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Development of framework for assessment of impact of climate change in a command of water resource project

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A framework comprising of four interdependent modules has been developed to analyse demand–supply scenarios under future uncertainties of climate change in an irrigation command where any mismatch can affect sustainability and wellbeing of the rural population. In the absence of runoff records, the water balance module of framework computes daily runoff from catchment considering all inputs, outputs and losses from the system. The climatic parameters and rainfall were forecasted for three future projected periods using statistical downscaling for six different climate projections. The Soil and Water Analysis Tool (SWAT), a physically based spatially distributed hydrological model and SWAT-CUP, an application for calibration and uncertainty analysis of SWAT model have been used to calibrate and validate a model for the base period (BP:1981–2015) and further applied to generate multiple future runoff series to asses water availability. The module-IV was designed to compute evapotranspiration using ETo calculator (a software to compute evapotranspiration) and then irrigation demand for Tandula command in the Chhattisgarh state of India considering present overall efficiency of 51% for the base (1991–2015) and future assessment periods. The analysis of all projected scenarios suggested an increase of annual temperature from present 26.2°–27.1°, 27.3° and 27.8°C during near (FP-1: 2020–2035), mid (FP-2: 2046–2064) and far century (FP-3: 2081–2099) periods, respectively, may demand more water which could be adversely affected by reduced rainfall. The water requirement may vary in the range of 410.4–464 MCM and supply from 426.2 to 453.2 MCM based on future projection from GCMs.

Keywords. GCM; downscale; climate change; crop water requirement; evapotranspiration; demand–supply analysis.

1. Introduction

Climate change likely to affect almost all the sectors of life and society (Rosenzweig *et al.* 2004; Scibek and Allen 2006; Githui *et al.* 2009; IPCC 2008, 2012, 2013; Liew *et al.* 2014; Segura *et al.* 2014; Kulkarni *et al.* 2016). Lugina *et al.* (2006) analyzed mean monthly and annual temperatures and concluded that the 12 out of 15 warmest years recorded in the history occurred after 1990. Mendelsohn (2008) reviewed various economic studies to assess the impact of climate change on agriculture in developing countries like India, Brazil, South Africa and South America and developed

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countries like the USA using Ricardian analysis and concluded that the agriculture in developing countries of tropical and sub-tropical regions is more sensitive than temperate agriculture. As climate change can significantly affect the demand of water, for the command and availability of water in the reservoir and other sources, it is desirable to carry out climate change assessment studies where irrigation demand and water availability should be computed using projections from general circulation models (De Silva *et al.* 2007; Shahid 2011).

The general circulation models (GCMs) are the most reliable tools intended to simulate climatic time series under future greenhouse gases (GHGs) concentrations used for different hydrologic and impact assessment studies (Ghosh and Mujumdar 2008; Chen *et al.* 2014; Alfieri *et al.* 2015; Panday *et al.* 2015). The GCMs are designed to project climate data, for coarse grids cannot be used directly on regional and basin scale. The statistical downscaling techniques link the coarse grid atmospheric conditions with local scale climatic data (Fowler *et al.* 2007; Tisseuil *et al.* 2010), while physically based models are used in dynamic downscaling techniques suitable for the limited area only (Giorgi and Mearns 1999). The dynamic downscaling models are suffered from the major drawback of complexity, high cost of the model run (Anandhi *et al.* 2008) and proliferation of systematic bias from GCM to RCM (Salathe 2003). The statistical downscaling is reasonably precise, simple, flexible, less costly and computationally less demanding has proved its reliability and compatibility in future projections (Lopez *et al.* 2009; Ethan *et al.* 2011).

The statistical downscaling model (SDSM) is one of the most commonly used software for downscaling climate variables. Wilby *et al.* (2014) developed and demonstrated new functionality of the Decision Centric (DC) version of the Statistical Down Scaling Model (SDSM-DC) having the facility of cross-validation and synthesis of daily weather climate series. Mahmood and Jia (2016) have assessed the impact of climate change on water resource availability in transboundary Jhelum river of Pakistan under A2 and B2 scenarios of the HADCM3 model using SDSM. From the analysis, it has been found that mean annual flow will increase by 4–15% under both A2 and B2 scenarios. Similarly, several other researchers (Wilby and Wigley 2000; Wilby *et al.* 2002; Khan *et al.* 2006; Fiseha *et al.* 2012; Tukimat and Harun 2013; Mahmood and Babel 2014) applied easy to use and convenient SDSM for downscaling of precipitation and climatic parameters.

The development of relationship between rainfall and runoff using hydrological modelling is the earliest, simplest and most commonly used method to quantify the contribution of climate changes, land use and other intervention on runoff and management of water resources (Tripathi *et al.* 2004, 2006; Lin *et al.* 2007, 2010). To quantify the impact of climate change and other anthropogenic activities, the rainfall-runoff modelling in association with the known quantum of climate change is one of the earliest and most commonly applied techniques (Jones *et al.* 2006). AGNPS (Young *et al.* 1989), ANSWERS (Beasley *et al.* 1980), MIKE SHE (Xevi *et al.* 1997), WEEP, SWAT (Arnold *et al.* 1998a, b; Neitsch *et al.* 2001), etc., are commonly used agricultural watershed models for runoff and sediment modelling. The SWAT model being simple, possibilities of changing source code has been widely used for scenarios assessment and impact of different hydrological components in watershed under land use/land cover (LULC) and climate change conditions (Gassman *et al.* 2007; Ghaffari *et al.* 2010). Glavan and Pinter (2012) described the strength, weakness, opportunities and threat (SWOT) of SWAT model and described it as easily available on-line model, which can combine water quality, quantity, agriculture land management, and climate change. Pandey *et al.* (2017) applied semi-distributed SWAT model for computation of water balance components of Armur watershed in Godavari river basin of India for the baseline (1961–1990) and future projected period (2071–2100) using A2 and B2 scenarios of Hadley Centre Regional Climate Model (HADRM3). The results of the analysis confirmed an increase of 3.25°C, 28, 28 and 49% in annual temperature, rainfall, evapotranspiration and water yield, respectively, during the future period (2071–2100) from the base period (1961–1990).

Assessment of climate change impact on crop water requirement is essential to develop adaptation strategies and sustainable management. Putthividhya and Sukgerd (2015) used GIS and CROPWAT for Ban Khai irrigation project in Thailand for assessment of spatially distributed crop water requirement and observed a deficit of water and reduction of yield. They suggested supplemental irrigation requirement under the wide spectrum of scenarios. Hashim *et al.* (2012) used neutron probe and lysimeter for computation of crop water requirement of wheat, broad beans, corn, cowpea, millet, okra and eggplant as seasonal crops, grasses and alfalfa as forage crops in Makkah region of Saudi Arabia and found that water requirement for seasonal crops may vary from 303 to 727.8 mm and the same for forage crops will be from 436.7 to 1821.94 mm. Lee *et al.* (2016) assessed the impact of climate change on translating and growing season for paddy crops in South Korea and optimized transplantation date and found that 923 MCM water can be saved if transplantation date is changed. Sposito *et al.* (2010) developed a decision-making framework for modelling adaptation due to climate change in rural agriculture production in the southwest region of Australia. The results obtained from regional downscaling of SRES scenarios B1, A2 and A1FI (IPCC 2000) were used to suggest adaptation strategies. Shrestha *et al.* (2014) applied SDSM coupled AquaCrop model for computation of irrigation water requirement and crop yield for rainfed and irrigated paddy in the southern region of Myanmar and found decreasing water demand in future due to shifting of climate pattern. Mainuddin *et al.* (2015) assessed the impact of climate change on dry irrigation for boro rice in Bangladesh using the A1B emission scenario for future periods of 2030 and 2050. They concluded that the average irrigation water requirement may increase by 3% for rice and 1–5% for other crops for the dry scenario. Bhatti *et al.* (2019) predicted future climate for A2 emission scenarios and applied in climate-based models to analyse variation in rainfall pattern and resulting crop growth in the Hakra branch canal of Pakistan.

Climate change has already instigated the negative impact on agriculture in many parts of the world because of more intense weather pattern. An increase in average global temperatures of just 2–4°C than pre-industrial levels could reduce crop yields by 15–35% in Africa and western Asia, and by 25–35% in the Middle East (FAO 2001). The latest economic survey of India of 2018 gave a warning that as per the prediction of IPCC of increasing temperature of 3–4°C by the end of the century may lower annual irrigation revenue by 12% in irrigated and 18% in rain-fed areas of the country. Mall *et al.* (2006) in their comprehensive review on impacts of climate change on Indian agriculture explained the large range of uncertainties in projected future temperature and precipitation over India and showed a significant warming trend in most of the places; however, rainfall may not be changed significantly. The water resources projects which are created to serve society for several decades have substantial risk for performance and now increasingly planned to sustain the potential impacts of climate change (Amell and Delaney 2006; Millner and Dietz 2015). Several different studies have been carried out by researchers (Kiparsky *et al.* 2014; Bhave *et al.* 2016; Shrestha and Shrestha 2016; Han *et al.* 2017; Asghar *et al.* 2019) with the objectives of impact assessment of climate change and development of adaptive measures on basin and project scales.

Under plausible climate change with increased climate variability, the farmers of developing countries like India are highly vulnerable and building their resilience is one of the most important challenges for planners and scientists. The crop income of farmers in irrigation projects may be under constant threat due to higher input cost in the belief of assured water supply may be under constant threat due to changing climate. The Chhattisgarh state of India is well known for its natural resources including water and working hard to manage judiciously. The agriculture is the main stem of the rural population in Chhattisgarh where 46.77 lakh ha land comes under cultivation. Non-availability of runoff data is a real challenge to assess supply and rainfall-runoff modelling for which a comprehensive water balance is required to determine runoff from the catchment. The review of literature has suggested that most of the studies on impact of climate change focused on either water availability or demand management in water resource project. In this study, a framework of four interconnected modules has been suggested and implemented to assess demand–supply analysis under changing climate conditions for command of water resource project in India.

2. Material and method

2.1 *Study area and data used*

The Tandula dam is situated on the confluence of river Tandula and Sukha Nala near Balod district of Chhattisgarh state of India having gross and live storage capacity of 312.25 and 302.28 MCM, respectively (figure 1). The catchment area of Tandula dam is 827.2 km^2. The design cropping pattern of Tandula command is 68,219 ha of paddy

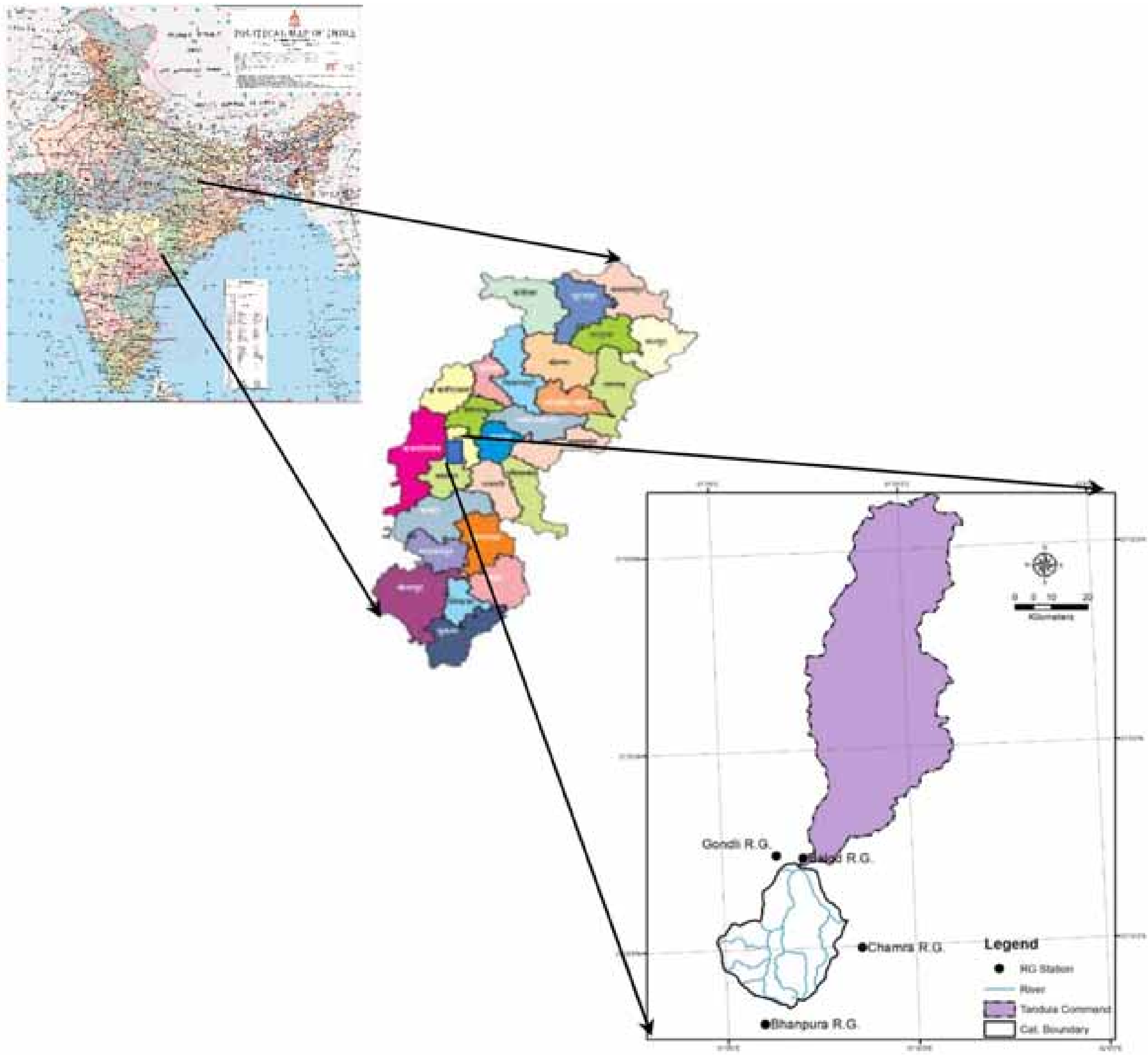

Figure 1. Base map showing Tandula dam and command in Chhattisgarh state (India).

in kharif season which was extended to 82,095 ha, now facing problems of water shortage. As complete cropping area in command cannot be shown at once, the total cropping area of paddy has been divided into two equal parts grown on June 15 and July 1 each year. The cropping pattern of Tandula command is given below.

Crop	Jun-1	Jun-2	Jul-1	Jul-2	Aug-1	Aug-2	Sept-1	Sept-2	Oct-1	Oct-2	Nov-1	Nov-2
Paddy-1 41048 ha		S							H			
Paddy-2 41047 ha			S							H		

The historical daily minimum temperature, maximum temperature and pan evaporation of Raipur Observatory for the period 1971–2015 collected from Indira Gandhi Agriculture University, Raipur and concurrent 26 NCEP/NCAR reanalysed predictors set (Kalnay *et al.* 1996) were used in the analysis. The rainfall series of Balod, Chamra, Bhanpura and Gondli R.G. stations for the period of 25 years (1991–2015) collected from the Water Resources Department (WRD) Raipur has been used in the study. Different predictors of A1B and A2 scenarios of CGCM, RCP 2.6, 4.5 and 8.5 of CANESM2 from the website http://climate-modelling.canada.ca and A2 and B2 scenarios of HADCM3 from the website https://catalogue.

ceda.ac.uk for the period of 2003 to 2099 were used for projection of climate and rainfall data. The daily reservoir levels, overflow from the spillway, canal releases of Tandula reservoir, transfer of water from adjoining Gondli reservoir from 1991 to 2015 and elevation-capacity table were collected from WRD Raipur for the water balance of Tandula reservoir.

2.2 *Methodology*

The proposed framework for demand–supply analysis consists of four interrelated modules including water balance of reservoir for computation of runoff from the catchment in module-I, future projection of climatic parameters and rainfall using the statistical downscaling technique in module-II. The rainfall-runoff modelling for water availability analysis of base period has been carried out in module-III, which further used to forecast future water availability using inputs from module-I and II. The module-IV is designed for assessment of present and future crop water requirement using inputs from module-II to analyse demand–supply scenarios. In the present study, demand–supply analysis has been carried out for three future periods (FP-1: 2020–2035, FP-2: 2046–2064 and FP-3: 2081–2099) considering projection, downscaling and modelling uncertainties. The workflow under these modules has been presented in figure 2 and described in the following sections.

2.2.1 *Module-I: Water balance of reservoir*

The water balance study of catchments, reservoirs, lakes, groundwater basins can be used for

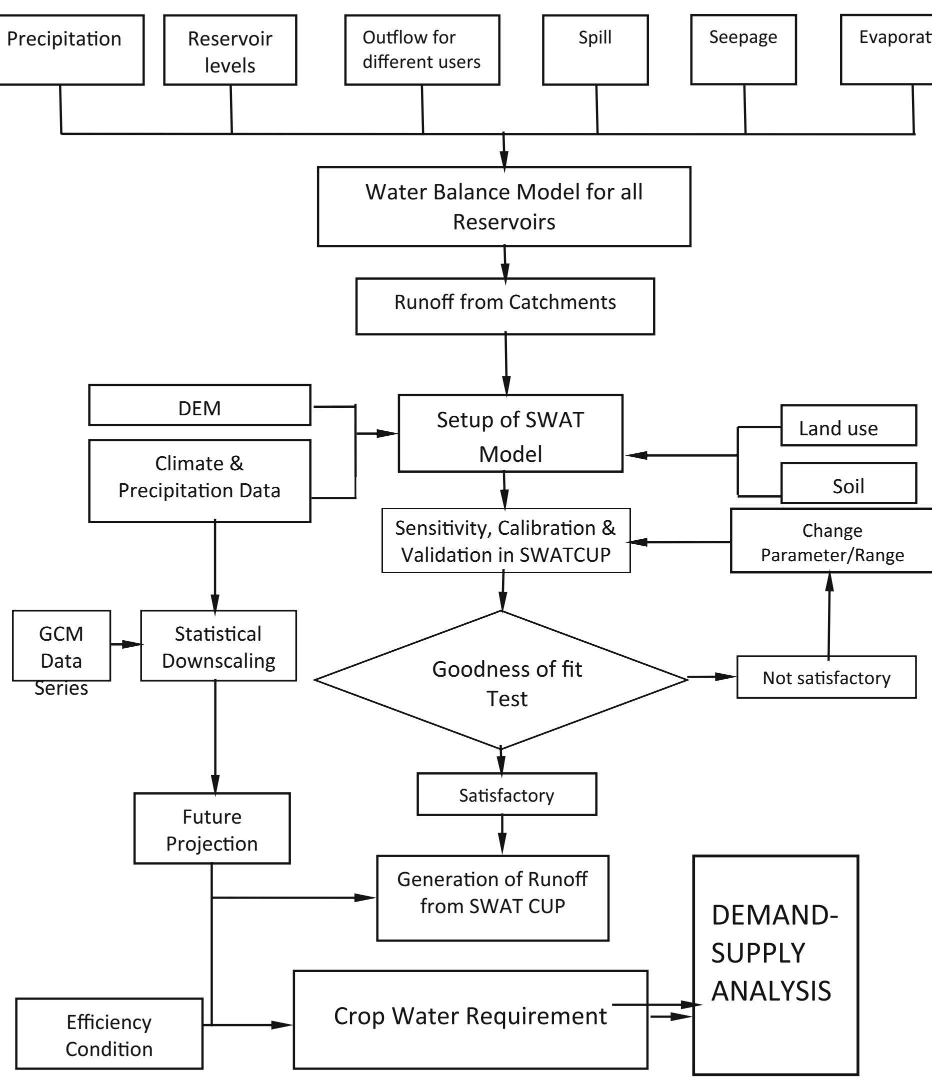

Figure 2. Work flow for proposed methodology under RDM framework.

allocation, control and redeployment and rational use of water resources in space and time (Sokolov and Chapman 1974). The water balance is a form of 'book-keeping' of a basin or reservoir where all significant components are considered for a specific period of time. The basic continuity equation for the water balance of a system can be written as:

$$\begin{bmatrix}\text{Input}\\ \text{to the}\\ \text{System}\end{bmatrix} - \begin{bmatrix}\text{Outflow}\\ \text{from the}\\ \text{System}\end{bmatrix} = \begin{bmatrix}\text{Change}\\ \text{in}\\ \text{Storage}\end{bmatrix}. \quad (1)$$

The hydrologic balance in case of water bodies provides stored water in controlled section and inflows from the basin using simple mass balance where the sum of all outflows deducted from the sum of inflows provides change in stored volume over a specific period of time (Chapra 1997; Fetter 2001; D'Urquiza-Díaz *et al.* 2009, etc.). The components of water balance in a reservoir can be summarized as:

$$V_t = V_{t-1} + (Q_{\text{in}})_t - (Q_{\text{out}})_t - U_t - (P_t - E_t - S_t)A_t, \quad (2)$$

where V_t and V_{t-1} are the volumes of water at any time t and t−1, respectively. $(Q_{\text{in}})_t$ and $(Q_{\text{out}})_t$ are the inflow and outflow volume from the reservoir, P_t, E_t and S_t are the depth of precipitation, evaporation and seepage from the reservoir and A_t is the area of reservoir at time t and U_t is the volume of water passes through the waste weir. The daily reservoir data including reservoir levels, elevation-area-capacity, spillway capacity tables, outflows including irrigation release, seepage loss, transfer to the other reservoir if any and evaporation data were used to determine daily runoff from the catchment of Tandula reservoir.

2.2.2 *Module-II: Statistical downscaling of climatic parameters and rainfall*

In the present study, statistical downscaling using SDSM-DC software (Wilby *et al.* 2014) has been carried out for the generation of future climatic scenarios for climatic variables and rainfall at different R.G. stations in Tandula command and catchment. In the statistical downscaling technique, the climatic parameters like temperature which are not dependent on any intermediate processes are modelled through unconditional multiple linear regression assuming a direct link between regional-scale predictors and local predictand, while precipitation is modelled through a conditional process because of its regulation by the intermediate process of wet day occurrence (Wilby *et al.* 2001). For the unconditional process of climatic parameters, the following equation is used to develop a direct relationship between climatic predictor (C_i) and chosen predictors (X_{ij}) along with regression constants, $\gamma_0, \gamma_1, \ldots, \gamma_j$ and e_i as the model error.

$$C_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j X_{ij} + e_i. \quad (3)$$

In case of precipitation, the wet day occurrence on an ith day can be determined by computing a candidate using random process generator (W_i) that varies from 0 to 1 and depends on n number of predictors (X_{ij}) using the following equation.

$$W_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j X_{ij}. \quad (4)$$

Statistically, the precipitation on any day is considered to be occurred if $W_i \le r_i$, where r_i is a stochastic output of the linear random generator. When the wet day is confirmed, the following equation can be used for downscaling of precipitation total (P_i) on a wet day:

$$P_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + e_i. \quad (5)$$

where, β_0, β_1, …, β_j are the regression coefficients and e_i is the model error (stochastically generated normally distributed number). The details of the statistical modelling process can be seen in Wilby *et al.* (2014) where the importance of the selection of the appropriate set of predictors was emphasized in statistical downscaling. The application of SDSM along with the strength and weakness can be found in Wilby *et al.* (2002, 2004), Gachon *et al.* (2005), Wilby and Dawson (2012), etc.

The selection of a set of appropriate predictors is one of the most important tasks in downscaling where knowledge of the physical atmospheric process and physically sensible predictors are crucial (Huang *et al.* 2011). Several methods were propagated by different researchers for selection of an appropriate set of predictors (Benestad 2002; Shongwe *et al.* 2006) and in the present study, percentage reduction method (Mahmood and Jia 2016) along with scatter diagram has been used where the top 10 predictors in the rank of correlation coefficient were selected and the predictor having the highest correlation coefficient called first super predictor. The absolute correlation coefficient, absolute partial correlation and percentage reduction (PR) can be computed for the remaining nine predictors using the following equation (Pallant 2007).

$$PR = \frac{P_r - R}{R}, \tag{6}$$

where P_r and R are the partial and absolute correlation coefficient, respectively. The predictors having P-value more than 0.05 and absolute correlation coefficient with super-predictor more than 0.70 have been removed to avoid multi-colinearity. The predictor having the lowest PR value has been recognized as the second super-predictor. A similar process is applied to get third predictors with a limiting a number of predictors up to three (Wilby *et al.* 2002; Chu *et al.* 2010). After selecting a set of suitable predictors, empirical relationships between predictand and selected predictors were developed using appropriate transformation and unconditional process for climatic parameters, while the conditional process for rainfall. The monthly, seasonal or annual models have been developed in SDSM using K-fold cross-validation technique (Markatou *et al.* 2005; Casanueva *et al.* 2014). In K-fold cross-validation, whole data series is divided into two parts and the first $((K–1)/K)$ part is taken for calibration to develop statistical relationships, while the remaining $(1/K)$ part is used for validation purpose. The generated series was debiased using linear scaling technique for precipitation (Lenderink *et al.* 2007; Fang *et al.* 2015) and linear difference for other climatic parameters. After debiasing, various goodness-of-fit criterions including statistics coefficient of correlation (C_c), adjusted R^2 (adj R^2), Nash–Sutcliff efficiency (η) (Nash and Sutcliffe 1970) for monthly rainfall of monsoon season have been used for selection of the best-suited model.

The uncertainty analysis is carried out to ascertain how closely the GCM data can reproduce the current climate of station/region with the help of the proposed statistical model. Wilcoxen's test has been used to test the hypothesis that two sets of data are significantly different from each other (Ogungbenro and Morakinyo 2014). Let S1 (X_1, $X_2, X_3, \ldots, X_n$) and S2 ($Y_1, Y_2, Y_3, \ldots, Y_n$) are two paired samples. The test statistics (V_s) of this test can be computed by the following equation.

$$V_s = \sum_{i=1}^{n_r} \mathrm{sign}(Y_i - X_i) R_i, \tag{7}$$

where, R_i is the rank of the pair and n_r is the number of non-zero pairs. Under the null hypothesis, V_s follows a distribution with expected value $E(V_s) = \frac{(n_r(n_r+1))}{4}$ and variance $V(V_s) = \frac{(n_r(n_r+1)(2n_r+1))}{6}$. For this test, p-value suggested by Lehmann (1975) has been used and given by the following equation:

$$P(V_s \le v) \approx \emptyset \left[\frac{v - E(V_s) + c}{\sqrt{V(V_s)}} \right], \tag{8}$$

where, $\emptyset$ and c is the distribution function and continuity correction, respectively. The null hypothesis (H_0) is defined as there is no inequality in the difference between observed and simulated variables at a critical p-value of 0.05 (95% confidence level here) (Pervez and Henebry 2014). After calibration, validation and uncertainty analysis, the weather generator of SDSM has been used for generation of multiple series of minimum and maximum temperature of Raipur and rainfall of four rain gauge stations in and around the Tandula catchment for three future periods namely near-century (2020–2035), mid-century (2046–2064) and far century period (2081–2099).

2.2.3 *Module III: Rainfall-runoff modelling*

In the present study, the SWAT model coupled with SWAT-CUP extension has been used for modelling hydrological processes in the catchment of Tandula reservoir considering its suitability for gauged as well as ungauged catchments. SWAT is a physically based model capable to predict the impact of management practices on runoff, sediment, chemical yields and nutrients on the basin and sub-basin scales (Arnold *et al.* 1998b; Neitsch *et al.* 2002). For modelling purpose, SWAT model divides a basin into a number of sub-basins and hydrological response units (HRUs). Sub-basin has a number of HRUs and each HRU is a lumped land area having a unique slope, land use, soil and management practices within the sub-basin. The following formulae are used in the SWAT model to predict surface runoff using the SCS-CN method.

$$Q = \frac{(P - I_a)^2}{(P - I_a + S)}, \tag{9}$$

where, $I_a = 0.2S$ for antecedent moisture condition II (AMC II), Q is the surface runoff in mm, P is the rainfall in mm, I_a is the initial abstraction, S is the surface retention can be computed by the following equation.

$$S = \frac{25400}{CN} - 254, \tag{10}$$

where, CN is the curve number depends on soil type, land use, management practices and antecedent moisture condition. The setting up of SWAT model can be done using six different menus present in Arc SWAT GUI including SWAT project setup, Watershed Delineator, HRU Analysis, Write Input Tables, Edit SWAT Input and SWAT Simulation. The SWAT model has been set up using ARC SWAT 2009 and sensitivity, calibration and validation have been carried out in SWAT-CUP, an associated public domain program having several optimization techniques like SUFI2, PSO, GLUE, Parasol, and MCMC. The full details regarding the application of SWAT-CUP can be seen in Abbaspour *et al.* (2007). The sensitivity analysis in SWAT-CUP can be carried out using Latin Hypercube generated One-factor-at-a-Time (LH-OAT) technique which regressed through a multiple regression system to get *t*-stat and *p*-value for a parameter. The *t*-stat value of a parameter can be compared with Student's *t* distribution and used to test how the mean of a sample of certain numbers is expected to behave. The *p*-value of each parameter is used to test the null hypothesis which indicates the low value (generally less than 0.05) can reject the hypothesis which finally gives the impression that the parameter is not very sensitive.

The uncertainty and calibration are carried out in the modelling process to determine the degree to which all uncertainties are accounted for and represented by *p*-factor and *r*-factor in SWAT-CUP application. The *p*-factor is a measure to represent how well-measured data lie within the data bracket of, by 95% prediction uncertainty (95 PPU) (Arnole *et al.* 2012), while *r*-factor may be defined as the ratio of the average width of 95 PPU band and standard deviation of the observed data. The *r*-factor value varies from 0 to infinity indicated the quality of the calibration. The *p*-factor as 100% and *r*-factor as 0 can be considered as a perfect match where simulated data exactly replicate the observed data during calibration. Generally, when the value of *p*-factor is increased, corresponding *r*-factor is also increased, so during calibration, a balance between two is maintained and tried to get the maximum value of *p*-factor with a minimum value of *r*-factor in combination. After successful calibration and validation of the model, the developed model with the best-fit values of parameters has been used to determine runoff series from catchments. For each scenario of different GCMs, three randomly selected climatic and rainfall series were generated in module-II, selected and used in SWAT-CUP application for generation of future runoff series. The average runoff from these three series has been computed and considered as average yearly runoff from the catchment.

2.2.4 *Module-IV: Computation of crop water demand*

The crop water requirement is the main demand on Tandula reservoir for which evapotranspiration for reference crop is computed using ETo calculator software (http://www.fao.org/land-water/databases-and-software/eto-calculator/en/) in module-IV. The ETo calculator uses the Penman–Monteith equation suggested by Food and Agriculture Organization (FAO). The ETo calculator uses minimum, maximum temperature, sunshine hours, wind speed and relative humidity and alternatively only temperature data along with location can be used to compute evapotranspiration. The crop water requirement for a crop consists of water needs to be supplied from source to meet all requirements including evapotranspiration, field preparation, nursery, leaching and losses during conveyance and application. The paddy is the only crop in the kharif season where water is supplied from Tandula reservoir. The standard depth of water as per prevailing norms for the nursery (100 mm each for first two 10-daily periods) and transplantation (150 mm for the third 10-daily period) have been considered for computation of crop water requirement (WAPCOS 2015). The total water requirement from multiple generated series of climatic parameters obtained from module-II for three future periods have been determined considering losses during conveyance and application and compared with corresponding supplies during the base period (BP: 1981–2015) under a similar situation. Presently, this region has conveyance efficiency as 75% (seepage and evaporation losses from mains and distributaries: 15% and operation losses: 10%) and application efficiency as 68% (field channel losses: 15% and filed losses: 20%) that make system efficiency as 51% (WAPCOS 2015).

3. Results and discussion

A framework consisting of four modules has been formulated and applied for the demand–supply analysis in Tandula command to deal with the uncertainties of climate change for three future assessment periods, i.e., FP-1: 2020–2035, FP-2: 2046–2064 and FP-3: 2081–2099.

3.1 *Module I: Water balance of reservoir*

The availability of water from the catchments of medium and small projects is one of the major problems for water resources management in developing countries. The water balance of Tandula reservoirs has been carried out on a daily time scale in module-I. The water balance analysis has been carried out from 1991 to 2015 for reservoir and all positive and negative components of water balance have been computed on daily basis and used in mass conservation equation to determine inflow from the catchment. In order to check water balance, the percentage error was computed using change in storage from water balance and reservoir levels for water year period (June 1 to May 31). Different components of the water balance of Tandula reservoir has been presented in figure 3.

From the analysis, it has been observed that percentage errors in water balance varied in the range of −6.87 to 4.04% for Tandula reservoir, which is $< 10\%$ of inflow and hence the inflow computed from water balance of reservoirs can be used in module-III for rainfall-runoff modelling. The seepage and evaporation are the major losses in the reservoir depending on the area of contact and water spread, respectively. The results of water balance for reservoirs indicated average annual flow may be 483 ± 202.8 MCM from Tandula catchment.

3.2 *Module II: Future projection of climatic parameters and rainfall*

The module-II has been used to forecast minimum and maximum temperature and rainfall of Balod, Bhanpura, Chamra and Gondli rain gauge stations. The SDSM-DC software has been used for selection of predictors, calibration and validation of statistical models which were further used to generate multiple series (10 for each) from seven different future climate forcing conditions including A1B and A2 scenarios of CGCM, RCP2.6, RCP4.5 and RCP8.5 of CANESM2 and A2 and B2 scenarios of HADCM3, GCMs for three future periods namely early century as FP-1 (2020–2035), mid-century as FP-2 (2046–2081) and far century as FP-3 (2081–2100).

During calibration of models in SDSM, different combinations of transformations and model types were tested and a series of climatic parameters for the calibration period was generated and debiased. The generated and observed climatic data were taken outside of SDSM and the coefficient of correlation (C_c), adjusted R^2 and Nash–Sutcliffe efficiency (η) for calibration period were computed on monthly basis for all the combinations. Few best-fit combinations of predictors selected during calibration were used to generate series with independent series of predictors for validation periods and goodness-of-fit measures were determined to assess the model performance. The Nash–Sutcliffe efficiencies have been worked out as 98.5 and 99.8% for minimum temperature, 91.3 and 91.5% for maximum temperature during calibration and

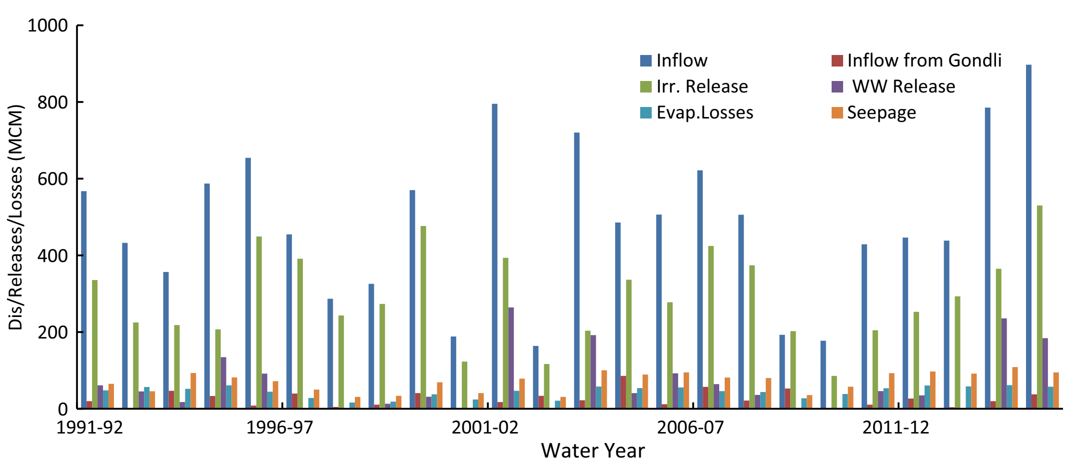

Figure 3. Different components of water balance of Tandula reservoir.

Table 1. *Goodness-of-fit measures for the statistical model for different climatic variables.*

Sl. no.	Climatic variables	Selected predictors	Model type/ transformation	Calibration C_c	Calibration Adj R^2	Calibration η	Validation C_c	Validation Adj R^2	Validation η
1	Minimum temperature	ncepp_fgl, ncepp500gl, nceps850gl	Monthly/none	0.96	0.91	91.3	0.96	0.92	91.5
2	Maximum temperature	ncepp5_zgl, ncepp500gl, ncepp8zhgl	Monthly/none	0.73	0.73	98.5	0.84	0.70	99.8
3	Relative humidity	nceps500gl, nceps850gl, ncepshumgl	Monthly/none	0.97	0.94	93.7	0.73	0.52	91.7
4	Wind speed	ncepmslpgl, ncepp5_ugl, ncepp_zgl,	Monthly/none	0.96	0.92	83.5	0.91	0.83	79.0
5	Sunshine hour	nceps500gl, nceps850gl, ncepshumgl	Monthly/none	0.90	0.84	82.9	0.87	0.75	78.9
6	Evaporation	ncepmslpgl, ncepshumgl, nceptempgl	Monthly/fourth root	0.71	0.51	93.1	0.90	0.87	99.5
7	Rainfall at Balod	ncepp5_ugl, ncepp8_ugl, ncepp850gl	Monthly/none	0.69	0.55	85.9	0.66	0.66	75.3
8	Rainfall at Bhanpura	ncepp5_ugl, ncepp5_zgl, ncepp8_zgl	Seasonal/none	0.66	0.58	64.6	0.88	0.45	49.6
9	Rainfall at Chamra	ncepp5_ugl, ncepp8_ugl, ncepp850gl	Seasonal/none	0.67	0.58	96.7	0.77	0.44	69.5
10	Rainfall at Gondli	ncepp_fgl, ncepp5_ugl, ncepp8_ugl	Seasonal/none	0.69	0.54	76.6	0.61	0.68	52.6

C_c = coefficient of correlation, Adj R^2= adjusted coefficient of determination, η = Nash–Sutcliffe efficiency.

validation, respectively. Similarly, the efficiencies for different rain gauge stations varied from 64.6 to 96.7% during calibration and from 49.4 to 75.3% during validation. The list of selected predictors, model type, transformation and different goodness-of-fit measures for different climatic variables have been presented in table 1.

In the uncertainty analysis, the developed statistical models for minimum, maximum temperature and rainfall were used to generate series for the period of 2001 to 2013 for A1B and A2 scenarios of CGCM, A2 and B2 of HADCM3 and from 2006 to 2013 for RCP2.6, RCP4.5 and RCP8.5 and debiased for application of Wilcoxon's signed-rank test. The computed p-value of the test has been compared which is the probability level to which the null hypothesis H_0 can be accepted. As all p-values were found equal or greater than significance level 0.05 (95% confidence level), it may be concluded that the developed models have no significant uncertainty and can be used for generation of future temperature and rainfall series. After uncertainty analysis, the developed statistical models were used to generate multiple series for temperature and rainfall using forecasted GCMs predictors selected for the models. Ten different series for minimum temperature, maximum temperatures and rainfall of four R.G. stations have been generated for three assessment periods. The graphical representations of ranges of minimum and maximum temperature during different projected periods have been depicted in figure 4(a and b), while projected seasonal rainfall in table 2.

The analysis of multiple projected scenarios suggested an increase of mean monthly minimum temperature in the months of February–May and October–December in all three future periods. The increasing minimum temperature in the month October–December may impact kharif water requirement in the region. The annual minimum temperature for the base period, 19.8°C may increase to 20.1, 20.0 and 20.3°C, respectively, during early, mid and far century periods, respectively. The results of the analysis of maximum temperature projection from different GCMs indicated a rising trend in all the months in the range of 0.27–18.49% during the near-century period, 0.18–30.73% during the mid-century period and 0.48–37.74% during far century period except in the month of December. The more intense heatwave in summer months may create health as well as water-related problems and more water for crops in rabi and kharif seasons in the region.

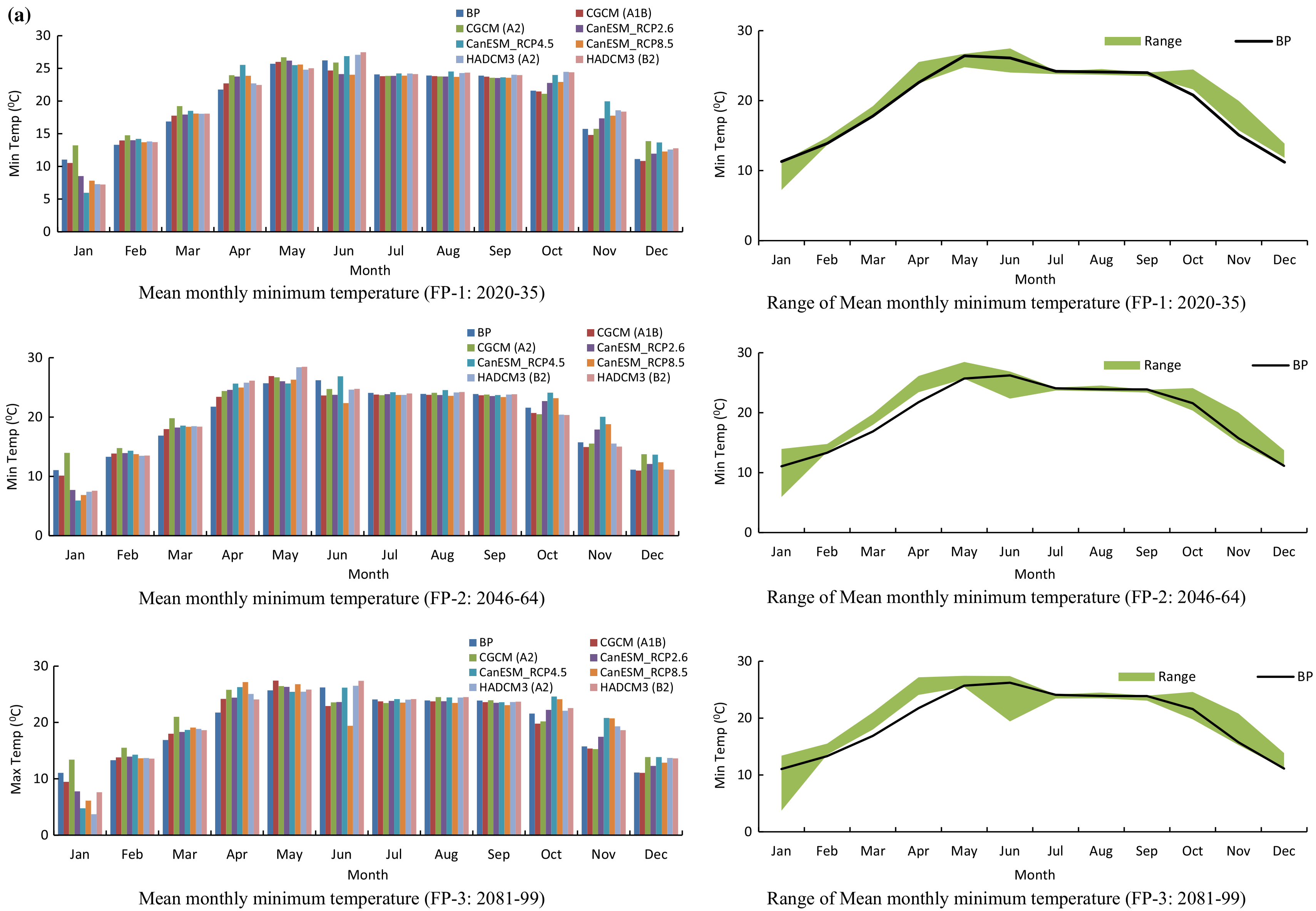

Figure 4. (**a**) Mean monthly minimum temperature and its range from different scenarios in three future projection periods. (**b**) Mean monthly maximum temperature (°C) and its range from different scenarios in three future projection periods.

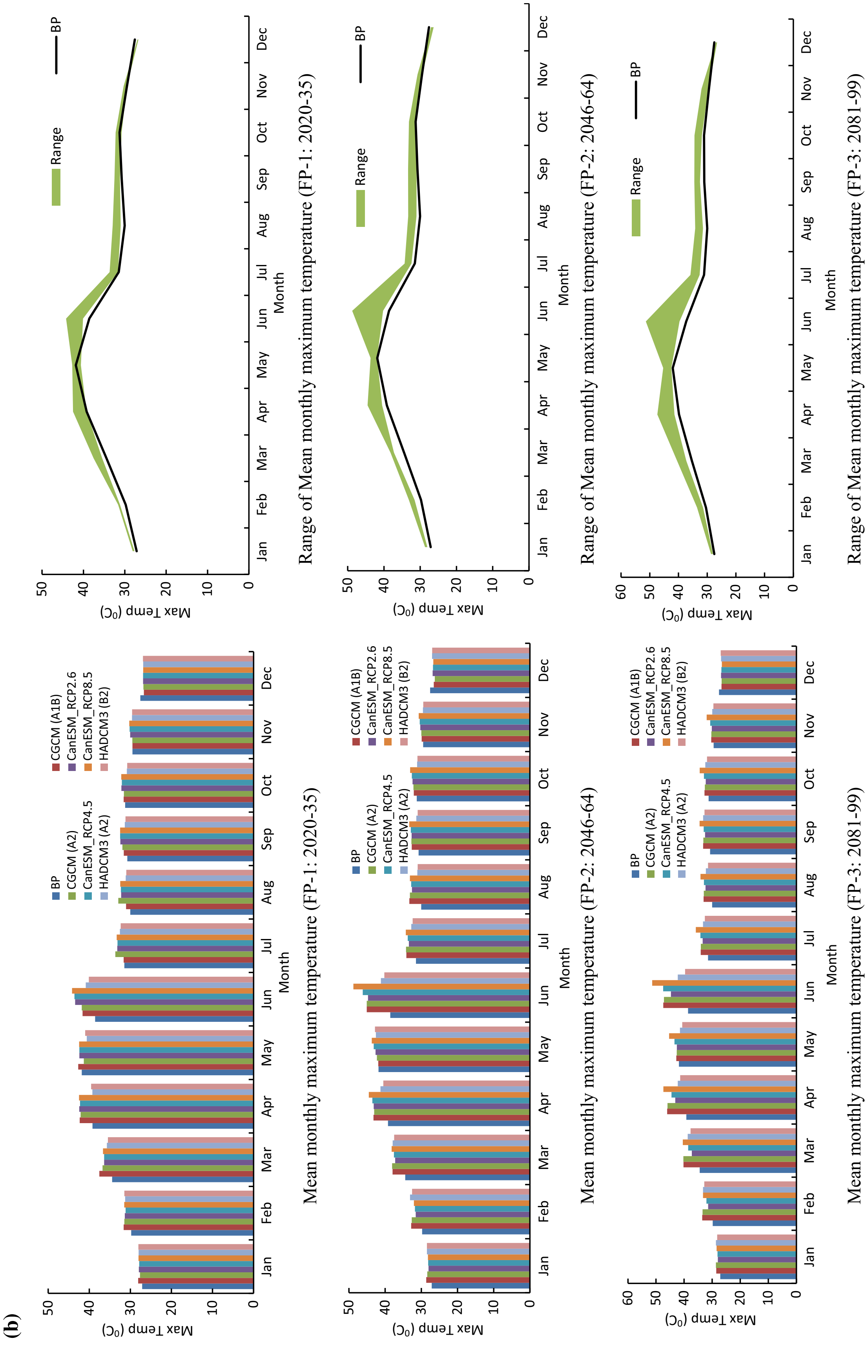

Figure 4. (Continued.)

Table 2. *Comparison of the base period and future projected mean seasonal rainfall.*

Rain gauge station	Base period (BP)	FP-1 2020–2035	FP-2 2046–2064	FP-3 2081–2099	FP-1 2020–2035	FP-2 2046–2064	FP-3 2081–2099
		CGCM-A1B			CGCM-A2		
Balod	936.3	1043.8	907.8	843.9	1009.2	863.4	915.6
Bhanpura	1484.5	1385.0	1413.3	1386.1	1369.4	1450.6	1375.2
Chamra	1095.1	1076.4	1094.2	913.9	1104.5	980.2	869.8
Gondli	824.6	719.5	744.5	727.4	701.3	767.2	780.9
		CANESM2-RCP2.6			CANESM2-RCP4.5		
Balod	936.3	999.6	902.2	970.4	847.0	836.5	801.4
Bhanpura	1484.5	1106.4	1083.0	1024.0	1201.0	1055.2	1078.3
Chamra	1095.1	1043.9	1004.2	898.2	941.8	971.6	956.6
Gondli	824.6	719.5	738.2	680.0	745.3	683.3	706.8
		CANESM2-RCP8.5			HADCM3-A2		
Balod	936.3	984.3	884.3	736.4	941.9	877.7	981.5
Bhanpura	1484.5	1108.4	983.7	873.0	1388.5	1070.2	1016
Chamra	1095.1	1012.4	938.2	928.7	1087.6	1224.5	1022.4
Gondli	824.6	678.8	682.3	662.8	896.5	830.4	883.5
		HADCM3-B2					
Ambagarh	1107.6	1100.7	1109.6	1117.2			
Balod	936.3	962.6	928.8	900.9			
Bhanpura	1484.5	1395.7	1100.5	1005			
Chamra	1095.1	1076.8	1221.9	1141.9			
Gondli	824.6	893.5	852.1	880.8			

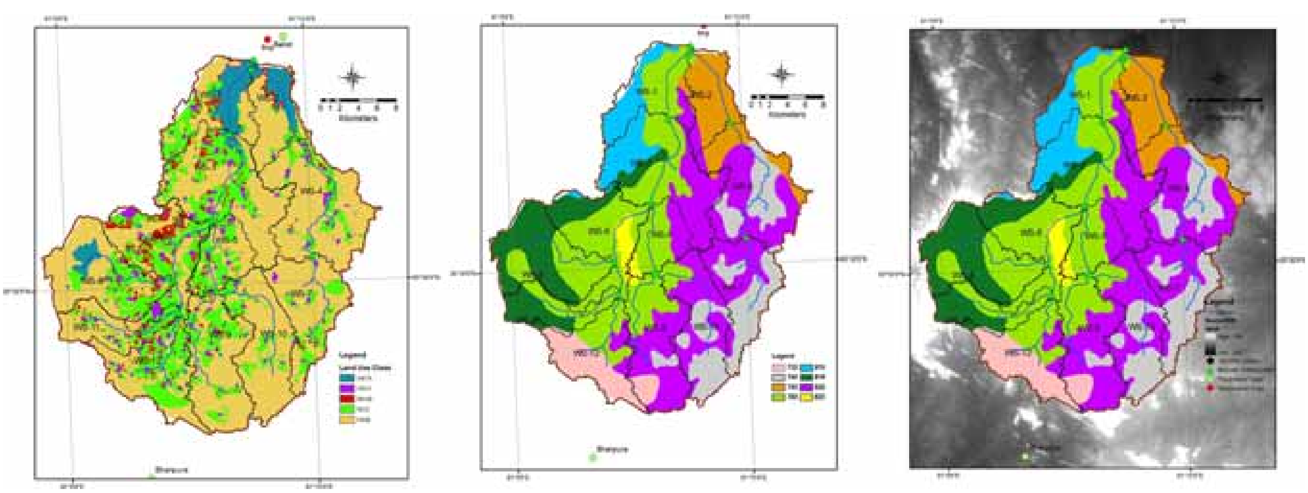

Figure 5. Land use, soil, DEM with SWAT setup for Tandula reservoir catchment.

The seasonal rainfall at Balod R.G. is about 936 mm during the base period, which will not affect much in the early century period (FP-1: 2020–2035) with an average of 970 mm and then reduce to 886 and 879 mm, respectively, during mid and far century periods. The seasonal rainfall at Bhanpura R.G. station is 1585 mm, the highest among all R.G. stations during the base period may receive less seasonal rainfall with an average of 1279 mm during FP-1 period, 1165 mm during FP-2 period and 1108 mm during FP-3 period. Chamra R.G. station's seasonal rainfall during the base period is 1095 mm will reduce in the range of 1049, 1062 and 962 mm during near, mid and far century periods, respectively. Gondli R.G. station having least seasonal rainfall during the base period as 825 mm will get 765 mm during near-century, 757 mm during mid-century and 760 mm rainfall during far century periods. The analysis suggested that all R.G. stations in and around the

Tandula catchment will receive lesser rainfall in future mostly in August and September months of the monsoon season.

3.3 *Module III: Rainfall-runoff model for the catchment of the reservoir*

In module-III, the SWAT model for Tandula reservoir catchment was developed using digital elevation model (DEM) from ASTER DEM refined through toposheets, land use and soil maps. A weather generator has been prepared using available climatic data of minimum and maximum temperature, wind speed, sunshine hour and rainfall. The land use, soil, DEM and SWAT setup for Tandula catchment have been presented in figure 5. The land uses have been divided in five groups namely deciduous forest (500.2 km^2), low density urban (27.8 km^2), scrub (36.6 km^2), agriculture (218.5 km^2) and water body (42.7 km^2). The soils in the study area have been divided into three hydrological soil groups (A: 249.3 km^2, B: 20.3 km^2, C: 364.1 km^2) (Tamgadge *et al.* 2002; Kumar *et al.* 2015). Using DEM of these catchments, the slope map was divided into five groups namely 0–2%, 2–5%, 5–10%, 10–25% and > 25%. After setting up the model, weather generator for the model was set up and all the files were written with default values. The model was then imported in SWAT-CUP software for sensitivity analysis, calibration and validation of the model.

3.3.1 *Sensitivity, calibration and validation*

The rainfall-runoff modelling for Tandula catchment was carried out using data from 1991 to 2015. The data from 1991 to 1994 was used for the warm-up of the model, while 1995 to 2007 for considered for calibration and 2008 to 2015 for validation. From the analysis of sensitivity analysis using *t-stat* (larger absolute value) and *p-stat* (smaller absolute value), *r_CN2, sol_k, sol_AWC, ch_N2, Alpha_BF*, *ESCO* and *GWQMN* were found to be the most sensitive for Tandula reservoir catchment (table 3). In the present study, sequential uncertainty fitting (SUFI2) algorithm has been used for the optimization of parameters. The uncertainty, calibration and validation of the model have been carried out with the help of some selected goodness of fit criterions such as *p*-factor, *r*-factor, bR^2 and Nash–Sutcliff efficiency. The 95 PPU graph for Tandula catchment during calibration and validation has been presented in figure 6. The Nash–Sutcliff efficiency during calibration and validation was found 0.75 and 0.65, respectively, and can be considered as satisfactory performance.

3.3.2 *Projected water availability from Tandula catchment*

The water availability from catchments plays an important role in water resource management as it is the main source of supply to meet different demands. In the present study, three sets of climatic and precipitation series obtained from module-II have been used in SWAT-CUP application for the computation of predicted runoff from the catchment. The average water availability in the base period (1991–2015) for Tandula is about 460 Mm^3 that varies in the range of 152.8–913.5 Mm^3. The projected average water availability from Tandula reservoir catchment may vary in the range of 388.42 (HADCM3-A2 scenario) to 553.96 MCM (CANESM2-RCP4.5 scenario) during FP-1 period, 409.17 (CANESM2-RCP2.6 scenario) to 518.69 MCM (CGCM-A1B scenario) during FP-2 period and 351.6 (HADCM3-A2 scenario) to 513.47 MCM (CGCM-A2 scenario) during FP-3 period. It

Table 3. *Results of sensitivity, calibration and validation for Tandula catchment.*

Parameter name	Description of parameter	Sensitivity results		Calibration and validation results	
		t-stat	*P*-value	Best value	Range
r_CN2	SCS curve number	− 14.429	0.00	− 0.015	− 0.1226 to 0.0927
Sol_k	Saturated hydraulic conductivity	− 13.648	0.00	0.748	0.0267 to 1.5227
Sol_AWC	Soil antecedent water content	− 1.449	0.015	0.058	− 0.3133 to 0.4293
Ch_N2	Manning's *N* for main channel	− 1.341	0.018	0.032	0.001 to 0.1662
Alpha_BF	Base flow alpha factor	− 0.988	0.032	0.514	0.2567 to 0.7713
ESCO	Soil evaporation compensation factor (days)	− 0.914	0.036	0.773	0.3858 to 1.1591
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	− 0.676	0.050	33.75	33.75 to 2268.801

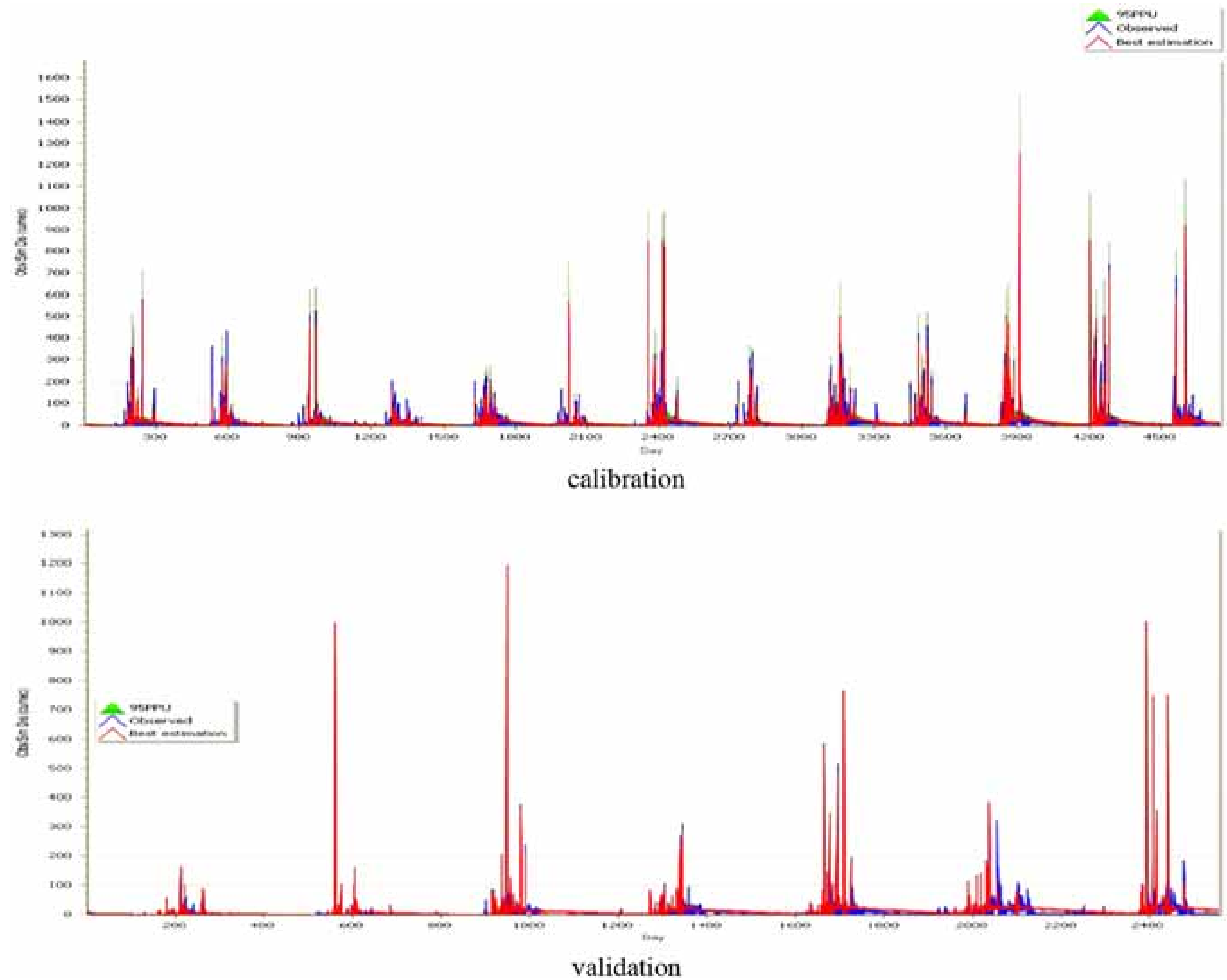

Figure 6. Comparison of observed and computed runoff with 95 PPU during calibration and validation.

has been observed that all other projections except the RCP4.5 scenario produced less water availability during the near-century period (FP-1: 2020–2035) than the average water availability during the base period. The water availability may increase during the mid-century period in comparison with the near-century period and may be more or less similar to the base period. The water availability will further reduce during far century period (FP-3: 2081–2099) where except A1B and A2 scenarios of CGCM, all other scenarios expressed lower water availability from Tandula catchment.

3.4 *Module-IV: Crop water requirement*

The module-IV has been used to compute crop water requirement for paddy crop in design cropping period of 82,095 ha paddy crop during kharif season in Tandula command for the base as well as three future assessment periods. The minimum, maximum temperature and rainfall series have been used to compute crop evapotranspiration with the help of ETo calculator and used to compute crop and gross water requirement for different 10-daily periods considering overall efficiency of 51%. From the analysis, it has been observed that the average gross water requirement may vary from 329.9 to 587.4 MCM with an average of 410.4 MCM during FP-1, 375.5–558.7 MCM with average of 464 MCM during FP-2 and 350.7–618.4 MCM with average of 448.4 MCM during FP-3 period when compared with average crop water requirement of 433.7 MCM during base period. The future projection and computation of crop water requirements concluded that gross water requirement will increase during the mid-century period (FP-2) and reduce in the last period of this century (FP-3).

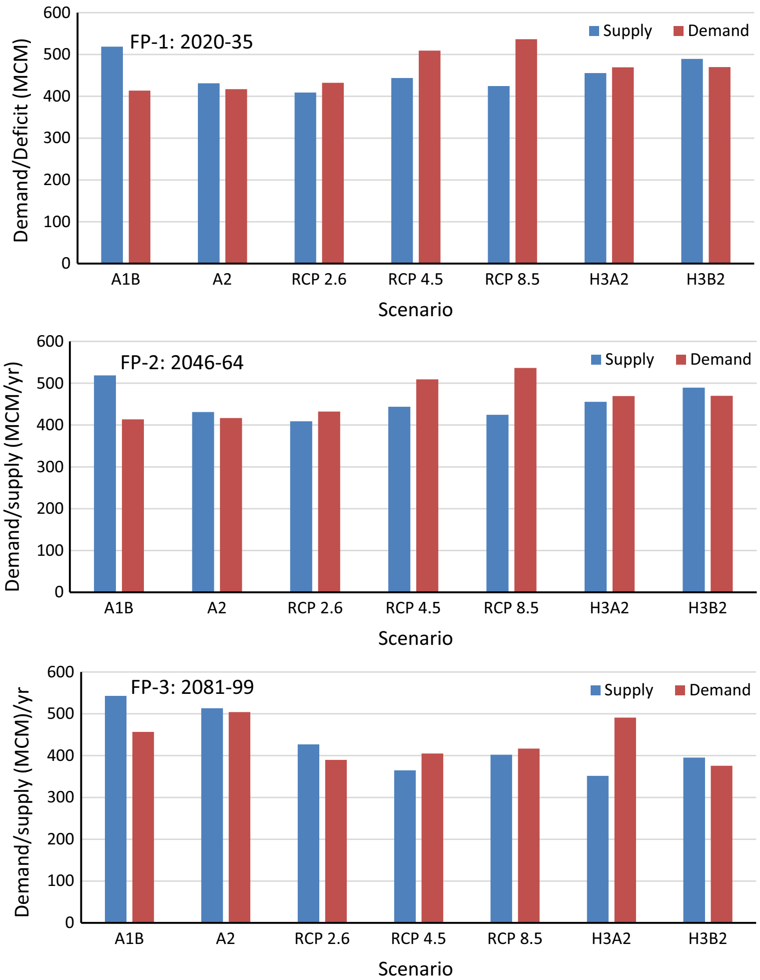

Figure 7. Demand–supply scenarios of Tandula project for near, mid and far century periods.

3.5 *Demand supply analysis*

The demand–supply analysis is essential for sustainable water management and development of the adaptation plan under climate change condition. The average yearly demand and supply under different projected climate scenarios during all three future assessment periods has been presented in figure 7. From the analysis, it has been observed that the projected average yearly supply from the catchment during the near-century period (FP-1: 2020–2035) will be about 426 MCM against average crop water requirement of 410 MCM showed overall no gaps in supply. The situation may change as multiple scenarios suggested higher average yearly demand of 464 MCM against the supply of 453 MCM during the mid-century period (FP-2: 2046–2064) and demand of 448 MCM against the supply of 428 MCM during far century period. The gap of demand and supply varied widely in mid and far century periods where four out of six scenarios indicated gaps in demand and supply.

4. Conclusions

The worldwide consensus on climate change compels countries and society to device different measures to cope up the harmful effects of climate change. Generally, the demands and supplies are considered as stationary to design and operate water resource projects and any significant change in climate may affect sustainability and benefits from the project. In this study, a framework has been suggested and applied for the development of scenarios-based demand–supply analysis for optimal planning under deep uncertainties of climate change in the command of Tandula reservoir in the Chhattisgarh state of India. The framework uses water balance for determining runoff from the catchment, SDSM for downscaling of climate, SWAT and SWAT-CUP for rainfall-runoff modelling and ETo calculator/programming to accomplish crop water requirement which may be helpful to analyse demand–supply scenarios.

The future projection of maximum temperature pointed towards the rise of temperature in all the months except December and increase of minimum temperature in all the months except January in all three future predictive periods may indicate rising demands for different uses in the region, while reduced rainfall may affect supplies from the catchment of Tandula reservoir. The curve number has been found as the most sensitive parameter in the assessment of runoff from the SWAT model. The average annual demand of Tandula command in near-century period may be less than corresponding base period demand, while it increased slightly by 2.3% in mid-century (FP-2: 2046–2064) and 3.8% in far century (FP-3: 2081–2099) period. The supply situation confirmed just higher average annual inflows in the mid-century period, while lesser supply than the base period corresponding supply during near and far century periods. Overall, the gaps in demand and supply may widen in mid and far century periods. Most of the RCP future scenarios confirmed widening of the gap between demand and supply in the future need to be addressed using efficient irrigation techniques.

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