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# Challenges in Soil Carbon Modelling and Measurement: A Decade of Experimental Data vs. RothC Simulations in an Organic Olive Grove

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**Abstract.** Modelling the persistence of soil organic carbon (SOC) is currently recognised as a key approach to enhance our understanding of its potential contribution to climate change mitigation. Despite its value, SOC modelling is challenged by soil heterogeneity and the limited availability of reliable data for model calibration and validation, often resulting in discrepancies between simulated and measured SOC dynamics. This study employs a modified version of the RothC model, adapted for amended soils, to simulate soil C dynamics under an 11-year experiment in an organic olive grove. The experiment evaluated four treatments of soil amendment: Compost, Biochar, a Mixture of both, and a control soil without amendment. By comparing the SOC data simulated by the RothC model with experimental field-sampling data, we assessed the model's accuracy in estimating SOC accumulation and stability in the soil. Both field measurements and RothC simulations consistently identified biochar as the most effective amendment for soil carbon accumulation over the 11-year period, followed by the Mixture and Compost treatments. Estimated soil carbon sequestration rates ranged from 1.67 to 2.66 Mg C ha$^{-1}$ yr$^{-1}$ based on field measurements and from 2.88 to 5.30 Mg C ha$^{-1}$ yr$^{-1}$ according to model simulations. However, treatment-dependent discrepancies were observed between modelled and field-based SOC stocks. While Compost and Mixture showed close agreement, Biochar exhibited the largest mismatch, likely due to its intrinsic properties that complicate field quantification and are not fully represented in current SOC models, posing challenges for monitoring and verification within carbon accounting frameworks.

## 1 Introduction

Soil Organic Carbon (SOC) is a fundamental component of the global biogeochemical carbon cycle and a central target for carbon management in agricultural systems (Peralta et al., 2022; Witzgall et al., 2021). Soil Carbon Sequestration (SCS) through the application of organic amendments aims to store carbon in stable organic forms within the soil, contributing to

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both short- and long-term carbon storage. Consequently, SCS is increasingly recognized as a potential strategy for atmospheric $CO_2$ removal and climate change mitigation (Don et al., 2024; Lal et al., 2018; Smith et al., 2020).

Field experiments involving SOC quantification based on soil sampling and analysis have long been fundamental for evaluating SOC dynamics under different management practices. Compared with laboratory experiments, their longer-term nature provides the empirical foundation for SOC assessments worldwide, offering critical insights into carbon stabilization mechanisms, soil quality improvement, and the role of microbial activity in carbon cycling. However, the high costs associated with spatial heterogeneity and repeated sampling limit the scope of these studies, hindering their ability to represent long-term, large-scale carbon dynamics. Understanding SOC behavior, therefore, requires integrating experimental observations with process-based simulations, as each provides complementary insights into carbon turnover. This integration is particularly relevant in soils receiving exogenous organic matter (EOM), which is widely applied as an effective strategy to enhance SOC levels in agricultural systems (Dai et al., 2021; Rasmussen and Parton, 1994; Van-Camp et al., 2004). The addition of organic amendments temporarily alters soil properties and carbon stabilization mechanisms, increasing heterogeneity and challenging the accurate monitoring of SOC changes. In this context, soil carbon modelling offers a valuable complementary approach to simulate SOC dynamics beyond the spatial and temporal limitations of field measurements, enabling a more comprehensive understanding of long-term carbon processes in managed agroecosystems.

Carbon turnover modelling is an approach that simulates soil dynamics and carbon persistence over a specific time scale (Coleman et al., 1997). It serves as a powerful tool to replicate various scenarios under different land management practices, climatic conditions, soil texture characteristics, and land uses. These models are based on the decomposition of organic matter and its transformation that can lead either to the stabilisation of organic carbon in the soil or to its release into the atmosphere as $CO_2$ (Coleman et al., 1997; Nemo et al., 2017; Stockmann et al., 2013). Several models have been successfully applied to simulate carbon turnover dynamics in soils, the most widely used C models including organic amendments are: the Rothamsted Carbon Model (Keel et al., 2023; Mondini et al., 2017a; Peltre et al., 2012; Peralta et al., 2022; Senapati et al., 2014; Shirato et al., 2011), CENTURY (Badewa et al., 2023; Paustian et al., 1992), DAISY (Delhez et al., 2025; Peltre et al., 2016; Rydgård et al., 2024), and NCSOIL (Antil et al., 2011; Noirot-Cosson et al., 2016).

Modelling carbon turnover requires long-term validation based on experimental field data (FAO, 2019; Pulcher et al., 2022; Shirato et al., 2005). This presents a challenge, as the approach demands significant infrastructure and resources, including experimental plots, analytical equipment and the implementation of field treatments. The limited number of long-term studies comparing SOC evolution in field experiments poses a limitation for SOC assessments. This gap in research affects the ability to evaluate SOC dynamics in response to land-use changes, climate variations and the application of different amendments, highlighting the critical need for studies that integrate both field measurements and modelling approaches to improve the accuracy and applicability of SOC predictions.

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The complementarity between simulated and measured carbon monitoring approaches is an increasing requirement within the accreditation framework of the voluntary carbon market (VCM). In the context of agricultural soils, various methodologies establish procedures to quantify, model, and verify changes in SOC resulting from the adoption of sustainable land management practices (Soil Organic Carbon Framework Methodolgy. Gold Standard for the Global Goals v.1.0, 2025; VM0042 Improved Agricultural Land Management, v2.1, 2025). These protocols require independent verification and the explicit assessment of the uncertainty associated with both biogeochemical models and field measurements (VMD0053 Model Calibration, Validation and Uncertainty Guidance for Biogeochemical Modeling for Agricultural Land Management Projects, v2.1, 2025). Therefore, the design and establishment of a globalised and reliable monitoring, reporting and verification (MRV) platform is a necessity (Smith et al., 2020). Recent European regulatory initiatives under development (CIR-EU, 2025) aim to address persistent challenges in quantifying soil carbon accumulation by acknowledging structural limitations in conventional approaches. In particular, these frameworks seek to avoid the establishment of SOC stock baselines derived from soil sampling, recognising that soil sampling often captures spatial variability rather than true changes in soil carbon sequestration. Moreover, these regulations explicitly acknowledge that certain EOMs, such as biochar, exhibit physicochemical characteristics that prevent their accurate quantification through field-based measurements alone (Chiaramonti et al., 2026).

This study assesses the agreement between field measurements and SOC modelling in quantifying soil carbon and examines the implications of observed discrepancies for accurate carbon accounting under current regulatory frameworks. To this end, experimental SOC data from an 11-year field experiment under organic amendment application are compared with SOC estimates generated by the RothC model. The analysis assesses the model's predictive capacity and its suitability for supporting sustainable soil management and climate change mitigation strategies, while identifying key limitations and sources of uncertainty in both field-based and modelling approaches, to inform methodological improvements for more robust agronomic and environmental decision-making.

## 2. Materials and Methods

### 2.1. Field experiment

The experiment was conducted from 2013 to 2024 in an organically managed olive grove located in the Murcia region, in the Southeastern part of the Iberian Peninsula, Spain (Sánchez-Garcia et al., 2021).

#### 2.1.1. Site description

The experiment site was located in the municipality of Jumilla (1° 22′ 41.9″ W, 38° 24′ 0.63″ N), at an altitude of 423 meters above sea level (Figure 1), and with a mean slope of 1.42°. The climate is dry typically Mediterranean, classified as cold semiarid/steppe climate (BSk), according to the climatic classification Koppen-Geiger (Kottek et al., 2006), with an average annual temperature of 16.3°C and an average annual precipitation of 263 mm per year. The orchard follows a tree density of 325 trees·ha$^{-1}$, with 4 m spacing between trees within the row and 7 m between rows. The soil at the experimental site is Haplic Calcisol (IUSS Working Group WRB, 2022), with a texture classified as Sandy Loam: sand content of 57%, silt 27% and clay 16%. The organic C content is 1.30%, and the soil has an alkaline pH of 8.12%.

The olive grove, established 30 years ago, has been consistently managed under certified organic practices with the application of organic amendments, primarily compost. No chemical fertilizers, herbicides or pesticides have been applied during this period. The grove is equipped with a drip irrigation system, which is only used during periods of high-water demand throughout the year. The tillage method used was minimum or reduced tillage, which involves shallow soil disturbance while avoiding soil inversion.

#### 2.1.2. Experimental design and treatment description

The field experiment follows a randomized complete block design, comprising 12 plots with four treatments replicated across three blocks to account for spatial variability across the site. The treatments included Biochar, Compost, a Mixture of 90% compost and 10% biochar, and a Control without addition of any amendment. Each plot contained six olive trees, with plots' perimeters separated by a single row of trees serving as a buffer (Figure 1). The amendments were applied throughout the duration of the experiment, with a total of five applications conducted in 2013, 2015, 2017, 2021, and 2023. These applications were carried out at the end of spring in each of those years, and were applied exclusively to moist soil along the drip lines.

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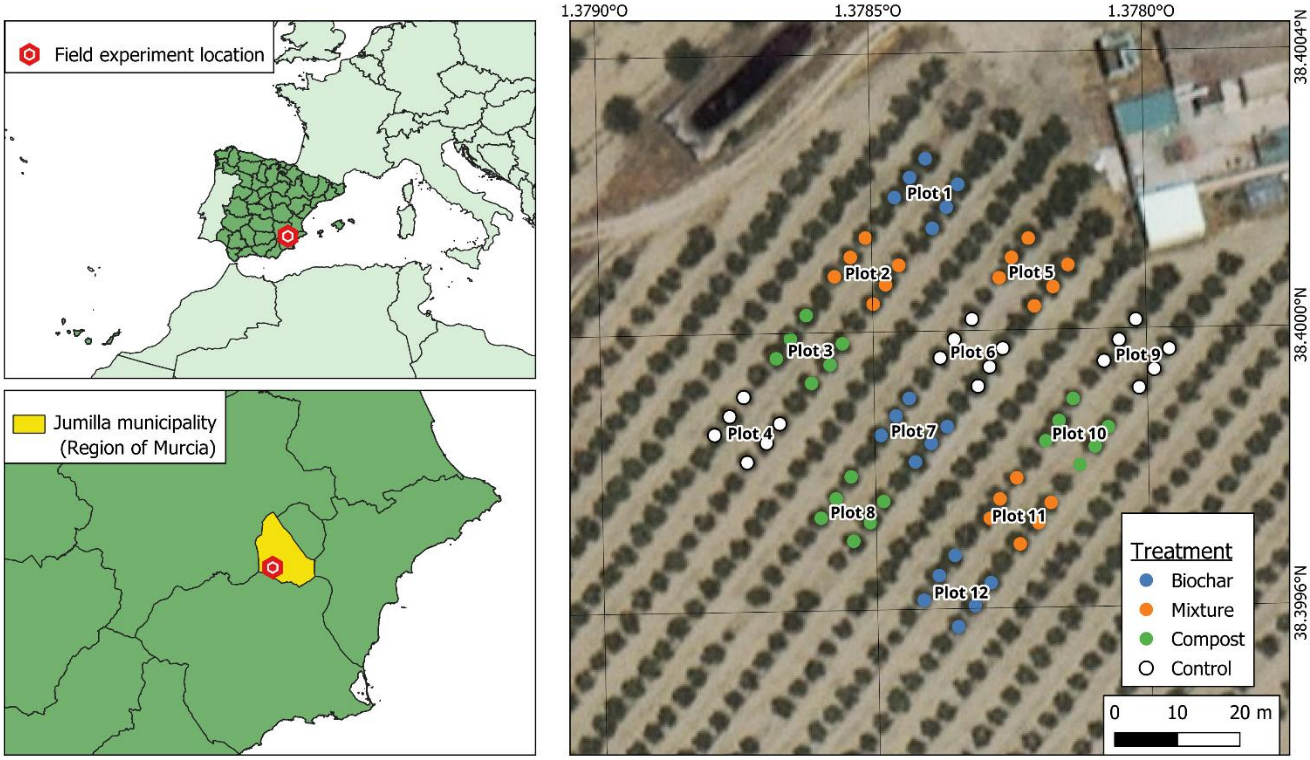


**Figure 1. Field experiment location, and experimental design for the treatments: Biochar, Mixture of Compost and Biochar, and Compost. Orthophoto study area: Plan Nacional de Ortofotografía Aérea (PNOA), © Instituto Geográfico Nacional**

The amendments were applied at a rate of 20 Mg ·ha$^{-1}$ (dry matter basis) distributed in a 1-m-wide strip along the entire tree row and manually incorporated into the soil to facilitate the homogenization of the added materials with the soil. The materials differed in their organic carbon content. Biochar had the highest organic carbon content, and two different types of biochar were used. The biochar applied during the first three amendment events was produced from oak wood feedstock and contained 67.3% organic carbon, with an H/C ratio of 0.32, corresponding to a carbon application rate of 13.46 Mg C ha$^{-1}$. The biochar used in the fourth and fifth applications was derived from vine shoots, contained 47.5% organic carbon, and exhibited a lower H/C ratio of 0.21, corresponding to a carbon application rate of 9.5 Mg C ha$^{-1}$. The compost was produced by on-farm windrow composting over a six-month period using two-phase olive mill waste, olive tree pruning and sheep manure; this amendment contained 35.8% organic carbon, equivalent to a rate of 7.16 Mg C·ha$^{-1}$. The mixture of compost (90%) and biochar (10%) resulted in an application rate of 7.79 Mg C·ha$^{-1}$ for the first three additions and 7.39 Mg C·ha$^{-1}$ for the fourth and fifth additions.

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### 2.2. Soil sampling, SOC analysis and data filtering

Soil samples were collected with a spade from the top 20 cm of soil within each experimental plot. A total of 17 sampling campaigns were conducted throughout the 11-year experimental period, except in 2018, 2019, and 2020, when no soil sampling or treatment applications took place. For each sampling date, at least four subsamples were randomly collected within the amended area along the drip lines of each plot to obtain a representative sample per plot.

Samples were air-dried, homogenized and sieved through a 2 mm mesh to remove coarse fragments. Subsequently, the fine-earth fraction was milled to a fine powder using a ball mill before SOC determination.

SOC concentration was determined by dry combustion following acid pre-treatment with 2 N HCl to remove inorganic carbon. SOC was primarily analysed using a LECO CHNS-932 elemental analyser (LECO Corporation, USA). From 2021 onwards, a subset of samples was additionally analysed in a second laboratory using an alternative elemental analyser (TRUSPEC CN628).

SOC data were filtered to remove outliers using the Median Absolute Deviation (MAD) method, which is a robust approach for handling extreme values and is therefore well-suited for detecting outliers in experimental datasets with limited replication (Miller and Miller, 1994). A MAD threshold of 4 was applied, such that SOC measurements showing a deviation greater than four times the MAD from the median value of the corresponding sampling date were classified as outliers and excluded from the analysis.

Bulk density (BD) was measured at the beginning and at the end of the experiment for each plot. Results showed that BD remained stable, showing no temporal variation and no differences among treatments. Therefore, a constant BD value was assumed for SOC stock calculations. The BD value used to convert SOC concentrations to SOC stocks was 1.20 $g \cdot cm^{-3}$.

SOC concentrations were converted to SOC stocks using the following equation (Eq.1):

$$SOC(Mg \cdot ha^{-1}) = SOC(g \cdot 100g^{-1}) \times BD(g \cdot cm^{-3}) \times Depth(cm) \quad (1)$$

where SOC ($Mg \cdot ha^{-1}$) is the soil organic carbon stock; SOC ($g \cdot 100\ g^{-1}$) is the soil organic carbon concentration; BD ($g \cdot cm^{-3}$) is the bulk density (constant value of 1.20 $g \cdot cm^{-3}$); and Depth (cm) corresponds to the sampling depth of the field experiment (20 cm).

For the analysis of soil carbon sequestration, the final SOC stock was defined as the average of the last three field sampling dates, collected over a one-year period spanning late 2023 and the first half of 2024. This reference period was used to reduce short-term variability in SOC measurements. The final SOC stock was calculated after applying a median absolute deviation (MAD) filter to these three measurements, thereby minimizing the uncertainty associated with reliance on a single

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sampling event. The remaining EOM was estimated as the difference between the final SOC stock of each amended treatment and that of the control. The fraction of added carbon remaining in the soil was calculated as the ratio between the remaining EOM and the total carbon input. The soil carbon sequestration (SCS) rate was then derived by dividing the remaining EOM by the duration of the experiment. For the comparative analysis between measured and modelled SOC, data from the first five months following amendment application were excluded to avoid potential outliers and to ensure that the organic amendments were fully integrated into the soil.

## 2.3. SOC Modelling

The Rothamsted Carbon Model (RothC) was used for SOC modelling in this study since it is appropriate for soil receiving organic amendments (Coleman et al., 1997; Jenkinson and Rayner, 1977). RothC is a multi-compartmental model that divides organic carbon into five distinct pools. Four of these pools are active and decompose at rates defined by the standard model, referred to as kinetic decay, while one pool represents inert material that does not decompose.

The RothC model allows for the inclusion of the amount of carbon added through organic amendments; however, the partitioning of added material into pools of different decomposability and their decomposition rates are fixed, therefore limiting its accuracy in representing the dynamics of added EOM. To overcome this limitation, a modified version of the RothC model developed by Mondini et al. (2017) was used, in which it is possible to specify the size and the decomposition rate of 3 additional EOM pools, namely decomposable (DEOM), resistant (REOM) and humified (HEOM) exogenous organic matter. This modified version operates similarly to the standard RothC model, but the additional pools allow for the simulation of the decomposition of extra materials.

### 2.3.1. Pools of Exogenous Organic Matter (EOM)

The EOMs were considered to be composed by two or three pools, depending on the physicochemical complexity and stability of the added material, according to Mondini et al. (2017). Biochar, for instance, is considered a relatively simple material in terms of stability, being highly stable over the long term, with a large fraction belonging to the most stable pool (Chiaramonti et al., 2024) and, a smaller fraction that decomposes more rapidly.  Therefore, in this study, biochar was considered as a material composing by two pools: one more decomposable (*DEOM*) and a very stable resistant fraction (*REOM).* The readily degradable fraction (DEOM) is generally assumed to be comparable to the Decomposable Plant Material (DPM) pool in the standard RothC model, with a degradation rate of 10 $yr^{-1}$ (Keel et al., 2023).

The compost was modelled as an EOM with three pools: DEOM, REOM, and HEOM. The mixture of compost and biochar was assumed to decompose independently, without interactive effects between them. The two amendments were modelled separately, and the amount of decomposed mixture at each time was obtained from the sum of decomposed biochar and compost at the same time.

### 2.3.2. EOM pools parameters estimation

Differently to the standard RothC, in the modified RothC for amended soil, there is the necessity to define the size and the decomposition rate of the EOM pools. This was obtained by model inversion (Mondini et al., 2017). This approach estimates the EOM pool parameters by minimizing the differences between the outputs from the RothC model simulations and experimental data on compost mineralization. The experimental data consisted in $CO_2$ fluxes measured in incubation experiments with composts of similar composition to those applied in the field experiment (Serramiá et al., 2012). These measurements were used to estimate the partitioning factors (*f*) and the decomposition rates (*k*) of each pool via inverse modelling based on SoilR package (Sierra et al., 2012) to simulate C turnover. The details of the model inversion are explained in the Supplementary Information Text (a).

The compost (Co) was prepared from raw materials derived from the olive and agricultural sectors, such as Two-Phase Olive Mill Waste (TPOMW), Sheep Manure, and Olive Tree Pruning (Serramiá et al., 2012), following a procedure similar to that used for the compost applied as a soil amendment in the field experiment. The compost was incubated in three contrasting soils to ensure robust estimation of partitioning and decomposition rates parameters, allowing the behaviour of the compost to be evaluated across soils with differing physicochemical properties. All soils were Mediterranean calcareous soils, with clay contents ranging from 6.5 to 14.4%, organic carbon contents between 0.6 and 1.0%, and overall low soil organic matter levels. The description of the compost and soils used for the RothC model inversion is specified in Table S1. The EOM pools parameters obtained from each soil were averaged and used in the RothC simulations.

We did not follow the same procedure for the biochar treatment because the $CO_2$ emissions after biochar amendment were too low to achieve a reliable fit between the simulation with the measured curve. Therefore, for the biochar treatment, we used the kinetic parameters proposed by Keel et al. (2023): *f*DEOM: 0.02; *f*REOM: 0.98; *k*DEOM: 10 $yr^{-1}$; *k*REOM: 0.0010 $yr^{-1}$. This approach is based on the fact that the size of the biochar pools and their decay are directly related to the pyrolysis temperature and the biochar H/C molar ratio.

### 2.3.3. RothC simulations

The basic inputs required by the model are climate, soil parameters and data on soil properties and soil management practices data (Peralta et al., 2022). In addition, RothC requires the specification of the initial carbon contents for each pool; therefore, to determine these initial values, RothC was run at long-term equilibrium. Model initialization is a critical step in the simulation process and a known source of uncertainty, as the size of the SOC pools cannot be directly measured (Dimassi et al., 2018). This initialization phase allows the estimation of both the steady-state (at equilibrium) pool sizes and the annual carbon inputs from plant residues. The model was run under equilibrium conditions for a period of 1000 years to achieve stabilization of the pools and input (Mondini et al., 2018; Peralta et al., 2022).

Subsequently, "Forward" simulations were carried out to simulate the real field experiment conditions. The climate data were obtained by the weather station "Cañada del Judío" (JU12) and extracted by the SIAM platform (Sistema de Información Agrario de Murcia, 2025). The climate parameters extracted were: average temperature, monthly accumulated precipitation, and monthly evapotranspiration (Allen et al., 1998; Peralta et al., 2022). The RothC parameter "DPM/RPM ratio", which describes the quality of plant-derived inputs, was set to 0.25, a value representative of inputs from woody vegetation. A constant plant cover was assumed for the corresponding "Plant Cover" parameter.

RothC "Forward" simulations were performed using the modified RothC model for amended soils. As the modified model requires carbon inputs from EOM material, the actual carbon content added with each type of amendment was included for every application and treatment, to bring the modelling closer to real-world conditions. Figure 2 shows the date of the treatment application events and SOC measurement events. Model performance in comparison to measured data was evaluated using $R^2$, RMSE, and Bias according to the criteria proposed by Smith et al. (1996).

## 3. Results

### 3.1. Field-measured SOC concentration and temporal trends

The dynamics of climate and SOC are expressed in Figure 2, which also indicates the timing of the organic amendment applications. The average monthly air temperature exhibited relatively stable seasonal patterns, whereas precipitation showed strong variability, with intense rainfall events concentrated in specific months, contrasting with periods of very low rainfall.

The SOC measurements collected over the 11-year field experiment showed an increase across all treatments, including the control without amendments. SOC contents ranged from 1.24 to 6.32 $g \cdot 100g^{-1}$ throughout the study (Figure 2), with final values after 11 years of 1.80, 2.56, 2.84, and 3.01 $g \cdot 100g^{-1}$, for the control, compost, mixture and biochar treatments, respectively (Table S2). The control treatment displayed a slight SOC increase over time, with an upward trend corresponding to an annual increase rate of 0.04 $g \cdot 100g^{-1} \cdot yr^{-1}$ (Table S2) when comparing baseline SOC with measurements from 2024. In contrast, all amendment treatments showed a higher and fairly consistent SOC accumulation rate, ranging from 0.11 to 0.16 $g \cdot 100g^{-1} \cdot yr^{-1}$ as shown in Table S2.

Plot-level (replicates) variability within the same treatment groups was also found to be considerable. Table S2 summarizes the mean standard deviation for each treatment. The control treatment exhibited consistent variability, with a mean standard deviation of approximately 0.27 $g \cdot 100g^{-1}$. In contrast, treatments such as biochar demonstrated notably higher variability, with a mean standard deviation of 0.46 $g \cdot 100g^{-1}$. Compost and the compost-biochar mixture displayed intermediate

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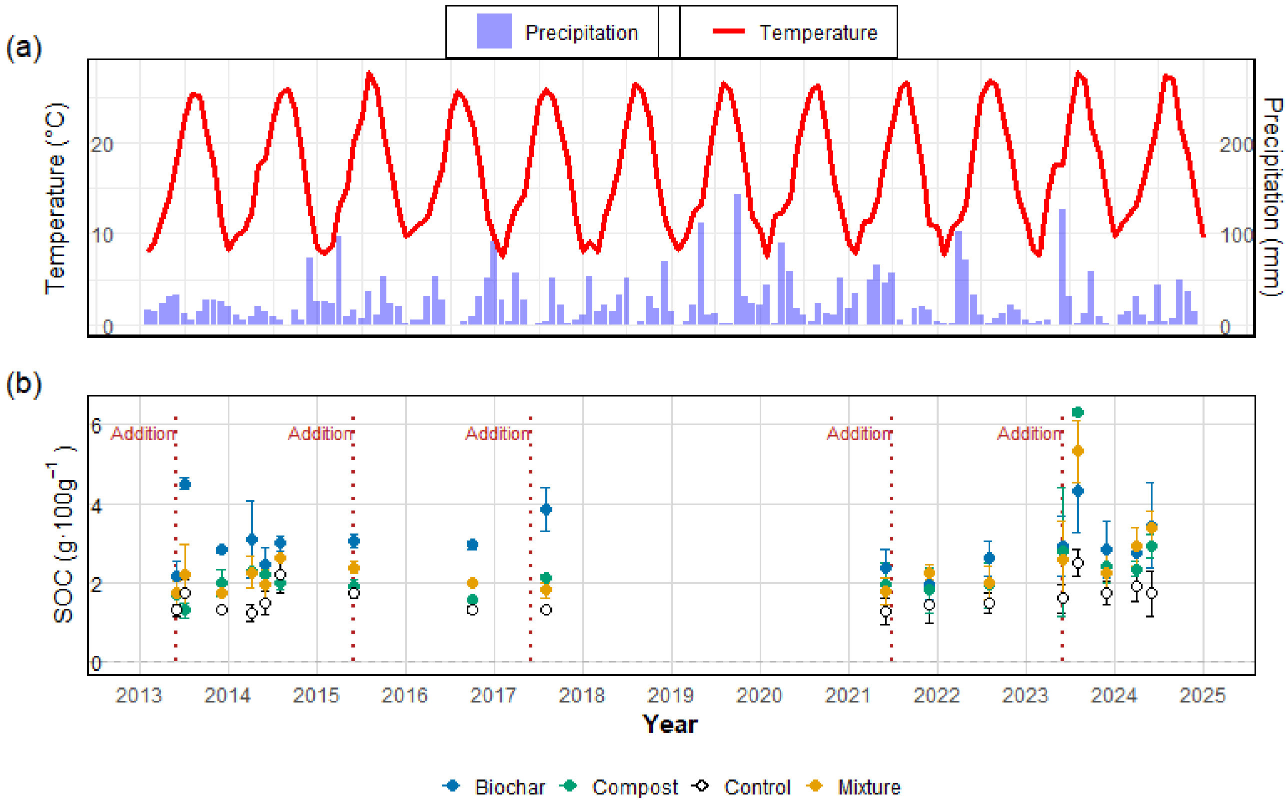
variability, with standard deviations of 0.34 and 0.37 g·100g⁻¹, respectively. Regarding the coefficients of variation (CV), replicates showed a regular pattern, with values ranging from 15.5% to 16.9%.




240 **Figure 2. The upper panel (a) shows the average monthly temperature and the monthly accumulated precipitation during the experiment period. Bars represent standard deviation. The lower panel (b) shows the experimental events chronology. The term Addition refers to the date when the amendment (compost, biochar or mixture) was applied to soil. Dots represent averaged SOC concentrations for each treatment after applying median absolute deviation (MAD) filter < 4. Dot colors are used to differentiate between the treatments**

245 ## 3.2. Modelling of SOC dynamics

### 3.2.1. Estimation of pool parameters for exogenous organic matter (EOM)

The estimation of the pools size *(f)* and the decomposition rate *(k)* for compost was achieved through the adjustment of the model to cumulative $CO_2$-C measured during compost (Co) incubations in three different soil types (Co-S1, Co-S2, and Co-S3; Figure 3) and averaging the results from the three incubations.

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Cumulative $CO_2$–C data were obtained from three different soils to achieve a more robust parameterization, as RothC allows model inversion while explicitly accounting for soil texture differences through clay content. The smallest pool corresponds to the labile fraction (*fDEOM = 0.04)* that corresponds to 4% of the total organic carbon added with the EOM. This pool exhibited the highest decay rate, *k*DEOM = 14.12 $yr^{-1}$, contributing to the sharp increase in $CO_2$-C release observed at the beginning of the incubation. The more stable pools (*fREOM* and *fHEOM*) represent carbon fractions that are more resistant to decomposition. The *fREOM* pool was predominant in Co-S1 (Jaén soil) and Co-S2 (Jumilla soil), while in Co-S3 (Santomera soil), *fHEOM* became the dominant fraction. This variation is attributable to the Santomera soil, which displayed a distinct $CO_2$-C flux pattern with lower overall C release compared to Co-S1 and Co-S2 (Figure 3) The average values for the *fREOM* and *fHEOM* pools of the compost were estimated at 0.51 and 0.45 with decay rate *kREOM* of 0.09 $yr^{-1}$ (Table 1). For the humified EOM pool, *k*HEOM of 0.02 $yr^{-1}$ is assumed according to the standard RothC for the humified pool of the soil organic carbon.

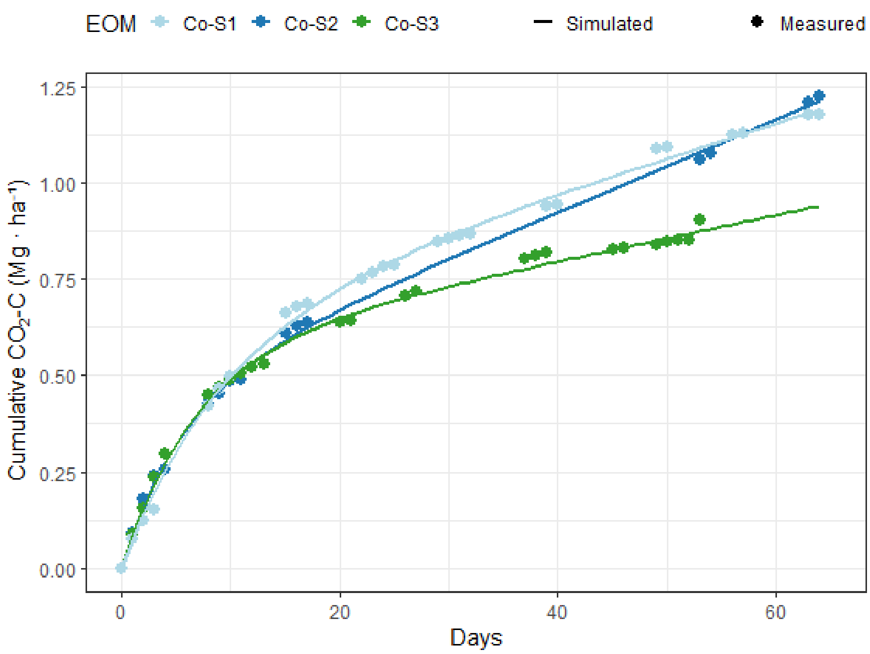


**Figure 3. CO2 emissions by compost amendment for different soils: measured (dots) and RothC-simulated (lines) cumulative $CO_2$–C (Mg $ha^{-1}$)**

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**Table 1. Kinetic parameters obtained by the RothC inversion using accumulated respiration flux (CO2-C flux)**

| | Incubated soil properties | | | | RothC optimized parameters | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **EOM** | **Soil** *Location* | **Sand** *(%)* | **Clay** *(%)* | **TOC** *(%)* | ***f*DEOM** *(unitless)* | ***f*REOM** *(unitless)* | ***f*HEOM** *(unitless)* | ***k*DEOM** *($yr^{-1}$)* | ***k*REOM** *($yr^{-1}$)* |
| Co-S1 | Jaén | 70.5 | 13.7 | 0.87 | 0.04 | 0.64 | 0.32 | 10.47 | 0.08 |
| Co-S2 | Jumilla | 87.8 | 6.5 | 0.58 | 0.03 | 0.59 | 0.39 | 17.80 | 0.11 |
| Co-S3 | Santomera | 75.5 | 14.4 | 0.99 | 0.04 | 0.31 | 0.65 | 14.10 | 0.07 |
| *mean* | | *77.9* | *11.5* | *0.81* | *0.04* | *0.51* | *0.45* | *14.12* | *0.09* |

270 **TOC**: Total Organic Carbon; **EOM**: exogenous organic matter; **DEOM**: decomposable EOM; **REOM**: resistant EOM; **HEOM**: humified EOM; ***f***: partitioning factor (unitless); ***k***: decomposition rate ($yr^{-1}$)

### 3.2.2. RothC model simulations vs. field data

The model was run for each treatment with the optimized pool parameters (Table 1) to evaluate its performance by comparing simulated SOC with field measurements. The initial SOC (baseline) was set as the mean value of the control plots on the first sampling date.

Figure 4 presents the comparison between field measurements and RothC simulations across all treatments, showing the $R^2$ coefficients, RMSE, Bias, and the 95% confidence interval. Additionally, regression analyses illustrate the SOC dynamics for measured SOC values. RothC simulations showed an increase in SOC dynamics over time across all amended treatments, with the increment being more pronounced for biochar than for compost and the compost-biochar mixture. This pattern is consistent with the field observations of annual SOC increases; however, the model did not reproduce the increase in SOC dynamics observed for the control treatment. Figure 4 includes shaded areas representing the 95% confidence interval, within which most data points are contained.

Overall, the comparison reveals a high degree of variability between the two approaches. The Root Mean Square Error (RMSE) is generally high, with a mean RMSE across all treatments, including the control, of approximately 12.35 $Mg \cdot ha^{-1}$. As observed in Figure 4, several parts of the line of modelled data lie outside the confidence interval, highlighting the discrepancies between the modelled and the experimental data.

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In the case of the control treatment, discrepancies were observed between the RothC-simulated SOC and the field measurements. While the agreement between simulated and measured values was good during the initial years of the experiment, deviations became apparent toward the end of the study period, with simulated values falling below the observed SOC levels. The RMSE for the control treatment was 9.46 Mg C·ha$^{-1}$. Notably, field measurements tended to be consistently higher than the model outputs, a trend reflected in the positive slope of the regression line. This suggests a potential increase in SOC even in the absence of organic amendments.

Among all treatments, compost and the mixture demonstrated the best agreement between simulated and observed SOC values. The coefficient of determination ($R^2$) for the average of all plots was 0.42, and 0.38 for compost and the mixture, respectively. These relatively higher $R^2$ values indicate a better agreement compared to the biochar treatment, which exhibited a substantially lower $R^2$ of 0.10.

The biochar treatment exhibited the highest level of divergence between the two approaches, as clearly seen in the model fitting results. The mean RMSE for this treatment reached 19.95 Mg C·ha$^{-1}$, the highest among all tested treatments, accompanied by the lowest $R^2$ values.

Overall, the bias analysis indicated that the Biochar treatment was the only treatment in which SOC measurements were overestimated by the RothC model. In contrast, the Control, Compost, and Mixture treatments exhibited positive bias, with measured SOC values consistently exceeding those predicted by the model.

**Table 2. Summary of comparison of measured and RothC-simulated Total SOC increase, annual accumulation rate, final SOC stock, Remaining EOM and SCS rate for each treatment. Measured uncertainties (±) represent the standard error (SE) estimated through a non-parametric bootstrap (n = 5000), obtained by independently resampling initial and final SOC datasets to incorporate both within-plot and between-plot variability.**

| | Measured | | | | | | Modelled | | |
|---|---|---|---|---|---|---|---|---|---|
| **Treatment** | **Total SOC increase** *(Mg·ha$^{-1}$)* | | **SOC increase per year** *(Mg·ha$^{-1}$· yr$^{-1}$)* | | **Final SOC stock** *(Mg·ha$^{-1}$)* | | **Total SOC increase** *(Mg·ha$^{-1}$)* | **SOC increase per year** *(Mg·ha$^{-1}$· yr$^{-1}$)* | **Final SOC stock** *(Mg·ha$^{-1}$)* |
| **Control** | 11.73 | *±3.01* | 1.06 | *±0.27* | 43.09 | *±2.38* | -1.26 | -0.11 | 30.10 |
| **Compost** | 30.13 | *±3.05* | 2.74 | *±0.27* | 61.49 | *±2.37* | 30.40 | 2.76 | 61.76 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Mixture** | 36.91 *±4.47* | 3.36 *±0.41* | 68.27 *±4.02* | 33.06 | 3.01 | 64.42 |
| **Biochar** | 40.98 *±5.41* | 3.73 *±0.49* | 72.34 *±4.98* | 57.02 | 5.18 | 88.38 |

| | **Remaining EOM-C** | | **SCS rate** | **SCS rate*** | **Remaining EOM-C** | | **SCS rate** | **SCS rate*** |
|---|---|---|---|---|---|---|---|---|
| | ***(Mg·ha$^{-1}$)*** | ***% of added C*** | ***(Mg·ha$^{-1}$ yr$^{-1}$)*** | | ***(Mg·ha$^{-1}$)*** | ***% of added C*** | ***(Mg·ha$^{-1}$ yr$^{-1}$)*** | |
| **Compost** | 18.40 | 51.40 | 1.67 | 0.51 | 31.66 | 88.44 | 2.88 | 0.88 |
| **Mixture** | 25.18 | 65.99 | 2.29 | 0.66 | 34.32 | 89.94 | 3.12 | 0.90 |
| **Biochar** | 29.25 | 49.26 | 2.66 | 0.49 | 58.28 | 98.15 | 5.30 | 0.98 |

**Total SOC increase:** SOC increment at the end of the experiment with respect to the initial baseline; **Final SOC stock**: mean SOC after a minimum of 5 months with respect to the last amendment application; **Remaining EOM-C**: C added with EOM that remains in the soil at the end of the experiment with respect to the control; **SCS rate**: Soil Carbon Sequestration rate with respect to the control; **SCS rate*:** Soil Carbon Sequestration rate with respect to the control, standardized/normalized for addition of 1Mg C · ha$^{-1}$·yr$^{-1}$.

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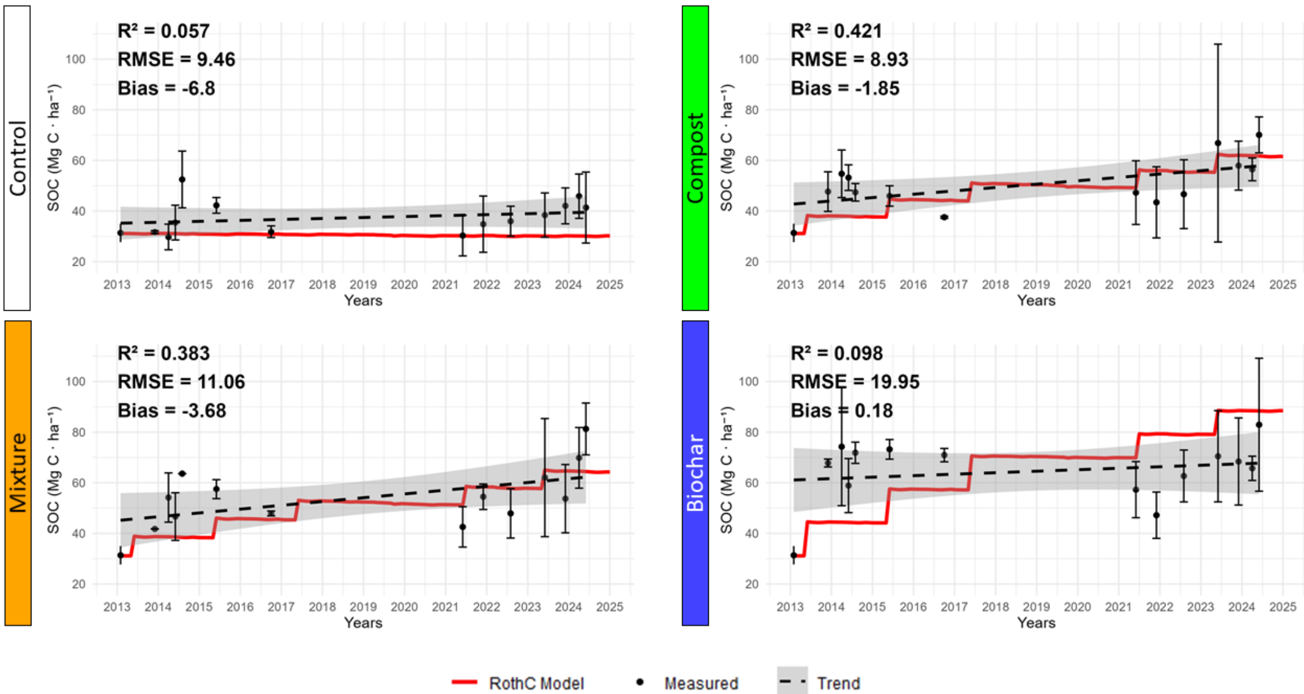


**Figure 4. Comparative analysis of RothC model simulations (red line) against sampled SOC data (black dots) for each treatment. Error bars represent the standard deviation. The black dashed line represents the regression line calculated from the measured values, with the shaded area showing 95% confidence interval. Model performance statistics ($R^2$, RMSE, and Bias) are reported. The RMSE and Bias metrics are expressed in (Mg C · $ha^{-1}$)**

RothC simulations were used to estimate net annual SOC sequestration rates over the experimental period, enabling a quantitative comparison among organic amendment treatments and with field-derived SOC data. Modelled sequestration rates were 2.9, 3.1, and 5.3 Mg C $ha^{-1}$ $yr^{-1}$ for the Compost, Mixture, and Biochar treatments, respectively (Table 2). In contrast, field measurements produced substantially lower sequestration rates of 1.7, 2.3, and 2.7 Mg C $ha^{-1}$ $yr^{-1}$ for the corresponding treatments.

According to the measured data, the proportion of added carbon remaining in the soil at the end of the experimental period was 51.4%, 66.0%, and 49.3% for the Compost, Mixture, and Biochar treatments, respectively. The corresponding values estimated by the model were markedly higher, reaching 88.4%, 89.9%, and 98.1%. When simulations were extended to a 100-year time horizon, the percentage of added carbon remaining in the soil decreased to 55.3% and 61.8% for the Compost and Mixture treatments, respectively, while remaining high for Biochar (96.8%). Accordingly, $F_{perm}$, defined as the fraction of added carbon remaining in the soil after 100 years (Rodrigues et al., 2023), was estimated at 32.45%, 43.0% and 95.4% for Compost, Mixture and Biochar, respectively.

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## 4.Discussion

### 4.1. Comparison of field-measured and RothC modelled SOC dynamics

Field measurements and RothC simulations showed comparable temporal trends in SOC dynamics across the different organic amendment treatments over the 11-year experimental period. Both approaches consistently ranked the amendments according to their relative carbon sequestration potential. However, RothC systematically overestimated SOC stocks compared to field measurements, with the magnitude of the discrepancy varying among amendment types and over time.

Monitoring the SOC for long-term is a complex task prone to errors, particularly in sampling procedures that involve extracting solid samples from a vertical soil profile (Poeplau et al., 2022). The inherent variability in field measurements often introduces significant uncertainties in both soil sampling and analysis that are challenging to control and manage. In calcareous soils with low organic carbon contents, such as the studied here, this uncertainty is further increased because small absolute changes in SOC can lead to relatively large analytical variability. The variability among plot replicates clearly dominated the overall uncertainty, reflecting pronounced variability even at short horizontal distances, a phenomenon referred to as fine-scale horizontal variability (Hoffmann et al., 2014).

Modelling offers notable advantages over field-based carbon measurements in terms of speed, resource efficiency, and time requirements (Peralta et al., 2022). Several studies have shown successfully that field-measured SOC can be well aligned with model-derived SOC estimates (Romanenkov et al., 2019; Thiagarajan et al., 2022), and, particularly in the case of soil respiration simulations, which successfully reproduced the overall dynamics (Pulcher et al., 2022). However, field data often exhibit considerable uncertainties, particularly in cases where external organic matter (EOM) was added to the soil, such as those examined in this study. Overall, studies applying both empirical measurements and SOC modelling consistently show that carbon-turnover models are generally able to capture the direction of SOC changes over time (Kröbel et al., 2011). However, substantial differences have also been reported among modelling frameworks and measurement approaches (Campbell et al., 2007; Congreves et al., 2015; He et al., 2021; Smith et al., 2012). These discrepancies are typically attributed to differences in calibration procedures and model input data, both of which must be carefully tailored to the specific conditions of each study site. Model performance can therefore vary considerably depending on how well these parameters reflect local environmental and management conditions. In semi-arid environments, calibration becomes particularly critical, as SOC dynamics are strongly governed by carbon inputs (Campbell et al., 2007). In this study, the model was adapted to site-specific conditions, with particular attention to the parameterization of organic amendment decomposition, to reduce uncertainty in SOC simulations.

A discrepancy between measured and modelled data was observed in the control treatment, with field data indicating an increasing SOC trend over time that was not reflected in the model simulations. Over the eleven-year experimental period,

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the olive grove experienced continuous growth, which likely influenced the potential increase in tree productivity and, consequently, in organic matter inputs. This may explain the observed trend of increasing SOC in the control treatment (Figure 4), which was not captured in the model under the plant input estimation approach adopted in this study, assuming constant plant inputs.

Some studies determined carbon inputs, also referred to as plant inputs, either by using traps to capture organic matter from the aboveground portion of vegetation (Pulcher et al., 2022) or by supplying external organic matter in a controlled manner (Jiang et al., 2013). Such approaches are particularly effective for model calibration, as they enable more accurate simulations by constraining carbon inputs. In this study, monthly plant carbon inputs were derived from the equilibrium carbon inputs obtained during the model equilibrium run (Mondini et al., 2018; Peralta et al., 2022), which represents a reasonable approximation under field conditions where direct measurements of plant-derived carbon inputs are unavailable. However, this approach was developed for herbaceous crops and may not fully capture the temporal variability and gradual increases in carbon inputs associated with vegetation growth under perennial systems. In agroecosystems subject to human management, a more realistic model calibration would therefore benefit from approximating actual vegetation-derived carbon inputs as closely as possible. Based on the outcomes of this study, future verification-oriented applications would be strengthened by incorporating field-based measurements of plant carbon inputs, thereby improving the representation of in-field processes within biogeochemical models.

Compost exhibited the best alignment between field measurement and RothC simulations, whereas treatments with biochar alone exhibited large discrepancies. The Compost–Biochar mixture performed slightly worse than pure compost, likely due to the relatively low biochar content in the mixture. This suggests that amendments dominated by compost are more predictable and, therefore, easier to quantify and validate under field conditions compared with biochar-based treatments.

### 4.2. Impact of EOM type and quality on Soil Carbon Sequestration (SCS)

Both field measurements and model simulations were able to distinguish the effects of amendment quality and consistently revealed substantial differences in their impact on soil carbon dynamics and stocks. Although modelled values were generally higher than field measurements, the relative differences among amendment types were consistently preserved. Biochar emerged as the most effective treatment for C sequestration, whereas the compost used in this experiment also showed a strong potential to enhance soil carbon stocks.

The C sequestration rate measured in the compost-amended plots (1.7 Mg C $ha^{-1}$ $yr^{-1}$) was calculated relative to the control treatment, in order to isolate the effect of compost application on SOC dynamics and to minimise the influence of other confounding factors, such as background carbon inputs associated with tree growth and routine agricultural practices during the experimental period. Previous studies have estimated compost-induced SOC sequestration rates ranging from 0.13 to

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0.55 Mg C $ha^{-1}$ $yr^{-1}$ under different soil and management conditions (Arrouays et al., 2002; Mondini et al., 2012, 2017; Peltre et al., 2012b; Smith et al., 2005), while the Carbo Pro tool (Peltre et al., 2012a) predicts a maximum rate of approximately 0.27 Mg C $ha^{-1}$ $yr^{-1}$ for highly stabilized composts. However, SOC sequestration rates are strongly influenced by compost application rates, which vary widely among studies. In the present experiment, the total compost-C input corresponded to an annual application rate of 3.3 Mg C $ha^{-1}$ $yr^{-1}$. When normalized to a standard input of 1 Mg C $ha^{-1}$ $yr^{-1}$, the resulting sequestration rate (0.51 Mg C $ha^{-1}$ $yr^{-1}$) falls within the range reported in the literature. In addition, the compost used in this study was produced from TPOMW-based feedstocks, resulting in a highly stabilized, lignocellulosic-rich material that is known to degrade slowly in soil (Sánchez-Monedero et al., 2008), further contributing to the observed sequestration rates.

The rate of C sequestration for biochar (0.49 Mg C $ha^{-1}$ $yr^{-1}$), calculated on the basis of an addition rate of 1 Mg C $ha^{-1}$ $yr^{-1}$, was comparable to that of compost (0.51 Mg C $ha^{-1}$ $yr^{-1}$). However, this apparent similarity contrasts with the well-established role of biochar as one of the most effective organic amendments for long-term carbon sequestration (Chiaramonti et al., 2024; Keel et al., 2023; Leng et al., 2019). In this study, field-based SOC measurements likely underestimate biochar-derived carbon due to the intrinsic spatial heterogeneity of this amendment and the randomness associated with manual soil sampling (Chiaramonti et al., 2026), which limits its suitability for accurately capturing biochar-C stocks. Conversely, RothC simulations may tend to overestimate biochar sequestration, as biochar decomposition kinetics are parameterized using the H/C molar ratio (Keel et al., 2023), which may not fully represent the complex and highly recalcitrant behaviour of biochar under field conditions.

Modelled results confirmed the observed trends in the influence of EOM quality on soil carbon stocks, although simulated sequestration rates were consistently higher than those derived from field measurements. In the case of modelled values, the SCS rate calculated for an EOM addition rate of 1 Mg C $ha^{-1}$ $y^{-1}$ were 0.88 and 0.98 Mg C $ha^{-1}$ $y^{-1}$ for compost and biochar, respectively. The values of biochar are consistent with those of Keel et al. (2023), while the SCS potential of compost is significantly higher with respect to the previous estimation. This could be explained by the specific compost utilized in the trials as TPOMW compost is known to be particularly resistant to degradation, and by a bias in parameter optimization, considering that in the optimization procedure, soils and composts similar to those of the field experiment were used, but not exactly the same.

$F_{perm}$ for compost estimated by the model was 32.4%, which is consistent with the reported values in the literature for compost of a wide range of feedstocks and the process condition: Ronchin et al. (2024): 44.16%; Mondini et al. (2017): 34.50%; Leifeld et al. (2024): 8.8%. Furthermore, Boldrin et al. (2009) calculated that only 2-14% of added carbon remains after 100 years. In this context, the compost used in this trial lies toward the upper end of the reported range, likely due to the use of TPOMW, which confers high stability to the compost.

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$F_{perm}$ for biochar is high (98%), a value consistent with findings from previous studies. $F_{perm}$ for biochar have been estimated to range from 70 to 98%(Hammond et al., 2011; Ibarrola et al., 2012; Shackley et al., 2012; Woolf et al., 2021). A similar range was proposed by IPCC (2019). Wolf et al. (2021), considering several field and lab studies (87 data points) on biochar amended soil with a minimum of 1 year of decomposition data, showed a mean $F_{perm}$ of about 0.70 (± 0.20 standard deviations). The maximum $F_{perm}$ reported in their article was 0.98, similar to that found in the present work.

Results from our field measurements highlight the difficulty of achieving fully reliable SOC estimates due to inherent soil spatial variability and inconsistencies in trial management, as repeated applications were not always performed with materials of identical characteristics, thereby increasing uncertainty in the experimental data. In contrast, modelled estimates consistently preserved the relative ranking of EOM stability, in agreement with the literature and with laboratory incubation studies of amended soils. However, the results also indicate the need to further improve model optimization procedures. Consequently, while modelling approaches provide valuable insight into long-term trends and relative treatment performance, absolute SOC values should be interpreted with caution and complemented by empirical observations and more comprehensive modelling frameworks (Maslouski et al., 2025).

**4.3. Biochar as amendment: challenges for field and modelled based C assessment and certification**

Based on model simulations, biochar appears to be the most effective amendment for C sequestration and a unique case in terms of stability. The high persistence of biochar estimated by the model is confirmed by other approaches. Keel et al. (2023) suggested to use pyrolysis temperature as a proxy to estimate the decay rate of the recalcitrant carbon pool. This method assumes that higher pyrolysis temperatures result in a lower H/C ratio, thereby enhancing biochar's stability (Zhang et al., 2024). A common assumption in the biochar's assessment is that higher biochar aromaticity results in greater carbon sequestration potential due to the increased stability of the material. A clear example is provided by Chiaramonti et al. (2024), who unearthed a biochar that had been applied to soil for 15 years and analysed its physicochemical properties. They found that its recalcitrant fraction (*f*REOM) had lost only 7% of its carbon over this period, corresponding to a field-derived decay rate of $k$REOM = 0.0048 $yr^{-1}$. This value is consistent with the decomposition rates proposed by Keel et al. (2023), indicating that highly aromatic biochars can indeed exhibit substantial persistence under real field conditions. The high biochar persistence is further supported by Kuzyakov et al. (2014) who compared biochar mineralization determined via $CO_2$ efflux and derived from $^{14}C$ in an 8.5 years incubation experiment.

Despite the promising results of the modelling approach for biochar amended soil, its reliable applicability remains a challenging and unresolved issue mainly due to the lack of long term field experiments for model parameterization and validation.

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Biochar is often modelled using a simple exponential decay function to represent its decomposition rate. This approach has been incorporated into carbon turnover models such as RothC and Century, but its representation remains underdeveloped (Lefebvre et al., 2020; Mondini et al., 2017; Woolf and Lehmann, 2012). The two-pool decay model has also been tested, but the labile fraction is typically minimal, causing the model to behave similarly to a single-pool system. As a result, this may lead to an incorrect assessment of biochar's persistence in the soil (Sanei et al., 2025).

The results of field experiment suggests that biochar also demonstrated the lowest predictability among treatments in the field experiment, as it showed a stability comparable to compost, in disagreement with the generally acknowledged high resistance of biochar to decomposition. As a matter of fact, there was a low agreement between measured and modelled data ($R^2 = 0.10$) for the biochar treatment. This highlights the high degree of uncertainty associated with the practical challenges of biochar application and its measurement under field conditions. Among the most distinguishing physical characteristics of biochar are its granular texture and its high carbon concentration (Chiaramonti et al., 2026), which complicates its integration into the soil matrix and may increase susceptibility to losses through wind or water transport compared with compost (Rumpel et al., 2009). In contrast, compost shows a more homogeneous distribution and has demonstrated an intimate association with the soil environment.

The limitations outlined above about the assessment of C stocks dynamics in biochar amended soil are particularly relevant, as biochar is increasingly recognised as a promising carbon dioxide removal (CDR) technology. Despite its high SCS potential, biochar presents specific challenges for both field-based quantification and biogeochemical modelling. Its heterogeneous spatial distribution and highly concentrated carbon content introduce substantial uncertainty in soil sampling approaches (Chiaramonti et al., 2026), while current SOC models, such as RothC, remain limited in their ability to fully represent its long-term stability and decomposition dynamics. For carbon credit certification schemes, this dual source of uncertainty complicates the robust quantification of long-term climate benefits and increases uncertainty in permanence estimates. Consequently, a cautious approach is required when allocating carbon credits to biochar-based interventions, emphasising the need to integrate field measurements, adapted modelling strategies (VMD0053 Model Calibration, Validation and Uncertainty Guidance for Biogeochemical Modeling for Agricultural Land Management Projects, v2.1, 2025), and upstream biochar characterisation to ensure reliable long-term carbon accounting.

## 5. Conclusions

The comparison between field measurements and model simulations revealed differences in the representation of SOC dynamics across approaches over the 11-year experimental period. The application of EOM accentuated these differences, with contrasting responses depending on the type of amendment. Compost showed the strongest agreement between measured and simulated SOC dynamics, indicating a consistent representation of its decomposition and its homogenization in the soil. In contrast, biochar proved more challenging to represent, reflecting its distinctive physicochemical properties and the resulting difficulties in both field quantification and model parameterization.

Soil sampling was identified as a major source of uncertainty, mainly due to the high variability observed among replicate plots, an issue that becomes particularly critical for heterogeneous amendments such as biochar. At the same time, modelling proved effective in capturing long-term SOC trends, but its performance for biochar was constrained by the need to adequately represent amendment-specific decomposition behaviour. In this regard, biochar stability appears highly sensitive to the parameterization of decomposition processes based on its intrinsic properties. In addition, model outputs were strongly influenced by the initialisation procedure and by assumptions related to plant carbon inputs, which are inherently variable under field conditions and difficult to constrain accurately.

Overall, this work does not aim to favour or invalidate either field-based measurements or modelling approaches for carbon accounting, but rather to clarify their respective strengths and limitations. From a practical perspective, modelling performs as a powerful and efficient tool for assessing SOC dynamics at larger spatial and temporal scales, while field sampling remains essential for validating observed trends. However, our results indicate that these approaches are not equally suitable for all types of organic amendments. In particular, biochar presents specific challenges for field-based verification of carbon sequestration, largely due to its heterogeneous spatial distribution and highly particulate nature, which amplify sampling-related uncertainty. In contrast, compost showed more consistent and reproducible behaviour across both approaches. Recognising these amendment-specific constraints is therefore critical to improving the robustness of SOC assessments and advancing reliable carbon accounting methodologies.

## Code, data, or code and data availability

Data and code are available upon request from the corresponding author.

## Author contributions

**F. Contreras**: Writing – review & editing, Supervision, Investigation, Conceptualization. **M.L. Cayuela**: Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization, Resources. **M. Sánchez-García:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization, Resources. **E. Ronchin:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization, Resources, Software. **C. Mondini:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization, Resources, Software. **M.A. Sánchez-Monedero:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization, Resources.

## Competing interests

The authors declare that they have not conflict of interest

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