ABSTRACT

The present study assessed the impact of climate change in the Anandapur catchment of Baitarani River basin, India, using the Soil and Water Assessment Tool (SWAT) hydrological model. The future climatic alterations under two Representative Concentration Pathways (RCPs), i.e. 4.5 and 8.5 scenarios, are quantified by an ensemble of two different CMIP5 models, i.e. CNRM-CM5.0, GFDL-CM3.0. The outcomes of this study reveal that the future rainfall and temperature may experience an increasing trend with gradual shifting of monsoon from mid-June to mid-May. The average annual streamflow experienced the highest increase during the period 2071–2095, whereas the highest average annual evapotranspiration (ET) is observed for the period 2046–2070 under both the RCPs and resulting in comparatively slower groundwater recharge (GWR) over the basin. In order to implement suitable adaptation strategies for a possible flood scenario on the concerned study basin, three critical sub-basins, namely, sub-basin 1, 4, and 5, were identified. Furthermore, the altered streamflow and ET dynamics may result in a significant shifting in the conventional agricultural practice in the coming future time scales. Conclusively, the outcomes of this study have potential implications for policy makers in formulating the policies related to sustainable water resources management in future scenarios.

Key words | climate change, ensemble, GCM, RCP, streamflow, SWAT

INTRODUCTION

Water is the most important natural resource for human beings due to its wide application in the field of domestic use, irrigation water supply and hydroelectric power generation (Chan 2012). Global climate change has exerted a considerable impact on the hydrological cycle that has subsequently affected the available water resources (Everett et al. 1996). The variation in precipitation patterns, floods, droughts, and evapotranspiration rate over different regions is caused by climate change (Frederick & Major 1997; Ficklin et al. 2012). The Intergovernmental Panel on Climate Change (IPCC) has reported that water resources are adversely affected due to the changing pattern of precipitation and temperature. Large variations of streamflow in a basin are due to the changing pattern of precipitation. In a basin scale, the streamflow varies nonlinearly with an alteration in precipitation (Sankarasubramanian & Vogel 2003). In arid regions, a marginal increase in temperature associated with an increase in evapotranspiration can cause a large variation of streamflow (McCabe & Wolock 2011). Meanwhile, in humid regions, any change in precipitation causes a large variation of streamflow (Sankarasubramanian & Vogel 2003). Hence, a basin-level hydrologic analysis is very important to evaluate the sensitivity of a basin to climate change scenarios and to
develop better water management systems and climate adaptation strategies.

In the current state of the art, General Circulation Models (GCMs) have proven to be the most reliable tools to predict future water resources changes in a hydrological basin (Xu 1999). Recently, the future climate change has been projected by using different GCMs of the Coupled Model Intercomparison Project Phase 5 (CMIP5), which are based on the Representative Concentration Pathways (RCPs) of greenhouse gases (IPCC 2014). The coarse resolution GCMs-derived climate data cannot be used directly for future climate change scenarios due to the limitation in resolving small scale features that impact rainfall characteristics (Hansen et al. 2006; Sharma et al. 2007; Chen et al. 2011; Salvi et al. 2013). Therefore, downscaling of GCMs is quite essential to perform a climate change impact assessment on a small scale (Silberstein et al. 2012). Two popular downscaling approaches, i.e. statistical (Anandhi et al. 2008) and dynamical (Misra et al. 2005; Dominguez et al. 2012) downscaling have been adopted to downscale large atmospheric variables of GCMs to the regional scale. The statistical downscaling method is preferred over dynamic downscaling because it is computationally more efficient and easy to implement (Hewitson & Crane 1996).

Downscaled meteorological data are widely used to evaluate the future projections of water resources (Chang & Jung 2010). There is a large amount of uncertainty associated in future projections when GCMs data are used as the input to hydrological models. The GCMs uncertainty is associated with the climate model structure and the inherent model parameterization (Teng et al. 2012). Climate projections are based on the greenhouse gas (GHG) emission scenarios under different conditions of economic and technological development. A significant increase in the concentration of GHG causes uncertainty in quantifying the emission scenarios, and thereby realistic assessment of climate change impact becomes difficult. Furthermore, large uncertainty arises due to the use of a single GCM in the hydrological model (Wilby & Harris 2006) for climate change impact assessments. Though the GCM models belong to the same experimental family, the output varies with varying boundary conditions of different models (Srinivasa Raju et al. 2017). Hence, an ensemble of multi-model GCMs has been used by many researchers for future climate projections (Tebaldi & Knutti 2007). The multi-model mean gives a better simulation of climate variables than a single model projection (Gleckler et al. 2008; Knutti et al. 2010; Zhang & Huang 2015).

Hydrologic models have proven to be useful in evaluating the climate change impact on water resources (Liuzzo et al. 2014). In the past, various studies have been carried out on climate change impacts on water resources using hydrologic models and some of the recent studies are discussed here. Shrestha et al. (2016) estimated the impact of climate change on hydrology and water resources in the Indrawati River Basin, Nepal, using the Soil and Water Assessment Tool (SWAT). The study shows that there is an increase in annual discharge in the river basin, but the monthly analysis reveals that the changes are not uniform. Mudbhaktal et al. (2017) assessed the impact of climate change on the Malaprabha and Nethravathi River catchments of southern India using SWAT. They found an increasing trend in high flows in Malaprabha, but a decreasing trend for Nethravathi. Meenu et al. (2013) evaluated the hydrologic impact of climate change in the Tunga–Bhadra river basin using the Hydrologic Engineering Center’s Hydrologic Modeling System Version 3.4 (HEC-HMS 3.4) and showed that the precipitation, runoff, and actual evapotranspiration have increased over the sub-basins as a consequence of climate change. Choi et al. (2014) estimated the hydrological impacts of warmer and wetter climate in Troutlake and Sturgeon River Basins in Central Canada using the Semi-Distributed Land Use-based Runoff Processes (SLURP) model and found that the total annual precipitation does not necessarily translate into similar changes in runoff whereas the seasonal precipitation significantly changes the runoff. Das & Umamahesh (2018) evaluated the climate change impact on hydrological components on a spatial and temporal scale using a macro scale, semi-distributed three-layer Variable Infiltration Capacity (VIC-3 L) model over the Wainganga River basin and reported that the rainfall, evapotranspiration, and runoff have not changed spatially, while there is an increasing trend temporally.

The past integrated climate change impact assessment studies suggest that there exists a clear bias towards the selection of a suitable hydrological model. The hydrological models are classified based on the degree of complexity in conceptualizing the catchment scale hydrological processes.
and scale of application. However, out of such a diversified list of hydrological models, the SWAT model has proven its capability in modelling different hydrological extremes such as floods and droughts in varying topographic and climatic conditions across the world (Shrestha et al. 2016; Dash et al. 2019). Because of its wide utility and applicability (Gassman et al. 2014), SWAT has been used successfully for hydrologic modeling (Kumar et al. 2014; Abbaspour et al. 2015; Dash et al. 2018) and climate change impact studies on streamflow (Githui et al. 2009; Mango et al. 2011). Considering the inherent applicability of the SWAT model, the present study undertakes the SWAT model for an integrated catchment scale climate change impact assessment.

Based on the identified research gaps, the specific objectives of this study are: (1) to set up the SWAT model for the study catchment during the base period within the acceptable uncertainty limits; (2) to evaluate the future climate change on different hydrological fluxes in spatial and temporal scale by using downscaled meteorological data from an ensemble of two GCMs.

The multi-model ensemble based approach will be helpful in formulating a more realistic future climate scenario for the concerned study area. The sub-basin scale water resources assessment will be helpful in formulating sustainable management policies under changing climate and land use scenarios. The integrated hydrological model based futuristic water balance assessment will formulate a flexible modelling framework and can be extended to many worldwide river catchments. Thus the outcomes of this study will be beneficial for policymakers to accurately estimate the available water resources in future climate scenarios and, subsequently, the supply–demand mechanism in a water distribution system can be managed more effectively.

**METHODOLOGY**

**Study area and data**

The Anandapur catchment of Baitarani River Basin, which is situated in between 85°00′ to 86°30′0″ E longitude and 21°00′ to 22°30′N latitude is selected as the study area and is situated in the Keonjhar district of Odisha state, India (Figure 1). The catchment area is 8,645 km² with topographic elevation ranging from 32 to 1,181 m above mean sea level (MSL). The basin experiences an undulated topography with average slope varying between 0 and 2%. Average rainfall in the basin is 1,628 mm with sub-humid tropical climate predominating over the complete basin. As per the information of the India Meteorological Department, the basin experiences four climatic seasons in a year, i.e. winter (January and February), pre-monsoon (March–May), monsoon (June–September) and post-monsoon (October–December). About 80% of rainfall occurs during the monsoon, i.e. between June and September. Temperature varies between 30 and 36 °C during the summer and 16–17 °C during winter. Two land use types, i.e. forest and farmland, are predominant in the catchment. Being an agriculture dominant basin, rice, maize, green gram, wheat, groundnut, and vegetable crops are cultivated throughout the year.

In general, four primary inputs, viz., the Digital Elevation Model (DEM), land use map, soil map and meteorological inputs (rainfall, temperature, solar radiation, relative humidity, and wind speed) are desired for running the SWAT model and a detailed description is given below. The DEM was collected from the Shuttle Radar Topography Mission (SRTM90) of USGS (http://srtm.csi.cgiar.org). The decadal land use maps for the years 1985, 1995 and 2005 for India were collected from ORNL DAAC (https://daac.ornl.gov/VEGETATION/guides/Decadal_LULC_India.html) for analysing the impact of land use change on water resource components (Roy et al. 2016). The soil map was obtained from the Harmonized World Soil Database (HWSD) that is developed by the Food and Agriculture Organization of the United Nations (FAO-UN) (Nachtergaele et al. 2010). Daily gridded rainfall and temperature data (1 × 1°) for the period 1980–2013 were collected from the India Meteorological Department (IMD), Pune. Further, the daily streamflow data for the Anandapur gauge station (1980–2013) was collected from the Water Resources Information System of India (India-WRIS) which is maintained by the Central Water Commission (CWC), India.

Data from the two best performing GCMs, namely the Centre National de Recherches Météorologiques (CNRM-CM5.0) and Geophysical Fluid Dynamics Laboratory
(GFDL-CM3.0) models, under the Coordinated Regional Downscaling Experiment (CORDEX) for South Asia were procured from the Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM) (http://cccr.tropmet.res.in/cordex/) and were selected based on the model evaluation works by Sperber et al. (2012) and Hasson et al. (2014). The performance of CMIP3 and CMIP5 models was evaluated by Sperber et al. (2012) in simulating the Asian summer monsoon. The study concluded that the accuracy of GCMs is still low in simulating the Indian monsoon based on the statistical metrics. However, they found that CNRM-CM5.0 and GFDL-CM3.0 models simulate the June–September summer rainfall climatology more accurately over the Indian monsoon region. Hence, the CNRM-CM5.0 and GFDL-CM3.0 models of CMIP5 versions have been selected for this study.

RCP 4.5 and RCP 8.5 represent the intensity of future climate change scenario in terms of the radiative forcing concentration as defined by IPCC AR5. The RCP 4.5 represents a scenario where the radiative forcing value is stabilized at 4.5 W/m² by the end of the year 2100 and is representative of a future having a relatively ambitious reduction of emissions equivalent to the SRES B1 scenario. Conversely, the RCP 8.5 corresponds to a future with zero policy regulation to reduce emissions and is equivalent to the SRES A1F1 scenario of IPCC AR4. The radiative forcing value in this scenario rises to a maximum value of 8.5 W/m² by the end of 2100. Furthermore, these two scenarios represent the two extreme future projections thereby depicting the role of radiative forcing in regulating greenhouse gas emission. Hence, based on the previously discussed relevance and common period of data availability of the GCMs, RCP 4.5 and 8.5 were chosen for this study.

Hydrological modelling

SWAT is a semi-distributed catchment-scale hydrological model and is capable of simulating the catchment hydrologic processes at daily and sub-daily time steps (Arnold et al. 1998). The model simulates basin level hydrologic...
characteristics based on varying land use and climate conditions, and it is widely used for climate change impact analysis (Wang et al. 2008; Bae et al. 2011; Ficklin et al. 2012). On the basis of a basic water balance approach, as given in Equation (1), SWAT partitions precipitation into different hydrological components such as surface runoff, evapotranspiration, lateral flow, percolation, base flow, and deep aquifer loss components (Neitsch et al. 2011). In this study, surface runoff is simulated using the Soil Conservation Service (SCS) curve number equation (Arnold 1972). CO2 concentration on leaf stomatal conductance on evapotranspiration (Neitsch et al. 2011). The Penman–Monteith method is used for the simulation of potential evapotranspiration (PET) (Monteith 1965; Allen 1986). Here, the Penman–Monteith method is preferred over the other three PET simulation options offered by the SWAT, because this method accounts for the effects of CO2 concentration on leaf stomatal conductance on evapotranspiration (Neitsch et al. 2011, which is important from a climate change perspective:

\[ SW_i = SW_0 + \sum_{j=1}^{t} (R_{day,j} - Q_{surf,i} - E_a,i - W_{seep,i} - Q_{gw,i}) \]  

where \( SW_i \) is the final soil water content (mm) at the end of day \( i \), \( SW_0 \) is the initial soil water content at the beginning of day \( i \) (mm), \( R_{day,j} \) is the amount of precipitation on day \( i \) (mm), \( Q_{surf,i} \) is the amount of surface runoff on day \( i \) (mm), \( E_a \) is the amount of evapotranspiration on day \( i \) (mm), \( W_{seep} \) is the amount of water entering the vadose zone from the soil profile on day \( i \) (mm), \( Q_{gw} \) is the amount of return flow on day \( i \) (mm), and \( t \) is the time of day.

Model set-up, calibration, and validation for streamflow

The DEM, land use, soil data and weather data (rainfall and temperature) are used as input to SWAT for hydrological modelling in the Anandapur catchment. The catchment is delineated into sub-basins using DEM data. Further, the sub-basins are divided into Hydrologic Response Units (HRUs) using land use, soil, and slope of the catchment. The minor percentage of land use, soil, and slope of each sub-basin are ignored by considering threshold values of the land use of 10%, soil and slope of 10 and 5% respectively (Winchell et al. 2013), which have been helpful to minimize the error in HRUs aggregation. The agricultural practice of the study region is certainly paddy-centric in nature. The presence of standing water inside the paddy field throughout the growing season imparts significant alternation to the catchment hydrology. To account for this effect, the SWAT model has an inbuilt pothole module and is used for the paddy land uses during the model simulation. First, the paddy HRUs are identified inside the study area, and subsequently assigned as the pothole HRUs in the management module. Further, the pothole parameters are updated inside the management module and model simulation is performed. Moreover, the agricultural management operations such as crop beginning period, irrigation, fertilizer application, and harvesting time are defined as per the local practice to make the model conceptualization more realistic.

The SWAT-CUP interface is coupled with the SWAT model for calibration and validation of the model (Abbaspour et al. 2007). The Sequential Uncertainty Fitting (SUFI-2) is linked to the SWAT through the SWAT-CUP and is used for investigating the sensitivity and uncertainty in streamflow prediction. SWAT is calibrated and validated for monthly streamflow by comparing the observed streamflow at the Anandapur outlet. Three years of data from 1980 to 1982 are considered for the warm-up of the model and subsequently, the periods 1983–2003 and 2004–2012 are selected as calibration and validation periods, respectively. The performance of the model is evaluated to check the reliability of its output through various statistical indicators (Moriasi et al. 2007). In this study the Nash–Sutcliffe efficiency (NSE) (Equation (2)), coefficient of determination \( R^2 \) (Equation (3)) and percent bias (PBIAS) (Equation (4)) statistical indicators are used in the model performance evaluation. Performance of the model is good when the PBIAS is within \( \pm 15\% \), NSE is above 0.75 (Moriasi et al. 2007) and \( R^2 \) is close to one:

\[ NSE = 1 - \frac{\sum_{i=1}^{N} (O_i - S_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2} \]  

\[ R^2 = \left( \frac{\sum_{i=1}^{N} (O_i - \bar{O})(P_i - \bar{P})}{\left[ \sum_{i=1}^{N} (O_i - \bar{O})^2 \right]^{0.5} \left[ \sum_{i=1}^{N} (P_i - \bar{P})^2 \right]^{0.5}} \right)^2 \]  

\[ PBIAS = 100 \times \frac{\sum_{i=1}^{N} (O_i - S_i)}{\sum_{i=1}^{N} O_i} \]
where $O_i$ is the $i$th observed data, $S_i$ is the $i$th predicted value, $P_i$ is the $i$th predicted data, $\bar{O}$ is the mean of measured data, $\bar{P}$ is the mean of model estimated data, and $N$ is the total number of simulation periods.

**Sensitivity analysis**

Sensitivity analysis is one of the pre-processing steps that helps to understand the change in model outputs concerning change in model inputs (Gassman et al. 2007). The sensitivity of model parameters has been measured using $t$-stat and $p$-value (Abbaspour 2011). The sensitivity of model parameters has been measured using $t$-stat and $p$-value (Abbaspour 2011). The parameters which have larger values of $t$-stat and smaller values of $p$ are the most sensitive. The selected SWAT parameters are presented in Table 1 with their respective $t$-stat and $p$-value.

Parameter uncertainty was expressed in terms of a 95% prediction uncertainty (95PPU) band. The lower limit of 95PPU is 2.5% and the upper limit is 97.5%. Initially, parameter uncertainty remains large, but after each iteration parameter uncertainty decreases. In the case of a more sensitive parameter, there is a large uncertainty reduction in comparison to that for the less sensitive parameter. The 95PPU is quantified by the P-factor (0–1) and the R-factor (0–$\infty$). The P-factor is the percentage measured data bracketed by the band of 95PPU, whereas the R-factor is the ratio of the average width of the band to the standard deviation of the corresponding measured variable (Abbaspour et al. 2007). When the P-factor is 1 and R-factor is 0, the simulated value perfectly matches the observed value (Abbaspour 2011).

### Multi-model ensemble projection under the future scenarios

SWAT is used for hydrological modelling, and future streamflow projections are obtained for the period 2021–2095 under the two Representation Concentration Pathways (RCPs) 4.5 and 8.5 scenarios. The future period is divided into three time slices, i.e. near (2021–2045), mid (2046–2070) and far (2071–2095) future. The impact of climate change on the hydrology of the catchment is evaluated using future climate data from the two GCMs by comparing the hydrologic response in future time periods with that obtained for the observed data. The climate model projections are qualitative, and hence give a low level of confidence and high level of uncertainty (Visser et al. 2000). Therefore, the quantification of the uncertainty is required to assess future climate projections. Since the output of one GCM is not reliable enough in evaluating future climate change impacts, a multi-GCM ensemble study is approached in this study. The ensemble average of simulated streamflow from two GCMs is evaluated using a

| Sl. no. | Parameter | Description | Minimum | Maximum | Fitted value | $t$-stat | $p$-value |
|--------|-----------|-------------|---------|---------|-------------|---------|-----------|
| 1      | V_ALPHA_BF.gw | Base flow recession alpha factor (days) | 0.25    | 0.76    | 0.42        | 34.32   | 0.00      |
| 2      | V_CH_K2.rte  | Channel effective hydraulic conductivity (mm/h) | 38.58   | 115.76  | 49.58       | -4.70   | 0.00      |
| 3      | V_CH_N2.rte  | Manning’s $n$ value for the main channel | 0.12    | 0.35    | 0.21        | -1.95   | 0.05      |
| 4      | V_SURLAG.bsn | Surface runoff lag time (day) | 1.43    | 3.81    | 3.72        | 1.06    | 0.28      |
| 5      | R_SOL_AWC(..).sol | Available water capacity (mm/mm) | -0.02   | 0.41    | 0.17        | -0.74   | 0.45      |
| 6      | V_ESCO.hru | Soil evaporation compensation factor | -0.25   | 0.58    | 0.10        | 0.69    | 0.48      |
| 7      | A_GW_DELAY.gw | Groundwater delay (day) | 188.60  | 565.89  | 380.83      | -0.58   | 0.55      |
| 8      | A_GWQMN.gw  | Threshold water depth in the shallow aquifer required for return flow to occur (mm) | 1,000   | 2,531.42| 2,277.12    | 0.52    | 0.59      |
| 9      | R_SOL_K(..).sol | Saturated hydraulic conductivity (mm/h) | -0.25   | 0.25    | -0.07       | -0.26   | 0.79      |
| 10     | R_CN2.mgt   | Soil Conservation Service curve number for AMC II | -0.002  | 0.09    | 0.08        | -0.05   | 0.95      |
weighted ensemble average approach. This study adopts a Reliability Assembling Averaging (REA) approach to assign appropriate weight to individual GCM model based on performance and convergence criteria (Giorgi & Mearns 2002). Moreover, a Cumulative Distribution Function (CDF) based approach was used to evaluate the reliability criteria as described by the study conducted by Chandra et al. (2015). The individual weights for each GCM grid point during RCP 4.5 and 8.5 are computed by applying the REA technique to all the atmospheric variables. The efficiency of GCMs outcomes in simulating the historical precipitation and temperature variables was used to compute the initial weight in terms of Mean Absolute Relative Error (MARE) as given in Equations (5) and (6):

\[
MARE = \frac{P_{\text{hist}} - GCM_{\text{hist}}}{GCM_{\text{hist}}}
\]

\[
w_i = \left( \frac{1}{MARE_i} \right) / \left( \sum_{i=1}^{n} \frac{1}{MARE_i} \right)
\]

where \(P_{\text{hist}}\) is the historical period precipitation, \(GCM_{\text{hist}}\) is historical GCM simulated precipitation, \(W_i\) is initial weight, \(n\) is number of GCM models and \(i\) is the model index.

Further, by multiplying the computed weight with the future precipitation CDF, the weighed mean CDF is calculated. Then the subsequent MARE and weight are computed until the final weight for the different GCM remains the same as that of the previous iteration.

**Bias correction and downscaling**

Before entering the meteorological inputs to the hydrological model, the bias correction of GCM output is essential due to the associated systematic and random model errors (Teutschbein & Seibert 2013; Fiseha et al. 2014). The existing bias can be reduced by adopting both parametric and non-parametric bias correction techniques. Among both techniques, non-parametric transformation is more efficient to reduce the systematic bias associated with the GCM outputs (Gudmundsson et al. 2012). In this study, the non-parametric quantile mapping bias correction method is used to remove systematic and random model errors from weighed climatic variables (Gudmundsson et al. 2012). The non-parametric quantile mapping bias correction method is based on the following Equation (7). The Cumulative Distribution Function (CDF) of the ensemble GCM and downscaled GCM precipitation data is shown in Figure 2(a), justifying the suitability of quantile mapping approach in bias correction. Furthermore, the scatter plot shown in Figure 2(b) indicates a greater degree of correlation among the GCM and downscaled precipitation data for the period 2071–2095:

\[
P_{\text{obs}} = F_{\text{obs}}^{-1}(F_{\text{wet}}(P_{\text{wet}}))
\]

where \(P_{\text{obs}}\) and \(P_{\text{wet}}\) are observed and weighted precipitation, \(F_{\text{wet}}\) is the CDF of \(P_{\text{wet}}\) and \(F_{\text{obs}}^{-1}\) is the inverse CDF corresponding to \(P_{\text{obs}}\).

The Statistical Downscaling Model (SDSM) based hybrid approach that forces synoptic-scale climate variables into station scale variables using a suitable statistical relationship is adopted in this study for downscaling the GCM outputs. The station-wise predictor variables were chosen from the partial correlation coefficient value carried out at 5% level of significance. The downscaling process was further enhanced by using the Climate Forecast System Reanalysis (CFSR) data products as the predictor variable. The commonly identified predictor variables for multiple stations include precipitation, relative humidity, temperature at 700 hPa pressure level and atmospheric pressure. Upon considering the above said predictor variables, the daily precipitation and temperature data were downscaled to the respective stations for the desired future time-scales. Details about the SDSM theoretical framework given by Wilby et al. (2002) can be explored further for downscaling.
of different meteorological, hydrological, and environmental variables.

RESULTS AND DISCUSSION

Calibration and validation of the SWAT model

Parameters involved in the simulation of monthly streamflow and their final fitted values are listed in Table 1. The sensitivity of the parameters is quantified according to the ranking of the parameters. The parameters such as ALPHA_BF, CH_K2, CH_N2, and SURLAG are more sensitive than other calibration parameters for streamflow simulation. The measured and simulated streamflow for both calibration and validation has a similar trend at the Anandapur gauging station (Figure 3(a)). The P and R factors of model uncertainty analysis are found to be 0.84 and 0.87, respectively, during the calibration and 0.70 and 0.69, respectively, during the validation, which indicates the model performance is satisfactory during both calibration and validation. The NSE, R2 and PBIAS values during calibration are 0.91, 0.92 and –1.9, respectively, and become 0.96, 0.97 and –0.2 during the validation period, respectively. The statistical analysis results indicate that the observed streamflow satisfactorily replicates (>0.50) the simulated streamflow. The scatter plot shown in Figure 3(b) shows a mixed behaviour of underestimation and overestimation during the course of the simulation. However, most of the time underestimation was found to be dominant in the simulation process. During the monsoon months of the years 2000, 2007 and 2008, significant underestimation is observed. Acceptable values of the goodness of fit statistics and similar temporal behaviour between observed and simulated streamflow values indicate that the performance of the model is quite adequate and can be used for impact analysis study in the Anandapur catchment.

Historical climate and land use and land cover (LULC) trend analysis

The Mann–Kendall test, a popular non-parametric trend analysis approach, has been used in this study to detect the trend in the historical time series of the above three variables. The outcomes of this analysis reveal that no significant trend is present for either temperature or precipitation time series and is evidenced by a Sen’s slope value of 9.41 mm/y and 0.021 ºC, respectively. To confirm the role of weather variables on controlling the groundwater recharge flux, the trend analysis approach was further extended for the groundwater recharge (GWR) and, certainly, the results also indicate absence of any significant trend. In general, it can be inferred from this analysis that the historical period was quite normal from the context of both the meteorological and hydrological variability and was supported further by the minimal variation in the land use of the concerned study area.

Land use is the most important variable in water balance studies of a catchment and the assessment of land use changes in a catchment is highly essential (Lu et al. 2013; Paul et al. 2016). Three land use maps for the years 1985, 1995 and 2005 (Figure 4(a)–4(c)) are considered for decadal changes in land use patterns. The land use classes included for the catchments are a deciduous forest, cropland, built-up land, mixed forest, shrub land, fallow land, wasteland, water body, and plantations and are shown in Table 2. From Table 2 it can be surmised that there is no significant change in land use over the past three decades. Therefore, it can be assumed that the future water balance components are mainly affected by climate change and accordingly the following analyses were carried out.

Impact of climate change on precipitation and temperature

The variation in all the previously mentioned meteorological variables sought to affect the future water resources of Anandapur catchment (AC) both quantitatively and qualitatively. However, due to availability of information of only precipitation and temperature for the future projections, this study is confined to evaluate the role of only these two variables in assessing the future water resources. Thus the variability of precipitation and temperature for the AC was analysed for the RCP 4.5 and RCP 8.5 scenarios in three future time slices of 2021–2045, 2046–2070 and 2071–2095 (Figures 5 and 6). It can be envisaged from Figure 7(a)–7(d) that the decrease in projected precipitation is maximum during the 2071–2095 time horizon for both RCP scenarios. The maximum increase in the projected
precipitation is observed during the near future scenario, i.e. 2021–2045; wherein more than three sub-basins experience >15% increase in projected precipitation. Furthermore, the inter-time horizontal variation of precipitation is more significant as compared to inter RCP variations. Moreover, the seasonal analysis of precipitation variability reveals that the increase in precipitation across all the future time scales could be attributed to the increase in precipitation magnitude during the non-monsoon periods and indicates a shifting in precipitation magnitude from the base season monsoon

Figure 3 | (a) Comparison of observed and simulated monthly streamflow during calibration and validation of the catchment. (b) Scatter plot of monthly streamflow simulation at the Anandapur outlet.
The precipitation behaviour as evidenced from the future GCM projections is found to be in line with the outcomes of the study carried out by Annamalai et al. (2016), wherein the reduction in monsoon rainfall was caused due to the lowering of the western Indian Ocean sea level pressure and the weakening of low-level monsoon wind. The increased global warming and sea surface temperature could disturb the monsoon convection and may result in increased precipitation over the western specific compared to South Asia.

Figure 7(e)–7(h) reveals that the mean seasonal temperature increases in all the future time periods, the highest being observed in the RCP 8.5 scenario of far future time horizon. The increase in the average annual maximum and
minimum temperature from the base period for RCP 4.5 and RCP 8.5 are summarised in Table 3. It can be surmised that the rate of increase in the average minimum temperature will be higher than that of average maximum temperature in the future climate change scenario. The highest increase in maximum temperature is found to be 1.2°C and 1.6°C for
Figure 7 | Seasonal variation of precipitation (a)–(d) and temperature (e)–(h) for different scenarios.

Table 3 | Average annual variation of the precipitation and temperature in the future time scale with respect to the base period

| Climate variable | RCP 4.5 (21–45) | RCP 4.5 (46–70) | RCP 4.5 (71–95) | RCP 8.5 (21–45) | RCP 8.5 (46–70) | RCP 8.5 (71–95) |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Max. temperature (°C) | +0.4 | +0.9 | +1.2 | +0.9 | +1.1 | +1.6 |
| Min. temperature (°C) | +0.5 | +1.5 | +1.7 | +0.6 | +1.8 | +2.1 |
| Precipitation (mm) | +427.17 | +359.56 | +301.69 | +480.86 | +367.08 | +343.84 |
the RCP 4.5 and RCP 8.5, respectively, and thereby signifying the period 2071–2095 to be more intense in terms of temperature rise. Similarly, the rise in average minimum temperature is also higher during the RCP 8.5 scenario of 2071–2095. Unlike precipitation, the temperature does not exhibit any seasonal shift between the base and future periods. However, the earlier pre-monsoon average maximum temperature of 39°C increases to 40.36°C in the case of the RCP 8.5 of 2071–2095 realizing a possible acute water shortage scenario during the pre-monsoon season of 2071–2095. Conversely, the seasonal fluctuation of the average maximum temperature is more pronounced during the RCP 4.5 scenario of all future time scales, making the climatic conditions comparatively less stable. As a consequence of temperature rise, the water holding capacity of the atmosphere increases which increases the evaporation rate resulting in intense localized precipitation (IPCC 2007).

**Spatial distribution of water resources in future time periods**

Spatial distribution of water resource components for the two water balance components, i.e. streamflow and evapotranspiration (ET), in the catchment are presented in Figure 8. The percentage change of the two components from the base periods are evaluated for future time periods under both RCP 4.5 and RCP 8.5 scenarios. The highest change of precipitation is observed for the period 2021–2045 under both scenarios (Figure 5). The trend gradually decreases towards the end of the future time periods. The spatial distribution of precipitation is quite similar in all time periods. The depth of precipitation increases at the lower reach of the catchment. The highest increased depth is 46.61% which is noticed for the period 2021–2045 under RCP 4.5, and 47.45% under RCP 8.5. The lowest change in depth is 35.59% for the period 2071–2095 under RCP 4.5, and 38.13% under RCP 8.5. Similarly, the spatial distribution of ET in future time periods is shown in Figure 8(g)–8(l)). The maximum increase in annual ET of 19.55% is observed in the period 2046–2070 under RCP 4.5, and 17.38% during 2046–2070 under RCP 8.5. The variation of ET is similar to that of precipitation in the periods 2021–2045 and 2046–2070 under both scenarios. However, the variation of ET is uneven in the period 2071–2095 for both scenarios. The lowest increase in ET of 6.25% is observed in this period for RCP 4.5, and 6.51% for RCP 8.5. The variation of ET is directly proportional to change in precipitation (Solomon 1967; Mishra & Lilhare 2016). Here, the ET is estimated using the Penman–Monteith method that depends on various climatic variables including temperature, wind speed, solar radiation, relative humidity, and ground heat flux and air density. Hence, though the increase in precipitation is less in the period 2046–2070 than the period 2021–2045, the ET is maximum in the period 2046–2070 due to increase in temperature. On the contrary, the increase in ET is less at the end of the period due to a lower increase in rainfall than the other two periods.

The spatial distribution of streamflow is shown in Figure 8(a)–8(f). The depth of discharge in future time periods is increasing as compared to the base period. The highest increase in depth of 71.05% is observed in the period 2071–2095 under RCP 4.5, and 65.77% under RCP 8.5. Similarly, the lowest increase in depth of 41.45% is noticed in the period 2021–2045 for RCP 4.5 and 60.52% for RCP 8.5. The spatial distribution of the streamflow is quite similar to the spatial pattern of precipitation; hence, the variation of the discharge is attributed to the alteration in the precipitation only. The maximum increase in depth is noticed in the lower reach of the catchment. The increase in depth in that region may be due to the higher intensity of the precipitation. Furthermore, Figure 9(a)–9(f) indicates the variation of groundwater recharge during all the future RCP scenarios of all the time periods. This shows a contrasting trend to that of variation of streamflow and ET across all the future time-scales. This may be attributed to the significant increase in the other two water balance components.

**Temporal analysis of climate change impact on water resources**

The projected future precipitation and temperature variables were forced into the calibrated and validated SWAT model, and subsequent model simulations were carried out to estimate different hydrological flux components for the desired future time horizon. It can be surmised from Table 4 that both streamflow and ET exhibit an increasing
trend for all the RCP scenarios of the future time scales except for during the period 2046–2070 for both the RCP scenarios, wherein a significant decrease in streamflow is predicted and is found to be in accordance with the trend of precipitation variation. As discussed earlier, the increased precipitation during the non-monsoon periods resulted in shifting in the high streamflow values from the month of August to July across all the future time horizons, i.e. 2021–2045, 2046–2070 and 2071–2095 for both the RCP 4.5 and RCP 8.5. This contrasting water availability scenario
seems to alter the present practice of rice transplantation during the end of July to the middle of August in the study basin to prevent the acute water shortage during the cropping period. It can be inferred from Table 4 that the temporal variability of streamflow across both the RCPs are in the order of 2046–2070 → 2021–2045 → 2071–2095 and depicting the mid-future time horizon to be the driest time horizon in terms of water availability, thereby needing considerable attention from policy makers.

Similarly, the increasing pattern in ET across all the time horizons could be a consequence of the increased precipitation and temperature estimates. Unlike the shift in precipitation, the ET variability is similar among both base and future climate change scenarios, the highest ET being observed in the month of August. However, the percentage change in ET with respect to the base period is more intense during the non-monsoon periods. It can be envisaged from Table 4 that the average annual ET value across all the future projections is > 1,000 mm with respect to a magnitude of 986.70 mm during the baseline scenario, demanding the attention of agriculture policy makers; however, a decrease in ET was observed during the 2071–2095 scenario of RCP 4.5. Furthermore, a high ET requirement may lead to acute water stress conditions in the crop root zone, thereby affecting the crop yield adversely. This future water crisis may demand effective supply-demand management through irrigation activity for sustainable crop growth.

Surprisingly, a slower increase in the average annual GWR is observed in comparison to its two drivers, i.e. streamflow and ET, which experienced a significant increase in magnitude with respect to the base period (Figures 5 and 6). The substantial reduction rate in the GWR could be attributed to the increased magnitude of ET, thereby causing less water available for percolation. Moreover, the decreasing trend of forest cover and increased urbanization exacerbate this situation further resulting in lesser recharge of groundwater and substantial depletion of the water table in the future time scale. The three larger sub-basins

**Figure 9** | Spatial distribution of groundwater recharge for RCP4.5 during (a) 2021–2045, (b) 2046–2070, (c) 2071–2095, and for RCP 8.5 during (d) 2021–2045, (e) 2046–2070, (f) 2071–2095.
constitute approximately 70% of the total catchment area and may experience only a 0–20% increase in the GWR with respect to the base period, whereas the smaller two sub-basins comprising only 15% of the catchment area may result in a 21–40% increase. The inter-seasonal variation of the GWR indicates that the rate of increase in the groundwater recharge is highest during the post-monsoon season for all the RCP scenarios and corresponds to a delayed groundwater flow scenario in the future. Similar to the shift in the monsoon rainfall, the delayed groundwater flow will have an adverse impact on the plant water uptake, thereby affecting the agricultural production.

To encapsulate this temporal variability pattern of the three fluxes, it can be observed that the ET experiences more variability across different RCP scenarios of the future time scale and demands the major attention of policy makers. Furthermore, since streamflow is expected to experience a maximum increase with respect to the base period, the future time scale is raising concerns for probable flood conditions and requires substantial performance enhancement of the existing reservoir and flood control structures. Moreover, the slower GWR trend corresponds to reduced fresh water availability in the coming future; hence the potential sites for managed aquifer recharge should be identified well in advance. Among the three discussed variables in the future climate change scenario, only increased streamflow causes a flood hazard in the basin. Hence, the critical sub-basins identified in this study include only three sub-basins (sub-basins 3, 4, and 7), considering their overall magnitude among all the future time scales, and special emphasis must be given to these three sub-basins while formulating management policies.

**CONCLUSIONS**

The impact of climate change on water resources in the Anandapur catchment has been analysed using the future climatic dataset under different scenarios. It has been noticed that the spatial and temporal variation of water balance components are affected due to extreme climatic alterations. Both the streamflow and ET are found to be increasing, whereas the GWR is decreasing in future time periods. The streamflow is attributed mainly to
precipitation and the ET is influenced by both precipitation and temperature. The slower GWR is attributed to more ET losses and increased urbanization in the future time periods, thereby leading to substantial depletion of the water table.

Overall, the decreasing trend of water availability in the catchment is likely to intensify further with fewer runoff losses in the form of streamflow. On the other hand, the crop is expected to suffer from moisture stress owing to frequent alternate dry spells and unexpected inundation due to frequent flash floods, due to intensive rainfall across the basin during monsoon season. Frequent irrigation is required during the non-monsoon period because of increased ET in this period. Therefore, for achieving sustainable crop production in order to meet the food grain demand of a growing population, the following suggestions may be incorporated by policymakers:

- Climate-resilient cropping pattern is to be adapted to utilize the monsoon rain effectively.
- More storage structures across the basin are required to be built to restrict the streamflow and harvest the excess water for irrigation during severe dry spells.
- Heavy duty crops grown at present across the basin may be substituted by light duty ones or low duration varieties to mitigate the higher irrigation demand of the crops accentuated under the increasing trend of evapotranspiration.
- Emphasis on more afforestation, and soil and water conservation measures would help in reducing the runoff losses across the basin and thereby increase the in-situ soil moisture storage and groundwater recharge.

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CONFLICT OF INTEREST

On behalf of all the authors, the corresponding author states that there is no conflict of interest.

REFERENCES

Abbaspour, K. C. 2011 SWAT-CUP: SWAT Calibration and Uncertainty Programs – A User Manual. Swiss Federal Institute of Aquatic Science and Technology, Duebendorf, Switzerland, p. 103.

Abbaspour, K. C., Vejdani, M., Haghighat, S. & Yang, J. 2007 SWAT-CUP calibration and uncertainty programs for SWAT Fourth International SWAT Conference 1596–1602. Adv. Water Resour. 54, 11–21.

Abbaspour, K. C. 2013 SWAT Calibration and Uncertainty Programs – A User Manual. Swiss Federal Institute of Aquatic Science and Technology. Duebendorf, Switzerland.

Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H. & Kløve, B. 2015 A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J. Hydrol. 524, 733–752.

Allen, R. G. 1986 A penman for all seasons. J. Irrig. Drain. Eng. 112 (4), 348–368.

Anandhi, A., Srinivas, V. V., Nanjundiah, R. S. & Kumar, N. D. 2008 Downscaling precipitation to river basin in India for IPCC SRES scenarios using Support Vector Machine. Int. J. Climatol. 28, 401–420.

Annamalai, H., Hafner, J., Sooraj, K. P. & Pillai, P. 2013 Global warming shifts the monsoon circulation, drying South Asia. J. Climatol. 26, 2701–2718.

Arnold, J. G., Srinivasan, R., Muttiah, R. S. & Williams, J. R. 1998 Large area hydrologic modeling and assessment part 1: model development. Water Resour. Assoc. 34, 73–89.

Bae, D. H., Jung, I. W. & Lettenmaier, D. P. 2011 Hydrologic uncertainties in climate change from IPCC AR4 GCM simulations of the Chungju Basin, Korea. J. Hydrol. 401, 90–105.

Bouraoui, F., Benabdallah, S., Jrad, A. & Bidoglio, G. 2005 Application of the SWAT model on the Medjerda river basin (Tunisia). Phys. Chem. Earth 30, 497–507.

Chan, N. W. 2012 Managing urban rivers and water quality in Malaysia for sustainable water resources. Int. J. Water Resour. 28 (2), 343–354.

Chandra, R., Saha, U. & Mujumdar, P. P. 2015 Model and parameter uncertainty in IDF relationships under climate change. Adv. Water Resour. 79, 127–139.

Chang, H. & Jung, I. W. 2010 Spatial and temporal changes in runoff caused by climate change in a complex large river basin in Oregon. J. Hydrol. 388, 186–207.

Chen, J., Brissette, F. P. & Leconte, R. 2011 Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. J. Hydrol. 401 (3–4), 190–202.

Choi, W., Kim, S. J., Lee, M., Koenig, K. & Rasmussen, P. 2014 Hydrological impacts of warmer and wetter climate in Troutlake and Sturgeon River Basins in Central Canada. Water Resour. Manage. 28 (15), 5319–5333.
Das, J. & Umamahesh, N. V. 2018 Spatio-temporal variation of water availability in a river basin under CORDEX simulated future projections. Water Resour. Manage. 32 (4), 1399–1419.

Dash, S. S., Sahoo, B. & Raghuvanshi, N. S. 2018 Comparative Assessment of Model Uncertainties in Streamflow Estimation From A Paddy-Dominated Integrated Catchment-Reservoir Command. AGU Fall Meeting, Washington, D.C.

Dash, S. S., Sahoo, B. & Raghuvanshi, N. S. 2019 A SWAT-Copula based approach for monitoring and assessment of drought propagation in an irrigation command. Ecol. Eng. 127, 417–430.

Dominguez, F., Rivera, E., Lettenmaier, D. P. & Castro, C. L. 2012 Changes in winter precipitation extremes for the western United States under a warmer climate as simulated by regional climate models. Geophys. Res. Lett. 39, 5.

Everett, J. T., Krovnin, A., Lluch-Belda, D., Okemwa, E., Regier, H. A., Troade, J. P. & Strzepek, K. M. 1996 Fisheries. In: Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analyses – Contribution of Working Group II to the Second Assessment Report of the Intergovernmental Panel on Climate Change (R. T. Watson, M. C. Zinyowera & R. H. Moss, eds). Cambridge University Press, Cambridge, pp. 511–537.

Ficklin, D. L., Stewart, I. T. & Maurer, E. P. 2012 Effects of projected climate change on the hydrology in the Mono Lake Basin, California. Clim. Change 116, 111–131.

Fisheha, B. M., Setegn, S. G. & Melesse, A. M. 2014 Impact of climate change on the hydrology of upper Tiber River basin using bias corrected regional climate model. Water Resour. Manage. 28, 1327–1343.

Frederick, K. D. & Major, D. C. 1997 Climatic change and the water resources. Clim. Change 37 (1), 7–23.

Gassman, P. W., Reyes, M. R., Green, C. H. & Arnold, J. G. 2007 The soil and water assessment tool: historical development, applications, and future research directions. Trans. ASABE 50 (4), 1211–1250.

Gassman, P. W., Sadeghi, A. M. & Srinivasan, R. 2014 Applications of the SWAT model special section: overview and insights. J. Environ. Qual. 43, 1–8.

Giorgi, F. & Mearns, L. O. 2002 Calculation of average, uncertainty range, and reliability of regional climate change from AOGCM simulations via the ‘reliability ensemble averaging’ (REA) method. J. Clim. 15, 1141–1158.

Githui, F., Gitau, W., Mutua, F. & Bauwens, W. 2009 Climate change impact on SWAT simulated streamflow in western Kenya. Int. J. Climatol. 29, 1823–1834.

Gleckler, P. J., Taylor, K. E. & Doutriaux, C. 2008 Performance metrics for climate models. J. Geophys. 113, 6.

Gudmundsson, L., Bremnes, J. B., Haugen, J. E. & Engen-Skaugen, T. 2012 Technical note: downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods. Hydrol. Earth Syst. Sci. 16, 3383–3390.

Hansen, J. W., Challinor, A., Ines, A., Wheeler, T. & Moron, V. 2006 Translating climate forecasts into agricultural terms: advances and challenges. Clim. Res. 33, 27–41.

Hasson, S., Lucarini, V., Pascale, S. & Böhner, J. 2014 Seasonality of the hydrological cycle in major South and Southeast Asian river basins as simulated by PCMDI/CMIP3 experiments. Earth Syst. Dyn. 5, 67–87.

Hewitson, B. C. & Crane, R. G. 1996 Climate downscaling: techniques and application. Clim. Res. 7, 85–95.

IPCC Climate Change 2007 The Physical Sciences Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

IPCC Climate Change 2014 Impacts, Adaptation and Vulnerability: Regional Aspects. Cambridge University Press, Cambridge.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J. & Meehl, G. A. 2010 Challenges in combining projections from multiple climate models. J. Climatol. 23, 2739–2758.

Kumar, S., Mishra, A. & Raghuvanshi, N. 2014 Identification of critical erosion watersheds for control management in data scarce condition using the SWAT model. J. Hydrol. Eng. 20 (6), 1–8.

Luizzo, L., Noto, L. V. & Arnone, E. 2014 Modifications in water resources availability under climate changes: a case study in a Sicilian Basin. Water Resour. Manage. 29, 1117–1135.

Lu, G. H., Xiao, H. & Wu, Z. Y. 2013 Assessing the impacts of future climate change on hydrology in Huang-Huai-Hai region in China using the PRECIS and VIC models. J. Hydrol. Eng. 18, 1077–1087.

Mango, L. M., Melesse, A. M., McClain, M. E., Gann, D. & Setegn, S. G. 2011 Land use and climate change impacts on the hydrology of the upper Mara River Basin, Kenya: results of a modeling study to support better resource management. Hydrol. Earth Syst. Sci. 15, 2243–2258.

McCabe, G. J. & Wolock, D. M. 2011 Independent effects of temperature and precipitation on modeled runoff in the conterminous United States. Water Resour. Res. 47 (11), 1–11.

Meenu, R., Rehana, S. & Mujumdar, P. P. 2015 Assessment of hydrologic impacts of climate change in Tunga–Bhadra river basin, India with HEC-HMS and SDSM. Hydrol. Process. 27 (11), 1572–1589.

Mishra, V. & Lilhare, R. 2016 Hydrologic sensitivity of Indian subcontinental river basins to climate change. Glob. Planet Change 139, 78–96.

Misra, V., Dirmeyer, P. A. & Kirtman, B. P. 2005 Dynamic downscaling of seasonal simulations over South America. J. Clim. 16, 103–117.

Monteith, J. L. 1965 Evaporation and environment. Symp. Soc. Exp. Biol. 19, 205–234.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Binger, R. L., Harmel, R. D. & Veith, T. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.

Muddhatkal, A., Raiker, R. V., Venkatesh, B. & Mahesh, A. 2017 Impacts of climate change on varied river-flow regimes of southern India. J. Hydrol. Eng. 22 (9), 1–13.
Nachtsgaede, F., Velthuizen, H., van Verelst, L., Batjes, N. H., Dijkshoorn, K., Engelen, V. W. P., van Fischer, G., Jones, A. & Montanarela, L. 2010 The Harmonized World Soil Database. In: Proceedings of 19th World Congress of Soil Science, Soil Solutions for A Changing World, 1–6 August 2010, Brisbane, Australia, pp. 34–37.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R. & Williams, J. R. 2011 Soil & Water Assessment Tool. Theoretical Documentation, Version 2009. Grassland, Soil and Water Research Laboratory, Agricultural Research Service Blackland Research Center – Texas AgriLife Research, Texas Water Resources Institute, Texas, pp. 1–647.

Paul, S., Ghosh, S. & Oglesby, R. 2016 Weakening of Indian summer monsoon rainfall due to changes in land use land cover. Sci. Rep. 6, 32177.

Roy, P. S., Meiyappan, P., Joshi, P. K., Kale, M. P., Srivastav, V. K., Srivasatava, S. K., Behera, M. D. & Roy, A. 2016 Decadal Land Use and Land Cover Classifications Across India, 1985, 1995, 2005. ORNL DAAC, Oak Ridge, Tennessee, USA.

Salvi, K., Kannan, S. & Ghosh, S. 2013 High resolution multi-site daily rainfall projections in India with statistical downscaling for climate change impact assessment. J. Geophys. Res. Atmos. 118, 3557–3578.

Sankarasubramanian, A. & Vogel, R. M. 2005 Hydroclimatology of the continental United States. Geophys. Res. Lett. 30 (7), 1363.

Sharma, D., Das Gupta, A. & Babel, M. S. 2007 Spatial disaggregation of bias corrected GCM precipitation for improved hydrologic simulation: ping river basin, Thailand. Hydrol. Earth Syst. Sci. 11 (4), 1373–1390.

Shrestha, S., Shrestha, M. & Babel, M. S. 2016 Modelling the potential impacts of climate change on hydrology and water resources in the Indrawati River Basin, Nepal. Environ. Earth Sci. 75 (4), 1–13.

Silberstein, R. P., Aryal, S. K., Durrant, J., Pearcey, M., Braccia, M., Charles, S. P., Boniecka, L., Hodgson, G. A., Bari, M. A., Viney, N. R. & McFarlane, D. J. 2012 Climate change and runoff in south-western Australia. J. Hydrol. 475, 441–455.

Solomon, S. 1967 Relationship between precipitation, evaporation, and runoff in tropical equatorial regions. Water Resour. Res. 3, 163–172.

Sperber, K. R., Annamalai, H., Kang, I. S., Kitoh, A., Moise, A., Turner, A., Wang, B. & Zhou, T. 2012 The Asian summer monsoon: an intercomparison of CMIP5 vs. CMIP3 simulations of the late 20th century. Clim. Dyn. 41, 2711–2744.

Srinivasa Raju, K., Sonali, P. & Nagesh Kumar, D. 2017 Ranking of CMIP5-based global climate models for India using compromise programming. Theor. Appl. Climatol. 128, 563–574.

Tebaldi, C. & Knutti, R. 2007 The use of the multi-model ensemble in probabilistic climate projections. Philosophical Transactions of the Royal Society: Math. Phys. Eng. Sci. 365 (1857), 2053–2075.

Teng, J., Vaze, J. & Chiew, F. H. S. 2012 Estimating the relative uncertainties sourced from GCMs and hydrological models in modeling climate change impact on runoff. J. Hydrometeorol. 13, 122–139.

Teutschbein, C. & Seibert, J. 2013 Is bias correction of regional climate model (RCM) simulations possible for nonstationary conditions. Hydrol. Earth Syst. Sci. 17, 5061–5077.

Visser, H., Folkert, R. J. M., Hoekstra, J. & de Wolff, J. J. 2000 Identifying key sources of uncertainty in climate change projections. Clim. Change 45, 421–457.

Wang, S., Kang, S., Zhang, L. & Li, F. 2008 Modelling hydrological response to different land-use and climate change scenarios in the Zamu River basin of northwest China. Hydrol. Process. 22, 2502–2510.

Wilby, R. L. & Harris, I. 2006 A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the river Thames, UK. Water Resour. Res. 42, W02419.

Wilby, R. L., Dawson, C. W. & Barrow, E. M. 2002 SDSM – a decision support tool for the assessment of regional climate change impacts. Environ. Model. Softw. 17 (2), 145–157.

Winchell, M., Srinivasan, R., Luzio, M. D. & Arnold, J. 2013 ARCSWAT Interface for SWAT2012: User’s Guide. Blackland Research and Extension Center Texas Agrilife Research, Texas, USA.

Xu, C. Y. 1999 Climate change and hydrologic models: a review of existing gaps and recent research developments. Water Resour. Manage. 13 (5), 369–382.

Zhang, H. & Huang, G. H. 2013 Development of climate change projections for small watersheds using multi-model ensemble simulation and stochastic weather generation. Clim. Dyn. 40, 805–821.

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