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Impact of Climate Change on Groundwater Recharge in Cotton Irrigated Fields under Agronomical Practices

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ABSTRACT

Cotton crop is one of the major water consumers in the Indus basin region. Accurate groundwater recharge estimation is a provoking duty due to hydrologic and environmental applications under climate change in the agricultural sector. An utmost region that is vulnerable to climate change and cotton production is declining, consequently. Here, historical trends (1975-2005) and future variability (2021-50 and 2051-80) of climate parameters were analyzed and predicted by SDSM for three emission scenarios (RCP 2.6, RCP 4.5, and RCP 8.5) for the semi-arid region Faisalabad, Pakistan. Results revealed a rise in maximum (minimum) temperature and a decline in rainfall, relative humidity, and wind speed for both 2021-50 and 2051-80 using different NCEP parameters ($p < 0.05$). The groundwater recharge was simulated using the Hydrus-1D unsaturated flow model. Hydrus-1D unsaturated flow model simulated the groundwater recharge under six treatments. A 41 cm reduction of groundwater recharge was observed under all scenarios. The highest recharge was observed 71 cm under RCP 2.6, and the lowest recharge was 30 cm under RCP 8.5, a maximum of 23% groundwater recharge controlled by climate variables with the weak relationship among them. Cotton sowing method T₆(bed planting without mulch) showed the highest yield (1,066 kg.ha⁻¹). It further indicates that rather than climate change, the agronomical practice may have a more significant impact on groundwater recharge and cotton yield. Findings highlight the significance of both climate change and the cotton sowing method while accessing future water resources in irrigated Indus basin agriculture.

Keywords: Groundwater, Recharge flux, Climate Change, Hydrus-1D, Cotton.

INTRODUCTION

Global cotton production requires 250 billion tons of water annually. In most developed countries, like Japan 95%, European Union 84%, and the United States over 50% water footprint from cotton consumption is cross-border, with impacts highest in Pakistan, India, China, and Uzbekistan. Pakistan is the fourth producer of cotton globally (Abbas 2020), the third-largest exporter of raw cotton, contributing up to 10% of GDP. Among top countries most vulnerable to climate change and most intensively cultivated region on Earth (Vinca et al. 2020). The production and annual growth rate of Pakistan cotton are presented in Fig. 1 based on historical data since 1960. One significant reason for the long-term decline in Pakistan's cotton production is climate change and the non-availability of quality seeds (Rehman 2021). Cotton crop cultivated in arid to semiarid (Punjab and Sindh province under Indus Delta) is more sensitive to climate risk (Abbas 2020). Rising temperature is not only decreasing Pakistan's cotton yield while also exerting additional stress on water demands for the agricultural (cotton) and socio-economic sectors in the agro-ecological zone (Naheed and Rasul 2005; Abbas 2020; Saleem et al. 2021). Meanwhile, in a semiarid or arid region for the agricultural sector, groundwater plugs the gaps of crop water requirement or canal (allocated) water supplies, has caused a lowering of depth to the water table from 10 to 25 m (Khan et al. 2017; Maqbool et al. 2021). That leads to adopting mitigation techniques to increase water conservation for cotton's environmentally friendly production. It is significant to access the groundwater recharge under future climate change in an irrigated cotton field to sustain natural resources for rural socio-economic development for a consistent cotton growth rate (Fig.1).

Groundwater recharge is water that crosses or punctuates the aquifer from surface or subsurface water ponding via terrestrial infiltration, leading to a bouncy source of freshwater

(Anderson et al., 2015). Accurate estimation of groundwater recharge is one of provoking duties due to hydrologic and environmental applications, influenced by several factors such as stochastic characteristics of rainfall, climatic parameters, and strata's infiltration capacity. It is interactively inflated by evapotranspiration, natural vegetation and crop patterns, flood frequency, and soil organic matter, particularly in agricultural problems, and their vulnerability is attributed to climate change (Şen 2015; Boughanmi et al. 2018; Wakode et al. 2018). Agriculture has a substantial impact on groundwater recharge quality and quantity, with the input of irrigation and fertilizer that may alter groundwater recharge fluxes and mobility of salts/pollutants from unsaturated zone to groundwater (Turkeltaub et al. 2014). Insufficient groundwater abstraction has waterlogged the land that creates a salinity problem (Maqbool et al. 2021); contrary, excessive pumpage has caused depletion of groundwater resources in a semi-arid agricultural region (Khaliq et al. 2021). The sustainability of water resources depends on evaluating water footprint accounting in irrigated fields (Xu and Li 2020). Previously found, groundwater recharge is very sensitive to potential future climate changes (Ficklin et al. 2010; Turkeltaub et al. 2014; Batalha et al. 2018). Increasing temperature (5.7 °C annually by the late 21st century) and declining rainfall (11.9% in the mid-21st century) were reported (Dahri et al. 2021). Erratic climate change exploits groundwater recharge estimation and could create hyper stress on groundwater recharge under the irrigated agricultural field.

Figure 1: cotton annual growth rate (%) and production (1000 480 lb. Bales) in Pakistan from 1960 to 2020. Source: www.indexmundi.com

Crop models and hydrologic models can access water variability in agro-hydrologic development themes for groundwater recharge (Siad et al. 2019). Hydrologic models are emphasized more due to continuous and mechanistic processes of soil water movement (Tenreiro et al. 2020). HYDRUS-1D can simulate the solute movement in the vadose zone and recharge flux below the root zone (Šimůnek et al. 2013). Turkeltaub et al. (2014) used HYDRUS-1D to develop a vertical unsaturated flow model and reported a 44% drop in groundwater recharge under agricultural (orchard and crop) fields following climate change scenarios. Increased daily temperatures from 1.1 to 6.4 °C can decrease the cumulative groundwater recharge due to reduced water use efficiency by the crops (Ficklin et al. 2010). Kambale et al. (2017) simulated the groundwater recharge by HYDRUS-1D in the semiarid region (northern India) reported that recharge flux would decrease by .0.090 to .0.210 m under Inter-Governmental Panel for Climate Change (IPCC) and .0.110 m under Indian Network for Climate Change Assessment (INCCA) for projected temperatures 2100s and 2030s, respectively. Meanwhile, the HYDRUS-1D model could provide better insight into groundwater recharge simulation, including capillary rise, hysteresis, preferential flow, subsurface lateral flow, and surface outflow for spatial water processes (vadose

zone process or data) (Tenreiro et al. 2020). Besides, statistical downscale modeling (SDMS) is a reliable decision support tool to generate future climatic parameters based on historical trends for a potential climate-driven impact assessment on groundwater recharge (Azam et al. 2020; Wu et al. 2020).

Trends and variability of groundwater recharge in the agricultural sector of Pakistan remain unidentified under future climate change. A series of studies relating to groundwater recharge is available under changing climate scenarios considering only a temperature rise (Kambale et al. 2017; Rahman et al. 2019; Wu et al. 2020). Nevertheless, some studies have described quantifying the impact of climate change on groundwater recharge by considering unsaturated zone processes. It is important to look at an irrigated cotton field because climate change is not homogenous across the Indus Basin region and different strategies need to adopt for increasing cotton yield and water use efficiency to mitigate their impact. The current study addresses this knowledge gap by investigating the groundwater recharge in an irrigated cotton field in a semi-arid area of Pakistan.

In this paper, first, historical trend analysis from 1975 to 2005 of climate parameters, i.e., minimum and maximum temperature, rainfall, relative humidity, and wind speed by SDMS and predicted their variability for future 2021-2050 and 2051-80 under representative concentration pathway (RCP) 2.6, RCP 4.5, and RCP 8.5, respectively. Secondly, to simulate groundwater recharge from irrigated cotton fields using numerical unsaturated flow modeling under different agronomical practices with or without mulch. Thirdly, perform the regression and correlation analysis to evaluate the relationship between groundwater recharge and climate variables. Lastly, different agronomical practices also accessed the cotton yield.

DATA AND METHODS

Study area

The study was conducted under a cotton (*Gossypium*) field, located in Rechna doab upland of Punjab at Water Management Research Center (WMRC), Faisalabad (31.3872° N latitude and 73.0121° E longitude, Fig. 1). Semi-arid climate in Köppen-Geiger classification of this area, with very hot and humid summers (April-October) and dry, cool winters (November-March). The maximum temperature in the hottest month is 50 °C (June), and the minimum temperature in the coldest month is 8 °C (December), an altitude of 184 m above mean sea level based on the nearest (under 2-km of research site) station's data provided by National Institute for Agriculture and Biology (NIAB), Faisalabad and. The average rainfall in the area is 283 mm, and the maximum rainfall event occurred during July. Study area falls in a mixed cropping zone of the Punjab Agro-Ecological zone, including wheat, rice, cotton, sugarcane, and maize are to be grown (AMIS 2016). Cropping intensity of the Faisalabad district now reaches ~150% due to the high demands of food (edible) crops. The study area part of the Indus plain that comes under the area has fertile land due to the alluvial soil genesis of Chenab Delta. The soil type is medium texture and homogenous structure up to 4 m depth. This plain is underlain by thick sandy loam to loamy sand with high hydraulic conductivity (Kelleners et al. 1999). According to the soil survey of Pakistan, the site's soil has low organic matter and pH (7.0 - 7.9), which is feasible for various crops.

Figure-2: Cotton irrigated crop sampling sites at Water Management Research Center (WMRC), Faisalabad.

Experimental setup and data collection

The experiment was conducted by Randomized Complete Block Design (RCBD), the sowing method, and land cover. The three sowing methods were studied, i.e., flat sowing, ridge sowing, and bed sowing with mulch and non-mulch land cover. There were six treatments, i.e., T₁ (flat sowing with mulch), T₂ (flat sowing without mulch), T₃ (ridge sowing with mulch), T₄ (ridge sowing without mulch), T₅ (bed planting with mulch), and T₆ (bed planting without mulch), respectively with three repetitions. The plot size was 6 m × 4.5 m, and the total experimental area was about 0.141 ha. The cotton crop was sown on June 13, 2017, and harvested on November 20, 2017, with three replication of each treatment. Therefore, the total simulation period for groundwater recharge flux was 150 days.

Moisture content data was collected from the fields at seven-day intervals. The soil sampling was done at 0-30 cm, 30-60cm, and 60-90 cm depth from each treatment plot with a fixed interval-soil sample collected by a vertical borehole (auger-hole) drilling method (Fig. 2). The moisture content of the soil sample was measured using the oven-dry method for 24 hours at 105 °C. Gravimetric moisture content (θ_g) was obtained, and volumetric moisture content (θ_v) calculated by $\theta_v = \theta_g \times \text{apparent specific gravity}$. Meanwhile, apparent specific gravity is the ratio of ρ_s = bulk density of soil (g/cm³); and ρ_w = bulk density of water (g/cm³).

The irrigation water was applied as a rotational program followed by the Extension and Adaptive Research Wing of the Punjab Agriculture Department. Detailed rotational methods can be found elsewhere (Maqbool et al. 2021). The department has fixed the irrigation interval based on the sowing method; the irrigation interval is seven days for bed and ridge sowing and flat sowing ten days of the cotton crop. Irrigation depth was calculated by following expression $QT =$

AD, where Q = discharge of the outlet/ tubewell (cusec); T = time of irrigation (hour); A = area to be irrigated (acre); and D = depth of applied irrigation (inch)¹.

Downscaling techniques

Statistical downscaling is a promising approach to formulate specific, local-scale, or level climatic predictions (Laflamme et al. 2015). Statistical downscaling is a computationally less intensive practice to accomplish diverse results at the local scale over dynamics downscaling. It has a two-step process comprising 1) establishing statistical relationships between local-scale climatic variables and large-scale predictors and 2) the implication of corresponding relationships to produce large-scale output to predict local-scale climatic features for the future (Hoar and Nychka 2008). Statistical downscaling modeling (SDSM) is a hybrid decision support tool to examine the impact of climate change. It includes future scenarios, weather generators, and multiple linear regression (MLR) methods for future climate predictions at local, regional, or cross-border (Kazmi et al. 2016; Gebrechorkos et al. 2019; Pomee et al. 2020). Here, CanESM2 climatic variables are used and acquired from <https://climate-scenarios.canada.ca/>. CanESM2 has historical data of 26 climatic parameters from 1976 to 2005, respectively. Grid data 27 X and 44 Y of CanESM2 were downloaded from the above link. In addition, observed climate data of the Faisalabad station was acquired from Pakistan Metrological Department (PMD). Moreover, it gives future climatic data under different Representative Concentrations Pathways (RCP) scenarios from 2006 to 2100, respectively. These scenarios are based on future projections of GHG (greenhouse gas) emissions. First scenario, RCP 2.6 is based on very low emission of GHG concentration. Second scenario, RCP 4.5, is considered a steady-state scenario to reduce GHG emissions to keep entire radioactive forces stable before 2100 by implementing numerous

¹ Units of the parameters are interchangeable on the basis of required unit of depth.

technologies and strategies. Third scenario, RCP 8.5 is characterized as constantly rising GHG emission for time series. The data is accessible at a grid resolution of 2.8125° latitude $\times$ 2.8125° longitudes, respectively.

Predictor's screening: the most relevant atmospheric parameters were chosen with the assistance of the MLR model. Selection was based on p-value, histograms, scatterplots, correlation matrix, and partial correlation. A correlation matrix was preferred between predictands and CanESM2 predictors (Kobuliev et al. 2021). A predictor parameter, which was positively correlated, has a significant representation in the scatterplot and minimum p-value. Therefore, it was cautiously chosen for maximum and minimum temperature, rainfall, relative humidity, and wind speed. NCEP (National Centers for Environmental Prediction) predictands were different for each parameter and selected based on p-value and partial r-value, respectively.

Calibration and validation of SDSM: the model was calibrated for data from 1976 to 1995 and validated from 1996 to 2005. The model was developed for the daily downscaling of rainfall. A monthly regression equation was applied in eight stations, and a sub-model was used conditionally. Ordinary Least Square (OLS) was used to optimize the model. Data for the calibration period (1976-1995) is used as a base and simulates the daily maximum and minimum temperature, rainfall, relative humidity, and wind speed for the validation period (1996-2005) with the induction of NCEP and CanESM2 predictors, respectively. For better agreement with the results, 100 ensembles were used to obtain the average. In literature, some other studies also evaluated the good performance of SDSM compared to other methods; that's why this statistical downscaling approach was used (Kazmi et al. 2016; Khan et al. 2018; Kobuliev et al. 2021). Performance of the model was evaluated by the root mean square error (RMSE), coefficients of correlation (R^2), and Nash-Sutcliffe Efficiency (NSE) and calculated by Eqs. 1, 2 & 3 as follows:

$$RMSE = \sqrt{\frac{1}{2} \sum_{k=1}^n (X_k - Y_k)^2} \quad (1)$$

$$R^2 = \frac{\sum_{k=1}^n (X_k - \bar{X})^2 \cdot \sum_{k=1}^n (Y_k - \bar{Y})^2}{\sqrt{\sum_{k=1}^n (X_k - \bar{X})^2 \cdot \sum_{k=1}^n (Y_k - \bar{Y})^2}} \quad (2)$$

$$E_f = 1 - \frac{\sum_{k=1}^n (Y_k - X_k)^2}{\sum_{k=1}^n (X_k - \bar{X})^2} \quad (3)$$

where X is the observed value, Y is simulated value removal, the $\bar{(-)}$ represents the mean value, and n is the number of samples.

Scenario Generator: is used to simulate the results of future climate scenarios, i.e., RCP2.6, RCP4.5, and RCP8.5, respectively. First, the future climate data of maximum temperature, minimum temperature, rainfall, relative humidity, and wind speed were predicted for 2006 to 2100 on a daily basis. Afterward, this data was used to estimate the groundwater recharge flux under different sowing conditions for the cotton field for the two periods, i.e., 2021 to 2050 and 2051 to 2080.

HYDRUS-1D: Estimation of Recharge Flux

To simulate groundwater recharge flux, unsaturated flow models were developed for each treatment, i.e., T₁, T₂, T₃, T₄, T₅, and T₆, respectively. Richard's convection-dispersion equations were espoused to account for the water flow under the cotton field. HYDRUS-1D code was run to simulate the one-dimensional flow based on Eq. 4 (Šimůnek et al. 2013). HYDRUS-1D was acquired from the public domain [PC-PROGRESS - Hydrus-1D \(pc-progress.com\)](http://pc-progress.com).

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left[K(h) \frac{\partial h}{\partial z} + K(h) \right] - S(h) \quad (4)$$

where θ is the volumetric soil water content ($\text{cm}^3 \text{ cm}^{-3}$); t is time (day); h is the soil-water pressure head (cm); z is the gravitational head as well as the vertical coordinate (cm, upwards is positive);

K(h) is the unsaturated hydraulic conductivity (cm d⁻¹), and S is the soil water extraction rate by plant roots (cm³ cm⁻³ d⁻¹).

The soil hydraulic properties of soil were elucidated by the Mualem-van Genuchten formulation (Mualem 1976; van Genuchten 1980), based on the pore-size distribution in the model by Eq 5 & 6, respectively;

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = (1 + \alpha_r |h|^n)^{-m} \quad (5)$$

$$K(h) = K_s S_e^l \left[1 - (1 - S_e^{1/m})^m \right]^2 \quad (6)$$

where S_e is effective saturation [-]; θ_r and θ_s are residual and saturated water contents [cm³ cm⁻³], respectively; and α_r [cm⁻¹], m [-] and n [-] are shape parameters. K_s is the saturated hydraulic conductivity [cm d⁻¹]; l [-] is a pore connectivity parameter; and m=1-1/n, when n>1. The percentage of sand, silt, and clay and Bulk density and van Genuchten parameters were given in Table-1.

Table-1: Soil properties of experimental site including particle-size distribution at different depths by weight percentage of particle-diameter intervals (sand, silt, and clay), and van Genuchten parameters

Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Bulk Density (g cm ⁻³)	θ _i (cm ³ cm ⁻³)	θ _r (cm ³ cm ⁻³)
0-30	74.25	12.35	13.40	1.660	0.0809	0.04
30-60	73.33	12.62	14.05	1.650	0.1401	0.05
60-90	73.5	12.80	13.75	1.642	0.1408	0.05

At first, the model's domain and soil parameters were conventional taken into account by the measured particle-size distributions (Table 1) and monitored moisture contents at different depths (0-30, 30-60, and 60-90 cm), respectively. Subsequently, undergoing model calibration, soil parameters were slightly modified to best fit corresponding observations and model predictions.

Flow model: Boundary and Initial Conditions

The top boundary condition was selected as a cotton crop field that ultimately depended upon evapotranspiration, irrigation, and rainfall. For this study, reference evapotranspiration (ET_0) was estimated with the Penman-Monteith equation using the NIAB meteorological station's recorded data. The bottom boundary condition was selected as a free drainage boundary condition to estimate the root zone's recharge flux. To calculate the root water uptake (transpiration), the proposed method to include osmotic stress was applied as represented in Eq. 7 (van Genuchten 1987). In the current study, the multiplicative threshold model was used.

$$\alpha(h, h_\phi) = \frac{1}{1 + (h/h_{50})^{p_1}} \frac{1}{1 + (h_\phi/h_{\phi 50})^{p_2}} \quad (7)$$

where p_1 , p_2 are experimental constants; h_{50} is the pressure head at which the water extraction rate is reduced by 50 % during conditions of negligible osmotic stress, and $h_{\phi 50}$ is the osmotic head at which the water extraction rate is reduced by 50 % during negligible water stress. The Feddes parameter values for root water uptake for the cotton crop were estimated by is given in **Table 2**.

Table 2: Root Water Uptake Parameters for Cotton Crop.

P.O. (cm): Value of the pressure head below which roots start to extract water from the soil.	-10
POpt (cm): Value of the pressure head below which roots extract water at the maximum possible rate	-25
P2H (cm): Value of the limiting pressure head below which roots can no longer extract water at the maximum rate (assuming a potential transpiration rate of $r2H$).	-200
P2L (cm): As above, but for a potential transpiration rate of $r2L$.	-600
P3 (cm): Value of the pressure head below which root water uptake ceases (usually taken at the wilting point).	-14,000
$r2H$ (cm/days): Potential transpiration rate [LT^{-1}] (currently set at 0.5 cm/day).	0.5
$r2L$ (cm/days): Potential transpiration rate [LT^{-1}] (currently set at 0.1 cm/day).	0.1

The water balance of the vertical soil domain covered by vegetation for a given period is the governing equation. There was no runoff during irrigation. The cotton plants' interception of rainwater was also neglected due to low rainfall amounts during the vegetation period. Potential

evapotranspiration (ET_o) was calculated by FAO-56 standards using the Penman-Monteith method. Meanwhile, crop evapotranspiration (ET_c) was computed by defining the regional crop coefficient (K_c) based on initial-season, mid-season, late-season, and evaporation soil, respectively. Evaporation from the soil is predicted by the estimation of energy available at the soil surface.

Model Calibration and prediction

Model calibration is typically defined as turning a model by interpreting the input parameters, i.e., soil hydraulic parameters and boundary and initials conditions. The foremost objective of the flow model's calibration is to fit the simulated model results and the observed value of soil moisture or water content under the cotton field. Inverse estimation methods were used to achieve the objective by determining unsaturated soils' hydraulic properties (Bitterlich et al. 2004). The water flows and salt transport are case sensitive to soil hydraulic functions [$\theta(h)$ and $K(\theta)$]. Meanwhile, pedotransfer functions were applied to predict water retention parameters and saturated hydraulic conductivity from soil texture and bulk density (Van Looy et al. 2017). These estimations were refined by induction of input data of one or two water retention points. Consequently, the hydraulic properties were calibrated to site-specific conditions. For this purpose, soil moisture, tension, and salinity data were measured every fifth day before and after irrigation.

The HYDRUS-1D model was calibrated against the moisture content during the cotton crop period. Results were evaluated against two statistical parameters: R^2 and RMSE, calculated by Eq. 1 & 2 for calibration and validation. The calibration parameter is the soil moisture content that was taken at a regular interval of time.

Statistical analysis

A correlation and multivariate regression model were conditioned to affirm the impact of climate change on groundwater recharge. Microsoft Excel® 2019 ads-in data analysis tool was used to develop a correlation and multivariate regression model. The linear relationship between tended groundwater recharge and climate variables was established to determine the groundwater recharge flux. These relationships were resultant as follows:

$$\Delta X = constant + \beta_1 \Delta T_{max} + \beta_2 \Delta T_{min} + \beta_3 \Delta R_f + \beta_4 \Delta R_H + \beta_5 \Delta W_s \quad (7)$$

where, ΔX is the groundwater recharge flux in cotton crop, β_1 , β_2 , β_3 , β_4 , and β_5 are the coefficient of maximum temperature (T_{max}), minimum temperature (T_{min}), rainfall (R_f), relative humidity (R_H), and wind speed (W_s), respectively. While Δ representing the change in climate variables.

RESULTS AND DISCUSSIONS

Future Climate Trends

The downscaling was performed using SDSM for the Faisalabad station. The 30 years (1975-2005) data were used for calibration (1975-1995) and validation (1996- 2005). Robustness of downscaling was evaluated by R^2 , RMSE, and NSE for both calibration and validation phases (Table 3). The results show that accuracy downscaling in the reproduction of climate parameters is based on high R^2 (>0.96) and low RMSE (<0.4) for both calibration and validation period, consequently. Besides, Nash-Sutcliffe Efficiency ($>0.95\sim 1.0$) is elucidated the good efficiency or better fitting of data. This performance analysis has shown better agreement than the previous study (Bessah et al. 2021). The CanSME2 GCM data was used for future climate generation under three emission scenarios, i.e., RCP 2.6, RCP 4.5, and RCP 8.5. The different NCEP predictors

were used for each parameter with the correlation method and the confidence level of 95 % for every climatic parameter. Long-term discrepancies in climate change parameters were investigated, i.e., maximum and minimum temperature, rainfall, relative humidity, and wind speed, respectively, for future 2021-2050 and 2051-80 under three emission scenarios, i.e., RCP 2.6, RCP 4.5, and RCP 8.5.

Table 3: Evaluation of climatic parameters for calibration (1975-1995) and validation (1996-2005) phase

Climate parameters	Calibration			Validation		
	R ²	RMSE	NSE	R ²	RMSE	NSE
Maximum temperature	0.965	0.348	0.973	0.975	0.221	0.981
Minimum temperature	0.997	0.033	0.996	0.961	0.365	0.979
Rainfall	0.976	0.343	0.884	0.959	0.376	0.879
Relative humidity	0.980	0.113	0.959	0.986	0.110	0.968
Wind speed	0.988	0.077	0.986	0.973	0.367	0.969

The average annual maximum (minimum) temperatures will be increased by 2.03 (0.80) °C, 2.11 (0.91) °C, and 2.18 (1.07) °C under RCP 2.6, RCP 4.5, and RCP 8.5, respectively, for 2021-50 (Table 4). During 2051-80, this annual increment in maximum (minimum) temperatures was higher significantly 3.40 (1.06) °C, 3.64 (1.51) °C, and 4.04 (2.18) °C under RCP 2.6, RCP 4.5, and RCP 8.5, respectively. This increasing trend of temperature is similar to previous reports lately (Arshad et al. 2019; Saddique et al. 2020). Meanwhile, the maximum (minimum) temperature range is projected to increase between 5.7 (0.8) °C annually by the late 21st century (Dahri et al. 2021). However, the expected rise of maximum (minimum) temperature by 2.03 to 4.04 (0.8 to 2.18) °C, that's the proximity of global emission consequence by 3 to 5 °C rise in temperature in Pakistan (Chaudhry 2017). Rainfall decline gradually, 48.22 to 41.68 mm, 47.92 to 41.41 mm, and

47.75 to 40.18 mm under RCP 2.6, RCP 4.5 RCP 8.5, respectively. Noteworthy, the moon season of the study would also be shifted from June-July to early April-May. Relative humidity and wind speed declined significantly from 10.20 to 10.53 % and 0.95 to 0.69 km.hr⁻¹ for the 2051-80 periods (Table 4). These climate variables are influential in evaluating the blue water footprint under cotton fields (Huang et al. 2019) and may cause a diminution of groundwater recharge.

Table 4: Predicted relative changes in average values future climatic parameters under RCP 2.6, RCP 4.5, and RCP 8.5

Parameters	2021-2050			2051-2080		
	RCP 2.6	RCP 4.5	RCP 8.5	RCP 2.6	RCP 4.5	RCP 8.5
Max. temperature (°C)	2.03	2.11	2.18	3.40	3.64	4.04
Min temperature (°C)	0.80	0.91	1.07	1.06	1.51	2.18
Rainfall (mm)	48.22	47.92	47.75	41.68	41.41	40.18
Relative humidity (%)	-4.52	-4.42	-4.37	-10.20	-10.33	-10.35
Wind speed (km/hr)	-0.40	-0.37	-0.35	-0.95	-0.85	-0.69

Calibration of HYDRUS-1D

The HYDRUS-1D model's calibration was undertaken by comparing the observed and simulated moisture content at 30 cm, 60 cm, and 90 cm depth, respectively. Observations nodes on experimental data of pressure heads were shown maximum hydraulic head at 30 cm and minimum hydraulic head at 90 cm depth with a seven-day interval of moisture content of the entire cotton season. Observation nodes of simulated moisture content were shown homogenous pattern (Fig. 3) of moisture content at 30 cm, 60 cm, and 90 cm respectively under six treatments (T₁, T₂, T₃, T₄, T₅, and T₆) into the soil profile. Consequently, maximum water content was simulated at 30 cm depth, and minimum water content was simulated at 90 cm depth regardless of the mulching and sowing method. The cotton field's water content exhibited erratic fluctuations in water content

during the season due to surface water inducing irrigation and rainfall. Herein, HYDRUS-1D made an efficient operation by predicting the time which water content arises. Nevertheless, the observed data showed a faster decrease in water content than predicted by HYDRUS-1D. This discrepancy in the top layer (30 cm) would be ascribed to more rapid drainage (sandy loam soil) or higher evapotranspiration rates by cotton plants. The model was run under a ten-time step (0-10) and generated a hydraulic conductivity profile and soil layers' hydraulic capacity. Hydraulic conductivity increased to a certain depth of soil after it became constant (Fig. 4a). It is a critical parameter to access the water flow into the soil stratum. Hydraulic capacity represented the amount of water conveyed through steady and uniform gravity flow (Fig. 4b).

In general, the simulated moisture content ($\text{cm}^3.\text{cm}^{-3}$) by HYDRUS-1D at 30 cm, 60 cm, and 90 cm depths corresponded in close proximity to the observed moisture content ($\text{cm}^3.\text{cm}^{-3}$) for six treatments. Nevertheless, deviations between simulated and observed moisture content exhibited at certain depths (e.g., 60 cm depth) at treatment T_6 . Moreover, the observed moisture content was apparently higher than the simulated moisture content at 30 cm depth for T_4 and T_6 . It could be due to the sowing of cotton without mulching. The robustness of the HYDRUS-1D is evaluated based on R^2 and RMSE values, as shown in Table 5. The R^2 and RMSE values for the HYDRUS-1D model were ranged between 0.81 and 0.92, and $3.40\text{E-}3$ and $6.55\text{E-}5$, respectively. Overall, the average R^2 (0.875) and RMSE ($5.24\text{E-}4$) were reliable through the whole soil profile. These results show consistency with previously groundwater recharge flux estimation using HYDRUS-1D under agricultural fields (Turkeltaub et al. 2014; Xi et al. 2016; Boughanmi et al. 2018). Thus, calibrated HYDRUS-1D model has indicated excellent performance, afterward used to simulating the one-dimensional soil water dynamics in cotton irrigated fields for all six treatments.

Figure 3: observations nodes of simulated water content at N₁ (30 cm), N₂ (60 cm), and N₃ (90 cm) under six treatments (T₁, T₂, T₃, T₄, T₅, and T₆).

Figure 4: profile information of soil (a) hydraulic conductivity and (b) hydraulic capacity under ten-time step

Table-5: R^2 and RMSE values between observed and simulated moisture content at different depths and treatments.

Treatment /Depth	R^2			RMSE		
	30 cm	60 cm	90 cm	30 cm	60 cm	90 cm
T ₁	0.89	0.86	0.85	1.00E-3	1.50E-3	1.50E-4
T ₂	0.92	0.91	0.87	1.20E-4	2.50E-4	4.20E-5
T ₃	0.85	0.89	0.82	6.55E-5	1.50E-4	3.25E-5
T ₄	0.92	0.86	0.91	6.55E-5	1.80E-4	3.22E-5
T ₅	0.91	0.86	0.87	2.77E-5	6.55E-5	1.40E-3
T ₆	0.89	0.82	0.85	3.40E-3	5.40E-4	4.10E-4

Groundwater recharge

The calibrated HYDRUS-1D model for the irrigated cotton field was run over 150 days at a daily resolution to estimate all fluxes, including actual root water uptake, bottom flux, surface runoff, infiltration rate, cumulative evaporation, and soil water storage into the root zone. Boundary fluxes under the flat sowing of the cotton crop with mulch cover in Fig. 5 during the season. Actual root water uptake (cm.day^{-1}) was minimum during 20-40 days and maximum at the 130th day after cotton sowing (Fig. 5a). The cotton crop's cumulative root water uptake is about 62 cm during the 150th day after sowing (Fig. 5b). Bottom flux (cm.day^{-1}) below the root zone was simulated (Fig. 5c); maximum bottom flux was 5 (cm.day^{-1}) during the initial stage under T₁. The cumulative/ total recharge flux was 55 cm approximately during the cotton season under T₁ (Fig. 5d). The amount of water that infiltrates below the root zone directly or indirectly turns into groundwater recharge.

Recharge during irrigated crop season has a fractional amount under a seven-day rotational program (warabandi system) based on the supply instead of the demand. Daily soil water storage under T₁ has a maximum value of 25 cm on the 20th day and a minimum value of 5 cm on the 138th day after cotton sowing (Fig. 5e). The soil moisture content store at this layer could maximize the cotton yield and water productivity (Wang et al. 2020). This stored water content is used by the cotton crop when a deficit of irrigation. The total depth of water infiltrated from the ground surface to the subsurface (Fig. 5f), approximately 110 cm during crop duration under T₁. In this circumstance, the surface runoff is negligible due to small land units or small experimental plots and low rainfall during the simulation period. However, the surface runoff may be increased under changing climate scenarios. Cumulative evaporation from the ground surface is minimum (Fig. 5g); approximately 0.6 cm of water was evaporated from the soil surface into the atmosphere. All

boundary fluxes are shown in Fig. 5h, including potential and actual surface flux, potential and actual root water uptake, and actual bottom flux. It reflects that the potential root water uptake is higher than the actual root water uptake. All fluxes were estimated in the vadose zone of soil using the water budget approach in HYDRUS-1D (Fig. 6).

Similarly, all fluxes were estimated for the remaining five treatments T₂, T₃, T₄, T₅, and T₆ using HYDRUS-1D. Cumulative recharge, cumulative actual water uptake, cumulative infiltration for all the six treatments have been calculated and compared (Fig. 7). Noteworthy, the maximum cumulative recharge was occurred under T₂ (75 cm), followed by T₄ (70 cm) and T₅ (62 cm). Moreover, the crop's cumulative actual root water uptake was highest under T₆ (83 cm), followed by T₅ (78 cm) and T₄ (72 cm). The estimated cumulative infiltration was observed maximum under T₂ (140 cm) and T₄ (140 cm). Mulching of cotton crops under T₁, T₃, and T₅ has reduced soil water content drainage due to climate variability, i.e., rainfall. Mulching has a decisive influence on a water-saving strategy to mitigate water stress in agriculture in rain-fed or semi-arid crop cultivation areas. Meanwhile, the cumulative water fluxes were reported more in flood irrigation over mulched drip irrigation (Jin et al. 2018). Besides, the bed planting (conventional row spacing) of cotton has shown ameliorative plant growth, nutrients uptake, and efficient use of available water resources (Hussain et al. 2021). Therefore, the estimated results strengthen all other advantages of bed planting, i.e., water-saving, uniform distribution, good crop. It also highlighted the disadvantages of flat sowing's higher water loss.

Figure 5(a-h): Boundary fluxes under flat sowing with mulch

Figure 6: Fluxes simulated using HYDRUS-1D for six treatments

Figure 7: all cumulative simulated fluxes of irrigated cotton field using HYDRUS-1D under T₂, T₃, T₄, T₅, and T₆

Impact of Climate Change on Groundwater Recharge

Herein, climate change on groundwater recharge with mulching was not calculated because of two factors: continuously reporting the plastic mulching's detrimental effect in the agrosystem (Qi et al. 2020; Amare and Desta 2021). That may lead to a ban in the future—another one, the insight that groundwater recharge won't be attained via plastic mulching. Therefore, the impact of climate change on groundwater recharge was calculated without mulching under treatment T₂, T₄, and T₆ for 2021-50 and 2061-80 under RCP 2.6, RCP 4.5, and RCP 8.5 in terms of recharge rate, root water uptake, infiltration rate, and evaporation (Fig. 8). The cumulative actual root water uptake (cm) increased for treatment T₂ and T₄ gradually for 2021-50 and 2051-80 (Fig. 8a & e). Cumulative recharge flux (cm) decreased under T₂, T₄, and T₆ (Fig. 8b, f, & j). Reduction of groundwater recharge flux could be a potential threat to the socio-ecological balance of the region (Rodríguez-Huerta et al. 2020), up to a 6.6% decrease in groundwater recharge reported under flood irrigation in the Mediterranean region (Pool et al. 2021). The highest recharge was observed 71 cm for 2051-80 under T₂ for RCP 2.6 (Fig. 8b), while the lowest recharge was 30 cm for 2021-50 under T₆ for RCP 8.5 (Fig. 8j). Overall, a maximum of 41 cm of recharge reduction was observed. There wasn't any significant change in cumulative infiltration for 2021-50 and 2051-80 (Fig. 8c, g & k). Cumulative evaporation increased significantly for 2021-50 and 2051-80 under treatment T₂, T₄, and T₆ (Fig. 8d, h & l). Overall, the magnitude of actual root water uptake, recharge flux, infiltration, and evaporation of 2051-2080 was more than 2021-50 for RCP 2.6, RCP 4.5, and RCP 8.5 under treatment T₂, T₄, and T₆. The increment in actual root water uptake and evaporation may attribute to an increase in temperature for 2021-50 and 2051-80. Meantime, the top layer of soil (0-20 cm) has a higher temperature (3-6°C) with an exponential functional relationship between temperature and root water uptake, increasing water uptake (Lv et al. 2013;

Resende et al. 2019). As water is allocated in the region, increased water uptake and evapotranspiration could create uncertainties in sustainable water resource management (Maqbool et al. 2021; Pool et al. 2021). The study area has coarse-textured soils that led to lowering groundwater recharge with time series of meteorological data (Batalha et al. 2018). Consequently, the recharge and infiltration fluxes declined for 2021-50 and 2051-80.

Figure 8: comparison of RCP 2.6, RCP 4.5, and RCP 8.5 for future (2021-2050 and 2051-2080) cumulative actual root water uptake (cm), cumulative recharge fluxes (cm), cumulative infiltration (cm), and cumulative evaporation (cm) under treatment T₂ flat sowing (a-d), treatment T₄ ridge sowing (e-h), and treatment T₆ bed planting (i-l) method of irrigated cotton field without mulching practice.

The multi-linear regression analysis for climate emission scenario (RCP 2.6, RCP 4.5, and RCP 8.5), agronomical practices (T₂, T₄, and T₆), and future (2021-50 and 2051-80) climate

variable results are shown in Table 6. Results revealed that the model is only bound to elucidate the variation groundwater recharge under cotton corps ranging from 23 % (0.2378) in T₆-RCP2.6_2050 to 5% (0.512) case of T₄-RCP4.5_2050. Correlation coefficient (r) results show weak uphill linear relationships between groundwater recharge and climate variables. These coefficients can quantify the real impact of climate variables in the changes in groundwater recharge. Moreover, the sign of coefficients indicates that future climate changes would be heterogeneous in the groundwater recharge versus climate variable. In the case of T₂- RCP4.5, climate variables account for only 23.11% of groundwater recharge flux, whereas 76.89% of the variation in recharge flux could be explained by other influential factors (fate and transport of solute, drainage practice, and soil texture along with soil organic matter). Recharge flux is controlled by 1-4% of annual average rainfall (Sandoval et al. 2018). Likewise, the regression analysis point to R² (coefficient of determination) of 0.2109, implying that the impact of climate variables explains 21.09% of the recharge flux changes in T₄- RCP8.5, while 78.91% controlled by other factors such as flood and drought. Reinecke et al. (2020) reported that the uncertainty range in climate change is large, and predictions with confidence with groundwater recharge can only be made for a specific region.

Table 6: Multivariate regression analysis of groundwater recharge in terms of climate parameters

Treatments & Scenarios	Coefficients					r	R ²
	T _{max}	T _{min}	R _f	R _H	W _s		
T ₂ - RCP2.6_2050	-0.4724	0.2867	1.1948	-0.0531	-1.231	0.379	0.144
T ₄ - RCP2.6_2050	0.1356	-0.0758	0.3322	0.0258	-0.0244	0.2403	0.0577
T ₆ - RCP2.6_2050	0.2260	-0.2	2.3135	0.0239	0.1416	0.4876	0.2378
T ₂ - RCP4.5_2050	0.0290	-0.0605	2.7084	0.0572	-1.0409	0.4807	0.2311
T ₄ - RCP4.5_2050	0.0904	-0.0931	0.2538	0.0071	0.0143	0.1455	0.0512
T ₆ - RCP4.5_2050	-0.1618	-0.0066	0.7273	-0.0542	-0.3692	0.2691	0.0724
T ₂ - RCP8.5_2050	0.5207	-0.3450	0.6784	0.2086	0.7801	0.4579	0.2097
T ₄ - RCP8.5_2050	0.1724	-0.1463	0.4760	0.0267	0.1245	0.2822	0.0796

T₆- RCP8.5_2050	-0.0034	-0.0028	1.3989	-0.0115	-0.1705	0.2346	0.0550
T₂- RCP2.6_2080	0.5037	-0.1978	1.1592	-0.1776	-0.0648	0.2101	0.0841
T₄- RCP2.6_2080	0.0904	-0.0931	0.2538	0.0071	0.0143	0.2777	0.0771
T₆- RCP2.6_2080	0.0934	-0.0069	0.1552	0.1214	-0.0151	0.1484	0.0520
T₂- RCP4.5_2080	0.3669	-0.3275	1.5760	0.0468	1.0508	0.4046	0.1637
T₄- RCP4.5_2080	-0.7728	0.3510	0.4367	-0.2107	0.5417	0.4057	0.1646
T₆- RCP4.5_2080	0.0631	-0.1600	0.3921	-0.0546	0.6086	0.2951	0.0871
T₂- RCP8.5_2080	-0.0909	0.0510	2.1426	0.0417	-1.1370	0.3936	0.1549
T₄- RCP8.5_2080	-0.5533	0.3666	0.7395	-0.0521	0.0489	0.4592	0.2109
T₆- RCP8.5_2080	-0.3018	0.7681	0.1489	-0.0330	-0.6301	0.3887	0.1511

(p>0.05; significant level 95%)

Figure 9: cotton yield in terms of sowing methods and treatments

Climate change decreases cotton yield from 699 to 534 kg.ha⁻¹ and elevates cotton irrigation requirement from 960.1 to 1048.9 mm in Pakistan (Arshad et al. 2019; Abbas 2020; Rehman 2021). However, from T₁ to T₆, cotton yield per hectare increased (Fig. 9). Bed planting without mulch (T₆) cotton sowing method has shown the highest cotton yield (1066 kg. ha⁻¹) followed by ridge planting without mulch (T₄, 1019 kg. ha⁻¹). It elucidates two significant facts; first, under-bed planting is less recharge flux and infiltration (Fig. 8j&k) and more cotton yield. Second, others without plastic mulch cotton have a greater yield than mulch. Therefore, existing agronomical should be replaced by adopting bed planting and without mulch regardless of the

cotton sowing method. As the future climate seems to get warmer, it needs to find such phenotypes variety of cotton crop that survive and yield good results under climate warming (high-yielded crop varieties are needed for a region with arid to semi-arid climate). Besides, it is equally important to adopt climate change adaptation measures for sustainable water resources management to avoid food security risks in the future.

Across Pakistan, groundwater contribution is estimated at 60 % for agriculture, while 60% of irrigation water is lost due to poor infrastructure of conveyance and inadequate application in the field (Imran 2019). In Abu Dhabi (United Arab Emirates), 76% of farmers rely on groundwater as a primary source with low water productivity (Al Tenaiji et al. 2021). Adopting climate-smart agriculture in water stress regions (arid and semi-arid) would combat climate change, water scarcity, and groundwater depletion that can enhanced cotton yield (90 kg.ha^{-1}) (Jamil et al. 2021). On the other hand, cotton farmers in Pakistan have a less yield and inefficient use of resources; thereby, irrigation water, soil, and agronomical management practices and technologies are economical, financially, and environmentally desirable for rural socio-economic development. Therefore, there is a need to develop and implement effective strategies to maintain groundwater and agricultural development sustainability.

Conclusion

Downscaling technique was used to calibrate and predict future climate parameters under climate change scenarios RCP 2.6, RCP 4.5, and RCP 8.5 for 2021-50 and 2051-80. That shows the gradual increase in maximum (minimum) temperature and decreased rainfall, relative humidity, and wind speed. Hydrus-1D unsaturated flow model was calibrated underlying the cotton crop with six different agronomical practices. Maximum cumulative recharge was occurred under T₂ (75 cm), followed by T₄ (70 cm), and actual root water uptake was highest under T₆ (83

cm). Cumulative recharge flux under climate change decreased for 2021-50 and 2051-80. The highest recharge was observed at 71 cm for 2051-80 under RCP 2.6 (T₂). Multivariate regression analysis revealed that only 5-23% of groundwater recharge controlled by climate variables, has a weak (positive) relationship between groundwater recharge and climate variables. Bed planting without mulch (T₆) cotton sowing method has shown the highest cotton yield (1066 kg. ha⁻¹) and, under future climate changes, has less recharge flux and infiltration. Therefore, it is equally important to adopt climate change adaptation measures for sustainable water resources management to avoid food security risks in the future. It is recommended that the current agronomical practice of cotton sowing shall be replaced with bed planting, and mulching practice should be prohibited for greater cotton yield to achieve sustainable development.

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