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Exploring adaptive capacities in Mediterranean agriculture: Insights from Central Italy's Ombrone catchment

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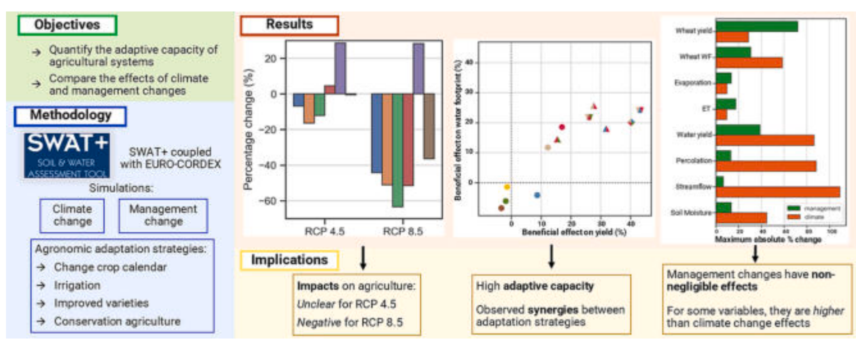
HIGHLIGHTS

- Mediterranean countries will face severe climate change impacts due to rising temperatures and altered rainfall patterns.
- The adaptive capacity of the agricultural system in Central Italy is comprehensively evaluated with the SWAT+ model.
- Autonomous agronomic adaptation strategies will be essential to tackle climate change in the Ombrone catchment.
- The impact of management changes on some specific water balance components should not be neglected.
- Impact assessments cannot be limited to the evaluation of future yield and should be as comprehensive as possible.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Climate change's profound implications for Mediterranean agriculture underscores the urgency of adaptation strategies. These strategies, whether incentivized or farmer-driven, are pivotal in mitigating crop yield losses and harnessing evolving climatic conditions. While the influence of agronomic adaptations on crop yields is well-explored, the implications for water footprint and water balance components remain largely unexplored.

OBJECTIVE: With this study, we aim to conduct a comprehensive assessment of the adaptive capacity of agricultural systems in the Ombrone catchment, Tuscany. We estimate the impacts of both climate change and adaptation strategies - also referred to as management changes - on crop yields, water footprint and water

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Management change
Land use change

balance components by comparing simulations with historical and future climate and with and without adaptation strategies.
METHODS: A Soil and Water Assessment Tool (SWAT+) agro-hydrological model of the Ombrone catchment is calibrated for crop yields of durum wheat, sunflower and irrigated maize. The impacts of climate change are then assessed by forcing the calibrated model with climate data from five bias-corrected regional climate models under Representative Concentration Pathways (RCPs) 4.5 and 8.5. Subsequently, we simulate six autonomous agronomic adaptation strategies (earlier and later sowing, supplemental irrigation, longer crop cycles, zero tillage and cover crops). We quantify their impacts on crop yield, water footprint and water balance components, such as evaporation, water yield and soil moisture.
RESULTS AND CONCLUSIONS: Our findings reveal negligible and adverse impacts on crop yields under RCPs 4.5 and 8.5 respectively. Agricultural systems show strong adaptive capabilities under both RCPs, particularly when multiple strategies are combined. The most impactful strategies include earlier sowing and extended cropping cycles. Supplemental irrigation and cover crops are beneficial only with specific combinations of climate models and RCPs. While management changes have limited impact on basin-scale water balance components, they induce an average 27% reduction in water yield at the cropland scale, attributed to practices like zero tillage and cover crops.
SIGNIFICANCE: Despite the uncertain impacts of climate change, our research reveal that changing the management - hence applying adaptation strategies - will be sufficient to maintain or improve current crop yields. Furthermore, we also underscore the non-negligible influence of management changes related to conservation agriculture on water balance components in agricultural catchments. Future adaptation strategy assessments should encompass comprehensive integration to evaluate broader impacts on water resources.

1. Introduction

Agriculture in the Mediterranean region is highly susceptible to climate change as yield losses are projected for most crops, mainly caused by the expected impacts on water resources (Iglesias et al., 2011; Ludwig et al., 2011; Pasqui and Di Giuseppe, 2019). Increasing temperatures will shorten the crop cycle length, reducing yields due to the shorter time to accumulate biomass, while water deficiencies will affect future yields, especially when occurring during sensible phases of the crop cycle. Pests, crop diseases, weeds, droughts, floods, cold and heat waves are among the various factors that could potentially be impacted by climate change, leading to detrimental effects on crop yield (Bindi and Olesen, 2011; Ciscar et al., 2018; Giannakopoulos et al., 2009; Spano et al., 2020). In general, summer crops are expected to be more affected by climate change compared to winter crops, mainly due to projected increases in drought stress (Webber et al., 2018). However, CO_2 rising could benefit crop yields, especially C3 crops (Ainsworth and Long, 2005; Webber et al., 2018). Also, local processes or characteristics might modify or mitigate the effects of climate change and, since adaptation strategies are planned considering the local characteristics, climate change impacts need to be addressed at the local scale (Iglesias et al., 2011; Pasqui and Di Giuseppe, 2019). In Northern and Central Italy, climate change impacts are uncertain since the General Circulation Models (GCMs) and the downscaled Regional Climate Models (RCMs) do not provide clear and robust projections regarding precipitation. This region lies within the transitional boundary separating the arid climate of North Africa and the humid climate of Central Europe. Previous research indicates that the precipitation equilibrium line typically intersects this area (Mariotti et al., 2015; PNACC, 2023; Spano et al., 2020). Regardless of the sign and magnitude of climate change, adaptation strategies will have a crucial role in limiting crop yield losses or enhancing the unlikely positive impact of climate change (Bindi and Olesen, 2011; Reidsma et al., 2015).

Agricultural adaptation strategies can be categorized as planned and autonomous, where planned adaptations refer to major structural changes at larger scales that generally require huge investments and longer times, while autonomous adaptations consist of adjustments at smaller and shorter scales to optimize production (Bindi and Olesen, 2011). Numerous agronomic practices have been proposed to adapt to changes in climate to improve crop yield, crop water productivity and water savings (Jovanovic et al., 2020; Van Opstal et al., 2021). Some of the commonly proposed or used adaptation strategies include: developing or selecting crops and varieties that perform better in modified climate conditions, shifting the crop calendar, conservation tillage, mulching, adjusting plant densities and including cover crops in crop rotations (Adeux et al., 2021; Iocola et al., 2017; Liebhard et al., 2022; Monaco et al., 2014; Noreika et al., 2022; Nouri et al., 2019; Sapkota et al., 2012; Schipanski et al., 2014; Stewart and Peterson, 2015). These and other autonomous agronomic adaptation strategies, which are generally overlooked by decision-makers, might have important roles in tackling climate change as they are, in most cases, highly accepted and will be easily implemented by farmers themselves (Bonzanigo et al., 2016; Varela-Ortega et al., 2016). Certainly, many of these adaptation strategies are just best management practices and their adoption would benefit also current agricultural systems. For example, the recent Italian plan for climate change adaptation (PNACC, 2023) recommended actions to tackle climate change including practices such as efficient irrigation systems, conservation agriculture and improved varieties, among others. Having this in mind, in the rest of the paper the terms adaptation strategies and management changes are used interchangeably.

In combination with climate models such as GCMs or RCMs, crop-growth models are typically used to estimate future crop yields and the effects of agronomic adaptation strategies. These process-based models represent the state of the art in our current understanding of crop processes (Ewert et al., 2015). Despite the great improvements in the last decades, these models still have important weaknesses that limit their application in integrated assessments. Some conditions that might affect future crop yield such as waterlogging or extreme temperatures are ignored or simplistically represented. Additionally, most of the studies focus on few crops, and the required data to accurately set up, calibrate and validate these models are often not available (Ewert et al., 2015). Another major issue involves scaling up point-scale outputs from crop-growth models to encompass field and catchment scales (Ahuja et al., 2019; Tenreiro et al., 2020).

To carry out useful impact assessments concerning food security, the output variables of crop-growth models might not be sufficient. For example, in addition to crop yield, a typical output derived from crop-growth models commonly used in agricultural water management is the Water Footprint (WF) (Gobin et al., 2017; Kersebaum et al., 2016). WF, defined as “the volume of freshwater used to produce the product, measured over the full supply chain” (Hoekstra et al., 2011), is a simple and universal metric that can be easily calculated. However, it has some shortcomings when trying to analyse the local contexts or consider the impacts of water use downstream (van Noordwijk et al., 2022). More specifically, WF is limited to vertical exchanges of water and does not consider the lateral, or horizontal, flows that are instead included when applying hydrological models (van Noordwijk et al., 2022). Hence, considering the processes and the outputs of hydrological models is surely helpful to better describe soil-water interactions at scales larger than the point-scale (Tenreiro et al., 2020), and the coupling of crop-growth and hydrological models is often promoted as an optimal solution (Siad et al., 2019; Van Gaelen et al., 2017). Agro-hydrological models, such as the Soil and Water Assessment Tool (SWAT), might offer solutions to most of the issues highlighted in the previous paragraphs. Agro-hydrological models generate a higher number of outputs that can be used to assess more comprehensively the impacts of climate change on food security and water resources, such as crop yield, WF and water balance components. By using the discretization of the hydrological model, crop yields can be spatially simulated for each specific crop, variety, soil, climate and management conditions. As integrated models are directly created with multiple modules, the problems related to coupling and the compatibility of the different processes, inputs, and outputs are largely avoided.

The SWAT/SWAT+ modelling suite has been already used to evaluate not only climate change impacts on crop yield, WF and water balance components but also the effect of many management changes (e.g.D'Ambrosio et al., 2020; Garg et al., 2012; Marcinkowski and Piniewski, 2018; Nkwasa et al., 2023; Pacetti et al., 2021; Parajuli et al., 2013; Salmoral et al., 2017; Sun and Ren, 2014; Vaghefi et al., 2017). Climate and land cover changes are known to affect the water balance and their impacts have been largely studied also with the SWAT model (e.g. Castelli et al., 2017; Mori et al., 2021). However, the effects of the management changes on the water balance have been mostly neglected (Noreika et al., 2021), especially when focusing on autonomous, farmer-led, agronomic practices (Chen et al., 2021). These effects need to be assessed as they might be significant, possibly changing the evaluation of the adaptation strategies if we were to consider only crop yield and WF. For example, it was demonstrated that the mechanization of agriculture in hilly areas led to increased runoff and erosion, reducing the resilience of the catchments (Napoli et al., 2017; Tarolli et al., 2014).

Thus, this study aims to evaluate climate change impacts on crop yield and WF of three representative crops and the adaptive capacity of the agricultural systems in the Ombrone catchment, Central Italy, through autonomous agronomic adaptation strategies. We re-calibrate an existing SWAT+ model for the Ombrone catchment in which durum wheat is selected as the representative rainfed winter crop, while sunflower and maize are selected as the rainfed and irrigated spring crops respectively. The adaptive capacity of the agricultural system is then evaluated with scenarios simulating management changes in sowing dates, supplemental irrigation, conservation tillage, cover crops and longer cycle varieties. Future simulations are performed encompassing the whole set of management changes, while irrigation of rainfed crops, no-tillage and cover crops are tested also for the historical scenario. For the future period, the most promising combinations of adaptation strategies, an aspect which is also often overlooked, are explored by analysing the synergies and trade-offs among them. Finally, the impacts of management changes via the proposed adaptation strategies on water balance components are assessed, testing the hypothesis that management changes could have a significant impact on the water balance in agricultural catchments.

2. Methodology

2.1. The SWAT+ model

The SWAT+ model is a renovated and improved version of the SWAT model (Bieger et al., 2017; Čerkasova et al., 2023). SWAT+ discretizes the catchment into sub-catchments and Hydrological Response Units (HRUs), which are spatial units with homogeneous characteristics of soil, land use and slope. Compared to the previous version, SWAT+ offers greater flexibility in the definition of water and agricultural management practices, since it includes the possibility to use decision tables, which allow for the specification of complex rules to simulate more realistic operations (Arnold et al., 2018; Čerkasova et al., 2023; Nkwasa et al., 2022).

To simulate crop yield, SWAT+ uses a module which is a simplified version of the EPIC model (Neitsch et al., 2011). Daily biomass accumulation (Δbio_{act}), simulated with eq. 1, is adjusted for the plant growth factor (γ_r) that quantifies the water, temperature and nutrient stresses (eq. 2). The total biomass (*bio*) and crop yield (*yld*) are then calculated with eqs. 3 and 4.

$$\Delta bio_{act} = \left(0.5 \times I_d \times RUE \times \left(1 - exp\left(-k_j \times LD\right)\right)\right) \times \gamma_r \tag{1}$$

$$\gamma_r = 1 - MAX(wstrs, tstrs, nstrs, pstrs) \tag{2}$$

$$bio = \sum_{i=1}^{d} \Delta bio_{act} \tag{3}$$

$$yld = bio_{agg} \times HI \; for \; HI \leq 1 \tag{4}$$

where I_d is the photosynthetically active radiation, *RUE* is the radiation use efficiency, K_j is the light interception and *LD* is the leaf area index development. *Wstrs*, *tstrs*, *nstrs* and *pstrs* represent water, temperature, nitrogen and phosphorous stresses, respectively. "MAX" is a mathematical function that returns the maximum value. *D* is days, bio_{agg} is the above-ground biomass and *HI* is the harvest index.

SWAT+ also simulates the CO_2 fertilization and stomatal conductance suppression modifying RUE and canopy resistance (r_c) with eqs. 5 (Stockle et al., 1992) and 6 (Easterling et al., 1992), respectively. The CO_2 effect on stomatal conductance is only included when using the Penman-Monteith approach to calculate potential evapotranspiration. It is important to underline that the equation is based on an experiment that reached 660 ppm (Morison, 1987) and that its validity above this threshold is dubious (Lemaitre-Basset et al., 2022).

$$RUE = \frac{100 \times CO_2}{CO_2 + exp(r_1 - r_2 \times CO_2)} \tag{5}$$

$$r_c = \frac{r_l}{(0.5 \times LD) \times \left(1.4 - 0.4 \times \frac{CO_2}{330}\right)} \tag{6}$$

where CO_2 is the concentration of carbon dioxide in the atmosphere, r_l is the minimum effective stomatal resistance of a single leaf, r_1 and r_2 are the shape coefficients.

2.2. The Ombrone catchment model

The study area is the Ombrone catchment (Fig. 1), a medium-sized coastal catchment located in Central and Southern Tuscany. The catchment is almost entirely included in the Grosseto and Siena provinces, has a maximum elevation of 1738 m a.s.l. and an area of 3552 km^2. Significant parts of the catchment are characterized by hilly and mountainous areas with slopes of over 20% (Diodato et al., 2023), where the most cultivated crops are cereals, forage crops, grapevine and olive groves (Napoli et al., 2014; Napoli and Orlandini, 2015). In the coastal areas horticultural and irrigated crops are more common. The Ombrone catchment is considered prone to agricultural drought (Diodato and Bellocchi, 2008; Villani et al., 2022) and receives lower precipitation and experiences increased dry spell occurrence compared to other parts of Tuscany (Bartolini et al., 2022). Herbaceous annual crops cover an area of 46.9% according to the Corine Land Cover of 2018 used in this study.

The same model of the Ombrone catchment prepared for the previous hydrological and climatological study was used for the simulations. For this study, the model was initially set up for 13 years for calibration and validation with one year of warm up. The 2637 HRUs with herbaceous cropland were split to represent the typical cropping pattern of the area, considering durum wheat as the rainfed winter crop (30% of the

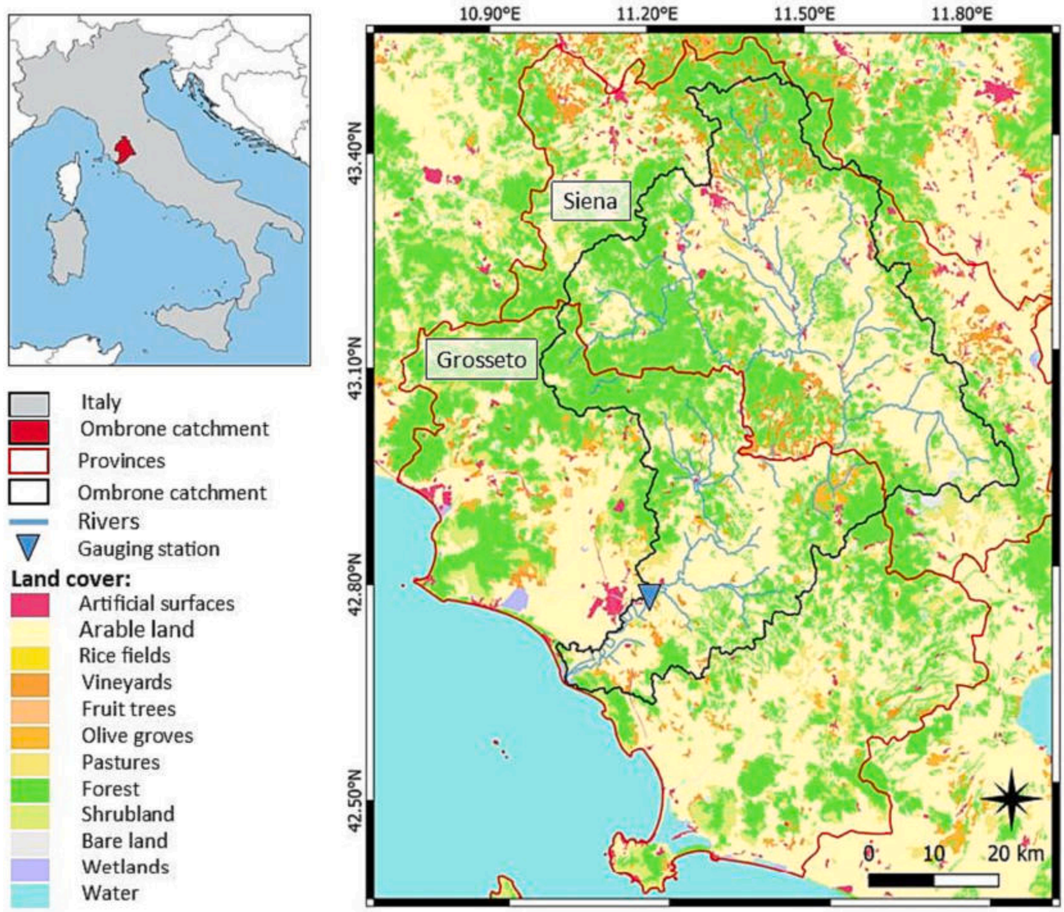

Fig. 1. The Ombrone catchment with the provinces of Siena and Grosseto, the catchment boundaries, the Istia gauging station and the land cover retrieved from the Corine Land Cover of 2018 used in this study.

HRU), sunflower as the rainfed spring crop (15%), maize as irrigated spring crop (15%), and alfalfa as the forage crop (40%). More detailed information about the model setup can be found in the supplementary materials, part 1.

2.3. Calibration and validation

In this study, we performed a new calibration and validation for crop yield. We used 12 years of provincial crop yield, spanning from 2010 to 2021, retrieved from the National Institute of Statistics (ISTAT) for the provinces of Siena and Grosseto; odd years were used for calibration while even for validation. Since the focus of this study was on crop yield, in addition to the sensitive crop parameters (Table S2), we also included the soil evaporation compensation factor (*esco*), the plant evaporation compensation factor (*epco*) and available water capacity (*awc*) to calibrate the model as in Sinnathamby et al. (2017). *Esco* and *epco* in the previous study were included in the automatic calibration performed for streamflow, while *awc* was not considered since it was not sensitive enough. As we modified two parameters that were originally included in the calibration for streamflow, we performed an additional calibration and validation also for monthly streamflow modifying the *cn2* parameter of the whole catchment and *esco* and *epco* of the HRU other than cropland. To evaluate model performance, we used the Nash-Sutcliffe Efficiency (NSE), the Normalized Root Mean Square Error (NRMSE) and the per cent bias (PBIAS) with the criteria of Jamieson et al. (1991) for NRMSE and Moriasi et al. (2007) for NSE and PBIAS, reported in Table S3.

2.4. Climate projections and management

We used five bias-corrected EURO-CORDEX climate models to simulate the future climate referred to as (1) CNRM-CM5-ALADIN63, (2) CNRM-CM5-RACMO22E, (3) EC-EARTH-RACMO22E, (4) MPI-ESM-LR-RCA4 and (5) NorESM1-M-REMO2015. We performed the simulations for 30-year periods comparing the historical simulation (1976–2005) with the long-term future period (2071–2100) of the same climate model for the Representative Concentration Pathways (RCPs) 4.5 and 8.5. Considering two years of warm up, the analyses were performed for periods of 28 years. The CO_2 value that could be used as input was constant for each simulation, and therefore we considered the average value for the different periods and RCPs considered in the study. We used the most updated values about CO_2 concentration projections (Büchner and Reyer, 2022), and it is important to underline that the value for the period 2071–2100 under RCP 8.5 is 939 ppm, much higher than the upper threshold of 660 ppm of the Morison experiment (Morison, 1987).

The climatological analysis performed in the previous study showed that the temperature is predicted to increase consistently according to the five climate models, more when considering RCP 8.5. On the other hand, precipitation projections are much more uncertain, with the models showing constant or slightly increasing values, except for NorESM1-M-REMO2015 which predicts decreasing values under RCP 8.5. The precipitation-related variables such as soil moisture, percolation, streamflow, and water yield vary accordingly with rainfall. The uncertainty when using climate models is further increased when dealing with evapotranspiration since it is highly influenced by CO_2 concentration (Lemaitre-Basset et al., 2022). When considering the CO_2

increase, as in this study, the potential evapotranspiration is predicted to have similar average values in the long-term future for RCP 4.5, while lower and probably unrealistic for RCP 8.5.

The crop module of the SWAT+ model is based on heat units but, differently from the original SWAT model, the input to specify the length of the crop cycle is days to maturity (Nkwasa et al., 2023). Hence, to consider the same variety with the future increase in temperature, we calculated the heat units required by the crops for the calibration period 2010–2021, and then we retrieved the days to maturity for the historical (1976–2005) and future (2071–2100) periods, both for RCPs 4.5 and 8.5. We calculated the days to maturity averaging the maximum and minimum temperatures of the five climate models since they were very similar after bias correction.

The crop management applied for calibration and validation and in the "no adaptation" (0.NA) scenario simulations is reported in Table S4. The management for the three crops considered is representative of the current practices and was checked with published papers and guidelines from the Tuscany Region (Dalla Marta et al., 2010; Giannini and Bagnoni, 2000; Orlando et al., 2015; Tuscany region, 2010). Since detailed information about the irrigation schedule was not available, we applied automatic sprinkler irrigation for maize using the default decision table available in the model, with a water stress threshold of 0.6. To simulate the optimal soil humidity conditions for sowing, we used the default decision tables automatically generated by the model, adjusted to obtain realistic sowing dates. Moreover, in SWAT+ the crops are automatically harvested at the end of the crop cycle, but we also specified the latest harvesting dates in the decision tables.

2.5. Simulation of management changes

To estimate the adaptive capacity of agricultural systems, we simulated several agronomic management changes (Table 1) such as earlier and later sowing dates (1.ES, 2.LS), supplemental irrigation (3.SI), longer crop cycle (4.LCC), and practices belonging to conservation agriculture, such as zero tillage (5.ZT) and cover crops (6.CC). In addition, we simulated the effect of combining the most effective practices (7.SI-LCC, 8.ES-LCC, 9.LCC-CC, 10.ES-SI-LCC, 11.ES-LCC-CC, 12.ES-SI-LCC-CC). Considering the RCPs, periods and management scenarios, we conducted a total of 150 simulations (five historical simulations +three management scenarios x five climate models +two RCPs × thirteen future management scenarios x 5 climate models). Overall, most of the practices considered are simple and will be easily and autonomously adopted by farmers, while others might need institutional support. The supplemental irrigation scenario is simulated regardless of water availability. Even if this is a simplification, the analysis of the outcomes of these simulations is certainly valid for crops at the field scale. It is also important to note that we simulated supplemental and not full irrigation, as the irrigation events were triggered by the water stress threshold. Furthermore, lower irrigation amounts were expected because the ensemble mean of the five climate models showed an increasing sign in annual precipitation and the crop cycles were shortened. Conservation agriculture practices are simulated as indicated in Arabi et al. (2008) and Kalcic et al. (2015) by reducing CN by two points, modifying Manning's roughness coefficient for overland flow (OV_N) and including a cover crop. We did not modify the USLE cover factor as it was not relevant to our research objectives.

After the simulations, we elaborated the outputs of the model for each RCP and management change. In this study, we report the impacts of climate and management changes on crop yield and WF and the effect of the management changes on the water balance components. The impacts of climate change on crop yields were evaluated by analysing the 28-year average yield for each HRU and comparing the future period (2071–2100) with the historical simulation of the same climate model, considering RCPs 4.5 and 8.5. A similar comparison was carried out for WF, which was calculated as the ratio of evapotranspiration and crop yield, expressed in $m^3\ kg^{-1}$, considering the annual average output files. To evaluate the effect of the management changes, we evaluated the relative percentage difference between the outputs of the no adaptation and adaptation scenarios. We performed this analysis for all the management changes only for the 2071–2100 future period, under both RCPs, while we evaluated the effect of supplemental irrigation, zero tillage and cover crops also in the historical scenarios. Concerning the agricultural impacts, we considered annual average crop yield and WF. Additionally, we analysed the drought and temperature stresses (DS, TS) that are direct outputs of the SWAT+ model. For the impacts on the water balance, we evaluated annual average evaporation, actual evapotranspiration, soil moisture, water yield and percolation at the cropland and catchment scales. The cropland is represented by the HRUs with durum wheat, sunflower and maize where the management changes were implemented. Synergies (trade-offs) were investigated by assessing if the effect of combinations of management changes was higher (lower) than the algebraic sum of the individual practices. For agricultural outputs, we considered a synergy (trade-off) if the values were higher (lower) than 3%, while for water balance components if they were higher (lower) than 2%. Of course, we considered the opposite when the negative changes were the beneficial ones, like for evaporation and water footprint. We also analysed the outputs in terms of beneficial changes, namely increasing crop yield and decreasing WF, evaporation and water yield. Finally, we evaluated the magnitude of the changes caused by management and climate on the agricultural – yield, WF, DS and TS – and hydrological – the water balance components at the cropland scale – variables, by comparing the absolute maximum percentage changes considering all the future simulations performed.

Table 1
The management changes considered in the study, with the description and SWAT+ input files change.

Code	Management change	Description	Input files changed
1.ES	Earlier sowing	Sowing window anticipated by 15 days, as well as tillage and fertilization operations	lum.dtl management.sch
2.LS	Later sowing	Sowing window delayed by 15 days, as well as tillage and fertilization operations	lum.dtl management.sch
3.SI	Supplemental irrigation	Automatic irrigation applied also to wheat and sunflower	management.sch
4.LCC	Longer crop cycles	Crop cycle increased by 15 days	plants.plt landuse.lum
5.ZT	Zero tillage	Conventional tillage changed to zero tillage. OV_N changed to "notill_2-9res". CN reduced by two points	management.sch cntable.lum landuse.lum
6.CC	Cover crops	Sowing and killing a leguminous crop (clover) when the main crop is not cultivated. Mouldboard tillage is also removed and harrow tillage is maintained. OV_N changed to "notill_2-9res". CN reduced by two points	management.sch plant.ini cntable.lum

Table 2
The parameters selected for calibration, the type of change, and the change in terms of percentage or new value.

Parameters crop yield	Type of change	Final change					
		Durum wheat		Sunflower		Maize	
		Siena	*Grosseto*	*Siena*	*Grosseto*	*Siena*	*Grosseto*
days_mat	*Replace*	180	180	110	90	120	120
bm_e	*Percentage*	–	–	5%	–	- 15%	- 10%
harv_idx	*Percentage*	–	- 2.5%	5%	–	- 17.5%	- 10%
lai_pot	*Percentage*	–	- 2.5%	5%	–	- 17.5%	- 10%
ext_co	*Percentage*	–	–	5%	–	- 15%	- 10%
hu_lai_decl	*Percentage*	–	–	5%	–	–	–
dlai_rate	*Percentage*	–	–	- 5%	–	–	–
frac_hu1	*Replace*	–	–	–	–	0.17	0.17
frac_hu2	*Replace*	–	–	–	–	0.55	0.55
lai_max1	*Replace*	–	–	–	–	0.13	0.14
lai_max2	*Replace*	–	–	–	–	0.9	0.92
esco	*Replace*	0.5	0.9	1	0.35	0.70	1
epco	*Replace*	1	0.6	1	0.60	1	1

Table 3
Model performances expressed as NRMSE (%) and PBIAS (%) for calibration and validation for durum wheat, sunflower, and maize in the Siena and Grosseto provinces.

Crop	Province	Calibration		Validation	
		NRMSE	*PBIAS*	*NRMSE*	*PBIAS*
Durum wheat	*Siena*	27.50% [3]	−5.08% [1]	28.61% [3]	7.23% [1]
	Grosseto	26.21% [3]	2.97% [1]	17.41% [2]	−0.05% [1]
Sunflower	*Siena*	6.68% [1]	−1.97% [1]	24.23% [3]	2.08% [1]
	Grosseto	20.26% [3]	15.97% [3]	28.86% [3]	−2.97% [1]
Maize	*Siena*	16.87% [2]	−0.27% [1]	22.09% [3]	0.17% [1]
	Grosseto	9.34% [1]	−0.22% [1]	15.32% [2]	−0.84% [1]

[1] Very good; [2] Good; [3] Satisfactory.

Table 4
Days to maturity for durum wheat, sunflower and maize used in the simulations.

Crop	Province	Calibrated (2010–2021)	Historical (1976–2005)	Future (2071–2100)	
				RCP 4.5	*RCP 8.5*
Durum wheat	*Siena*	180	187	163	143
	Grosseto	180	187	163	143
Sunflower	*Siena*	110	112	99	89
	Grosseto	90	91	80	72
Maize	*Siena*	120	122	107	96
	Grosseto	120	122	107	96

3. Results

3.1. SWAT+ calibration and validation

The calibrated values for crop yields are reported in Table 2, while the results in terms of calibration and validation performances are in Table 3. Overall, we obtained at least satisfactory performances for the three crops in the two provinces. For durum wheat and sunflower, changing only the *days to maturity*, *esco* and *epco* was almost sufficient to obtain the best parameter set, and few additional modifications were needed. On the other hand, for maize, we had to strongly reduce most of the parameters since the model overestimated yields. Because of the known limitations of the model, the aggregated statistical data used and the approximations in the model setup, we consider our model validated for the average annual crop yield, as done in other studies that applied the SWAT/SWAT+ model for crop yield estimation (Musyoka et al., 2021; Nkwasa et al., 2023; Srinivasan et al., 2010). Then, we calculated the heat units to retrieve the days to maturity for the historical (1976–2005) and future (2071–2100) periods, which were drastically reduced, in particular for RCP 8.5 (Table 4). Finally, modifying *cn2* of the whole catchment and *esco* and *epco* of the HRUs other than cropland, we obtained at least satisfactory performances for monthly streamflow (NSE > 0.5 and PBIAS <25%) according to Moriasi et al. (2007) as shown in Table S5, except for PBIAS during calibration in the most downstream gauging station of Istia, for which there is probably an error in the reported observed flows.

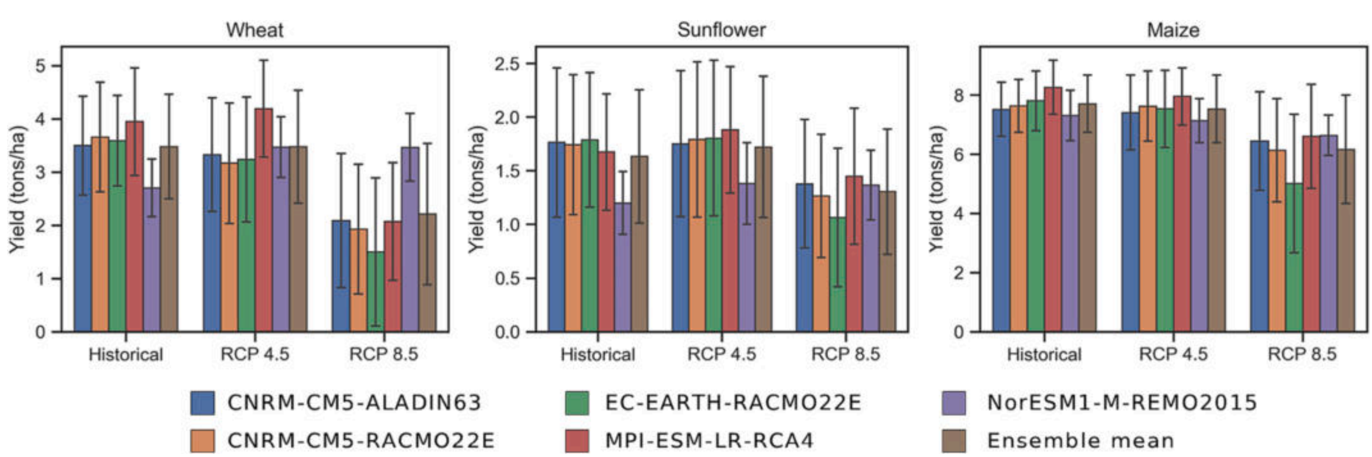

Fig. 2. Climate change impact on crop yield. Durum wheat, sunflower and maize yield plots are created with the absolute values for the historical and RCPs 4.5 and 8.5 simulations. The plots are created using the annual average yield for the respective periods considering all the HRUs with cropland.

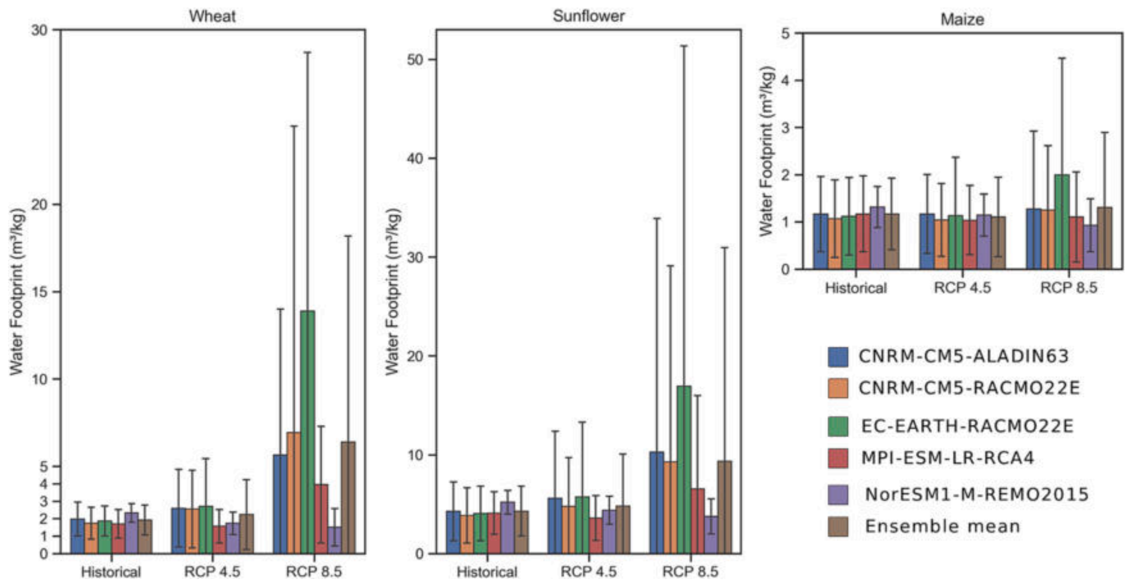

Fig. 3. Climate change impacts on water footprint. Durum wheat, sunflower and maize water footprint plots are created with the absolute values for the historical and RCPs 4.5 and 8.5 simulations. The plots are created using the annual average water footprint for the respective periods considering all the HRUs with cropland.

3.2. Climate change impacts on crop yield and water footprint

For durum wheat, the rainfed winter crop, three climate models (CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E, and EC-EARTH-RACMO22E) predicted decreases in crop yield up to −16.4% under RCP 4.5 and −63.4% for RCP 8.5 considering the most pessimistic model. MPI-ESM-LR-RCA4 simulations disagreed since when considering RCP 4.5 yields were predicted to slightly increase, while they dropped under RCP 8.5. Instead, wheat yields simulated with NorESM1-M-REMO2015 increased by almost 30% under both RCPs. The ensemble mean for durum wheat yield was predicted to remain constant under RCP 4.5 and to decrease by almost −40% under RCP 8.5 (Fig. 2). As expected, wheat WF showed the opposite trend of crop yield, with the ensemble mean increasing by 24.1% and 265.3% under RCPs 4.5 and 8.5, respectively (Fig. 3). Analysing the distributions, we can assess that low values for wheat yield will be much more frequent compared to the historical simulations under RCP 8.5, explaining the significant increase observed for WF. Specifically, in the worst-case scenario (EC-EARTH-RACMO22E, RCP 8.5), a sevenfold increase in mean WF was predicted as a result of the very low yield, in many HRUs below one ton ha^{-1}. Considering most of the simulations, because of the very low annual average yields in many HRUs, especially under RCP 8.5, we can affirm that some parts of cropland might become unsuitable for wheat growth.

For sunflower, the absolute magnitudes of changes were much smaller compared to durum wheat. Under RCP 4.5, sunflower yields were predicted to remain constant or increase, with ensemble mean increases of almost 5.1%. On the other hand, under RCP 8.5 all the models predicted decreasing yields except for NorESM1-M-REMO2015. The ensemble mean was predicted to decrease by almost −21.7% under RCP 8.5 (Fig. 2). Considering WF under RCP 4.5, CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E and EC-EARTH-RACMO22E predicted increasing values by up to 53.8%, while MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015 decreasing values by up to −15.9%. Under RCP 8.5, all the models predicted increases in sunflower WF up to 313% for EC-EARTH-RACMO22E except for NorESM1-M-REMO2015 which showed decreased WF by −26%. The ensemble means for sunflower WF were predicted to increase by 20.6% under RCPs 4.5 and to double under RCP 8.5 (Fig. 3). The reductions in sunflower yield predicted in the simulations were not as widespread and significant in magnitude as for durum wheat. Hence, no cropland is expected to become unsuitable for sunflower cultivation.

Maize is an irrigated spring crop and, therefore, it is not drastically affected by changes in precipitation and, in our study, the role of irrigation was not as important as depicted by other studies in the Mediterranean region. Considering RCP 4.5, maize yields remained almost constant with all the climate models, while for RCP 8.5 yields were predicted to significantly decrease. The decrease reached almost −40% for EC-EARTH-RACMO22E, with an ensemble-mean decrease of −21.2% (Fig. 2). WF was consistent with maize yield and, overall, higher variability in WF is expected in the future, but the magnitude of changes (absolute and relative) was not as high as for sunflower and durum wheat. In particular, under RCP 8.5 the maximum increase and decrease in maize WF were simulated by EC-EARTH-RACMO22E (>75% increase) and NorESM1-M-REMO2015 (almost −30% decrease), respectively, with a moderate ensemble-mean increase of 14.9% (Fig. 3). Even if in some simulations strong reductions in maize yield were predicted, regardless of economic considerations no cropland is expected to become unsuitable for maize cultivation.

3.3. The effect of management changes in the historical scenarios

Supplemental irrigation (3.SI) was highly beneficial for wheat and sunflower yields, with ensemble increases of 36.1% and 45.4% respectively. For NorESM1-M-REMO2015, yields reached values up to 73.2% and 93.4% for the two rainfed crops. Basin evapotranspiration also moderately increased (5.6%). However, WF showed improvements as it decreased for both crops (−12.2% and −11.5%). As expected, consistent decreases of more than −50% in drought stress were observed.

The inclusion of cover crops (6.CC) and the application of zero tillage (5.ZT) had a minor effect on all the variables analysed, except for water yield which was drastically reduced (−6.1% and −35.5% at the basin and cropland scales, respectively). The effects on crop yield and other variables were mostly negligible (<5% changes), except for 6.CC for sunflower which resulted in an 8.8% yield increase.

3.4. The adaptive capacity of agricultural systems in the future scenarios

The effects of management changes on crop yield, WF, DS, TS, evaporation, actual evapotranspiration, soil moisture, water yield, percolation and streamflow are reported as heatmaps in Figs. 4–7 and Table 5. As anticipated in the methodological section, the calculation of potential evapotranspiration with CO_2 concentration values above 660

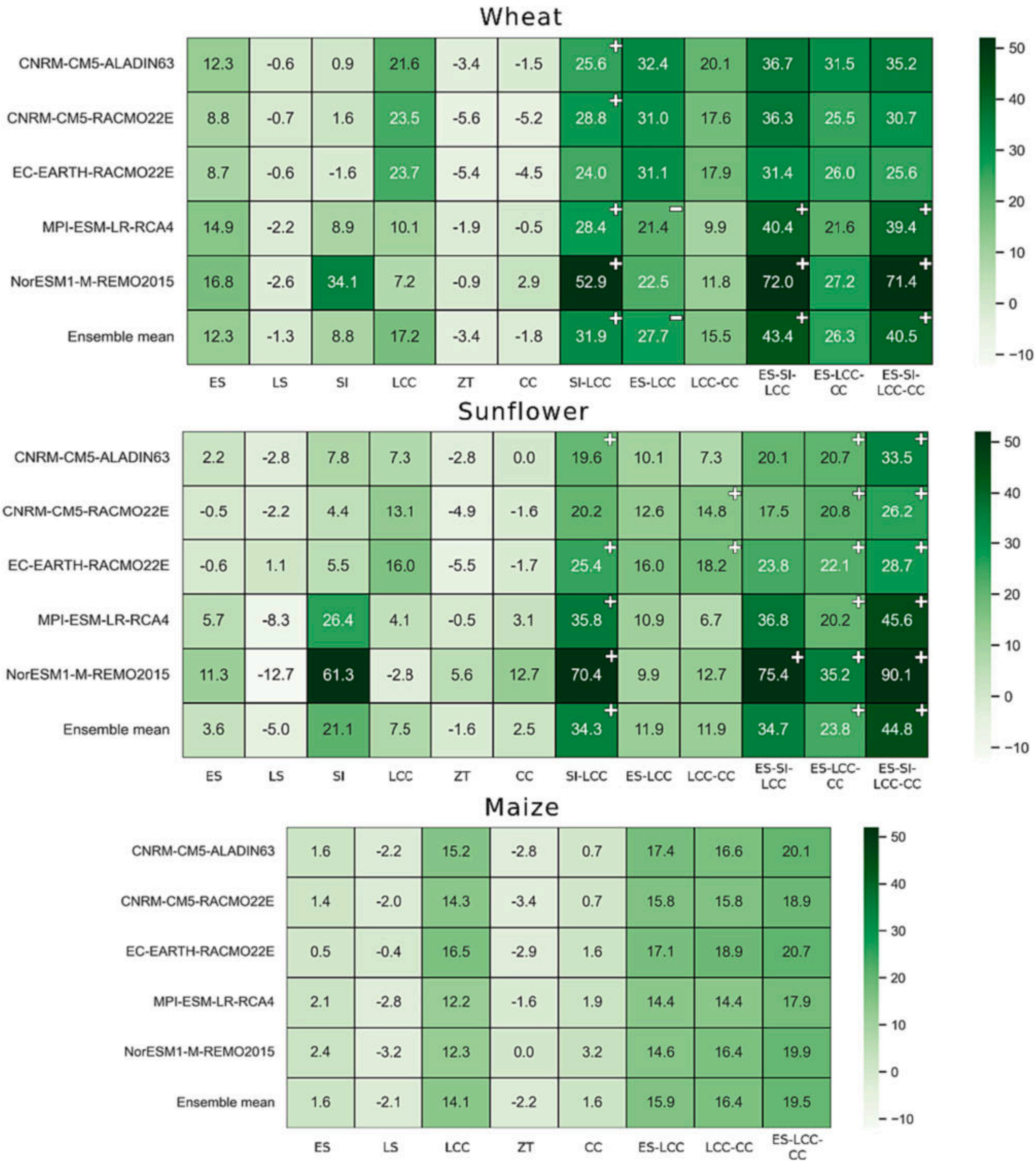

Fig. 4. Effect of management changes on crop yield. Heatmaps created with the percentage changes for durum wheat, sunflower and maize yields, calculated considering the "no adaptation" and the different adaptation scenarios, for RCP 4.5. In the combinations of management changes, the synergies are indicated with the "+" symbol and trade-offs with "-".

ppm in the SWAT+ model is questionable. Hence, we opted to focus mainly on RCP 4.5 outputs. Still, some outputs of RCP 8.5 simulations are discussed, and the heatmaps are available in the supplementary materials (Fig. S4-S7). Fig. 8 reports the effects of management changes on water balance components at catchment and cropland scales. The beneficial effects of the use of adaptation strategies and their combination are plotted in Fig. 9 for wheat, sunflower and maize. We considered as beneficial effects increased crop yield and reduced WF, evaporation and water yield. For this figure, again we considered only the outputs of RCP 4.5. Fig. 10 shows the maximum absolute impacts caused by climate and management changes on each variable that we considered in this study, under RCP 4.5.

3.4.1. *Effect of management changes on crop yield*

Overall, durum wheat yield had the highest relative losses predicted without adaptation strategies (Fig. 2). Nonetheless, the adaptive capacity for this crop was high (Fig. 4), reaching similar or increased yields compared to the historical simulations. The most effective management change was 4.LCC, especially when considering the climate models that predicted yield decreases (CNRM-CM5-ALADIN63, CNRM-CM5-

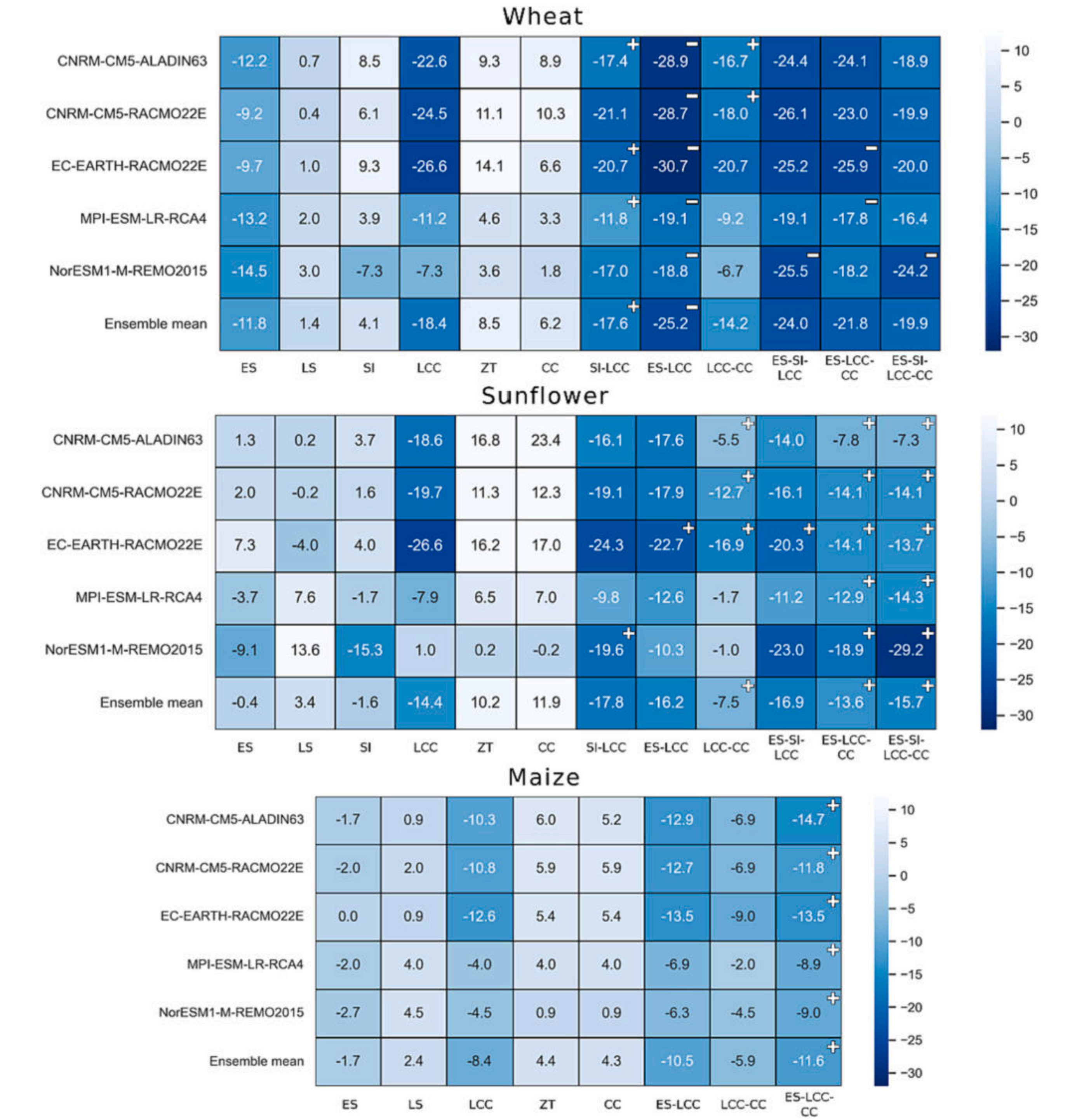

Fig. 5. Effect of management changes on water footprint. Heatmaps created with the percentage changes in WF of wheat, sunflower, and maize, calculated considering the "no adaptation" and the different adaptation scenarios, for RCP 4.5. In the combinations of management changes, the synergies are indicated with the "+" symbol and trade-offs with "-".

RACMO22E and EC-EARTH-RACMO22E). Among the crops that we considered, wheat had the longest crop cycle and, consequently, also the highest reductions due to increased temperatures, explaining why 4.LCC was particularly beneficial. 1.ES also had positive effects, higher when considering MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015, while 5. ZT and 6.CC had a negligible effect. 3.SI was particularly useful in NorESM1-M-REMO2015, but it had little or no positive effect when considering the other models. For the individual adaptation strategies, the magnitudes of change were higher when considering RCP 8.5, except for 3.SI (Fig. S4). The effect of the combinations of management changes allowed to achieve >70% gained yields. Furthermore, we observed some significant synergies combining 3.SI with 1.ES and 4.LCC. As a final recommendation, 1.ES and 4.LCC should be always implemented regardless of the climate model, while 3.SI is suggested only with drier conditions.

A good adaptive capacity was observed for sunflower (Fig. 4). 4.LCC was effective with CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E and EC-EARTH-RACMO22E, even if percentages of gained yields were lower compared to durum wheat. 1.ES, 3.SI and 6.CC had positive effects when considering MPI-ESM-LR-RCA4 and even more NorESM1-M-

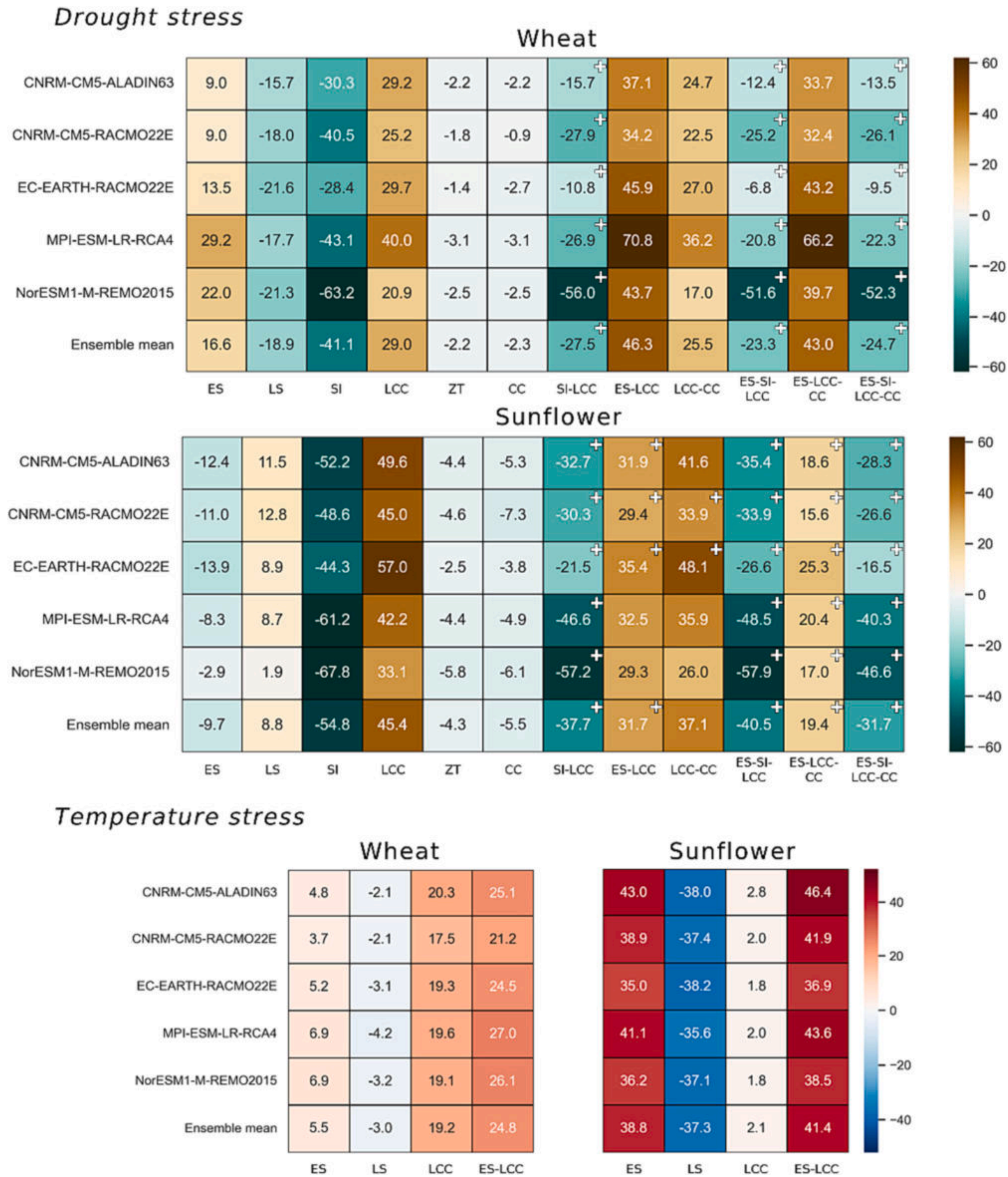

Fig. 6. Effect of management changes on drought and temperature stress. Heatmaps created with the percentage changes in DS and TS of wheat and sunflower, calculated considering the "no adaptation" and the different adaptation scenarios, for RCP 4.5. For TS, we reported only the strategies that affected it. In the combinations of management changes, the synergies are indicated with the "+" symbol and trade-offs with "-".

REMO2015. The change in sowing date had no significant effect in CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E and EC-EARTH-RACMO22E. In MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015, under RCP 4.5, the effect of 4.LCC was negligible. However, we observed synergies when 4.LCC was combined with 3.SI and 6.CC. Overall, the potential gained yields with management changes were lower compared to durum wheat, but the maximum reached >90% when considering the complete combination of management changes, RCP 4.5, and NorESM1-M-REMO2015. Different from durum wheat, for sunflower the positive effect of combining 3.SI and 6.CC was much clearer and not alternative, especially for the MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015. Resuming the outcomes for sunflower, we can affirm that 4.LCC should always be taken into consideration, while 1.ES, 3.SI, and 6.CC especially if the climate will get drier.

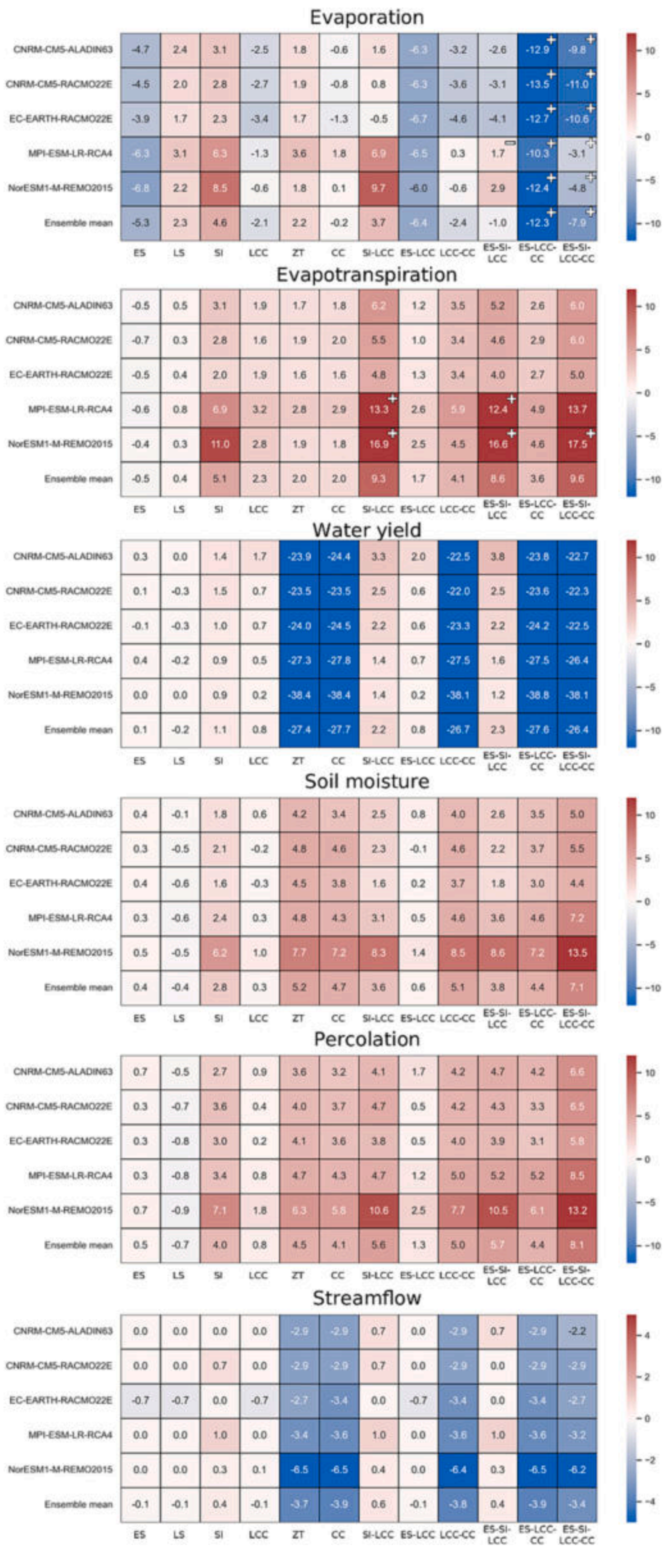

Fig. 7. Effect of management changes on evaporation, evapotranspiration, water yield, soil moisture and percolation, considering only cropland, and streamflow at the outlet. Heatmaps created with the percentage changes, calculated considering the adaptation and no adaptation scenarios, for RCP 4.5. In the combinations of management changes, the synergies are indicated with the "+" symbol and trade-offs with "-".

Table 5
Ensemble percentage changes, with standard deviation, after simulating the management changes without combinations for the crop and hydrological variables considered in this study. When referring to water balance components, here we consider the outputs at the cropland scale.

Management change	1.ES	2.LS	3.SI	4.LCC	5.ZT	6.CC
RCP 4.5						
Wheat yield	12.3 ± 3.2%	−1.3 ± 0.9%	8.8 ± 13.1%	17.2 ± 7.1%	−3.4 ± 1.9%	−1.8 ± 2.9%
Maize yield	1.6 ± 0.6%	−2.1 ± 1%	/	14.1 ± 1.7%	−2.2 ± 1.2%	1.6 ± 0.9%
Sunflower Yield	3.6 ± 4.5%	−5 ± 4.9%	21.1 ± 21.6%	7.5 ± 6.7%	−1.6 ± 4%	2.5 ± 5.4%
Wheat WF	−11.8 ± 2%	1.4 ± 1%	4.1 ± 6%	−18.4 ± 7.7%	8.5 ± 3.9%	6.2 ± 3.2%
Maize WF	−1.7 ± 0.9%	2.4 ± 1.5%	/	−8.4 ± 3.5%	4.4 ± 1.9%	4.3 ± 1.8%
Sunflower WF	−0.4 ± 5.6%	3.4 ± 6.3%	−1.6 ± 7.2%	−14.4 ± 9.7%	10.2 ± 6.2%	11.9 ± 8.1%
Wheat DS	16.6 ± 7.9%	−18.9 ± 2.3%	−41.1 ± 12.4%	29 ± 6.3%	−2.2 ± 0.6%	−2.3 ± 0.7%
Sunflower DS	−9.7 ± 3.9%	8.8 ± 3.8%	−54.8 ± 8.6%	45.4 ± 7.9%	−4.3 ± 1%	−5.5 ± 1.2%
Wheat TS	5.5 ± 1.2%	−3 ± 0.8%	/	19.2 ± 0.9%	/	/
Sunflower TS	38.8 ± 3%	−37.3 ± 0.9%	/	2.1 ± 0.4%	/	/
Streamflow	−0.1 ± 0.3%	−0.1 ± 0.3%	0.4 ± 0.4%	−0.1 ± 0.3%	−3.7 ± 1.4%	−3.9 ± 1.4%
Water yield	0.1 ± 0.2%	−0.2 ± 0.1%	1.1 ± 0.2%	0.8 ± 0.5%	−27.4 ± 5.6%	−27.7 ± 5.5%
Evapotranspiration	−0.5 ± 0.1%	0.4 ± 0.2%	5.1 ± 3.4%	2.3 ± 0.6%	2 ± 0.4%	2 ± 0.4%
Evaporation	−5.3 ± 1.1%	2.3 ± 0.5%	4.6 ± 2.4%	−2.1 ± 1%	2.2 ± 0.7%	−0.2 ± 1.1%
Soil moisture	0.4 ± 0.1%	−0.4 ± 0.2%	2.8 ± 1.7%	0.3 ± 0.5%	5.2 ± 1.3%	4.7 ± 1.3%
Percolation	0.5 ± 0.2%	−0.7 ± 0.1%	4 ± 1.6%	0.8 ± 0.6%	4.5 ± 0.9%	4.1 ± 0.9%
RCP 8.5						
Wheat yield	21.1 ± 1.7%	−4.1 ± 1.2%	−1.6 ± 5%	25.3 ± 4.3%	−4.3 ± 0.9%	−2.1 ± 2.1%
Maize yield	1.2 ± 1.6%	−2.5 ± 1%	/	19.7 ± 2.2%	−5.2 ± 2%	−1.1 ± 1.8%
Sunflower Yield	0.5 ± 5.7%	−2 ± 4.6%	7.3 ± 15%	19.2 ± 3.7%	−6.5 ± 3%	−2.1 ± 4%
Wheat WF	−26.8 ± 5.2%	5.1 ± 1.7%	15.2 ± 5.7%	−25.7 ± 5.2%	12.2 ± 4.3%	4.5 ± 2.1%
Maize WF	0.7 ± 3.3%	1.1 ± 2.1%	/	−18.2 ± 5.3%	10.9 ± 4.4%	11.2 ± 5.3%
Sunflower WF	3.5 ± 8%	−2.1 ± 7.4%	1.3 ± 5.2%	−25 ± 6.6%	12.9 ± 4.7%	13.8 ± 5.6%

(*continued on next page*)

Table 5 (*continued*)

Management change	1.ES	2.LS	3.SI	4.LCC	5.ZT	6.CC
Wheat DS	24.7 ± 13.2%	−34.6 ± 5.7%	−33.1 ± 13.4%	28.3 ± 4.1%	−0.6 ± 1.3%	0.6 ± 1.6%
Sunflower DS	−12.7 ± 7.8%	21.7 ± 9%	−38.1 ± 14.7%	56.3 ± 13.7%	−2.9 ± 2%	−4.4 ± 1.7%
Wheat TS	13.5 ± 3.1%	−6.3 ± 0.8%	/	18.5 ± 1.3%	/	/
Sunflower TS	44.4 ± 3.5%	−39.5 ± 1.1%	/	3.2 ± 0.4%	/	/
Streamflow	0.6 ± 0.2%	0 ± 0%	0.7 ± 0.3%	0.4 ± 0.3%	−2.9 ± 1.8%	−3.4 ± 1.7%
Water yield	1 ± 0.4%	−0.2 ± 0.2%	0.9 ± 0.3%	1 ± 0.5%	−23.1 ± 10%	−23.8 ± 9.8%
Evapotranspiration	−0.6 ± 0.2%	0.5 ± 0.1%	2.2 ± 2.1%	0.9 ± 0.7%	1.9 ± 0.2%	2.3 ± 0.1%
Evaporation	−6.4 ± 0.8%	2.8 ± 0.4%	2.4 ± 1.6%	−2.6 ± 0.6%	1.8 ± 0.1%	−1.1 ± 0.2%
Soil moisture	1.6 ± 0.8%	−0.7 ± 0.5%	1.7 ± 1.8%	1 ± 0.4%	4.6 ± 1.7%	3.7 ± 1.4%
Percolation	1.9 ± 0.8%	−1 ± 0.5%	2.8 ± 2.3%	1 ± 0.7%	4.3 ± 1.3%	3.2 ± 1.1%

The climate change impacts on irrigated maize yields were mainly determined by the changes in the climate variables other than precipitation. Hence, the adaptive capacity for this crop was lower and it was strictly linked with the crop cycle start and length (Fig. 4). As expected, the magnitude of gained yields was much lower, reaching no more than 25.9% under RCP 8.5 (Fig. S4). Compared to sunflower, the positive effects of 4.LCC under both RCPs and 1.ES under RCP 8.5 were much clearer (Fig. S4). No significant synergies or trade-offs were observed for maize.

3.4.2. Effect of management changes on water footprint

WF showed consistent opposite values compared to crop yield (Fig. 5). Overall, the changes reported for RCP 4.5 for the three crops considered were slightly lower in magnitude compared to RCP 8.5 (Fig. S5). The management changes with increased water use, such as 3.SI and 6.CC, showed an increase in WF, more accentuated when these strategies had no significant positive impact on yields. Instead, it is interesting to point out that WF decreased for sunflower when considering NorESM1-M-REMO2015, meaning that the increase in water used by these strategies was justified by the increase in crop yield. WF decreased also for wheat with NorESM1-M-REMO2015 when applying supplemental irrigation. 4.LCC was shown to be crucial in reducing WF since it increased crop yield without significantly increasing the annual evapotranspiration, with beneficial effects that were higher in CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E and EC-EARTH-RACMO22E. In MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015, 1.ES was effective in reducing the WF of durum wheat and sunflower. For durum wheat, a reduction was also observed with the other climate models. In CNRM-CM5-ALADIN63, CNRM-CM5-RACMO22E and EC-EARTH-RACMO22E, for sunflower and under RCP 4.5, 2.LS was more beneficial than 1.ES, even if with low-magnitude changes. Under RCP 8.5 for sunflower, 2.LS consistently reduced WF while 1.ES increased it, according to all climate models except for NorESM1-M-REMO2015 (Fig. S5). Due to lower crop yields and increased water retention, 5.ZT always showed minor increases in WF, negligible for NorESM1-M-REMO2015 for sunflower and maize. For durum wheat, a huge ensemble decrease in WF of −39.1% was achieved when simultaneously implementing 1.ES and 4.LCC under RCP 8.5 (Fig. S5), even if a trade-off was observed (Fig. 5). On the other hand, when combining management changes that decreased WF with others that increased it, such as 4.LCC with 3.SI or 6.CC, synergies were observed for the three crops. For sunflower, the best outcomes regarding WF were obtained mainly because of 4.LCC, with the highest decrease being −25% considering the ensemble mean and RCP 8.5 (Fig. S5). Similarly, for maize, the strongest reductions in WF were also achieved with 4.LCC, with a maximum decrease of −18.2% considering the ensemble mean and RCP 8.5 (Fig. S5).

3.4.3. Effect of climate and management changes on drought and temperature stress

Overall, DS and TS decreased compared to historical simulations. This was expected for DS since most climate models predicted minor increases in precipitation and the crop cycles were shortened due to the

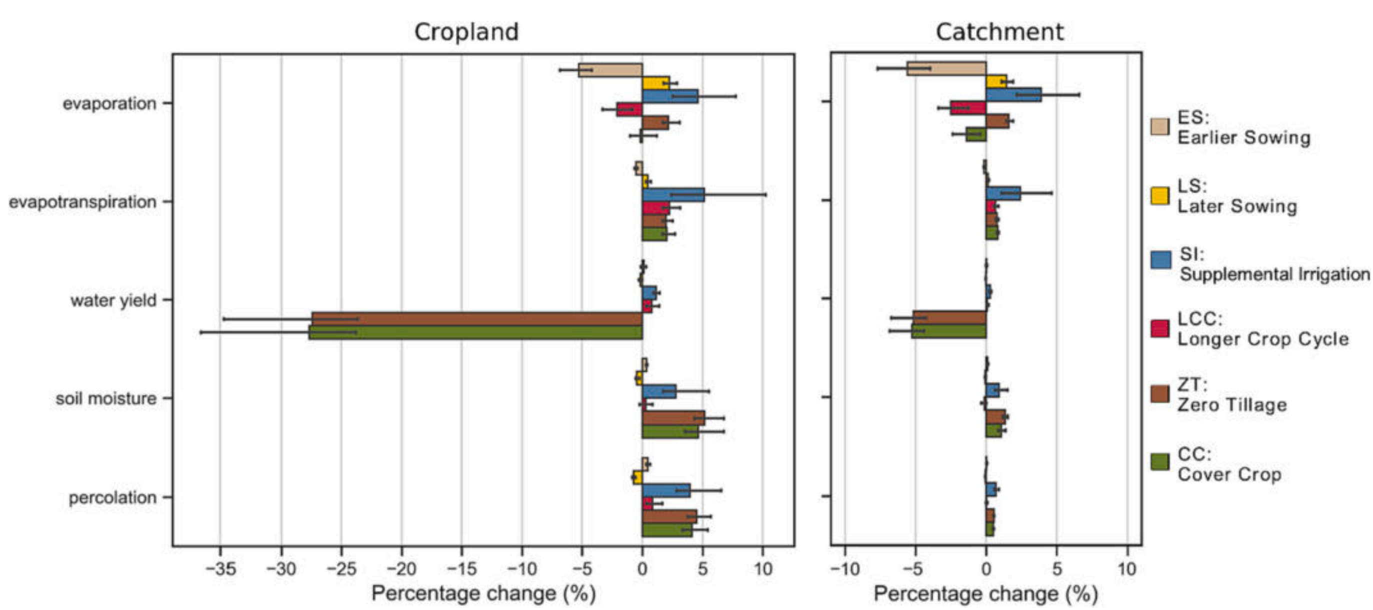

Fig. 8. Comparison of the effects of management changes on water balance components for the whole catchment and only for cropland where the agricultural practices are implemented. The bar plots are created considering the percentage relative differences between adaptation and no-adaptation scenarios. The graphs use outputs of RCP 4.5 simulations.

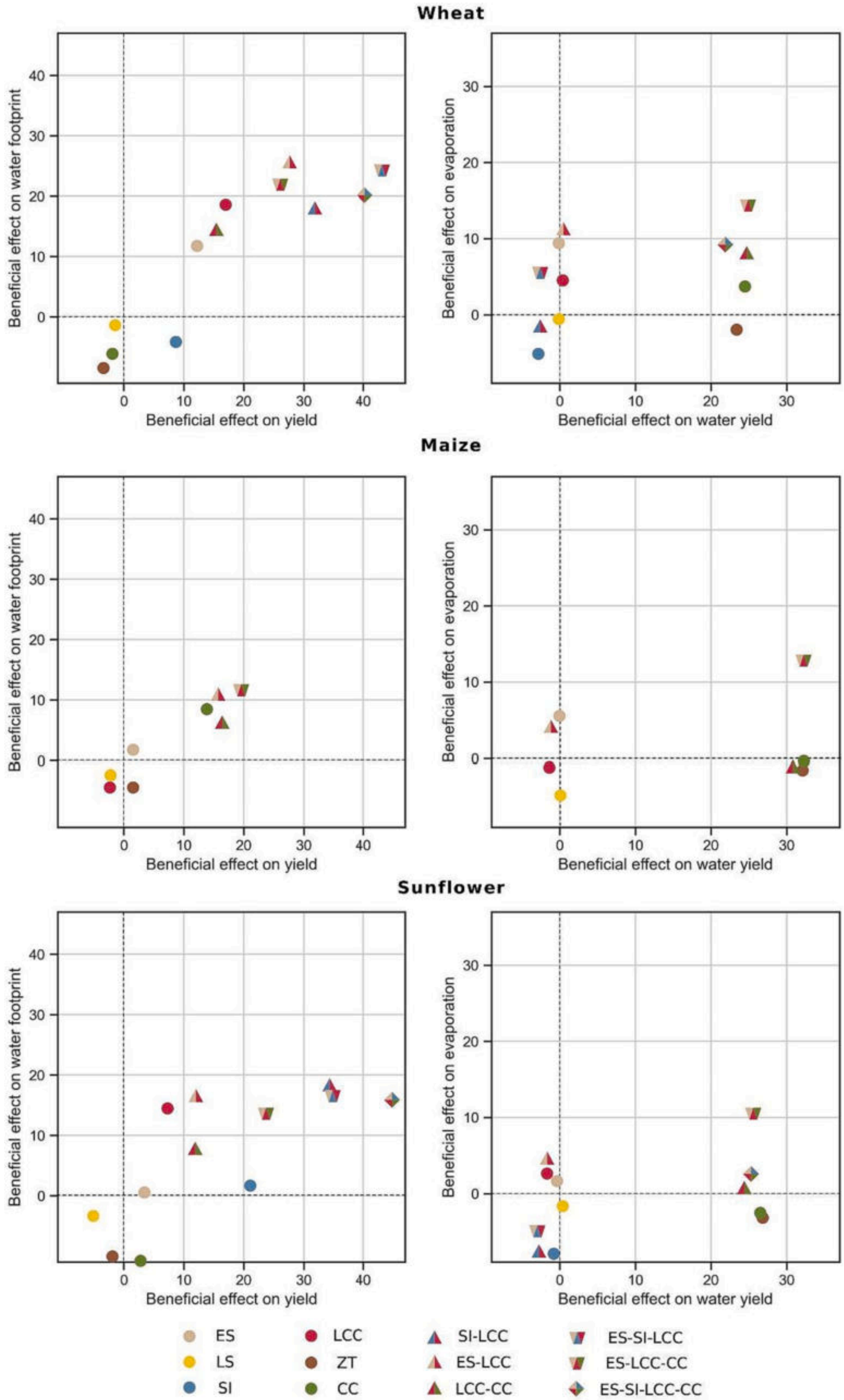

Fig. 9. The beneficial effects of adaptation strategies and their combinations for wheat, sunflower and maize, considering the ensemble mean. We selected as beneficial effect on agricultural outputs increased crop yield and reduced WF, while for the water balance reduced evaporation and increased water yield. For this figure, we considered only the outputs of RCP 4.5 and the cropland scale.

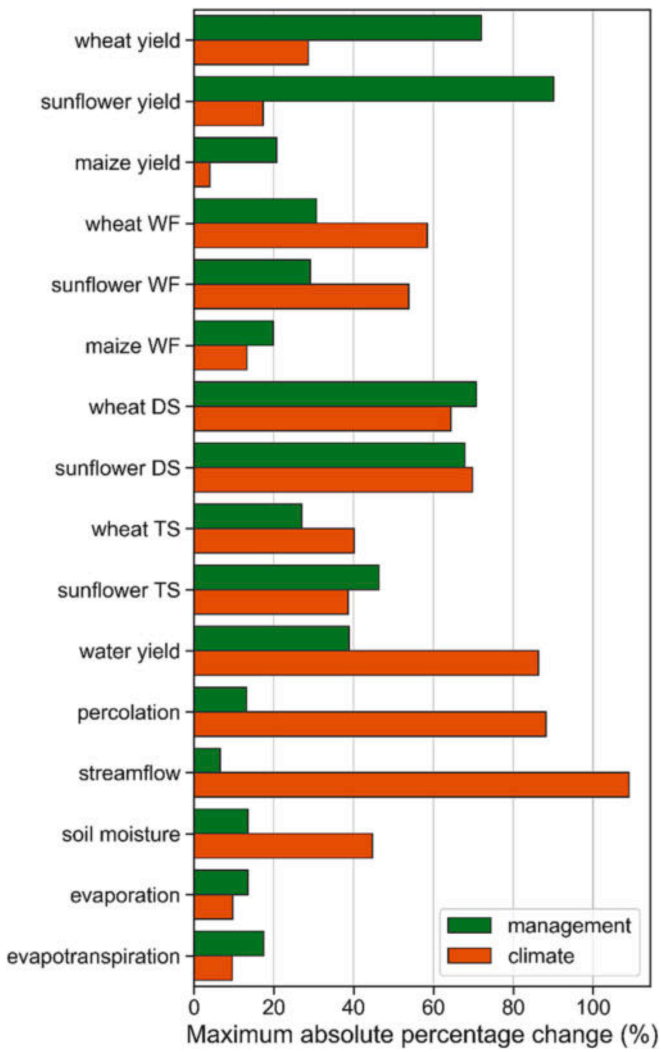

Fig. 10. Comparison of the management and climate change effects on the agricultural and hydrological variables considered in this study, under RCP 4.5. The bar plot is created using the maximum absolute percentage change of the simulations performed in this study. For the water balance components, we considered the outputs at the cropland scale and for Streamflow the Sasso d'Ombrone gauging station.

heat units' requirements that were reached much faster in a warmer climate. Instead, for TS this was surprising since the decrease was only partially explained by the shorter crop cycles. Hence, the TS was largely caused by low temperatures, as also discussed by Wang et al. (2017). The results for TS are similar when considering the two RCPs and the spring crops maize and sunflower. Hence, in Fig. 6, we reported only the outputs of the simulations under RCP 4.5 for durum wheat and sunflower.

DS was significantly influenced by the change in the sowing date, especially for wheat. As expected, 1.ES increased the DS for the winter crop and decreased it for the spring crop, while 2.LS showed consistent opposite results. 3.SI strongly reduced DS with ensemble-mean reductions of −41.1% and −54.8% for wheat and sunflower, respectively. Furthermore, 4.LCC significantly increased DS by 29% and 45.4% for wheat and sunflower respectively. Notably, 6.CC did not increase DS but slightly reduced it. Regarding TS, 1.ES increased while 2.LS decreased it, especially for the spring crop, confirming that lower temperature mainly contributed to TS. Moreover, 4.LCC increased TS mainly for the winter crop with an ensemble-mean increase of 19.2%. Consistently with the synergies observed for crop yield, we found synergies between 1.ES and 4.LCC only for sunflower, while between 3.SI and 4.LCC for both crops. Instead, no synergies or trade-offs were found for TS.

3.5. Effects of management changes on the water balance components

Results showed that the impacts of some management changes on some components of the water balance were significant, especially at the cropland scale (Figs. 7, 8) but also at the catchment scale (Fig. 8).

At the cropland scale (Figs. 7, 8), the impacts of management changes on the water balance components were consistent in sign and generally higher in magnitude compared to the catchment scale (Fig. 8). The impact of 3.SI was reduced when considering the catchment scale, especially for evapotranspiration, water yield, soil moisture and percolation, while it remained almost the same for evaporation. For 4.LCC, 5.ZT and 6.CC we also observed reduced changes for evapotranspiration, as well as for soil moisture and percolation for 5.ZT and 6.CC. However, these described percentage changes refer to magnitudes <5%. Instead, the effect of 5.ZT and 6.CC on water yield was very high in cropland, with average reductions of −27% under RCP 4.5. This effect was drastically reduced to approximately −5% at the catchment scale. Synergies between management changes were found for evaporation and evapotranspiration, mainly with 3.SI and 4.LCC (Fig. 7).

The most impacted water balance component at the catchment scale was evaporation, which was affected mainly by 1.ES and 3.SI in some specific simulations (Fig. 8). More precisely, evaporation was decreased by earlier sowing, longer crop cycle varieties and cover crops, while it was increased mainly with supplemental irrigation, but also with later sowing dates and zero tillage. Supplemental irrigation also increased catchment actual evapotranspiration. Water yield was affected to some extent by 5.ZT and 6.CC, while for evapotranspiration, percolation and soil moisture the impacts were negligible.

4. Discussion

4.1. Crop yield estimation with SWAT+

Model performances for estimating crop yield are generally lower compared to monthly streamflow. This is a known issue reported in other studies in which the long-term annual average was coherent with the observed data, but not the inter-annual variation (Musyoka et al., 2021; Nkwasa et al., 2023). Certainly, using an aggregated representation of cropland and management is an approximation that has an impact on the model performance (Abbaspour et al., 2015; Srinivasan et al., 2010). Moreover, controlled experimental yields are usually preferred to actual yields since agricultural models cannot simulate yield losses due to pests and factors other than nutrients, water, and temperature stresses. Finally, it is important to consider that the provincial average yields provided by ISTAT have large uncertainties, even if they are commonly used in research conducted in Italy (Bocchiola et al., 2013; Diodato and Bellocchi, 2008; Monteleone et al., 2022; Toscano et al., 2012). The higher variability of the simulated yields compared to observed yields can be also explained by the fact that aggregated observed data tend to reduce the variability of the farm scale (Eini et al., 2023). Often, the simulated larger variability is caused by a higher number of extremely low yields (Wang et al., 2017), as in our study. Nevertheless, given all these limitations, the performances of the SWAT+ model were overall at least satisfactory according to the performance criteria selected for this research.

4.2. Uncertain impacts of climate change on crops

In our study, the ensemble means showed negligible changes for future yields under RCP 4.5 while strong decreases (>|20%|) under RCP 8.5. Nonetheless, crop yields were highly dependent on the different climate models used. More in detail, NorESM1-M-REMO2015 showed contrasting values with the other climate models. This was mainly caused by the very low historical yields simulated, which resulted in considerable percentage increases in the future even if the absolute values were in line with the observed yields and the other simulations

(Fig. 2). These variable outputs represent a problem for planning future strategies. For this, it is also important to consider ensembles of climate models and compare results with other studies, as well as being able to communicate and deal with uncertainty. The uncertainty observed in our results is also reflected in analysing literature about climate change impacts in the Mediterranean region. For durum wheat, for example, the percentage changes range from a −60% decrease to a 30% increase according to the specific location, scenario, methodologies, RCP, climate and crop models considered (Bird et al., 2016; El Afandi et al., 2010; Garofalo et al., 2019; Pirttioja et al., 2015; Ruiz-Ramos et al., 2018; Ventrella et al., 2015). For our study area, the European-scale study of Moriondo et al. (2010) simulated minor changes in wheat yield, while in the analysis at the national scale reported by Spano et al. (2020), moderate increases were predicted under RCP 8.5. The moderate increases were confirmed also by the draft of the PNACC (2018) while constant values were predicted for RCP 4.5. Fewer specific studies are available for sunflower, which is considered highly vulnerable since it is a rainfed spring crop (PNACC, 2018; Spano et al., 2020). However, the climate change analysis of Moriondo et al. (2010) reported minor changes in sunflower yields for our study area. This is in line with our outputs that showed constant and decreasing sunflower yields for RCPs 4.5 and 8.5, respectively. Many studies evaluated the impacts of climate change on maize and, in general, more consistent values are reported in the literature. This can be attributed to the fact that maize as an irrigated crop is less affected by precipitation variability. Decreasing maize yields are generally predicted for the Mediterranean region (e.g. Bocchiola et al., 2013; El Afandi et al., 2010; Gabaldón-Leal et al., 2015; Rey et al., 2011; Torriani et al., 2007; Tubiello et al., 2000). However, in Bocchiola et al. (2013), with sufficient irrigation or precipitation and increases in temperature of <2 °C, constant or increasing maize yields were predicted. The outcomes of the simulations summarized in Spano et al. (2020) and PNACC (2018) confirmed the moderate decreases in maize yields in Southern Tuscany. Our results are in line with those reported in maize literature since we found yield decreases under RCP 8.5 and minor changes under RCP 4.5.

WF is a common metric to estimate agricultural water consumption which entails a high degree of uncertainty due to the different approaches to account for the water used (Feng et al., 2021). This uncertainty escalates when considering future WF in the context of climate change (Wang et al., 2023) and the large range observed in our results seems to confirm this statement (Fig. 3). Global estimates of WF, considering the sum of blue and green water, were estimated by Mekonnen and Hoekstra (2011, 2012) as 1.6 m^3 kg^{-1}, 1.0 m^3 kg^{-1} and 2.2 m^3 kg^{-1} for wheat, maize and oil crops, respectively. Feng et al. (2021) reported lower values for WF global averages, estimated at 1.1 m^3 kg^{-1} and 0.7 m^3 kg^{-1} for wheat and maize, respectively, with the ranges of uncertainty that increased considerably when considering smaller scales. Values reported in studies conducted in Italy for rainfed winter durum wheat range from 0.9 m^3 kg^{-1} and 2.7 m^3 kg^{-1} (Garofalo et al., 2019; Ventrella et al., 2015). The irrigated maize WF in Northern Italy was estimated by Nana et al. (2014) at 0.5 m^3 kg^{-1}. Bocchiola et al. (2013) found minor changes in future total WF, with green and blue water compensating for each other in response to precipitation variability. Nevertheless, in the worst-case scenario, WF decreased due to the drop in maize yield (Bocchiola et al., 2013). Specific studies on sunflower are less common and the WF varies a lot according to the different climates. In the studies discussed by Bulut (2023) about sunflower WF, the values range between 1.3 and 3.3 m^3 kg^{-1}, with huge differences in green and blue WFs. Brouziyne et al. (2018) performed a water productivity analysis in Morocco and found a decrease in future water productivity for both rainfed wheat and sunflower due to climate change. The ensemble means of total WFs estimated in our study were 1.9 m^3 kg^{-1}, 4.2 m^3 kg^{-1} and 1.1 m^3 kg^{-1} for durum wheat, sunflower and maize, respectively, slightly higher than WF values found in the literature. Nonetheless, our WF values are still in the range of uncertainty reported in the literature, and it is important to keep in mind that we calculated WF considering the annual average actual evapotranspiration as water used, and not only referring to the months in which the crop is grown. This approach allowed us to compare the WF of other adaptation strategies such as cover crops. Considering RCP 4.5, WFs slightly decreased for maize and increased for the rainfed crops, while for RCP 8.5 the ensemble means showed minor increases for maize but increased substantially for durum wheat and sunflower due to the significant drop in crop yield in many HRUs. These very low yields predicted for durum wheat (<1 ton ha^{-1}) in many HRUs of the Ombrone catchment led us to conclude that, without adaptation, part of the catchment will become unsuitable for wheat growth under the worst scenarios. Nevertheless, it is important to underline that SWAT+ outputs when considering CO_2 values higher than 660 ppm, as in our case for RCP 8.5, are prone to large uncertainties.

The analysis reported by Webber et al. (2018) showed that heat stress will not harm future wheat and maize yields. These results are consistent with our study since we found decreasing temperature stress due to reduced crop cycle length and increased temperature. This seems counterintuitive but the optimal temperatures are quite high – 15 °C for durum wheat and 25 °C for sunflower and maize – and, consequently, the temperature stress is largely caused by low temperatures, as found and discussed also in Wang et al. (2017). Considering drought stress, Webber et al. (2018) reported negative impacts on maize yield in our study area. Our results showed maize yield reduction under RCP 8.5, but these were not strictly related to drought stress which was negligible due to supplemental irrigation. Regarding future irrigation, despite the rising temperatures and the consequent increase in evapotranspiration, other studies found reduced irrigation requirements for maize by up to −25% mainly due to the shortening of the crop cycle (Gabaldón-Leal et al., 2015; Rey et al., 2011). These reductions were confirmed also in our study and the role of supplemental irrigation was not so important since climate models predicted slight increases in precipitation.

4.3. The effectiveness of management changes

In response to reduced precipitation, irrigation is likely to be needed in the Northern Mediterranean countries for typically-rainfed crops, such as wheat (Saadi et al., 2015) and sunflower (Giannini et al., 2022). Many studies conducted within the Mediterranean region confirmed the positive role of supplemental irrigation for wheat (Bird et al., 2016; El Afandi et al., 2010; Garofalo et al., 2019; Moriondo et al., 2010; Ruiz-Ramos et al., 2018; Ventrella et al., 2012b; Ventrella et al., 2015). Furthermore, changes in sowing date drastically affect future yields, with variations of up to 40% found in Southern Italy in the study of Ventrella et al. (2012a). However, contrasting results can be found in the literature. For example, El Afandi et al. (2010) reported positive effects of earlier sowings, while Bird et al. (2016) and Moriondo et al. (2010) claimed the benefits of delayed sowing. Crop rotation (Ventrella et al., 2012c), mulching (Bird et al., 2016) and longer crop cycles (Moriondo et al., 2010) also showed positive effects on wheat yield. For sunflower, the study of Giannini et al. (2022) in Sardinia reported that earlier sowing and supplemental irrigation have beneficial effects on yield. Focusing on our study area, the analysis of Moriondo et al. (2010) confirmed that anticipated sowing dates led to moderate increases in sunflower yields, comparable to those of longer crop cycle varieties. In the same study, the increase caused by the application of supplemental irrigation on future sunflower yields was higher than 75%. Maize is typically irrigated in Italy and an appropriate irrigation strategy is fundamental to avoid water stresses during the most critical phases (El Afandi et al., 2010; Gabaldón-Leal et al., 2015; Monteleone et al., 2022). Furthermore, longer crop cycles and earlier sowing dates showed positive effects on maize yield (Rey et al., 2011; Torriani et al., 2007; Tubiello et al., 2000), quantified in an increase of 14% in the study of Gabaldón-Leal et al. (2015). Regarding the impacts of irrigation on WF, Bocchiola et al. (2013) showed a strong relation between blue water and precipitation for maize in Northern Italy. The historical and future WFs of the irrigated simulations for winter wheat in Southern Italy reported in the studies of Ventrella et al. (2015) and Garofalo et al. (2019) were lower as compared to the WFs of the rainfed crop, demonstrating the beneficial impact of irrigation reducing WF by increasing crop yields. Our results confirmed that, when irrigation increased crop yield for wheat and sunflower, WF consistently decreased. The water productivity analysis of Brouziyne et al. (2018) in Morocco showed the beneficial impact of no-tillage on the water productivity of wheat and sunflower, while anticipating sowing of 10 days was beneficial for wheat and unclear for sunflower. Their results about earlier sowing were consistent with our WF outcomes, while the beneficial impacts of zero tillage were not confirmed in our study.

According to our results, adaptation strategies were shown to be essential to maintain the historical crop yields. Furthermore, in some cases, especially when considering combinations of adaptation strategies, the SWAT+ model predicted increases in future yields and decreases in WF (Fig. 9). Synergies between adaptation strategies should not be disregarded, as shown in our study. As for climate change impacts, also the effects of management changes showed some degree of uncertainty, both in our study and checking available literature. Nevertheless, the adaptation strategies that we simulated are simple ones and they can mostly be adopted easily by farmers without the need for significant planning. Considering the effect of adaptation strategies on agricultural outputs, namely crop yield and WF, the most promising adaptation strategies for durum wheat were earlier sowings and longer crop cycles, while supplemental irrigation had beneficial effects only with MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015. For sunflower, longer crop cycles were always useful while earlier sowing, supplemental irrigation and cover crops only with MPI-ESM-LR-RCA4 and NorESM1-M-REMO2015. Similar recommendations can be provided for maize, with longer crop cycles being the most effective strategy both in increasing crop yield and in reducing WF. Overall, we can affirm that in our case study, the effect of some adaptation strategies was comparable to the impacts of climate change. Comparing the magnitudes of change in Fig. 10, it is possible to observe that the maximum absolute percentage increases for crop yields are much higher for management changes than the changes caused by climate change under RCP 4.5. The increased magnitude changes of management as compared to climate are more evident when considering combinations of adaptation strategies in some climate models, mainly NorESM1-M-REMO2015. On the other hand, the impacts of climate change on WF are much higher compared to those of adaptation strategies, except for total WF for maize that showed similar magnitudes of change as compared to the maximum management changes (Fig. 10). Finally, the maximum absolute changes were also similar when considering DS and TS (Fig. 10).

In this study, we mostly focused on the management changes applied in the future and framed them as adaptation strategies. Nevertheless, it is clear that most of these changes would be beneficial also in the present. We refer to the management changes as adaptation strategies since, in the simplification of the current agricultural systems, we assume that these practices are not widely implemented in the whole catchment and might be adopted in the future, as also recommended in the recent PNACC (2023). For the management changes that we simulated in the historical scenarios, namely supplemental irrigation and the practices of conservation agriculture (zero tillage and cover crops), as expected the changes have the same sign as compared to the future ones. Interestingly, they mostly have a higher magnitude of changes. For example, the ensemble mean yield increases after simulating supplemental irrigation were >20% higher in magnitude in the historical as compared to RCP 4.5 future simulations. As a consequence, beneficial decreases in WF were observed for both rainfed crops, while in future scenarios, these were not clear. Similarly, the decrease in basin water yield was higher in the historical scenarios when applying zero tillage and cover crops. The amplified effect in the historical scenarios can be attributed to the fact that, on average, a slight increase in precipitation is predicted by the five climate models. Also, in the future the crop cycle is reduced due to increased temperatures, reducing the potential benefits of supplemental irrigation. This last statement is confirmed also by the synergy that we observed when applying supplemental irrigation with longer crop cycle varieties in the future.

4.4. The impact of management changes on water balance components

The use of an agro-hydrological model to spatially simulate crop growth and the possible management changes allowed for the evaluation of their impacts on water balance components, such as evaporation, actual evapotranspiration, water yield, percolation and soil moisture. Certainly, the SWAT+ model simplifies the processes influenced by management changes and further research is necessary. In our study, the area with herbaceous crops where the adaptation strategies were implemented corresponds to approximately one-third of the whole catchment, and it is interesting to note that the changes were not always reduced proportionally (Fig. 8). The outputs regarding the beneficial effects of the simulations on evaporation and water yield are also plotted in Fig. 9. To quantify how much the management changes influenced the water balance components, the comparison with the changes induced by climate change is displayed in Fig. 10.

The impacts of adaptation strategies on water balance components are usually neglected and there are few studies in the literature. One example is the water productivity analysis carried out with the SWAT model by Brouziyne et al. (2018), which showed that earlier sowing caused a reduction in water yield <5%, while zero tillage yielded minor changes (<1%). Salmoral et al. (2017) evaluated the impact of contour tillage on water balance components and found no significant changes, different from when considering afforestation – a land cover change – which drastically influenced basin evapotranspiration and evaporation. In a field-scale study about the full adoption of rapeseed for biofuel, Noreika et al. (2020) found significant changes in evapotranspiration, soil moisture and flow by −11.8%, 20% and 36.1%, respectively. According to Noreika et al. (2022), residue incorporation, contour farming and conservative tillage reinforced the small water cycle both at the field and catchment scales, except for streamflow at the outlet. Their results showed that soil moisture and evapotranspiration were higher with conservation practices compared to conventional tillage, while the opposite occurred for runoff and lateral flow, with runoff that was more than double with conventional tillage. Interestingly, they found that the scale of adoption of the practices and the distribution in the catchment did not affect the water balance components. Ullrich and Volk (2009) found decreases of up to −30% in surface runoff and more than −10% in water yield applying no-tillage compared to conventional tillage, with differences according to the crops and tillage dates considered. Chen et al. (2021) performed a comprehensive analysis of irrigation at different depths, earlier and later sowing. For irrigated maize, they found that earlier sowing moderately increased (<5%) evapotranspiration, soil moisture, runoff and water yield, while later sowing decreased them by almost the same magnitude, except for soil water for which they reported a decrease of −7.8%. For irrigated wheat, with earlier sowing they observed an increase of 7.3% in evapotranspiration and decreases of more than −10% in soil moisture, runoff and water yield, while opposite changes were found for later sowing dates. For rainfed wheat, except for evapotranspiration which remained almost constant, they reported significant decreases in soil moisture, runoff and water yield for earlier sowing, while consistent opposite for later sowing, with increases reaching 77.3% in soil moisture.

In our study, while the effects of adaptation strategies on crop yield and WF were significant, the impacts on the water balance were generally low when considering the relative changes at the catchment scale (Fig. 8). However, in some cases and especially when considering the cropland scale, the impacts were significant and should not be neglected when comprehensively evaluating agronomic adaptation strategies. For example, water yield in cropland was significantly reduced by almost −40% when applying zero tillage and cover crops in one specific climate model under RCP 4.5 (Fig. 7). Combinations of adaptation strategies were more beneficial compared to individual ones (Fig. 9), and some synergies were observed. Furthermore, for some water balance components such as evaporation and actual evapotranspiration, we observed minor changes caused by climate change, comparable to the ones obtained for management changes, while the impacts of climate change were much higher as compared to those caused by management changes for water yield, soil moisture, percolation and streamflow (Fig. 10). At the catchment scale, the adaptation strategies had impacts of a few percentiles, with ensemble-mean changes mostly lower than 5%, with some exceptions (Fig. 8). These changes might seem negligible, but it is important to underline that we simulated very small changes. For example, sowing dates were shifted by only 15 days and the crop cycles were increased by the same number of days. As already discussed, supplemental irrigation was not so important in our study, but still, we could observe some impact on the water balance. With more significant management changes the impacts on the water balance components at the catchment scale could further increase.

5. Conclusion

Despite the limitations of integrated models, distributed agro-hydrological models such as SWAT+ can be very useful for carrying out comprehensive climate change impact assessments since their outputs are related to food security and water resources at both field and catchment scales. Our results showed that projected crop yield changes were highly variable and dependent on the crop, RCP and climate model considered. This uncertainty, which emerged not only from our study but also from analysing the literature, complicates the role of decision-makers who have to plan future policies to deal with this challenge. On the other hand, the positive insight from our research is related to the high adaptive capacity of the agricultural systems after the adoption of simple, autonomous changes in management, that will be in most cases easily implemented by farmers. Many combinations of adaptation strategies showed interesting synergies that enhanced the positive effects or reduced the negative ones, but in some cases, we also observed trade-offs that should be considered. Our results also suggest that the impacts of some management changes in some agricultural catchments cannot be neglected when trying to assess the adaptive capacity of agricultural systems. Hence, climate change impact assessment should be as integrated and comprehensive as possible by also considering the impacts at scales larger than the field scale, not only to include more climate, soil, crop and management variabilities but also to simulate catchment-scale processes and impacts.

CRediT authorship contribution statement

Lorenzo Villani: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Giulio Castelli:** Conceptualization, Methodology, Writing – review & editing. **Estifanos Addisu Yimer:** Methodology, Writing – review & editing. **Albert Nkwasa:** Methodology, Writing – review & editing. **Daniele Penna:** Conceptualization, Supervision, Writing – review & editing. **Ann van Griensven:** Conceptualization, Supervision, Writing – review & editing. **Elena Bresci:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.103903.

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