Modeling the Impact of Climate Change on Evapotranspiration and Irrigation Requirements of Rice in Chandauli Using NEX-GDDP and CROPWAT

Abstract

A study was conducted to evaluate the impact of climate change on the water requirements of rice crops in the Chandauli district of Uttar Pradesh, where rice is a principal cereal crop. Climate change poses serious threats to food security and water resources, necessitating such assessments. The research employed the CROPWAT 8.0 model to estimate evapotranspiration (ET) and irrigation water requirements (IWR) for rice cultivation. Climate data, including maximum temperature (Tmax), minimum temperature (Tmin), and rainfall, were derived from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) for both the baseline period (1981–2015) and the future period (2020–2040), under the RCP 4.5 scenario. Due to inherent biases in General Circulation Models (GCMs), two bias correction methods—linear scaling and modified difference—were tested, with linear scaling proving more effective. Climate projections indicate an approximate increase of 1.7 °C in both Tmax and Tmin by 2040. Although total rainfall may rise, effective rainfall (ER) is projected to fluctuate. The study predicts an 8.8% increase in crop water requirements (CWR) by 2040 due to rising temperatures. Meanwhile, irrigation water requirements (IWR) are expected to vary: increasing by 19% in 2020, decreasing by 9% in 2030, and rising again by 2.9% in 2040. These findings underscore the importance of adaptive water management and agricultural planning to mitigate climate change impacts on rice production in the region.

***Keywords**:* Bias correction, Climate change, Crop water requirement,

1. INTRODUCTION

Efficient use of freshwater is becoming increasingly critical as global demand continues to rise. Freshwater is one of the most essential natural resources, and it is estimated that nearly two-thirds of the global population could face severe freshwater shortages within the next quarter century if water is not managed wisely. In India, the agricultural sector accounts for approximately 81% of total water consumption, making efficient water use in farming a top priority (Surendran et al., 2015). Agriculture requires water primarily for irrigation to meet the evapotranspiration demand necessary for vital metabolic processes such as photosynthesis. These physiological activities are crucial for healthy plant growth and higher crop yields. Maintaining an appropriate air-to-water ratio in the plant root zone is essential to create a favorable environment for plant development. These physiological processes are highly dependent on the availability of water, especially during key developmental phases. Crops are particularly vulnerable to water stress during their critical growth stages; hence, maintaining adequate soil moisture in the root zone is essential to prevent yield reduction or crop failure. Accurate estimation of crop water requirement (CWR) and the implementation of efficient irrigation scheduling are vital components of effective irrigation planning and water resource management. In this context, estimating the irrigation water requirement (IWR) under varying cropping patterns has become an increasingly important task for water resource managers and planners (Darren et al., 2014). Moreover, any changes in the average weather conditions of a region—such as shifts in temperature or rainfall patterns—can significantly influence crop growth and productivity. Climate change has emerged as one of the major challenges for humanity in the 21st century, particularly because agriculture is highly dependent on weather and climatic conditions (Neill et al., 2017). Among various climatic variables, rainfall is especially significant due to its non-uniform distribution across time and space (Parthasarathy, 1984). Having prior knowledge of regional weather parameters is essential for efficient and effective irrigation scheduling. Numerous studies have been conducted at both national and international levels—across farm and non-farm sectors—using time series data to forecast weather variables.

Climate models serve as critical tools for projecting future climate scenarios. The Coupled Model Intercomparison Project Phase 5 (CMIP5) offers the most extensive and recent collection of meteorological datasets for analyzing historical trends and simulating future climate conditions (Taylor et al., 2012). However, applying these global simulations at the regional scale poses challenges due to their coarse spatial resolution, which may not accurately capture localized climate variability. The CMIP5 climate models are known to exhibit considerable biases in simulating seasonal averages, which differ across geographical regions and among various models (Sengupta and Rajeevan, 2013). Research has shown that these discrepancies tend to be more pronounced for precipitation than for temperature (Andreasson et al., 2004). As a result, it is essential to apply bias correction techniques to raw model outputs to improve their accuracy for regional applications (Sharma et al., 2007; Hansen et al., 2006; Feddersen and Andersen, 2005). In addition, to enhance the spatial resolution and reliability of regional climate projections, a variety of dynamical and statistical downscaling methods have been developed and widely used.

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The NEX-GDDP dataset, derived from CMIP5-generated GCM simulations, provides statistically downscaled climate scenarios with a global, high-resolution, bias-corrected set of climate projections. These projections are particularly useful for assessing the impacts of climate change at finer spatial scales. The dataset has a spatial resolution of 0.25° (25 km × 25 km). In this study, the applicability of the NEX-GDDP dataset for the Chandauli district, India, is evaluated using rainfall and temperature data from the Banaras Hindu University observatory. To minimize random errors inherent in individual models and reduce internal variability, the study employs the multi-model averaging approach (Jain et al., 2019; Harrison et al., 1995).

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2. Materials and Methods

2.1 Description of study area

Chandauli district, situated in the southeastern region of Uttar Pradesh, India, is an important administrative unit within the Varanasi Division. Geographically, it lies between 24°56′N to 25°35′N latitude and 83°02′E to 83°42′E longitude presented in Fig.01. The district shares its boundaries with Varanasi to the west, Sonbhadra to the south, Bihar state to the east, and Ghazipur to the north. Covering an area of approximately 2,484 square kilometers (District survey report, 2020), the administrative headquarters is located in Chandauli town. The district features varied topography, comprising fertile alluvial plains in the northern part and undulating hills associated with the Vindhyan range in the south. Major rivers such as the Ganga, along with its tributaries, the Karmanasa and Chandraprabha, significantly influence the region's hydrology and enhance its agricultural potential. Climatically, Chandauli experiences a sub-tropical monsoon climate, characterized by hot summers, mild winters, and a well-defined monsoon season from June to September. The district receives average annual rainfall between 1000 mm and 1200 mm, primarily from the southwest monsoon. Temperature variations range from around 5°C in winter to above 40°C during peak summer. According to the 2011 Census of India, Chandauli has a population of approximately 1.95 million, with a population density of 785 persons per square kilometer. The district is predominantly rural, with more than 85% of the population dependent on agriculture and allied sectors for livelihood. Agriculture serves as the cornerstone of Chandauli's economy. Due to its substantial rice production, it is often referred to as the "Dhaan Ka Katora" (Rice Bowl) of Uttar Pradesh (CRIDA Contingency report, 2019). The availability of fertile soil, abundant water resources, and favorable climate conditions contribute to the region's high suitability for paddy cultivation. Besides rice, other key crops include wheat, pulses, and horticultural produce. Nonetheless, variability in monsoon patterns and rising temperatures pose emerging challenges to sustainable agricultural development.

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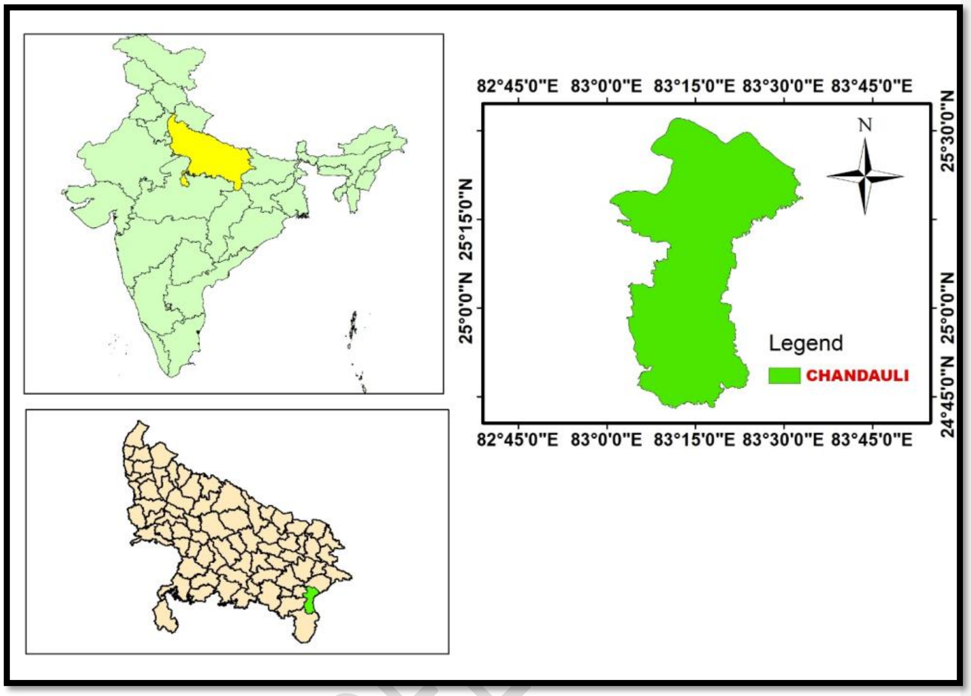

Fig. 01: Study area Map

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2.2 Retrieval of climate data

The recently released NEX-GDDP dataset was utilized to obtain site-specific daily rainfall and temperature data for two time periods: the baseline (1981–2015) and the future projection period (2020–2040). To enhance the reliability of the projections, the multi-model averaging approach was applied, which helps to minimize random errors and reduce internal variability. A total of seven General Circulation Models (GCMs) from the CMIP5 archive were selected to generate the downscaled NEX-GDDP dataset (Table 01). These models were combined into an ensemble to further reduce uncertainties associated with individual model outputs.

Table 01. Seven CMIP5 general circulation models (GCMs) used in the study

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S. No.	Model	Institute	Resolution

1.	CanESM2	Canadian Centre for Climate Modelling and Analysis	2.8˚ × 2.8˚
2.	CCSM4	National Centre for Atmospheric Research, USA	0.95˚ × 1.25˚
3.	GFDL-CM3	Geophysical Fluid Dynamic laboratory, USA	2˚ × 2.5˚
4.	GFDL-ESM2M	Geophysical Fluid Dynamic laboratory, USA	2˚ × 2.5˚
5.	INMCM4	Institute of Numerical Mathematics of the Russian Academy of Sciences	2.5˚× 2˚
6.	MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M), Germany	1.87˚ × 1.87˚
7.	MRI-CGCM3	Meteorological Research Institute, Japan	1.12˚ × 1.12˚

2.3 Assessment of the NEX-GDDP Dataset for Regional Climate Analysis

Evaluating model data against observed data during the baseline period is essential for assessing the predictive capability of the model for future projections. In this study, the performance of the NEX-GDDP dataset was evaluated using three statistical performance indicators: the correlation coefficient (r), root mean square error (RMSE), and percent bias (Pbias), as presented in Table 03. These indices are commonly used in the evaluation of climate models (Jain et al., 2019). The correlation coefficient (r) indicates the strength and direction of the linear relationship between observed and predicted values. RMSE measures the accuracy of the model's predictions by quantifying the average magnitude of the errors. Pbias assesses the average tendency of the simulated values to overestimate or underestimate the observed data.

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Table 01. Detailed equations and variables used for the evaluation of model dataset

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Statistical Metric	Equation	Description	Unit
Correlation Coefficient (r)	$r = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2}\sqrt{\sum(Y-\bar{Y})^2}}$	$\bar{X}$ denotes mean of X variable variable $\bar{Y}$ denotes mean of Y variable	---
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{n}}$	X_i denotes observed value, Y_i denotes model value, and n denotes Total number of	mm or ˚C
Percent Bias (Pbias)	$Pbias = \frac{\sum(Y_i - X_i)}{n} \times 100$	Same as RMSE description	%

2.4 Bias reduction

Model recorded dataset are not perfect in providing simulated climatology. They will differ from observed climatology (Sharma et al., 2004). For this reason, the nearterm climate predictions are usually bias-reduction. In this study two bias reduction methods i.e. linear scaling (LS) and modified difference approachare compared in this study. Bias reduction wasdone on the monthly basis. The monthly correction factors were developed from observed and model data for the year 2001-2015. After bias reduction of baseline dataset, the method obtaining lower Pbias is considered as the best and same correction factors were applied for bias reduction of the future data. Both bias reduction methods to correct model dataset areas follows.

2.4.1 Linear scaling method

This method is based on the principle of aligning the monthly mean of corrected model values with that of the observed data (Lenderink et al., 2007). It involves adjusting the model simulations through either multiplication or addition, depending on whether the variable is rainfall or temperature. Monthly correction factors were derived for rainfall and temperature using Equation (1) and Equation (2), respectively.

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For rainfall

$$R_{cor,m} = R_{uncor,m} \times \frac{\overline{R_{obs}}}{\overline{R_{uncor,m}}} \qquad \ldots(1)$$

For temperature

$$T_{cor,m} = T_{uncor,m} + \frac{\overline{T_{obs}}}{\overline{T_{uncor,m}}} \qquad \ldots(2)$$

2.4.2 Modified Difference Approach

To generate monthly correction factors for rainfall and temperature, the modified difference approach was applied using Equation (3) and Equation (4), respectively. While conceptually similar to the standard difference method, this approach enhances the correction process by incorporating additional statistical parameters. In the case of temperature, for example, adjustments to the mean (μ) and standard deviation (σ) were introduced to shift and scale the data, thereby refining the representation of both central tendency and variability in the corrected dataset (Leander and Buishand, 2007).

For rainfall

$$R_{cor,m} = \left(R_{uncor,m} + (\triangle\, x)\right) \times \frac{\sigma(R_{obs})}{\sigma(R_{uncor,m})} \qquad \ldots(3)$$

For temperature

$$T_{cor,m} = \overline{T_{obs}} + \left(T_{uncor,m} - \overline{T_{obs}}\right) \times \frac{\sigma(T_{obs})}{\sigma(T_{uncor,m})} + (\overline{T_{obs}} - \overline{T_{uncor,m}}) \qquad \ldots(4)$$

Where $R_{cor,m}$ and $T_{cor,m}$ are the model corrected value of rainfall and temperature , $R_{uncor,m}$ and $T_{uncor,m}$ are the model uncorrected rainfall and temperature, $\overline{R_{obs}}$ and $\overline{T_{obs}}$ are the average value of observed rainfall and temperature, and $\sigma(R_{obs})$ and $\sigma(T_{obs})$ are standard deviation of observed rainfall and temperature values, and $\sigma(R_{uncor,m})$ and $\sigma(T_{uncor,m})$ are the standard deviation of model uncorrected rainfall and temperature values, and $(\triangle\, x)$ is a average daily difference of observed and modelled values.

2.5 Simulated Climate Variability in Rainfall and Temperature (2020–2040)

Daily temperature and rainfall values for the years 1981–2015 (baseline), as well as for 2020, 2030, and 2040, were derived from the NEX-GDDP dataset. Monthly correction factors, developed using data from 2001 to 2015, were applied to reduce biases in the NEX-GDDP projections for the future years (2020, 2030, and 2040). To evaluate the potential impacts of climate change, comparisons were conducted between baseline and projected future values of temperature and rainfall.

2.6 Determination of Irrigation Water Requirement under Changing Climate

In this study, the CROPWAT 8.0 model is utilized to estimate the water requirement for rice. Previous research has demonstrated that CROPWAT 8.0 is a reliable tool for determining crop water requirements (CWR). Developed by the FAO in 1990, CROPWAT 8.0 is designed to support the planning and management of irrigation projects. It is an effective tool for analyzing the complex interactions between various farm parameters, including soil, crop, and climate, to determine CWR. The model consists of five input modules: climate, rainfall, crop, soil, and cropping pattern. The climate data required include maximum temperature (Tmax), minimum temperature (Tmin), wind speed (u), relative humidity (RH), and sunshine hours. To calculate reference evapotranspiration (ET0), the CROPWAT 8.0 model employs the FAO Penman-Monteith formula.

$$ET_0 = \frac{0.408(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)} \qquad \ldots(5)$$

where,

ET_0 = Reference evapotranspiration (mm day^{-1})

R_n = Net radiation at the crop surface (MJ m^{-2} day^{-1})

e_s = Saturation vapour pressure (kPa)

e_a = Actual vapour pressure (kPa)

(e_s- e_a) = Saturation vapour pressure deficit (kPa)

Δ = Slope vapour pressure curve (kPa °C^{-1})

γ = Psychrometric constant (kPa °C^{-1})

G = Soil heat flux density (MJ m^{-2} day^{-1})

T = Air temperature at 2 m height (°C)

U_2 = Wind speed at 2 m height (m s^{-1})

The water requirement for rice was calculated by multiplying the crop coefficient (Kc) with the reference evapotranspiration (ET0), along with an additional component to account for puddling, as suggested by Kung (1971). The irrigation water requirement (IWR) for rice was then estimated by factoring in the effective rainfall specific to the location, assuming an irrigation efficiency of 60% (FAO, 2007).

$$IWR = (ET_c - ER) \times (\text{irrigation efficiency}) \qquad \ldots(6)$$

In the present study, the USDA Soil Conservation Service (SCS) method (Smith, 1991) is used for computation of effective rainfall (ER) The salient details of the rice crop and sandy loam soil for the study are taken are as per FAO.

2.7 Evaluating Climate-Induced Variability in Irrigation Demand

CROPWAT 8.0 software was employed to evaluate the impact of climate change on the crop water requirement (CWR) for rice in the Chandauli district. Future projections of temperature and rainfall for the years 2020, 2030, and 2040 were obtained using the NEX-GDDP dataset and used as input weather data in the CROPWAT 8.0 model. As noted by Shahid (2009), rising temperatures in the future are expected to significantly contribute to increased reference evapotranspiration (ET0). Therefore, in this study, only temperature changes were considered for calculating future crop evapotranspiration (ETc), while other climatic parameters such as wind speed, relative humidity, and sunshine hours were assumed to remain constant at baseline values. By inputting climate, rainfall, soil, and crop data, the model was used to analyze changes in effective rainfall and irrigation water requirements (IWR) for the years 2020, 2030, and 2040.

3. RESULTS AND DISCUSSION

3.1 Appraisal of NEX-GDDP dataset

Observed daily temperature and rainfall data from 1981 to 2015 were used as the reference dataset to evaluate the performance of the NEX-GDDP model. The correlation coefficient, root mean square error (RMSE), and percent bias (Pbias) for this evaluation are presented in Table 03. The correlation between the observed and NEX-GDDP data was stronger for temperature variables—0.880 for maximum temperature (Tmax) and 0.872 for minimum temperature (Tmin)—but notably weaker for rainfall, which showed a correlation of only 0.212. The lower correlation for rainfall may be attributed to its irregular temporal and spatial distribution, as noted by Mooley et al. (1984). Similarly, Andreasson et al. (2004) observed that model biases are more significant for rainfall than for temperature. The RMSE values were found to be 3.197°C for Tmax, 3.757°C for Tmin, and 12.301 mm for rainfall. The Pbias between observed and modeled data was calculated at 3.92% for Tmax, 1.88% for Tmin, and 11% for rainfall.

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Table 02: Evaluation of model dataset

Statistical matrices	Observed & model data
T_{max} (˚C)	
Correlation coefficient	0.880
RMSE	3.197 ˚C
Pbias	3.92%
T_{min} (˚C)	
Correlation coefficient	0.872
RMSE	3.757 ˚C
Pbias	1.88%
Rainfall (mm)	
Correlation coefficient	0.212
RMSE	12.301 mm
Pbias	-11%

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3.2 Bias correction in the NEX-GDDP dataset

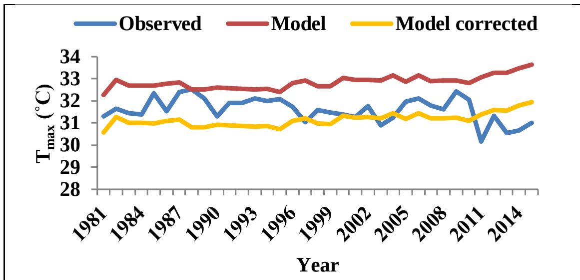
To develop an appropriate correction function, two bias correction methods—linear scaling (LS) and the modified difference approach—were compared. The linear scaling method significantly improved the Pbias values, bringing the model-simulated temperature data closer to the observed values. Specifically, the Pbias for maximum temperature (Tmax) improved from 3.92% to -1.43%, and for minimum temperature (Tmin), it improved from 1.88% to 0.33% (Table 04). The differences in mean and standard deviation between the observed and corrected model data were also reduced compared to those between the observed and uncorrected model data (Table 04). For rainfall, the correction functions based on the LS method showed a reduction in the difference of mean and standard deviation values between corrected and observed datasets (Fig. 2). The Pbias for rainfall improved from -11% to -2.4% (Table 04).

Monthly correction functions for Tmax and Tmin were developed using the modified difference approach to align the model-simulated data with the observed values. However, the results indicated that this method did not significantly improve the model output, as illustrated in Fig. 02. The Pbias for Tmax increased from 3.92% to 6.47%, and for Tmin, it rose from 1.88% to 2.40% (Table 04). For rainfall, the Pbias improved marginally, shifting from -11% to -7% (Table 04). It was observed that the linear scaling (LS) method produced greater reductions in discrepancies between observed and corrected model values for Tmax, Tmin, and rainfall. Therefore, the LS-derived correction factors were used for bias correction of the future climate dataset. Similar findings were reported by Dar et al. (2017), who noted the superior performance of the LS method over the modified difference approach. Kaur et al. (2015) evaluated statistical bias correction methods and found that the modified difference approach was more effective than the simple difference method at the monthly scale. In a comparative study of six bias correction techniques, Chen et al. (2013) concluded that distribution-based methods (such as daily translation, daily bias correction, empirical quantile mapping, and gamma quantile mapping) outperform mean-based approaches like linear scaling and the local intensity method.

Table 03: Statistical analysis of observed, model, and model corrected Tmax, Tmin, and rainfall by linear scaling method and modified difference approach

Parameters	Observed	Model	Linear scaling	Modified approach
		T_{max} (˚C)		
Mean (µ)	31.60	32.84	31.14	33.64
Standard deviation (σ)	6.20	5.34	5.75	5.93
Pbias (%)	--	3.92	-1.43	6.47
		T_{min} (˚C)		
Mean (µ)	19.57	19.94	19.63	20.04
Standard deviation (σ)	7.65	6.62	6.78	7.59
Pbias (%)	--	1.88	0.33	2.40

Rainfall (mm)				
Mean (μ)	2.74	2.43	2.67	2.44
Standard deviation (σ)	12.41	4.65	4.94	4.71
Pbias (%)	--	-11	-2.4	-7.0



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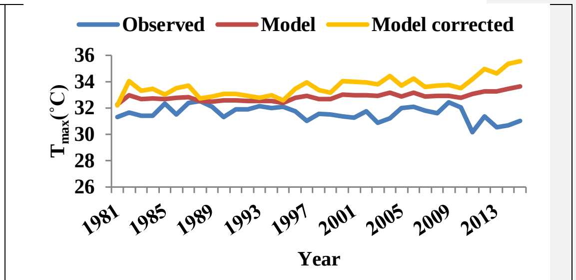

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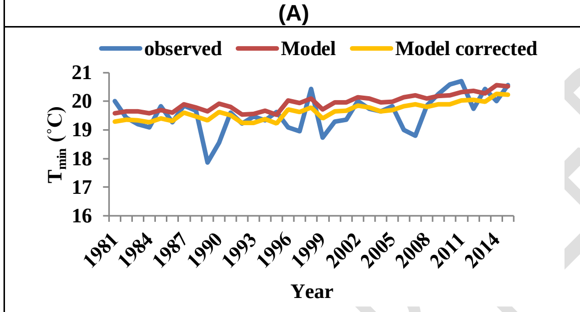

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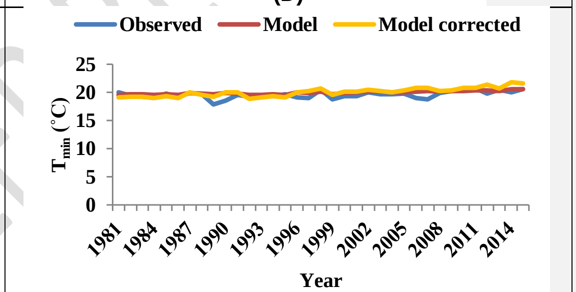

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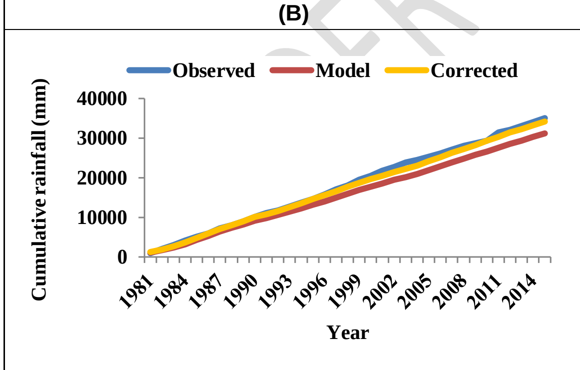

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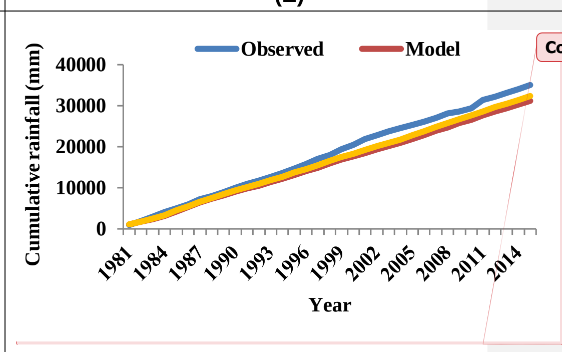

(F)

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Fig.2 Observed, model, and model corrected (A)maximum temperature (B) minimum temperature (C) Cumulative rainfall by linear scaling method and model corrected (D)maximum temperature (E) minimum temperature (F) Cumulative rainfall by modified difference approach

3.3 Future climate scenarios

Future projection of NEX-GDDP dataset for the Chanduali district suggest a rise in minimum and maximum temperature both. A steady increase in T_{max} and T_{min} has estimated by model. Analysis showed an increase in T_{max} of 0.58˚C, 0.84˚C and 1.42˚C in 2020, 2030, & 2040 respectively as compare to baseline (Fig.03). For T_{min} an increase of 0.8˚C in 2020, 1.37˚C in 2030, and 2˚C in 2040 was predicted by model as shown in Fig. 04. In case of rainfall no particular trend followed by model. Model predicteda reduction in rainfall of 123 mm in 2020 but an increase in rainfall of 223 mm in 2030 and 88.75 in 2040 was predicted by model (Fig 04). Projected T_{max}, T_{min} and rainfall during the irrigation month in a year 2020, 2030, and 2040 are presented in Table 04. These T_{max}, T_{min} and rainfall value are used to estimate change in ET_c and IWR. Kumar et al.,(2010) reported in India historical temperature is continuously increasing but rainfall is trendless. At the end of 21st century average temperature is projected to elevate by 3 to 6˚C and future rainfall may be higher by 15 to 40% from baseline period (1961-90) (IPCC, 2007).

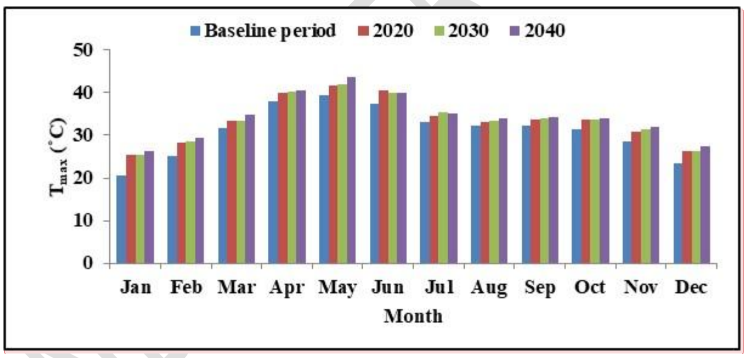

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Fig. 03: Comparison of T_{max} during baseline and future for the year 2020, 2030, & 2040

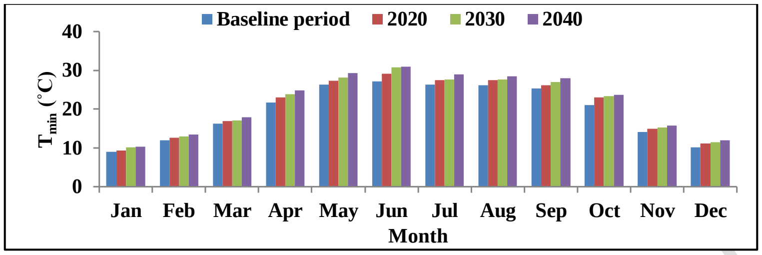

Fig.04: Comparison of T_{min} during baseline and future for the year 2020, 2030, & 2040

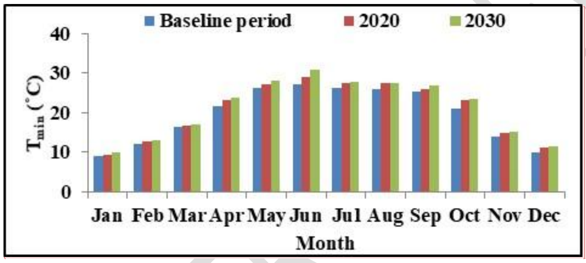

Fig.05: Comparison of rainfall during baseline and future for the year 2020, 2030, & 2040

3.4 Estimation of Irriagtion water requirement (IWR)

The irrigation water requirement (IWR) for rice cultivation in Chandauli district was estimated using the CROPWAT 8.0 software. Monthly average rainfall and temperature data from the baseline period (1981–2015) were utilized for this purpose. The average seasonal crop water requirement (CWR) and irrigation water requirement were calculated to be 860.5 mm and 380.9 mm, respectively, assuming an irrigation efficiency of 60%. It was observed that evapotranspiration (ETc) losses were highest during the early growth stages of rice, as this period demands significant water input to support critical physiological functions. Inadequate water supply during this stage can adversely impact crop yield. Therefore, efficient irrigation strategies that enhance water productivity should be promoted. Ramesh et al. (2019) reported average seasonal rice water requirements of 383.3 mm and 403.8 mm for Lakhimpur Kheri and Sitapur districts, respectively. Crops cultivated under hot and sunny climatic conditions typically have higher daily water demands compared to those grown in cooler environments. Dar et al. (2017) estimated an average seasonal IWR of 1495.3 mm for rice in Ludhiana district. Similarly, Banerjee et al. (2016) found that a temperature rise of 2°C and 3°C led to an increase in the IWR for potato crops by 0.06 mm/day and 0.16 mm/day, respectively, in the lower Gangetic plains. Chatterjee et al. (2012) also projected a 7–8% increase

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in potato IWR by 2020, which could rise to approximately 14–15% by 2050 in the Ganga River Basin, West Bengal.

3.5 Impact Analysis of Changing Climate Conditions

3.5.1 Evapotranspiration

Evapotranspiration (ET) represents a significant component of water loss within the water balance system. In this study, ET losses for rice crops were estimated using the CROPWAT 8.0 model for both the baseline period and projected future years—2020, 2030, and 2040. During the baseline period (1981–2015), the monthly reference evapotranspiration (ET_0) ranged between approximately 65.72 mm and 276.12 mm. The lowest ET_0 occurred in January (65.72 mm), while the highest was recorded in May (276.12 mm). A gradual increase in ET_0 was observed from January, peaking in May, followed by a steady decline to around 72.54 mm in December. A comparison of baseline and future ET_0 values indicated projected increases of 6.2%, 6.8%, and 8.8% in the years 2020, 2030, and 2040, respectively, as illustrated in Fig. 06. Similar findings were reported by Singh et al. (2020), where maximum ET_0 occurred in May and the minimum in January. The observed increase in ET_0 during sunnier months can be attributed to elevated temperatures, stronger winds, and lower relative humidity levels.

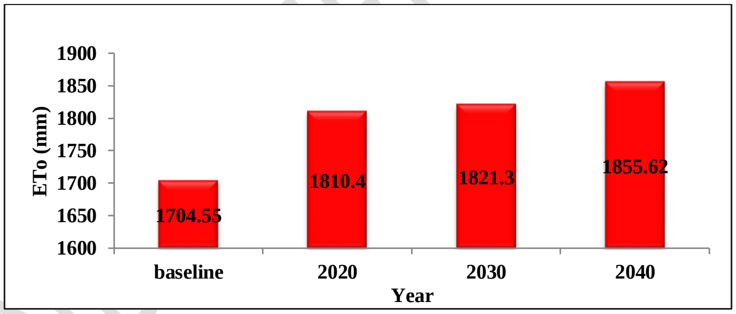

Fig. 06: ET. From base line to projected period

3.5.2 Effective rainfall

In this study, the USDA Soil Conservation Service (SCS) method is used for the determination of ER for baseline and future period for the year 2020, 2030, & 2040 over the Chanduali District. This will be helpful in estimation of IWR of rice crop for the same area. Results suggested that for the baseline period the maximum and minimum ER would be in the month of July (153 mm) and December (0.9 mm). It has found that in future, maximum ER would be in July in 2020 (153 mm), 2030 (159.4 mm), 2040 (161.3 mm) and minimum ER would be in December in 2020 (0 mm), 2030 (0 mm)& 2040 (0 mm).Effective rainfall would not follow a particular trend in future. The average value of ER will decreased from 69 mm in 2020, then increased by 223 mm in 2030, and again decreased by 12.4 mm in 2040 as shown in Fig.07. Numerous studies relating to rainfall changing pattern over India have observed large variation in rainfall over the century (Mooley *et al*., 1984). Obtained results are in line with previous studies. Singh *et al.,* (2019) estimated ER using USDA-SCS method over Buxer district in Bihar and found maximum ER in August (153.8 mm) and minimum in December (3 mm). Singh *et al.,* (2020) used the USDA-SCS method to calculate ER and found maximum and minimum ER in the month of July (143 mm) and December (22.3 mm) respectively over Dehradun district.

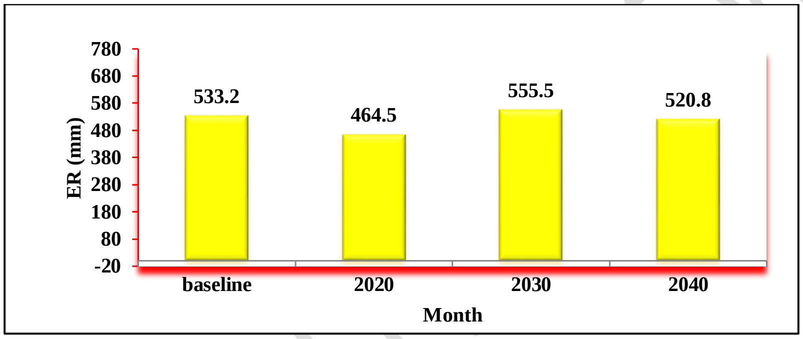

Fig. 07: Effective rainfall for projected month

3.6 Irrigation water requirement (IWR)

Using weather data from the Chandauli region, irrigation water requirements (IWR) were estimated for the baseline period (1981–2015) and projected for the years 2020, 2030, and 2040. In Chandauli district, rice is typically grown from mid-July to mid-November, with a growth duration ranging from 105 to 110 days. The average irrigation demands for different years are illustrated in Fig.08. The results indicate that the IWR for rice does not follow a consistent trend over time. The average IWR is projected to rise from 380.9 mm during the baseline period to 455.5 mm in 2020, followed by a decrease to 345.3 mm in 2030, and then a slight increase to 369.7 mm by 2040. This fluctuation is likely attributed to variations in future effective rainfall. Similar trends in rice water demand have been reported by other researchers (Shahid et al., 2011). Rising temperatures are expected to increase evaporation and transpiration rates, thereby impacting IWR. According to Kumar et al. (2017), the water requirement for paddy during the growing period ranges between 546 mm and 660 mm. The findings of this study align with that range, with simulated water requirements for rice falling between 620.5 mm and 652.5 mm. Recent research also highlights that shifts in temperature and precipitation patterns can substantially affect irrigation demands.

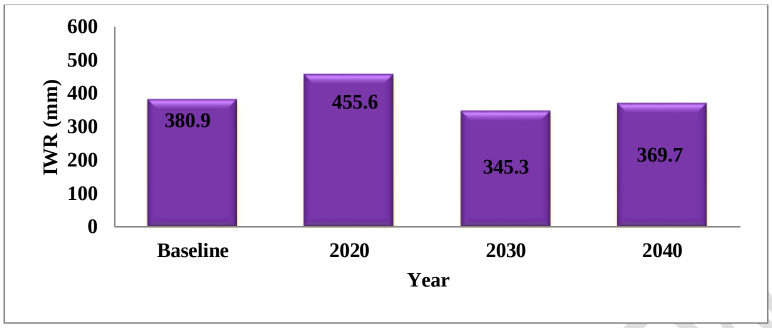

Fig. 08: Irrigation Water Requirment for projected period

Table 4: Simulated reference evapotranspiration (ET$_0$), effective rainfall (ER), crop water requirement (CWR) and irrigation water requirementof rice crop in Chanduali district during baseline period and future for the year 2020, 2030, and 2040

Parameters	Baseline (1981-2015)	Future		
		2020	2030	2040
Reference evapotranspiration (mm)	1704.55	1810.4	1821.3	1855.62
Effective rainfall (mm)	533.2	464.5	555.5	520.8
Crop water requirement (mm)	860.5	885.4	889.5	892.5
Irrigation water requirement (mm)	380.9	455.6	345.3	369.7

4. CONCLUSION

This study presents a comprehensive assessment of the potential impacts of climate change on the irrigation water requirement (IWR) of rice in Chandauli district, Uttar Pradesh, using statistically downscaled projections from the NEX-GDDP dataset under the RCP 4.5 scenario. Climate variables, including daily maximum and minimum temperatures and rainfall, were analyzed for the baseline period (1981–2015) and projected future periods (2020, 2030, and 2040). Model validation against observed data showed strong agreement for temperature (r = 0.85), while rainfall exhibited lower correlation (r = 0.18), likely due to its inherent spatial and temporal variability.

To improve the reliability of model outputs, two bias correction techniques—Linear Scaling (LS) and Modified Difference Approach (MDA) were applied and evaluated. The LS method proved more effective in minimizing biases and was thus employed for correcting future projections. These corrected datasets were then used in the CROPWAT 8.0 model to simulate reference evapotranspiration (ET_0), crop water requirement (CWR), and IWR for rice cultivation. Findings indicate a projected increase in maximum and minimum temperatures by 1.42°C and 2.0°C, respectively, by 2040. This rise in temperature is expected to increase ET_0, thereby elevating crop water demand. The seasonal CWR is anticipated to rise by 3.7% by 2040 compared to the baseline, with the highest water requirement observed in July—coinciding with peak evapotranspiration and critical crop growth stages. However, the IWR does not follow a uniform trend, largely due to projected variability in effective rainfall across future periods. These fluctuations underline the importance of localized water management strategies.

The outcomes of this study provide crucial insights for agricultural planning under changing climatic conditions. The results underscore the need for adaptive water resource management strategies, such as the development of on-farm water storage systems, efficient irrigation scheduling, and soil moisture conservation techniques, particularly for water-intensive crops like rice. These measures will be essential for sustaining crop productivity and ensuring water security in the face of future climate variability. The findings can serve as a scientific foundation for policymakers and stakeholders in designing region-specific climate-resilient agricultural practices.

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