UNIVERSITÀ DEGLI STUDI DI SASSARI

CORSO DI DOTTORATO DI RICERCA
Scienze Agrarie

Produttività delle piante coltivate

Ciclo XXIX

PAST EXPERIENCE SUPPORTS FUTURE CHOICES FOR CROPPING SYSTEMS MANAGEMENT: THE ITALIAN LONG-TERM AGRO-ECOSYSTEM EXPERIMENTS (LTAEs) THROUGH THE IC-FAR NETWORK

Ileana Iocola

Coordinatore del Corso Prof. Antonello Cannas
Referente di Curriculum Prof. Giovanna Attene
Docente Guida Prof. Pier Paolo Roggero

Anno accademico 2015- 2016

TABLE OF CONTENTS

Introduction

The field experiments have always been considered of fundamental importance for agro-ecosystem understanding. But, although there are several long-term agroecosystem experiments (LTAE), short-term studies are much more common (Tilman 1989) because it is very difficult to sustain long-term experiments over the time. Furthermore, LTAEs are more susceptible to be interrupted because they required more organization and collaboration among scientists of different generations (Richter, 2007). The principal difference existing between long and short-term experiments is that LTAEs can provide insight into causes and magnitudes of changes occurring over the long-term processes, while short-term studies are mostly focused on the initial trajectories of the processes (Alan et al., 2012). For instance, the stock of soil organic carbon (SOC) changes very slowly because it is influenced by long-term processes and it can be detected with a 90% level of confidence after at least 6-10 years (Smith, 2004). Thus, data from long-term experimental sites are the only reliable ground proof for assessing these changes. Other than for understanding and linking short-term processes with longer temporal dynamics, data coming from LTAEs can be also considered reliable instruments to inform and validate mechanistic models for assessing the resilience of cropping systems and predict these dynamics across time or space.

The three years (2013-2016) research project IC-FAR – "llnking long term observatories with Crop systems modeling For a better understanding of climate change impact and Adaptation stRategies for Italian cropping systems" (www.icfar.it), funded by the Italian Ministry of Education, University and Research (MIUR), was designed with the idea to ensure continuity to the Italian LTAEs and evaluate if the old LTAEs, designed many years ago, can provide opportunities to address nowadays research questions and challenges that were not part of the original motivation of the experiment (Roggero, 2016). Furthermore, the main objective of the IC-FAR project was to connect the LTAEs managers with the crop and climate modelling communities in order to create an ideal platform for model calibration and validation using the long term datasets and for better understanding of how cropping system management can adapt to and mitigate the impacts of climate changes. The IC-FAR project provided answers to these questions by collecting data and analyzing sixteen LTAEs located in six different locations (Fig. 1) over a Nord-South transect across Italy. These experiments were originally designed for a variety of different purposes, principally for studying the long term effects of different agronomic management strategies (i.e, tillage practices, type and rate of nitrogen fertilization, crop rotation schemes) on crop yield and SOC and nitrogen dynamics.

A common database (Ginaldi et al., 2016) was created to harmonize, assemble, ensure comparability and quality of data and make information readily available to the wider research community. The IC-FAR database was designed in a way to be compatible with other international databases for model inter-comparison protocols proposed by international research modelling communities (i.e., AgMIP, Macsur) to which IC-FAR is linked. In fact, the IC-FAR partnership was composed by several Italian research teams (10 Universities - Basilicata, Bologna, Firenze, Marche, Padova, Perugia, Pisa, Sassari, Torino, Udine, the National Research Council - CNR Ibimet of Rome and the Agricultural Research Coucil - CRA SCA of Foggia) organized in a network with multiple international institutions from Europe and United States.

Fig. 1. Location of IC-FAR sites. The years of the establishment of the experiments are reported as labels

This PhD thesis was entirely developed in the IC-FAR framework, thus benefiting from the presence of numerous expertise in climate data management, advanced statistical analysis and crop modelling. Using the long-term experimental data of the IC-FAR project and integrating different methodological approaches such as data mining, multi model ensemble and future climate scenarios, it was evaluated the relevance of the long term datasets in generating new knowledge and understanding on processes that act at different temporal scales and how these processes interact with the environment and the agronomic management practices.

The work is divided into two chapters which in fact represent two different scientific papers. The first chapter reports a study that has been published during the PhD course on the European Journal of Agronomy (Seddaiu et al., 2016). In this study, using data from the LTAE located in Ancona and a recursive partitioning analysis (Strobl et al., 2009), we explored how long term tillage practices, N fertilization rate and their interaction with some meteorological factors (monthly temperatures and precipitations) can explain the crop inter-annual yield variability in a cereal two-year rotation under rainfed Mediterranean conditions. The identification of the main key factors driving crop yields can be useful to target further research and to support adaptive crop management responses to climate variability and to design policy interventions for rainfed cropping systems in the Mediterranean areas. In particular in this work, the PhD student has contributed to design and contextualize the analysis of the data using the recursive repartition approach, to write the manuscript and to discuss the results.

The second chapter reports a study on SOC stock dynamics which has been already submitted to the European Journal of Agronomy. Conservation tillage practices are frequently proposed as mitigation strategies, because they can contribute to increase SOC compared to conventional mouldboard ploughing. We assessed the long-term effects of different tillage management practices on crop yield and SOC stock dynamics in Mediterranean rainfed cereal cropping systems under current and future climate scenarios, using two LTEs dataset (AN and PI2) taken from the IC-FAR database and an ensemble of four crop models (APSIM, DSSAT, EPIC, SALUS). The multi-model mean was able to better reproduce and with less uncertainty the SOC dynamics than each single model, hence better SOC predictions are also expected to occur in the future assessment. In this study, the PhD student has given a substantial contribution to the conception, design, analysis, interpretation of data, perform the simulations with DSSAT and SALUS models, and write the manuscript.

The different methodologies used in this thesis for the analysis of the available IC-FAR datasets have underlined the relevance and opportunities that LTAEs can provide in identifying the relevant factors (weather, management and their interaction) influencing the inter-annual variability of crop yields and in understanding the processes controlling agroecosystem long term dynamics of sustainability indicators such as SOC content in the topsoil. The long term datasets also showed to be an invaluable source of information for cropping system modelling approaches, as they allow a robust calibration of model simulations of the long-term sustainability of cropping systems. Crop models are the only available tools to predict and effectively assess the potential for adaptation/mitigation responses in addressing the resilience of agroecosystems to climate change pressures. Obviously, the longer an experiment is conducted, the more valuable it becomes as it can provide more variable conditions (e.g. weather extremes, pathogens) capturing also some infrequent extreme events. The changes of the environmental conditions over time could also support and produce new ideas and insights and feed new inspiring experiments.

Last but not least, the modelling approaches applied to the LTAEs datasets provided an opportunity for harmonizing the data collection protocols, which is a prerequisite for the networking of the experimental sites and the further development of the fruitful interactions between the agronomic communities of modelers and LTAE managers.

References

Alan K. K., Smith D. M., Hobbie S.E., Collins S. L., Fahey T.J., Hansen G.J.A., Landis D.A., La Pierre K. J., Melillo J.M., Seastedt, T.R., Shaver G. R., Webster J.R., 2012. Past, Present, and Future Roles of Long-Term Experiments in the LTER Network. BioScience 62 (4), 377-389. doi: 10.1525/bio.2012.62.4.9

Ginaldi F., Bindi M., Dalla Marta A., Ferrise R., Orlandini S., Danuso F., 2016. Interoperability of agronomic long term experiment databases and crop model intercomparison: the Italian experience, Eur. J. Agron, 77, 209-222

Richter, D. deB., M. Hofmockel, M. A. Callaham, D. S. Powlson, and P. Smith. 2007. Long-Term Soil Experiments: Keys to Managing Earth's Rapidly Changing Ecosystems. Soil Sci. Soc. Am. J. 71:266-279. doi:10.2136/sssaj2006.0181

Roggero P.P., 2016. Introduction to the EJA special issue on "IC-FAR - Linking long term observatories with crop system modelling for a better understanding of climate change impact and adaptation strategies for Italian cropping systems". Eur. J. Agron, 77: 136-137

Seddaiu G., Iocola I., Farina R., Orsini R., Iezzi G., Roggero P.P., 2016. Long term effects of tillage practices and N fertilization in rainfed Mediterranean cropping systems: durum wheat, sunflower and maize grain yield. Eur. J. Agron, 77:166-178

Smith, P. 2004. How long before a change in soil organic carbon can be detected?. Global Change Biology, 10, 1878–1883. doi:10.1111/j.1365-2486.2004.00854.x

Strobl, C., Malley, J., Tutz, G., 2009. An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random forests. Psychol. Methods. 14(4), 323-348.

Tilman D., 1989. Ecological experimentation: Strengths and conceptual problems. Likens GE, ed. Long-Term Studies in Ecology. Springer, 136–1

CHAPTER 1

Long term effects of tillage practices and N fertilization in rainfed Mediterranean cropping systems: durum wheat, sunflower and maize grain yield

Giovanna Seddaiu[a,b,*], Ileana Iocola[b], Roberta Farina[c], Roberto Orsini[d], Giuseppe Iezzi[d], Pier Paolo Roggero[a,b]

[a]Dipartimento di Agraria, University of Sassari, Viale Italia 39, 07100 Sassari, Italy; [b]Nucleo di Ricerca sulla Desertificazione-NRD, University of Sassari, Viale Italia 39, 07100 Sassari, Italy; [c]Centro di ricerca per lo studio delle relazioni tra pianta e suolo, Consiglio per la Ricerca in Agricoltura, via della Navicella 2-4, Rome, Italy; [d]Dipartimento di Scienze Agrarie Alimentari e Ambientali, Università Politecnica delle Marche, via Brecce Bianche, 60131 Ancona, Italy.

http://doi.org/10.1016/j.eja.2016.02.008

Abstract

Long term investigations on the combined effects of tillage systems and other agronomic practices such as mineral N fertilization under Mediterranean conditions on durum wheat are very scanty and findings are often contradictory. Moreover, no studies are available on the long term effect of the adoption of conservation tillage on grain yield of maize and sunflower grown in rotation with durum wheat under rainfed Mediterranean conditions. This paper reports the results of a 20-years experiment on a durum wheat-sunflower (7 years) and durum wheat–maize (13 years) two-year rotation, whose main objective was to quantify the long term effects of different tillage practices (CT = conventional tillage; MT = minimum tillage; NT = no tillage) combined with different nitrogen fertilizer rates (N0, N1, N2 corresponding to 0,45 and 90 kg N ha^{-1} for sunflower, and 0, 90 and 180 kg N ha^{-1} for wheat and maize) on grain yield, yield components and yield stability for the three crops. In addition, the influence of meteorological factors on the interannual variability of studied variables was also assessed. For durum wheat, NT did not allow substantial yield benefits leading to comparable yields with respect to CT in ten out of twenty years. For both sunflower and maize, NT under rainfed conditions was not a viable options, because of the unsuitable (i.e., too wet) soil conditions of the clayish soil at sowing. Both spring crops performed well with MT. No significant N × tillage interaction was found for the three crops. As expected, the response of durum wheat and maize grain yield to N was remarkable, while sunflower grain yield was not significantly influenced by N rate. Wheat yield was constrained by high temperatures in January during tillering and drought in April during heading. The interannual yield variability of sunflower was mainly associated to soil water deficit at flowering and air temperature during seed filling. Heavy rains during this latter phase strongly constrained sunflower grain yield. Maize grain yield was negatively affected by high temperatures in June and drought in July, this latter factor was particularly important in the fertilized maize. Considering both yield and yield stability, durum wheat and sunflower performed better under MT andN1 while maize performed better

under both CT and MT and with N2 rates. The results of this long term study are suitable for supporting policies on sustainable Mediterranean rainfed cropping systems and also for cropping system modelling.

Keywords: No tillage; Minimum tillage; Silty-clay soil; Yield stability; Recursive partitioning analysis; Rainfed cropping systems

1. Introduction

Rainfed cereal cropping systems based on rotations between wheat and a spring crop are widespread in Mediterranean Europe. In the southern Mediterranean countries, winter cereals are grown as monoculture or in rotation with other autumn–spring crops such as pulses, fallow pasture, hay crops or other minor cereals. In the northern Mediterranean countries, the rainfall regime and the high water holding capacity of the arable soils allow the cultivation ofspring-summer crops such as sunflower, sorghum or maize under rainfed conditions. Conservation agricultural practices (CA) such as reduced or no tillage, characterized by a low disturbance of soil, coupled with crop residues retention, are increasingly widespread for cultivating cereals and industrial crops in the regions with dry Mediterranean climate (Kassam et al., 2012). CA in the Mediterranean dry areas can have positive effects on crop productivity due to increased soil moisture and nutrient availability (López-Garrido et al., 2011) and can contribute to reduce soil erosion, nitrate leaching, greenhouse gas emissions and fuel costs (Kassam et al., 2012). Site specific effects of CA (i.e., related to soil and climate types) on soil water retention (e.g., De Vita et al., 2007), soil aggregation stability (e.g.,Hernanz et al., 2002), microbial activity (Pastorelli et al., 2013) and weed dynamics (De Sanctis et al., 2012) can largely explain the various impacts of CA on crop yields. However, evidences on long term effects of CA practices on crop yield and stability are less frequent and sometimes contradictory. More than 50% of durum wheat cultivated worldwide lies in the Mediterranean region (Bozzini, 1988) where it represents one of the most important crops in rainfed cropping systems. In these areas, wheat grain yield is characterized by a high interannual variability due to erratic seasonal weather patterns, particularly irregular rainfall distribution and high temperatures during thegrain filling stage (Lopez-Bellido et al., 1996). Under rainfed semi-arid Mediterranean conditions, Amato et al. (2013) and Ruisi et al.(2014) showed that durum wheat yield was higher under no tillage than conventional tillage only when water stress was high and that N fertilizer requirements increase with no tillage compared with conventional tillage, because of changes in N cycling that lead to are duction in plant-available soil N. Sunflower, together with other oilseed crops, is recently drawing a renewed commercial and scientific attention because of its role as energy crop in the cereal-based cropping systems (Barontini et al., 2015 and references therein). Under Mediterranean rainfed conditions, sunflower production is heavily constrained by summer water stress, hence it is practiced as a rainfed crop only in the clayey soil of the northern areas, where the spring-summer rainfall regime is favorable and soil water holding capacity can buffer crop water availability. Under Mediterranean rainfed conditions in southern Spain, CA did not exert a beneficial influence on sunflower grain yields (López-Bellido et al., 2003;Murillo et al., 1998), although a high interannual variability was observed, mainly influenced by soil water conditions throughout the crop cycle.CA practices may have site-specific impacts on rainfed grain maize yields. CA practices in well drained soils and under high N fertilization inputs and crop rotation may improve maize yield, and yield stability seems to be not significantly affected by reduced tillage (Rusinamhodzi et al., 2011). Rainfall was confirmed as the most important determinant of maize yield under rainfed conditions. The meta-analysis of Rusinamhodzi et al. (2011) clearly revealed that the success of CA in improving maize yields depends on the adoption of other good agronomic practices such as targeted site-specific fertilizer application, timely weeding and crop rotations. To our knowledge, no studies are available on the long term effect of conservation tillage on the productivity of rainfed maize and sunflower under Mediterranean conditions. The duration of such studies on sunflower ranged from one (Lopez-Garrido et al.,2014) to four years (López-Bellido et al., 2003). In the case of grain maize, the available long term studies on the role of tillage systems on yields are referred to a range of climate conditions, from a typical Northern-Central USA climate (Karlen et al., 2013), to the subhumid temperate climate in the Pampas of Argentina (Diaz-Zorita et al., 2002), to the semi-arid, subtropical climate of highlands of Central Mexico (Verhulst et al., 2011) and to the cold semi-arid and humid subtropical climate of Northern China (Wang et al., 2012), none of which comparable to the Mediterranean climate type. The long-term impact of conservation tillage practices for durum wheat under Mediterranean conditions was instead analysed by several scholars (e.g., Amato et al., 2013; Lopez-Bellido et al., 1996, 2000, 2001; Mazzoncini et al., 2008). However, findings were often contradictory due to differences among the experimental sites in terms of climatic conditions, soil type, management practices, agronomic history and duration of experiments. Hence the effectiveness of various tillage systems is highly site specific and the impact of yield-limiting factors may vary significantly depending on the environmental conditions and on the interactions between them and the management practices (Subedi and Ma, 2009). Moreover, very few long term investigations have been conducted to study the combined effects of tillage systems and other agronomic practices such as mineral N fertilization under Mediterranean conditions (Lopez-Bellido et al., 1996, 2001). In the context of rainfed cereal cropping systems of the clayey hills of central Italy, in approximately 300,000 ha of arable hill-slope land, the rotation of wheat and a spring-summer crop such as sunflower or maize implies about 8–9 months of intercropping period between the wheat harvest (early

July) and the seeding of sunflower (March) or maize (April). Because of the high soil clay content (up to 50%) and the seasonal rainfall/evapotranspiration regime, the main tillage under the conventional practice (i.e.,30–40 cm deep ploughing) is made in the summer, in order to exploit the structuring effect of thermal and water regimes in the soil during autumn–winter. Moreover, tillage practices during autumn may be difficult due to the high plasticity of the clayey soils when autumn is wet. Further harrowing is practiced during inter-cropping to prepare the maize or sunflower seedbed. Therefore, the conventional practice exposes the bare soil to erosion (Roggero and Toderi, 2002) and nitrate leaching (De Sanctis et al., 2009) during the wet and cool season. CA techniques including no tillage and reduced N fertilization rates can provide options to mitigate such undesirable processes, but are considered by farmers as not reliable enough to ensure yield targets and stability, particularly in the case of the spring–summer crops. In this paper we explore the implications for adopting CA practices from a Long Term Experiment (LTE) based on a two-year rotation of durum wheat and sunflower or maize under rainfed Mediterranean conditions and heavy clayey soils. The aims of this study were to (i) assess the long term influence of tillage systems and N fertilization rates on yield, yield components and stability of durum wheat, sunflower and maize under Mediterranean rainfed conditions of the hilly areas of Central Italy and (ii) analyse at what extent the meteorological factors can influence the interannual variability of yield for the three crops.

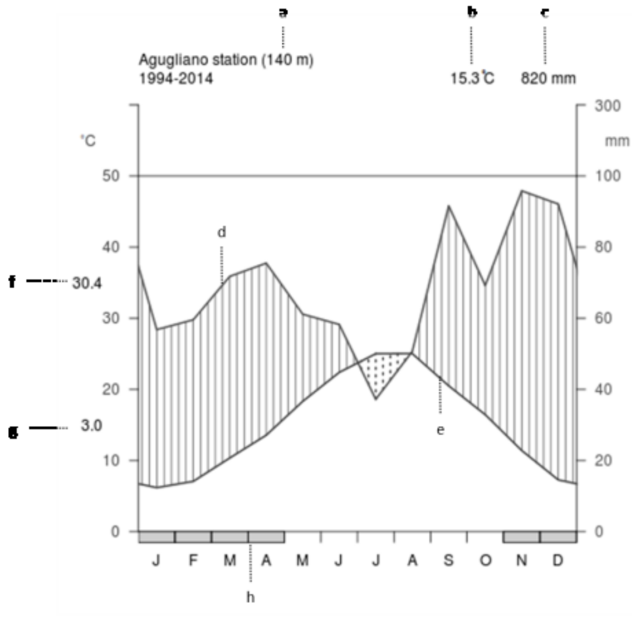

Fig. 1. Walter and Lieth climate diagram of Agugliano weather station. Period of observation: 1994–2014. (a) Elevation, (b) annual average of temperature, (c) annual average of precipitation, (d) monthly mean temperatures, (e) monthly mean precipitation, (f) mean daily maximum temperature of the warmest month, (g) mean daily minimum temperature of the coldest month, (h) indication of potential frost periods (months with absolute monthly minimum temperature below 0◦C). Vertical lines: humid period, dotted area: dry period.

2. Materials and methods

2.1. Experimental site

The LTE is located at the “Pasquale Rosati” experimental farm of the Polytechnic University of Marche in Agugliano, Italy (43◦32_N,13◦22_E, 100 m a.s.l.), on a silty-clay soil classified as Calcaric Gleyic Cambisols (FAO, 2006), almost free of gravel, with a high clay (49%) and calcium carbonate (31%) content, pH of 8.3, a low soil organic carbon (SOC) content (0.7%) and a slope of about 10%. The climate of the experimental site is Mediterranean (Fig. 1), with a mean annual rainfall of 820 mm, mostly distributed in the autumn and winter (54%) and in the spring (24%). The mean air temperature is 15.3◦C, with monthly means ranging from 6.2◦C in January to 25◦C in August. The mean annual evapotranspiration (ET0), estimated at daily basis over the 20-years period with the FAO Penman–Monteith formula by using the computer tool ET0Calculator (Annandale et al., 2002), was 1068 mm (standard deviation (SD) = 75 mm), producing an average aridity index(Rain/ETo) of 0.76 (SD = 0.16).

2.2. Experimental design and crop management

The LTE was established in 1994 and is still on-going consisting on a rainfed 2-years rotation with durum wheat (*Triticum durum* L. cv. Grazia, ISEA) in rotation with sunflower (*Helianthus annuus* L.,cv. Starsol, ISEA) until 2001 or maize (*Zea mays* L., DK440 hybrid, Dekalb Monsanto, FAO class 300) from 2002 onwards. The crop rotation was duplicated in two adjacent fields to allow for all crops to be present each year. Within each field, three tillage (T, main plot,1500 m^2) and three nitrogen fertilizer (N, sub-plot, 500 m^2) treatments were repeated in the same plots every year and arranged according to a split plot experimental design with two replications. The conventional tillage (CT), that is representative of the business as usual tillage practice in the study area, and the minimum tillage (MT) plots were ploughed along the maximum slope every year by a mouldboard (with 2 plows) at a depth of 40 cm or a chisel at a depth of 25 cm respectively in autumn for wheat and in summer for maize. The seedbed was prepared with double harrowing before the sowing date. The no tillage (NT) soil was left undisturbed except for crop residues and weed chopping and total herbicide spraying prior to direct seed drilling. The three N fertilizer treatments (N0,N1 and N2) corresponded to 0, 90 and 180 kg N ha^{-1} distributed in two rates for wheat and at seeding for maize, while sunflower received 0, 45 and 90 kg N ha^{-1} about one month after sowing. The N1 treatment was compliant with the agri-environmental measures adopted within the Rural development Plans at local scale. The N2 treatment was the business as usual N rates in the study area at the start of the experiment. The N0 treatment was chosen as a control. Dates of the agronomic management practices for all the three crops are reported in Table 1.

2.3. Measurements

At crop maturity, grain yield for all the studied crops was measured in each plot through combine harvesters and it was expressed on a dry matter content basis. Twenty (1995–2014), seven (1995–2001) and thirteen (2002–2014) years of grain yield data were collected respectively for durum wheat, sunflower and maize. Yield components were determined on thirteen (1995–2001, 2007–2008, 2011–2014), seven (1995–2001) and nine (2002–2003, 2006–2008, 2011–2014) years respectively for durum wheat, sunflower and maize. For durum wheat, the number of spikes m^{-2} was determined by counting the number of spikes along two adjacent 1-m long rows. The grain weight per spike and the 100 grains weight were estimated on 30 spikes randomly collected per subplot. For sunflower and maize, yield components were assessed on three random samples per subplot of 10 plants each for a total of 30 plants sampled in each subplot.

Table 1. Number of days from the first of January (median, minimum and maximum) of the agronomic management practices adopted during the experimental years.

Agro-technique	Durum wheat	Sunflower	Maize
Ploughing (40 cm) ^{CT}	285 (223-304)	250 (233-297)	249 (235-260)
Ripping (70 cm) ^{MT}	272 (228-291)	258 (242-306)	245 (231-312)
Harrowing and seed bed preparation $^{CT, MT}$	303 (261-330)	73 (58-92)	94 (36-138)
P fertilization (70 kg P_2O_5 ha^{-1})	319 (296-345)	69 (43-89)	92 (58-138)
Sowing	327 (293-339)	90 (81-100)	103 (91-139)
Gliphosate application ^{NT} *	90 (70-122)	89 (91-101)	134 (99-172)
1st N fertilization **	67 (35-94)	115 (105-151)	126 (98-169)
2nd N fertilization **	101 (76-116)	-	-
Harvest	188 (178-197)	251 (235-276)	274 (255-283)

CT: Conventional tillage; MT: Minimum tillage; NT: No-tillage
*****at a rate of 2.25 l ha^{-1}
****** for durum wheat 50 % of N distribution for each date

For each plant the grains weight per inflorescence and the 100 grains weight were determined. Plant density of sunflower and maize was determined by counting the number of plants along two adjacent 10-m long rows. Meteorological data were obtained from the Agugliano (43◦32_N, 13◦22_E, elevation: 140 m) weather station of the Agrometeorological Regional Service of Marche (ASSAM) that is located nearby the experimental site. E-OBS dataset (Haylock et al.,2008) from the EU-FP6 project ENSEMBLES (http://ensembles-eu.metoffice.com) was used for retrieval of the missing data related to daily precipitations, minimum and maximum temperatures.

2.4. Data analyses

All data were submitted to the PROC MIXED procedure in SAS (SAS Institute, 1999), suitable for analyzing mixed effects and repeated measures with non-constant variance and any covariance structure models. The independence assumption on the error terms required for the ANOVA of a factorial model (Montgomery, 1997) was in fact likely not met. The appropriate mixed model was built following Onofri et al., 2016 and considering "year" as a repeated factor and for each year, tillage (T) and N fertilisation (N) as randomised treatment factors. The appropriate variance–covariance structure for this particular model was selected fitting all possible models and making an 'a posteriori' selection, based on those statistics which put a penalty on 'complexity', such as the Akaike Information Criterion (AIC: Akaike, 1974). For assessing the yield stability over the experimental years, the Shukla's (1972) stability variance was calculated by applying the R code reported by Onofri et al., 2016. The closer to zero is the Shukla's stability variance the more stable is the yield. We tested the null hypothesis of any grain yield trend over time associated to the repeated T and N fertilization treatments by fitting a simple linear regression of yield *vs*. years as suggested by Piepho et al. (2014) The treatment (T × N) effect was regarded as fixed as well as the treatment-dependent slopes, while the year effect and the year × treatment interactions as random. The robustness of this analysis increases with the duration of the experiment (Onofri et al., 2016), hence is higher for the durum wheat experiment than for maize (13-years trial). For this reason, this analysis was not performed for sunflower. For all the studied crops, three agro-meteorological variables were calculated and analysed on monthly basis starting from sowing until crop harvest: mean temperature (Tmean), rainfall amount (Rain) and cumulated reference evapotranspiration (ET0). Linear correlation coefficients (Pearson r) were then used to determine the effect of each meteorological variable on yields considering both yields of all treatments and yields related to each singular management factor (CT, MT, NT and N0, N1, N2). Only the meteorological variables that were statistically significant in at least one treatment, together with the categorical factors T and N, were submitted as inputs in a recursive partitioning analysis. The inter-annual variability of these variables is shown in Table 2. The recursive partition explores the structure of a dataset, developing decision rules for predicting a categorical (classification tree) or continuous (regression tree) variable (Rokach and Maimon, 2008; Strobl et al., 2009). In our study, we used the regression tree function *ctree* available in the party R package (Hothorn et al., 2006) to explore the variation of yield as influenced by several explanatory (meteorological and management) variables. Regression trees are constructed by recursively splitting the response variable (i.e., grain yield) into two groups on the basis of the explanatory variables (Tmean, Rain, ET0) so as to minimize variability within a group and maximizing variability between groups. At the end, the terminal node (leaves) is characterized by the mean values of the response variable.

Ctree function bases its node splitting on statistical tests providing a P value for the significance of its splitting. Although *ctree* was used in this study just to explore the interactions among explanatory variables and not as a predictive tool, we estimated anyway the performance of the regression using the root-mean-square error (RMSE) and the mean absolute error (MAE).

RMSE was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{obs,i} - y_{model,i})^2}{n}}$$

and MAE was given by:

$$MAE = \frac{\sum_{i=1}^{n}| y_{obs,i} - y_{model,i} |}{n}$$

where y_{obs} is the observed crop yield, y_{model} is the modelled yield at $year_i$ and n is the number of observations.

Table 2. Annual variability of the monthly statistically significant meteorological variables selected by ctree tool for the three studied crops. Period of observation: 1994-2014.

Year	M1_Tmean	M4_Rain	M4_ET0	M5_Tmean	M6_Tmean	M6_ET0	M7_Tmean	M7_Rain	M8_Rain
1994	7.0	77.6	91.6	17.2	20.8	147.2	24.3	68.6	4.4
1995	5.8	93.4	93.0	16.9	19.4	152.5	24.5	40.8	97.6
1996	6.0	82.0	95.0	17.5	22.2	165.5	23.3	28.2	181.2
1997	6.0	103.6	92.4	18.4	22.4	158.1	23.6	27.8	67.8
1998	5.7	95.0	91.1	17.1	23.2	157.5	26.0	14.8	24.0
1999	7.0	87.6	86.5	19.7	22.5	143.8	24.3	54.4	39.2
2000	4.7	51.2	87.5	19.7	22.9	162.5	23.5	53.8	15.2
2001	7.4	82.6	91.1	18.8	21.8	156.7	25.1	4.4	67.8
2002	4.5	67.8	83.4	18.4	23.3	164.9	23.9	94.4	78.8
2003	6.2	29.0	89.8	19.5	26.2	166.9	26.9	14.2	43.4
2004	5.3	75.6	75.6	15.9	21.7	139.4	25.1	12.8	18.0
2005	4.8	73.6	92.6	18.8	22.0	147.7	25.0	45.0	77.6
2006	4.1	109.8	89.8	18.4	22.4	147.5	25.0	51.4	95.0
2007	9.5	30.0	111.1	20.0	23.8	152.7	27.1	1.0	89.2
2008	7.5	95.4	102.8	18.9	23.2	155.0	26.0	38.0	1.4
2009	5.7	70.8	90.5	21.2	22.4	143.3	25.8	26.6	24.4
2010	4.4	90.2	89.3	18.2	22.0	151.0	25.6	17.2	79.4
2011	5.1	48.6	108.2	18.4	22.8	152.1	24.4	50.2	0.2
2012	6.5	114.0	95.2	16.8	21.3	152.3	28.1	6.8	35.8
2013	7.0	28.6	90.3	17.6	21.6	135.2	24.6	23.2	19.4
2014	9.2	79.0	79.2	17.7	22.5	138.7	23.4	108.4	4.4
Mean	*6.2*	*75.5*	*91.7*	*18.3*	*22.4*	*151.9*	*25.0*	*37.2*	*50.7*
SD	*1.5*	*25.4*	*8.2*	*1.3*	*1.3*	*9.0*	*1.3*	*28.4*	*44.7*

Tmean= mean monthly temperature (°C), Rain = monthly precipitation (mm), ET0 = cumulated monthly reference evapotranspiration (mm), M = Month from 1 (January) to 8 (August).

3. Results

3.1. Durum wheat yield, yield components and yield stability

Significant year × T and year × N interactions were observed, while no significant T × N interaction was observed (Table 3). Grain yields ranged from 1.3 (CT 2004) to 5.0 t ha^{-1}(CT 2013) and from 0.6 (N0 2007) to

5.9 t ha^{-1}(N2 2004). Grain yield under NT was significantly higher than CT in one out of twenty years, while CT and NT were not significantly different in ten out of twenty years (Table 4). MT differed significantly from CT in eight out of twenty years being significantly higher and lower in three and five years respectively. Wheat grain yields were higher under MT than NT in seven out of twenty years throughout the experiment. N2 showed higher grain yields than N1 in sixteen out of twenty years. Among the four years with no significant differences between N2 and N1, two years were the least productive ones.

On average, NT resulted in lower spikes m^{-2} than MT and CT by about −13% (313 *vs*. 359). A significant relationship was found between spikes m^{-2} and grain yield independently of the tillage treatment averaged for all N levels, while the same relationship was significant only for N2 (Fig. 2). The number of kernels per spike and the 100 kernels weight were significantly influenced by the tillage × year and nitro-gen × year interactions (Table 3). The number of kernels per spike ranged between 21 and 42 with NT showing a slight higher value than CT and MT (33 vs. 29). In 70% of the years when the number of kernels per spike was determined, N2 had about 6 kernels per spike more (+20%) than N1. In about half of the years, 100 kernels weight showed significant higher values under NT than CT.

Table 3. Results of the repeated measures mixed model for durum wheat traits. Bold numbers in columns indicate significant P values (≤ 0.05) of the F tests.

Factors	df	Grain yield	Spikes m^{-2}	nr. kernels per spike	100 kernels weight
Tillage (T)	2	0.11	0.05	0.05	0.17
N rate (N)	2	**<0.01**	0.11	**<0.01**	**0.02**
Year (Y)	19	**<0.01**	**<0.01**	**<0.01**	**<0.01**
T x N	4	0.09	0.88	0.26	0.16
T x Y	38	**<0.01**	0.34	**0.05**	**0.02**
N x Y	38	**<0.01**	0.06	**<0.01**	**<0.01**
T x N x Y	76	0.76	0.59	0.11	0.16
CV (%)		*12*	*11*	*9*	*2*

The stability analysis (Fig. 3) showed that the most productive treatment (CT N2) was the least stable in terms of grain yield, while CT N1 and, even more, MT N1 characterized by intermediate yields were the most stable. Also NT N0 had very stable grain yields that were however associated to low yields. No significant time trend was found for grain yield for any of the T × N fertilization combinations.

The correlation analysis between the meteorological variables and grain yield selected the following significant variables (Table 5): mean temperature of January (M1 Tmean), mean temperature (M3 Tmean) and rainfall (M3 RAIN) of March, mean temperature (M4 Tmean), rainfall (M4 RAIN) and reference evapotranspiration (M4 ET0) of April and mean temperature of May (M5 Tmean).

Table 4. Durum wheat grain yield (kg ha^{-1}) as influenced by tillage and N fertilization systems over twenty years.

	Tillage			N fertilization		
Year	CT	MT	NT	N0	N1	N2
1995	2907 a	2674 a	2253 b	1585 b	3069 a	3181 a
1996	2613 a	2033 b	2073 b	1078 c	2585 b	3057 a
1997	3299 a	3106 ab	3015 b	1417 c	3505 b	4497 a
1998	2904 a	2878 a	2890 a	1422 c	3404 b	3846 a
1999	2294 a	2081 a	1688 b	1088 c	2206 b	2769 a
2000	2244 a	2132 a	2028 a	930 c	2529 b	2943 a
2001	1748 ab	2017 a	1638 b	1036 b	2291 a	2077 a
2002	3778 a	3219 b	2371 c	2168 c	3315 b	3885 a
2003	2793 ab	2679 b	3154 a	1379 c	3331 b	3917 a
2004	5003 a	3932 b	4435 ab	2536 b	4910 b	5924 a
2005	3285 a	3440 a	3217 a	2103 b	3717 a	4122 a
2006	3852 a	3205 b	3420 b	1779 c	3585 b	5113 a
2007	2265 a	1822 b	1478 c	570 c	1912 b	3082 a
2008	3181 a	2954 ab	2546 b	1414 c	2951 b	4316 a
2009	2812 b	3354 a	3700 a	1493 c	3831 b	4543 a
2010	3573 a	3504 a	2752 b	1029 c	3360 b	5439 a
2011	2103 b	2968 a	2449 ab	1582 c	2541 b	3397 a
2012	2906 a	3073 a	3513 a	1511 c	3122 b	4860 a
2013	1252 b	1742 a	1306 b	972 b	1540 a	1788 a
2014	2123 a	2259 a	2379 a	986 c	2430 b	3345 a
Mean	*2847*	*2754*	*2615*	*1404*	*3007*	*3805*

Means within a row for tillage and N fertilization factors separately that are followed by the same letter are not significantly different at $P \leq 0.05$.

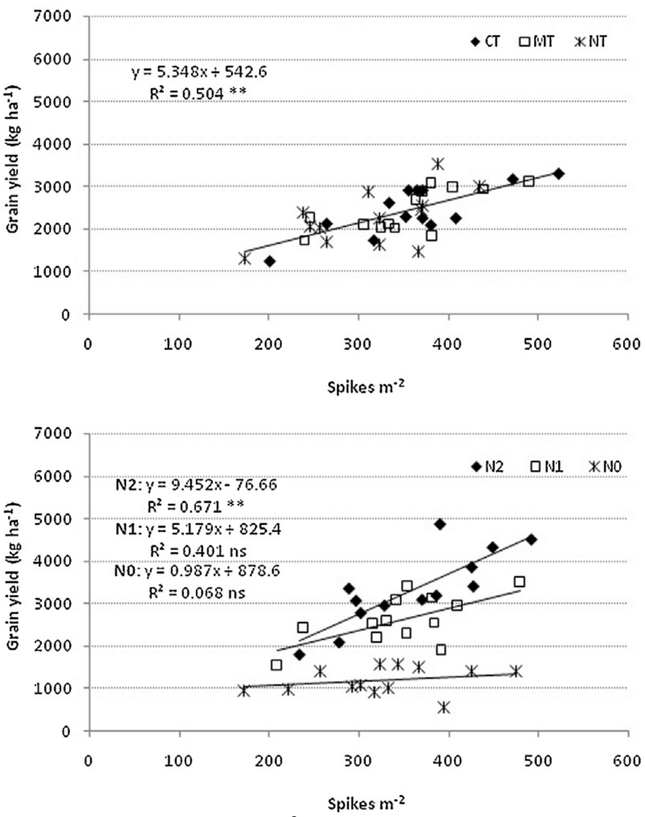

Fig. 2. Relationships between mean grain yield and spikes m^{-2} for durum wheat as influenced by tillage techniques (top) or by N fertilization rates (bottom). Data on spikes m^{-2} are referred to thirteen years from 1995 to 2001, from 2007 to 2008 and from 2011 to 2014.

The decision tree obtained considering these significant meteorological variables, together with T and N factors, is reported in Fig. 4. The first important factor was N fertilization, with N0 associated to the lowest yields. M1 Tmean was the second most important factor independently of the N fertilization rate, and 6.5◦C represented the partitioning threshold. The group identified by N2 and N1 and M1 Tmean ≤ 6.5◦C was further split according to the N fertilization rate and both subgroups obtained were divided by a M4 ET0 value of 91 mm. Other important meteorological factors were M4 Rain for the group firstly identified by N2and N1 and M1 Tmean > 6.5◦C, and the M5 Tmean for the group identified by N0 and M1 Tmean ≤ 6.5◦C. The lowest wheat grain yield was associated to N0 and M1 Tmean > 6.5◦C, while the highest yield to M1 Tmean ≤ 6.5◦C, N2 and M4 ET0 ≤ 91 mm. The two indicators of the model performance RMSE and MAE were respectively 694 kg ha^{-1}and 525 kg ha−1. Similarly to what found with the mixed model analysis, the effect of tillage on wheat grain yield was not significant also for the decisional tree approach.

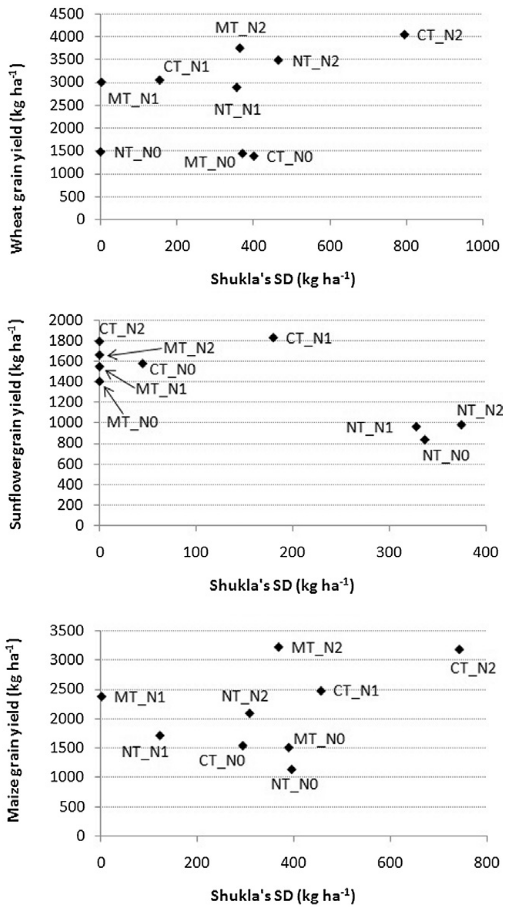

Fig. 3. Relation between yield and yield stability (Shukla SD) for durum wheat (top), sunflower (middle) and maize (bottom).

Table 5. Correlation coefficients among wheat grain yields and selected monthly meteorological variables.

	ALL		N2		N1		N0		CT		MT		NT	
M1_Tmean	-0.30	***	-0.43	***	-0.52	***	-0.52	***	-0.29	*	-0.32	*	-0.30	*
M3_Tmean	-0.20	**	-0.30	*	-0.34	**	-0.34	**	-0.23		-0.15		-0.23	
M3_RAIN	-0.16	*	-0.14		-0.37	**	-0.31	*	-0.18		-0.11		-0.20	
M4_Tmean	-0.20	**	-0.23		-0.43	***	-0.35	**	-0.25		-0.16		-0.19	
M4_RAIN	0.23	**	0.43	***	0.36	**	0.24		0.24		0.20		0.24	
M4_ET0	-0.18	*	-0.20		-0.37	**	-0.32	*	-0.20		-0.12		-0.21	
M5_Tmean	-0.15	*	-0.20		-0.22		-0.33	*	-0.18		-0.11		-0.15	

where ALL = yields of all treatments; N2, N1, N0 = yields for 180, 90, 0 kg N ha^{-1}; CT= yields for conventional tillage; MT = yields for minimum tillage; NT = yields for no tillage; M = Month from 1 (January) to 5 (May).
*: significant at P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.

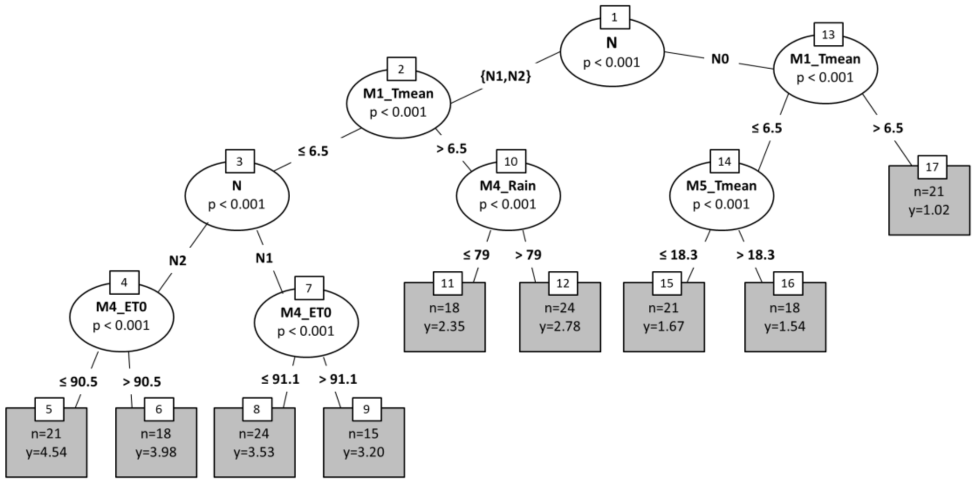

Fig. 4. Regression tree showing the emerging drivers of the durum wheat grain yield interannual variation: meteorological variables (Tmean = mean monthly temperature, RAIN = monthly precipitation, ET0 = cumulate monthly reference evapotranspiration; M = month from 1-January to 5-May) and N fertilization rate (0, 90, 180 N kg ha^{-1}). n = number of observations and y = t ha−1) in each terminal node.

Table 6. Results of the repeated measures mixed model for sunflower traits. Bold numbers in columns indicate significant P values (≤ 0.05) of the F tests.

Factors	df	Grain yield	Plants m^{-2}	Achenes weight per flower head	1,000 achenes weight
Tillage (T)	2	**0.01**	<0.01	0.14	0.06
N rate (N)	2	0.10	0.69	**0.04**	**0.05**
Year (Y)	6	**<0.01**	**<0.01**	**<0.01**	**0.01**
T x N	4	0.61	0.91	0.33	0.42
T x Y	12	**<0.01**	**<0.01**	**<0.01**	**<0.01**
N x Y	12	0.66	0.74	0.88	0.10
T x N x Y	24	0.97	0.93	0.77	0.03
CV (%)		*17*	*14*	*17*	*7*

Table 7. Sunflower grain yield (kg ha^{-1}) as influenced by tillage and N fertilization systems over seven years.

	Tillage			N fertilization		
Year	CT	MT	NT	N0	N1	N2
1995	1366 a	564 b	415 b	653	804	887
1996	883 a	640 b	266 c	593	599	597
1997	1419 a	1138 b	1374 ab	1179	1390	1362
1998	3270 a	3106 a	1982 b	2415	3037	2906
1999	2350 a	2113 a	1327 b	1641	1931	2218
2000	1888 a	1789 a	457 b	1219	1401	1514
2001	1271 a	1339 a	498 b	860	1040	1207
Mean	*1778*	*1527*	*903*	*1223*	*1457*	*1527*

Means within a row for the tillage factor that are followed by the same letter are not significantly different at P ≤ 0.05.

3.2. Yield, yield components and yield stability in sunflower

Sunflower grain yield showed a high interannual variability ranging from 0.6 to 2.8 t ha^{-1} (Table 6). A significant year × T interaction was found while no effect of N was observed (Table 6). Grain yield under NT was always significantly lower than CT (Table 7) except for one year out of seven (1997). In the last four years of sunflower cultivation, MT showed similar yields to CT and higher than NT. Plants m^{-2}, achenes weight per flower head and the 1000 achenes weight showed a significant T × year interaction (Table 6). On average (data not shown), under NT the number of plants per m^{-2} were lower by 54% than CT (2.6 vs 5.6). In two out of seven years (1996 and 1998), the number of plants per m^{-2} under NT was more than 80% lower than under CT. Under MT, plant density was significantly lower than under CT in six out of seven years, on average−12% (from −3 to −18%), while it was slightly higher only in 1998. The achenes weight per flower head (data not shown) ranged from 8.6 to 67.7 g under NT in 1995 and CT in 1999 respectively. However, on average, NT showed a +13% higher achenes weight per flower head with respect to CT.

The results of the stability analysis (Fig. 3) showed that CT N2 and MT N2 were on average the most productive treatments and, at the same time, with the least unstable yields. All the NT treatments independently of the N fertilizer rate had the lowest stability. The correlation analysis between sunflower grain yields and the meteorological variables selected the following significant variables (Table 8): mean temperature (M4 Tmean) and precipitation (M4 Rain) of April, the reference evapotranspiration of May (M5 ET0), the mean temperature (M6 Tmean) and reference evapotranspiration of June (M6 ET0), mean temperature of July (M7 Tmean), mean temperature (M8 Tmean), precipitation (M8 Rain) and reference evapotranspiration (M8 ET0) of August. The significant meteorological variables together with N and T factors were used as input in the regression tree analysis illustrated in Fig. 5. The first most important factor was M7 Tmean followed by the T factor with higher sunflower yields associated to CT and MT. This group was further split according to a threshold value of 39.2 mm for the M8 Rain, while the NT group was split according to the M6 ET0. The highest sunflower grain yield was associated to M7 Tmean ≤ 25.1◦C, CT or MT and M8 Rain ≤ 39.2 mm, while the lowest yield to M7 Tmean ≤ 25.1◦C, NT and M6 ET0 > 156.7 mm.

The performance indicators RMSE and MAE were respectively475 kg ha^{-1} and 398 kg ha^{-1}. According to what found with the mixed model analysis, the N fertilization rate was not considered a significant explanatory variable also in the recursive partition approach.

Table 8. Correlation coefficients among sunflower grain yields and selected monthly meteorological variables.

	ALL	N2	N1	N0	CT	MT	NT
M4_Tmean	0.29 *	0.32	0.28	0.29	0.45 *	0.50 *	-0.07
M4_Rain	0.11	0.09	0.13	0.10	0.05	-0.06	0.46 *
M5_ET0	-0.38 **	-0.40	-0.40	-0.36	-0.52 *	-0.47 *	-0.25
M6_Tmean	0.47 ***	0.46 *	0.47 *	0.50 *	0.44 *	0.65 **	0.45 *
M6_ET0	-0.30 *	-0.37	-0.28	-0.26	-0.38	-0.26	-0.39
M7_Tmean	0.54 ***	0.55 **	0.58 **	0.52 *	0.64 **	0.62 **	0.54 *
M8_Tmean	0.43 ***	0.47 *	0.42	0.42	0.46 *	0.68 ***	0.23
M8_Rain	-0.46 ***	-0.51 *	-0.45 *	-0.44 *	-0.53 *	-0.63 **	-0.35
M8_ET0	0.20	0.15	0.24	0.22	0.16	0.03	0.57 **

where ALL = yields of all treatments; N2, N1, N0 = yields for 180, 90, 0 kg N ha^{-1}; CT= yields for conventional tillage; MT = yields for minimum tillage; NT = yields for no tillage; M = Month from 1 (January) to 5 (May).
*: significant at P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.

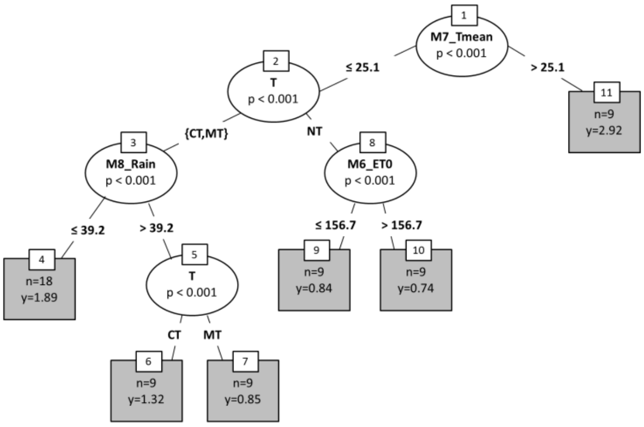

Fig. 5. Regression tree showing the emerging drivers of the sunflower grain yield interannual variation: meteorological variables (Tmean = mean monthly temperature; RAIN = monthly precipitation; M = month from 6-June to 8-August) and management factors (T—Tillage: CT = conventional tillage, MT = minimum tillage; NT = no tillage). n = number of observations and y = mean yield (t ha^{-1}) in each terminal node.

3.3. Yield, yield components and yield stability in maize

Maize grain yield showed an irregular pattern over the thirteen years period ranging from very low values (2003 and 2007 for NT) up to 5.0 t ha^{-1} (2012 for MT). The interactions between both year × T and year × N were significant (Table 9). In 2003 and 2007, grain yields under NT were almost zero, due to the very low plant density that did not allow mechanical harvest (Table 10). In more than half of the years, NT showed a lower yield than CT (−40%). MT differed significantly from CT in eight out of thirteen years being significantly higher and lower in four years respectively. N2 showed comparable grain yields to N1 in 30% of years. N1 in none of the years showed significantly higher yield than N2.In terms of plants m^{-2}, NT showed always lower values (3.4 plants m^{-2}) by about −45% (from −20% to −96%) compared to CT and MT (data not shown). Plant density was positively correlated with grain yield (Fig. 6) with data grouped by T treatments. By considering the relationship with data grouped by N treatments, a weaker correlation was found (r = 0.54, P = 0.003). The 100 grains weight was significantly influenced by T × year interaction (Table 9) and ranged from 7.7 g (MT 2014) to 24.1 g (NT2008) with a mean of 18.5 g. No significant differences were found among T treatments along the experimental period with the exception of 2008 when 100 grains weight was +11% higher in NT than in CT and MT.

Table 9. Results of the repeated measures mixed model for maize traits. Bold numbers in columns indicate significant P values (≤ 0.05) of the F tests.

Factors	df	Grain yield	Plants m^{-2}	100 grains weight
Tillage (T)	2	**0.05**	**<0.01**	0.09
N rate (N)	2	**<0.01**	0.26	0.67
Year (Y)	12	**<0.01**	**<0.01**	**<0.01**
T x N	4	0.26	0.64	0.44
T x Y	22	**<0.01**	**<0.01**	**<0.01**
N x Y	24	**0.02**	**0.02**	0.41
T x N x Y	44	0.99	0.07	0.51
CV%		*24*	*7*	*3*

Table 10. Maize grain yield (kg ha^{-1}) as influenced by tillage and N fertilization systems over thirteen years

Year	CT	MT	NT	N0	N1	N2
2002	1612 a	881 b	1159 ab	715 b	1322 a	1614 a
2003	637 a	497 a	25 b	544 a	508 a	649 a
2004	1565 a	1757 a	854 b	1097 b	1428 ab	1651 a
2005	4453 a	2836 b	1791 c	2072 c	3073 b	3935 a
2006	2165 b	2798 a	1520 c	1330 b	1828 b	3325 a
2007	1256 a	792 b	28 c	545 c	1047 b	1479 a
2008	2064 a	2268 a	1918 a	1208 c	2250 b	2793 a
2009	3430 a	2903 b	2249 c	1883 c	2824 b	3876 a
2010	2032 b	2859 a	2358 ab	1523 c	2453 b	3273 a
2011	2320 a	2219 ab	1642 b	1222 c	2110 b	2849 a
2012	3778 b	4956 a	4919 a	3509 c	4556 b	5588 a
2013	1480 a	1549 a	661 b	611 b	1334 a	1745 a
2014	3810 b	4514 a	3667 b	2333 c	4379 b	5279 a
Mean	*2354*	*2371*	*1489*	*1430*	*2307*	*2927*

Means within a row for tillage and N fertilization factors separately that are followed by the same letter are not significantly different at P ≤ 0.05.

The results of the stability analysis (Fig. 3) showed that the most productive treatment (CT N2) was the least stable in terms of grain yield, while the highest yield stability was found for MT N1 and NT N1. Unfertilized treatments had intermediate stability. MT and NT combined with N2 or N1 showed a significant positive trend in terms of grain yield over time (NT N1: slope 231 kg ha^{-1} y^{-1}; P-value 0.02; MT N2: slope 301 kg ha^{-1} y^{-1}; P-value 0.01).

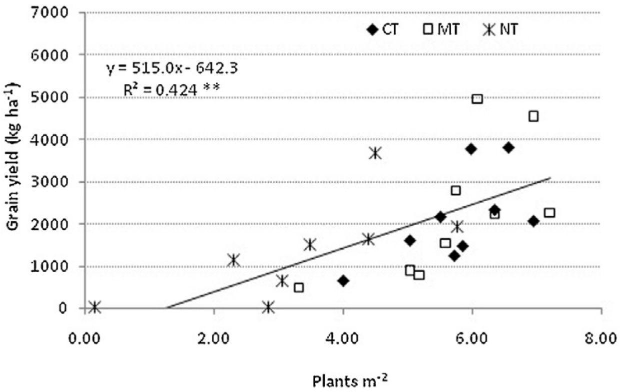

Fig. 6. Linear regression between grain yield and plants m−2for maize as influenced by tillage techniques. Data on plants m^{-2} are referred to nine years from 2002 to 2003, from 2006 to 2008 and from 2011 to 2014.

Through the correlation analysis between the meteorological variables and maize yield, the following significant variables were identified (Table 11): mean temperature (M4 Tmean) and reference evapotranspiration (M4 ET0) of April, mean temperature (M6 Tmean), precipitation (M6 Rain), and reference evapotranspiration (M6 ET0) of June, rain of July (M7 Rain) and reference evapotranspiration of August (M8 ET0).

The significant meteorological variables and the management factors (T and N) were used for obtaining the conditional regression tree for maize yield reported in Fig. 7. The meteorological variables explaining most the yield performances in maize were M6 Tmean (threshold values ranging from 22.0 to 23.3◦C) and M7 Rain (50.2 mm). Both management factors were found to be significant. The lowest maize grain yield was associated to M6 Tmean > 23.2◦C and MT and NT practices, while the highest values to M6 Tmean ≤ 23.2◦C, N2 or N1 and M7 Rain > 50.2 mm. RMSE and MAE obtained with the regression tree for maize were respectively 936 kg ha^{-1} and 785 kg ha^{-1}. According to the mixed model analysis, also this decisional tree found that both T management and N fertilization rates were significant for maize yield.

Table 11. Correlation coefficients among maize grain yields and selected monthly meteorological variables.

	ALL		N2		N1		N0		CT		MT		NT	
M4_Tmean	-0.22	*	-0.21		-0.30		-0.25		-0.17		-0.26		-0.25	
M4_ET0	-0.41	***	-0.43	**	-0.50	**	-0.44	**	-0.25		-0.50	**	-0.48	**
M6_Tmean	-0.49	***	-0.56	***	-0.55	***	-0.53	***	-0.46	**	-0.53	***	-0.51	***
M6_Rain	0.22	*	0.32	*	0.22		0.17		0.24		0.28		0.17	
M6_ET0	-0.28	**	-0.34	*	-0.33	*	-0.24		-0.30		-0.36	*	-0.20	
M7_Rain	0.21	*	0.27		0.28		0.10		0.25		0.17		0.21	
M8_ET0	-0.20		-0.24		-0.20		-0.10		-0.30	*	-0.10		-0.07	

where ALL = yields of all treatments; N2, N1, N0 = yields for 180, 90, 0 kg N ha^{-1}; CT= yields for conventional tillage; MT = yields for minimum tillage; NT = yields for no tillage; M = Month from 1 (January) to 5 (May).
*: significant at P ≤ 0.05; **: P ≤ 0.01; ***: P ≤ 0.001.

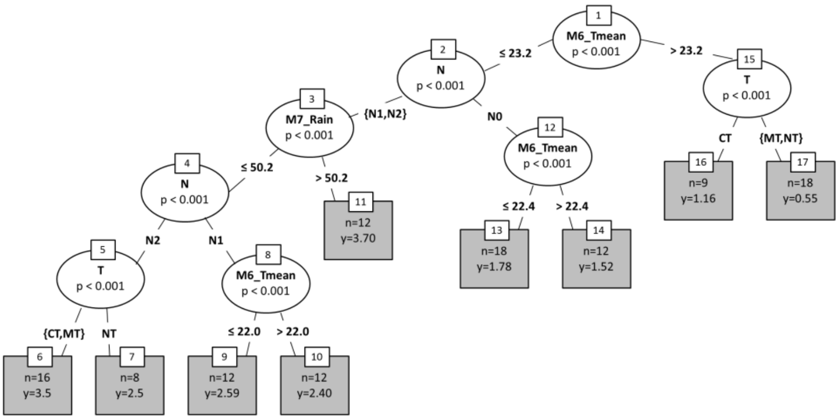

Fig. 7. Regression tree showing the effect of emerging drivers of the maize grain yield interannual variation: meteorological variables (Tmean = mean monthly temperature; RAIN = monthly precipitation; M = month from 6-June to 7-July) and management factors (N—nitrogen fertilization rate: 0, 90, 180 N kg ha^{-1}; T—Tillage: CT = conventional tillage, MT = minimum tillage; NT = no tillage). n = number of observations and y = mean yield (t ha−1) in each terminal node.

4. Discussion

4.1. Effects of tillage and fertilization systems on durum wheat yield traits

Our results show that NT did not provide any substantial advantage or disadvantage to durum wheat grain yield in comparison to CT or MT. This finding is consistent to the evidences reported in the European meta-analysis by Van den Putte et al. (2010), showing an average grain yield of −8.5% for NT compared to CT. Similarly, in a 16-years long term experiment made in Central Italy on poorly drained silt-loam soil, Mazzoncini et al. (2008) reported a mean loss of wheat grain yield of −8.9% under NT vs. CT. Lopez-Bellido et al. (2000, 2001) and De Vita et al. (2007), in the Vertisols of Spain and Italy respectively, found that wheat under CT performed better only in the wet years, while in the dry years, wheat grain yield was higher under NT. Our results do not confirm these findings and our interpretation is that we rarely experienced extremely dry years (i.e. less than 350 mm of rainfall during the wheat cycle) and because the soil of the experimental field was not a Vertisol, which would have been characterized by self-structuring capacity. In a 20-years experiment carried out on a Vertisol, under semiarid Mediterranean conditions, Ruisi et al. (2014) did not observe significant differences between CT and NT, although they also found a tendency for NT to guarantee superior grain yields under water stress conditions during the crop cycle. However, similarly to our findings, Ruisi et al. (2014) found a great interannual variability in durum wheat productivity, that they interpreted as mainly associated to the interactions between tillage and other agronomic factors, in particular crop sequence. A yield superiority of NT com-pared to CT was in fact observed only when wheat was grown in a 2-years rotation, while, when grown continuously, it performed better under CT. In our experiment, the 2-years rotation of wheat with a spring crop might have contributed to prevent from the potential progressive increased incidence of pests and diseases, which are often the main drivers causing differences between tillage systems under monocropping. It is interesting to highlight that durum wheat grain yield under NT did not show any significant increasing trend over time, although in the same LTE, De Sanctis et al. (2012) measured an increment of soil organic matter in the top soil in the first twelve experimental years. The possible positive effects on soil quality due to no tillage, as improved water retention (De Vita et al., 2007), aggregation stability (Hernanz et al.,2002), improved biological and biochemical soil processes (Acosta-Martinez and Tabatabai, 2001) did not result into a higher crop productivity. Soil compaction is also an important constraint for wheat grain yield under NT, as documented in the same LTE by Pastorelli et al.(2013). The negative effects of soil compaction on root development and tillering are well documented (e.g., Atwell, 1990) andmconfirmed by the lower number of spikes m^{-2} under NT in our experiment (−14% with respect to CT). However, this seems in contrast to the findings of other scholars who measured similar soil bulk density and root density values under NT and CT (e.g., Munoz-Romero et al., 2010; Plaza-Bonilla et al., 2014) but on Vertisols, where the self-structuring nature and the better soil water conditions allow sufficient conditions for root growth and tillering also under NT (e.g., López-Bellido et al., 2007). The most relevant factor influencing wheat yield was N fertilization, which provided an advantage of about +30% in terms of grain yield when doubling the N rate from 90 to 180 kg ha^{-1} N. In southern Spain, also Lopez-Bellido et al. (2001) reported a more significant impact of N fertilization than tillage on grain yield, with no additional response to N fertilizer at rates above 100 kg ha^{-1}. In our study, grain yields were more stable with 90 kg N ha^{-1}than with180 kg N ha^{-1}. Therefore, the decision about the about the optimal N fertilizer rate to adopt will depend on the specific farming system context and associated trade-offs between productivity and stability targets.

The second important driver influencing the grain yield, as resulted from the decisional tree analysis, was the mean temperature of January. Low temperatures at early developmental stages(as it is in January in the experimental site) and in particular when plants are at the tillering stage, might delay the crop development determining an increase of the tillering duration. A greater number of tillers can lead therefore to a greater potential numbers of spikes m^{-2} and, hence, to a higher yield (Kazmi and Rasul, 2012). When N was not a limiting factor, the water availability in April, which depends on rainfall and evapotranspiration, was a key driver for grain yields. The earing and anthesis occurred mainly in April and these are the most critical phases in wheat for yield (Ozturk andAydin, 2004; Wheeler et al., 1996; Albrizio et al., 2010). A water stress in this period could have reduced the number of kernels per spike, leading to a significant reduction of grain yield. A significant sensitivity of durum wheat to high air temperature and water stress in April and May was also observed by Campiglia et al. (2015) who carried out a 6-years trial under similar soil and climate conditions to our study. They highlighted a different level of sensitivity to rainfall in spring depending also on the soil N availability associated to the compared cropping systems. This finding is consistent to the results of the decisional tree analysis that revealed a key role of April rainfall in constraining grain yield under sufficient N fertilizer application. In spring, the N availability is a main driver of the aerial biomass production and leaf area, hence under no limiting soil N, wheat may become more vulnerable to water stress and, at the same time, more able to exploit the benefits of water availability (Sadras et al., 2012) than an unfertilized crop. When N was not supplied, only air temperature in May, together with air temperature in January, were the main grain yield constraints. The grain filling period started during May. High temperatures throughout this stage, affecting kernel weight and accelerating grain maturity (Monpara, 2011), may lower grain yield. Overall, temperature in the early growth stages, soil moisture during flowering and anthesis and their interaction with N nutrition explained most of the inter-annual durum wheat yield variability.

4.2. Effects of tillage and fertilization systems on sunflower yield traits

The most important yield-limiting factor for sunflower in the specific environmental conditions, characterized by clayey soils that are not Vertisols, was the application of NT practices. The substantial failure of NT was strongly related to poor crop establishment under unsuitable soil moisture conditions at sowing time, as already highlighted by Farina et al. (2011) in the same LTE. In clayey soils, NT is constrained by the mechanical impedance of the seed-slot walls in compacted and wet soil conditions for plants emergence, as reported by some authors (e.g., Bayhan et al., 2002). This sunflower sensitivity to NT systems was also observed with less problematic soil texture as in loamy sand soils (Rühlemann andSchmidtke, 2015) and in sandy clay loam soils (Lopez-Garrido et al.,2014). In these latter conditions, the number of plants m^{-2} at the emergence and, in turn, the plant density at harvest were −97% less under NT than under CT. In our experiment, plant density with NT was on average 60% lower with NT than under CT. Plant density was independent of tillage systems (on average, 5.4 plants m^{-2}) only in 1997, when no yield differences were observed between CT and NT. This confirms the negative role of worsened physical soil conditions, such as high penetration resistance and low macroporosity (Pastorelli et al., 2013), under NT for seedling emergence. The low soil porosity may also restrict gaseous exchange creating unfavorable conditions for germination and seedlings establishment (Gantzer and Blake, 1978). In contrast to our findings, Halvorsonet al. (1999) reported a beneficial effect of NT on sunflower yields, although under more suitable soil texture conditions (silt-loamysoil) and no limiting soil N availability. Overall, the sunflower productivity measured in our long term experiment was rather low (1.4 t ha^{-1}) with high interannual variability associated to weather patterns. Under rainfed Mediterranean conditions, other scholars found higher yields by about + 1 t ha^{-1} (López-Bellido et al., 2003; Murillo et al., 1998), although with similar variations among years mainly related to soil water availability. When sunflower had received less than 100 mm of rainfall during the growing season, yields were dramatically lowered under soil inversion tillage (0.5 t ha^{-1}) while reduced tillage was able to keep reasonable growth and yields (1.5 t ha^{-1}). In the Northern Great Plains (USA), characterized by severe drought during the sunflower growing season (less than 250 mm of rainfall from April to September), this crop produced extremely low yields (always lower than 0.5 t ha^{-1}) (Lenssen et al., 2007). Under water-limiting conditions, i.e., some 400 mm of rainfall from May to August, Krupinsky et al. (2006) observed around 1.4 t ha^{-1} of achene yield for sunflower grown in rotation with spring wheat. In our experimental conditions, rainfall from April to September ranged between 280–520 mm during the seven years of the trial and the least productive year corresponded to the least rainfall amount in the period June–July when flowering occurred. The main weather driver influencing sunflower yield identified through the recursive partition analysis was the mean temperature of July, followed by evapotranspiration in June and rainfall amount in August. Mean temperatures of July in the range 25–30◦C determined higher grain yields. In fact, the optimum temperatures for sunflower seed filling range from 23 to 28◦C. Above this range grain filling is constrained (Chimenti et al., 2001). Moreover, sunflower sensitivity to heat stress decreases as grain filling proceeds (Rondanini et al., 2003). Regarding soil water deficit, the most critical period occurs soon before and after flowering (Rao et al., 1977). According to this, we found that lower evapotranspiration values in June when flowering initiates, are among the main weather factors influencing yield in particular under NT. Rainfall amount in August was negatively correlated with grain yield. In fact, sun-flower in August is usually at the end of the grain filling phase and adverse conditions during this period could affect the achene viability. In particular, the heavy rains that occurred in August 1996 could have lead to the detachment of the achenes from the flower head and likely to the occurrence of diseases and other biotic stresses, resulting in severe production losses. The effect of N fertilization was not significant and independent of the tillage system, although the high error variance is likely to conceal a type II error in the F test as the grain yield of the unfertilized crop was on average −18% than that of the fertilized ones. On the contrary, Halvorson et al. (1999) and De Vuyst and Halvorson (2004) reported a significant tillage × N interaction under CT combined with 100 kg N ha^{-1} which led to the highest 12-year average grain yields. The lack of significant effect of the N input in our experimental conditions may support the empirical considerations of many farmers growing rainfed sunflower in rotation with wheat in Mediterranean basin areas who do not apply N fertilizers directly to sunflower but to durum wheat, since they experienced a lack of significant response of sunflower to N (López-Bellido et al., 2003). Considering the sunflower productivity, the highest N fertilizer rate under MT and CT reached higher yields (on average, 1.8 t ha^{-1}) and were characterized by high stability. Yield stability results indicate however a relatively good performance of sunflower cropped under MT and intermediate N fertilizer rates, as it was shown for durum wheat.

4.3. Effects of tillage and fertilization systems on maize yield traits

Similarly to what discussed for sunflower, the most relevant yield-limiting factor for maize grain yields was the NT application. Similarly to what discussed for sunflower, this was mainly associated to unsuitable soil conditions for direct seed drilling operations, that constrained seed germination, as revealed by the lower mean plant density (−50%) under NT vs. CT. The retention of previous crop residues in the surface soil with NT might also have delayed seedling emergence because of a longer duration of low temperatures as compared to tillage practices with residue incorporation. This interpretation is supported by the findings of Cai and Wang (2002) and Wang et al. (2012) who found a lower surface soil temperature of −2 to −6◦C under NT with residue retention systems with respect to residue removal or incorporation, leading to lower emergence and grain yield in maize. Soil texture is another important factor influencing the outcomes of NT practices with the worst results or nihil benefits usually obtained with fine-textured soils (Tabaglio and Gavazzi, 2009; Verhulst et al., 2011) as it was for our clayish soil. In these soil types long term NT result in increased soil bulk density (Pastorelli et al., 2013) that, in turn, constrains root growth in the subsoil contributing to limited water and nutrient uptake capability of maize, particularly after the tasseling stage (Wang et al., 2015). The lower productivity of rainfed maize under NT was constantly observed along the 13-years experiment with very few exceptions, although we observed very high interannual variations, as also demonstrated by the lower yield stability of NT as compared to CT or MT systems. However, a significant upward trend was found over time in terms of maize grain yield for MT and NT with both N2 and N1 rates. These results need to be confirmed when the duration of the maize trial will reach an appropriate length for the fertility trend analysis to be sufficiently reliable (at least 20 years). Other authors observed an increasing trend of yields after at least two to four years since the start of NT adoption that were considered a minimum time period for creating better soil structure and, hence, better soil and plant water status (Karunatilake et al., 2000; Diaz-Zorita et al., 2002). Also Colvin et al. (2001) raised several concerns regarding consistently lower maize yields under NT than under CT or MT systems in the first period after conversion to NT, while in the same environment but in the long term, Karlen et al. (2013) found similar yields among tillage systems. Even though NT maize, in our experimental conditions, followed seven years of continuous NT in the context of the wheat-sunflower rotation and showed a slight increasing trend over the thirteen years of the trial, the level of productivity remained quite low. This suggests that, although soil available water might had been higher in the topsoil (Wang et al., 2015), yield was likely constrained by a combination of unsuitable soil conditions for sowing, reduced water uptake ability or soil nutrient deficit. Tabaglio and Gavazzi (2006, 2009) in Northern Italy reported opposite yield results with NT depending on soil fertility traits, with better maize performances in the most nutrient-rich soil. On the contrary, we did not find a significant interaction between T and N fertilization systems. However, the highest N rate (180 kg N ha^{-1}) was far lower than the common rate in the maize-based cropping systems in Italy (about 250 kg N ha^{-1}) under irrigation or in wetter climates and this could have flattened the maize performance particularly in more humid years. In terms of yield stability and yield outcomes over the thirteen years of the experiment, the best performance was achieved with the intermediate N rate and MT. Nevertheless, the overall mean productivity (2.1 t ha^{-1}) was rather low if compared to what reported by other scholars for rainfed maize grown under more suitable rainfall pat-terns (9 t ha^{-1} in Northern Italy by Tabaglio and Gavazzi, 20098 t ha^{-1} in Northern-Central USA by Karlen et al., 2013; 5 t ha^{-1} in Central Mexico by Verhulst et al., 2011; 5 t ha^{-1} in Northern China by Wang et al., 2012). In our experimental conditions, weather factors affected negatively maize yields, particularly high mean temperatures in June (>23.2◦C) and drought conditions in July. This latter factor is particularly important when N was less limiting. In these periods, maize sensitivity to high temperatures was associated to high evapotranspiration and low soil moisture during anthesis (Sánchez et al., 2014) when potential total number of kernels per plant is defined. Two of the most vulnerable developmental stages of maize to water stress, i.e., the end of the flowering and the beginning of the grain filling, occurred in July. In rainfed systems, water stresses are recognized to be responsible of maize yield losses particularly if they occur after tassel initiation, at anthesis and during the grain filling (Tollenaar and Bruulsema, 1988).

5. Conclusions

In this study we investigated how long term tillage management and N fertilization strategies and their interaction with some meteorological factors, especially temperature and precipitation, can explain the interannual yield variability of durum wheat, sunflower or maize in a rainfed Mediterranean 2-year crop rotation. The identification of the key drivers that influence wheat, sunflower and maize yields will be useful to target further research and to support adaptive crop management responses to climate variability and to design policy interventions for these important rainfed cropping systems in the Mediterranean hill-slopes. Moreover, this long term evaluation can represent an important and robust source of data and information for cropping system modelling approaches.

Long term NT systems did not provide any additional advantage or disadvantage to durum wheat productivity and no tillage × N fertilization interaction was observed. Consequently, the decision to adopt conservation tillage methods will depend rather than just on productivity objectives, on the specific farming system context and related potential benefits in terms workload or production costs. The interannual wheat grain yield variability was constrained by the temperatures in the early growth stages, in relation to the tillering enhancement effect, and by the water stress during the reproduction phase in spring. The long term experimental results clearly indicate that in the non-Vertisols clayish soils of the study area the adoption of continuous NT under rainfed conditions is not a viable options for sunflower and maize. In particular for sunflower, N fertilization seemed to be not sufficient to compensate for the yield penalty associated to NT practices. This finding is strongly associated to the site-specific characteristics of the study area that constrained the success of the direct seed drilling. MT proved instead to be aviable option for both maize and sunflower crops particularly to enhance grain yield stability. However, the overall productivity of both sunflower and maize, independently of the tillage and N fertilization systems, was found to be rather low in absolute terms, even if it was consistent to yields observed for sunflower grown under rainfed conditions in semi-arid environments. Maize yields were instead absolutely not satisfactory, considering the high productivity potential of this crop. This indicates that in the study area, the severe water stress during the reproductive phases heavily constrains maize productivity under rainfed conditions. However, our findings on rainfed maize productivity under conservation tillage represent, to our knowledge, a unique attempt to assess the role of these tillage systems in the Mediterranean environments.

Acknowledgments

This study was conducted in the context of the IC-FAR project (prot. 2010FRE7J4, PRIN Funding scheme of the Italian Ministry of Education, University and Research 2010–11). The following research grants supported the long term field experiment over the years: Regione Marche, Polytechnic University of Marche, Ministry of Agricultural, Food and Forestry policies (Agroscenari project, D.M. 8608/7303/2008—www.agroscenari.it; FACCE JPI knowledge hub “MACSUR”, D.M. 2660/7303/2012—www.macsur.eu); Italian Ministry of Education, University and Research (SOILSINK project,D.D. 286 20/2/2006—www.soilsink.it). Weather data were pro-vided by the Marche Agrometeoservice (www.meteo.marche.it); soil analysis were conducted by the ASSAM soil lab (www.assam.marche.it). Soil sampling was designed in collaboration with Giuseppe Corti (Polytechnic University of Marche). The contribution of Ileana Iocola was provided in the context of the PhD Course “Agricultural Science” of the University of Sassari (XXIX cycle).

References

Akaike, H., 1974. A new look at the statistical model identification. IEEE Trans. Autom. Control 19, 716–723.

Albrizio, R., Todorovic, M., Matic, T., Stellacci, A.M., 2010. Comparing the interactive effects of water and nitrogen on durum wheat and barley grown in a Mediterranean environment. Field Crop Res. 115, 179–190.

Almaraz ,J., Mabood,F., Zhou,X., Gregorich, E., Smith, D., 2008. Climate change, weather variability and corn yield at a higher latitude locale: Southwestern Quebec. Climatic Change 88(2), 187–197.

Amato, G., Ruisi, P., Frenda, A. S., Di Miceli, G., Saia, S., Plaia, A., Giambalvo, D. ,2013. Long-term tillage and crop sequence effects on wheat grain yield and quality. Agron. J. 105(5), 1317-1327.

Annandale, J. G., N. Z. Jovanic, N. Benade, Allen, R.G., 2002. Software for missing data error analysis of Penman-Monteith reference evapotranspiration. Irrig. Sci. 21, 57–67.

Barberi, P., Aendekerk, R., Antichi, D., Armengot, L. Berner, A., Bigongiali, F., Blanco-Moreno, J. M., Carlesi, S., Celette, F., Chamorro, L., Crowley, O., Döring, T., Grosse, M., Haase, T., Hess, J., Huiting, H., José-Maria, L., Klaedtke, S., Kranzler, A., Luik, A., Peigne, J., Sukkel, W., Surböck, A., Talgre, L., Sans, F. X., 2014.. Reduced tillage and cover crops in organic arable systems preserves weed diversity without jeopardising crop yield. Building Organic Bridges 3, 765-768.

Bayhan, Y., Kayisoglu, B., Gonulol, E., 2002. Effect of soil compaction on sunflower growth. Soil Till. Res. 68, 31–38.

Barontini, F., Simone, M., Triana, F., Mancini, A., Ragaglini, G., Nicolella, C., 2015. Pilot-scale biofuel production from sunflower crops in central Italy. Renew. Energ. 83, 954-962.

Bozzini, A., 1988. Origin, distribution, and production of durum wheat in the world, in: Fabriani, G., Lintas, C., (Eds.), Durum wheat: Chemistry & Technology. Am. Assoc. Cereal Chem., St. Paul, MN., pp. 1-16.

Cai, D.X., Wang, X.B., 2002. Conservation tillage systems for spring maize in the semihumid to arid areas of China, in: Stott, D.E., Mohttar, R.H., Steinhardt, G.C. (Eds.), Sustaining the Global Farm—Selected Papers from the 10th International Soil Conservation Organization Meeting held May 24–29, 1999 at Purdue University and the USDA-ARS National Soil Erosion Research Laboratory, IN., pp. 366–370.

Campiglia, E., Mancinelli, R., De Stefanis, E., Pucciarmati, S., Radicetti, E., 2015. The long-term effects of conventional and organic cropping systems, tillage managements and weather conditions on yield and grain quality of durum wheat (*Triticum durum* Desf.) in the Mediterranean environment of Central Italy. Field Crop Res. 176, 34-44.

Chimenti, C., Hall, A.J., Lopez, M., 2001. Embryo-growth rate and duration in sunflower as affected by temperature. Field Crop Res. 69, 81–88.

Colvin, T.S., Meek, D.W., Cook, J.D., Baker, J.L., Cruse, R.M., 2001. Analysis of long term experiment record. American Society of Agricultural Engineers (ASAE) Meeting Presentation No. 01-AETC-01. ASAE, St. Joseph, MI.

Deepak, K. R., Gerber, J.S., MacDonald, G.K., West, P.C, 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6, Article number: 5989. doi:10.1038/ncomms6989.

De Sanctis, G., Toderi, M., Orsini, R., Iezzi, G., Roggero, P. P., Jones, J.W., 2009. Nitrogen losses and nitrates content in the water surplus: simulation of DSSAT model, in: Proceedings of the 16th Nitrogen Workshop-Connecting different scales of nitrogen use in agriculture. June 28th to July 1st, pp. 517-518.

De Sanctis, G., Roggero, P.P., Seddaiu, G., Orsini, R., Porter, C.H., Jones, J.W., 2012. Long term no tillage increased soil organic carbon content of rain-fed cereal systems in a Mediterranean area. Eur. J. Agron. 40, 18-27.

De Vita, P., Di Paolo, E., Fecondo, G., Di Fonzo, N., Pisante, M., 2007. No-tillage and conventional tillage effects on durum wheat yield, grain quality and soil moisture content in southern Italy. Soil Till. Res. 92, 69-78.

DeVuyst, E.A., Halvorson, A.D., 2004. Economics of Annual Cropping versus Crop–Fallow in The Northern Great Plains as Influenced by Tillage and Nitrogen. Agron. J. 96, 148-153.

Diaz-Zorita, M., Duarte, G.A., Grove, J.H., 2002. A review of no-till systems and soil management for sustainable crop production in the subhumid and semiarid Pampas of Argentina. Soil Till. Res. 65, 1-18.

Douglas, W.S., Lianne, M. D., Lor, I.L.C., 1998. Phenological Temperature Response of Maize. Agron. J. 90, 73–79.

FAO, 2006. World Reference Base for Soil Resources. World Soil Resources Report 103. IUSS, ISRIC, FAO, Rome, 145 pp.

Farina, R., Seddaiu, G., Orsini, R., Stieglich, E., Roggero, P.P., Francaviglia, R., 2011. Soil carbon dynamics and crop productivity as influenced by climate change in a rainfed cereal system under contrasting tillage using EPIC. Soil Till. Res. 112 (1), 36-46.

Gantzer, C.J., Blake, G.R., 1978. Physical characteristics of Le Sueur clay loam soil following no-till and conventional tillage. Agron. J. 70, 853-857.

Halvorson, A.D., Black, A.L., Krupinsky, J.M., Merrill, S.D., Tanaka, D.L., 1999. Sunflower response to tillage and nitrogen fertilization under intensive cropping in a wheat rotation. Agron. J. 91, 637-642.

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., New, M., 2008. A European daily high-resolution gridded dataset of surface temperature and precipitation. J. Geophys Res-Atmos. 113, doi:10.1029/2008JD10201.

Hernanz, J.L., Lopez, R., Navarrete, L., Sanchez-Giron, V., 2002. Long-term effects of tillage systems and rotations on soil structural stability and organic carbon stratification in semiarid central Spain. Soil Till. Res. 66, 129-141.

Hothorn, T., Hornik, K., Zeileis, C., 2006. Unbiased recursive partitioning: A conditional inference framework. J. Comput. Graph. Stat. 15, 651–674.

Isik, M, Devadoss, S., 2006. An Analysis of the Impact of Climate Change on Crop Yields and Yield Variability. Appl. Econ. 38, 835–844.

Kandel, H.J., Schneiter, A.A., Johnson, B.L., 1997. Intercropping legumes into sunflower at different growth stages. Crop Sci 37, 1532–1537.

Karlen, D.L., Kovar, J.L., Cambardella, C.A., Colvin, T.S., 2013. Thirty-year tillage effects on crop yield and soil fertility indicators. Soil Till. Res. 130, 24-41.

Karunatilake, U., van Es, H.M., Schindelbeck, R.R., 2000. Soil and maize response to plow and no-tillage after alfalfa-to-maize conversion on a clay loam soil in New York. Soil Till. Res. 55, 31-42.

Kassam, A., Friedrich, T., Derpsch, R., Lahmar, R., Mrabel, R., Basch, G., Gonzalez-Sanchez, E.J., Serraj, R., 2012. Conservation agriculture in the dry Mediterranean climate. Field Crop Res. 132, 7-17.

Kazmi, D., Rasul, G., 2012. Agrometeorological wheat yield prediction in rainfed Potohar region of Pakistan. Agricultural Sciences, 3, 170-177. doi: 10.4236/as.2012.32019.

Krupinsky, J.M., Tanaka, D.L., Merrill, S.D., Liebig, M.A., Hanson, J.D., 2006. Crop sequence effects of 10 crops in the northern Great Plains. Agr. Sys., 88, 227-254.

Lenssen¸ A.W. Waddell, J.T., Johnson, G.D., Carlson, G.R., 2007. Diversified cropping systems in semiarid Montana: Nitrogen use during drought. Soil Till. Res. 94, 362–375.

Lobell, D., Cahill, K., Field, C., 2007. Historical Effects of Temperature and Precipitation on California Crop Yields. Climatic Change 81, 2, 187–203.

Lopez-Bellido, L., Fuentes, M., Castillo, J.E., Lopez-Garrido, F.J., Fernandez, E.J., 1996. Long-term tillage, crop rotation, and nitrogen fertilizer effects on wheat yield under Mediterranean conditions. Agron. J. 88, 783–791.

Lopez-Bellido, L., Lopez-Bellido, R.J., Castillo, J.E., Lopez-Bellido, F.J., 2000. Effects of tillage, crop rotation, and nitrogen fertilization on wheat under rainfed Mediterranean conditions. Agron. J. 92, 1054-1063.

Lopez-Bellido, L., Lopez-Bellido, R.J., Castillo, J.E., Lopez-Bellido, F.J., 2001. Effects on long-term tillage, crop rotation and nitrogen fertilization on bread-making quality of hard red spring wheat. Field Crop Res. 72(3), 197-210.

López-Bellido, R.J., López-Bellido, L., Castillo, J.E., López-Bellido, F.J., 2003. Nitrogen uptake by sunflower as affected by tillage and soil residual nitrogen in a wheat–sunflower rotation under rainfed Mediterranean conditions. Soil Till. Res. 72 (1), 43–51.

López-Bellido, R.J., López-Bellido, L., Benítez-Vega, J., López-Bellido, F.J., 2007. Tillage system, preceding crop, and nitrogen fertilizer in wheat crop: II. Water utilization. Agron. J. 99, 66–72.

López-Garrido, R., Madejón, E., Murillo, J. M., Moreno, F., 2011. Short and long-term distribution with depth of soil organic carbon and nutrients under traditional and conservation tillage in a Mediterranean environment (southwest Spain). Soil use and Manage. 27, 177-185.

Lopez-Garrido, R., Madejon, E., Leon-Camacho, M., Giron, I., Moreno, F., Murillo, J.M., 2014. Reduced tillage as an alternative to no-tillage under Mediterranean conditions: A case study. Soil Till. Res.140, 40-47.

Mazzoncini, M., Di Bene, C., Coli, A., Antichi, D., Petri, M., Bonari, E., 2008. Rainfed wheat and soybean productivity in a long-term tillage experiment in central Italy. Agron. J. 100(5), 1418-1429.

Mazzoncini, M., Sapkota, T.B., Bàrberi, P., Antichi, D., Risaliti, R. ,2011. Long-term effect of tillage, nitrogen fertilization and cover crops on soil organic carbon and total nitrogen content. Soil Till. Res.114(2), 165-174.

Montgomery, D.C., 1997. Design and Analysis of Experiments, fourth edition New York, NY, Wiley.

Munoz-Romero, V., Benítez-Vega, J., López-Bellido, L., López-Bellido, R.J., 2010. Monitoring wheat root development in a rainfed vertisol: Tillage effect. Eur. J. Agron. 33, 182-187.

Murillo, J.M., Moreno, F., Pelegrin, F., Fernandez, J.E., 1998. Responses of sunflower to traditional and conservation tillage under rainfed conditions in southern Spain. Soil Till. Res. 49, 233-241.

Onofri, A., Seddaiu, G., Piepho, H-P., 2015. Long-term experiments with cropping systems: case studies on data analysis. In this special issue.

Ozturk, A., Aydin, F., 2004. Effect of Water Stress at Various Growth Stages on Some Quality Characteristics of Winter Wheat. J. Agron. Crop Sci. 190, 93–99. doi: 10.1046/j.1439-037X.2003.00080.x.

Pastorelli, R., Vignozzi, N., Landi, S., Piccolo, R., Orsini, R., Seddaiu, G., Roggero, P.P., Pagliai, M., 2013. Consequences on macroporosity and bacterial diversity of adopting a no-tillage farming system in a clayish soil of Central Italy. Soil Biol. Biochem. 66, 78-93.

Plaza-Bonilla, D., Álvaro-Fuentes, J., Hansen, N.C., Lampurlanés, J., Cantero-Martínez, C., 2014. Winter cereal root growth and aboveground–belowground biomass ratios as affected by site and tillage system in dryland Mediterranean conditions. Plant Soil 374, 925-939.

Porter, J.R., Semenov, M. A., 2005. Crop responses to climatic variation. Philos. T. R. SocB, 360, 1463, 2021–2035.

Rao, M., Seshachalam, N., Rao, V.R., Ramachandram, M., 1977. Critical stages for moisture stress in different crops. Mysore J. Agr. Sci. 11, 494-500.

Rokach, L., Maimon, O., 2008. Data mining with decision trees: theory and applications. World Scientific Pub Co Inc. ISBN 978-9812771711.

Roggero, P. P., Toderi, M., 2002. Impact of cropping systems on soil erosion in the clay hills of central Italy. Advances in Geoecology, 35, 471-80.

Rondanini, D., Savin, R., Hall, A.J., 2003. Dynamics of fruit growth and oil quality of sunflower (*Helianthus annuus* L.) exposed to brief intervals of high temperature during grain filling. Field Crop Res. 83(1), 79-90.

Ruisi, P., Giambalvo, D., Saia, S., Di Miceli, G., Frenda, A.S., Plaia, A., Amato, G., 2014. Conservation tillage in a semiarid Mediterranean environment: results of 20 years of research. Ital. J. Agron. 9, 1-9.

Rühlemann, L., Schmidtke, K., 2015. Evaluation of monocropped and intercropped grain legumes for cover cropping in no-tillage and reduced tillage organic agriculture. Eur. J. Agron. 65, 83-94.
Rusinamhodzi, L., Corbeels, M., van Wijk, M.T., Rufino, M. C., Nyamangara, J., Giller, K.E., 2011. A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. Agron. Sustain. Dev. 31(4), 657-673.
Sánchez, B., Rasmussen, A. Porter, J.R., 2014. Temperatures and the growth and development of maize and rice: a review.Glob. Change Biol. 20, 408–417. doi: 10.1111/gcb.12389.
SAS Institute, 1999. SAS/STAT User's Guide, Version 8. SAS Institute, Inc., Cary, NC.
Schoper, J.B., Lambert, R.J., Vasilas, B.L., 1987. Pollen variability, pollen shedding, and combining ability for tassel heat tolerance in maize. Crop Sci. 27, 27-37.
Shukla, G.K., 1972. Some statistical aspects of partitioning genotype-environmental components of variability. Heredity, 29, 237-245.
Strobl, C., Malley, J., Tutz, G., 2009. An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random forests. Psychol. Methods. 14(4), 323-348.
Tabaglio, V., Gavazzi, C., 2006. Yield performance of maize (Zea mays L.) cropped under conventional tillage and no-tillage in Northern Italy. Agr. Med. 136, 198-205.
Tabaglio, V., Gavazzi, C., 2009. Monoculture maize (Zea mays L.) cropped under conventional tillage, no-tillage and N fertilization: (I) Three years yield performances. Ital. J. Agron., 3, 61-67.
Tollenaar, M., Bruulsema, T.W. 1988. Efficiency of maize dry matter production during periods of complete leaf-area expansion. Agron. J. 80, 580-585.
Van den Putte, A., Govers, G., Diels, J., Gillijns, K., Demuzere, M., 2010. Assessing the effect of soil tillage on crop growth: A meta-regression analysis on European crop yields under conservation agriculture. Eur. J. Agron. 33, 231–241.
Verhulst, N., Nelissen, V., Jespers, N., Haven, H., Sayre, K.D., Raes, D., Deckers, J., Govaerts, B., 2011. Soil water content, maize yield and its stability as affected by tillage and crop residue management in rainfed semi-arid highlands. Plant Soil 344, 73-85.
Wang, X., Wu, H., Dai, K., Zhang, D., Feng, Z., Zhao, Q., Wu, X., Jin, K., Cai, D., Oenema, O., Hoogmoed, W.B., 2012. Tillage and crop residue effects on rainfed wheat and maize production in northern China. Field Crop Res. 132, 106-116.
Wang, X., Zhou, B., Sun, X., Yue, Y., Ma, W., Zhao, M., 2015. Soil Tillage Management Affects Maize Grain Yield by Regulating Spatial Distribution Coordination of Roots, Soil Moisture and Nitrogen Status. Plos One, 10(6), e0129231.
Weiss, E.A., 2000. Oilseed crops. Blackwell Science, Oxford.
Wheeler, T.R., Batts, G.R., Ellis, R.H., Hadley, P., Morison, J.I.L., 1996. Growth and yield of winter wheat (Triticum aestivum) crops in response to CO2 and temperature. J. Agric. Sci. 127, 37-48

CHAPTER 2

Conservation tillage can mitigate climate change impacts in Mediterranean cereal systems: an integrated SOC assessment using long term experimental data

Ileana Iocola[a], Simona Bassu[a], Roberta Farina[b], Daniele Antichi[c], Bruno Basso[d], Marco Bindi[e], Anna Dallamarta[e], Francesco Danuso[f], Luca Doro[g,h], Roberto Ferrise[e], Luisa Giglio[i], Fabrizio Ginaldi[j], Marco Mazzoncini[c], Laura Mula[a,g], Roberto Orsini[k], Massimiliano Pasqui[l], Giovanna Seddaiu[a,g], Rodica Tomozeiu[m], Domenico Ventrella[i], Giulia Villani[m], Pier Paolo Roggero[a,g]

[a]Nucleo Ricerca Desertificazione - NRD, University of Sassari, Viale Italia 39,07100 Sassari, Italy; [b]Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Centro di ricerca Agricoltura e Ambiente, CREA-AA, via della Navicella2-4, Rome, Italy; [c]Dipartimento di Scienze Agrarie Alimentari ed Agro-Ambientali -DISAAA-a, University of Pisa, Via del Borghetto 80, 56124 Pisa, Italy; [d]Department of Geological Sciences, Michigan State University, 288 Farm Lane, East Lansing, MI 48824, USA; [e]Dipartimento di Scienze Produzioni Agroalimentari e dell'Ambiente- DISPAA, University of Florence, Piazzale delle Cascine 18, 50144 Florence, Italy; [f]Dipartimento di Scienze Agroalimentari, Ambientali ed Animali – DI4A, University of Udine, via delle Scienze 6, 33100 Udine, Italy; [g]Dipartimento di Agraria, University of Sassari, Viale Italia 39,07100 Sassari, Italy; [h]Blackland Research & Extension, 720 East Blackland Road Temple, TX 76502, USA; [i]Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria, Centro di ricerca Agricoltura e Ambiente, CREA-AA, Via Celso Ulpiani 5, 70125 Bari, Italy; [j]CREA-Research Center for Agriculture and Environment, Via di Corticella, 133 - 40128 Bologna, Italy; [k]Dipartimento di Scienze Agrarie, Alimentari ed Ambientali, Marche Polytechnic University, via Brecce Bianche, 60131 Ancona, Italy; [l]Centro Nazionale delle Ricerche, Istituto di Biometeorologia CNR-Ibimet, Via Taurini, 19, 00185 Roma, Italy; [m]Agenzia regionale per la prevenzione, l´ambiente e l´energia dell´Emilia-Romagna, Servizio Idro-Meteo-Clima di Bologna Emilia-Romagna Arpae-SIMC, Viale Silvani 6, 40122 Bologna, Italy.

Abstract

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

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

1. Introduction

Soil organic carbon (SOC) is important to crop production because it mediates nutrient cycling, and affects soil fertility (Bolinder et al., 2010; Lal et al., 2009), and soil water-holding capacity (Huntington, 2007). Sequestration of C 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 practices (i.e., Reduced tillage – RT and no till – NT), have been adopted to reduce these negative impacts although sometimes lower yields have been associated to these practices (Van den Putte et al., 2010). There is still uncertainty of the merit of conservation tillage to contribute to increasing the resilience of cropping systems to climate change (Powlson et al., 2016) and to increasing SOC compared with CT practices (Gonzalez-Sanchezet al., 2012; Haddaway et al., 2016). In fact, SOC significantly increases in the layers closest to the soil surface under conservation tillage but does not always increase in the deeper soil profile where, conversely, SOC content tends to increase under conventional tillage, particularly near or at the bottom of the plowed layer (Alvarez, 2005; Angers and Eriksen-Hamel, 2008; De Sanctis et al., 2012). These results highlight the importance of evaluating the entire soil profile or, at least, the depth of the plowed layer to compare the effect of contrasting tillage practices on SOC stocks.

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

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

Furthermore, many studies of multi model ensembles (MME) under current climate conditions have shown that the mean or median of the ensemble's simulated values reproduce the measured crop yields better than any individual model (Asseng et al., 2014; Li et al., 2015; Martre et al., 2015; Palosuo et al., 2011; Rötter et al., 2012). Given the improved performance of crop model ensembles over single models under current conditions, Wallach et al. suggest (2016) that better predictions under future climate conditions can be obtained with the mean or median of the model ensemble, even without improving the present-day crop models. Nevertheless, while some research has assessed MME to predict crop yield, no MME studies are currently available that evaluate the ensemble mean or median to simulate SOC dynamics. Many studies have used biogeochemical models (Alvaro-Fuentes et al., 2012; Lugato et al., 2007; Tornquist et al., 2009) to assess the impact of climate change on SOC, but because these models have simplified processes for crop growth simulation, they could produce unreliable impacts on crop productivity and, consequently, on soil C-input. Crop biophysical models have been used mainly for assessing climate change impacts on crop production (Asseng et al., 2014; Bassu et al., 2014; Long et al., 2006) and are focused on one single crop. These models typically involved re-initializing the soil conditions to the same state each year without considering SOC dynamics that may change as a result of crop management. In contrast, recent studies (Basso et al., 2015; Kollas et al., 2015; Teixeira et al., 2015) have highlighted the importance of reproducing the entire crop sequence with continuous simulation to take in account any additive (or subtractive) effects that may influence soil nutrients, SOC, and consequently, crop yields. This is particularly important under limited growing conditions such as in rainfed cropping systems with low SOC content. As a matter of fact, SOC can vary by year in response to agronomic management decisions and climate. These changes in SOC then affect soil water holding capacity and nitrogen and, at the same time, crop performance which, in turn, affects additional input of SOC. Moreover, continuous simulations can also allow more accurate evaluation of agronomic management practices such as tillage and offer insight into long-term adaptation and mitigation strategies (Basso et al., 2006; 2015).

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

2. Material and methods

2.1 Description of the long-term datasets

The data from two rainfed long-term experiments (LTEs) were utilized for this study: the AN site located in Agugliano (Ancona, Marche, 43°32’N, 13°22’E) and the PI2 site in San Piero a Grado (Pisa, Toscana, 43°41’N, 10°23’E). These sites are characterized by contrasting tillage practices and belong to the IC-FAR national network (Linking Long Term Observatories with Crop Systems Modeling For a better understanding of Climate Change Impact and Adaptation StRategies for Italian Cropping Systems). The climate of the both AN and PI2 sites is Mediterranean with a bimodal distribution of cumulated monthly precipitation in spring and autumn, mild winters and warm dry summers.

2.1.1 LTE AN

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

The conventional tillage (CT) and no till (NT) treatments were used to calibrate the crop models in the durum wheat-maize rotation (2002-2014). CT plots were ploughed each year by moldboard to a depth of 40 cm in October for wheat and at the end of August for maize. The seedbed was prepared with double harrowing to a depth of 15 cm before the sowing date. NT plots were left undisturbed except for sod seeding, chopping of crop and weed residues and herbicide spraying before seeding. Both CT and NT treatments were fertilized with 90 kg N ha^{-1}. Mineral N was distributed as ammonium nitrate in two equal rates in February and March for wheat and in one rate at seeding for maize. Crop residues were left in the field for both tillage systems.

Measured crop data consisted of phenology (flowering, and physiological maturity dates), leaf area index (LAI), and productivity (aboveground biomass and grain yield) from 2002 to 2014. SOC samples of the soil profile were collected in 1996, to a depth of 40 cm in 2002 and to a depth of 100 cm in 2006 and 2010 in both the CT and NT treatments. Physical soil characteristics and hydraulic proprieties were measured in 2006 and used to define the main soil characteristics of the site (Table 1).

2.1.2 LTE PI2

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

In this study we used a subset of treatments of the PI2 LTE (1994 to 2008) where durum wheat and maize were grown without cover crops, to evaluate the effects of the different tillage systems on SOC dynamics. The CT consisted of annual moldboard ploughing to a depth of 30-35 cm followed by secondary tillage with disk and rotary harrows. The RT was characterized by no-tillage for wheat and shallow harrowing for seedbed preparation for maize to a depth of 10-15 cm. Plots of durum wheat and maize were fertilized with 180 and 300 kg N ha^{-1}, respectively. In both systems, crop residues were chopped after harvest and left in the field. Weed control was based on post-emergence herbicide application in the CT system while pre-sowing glyphosate was also applied in the RT. FAO class 300 were used from 1994 to 2000 and class

500 from 2002 to 2006, while Cirillo and Duilio were used for durum wheat in 1999 and from 2001 to 2007. Aboveground biomass and crop yield were measured each year at harvest. Soil analyses were conducted on soil samples collected at the depths of 0-10 and 10-30 cm at the end of September in 1993 (at the beginning of the experiment), 1998 and 2008. In 2015, soil was sampled down to 90 cm to assess properties of the deeper soil layers. Data from 1993, coupled with data from the deeper layers collected in 2015 were used to define the main soil characteristics of the PI2 site (Table 1). Soil hydraulic properties were estimated using the pedo-transfer functions of Ritchie et al. (1999).

Table 1. Main physical and hydrological properties of the soils in AN and PI2 as reported in the IC-FAR database.

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

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

2.2 Setup of the crop models

Experimental and weather data collected and harmonized in the common IC-FAR database (Ginaldi et al., 2016) were used to inform and validate four process-based crop models to assess their ability to simulate SOC dynamics in different tillage systems and reproduce reliable crop residue-C inputs. Table 2 provides a list of the models used and the various biophysical approaches used in each model. A general flow chart describing the soil properties modified by the change in SOC and tillage events in the crop models is reported in Annex 1 (Fig.A1). Models simulated the long-term datasets of the experimental treatments with a continuous run, that is, without re-initialization at the onset of each growing season. In APSIM-NWheat, the simulation of maize was replaced by adding to the soil the observed amounts of residues left by the maize crop each year.

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

Before the start of the experiment in 1994, De Sanctis et al. (2012) reported the AN site had previously experienced a two-year durum wheat-maize rotation for 44 years (1950-1994) with an average N fertilizer rate of 140 kg ha^{-1}, initiated on grassland. Therefore, before simulating the cropping system for 1994-2014, the models were run over 44 years with an antecedent simulation based on a wheat-maize rotation. The total SOC in the upper 40 cm in 1950 was iteratively estimated by fitting the simulated value with the observed measured SOC in 1996, that was considered as initial value for the simulations starting in 1994. In the Century-based models (EPIC, DSSAT, SALUS), the SOC fractions at the AN site were initialized following the procedures suggested by Basso et al. (2011) considering 2%, 64% and 34% for the active, the slow and the passive pools, respectively. The final simulated fractions of the passive pool for each soil depth were then used as inputs in the simulation starting in 1994. A wheat-maize rotation was also simulated over the period 1994-2001 although in the same years sunflower was sown instead of maize but the amount of residues left by sunflower was similar to that left by maize in this rainfed system (De Sanctis et al., 2012). In the APSIM-NWheat model, inputs to set the amounts of the initial labile pool (biom) and the rest of the soil organic matter (hum) in each layer for year 1994 were set in order to minimize the root mean square error between simulated and measured values at both 0-15 and 15-40 cm for the two treatments (i.e., tillage and no tillage).

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

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

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

The PI2 site was initiated on grass land in 1930. A pre-run simulation over 63 years (1930-1993) was performed on a rain-fed biannual *durum* wheat-maize rotation fertilized with 180 kg N ha^{-1} for the winter crop and 300 kg N ha^{-1} for the summer crop. Total SOC in the upper 30 cm in 1930 was estimated iteratively until the measured SOC value in 1993 was adequately predicted by the simulation. Following the procedure of Basso et al. (2011), the same initial SOC fractions used in AN for the Century-based models were used also for PI2 in 1930. At the end of the 63 year period, the final simulated fractions obtained for the passive pool in each model were then used to initialize simulations starting in 1993. In APSIM-NWheat, the initial amounts of biom and hum in 1993 were defined so that root squared errors between simulated and measured SOC values were minimized.

The approach used by De Sanctis et al. (2012) was applied at the AN site for the DSSAT model in order to consider the presence of weeds in the conservation tillage systems. The simulations under NT were carried out with the weed contribution during the fallow period from wheat harvest (July) to maize sowing (April). Plant parameters for Bahia grass (*Paspalum notatum* Flüggé) were used to simulate green foxtail (*Setaria viridis* L.), the most frequent weed species observed at the experimental site, because Bahia grass is a C4 plant included within DSSAT that is similar to foxtail. In PI2, as the simulation of weed growth during the fallow period was limited by the presence of tillage, weed contribution to SOC was simulated in the RT system adding also an amount of 1500 kg ha^{-1} of bahia grass crop residue at the onset of each maize growing seasons. This average amount per year was taken from Mazzoncini et al. (2011) considering the total weed biomass contribution over the experimental period 1994-2008.

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

2.3 Evaluation of model performance

The performance of each model to simulate SOC was evaluated by calculating complementary indicators following the method proposed by Smith et al. (1997), but only one indicator was selected for each statistical aspect of the simulation so that the same weight was given in the evaluation of the model's overall ability.

The total difference between simulated and measured values were calculated as the relative root mean square error (RRMSE):

$$RRMSE = \frac{100}{\bar{O}} \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

where the relative difference between the predicted (P_i) and the observed (O_i) value is weighted as a percentage of the mean value of observed data ($\bar{O}$). The lowest possible value of RRMSE is zero when there is no difference between simulated and observed data.

The statistical significance of RRMSE was estimated calculating the $RRMSE_{95\%}$:

$$RRMSE_{95\%} = \frac{100}{\bar{O}} \sqrt{\frac{\sum_{i=1}^{n}(t_{(n-2)95\%_i} * S_e(i))^2}{n}}$$

where $t_{(n-2)95\%i}$ is the Student's *t* distribution with n-2 degree of freedom and two-tailed P-value of 0.05 and $S_e(i)$ is the standard error of the measurements. When RRMSE value is less than $RRMSE_{95\%}$ the prediction is within the 95% confidence interval for those measurements.

Modeling efficiency (EF) was used to evaluate the efficiency of the model to describe the data compared to the mean of the observations:

$$EF = \frac{(\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2)}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

A positive EF value indicates that the predicted values describe the trend in the measured data better than the mean of the observations. A maximum value for EF of 1 is reached when the simulated values are perfectly equal to the measured data. A negative EF value indicates that the simple mean of the observations performs better than the model.

Bias was evaluated using the relative error E:

$$E = \frac{100}{n}\sum_{i=1}^{n}\frac{(O_i - P_i)}{O_i}$$

and its significance was determined calculating the $E_{95\%}$:

$$E_{95\%} = \frac{100}{n}\sum_{i=1}^{n}\frac{(t_{(n-2)95\%_i} * S_e(i))}{O_i}$$

An E value greater than $E_{95\%}$ shows that the bias in the simulation is greater than the 95% confidence interval of the observations.

Finally, the correlation coefficient, *r*, was determined to evaluate the degree of association between the simulation and the observations:

$$r = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}$$

where $\bar{P}$ is the mean value of predicted data. Values of *r* are between -1 and +1.A model that perfectly reproduces observed data will have an *r* value of +1.

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

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

To evaluate whether the crop growth modules of each model correctly simulated the annual C input to the soil from crop residues, the mean measured and simulated aboveground biomass (AGB) and yield for the two crops were compared under conventional and conservational tillage systems at both sites. The simulation bias for AGB and yield were also evaluated by calculating the mean difference between measured and simulated data with the Mean Bias Error (MBE) which immediately provides information on model overestimation (positive values) or underestimation (negative ones), as follows:

$$MBE = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n}$$

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

2.4 Simulation scenarios

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

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

(Scoccimarro et al., 2011) were entered into the statistical scheme in order to estimate the future local climate. Two emission scenarios were used: RCP4.5 and RCP8.5 (Moss et al., 2008), while the projections were constructed over the period 2021-2050 (CF: Future Climate) with respect to 1971-2000 (CP: Present Climate). Seasonal projections were used as input in a Richardson-based weather generator (Richardson and Wright, 1984) to preserve the correlation between weather variables in order to generate daily time series of precipitation (PREC), maximum and minimum air temperature (Tmax, Tmin) for both AN and PI2 sites. Daily generated datasets were bias-corrected with monthly correction factors obtained by comparing the overlapping periods of the CP and the available local weather stations. Finally, daily radiation was estimated by the RadEst model (Donatelli et al., 2003) from Tmax and Tmin for all climate scenarios. A CO_2 concentration of 360 ppm was considered for the CP scenario, while values of 460 ppm and 490 ppm were projected for both RCP4.5 and RCP8.5 CF scenarios up to 2050.

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

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

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

*CT= Conventional Tillage; **NT= No Tillage; ***RT= Reduced Tillage.

3. Results

3.1 Model Evaluation

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

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

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

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

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

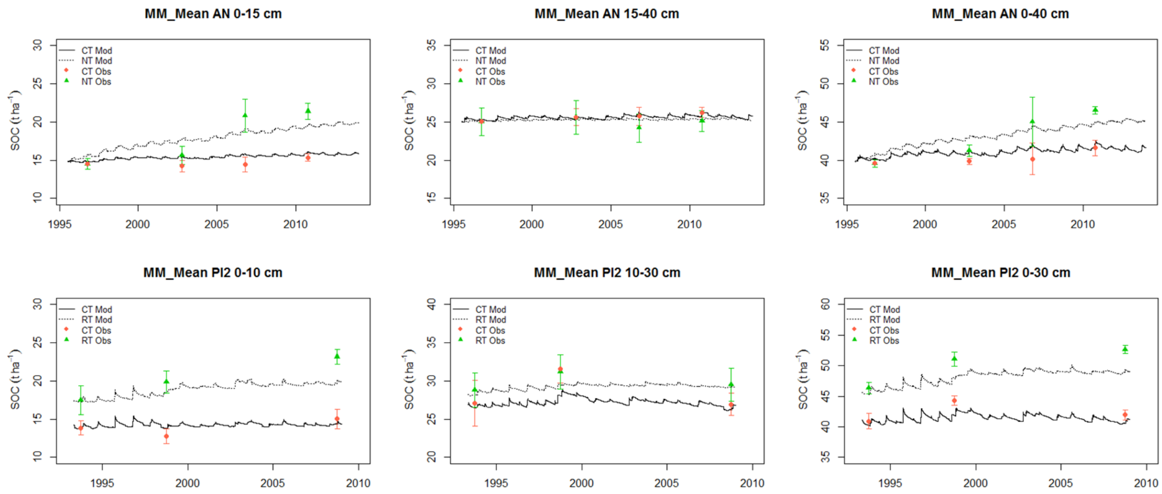

Fig. 1. Soil organic carbon (SOC, t ha^{-1}) dynamics simulated (Mod) by the multi model mean (MM_Mean) in different tillage systems (CT= Conventional tillage, NT= No till, RT= Reduced tillage) at different soil depths in the two sites (AN: 0-15cm, 15-40cm, 0-40cm; PI2: 0-10cm, 10-30cm, 0-30cm) in comparison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

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

3.2 Simulation scenarios: CP vs CF

3.2.1 Climate scenarios

The CP scenario reproduced the mean monthly values of all indices very well (Tmax, Tmin and PREC) for the local observed climate from 1971 to 2000 in both sites (Supplementary material, Table S1). The CF scenarios RCP4.5 and RCP8.5 (Fig. 2) showed that an increase of temperatures is likely to occur during the period 2021-2050 in all seasons in both sites. In particular, an annual mean temperature increase of +1.8°C in RCP4.5 and +2.1°C in RCP8.5 was projected for AN and increases of +1.9°C (RCP4.5) and +2.1°C (RCP8.5) were projected for PI2. The biggest changes mainly occurred during the summer when temperatures reached their maximum level, in particular in August for AN (+ 2.6°C RCP4.5 and +2.7°C in RCP8.5) and in July for PI2 (+2.9°C in RCP4.5 and +3.1°C in RCP8.5).

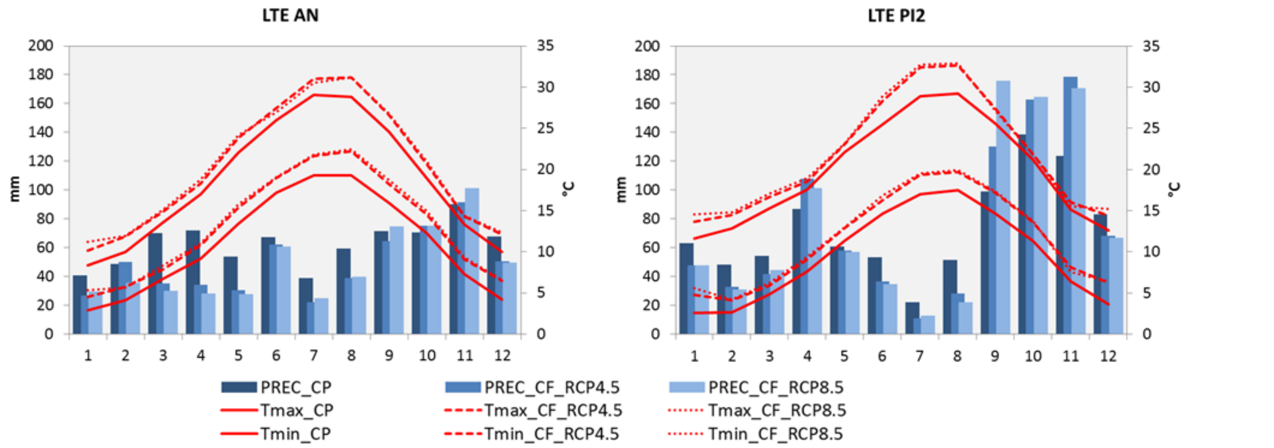

Fig. 2. Climate scenarios for the three time spans: CP (Present Climate), CF (Future Climate) RCP4.5, and RCP8.5 in AN and PI2 sites. PREC: monthly mean precipitation, Tmax: monthly maximum temperature and Tmin: monthly minimum temperature.

The pattern of changes in precipitation was more complex and different from season to season and in the two sites. With regard to AN, the mean annual precipitation was of 750 mm in the CP scenario while, in the future, this value decreased by -22.5% in RCP4.5 and -23.0% in RCP8.5, with the highest reduction occurring from March to May (-49.0 % in RCP4.5 and -56.1% in RCP8.5) and during the summer, especially from July to August (-38.0% in RCP4.5 and -34.1% in RCP8.5). On the other hand, a slight increase in precipitation occurred in autumn mostly from October to November (+3.7% in RCP4.5 and +9.9% in RCP8.5).

In PI2, the climate scenarios showed a mean total annual precipitation of 884 mm during the CP period and a modest increase of 2.1% in RCP4.5 and 4.9% in RCP8.5 was observed under projected climate change scenarios. The largest increase occurred in April (+24.0 % in RCP4.5 and +16.9% in RCP8.5) and during autumn from September to November (+30.5% in RCP4.5 and +41.4% in RCP8.5). As already observed for

AN, a strong reduction of rainfall occurred in summer from July to August (-47.0% in RCP4.5 and -52.7% in RCP8.5).

3.2.2 MM Mean simulation scenarios

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

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

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

* mean values of simulations with a CO_2 concentration of 460 ppm and 490 ppm

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

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

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

At the AN site, under CP conditions, the SOC stock increased at an annual rate of +0.28% with CT and +0.73% with NT, corresponding to gains of +0.11 (CT) and +0.29 (NT) t C ha^{-1} $year^{-1}$ in the uppermost 40 cm of soil. Over 30 years of simulation under future scenarios, no significant changes in the SOC stock were observed with CT, while the SOC stock increased at an average annual rate +0.16 t C ha^{-1} $year^{-1}$ with NT, corresponding to a relative annual gain of +0.4% of SOC. When compared to SOC dynamics under CP and same tillage technique, after 30-years of simulation we observed a SOC decrease of -3.1 t ha^{-1} with CT (-7.3%) and -3.8 t ha^{-1} with NT (-7.9%), with greater losses in the top (-10.2%) vs bottom (-5.5%) layers only in the case of NT.

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

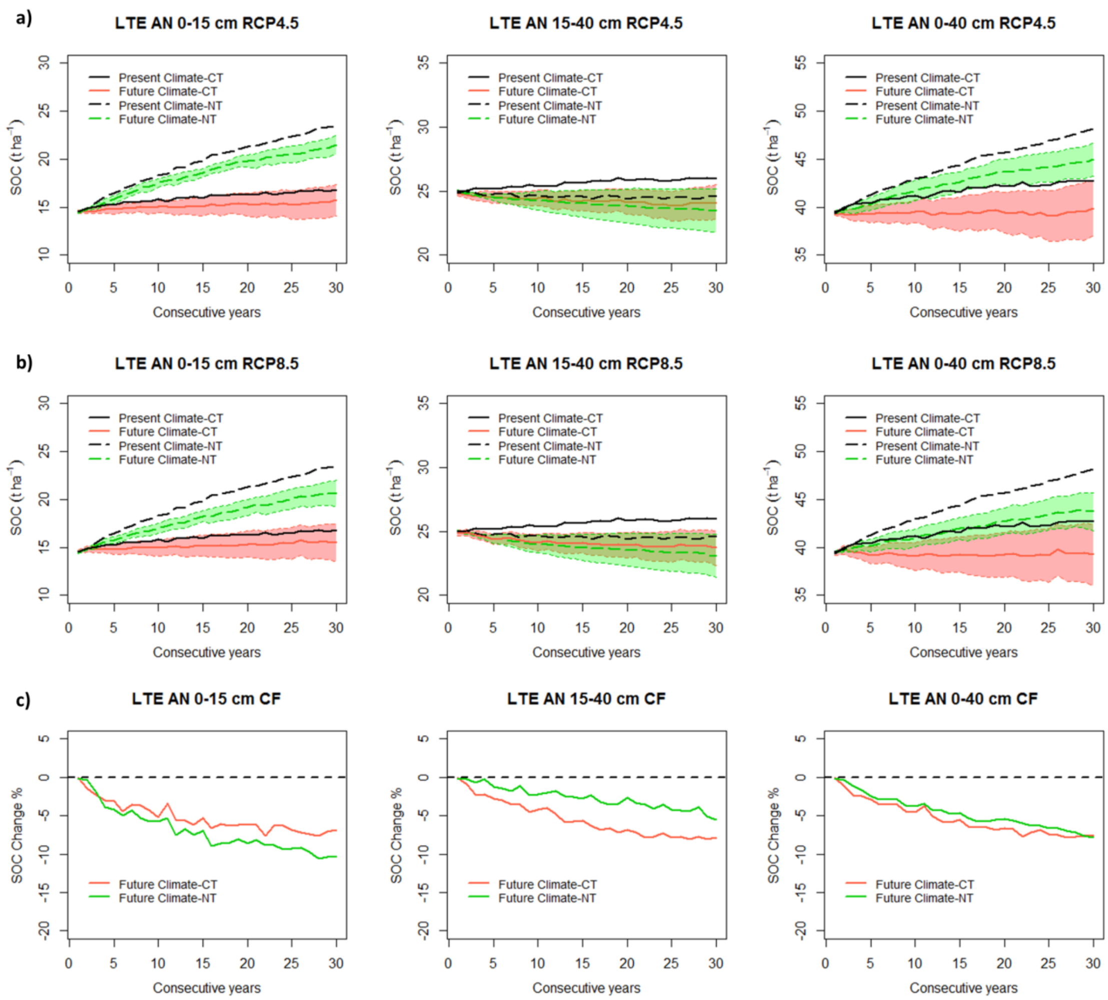

Fig. 3. Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM_Mean) in present and future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or No Tillage - NT practices in AN;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

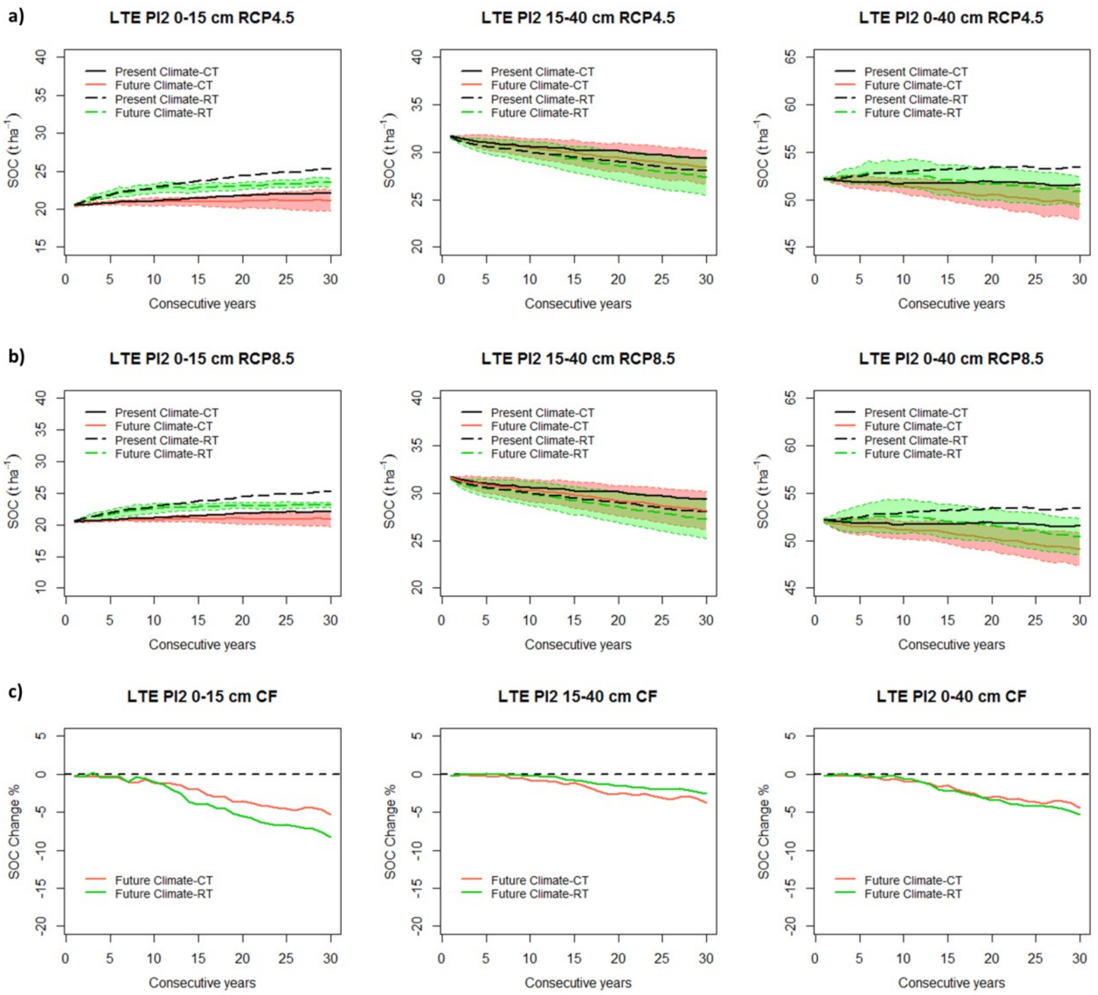

Fig. 4. Soil organic carbon (SOC) trends and climate change impacts over different soil layers (0-15 cm, 15-40 cm and 0-40cm) simulated by the multi model ensemble (MM_Mean) in present and future climate scenarios (RCP4.5 and RCP8.5) using Conventional Tillage - CT or Reduced Tillage - RT practices in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

4. Discussion

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

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

Temperature and precipitation are the main climatic drivers that influence, both directly and indirectly, organic carbon trends in the soil (Fantappiè et al., 2011; Saby et al., 2008; Smith et al., 2005). Because the monthly mean temperature is expected to increase around +2.0°C under future scenarios at both sites, soil biological activity will likely be stimulated which increases the decomposition rate and facilitates SOC losses through heterotrophic respiration (Ugalde et al., 2007). Leiros et al. (1999) showed that the positive effect on soil decomposition rate caused by a 2°C temperature increase is usually limited by a concurrent -10% decrease in soil moisture. Moreover, according to Gottschalk et al. (2012), C mineralization is constrained by both low or high values of soil water content, which is mainly influenced by precipitation. The two sites were characterized by similar increase of temperatures but diverse patterns of precipitation (on average -22.7 % in AN and +3.5% in PI2). Hence, the interaction of both factors affected the organic carbon decomposition differently at the two sites under the future scenarios, and led to lower SOC impact in PI2. However, the impact of climate change at AN was constrained by a higher clay content which physically protects SOC from microbial decomposition (Baldock and Skjemstad, 2000; Six et al., 2002; Xu et al., 2016).

These interactions are taken into account by the models which control SOC stock dynamics considering a variety of management, soil proprieties and climate factors.

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

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

CT and conservation tillage (both NT and RT) resulted in different redistributions of SOC among soil horizons. However, considering the total SOC of the 0-40 cm depth, the conservation tillage systems were able to stock more SOC than CT also under future scenarios. In fact, as conservation tillage practices decrease SOC decomposition by reducing soil CO_2 emissions (Powlson et al., 2011), they are suggested for climate change mitigation. A meta-analysis review by Angers and Eriksen-Hamel (2008) reported that the difference in SOC stocks between NT and CT at the depth of 0-30 cm is an average of 4.9 t ha^{-1} and that the difference in favor of NT increases over time until ~25-30 years, when NT usually reaches a new steady state (Alvarez et al., 2005). The same difference, 4.9 t ha^{-1}, was observed in the experimental dataset from the AN site for the period 1996-2010 in the 0-40 cm soil layer. In the CP scenario the difference between NT and CT was 5.4 t ha^{-1} after 30 years of simulation. The difference still remained high in the future scenarios with a value of 4.7 t ha^{-1}. The higher SOC stock with NT was not only due to the reduction in the decomposition coefficient but also to the weed biomass contribution, considered by the models, as also shown by De Sanctis et al. (2012). The RT system in PI2 was not so as performant as NT in AN, even if it showed slightly higher SOC values than CT with a positive difference of 1.8 t ha^{-1} in CP period and 1.3 t ha^{-1} in future scenarios. The SOC dynamic in this site was reproduced with higher uncertainty as the MM_Mean showed a high RMSE value mainly due to an underestimation of observed data under RT.

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

5. Conclusions

In this study an ensemble of four biophysical crop models (APSIM-NWheat, DSSAT, EPIC, SALUS) was used to assess the impacts of climate change on SOC stock changes under conventional and conservation tillage practices in two long-term Mediterranean rainfed durum wheat-maize rotation systems under different climate scenarios. The multi-model mean reproduced SOC dynamics better and with less uncertainty than single simulation models did and provides a more reliable prediction of SOC dynamics under future climate scenarios. Even if conservation tillage systems were more impacted by climate change than conventional tillage systems, they were still able to retain more SOC than CT, so these practices can be considered viable options for contributing to mitigate climate change through C sequestration. However further studies are necessary to complement these results and provide additional insights on the tradeoff between mitigation and adaptation and on the comprehensive GHG emissions including nitrous oxide under conservation tillage systems. The C saturation capacity of soils in relation to their texture and the effects of the change in SOC on soil hydraulic proprieties and crop yield are other aspects that need to be investigated under Mediterranean conditions.

Acknowledgments

This research is part of the IC-FAR project (prot. 2010FRE7J4, PRIN Funding scheme of the Italian Ministry of Education, University and Research 2010–11). The contribution of Ileana Iocola was provided in the context of the PhD Course "Agricultural Science" of the University of Sassari (XXIX cycle). We wish to greatly acknowledge the efforts of all LTAE designers, LTAE managers, researchers and students that have ensured the continuity to the long-term experiments in AN and PI2 sites over the time.

References

Albrizio, R., Todorovic, M., Matic, T., Stellacci, A.M., 2010. Comparing the interactive effects of water and nitrogen on durum wheat and barley grown in a Mediterranean environment. Field Crop Research 115, 179-190.

Alvarez R., 2005. A review of nitrogen fertilizer and conservation tillage effects on soil organic carbon storage. Soil Use and Management 21(1), 38-52.

Alvaro-Fuentes, J., Morel, F.J., Plaza-Bonilla, D., Arrue, J.L., Cantero-Martinez, C., 2012. Modelling tillage and nitrogen fertilization effects on soil organic carbon dynamics. Soil & Tillage Research 108, 32-39.

Angers, D., Eriksen-Hamel, N., 2008. Full-inversion tillage and organic carbon distribution in soil profiles: a meta-analysis. Soil Science Society of America Journal,72, 1370-1374.

Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., Kimball, B.A., Ottman, M. J., Wall, G. W., White, J. W., Reynolds, M. P., Alderman, P. D., Prasad, P. V. V., Aggarwal, P. K., Anothai, J., Basso, B., Biernath, C., Challinor, A. J., De Sanctis, G., Doltra, J., Fereres, E., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L. A., Izaurralde, R. C., Jabloun, M., Jones, C. D., Kersebaum, K. C., Koehler, A-K., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J. E., Palosuo, T., Priesack, E., Eyshi Rezaei, E., Ruane, A. C., Semenov, M. A., Shcherbak, I., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Thorburn, P. J., Waha, K., Wang, E., Wallach, D., Wolf, J., Zhao, Z., Zhu, Y., 2014. Rising temperatures reduce global wheat production. Nature Climate Change. 5, 143-147.

Baldock, J.A., Skjemstad, J.O., 2000. Role of the soil matrix and minerals in protecting natural organic materials against biological attack. Org. Geochem. 31, 697-710.

Basso, B., Ritchie, J.T., Grace, P.R., Sartori, L., 2006. Simulation of tillage systems impact on soil biophysical properties using the SALUS model. Italian Journal of Agronomy, 1(4), 677-688.

Basso, B., Gargiulo, O., Paustian, K., Robertson, G.P., Porter, C., Grace, P.R., Jones, J.W., 2011. Procedures for initializing soil organic carbon pools in the DSSAT CENTURY model for agricultural Systems. Soil Science Society of America Journal. 75, 69-78.

Basso, B., Ritchie, J.T., 2015. Simulating Crop Growth and Biogeochemical Fluxes in Response to Land Management using the SALUS Model. In S. K. Hamilton, J. E. Doll, and G. P. Robertson, editors. The ecology of agricultural landscapes: long-term research on the path to sustainability. Oxford University Press, New York, NY USA.

Basso, B., Hyndman, D.W., Kendall, A.D., Grace, P.R., Robertson, G.P., 2015. Can Impacts of Climate Change and Agricultural Adaptation Strategies Be Accurately Quantified if Crop Models Are Annually Re-Initialized? PLoS ONE, 10 (6): e0127333. doi:10.1371/journal.pone.0127333.

Bassu, S., Brisson, N., Durand , J.L., Boote, K., Lizaso, J., Jones, J.W., Rosenzweig, C., Ruane , A.C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis , G., Gayler, S., Grassini, P., Hatfield, J., Hoek S., Izaurralde, C., Jongschaap, R., Kemanian, A.R., Kersebaum, K.C., Kim, S.H., Kumar, N.S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M.V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., Waha, K., 2014. How do various maize crop models vary in their responses to climate change factors? Global Change Biology, 20 (7), 2301-2320.

Bertolino, A.V.F.A., Fernandes, N. F., Miranda, J. P.L., Souza, A. P., Lopes, M. R.S., Palmieri, F., 2010. Effects of plough pan development on surface hydrology and on soil physical properties in Southeastern Brazilian plateau, Journal of Hydrology, 393, 1-2, 2010, 94-104.

Bolinder, M., Kätterer, T., Andrén, O., Ericson, L., Parent, L.E., Kirchmann, H., 2010. Long-term soil organic carbon and nitrogen dynamics in forage-based crop rotations in Northern Sweden (63–64 N). Agriculture Ecosystems & Environment, 138 (3), 335-342.

Campiglia, E., Mancinelli, R., De Stefanis, E., Pucciarmati, S., Radicetti, E., 2015. Thelong-term effects of conventional and organic cropping systems, tillage managements and weather conditions on yield and grain quality of durum wheat (Triticum durum Desf.) in the Mediterranean environment of CentralItaly. Field Crop Research 176, 34-44.

De Sanctis, G., Roggero, P.P., Seddaiu, G., Orsini, R., Porter, C. H., Jones, J.W., 2012. Long-term no tillage increased soil organic carbon content of rain-fed cereal systems in a Mediterranean area. European Journal of Agronomy, 40, 18-27.

Donatelli, M., Bellocchi, G., Fontana, F., 2003. RadEst3.00: software to estimate daily radiation data from commonly available meteorological variables. European Journal of Agronomy 18, 363–367.

Doran, J.W., 1980. Soil microbial and biochemical changes associated with reduced tillage. Soil Science Society of America Journal 44, 765-771.

Ewert , F., Angulo, C., Rumbaur, C., Lock, R, Enders, A., Adenauer, M., Heckelei, T., van Ittersum, M., Wolf, J., Rötter, R., 2011. Scenario development and assessment of the potential impacts of climate and market changes on crops in Europe. AgriAdapt project reports, no. 2 & 3, 49 pp.

Fantappiè, M., L'Abate, G., Costantini, E.A.C., 2011.The influence of climate change on the soil organic carbon content in Italy from 1961 to 2008. 135, 343-352.

Farina, R., Seddaiu, G., Orsini, R., Steglich, E., Roggero, P.P., Francaviglia, R., 2011. Soil carbon dynamics and crop productivity as influenced by climate change in a rainfed cereal system under contrasting tillage using EPIC, Soil and Tillage Research, 112, 36-46.

Ginaldi, F., Bindi, M., Dalla Marta, A., Ferrise, R., Orlandini, S., Danuso, F., 2016. Interoperability of agronomic long term experiment databases and crop model intercomparison: the Italian experience, European Journal of Agronomy, 77, 209-222.

González-Sánchez, E. J., Ordóñez-Fernández, R., Carbonell-Bojollo, R., Veroz-González, O., Gil-Ribes, J.A., 2012. Meta-analysis on atmospheric carbon capture in Spain through the use of conservation agriculture. Soil Tillage Res., 122, 52-60.

Gottschalk, P., Smith, J.U., Wattenbach, M., Bellarby, J., Stehfest, E., Arnell, N., Osborn, T. J., Jones, C., Smith, P., 2012. How will organic carbon stocks in mineral soils evolve under future climate? Global projections using RothC for a range of climate change scenarios. Biogeosciences, Vol.9, 8: 3151-3171.

Haddaway N.R., Hedlund, K., Jackson, L. E., Kätterer, T., Lugato, E., Thomsen, I. K., Jørgensen, H. B., Isberg, P., 2016. How does tillage intensity affect soil organic carbon? A systematic review protocol. Environmental Evidence, 5(1).

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones P.D., New, M., 2008. A European daily high-resolution gridded dataset of surface temperature and precipitation. J. Geophys. Res (Atmospheres), 113, D20119, doi:10.1029/2008JD10201.

Harris G.R., Collins M, Sexton D.M.H., Murphy, J. M., Booth, B. B. B., 2010. Probabilistic projections for twenty-first century European climate. Nat Hazards Earth Syst Sci. 10, 2009–2020.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.I., White J.W., Uryasev, O., Ogoshi, R., Koo, J., Shelia, V., Tsuji, G.Y., 2015. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6 (http://dssat.net). DSSAT Foundation, Prosser, Washington.

Huntington, T. G. 2007. Available Water Capacity and Soil Organic Matter. In Encyclopedia of Soil Science, Second Edition. Taylor and Francis: New York, Published online: 12 Dec 2007, 139-143.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., Quiroga Jakas, M. C., 2006. Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecol. Modelling. 192(3-4), 362-384.

Jones, C.A., Kiniry, J.R., 1986. CERES-Maize: A Simulation Model of Maize Growth and Development. Texas A&M University Press, College Station, Texas.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy 18, 267-288.

Knapp, A. K., Smith, M.D., Hobbie, S.E., Collins, S. L., Fahey, T. J., Hansen, G. J. A., Landis, D. A., La Pierre, K. J., Melillo, J. M., Seastedt, T. R., Shaver, G. R., Webster, J. R., 2012. Past, Present, and Future Roles of Long-Term Experiments in the LTER Network. BioScience. 62, 377-389.

Kollas, C., Kersebaum, K., C., Nendel, C., Manevski, K., Müller, C., Palosuo, T., Armas-Herrera, C. M., Beaudoin, N., Bindi, M., Charfeddine, M., Conradt, T., Constantin, J., Eitzinger, J., Ewert, F., Ferrise, R., Gaiser, T., Garcia de Cortazar-Atauri, I., Giglio, L., Hlavinka, P., Hoffmann, H., Hoffmann, M. P., Launay, M., Manderscheid, R., Mary,B., Mirschel, W., Moriondo, M., Olesen, J. E., Öztürk, I., Pacholski, A., Ripoche-Wachter, D., Roggero, P. P., Roncossek, S., Rötter, R. P., Ruget, F., Sharif , B., Trnka, M., Ventrella, D., Waha, K., Wegehenkel, M., Weigel, H-J, Wu, L., 2015. Crop rotation modelling—A European model intercomparison, European Journal of Agronomy. 70, 98-111.

Körschens, M., 1996. Long-term data sets from Germany and Eastern Europe. Chapter in Evaluation of Soil Organic Matter Models. Volume 38 of the series NATO ASI Series pp 69-80.

Lal, R., Follett, R. Soils and climate change. In: Lal R, Follett R, editors. Soil carbon sequestration and the greenhouse effect, vol. 57. 2nd ed. Madison: SSSA Special Publication; 2009.

Le Foll, S., 2015. 4 per 1000: A New Program for Carbon Sequestration in Agriculture. Paris, France: French Minister of Agriculture, Agrifood and Forestry.

Leiros, M.C., Trasar-Cepeda, C., Seoane, S., Gil-Sotres, F., 1999. Dependence of mineralization of soil organic matter on temperature and moisture. Soil Biology and Biochemistry, 31, 327-335.

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K., Adam, M., Bregaglio, S., Buis, S., Confalonieri, R., Fumoto, T., Gaydon, D., Marcaida, M., Nakagawa, H., Oriol, P., Ruane, A. C., Ruget, F., Singh, B.-., Singh, U., Tang, L., Tao, F., Wilkens, P., Yoshida, H., Zhang, Z., Bouman, B., 2015. Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. Glob Change Biol. 21, 1328–1341.

Long, S., Ainsworth, P., Leakey, E.A., Nösberger, A.D.B., Ort, D.R., 2006. Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising CO2 Concentrations. Science. 312, 5782 pp. 1918–1921. PMID: 16809532.

Lugato, E., Paustian, K., Giardini, L., 2007. Modelling soil organic carbon dynamics in two long-term experiments of north-eastern Italy. Agriculture, Ecosystems & Environment, 120 (2), 423-432.

Lugato, E., Panagos, P., Bampa, F., Jones, A., Montanarella, L., 2014. A new baseline of organic carbon stock in European agricultural soils using a modelling approach. Global Change Biology, 20, 313-326.

Lugato, E., Bampa, F., Panagos, P., Montanarella, L., Jones, A., 2015. Potential carbon sequestration of European arable soils estimated by modelling a comprehensive set of management practices. Global Change Biology, 20, 3557–3567.

Mackenzie, A.F., Fan, M.X., Cardin, F., 1998. Nitrous oxide emission in three years as affected by tillage, corn-soybeans-alfalfa rotations, and nitrogen fertilization. Journal of Environmental Quality. 27, 698-703.

Marraccini, E., Debolini, M., Di Bene, C., Rapey, H., Bonari, E., 2012. Factors affecting soil organic matter conservation in Mediterranean hillside winter cereals-legumes cropping systems. Italian Journal of Agronomy, 7(3), 38.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J. W., Rötter, R. P., Boote, K. J., Ruane, A. C., Thorburn, P. J., Cammarano, D., Hatfield, J. L., Rosenzweig, C., Aggarwal, P. K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A. J., Doltra, J., Gayler, S., Goldberg, R., Grant, R. F., Heng, L., Hooker, J., Hunt, L. A., Ingwersen, J., Izaurralde, R. C., Kersebaum, K. C., Müller, C., Kumar, S. N., Nendel, C., O'leary, G., Olesen, J. E., Osborne, T. M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M. A., Shcherbak, I., Steduto, P., Stöckle, C. O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., White, J. W. and Wolf, J., 2015. Multimodel ensembles of wheat growth: many models are better than one. Glob Change Biol, 21, 911–925.

Mazzoncini, M., Sapkota, T.B., Barberi, P., Antichi, D., Risaliti, R., 2011. Long-term effect of tillage, nitrogen fertilization and cover crops on soil organic carbon and total nitrogen content. Soil & Tillage Research, 114, 165–174.

Mondini, C., Coleman, K., Whitmore, A.P., 2012. Spatially explicit modelling of changes in soil organic C in agricultural soils in Italy, 2001–2100: Potential for compost amendment, Agriculture, Ecosystems & Environment, 153, 24-32.

Moss, R., Babiker, M., Brinkman, S., Calvo, E., Carter, T., Edmonds, J., Elgizouli, I., Emori, S., Erda, L., Hibbard, K., Jones, R., Kainuma, M., Kelleher, J., Lamarque, J. F., Manning, M., Matthews, B., Meehl, J., Meyer, L., Mitchell, J., Nakicenovic, N., O'Neill, B., Pichs, R., Riahi, K., Rose, S., Runci, P., Stouffer, R., van Vuuren, D., Weyant, J., Wilbanks, T., Pascal van Ypersele, J., Zurek, M., 2008. Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies. Geneva: Intergovernmental Panel on Climate Change. p. 132.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takáč, J., Trnka, M., Bindi, M., Çaldağ, B., Ewert, F., Ferrise, R., Mirschel, W., Şaylan, L., Šiška, B., Rötter, R., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: a comparison of eight crop growth models. Eur J Agron. 35, 103–114.

Parton, W.J., Stewart, J.W.B., Cole, C.V., 1988. Dynamics of C, N, P and S in grassland soils: a model. Biogeochemistry 5, 109-131.

Parton, W.J., Ojima, D.S., Cole, C.V., Schimel, D.S., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: Bryant, R.B., Arnold, R.W. (Eds.), Quantitative Modeling of Soil Forming Processes (Special Publication 39). SSSA, Madison, WI, 147-167.

Pastorelli, R., Vignozzi, N., Landi, S., Piccolo, R., Orsini, R., Seddaiu, G., Roggero, P.P., Pagliai, M., 2013. Consequences on macroporosity and bacterial diversity of adopting a no-tillage system in a clayish soil of Central Italy. Soil Biolology and Biochemistry, 66, 78-93.

Powlson, D.S., Stirling, C. M., Thierfelder, C., White, R. P., Jat, M.L., 2016. Does conservation agriculture deliver climate change mitigation through soil carbon sequestration in tropical agro-ecosystems? Agriculture, Ecosystems & Environment, 220, 164-174.

Powlson, D. S., Whitmore, A. P., Goulding, K. W. T., 2011. Soil carbon sequestration to mitigate climate change: a critical re-examination to identify the true and the false. European Journal of Soil Science, 62, 42–55.

Richardson, C. W., Wright, D. A. WGEN.,1984: A model for generating daily weather variables. USDA, ARS, publication ARS-8.

Ritchie, J.T., Gerakis, A., Suleiman, A., 1999. Simple model to estimate field-measured soil water limits. Transactions of the American Society of Agricultural Engineers.42, 1609–1614

Rötter, R.P., Timothy, R.C., Jørgen, E.O., Porter, J.R., 2011. Crop-climate models need an overhaul. Nature Climate Change, 1, 175-177.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J. E., Patil, R. H., Ruget, F., Takáč, J., Trnka, M., 2012. Simulation of spring barley yield in different climatic zones of northern and Central Europe: a comparison of nine crop models. Field Crop Research, 133, 23–36.

Ruisi, P., Giambalvo, D., Saia, S., Di Miceli, G., Frenda, A. S., Plaia, A., Amato, G., 2014. Conservation tillage in a semiarid Mediterranean environment: results of 20 years of research. Italian Journal of Agronomy, 9, 1-7.

Rusu T., 2014. Energy efficiency and soil conservation in conventional, minimum tillage and no-tillage, International Soil and Water Conservation Research, Volume 2, Issue 4, 42-49.

Saby, N.P.A. , Arrouays, D., Antoni, V., Lemercier, B., Follain, S., Walter, C., Schvartz, C., 2008. Changes in soil organic carbon in a mountainous French region, 1990-2004. Soil Use and Management 24, 254-262.

Sánchez, B., Rasmussen, A., Porter, J.R., 2014. Temperatures and the growth and development of maize and rice: a review. Global Change Biology 20, 408–417.

Scoccimarro, E., Gualdi, S., Bellucci, A., Sanna, A., Fogli, P.G., Manzini, E., Vichi, M., Oddo, P., Navarra, A., 2011. Effects of Tropical Cyclones on Ocean Heat Transport in a High Resolution Coupled General Circulation Model. Journal of Climate. 24, 4368-4384.

Seddaiu, G., Iocola, I., Farina, R., Orsini, R., Iezzi, G., Roggero, P.P., 2016. Long term effects of tillage practices and N fertilization in rainfed Mediterranean cropping systems: durum wheat, sunflower and maize grain yield. European Journal Of Agronomy, 77, 166-178.

Six, J., Conant, R.T., Paul, E.A., Paustian, K., 2002. Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. Plant Soil, 241,155-176.

Smith, J., Smith, P., Wattenbach, M., Zaehle, S., Hiederer, R., Jones, R. J.A., Montanarella, L., Rounsevell, M.D.A., Reginster, I., Ewert, F., 2005. Projected changes in mineral soil carbon of European croplands and grasslands, 1990–2080. Global Change Biology, 11, 2141–2152.

Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., Coleman, K.C., Franko, U., Frolking, S., Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek, H., Komarov, A.S., Li, C., Molina, J.A., Mueller, T., Parton, W.J., Thornley, J.M., Whitmore, A.P., 1997. A comparison of the performance of nine soil organic matter models using seven long-term experimental datasets. Geoderma, 81, 153-225.

Tao, F., Yokozawa, M., Zhang, Z., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. Agricultural and Forest Meteorology, 149, 831-850.

Teixeira, E.I., Brown, H.E., Sharp, J.M., Meenken, E.D., Ewert, F., 2015. Evaluating methods to simulate crop rotations for climate impact assessments - a case study on the Canterbury plains of New Zealand. Environmental Modelling & Software. 72, 304-313.

Tomozeiu, R., Agrillo, G., Cacciamani, C., Pavan, V., 2014. Statistically downscaled climate change projections of surface temperature over Northern Italy for the periods 2021-2050 and 2070-2099, Nat.Hazards, 72, 143-168.

Tornquist, C.G., Mielniczuk, J., Pellegrino Cerri, C.E., 2009. Modeling soil organic carbon dynamics in Oxisols of Ibirubá (Brazil) with the Century Model, Soil and Tillage Research. 105, 33-43.

Ugalde, D., Brungs, A., Kaebernick, M., McGregor, A., Slattery, B., 2007. Implications of climate change for tillage practice in Australia. Soil and Tillage Research 97, 318–330.

Wang, J., Wang, X., Xu, M., Feng, G., Zhang, W., Yang, X., & Huang, S., 2015. Contributions of wheat and maize residues to soil organic carbon under long-term rotation in north China. Scientific Reports, 5, 11409.

Van den Putte, A., Govers, G., Diels, J., Gillijns, K., Demuzere, M., 2010. Assessing the effect of soil tillage on crop growth: a meta-regression analysis on European crop yields under conservation agriculture. European Journal of Agronomy, 33, 231-41.

Wallach, D., Mearns, L.O., Ruane, A.C., Rötter, R.P., Asseng, S., 2016. Lessons from climate modeling on the design and use of ensembles for crop modeling Climatic Change. doi:10.1007/s10584-016-1803-1

White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W. 2011. Methodologies for simulating impact of climate change on crop production. Field Crops Research. 124, 357–368.

Wiesmeier, M., Poeplau, C., Sierra, C.A., Maier, H., Frühauf, C., Hübner, R., Kühnel, A., Spörlein, P., Geuß, U., Hangen, E., Schilling, B., von Lützow, M., Kögel-Knabner, I., 2016. Projected loss of soil organic carbon in temperate agricultural soils in the 21st century: effects of climate change and carbon input trends. Scientific Reports 6, Article number: 32525

Williams, J. R., Sharpley, A.N., 1989. EPIC-Erosion/productivity impact calculator: 1. Model documentation. Technical Bulletin No. 1768. USDA Agricultural Research Service, Washington, D.C.

Xu, X., Shi, Z., Li, D., Rey, A., Ruan, H., Craine, J. M., Liang, J., Zhou, J., Luo, Y., 2016. Soil properties control decomposition of soil organic carbon: Results from data-assimilation analysis. Geoderma, 262, 235-242.

Supplementary Materials

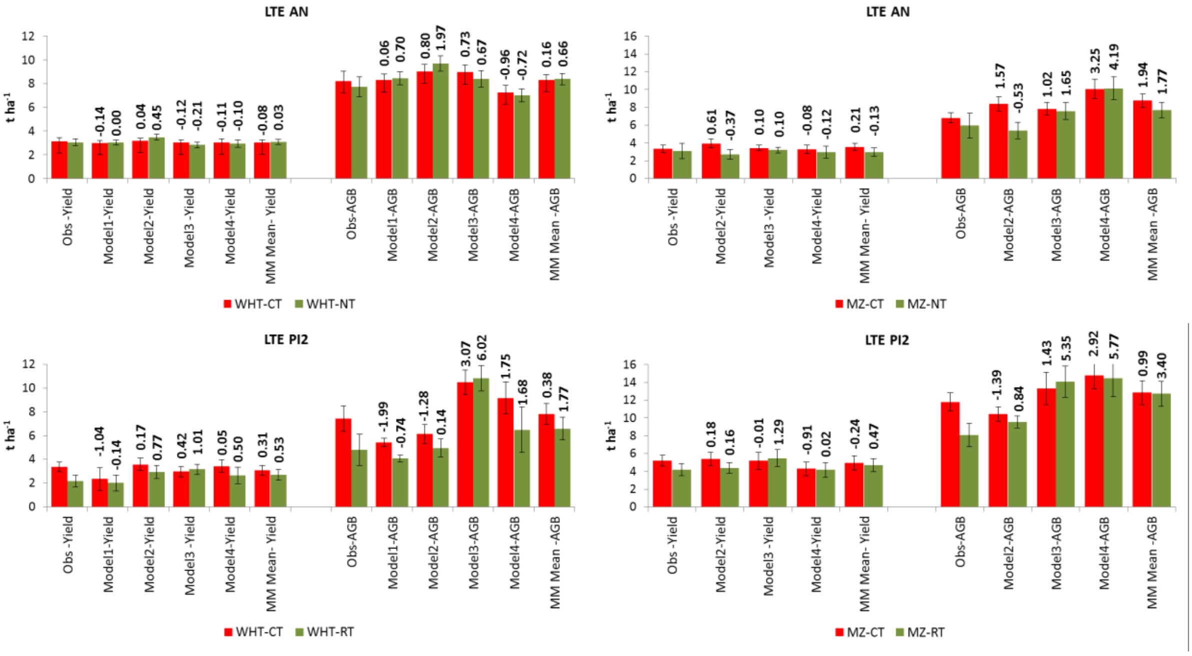

Fig. S1. Comparison of average observed and simulated data (yield and aboveground biomass -AGB-, as dry matter in t ha^{-1}). Four models (Model 1, 2, 3, 4, plus their global MM_Mean) and different tillage systems (CT: Conventional Tillage, NT: No Till, RT: Reduced Tillage) were considered in each sites, over 2002-2014 for AN and 1994-2007 for PI2. Standard errors for observed and simulated values are shown as error bars. The Mean Bias Errors (MBE) are reported as labels.

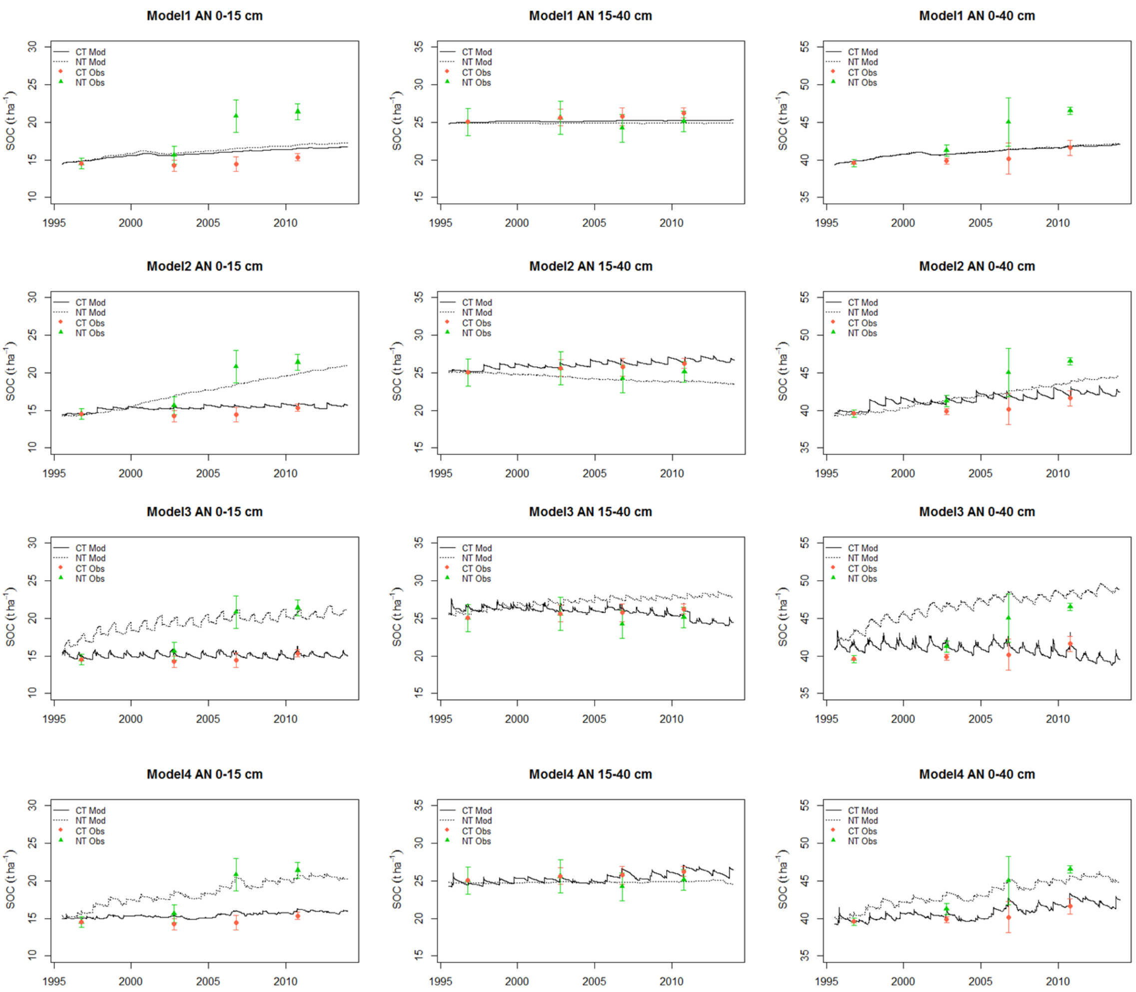

Fig. S2. Soil organic carbon (SOC, t ha^{-1}) dynamics simulated (Mod) by the four crop models (Model1, 2, 3, and 4) in different tillage systems (CT= Conventional tillage, NT= No till) at different depths (0-15 cm, 15-40 cm, 0-40 cm) in AN site in comparison with the observed (Obs) SOC values. Vertical bars are the standard errors.

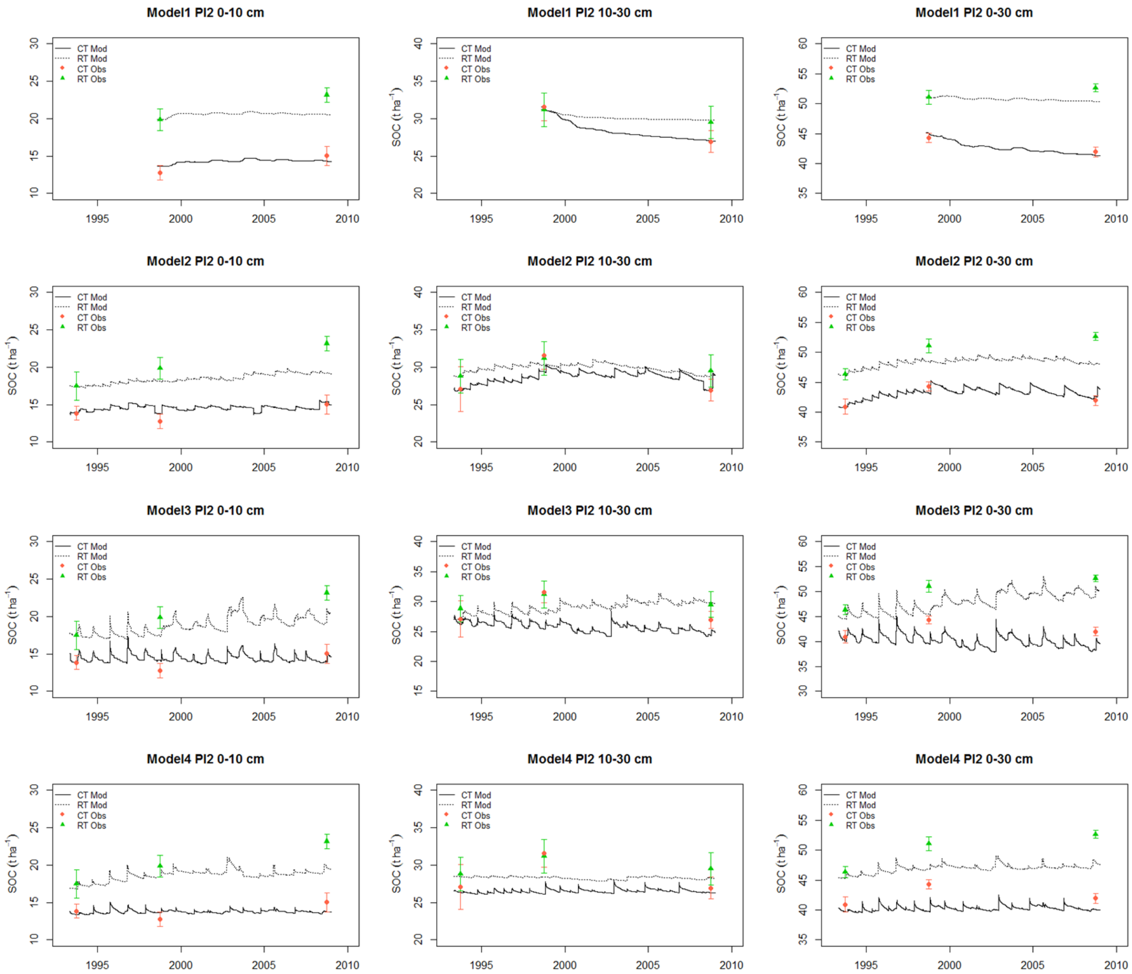

Fig. S3. Soil organic carbon (SOC, t ha^{-1}) dynamics simulated (Mod) by the four crop models (Model1, 2, 3 and 4) in different tillage systems (CT= Conventional tillage, RT= Reduced tillage) at different depths (0-10 cm, 10-30 cm, 0-30 cm) in PI2 site in comparison with the observed (Obs) SOC values. Vertical bars are the standard errors.

Table S1. Observed (Obs) and simulated (CP) climate scenarios for the period 1971-2000 in AN and PI2 sites. PREC: monthly mean total precipitation, Tmax: monthly maximum air temperature and Tmin: monthly miminum air temperature.

	Obs - AN			**CP - AN**			**Obs - PI2**			**CP - PI2**		
	Tmin	**Tmax**	**PREC**	**Tmin**	**Tmax**	**PREC**	**Tmin**	**Tmax**	**PREC**	**Tmin**	**Tmax**	**PREC**
1	2.90	8.29	40.79	2.91	8.32	40.88	2.55	11.56	62.61	2.57	11.57	62.61
2	4.09	9.92	48.66	4.11	9.99	48.53	2.65	12.76	48.43	2.66	12.81	48.43
3	6.75	13.49	70.22	6.72	13.53	70.07	4.85	15.27	54.27	4.88	15.24	54.27
4	9.19	16.94	71.58	9.19	16.95	71.75	7.63	17.57	87.06	7.62	17.59	87.06
5	13.34	22.01	53.72	13.36	22.01	53.67	11.38	22.12	61.02	11.40	22.09	61.02
6	17.10	25.87	67.07	17.14	25.92	67.20	14.63	25.44	53.20	14.61	25.43	53.20
7	19.30	29.08	38.89	19.26	29.08	38.93	17.00	28.90	22.10	17.03	28.90	22.10
8	19.31	28.77	59.22	19.31	28.79	59.39	17.49	29.18	51.52	17.48	29.24	51.52
9	15.97	24.59	71.62	15.96	24.59	71.62	14.59	25.54	99.33	14.59	25.53	99.33
10	12.26	19.00	70.21	12.30	18.97	70.59	11.32	21.11	139.07	11.30	21.12	139.07
11	7.25	13.22	90.57	7.28	13.28	90.12	6.37	15.13	123.96	6.39	15.12	123.96
12	4.18	10.01	67.52	4.22	10.01	67.59	3.68	12.58	82.65	3.66	12.61	82.65
	10.97	**18.43**	**750.07**	**10.98**	**18.45**	**750.34**	**9.51**	**19.76**	**885.22**	**9.52**	**19.77**	**885.22**

Annex 1

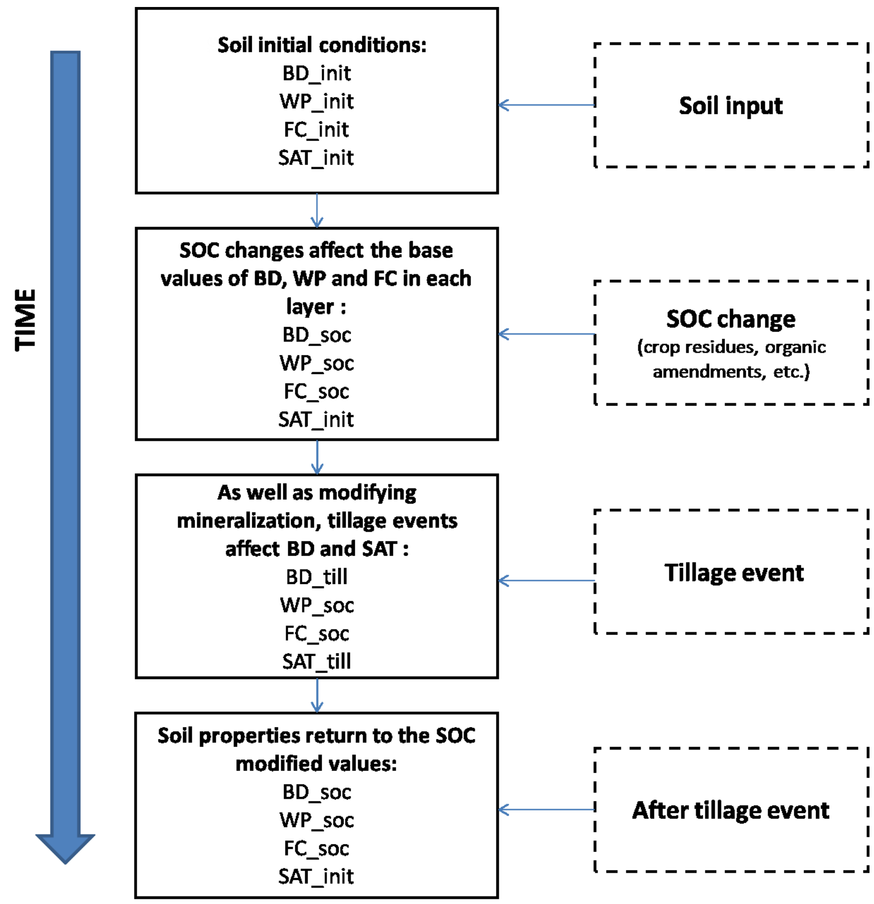

Fig. A1. Simplified flow chart describing the modification of soil properties in relation to SOC changes and tillage events in crop simulation models. WP = Soil water content at wilting point; FC = Soil water content at field capacity; SAT = Saturated water content; BD = Bulk Density.