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RESEARCH

Vulnerability Assessment of Wheat Yield Under Warming Climate in Northern India Using Multi-model Projections

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Abstract

Climate change impact on crop production using different climate model projections varies considerably and it is challenging to choose a suitable climate scenario for risk assessment. This study aims to assess the climate change impact on the wheat crop in nine agro-climatic zones (ACZs) of Uttar Pradesh (UP) in Northern India using the CERES-Wheat crop model, driven by high resolution projected climate from different regional climate models (RCMs). The results show that the vegetative growth period would be shortened across the ACZs and scenarios where higher reductions will be witnessed under RCP 8.5 viz., up to 10 days in the 2050s (2040–2069), and 14 days in the 2080s (2070–2099). Also, in the 2080s shortening up to 17 days will be observed in the total growth period under RCP 8.5. When elevated CO_2 concentration was not considered the wheat yields were found to reduce up to 20.5 and 30% under RCP 4.5 and RCP 8.5, respectively, in the 2050s. In the 2080s, the losses will be more pronounced reaching up to 41.5% under RCP 8.5. With the consideration of $CO_{2,}$ the yield reductions will be up to 14 and 18% under RCP 4.5 and RCP 8.5 respectively in the 2080s. Uncertainty associated with climate model revealed that ACCESS 1-0 and MPI-ESM-LR predicted higher mean yield reductions while CNRM-CM5 has shown a mild effect. Present study concluded that eastern UP is a vulnerable region for wheat production in the 21st century. The results suggest that there is an urgent need for developing suitable adaptation strategies to ameliorate the adverse effects on wheat production in UP through regional policy planning.

Keywords Wheat · Climate change · Multi-model projection · CERES-wheat · Model uncertainty · Impact assessment

Introduction

Climate change, an anthropogenic phenomenon leading to a rise in temperature, irregular precipitation, and other weather extremes, has adverse impacts across the globe (IPCC 2021). Its direct impact is evident on agriculture, thus affecting food production and hence, food security (Lobel et al., 2011; Rosenzweig et al., 2014; Lesk et al., 2016; Asseng et al., 2015; Mall et al., 2021). It is projected that by the 2050s if the carbon emissions are not controlled, the global temperature will rise by 1.5 °C and India would be among the hardest-hit countries. The ramifications will be witnessed in form of reduced crop production, increased heat waves, negative impact on livestock, disease outbreaks, economic losses, etc. (IPCC 2018; Singh et al., 2021a). Globally, India is the second-largest producer of wheat with a production share of – 14% grown in 13% of the global wheat area (DES 2021). India has made remarkable progress in wheat production by reaching a record production of 107 million tonnes in 2019–20 from a minimal production of 6.46 million tonnes in 1950–51 with a marginal increase in area under wheat cultivation from 9.75 million ha in 1950–51 to 31.45 million ha in 2019–20 (DES 2021). Among the wheat-producing states of India: Uttar Pradesh (UP) contributes 32.7% of the cultivated area of – 30% of total wheat production (DES 2021). It is the staple diet of the country and an undeniable crop for nutritional as well as the economic security of the nation.

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Wheat is sensitive to temperature fluctuation and temperature stress (> 30 °C) during flowering may lead to sterility and poor grain set (Alghabari et al., 2014). Supra-optimal temperature and heat stress affect yield, phenology, grain nitrogen content, and grain mass of wheat (Asseng et al., 2011; Song et al., 2018, 2020; Chakrabarti et al., 2021; Osman et al., 2020; Teixeira et al., 2013). The heat stress affects the plant physiology by reducing the number of tillers, reduced leaf area index, breakdown of chlorophyll, photosynthesis inhibition, increased photorespiration, loss of osmotic potential, rise in rate of evapotranspiration, reduced net carbon assimilation, deactivation of Rubisco and increased root respiration (Akter & Islam, 2017; Dhyani et al., 2013; Farooq et al., 2011; Zampieri et al., 2017; Kumari et al., 2019). The unequivocal sensitivity of wheat to temperature and precipitation changes will have a negative impact on wheat growth globally (Asseng et al., 2015). In Indo-Gangetic Plain (IGP) and Northwestern India, there is a declining trend in the yield of wheat which has raised serious concern about the region's food supply (Sonkar et al., 2019). It thus becomes imperative to understand the impacts of climate change on agricultural production to develop suitable adaptation options to strengthen resilience (Aggarwal & Sivakumar, 2010; Yadav et al., 2015; Campbell et al., 2016; Richardson et al., 2018; Mall et al., 2019; Bhatt et al., 2019; Sonkar et al., 2020).

Climate change impact assessment can be done through statistical analysis, experiment-based studies, and process-based crop models (Liu et al., 2016; Mall et al., 2018; Zhang et al., 2019; Ye et al., 2021). Process-based crop simulation models integrate the underlying mechanism of crop response to environment i.e., the genotype & phenotype (genotype × environment interaction). Projections made by climatic models, hence are widely used in assessing the climate impact. The prediction of future climate impacts with precision is difficult and subject to the climate model complexities, use of crop models, climate scenarios considered, cascading the uncertainty in predictions (Deser et al., 2012; Maslin & Austin, 2012; Wang et al., 2020a). Also, there are significant biases in the Global Climate Models projections, making it imperative to correct the bias. Furthermore, impact assessments using gridded climate data are region specific (He et al., 2020; Wilcox & Makowski, 2014). Apart from this, an understanding of crop response at elevated CO_2 levels rather than only temperature is required to produce robust impact assessments as the former situation sounds more realistic (Lobell & Gourdji, 2012). Hence, the use of a combination of climate models under different scenarios proves more effective to deploy reliable decision support in climate change impact and agricultural system vulnerability assessment (Asseng et al., 2013; Martre et al., 2015; Mereu et al., 2021; Singh et al., 2018; Toreti et al., 2020). There have been studies on the impact of climate change on wheat yields, phenology, grain quality, and nutrient management, at global and country-level but region-specific studies with multiple scenarios in India are limited.

Therefore, in the light of the above, this study was designed to investigate the impacts of climate change on wheat in different agro-climatic zones (ACZs) of UP in northern India using multiple regional climate model simulations under two emission scenarios (RCP 4.5 and RCP 8.5) in combination with well-established crop simulation model CERES-Wheat for two time periods 2050s (2040–2069) and 2080s (2070–2099) with different CO_2 concentrations. The specific goals of this study were to analyze the observed and projected climatic variables and quantify the potential impacts of future climate change on wheat phenology and production in UP. This will be instrumental in assessing the response of wheat to climate change more reliably in northern India. Any change in agriculture production has huge socio-economic implications which directly affect the population. Hence, the study may play a decisive role in framing agro-centric policies by the government and concerned stakeholders.

Materials and Methods

Study Site

The study was conducted for Uttar Pradesh (UP) state (23° 50′-30° 45′ N latitude to 77° 04′-84° 38′ E longitudes) in northern India covering an area of 29.4 million hectares of the Indo-Gangetic plains and characterized by humid subtropical climate. The novelty of this research lies in the zone-wise assessment of the whole region at 0.5 × 0.5 km resolution using different regional climate models and CO_2 concentrations to understand the regional disparity in distribution of meteorological variables and their impacts on wheat production. The analysis was done for the nine agro-climatic zones (ACZs) of UP namely, Bhabhar and Tarai Zone (BTZ), Bundelkhand Zone (BKZ), Central Plain Zone (CPZ), Eastern Plain Zone (EPZ), Mid-Western Plain Zone (MWPZ), North-Eastern Plain Zone (NEZ), South-Western Semi-Arid Zone (SWSAZ), Western Plain Zone (WPZ), and Vindhyan Zone (VZ) (Fig. 1). Specific characteristics i.e., area, climate, wheat production statistics, etc., of each zone, are illustrated in Table 1. Here, the spring wheat is sown in the rabi season (November to April) under irrigated and unirrigated conditions.

Climate Data

Long-term observed daily meteorological data i.e. maximum temperature, minimum temperature, and rainfall for a period of 1980–2009 (baseline period) at a resolution of 0.5° × 0.5° for the nine ACZs of UP were obtained from the Indian

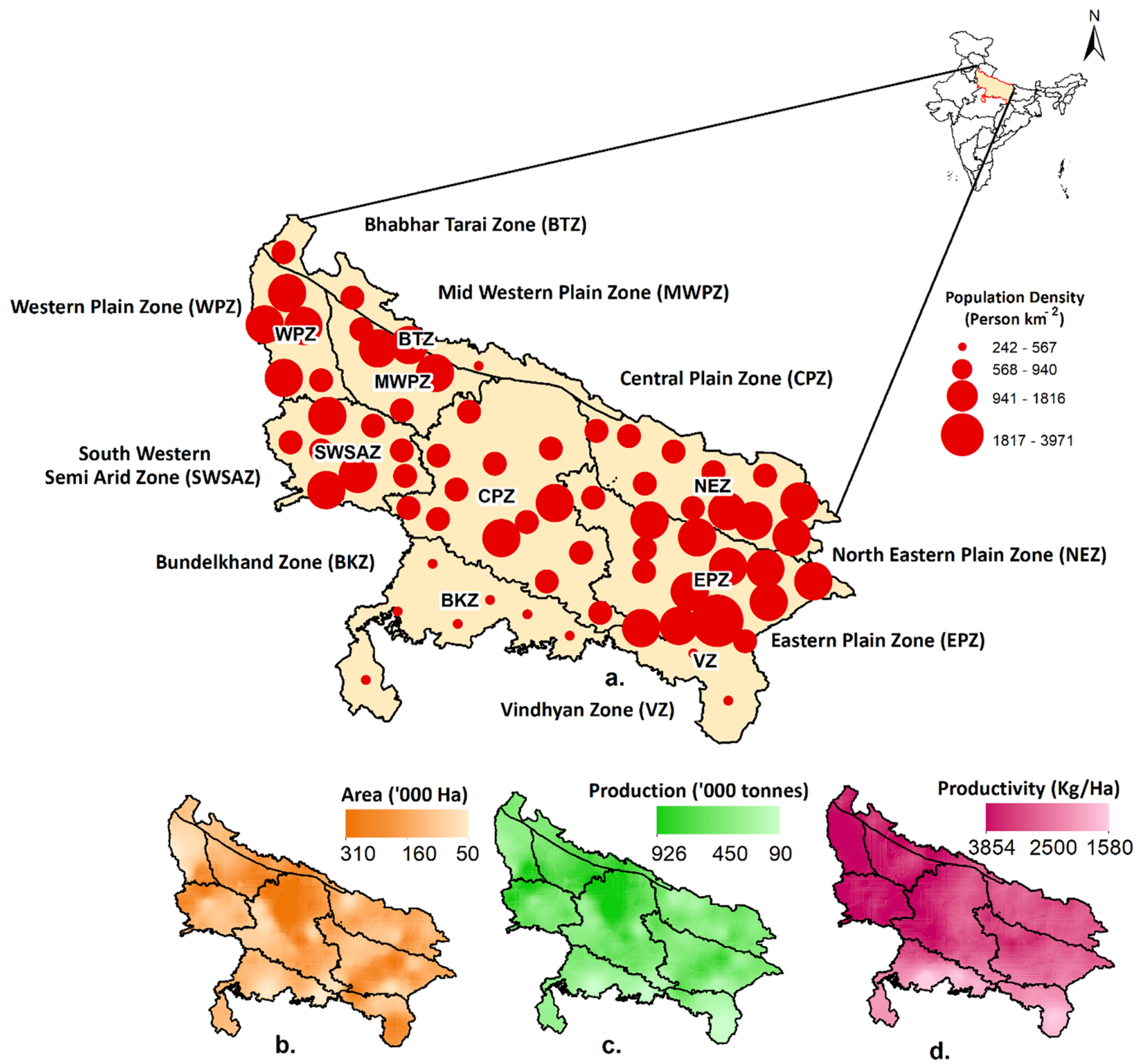


Fig. 1 Description of agro-climatic zones of Uttar Pradesh. **a** Population density **b** Area under wheat cultivation **c** Wheat production and **d** Productivity of wheat. Data is an average for a period of 1997–98 to 2018–19. Population data collected from Population Census 2011

Table 1 General information about different agro-climatic zones of Uttar Pradesh

Agro-climatic zone	Area (in Ha)	Climate	Soil type	Maximum temperature	Minimum temperature
BKZ	29,61,006	Dry sub-humid to arid	Mixed red & black soil	23.3–38.93 °C	8.20–21.62 °C
BTZ	16,97,125	Sub-humid	Clay & sandy loam, alluvial	19.26–33.98 °C	6.75–18.38 °C
CPZ	56,47,307	Dry sub-humid to semi-arid	Clay & sandy loam, silty clay	21.84–37.74 °C	8.21–21.12 °C
EPZ	38,08,718	Dry sub-humid	Sandy loam, clay loam, alluvial	22.55–38.11 °C	8.59–21.21 °C
MWPZ	16,97,125	Sub-humid	Clay & sandy loam, alluvial	20.20–35.74 °C	7.04–19.46 °C
NEPZ	29,55,485	Humid-sub tropical	Sandy loam, silty loam	22.27–37.60 °C	8.57–21.07 °C
SWSAZ	22,34,222	Semi-arid	Sandy loam, sandy soil, alluvial	21.44–38.07 °C	7.39–21.27 °C
VZ	13,81,840	Sub-humid	Red laterite & black Soil	23.39–38.50 °C	8.71–21.26 °C
WPZ	16,37,424	Semi-arid	Sandy loam, loam, silty loam	19.97–35.58 °C	6.93–19.60 °C

Meteorological Department (IMD). On the other hand, daily surface solar radiation data (MJ/m^2/day) was computed using the Hargreaves and Samani method (Hargreaves & Samani, 1982, 1985).

For future, the study used five Global Climate Models (GCMs) output for dynamically downscaled climate projections using two Regional Climate Models (RCMs) first, Regional Climate Model (RegCM) and second, Conformal-Cubic Atmospheric Model (CCAM). An ensemble of four dynamically downscaled projections at a resolution of 0.5° × 0.5° was obtained using CCAM by forcing the boundary conditions from four different Global Climate Models (GCMs) namely ACCESS1-0, CNRM-CM5, NorESM1-M, MPI-ESM-LR (Online Resource 1). On the other hand, RegCM was used to generate dynamically climate projections from global climate model MPI-ESM-MR. These GCMs output (using RCMs for downscaling) are found to be suitable for impact assessment studies over Indian region because of their efficient performance (Mall et al., 2018; Singh et al., 2021b; Jaiswal et al., 2022). The CCAM data from Coordinated Regional Climate Downscaling Experiment -South Asia (CORDEX-SA) experiment was obtained from the Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India. The downscaled RegCM simulations at 0.25° × 0.25° resolution were simulated at DST-Mahamana Centre of Excellence in Climate Change Research (MCECCR), Banaras Hindu University, India. This was then regridded to 0.5° × 0.5° resolution using the bilinear interpolation method to bring all the models to same spatial resolution (Singh et al., 2021b; Voropay et al., 2021). Solar radiation was then computed using the same methods as used for the baseline period. The data was obtained for two time periods: the 2050s (2040–2069) mid-century and the 2080s (2070–2099) end-of-century under two RCP scenarios 4.5 and 8.5 each. RCP 4.5 (optimistic scenario) and 8.5 (pessimistic scenario) correspond to an anthropogenic radiative forcing reaching 4.5 and 8.5 W/m2, respectively, in relation to the pre-industrial level by 2100.

Uncertainties in climate projections arising through global climate model, call for bias correction for accurate and reliable representation of regional climate information (Mall et al. 2018; Laux et al., 2021). The climate dataset used in the study was bias-corrected using Variance scaling approach to remove bias associated with temperature data and Local Intensity Scaling method for rainfall (Jaiswal et al., 2022; Teutschbein & Seibert, 2012). The monthly and seasonal mean of solar radiation (SRad) and bias-corrected maximum temperature (T_{max}) and minimum temperature (T_{min}) of wheat growing season were used to compare the changes in temperature and solar radiation in the future with respect to the baseline period. The use of multiple GCMs output establishes the range of uncertainty which will help in investigating inter-model variability during the assessment of climate change impacts on crops.

CERES-Wheat Model

The wheat yield simulations were done using CERES-Wheat module of the Decision Support System for Agro technology Transfer (DSSAT) version 4.7 cropping system model (Hoogenboom et al., 2017; Jones et al., 2003). It is one of the most widely used models and has been validated in a wide variety of environments (Basso et al., 2016). The model requires daily climate data (maximum and minimum temperatures, solar radiation, and rainfall), soil physical properties (pH, EC, bulk density, organic carbon, etc.), and phenological information such as date of planting, seedling emergence, flowering and maturity, yield, biomass, grain number, LAI, etc., and genetic traits specific for the cultivar. The ability of this model to simulate phenology, dry matter, nitrogen dynamics, soil moisture/water balance, and environmental modification, etc., under a wide variety of conditions has been proven for a range of crops, regions, and applications.

Simulation and Impact Assessment

The CERES-Wheat model has been validated by Mall et al. (2016) for this region. A popular wheat variety of UP, HUW-234 was used for simulations. It is a late sown variety of 110–120-day growth period and is sown after harvesting of rice and sugarcane in eastern and western regions of UP respectively. Since, the study was done solely to assess the impact of climatic variables on wheat yield, all other optimum crop management practices like sowing date, irrigation, fertilization, etc., used as an input in the model were kept the same for all the ACZs. The simulations were done at sowing date of 15 November, and a plant population density of 100 plants/m^2. Already calibrated and validated genetic coefficient generated and used by Forecasting units of Indian Meteorological Department was used for the simulations (AMFU, 2020). The simulations were done with no nutrient or water stress at all the locations for baseline and future periods with and without CO_2 effects.

The effect of CO_2 was studied by conducting simulations at two different CO_2 concentrations in order to cover all the possible scenarios, likely to occur in the future. A concentration of 380 ppm was used in the baseline as well as for future simulations without CO_2 effect, in the 2050 and 2080s under RCP 4.5 and 8.5 scenarios as suggested. For simulations with CO_2 effect, under RCP 4.5, the 2050 and 2080s corresponded to an elevated CO_2 of 499 and 532 ppm respectively and in RCP 8.5, 2050 and 2080s corresponded to an elevated CO_2 of 571 and 801 ppm respectively. This provided 40 climate change scenarios (5 climate model outputs × 2 RCPs × 2 study periods × 2 CO_2 concentrations) for impact assessment.

The detailed information on different scenarios can also be accessed from agmip.org (Rosenzweig et al., 2015).

Climate variables have a direct impact on crop growth, any deviation from the optimum range of temperature can lead to a significant change in yield of wheat. Thus, the response of wheat yield and phenology in 40 different climate change scenarios was analysed with respect to the baseline period using projected and observed climate data. In the study, simulations were performed for the baseline period as well as for the 40 climate change scenarios at each grid, and then analysis was done at grid level and later clustered under respective ACZs.

The weather variables were first checked for the presence of any multicollinearity using Pearson's correlation test (r), which may influence the cause-effect relationship between yield and weather variables in the study. Two or more variables are considered correlated if the correlation coefficient between the variables remains > 0.7, in such case the uncorrelated variables were considered in the regression model as explanatory variables.

The association between baseline climate variables and wheat yield was then established using generalized additive mixed-effect modeling (gamm). The model was a multivariate regression model that took into consideration the minimum and maximum temperature, and solar radiation and rainfall as independent variables against wheat yield, a dependent variable that makes the core model. The core model was adjusted for district fixed effects and the potential confounding of long-term time trend considering quasi-poisson distribution. The following regression model was used:

$$\{E[(Y_{dt})]\} = C_{dt} + \beta_1 T\max_{dt} + \beta_2 T\min_{dt} + \beta_3 \mathrm{SRAD}_{dt} + \beta_4 \mathrm{Rainfall}_{dt} + f(\mathrm{Time}_t) + b_i$$

where $E[(Y_{dt})]$ denotes the wheat yield in district "d" at time "t"(here, year);c is the intercept that adjusts the district-specific effect, β is the regression coefficients; f refers to the smoothed function of time (penalized cubic smoothing spline) that adjusts confounding effect of recent capital and technical achievements in wheat cropping system during these years and, bi ~ N(0,σb 2) is a random-effects intercept for each grid i that accounts for grid-specific variations. The result is expressed in the form of a percent change in yield per unit change in weather variables with a 95% confidence interval (CI). The models were fit using the gamm function from the "MASS" library in R.

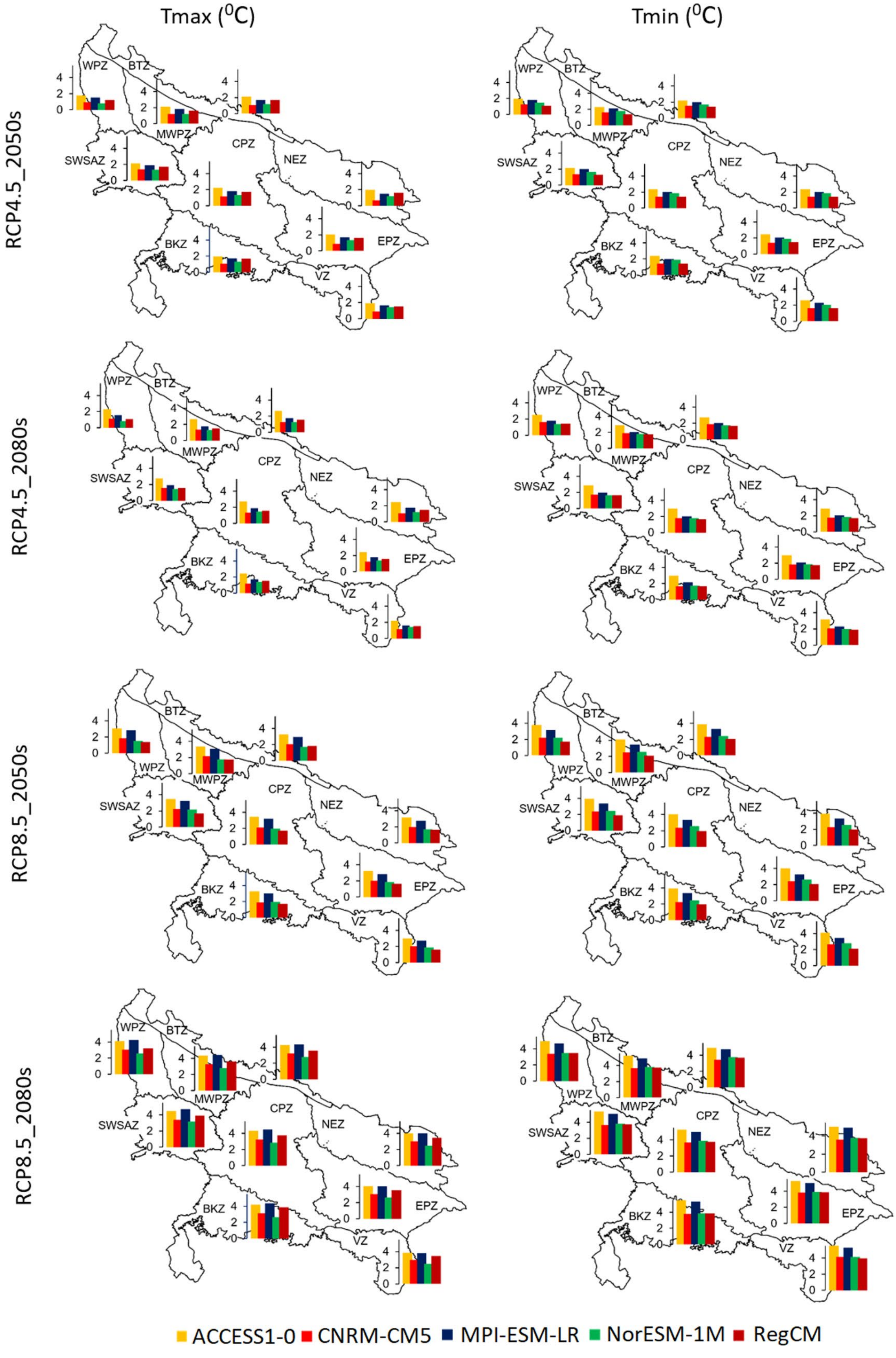
Results

Projected Changes in Climate Variables During Wheat Growth Season

The rabi season baseline average T_{max} and T_{min} were 26.8 and 11.7 °C respectively, whereas the mean seasonal temperature was 19.25 °C. The model ensemble showed that during wheat growing season T_{max} and T_{min} will increase in all climate change scenarios (Online Resource 2). Under RCP4.5, T_{min} is expected to increase by 1.79 °C in the 2050s and 2.04 °C in 2080s, and under RCP8.5 by 2.83 °C in 2050s and 4.30 °C in 2080s across the nine agro-climatic zones. On the other hand, T_{max} is expected to increase by 1.52 °C in the 2050s and 1.66 °C in 2080s under RCP4.5 and under RCP 8.5 by 2.36 °C in 2050s and 3.58 °C in 2080s, showing a drastic change in temperature with a wider range.

The downscaled projections at individual level, however, show significant heterogeneity in temperature changes across all the zones with variable magnitude (Fig. 2). Under RCP 4.5, the seasonal average T_{max} is expected to rise by 0.66 °C (CNRM-CM5) in NEZ to 2.20 °C (ACCESS 1-0) in CPZ and 0.84 °C (NorESM1-M) in WPZ, to 2.72 °C (ACCESS 1–0) in NEZ in the 2050 and 2080s, respectively. While the rise in average seasonal T_{min} will be comparatively higher ranging from 1.09 °C (RegCM) in WPZ to 2.59 °C (ACCESS1-0) in VZ and 1.40 °C (NORESM1-M) in WPZ to 3.19 °C (ACCESS1-0) in VZ in the 2050 and 2080s, respectively. Extreme changes were witnessed under RCP 8.5, where the seasonal average T_{max} will rise by 1.39 °C (RegCM) in WPZ to 3.47 °C (ACCESS1-0) in SWZ, and 2.46 °C (NORESM1-M) in NEZ, to 4.69 °C (MPI-ESM-MR) in SWZ, in the 2050s and 2080s, respectively. The rise in seasonal average T_{min} will range from 1.72 °C (RegCM) in WPZ to 4.12 °C (ACCESS1-0) in VZ, and highest increment of 3.38 °C (CNRM-CM5) in WPZ to 5.52 °C (ACCESS1-0) in VZ in the 2050 and 2080s, respectively. Varied results were obtained in the case of T_{max} with no zonal distinction. An increase in T_{min} was observed from western to eastern UP, where maximum rise in T_{min} will be witnessed in VZ. ACCESS 1-0 is associated with higher temperature increment while RegCM and NorESM1-M are associated with a lower rise in temperature as compared to baseline.

The analysis of projected monthly average T_{min} and T_{max} along with baseline temperature over the nine ACZs of UP for the wheat season is shown in Fig. 3. The trend revealed that the monthly T_{max} and T_{min} are uniformly increasing among all the climate models compared to baseline across the zones. However, the magnitude of temperature rise will be higher in April followed by January as compared to other months across the zones. It is noteworthy that terminal spikelet development takes place around January and grain



Tmax (^{0}C)
Tmin (^{0}C)
RCP4.5_2050s
RCP4.5_2080s
RCP8.5_2050s
RCP8.5_2080s
WPZ
BTZ
MWPZ
SWSAZ
CPZ
NEZ
BKZ
EPZ
VZ
ACCESS1-0
CNRM-CM5
MPI-ESM-LR
NorESM-1M
RegCM

◂**Fig. 2** Change in mean seasonal maximum temperature (Tmax, °C) and minimum temperature (Tmin, °C) as projected by climate models relative to baseline period (1980–2009) under different representative pathways during mid-century (2050s) and end-of-century (2080s) for 9 agro-climatic zones of Uttar Pradesh

filling in March–April. Under RCP 4.5 during the 2050s the T_{min} in January will rise from 1.30 °C (RegCM) in WPZ to 2.96 °C (ACCESS 1-0) in VZ (Fig. 3a). March and April are crucial for grain filling and Tmax will increase up to 2.40 °C (RegCM) in SWSAZ and 2.36 °C (RegCM) in BTZ, respectively. In the 2080s the magnitude of rise in T_{min} will be highest in January month across all the zones ranging from 1.44 °C (NORESM1-M) in BTZ to 3.38 °C (ACCESS1-0) in VZ. ACCESS1-0 model projected the highest T_{max} reaching 41.6 °C during April in BKZ while the lowest T_{max} will be 20.1 °C as per NORESM1-M during January month in WPZ (Fig. 3b).

Under RCP 8.5 similar trends are observed but with a higher magnitude. In the 2050s, T_{min} ranged from 8.9 °C (RegCM) in BTZ in January to 25.4 °C (ACCESS1-0) in BKZ in April (Fig. 3c). While T_{max} will range from 20.9 °C (NORESM1-M) in BTZ in January to 42.1 °C (ACCESS1-0) in BKZ during April. In the 2080s, the T_{min} will range from 10.4 °C (CNRM-CM5) in January in BTZ to 27.2 °C (ACCESS1-0) in BKZ (Fig. 3d). Here, ACCESS1-0 is associated with a higher increment of weather variables while RegCM and CNRM-CM5 are associated with a moderate increment in weather variables as compared to baseline. Apart from Tmax and Tmin, the analysis of SRad revealed that there will be a marginal decrease (upto 1.67 W/m^{-2}/day) in SRad over all the climate change scenarios as compared to the baseline (Online Resource 3). The rainfall on the other hand, has shown irregular variations. The month wise analysis of rainfall showed that the changes (mm/day) in all the climate change scenarios are marginal but heterogeneous viz − 0.03 mm/day in month of February in the 2080s under RCP8.5 in MWPZ to + 2 mm/day in February in the 2080s under RCP4.5 in WPZ (Online Resource 4).

Projected Change in Wheat Phenology

In this study, we found that vegetative growth period as well as total growth period would be shorter in the future across the nine ACZs (Fig. 4). In the 2050s under RCP4.5, the average vegetative growth period would shorten to the maximum extent in VZ with ACCESS1-0 predicting an extreme shortening of 6.4 days to CNRM-CM5 showing a minimum shortening of 2.8 days. On the other hand, zones like WPZ and MWPZ would have a minimum shortening of vegetative growth period ranging from 0.6 to 1.1 days and 0.6 to 0.8 days respectively. The vegetative growth period shortening under RCP 8.5 would be more prominent but following the same zonal pattern where VZ will have the highest shortening of 5–10.7 days followed by BKZ (3.9–9.2 days) and WPZ showing the lowest reduction of 0.7–2.5 days.

During the 2080s, the vegetative growth period will shorten by 7.7 days in VZ followed by BKZ (1.8–6.6 days), and EPZ (2–6 days) to a minimum shortening of 0.5–1.4 days in WPZ and 0.8–2 days in MWPZ under RCP 4.5. Severe shortening is observed under RCP 8.5 up to 9.3 to 13.7 days in VZ and 2.2–6.2 days in WPZ. In this case, ACCESS1-0 (2.8–10.9 days) and MPI-ESM-LR (2.5–10.9 days) have shown extreme shortening of vegetative growth period among both RCPs in nine ACZs on an average, conceivably because the temperature increase shown by these models are much higher than the rest of the climatic models. While as per CNRM-CM5 the shortening will be 0.4–6.6 days and as per NorESM1-M it will be 1.4–6.4 days across all the scenarios.

Overall, the total growth period will shorten by 2–3 weeks in UP while significant variation will be observed among different climate change scenarios and ACZs individually (Fig. 4). Extreme shortening of total growth period is expected under RCP 8.5 ranging from 1.1 to 14 days in the 2050s and 3.6 to 17.3 days in the 2080s. While under RCP 4.5 the shortening of the total growth period would range from 0.6 to 10.7 days and 0.4 to 10.5 days in the 2050 and 2080s respectively. Among the ACZs, the shortening of the total growth period in the 2050s will be up to 10.7 days under RCP 4.5 and 13.9 days under RCP 8.5 in VZ as per ACCESS1-0 model. While during the 2080s, maximum reduction will be witnessed as per ACCESS1-0 model, again in VZ up to 10.4 and 17.3 days under RCP 4.5 and 8.5 respectively. Like the vegetative growth period, the shortening of total growth period is following the same pattern. It can be said that, ACCESS1-0 (5.1–13 days) and MPI-ESM-LR (4.1–13 days) showed the highest reduction while results from CNRM-CM5 (2.4–8.7 days) and NorESM1-M (3.3–8.4 days) reveal comparatively lesser shortening. The changes in total growing period have wide variations across the zones and majorly between the model projections, showing a longitudinal increase in magnitude as we move towards zones like EPZ, BKZ, NEZ, and VZ in eastern UP. It agrees with the incremental rise of temperature in eastern UP as compared to western UP in the 2050s and 2080s as shown earlier.

Impacts of Climate Change Projection on Wheat Yield

Results considering the model ensemble show that, when CO_2 effects were not considered, the wheat yields would be reduced by 13.3–31% under RCP 8.5 across all the zones in the 2050 and 2080s (Online Resource 5). Since higher CO_2 levels offset the detrimental effect of higher temperatures

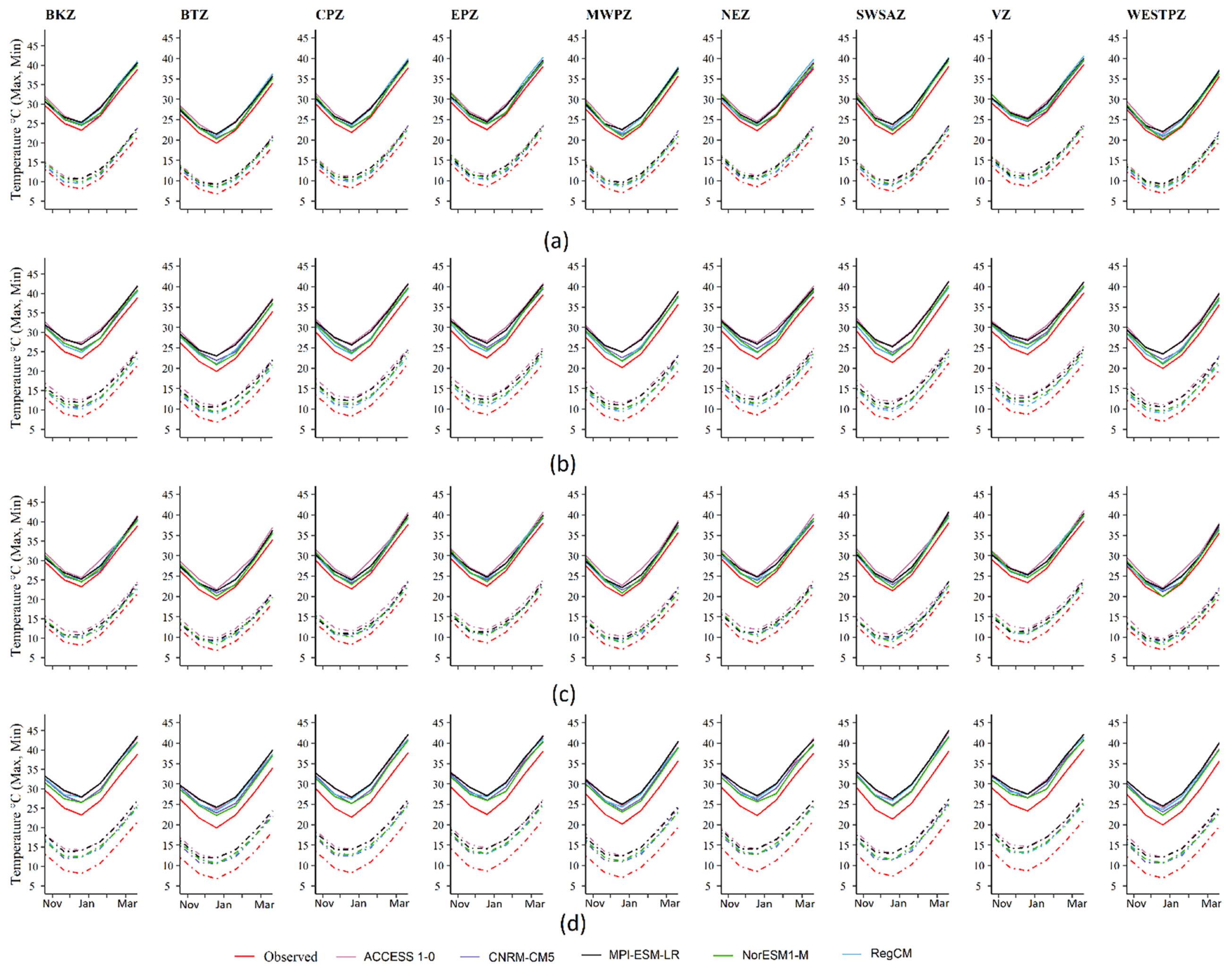


Fig. 3 Average monthly (wheat growing season) maximum temperature (T_{max}) and minimum temperature (T_{min}) during baseline period (1980–2009) and **a** mid-century (2050s) under RCP 4.5 **b** end-of-century (2080s) under RCP 4.5 **c** mid-century (2050s) under RCP 8.5 and **d** end-of-century (2080s) under RCP 8.5, as projected by different climate models in 9 agro climatic zones of Uttar Pradesh. Here the solid lines represent the T_{max} and dashed lines represent the T_{min}

in wheat and other crops as well, yield benefit had been seen when increased CO_2 effect is considered and a marginal increase in yield was found in two zones BTZ (0.4–2.2%) and WPZ (1.6–3%) while the lower reductions in other zones from 0.2% in MWPZ to 13.2% in VZ, under both the scenarios.

Results indicated a reduction in wheat yield with a significant amount of variation among ACZs (Fig. 5). When effects of CO_2 were not considered the yield was reduced invariably in the 2050s with extreme reduction witnessed in VZ as all climate models reveal highest reduction of 20.5% under RCP 4.5 and 30% under RCP 8.5 as projected by ACCESS1-0. The lowest yield reduction is observed in WPZ with the lowest magnitude of 1.9% under RCP4.5 and 5.7% under RCP 8.5 as per RegCM. In the same time period, when effects of CO_2 are considered the yield is reduced (0.5–16%) in all zones as per ACCESS1-0 with the highest reduction in VZ followed by NEZ. While BTZ and WPZ will have a slight increase in mean yield with the remaining four climate models. RegCM showed an increase in yield up to 6.7% under RCP4.5 and 8.6% under RCP 8.5 in BTZ and 8.7–11% under RCP 4.5 and 8.5 respectively in WPZ.

The losses in wheat yield during the 2080s, when CO_2 effect was not considered would range from 6 to 25% under RCP 4.5 with more reductions under RCP 8.5 ranging from 23 to 41.5% across the zones due to more temperature extremes expected in this period (Fig. 5). Higher reductions are expected in VZ (> 17%), NEZ (> 13%), and BKZ (> 12%) according to ACCESS1-0, CNRM-CM5, and MPI-ESM-LR under RCP 4.5. Similarly, severe reductions under RCP 8.5 would be seen in VZ (> 33%), BKZ (> 29%), and NEZ (> 28%) with ACCESS 1–0, MPI-ESM-LR, and

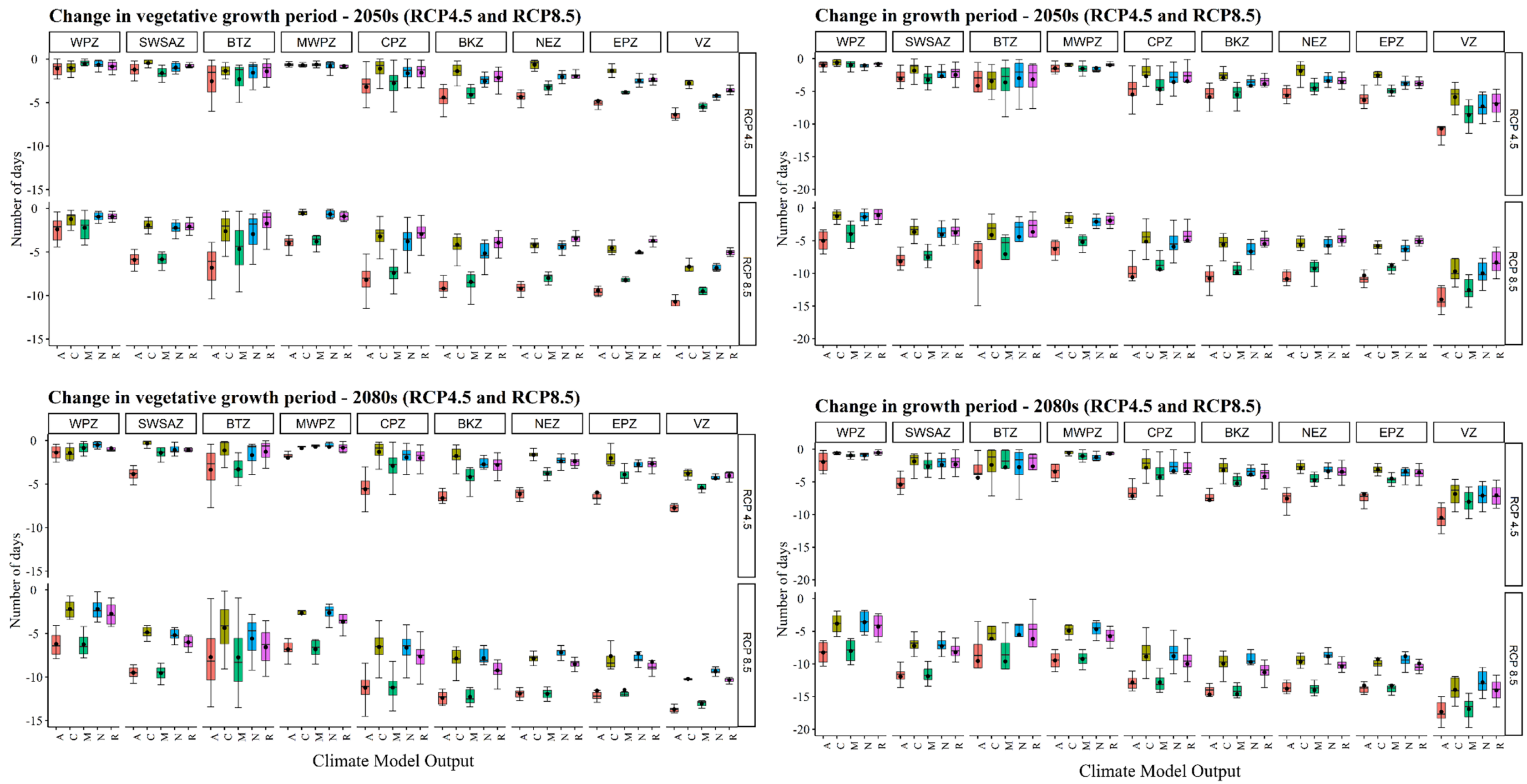


Fig. 4 Simulated change in vegetative growth period and total growth period (compared with baseline 1980–2009) in mid-century (2050s) and end-of-century (2080s) under RCP 4.5 and RCP 8.5 using different climate models for 9 agro-climatic zones of Uttar Pradesh. The point within the boxplot presents the mean value and median is given by line. Here, A- ACCESS1-0, C- CNRM-CM5, M-MPI-ESM-LR, N-NorESM1-M, R-RegCM

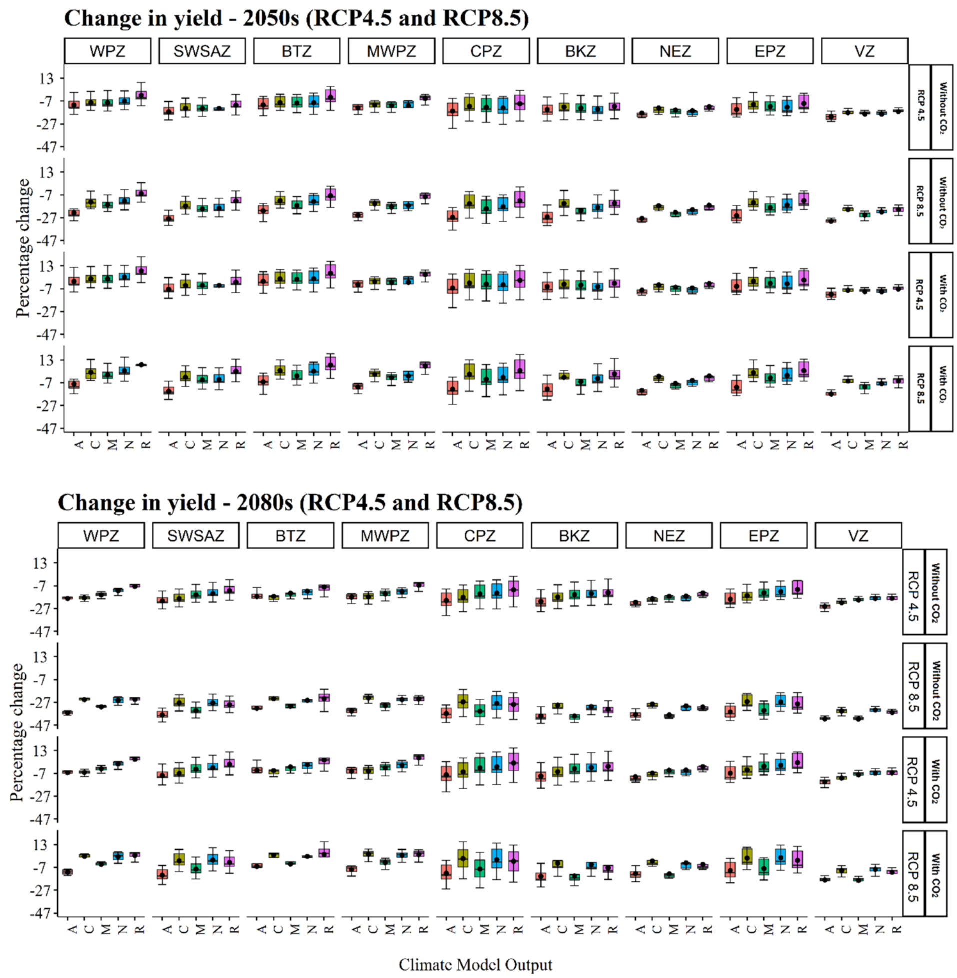


Fig. 5 Simulated wheat yield change in mid-century (2050s) and end-of-century (2080s) under RCP 4.5 and RCP 8.5 compared with baseline (1980–2009) using different climate models for 9 agro-climatic zones of Uttar Pradesh. The point within the boxplot presents the mean value and median is given by black line. Here- A- ACCESS1-0, C- CNRM-CM5, M-MPI-ESM-MR, N-NorESM1-M, R-RegCM

NorESM1-M. ACCESS 1.0, CNRM-CM5 and MPI-ESM-LR predicted a yield loss ranging from 0.7 (EPZ) to 14.3% (VZ) across the zones under RCP 4.5. NorESM1-M predicted a rise in yield of 0.2–1.3% in BTZ, EPZ, MWPZ, WPZ, and RegCM revealed a positive increase of 2.2–6.7% in CPZ, EPZ, BTZ, WPZ, and MWPZ. Higher yield reduction is predicted under RCP 8.5 with ACCESS1-0 and MPI-ESM-LR, ranging from 3% in MWPZ to 18% in VZ. A minor increase up to 4.5% in mean yield was noticed in three zones BTZ, MWPZ, and WPZ, as per CNRM-CM5, NorESM1-M, and RegCM.

Response of Wheat Yield to Climate Variables

The correlation between wheat yield and weather variables was heterogeneous across the zones (Online resource 6). The regression results indicate that rainfall has no significant effect on wheat yield but there is a negative relationship between yield with minimum and maximum temperature (Table 2). A unit rise in T_{min} will reduce yield across the zone by 3–7.8% and a unit rise in T_{max} will reduce yield by 1.9–6%. SRad however has a positive relationship with wheat yield and a unit rise in it will increase it by 5.4–10.5%. This cumulative effect of each variable hence had an impact on the yield.

Dose–Response Relationship

In general, a linear association between T_{max} and T_{min} and wheat yield was noted with an overall decrease in crop yield with increasing temperature (Fig. 6). However, for T_{min}, the relationship was not necessarily linear. For most of the zones, as T_{max} rises above 24 °C, and T_{min} above 10 °C, the wheat yield starts to decline. SRad on the other hand shows a positive but linear relationship with the wheat yield, with an overall increase in crop yield with increasing solar radiation. As the SRad rises above 14 MJ/m^2/day, the crop yield increases. The association with the rainfall was not very robust, as was evident with a wide confidence interval, thus, the wheat yields are more associated with temperature and radiation than rainfall.

Table 2 Percentage change in yield due to unit rise in weather variables obtained from regression estimates in different agro-climatic zones of Uttar Pradesh

Zone	Tmax	Tmin	SRAD
BKZ	– 3.0***	– 5.7***	7.2***
BTZ	– 1.9**	– 6.0***	6.2***
CPZ	– 2.2***	– 6.2***	6.5***
EPZ	– 2.9***	– 5.2***	7.2***
MWPZ	– 2.0*	– 7.8***	5.6***
NEZ	– 1.9*	– 5.6***	5.4***
SWZ	– 3.6***	– 4.1***	7.8***
VZ	– 2.5*	– 8.6***	6.3***
WPZ	– 6.0*	– 3.0***	10.5***

The values with '***' are significant at $p < 0$, '**' at $p<0.001$ and '*' at $p <0.05$. Rainfall was not found to be significant

Discussion

Change in Wheat Phenology Under Different Climate Change Scenarios

Wheat is a C3 crop and is sensitive to heat stress as well as carbon dioxide concentration. Results show that there will be a rise in T_{max} and T_{min} during the total growth period and yield would be decreased. Supra optimal temperatures increase the risk of heat stress at critical crop growth stages and this sensitivity could negatively impact wheat production (Teixeira et al., 2013; Wahid et al., 2007). Porter & Gawith, 1999 have reported that the limit for T_{max} for anthesis and grain filling is 31 and 35.4 °C. The findings of the study revealed that T_{max} during germination to terminal spikelet development, end of spikelet to beginning of grain filling and grain filling period in baseline was 22, 31 & 34.7 °C respectively. In the future during germination to terminal spikelet T_{max} ranged from 23.6 to 24.7 °C; 23.5 to 25 °C (the 2050s) and 24 to – 26 °C; 25 to – 27 °C (the 2080s) under RCP 4.5 and RCP 8.5 respectively. The T_{max} range during grain filling period was 35 to – 36 °C; 35 to – 36.5 °C (the 2050s) and 35 to – 36 °C; 36 to – 37 °C (the 2080s) under RCP 4.5 and RCP 8.5 respectively. Concluding that the temperature in climate change scenario will be higher than optimum. It is noteworthy that wheat requires 2200 Growing Degree Days for crop maturity, a rise in T_{max} and T_{min} will lead to rapid accumulation of growing degree days reducing the phenological phase. There is a general agreement that a rise in temperature leads to a shortening of the vegetative growth period and total growth period of wheat (Ren et al., 2019; Qaseem et al., 2019).

Change in Wheat Yield Under Different Climate Change Scenarios

Under optimum conditions, wheat crop requires a temperature of 22 °C during vegetative phase, 21 °C during reproductive phase, and a threshold of 35.4 °C for grain filling (Porter & Gawith, 1999). A Seasonal mean temperature of more than 32 °C leads to death of flowers and zero yields

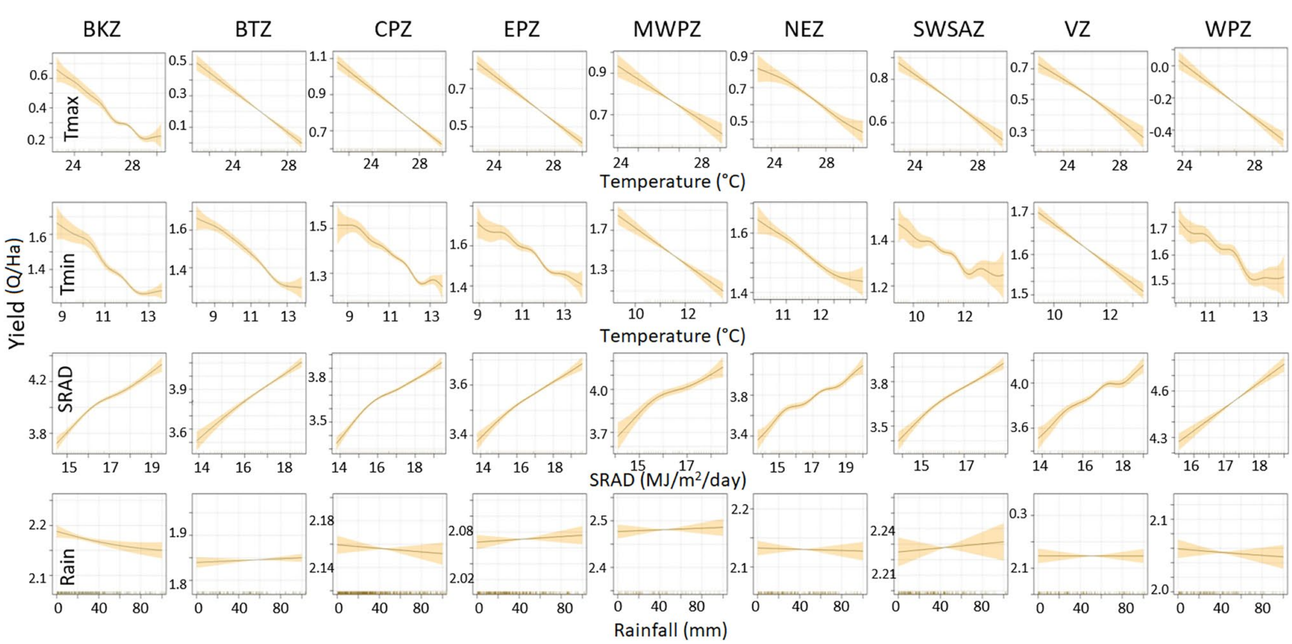


Fig. 6 Wheat yield using penalized cubic spline against different climatic variables for nine Agro-climatic zones of Uttar Pradesh. The shaded region indicates 95% confidence interval

(Asseng et al., 2015). The regression analysis revealed that a unit rise in Tmax and Tmin will reduce the wheat yield. Similar finding has also been reported by Akhter & Islam (2017) that there will be a 6% decrease in wheat yield with a unit rise in temperature. Our simulation analysis revealed yield reductions with zonal and modular variations. The findings of this study are consistent with other studies which have also shown a declining trend in wheat yield in different Indian regions (Asseng et al., 2015; Dubey et al., 2020; Daloz et al., 2021). Studies done by (Liu et al., 2016) have shown that unit rise in temperature leads to decline in wheat yield.

The increased CO_2 levels stimulate the growth of wheat plant provided that water and nutrient stress does not exist (Amthor, 2001). Zones like BTZ, and WPZ have shown a slight positive deviation in the average wheat yield. The less pronounced yield reduction and increase in some zones is due the fact that are higher concentrations of CO_2 (499, 532, 517 and 801 ppm) increase the photosynthetic activity and compensating for the detrimental effects of increasing temperatures. Our findings are in agreement with other studies that have shown a decrease in wheat yield due to a rise in temperature when CO_2 effects are not considered but the increased CO_2 concentrations have a positive effect on wheat yield by increased photosynthesis (Liu et al., 2019; Wang et al., 2020b). Here eastern UP emerged as a vulnerable zone in terms of yield reductions. This impact will not only affect the wheat production of the state but also the income of the stakeholders as the population is high and their major dependence is on agriculture (Fig. 1).

Uncertainty and Limitations of the Study

The uncertainty in yield prediction is associated with the crop simulation model used, choice of GCM, downscaling method adopted, crop management practices, and other related assumptions (Lobell et al., 2012; Wang et al., 2017, 2020a). Uncertainty can be measured by the range of potential outcomes obtained in impact assessment. For the development of robust decision support in such studies, the use of multiple climate change scenarios provides reliable solutions. In our study, we used 5 GCMs output (downscaled projections using RCMs), two emission scenarios, and two time periods in combination with a crop simulation model to quantify the range of potential outcomes. Our study revealed that there is clear evidence of wheat yield reductions but different climate scenarios revealed a wide variation in the impact and behavior of outcomes at the nine ACZs of UP. For example, when elevated CO_2 concentration were not considered the yield varies − 1.9 to − 20.5% and − 6 to − 25% in 2050 and 2080s respectively under RCP 4.5 and − 5.7 to − 30% and − 23% and − 41.5% in 2050s and 2080s respectively under RCP 8.5 among different climate models (Fig. 5). While an increase in yield can be seen in the case of elevated CO_2 concentrations. In the case of variation over RCP, when elevated CO_2 concentrations were not considered, the yield varied from − 7.2 to − 23.2% and − 13.2 to − 37.3 in the 2050 and 2080s respectively. While in the case of elevated CO_2 concentration it was + 1.6 to -9.3 and + 0.1 to − 13.2 in the 2050 and 2080s respectively. This revealed that climate model output were the major source of uncertainty in the study. Our results are consistent with other studies that have revealed that when climate impact assessments are done, the climate model projections are one of the drivers of uncertainty (Rahman et al. 2018, Zhang et al., 2019; Zheng et al., 2020).

A few limitations this conundrum of assessing the response of wheat to climate shocks conceives are that the study has considered only single dominant variety of the state simulated on a single crop model, while other new varieties and crop models may give different results. The study assumed no stresses from water, nutrients, pests, diseases, and other weather events such as heat waves, cold waves, and diurnal temperature rhythm (DTR). Also, there lies a scope for using more climate models in order to reduce the uncertainty of impact assessment. This study, rely on climate and crop model for the assessment of wheat yield in future climate (Maiorano et al., 2017; Tao et al., 2018; Zhang et al., 2019), hence optimizing different model parameters, improving model structure, and selecting the well-validated crop model best suited for regional impact study should be helpful.

Conclusions

All the climate projections predicted a progressive increase in T_{max} and T_{min} of the total growing season on an average, and individual months also in the 2050, 2080s, and under both RCP 4.5 and 8.5. The impact assessment revealed that the vegetative growth period of wheat will be reduced across all the zones by 0.4–13 days and the total growth period will be shortened by 0.6–17 days showing a negative impact on wheat phenology. This will lead to reductions in average wheat yield over all the nine zones ranging from 2 to 41% when CO_2 effect was not considered, and comparatively less reduction of 0.3–18% with consideration of CO_2 where some zones have shown a positive change in the yield (Fig. 5). Uncertainty was majorly associated with climate model outputs. It was revealed that ACCESS1-0 and MPI-ESM-LR have predicted a higher yield reduction across all the zones and scenarios while CNRM-CM5 has shown lower yield reductions. It was concluded that eastern UP represents the most vulnerable region for wheat production during the mid and late 21st century within the study site. Looking at the ramifications, the loss in wheat yield will reduce the incomes of farmers thus hampering their livelihood. The decreased production will affect livestock by lack of fodder or a rise in fodder prices. This scarcity of resources combined with an increase in the population of the country will require better solutions to meet the food demand with lesser inputs. It is noteworthy that climate resilience is driven by region-specific drivers demanding segregated adaptive measures. There is a dire need for appropriate interventions like suitable adaptation practices, adaptive varieties, location-specific strategies, the introduction of new cropping patterns, and the diversification of food basket/habits, etc. to be developed for UP in order to ensure food and income security of the region.

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Author contributions RKM: Conceptualize, Supervision and project management, methodology, interpretation of the results as well as review and editing of the draft; resources; funding acquisition. SP: Methodology, investigation, formal analysis, interpretation of the results, and writing of the original draft. RJ: Methodology, data analysis, visualizations & interpretation of the results. RS: Supervision, review, and editing of the draft. RC: Conceptualization, interpretation of the results, review, and editing of the draft.

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Data availability Authors declare that all data and materials support their published claims and comply with field standards. Authors promote data transparency and agree to provide in case of a request from the journal.

Declarations

Conflict of interest The authors declare no conflict of interest relating to the material presented in this article. Its contents, including any opinions and/or conclusions expressed, are solely those of the authors.

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