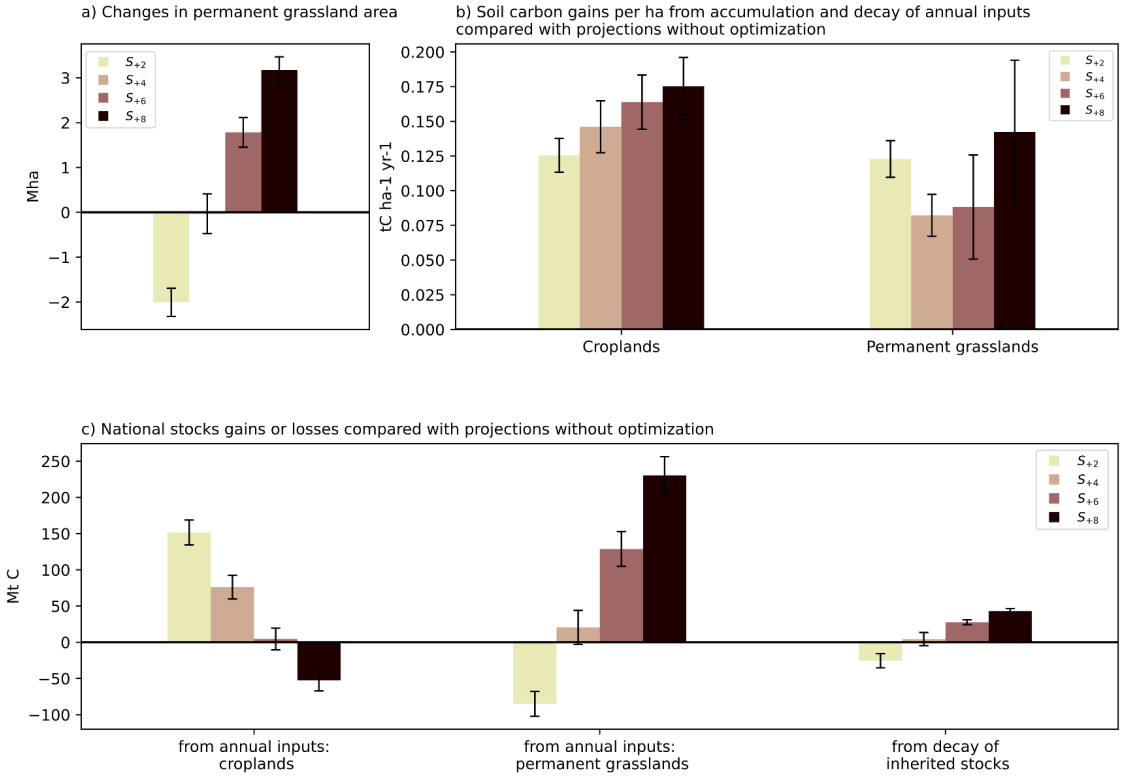

586

587 **Figure 5. (a) National changes in permanent grasslands areas compared with the initial state. (b) Soil carbon gains from changes in annual carbon**
588 **inputs from optimization, compared with projections without optimization of land use or management. (c) Total soil gains or losses from**
589 **optimization compared with stocks projected without optimization.** In panel (b) positive values indicate a greater accumulation of soil organic carbon
590 compared with stocks projected over a 30 year time horizon without optimization (i.e., assuming fixed initial areas and management). Croplands values are
591 expressed per ha of cropland (left) and permanent grasslands values per ha of permanent grassland (right). In panel (c), the changes in total stocks result
592 from the combination of area changes (panel a) and changes in accumulation rates (panel b). In all panels, bars and whiskers show the mean differences and
593 standard deviation of changes, respectively, across all simulations. .

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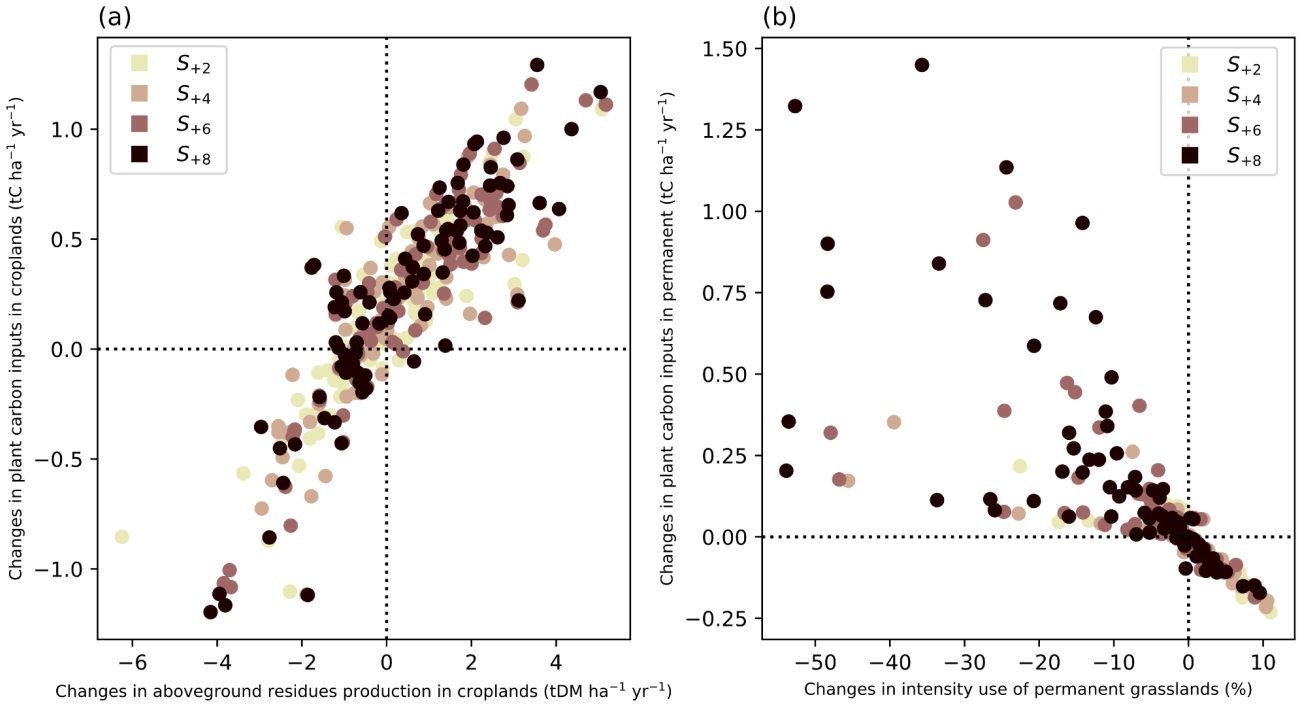

Figure 6. (a) scatterplot showing changes in crop residue production per ha (x-axis) and changes in plant carbon inputs in croplands (y-axis) in the optimized scenarios compared with the initial state. (b) scatterplot showing the changes in intensity use of permanent grasslands (x-axis) and change in plant carbon inputs per ha in permanent grasslands. Each dot represents a spatial unit. The reported values are the mean differences across simulations compared with the initial state.

5.4 Strengths, applicability and limitations

In this section, we assess the main strengths and limitations of the model.

First, one of the key strengths of MMALO is its differentiation between crop types, which can provide decision-makers with short-term flexible options for land-use planning (Xie et al., 2023). Indeed, switching between crops is more flexible and faster to implement than converting cropland to perennial systems such as forests. In particular, we show that crop switching enables greater accumulation rates of soil carbon in croplands (Fig 5.b). The model also accounts for land use changes effects between cropland and permanent grassland, which are key mechanisms affecting soil carbon (Li et al., 2018). Doing so, we show that land planning flexibility mainly holds for modest soil carbon targets, whereas higher targets increasingly require land conversion toward permanent grasslands.

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Another key contribution of MMALO is the explicit integration of temporal stability. By considering the interannual variance of agricultural production, MMALO can identify which land allocations reduce exposure to yield shocks, which is crucial for decision-makers.

Last, the model is computationally lightweight and flexible, which supports its broad applicability. The crop and grassland types included in the optimization can be easily modified. For instance, permanent grassland areas can be fixed to explore strategies to increase soil carbon only in croplands. The framework can also be extended to include agricultural management practices. For example, we implemented the option to optimize crop residue management and grassland use intensity, two practices that have been proposed to increase soil carbon stocks in agricultural lands (Soussana & Lemaire, 2014; Herzfeld et al., 2021; Lin et al., 2024). Model constraints can also be adapted to reflect specific policies in different regions. For instance, constraints could be differentiated across spatial units to reflect designated production areas or areas where land conversion between permanent grasslands and croplands is restricted. Minimum national production targets could also be implemented to apply the model in regions where agricultural production is regulated. However, applying the model to other regions would require data that may not be readily available, especially on long-term agricultural yields and soil carbon stocks at the appropriate spatial resolution.

A key limitation of the framework concerns our ability to represent soil carbon turnover using a parsimonious set of data, which is a source of important uncertainties discussed throughout this article. First, our approach to the calculation of turnover times assumes that soil carbon stocks have been built from inputs similar to those estimated for the period 2000-2020, which is an important simplification (Sierra et al., 2017). This approach neglects historical changes in agricultural systems that likely had opposing effects on soil carbon inputs and losses, such as the important increase of arable yields in France since the 19th century (Le Noë et al., 2018; Schauberger et al., 2018) and the historical increase in harvest index permitted by crop breeding programs (Ruiz et al., 2023). Accounting for these historical dynamics would require annual reconstruction of land use, agricultural production and management practices over long time periods. However, available datasets at the appropriate resolution are scarce and remain limited to yields and to a small number of crops (Schauberger et al., 2018). Moreover, turnover time is supposed to be constant, implying that the relationships between soil carbon inputs, stocks and turnover times estimated under current conditions would remain valid over the whole period. This assumption overlooks potential limits to the capacity of soils to stabilize additional carbon under increased inputs, related to biological and physical stabilization mechanisms (Cotrufo et al., 2019; Breure et al., 2025). Last, erosion processes are accounted for only indirectly through the calculation of turnover times. This limited representation could result in an underestimation of soil carbon losses, particularly if the model allocates a larger share of land to intensively tilled crops, such as sugar beet (Juřicová et al., 2025).

The spatial resolution adopted in this work also comes with important limitations. The aggregation of soil carbon measurements at the NUTS3 level masks local spatial heterogeneity in soil carbon stocks. Although higher-resolution data are available for soil carbon stocks in France (Chen et al., 2018), NUTS3 is the finest spatial resolution for which sufficiently

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long term annual yield data are available in agricultural statistics. We therefore adopted this coarser resolution to account for temporal variability in yields.

In its current version, the model allocates agricultural land to individual crop and grassland types. Allocating land to crop sequences instead could improve the realism of the optimization, by representing management options that are more representative of how agricultural systems are organized in practice. A recent dataset of crop sequence types in Europe could be used to support such developments (Ballot et al., 2023). Relatedly, constraints on land use changes between cropland and permanent grassland could be improved to better account for spatial heterogeneity in land suitability, as not all permanent grasslands are suitable for conversion to cropland. Future developments could build on spatially explicit land suitability indices to provide more realistic constraints on the maximum extent of land conversion (e.g. Fischer et al., 2021).

Because it relies on historical yields to calculate production variability, the current version of MMALO does not account for future climate conditions or their potential impacts on agricultural productivity and soil carbon dynamics. The model could be extended to explore the implication of future land use planning under different climate scenarios, accounting for reductions in turnover time with warming (Varney et al., 2020) and building on projections of agricultural yields (e.g., Minoli et al., 2022). However, yield projections generally cover only a limited number of crops, which may strongly constrain the range of crop types that can be represented.

Finally, our framework does not account for potential trade-offs between soil carbon accrual and greenhouse gas emissions, such as increased nitrous oxide emissions associated with greater residue returns (Guenet et al., 2021). Estimating changes in greenhouse gas emissions associated with the different scenarios would provide a more comprehensive appraisal of their potential climate benefits.

6. Conclusions

We presented MMALO, a new multi-objective optimization model which provides a framework for identifying land planning strategies addressing simultaneously three objectives: (1) maximizing mean annual food crops production; (2) minimizing interannual variability in plant production; (3) achieving a predefined soil carbon stock accrual target over a 30 years time horizon. The model resolves synergies and trade-offs among the objectives, showing that an increase in soil carbon can be achieved without compromising with food production and stability in France. We identified a progressive decline in potential food production as the soil carbon accrual target increased, with food production falling below the current level at the highest target of +8 MtC per year for 30 years. In addition, we evaluated two data-driven approaches for calibrating the turnover times of soil carbon and show that the choice is associated with differences in optimized food production up to 19%. We stress that both approaches come with important uncertainties. Nonetheless, the spatial structures of the optimized land allocations were robust to these uncertainties, which supports the use of MMALO to compare alternative cropland and grassland allocation strategies with regards to distinct soil carbon objectives. In the French context, and over a relatively short-term horizon of 30 years, we recommend using the non-equilibrium approach to better account for currently observed

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soil carbon dynamics. The soil equilibrium assumption provides a practical alternative where data are lacking, but users should acknowledge that it likely overestimates soil carbon changes in French croplands. Critical next steps towards addressing the limitations of the first version of MMALO include a refinement of input data to account for crop sequences and spatial variability of soil carbon stocks and yields, as well as the extending the framework to account for changes in greenhouse gas emissions. Other avenues for future development include the consideration of additional management practices, such as cover cropping and agroforestry (Paustian et al., 2016, Helfenstein et al., 2025), crop variety selection (Chenu et al., 2019), and soil amendments from external sources (e.g. biochar; Paustian et al., 2016).

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7. Appendices

Table A1. Output variables in MMALO, in order of appearance in the equations, and classified as optimized (O) or induced (I) variables. Some variables can belong to either category depending on whether the user chose to optimize agricultural management. EJ : Exajoules. Mt C : million tons organic carbon. Mha : million ha. Mt DM : million tons dry matter.

Variable	Unit	Description	Optimized/Induced
S	No unit	Share of agricultural area	O
$P_{food}(S)$	EJ yr^{-1}	Mean annual crop-based caloric food production	I , objective #1
$V(S)$	EJ^2 yr^{-2}	Interannual variance of plant production	I, objective #2
$C(S)$	Mt C	Projected soil carbon stocks in topsoils	I , objective #3
$A_{i,j}$	Mha	Area allocated to each *j* in each *i*	I
$P_{i,j}$	MtDM yr^{-1}	Production	I
$P_{crop\ res\ i,j}$	MtDM yr^{-1}	Production of crop residues	I
$P_{crop\ res\ exp\ i,j}$	MtDM yr^{-1}	Crop residues harvested	I
$P_{crop\ res\ left\ i,j}$	MtDM yr^{-1}	Crop residues left on fields	I/O
$P_{grass\ graz\ i,j}$	MtDM yr^{-1}	Grass grazed	I
$P_{grass\ harvest\ i,j}$	MtDM yr^{-1}	Grass harvested	I
$P_{grass\ left\ i,j}$	MtDM yr^{-1}	Grass left on fields	I/O
$I_{i,i}$	MtC yr^{-1}	Annual soil carbon inputs	I
$I_{plant\ i,j}$	MtC yr^{-1}	Annual soil carbon inputs from plant materials	I
$I_{man\ graz\ i,j}$	MtC yr^{-1}	Annual soil carbon inputs from livestock manure deposited during grazing	I
$I_{man\ crop\ +\ grass\ i,i}$	MtC yr^{-1}	Annual soil carbon inputs from livestock manure applied as fertilizer	I
$P_{root\ i,j}$	MtDM yr^{-1}	Belowground production (roots)	I
$C(0)_{i,k}$	MtC	Inherited soil carbon partitioned between land use classes, after land use changes between croplands and permanent grasslands	I
ΔA	Mha	Land use changes	I

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693 **Table A2. Input variables in MMALO, in order of appearance in the equations.** Mt C : million tons organic carbon. EJ :
694 Exajoule. TJ: Terrajoule. Mha : million ha. LU : Livestock units.
695

Input variable	Unit	Description	Source
A_i	Mha	Total agricultural areas	Annual agricultural statistics 2000-2020 (Agreste, 2025b)
$p_{i,j}$	tDM ha^{-1} yr^{-1}	Yields	Annual agricultural statistics 2000-2020 (Agreste, 2025b)
e_j	TJ tDM^{-1}	Gross energy content	AFZ, 2017
$P_{feed\ tot}$	EJ yr^{-1}	Feed uses of non-fodder crops	This study, from national agricultural commodities balance sheets (Agreste, 2025a) and technical conversion factors (FAO, 2000)
Γ	TJ^2 ha^{-2}	Variance covariance matrix of annual yields converted in gross energy equivalent	Annual agricultural statistics 2000-2020 (Agreste, 2025b)
λ	No unit	Weight given to minimizing plant production variance over maximizing annual mean food-crop production	User-defined
Δ	Mt C	Soil carbon accrual target	User-defined
$S_{max\ j}$	No unit	Maximum share of areas allocated to each *j*	This study, Sect. 2.2
rpr_j	tDM tDM^{-1}	Residues production ratio	This study, as 1/harvest index (harvest index taken from Wolf et al., 2015).
$L_{i,j}$	No unit	Observed fraction of crop residues left on fields	National Observatory of of Biomass Resources 2019-2021 (FranceAgriMer, 2025)
$L_{max\ i,i}$	No unit	Maximum fraction of crop residues left on fields	Available fraction at the NUTS1 level for years 2019-21 from the National Observatory of of Biomass Resources (FranceAgriMer, 2025)
$gui_{i,i}$	No unit	Grassland use intensity (fraction of aboveground production harvested or grazed)	This study, Sect. 3.1
$REQ_{g\ graz\ i}$	Mt DM yr^{-1}	Livestock requirement for grazing grass	Livestock numbers : Agreste, 2025b Requirements per LU : Devun et al. (2012) , Jousseins et al. (2014) and Bossis et al. (2015)
$REQ_{g\ harvest\ i}$	Mt DM yr^{-1}	Livestock requirement for harvested grass	Livestock numbers : Agreste, 2025b Requirements per LU : Devun et al. (2012) , Jousseins et al. (2014) and Bossis et al. (2015)
$REQ_{f\ i}$	Mt DM yr^{-1}	Livestock requirement for annual fodder crops	Livestock numbers : Agreste, 2025b Requirements per LU : Devun et al. (2012) , Jousseins et al. (2014) and Bossis et al. (2015)
$REQ_{o\ j}$	Mt DM yr^{-1}	Livestock requirement for non fodder crops	National agricultural commodities balance sheets (Agreste, 2025a)
REQ_{res}	Mt DM yr^{-1}	Harvested residues requirements for human activities	National Observatory of of Biomass Resources 2019-2021 (FranceAgriMer, 2025)
f_0	No unit	fraction of food crop j in the total food calorie production	This study, Sect 2.2
$c_{res\ j}$	tC tDM^{-1}	Carbon content of aerial residues	Thiébeau et al., 2021
$c_{root\ j}$	tC tDM^{-1}	Carbon content of roots	Thiébeau et al., 2021
$M_{graz\ i}$	Mt C yr^{-1}	Livestock manure deposited during grazing	This study, Sect. 3.2
$m_{farm\ r}$	t C $ha^{-1}yr^{-1}$	Application rates of livestock manure collected in buildings, after accounting for losses	This study, Sect. 3.2

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$\tau_{i,k}$	years	Soil carbon mean turnover time	This study, Sect 4.
t	years	Time horizon for projecting soil carbon changes	User-dependant (by default 30 years)
$c(0)_{i,k}$	tC ha^{-1}	Carbon density in the initial state	This study, Sect. 3.4 from RMQS (INRA et al., 2021)
$A_{0\,i,k}$	Mha	Initial areas of croplands and permanent grasslands	Annual agricultural statistics 2000-2020 (Agreste, 2025b)

Table A3. Mean proportion of spatial units showing an increase in plant carbon input and permanent grassland area relative to the initial level. Values in parentheses indicate the standard deviation across simulations.

Variable	S_{+2}	S_{+4}	S_{+6}	S_{+8}
Increase plant carbon inputs per ha in croplands	0.73 (0.02)	0.76 (0.02)	0.76 (0.02)	0.74 (0.04)
Increase plant carbon inputs per ha in permanent grasslands	0.69 (0.03)	0.67 (0.03)	0.63 (0.05)	0.65 (0.05)
Increase permanent grasslands area	0.28 (0.02)	0.40 (0.03)	0.52 (0.03)	0.60 (0.03)

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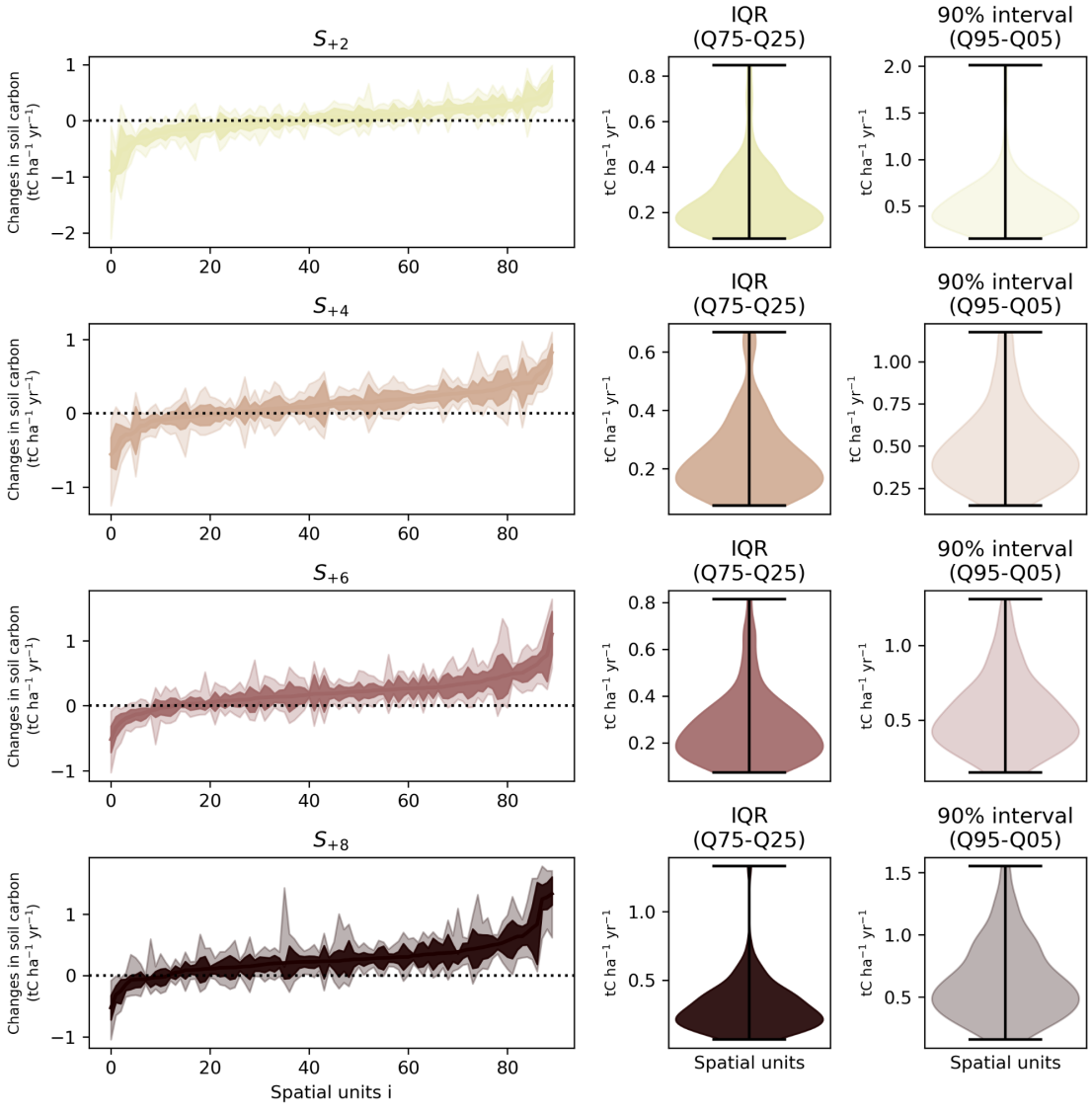

Figure A1. Estimated variability in soil carbon stocks changes (y-axis) across spatial units (x-axis) in the sensitivity analysis experiments. Changes in soil carbon stocks refer to the difference between the simulated stocks from optimized land allocation and the initial stocks. In the left panels, the coloured bands represent the 25th to 75th percentiles. For clarity, departments are ordered along the x-axis from lowest to highest mean soil carbon change. The middle panels present the distribution of the interquartile range of simulated soil carbon changes across simulation for each spatial unit. The right panels present the distribution of the 90% interval of soil carbon changes across simulations for each spatial unit.

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Code and data availability

The model code and data are publicly available on the following repository : https://doi.org/10.5281/zenodo.22798369 (Borghino et al., 2026)

Public datasets used for this study include the following :
(i) Agricultural commodities balance sheets and annual agricultural statistics from the Statistics and Foresight Service (SSP) of the French Ministry of Agriculture, retrieved at: https://www.data.gouv.fr/datasets/agreste-bilans-d-approvisionnement (Agreste, 2025a) and https://www.data.gouv.fr/datasets/agreste-statistique-agricole-annuelle-saa (Agreste, 2025b)
(ii) Soil carbon concentration and bulk density from the French Soil Monitoring Network (RMQS), retrieved at : https://doi.org/10.15454/QSXKGA (INRA et al., 2021) and https://doi.org/10.57745/7Y3G5W (INRA et al., 2024)
(iii) Biomass and chemical quality of crop residues from European areas, retrieved at https://doi.org/10.15454/LBI3U7 (Thiébeau et al., 2021)
(iv) Crop residues management from the National Observatory of Biomass Resources , retrieved at : https://visionet.franceagrimer.fr/Pages/Statistiques.aspx?sousmenu=multi-filieres (FranceAgriMer, 2025)

Author contributions

N.B., D.M., D.G., and P.C. designed the study. N.B., D.M, D.G, Y.W, X.W, and P.C were involved in the development of the modelling framework. N.B coded the model and performed the simulations. N.B and B.Y. collected data. All authors were involved in the analysis of the results. N.B. prepared the first draft of the manuscript with support from all authors. D.M, D.G., and P.C. supervised the work. P.C. acquired the funding. All authors contributed to the final manuscript and approved its publication.

Competing interests

The authors declare no competing interests.

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