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Adapting agriculture to climate shifts: managing crop water needs for environmental resilience in Sindh, Pakistan

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Abstract. Sindh is an important hub for the agricultural production in Pakistan. Therefore, this study was aimed to model the air temperature trend in Sindh and its impacts on the seasonal water requirement for Rice, Wheat, and Sugarcane under the Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios. In this study, RegCM4 with GFDL-ESM2M was used and the bias correction of RegCM4 simulations was done using Quantile Mapping. As per the analysis, the average annual temperature over the study area may rise by about 1.2 to 1.8 °C and 2.8 to 3.3 °C under RCP 4.5 and 8.5 scenarios respectively. Seasonally, warming is expected to be higher in spring and winter seasons, whereas, diurnally, the daytime temperature may increase by about 1.2 to 1.7 °C and 2.6 to 3.2 °C, while the nighttime temperature may rise by about 1.4 to 2.7 °C and 3.0 to 3.5 °C under the RCP 4.5 and 8.5 scenarios respectively. Consequentially, the seasonal water requirement for Rice in Sindh may increase by about 50–100 mm and 100–200 mm under RCP 4.5 and 8.5 scenarios respectively. For Wheat, the water requirement may rise by about 60 mm and 100 mm, whereas for Sugarcane, it may soar by about 100–150 mm and 150–200 mm under RCP 4.5 and 8.5 scenarios respectively. Conclusively, the rising crop water consumption may cause increased irrigation requirements, low crop water productivity and yield, and rising local water disputes thereby endangering the crop production and water security in the province.

Key words: climate change, crop water requirement, CROPWAT, CORDEX, food security, quantile mapping, RegCM4, SDG 13.

INTRODUCTION

Climate variability has turned out to be one of the most pressing issues for the world community due to its adverse impacts on the freshwater resources, agriculture, human health, and the overall ecosystem. Climate change is legitimately blamed to be human-induced with the main reasons including the land cover changes and unplanned development, deforestation, industrialization, burning of fossil fuels and rising Greenhouse Gases (GHGs) which destabilizes the global radiation balance and leads to the changing climate regime (Chong et al., 2021; Abbas et al., 2022). Globally, the unfavourable impacts of varying climate have been witnessed in the form of soaring temperatures, extreme meteorological events, seasonal shifts, melting glaciers, flash floods, and rising sea levels (Raihan, 2023). For instance, during the past 100 years, the mean global temperature has soared by about 0.74 °C, where in South Asia, warming increased by about 0.75 °C (Shah et al., 2020; Penev et al., 2021). Temporally, warming has been higher during the later years of century, where the earth temperature heated by about 0.18 °C per decade since 1981 alone (Akaev & Davydova, 2023). Due to the significant dependence on the natural resources and agriculture, lack of climate chnage adaptation and mitigation capacity, high population growth rate and poverty, the climate change adversities are expected to be worst in Asia, where as per the Intergovernmental Panel on Climate Change (IPCC), some parts of Asia have warmed up by 2 °C than the pre-industrial period (1850–1900), that is higher than global temperature anomaly (+1.1 °C) (You et al., 2022).

Table 1. Temporal change in global GHG levels with life span and warming potential

GHG	Level in 1870	Level in 2007	Level in 2022	Life Span in years	Warming potential (Relative to CO_2)
CO_2	280 ppm	399 ppm	420 ppm	300–1,000	1
CH_4	700 ppb	1,745 ppb	1,932 ppb	12	72
NO	270 ppb	314 ppb	334 ppb	114	310
SF6	0	3.5 ppt	10.5 ppt	3,200	16,300

Source: Rasul et al., 2012); ppt: parts per trillion; ppb: parts per billion; ppm: parts per million.

Among all major anthropogenic factors reprehensible for the changing climate patterns, the rising GHG concentrations across the globe (as shown in Table 1) is the prime cause behind the destabilizing global heat balance and consequently varrying climate patterns. For capturing the climate patterns under different GHG emission scenarios and to forumulate climate change adaptative and mitgation policy accordingly, IPCC in its 5th Assessment Report (2014) has adopted four (04) radiative forcing scenarios known as the Representative Concentration Pathways (RCPs) which depend on the magnitude of GHG concentrations and the mitigative measures adopted by the world community in the coming decades (Pedersen et al., 2022). Radiative forcing generally refers to the difference between the incoming and outgoing solar heat energy (in Watt m^{-2}), with greater the difference, the more will be the entrapped heat and warmer will be the earth temperature. RCPs are categorized as RCP 2.6, 4.5, 6.0, and 8.5. As per IPCC, RCP 2.6 is a scenario under which the radiative forcing (global) may touch 2.6 Watt m^{-2} by 2100. Further, this scenario assumes that the CO_2 emissions begin to decrease by 2020 and drops to zero by 2100. Further, it also expects Sulphur dioxide (SO_2) emissions to around 10% of 1980 to 1990 levels, and CH_4 reduction to about half of 2020 levels by 2100. Under this scenario, the mean global temperature is expected to climb by about 1.5 to 2.0 °C by 2100 than the pre-industrial baseline. RCP 4.5 is a scenario under which the radiative forcing may reach to about 4.5 Watt m^{-2}, with the global CO_2 levels heading to 550 to 600 ppm by the end of 21st century. This scenario calls for a decline in CO_2 levels from 2045, so as to attain half of the levels of 2050 by 2100. Similarly, CH_4 emissions also need to be ceased by 2050 and decline to about 75% of CH_4 levels of 2040, while SO_2 levels are assumed to reach 20% of levels of 1980 to 1990 by 2100. In this scenario, the global temperature may warm by about 2.5 to 3.0 °C. RCP 8.5 is the worst-case scenario with no formulation and implementation of climate change mitigation policies by the world community and the global CO_2 levels marching to approximately 1,200 ppm by 2100. Under this scenario, the global temperature is expected to rise by about 5 °C by the end of century (Pedersen et al., 2022).

In order to computationally project the climate patterns under the different RCP scenarios, numerical climate models have been used (Panfilova et al., 2020). These models are categorized spatially as the Global Climate Model (GCM) and the Regional Climate Model (RCM). GCMs have a coarser (lower) spatial resoutlion (typically 150–300 km) and project the climate patterns on the global-scale, while RCMs (spatial resoultion as 20–60 km) project the climate patterns on a regional scale by using the Initial Conditions (ICs) and the Lateral Boundary Condtions (LBCs) of a GCM, and better captures the region-specific climate patterns (Barnes et al., 2024; Gutierrez et al., 2024). As per the literature, RCM projections are basically the transformed outcomes of GCMs on a finer resolution via downscaling. Downscaling refers to the transformation of lower resolution GCM outputs to a higher resolution climate data and is done using the Statistical or Dynamical appraoch (Boe et al., 2023; Zhang et al., 2023). Dynamical downscaling involves the use of a finer resolution RCM to dynamically transform the GCM projections, while in statistical downscaling, a statistical nexus is etablished between the past global and local climate trends to understand how the local climate is responding to the planetary-scale climate variability. This statistical relation is then applied on the GCM datasets to regionalize the model outcomes.

As discussed above, GCMs due to the coarser resolution are suitable only for planetary-scale climate projections as it miss the region-specific climate features and may ultimately mislead the regional climate analysis. Therefore, RCMs due to the higher resolution have been suggested and employed in various studies to conduct regional climate change assessement. For example, Raul (2017) used a RCM called REMO (2009) with the GCM named MPI-ESM-LR to study the agricultural susceptibility over Maharashtra in the Western India under the changing climate scenarios for the period 2015 to 2100. The model outcomes projected a rise in precipitation by about 80 to 250 mm and the temperature increment of about 0.5 to 2.5 °C over the study area by 2099. Ali et al. (2021) employed a RCM named RegCM4, with three (03) GCMs from the Coupled Model Intercomparison Project 5th Phase (CMIP5) namely MPI-ESM-MR, NorESM1-M and MICROC5 to determine the shift in the Monsoon rainfall over the Upper Indus Region and Pakistan. The results indicated a greater strength gain in

Monsoon under RCP 8.5 over the UIB than RCP 2.6. For Pakistan overall, a slight decline (increase) in precipitation is projected under the RCP 8.5 (RCP 2.6) scenario. Hassan et al. (2014) employed the RegCM, utilizing two experiments with ECMWF's Reanalysis data (ERA-40) and ECHAM5 for the period 1971–2000, confirming the model's accurate reproduction of air temperatures and effective analysis of Monsoon precipitation in South Asia.

RegCM is a Regional Climate Model developed by the Italy's International Center for Theoretical Physics (ICTP) for extended regional climate studies. The model solves a set of dynamical equations describing the atmosphere dynamics along with the parameterization for physical climate processes including radiation, convection, turbulent diffusion, clouds and precipitation, soil moisture and ocean fluxes, and tracer transport and chemistry to capture the atmospheric state of a region (Eghbali et al., 2022). Nevertheless, due to the regionally varyig topography and climate features, the RCM simulations often yield errors known as the Biases, which may question the reliability and raise uncertainty in the model outcomes. Therefore, different bias correction techniques have been proposed including Linear Scaling (LS), Power Transformation (PT), Local Intensity Scaling (LOCI), Distribition Mapping (DM), and the Quantile Mapping (QM) method as shown in the Table 2 (Fang et al., 2015). As per the past studies, the QM approach works well to remove biases from daily as well as monthly climate model simulations (Xue et al., 2022; Rajulapati & Papalexiou, 2023).

Table 2. Mathaemtical expressions for the commonly used bias correction methods

Bias Correction Method	Equation	
	Temperature	Precipitation
Linear scaling	$T_{corrected} = T_{Sim} + \mu(T_{obs}) - \mu(T_{sim})$	$P_{corrected} = P_{sim} \cdot \frac{\mu(P_{obs})}{\mu(P_{sim})}$ where $P_{corrected} = 0$, if $P_{sim} < P_{Thres}$
Local intensity scaling (LOCI) of precipitation	-	$P_{corrected} = P_{sim} \times S_m$ where $S_m = \frac{\mu(P_{obs}\vert P_{obs}>0)}{\mu(P_{sim}\vert P_{sim}>P_{Thres}}$
Power transformation (PT) of precipitation	-	$P_{corrected} = S_m \cdot P_{LOCI}{}^{b}$ where $S_m = \frac{\mu(P_{obs})}{\mu(P_{LOCI}{}^{b})}$ $f(b) = \frac{\sigma(P_{obs})}{\mu(P_{obs})} - \frac{\sigma(P_{LOCI}{}^{b})}{\mu(P_{LOCI}{}^{b})}$
Variance scaling (VARI) of temperature	$T_{corrected} = [T_{sim} - \mu(T_{sim})] . \frac{\sigma(T_{obs})}{\sigma(T_{sim})} + \mu(T_{obs})$	-
Distribution/ Mapping (DM)	$T_{corrected} = F_N{}^{-1}(T_{sim} \vert \mu_{sim}, \sigma_{sim}) \vert \mu_{obs}, \sigma_{obs})$ where $f_N(x\vert\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} . e^{\frac{-(x-\mu)^2}{2\sigma^2}}$; $x \in R$	$P_{corrected} = F_r{}^{-1}(F_r(P_{LOCI} \vert \alpha_{LOCI}, \beta_{LOCI})\vert \alpha_{obs}, \beta_{obs})$ where $f_r(x\vert\alpha,\beta) = x^{\alpha-1} x \frac{1}{\beta^{\alpha}} \cdot e^{\frac{-x}{\beta}}$; $x \geq 0, \alpha, \beta > 0$
Quantile Mapping (QM)	$T_{Corrected} = x_{ms} + F_{oh}^{-1}(F_{ms}(x_{ms})) - F_{mh}^{-1}(F_{ms}(x_{ms}))$	$P_{corrected} = F_{oh}{}^{-1}(F_{mh}(x_{ms}))$, $x_{ms} \geq x_{th}$

Source: Fang et al., 2015.

The agriculture sector is highly susceptible to climate change due to its heavy reliance on the climate patterns and water availability (Mokrikov et al., 2019; Horváth et al., 2021; Talukder et al., 2022; Viikoja et al., 2023). Globally, agriculture is the largest consumer of freshwater as it consumes about 72% of the yearly global freshwater withdrawals (Bazrafshan et al., 2022; Rosa, 2022). A crop usually meet its water requirement through Evapotranspiration (ET). According to the Food and Agriculture Organization (FAO), Crop Water Requirement (CWR) is the depth of water required by a crop for ET (Ehteram et al., 2021; Pereira et al., 2021). Thermodynamically, evaporation only depends on weather conditions (temperature, humdity, windspeed, and solar radiation), while for transpiration, climate as well as soil properties, crop type and its growth phase, land treatment practice, and position of watertable are the influential factors (Paul et al., 2022). Furthermore, poor land fertility and soil management, high soil pH, limited and inadequate use of fertilizers, lack of disease and pest control, and low water availability also impacts (lowers) transpiration.

For crop water requirement, Reference Evapotranspiration (ET_o) is estimated which shows the evaporating potential or evaporatice demand of atmosphere and depends only on the weather conditions of region. According to FAO, ET_o is the ET from a reference crop surface (typically grass or alfalfa) 0.12 m tall, 70 s m^{-1} of surface resistance, surface albedo of 0.23, and having suffecient water on the field with non-restricting soil conditions (Srdić et al., 2023). Due to the sufficient water on the reference crop surface, the soil and crop properties do not interfere with the ET process, and thus ET_o solely indicates the energy available in the atmosphere to evaporate water from the surface. Apart from climate, the influence of soil texture, depth to water table, management practice, and the crop growth stage on crop ET is accounted with the help of a crop parameter known as Crop Coefficient (K_c). As per FAO, K_c is the ratio of actual ET from the crop field measured using the lysimeter to ET_o under the same environmental conditions. K_c is an empirical parameter and is estimated by conducting the lysimetric studies. The value of K_c noticeably varies with the crop growth stage as the crop ET is lowest during the sowing stage, starts increasing with the development phase, reaches its maximum during the late stage, and then declines as the crop march towards its harvesting phase after gaining full maturity (Liu et al., 2023).

For ET_o, FAO Penman-Monteith (PM) equation is the most reliable and widely used approach to estimate the daily as well as monthly ET_o under different climate conditions (Xing et al., 2023; Zerihun et al., 2023). For instance, Abeysiriwardana et al. (2022) used the FAO PM method to estimate ET_o in different parts of Sri Lanka. Awal et al. (2020) used the PM equation to determine ET_o over the Western Texas in USA. Ndule & Ranjan (2021) also used the PM equation to estimate ET_o over the semi-arid southern Manitoba (Canada). However, due to the large soil, crop, and weather data required for the equation which might not be available for all regions and time period, the equation proposed by Hargreaves and Samani (1985) known as the Hargreaves (HG) equation can be used for ET_o. However, the method overestimates ET_o under the humid climate conditions and underestimates under the semi-arid conditions, whereas spatially, the equation underestimates ET_o over the inland areas and overestimates nearer to the coastal zones. In order to overcome this limitation, the previous studies have proposed the local calibration of HG equation. For example, Lujano et al. (2023) calibrated the HG equation for computing ET_o in the Peruvian Altipano (Peru) by taking FAO PM equation as a reference. Ramírez et al. (2023) used the HG equation after local adjustment for computing ET_o in the semi-arid region of Mexico. Al-Asadi et al. (2023) also used FAO PM equation as a benchmark to calibrate HG equation so as to estimate ET_o in different parts of Iraq.

Pakistan is an agrarian country with nearly 24 Million hectares (Mha) of its area under cultivation, 25% of its Gross Domestic Product (GDP) depends on the agricultural and livestock sector, and more than 90% of its freshwater resources are utilized for the agricultural and livestock production (Raza et al., 2023a). As per the Pakistan Agricultural Research Council (PARC), about 90% of the agricultural production in Pakistan depends on irrigation, as the country's precipitation can meet only 10 to 15% of the water requirements (Qureshi, 2020). The major source of freshwater in Pakistan is the mighty Indus Basin having the mean annual runoff of 146 million Acre-ft (MAF), where about 50 to 70% of its annual flow comes from the glacier and snowmelt runoff and remaining from the Monsoon and winter precipitation (Romshoo & Marazi, 2022). Apart from surface water, Pakistan also relies on groundwater for its domestic and agricultural water needs. As per the Water and Power Development Authority (WAPDA) of Pakistan, the mean annual groundwater recharge from the Indus Basin in Pakistan is about 55 MAF, where the country extracts nearly 50 MAF every year. In addition, Pakistan is the world's 3rd largest consumer of groundwater for agriculture, where approximately 73% of its irrigated area relies on groundwater. For crop production, Pakistan has two growing seasons namely Kharif (May to September) and Rabi (October to April), with the country's major crops including Rice, Wheat, Sugarcane, Cotton, chilies, fruits, and vegetables that serve as a major source of foreign exchequer to the national economy and livelihoods for the local farmers (Qureshi, 2020).

Rice is a major Kharif crop of Pakistan grown on an area of about 2.7 Mha in the country, with the per hectare yield of 2.95 tonnes and the mean annual production of 8.0 million tonnes (Ghani et al., 2023). The crop is among the highest water consuming crops consuming about 70% of the irrigation withdrawals in the country due to a continuous submergance required for its growth (Akbar et al., 2023). In Sindh, Rice is grown in between July to September on an area of about 0.75 Mha, with the annual production of about 2 million tonnes. In Sindh, the seasonal water requirement of Rice is higher than Punjab due to warmer climate, where about 1,200 to 1,500 mm is consumed in the former for Rice production (Joyo et al., 2023). Wheat is an important Rabi crop of Pakistan grown on an area of about 9.2 Mha in the country, with the mean annual production of 26 million tonnes and the per hectare yield of about 2.8 tonnes. In Sindh, Wheat is grown on an area of about 1.12 Mha in between November to March, with the mean annual production of about 4 million tonnes and the seasonal water consumption of about 400 mm (Nangraj et al., 2023). Contrarily to Rice and Wheat, Sugarcane is a perenial crop grown on an area of about 1.2 Mha in Pakistan, with the mean annual production of 64 million tonnes. In Sindh, Sugarcane is grown on an area of 0.3 Mha, with the seasonal crop water consumption in the province as 1,700 to 2,000 mm (Raza et al., 2023b).

Pakistan has repeatedly been considered among the topmost countries that are at high risk of climate change. As per IPCC, warming in Pakistan is expected to be more than the global average in coming years, where the mean temperature may increase by about 5.3 °C by the end of 21st century, that is more than the global predicted temperature rise (3.7 °C) (Gul et al., 2022). According to the Global Change Impact Studies Centre (GCISC), warming may soar by about 4.6 °C in Sindh, 5.04 °C in Balochistan, 5.06 °C in Punjab, 5.4 °C in KPK, and 5.8 °C in Gilgit-Baltistan under RCP 8.5 scenario (Javed & Khan, 2019). Different studies have been conducted in the past to assess the climate change impacts on the crop water requirements in Pakistan. For instance, Shafeeque & Amna (2023) modeled the seasonal CWR in different parts of Pakistan under CMIP6 scenarios. As per the study, under SSP245 scenario, the Kharif seasonal CWR may increase by 0.48–0.74 mm year^{-1}, whereas in Rabi season, the CWR may increase by 0.47–0.64 mm year^{-1}. Under SSP845 scenario, the Kharif CWR may increase by 1.26–1.54 mm year^{-1}, whereas the Rabi seasonal CWR in the country may increase by 0.98–1.20 mm year^{-1} by 2100. Similarly, Ahmad et al. (2021) modeled the seasonal CWR in Rice-Wheat Punjab under RCP 4.5 and 8.5 scenarios for the period 2021–2050 and 2051–2080. The analysis projected the Wheat seasonal ET to increase by 10–13 mm and 26–37 mm during 2021–2050 and 2051–2080 respectively, whereas the Rice seasonal ET may increase by 5–22 mm and 5–25 mm during 2021–2050 and 2051–2080 respectively. Ahmed & Choi (2018) also modeled the climate change influence on ET_o over the Upper Chenab Command area of Punjab under the A1B scenario. The study projected the winter seasonal ET_o to raise by 21–26 mm and 45–55 mm during 2021–2050 and 2051–2080 respectively, while the summer seasonal ET_o may raise by 16–21 mm and 51–63 mm during 2021–2050 and 2051–2080 respectively.

The Sindh province is worst affected by climate extremes during the past decades. Therefore, this study was conducted to model the air temperature patterns in Sindh and its impacts on the seasonal CWR for Rice, Wheat, and Sugarcane under RCP 4.5 and 8.5 scenarios. The outcomes of this study may help in understanding the future climate variability and its impacts on the crop water demand and freshwater resources in Sindh, and to formulate holistic and well-integrated climate change adaptation and freshwater management measures for ensuring food and water security in the province under the climate change scenarios.

MATERIALS AND METHODS

Study Area

Sindh is an important contributor to the agricultural and livestock sector of Pakistan after Punjab. Geographically, Sindh lies in the Sub-tropical region between the latitudes 23° to 29 °N and between the longitudes 67° to 70°E, spanning on an area of about 14.09 Mha as shown in the Fig. 1. The Gross Command Area (GCA) of Sindh is about 5.53 Mha, out of which 4.87 Mha is under cultivation (Mangan et al., 2021). However, due to the poor drainage infrastructure, about 36% of GCA in the province is waterlogged and is affected by high soil salinity, with the dominant water table depth ranging from about 1.5 to 3.0 m. Climatologically, Sindh is characterized with hot and rainy summers and cold dry winters, with the maximum temperature often touches 46 °C in May, and minimum temperature as low as 2 °C during winter (January). Sindh is predominantly arid with the annual precipitation across the province ranging from about 150–350 mm, where the major fraction of its yearly rainfall is recieved during Summer season (July–September) from the Southwest Monsoon system (Kumar et al., 2023).

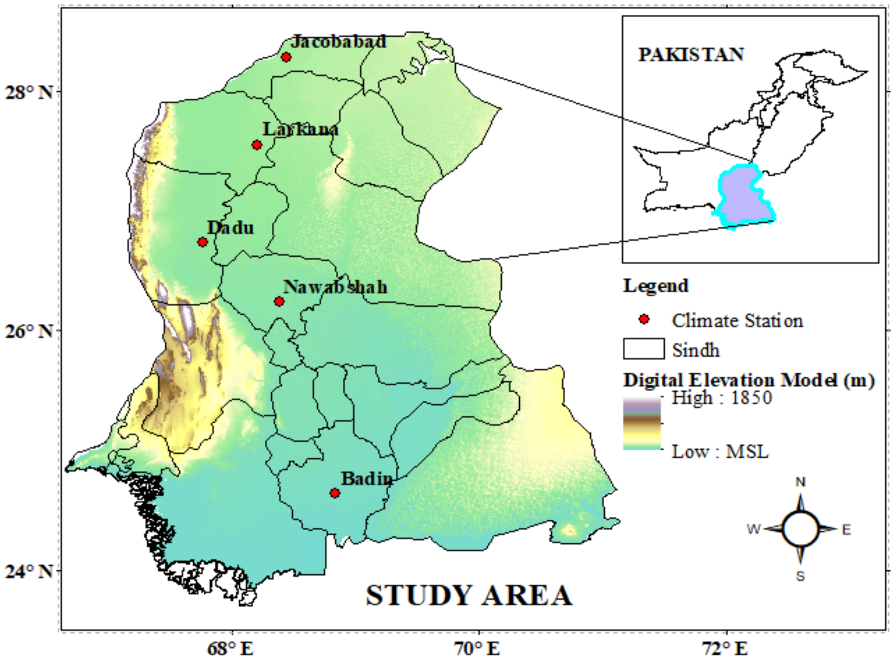

Figure 1. Study area and the selected stations.

Lithologically, based on the FAO soil classification, Sindh is classified into ten (10) different soil classes as shown in the Fig. 2, with clayey loam is the dominant soil texture, which favour crop yields due to high field capacity (as shown in Table 3).

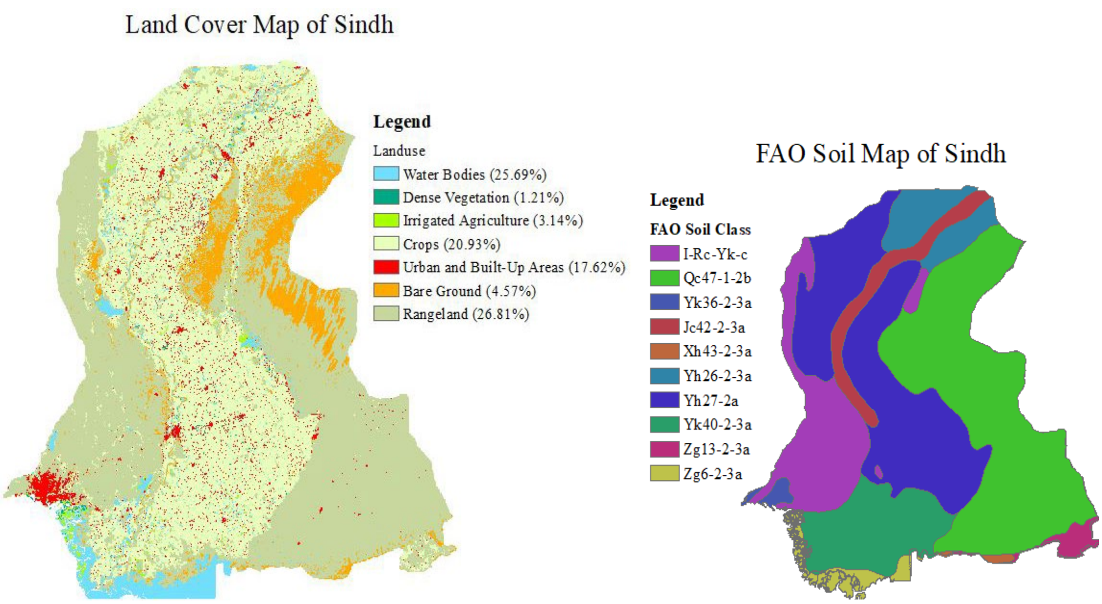

Figure 2. Landuse and FAO soil classification of Sindh, Pakistan.

On the other hand, based on the Sentinel-02 landuse classification, the dominant land cover of Sindh comprises of water bodies (25.69%), irrigated and rainfed cropfields (20.93%), urban areas (17.62%), and rangeland mainly consisting of moderate to sparse bushes, Mangrooves, shrubs and grass tufts, and savannas with less grasses, trees and other plants (26.81%).

Table 3. Representative physical properties of FAO soil classes in Sindh

FAO Soil Class	Soil texture	Soil composition			Specific gravity	Porosity (%)	Infiltration rate (mm h^{-1})	Field capacity (%)	Crop extractable water (%)
		Sand (%)	Silt (%)	Clay (%)					
I-Rc-Yk-c	Loam	35	39	26	1.3–1.5	43–49	8–20	25–36	11–17
Qc47-1-2b	Sandy Loam	79	12	9	1.4–1.6	40–47	13–76	15–27	6–12
Yk36-2-3a	Clay Loam	35	35	30	1.3–1.4	47–51	2.5–15	31–42	15–20
Jc42-2-3a	Clay Loam	27	44	29	1.3–1.4	47–51	2.5–15	31–42	15–20
Xh43-2-3a	Loam	32	42	26	1.35–1.5	43–49	8–20	25–36	11–17
Yh26-2-3a	Loam	44	30	26	1.35–1.5	43–49	8–20	25–36	11–17
Yh27-2a	Sandy Loam	52	32	16	1.4–1.6	40–47	13–76	15–27	6–12
Yk40-2-3a	Clay Loam	36	33	31	1.3–1.4	47–51	2.5–15	31–42	15–20
Zg13-2-3a	Clay Loam	26	35	39	1.3–1.4	47–51	2.5–15	31–42	15–20
Zg6-2-3a	Clay	25	27	48	1.2–1.3	51–55	0.1–1	39–49	19–24

(Source: Cuenca, 1987).

Hydrologically, as per the Indus River System Authority (IRSA) of Pakistan, Sindh receives about 48.76 MAF annually from the Indus River, with 33.94 MAF in Kharif season and 14.82 MAF in Rabi season. The Indus Basin Irrigation System (IBIS) has the province as one of its main beneficiaries with three (03) barrages in the province, diverting 48.76 MAF annually to the 14 main canal commands with a complex system of 117 branch canals, 1,400 distributaries and minors, and about 42,000 water courses across the province (Simons et al., 2020). Based on the crop type, climate, water availability, and cropping practice, Sindh has two major agro-climatic zones including Cotton-Wheat Sindh and Rice-Other Sindh. Cotton-Wheat Sindh serves as a major zone for cultivating Cotton, Sugarcane, Wheat, And Rice in the province, while in Rice-Other Sindh, Barley, Rice, Sugarcane, Wheat, pulses, vegetables, and fruits are the prominent crops (Sadiq et al., 2019).

For this study, a number of five (05) stations in Sindh namely Badin, Dadu, Jacobabad, Larkana, and Nawabshah having rich growing fields of Rice, Wheat, and Sugarcane were selected. The climate data needed for this purpose was taken from the Pakistan Meteorological Department (PMD) for the years 1990–2022. The climate normal for the selected stations are shown in the Fig. 3.

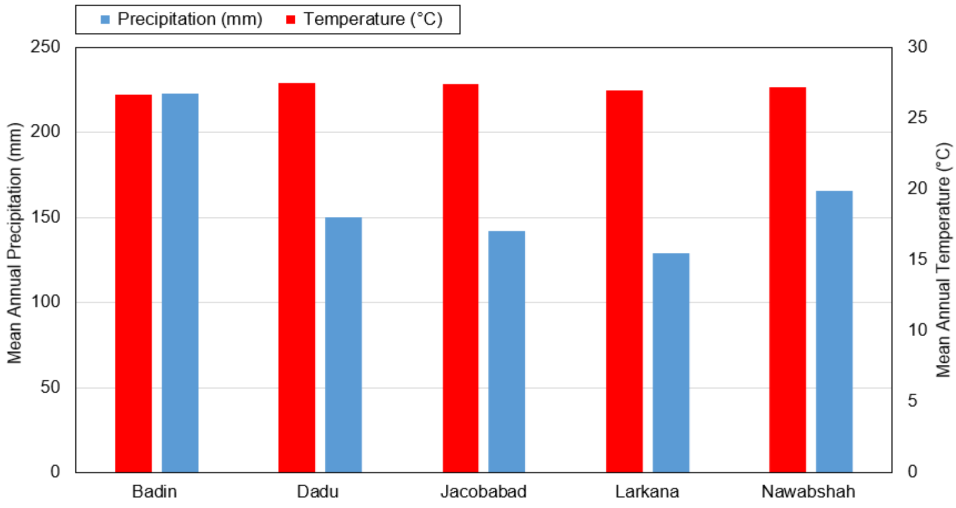

Figure 3. Mean annual precipitation (mm) and temperature (℃) of the selected stations.

Methodology

Selection of Regional Climate Model

In this study, the Regional Climate Model Version 4 (RegCM4) was selected with NOAA-GFDL-ESM2M as the driving Atmosphere-Ocean Global Circulation Model (AOGCM). The daily historical and future RegCM4 climate projections for the study area were acquired from the CORDEX data portal (https://cordex.org/data-access/regional-data-portals) for both RCP 4.5 and 8.5 scenarios. The Coordinated Regional Downscaling Experiment (CORDEX) is a program supported by the World Climate Research Program (WCRP) to forumulate a modifed framework via global co-ordination with a prime aim to generate the regional-scale downscaled climate projections for different regions of the world by considering the region-specific climate features, so as to faciltate the impact assessment studies on the regional scale. The climate data was obtained for the period 1990 to 2099, with 1990 to 2005 taken as the validation period, and 2020 to 2099 was taken as the modeling period as shown in the Table 4.

Table 4. Description of RCM-GCM combination used in the study

RCM	CORDEX Domain	Driving GCM	Spatial resolution	Climate variables	Temporal resolution	Time period
RegCM4	WAS-44i	NOAA-GFDL-ESM2M	50 km	T_{max} and T_{min}	Daily	1990–2099

Bias Correction of RCM Simulations

As discussed earlier, the RCM climate simulations often contain biases that result in misinterpretation and erroneous reproduction of local climate features and may ultimately mislead the analysis. In this study, the air temperature (T_{min} and T_{max}) simulated by RegCM4 showed the presence of warm biases (overestimation) for all stations during the validation period. Therefore, in order to remove biases from the RegCM4 temperature simulations, the Quantile Mapping (QM) technique was used.

Quantile mapping (QM)

In this study, QM technique was used to bias correct the daily temperature projections for all stations. The method works by establishing a statistical nexus between the histroical model simulations and the actual data of same period by replacing the model values with the actual data at the same Cumulative Density Function (CDF) of the employed distribution, and this statsitical relation is then applied on the future climate dataset of the climate model to obtain statisitcally improved projections. In QM approach, Gamma distribution is used to correct precipitation, Normal distribution for temperature, and Beta distribution for the solar radiation. The mathematical expression employed by QM for correcting the temperature values (historical as well as the future values) is shown in the Eq. 1 as under (Gupta et al., 2019):

$$\bar{x}_{ms.corr}\ (\text{Temperature}) = x_{ms} + F_{oh}^{-1}\left(F_{ms}(x_{ms})\right) - F_{mh}^{-1}\left(F_{ms}(x_{ms})\right) \qquad (1)$$

where, F is the Cumulative Density Function (CDF), F^{-1} is its inverse, and subscripts o is the actual data, m is the model predicted value, s and h are the simulation and past period respectively, and $\bar{x}_{ms.corr}$ is the bias corrected value.

Estimation of reference evapotranspiration (ET_o)

FAO Penman-Monteith equation

The FAO PM Equation for ET_o is shown in the Eq. 2 as under:

$$ET_o = \frac{0.408\Delta(R-S)+\gamma\frac{900}{T+273}v(e_s-e_a)}{\Delta+\gamma(1+0.34v)} \qquad (2)$$

where S is the soil heat flux density (MJ m^{-2} per day), R is net solar radiation at the field surface (MJ m^{-2} per day), Δ is the slope of vapour pressure curve (KPa °C^{-1}), γ is the psychometric constant (KPa °C^{-1}), T is the average daily air temperature at 2 m altitude (°C), v is the wind speed at 2 m height (m s^{-1}), e_s and e_a are the saturation and actual vapour pressures (KPa) respectively. Herein, this study involved the utilization of a computer model called CROPWAT 8.0 to assess ET_o following the FAO PM equation (Ma et al., 2023).

Hargreaves equation

The Hargreaves Equation is shown in the Eq. 3 as under:

$$ET_o = BR_a\,(T+17.8)(T_{max} - T_{min})^{0.5} \qquad (3)$$

where, B is a constant assigned the value 0.0023, ET_o represents reference evapotranspiration (in millimeters per day), Ra denotes extraterrestrial solar radiation (in Mega-joules per square meter per day), and T, T_{max}, and T_{min} refer to the mean, maximum, and minimum air temperatures, respectively, measured in degrees Celsius (Habeeb et al., 2021).

Calibration of Hargreaves equation

The calibration process (with 2005–2019 taken as the calibration period) involved the estimation of a calibration factor (B) for all selected stations so as to adjust the HG equation on monthly scale, and to align with the specific climatic conditions of the locality by taking PM equation as a reference.

$$ET_o\ (PM) = B\ ET_o\ (HG)$$

$$ET_o\ (PM) = BR_a\,(T+17.8)(T_{max} - T_{min})^{0.5}$$

By taking Y= ET_o (PM) and X= ET_o (HG), the expression can be rewritten as: Y = BX.

Afterwards, by calculating the Coefficient of determination (R^2) and the Root Mean Square Error (RMSE) between the ET_o estimates of HG and PM equations for each year within the calibration period, the calibration factor 'B' was determined for each station. The parameter B was selected based on the year exhibiting the highest R^2 and the lowest RMSE value. The equations used for the estimation of R^2 and RMSE as under (Majeed et al., 2017):

$$R^2 = \frac{[\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})]^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \quad (5)$$

where 'yi' denotes the estimated average monthly reference evapotranspiration (ET_o) using the PM equation for month 'i' in millimeters per day, 'xi' represents the estimated average monthly ET_o using the HG equation for month 'i' in millimeters per day, and '$\bar{x}$ and $\bar{y}$' signify the averages of xi and yi, respectively.

Computation of seasonal crop water requirement

As per FAO, the equation used to estimate the daily water requirement for a crop is given in Eq. 6 as below:

$$\text{Crop Water Requirement (CWR)} = ET_o \times K_c \quad (6)$$

In this study, the monthly and seasonal water requirements for the selected crops under RCP 4.5 and 8.5 scenarios were estimated using Eqs 7 and 8 respectively given as under:

$$\text{Monthly Crop Water Requirement} = \sum \text{Daily Crop Water Requirement} \quad (7)$$

$$\text{Seasonal Crop Water Requirement} = \sum \text{Monthly Crop Water Requirement} \quad (8)$$

RESULTS AND DISCUSSION

Bias correction of RCM simulations

In this study, the RegCM4 simulations for the study area were bias corrected using the QM approach for the period 1990 to 2005. The evaluation of bias corrected outputs was performed using the two statistical parameters as RMSE and R^2 between the historical actual and simulated data to validate how close the simulated values are to the actual climate data after bias correction. The validation results are shown as under:

Table 5. Goodness of fit between the observed and simulated climate data before and after bias correction for RCP 4.5 scenario

Station	Nawabshah		Dadu		Badin		Jacobabad		Larkana	
	T_{min} (°C)									
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Before Bias Correction	4.91	0.76	5.25	0.81	4.23	0.77	5.86	0.74	4.66	0.82
After Bias Correction	3.26	0.80	2.87	0.85	2.56	0.84	2.97	0.88	1.85	0.90
	T_{max} (°C)									
Before Bias Correction	6.91	0.67	3.61	0.74	4.50	0.65	5.43	0.67	3.60	0.74
After Bias Correction	2.71	0.78	2.48	0.88	2.09	0.86	2.98	0.79	2.05	0.89

Table 6. Goodness of fit between the observed and simulated climate data before and after bias correction for RCP 8.5 scenario

Station	Nawabshah		Dadu		Badin		Jacobabad		Larkana	
	T_{min} (°C)									
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Before Bias Correction	3.32	0.79	4.10	0.79	3.22	0.78	4.31	0.79	4.13	0.81
After Bias Correction	2.03	0.85	1.80	0.89	1.55	0.89	2.07	0.88	1.60	0.90
	T_{min} (°C)									
Before Bias Correction	5.65	0.68	3.78	0.70	4.31	0.65	5.20	0.69	3.82	0.70
After Bias Correction	1.63	0.84	2.46	0.86	2.22	0.70	2.85	0.81	2.23	0.87

Temperature projections in study area under the climate change scenarios

In this study, after the removal of biases from the RegCM4 temperature projections, the temperature patterns under the RCP 4.5 and 8.5 scenarios in the selected stations were comprehensively analysed using the Sen's Slope method for the period 2020 to 2099 using R (a programming language). The results obtained from the analysis are shown as under:

Table 7. RegCM4 projected temperature change (°C) over the selected stations under RCP 4.5 scenario

S.No.	Station	Temperature Change (°C)			
		Annual	Spring	Summer	Winter
1	Badin	+1.8	+2.4	+0.7	+4.9
2	Dadu	+1.3	+1.8	+0.9	+3.3
3	Jacobabad	+1.6	+3.5	+0.3	+4.3
4	Larkana	+1.3	+2.0	+0.3	+3.1
5	Nawabshah	+1.6	+3.0	+0.5	+4.7

Table 8. RegCM4 projected temperature change (°C year^{-1}) over the selected stations under RCP 8.5 scenario

S.No.	Station	Temperature Change (°C)			
		Annual	Spring	Summer	Winter
1	Badin	+3.1	+4.0	+0.9	+5.7
2	Dadu	+3.0	+3.7	+1.5	+4.5
3	Jacobabad	+3.3	+5.7	+0.5	+5.4
4	Larkana	+2.8	+3.6	+1.3	+4.3
5	Nawabshah	+3.3	+4.9	+0.7	+5.9

The above analysis showed a significant rise in air temperature in the selected stations. Annually, the air temperature over the study area may rise by about 1.3–1.8 °C under the RCP 4.5 scenario as shown in the Table 7, whereas under the RCP 8.5 scenario, warming may soar by about 2.8–3.3 °C by the end of century as shown in the Table 8. It is pertinent to understand that the seasonal temperatures also hold significance for agriculture. For instance, for Rabi crops, winter and the early spring temperatures govern the crop water needs, crop water productivity, soil moisture availability, and the crop yield. While for the Kharif crops, the late spring and summer seasonal temperatures are highly influential. As per the analysis, for Spring season, temperature may increase by about 1.8–3.5 °C under RCP 4.5 scenario, whereas under the RCP 8.5 scenario, warming may increase by about 3.5–5.7 °C by the year 2100. For summer season, temperature may increase by about 0.3–0.9 °C under RCP 4.5 scenario, while under the RCP 8.5 scenario, temperature may warm by about 0.7–1.5 °C. For winter season, a rise of about 3.1–4.9 °C under the RCP 4.5 scenario may be recorded, whereas under the RCP 8.5 scenario, warming may soar by about 4.3–5.9 °C.

Apart from the mean daily temperature, the maximum (daytime) and minimum (nighttime) temperatures of a day also holds a significant importance for the crops, as the best photosynthesis is linked to high daytime and low nighttime temperatures. Moreover, the maturing of crops is also effected due to variations in the nighttime temperature. In this study, RegCM4 projected a higher magnitude of warming of nighttime temperature in Sindh than the daytime temperature. Under RCP 4.5 scenario, the daytime temperature in the province may increase by about 1.2 to 1.7 °C, while the nighttime temperature may increase by about 1.4 to 2.8 °C by the year 2100 as shown in the Table 9. On the other hand, under RCP 8.5 scenario, the daytime temperature may increase by about 2.6 to 3.2 °C, whereas the minimum temperature may increase by about 3.0 to 3.5 °C.

Table 9. RegCM4 projected daytime and nighttime temperature change (°C) over the selected stations under RCP 4.5 and 8.5 scenarios

S.No.	Station	RCP 4.5		RCP 8.5	
		T_{max}	T_{min}	T_{max}	T_{min}
1	Badin	+1.7	+2.8	+3.0	+3.3
2	Dadu	+1.2	+1.4	+2.8	+3.1
3	Jacobabad	+1.6	+1.5	+3.2	+3.3
4	Larkana	+1.2	+1.4	+2.6	+3.0
5	Nawabshah	+1.5	+1.7	+3.1	+3.5

Conclusively, it is pertinent to mention that the selected stations in this study serve as the major agricultural zones in Sindh province for growing important food and horticultural crops in the country. Therefore, the warming air temperature patterns as projected by the analysis may adversely impact the agricultural production in the province, as the rising temperatures may result in increased evapotranspiration and consequently more crop water consumption, soil moisture desiccation, declining crop-water use efficiency, crop water stress conditions, and ultimately reduced crop yield, thereby threatening the food as well as the water security in the country.

Calibration of Hargreaves equation

In this study, HG equation was calibrated for all selected stations on the monthly scale to minimize the overestimation of ET_o. The results of local calibration are shown as under:

Table 10. Summary of Hargreaves Equation local calibration for selected stations in Sindh

Station	Nawabshah		Dadu		Badin		Jacobabad		Larkana	
	Tmin (°C)									
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Before Bias Correction	6.72	0.93	6.83	0.89	3.87	0.80	7.71	0.87	7.22	0.90
After Bias Correction	0.93	0.96	0.82	0.92	0.80	0.85	0.85	0.92	0.99	0.92

The above calibration results (Table 10) indicated that RMSE was higher and the value of R^2 was comparatively lower between the results of the original HG equation and the FAO PM equation before calibration. However, after the calibration of HG equation by finding the calibration factor (B), the correlation in results between the two methods improved statistically and the deviation in results (RMSE) dropped significantly, with the correlation (R^2) improved further. Thus, the calibrated Hargreaves equations showed a good match of ET_o estimates with that of FAO PM equation. The resulting calibrated HG equations to estimate the monthly ET_o are shown in the Table 11 as under.

The above calibrated Hargreaves equations were then used to estimate ET_o over the selected stations under the RCP 4.5 and 8.5 scenarios.

Table 11. Calibrated Hargreaves equations for the selected stations

Station	Calibrated Hargreaves equation
Badin	$ET_o = 0.0013\, R_a\, (T+17.8)(T_{max} - T_{min})^{0.5}$
Jacobabad	$ET_o = 0.00125\, R_a\, (T+17.8)(T_{max} - T_{min})^{0.5}$
Dadu	$ET_o = 0.00123\, R_a\, (T+17.8)(T_{max} - T_{min})^{0.5}$
Larkana	$ET_o = 0.00115\, R_a\, (T+17.8)(T_{max} - T_{min})^{0.5}$
Nawabshah	$ET_o = 0.00127\, R_a\, (T+17.8)(T_{max} - T_{min})^{0.5}$

Projected seasonal ET_o in study area under the climate change scenarios

In this study, after the local calibration of Hargreaves equation for the selected stations, the change in seasonal reference evapotranspiration was estimated for Kharif and Rabi seasons for all stations under the RCP 4.5 and 8.5 scenarios using the calibrated HG equations. The results obtained from the analysis are shown as under.

Table 12. Projected station-wise change in seasonal ET_o in mm year^{-1} under the climate change scenarios

Station	RCP 4.5		RCP 8.5	
	Kharif	Rabi	Kharif	Rabi
Badin	+0.76	+0.73	+1.04	+1.72
Dadu	+0.95	+0.48	+1.63	+1.63
Jacobabad	+0.82	+0.38	+1.61	+1.20
Larkana	+0.98	+0.44	+1.62	+1.18
Nawabshah	+0.80	+0.49	+1.14	+1.30

As discussed earlier, ET_o indicates the eveporative demand of atmosphere at a location and greatly influence the crop water requirements. The above results (Table 12) showed that under the RCP 4.5 scenario, the ET_o for the Kharif season in the study area may increase by about 60 to 80 mm at the rate of about 0.7 to 1.0 mm year^{-1} by 2100. Under RCP 8.5 scenario, the ET_o for Kharif season may increase by about 80 to 130 mm at the rate of about 1.0 to 1.7 mm year^{-1} by the end of century. For Rabi season, ET_o in the study area may increase by about 30 to 60 mm under the RCP 4.5 scenario, whereas under RCP 8.5 scenario, ET_o is expected to increase by about 90 to 140 mm at the rate of about 1.3 to 1.7 mm year^{-1} by the year 2100.

Projected seasonal crop water requirements in study area under the climate change scenarios

In this study, the calibrated Hargreaves equations along with the bias corrected temperature data were used to compute ET_o for the modelling period. After the estimation of ET_o, the seasonal water requirements for Rice, Wheat, and Sugarcane were estimated using Eq. 8 under the RCP 4.5 and 8.5 scenarios. The results obtained from the analysis are shown as under.

Projected seasonal water requirement of rice in study area under the climate change scenarios

The projected seasonal crop water requirement of Rice under RCP 4.5 and 8.5 scenarios over the study area are shown in the Figs 4−8 as under:

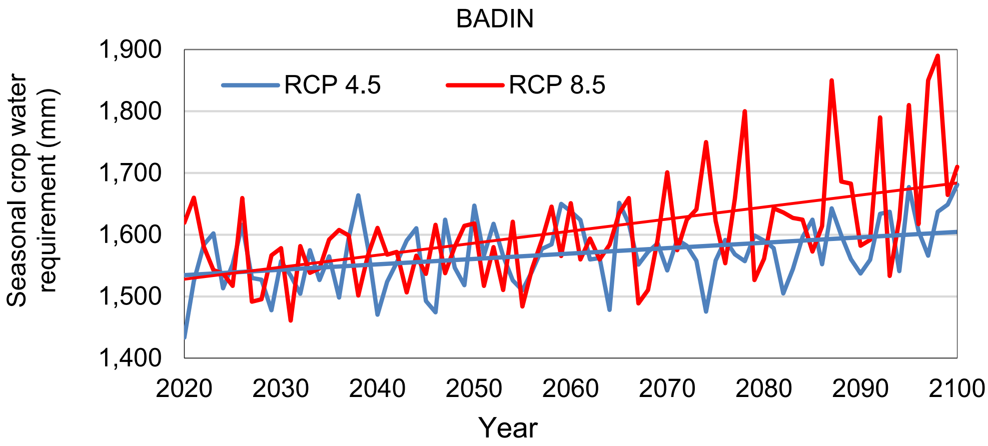

Figure 4. Projected Seasonal water requirement of Rice in Badin under RCP 4.5 and 8.5 scenarios.

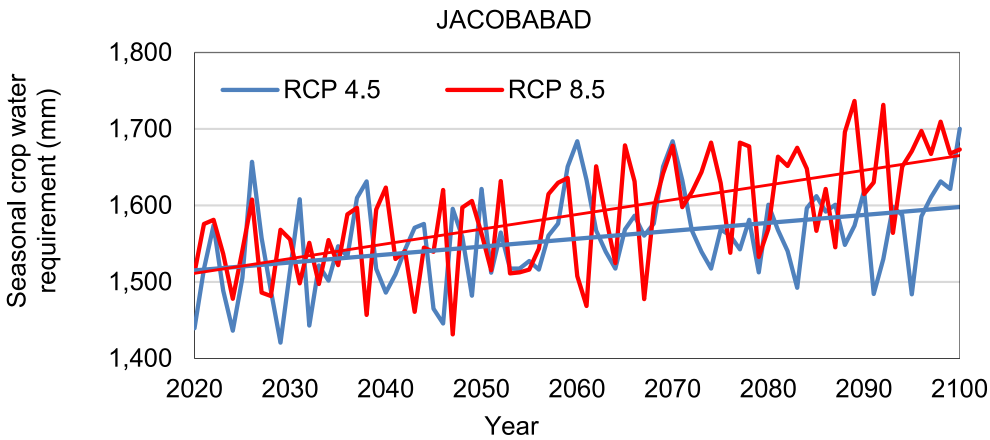

Figure 5. Projected Seasonal water requirement of Rice in Jacobabad under RCP 4.5 and 8.5 scenarios.

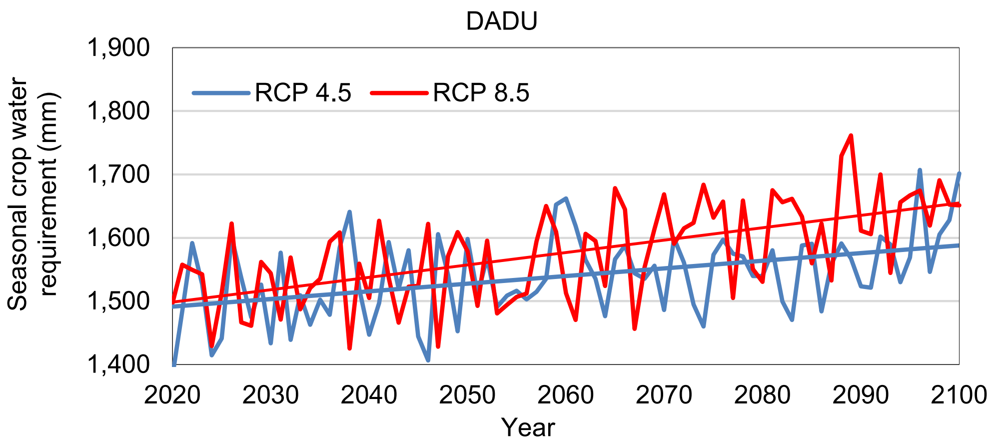

Figure 6. Projected Seasonal water requirement of Rice in Dadu under RCP 4.5 and 8.5 scenarios.

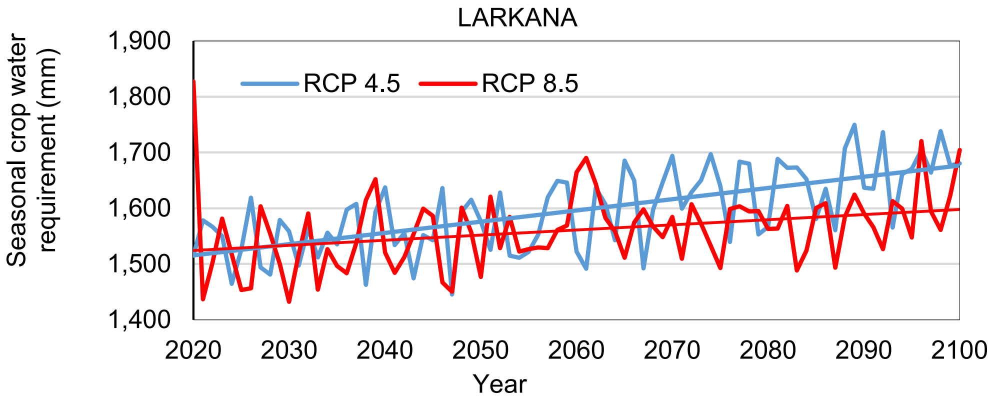

Figure 7. Projected Seasonal water requirement of Rice in Larkana under RCP 4.5 and 8.5 scenarios.

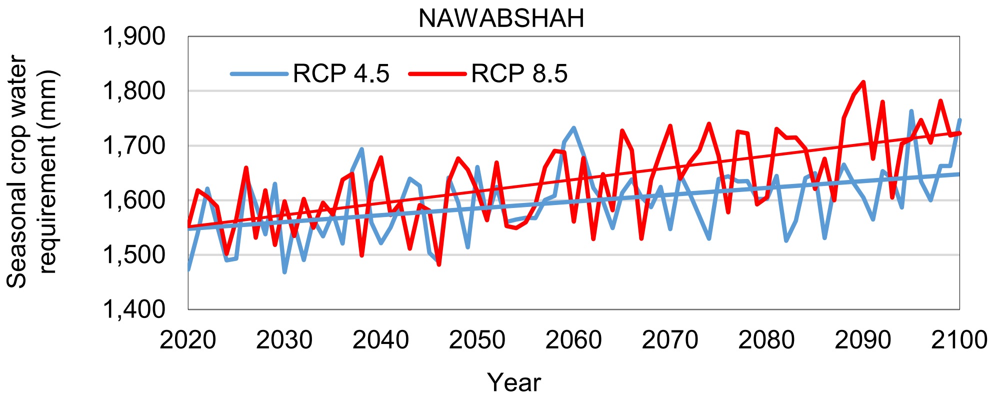

Figure 8. Projected Seasonal water requirement of Rice in Nawabshah under RCP 4.5 and 8.5 scenarios.

Projected seasonal water requirement of wheat in study area under the climate change scenarios

The projected seasonal crop water requirement of Wheat under RCP 4.5 and 8.5 scenarios in the study area are shown in the Figs 9−13 as under:

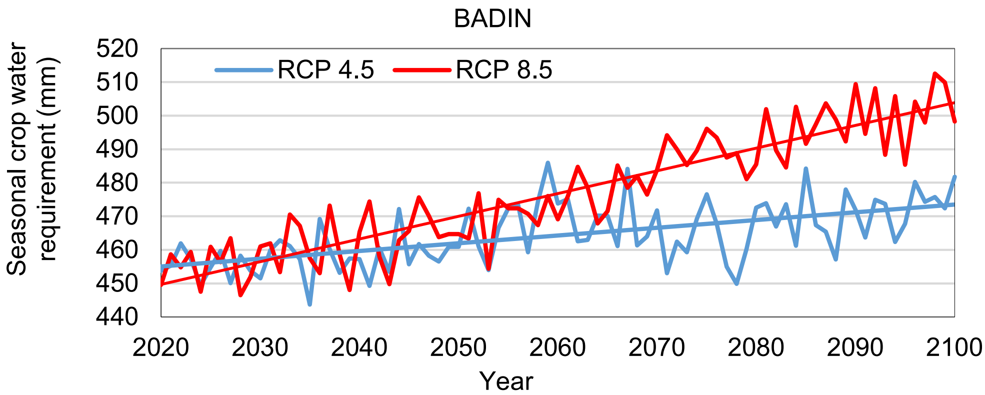

Figure 9. Projected Seasonal water requirement of Wheat in Badin under RCP 4.5 and 8.5 scenarios.

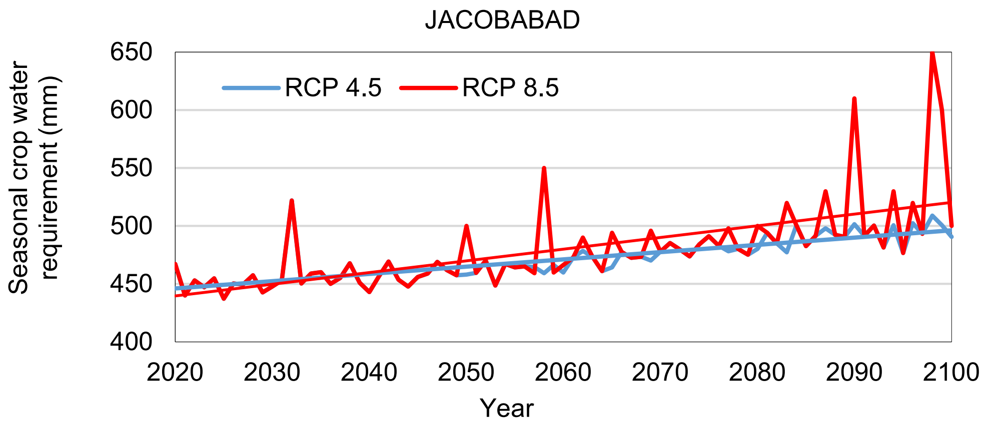

Figure 10. Projected Seasonal water requirement of Wheat in Jacobabad under RCP 4.5 and 8.5 scenarios.

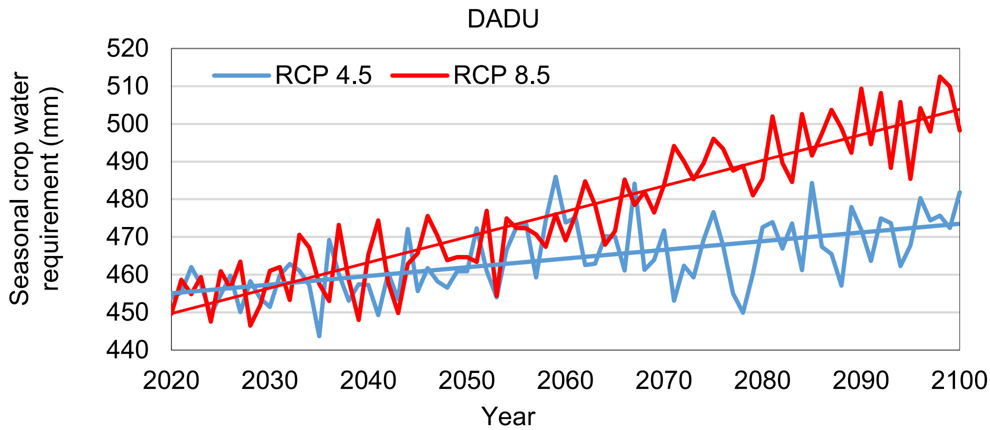

Figure 11. Projected Seasonal water requirement of Wheat in Dadu under RCP 4.5 and 8.5 scenarios.

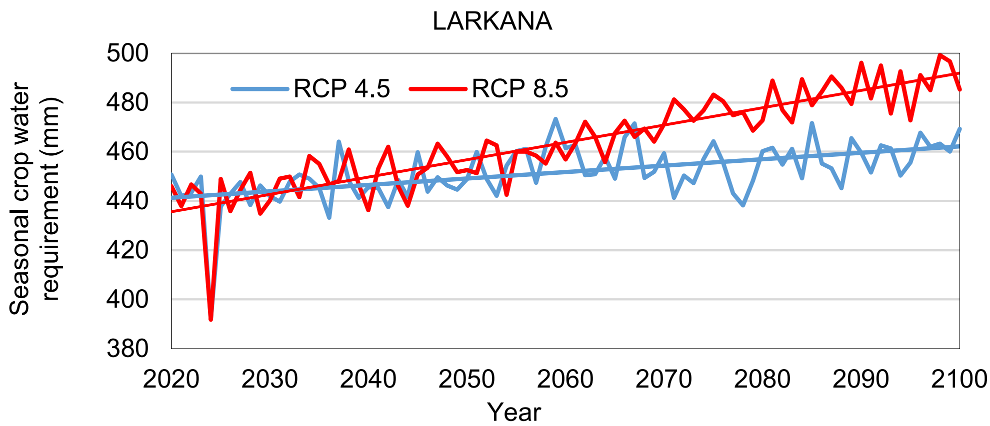

Figure 12. Projected Seasonal water requirement of Wheat in Larkana under RCP 4.5 and 8.5 scenarios.

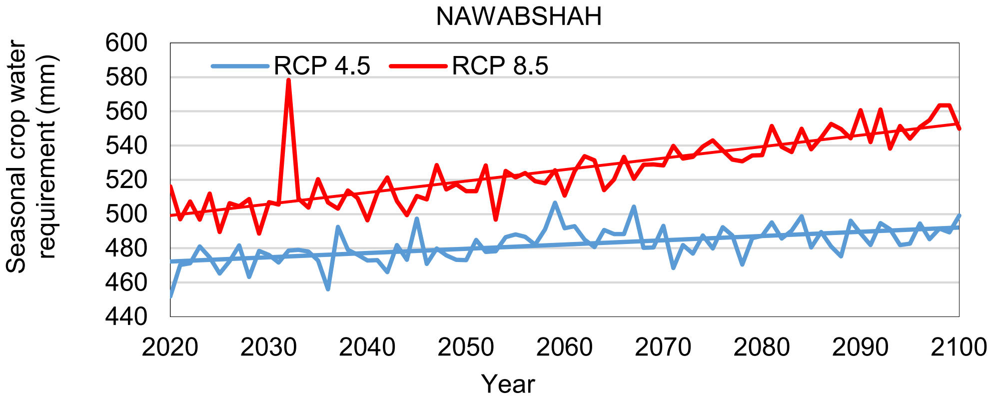

Figure 13. Projected Seasonal water requirement of Wheat in Nawabshah under RCP 4.5 and 8.5 scenarios.

Projected seasonal water requirement of sugarcane in study area under RCP 4.5 and 8.5 scenarios

The projected seasonal crop water requirment of Sugarcane under RCP 4.5 and 8.5 scenarios in the study area are shown in the Figs 14–18 as under:

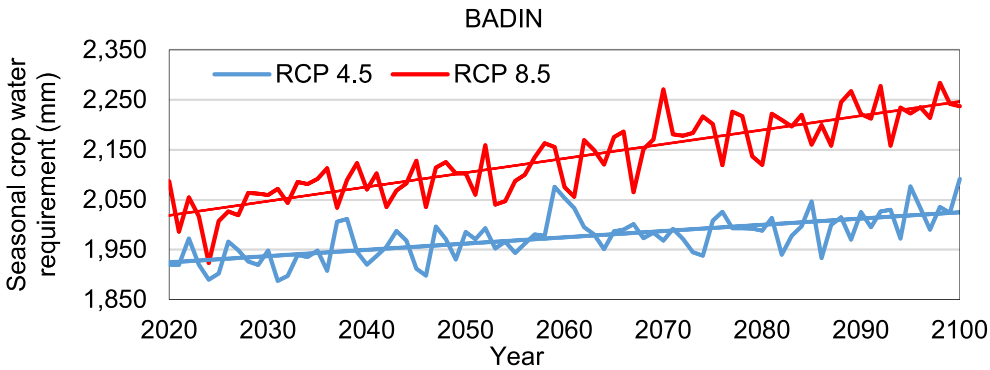

Figure 14. Projected Seasonal water requirement of Sugarcane in Badin under RCP 4.5 and 8.5 scenarios.

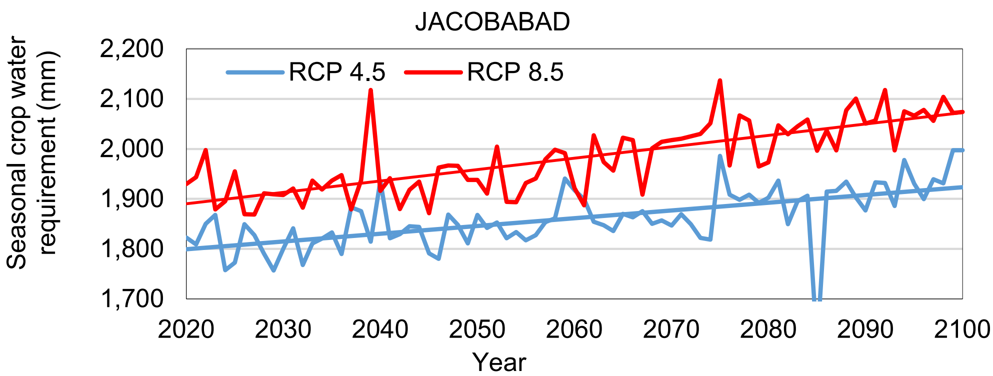

Figure 15. Projected Seasonal water requirement of Sugarcane in Jacobabad under RCP 4.5 and 8.5 scenarios.

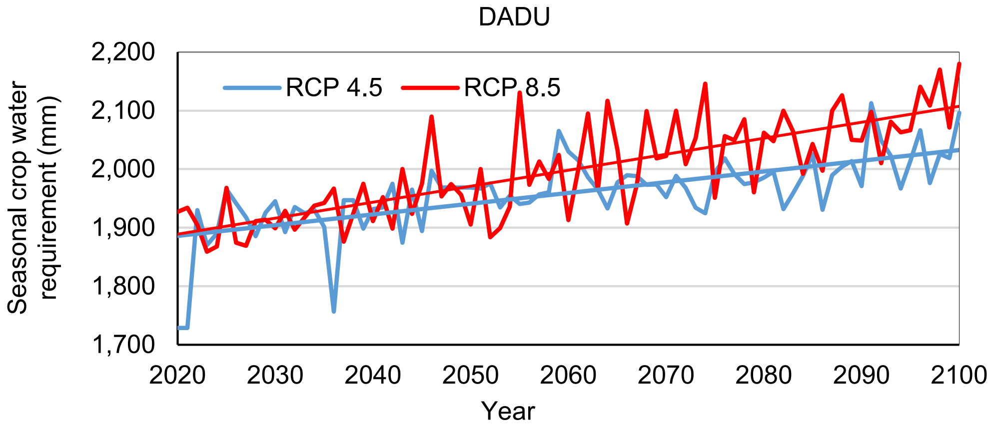

Figure 16. Projected Seasonal water requirement of Sugarcane in Dadu under RCP 4.5 and 8.5 scenarios.

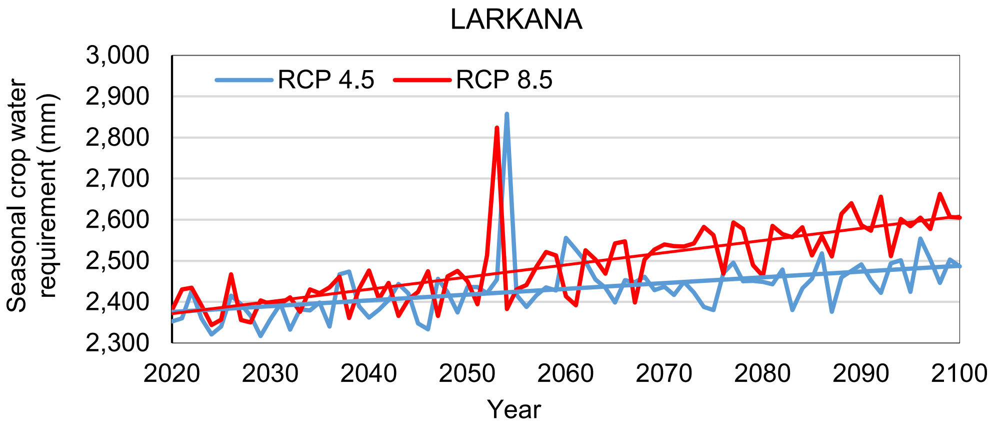

Figure 17. Projected Seasonal water requirement of Sugarcane in Larkana under RCP 4.5 and 8.5 scenarios.

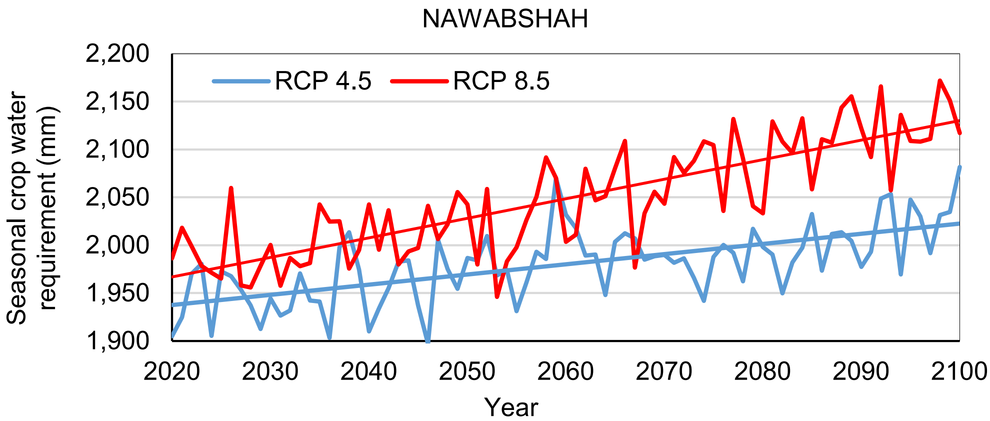

Figure 18. Projected Seasonal water requirement of Sugarcane in Larkana under RCP 4.5 and 8.5 scenarios.

The above analysis projected a noticeable rise in the seasonal water requirements for Rice, Wheat, and Sugarcane in Sindh under the climate change scenarios. For Rice, the seasonal crop water requirement may increase from about 1,500 to 1,550 mm currently to about 1,600 to 1,650 mm in Sindh under RCP 4.5 scenario, while under RCP 8.5 scenario, the water consumption may increase to about 1,700 mm, as shown in the Figs 4 and 5. For Wheat, the seasonal crop water requirement may increase from about 400 to 450 mm currently to about 500 mm under the RCP 4.5 scenario, while under the RCP 8.5 scenario, the water requirement may reach to about 550 mm, as shown in the Figs 6 and 7. For Sugarcane, the seasonal crop water requirement may increase from about 1,700 to 1,900 mm currently to about 2,000 to 2,050 mm under the RCP 4.5 scenario, whereas under the RCP 8.5 scenario, the water requirement may reach to about 2,100 mm by the end of century as shown in the Figs 8 and 9.

Conclusively, Rice, Wheat, and Sugarcane are among the major crops of Pakistan, consuming significant amount of irrigation withdrawals in the country, and serve as livelihood for the local farmers and an important source of foreign exchequer for the national economy. Therefore, the increasing crop water requirements due to climate change as predicted in this study may cause increased freshwater consumption in Sindh for crop production, pressurizing the already stressed freshwater resources of the country and rise in local water disputes, ultimately posing an eminent threat to the country's food and water security.

CONCLUSION AND RECOMMENDATIONS

The prime objective of this study was to model the temperature patterns over the Sindh province and to project its impacts on the reference evapotranspiration and seasonal water requirements for the major crops of country including Rice, Wheat, and Sugarcane under the climate change scenarios. Following conclusions have been made based on the analysis performed:

1. The RegCM4 bias corrected outputs showed that under RCP 4.5 scenario, the average annual temperature in Sindh may warm by about 1.3–1.8 °C, while about 2.8–3.3 °C under the RCP 8.5 scenario by the end of 21st century. Seasonally, warming was projected to be mainly focused on the spring and winter seasons. For spring season, temperature may increase by about 1.8–3.5 °C under RCP 4.5 scenario, and about 3.5–5.7 °C under RCP 8.5 scenario. For winter season, warming may increase by about 3.1–4.9 °C under RCP 4.5 scenario, and about 4.3–5.9 °C under RCP 8.5 scenario.

2. Diurnally, RegCM4 projected a higher increase in nighttime temperature as compared to the daytime temperature. As per the model outputs, the daytime temperature may increase by about 1.2–1.7 °C, while the nighttime temperature may increase by about 1.4–2.8 °C under RCP 4.5 scenario. Under RCP 8.5 scenario, the maximum temperature may rise by about 2.6–3.2 °C, while the minimum temperature may increase by about 3.0–3.5 °C by the end of century.

3. For ET_o, the analysis revealed that under the RCP 4.5 scenario, the Kharif seasonal ET_o may increase by about 60–80 mm, while the Rabi seasonal ET_o may increase by about 30–60 mm by 2100. Under RCP 8.5 scenario, the Kharif seasonal ET_o may increase by about 80–130 mm, whereas the Rabi seasonal ET_o may soar by about 90–150 mm by the end of century.

4. Due to the warming air temperatures, a noticeable rise in crop water consumption in the province was predicted. For Rice, the seasonal water requirement may increase by about 50–100 mm under the RCP 4.5 scenario, and about 100–200 mm under the RCP 8.5 scenario. For Wheat, the seasonal water requirement may increase by about 60 mm under the RCP 4.5 scenario, and about 100 mm under RCP 8.5 scenario. For Sugarcane, the water requirement may increase by about 100–150 mm and 150–200 mm under RCP 4.5 and 8.5 scenarios respectively.

5. In view of the study outcomes, the authors recommend the formulation of a holistic and well-integrated climate change adaptation and mitigation strategy to deal with the unfavorable aspects of the global climate shift in the country. Moreover, to cater the increasing agricultural water demand under the warming scenarios, a timely shift to conservative utilization and management of water resources is suggested.

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