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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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 21st 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

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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

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　(Izaurralde 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^{-1}. 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^{-1}, 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^{-1}, 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^{-1} for the winter crop and 300 kg N ha^{-1} 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^{-1} 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^{-1} 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[1], and predictands

327   represented by the seasonal indices of temperature and precipitation over the case studies,

328   computed from E-OBS gridded dataset[2] (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 $1.125° \times 1.125°$. 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_2 concentration of 360 ppm was used for the present climate scenario considering a mean

346   CO_2 value recorded at Mauna Lao Observatory (NOAA ESRL Global Monitoring Division, 2015)

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[1] http://www.ecmwf.int/products/
[2] 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^{-2} for durum wheat in AN and PI2 (all tillage systems)

355 respectively, and 7 and 6 plants m^{-2} for maize under all tillage systems in PI2 and under CT in AN

356 site. Maize seedling emergence was reduced to 3 plants m^{-2} 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^{-1} year^{-1} 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^{-1} year^{-1} 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^{-1} with CT (-7.3%) and -3.8 Mg ha^{-1} 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^{-1} year^{-1} 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^{-1} year^{-1} with CT

454 and -0.06 Mg C ha^{-1} year^{-1} 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^{-1} in CT (-4.4 %) and -2.8 Mg ha^{-1} 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 21th 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^{-1} 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^{-1} up to -6.1 Mg ha^{-1}

489   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

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 proprieties 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 CO2 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_2 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_2 emissions (Powlson 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[-1] 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[-1], 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^{-1} after 30 years of simulation. The

548 difference still remained high in the future scenarios with a value of 4.7 Mg ha^{-1}. 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^{-1} in CP period and 1.3 Mg ha^{-1} 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 21st 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 proprieties 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.

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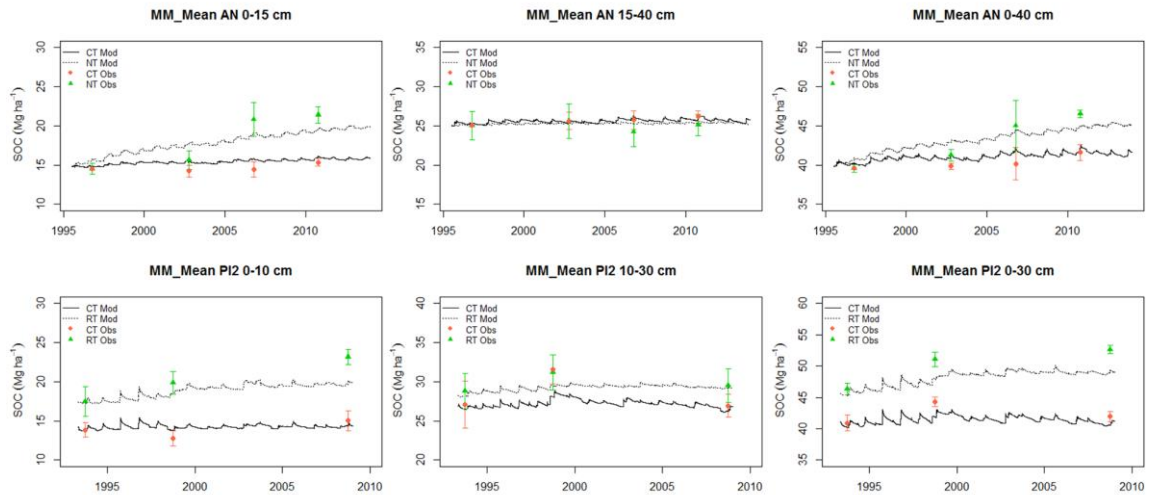
Fig. 1. Soil organic carbon (SOC, Mg ha^{-1}) dynamics simulated (Mod) by the multi model mean

(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.

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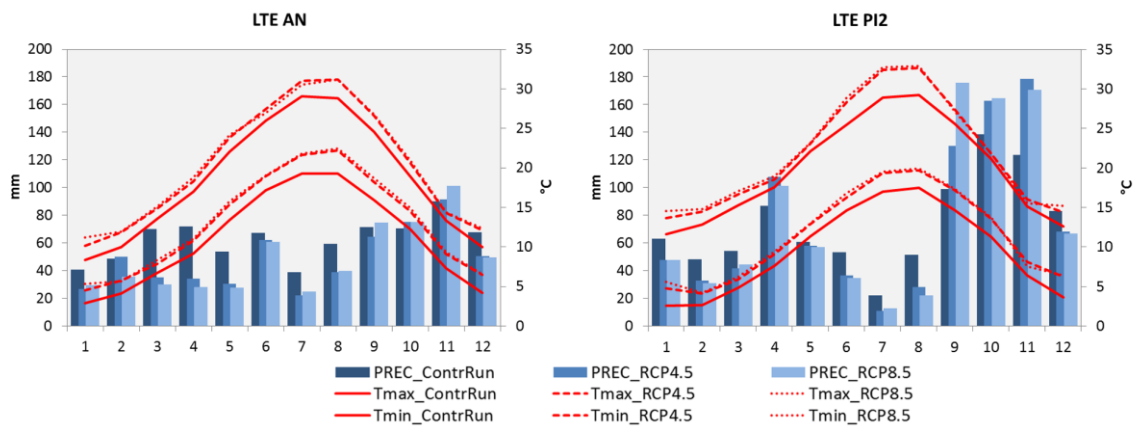
Fig. 2. Climate scenarios for the three time spans: CP (Present Climate), CF (Future Climate)

RCP4.5, and RCP8.5 in AN and PI2 sites. PREC: monthly mean precipitation, Tmax: monthly
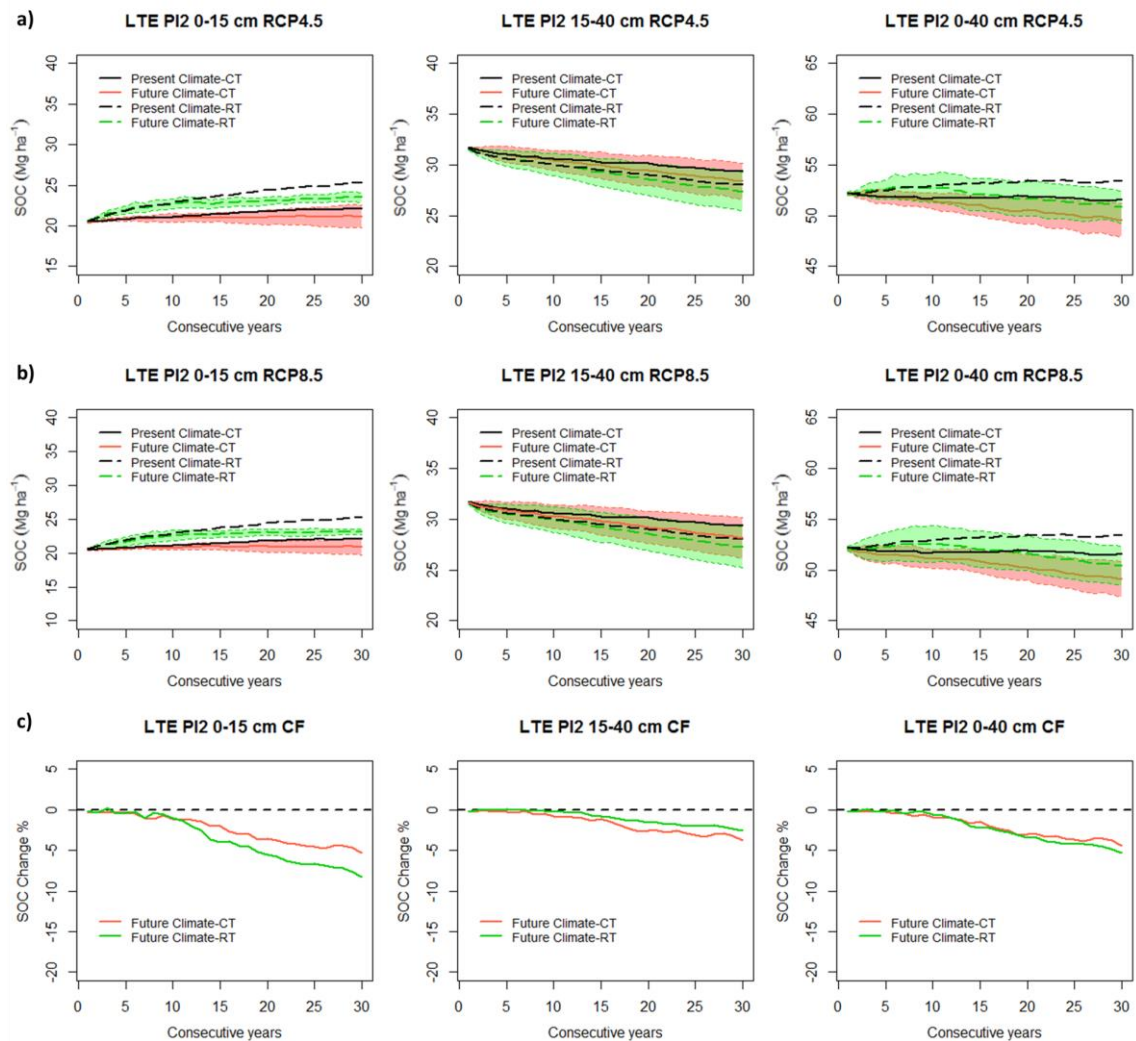
maximum temperature and Tmin: monthly minimum temperature.

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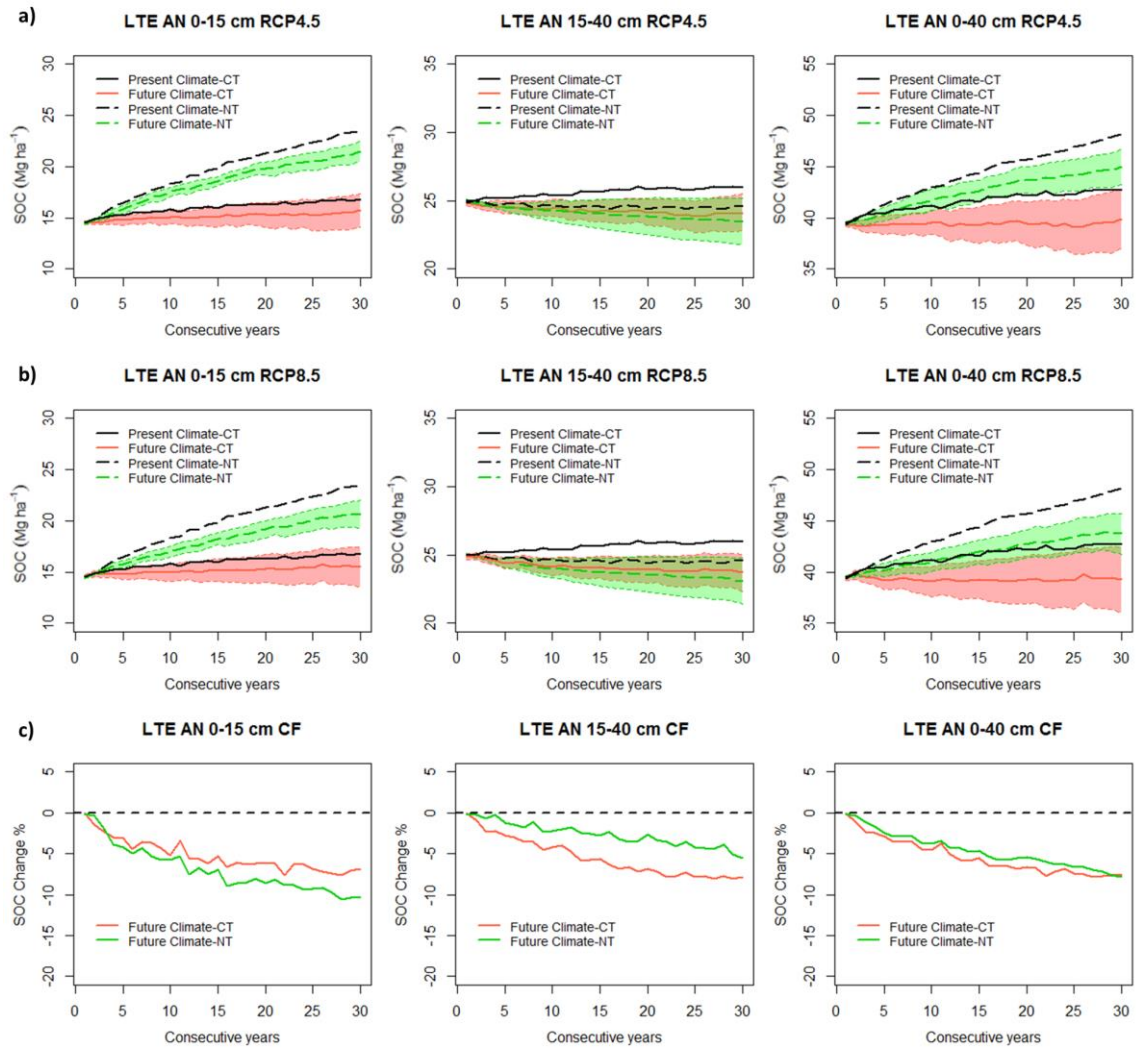
Fig. 3. Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-
15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM_Mean) in present and
future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or No Tillage -
NT practices in AN; 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.

920

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.

930   **Table 1.** Main physical and hydrological properties of the soils in AN and PI2 as reported in the

931   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

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

933   Saturated water content; BD = Bulk Density.

934

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

936 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

937 a) Biomass growth or light utilization: RUE = Radiation use efficiency approach; b)Yield

938 formation depending on: HI = harvest index, B = total above-ground biomass, Gn = number of

939 grains and grain-growth rate; c) Model of root distribution over depth: linear (Lin), exponential

940 (Exp), sigmoidal (Sig); d) Soil dynamic based on Ceres (Jones and Kiniry, 1986) or Century

941 model (Parton et al., 1988; Parton et al., 1994); e) Number of soil organic carbon pools: 2 (labile

942 pool and the rest of the soil organic matter), 3 (active, slow, and passive); f) FOM (fresh organic

943 matter) pools: 2 (structural and metabolic), 3 (carbohydrate, cellulose, and lignin).

944 **Table 3.** Dates of the agronomic management practices used in AN and PI2 sites for the
945 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)	

946 *CT= Conventional Tillage; **NT= No Tillage; ***RT= Reduced Tillage; N= Nitrogen

947 fertilization rate (kg ha^{-1} year^{-1}).

948 **Table 4.** Evaluation of the four models (Model1, 2, 3 and 4) and the multi model mean

949 (MM_Mean) in simulating the soil organic content (SOC, Mg ha^{-1}) in AN and PI2 sites

950 considering the available observed measurements (AN: 2002, 2006, 2010; PI2: 1998, 2008) until

951 the depth of ploughing (0-40cm for AN and 0-30 cm for PI2) under both conventional and

952 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*

953 RMSE= root mean square error; RRMSE95% = 95% confidence interval of RRMSE; EF =

954 modeling efficiency; E = the relative error; E95% = 95% confidence interval of E; *r* = Pearson

955 correlation coefficient; * is the r statistical significance at 95% confidence level, (-) means no

956 data. The numbers in brackets indicate the ranks obtained by models in relation to the performance

957 of each indicator. RankMean is the mean of the ranks for each model.

958 **Table 5.** Mean values (Mg ha^{-1}) of aboveground biomass (AGB) and yield for maize (MZ) and

959 wheat (WHT) between CP (Present Climate) and future scenarios CF (RCP4.5 and RCP8.5) under

960 conventional and conservation tillage systems in AN and PI2 sites. The numbers in brackets are

961 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	4.0	8.5	3.2	8.4	3.4	8.6	3.2
	(15.7%)	(21.6%)	(8.9%)	(8.5%)	(14.3%)	(17.2%)	(7.9%)	(8.2%)
CF RCP4.5_AN	7.9	3.2	7.0	2.5	6.7	2.7	7.2	2.7
	(23.1%)	(32.7%)	(16.2%)	(19.7%)	(24.9%)	(22.1%)	(16.1%)	(19.0%)
CF RCP8.5_AN	7.7	3.2	6.8	2.4	6.6	2.6	7.1	2.6
	(23.9%)	(30.7%)	(17.9%)	(19.5%)	(29.6%)	(27.9%)	(15.9%)	(17.1%)
CP_PI2	10.5	4.1	9.1	4.4	10.9	4.3	8.5	4.1
	(14.1%)	(25.0%)	(14.2%)	(18.6%)	(12.7%)	(23.6%)	(13.4%)	(17.6%)
CF RCP4.5_PI2	9.0	2.9	8.6 (19.8%)	4.2	9.3	3.2	7.6	3.77
	(19.0%)	(31.2%)		(22.7%)	(16.0%)	(27.3%)	(22.3%)	(23.48%)
CF RCP8.5_PI2	9.2	2.9	8.0	3.7	9.3	3.1	7.0	3.4
	(11.7%)	(25.0%)	(14.4%)	(18.0%)	(12.4%)	(23.1%)	(18.7%)	(20.2%)

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