Modeling future irrigation water demands in the context of climate change: a case study of Jayakwadi command area, India

Akshay Sunil, B. Deepthi, A. B. Mirajkar & S. Adarsh

Modeling Earth Systems and Environment

ISSN 2363-6203

Model. Earth Syst. Environ.
DOI 10.1007/s40808-020-00955-y

ONLINE FIRST

Springer

Modeling Earth Systems and Environment
https://doi.org/10.1007/s40808-020-00955-y

ORIGINAL ARTICLE

Modeling future irrigation water demands in the context of climate change: a case study of Jayakwadi command area, India

Akshay Sunil[1] · B. Deepthi[1] · A. B. Mirajkar[1] · S. Adarsh[2]

Received: 22 May 2020 / Accepted: 25 August 2020

Abstract
In the present study, the downscaled future climate data from the General Circulation Model (GCM), CanESM2 has been used to calculate the monthly crop water requirements of the major crops cultivated in the Jayakwadi command area, Maharashtra, India. Statistical downscaling was carried out using the statistical downscaling model and the future irrigation demands were estimated using the CROPWAT model. Statistical downscaling of the CanESM2 GCM model and prediction of the future temperature and precipitation was done for two representative concentration pathways (RCP) scenarios namely the RCP 4.5 and RCP 8.5. Further, the future irrigation demands were estimated under the RCP 4.5 and 8.5 scenarios for the period 2011–2100 with three-time spells of 30 years centered on the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100). The results indicated an increase in temperature and precipitation over time spells when compared to the base period (1961–2005). The annual average temperature has been projected to increase by 0.306 °C and 0.358 °C by the 2080s when compared to the base period under the RCP 4.5 and RCP 8.5 scenarios, respectively. The annual average precipitation has been projected to increase from 856.58 mm in the base period to 1410.11 mm and 1784.06 mm under RCP 4.5 and RCP 8.5, respectively. The average reference evapotranspiration (ET_o) values showed an increase from 5.41 mm/day to 5.45 mm/day, 5.53 mm/day, and 5.57 mm/day for the periods 2020s, 2050s and 2080s respectively in the RCP 8.5 scenario. The average annual irrigation demand showed a reduction of 14.07% and 14.72% for RCP 4.5 and RCP 8.5 scenarios respectively. The estimated variations in demand values can be used for optimal irrigation planning in the culturable command area of the Jayakwadi reservoir.

Keywords Climate change · Crop water requirements · General circulation model · Statistical downscaling · CROPWAT

Introduction

Indian economy is highly reliant on agriculture and the major share of the reservoir storage in India is used for irrigation purposes. The irrigation demand has a strong relationship with the climate of an area (Tukimat et al. 2017). The rainfall trend, temperature, relative humidity, solar radiation, and wind speed are some of the climatic parameters that affect the irrigation water requirement and agricultural production of a region (Rehana and Mujumdar 2012; Battude et al. 2016). Therefore, the fluctuations in irrigation demand are highly dependent on the ever-changing climatic scenarios. Understanding the future irrigation demand under changing climate may help in developing proper adaptation strategies for food security and crop modeling (Islam et al. 2020). Proper modeling of irrigation demand in the context of climate change may also be essential for devising an optimal release policy of reservoirs in the long term.

The changing pattern in climate has led to serious concerns at the global level and researchers often use general circulation models (GCM) to downscale future temperature and precipitation at the local and regional scales. GCM projections are translated for regional impact assessment using

✉ Akshay Sunil
akshaysunil172@gmail.com

B. Deepthi
deepthibhadran2@gmail.com

A. B. Mirajkar
ashmirajkar@gmail.com

S. Adarsh
adarsh_lce@yahoo.co.in

[1] Department of Civil Engineering, Visvesvaraya National Institute of Technology, Nagpur 440010, India

[2] Department of Civil Engineering, TKM College of Engineering, Kollam, India

Published online: 30 August 2020

either statistical or dynamic downscaling. Several methodologies are developed for assessing the hydrologic impacts of climate change, giving importance to statistical techniques for assessing the regional impact (Mujumdar and Ghosh 2008). Observed relationships between large-scale climate phenomenon and local conditions are used in the statistical downscaling method to generate fine-grain projections from GCM output (Wilby et al. 2002). The methods of the transfer function and linear regression are used for statistical downscaling of the GCM by the statistical downscaling model (SDSM) model to generate stochastic meteorological data (Wilby et al. 2002). As per the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), climate projections are available for four representative concentration pathways (RCPs) namely RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5 for up to 2100 (IPCC 2014). In the past decade, several researchers considered the RCP scenarios for modelling the impact of climate change on water resources, in different parts of the globe (Chaturvedi et al. 2012; Khadka and Pathak 2016; Abbasnia and Toros 2016; Yadeta et al. 2020).

The future downscaled temperature and precipitation showed an increasing trend in the Marsyangdi river basin, Nepal using the CanESM2 dataset for the RCP 2.6, RCP 4.5, and RCP 8.5 scenarios (Khadka and Pathak 2016). The projected increase in the annual precipitation values in the future showed an inverse relationship with station points located at higher elevations. The SDSM model was used in downscaling the weather data for the upper Godavari river basin, Maharashtra (Saraf and Regulwar 2016). The average maximum temperature statistically downscaled using CGCM3 outputs showed an increase between 0.3 and 3.5 °C for the future periods 2041–2070 and 2071–2099, respectively, for 7 selected stations over Iran (Abbasnia and Toros 2016). The increase in temperature has a strong correlation with the evapotranspiration losses resulting in irrigation demand fluctuations. The results obtained from the outputs of 17 global climate models ensemble under the RCP 4.5 and 8.5 emission scenarios indicated that the rise in temperature resulted in an increase in the predicted evapotranspiration for the future at Aleltu Agriculture stations, Ethiopia (Yadeta et al. 2020).

One of the basic needs for crop planning on a farm and the planning of any irrigation project is the estimation of the water requirement of crops (Dhamge et al. 2008). Proper understanding of the impacts of climate change on crop water requirements (CWR) is essential in tackling problems of food security and sustainable use of water resources in the future (Zhou et al. 2017). The changing climatic conditions have serious impacts on the availability of water resources in an area. Several studies have been carried out to estimate the fluctuations in ET_o and CWR values that occur as a result of the changes in climatic parameters, namely the temperature and precipitation under the different RCP scenarios. The predicted values of temperature and precipitation have been used to assess the variations in ET_o and regional crop water requirements in Hetao Irrigation District (HID), China. The results indicated that the predicted increase in temperature and precipitation extremes has led to a direct increase in future ET_o values by 4% to 7% in the HID (Zhou et al. 2017). The ET_o values were determined by inputting the climatological records of the sunshine duration, maximum and minimum temperatures, humidity, and wind speed at 2 m height into the CROPWAT 8.0 modeling software (Rahimi et al. 2018), and multiple linear regression techniques were used further to devise a model that predicts the reference evapotranspiration using the meteorological data.

Recently, several studies have been conducted by researchers to estimate the fluctuations in crop irrigation demands under the changing climatic scenarios. The CROPWAT model is an effective tool that estimates the ET_o and CWR values from the predicted climatic parameters. The sensitivity analysis results of the Penman–Monteith equation to the different climatic variables indicated good performance when the minimum and maximum temperatures were used in the estimation of the reference evapotranspiration (Koudahe et al. 2018). The variations in the crop yield and the irrigation demands have been studied for various cultivated areas and river basins across the globe under the different CO_2 emission scenarios. The projected climatic parameters can be suitably used to estimate the future irrigation demands of an area (Ashofteh et al. 2015). The CROPWAT 8.0 model uses the FAO Penman–Monteith method (Allen et al. 2001) for determining the ET_o and the United States Department of Agriculture (USDA) soil conservation (S.C.) method was used to estimate the effective rainfall (Djaman et al. 2018; Mehta and Pandey 2016; Patidar et al. 2020). The CROPWAT model has been used in calculating the CWR and in planning irrigation scheduling worldwide, such as in India (Surendran et al. 2015) and in Iraq (Ewaid et al. 2019), Ontario (Doria et al. 2006). Numerical simulation results show that an increase in the CO_2 emission and the resultant rise in temperature substantially decrease the wheat crop yield (Verma and Misra 2017). The future irrigation demand in a tropical paddy cultivated area was found to decrease due to the increase in rainfall in the catchment for the Muda Irrigation Project, Malaysia (Tukimat et al. 2017). The future climate simulations in the study area were done using the SDSM model under the A2 scenario of the Special Report on Emissions Scenarios (SRES). The future irrigation requirements were simulated for nine selected locations enclosing the Bhadra reservoir command area by a multivariable downscaling technique named canonical correlation analysis (CCA) (Rehana and Mujumdar 2012). The study indicated that the future irrigation requirements in the command area increased even though the projected rainfall in the catchment area showed an increasing trend. This increase in the simulated irrigation demands was because of the projected fluctuations in the predicted climatic parameters, namely the temperature, relative humidity (RH), solar radiation, and wind speed. The irrigation water requirement of the rice crop was forecasted based on the projected meteorological data of HadCM3 under the A2 scenario (Gilanipour and Gholizadeh 2016), the future irrigation demands for the rice crop showed a decreasing trend for the projected increase in precipitation.

From the literature, it can be seen that numerous studies have been carried out to assess the impacts of climate change on reference evapotranspiration and crop irrigation requirements at both the regional and basin level. However, there is no evidence of detailed studies involving the estimation of future irrigation demands under the RCP scenarios at the command area level of a reservoir in the Indian context. Thus, the present study investigates the effect of climate change on future irrigation demands in the Jayakwadi command area, located in Maharashtra, India, using GCM data under the medium emission RCP 4.5 and high emission RCP 8.5 scenarios. The assessments in demand fluctuations can be suitably used as recommendations in irrigation planning and modeling reservoir operations for the Jayakwadi command area in the future.

Materials and methods

Study area

The Jayakwadi Project Stage-I is located within the Upper Godavari basin, a sub-basin of the Godavari basin in India. The Upper Godavari sub-basin has a catchment area of 21,774 km^2 extending between 19° and 20°30′ N latitude and 73°27′ to 75°30′ E longitude within the state of Maharashtra. The observed average yearly rainfall was found out to be 856.57 mm and the annual average temperature is 25.75 °C for the baseline period 1961–2005. The location of the study area within the Godavari basin is shown in Fig. 1. The Jayakwadi Project Stage-I has a total gross storage of 2909 million cubic meters (MCM), live storage of 2171 MCM, and dead storage of 738 MCM.

The gross command area and the culturable command area of the project are 2,03,960 ha, and 1,83,560 ha respectively [Command Area Development Authority (CADA) office, Aurangabad]. The annual cropped area (ACA) is 1,45,180 ha with three major cropping seasons namely the Kharif, Rabi and hot weather cropping seasons (CADA. Aurangabad). Hybrid Jowar and Paddy form the major Kharif crops with a cropping area of 12% and 10% of the total ACA, while the major Rabi crops are wheat, maize, and gram with a percentage share of 25%, 15%, and 5%. The major hot weather (HW) crop is HW groundnut with a percentage share of 3%. Cotton is cultivated as a two seasonal crop (predominantly Kharif) in the command area with a percentage share of 2%. Sugarcane is a perennial crop in the command area with a percentage allocation of 5% of the command area. In the present study, the cotton crop is treated as a Kharif crop for its future irrigation demand estimation.

Dataset used in the study

The crop data including the major (season wise) crops in the cultivated area and its cropping pattern in the catchment area were obtained from the Command Area Development Authority (CADA), Aurangabad. Crop data such as crop coefficient (K_c), development length stages (days), root zone depth (m), sowing and harvesting dates, and yield response were obtained from detailed reports of CADA, Aurangabad and Food and Agriculture Organization (FAO) Irrigation and Drainage Paper No. 56 (Allen et al. 2001). The daily gridded observed rainfall and temperature data of 0.25° × 0.25° resolution was obtained from the India Meteorological Department (IMD) for the period 1961–2005. The data included the minimum and maximum temperatures, and the daily precipitation values. The future climate change projection has been made using the Second Generation of Earth System Model (CanESM2) developed at the Canadian Centre for Climate Modeling and Analysis (CCCma) (Hua et al. 2015; Genesse and Braun 2019). The approximate spatial resolution in latitude and longitude is 2.8° × 2.8°. The CanESM2 projection under the RCP 4.5 and 8.5 scenarios for the period 2006–2100 was also obtained from the CCCSN website. The National Center for Environmental Prediction (NCEP) reanalysis data set for 1961–2005 was used to train the downscaling model (Ahmadi et al. 2014). A long-term baseline period of 45 years from 1961 to 2005 was selected for the study. For the statistical downscaling model, a calibration period of 25 years (1961–1985) and a validation period of 20 years (1986–2005) was adopted for rainfall and temperature.

Statistical downscaling model (SDSM)

The SDSM model is one of the most credible and popular tool used for statistical downscaling of seasonal temperature and precipitation over the years (Wilby et al. 2002). SDSM allows the spatial scale reduction of coarse resolution data of GCMs for the assessment of regional impacts of global warming. It is developed on the basis of multiple linear regression models. To simulate the climatic parameters, linear regression model is developed between the predictands and the large scale predictors. The SDSM model consists

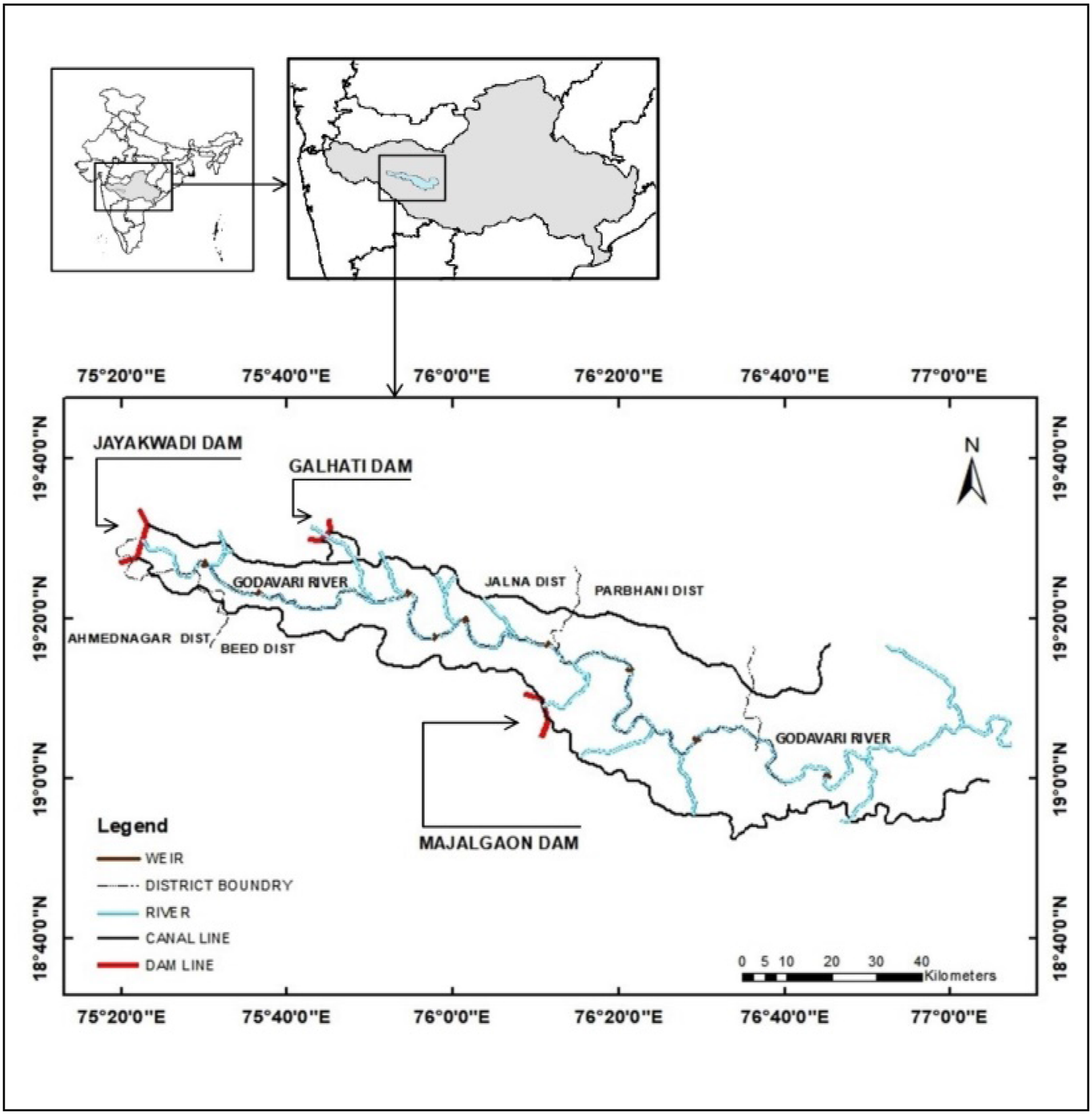

Fig. 1 Index map of Jayakwadi project stage- I and II in the Godavari basin

of mainly four steps namely; screening of predictors, model calibration, weather generator and scenario generation. The present and future daily climatic parameters can be simulated through the combination of these developed regression equations and the weather generators provided by the GCMs,

Screening of predictors

Daily data of rainfall, maximum temperature and minimum temperature are taken as the predictand and NCEP/NCAR reanalysis data as the large scale predictors. Screening of predictors is done to select suitable predictors with the strongest correlation with each of these predictands from the NCEP/NCAR reanalysis data. These predictors are selected on the basis of partial correlation; percentage of explained variance as well as the scatter plot between the predictand and the predictors (Wilby and Dawson 2013). The statistical relationship is established these selected predictors and the corresponding predictands. In this study, suitable predictors are selected on the basis of its correlation with the predictands.

Calibration and validation of SDSM

The observed datasets of rainfall, maximum temperature and minimum temperature from 1961 to 2005 were used for the calibration and validation of SDSM. The 45 years of datasets were divided into two groups. The first 25 years (1961–1985) were used for calibration and the remaining 20 years (1991–2005) were used for validation of the SDSM model. The calibration option in SDSM software was used to develop the statistical relationship between the predictands and the selected predictors for the calibration period. The weather generator option in SDSM was used to simulate the daily values of rainfall, the maximum and minimum temperature for the calibration and validation period. The performance of the SDSM during the calibration and validation period was evaluated on the basis of statistical parameters like the coefficient of determination (R^2), Root Mean Square Error (RMSE) and Nash–Sutcliffe Efficiency (NSE). The coefficient of determination (R^2) compares the explained variance of modelled data with the total variance of the observed data and the value ranges from 0 to 1. The higher value represents better model performance. The NSE determines the relative magnitude of the variance of residues and measured data. It ranges from $-\infty$ to 1 with 1 being the ideal value for best performance. The values below 0 represent unacceptable performance whereas values within 0–1 indicate acceptable levels of performance. The RMSE is used to measure the difference between observed and simulated values. The RMSE value of 0 represents the good performance of the model theoretically. Statistical evaluation of SDSM helps us to ensure whether the relationship established between the predictands and selected predictors during the calibration period have the accuracy to predict the future daily rainfall, maximum and minimum temperature.

Scenario generation

After the validation of SDSM software, the regression equation developed during the calibration of SDSM was used for the process of downscaling using the outputs of the CanESM2 model as large scale predictors under different RCP scenarios. For the process of downscaling, the scenario generation option in SDSM was used. The future climatic variables were predicted up to the year 2100 with three periods of 30 years centered on the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100).

CROPWAT model

In the present study, the CROPWAT model was used to calculate the future irrigation demands of the Jayakwadi command area. The CROPWAT 8.0 simulation software was attached to CLIMWAT 2.0 tool and the crop water requirements (CWR) of the major crops in the study area have been calculated (Ewaid et al. 2019; Surendran et al. 2015; Doria et al. 2006). The reference evapotranspiration (ETo) (FAO Penman–Monteith method) and the effective rainfall (R_{eff}) (USDA soil conservation service method) were calculated from the CROPWAT model for the future scenarios (Shreedhar et al. 2015). The FAO Penman–Monteith method and USDA soil conservation service method are referred from the Food and Agriculture Organization (FAO) Irrigation and Drainage Paper No. 56 (Allen et al. 2001).

Equation 1 shows the Penman–Monteith equation used in the study to compute the $\mathrm{ET_o}$ values for future climatic scenarios:

$$\mathrm{ET_o} = \frac{0.408\Delta(\mathrm{Rn} - G) + \left(\gamma \frac{900}{T+273} u_2(\mathrm{es} - \mathrm{ea})\right)}{\Delta + \gamma(1 + 0.34u_2)} \tag{1}$$

where $\mathrm{ET_o}$ is the reference evapotranspiration (mm day−1), Δ is the slope of vapor pressure curve (kPa C^{-1}), Rn is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), γ is the psychrometric constant (kPa $°\mathrm{C}^{-1}$), T is the mean daily air temperature at 2 m height (°C), u_2 is the wind speed at 2 m height (m s^{-1}), es is the saturation vapor pressure and ea is the actual vapor pressure (kPa), es − ea is the saturation vapor pressure deficit (kPa). Reference evapotranspiration ($\mathrm{ET_o}$) was considered as the key variable for the estimation of crop evapotranspiration ($\mathrm{ET_c}$) (Poddar et al. 2018). The $\mathrm{ET_c}$ is calculated from $\mathrm{ET_o}$ and crop coefficient (K_c) using Eq. 2 under standard conditions. The standard conditions mean that there are no limitations in the crop growth including a sufficient supply of water and crops should be free from diseases and pest infections (Doria et al. 2006):

$$\mathrm{ET_c} = \mathrm{ET_o} \times K_c \tag{2}$$

The daily $\mathrm{ET_c}$ values computed were summed up for different growth stages of the crop to obtain the seasonal CWR. The future CWR of the major crops for RCP 4.5 and RCP 8.5 scenarios has been calculated using the CROPWAT model. The future total irrigation demands for the command area were computed using the estimated

CWR (Ahmadi and Azizzadeh 2020). The net irrigation water requirement (NIWR) is the difference between the ET_c and effective precipitation (R_{eff}). The total irrigation water demands for each crop is estimated by taking the product of the NIWR and the present area under cultivation provided by the CADA office, Aurangabad. The flow chart showing the methodology for estimation of the future irrigation demands using SDSM and CROPWAT models is provided in Fig. 2.

In the present study, the predicted climatic parameters from the SDSM output were used as an input into the CROPWAT model for future irrigation demand estimation. The CROPWAT model was validated using historical data before the computation of crop irrigation demands. The reference evapotranspiration was computed using the simulated temperature and precipitation data using the CROPWAT model. It was assumed that the climatic parameters like wind speed, relative humidity, and sunshine hours remain constant throughout the entire period of study.

Results and discussions

Selection of predictors

The climatic parameters namely, the maximum temperature (T_{max}), minimum temperature (T_{min}), and precipitation (PCP) for the baseline period were downscaled using the SDSM model. The monthly correlation values (R) between predictor-predictand relationships have been used to select the predictors in the study (Tukimat et al. 2017). A set of suitable predictor variables were selected for each climatic parameters based on a combination of the correlation matrix,

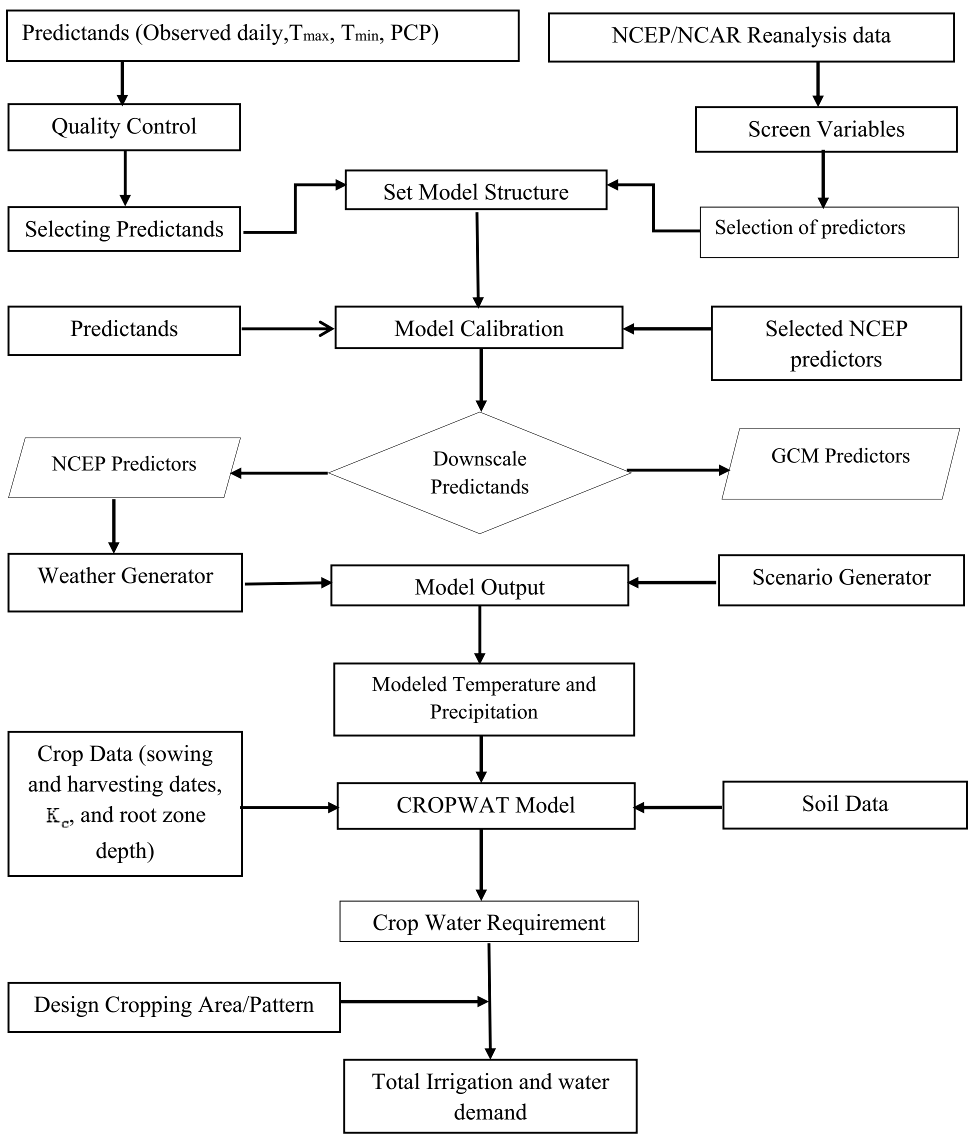

Fig. 2 Flow chart for the steps involved in the estimation of future irrigation demands for the different RCP scenarios using SDSM and CROPWAT models

partial correlation, and p value at a significance level of 0.05 (Mahamood and Babel 2012). Through this process, a set of five predictors having the highest correlation, partial correlation, and the least p value with the predictand were selected to simulate the maximum and minimum temperatures. Similarly, a set of four predictors were selected to simulate the precipitation (Hussain et al. 2017). The set of predictors chosen for temperature simulation were wind direction at surface (p1_th), divergence at surface (p1_zh), vorticity at 500 hPa (p5_z), zonal velocity component at 850 hPa (p8_u), and the mean temperature at 2 m (temp). Similarly, the predictors chosen for precipitation are vorticity at surface (p1_z), geostrophic air flow velocity at 500 hPa (p5_f), vorticity at 850 hPa (p8_z), and the near surface specific humidity (shum).

Performance evaluation of SDSM

The calibration period of the SDSM model was from 1961 to 1985 and the results have been validated from 1986 to 2005. The coefficient of determination (R^2) was calculated to evaluate the accuracy of the SDSM model (Pichuka and Maity 2016). In this study, the statistical parameters namely R^2, NSE and RMSE were determined for the performance evaluation of SDSM. The calculated values for each of these parameters indicated that the downscaled temperature and precipitation statistics during calibration (1961–1985) and validation (1986–2005) period were in close agreement with the observed values during the baseline period (1961–2005). Table 1 shows the values of R^2, NSE and RMSE for monthly simulated precipitation, maximum and minimum temperature during the calibration and validation period.

Both during the calibration and validation period, the maximum temperature simulated by SDSM using NCEP/NCAR reanalysis data is showing a good correlation with the observed dataset as compared to precipitation and minimum temperature. From Table 1 it is clear that the RMSE value is more for precipitation indicating that the SDSM model is more suitable for the simulation of temperature. The R^2 values for the simulated monthly maximum and minimum temperature during the calibration period were 0.94 and 0.86 respectively to the observed values. The R^2 values for the simulated monthly maximum and minimum temperature during the validation period were 0.85 and 0.83, respectively. Similarly, the R^2 values computed for monthly average precipitation (PCP) were 0.61 and 0.56 for the calibration and validation phases. The RMSE values obtained during the calibration period is less compared to the validation. Among the three climatic parameters, the maximum temperature simulated by SDSM is showing less RMSE value. This means that the difference between observed and simulated values during the observation period is also less. In the case of NSE value also the maximum temperature is having higher value as compared to the other two climatic parameters.

Therefore, there exists a good agreement between the simulated and observed values for both the temperature and rainfall and the CanESM2 predictors were further used to forecast the climatic parameters for the future RCP scenarios (Zhang et al. 2016). The average monthly temperatures for the calibration and validation periods were obtained by taking the simple average of the maximum and minimum temperature from the SDSM simulated results. The graphical comparison of the downscaled and the observed monthly climatic parameters during the calibration and validation periods are shown in Figs. 3 and 4 respectively.

Future climate simulations and projections

The calibrated parameters of selected predictors were further used in the statistical downscaling of the GCM scenario in the present and future (Bothale and Katpatal 2017). The future climate scenario up to the year 2100 with three periods of 30 years centered on the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100) was obtained from the model. The projected future temperature and precipitation data were compared with the baseline period (1961–2005) data and the changes in different RCP scenarios were noted. The CanESM2 projected mean monthly maximum temperature (T_{max}) and minimum temperature (T_{min}) under the RCP 4.5 and RCP 8.5 scenarios for the 2020s, the 2050s and 2080s are shown in Fig. 5. The projected maximum temperature (T_{max}) and minimum temperature (T_{min}) also showed an increasing trend for both scenarios as shown in Fig. 5. The results indicated that the annual average maximum temperature (T_{max}) will increase by 0.16 °C and 0.214 °C under the RCP 4.5 and RCP 8.5 scenarios, respectively, by the 2100s. However,

Table 1 Statistical evaluation of SDSM during calibration (C) and validation (V)

Parameters	Precipitation		Maximum temperature		Minimum temperature	
	C	V	C	V	C	V
R^2	0.61	0.56	0.94	0.85	0.86	0.83
NSE	0.72	0.66	0.84	0.79	0.82	0.76
RMSE	3.83	4.13	2.67	3.12	2.78	3.24

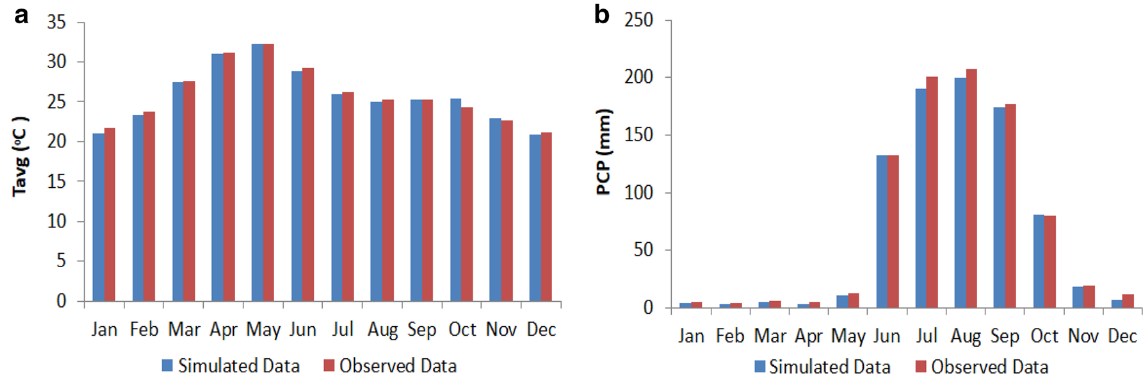

Fig. 3 Comparison of the model-simulated and observed average temperature (**a**), and precipitation (**b**) for the calibration period in the Jayakwadi command area

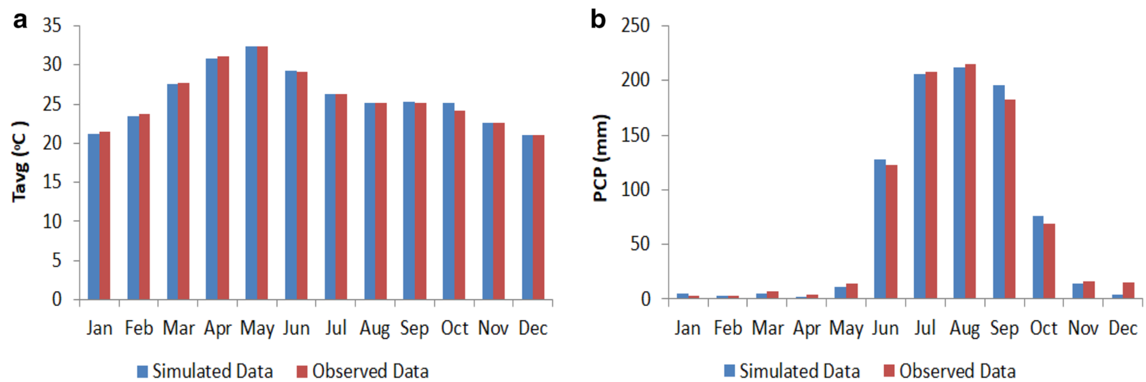

Fig. 4 Comparison of the model-simulated and observed average temperature (**a**), and precipitation (**b**) for the validation period in the Jayakwadi command area

the projected increase in the annual minimum temperature (T_{min}) indicated a higher increase under the RCP 4.5 and RCP 8.5 scenarios with values of 0.452 °C and 0.502 °C, respectively. The projected mean monthly average temperature (T_{avg}) and average precipitation (PCP) under the RCP 4.5 and RCP 8.5 scenarios for the 2020s, the 2050s and 2080s are shown in Fig. 6. The average monthly temperature showed an increasing trend for both scenarios as indicated in the figure. The maximum increase in the mean monthly temperature by the 2080s was obtained under the RCP 8.5 scenario with an increase of 0.358 °C to the baseline period. The annual average precipitation also showed an increasing trend with the highest precipitation value of 1784.06 mm for the period of the 2080s under the RCP 8.5 scenario. The average rainfall is expected to rise by 3.95% and 6.6% per decade for the RCP 4.5 and RCP 8.5 scenarios, respectively. The rise in temperature results in an increase in the rate of evapotranspiration and can affect healthy vegetation. From the results, it was observed that both the temperature as well as rainfall will increase in the Jayakwadi command area under both the RCP scenarios with the RCP 8.5 scenario having the maximum increase. The results obtained in the present study are in line with those simulated by Dahal et al. (2016).

Simulation of reference evapotranspiration

The variations in reference evapotranspiration (ET_o) for the future scenarios were also computed from the downscaled climatic parameters using the CROPWAT model. The CROPWAT model uses the FAO Penman–Monteith equation for the future ET_o computation and has been used in the study because of its wide acceptability for all crops (Ashofteh et al. 2015). The ET_o value depends on the climatic parameters including the maximum and minimum temperature and is independent of the crop parameters. The predicted monthly means of the simulated daily data series of maximum temperature (T_{max}), minimum temperature (T_{min}), and precipitation (PCP) were used to simulate future demands from the CROPWAT model (Doria et al. 2006).The simulated climatic parameters were added to the CROPWAT model and the future ET_o values were estimated for both

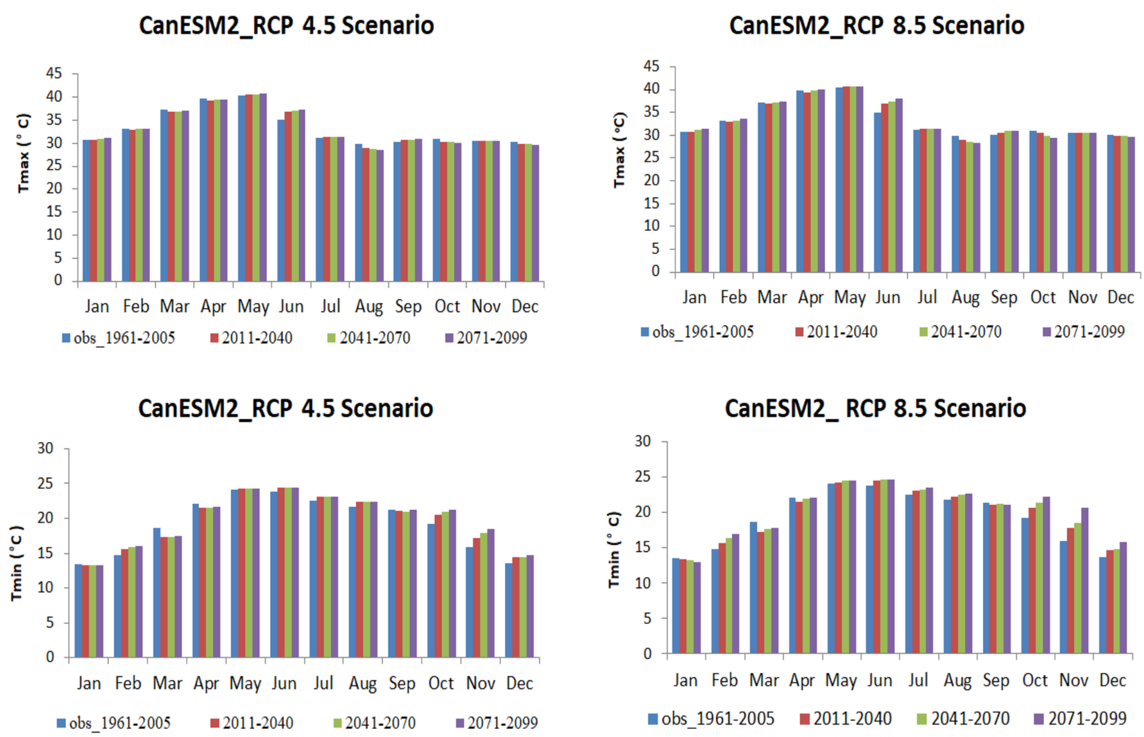

Fig. 5 Mean monthly changes in the projected maximum temperature (T_{max}) and minimum temperature (T_{min}) under RCP 4.5 and RCP 8.5 scenarios of the CanESM2 model

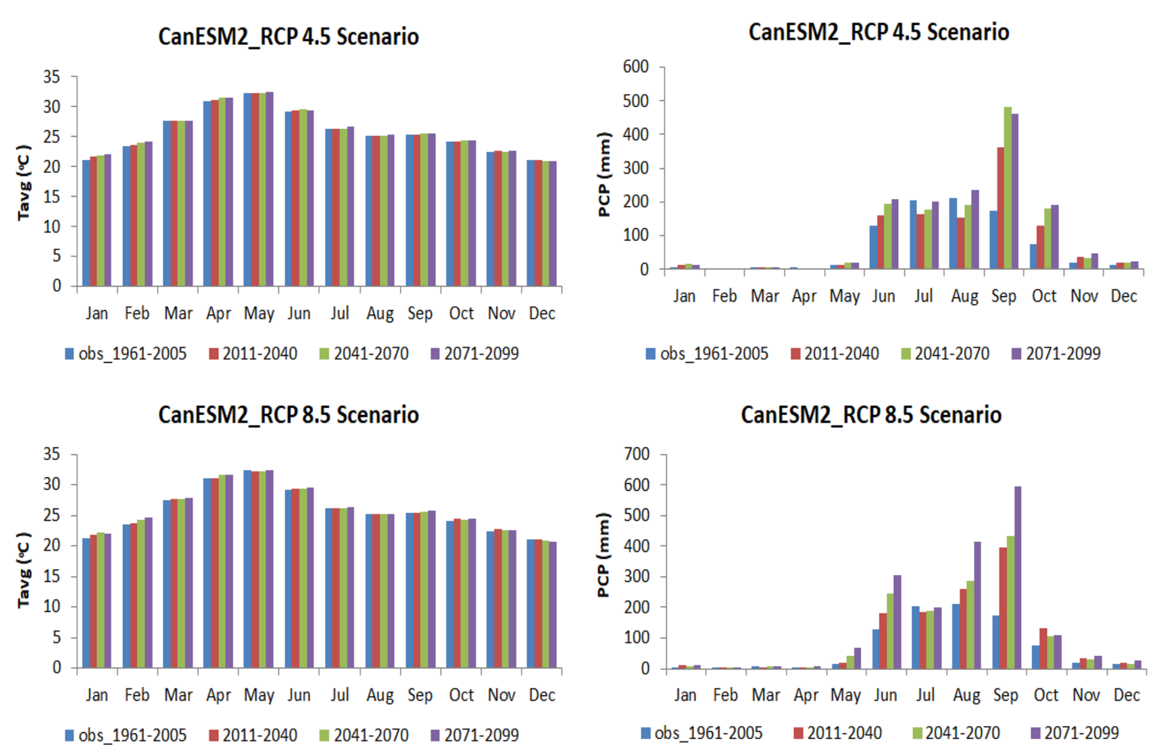

Fig. 6 Mean monthly changes in the projected average temperature (T_{avg}) and precipitation (PCP) under RCP 4.5 and RCP 8.5 scenarios of the CanESM2 model

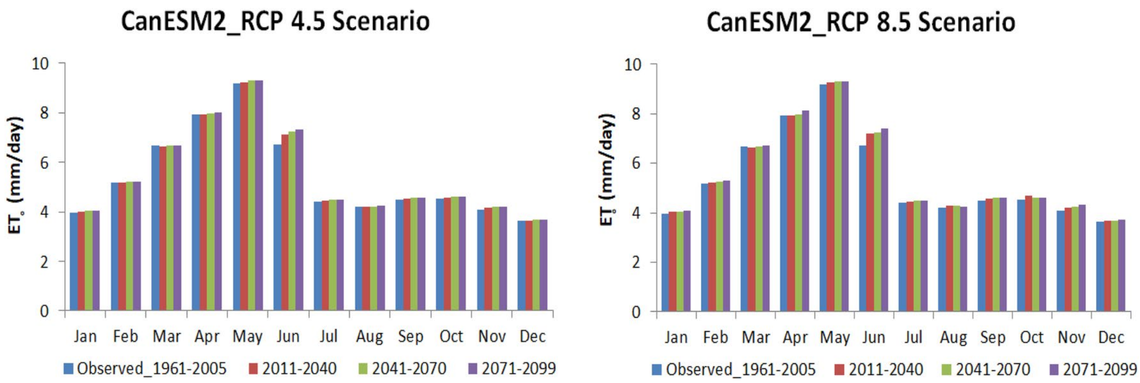

Fig. 7 Mean daily variation of reference evapotranspiration (ET_o) under RCP 4.5 and RCP 8.5 scenarios

the intermediate emission RCP 4.5 and the high emission RCP 8.5 scenarios. The variation in ET_o for the periods the 2020s, 2050s, and 2080s for both the RCP scenarios are shown in Fig. 7. The monthly reference evapotranspiration values showed an increasing trend in the future for both the RCP scenarios. The maximum increase in the monthly ET_o by the 2080s was observed in June with a monthly increase of 0.67 mm/day and 0.7 mm/day under the RCP 4.5 and RCP 8.5 scenarios, respectively. The maximum ET_o was observed in the month of May for both the RCP scenarios while December had the least ET_o value. The increasing trend in the future ET_o values as estimated from the model is a result of an increase in the predicted (T_{max}) and (T_{min}) values. This increasing trend in future ET_o may lead to an increase in future crop irrigation requirements. The CROPWAT model was further used in the simulation of crop water demands for future scenarios using the obtained climatic parameters.

Simulations of irrigation water demands

The crop water requirements (CWR) were simulated for all the major crops in the Jayakwadi command area using the CROPWAT 8.0 model and the variation in irrigation demands for the RCP 4.5 and 8.5 scenarios were analyzed. The Net Irrigation Water Requirement (NIWR) of a crop is the quantity of water required for crop growth and it depends on the type of crop and the climate of the study area. The irrigation requirements of crops were found out for the three major cropping seasons, namely the Kharif (Kh), Rabi (Rb), and Hot weather (HW) season. The crop evapotranspiration (ET_c) during the different crop-growth stages depends on the crop coefficient (K_c). The crop data were added to the CROPWAT model for the future CWR estimation in the CCA of the Jayakwadi reservoir. The CWR requirements of different crops for the RCP 4.5 and RCP 8.5 scenarios are given in Figs. 8 and 9, respectively. As shown in the figures, the irrigation demands for the major Kharif crops, namely Hybrid Jowar, Paddy, and Cotton showed a considerable loss during the Kharif months of June to September. The annual Irrigation requirement of Paddy shows a decrease of 11.2% and 29.4% by the 2100s for the RCP 4.5 and RCP 8.5 scenarios, respectively. The decrease in irrigation requirement is because of the increasing trend in the predicted rainfall for the future scenarios in the Kharif season. The future irrigation requirements of cotton crops showed a decrease of 13.6% and 18.3% while the Hybrid Jowar indicated a decrease of 11.1% and 26.6% for the RCP 4.5 and RCP 8.5 scenarios respectively by the 2080s. The results indicate that the net irrigation water requirement (NIWR) of the Kharif crops heavily depends on the effective rainfall in the command area.

The future irrigation requirements of the major Rabi crops, namely Wheat, Maize, and Gram also showed a decrease in irrigation requirements for future scenarios. Unlike in the case of Kharif crops, the NIWR for the Rabi crops showed a much greater decrease for the RCP 4.5 scenario than the RCP 8.5 scenario. It was observed that by the 2080s, the CWR of the wheat crop showed a decrease of 7.38% and 7.1% while Maize showed a decrease of 20.7% and 16.5% for the RCP 4.5 and 8.5 scenarios, respectively. The decrease in CWR for the Gram, a major pulse crop (Rb) in the command area was also obtained to be more for the RCP 4.5 scenario with a decrease of 29.3%. The CWR for the Gram crop during the baseline period was 245.7 mm/yr and was showed to decrease to a value of 173.5 mm/yr by the 2080s for the RCP 4.5 scenario. The irrigation demands of the Rabi crops were governed by the rise in temperature and evapotranspiration losses for future scenarios along with the increase in rainfall pattern; hence the irrigation requirements were slightly higher for the RCP 8.5 scenario compared to the RCP 4.5 scenario. The results indicate that even though the future rainfall indicates an increasing trend, the rainfall that occurs just before monsoon period will not be available

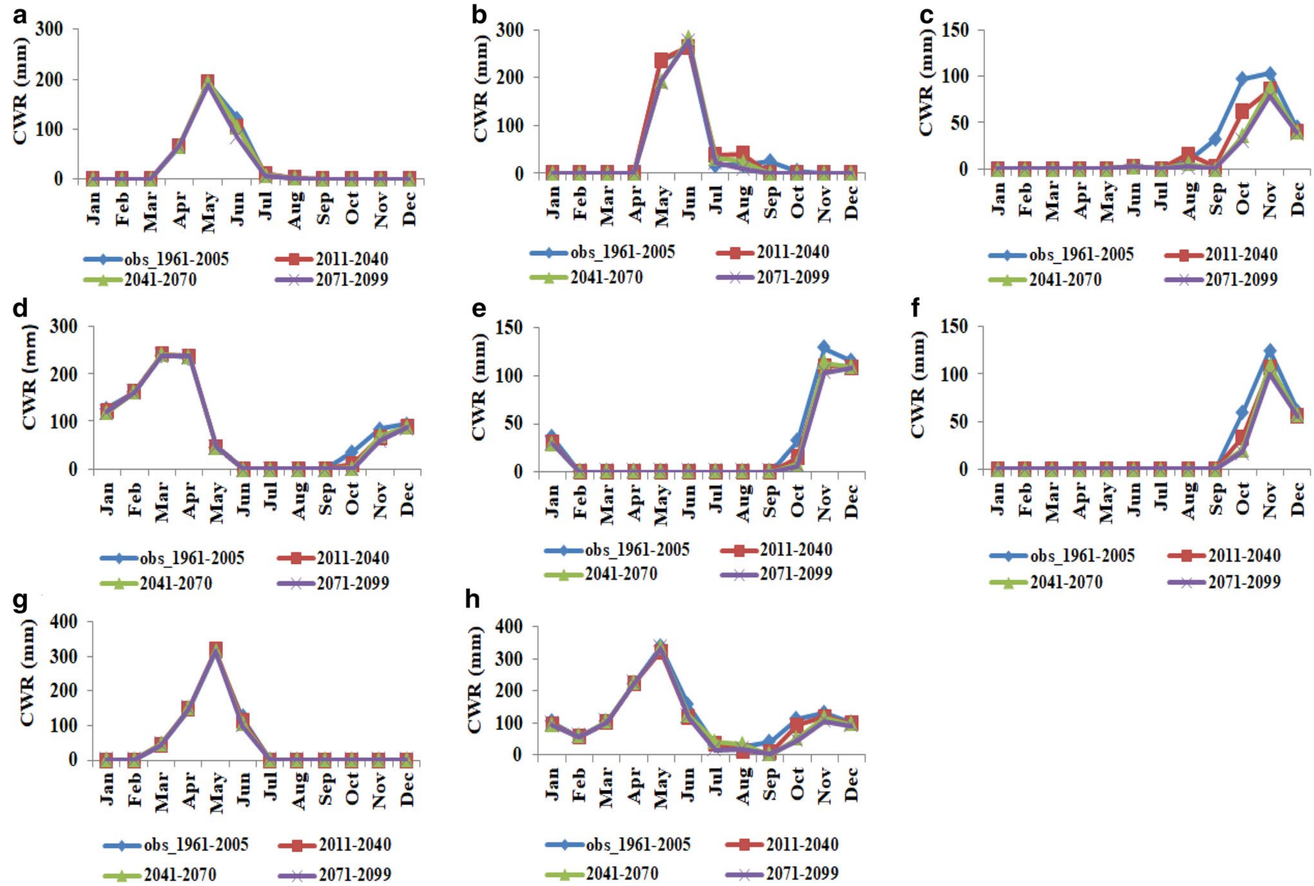

Fig. 8 Crop water requirement of hybrid jowar (**a**), paddy (**b**), cotton (**c**), wheat (**d**), maize (**e**), gram (**f**), HW groundnut (**g**) and sugarcane (**h**) in the Jayakwadi command area for the RCP 4.5 scenario

to satisfy the crop water demands due to the increase in the evaporation and transpiration losses.

The irrigation requirements of the HW groundnut and sugarcane crops were also estimated to decrease for the future RCP scenarios. Sugarcane is a perennial crop with an annual NIWR 1410 mm showed a considerable decrease in demand during the Kharif months. The NIWR values of sugarcane were found out to be 1202.1 mm/yr and 1182.9 mm/yr by the 2080s for the RCP 4.5 and RCP 8.5 scenarios respectively. A major decrease in irrigation water demands was observed during the Kharif months of August, September, and October for the sugarcane crop as indicated in the figures.

The monthly variation in the total irrigation water demands (MCM) for the different RCP scenarios is shown in Fig. 10. The monthly deviations in the total irrigation demands with reference to the baseline period for both the RCP scenarios are shown in Fig. 11. The figures show that future water demands will be the highest in the hot weather months of April and May, as before. The higher irrigation requirements estimated for the hot weather season should be taken into concern while devising better irrigation strategies in the future. The monthly deviations in irrigation demands were observed to be more during the Kharif months while the Rabi months showed lesser deviations. The future irrigation demand values show a considerable decrease for the Kharif months (June–October). The irrigation demands for February, March, and April show lesser deviation for future scenarios with a slight increase in demand values for the period of the 2020s under both RCP scenarios. The positive deviations in irrigation requirements during these months may lead to a drought-like situation and proper interventions in management policies should be adopted during this period for attaining a fairly equitable share of water. However, the demands during these months show a decreasing trend for the period of 2050 and 2080s.

The fluctuations in the future irrigation demands can be satisfied by developing a suitable release policy taking into

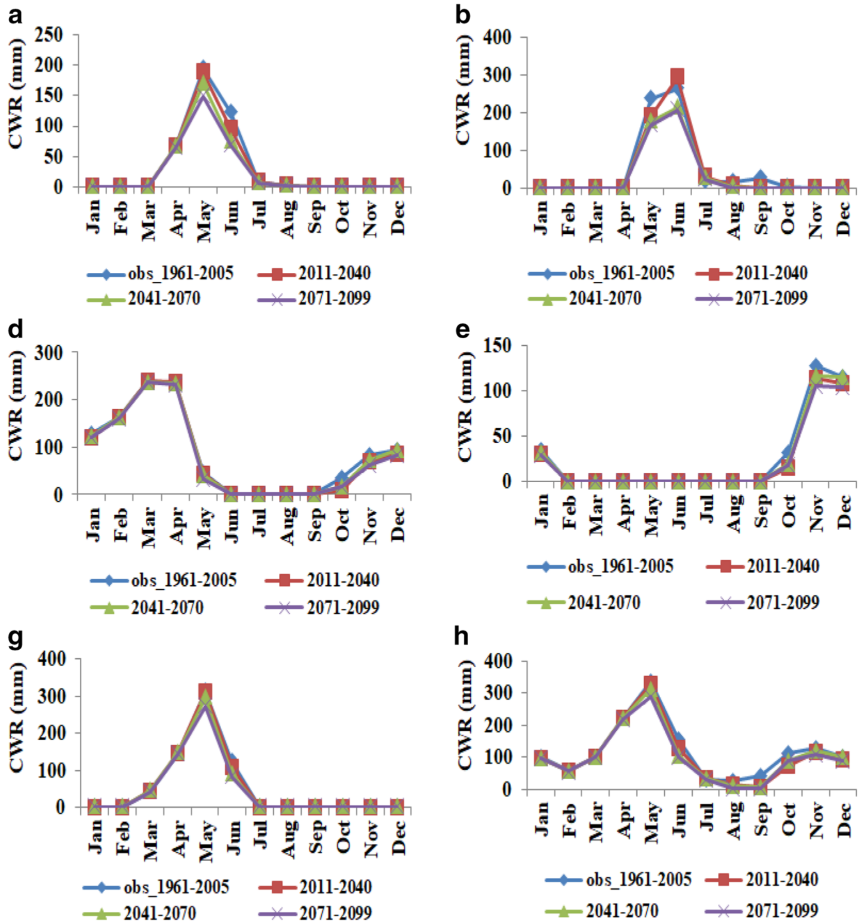

Fig. 9 Crop water requirement of hybrid jowar (**a**), paddy (**b**), cotton (**c**), wheat (**d**), maize (**e**), gram (**f**), HW groundnut (**g**) and sugarcane (**h**) in the Jayakwadi command area for the RCP 8.5 scenario

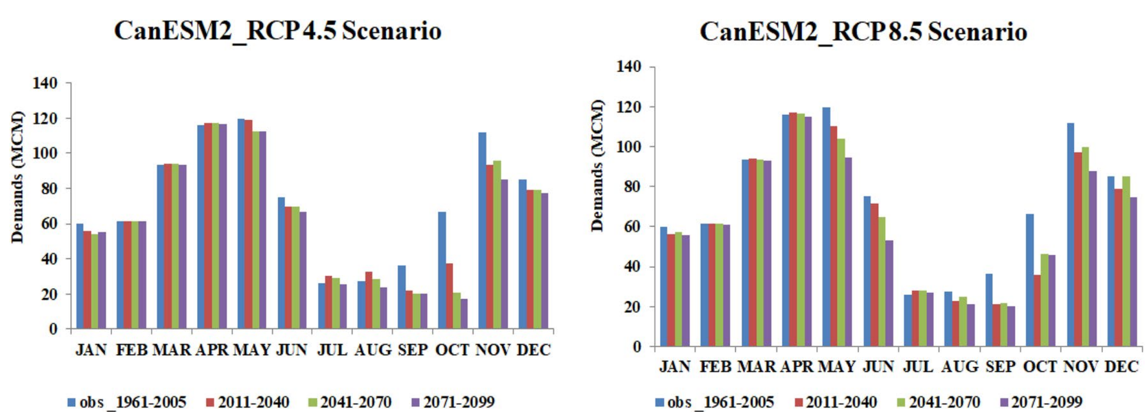

Fig. 10 The monthly variation in total irrigation water demand simulated using CROPWAT for future RCP scenarios in the Jayakwadi command area

account the variations in the demand pattern. Multi-objective optimization should be done for optimizing the reservoir releases and the cropping pattern, considering the variability in irrigation demand (Ikhar et al. 2017). The results can be used in proper reservoir planning and a further study in the rainfall trend and its non-stationary behavior can be done for optimizing the water required for irrigation, urban and industrial purposes, and hydropower generation (Ahmadi

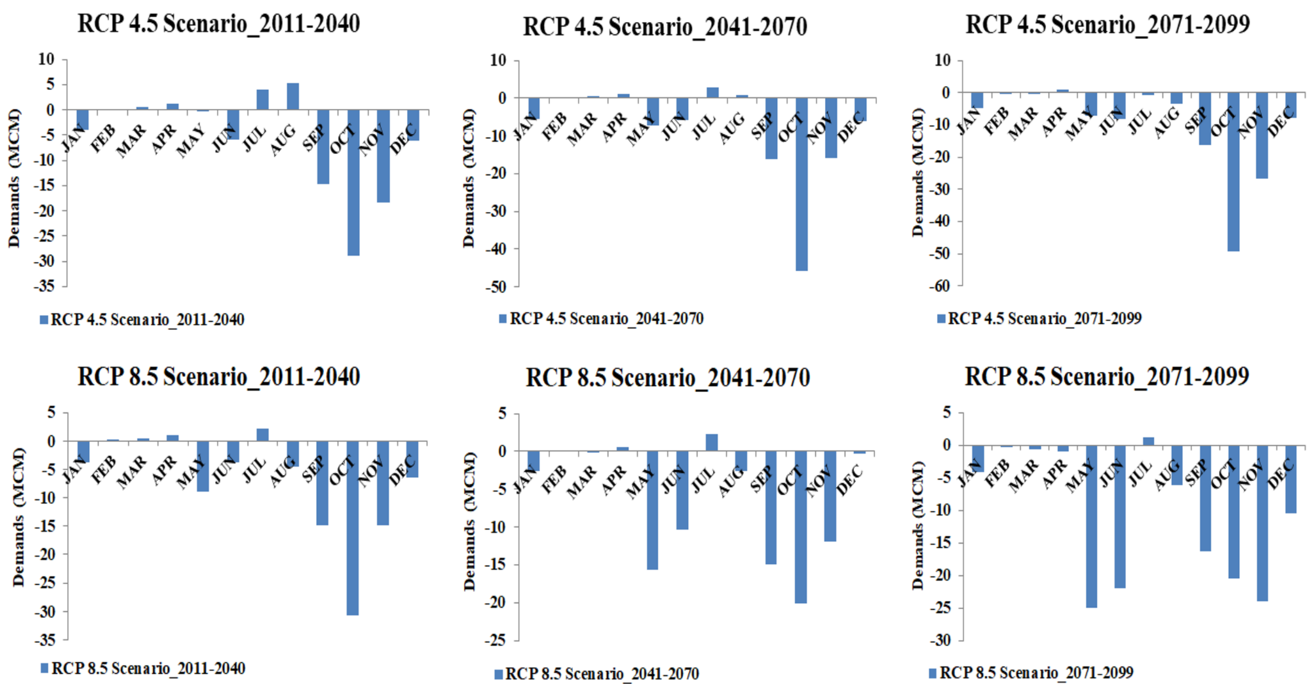

Fig. 11 The monthly deviations in total irrigation demand with reference to the baseline period for the future RCP scenarios in the Jayakwadi command area

and Azizzadeh 2020). Therefore, the results inferred from the study can be used by the planning authorities and policy-makers in understanding the impacts of climate change and in adopting policy responses to tackle the issues of fluctuations in future irrigation demand.

Conclusions

This study estimated the future irrigation demands for the Jayakwadi command area, Maharashtra India under a changing climate scenario. The future climatic parameters predicted using the SDSM model was used as an input for the CROPWAT model. The results indicated that there will be an increase in temperature and precipitation for the different RCP scenarios provided by the IPCC. The reference evapotranspiration simulated for the periods of the 2020s, 2050s, and 2080s also showed a rise in the future. Both the predicted temperature and reference evapotranspiration showed their peak value in May. The predicted rainfall showed an increasing trend especially during the Kharif months namely August, September, and October. The future irrigation water demands were found to show a significant decrease for the Kharif crops because of the increase in rainfall trend especially during June, July, August, and September. For the Kharif crops, the irrigation demands by the 2080s under the RCP 4.5 scenarios were greater as compared to the demands under the RCP 8.5 scenario. The higher values of demands obtained under the RCP 4.5 scenario for the Kharif season was because of the higher intensity of the predicted rainfall values under the RCP 8.5 scenario compared to the RCP 4.5 scenario. Despite the rise in temperature, the availability of water in the Jayakwadi command area is not expected to be reduced for the predicted future scenarios. The increase in the predicted rainfall may be an indication of flooding in the study area. The future irrigation water requirements for Rabi crops were also estimated to reduce with reference to the baseline period for both the RCP scenarios. The average Rabi crop irrigation demands forecasted under the RCP 4.5 scenario were lesser compared to the RCP 8.5 scenario even though the predicted rainfall showed higher values for the RCP 8.5. This increase in irrigation demands under the RCP 8.5 scenario compared to the RCP 4.5 scenario is because of the greater increase in the temperature rise for the predicted maximum and minimum temperatures for the study area. The increase in temperature leads to a direct increase in the reference evapotranspiration values leading to a higher demand for water. The future crop-wise irrigation requirements for the major crops has been discussed in the study and can be used as a source for optimizing the cropping area as well as the irrigation releases from the reservoir for the future scenarios.

Acknowledgements The authors are thankful to the Science and Engineering Research Board (SERB-ECR/2016/001409) affiliated to the

Department of Science and Technology (DST), New Delhi, for providing necessary funds for the present study. Authors also thank the CADA (Aurangabad) for providing the relevant data required for the analysis in the present study.

References

Abbasnia M, Toros H (2016) Future changes in maximum temperature using the statistical downscaling model (SDSM) at selected stations of Iran. Model Earth Syst Environ 2:68. https://doi.org/10.1007/s40808-016-0112-z

Ahmadi H, Azizzadeh J (2020) The impacts of climate change based on regional and global climate models (RCMs and GCMs) projections (case study: Ilam province). Model Earth Syst Environ 6:685–696. https://doi.org/10.1007/s40808-020-00721-0

Ahmadi A, Moridi A, Lafdani EK, Kianpishesg G (2014) Assessment of climate change impacts on rainfall using large scale variables and downscaling models—a case study. J Earth Syst Sci 123:1603–1618. https://doi.org/10.1007/s12040-014-0497-x

Allen RG, Smith M, Pereira LS, Raes D, Wright JL (2001) Revised FAO procedures for calculating evapotranspiration: irrigation and drainage paper no. 56 with testing in Idaho. In: Watershed management and operations management. https://doi.org/10.1061/40499(2000)125

Ashofteh P, Haddad O, Marino M (2015) Risk analysis of water demand for agricultural crops under climate change. J Hydrol Eng. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001053

Battude M, Bitar AA, Morin D, Cros J, Huc M, Sicre CM, Dantec VL, Demarez V (2016) Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. Remote Sens Environ. https://doi.org/10.1016/j.rse.2016.07.030

Bothale RV, Katpatal YB (2017) Impact of climate change scenarios on hydrologic response of Upper Wardha catchment, Central India. Int J Glob Warm 13:32–56. https://doi.org/10.1504/IJGW.2017.085783

Chaturvedi RK, Joshi J, Jayaraman M, Bala G, Ravindranath NH (2012) Multi-model climate change projections for India under representative concentration pathways. Curr Sci 103:791–802

Dahal V, Shakya NM, Bhattarai R (2016) Estimating the impact of climate change on water availability in Bagmati basin, Nepal. Environ Process 3:1–17. https://doi.org/10.1007/s40710-016-0127-5

Dhamge NR, Badar AM, Baiswarey NZ (2008) Crop water requirement by modified Penman method using HYMOS. ISH J Hydraul Eng 14:28–42. https://doi.org/10.1080/09715010.2008.10514920

Djaman K, Oneill M, Owen CK, Smeal D, Koudahe K, West M, Allen S, Lombard K, Irmak S (2018) Crop evapotranspiration, irrigation water requirement and water productivity of maize from meteorological data under semiarid climate. Water 10:405. https://doi.org/10.3390/w10040405

Doria R, Madramootoo C, Mehdi B (2006) Estimation of future crop water requirements for 2020 and 2050, using CROPWAT. In: 2006 IEEE EIC climate change conference. https://doi.org/10.1109/eicccc.2006.277194

Ewaid SH, Abed SA, Ansari N (2019) Crop water requirements and irrigation schedules for some major crops in Southern Iraq. Water 11:756. https://doi.org/10.3390/w11040756

Genesse RG, Braun M (2019) Impact of internal variability on climate change for the upcoming decades: analysis of the CANESM2-LE and CESM-LE large ensembles. Clim Change 156:299–314. https://doi.org/10.1007/s10584-019-02550-2

Gilanipour J, Gholizadeh B (2016) Prediction of rice water requirement using FAO-CROPWAT Model in North Iran under future climate change. https://doi.org/10.20944/preprints201610.0134.v1

Hua W, Chen H, Sun S, Zhou L (2015) Assessing climatic impacts of future land use and land cover change projected with the CanESM2 model. Int J Climatol 35:3661–3675. https://doi.org/10.1002/joc.4240

Hussain M, Yusof KW, Mustafa MR, Mahmood R, Shaofeng J (2017) Projected changes in temperature and precipitation in Sarawak state of Malaysia for selected CMIP5 climate scenarios. Int J Sustain Dev Plan 12:1299–1311. https://doi.org/10.2495/SDP-V12-N8-1299-1311

Ikhar P, Regulwar DG, Kamodkar RU (2017) Optimal reservoir operation using soil and water assessment tool and genetic algorithm. ISH J Hydraul Eng 24:1–9. https://doi.org/10.1080/09715010.2017.1417754

Intergovernmental Panel on Climate Change (IPCC) (2014) Climate change: synthesis report. In: Core Writing Team, Pachauri RK, Meyer LA (eds) Contribution of working groups I, II and III, to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC, Geneva

Islam R, Islam MM, Islam MN, Islam MN, Sen S, Faisal RF (2020) Climate change adaptation strategies: a prospect toward crop modelling and food security management. Model Earth Syst Environ 6:769–777. https://doi.org/10.1007/s40808-019-00708-6

Khadka D, Pathak D (2016) Climate change projection for the marsyangdi river basin, Nepal using statistical downscaling of GCM and its implications in geodisasters. Geoenviron Disasters 3:15. https://doi.org/10.1186/s40677-016-0050-0

Koudahe K, Djaman K, Adewumi JK (2018) Evaluation of the Penman–Monteith reference evapotranspiration under limited data and its sensitivity to key climatic variables under humid and semiarid conditions. Model Earth Syst Environ 4:1239–1257. https://doi.org/10.1007/s40808-018-0497-y

Mahamood R, Babel MS (2012) Evaluation of SDSM developed by annual and monthly sub-models for downscaling temperature and precipitation in the Jhelum basin, Pakistan and India. Theor Appl Climatol 113:27–44. https://doi.org/10.1007/s00704-012-0765-0

Mehta R, Pandey V (2016) Crop water requirement (ETc) of different crops of middle Gujarat. J Agrometeorol 18:83–87

Mujumdar PP, Ghosh S (2008) Climate change impact on hydrology and water resources. ISH J Hydraul Eng 14:1–17. https://doi.org/10.1080/09715010.2008.10514918

Patidar R, Mohanty M, Sinha NK, Gupta SC, Somasundaram J, Chaudhary RS, Soliya R, Hati KM, Prabhakar M, Reddy SK, Patra AK, Rao S (2020) Potential impact of future climate change on maize under rainfed condition in Central India. J Agrometeorol 22:18–23

Pichuka S, Maity R (2016) Spatio-temporal downscaling of projected precipitation in the 21st century: indication of a wetter monsoon over the Upper Mahanadi Basin, India. Hydrol Sci J 62:467–482. https://doi.org/10.1080/02626667.2016.1241882

Poddar A, Gupta P, Kumar N, Shankar V, Ojha CSP (2018) Evaluation of crop evapotranspiration methods and sensitivity analysis of climatic parameters for sub-humid sub-tropical locations in western Himalayas (India). ISH J Hydraul Eng 10(1080/09715010):1551731

Rahimi J, Khalili A, Bazrafshan J (2018) Modeling uncertainty of statistical downscaling methods in quantifying the climate change impacts on late spring frost risk over Iran. Model Earth Syst Environ 4:421–435. https://doi.org/10.1007/s40808-018-0416-2

Rehana S, Mujumdar PP (2012) Regional impacts of climate change on irrigation water demands. Hydrol Process. https://doi.org/10.1002/hyp.9379

Saraf VR, Regulwar DG (2016) Assessment of climate change for precipitation and temperature using statistical downscaling methods in Upper Godavari River Basin, India. J Water Resour Prot 8:31–45. https://doi.org/10.4236/jwarp.2016.81004

Shreedhar R, Hiremath CG, Shetty GG (2015) Optimization of cropping pattern using linear programming model for Markandeya command area. Int J Sci Eng Res 6:1311–1325

Surendran U, Sushanth CM, Mammen G, Joseph EJ (2015) Modelling the crop water requirement using FAO-CROPWAT and assessment of water resources for sustainable water resource management: a case study in Palakkad district of humid tropical Kerala, India. Aquat Procedia 4:1211–1219. https://doi.org/10.1016/j.aqpro.2015.02.154

Tukimat NN, Harun S, Shahid S (2017) Modelling irrigation water demand in a tropical paddy cultivated area in the context of climate change. J Water Resour Plan Manag 143:05017003. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000753

Verma M, Misra AK (2017) Effects of elevated carbon dioxide and temperature on crop yield: a modelling study. J Appl Math Comput 58:503–526. https://doi.org/10.1007/s12190-017-1154-8

Wilby RL, Dawson CW (2013) The statistical downscaling model: insights from one decade of application. Int J Climatol 33:1707–1719. https://doi.org/10.1002/joc.3544

Wilby RL, Dawson CW, Barrow EM (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. Environ Model Softw 17:147–159. https://doi.org/10.1016/S1364-8152(01)00060-3

Yadeta D, Kebede A, Tessema N (2020) Potential evapotranspiration models evaluation, modelling, and projection under climate scenarios, Kesem sub-basin, Awash River basin, Ethiopia. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-00831-9

Zhang Y, You Q, Chen C, Ge J (2016) Impacts of climate change on streamflows under RCP scenarios: a case study in Xin River Basin, China. Atmos Res 5:6. https://doi.org/10.1016/j.atmosres.2016.04.018

Zhou T, Wu P, Sun S, Li X, Wang Y, Luan X (2017) Impact of future climate change on regional crop water requirement: a case study of Hetao irrigation district, China. Water 9:429. https://doi.org/10.3390/w9060429