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Assessment of climate change impact on rainfed corn yield with adaptation measures in Deep South, US

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ABSTRACT

Invariable warming trends of global climate and increase in uncertainties in seasonal precipitation are major threats to crop production and subsequently, to food security. Simulation is needed to understand the suitability of potential adaptation strategies to mitigate the impacts of uncertain climate change scenarios on agricultural production. This study investigates the influence of climate change on maize yield in the Mobile River Basin (MRB) in the southeastern United States using the Decision Support System for Agrotechnology Transfer (DSSAT) crop model. We use four climate models from Coupled Model Intercomparison Project Phase 6 (CMIP6) under two Shared Socio-economic Pathways (SSPs) of SSP245 and SSP585 to represent future changes in solar radiation, precipitation and temperature. In this study, we simulate crop yields using climate data from the past (1985–2010), the experimental period (2011–2017), and future projections (2026–2050, 2050–2075, and 2076–2100). The simulated crop yields are compared to historical yields to evaluate the adaptation measures selected to mitigate the impact of future climate scenarios, assuming no effective adaptation measures or changes in farming practices. The findings indicated that by end of the 21st century, maize yield will fall by 8.2 % (-842 $kg \cdot ha^{-1}$) and 16.4 % (-1684 $kg \cdot ha^{-1}$) under the SSP245 and SSP585 scenarios, respectively. Future climate change will have a significant impact on maize production in MRB, and will require optimal adaptation measures to manage agricultural production loss. We evaluate several adaptation strategies including optimization of planting date, fertilizer application date, implementing supplemental irrigation and modification of fertilizer doses. The study concludes that significant improvement in corn yield under the changed climatic patterns assumed as per the SSPs considered, is possible by planting one week ahead, fertilizing two weeks ahead, and using suitable supplementary irrigation during the cropping season. The findings of this study can be utilized in adapting to climate change and advancing sustainable agricultural development in the MRB.

1. Introduction

Food security is an essential component of sustainable development, and a range of threatening factors including population growth and climate change are proven to affect food security. With rising trend of temperature and increased incidence of extreme weather, crop yield is expected to face more challenges in the future (Hameed et al., 2019; Arunrat et al., 2020). Since climatic factors significantly impact agricultural productivity, any change in climate variables such as temperature and precipitation might jeopardize nations' food security objectives. Various forecasting methods confirm that the global climate change will negatively impact yield of major food grains, such as corn, wheat, soybean, and rice (Abbaszadeh et al., 2022; Gavahi et al., 2021; Wang et al., 2018).

Climate change has far-reaching implications for agricultural production. Global temperature increases can significantly reduce wheat and maize yields, with predictions of up to 6 % yield reductions for every degree of temperature rise (Liu et al., 2016). Concurrently, optimal locations for planting various crops will shift due to climate changes, necessitating adjustments in crop management and cultivar selection (Pugh et al., 2016). Elevated CO_2 concentrations, while beneficial in some respects by enhancing yield and drought resilience in plants, can compromise the nutritional quality of C3 crops (Myers et al., 2014; Uddling et al., 2018). Extreme climatic events, such as floods and heatwaves, have historically slashed global cereal yields by up to 10 % (Lesk et al., 2016). For instance, warmer temperatures reduced wheat

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yields by 5.2 % in India between 1981 and 2009, while regional anomalies like high rainfall or droughts have caused massive fluctuations in yields in areas such as East Africa, the US, and Australia (Gupta et al., 2017; Huntington et al., 2017). The United States is the largest maize producer, accounting for about 30 % of global output. Since 1980, however, the United States has suffered a considerable rise in heat, drought, and harsh weather, resulting in substantial losses to maize yield (Asseng et al., 2015; Li and Troy, 2018; Mazdiyasni and AghaKouchak, 2015; Wuebbles, 2021; Yarveysi et al., 2023; Zipper et al., 2018).

Drought was the leading cause of maize crop losses in the United States from 1989 to 2016, totaling $18 billion (Baharanyi et al., 2012; Li et al., 2019). Zipper et al. (2016) evaluated the sensitivity of U.S. maize output to drought from 1958 to 2007 and found that drought was responsible for 13 % of the fluctuation in crop yield, with the Southeast area being the most vulnerable. As the frequency and intensity of severe weather events are projected to rise in the future, the security of maize production is evidently under threat (Elahi et al., 2021; Praveen and Sharma, 2019; Prein et al., 2020; Wuebbles et al., 2014; Zipper et al., 2018). The southeastern United States has experienced intense and frequent droughts in recent decades (Gavahi et al., 2020). Since drought has a significant negative impact on maize yields in the United States, particularly during crop development, the southern states aim to improve irrigation facilities and other measures in the future to prevent crop yield losses (Du et al., 2018; Yang et al., 2020). In addition, climate forecast studies show that the southeastern United States will experience scarcity of clean water (Boretti and Rosa, 2019; Griffith and Gobler, 2020). As a result, wise choice of adaptation measures is critical for achieving potential crop yields and regional food security, especially in the face of climate change (Cao et al., 2018; Kadiresan and Khanal, 2018; Karthikeyan et al., 2020).

To increase crop resilience in response to the detrimental effects of climate change on crops, appropriate adaptation methods must be developed (Ahmad and Afzal, 2020; Boonwichai et al., 2018; Gul et al., 2022; Mirfenderski et al., 2022; Xu et al., 2020). In recent years, a popular research topic has been how agriculture responds to climate change. A large number of studies have used crop models to examine the effect of climate change on crops and adaptation measures (Challinor et al., 2018; Muller et al., 2021; Peng et al., 2020; Sultan et al., 2019; Xiao et al., 2021). The combined impacts of climate, soil, and farm management methods on crop growth and development can be investigated through crop model simulations, as these models simulate the plant-water-soil-atmosphere system holistically (Cochand et al., 2021; Ding et al., 2021; Mainuddin et al., 2021). Consequently, crop models not only can anticipate the impact of future changes in climatic patterns on crop yields, but also can be used to evaluate effective adaptation measures to mitigate the impacts of climate change (Pakmehr et al., 2021; Zobeidi et al., 2022). Multiple studies have shown the effects of climate change on corn output in the United States, but few have proposed adaptive strategies to counteract these effects. Consequently, it is of great theoretical and practical importance to accurately assess the impact of climate change on maize production in the Mobile River Basin (MRB) and to formulate corresponding adaptive measures to mitigate the impact of climate change and ensure the sustainable development of local agriculture.

DSSAT is renowned for its multipurpose applications, from simulating crop development facets like phenology, biomass, and yield production to predicting yield responses under various irrigation scenarios and climate change impacts. The CERES-Maize model within DSSAT has been recognized for its accuracy in diverse climatic conditions, from monsoonal to semiarid and continental (Ben Nouna et al., 2000; Soler et al., 2007; Wang et al., 2011). Numerous studies have successfully validated DSSAT models, especially in the context of climate change impacts on growth (Ines et al., 2013; Jiang et al., 2021; Shrestha et al., 2017; Soler et al., 2007). Given this extensive validation and its modular structure encompassing weather, soil, and management modules, DSSAT emerges as an invaluable tool for developing strategies to mitigate the repercussions of climate change on crop yields. Additionally, existing research has conducted in-depth sensitivity analyses of the DSSAT model, highlighting that factors such as water stress, P5 (grain filling duration under optimal conditions), G3 (kernel filling rate under optimal conditions), and P2 (thermal time from silking to physiological maturity) significantly affect yield (Corbeels et al., 2016; Wang et al., 2021). This is particularly the case in the United States, due to more extensive data availability and better validation of the models for crops and conditions prevalent in this region (Akumaga et al., 2023; Valli, 2019).

In the face of climate change's influence on maize output, developing realistic adaptation measures is an important means of mitigating and coping with climate change (Ahmad and Afzal, 2020; Deb et al., 2015; Mirhosseini and Srivastava, 2016; Zhao et al., 2017). Crops can achieve the optimum yield with precipitation, temperature, and solar radiation during the growth period by altering the planting and fertilization dates (Jiang et al., 2021; Ojeda et al., 2021; Price et al., 2022). Supplemental irrigation and fertilization at important periods, in addition to altering sowing and fertilization dates, can be a very efficient adaptive approach (Ahmad et al., 2022; Bondesan et al., 2023; Xia et al., 2021). DSSAT model is implemented here to develop the optimal climate change adaptation plan for the four adaptation measures including, changing planting dates, fertilization dates, fertilization doses and irrigation water supply, ensuring the long-term growth of local agriculture.

Four climate models provided by the Coupled Model Intercomparison Project Phase 6 (CMIP6) were adopted in this study to assess the impact of climate change on maize production over the next three periods (2030s:2026–2050, 2060s:2051–2075 and 2090s:2076–2100) under SSP245 (intermediate stable state) and SSP585 (maximum greenhouse gas emission state) scenarios. Four potential adaptation were evaluated in the MRB using the DSSAT crop simulation model for efficient adaptation under climate change conditions. The results of this study can potentially help policymakers and researchers plan future management practices in the field.

2. Materials and methods

2.1. Study area

The MRB, located in the southeast portion of the U.S., is the sixth-largest basin in the U.S. (Iwanowicz et al., 2016). There are four states in its catchment region, which is around 115,200 square miles. The Upper Appalachian Plateau generates flow to the north, which flows into Mobile Bay to the south. Some of the most important crops are corn, soybeans, cotton, and hay. Pioneer 1319 is MRB's most popular maize cultivar/variety (Deb et al., 2022). More than 65 % of the annual precipitation is received during the corn-growing season, which averages between 1270 mm and 1524 mm. Mean temperature varies from 15 to 21 degrees Celsius from north to south (Jimenez et al., 2021). In this study, four catchments in the MRB were selected for simulation to reflect the growth status of maize in the study area (Fig. 1). The four catchments were meticulously selected to represent the diverse agro-climatological conditions prevalent in the basin. These catchments exhibit varying characteristics in terms of soil type, precipitation, temperature, and growing conditions which significantly influence maize cultivation. In addition, there are corresponding agricultural experiment sites for each of the four catchments including Tennessee Valley Res. and Ext. Ctr., Sand Mountain Res. and Ext. Ctr., Prattville Experiment Field and Brewton Experiment Field. By focusing on these specific catchments, this study aims to capture a comprehensive understanding of maize growth across different environmental conditions in the MRB.

2.2. Climate data

Several datasets were used comprising meteorological data, maize information, and its agronomic treatment for the current study.

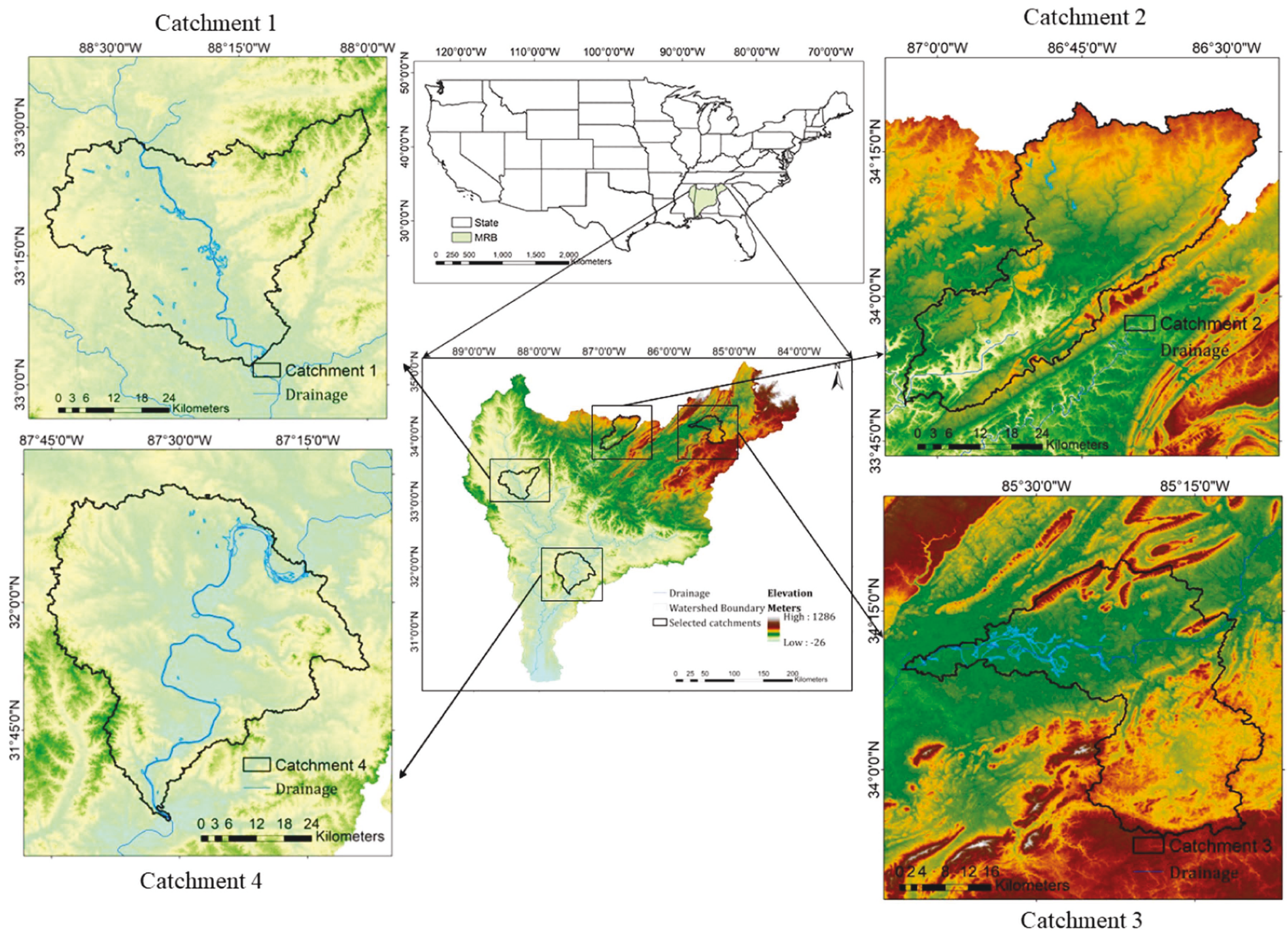

Fig. 1. Location of Mobile River Basin and four study catchments.

Parameter-elevation Relationships on Independent Slopes Model (PRISM) was used to obtain meteorological data, including precipitation data, minimum and maximum temperature, and solar radiation, at a daily timescale. Parameter-elevation Relationships on Independent Slopes Model (PRISM), which interpolates observations from a network of weather stations to estimate climate variables such as precipitation, minimum and maximum temperatures, and solar radiation at a daily resolution, adjusts for factors like elevation and topographic exposure to provide detailed climate estimates at specific area (Daly et al., 2008). The historical weather data from 1986 to 2010 were used to project the future climate conditions. Trend examination was conducted via linear regression, enabling the identification of increasing trends. Statistical significance, determined through methods such as t-tests, was recognized at a p-value less than 0.05.

The four chosen GCMs are CNRM, HAD, IPSL, and UKES (Lurton et al., 2020; Yang et al., 2020; Zhu and Yang, 2020). According to a previous study analyzing 31 GCMs over the CONUS, these four models were determined to be best represent the southeast region of the CONUS (Almazroui et al., 2021). Although in the absence of this information one can use an objective approach for GCM selection (Ahmadalipour et al., 2017). Bias correction was applied to the raw GCM data using a quantile mapping approach, which is a statistical technique that adjusts the distribution of simulated data to match that of observed data, where precipitation data were obtained from the observed historical data from PRISM (Huang et al., 2021; Patel et al., 2022). GCM results are bias-corrected at a 4 km resolution before being spatially aggregated to reflect the socio-economic pathway (SSP) 245 and 585 scenarios. This dataset is regarded superior to the Representative Concentration Pathways (RCP) scenarios (Shrestha and Roachanakanan, 2021). Temperature, solar radiation, and precipitation for three future periods under two sample concentration pathways were compared to the observed data for the period 1986–2010. To simulate grain yield, the research utilized historical (1986–2010), experimental (2011–2017), and future (2030 s, 2060 s and 2090 s) climate data.

2.3. Crop and management data

DSSAT was calibrated and validated using meteorological data from 1986 to 2017 from PRISM (Jones et al., 2003).Information on corn growing season and its agronomic management practices (Table 1), such as corn varieties, planting methods, planting dates, harvest dates, fertilizer application dates and dosages, and corn yield data, were obtained from two state agricultural research centers, namely the Auburn University Alabama Agricultural Experiment Station and the University of Georgia Cooperative Extension on Crop and Soil Sciences (Georgia)(Da Cunha Leme Filho et al., 2020; Jenda and Weisbrod, 2013; Pearson and Atucha, 2015). These research centers publish annual crop yield datasets for their research stations under rain-fed conditions.

Specifically, the corn-growing season typically stretches from April to September, with planting usually beginning in early April and harvests commencing by early September. Fertilization, predominantly using nitrogen fertilizer, is synchronized with the sowing time to optimize growth and yield. Agronomic management practices are consistent across four catchments. Corn's growth begins with the Seedling Stage,

Table 1
Information of corn growing season and its agronomic management practices.

Corn -growing season	fertilizer	fertilizer dates	Nitrogen Rate (lbs/ac)	Plant pop. (seeds/ac)	Herbicides used
April to September	nitrogen	April	120–160	25000–30000	Atrazine/Dual

Table 2
Calibrated genetic coefficients for maize in 4 catchments.

Catchment	P1	P2	P5	G2	G3	PHINT
1	253	0.9	957	812	10.6	50.8
2	255	0.85	951	884	10.4	53.5
3	278	0.8	976	761	8.9	53.8
4	237	0.75	938	957	11.2	51.1

where young plants emerge and establish foundational leaves. This progresses to the Ear Stage, marked by the critical tasseling phase, where pollen-producing structures appear, ensuring kernel formation. Finally, in the Kernel Stage, kernels mature on the cob, with the grain-filling period playing a pivotal role in determining yield as kernels accumulate starches and nutrients. Both tasseling and grain-filling are crucial junctures in corn's development cycle, greatly influencing final yield outcomes.

2.4. Simulation scenarios

The DSSAT was used to determine the optimal adaptation measures for maize to future climate change. Developed by the United States Department of Agriculture, the DSSAT model is adept at simulating vegetative and reproductive growth, as well as physiological, ecological processes, and daily soil water balance. The model's input data encompasses four fundamental categories: meteorological data, crop-specific data, soil properties, and agricultural management practices (Jones et al., 2003).

The DSSAT model was calibrated and validated using maize yield experiment data gathered from agricultural stations. The model is calibrated for the period of 1986–2010 and then validated during the years 2011–2017. As used in crop models, crop genetic coefficients are mathematical constructs designed to mimic the phenotypic outcome of genes under different environments to influence. Six crop genetic coefficient factors were used to calibrate the DSSAT model for maize, focusing on both phenological aspects and yield potential. The coefficients include: P1, which measures photoperiod sensitivity affecting the timing of flowering based on day length; P2, the thermal time required from silking to maturity, impacting the grain-filling period; and P5, which determines the duration of grain filling under optimal conditions, influencing kernel weight. Additionally, G2 represents the potential kernel number per plant, a key determinant of yield capacity; G3 assesses the kernel filling rate under optimal conditions, affecting the speed and efficiency of grain filling; and PHINT, the phyllochron interval, or the time between the emergence of successive leaves, which influences overall plant development and canopy structure. These six parameters were examined for sensitivity using the t-stat and p-values. The effectiveness of model calibration was assessed using the coefficient of determination (R^2), root mean square error (RMSE), and Kling-Gupta Efficiency (KGE) (Esmaeili-Gisavandani et al., 2021).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{2}$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \tag{3}$$

Where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ the mean of the observed data and n is the number of observations. r is the correlation coefficient between observed and simulated data, β is the ratio of the mean simulated value to the mean observed value and γ is the ratio of the coefficient of variation of the simulated data to that of the observed data.

The DSSAT 4.8 crop model forecasted maize production under climate change scenarios for the following three time periods (2030 s, 2060 s and 2090 s). The model was used to estimate the impact of four distinct adaptation measures on crop yield, including, changing planting dates, fertilization dates, fertilization doses and irrigation water supply. The effects of the chosen adaptation measures were then determined by comparing the simulated crop yields with and without adaptation measures. In the study, the DSSAT model demonstrated the impacts of various adaptation measures on maize production, providing a theoretical foundation for maize adaptation to climate change and sustainable development in the region.

3. Results

3.1. DSSAT model calibration and validation

Corn yield was used to compute the genetic coefficient with the help of the Genotype coefficient calculator (GENCALC) tool of the DSSAT model. We performed a calibration and validation of the DSSAT model over the four catchment, following the methods (GENCALC) described in previous studies (Gunawat et al., 2022; Tooley et al., 2021). For calibration, 25 years of field yield data (1986–2010) were used in this work. Then, the next seven years of data were utilized for model validation (2011–2017). Fig. 2 depicts all the statistical measures obtained throughout the calibration and validation. As shown in Fig. 2, the RMSE ranges for calibration and validation are 1282–2399 (kg/ha) and 883–1726 (kg/ha), respectively. The R^2 and KGE ranges for calibration are 0.71–0.80 and 0.69–0.87 followed by 0.79–0.85 and 0.64–0.88, for validation, respectively. The better performance statistics for the validation as compared to the calibration is most possibly due to the enhanced performance of the input climatic dataset in the recent years. Given the reasonable range of statistical measures, we found the model ready for forecasting corn yield in the MRB under climate change scenarios.

3.2. Future climate change trends

The climatological (1986–2010) average annual precipitation in the study area is 1306.5 mm. As shown in Fig. 3, the trend of precipitation may not be obvious in the future under the two scenarios considered, and there is no significant difference between the two precipitation scenarios. The future period is divided into three phases (early or 2030 s: 2026–2050), middle or 2060 s: 2051–2075), and late or 2090 s: 2076–2100) to quantitatively analyze its changing trend. Under the SSP245 scenario, precipitation in the early and middle 21st century rises by 0.6 % and 2.4 %, respectively. Compared with the baseline, precipitation decreases near the end of the 21st century. The average trend rate was −6.1 millimeters per decade (mm/10a). However, the precipitation in the early and middle periods showed an upward trend, and the trend rates were 6.1 mm/10a and 2.7 mm/10a, respectively. Under the SSP585 scenario, early and late 21st-century precipitation drops by

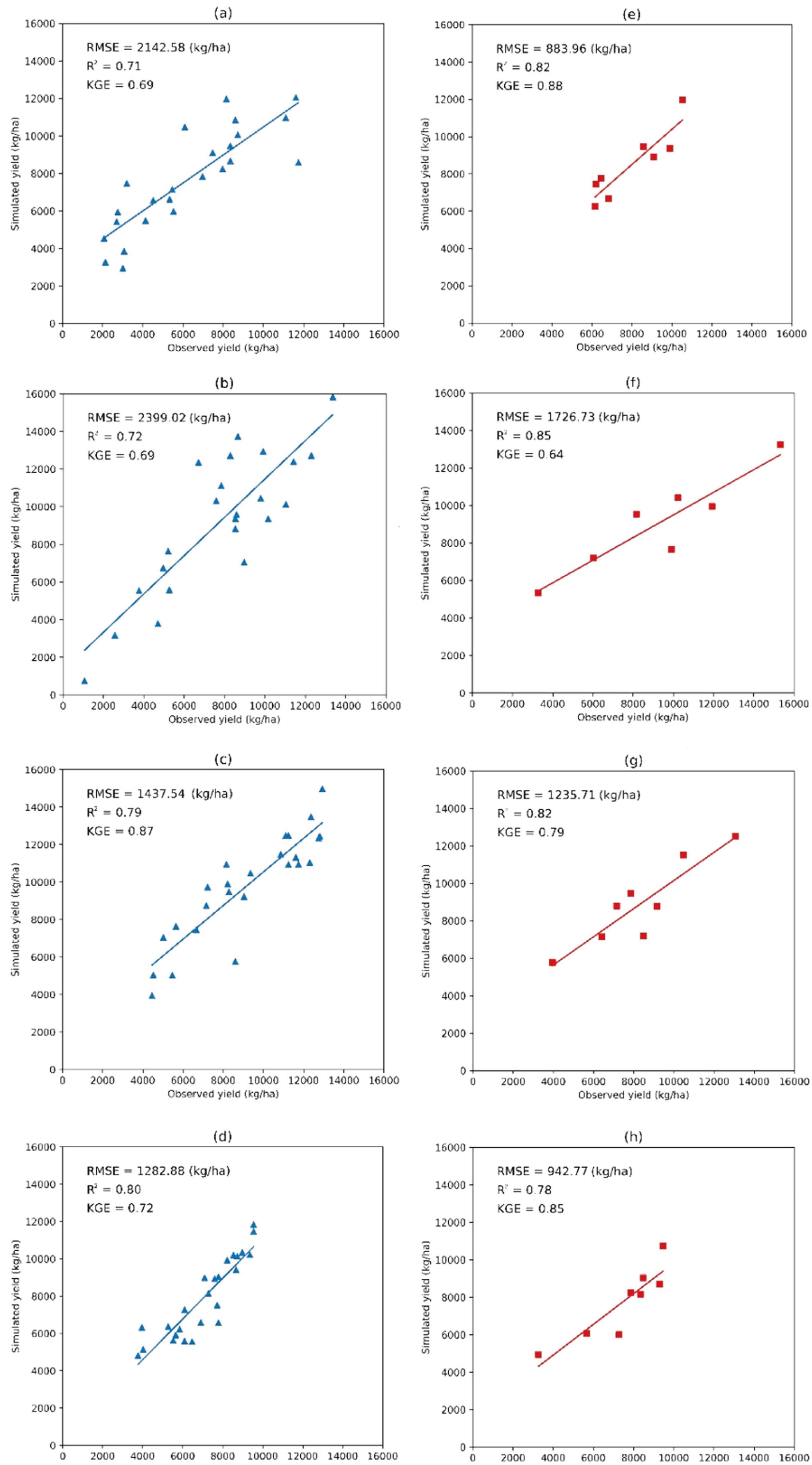

Fig. 2. Calibration and validation of the DSSAT model. (a) catchment1 calibration; (b) catchment2 calibration; (c) catchment3 calibration; (d) catchment4 calibration; e) catchment1 validation; (f) catchment2 validation; (g) catchment3 validation; (h) catchment4 validation.

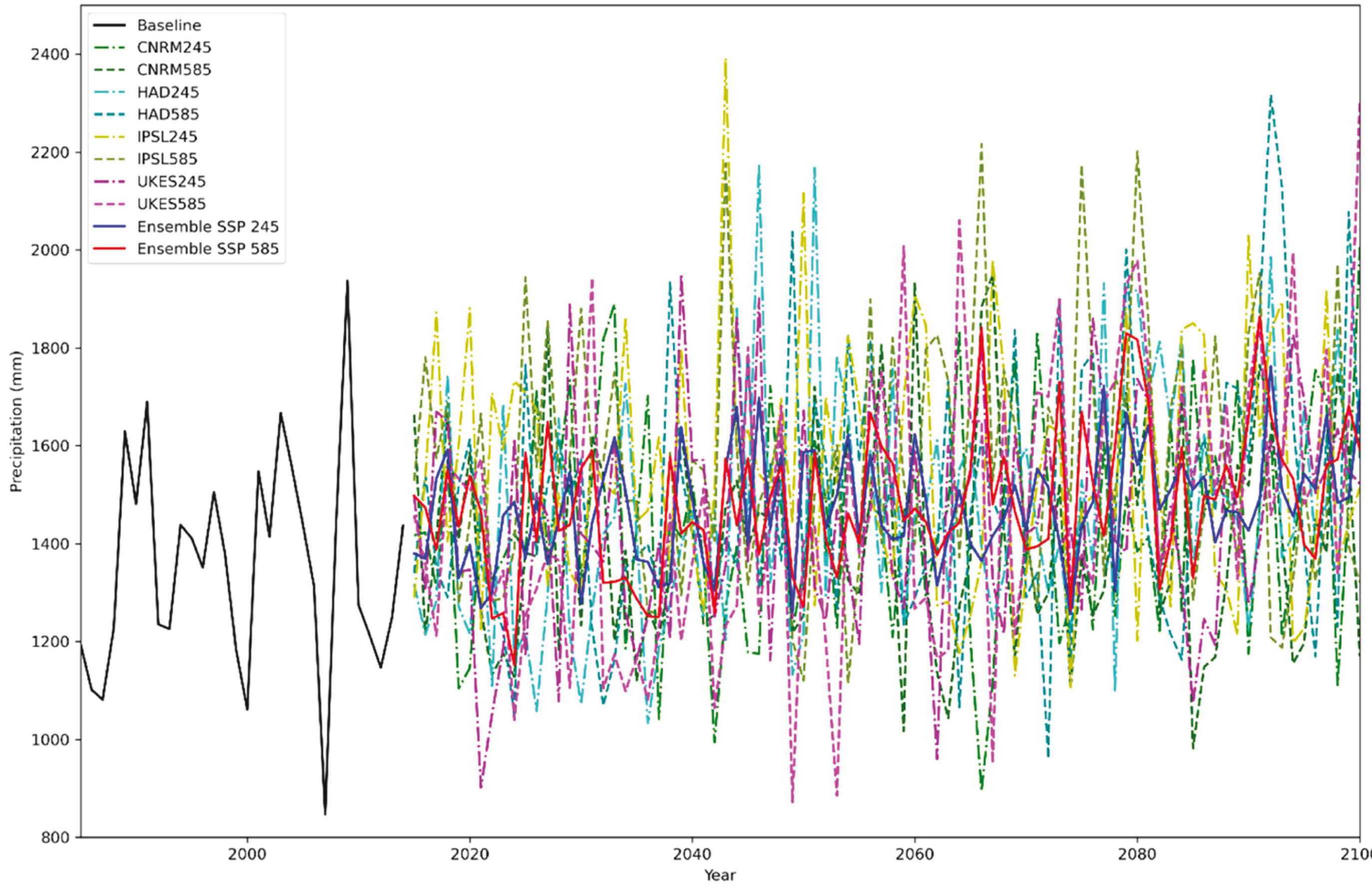

Fig. 3. Historical and projected annual rainfall under SSP245 and SSP585 scenarios.

3.7 % and 1.8 %, respectively, which corresponds to trend rates of −0.4 mm/10a and −4.02 mm/10a. In contrast, precipitation in the middle 21st century is projected to rise by 6.3 %. The rate of increase is 6.1 mm/10a and it is determined that the two scenarios would increase or decrease in the future but the changing trend in each stage is not statistically significant. However, future precipitation is shown to be more variable, ranging from 845 mm to 2287 mm, especially in the SSP585 scenarios.

In this study, all historical weather data the study area from 1985 to 2010 were selected as the historic trend. Figure S1-S2 in Supplementary information showed the future weather data projected by the CMIP6 multi-model ensemble through 2100 and the interannual variations in maximum and minimum temperature. In the MRB, the interannual average maximum and minimum temperature (1986–2017) are 23.8 °C and 10.37 °C, respectively. Both the maximum and minimum temperatures will increase in the future, with the warming being more pronounced under the SSP585 scenario. Under the SSP245 scenario, the maximum temperature increases by 1.22 °C, 1.92 °C, and 3.17 °C in the early, middle, and late 21st century, respectively. Similarly, the corresponding minimum temperature will be 0.94 °C, 1.85 °C, and 2.13 °C for the three horizons, respectively. While significant warming is projected under this scenario, the rate of warming appears to decrease over time, as indicated by the lower increment in the late 21st century compared to the middle period. Under the SSP585 scenario, the maximum and minimum temperature variation ranges are higher than those under the SSP245 scenario. In the early, middle, and late 21st century, the maximum temperature increases by 1.87 °C, 3.52 °C, and 5.67 °C, while the minimum temperature climbs by 1.38 °C, 2.97 °C, and 5.12 °C, respectively. Under the two scenarios, the maximum temperature is projected to increase by 13.4 % and 23.8 % by the end of the 21st century, respectively.

In order to study the impact of climate change on the corn-growing season (April-September), monthly statistical analysis was conducted on different meteorological elements in four catchments. Figure S3 in Supplementary Information shows the changes in monthly maximum and minimum temperatures, precipitation, and solar radiation in the study region predicted by the CMIP6 multi-model combination for two SSP scenarios in the early, mid, and late 21st century. The monthly maximum temperature in all future periods is higher than the baseline. The monthly maximum temperature shows a slightly increasing trend, but the increase is more obvious in the second half of the year. During the corn growing season, the temperature increase range in May, June and July was relatively gentle, while the temperature increase range in August and September was most obvious. By the end of the 21st century, the baseline's monthly maximum temperature changes from July to August. The trend of monthly minimum temperature and maximum temperature is consistent in the future, and the temperature increase from July to December is still greater than that of January to June, but the minimum temperature increase is greater than that of the maximum temperature. During the corn growing season, the temperature rise was most significant from July to September.

Monthly precipitation in the future is shown in Figure S3, with a large overall variation observed in range of precipitation. Under all scenarios, monthly precipitation is projected to increase as compared to that in baseline, for months from January to June and from September to December, in all situations, but it falls from July to August. Precipitation is projected to increase overall during the corn growing season, with more significant increases in May, August, and September; but rainfall in June and July is projected to reduce.

Future solar radiation exhibits a decreasing trend from January to May and a rising trend from June to December when compared to the baseline. Except for May, when it is below the baseline, solar radiation generally increases over the corn growing season. In summary, the projected maximum and minimum temperature, and solar radiation will rise during the corn growing season, while precipitation and solar radiation will decrease from June to July and May, respectively.

3.3. Future maize yield trends

An ensemble simulation of future maize yield was conducted, utilizing projections from four CMIP6 models, to investigate the impact of climate change on maize yield across four catchments within the MRB. Other field management measures, such as planting density, tillage, crop rotation, and residue management, were consistently applied, with existing management practices maintained unaltered throughout the study. Averaging yields over each decade rather than one year helps minimize short-term fluctuations and clarifies longer-term trends. Fig. 4 shows the simulation results of corn yield in various future periods under two different climate scenarios.

The baseline maize yields in the four catchments are 10274 kg per hectare ($kg \cdot ha^{-1}$), 10179 $kg \cdot ha^{-1}$, 10087 $kg \cdot ha^{-1,}$ and 10543 $kg \cdot ha^{-1}$, respectively. According to the simulation results, future climate change will constrain the rainfed maize yield. Compared with the baseline, under the SSP245 scenario, the average maize yields in catchments 1, 2 and 3 changes by 6.7 %(688 $kg \cdot ha^{-1}$), -4.7 %(-482 $kg \cdot ha^{-1}$), and -8.2 %(-842 $kg \cdot ha^{-1}$), in the 2030 s, 2060 s and 2090 s, respectively. However, rainfed maize yields will increase by 3.9 %(411 $kg \cdot ha^{-1}$), in catchment 4. Under the SSP585 scenario, the average maize yield of the 4 catchments in 2030 s, 2060 s and 2090 s changes to 3.7 % (482 $kg \cdot ha^{-1}$), -6.9 %(-708 $kg \cdot ha^{-1}$) and -16.4 %(-1684 $kg \cdot ha^{-1}$), respectively. Excluding catchment 4, future climate change will cause a slight increase in rainfed maize yield in the early twenty-first century but has varying degrees of negative effects on the following two periods with a significant difference (P-value <0.01), with the trend of production reduction being particularly pronounced under SSP585 scenario. The overall reduction in maize yield can be attributed to increased evapotranspiration rates caused by rising temperatures (resulting in increased crop water requirements). In addition, this reduction might partly be attributed to shortened growing periods, a consequence of increased stomatal closure in response to higher temperatures.

3.4. Adaptation measures for improving corn yield

3.4.1. Effect of planting date on yield

This study, based on the traditional sowing time of the agricultural experimental station (B0) and spanning one week, establishes a total of eight sowing periods ranging from four weeks earlier to four weeks later. The effects of different sowing dates on maize yield in different catchments, different scenarios and different periods were evaluated. Fig. 5 shows the simulated results of maize production at various planting dates throughout the three periods in 21st century under the SSP245 and SSP585 scenarios. For rainfed corn, the best sowing date under the two scenarios is found consistent with the traditional sowing date in 2030 s. For the 2060 s and 2090 s, optimal sowing dates are anticipated to shift earlier, likely within the first week of the traditional planting season. High temperature periods are expected to increase in the future. Therefore, an earlier sowing date can avoid increased evapotranspiration due to high temperatures, especially during the grain filling stage - a critical phase in the crop's lifecycle where the grain accumulates carbohydrates, proteins, and other essential nutrients post-pollination, directly influencing final grain yield and quality. Compared with the local traditional sowing date, the optimal sowing date could increase rainfed maize yield in MRB in 2060 s and 2090 s by 8.5 %, 16.8 % and 7.5 %, 20.5 % reference to the baseline yield under SSP245 and SSP585 scenarios, respectively. production, and the improvement under SSP585 is greater than that of the SSP245.

3.4.2. Effect of irrigation water on yield

Water is an important factor limiting the yield of crop. Therefore, supplementary irrigation is considered another effective adaptive measure for sustaining corn yield under climate change in the MRB. In this study, five different irrigation volumes are considered, namely 5 mm (I1), 10 mm (I2), 20 mm (I3), 30 mm (I4) and 40 mm (I5). These volumes represent the total amount of water applied. They were administered to simulate varying levels of deficit irrigation, where each volume was applied whenever the soil moisture content reached a predetermined threshold level. This approach was designed to closely mimic real-world irrigation practices where water application is often adjusted based on the crop's water needs and prevailing weather conditions. Fig. 6 shows that maize yield can be significantly improved by supplementary irrigation. Under SSP245 and SSP585 scenarios, maize yield can be increased by 13 % - 16 % when the water supply is 20 mm and 40 mm, respectively, in the next three periods.

3.4.3. Effect of fertilizer application date on yield

The timing of fertilizer application significantly affects maize yield. This study was based on the standard fertilizer application period (B0) at the agricultural experiment station with one week of fertilizer application. Six fertilizer application periods were selected: one week earlier (F1), two weeks earlier (F2), three weeks earlier (F3), one week later (B1), two weeks later (B2), three weeks later (B3), and three weeks later (B4). Fig. 7 shows the simulated results of maize yield under the SSP245 and SSP585 scenarios with different fertilizer application times in the three future periods. For rainfed corn, the best fertilization time is found as two weeks in advance under both scenarios, closely aligned with the planting date findings. This synchronization between planting and fertilization dates is crucial for enhancing fertilizer efficiency, particularly as changes in rainfall and temperature impact soil moisture. These results suggest that an early and well-coordinated application of fertilizer, in tandem with strategic planting dates, is an effective adaptation strategy to mitigate climate change's effects on maize yield.

3.4.4. Effect of fertilizer application dose on yield

Fertilizer application dose is critical for crop development and yield. In this study, four different fertilizer application doses were set up for comparison experiments. 5 kg N/ha (F1), 10 kg N/ha (F2), 15 kg N/ha (F3), and 20 kg N/ha (F4). As seen in Fig. 8, fertilizer application did not contribute substantially to maize yield. At SSP245 and SSP585, fertilizer applications of 10 kg N/ha and 15 kg N/ha only increased maize yield by 2.3–6.8 %. Maize yield is found to increase only slightly with the increase in fertilizer use. Excessive fertilizer use can cause toxicity and reduce crop development, threaten the ecosystem, pollute drinking water, and become dangerous to human health. Therefore, the real circumstances of each farm should be considered to determine the precise quantity of fertilizer application.

4. Discussion

In this study, the DSSAT model is applied to the southeastern United States to suggest adaptation strategies to negate the adverse impacts of climate change on the yield of corn. The model was calibrated and validated based on field test data from state agricultural research centers. CMIP6 was utilized to quantitatively examine the influence of climate change on the MRB maize yield. Simultaneously, a multi-point simulation, which refers to the process of conducting simulations at multiple locations within the MRB, was performed to ensure that the findings were representative of the entire MRB. Given the negative effects of future climate change, this study developed four optimal measures to adapt to climate change. The effects of different adaptation measures on reducing maize yield were investigated and the optimal measures to adapt to climate change were proposed.

Temperature is a significant meteorological component that influences maize growth and development. The maize production in MRB

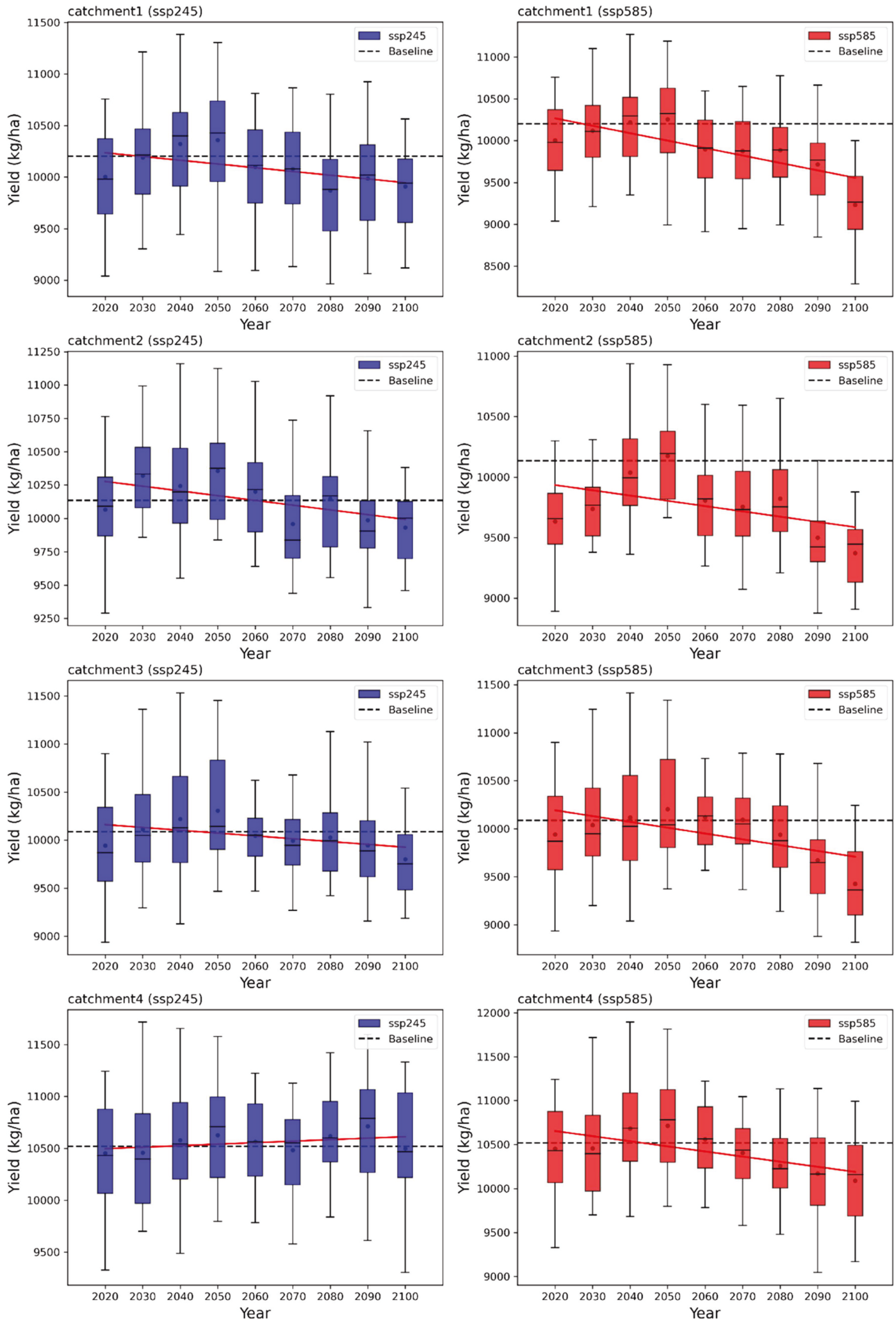

Fig. 4. Simulation of corn yield during 2020s–2100 s for four catchments under SSP245 and SSP585 scenarios; the black line within the box represents the average of historical yield and dots represent mean. The red lines represent the estimated yield trends.

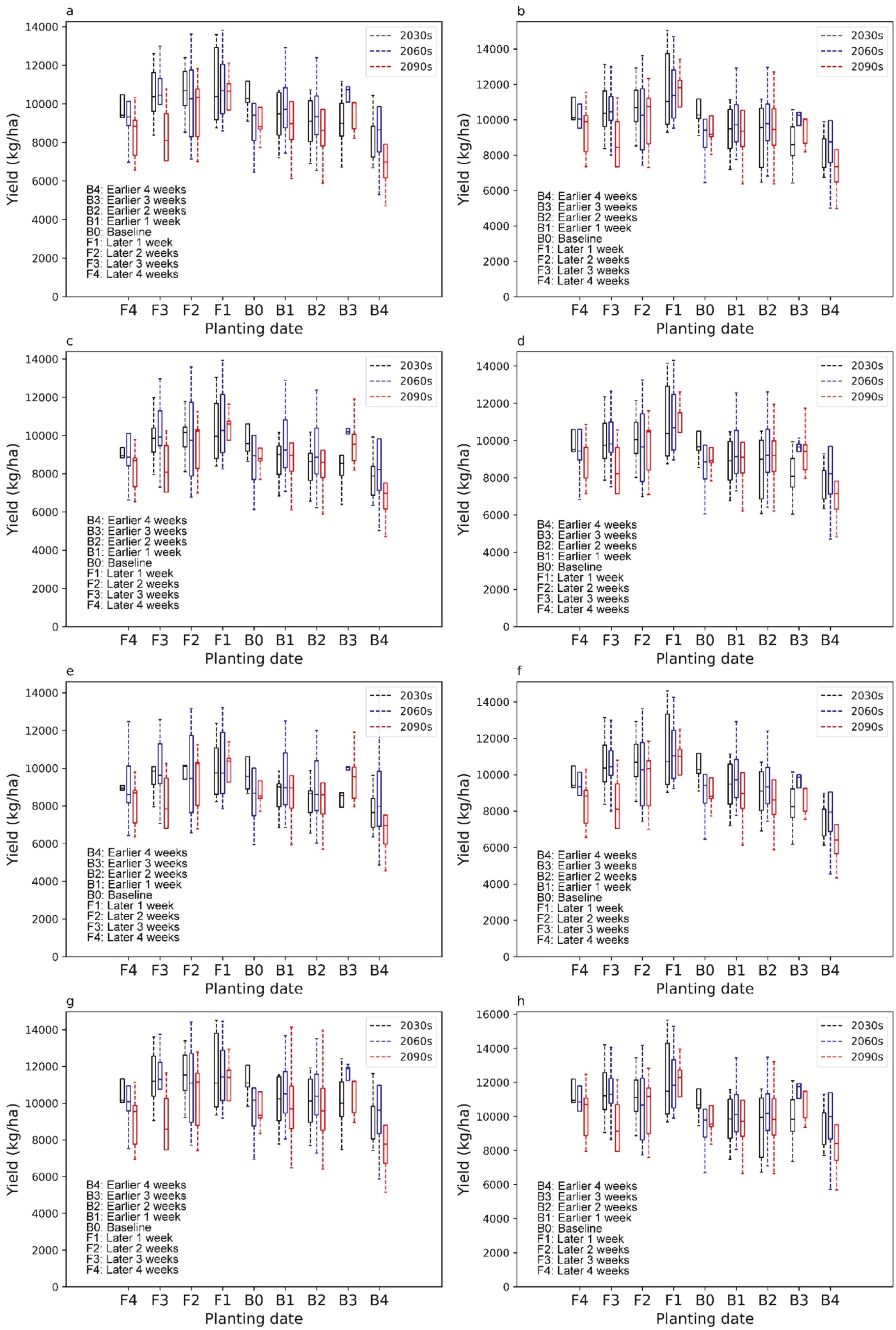

Fig. 5. Rainfed corn yield for adaptation measures of change in planting date (shift earlier 1, 2, 3, 4 weeks, baseline, and shift later 1, 2, 3, 4 weeks) for 2030 s, 2060 s and 2090 s. (a) catchment 1 SSP245; (b) catchment 1 SSP585; (c) catchment 2 SSP245; (d) catchment 2 SSP585; (e) catchment 3 SSP245; (f) catchment 3 SSP585; (g) catchment 4 SSP245; (h) catchment 4 SSP585.

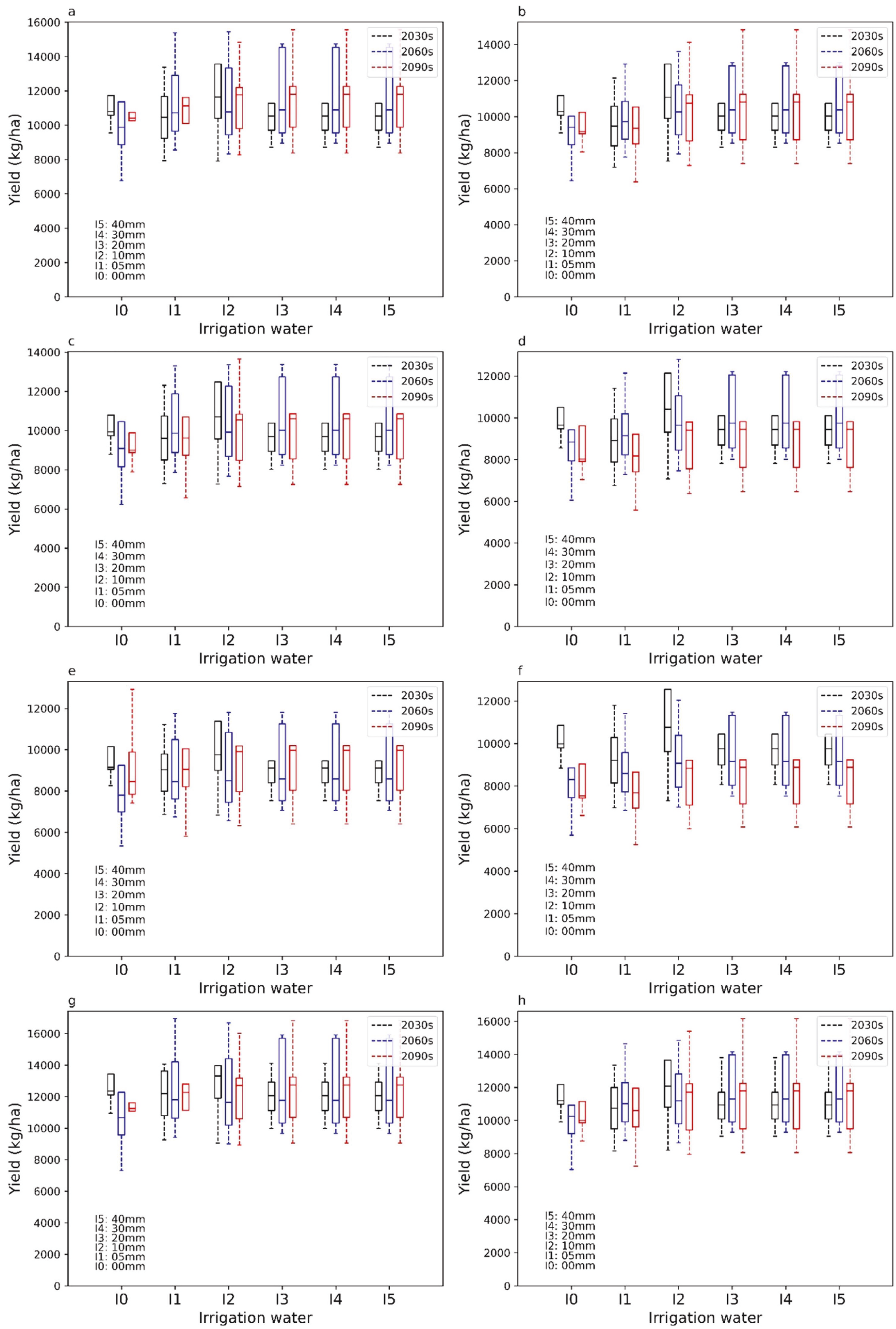

Fig. 6. Rainfed corn yield for adaptation measures of supplying irrigation water (only rainfall, 5, 10, 20, 30, and 40 mm for 2030 s, 2060 s and 2090 s. (a) catchment 1 SSP245; (b) catchment 1 SSP585; (c) catchment 2 SSP245; (d) catchment 2 SSP585; (e) catchment 3 SSP245; (f) catchment 3 SSP585; (g) catchment 4 SSP245; (h) catchment 4 SSP585.

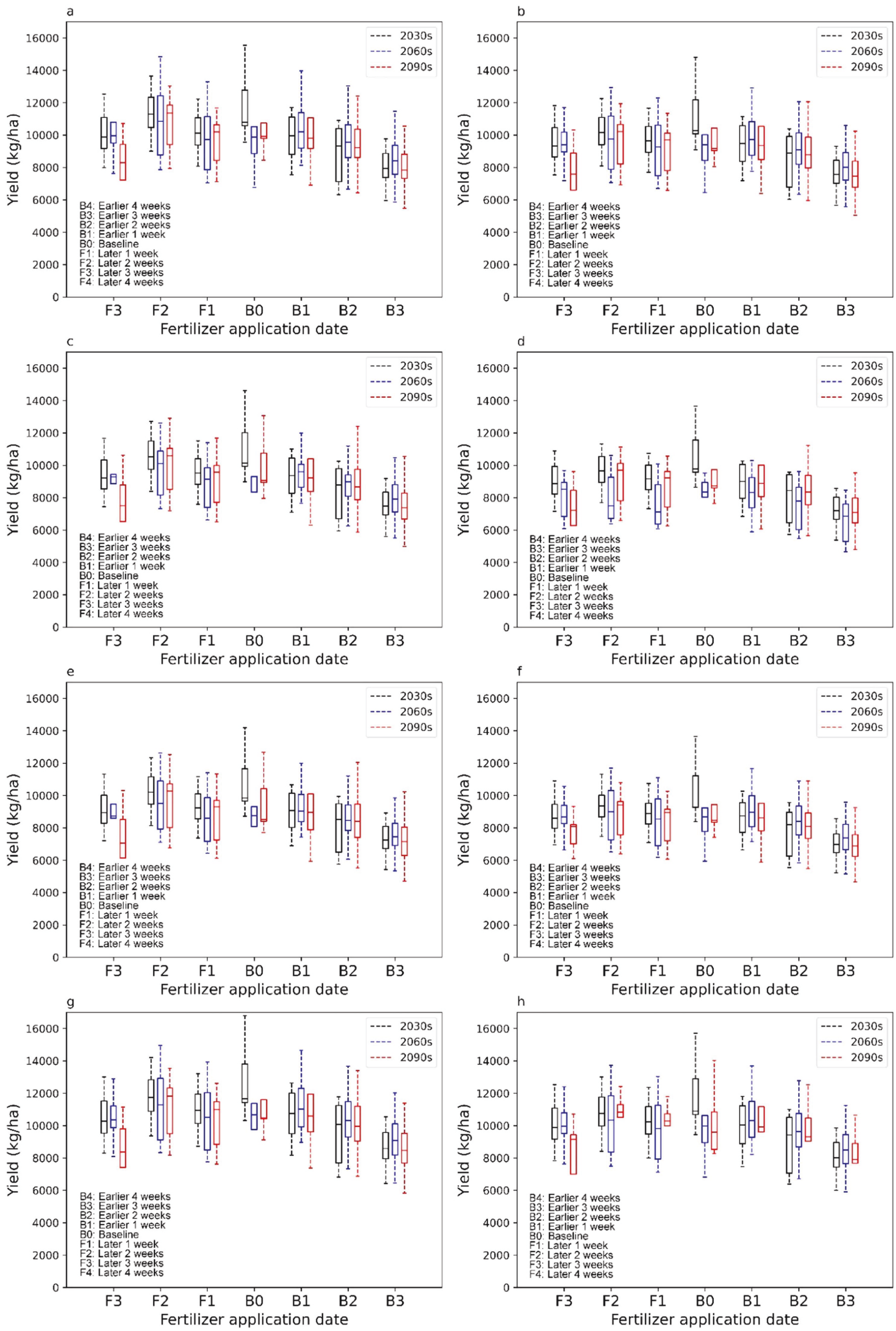

Fig. 7. Rain-fed corn yield for adaptation measures of change in fertilizer application date (shift earlier 1, 2, 3 weeks, baseline, and shift later 1, 2, 3 weeks) under SSP245 and SSP585 scenarios for 2030 s, 2060 s and 2090 s. (a) catchment 1 SSP245; (b) catchment 1 SSP585; (c) catchment 2 SSP245; (d) catchment 2 SSP585; (e) catchment 3 SSP245; (f) catchment 3 SSP585; (g) catchment 4 SSP245; (h) catchment 4 SSP585.

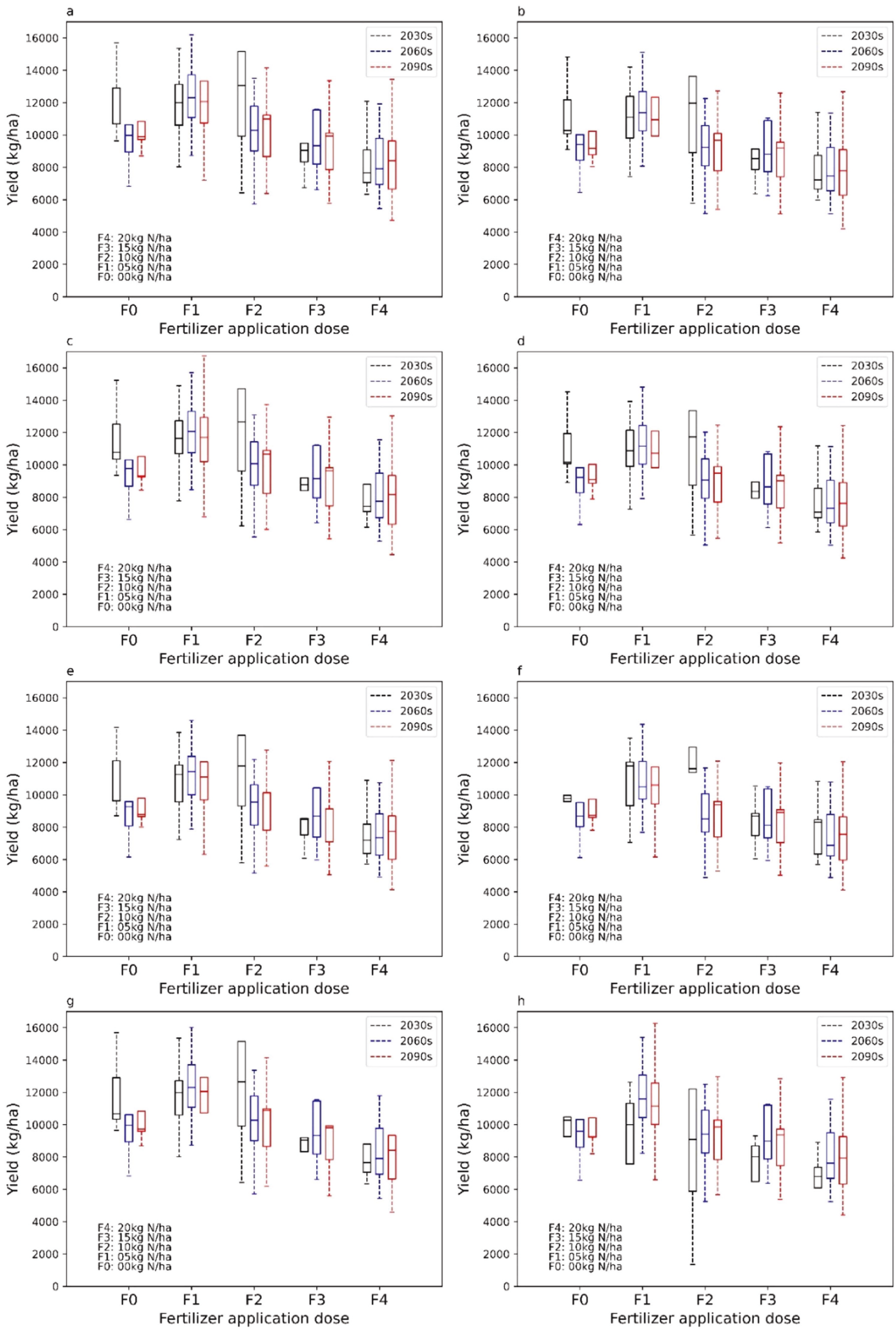

Fig. 8. Rain-fed corn yield for adaptation measures of change in fertilizer application dose (5, 10, 15, and 20 kg N/ha) for 2030 s, 2060 s and 2090 s. (a) catchment 1 SSP245; (b) catchment 1 SSP585; (c) catchment 2 SSP245; (d) catchment 2 SSP585; (e) catchment 3 SSP245; (f) catchment 3 SSP585; (g) catchment 4 SSP245; (h) catchment 4 SSP585.

exhibits increased vulnerability to climate change, particularly under the SSP585 scenario. In dry and semi-arid locations, the key limiting factor of rainfed maize yield is precipitation. Future climate change is not favorable to the growth and development of rainfed maize, owing to increased variability in temperature and precipitation, causing maize production to be unstable, especially under the SSP585 scenario (Arunrat et al., 2022; Dang et al., 2022). Additionally, in the critical period of maize growth (the filling stage), higher temperatures and less precipitation caused by climate change considerably affect corn yield.

Similar to other rainfed contexts (Jain et al., 2015), changing the planting date in the MRB is a simple and practical strategy to address future climate change. The shift of sowing date primarily influences the precipitation, temperature, and solar radiation received throughout the growing period, influencing maize growth and development. Choosing the optimal sowing date at different times might help maize yield the optimal use of water, heat, and light resources based on changes in future climatic components. Meanwhile, the ideal sowing date defines the best time for biomass increase, blooming, and filling.

According to the simulation results, supplemental watering at the Tasseling and grain filling stages was the most effective supplementary irrigation method. Tassel is a vital step in maize development. Male and female ears cannot grow normally if water is scarce during this period. If supplementary irrigation at this stage can significantly increase the number of grains per ear of maize, improving maize biomass after silking will lead to yield increase (Gao et al., 2017). To ensure sustainable irrigation, water sources in the region, such as rivers, ponds, and groundwater, should also be considered when determining the amount of irrigation water. Excessive irrigation instead has a more negative impact on the local ecosystem.

Increasing the frequency of fertilization, distinct from the timing and dosage, has been shown to mitigate the impact of climate change on maize production (Han et al., 2023). However, the Length of fertilizer intervals is mostly determined by local circumstances and crop types. Yields may only be increased by increasing fertilizer application if nutrient insufficiency is one of the primary limiting factors affecting crop growth (Guo et al., 2022). Therefore, it is crucial to balance the increased frequency with the crop's actual nutrient needs and to account for soil conditions and potential long-term buildup of fertilizers.

Planting dates are adjusted to simulate the impact of different sowing times on crop exposure to climatic variables like water, temperature, and solar radiation, affecting the entire growth cycle. Fertilization time is varied to explore how changes in nutrient application timing influence crop development, particularly under shifting precipitation and temperature patterns. Irrigation schedules are modeled by setting soil moisture thresholds that trigger irrigation, assessing the impact of water supplementation during critical growth stages such as tasseling and grain filling. Finally, fertilizer dosages are manipulated to study the yield sensitivity to different nutrient levels, providing insights into how nutrient optimization can counteract climate-related stressors. Together, these adjustments in the DSSAT model offer a comprehensive view of how strategic changes in farming practices can mitigate the adverse effects of climate change on maize production. Sensitivity analysis is essential for identifying which model parameters are most influential under varying climatic and management conditions. Our study integrates a sensitivity analysis, referencing established research that pinpoints water stress, P5 (grain filling duration under optimal conditions), G3 (kernel filling rate under optimal conditions), and P2 (thermal time from silking to physiological maturity) as critical factors affecting maize yield. Particularly, our analysis focuses on how variations in these parameters under different scenarios of water availability and nutrient supply influence crop growth outputs and yield predictions (Wang et al., 2021). This approach helps in understanding the relative importance of each parameter and their interactions under climate stress conditions.

The findings of this study, while indicating potential avenues for enhancing maize yield through adjusted planting and fertilization strategies, must be contextualized within the practical realities of farming in the MRB. The limitations of the current study include assumption of homogeneity of agricultural management, fertilization, soil qualities, and initial maize types. The impacts of extreme weather, such as hurricanes and floods, extreme heat and prolonged drought, pests and diseases on maize were also not considered here. A critical factor influencing the feasibility of these strategies is the region's climatic patterns, particularly its early spring precipitation. In the MRB, high precipitation levels often result in saturated or even flooded fields, which can significantly hinder the ability of farmers to adhere to the identified optimal sowing dates. This challenge underscores the importance of developing flexible adaptation strategies that can accommodate the variability and unpredictability of field conditions (Price et al., 2022). Additionally, the increasing frequency of temperature extremes presents a dual challenge: not only are the high temperatures of concern, but also the shift in frost dates. For instance, a late frost event in March (2023) significantly impacted Alabama's harvest this year, highlighting the need for strategies that can mitigate risks associated with both ends of the temperature spectrum. Beyond agronomic considerations, there are also socioeconomic factors at play. While certain strategies such as increased irrigation might be theoretically effective, their practical implementation faces significant barriers in the MRB. Issues like restrictive riparian rights laws, deep groundwater sources in areas like the Black Belt, limited existing irrigation infrastructure, and overall financial constraints among farmers severely limit the widespread adoption of such measures (Pathak and Magliocca, 2022).

The study's findings highlight the need for comprehensive policy strategies that integrate multiple adaptation measures to mitigate the impacts of climate change on maize production. Specifically, advancing planting and fertilization dates could optimize crop yield, suggesting that policymakers should promote agricultural practices that are adaptable to climatic predictions. Additionally, the positive role of irrigation in enhancing yield underscores the importance of supporting robust irrigation infrastructure and efficient water management policies. However, the limited impact of varying fertilizer doses indicates that other factors may be more critical, pointing to the necessity for ongoing research and development in crop management and fertilization techniques. Collectively, these insights can guide policymakers in crafting effective climate adaptation strategies and agricultural policies to ensure sustainable food production.

5. Conclusion

The analysis of the four different adaptation measures led to the following conclusions:

a) The findings suggest that it will be challenging for a single adaptation mechanism to fully compensate for the adverse effects of climate change on irrigated maize.
b) In the SSP245 and SSP585 scenarios, advancing the planting date by one week and advancing the fertilization date by two weeks would maximize the benefits.
c) The availability of irrigation water can help increase corn production.
d) The amount of fertilizer dose did not have a significant effect on corn yield under any conditions.

This opens opportunities for future research to look into the effect of these factors on corn yield and devise adaptation measures accordingly. Overall, the results of this study show that corn yields can be affected by climate change, and also highlights the importance of carefully considering adaptation measures. The results of this study can be used as a reference for maize adaptation to climate change and sustainable agricultural growth in the MRB.

CRediT authorship contribution statement

Hamid Moradkhani: Writing – review & editing, Supervision, Methodology, Conceptualization. **Xiaoliang Han:** Writing – original draft, Methodology, Data curation. **Adrija Roy:** Writing – review & editing, Methodology. **Nicholas Magliocca:** Writing – review & editing. **Mesfin Mekonnen:** Writing – review & editing. **Pouya Moghaddasi:** Writing – review & editing. **Hamed Moftakhari:** Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Hamid Moradkhani reports financial support was provided by The U.S. National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2024.109230.

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