Implications of future climate change on crop and irrigation water requirements in a semi-arid river basin using CMIP6 GCMs (Postprint)

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Abstract

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Full Text

Preamble

Implications of Future Climate Change on Crop and Irrigation Water Requirements in a Semi-Arid River Basin Using CMIP6 GCMs

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Abstract: Agriculture faces increasing risks from climate change, particularly in semi-arid regions. A lack of understanding of crop water requirement (CWR) and irrigation water requirement (IWR) under changing climate conditions may lead to crop failure and socioeconomic problems that can prove detrimental to agriculture-based economies in emerging nations worldwide. Previous research on CWR and IWR has largely focused on large river basins using scenarios from the Coupled Model Intercomparison Project Phase 3 (CMIP3) and Phase 5 (CMIP5). However, smaller basins are more susceptible to regional climate change, with more significant impacts on crops. This study estimates CWRs and IWRs for five crops (sugarcane, wheat, cotton, sorghum, and soybean) in the Pravara River Basin (area of 6537 km^2) of India using outputs from the most recent Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Models (GCMs) under Shared Socio-economic Pathway (SSP) 245 and SSP585 scenarios. An increase in mean annual rainfall is projected under both scenarios in the 2050s and 2080s using ten selected CMIP6 GCMs. CWRs for all crops may decline in almost all of the CMIP6 GCMs in the 2050s and 2080s (with the exceptions of ACCESS-CM-2 and ACCESS-ESM-1.5) under SSP245 and SSP585 scenarios. The availability of increasing soil moisture in the root zone due to increasing rainfall and a decrease in the projected maximum temperature may be responsible for this decline in CWR. Similarly, except for soybean and cotton, the projected IWRs for all other three crops under SSP245 and SSP585 scenarios show a decrease or a small increase in the 2050s and 2080s in most CMIP6 GCMs. These findings are important for agricultural researchers and water resource managers to implement long-term crop planning techniques and to reduce the negative impacts of climate change and associated rainfall variability to avert crop failure and agricultural losses.

Keywords: climate change; crop water requirement; irrigation water requirement; CMIP6 GCMs; emission scenario; Pravara River Basin

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1 Introduction

India's agricultural sector contributes 17.90% to the gross value added and provides employment to 56.40% of the country's total workforce (Economic Survey, 2021). Indian agriculture is heavily climate-dependent with notable regional and climatic variability, and rain-fed area accounts for approximately 54.00% of the gross cropped area despite notable efforts to increase the area under irrigation (Gulati et al., 2018). The agricultural sector faces multi-dimensional pressure from many stressors, such as climate change and socio-economic factors (e.g., population growth, unbounded urbanization, and industrialization) (Dai et al., 2013; Yu et al., 2019). Additionally, potential implications of climate change vary from regional to local population scales (Farooq et al., 2022). Changes in climate, primarily in the forms of rainfall, temperature, and radiation, will impact the availability of water resources and water requirements for both irrigated and rain-fed crops (Jain and Singh, 2020). Masia et al. (2021) found that evaporative demand will increase in tandem with rising global temperature, thus increasing crop evapotranspiration. Crop water requirement (CWR) varies depending on the cropping system, and climate change may have a substantial impact on CWR (Sun et al., 2013; Ye et al., 2015). Elgali et al. (2007) found that CWR and irrigation water requirement (IWR) are very sensitive to changes in climatic variables and will vary due to climate change. Thus, climate change is increasingly threatening major crop production systems (Farooq et al., 2022). Ahmad et al. (2021) revealed that the risk of crop failure will be higher due to projected climate change under Coupled Model Intercomparison Project Phase 5 (CMIP5) General Circulation Models (GCMs). However, the actual impacts of climate change on CWR are complex and difficult to predict (Jain and Singh, 2020).

According to the Fifth Assessment Report (AR5) of IPCC (2014), surface temperature will increase during the 21st century under all emission scenarios, and this will adversely impact agriculture, land and water resources, environment, ecosystems, biodiversity, and even society (Singh et al., 2015a; Jain and Singh, 2020). Therefore, it is vital to explore the links between agricultural water management and climate change, looking into the regional and local variability of food and water security. Döll (2002) applied a global irrigation model to assess the impacts of climate change on net IWR and found that there may be an increase in global net IWR of 5.00%–8.00% by the end of the 2070s, with the largest increase in the South Asia region. Wada et al. (2013) used CMIP5 GCMs and applied seven global hydrological models to evaluate the impacts of climate change on CWR and pointed out that there would be an increase in CWR and a decrease in water availability by the 2080s with pronounced regional patterns. Rehana and Mujumdar (2013) found that there will probably be an increase in CWR due to climate change. Elliott et al. (2014) revealed that there might be an inversion of 2.0$\times 10^{\{4\}-6.0\times 10}\{4\}$ km^2 of cropland from irrigated to rainfed systems due to limitations of freshwater availability, mostly in the irrigated regions of western United States, China, and West, South, and Central Asia.

According to Jain and Singh (2020), the correlation between global CWR and global warming is high, and the benefits of increasing rainfall for irrigation are small. Haz-Amor et al. (2020) used CMIP5 GCMs with the CROPWAT model and found an increase in IWR based on scenario projections. Shrestha et al. (2013) also used a coupled CROPWAT model with HadCM3 GCM (A2 and B2 scenarios) for future projections and found that IWR varied with physiographic regions and growth stages of crops. The IWRs in the middle and high hills of Nepal were found to have a decreasing trend, while IWR in the Terai region showed an increasing trend. De Silva et al. (2007) predicted the impacts of climate change by coupling the CROPWAT model with HadCM3 GCM under A2 and B2 scenarios and found that IWR increased by 23.00% and 13.00% for paddy crop, respectively. Das et al. (2020) assessed the impacts of climate change on crop yield in the eastern Himalayas. More recently, Abdoulaye et al. (2021) and Poonia et al. (2021) assessed the impacts of climate change on CWR and IWR using the CROPWAT model coupled with CMIP5 and Coordinated Regional Downscaling Experiment (CORDEX) GCMs, respectively, for river basins in Niger and the eastern Himalayan region. Some other important work in this domain includes the study of Li et al. (2020), who developed a structure for "water suitable" agriculture by analyzing factors affecting IWR. Overall, it can be stated that the climate change-induced increase in water demand will bring further challenges to farmers to irrigate and grow crops with limited water availability. However, the studies done by Flörke et al. (2018) and Gondim et al. (2018) opined that improvements in agricultural water use efficiency through improved technological and scientific interventions will help compensate for the adverse impacts of climate change and may supply enough water to meet demands of other sectors. For improving water use efficiency, it is critical to understand how much water crops require at different times of the year, as well as to develop rational irrigation schedules for irrigated areas. Tubiello and Fischer (2007) found that an alleviated climate may reduce the impacts of climate change on agricultural water requirements by about 40.00%, or 125$\times 10^{\{8\}-160\times 10}\{8\}$ m^3, compared with an unmitigated climate.

Schwaller et al. (2021) underscore the importance of effective agricultural water management through a comprehensive understanding of CWR and IWR, but this information is frequently not readily available. Therefore, it is of paramount importance to understand the variability of climate-induced CWRs and IWRs of different crops for effectively managing agricultural water resources and mitigating the adverse impacts of climate change on agriculture.

However, previous studies, as discussed above, have used climate projections mainly from Coupled Model Intercomparison Project Phase 3 (CMIP3) GCMs and CMIP5 GCMs to assess future CWR and IWR, which inherited limitations, particularly in simulating extreme rainfall events (Kim et al., 2020). This bias in rainfall estimation results in higher uncertainties in projected CWR and IWR. More recently, a new generation of Coupled Model Intercomparison Project Phase 6 (CMIP6) framework has been introduced (Eyring et al., 2016; Gupta et al., 2020; Mishra et al., 2020) to overcome the drawbacks of CMIP3 and CMIP5 models and fulfill the needs of a growing climate community. Therefore, in this study, downscaled and bias-corrected GCM outputs of different climatic parameters generated within new Shared Socio-economic Pathways (SSPs) developed as part of the CMIP6 GCM framework were applied for the estimation of CWR and IWR using the CROPWAT model for five crops (i.e., sugarcane, cotton, soybean, wheat, and sorghum) of varying growth periods in a semi-arid river basin located in the state of Maharashtra, India for future periods (2050s and 2080s). This study will aid in understanding the long-term impacts of climate change on agriculture and in developing adaptation plans for local agricultural water management by local water managers, researchers, and policymakers.

2.1 Study Area

The selected study area is the Pravara River Basin (PRB; Fig. 1 [Figure 1: see original paper]), located in the Ahmednagar District of Maharashtra State, India. Ahmednagar is one of the worst drought-hit districts in India. It is home to 4.5×10^{6} people, of which about 80.00% are rural. Agriculture and animal husbandry are the prime economic activities and contribute significantly to the total income of the region.

The Pravara River is one of the smallest tributaries of the Godavari River (the second largest river system in Peninsular India) that originates near Akola on the eastern slopes of the Sahyadris (19°31′45″N, 73°45′05″E; 750 m) in the western Ghats. It is a rain-fed and intermittent river that generally dries out in summer. Mahalungi and Mula are two important left and right bank tributaries of the Pravara River that join at Sangamner and Nevasa, respectively.

The river flows approximately 208 km from its origin in the Sahyadri to its mouth at Pravara Sangam (19°37′00″N, 75°01′00″E; 531 m) and forms a basin with an area of approximately 6537 km^{2}
The entire basin is made up of Cretaceous–Tertiary extrusive basalt flows known as the Deccan Volcanic Province (Wellman and McElhinny, 1970; Alexander, 1981; Widdowson and Mitchel, 1999; Hooper et al., 2010). The major soil categories include shallow alluvium soil, medium black soil, deep black soil, and reddish soil, which account for nearly 38.00%, 48.00%, 13.00%, and 0.80% of the total cultivated area, respectively (http://www.kvk.pravara.com/).

Topographically, moderate relief variation is found in the basin, where

altitude ranges from 404 to 1424 m. The western section of the basin has a hilly landscape, whereas the eastern section is a relatively flat plateau. Because of its geographical location, the PRB has a semi-arid climate. The basin's average annual rainfall based on gridded rainfall data (0.25°×0.25°) from the India Meteorological Department for 30 years (1991–2020) is 593.3 mm. The seasonal mon
m^3) upstream of the river in 1926. It is one of the major irrigation projects in the Ahmednagar District, accounting for nearly 8.70% (570 km^2) of the total basin area. Sugarcane, cotton, soybean, wheat, and sorghum are important crops grown in the region (Table 1). Sugarcane has become the dominant commercial crop in this area, and the Pravara River serves as the primary irrigation source for agriculture. The region is vulnerable to climate change and has experienced persistent multi-year droughts in the recent past. Therefore, it is of paramount importance to understand the variability of climate-induced CWRs and IWRs of different crops for effectively managing agricultural water and mitigating the adverse impacts of climate change on agriculture in the PRB.

Fig. 1 Overview of the Pravara River Basin (PRB) as well as the important places (cities, towns, and dams) in the basin

Table 1 Planting and harvesting dates for the major crops grown in the Pravara River Basin (PRB)

Crop	Scientific name	Planting–harvesting date	Critical depletion factor	Rooting depth (cm)	Length of crop growth stage (d)
Wheat	Triticum aestivum	15 Oct–11 Feb	-	-	Initial: Developing: Middle season: -
Sorghum	Sorghum bicolor	15 Oct–16 Feb	-	-	Initial: Developing: Middle season: -
Sugarcane	Saccharum officinarum	15 July–14 July	-	-	Initial: Developing: Middle season: -
Cotton	Gossypium	15 July–10 Jan	-	-	Initial: Developing: Middle season: -
Soybean	Glycine max	15 July–1 Dec	-	-	Initial: Developing: Middle season: -

2.2 Agro-Meteorological Data

Figure 2 [Figure 2: see original paper] shows a schematic of the methodology and data adopted in this study. Data used for the calculations of CWR and IWR, including climatic variables, soil parameters, and crop parameters, were input into the CROPWAT 8.0 model. Meteorological data including temperature (Tmax and Tmin), rainfall, wind speed, mean relative humidity, and sunshine hours were obtained on a daily time scale from the India Meteorological Department (http://www.imdpune.gov.in/). Rainfall data were available at a grid resolution of 0.250°$×0.250°, whileotherclimaticvariableswereofferedataspatialresolutionof0.500°×$0.500°. Soil data (total available moisture content, maximum rain infiltration rate, maximum rooting depth, initial soil moisture depletion, and initial available soil moisture) and crop parameters (planting date, length of crop growth stage, crop coefficient, rooting depth, critical depletion factor, yield response factor, and crop height) were obtained from the Food and Agriculture Organization (FAO) Manual 56 available at http://www.fao.org/land-water/database.

Fig. 2 Flowchart showing the adopted methodology for estimating and investigating the implications of future climate change on CWRs and IWRs for major crops in the PRB. CWR, crop water requirement; IWR, irrigation water requirements; Kc, crop coefficient; CMIP6, Coupled Model Intercomparison Project Phase 6; GCMs, General Circulation Models; SSP, Shared Socio-economic Pathway; MK, Mann-Kendall; ET0, reference crop evapotranspiration; FAO, Food and Agriculture Organization; ETc, crop evapotranspiration; Reff, effective rainfall.

2.3 Scenario Data of CMIP6 GCMs

In this study, we used the bias-corrected downscaled CMIP6 GCM datasets developed by Mishra et al. (2020) for South Asia to investigate the impacts of future climate change on CWR and IWR. They developed these bias-corrected datasets based on the Empirical Quantile Mapping approach for the historical (1951–2014) and future (2015–2100) periods under four scenarios: Shared Socio-economic Pathway (SSP) 126, SSP245, SSP370, and SSP585. In this study, downscaled high spatial resolution (approximately 0.250°$×0.250°)dataoftenCMIP6GCMs(Table2)wereusedtorevealthemiddle(2041–2070)andfar(2071–2100)
economicchangesthatwilltakeplaceby2100(Riahietal., 2017).Theypresentsocio−
economicandtechnologicaltrajectorieswithabaselineinwhichnoclimatepoliciesareenactedafter2010, resultin
industriallevelsby2100.Inaddition, thefourSSPscanbelinkedtoclimatepoliciestogeneratedifferentoutcomes
in 2100.

Table 2 Detailed description of Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Models (GCMs) used in this study

CMIP6 GCM	Description	Spatial resolution	Institution
ACCESS-ESM-1.5	Australian Community Climate and Earth System Simulator-Earth System Model Version 1.0	1.250°$×1.875°|CommonwealthScientificandIndustrialOrganisation(CS… CM−2|AustralianCommunityClimateandEarthSystemSimulator−CoupledModelVersion2.0|1.250°×1.875°|CommonwealthScientificandIn… CSM2−MR|BeijingClimateCentreClimateSystemModelVersion2.0|1.100°×1.10… Earth3|EarthConsortium−Earth3Model|0.350°×0.350°|Twenty−sevenresearchinstitutesfrom10Europeancountries||EC−Earth3−Veg|EarthConsortium−Earth3VegModel|0.350°×0.350°|Twenty−sevenresearchinstitutesfrom10Europeancountries||INM−CM4−8|InstituteforNumericalMathematicsClimateModelVersion4.8|2.000°×… CM5−0|InstituteforNumericalMathematicsClimateModelVersion5.0|2.000°×… ESM1−2−HR|MaxPlanckInstituteforMeteorologyEarthSystemModelVersion1.2… ESM2.0|MeteorologicalResearchInstituteEarthSystemModelVersion2.… MM|NorwegianEarthSystemModelVersion2.0withmediumresolution|2…	Norwegian Community Earth System Model, Norway

2.4 Screening of Data and Trend Analysis

Inhomogeneity in time series introduces statistical errors that may lead to false analysis and interpretation of climatic events (Peterson et al., 1998; WMO, 2011). Therefore, initial data quality checks (e.g., screening data for outliers, trends, and discontinuities) are recommended for time series (monthly, seasonal, and annual) of climatic variables (WMO, 2011). Outliers and inhomogeneity in the historical data were detected using the generalized Extreme Studentized Deviate (ESD) test (Rosner, 1983) and Buishand's Range test (Buishand, 1982) methods, respectively.

The ESD method was used to test the null hypothesis (H_0) that there are no outliers versus the alternative hypothesis (H_1) that there are 'r' outliers in the dataset. The test statistic 'r' was defined by the following equation:

$$r = \max_i \frac{|x_i - \bar{x}|}{s}$$

where $\bar{x}$, x_i, and s are the sample mean, the ith observation of the sample, and standard deviation, respectively. The r test value is compared with the tabulated critical value at a given level of significance (5% significance level).

The null hypothesis that the suspected value is not an outlier is rejected if the r test value is greater than the tabulated critical value.

In Buishand's Range test method, the test statistic adjusted partial sum (S_k) was calculated by:

$$S_k = \sum_{i=1}^{k} (x_i - \bar{x}), \quad 1 \leq k \leq n$$

It is a measure of cumulative deviation from the mean for the kth observation in time series $(x_1, x_2, \dots, x_i, \dots, x_n)$. The series is homogeneous without any change point if S_k fluctuates around zero. When a break point is present in the series, S_k reaches a maximum value (negative shift) or minimum value (positive shift) for the year $i = k$. The significance of shift was tested using rescaled adjusted range (R) defined by the following equation:

$$R = \max(S_k) - \min(S_k)$$

The ratio of R to square root of n was compared with the tabulated critical values (Buishand, 1982) at a given significance level (Table 3). It should be noted that 'n' represents the total number of observations in the time series. The null hypothesis of no change point is rejected if the ratio is less than the critical value (1.43) at 5% significance level. These time series of observations were further homogenized using a multistep process based on non-parametric statistics as described in Peterson and Easterling (1994).

Table 3 Statistical information of annual and seasonal climatic variables averaged over 1991–2020 in the PRB

Climatic variable	Standard deviation	Coefficient of skewness	Coefficient of kurtosis	Coefficient of variance	Buishand's Range test	Cumulative deviation/square root (n)	R/square root (n)	Break
Annual Tmax (°C)	-	-	-	-	1.99*	-	-	-
Tmin (°C)	-	-	-	-	1.51*	-	-	-
Rainfall (mm)	593.38	-	-	-	1.70*	-	-	-

Climatic variable	Standard deviation	Coefficient of skewness	Coefficient of kurtosis	Coefficient of variance	Buishand's Range test	Cumulative deviation/square root (n)	R/square root (n)	Break
Pre-monsoon season (March–May) Tmax (°C)	-	-	-	-	1.65*	-	-	-
Tmin (°C)	-	-	-	-	1.53*	-	-	-
Rainfall (mm)	-	-	-	-	1.87*	-	-	-
Monsoon season (June–September) Tmax (°C)	-	-	-	-	1.60*	-	-	-
Tmin (°C)	-	-	-	-	-	-	-	-
Rainfall (mm)	470.25	-	-	-	-	-	-	-
Post-monsoon season (October–November) Tmax (°C)	-	-	-	-	-	-	-	-
Tmin (°C)	-	-	-	-	-	-	-	-
Rainfall (mm)	98.17	-	-	-	-	-	-	-

Climatic variable	Standard deviation	Coefficient of skewness	Coefficient of kurtosis	Coefficient of variance	Buishand's Range test	Cumulative deviation/square root (n)	R/square root (n)	Break
Winter season (December–February) Tmax (°C)	-	-	-	-	-	-	-	-
Tmin (°C)	-	-	-	-	-	-	-	-
Rainfall- (mm)		-	-	-	-	-	-	-

Note: Tmax, maximum temperature; Tmin, minimum temperature; R, rescaled adjusted range.

After screening the data, the non-parametric Mann-Kendall (MK) test and Sen's slope estimator methods were employed for detecting trends in climatic variables. A detailed description of the methods can be found in Singh et al. (2015b).

2.5 Estimations of Reference Crop Evapotranspiration (ET_0), Effective Rainfall (Reff), CWR, and IWR

The CROPWAT 8.0 model was used to estimate ET_0, Reff, and water requirements (CWR and IWR) for the different investigated crops. CROPWAT 8.0 calculates ET_0, Reff, CWR, and IWR based on climate, crop, and soil data. It has been widely used as a decision-support tool in international settings to calculate regional irrigation needs (Smith et al., 2002; Poonia et al., 2021). The model uses the Penman-Monteith (FAO 56 PM) equation (Savva et al., 2002; Schwaller et al., 2021) to calculate ET_0. This equation uses Tmax, Tmin, humidity, wind speed, and sunshine hours as input data, and CROPWAT uses these data to calculate ET_0 by the following expression (Allen et al., 1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)}$$

where ET_0 is the reference crop evapotranspiration (mm/d); R is the mean daily net radiation (MJ/(m^2 · d)); G is the soil heat flux density (MJ/(m^2 · d)); γ is the psychrometric constant (0.067 kPa/°C); T is the mean daily air temperature (°C), and the value of (Tmax+Tmin)/2 was measured between 1.5 and 2.0 m height above the ground; U_2 is the wind speed at 2.0 m height above the ground (m/s); e is the saturation vapour pressure (kPa); e is the actual vapour pressure (kPa); (e –e) is the vapour pressure deficit (kPa); and Δ is the slope of vapour pressure curve (kPa/°C).

Similarly, Reff was estimated using the following relationship for the two conditions (when Rmonth < 250.00 mm and Rmonth > 250.00 mm, where Rmonth is the monthly average rainfall (mm)) as described in Moseki et al. (2019):

$$Reff = \begin{cases} 0.6R_{month} - 10 & \text{if } R_{month} < 250.00 \text{ mm} \\ 0.8R_{month} + 125 & \text{if } R_{month} > 250.00 \text{ mm} \end{cases}$$

The CWR was calculated using the FAO 56 PM equation coupled with the single crop coefficient method as follows (Allen et al., 1998; Luo et al., 2022):

$$ET_c = K_c \times ET_0$$

where ETc and Kc are the crop evapotranspiration (crop water requirement; mm/d) and crop coefficient, respectively. The Kc was determined from the variation in climatic variables, crop types, and growing stages of crops. Notably, in this work, CWR was computed during the whole growth period for all five crops: sugarcane, wheat, cotton, soybean, and sorghum. Further, IWR was estimated by subtracting Reff from ETc (Moseki et al., 2019; Poonia et al., 2021):

$$IWR = ET_c - Reff$$

3.1 Trends in Climatic Variables for Historical Period (1991–2020)

Temporal variability in temperature (Tmax and Tmin) and rainfall directly affects the sowing and growing stages of crops. The best way to explain this variability is to look at anomalies in Tmax, Tmin, and rainfall and analyze their patterns during the study period (Singh et al., 2016). In this study, anomalies in temperature and rainfall were calculated by subtracting the annual and seasonal time series from the yearly mean averaged for the years 1991–2020 (historical period).

Using MK and Sen's slope estimator methods, we determined the magnitudes and directions of changes in Tmax, Tmin, and rainfall. The results of MK test (Zs) and Sen's slope test (Q) are given in Table 4 . At the annual scale, statistically insignificant decreasing trends in Tmax and rainfall are observed in the PRB for the study period. However, no definite trend in annual Tmin is detected. Similar patterns are observed for these variables in the post-monsoon season but with varying magnitudes. During the monsoon season, statistically insignificant increasing trends in Tmax and Tmin are detected, while rainfall reveals a decreasing trend. However, during winter, no trend in rainfall but a decreasing trend in temperature are observed.

Table 4 Annual and seasonal trends in temperature and rainfall anomalies in the PRB for historical period (1991–2020)

Period	Tmax	Tmin	Rainfall
	Zs	Q (°C/a)	Zs
Annual	-	-	No trend
Monsoon	-	-	-
Pre-monsoon	No trend	-	No trend
Winter	-	-	-
Post-monsoon	-	-	No trend

Note: Zs, Mann-Kendall (MK) test; Q, Sen's slope test.

These results show dissimilarity with previous studies of Guhathakurta et al. (2013) and Singh et al. (2021) where a statistically insignificant decreasing trend of rainfall in winter and an increasing trend of rainfall in pre-monsoon, monsoon, and post-monsoon and annual rainfall are reported in the Ahmednagar District. However, a recent report "Observed Rainfall Variability and Changes over Maharashtra State" published in 2020 by the India Meteorological Department shows a decreasing trend in mean annual and monsoonal rainfall in the Ahmednagar District (Guhathakurta et al., 2020). The difference in these results might be attributed to the length of the data period used for trend analysis. Specifically, Guhathakurta et al. (2013) and Singh et al. (2021) used long-term gridded data obtained from the India Meteorological Department for 1901–2006 and 1901–2018, respectively, while the data period in the report was 1989–2018. Furthermore, the decreasing trend observed in rainfall can be attributed to the decreased number of rainy days recorded in the Ahmednagar District in recent decades (1990–2020s).

3.2 Changes in Climatic Variables under SSP245 and SSP585 Scenarios in the 2050s and 2080s

Figures 3 and 4 show projected changes in mean annual Tmax, Tmin, and rainfall under SSP245 and SSP585 scenarios for future periods 2041–2070 (2050s) and 2071–2100 (2080s) with respect to the baseline period 1991–2020. All models under both scenarios predict rises in mean annual Tmin and rainfall in the 2050s and 2080s. The increasing ranges are 0.59°C–3.47°C in the 2050s and 1.21°C–6.47°C in the 2080s for Tmin, and 11.70%–73.05% in the 2050s and 2.80%–163.80% in the 2080s for rainfall. Within scenarios, relatively high increases in mean annual Tmin and rainfall are observed under the SSP585 scenario compared to the SSP245 scenario. However, in general, eight out of ten models predict a decrease in mean annual Tmax under all scenarios in all future periods except for a higher emission scenario (i.e., SSP585) in the 2080s.

Projected changes in seasonal rainfall under both SSP245 and SSP585 scenarios were investigated. In general, nine out of ten CMIP6 GCMs predict a significant increase in monsoonal rainfall under both scenarios in the 2050s and 2080s. Specifically, the increasing ranges are 21.00%–73.00% in the 2050s and 4.00%–99.00% in the 2080s under the SSP245 scenario, and 17.00%–94.00% in the 2050s and 17.00%–176.00% in the 2080s under the SSP585 scenario. However, a decrease in post-monsoonal rainfall ranging from –0.02% to –73.00% is projected under the SSP245 scenario in the 2050s. Similarly, the analysis of future scenarios in general reveals a decrease in Tmax for all seasons under a lower emission scenario of SSP245 in the 2050s; however, an increase in Tmax is predicted under a higher emission scenario of SSP585 for all seasons in the 2080s. Opposite to this, an increase in Tmin is predicted for all seasons under both scenarios for most models in the 2050s and 2080s. The predicted increase is relatively high for Tmin compared to Tmax under both scenarios for all seasons. The results discussed here are in accordance with previous work of Todmal et al. (2021) who reported increases in mean annual and monsoonal rainfall and minimum temperature over the state of Maharashtra in India for the future period (2015–2100) using the REgional MOdel (REMO).

Fig. 3 Projected changes in annual Tmin (a–d) and Tmax (e–h) in the PRB using different CMIP6 GCMs under SSP245 and SSP585 scenarios in the 2050s and 2080s. Tmin, minimum temperature; Tmax, maximum temperature.

3.3.1 ET_0 and Reff

Table 5 presents ET_0 and Reff estimated for different months using data from 1991–2020. ET_0 exhibits variations across months. Due to high temperature in summer, it reaches its maximum value in April (7.92 mm/d); however, the minimum value occurs in August (4.12 mm/d) as temperature is likewise low in this month. From 1991 to 2020, the long-term yearly average of ET_0 is 5.27 mm/d. The volatility in ET_0 is attributed to changes in other climatic variables. Low humidity, high wind speed, and high temperature cause ET_0 to reach its highest level during the summer season (i.e., dry season). Reff experiences similar variations throughout the year owing to variations in rainfall, with September having the highest value (113.34 mm/month) and January having the lowest value (1.02 mm/month). The long-term (1991–2020) yearly average of Reff is 492.21 mm/month.

Fig. 4 Projected changes in mean annual rainfall in the PRB using different CMIP6 GCMs under SSP245 and SSP585 scenarios in the 2050s (a and b) and 2080s (c and d).

Table 5 Estimations of monthly reference crop evapotranspiration (ET_0) and effective rainfall (Reff) in the PRB from meteorological data averaged over 1991–2020

Month	Temperature (°C)	Humidity	Wind speed (km/d)	Sunshine hours (h)	Rn (MJ/(mm/d))	Rainfall (mm/month)	Reff (mm/month)	Average

Note: Rn, mean daily net radiation.

3.3.2 Estimations of CWRs and IWRs for Different Crops

CWR of any crop is the total amount (depth) of water lost owing to evapotranspiration and is determined from ETc. Every crop has various water requirements depending on location, climatic conditions, soil type, cultivation technique, and Reff (Ewaid et al., 2019). Tables 6–10 show that Reff, CWR, and IWR fluctuate across the developmental stages of all crops. Moreover, Kc values are not constant at any development stage, indicating seasonal crop water needs (Allen et al., 1998; Azevedo et al., 2007; Irmark et al., 2013). ETc increases during the growth stage and lowers significantly during later phases based on Kc values. Tables 6–10 indicate that ETc values are lower in the early and late stages when crops are in the productive stage and higher in the middle stage. IWRs for all five crops in 10-day periods descend in the order of 1707.00 mm/10 d (sugarcane) > 500.80 mm/10 d (wheat) > 401.60 mm/10 d (cotton) > 381.50 mm/10 d (sorghum) > 212.80 mm/10 d (soybean), as shown in Tables 6–10.

Table 6 Estimations of CWR and IWR for wheat in the PRB for historical period (1991–2020)

Month	Number of cycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
		Initial					
		Developing					
		Developing					
		Developing					
		Middle					
		Middle					
		Middle					
		Middle					
		Middle					
	Average						

Note: Kc, crop coefficient; CWR, crop water requirement; IWR, irrigation water requirement.

Table 7 Estimations of CWR and IWR for sorghum in the PRB for historical period (1991–2020)

Number of Monthcycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
	Initial					
	Initial					
	Developing					
	Developing					
	Developing					
	Middle					
	Middle					
	Middle					
	Middle					
Average						

Table 8 Estimations of CWR and IWR for soybean in the PRB for historical period (1991–2020)

Number of Monthcycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
	Initial					
	Initial					
	Initial					
	Developing					
	Developing					
	Developing					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
Average						

Table 9 Estimations of CWR and IWR for sugarcane in the PRB for historical period (1991–2020)

Number of Monthcycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
	Initial					
	Initial					
	Initial					

Number of Monthcycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
	Developing					
	Developing					
	Developing					
	Developing					
	Developing					
	Developing					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
To be continued						

Table 9 (continued)

Number of Monthcycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
	Middle					
Continued Average						

Table 10 Estimations of CWR and IWRs for cotton in the PRB for historical period (1991–2020)

Month	Number of cycles per 10 d	Growth stage	Kc	ETc (mm/d)	CWR (mm/10 d)	Reff (mm/10 d)	IWR (mm/10 d)
		Initial					
		Initial					
		Initial					
		Developing					
		Developing					
		Developing					
		Developing					
		Middle					
		Middle					
		Middle					
		Middle					
		Middle					
	Average						

3.4.1 ET_0 and Reff

Using the CROPWAT 8.0 model, we calculated ET_0 for different months in the 2050s and 2080s under SSP245 and SSP585 scenarios, as shown in Tables 11 and 12. In the 2050s and 2080s, ET_0 is highest in April and lowest in August compared to other months for both scenarios. The volatility in ET_0 is attributed to changes in climatic variables. Low humidity, high wind speed, and high temperature cause ET_0 to reach its highest level during the summer season (i.e., dry season). Here, it can be deduced that ACCESS-CM-2 GCM consistently projects the highest average ET_0 compared to the rest of the CMIP6 GCMs under both scenarios (SSP245 and SSP585) in the 2050s and 2080s.

Table 11 Projected estimations of monthly ET_0 using different CMIP6 GCMs in the PRB under SSP245 and SSP585 scenarios in the 2050s

Month	ACCESS-ESM-1-5	ACCESS-CM-2	BCC-CSM2-MR	EC-Earth3	EC-Earth3-Veg	INM-CM4-8	INM-CM5-0	MPI-ESM1-2-HR	MRI-ESM2-0	NorESM2-MM	Baseline period ET_0 (mm/d)	SSP245 scenario Average	SSP585 scenario Average

Note: The baseline period is from 1991 to 2020.

Table 12 Projected estimations of monthly ET_0 using different CMIP6 GCMs in the PRB under SSP245 and SSP585 scenarios in the 2080s

Month	ACCESS-ESM-1.5	ACCESS-CM-2	BCC-CSM2-MR	EC-Earth3	EC-Earth3-Veg	INM-CM4-8	INM-CM5-0	MPI-ESM1-2-HR	MRI-ESM2-0	NorESM2-MM	Baseline period ET_0 (mm/d)	SSP245 scenario Average	SSP585 scenario Average

Note: The baseline period is from 1991 to 2020.

Further, Figure 5 [Figure 5: see original paper] shows the percentage change in ET_0 under SSP245 and SSP585 scenarios in the 2050s and 2080s. For all CMIP6 GCMs, the percentage change in ET_0 is negative (i.e., ET_0 is decreasing) under the SSP245 scenario in the 2050s and 2080s, except for three CMIP6 GCMs: ACCESS-CM-2, MRI-ESM2-0, and ACCESS-ESM-1.5, in which the percentage change in ET_0 is positive (2.70% and 4.60%, respectively) in the 2050s and 2080s with respect to average ET_0 in the baseline period (1991–2020). Specifically, in the 2080s, only two CMIP6 GCMs (ACCESS-CM-2 and ACCESS-ESM-1.5) predict a positive increase in ET_0 under the SSP245 scenario. Mondal et al. (2021) reported an increase of 4.00% in ET_0 over the Indus River Basin under the medium emission scenario (SSP245). A similar pattern is observed under the SSP585 scenario in the 2050s in this study, where for almost all CMIP6 GCMs, the percentage change in ET_0 is negative (i.e., ET_0 is decreasing), except for two CMIP6 GCMs: ACCESS-CM-2 and ACCESS-ESM-1.5, in which the percentage change in ET_0 is positive (3.80% and 1.70%, respectively) with respect to average ET_0 in the baseline period (1991–2020). However, under the SSP585 scenario in the 2080s, all CMIP6 GCMs consistently reveal a positive change in ET_0 (i.e., ET_0 is increasing), up to 20.30%, which is much higher than the percentage increase in ET_0 (4.60%) under the SSP245 scenario in the 2080s. Overall, ET_0 is predicted to increase for all ten CMIP6 GCMs under the SSP585 scenario (high emission scenario) in the 2080s, while both increasing and declining trends are observed with a decreasing pronounced pattern for the remaining periods and scenarios.

Fig. 5 Projected percentage change in ET_0 using different CMIP6 GCMs in the PRB under SSP245 (a and b) and SSP585 (c and d) scenarios in the 2050s and 2080s

3.4.2 Estimations of CWRs and IWRs for Different Crops

Table 13 shows CWR estimates for different crops using ten CMIP6 GCMs under two scenarios (SSP245 and SSP585) in the 2050s and 2080s. It can be observed from Table 13 that two CMIP6 GCMs, namely ACCESS-CM-2 and ACCESS-ESM-1.5, project increases in CWRs for cotton and soybean crops under both SSP245 and SSP585 scenarios compared to the rest of the eight CMIP6 GCMs, which estimate decreases in CWRs for all crops in the 2050s and 2080s. However, the overall averages of projected CWRs for cotton, sorghum, sugarcane, soybean, and wheat for all ten models are 667.80, 417.20, 2102.40, 501.20, and 542.80 mm in the 2050s, and 671.70, 420.50, 2112.40, 500.90, and 547.50 mm in the 2080s, respectively. These values are comparatively lower than those during the historical period (1991–2020).

Figure 6 [Figure 6: see original paper] also shows the projected percentage change (percentage increase or decrease) of CWRs for all crops using the ten CMIP6 GCMs under SSP245 and SSP585 scenarios in the 2050s and 2080s, with respect to the baseline period 1991–2020. With the exceptions of ACCESS-CM-2 and ACCESS-ESM-1.5, which predict increases in CWRs for soybean, cotton, and wheat under the SSP245 scenario in the 2050s and 2080s, decreases in the estimated percentage change of CWRs for all crops are found for nearly all CMIP6 GCMs. Similarly, under the SSP585 scenario, there are decreases in the projected percentage change of CWRs for almost all CMIP6 GCMs in the 2050s, except for ACCESS-CM-2 and ACCESS-ESM-1.5. However, a detailed analysis shows that there exist increases in the projected percentage change of CWRs for all crops under the SSP585 scenario in the 2080s compared to the SSP245 scenario in the 2050s. This could be related to the rise in Tmax during this period. Additionally, results of ACCESS-CM-2 and ACCESS-ESM-1.5 indicate that there are larger increases in the projected percentage change of CWRs for soybean, cotton, and wheat than for sugarcane and sorghum under both scenarios in the 2050s and 2080s. Overall, the results show that the projected percentage change of CWR is decreasing for almost all CMIP6 GCMs (except for ACCESS-CM-2 and ACCESS-ESM-1.5) under the SSP245 scenario in the 2050s and 2080s. However, under the SSP585 scenario, the projected percentage change of CWRs for all crops may increase for five GCMs (ACCESS-ESM-1.5, ACCESS-CM-2, BCC-CSM2-MR, INMCM4-8, and NorESM2-MM) in the 2080s. As an example, by using MRI-ESM2-0, the projected percentage change of CWR for sugarcane is –2.30%, whereas the values are –4.60%, –3.90%, –3.60%, and –2.30%, respectively, for sorghum, wheat, cotton, and soybean.

Table 13 Projected CWRs of five crops using different CMIP6 GCMs in the PRB under SSP245 and SSP585 scenarios in the 2050s and 2080s

CMIP6 GCM	Scenario	2050s					2080s				
		Cotton	Sorghum	Sugarcane	Soybean	Wheat	Cotton	Sorghum	Sugarcane	Soybean	Wheat
ACCESS-ESM-1.5	SSP245	702.80	419.30				703.30	421.10			
	SSP585										
ACCESS-CM-2	SSP245	710.80	426.00				713.00	426.70			
	SSP585										

CMIP6 GCM	Scenario	2050s					2080s				
BCC-CSM2-MR	SSP245	673.60	426.10				678.90	427.80			
	SSP585										
EC-Earth3	SSP245	644.60	411.40				649.00	412.80			
	SSP585										
EC-Earth3-Veg	SSP245	646.30	411.70				650.60	414.90			
	SSP585										
INMCM4-8	SSP245	664.70	412.60				673.80	420.20			
	SSP585										
INMCM5-0	SSP245	655.20	417.30				662.60	420.70			
	SSP585										
MPI-ESM1-2-HR	SSP245	654.80	414.10				667.50	417.20			
	SSP585										
MRI-ESM2-0	SSP245	659.00	411.40				653.70	413.40			
	SSP585										
NorESM2-MM	SSP245	666.90	421.60				676.40	426.00			
	SSP585										
Average CWR (mm)		667.80	417.20	2102.40	501.20	542.80	671.70	420.50	2112.40	500.90	547.50

Fig. 6 Projected percentage change in CWRs of five crops using different CMIP6 GCMs in the PRB under SSP245 (a and b) and SSP585 (c and d) scenarios in the 2050s and 2080s

However, the overall averages of the projected percentage decrease of CWRs for all five crops using the ten CMIP6 GCMs reveal that cotton has the largest percentage decrease of CWR (–3.70%), followed by sorghum (–3.60%), sugarcane (–3.30%), soybean (–3.30%), and wheat (–2.9%) under the SSP245 scenario in the 2050s and 2080s (Fig. 6), with respect to the baseline period (1991–2020) as given in Tables 6–10. Similarly, under the SSP585 scenario, sugarcane shows the largest percentage decrease in projected CWR (–3.10%), followed by cotton (–2.80%), sorghum (–2.80%), soybean (–2.50%), and wheat (–2.00%) (Fig.

6). This indicates that the pattern of percentage decrease in CWRs for all five crops is similar in the 2050s under both scenarios (i.e., SSP245 and SSP585), except for sugarcane, which shows a larger percentage decrease in CWRs under the SSP585 scenario in the 2050s compared to other crops. Similarly, in the 2080s, the overall averages of the projected percentage decrease of CWRs for all five crops using the ten CMIP6 GCMs show that soybean exhibits the largest percentage decrease in projected CWR (–3.70%), followed by cotton (–3.30%), sugarcane (–3.00%), sorghum (–2.90%), and wheat (–2.20%) under the SSP245 scenario. The availability of increasing soil moisture in the root zone due to increasing rainfall and a decrease in projected Tmax may be responsible for this decline in CWR.

Figure 6 indicates that the percentage decreases in CWR for wheat crop under both SSP245 and SSP585 scenarios in the 2050s and 2080s are lower compared to other crops for most CMIP6 GCMs, in which CWR is projected to increase. This shows that crops like wheat and sugarcane will have higher CWRs in the future than other crops in the PRB. However, at the same time, if we look into the CWRs projected by ACCESS-ESM-1.5 and ACCESS-CM-2 GCMs, CWRs of cotton and soybean will increase under both SSP245 and SSP585 scenarios in the 2050s and 2080s. Acharjee et al. (2017) found that future CWRs are projected to fluctuate and depend on the rainfall pattern. Overall, our results imply that projected CWRs are decreasing for most CMIP6 GCMs (except for ACCESS-CM-2 and ACCESS-ESM-1.5) under the SSP245 scenario in the 2050s and 2080s. However, under the SSP585 scenario, projected CWRs for all crops show increases for half of the CMIP6 GCMs in the 2080s in comparison to the 2050s. This analysis indicates that crops such as wheat and sugarcane have lower decreases in CWRs compared to other crops in the PRB in comparison to the baseline period (1991–2020).

Table 14 shows the estimations of future IWRs for the five selected crops using ten CMIP6 GCMs under two different scenarios (SSP245 and SSP585) in the 2050s and 2080s. The overall averages of projected IWRs for cotton, sorghum, sugarcane, soybean, and wheat in the 2050s for all CMIP6 GCMs are 415.00, 357.30, 1730.70, 249.60, and 471.10 mm under the SSP245 scenario, and 367.40, 317.80, 1562.90, 213.10, and 430.00 mm under the SSP585 scenario, respectively. Similarly, projected IWRs in the 2080s are 405.30, 350.60, 1720.80, 230.80, and 474.40 mm under the SSP245 scenario, and 354.30, 318.30, 1575.80, 196.9, and 427.5 mm under the SSP585 scenario, for cotton, sorghum, sugarcane, soybean, and wheat crops. In general, there is a decrease in the overall projected IWRs for both scenarios in the 2050s and 2080s with respect to the baseline period (1991–2020).

We evaluated the percentage deviation between the overall average of projected IWRs for all five crops under SSP245 and SSP585 scenarios with respect to the baseline period (1991–2020). The results show that under the SSP245 scenario, sorghum has the largest percentage decrease in projected IWR (–6.30%), followed by wheat (–5.90%) compared to other crops, whereas soybean has the largest percentage increase in projected IWR (17.30%), followed by cotton (3.30%) in the 2050s. Under the SSP585 scenario, again, sorghum crop has the largest decrease in projected IWR (–16.70%) with respect to the baseline period, followed by wheat (–14.40%), cotton (–8.50%), and sugarcane (–8.40%) in the 2050s.

Similarly, Figure 7 [Figure 7: see original paper] shows the projected percentage change in IWRs for all crops under SSP245 and SSP585 scenarios in both periods. In general, the projected percentage change of IWRs for all crops under SSP245 and SSP585 scenarios are decreasing or slightly increasing, except for soybean and cotton, which have the largest increase in IWRs (up to 51.30% and 24.50%, respectively) in the 2050s under the SSP245 scenario. Sorghum has the largest percentage decrease in IWR (–25.00%) in the 2050s under both SSP245 and SSP585 scenarios (Fig. 7). A similar pattern (with slight increase or decrease) is observed for this crop in the 2080s under both scenarios. The main reason for the decrease in projected IWR may be attributed to the increase in average annual rainfall. The projected percentage change of IWR shows high variations under SSP245 and SSP585 scenarios in the 2050s and 2080s mainly due to large variability in projected rainfall.

Figure 7 further indicates that in general there are increases in the projected percentage change of IWRs in the 2050s and 2080s under both scenarios for soybean and cotton using five CMIP6 GCMs (ACCESS-ESM-1.5, ACCESS-CM-2, BCC-CSM2-MR, INMCM4-8, and INMCM5-0). Konzmann et al. (2013) observed that increased rainfall resulted in a modest drop in irrigation needs in several regions worldwide, including southeastern China and India. There is also the argument that structural crop responses caused by elevated CO_2 concentrations may offset the negative impacts of climate change on agriculture, which would result in lower IWRs in many parts of the world (Konzmann et al., 2013).

Fig. 7 Projected percentage change in IWRs using different CMIP6 GCMs in the PRB under SSP245 (a and b) and SSP585 (c and d) scenarios in the 2050s and 2080s

Table 14 Projected IWRs of five crops using different CMIP6 GCMs in the PRB under SSP245 and SSP585 scenarios in the 2050s and 2080s

CMIP6 GCM	Scenario	2050s					2080s				
		Cotton	Sorghum	Sugarcane	Soybean	Wheat	Cotton	Sorghum	Sugarcane	Soybean	Wheat
ACCESS-ESM-1.5	SSP245	453.90	395.90				397.30	259.00			
	SSP585										
ACCESS-CM-2	SSP245	416.30	286.20				374.20	290.00			
	SSP585										

CMIP6 GCM	Scenario	2050s					2080s				
BCC-CSM2-MR	SSP245	499.80	408.80				495.80	411.20			
	SSP585										
EC-Earth3	SSP245	352.60	353.20				346.90	356.30			
	SSP585										
EC-Earth3-Veg	SSP245	360.10	350.10				365.60	355.20			
	SSP585										
INMCM4-8	SSP245	454.70	314.00				472.70	349.40			
	SSP585										
INMCM5-0	SSP245	445.30	370.80				431.80	376.10			
	SSP585										
MPI-ESM1-2-HR	SSP245	389.20	378.10				396.30	382.40			
	SSP585										
MRI-ESM2-0	SSP245	397.30	337.20				371.90	344.10			
	SSP585										
NorESM2-MM	SSP245	380.60	379.10				389.30	371.50			
	SSP585										
Average IWR (mm)		415.00	357.30	1730.7[illegible]	[illegible]49.60	471.10	405.30	350.60	1720.8[illegible]	[illegible]30.80	474.40

4 Conclusions

In this study, multi-scenario projections from CMIP6 GCMs were used to investigate the impacts of climate change on CWR and IWR in a semi-arid river basin of India under two future scenarios (SSP245 and SSP585) in the 2050s and 2080s. We found that projected CWRs decrease for all five crops for almost all CMIP6 GCMs (except for ACCESS-CM-2 and ACCESS-ESM-1.5 for soybean and cotton) under SSP245 and SSP585 scenarios in the 2050s and 2080s. The increase in CWRs observed for ACCESS-CM-2 and ACCESS-ESM-1.5 under both scenarios is more pronounced in the 2080s. The study also found that CWRs in crops such as sugarcane, sorghum, and wheat would decrease for all ten CMIP6 GCMs under both scenarios in the 2050s and 2080s. This could be attributed to the projected decrease in Tmax.

Similarly, projected IWRs for all five crops under the SSP245 scenario would decrease or slightly increase in the 2050s and 2080s, except for soybean and cotton. For about four CMIP6 GCMs (EC-Earth3, EC-Earth3-Veg, MPI-ESM1-2-HR, and NorESM2-MM), a decrease in IWR is found in the 2050s and 2080s under both scenarios. Sorghum crop has the largest decrease in IWR in the 2050s and 2080s under both scenarios, followed by wheat and sugarcane. However, at the same time, soybean exhibits the largest increase in IWR in the 2050s and 2080s under both scenarios, followed by cotton. The main reason for the drop in IWRs may be attributed to the increase in average annual rainfall. The results further show that crops like cotton and soybean are more vulnerable to climate change than other crops in the PRB. This implies that farmers may opt to increase the acreage of sorghum and wheat compared to soybean and cotton. These results will be of great assistance to agricultural researchers and water resource managers in adopting long-term crop planning techniques to lessen the detrimental impacts of climate change on water resources management in agricultural semi-arid regions like the PRB.

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Note: Figure translations are in progress. See original paper for figures.