Received: 10 October 2023 | Revised: 5 March 2024 | Accepted: 8 March 2024

DOI: 10.1111/sum.13050

RESEARCH ARTICLE

Soil Use and Management | BRITISH SOCIETY OF SOIL SCIENCE | WILEY

Soil tillage reduction as a climate change mitigation strategy in Mediterranean cereal-based cropping systems

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Funding information

Horizon Project SolaQua ID. 952879; PSR Marche 2014/2020 Agricoltura di precisione cerialicola ID 29000; Progetto Strategico Università Politecnica delle Marche 2017

Abstract

According to climate change projections, global temperatures would increase by 2°C by 2070, and agriculture is expected to be among the most affected sectors, particularly intensive field crops like cereals. Therefore, researchers need to investigate the most cost-effective agricultural strategies that can prevent production losses and ensure global food security. This study aimed to identify the limiting factors of durum wheat (*Triticum turgidum* L. subsp. *Durum* (Desf.) Husn.) yield production under Mediterranean conditions. Durum wheat yield data of over 5 years (2017–2022), from a 30-year rainfed long-term experiment conducted in the 'Pasquale Rosati' experimental farm of the Polytechnic University of Marche in Agugliano, Italy (43°32' N, 13°22′ E, 100 a.s.l.) on Calcaric Gleyic Cambisols with a silt-clay texture, were analysed and compared with the recorded thermo-pluviometric trend. The field trial included two soil managements (no tillage vs. conventional tillage) and three Nitrogen (N) fertilization levels (0, 90, and 180 kg N ha^{-1}). The most important driver for durum wheat production was N fertilization. However, in the absence of N fertilization, no tillage showed a higher yield (+1.2 t ha^{-1}) than conventional tillage due to the accumulation of organic matter in the soil. When wheat was fertilized with 90 kg N ha^{-1}, no tillage resulted in 25% yield more than conventional tillage (+1.2 t ha^{-1}), but this occurred only when the increase in temperatures was constant from January until harvest (this happened in 3 of 5 years of monitoring). The non-constant increase in temperature from January to wheat harvest may hamper crop phenological development and reduce the potential yield. The highest fertilization rate (180 Kg N ha^{-1}) resulted in the highest wheat yields regardless of soil management and thermo-pluviometric trends (5.78 t ha^{-1}). After N fertilization and soil management, the minimum and maximum temperature in February and the maximum temperature in April were crucial for durum wheat production under Mediterranean condition. When there is non-constant increase in temperature from January to wheat harvest no-tillage should be preferred over conventional tillage because wheat yields did not reduce under no tillage. Thus, agricultural policies that support the switch from conventional tillage to no-tillage management should be promoted to enable food security in Mediterranean environments.

KEYWORDS

conventional tillage, durum wheat yield, nitrogen fertilization, no tillage, thermo-pluviometric trend

1 | INTRODUCTION

Climate change is one of the greatest threats to human health in the 21st century (Vicedo-Cabrera et al., 2021; Zhao et al., 2021). Global surface temperatures are increasing, and the frequency and intensity of extreme weather events, such as heatwaves, droughts, floods, and storms, are expected to increase in the future (Rocha et al., 2022). Crop production is vulnerable to climate variability, and climate change associated with increases of +2°C by 2070, atmospheric CO_2 increase, and changing rainfall patterns may lead to a significant decline in crop production. Enhancing crop production to meet increasing demands due to population growth and the risk posed by climate change is a challenging task (Bhadouria et al., 2019).

Cereal grains have been the major component of human diet for thousands of years and have played a major role in shaping human civilization. Grains such as wheat, rice, and maize are essential to the daily sustenance of billions of people worldwide, and the consumption of cereal grains account for more than 50% of the world daily calorie (Awika, 2011).

As with other cereals, temperature variations can cause durum wheat (Triticum turgidum L. subsp. Durum (Desf.) Husn.) to grow at different times of the year and undergo phenological development shift. It has been suggested that an increase in temperature by 1°C during the cultivation of wheat could reduce yields by 3%–10% (Sabella et al., 2020). Strategies to limit the potential damage of climate change (O'Brien et al., 2021) include: (i) precision agriculture, (ii) canopy-cooling irrigation strategy, and (iii) conservation agriculture (Pittelkow et al., 2015).

Precision agriculture can be defined as the application of modern information technologies to provide, process, and analyse multisource data of high spatial and temporal resolution for decision making and operations (Fuglie, 2016). Precision agriculture can optimize the use of agronomic inputs via geo-spatial analysis (Manzione et al., 2021), machine (Chlingaryan et al., 2018) and deep learning approach (Kamilaris & Prenafeta-Boldú, 2018; Schillaci et al., 2021), and mitigation of greenhouse gas emissions from agriculture (Fellmann et al., 2021; Medel-Jiménez et al., 2022) to reduce the impact of climate change from agriculture.

Farmers may maximize productivity, revenue, and global food security (Gounden et al., 2015) by providing only 'what, where, and when it is needed' agronomic inputs (Mulla & Schepers, 2015), which reduces the impact of climate change from agriculture (Cisternas et al., 2020).

To apply precision agriculture, spatio-temporal data acquisition of the whole system of soil (Schillaci et al., 2021), plant (Fiorentini et al., 2021), and weather (Xu et al., 2022) is needed to optimize the process.

Despite the importance of precision agriculture in optimization of crop productions (Denora, Amato, et al., 2022) and reduction of agricultural environmental impact (Sapkota et al., 2014), crop critical issues such as air temperature are not solved by precision agriculture. In fact, when air temperature exceeds the crop limit, stomata closes, evapotranspiration collapses, and the plant may become susceptible to phototranspiration, which depletes the reserve of the plant and causes an irreversible loss of production (Greer, 2017).

An example of agronomic management to be able to mitigate high air temperatures is a canopy cooling irrigation system, which uses water to reduce the perceived leaf temperature and restore a temperature suitable for photosynthesis and evapotranspiration of globe artichoke (Deligios et al., 2019) and durum wheat (Thakur et al., 2022) demonstrated promising results.

However, plants are not only affected by leaf temperature but also affected by soil temperature, moisture, biological activity, and nutrient availability (Li et al., 2013). Conservation agriculture can influence all these mentioned soil parameters to improve plant growth conditions (Devkota et al., 2022; Orsini et al., 2020; Shen et al., 2018).

As observed by several authors under different pedoclimatic conditions, no-tillage can reduce soil temperature by 1.5°C (Shen et al., 2018), surface crust, and runoff (Stagnari et al., 2009). Compared with conventional tillage, no tillage can improve microbiological activity (Morugán-Coronado et al., 2022), soil organic carbon (De Sanctis et al., 2012), nitrogen availability (Alam et al., 2020), and water infiltration (Mhlanga & Thierfelder, 2021). These positive effects are generated by conservation agriculture when applied for several years consecutively, as suggested by a recent study that estimated an average soil organic carbon accumulation of 0.04% y^{-1} (Valkama et al., 2020).

Compared with precision farming and climate-controlled irrigation, conservation agriculture requires a lower initial economic investment, and the soil management needs to be performed annually by the farmer (Bellotti & Rochecouste, 2014; Capmourteres et al., 2018; Parihar et al., 2022; Paudel et al., 2023).

The aim of this study was to identify the limiting factors affecting durum wheat yield under Mediterranean conditions. We aimed to evaluate the impact of repeated years of different soil management (conventional tillage vs. no tillage), combined with different nitrogen fertilization rates, and assess the influence of the last five years trends of thermo-pluviometric. Additionally, our study aimed to propose agricultural policies that could optimize cereals cropping systems under Mediterranean conditions.

2 | MATERIALS AND METHODS

2.1 | Long-term experiment description

The long-term experiment was performed at the 'Pasquale Rosati' experimental farm of the Polytechnic University of Marche in Agugliano (Figure 1), Italy (43°32′ N, 13°22′ E, 100 a.s.l.) (Seddaiu et al., 2016).

The long-term experiment, established in 1994 and still on-going (Orsini et al., 2019), consists of a 2-year rainfed rotation of durum wheat (*Triticum turgidum* L. subsp. durum Desf.) cv. Tyrex (Apsov Sementi, Voghera, Italy) and maize (*Zea mays* L.) cv. DK440 (hybrid, FAO Class 300, Dekalb-Monsanto Agricoltura Italia S.p.A, Milano, Italy). The crop rotation was duplicated in two adjacent fields to allow for all crops to be present each year. Within each field, two soil management systems (conventional tillage and no tillage) and three nitrogen (N) fertilizer levels (0, 90, and 180 kg N ha^{-1}) were applied according to a split-plot experimental design (main and sub plots: 1500 and 500 m^2, respectively).

In the conventional tillage plots (CT), which represents the typical tillage practice in the study area, the soil was annually ploughed along the maximum slope using a mouldboard (with 2 ploughs) at a depth of 0.4 m during the autumn season. Double harrowing was used to prepare the seedbed before the sowing date.

In the no tillage plots (NT), the soil remained undisturbed except for sod seeding, crop residue and weed chopping, and total herbicide spraying prior to seeding.

FIGURE 1 Long-term experimental spatial location.

The three N-fertilizer treatments were N0, N90, and N180, which corresponded to 0, 90, and 180 kg N ha^{-1} distributed in two split applications (Table 1).

The N90 treatment was consistent with the agri-environmental measures adopted within the Rural Development Program at local scale. The N180 treatment was the business-as-usual N rates in the study area.

Durum wheat was sown in autumn at a seeding rate of 220 kg ha^{-1}, with a distance between rows of 0.17 m. Each year, N fertilization in the form of urea (46% of N) was split in two applications: 50% at the end of tillering and 50% before head emergence. Weeds, pests, and diseases were chemically controlled. The sequence of agronomic practices applied in the long-term experiment is presented in Table 1.

According to the Walter & Leith climatic classes (Walter & Leith, 1967), the climate of the study area (Figure 2) is attenuated meso-Mediterranean, and it is characterized by a mean annual rainfall of ca. 758 mm and a mean annual temperature of 15.9°C, with monthly means ranging from 7.4°C in February to 24.1°C in August.

The soil in the study area is classified as Calcaric Gleyic Cambisols (Micheli et al., 2006). It exhibits a silt-clay texture, with sand content of 123.5 g kg^{-1}, silt of 403.5 g kg^{-1}, and clay of 473 g kg^{-1}. Additionally, the soil composition includes 9.1 g kg^{-1} of organic carbon, 13.8 mg kg^{-1} of phosphorus, and 323.2 mg kg^{-1} of potassium. The soil properties has a cation exchange capacity of 26.7 cmol kg^{-1}, a pH level of 8.1, a soil bulk density of 1.30 g cm^{-3}, and a slope of ca. 10%.

2.2 | Measurements

For each subplot, three test areas were randomly selected and georeferenced (Figure 3) using a Leica Zeno 20 (Leica Geosystem, Heerbrugg, Canton St. Gallen, Switzerland). At crop maturity, fresh biomass was sampled and divided into the yield components for each test areas (1 m^2) using a laboratory thresher. The grain were dried in the oven for 48 h at 100°C and weighed to determine grain yield (t ha^{-1}). The grain yield (t ha^{-1}) was estimated using the following formula (Equation 1):

$$\text{Grain yield}\left(\frac{t}{ha}\right) = \text{g (dry grain yield biomass)} * 0.0001 \text{ (conversion factor from square meters to hectares)}. \quad (1)$$

Daily meteorological data (mean, maximum, and minimum daily air temperature and sum of daily rainfall) were obtained from the Agugliano (43°32′ N, 13°22′ E, elevation: 140 m) weather station of the Agrometeorological Regional Service of Marche (AMAP), which is located near the experimental site (around 600 m distance).

Soil sampling was conducted using a hand auger (model: Suelo HA-3, Zhejiang Lujian Instrument Equipment Co.,

TABLE 1 Agronomic management practices adopted during the experimental monitoring (mm/dd/yyyy).

Management practice	Application	Cropping season				
		2017–2018	2018–2019	2019–2020	2020–2021	2021–2022
Ploughing		10/02/2017	09/26/2018	11/11/2019	11/14/2020	11/04/2021
Harrowing and seed bed preparation		11/20/2017	11/01/2018	11/05/2019	11/02/2020	11/02/2021
Sowing		11/21/2017	11/30/2018	11/14/2019	11/10/2020	11/15/2021
Weed control: Pinoxaden[a]		03/28/2018	03/08/2019	02/10/2020	02/14/2021	02/06/2022
N fertilization	1st	03/29/2018	03/18/2019	02/25/2020	02/28/2021	02/21/2022
	2nd	04/30/2018	05/02/2019	04/09/2020	04/15/2021	04/09/2022
Pest control: Azoxystrobin, Cyproconazole[b]		04/24/2018	04/22/2019	04/20/2020	04/26/2021	04/28/2022
Harvest		07/06/2018	07/07/2019	07/06/2020	07/02/2021	07/10/2022

[a]Dose: 30 g ha^{-1} of active ingredient.

[b]Dose: 0.16 L ha^{-1} of active ingredient.

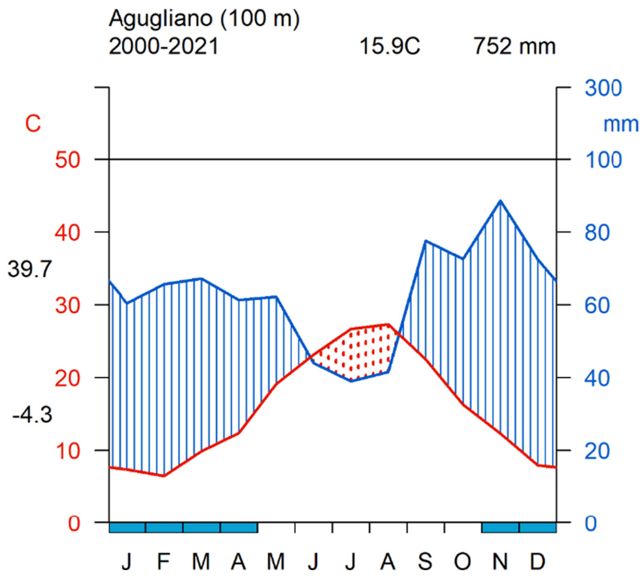


FIGURE 2 Walter & Leith climate diagram (2000–2021).

Ltd., Zhejiang, China, diameter 5.5cm) immediately before sowing. Two samples were obtained from each subplot at a depth of 0–0.20m and geo-referenced using the Leica Zeno 20 (Leica Geosystem, Heerbrugg, Canton St. allen, Switzerland). The sand content ($g\,kg^{-1}$), silt content ($g\,kg^{-1}$), and clay content ($g\,kg^{-1}$) for each sample were measured using the hydrometer method (Beverwijk, 1967). The pH was measured with a pH metre, organic matter ($g\,kg^{-1}$) was determined using the Walkley–Black chromic acid wet oxidation method (Walkley & Black, 1934), total N ($g\,kg^{-1}$) was analysed with the Kjeldahl method (Bremner, 1960), and the C/N ratio was calculated based on the previous measurements. The available water was calculated as difference between the field capacity (% Vol.) and Oven Dried (% Vol.). In details, the soil samples (n.12 for each soil management) were extracted at 20cm depth with Undisturbed Cylinder Method (Hillel, 2003) immediately after the macroplot outlet rill water surplus evacuation assuming that the 0.2m soil depth was at field capacity. The soil samples after the extraction were placed in plastic bag and carried to laboratory to determine fresh and dry weight (g) determined by analytical balance, after placing in ventilated oven at 105°C for 72h until constant dry weight determination. The results of the soil analysis are shown in Table 2 (Fiorentini et al., 2021).

More details on the trends in soil chemical and physical parameters from 1994 to 2012 are found in Iocola et al. (2017).

2.3 | Statistical analysis

All statistical analyses were performed using R statistical software (Core Team, 2014). All potential models were constructed to determine which one would fit the data the best, and the best model was then chosen based on statistics that put a penalty on 'complexity', such as the Akaike Information Criterion (Akaike, 1974), Bayesian Information Criterion (Schwarz, 1978), and likelihood ratio tests (Wilks, 1938). The best model that fit better with the data was the mixed model, as reported in several studies (Fiorentini et al., 2019; Piepho et al., 2004; Pro et al., 2021; Seddaiu et al., 2016). Based on the dataset structure, the soil management, N input, and year were set as fixed factors, whereas block and plots were set as random factors of the mixed model. In addition, yield was analysed using nitrogen and soil management as fixed factors, respectively.

Further, we confirmed whether the model satisfies the assumptions of the analysis of variance (ANOVA) before performing the ANOVA. The normality distribution of the model residual was checked both graphically (QQ-plot) and by performing the Shapiro–Wilk normality test. The homoscedasticity was checked using the Levene test. The 'emmeans' function with the Bonferroni correction of the emmeans R package was used to perform the estimated marginal means post-hoc analysis only when the ANOVA revealed a significant difference between the components (p-value $< .05$) (Lenth, 2019).

2.4 | Conditional inference trees

Four agro-meteorological variables (mean temperature °C, absolute minimum temperature °C, absolute maximum temperature °C, and rainfall amount mm), soil management, and N input levels were used as inputs in a recursive partitioning analysis in which the target variable was the grain yield ($t\,ha^{-1}$). The four agro-meteorological variables were analysed on monthly basis starting from sowing (November) until harvest (July).

Soil management was considered as a categorical variable (CT or NT), and the N input was considered as a numerical variable based on the amount of N provided to the crop (0, 90, and 180 $kg\,ha^{-1}$) (Figure 3 and Table 1).

The recursive partition explores the structure of a dataset to develop decision rules for predicting a categorical (classification tree) or continuous (regression tree) variable (Rokach & Maimon, 2008; Strobl et al., 2009). This study 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 variables (meteorological, soil, and N management).

FIGURE 3 Long-term experimental design and yield sample spatial positions.

Regression trees are constructed by recursively splitting the response variable (grain yield, t ha^{-1}) into two groups based on the explanatory variables to minimize variability within a group and maximize variability between groups.

At the end, the terminal node (leaves) was characterized using the mean values of the response variable. The 'ctree' function uses statistical tests to split nodes and provides a P-value that indicates how significant the splitting is. In this study, the 'ctree' function was used to explore the interactions among explanatory variables and not as a predictive tool.

Three different datasets were used to perform the recursive partitioning analysis: one dataset with all the soil management and the other two datasets were created by excluding either soil management to highlight different behaviours.

3 | RESULTS

3.1 | Weather data

All the weather data were analysed on monthly basis starting from November (durum wheat sowing) until July (harvest), and they are presented in Table 3.

Considering the thermal data, the growth seasons analysed (2017–2022) showed higher mean temperature (+1.2°C), minimum temperature (+1.4°C), and maximum temperature (+1.9°C) than the long-term data (1950–2023). The rainfall during the growing season decreased by 89.36 mm compared with that of the long-term data (Table 3).

The 2017–2018 growing season recorded the lowest mean temperature (13.79°C), absolute minimum

TABLE 2 Soil data of the no-tillage and conventional tillage plots.

Soil management	Sand ($g\,kg^{-1}$)	Silt ($g\,kg^{-1}$)	Clay ($g\,kg^{-1}$)	pH	C/N	Organic matter ($g\,kg^{-1}$)	Total nitrogen ($g\,kg^{-1}$)	Available water (% Vol.)
CT	423 (±44) a	126 (±20) a	451 (±58) a	7.8 (±0.2) a	7.9 (±0.5) b	13.20 (±1.07) b	0.98 (±0.04) b	11.8 (±0.8) b
NT	436 (±42) a	121 (±20) a	443 (±39) a	7.8 (±0.2) a	8.6 (±0.5) a	21.52 (±6.40) a	1.44 (±0.36) a	17,5 (±1.1) a

Note: Means within column that are followed by the same letter are not significantly different at $p < .05\%$.

Abbreviations: CT, conventional tillage; NT, no-tillage.

temperature (−7.80°C), and absolute maximum temperature (32.70°C) and the highest rainfall (746.40 mm) compared with the other growing seasons. The highest mean temperature (14.53°C) was recorded during the 2019–2020 growing season, and the highest temperature recorded during the 2020–2021 growing season was 37.50°C (Figure 4). The rainfalls recorded during the 2018–2019, 2019–2020, 2020–2021, and 2021–2022 growing seasons were 69%, 51%, 46%, and 77% lower compared with the 2017–2018 growing season, respectively.

Three of the five studied growing seasons showed a non-constant trend with increasing temperatures from January to March (Figure 4). Particularly, a higher mean temperature in January (8.54°C), lower mean temperature in February (4.79°C), and higher mean temperature in March (8.93°C) were observed during the 2018–2019 growing season.

During the 2019–2020 and 2021–2022 growing seasons, the temperature recorded in February (11.04°C and 9.31°C, respectively) was higher than that recorded in March (10.23°C and 8.43°C, respectively). It should be noted that two of the five studied growing seasons (i.e., 2018–2019 and 2020–2021 growing seasons) showed a linear trend with increasing temperature from January to July (Figure 4).

3.2 | Grain yield data

The ANOVA applied to the mixed model fitted with the grain yield ($t\,ha^{-1}$), indicating that the single effect of N input, soil management, and year are significant (Table 4).

Moreover, the combined effect of N input, soil management, and year showed a significant difference in the grain yield ($t\,ha^{-1}$) while no significant interaction emerged between the three factors (N × SM × Y) (Table 4).

As the N fertilization level increases, the yield increases significantly, with an average value of 2.08 $t\,ha^{-1}$, 4.06 ha^{-1}, and 5.77 ha^{-1}, respectively for N0, N90, and N180. For the unfertilized treatment, the NT (2.69 ha^{-1}) achieved a significantly higher grain yield value than CT (1.46 ha^{-1}) for each growing season (Table 5).

Considering the N90 level of fertilization, in two of the five growing seasons, NT resulted in significantly higher yield than CT (+16.14% and + 33.76% $t\,ha^{-1}$, respectively). In these two growing seasons (2018–2019 and 2020–2021), a constant and gradual increase in temperature from January to July was observed (Figure 4). Conversely, in the remaining growing seasons, when the temperature did not constantly increase from January to July, the average grain yield for NT (4.27 $t\,ha^{-1}$) was not statistically different from that for CT (3.98 $t\,ha^{-1}$) (Table 5). No

TABLE 3 Comparison between thermo-pluviometric trends and historical data recorded by the Agugliano weather station during the studied growing seasons (2017–2022) and historical data (1950–2023).

	Mean air T (°C)									
	November	December	January	February	March	April	May	June	July	Mean
Studied growing season (2017–2022)	11.8	7.7	6.7	8.5	9.8	13.7	18.2	24.1	25.9	14.0
Historical data (1950–2023)	10.71	6.71	5.44	6.84	9.51	12.93	17.72	21.88	24.15	12.9
Δ (Studied growing season–Historical data)	1.1	1.0	1.3	1.7	0.3	0.8	0.5	2.2	1.8	1.2
	Max Air T (°C)									
	November	December	January	February	March	April	May	June	July	Max
Studied growing season (2017–2022)	22.20	18.30	18.70	20.00	22.30	26.30	29.60	35.20	35.00	35.2
Historical data (1950–2023)	21.22	16.77	15.77	18.13	21.83	23.61	30.14	32.97	34.49	34.5
Δ (Studied growing season–Historical data)	0.98	1.53	2.93	1.87	0.47	2.69	−0.54	2.24	0.51	1.4
	Min Air T (°C)									
	November	December	January	February	March	April	May	June	July	Min
Studied growing season (2017–2022)	2.90	0.10	−0.60	−1.30	0.40	3.30	8.00	12.50	16.70	−1.30
Historical data (1950–2023)	0.79	−1.89	−3.04	−3.14	−1.96	1.75	7.65	10.99	13.96	−3.14
Δ (Studied growing season–Historical data)	2.11	1.99	2.44	1.84	2.36	1.55	0.35	1.51	2.75	1.9
	Rainfall (mm)									
	November	December	January	February	March	April	May	June	July	Sum
Studied growing season (2017–2022)	94.90	90.00	42.10	58.80	57.20	49.60	70.30	32.20	17.60	512.70
Historical data (1950–2023)	79.07	78.14	57.13	66.62	87.65	71.59	66.79	58.79	36.29	602.06
Δ (Studied growing season–Historical data)	15.83	11.86	−15.03	−7.82	−30.45	−21.99	3.51	−26.59	−18.69	−89.36

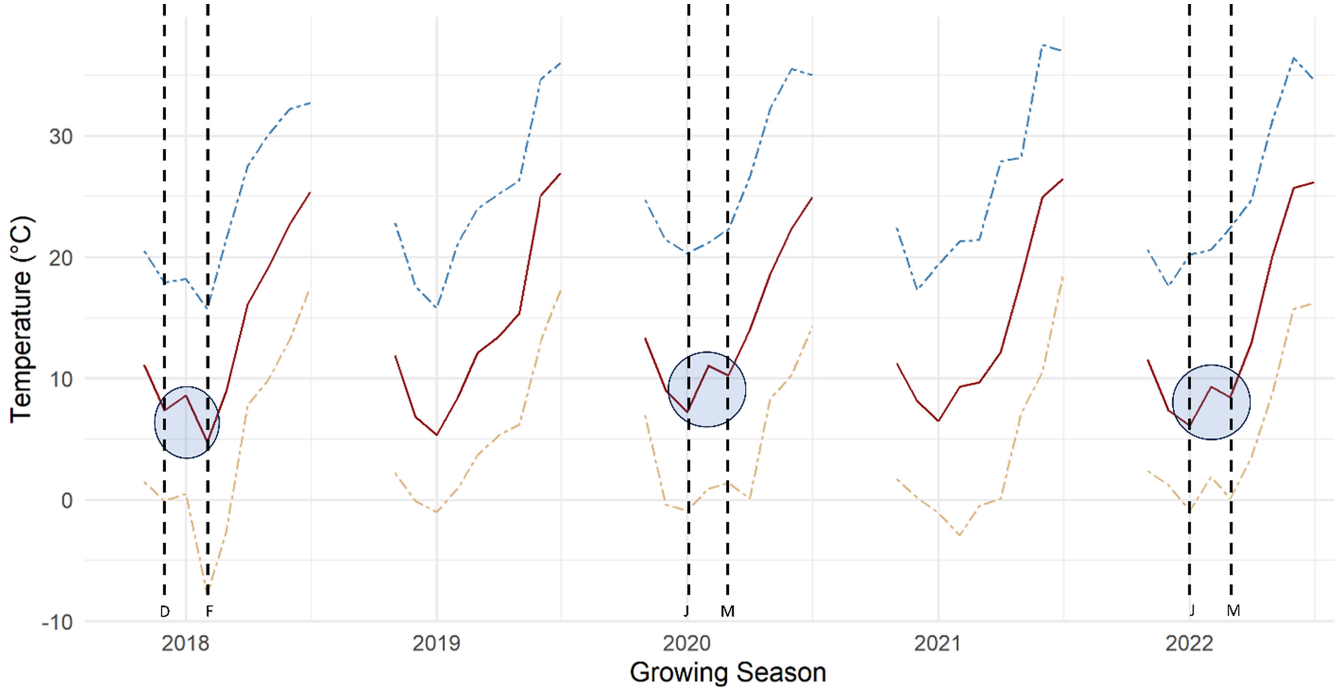


FIGURE 4 Monthly mean temperature (red line), absolute maximum temperature (blue dash line), and absolute minimum temperature (orange dash line) trend during the growing seasons starting from November until July. The blue circle is used to indicate the growing season that have a non-constant increase in temperatures from December (D) until March (M).

TABLE 4 ANOVA results applied to the mixed model.

		Grain yield t ha^{-1}	
Factors	***df***	***p*-value**	***F*-value**
N	2	***	440.21
SM	1	***	88.18
Y	4	***	21.65
N×SM	2	**	12.51
N×Y	8	**	4.09
SM×Y	4	*	2.82
N×SM×Y	8	0.51	0.91

Abbreviations: *df*, degree of freedom; N, Nitrogen fertilization; SM, soil management; Y, year.

*Significant at p < .05%; **Significant at p < .01%; ***Significant at p < .001%.

significant difference was observed between soil management for N180 in all the five studied growing seasons and the mean values were 5.85 t ha^{-1} and 5.70 t ha^{-1} for CT and NT, respectively.

Considering the average yield obtained for each year, the 2020 (4.43 t ha^{-1}) and 2022 (4.24 t ha^{-1}) growing seasons reached a significantly higher value than the 2018 (3.18 t ha^{-1}) growing season due to a late snowfall that characterized the month of February during which the minimum temperature (2°C) were observed to be significantly lower than the average (5.5°C). However, no statistically significant differences were shown between the 2022, 2021, 2020, and 2019 growing seasons (Table 5).

3.3 | Conditional inference trees

A conditional inference tree with nine leaves and seven internal nodes was created using the dataset with both soil managements (Figure 5). The root node was based on the amount of N provided to the crop. If no N was provided to the crop, a new internal node is created based on the soil management used. When the soil management was NT, the grain yield was 2.69 t ha^{-1}, but when the soil management was CT, a new internal node was created based on the maximum temperature in April. When the maximum temperature in April was lower than 25.2°C, the grain yield was 1.62 t ha^{-1}, but when the maximum temperature in April was higher than 25.2°C, the grain yield was 1.028 t ha^{-1} (Figure 5).

For the root node, when the N applied to the crop was higher than 0 kg N ha^{-1}, a new internal node was created based on whether the N supplied to the crop was greater or less than 90 kg N ha^{-1}. When the N applied to the crop was higher than 90 kg N ha^{-1}, a new internal node was created based on the minimum temperature in February. When the minimum temperature in February was higher than −2.9°C, the grain yield

TABLE 5 Estimated marginal mean analysis results of the grain yield ($t\,ha^{-1}$) for each growing season.

Growing season	Nitrogen input	Soil management	Grain yield t ha^{-1}	Grain yield t ha^{-1} (grand mean)
2018	0	CT	1.32 (±0.22) d	3.18 (±2.48) B
		NT	2.53 (±0.17) c	
	90	CT	3.22 (±0.36) b	
		NT	3.71 (±0.32) b	
	180	CT	4.55 (±1.49) a	
		NT	4.26 (±0.31) a	
2019	0	CT	1.51 (±0.64) e	3.94 (±2.72) AB
		NT	2.32 (±0.41) d	
	90	CT	3.69 (±0.50) c	
		NT	4.40 (±0.47) b	
	180	CT	6.45 (±1.31) a	
		NT	6.25 (±1.00) a	
2020	0	CT	1.21 (±0.25) d	4.43 (±2.58) A
		NT	2.95 (±0.69) c	
	90	CT	4.08 (±0.54) b	
		NT	4.45 (±0.41) b	
	180	CT	6.25 (±1.17) a	
		NT	6.62 (±0.42) a	
2021	0	CT	1.55 (±0.10) e	3.49 (±2.55) AB
		NT	2.60 (±0.32) d	
	90	CT	3.08 (±0.75) c	
		NT	4.65 (±0.91) b	
	180	CT	5.63 (±0.88) a	
		NT	5.43 (±0.32) a	
2022	0	CT	1.73 (±0.37) d	4.24 (±2.55) A
		NT	3.05 (±0.44) c	
	90	CT	4.69 (±0.70) b	
		NT	4.64 (±0.42) b	
	180	CT	6.36 (±0.92) a	
		NT	5.95 (±0.45) a	

Note: Means within year and column that are followed by the same lowercase letter are not significantly different at $p < .05\%$. Means within year and column that are followed by the same uppercase letter are not significantly different at $p < .05\%$.

was 6.15 $t\,ha^{-1}$, but when the minimum temperature in February was lower than −2.9°C, the grain yield was 4.72 $t\,ha^{-1}$ (Figure 5).

When the N applied to the crop was higher than 90 $kg\,N\,ha^{-1}$, a new internal node was created based on the soil management adopted. When the soil management was CT, a new terminal node was created based on the minimum temperature in February. When the minimum temperature in February was higher than −2.9°C, the grain yield was 3.82 $t\,ha^{-1}$, but when the minimum temperature in February was lower than −2.9°C, the grain yield was 2.90 $t\,ha^{-1}$ (Figure 5). For the soil management, when the soil management was NT, a new internal node was created based on the mean temperature in February. When the mean temperature in February was higher than 8.47°C, the grain yield was 4.91 $t\,ha^{-1}$, but when the mean temperature in February was lower than 8.47°C, the grain yield was 4.06 $t\,ha^{-1}$.

A conditional inference tree with four leaves and three internal nodes was created using the dataset with only no tillage (Figure 6).

The root node is based on the amount of N provided to the crop. When the N provided to the crop was not higher than 0 $kg\,N\,ha^{-1}$, the grain yield was 2.69 $t\,ha^{-1}$. When the N provided to the crop was higher than 0 $kg\,N\,ha^{-1}$, a new internal node was created based on the mean temperature

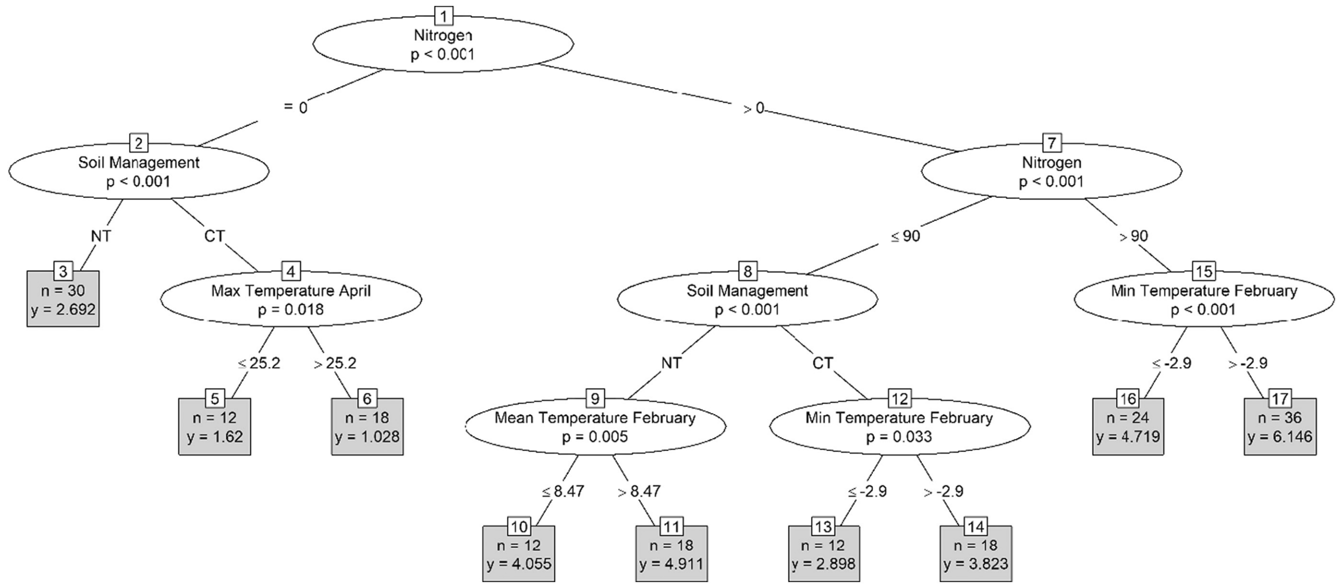
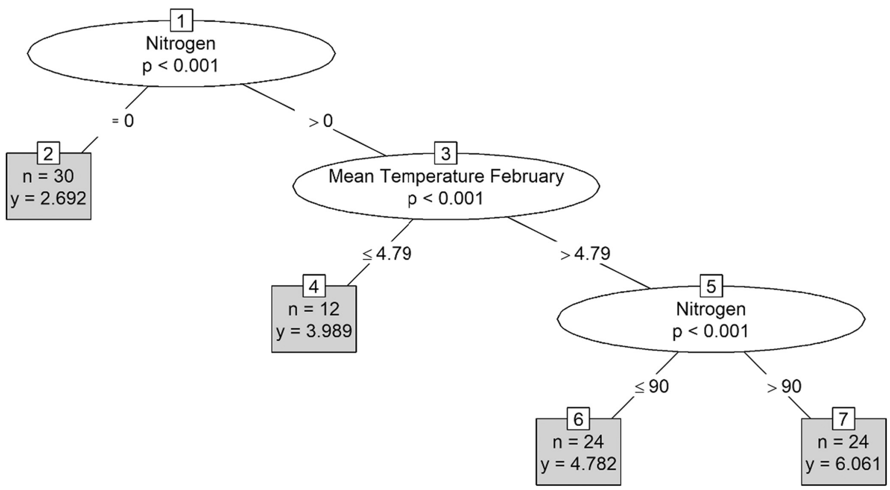


FIGURE 5 Conditional inference tree showing the emerging drivers of the durum wheat grain yield inter-annual variation: meteorological variables, nitrogen input (0, 90, and 180 N kg ha^{-1}), and both soil management.

FIGURE 6 Conditional inference tree showing the emerging drivers of the durum wheat grain yield inter-annual variation under no tillage soil management condition: meteorological variables and N input (0, 90, and 180 N kg ha^{-1}).



in February (Figure 6). When the mean temperature in February was lower than 4.79°C, the grain yield was 3.99 t ha^{-1}, but when the mean temperature in February was higher than 4.79°C, a new internal node was created based on the N provided to the crop. When the N provided to the crop was lower than 90 kg N ha^{-1}, the grain yield was 4.78 t ha^{-1}, but when the N provided to the crop was higher than 90 kg N ha^{-1}, the grain yield was 6.06 t ha^{-1} (Figure 6).

A conditional inference tree with five leaves and three internal nodes was created using the dataset with only CT (Figure 7).

The root node is based on the amount of N provided to the crop. When the N provided to the crop was not higher than 0 kg N ha^{-1}, a new internal node was created based on the maximum temperature in April (Figure 7). When the maximum temperature in April was lower than 25.2°C, the grain yield was 1.62 t ha^{-1}, but when the maximum temperature in April was higher than 25.2°C, the grain yield was 1.03 t ha^{-1}. When the amount of N provided to the crop was higher than 0 kg N ha^{-1}, a new internal node was created based on the amount of N provided to the crop. When the N provided to the crop was lower than 90 kg N ha^{-1}, the grain yield was 5.50 t ha^{-1}, but when the N provided to the crop was higher than 90 kg N ha^{-1}, a new internal node was created based on the minimum temperature in February. When the minimum temperature in February was lower than 2.9°C, the grain yield was 2.90 t ha^{-1}, but when the minimum temperature in February was higher than 2.9°C, the grain yield was 3.82 t ha^{-1} (Figure 7).

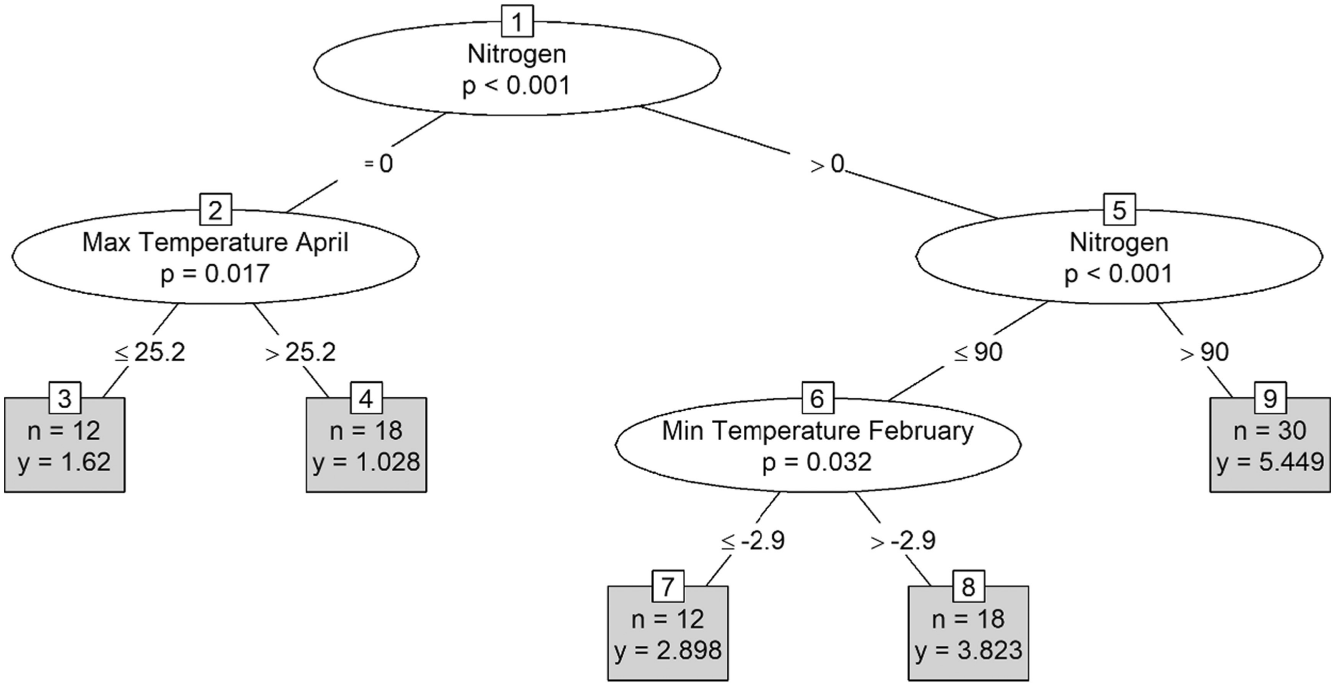


FIGURE 7 Conditional inference tree showing the emerging drivers of the durum wheat grain yield inter-annual variation under conventional soil tillage management condition: meteorological variables and N input (0, 90, and 180 N kg ha^{-1}).

4 | DISCUSSION

4.1 | Impact of weather trends

Research has shown that after water and N, temperature trends during the growing season are one of the main limiting factors of durum wheat yield (Fiorentini et al., 2022). An understanding of the impact of temperature trends on crop development and related variation to achieve high yield is crucial for global food security. Vargas Zeppetello et al. (2022) predicted an increase of 2°C on a global scale, which may result in a shift in growing areas of many crops.

The results of this study showed that temperature increase was not constant from January to July (i.e., wheat harvest) in three out of the five studied cropping seasons, and this hindered the crop phenological development and resulted in low yields (Bożek et al., 2021).

In the studied area, tillering occurred from January until March. This phenological stage is critical in determining the final yield, and durum wheat requires an ever-increasing temperature to continue its phenological progression (Al-Karaki, 2012; Morales-Coronado et al., 2019). Therefore, the yield may reduce if increased and decreased temperatures are observed during the crop growing period.

These results are in line with that of Sabella et al. (2020) who simulated the phenological development of durum wheat in a climate chamber, using the predicted climatic conditions for 2070 (a temperature increase of 2.5°C). The authors observed that the crop cycle was significantly shorter due to the physiological strategy of the plant to adapt to the high summer temperatures through early ripening of the kernels (Sabella et al., 2020).

Ercoli et al. (2009) compared two durum wheat varieties (Appio and Creso), which were grown in controlled environment conditions and in pots with three rates of N fertilizer (0, 120, and 180 kg N ha^{-1}) and two air temperature regimes during grain filling (20/15°C and 28/23°C day/night). Their study showed contrasting results because the durum grain yield and kernel weight were higher at 20/15°C than at 28/23°C, and the grain protein concentration was higher under the 28/23°C temperature regime than under the 20/15°C temperature regime.

Fiorentini et al. (2022) applied a machine learning approach to forecast durum wheat yield using a multi-data source approach and showed that temperature and rainfall are the third and fourth most important factors for durum wheat yields, respectively. Durum wheat, being a C3 crop species, has a low temperature at which photosynthetic activities shut down (ca. 25°C) (Yamori et al., 2014), and this was recorded in each year from April to harvest in this study. Moreover, a temperature higher than 30°C was recorded in the last two months of crop development (May–June) in each year of monitoring, and it probably resulted in crop photorespiration, which burned the reserves and consequently reduced the potential yield (Sabella et al., 2020).

4.2 | Grain yield

Nitrogen is the main key driver of durum wheat production in the Mediterranean area, because as the level of N fertilization increases, durum wheat yield increases (Denora, Fiorentini, et al., 2022).

As suggested by Grahmann et al. (2014), to achieve high quantity and quality of durum wheat yield, it is necessary to provide an amount of N above of 150 kg ha^{-1} when initial soil N content is low (0.53 total N g kg^{-1} soil).

However, it is also important to avoid the application of more N fertilizer than is necessary because, as observed by Abad et al. (2004), high N fertilization (200 kg N ha^{-1}) can increase the risks of nitrate leaching.

With regards to the unfertilized treatment (0 kg N ha^{-1}), repeated years of no-tillage increased production level than CT (Orsini et al., 2020). This was attributed to the CT, which inverted the soil horizons and caused an oxidation of microorganisms and soil organic matter (Jacobs et al., 2010); hence, the soil N available to the crop and water-hold capacity reduced. NT does not invert soil horizons or affect organic matter and related microorganisms in the soil; hence, NT preserves the soil organic matter levels and ensures the more N to the crop (Wacker et al., 2022).

Several authors showed that NT can slightly increase the annual soil organic carbon at a rate of 0.40% yr^{-1} (Valkama et al., 2020) and 0.69% yr^{-1} (Wacker et al., 2022), and the combination of crop residues and NT can result in a higher annual sequestration rate (Page et al., 2020).

For 90 kg N ha^{-1} treatment, NT resulted in higher yield levels than CT during the cropping seasons when the temperature rise was constant from January to harvest (Figure 4 and Table 4) but did not show significant difference during the remaining cropping seasons. For full fertilized treatment (180 kg N ha^{-1}), neither variation in soil management nor thermo-pluviometric trend showed any difference in production, corroborating what was observed in previous studies (Fiorentini et al., 2021). The full fertilized treatment eliminated all variations that may result from varying soil management and fluctuating thermo-pluviometric trends (Orsini et al., 2019).

4.3 | Conditional inference trees

Conditional inference tree analysis confirmed the results of the ANOVA fitted using soil management, N fertilization, and weather data. The root node of each tree, as the main factors of the potential yield, indicated whether the crop received mineral N fertilization, and N fertilization is the key driver of durum wheat production (Fiorentini et al., 2021).

Specifically, N fertilization, minimum and maximum temperatures in February, and the maximum temperature in April were the most important factors that impacted the potential yield of durum wheat.

Seddaiu et al. (2016) used the conditional inference tree approach and showed that the N fertilization and cumulate monthly reference evapotranspiration recorded in April were two of the most important key drivers for durum wheat production. These results indicate that February and April are important months for durum wheat production under Mediterranean conditions because two critical phenological stages for durum wheat, namely tillering and stem elongation occurred during those periods (Fiorentini et al., 2022).

The conditional inference tree generated using the entire dataset indicates that NT is not linked to reduced wheat yields, even in the event of a temperature increase of +2°C as reported by numerous authors (Abdulla, 2020; Hasegawa et al., 2022; Wang, Hou, et al., 2021; Wang, Zhang, et al., 2021). Conversely, CT can increase susceptibility to increase in temperatures.

Increased amount of soil organic matter and crop residues may be two reasons for the reduced vulnerability to increase in temperatures by NT (Valkama et al., 2020; Wacker et al., 2022). In particular, the high amount of soil organic matter in NT increases the N available to the crop and increases its resistant to biotic and abiotic stresses (Orsini et al., 2020).

Moreover, crop residues can alter the relative temperature of the soil, which in turn alters soil microbial activity and mineralization of organic matter (Shen et al., 2018). Such alteration does not occur or is less pronounced in CT, where soil temperature depends mainly on the variation in air temperature (Jat et al., 2019).

As observed by Motaroki et al. (2021), NT is one of the agronomic management adaptations to climate change. Indeed, the results of conditional inference tree created using the NT data show that mean temperature in February is the only factor that affected wheat yield, and an increase in yield is anticipated if the temperature increases by 2°C.

Conditional tree created with the CT data shows that the grain yield depends on two thermal conditions: the maximum temperature in April and minimum temperature in February. The amount and frequency of rainfall during the five monitored growing seasons were sufficient to cover the entire wheat water need (Table 2), and with an expected temperature increase of +2°C, the adoption of CT would likely reduce the potential yield because it is more dependent on air thermal alterations (Li et al., 2022). Since there are not many notable changes between the growing season and historical data, rainfall had little effect. It can be inferred that rainfall aided the effects that different levels of N fertilization had on the yields because N showed significant effect. The significance that year showed was mainly due to the temperature trend.

5 | CONCLUSIONS

This study aimed to identify the limiting factors of durum wheat yield production under Mediterranean conditions. In this study carried out in central Italy under rainfed condition, five growing seasons of durum wheat (2018–2023) from a 30-year long-term experiment were analysed. The most important limiting factors for the grain yield were N, minimum and maximum temperature in February, and maximum temperature in April. Owing to the anticipated increase in temperature predicted by several authors, it is recommended that NT soil management be preferred and supported by policies such as Rural Development Programs, because it would stabilize wheat yield and thus enable Mediterranean food security.

ACKNOWLEDGEMENTS

We kindly appreciate the Marche Polytechnic University, trough University Strategic Project (PSA 2017) 'PFRLab: Setting of a Precision Farming Robotic Laboratory for cropping system sustainability and food safety and security' and Marche Region trough measure 16.1 Action 2 of the Rural Development Plan (PSR 2014/2020) 'Precision agriculture: reduction of the environmental impact of production systems' (project ID 29000). HORIZON 2020 Project (H2020) number 952879, SolAcqua for the support received for this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article: Fiorentini, M., Orsini, R., Zenobi, S., Francioni, M., Rivosecchi, C., Bianchini, M., di Tella, B., D'Ottavio, P., Ledda, L., Santilocchi, R., & Deligios, P. (2024). Soil tillage reduction as a climate change mitigation strategy in Mediterranean cereal-based cropping systems. *Soil Use and Management*, *40*, e13050. https://doi.org/10.1111/sum.13050