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In-silico evidence for improving irrigated maize productivity in the Great Plains: A high-resolution spatial simulation approach

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ABSTRACT

Food security and the depletion of water resources have become the two main concerns for the future of agricultural sustainability. Climate change, on the other hand, challenges global agricultural productivity, making target agricultural zones less productive. However, increasing yield potential through adaptation is crucial for improving global agricultural production. In this study, an approach for studying the impacts of future climate conditions and adaptation strategies on yield and water use dynamics of maize in the Eastern Kansas River Basin (EKSRB) of the US Great Plains, based on different future climate scenarios and deficit irrigation water management at a 4 km spatial resolution was presented. Using the spatially-adapted CERES-Maize model, the combination of impacts of in silico genotype-specific adaptations for selected genotype-specific parameters, treated as quantitative traits (improved canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and no nutrient limitation [NNL]) on yield and irrigation water use were explored. In addition, we assessed the integration of the individual genotype-specific and agronomic adaptation strategies to understand the co-benefits and trade-offs on yield improvement and water savings. Future climate scenarios for the region were created for two Representative Concentration Pathways (RCPs) (4.5 and 8.5) over three 25-year future periods (2025–2100) and compared to the historical climate (1991–2015). Results showed that future maize yield declined by approximately 34 % to 43 % (early and late century time periods, respectively) under RCP 4.5, and 33 % to 68 % (early and late century time periods, respectively) under RCP 8.5. Despite the yield declines, we found water use savings ranging from 9 % to 20 % (early and late century time periods, respectively) under RCP 4.5, and 13 % to 18 % (early and late century time periods, respectively) under RCP 8.5. We observed that integrated adaptation strategy linked to improved RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4), resulted in the early 21st century average yield gain of 0.6 to 3 % (RCPs 4.5 and 8.5, respectively), with water savings of 10 to 13 % (RCPs 4.5 and 8.5, respectively), relative to historical condition. However, going forward into the 21st century, we found marginal yield deviations (especially under RCP 4.5) with further increases in water savings, more than observed under the no-adaptation scenario. This suggests the need to re-examine and re-design these adaptation strategies for further yield improvement, while leveraging the benefits of water savings under future climate conditions. Our findings emphasize the transformative potential of all-inclusive integrated adaptation strategies in mitigating the impacts of future climate conditions on irrigated maize production in the Great Plains.

1. Introduction

The projected increases in growing season climate variables due to changes in our climate (IPCC, 2023; Kothari et al., 2019; Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025; Stella et al., 2023; Onyekwelu et al., 2023; Igwe et al., 2025), challenge the future of three key crops – maize, wheat, and rice – which supply nearly two-thirds of 90 % of the global human calorie consumption (Kastner et al., 2012; Stewart & Lal,

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2018). Projected increase in future population, on the other hand, challenges food security in major regions of the world, stretching the need to intensify food production in target/high-yielding regions (FAO, 2023a, 2023b). Maize, for example, will suffer severe yield shock due to future climate change, with the majority of studies recommending adaptation as one of the key strategies for yield improvement in high-yielding regions (Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025; Sen et al., 2024; Yang & Wang, 2023). The US Great Plains and broader Midwest region, as one of the world's high-yielding regions and leading maize producers, face significant challenges as irrigation practices deplete the High Plains Aquifer (Ogallala Aquifer), which is the largest aquifer in the US and the Great Plains (Araya et al., 2017; McGuire, 2012; Scanlon et al., 2012). Studies have shown that irrigation demand for maize in the Great Plains will increase amid uncertain rainfall conditions, leading to further depletion of the High Plains Aquifer. For example, Onyekwelu et al. (2025) have shown that maize irrigation water use under early to late 21st-century climate conditions will increase by 30 to 32 %, without yield improvement. In the same study, they found that deficit irrigation may offer benefits of water savings reaching up to 15 % without further diminishing productivity, while maintaining water resources needed to improve aquifer recovery. However, solutions for implementing maize adaptation to future climate conditions that are aimed at improving spatiotemporal yield and maintaining irrigation water savings are still lacking.

While the US Great Plains and broader Midwest remain one of the world's high-yielding and leading maize-producing regions, John Powell, as early as 1879 (Powell, 1879), defined the east–west aridity gradient that characterizes the region's agriculture and water use. Amidst the east–west aridity gradient, John Powell noted the 100th meridian, which is the symbolic hydroclimatic dividing line between the moist eastern part of the United States and the drier western plains (Seager et al., 2018), and where precipitation is approximately equal to potential evapotranspiration (Seager et al., 2018). While the 100th meridian holds the true hydroclimatic divide of the United States and is realized in terms of farm size and settlement, recent studies have shown that the hydroclimatic conditions that characterize this line are shifting eastwards, thereby creating drier conditions to the east of the 100th meridian (Krajick, 2018; Seager et al., 2018). The implications of this eastward migration on irrigated maize response to different climate scenarios and adaptation strategies remain uncertain in the region, as further eastward migration is expected over the next decades (Krajick, 2018; Seager et al., 2018).

As climate changes with anticipated negative consequences (Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025; Onyekwelu, 2025), it is widely agreed that agricultural crop production will not be on track to meet the production doubling needed by 2050 for humanity to avoid significant food security disruption (Godfray et al., 2010). Researchers have recognized climate adaptation strategies to include accelerating genetic gains through breeding and employing improved in-field production methods and agronomic management, such as adjusting planting dates, managing nutrient application and allocation of biologicals, and precision agriculture (Guarin et al., 2022, 2023; Kothari et al., 2019, 2020; Martre et al., 2024; Onyekwelu & Sharda, 2024b; Poudel et al., 2023; Stella et al., 2023; Onyekwelu, 2025). While accelerating yield gains through breeding and agronomic management are essential adaptation strategies for improving crop production, the time horizon between identifying high-performance traits in crop genotypes or cultivars and stable agronomic management practices for yield improvement and water use savings may be long under field or laboratory experiments. In some cases, field or laboratory experiments may not be readily feasible to test these strategies due to intensive financial investment and labor requirements (Battisti et al., 2017; Onyekwelu & Sharda, 2024b; Sinclair et al., 2010; Onyekwelu, 2025). In addition, field or laboratory experiments lack the advanced time horizon and field-to-regional scalability needed to achieve future agricultural sustainability and assess location-specific impacts of various strategies under different future climate scenarios and environmental variability.

Process-based crop models are powerful tools that allow multiple scenario analysis under different climates and environmental conditions and can facilitate testing of modified cultivar traits and agronomic management practices, and evaluate how they can impact crop production, especially under future climate conditions (Battisti et al., 2017; Onyekwelu & Sharda, 2024b; Sinclair et al., 2010). For example, Guarin et al. (2022) tested the best-performing doubled haploid crosses of wheat with improved RUE, KCAN, fruiting efficiency, grain filling duration, and grain size using a multi-model ensemble of process-based wheat models in 34 global locations. They found that global wheat production is projected to increase without cropland expansion. In another study, Tesfaye et al. (2018), assessed the potential benefits of drought and heat tolerance traits of maize cultivars using the CERES-Maize model. They reported that incorporating drought and heat tolerance traits into benchmark maize cultivars increased maize yield under future climate conditions. By adjusting planting dates as an adaptation strategy, Getachew et al. (2021) found that early planting of sorghum resulted in better yield compared to the baseline planting dates based on simulated results from two sites in Ethiopia. Overall, these studies concluded that adaptation is key to sustaining agricultural crop production under future climate conditions.

Given that numerous studies have tested different adaptation strategies for improving crop productivity under future climate conditions using process-based crop models, studies testing individual adaptation levels (genotype-specific traits or agronomic management practices), alongside integration of genotype-specific and agronomic adaptation strategies on irrigated maize production are still lacking. In addition, the scale of most climate impact and adaptation studies remained point-scale, given that most process-based crop models run at point-scale to simulate a homogenous unit, such as a field (Onyekwelu et al., 2025; Onyekwelu, 2025). This has limitations when considering the spatial heterogeneity of environmental conditions (e.g., soil and climate), and how different adaptation strategies may respond to different landscape conditions at a regional scale. Moreover, spatial information on irrigation water use of maize and response under different adaptation strategies is lacking. Adapting point-scale crop models for spatial simulation of crop productivity offers many advantages (Onyekwelu et al., 2025). For instance, spatial simulations provide location-specific insights, which can be used to target the combination of high-yielding and low water use locations under different adaptation strategies for resource management. In addition, spatial simulation of crop productivity can be used to optimize input resources (e.g., irrigation, fertilizer, etc.) for profit maximization (Onyekwelu et al. 2025) and to assess co-benefits and trade-offs among different ecosystem services (Qiu et al., 2018, 2019). By integrating gridded outputs from regional crop models with spatial soil distributions and seasonal climate data under different adaptation strategies, valuable insights into key factors influencing crop yield and irrigation water use can be drawn to improve agricultural management zones (Onyekwelu et al., 2025). This approach enhances the understanding of how landscape and atmospheric conditions shape regional agricultural productivity. It also supports the development of effective adaptation and management strategies aimed at improving crop sustainability and resource use efficiency (Onyekwelu et al., 2025).

In our previous study, we developed a fine-scale spatial protocol for adapting a point-scale crop model for spatial simulation of irrigated maize productivity (yield, water use, water productivity, and farmers' net returns) under different climate scenarios, using Shawnee County in EKSRB of the Great Plains as a case study (Onyekwelu et al., 2025). Based on our spatial protocol, a novel crop modeling study was developed and evaluated across the entire EKSRB (comprising 17 counties) to understand the impacts of different future climate scenarios and adaptation strategies on irrigated maize yield and water use. Thus, the objectives of this study were to: (1) determine the spatial and temporal patterns of irrigated maize yield and water use responses to future climate conditions and deficit irrigation strategy in the EKSRB, (2) determine the impacts of in silico genotype-specific adaptations for selected genotype-specific parameters, treated as quantitative traits (improve canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and no nutrient limitation [NNL]) on yield and irrigation water use. In addition, we assessed the integration of the genotype-specific and agronomic adaptation strategies to understand the co-benefits and trade-offs on yield improvement and water savings. By accounting for spatial heterogeneity, we quantified location-specific impacts of future climate conditions and adaptation strategies on irrigated maize production, offering valuable insights for other regions in the Great Plains and around the world facing climate change uncertainty.

2. Materials and methods

2.1. Study area

This study was carried out in the Eastern Kansas River Basin (Fig. 1; EKSRB, hereafter), which represent the watershed of the Kansas River, spanning from the confluence of the Smoky Hill and Republican rivers in the west, to its terminus at the Missouri river in Kansas City (Onyekwelu & Sharda, 2024a, 2024b; Sen et al., 2023, 2024). More details on the region's hydrology are reported in (Onyekwelu & Sharda, 2024a, 2024b; Onyekwelu et al., 2025). The basin represents an exemplar region in the Great Plains exposed to potential impacts of aridity increase due to climate change on crop production and ecosystem function. With the 100th meridian (Powell, 1879) lying adjacent to its western edge, projected aridity increases (Seager et al., 2018) are expected to encroach into the basin, continuing eastwards; thus, making the region a perfect location to develop sustainable solutions for climate impact mitigation and adaptation strategies for the broader Great Plains agricultural system.

There are seventeen counties in EKSRB (Fig. 1, S1, S2, and S3), with the basin covering an area of over two million acres (Fig. 1; larger than the State of Connecticut in the United States). Crop production in EKSRB comprises a mix of rainfed and irrigated croplands, with irrigation playing a crucial role in growing water-demanding crops such as maize and soybean. There are over 2,900 irrigated maize fields in EKSRB, resulting in over 55,000 acres. It is important to note that the majority of the large irrigated fields are located in the alluvial plain of the Kansas River (Fig. 1; Onyekwelu et al., 2025). There are over 100 unique dominant soil types, with variable distributions of different textures as shown in Fig. 1.

The average growing season rainfall (between April and September) in EKSRB ranges from 472 mm in the west and 520 mm in the east, showing an increasing trend from west to east (Onyekwelu & Sharda, 2024b). Growing season temperatures (Tmin and Tmax) increase from east to west, with values ranging from 16 to 17.5 °C and 28.5 to 30 °C, respectively. Solar radiation (SRAD), on the other hand, is fairly stable, with an average value of 22.2 $MJm^{-2}d^{-1}$ in the west and 21.3 $MJm^{-2}d^{-1}$ in the east (Onyekwelu & Sharda, 2024b).

2.2. CERES-Maize model: Spatial implementation

The present study used the CERES-Maize model within the Decision Support System for Agrotechnology Transfer (DSSAT version 4.7.5, hereafter), for simulating maize yield and irrigation water use under different future climate scenarios and adaptation strategies (Jones et al., 2003; Onyekwelu & Sharda, 2024b; Ritchie et al., 1998). As it is quite common with this class of models, it assumes a homogeneous unit of land for simulating crop growth and development, taking into account different management practices and weather variables (Jones et al., 2003). The DSSAT application software currently comprises over 40

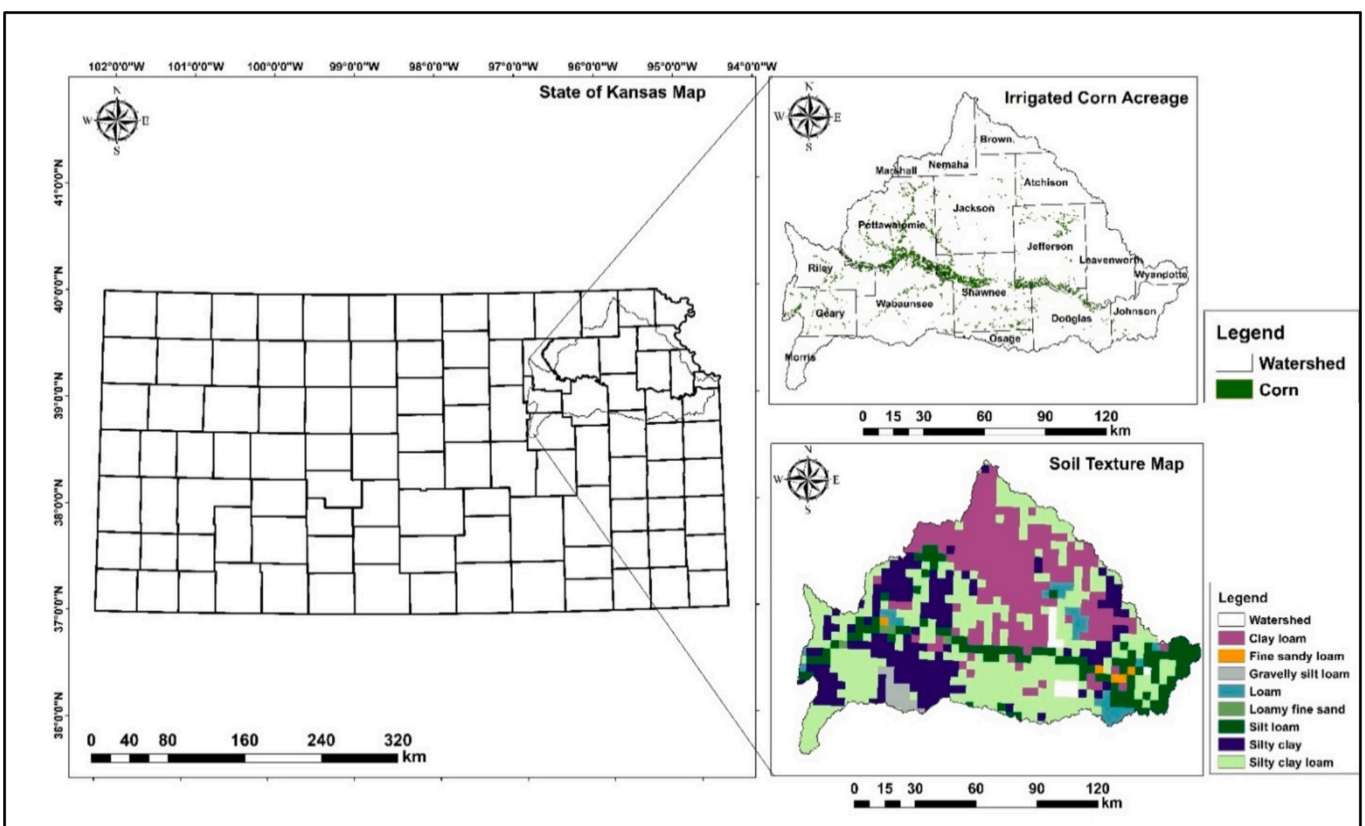

Fig. 1. Inset map of the study area (EKSRB in the State of Kansas map) with irrigated maize acreage and spatial soil textures shown in the upper and lower right, respectively.

crop simulation models, with new modules being developed for handling different processes, such as yield forecasting (Hoogenboom et al., 2019). The minimum climate datasets required to run the CERES-Maize model include daily minimum and maximum air temperatures, rainfall, and SRAD. The model also accounts for soil information, management data (irrigation, nutrients, and planting conditions), initial conditions at planting, and cultivar characteristics represented as genotype-specific coefficients (Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025). Thus, it is possible to use this model for evaluating the effects of various genotype-specific traits and agronomic management on irrigated maize yield and water use, and for designing maize ideotypes for climate change mitigation (Onyekwelu & Sharda, 2024b).

While the DSSAT and its suites of crop simulation models have been used extensively across a wide range of studies, they are designed to run at a point scale for representing a homogeneous agricultural unit and, as such, lack any spatially distributed or spatial-oriented user interface for location-specific simulation of cropping systems. In addition, because climate change impacts are spatially variable, understanding how different locations respond to varying management and atmospheric conditions is necessary for designing strategic adaptation to mitigate climate impacts. As a result, the DSSAT spatial execution file (*.GSX) was used to link grid-level soil and climate inputs to simulate grid-specific impacts. A top-down spatial protocol reported by Onyekwelu et al. (2025) was adopted to simulate irrigated maize productivity in EKSRB. The region was first divided into 4 km grids, representing the finest resolution possible for matching the input meteorological datasets required to run the model (Fig. 2). This approach resulted in 1024 grids in the region, with unique soil and atmospheric conditions (Fig. 2). The grid information were then used to access areas in the region where irrigated maize grows utilizing a combination of the USDA CropScape Crop Data Layer (https://nassgeodata.gmu.edu/CropScape; Han et al., 2012) for total maize (rainfed and irrigated) acreage, gSSURGO (Gridded Soil Survey Geographic) for detailed spatial soil distribution (Soil Survey Staff, 2022), and Landsat-based irrigation dataset (LANID) for cropland irrigation in the contiguous United States (Xie et al., 2021; Xie & Lark, 2021). To filter only irrigated maize fields in the region, a geoprocessing operation in ArcMap 10.7 was performed to compute geometric intersections between maize fields that overlap the irrigation map (LANID) and the attendant soil information. Irrigated maize-growing grids were assigned by linking the resulting irrigated fields with the 1024 regional grid counts using zonal statistics (Onyekwelu et al., 2025). The final result was 402 grids, representing unique locations where irrigated maize grows for the model simulation in the region (Fig. 2).

The updated spatial grid information was used to retrieve weather variables and crop management inputs required for model simulation. Model outputs were spatially integrated to each unique grid location using the corresponding grid centroids. All spatial mapping and analytical procedures were conducted within the Python programming environment, leveraging the GeoPandas, Pandas, Cartopy, and Matplotlib libraries (Jordahl et al., 2021; Hunter, 2007; Onyekwelu et al., 2025).

2.3. Model input preparation and long-term spatial simulation

We developed sets of Python scripts to retrieve and convert grid-level weather and soil datasets into DSSAT-compatible formats (*.WTH and *.SOL, respectively). Soil data retrieved from the gSSURGO at 30 m were regridded to 4 km to match the scale of our modeling unit. Similarly, historical climate information at 4 km were retrieved for each grid from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) (PRISM Climate Group, 2014) Group for a period of 25 years (1991 – 2015).

A previously calibrated and validated regional CERES-Maize model, using 13 site-years of maize yield data and 10 years of irrigation water use data from 92 wells (Onyekwelu et al., 2025), was used. As it has been observed for the CERES class models in DSSAT, the issue of equifinality of genotype-specific parameters was reported by Onyekwelu et al. (2025), and as documented by (Lamsal et al., 2018). However, since the interest of this study is focused on assessing in-silico climate impacts and adaptation strategies on yield and resource use without inferring any underpinning genetics for immediate breeding, the impact of equifinality is not a concern (Lamsal et al., 2018). In addition, several other studies have explored in-silico adaptation methods to provide insights into potential yield improvements and resource maximization under climate change (Kothari et al., 2019, 2020; Onyekwelu & Sharda, 2024b; Singh et al., 2014).

To conduct long-term simulations, spatially dependent (county-

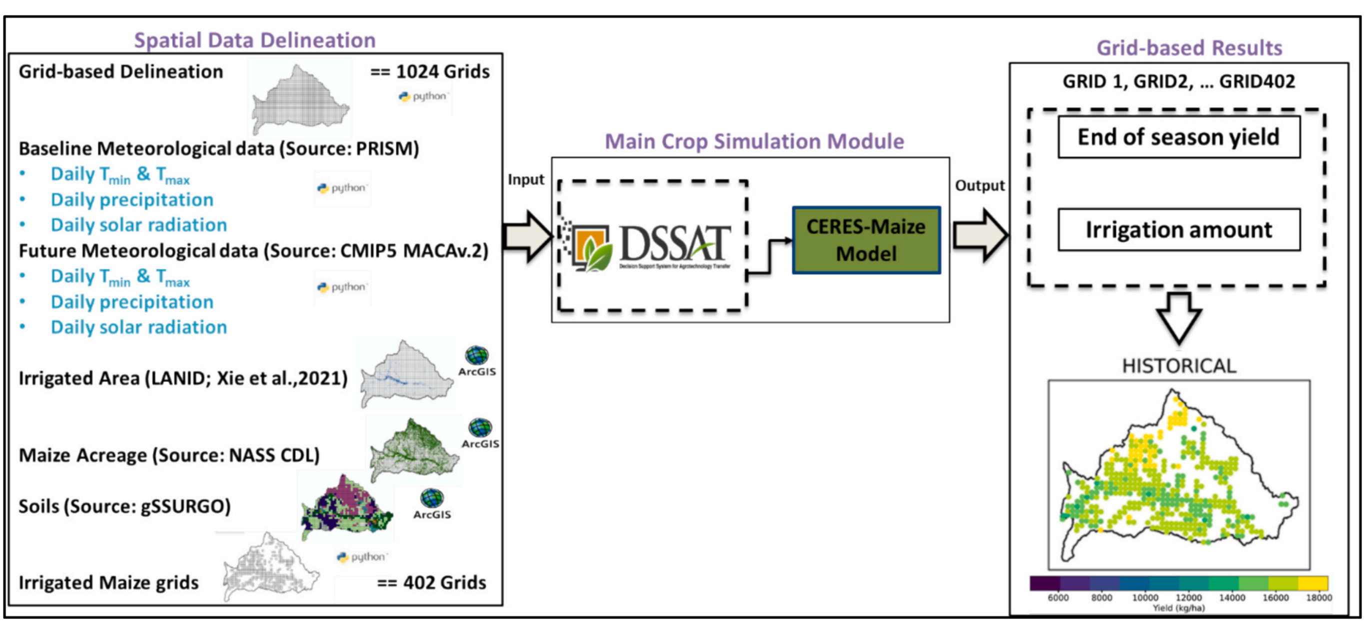

Fig. 2. Workflow for spatially distributed irrigated maize simulation using the DSSAT CERES-Maize model by integrating grid-based inputs to generate grid-specific results (yield, and irrigation water use), visualized as grid-specific spatial output maps.
Adapted from Onyekwelu et al. (2025).

scale) management practices for maize production in the region were implemented based on the information reported in Table S1 and Fig. S4 (K-State Extension 2022). According to K-State Extension (2022), there are two planting zones (zone 2 and 3) in the region, with planting dates ranging from 15th April to 10th May for zone 2, and 1st April to 5th May for zone 3 (Table S1). Maize was planted in each grid at a seeding rate of 10 plants/m^2, row spacing of 76 cm, and planting depth of 5 cm (Table S1, K-State Extension, 2022; Lingenfelser et al., 2015; Onyekwelu & Sharda, 2024b; Sassenrath et al., 2021). Since each grid in the model is a unique combination of soil and climate, no two grids share the same input. Therefore, we treated each grid as a spatially independent unit, capable of providing location-specific insight. Initial soil moisture conditions assumed that the grid-level soil profiles were at field capacity at planting. In addition, the initial soil nitrogen was set to 25 kg Nha^{-1}, assuming 1 % soil organic matter content (Onyekwelu & Sharda, 2024b). In-season fertilizer applications were set according to regional recommendations (K-State Extension, 2007, 2022) and as per the variety trial reports (Lingenfelser et al., 2015; Sassenrath et al., 2021). Under historical conditions, irrigation allocation in each grid was managed at 50 % management allowable depletion (MAD), which represents the current farmers' choice water management regime required to fill the soil profile to field capacity (FC) in the region (Onyekwelu et al., 2025). However, deficit irrigation approach was adopted under future climate conditions based on our previous study in the region reporting substantial irrigation increase (up to 32 %) under full irrigation without yield improvement (Onyekwelu et al., 2025). The deficit irrigation strategy was achieved by managing irrigation allocation in each grid at 75 % MAD, allowing 25 % of soil water before the next irrigation event automatically returned it to FC (Onyekwelu et al., 2025). This strategy represents the greatest potential for improved water management for balancing hydrologic and agronomic trade-offs under future climate conditions (Onyekwelu et al., 2025).

To accurately capture the effects of CO_2 on seasonal biomass accumulation and transpiration, dynamic CO_2 values were used. To evaluate historical and future climate impacts on maize productivity, the model was run from 1991 to 2099, driven by historical climate information and future climate data from the CMIP5 model family. Details on the future climate scenarios and the global climate models (GCMs) used are presented in the following section.

2.4. Future climate scenarios

Future climate scenario impacts on irrigated maize production were simulated for each of the 402 unique grids in the region. We selected the scenarios based on RCPs 4.5 and 8.5, divided into three time slices: 2030 s (early century), 2060 s (mid-century), and 2090 s (late century). Details on the RCPs (4.5 and 8.5) have been reported in our previous study (Onyekwelu et al., 2025). Daily weather variables (SRAD, rainfall, Tmin, and Tmax) were obtained for CMIP5 GCMs available from the MACA-2 database at https://climate.northwestknowledge.net/MACA/data_portal.php (Abatzoglou, 2013; Abatzoglou & Brown, 2012). These datasets are available at 4 km resolution and cover the conterminous United States. In addition, the resolution of this dataset matches the resolution of our modeling unit. The datasets have been statistically downscaled and bias-adjusted using the Multivariate Adaptive Constructed Analogs (MACA v2) method (Abatzoglou, 2013; Abatzoglou & Brown, 2012), and have been used by several studies (Onyekwelu et al., 2024; Kothari et al., 2020, 2021; Yang & Wang, 2023; Sen et al., 2024).

While the CMIP6 climate models represent the current update in future atmospheric climate simulations, recent studies have used CMIP5 climate models for climate impact studies and have shown comparable results to CMIP6 (Dahri et al., 2024; Dehghan Moroozeh et al., 2024; Guarin et al., 2022, 2023; Hamlet et al., 2024; Jha et al., 2024; Stella et al., 2023; Trancoso et al., 2024; Try et al., 2022; Onyekwelu et al., 2025). The results from these studies suggest that the selection of CMIP5 in this study, instead of CMIP6, likely does not have any substantial impact on our findings. However, to ensure robust model simulation and to account for GCM-related uncertainty, five GCMs spanning the full range of climate sensitivities were used. This was based on sensitivity labeling reported by Onyekwelu et al. (2025) and Yang & Wang (2023), and as shown in Table 1 below. CO_2 impacts on biophysical processes were captured using dynamic CO_2 values for the two RCPs from 2025 to 2099. After model simulation, maize productivity outcomes (yield and irrigation water use) for the five selected GCMs were averaged per grid across different time slices and RCPs to obtain ensemble averages, which were then compared with the historical period (1991–2015). In addition, we conducted regression analysis to understand the effect of changes in growing season length on yield in the region under both RCPs.

2.5. Climate impact adaptation strategies

According to Lobell (2014), adaptation is any agricultural practice or activity that reduces negative climate impacts while enhancing positive impacts (Onyekwelu & Sharda, 2024b). Based on this definition, one of the objectives of this study was to assess the impacts of different in silico adaptation strategies on maize yield and irrigation water use under future climate conditions. Model simulations were first conducted under a no-adaptation strategy to benchmark the impacts of future climate on yield and irrigation water use in the region. A set of adaptation strategies was implemented under three categories (Fig. 3): genotype-specific adaptations (Ge), agronomic adaptations (Ag), and integrated adaptations (Int). These adaptation strategies were implemented based on evidence found in the literature, preliminary analysis, and the need to improve yield to meet the expected grain demand to feed the growing population (Ciampitti & Lemaire, 2022; Getachew et al., 2021; Guarin et al., 2022, 2023; Liu et al., 2013; Martre et al., 2024; Stella et al., 2023; Tesfaye et al., 2017, 2018). A total of 10 climate adaptation strategies aimed at improving maize yield and maintaining irrigation water savings were assessed. Each adaptation strategy simulation was executed based on the five GCMs, two RCP scenarios, 402 maize-growing grids, one irrigation scenario, and over 75 years of simulation in the future; thus, making a total of 301,500 runs per adaptation. Details of different adaptation categories are presented below (Fig. 3).

2.5.1. Genotype-specific adaptation strategies (Ge)

The "cultivar", "species", and "ecotype" parameters in the CERES-Maize model are collectively referred to as genotype parameters (Hoogenboom et al., 2019). The genotype-specific adaptations were termed "ideotypes" to refer to combinations of ideal traits needed to achieve yield improvement and water savings under future climate conditions (Mi et al., 2016). These genotype-specific adaptation strategies were based on evidence reported for improved maize varieties, with improved canopy photosynthesis (radiation use efficiency; RUE), improved light extinction (KCAN), and heat tolerance under extreme air temperatures (Guarin et al., 2022, 2023; Martre et al., 2024; Mi et al., 2016; Stella et al., 2023; Tesfaye et al., 2017).

2.5.1.1. Ideotype I – Radiation use efficiency (RUE). An ideotype with improved canopy photosynthesis was created by increasing the benchmark RUE value of the reference cultivar by 20 %. This approach is consistent with findings in the literature for high-yielding maize cultivars around the globe. For example, studies in the US have shown that recent advances in maize genetics have seen RUE values ranging from 3 to 5.5 g MJ^{-1} (Shi et al., 2022). According to Shi et al. (2022), RUE values obtained from different field experiments around the world range from 1.05 to 5.74g MJ^{-1}. Loomis & Amthor (1999) has indicated that the maximum RUE value of a closed maize canopy is around 5.5g MJ^{-1}. The benchmark values for RUE of reference cultivars in the CERES-Maize model range from 2.0 to 4.5 g MJ^{-1}, with a mean value of 4.1 g

Table 1
List of selected CMIP5 GCMs.

GCM	Country	Climate sensitivity	Ensemble member	Native Resolution (deg. lon x deg. lat)	Downscaled Resolution (km x km)	Reference
BCC-CSM1-1	China	Low	r1i1p1f1	2.8 x 2.8	4 x 4	(Abatzoglou, 2013)
GFDL-ESM2M	USA	Low	r1i1p1f1	2.5 x 2.0	4 x 4	(Abatzoglou, 2013)
CanESM2	Canada	High	r1i1p1f1	2.8 x 2.8	4 x 4	(Abatzoglou, 2013)
CNRM-CM5	France	High	r1i1p1f1	1.4 x 1.4	4 x 4	(Abatzoglou, 2013)
CCSM4	USA	Medium	r6i1p1f1	1.25 x 0.94	4 x 4	(Abatzoglou, 2013)

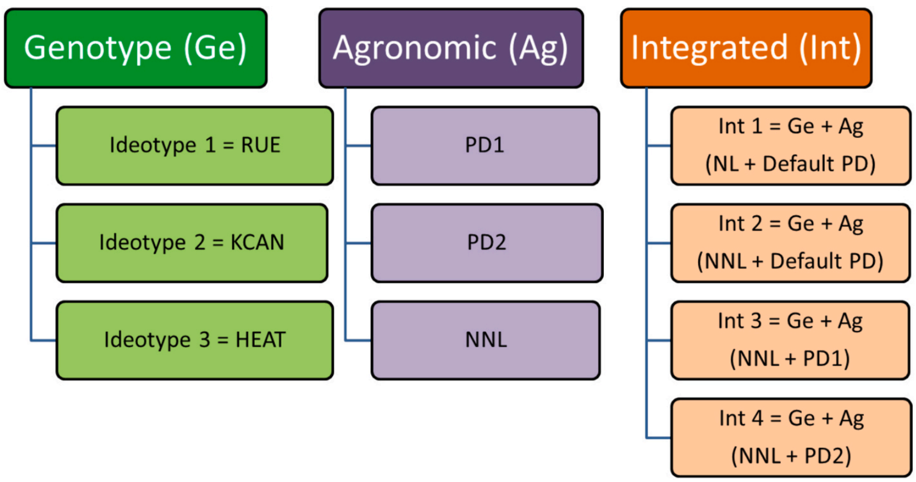

Fig. 3. Adaptation strategies based on genotype designed as ideotypes, agronomic management, and integrated, designed by linking genotype-specific adaptations with agronomic managements.

MJ^{-1} after calibration (Hoogenboom et al., 2019; Onyekwelu et al., 2025). This value was increased to 4.92 g MJ^{-1} (20 % increase) and was within the limits of RUE estimated from field experiments (Shi et al., 2022; Wei et al., 2017).

2.5.1.2. Ideotype II – Light extinction coefficient (KCAN). Studies across different fronts have shown that recent advances in breeding have improved KCAN (Guarin et al., 2022, 2023; Martre et al., 2024; Stella et al., 2023). According to Guarin et al. (2022), advances in doubled-haploid wheat varieties relative to traditional varieties have seen KCAN increased by 10 %; thus, supporting evidence for increasing yield potential, especially under climate change. Successful modeling of plant growth relies on adequate description of KCAN for intercepted photosynthetically active radiation distribution (Wei et al., 2017). The benchmark value for KCAN within the CERES-Maize model is 0.85 after calibration. An ideotype with improved KCAN was created by increasing the benchmark value by 9 %.

2.5.1.3. Ideotype III – Heat tolerance (HEAT). Although maize is a summer crop, it is very sensitive to high daily temperatures during the growing season (Tesfaye et al., 2018). With increasing temperatures under future climate scenarios, optimal growing temperatures for maize may fluctuate between day and night and over the growing season. The sensitivity of maize to high temperatures affects grain-filling rate and duration. Therefore, a heat-tolerant ideotype was created by modifying the optimum and maximum temperature parameters (Topt and Tmax, respectively) that affect relative grain-filling rate (RGFIL). In the CERES-Maize model, the RGFIL is a daily timestep temperature function (Hoogenboom et al., 2019) with values ranging from 0 to 1 (for limiting and non-limiting conditions, respectively). Accordingly, the heat-tolerant ideotype was created by increasing the Topt and Tmax parameter values of the reference cultivar by 2 °C. This is similar to the methods used by Singh et al. (2014) and Tesfaye et al. (2018) in CERES-Sorghum and CERES-Maize models, respectively.

2.5.2. Agronomic adaptation strategies (Ag)

The agronomic adaptation strategies came from the awareness of risk-averse cropping systems and were implemented to explore changes in management practices that could lead to yield improvements and water savings under future climate conditions. Details of the individual implementations are found below.

2.5.2.1. Planting dates – PD1 and PD2. Early planting has been shown to mitigate yield losses due to climate change. In a study conducted in Ethiopia, they found that early planting of sorghum resulted in better yield compared to the baseline planting dates (Getachew et al., 2021). In this study, two early planting strategies were created as follows: PD1 and PD2 (Fig. 3, planting dates 1 and 2, respectively) implemented by shifting the baseline county-level planting dates (presented in Table S1) behind by one week and two weeks (7 and 14 days), respectively.

2.5.2.2. No nutrient limitation – NNL. No nutrient limitation condition was implemented by turning off the nutrient balance and simulation routines in the CERES-Maize model to ensure potential nutrient allocation throughout the growing season, while mimicking strategic nutrient allocation as needed and when the plant needs them. Studies have shown that nutrient management and needs will increase for some crops, especially under future climate conditions. For example, Martre et al. (2024) reported that global nitrogen fertilizer needs for wheat yield improvement will increase under climate change. In another study, Liu et al. (2016) reported that maize yield gap of up to 40 % could be reduced by improving local agronomic management (fertilizer input and selecting high-yielding cultivars). Overall, the choice of implementing NNL as an adaptation strategy represents a real opportunity to maximize maize production in the face of climate risks and soil degradation.

2.5.3. Integrated adaptation strategies (Int)

The genotype-specific and agronomic adaptation strategies were stacked to develop different levels of integrated adaptation strategies (Fig. 3). The strategies were implemented to ensure that targeting yield improvement and water savings may not be realized in isolation or through a single farming practice. Based on that, four levels of integrated adaptation strategies (Int) were implemented as follows: Ge + Ag (Int 1; NL + Default PD), Ge + Ag (Int 2; NNL + Default PD), Ge + Ag (Int 3; NNL + PD1), and Ge + Ag (Int 4; NNL + PD4). Int 1 (NL + Default PD). Int 1 integrated all levels of genotype-specific adaptation with limiting nutrient (NL; default nutrient recommendation) condition and county-level baseline planting dates (Default PD) to assess its impact on yield and water use. Similarly, Int 2 (NNL + Default PD) combined all levels of genotype-specific adaptation with a no nutrient limitation (NNL) condition and county-level baseline planting dates (Default PD). Int 3 and Int 4 (NNL + PD1 and NNL + PD2, respectively) linked all genotype-specific and NNL adaptation strategies, but with county-level baseline planting dates shifted by 7 and 14 days early, respectively. It is important to note that the level of adaptation strategies, coupled with the spatially distributed modeling approach presented here, is the first of its kind in the Great Plains.

3. Results and discussion

3.1. Growing season future climate deviations in EKSRB

Figs. 4–6 show future climate deviations from historical conditions for Tmin, Tmax, and rainfall, respectively. We defined deviation as the difference between future climate conditions and the historical averages of each variable (minimum and maximum temperatures, and rainfall) per grid. Climate deviations are shown for both RCPs 4.5 and 8.5 over three future time periods (2030 s, 2060 s, and 2090 s). The spatial distribution of Tmin deviation under RCP 4.5 ranges from 0.9 to 1.5 °C under 2030 s, 1 to 2 °C under 2060 s, and 1.5 to 2.5 °C under 2090 s time periods (Fig. 4). These deviations, except under 2090 s, are consistent with the Paris Agreement (United Nations, 2015), which aims to stabilize temperatures well below 2 °C. The Paris Agreement pursues efforts to limit the temperature increase to 1.5 °C (Brown et al., 2018; United Nations, 2015); however, studies have shown the impacts of temperature increase at 1 to 1.5 °C on cropping systems without adaptation. For instance, Onyekwelu & Sharda (2024b) showed that for a 1 °C rise in Tmin, a 14 % to 25 % maize yield loss was observed in eastern Great Plains under rainfed conditions. Tmin deviation under RCP 8.5 (Fig. 4) ranges from 0.9 to 1.7 °C in 2030 s, 2.0 to 3.2 °C in 2060 s, and 3.2 to 4.0 °C in 2090 s. These deviations are far from the Paris Agreement's 2.0 °C stabilization target, especially in the 2060 s and 2090 s.

The gradual increase in Tmin deviation observed under RCP 4.5 was absent under RCP 8.5, suggesting strong atmospheric forcing in the high-emission pathway. It is important to note that Tmin deviations increase from east to west, a trend consistent with the regional aridity gradient of the Great Plains (Onyekwelu & Sharda, 2024b; Seager et al., 2018).

Fig. 5 shows the Tmax spatial deviations under RCPs 4.5 and 8.5, with values ranging from 0.9 to 1.5 °C under 2030 s (both 4.5 and 8.5), 1.2 to 2 °C and 2 to 3.2 °C under 2060 s (4.5 and 8.5, respectively), and 2 to 2.5 °C and 3.2 to > 5.0 °C under 2090 s (4.5 and 8.5, respectively) time periods (Fig. 5). The deviations observed for Tmax follow similar patterns found in Tmin, especially under RCP 8.5, but largely deviates under RCP 4.5. This suggests that atmospheric forcings mediating Tmin and Tmax changes under RCP 8.5 might be similar; however, because Tmax values are higher, the separation of these forcing mediation effects is more distinct and pronounced in the region. It is important to note that, similar to Tmin under RCP 4.5, the deviations found in Tmax under RCP 4.5 are consistent with the Paris Agreement (United Nations, 2015; Onyekwelu et al., 2025). However, the impact of a 1 °C rise in Tmax has been found to result in maize yield loss ranging from 10 % to 18 % (Onyekwelu & Sharda, 2024b).

While the spatial distribution of Tmax deviation under all RCPs increases from east to west, the gradual increase observed under RCP 4.5 was absent in RCP 8.5, indicating significant atmospheric forcing

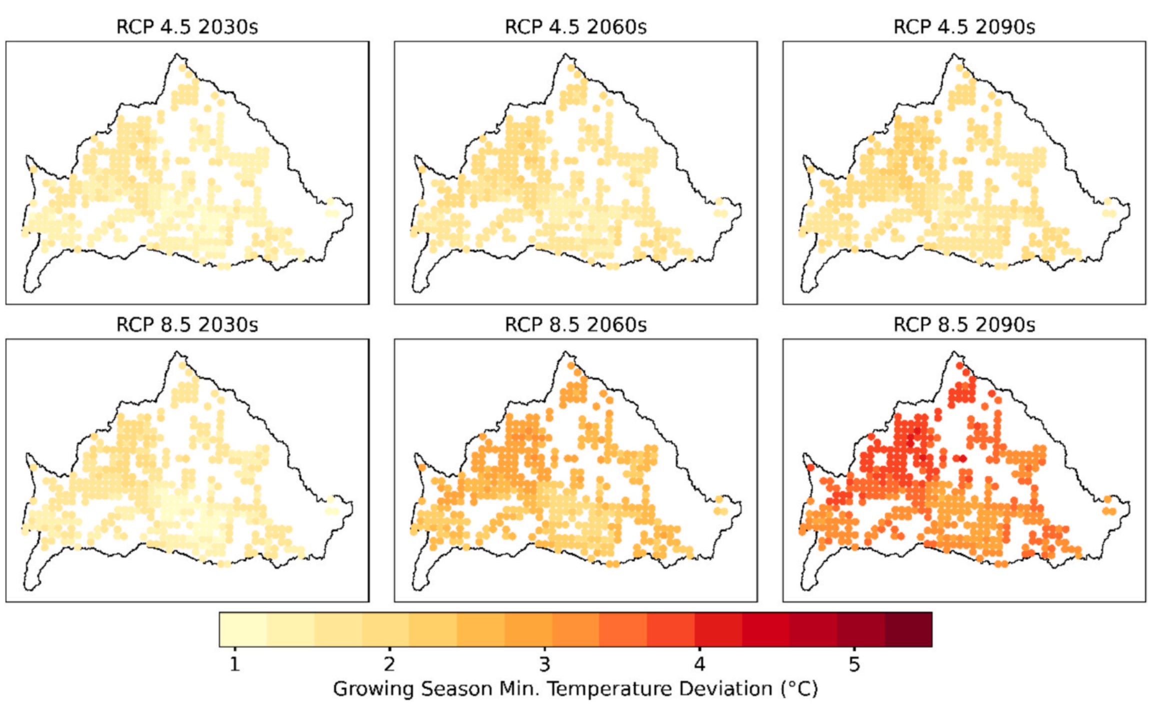

Fig. 4. Growing season minimum temperature deviation for RCPs 4.5 and 8.5 over three future time periods (2030 s, 2060 s, and 2090 s).

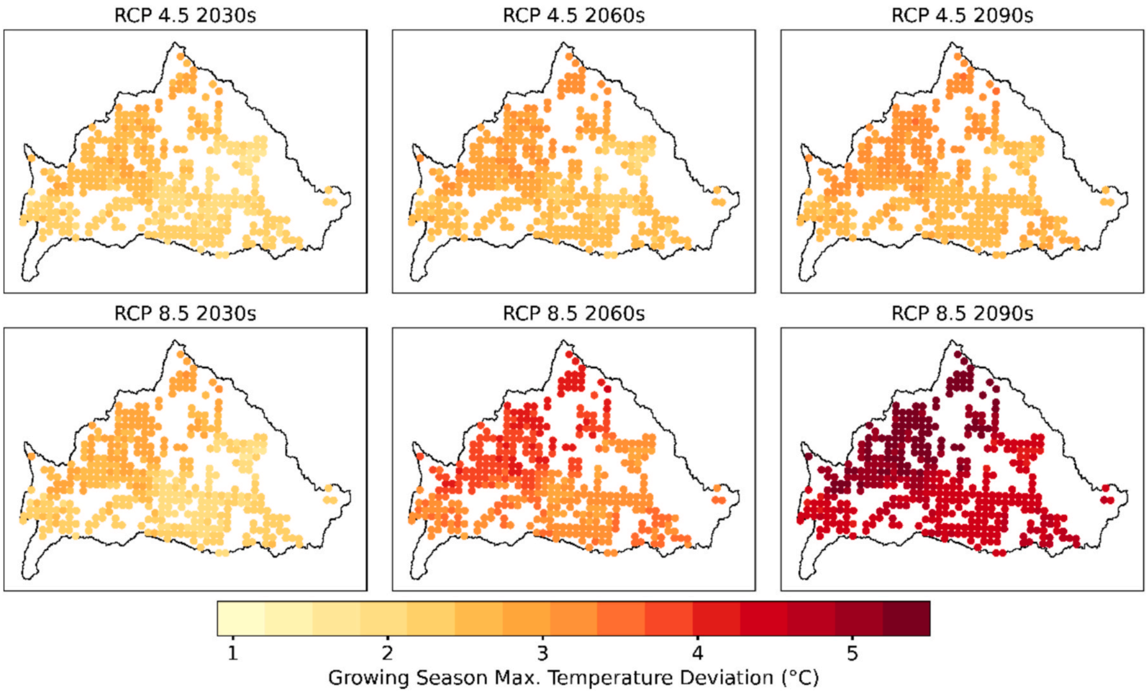

Fig. 5. Growing season maximum temperature deviation for RCPs 4.5 and 8.5 over three future time periods (2030 s, 2060 s, and 2090 s).

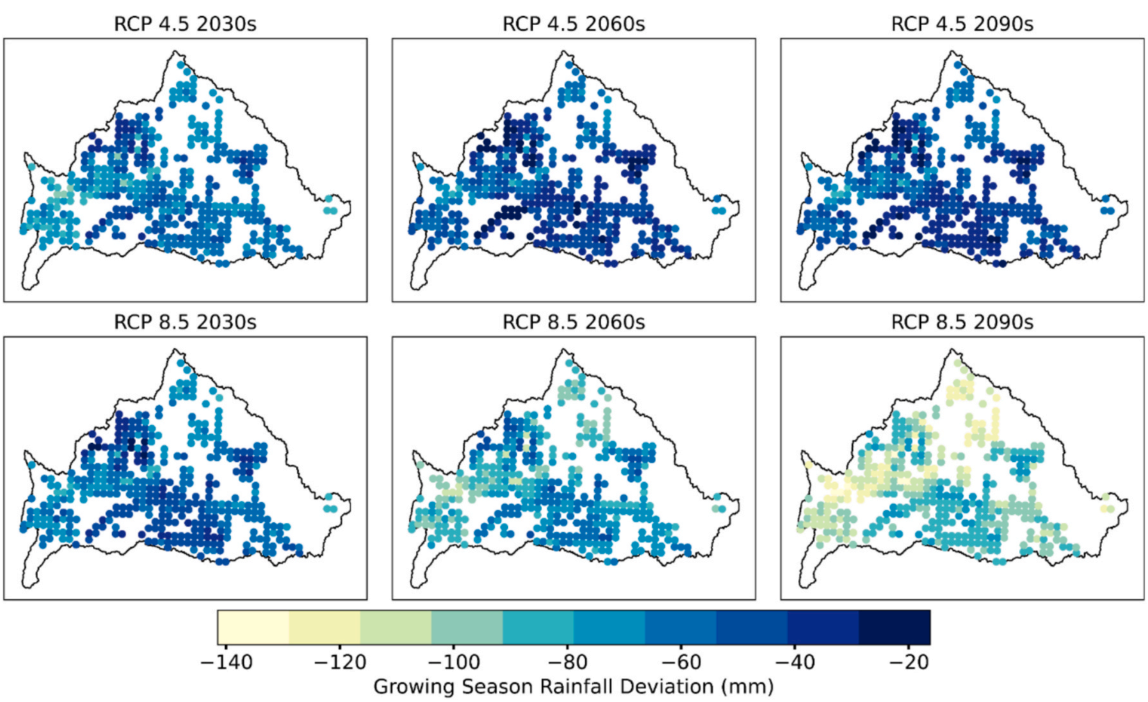

Fig. 6. Growing season rainfall deviation for RCPs 4.5 and 8.5 over three future time periods (2030 s, 2060 s, and 2090 s).

present under high-emission scenarios of 8.5. Previous studies have reported results similar to those observed in this study. For example, Ruosteenoja et al. (2016) found that climate change projections for Finland over the next few decades are fairly similar across all RCP scenarios. However, in the second half of the century, they reported that regional climate evolution is highly dependent on greenhouse gas emissions. They also found that summer warming deviation ranges from 1 to 4 °C, similar to growing season Tmax deviation found in this study.

The spatial deviation of growing season rainfall from the historical conditions shows declining values under all RCPs and the three time periods in the future (Fig. 6). Results revealed that deviation values decreased going into the future under RCP 4.5, with deviation range in the 2090 s potentially insignificant (−60 mm to −15 mm) compared to 2060 s (−75 mm to −20 mm) and 2030 s (−100 mm to −30 mm; Fig. 6). This pattern of rainfall deviation can be attributed to several mechanisms, driven by climate dynamics, atmospheric composition, and regional feedback. For instance, under RCP 4.5, greenhouse gas concentrations continue to rise until mid-century before stabilization (IPCC, 2023). Based on atmospheric feedback, a warming atmosphere can hold more water vapor due to the Clausius-Clapeyron relationship, increasing atmospheric moisture content by approximately 7 % per °C of warming (Trenberth, 2011). This could be the reason for the lesser decline in growing-season rainfall observed later in the 21st century under RCP 4.5 in this study. Conversely, the pattern of growing season rainfall deviation under RCP 8.5 shows a further decrease in spatial trend in future time periods (2030 s to 2090 s; Fig. 6). Bhatta et al. (2019) reported that under RCP 8.5 during the late 21st century, rainfall is projected to decrease by 4.5 %. Since RCP 8.5 represents a high-emission scenario leading to significant global warming, intensified warming under this scenario may disrupt atmospheric circulation systems, leading to uncertain and drastic decline in rainfall (Trenberth & Asrar, 2014; Trenberth, 2011). It is important to note that the pattern of growing season rainfall deviation is stronger in the west than in the eastern portion of the region; a spatial trend consistent with the regional rainfall gradient of the Great Plains (Onyekwelu & Sharda, 2024b; Seager et al., 2018).

With temperature and rainfall deviations from the historical reaching up to 5 °C and −140 mm, growing irrigated maize under these climate conditions without adaptation may result in yield failure and reduced irrigation water productivity. Therefore, implementing adaptation strategies aimed at improving maize yield and maintaining irrigation water savings under these climate conditions is essential for meeting the expected grain demand while also conserving water resources to ensure gradual improvement in aquifer recovery.

3.2. Yield and irrigation sensitivities to future climate and adaptation in the early 21st century (2030 s)

Figs. 7 and 8 show maize yield sensitivity to historical and future climate conditions, and different adaptation strategies under RCPs 4.5 and 8.5. We observed no significant spatial pattern in the historical (HISTORICAL) yield distribution; however, high yield values dominated in the northern part of the region. This suggests that irrigated yield distribution under historical conditions might be controlled by a myriad of factors, including spatial soil textures and climate variables, county-level planting conditions, irrigation, and so on. Previous studies have shown that irrigated maize yield in the region is primarily controlled by soil type and growing season climate conditions (Onyekwelu et al., 2025).

It was observed that maize yield in the early 21st century declined (relative to historical yield) by −34 % under RCP 4.5 (Fig. 7, Table 2) and –33 % under RCP 8.5 (Fig. 8, Table 2). Yield decline may have occurred primarily due to warming-induced stresses and shortened growing season length (GSL). We observed in this study that GSL shortened by 12 to 18 days under RCP 4.5, and 12 to 20 days under RCP 8.5 in the early 21st century. These results agree with findings reported in the literature. For example, Araya et al. (2017) found that maize yield decline in Western Kansas ranged from 10 % to 60 % and 5 % to 80 % (RCPs 4.5 and 8.5, respectively). In addition, they observed that shortened GSL in the range 18–24 days may have triggered yield loss under future climate conditions. Interestingly, our further analysis using regression analysis revealed that a one day short in GSL may result in about 243 kgha^{-1} yield loss under RCP 4.5, and 321 kgha^{-1} under RCP 8.5 (Fig. 9). This suggests that while decline in GSL may result in maize production losses under current seed varieties, breeding strategies that prioritize early maturing hybrids may adapt to shorter growing seasons and help stabilize or even enhance yield under changing climatic conditions.

The similar decline responses found between RCPs 4.5 and 8.5, as reported previously, suggest comparable climatic controls in the region under both RCPs. For example, our findings in this study revealed that growing season Tmin and Tmax distributions show similar pattern in the region (Figs. 4 and 5). The 1 % marginal gain under RCP 8.5 may be due to CO_2 fertilization effects (Tubiello & Ewert, 2002; Onyekwelu et al., 2025), resulting partly due to higher CO_2 emission under RCP 8.5,

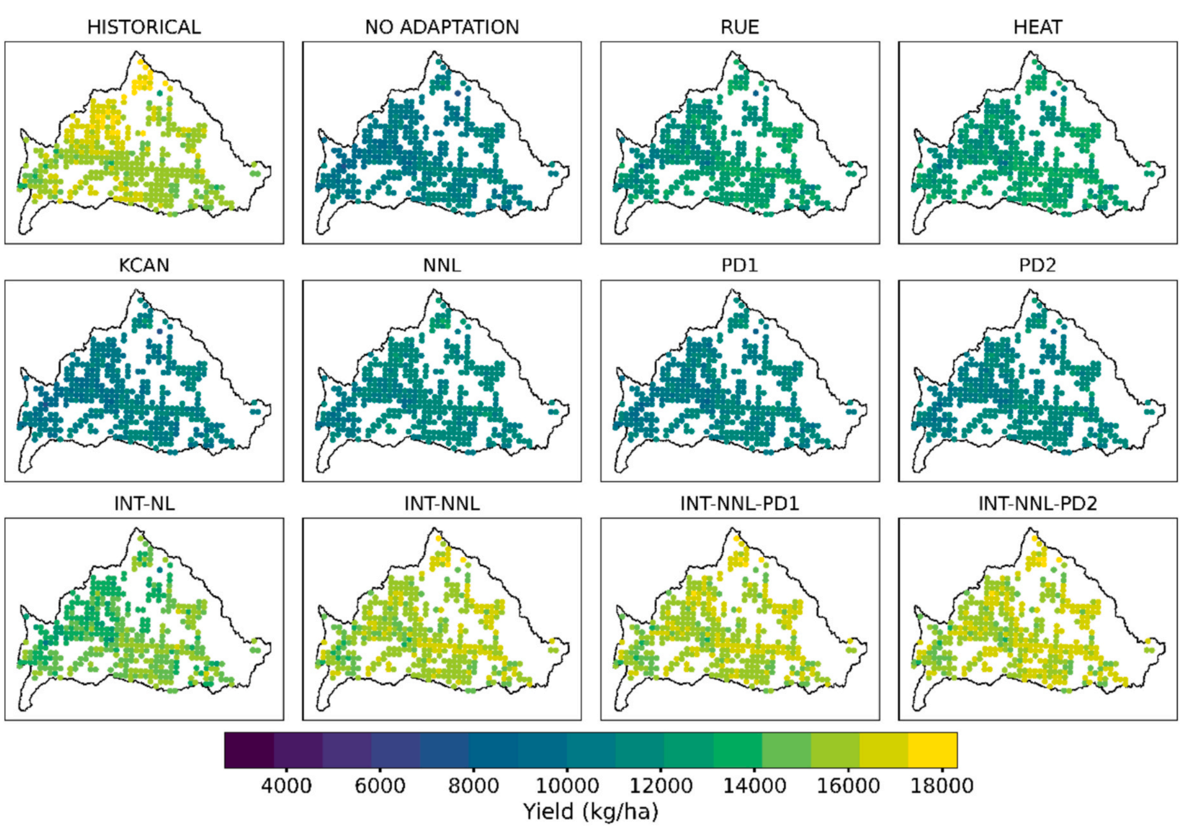

Fig. 7. Yield sensitivity under RCP 4.5 (2030 s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

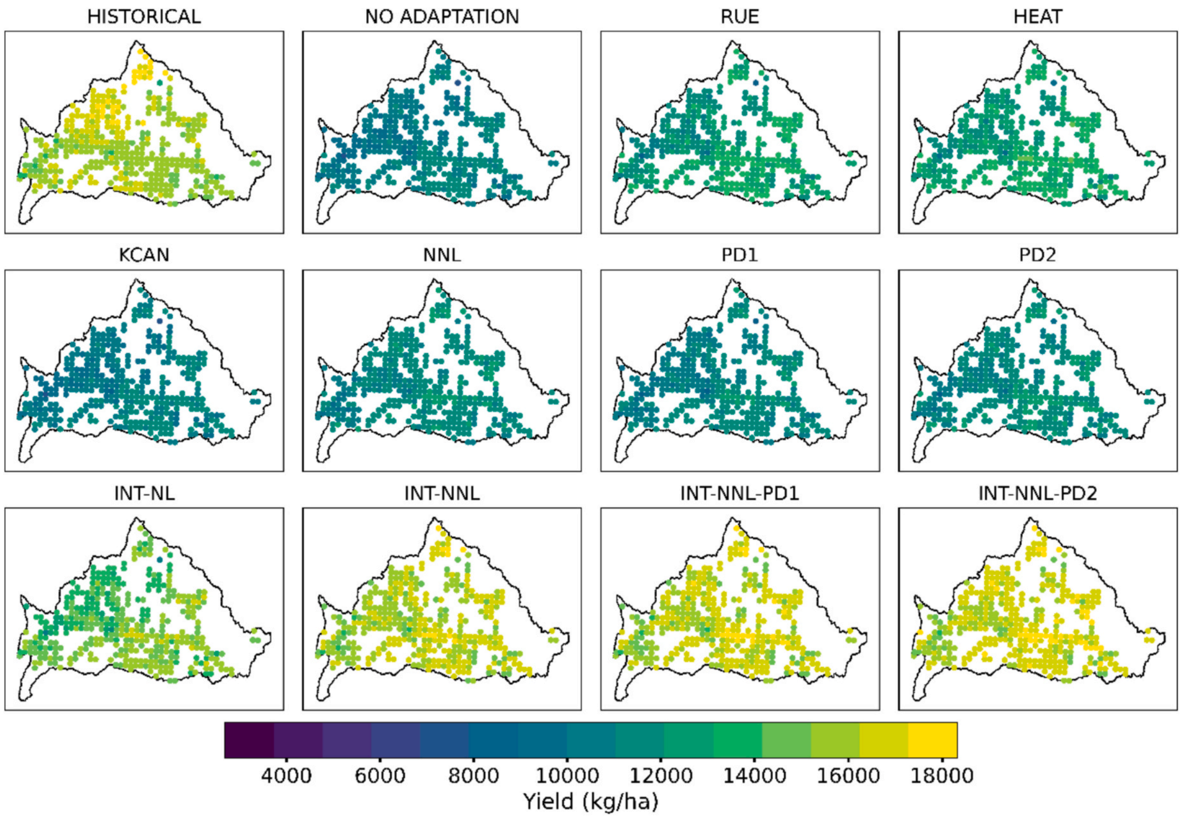

Fig. 8. Yield sensitivity under RCP 8.5 (2030 s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

Table 2
Simulated mean changes (%) in yield and irrigation water use in EKSRB under different climate scenarios and adaptation strategies with respect to historical conditions.

		Grain yield changes (%)						Irrigation water use changes (%)					
		2030s		2060s		2090s		2030s		2060s		2090s	
Adaptation Strategies	**RCP Scenarios**	**4.5**	**8.5**	**4.5**	**8.5**	**4.5**	**8.5**	**4.5**	**8.5**	**4.5**	**8.5**	**4.5**	**8.5**
	No Adaptation	-34	-33	-38	-51	-43	-68	-9	-13	-13	-15	-20	-18
Genotype	Ideotype 1 (RUE)	-23	-22	-28	-43	-33	-64	-11	-15	-15	-17	-22	-20
	Ideotype 2 (KCAN)	-34	-33	-39	-51	-42	-69	-8	-11	-12	-13	-19	-16
	Ideotype 3 (HEAT)	-21	-20	-25	-36	-28	-55	-7	-11	-12	-11	-16	-10
Agronomic	PD1	-32	-30	-36	-48	-40	-65	-10	-12	-13	-15	-20	-17
	PD2	-30	-28	-34	-45	-37	-62	-9	-12	-13	-15	-20	-16
	NNL	-29	-29	-34	-46	-38	-64	-9	-13	-13	-13	-19	-14
Integrated	Int 1 (INT-NL)	-9	-8	-13	-26	-17	-48	-8	-12	-12	-12	-16	-10
	Int 2 (INT-NNL)	-0.9	0.6	-5	-17	-9	-39	-7	-11	-11	-10	-15	-6
	Int 3 (INT-NNL-PD1)	-0.2	1.8	-3	-15	-7	-36	-9	-12	-13	-12	-16	-8
	Int 4 (INT-NNL-PD2)	0.6	3	-2	-13	-6	-33	-10	-13	-14	-13	-18	-10

although having similar temperature range to RCP 4.5 (Figs. 4 and 5). Relative to the historical yield distribution (Figs. 7 and 8), there are clear east-to-west gradients in yield distributions, with lower yields towards the western side of the region under both RCPs, suggesting potential temperature-mediated impacts. These findings agree with the previously observed temperature gradient in the region (Figs. 4 and 5).

By integrating adaptation strategies, we found significant improvements in yield relative to no adaptation scenario (NO ADAPTATION; under RCPs 4.5 and 8.5), with highest individual improvement reported for heat tolerant ideotype (Table 2, Figs. 7 and 8; HEAT) under genotype-specific adaptation, no nutrient limitation (Table 2, Figs. 7 and 8; NNL) under agronomic adaptation, and Int 4 (Table 2, Figs. 7 and 8; INT-NNL-PD2) under integrated adaptation strategies. While significant yield improvements were reported for individual adaptations across different categories (Table 2), KCAN, as an adaptation strategy, showed no yield improvement under both RCPs, suggesting probable light

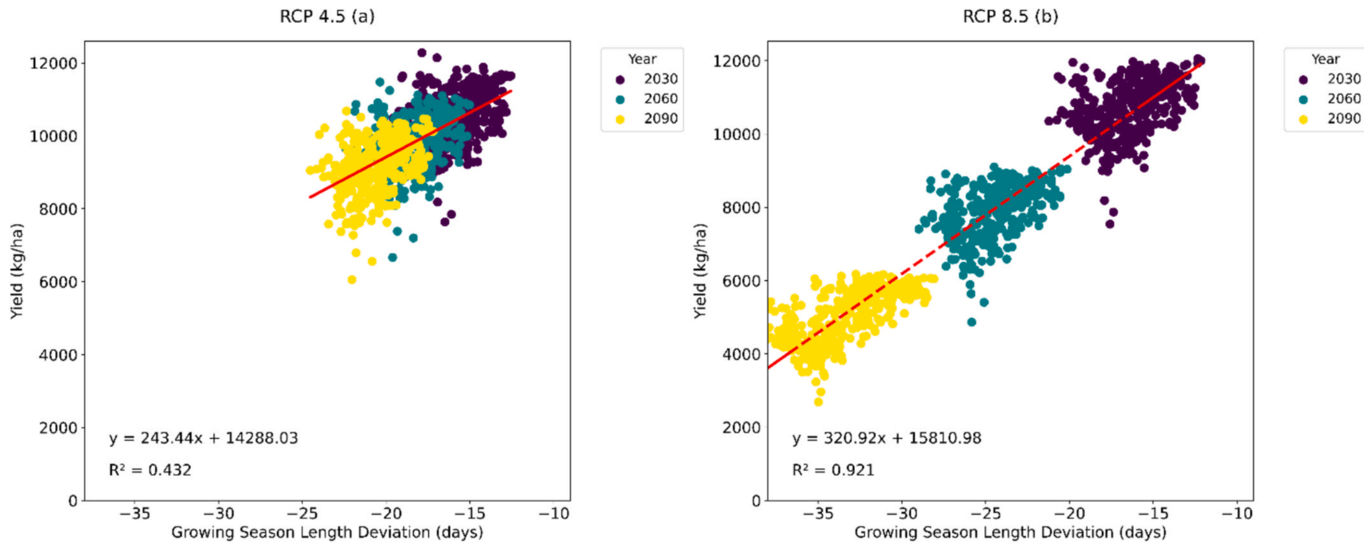

Fig. 9. Regression analyses between yield (kg/ha) and growing season length deviations (GSL, days) under RCPs 4.5 (a) and 8.5 (b).

extinction saturation at peak KCAN values, consistent with findings from previous studies. For example, Stella et al. (2023) found in their *in-silico* study of wheat response to doubled-haploid traits modification under future climate scenarios that altered KCAN values had the least effect on yield levels, with no effect under rainfed conditions.

Interestingly, we found that all the integrated adaptation strategies (INT-NNL [Int 2], INT-NNL-PD1 [Int 3], and INT-NNL-PD2 [Int 4]), with the exception of Int 1 (INT-NL), resulted in yield improvements, which are either higher or substantial relative to the historical yield distribution (Table 2, Figs. 7 and 8). However, a global optimum for the integrated adaptation was found corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2, regarded as INT-NNL-PD2 (Int 4, Figs. 7 and 8) under both RCPs. This strategy resulted in average yield gain of 0.6 % under RCP 4.5, and 3 % gain under RCP 8.5, relative to historical yield distribution. The higher yield gain under RCP 8.5 indicates the potential benefits of CO_2 fertilization in the early 21st century (2030 s). Interestingly, we found that yield values under this adaptation increase from west to east, potentially mediated by the two weeks (PD2) early planting window coupled in the adaptation. This may have resulted in expanding the range of optimum temperatures early on

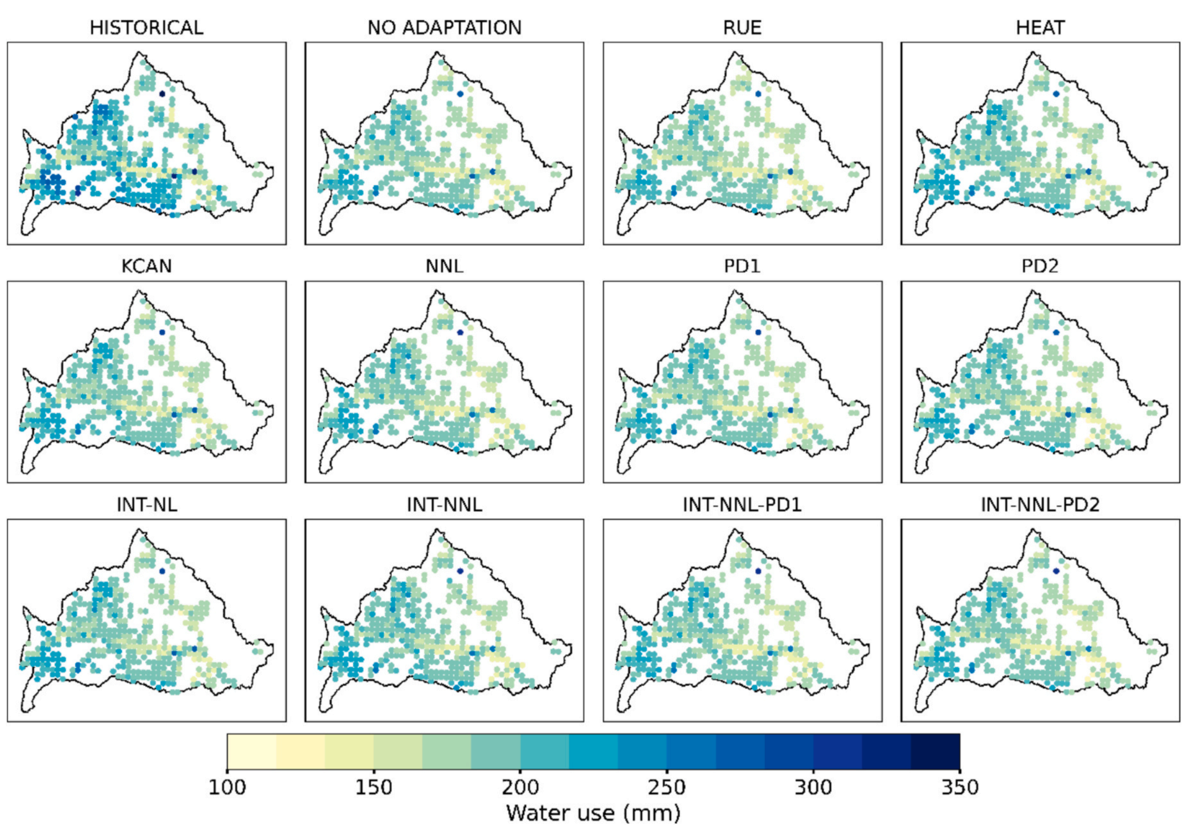

Fig. 10. Irrigation sensitivity under RCP 4.5 (2030 s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

in the growing season; thus, giving more opportunity for proper utilization of nutrients, and for the HEAT and RUE traits to dominate for yield improvement. Studies have shown that early planting and improved nutrient management towards non-limiting condition, are great agronomic adaptations for managing cropping systems (Getachew et al., 2021; Martre et al., 2024). The consistency of this adaptation strategy towards yield improvement in the region, especially under RCP 8.5, indicates that the combination could be a successful strategy for developing resilient cultivars and agronomic management for sustainable maize production in the region.

Irrigation sensitivity to historical and future climate conditions, and different adaptation strategies are presented in Figs. 10 and 11. Irrigation water use under historical and future climate conditions follows a similar spatial gradient to that observed for growing-season rainfall deviation (Fig. 6) in this study, with more water use in the western part of the region than in the eastern part. Similarly, we found comparable irrigation water use patterns under future climate without adaptation and with adaptation strategies (Figs. 10 and 11).

Under future climate without adaptation, irrigation water use declined relative to historical conditions, with average water savings of −9% under RCP 4.5, and −13 % under RCP 8.5. Our previous study reported that full irrigation under future climate conditions resulted in increased water use by 32 % without improving productivity. The decline in irrigation water use observed under deficit irrigation (75 % MAD) likely provides additional evidence that higher CO_2 concentrations, especially under RCP 8.5 in the early 21st century, drive physiological changes in plants, including stomatal closure, which reduces transpiration rates. Stomatal closure occurs as plants optimize their water use efficiency (WUE) in response to stress and increased CO_2 availability for photosynthesis. Reduced transpiration leads to lower water requirements for maintaining plant growth, as documented in previous studies (Kirschbaum & McMillan, 2018; Serna, 2022; Tubiello & Ewert, 2002).

Under adaptation strategies, we found that irrigation water use increases from east to west, similar to our observation under historical and future climate (without adaptation) conditions (Figs. 10 and 11). Individual adaptation strategies under future climate (RCPs 4.5 and 8.5) reduced irrigation water use relative to historical conditions, with the highest water savings observed for RUE under genotype-specific adaptation, PD1 under agronomic adaptation, and Int 4 (INT-NNL-PD2) under integrated adaptation (Table 2, Figs. 10 and 11). While there are significant water savings under all adaptation strategies relative to historical water use, we found that adaptation strategies such as KCAN, HEAT, and Int 2 (INT-NNL) increased water use by 2 % relative to the no adaptation scenario (NO ADAPTATION). With respect to the HEAT ideotype, this might be due to the cooling effect of irrigation under a high temperature scenario, thereby increasing irrigation water use. Overall, achieving a 0.6 to 3 % average yield gain and water savings of 10 to 13 % relative to historical conditions in the early 21st century climate conditions requires an integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

3.3. *Yield and irrigation sensitivities to future climate and adaptation in the mid-21st century (2060 s)*

Yield sensitivities to different climate scenarios and adaptation strategies in the mid-21st century are presented in Figs. S5 and S6, and Table 2. We found that maize yield under no adaptation in the mid-21st century further declined (relative to historical yield) than previously reported for the early 21st century, with mean values ranging from −38 % under RCP 4.5, and −51 % under RCP 8.5 (Table 2). As previously reported, we inferred that yield decline in the mid-21st century might be linked to shortened GSL and warming-induced stresses. Under the mid-

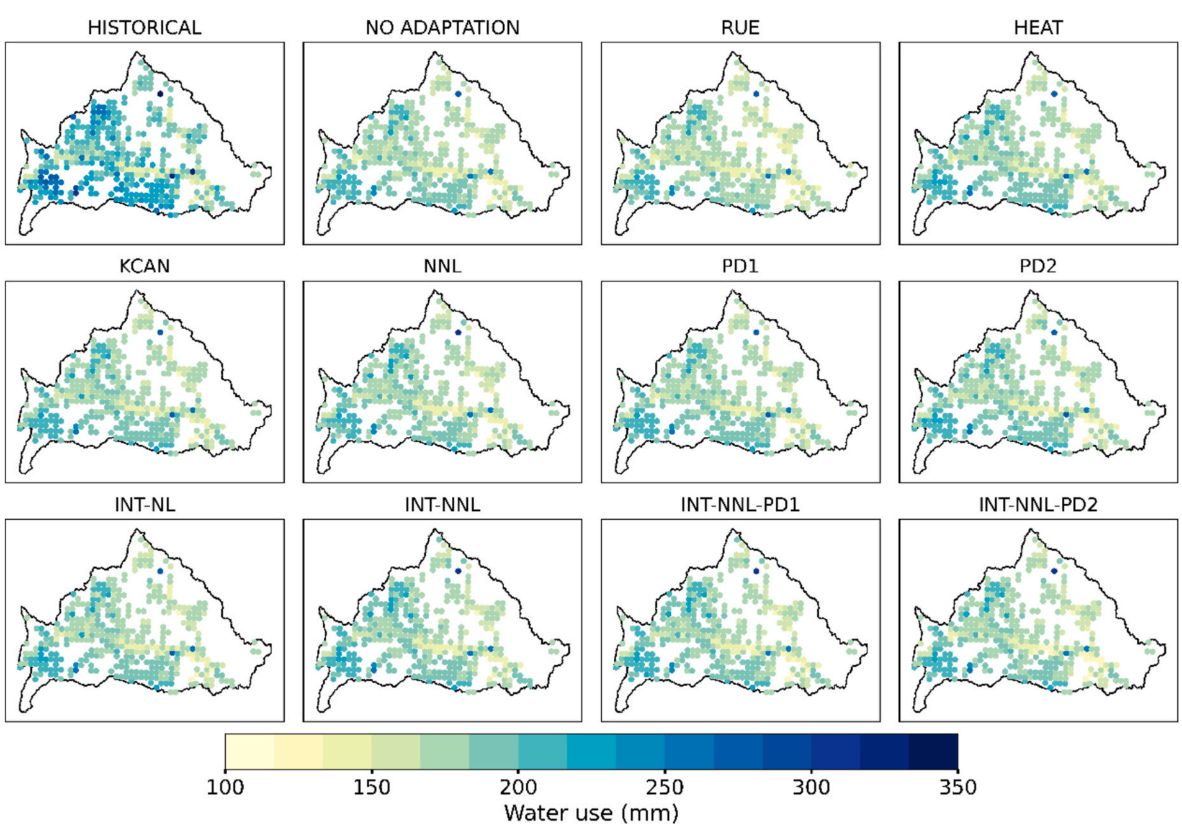

Fig. 11. Irrigation sensitivity under RCP 8.5 (2030 s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

21st century climate conditions, we found that GSL was reduced by 15 to 25 days under RCP 4.5, and 17 to 30 days under RCP 8.5 (Fig. S13), and agrees with previous studies (Araya et al., 2017).

The dissimilar decline responses found between RCPs 4.5 and 8.5 suggest divergent climatic controls under both RCPs in the region. We recall that, under both scenarios, growing-season Tmin and Tmax deviations show disparate patterns across the region (Figs. 4 and 5). In addition, the greater increases in Tmin and Tmax under RCP 8.5, compared with RCP 4.5, may have resulted in such a wide margin. Furthermore, there are clear patterns of yield decline increasing from east to west under both RCPs, suggesting temperature-mediated effects, which agree with the established temperature gradient in the region.

Incorporating different levels of adaptation strategies resulted in significant yield improvements relative to the no-adaptation scenario (NO ADAPTATION, Figs. S5 and S6). However, KCAN under genotype-specific adaptation resulted in a 1 % increase in yield decline (Table 2). This is similar to earlier stated reasons, which might be linked to light extinction saturation at peak KCAN values, especially under high temperatures. Similar to our observation in the early 21st century simulations, we found that the global optimum adaptation in the mid-century for improving yield matches the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4); however, there were substantial yield improvements, especially under RCP 4.5, with a marginal mean deviation of −2% under RCP 4.5, and −13 % under RCP 8.5 (Table 2). Interestingly, under RCP 4.5, we found significant yield improvement towards the eastern portion of the region, suggesting a possible effect of early planting (PD2) coupled with the adaptation (Fig. S5). The climate mitigation effect of this adaptation strategy was gradually masked out under RCP 8.5 in the region (Fig. S6), indicating high temperature impacts and reduced interconvertibility of CO_2 fertilization benefits.

Irrigation sensitivities to future climate conditions and different adaptation strategies are presented in Figs. S7 and S8, and Table 2. Similar to our findings in the early 21st century, we found that irrigation water use savings increase from west to east both under the future climate without and with adaptation strategies. In general, significant water savings under no adaptation were observed relative to historical conditions, with average values of −13 % under RCP 4.5 and −15 % under RCP 8.5. The higher water savings under RCP 8.5 might have been due to previously documented reasons, including stomatal closure, which reduces transpiration rates, especially under high CO_2 emission scenario (Kirschbaum & McMillan, 2018; Serna, 2022; Tubiello & Ewert, 2002). It is important to note that water savings increased through time, with higher savings observed in the mid-21st century than in the early 21st century.

We found that individual adaptation strategies yielded additional savings in irrigation water use compared with historical levels. The highest water savings were observed for strategies focused on RUE under genotype-specific adaptation, planting date adjustments (PD1 and PD2) under agronomic adaptation, and integrated approach combining multiple strategies (INT-NNL-PD2; Int 4), see Table 2. Although all adaptation strategies resulted in significant water savings relative to historical and future climate with no adaptation water use, some strategies, such as KCAN, HEAT, Int 1 (INT-NL), Int 2 (INT-NNL), and Int 3 (INT-NNL-PD1) slightly increased water use by 1 to 2 % compared to no adaptation scenario under both RCPs (Table 2). This might be linked to increasing temperature in the mid-21st century, in combination with light extinction saturation due to KCAN, and shifts in planting dates to further expand the optimum growing season length. In summary, achieving yield improvement in the mid-21st-century climate, with average marginal deviations of −2% under RCP 4.5 and −13 % under RCP 8.5, may result in significant water savings of −13 to −14 % relative to historical conditions. This will require an integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

3.4. Yield and irrigation sensitivities to future climate and adaptation in the late 21st century (2090 s)

Future yield distributions under adaptation and no adaptation are shown in the Figs. S9 and S10 for RCPs 4.5 and 8.5, respectively. Yield decline under no adaptation shows strong consistency through time, with further decline observed in the late century. We found decline values ranging from −43 % under RCP 4.5 to −68 % under RCP 8.5. As expected, GSL deviation was higher under RCP 8.5 than in RCP 4.5, with values ranging from 32 to 40 days and 20 to 28 days, respectively (Fig. S13).

While adaptation may offer solutions to reduce drastic yield decline and shock caused by future climate conditions in the late 21st century, we found that under the present condition being tested, individual adaptation strategies targeted towards improving canopy photosynthesis (RUE), light extinction (KCAN), and shifting planting dates (PD1 and PD2) may no longer be beneficial for yield improvement, especially under RCP 8.5 (Table 2). Interestingly, we observed that the HEAT ideotype (HEAT) significantly outperformed all genotype-specific and agronomic adaptations, with deviations from historical conditions ranging from −28 % (RCP 4.5) to −55 % (RCP 8.5). However, integrated adaptation strategies, especially the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4), may be useful for significant yield improvement, with a marginal deviation of −6% relative to the historical condition (Table 2). This is only true for RCP 4.5 scenario, in which changes in atmospheric conditions are more gradual than under RCP 8.5. Under RCP 8.5, we found a yield deviation of –33 % relative to the historical condition, indicating that a suitable adaptation strategy under the RCP 8.5 scenario might be one that is more adaptable to high temperatures. It is important to note that while we tested the combination of RUE, HEAT, KCAN, NNL, and PD2 to be the best strategy, we infer that, given the present results and evidence, a combination of HEAT ideotype, NNL, and PD2 will make a great strategy for improving yield, especially under the RCP 4.5 scenario. Therefore, heat-tolerant cultivars beyond those tested in this study, coupled with optimal nutrient allocation and early planting conditions, may adapt well to climate forcings in the late 21st century.

While drastic yield decline was observed under the late century climate condition without adaptation, we found further increment in water savings under both RCP scenarios, with water savings increasing from west to east (Figs. S11 and S12). Under no adaptation, average water savings relative to historical conditions range from −20 % and −18 % (RCPs 4.5 and 8.5, respectively). The higher water savings under RCP 4.5 more than in RCP 8.5 indicate the benefits of gradual warming conditions and relatively high CO_2 values without quickly hitting the saturation level of maize CO_2 assimilation for photosynthesis. Studies have shown that CO_2 saturation of maize ranges from 400 to 550 ppm (Leakey et al., 2006). Under elevated and ambient CO_2 using Free-Air Concentration Enrichment technology (FACE), Leakey et al. (2006) found that elevated CO_2 beyond 550 ppm does not affect photosynthesis, productivity, and yield of maize. In addition, they observed that stomatal conductance was lower by −34 %, with high soil moisture reaching up to 31 %; hence, reduced crop water use. This implies that the increasing CO_2 levels may not deliver the full benefits to the Great Plains maize production under the RCP 8.5 climate conditions expected in the late 21st century.

Individual adaptation strategies showed further water savings compared to historical levels. Similar to previous results in the early and mid-21st century time periods, we found the highest water savings with strategies focused on RUE under genotype-specific adaptation, planting date adjustments (PD1 and PD2) under agronomic adaptation, and integrated approach combining multiple strategies (INT-NNL-PD2; Int 4), see Table 2. Adaptation strategies, such as HEAT, Int 1 (INT-NL), Int 2 (INT-NNL), and Int 3 (INT-NNL-PD1), further increased water use by 5 to 12 % (RCPs 4.5 and 8.5, respectively) relative to the no adaptation scenario (Table 2). This indicates that the adaptation strategy linked to heat tolerance in the late century might increase water use beyond the limits observed under the no-adaptation scenario. In conclusion, achieving yield improvement in the late 21st century climate may require re-examination of the current adaptation implementation for potential improvement, especially under RCP 8.5. However, we found that, under current conditions, the simulated marginal yield deviation is −6% relative to historical conditions under RCP 4.5, resulting in water savings of −18 %. This will require an integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

3.5. Limitations of the study

This study assessed the spatiotemporal pattern of irrigated maize productivity under different future climate scenarios and adaptation strategies in the Great Plains. Given that the present study is an extension of our previous study (Onyekwelu et al., 2025) in the region, it shares similar assumptions, which were substantially addressed in the previous study. However, an important assumption that was not included and was not part of the previous study was the selection of early planting dates and adjustments. We selected early planting date adjustments as one of the adaptation strategies under the agronomic management scenario. The adjustments were based solely on the literature and the plausible benefits of early planting in ameliorating yield loss due to climate change (Getachew et al., 2021). However, due to the scale and scope of this study, the potential impacts of spring freeze due to low soil and air temperatures below the maize base temperature of 10 °C were not considered. Typical planting dates in the region range from April 1 to May 15. A baseline planting date selection of April 1, for example, and adjusted to occur one or two weeks earlier, will see maize planted around March 25th or 18th, respectively.

While this is plausible to escape potential heat stress during reproductive stages (Waqas et al., 2021), the chilling stress due to potential low temperatures may have an impact on the plant cell or tissue (Waqas et al., 2021). However, a three-year study in the region showed that yield values remained either stable or increased when planting was done in late March compared to planting in mid-to-late April and early-to-mid May (Adee et al., 2024). In addition, we selected early planting as an adaptation because of the probable benefits of moderate climate-induced warming, which could expand the range of optimal temperatures early in the growing season. Nonetheless, there are biological solutions for seed treatment, especially for risk-averse farmers to protect seeds against uncertain soil conditions during the critical early growth period, pests, and disease (Corteva Agriscience, personal communication). In addition, incorporating early vigor traits in maize hybrids could lead to significant agronomic and yield benefits (Capo et al., 2023; Dadrasi et al., 2024).

4. Conclusions

This study offers a first-time comprehensive insight through a fine-scale spatial analysis of the impacts of future climate scenarios and adaptation strategies on irrigated maize production in the Great Plains. Under future climate without adaptation, maize yield declined by 34 % and 43 % (2030 s and 2090 s, respectively) under RCP 4.5, and by 33 %-68 % (2030 s and 2090 s, respectively) under RCP 8.5. The decline in yield values under future climate conditions were primarily due to shortened growing season length and warming-induced stresses due to high growing season temperatures. Despite yield declines, we found water use savings ranging from 9 % to 20 % (early and late century time periods, respectively) under RCP 4.5, and 13 % to 18 % (early and late century time periods, respectively) under RCP 8.5. By integrating agronomic and genotype-specific adaptations, our findings underscore the critical role of tailored adaptation strategies in mitigating the adverse effects of climate change on irrigated maize production systems in the Great Plains. We found that individual adaptation categories, such as genotype-specific and agronomic adaptations, demonstrated significant improvements in maize yield compared to the no-adaptation scenario. However, integrated adaptation strategies yielded significantly greater benefits, indicating that an all-inclusive approach is more effective at addressing the complex challenges posed by future climate conditions in the Great Plains. These integrated strategies not only enhanced maize yield but also contributed to substantial water savings — a critical factor for sustaining the region's water resources and ensuring long-term agricultural viability. In quantitative terms, we found that the integrated adaptation strategy linked to improved RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4) resulted in the early 21st century yield gain of 0.6 to 3 % (RCPs 4.5 and 8.5, respectively), with water savings of −10 to −13 % (RCPs 4.5 and 8.5, respectively), relative to historical condition. However, going forward into the 21st century, we observed marginal yield deviations and a further increase in water savings, more than observed under no-adaptation scenarios, suggesting the need to re-examine and redesign these adaptation strategies to deliver co-benefits of further yield gains and improvements while delivering water-savings benefits.

Our study further highlights the dual importance of productivity and sustainability in the Great Plains. While yield improvements are vital to meet food security needs, the water savings achieved through adaptation strategies underscore the necessity of water resource conservation to support aquifer recovery. This balance between adaptation and resource management is essential for promoting resilience in agricultural systems under future climate uncertainties. In addition, the insights drawn from this study have important implications for farmers, breeders, and policymakers. For farmers, our findings provide actionable guidance on selecting and implementing effective adaptation strategies tailored to specific environmental and agronomic management, given our spatial model framework. For breeders, the study underscores the value of developing climate-resilient genotypes that complement broader adaptation frameworks. Policymakers can use these insights to develop targeted interventions and support systems that promote sustainable agricultural practices in the face of climate risks. Our findings emphasize the transformative potential of integrated adaptation strategies in mitigating the impacts of future climate conditions on irrigated maize production in the Great Plains. This work serves as a crucial step toward building resilient cropping systems capable of thriving under future climate conditions, offering a useful analog to other regions in the Great Plains and around the globe facing similar threats to food security and water resources.

CRediT authorship contribution statement

Ikenna Onyekwelu: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sam Zipper:** Writing – review & editing, Resources, Project administration, Methodology, Funding acquisition. **Stephen Welch:** Writing – review & editing. **Xiaomao Lin:** Writing – review & editing. **Vaishali Sharda:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2025.111138.

Data availability

Data will be made available on request.

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