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A novel approach to use the DayCent model for simulating agroforestry systems with multiple components

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Abstract Agroforestry can offer carbon sequestration, higher system productivity and biodiversity. However, a limited number of field experiments exist to study their feasibility and trade-offs for large scale deployment. Agroecosystem models could represent a valuable tool for their ex ante assessment. Here, we present ZonalCent, a novel approach to use the DayCent model to simulate multi-component agroforestry systems by splitting them into several independent zones, and simulating each zone individually. We used six agroforestry sites in France to evaluate how well ZonalCent represented carbon sequestration in tree biomass, soil organic carbon stocks and in the total system. This proved promising because with the default parameter set of DayCent, ZonalCent was highly suitable to represent tree carbon sequestration (Nash–Sutcliffe modelling efficiency; NSE of 0.86), and suitable for total system carbon sequestration potential (NSE of 0.55), despite a tendency to overestimate SOC stocks (NSE of 0.38). Only one site had yield data and there, ZonalCent approach could approximate the mean yield reduction—yet more detailed evaluation is necessary. Negative correlations showed that simulated yield was most strongly affected by (a) shading by mature trees and (b) the loss of arable area due to grass strips. While more detailed models may be needed for a detailed process understanding, ZonalCent includes the most important interactions (light, water, nutrients, temperature) in a simple but effective way and can be readily used—because it is based on DayCent—to estimate the potential carbon sequestration of agroforestry systems at larger scales.

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Introduction

In recent years, modern or mechanized temperate agroforestry systems, such as alley cropping systems, have received considerable attention due to their potential to act as a carbon sink (Cardinael et al. 2017; Kim et al. 2016; Mayer et al. 2022; Terasaki Hart et al. 2023), increase biodiversity and reduce nutrient leaching (Tully and Ryals 2017). Furthermore, these systems have been found to be more productive monocultures in several cases (Arenas-Corraliza et al. 2018; Temani et al. 2021; Lehmann et al. 2020; Bai et al. 2016; Graves et al. 2011). However, despite considerable claims of their sustainability (Wilson and Lovell 2016), there are only few experiments that study temperate agroforestry in sufficient detail (Dupraz et al. 2019). This limits our understanding of how temperate agroforestry systems behave on different soils, under different climates and with different system setups, including different tree species, spacing, and crop rotations.

Despite the spike of interest in the recent decade, newly established temperate agroforestry systems are not suitable to study the long-term effect of agroforestry on carbon sequestration, crop yield and interactions in detail. The reason for this is the slow growth of trees, and thus it takes at least one to two decades before an agroforestry system is mature, the crown of trees is fully developed, and the effect on yield is fully unfolded (Dupraz et al. 2019).

With a limited number of temperate long-term experiments (e.g., Wotherspoon et al. 2014; Thevathasan et al. 2020; Cardinael et al. 2017), agroecosystem models can present a valuable tool for ex ante assessment of potential trade-offs between ecosystems services such as acting as a carbon sink and providing a crop yield (Luedeling et al. 2016). They build on our most current understanding of the complex interactions in ecosystems (Necpalova et al. 2018). Therefore, if they represent the long-term experiments well they can be used to extrapolate the results to larger areas. For example, they have been used for ex ante assessment of yield potential (Saito et al. 2021) and carbon sequestration capacity (Lee et al. 2020).

These models can simulate the effects of important driving variables on yield formation and carbon sequestration, using semi-mechanistic functions that have been improved through decades of agronomic and soil research. They can also simulate competition for light and nutrients. However, because agricultural models usually fail to represent the most important global drivers with a single parameter set, they must be evaluated for local conditions (Necpálová et al. 2015) whenever applying them to new conditions or systems, such as agroforestry.

Applying agroecosystem models to simulate carbon sequestration potentials of agroforestry has been done; for example, CENTURY has been applied to simulate the arable component of temperate and tropical agroforestry systems by adding prunings manually (Oelbermann and Voroney 2011). Cardinael et al. (2018) developed the CARBOSAF model to simulate the two dimensional distribution of soil organic carbon stocks in agroforestry plots and based this on horizontal and vertical distribution of C inputs in the plot. Yet, these approaches only considered individual components of the agroforestry system and ignored others, such as simulating tree biomass.

While there are a range of integrated agroforestry models such as WaNuLCAS, Yield-SAFE and Hi-SAFE, they are often either too complex or too simple (Luedeling et al. 2016). For example, WaNuLCAS, the most complex agroforestry model to date has in fact been too complex for most users, which most likely hindered widespread adoption and ex ante analysis in new systems (Luedeling et al. 2016). Very simple approaches, such as Yield-SAFE (van der Werf et al. 2007) on the other hand are too simplistic for any simulation of carbon sequestration potential, because of a lack of a SOC pool. There has been an attempt to couple Yield-SAFE with RothC (Palma et al. 2018), however it has only included litter inputs into the soil, but not the effect of SOC and N mineralization on tree growth, or shading on crops. Overall, the use of these models remains a niche (Luedeling et al. 2016), e.g., the search term "Hi-SAFE" at the time of writing yielded 4 studies in Scopus that applied the model to temperate conditions (Artru et al. 2017; Dupraz et al. 2019; Huo et al. 2021; Reyes et al. 2021); the terms "WaNuLCAS AND temperate" yielded no studies.

That the models remain niche, limits their robustness for larger scale predictions, especially for carbon sequestration, because neither their soil carbon nor tree carbon pools have been calibrated or evaluated against a large range of ecosystems and soils. On the other hand, well-established and globally tested models such as DayCent (Parton et al. 1998; Del Grosso et al. 2001) should be more robust for larger scale predictions of carbon sequestration potential, but they are often limited in the complexity of their interactions.

Here, we present and test a novel approach to use the DayCent model to simulate multi-component agroforestry systems. The DayCent model is a widely used model that can adequately simulate crop yields, soil organic carbon, soil N and N_2O emissions in temperate systems (Del Grosso et al. 2005; Necpálová et al. 2015; Necpalova et al. 2018; Gurung et al. 2020, 2021). However, to our knowledge it has never been used to simulate complex temperate agroforestry systems. In fact, the default DayCent model considers homogeneity at the plot level, and can only accommodate one crop and one tree component at the same time for each plot. It is therefore not able to simulate most modern agroforestry systems, such as alley cropping systems, that have at least three components (tree, grass strip and crop). Also, since it does not have a spatial component within plots, it cannot accommodate for different tree densities in agroforestry systems.

To overcome these limitations, we developed the ZonalCent approach. It uses DayCent to simulate complex agroforestry systems by separating them into several zones and simulating each zone individually. In this article, we first present a technical description, followed by a test of ZonalCent, simulating the carbon sink potential of six different French agroforestry systems of ages between six and 41 years and evaluating the simulated carbon sink potential in different system components against measured data from a detailed study Cardinael et al. (2017). Finally, we provide an outlook on the expected effects of system setup on yield, sensitivity of yield and carbon sink potential.

Material and methods

Simulating multi-component agroforestry systems by an area splitting approach

DayCent model description

DayCent (version 2020 of DD_EVI) is an agroecosystem model with intermediate complexity (Del Grosso et al. 2001) that represents the dynamics of plant growth, soil organic carbon (SOC) and nitrogen (N) cycling, as well as the effect of soil moisture and temperature on these processes. Simplified phenology, genetic potential and stress factors influence the plant growth and productivity. The pools that simulate SOC and N dynamics are purely conceptual and separated into active, slow, and passive pools (Parton et al. 1987) and they only represent the topsoil. We left all DayCent model parameters at their default for the utilized model version, with the exception of SOC turnover rates. For these we took the median parameter values of the recent Bayesian calibration by Gurung et al. (2020, Table 4). This calibration made DayCent representative of the 0–30 cm topsoil (instead of the standard 0–20 cm), aligning it with IPCC standards (IPCC 2019). Specifically, the parameters were set to the following values: 0.0035 d^{-1} for the turnover rate of the passive pool (DEC4), 0.0991 d^{-1} for the turnover rate of the slow pool (DEC5(2)), 0.5577 g g^{-1} for the fraction of C lost as CO_2 when the slow soil organic matter pool decomposes (P2CO2(2)), 0.5383 g g^{-1} for the fraction of C lost as CO_2 when the soil metabolic litter pool decomposes (PMCO2(2)), 0.0481 g g^{-1} for the effect of clay on SOC stabilization (PS1S3(2)). Further, the temperature effect on decomposition were set to 17.0523 °C for TEFF(1) and 0.1411 °C for the TEFF(4) parameter. Finally, the decompositions multiplier for the months after plowing were set to and 11.8702 (unitless; CLTEFF(1), CLTEFF(2) and CLTEFF(4)).

The growth of trees and crops in DayCent are represented by different sub-modules. They are similar in having a maximum radiation use efficiency and a reduction of the radiation use efficiency under stress. The crop module has only three carbon pools (aboveground biomass, mature roots and juvenile roots) while trees have six pools (leaves, branches, large wood, juvenile fine roots, mature fine roots and coarse roots). Maintenance respiration and a death rate of leaves exist in both sub-modules.

To allow for the simulation of multi component agroforestry system, DayCent needs to be run in savanna mode, which allows for one herbaceous and one woody component to be simulated at the same time (both sub-modules active). Savanna mode also simulates competition for soil nutrients (in this article only N), increased transpiration, and shading of the herbaceous component by the woody component including reductions in soil temperature. The user can specify how much fertilizer is available to the woody component vs the herbaceous component by specifying an orchard tree fraction event (OTRF). This event sets how much of mineral N will be available to the woody component (between 0 and 1) while there is limitation and competition, the remainder will be allocated to the herbaceous part (personal communication DayCent developers). Hence, the OTRF event can be used to proxy the effects of plant density in the tree affected zone.

We used the NASA POWER product (https://power.larc.nasa.gov/docs/methodology/) to drive the daily climate data needed to run DayCent. To derive the hydraulic conductivity parameters from the given texture data (i.e., volumetric field capacity, wilting point, and saturated hydraulic conductivity K_s), we used the widely applied pedotransfer function of Saxton and Rawls (2006).

Description of the ZonalCent approach

Using a zonal approach allows to simulate multi component agroforestry systems in DayCent. This approach was inspired by the approach that Feuerbacher et al. (2021) developed to simulate the economic feasibility of multi component agrivoltaic systems, by splitting the area under agrivoltaic into different zones. The basis of the ZonalCent approach is the separation of the agroforestry systems into different zones where each zone has a maximum of one herbaceous and one woody plant. Currently those are three zones to represent alley cropping, but more are possible. Those three zones are the grass strip zone (A_G), the total zone which is affected by the tree crown (A_C) and the zone that is not affected by the tree crown (1-A_C). All zones are expressed as fraction of the total area, so by definition they range between 0 and 1. The total area consists of A_C and 1-A_C, while A_G is a sub-zone of A_C (Fig. 1). A classical arable system could be seen as a special case where A_G and A_C are both zero. A dense silvopasture system would have A_G as zero (because the grass would in this case be considered the main crop) and A_C would be 1. The fraction of each zone can be derived from three simple variables, the width of the grass strip (l), the width of the arable part of the field (L), and the three dependent maximum radius of the tree crown (r_{max}). The following equations are used to derive the fractions:

$$A_G = l/(l + L) \tag{1}$$

$$A_C = \frac{2r_{max}}{(l + L)} \tag{2}$$

The orchard tree faction (OTRF), i.e., the competitiveness of the tree for N in A_C and A_G are scaled

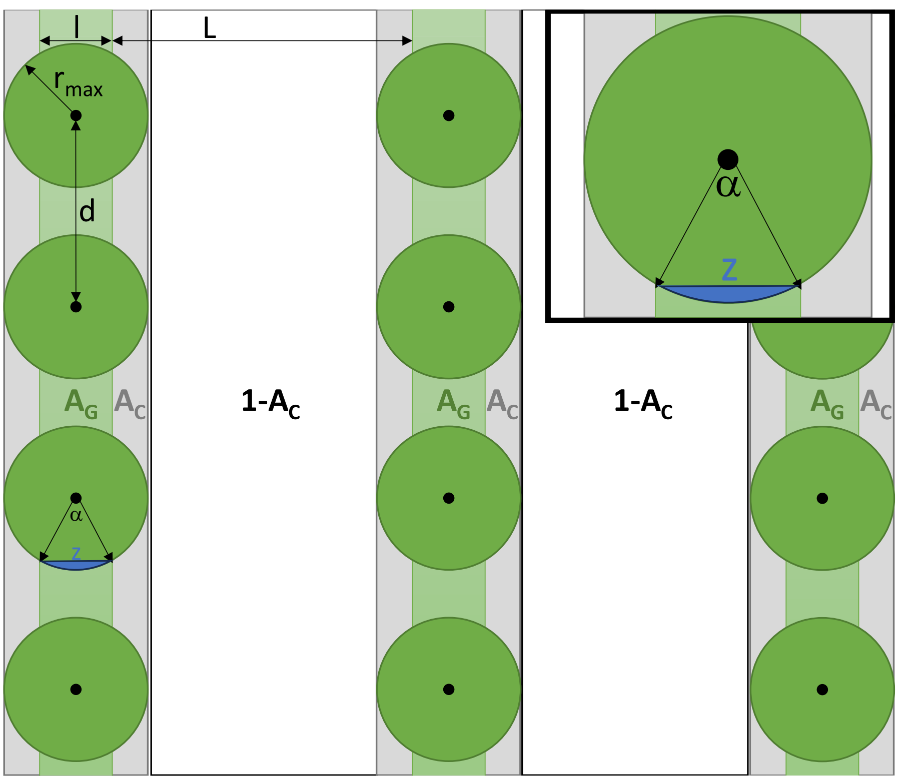

Fig. 1 Illustration of the different simulation components needed to simulate more than two components of agroforestry systems in DayCent. The system consists of three zones. The grass strip zone (A_G), the total crown affected zone (A_C) and the zone that is not affected by the crown (1-A_C). The size of each zone depends on the width of the grass strip (l), the width of the arable part of the field (L), and the maximum radius of the tree crown (r_{max}). The top right corner represents a zoomed in version of the tree area. The distance between trees in row (d), α, and Z are helper variables that are needed to compute the competitiveness of the tree for N in the zones A_G and A_C

based on the relative surface area that can maximally be covered by the crown in each area (when the tree crown has reached r_{max}). Hence, it is an approximation that assumes that the roots cover a similar area as the crown:

$$OTRF_{Crown} = \frac{\pi r_{max}^2}{(d * 2r)} \tag{3}$$

For the grass strip, the OTRF is even larger, because the crown is usually wider than the grass strip.

$$OTRF_{Grass} = \frac{Z + \sqrt{r_{max}^2 - (0.5l)^2} * l}{0.5d * l} \tag{4}$$

with Z being the rounded part of the crown which is not captured by the area $\sqrt{r_{max}^2 - (0.5l)^2} * l$ (Fig. 1). It can be calculated as follows

$$Z = \pi * r_{max}^2 * \frac{\alpha}{360} - 0.5l * \sqrt{r_{max}^2 - (0.5l)^2} \tag{5}$$

and

$$sin\frac{1}{2}\alpha = \frac{0.5l}{r_{max}}; \alpha = 2 * sin^{-1}\left(\frac{0.5l}{r_{max}}\right) \tag{6}$$

After assigning the zones, each zone is run individually in DayCent. The spatial distribution of fertilizer inputs should also be determined (.e.,g whether the grass strips receive fertilizer or not). In our case it was assumed that they do not receive any mineral fertilizer (according to communications with the managing farmers).

Then, the yield, the biomass carbon and differences in SOC stocks can be calculated as follows:

$$C_{Tree}\ (g\ C\ m^{-2}) = TBM\_C_{A_C} * A_C \tag{7}$$

$$\Delta SOC\ (g\ C\ m^{-2}) = (SOC_{A_G} * A_G + SOC_{A_C} * (A_C - A_G) + SOC_{(1-A_C)} * (1 - A_C)) - SOC_{(1-A_C)} \tag{8}$$

Here, C_{Tree} is the carbon stocks of the trees of the agroforestry system (that can also be separated into components such as aboveground and belowgound stocks) and $TBM\_C_{A_C}$ is the carbon stocks in the trees in the A_C zone. ΔSOC is the difference in SOC between the agroforestry and the control plot, while $C_{Tree} + \Delta SOC$ would be the total carbon sequestration of the agroforestry system. SOC_{A_C}, SOC_{A_G} and $SOC_{(1-A_C)}$ are the simulated SOC stocks in the zones A_G, A_C and (1-A_C), respectively.

The relative yields for the total area rY_T and only the arable part of the plot rY_A are calculated as follows:

$$rY_T\ (g\ g^{-1}) = \frac{\bar{Y}_{A_C} * (A_C - A_G) + \bar{Y}_{(1-A_C)} * (1 - A_C)}{\bar{Y}_{(1-A_C)}} \tag{9}$$

$$rY_A\ (g\ g^{-1}) = \frac{\bar{Y}_{A_C} * (A_C - A_G) + \bar{Y}_{(1-A_C)} * (1 - A_C)}{\bar{Y}_{(1-A_C)} * (1 - A_G)} \tag{10}$$

Here, $\bar{Y}_{A_C}$, and $\bar{Y}_{(1-A_C)}$ are the mean yield of the areas A_C and (1-A_C), respectively.

ZonalCent evaluation

Site description

The six sites (Table 1) that were used to evaluate the ZonalCent approach represent a unique compilation of French short- to long-term agroforestry sites ranging from 6 to 41 years of age at the time of study (Cardinael et al. 2017). Of the six sites, five (i.e., Restinclières, Châteaudun, Melle, Saint-Jean d'Angely, and Vézénobres) were silvoarable systems, while the sixth site (i.e., Theix), was a silvopastoral system. The mean annual temperature ranged from 8 °C (Theix) to 15 °C (Restinclières and Vézénobres), with the other sites having a mean annual temperature between 11 and 13 °C. The mean annual precipitation ranged from 600 mm (Châteaudun) to 1040 mm (Vézénobres) and for the rest of the sites, it was between 800 and 870 mm. The soils included Fluvisols, Luvisols and one Andosol (Theix) with 10–56% of clay and 7–48% of sand (further details in Cardinael et al. 2017, Table 1). Each site consists of an agroforestry and an agricultural control plot without trees and both of these types of plots were subject to the exact same management. In all sites, except the silvopastoral system, a strip with sown grass or natural herbaceous vegetation of 2 m (l) was established in the arable fields and the trees were planted in the middle of this strip.

Table 1 Overview of the size measures of the different zones of the agroforestry systems studies in this assessment

Site	Tree	Age (yr)	Density (trees ha^{-1})	r_{max} (m)	d (m)	L (m)	l (m)	α (°)	Z (m^2)	A_C	A_G	OTRF$_{grass}$	OTRF$_{crown}$	Crops
Châteaudun	Walnut	6	34	3.5	10	24	2	33.2	0.2	0.27	0.08	0.69	0.55	Wheat, rapeseed
Melle	Walnut	6	35	3.5	8	27	2	33.2	0.2	0.24	0.07	0.86	0.69	Wheat, rapeseed, sunflower
Saint-Jean d'Angely	Walnut	41	102	3.5	7	12	2	33.2	0.2	0.50	0.14	0.99	0.79	Sunflower, wheat, barley
Vézénobres	Walnut	18	100	3.5	10	9	2	33.2	0.2	0.64	0.18	0.69	0.55	Durum wheat, rapeseed, chickpea
Restinclières	Walnut	18	110	3.5	8	11	2	33.2	0.2	0.54	0.15	0.86	0.69	Rapeseed, wheat, potato
Theix	Cherry	26	200	3.5	7	7	0	–	–	1.00	–	0.79	0.79	Ryegrass, fescue

r_{max}, maximum radius of the tree crown; d, distance between the trees in the row; L, width of the arable part of the field; l, width of the grass strip; Z, rounded part of the crown area overlapping the grass strip; α, auxiliary angle needed for the calculation of Z; A_G, grass strip zone; A_C, total crown affected zone; OTRF$_{Grass}$, competitiveness factor of the tree for N in A_G; OTRF$_{Crown}$, competitiveness factor of the tree for N in A_C

Simulation assumptions

To initialize the SOC and N pools of DayCent, we followed the approach suggested by Mathers et al. (2023) for a robust initialization. This approach uses measured SOC stocks to initialize the pools, while the DayCent-typical spin-up and site history simulation are only used to distribute the measured SOC stocks between the pools. A spin-up run of 2000 years was used to bring the SOC pools to steady state and was followed by simulating a general site history. Because detailed site data was not available, we simulated an approximate agricultural site history with temperate deciduous forest until the 14th century, followed by low input agriculture and after the agricultural revolution an increased intensification (Necpalova et al. 2018). Because we had no data of the initial SOC stocks at the time of agroforestry establishment, we used the value of the control site (which had remained unchanged since tree planting) to initialize SOC stocks (Table 3). Additionally, any SOC stock gains from agroforestry were expressed as the difference between agroforestry and a control without agroforestry. This, together with SOC pool initialization based on measured data, limits the influence of the site history. Expressing SOC stock gains or losses as the difference with a reference scenario is the common way to simulate SOC changes due to management with DayCent, and was deemed the most suitable for certification of greenhouse gas mitigation (Mathers et al. 2023).

During the simulation period of the agroforestry system, we simulated the control and the agroforestry system with the crop rotations (Table 1) as they were specified by Cardinael et al. (2017). Because exact dates of planting, fertilizer application and harvesting, as well as amounts of fertilizer applied were not available, we used typical dates and amounts for European cropping systems per crop type (based on KTBL 2020). The detailed assumptions are displayed in Table 2. The grass species used for the inter-row depended on the site; in Saint-Jean d'Angely, Vézénobres and Restinclières, they consisted of spontaneous herbaceous vegetation, while in Châteaudun and Melle, a rye grass and fescue was planted (Cardinael et al. 2017). Spontaneous vegetation was represented by grasses with low productivity (G1 parameterization of Crop.100 file in DayCent), while planted grasses were represented by grasses with high

Table 2 Crop calendars assumed per crop type and crop specific amounts of fertilizer N applications.

Crop	Crop.100 name	Sowing date (DoY)	Harvest date (DoY)	Day of year (amount of N fertilizer; kg N ha^{-1} yr^{-1}) 1st application	2nd application	3rd application	Total N fertilizer (kg N ha^{-1} yr^{-1})
Wheat	W3	October 26 (299)	July 14 (195)	75(50)	100(70)	130(50)	170
Durum Wheat	W2	October 26 (299)	July 14 (195)	75(50)	100(70)	x	120
Barley	BAR2	October 1 (274)	June 29 (180)	75(50)	100(70)	x	120
Sunflower	SUN	March 31 (90)	September 1 (244)	120(40)	150(50)	x	90
Rapeseed	RAPE	September 12 (255)	June 29 (180)	257(30)	80(90)	x	120
Potato	POT	April 25 (115)	September 2 (245)	130(60)	160(100)	x	160
Chickpea	PEA	March 16 (75)	August 18 (230)	0			

Assumptions are based on the recommendations of KTBL (2020). Abbreviations: DoY, day of year; Crop.100 name, name of the parameterization in DayCent

Table 3 Overview of the data used for the evaluation of Zonal Cent

Site	Tree	Age (yr)	SOC AF (t C ha^{-1}) (0–30 cm)	SOC CP (t C ha^{-1}) (0–30 cm)	ΔSOC (t C ha^{-1}) (0–30 cm)	AF tree AGB (t C ha^{-1})	AF tree BGB (t C ha^{-1})
Châteaudun	Walnut	6	46.7	45.0	1.7	0.02	0.01
Melle	Walnut	6	40.7	40.1	0.5	0.07	0.03
Saint-Jean d'Angely	Walnut	41	94.3*	64.3*	30*	19.9	5.6
Vézénobres	Walnut	18	42.8	40.8	2.0	26.6	6.6
Restinclières	Walnut	18	40.3	35.8	4.5	10.9	3.0
Theix	Cherry	26	110.2	114.3	−4.1	36.7	9.1

The data is based on Cardinael et al. (2017, Table 4 and 5). Abbreviations: AF, agroforestry; CP, control plot (without agroforestry); AGB, aboveground biomass; BGB belowground biomass

*calculated by linear extrapolation of 0–10 and 0–20 cm layers to the 0–30 cm layer (due to absence of measured data below 20 cm because of stones)

productivity (GI1 parameterization). Trees were represented by the WALNUT and CHERRY parameterizations of DayCent.

Evaluation of the ZonalCent appraoch

The specific data used to evaluate the ZonalCent approach were (i) the measured difference in SOC stocks (0–30 cm) between the agroforestry and the control plot and (ii) the measured carbon stocks in the trees (Table 3). The SOC stocks were measured in a 2014 sampling campaign, with the exception of the Restinclières site, where they were from 2013. The measurements were based on the equivalent soil mass approach (Lee et al. 2009), with soil masses representing the typical soil mass from 0 to 30 cm per site (Cardinael et al. 2017). In the agroforestry plots, they represented a weighted average of SOC stocks which were measured in the grass strip and in the crop/grass alley. The tree carbon stocks were estimated by measuring the volume of the trunks and branches of 10–20 trees per site, and multiplying their volume with species-specific wood density values (Chave et al. 2009) and measured C concentrations. Belowground tree carbon stocks were estimated using the allometric equations of Cairns et al. (1997).

The evaluation statistics used to compare measured and modelled values were based on Loague and Green (1991):

$$MSE_y = \frac{1}{n}\sum_{z=1}^{n}(O_{yz} - P_{yz})^2 \quad (11)$$

$$rRMSE_y = \frac{\sqrt{MSE_y}}{\bar{O}_y} \quad (12)$$

$$NSE_y = 1 - \frac{\sum_{z=1}^{n}(O_{yz} - P_{yz})^2}{\sum_{z=1}^{n}(O_{yz} - \bar{O}_y)^2} \quad (13)$$

Here, MSE_y is the mean-squared-error and $rRMSE$ is its root in relative terms. NSE_y is Nash–Sutcliffe modelling efficiency, O_{yz} is the measured value of the z-th measurement of the y-th type of measurement. The $\bar{O}_y$ stands for the mean of all measured values from the y-th type of measurement while P_{yz} is the model predicted value corresponding to O_{yz}. To gain a better understanding of the model mismatch, we divided MSE_y into squared bias (SB), nonunity slope (NU) and lack of correlation (LC). This was suggested by Gauch et al. (2003). These three measures were expressed in relative terms, i.e., they were divided by the MSE_y:

$$SB_y(\%) = \frac{(\bar{O}_y - \bar{P}_y)^2}{MSE_y} * 100 \quad (14)$$

$$NU_y(\%) = \frac{(1 - b_y)^2 * (\frac{\sum_{z=1}^{n}(O_{yz}^2)}{n})}{MSE_y} * 100 \quad (15)$$

$$LC_y(\%) = \frac{(1 - r_y)^2 * (\frac{\sum_{z=1}^{n}(P_{yz}^2)}{n})}{MSE_y} * 100 \quad (16)$$

Here, $\bar{P}_y$ is the mean simulated value of the y-th measurement type, b the slope of the regression of P on O. The term r stands for the correlation coefficient between O and P. These measures, i.e., LC, SB and NU indicate if the model errors are mostly random (high LC), or to which degree there is systematic bias (high SB), and if model sensitivity is too high or low (high NU).

Finally, we used a statistical (linear) model to determine the contribution of the different components of the agroforestry system to simulated reductions in yield, simulated carbon sequestration in tree biomass, and to the simulated total carbon sequestration. To do so, we fit an additive linear model with relative yield or total carbon sequestration as the dependent variable and A_G, agroforestry age and tree density as explanatory covariates (A_C was not included because of a perfect correlation of 0.98 with tree density and because tree density proved the better covariate). To derive an indication of their relative importance, we assessed the reduction in R^2 when removing each of the covariates from the full model in combination with the Akaike information criterion (AIC) of each model.

Results

Evaluation of ZonalCent predicting differences in carbon stocks

The ZonalCent approach performed well in simulating the measured carbon stored in the aboveground biomass (NSE of 0.86, rRMSR of 33%) and belowground biomass (NSE of 0.65, rRMSE of 49%) of the trees across the six sites (Fig. 2). In contrast, the differences in SOC stocks in the top 30 cm were not simulated as well (NSE of 0.38, rRMSR of 152%) and ZonalCent predicted a faster increase in SOC stocks in agroforestry plots compared to arable plots than what was observed. The ZonalCent approach also had very little bias (SB of 6%) for aboveground biomass carbon stocks in trees and little bias (SB of 29%) for belowground tree biomass carbon stocks. In contrast, the difference in SOC stocks between agroforestry and arable plots was biased towards too high SOC stocks in agroforestry plots (SB of 69%) and the nonunity slope (NU of 26%) indicated that the simulated SOC stocks were on average too high compared to measurements. Interestingly, ZonalCent could predict the lower SOC stocks in the agroforestry plot compared to the arable plot of the Theix site, which was the only site with a silvopastoral system. In fact, it predicted it rather well with the simulated difference being -4.1 g C m^{-2} and the measured one being -3.8 g C m^{-2}. Despite the bias in SOC stocks, the overall carbon sequestration potential of the different

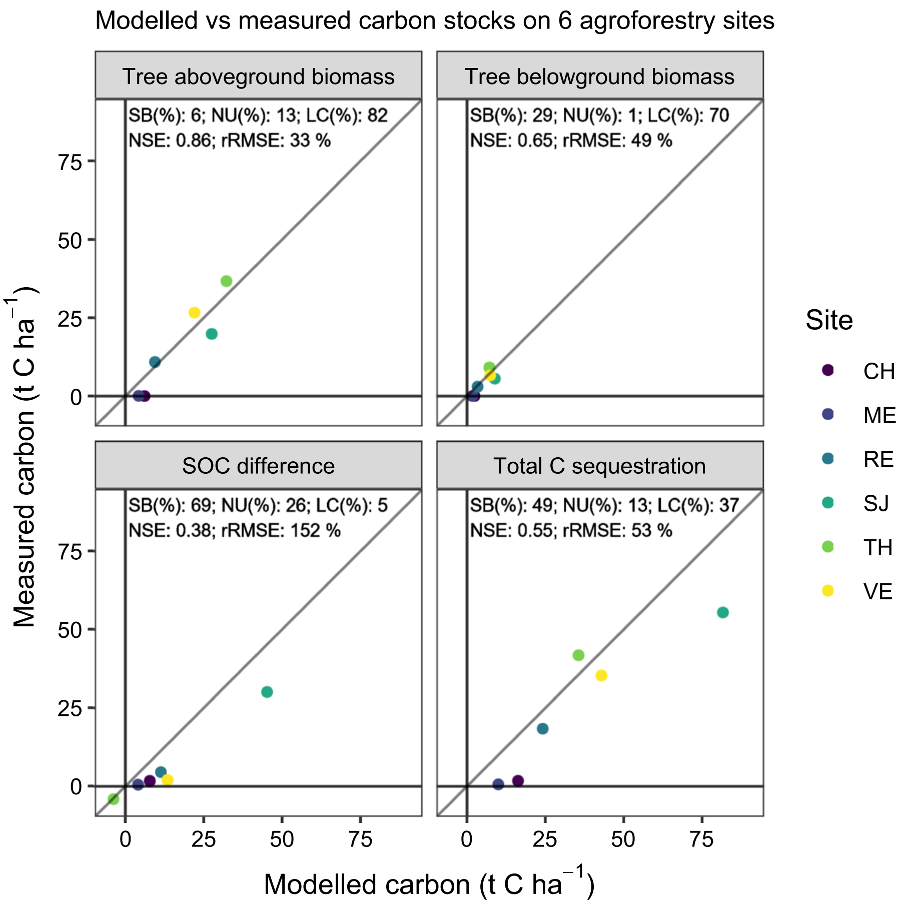

Fig. 2 Simulated compared to measured differences in carbon stocks in aboveground biomass, belowground biomass and SOC stocks (the latter in 0–30 cm soil depth). Abbreviations: NSE, Nash–Sutcliffe modeling efficiency; rRMSE, relative root mean squared error; SB, squared bias; NU, non-unity slope; LC, lack of correlation. Site names: RE, Restinclières; CH, Châteaudun; ME, Melle; SJ, Saint-Jean d'Angely; VE, Vézénobres; TH, Theix

systems was simulated acceptably (NSE of 0.55, rRMSE of 53%), with some bias (SB of 49%) and nonunity slope (NU of 13%). Interestingly, three of the six sites, i.e., Theix, Restinclières and Vézénobles were along the 1 to 1 line, while Saint-Jean-d'Angély had the strongest mismatch (mostly originating from SOC).

The simulated effect of agroforestry on yield

The ZonalCent approach predicted a strong correlation between the relative crown area of the different agroforestry plots (A_C) with the relative yield of the arable part of the agroforestry plots compared to the arable plots (Fig. 3).

The original study of Cardinael et al. (2017) focused on carbon stocks and did not report any yields. However, data on yield reduction were available for the Restinclières site via Cardinael et al. (2018), who provided a linear regression model to

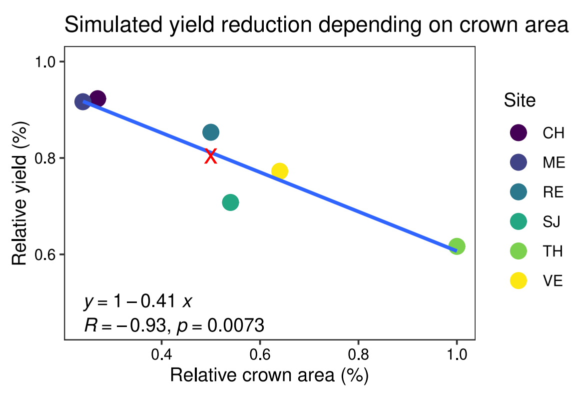

Fig. 3 Simulated relative yield of the arable area in the agroforestry plots as a function of the relative crown area. The regression and correlation coefficient (R) with significance level are also displayed. Site names: RE, Restinclières; CH, Châteaudun; ME, Melle; SJ, Saint-Jean d'Angely; VE, Vézénobres; TH, Theix. The red "x" displays the measured value for the Restinclières site

estimate the relative yield in the arable part of the agroforestry plot as a function of the distance from the tree. The distance between the tree rows in Restinclières was 13 m with a grass strip of 2 m width. Consequently, traversing the arable portion of the plot with 1 m steps would result in distances to the next tree of 1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 5.5, 4.5, 3.5, 2.5, and 1.5 m. Applying these values to their regression formula (Cardinael et al. 2018, Fig. 3 and equation 28) and averaging the results, resulted in an average value of 81% relative yield for the arable part of the agroforestry plot compared to the control plot. It also needs to be considered that the grass strip occupied 2 m on which yield loss was 100 %. Therefore, the relative yield for the full area, based on the formula by Cardinael et al. (2018), would only be 69% (= 81% * 11/13). The relative yields predicted by the ZonalCent approach in Restinclières were 85 and 72% for arable area and full area, respectively, (Fig. 3) and were thus rather similar to the relative yield values calculated with the formula of Cardinael et al. (2018), especially given the broad assumptions of fertilizer applications and crop rotations that were necessary in modelling the yields with the ZonalCent approach in the absence of detailed information.

Sensitivity of ZonalCent to different agroforestry system components

The linear statistical model on simulated yield reduction could explain 96% of the variation by the combined effects of tree density, tree age and the relative size of the grass strip (AIC: −19.47). For this model, the R^2 was reduced most drastically when removing tree density (−67%; new AIC: −4.20), followed by removing the area of the grass strip (−31%; new AIC: −8.40) and the tree age (−11%; new AIC: −13.48). The linear statistical model on total carbon sequestration (sum of trees aboveground, belowground and difference in SOC stocks) could only explain 58% of the variation in total carbon sequestration by the combined effects of tree density, tree age and the relative size of the grass strip (AIC: 59.69). The R^2 of this model was reduced most strongly (−47%; AIC: new 62.18) when removing tree density, followed by removing the area of the grass strip (−44%; AIC: new 61.99) and the tree age (−23%; AIC: 60.37). In contrast, when only looking at the carbon sequestered in the biomass, the linear model could explain 94% of variation (AIC: 41.75), with the reduction in R^2 being again strongest when removing tree density (−83%; AIC: 55.56), followed by removing the tree age (−27%; new AIC: 49.60) and the area of the grass strip (−20%; new AIC: 48.25). These analyses were also in line with simple linear regressions built per covariate (Fig. 4). The strongest correlations of all three dependent variables existed with tree density (absolute value of r between 0.37 and 0.80).

Discussion

ZonalCent as a simple and flexible way to simulate agroforestry systems of various complexities

With the ZonalCent approach, we present a novel and flexible way to use the well-established DayCent model for the simulation of agroforestry systems of various complexities. Our approach adheres to the most important requirements for agroforestry models, as specified by Luedeling et al. (2016): it is flexible, simple to implement, and, because it builds on one of the most used agroecological models, software quality, interoperability and longevity of the approach are high. The good model performance statistics in simulating tree carbon stocks above (NSE of 0.86) and below ground (NSE of 0.65) and the acceptable model performance statistics of total carbon sequestration (NSE of 0.55), notably without any additional adjustment of DayCent model parameters, provide compelling evidence of the suitability of ZonalCent (Fig. 2). Yet, the SOC module needs some further improvement, because it tends to overestimate SOC sequestration. At this point, it is not clear what drove the model bias in the difference in SOC between the agroforestry and arable plots, but it could be related to the choice of grass species that was simulated (i.e., the sites with the strongest mismatch were Saint-Jean d'Angely, Vézénobres, and Restinclières; at these sites the grass area was natural herbaceous vegetation). Another reason for the overestimation of SOC by DayCent could be that by only simulating the 0–30 cm topsoil, the model adds too much dead root biomass of the trees to the SOC pools. It is known that trees root much deeper than 30 cm but DayCent assumes all dead root material to become part of the litter part of the SOC pool. However, with no further information on this, we decided not to alter the

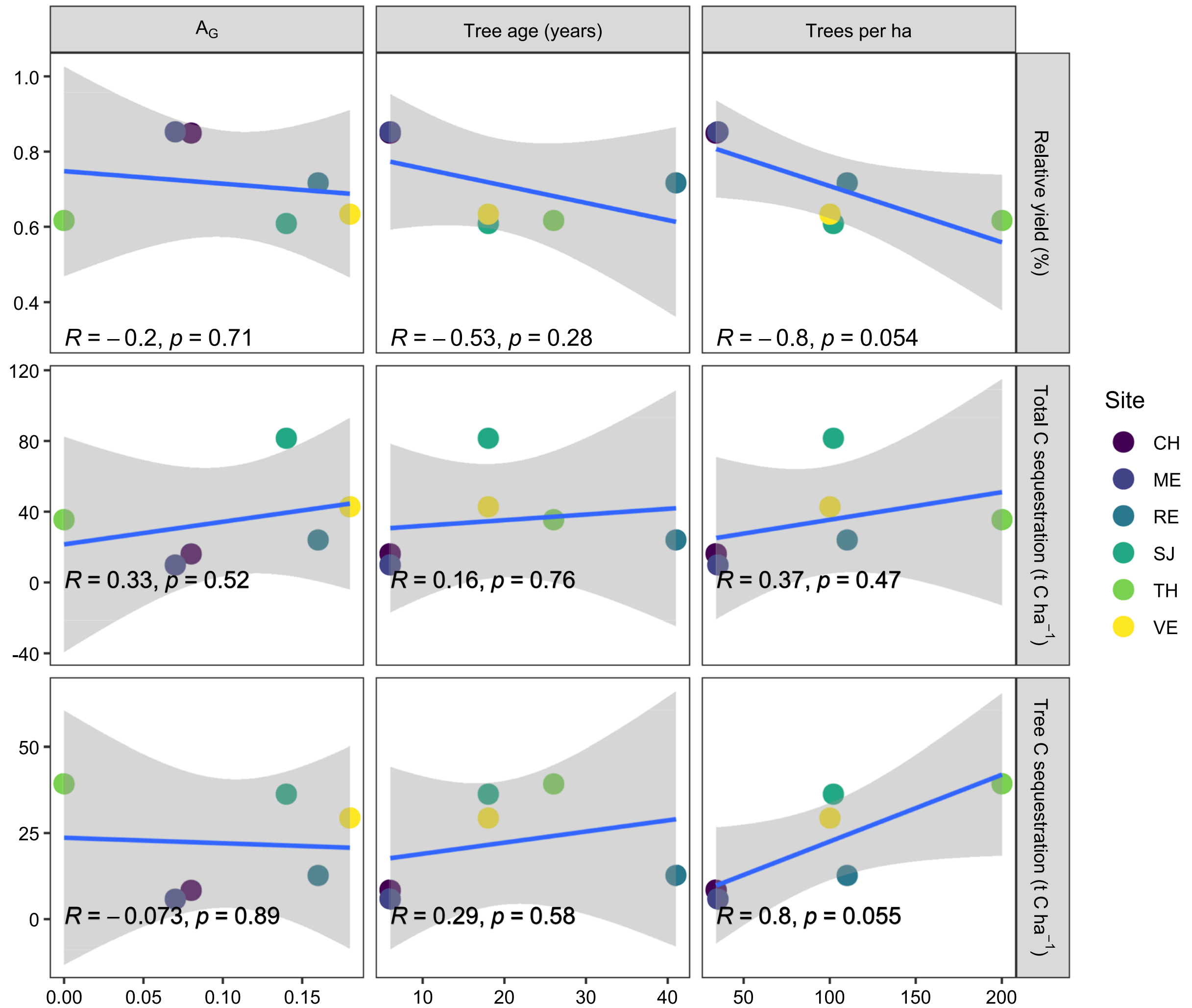

Fig. 4 Correlations between ZonalCent-simulated yield reduction, sequestered carbon in the trees and total sequestered carbon with the area fraction of the grass strip A_G, tree age and tree density (trees per ha). Site names: RE, Restinclières; CH, Châteaudun; ME, Melle; SJ, Saint-Jean d'Angely; VE, Vézénobres; TH, Theix

model settings to improve the model results further. First, we wanted to avoid an after the fact fine tuning that would give overly optimistic results. Second, the parameter values of Gurung et al. (2020) are based on a combination of eight long-term experiments with long time series of SOC stocks and several management types, and therefore some of the most reliable values currently available. In that sense, while our results indicate that SOC stock differences should be assessed most critically, the overall model performance is already very good and in the range of what many modelling approaches achieve for the evaluation dataset after a calibration (e.g., Lee et al. 2012; Necpálová et al. 2015; Necpalova et al. 2018; Gurung et al. 2020; dos Reis Martins et al. 2022; Laub et al. 2024).

It is interesting and biologically reasonable that simulated yields were strongly related to the relative area of the crown (Fig. 3). While for the Restinclières site, the only site with yield information, the model predictions for yield reduction by ZonalCent proved valid, the yield aspect of the ZonalCent approach clearly needs to be further evaluated in other mature agroforestry systems. Unfortunately, there only is a very limited number of these sites (Dupraz et al. 2019). The less-than proportional and almost linear decline of yield with increasing crown area is, however, roughly in alignment with recent meta-analyses that found moderate sensitivities of cereals and legumes already at low levels of shading (Ivezić et al. 2021; Laub et al. 2022).

In general, while the complexity of interactions at the root level is high in agroforestry systems, the gain by simulating these in detail is often not worth the cost in computation, parameterization, and additional data needed to do so (Luedeling et al. 2016). Another argument for the simplifications by ZonalCent, to disaggregate the agroforestry system into different zones with no interactions, is that many agroforestry systems are designed in a way that minimizes root competition, e.g., via root pruning (Kumar et al. 2022). The good performance of the ZonalCent approach for the six sites in France without any model calibration substantiates that simple approaches such as ZonalCent that rely on simulating only the most crucial interactions (nutrient, water and light competition close to the trees as well as temperature regulation), and only between two components at a time, may be superior in many cases, especially in ex ante simulations. Overall, our results clearly showed that the ZonalCent approach is suitable for estimating the carbon sequestration potential of temperate agroforestry systems, and it provided some initial indications that it may be suitable to predict yield as well.

Limited interactions of ZonalCent components

The ZonalCent approach, with its intermediate complexity to simulate nutrient, light, water and temperature interactions (by zone only) is a rather straightforward approach for agroforestry simulations. Because DayCent is widely used across scales and well parameterized, ZonalCent is ideal for ex ante assessment at larger scales. Further, DayCent contains modules for soil and biomass C, crop and tree biomass and yield of both, and it thus simulates all essential competition/interactions (nutrient, water, microclimate, shading). The approach is clearly not as detailed as for example the Hi-SAFE model (Dupraz et al. 2019), which considers the 3d assembly of complex agroforestry systems. However, this complexity of Hi-SAFE makes it very data hungry for parameterization and validation (Luedeling et al. 2016), which for most approaches outside of research experiments can be a serious limitation. The theoretical advantage of complex nutrient and water uptake routines that consider, for example, root length in different zones and competitiveness of roots for nitrogen and water uptake, may thus become a disadvantage under data scarce conditions or at least irrelevant for systems that are typically well nourished and mostly under humid conditions. In fact, it is likely that for most ex ante applications, the higher number of parameters compared to available measurements would increases rather than decreases simulation error, because model complexity and data availability/quality always need to be balanced (Rompaey and Govers 2002). Thus, given the scarcity of datasets of temperate agroforestry systems, ZonalCent is arguably more robust for upscaling and ex ante assessment compared to complex models, primarily because it is less likely subject to major model errors resulting from overparameterization. The ZonalCent approach is thus a good model for intermediate complexity and for upscaling exercises, because of its flexibility, and because it builds on DayCent which has been parameterized for a large range of environmental conditions, crops and trees.

We recommend that the yield component of ZonalCent should be further tested (including the yield component of the tree, which can also be simulated by DayCent but has not been done here). The yield data used here and largely used across agroforestry models is the one based on the Restinclières field, which is rather dense compared to what is being implemented at the moment in temperate Europe (generally 24–30 m between tree rows), and may be quite far from what can be expected in the future. In case that yield is not predicted well, it would be possible to add even more than the three zones, e.g., a fourth zone of the cropped area that is not subject to nutrient competition, but to shading, where reduced daily radiation could simply be calculated based on simulated tree biomass. Further, r_{max} may also need to be altered for different tree species; in this study, the 3.5 m was based on the minimal distance between two trees (7 m) and led to good results, but it may be different for different tree species.

The simplicity of DayCent, i.e., that it does not include any spatial component could also be a strength because one could create in theory an unlimited amount of zones with one tree and one crop each to represent more diverse and spatially complex agroforestry systems without the need to alter the model itself. The ZonalCent approach could also be extended to any model that can simulate a tree and a crop in the same plot. It should even be possible to include agroforestry systems with intercropping with the Tcrop appraoch (Della Chiesa et al. 2022), but one limitation for agroforestry system complexity would be that DayCent can currently only simulate one type tree per plot.

On the other hand, ZonalCent should not be used for agroforestry systems that are subject to heavy pruning or pollarding. The reason is that DayCent, for the calculation of light interception, only considers a theoretical leaf area for trees, which is based on tree biomass and ignores the leaf biomass for this calculation. This is a workaround because DayCent does not have a reserve pool for carbohydrates. Thus, despite its potential to simulate tree management, DayCent is poorly suited for simulating any systems where leaf interception of light is purposefully reduced without a major reduction in tree biomass, and would overestimate the light competition.

Tree density and grass strip size as the major components that influence yield reduction and carbon sequestration

Factors that influence crop yield and carbon sequestration in temperate agroforestry systems have not been disentangled in detail, but clearly, shading (Abbasi Surki et al. 2020), nutrient competition (Hussain et al. 2016; Qiao et al. 2019) and loss of area due grass strips (Feuerbacher et al. 2021) play a crucial role. The negative correlation between trees per ha and simulated yield illustrates a trade-off in temperate agroforestry systems between yield (Carrier et al. 2019; den Hond-Vaccaro et al. 2023) and carbon sequestration in biomass and soil (Mayer et al. 2022). In fact, optimizing such trade-offs is key for a productive agroforestry system (Blaser et al. 2018). With a higher number of trees grown per area, more carbon can be sequestered, even though the use of the wood in the end determines the real lifetime of the carbon sink (Keel et al. 2023). Yet, the higher the number of trees, the more shade and competition exists with crops—and a high density of trees can only be achieved with a small distance between two tree rows, which reduces arable land. So while temperate agroforestry systems can be a cost-efficient carbon sink, the whole system profitability, high establishment costs, and especially the yield reduction must also be considered (Bamière et al. 2023). In fact the combination of yield reduction and higher machine operation cost could even lead to negative contribution margins (Feuerbacher et al. 2021, 2022), a negative consequence which should be avoided as much as possible.

In this regard, silvopastoral systems, ideally under grazing, may represent the optimal solution for carbon sequestration through tree biomass. They are already under grass, thus avoiding the need to divert additional land from production. Moreover, grasses and forages can tolerate up to 30% of shade without experiencing a loss in green biomass yield (Laub et al. 2022). Besides, other factors that DayCent cannot simulate, such as pollination, reduced nutrient loss, improved micro-climate and species richness (Torralba et al. 2016; Kay et al. 2019, 2020; Blaser et al. 2018), may also need to be considered.

Our results show clearly that the relative crown area plays a strong role for the reduction of relative yield. Indeed, the straightforward yet robust correlation between relative crown area (or, indeed, the almost perfectly correlated tree density) and simulated yield in the arable area (r of -0.94; Fig. 3) could be employed in the most basic form of ex ante analysis, even in the absence of a clear understanding of the extent of reduction in solar radiation due to the presence of the trees (Laub et al. 2022). Nevertheless, as five of the six sites of this study utilized walnut trees, it is probable that such a straightforward calculation would be feasible only with walnut trees. For other species, the development of tree-specific regressions would be necessary. Carbon sequestration on the other hand is probably the most difficult to estimate, because it depends also on site conditions, texture, climate, and initial SOC status. This is where more complex approaches, such as ZonalCent may be needed. DayCent incorporates all these effects on a) the growth rates of trees and the productivity of the crops/grasses and b) the efficiency to stabilize carbon in the soil, all as a function of texture, climate, management and initial SOC content. On the other hand, a large portion of SOC sequestration in agroforestry systems happens in the subsoil (Cardinael et al. 2017) and DayCent, which simulates only the top 30 cm of SOC, is thus limited in capturing the full carbon sequestration potential and mostly simulates the effect of the grass vegetation on soil carbon. It would therefore be desirable in the future to expand the simulation with ZonalCent to deeper soil depths.

Conclusion

In this article, we presented ZonalCent, a novel approach that allows to use the widely applied DayCent model to simulate multi-component agroforestry systems by splitting them into different independent zones, simulating each of them individually and calculating system performance as weighted average of the different zones. We used a collection of six short- to long-term agroforestry sites in France to evaluate the suitability of the ZonalCent approach to represent carbon sequestration in tree biomass, SOC stocks and total sequestration at the system level. DayCent was applied without any parameter adjustments. Our evaluation showed that the ZonalCent approach is highly suitable to represent tree carbon sequestration but biased to overestimate sequestration in SOC stocks. This leads to an overall acceptable representation of total system carbon sequestration, which could be further improved by reducing the SOC bias. Due to lack of yield data, we could only compare the simulated and observed yield reduction for one site, where ZonalCent captured the average yield reduction. Further investigation is needed to test the capacity of ZonalCent to predict yield reductions, but unfortunately datasets of mature temperate agroforestry systems are very scarce. The strong negative correlation between tree density and simulated relative yield in the agroforestry system, however, suggested that the main components that influence yield in agroforestry system are related to light and nutrient competition by the trees (and the obvious loss of arable area due to grass strips). Consequently, the highest carbon sequstration potential might be in silvopasture or similar systems where a high tree density can be achieved, no additional "grass strips" are needed (Thevathasan et al. 2020) and where rather shade tolerant forages and grasses are grown. The ZonalCent approach with its flexibility and limited complexity is thus very suitable for rapid ex ante assessments at larger scales.

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Author contributions ML and JS developed the initial idea to use DayCent to simulate temperate agroforestry systems. ML, ULG, RC and MP developed concrete idea for simulating the six french case studies. ML and MP developed the ZonalCent approach and conducted the simulations. ML prepared the original draft of the manuscript. All coauthors except MP contributed in writing and editing of the final submitted article.

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Data availability All the data used for the simulations of this article are from the study of Cardinael et al. (2017), and can be retrieved directly from the tables in their article.

Declarations

Conflict of interest The authors know of no Conflict of interest.

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