



Impact of climate change on crop water and irrigation requirements over eastern Himalayan region

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Accepted: 19 November 2020 / Published online: 2 January 2021
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Abstract

Due to climate change, the agricultural and socio-economic development over the eastern Himalayan region of India is greatly affected. The present study has been carried out to investigate the implications of climate change on regional crop water requirements (CWR) and crop irrigation requirement (CIR) of major crops (maize, wheat and, rice) over a Himalayan state, i.e., Sikkim. Daily climatic datasets such as rainfall, minimum temperature, maximum temperature, wind speed, sunshine hours, and relative humidity are used for this analysis along with crop and soil data. For future period (2021–2099), climatic datasets are collected from the four climate models (ACCESS1-0, CCSM4, CNRM-CM5 and MPI-ESM-LR) of CORDEX under two different scenarios, i.e., Representative Concentration Pathway (RCP) 4.5 and 8.5. CWR & CIR of maize, wheat and rice crops are projected for three-time windows, i.e. start term (2021–2046), mid-term (2047–2073), and end term (2074–2099) by taking 1998–2015 as baseline period. In addition, uncertainty and sensitivity analysis is carried out. The outcomes from the study suggest an increase in the CWR towards the end of the twenty-first century for rice and wheat over West (8% and 39%) and South (11% and 37%) Sikkim with respect to baseline period. In case of Maize, a decreasing trend is noticed over West (– 4%) and East (– 15%) Sikkim. For all the crops in East Sikkim, a declining trend is likely to occur. In most of the cases, the CIR has increased towards the end of the twenty-first century. The uncertainty analysis reveals RCP 4.5 as the possible scenario over the study area. The outcomes from the study facilitate the agricultural and water managers for adopting effective measures to ensure sustainability.

Keywords Climate change · Crop water requirement · Crop irrigation requirement · Himalayan region · Uncertainty analysis

1 Introduction

Potential changes in climate variability and its extremes are emerging as key determinants for agricultural and socio-economic development. Due to the dual pressure of climate change and growing population demand, the agricultural sector has become more vulnerable. The observed warming climate over last several decades is directly associated with the variability in the hydrological components such as

occurrence and intensity of precipitation, available soil moisture, rate of evaporation, runoff generation, and many more (Rao et al. 2011). Further, the changes in the hydrological components can be considered as one of the principal sources of fluctuation in the agricultural sector in many parts of the world affecting plant water use, crop growth, development, quantity of irrigation and productivity (Moonen et al. 2002; Todisco and Vergni 2008; Wei et al. 2014). In conjunction with the prevailing warming conditions, it has been projected an increase in the average global surface temperature by 4.8 °C by the end of twenty-first century with latitudinal variations in the precipitation pattern (IPCC 2014). Therefore, rising temperature with precipitation uncertainty has a substantial influence on future water availability and irrigation water requirement worldwide (Boonwichai et al. 2018).

India, an agrarian country, shares about 18% of the total world population and having 9% of the world's arable land.

Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s00477-020-01942-6>) contains supplementary material, which is available to authorized users.

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In addition, about 56% of its agricultural land is rainfed (Goyal and Surampalli 2018). With a limited amount of resources and in the scenario of climate change the sustainable management of the agricultural sector has become paramount importance (Jha et al. 2019) and even more challenging in the mountain regions (Das et al. 2020a). A report by the International Center for Integrated Mountain Development states a widespread increase in the warming trend about 0.01–0.04 °C per year over Eastern Himalayas (Sharma et al. 2009). Due to increasing uncertainty, the Himalayan agriculture is being impacted substantially (Das et al. 2020b). Moreover, water storage for irrigation is consistent problem due to undulated topography and rocky terrain; hence, rainfed agriculture is dominant over the hilly areas. The mountain cultivators are facing challenges and unpredictable scenarios due to climate change, which further worsen the life and livelihood of the mountain communities (Goswami et al. 2018a, b). In this sense, it is indispensable to understand the crop water demand and irrigation requirement under the climate change circumstances for effective agricultural water management in the mountain regions.

Realizing the importance of agricultural water management, in this study we have analyzed the spatio-temporal variability of the crop water requirement (CWR) and crop irrigation requirement (CIR) of different major crops under the climate change scenarios. Water required by different crops depends upon various factors such as location, atmosphere, and type of soil, valuable precipitation and techniques used for development. According to Food and Agriculture Organization (FAO), the term CWR is defined as the depth of water which is equivalent to the amount of evapotranspiration from a healthy crop under non-restricting soil conditions and given growing environment. In other words, it is the amount of water required by the crop for the optimal growth (Song et al. 2018). Over long-term, the climate variability is likely to affect agriculture in various ways, including the CWR (Todisco and Vergni 2008). Similar to the CWR, CIR indicates the extra amount of water that is supplied through irrigation for promising optimal growth condition for crop and is closely related to CWR. Moreover, the irrigation water requirements vary according to the available soil moisture condition in the soil and the balance between the precipitation and evapotranspiration (De Silva et al. 2007). Therefore, water availability and distribution under climate change will greatly affect the CIR as well. Future quantification of spatio-temporal variability of CWR and IR can improve water management efficiency. In an effort to analyze the future CWR and IR, limited studies have been carried out by the researchers from various parts of the world and the examples include but are not limited to, De Silva et al. (2007), Döll (2002), Droogers (2004), Shen et al. (2013), Shrestha et al. (2013), Song et al. (2018), Tubiello et al. (2000), Zhou et al.

(2017), among others. However, most of the studies are carried out without ascertaining the uncertainty associated with the climate models and scenarios.

Under this understanding, the present analysis incorporated CROPWAT model to estimate the CWR and CIR over the Eastern Himalayan region. The CROPWAT, as an irrigation planning and management tool, is developed by the Water and land Development Department of FAO. The CROPWAT uses the spatio-temporal heterogeneity of soil, climate, and crop inputs to compute the CWR and CIR. Over the Asian countries, the use of CROPWAT model is prominent over China and Nepal (Shrestha et al. 2013; Zhou et al. 2017; Song et al. 2018). However, over the agrarian country like India, the use of CROPWAT is limited with reference to evaluate the future changeability of CWR and CIR. In order to account the uncertainty, the past studies employed methodology such as imprecise probability (Ghosh and Mujumdar 2009), Bayesian analysis (Das and Umamahesh 2018b), sensitivity analysis (Mearns et al. 1996), among others. The present analysis adopts the possibilistic approach to assess the uncertainty associated with incomplete or partial knowledge (Zadeh 1999). However, the probability theory is adopted to the dataset with complete information. The outputs from the GCMs under different scenarios can be related to the datasets with incomplete information. The adopted technique is simple and inexpensive.

The aim of the present paper is to assess the spatio-temporal variation of the climate change impact on CWR and CIR of major crops over one of the northeastern Himalayan states, namely Sikkim. For the future projection under different possible scenarios, we have used outputs from the GCMs developed as a part of the fifth phase Coupled Model Intercomparison Project (CMIP5). The inherent bias in the GCM outputs is corrected using the distribution mapping method. To the best of the authors' knowledge, evaluation of GCM and scenario uncertainty is very limited in the past studies on CWR and CIR. In addition, sensitivity analysis by shifting the crop planting periods is demonstrated to identify the implications on CWR for all the major crops. The reliable estimates of CWR and CIR of different major crops over the northeastern Himalayan region would help greatly in rational utilization of available water resources for irrigation, effective planning of irrigation schemes for water conservation and management practices.

2 Materials and methods

2.1 Study area description

The selected study site, Sikkim (Fig. 1), lies in the north-east part of Himalaya, which is landlocked by Bhutan,

Nepal and China. The study is conducted on three major areas in Sikkim namely, Gangtok (East Sikkim), Geyzing (West Sikkim), and Namchi (South Sikkim). The location map of Sikkim and digital elevation map of Sikkim is shown in Fig. 1a, c. Figure 1b represents three chosen reference locations of east, west and south Sikkim, respectively. Geographical latitudes of the study area are 27° 07' N and 28° 13' N and longitudes 88° 01' E and 88° 92' E. The altitude of Sikkim ranges from 192 m, and 7403 m above mean sea level (msl). Rainfall mainly occurs in monsoon season (May–September) with an average annual rainfall of 3300–3600 mm. Absolute maximum temperature (Tmax) and minimum temperature (Tmin) ranges from 17–24 to 9–13 °C, respectively (Deb et al. 2015).

The undulated geology and rough, rock-bounded topography of Sikkim make it difficult for agricultural practice. Yet, in spite of such impediments, farming

practices are done by changing rocky and undulated topography to agrarian land by means of terraces. Major crops grown in Sikkim are maize, rice and wheat. Although Sikkim’s economy is largely dependent on agriculture, most of cultivation is rainfed with traditional system and low-level inputs. Due to lack of adequate harnessing techniques, the total area under agriculture is not more than 11% in Sikkim. However, about 70% of Sikkim’s population depends on agricultural activity for their livelihood (Azhoni and Goyal 2018).

2.2 Data

2.2.1 Meteorological data

Meteorological datasets such as precipitation and temperature series at 0.5° × 0.5° grid resolution are obtained from India Meteorological Department (IMD) during

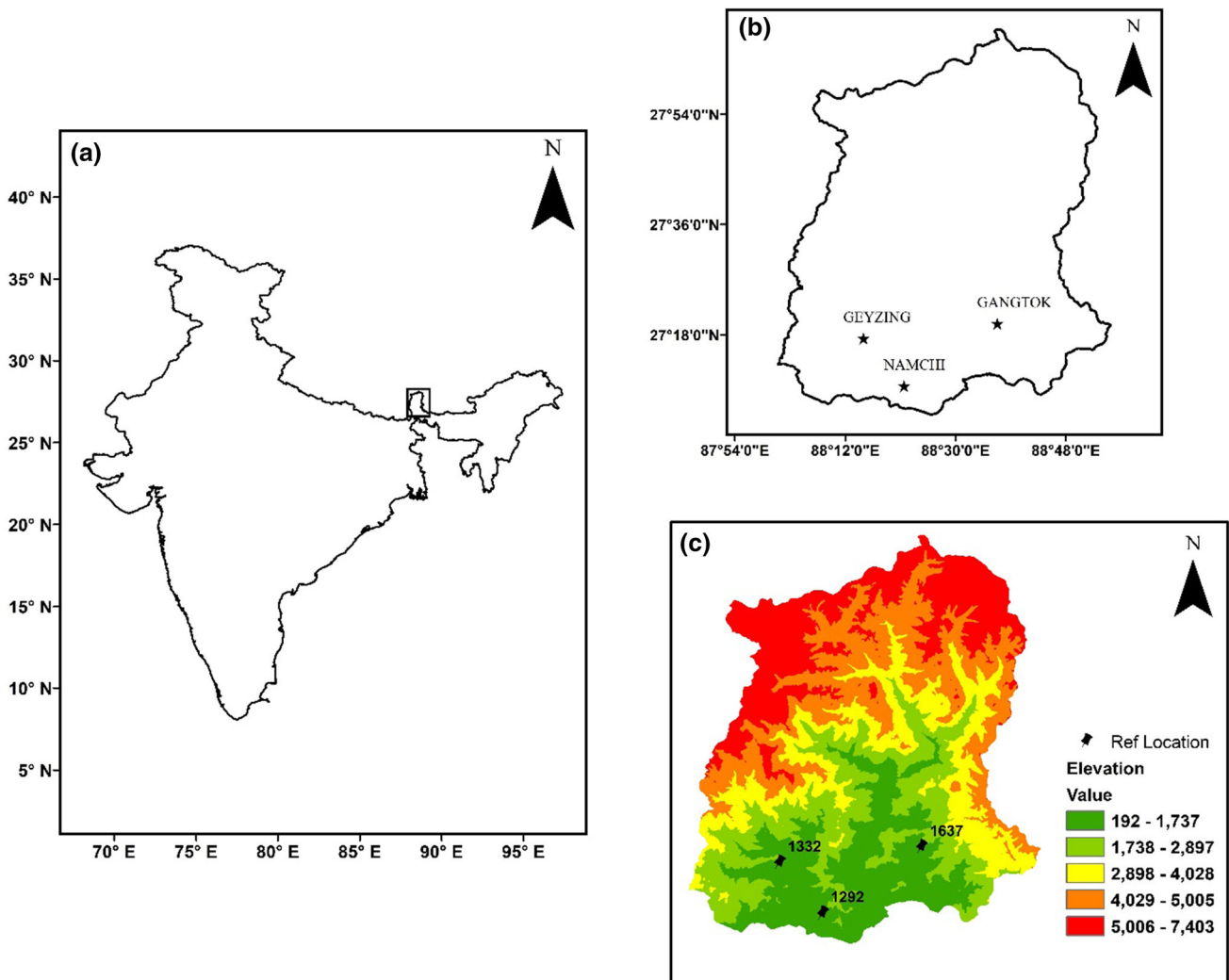


Fig. 1 Location and elevation map of the study area. **a** Sikkim map superimposed over India, **b** location of the chosen three districts over Sikkim, **c** elevation map of the Sikkim

1970–2015. The wind speed data are collected from the Terrestrial Hydrology Research Group, Princeton University website and are available at $0.5^\circ \times 0.5^\circ$ resolution (<http://hydrology.princeton.edu/getdata.php?dataid=1>). Relative humidity data are obtained from the National Center for Environmental Prediction/ National Center for Atmospheric Research (NCEP/ NCAR) re-analysis dataset (<https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.pressure.html>).

2.2.2 GCM simulated dataset

In order to understand the regional climate change and its impact in the foreseen future, Global Climate Models/General Circulation Models (GCMs) are used as most credible tools that projects different hydro-meteorological variables in future under different possible climate scenarios (Das and Umamahesh 2018a). However, the lower spatial resolution outputs from the GCM are incapable of capturing the regional information. To make up the inability of the GCMs in predicting regional climate, different downscaling techniques such as statistical and dynamic downscaling are widely adopted (Ghosh and Mujumdar 2008; Goyal and Ojha 2012; Wilby et al. 2014; Das and Umamahesh 2016, 2018a). Therefore, in order to avail the high-resolution datasets, several experimental groups help the research community in providing the datasets with regional interest.

In the present study, we have used outputs from four different GCMs under two different climate scenarios (Representative Concentration Pathways (RCP) 4.5 and 8.5) with a resolution of $0.5^\circ \times 0.5^\circ$ are downloaded from the Coordinated Regional Climate Downscaling Experiment (CORDEX) for South Asia from the Indian Institute of Tropical Meteorology, Pune (IITM) (Das and Umamahesh 2018b). To incorporate the diversity among the GCMs, we have selected four different models, namely Community Climate System Model, version 4 (CCSM4), Australian Community Climate and Earth-System Simulator version 1.0 (ACCESS1.0), Max Planck Institute for Meteorology Earth System Model LR (MPI-ESM-LR), Centre National de Recherches Météorologiques Coupled Global Climate Model, version 5 (CNRM-CM5). The future projections of the datasets (precipitation, temperature) are obtained under stabilized (RCP4.5) and high emission (RCP8.5) scenarios during 2006–2099. It is worth mentioning that historical datasets from 1970 to 2005 from all the models are downloaded to incorporate bias-correction in the datasets.

2.3 Research methodology

To accomplish the motive of the study, the proposed methodology is briefly presented in the form of a

flowchart (Fig. 2). The meteorological datasets, namely, precipitation, maximum and minimum temperature, relative humidity, and wind speed for the historical period are collected. The reference evapotranspiration (ET_0) is computed using the Penman–Monteith method. Based on the observed historical data, the inherent bias in the outputs from the GCMs are corrected and applied for the future simulation (2006–2099) for two different scenarios. Next, the CWR and IR are computed using the crop coefficient for different major crops over three different locations over the Sikkim using the bias corrected future simulations. To ascertain the GCM and both GCM and scenario uncertainty, we have adopted possibilistic approach. In addition, we have also considered the multiple model ensemble method to minimize the uncertainty. Subsequently, sensitivity analysis is carried out through shifting the growing periods of different major crops under different possible climate change scenarios.

2.3.1 Bias correction

Although GCMs are used as a major tool to evaluate climate change, a robust assessment of climate change impact requires unbiased input (Maraun 2016). The high-resolution outputs from the GCMs are associated with substantial deviations from the actual data due to the random and systematic errors (Teutschbein and Seibert 2013). In order to bridge the gap between the simulated and observed variables, bias correction is indispensable. In the present analysis, distribution mapping is used to correct the bias in precipitation and temperature datasets. In other words, distribution mapping is also known as quantile-quantile mapping (Johnson and Sharma 2011), probability mapping (Block et al. 2009), and histogram equalization (Rojas et al. 2011). In order to correct the bias in precipitation and temperature series, gamma and Gaussian distributions are used, respectively. The gamma distribution (Thom 1958) has been proven to be suitable for precipitation analysis (Block et al. 2009; Piani et al. 2010). Similarly, the gaussian distribution (Cramér 1999) is generally assumed to be best fit for temperature analysis (Schoenau and Kehrig 1990). The motive of distribution mapping is to correct the probability distribution function of the model simulated series to match the distribution of observed series. In this study, cumulative distribution functions (CDFs) are obtained for both the baseline and GCM-simulated historical values for all the days within a certain month. Next, the value of the GCM-simulated variables, i.e., temperature/precipitation of day d within month m is investigated on the empirical CDF of the GCM simulations along with its corresponding cumulative probability. Subsequently, the value of temperature/precipitation corresponds to the same cumulative probability is located on the empirical CDF of

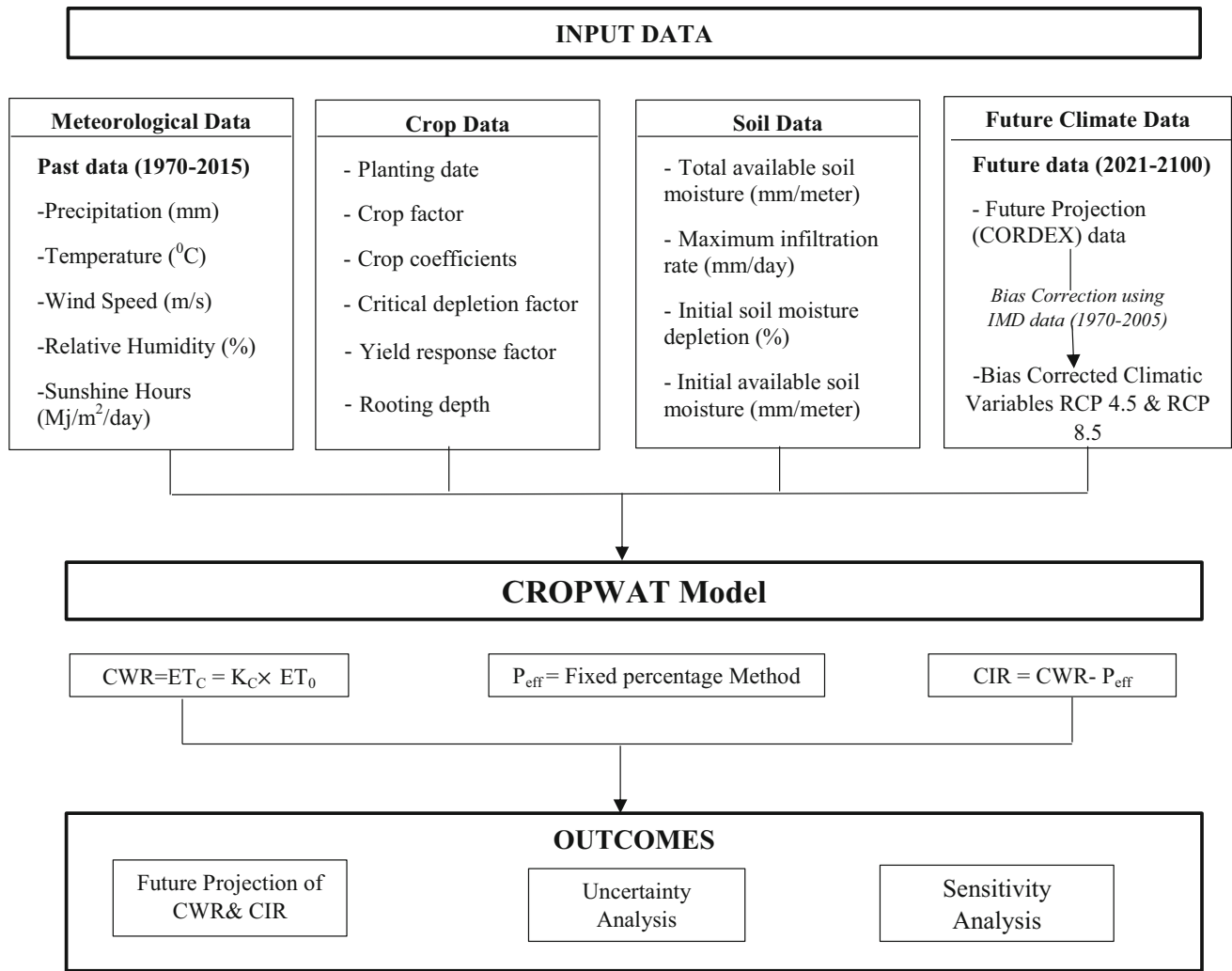


Fig. 2 Flow chart of the proposed methodology

observed dataset. Lastly, this value is considered as corrected value during the baseline period for the GCM simulation. This procedure is performed using gamma distribution for precipitation and Gaussian (normal) distribution for temperature. The equations used to correct precipitation and temperature series are presented in Eqs. 1 and 2 (Teutschbein and Seibert 2012). Based on these corrections, the future projected datasets of multiple GCMs are corrected before analyzing the impact of climate change on crop water requirement and irrigation requirement.

$$\begin{aligned}
 P_{con}^*(d) &= F_{\gamma}^{-1}(F_{\gamma}(P_{con}(d)|\alpha_{con,m}, \beta_{con,m})|\alpha_{obs,m}, \beta_{obs,m}) \\
 P_{fut}^*(d) &= F_{\gamma}^{-1}(F_{\gamma}(P_{fut}(d)|\alpha_{con,m}, \beta_{con,m})|\alpha_{obs,m}, \beta_{obs,m})
 \end{aligned}
 \tag{1}$$

$$\begin{aligned}
 T_{con}^*(d) &= F_N^{-1}(F_N(P_{con}(d)|\mu_{con,m}, \sigma_{con,m}^2)|\mu_{obs,m}, \sigma_{obs,m}^2) \\
 T_{fut}^*(d) &= F_N^{-1}(F_N(P_{fut}(d)|\mu_{con,m}, \sigma_{con,m}^2)|\mu_{obs,m}, \sigma_{obs,m}^2)
 \end{aligned}
 \tag{2}$$

Different symbols and notation used in Eqs. 1 and 2: con—control period (GCM simulated under baseline period, i.e., 1970–2005); fut—future; obs—observed; (d)—daily; m—monthly interval; P—precipitation; T—temperature; γ —Gamma distribution; N—Normal distribution; α and β —shape and scale parameter of the Gamma distribution; μ and σ —location and scale parameters of the Gaussian distribution; *—denotes bias-corrected. For example, before and after bias correction of precipitation, maximum and minimum temperature during the baseline period for the reference location over South Sikkim (Namchi) is presented in Fig. 3 as quantile–quantile plot for MPI-ESM-LR model. In can be noted from the figure that different

meteorological series has been significantly improved as compared to the observed dataset after removal of the bias.

2.3.2 CROPWAT model

The crop water requirement varies extensively and is affected by types of crop, properties of soil, weather conditions, etc. The amount of water lost by the crop represents by the crop evapotranspiration (ET_c) and CWR represents the extra amount of water that has to be supplied for growth of crop. In the present study, CROPWAT model is used to compute the CWR for different major crops over Sikkim. According to Smith et al. (2002), the model requires less number of input datasets as compared to the other models. The model uses Penman–Monteith method (Eq. 3) to compute ET_o , crop evapotranspiration and irrigation requirement (Smith 1991; Allen et al. 1998). At present, there are different methods that are being used to compute the CWR in water resources research. For instance, the Blaney–Criddle, Penman–Monteith, radiation, and pan evaporation methods are commonly used to compute CWR for different crops. Moreover, the choice of methods is based on the precision required to compute the water needs and availability of climatic datasets. Due to the excellent performance and inclusion of physical theory in computation, Penman–Monteith method is widely used (Pereira et al. 2015). In addition, this method offers minimum percentage of error as compared to the other method, i.e. $\pm 10\%$ in summer and up to 20% under low evaporative condition (Doorenbos and Pruitt 1977). Therefore, in the present paper, we have used Penman–Monteith method to analyze spatio-temporal variability of CWR for different major crops. To do so, CROPWAT, which has been highly recommended by FAO to better estimate of CWR under different climate change scenarios (Smith 1992), is used.

$$ET_o \text{ (mm/day)} = \frac{0.408\Delta(R_n - G) + \gamma \times \frac{900}{T+273} \times U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (3)$$

where Δ is the slope of the saturation vapor pressure temperature relationship (KPa/°C); R_n is the net radiation at the crop surface (MJ/m²/day); G is soil heat flux density (MJ/m²/day); γ is psychrometric constant (KPa/°C), U_2 is the measured wind speed at 2 m height (m/s); e_s and e_a are saturation and actual vapor pressure in KPa, respectively; T is the mean daily air temperature (in °C).

The model requires different input data modules, namely, climate data, crop data, soil data, and crop pattern data. The climate data include precipitation, temperature (minimum and maximum), windspeed, relative humidity, sunshine hours, etc. In the absence of relative humidity and sunshine hours, CROPWAT can estimate ET_o using latitude, longitude, altitude, maximum and minimum temperature of location. Similar to the climate data, the crop data such as maximum rooting depth, crop description, crop factor, rooting depth, growing days, etc. are needed. The crop development stages with different crop properties are mentioned in Table 1. The soil properties, namely, soil moisture availability, maximum infiltration rate, maximum rooting depth and initial soil moisture depletion are given as inputs to CROPWAT model. Loamy soil is more dominated in the study area. The soil and crop data are collected from the literature (Deb et al. 2015; Dubey and Sharma 2018; Allen et al. 1998). The CWR is computed using Eq. 4.

$$ET_c = K_c \times ET_o \quad (4)$$

where K_c is the crop coefficient that depends on various factors like soil, crop height, albedo, wind speed and its direction, etc. Moreover, K_c varies for the types of crop and growing stages of crop.

To compute the crop irrigation requirement (CIR), effective rainfall ($P_{\text{effective}}$) is computed based on the fixed

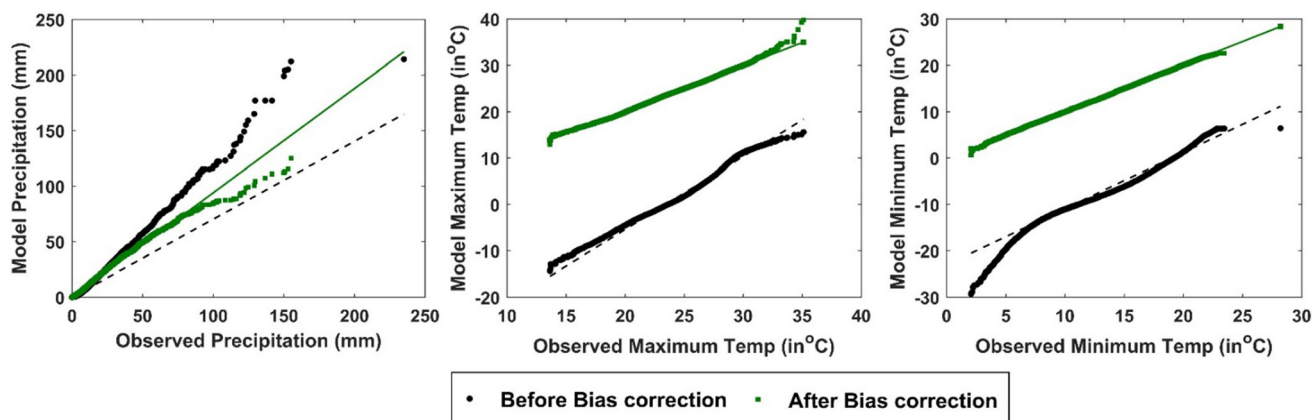


Fig. 3 Before and after bias-correction of precipitation, maximum and minimum temperature over South Sikkim for MPI-ESM-LR

Table 1 Crop development stages of maize, rice and wheat

Crop & it's characteristics	Initial	Crop development	Mid-season	Late	Total	Sowing date
<i>Maize</i>						
Stage length days	20	35	40	30	125	April–May
Root depth	0.3	>>	>>	1		
Crop coefficient	0.4	–	1.2	0.5	–	
Yield response factor	0.4	0.4	1.3	0.5	1.25	
<i>Rice</i>						
Stage length days	30	40	35	20	125	July–August
Root depth	0.1	>>	>>	0.6		
Crop coefficient wet	1.7	–	1.7	0.4	–	
Crop coefficient dry	0.5	–	1.05	0.7	–	
Yield response factor	1	1.09	1.32	0.5	1.1	
<i>Wheat</i>						
Stage length days	15	25	50	30	120	October–November
Root depth	0.3	>>	>>	1.2		
Crop coefficient	0.3	–	1.15	0.4	–	
Yield response factor	0.2	0.65	0.55	0.1	1.05	

percentage method. In Indian condition, it is advised to consider 50–80% of the total rainfall as effective (Dastane 1974). In the present study, we have chosen 65% as effective precipitation considering the undulated topography of the study area. The amount of irrigation requirement is calculated by subtracting estimated effective rainfall from calculated crop water requirement (Eq. 5).

$$CIR = CWR - P_{effective}. \tag{5}$$

2.3.3 Linear trend analysis

To identify the linear trend in the CWR and CIR time series, we have used a non-parametric method named as Sen’s slope estimator proposed by Sen (1968). This method computes the slope of the trend and the corresponding intercept of the time series. The slope of the time series is computed by using Eq. 6.

$$S = \frac{y_j - y_k}{j - k}, \quad \text{for } j = 1, \dots, n - 1, n; \quad k = 1, \dots, j - 1 \tag{6}$$

where S is the slope, y_j and y_k are the data points at time j and k where ($j > k$). With total number of data points n, the possible slope estimates can be $n(n - 1)/2$ (Zaifoğlu et al. 2017). After computing all the possible slope values, the values of S are ranked in an increasing order. If the total count of slope is an odd number, then the middle value of will be the median of slope otherwise the median value will be the mean of the two values at the center.

2.3.4 Uncertainty analysis

Climate change impact assessment is carried out at a regional scale and impact estimation at finer spatial scales is burdened with a substantial amount of uncertainty resulting from several sources (Mujumdar and Ghosh 2008). In addition, due to the availability of several climate models and scenarios, there is always existence of uncertainty in climate change impact analysis (Najafi and Heshami Kermani 2017). Due to the uncertainty that is involved in climate modelling, the outputs cannot be used directly for proposing different adaptation strategies and decisions (Pielke and Wilby 2012; Huth 2004) characterized different level of uncertainty such as (1) scenario uncertainty, (2) GCM uncertainty, (3) due to downscaling methods, and (4) different realizations of a single GCM due to parameter uncertainty (intramodel uncertainty). In the present study, we have analyzed the GCM and scenario uncertainty using possibility theory. Here, the possibility approach is based on the capability of the climate model and scenario to simulate CWR and IR in the prevailing climate changing scenario over different parts of Sikkim. The mathematical expression of the possibility theory can be presented as

$$\prod_X(x): \Omega \rightarrow [0, 1]. \tag{7}$$

If $x = 0$ represents $X = x$ is not possible, whereas, $x = 1$ denotes $X = x$ is possible without any restriction. The restriction refers to the absence of any value other than x that X can take with high possibility. According to the

normalization property, there must be one \tilde{x} such that $\prod_X(\tilde{x}) = 1$ (Spott 1999). A detailed presentation of the possibility approach is given in Das et al. (2018), Mujumdar and Ghosh (2008) and the interested readers are advised to follow the publications for better understanding. In the present study, the uncertainty analysis using possibilistic approach is performed by considering climate change evidence in the recent past, i.e., 2006–2015. Therefore, uncertainty related to GCMs and scenario is evaluated during this period. The CWR and IR computed using the observational datasets are considered as historical observation of CWR and IR during 2006–2015. Next, the bias corrected model simulations during the recent past are used to compute CWR and IR under different climate change scenarios. The performance index (C) is calculated to assess the performance of the model simulated CWR and CIR with historical CWR and CIR using Eq. 8.

$$C = 1 - \frac{\sum_t (CWR/CIR_{obs(t)} - CWR/CIR_{sim(t)})^2}{\sum_t (CWR/CIR_{obs(t)} - CWR/CIR_{obs})^2} \quad (8)$$

According to the normalization property, the possibility value for a particular GCM and scenario is computed by dividing the largest C value with computed C values of that GCM and scenario.

3 Results and discussion

3.1 Precipitation and temperature variability

The quality of the meteorological outputs from the GCMs are improved significantly after the bias-correction and the annual variation in the precipitation and temperature for baseline and future projected period under both climate change scenarios for the east, west and south Sikkim is presented in a Supplementary information under Figure S1. The shaded area represents the mean ensemble of projected future climatic variables, i.e. precipitation and temperature while solid line denotes ensemble mean under both scenarios during 2021–2099. It can be seen that annual precipitation showing a decreasing trend over West and South Sikkim, while there is no significant change over East Sikkim is observed under both scenarios. In case of temperature, increasing trend is observed in minimum and maximum temperature under both scenarios RCP 4.5 and 8.5. This variation is observed higher in high emission pathways as compared with the stabilized scenario pathways. Moreover, highest deviation in maximum temperature is observed over South Sikkim and the lowest deviation is observed in East Sikkim. However, there is no significant variability in minimum temperature observed among the three districts of Sikkim. Therefore, only

precipitation and maximum temperature variability are presented in Figure S1.

3.2 Past and future trend of CWR

This section deals with the CWR of three major crops, namely, maize, wheat, and rice over three different locations of Sikkim. The historical CWR is computed based on the observed meteorological datasets and the future projections are obtained using the bias corrected outputs from the four selected GCMs under RCP 4.5 and 8.5 scenarios. It is worth mentioning that all the supplementary figures and tables can be identified in the main text Figure S (figure number) and Table S (table number), respectively. The CWR of maize, wheat, and rice during their growth period for the baseline and future projected period for all three parts of Sikkim is presented in Figure S2 for Maize, S3 for Wheat and S4 for Rice. Moreover, the linear trend magnitude obtained from Sen's slope analysis of CWR of different crops is depicted in Figure S5.

An increasing trend of CWR for maize from 1998 to 2015 is observed for all the three parts of Sikkim and can be noted from Figure S2. Further, the findings can be supported by the positive linear magnitude of slope in Figure S5(a). In future projection, a significant decreasing trend is observed for all the models under both scenarios. However, a higher decreasing trend (-0.19 to -0.35 mm/year) is observed in case of RCP 4.5 than 8.5. More interestingly, the CWR trend is likely to increase under both the scenarios for all the models over West (0.29 – 0.5 mm/year for RCP 4.5) and South (0.32 – 0.61 mm/year for RCP 4.5) Sikkim. In case of RCP 8.5 scenario, the highest change in the CWR is observed in CNRM-CM5 (1.52 mm/year) over West Sikkim and in MPI-ESM-LR (1.96 mm/year) over South Sikkim. The decrease in CWR over East Sikkim can be attributed to the future changes in the precipitation and temperature. Over East Sikkim, there is no significant change in the precipitation from the historical period as compared to the West and South. Furthermore, the temperature has not significantly increased under the climate change scenarios with respect to the past records and as compared to the other two locations. Therefore, the ET_o is not going to increase more significantly over East Sikkim resulting in less CWR.

In case of Wheat, a significant decreasing trend is noticed over West and South Sikkim for the baseline period. However, an insignificant increasing trend is observed over East Sikkim. In most of the cases, the future projections of CWR have shown an increasing trend under both the scenarios with maximum increase in case of RCP 8.5. The highest increasing rates are 0.78 , 1.61 , and 1.35 mm/year for East, West and South Sikkim, respectively. All the above-said results can be noticed under the Figure S3 and

Figure S5(b). It can be noted from Figure S4 and S5(c) that there is an increase in the CWR of rice during the baseline period. Similar to the wheat, the CWR of rice during the 2021–2099 has increased under both the scenarios for most of the cases. The highest increasing rates are 0.63, 1.54, and 3.69 mm/year for East, West and South Sikkim, respectively.

3.3 Past and future trend of CIR

The CIR of wheat and rice during the baseline and future period over three regions of Sikkim are shown in Figure S6 for wheat and S7 for rice. The Sen Slope results of a crop irrigation requirement are also shown in Figure S8. It should be noted that maize crop is considered as rainfed and hence CIR is not computed for the same.

Figure S6 demonstrates the decreasing trend in CIR for wheat crop during 1998–2015 in West and South Sikkim while the increasing trend is observed over East Sikkim. A similar trend can also be observed in Fig S8 (a). An increasing trend is observed for East and West Sikkim under RCP 4.5 and 8.5 scenarios for most of the GCMs. On the other hand, in South Sikkim although the CIR is likely to increase in future, there is no visible difference observed between RCP 4.5 and 8.5 for all GCMs except MPI-ESM-LR. The highest increasing rates are noticed as 0.77, 1.51, and 0.74 mm/year for East, West and South Sikkim, respectively.

The future projection and its linear trend are presented in Figure S7 and S8(b). An increasing trend with magnitude 0.35–1.54 mm/year and 0.73–1.84 mm/year is observed over West and South Sikkim, respectively under both scenarios. However, an insignificant linear trend of – 0.06 to 0.15 mm/year is noticed over East Sikkim under RCP 4.5 and 0.42–0.85 under RCP 8.5. The highest positive rates are obtained from ACCESS-1.0, CNRM-CM5, and MPI-ESM-LR models for East, West and South Sikkim, respectively. The decrease in CIR over East Sikkim can be attributed to the insignificant changes in the future CWR. Over East Sikkim, there is no significant change in the CWR of Rice as compared to the West and South. Therefore, the CWR is not going to increase more significantly over East Sikkim resulting in less CIR.

3.4 Uncertainty analysis of future CWR & CIR

It is important to note that the results discussed in Sects. 3.2 and 3.3 are not analyzed for the uncertainty. As uncertainty analysis in the climate change impact study is essential to minimize the errors, in the present section we are presenting the future outcomes of CWR and CIR after the uncertainty analysis using possibilistic approach as discussed in Sect. 3.4.

The performance measure C is calculated for multiple GCMs under both scenarios based on their simulation during 2006–2015. Table S1 presents the unnormalized C value to assess both GCM and scenario uncertainty. The highest C values are marked as bold in Table S1 for three major crops and districts of Sikkim. The possibility value after normalization for both scenario and GCM uncertainty is presented in Table 2.

It can be found from Table 2 that the RCP 4.5 scenario exhibits the highest possibility value (11 out of 15 cases) which implies that stabilized scenario pathway is identified as the most possible scenario for regional climate change impact assessment in our study areas for CWR and CIR. It is important to note that for other agro-meteorological variables except CWR and CIR, the possibility distribution can be different for the same region. Since the climate forcing is not very significant during the recent past (2006–2015) and therefore significant difference in GCMs output is not found between RCP 4.5 & 8.5 scenarios. The possibility value of 1 does not mean that the particular GCM and scenario projects the best climate change assessment over the study area. However, with the available GCM and scenario projections the particular selected GCM under the scenario is likely to prevail in the selected study area.

3.5 Future projection of CWR & CIR with uncertainty analysis

Future projection of CWR and CIR of different crops among three districts of Sikkim with best possible GCM and scenario is presented in Figs. 4 and 5, respectively.

The percentage change in CWR of wheat crop in the future increases from 32–39 to 23–37% over West and South Sikkim, respectively as compared to the baseline period. Whereas the percentage change is likely to decrease from – 11 to – 6% over East Sikkim during 2021–2099. In the case of maize, the CWR change is likely to decline between – 15 to – 9%, – 8 to – 4% and – 5 to 3% over East, West and South Sikkim, respectively. Similarly, the percentage increase in the projected CIR ranges from 24–58 to 20–27% over West and South Sikkim while decreasing trend from – 12 to – 5% is observed over East Sikkim during 2021–2099. On the other hand, the percentage change in the CWR of rice ranges from – 6 to – 3, – 2 to 8, to – 0.5 to 11% over East, West, and South Sikkim, respectively. However, CIR of rice crop has shown an increasing trend among the three districts of Sikkim ranges from 4–25, 2–35 to 2–36% over East, West and South Sikkim, respectively. It is worth mentioning that the future variability of the CWR and CIR primarily depends on the meteorological changeability as the constituent of the soil profile over the study area is assumed to be

Table 2 Possibility values after normalization for different crops over different regions

Crop	GCM/scenarios	ACCESS1.0		CCSM4		CNRM-CM5		MPI-ESM-LR	
		RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Maize	East Sikkim	0.86	0.59	0.47	0.89	0.55	0.89	1.00	0.63
	West Sikkim	0.87	0.46	0.59	0.56	0.96	0.62	1.00	0.73
	South Sikkim	1.00	0.50	0.81	0.90	0.97	0.75	0.46	0.72
Rice	East Sikkim	0.75	0.85	0.69	0.54	1.00	0.83	0.77	0.48
	West Sikkim	0.56	1.00	0.62	0.65	0.43	0.56	0.55	0.45
	South Sikkim	0.58	0.73	0.92	1.00	0.78	0.53	0.56	0.47
Wheat	East Sikkim	1.00	0.62	0.72	0.69	0.87	0.82	0.63	0.64
	West Sikkim	0.77	0.54	0.70	0.55	1.00	0.57	0.67	0.51
	South Sikkim	0.54	0.83	0.98	0.67	1.00	0.49	0.98	0.70
Rice CIR	East Sikkim	1.00	0.54	0.96	0.92	0.73	0.72	0.97	0.68
	West Sikkim	0.84	1.00	0.62	0.90	0.80	0.62	0.59	0.55
	South Sikkim	0.95	0.73	1.00	0.72	0.64	0.69	0.58	0.52
Wheat CIR	East Sikkim	1.00	0.75	0.86	0.51	0.83	0.96	0.88	0.71
	West Sikkim	0.53	0.92	0.55	0.73	0.78	0.53	0.84	1.00
	South Sikkim	1.00	0.58	0.73	0.82	0.73	0.62	0.58	0.55

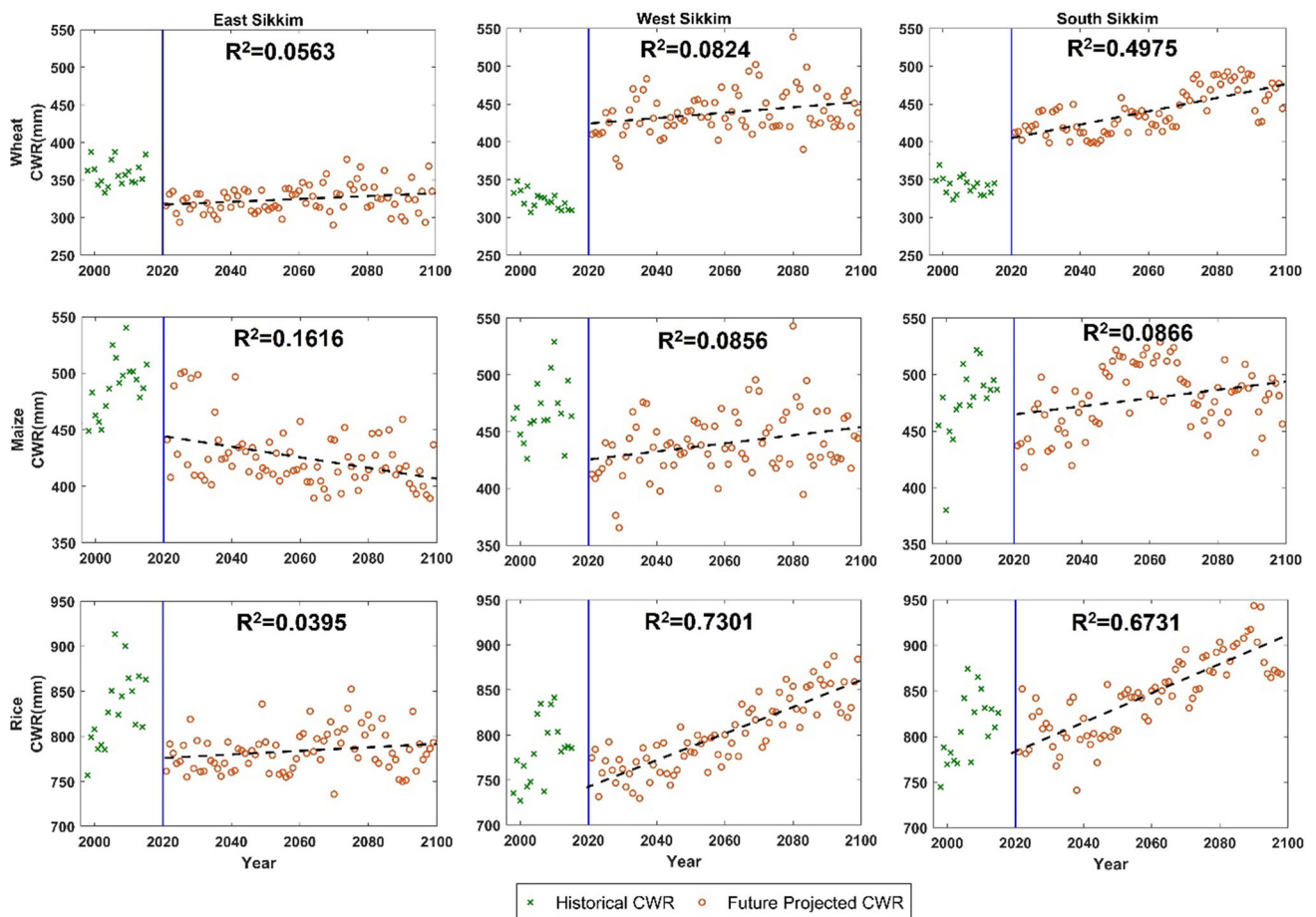


Fig. 4 Observed and future projections of CWR for different crops over East, West, and South Sikkim after GCM and scenario uncertainty analysis

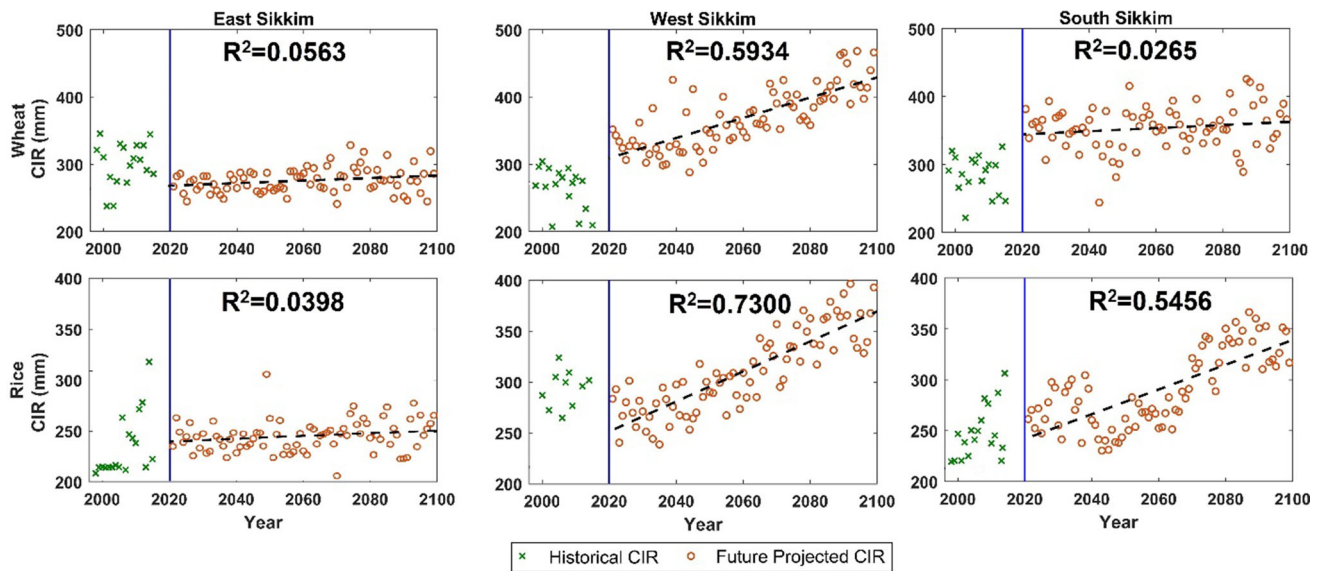


Fig. 5 Observed and future projections of CIR for wheat and rice over East, West, and South Sikkim after GCM and scenario uncertainty analysis

constant in the future period. Due to the spatio-temporal variability of meteorological variables, the soil moisture profile over the study area is likely to change resulting in variable CWR and CIR.

3.6 Sensitivity analysis

With increasing greenhouse gas emission and climate change forcings, it is necessary to find out the way for the opportunity to decrease CWR in terms of water conservation. Therefore, we have carried out sensitivity analysis by altering the growth period of different crops over three different districts of Sikkim. In Sikkim, the growing period of maize starts from mid-April. In addition to the current condition, five different scenarios based on the growth period of the crop are proposed such as Case I (30 March), Case II (30-April), Case III (15 May), Case IV (30 May) and Case V (15 June), i.e. growing period of maize is shifted from mid-April to mid-June. For Case I, maize has shown an increasing trend in CWR whereas for other cases such as Case II to Case V, CWR is likely to decrease, under both RCP 4.5 and 8.5 scenarios for all 3 parts of Sikkim (Fig. 6, Figure S9, & Figure S10). A significant amount of water conservation is noticed from case II to case V whereas no conservation is observed in case I. Case V projects the lowest CWR and hence identified as highest level of water conservation. The growing seasons of Maize are shifted from April to June, indicating conservation of 10 to 60, 12 to 86, and 12 to 108 mm/year under both scenarios for East, West, and South Sikkim, respectively.

Also, the growing seasons of Wheat (Figure S11) are shifted from 20 October to 5 December, i.e., Case I (5 October), Case II (20 October), Case III (5 November),

Case IV (20 November) and Case V (5 December). For East and South Sikkim, case I, II & V clearly indicate increasing trend of CWR while a decrease is observed over case III & IV. However, for West Sikkim, CWR decreases over Case III, IV, & V. This clearly indicates that the wheat growth period is suitable to shift from 5th to 20th day of November from the current scenarios or else no water conservation is possible. The growing seasons of wheat are shifted from October to November, indicating conservation of 1–11, 18–29, and 3–95 mm/year for East, West, and South Sikkim, respectively.

Similarly, for the rice crop (see Figure S12), in addition to current condition i.e. 1st week of July, 5 newly added growing periods are proposed viz., Case I (15 June), Case II (15 July), Case III (30 July), Case IV (15 August) and Case V (30 August). From Case II to Case V, CWR of rice shows a decreasing trend both scenarios over all three parts of Sikkim. After adopting the newly developed growing period from July to August, water conservation of 13–102, 4–102 and 11–88 mm/year under both RCP 4.5 & 8.5 scenarios for East, West and South Sikkim, respectively.

It should be noted that the sensitivity analysis through changing the growing periods of different crops is carried out to understand the implications on CWR under different climate change scenarios. Moreover, authors have assumed 15 days gap from one case to another, which may not affect the crop management practices over the study area drastically. In the present scenario of climate change, the spatio-temporal variability of precipitation is well understood. Therefore, the shift in the crop producing periods, would help in coping with the changeability in the precipitation pattern. However, adaptation of such conditions would be a decision-based approach (can't be straight

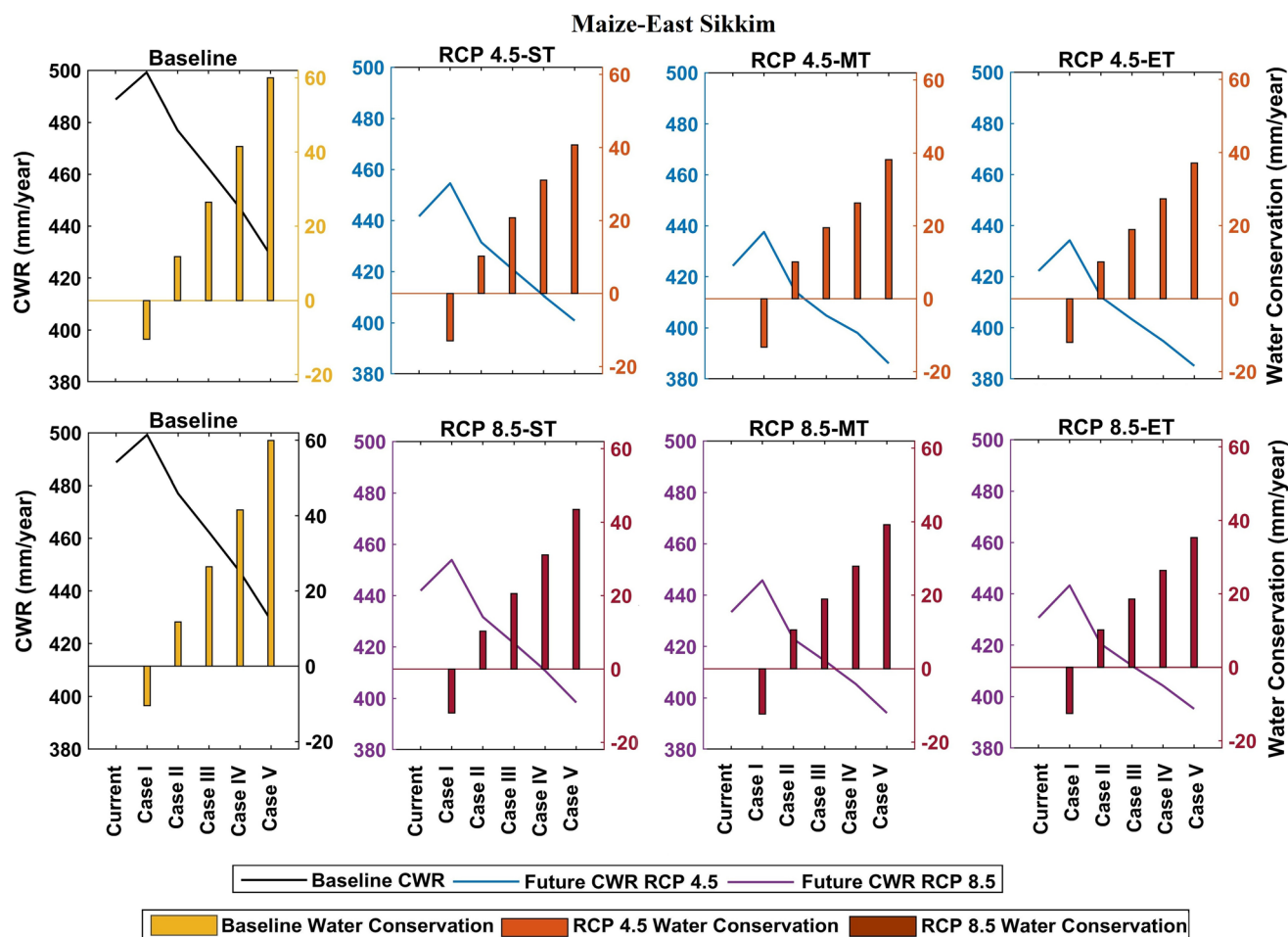


Fig. 6 Sensitivity analysis on CWR for different growing periods of Maize in East Sikkim

forward) that depends on the crop yields, feasibility, marketing values of different crops, among others.

4 Conclusions

The present study investigates the climate change implications on CWR and CIR in three districts of Sikkim, namely East, West, and South Sikkim. Additionally, uncertainty analysis of both GCM and scenario is also carried by using the possibility approach. The outcomes of the study are as follows:

- The future projection of regional CWR in the total growth stage of maize, wheat, and rice is likely to decrease over East Sikkim. On the other hand, CWR (except for maize in West Sikkim) over West and South Sikkim is expected to increase during 2021–2099.
- The future trends of CIR of wheat and rice show a significant increasing trend in West and South Sikkim, whereas, over East Sikkim CIR is likely to decrease (increase) for wheat (rice).

- It is noted that shifting growth period may reduce CWR in the study region.
- The uncertainty analysis reveals RCP 4.5 as the most possible scenario for the regional climate change impact assessment on CWR and CIR over the study area.

The outcomes from the study would provide a framework for the agricultural and water engineering over Sikkim for effective management of water resources for sustainable agriculture. Adaptation of different cropping pattern is necessary to combat climate change. However, its impact on the crop yield and marketing values under the stressed scenario of climate change and population growth should be analyzed and hence provides a new direction to pursue future research.

Acknowledgements The authors acknowledge the financial support provided by the Department of Science & Technology (DST), Government of India under research Project DST/CCP/MRDP/98/2017(G).

Data availability Some or all data, models, or code generated or used during the study are available from the corresponding author by request. The list of the items, which can be availed, are historical meteorological data and outputs from the GCMs under future possible scenarios. Moreover, the code for the bias correction is available from the corresponding author by request.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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