



Eddy covariance diverges from inventory and model-based estimates of soil organic carbon stock change across five crop rotations in Belgian cropland

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Abstract. Quantifying long-term soil organic carbon (SOC) dynamics in croplands is critical to evaluate their climate
15 mitigation potential. We assessed SOC stock changes over 21 years at the BE-Lon ICOS cropland (Belgium) by comparing
decadal soil inventories, RothC model simulations, and eddy covariance (EC) flux measurements, supported by comprehensive
uncertainty propagation. Soil inventories and RothC indicated near-equilibrium SOC stock dynamics, with a non-significant
loss and a gain of $19.7 \pm 30.3 \text{ gC m}^{-2} \text{ yr}^{-1}$, respectively. In contrast, EC-derived carbon budgets suggested mean annual SOC
20 losses of $69.8 \pm 19.2 \text{ gC m}^{-2} \text{ yr}^{-1}$. Uncertainty in the flux-based approach was distributed evenly among spectral corrections,
friction velocity thresholds, and lateral carbon flux estimates; yet it remained substantially smaller than the cumulative flux
signal. A systematic positive discrepancy between EC-derived budget and RothC simulations suggests an underestimation of
net carbon sequestration by the EC technique, which is consistent with the well-documented energy balance non-closure at
cropland sites. Despite these methodological discrepancies, both EC and RothC consistently highlighted the critical role of
management practices. Notably, both approaches identified the winter wheat–cover crop sequence as a moderate net carbon
25 source in the absence of organic amendments. Conversely, manure application emerged as the primary driver of SOC stock
accumulation. More broadly, this study highlights the necessity of combining process-based models, multi-decadal inventories,
and EC flux measurements to reliably constrain SOC budgets and identify robust management drivers in cropland ecosystems.



1 Introduction

The management of soil organic carbon (SOC) plays a dual role in sustaining agricultural productivity and regulating the global carbon cycle. While soil represents the largest carbon pool within the terrestrial biosphere, storing two to four times more carbon (C) than the combined total of vegetation and the atmosphere (Lehmann and Kleber, 2015; Terrer et al., 2021), even minor changes in SOC content can either exacerbate or mitigate climate change through their effects on atmospheric CO₂ concentrations (Köchy et al., 2015). As a vital component of agricultural productivity, high stocks of SOC improve soil structure, supply nutrients, enhance water retention, and support crop performance (Lal, 2020; Pan et al., 2009). Furthermore, SOC sequestration is increasingly recognized as a viable negative emission method, capable of offsetting one-sixth to one-third of annual net anthropogenic CO₂ emissions (Friedlingstein et al., 2022; Fuss et al., 2018).

Agricultural soils cover an area of more than 1.2 M ha, spanning across a wide range of climate zone and edaphic conditions (Potapov et al., 2021). The heterogeneity of agricultural landscapes complicates the assessment of SOC changes over space and time (Penko Seidl and Golobič, 2020; Sulman et al., 2020). In particular, SOC dynamics in croplands are influenced by agricultural practices, including tillage, crop rotation, residue management, and fertilization, which collectively influence nutrient cycling, soil fertility, and greenhouse gas emissions (Ren et al., 2020). Comprehensive and robust methods for SOC assessment are essential to support sustainable agricultural management and to mitigate climate change through the implementation of monitoring, reporting, and verification (MRV) tools (Smith et al., 2020).

Traditional SOC assessment methods rely on direct soil sampling and laboratory analyses, providing detailed but spatially and temporally limited estimates of carbon stocks, lacking the temporal resolution required to capture SOC dynamics (Raffeld et al., 2024; Smith et al., 2020). Additionally, the variability of bulk density and SOC concentration on croplands may also complicate the assessment of SOC stock changes from soil inventories (Goidts et al., 2009). Flux tower measurements offer an alternative method for assessing CO₂ exchange at the ecosystem–atmosphere interface through the eddy covariance (EC) technique, which delivers high-frequency observations of net CO₂ fluxes across multiple interacting pools, referred to as net ecosystem exchange (NEE) (Baldocchi, 2014). To date, over 800 site-years of data from more than 130 cropland sites have been collected by the FLUXNET network (Pastorello et al., 2020), thereby offering powerful datasets for studying carbon dynamics in croplands. Additional measurement of lateral CO₂ fluxes from farming activities (e.g., farmyard manure application, harvest) enables calculation of the net biome productivity (NBP), which should theoretically correspond to changes in SOC stocks if dissolved organic and inorganic carbon fluxes are negligible (Aubinet et al., 2009). However, the extensive post-processing of EC data can introduce additional uncertainties (Aubinet et al., 2012; Hemes et al., 2021). Although substantial progress has been achieved through the development of standardized quality-control procedures in centralized data-processing pipelines (Pastorello et al., 2020), comprehensive uncertainty analysis across all steps of the EC data processing chain remains essential to ensure robust estimates of carbon fluxes and derived budgets. Process-based SOC models estimate SOC stocks by simulating soil carbon cycling processes and their interactions with climate, soil properties and management practices to predict SOC dynamics over time under changing environmental and land-



65 use conditions (Smith et al., 2020). The Rothamsted Carbon Model (RothC - Coleman and Jenkinson, 1996) has been widely
used under varying land-use, management scenarios, and climate conditions to predict SOC stocks at local (Dechow et al.,
2019; Geremew et al., 2024; Ingwersen et al., 2024; Zimmermann et al., 2007) and large scales (Gutierrez et al., 2023; Jordon
and Smith, 2022; Morais et al., 2019; Muhammed et al., 2018). RothC is currently used for estimating national-scale CO₂
emissions and removals as a Tier 3 approach in Japan, Switzerland and Australia (Forrester et al., 2024, 2024; Wüst-Galley
70 et al., 2020; Yokozawa et al., 2010), is recommended by the Food and Agriculture Organization of the United Nations (FAO)
as a baseline model for mapping SOC sequestration potential (Peralta et al., 2022), and has been integrated into Earth system
models (Clark et al., 2011).

This study assesses changes in SOC stocks over 21 years in a typical 4-year crop rotation at the Lonzée EC station in Wallonia,
Belgium. The joint comparison of soil inventories, EC-derived carbon budgets, and RothC simulations provides a unique
75 opportunity to evaluate the consistency of independent approaches, identify potential biases, and improve confidence in SOC
stock change estimates. The objectives were to (1) quantify long-term SOC stock changes across methods, (2) assess associated
uncertainties, and (3) examine the influence of agricultural management practices on SOC stock dynamics.

2 Material and methods

2.1 Study site

80 The study site is located in Lonzée, Belgium (50°33'05.8"N 4°44'46.4"E, 167 m asl). The cropland has been cultivated for
more than 80 years. Since 2004, the main crops have been sugar beet (SB - *Beta vulgaris* L.), winter wheat (WW - *Triticum*
aestivum L.) and seed potato (SP - *Solanum tuberosum* L), grown in a four-year rotation system typical of central Belgium
under conventional tillage. Fertilization varied with crop and year but was dominated by repeated nitrogen (N) applications,
mainly as liquid N, nitrate, ammonitrate or urea-based fertilizers. The average mineral and organic nitrogen fertilization were
85 respectively 161 kg N_{min} ha⁻¹ yr⁻¹ and 23.2 kg N_{org} ha⁻¹ yr⁻¹. In addition, potassium, calcium, sulfur, boron, and magnesium
were applied intermittently and some rotations also received organic amendments such as cow manure and lime-based
products. Farming activities associated with these rotations are given in **Table S1**.

The Lonzée site has been part of the FLUXNET network since 2004 and was labelled 'class 2' station in the Integrated Carbon
Observation System (ICOS) network in 2017 (site code BE-Lon). The climate is temperate oceanic (Köppen classification
90 Cfb) with annual mean precipitation and temperature of 742 mm and 10.2 °C respectively. The soil is classified as a Stagnic
Luvisol (WRB, 2022, Mantel et al., 2023). Texture shows a clear vertical gradient: silt dominates the topsoil (>80 % in 0–30
cm), sand content decreases with depth, and clay content increases correspondingly. SOC content follows the typical
exponential decline with depth observed in ploughed agricultural soils, from 10.9 gC kg⁻¹ in 0–30 cm to 3.96 and 1.80 gC kg⁻¹
in the 30–60 and 60–100 cm layers, respectively (measured in 2017; **Table A1**).

95 This paper focuses on the 2004–2024 period, thereby including five rotations starting in April 2004. The first (2004–2008),
second (2008–2012) and fourth (2016–2020) rotations followed the typical scheme: SB-WW-SP-WW. Cover crops (mustard



MU - *Sinapsis alba* L.; oat OAT - *Avena sativa* L.; faba bean FAB - *Vicia faba* L., phacelia PHA - *Phacelia tanacetifolia* L., clover CLO - *Trifolium repens* L.) were sown after harvesting WW except in 2005, 2007 and 2011. The third (2012-2016) and fifth (2020-2024) rotations diverged from this cropping sequence: in 2012 silage maize (MA - *Zea mays* L.) replaced SB, and 100 spinach (SPI - *Spinacia oleracea* L.) and green dwarf beans (GWB - *Phaseolus vulgaris* L. var. *nanus*) were sown in 2021 to achieve higher economic returns. Due to technical constraints, the spinach crop was not harvested and was instead crushed and incorporated into the soil in May 2021. Consequently, we classified it as a cover crop in our analysis, as all aboveground biomass were returned to the soil. Green dwarf beans were subsequently sown in August 2021 and harvested in October 2021. Consequently, rotation 5 was extended beyond the typical cycle, concluding with the crushing of a mix of phacelia and clover 105 as cover crops after winter wheat harvest until the end of 2024. Due to lack of data availability, the three months of bare soil preceding the end of rotation 5 from January 20225 to March 2025 were not included in the analysis. The study period therefore ended with phacelia-clover crushing in December 2024. The crop calendar is given in **Figure 1**.

2.2 Data processing

The Lonze station is equipped with a sonic anemometer (Solent Research R3 before 2014 and Solent Research HS-50 after 110 2014, Gill Instruments, Lymington, UK) and an infrared gas analyzer (LI-7000 before 2014 and LI-7200 after 2014, LI-COR Inc., Lincoln, NE, US) allowing to quantify the turbulent exchange of CO₂ (NEE), latent heat (LE) and sensible heat (H) from high-frequency (10-20 Hz) measurements of vertical wind speed and gas concentrations. The complete list of sensors is given in **Table S2**. All variables used in this study, except CO₂ fluxes, can be found in Dumont et al. (2026a). The processing of CO₂ flux data, which is different than the standard FLUXNET pipeline, is described below.

115 Half-hourly fluxes were calculated from raw data following the methodology described in Aubinet et al. (2012). Block averaging was used for the estimation of fluctuations, double rotation was applied to align the wind vector to the streamlines, and time lag was estimated by covariance maximization. One important step in flux computation consists of applying a spectral correction on CO₂ flux observations. In particular, the EC system acts as a low pass filter due to its limited ability to resolve small-scale variations in vertical wind speed and CO₂ concentration, resulting in attenuation of the measured co-spectra at high 120 frequencies (Aubinet et al., 2012). This signal loss is compensated during post-processing by means of a correction factor (CF), which is used to estimate the true, unattenuated covariance from the measured covariance. Assuming co-spectral similarity among scalar fluxes, CF can be estimated empirically as the ratio of the integrated unbiased wind speed (w_s) – sonic temperature (T_s) co-spectrum to the integrated biased w_s – CO₂ concentration co-spectrum. The latter is modeled as the product of a transfer function and the unbiased w_s – T_s co-spectrum. The transfer function was obtained by fitting a Lorentzian 125 function, characterized by a single fitting parameter corresponding to the cut-off frequency (f_c), to the ratio between high-quality biased and unbiased co-spectra (Ibrom et al., 2007). Beyond this general framework, several implementation choices are possible. In this study, we followed the co-spectral approach described in Faurès et al. (pers. comm.). Co-spectra were preferred over spectra for the estimation of f_c . Recent developments by (Peltola et al., 2021), highlighting the need to account for an additional filtering linked to the lag search by covariance maximization, were also included. The estimation of f_c and



130 CF was based on binned, class-averaged co-spectra, with atmospheric stability and wind speed used as sorting variables. CF were then used to correct half-hourly CO_2 for compensating high-frequency losses. Co-spectra were computed using the EddyPro software (LI-COR Biosciences, Lincoln, NE, USA, v7.0.9), and subsequent analysis was performed with the Python tool FreqCor v1.3 (<https://github.com/BernardHeinesch/FreqCor>).

Because f_c and CF also depend on the effective measurement height and on instrumental setup characteristics—such as the
135 distance between the sonic anemometer sensing volume and the gas inlet, flow rate, tube length, and filter and rain cap configurations—the analysis was conducted separately for periods during which these characteristics remained constant. The effective measurement height was discretized into three classes split around 1.5 and 2.3 m, resulting in 34 sub-periods over the 21-year study period. Additional information on uncertainty calculations can be found in section 2.4.

After spectral corrections, post-processing of NEE data included (i) determination of friction velocity (u^*) thresholds, and (ii)
140 gap-filling of missing or discarded data under low turbulence, following the REdDyProc routine (version 1.3.3; Wutzler et al., 2018). Compared to the typical REdDyProc workflow, we implemented several adaptations to account for the crop rotation structure of the Lonzée site. Instead of relying on fixed three-months yearly seasons, we defined a seasonal stratification based on harvest and sowing dates of each crop, reflecting the aerodynamic characteristics of each cropping period. Within each sowing-to-harvest sequence, the following typical data treatment was applied. First, u^* thresholds were determined using the
145 moving point detection method (Papale et al., 2006). Second, to propagate the uncertainty associated with the u^* threshold estimation, five equiprobable u^* scenarios corresponding to the 5th, 16th, 50th, 84th and 95th percentiles of the bootstrapped u^* threshold distribution ($n = 200$ bootstrap samples) were generated. Third, after discarding data under low turbulence (i.e., $u^* < u^*$ thresholds), gap-filling was performed by applying the standard MDS (Marginal Distribution Sampling) algorithm (Reichstein et al., 2005), using shortwave incoming radiation, air temperature, and vapor pressure deficit as auxiliary
150 meteorological variables. The MDS method consists in replacing missing data with the average of half-hourly CO_2 flux measurements under similar meteorological variables within sliding time-windows. The MDS method was applied for each u^* threshold scenario, yielding an ensemble of five gap-filled NEE time series from which half-hourly uncertainty envelopes (5th–95th percentile range) were derived.

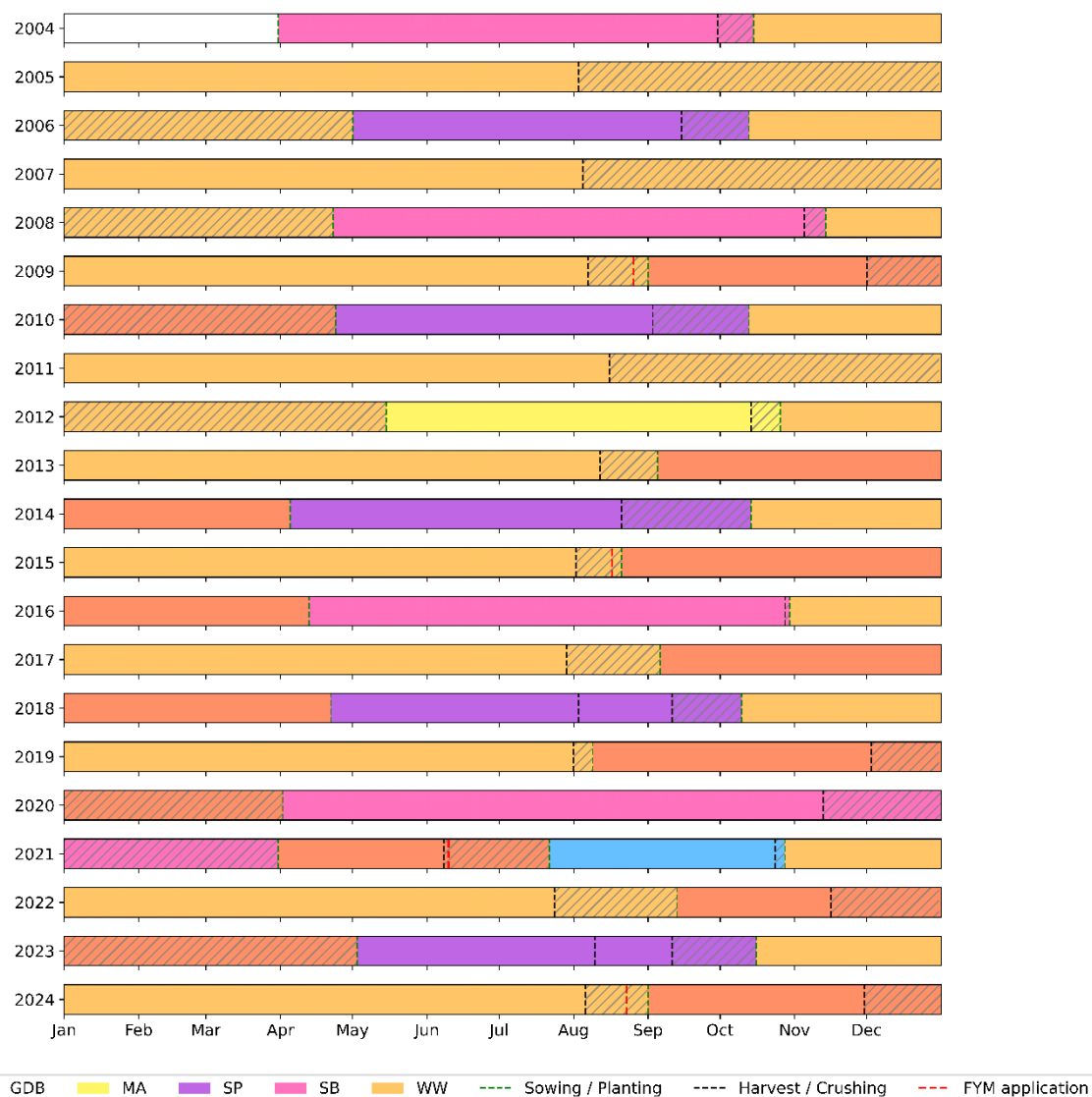


Figure 1. Summary of five crop rotations (2004–2024) at BE-Lon. Each crop period spans from sowing to the sowing of the subsequent crop. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean. Rotations ran from 31 March to 31 March four years later, except Rotation 5, which ended on 31 December 2024. For cover crops: oat–faba bean (2019–2020), spinach (2021), and phacelia–clover (2024); mustard was used in all other years. FYM is farmyard manure. Hatches show bare soil periods between harvest/crushing and sowing/planting events.



Unlike standard implementations of REddyProc, which treat the full time series as a homogeneous pool for MDS gap-filling, this pipeline segmented the data by crop group prior to gap-filling. This segmentation inevitably reduced pool sizes at crop transitions or at the edges of the dataset, necessitating an alternative approach where standard MDS would have failed for gap-filling discarded or missing data. For instance, at the onset of a winter wheat period, only a few days of observations are available within that crop group, making it impossible for MDS to identify a sufficient number of meteorologically similar half-hours within the required window. For these cases, we implemented a fallback that extended the search of similar conditions periods to all years of the dataset while preserving the crop-group consistency. Candidate observations were drawn from the same crop group across the full record and matched using the standard MDS meteorological similarity criteria. The gap-filled value was the arithmetic mean of all retained observations, and a quality flag (fqc = 4–6) was assigned to reflect the level of constraint relaxation, extending the REddyProc flag convention (fqc 0 : measured data, fqc 1–3, gap-filled depending on the availability of meteorological drivers). Of the 363,841 half-hourly timesteps retained in the analysis, 67.0 % corresponded to fqc = 0, 29.4 % to fqc = 1–3, and 3.52 % to fqc = 4–6.

2.3 EC-based C budget

Assuming that all dissolved organic and inorganic carbon in precipitation, runoff, percolation and drainage are negligible, the SOC stock budget of an agricultural field over a specific time interval (t to t') can be written as (Baker and Griffis, 2005; Zhou et al., 2025):

$$NBP = \sum_t^{t'} (NEE - C_{imp} + C_{exp}) \quad (1)$$

with NBP the net biome productivity, C_{imp} the carbon imported (e.g., farmyard manure), C_{exp} the carbon exported (e.g., harvest), all expressed in mass density (kg C m^{-2}). Carbon gain was counted negative and carbon loss positive, following the EC flux sign convention. Since the study period encompasses five full crop rotations, we assumed that residue-derived carbon inputs were considered effectively balanced across the study period and unlikely to introduce systematic bias in the long-term carbon budget estimates.

The time interval from t to t' in Eq. 1 extends from the sowing of one crop to the sowing of the subsequent crop. This sowing-to-sowing definition ensured that most of CO_2 emissions arising from post-harvest crop residue decomposition were attributed to the crop of origin rather than to the following crop, thereby enabling a more robust estimation of the influence of crop species on SOC stock variations. The calculation of the fraction of crop residues that have been decomposed between harvest of the crop and sowing of the next crop will be described in section 2.6.2.

C_{imp} from farming practices consisted in the addition of farmyard manure (FYM), limes (SL) and seeds or mother tubers. FYM was added in 2009 (Rotation 2), 2015 (Rotation 3), 2021 and 2024 (Rotation 5, **Table 1**). C added from FYM ($C_{imp,FYM}$) was calculated as follows:

$$C_{imp,FYM} = FM_{FYM} \cdot [C]_{FYM} \cdot f_{FM2DM} \quad (2)$$



where FM_{FYM} is fresh matter FM of FYM (communicated by the farmer – kg m⁻²), $[C]_{FYM}$ is C content (kg C kg⁻¹ of dry matter DM) and f_{FM2DM} is the conversion factor from FM to DM, which is the inverse of the dry matter content (kg DM kg⁻¹). $[C]_{FYM}$ and f_{FM2DM} were measured in 2009 and 2021. In practice, samples of FYM were collected at three different depths within the heap of manure (3 repetitions) and dried at 65 °C to determine f_{FM2DM} . $[C]_{FYM}$ was measured by dry combustion (ISO 10694:1995). f_{FM2DM} was 0.29 in 2009 and 0.24 ± 0.07 in 2021 (no standard deviation on f_{FM2DM} available in 2009). $[C]_{FYM}$ was 0.33 ± 0.02 and 0.37 ± 0.02 in 2009 and 2021 respectively $[C]_{FYM}$ and f_{FM2DM} were therefore set to 0.35 ± 0.01 and to 0.27 ± 0.07 (average of the two campaigns assuming independent measurements). C added from slimes ($C_{imp,SL}$) was calculated as follows:

$$C_{imp,SL} = m_{SL} \cdot \frac{M_C}{M_{SL}} \quad (3)$$

where m_{SL} is the mass density of slimes added to the cropland (communicated by the farmer – kg m⁻²), M_C is the molar mass of C, and M_{SL} is the molar mass of lime (either CaCO₃ or MgCO₃ – kg mol⁻¹). C imported from sowing ($C_{imp,SE}$) was calculated as follows:

$$C_{imp,SE} = m_{SE} \cdot SD \cdot [C]_{SE} \quad (4)$$

with SD the density of seeds (communicated by the farmer – m⁻²), m_{SE} the mass of seeds (kg) and $[C]_{SE}$ the carbon content of seeds (kg C kg⁻¹ DM). m_{SE} was set to 20 mg (Heimbach, 2018) and $[C]_{SE}$ was set to 45% (Ma et al., 2018). For potato, $C_{imp,SE}$ was calculated from dry matter of mother tubers and C content similarly to exports of C (C_{exp}) as follows:

$$C_{exp} = DM_H \cdot [C]_H \quad (5)$$

with DM_H the dry matter of harvested material (kg m⁻²) and $[C]_H$ the C content (kg C kg⁻¹ DM) of harvested material (being tubers for SP and SB, grains and a variable fraction of straws for WW, grains and straws for MA, grain legumes for GDB). DM_H was obtained after drying fresh matter harvested in an oven at 65°C until constant weight. $[C]_H$ was measured by dry combustion (ISO 10694:1995). Missing measurements of $[C]_H$ were replaced by the average of measurements for similar crops. C_{imp} associated to FYM and SL are shown in **Table 1**. DM_H , $[C]_H$ and SD used to calculate C_{imp} and C_{exp} are provided in **Table A2**. All ancillary data collected at BE-Lon follows ICOS standard protocols (Gielen et al., 2018) and can be found in Dumont et al. (2026b) for the period 2017-2024. For the period 2004-2017, the protocol for ancillary data collection is described in Buysse et al. (2017).



Table 1. Carbon inputs added over the five-rotation period at BE-Lon. FM_{FYM} is fresh matter of farmyard manure (FYM), m_{SL} is the density of slimes (SL) and C_{imp} is the corresponding input of carbon (Eq. 2-4). All uncertainties are cumulative standard deviation.

Date	Rotation	C_{imp} type (FYM/SL)	FM_{FYM} or m_{SL} (kg m ⁻²)	C_{imp} (kg C m ⁻²)
10-09-07	1	SL (CaCO ₃)	0.45	0.05
10-09-07	1	SL (MgCO ₃)	0.02	
20-08-11	2	SL (CaCO ₃)	0.68	0.09
20-08-11	2	SL (MgCO ₃)	0.03	
21-08-15	3	SL (CaCO ₃)	0.45	0.05
21-08-15	3	SL (MgCO ₃)	0.02	
07-08-19	4	SL (CaCO ₃)	0.45	0.05
07-08-19	4	SL (MgCO ₃)	0.02	
26-08-09	2	FYM	2.80	0.27 ± 0.03
17-08-15	3	FYM	5.0	0.44 ± 0.14
10-06-21	5	FYM	3.93	0.35 ± 0.11
22-08-24	5	FYM	3.31	0.29 ± 0.09

215 2.4 Uncertainty on EC-based C budget

The half-hourly uncertainty on NBP ($\sigma_{NBP,30}$) was calculated as the square root of the sum of squares of all individual half-hourly uncertainties on NEE ($\sigma_{NEE,30}$), C_{imp} ($\sigma_{C_{imp},30}$) and C_{exp} ($\sigma_{C_{exp},30}$) as:

$$\sigma_{NBP,30} = \sqrt{(\sigma_{NEE,30})^2 + (\sigma_{C_{imp},30})^2 + (\sigma_{C_{exp},30})^2} \quad (6)$$



Eq. 6 explicitly considers that the covariance between all uncertainties is negligible, that is, errors are assumed independent.

220 $\sigma_{NEE,30}$ was calculated as the combination of uncertainties related to the low turbulence filtering procedure ($\sigma_{NEE,u^*,30}$), to the spectral correction procedure ($\sigma_{NEE,spcorr,30}$) and to the random error in NEE measurement ($\sigma_{NEE,meas,30}$) (Aubinet et al., 2012). As the MDS approach generally yields results comparable to alternative methods (Teng et al., 2020; Zhao and Huang, 2015), particularly at sites below 60°N and in the absence of prolonged data gaps (Vekuri et al., 2023, 2025), the uncertainty in gap-filling was neglected in the analysis. Eq. 6 then becomes:

$$225 \quad \sigma_{NBP,30} = \sqrt{(\sigma_{NEE,meas,30})^2 + (\sigma_{NEE,u^*,30})^2 + (\sigma_{NEE,spcorr,30})^2 + (\sigma_{C_{imp},30})^2 + (\sigma_{C_{exp},30})^2} \quad (7)$$

The calculation of each term of Eq. 7 and the propagation of uncertainty over long-term budgets is described below.

2.4.1 Uncertainty on lateral C fluxes

$\sigma_{C_{imp},30}$ and $\sigma_{C_{exp},30}$ were calculated using Eq. 2-5 and the Gaussian error propagation (Ku, 1966), giving for C_{exp} as an example :

$$230 \quad \sigma_{C_{exp},30} = \sqrt{([C]_H \cdot \sigma_{DM_H})^2 + (DM_H \cdot \sigma_{[C]_H})^2} \quad (8)$$

For $\sigma_{C_{imp},30}$, no standard deviations on FM_{FYM} (Eq. 2) and m_{SL} (Eq. 3) were available. The uncertainty on FM_{FYM} was set to $\pm 10\%$ to account for optimistic typical field-scale deviations caused by variations in manure density, volume estimation, and spreader calibration (Thirion and Chabot, 2003). These uncertainties were attributed to the median half-hour of the day (i.e., 12h GMT+1) when measurements were performed.

235

2.4.2 Uncertainty on NEE

$\sigma_{NEE,u^*,30}$ was calculated as (Pastorello et al., 2020) :

$$\sigma_{NEE,u^*,30} = \frac{NEE_{U84_f} - NEE_{U16_f}}{2} \quad (9)$$

240 where NEE_{U84_f} and NEE_{U16_f} are respectively the half-hourly gap-filled NEE after applying a u^* threshold corresponding to the 84th and 16th percentile of the threshold distribution within a sowing-to-harvest period (see section 2.2).

$\sigma_{NEE,meas,30}$ was calculated as the standard deviation of the measured NEE fluxes following the method described in Hollinger and Richardson (2005).

245 $\sigma_{NEE,spcorr,30}$ corresponds to the total uncertainty related to the spectral correction applied on CO₂ flux measurements, which consists of two components: (i) one related to the cut-off frequency resulting from the fitting of the Lorentzian function, referred to as the transfer function uncertainty σ_{tf} , and (ii) one related to the aggregation of correction factors within wind speed and stability classes, referred to as the spectral class uncertainty σ_{cl} . σ_{tf} corresponds to the square root of the diagonal of the covariance matrix associated with the fitted Lorentzian parameters, while σ_{cl} was calculated as the standard deviation



of the population of correction factors CF for a given wind speed and stability class within a spectral correction period. These two uncertainty sources are physically independent: σ_{tf} depends solely on the uncertainty in the cut-off frequency f_c derived from the Lorentzian fitting procedure, while σ_{cl} reflects the residual variability of individual correction factors within each class, which can be attributed to other factors such as like crop height or wind direction.

2.4.3 Propagation of uncertainties

The general framework of uncertainty propagation posits that systematic errors accumulate linearly and random errors accumulate in quadrature (Richardson et al., 2012). Therefore, the cumulative uncertainty on NEE and ultimately on NBP strongly depends on the categorization of each uncertainty term as systematic or random.

For $\sigma_{NEE,spcorr,30}$, we considered each spectral correction period as an independent correction unit, within which we applied a nested error structure reflecting the nature of the spectral correction procedure. Within each wind speed – stability class combination (k) for a given spectral correction period, since $\sigma_{tf,k}$ originates from a single cut-off frequency estimate derived from the Lorentzian fitting procedure and applied identically to all half-hours of class k , it was treated as systematic and propagated linearly over the cumulated NEE of the class (Richardson et al., 2012). The uncertainty on NEE related to the cut-off frequency for each class ($\sigma_{NEE,tf,k}$) was therefore calculated as:

$$\sigma_{NEE,tf,k} = \sigma_{tf,k} \cdot \sum_{t \in k} |NEE_t| \quad (10)$$

In contrast, $\sigma_{NEE,cl,k}$ was treated as random, assuming that variability of co-spectra within a wind speed – stability class is uncorrelated between half-hours, and was therefore propagated quadratically:

$$\sigma_{NEE,cl,k} = \sigma_{cl,k} \cdot \sqrt{\sum_{t \in k} (NEE_t)^2} \quad (11)$$

The composite uncertainty for each class k was then obtained by combining these two independent contributions quadratically:

$$\sigma_{NEE,spcorr,k} = \sqrt{(\sigma_{NEE,cl,k})^2 + (\sigma_{NEE,tf,k})^2} \quad (12)$$

Since wind speed – stability classes capture distinct turbulent regimes, their associated errors can be considered independent across classes. The total standard deviation on cumulated NEE within a spectral correction period p containing n_k wind speed classes was therefore obtained as the square root of the sum of squares of class-level contributions:

$$\sigma_{NEE,spcorr,p} = \sqrt{\sum_{k=1}^{n_k} (\sigma_{NEE,spcorr,k})^2} \quad (13)$$

For simplicity, the class-level uncertainty $\sigma_{NEE,k}$ was redistributed to each half-hour in proportion to its absolute NEE value, normalized by the root-sum-of-squares of NEE within the class. This provides an estimate of the half-hourly uncertainty in



NEE due to the spectral correction procedure ($\sigma_{NEE,spcorr,30}$). This redistribution enables that the quadratic sum of half-hourly
275 uncertainties exactly recovers $\sigma_{NEE,spcorr,k}$, and by extension $\sigma_{NEE,spcorr,p}$ at every aggregation level.

A very similar approach was applied to the uncertainty on u^* threshold determination. Since a single u^* threshold is applied
uniformly to all half-hours within a given crop season, this uncertainty is systematic in nature within each season. Accordingly,
errors were accumulated linearly within each season to yield a seasonal u^* uncertainty. Since crop seasons are determined
independently and their respective thresholds are estimated from non-overlapping datasets, seasonal uncertainties are treated
280 as independent and combined in quadrature across seasons. Half-hourly values were then redistributed from the seasonal
budget in proportion to their individual contribution, preserving quadratic consistency with the total uncertainty related to u^*
threshold procedure, and giving $\sigma_{NEE,u^*,30}$. $\sigma_{NBP,30}$ calculated using Eq. 7 was then propagated in quadrature over a specified
period (d) following:

$$\sigma_{NBP,d} = \sqrt{\sum_{t \in d} (\sigma_{NBP,30,t})^2} \quad (14)$$

285 where t is the number of half-hourly data within the corresponding time window d . As the covariance was neglected, the
reported NBP uncertainty should therefore be considered as a higher bound on the true uncertainty.

2.5 Soil inventories

Soil samples were collected in 2007 and 2017. In 2007, the sampling scheme corresponding to a systematic grid covered a
rectangular area of 0.6 hectares around the EC flux tower (Rodeghiero et al., 2010; Schrumpf et al., 2011). The 61 cores
290 extracted at the node of the sampling grid were each divided into 2–3 pedogenetic horizons, reaching a mean maximum depth
of 60 cm. In 2017, the sampling scheme covered the entire cropland area (14 ha), which corresponded to a stratified random
sampling where the sampling domain was divided into six strata of equal area. 20 sample locations were selected from the
sampling domain from which 100 samples were extracted over 5 depths (0–5, 5–15, 15–30, 30–60, 60–100 cm) following ICOS
protocols (Arrouays et al., 2018). As the carbonate content was below 0.70 g C inorganic kg^{-1} (0.34, 0.36, 0.47 g C inorganic
295 kg^{-1} over 0–5, 5–15 and 15–30 cm, **Table A1**), SOC concentration was calculated as the difference between total and carbonate
concentration (Arrouays et al., 2018). In 2007, no information on carbonate concentration was available. Since the soil is
classified as Stagnic Luvisoil (Mantel et al., 2023) developed under leaching conditions and inherently non-calcareous;
carbonate contents are therefore negligible, and total carbon is taken as equivalent to SOC for the 2007 campaign.

SOC stocks were computed on an equivalent soil mass basis (ESM; Lee et al., 2009) using the simpleESM R script (Ferchaud
300 et al., 2023) with reference soil masses of 384 and 436 Mg ha^{-1} in ~0–30 cm and ~30–60 cm layers. The mean and standard
deviation of SOC stocks over these layers were then computed using a design-based approach (Loustau et al., 2017). Because
the soil was relatively homogeneous, a reduced dataset was reconstructed by selecting spatially co-located sampling points
from 2007 and 2017 to ensure a reliable comparison between the two datasets (**Fig. A1**) (Loubet et al., 2026). Differences in
SOC stocks over the ~0–30 cm and ~30–60 cm layers between 2007 and 2017 within the reduced area were quantified using



305 Hedges' g effect size estimates, allowing to correct standardized mean difference for small-sample bias (Hedges, 1981). Confidence intervals on Hedges' g were obtained using 10,000 nonparametric bootstrap resamples and estimated with the bias-corrected and accelerated method (Kirby and Gerlanc, 2013). More information on the statistical analysis on SOC stock comparison can be found in Loubet et al. (2026).

2.6 Process-based modelling of SOC

310 2.6.1 The RothC model

The RothC model (Coleman and Jenkinson, 1996) was used to simulate SOC stock changes in the topsoil (i.e., over 0-23 cm, as the model was calibrated and validated in this soil layer) between 2004 and 2024. RothC divides SOC into five conceptual pools: decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), humified organic matter (HUM) and inert organic matter (IOM) pools. SOC stock depletion within each pool are influenced by rate modifying factors which depend on climate conditions, land use and pool characteristics (Coleman and Jenkinson, 1996). RothC requires the following inputs: initial SOC stock, precipitation, open-pan evaporation, air temperature, clay content, decomposability of incoming plant material (expressed as the DPM/RPM ratio and set to 1.44 for croplands), soil cover (either 0.6 for vegetated soil or 1.0 for bare soil) and C inputs from farmyard manure and plant biomass (in kg C m^{-2}). The latter includes all plant material returned during the cultivation period, including both above ground biomass as crop residues and belowground biomass as C exudates or unharvested root biomass. In practice, fractions of carbon returned to the soil as belowground biomass (BGB) were estimated from the sum of plant carbon in root tissues (C_R) and root exudates (C_E) (Bolinder et al., 2007):

$$C_{BGB} = C_R + C_E \quad (15)$$

where C_E represents 65% of C_R (Bolinder et al., 2007). For silage maize and winter wheat, C_R was estimated from carbon exported from the main agricultural product (C_P), shoot-to-root ratio ($S:R$) and harvest index (HI) (Bolinder et al., 2007; Keel et al., 2017):

$$C_R = \frac{C_P}{S:R \cdot HI} \quad (16)$$

HI was calculated from the ratio of harvested grain to total biomass harvested and $S:R$ was quantified during a 2022 pre-harvest field campaign on winter wheat. Measurements were conducted at four randomly selected locations across the cropland, following established protocols for both shoot biomass (Gielen et al., 2018) and root biomass (Frasier et al., 2016; Noordwijk et al., 1985). Root biomass was measured by collecting soil samples at six depth intervals within the 0-100 cm layer using hand augers. Roots were separated from soil using a saline solution (NaCl), followed by sieving (2 mm, 1 mm and 0.5 mm). The samples were then dried at 65°C until constant weight was achieved. Total root biomass was calculated by normalizing root weight by the soil sampling area across the entire soil profile. Shoot biomass was determined by harvesting 5 randomly selected plants at each sampling location. All aboveground organs were dried at 65°C until reaching constant weight. Final shoot biomass was calculated as the ratio of dry organ weight to the sampled soil surface area. $S:R$ was 12.3 which in the upper end of the values reported by Bolinder et al. (2007). $S:R$ for silage maize was assumed to be equivalent to



that of winter wheat (Bolinder et al., 2007). For the other crops, Bolinder coefficients were used to determine C_R and C_E from yield or from crushed aboveground biomass for cover crops (Bolinder et al., 2007). C_{BGB} was rescaled to 23 cm to match RothC layers definition (Dechow et al., 2019; Keel et al., 2017).

340 2.6.2 Initialization and simulation phases

Reactive carbon pools in RothC were initialized as a function of clay content and initial SOC stock (Falloon et al., 1998; Morais et al., 2019; Weihermüller et al., 2013). The initial SOC stock in 2004 was set to the 2007 inventory measurement, since significant changes in SOC stocks are generally detectable only after at least 10 years (Schrumpf et al., 2011; Smith, 2004). All model parameters were chosen accordingly to the original version of RothC (Coleman and Jenkinson, 1996). The
345 decomposition rate constants related to pool characteristics were not modified (10 year⁻¹ for DPM, 0.3 year⁻¹ for RPM, 0.66 year⁻¹ for BIO and 0.02 year⁻¹ for HUM). The model was then run between 2004 and 2024 using observed meteorological data, C inputs from plant biomass and from FYM. Potential evapotranspiration was calculated using the FAO Penman-Monteith equation (Allen, 1998; Cai et al., 2007) based on wind speed, vapor pressure deficit, and net radiation. Open-pan evapotranspiration was calculated by dividing potential evapotranspiration by 0.75 (Coleman and Jenkinson, 1996). For winter
350 wheat, maize and cover crops, carbon inputs were calculated as the sum of measured aboveground crop residues after harvest (Table A3) and estimated belowground biomass (C_{BGB} – Eq. 15). For tuber crops, measured harvest residues were selected as carbon inputs. For each simulated month, the difference between the initial SOC stock was calculated (ΔSOC_{RothC}).

To draw meaningful conclusions regarding the influence of crop species on SOC stock variations over the sowing-to-sowing crop period, a large fraction of crop residues must be mineralized within the defined interval. To verify this condition, we
355 calculated the fraction of C input allocated to the DPM pool in RothC (C_{DPM}) that was mineralized (f_{DPM}) over the sowing-to-sowing period (from t to t') as follows:

$$f_{DPM} = 1 - \frac{C_{DPM}(t')}{C_{DPM}(t)} = 1 - e^{-k_{DPM} \sum \xi_i} \quad (17)$$

where ξ_i is the product of RothC rate modifiers for temperature, soil moisture and soil cover respectively calculated at time t , and k_{DPM} is the decomposition rate constant of the DPM pool (10 yr⁻¹ = 0.83 month⁻¹). i denotes the number of months within
360 a period. Since RPM, BIO and HUM have substantially lower decomposition rates, their variation of SOC stocks over a sowing-to-sowing interval remains negligible. Therefore, DPM constitutes the only source of bias that might influence the significance of C budget of each sowing-to-sowing periods. For periods where f_{DPM} was low, the C balance remained open at the end of the period — a substantial fraction of fresh organic inputs had not yet been mineralized. In such cases, both NBP and ΔSOC_{RothC} underestimated the true C loss, and the sink or source classification should be interpreted with caution. A
365 threshold of $f_{DPM} > 70\%$ was considered to have a sufficiently closed C budget for reliable assessment of the sink or source strength of the crop period, as less than 30% of fresh DPM inputs remained undecomposed at the end of the accounting period.



2.7 Uncertainty on RothC simulations

Monte Carlo (MC) simulations represents a powerful probabilistic framework for quantifying the uncertainties related to inputs, parameters, model structure, and initial conditions (Pierson et al., 2022). MC methodology was applied to RothC by propagating uncertainties through the model via repeated random sampling in probability distribution over 10 000 simulations (Stamati et al., 2013). The process notably involves selecting the range and probability distributions of selected factors, generating random samples, running the model for each sample, and then conducting uncertainty analysis (Saltelli et al., 2000). Since all model inputs were obtained from measurements, statistical distributions of inputs were defined based on a Gaussian distribution ranging from one measured standard deviation on each side of the mean. Finally, statistical distributions of RothC parameters (decomposition rates, temperature and bare soil moisture deficit rate modifiers) were also defined based on a Gaussian distribution but within a 10 % margin, which is a typical approach when uncertainty around parameters is not known (Delhez et al., 2025). For each MC simulation, the monthly total SOC and the corresponding difference with initial SOC were calculated. All monthly predictions are then pooled to derive typical statistical parameters such as the mean, standard deviation and 95% confidence bounds. RothC was run in R using the SoilR package (Sierra et al., 2012).

2.8 Comparison between NBP and SOC stocks simulated by RothC

Unlike inventories, which measure changes in SOC stock between two discrete sampling campaigns, NBP and $\Delta\text{SOC}_{\text{RothC}}$ provide continuous estimates of SOC stock variations. However, the two methods rely on fundamentally different principles: NBP integrates NEE, capturing the net CO_2 exchange between vegetation and the atmosphere, and thus directly reflecting crop carbon sequestration after accounting for autotrophic and heterotrophic respiration. In contrast, RothC does not simulate plant uptake explicitly; instead, it requires estimated carbon inputs and focuses on the decomposition and turnover of organic matter within the soil. Therefore, the comparison between NBP and $\Delta\text{SOC}_{\text{RothC}}$ consisted in two parts: first comparing their dynamics to identify systematic trends or biases over the five-rotation period, and second, the calculation of variations of NBP and $\Delta\text{SOC}_{\text{RothC}}$ over individual sowing-to-sowing periods. In particular, the net change in each variable was computed as the difference between cumulative values at the end and beginning of the period.

As RothC operates at a monthly time step while EC measurements are provided at half-hourly resolution, NBP and its associated uncertainty were aggregated to a monthly basis prior to comparison. For each sowing-to-sowing period, cumulative NBP was extracted at the exact day of transition between consecutive periods within the month, thereby capturing the net carbon exchange integrated over the sowing-to-sowing periods, including post-harvest residue mineralization. Because both NBP and $\Delta\text{SOC}_{\text{RothC}}$ time series carry correlated uncertainties (each monthly value inheriting the accumulated error of all preceding timesteps) the variance of the difference between the two stocks $\Delta S = S(t) - S(t_0)$ reduces to $\sigma^2(\Delta S) = \sigma^2(S_t) - \sigma^2(S_{t_0})$. The resulting standard deviation $\sigma(\Delta S)$ was used as the uncertainty estimate for each period. The average difference between NBP and $\Delta\text{SOC}_{\text{RothC}}$ variations was calculated within each period to quantify agreement between the two estimates. This comparison helps determine whether both methods converge on the same source–sink pattern for a given crop period,



provided that the underlying f_{DPM} estimate meets the 70% robustness criterion. RothC simulations and soil inventories
400 followed the same sign convention as NBP, in which carbon gains were considered negative and carbon losses positive.

3 Results

3.1 Eddy covariance-based carbon budget

Winter wheat was the crop with the longest cumulative cultivation period over the five-rotation period for a total of 129.1
months, followed by cover crop (53.8 months), sugar beet (32.2 months), potato (28.8 months), maize (5.46 months) and green
405 dwarf bean (3.13 months). Carbon exports were highest for winter wheat ($5.49 \pm 0.13 \text{ kg C m}^{-2}$), followed by sugar beet (3.64 ± 0.22), seed potato (1.55 ± 0.01), maize (0.78 ± 0.01), and green dwarf bean (0.04 ± 0.00) (Table 2; Fig. 2).

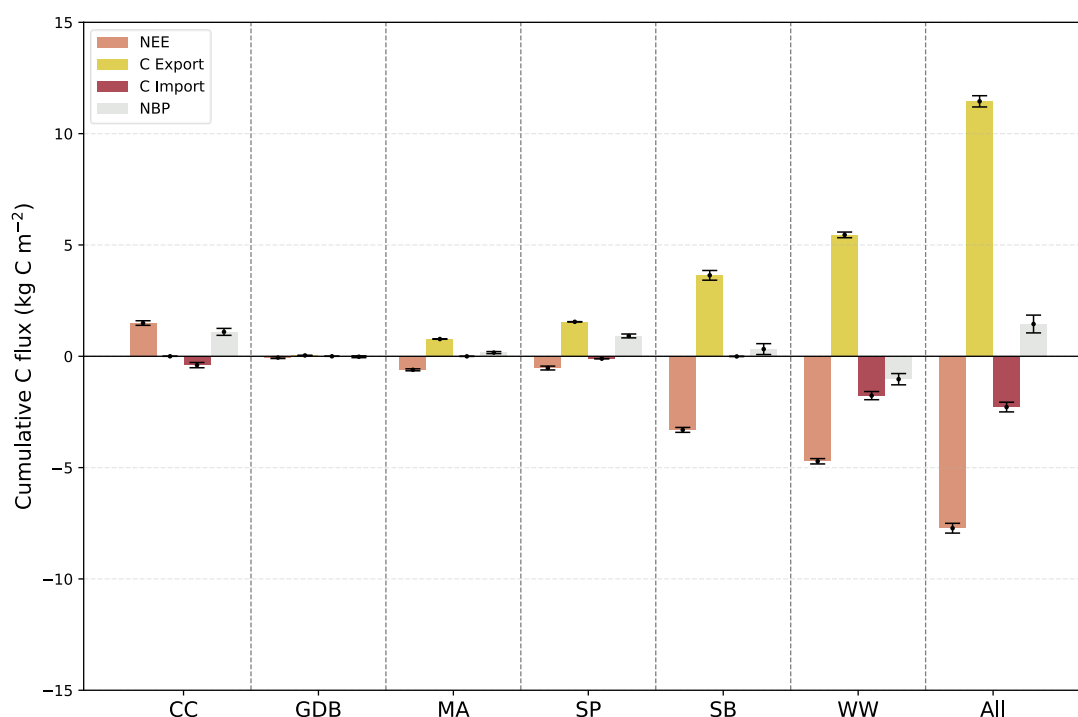


Figure 2. Cumulative net ecosystem exchange (NEE), exports of carbon (C_{exp}), imports of carbon (C_{imp}) and net biome production (NBP) for each crop over the five-rotation period. The error bars on the bar plots show cumulative standard deviations on each budget term. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean.



Farmyard manure was the main external
 410 carbon input across the study period, with
 applications restricted to rotations 2, 3 and
 5 (**Table 2**). Cumulative NEE differed
 markedly among crops: it was strongly
 negative (i.e. net C uptake) under winter
 415 wheat and sugar beet, near zero under
 potato, silage maize and green dwarf bean,
 and positive (net C release) under the cover
 crop (**Table 2**). As manure application
 occurred after winter wheat harvest in 2009,
 420 2015 and 2024 and after cover crop
 crushing in 2021 (**Fig. 1; Table 1**), the NBP
 of these crops was therefore reduced (**Table**
A3). In particular, the NBP of winter wheat
 was negative ($-1.02 \pm 0.25 \text{ kg C m}^{-2}$) while
 425 other crops exhibited NBP values ranging
 from near equilibrium to a moderate carbon
 source (**Fig. 2; Table 2**). Positive NBP
 values were observed for maize ($0.16 \pm$
 0.05 kg C m^{-2}), potato ($0.91 \pm 0.09 \text{ kg C}$
 430 m^{-2}), sugar beet ($0.32 \pm 0.24 \text{ kg C m}^{-2}$) and
 cover crops ($1.10 \pm 0.16 \text{ kg C m}^{-2}$) whereas
 NBP of green dwarf bean ($-0.02 \pm 0.04 \text{ kg}$
 C m^{-2}) did not differ significantly from zero
 (**Table 2**).
 435 Over the five rotations (252 months), 11.5
 $\pm 0.25 \text{ kg C m}^{-2}$ were exported at harvest
 while $-7.72 \pm 0.22 \text{ kg C m}^{-2}$ was
 sequestered by vegetation and -2.28 ± 0.21
 kg C m^{-2} was added as FYM, slimes, seeds
 440 and mother tubers, giving a total NBP of
 $1.45 \pm 0.40 \text{ kg C m}^{-2}$ (**Table 1; Table 2**). It
 corresponds to a yearly loss of 69.8 ± 19.2

Table 2. Cumulative values of net ecosystem exchange (NEE), imports of carbon (C_{imp}), exports of carbon at harvest (C_{exp}), net biome production (NBP) for each rotation and each crop over the five-rotation period. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean. Crops are mentioned with the corresponding year. All uncertainties are cumulative standard deviation.

	<i>NEE</i> (kg C m ⁻²)	<i>C_{imp}</i> (kg C m ⁻²)	<i>C_{exp}</i> (kg C m ⁻²)	<i>NBP</i> (kg C m ⁻²)
Total per rotation				
Rot. 1	-1.77 ± 0.08	-0.18 ± 0.00	2.08 ± 0.08	0.13 ± 0.11
Rot. 2	-1.76 ± 0.12	-0.48 ± 0.03	2.37 ± 0.14	0.13 ± 0.19
Rot. 3	-1.31 ± 0.07	-0.60 ± 0.14	2.27 ± 0.05	0.35 ± 0.17
Rot. 4	-1.50 ± 0.07	-0.20 ± 0.00	2.40 ± 0.12	0.70 ± 0.13
Rot. 5	-1.38 ± 0.14	-0.81 ± 0.15	2.33 ± 0.15	0.14 ± 0.25
Total per crop				
WW	-4.72 ± 0.12	-1.77 ± 0.18	5.45 ± 0.13	-1.02 ± 0.26
SB	-3.30 ± 0.11	-0.01	3.64 ± 0.22	0.32 ± 0.24
SP	-0.53 ± 0.09	-0.11	1.55 ± 0.01	0.91 ± 0.09
CC	1.49 ± 0.10	-0.40 ± 0.12	-	1.09 ± 0.15
MA	-0.61 ± 0.04	-0.00	0.78 ± 0.01	0.17 ± 0.05
GDB	-0.06 ± 0.05	-0.05	0.04 ± 0.00	-0.02 ± 0.05
Total	-7.72 ± 0.22	-2.28 ± 0.22	11.45 ± 0.25	1.45 ± 0.40



gC m⁻² on average. The uncertainty in NBP was distributed relatively evenly across all components of the carbon budget. The cumulative $\sigma_{C_{imp}}$ and $\sigma_{C_{exp}}$ were 0.25 kg C m⁻² and 0.21 kg C m⁻², respectively. The uncertainty on cumulative related to u* filtering (σ_{NEE,u^*}) reached 0.17 kg C m⁻² while $\sigma_{NEE,spcorr}$ amounted to 0.13 kg C m⁻², leading to σ_{NEE} of 0.22 kg C m⁻² (Table 2).

NBP was the highest for Rotation 4, which is explained by the highest exports of C in the five-rotation period (Fig. 3, Table 2). Despite no cover crops being grown and no manure being applied, rotation 1 had a NBP which remained close to equilibrium (Fig. 3, Table 2). Compared to Rotation 1, Rotation 2 received an additional 0.30 kg C m⁻² of C inputs via manure (Fig. 3, Table 2). As explained in Section 2.1, three months of bare soil following cover crop crushing were not included in Rotation 5 between January and April 2025, which would have slightly increased the NBP due to heterotrophic soil respiration. Other rotations showed higher positive NBP trends despite manure applications in 2009 and 2015 (Fig. 3). Overall, the persistent positive trend across the observation period indicates a long-term carbon source pattern. Cumulative carbon fluxes for each crop-period are given in Table A3.

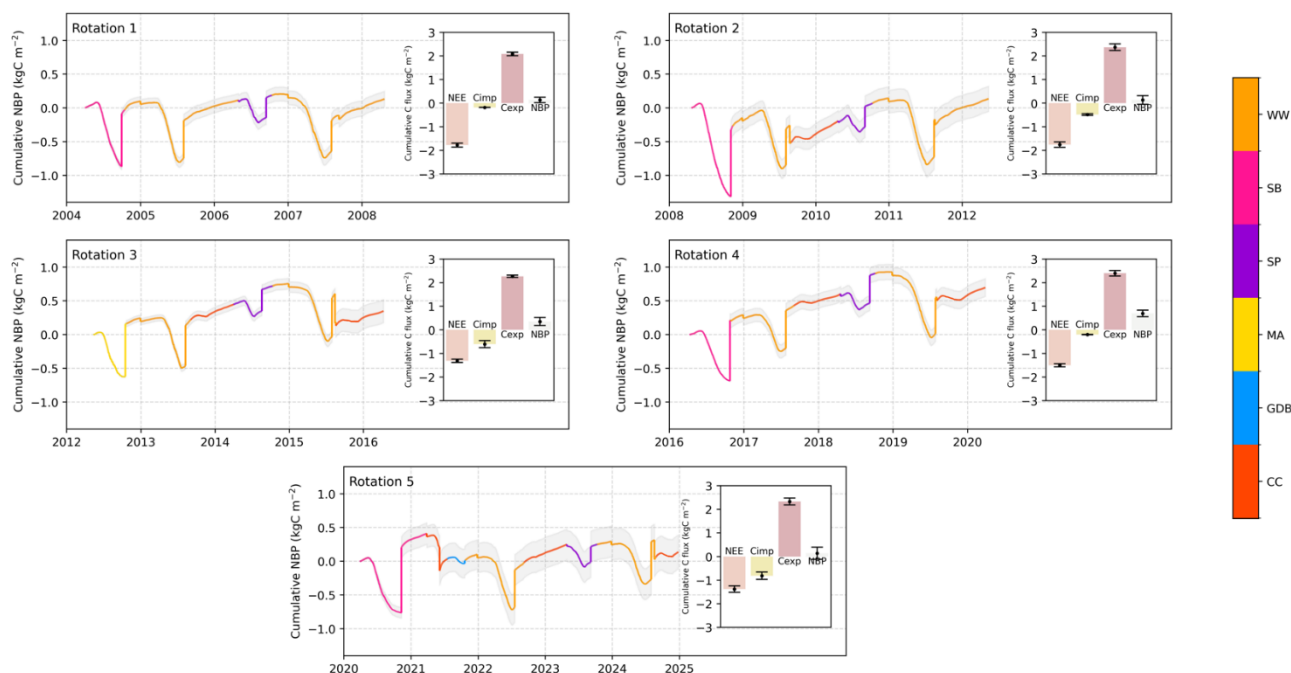


Figure 3. Cumulative net ecosystem exchange (NEE), exports of carbon (C_{exp}), imports of carbon (C_{imp}) and net biome production (NBP) for each rotation over the five-rotation period. The shaded curve represents the cumulative sum of standard deviation on NBP (σ_{NBP}) over each rotation. The error bars on the bar plots show cumulative standard deviations on NEE, C_{imp} and C_{exp} , calculated using Eq. 14-16. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean.



3.2 Comparison between RothC simulations, NBP and inventories

The fraction of DPM mineralized (f_{DPM}) calculated from RothC SOC stock simulations, varied widely across crop-periods (Table 3). As C inputs in RothC are attributed to the harvest month and the three preceding months, f_{DPM} was driven primarily by the length of the harvest-to-sowing period and the corresponding meteorological conditions (Table 3).

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Table 3. Harvest-to-sowing intervals and fraction of mineralization of the DPM pool (f_{DPM}). Bold text for Total C input highlight the application of farmyard manure. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean.

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Crop	Harvest-to-sowing interval (month)	f_{DPM} (%)	Crop	Harvest-to-sowing interval (month)	f_{DPM} (%)
SB 04	0.49	65.54	CC 19-20	3.94	77.53
SB 08	0.3	12.14	CC 21	1.45	68.59
SB 16	0.07	3.16	CC 22-23	5.52	94.87
SB 20-21	4.57	79.3	CC 24	3.65	31.76
SP 06	0.92	24.63	WW 04-06	8.90	95.24
SP 10	1.31	35.98	WW 06-08	8.57	99.81
SP 14	1.77	95.19	WW 08-09	0.82	21.59
SP 18	0.95	17.84	WW 10-12	8.94	96.02
SP 23	1.15	73.84	WW 12-13	0.79	69.62
MA 12	0.39	21.62	WW 14-15	0.62	23.56
GDB 21	0.13	5.88	WW 16-17	1.28	49.01
CC 09-10	4.73	78.17	WW 18-19	0.26	34.39
CC 13-14	4.63	83.34	WW 21-22	1.68	86.69
CC 15-16	4.17	83.72	WW 23-24	0.85	32.42
CC 17-18	4.50	76.78			



Cover crop periods consistently showed high f_{DPM} , as residues were crushed in winter under conditions favorable to early-
490 spring mineralization, except for 2024 due to the truncation of the study period on 31 December. Similarly, winter wheat
periods without cover crops (2004–2006, 2006–2008, 2010–2012) yielded harvest-to-sowing interval exceeding 8 months
and $f_{DPM} > 90\%$. Conversely, short harvest-to-sowing interval associated with winter wheat (2008–2009, 2014–2015, 2018–
2019, 2023–2024), maize (2012), sugar beet (2016), seed potato (2018) and green dwarf bean (2021) resulted in markedly
lower mineralized fractions (**Table 3**). Interestingly, when the short winter wheat harvest-to-sowing intervals of 2008–2009,
495 2014–2015, and 2018–2019 were combined with their immediately following cover crop periods to form full rotation
sequences, the duration-weighted fraction of mineralized DPM increased substantially, reaching 69.8%, 75.9%, and 74.9%,
respectively — all exceeding the 70% robustness threshold (data not shown). The exception was the 2023–2024 sequence
(31.9%), for which the cover crop period itself remained largely incomplete at the time of analysis, preventing the identification
of the source or sink trend of the period. Taken together, these results demonstrate that the WW–CC sequence consistently
500 achieves a high f_{DPM} , ensuring that only a small residual pool of labile C remains at the onset of the next cropping period. This,
in turn, strengthens the reliability of the NBP and RothC simulated carbon balance, as the sink or source status of the crop-
period is not confounded by undecomposed DPM across interval boundaries. Note that regrouping winter wheat and cover
crops in the EC-based budget would have led to a NBP of $0.07 \pm 0.30 \text{ kg C m}^{-2}$ for the combined sequence, suggesting near-
equilibrium. Overall, f_{DPM} was strongly and positively correlated with harvest-to-sowing interval length across all crop-
505 periods (Pearson $r = 0.74$, $p < 0.001$), confirming that interval duration is the primary control on DPM mineralization at BE-
Lon. No significant additional effect of harvest timing was detected after controlling for interval length (partial $r = -0.16$, $p =$
 0.42).

RothC simulations yielded a final ΔSOC of $-0.39 \pm 0.63 \text{ kg C m}^{-2}$ over the five-rotation period (**Fig. 4**). The large standard
deviation reflects an uncertain carbon balance, ranging from moderate sink to source. Increase in $\Delta\text{SOC}_{\text{RothC}}$ stocks occurred
510 either due to manure application or during the three months preceding and including the harvest month due to crop residues
and root exudates (**Fig. 4**). On the other hand, positive $\Delta\text{SOC}_{\text{RothC}}$ (i.e., decrease in SOC stocks) notably occurred after harvest,
where CO_2 emissions were solely driven by heterotrophic respiration resulting from crop residues (**Fig. 4**).

Cumulative SOC stocks over the ~0–60 cm profile (820 kg m^{-2} of fine earth), derived from inventories on an equivalent soil
mass basis, were $5.99 \pm 0.14 \text{ kg C m}^{-2}$ in 2007 and $5.93 \pm 0.22 \text{ kg C m}^{-2}$ in 2017. Corresponding stocks in the topsoil (~0–30
515 cm) were $3.81 \pm 0.38 \text{ kg C m}^{-2}$ and $3.79 \pm 0.21 \text{ kg C m}^{-2}$, respectively, while subsoil (~30–60 cm) stocks were $2.18 \pm 0.48 \text{ kg}$
 C m^{-2} and $2.17 \pm 0.28 \text{ kg C m}^{-2}$, respectively. The magnitude of change between the two inventories ($\Delta\text{SOC}_{\text{inv}}$) was negligible,
as indicated by Hedges' g values overlapping zero for both layers (topsoil: -0.05 , with a 95% CI from -0.45 to 0.40 ; subsoil: $-$
 0.02 , with a 95% CI from -0.38 to 0.43). Therefore, $\Delta\text{SOC}_{\text{inv}}$ was not significantly different from 0 over the period 2007–2017.
 $\Delta\text{SOC}_{\text{RothC}}$ in 2017 ($-0.28 \pm 0.48 \text{ kg C m}^{-2}$) was of similar magnitude to the inventory change, whereas NBP over the same
520 period was higher than 1.0 kg C m^{-2} (**Fig. 4**).

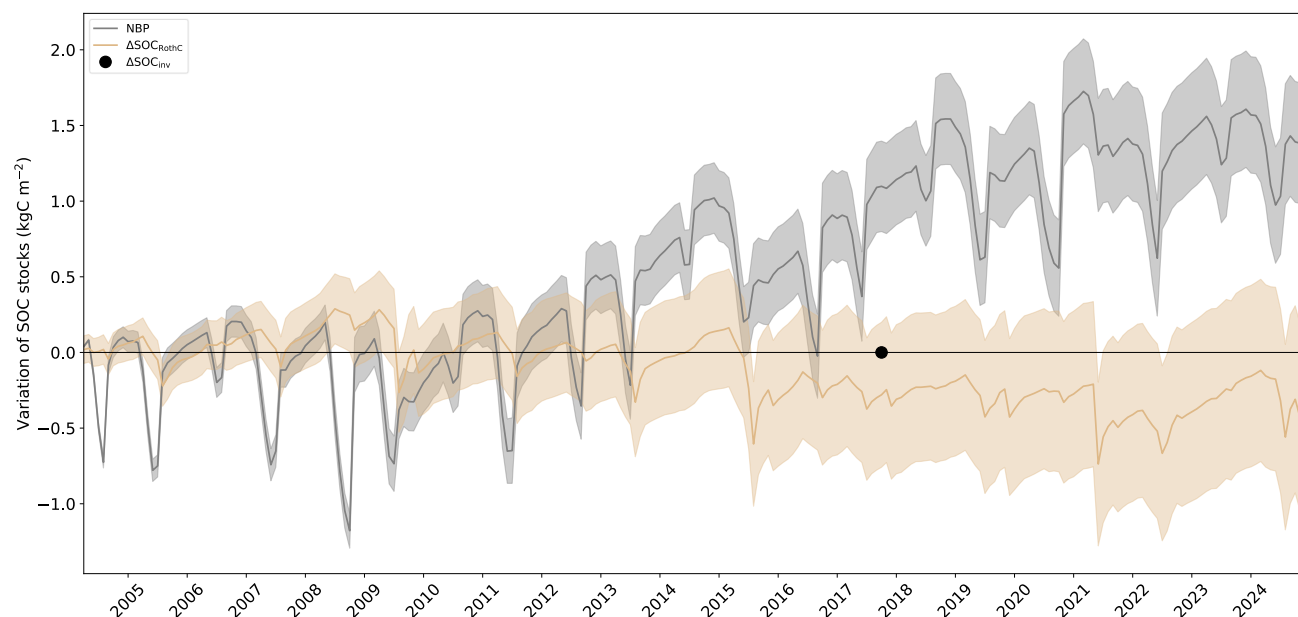


Figure 4. Cumulative net biome production (NBP), simulation of SOC stock variation by RothC ($\Delta\text{SOC}_{\text{RothC}}$). Vertical lines indicate farmyard manure application. The shaded curves represent the cumulative sum of standard deviation over the study period. The black circle indicates the difference between the SOC stocks measured in 2007 and 2017 ($\Delta\text{SOC}_{\text{inv}}$). Note that the grey curve corresponds to the cumulated NBP per month, which leads to a monthly aggregation of events (e.g., FYM and harvest if occurring the same month).

By the end of the five-rotation period, the discrepancy between $\Delta\text{SOC}_{\text{RothC}}$ and NBP reached $1.84 \pm 0.74 \text{ kg C m}^{-2}$. The comparison between variations of NBP and $\Delta\text{SOC}_{\text{RothC}}$ for each crop periods showed a systematic positive discrepancy between the two variables as highlighted by the positive mean difference for maize, seed potato and winter wheat with respectively $0.24 \pm 0.03 \text{ kg C m}^{-2} \text{ period}^{-1}$, $0.12 \pm 0.01 \text{ kg C m}^{-2} \text{ period}^{-1}$, and $0.16 \pm 0.03 \text{ kg C m}^{-2} \text{ period}^{-1}$ (**Fig. 5**). For sugar beet, the mean difference was $0.07 \pm 0.06 \text{ kg C m}^{-2} \text{ period}^{-1}$, which was strongly influenced by the year 2008 with a negative NBP of $-0.27 \pm 0.14 \text{ kg C m}^{-2}$ while $\Delta\text{SOC}_{\text{RothC}}$ was close to zero (**Fig. 5, Table A3**). In particular, the cumulative NEE for this crop over the active vegetation period in 2008 (from sowing to harvest) was $-1.26 \pm 0.03 \text{ kg C m}^{-2}$, which was 36%, 85%, and 129% higher in absolute value than in 2004 ($-0.81 \pm 0.05 \text{ kg C m}^{-2}$), 2016 ($-0.68 \pm 0.02 \text{ kg C m}^{-2}$), and 2021 ($-0.55 \pm 0.08 \text{ kg C m}^{-2}$), respectively (data not shown). In the meantime, the yield and crop residues did not follow the same magnitude (**Table A3**), which might indicate an underestimation of biomass measured at harvest in 2008.

A strong agreement between variations of NBP and $\Delta\text{SOC}_{\text{RothC}}$ was found for cover crop, with a mean difference of $0.03 \pm 0.02 \text{ kg C m}^{-2}$, which persisted whether farmyard manure was added or not (**Fig. 5 (a)**). The point at negative NBP and $\Delta\text{SOC}_{\text{RothC}}$ variations corresponds to the phacelia – clover crop in 2024, which was truncated in December 2024, resulting in a partial mineralization of C residues after crushing (**Fig. 5 (a)**). All other cover crop periods had a positive variation of NBP



and $\Delta\text{SOC}_{\text{RothC}}$, highlighting SOC stock decrease. Only green dwarf bean showed a negative mean difference of -0.08 ± 0.00 kg C m⁻² period⁻¹, but the interpretation is limited with only one crop period in 2021 (**Fig. 5 (b)**).

540 Winter wheat was an important driver of the discrepancy between NBP and $\Delta\text{SOC}_{\text{RothC}}$ over the five-rotation period, with a marked underestimation of C sequestration via NBP compared to RothC over the 10 crop periods (**Fig. 5 (f)**). However, low f_{DPM} indicated that not all crop residues were sufficiently mineralized to conclude that winter wheat significantly sequesters C in the soil. The same observation regarding f_{DPM} applies to all crops except cover crops (**Fig. 5 (b),(c),(d),(e)**). Since cover crop and winter wheat are part of the same agronomic sequence which aims to cover the soil before the next spring crop (sugar beet or potato), one could group these two crops together to form a unique winter wheat – cover crop sequence spanning from

545 sowing of winter wheat to sowing of the next main crop after cover crop crushing. The mean difference between NBP and $\Delta\text{SOC}_{\text{RothC}}$ of these new sequences was lower than all winter wheat crop periods alone, while still driving the positive discrepancy between NBP and $\Delta\text{SOC}_{\text{RothC}}$ (0.10 ± 0.05 kg C m⁻² period⁻¹, **Fig. 6 (a),(b)**). Importantly, the extension of the sowing-to-sowing period resulted in a higher degree of mineralization, enabling complete mineralization of all residues within

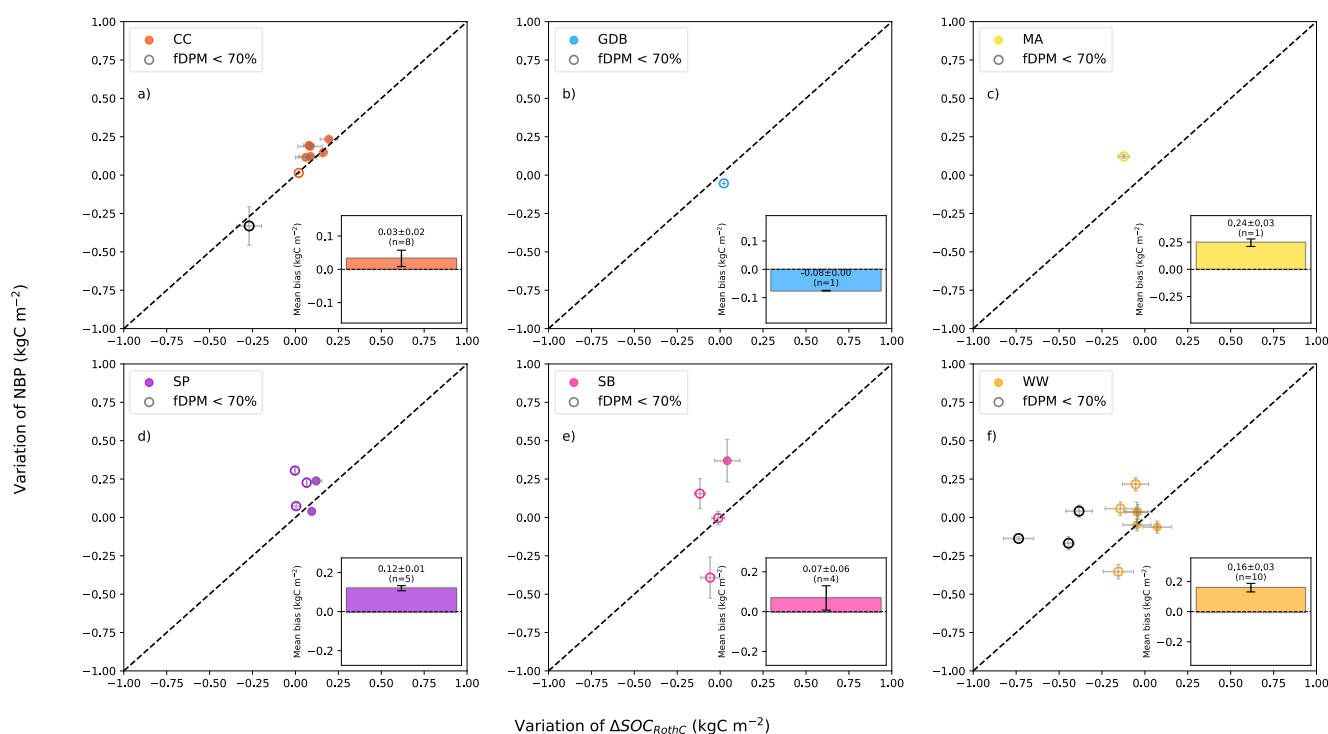


Figure 5. Variation of net biome productivity (NBP) and variations of SOC stock modelled by RothC ($\Delta\text{SOC}_{\text{RothC}}$) for cover crop (panel a), green dwarf bean (panel b), silage maize (panel c), seed potato (panel d), sugar beet (panel e) and winter wheat (panel f). The mean bias between the two variables is shown in the inset. Black circles indicate farmyard manure application. Open circles indicate fraction of mineralization of the DPM pool (f_{DPM}) lower than 70%. Open black circles indicate both farmyard manure application and f_{DPM} lower than 70%. n is the number of sowing-to-sowing periods per crop. Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean.



the sequence (**Fig. 6 (b)**). Without farmyard manure application, these sequences were from neutral to moderate net C source (**Fig. 6 (b)**). Addition of farmyard manure achieved negative variations of NBP and $\Delta\text{SOC}_{\text{RothC}}$ associated with high mineralization rate for two periods in 2009-2010 and 2015-2016 (**Fig. 6 (b)**). Only one winter wheat – cover crop sequence, corresponding to the phacelia – clover crop in 2024, was a net C sink due to farmyard manure application but still achieved an incomplete mineralization (**Fig. 6 (b)**). The three remaining winter wheat crop periods alone were the ones in Rotation 1 (2004-2006, 2006-2008 and 2010-2012) when no cover crops were sown after harvest and bare soil was there until sowing of the seed potato, sugar beet and maize respectively (**Fig. 6 (a)**). For these three winter wheat crops, no significant sink or source pattern, nor bias between NBP and $\Delta\text{SOC}_{\text{RothC}}$ could be observed (**Fig. 6 (a)**).

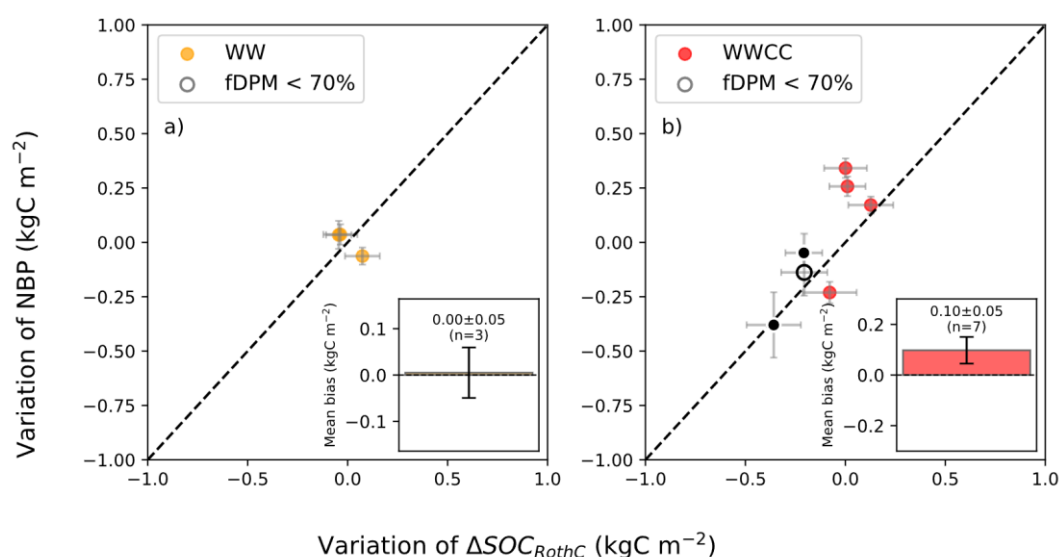


Figure 6. Variation of net biome productivity (NBP) and variations of SOC stock modelled by RothC ($\Delta\text{SOC}_{\text{RothC}}$) for winter wheat without subsequent cover crops (panel a) and for the winter wheat – cover crop sequence (panel b). The mean bias between the two variables is shown in the inset. Open circles indicate fraction of mineralization of the DPM pool (f_{DPM}) lower than 70%. Closed circles indicate f_{DPM} higher than 70%. Black circles indicate farmyard manure application. n is the number of sowing-to-sowing periods per crop. Black edge circles correspond to farmyard manure application. Abbreviations: WW, winter wheat; CC, cover crop.

4 Discussion

4.1 Discrepancies between RothC simulations and EC

The annual SOC stock loss rate derived from NBP was estimated at approximately $0.07 \text{ kg C m}^{-2} \text{ yr}^{-1}$ on average. At this rate, the initial SOC stock in the 0–60 cm soil profile (5.99 kg C m^{-2}) would theoretically be depleted within about 85.6 years, assuming a linear and uninterrupted loss. However, this simple projection should be interpreted with caution, as it does not fully reflect long-term soil carbon dynamics. In particular, the site has been under continuous cultivation for nearly a century,



with the current crop rotation maintained for at least 40 years. Under such stable management conditions, SOC dynamics are more likely to approach a quasi-equilibrium state rather than follow a sustained linear decline over time. For instance, Buysse et al. (2013) demonstrated at a long-term experimental site near Lonzée that SOC stock equilibrium is typically achieved after 20 years of constant farmyard manure and crop residue treatments, resulting in minimal subsequent effects on SOC concentration. While these observations suggest that the EC-derived SOC loss rate may be overestimated, these results on NBP lie within the range of previous studies conducted on similar crop rotations using EC data. For instance, Poyda et al. (2019) found an annual loss of 0.12 kg C m^{-2} for six intensive crop rotations over a period of eight years in Germany. Emmel et al. (2018) showed that the Oensingen site in Switzerland (site code CH-Oe2) behaved as a net carbon source with a loss of $0.12 \text{ kg C m}^{-2} \text{ yr}^{-1}$ over 13 years for a crop rotation including winter barley, winter wheat, winter rapeseed, peas and potato. Similar results were found across Europe for similar rotations under similar climate (Kutsch et al. (2010) – $0.10 \text{ kg C m}^{-2} \text{ yr}^{-1}$, Ceschia et al. (2010) – $0.14 \text{ kg C m}^{-2} \text{ yr}^{-1}$, Buysse et al. (2017) – $0.09 \text{ kg C m}^{-2} \text{ yr}^{-1}$, Loubet et al. (2011) – $0.13 \text{ kg C m}^{-2} \text{ yr}^{-1}$). In Wallonia, these findings strongly contrast with SOC stock variations derived from regional inventories. For instance, historical soil databases (Goidts and Van Wesemael, 2007) and modelling (Meersmans et al., 2011) have shown that croplands have lost on average $0\text{--}0.02 \text{ kg C m}^{-2} \text{ yr}^{-1}$ in the plough layer over 50 years in Wallonia, reflecting a moderate-to-null decline. Although this trend was supported by RothC simulations and soil inventories at the Lonzée cropland (**Fig. 4**), our results show large uncertainty bounds in $\Delta\text{SOC}_{\text{RothC}}$ over the five-rotation period, underscoring the need for cautious interpretation. Furthermore, the comparison between $\Delta\text{SOC}_{\text{RothC}}$ and cumulative NBP may be biased by the omission of subsoil carbon dynamics in RothC. While EC fluxes integrate CO_2 exchange across the entire soil profile, RothC simulations only accounted for the top 23 cm of soil (Coleman and Jenkinson, 1996). C inputs from belowground biomass for winter wheat and silage maize were estimated using measured shoot-to-root ratios and harvest index values. These estimates were aligned with the RothC vertical discretization by assigning root-derived inputs to the topsoil layer, under the assumption that most root biomass is concentrated within this horizon (Bolinder et al., 2007). As a result, all carbon inputs were conceptually added into the topsoil and no inputs to the subsoil were considered. Although evidence suggests that most CO_2 efflux in croplands originates from the topsoil (Khan et al., 2023; Wang et al., 2018; Wiaux et al., 2015) and that subsoil SOC stocks are relatively stable due to slow turnover rates (Alcántara et al., 2017) or textural protection (Sierra et al., 2024), recent studies indicate that root–subsoil interactions, particularly in cereals, can substantially contribute to changes in subsoil carbon stocks (Jones et al., 2026; Kätterer et al., 2014; Patra et al., 2022, 2024). In the present study, measurements conducted during pre-harvest field campaign in 2022 showed that winter wheat root biomass in the subsoil (30–100 cm) accounted for $16.5 \pm 4.2\%$ of the total root biomass over the whole soil profile. Therefore, a significant part of C inputs for winter wheat and maize could have been attributed to a subsoil layer, which could have exacerbated the difference between RothC simulations and NBP (loss of C) by enhancing SOC sequestration due to greater stabilization with depth, thus widening the gap with NBP. On the other hand, this could also decrease $\Delta\text{SOC}_{\text{RothC}}$ if priming of older carbon, enhanced mineralization, or lateral exports dominated. To resolve this uncertainty, future work should assess the sensitivity of overall ΔSOC to belowground carbon allocation, depth-dependent turnover rates, and priming effects. Recent modeling frameworks have started to address these processes explicitly — including



the implementation of RothC within JULES across a 3 m soil profile (Nakhavali et al., 2018), rCTOOL (Giannini-Kurina et al., 2025), and ORCHIDEE-SOM (Camino-Serrano et al., 2018). While SOC stock measurements for topsoil and subsoil are available at our site and could support such an extension, implementing and validating a multi-layer model was beyond the scope of the present study, which focused on the topsoil carbon budget over observed rotation sequences. Coupling these multi-layer approaches with the long-term eddy covariance and soil inventory dataset presented here therefore constitutes a particularly well-constrained opportunity for future work.

A complementary avenue to further constrain SOC stock dynamics at BE-Lon would be the measurement of functional soil organic matter fractions, such as particulate organic matter (POM) and mineral-associated organic matter (MAOM). Bulk SOC stock measurements integrate pools with contrasting turnover times and stabilization mechanisms, and may therefore mask compensating changes between a labile, plant-derived POM pool and a more persistent, mineral-stabilized MAOM pool (Cotrufo et al., 2019; Lavalée et al., 2020). Partitioning SOC into these measurable fractions would provide a more mechanistic basis for interpreting the near-equilibrium trend observed here and would offer observational constraints that map more directly onto recent process-based models structured around measurable pools (e.g. MEMS, Millennial; Abramoff et al., 2022) than the kinetically defined pools of RothC. Additionally, constraining model uncertainty using supplementary observational data, such as mineralization curves to improve process representation in RothC (Mondini et al., 2017), or adopting an ensemble approach with multiple soil carbon models (Farina et al., 2021) would support more robust conclusions.

Finally, an important step in the calculation of NBP from NEE and lateral C fluxes was the omission of total dissolved organic and inorganic carbon (DIC-DOC) in Eq. 1, due to a lack of available measurements and limited representation in the model framework. Notably, DOC and DIC fluxes have been shown to be non-negligible in croplands and can represent a significant component of the carbon budget (Nakhavali et al., 2021, 2024). Yearly losses yielded $12.5 \text{ g C m}^{-2} \text{ yr}^{-1}$, $16.0 \text{ g C m}^{-2} \text{ yr}^{-1}$ and $11.2 \text{ g C m}^{-2} \text{ yr}^{-1}$ at the cropland ICOS sites of Grignon, Klingenberg and Carlow, respectively (Kindler et al., 2011). Comparable flux magnitudes have been reported in other croplands (Manninen et al., 2018; Walmsley et al., 2011) as well as in large-scale modelling studies across Europe (Gommet et al., 2022; Janssens et al., 2003). Including DIC and DOC fluxes in the EC-derived C budget would therefore increase the discrepancy between NBP and $\Delta\text{SOC}_{\text{RothC}}$, while leaving unchanged the conclusions of the present study regarding the differences observed among the SOC stock-based methods.

4.2 Uncertainty propagation and its impact on trend significance

The large uncertainty bounds on $\Delta\text{SOC}_{\text{RothC}}$ indicates that RothC simulations must be interpreted with caution. By the end of the simulation period, the standard deviation of simulated SOC stock variation (0.63 kg C m^{-2}) was larger than the corresponding increase in SOC stock ($-0.39 \text{ kg C m}^{-2}$), underscoring considerable predictive uncertainty regarding the sink status of the Lonzée cropland. The variability observed here exceeded that reported in previous studies (Filip et al., 2025; Morais et al., 2019; Pesce et al., 2024), likely because, in addition to C inputs and meteorological drivers, we also accounted for a moderate hypothesized uncertainty in the model's functional relationships (10 % on model parameters, section 2.6). While the trend of sink or source pattern could not be statistically confirmed, the 2017 SOC stock measured by physical



sampling fell within the simulated range, thereby supporting the overall trend of equilibrium of SOC stocks at BE-Lon over
650 the 21-year period. Confirmation of the apparent long-term stability requires additional SOC measurements, ideally at least
ten years after the 2017 sampling (Schrumpf et al., 2011), which is required in the ICOS protocols.

Error propagation in EC measurements is critical for reliable carbon budgets, as uncertainties arise from instrumental
limitations, missing data and gap-filling. Comprehensive evaluation and propagation of errors ensure the reliability of long-
term NEE estimates. In this study, we quantified uncertainty contributions from key processing steps over the five-rotation
655 period. Random measurement errors contributed minimally to the total error on NEE ($0.98 \text{ g C m}^{-2} \text{ yr}^{-1}$), consistent with
literature values ($0\text{--}5 \text{ g C m}^{-2} \text{ yr}^{-1}$) (Du et al., 2014; Vekuri et al., 2023). The u^* threshold uncertainty reached 8.09 g C m^{-2}
 yr^{-1} , which is slightly lower than the range of reported values ($10\text{--}100 \text{ g C m}^{-2} \text{ yr}^{-1}$) (Papale et al., 2006) likely thanks to
sowing-to-harvest seasons in REdDyProc that constrained surface roughness variability. Spectral correction uncertainty was
comparable at $6.29 \text{ g C m}^{-2} \text{ yr}^{-1}$, reflecting methodological robustness of the spectral correction workflow. These two dominant
660 sources on NEE uncertainty (u^* filtering and spectral correction) together accounted for $\sim 30\%$ of the total annual uncertainty
on NBP, the other 70% being shared by the uncertainty on C_{imp} and C_{exp} . The total cumulative standard deviation on NEE
represented a very small fraction of the cumulative flux (3% on the $-7.61 \text{ kg C m}^{-2}$), thereby indicating that the post-processing
workflow of EC data minimized the uncertainty associated with flux estimation and ensured a high level of confidence in the
derived cumulative carbon balance.

665 4.3 Potential underestimation of C sequestration

This study showed a systematic underestimation of NBP when compared to $\Delta\text{SOC}_{\text{RothC}}$, which was observed for winter wheat,
maize, seed potato and sugar beet (**Fig. 5**), and suggested a potential underestimation of C sequestration by the EC technique.
To further investigate the mismatch between the flux-based approach and the SOC modelling approach, we calculated the
carbon balance ratio (CBR), which is defined as the ratio of the integrated NEE to the difference between the carbon exported
670 and imported plus the difference between final and initial SOC (Baker and Griffis, 2005). In the absence of SOC stock changes,
the vertical CO_2 flux balance should match the net lateral carbon balance, leading to a CBR of ~ 1 . At the Lonzée site, the CBR
over five full rotations was $\sim 82.5\%$, suggesting that EC measurements likely captured only a part of the true CO_2 exchange
over the cropland, assuming no systematic biases affected lateral carbon fluxes or inventory estimates. This finding for CO_2
fluxes is consistent with the well-documented non-closure of the surface energy balance, where the sum of turbulent sensible
675 and latent heat fluxes is likely smaller than the available energy (Aubinet et al., 2012; Foken, 2008; Oncley et al., 2007; Twine
et al., 2000). The energy balance ratio (EBR) at BE-Lon was 60.8% over the five-rotation period (Arquin, pers. comm.), which
falls within the lower range of values typically reported for croplands (Nicolini et al., 2026; Stoy et al., 2013). One commonly
proposed explanation is the contribution of large-scale turbulent structures with timescales exceeding the EC averaging period,
which generate dispersive fluxes that are not captured by single-tower measurements (Foken et al., 2011; Gao et al., 2019;
680 Mauder et al., 2020; Wohlfahrt and Widmoser, 2013). It has also been suggested that missing terms in the classical energy
balance equation may contribute to the observed imbalance (Durand, 2022; Sun et al., 2021; Sun and Tribbia, 2025). However,



whether such energy balance non-closure can be directly translated into corrections for NEE remains uncertain (Mauder et al., 2024; Zhou et al., 2024). As this correction would apply to both photosynthesis and respiration-driven NEE, the impact on NBP remains uncertain. These findings therefore call for caution when interpreting absolute NEE-derived carbon budgets, while highlighting the value of independent model-based approaches, such as RothC, to benchmark and contextualize EC measurements.

4.4 The role of amendments and cover crops on SOC sequestration

This study demonstrates that farmyard manure application during a winter wheat – cover crop sequence led to a significant increase in SOC stocks, as consistently indicated by both NBP and $\Delta\text{SOC}_{\text{RothC}}$ variations under high DPM mineralization conditions (**Fig. 6-b**). In contrast, without manure amendment, the additional carbon inputs from cover crop incorporation and winter wheat harvest residues appeared insufficient to offset heterotrophic respiration losses, resulting in a moderate net carbon loss (**Fig. 6-b**). Manure applications can enhance SOC stocks through two non-exclusive pathways: (i) by boosting crop productivity and cover crop growth, thereby increasing the amount of plant residues and rhizodeposition returned to the soil (Stewart et al., 2007); and (ii) by directly supplying organic matter with a composition and nutrient content that promote the stabilization of a larger fraction of input C in soil organic matter compared to crop residues alone, as suggested by global syntheses of manure effects on SOC (Maillard and Angers, 2014). These findings highlight the critical role of organic amendments in enhancing the carbon sequestration potential of the BE-Lon cropland and raise important questions regarding the capacity of cover crops alone—in the absence of external organic inputs—to drive net SOC accumulation under the prevailing climatic and management conditions.

The potential to further enhance carbon sequestration through increased manure application depends on factors such as soil and climate adaptability, economic feasibility for farmers, impacts on food production, and the extent to which these practices are already implemented. It is well known that manure applications have been shown to increase SOC stocks (Bolinder et al., 2020; Poulton et al., 2018; Sail et al., 2025), making organic amendments a promising strategy to increase SOC stocks in agricultural systems (Bai et al., 2023; Chenu et al., 2019). However, the potential for further SOC gains from increasing manure application depends on the soil's capacity to stabilize added carbon. This capacity is determined by the number of mineral binding sites, which is closely related to the proportion of fine silt and clay particles (Carter et al., 2003). Soils are therefore expected to have a finite carbon storage capacity in aggregate fractions, with an estimated upper limit of approximately 50 g C kg⁻¹ for European soils (Cotrufo et al., 2019). Consequently, soils with low initial SOC content in the fine fraction typically have high carbon sequestration potential due to a greater capacity for long-term stabilization in association with the mineral phase (Georgiou et al., 2022; Gross and Glaser, 2021). However, recent studies indicate that soils with high initial SOC can continue to sequester carbon when carbon inputs increase (Orgill et al., 2017). It is therefore expected that increasing manure applications leads to measurable gains in SOC stocks (Joona et al., 2024; Koga, 2017; Liang et al., 2023; Shakoor et al., 2021). The role of cover crops in enhancing the carbon sink capacity of croplands remains debated in the literature, with studies reporting a wide range of outcomes from net carbon gains to neutral or slightly negative balances. For instance, a long-term



715 experiment in France demonstrated that residue incorporation from cover crops was largely compensated by the associated
CO₂ respiration flux following crushing, in a cropland with a SOC content comparable to BE-Lon (Breil et al., 2023). Meta-
analyses notably consistently report SOC stock gains under cover crops relative to bare soils (McClelland et al., 2021; Poeplau
and Don, 2015; Scavo et al., 2022). Process-based model simulations in Flanders (Spotorno et al., 2024) or Germany (Seitz et
al., 2023) similarly suggest beneficial effects on SOC stocks. However, other studies point to more limited or inconsistent
720 outcomes. Blanco-Canqui (2022) reported only minor effects of cover crops on SOC sequestration, a 65-year long-term
experiment in Belgium found marginal SOC increases attributable to cover crops (Sail et al., 2025), and Schepens et al. (2025)
concluded that winter cover crops do not systematically increase SOC stocks across Northwestern Europe. The extent to which
cover crops enhance the carbon sink capacity of croplands is therefore site-specific, and depends on factors including the
duration of cover crop integration, initial SOC content, soil texture, climate and, critically, plant species (Blanco-Canqui, 2022;
725 Breil et al., 2023; Zhang et al., 2022). At BE-Lon, mustard accounted for more than 80% of cover crop periods, with oat and
faba bean mixtures comprising the remainder. Mustard appears to have limited SOC sequestration potential (Antosh et al.,
2020), in contrast to ryegrass — also used in Western Europe (Smit et al., 2019) — which can substantially enhance SOC
stocks (Jensen et al., 2022; Poeplau et al., 2015). The dominance of a low-sequestration cover crop species at the BE-Lon site
may therefore partly explain the absence of a net carbon sink effect from cover cropping. Furthermore, incorporating N-rich
730 cover crops like faba beans may lead to increased N₂O emissions offsetting the carbon storage benefits (Li et al., 2024).
This study could not confirm whether winter wheat or maize as contributors to SOC sequestration, owing to the incomplete
mineralization of the DPM pool following harvest (**Fig. 5**). When winter wheat data were pooled with the subsequent cover
crop periods to achieve higher DPM mineralization rates over a unique agronomic sequence, both NBP and $\Delta\text{SOC}_{\text{RothC}}$
consistently indicated a moderate net carbon source trend — except when farmyard manure was applied (**Fig. 6**). This pattern
735 is consistent with the broader finding that organic amendments, rather than crop rotation design alone, appear to be the primary
lever for SOC accumulation at BE-Lon. While the inclusion of cereal crops with deep root systems has been proposed as a
strategy to increase belowground C inputs and promote SOC gains in many studies (Patra et al., 2022, 2024; Poeplau et al.,
2021; Sun et al., 2018), this effect may be insufficient to counteract heterotrophic respiration losses under the management
and climatic conditions prevailing at this site. Under the conditions of this study, modifying the rotation to increase the
740 proportion of cereal crops does not therefore appear to be a sufficient strategy for improving net SOC sequestration.
Although this study showed that manure application was a key driver of SOC accumulation, the associated increase in
greenhouse gas emissions, particularly nitrous oxide (N₂O), may partially or even fully offset the climate benefits of enhanced
carbon sequestration (Guenet et al., 2021). In general, manure amendments lead to significantly higher N₂O emissions than
mineral nitrogen fertilization alone, with the magnitude of this effect strongly influenced by the C/N ratio of the applied
745 material (Zhou et al., 2017). While the present study did not quantify N₂O emissions following manure application, additional
inputs, even within the limits set by the European Union Nitrates Directive (91/676/EEC) and farm-level agronomic
constraints, could exacerbate ammonia volatilization, nitrate leaching, and N₂O emissions, thereby reducing or negating the
net greenhouse gas mitigation potential at the cropland scale (Maenhout et al., 2024). Moreover, manure use is constrained by



broader environmental concerns, including water contamination, nitrate leaching, the spread of antibiotic resistance, and risks to ecosystems functioning (Zhen et al., 2020, Wang et al., 2019). Overall, the net climate mitigation potential of manure application is likely limited, as many of its benefits reflect redistribution of existing carbon stocks rather than direct sequestration of atmospheric carbon into the soil (Powlson et al., 2011, 2012).

5 Conclusion

This study compared decadal soil inventories, RothC simulations, and eddy covariance measurements with lateral C flux inventories to assess SOC stock changes at BE-Lon across five crop rotations. EC-derived carbon budgets indicated high SOC losses inconsistent with the long-term agricultural and management history of the site, while RothC simulations and soil inventories supported near-equilibrium dynamics. The discrepancy between the two approaches likely reflects an underestimation of C sequestration by EC, which is consistent with the well-documented energy balance non-closure at cropland sites. A comprehensive uncertainty analysis revealed that uncertainties associated with spectral correction and u^* threshold determination were comparable in magnitude to the uncertainty in lateral C flux estimates within the EC-based budget. However, all remained smaller than the NBP signal, enabling the identification of a strong source trend. Comparison between NBP and $\Delta\text{SOC}_{\text{RothC}}$ variations revealed a systematic positive bias for winter wheat, maize, sugar beet, and seed potato, indicating a possible underestimation of carbon net sequestration by the EC technique. Both approaches consistently identified the winter wheat – cover crop sequence as a moderate net C source in the absence of organic amendments. Farmyard manure application emerged as the primary driver of SOC accumulation at the site, as shown by the convergence between NBP and $\Delta\text{SOC}_{\text{RothC}}$ variations under high DPM mineralization. However, evaluating the true mitigation potential of this practice requires accounting for potential trade-offs with N_2O emissions in the full greenhouse gas balance. More broadly, this study highlights the value of combining process-based models, multi-decadal soil inventories, and eddy covariance flux tower to constrain SOC budgets, and improve understanding of SOC stock drivers on croplands.



6 Appendix

Table A1. Soil characteristics at BE-Lon across the vertical profile: carbonates (CaCO_3), soil organic carbon content (SOC), organic matter (OM), nitrogen content (N), bulk density (BD), pH and granulometry. Samples were collected during the field campaign in 2017 following ICOS protocols.

Depth (m)	CaCO_3 (g kg ⁻¹)	SOC (g kg ⁻¹)	OM (g kg ⁻¹)	N (g kg ⁻¹)	BD (g cm ⁻³)	pH	Clay (%)	Silt (%)	Sand (%)
0 - 5	0.34	11.055	19.12	1.09	1.19	-	-	-	-
5 - 15	0.36	10.72	18.54	1.07	1.23	8.10	11.60	80.20	8.20
15 - 30	0.47	10.74	18.57	1.07	1.39	8.20	10.80	80.70	8.50
30 - 60	2.17	3.96	6.85	0.47	1.50	8.00	16.70	76.70	6.60
60 - 100	2.00	1.80	3.12	0.25	1.54	8.00	19.70	74.70	5.60

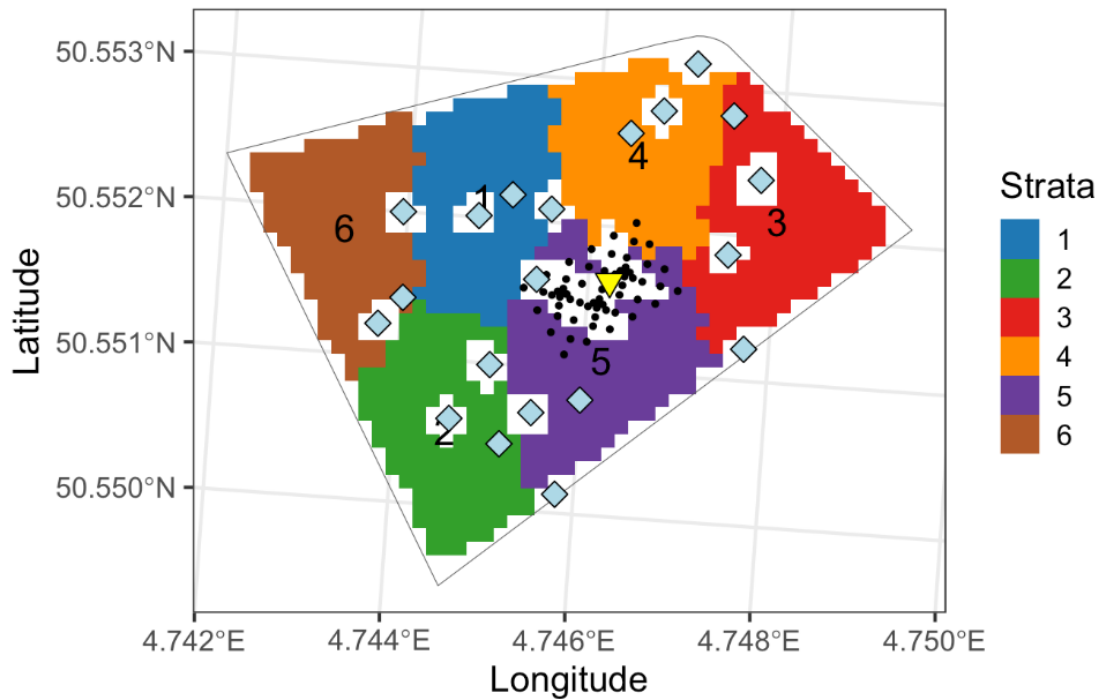


Figure A1. Spatial design of soil sampling in 2007 and 2017. The black points indicate 2007 samples location. The blue diamonds indicate 2017 samples locations labelled as ‘SP-I’. Strata were determined based on (Loubet et al., 2026).



Table A2. Seed density (SD), dry matter (DM_H), carbon content ($[C]_H$) of the harvested product and the corresponding export of carbon at harvest (C_{exp}) for the main crop periods. For abbreviations, WW: winter wheat, SP: seed potato, SB: sugar beet, MA: silage maize, GDB: green dwarf bean. All uncertainties are standard deviation.

Crop	SD (ha^{-1})	DM_H ($kg\ m^{-2}$)	$[C]_H$ ($g\ C\ kg^{-1}$)	C_{exp} ($kg\ C\ m^{-2}$)
SB 04	95 444	1.87 ± 0.11	413 ± 0.79	0.78 ± 0.03
WW 04-06	2 221 154	1.30 ± 0.12	421 ± 1.87	0.56 ± 0.06
SP 06	42 433	0.75 ± 0.00	392 ± 1.84	0.29 ± 0.00
WW 06-08	2 685 000	0.75 ± 0.04	414 ± 2.56	0.45 ± 0.02
SB 08	85 422	2.44 ± 0.07	404 ± 3.31	0.99 ± 0.13
WW 08-09	2 585 000	1.29 ± 0.08	412 ± 1.71	0.53 ± 0.04
SP 10	68 833	0.79	387 ± 1.34	0.31 ± 0.00
WW 10-12	2 424 000	1.37 ± 0.05	399 ± 0.72	0.55 ± 0.02
MA 12	106 917	1.96	407 ± 10.0	0.78 ± 0.01
WW 12-13	2 096 000	0.92 ± 0.01	/	0.60 ± 0.04
SP 14	46 944	0.76	421 ± 8.48	0.32 ± 0.01
WW 14-15	1 827 885	1.33 ± 0.02	/	0.58 ± 0.01
SB 16	105 000	2.22	/	0.90 ± 0.10
WW 16-17	1 723 077	0.86 ± 0.28	/	0.56 ± 0.04
SP 18	50 000	1.10	/	0.41 ± 0.00
WW 18-19	1 423 077	1.62	/	0.53 ± 0.05
SB 20-21	105 000	2.23	416 ± 3.30	0.97 ± 0.14
GDB 21	859 375	0.1	/	0.04 ± 0.04
WW 21-22	3 081 731	1.76	428 ± 2.4	0.55 ± 0.04
SP 23	56 000	0.6	373 ± 0.5	0.22 ± 0.00
WW 23-24	2 610 577	1.31	/	0.56 ± 0.04



Table A3. Cumulative values of net ecosystem exchange (*NEE*), imports of carbon (*C_{imp}*), exports of carbon at harvest (*C_{exp}*), net biome production (*NBP*) and aboveground crop residues at harvest (*CR*). Abbreviations: WW, winter wheat; SP, seed potato; SB, sugar beet; CC, cover crop; MA, silage maize; GDB, green dwarf bean. Crops are mentioned with the corresponding year. All uncertainties are cumulative standard deviation. Bold text for *C_{imp}* highlight the application of farmyard manure. Crop-periods are defined as from sowing to sowing of the next crop.

Crop	<i>NEE</i> (kg C m ⁻²)	<i>C_{imp}</i> (kg C m ⁻²)	<i>C_{exp}</i> (kg C m ⁻²)	<i>NBP</i> (kg C m ⁻²)	<i>CR</i> (kg C m ⁻²)
SB 04	-0.81 ± 0.06	-0.00	0.78 ± 0.03	-0.03 ± 0.06	0.19 ± 0.06
WW 04-06	-0.45 ± 0.05	-0.05	0.56 ± 0.06	0.06 ± 0.09	0.21 ± 0.07
SP 06	-0.20 ± 0.03	-0.02	0.29 ± 0.00	0.07 ± 0.02	0.06 ± 0.00
WW 06-08	-0.45 ± 0.04	-0.11 ± 0.01	0.45 ± 0.03	-0.11 ± 0.06	0.18 ± 0.06
SB 08	-1.26 ± 0.05	-0.00	0.99 ± 0.13	-0.27 ± 0.14	0.22 ± 0.07
WW 08-09	-0.31 ± 0.03	-0.32 ± 0.04	0.53 ± 0.04	-0.10 ± 0.07	0.18 ± 0.04
CC 0910	0.32 ± 0.01	-0.00	/	0.32 ± 0.01	/
SP 10	-0.02 ± 0.08	-0.02	0.31 ± 0.00	0.26 ± 0.08	0.03 ± 0.00
WW 10-12	-0.48 ± 0.09	-0.14 ± 0.01	0.55 ± 0.02	-0.07 ± 0.09	0.17 ± 0.02
MA 12	-0.61 ± 0.05	-0.00	0.78 ± 0.01	0.17 ± 0.05	0.02 ± 0.00
WW 12-13	-0.36 ± 0.03	-0.05	0.60 ± 0.04	0.18 ± 0.06	0.28 ± 0.02
CC 13-14	0.23 ± 0.02	-0.00	/	0.23 ± 0.02	/
SP 14	-0.05 ± 0.04	-0.00	0.32 ± 0.01	0.27 ± 0.04	0.01 ± 0.00
WW 14-15	-0.62 ± 0.02	-0.55 ± 0.15	0.57 ± 0.01	-0.59 ± 0.15	0.28 ± 0.02
CC 15-16	0.22 ± 0.03	-0.00	/	0.22 ± 0.03	/

Crop	<i>NEE</i> (kg C m ⁻²)	<i>C_{in}</i> (kg C m ⁻²)	<i>C_{exp}</i> (kg C m ⁻²)	<i>NBP</i> (kg C m ⁻²)	<i>CR</i> (kg C m ⁻²)
SB 16	-0.68 ± 0.02	-0.00	0.90 ± 0.01	0.21 ± 0.10	0.19 ± 0.05
WW 16-17	-0.28 ± 0.01	-0.05	0.56 ± 0.04	0.23 ± 0.05	0.10 ± 0.04
CC 17-18	0.18 ± 0.06	-0.00	/	0.18 ± 0.06	/
SP 18	-0.07 ± 0.03	-0.04	0.41 ± 0.00	0.3 ± 0.03	0.05 ± 0.01
WW 18-19	-0.82 ± 0.02	-0.11 ± 0.01	0.53 ± 0.05	-0.40 ± 0.05	0.19 ± 0.05
CC 19-20	0.19 ± 0.10	-0.00	/	0.19 ± 0.10	/
SB 20-21	-0.55 ± 0.09	-0.00	0.97 ± 0.14	0.41 ± 0.17	0.17 ± 0.07
CC 21 (SPI)	0.02 ± 0.08	-0.39 ± 0.12	/	-0.37 ± 0.14	/
GDB 21	-0.07 ± 0.02	-0.00	0.04 ± 0.00	-0.02 ± 0.02	/
WW 21-22	-0.52 ± 0.07	-0.05	0.55 ± 0.04	-0.03 ± 0.08	0.18 ± 0.04
CC 22-23	0.26 ± 0.01	-0.00	/	0.26 ± 0.01	/
SP 23	-0.20 ± 0.01	-0.02	0.22 ± 0.00	0.00 ± 0.01	0.03 ± 0.03
WW 23-24	-0.39 ± 0.01	-0.34 ± 0.10	0.56 ± 0.04	-0.18 ± 0.11	0.15 ± 0.04
CC 24 (PHA-CLO)	0.07 ± 0.00	-0.00	/	0.07 ± 0.00	/



7 Code and data availability

All eddy covariance-related and meteorological variables except CO₂ fluxes are accessible on the ICOS Carbon Portal at <https://hdl.handle.net/11676/1u2xQ5XcQoX0j2wJiZcyDP3M>. Biomass data after 2017 are accessible on the ICOS Carbon Portal at <https://hdl.handle.net/11676/99gAK7xqcSkk7SRKDwZz1KJT>. Biomass data before 2017 and raw CO₂ flux measurements over the 2004-2024 period were provided by the ICOS team of the Lonzée site and are accessible upon request. RothC is an open-source model available in the SoilR package (10.32614/CRAN.package.SoilR). FreqCor is a Python toolbox to compute and apply spectral/cospectral correction factors to eddy covariance fluxes and is available at <https://github.com/BernardHeinesch/FreqCor>.

8 Author contributions

QB, BH, and BL (Bernard Longdoz) designed the study. BH developed the spectral correction procedure. QB processed the eddy covariance data and conducted the EC-based budget calculations, RothC simulations, and all corresponding uncertainty analyses. BW performed the comparison between soil inventories and the associated uncertainty analyses. YZ provided guidance for running RothC. QB wrote the manuscript. All co-authors contributed to the revision process and to improving the manuscript, with BH and BL (Bernard Longdoz) playing an active role in revising the early versions.

9 Competing interests

The contact author has declared that none of the authors has any competing interests.

10 Disclaimer

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13 References

Abramoff, R. Z., Guenet, B., Zhang, H., Georgiou, K., Xu, X., Viscarra Rossel, R. A., Yuan, W., and Ciais, P.: Improved global-scale predictions of soil carbon stocks with Millennial Version 2, *Soil Biol. Biochem.*, 164, 108466, <https://doi.org/10.1016/j.soilbio.2021.108466>, 2022.

900 Alcántara, V., Don, A., Vesterdal, L., Well, R., and Nieder, R.: Stability of buried carbon in deep-ploughed forest and cropland soils - implications for carbon stocks, *Sci. Rep.*, 7, 5511, <https://doi.org/10.1038/s41598-017-05501-y>, 2017.

Allen, R. G. and Food and Agriculture Organization of the United Nations (Eds.): *Crop evapotranspiration: guidelines for computing crop water requirements*, Food and Agriculture Organization of the United Nations, Rome, 300 pp., 1998.

905 Antosh, E., Idowu, J., Schutte, B., and Lehnhoff, E.: Winter cover crops effects on soil properties and sweet corn yield in semi-arid irrigated systems, *Agron. J.*, 112, 92–106, <https://doi.org/10.1002/agj2.20055>, 2020.

Arrouays, D., Saby, N. P. A., Boukir, H., Jolivet, C., Ratié, C., Schrumpf, M., Merbold, L., Gielen, B., Gogo, S., Delpierre, N., Vincent, G., Klumpp, K., and Loustau, D.: Soil sampling and preparation for monitoring soil carbon, *Int. Agrophysics*, 32, 633–643, <https://doi.org/10.1515/intag-2017-0047>, 2018.

910 Aubinet, M., Moureaux, C., Bodson, B., Dufranne, D., Heinesch, B., Suleau, M., Vancutsem, F., and Vilret, A.: Carbon sequestration by a crop over a 4-year sugar beet/winter wheat/seed potato/winter wheat rotation cycle, *Agric. For. Meteorol.*, 149, 407–418, <https://doi.org/10.1016/j.agrformet.2008.09.003>, 2009.

Aubinet, M., Vesala, T., and Papale, D. (Eds.): *Eddy Covariance: A Practical Guide to Measurement and Data Analysis*, Springer Netherlands, Dordrecht, <https://doi.org/10.1007/978-94-007-2351-1>, 2012.

915 Bai, X., Tang, J., Wang, W., Ma, J., Shi, J., and Ren, W.: Organic amendment effects on cropland soil organic carbon and its implications: A global synthesis, *CATENA*, 231, 107343, <https://doi.org/10.1016/j.catena.2023.107343>, 2023.

Baker, J. M. and Griffis, T. J.: Examining strategies to improve the carbon balance of corn/soybean agriculture using eddy covariance and mass balance techniques, *Agric. For. Meteorol.*, 128, 163–177, <https://doi.org/10.1016/j.agrformet.2004.11.005>, 2005.



- 920 Baldocchi, D.: Measuring fluxes of trace gases and energy between ecosystems and the atmosphere - the state and future of the eddy covariance method, *Glob. Change Biol.*, 20, 3600–3609, <https://doi.org/10.1111/gcb.12649>, 2014.
- Blanco-Canqui, H.: Cover crops and carbon sequestration: Lessons from U.S. studies, *Soil Sci. Soc. Am. J.*, 86, 501–519, <https://doi.org/10.1002/saj2.20378>, 2022.
- 925 Bolinder, M. A., Janzen, H. H., Gregorich, E. G., Angers, D. A., and VandenBygaart, A. J.: An approach for estimating net primary productivity and annual carbon inputs to soil for common agricultural crops in Canada, *Agric. Ecosyst. Environ.*, 118, 29–42, <https://doi.org/10.1016/j.agee.2006.05.013>, 2007.
- Bolinder, M. A., Crotty, F., Elsen, A., Frac, M., Kismányoky, T., Lipiec, J., Tits, M., Tóth, Z., and Kätterer, T.: The effect of crop residues, cover crops, manures and nitrogen fertilization on soil organic carbon changes in agroecosystems: a synthesis of reviews, *Mitig. Adapt. Strateg. Glob. Change*, 25, 929–952, <https://doi.org/10.1007/s11027-020-09916-3>, 2020.
- 930 Breil, N. L., Lamaze, T., Bustillo, V., Marcato-Romain, C.-E., Coudert, B., Queguiner, S., and Jarosz-Pellé, N.: Combined impact of no-tillage and cover crops on soil carbon stocks and fluxes in maize crops, *Soil Tillage Res.*, 233, 105782, <https://doi.org/10.1016/j.still.2023.105782>, 2023.
- Buyse, P., Goffin, S., Carnol, M., Malchair, S., Debacq, A., Longdoz, B., and Aubinet, M.: Short-term temperature impact on soil heterotrophic respiration in limed agricultural soil samples, *Biogeochemistry*, 112, 441–455, <https://doi.org/10.1007/s10533-012-9739-7>, 2013.
- 935 Buyse, P., Bodson, B., Debacq, A., De Ligne, A., Heinesch, B., Manise, T., Moureaux, C., and Aubinet, M.: Carbon budget measurement over 12 years at a crop production site in the silty-loam region in Belgium, *Agric. For. Meteorol.*, 246, 241–255, <https://doi.org/10.1016/j.agrformet.2017.07.004>, 2017.
- 940 Cai, J., Liu, Y., Lei, T., and Pereira, L. S.: Estimating reference evapotranspiration with the FAO Penman–Monteith equation using daily weather forecast messages, *Agric. For. Meteorol.*, 145, 22–35, <https://doi.org/10.1016/j.agrformet.2007.04.012>, 2007.
- Camino-Serrano, M., Guenet, B., Luyssaert, S., Ciais, P., Bastrikov, V., De Vos, B., Gielen, B., Gleixner, G., Jornet-Puig, A., Kaiser, K., Kothawala, D., Lauerwald, R., Peñuelas, J., Schrumpf, M., Vicca, S., Vuichard, N., Walmsley, D., and Janssens, I. A.: ORCHIDEE-SOM: modeling soil organic carbon (SOC) and dissolved organic carbon (DOC) dynamics along vertical soil profiles in Europe, *Geosci. Model Dev.*, 11, 937–957, <https://doi.org/10.5194/gmd-11-937-2018>, 2018.
- 945 Carter, M. R., Angers, D. A., Gregorich, E. G., and Bolinder, M. A.: Characterizing organic matter retention for surface soils in eastern Canada using density and particle size fractions, *Can. J. Soil Sci.*, 83, 11–23, <https://doi.org/10.4141/S01-087>, 2003.
- 950 Ceschia, E., Béziat, P., Dejoux, J. F., Aubinet, M., Bernhofer, Ch., Bodson, B., Buchmann, N., Carrara, A., Cellier, P., Di Tommasi, P., Elbers, J. A., Eugster, W., Grünwald, T., Jacobs, C. M. J., Jans, W. W. P., Jones, M., Kutsch, W., Lanigan, G., Magliulo, E., Marloie, O., Moors, E. J., Moureaux, C., Oliso, A., Osborne, B., Sanz, M. J., Saunders, M., Smith, P., Soegaard, H., and Wattenbach, M.: Management effects on net ecosystem carbon and GHG budgets at European crop sites, *Agric. Ecosyst. Environ.*, 139, 363–383, <https://doi.org/10.1016/j.agee.2010.09.020>, 2010.
- Chenu, C., Angers, D. A., Barré, P., Derrien, D., Arrouays, D., and Balesdent, J.: Increasing organic stocks in agricultural soils: Knowledge gaps and potential innovations, *Soil Tillage Res.*, 188, 41–52, <https://doi.org/10.1016/j.still.2018.04.011>, 2019.
- 955 Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., Blyth, E., Boucher, O., Harding, R. J., Huntingford, C., and Cox, P. M.: The Joint UK Land Environment Simulator (JULES),



- model description – Part 2: Carbon fluxes and vegetation dynamics, *Geosci. Model Dev.*, 4, 701–722, <https://doi.org/10.5194/gmd-4-701-2011>, 2011.
- 960 Coleman, K. and Jenkinson, D. S.: RothC-26.3 - A Model for the turnover of carbon in soil, in: *Evaluation of Soil Organic Matter Models*, edited by: Powlson, D. S., Smith, P., and Smith, J. U., Springer Berlin Heidelberg, Berlin, Heidelberg, 237–246, https://doi.org/10.1007/978-3-642-61094-3_17, 1996.
- Cotrufo, M. F., Ranalli, M. G., Haddix, M. L., Six, J., and Lugato, E.: Soil carbon storage informed by particulate and mineral-associated organic matter, *Nat. Geosci.*, 12, 989–994, <https://doi.org/10.1038/s41561-019-0484-6>, 2019.
- 965 Dechow, R., Franko, U., Kätterer, T., and Kolbe, H.: Evaluation of the RothC model as a prognostic tool for the prediction of SOC trends in response to management practices on arable land, *Geoderma*, 337, 463–478, <https://doi.org/10.1016/j.geoderma.2018.10.001>, 2019.
- Delhez, L., Dumont, B., and Longdoz, B.: Leveraging temporal variability in global sensitivity analysis of the Daisy soil-plant-atmosphere model, *Eur. J. Agron.*, 165, 127533, <https://doi.org/10.1016/j.eja.2025.127533>, 2025.
- 970 Du, Q., Liu, H., Feng, J., and Wang, L.: Effects of different gap filling methods and land surface energy balance closure on annual net ecosystem exchange in a semiarid area of China, *Sci. China Earth Sci.*, 57, 1340–1351, <https://doi.org/10.1007/s11430-013-4756-5>, 2014.
- Dumont, B., Heinesch, B., Bodson, B., Bogaerts, G., Chopin, H., De Ligne, A., Demoulin, L., Douxfils, B., Engelmann, T., Faurès, A., Longdoz, B., Manise, T., Orgun, A., Piret, A., and Thyron, T.: Fluxnet Archive Product from Lonze, 2004–2024, FLUXNET [dataset], <https://hdl.handle.net/11676/1u2xQ5XcQoX0j2wJiZcyDP3M>, 2026a
- 975 Dumont, B., Heinesch, B., Bodson, B., Bogaerts, G., Chopin, H., Clément, T., De Ligne, A., Demoulin, L., Douxfils, B., Engelmann, T., Faurès, A., Longdoz, B., Manise, T., Orgun, A., Piret, A., and Thyron, T.: ETC L2 ARCHIVE from Lonze, 2017–2025, ICOS RI [dataset], <https://hdl.handle.net/11676/99gAK7xqcSkk7SRKDwZz1KJT>, 2026b
- Durand, P.: A Possible Reconciliation between Eddy Covariance Fluxes and Surface Energy Balance Closure, *Atmosphere*, 13, 1965, <https://doi.org/10.3390/atmos13121965>, 2022.
- 980 Emmel, C., Winkler, A., Hörtnagl, L., Revill, A., Ammann, C., D’Odorico, P., Buchmann, N., and Eugster, W.: Integrated management of a Swiss cropland is not sufficient to preserve its soil carbon pool in the long term, *Biogeosciences*, 15, 5377–5393, <https://doi.org/10.5194/bg-15-5377-2018>, 2018.
- European Commission, Directorate-General for Environment: Nitrates Directive 91/676/EEC – Status and trends of aquatic environment and agricultural practice: development guide for Member States’ reports, 2000.
- 985 Falloon, P., Smith, P., Coleman, K., and Marshall, S.: Estimating the size of the inert organic matter pool from total soil organic carbon content for use in the Rothamsted carbon model, *Soil Biol. Biochem.*, 30, 1207–1211, [https://doi.org/10.1016/S0038-0717\(97\)00256-3](https://doi.org/10.1016/S0038-0717(97)00256-3), 1998.
- 990 Farina, R., Sándor, R., Abdalla, M., Álvaro-Fuentes, J., Bechini, L., Bolinder, M. A., Brilli, L., Chenu, C., Clivot, H., De Antoni Migliorati, M., Di Bene, C., Dorich, C. D., Ehrhardt, F., Ferchaud, F., Fitton, N., Francaviglia, R., Franko, U., Giltrap, D. L., Grant, B. B., Guenet, B., Harrison, M. T., Kirschbaum, M. U. F., Kuka, K., Kulmala, L., Liski, J., McGrath, M. J., Meier, E., Menichetti, L., Moyano, F., Nendel, C., Recous, S., Reibold, N., Shepherd, A., Smith, W. N., Smith, P., Soussana, J., Stella, T., Taghizadeh-Toosi, A., Tsutsikh, E., and Bellocchi, G.: Ensemble modelling, uncertainty and robust predictions of organic carbon in long-term bare-fallow soils, *Glob. Change Biol.*, 27, 904–928, <https://doi.org/10.1111/gcb.15441>, 2021.



- 995 Ferchaud, F., Chlebowski, F., and Mary, B.: SimpleESM: R script to calculate soil organic carbon and nitrogen stocks at equivalent soil mass, INRAE, France, 9 pp., 2023.
- Filip, I. D., Peri, P. L., Banegas, N., Nasca, J., Sacido, M., Faverin, C., and Vibart, R.: Predicting Soil Organic Carbon Stocks Under Native Forests and Grasslands in the Dry Chaco Region of Argentina, *Sustainability*, 17, 5012, <https://doi.org/10.3390/su17115012>, 2025.
- 1000 Foken, T.: The energy balance closure problem: an overview, *Ecol. Appl.*, 18, 1351–1367, <https://doi.org/10.1890/06-0922.1>, 2008.
- Foken, T., Aubinet, M., Finnigan, J. J., Leclerc, M. Y., Mauder, M., and Paw U, K. T.: Results Of A Panel Discussion About The Energy Balance Closure Correction For Trace Gases, *Bull. Am. Meteorol. Soc.*, 92, ES13–ES18, <https://doi.org/10.1175/2011BAMS3130.1>, 2011.
- 1005 Forrester, D. I., England, J. R., Paul, K. I., Rosauer, D. F., and Roxburgh, S. H.: Modelling carbon flows from live biomass to soils using the full Carbon Accounting Model (FullCAM), *Environ. Model. Softw.*, 177, 106064, <https://doi.org/10.1016/j.envsoft.2024.106064>, 2024.
- Frasier, I., Noellemeier, E., Fernández, R., and Quiroga, A.: Direct field method for root biomass quantification in agroecosystems, *MethodsX*, 3, 513–519, <https://doi.org/10.1016/j.mex.2016.08.002>, 2016.
- 1010 Friedlingstein, P., O’Sullivan, M., Jones, M. W., Andrew, R. M., Gregor, L., Hauck, J., Le Quéré, C., Luijkx, I. T., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Alkama, R., Arneeth, A., Arora, V. K., Bates, N. R., Becker, M., Bellouin, N., Bittig, H. C., Bopp, L., Chevallier, F., Chini, L. P., Cronin, M., Evans, W., Falk, S., Feely, R. A., Gasser, T., Gehlen, M., Gkritzalis, T., Gloege, L., Grassi, G., Gruber, N., Gürses, Ö., Harris, I., Hefner, M., Houghton, R. A., Hurtt, G. C., Iida, Y., Ilyina, T., Jain, A. K., Jersild, A., Kadono, K., Kato, E., Kennedy, D., Klein Goldewijk, K., Knauer, J., Korsbakken, J. I., Landschützer, P., Lefèvre, N., Lindsay, K., Liu, J., Liu, Z., Marland, G., Mayot, N., McGrath, M. J., Metzl, N., Monacci, N. M., Munro, D. R., Nakaoka, S.-I., Niwa, Y., O’Brien, K., Ono, T., Palmer, P. I., Pan, N., Pierrot, D., Pocock, K., Poulter, B., Resplandy, L., Robertson, E., Rödenbeck, C., Rodriguez, C., Rosan, T. M., Schwinger, J., Séférian, R., Shutler, J. D., Skjelvan, I., Steinhoff, T., Sun, Q., Sutton, A. J., Sweeney, C., Takao, S., Tanhua, T., Tans, P. P., Tian, X., Tian, H., Tilbrook, B., Tsujino, H., Tubiello, F., Van Der Werf, G. R., Walker, A. P., Wanninkhof, R., Whitehead, C., Willstrand Wranne, A., et al.: Global Carbon Budget 2022, *Earth Syst. Sci. Data*, 14, 4811–4900, <https://doi.org/10.5194/essd-14-4811-2022>, 2022.
- 1015 1020 Fuss, S., Lamb, W. F., Callaghan, M. W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., De Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G. F., Rogelj, J., Smith, P., Vicente, J. L. V., Wilcox, J., Del Mar Zamora Dominguez, M., and Minx, J. C.: Negative emissions—Part 2: Costs, potentials and side effects, *Environ. Res. Lett.*, 13, 063002, <https://doi.org/10.1088/1748-9326/aabf9f>, 2018.
- 1025 Gao, Z., Liu, H., Missik, J. E. C., Yao, J., Huang, M., Chen, X., Arntzen, E., and McFarland, D. P.: Mechanistic links between underestimated CO₂ fluxes and non-closure of the surface energy balance in a semi-arid sagebrush ecosystem, *Environ. Res. Lett.*, 14, 044016, <https://doi.org/10.1088/1748-9326/ab082d>, 2019.
- 1030 Garnier, J., Billen, G., Tournebise, J., Barré, P., Mary, B., and Baudin, F.: Storage or loss of soil active carbon in cropland soils: The effect of agricultural practices and hydrology, *Geoderma*, 407, 115538, <https://doi.org/10.1016/j.geoderma.2021.115538>, 2022.
- Georgiou, K., Jackson, R. B., Vindušková, O., Abramoff, R. Z., Ahlström, A., Feng, W., Harden, J. W., Pellegrini, A. F. A., Polley, H. W., Soong, J. L., Riley, W. J., and Torn, M. S.: Global stocks and capacity of mineral-associated soil organic carbon, *Nat. Commun.*, 13, 3797, <https://doi.org/10.1038/s41467-022-31540-9>, 2022.



- Geremew, B., Tadesse, T., Bedadi, B., Gollany, H. T., Tesfaye, K., Aschalew, A., Tilaye, A., and Abera, W.: Evaluation of RothC model for predicting soil organic carbon stock in north-west Ethiopia, *Environ. Chall.*, 15, 100909, <https://doi.org/10.1016/j.envc.2024.100909>, 2024.
- Giannini-Kurina, F., Serra, J., Christensen, B. T., Eriksen, J., Hutchings, N. J., Olesen, J. E., and Jensen, J. L.: Modelling and validating soil carbon dynamics at the long-term plot scale using the rCTOOL R package, *Environ. Model. Softw.*, 183, 106229, <https://doi.org/10.1016/j.envsoft.2024.106229>, 2025.
- Gielen, B., Acosta, M., Altimir, N., Buchmann, N., Cescatti, A., Ceschia, E., Fleck, S., Hörtnagl, L., Klumpp, K., Kolari, P., Lohila, A., Loustau, D., Marañón-Jimenez, S., Manise, T., Matteucci, G., Merbold, L., Metzger, C., Moureaux, C., Montagnani, L., Nilsson, M. B., Osborne, B., Papale, D., Pavelka, M., Saunders, M., Simioni, G., Soudani, K., Sonnentag, O., Tallec, T., Tuittila, E.-S., Peichl, M., Pokorný, R., Vincke, C., and Wohlfahrt, G.: Ancillary vegetation measurements at ICOS ecosystem stations, *Int. Agrophysics*, 32, 645–664, <https://doi.org/10.1515/intag-2017-0048>, 2018.
- Goidts, E. and Van Wesemael, B.: Regional assessment of soil organic carbon changes under agriculture in Southern Belgium (1955–2005), *Geoderma*, 141, 341–354, <https://doi.org/10.1016/j.geoderma.2007.06.013>, 2007.
- Goidts, E., Van Wesemael, B., and Crucifix, M.: Magnitude and sources of uncertainties in soil organic carbon (SOC) stock assessments at various scales, *Eur. J. Soil Sci.*, 60, 723–739, <https://doi.org/10.1111/j.1365-2389.2009.01157.x>, 2009.
- Gommet, C., Lauerwald, R., Ciais, P., Guenet, B., Zhang, H., and Regnier, P.: Spatiotemporal patterns and drivers of terrestrial dissolved organic carbon (DOC) leaching into the European river network, *Earth Syst. Dyn.*, 13, 393–418, <https://doi.org/10.5194/esd-13-393-2022>, 2022.
- Gross, A. and Glaser, B.: Meta-analysis on how manure application changes soil organic carbon storage, *Sci. Rep.*, 11, 5516, <https://doi.org/10.1038/s41598-021-82739-7>, 2021.
- Guenet, B., Gabrielle, B., Chenu, C., Arrouays, D., Balesdent, J., Bernoux, M., Bruni, E., Caliman, J., Cardinael, R., Chen, S., Ciais, P., Desbois, D., Fouche, J., Frank, S., Henault, C., Lugato, E., Naipal, V., Nesme, T., Obersteiner, M., Pellerin, S., Powlson, D. S., Rasse, D. P., Rees, F., Soussana, J., Su, Y., Tian, H., Valin, H., and Zhou, F.: Can N₂O emissions offset the benefits from soil organic carbon storage?, *Glob. Change Biol.*, 27, 237–256, <https://doi.org/10.1111/gcb.15342>, 2021.
- Gutierrez, S., Grados, D., Møller, A. B., De Carvalho Gomes, L., Beucher, A. M., Giannini-Kurina, F., De Jonge, L. W., and Greve, M. H.: Unleashing the sequestration potential of soil organic carbon under climate and land use change scenarios in Danish agroecosystems, *Sci. Total Environ.*, 905, 166921, <https://doi.org/10.1016/j.scitotenv.2023.166921>, 2023.
- Hedges, L. V.: Distribution Theory for Glass's Estimator of Effect Size and Related Estimators, *J. Educ. Stat.*, 6, 107, <https://doi.org/10.2307/1164588>, 1981.
- Heimbach, U.: Variability of thousand grain weights of seed batches of important arable and some horticultural crops, *J. Cultiv. Plants*, 250-254 Seiten, <https://doi.org/10.5073/JFK.2018.08.03>, 2018.
- Hemes, K. S., Runkle, B. R. K., Novick, K. A., Baldocchi, D. D., and Field, C. B.: An Ecosystem-Scale Flux Measurement Strategy to Assess Natural Climate Solutions, *Environ. Sci. Technol.*, 55, 3494–3504, <https://doi.org/10.1021/acs.est.0c06421>, 2021.
- Hollinger, D. Y. and Richardson, A. D.: Uncertainty in eddy covariance measurements and its application to physiological models, *Tree Physiol.*, 25, 873–885, <https://doi.org/10.1093/treephys/25.7.873>, 2005.



- 1070 Ibrom, A., Dellwik, E., Larsen, S. E., and Pilegaard, K.: On the use of the Webb–Pearman–Leuning theory for closed-path eddy correlation measurements, *Tellus B Chem. Phys. Meteorol.*, 59, 937, <https://doi.org/10.1111/j.1600-0889.2007.00311.x>, 2007.
- Ingwersen, J., Poyda, A., Kremer, P., and Streck, T.: Harvest residues: A relevant term in the carbon balance of croplands?, *Agric. For. Meteorol.*, 349, 109935, <https://doi.org/10.1016/j.agrformet.2024.109935>, 2024.
- 1075 Janssens, I. A., Freibauer, A., Ciais, P., Smith, P., Nabuurs, G.-J., Folberth, G., Schlamadinger, B., Hutjes, R. W. A., Ceulemans, R., Schulze, E.-D., Valentini, R., and Dolman, A. J.: Europe’s Terrestrial Biosphere Absorbs 7 to 12% of European Anthropogenic CO₂ Emissions, *Science*, 300, 1538–1542, <https://doi.org/10.1126/science.1083592>, 2003.
- Jensen, J. L., Eriksen, J., Thomsen, I. K., Munkholm, L. J., and Christensen, B. T.: Cereal straw incorporation and ryegrass cover crops: The path to equilibrium in soil carbon storage is short, *Eur. J. Soil Sci.*, 73, e13173, <https://doi.org/10.1111/ejss.13173>, 2022.
- 1080 Jones, D. L., Cooledge, E. C., Alston, D., and Chadwick, D. R.: Agricultural management strategies to actively promote subsoil carbon storage, *Soil Tillage Res.*, 256, 106846, <https://doi.org/10.1016/j.still.2025.106846>, 2026.
- Joona, J., Liski, E., and Kahiluoto, H.: Manure increases soil organic carbon most when allocated to annual cropping, *CATENA*, 238, 107844, <https://doi.org/10.1016/j.catena.2024.107844>, 2024.
- 1085 Jordon, M. W. and Smith, P.: Modelling soil carbon stocks following reduced tillage intensity: A framework to estimate decomposition rate constant modifiers for RothC-26.3, demonstrated in north-west Europe, *Soil Tillage Res.*, 222, 105428, <https://doi.org/10.1016/j.still.2022.105428>, 2022.
- Kätterer, T., Börjesson, G., and Kirchmann, H.: Changes in organic carbon in topsoil and subsoil and microbial community composition caused by repeated additions of organic amendments and N fertilisation in a long-term field experiment in Sweden, *Agric. Ecosyst. Environ.*, 189, 110–118, <https://doi.org/10.1016/j.agee.2014.03.025>, 2014.
- 1090 Keel, S. G., Leifeld, J., Mayer, J., Taghizadeh-Toosi, A., and Olesen, J. E.: Large uncertainty in soil carbon modelling related to method of calculation of plant carbon input in agricultural systems, *Eur. J. Soil Sci.*, 68, 953–963, <https://doi.org/10.1111/ejss.12454>, 2017.
- Khan, Md. Z., Chabbi, A., Hicks Pries, C. E., Torn, M. S., and Rumpel, C.: Management impacts on whole soil warming responses of CO₂ production and efflux in temperate climate, *Geoderma*, 440, 116725, <https://doi.org/10.1016/j.geoderma.2023.116725>, 2023.
- 1095 Kindler, R., Siemens, J., Kaiser, K., Walmsley, D. C., Bernhofer, C., Buchmann, N., Cellier, P., Eugster, W., Gleixner, G., Grünwald, T., Heim, A., Ibrom, A., Jones, S. K., Jones, M., Klumpp, K., Kutsch, W., Larsen, K. S., Lehuger, S., Loubet, B., Mckenzie, R., Moors, E., Osborne, B., Pilegaard, K., Rebmann, C., Saunders, M., Schmidt, M. W. I., Schrumpf, M., Seyfferth, J., Skiba, U., Soussana, J., Sutton, M. A., Tefs, C., Vowinkel, B., Zeeman, M. J., and Kaupenjohann, M.: Dissolved carbon leaching from soil is a crucial component of the net ecosystem carbon balance, *Glob. Change Biol.*, 17, 1167–1185, <https://doi.org/10.1111/j.1365-2486.2010.02282.x>, 2011.
- Kirby, K. N. and Gerlanc, D.: BootES: An R package for bootstrap confidence intervals on effect sizes, *Behav. Res. Methods*, 45, 905–927, <https://doi.org/10.3758/s13428-013-0330-5>, 2013.
- 1105 Köchy, M., Hiederer, R., and Freibauer, A.: Global distribution of soil organic carbon – Part 1: Masses and frequency distributions of SOC stocks for the tropics, permafrost regions, wetlands, and the world, *SOIL*, 1, 351–365, <https://doi.org/10.5194/soil-1-351-2015>, 2015.



- Koga, N.: Tillage, fertilizer type, and plant residue input impacts on soil carbon sequestration rates on a Japanese Andosol, *Soil Sci. Plant Nutr.*, 63, 396–404, <https://doi.org/10.1080/00380768.2017.1355725>, 2017.
- 1110 Ku, H. H.: Notes on the use of propagation of error formulas, *J. Res. Natl. Bur. Stand. Sect. C Eng. Instrum.*, 263, 1966.
- Kutsch, W. L., Aubinet, M., Buchmann, N., Smith, P., Osborne, B., Eugster, W., Wattenbach, M., Schruppf, M., Schulze, E. D., Tomelleri, E., Ceschia, E., Bernhofer, C., Béziat, P., Carrara, A., Di Tommasi, P., Grünwald, T., Jones, M., Magliulo, V., Marloie, O., Moureaux, C., Olioso, A., Sanz, M. J., Saunders, M., Søgaaard, H., and Ziegler, W.: The net biome production of full crop rotations in Europe, *Agric. Ecosyst. Environ.*, 139, 336–345, <https://doi.org/10.1016/j.agee.2010.07.016>, 2010.
- 1115 Lal, R.: Soil organic matter and water retention, *Agron. J.*, 112, 3265–3277, <https://doi.org/10.1002/agj.2.20282>, 2020.
- Lavallee, J. M., Soong, J. L., and Cotrufo, M. F.: Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century, *Glob. Change Biol.*, 26, 261–273, <https://doi.org/10.1111/gcb.14859>, 2020.
- Lee, J., Hopmans, J. W., Rolston, D. E., Baer, S. G., and Six, J.: Determining soil carbon stock changes: Simple bulk density corrections fail, *Agric. Ecosyst. Environ.*, 134, 251–256, <https://doi.org/10.1016/j.agee.2009.07.006>, 2009.
- 1120 Lehmann, J. and Kleber, M.: The contentious nature of soil organic matter, *Nature*, 528, 60–68, <https://doi.org/10.1038/nature16069>, 2015.
- Li, L., Hong, M., Zhang, Y., and Paustian, K.: Soil N₂O emissions from specialty crop systems: A global estimation and meta-analysis, *Glob. Change Biol.*, 30, e17233, <https://doi.org/10.1111/gcb.17233>, 2024.
- 1125 Liang, S., Sun, N., Wang, S., Colinet, G., Longdoz, B., Meersmans, J., Wu, L., and Xu, M.: Manure amendment acts as a recommended fertilization for improving carbon sequestration efficiency in soils of typical drylands of China, *Front. Environ. Sci.*, 11, <https://doi.org/10.3389/fenvs.2023.1173509>, 2023.
- Loubet, B., Laville, P., Lehuger, S., Larmanou, E., Fléchar, C., Mascher, N., Genermont, S., Roche, R., Ferrara, R. M., Stella, P., Personne, E., Durand, B., Decuq, C., Flura, D., Masson, S., Fanucci, O., Rampon, J.-N., Siemens, J., Kindler, R., Gabrielle, B., Schruppf, M., and Cellier, P.: Carbon, nitrogen and Greenhouse gases budgets over a four years crop rotation in northern France, *Plant Soil*, 343, 109–137, <https://doi.org/10.1007/s11104-011-0751-9>, 2011.
- 1130 Loubet, B., Saby, N. P. A., Winck, B., Gebleh, M., Buysse, P., Chenu, J.-P., Ratié, C., Jolivet, C., Kalalian, C., Levvasseur, F., Munera-Echeverri, J.-L., Lafont, S., Loustau, D., Papale, D., Nicolini, G., and Arrouays, D.: Carbon soil stock change in an intensive crop field near Paris reveals significant carbon losses over a decade, *Biogeosciences*, 23, 2059–2077, <https://doi.org/10.5194/bg-23-2059-2026>, 2026.
- 1135 Loustau, D., Jolivet, C., Lafont, S., Loubet, B., Klumpp, K., Papale, D., and Arrouays, D.: ICOS Ecosystem Instructions for Soil Samples Collection and Preparation, Version 20230727, ICOS Ecosystem Thematic Centre, <https://doi.org/10.18160/k3yc-td6h>, 2017.
- Ma, S., He, F., Tian, D., Zou, D., Yan, Z., Yang, Y., Zhou, T., Huang, K., Shen, H., and Fang, J.: Variations and determinants of carbon content in plants: a global synthesis, *Biogeosciences*, 15, 693–702, <https://doi.org/10.5194/bg-15-693-2018>, 2018.
- 1140 Maenhout, P., Di Bene, C., Cayuela, M. L., Diaz-Pines, E., Govednik, A., Keuper, F., Mavsar, S., Mihelic, R., O’Toole, A., Schwarzmann, A., Suhadolc, M., Syp, A., and Valkama, E.: Trade-offs and synergies of soil carbon sequestration: Addressing knowledge gaps related to soil management strategies, *Eur. J. Soil Sci.*, 75, e13515, <https://doi.org/10.1111/ejss.13515>, 2024.



- Maillard, É. and Angers, D. A.: Animal manure application and soil organic carbon stocks: a meta-analysis, *Glob. Change Biol.*, 20, 666–679, <https://doi.org/10.1111/gcb.12438>, 2014.
- 1145 Manninen, N., Soenne, H., Lemola, R., Hoikkala, L., and Turtola, E.: Effects of agricultural land use on dissolved organic carbon and nitrogen in surface runoff and subsurface drainage, *Sci. Total Environ.*, 618, 1519–1528, <https://doi.org/10.1016/j.scitotenv.2017.09.319>, 2018.
- Mantel, S., Dondeyne, S., and Deckers, S.: World reference base for soil resources (WRB), in: *Encyclopedia of Soils in the Environment*, Elsevier, 206–217, <https://doi.org/10.1016/B978-0-12-822974-3.00161-0>, 2023.
- 1150 Mauder, M., Foken, T., and Cuxart, J.: Surface-Energy-Balance Closure over Land: A Review, *Bound.-Layer Meteorol.*, 177, 395–426, <https://doi.org/10.1007/s10546-020-00529-6>, 2020.
- Mauder, M., Jung, M., Stoy, P., Nelson, J., and Wanner, L.: Energy balance closure at FLUXNET sites revisited, *Agric. For. Meteorol.*, 358, 110235, <https://doi.org/10.1016/j.agrformet.2024.110235>, 2024.
- 1155 McClelland, S. C., Paustian, K., and Schipanski, M. E.: Management of cover crops in temperate climates influences soil organic carbon stocks: a meta-analysis, *Ecol. Appl.*, 31, e02278, <https://doi.org/10.1002/eap.2278>, 2021.
- Meersmans, J., Van Wesemael, B., Goidts, E., Van Molle, M., De Baets, S., and De Ridder, F.: Spatial analysis of soil organic carbon evolution in Belgian croplands and grasslands, 1960–2006: SPATIAL ANALYSIS OF SOIL ORGANIC CARBON EVOLUTION, *Glob. Change Biol.*, 17, 466–479, <https://doi.org/10.1111/j.1365-2486.2010.02183.x>, 2011.
- 1160 Mondini, C., Cayuela, M. L., Sinicco, T., Fornasier, F., Galvez, A., and Sánchez-Monedero, M. A.: Modification of the RothC model to simulate soil C mineralization of exogenous organic matter, *Biogeosciences*, 14, 3253–3274, <https://doi.org/10.5194/bg-14-3253-2017>, 2017.
- Morais, T. G., Teixeira, R. F. M., and Domingos, T.: Detailed global modelling of soil organic carbon in cropland, grassland and forest soils, *PLOS ONE*, 14, e0222604, <https://doi.org/10.1371/journal.pone.0222604>, 2019.
- 1165 Muhammed, S. E., Coleman, K., Wu, L., Bell, V. A., Davies, J. A. C., Quinton, J. N., Carnell, E. J., Tomlinson, S. J., Dore, A. J., Dragosits, U., Naden, P. S., Glendinning, M. J., Tipping, E., and Whitmore, A. P.: Impact of two centuries of intensive agriculture on soil carbon, nitrogen and phosphorus cycling in the UK, *Sci. Total Environ.*, 634, 1486–1504, <https://doi.org/10.1016/j.scitotenv.2018.03.378>, 2018.
- 1170 Nakhavali, M., Friedlingstein, P., Lauerwald, R., Tang, J., Chadburn, S., Camino-Serrano, M., Guenet, B., Harper, A., Walmsley, D., Peichl, M., and Gielen, B.: Representation of dissolved organic carbon in the JULES land surface model (vn4.4_JULES-DOCM), *Geosci. Model Dev.*, 11, 593–609, <https://doi.org/10.5194/gmd-11-593-2018>, 2018.
- Nakhavali, M., Lauerwald, R., Regnier, P., Guenet, B., Chadburn, S., and Friedlingstein, P.: Leaching of dissolved organic carbon from mineral soils plays a significant role in the terrestrial carbon balance, *Glob. Change Biol.*, 27, 1083–1096, <https://doi.org/10.1111/gcb.15460>, 2021.
- 1175 Nakhavali, M. (Andre), Lauerwald, R., Regnier, P., and Friedlingstein, P.: Historical trends and drivers of the laterally transported terrestrial dissolved organic carbon to river systems, *Sci. Total Environ.*, 917, 170560, <https://doi.org/10.1016/j.scitotenv.2024.170560>, 2024.
- Nicolini, G., Durden, D., Di Fiore, L., Florian, C., Sabbatini, S., Gielen, B., Iserbyt, A., Loubet, B., Mammarella, I., Mariotti, A., Op De Beeck, M., Slemmons, C., Trotta, C., Young, A., Chabbi, A., Feigenwinter, I., Heinesch, B., Kowalska, N., Mauder, M., Šigut, L., Van Der Molen, M., Bastos Campos, F., Berveiller, D., Brümmer, C., Cuntz, M., Domec, J., Dumont, B., Fares,



- 1180 S., Gianelle, D., Jensen, R., Kalalian, C., Kljun, N., Lange, H., Limousin, J., Lundin, E., Manco, A., Montagnani, L., Nemitz, E., Peichl, M., Rinne, E., Roland, M., Schmidt, M., Simioni, G., Thomas, A., Vincke, C., and Papale, D.: Bridging the Energy Balance Gap in Eddy-Covariance Measurements: Insights From Standardized Network Data, *Glob. Change Biol.*, 32, e70892, <https://doi.org/10.1111/gcb.70892>, 2026.
- 1185 Noordwijk, M. V., Floris, J., and Jager, A. D.: Sampling schemes for estimating root density distribution in cropped fields, *Neth. J. Agric. Sci.*, 33, 241–261, <https://doi.org/10.18174/njas.v33i3.16839>, 1985.
- Onckley, S. P., Foken, T., Vogt, R., Kohsiek, W., DeBruin, H. A. R., Bernhofer, C., Christen, A., Gorsel, E. V., Grantz, D., Feigenwinter, C., Lehner, I., Liebethal, C., Liu, H., Mauder, M., Pitacco, A., Ribeiro, L., and Weidinger, T.: The Energy Balance Experiment EBEX-2000. Part I: overview and energy balance, *Bound.-Layer Meteorol.*, 123, 1–28, <https://doi.org/10.1007/s10546-007-9161-1>, 2007.
- 1190 Orgill, S. E., Condon, J. R., Kirkby, C. A., Orchard, B. A., Conyers, M. K., Greene, R. S. B., and Murphy, B. W.: Soil with high organic carbon concentration continues to sequester carbon with increasing carbon inputs, *Geoderma*, 285, 151–163, <https://doi.org/10.1016/j.geoderma.2016.09.033>, 2017.
- Pan, G., Smith, P., and Pan, W.: The role of soil organic matter in maintaining the productivity and yield stability of cereals in China, *Agric. Ecosyst. Environ.*, 129, 344–348, <https://doi.org/10.1016/j.agee.2008.10.008>, 2009.
- 1195 Papale, D., Reichstein, M., Aubinet, M., Canfora, E., Bernhofer, C., Kutsch, W., Longdoz, B., Rambal, S., Valentini, R., Vesala, T., and Yakir, D.: Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation, *Biogeosciences*, 3, 571–583, <https://doi.org/10.5194/bg-3-571-2006>, 2006.
- Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y.-W., Poindexter, C., Chen, J., Elbashandy, A., Humphrey, M., Isaac, P., Polidori, D., Ribeca, A., Ingen, C., Zhang, L., Amiro, B., Ammann, C., Arain, M., Ardö, J., and 1200 Papale, D.: The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data, *Sci. Data*, 7, <https://doi.org/10.1038/s41597-020-0534-3>, 2020.
- Patra, R., Saha, D., and Jagadamma, S.: Winter wheat cover crop increased subsoil organic carbon in a long-term cotton cropping system in Tennessee, *Soil Tillage Res.*, 224, 105521, <https://doi.org/10.1016/j.still.2022.105521>, 2022.
- 1205 Patra, R., Saha, D., Neupane, A., and Jagadamma, S.: Deep-rooted winter wheat cover crop promotes subsoil organic carbon storage through improved microbial functional traits, *Appl. Soil Ecol.*, 199, 105413, <https://doi.org/10.1016/j.apsoil.2024.105413>, 2024.
- Peltola, O., Aslan, T., Ibrom, A., Nemitz, E., Rannik, Ü., and Mammarella, I.: The high-frequency response correction of eddy covariance fluxes – Part 1: An experimental approach and its interdependence with the time-lag estimation, *Atmos. Meas. Tech.*, 14, 5071–5088, <https://doi.org/10.5194/amt-14-5071-2021>, 2021.
- 1210 Penko Seidl, N. and Golobič, M.: Quantitative assessment of agricultural landscape heterogeneity, *Ecol. Indic.*, 112, 106115, <https://doi.org/10.1016/j.ecolind.2020.106115>, 2020.
- Pesce, S., Balugani, E., De Paz, J. M., Marazza, D., and Visconti, F.: A Modified Version of RothC to Model the Direct and Indirect Effects of Rice Straw Mulching on Soil Carbon Dynamics, Calibrated in Two Valencian Citrus Orchards, *Soil Syst.*, 8, 12, <https://doi.org/10.3390/soilsystems8010012>, 2024.
- 1215 Pierson, D., Lohse, K. A., Wieder, W. R., Patton, N. R., Facer, J., De Graaff, M.-A., Georgiou, K., Seyfried, M. S., Flerchinger, G., and Will, R.: Optimizing process-based models to predict current and future soil organic carbon stocks at high-resolution, *Sci. Rep.*, 12, 10824, <https://doi.org/10.1038/s41598-022-14224-8>, 2022.



- Poeplau, C. and Don, A.: Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis, *Agric. Ecosyst. Environ.*, 200, 33–41, <https://doi.org/10.1016/j.agee.2014.10.024>, 2015.
- 1220 Poeplau, C., Aronsson, H., Myrbeck, Å., and Kätterer, T.: Effect of perennial ryegrass cover crop on soil organic carbon stocks in southern Sweden, *Geoderma Reg.*, 4, 126–133, <https://doi.org/10.1016/j.geodrs.2015.01.004>, 2015.
- Poeplau, C., Don, A., and Schneider, F.: Roots are key to increasing the mean residence time of organic carbon entering temperate agricultural soils, *Glob. Change Biol.*, 27, 4921–4934, <https://doi.org/10.1111/gcb.15787>, 2021.
- 1225 Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., Song, X.-P., Pickens, A., Shen, Q., and Cortez, J.: Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century, *Nat. Food*, 3, 19–28, <https://doi.org/10.1038/s43016-021-00429-z>, 2021.
- Poulton, P., Johnston, J., Macdonald, A., White, R., and Powlson, D.: Major limitations to achieving “4 per 1000” increases in soil organic carbon stock in temperate regions: Evidence from long-term experiments at Rothamsted Research, United Kingdom, *Glob. Change Biol.*, 24, 2563–2584, <https://doi.org/10.1111/gcb.14066>, 2018.
- 1230 Powlson, D. S., Whitmore, A. P., and Goulding, K. W. T.: Soil carbon sequestration to mitigate climate change: a critical re-examination to identify the true and the false, *Eur. J. Soil Sci.*, 62, 42–55, <https://doi.org/10.1111/j.1365-2389.2010.01342.x>, 2011.
- Powlson, D. S., Bhogal, A., Chambers, B. J., Coleman, K., Macdonald, A. J., Goulding, K. W. T., and Whitmore, A. P.: The potential to increase soil carbon stocks through reduced tillage or organic material additions in England and Wales: A case study, *Agric. Ecosyst. Environ.*, 146, 23–33, <https://doi.org/10.1016/j.agee.2011.10.004>, 2012.
- 1235 Poyda, A., Witzmann, H.-D., Ingwersen, J., Eshonkulov, R., Högy, P., Demyan, M. S., Kremer, P., Wulfmeyer, V., and Streck, T.: Carbon fluxes and budgets of intensive crop rotations in two regional climates of southwest Germany, *Agric. Ecosyst. Environ.*, 276, 31–46, <https://doi.org/10.1016/j.agee.2019.02.011>, 2019.
- Raffeld, A. M., Bradford, M. A., Jackson, R. D., Rath, D., Sanford, G. R., Tautges, N., and Oldfield, E. E.: The importance of accounting method and sampling depth to estimate changes in soil carbon stocks, *Carbon Balance Manag.*, 19, 2, <https://doi.org/10.1186/s13021-024-00249-1>, 2024.
- 1240 Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Bernhofer, C., Buchmann, N., Gilmanov, T., Granier, A., Grunwald, T., Havrankova, K., Ilvesniemi, H., Janous, D., Knohl, A., Laurila, T., Lohila, A., Loustau, D., Matteucci, G., Meyers, T., Miglietta, F., Ourcival, J.-M., Pumpanen, J., Rambal, S., Rotenberg, E., Sanz, M., Tenhunen, J., Seufert, G., Vaccari, F., Vesala, T., Yakir, D., and Valentini, R.: On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm, *Glob. Change Biol.*, 11, 1424–1439, <https://doi.org/10.1111/j.1365-2486.2005.001002.x>, 2005.
- 1245 Ren, W., Banger, K., Tao, B., Yang, J., Huang, Y., and Tian, H.: Global pattern and change of cropland soil organic carbon during 1901–2010: Roles of climate, atmospheric chemistry, land use and management, *Geogr. Sustain.*, 1, 59–69, <https://doi.org/10.1016/j.geosus.2020.03.001>, 2020.
- Richardson, A. D., Aubinet, M., Barr, A. G., Hollinger, D. Y., Ibrom, A., Lasslop, G., and Reichstein, M.: Uncertainty Quantification, in: *Eddy Covariance*, edited by: Aubinet, M., Vesala, T., and Papale, D., Springer Netherlands, Dordrecht, 173–209, https://doi.org/10.1007/978-94-007-2351-1_7, 2012.



- 1255 Rodeghiero, M., Heinemeyer, A., Schrumpf, M., and Bellamy, P.: Determination of soil carbon stocks and changes, in: *Soil Carbon Dynamics*, edited by: Kutsch, W. L., Bahn, M., and Heinemeyer, A., Cambridge University Press, 49–75, <https://doi.org/10.1017/CBO9780511711794.005>, 2010.
- Sail, S., Huyghebaert, B., Vanwindekens, F., Abras, M., and Hardy, B.: Soil organic carbon stocks and dynamics under contrasting organic matter management practices – Results from a 65-year-old experiment in Belgium, *Eur. J. Agron.*, 170, 127709, <https://doi.org/10.1016/j.eja.2025.127709>, 2025.
- 1260 Saltelli, A., Tarantola, S., and Campolongo, F.: Sensitivity Analysis as an Ingredient of Modeling, *Stat. Sci.*, 15, 377–395, 2000.
- Scavo, A., Fontanazza, S., Restuccia, A., Pesce, G. R., Abbate, C., and Mauromicale, G.: The role of cover crops in improving soil fertility and plant nutritional status in temperate climates. A review, *Agron. Sustain. Dev.*, 42, 93, <https://doi.org/10.1007/s13593-022-00825-0>, 2022.
- 1265 Schepens, J. A. B., Koopmans, C. J., Heupink, D. T., Timmermans, B. G. H., Gentsch, N., Martens, S., De Haan, J., Creamer, R. E., and Moinet, G. Y. K.: From global trends to local realities: SOC accrual of improved management practices in northwestern Europe, *Geoderma Reg.*, 42, e00983, <https://doi.org/10.1016/j.geodrs.2025.e00983>, 2025.
- Schrumpf, M., Schulze, E. D., Kaiser, K., and Schumacher, J.: How accurately can soil organic carbon stocks and stock changes be quantified by soil inventories?, *Biogeosciences*, 8, 1193–1212, <https://doi.org/10.5194/bg-8-1193-2011>, 2011.
- 1270 Seitz, D., Fischer, L. M., Dechow, R., Wiesmeier, M., and Don, A.: The potential of cover crops to increase soil organic carbon storage in German croplands, *Plant Soil*, 488, 157–173, <https://doi.org/10.1007/s11104-022-05438-w>, 2023.
- Shakoor, A., Shakoor, S., Rehman, A., Ashraf, F., Abdullah, M., Shahzad, S. M., Farooq, T. H., Ashraf, M., Manzoor, M. A., Altaf, M. M., and Altaf, M. A.: Effect of animal manure, crop type, climate zone, and soil attributes on greenhouse gas emissions from agricultural soils—A global meta-analysis, *J. Clean. Prod.*, 278, 124019, <https://doi.org/10.1016/j.jclepro.2020.124019>, 2021.
- 1275 Sierra, C. A., Müller, M., and Trumbore, S. E.: Models of soil organic matter decomposition: the SoilR package, version 1.0, *Geosci. Model Dev.*, 5, 1045–1060, <https://doi.org/10.5194/gmd-5-1045-2012>, 2012.
- Sierra, C. A., Ahrens, B., Bolinder, M. A., Braakhekke, M. C., Von Fromm, S., Kätterer, T., Luo, Z., Parvin, N., and Wang, G.: Carbon sequestration in the subsoil and the time required to stabilize carbon for climate change mitigation, *Glob. Change Biol.*, 30, e17153, <https://doi.org/10.1111/gcb.17153>, 2024.
- 1280 Smith, P.: How long before a change in soil organic carbon can be detected?, *Glob. Change Biol.*, 10, 1878–1883, <https://doi.org/10.1111/j.1365-2486.2004.00854.x>, 2004.
- Smith, P., Soussana, J., Angers, D., Schipper, L., Chenu, C., Rasse, D. P., Batjes, N. H., Van Egmond, F., McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J. E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A., and Klumpp, K.: How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal, *Glob. Change Biol.*, 26, 219–241, <https://doi.org/10.1111/gcb.14815>, 2020.
- 1285 Spotorno, S., Gobin, A., Vanongeval, F., Del Borghi, A., and Gallo, M.: Carbon Farming practices assessment: Modelling spatial changes of Soil Organic Carbon in Flanders, Belgium, *Sci. Total Environ.*, 922, 171267, <https://doi.org/10.1016/j.scitotenv.2024.171267>, 2024.



- 1290 Stamati, F. E., Nikolaidis, N. P., and Schnoor, J. L.: Modeling topsoil carbon sequestration in two contrasting crop production to set-aside conversions with RothC – Calibration issues and uncertainty analysis, *Agric. Ecosyst. Environ.*, 165, 190–200, <https://doi.org/10.1016/j.agee.2012.11.010>, 2013.
- Stewart, C. E., Paustian, K., Conant, R. T., Plante, A. F., and Six, J.: Soil carbon saturation: concept, evidence and evaluation, *Biogeochemistry*, 86, 19–31, <https://doi.org/10.1007/s10533-007-9140-0>, 2007.
- 1295 Stoy, P. C., Mauder, M., Foken, T., Marcolla, B., Boegh, E., Ibrom, A., Arain, M. A., Arneth, A., Aurela, M., Bernhofer, C., Cescatti, A., Dellwik, E., Duce, P., Gianelle, D., van Gorsel, E., Kiely, G., Knohl, A., Margolis, H., McCaughey, H., Merbold, L., Montagnani, L., Papale, D., Reichstein, M., Saunders, M., Serrano-Ortiz, P., Sottocornola, M., Spano, D., Vaccari, F., and Varlagin, A.: A data-driven analysis of energy balance closure across FLUXNET research sites: The role of landscape scale heterogeneity, *Agric. For. Meteorol.*, 171–172, 137–152, <https://doi.org/10.1016/j.agrformet.2012.11.004>, 2013.
- 1300 Sulman, B. N., Harden, J., He, Y., Treat, C., Koven, C., Mishra, U., O'Donnell, J. A., and Nave, L. E.: Land Use and Land Cover Affect the Depth Distribution of Soil Carbon: Insights From a Large Database of Soil Profiles, *Front. Environ. Sci.*, 8, 146, <https://doi.org/10.3389/fenvs.2020.00146>, 2020.
- Sun, J. and Tribbia, J.: Total energy conservation for explaining discrepancies between field observations and the traditional thermal energy balance, *Q. J. R. Meteorol. Soc.*, 151, e5005, <https://doi.org/10.1002/qj.5005>, 2025.
- 1305 Sun, J., Massman, W. J., Banta, R. M., and Burns, S. P.: Revisiting the Surface Energy Imbalance, *J. Geophys. Res. Atmos.*, 126, e2020JD034219, <https://doi.org/10.1029/2020JD034219>, 2021.
- Sun, Z., Chen, Q., Han, X., Bol, R., Qu, B., and Meng, F.: Allocation of photosynthesized carbon in an intensively farmed winter wheat–soil system as revealed by $^{14}\text{CO}_2$ pulse labelling, *Sci. Rep.*, 8, 3160, <https://doi.org/10.1038/s41598-018-21547-y>, 2018.
- 1310 Teng, D., He, X., Wang, J., Wang, J., and Lv, G.: Uncertainty in gap filling and estimating the annual sum of carbon dioxide exchange for the desert Tugai forest, Ebinur Lake Basin, Northwest China, *PeerJ*, 8, e8530, <https://doi.org/10.7717/peerj.8530>, 2020.
- Terrer, C., Phillips, R. P., Hungate, B. A., Rosende, J., Pett-Ridge, J., Craig, M. E., Van Groenigen, K. J., Keenan, T. F., Sulman, B. N., Stocker, B. D., Reich, P. B., Pellegrini, A. F. A., Pendall, E., Zhang, H., Evans, R. D., Carrillo, Y., Fisher, J. B., Van Sundert, K., Vicca, S., and Jackson, R. B.: A trade-off between plant and soil carbon storage under elevated CO_2 , *Nature*, 591, 599–603, <https://doi.org/10.1038/s41586-021-03306-8>, 2021.
- Thirion, F. and Chabot, F.: Recommandations pour assurer la qualité d'épandage des produits organiques, *Ingénieries Eau-Agriculture-Territoires*, 35, 29–41, <https://hal.science/hal-00467509>, 2003.
- Twine, T. E., Kustas, W. P., Norman, J. M., Cook, D. R., Houser, P. R., Meyers, T. P., Prueger, J. H., Starks, P. J., and Wesely, M. L.: Correcting eddy-covariance flux underestimates over a grassland, *Agric. For. Meteorol.*, 103, 279–300, [https://doi.org/10.1016/S0168-1923\(00\)00123-4](https://doi.org/10.1016/S0168-1923(00)00123-4), 2000.
- Vekuri, H., Tuovinen, J.-P., Kulmala, L., Papale, D., Kolari, P., Aurela, M., Laurila, T., Liski, J., and Lohila, A.: A widely-used eddy covariance gap-filling method creates systematic bias in carbon balance estimates, *Sci. Rep.*, 13, 1720, <https://doi.org/10.1038/s41598-023-28827-2>, 2023.
- 1325 Vekuri, H., Tuovinen, J.-P., Kulmala, L., Aurela, M., Thum, T., Liski, J., and Lohila, A.: Improved uncertainty estimates for eddy covariance-based carbon dioxide balances using deep ensembles for gap-filling, *Agric. For. Meteorol.*, 371, 110558, <https://doi.org/10.1016/j.agrformet.2025.110558>, 2025.



- Walmsley, D. C., Siemens, J., Kindler, R., Kirwan, L., Kaiser, K., Saunders, M., Kaupenjohann, M., and Osborne, B. A.: Dissolved carbon leaching from an Irish cropland soil is increased by reduced tillage and cover cropping, *Agric. Ecosyst. Environ.*, 142, 393–402, <https://doi.org/10.1016/j.agee.2011.06.011>, 2011.
- Wang, Y., Li, X., Dong, W., Wu, D., Hu, C., Zhang, Y., and Luo, Y.: Depth-dependent greenhouse gas production and consumption in an upland cropping system in northern China, *Geoderma*, 319, 100–112, <https://doi.org/10.1016/j.geoderma.2018.01.001>, 2018.
- Wang, Y., Ying, H., Yin, Y., Zheng, H., and Cui, Z.: Estimating soil nitrate leaching of nitrogen fertilizer from global meta-analysis, *Sci. Total Environ.*, 657, 96–102, <https://doi.org/10.1016/j.scitotenv.2018.12.029>, 2019.
- Weihermüller, L., Graf, A., Herbst, M., and Vereecken, H.: Simple pedotransfer functions to initialize reactive carbon pools of the RothC model, *Eur. J. Soil Sci.*, 64, 567–575, <https://doi.org/10.1111/ejss.12036>, 2013.
- Wiaux, F., Vanclooster, M., and Van Oost, K.: Vertical partitioning and controlling factors of gradient-based soil carbon dioxide fluxes in two contrasted soil profiles along a loamy hillslope, *Biogeosciences*, 12, 4637–4649, <https://doi.org/10.5194/bg-12-4637-2015>, 2015.
- Wohlfahrt, G. and Widmoser, P.: Can an energy balance model provide additional constraints on how to close the energy imbalance?, *Agric. For. Meteorol.*, 169, 85–91, <https://doi.org/10.1016/j.agrformet.2012.10.006>, 2013.
- Wüst-Galley, C., Keel, S. G., and Leifeld, J.: A model-based carbon inventory for Switzerland’s mineral agricultural soils using RothC, *Agroscope*, <https://doi.org/10.34776/AS105E>, 2020.
- Wutzler, T., Lucas-Moffat, A., Migliavacca, M., Knauer, J., Sickel, K., Šigut, L., Menzer, O., and Reichstein, M.: Basic and extensible post-processing of eddy covariance flux data with REddyProc, *Biogeosciences*, 15, 5015–5030, <https://doi.org/10.5194/bg-15-5015-2018>, 2018.
- Yokozawa, M., Shirato, Y., Sakamoto, T., Yonemura, S., Nakai, M., and Ohkura, T.: Use of the RothC model to estimate the carbon sequestration potential of organic matter application in Japanese arable soils, *Soil Sci. Plant Nutr.*, 56, 168–176, <https://doi.org/10.1111/j.1747-0765.2009.00422.x>, 2010.
- Zhang, Z., Kaye, J. P., Bradley, B. A., Amsili, J. P., and Suseela, V.: Cover crop functional types differentially alter the content and composition of soil organic carbon in particulate and mineral-associated fractions, *Glob. Change Biol.*, 28, 5831–5848, <https://doi.org/10.1111/gcb.16296>, 2022.
- Zhao, X. and Huang, Y.: A Comparison of Three Gap Filling Techniques for Eddy Covariance Net Carbon Fluxes in Short Vegetation Ecosystems, *Adv. Meteorol.*, 2015, 1–12, <https://doi.org/10.1155/2015/260580>, 2015.
- Zhen, H., Jia, L., Huang, C., Qiao, Y., Li, J., Li, H., Chen, Q., and Wan, Y.: Long-term effects of intensive application of manure on heavy metal pollution risk in protected-field vegetable production, *Environ. Pollut.*, 263, 114552, <https://doi.org/10.1016/j.envpol.2020.114552>, 2020.
- Zhou, J., Shao, G., Li, L., Yang, X., Zamanian, K., Alharbi, S. A., Filimonenko, E., Liu, E., Mei, X., and Kuzyakov, Y.: The over-estimation of long-term mineral fertilizer on CO₂ release from soil carbonates, *Agric. Ecosyst. Environ.*, 392, 109737, <https://doi.org/10.1016/j.agee.2025.109737>, 2025.
- Zhou, M., Zhu, B., Wang, S., Zhu, X., Vereecken, H., and Brüggemann, N.: Stimulation of N₂ O emission by manure application to agricultural soils may largely offset carbon benefits: a global meta-analysis, *Glob. Change Biol.*, 23, 4068–4083, <https://doi.org/10.1111/gcb.13648>, 2017.



1365 Zhou, Y., Liu, H., Sühling, M., and Li, X.: Implications of energy balance non-closure on carbon dioxide flux uncertainties: Insights from large eddy simulations in convective boundary layers, *Agric. For. Meteorol.*, 358, 110211, <https://doi.org/10.1016/j.agrformet.2024.110211>, 2024.

Zimmermann, M., Leifeld, J., Schmidt, M. W. I., Smith, P., and Fuhrer, J.: Measured soil organic matter fractions can be related to pools in the RothC model, *Eur. J. Soil Sci.*, 58, 658–667, <https://doi.org/10.1111/j.1365-2389.2006.00855.x>, 2007.

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