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Optimizing cultivars enhances the climate resilience of oat production across China under future climate change

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Introduction: Oat (*Avena sativa* L.) is a vital grain and forage crop that supports global food security and sustainable diets. A comprehensive understanding of the adaptive potential of oat to climate change is urgently required in order to develop effective strategies for ensuring future agriculture and food security.

Methods: In this study, using the Agricultural Production Systems Simulator (APSIM)-Oat model and the CMIP6 shared socioeconomic pathway (SSP) scenarios, we investigated potential adaptation strategies through cultivar optimization across China, including Northeast China (NEC), North China Plain (NCP), Northwest China (NWC), and Southwest China (SWC).

Results: Under future climate scenarios, the rainfed oat biomass and yield are projected to decrease in the 2030s, with improvements emerging in the cooler northern regions such as NEC by the 2060s, with the southern regions including NCP, NWC, and SWC continuing to experience declines. Similar trends are observed under irrigated conditions. Cultivar optimization shows strong regional and water management specificity, and early-maturing cultivars are recommended for NEC under rainfed conditions, whereas middle- and late-maturing types suit NCP, SWC, and NWC. Under irrigation, early-maturing cultivars perform better across NEC, NCP, and NWC, with middle-maturing cultivars remaining preferable in SWC.

Discussion: Adopting optimal cultivars effectively mitigates the yield losses in vulnerable regions such as SWC and enhances the yield gains in other regions under both rainfed and irrigated systems. These findings highlight the importance of region-specific cultivar optimization in sustaining oat production, supporting climate-resilient agriculture, and safeguarding long-term food security.

KEYWORDS

climate change, cultivar maturing, yield, biomass, APSIM-oat

1 Introduction

Climate change, particularly rising temperature and shifting precipitation patterns, poses a significant threat to global food production and security (Wang et al., 2018). Increased temperature and altered precipitation during the crop-growing period exacerbate the frequency and severity of heat waves, drought, and other extreme events (Hakela et al., 2020). Furthermore, increasing temperature accelerates crop development, shortening the growing periods and reducing biomass accumulation, thereby challenging crop production worldwide (Adavi et al., 2018).

Oat (*Avena sativa* L.) is a vital grain and forage crop, particularly in semi-arid and arid regions such as the Tibetan Plateau, where it plays a critical role in alleviating livestock forage shortages during the cold season (Wang et al., 2022; Ma et al., 2024). In recent decades, oat has gained increasing attention as a dietary staple due to its health benefits and the growing demand for plant-based and non-dairy alternatives (Rasane et al., 2015; Hakela et al., 2020). Moreover, oat is well suited for gluten-free diets, and the recognition of the qualities/value of oat in human nutrition has contributed to its expanding cultivation worldwide (Kaukinen et al., 2013). However, sustainable oat production is now under threat from climate change, primarily driven by rising temperature, high variation of the precipitation patterns, and a decline in solar radiation (Kuang and Jiao, 2016; Ma et al., 2024).

Against the background of ongoing warming, the impacts of rising temperature on oat production have been revealed globally (O'Donnell and Adkins, 2001; Robertson et al., 2013). Oat exhibits critical maximum and minimum temperature thresholds of 28°C and 5°C, respectively, leading to regionally varying responses to climate change, particularly to temperature increases (Robertson et al., 2013). In the Northern Plains of the United States and Canada, the changes in temperature and precipitation have reduced oat yields (Klink et al., 2014). Similarly, in Germany, climate change has been negatively affecting oat production since the 1950s, alongside a rise in irrigation water demand (Drastig et al., 2016). Mediterranean areas face significant yield limitations due to high temperature and drought, with warming severely decreasing oat yield (Risipail et al., 2018). Conversely, climate warming has expanded the most suitable areas for oat production in North China (Qin et al., 2023). However, the majority of existing studies were concentrated on limited sites, and a comprehensive assessment of oat responses to future climate change remains limited.

The selection of nationally and locally appropriate management practices would be an effective strategy to mitigate the adverse effects of climate change on oat production (Peltonen-Sainio et al., 2021). A lot of research studies have been conducted to determine the efficacy of climate change adaptation measures in improving oat yield. For instance, Peltonen-Sainio et al. (2021) pointed out that optimizing the irrigation schedule could alleviate the early summer droughts and enhance the oat yield in Finland. Seidel et al. (2021) identified increased plant-available topsoil phosphorus as a viable measure to counteract the oat yield losses induced by rising temperatures. However, irrigation and fertilizer application would increase the

economic inputs for producers. In contrast, the selection of optimal cultivars and adjustment of the sowing dates represent two cost-effective adaptation strategies (Tang et al., 2022). Optimizing the sowing date could help avoid climatic stresses, such as drought and heat stress, during the critical growth periods under global warming (Zhang et al., 2019; Ma et al., 2024). In general, global warming shortens the oat growth period by accelerating the development rate, but the selection of late-maturing cultivars could compensate for this effect (Risipail et al., 2018). However, a lot of farmers face constraints in freely adjusting the sowing dates due to involvement in other industries. In such cases, the selection of suitable cultivars based on a fixed sowing time offers a practical solution.

Oat production in China is categorized into four sowing agro-ecological zones based on varying climatic conditions and agronomic practices (Bo et al., 2021). As a cool-season crop, oat performs well in cool and frost-free seasons, but exhibits poorer growth performance in hot environments (Zhou et al., 2021). Climate warming in China has been shown to reduce oat yields while simultaneously increasing the water requirements during the growing season, and combined with shifting precipitation patterns, the drought risks for oat are on the rise (Jia et al., 2019; Ma et al., 2024). China has experienced an average annual temperature increase of 1.2°C over the past five decades (Piao et al., 2010). In cooler regions such as Northeast China, where the spring and summer temperatures are typically low, this warming trend has expanded the optimal sowing window, enabling the selection of more cultivars and potentially benefiting oat production (Zhang et al., 2019). Conversely, in warmer regions such as Southwest China, rising temperature has emerged as a primary constraint for oat cultivation (Bo et al., 2021).

Despite the growing importance of oats, comprehensive studies on regional cultivar adaptation in China are limited. Investigation of the cultivar adaptation potential and mechanism under future climate scenarios could inform the optimization of oat planting layouts nationwide. Therefore, the objectives of this study were to evaluate the oat yield responses to future climate change and identify region-specific optimal cultivars.

2 Materials and methods

2.1 Study areas, historical climate data, and soil data

Based on variations in climatic conditions and cropping management practices, the oat cultivation areas in China were classified into four distinct zones: Northeast China (NEC), North China Plain (NCP), Northwest China (NWC), and Southwest China (SWC) (Figure 1). This study encompassed 205 representative sites across these regions, with distributions of 90 sites in NEC, 41 in NCP, 41 in NWC, and 33 in SWC (Figure 1).

Historical climate data for the 205 meteorological sites, including the maximum and minimum temperatures, precipitation, and sunshine hours from 1981 to 2020, are available from the China

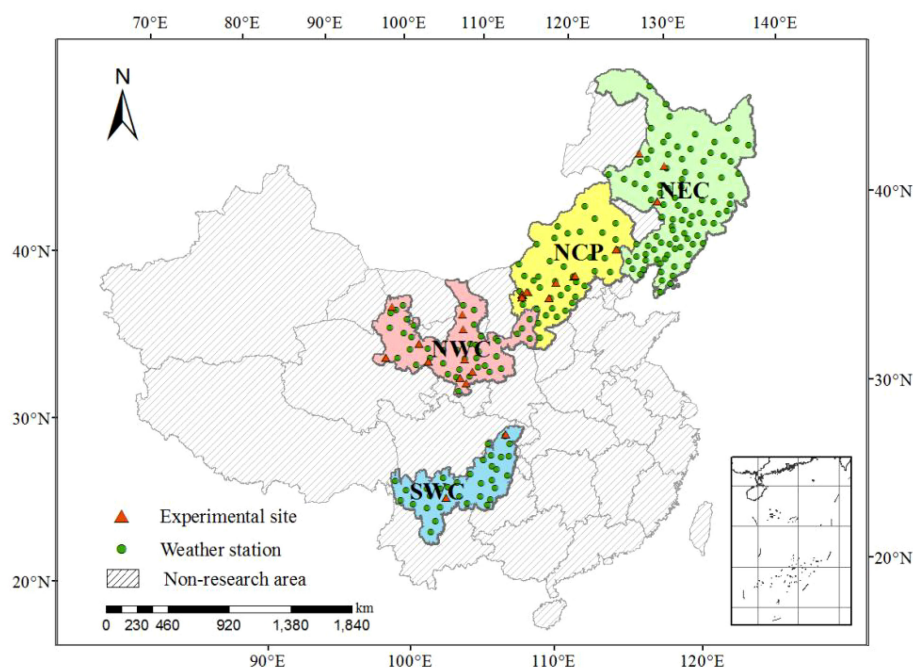


FIGURE 1

Oat cultivation zones, experimental sites, and meteorological stations used in this study. NEC, Northeast China; NCP, North China Plain; NWC, Northwest China; SWC, Southwest China.

Meteorological Administration. Daily solar radiation was calculated using the Ångström equation based on the sunshine hours (Tang et al., 2022). To account for spatial heterogeneity across the oat cultivation regions in China, 15 soil types were incorporated into the analysis. The spatial distribution and the characteristics of these soil types are presented in [Supplementary Figure S1](#) (Li et al., 2022).

2.2 Future climate data

Daily future climate projections (maximum/minimum temperature, precipitation, and solar radiation) were statistically downscaled from monthly gridded climate data ($2.5^\circ \times 2.5^\circ$) derived from the BCC-CSM2-MR (Beijing Climate Center, BCC) global climate model (GCM) of CMIP6. The GCM was selected for the following three reasons. Firstly, the GCM was developed by the BCC and has demonstrated strong performance in simulating historical climate over China, particularly for agriculture-relevant variables (Xiao et al., 2020; Tan et al., 2022). Secondly, it is compatible with the input requirements of the APSIM-Oat model. Lastly (but just as importantly), numerous previous studies have investigated the impacts of future climate change on agriculture based on this GCM, pointing out that it exhibits lower uncertainty compared with other GCMs in China (Song et al., 2019; Wang et al., 2020; Han et al., 2023). The climate projections were generated under the combined shared socioeconomic pathway (SSP) and representative concentration pathway (RCP) scenarios developed through integrated assessment

modeling (O'Neill et al., 2016). The downscaling process involved three key steps. Firstly, the monthly GCM simulations were spatially interpolated to individual stations using the inverse distance-weighted (IDW) method. For this step, a commonly used approach is to assign a site with a value corresponding to the GCM grid cell that it resides within. This is appropriate with very high-resolution gridded data, e.g., the higher spatial resolutions achieved by dynamic downscaling, in which the size of the grid cells is relatively small. Subsequently, systematic biases between the monthly observed data and the GCM-projected data were corrected through transfer functions derived from historical training periods. For this step, each climate variable and the calendar month values obtained in the spatial downscaling are sorted separately. The observed and the GCM data are then paired according to their rank, or quartile, and plotted to yield a $q-q$ plot. If the two distributions are linearly related, the points in the $q-q$ plot lie on a line. If all points in the $q-q$ plot lie on a 1:1 line, the two distributions are identical. Finally, the daily climate variables (including the maximum and minimum temperatures, precipitation, and radiation) for each site were generated from the bias-corrected monthly GCM projections using the WGEN stochastic weather generator. For this step, the amount of precipitation is modeled by a two-parameter gamma distribution. The parameters for the minimum and maximum temperatures are calculated in a similar fashion to precipitation. For a detailed description, refer to Liu and Zuo (2012). Moreover, we have validated the downscaling results at two typical sites: Zhangbei and Xilamuren ([Supplementary Figure S2](#)). Future CO_2 concentration was calculated as [Equation 1](#):

$$\begin{aligned}
[\text{CO}_2]_Y = & 62.044 + \frac{34.002 - 3.8702 \times Y}{0.24423 - 1.1542 \times Y^{2.4901}} + 0.028057 \\
& \times (Y - 1900)^2 + 0.00026827 \times (Y - 1960)^3 \\
& - 9.2571 \times 10^{-7} \times (Y - 1910)^4 - 2.2448 \times (Y - 2030)
\end{aligned} \quad (1)$$

where $[\text{CO}_2]_Y$ is the CO_2 concentration in year Y . Y is the calendar year with values of 1981, 1982, ..., 2100. The empirical equation was obtained by fitting the AR6 projected CO_2 concentration extracted from O'Neill et al. (2016). The nonlinear least-squares regression resulted in $R^2 = 0.99$ and RMSE = 5.0 ppm $[\text{CO}_2]$.

2.3 APSIM-Oat model and its validation

The Agricultural Production Systems sIMulator (APSIM) is a modular modeling framework developed by the Agricultural Production Systems Research Unit in Australia. Designed to simulate biophysical processes in agricultural systems, APSIM particularly focuses on the evaluation of the economic and ecological impacts of management practices under climate uncertainty. Within this framework, the APSIM-Oat model was adapted from the existing wheat model (Brown et al., 2014). The APSIM-Oat model operates on a daily time step, simulating oat development, biomass accumulation, and grain yield in response to environmental factors including temperature, photoperiod, solar radiation, soil water, and nitrogen availability. The model terminates crop growth at the first occurrence of late-season frost, regardless of whether physiological maturity has been reached (Barlow et al., 2015). The key driving variables for this model include temperature, precipitation, radiation, and CO_2 concentration. The model accommodates CO_2 levels ranging from 350 to 1,000 ppm, enabling simulations under various future climate scenarios and allowing for the assessment of the CO_2 fertilization effects on crop growth and yield formation. For oat, the CO_2 factors in the model are calculated by a function of the environmental CO_2 concentration (C , in parts per million) and the daily mean temperature (T_{mean}) as published by Reyenga et al. (1999) (Equation 2).

$$f_c = \frac{(c - c_i)(350 + 2C_i)}{(C + 2C_i)(350 - C_i)} \quad (2)$$

where C_i is the temperature-dependent CO_2 compensation point (in parts per million) and is derived from the Equation 3:

$$C_i = \frac{163 - T_{\text{mean}}}{5 - 0.1T_{\text{mean}}} \quad (3)$$

The phenological development of oats from sowing to maturity is divided into eight distinct growth phases, each characterized by key phenological stages, i.e., sowing, germination, emergence, end of juvenile stage, floral initiation, flowering, start of grain filling, end of grain filling, and maturity. The progression through each phase is determined by the accumulation of thermal time (TT), calculated using a triangular temperature response function based on three cardinal temperatures, i.e., base (T_b), optimum (T_o), and maximum (T_m) temperatures (Equation 4).

$$TT = \begin{cases} T - T_b & T_b < T \leq T_o \\ (T_m - T)T_o / (T_o - T_b) & T_o < T \leq T_m \\ 0 & T \ll T_b \text{ or } T \gg T_m \end{cases} \quad (4)$$

where T is the actual air temperature. T_b , T_o , and T_m are 0°C, 26°C, and 34°C, respectively, in the model.

Prior to flower initiation, the daily accumulated TT is adjusted by two cultivar-specific coefficients: f_v and f_D . f_v represents the vernalization sensitivity (ver_sens), while f_D reflects the photoperiod sensitivity (photop_sens). These coefficients are applied multiplicatively to the TT accumulation. Following floral initiation, f_v and f_D are fixed in the model.

The model simulates the potential leaf area through three key components: the leaf number per node, the potential leaf size, and the node appearance rate. The actual leaf area growth is calculated based on the potential constraint of carbon availability and is further modified by the effects of water and nitrogen stress. The daily biomass growth is calculated based on the radiation interception and the radiation use efficiency (RUE, in grams per megajoule), and the reduction factors include nitrogen and water stress. The grain biomass accumulation is simulated using a grain number- and size-based approach. The model determines the grain number based on the stem weight at anthesis and a cultivar-specific parameter (grains per unit stem weight). The potential grain filling rate is primarily driven by temperature and is constrained by the amount of biomass allocated to reproductive organs.

In this study, APSIM-Oat (version 7.10) was employed to assess the climate change adaptation potential in oat production through cultivar optimization. Model performance was evaluated using published experiment data spanning China's major oat cultivation regions. To ensure robust model calibration and validation, we selected representative cultivars encompassing the early-, medium-, and late-maturing types across all four planting regions to account for regional varietal differences. Field experiments were carefully chosen to minimize spatial heterogeneity effects. Data were partitioned into independent calibration and validation sets by region, cultivar, and year. The comprehensive cultivar information, including the maturity classifications, planting regions, experimental sites, and data sources, is detailed in Supplementary Table S1. For the calibration and validation of the APSIM-Oat model, 9, 12, 5, and 4 cultivars were selected in NEC, NCP, NWC, and SWC, respectively. In total, 16, 20, 8, and 8 sets of data, respectively, were generated for the validation across the four regions. In the model, 14 genetic parameters were adjusted based on previous studies (Supplementary Table S2) (Zhang et al., 2019). Each parameter was determined through a "trial-and-error" approach using field-measured biomass and yield data. Three statistics, i.e., the coefficient of determination (R^2) of the regression lines, the root mean square error (RMSE), and the relative root square error (normalized RMSE, NRMSE), were used to evaluate the performance of the APSIM-Oat model. The results showed that APSIM-Oat performed well in simulating the oat yield at each site in the four oat sowing regions with the calibrated cultivar parameters (Supplementary Figure S3). The NRMSEs

between the observed and the simulated oat yields were 13.3%, 14.3%, 6.5%, and 6.5% in NEC, NCP, NWC, and SWC (Supplementary Figures S3A, C, E, G), respectively, in the calibration year. For the validation years, the NRMSEs between the observed and the simulated oat yields were 8.4%, 11.6%, 6.1%, and 7.4% in NEC, NCP, NWC, and SWC (Supplementary Figures S3B, D, F, H), respectively.

2.4 Assessment of the impacts of future climate change on oat production

To evaluate the impacts of climate change on oat production, APSIM-Oat was driven by daily climate data for three periods, i.e., baseline (1981–2010), 2030s (2031–2060), and 2060s (2071–2100), under both rainfed and irrigated conditions. Under rainfed conditions, the sowing density were set at 400, 450, 390, and 380 plants per square meter in NEC, NCP, NWC, and SWC, respectively, based on local agronomic management practices, and the cultivars were set as currently managed. The irrigated treatment maintained identical management practices, except for supplemental irrigation applications of 30 mm at sowing and 90 mm at flowering (Sun et al., 2023a; Sun et al., 2023b). Across all regions, nitrogen fertilization maintained the soil mineral nitrogen (0- to 100-cm depth) above 300 kg N ha⁻¹ to prevent nitrogen limitation (Wei et al., 2018). For the single-cropping system in NEC and NCP, the initial 10 simulation years served as a spin-up period to eliminate the initial condition effects. In NWC and SWC, with multiple cropping systems, the soil water content at sowing was reset annually to 35% of the plant available water capacity to avoid residual effects from preceding crops.

The effects of future climate change on oat production, including biomass, yield, evapotranspiration (ET), and water use efficiency (WUE) under current management practices, were assessed by comparing the different projection periods (2030s and 2060s) against the baseline period (1981–2010), which was calculated as Equation 5:

$$\Delta Y_{2030s/2060s}(\%) = (Y_{2030s/2060s} - Y_b) / Y_b \times 100 \quad (5)$$

where $Y_{2030s/2060s}$ represents the simulated average index of oat under the future periods 2030s and 2060s. Y_b is the oat index under the baseline period with the cultivars used by local farmers.

2.5 Adaptation potential from optimizing the cultivar under future climate scenarios

To assess the adaptation potential of oat to future climate conditions, simulations were conducted using three representative cultivars spanning the early-, middle-, and late-maturing groups across the oat planting regions. Changes in the oat production indexes with different cultivars were calculated as follows (Equation 6):

$$\Delta Y_{2030s/2060s,C}(\%) = (Y_{2030s/2060s,C} - Y_b) / Y_b \times 100 \quad (6)$$

where $Y_{2030s/2060s,C}$ represents the simulated average index of oat with cultivar shift under the future periods 2030s and 2060s. Y_b is the index under the baseline period with the cultivars used by local farmers.

3 Results

3.1 Rainfed oat biomass, yield, water consumption, and water use efficiency in the baseline period

The rainfed oat biomass during the baseline period exhibited substantial regional variations across China's major oat sowing regions, which ranged 2,500–7,250 kg ha⁻¹ in NEC, 890–11,840 kg ha⁻¹ in NCP, 600–20,900 kg ha⁻¹ in NWC, and 1,060–21,800 kg ha⁻¹ in SWC (Figure 2A). The regional averages revealed SWC as the highest-producing region (9,900 kg ha⁻¹), followed sequentially by NWC (7,600 kg ha⁻¹), NEC (4,700 kg ha⁻¹), and NCP (4,400 kg ha⁻¹) (Figure 2A). Similar geographical patterns emerged for the rainfed oat yield (Figure 2B), with production ranges of 1,160–3,810 kg ha⁻¹ (NEC), 80–3,800 kg ha⁻¹ (NCP), 120–4,990 kg ha⁻¹ (NWC), and 460–9,530 kg ha⁻¹ (SWC). SWC maintained its productivity advantage with the highest average yield (3,250 kg ha⁻¹), followed by NEC (2,400 kg ha⁻¹), NWC (1,910 kg ha⁻¹), and NCP (1,540 kg ha⁻¹) (Figure 2B). The rainfed oat water consumption (ET) ranges were 168–280, 88–309, 58–330, and 162–330 mm in NEC, NCP, NWC, and SWC, respectively (Figure 2C). Averaged ET was highest in SWC (250 mm), followed by NCP (230 mm), NEC (210 mm), and NWC (200 mm) (Figure 2C). WUE demonstrated considerable spatial variability (Figure 2D), ranging from 5.40 to 21.10 kg ha⁻¹ mm⁻¹ in NEC, from 1.80 to 29.6 kg ha⁻¹ mm⁻¹ in NCP, from 2.04 to 19.80 kg ha⁻¹ mm⁻¹ in NWC, and from 1.50 to 30.00 kg ha⁻¹ mm⁻¹ in SWC (Figure 2D). The average WUE was remarkably similar between SWC (11.50 kg ha⁻¹ mm⁻¹) and NEC (11.30 kg ha⁻¹ mm⁻¹), with lower values found in NWC (8.30 kg ha⁻¹ mm⁻¹) and NCP (6.60 kg ha⁻¹ mm⁻¹) (Figure 2D).

3.2 Irrigated oat biomass, yield, water consumption, and water use efficiency in the baseline period

Under irrigated conditions during the baseline period, the oat biomass production showed significant regional variations, which ranged from 2,500 to 7,300 kg ha⁻¹ in NEC, from 3,000 to 12,000 kg ha⁻¹ in NCP, from 3,200 to 21,100 kg ha⁻¹ in NWC, and from 1,000 to 22,000 kg ha⁻¹ in SWC (Figure 3A). The highest biomass was achieved in SWC (12,000 kg ha⁻¹), followed by NWC (10,300 kg ha⁻¹), NCP (6,000 kg ha⁻¹), and NEC (4,800 kg ha⁻¹) (Figure 3A). For irrigated conditions, the yield ranges were 1,160–3,820 kg ha⁻¹ (NEC), 940–3,800 kg ha⁻¹ (NCP), 380–4,990 kg ha⁻¹ (NWC), and 460–9,670 kg ha⁻¹ (SWC) (Figure 3B). SWC produced the

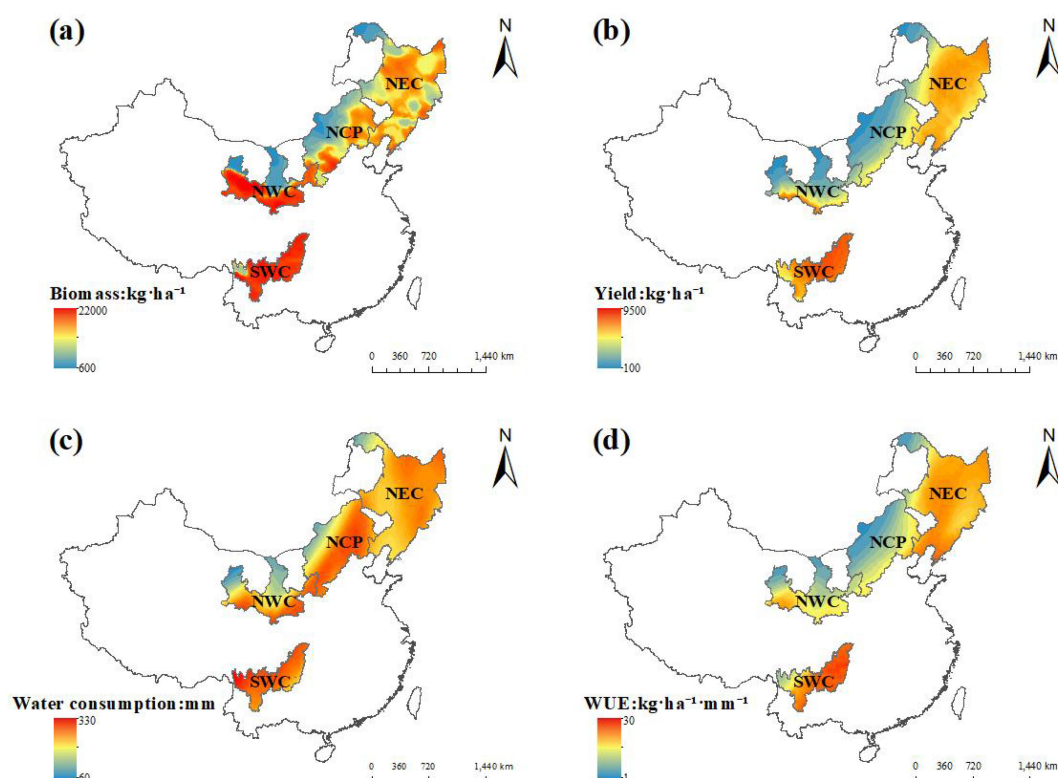


FIGURE 2
Rainfed oat biomass (A), yield (B), water consumption (C), and water use efficiency (WUE) (D) in different oat production zones in China in the baseline period (1981–2010).

maximum yield, with averaged yield of $5,110 \text{ kg ha}^{-1}$, followed by NEC ($2,430 \text{ kg ha}^{-1}$), NCP ($2,240 \text{ kg ha}^{-1}$), and NWC ($2,230 \text{ kg ha}^{-1}$) (Figure 3B). The ET ranges of irrigated oat were 178–280 mm (NEC), 129–328 mm (NCP), 143–342 mm (NWC), and 166–332 mm (SWC) (Figure 3C). Average ET was highest in SWC (288 mm), followed by NCP (267 mm), NWC (253 mm), and NEC (220 mm) (Figure 3C). The WUE ranges were $5.20\text{--}21.00 \text{ kg ha}^{-1} \text{ mm}^{-1}$ (NEC), $5.40\text{--}29.60 \text{ kg ha}^{-1} \text{ mm}^{-1}$ (NCP), $2.60\text{--}19.80 \text{ kg ha}^{-1} \text{ mm}^{-1}$ (NWC), and $1.45\text{--}29.90 \text{ kg ha}^{-1} \text{ mm}^{-1}$ (SWC) (Figure 3D). SWC achieved the highest average WUE ($17.40 \text{ kg ha}^{-1} \text{ mm}^{-1}$), followed by NEC ($11.03 \text{ kg ha}^{-1} \text{ mm}^{-1}$), NCP ($8.61 \text{ kg ha}^{-1} \text{ mm}^{-1}$), and NWC ($8.33 \text{ kg ha}^{-1} \text{ mm}^{-1}$) (Figure 3D).

3.3 Impacts of climate change on oat biomass, yield, and water use under rainfed condition in the future periods

Compared with the baseline period, the rainfed oat biomass exhibited distinct regional trends in the 2030s, with NEC showing wide variations but a minimal mean change (-1.5%), NCP declining moderately (-2.9%), NWC experiencing a substantial decrease (-16.6% , $p < 0.01$), and SWC showing a slight reduction (-4.2% , $p < 0.05$). By the 2060s, NEC demonstrated a modest increase (2.9%), with NCP remaining near the baseline (-1.0%), NWC maintaining a significant decline (-14.7% , $p < 0.01$), and SWC showing some

recovery (-2.0%) (Figure 4A). The rainfed oat yields displayed similar regional patterns. In the 2030s, NEC and SWC remained near the baseline (-0.5% and -0.2% , respectively), with NCP showing a minimal increase (0.9%) and NWC experiencing a marked decline (-14.7% , $p < 0.01$). By the 2060s, NEC shifted to moderate growth (2.0%), with NCP maintaining stability (0.9%), NWC persisting in a substantial reduction (-13.7% , $p < 0.01$), and SWC showing a definite decreasing trend (-4.9% , $p < 0.05$) (Figure 4B). The ET changes revealed consistent increases in NCP across both periods (3.4% in the 2030s and 5.4% in the 2060s). NEC showed minor reductions (from -1.5% to -3.4%), NWC transitioned from a slight decrease (-2.5%) to a modest increase (2.5%), while SWC remained relatively stable (from -2.6% to -0.5%) (Figure 4C). WUE demonstrated clear regional contrasts, with NEC showing a steady improvement ($2.0\%\text{--}3.9\%$), NCP exhibiting a consistent decline (-4.9% , $p < 0.05$), NWC experiencing substantial reductions (from -13.7% to -15.6% , $p < 0.01$), and SWC showing modest decreases (from -2.0% to -3.9% , $p < 0.05$) across both periods (Figure 4D).

3.4 Impacts of climate change on oat biomass, yield, and water use under irrigated condition in the future periods

Under irrigation conditions, the oat production indicators showed distinct regional patterns during the 2030s and the 2060s

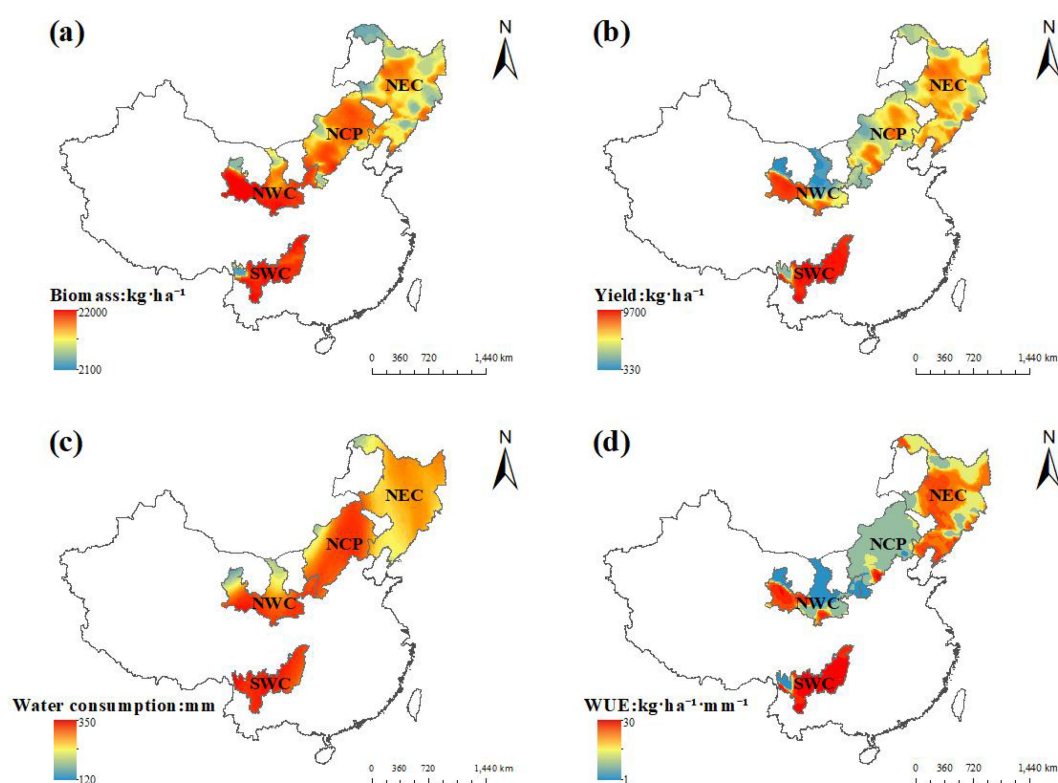


FIGURE 3
Irrigated oat biomass (A), yield (B), water consumption (C), and water use efficiency (WUE) (D) in the different oat production zones in China in the baseline period (1981–2010).

compared with the baseline period. For biomass, NEC transitioned from a minor decline (-0.50%) in the 2030s to a slight increase (1.00%) by the 2060s. In contrast, NCP and NWC experienced substantial reductions that intensified over time, from -9.80% to -14.70% ($p < 0.01$) and from -13.70% to -15.70% ($p < 0.01$), respectively. SWC maintained relatively stable but consistently negative values (from -3.90% to -3.00%) across both periods (Figure 5A). The yield patterns followed similar regional trends. NEC showed an improvement from 0.50% to 2.00% , while NCP and NWC faced significant declines, deteriorating from -10.80% ($p < 0.01$) to -14.70% ($p < 0.01$) and from -12.70% ($p < 0.01$) to -15.60% ($p < 0.01$), respectively. SWC remained consistently below the baseline, with values of -4.90% ($p < 0.05$) and -4.00% ($p < 0.05$) (Figure 5B). The ET changes revealed diverse responses, with NEC and SWC showing persistent minor reductions, while NCP improving from -4.30% ($p < 0.05$) to -1.00% . Notably, NWC transitioned from a significant decrease (-5.20% , $p < 0.05$) to a moderate increase (2.90%) by the 2060s (Figure 5C). WUE demonstrated striking regional contrasts. NEC maintained consistent improvements (4.40% in both periods), while NCP showed worsening conditions (from -10.30% to -13.10% , both $p < 0.01$). NWC exhibited the most remarkable shift, moving from a substantial reduction (-14.10% , $p < 0.01$) to a significant

improvement (7.30% , $p < 0.01$). SWC persisted with moderate declines (from -6.30% to -5.40% , both $p < 0.05$) throughout the study period (Figure 5D).

3.5 Optimal oat cultivar under future climate change in China

The climate change projections revealed distinct optimal cultivar strategies for maximizing the oat yields across the four growing regions in China (Table 1). For the rainfed conditions in the 2030s, yield optimization required early-maturing cultivars in NEC (4.4% increase), middle-maturing cultivars in both NCP (0.9% increase) and SWC (0.2% decrease), and late-maturing cultivars in NWC (6.2% increase) (Table 1). These cultivar preferences persisted in the 2060s for NEC (7.8% increase), NCP (0.9% increase), and NWC (5.5% increase), while SWC required a shift to late-maturing cultivars (1.5% decrease) (Table 1). Under irrigated conditions, early-maturing cultivars proved optimal in the 2030s for NEC (4.7% increase), NCP (3.1% increase), and NWC (6.0% increase), with middle-maturing cultivars performing best in SWC (4.9% decrease). By the 2060s, these same cultivar selections maintained their advantages, yielding increases of 8.2% (NEC),

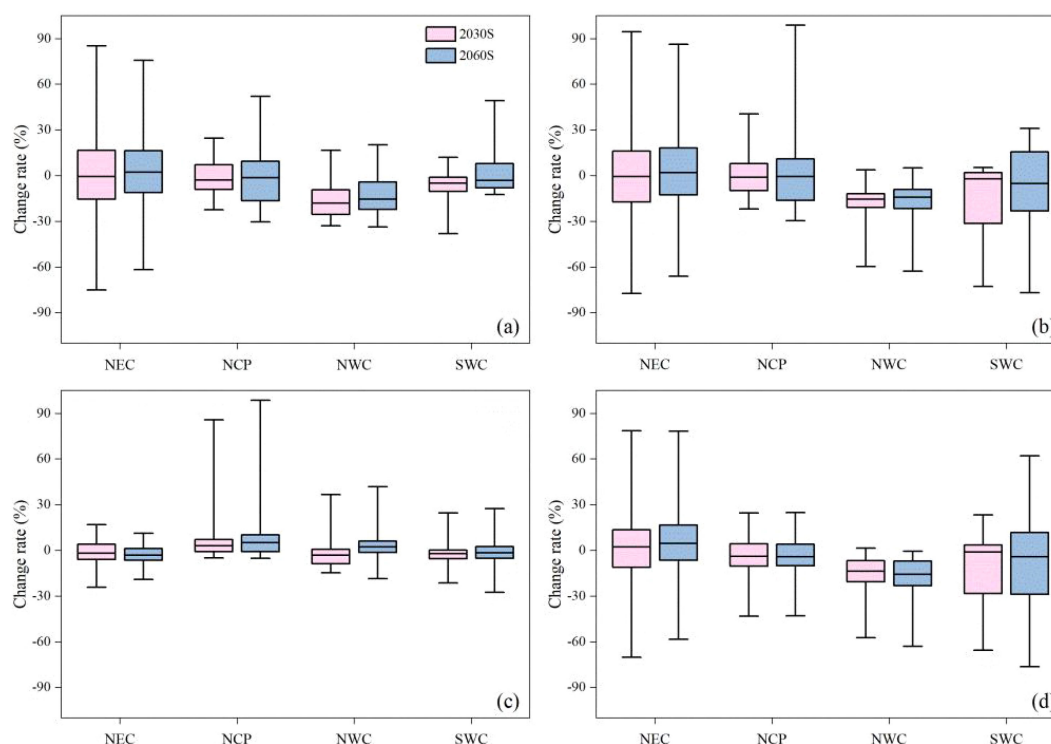


FIGURE 4

Impacts of future climate change on rainfed oat biomass (A), yield (B), water consumption (C), and water use efficiency (WUE) (D) in the 2030s (2031–2060) and the 2060s (2071–2100). Box boundaries indicate the 25th and 75th percentiles across the different regions; whiskers below and above the box indicate minimum and maximum values, respectively; and horizontal line inside the box represents the mean value.

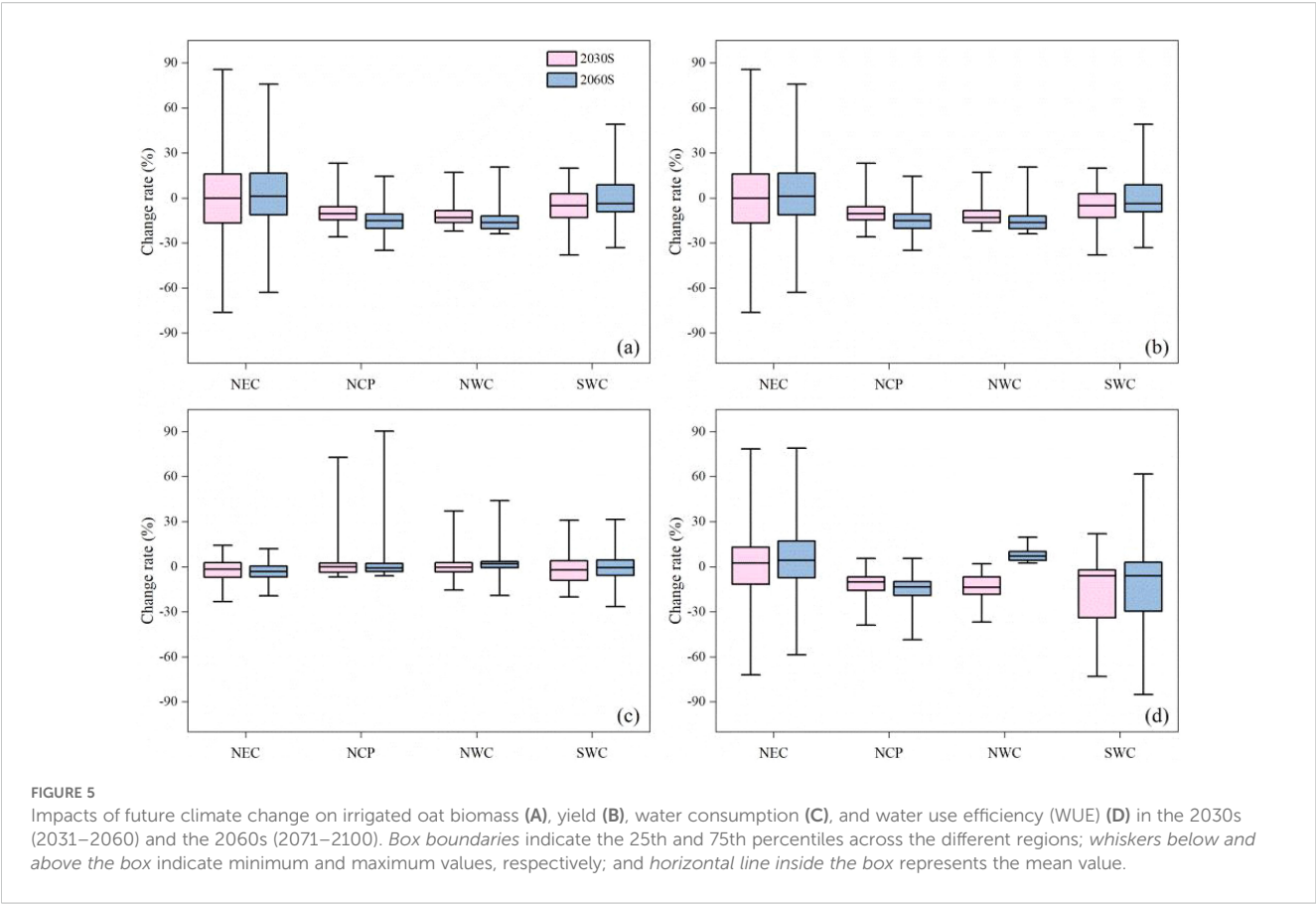
5.8% (NCP), and 4.0% (NWC), while the yield reduction in SWC moderated to just 1.2% with continued use of middle-maturing cultivars (Table 1).

4 Discussion

Oat serves as a crucial dual-purpose crop that is widely cultivated in dryland agricultural systems globally (Francia et al., 2006). As a typical dual-purpose crop, it is grazed by livestock during the vegetative phase before being allowed to regenerate for grain production (Sprague et al., 2021). Since biomass accumulation directly determines the forage potential, we first analyzed the oat biomass variations in the baseline period across China. Our results revealed that both the rainfed and irrigated oat biomass were highest in SWC. For rainfed oat, water availability represents the primary limiting factor, and the higher biomass in the region can be attributed to the better alignment between the precipitation patterns and the oat water requirement. Under the irrigated condition, where the water constraints were alleviated, the thermal conditions in the region more closely matched the optimal temperature range for oat photosynthesis, thereby enhancing biomass accumulation. This biomass advantage translated into higher grain yields, as the oat harvest index remained relatively stable across different management practices (Liu et al., 2023).

Consequently, the greater biomass production directly supported its superior yield performance compared with that of the other regions.

Climate change has exerted substantial impacts on the global oat production (Hakela et al., 2020). Our simulated results demonstrated declining trends for both rainfed and irrigated oat biomass across China in the 2030s, with only NEC increased by the 2060s. These changes can be attributed to several physiological mechanisms, with climate warming accelerating phenological development, thereby shortening the oat growing period (Robertson et al., 2013). More importantly, the effects of temperature on biomass accumulation are fundamentally determined by its relationship with the thermal thresholds of oat (Tang et al., 2024). Previous studies revealed optimal growth temperatures for oat around 18°C and critical maximum thresholds of 24–28°C (Robertson et al., 2013). During the 2030s, the average temperature during the oat growing period consistently exceeded the optimum range, while the maximum temperature surpassed the critical thresholds, resulting in widespread heat stress that reduced the biomass production nationwide. In NEC, increasing the CO₂ concentration and precipitation could offset the negative effects of climate warming, and the biomass would show an increasing trend in the 2060s. Conversely, in other regions, the detrimental effects of excessive temperatures outweighed these positive factors, causing continued biomass declines. Notably, the



yield changes closely mirrored the biomass patterns, as biomass accumulation serves as the fundamental determinant of the final grain yield in oat production systems.

The optimization of irrigation management hinges on accurately quantifying the crop water use (Allen et al., 2005; Droogers et al., 2010). For rainfed oat, ET was projected to increase solely in NCP in the 2030s, while expanded to both NCP and NWC by the 2060s. ET encompasses both crop transpiration and soil evaporation throughout the growing period (Stewart and

Peterson, 2015). Under future climate warming scenarios, soil evaporation was expected to rise, whereas crop transpiration might decline due to a reduced biomass accumulation. When the reduction in transpiration is outweighed by the increased amount of soil evaporation relative to the baseline period, the ET under rainfed conditions would show an increasing trend. For irrigated oat, ET was anticipated to decrease across China during the 2030s compared with the baseline period, and it would only increase in NWC in the 2060s. The underlying mechanisms driving these ET

TABLE 1 Impacts of the different maturing cultivars on the rainfed and irrigated oat yields across China under climate change scenarios in the 2030s and the 2060s.

Planting region		2030s			2060s		
		E	M	L	E	M	L
Rainfed	NEC	4.4	−0.5	−1.7	7.8	2.0	−0.8
	NCP	−3.4	0.9	−6.2	−8.0	0.9	−9.8
	NWC	−0.4	−14.7	6.2	3.9	−13.7	5.5
	SWC	−11.2	−0.2	−8.6	−5.7	−4.9	−1.5
Irrigated	NEC	4.7	0.50	−1.0	8.2	2.2	0.5
	NCP	3.1	−10.8	1.1	5.8	−14.7	0.4
	NWC	6.0	−12.7	−7.1	4.0	−15.6	−4.7
	SWC	−9.7	−4.9	−9.6	−3.8	−4.00	−1.2

E, early; M, middle; L, late; NEC, Northeast China; NCP, North China Plain; NWC, Northwest China; SWC, Southwest China.

changes were the same with those under rainfed conditions. The WUE of rainfed oats showed improvements only in NEC during both the 2030s and the 2060s, while irrigated oats exhibited enhanced WUE in both NEC and NWC during these periods. WUE is determined by crop yield and water consumption (Tang et al., 2018). When the yield reduction is proportionally smaller than the decrease in ET, WUE would show an increasing trend.

The effectiveness of cultivar adjustment as an adaptation measure would vary across regions under future global warming scenarios (Kumagai and Sameshima, 2014; Tao et al., 2014). Under future climate scenarios (2030s–2060s), early-maturing cultivars would be optimal for rainfed oats in NEC, mid-maturing cultivars in NCP and SWC, and late-maturing cultivars in NWC. The yields would only decrease in SWC. This divergence stems from the improved alignment of rainfall and water needs via cultivar adaptation in the majority of regions, whereas in SWC, the rising growing-season temperatures exceed the tolerance of oats, limiting the adaptation benefits. For irrigated oats, early-maturing cultivars would suit NEC, NCP, and NWC, with the mid-maturing types preferred in SWC. Yield declines only in SWC as irrigation alleviates the water constraints, but not heat stress. Persistent high temperatures during the growing season make cultivar adjustment ineffective, leading to yield losses. However, these projections face uncertainties related to climate model accuracy and cultivar responses. In addition, from a practical standpoint, farmer adoption faces challenges such as limited access to improved seeds, additional costs, and perceived risks associated with cultivar switching. In regions such as SWC, where climate vulnerability is high, structural constraints—including insufficient technical guidance, low awareness of adaptation strategies, and limited infrastructure—may further impede effective implementation. Thus, while cultivar adaptation shows theoretical potential, its real-world efficacy will depend on integrated support systems that address both agronomic and socioeconomic barriers.

In this study, we focused on optimizing oat cultivars for different sowing regions across China; therefore, consistent irrigation and nitrogen fertilizer applications were maintained. This management approach was adopted for two main reasons. Firstly, the irrigation and nitrogen application rates were based on recommendations from previous studies conducted in various oat sowing regions of China (Wei et al., 2018; Sun et al., 2013a; Sun et al., 2013b). Secondly, maintaining consistent management practices allowed for an effective comparison of the impacts of future climate change on oat production across the different regions. It should be noted, however, that the optimal irrigation and nitrogen (N) fertilization levels may vary with oat cultivars and climate conditions. Further research is needed to identify the optimal combination of irrigation and N fertilization for oat production under future climate conditions. In addition, CO₂ fertilizer was modeled in the simulation. Previous studies have revealed that the APSIM model could simulate the effects of CO₂ well (Vanuytrecht and Thorburn, 2017; Morel et al., 2021). Despite its adequate simulation of the CO₂ responses, a significant limitation of this model lies in its CO₂ module, which must be addressed through more extensive and detailed validation in subsequent studies.

While this study identified optimal oat cultivars for future warming scenarios across China, several uncertainties and limitations should be acknowledged. Firstly, we did not account for cultivars with enhanced heat or drought resistance, which could potentially improve the yields under climate stress (Frey, 1998). Secondly, although crop rotation systems significantly influence both soil water dynamics and nutrient availability (Ewing et al., 2024), our simulation only incorporated rotation effects through initial soil water resetting at sowing, without considering N fertilizer limitations. In practice, producers typically apply extensive rates of N fertilizer, which generally meets the nutritional requirements of oat (May et al., 2020; Qian et al., 2022). Thus, while our N fertilization assumptions align with common practices, optimal cultivar selection might vary under different fertilization regimes. In addition, our irrigation modeling did not incorporate efficiency variations among different methods, where flood irrigation is the least efficient, sprinkler irrigation intermediate, and drip irrigation the most water-efficient (Tian et al., 2022). Furthermore, government agricultural policies may influence management decisions, and this was not addressed in our study (Qin et al., 2023). Lastly (but just as importantly), only one GCM was employed in this study, which may have introduced uncertainty. However, a prior study demonstrated that the specific GCM utilized herein can effectively reduce uncertainty in future climate change simulations (Wang et al., 2020). Furthermore, multiple GCMs will be incorporated in our subsequent simulations. Despite these limitations, our findings provide valuable insights into adapting oat production systems across China to climate change.

5 Conclusions

This study employed the validated APSIM-Oat model to assess climate change impacts on oat production across China's major growing regions and to evaluate cultivar optimization as an adaptation strategy for the 2030s and the 2060s. The results revealed notable regional differences in oat responses to climate warming. Under rainfed conditions, both oat biomass and yield were projected to decline across the majority of regions during the 2030s, with only limited improvement observed in NEC by the 2060s. Under irrigation, biomass showed a comparable pattern of decline in the 2030s, followed by moderate increases in NEC during the 2060s, while yield improvements remained modest and largely confined to NEC in both periods. Cultivar optimization identified region-specific adaptation strategies, with early-maturing cultivars for NEC, medium-maturing types for NCP and SWC, and late-maturing varieties for NWC under rainfed conditions. Under irrigation, early-maturing cultivars were optimal in NEC, NCP, and NWC, whereas medium-maturing cultivars performed best in SWC. These findings suggest that targeted cultivar selection can serve as a regionally appropriate measure to partially offset the negative impacts of climate warming on oat production. To further advance this research, the following concrete steps are recommended. Firstly, multi-GCM ensemble simulations should be conducted to better quantify uncertainties in climate projections. Secondly, more detailed

field trials under realistic growing conditions should be carried out to validate the proposed cultivar strategies. Lastly (but just as importantly), socioeconomic analyses should be conducted to assess the practical feasibility and adoption potential of these adaptation measures.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

JT: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. HB: Data curation, Software, Writing – review & editing. HY: Data curation, Formal analysis, Resources, Writing – review & editing. XZ: Data curation, Methodology, Writing – review & editing. FG: Data curation, Methodology, Writing – review & editing. HZ: Data curation, Methodology, Writing – review & editing.

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Supplementary material

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