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Projected climate change impacts on future soil organic carbon dynamics and wheat yields under different agricultural management strategies for two contrasting environments in Iran

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Abstract

Understanding how agricultural practices and climate change impact crop yields and soil organic carbon (SOC) is crucial for maintaining agroecosystem functioning. In this study, MONICA model was used for assessing the impacts of agricultural strategies: conventional (CON), organic (ORG), and integrated (INT), and crop rotation systems: fallow-wheat (F-W), maize-wheat (M-W), sesame-wheat (S-W), and mung bean-wheat (B-W) on the yield and above ground biomass (AGB) of aforementioned crops and the change in SOC stocks for the semi-arid region of Ahvaz (Iran). We also assessed the impacts of CO₂ emissions of societal development pathways SSP245 (480 ppm) and SSP585 (600 ppm) on future (2030–2060) changes in yield, AGB, and SOC for a M-W rotation under the mentioned agricultural strategies in the contrasting climate zones of Ahvaz and Torbat-Heydareye. MAE and NRMSE values of the calibrated model were 0.4 Mg ha⁻¹ and 12% for wheat yield and 0.5 Mg ha⁻¹ and 10.4% for wheat AGB. The low NRMSE values for SOC simulations (7.7%) indicated that MONICA accurately reproduced observed SOC. Projected wheat yield and AGB, and SOC contents, influenced by elevated CO₂ levels and rising temperatures. In future scenarios, CO₂ enrichment and warming improved yield and SOC in the semi-arid cold climate (Torbat-Heydareye) but reduced both in the semi-arid warm climate (Ahvaz). Climate change had a stronger impact on SOC under CON than under organic-based management strategies at both sites. This highlights the need to assess agricultural strategies regionally, considering climate projections and soil types.

Keywords Simulation model · Climate change impacts · Crop yield · Soil organic carbon sequestration · Crop rotation · Crop residues

1 Introduction

Accelerating climate change, driven by rising greenhouse gas emissions, especially CO₂, has become a global concern. Among the various strategies for reducing emissions, agricultural management is increasingly recognized as a key approach (de Larminat 2016; Ray et al. 2020). This can be achieved by both minimizing emissions from farming practices (Johnson et al. 2007) and enhancing soil carbon sequestration (Lal 2004; Gangopadhyay et al. 2022). Agricultural soils, as the largest terrestrial carbon (C) sink, have the potential to play an important role in mitigating climate change by sequestering organic C in the soil (Lal 2008). The capability of the soil to retain C is 2.5 to 3 times higher than of the atmosphere (Fekete et al. 2021; Sommer and Bossio 2014). Soil organic carbon (SOC) stock is formed as a result of the long-term addition and accumulation of organic C in the soil by decomposing organic matter sources (Chen et al. 2015). It is an integral part of agroecosystems influencing soil quality and productivity, and, therefore, ensuring food, soil, water and energy security through controlling soil geochemical and biological processes and their interactions (Gerke 2022; Padarian et al. 2021). However, global change such as changes in precipitation patterns and warming, combined with land use and land management changes, have increased the vulnerability of SOC to losses (Pendall et al. 2008). This, together with the breakdown of soil structure, soil erosion and the decline in soil biodiversity, threatens crop productivity, particularly in semi-arid regions (Lal 2010). Therefore, addressing solutions such as improving soil fertility, biodiversity and land management to enhance SOC, thereby promoting soil structure and its water retention, improves the resilience of agroecosystems to climate change (Hashimi et al. 2023; Salehi et al. 2025; Smith 2008). Since arable lands occupy 37.5% of the earth's surface (Fuglie et al. 2024). Therefore, agricultural activities such as application of organic and inorganic fertilisers, management of crop residues, use of diverse crop rotation systems and tillage regimes have important roles to play in improving the resilience of agroecosystem to climate change through SOC sequestration (Caldiz et al. 2018; Gollany and Venterea 2018). A study in Funiu Mountain, central China, found that applying organic matter in cereal-cereal systems enhanced the formation of macro-aggregates and their association with organic carbon (Zhao et al. 2023). Additionally, research done by (Bansal et al. 2021) at the University of Tennessee showed that shifting from continuous legume or cereal monocultures to cereal-legume and legume-oilseed rotations increased SOC in both topsoil and subsoil due to slower carbon turnover.

However, agricultural systems, and thus crop yield, are directly affected by changes in climate. Therefore, recognising how climate change will affect crop productivity over the coming decade remains critical (Faye et al. 2023). For example, crop yields are strongly affected by changes in temperature, rainfall and carbon dioxide (CO₂). Although higher atmospheric CO₂ improves crop photosynthesis and productivity (Tubiello et al. 2007), a severe rise in temperature reduces crop yields due to faster crop development and shorter growing cycle, increased evapotranspiration, crop water demand, and heat stress (Adusei et al. 2022). Many researchers have investigated the potential influence of agricultural management strategies, e.g. organic, inorganic, and integrated use of fertilizers in combination with crop residues retention to the soil, on improving C sequestration and crop yield stability, but considerable uncertainty remains in their response to climate change (Matsumoto et al. 2021; Mohamad et al. 2016; Maltas et al. 2018). Faye et al. (2023) showed that the effects of climate change on the grain yield of C3 crops, e.g., winter wheat (*Triticum aestivum* L.),

winter barley (*Hordeum vulgare* L.) and winter rapeseed (*Brassica rapa* L.), were generally positive for the residue incorporation scenario. Others have shown that the gradual substitution of crops by better-suited ones may influence the production figures by simply increasing the production area (Nendel et al. 2023). More benefits of agricultural strategies are associated with the crop rotation systems. For instance, different rotation designs of small cereal grain, legumes, and perennial crops had an affirmative trace on SOC and agroecosystem profitability and adaptability (Chahal et al. 2021; Davis et al. 2012; Yang and Kay 2001). Understanding the multiple feedback mechanisms in the crop–soil–atmosphere nexus is challenging and often requires additional tools to facilitate it.

Digital tools that help to disentangle and reproduce the complex relationships between crop, soil, atmosphere and management are process-based crop models (hereafter referred to as crop models). They are commonly employed for assessing the impact of agricultural management in reducing the consequences of future climate change. These models allow us to test a range of scenarios aiming to develop modern site-specific management strategies adapted to climate change. Moreover, a crop model can be spatialized and used at scales other than that for which it was originally designed (Pasquel et al. 2022). There are ongoing efforts to accurately simulate crop yield and SOC changes in response to a wide range of management strategies and future climatic changes. Multiple crop models and platforms such as APSIM (Zhao et al. 2013), MONICA (Nendel et al. 2011), SIMPLACE (Enders et al. 2023), CQESTR (Nash et al. 2018), and DSSAT (Liu et al. 2017) have been equipped with crop growth modules to quantify and predict crop yield and SOC under different agricultural management and changing environments. Furthermore, to accurately predict future SOC pools in agroecosystems, changes in organic matter decomposition in response to agricultural management strategies and future climate change must be considered. Studies have discovered a decrease in SOC with increasing temperature and precipitation in response to climate change projections. This may be due to accelerated decomposition of soil organic matter and, hence, loss of C from the soil (Nash et al. 2018; Wang et al. 2014). Additionally, incorporating C inputs, e.g., manure, crop residue, and crop rotation can mitigate further SOC losses and enhance soil C sequestration amid climate change (Herzfeld et al. 2021). However, due to large uncertainties in regional climate change projections, crop and soil responses to environmental changes (precipitation, temperature, CO₂ concentration), and the role of adaptation strategies, the development of reliable agricultural strategies for future crop production remains a challenge (Challinor et al. 2007; Jiang et al. 2014).

Although farmers' attitudes toward sustainable land management strategies in Iran vary widely, ranging from completely favorable to unfavorable, with a general tendency toward disinterest (Abadi et al. 2020), their active involvement in soil conservation projects is crucial for the success of these initiatives, as they represent a new policy approach to combat soil degradation and promote sustainable agriculture (Mohammadi Golrang et al. 2017). This need for farmer engagement becomes even more critical when considering the widespread unsustainable practices currently in use. In Iran, the consistent use of inorganic fertilisers, harvesting of crop residues for livestock feeding and burning them to facilitate tillage for the next crop cultivation as well as lack of appropriate crop rotation systems has led to poor structure of the soil, decrease of SOC, and consequently low productivity of agricultural systems (Kabiri et al. 2016). This mismanagement, in combination with climate variability, could have serious implications for the country's future crop production. Addressing this issue requires an exploration of the ability of crop models to describe the interconnections between crop growth

and yield, SOC dynamics and potential agricultural management strategies under climate change projections. In this regard, several studies have investigated SOC changes and crop yield responses to crop residue management (Nash et al. 2018), timing of nitrogen application, growing condition (Webber et al. 2015), different crop rotation systems, and climate change (Adusei et al. 2022; Liu and Basso 2020; Wang et al. 2014). However, our study, for the first time attempted to apply the Model for Nitrogen and Carbon in Agroecosystems (MONICA) to simulate the simultaneous effects of different agricultural strategies combined with various crop rotation systems, and their response to the sensitivity of simulated climate change impacts simulated climate change impacts in a semi-arid warm region.

This study aims (i) to calibrate a process-based crop model, MONICA, to simulate the effect of agricultural strategies and crop rotation systems on SOC sequestration and crop productivity; (ii) to determine the response of SOC changes, wheat yield, and AGB to climate change under a range of future emission scenarios based on the latest climate model output from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The response of the following agricultural management strategies will be tested:

- a) Only use of inorganic fertilizers + crop residues removal (CON).
- b) Only use of organic fertilizers + incorporation of 30% of crop residues to the soil (ORG).
- c) Integrated use of organic and inorganic fertilizers + incorporation of 15% of crop residues to the soil (INT).

2 Data and methods

2.1 Study area

The study was conducted over a span of four growing seasons, from 2018 to 2020, encompassing both spring and winter crop-growing seasons. The research took place in Ahvaz, a region situated at the center of Khuzestan province in southwest Iran. The study area is located between 48° 41' E and 31° 20' N, with an elevation of 22.5 m, covering an area of 64,055 square kilometers. Khuzestan province is a leading wheat producer in Iran, annually yielding 1.37 million metric tons. The climate in the study region is predominantly hot and semi-arid with mild winters and an average annual rainfall of 213 mm, primarily occurring during the winter season from January to March. The average annual temperature is 25 °C, reaching a maximum of 48 °C in spring and dropping to a minimum of 4 °C in winter. The texture of the topsoil at the experimental site is classified as sandy-loam, consisting of 67% sand, 21% silt, and 12% clay. The soil analysis revealed nitrogen content of 0.039%, C content of 0.45%, available phosphorus content of 26 kg ha⁻¹, available potassium content of 318 kg ha⁻¹, electrical conductivity of 3.4 dS m⁻¹, and a pH value of 7.8 (Goroeei et al. 2023b; Nazari et al. 2021).

2.2 The MONICA model

The simulations were carried out with the MONICA model, which is the latest generation of the HERMES model versions (Kersebaum 2007; Nendel et al. 2011), extended for C cycle in plant-soil ecosystems. It simulates crop growth, the turnover of organic matter, water,

and nitrogen uptake. The model has been used to estimate the effect of crop management strategies (e.g., type of fertilization, irrigation, crop residues management), different crop rotation systems and climate change on crop growth and soil processes (Asseng et al. 2013; Nendel 2014; Nendel et al. 2023; Pohanková et al. 2024). In this model, depending on crop species and growth parameters, growth period is divided into six (e.g. wheat: emergence, begin stem elongation, double ridge, heading, anthesis, maturity) or seven developmental stages (e.g. maize: emergence, begin stem elongation, inflorescence emergence (heading), begin male anthesis, begin female anthesis, begin grain filling, maturity) from sowing to maturity. Similar to Allen et al. (1998) reference evapotranspiration is calculated using the Penman-Monteith method, which requires data on temperature, relative humidity, wind speed, and solar radiation. In addition, specific potential evapotranspiration is calculated using crop-specific factors (K_c) during the growing season. The organic matter turnover and the dynamics of C and N turnover are quantified based on the routines used in the DAISY model (Abrahamsen and Hansen 2000; Jensen et al. 2001). The model is able to estimate dynamics of SOC in different soil depths. It estimates the changes in different SOC pools characterized by different decomposition rates of fresh organic matter, humified organic matter (fast or slow) and microbial biomass. The MONICA model has been calibrated to simulate and predict the growth of the most important European crops (e.g. Rötter et al. 2012; Asseng et al. 2013; Bassu et al. 2014; Fleisher et al. 2017; Nendel et al. 2011; Nendel et al. 2023) and also organic C dynamics in soils (Stella et al. 2019a, b; Farina et al. 2021; Aiteew et al. 2024). More details about MONICA can be accessed at <https://github.com/za-lf-rpm/monica>.

2.3 Crop growth simulation under different agricultural management scenarios

2.3.1 Field experiments

Data for calibration and validation of the MONICA were obtained from irrigated experimental plots under three different management strategies (CON, ORG, INT) differing in applied amount of organic and inorganic fertilizers and various crop rotation systems. A total of 12 combinations of agricultural management and crop rotation systems were arranged in a split-plot randomized complete block design with three replications (Gorooei et al. 2023a). The fertilizer and crop residue management was comprised of: 1- *conventional (CON)*, The inorganic fertilizers applied for this management were nitrogen (Urea), phosphorus (H_2PO_4), and potassium (K_2SO_4) and all crop residues were removed after harvesting each crop (i.e. before sowing of the following crop); 2- *Organic (ORG)*, only organic fertilizers were applied in this management strategy i.e. compost and vermicompost produced from manure. After harvesting each crop (spring and winter crops) 30% of crop residues were incorporated back to the soil, and 3- *Integrate management strategy (INT)*, where a combination of inorganic and organic fertilizers was applied. In addition, 15% of the crop residues were returned to the soil.

Four wheat-based crop rotation systems comprising mung bean (*Vigna radiata* L.)-wheat, maize (*Zea mays* L.)-wheat, sesame (*Sesamum indicum* L.)-wheat, and fallow-wheat rotation were carried out. In these cropping systems, mung bean, maize, and sesame were planted in the spring and wheat was planted during the winter season. Furrows for summer cultivation were initially prepared using a moldboard plow to a depth of 20 cm. To

prevent mixing between experimental plots, shovels and rakes were used to simulate tillage for wheat row preparation. Irrigation was applied based on crop water requirements and soil moisture conditions using CROPWAT version 8.0, incorporating crop coefficients and evapotranspiration data. Seasonal irrigation requirements were 369 mm for wheat, 347 mm for maize, 337 mm for mung bean, and 315 mm for sesame. Detailed information on agronomic practices, including planting dates, fertilizer application schedules, and the chemical properties of organic fertilizers and crop residues are given in Table S1 as well as in (Gorooei et al. 2023a). A schematic presentation of the crop rotation systems is shown in Fig. 1A. Crop parameters, such as grain yield and total above-ground biomass (AGB), were assessed for all the spring and winter crops examined in this study (Gorooei et al. 2023a). Furthermore, the Walkley and Black (1934) method was utilized to quantify the total soil organic carbon (SOC) following the harvest of each spring and winter cultivation.

2.3.2 Data available for model calibration

The meteorological input data, representing daily climate conditions, was acquired from the meteorological station situated at Shahid Chamran University in Ahvaz, Iran. A comprehensive breakdown of the meteorological input is provided in Table S2. The initial soil data, presented in Table S2, were obtained by direct measurement of samples taken from the experimental plots, focusing on the top 20 cm of soil. To simulate the agricultural scenarios, crop data and various agricultural strategies, including tillage, fertilizer application (type, quantity, timing), irrigation amounts and timing, crop residue management, and individual crop rotation systems, were incorporated into the model (Fig. 1C). Table S2 presents the specific details of these inputs. For each crop rotation system (e.g., W-F, M-W, S-W, and B-W), the MONICA model was individually prepared with the corresponding agricultural management options (CON, INT, and ORG).

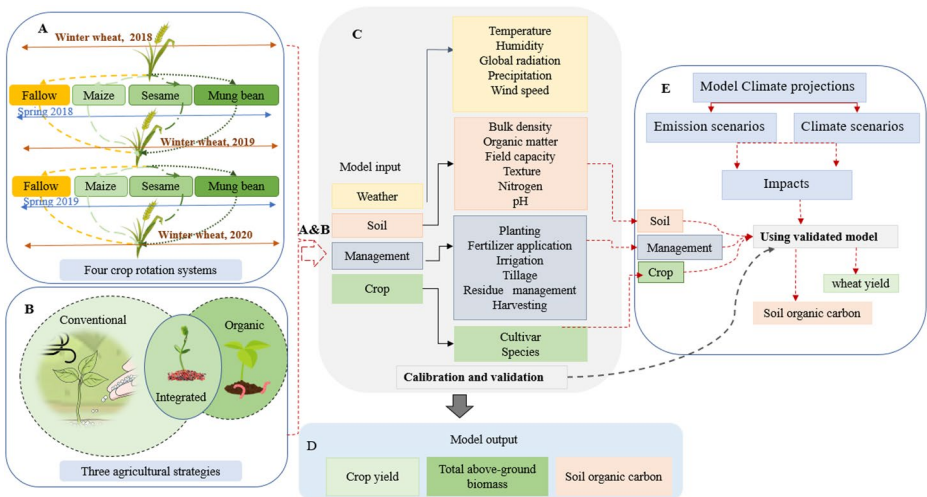


Fig. 1 The use of stage-based crop models can be a promising path to estimate the impact of different agricultural practices (A&B) on crop yield and soil geochemical processes (C&D) on the plant-soil ecosystem and their response to climate change scenarios (E)

2.3.3 Model calibration and validation

The crop model parameters were automatically calibrated using Python programming language specifically focused on the wheat-fallow system (W-F), using two years of data under the three agricultural strategies mentioned earlier. A Python script was created to calibrate the MONICA for each crop based on grain yield and AGB measured in the experiment described in Sect. 2.2. The calibration procedure started by defining the upper and lower ranges of the most influential model parameters e.g., specific leaf area (SLA). MONICA divides the development of crop growth into separate stages. Therefore, some crop parameters are assigned different values for different growth stages (Specka et al. 2015). The value ranges of the parameters were close to the default values of the model. The model parameters that were used for automatic model calibration are listed in Table 1. The python script ran the model 500 times. Each time it randomly set different values of the parameters and simulated the new value for the target variables (Kamali et al. 2022). Finally, the script selected the combination of parameter values that yielded the lowest value of normalized root mean square error (NRMSE).

The calibration process consisted of three distinct phases. Firstly, in the crop phenology-based calibration phase, the model parameters, such as the growing degree days (sum of daily air temperature to reach specific crop phenological stages) and base temperature influencing the crop's phenology period, were calibrated based on observed data, specifically the time of flowering for wheat monocropping under CON, ORG, and INT (refer to Table 1 for details).

The second phase involved a full calibration for the parameters related to crop growth. The parameters obtained from the first phase remained unchanged, and the calibration process focused on evaluating two crop variables: grain yield and AGB (total above-ground biomass). During this phase, additional model parameters were adjusted (see Table 1). The calibrated model parameters derived from the two calibration phases were kept constant for running the model across all agricultural strategies and the two experimental years. Similar calibration procedures were employed for spring crops, including sesame, maize, and mung bean. However, as there were no specific default crop parameter files available for sesame and mung bean in the MONICA model, the default parameters for cotton (oilseed) and field pea (legume) were modified according to available information on sesame and mungbean at relevant BBCH-scales (Elie et al. 2010; Nendel et al. 2014; Geetika et al. 2022; Langham et al. 2008). Based on the new crop parameter files, it was possible to simulate the yield, biomass, and SOC dynamics under sesame and mung bean, respectively. The changed parameters for this purpose are specified in Table 1.

The third phase involved calibrating the model for describing the SOC dynamics under the different crop management strategies and rotations. MONICA was used to estimate the temporal dynamics of SOC under various combinations of agricultural strategies and crop rotation systems over a short-term period. The calibrated model parameters from the first and second phase were applied to estimate SOC. As MONICA evaluates SOC dynamics based on the decomposition rate of organic matter e.g., crop residues and manure, the model parameters influencing the decomposition rate and SOC dynamics are highlighted in Table 1. In this research, it has been attempted to simulate the SOC values where crops have been grown under different fertilizer applications and crop residue management.

Table 1 MONICA's main factors that played a role in the variability of crop and soil parameters in this research

| Crop calibration | | Soil organic carbon calibration | |
|------------------------------|-------------------------------|---------------------------------------|--------------------------|
| Model parameters | | Model parameters | |
| Phase 1 | | Phase 3 | |
| Phase 2 | | Soil | |
| | | Manure | |
| | | Crop residues | |
| Stage sum temperature (TSUM) | Specific leaf area | AOM_SlowUtilizationEfficiency | AOM_DryMatterContent |
| Vernalization | Assimilate Partitioning Coeff | SOM_FastDecCoeffStandard ² | AOM_FastDecCoeffStandard |
| Base temperature | Organ Id ¹ | | CN_Ratio_AOM_Slow |
| | Maximum Assimilation Rate | | AOM_NH4Content |
| | NConcentrationB0 | | AOM_NO3Content |
| | NConcentrationPN | | AOM_SlowDecCoeffStandard |

¹Organ Id refers to the maximum allocation of produced dry matter to each crop organ at different growth stages: organ Id_1: root, organ Id_2: leaf, organ Id_3: stem, and organ Id_4: grain

²Organic carbon in rapidly decomposing humified matter at 0–10 cm of soil depth

The calibration was further validated using additional crop rotation systems, including B-W, S-W, and M-W. Validation of the model for grain yield, AGB and SOC content of spring crops was not performed because all spring crops were planted in rotation with the same crop (wheat). There was only one rotation for each of them and, hence, the amount of data for validation was not sufficient.

2.3.4 Statistical indices

Evaluation and comparison of the crop models performance have been widely discussed and done through different methods (Liben et al. 2018; Wallach et al. 2006). A set of statistical indices e.g., mean bias error, mean squared error (Rötter et al. 2012), and mean absolute error (MAE) have been used to assess the model performance. For assessing performance of the MONICA model and comparing its simulated values with the observed data, we considered two statistical indices as normalized root mean square error (NRMSE) and MAE (Palosuo et al. 2011):

$$NRMSE = \frac{\sum_{i=1}^n (Y_i - Y_s)^2}{\sum Y_i^2} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^n |Y_i - Y_s|}{n} \quad (2)$$

where n , Y_i , and Y_s refer to the number of observations, predicted values by the model, and observed values, respectively.

The NRMSE provides a percentage (%) of the difference between observed data versus simulated data. Model performance is considered great with $NRMSE \leq 10\%$, good if $10\% \leq NRMSE \leq 20\%$, fair if $20\% \leq NRMSE \leq 30\%$, and poor if $NRMSE \geq 30\%$ (Liben et al. 2018; Wallach et al. 2006). The MAE is a common measure of forecast error in time series analysis that measures the errors between pairs of observations.

2.4 Climate change scenarios and database description

Climate data were extracted based on the model requirements presented in Table S1 for two periods: the baseline (from 1990–2010) and the future scenario (from 2030–2060) for two target cities of Iran named Ahvaz (Latitude: 31°19'8.44"N and Longitude: 48°41'3.12"E) and Torbat-Heydareye (Latitude: 35° 16' 26.44" N and Longitude: 59° 13' 10.16" E), representing two important cities for wheat production (Fig. 2).

The data were made available from NEX-GDDP-CMIP6 (<https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6>) at a spatial resolution of 0.25 degrees \times 0.25 degrees, comprised of global downscaled and bias-corrected climate scenarios derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 6 (CMIP6) and across all four "Tier 1" greenhouse gas emissions scenarios known as Shared Socioeconomic Pathways (SSPs) namely SSP126, SSP245 and SSP585. The CMIP6 GCM runs were developed in support of the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR6). This dataset includes downscaled projections from ScenarioMIP model runs for which daily scenarios were produced and distributed through the Earth System Grid Federation.

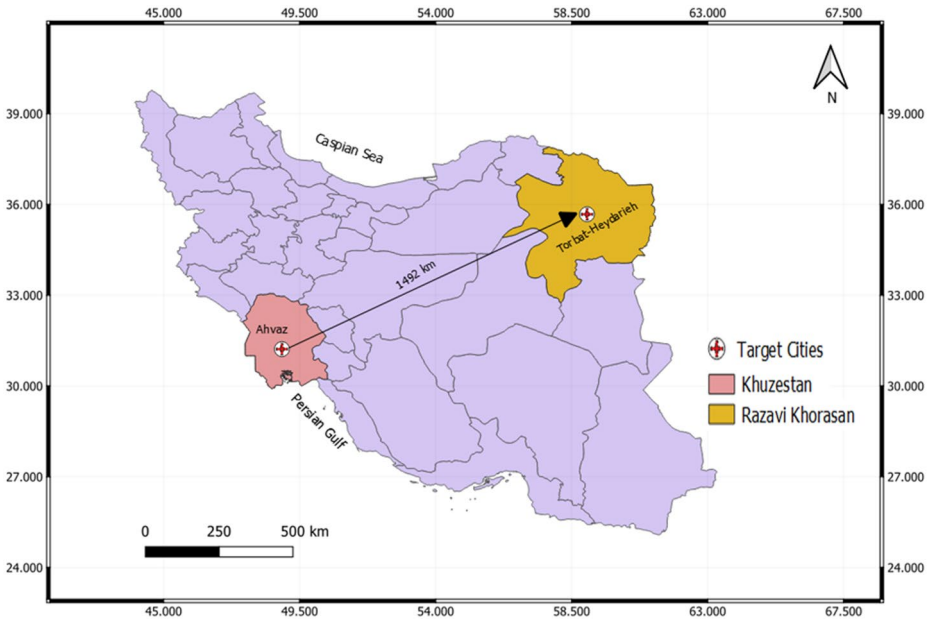


Fig. 2 The map shows Iran and two cities used for this study as Ahvaz in the south-west and Torbat-Heydarbeh in the north-east of Iran

The Bias-Correction Spatial Disaggregation (BCSD) method was used, a statistical downscaling technique that enhances the spatial resolution and statistical accuracy of GCM outputs, making them more suitable for regional and local climate impact assessments. This method involves two primary steps: bias correction and spatial disaggregation. The first step in the BCSD method is bias correction, which aims to align the statistical properties of the GCM outputs with observed data. A common approach, which was used, is quantile mapping, where the cumulative distribution functions (CDFs) of the GCM outputs are compared with those of historical observations from the Global Meteorological Forcing Dataset (GMFD) over a common reference period (e.g., 1960–2014) and adjusted to match the observed CDFs, effectively correcting biases in mean, variance, and other statistical moments.

After bias correction, the next step was spatial disaggregation, which enhances the spatial resolution of the GCM outputs. This was achieved by interpolating the bias-corrected data onto a finer grid, using bilinear interpolation. The goal was to add realistic spatial detail to the climate projections, preserving the large-scale trends of the original GCMs while providing finer spatial resolution suitable for impact studies. Together, these steps transform coarse-resolution GCM outputs into high-resolution, statistically consistent climate projections that are more suitable for regional and local impact assessments.

The following four GCMs were used in this study: (i) GFDL-ESM4: Geophysical Fluid Science Laboratory-Earth System Modelling (<https://www.gfdl.noaa.gov/earth-system-esm4/>); (ii) GFDL-ESM5: Earth System Models (<https://pcmdi.llnl.gov/index.html>); (iii) ACCESS-ESM1: Australian Community Climate and Earth System Simulator Earth System Model Version 1.5 (<https://www.cen.uni-hamburg.de/en/icdc/data/cryosphere/cmip6-sea-ice-area/access-esm1.html>); and (iv) INM-AM4-8: Institute for Numerical Math-

ematics - Climate Model Version 4 (<https://www.cen.uni-hamburg.de/en/icdc/data/cryosphere/cmip6-sea-ice-area/inm-cm.html>). The atmospheric CO₂ concentration used in the current study was set at 350, 450 and 600 ppm for the baseline, SSP245 and SSP585, respectively. The MONICA model was run for the described climate scenarios for three agricultural strategies were mentioned above and for maize-wheat rotation as the most common cropping system in the region. The mean temperature and mean radiation estimated by four GCMs for Ahvaz and Torbat-Heydareye for baseline and two future scenarios are shown in Fig. 5. All model parameters were kept the same for running MONICA for the two cities mentioned. With respect to the crop management, all field operations including full irrigation, which is the standard in these wheat production regions, were the same as during model calibration and validation, except for the sowing and harvesting dates in Torbat-Heydareye. Compared to Ahvaz, the sowing dates for spring maize (2nd July) and winter wheat (30th November) in Torbat-Heydareye were 8 and 20 days earlier respectively. Correspondingly, the harvest dates for spring maize (24th October) and winter wheat (1st August) changed at this location. Overall, the wheat growing season is longer in Torbat-Heydareye than in Ahvaz.

2.5 Determination of the changes in relative yield and soil organic carbon under climate change scenarios

The following formulae are used to calculate the changes in relative wheat yield, AGB, and relative SOC stocks for different agricultural strategies and for projected future climate change scenarios (Faye et al. 2023):

$$\Delta Y = \frac{Y_{\text{scenario}} - Y_{\text{baseline}}}{Y_{\text{baseline}}} * 100 \quad (3)$$

$$\Delta AGB = \frac{AGB_{\text{scenario}} - AGB_{\text{baseline}}}{AGB_{\text{baseline}}} * 100 \quad (4)$$

$$\Delta SOC = \frac{SOC_{\text{scenario}} - SOC_{\text{baseline}}}{SOC_{\text{baseline}}} * 100 \quad (5)$$

where Y_{scenario} , AGB_{scenario} , and SOC_{scenario} refer to the average values of the simulated wheat yield and SOC, respectively, over the future climate scenarios (2030–2060) and Y_{baseline} , AGB_{baseline} , and SOC_{baseline} represent the average values for the baseline period (1990–2010).

2.6 Statistical analysis

The results of simulations under different climate change scenarios were subjected to two factorial analysis of variance in a completely randomised design using SAS.v9.4. The two factors were considered to be climate change scenarios at three levels: baseline, SSP245 and SSP585, and agricultural strategies at three levels: CON, ORG, and INT. The means for yield, AGB, number of days to maturity and SOC and their relative changes were compared using Duncan's multiple range test. Factor effects were considered significant at $p \leq 0.05$.

The impact of the uncertainty in projected climate variables on wheat yield and SOC over an ensemble of 4 GCMs, i.e. average temperature (T_{avg}) and the ratio of actual evapotranspiration to potential evapotranspiration (ET_a/ET_p), which were computed by the MONICA model based on projected climate data, was assessed in relation to the annual mean changes in SOC stock and yield. This analysis utilized linear regression models in R (Fox and Weisberg 2018). The ensemble time series capturing the uncertainty in SOC stock and yield were computed for each climate scenario and agricultural strategy. To quantify this uncertainty, the 95% confidence intervals (CIs) across the climate projections and agricultural scenarios were calculated for the maize-wheat (M-W) rotation in R (Riggers et al. 2021).

3 Results

3.1 Model response to phenology-based calibration for wheat, mung bean, sesame, and maize under different agricultural strategies

Stage-Sum Temperature (TSUM) and base temperature were the parameters that were used for calibration of wheat phenology. Vernalization was considered to be zero for wheat due to the absence of low non-freezing temperatures in the winter season in the study area. The phenology-based calibration showed that overall the model was able to provide a satisfactory estimate of flowering date for all spring crops and winter wheat (Table S3). However, for winter wheat the day of flowering was slightly underestimated by the simulations in the first year of the experiment, ranging from 5 days for the CON to 6 days for the INT and ORG agricultural strategies.

3.2 Model response to yield, and above-ground biomass of wheat and spring crops

The MONICA model was calibrated on the W-F cropping system (wheat mono-cropping) (Fig. 3 A). For all treatments, the simulated wheat yield followed the order $CON > INT > ORG$ with NRMSE and MAE of 12% and 0.4 Mg ha^{-1} , respectively (Fig. 3 A). It confirms that the model is capable of simulating wheat yield under different organic and inorganic fertilizer sources as well as crop residue management (Fig. 3 A&B). In the INT treatment the model slightly overestimated the grain yield in one year. Although the model calibration illustrated acceptable accuracy in predicting above-ground biomass (AGB) for CON, an overestimation was observed in terms of AGB for INT ($+1.2 \text{ Mg ha}^{-1}$) and ORG ($+1.0 \text{ Mg ha}^{-1}$) in the first year of the experiment (Fig. 3 B). In general, the calibration outcomes for AGB demonstrated a favorable performance, as indicated by low NRMSE (Normalized Root Mean Square Error) and MAE (Mean Absolute Error) values between the observed and simulated data. Specifically, the NRMSE was found to be 10.4%, while the MAE stood at 0.5 Mg ha^{-1} (Fig. 3 C).

Simulation results of model validation indicated good to fair estimation of wheat yield and AGB for different crop rotation systems in various agricultural strategies (Fig. 3 B&D) with smaller values of NRMSE and MAE compared to model calibration. In addition, the model provided an overall accurate estimate of AGB, although it overestimated AGB for M-W in CON and INT (Fig. 3 D).

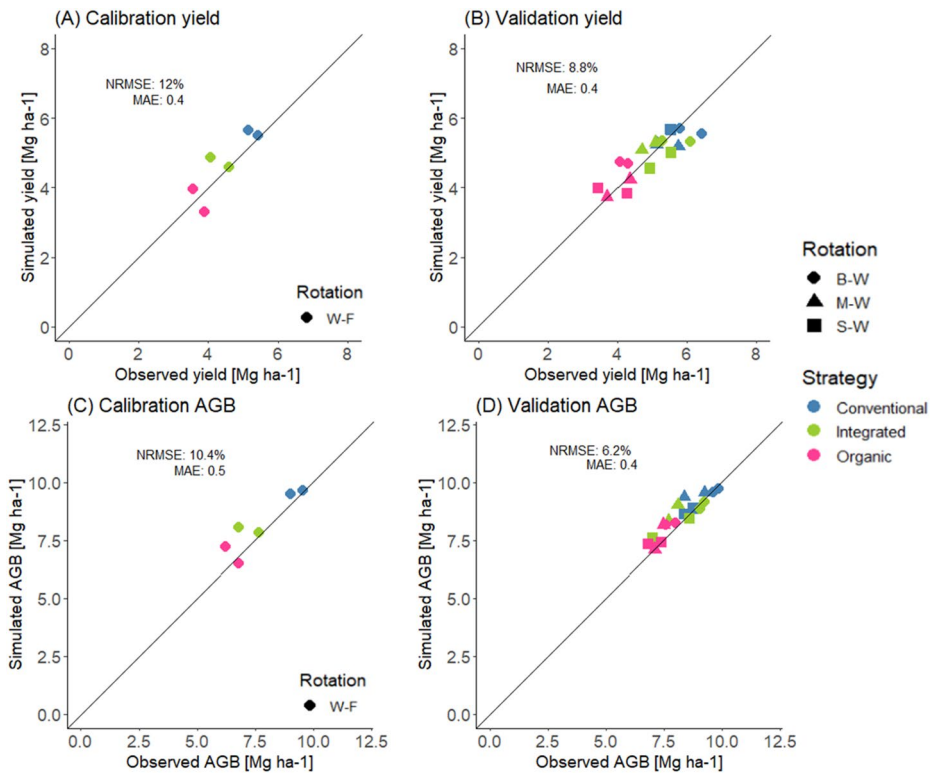


Fig. 3 The results of calibration (A&C) and validation (B&D) for wheat yield and aboveground biomass (AGB) in four crop rotation systems: fallow- wheat (W-F); mung bean-wheat (B-W), maize- wheat (M-W), and sesame- wheat (S-W) and three agricultural strategies comprising conventional, integrated and organic. NRMSE and MAE represent normalized root mean square error and mean absolute error, respectively

MONICA also was calibrated for three spring crops comprising sesame, mung bean, and maize. The crop parameters used for the calibration for these crops were shown in Table 1. The calibrated model successfully simulated the measured spring crop yields with NRMSE and MAE of 16.1% and 0.2 Mg ha⁻¹, respectively (Fig. S1 A). A detailed comparison of the estimated grain yield for sesame and mung bean with the observed values showed that the model perfectly reproduced the observations for the mentioned crops under all agricultural strategies, while the model underestimated maize yield for CON and INT. This increased the value of NRMSE (Fig. S1 A). According to Fig. S1 A, simulated yields for all spring crops widely varied among different agricultural strategies. Estimated values for spring crop yields ranged from 0.8 Mg ha⁻¹ for sesame in ORG to 4.8 Mg ha⁻¹ for maize in the CON strategy (Fig. S1 A).

In terms of AGB simulated values varied for different agricultural strategies after model calibration. The model performed well in the estimation of the final AGB (NRMSE: 9.9%, MAE: 0.4 Mg ha⁻¹). The model underestimated AGB for mung bean and sesame in all agricultural strategies, but overestimated it for maize (Fig. S1 B). However, the deviations between simulated and observed values were minor. In addition, the highest amount of AGB

for maize (7.4 Mg ha^{-1}), sesame (4.2 Mg ha^{-1}), and mung bean (5.6 Mg ha^{-1}) were simulated for the CON strategy, which was fully supported by mineral nitrogen.

3.3 Model calibration and validation for soil organic carbon in wheat-based rotation systems under three agricultural strategies

After model calibration, a good fit between measured and simulated SOC values over four cropping seasons for the W-F cropping system and all management strategies was observed. This means that after two years of organic fertilizer application and incorporation of crop residues into the soil in ORG and INT strategies, the model estimated adequately the increase in SOC values with an average of 5.1 g kg^{-1} and 5.5 g kg^{-1} for INT and ORG, respectively, at the end of the simulation period (Fig. 4 A). The lowest values of the simulated SOC after two years was estimated under the CON strategy, which was in high agreement with the observed data (Fig. 4 A).

Although the model validation process showed a slightly higher NRMSE (7.7%) compared to calibration when estimating SOC values for the other crop rotations, the simulations matched well with the observations and exhibited significant variations across different crop rotation systems and farming strategies (Fig. 4 B). Notably, the highest simulated SOC value of 6.1 g kg^{-1} was found for B-W under ORG, while the lowest simulated value of 4.3 g kg^{-1} was found for W-F under CON, which agreed well with the observations in the field. Our simulations demonstrated that the model accurately replicated the observed SOC values for the wheat-sesame rotation system under all agricultural strategies. The optimal values of the model parameters for SOC calibration determined based on the lowest NRMSE between the observed and simulated data are listed in Table 2.

Overall, the good model performance of SOC simulation for all spring crop rotation systems under three agricultural strategies was indicated by overall low NRMSE: 7.4% and low MAE: 0.3 g kg^{-1} . However, the model performance for simulating SOC was lower under sesame-, maize-, and mung bean-wheat rotations in the CON strategy, where no additional

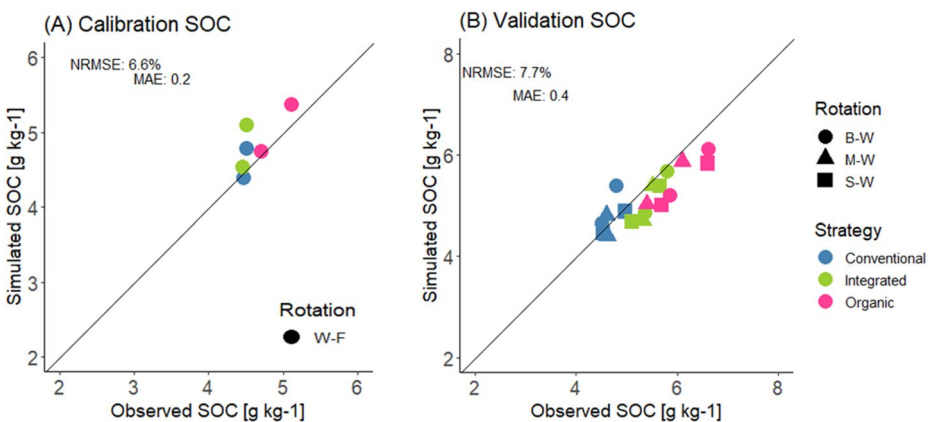


Fig. 4 (A) and (B) indicate the results of MONICA calibration and validation, respectively, of soil organic carbon content over time in four wheat-based rotation systems: fallow- wheat (W-F); mung bean-wheat (B-W), maize- wheat (M-W), and sesame- wheat (S-W) and three agricultural strategies comprising conventional, integrated and organic. NRMSE and MAE represent normalized root mean square error and mean absolute error, respectively

Table 2 List of crop residue, manure, and soil parameters considered in MONICA model for the calibration of soil organic carbon changes. W, M, B, and S refer to wheat, maize, mung bean, and Sesame

| Model parameters for soil organic carbon calibration | Unit | Default | | | | New | | | |
|--|---------------------|---------|-------|-------|-------|----------------------------|-------|-------|------|
| Crop residues | | W | M | B | S | W | M | B | S |
| AOM_SlowDecCoeffStandard | d ⁻¹ | 0.012 | 0.012 | 0.012 | 0.012 | 0.015 | 0.008 | 0.009 | 0.01 |
| CN_Ratio_AOM_Slow | | 200 | 225 | 47.7 | 75 | 100 | 130 | 25 | 32 |
| Manure | | Default | | | | New | | | |
| AOM_DryMatterContent | kg DM | 0.25 | | | | 0.25 (No changed) | | | |
| | kg FM ⁻¹ | | | | | | | | |
| AOM_FastDecCoeffStandard | d ⁻¹ | 0.0001 | | | | 0.0002 (Modified) | | | |
| AOM_NH4Content | kg N | 0.00006 | | | | 0.00006 (No changed) | | | |
| | kg DM ⁻¹ | | | | | | | | |
| AOM_NO3Content | kg N | 0.00006 | | | | 0.00006 (No changed) | | | |
| | kg DM ⁻¹ | | | | | | | | |
| AOM_SlowDecCoeffStandard | d-1 | 0.008 | | | | 0.0001 (Modified) | | | |
| CN_Ratio_AOM_Slow | | 130 | | | | 130 (No changed) | | | |
| Soil parameters | | Default | | | | New | | | |
| AOM_SlowUtilizationEfficiency | | 0.4 | | | | 0.2 | | | |
| SOM_FastDecCoeffStandard | d ⁻¹ | 0.00014 | | | | 0.00034 | | | |

organic matter was added compared to ORG. The values of the model parameters resulting from MONICA calibration for maize, sesame, and mung bean are given in Table 2.

3.4 Projected wheat yield and above-ground biomass under different climate change scenarios

Overall, all climate variables (e.g. mean temperature and total precipitation) projected by the GCMs for two cities with different climatic conditions, ranging from semi-arid warm in Ahvaz to semi-arid cold in Torbat-Heydareye, were likely to increase in the future. The magnitude of the incremental change in mean temperature and global radiation under the SSP585 was higher than that under the SSP245 (Fig. 5 A to D). Furthermore, the ratio of actual evapotranspiration (Eta) to potential evapotranspiration (ETp) computed by MONICA according to the baseline and projected climate scenarios, which represents the availability of soil water to crops over growing season, showed a higher values in Torbat-Heydareye compared to Ahvaz (Fig. 5 A&B).

The predicted wheat yield and AGB under two climate scenarios showed that grain yield and AGB in Ahvaz decreased significantly for all agricultural strategies for the future scenarios compared to the baseline (Fig. 6 A&B). Furthermore, the results of relative change indicated that this reduction was lower for organic-based strategies than for CON (Fig. 7 A&B). Although the relative change in yield and AGB was not significantly different between INT and ORG, the reduction was lower for INT (Fig. 7 A&B). In addition, SSP585 with the highest atmospheric CO₂ (600ppm) concentration and increased temperature had a greater negative impact on yield and AGB compared to SSP245. The simulations also showed that CON in Ahvaz is the most sensitive agricultural strategy to climate change.

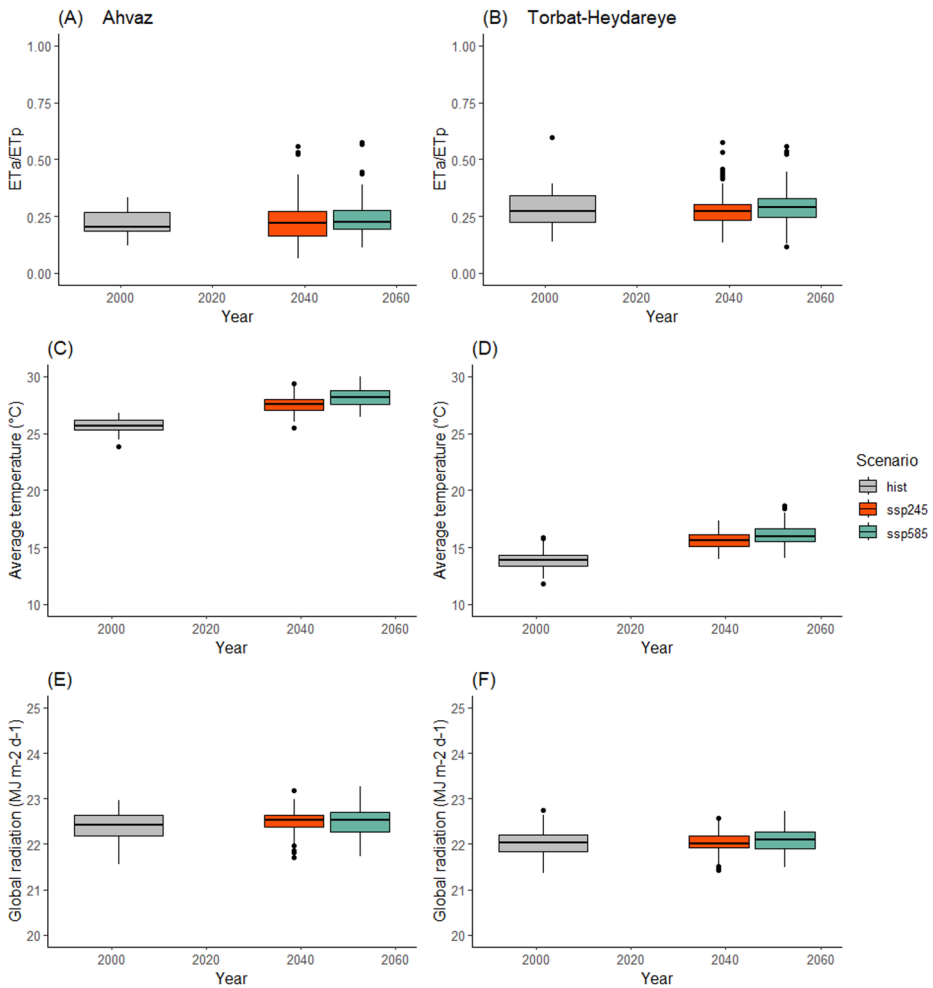


Fig. 5 Mean values of the actual evapotranspiration (Eta)/potential evapotranspiration (ETp) (A&B) calculated by MONICA, annual mean temperature (C&D), and global radiation (E&F) as projected by four different climate models for hist: baseline period (1990–2010; an average of 20 years) and future climate scenarios (2030–2060; an average of 30 years) under two shared socio-economic pathways with two concentrations of CO₂ emission (ssp245: 450 ppm and ssp585: 600 ppm) for two different locations in southwest (Ahvaz) and east (Torbat-Heydareye) of Iran

On the other hand, an increase in the simulated yield and AGB was observed under elevated CO₂ and increasing temperature for Torbat-Heydareye under all agricultural strategies compared to the historical period (Fig. 6B). However, the relative changes indicated a significant improvement in yield and AGB under organic-based strategies compared to CON for SSP245 and SSP585 (Fig. 7 C&D). The simulation results in Torbat-Heydareye indicated that the INT strategy, using a combination of organic and inorganic fertilizers and crop residue management, was more resilient to climate change than CON and ORG by producing higher yields and AGB under climate change scenarios (Fig. 7 C&D).

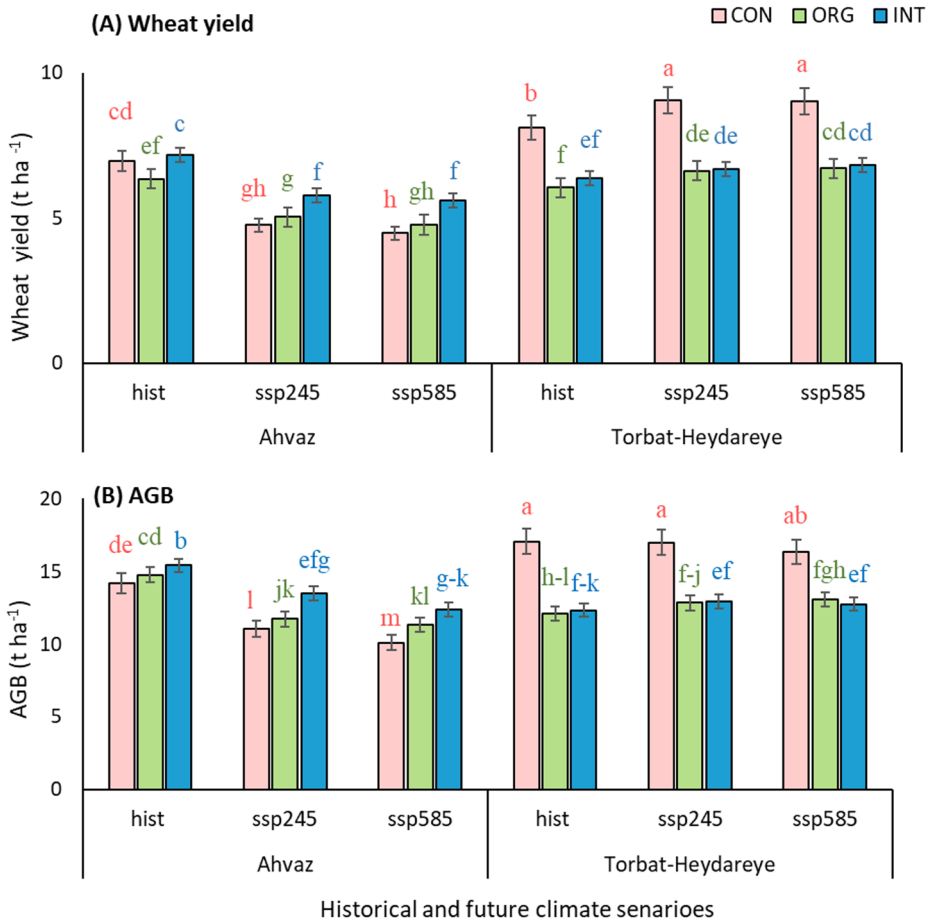


Fig. 6 (A) and (B) show simulated values of wheat grain yield and above ground biomass (AGB) for Ahvaz and Torbat-Heydareye under different projected climate change scenarios by four GCMs for hist: baseline period (1990–2010; an average of 20 years) and future climate scenarios (2030–2060; an average of 30 years) under two shared socio-economic pathways with two concentration of CO₂ emission as: ssp245: 450 ppm and ssp585: 600 ppm and three agricultural strategies: conventional (CON), integrated (INT) and organic (ORG). Significant differences between treatments at $p < 0.05$ based on Duncan’s multiple range test are indicated by different letters at the top of the bars

The estimated mean number of days from emergence to maturity revealed that the growing period in Torbat-Heydareye was significantly longer than in Ahvaz. In addition, in both locations, the growing period under different climate scenarios followed the order $hist \geq SSP245 \geq SSP585$ (Fig. S3). The number of days to maturity was reduced by up to 6 days for Ahvaz and up to 6 days for Torbat-Heydareye under future climate change compared to the historical period. The number of days from emergence to maturity was the same for all agricultural strategies.

Moreover, the 95% CIs for time series simulations revealed that yield at both locations was sensitive to Tavg and ETa/ETp. While the negative impact of increased temperature under the SSP245 scenario was more pronounced in Ahvaz, yield in Torbat-Heydareye ben-

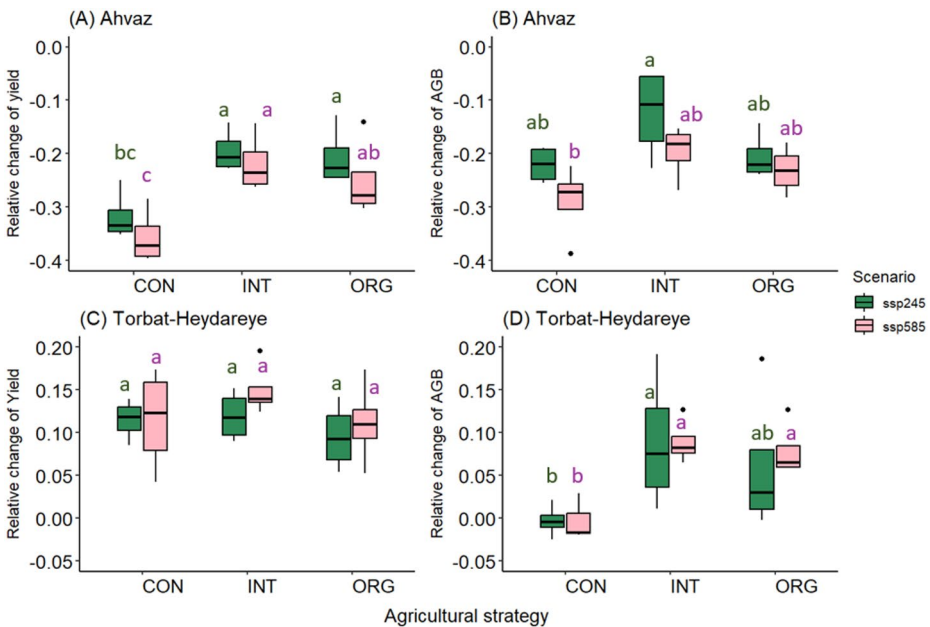


Fig. 7 Future relative change for SSP245 and SSP585 on wheat grain yield and above ground biomass (AGB) for Ahvaz (A&B) and Torbat-Heydareye (C&D) under three agricultural strategies: conventional (CON), integrated (INT), and organic (ORG). Significant differences between treatments at $p < 0.05$ based on Duncan's multiple range test are indicated by different letters at the top of the boxes

efited from the rise in temperature and enhanced CO_2 during the 2031–2040 and 2041–2050 periods under SSP245 (Fig. 8A). The impact of ETa/ETp on yield showed greater variability across locations, years, and scenarios compared to Tavg (Fig. 8B). The confidence intervals indicated a positive relationship between water availability and yield, which helps offset the negative impacts of climate change, especially when benefits from elevated CO_2 (SSP585, SSP245) are considered (Fig. 8B).

3.5 Projected change in soil organic carbon under different climate change scenarios

Predicted changes in SOC under climate change scenarios showed that the effect of agricultural strategies, such as the application of organic fertilizer and crop residues on SOC turnover was strongly dependent on climate conditions, especially temperature. For example, in Torbat-Heydareye with cooler temperature, although increasing temperature and elevated atmospheric CO_2 significantly reduced SOC under CON for SSP245 and SSP585 compared to historical period, the addition of organic fertilizer and incorporation of crop residues into the soil maintained SOC for ORG and INT under future climate scenarios (Fig. 9 A&C, Table 3). On the other hand, under the future climate scenarios, the predicted SOC in Ahvaz was significantly reduced by the increase in temperature (Fig. 10A). The trend of SOC reduction followed the order $\text{CON} \geq \text{INT} \geq \text{ORG}$. However, the highest decrease in SOC for both cities was predicted under SSP585 (Fig. 9 B&C), in which temperature was projected to be higher than under SSP245 and the historical period.

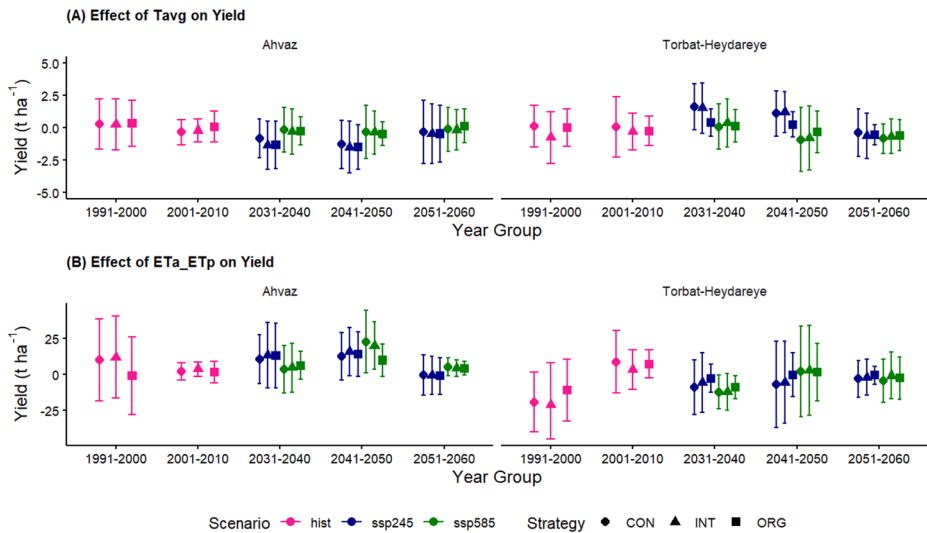


Fig. 8 (A) and (B) show the 95% confidence intervals for the impacts of average temperature (Tavg) and the ratio of ETa/ETp on wheat yield. These estimations were made for Ahvaz and Torbat-Heydareh, using climate projections for 1990–2010 (baseline) and 2030–2060 from 4 GCMs under two SSPs (ssp245: 450 ppm, ssp585: 600 ppm) and three agricultural strategies: conventional (CON), integrated (INT) and organic (ORG)

Time series simulations of projected SOC stocks indicated that increasing temperatures led to a decline in SOC levels in Ahvaz, as shown by the 95% CIs (Fig. 10A). This decline was significantly greater than the baseline, particularly during the 2031–2040 period. In contrast, temperature showed a slightly positive correlation with SOC changes in Torbat-Heydareye across all agricultural strategies, with a more substantial overall effect, as reflected by the 95% CIs (Fig. 10A). The results also revealed a wide 95% CIs when assessing SOC responses to changes in water availability (ETa/ETp). Unlike Tavg, water availability had a positive effect on SOC stocks in Ahvaz, especially under elevated CO₂ levels in the SSP585 scenario during the 2041–2050 period and across all agricultural strategies (Fig. 10B). Moreover, SOC stocks in Torbat-Heydareye under the ORG and INT strategies appeared more sensitive to water availability over time compared to the CON strategy.

4 Discussion

4.1 Model response to yield, and above-ground biomass of various crop rotation systems

The MONICA model was able to reproduce the observed yield and AGB for wheat under different management conditions with a high accuracy in this semi-arid warm region. In this research, having similar information on initial soil properties and climate conditions, the simulated wheat yield varied among the different agricultural strategies and crop rotation systems. This was due to differences in model inputs with respect to, for example, different amounts of applied organic and mineral fertilizer in the rotations of wheat with oilseeds,

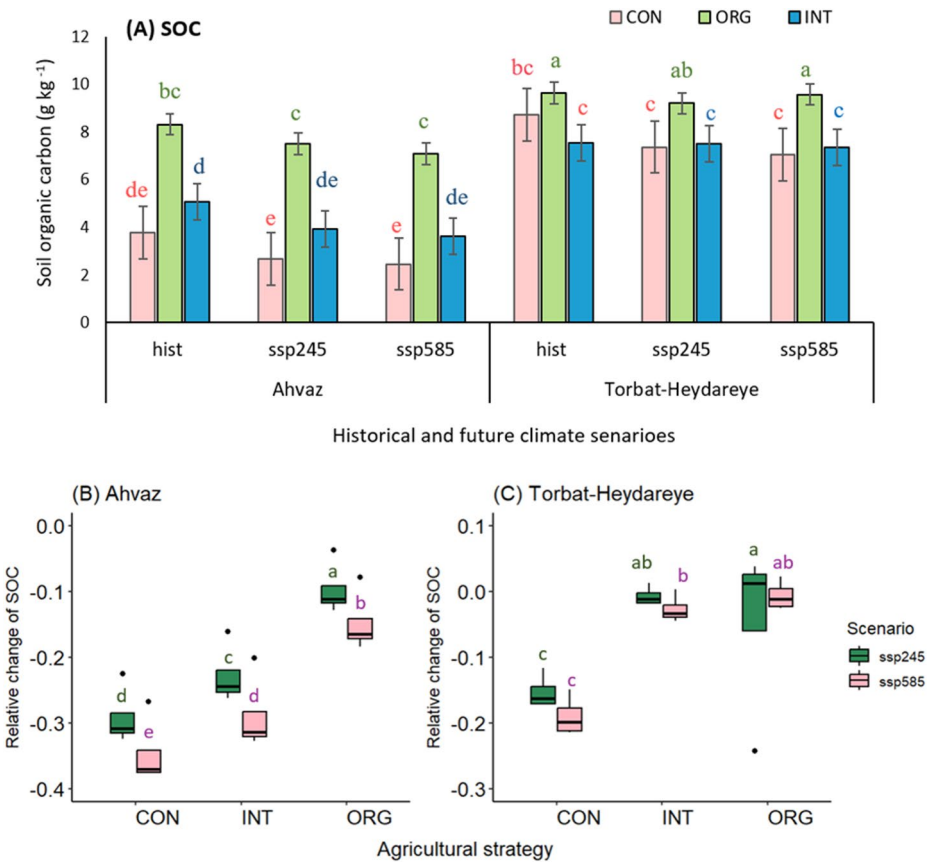


Fig. 9 Simulated values of soil organic carbon (SOC) for Ahvaz and Torbat-Heydareye under different projected climate change scenarios by four GCMs for hist: baseline period (1990–2010; an average of 20 years) and future climate scenarios (2030–2060; an average of 30 years) under two shared socio-economic pathways with two concentration of CO₂ emission as: ssp245: 450 ppm and ssp585: 600 ppm and three agricultural strategies: conventional (CON), integrated (INT) and organic (ORG) (A). Panels B and C refer to the relative change of SOC for SSP245 and SSP585 for Ahvaz and Torbat-Heydareye, respectively. Significant differences between treatments at $p < 0.05$ based on Duncan’s multiple range test are indicated by different letters at the top of the bars and boxes

legumes, and maize. The differences in the amounts of organic and mineral fertilizers as well as the amount of crop residues caused variations in the release and availability of nitrogen during the growing season, which was the reason for the variability in simulated yield under ORG, INT, and CON. Underestimation of simulated yield of wheat in response to nitrogen limitation was also reported by Salo et al. (2016) and Hakala et al. (2016). The different management strategies also affected the availability of mineral N in the soil. This can explain the differences between observed and estimated wheat yields under different agricultural strategies (Battisti et al. 2017). However, the model slightly overestimated the final AGB for organic-based agricultural strategies e.g., ORG and INT where manure and crop residues were applied. This was probably due to overestimated post-flowering nutrient release in ORG and INT strategies in the simulations (Maltas et al. 2018). In addition,

Table 3 The changes in predicted grain yield, aboveground biomass (AGBiom) and soil organic carbon (SOC) under two future climate scenarios (SSP245 and SSP585) compared to historical climate data for maize-wheat rotation under three agricultural strategies: conventional (CON), integrated (INT) and organic (ORG) in two cities of iran: Ahvaz and Torbat-Heydareye

| Climate scenarios | Agricultural strategies | Ahvaz | | | Torbat-Heydareye | | |
|-------------------|-------------------------|-----------|------------|---------|------------------|------------|---------|
| | | Yield (%) | AGBiom (%) | SOC (%) | Yield (%) | AGBiom (%) | SOC (%) |
| ssp245 | CON | -31.7 | -22.0 | -29.1 | 11.5 | -0.3 | -15.3 |
| | ORG | -22.1 | -21.9 | -10.2 | 9.2 | 5.3 | 0.5 |
| | INT | -19.5 | -12.4 | -22.8 | 11.9 | 8.8 | -0.7 |
| ssp585 | CON | -35.5 | -28.9 | -34.6 | 11.5 | -4.2 | -19.0 |
| | ORG | -24.9 | -23.1 | -14.8 | 11.1 | 7.9 | 0.0 |
| | INT | -21.8 | -19.4 | -27.9 | 13.9 | 7.5 | -2.1 |

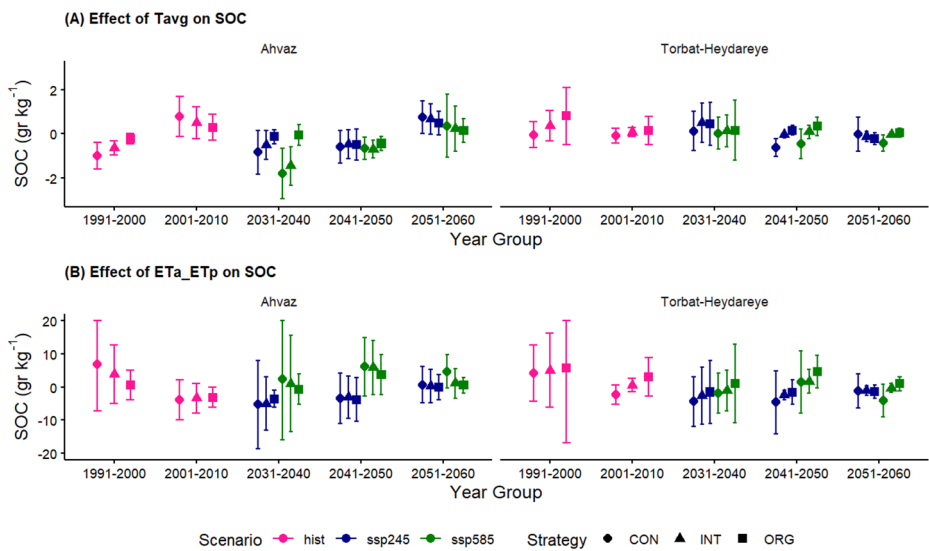


Fig. 10 (A) and (B) show the 95% confidence intervals for the impacts of average temperature and ETa/ETp SOC. These estimations were made for Ahvaz and Torbat-Heydarieh, using climate projections from 4 GCMs for 1990–2010 (baseline) and 2030–2060 under two SSPs (ssp245: 450 ppm, ssp585: 600 ppm) and three agricultural strategies: conventional (CON), integrated (INT) and organic (ORG)

improving the efficiency of solar radiation use in CO₂ assimilation during flowering and grain filling, and increasing the partitioning of carbohydrates produced to vegetative fractions such as leaves and stems, could be another explanations for the high simulation of AGB (Ding et al. 2021; Gilardelli et al. 2016; Liang et al. 2016).

During the calibration of MONICA for spring crops, the model successfully simulated the yield and AGB of sesame, mung bean, and maize under various agricultural management strategies. However, accurately simulating the effects of different agricultural management strategies, particularly when relying solely on organic fertilizer application, on yields and AGB poses a challenge, especially in semi-arid regions. This complexity arises from the interplay between climate conditions, crop characteristics, soil properties, and management practices. Nevertheless, MONICA adequately simulated the grain yield of mung

bean, sesame, and maize. Moreover, similar to wheat simulations, the simulated grain yield of mung bean, sesame, and maize varied across different agricultural strategies, highlighting the capacity of the model to simulate the effect of different fertilizer and crop residue management (Couëdel et al. 2024). MONICA, along with other crop models like DSSAT and EPIC, has been developed to capture the intricate interactions among climate, soil, and nutrient processes, enabling the simulation of multiple crops within a rotation system (Triacca et al. 2025; Di Bene et al. 2022; Ding et al. 2021; Kollas et al. 2015; Nendel 2016).

In this context, two parameters, SLA, which represents the ability of leaves to capture radiation and photosynthetic performance, and assimilate partitioning coefficient, were found to be important for all crops. They were identified as the two most influential model parameters in the partitioning of dry matter into reproductive crop organs, such as pods in sesame and mung bean, thereby influencing grain yield variations among different agricultural strategies. This observation is consistent with the findings of Gorooei et al. 2023b; Sieling et al. (2016). The importance of these parameters is further elucidated in Table S4.

4.2 Model response to soil organic carbon changes under agricultural strategies

Soils are one of the largest reservoirs for C, having the potential for C sequestration. In this study, the type of crop rotation, crop residue management, and fertilizer application affected C sequestration in experimental plots.

The incorporation of crop residues into the soil and the application of manures have multiple effects on soil temperature, moisture, nutrient availability and soil microorganisms. These practices serve as an energy source for soil microorganisms and enhance the decomposition rate of organic matter. Consequently, the increased amount of carbon input promotes the sequestration of C in the soil over time. Previous studies by Roozbeh and Rajaie (2021) and Zhao et al. (2013) have highlighted the positive impact of these practices on C sequestration. ORG and INT strategies under wheat-based rotation systems explained a larger proportion of the variability in SOC compared to CON. Although most of the simulated results were consistent with observed values, an overestimation in SOC for the ORG strategy under the M–W cropping system occurred. An increase in simulated SOC associated with low initial SOC content and 100% return of plant residues to the soil was demonstrated by MONICA (Stella et al. 2019a, b). According to basic soil information e.g., pH and C to N ratio as well as types of organic matter inputs such as shoot and root residues and manure application, the model considers two types of decomposable organic matter pools i.e. passive (slow turnover) and active (fast turnover) pool (Clivot et al. 2017, 2019; Godde et al. 2016; Gorooei et al. 2024). In this research, MONICA also simulated SOC based on the rate of decomposition and utilization of the organic matter as well as the fast and slow turnover of organic matter (Aiteew et al. 2024). On the other hand, simulation results indicate that the model is more sensitive to carbon input values than to their decomposition rates (Riggers et al. 2019). Moreover, our findings align with previous studies that have estimated higher levels of soil organic carbon (SOC) under high C inputs (Nyawira et al. 2021).

Since C measurements were conducted only twice per year, whereas MONICA simulates SOC turnover on a daily time scale, the selection of appropriate model performance metrics was limited (Chu et al. 2018). Nevertheless, validation of the wheat-calibrated model using the remaining crop rotation systems, including spring crops, showed that the simulated and observed variables followed similar trends. For example, calibration revealed a

strong relationship between SOC stock change rates and C inputs from different fertilizer applications. The influence of C inputs on SOC dynamics became even more evident when the effects of spring crops were considered during validation. Additionally, variations in the nitrogen and C content of spring crop residues, together with differences in C turnover rates (AOM_SlowDecCoeffStandard and CN_Ratio_AOM_Slow, Table 2), further increased the model's sensitivity in simulating SOC pools (Aiteew et al. 2024).

However, studying SOC pools requires a deeper understanding of the processes that drive SOC dynamics, as SOC is distributed among multiple pools with distinct turnover and exchange rates. These include dead crop residues and roots, metabolic and structural litter, slow and passive humus, and microbial biomass. Carbon and nitrogen which influence SOC dynamics can also be lost from the system through erosion, leaching, denitrification and volatilization. The fluxes between these pools are influenced by several factors, including soil and crop management practices, soil hydrology, temperature, and soil depth. Although the MONICA model accounts for microbial activity and its influence on SOC turnover and residue decomposition (Stella et al. 2019a, b), this aspect was not the primary focus of the current study.

4.3 Climate change impacts on wheat productivity and soil organic carbon under three agricultural strategies in a maize-wheat rotation

Analysis of future climate projections, based on the average of four GCMs, indicates that both southwest Iran (Ahvaz) and eastern Iran (Torbat-Heydareye) will experience continued warming in the coming decades. While temperature increases are projected to be significant overall (Schlenker and Lobell 2010), the comparison of average Eta/ET_p values during the reference period (1990–2010) with projected changes under future climate scenarios (SSP245 and SSP585) reveals that global warming will more severely impact soil water availability in warmer, semi-arid regions like Ahvaz, compared to cooler areas such as Torbat-Heydareye.

Changes in temperature, precipitation, radiation and CO₂ emissions are driving the changes in yield, AGB and SOC (Bai et al. 2022). Elevated CO₂ and slight increases in radiation, as projected by the GCMs, improved wheat yield in Torbat-Heydareye by 9–11.9% under SSP245 and 11–13.9% under SSP585, with AGB increases of 5.8–8.8% and 7.8–7.9%, respectively. In contrast, rising temperatures in Ahvaz shortened the growing season, leading to yield losses of 19–35% and AGB reductions of 12–28% (Stella et al. 2023). In addition, the reduction in days from emergence to maturity confirmed that the future wheat growing season will be shorter than the baseline. Zhang et al. (2022) reported that wheat yield reduced by 1–8% for SSP245 and 4–23% for SSP585 scenario relative to baseline under a warm-temperate climate condition. The notable reduction in projected SOC pools, combined with changes in climate variables in Ahvaz, may also contribute to the predicted losses in yield and AGB. Management practices that increase SOC enhanced soil fertility by improving water retention and supporting soil biodiversity. These benefits help sustain productivity and stabilize yields in the face of climate change. In contrast, declining SOC levels can result in significant yield losses (Herzfeld et al. 2021; Liu and Basso 2020).

These negative and positive effects varied not only across sites but also among different management strategies. For example, organic-based agricultural strategies showed more flexibility to climate change scenarios compared to CON (Thakur et al. 2022). The INT

strategy, by adding a combination of organic and inorganic fertilizers and incorporating 15% of crop residues into the soil, reduced the negative effects of climate change on yield and AGB in Ahvaz, and promoted higher wheat yields in Torbat-Heydareye compared to CON and ORG under projected climate scenarios. Including soil–crop feedbacks from organic matter application had a substantial effect on simulated grain yield (Song et al. 2015). However, for all agricultural strategies, the relative change in yield and AGB compared to baseline was higher for SSP245 than for SSP585 at both sites. Although the increase in CO₂ results in higher yield, the higher temperature under SSP585 should have the opposite effect due to a reduction in the length of the crop growth cycle (Roudier et al. 2011) (Fig. 7). In Ahvaz, the reduction in length of growth cycle caused a decrease in yield and AGB inspite of higher CO₂ concentrations. Since this research was conducted under irrigated condition, yield improvement or loss was due to variability of climate factors, elevated CO₂, and day from emergence to maturity as well as heat stress (Adusei et al. 2022; Bai et al. 2022). Especially in Ahvaz, where wheat was subjected to heat stress during the last 10 days of growth, our projection results contribute to the body of knowledge to understand how future climate change will affect SOC content under different crop management strategies. The predicted simulations showed that increasing temperature in SSP585 reduced SOC stocks in both locations, irrespective of the type of agricultural strategies and the incorporation of crop residues into the soil. This results were in line with the research has done by Faye et al. (2023). The higher temperature is likely to have increased C mineralization in the active and intermediate pools (Poepflau et al. 2017), which is more evident for the irrigated experimental plots in Ahvaz, where the warm climate condition dominates.

In addition, in the warm semi-arid conditions, increasing temperature led to more soil respiration and therefore to loss of C from the soil in the form of CO₂ (Goroeei et al. 2023a; Thuille et al. 2000). Although elevated atmospheric CO₂ has been shown in the literature to enhance C sequestration more than soil respiration and C loss (Black et al. 2017; Zhang et al. 2022), its combination with an increase in temperature had the opposite effect on C sequestration. Nevertheless, the higher relative change in SOC pools under future climate data compared to baseline showed that incorporating 15% of crop residues into the soil for INT and 30% for ORG and applying organic matter reduced SOC losses in both locations in a long-term simulation (Stella et al. 2019a, b). Also in Torbat-Heydareye, the increase in AGB led to an increase in the proportion of crop residues in the soil and will therefore contribute to maintaining SOC levels in the soil.

5 Conclusion

The calibrated model was able to successfully simulate yield and AGB for winter and spring crops under different crop management strategies as evidenced by low NRMSE values of 12% and 8.8% for yield and AGB of wheat. Although the model slightly overestimated SOC values under ORG and INT, the inclusion of mung bean in a wheat-mung bean rotation system had a negative impact on SOC values when inorganic fertilizers were applied. The predicted results under different climate projections for maize-wheat rotations showed that wheat yield and AGB were differentially affected by increasing temperature and elevated CO₂ in two different locations and for the three crop management strategies. In Torbat-Heydareye, an increase in temperature and CO₂ led to a partial improvement in yield and AGB, while in Ahvaz it

led to a decrease, as the temperature regime in Ahvaz is already around the optimum range for photosynthesis, and would leave this range with future elevated temperatures. The CON management was more sensitive to changing climate compared to the organic-based strategies. Regarding the response of SOC pools to climate projections, overall, increasing temperatures increased C losses irrespective of the agricultural strategies considered at both sites. This reduction was more pronounced for SSP585 than SSP245. However, C losses due to increased temperature were partly balanced by incorporating crop residues into the soil and by applying organic matter in both locations. The higher crop residue inputs in the INT and ORG strategies together with the cooler climate in Torbat may be able to maintain future SOC content at the current level. This research at two locations indicates that there seems to be a potential benefit of the tested agronomic strategies for the entire province of Khuzestan and even larger areas in the semi-arid zone. Time series data on crop yields and SOC dynamics across this region could help to test the potential of these strategies in a larger region and investigate the spatio-temporal patterns of their impact. Agricultural strategies and crop rotation systems remain underexplored for their potential to increase soil fertility and mitigate climate change in the semi-arid areas of Iran, particularly for different the soil types under agricultural use.

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Author contributions Aram Gorooei: Writing the original draft, conceptualization, methodology, data collecting, data modeling, parametrising and calibrating the model. Thomas Gaiser and Amit Kumar Srivastava: Writing, review & editing, conceptualization, methodology, review and support in model calibration results, data processing. Farshid Jahanbakhshi: review & editing. Ali Ahmadi: Supporting in model calibration and Python codes. Amir Aynehban: Methodology and data collecting. Claas Nendel: review & editing, conceptualization, methodology, support in model parameterization and calibration, Bahareh Kamali: conceptualization, methodology and support in model calibration.

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Data availability The experimental data supporting this study will be available upon reasonable request to the corresponding author.

Code availability The Python and R codes used in this research are available upon reasonable request from the corresponding author.

Declarations

Ethics approval This research follows the framework of research ethics and the authors declare their responsibility and accountability for this research.

Consent to participate All listed authors agreed to participate as co-authors in this article.

Consent for publication All authors contributing to this research hereby declare their consent for submitting the article to the Journal of Mitigation and Adaptation Strategies for Global Change.

Conflict of interest The authors have no conflict of interest.

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