

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

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1 **Can conservation tillage mitigate climate change impacts in Mediterranean cereal systems?**

2 **A soil organic carbon assessment using long term experiments**

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4 Ileana Iocola<sup>a</sup>, Simona Bassu<sup>a</sup>, Roberta Farina<sup>b</sup>, Daniele Antichi<sup>c</sup>, Bruno Basso<sup>d</sup>, Marco Bindi<sup>e</sup>,

5 Anna Dalla Marta<sup>e</sup>, Francesco Danuso<sup>f</sup>, Luca Doro<sup>g,h</sup>, Roberto Ferrise<sup>e</sup>, Luisa Giglio<sup>i</sup>, Fabrizio

6 Ginaldi<sup>j</sup>, Marco Mazzoncini<sup>c</sup>, Laura Mula<sup>a,h</sup>, Roberto Orsini<sup>k</sup>, Giuseppe Corti<sup>k</sup>, Massimiliano

7 Pasqui<sup>l</sup>, Giovanna Seddaiu<sup>a,h</sup>, Rodica Tomozeiu<sup>m</sup>, Domenico Ventrella<sup>i</sup>, Giulia Villani<sup>n</sup>, Pier Paolo

8 Roggero<sup>a,h</sup>

9

10 <sup>a</sup>Nucleo Ricerca Desertificazione - NRD, University of Sassari, Viale Italia 39,07100 Sassari, Italy

11 <sup>b</sup>Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Centro di ricerca  
12 Agricoltura e Ambiente, CREA-AA, via della Navicella 2-4, Rome, Italy

13 <sup>c</sup>Dipartimento di Scienze Agrarie Alimentari ed Agro-Ambientali - DISAAA-a, University of Pisa,  
14 Via del Borghetto 80, 56124 Pisa, Italy

15 <sup>d</sup>Department of Geological Sciences, Michigan State University, 288 Farm Lane, East Lansing,  
16 MI 48824, USA

17 <sup>e</sup>Dipartimento di Scienze delle Produzioni Agroalimentari e dell'Ambiente - DISPAA, University  
18 of Florence, Piazzale delle Cascine 18, 50144 Florence, Italy

19 <sup>f</sup>Dipartimento di Scienze Agroalimentari, Ambientali ed Animali - DI4A, University of Udine, via  
20 delle Scienze 6, 33100 Udine, Italy

21 <sup>g</sup>Blackland Research & Extension, 720 East Blackland Road Temple, TX 76502, USA

22 <sup>h</sup>Dipartimento di Agraria, University of Sassari, Viale Italia 39,07100 Sassari, Italy

23 <sup>i</sup>Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Centro di ricerca  
24 Agricoltura e Ambiente, CREA-AA, Via Celso Ulpiani 5, 70125 Bari, Italy

25 <sup>j</sup>Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Centro di ricerca  
26 Agricoltura e Ambiente, CREA-AA, Via di Corticella, 133 - 40128 Bologna, Italy

27 <sup>k</sup>Dipartimento di Scienze Agrarie, Alimentari ed Ambientali, Marche Polytechnic University, via  
28 Brecce Bianche, 60131 Ancona, Italy

29 <sup>l</sup>Centro Nazionale delle Ricerche, Istituto di Biometeorologia CNR-Ibimet, Via Taurini, 19, 00185  
30 Roma, Italy

31 <sup>m</sup>Agenzia regionale per la prevenzione, l'ambiente e l'energia dell'Emilia-Romagna, Servizio  
32 Idro-Meteo-Clima di Bologna Emilia-Romagna Arpae-SIMC, Viale Silvani 6, 40122 Bologna,  
33 Italy

34 <sup>n</sup>Dipartimento di Scienze e Tecnologie Agro-Alimentari, University of Bologna, Viale G.Fanin 50,  
35 40127 Bologna, Italy

36

37 *Email address:* iiocola@uniss.it (I. Iocola), sbassu@uniss.it (S. Bassu), roberta.farina@crea.gov.it  
38 (R. Farina), daniele.antichi@avanzi.unipi.it (D. Antichi), basso@msu.edu (B. Basso),  
39 marco.bindi@unifi.it (M. Bindi), anna.dallamarta@unifi.it (A. Dallamarta),  
40 francesco.danuso@uniud.it (F. Danuso), ldoro@uniss.it (L. Doro), roberto.ferrise@unifi.it (R.  
41 Ferrise), luisa.giglio@crea.gov.it (L. Giglio), fabrizio.ginaldi@crea.gov.it (F. Ginaldi),  
42 marco.mazzoncini@unipi.it (M. Mazzoncini), lmula@uniss.it (L. Mula), r.orsini@univpm.it (R.  
43 Orsini), g.corti@univpm.it (G.Corti), m.pasqui@ibimet.cnr.it (M. Pasqui), gseddaiu@uniss.it (G.  
44 Seddaiu), rtozeiu@arpae.it (R. Tomozeiu), domenico.ventrella@crea.gov.it (D. Ventrella),  
45 gvillani@arpae.it (Giulia Villani), pproggero@uniss.it (P.P. Roggero)

46

47 \*Corresponding author at: Nucleo Ricerca Desertificazione - NRD, University of Sassari, Viale  
48 Italia 39,07100 Sassari, Italy. Tel: +39079213101

49 E-mail address: iiocola@uniss.it (I. Iocola)

50

51 **Abstract**

52 Simulation models, informed and validated with datasets from long term experiments (LTEs), are  
53 considered useful tools to explore the effects of different management strategies on soil organic  
54 carbon (SOC) dynamics and evaluate suitable mitigative options for climate change. But, while  
55 there are several studies which assessed a better prediction of crop yields using an ensemble of  
56 models, no studies are currently available on the evaluation of a model ensemble on SOC stocks.  
57 In this study we assessed the advantages of using an ensemble of crop models (APSIM-NWheat,  
58 DSSAT, EPIC, SALUS), calibrated and validated with datasets from LTEs, to estimate SOC  
59 dynamics. Then we used the mean of the model ensemble to assess the impacts of climate change  
60 on SOC stocks under conventional (CT) and conservation tillage practices (NT: No Till; RT:  
61 Reduced Tillage). The assessment was completed for two long-term experiment sites (Agugliano -  
62 AN and Pisa - PI2 sites) in Italy under rainfed conditions. A durum wheat (*Triticum turgidum*  
63 subsp. *durum* (Desf.) Husn.) - maize (*Zea mays* L.) rotation system was evaluated under two  
64 different climate scenarios over the periods 1971-2000 (CP: Present Climate) and 2021-2050 (CF:  
65 Future Climate), generated by setting up a statistical model based on canonical correlation  
66 analysis. Our study showed a decrease of SOC stocks in both sites and tillage systems over CF  
67 when compared with CP. At the AN site, CT lost -7.3% and NT -7.9% of SOC stock (0-40 cm)  
68 under CF. At the PI2 site, CT lost -4.4% and RT -5.3% of SOC stocks (0-40 cm). Even if  
69 conservation tillage systems were more impacted under future scenarios, they were still able to  
70 store more SOC than CT, so that these practices can be considered viable options to mitigate  
71 climate change. Furthermore, at the AN site, under CF, NT demonstrated an annual increase of  
72 0.4%, the target value suggested by the 4 per thousand initiative launched at the 21<sup>st</sup> meeting of the  
73 Conference of the Parties in Paris. However, RT at the PI2 needs to be coupled with other  
74 management strategies, as the introduction of cover crops, to achieve such target.

75

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

78

## 79 **1. Introduction**

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

91 Less intensive tillage management, also referred to as conservation agriculture (i.e., Reduced  
92 tillage – RT and no till – NT), has been adopted to reduce these negative impacts although  
93 sometimes lower yields have been associated to these practices (Van den Putte et al., 2010). There  
94 is still uncertainty of the merit of conservation tillage to contribute to increasing the resilience of  
95 cropping systems to climate change (Powelson et al., 2016) and to increasing SOC compared with  
96 CT practices (Gonzalez-Sanchez et al., 2012; Haddaway et al., 2016). In fact, SOC significantly  
97 increases in the layers closest to the soil surface under conservation tillage but does not always  
98 increase in the deeper soil profile where, conversely, SOC content tends to increase under  
99 conventional tillage, particularly near or at the bottom of the plowed layer (Alvarez, 2005; Angers

100 and Eriksen-Hamel, 2008; De Sanctis et al., 2012). These results highlight the importance of  
101 evaluating the entire soil profile or, at least, the depth of the plowed layer to compare the effect of  
102 contrasting tillage practices on SOC stocks.

103 However, because changes in SOC can occur very slowly (Smith et al., 1997), the relationship  
104 between tillage practices and SOC sequestration should be evaluated over a sufficiently long  
105 period of time. Long-term experimental sites (LTEs) at research facilities thus represent the ideal  
106 setting to assess processes and factors that may affect SOC content over a long period of time  
107 because there are long-term datasets associated with these sites (Korschens, 1996; Ruisi et al.,  
108 2014). In fact, while short-term experiments can support research that focuses on the initial stages  
109 of a process, LTEs permit evaluation of the magnitude of change over a longer period of time and  
110 allows understanding the cause of these changes at the same time (Knapp et al., 2012). For this  
111 reason, data coming from LTEs play a key role in informing and validating crop simulation  
112 models. Furthermore, as LTEs permit understanding the relationship of short- and long-term  
113 processes, they are crucial to improving the ability of current crop simulation models to simulate  
114 future scenarios. Powerful tools can be developed from this process that permit researchers and  
115 policymakers to explore management strategies that increase SOC and define suitable adaptation  
116 and mitigation options to reduce the impact of climate change on cropping systems (Ewert et al.,  
117 2011; White et al., 2011). Models were successfully used to simulate contrasting tillage  
118 management in agroecosystems under current (Chang et al., 2013; De Sanctis et al., 2012; Franko  
119 and Spiegel, 2016; Leite et al., 2009; Tan et al., 2007) and future climates (Bhattarai et al., 2017;  
120 Farina et al., 2011).

121 Given the growing interest in assessing uncertainty, in particular under future scenarios (Wallach  
122 et al., 2016), both the climate and crop modeling communities have proposed the use of an  
123 ensemble of models to obtain a probability distribution of projections (Harris et al., 2010) rather  
124 than a single model. In fact, crop models can vary in structure and parameterization and formalize

125 bio-physical and physiological processes differently. For this reason, they may respond in different  
126 way to future climate scenarios, thereby projecting different impacts of climate change on SOC  
127 and crop yield, even if they had been able to reproduce quite well the observed values under past  
128 conditions (Bassu et al., 2014). As a result, an assessment of climate change impacts based on an  
129 ensemble of outcomes from multiple model simulations is more reliable than one obtained from a  
130 single model (Rötter et al., 2011; Tao et al., 2009).

131 Furthermore, many studies of multi model ensembles (MME) under current climate conditions  
132 have shown that the mean or median of the ensemble's simulated values reproduce the measured  
133 crop yields better than any individual model (Asseng et al., 2014; Li et al., 2015; Martre et al.,  
134 2015; Palosuo et al., 2011; Rötter et al., 2012). Given the improved performance of crop model  
135 ensembles over single models under current conditions, Wallach et al. (2016) suggest that better  
136 predictions under future climate conditions can be obtained with the mean or median of the model  
137 ensemble, even without improving the present-day crop models. Nevertheless, while some  
138 research has assessed MME to predict crop yield, no MME studies are currently available that  
139 evaluate the ensemble mean or median to simulate SOC dynamics. Many studies have used  
140 biogeochemical models (Alvaro-Fuentes et al., 2012; Gottschalk et al., 2012; Lugato et al., 2007;  
141 Meersmans et al., 2016; Muñoz-Rojas et al., 2013; Tornquist et al., 2009) to assess the impact of  
142 climate change on SOC, but because these models have simplified processes for crop growth  
143 simulation, they could produce unreliable impacts on crop productivity and, consequently, on soil  
144 C-input. Most climate change impact studies using crop process based models have focused on the  
145 crop-atmosphere interaction of single crops alone (Asseng et al., 2014; Bassu et al., 2014; Long et  
146 al., 2006) while, more recently, studies emerge which consider the entire system of soil-crop-  
147 atmosphere interaction (Basso et al., 2015; Kollas et al., 2015; Nendel et al., 2014; Teixeira et al.,  
148 2015). This is particularly important under limited growing conditions such as in rainfed cropping  
149 systems with low SOC content. As a matter of fact, SOC can vary by year in response to agronomic

150 management decisions and climate. These changes in SOC then affect soil water holding capacity  
151 and nitrogen and, at the same time, crop performance which, in turn, affects additional input of  
152 SOC.

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

167

## 168 **2. Material and methods**

### 169 **2.1 Description of the long-term datasets**

170 The data from two rainfed long-term experiments (LTEs) were utilized for this study: the AN site  
171 located in Agugliano (Ancona, Marche, 43°32'N, 13°22'E) and the PI2 site in San Piero a Grado  
172 (Pisa, Toscana, 43°41'N, 10°23'E). These sites are characterized by contrasting tillage practices  
173 and belong to the IC-FAR national network (Linking long term observatories with crop systems  
174 modeling for a better understanding of climate change impact and adaptation strategies for Italian

175 cropping systems). The climate of the both AN and PI2 sites is Mediterranean with a bimodal  
176 distribution of cumulated monthly precipitation in spring and autumn, mild winters and warm dry  
177 summers.

### 178 **2.1.1 LTE AN**

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

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

195 Measured crop data consisted of phenology (flowering, and physiological maturity dates), leaf area  
196 index (LAI), and productivity (aboveground biomass and grain yield) from 2002 to 2014. SOC  
197 samples of the soil profile were collected to a depth of 40 cm in 1996 and 2002 and to a depth of  
198 100 cm in 2006 and 2010 in both the CT and NT treatments. Physical soil characteristics and  
199 hydraulic proprieties were measured in 2006 and used to define the main soil characteristics of the

200 site (Table 1). As the experiment was initialized on a CT system, we used 2006 data of the CT  
201 N90 treatments as a reference for the main soil characteristics of AN site assuming that these did  
202 not substantially change since the beginning of the experiment as reported by De Sanctis et al.  
203 (2012).

#### 204 **2.1.2 LTE PI2**

205 The PI2 LTE (Mazzoncini et al., 2011) is located in a lowland coastal area with an alluvial loam  
206 soil. The experimental design includes two tillage systems (CT – annual plough *vs* RT – reduced  
207 tillage), four mineral N fertilization rates and four soil cover types factorially combined in a split-  
208 split-plot design with four replications. The design included a continuous maize crop from 1994 to  
209 1998 followed by a two-year durum wheat-maize rotation until 2004. After 2005 the LTE was  
210 changed to a four-year crop rotation of durum wheat-maize-durum wheat-sunflower. Over the 15  
211 years include in this research (1994-2008), mean annual precipitation at this site was 826 mm and  
212 the mean annual air temperature was 14.6 °C.

213 In this study we used a subset of treatments of the PI2 LTE (1994 to 2008) where durum wheat  
214 and maize were grown without cover crops, to evaluate the effects of the different tillage systems  
215 on SOC dynamics. The CT consisted of annual moldboard ploughing to a depth of 30-35 cm  
216 followed by secondary tillage with disk and rotary harrows. The RT was characterized by no-  
217 tillage for wheat and shallow harrowing for seedbed preparation for maize to a depth of 10-15 cm.  
218 Plots of durum wheat and maize were fertilized with 180 and 300 kg N ha<sup>-1</sup>, respectively. In both  
219 systems, crop residues were chopped after harvest and left in the field. Weed control was based on  
220 post-emergence herbicide application in the CT system while pre-sowing glyphosate was also  
221 applied in the RT. FAO class 300 were used from 1994 to 2000 and class 500 from 2002 to 2006,  
222 while Cirillo and Duilio were used for durum wheat in 1999 and from 2001 to 2007. Aboveground  
223 biomass and crop yield were measured each year at harvest. Soil analyses were conducted on soil  
224 samples collected at the depths of 0-10 and 10-30 cm at the end of September in 1993 (at the

225 beginning of the experiment), 1998 and 2008. During the IC-FAR project, additional soil data  
226 were collected in 2015 from a depth of 30 to 90 cm to characterize the soil texture of the deeper  
227 layers assuming that texture values did not change from the beginning of the experiment. Data  
228 from 1993, coupled with texture data from the deeper layers collected in 2015 were used to define  
229 the main soil physical characteristics of the PI2 site (Table 1). Soil hydraulic properties were  
230 estimated using the pedo-transfer functions of Ritchie et al. (1999).

231

## 232 **2.2 Setup of the crop models**

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

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

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

250 Century-based models (EPIC, DSSAT, SALUS), the SOC fractions in 1950 were initialized  
251 following the procedures suggested by Basso et al. (2011) considering 2%, 64% and 34% for the  
252 active, the slow and the passive pools, respectively. The final simulated fractions of the passive  
253 pool for each soil depth obtained at the end of the antecedent simulation were then used as inputs  
254 in the simulation starting in 1994. A wheat-maize rotation was also simulated over the period  
255 1994-2001 although in the same years sunflower was sown instead of maize but the amount of  
256 residues left by sunflower was similar to that left by maize in this rainfed system (De Sanctis et al.,  
257 2012). In the APSIM-NWheat model, inputs to set the amounts of the initial labile pool (biom) and  
258 the rest of the soil organic matter (hum) in each layer for year 1994 were set in order to minimize  
259 the root mean square error between simulated and measured values at both 0-15 and 15-40 cm for  
260 the two treatments (i.e., tillage and no tillage).

261 In the PI2 site, before the start of the experiment in 1993, a pre-run simulation over 63 years  
262 (1930-1993) was performed on a rainfed biannual *durum* wheat-maize rotation fertilized with 180  
263 kg N ha<sup>-1</sup> for the winter crop and 300 kg N ha<sup>-1</sup> for the summer crop. The biannual rotation was  
264 initialized in 1930 on grassland. Total SOC in the upper 30 cm in 1930 was estimated iteratively  
265 until the measured SOC value in 1993 was adequately predicted by the simulation. Following the  
266 procedure of Basso et al. (2011), the same initial SOC fractions used in AN for the Century-based  
267 models were used also for PI2 in 1930. At the end of the 63 year period, the final simulated  
268 fractions obtained for the passive pool in each model were then used to initialize simulations  
269 starting in 1993.

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

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

275 NT were carried out with the weed contribution during the fallow period from wheat harvest (July)  
276 to maize sowing (April). Plant parameters for Bahia grass (*Paspalum notatum* Flüggé) were used  
277 to simulate green foxtail (*Setaria viridis* L.), the most frequent weed species observed at the  
278 experimental site, because Bahia grass is a C4 plant included within DSSAT that is similar to  
279 foxtail. In PI2, as the simulation of weed growth during the fallow period was limited by the  
280 presence of tillage, weed contribution to SOC was simulated in the RT system adding also an  
281 amount of 1500 kg ha<sup>-1</sup> of bahia grass crop residue at the onset of each maize growing seasons.  
282 This average amount per year was taken from Mazzoncini et al. (2011) considering the total weed  
283 biomass contribution over the experimental period 1994-2008.  
284 In the APSIM-NWheat, EPIC, and SALUS models, the weed biomass was added to the initial  
285 input residues and set to 1500 kg ha<sup>-1</sup> at both AN and PI2 sites as reported in De Sanctis et al.  
286 (2012) and Mazzoncini et al. (2011), respectively.

287

### 288 **2.3 Evaluation of model performance**

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

296 Statistics were calculated in each site considering the available observed SOC measurements (AN:  
297 2002, 2006, 2010; PI2: 1998, 2008) to a depth of up to 40 cm for both tillage systems but not  
298 including the initial observed SOC values used as model inputs (1996 and 1993 respectively for

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

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

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

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

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

318

#### 319 **2.4 Simulation scenarios**

320 Climate scenarios were generated by setting up a statistical downscaling model over the case  
321 studies, represented by a multivariate regression (Tomozeiu et al., 2014). The statistical scheme  
322 was based on the assumption that the local climate variability is determined by the variability of  
323 large scale fields and local features. The link between local predictors and large scale predictors

324 has been determined by Canonical Correlation Analysis (CCA). The most important patterns that  
325 resulted from CCA were then used as input of the multivariate regression scheme. The setup of the  
326 statistical model was done using predictors from ERA40 and ERA-Interim<sup>1</sup>, and predictands  
327 represented by the seasonal indices of temperature and precipitation over the case studies,  
328 computed from E-OBS gridded dataset<sup>2</sup> (Haylock et al., 2008). The large-scale predictors tested  
329 were: mean sea level pressure (MSLP), geopotential height at 500 hPa (Z500) and temperature at  
330 850 hPa (T850), spatially ranging between 90°W to 90°E in longitude and 20°N to 80°N in  
331 latitude, with a horizontal resolution of  $1.125^\circ \times 1.125^\circ$ . The set-up of the statistical model was  
332 done over the 1958-2010 period. Once the most skillful model was detected for each season and  
333 index (local temperature or precipitation), the predictors simulated by the CMCC-CM global  
334 climate model (Scoccimarro et al., 2011) were entered into the statistical scheme in order to  
335 estimate the future local climate. Two emission scenarios were used: RCP4.5 and RCP8.5 (Moss  
336 et al., 2008), while the projections were constructed over the period 2021-2050 (CF: Future  
337 Climate) with respect to 1971-2000 (CP: Present Climate).

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

345 A CO<sub>2</sub> concentration of 360 ppm was used for the present climate scenario considering a mean  
346 CO<sub>2</sub> value recorded at Mauna Lao Observatory (NOAA ESRL Global Monitoring Division, 2015)

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<sup>1</sup> <http://www.ecmwf.int/products/>

<sup>2</sup> <http://eca.knmi.nl/download/ensembles/ensembles.php>

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

349 The four validated crop models were run using the CP and CF scenarios in both LTEs to assess the  
350 climate change impacts on SOC stocks. Models were run with the management practices reported  
351 in Table 3 and simulating two rotations (Rot1: wheat-maize, Rot2: maize-wheat) to allow the  
352 presence of both crops in each year. Seedling emergence was set according to the most frequent  
353 values observed in the field as measured by Seddaiu et al. (2016) for AN and by Mazzoncini et al.  
354 (2011). It was set at 300 and 350 plants m<sup>-2</sup> for durum wheat in AN and PI2 (all tillage systems)  
355 respectively, and 7 and 6 plants m<sup>-2</sup> for maize under all tillage systems in PI2 and under CT in AN  
356 site. Maize seedling emergence was reduced to 3 plants m<sup>-2</sup> under NT as observed for the LTE in  
357 AN. The crop harvest date was set at maturity in the crop models. The SOC measured in 1996 (for  
358 AN) and 1993 (PI2) were used as initial values in all scenarios. The SOC fractions were initialized  
359 with the same procedures described in the set-up phase. SOC changes to a depth of 0-40 cm,  
360 aboveground biomass, and yield were assessed using the MM\_Mean in both sites over the  
361 simulation periods CP and CF, for the different applied tillage management (Table 3) and climate  
362 change scenarios.

363

### 364 **3. Results**

#### 365 **3.1 Model Evaluation**

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

369 Table 4 shows statistics that describe the performance of all the models tested to simulate the SOC  
370 dynamics in the upper 40 cm and the MM\_Mean for all of the models. At the AN site, RRMSE for  
371 all of the models was less than the RRMSE95% which indicates that even if some of the models

372 generated some simulation values outside the measured standard errors (Supplementary material,  
373 Fig. S2), they were still within the 95% confidence interval when the entire dataset was examined.  
374 Model 3 (RRMSE= 7.44) had the worst performance and strongly overestimated SOC in NT.  
375 Model1 (RRMSE= 5.85) presented a flat trend in NT SOC dynamic, with most of the values  
376 laying below the observed ones. A similar pattern of model performance was reflected by the EF  
377 indicator that showed a negative value (EF= -0.60) only for Model3. Model1 produced an EF  
378 value very close to zero. E values for all of the models were within the 95% confidence interval of  
379 E95%, and Model3 had the highest bias (E= -6.57). All models, excluding Model1, presented  
380 significant *r* values. Considering the overall statistics, the best performance in the simulation of  
381 SOC dynamic in AN was achieved by the MM\_Mean which showed the lowest value of the  
382 RankMean. The good performance of MM\_Mean was also supported by the qualitative graphical  
383 representation reported in Fig. 1 in which the SOC dynamics simulated by the MM\_Mean were  
384 very close to the measured data in both tillage systems and better than those shown by the other  
385 crop models (Supplementary material, Fig. S2) in both total (0 - 40 cm), superficial (0 - 15 cm),  
386 and deeper layers (15 - 40 cm).

387 In PI2, only Model1 showed a RRMSE within the 95% confidence interval of the measured data,  
388 although all models presented positive values of EF. Considering the EF statistics, only Model1  
389 (EF=0.90), MM\_Mean (EF= 0.65), and Model2 (EF= 0.62) reached values close to 1. In fact,  
390 these models better reproduced the measured data for CT system in 1998 (Supplementary material,  
391 Fig. S3), while all models showed an underestimation of the observed data under RT. Considering  
392 model bias evaluation, only Model3 and Model4 showed E values greater than E95% (E=8.28 and  
393 E=7.95, respectively). All models, except Model1, for which it was not possible to calculate the  
394 statistical significance of *r* given the low numbers of observations (n=2), showed high positive and  
395 significant correlations between measurements and simulated data. Considering overall statistics,  
396 the best performance in the simulation of SOC in PI2 was obtained by Model1 (RankMean= 1.0),

397 but its simulation started in 1998, and it could not be statistically compared with the other models.  
398 The second best rank was reached by the MM\_Mean (RankMean= 2.0). MM\_Mean showed a  
399 better representation of CT system (Fig. 1) than other single models (Supplementary material, Fig.  
400 S3) but it was not able to reproduce the high SOC value observed in RT.

401

## 402 **3.2 Simulation scenarios: CP vs CF**

### 403 **3.2.1 Climate scenarios**

404 The CP scenario reproduced the mean monthly values of all indices very well (Tmax, Tmin and  
405 PREC) for the local observed climate from 1971 to 2000 in both sites (Supplementary material,  
406 Table S2). The CF scenarios RCP4.5 and RCP8.5 (Fig. 2) showed that an increase of temperatures  
407 is expected during the period 2021-2050 in all seasons in both sites: +1.8°C annual mean T in  
408 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  
409 highest increases in the summer.

410 The changes in precipitation pattern were different from season to season in the two sites. At AN,  
411 the mean annual precipitation (750 mm under CP) decreased by -22.5% in RCP4.5 and -23.0% in  
412 RCP8.5, with the highest reduction occurring in spring (up to -49.0 % in RCP4.5 and -56.1% in  
413 RCP8.5) and summer months (up to -38.0% in RCP4.5 and -34.1% in RCP8.5). At PI2, the mean  
414 annual precipitation under CP (884 mm) is expected to slightly increase of 2.1% in RCP4.5 and  
415 4.9% in RCP8.5. The largest increase is expected in April (+24.0 % in RCP4.5 and +16.9% in  
416 RCP8.5) and in the autumn months (+30.5% in RCP4.5 and +41.4% in RCP8.5), while a strong  
417 reduction of rainfall is expected in the summer months (47.0% in RCP4.5 and -52.7% in RCP8.5).

418

### 419 **3.2.2 Multi-model mean simulation scenarios**

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

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

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

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

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

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

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

460

#### 461 **4. Discussion**

462 Our results confirm the hypothesis that under current climatic conditions, the MM\_Mean  
463 reproduces SOC dynamic better than a single simulation model and with less uncertainty as  
464 demonstrated by lower RMSE and standard error values. Hence the model ensemble (MME)  
465 provides a better prediction of SOC change in relation to climate change. In contrast with other  
466 studies (Alvaro-Fuentes et al., 2012; Lugato et al., 2007; Tornquist et al., 2009), we used crop  
467 models rather than biogeochemical ones to assess the impact of future scenarios on crop  
468 productivity and yield in order to reliably reproduce soil C-input and, at the same time, evaluate  
469 climate change impacts on crop yields. Several studies have used simulation models as effective  
470 tools to assess changes in SOC stocks under current and future scenarios in order to identify

471 effective agronomic practices (Farina et al., 2011; Lugato et al., 2015; Tornquist et al., 2009;  
472 Wiesmeier et al., 2016) that reduce soil C emissions and increase C stock, thereby mitigating  
473 climate change. The added value of this work is the robustness of the results we obtained given the  
474 use of an ensemble of models that were validated using long-term experimental datasets and able  
475 to adequately assess the long-term processes that affect SOC dynamics.

476 Our results are generally in agreement with the SOC trends reported by other authors (Farina et al.,  
477 2011; Lugato et al., 2014; Mondini et al., 2012; Smith et al., 2005) which projected a negative  
478 trend on SOC stock dynamics in cropland across the 21st century. However the results obtained by  
479 other studies are not always directly comparable with the ones of this work due to the differences  
480 in spatial and temporal scale, soil profiles, climate scenarios, and methodologies. Lugato et al.  
481 (2014) reported in the short to medium term (2020) a decrease in SOC in agricultural soils of  
482 Central and Southern Italy and an expected net loss of about 2.5 Mg ha<sup>-1</sup> close to the end of the  
483 century in the Mediterranean region. Mondini et al. (2012) projected a loss of about 6.3% of SOC  
484 between 2001 and 2100 on arable land in Italy, while Smith et al. (2005) projected a SOC loss of  
485 between -14% and -10% over 1990-2080 on a high level (European croplands). Farina et al. (2011)  
486 applied a similar methodology at the same AN site using EPIC model coupled with two different  
487 general circulation models (GISS and HadCM3) for A2 and B2 emission scenarios. Considering  
488 the entire soil profile, the study showed a SOC loss ranging from -2.3 Mg ha<sup>-1</sup> up to -6.1 Mg ha<sup>-1</sup>  
489 in CT and from -2.1 Mg ha<sup>-1</sup> up to -7.4 Mg ha<sup>-1</sup> in NT, over the period 2040-2069 compared to the  
490 baseline 1956-2006.

491 Temperature and precipitation are the main climatic drivers that influence, both directly and  
492 indirectly, organic carbon trends in the soil (Fantappiè et al., 2011; Saby et al., 2008; Smith et al.,  
493 2005). Because the monthly mean temperature is expected to increase around +2.0°C under future  
494 scenarios at both sites, soil biological activity will likely be stimulated which increases the  
495 decomposition rate and facilitates SOC losses through heterotrophic respiration (Ugalde et al.,

496 2007). Leiros et al. (1999) showed that the positive effect on soil decomposition rate caused by a  
497 2°C temperature increase is usually limited by a concurrent -10% decrease in soil moisture.  
498 Moreover, according to Gottschalk et al. (2012), C mineralization is constrained by both low or  
499 high values of soil water content, which is mainly influenced by precipitation. The two sites were  
500 characterized by similar increase of temperatures but diverse patterns of precipitation (on average -  
501 22.7 % in AN and +3.5% in PI2). Hence, the interaction of both factors affected the organic  
502 carbon decomposition differently at the two sites under the future scenarios, and led to lower SOC  
503 impact in PI2. However, the impact of climate change at AN was constrained by a higher clay  
504 content which physically protects SOC from microbial decomposition (Baldock and Skjemstad,  
505 2000; Six et al., 2002; Xu et al., 2016). These interactions are taken into account by the models  
506 which control SOC stock dynamics considering a variety of management, soil properties and  
507 climate factors. In all the considered models the decomposition of the organic carbon is simulated  
508 with a first-order decomposition kinetics of the C mass (Jones and Kiniry, 1986; Parton et al.,  
509 1994; Parton et al., 1988). The decomposed carbon is partly lost to the atmosphere as CO<sub>2</sub> and  
510 transferred to another organic matter pool. The decomposition rates are computed daily and their  
511 values change in relation to some environmental modifiers such as temperature, moisture, litter  
512 quality, and soil texture (Basso et al., 2006; Gijsman et al., 2002; Izaurralde et al., 2006; Porter et  
513 al., 2009).

514 Temperature and precipitation indirectly influence SOC by affecting a number of physiological  
515 and biological processes that drive crop growth and development, and determine soil C input  
516 released by crop residues. Our results showed that the growing season length of both maize and  
517 wheat was significantly reduced during the period 2021-2050 in the two sites due to increased  
518 temperature. In both sites, maize grain and AGB production was also strongly constrained by the  
519 projected precipitation decrease occurring during summer season, when the crop is more  
520 vulnerable to water stress under rainfed conditions (Sánchez et al., 2014). In particular, maize was

521 more affected in PI2 than in AN due to the significant reduction of rainfall (around -50%) that is  
522 projected to occur during July and August at the PI2 site. Maize production at the AN site could be  
523 even more affected especially under NT system since the yield of this crop is low as it is affected  
524 by high variability and low seedling emergence (50% than with CT).

525 Wheat is mostly influenced by water availability during earing and anthesis phases occurring in  
526 the spring (Albrizio et al., 2010; Campiglia et al., 2015). At the AN site, the significant reduction  
527 in precipitation that was projected in the spring constrained wheat production under future  
528 scenarios, despite the positive effect of CO<sub>2</sub> atmospheric enrichment which offsets the rainfall  
529 impact. On the other hand, the expected increased precipitation at PI2 in April was able to limit the  
530 negative effect of the shortening of the growing season on both wheat yield and aboveground  
531 biomass, determining a concurrent lower decrease of available crop residue input into the soil.

532 CT and conservation tillage (both NT and RT) resulted in different redistributions of SOC among  
533 soil horizons. However, considering the total SOC of the 0-40 cm depth, the conservation tillage  
534 systems were able to stock more SOC than CT also under future scenarios. In fact, as conservation  
535 tillage practices decrease SOC decomposition by reducing soil CO<sub>2</sub> emissions (Powelson et al.,  
536 2011), they are suggested for climate change mitigation.

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

542 A meta-analysis review by Angers and Eriksen-Hamel (2008) reported that the difference in SOC  
543 stocks between NT and CT at the depth of 0-30 cm is an average of 4.9 Mg ha<sup>-1</sup> and that the  
544 difference in favor of NT increases over time until ~25-30 years, when NT may have reached a  
545 new steady state (Alvarez et al., 2005). The same difference, 4.9 Mg ha<sup>-1</sup>, was observed in the

546 experimental dataset from the AN site for the period 1996-2010 in the 0-40 cm soil layer. In the  
547 CP scenario the difference between NT and CT was 5.4 Mg ha<sup>-1</sup> after 30 years of simulation. The  
548 difference still remained high in the future scenarios with a value of 4.7 Mg ha<sup>-1</sup>. The higher SOC  
549 stock with NT was not only due to the reduction in the decomposition coefficient but also to the  
550 weed biomass contribution, considered by the models, as also shown by De Sanctis et al. (2012).  
551 The RT system in PI2 was not so as performant as NT in AN, even if it showed slightly higher  
552 SOC values than CT with a positive difference of 1.8 Mg ha<sup>-1</sup> in CP period and 1.3 Mg ha<sup>-1</sup> in  
553 future scenarios. The SOC dynamic in this site was reproduced with higher uncertainty as the  
554 MM\_Mean showed a high RMSE value mainly due to an underestimation of observed data under  
555 RT.

556 A reliable SOC stock assessment has been recently encouraged by the 4 per thousand initiative  
557 (4PT, Le Foll, 2015) launched at the 21<sup>st</sup> meeting of the Conference of the Parties in Paris. This  
558 initiative aims to mitigate climate change by increasing SOC stock at an annual rate of 0.4%  
559 through the adoption of best management practices. The results of this study showed that  
560 conservation tillage systems (NT and RT) in both sites were able to store more SOC than CT so  
561 these practices ought to be considered viable options to mitigate climate change in Mediterranean  
562 cereal systems. Furthermore, in AN, NT could provide the annual increase of 0.4% required by  
563 4PT also under climate change scenarios. The main problem related to NT in this silty-clay site is  
564 the lower average productivity of maize due to low establishment that was attributed to poor soil  
565 physical conditions at seeding. On the contrary, RT in PI2 needs to be coupled with other  
566 management strategies such as the introduction of cover crops to ensure higher SOC levels.  
567 However, the benefits of adopting conservation tillage to reduce the transfer of C to the  
568 atmosphere and enhance SOC sequestration, have to be verified for other greenhouse gas  
569 emissions in order to assess their overall impacts. Some studies have reported increased nitrous  
570 oxide emissions in no tillage systems (Mackenzie et al., 1998; Pastorelli et al., 2013) and more

571 abundant denitrifying bacteria in no-tilled soil (Doran, 1980). It is also important to consider that  
572 soils might have a potential limit for C accumulation mainly determined by their physical  
573 properties and clay content (Tornquist et al., 2009). Consequently, SOC sequestration can be only  
574 a short-term strategy for climate change mitigation but other long-term solutions have to be  
575 implemented.

576

## 577 **5. Conclusions**

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

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

593

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601

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900

901 **Fig. 1.** Soil organic carbon (SOC, Mg ha<sup>-1</sup>) dynamics simulated (Mod) by the multi model mean  
902 (MM\_Mean) in different tillage systems (CT= Conventional tillage, NT= No till, RT= Reduced  
903 tillage) at different soil depths in the two sites (AN: 0-15cm, 15-40cm, 0-40cm; PI2: 0-10cm, 10-  
904 30cm, 0-30cm) in comparison with the observed (Obs) SOC values in the LTEs. Vertical bars are  
905 the standard errors.

906

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

910

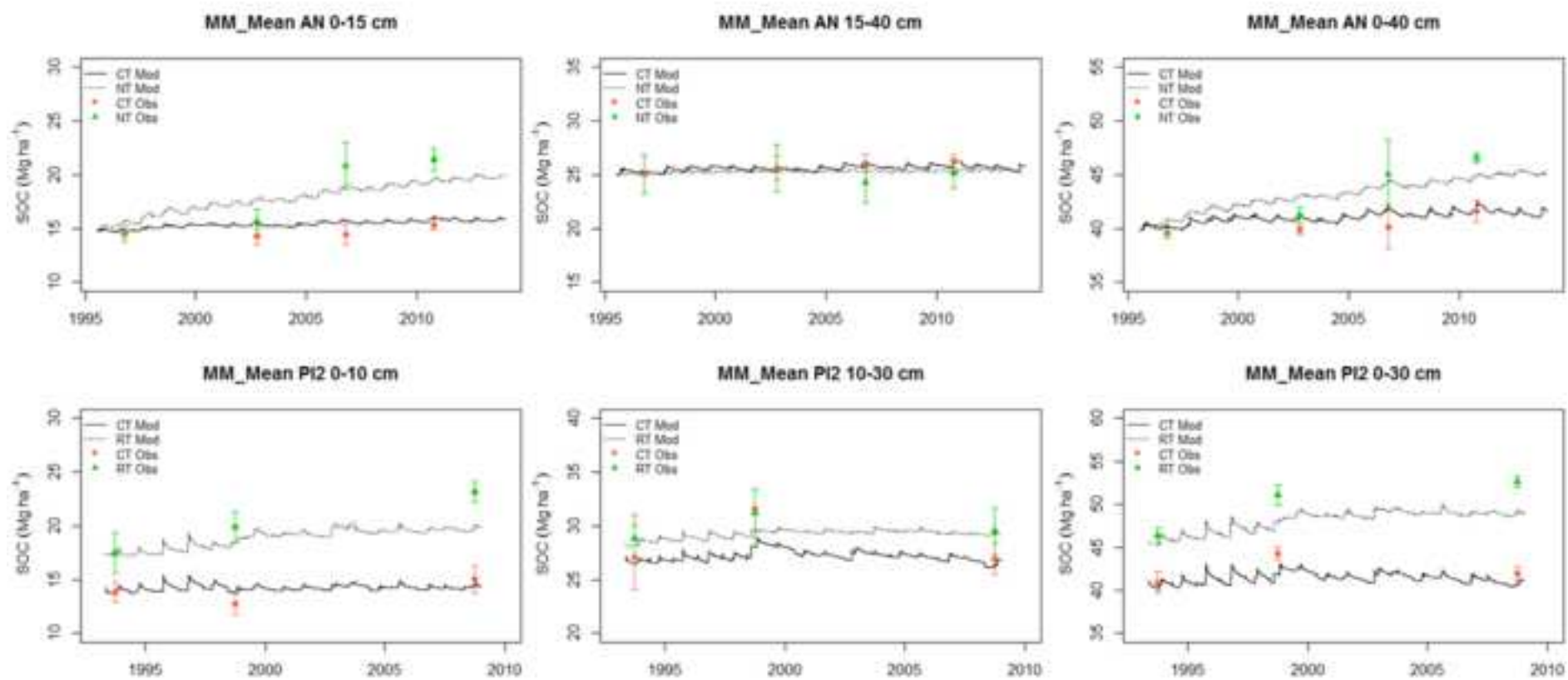
911 **Fig. 3.** Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-  
912 15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM\_Mean) in present and  
913 future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or No Tillage -  
914 NT practices in AN; a) RCP4.5 scenario; b) RCP8.5 scenario. The red and green regions delimited  
915 by the dashed lines are the standard errors of the simulations respectively obtained for CT and NT  
916 systems; c) Relative annual SOC change (%) observed in climate change scenarios (CF: mean  
917 values of RCP4.5 and RCP8.5) in relation to the present climate scenario.

918

919 **Fig. 4.** Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-  
920 15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM\_Mean) in present and  
921 future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or Reduced  
922 Tillage - RT practices in PI2; a) RCP4.5 scenario; b) RCP8.5 scenario. The red and green regions  
923 delimited by the dashed lines are the standard errors of the simulations respectively obtained for  
924 CT and NT systems; c) Relative annual SOC change (%) observed in climate change scenarios  
925 (CF: mean values of RCP4.5 and RCP8.5) in relation to the present climate scenario.

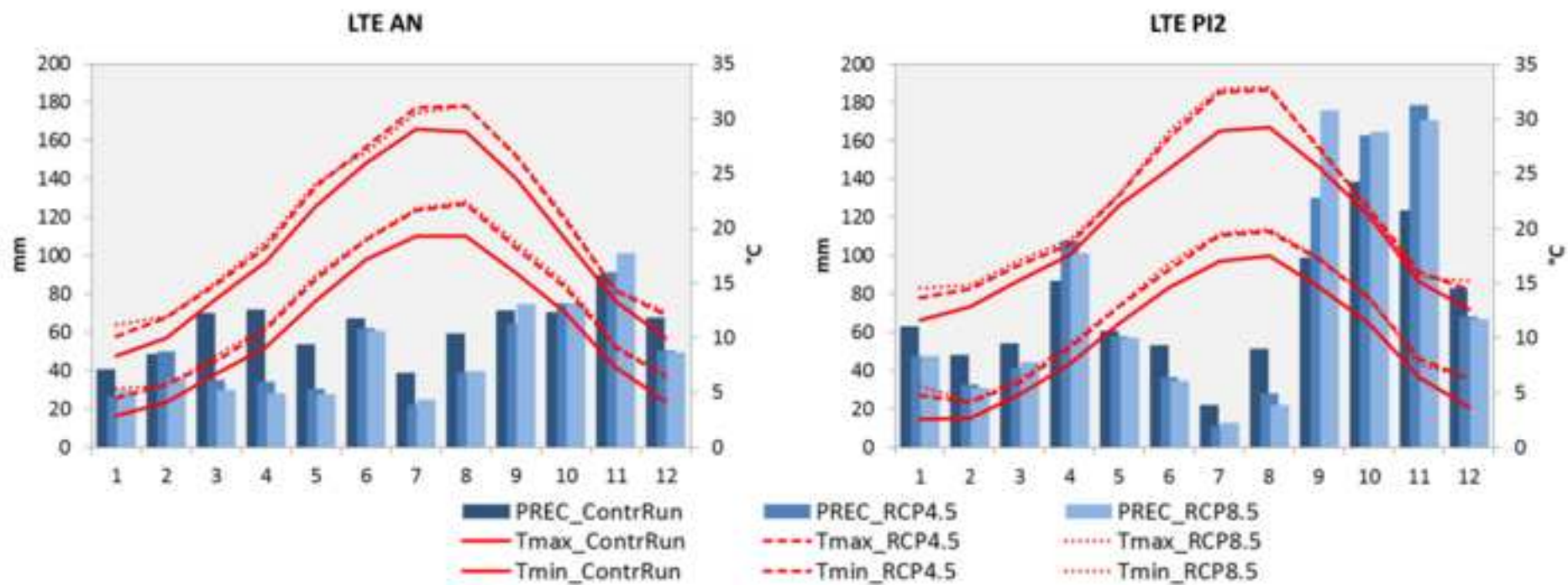
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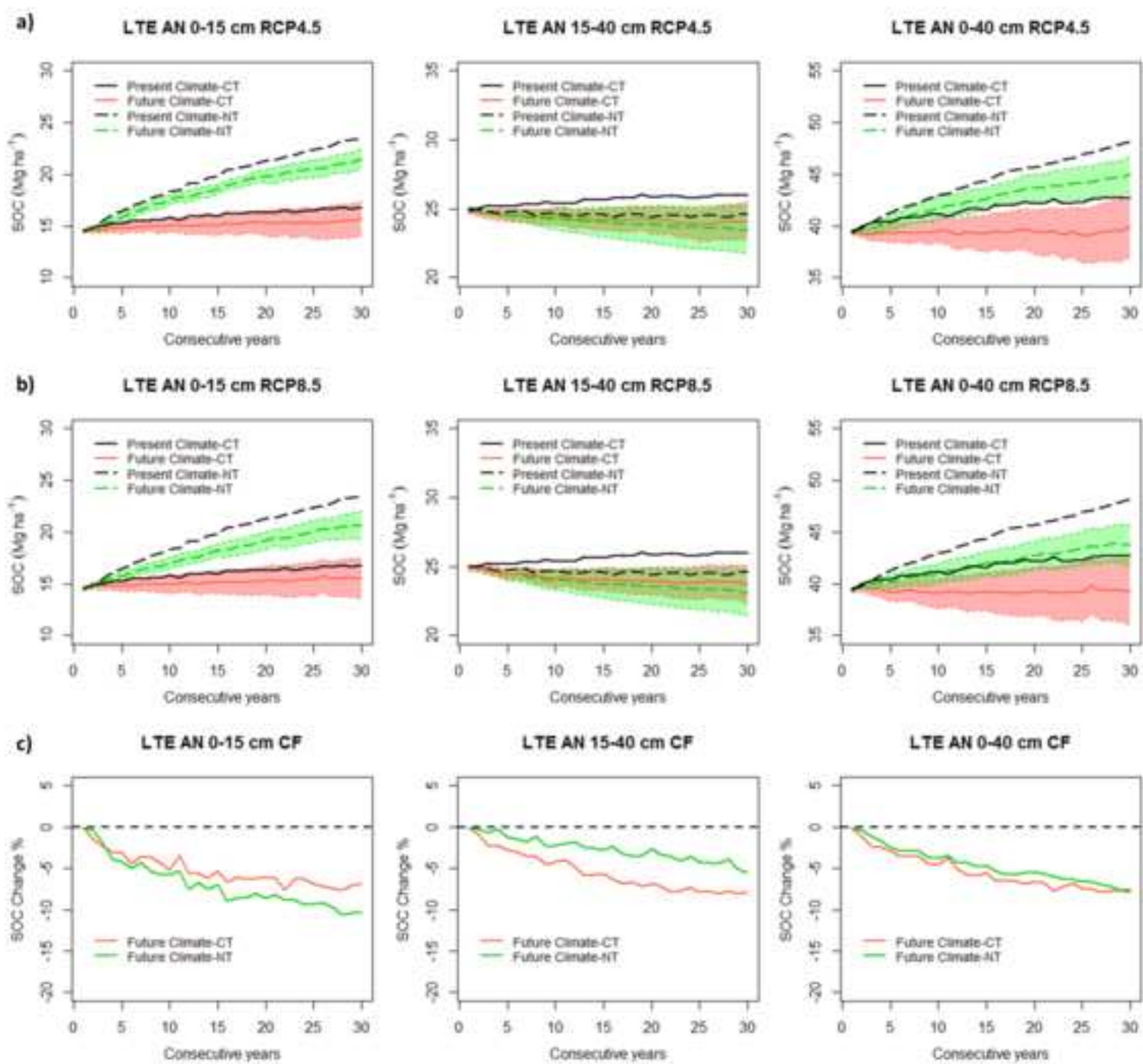


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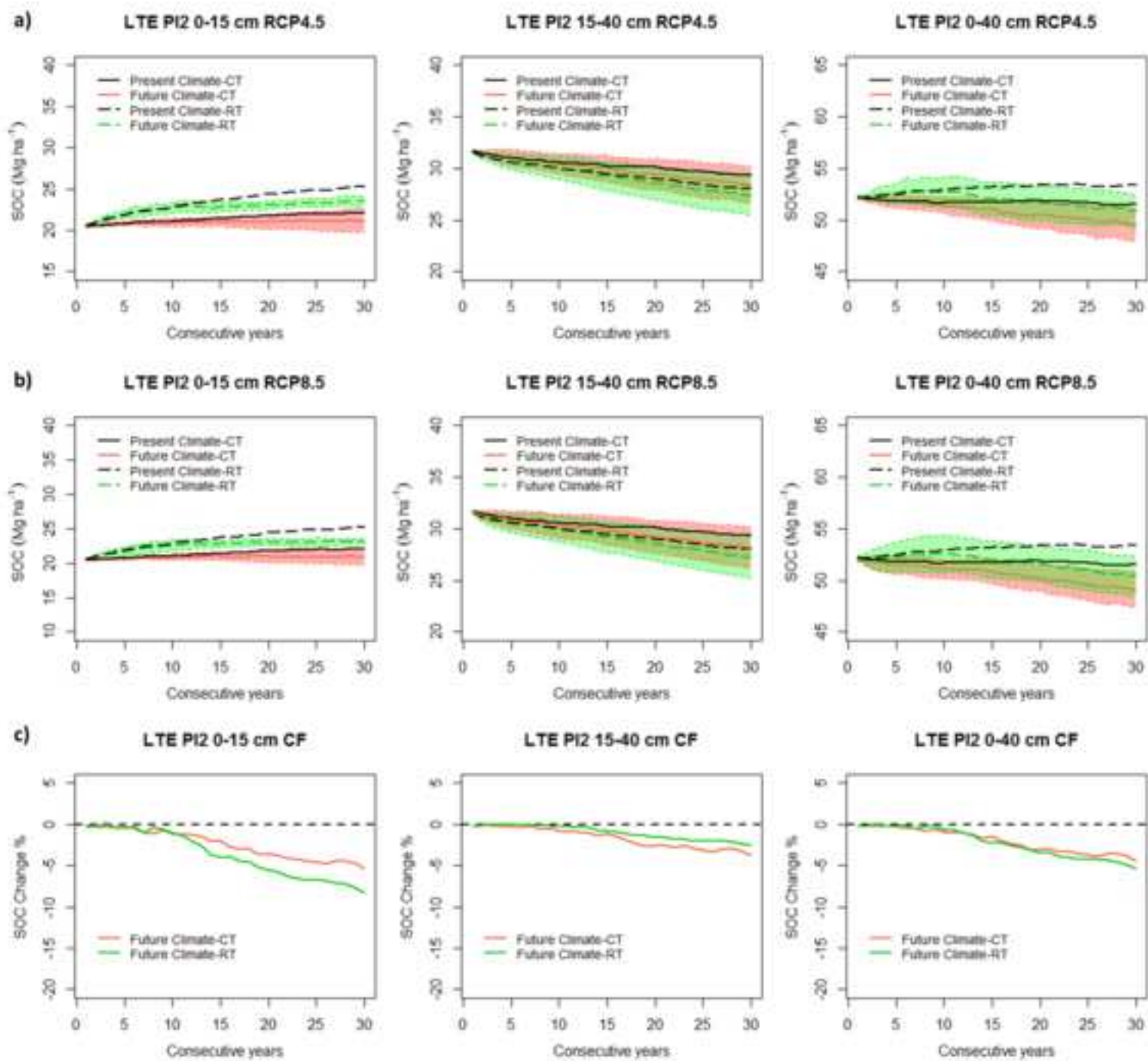
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- 1 **Table 1.** Main physical and hydrological properties of the soils in AN and PI2 as reported in the  
 2 IC-FAR database and used as inputs in the process based crop models.

	cm	%	%	%	$\text{g cm}^{-3}$	$\text{cm}^3 \text{cm}^{-3}$	$\text{cm}^3 \text{cm}^{-3}$	$\text{cm}^3 \text{cm}^{-3}$
<b>LTE</b>	<b>Depth</b>	<b>Clay</b>	<b>Silt</b>	<b>Sand</b>	<b>BD</b>	<b>WP</b>	<b>FC</b>	<b>SAT</b>
<b>AN</b>	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
<b>PI2</b>	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

- 3 WP = Soil water content at wilting point; FC = Soil water content at field capacity; SAT =

- 4 Saturated water content; BD = Bulk Density.

- 5

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

Model	Reference	Crop	Biomass growth <sup>a</sup>	Yield formation <sup>b</sup>	Root distribution <sup>c</sup>	Soil dynamic <sup>d</sup>	N° SOC pools <sup>e</sup>	N° FOM pools <sup>f</sup>
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

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

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

<b>AN (Tillage systems: CT* and NT**)</b>	<b>Wheat</b>	<b>Maize</b>
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) March 10 (45N)	April 25 (90N)
<b>PI2 (Tillage systems: CT* and RT***)</b>	<b>Wheat</b>	<b>Maize</b>
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) April 12 (90N)	May 10 (300N)

17 \*CT= Conventional Tillage; \*\*NT= No Tillage; \*\*\*RT= Reduced Tillage; N= Nitrogen  
 18 fertilization rate (kg ha<sup>-1</sup> year<sup>-1</sup>).

19 **Table 4.** Evaluation of the four models (Model1, 2, 3 and 4) and the multi model mean  
 20 (MM\_Mean) in simulating the soil organic content (SOC, Mg ha<sup>-1</sup>) in AN and PI2 sites  
 21 considering the available observed measurements (AN: 2002, 2006, 2010; PI2: 1998, 2008) until  
 22 the depth of ploughing (0-40cm for AN and 0-30 cm for PI2) under both conventional and  
 23 conservative tillage systems.

	Min	Max	Best		
	0.00	+inf.	0.00		
	-inf.	1.00	1.00		
	-inf.	+inf.	0.00		
	-1.00	1.00	1.00		
	<b>RRMSE</b>	<b>EF</b>	<b>E</b>	<b>r</b>	<b>RankMean</b>
<b>Site AN</b>	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
<b>Site PI2</b>	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

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

29 **Table 5.** Mean values (Mg ha<sup>-1</sup>) of aboveground biomass (AGB) and yield for maize (MZ) and  
 30 wheat (WHT) between CP (Present Climate) and future scenarios CF (RCP4.5 and RCP8.5) under  
 31 conventional and conservation tillage systems in AN and PI2 sites. The numbers in brackets are  
 32 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	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%)
RCP4.5_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%)
RCP8.5_AN	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%)
CP_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	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%)
RCP8.5_PI2								

33