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Modelling the impacts of climate change on the sustainability of rainfed and irrigated maize in Pakistan

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ABSTRACT

Maize is a globally significant food crop but its future sustainability under rainfed conditions is at risk due to climate change and increased climate uncertainty. In Pakistan most maize is rainfed but there is increasing interest in the role of supplemental irrigation to reduce the vulnerability of crop yields to future drought and climate risks. Using a crop model (DSSAT CERES-Maize) with downscaled data from a weather generator (LARS-WG) and for five selected GCMs, two RCPs (4.5 and 8.5) and two time slices (2050s and 2080s), this study assessed the impacts of climate change and climate variability on rainfed maize grown in the Pothwar region of Pakistan, and the extent to which irrigation could offset future yield reductions. Model simulations were calibrated and validated using experimental data from 2021 and 2022. The outputs showed that on average the yield of maize could be increased by 55% with a single irrigation of 60 mm during the reproductive stage. For the baseline (1991–2020) the average rainfed yield was 3370 kg/ha. The climate change scenarios for the 2050s indicated a −13.5% and −5.8% decline in rainfed yield under RCP4.5 and RCP8.5, respectively. Irrigation applications (between 162 mm and 180 mm) increased grain yields by 5615 kg/ha and 5732 kg/ha, respectively. For the 2080s scenarios there was a projected decrease in yield by -9.3% and -39.7% under RCP4.5 and RCP8.5, respectively. Modelling also confirmed significant reductions in maize biomass production which would negatively impact on feedstocks for both livestock and renewable energy generation.

1. Introduction

Agriculture plays a pivotal role in economic development and poverty reduction but socio economic development and population growth is threatening the ability of less developed countries to meet their future food demands (Godfray et al., 2011; Rao et al., 2022). Most agriculture globally is dependent on rainfed production (80%) and contributes to approximately two-thirds of the world's food production needs (Falkenmark et al., 2001). In Pakistan, about 4 million hectares of agricultural land (24 Mha) is rainfed (Baig et al., 2013) which underpins rural livelihoods and economic development (Adnan et al., 2009; Government of Pakistan, 2008). However, there is increasing recognition of the climate risks facing the agricultural sector and the need to develop and implement cost-effective adaptation strategies to improve productivity (Hafiza et al., 2022), particularly in key staple crops such as maize. Globally, maize (*Zea mays L.*) is one of the most important cereal crops and grown under both irrigated and rainfed production (Irshad et al., 2002). It represents 1.11 million ha in Pakistan with average annual production of 4.04 million tons and productivity of 3620 kg/ha. Maize yields remain very low in Pakistan compared to other countries such as Italy (9500 kg/ha), Canada (6600 kg/ha), China (4600 kg/ha) and Argentina (5700 kg/ha) (Chachar et al., 2020). Maize production is also particularly sensitive to drought stress and climate variability (Ahmed et al., 2018; Hafiza et al., 2022) with changes in temperature and precipitation responsible for shortening the growing season (Ahmed et al., 2018; ur Rahman et al., 2018) and reducing yields (Osman et al., 2021). Getachew et al. (2021) and Suryabhagavan (2017) reported that changes in the timing of monsoon seasons and increased frequency of

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extreme weather events (floods and droughts) can severely affect crop production. Ahmad et al. (2020) reported that a 3.4°C rise in maximum temperature and 3.8°C rise in minimum temperature under hot/dry conditions (RCP8.5) would lead to a 28% reduction in current production and a 29% decrease in future production by the middle of the century (2050).

To reduce the impacts of climate change on productivity, current management practices need to change (Abbas et al., 2017; Yang et al., 2019), including the introduction of irrigation (Ahmad et al., 2019, 2020; Babel and Turyatunga, 2015; ur Rahman et al., 2018). Supplemental irrigation (SI) helps buffer rainfall shortages during critical growth periods (Oweis and Hachum, 2009) to maximize yield and water use efficiency (Gao et al., 2017; Li and Sun, 2016). Igbadun et al. (2007) reported that more consistent yields can also be achieved by applying irrigation during the flowering stage, even if irrigation is limited during the vegetative and grain-filling stages. The challenge in understanding the potential yield benefits associated with SI and the changing relationships between crop, soil, environment and management is that conducting long-term field experiments is both time consuming and expensive (Hoogenboom et al., 2021; Jones et al., 2003). Scientists have therefore developed biophysical crop models including, for example, FAO AquaCrop (Steduto et al., 2012) and APSIM (Keating et al., 2003; McCown et al., 1996). The DSSAT (Decision Support System for Agrotechnology Transfer) suite of models has also been widely used to assess different agricultural systems under a range of alternate climate and agro-economic futures (Ahmed et al., 2018; Amiri et al., 2022; Chisanga et al., 2022; Hoogenboom et al., 2019; Jones et al., 2003). The Crop-Environment-Resource-Synthesis (CERES)-Maize model embedded within DSSAT has also been extensively used to develop management strategies to assess climate impacts on maize productivity (Abbas et al., 2023; Akumaga et al., 2023; Cecil et al., 2023; Wang et al., 2023; Yang et al., 2023; Zhu et al., 2023). To design future adaptation strategies, many researchers have typically coupled crop models with future climate scenarios developed through General Circulation Models (GCMs) for selected Representative Concentration Pathways (RCPs) (Mohammed et al., 2022; Quan et al., 2022; Rao et al., 2022). Such an integrated approach was adopted for this study.

Assessing climate variability is essential for decision-making in climate-sensitive sectors such as agriculture (Abbas et al., 2017). Future yield projections therefore need to account for different weather forecasting models and scales (general and regional circulation models, GCM and RCM) and for different wetting and drying uncertainties (Baigorria et al., 2008; Ferrise et al., 2015; Jha et al., 2019). In conjunction with GCM developments, weather generators have been developed and widely used, including the LARS-WG to simulate and downscale weather data for current and future periods for different GCMs and RCPs (Khalaf et al., 2022; Mirshekarnezhad, 2023; Semenov et al., 2002). Whilst there is extensive data on the impacts of climate change on maize in Africa (Knox et al., 2012) and irrigation on crop productivity, there is much less reported evidence of these combined impacts on maize in Pakistan, where it constitutes a crop of major economic importance. The aim of this study was therefore to investigate the impacts of climate change on rainfed maize in the Pothwar region of Pakistan, and the extent to which supplemental irrigation could mitigate future yield reductions due to abiotic stress.

2. Materials and methods

In summary, experimental trials were conducted in 2021 and 2022 to assess the effects of supplemental irrigation on maize during the vegetative, reproductive and maturity growth stages. Soil characteristics including changes in soil moisture, local weather data, crop management inputs, crop phenology, biomass and yield data were collected. Field data were used to calibrate and validate the CERES-Maize model of DSSAT version 4.8.0 (Hoogenboom et al., 2023). The impacts of climate change on biomass, yield and irrigation needs were simulated for the baseline (30 years historical weather), and for the near (2050s) and far (2080s) futures. To assess climate uncertainties, five GCMs were selected using GCMeval (www.gcmeval.met.no) and the LARS-WG used to derive future climatology. A schematic of the integrated methodology is given in Fig. 1 and a brief description of the experimental site, data collection, and crop and climate modelling approaches are provided below.

2.1. Study site and experimental design

The study was conducted at the National Agricultural Research Centre (NARC) Islamabad in northern Pakistan which has a humid subtropical climate. The experimental site is located at 33.677371° N and 73.132374° E (altitude 498 m above mean sea level). The crops grown in the Pothwar region include wheat, maize, barley, bajra, gram and groundnut (Imran et al., 2021; Rashid and Rasul, 2011). Fig. 2 shows the location of the experimental site and soil characteristics are given in Table 1. Islamabad has four distinct agroclimatic seasons: a hot summer, a monsoon season, a mild autumn, and a cool winter (Rashid and Rasul, 2011). The average maximum and minimum temperatures during the summer maize season were 36.2 °C and 8.85 °C in June and March, respectively. Average (2011–20) maximum rainfall was recorded in March (119 mm) and the minimum in May (45 mm). On average, summer maize receives 280 mm of rainfall (Rafique et al., 2023; Rashid et al., 2014), but effective rainfall is only 214 mm (Rashid and Rasul, 2011). Except for a few rainy summers over the last decade (2014–16 and 2020), supplemental irrigation was required in 2011–13 and 2017–19 to achieve sustainable maize yields. Irrigation demand peaks during April and May. Figure SI-1 shows the weather conditions at the experimental site between 2021 and 2022.

Field experiments were conducted during the summer of 2021 and 2022. The trial was a randomized complete block design with a split plot arrangement. The plot size for each treatment was 25 m^2 (5 m × 5 m) with a 1 m gap between treatments. The local variety of maize (Haq Nawaz Gold) was sown at a rate of 49.40 kg/ha (recommended for row sowing). The total crop water requirement for maize in the Pothwar region is up to 400 mm (Rashid and Rasul, 2011; Rashid et al., 2014), which is traditionally applied as 5 separate irrigations (each 80 mm) on an interval of 18–21 days, through the season. Due to high rainfall variability in Islamabad, a single irrigation of 75% of 80 mm (i.e. 60 mm) and 50% of 80 mm (i.e. 40 mm) was applied at different growth stages, as suggested by Gao et al. (2017). The trial comprised of seven treatments, each with three replicates. These included a control or rainfed treatment (T_0), 60 mm additional irrigation at the vegetative stage (T_1), 40 mm additional irrigation at the vegetative stage (T_2), 60 mm additional irrigation at the reproductive stage (T_3), 40 mm additional irrigation at the reproductive stage (T_4), 60 mm additional irrigation at the maturity stage (T_5), and 40 mm additional irrigation at the maturity stage (T_6). This also helped to identify the critical growth stages at which irrigation for maize were needed (Aluoch et al., 2022; Gao et al., 2017; Igbadun et al., 2007; Li and Sun, 2016). The timing for irrigation for summer maize at the vegetative and reproductive stages in a semi-arid region were consistent with Wang et al. (2023). Figure SI-2 shows the experimental design.

2.2. Crop husbandry practices

Seeds were sown on 2nd and 1st March in 2021 and 2022, respectively. The seed rate was 16 plants/m^2, with a plant-to-plant spacing of 0.20 m and row-to-row spacing of 0.66 m (Hoogenboom et al., 2019; Jones et al., 2003). The recommended nitrogen dose in the form of urea was 155 kg N/ha (divided into five applications) based on Wang et al. (2023), phosphorous (in the form of DAP) was applied at a rate of 57 kg P/ha (one application at sowing) and potassium (in the form of potassium sulphate) at a rate of 30 kg K/ha, was equally applied to all treatments. Weed, pest, and disease control measures were maintained

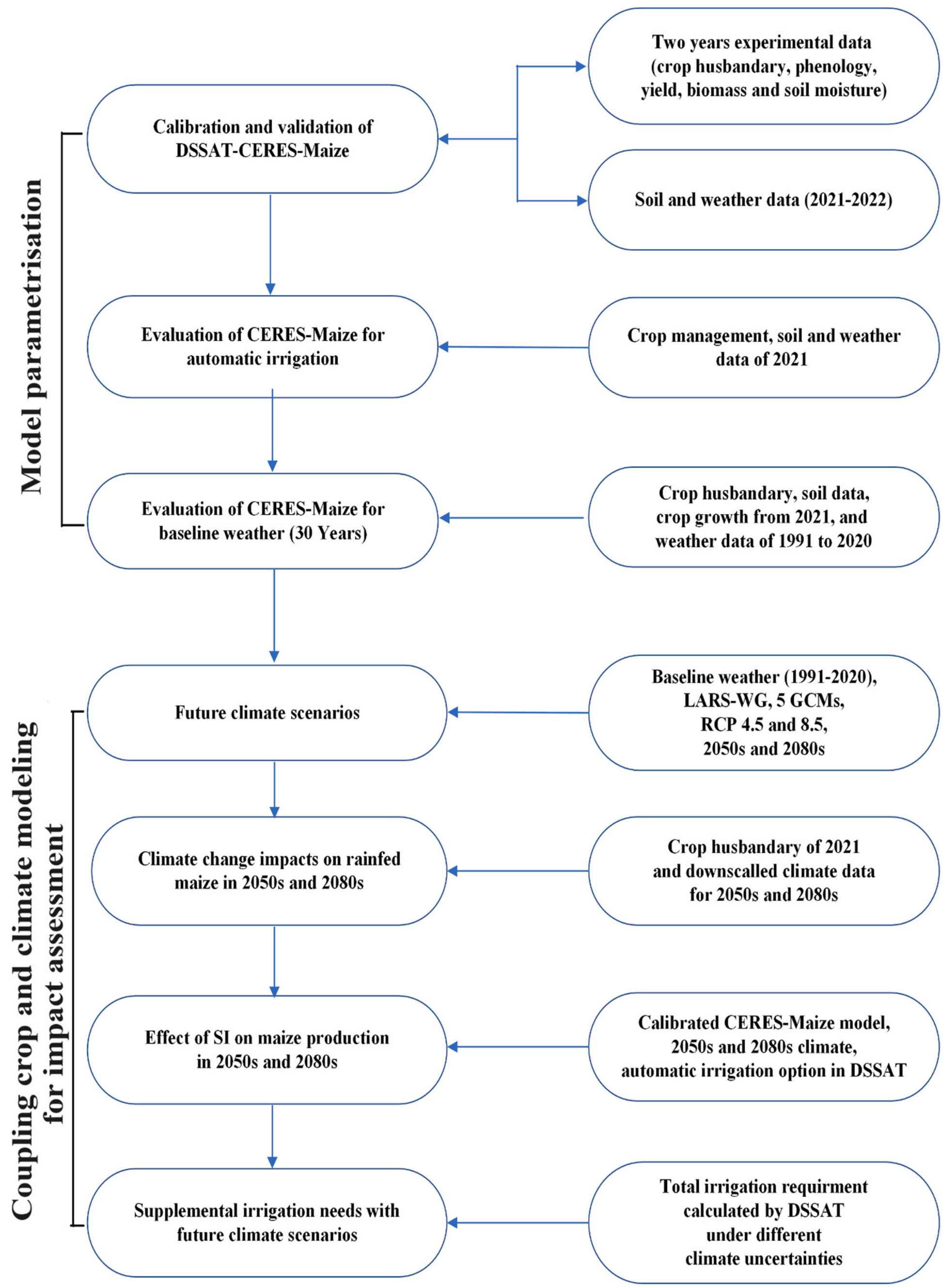

Fig. 1. Schematic showing the methodological framework for coupling experimental fieldwork with crop and climate modelling to assess impacts on maize yields and irrigation needs.

across all treatments. Irrigation was applied once at the specified amount in each treatment. Table 2 summarises the dates and irrigation applied in each treatment. Crop harvest was completed on 10th and 9th June in 2021 and 2022, respectively. The management practices (except irrigation) were similar to those adopted by local farmers.

2.3. Brief description of CERES-Maize model

The CERES-Maize model, embedded within the Decision Support System for Agrotechnology Transfer (DSSAT) programme, encompasses elements including vegetative and reproductive development, and carbon, water, and nitrogen balances, making it a comprehensive tool for simulating maize crop growth and development under contrasting environmental and resource conditions (Hoogenboom et al., 2019; Jones et al., 2003). The CERES -Maize model has been used internationally to assess climate impacts and adaptation strategies for maize in numerous countries including China (Huang et al., 2022; Quan et al., 2022), Ethiopia (Getachew et al., 2021), Hungary (Zelenák et al., 2022), Pakistan (Ahmad et al., 2020; Hafiza et al., 2022), USA (Amiri et al., 2022), and Zambia (Chisanga et al., 2022), and to design management practices considering various integrated approaches (Hoogenboom et al., 2019; Wang et al., 2023; Yang et al., 2023). To run the CERES-Maize model, data relating to the local weather, soil characteristics and crop management were required. The genetic coefficients for maize were defined using the GLUE (Generalized Likelihood Uncertainty Estimator) and sensitivity tool in DSSAT V4.8 (Abbas et al., 2023; Rafique et al., 2023).

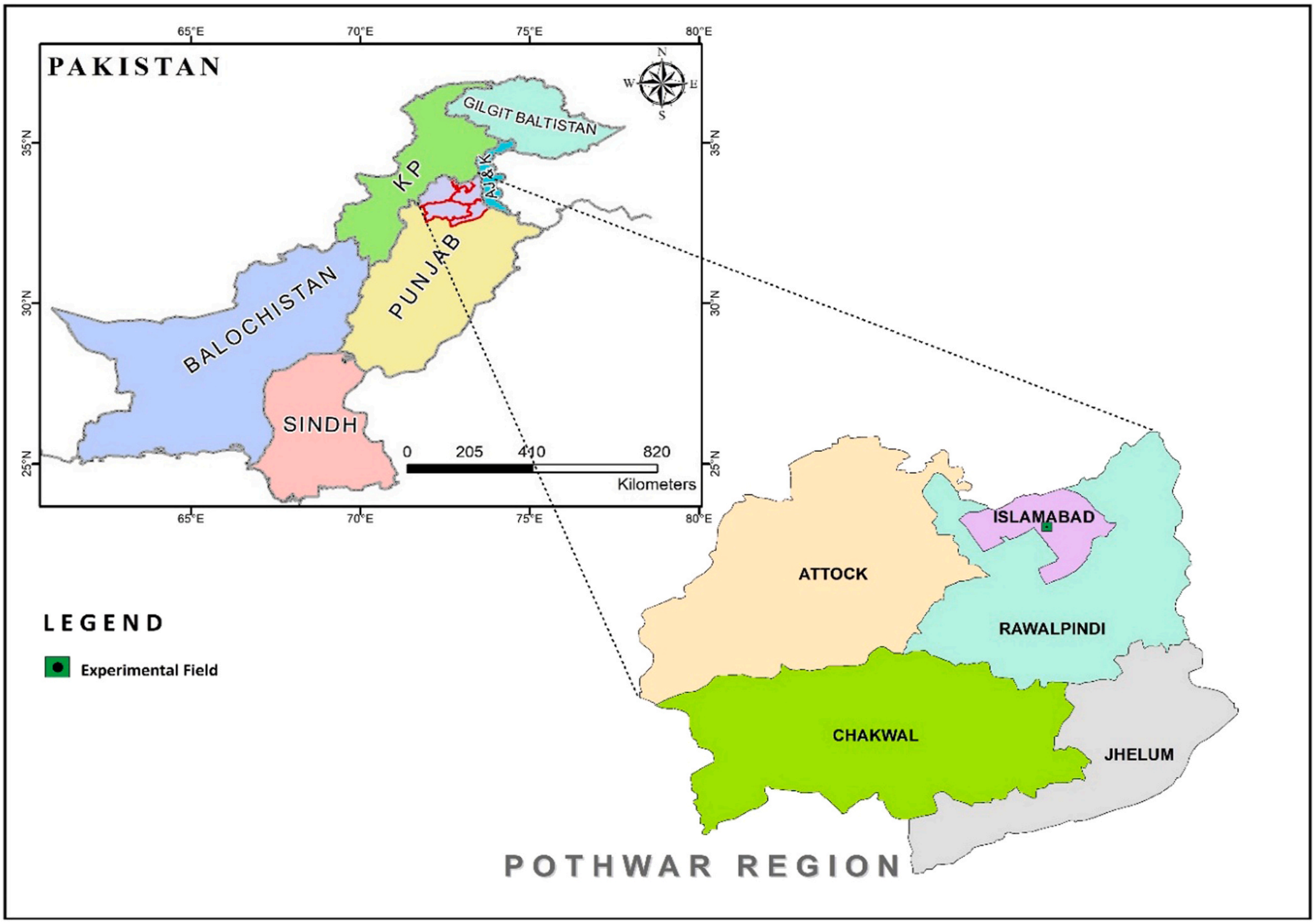

Fig. 2. Location map of the experimental site.

Table 1
Physical, chemical, and hydrological characteristics of the experimental site, incorporated in CERES-Maize model.

Depth (cm)	Clay (%)	Silt (%)	LL	DUL	SWC	BD	HC	pH in water	OC	$CaCO_3$	SRGF
0 – 15	35.1	53.2	0.12	0.29	0.36	1.47	1.29	8.3	0.75	7.5	1.00
15 – 30	34.7	52.1	0.10	0.32	0.39	1.52	1.33	8.0	0.65	4.5	0.65
30–45	34.2	54.1	0.09	0.34	0.41	1.54	1.35	7.7	0.44	2.2	0.35

LL is lower limit (permanent wilting point), DUL is drained upper limit (field capacity), SWC is saturated water content, BD is bulk density (g/cm3), SWC is saturated hydraulic conductivity (cm/hr), OC is organic carbon (%), CacO3 is calcium carbonate (g/kg), SRGF is soil root growth factor.

Table 2
Additional irrigation applications (number and volume) applied in each experimental treatment.

Treatment	**Irrigation applications (days after planting)**		**Irrigation depth (mm)**
	2021	**2022**	
T_1 (vegetative stage)	24	24	60
T_2 (vegetative stage)	24	24	40
T_3 (reproductive stage)	57	40	60
T_4 (reproductive stage)	57	40	40
T_5 (maturity stage)	88	80	60
T_6 (maturity stage)	88	80	40

2.4. CERES-Maize model parameterisation

The growth and production assessment in CERES-Maize required management, weather and soils data and details on the genetic characteristics of the cultivar (Hoogenboom et al., 2019). Weather data including maximum and minimum temperature (°C), rainfall (mm), solar radiation (MJ/m^2/day), relative humidity (%), and sunshine (hrs) for a 30 year (1991–2020) historical period and for the experimental years (2021–22) were collated. Management data included factors such as the previous crop planted, the weight of remaining crop and root residue, as well as various aspects of crop management including timing of planting, tillage practices, fertilizer and irrigation quantities, and the harvest date. The only variable that was modified was the soil root growth factor (SRGF) as the soil profile (0.45 m) was shallow compared to the typical rooting depth for maize (1.2 m). For a shallow soil profile, the SRGF plays critical role in calibration, especially for water stressed treatments (Hoogenboom et al., 1999). In our study, we simulated different SRGFs in DSSAT, with different combinations ranging between 0.01 and 1.0 for each of the three soil depths. This resulted in good agreement between measured and simulated values, where the SRGF was 1.0, 0.65 and 0.30 in the upper (0 – 15 cm), middle (15 – 30 cm) and lower (30 – 45 cm) soil layers. All other inputs, including management practices, were the same as for the experimental conditions as recommended by Hoogenboom, et al. (2019). The CERES-Maize model was then used to assess production traits (assuming current management practices) for future climate scenarios (using weather data generated via LARS-WG) for both rainfed and irrigated conditions under RCP4.5 and RCP8.5 (Abbas et al., 2023; Yasin et al., 2022).

2.5. CERES-Maize model calibration and validation

Calibration of the CERES-Maize model was completed using the phenology, dry grain yield, dry biomass, and soil moisture data from the experimental treatments conducted in 2021. The calibration process was divided into two parts, firstly a calibration with the low stressed treatment data (T_3 2021) followed by full model calibration with the other treatments from 2021, as recommended by Hoogenboom et al. (2019). After calibration, the treatments from 2022 were then used for model validation to assess the statistical goodness of fit. Weather data for the experimental years and for the 30-year period (1991–2020) were obtained from a weather station at NARC, Islamabad. The experimental data collected during 2021 and 2022 included soil moisture content (cm^3/cm^3), crop yield (kg/ha), crop biomass or tops weight (kg/ha) and crop phenology. Soil samples were collected every 2 weeks from three horizons (0–15, 15–30, and 30–45 cm) and from each treatment (Gao et al., 2017; Oweis and Hachum, 2009). The soil samples were oven dried at 105 °C for 24 h to determine dry weight (Jiang et al., 2016) and Eq. 1 used to estimate soil moisture content (cm^3/cm^3) on a dry weight basis. The threshed grain yield and dry biomass were obtained after harvest. The phenological information (emergence, anthesis and maturity) was recorded at each growth stage, involving 12 plants being marked within the central two rows of each experimental plot to monitor their duration of development until they reached 50% tasseling, silking, and the days required for maturity (Abbas et al., 2023; Ahmed et al., 2018; Srivastava et al., 2022). This 2021 data was used to calibrate the CERES Maize model (2021) and then data from 2022 used for validation. Following the calibration process, genetic coefficients were derived (Table 3) using GLUE, a coefficient estimator in DSSAT (Hoogenboom et al., 2019; Jones et al., 2003). The 30 years weather data was used to generate a historical baseline for rainfed yield and biomass, which was then compared against the simulated yield and biomass for the two future periods (2050s and 2080s).

$$\theta_v\left(\frac{cm^3}{cm^3}\right) = \frac{W_{w-}W_d}{W_d} \times \rho_b \times \rho_w \tag{1}$$

where; θ_v was the volumetric soil moisture content, w_w was the wet weight of soil (g), w_d was the dry weight of soil (g), ρ_b was the bulk density of soil (g/cm^3), and ρw was the density of water (g/cm^3).

Model calibration involved assessing the goodness of fit between the paired values of observed and simulated moisture content (cm^3/cm^3), grain yield (kg/ha), and harvested biomass (kg/ha) using field data for 2021. Model validation used datasets for the same variables for 2022 but excluded the T3 treatment which had been used for model calibration.

Table 3
Genotype parameters used in CERES Maize for the local maize variety (Haq-Nawaz-Gold).

Parameter	Description	Value	Unit
Development variable			
P1	Thermal time from seedling emergence to end of juvenile phase	26.5	days
P2	Photoperiod sensitivity (0–1)	0.913	days
P5	Thermal time from silking to physiological maturity (days)	759.7	days
Growth variable			
G2	Maximum kernel number per plant	819.3	unitless
G3	Kernel growth rate under optimum condition	12.76	mg/day
Phint	Thermal time between successive leaf tip to emergence	45.00	^{0}C days/tip

The statistical tests included root mean-squared error (RMSE) (Eq. 2) and relative-root mean-squared error (RRMSE) (Eq. 3):

$$RMSE = \sqrt{\left(1 \Big/ n^* \sum_{i=n}^{n} (S_i - O_i)^2\right)} \tag{2}$$

$$\mathrm{RRMSE} = 100 \Big/ \mathrm{M}^* \sqrt{\left(1 \Big/ \mathrm{n}^* \sum_{i=n}^{n} (\mathrm{S_i} - \mathrm{O_i})^2\right)} \tag{3}$$

where; S_i is the simulated and O_i is the observed value, and M is the mean of the observed value. Model performance was considered to be excellent if the RRMSE was < 10%, good if it ranged between 10% and 20%, fair if it was > 20% and < 30%, and poor if it was > 30% (Pérez-Ortolá et al., 2015; Jamieson, 1991). In addition, linear regressions and their coefficients of determination (R^2) were calculated for each treatment (observed) and its corresponding CERES Maize simulated values. A paired t-test on the simulated and observed means for dry biomass and grain yield were also calculated, where the simulated values were deemed not to be statistically significantly different from the observed values if the calculated t-values were lower than the critical t-value.

The CERES-Maize model was also used to assess the impacts of irrigation on grain yield and biomass for both experimental years. using the automatic mode in the simulation (Jiang et al., 2016). Automated irrigation was configured assuming a managed allowable depletion (MAD) value of 0.5. This assumes that when half of the available water in the root zone has been used, then an irrigation is triggered to replenish the soil back to field capacity (Chen et al., 2020; Malik and Dechmi, 2019). The other management options were kept the same as in the experimental conditions.

2.6. GCM selection and statistical downscaling

The historical weather data were used to generate future climatology for two RCPs (4.5 and 8.5) and for two time slices (near (2050s) and far (2080s) futures). A similar approach was adopted elsewhere globally by Mohammed et al. (2022), Quan et al. (2022) and Srivastava et al. (2022). Given the wide range of GCMs available it is important to select an appropriate ensemble for a specific location (Abbas et al., 2017). In this study, the GCMeval tool was used (Brunton et al., 2023; Parding et al., 2020). The evaluation technique in GCMeval is based on concepts described in McSweeney and Jones (2016). The tool evaluates the CMIP5 climate model ensemble in terms of how well each model simulates the current climate in each region (Parding et al., 2020), considering factors such as seasons, climate variables (precipitation and temperature), and skill scores (bias, spatial correlation, spatial SD ratio, and RMSE of annual cycle). The ensemble selection using GCMeval was then further verified by reviewing relevant literature that reported which GCMs had been used for modelling climate impacts in Pakistan (see Supplementary Information). We ultimately selected 5 GCMs including MIROC5, INMCM4, MPI_ESM_MR, CanESM2, and GFDL_CM3 to represent the climate uncertainty of cold/wet, cold/dry, middle, hot/wet, and hot/dry climates, respectively. Table 4 summarises the characteristics of the selected GCMs, and Table 5 summarises the projected changes in precipitation and temperature for the near and far futures for the 5 GCMs under the RCP 4.5 and RCP 8.5, respectively.

A weather generator known as LARS-WG (Semenov et al., 2002) was then used to statistically downscale the GCM data for the five GCMs. The LARS-WG includes 19 climate models based on the CMIP5 ensemble as used in the IPCC 5th Assessment Report (Semenov et al., 2013). The model produces histograms from the observed historical climatology to categorize daily maximum and minimum temperature and precipitation, as well as assessing the durations of dry and wet day sequences (Osman et al., 2022). For each future scenario, 30 years of synthetic

Table 4
General information of the GCM's selected in this study (Zhang et al. 2020). Details for each GCM can be found online (https://www.ametsoc.org/PubsAcronymList).

Model name	Institute	Country	Resolution
MIROC5	Atmosphere and Ocean Research Institute (AORI)	Japan	1.5° × 1.5°
INMCM4	Institute of Numerical Mathematics	Russia	1.5° × 2°
MPI_ESM_MR	Max Planck Institute for Meteorology	Germany	1.875° × 1.875°
CanESM2	Canadian Centre for Climate Modelling and Analysis (CCCma)	Canada	2.8° × 2.8°
GFDL_CM3	Geographical Fluid Dynamics Laboratory (GFDL)	USA	2.5° × 2.0°

Table 5
Projected changes in temperature and precipitation for selected GCM's for the near (2050 s) and far (2080 s) futures.

RCP	Climate Uncertainty	Global climate model (GCM)	Change	
			Temperature (^{0}C)	Precipitation (mm/day)
Near Future (2050 s)				
4.5	Cold/wet	MIROC5	+0.96	+0.33
	Cold/dry	inmcm4	+0.36	-0.09
	Middle	MPI_ESM_MR	+1.0	+0.15
	Hot/wet	CanESM2	+1.31	+0.33
	Hot Dry	GFDL_CM3	+1.49	+0.12
8.5	Cold/wet	MIROC5	+1.04	+0.21
	Cold/dry	inmcm4	+0.68	+0.04
	Middle	MPI_ESM_MR	+1.15	+0.15
	Hot/wet	CanESM2	+1.56	+0.29
	Hot Dry	GFDL_CM3	+1.57	+0.14
Far Future (2080 s)				
4.5	Cold/wet	MIROC5	+1.81	+0.60
	Cold/dry	inmcm4	+1.09	+0.09
	Middle	MPI_ESM_MR	+1.75	+0.32
	Hot/wet	CanESM2	+2.25	+0.30
	Hot Dry	GFDL_CM3	+2.83	+0.41
8.5	Cold/wet	MIROC5	+3.06	+0.84
	Cold/dry	inmcm4	+2.47	+0.22
	Middle	MPI_ESM_MR	+3.70	+0.38
	Hot/wet	CanESM2	+4.16	+0.55
	Hot Dry	GFDL_CM3	+4.58	+0.55

weather data were generated and used as an input into the CERES-Maize model. The model was run firstly for the baseline and then for each future scenario to assess projected changes in dry biomass, dry grain yield (threshed) and irrigation need.

3. Results and discussion

3.1. CERES Maize model calibration and validation

The model was initially calibrated using the T_3 treatment (less stressed treatment) data for 2021 for crop phenology, dry grain yield, dry biomass, and soil moisture (Table 6), because the T_3 treatment was used to derive the cultivar coefficients using the GLUE estimator within the DSSAT software. The other treatments from 2021 were then used for full model calibration (Table 7). The model simulated production traits with a high degree of accuracy (97.03% and 97.55%). Based on the T_3 calibration, the CERES Maize model predicted emergence, anthesis and maturity with a high degree of statistical confidence. The RMSE values obtained in this study for days to anthesis and days maturity were consistent with those of Ahmed et al. (2018) who reported a RMSE of 2.73 days and 2.44 days for days to anthesis and days to maturity, respectively. Amouzou et al. (2018) reported RMSE (and nRMSE) values of 1 day (2%) and 1 day (1%) for predicting anthesis and maturity dates for maize. Kadiyala et al. (2015) reported RMSE (and nRMSE) values for predicting anthesis, maturity, grain yield and biomass as 1.4 days (2%), 1.15 days (9%), 1.55 tons/ha (18.4%) and 0.23 tons/ha (3.60%), respectively. For biomass, the calibrated values were also in close agreement with Ahmed et al. (2018), their RMSE values ranging between 449 and 1172 kg/ha and with Amouzou et al. (2018) for grain yield (RMSE 47–413.6 kg/ha and RRMSE 2–19%). Malik and Dechmi (2019) reported the RMSE (and nRMSE) values for predicting grain yield and biomass as 694 kg/ha (5%) and 2522 kg/ha (22%), respectively. The simulated soil moisture was close to the measured values (Fig. 3) for both calibration and validation periods. For soil moisture in the top layer (0–15 cm) in T_3 2021, the CERES-Maize model simulated values for RMSE and RRMSE were 0.013 cm^3/cm^3 and 7.83%, respectively. For the 15–30 cm layer, the equivalent values were 0.011 cm^3/cm^3 and 6.28%, and for the 30–45 cm layer, values of 0.01 cm^3/cm^3 and 5.47% were obtained.

For full model calibration, the simulated yields from CERES-Maize showed very good statistical performance with minimum and maximum RMSE values of 85 and 272 kg/ha, and RRMSE of 3.12 and 6.55%, respectively. The maximum and minimum RMSE and RRMSE values while predicting the biomass were 296 and 642 kg/ha, 3.54 and 6.54%, respectively. The findings from our study for predicting the maize yield and biomass are in close agreement with studies conducted by Abbas et al. (2023), Ahmed et al. (2018), Amouzou et al. (2018) and Tovihoudji et al. (2019). Abbas et al. (2023) reported a slightly higher RMSE (391–476 kg/ha) for yield and RMSE of 572.5–779.5 kg/ha for biomass. Ahmed et al. (2018) reported an RMSE for biomass (tops weight) and grain yield as 449–1172 kg/ha, and 451–963 kg/ha for their calibration based on experimental treatments. Amouzou et al. (2018) reported a very close agreement with our findings for grain yield and biomass. They showed an RMSE (and nRMSE) of 47–252 kg/ha (2–7%) and 253–621 kg/ha (3–7%), respectively. Tovihoudji et al. (2019) reported a CERES-Maize calibration with an RMSE (and RRMSE) for above ground biomass and yield of 569 kg/ha (8%) and 327 kg/ha (12%), respectively. There were no directly comparable results of model efficiency. The model performance for calibrating soil moisture content was also very good. The RMSE was up to 0.014 cm^3/cm^3 and RRMSE was up to 7.83%. Amouzou et al. (2018) reported RMSE values for soil moisture ranging from 6% to 13% which was within the range of our RRMSE values for 2021. Jiang et al. (2016) also reported RMSE values for CERES-Maize for predicting soil water content as 11.5% (0–5 cm depth), 11.8% (5–20 cm), 10.3% (20–40 cm) and 8.7% (for 40–120 cm).

The grain yield, biomass, and soil moisture content data from 2022 were then used to validate the CERES-Maize model. Table SI-3 summarises the RMSE and RRMSE values for the validation. Across all experimental treatments, the RMSE for grain yield ranged between 79 and 140 kg/ha. The RRMSE values ranged between 3.29% and 10.85%, respectively. For biomass, the RMSE and RRMSE ranges were 123–384 kg/ha and 2.15–4.75%, respectively. These results confirm a very good level of accuracy for the CERES-Maize model in predicting production traits. For soil moisture content (cm^3/cm^3) in 0–15 cm layer, the RMSE and RRMSE values were 0.006–0.009 cm^3/cm^3 and 3.39–5.16%. For soil depth of 15–30 cm, the values for RMSE and RRMSE were 0.006–0.008 cm^3/cm^3, and 3.23–6.56%, respectively. For 30–45 cm depth, the equivalent values were 0.005–0.007 cm^3/cm^3 and 3.15–5.07%. Finally, a summary of the linear regressions, coefficients of determination (R^2), and paired t-test statistics using the simulated and

Table 6
Observed and simulated crop phenology, dry grain yield and dry biomass for a less stressed treatment (T_3) in 2021.

Date	Observed range	Simulated	RMSE	RRMSE (%)
Emergence	10th Mar ± 1 days	10th Mar	0.82 days	10.21
Anthesis	15th Apr ± 2 days	13th Apr	2.58 days	5.94
Maturity	30th May ± 2 days	25th May	3.42 days	3.96
Yield (kg/ha)	4932–5196	5283	229	4.51
Biomass (kg/ha)	10852–11432	11622	502	4.49

Table 7
Statistical performance indicators of CERES-Maize for simulating dry grain yield and dry biomass for the calibration period (2021).

Treatment	Productiontrait (kg/ha)	Observed range	Simulated value	RMSE (kg/ha)	RRMSE (%)
T_0	Yield	2560–2784	2731	114	4.277
	Biomass	7652–8324	8163	341	4.28
T_1	Yield	2768–3044	2967	127	4.375
	Biomass	7988–8680	8312	296	3.54
T_2	Yield	2712–2988	2967	162	5.681
	Biomass	7796–8396	8312	305	3.75
T_4	Yield	4036–4264	4399	272	6.554
	Biomass	9564–10104	10423	642	6.54
T_5	Yield	2672–2904	2731	121	4.302
	Biomass	7756–8528	8163	316	3.87
T_6	Yield	2608–2808	2731	85	3.121
	Biomass	7596–8372	8163	363	4.54

observed data for biomass and grain yield are summarised in Table 8. For all treatments the R^2 values were very high (>0.9), and the paired t-tests confirmed that the simulated and observed means were not significantly different ($P < 0.05$) since the calculated t-values were lower than the critical t-value for both biomass and yield. This statistical analysis in conjunction with the RMSE and RRMSE values described above confirmed that the validated model was suitable for assessing climate change impacts on maize in the Pothwar region of Pakistan.

3.2. Impacts of supplemental irrigation on production traits

Based on irrigation applications of 60 mm and 40 mm at the reproductive stage for the T_3 and T_4 treatments, maize yields were found to increase by +55.5% and +34.1%, and biomass by +40.7% and +24.3%, respectively (Fig. 4). The same irrigation applications at the vegetative stage (T_1 and T_2) also improved yields (+10% and +5.29%) and biomass (+10% and +7%) production. However, at maturity there was only a negligible impact in both years (+2.4% in 2021; +1.7% in 2022). These findings are consistent with Igbadun et al. (2007) and Li and Sun (2016) who reported that the reproductive stage (tasseling and grain filling) is the most critical growth stage of maize in semi-arid regions and is highly sensitive to water stress. An adequate irrigation at this stage can therefore increase yield. Gao et al. (2017) reported that a single supplemental irrigation applied at the vegetative (such as V_6, and V_{12}) and reproductive (tasseling and silking) stages improved maize productivity compared to un-irrigated experiments. Similar findings were reported by Babel and Turyatunga (2015), Hammad et al. (2018), Jiang et al. (2016), Khan et al. (2021a), (2021b) and Wang et al. (2023).

3.3. Evaluation of DSSAT automatic irrigation on experimental conditions

The calibrated CERES-Maize model was used to assess the impacts of supplemental irrigation on grain yield and biomass through an automatic irrigation option. The rainfed production traits were then compared with the simulations assuming automatic irrigation. Under rainfed conditions in 2021 and 2022, maize yields and biomass were 2731 kg/ha and 1168 kg/ha, and 8163 kg/ha and 5672 kg/ha. In 2021, automatic irrigation (182 mm applied across 5 events) increased grain yield and biomass to 7186 kg/ha (+62%) and 14,021 kg/ha (+42.5%), respectively. During 2022, the automatic irrigation (258 mm applied across 7 events) increased grain yield and biomass by 85.8% (up to 8230 kg/ha) and 64.6% (up to 16,009 kg/ha), respectively. Chen et al. (2020) assessed the application of the automatic irrigation option in the CERES-Maize model and reported that rainfed grain yield could be increased by between 6153 kg/ha (119 mm irrigation) to 12,077 kg/ha (280 mm irrigation). Kadiyala et al. (2015) also evaluated automatic irrigation at 60% threshold of field capacity in CERES- Maize and observed an increase in grain yield of up to 7960 kg/ha.

3.4. Projected changes in climate for RCP 4.5 and 8.5

The projected climate changes under RCP 4.5 in Islamabad indicate a rise in both temperature and precipitation. The maximum temperature and precipitation increase for the near future (2050s) was +1.49 °C in hot/dry (GFDL_CM3) conditions and +0.33 mm/day in both cold/wet (MIROC5) and hot/wet conditions (CanESM2). The MPI_ESM_MR model (middle/average uncertainty) indicates a rise in temperature and precipitation by +1.0 °C and +0.15 mm/day, respectively. For the far future (2080 s), the maximum increase in temperature and precipitation was +2.83 °C in hot/dry conditions and +0.66 mm/day under cold/wet conditions. The minimum increase in temperature was observed under the cold/dry (INMCM4) conditions for both periods, i.e., 2050s (+0.36 °C) and 2080s (+1.09 °C). However, the cold/dry conditions for the near future indicates a precipitation decline of -0.09 mm/day. Ali et al. (2019) estimated the projected rise in minimum temperature across different regions in Pakistan to be +1.5 °C (+2.5 °C) and +2.2 °C (+4.5 °C) under the RCP4.5 (RCP 8.5) in the 2050 s and 2080 s, respectively. Such changes in temperature and precipitation for Islamabad have been reported by Bint-e-Mehmood et al. (2023). Table 5 summarises the projected temperature and precipitation changes for each climate condition for both future time periods.

The RCP8.5 scenarios depict significant increase in temperature and precipitation specially in far future (2080s). The climate projections show +4.58 °C as the maximum increase in temperature for hot/dry conditions in the far future and +2.47 °C as the minimum temperature increase under cold/dry conditions. The maximum increase in precipitation for the cold/wet condition showed an increase of +0.84 mm/day and a minimum of +0.22 mm/day for the cold/dry condition. For the near future (2050s), the projections show maximum and minimum increases in temperature of up to +1.57 °C and +0.68 °C under the hot/dry and cold/dry conditions, respectively. The mid-range uncertainty (MPI_ESM_MR model) projects a rise in temperature and precipitation of +1.0 °C and +0.15 mm/day, respectively. Janes et al. (2019) projected an increase in temperature of +4.5 °C in summer for 2070–2099, over South Asia by downscaling data from three GCMs. Similarly, Pakistan is likely to experience a rise in minimum temperature and summer days +1.3 to +1.9 °C and 6–20 days under RCP4.5 and RCP8.5, respectively (Sajjad and Ghaffar, 2019). Table summarises the projected changes in temperature and precipitation for the selected GCM models under different climate uncertainties.

3.5. Climate change impacts on maize yield in the 2050 s and 2080 s under RCP4.5

Fig. 5 shows the projected impacts of climate change on rainfed and irrigated maize yield in the 2050s and 2080s under RCP4.5. The modelling shows that the average rainfed yield in the 2050s would decrease by −13.5% and −4.2% in cool/wet and cool/dry scenarios, respectively, compared to the baseline yield (3370 kg/ha). These results are consistent with Tesfaye et al. (2016) who reported that grain yields

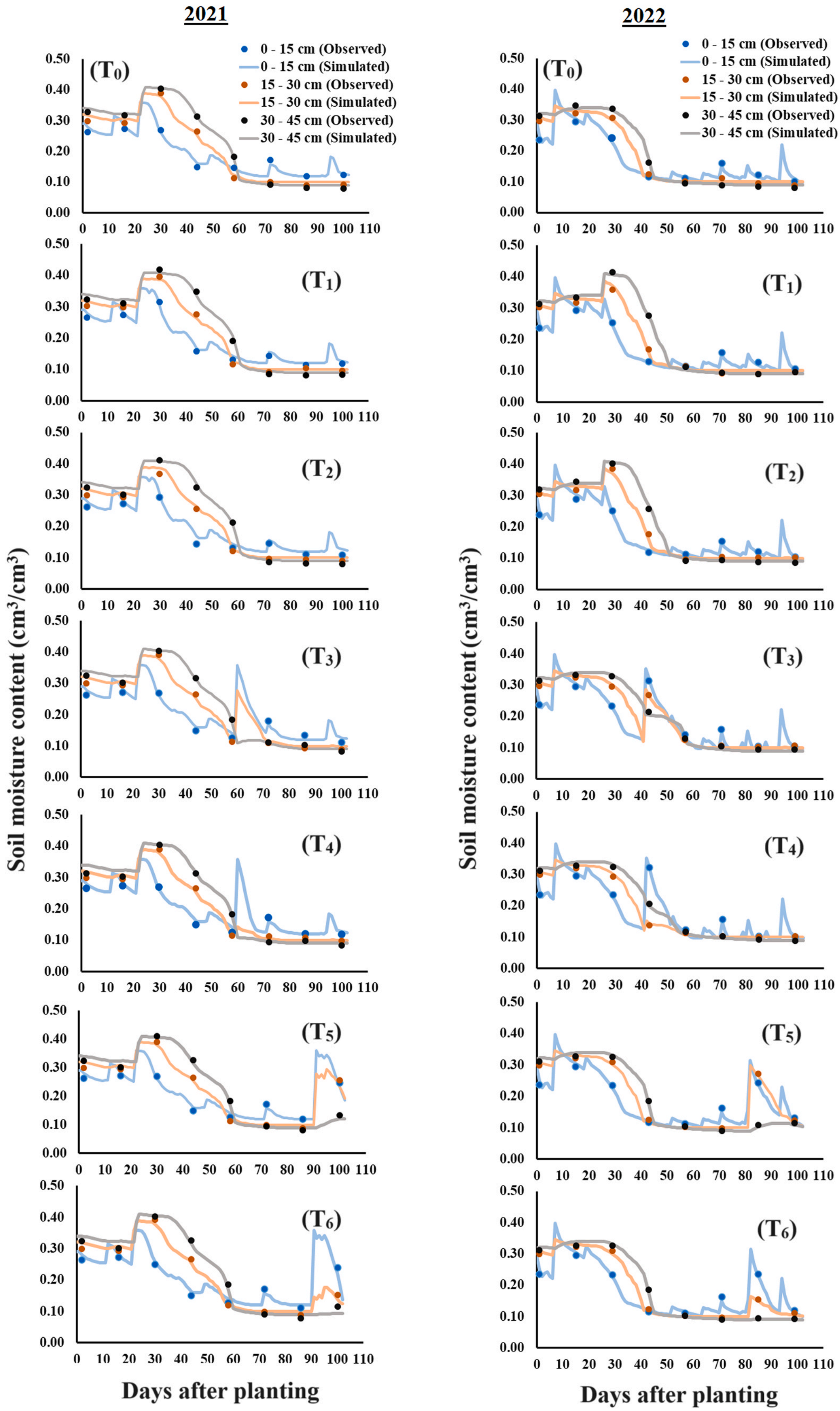

Fig. 3. Observed and simulated soil moisture content (cm^3/cm^3) in 0–15 cm, 15–30 cm, and 30–45 cm soil depths, for each treatment for the calibration (2021) and evaluation (2022) periods.

Table 8
Summary statistics for the CERES-Maize model validation for dry grain yield and dry biomass (R = replicate (observed); n = 5, p<0.05).

Statistic	Dry biomass	Dry grain yield
Regression and coefficient of determination (R^2)		
R1 v simulated	$y = 1.074x - 1063$ $R^2 = 0.997$	$y = 1.0134x - 175.38$ $R^2 = 0.998$
R2 v simulated	$y = 0.6704x + 2963.5$ $R^2 = 0.984$	$y = 0.8103x + 619.37$ $R^2 = 0.997$
R3 v simulated	$y = 0.85x + 1123.8$ $R^2 = 0.958$	$y = 0.8949x + 275.38$ $R^2 = 0.987$
Paired t-test (two-tailed) on simulated and observed means		
P value	0.0785	0.1436
t-statistic	2.206	1.733
Critical value	2.571	2.571

in South Asia would reduce by −5% to −12.5% if existing cultivars were grown under a future climate. A large part of South Asia may face reductions in grain yield of more than −25% by 2050. Our results are also in agreement with research by Mohammed et al. (2022) in Ethiopia which reported that grain yield could decrease by up to −26% in the 2050 s under RCP4.5. Srivastava et al. (2021) reported that the reduction in rainfed yield in eastern India would range between −7.5% and −10.5% and −4.3% to −10.6% in the 2050s and 2080s, respectively. For hot/wet, hot/dry, and middle scenarios we observed a slight increase in rainfed yield of up to +14.2%, +6.7%, and +6.1%, respectively. Han et al. (2021) observed that rainfed yields in China could increase by +16.4% and +12.6% by 2060 and 2090, respectively. Supplemental irrigation could improve average grain yields by +30.1% to +69.8% under all scenarios for RCP4.5 for the 2050s. In India, Rao et al. (2022) reported that supplemental irrigation of 50 mm could increase maize yields from +5% to +15% by the mid-century. For the 2080s, our modelling shows a decline in rainfed yield by −3.3%, −9.3% and −1.3%

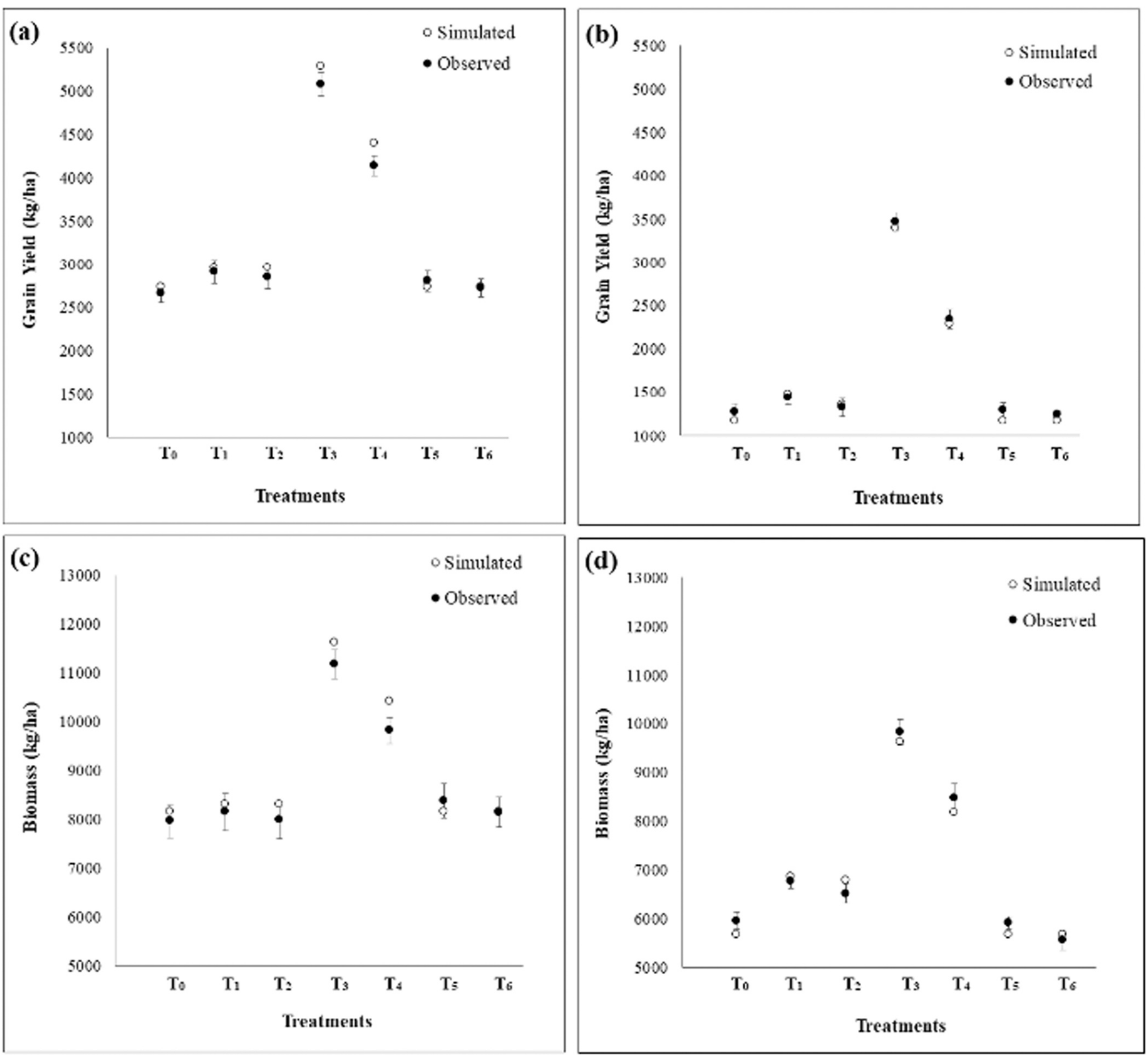

Fig. 4. CERES-Maize simulated and observed dry grain yields (a and b) and dry biomass (c and d) for each treatment for the calibration (2021) and evaluation (2022) periods.

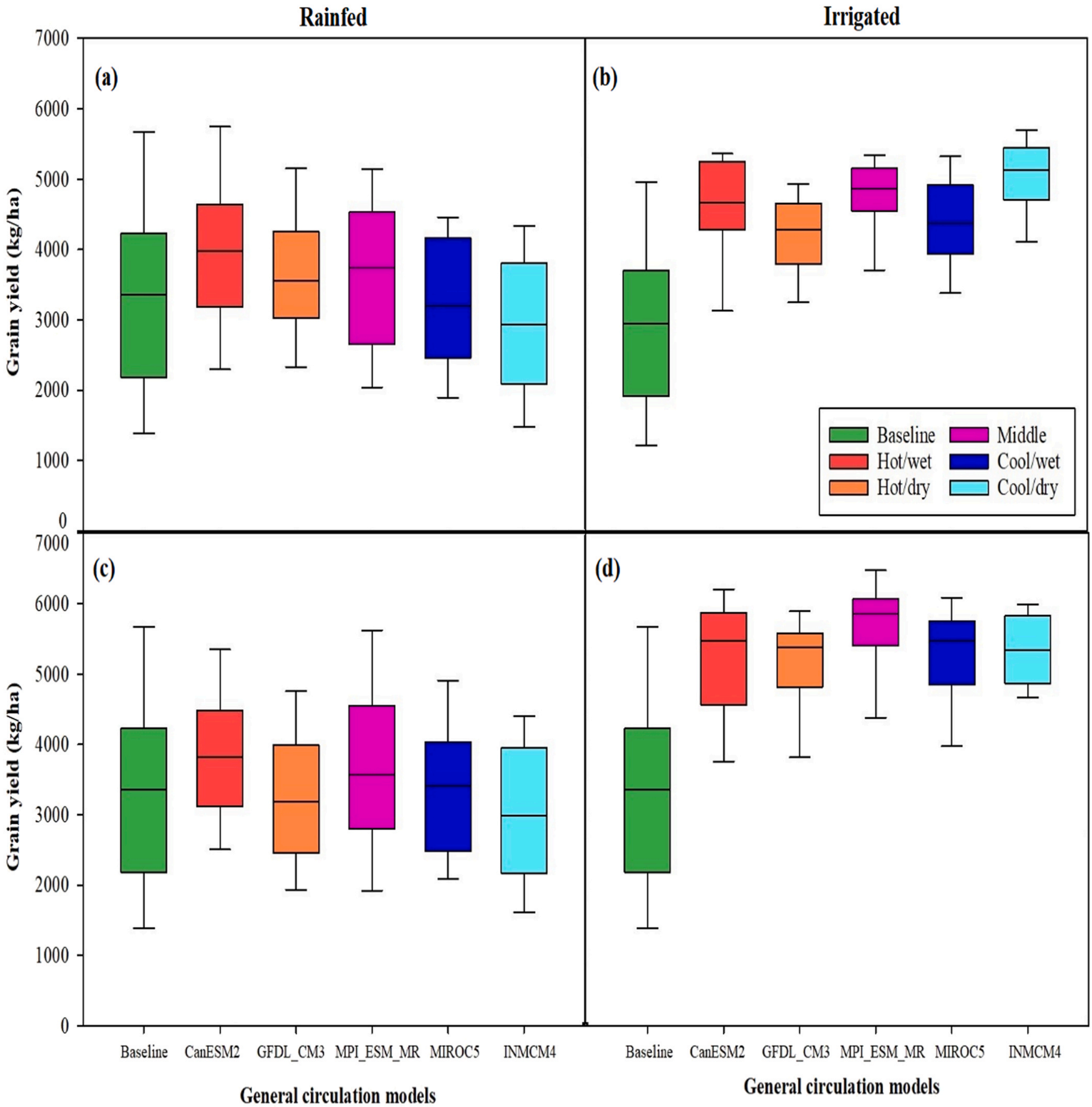

Fig. 5. Modelled impacts of climate change on dry grain yield for the near (2050 s) and far (2080 s) under rainfed conditions (top panel (a) and (b), and under supplemental irrigation (lower panel) (c) and (d) under RCP 4.5.

for the hot/dry, cool/dry, and cool/wet condition uncertainties, respectively. However, a subsequent increase in rainfall coupled with increased temperature shows that grain yield could increase by +12.9% and +7.9% under hot/wet and middle conditions, respectively. Moradi et al. (2013) reported that grain yields in Iran could decline by −11% to −38% with climate change. Rao et al. (2022) reported that rainfed grain yields in India could reduce from −16% to −46% under a future climate scenario of RCP4.5. Similarly, research by Xiao et al. (2020) showed that grain yields could reduce by −3.5% to −19.7% in the 2080s under RCP8.5. Xiao et al. (2020) also reported yield reductions of −4.1% to −14% in China using a multi-GCM approach for the 2040s and 2080s. Supplemental irrigation has been shown to increase grain yields by +34.1 to 56.7% under all climate uncertainties for RCP8.5. Grain yields are highly sensitive to temperature, so increases in temperature lead to greater reductions in yield. Table SI-4 summarises the impacts of climate change on grain yield under rainfed and irrigated conditions for RCP4.5.

3.6. *Climate change impacts on maize yield in the 2050 s and 2080 s under RCP8.5*

Fig. 6 shows the impacts of climate change on rainfed and irrigated maize yield the in 2050s and 2080s under RCP8.5. For 2050s, the average rainfed yield is expected to decrease by −5.8% in the cool/dry condition. The increased rainfall and temperature would increase grain yield by +9.2%, +8.5%, +7.2%, and +6.9% in the hot/wet, hot/dry, middle, and cool/wet climate condition uncertainties, respectively. Our

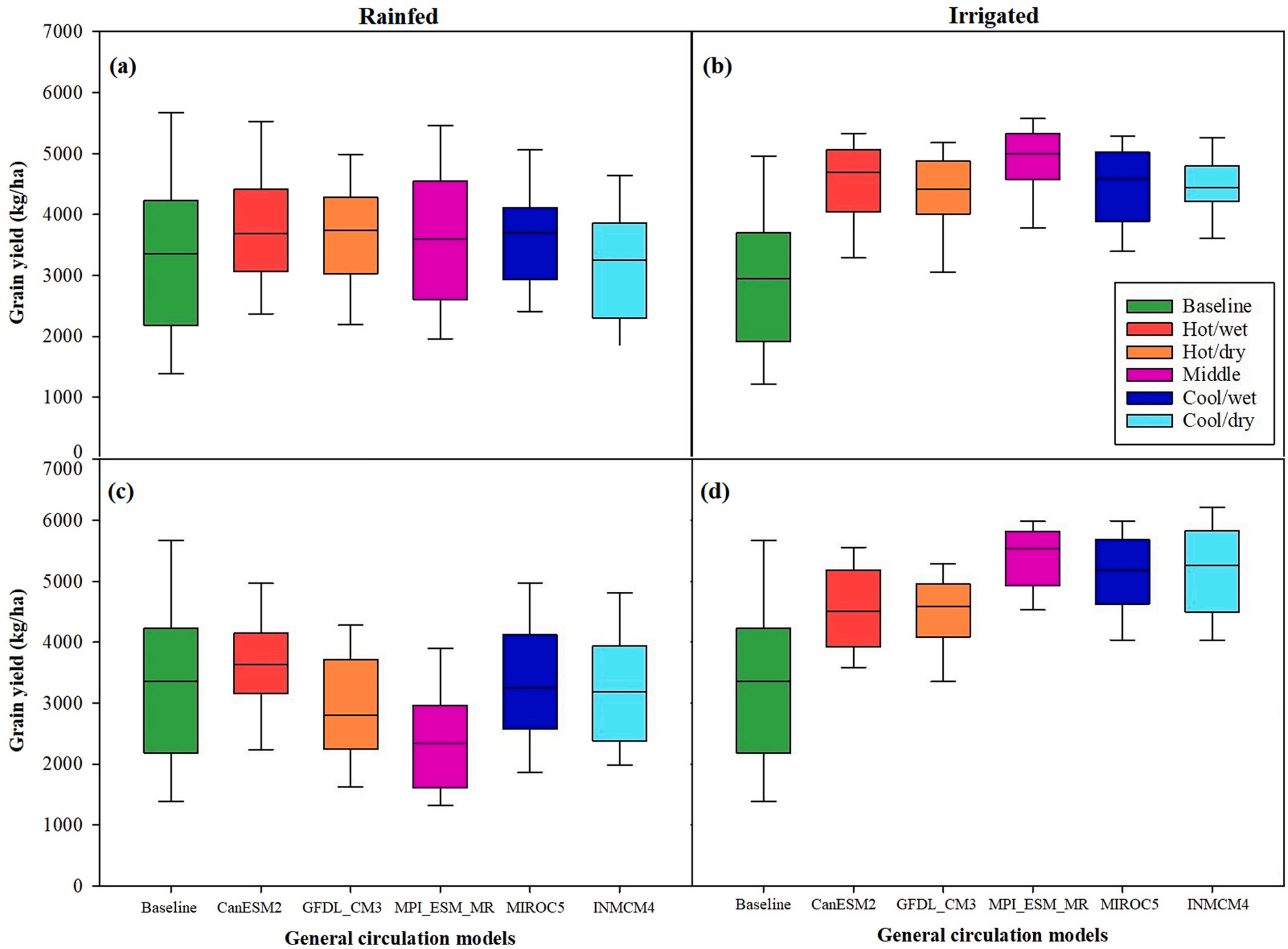

Fig. 6. Modelled impacts of climate change on rainfed yield (dry) for the near future (a), impacts of supplemental irrigation on dry grain yield in near future (b), climate change impacts on rainfed grain yield (dry) in far future under (c), impacts of supplemental irrigation on dry grain yield in far future (d), under RCP8.5.

findings are consistent with Yasin et al. (2022) who reported that projected grain yields in Pakistan would decrease by −8% to −55% due to climate change in the mid-century (2050s) under RCP8.5. Ahmad et al. (2020) reported that grain yields in Faisalabad (an irrigated region of Pakistan) were expected to decline by up to −28% by the mid-century (2050s), under RCP 8.5. Mohammed et al. (2022) reported that maize yield in Ethiopia could reduce by −29% in the 2050s under RCP8.5. Rao et al. (2022) reported that the grain yield of rainfed maize in India could reduce by −21% to −80% under a future climate scenario in RCP8.5. Supplemental irrigation could increase grain yield by +34.7%, +32.1%, +40%, +34.1%, and +50.8% for the climate uncertainties projected by CanESM2, GFDL_CM3, MPI_ESM_MR, MIROC5, and INMCM4 models, respectively. For the 2080 s, the combination of increased temperature with comparatively less rainfall would decrease grain yields by up to −16.9%, −39.7%, −2.6%, and −5.6% under the hot/dry, middle, cool/wet, and cool/dry climate condition scenarios. A +6.9% increase in grain yield was observed for the hot/wet climate. Our study findings are consistent with those of Abbas et al. (2023) who estimated that grain yields would decrease by −17% to −29% in Multan under future climate change scenarios of RCP8.5. Supplemental irrigation would help to increase grain yields by between +24.4% and +54.2% for all climate condition uncertainties. These results are consistent with Babel and Turyatunga (2015) who predicted that supplemental irrigation (80 mm) could increase maize yields in Iran by between +28.6% and +42.1% across all future climate scenarios for the 2050s and 2080s. Kassie et al. (2015) and Moradi et al. (2013) also reported on the benefits of supplemental irrigation in mitigating the adverse impacts of climate change during the moisture-sensitive growth stages of maize production. Adaptation strategies including the increased reliance on supplemental irrigation will be needed to offset the negative impacts of climate change on maize yields. Table SI-5 summarises the impacts of climate change on rainfed and irrigated maize yields under the RCP8.5 scenario.

3.7. Climate change impacts on maize biomass under RCP 4.5 and 8.5

Understanding the climate impacts on maize biomass is also critical given its use both as a feedstock for livestock and as a fuel supply for renewable energy generation. The experimental trials conducted in this study confirmed that a single irrigation (60 mm) could increase average biomass production by +35.2%. Reduced rainfall in the future could result in reduction of biomass by up to −7% compared to the baseline. Figure SI-6 summarises the projected impacts of climate change on biomass production for future time periods under RCP4.5. Rainfed biomass production in the 2080 s is more affected than in the 2050 s where decreases by −1.9% and −6.3% in cool/wet and cool/dry conditions were projected. The increase in rainfall and temperature in the hot/wet, hot/dry, and middle climate condition scenarios increases biomass by up to +9.5%, +4.6%, and +4.2%, respectively. Supplemental irrigation of 131–180 mm increases biomass production by +21.2 to +41.2% under all future scenarios. In the 2080 s, the only decrease in rainfed biomass is observed under the cool/dry climate conditions by −4.7%. The increased rainfall in the far future increases biomass by +7.9%, and +6.1% in the hot/wet and middle climate condition uncertainties, respectively. However, there would be a smaller increase (+0.6%) and negligible decrease (-0.2%) in rainfed biomass under the cool/wet and hot/dry conditions, respectively. Supplemental irrigation ranging from 134 mm to 171 mm as an adaptation strategy in the far future could increase biomass by +23.9 to +34.6%. Table SI-7 summarises the impacts of climate change on rainfed and irrigated maize biomass under RCP4.5.

Figure SI-8 shows the impacts of climate change on biomass production in 2050 s and 2080 s under RCP8.5. In the 2050 s, a modest increase in rainfed biomass production is observed by +5.8%, +6.4%, +4.9%, and +4.2% in the hot/wet, hot/dry, middle, and cool/wet climate condition scenarios, respectively. The only biomass reduction was under the cool/dry conditions (-3.4%). Compared to the baseline, supplemental irrigation can increase biomass by +23.9%, +22.9%, +28.4%, +23.5%, and +30.7% as projected by the CanESM2, GFDL_CM3, MPI_ESM_MR, MIROC5, and INMCM4 models, respectively. In 2080 s, the biomass under rainfed conditions will be affected by climate change. There was a projected decrease in rainfed biomass of up to −6.6%, −15.5%, and −2.6% for the hot/dry, middle, and cool/dry climate conditions, respectively. The hot/wet and cool/dry scenarios show an increase in biomass production of +4.8%, and +0.7%, respectively. However, supplemental irrigation could increase biomass by +17.9%, +18.8%, +26.3%, +23.9%, and +32.2% under the hot/wet, hot/dry, middle, cool/wet, and cool/dry scenarios, respectively. Table SI-9 summarises the impacts of climate change on biomass under rainfed and irrigated conditions for RCP8.5.

3.8. Projected changes in irrigation needs

Fig. 7 summarises the irrigation needs (mm) for the near and far futures under both RCP's (4.5 and 8.5). For the 2050 s, the RCP4.5 results show that the average grain yield could increase to 5239 kg/ha (+35.7%), 4823 kg/ha (+30.1%), 5464 kg/ha (+38.3%), 5016 kg/ha (+32.8%), and 5723 kg/ha (+69.8%) if irrigations amounting to between 131 mm and 180 mm were applied during the season under the five future climate conditions. In contrast with Rao et al. (2022), our results are much higher. They reported that irrigated grain yields by the mid-century (2050 s) would only increase by +5–15% assuming a single irrigation of 50 mm, under the RCP4.5 scenarios. This might be because of the different climate and irrigated conditions. For the 2080 s (RCP4.5), the average grain yield could increase by up to 5215 kg/ha, 5116 kg/ha, 5655 kg/ha, 5249 kg/ha, and 5252 kg/ha, if supplemental irrigation was applied ranging between 134 mm and 171 mm during the season, under the five climate condition scenarios. The findings of Umesh et al. (2022) are more consistent with our study. They observed that supplemental irrigation of 50 mm could increase rainfed yields by +28.4% (near mid-century) to +74.8% (end century) under future climate change scenarios of RCP4.5. For the 2050 s under RCP8.5, we observed an increase in grain yield (kg/ha) of up to 5161, 4963, 5615, 5115, and 5082 kg/ha when supplemental irrigation (mm) was applied (142, 134, 156, 149 and 162 mm) under the projected changes in

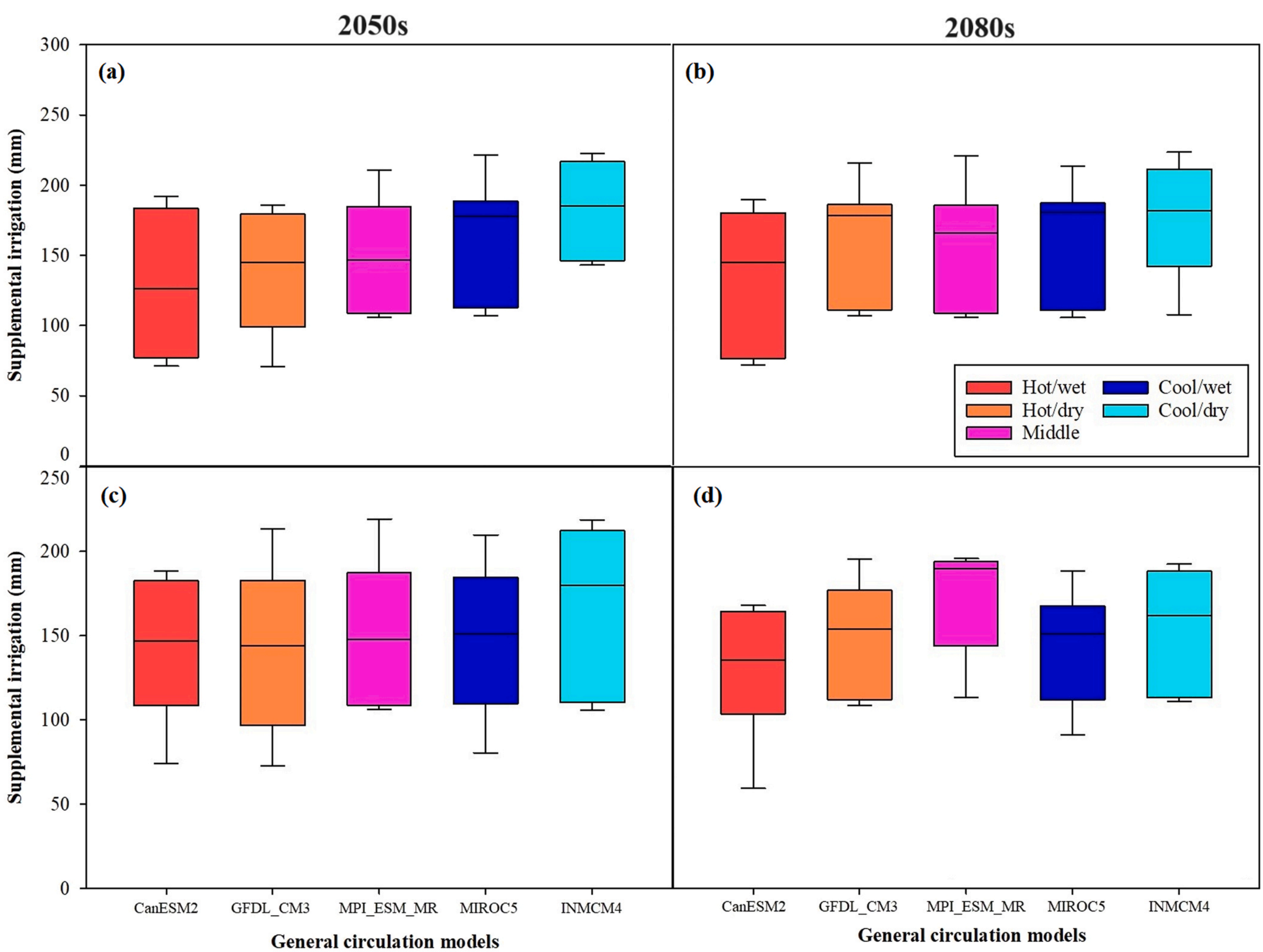

Fig. 7. Modelled supplemental irrigation requirements (mm) in 2050 s under RCP4.5 (a), supplemental irrigation requirements in 2080 s under RCP4.5 (b), supplemental irrigations requirements in 2050 s under RCP8.5 (c), and supplemental irrigation requirements in 2080 s under RCP8.5 (d).

weather by CanESM2, GFDL_CM3, MPI_ESM_MR, MIROC5, and INMCM4, respectively. For the 2080 s, supplemental irrigation of between 127 mm and 165 mm, could increase yields (kg/ha) by up to 4554, 4459, 5336, 5114, and 5196 kg/ha for the five climate condition scenarios, respectively. The results of our study agree with Babel and Turyatunga (2015) who predicted that supplemental irrigation of 80 mm in Iran could increase maize yields by +28.6% to +42.1% under all future climate scenarios for the 2050s and 2080s. Umesh et al. (2022) also reported that supplemental irrigation of 50 mm for a rainfed region in India could increase maize yields by +34.8% (in 2025) to +85.9% (in 2090) under RCP8.5.

3.9. Methodological limitations

This modelling study has a number of inherent limitations and assumptions. It was a single site experiment so extrapolation to other regions within Pakistan or elsewhere in South Asia should be exercised with caution. For different soils, weather, and management options the climate and impacts adaptation strategies would be different. In this study, climate projections based on climate models were derived, which have implicit uncertainties, due to the complex and incomplete understandings of the climate systems and coarse resolution. The study findings are contingent on the accuracy of these models, and any biases or limitations in the models can influence the outputs. Moreover, the assumption of stationarity in certain aspects of climate and crop response may not hold true under changing climate conditions, potentially affecting the reliability of long-term predictions (Ali et al., 2019). The crop model used to simulate maize growth and yield were based on assumptions regarding crop physiology and response to environmental factors, which may not fully capture the complexity of real-world agricultural systems. Furthermore, the study's findings were specific to the geographical area and period studied and generalizing them to other regions or future timeframes may require additional research and consideration of local factors. Socioeconomic factors, such as farmers' decision-making and adaptation strategies, are also critical but may not be fully integrated into the analysis. Finally, the study may not fully explore the impact of extreme weather events, such as droughts or floods, on maize sustainability, despite their potential severity and significance in a changing climate.

3.10. Implications for future sustainability of maize production

From the findings of this study, it is understood that the production of rainfed maize in Pothwar region is not sustainable. The grain yield and biomass could be extensively increased with adequate irrigation applications, especially if applied during critical growth stages. There is a need for policy reforms and irrigation management in the study region to take maximum economic benefits from the maize production with very less input or human efforts. Rainwater harvesting (construction of ponds/reservoirs) should be adopted in the region to avoid water losses during extreme rainy seasons/monsoon, which can be used to irrigate the crops in dry spells of the summer season. The solar water pumps could also be installed for supplemental irrigation purposes in rainfed regions to avoid production losses (Ali Shah and Akbar, 2021). Climate change can severely impact the maize yield by shortening the crop season through increased temperature and less precipitation. The inadequate rainfall is projecting an agitate scenario for irrigation developments in 2050 s and 2080 s to achieve sustainable production targets. Shifts in sowing and harvesting dates and climate resilient management practices should be studied to generate adaptation measures for future periods. The services of non-governmental organizations (NGO's), research and development foundations and extension workers need to be invoked to train local farmers for climate-smart irrigation management to minimize the region's economic loss. Despite of highly precipitated region of Pakistan there is still need for irrigating summer crops in the Pothwar region, which indicates that other rainfed regions are at the risk of production-related economic losses. Therefore, this study will provide a useful basis for understanding the impacts of climate change on both rainfed and irrigated maize and evaluating the beneficial impacts of supplemental irrigation on grain yield in other rainfed regions of Pakistan.

4. Conclusions

Supplemental irrigation is necessary to achieve sustainable production of cereal crops in rainfed regions, like Pothwar. Especially in summer season, the crop yields are severely affected due to water stress (due to less rainfall) in critical growth stages. In comparison of rainfed yield, the single supplemental irrigation of 60 mm and 40 mm applied at reproductive stage of maize revealed a significant increase in grain yield up to 5083 kg/ha and 3472 kg/ha, followed by the vegetative growth stage (increased by 9.98% and 5.19%), respectively. The results confirm that the reproductive stage is most critical for water stress. The climate change assessment shows the hot/dry scenario has maximum increase in temperature. The maximum increase in temperature would be 4.58 °C and 2.83 °C in 2080s under RCP 4.5 and 8.5 with a minimal increase in precipitation of 0.14 mm/day (15.4 mm/season) and 0.55 mm/day (60.5 mm/season), respectively. These climate projections have resulted the higher irrigation demands in hot/dry conditions compared to other uncertainties. These climate change scenarios suggest the rainfed yield could be reduced by 4.2–13.5% in RCP 4.5 and 2.6–39.7% in RCP 8.5. The irrigation-based adaptations developed in this study suggest the grain yield could be increased by 30.1–69.8% in RCP 4.5 and 24.4–54.2% in RCP8.5. The maximum increase in grain yield was recorded with the middle uncertainty when supplemental irrigation is applied. In the Pothwar region, rainfed maize will be negatively affected by climate change but supplemental irrigation could mitigate these impacts if implemented as an adaptation management strategy.

CRediT authorship contribution statement

Jerry William Knox: Writing – review & editing, Visualization, Validation, Supervision, Investigation, Formal analysis. **Shahzad Hussain Dahri:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Irfan Ahmed Shaikh:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Zakir Hussain Dahri:** Writing – review & editing, Resources, Investigation, Data curation. **Gerrit Hoogenboom:** Writing – review & editing, Validation, Supervision, Formal analysis. **Mashooque Ali Talpur:** Writing – review & editing, Resources, Conceptualization. **Munir Ahmed Mangrio:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, 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.

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.agwat.2024.108794.

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