Can conservation tillage mitigate climate change impacts in Mediterranean cereal systems? A soil organic carbon assessment using long term experiments

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Abstract

Simulation models, informed and validated with datasets from long term experiments (LTEs), are considered useful tools to explore the effects of different management strategies on soil organic carbon (SOC) dynamics and evaluate suitable mitigative options for climate change. But, while there are several studies which assessed a better prediction of crop yields using an ensemble of models, no studies are currently available on the evaluation of a model ensemble on SOC stocks. In this study we assessed the advantages of using an ensemble of crop models (APSIM-NWheat, DSSAT, EPIC, SALUS), calibrated and validated with datasets from LTEs, to estimate SOC dynamics. Then we used the mean of the model ensemble to assess the impacts of climate change on SOC stocks under conventional (CT) and conservation tillage practices (NT: No Till; RT: Reduced Tillage). The assessment was completed for two long-term experiment sites (Agugliano - AN and Pisa - PI2 sites) in Italy under rainfed conditions. A durum wheat (*Triticum turgidum* subsp. *durum* (Desf.) Husn.) - maize (*Zea mays* L.) rotation system was evaluated under two different climate scenarios over the periods 1971-2000 (CP: Present Climate) and 2021-2050 (CF: Future Climate), generated by setting up a statistical model based on canonical correlation analysis. Our study showed a decrease of SOC stocks in both sites and tillage systems over CF when compared with CP. At the AN site, CT lost -7.3% and NT -7.9% of SOC stock (0-40 cm) under CF. At the PI2 site, CT lost -4.4% and RT -5.3% of SOC stocks (0-40 cm). Even if conservation tillage systems were more impacted under future scenarios, they were still able to store more SOC than CT, so that these practices can be considered viable options to mitigate climate change. Furthermore, at the AN site, under CF, NT demonstrated an annual increase of 0.4%, the target value suggested by the 4 per thousand initiative launched at the 21st meeting of the Conference of the Parties in Paris. However, RT at the PI2 needs to be coupled with other management strategies, as the introduction of cover crops, to achieve such target.

Keywords: Soil organic carbon; Model ensemble; Tillage; Wheat-maize rotation; Prediction; Mitigation strategies.

1. Introduction

Soil organic carbon (SOC) is important to crop production because it mediates nutrient cycling, and affects soil fertility (Bolinder et al., 2010; Lal et al., 2009), and soil water-holding capacity (Huntington, 2007). Sequestration of carbon in soil by increasing SOC is also considered one way to mitigate climate change as SOC represents the main C sink in terrestrial ecosystems (Wang et al., 2015). Different tillage practices affect both sequestration capacity and the distribution of organic C in soil and can contribute to mitigative adaptation strategies to climate change in a variety of ways (Marraccini et al., 2012). In general, benefits associated with tillage include topsoil aeration, ease of seed emergence, effective weed control and incorporation of crop residue into the soil. However, conventional tillage (CT), characterized by traditional moldboard ploughing, can stimulate rapid mineralization of SOC, increase soil erosion, create a plough pan and increase the use of energy for mechanical operations (Bertolino et al., 2010; Rusu, 2014).

Less intensive tillage management, also referred to as conservation agriculture (i.e., Reduced tillage – RT and no till – NT), has been adopted to reduce these negative impacts although sometimes lower yields have been associated to these practices (Van den Putte et al., 2010). There is still uncertainty of the merit of conservation tillage to contribute to increasing the resilience of cropping systems to climate change (Powlson et al., 2016) and to increasing SOC compared with CT practices (Gonzalez-Sanchezet al., 2012; Haddaway et al., 2016). In fact, SOC significantly increases in the layers closest to the soil surface under conservation tillage but does not always increase in the deeper soil profile where, conversely, SOC content tends to increase under conventional tillage, particularly near or at the bottom of the plowed layer (Alvarez, 2005; Angers and Eriksen-Hamel, 2008; De Sanctis et al., 2012). These results highlight the importance of evaluating the entire soil profile or, at least, the depth of the plowed layer to compare the effect of contrasting tillage practices on SOC stocks.

However, because changes in SOC can occur very slowly (Smith et al., 1997), the relationship between tillage practices and SOC sequestration should be evaluated over a sufficiently long period of time. Long-term experimental sites (LTEs) at research facilities thus represent the ideal setting to assess processes and factors that may affect SOC content over a long period of time because there are long-term datasets associated with these sites (Korschens, 1996; Ruisi et al., 2014). In fact, while short-term experiments can support research that focuses on the initial stages of a process, LTEs permit evaluation of the magnitude of change over a longer period of time and allows understanding the cause of these changes at the same time (Knapp et al., 2012). For this reason, data coming from LTEs play a key role in informing and validating crop simulation models. Furthermore, as LTEs permit understanding the relationship of short- and long-term processes, they are crucial to improving the ability of current crop simulation models to simulate future scenarios. Powerful tools can be developed from this process that permit researchers and policymakers to explore management strategies that increase SOC and define suitable adaptation and mitigation options to reduce the impact of climate change on cropping systems (Ewert et al., 2011; White et al., 2011). Models were successfully used to simulate contrasting tillage management in agroecosystems under current (Chang et al., 2013; De Sanctis et al., 2012; Franko and Spiegel, 2016; Leite et al., 2009; Tan et al., 2007) and future climates (Bhattarai et al., 2017; Farina et al., 2011).

Given the growing interest in assessing uncertainty, in particular under future scenarios (Wallach et al., 2016), both the climate and crop modeling communities have proposed the use of an ensemble of models to obtain a probability distribution of projections (Harris et al., 2010) rather than a single model. In fact, crop models can vary in structure and parameterization and formalize bio-physical and physiological processes differently. For this reason, they may respond in different way to future climate scenarios, thereby projecting different impacts of climate change on SOC and crop yield, even if they had been able to reproduce quite well the observed values under past conditions (Bassu et al., 2014). As a result, an assessment of climate change impacts based on an ensemble of outcomes from multiple model simulations is more reliable than one obtained from a single model (Rötter et al., 2011; Tao et al., 2009).

Furthermore, many studies of multi model ensembles (MME) under current climate conditions have shown that the mean or median of the ensemble's simulated values reproduce the measured crop yields better than any individual model (Asseng et al., 2014; Li et al., 2015; Martre et al., 2015; Palosuo et al., 2011; Rötter et al., 2012). Given the improved performance of crop model ensembles over single models under current conditions, Wallach et al. (2016) suggest that better predictions under future climate conditions can be obtained with the mean or median of the model ensemble, even without improving the present-day crop models. Nevertheless, while some research has assessed MME to predict crop yield, no MME studies are currently available that evaluate the ensemble mean or median to simulate SOC dynamics. Many studies have used biogeochemical models (Alvaro-Fuentes et al., 2012; Gottschalk et al., 2012; Lugato et al., 2007; Meersmans et al., 2016; Muñoz-Rojas et al., 2013; Tornquist et al., 2009) to assess the impact of climate change on SOC, but because these models have simplified processes for crop growth simulation, they could produce unreliable impacts on crop productivity and, consequently, on soil C-input. Most climate change impact studies using crop process based models have focused on the crop-atmosphere interaction of single crops alone (Asseng et al., 2014; Bassu et al., 2014; Long et al., 2006) while, more recently, studies emerge which consider the entire system of soil-crop-atmosphere interaction (Basso et al., 2015; Kollas et al., 2015; Nendel et al., 2014; Teixeira et al., 2015). This is particularly important under limited growing conditions such as in rainfed cropping systems with low SOC content. As a matter of fact, SOC can vary by year in response to agronomic management decisions and climate. These changes in SOC then affect soil water holding capacity and nitrogen and, at the same time, crop performance which, in turn, affects additional input of SOC.

Considering all of the issues mentioned above, we hypothesized that using an ensemble of models to estimate SOC in agricultural soils provides an advantage in terms of simulation accuracy, an approach that has not been used in previous studies. Moreover, we assumed that the use of process-based crop models for the dynamic estimation of plant C inputs to soil, varying year by year according to soil and climate variability and considered the main driver of SOC dynamic (Izaurralde et al., 2006), greatly improves the reliability of SOC simulations. We tested our hypothesis with four process-based crop models that were calibrated and evaluated with a set of data from selected Italian LTEs where different tillage options had been applied to cereal-based cropping systems in rainfed conditions. Thereafter we used MME to assess the long-term effects of contrasting tillage practices on changes in SOC stocks, considering both superficial (0-15 cm) and deeper layers (15-40 cm), in rainfed durum wheat (*Triticum turgidum* subsp. *durum* (Desf.) Husn.) - maize (*Zea mays* L.) rotations. These simulations were completed under both current and future climate scenarios. In this way we were able to assess the impact of future scenarios on both SOC and crop yield.

2. Material and methods

2.1 Description of the long-term datasets

The data from two rainfed long-term experiments (LTEs) were utilized for this study: the AN site located in Agugliano (Ancona, Marche, 43°32'N, 13°22'E) and the PI2 site in San Piero a Grado (Pisa, Toscana, 43°41'N, 10°23'E). These sites are characterized by contrasting tillage practices and belong to the IC-FAR national network (Linking long term observatories with crop systems modeling for a better understanding of climate change impact and adaptation strategies for Italian cropping systems). The climate of the both AN and PI2 sites is Mediterranean with a bimodal distribution of cumulated monthly precipitation in spring and autumn, mild winters and warm dry summers.

2.1.1 LTE AN

The AN LTE (Seddaiu et al., 2016) was established in 1994 in a hilly area with silt-clay soil. The rotation included two years of durum wheat (cv. Grazia, ISEA) followed by sunflower (*Helianthus annuus* L., cv. Starsol, ISEA) until 2001. After 2002 the sunflower crop in the rotation was replaced by maize (DK440 hybrid, Dekalb Monsanto, FAO class 300). These rotations were replicated twice in adjacent fields to allow production of all crops each year. Over the experimental period (1994-2014), the AN experiment site experienced mean annual rainfall of 820 mm and mean annual air temperature of 15.3°C.

The conventional tillage (CT) and no till (NT) treatments were used to calibrate the crop models in the durum wheat-maize rotation (2002-2014). CT plots were ploughed each year by moldboard to a depth of 40 cm in October for wheat and at the end of August for maize. The seedbed was prepared with double harrowing to a depth of 15 cm before the sowing date. NT plots were left undisturbed except for sod seeding, chopping of crop and weed residues and herbicide spraying before seeding. Both CT and NT treatments were fertilized with 90 kg N ha^{-1}. Mineral N was distributed as ammonium nitrate in two equal rates in February and March for wheat and in one rate at seeding for maize. For both tillage systems crop residues were not removed from the field and incorporated in soil under CT by ploughing.

Measured crop data consisted of phenology (flowering, and physiological maturity dates), leaf area index (LAI), and productivity (aboveground biomass and grain yield) from 2002 to 2014. SOC samples of the soil profile were collected to a depth of 40 cm in 1996 and 2002 and to a depth of 100 cm in 2006 and 2010 in both the CT and NT treatments. Physical soil characteristics and hydraulic proprieties were measured in 2006 and used to define the main soil characteristics of the site (Table 1). As the experiment was initialized on a CT system, we used 2006 data of the CT N90 treatments as a reference for the main soil characteristics of AN site assuming that these did not substantially change since the beginning of the experiment as reported by De Sanctis et al. (2012).

2.1.2 LTE PI2

The PI2 LTE (Mazzoncini et al., 2011) is located in a lowland coastal area with an alluvial loam soil. The experimental design includes two tillage systems (CT – annual plough *vs* RT – reduced tillage), four mineral N fertilization rates and four soil cover types factorially combined in a split-split-plot design with four replications. The design included a continuous maize crop from 1994 to 1998 followed by a two-year durum wheat-maize rotation until 2004. After 2005 the LTE was changed to a four-year crop rotation of durum wheat-maize-durum wheat-sunflower. Over the 15 years include in this research (1994-2008), mean annual precipitation at this site was 826 mm and the mean annual air temperature was 14.6 °C.

In this study we used a subset of treatments of the PI2 LTE (1994 to 2008) where durum wheat and maize were grown without cover crops, to evaluate the effects of the different tillage systems on SOC dynamics. The CT consisted of annual moldboard ploughing to a depth of 30-35 cm followed by secondary tillage with disk and rotary harrows. The RT was characterized by no-tillage for wheat and shallow harrowing for seedbed preparation for maize to a depth of 10-15 cm. Plots of durum wheat and maize were fertilized with 180 and 300 kg N ha^{-1}, respectively. In both systems, crop residues were chopped after harvest and left in the field. Weed control was based on post-emergence herbicide application in the CT system while pre-sowing glyphosate was also applied in the RT. FAO class 300 were used from 1994 to 2000 and class 500 from 2002 to 2006, while Cirillo and Duilio were used for durum wheat in 1999 and from 2001 to 2007. Aboveground biomass and crop yield were measured each year at harvest. Soil analyses were conducted on soil samples collected at the depths of 0-10 and 10-30 cm at the end of September in 1993 (at the beginning of the experiment), 1998 and 2008. During the IC-FAR project, additional soil data were collected in 2015 from a depth of 30 to 90 cm to characterize the soil texture of the deeper layers assuming that texture values did not change from the beginning of the experiment. Data from 1993, coupled with texture data from the deeper layers collected in 2015 were used to define the main soil physical characteristics of the PI2 site (Table 1). Soil hydraulic properties were estimated using the pedo-transfer functions of Ritchie et al. (1999).

2.2 Setup of the crop models

The experimental and weather data collected and harmonized in the common IC-FAR database (see details in Ginaldi et al., 2016) were used to inform and validate four process-based crop models to assess their ability to simulate SOC dynamics in different tillage systems and reproduce reliable crop residue-C inputs. Table 2 provides a list of the models used and the various biophysical approaches used in each model. In APSIM-NWheat, the simulation of maize was replaced by adding to the soil the observed amounts of residues left by the maize crop each year.

SOC is commonly divided up in these crop models into several different pools (Table 2) based on the residence time. In order to properly estimate SOC distribution across pools, soil carbon initialization was carried out considering the land use history of the experimental sites.

Before the start of the experiment in 1994, De Sanctis et al. (2012) reported the AN site had previously experienced a two-year durum wheat-maize rotation for 44 years (1950-1994) with an average N fertilizer rate of 140 kg ha^{-1}, initiated on grassland. Therefore, before simulating the cropping system for 1994-2014, the models were run over 44 years (since 1950) with an antecedent simulation based on a wheat-maize rotation. The total SOC in the upper 40 cm in 1950 was iteratively estimated by fitting the simulated value at the end of the simulation with the first observed measured SOC available in 1996 that was considered as initial value of the LTE assuming that it did not substantially change from the beginning of the experiment in 1994. In the

Century-based models (EPIC, DSSAT, SALUS), the SOC fractions in 1950 were initialized following the procedures suggested by Basso et al. (2011) considering 2%, 64% and 34% for the active, the slow and the passive pools, respectively. The final simulated fractions of the passive pool for each soil depth obtained at the end of the antecedent simulation were then used as inputs in the simulation starting in 1994. A wheat-maize rotation was also simulated over the period 1994-2001 although in the same years sunflower was sown instead of maize but the amount of residues left by sunflower was similar to that left by maize in this rainfed system (De Sanctis et al., 2012). In the APSIM-NWheat model, inputs to set the amounts of the initial labile pool (biom) and the rest of the soil organic matter (hum) in each layer for year 1994 were set in order to minimize the root mean square error between simulated and measured values at both 0-15 and 15-40 cm for the two treatments (i.e., tillage and no tillage).

In the PI2 site, before the start of the experiment in 1993, a pre-run simulation over 63 years (1930-1993) was performed on a rainfed biannual *durum* wheat-maize rotation fertilized with 180 kg N ha^{-1} for the winter crop and 300 kg N ha^{-1} for the summer crop. The biannual rotation was initialized in 1930 on grassland. Total SOC in the upper 30 cm in 1930 was estimated iteratively until the measured SOC value in 1993 was adequately predicted by the simulation. Following the procedure of Basso et al. (2011), the same initial SOC fractions used in AN for the Century-based models were used also for PI2 in 1930. At the end of the 63 year period, the final simulated fractions obtained for the passive pool in each model were then used to initialize simulations starting in 1993.

APSIM-NWheat started the simulation in 1998 when the continuous maize system was replaced by the wheat-maize rotation. The initial amounts of biom and hum in 1998 were defined so that root squared errors between simulated and measured SOC values were minimized.

The approach used by De Sanctis et al. (2012) was applied at the AN site for the DSSAT model in order to consider the presence of weeds in the conservation tillage systems. The simulations under

NT were carried out with the weed contribution during the fallow period from wheat harvest (July) to maize sowing (April). Plant parameters for Bahia grass (*Paspalum notatum* Flüggé) were used to simulate green foxtail (*Setaria viridis* L.), the most frequent weed species observed at the experimental site, because Bahia grass is a C4 plant included within DSSAT that is similar to foxtail. In PI2, as the simulation of weed growth during the fallow period was limited by the presence of tillage, weed contribution to SOC was simulated in the RT system adding also an amount of 1500 kg ha^{-1} of bahia grass crop residue at the onset of each maize growing seasons. This average amount per year was taken from Mazzoncini et al. (2011) considering the total weed biomass contribution over the experimental period 1994-2008.

In the APSIM-NWheat, EPIC, and SALUS models, the weed biomass was added to the initial input residues and set to 1500 kg ha^{-1} at both AN and PI2 sites as reported in De Sanctis et al. (2012) and Mazzoncini et al. (2011), respectively.

2.3 Evaluation of model performance

The performance of each model to simulate SOC was evaluated by calculating complementary indicators following the method proposed by Smith et al. (1997), but only one indicator was selected for each statistical aspect of the simulation so that the same weight was given in the evaluation of the model's overall ability. We selected the relative root mean square error (RRMSE), its statistical significance RRMSE $_{95\%}$, the modeling efficiency (EF), the relative error E with its statistical significance E $_{95\%}$. and the correlation coefficient (*r*) . A full description of each indicator is provided in the Supplementary material.

Statistics were calculated in each site considering the available observed SOC measurements (AN: 2002, 2006, 2010; PI2: 1998, 2008) to a depth of up to 40 cm for both tillage systems but not including the initial observed SOC values used as model inputs (1996 and 1993 respectively for

AN and PI2). The performance of APSIM-NWheat was evaluated in PI2 considering only the observed SOC of CT and RT in 2008.

The multi model mean (MM_Mean) of the individual simulations was also considered to evaluate the performance of the MME. All previously mentioned statistics were also determined for this multi model estimator. The single models and the MM_Mean were then ranked in relation to the performance obtained for each indicator and the mean of ranks (RankMean) over all the statistics was taken into account to evaluate the overall skill of the simulations.

To evaluate whether the crop growth modules of each model correctly simulated the annual C input to the soil from crop residues, the mean measured and simulated aboveground biomass (AGB) and yield for the two crops were compared under conventional and conservational tillage systems at both sites. The simulation bias for AGB and yield were also evaluated by calculating the mean difference between measured and simulated data with the Mean Bias Error (MBE, see Supplementary material).

Hereafter, the names of models APSIM-NWheat, DSSAT, EPIC, SALUS are reported as Model1, Model2, Model3, Model4, respectively, in order to remove any sense of endorsement of any of these models, since that is outside the scope of this research.

An uncertainty analysis was also carried out calculating the mean standard errors of the estimated SOC values until the ploughing depth over the calibrated periods in both sites and tillage systems with the increase of the number of the simulation models (Supplementary material, Table S1).

2.4 Simulation scenarios

Climate scenarios were generated by setting up a statistical downscaling model over the case studies, represented by a multivariate regression (Tomozeiu et al., 2014). The statistical scheme was based on the assumption that the local climate variability is determined by the variability of large scale fields and local features. The link between local predictors and large scale predictors has been determined by Canonical Correlation Analysis (CCA). The most important patterns that resulted from CCA were then used as input of the multivariate regression scheme. The setup of the statistical model was done using predictors from ERA40 and ERA-Interim[1], and predictands represented by the seasonal indices of temperature and precipitation over the case studies, computed from E-OBS gridded dataset[2] (Haylock et al., 2008). The large-scale predictors tested were: mean sea level pressure (MSLP), geopotential height at 500 hPa (Z500) and temperature at 850 hPa (T850), spatially ranging between 90°W to 90°E in longitude and 20°N to 80°N in latitude, with a horizontal resolution of 1.125° × 1.125°. The set-up of the statistical model was done over the 1958-2010 period. Once the most skillful model was detected for each season and index (local temperature or precipitation), the predictors simulated by the CMCC-CM global climate model (Scoccimarro et al., 2011) were entered into the statistical scheme in order to estimate the future local climate. Two emission scenarios were used: RCP4.5 and RCP8.5 (Moss et al., 2008), while the projections were constructed over the period 2021-2050 (CF: Future Climate) with respect to 1971-2000 (CP: Present Climate).

Seasonal projections were used as input in a Richardson-based weather generator (Richardson and Wright, 1984) to preserve the correlation between weather variables in order to generate daily time series of precipitation (PREC), maximum and minimum air temperature (Tmax, Tmin) for both AN and PI2 sites. Daily generated datasets were bias-corrected with monthly correction factors obtained by comparing the overlapping periods of the CP and the available local weather stations. Finally, daily radiation was estimated by the RadEst model (Donatelli et al., 2003) from Tmax and Tmin for all climate scenarios.

A CO_2 concentration of 360 ppm was used for the present climate scenario considering a mean CO_2 value recorded at Mauna Lao Observatory (NOAA ESRL Global Monitoring Division, 2015)

[1] http://www.ecmwf.int/products/
[2] http://eca.knmi.nl/download/ensembles/ensembles.php

over the CP period, while values of 460 ppm and 490 ppm were projected for RCP4.5 and RCP8.5 CF scenarios up to 2050.

The four validated crop models were run using the CP and CF scenarios in both LTEs to assess the climate change impacts on SOC stocks. Models were run with the management practices reported in Table 3 and simulating two rotations (Rot1: wheat-maize, Rot2: maize-wheat) to allow the presence of both crops in each year. Seedling emergence was set according to the most frequent values observed in the field as measured by Seddaiu et al. (2016) for AN and by Mazzoncini et al. (2011). It was set at 300 and 350 plants m^{-2} for durum wheat in AN and PI2 (all tillage systems) respectively, and 7 and 6 plants m^{-2} for maize under all tillage systems in PI2 and under CT in AN site. Maize seedling emergence was reduced to 3 plants m^{-2} under NT as observed for the LTE in AN. The crop harvest date was set at maturity in the crop models. The SOC measured in 1996 (for AN) and 1993 (PI2) were used as initial values in all scenarios. The SOC fractions were initialized with the same procedures described in the set-up phase. SOC changes to a depth of 0-40 cm, aboveground biomass, and yield were assessed using the MM_Mean in both sites over the simulation periods CP and CF, for the different applied tillage management (Table 3) and climate change scenarios.

3. Results

3.1 Model Evaluation

All models suitably reproduced the mean observed yield and AGB values of both crops, demonstrated by low MBE values in the different tillage systems of both sites. This was particularly true for crop yields (Supplementary material, Fig. S1).

Table 4 shows statistics that describe the performance of all the models tested to simulate the SOC dynamics in the upper 40 cm and the MM_Mean for all of the models. At the AN site, RRMSE for all of the models was less than the RRMSE95% which indicates that even if some of the models generated some simulation values outside the measured standard errors (Supplementary material, Fig. S2), they were still within the 95% confidence interval when the entire dataset was examined. Model 3 (RRMSE= 7.44) had the worst performance and strongly overestimated SOC in NT. Model1 (RRMSE= 5.85) presented a flat trend in NT SOC dynamic, with most of the values laying below the observed ones. A similar pattern of model performance was reflected by the EF indicator that showed a negative value (EF= -0.60) only for Model3. Model1 produced an EF value very close to zero. E values for all of the models were within the 95% confidence interval of E95%, and Model3 had the highest bias (E= -6.57). All models, excluding Model1, presented significant *r* values. Considering the overall statistics, the best performance in the simulation of SOC dynamic in AN was achieved by the MM_Mean which showed the lowest value of the RankMean. The good performance of MM_Mean was also supported by the qualitative graphical representation reported in Fig. 1 in which the SOC dynamics simulated by the MM_Mean were very close to the measured data in both tillage systems and better than those shown by the other crop models (Supplementary material, Fig. S2) in both total (0 - 40 cm), superficial (0 - 15 cm), and deeper layers (15 - 40 cm).

In PI2, only Model1 showed a RRMSE within the 95% confidence interval of the measured data, although all models presented positive values of EF. Considering the EF statistics, only Model1 (EF=0.90), MM_Mean (EF= 0.65), and Model2 (EF= 0.62) reached values close to 1. In fact, these models better reproduced the measured data for CT system in 1998 (Supplementary material, Fig. S3), while all models showed an underestimation of the observed data under RT. Considering model bias evaluation, only Model3 and Model4 showed E values greater than E95% (E=8.28 and E=7.95, respectively). All models, except Model1, for which it was not possible to calculate the statistical significance of *r* given the low numbers of observations (n=2), showed high positive and significant correlations between measurements and simulated data. Considering overall statistics, the best performance in the simulation of SOC in PI2 was obtained by Model1 (RankMean= 1.0), but its simulation started in 1998, and it could not be statistically compared with the other models. The second best rank was reached by the MM_Mean (RankMean= 2.0). MM_Mean showed a better representation of CT system (Fig. 1) than other single models (Supplementary material, Fig. S3) but it was not able to reproduce the high SOC value observed in RT.

3.2 Simulation scenarios: CP vs CF

3.2.1 Climate scenarios

The CP scenario reproduced the mean monthly values of all indices very well (Tmax, Tmin and PREC) for the local observed climate from 1971 to 2000 in both sites (Supplementary material, Table S2). The CF scenarios RCP4.5 and RCP8.5 (Fig. 2) showed that an increase of temperatures is expected during the period 2021-2050 in all seasons in both sites: +1.8°C annual mean T in RCP4.5 and +2.1°C in RCP8.5 at AN and +1.9°C (RCP4.5) and +2.1°C (RCP8.5) at PI2, with highest increases in the summer.

The changes in precipitation pattern were different from season to season in the two sites. At AN, the mean annual precipitation (750 mm under CP) decreased by -22.5% in RCP4.5 and -23.0% in RCP8.5, with the highest reduction occurring in spring (up to -49.0 % in RCP4.5 and -56.1% in RCP8.5) and summer months (up to -38.0% in RCP4.5 and -34.1% in RCP8.5). At PI2, the mean annual precipitation under CP (884 mm) is expected to slightly increase of 2.1% in RCP4.5 and 4.9% in RCP8.5. The largest increase is expected in April (+24.0 % in RCP4.5 and +16.9% in RCP8.5) and in the autumn months (+30.5% in RCP4.5 and +41.4% in RCP8.5), while a strong reduction of rainfall is expected in the summer months (47.0% in RCP4.5 and -52.7% in RCP8.5).

3.2.2 Multi-model mean simulation scenarios

The projected effects of climate change on crops were similar for both RCP4.5 and RCP8.5 scenarios with a slightly higher impact of the latter (Table 5).

On average for both future scenarios, maize at the AN site had a growing season that was shorter by 14 days with decreased both AGB (-20.8 % in CT and -20.2% in NT) and yield (-19.2% in CT and -21.5% in NT). The growing season for wheat was also shorter (-11 days) which resulted in a decrease in both AGB (-18.8% in CT and -16.8% in NT) and yield (-21.4% in CT and -18.4% in NT) but with more stable results as evidenced by the lower coefficient of variation (CV) values (Table 5).

Maize at the PI2 site was strongly affected by the impact of a shorter growing season (-15 days). Yield decreased by 27.5% with CT and 26.6% with RT, and AGB was reduced by -13.5% with CT and -14.6% with RT. However, the effect of climate change on wheat appears less important. The growing season had a comparable reduction (-11 days) to AN but a lower relative decrease of AGB (-9.6% in CT and -14.3% in RT) and yield (9.5% in CT and 13.8% in RT) than in AN.

In general, this study showed a decrease of SOC stocks to the depth of 0-40 cm in both sites and tillage systems under CF scenarios when compared with CP and a standard error increasing with time (Fig. 3 and 4). The deviations of the single models from MM_Mean simulation under CF were generally smaller in the 0-15 cm layer than the 15-40 cm layer. This is evidenced in Fig. 3 and 4 by the larger red and green areas for conventional and conservation systems, respectively, in deeper layers in both sites.

At the AN site, under CP conditions, the SOC stock increased at an annual rate of +0.28% with CT and +0.73% with NT, corresponding to gains of +0.11 (CT) and +0.29 (NT) Mg C ha^{-1} year^{-1} in the uppermost 40 cm of soil. Over 30 years of simulation under future scenarios, no significant changes in the SOC stock were observed with CT, while the SOC stock increased at an average annual rate +0.16 Mg C ha^{-1} year^{-1} with NT, corresponding to a relative annual gain of +0.4% of SOC. When compared to SOC dynamics under CP and same tillage technique, after 30-years of simulation we observed a SOC decrease of -3.1 Mg ha^{-1} with CT (-7.3%) and -3.8 Mg ha^{-1} with

NT (-7.9%), with greater losses in the top (-10.2%) vs bottom (-5.5%) layers only in the case of NT.

In PI2, under CP scenario, the SOC stock decreased at an annual rate of -0.04% with CT and increased at the rate of +0.07% with RT, corresponding to a loss of -0.02 (CT) and a gain of +0.04 (RT) Mg C ha^{-1} year^{-1} in the 0-40 cm soil layer. Under CF scenarios, SOC values obtained at PI2 after 30 years of simulation were lower than stocks reported in CP but, in contrast with AN, the difference between initial and final values were always negative. In fact, on average with both future scenarios, the SOC stock declined at a mean annual rate of -0.10 Mg C ha^{-1} year^{-1} with CT and -0.06 Mg C ha^{-1} year^{-1} with RT in the 0-40 cm soil layer, corresponding to a relative annual SOC losses of -0.19% (CT) and -0.11% (RT). Comparing the future soil dynamics to those obtained with same tillage technique under CP scenario, after 30 years of simulation SOC reductions of -2.1 Mg ha^{-1} in CT (-4.4 %) and -2.8 Mg ha^{-1} in RT (-5.3%) were observed. According to AN site, the conservation tillage system (RT) showed a greater loss of SOC in the top (-8.3%) layer than in the bottom (-2.5%).

4. Discussion

Our results confirm the hypothesis that under current climatic conditions, the MM_Mean reproduces SOC dynamic better than a single simulation model and with less uncertainty as demonstrated by lower RMSE and standard error values. Hence the model ensemble (MME) provides a better prediction of SOC change in relation to climate change. In contrast with other studies (Alvaro-Fuentes et al., 2012; Lugato et al., 2007; Tornquist et al., 2009), we used crop models rather than biogeochemical ones to assess the impact of future scenarios on crop productivity and yield in order to reliably reproduce soil C-input and, at the same time, evaluate climate change impacts on crop yields. Several studies have used simulation models as effective tools to assess changes in SOC stocks under current and future scenarios in order to identify effective agronomic practices (Farina et al., 2011; Lugato et al., 2015; Tornquist et al., 2009; Wiesmeier et al., 2016) that reduce soil C emissions and increase C stock, thereby mitigating climate change. The added value of this work is the robustness of the results we obtained given the use of an ensemble of models that were validated using long-term experimental datasets and able to adequately assess the long-term processes that affect SOC dynamics.

Our results are generally in agreement with the SOC trends reported by other authors (Farina et al., 2011; Lugato et al., 2014; Mondini et al., 2012; Smith et al., 2005) which projected a negative trend on SOC stock dynamics in cropland across the 21th century. However the results obtained by other studies are not always directly comparable with the ones of this work due to the differences in spatial and temporal scale, soil profiles, climate scenarios, and methodologies. Lugato et al. (2014) reported in the short to medium term (2020) a decrease in SOC in agricultural soils of Central and Southern Italy and an expected net loss of about 2.5 Mg ha^{-1} close to the end of the century in the Mediterranean region. Mondini et al. (2012) projected a loss of about 6.3% of SOC between 2001 and 2100 on arable land in Italy, while Smith et al. (2005) projected a SOC loss of between -14% and -10% over 1990-2080 on a high level (European croplands). Farina et al. (2011) applied a similar methodology at the same AN site using EPIC model coupled with two different general circulation models (GISS and HadCM3) for A2 and B2 emission scenarios. Considering the entire soil profile, the study showed a SOC loss ranging from -2.3 Mg ha^{-1} up to -6.1 Mg ha^{-1} in CT and from -2.1 Mg ha^{-1} up to -7.4 Mg ha^{-1} in NT, over the period 2040-2069 compared to the baseline 1956-2006.

Temperature and precipitation are the main climatic drivers that influence, both directly and indirectly, organic carbon trends in the soil (Fantappiè et al., 2011; Saby et al., 2008; Smith et al., 2005). Because the monthly mean temperature is expected to increase around +2.0°C under future scenarios at both sites, soil biological activity will likely be stimulated which increases the decomposition rate and facilitates SOC losses through heterotrophic respiration (Ugalde et al., 2007). Leiros et al. (1999) showed that the positive effect on soil decomposition rate caused by a 2°C temperature increase is usually limited by a concurrent -10% decrease in soil moisture. Moreover, according to Gottschalk et al. (2012), C mineralization is constrained by both low or high values of soil water content, which is mainly influenced by precipitation. The two sites were characterized by similar increase of temperatures but diverse patterns of precipitation (on average -22.7 % in AN and +3.5% in PI2). Hence, the interaction of both factors affected the organic carbon decomposition differently at the two sites under the future scenarios, and led to lower SOC impact in PI2. However, the impact of climate change at AN was constrained by a higher clay content which physically protects SOC from microbial decomposition (Baldock and Skjemstad, 2000; Six et al., 2002; Xu et al., 2016). These interactions are taken into account by the models which control SOC stock dynamics considering a variety of management, soil proprieties and climate factors. In all the considered models the decomposition of the organic carbon is simulated with a first-order decomposition kinetics of the C mass (Jones and Kiniry, 1986; Parton et al., 1994; Parton et al., 1988). The decomposed carbon is partly lost to the atmosphere as CO_2 and transferred to another organic matter pool. The decomposition rates are computed daily and their values change in relation to some environmental modifiers such as temperature, moisture, litter quality, and soil texture (Basso et al., 2006; Gijsman et al., 2002; Izaurralde et al., 2006; Porter et al., 2009).

Temperature and precipitation indirectly influence SOC by affecting a number of physiological and biological processes that drive crop growth and development, and determine soil C input released by crop residues. Our results showed that the growing season length of both maize and wheat was significantly reduced during the period 2021-2050 in the two sites due to increased temperature. In both sites, maize grain and AGB production was also strongly constrained by the projected precipitation decrease occurring during summer season, when the crop is more vulnerable to water stress under rainfed conditions (Sánchez et al., 2014). In particular, maize was more affected in PI2 than in AN due to the significant reduction of rainfall (around -50%) that is projected to occur during July and August at the PI2 site. Maize production at the AN site could be even more affected especially under NT system since the yield of this crop is low as it is affected by high variability and low seedling emergence (50% than with CT).

Wheat is mostly influenced by water availability during earing and anthesis phases occurring in the spring (Albrizio et al., 2010; Campiglia et al., 2015). At the AN site, the significant reduction in precipitation that was projected in the spring constrained wheat production under future scenarios, despite the positive effect of CO_2 atmospheric enrichment which offsets the rainfall impact. On the other hand, the expected increased precipitation at PI2 in April was able to limit the negative effect of the shortening of the growing season on both wheat yield and aboveground biomass, determining a concurrent lower decrease of available crop residue input into the soil.

CT and conservation tillage (both NT and RT) resulted in different redistributions of SOC among soil horizons. However, considering the total SOC of the 0-40 cm depth, the conservation tillage systems were able to stock more SOC than CT also under future scenarios. In fact, as conservation tillage practices decrease SOC decomposition by reducing soil CO_2 emissions (Powlson et al., 2011), they are suggested for climate change mitigation.

In all the used models the effects of tillage on soil proprieties are based on the procedures developed by Dadoun (1993) in the Ceres-Till model. Tillage directly affect the soil organic carbon decomposition modifying a cultivator factor. This factor accelerates the decomposition rates in particular more after ploughing than other tillage practices. While, in NT systems, there is no direct effect on the decomposition rates.

A meta-analysis review by Angers and Eriksen-Hamel (2008) reported that the difference in SOC stocks between NT and CT at the depth of 0-30 cm is an average of 4.9 Mg ha^{-1} and that the difference in favor of NT increases over time until ~25-30 years, when NT may have reached a new steady state (Alvarez et al., 2005). The same difference, 4.9 Mg ha^{-1}, was observed in the experimental dataset from the AN site for the period 1996-2010 in the 0-40 cm soil layer. In the CP scenario the difference between NT and CT was 5.4 Mg ha^{-1} after 30 years of simulation. The difference still remained high in the future scenarios with a value of 4.7 Mg ha^{-1}. The higher SOC stock with NT was not only due to the reduction in the decomposition coefficient but also to the weed biomass contribution, considered by the models, as also shown by De Sanctis et al. (2012).

The RT system in PI2 was not so as performant as NT in AN, even if it showed slightly higher SOC values than CT with a positive difference of 1.8 Mg ha^{-1} in CP period and 1.3 Mg ha^{-1} in future scenarios. The SOC dynamic in this site was reproduced with higher uncertainty as the MM_Mean showed a high RMSE value mainly due to an underestimation of observed data under RT.

A reliable SOC stock assessment has been recently encouraged by the 4 per thousand initiative (4PT, Le Foll, 2015) launched at the 21st meeting of the Conference of the Parties in Paris. This initiative aims to mitigate climate change by increasing SOC stock at an annual rate of 0.4% through the adoption of best management practices. The results of this study showed that conservation tillage systems (NT and RT) in both sites were able to store more SOC than CT so these practices ought to be considered viable options to mitigate climate change in Mediterranean cereal systems. Furthermore, in AN, NT could provide the annual increase of 0.4% required by 4PT also under climate change scenarios. The main problem related to NT in this silty-clay site is the lower average productivity of maize due to low establishment that was attributed to poor soil physical conditions at seeding. On the contrary, RT in PI2 needs to be coupled with other management strategies such as the introduction of cover crops to ensure higher SOC levels. However, the benefits of adopting conservation tillage to reduce the transfer of C to the atmosphere and enhance SOC sequestration, have to be verified for other greenhouse gas emissions in order to assess their overall impacts. Some studies have reported increased nitrous oxide emissions in no tillage systems (Mackenzie et al., 1998; Pastorelli et al., 2013) and more abundant denitrifying bacteria in no-tilled soil (Doran, 1980). It is also important to consider that soils might have a potential limit for C accumulation mainly determined by their physical proprieties and clay content (Tornquist et al., 2009). Consequently, SOC sequestration can be only a short-term strategy for climate change mitigation but other long-term solutions have to be implemented.

5. Conclusions

In this study an ensemble of four process based crop models (APSIM-NWheat, DSSAT, EPIC, SALUS) was used to assess the impacts of climate change on SOC stock changes under conventional and conservation tillage practices in two rainfed long-term wheat-maize rotational cropping systems under different Mediterranean climate scenarios. Our results clearly showed that the multi-model mean reproduced SOC dynamics better and with less uncertainty than single simulation models and provided a more reliable prediction of SOC dynamics under future climate scenarios. Under changed climate, conservation tillage systems were still able to retain more SOC than CT, with only the NT reaching the target of 4PT. The contribution of weeds, considered by models and covering the soil in the fallow period between the wheat harvest and maize seeding, was also relevant in providing an extra C input to the soil under conservation tillage systems.

Although there is the potential for no tillage to strongly contribute to SOC sequestration, our study has also evidenced that, at the same time, NT systems could affect crop productivity in specific sites with silty clay soils, because of crop establishment problems. Further studies including more sites and more simulation models are necessary to achieve more general conclusions and to consider specific side-effects of contrasting tillage practices.

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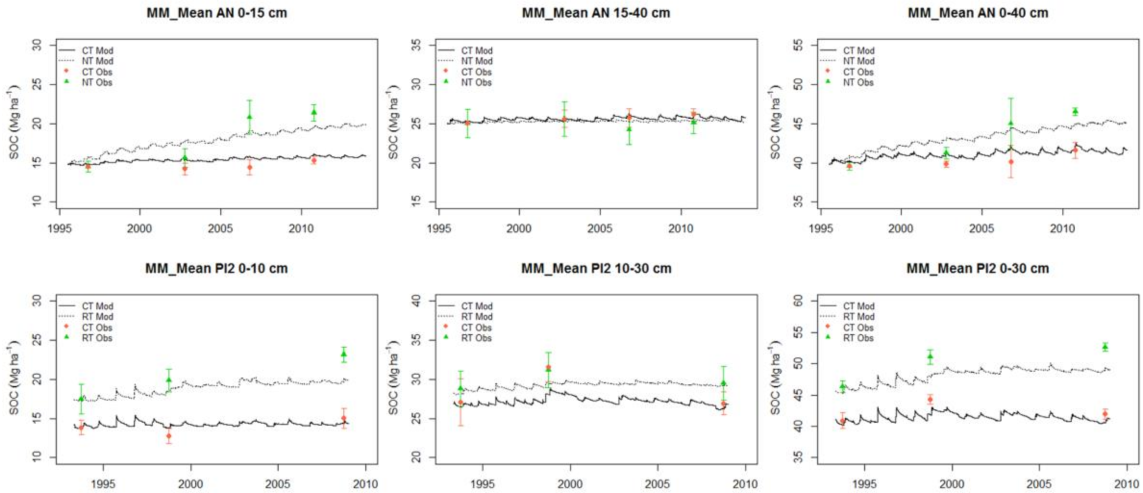

Fig. 1. Soil organic carbon (SOC, Mg ha^{-1}) dynamics simulated (Mod) by the multi model mean (MM_Mean) in different tillage systems (CT= Conventional tillage, NT= No till, RT= Reduced tillage) at different soil depths in the two sites (AN: 0-15cm, 15-40cm, 0-40cm; PI2: 0-10cm, 10-30cm, 0-30cm) in comparison with the observed (Obs) SOC values in the LTEs. Vertical bars are the standard errors.

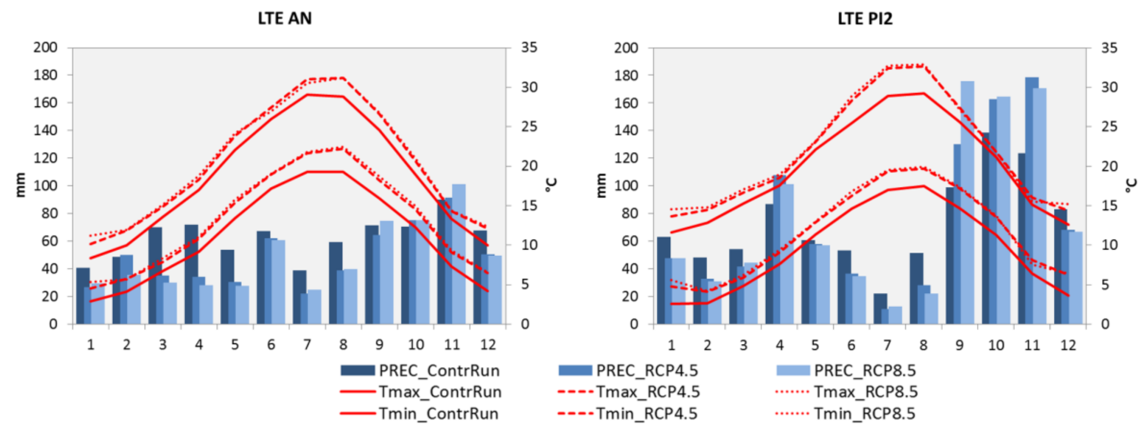

Fig. 2. Climate scenarios for the three time spans: CP (Present Climate), CF (Future Climate) RCP4.5, and RCP8.5 in AN and PI2 sites. PREC: monthly mean precipitation, Tmax: monthly maximum temperature and Tmin: monthly minimum temperature.

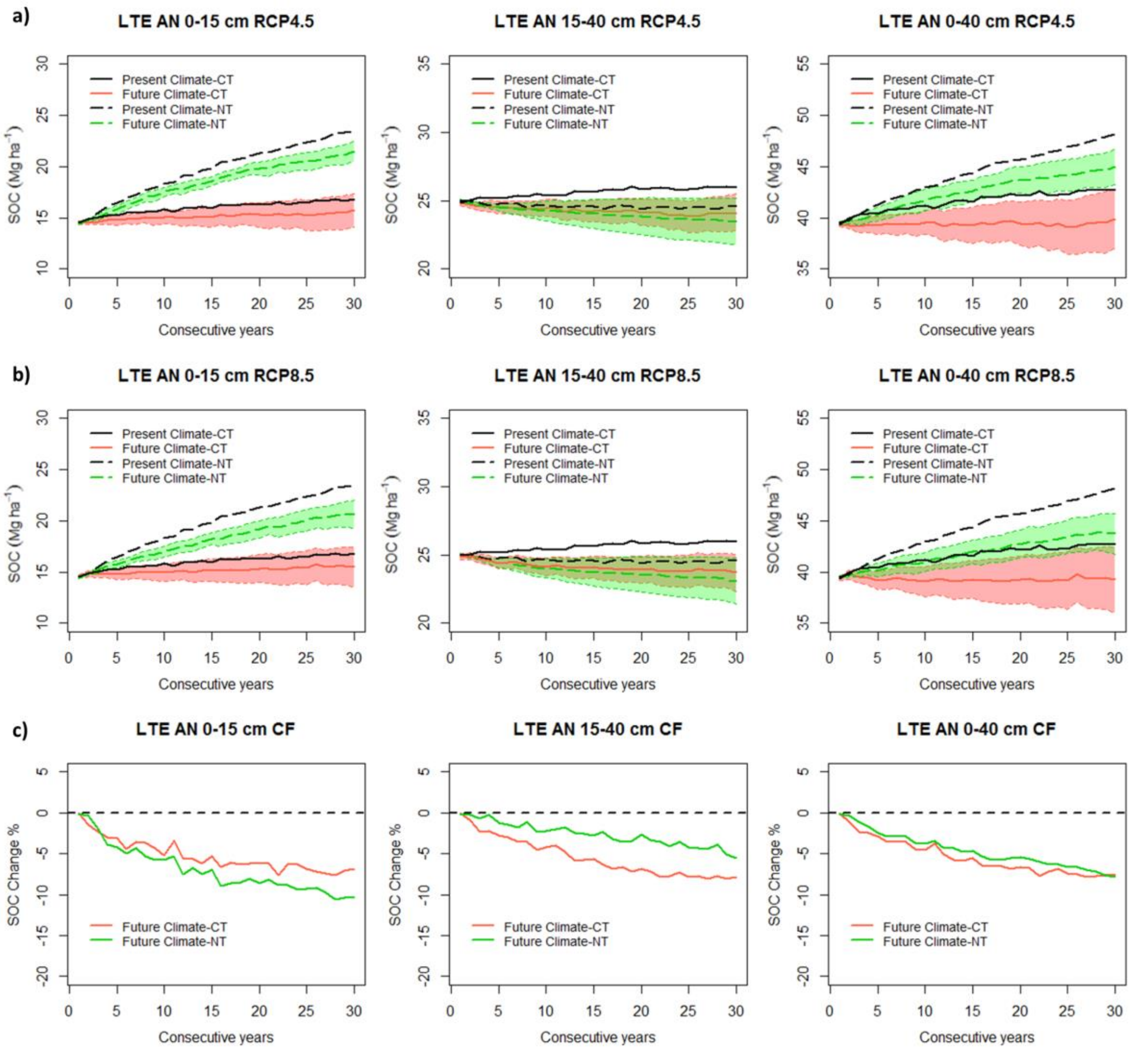

Fig. 3. Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM_Mean) in present and future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or No Tillage - NT practices in AN; a) RCP4.5 scenario; b) RCP8.5 scenario. The red and green regions delimited by the dashed lines are the standard errors of the simulations respectively obtained for CT and NT systems; c) Relative annual SOC change (%) observed in climate change scenarios (CF: mean values of RCP4.5 and RCP8.5) in relation to the present climate scenario.

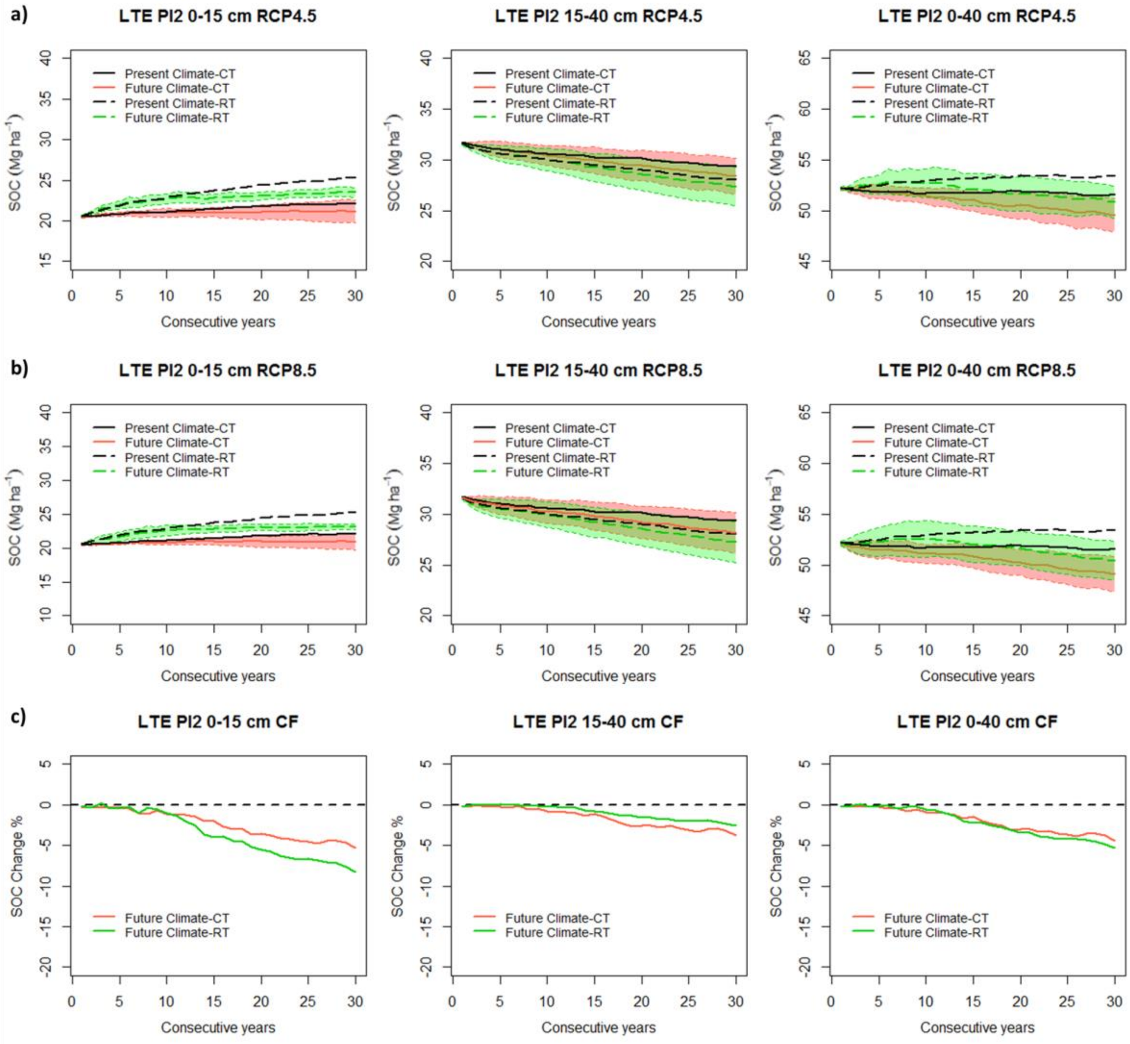

Fig. 4. Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM_Mean) in present and future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or Reduced Tillage - RT practices in PI2; a) RCP4.5 scenario; b) RCP8.5 scenario. The red and green regions delimited by the dashed lines are the standard errors of the simulations respectively obtained for CT and NT systems; c) Relative annual SOC change (%) observed in climate change scenarios (CF: mean values of RCP4.5 and RCP8.5) in relation to the present climate scenario.

Table 1. Main physical and hydrological properties of the soils in AN and PI2 as reported in the IC-FAR database and used as inputs in the process based crop models.

	cm	%	%	%	g cm^{-3}	cm^3 cm^{-3}	cm^3 cm^{-3}	cm^3 cm^{-3}
LTE	**Depth**	**Clay**	**Silt**	**Sand**	**BD**	**WP**	**FC**	**SAT**
AN	0-5	49.8	41.4	8.7	1.27	0.293	0.427	0.518
	5-15	49.1	41.2	9.7	1.30	0.289	0.424	0.514
	15-40	49.4	42.3	8.4	1.37	0.290	0.425	0.517
	40-60	49.9	42.1	8.0	1.48	0.293	0.422	0.519
	60-100	51.1	40.7	8.2	1.56	0.300	0.424	0.519
PI2	0-10	28.3	24.2	47.4	1.37	0.116	0.253	0.430
	10-30	27.9	23.3	48.8	1.38	0.114	0.251	0.430
	30-60	21.5	35.1	43.3	1.44	0.116	0.250	0.420
	60-90	14.2	26.5	59.3	1.47	0.100	0.230	0.390

WP = Soil water content at wilting point; FC = Soil water content at field capacity; SAT = Saturated water content; BD = Bulk Density.

Table 2. Crop models applied and their modeling approaches to determine crop growth and SOC dynamic.

Model	**Reference**	**Crop**	**Biomass growth**[a]	**Yield formation**[b]	**Root distribution**[c]	**Soil dynamic**[d]	**N° SOC pools**[e]	**N° FOM pools**[f]
APSIM-NWheat	Keating et al., 2003	Wheat	RUE	Gn	Exp	Ceres	2	3
DSSAT 4.6	Hoogenboom et al., 2015	Wheat, Maize	RUE	Gn,B	Exp	Century	3	2
EPIC	Williams and Sharpley, 1989	Wheat, Maize	RUE	HI, B	Lin	Century	3	2
SALUS	Basso and Ritchie, 2015	Wheat, Maize	RUE	Gn,B	Exp	Century	3	2

a) Biomass growth or light utilization: RUE = Radiation use efficiency approach; b)Yield formation depending on: HI = harvest index, B = total above-ground biomass, Gn = number of grains and grain-growth rate; c) Model of root distribution over depth: linear (Lin), exponential (Exp), sigmoidal (Sig); d) Soil dynamic based on Ceres (Jones and Kiniry, 1986) or Century model (Parton et al., 1988; Parton et al., 1994); e) Number of soil organic carbon pools: 2 (labile pool and the rest of the soil organic matter), 3 (active, slow, and passive); f) FOM (fresh organic matter) pools: 2 (structural and metabolic), 3 (carbohydrate, cellulose, and lignin).

Table 3. Dates of the agronomic management practices used in AN and PI2 sites for the simulations.

AN (Tillage systems: CT* and NT)**	**Wheat**	**Maize**
CT: Plowing (40 cm)	October 20	August 30
CT: Harrowing (15 cm)	October 30, November 10	November 15, April 5
All: Sowing	November 20	April 10
All: Nitrogen fertilization	February 15 (45N)	April 25 (90N)
	March 10 (45N)	
PI2 (Tillage systems: CT* and RT*)**	**Wheat**	**Maize**
CT: Plowing (30 cm)	October 5	August 30
All: Harrowing (15 cm)	November 8, November 30	May 7, May 10
All: Sowing	December 6	May 10
All: Nitrogen fertilization	February 18 (90N)	May 10 (300N)
	April 12 (90N)	

*CT= Conventional Tillage; **NT= No Tillage; ***RT= Reduced Tillage; N= Nitrogen fertilization rate (kg ha^{-1} $year^{-1}$).

Table 4. Evaluation of the four models (Model1, 2, 3 and 4) and the multi model mean (MM_Mean) in simulating the soil organic content (SOC, Mg ha^{-1}) in AN and PI2 sites considering the available observed measurements (AN: 2002, 2006, 2010; PI2: 1998, 2008) until the depth of ploughing (0-40cm for AN and 0-30 cm for PI2) under both conventional and conservative tillage systems.

Min	0.00	-inf.	-inf.	-1.00	
Max	+inf.	1.00	+inf.	1.00	
Best	0.00	1.00	0.00	1.00	
	RRMSE	**EF**	**E**	**r**	**RankMean**
Site AN	RRMSE95%=8.36		E95%= ±6.63		
Model1	5.85 *(4)*	0.01 *(4)*	2.26 *(3)*	0.63 *(5)*	*4.0*
Model2	4.60 *(3)*	0.39 *(3)*	0.31 *(1)*	0.83* *(4)*	*2.8*
Model3	7.44 *(5)*	-0.60 *(5)*	-6.57 *(5)*	0.86* *(3)*	*4.5*
Model4	3.77 *(2)*	0.59 *(2)*	-2.64 *(4)*	0.91* *(2)*	*2.5*
MM_MEAN	3.46 *(1)*	0.65 *(1)*	-1.66 *(2)*	0.95* *(1)*	*1.3*
Site PI2	RRMSE95%=5.43		E95%=±5.35		
Model1	3.54 *(1)*	0.90 *(1)*	2.91 *(1)*	-	*1.0*
Model2	5.80 *(3)*	0.62 *(3)*	3.71 *(2)*	0.977* *(3)*	*2.8*
Model3	8.68 *(5)*	0.15 *(5)*	8.28 *(5)*	0.962* *(4)*	*4.8*
Model4	8.39 *(4)*	0.20 *(4)*	7.95 *(4)*	0.978* *(2)*	*3.5*
MM_MEAN	5.55 *(2)*	0.65 *(2)*	5.22 *(3)*	0.999* *(1)*	*2.0*

RMSE= root mean square error; RRMSE95% = 95% confidence interval of RRMSE; EF = modeling efficiency; E = the relative error; E95% = 95% confidence interval of E; *r* = Pearson correlation coefficient; * is the r statistical significance at 95% confidence level, (-) means no data. The numbers in brackets indicate the ranks obtained by models in relation to the performance of each indicator. RankMean is the mean of the ranks for each model.

Table 5. Mean values (Mg ha^{-1}) of aboveground biomass (AGB) and yield for maize (MZ) and wheat (WHT) between CP (Present Climate) and future scenarios CF (RCP4.5 and RCP8.5) under conventional and conservation tillage systems in AN and PI2 sites. The numbers in brackets are the coefficients of variation.

	Conventional Tillage				Conservation Tillage			
	MZ_AGB	MZ_Yield	WHT_AGB	WHT_Yield	MZ_AGB	MZ_Yield	WHT_AGB	WHT_Yield
CP_AN	9.9 (15.7%)	4.0 (21.6%)	8.5 (8.9%)	3.2 (8.5%)	8.4 (14.3%)	3.4 (17.2%)	8.6 (7.9%)	3.2 (8.2%)
CF RCP4.5_AN	7.9 (23.1%)	3.2 (32.7%)	7.0 (16.2%)	2.5 (19.7%)	6.7 (24.9%)	2.7 (22.1%)	7.2 (16.1%)	2.7 (19.0%)
CF RCP8.5_AN	7.7 (23.9%)	3.2 (30.7%)	6.8 (17.9%)	2.4 (19.5%)	6.6 (29.6%)	2.6 (27.9%)	7.1 (15.9%)	2.6 (17.1%)
CP_PI2	10.5 (14.1%)	4.1 (25.0%)	9.1 (14.2%)	4.4 (18.6%)	10.9 (12.7%)	4.3 (23.6%)	8.5 (13.4%)	4.1 (17.6%)
CF RCP4.5_PI2	9.0 (19.0%)	2.9 (31.2%)	8.6 (19.8%)	4.2 (22.7%)	9.3 (16.0%)	3.2 (27.3%)	7.6 (22.3%)	3.77 (23.48%)
CF RCP8.5_PI2	9.2 (11.7%)	2.9 (25.0%)	8.0 (14.4%)	3.7 (18.0%)	9.3 (12.4%)	3.1 (23.1%)	7.0 (18.7%)	3.4 (20.2%)