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Deep SOC stock dynamics under contrasting management systems: Is the EPIC model ready for carbon farming implementation?

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ABSTRACT

Process-based models have been recognized as cost-effective tools to assess carbon farming mechanisms through quantifying the C fluxes in the agroecosystems. A result-based approach is suggested however the wide variability of agricultural environments makes further model implementation necessary to limit the uncertainty of the results, especially on deep soil organic carbon (SOC) stock estimation and stratification and in agroecosystems characterized by a shallow water table. In this study, a comprehensive soil and crop dataset collected over a seven-year period from different pedoclimatic conditions across the Veneto Region (NE Italy) was used for EPIC model calibration and validation of SOC stock dynamics. Experimental data included yields from several crops (corn, winter and spring wheat, rapeseed, and soybean), continuous monitoring of soil water content, and SOC stocks (1872 total samples within the 0–50 cm soil profile) under conventional, cover crop and conservation agriculture systems. Modelling was performed by testing two N-C sub-models (CENTURY and PHOENIX), which differentiated in terms of mineralization/immobilization rates.

Results showed that the procedure was able to obtain parameters valuable for most of the management system and pedoclimatic condition, reproducing well the tested variables. The EPIC model acceptably captured soil water dynamics (Nash-Sutcliffe coefficient – NSE – was up to 0.26), especially in the topsoil. Furthermore, simulation of weed—crop competition in conservation agriculture strongly contributed to properly explain the variability in crop production among the contrasting agricultural systems (R^2 ranged from 0.51 to 0.71). Likewise, EPIC skillfully simulated SOC stocks within the 0–50-cm profile regardless of the sub-model used (NSE was up to 0.64). Moreover, the model acceptably captured the profile SOC stratification among the different management practices. This study highlights the EPIC robustness for predicting SOC stocks and assessing with high accuracy carbon farming results.

1. Introduction

There is renewed interest in carbon (C) farming, a strategy that encompasses the management of carbon pools, flows, and greenhouse gas (GHG) fluxes at the farm level. To address this issue within the "Farm to Fork Strategy", the EU is called upon to implement effective monitoring, reporting, and verification (MRV) scheme that will provide incentives to farmers and landowners based on the results achieved (COWI, 2021). At the field scale, the challenge is to ensure rapid accounting of soil organic carbon (SOC) stock, and its variability over space and time (Montanarella and Panagos, 2021).

Several agricultural practices have been identified to enhance SOC stock (Abbas et al., 2020; Chenu et al., 2019; Stockmann et al., 2013). However, accurate evaluation of their effectiveness is complex and highly site-specific. The SOC spatial variability is often greater than its variability over time, introducing unavoidable uncertainties in detecting

Abbreviations: MRV, monitoring, reporting, and verification; CA, conservation agriculture; CC, cover cropping; CNT, CENTURY; CV, conventional agriculture; JHGR, johnsongrass; NSE, Nash-Sutcliffe coefficient of efficiency; PBIAS, percentage of bias; PHO, PHOENIX; PRMT, parameter; SOC, soil organic carbon; SOYB, soybean; SWC, soil water content; SWHT, spring wheat; WWHT, winter wheat.

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changes in SOC stocks (Morari et al., 2019).

Proper sampling protocols can be adopted to maximize the accuracy to field-level soil changes. These methods produce accurate estimates of SOC stock –even minimizing the number of samples (Longo et al., 2020; Smith et al., 2020)– although MRV costs can still be high. Moreover, simply scaling up data to a greater spatial level, or extending data from one to another agroecosystem, can generate uncertainty due to variations in soil, climate, crop, and management practices (Hoffmann et al., 2016; Manivasagam and Rozenstein, 2020).

Modeling approaches represent promising solutions for a trade-off between monitoring accuracy and costs. Process-based agroecosystem models are among the best tools to estimate biogeochemical fluxes and predict agronomic and environmental performances of different farm management (Oteng-Darko et al., 2013).

However, reliable reproduction of SOC dynamics and nutrient cycling still need thorough testing with monitored data to overcome the uncertainties associated with their theoretical background. For instance, Brilli et al. (2017), by reviewing several studies, found that flux discrepancies arose from errors in the simulation of soil water content (SWC), underlining the importance of adequately describing peculiar agroecosystem conditions such as a shallow water table, or thawing and ponding. Moreover, current models typically represent soils in a simplified way that limits the correct representation of deep SOC dynamics (Braakhekke et al., 2013; Jones et al., 2017; LeDuc et al., 2017), e.g., actual SOC accumulation versus SOC stratification under no-till conditions (Morari et al., 2019; Powlson et al., 2014) or dissolved organic carbon leaching (Montanarella and Panagos, 2021).

Among process-based biogeochemical models, EPIC (Williams, 1990) has been recently upgraded with advanced physical methods for accurate simulation of soil water dynamics and microbial denitrification. First, an efficient yet accurate solution of the Richards equation (Richards, 1931) was included to overcome the cascade model (Gowdish and Muñoz-Carpena, 2009; Jones et al., 2021). The updated model was tested on a series of lysimeters that were managed according to different shallow groundwater depths, showing considerable improvements in SWC predictions (Longo et al., 2021b). Second, a state-of-the-art C/N modeling based on CENTURY (Izaurralde et al., 2006; Parton et al., 1998) was upgraded by introducing a microbial denitrification N-C sub-model (Izaurralde et al., 2017) based on PHOENIX approach (McGill et al., 1981). However, the above-mentioned studies did not test such sub-models in terms of C dynamics while they focused on water and N cycles, despite they could be pivotal for refining SOC stock estimates.

Since 2000, the Veneto Region Government (NE Italy) has subsidized several agri-environmental schemes with the general goal to reduce the environmental impact of agriculture and enhance the delivery of ecosystem services. Recent research has shown that there are significant benefits for the agroecosystem from adopting such practices (Dal Ferro et al., 2017; Longo et al., 2021a; Piccoli et al., 2019), especially on the water quality in the low-lying regional plain that exhibits shallow water table conditions (Borin et al., 2000; Camarotto et al., 2018; Morari et al., 2012). However, the *ex-ante* and *ex-post* evaluations of sustainable agricultural practices require further refinement to comply with the MRV requirements of carbon farming. For instance, previous estimates of SOC stock potential under conservation practices in Veneto Region generated uncertainty due to the model underrepresentation of SOC profile distribution, especially in deep layers (Longo et al., 2021a).

Here, we hypothesize that recent upgrades in EPIC concerning SWC dynamics and N-C processes can improve the prediction of biogeochemical dynamics at the field scale, and in turn refine SOC stock estimates within the soil profile. The general objective of this paper is to test the robustness of recently-improved EPIC under the peculiar environment of the low-lying Venetian plain, by using a large dataset of 44 agricultural fields across the region covering contrasting tillage and soil cover managements. Our specific aims were: i) to assess the ability of the Richards sub-model to model soil water dynamics under shallow water table conditions, and ii) to test the EPIC PHOENIX-based sub-model to simulate SOC using the standard EPIC CENTURY-based sub-model as a benchmark.

2. Materials and methods

2.1. Study area

The experimental data used for calibrating and validating the EPIC model were collected from three farms in the Veneto Region in northeast Italy during the period 2011–2017. The "Vallevecchia" (F1) farm was located on the Adriatic Coast (45° 38.350′N 12° 57.245′E, −2 m a.s.l.) (Fig. 1): the soil was Gleyic Fluvisol or Endogleyic Fluvic Cambisol (FAO-UNESCO, 1990) with texture ranging from silty-clay to sandy-loam (Table 1) and bulk density of 1.439 g cm^{-3}, on average. The "Diana" (F2) and "Sasse Rami" (F3) farms were situated further west, on the central (45° 34.965′ N 12° 18.464′ E, 6 m a.s.l.) and southern (45° 2.908′ N 11° 52.872′ E, 2 m a.s.l.) regional plains, respectively. Both F2 and F3 were characterised by Endogleyic Cambisol (FAO-UNESCO, 1990) silty-loam soils with an average bulk density of 1.426 and 1.451 g cm^{-3} (Table 1). During the study period annual precipitations were 756 (±96), 953 (±60), and 703 (±54) mm in F1, F2 and F3, respectively (Fig. 2). Mean yearly temperatures were 14.1 °C (±0.1 °C), 14.4 °C (±0.1 °C), 13.7 °C (±0.2 °C), with the coldest (January) and warmest (July) months having average minimum temperatures of 0.6 °C (±1.0 °C), − 0.2 °C (±1.2 °C), and 0.0 °C (±1.2 °C) and maximum temperatures of 28.6 °C (±2.9 °C), 29.8 °C (1.0 °C), and 30.2 °C (±1.8 °C) in F1, F2 and F3, respectively (Fig. 2). Reference evapotranspiration (ET_0) exceeded rainfall from May to September in F1 and F2, from May to October in F3.

2.2. Cultivation practices

Since 2010, a conventional agricultural system (CV) has been established in a comparison with cover crop (CC) –it followed the same agronomic protocol as CV with the addition of cover crops between the main crops– and conservation agriculture (CA) managements. CA and

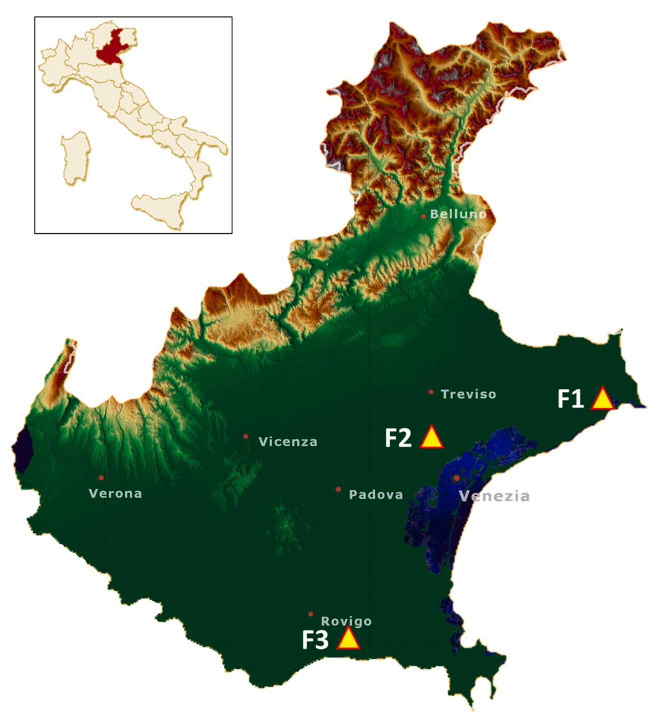

Fig. 1. Experimental sites in the Veneto region low plain, northeast Italy. Farm positions are marked with triangles (Vallevecchia, F1; Diana, F2, Sasse Rami, F3).

Table 1
Main soil physicochemical characteristics of the three farms in the 0–50 cm soil profile (Vallevecchia, F1; Diana, F2, Sasse Rami, F3).

Soil property	Unit	F1	F2	F3
Sand	g 100 g^{-1}	34.2	8.3	18.4
Silt	g 100 g^{-1}	42.6	66.1	57.8
Clay	g 100 g^{-1}	23.2	25.6	23.8
Bulk density	g cm^{-3}	1.439	1.426	1.451
pH		8.3	8.0	8.6
Total Carbonate	g 100 g^{-1}	53.0	4.0	13.0
Active carbonate	g 100 g^{-1}	3.0	1.0	3.0
SOC	g 100 g^{-1}	1.0	0.9	0.8
Available P	mg kg^{-1}	32.0	22.0	6.0
Exchangeable Ca	cmol(+) kg^{-1}	24.7	21.7	15.5
Exchangeable Mg	cmol(+) kg^{-1}	3.2	3.4	1.4
Exchangeable K	cmol(+) kg^{-1}	0.5	0.3	0.2

CC were agri-environmental measures that followed the rules established by the Rural Development Programme for the Veneto Region.

A total of 44 experimental fields (ca. 400 m long × 30 m wide) were included in this study, evenly separated between farms and agricultural systems (Table S1). Tillage operations for CV and CC included moldboard plow 35-cm deep and a 15-cm deep seedbed was prepared by disk harrow. The CA was managed with no tillage, direct sowing, and crop residues left on the field after harvest. Each system underwent the same crop rotation since 2010: winter wheat (*Triticum aestivum* L.), oilseed rape (*Brassica napus* L.), soybean (*Glycine max* (L.) Merr.) and corn (*Zea mays* L.) were the main crops, after which in 2015, the rotation was simplified by abandoning rapeseed cultivation (Table S1 and Table S2). In a few instances, winter wheat sowing was delayed until the spring season. In both CA and CC, the permanent soil cover was performed with cover crops: sorghum-sudangrass (*Sorghum x drummondii* (Nees ex Steud.) Millsp. & Chase) in the spring-summer season and a mixture of barley and vetch (*Hordeum vulgare* L., *Vicia sativa* L., until 2014) or winter wheat (after 2014) during autumn-winter (Table S1).

Soil remained bare between the main CV crops. Crop protection was based on Integrated pest management (IPM) practices following indications from Annual Crops Bulletin (https://www.venetoagricoltura.org/argomento/bollettino-colture-erbacee/) which exploits several development models, DSS and monitoring procedures. When a IPM decision was taken, it was applied to all the CA, CC and CV fields.

2.3. In-field data collection

A total of nine soil water monitoring stations were installed to cover all the different treatments at the three farms. At each farm, volumetric SWC (m^3 m^{-3}) was recorded daily from November 2013 to May 2015 via WaterScout SMEC 300 sensors (Spectrum Technologies, Aurora, IL, USA) positioned at depths of 10, 30, and 50 cm. Prior to field installation, the SMEC 300 sensors were calibrated in the laboratory to an accuracy of ±5%. Weather data were collected from nearby stations operated by the Environmental Protection Agency of the Veneto Region (ARPAV).

As of March 2016, additional nine soil water monitoring stations were installed in three experimental fields only of F3, such that the CV, CC, and CA systems were monitored with three monitoring stations each. Each station was equipped with multi-sensor probes (HD3510.2, Delta OHM, GHM GROUP, Selvazzano Dentro, IT) that continuously monitored soil temperature (°C) and volumetric soil water content (m^3 m^{-3}) at 10, 30, and 55 cm depths. It follows that monitoring of soil water dynamics in each agricultural system was replicated three times at all the depths. All soil moisture sensors were previously calibrated in the laboratory to an accuracy of ±3%. An additional weather station was also installed that was equipped with a thermometer, hygrometer, anemometer, pyranometer, and rain gauge. Across farms and cultivation systems, phreatic wells (3.5 m depth) were installed to monitor the water table level.

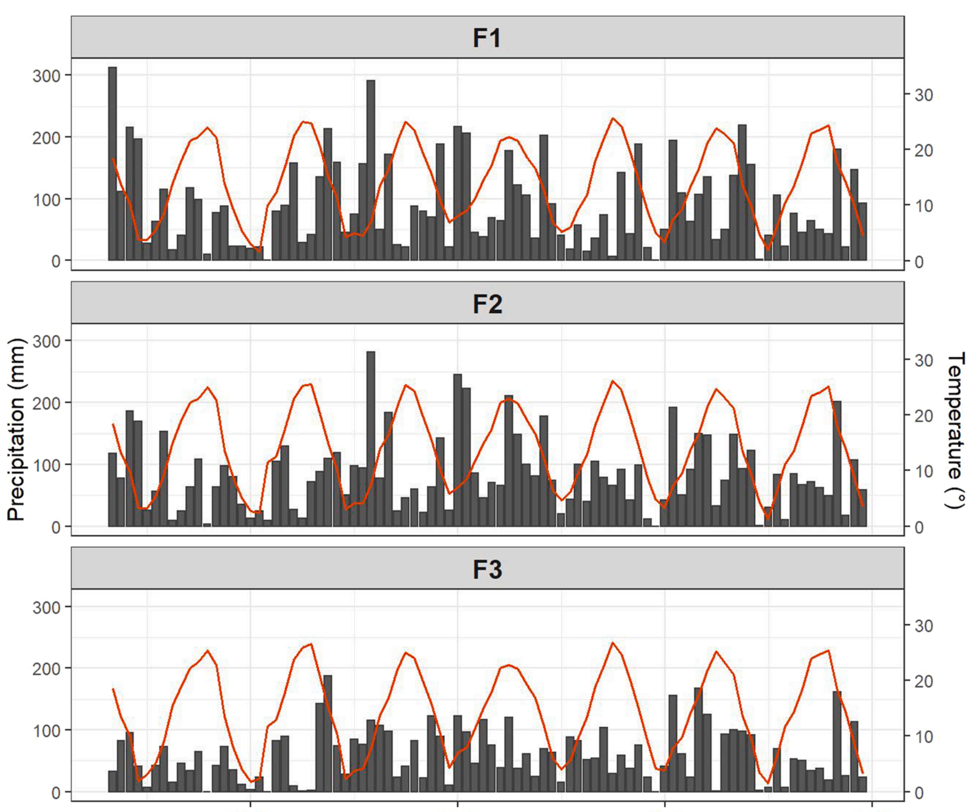

Fig. 2. Monthly precipitation (bars, mm) and average temperature (red line, Celsius) by farm.

Crop biomass and residue samples were collected annually from three 2 m^2 areas in each of the 44 fields. The biomass samples were dried at 65 °C in a forced draft oven for 72 h for dry weight determination.

Three comprehensive soil sampling campaigns were undertaken in the spring of 2011, 2014, and 2017 (Camarotto et al., 2020) to evaluate the effects of soil cover and undisturbed soil management on SOC stocks. In 2014, sampling was conducted only on CA and CV fields, while in 2011 and 2017 all agricultural systems were investigated. Undisturbed soil cores (0–50 cm) were taken by hydraulic sampler following the methodology reported in Dal Ferro et al. (2020) from six systematically chosen locations in each field and cut into three distinct layers, 0–5, 5–30 and 30–50 cm (Piccoli et al., 2016). Briefly, a tractor-mounted double-cylinder core sampler was used to minimize compaction by slowly drilling soil layers. After sampling, each soil core was measured to verify it matched the full length of the hole. A total of 1872 samples were collected and later analyzed to estimate SOC concentration (with CNS elemental analyzer Vario Max, Elementar Americas, Inc., DE), particle size distribution (with laser diffraction, Malvern Mastersizer 2000, Malvern, UK) and dry bulk density by the core method.

2.4. The EPIC model

The EPIC model was originally developed in the early 80 s by the USDA with the main purpose of assessing the impact of erosion on soil productivity (Williams et al., 1984). After the addition of various modules over the past 20 years, EPIC is now suitable to simulate a wide range of processes in the agroecosystems, such as crop growth and yield, nutrient cycling, water balance, and many agronomic techniques (Gassman et al., 2004).

The standard coupled C-N subroutine (CNT) reflects an approach similar to that of CENTURY (Izaurralde et al., 2006), in which C and N compounds are allocated to biomass, slow, or passive pools. In the recent version, a second module (PHO) based on the approach used in both the CENTURY and PHOENIX models (McGill et al., 1981) was also added (Izaurralde et al., 2017). Here, mineralization and immobilization rates vary with fluctuating C/N ratios of aggregated microbial biomass (i.e., bacterial and fungi are not treated separately). Gas diffusivity was improved as well when using PHO. Instead of a generalized function of depth or carbon/clay fractions, diffusion of O_2 and CO_2, along with N_2O and N_2, are simultaneously simulated using the gas transport equation (Šimůnek and Suarez, 1993). The upgraded sub-model also contains a decomposition feedback mechanism (Izaurralde et al., 2012), which is reduced sufficiently such that actual decomposition produces an electron supply equal to the total of electrons that can be accepted by O_2 and oxides of N. Both CNT and PHO sub-models simulate C-N dynamics for all soil layers.

The EPIC model simulates SWC dynamics through a cascade model approach, which showed to be inaccurate for near-saturated conditions (Longo et al., 2021b). To overcome this, the EPIC code has been recently upgraded with subroutines for simulating SWC dynamics intended to better handle conditions above the field capacity. The subroutines use the Ross method (Ross, 2006) to reproduce a fast analytical solution of the Richards equation (Jones et al., 2021), which is:

$$\frac{\partial\theta}{\partial t} = \frac{\partial}{\partial z}\left[K(\theta)\left(\frac{\partial \mathrm{h}}{\partial z}+1\right)\right] \quad (1)$$

where θ is the volumetric soil water content ($m^3\ m^{-3}$), t is time (s), K is the hydraulic conductivity (m s^{-1}), z is the elevation (m), and h is the matric head (m).

The Richards sub-model drives daily vertical water flows through the soil following infiltration and evaporation from the surface soil layer, and root water extraction from root-penetrated soil layers. Due to its application for independent modeling units, horizontal inflows and outflows are assumed to be balanced in EPIC. Percolation from the deepest soil layer is assumed to occur as free gravitational drainage. The two bottom boundary conditions available in the module are free drainage and constant head. Soil hydraulic parameterization employs the modified van Genuchten-Mualem models (Schaap and van Genuchten, 2006) to characterize the soil water retention and unsaturated hydraulic conductivity functions. The soil hydraulic characteristics can either be input or estimated by the pedotransfer functions in the code.

2.5. Model input data

Model input parameters were daily weather data from which crop potential evapotranspiration was calculated using Penman-Monteith equation (Allen et al., 1998). Soil profiles were set down to 1.5 m. Dry bulk density, particle size distribution, pH, and SOC concentration measured on samples within the 0–50 cm profile were fed into the model. The other soil parameters required by the model, and those below 50 cm deep, came from the Veneto Region soil map (Regione Veneto, 2005) (Table 1). Model SOC fraction pools were initialized with a 100-yr spin-up of crop rotations (Izaurralde et al., 2012) typical in the area as in Dal Ferro et al. (2016). Minimum and maximum shallow water table depths were also added as input parameters. Pedotransfer functions were used to estimate soil hydraulic parameters according to (Jones et al., 2014).

The dates, operational details, and quantities of the agricultural management practices, such as tillage, fertilizations, and harvesting came from experimental protocols. Crop and cover crop parameters embedded in the plant species file (CROPCOM.DAT) were adjusted to the specific vegetation conditions of the Veneto Region. Corn (CORN), soybean (SOYB), and winter wheat (WWHT) parameterization was based on the studies of Giardini et al. (1998) and Causarano et al. (2008) (Table S3). Spring wheat (SWHT) was used in the instances when the sowing of winter wheat was delayed. For this crop and in the case of rapeseed (RAPE), crop parameters were sourced from the EPIC database (Williams, 1995). Some CA systems experienced high competition from weeds, which led to significant lower yields than weed-free fields. Here, Johnsongrass (JHGR) was simulated to reproduce the effect of weeds competing with the main crop.

2.6. Calibration and validation

Calibration and validation were performed by comparing experimental and simulated crop yields, SWC dynamics, and SOC contents within the 0–50 cm profile throughout the 7-year experiment (2011–2017). Calibration and validation datasets of crop yields and SOC were built to represent the whole range of pedo-climatic and management conditions. Hence, for each farm-management practice combination, half of the experimental fields were randomly selected for calibration, the remaining half was used for validation. It follows that in total 22 out of 44 fields were used for calibration.

Water dynamics, available in nine fields from November 2013 to October 2014, were used for calibration; values from November 2014 to April 2015 were used for validation. In F3 farm, the March 2016-to-December 2017 period was also used for water dynamics validation. Soil layer depths differed between measured and simulated values. To match them, simulated SOC stocks were determined by fitting an equal-area spline to estimate the 1 cm variation in bulk density and SOC concentration along the soil profile (Longo et al., 2020), and by calculating the cumulative stock in the 50 cm depth and the stock in the 0–5, 5–30 and 30–50 cm depth.

A first set of potentially calibrated parameters was selected based on expert knowledge of EPIC, which most influence SWC, yield, and SOC (Table S4). Selected SWC parameters mainly affected the Penman-Monteith equation and runoff. Most of the parameters regarding crop yield adjustments were related to the influence of stresses caused by water deficit and soil strength. SOC parameters regarded SOC pool transformation and decay rate, the effect of tillage, and soil biological mixing (e.g., earthworms). After that, a sensitivity test using the Morris elementary screening method (Campolongo et al., 2007) was performed to identify the most sensitive parameters requiring calibration. The method involves two main steps. First, it discretizes the input space for each variable, then it performs a set number of designs as each input is varied while holding the others fixed (one-at-time design) (Iooss and Lemaître, 2015).

Final sensitivity is expressed as the mean of absolute value (μ^*) and the standard deviation (σ) of the elementary effect of the tested parameter (Iooss and Lemaître, 2015). The larger the μ^* is, the more the parameter contributes to output dispersion. The smaller is σ, the more negligible the parameter effect becomes when interacting with others. The screening method considered the influence of the selected parameters on model skill for simulating yield, SWC and SOC, according to the Nash-Sutcliffe coefficient of efficiency (NSE) (Nash and Sutcliffe, 1970), with the average NSE utilized for a balanced assessment. The parameter selection method was conducted for both PHO and CNT subroutines, which were executed for 420 iterations (20 parameters $\times$ 20 +1 repetitions) at 22 fields (totally 18480 simulations). Parameters whose relative sensitivity –the ratio between each μ^* and the maximum μ^* – was < 0.05 were excluded from calibration.

A multi-objective genetic parameter estimation algorithm (NSGA-II; Deb et al., 2002) was used to automatically find the best parameter set. The optimization procedure aimed to maximize the NSE coefficient of yield, SWC and SOC of the 22 selected fields, so that the procedure simultaneously optimized three NSE values. The parameter set that maximized the average NSE was then selected. The model was executed for 66000 iterations (number of generations=30, population size=100, fields=22) for each N-C sub-model (132000 in total).

As for validation, the coefficient of determination (R^2), the NSE, and the percent bias (PBIAS) coefficients (Tonitto et al., 2010) were calculated between experimental and simulated results.

The NSE coefficient (Nash and Sutcliffe, 1970) was expressed as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(\mathrm{Obs}_i - \mathrm{Sim}_i)^2}{\sum_{i=1}^{n}(\mathrm{Obs}_i - \overline{\mathrm{Obs}})^2} \tag{2}$$

where Obs_i is the i-th observation of the variable being evaluated, Sim_i is the i-th simulated value of that variable, $\overline{\mathrm{Obs}}$ is the mean of observed values, and n is the total number of observations. Model outcomes produce good approximations when NSE is positive, with NSE= 1 representing the best fit.

The PBIAS coefficient measures the average tendency of the simulated data to be larger or smaller than their observed counterparts and was expressed as:

$$PBIAS = \frac{\sum_{i=1}^{n}(\mathrm{Obs}_i - \mathrm{Sim}_i) \times 100}{\sum_{i=1}^{n}\mathrm{Obs}_i} \tag{3}$$

Both automated calibration and validation procedures were conducted in R version 3.6.0 (R Core Team, 2017).

3. Results

3.1. Sensitivity analysis and model calibration

The sensitivity analysis using the Morris method revealed greater sensitivity for SWC-related parameters than SOC and yield, regardless the implementation of PHO or CNT sub-models. Of all SWC parameters, only PRMT(75) –which affects the residue influence on runoff (Table S4)– was excluded from the calibration process. The greatest effect was associated with the "adjustment factor of the Penman-Monteith equation" (PRMT(74)), a parameter that contributed (PHO, $\mu^* = 0.29$; CNT, $\mu^* = 0.30$) and interacted (PHO, $\sigma = 0.27$; CNT, $\sigma = 0.28$) more than others to the model output (Table S4) or (Table S5). Considering SOC parameters, the Morris method selected PRMT(20), PRMT(47), and PRMT(51), which represent the microbial decay rate coefficient, the slow humus transformation rate, and the microbial activity in topsoil layer, respectively. Regarding crop, the selection procedure highlighted high sensitivity for root growth against soil strength (PRMT(2)). In total, eight parameters out of 20 were excluded from the calibration process.

The model calibration produced similar results between CNT and PHO sub-models. In only a few exceptions did parameters relatively vary much from their initial values. For example, runoff related PRMT(81) increased from 0.10 to 0.52 (PHO) and 0.19 (CNT). The PRMT(20) rose from 1.00 to 1.34 (PHO) and 1.20 (CNT).

3.2. Soil water content dynamics

Experimental SWC had generally higher values during winter, followed by a gradual decrease until minima that were observed during summer (Fig. 3). This dynamic was more pronounced in F2 regardless the agricultural system and the soil depth. Similar, F1 dynamics were more noticeable under CC and CV than CA as well as at 10 and 30 cm than 55 cm depth. SWC increased with depth, averaging 0.26 (SD $= \pm 0.004$), 0.30 (± 0.004), and 0.29 (± 0.003) m^3 m^{-3} at 15 cm in F1, F2, and F3, respectively, and 0.35 (± 0.003), 0.34 (± 0.003), 0.38 (± 0.002) m^3 m^{-3} at 55 cm depth. Prolonged periods of SWC > 0.30 m m^{-3} were observed at all depths in F1 and F2, which increased to values > 0.40 m m^{-3} in F3. Here, it was also monitored the highest SWC that reached values up to 0.48 m m^{-3} during the winter of 2014. In contrast, the lowest SWC was measured in F2 during July 2014, when a prolonged dry period combined with high temperatures and evapotranspiration dropped SWC down to 0.08 m m^{-3} in the surface layer (Fig. 3b). Regarding management, SWC varied little on average, with values equal to 0.31 (± 0.003) m m^{-3} for CC and 0.33 (± 0.002) m m^{-3} for both CV and CA.

Little SWC variations were observed between CNT and PHO, and similar dynamics were simulated by the two sub-models (Fig. 3 and S1). Overall, both sub-models predicted average SWC values of 0.32 m^3 m^{-3} across all depths along the experiment, while observations showed averages equal to 0.27, 0.30, and 0.36 m^3 m^{-3} at 15, 30 and 55 cm depth, respectively. A brief description for only PHO is reported hereafter. Simulations with PHO led to good representation of experimental SWC at 15-cm depth across farms and managements (NSE=0.07). Results also agreed well at 30-cm depth, despite some misrepresentations. For instance, the experimental SWC fluctuation under CC in F2 was not caught by EPIC with observations ranging between 0.10 and 0.36 m^3 m^{-3}, and simulations between 0.27 and 0.44 m^3 m^{-3} (Fig. 3b). Larger differences were observed at 55-cm depth for all treatments. In fact, EPIC often simulated quick changes in saturated and unsaturated SWC fluctuations along the full soil profile, even though only slight changes were monitored. In this context, some prolonged soil saturation conditions during winter at 55-cm depth were not predicted, probably because of a model neglection of upward movements (Fig. 3a, b).

The SWC dynamics found during calibration were confirmed in the validation, highlighting a good sensitivity to detect soil moisture changes especially in the surface and intermediate layers. Also, the model was accurate to describe SWC dynamics in the surface layer of F2 and F3 (NSE equaled 0.26 and 0.13, respectively). Accuracy decreased with depth: at 30-cm depth, some higher SWC was predicted compared with the observed at both F1 and F2, especially for the summer months when EPIC probably underestimated the evapotranspiration, failing in turn to reproduce the observed low SWCs; at 55-cm depth some SWC underestimation was found in F1 CA and F3 regardless the management system.

Soil water content for validation period was underestimated in CA and CV (PBIAS=−8.8% and −3.7%), while it performed better for CC, which PBIAS showed a slightly overprediction (1.1%).

At F3, EPIC performed well at 10 and 30 cm in CC, successfully

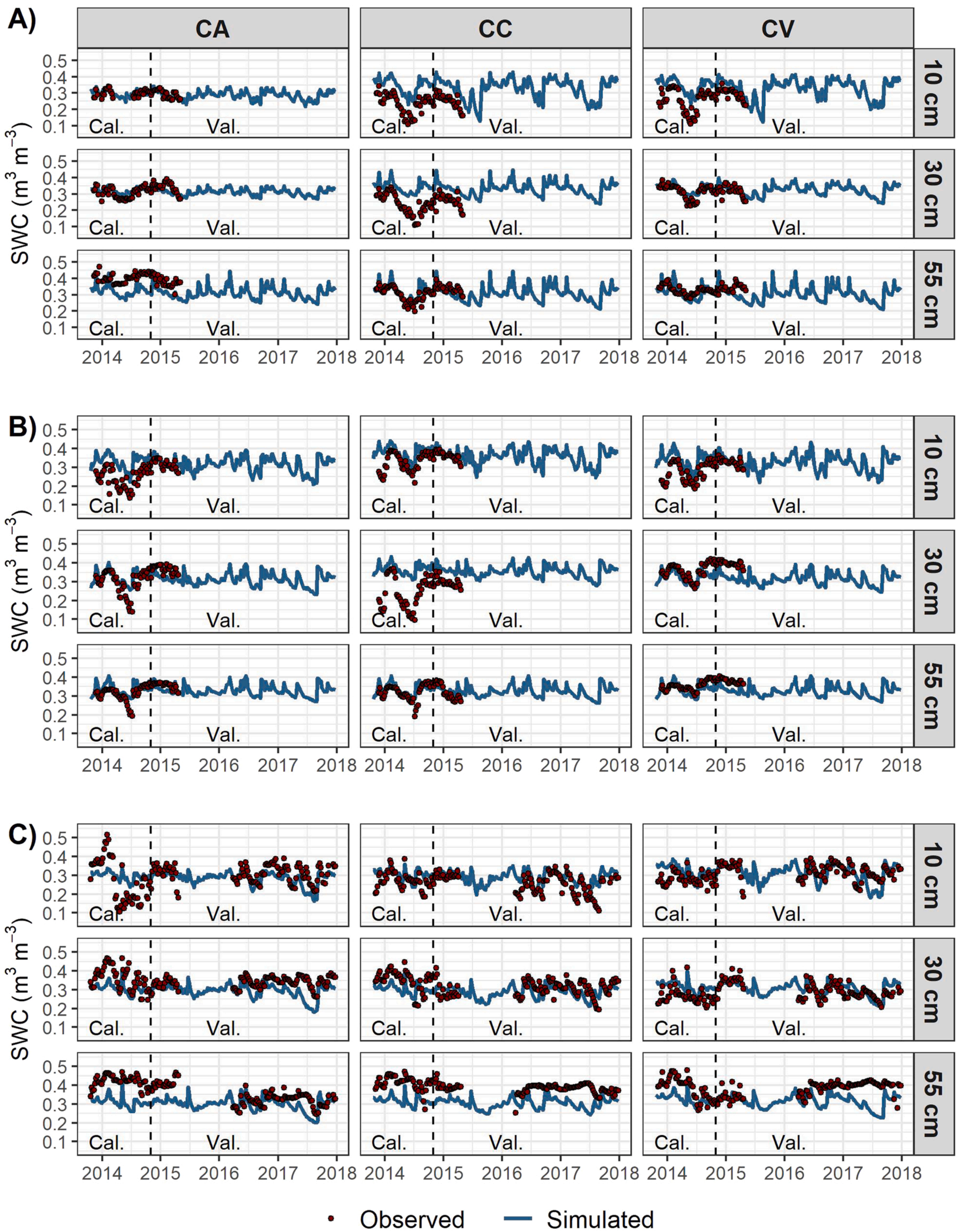

Fig. 3. Observed and simulated daily SWC (soil water content, m^3 m^{-3}) by management system and depth at a) F1 farm, b) F2 farm, and c) F3 farm using the PHO submodel. Observed and simulated values were reported during calibration (Cal) and validation (Val).

capturing both dynamics and range. Nonetheless, it failed at the deepest layer, when accuracy rapidly dropped as a result of upward movement underestimations. SWC dynamics for CNT are reported in Supplementary material (Fig. S1).

Little SWC variations were observed between CNT and PHO, and similar dynamics were simulated by the two sub-models (Fig. S1). Overall, they both predicted average SWC values were 0.32 m^3 m^{-3} for all depths all along the experiment, while observations showed averages equal to 0.27, 0.30, and 0.36 m^3 m^{-3} at 15, 30 and 55 cm depth, respectively.

3.3. *Crop yields*

During the 7-year experiment different crops, management systems, and farms, determined high yield variability. For instance, corn (CORN) yield averaged 7.79 Mg DM ha^{-1} (SD = 2.88 Mg DM ha^{-1}) while soybean (SOYB) averaged 2.75 Mg DM ha^{-1} (SD = 1.51 Mg DM ha^{-1}). The highest CORN yields were observed under CA (14.3 Mg DM ha^{-1}, respectively). Substantial yield reductions were also observed in CA compared to CV and CC (−28.3% for CORN and −21.0% for SOYB, on average) in the fields where weed infestation of Johnsongrass (*Sorghum halepense* (L.) Pers.) was poorly controlled. Rapeseed (RAPE) and spring wheat (SWWHT) produced generally lower yields, with the former varying from values < 1.0–2.65 Mg DM ha^{-1} and the latter from 1.1 to 3.78 Mg DM ha^{-1} (Fig. 4). Winter wheat (WWHT) averaged 5.45 Mg DM ha^{-1}, with SD = 1.74 Mg DM ha^{-1}.

Modeled yields using the PHO sub-model acceptably reproduced the experimental results, explaining overall 55% of the measured variability. However, some slight underestimation was observed in all systems, estimated by a general PBIAS = −6.9%. The best model performance was observed under CC (R^2 = 0.69). Under CA, EPIC initially simulated high soybean and corn yields that did not account for the experimental competition between main crops and weeds. The model adjustment with simultaneous growth of the main crops with weeds resulted in: i) crop yield predictions that were reduced from 8.84 to 3.68 DM Mg ha^{-1} (data in line with the observed average = 4.82 Mg DM ha^{-1}); ii) explained variability equal to 56% of the total one that was experimentally found (Fig. 4).

Among all crops, CORN was the best modelled (NSE = 0.15) followed by SOYB (NSE = 0.11), while the model performance dropped under RAPE(NSE =−0.6) despite a low PBIAS (= 1.2%).

When using the CNT sub-model (Fig. S3), some differences emerged compared to PHO. In particular, the model had better caught the observed variability, in particular in CA and CV, that increased the R^2 from 0.56 and 0.51 –using PHO– to 0.65 and 0.71 –using CNT. The coefficient of determination did not vary for CC fields (0.69). Predictions mostly differed for CORN and SOYB, whose NSE rose up to 0.43 and 0.27 (for PHO = 0.15 and 0.11). RAPE yield prediction worsened considerably, being PBIAS equal to 48.5%.

3.4. Soil organic carbon stocks

Soil organic carbon dynamics during the 2011–2017 experiment have been extensively reported in Camarotto et al. (2020). A brief description of main experimental results is reported here.

In 2011, observed SOC stocks along the 0–50 cm soil profile averaged 67.6, 71.9, and 79.1 Mg C ha^{-1} under CV, CA, and CC, respectively, and higher values in F1 (84.0 Mg C ha^{-1}) than in F3 (69.9 Mg C ha^{-1}) and F2 (61.1 Mg C ha^{-1}). During the second sampling campaign (2014) SOC content was determined only under CA and CV systems, leading to estimated stocks of 67.3 ± 6.6 and 70.6 ± 12.9 Mg C ha^{-1}, respectively. No samplings were performed in CC in 2014. In contrast, SOC stocks were greater in CA than CV in 2017, being respectively equal to 75.4 and 71.1 Mg C ha^{-1} (Fig. 5). The highest SOC stock in 2017 was measured under CC (80.1 Mg C ha^{-1}), despite a 3.74 Mg C ha^{-1} decrease with respect to initial conditions (2011). Instead, both CA and CV had an increase in stocks, equal to 2.08 and 2.59 Mg C ha^{-1}, respectively, from 2011 to 2017.

A SOC stratification was clearly observed within the soil profile. Final CA stocks were greater than those in the other systems in the surface layer (0–5 cm), being 9.28 (SD = 1.1) Mg C ha^{-1} against 7.7 (SD = 1.2 v) and 6.3 (SD = 1.6) Mg C ha^{-1} in CC and CV, respectively (Fig. 6). In the deeper layers, CC stocks outranked CV and CA both in 5–30 (37.6; SD = 78.5 Mg C ha^{-1}) and 30–50 cm layer (30.7; SD 2.6 Mg C ha^{-1}).

CNT and PHO sub-models were able to predict SOC stocks within the 0–50 cm in both 2014 and 2017, regardless the management system (Fig. 5). CNT sub-model slightly overestimated the SOC stocks in 2014 (PBIAS = 7.3%) compared to PHO (PBIAS =−1.7%) while in 2017 SOC stock were underestimated by PHO (PBIAS=−8.2%) with respect to CNT (PBIAS=2.6%). The high SOC stock values, particularly in F1, were underrepresented by PHO, which restricted the observed variability (86–103 Mg C ha^{-1}) in the range 67–76 Mg C ha^{-1}. Similarly, CNT underperformed in the same range but reaching an upper limit of 85 Mg C ha^{-1}. Considering the treatment, CNT outperformed PHO in CV in both the years, on the contrary PHO better simulated CA, as well confirmed by NSE coefficient (Table 2).

Over the experimental period, EPIC was less effective at predicting SOC stock layering. Indeed, in 2017 both sub-models slightly overestimated stratification in the 0–5 cm layer irrespective of management system (Fig. 6), and underestimated values in the 5–30 and 30–50 cm layers, especially for values above 40 Mg C ha^{-1}.

Considering the whole profile, SOC stock changes in time were better captured by PHO, which simulated an overall increase of 1.73 Mg ha^{-1} in the 2011–2017 period, against an observed value of 1.12 Mg ha^{-1}. Conversely, CNT highly overpredicted SOC stock changes (6.23 Mg ha^{-1}) despite a closer estimation of CV increases (2.59 vs. 2.46 Mg ha^{-1}, for observed and simulated values). Both PHO and CNT poorly reproduced the SOC depletion under CC. Regarding stock changes by layer, surface and 30–50 cm layers dynamics were better captured by PHO compared to CNT, despite they both overestimated the observed change: 0.54 Mg ha^{-1} vs 0.92 Mg ha^{-1} (PHO) and 1.60 Mg ha^{-1} (CNT) at 0–5 cm; 1.08 Mg ha^{-1} vs to 2.50 (PHO) and 5.08 Mg ha^{-1} (CNT) at 30–50 cm. Conversely, variations in the middle layer were better performed by CNT.

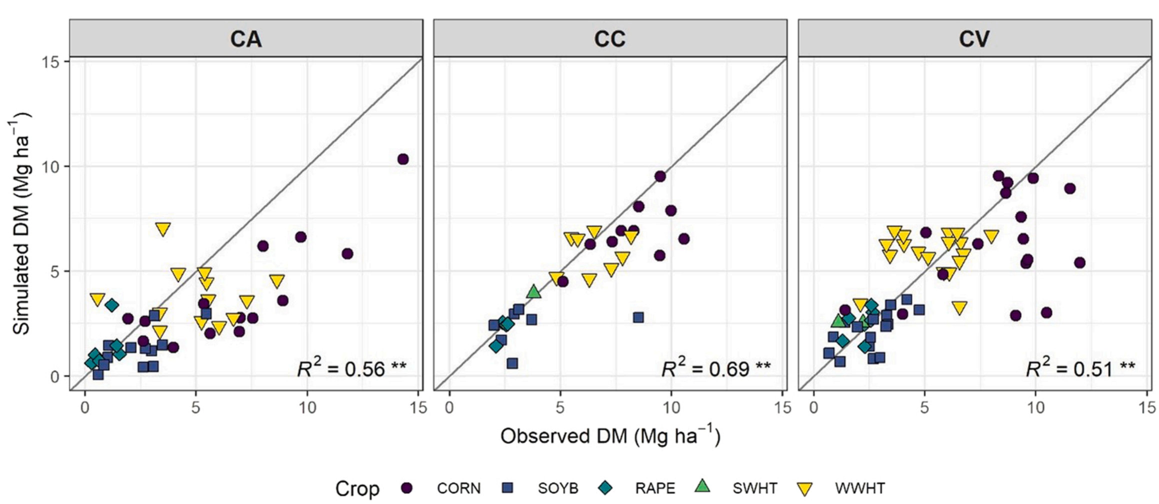

Fig. 4. Comparison of observed and simulated yields in the validation fields using the PHO sub-model. Significant relationships are labelled with asterisks (* = p < 0.05, ** = p < 0.01).

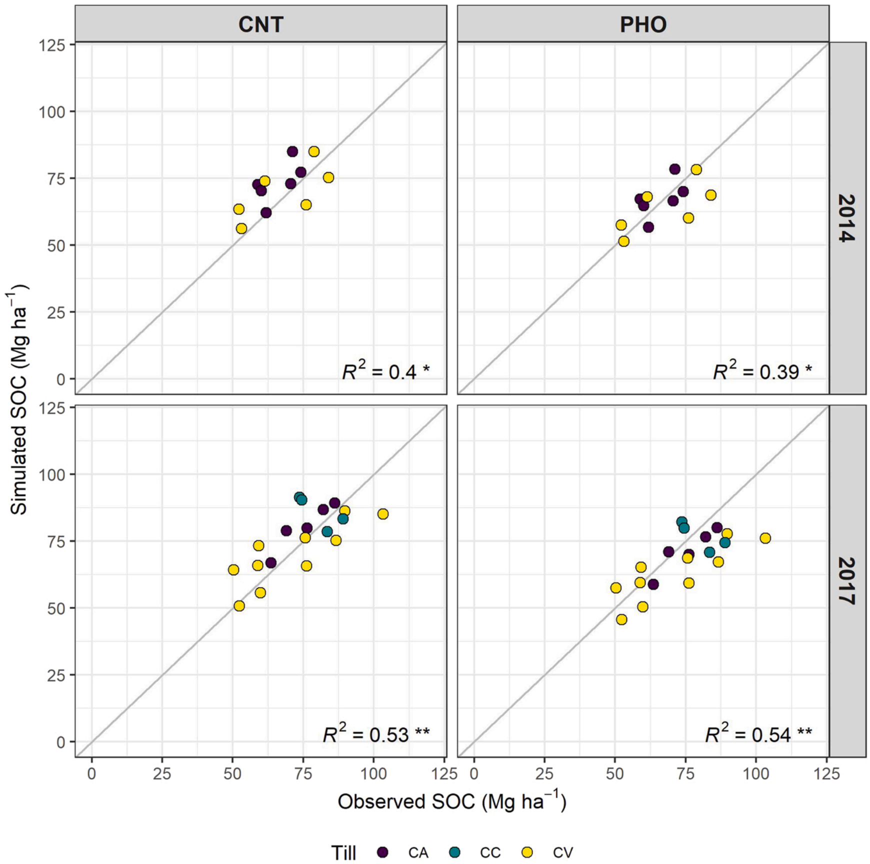

Fig. 5. Comparison of simulated and observed SOC stocks along the full profile (0–50 cm) by model used under different agricultural systems (CA: Conservation agriculture, CC: conventional cover crop practices, CV: conventional practices). One asterisk (*) indicates statistical significance at $p < 0.05$; two asterisks (**) indicates significance at $p < 0.01$.

4. Discussion

4.1. Model performance and description of biogeochemical cycles

The screening of sensitive and insensitive model parameters proved the Morris method ably minimized calibration efforts, as the influential parameters reduced with respect to those initially selected. Automated parameter optimization after Morris diagnosis resulted in an optimal set of parameters by overcoming the issues of manual calibration, such as time demands and consideration of parameter—parameter interactions (Balkovič et al., 2018; Causarano et al., 2007; Wang et al., 2005).

In terms of SWC, EPIC produced promising results, being that the model was generally able to describe the dynamics across farms, agricultural practices, and soil depths. Therefore, implementation of EPIC with the physically-based approach of Richards equation confirmed its ability in terms of soil water predictions. This advanced approach, implemented as either an internal subroutine or coupled to a hydraulic model, has yielded satisfactory results in several other studies (Diekkrüger et al., 1995; Doro et al., 2018; Shelia et al., 2018; Wang et al., 2015). Researchers have highlighted the success of the calibrated Richards solver to surmount SWC underestimations that can render cascade-based methods unsuitable for simulating soil water dynamics (Beheydt et al., 2007; Kröbel et al., 2010) and related ecosystem services (water cycle regulation, nutrient cycling, water filtering, etc.), especially at high SWC. In this study, underestimations were rarely observed by using the calibrated Richards solver, except during the initial period in F3 and at occasional events in the other farms, generally at the deepest soil layers. Previous modelling studies that were conducted in lysimeters (Longo et al., 2021b) showed that strictly controlled conditions of shallow water table level ensured considerably better description of SWC dynamics than those reported here. It is likely that lack of continuous groundwater data has limited model performance in the present experiment. More sophisticated model approaches could be helpful to reproduce water table fluctuations, such as in the recent coupling of DayCent biogeochemical and MODFLOW groundwater flow models (Deng et al., 2021a; Deng et al., 2021b).

EPIC provided satisfactory predictions of crop yield at levels comparable to those reported in other CA (Causarano et al., 2008; Jones et al., 2017), CC (Jones et al., 2018), and CV (Balkovič et al., 2013; Billen et al., 2009) modeling studies. Specifically, EPIC predicted the lower yields that resulted from resource competition between crops and weeds in no-tillage (CA) as opposed to the absence of competition in tillage (CC, CV) managements. However, it cannot be excluded that other factors such as the poor soil structure conditions and a higher bulk density (Camarotto et al., 2020) hindered the crop growth, especially in the short term (Constantin et al., 2010). Weed infestation is a common occurrence under conservation agriculture (Bajwa, 2014; Chauhan et al., 2012), especially when practiced with no-tillage and poorly-timed herbicide application. These results indicate that yields can be modeled successfully as long as needed information is available. Missing information about field crop—weed competition may partially explain the inter-annual variability that was observed within plots in the experiment, but that was not captured by the model. Other authors have also reported a limitation in the ability to predict year-to-year variability (Causarano et al., 2008; Kiniryt et al., 1995). Such findings highlight the dependency of the model on reliable boundary conditions and input parameters from experimental sites.

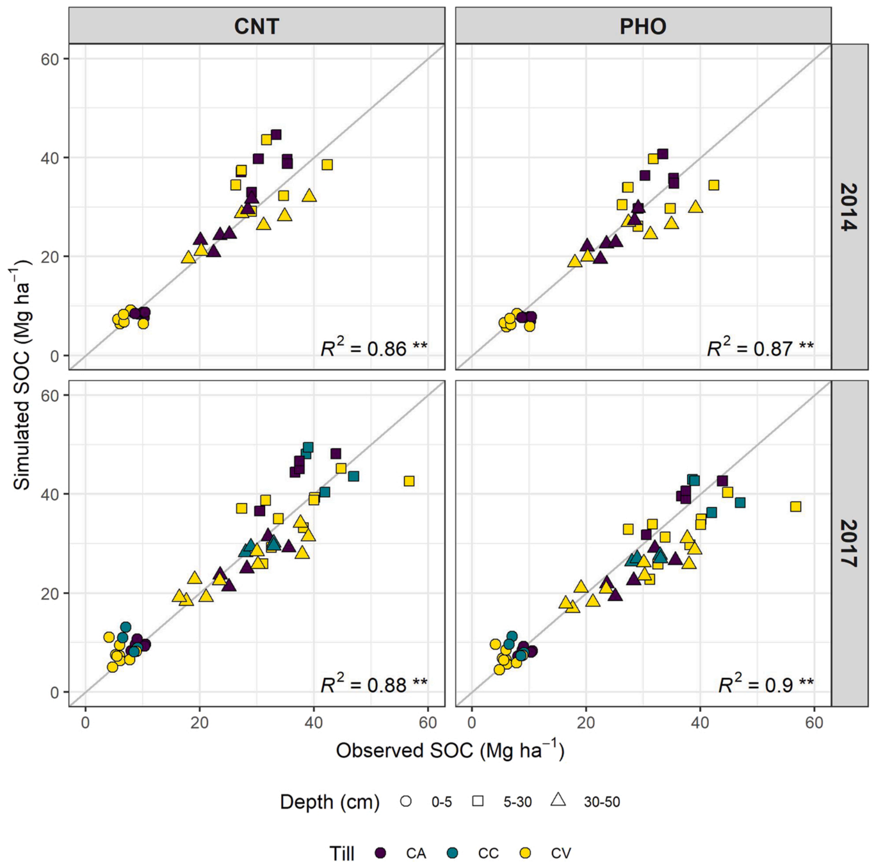

Fig. 6. Comparison of simulated and observed SOC stocks by depth (symbol) and tillage (color). All regression models were statistically significant ($p < 0.001$).

Table 2
Average observed and simulated soil organic carbon stocks within 50-cm soil depth using CENTURY (CNT) and PHOENIX (PHO).

		2014				2017			
Sub-model	Till	Observed SOC (Mg ha^{-1})	Simulated SOC (Mg ha^{-1})	NSE	PBIAS (%)	Observed SOC (Mg ha^{-1})	Simulated SOC (Mg ha^{-1})	NSE	PBIAS (%)
CNT	CA	66.0	73.4	-1.32	11.1	75.4	80.4	0.54	6.6
	CC	-	-	-	-	80.1	86.0	-2.83	7.4
	CV	67.5	69.9	0.44	3.5	71.1	69.9	0.64	-1.7
PHO	CA	66.0	67.3	0.07	1.9	75.4	71.4	0.63	-5.3
	CC	-	-	-	-	80.1	76.9	-1.84	-4.0
	CV	67.5	64.0	0.41	-5.2	71.1	62.8	0.38	-11.7

4.2. SOC stock estimates with EPIC

The usage of biogeochemical models, especially when accompanied by field auditing, has been suggested as the most robust method for carbon farming purposes and MRV scheme (COWI, 2021; Mattila et al., 2022; Nevalainen et al., 2022). Among the advantages of using such tools, models can also be applied to estimate co-benefits of carbon farming, such as increases in soil and water quality and economic services (Baumber et al., 2019; Lin et al., 2013). Indeed, most empirical studies focuses on the possible amount of GHGs mitigated, thereby neglecting any potential non-GHG environmental and social co-benefits of carbon farming (Tang et al., 2016).

The model was found to produce accurate predictions of SOC dynamics, which compared favorably with other studies (Jones et al., 2018, 2017; Zhao et al., 2013). The EPIC model was able to perform well across systems and years in two ways, first by capturing SOC stock variability affected by differing tillage systems, and second by highlighting its potential for SOC-related ecosystem services valuation (e.g., carbon sequestration and climate regulation, soil degradation limitation) (Jones et al., 2018). It is worth mentioning that soil compaction and bulk density variation are some examples of the difficulties in modeling soil carbon increases (Mattila et al., 2022). Despite EPIC did not include the effect of soil compaction on bulk density variation, experimental data did not show significant variation across years (Camarotto et al., 2020), substantiating the choice of using this model for reproducing SOC stock dynamics.

Despite the contrasting tillage/no-tillage practice, the model simulated well the experimental SOC stocks in the full soil profile, which accounted to an average of +2.08, +2.59, in CA and CV and –3.74 in CC, during the 2011–2017 trial.

It follows that calibrated soil parameters were able to describe the different conditions in CV and CA, for instance by adjusting the root growth-soil strength relationships and microbial decay rate coefficient (PRMT(2) and PRMT(20), respectively. In contrast, EPIC did not fully reproduce the SOC depletion experimentally observed under CC (Camarotto et al., 2020) for which it was claimed a priming effect due to the large burying of fresh biomass with a high C/N ratio. Finally, it is worth to note that the model calibration included most of the soil types and cropping systems that are representative of the low-lying Venetian plain soils. However, it did not cover the full pedo-climatic and management combinations that mostly occur, e.g., in the high plain and hilly areas of Veneto (grasslands, vineyards, etc.). This suggests that a wider model validation should be conducted to provide a comprehensive assessment of SOC stock dynamics across the agroecosystems of the region (Longo et al., 2021a). For instance, the requirement of specific calibrations/validations might be also hinted by the different C residence times between grassland vs. cropland (Guo et al., 2017).

The implementation of PHO sub-model showed similar results to CNT, despite the latter yielded slightly SOC stock overestimations in 2014 and 2017 when CC and CA were simulated. Le et al. (2018) already reported that EPIC overestimated SOC under a no-tillage in Cambodia. Most likely, CNT overestimated the potential decomposition rate of structural and metabolic surface SOC pools, even though an a priori 100-year spinning-up procedure was applied to equilibrate soil C. Several authors insist that the spinning-up procedure is often the most adequate and common SOC pool initialization method (Farina et al., 2020; Hashimoto et al., 2011; Nemo et al., 2017), others (e.g. Dimassi et al., 2018) argue that the spinning-up procedure has little effect. Thus, the outperformance on PHO in CA and CC may relate to its ability to represent plant residue decomposition well, as reported by Jans-Hammermeister and McGill (1997). Over time, interest has grown in models that use microbial biomass to drive decomposition rates (Berardi et al., 2020). Therefore, PHO may be preferred to CNT as it better combines N and C cycle simulations. Indeed, PHOENIX applies the deterministic Michaelis-Menten kinetic equation for simulating the N immobilization, N mineralization, and microbial O_2 uptake (Manzoni and Porporato, 2009). Wieder et al. (2013) underscored that the Michaelis-Menten kinetic-based modeling approach was able to generate more accurate projections of the C soil feedback on climate change. Similar microbial models also correctly reproduced ephemeral increases in the C decomposition due to warming, re-wetting, and root-priming events (Allison et al., 2010; Evans et al., 2016; Sulman et al., 2017). The DNDC model was recently upgraded by developing a microbial-mediated organic matter decomposition model, increasing the performance in capturing seasonal variations of net ecosystem exchange and SOC changes (Deng et al., 2021b; Deng et al., 2021a).

5. Conclusions

The EPIC model was calibrated and validated using a massive dataset from three farms that included crop yields, soil water content dynamics, and SOC stocks. Overall, the model was able to reproduce the tested variables under different pedo-climatic and management conditions over a seven-year period, which made clear it represents a promising tool to quantify ecosystem services provisioning across the Venetian Plain (9000 km^2). In fact, the Richards sub-model implementation made it possible to predict well the SOC stock dynamics even under shallow water table conditions, thus broadening its applicability to low-lying and coastal areas that are poorly represented by cascade-based biogeochemical models. The additional strength of the model was its ability to explain the variability in crop production, even when weed—crop competition was present. Some of the best performances by the model were observed for SOC simulations. The model described management systems that were characterized by different tillage practices, emphasizing its ability to simulate not only the SOC stock within the 0–50-cm profile regardless of sub-model used, but also the SOC stratification.

In terms of opportunities to improve the model, there are several. Soil water content simulations suffered from missing data that could not be used to set water table levels as a bottom boundary condition. Results in the 0–30 cm soil profile were generally acceptable, but less so in the deepest layer. Soil water content predictions in the model would benefit from modification and additional testing of the water table level routine with data from environments characterized by shallow water tables, such as those studied here.

On balance, we accept our hypothesis that recent EPIC implementations provide substantial improvements for predicting SOC dynamics, which allows refined estimates of agricultural practices to affect the SOC stocks in the perspective of carbon farming initiatives. The acceptance of our hypothesis comes with the recommendation to use the PHO sub-model in the future, since microbial C/N dynamics are more realistically modeled and provide far better outcomes when both the C and N cycles are combined and tested. To this end, future research will be required to test a wide range of ecosystem service provisioning models that embed both C and N cycles, allowing to account for the whole GHG balance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2023.126771.

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