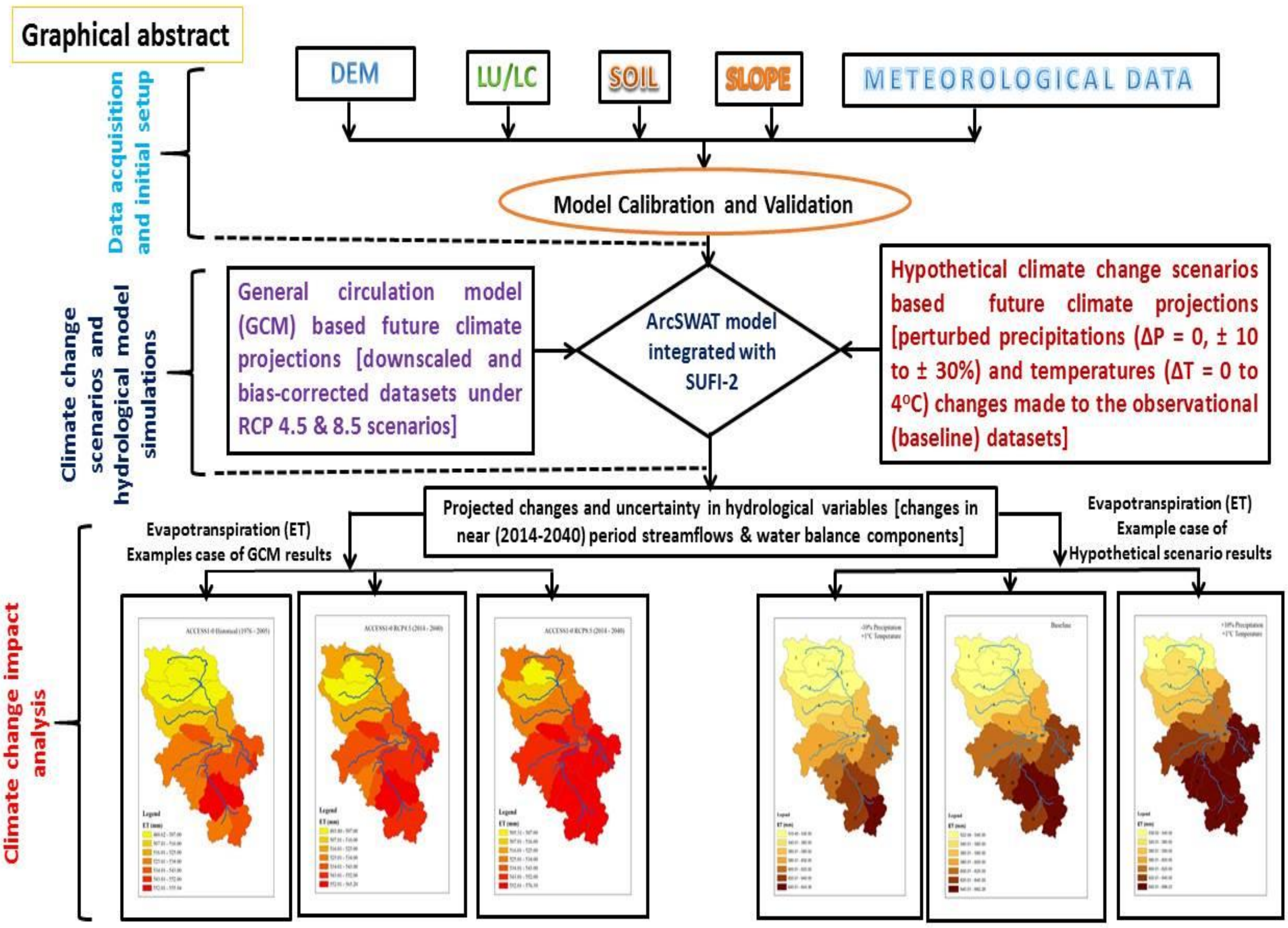
Assessment of hydrological response in Subarnarekha river basin under anticipated climate change scenarios

C. Madhusudana Rao[1], A. Bardhan[2], J. P. Patra[3]

[1]Department of Civil Engineering, National Institute of Technology Jamshedpur, Jamshedpur-831014, India. madhu_chintalacheruvu@yahoo.co.in, cmrao.civil@nitjsr.ac.in (corresponding author).

[2]Department of Civil Engineering, National Institute of Technology Jamshedpur, Jamshedpur-831014, India. bardhanavijit91@gmail.com

[3]Surface Water Hydrology Division, National Institute of Hydrology, Roorkee, Roorkee- 247667, India. patra.nih@gmail.com



Abstract

Two hydrological climate modelling techniques, general circulation model (GCM) and hypothetical climate change scenarios, were used to analyse the hydrological response to the anticipated climate change scenarios in the Subarnarekha river basin in Eastern India. Both models verified individually for the same river basin and a comparative performance of the models was evaluated to relate the two models for the near (2014-2040) period climate. The hydrological response under the anticipated climate change in the Subarnarekha river basin is well assessed by GCM under the RCP 8.5 scenarios compared to the RCPs 4.5. Results indicate GCM best suited over the hypothetical climate change scenarios as GCM has demonstrated their potential in accurately reproducing the past observed climatic changes. The strong performance of the hypothetical climate change scenarios model, particularly for warming climate scenarios, suggests that it may have distinct advantages for the analysis of water balance components in the river basin. The monthly streamflows of Subarnarekha river basin was simulated using a total of 14 years (2000-2013) daily observed streamflow data in the ArcSWAT model integrated with model calibration and uncertainty analysis by means of SUFI-2 algorithm. The results indicate during the calibration the coefficient of determination (R^2) and Nash-Sutcliff Efficiency (NSE) were reported as 0.98 and 0.97, respectively, while during the validation the R^2 and NSE were obtained as 0.94 and 0.94, respectively, confirms the hydrological model performance was very good both in calibration and validation. The obtained climate change water impact index (I_{CCWI}) values reveal the Subarnarekha river basin is more responsive to climate change. The reduction in precipitation along with the significant warming under the projected future climate is likely to reduce availability of water substantially in the study region. This work would be useful for the effective management of water resources for sustainable agriculture and in mitigating natural hazards such as droughts and floods in the study region.

Key Words: GCM, hypothetical climate change, ArcSWAT, SUFI-2, Subarnarekha river basin

1. Introduction

Investigation of effects of climate change scenarios on water resources of river basins using climate models has received significant interest by the researchers. Climate models are the main source of information for assessing the potential impacts of climate change at global and regional scales and can be used for assessing future changes in streamflows of river basins.

Two widely used climate models for assessing the impacts of climate change on hydrological performance as implemented in a number of former studies are: 1) general circulation model (GCM) through statistical downscaling techniques (e.g., Wilby and Wigley, 1997; Hassan *et al.*, 1998), 2) hypothetical climate change scenarios as input to hydrologic models (e.g., Nemec and Schaake, 1982; Gleick, 1986; Arnell, 1992; Ramadan *et al.*, 2013; Uniyal *et al.*, 2015). The GCM models through statistical downscaling approaches are considered the most reliable tools in studying climate change effects in the river basins (Goyal *et al.*, 2012; Sachindra *et al.*, 2014). The statistical downscaling relies on the empirical relationships derived between the GCM outputs (predictors of downscaling models) and the catchment scale hydro-climatic variables (predictands of downscaling models) such as precipitation, streamflow and evaporation (Hay and Clark, 2003).

However, there exist some discrepancy in the GCM approach i.e., GCM generate outputs at coarse grid scales in the order of a few hundred kilometres, their outputs cannot be directly used in catchment scale climate impact studies, which usually need hydro-climatic data at fine spatial resolutions (Sachindra *et al.*, 2014). This discrepancy indicates the scale mismatch between the GCM outputs and the hydro-climatic information needed at the catchment level. This may be considered as the major setback of the GCM model approach, even when it evidenced as the most reliable tool in assessing the climate change effects in the river basins.

Therefore, considering the discrepancy in the GCM model approach the hypothetical climate change scenarios for the initial stage of climate impact studies is widely used. Many researchers (e.g., Clinton, 1994; Bobba *et al.*, 1999; Mimikou *et al.*, 2000; Xu, 2000; Baltas and Mimikou, 2007; Rehana and Mujumdar, 2011; Ramadan *et al.*, 2013; Uniyal *et al.*, 2015) have employed hypothetical climate change scenarios to perform the sensitivity analysis on river basins. Hypothetical scenarios are executed by perturbing the baseline simulation (the validated simulation forced with observed station data) as input (Mengistu and Sorteberg, 2012). The increase in temperature is considered according to IPCC (Climate Change, 2014). These hypothetical climate change scenarios are often used as an alternate model approaches to the GCMs as they can avoid the complex statistical downscaling procedure when applied for the river basin studies. However, the model selection is the process of choosing one of the models as the final model that addresses the river basin problem and performs better under the climate changing scenarios. Therefore, it is inevitable to carry a comparative performance evaluation study between the climate models to relate their advantages and disadvantages in the model approaches.

In this study, a comparative performance evaluation is proposed to relate the climate models i.e., GCM model and the hypothetical climate change scenarios for their appropriate use in the river basin studies. Knowing the advantages and disadvantages of these two model approaches, one can sensibly apply them for assessment of hydrological response in river basin studies.

Further, the SWAT (Soil and Water Assessment Tool, Arnold *et al.*, 1998) model has been frequently used to carry out hydrologic modelling of river basins. The hydrological conditions are simulated to observe the climate change effect on water resources under the projected weather conditions in the river basins (Gosain *et al.*, 2006). In order to simulate the streamflows of river basin the ArcSWAT (a physically-based, semi-distributed hydrologic model) integrated with model calibration and uncertainty analysis by means of Sequential Uncertainty Fitting (SUFI-2) algorithm is widely used by many researchers (e.g., Abbaspour *et al.*, 2007; 2011; Gosain *et al.*, 2006; Fiseha *et al.*, 2014; Narsimlu *et al.*, 2015; Uniyal *et al.*, 2015; Mishra and Lilhare, 2016). The land use classification can easily be made in ArcSWAT model, whereas the SUFI-2 algorithm is used for model calibration, sensitivity and uncertainty analysis in streamflow prediction.

The Subarnarekha river basin in Eastern India needs effective management of water resources for sustainable agriculture and in mitigating natural hazards such as droughts and floods in the region. It is essential to assess the hydrological responses such as streamflows, water balance components, extreme flood events, variations in low flow across the basin under the anticipated climate change scenarios because this river basin is suffering from water shortage and natural hazards. Previous study focussed on annual streamflow assessment in this river basin together with the other river basins in India (Mishra and Lilhare, 2016). To the knowledge of the authors, no other notable work is seen in literature which focuses mainly on the comparative performance of the climate models used for assessment climate change effects for this river basin.

With this back ground, in the present study an effort is made to assess the climate change impact on hydrology of Subarnarekha river basin through the earlier described two climate model approaches such as GCM model and hypothetical climate change scenarios by setting two objectives (i) to calibrate and validate the ArcSWAT model for simulating monthly streamflows in the river basin, (ii) to evaluate the hydrological response to the anticipated climate changes in the river basin. This study provides support to water resource management for sustainable agriculture and in mitigating the natural flood and drought hazards in the river basin.

2. Study area

The Subarnarekha river basin is the smallest of the 14 major river basins in India and is passing through Jharkhand, West Bengal and Orissa states of Eastern India. The gauging station is located at a place called Ghatsila which is almost a peripheral boundary of Jharkhand state and is falling in the mid-reach of the river. The basin under consideration (Figure 1a) in the present study is up to Ghatsila gauging station in Jharkhand state, and is located between 21° 33' to 23° 32' North latitudes and 85° 09' to 87° 27' East longitudes in the North-East corner of the peninsular India. The total catchment area of the basin under consideration is about 14140 km^2 with high topographical variations ranging from 49 m to 1049 m above mean sea level.

The Digital Elevation Model (DEM) of the basin is given in Figure 1b. The map of the land use classes of the basin is given in Figure 1c. Nine land use classess were found in the basin namely forest land, agricultural land, barren land, Indian grass land, water body, low density residential area, industrial area, mid-to-low density residential area and mid density residential area. The major area is covered by agricultural land (60.49%), forest land (14.79%), and Indian grass land (13.63%) in the study region.

The present study uses the global soil data (Harmonized World Soil Data viewer-HWSD, version 1.2) from FAO (FAO, 2009). Figure 1d show the six different soil class namely I-Ne-3729, Nd50-2b-3819, Vc21-3b-3860, Lf32-1b-3788, I-bc-3735 and Lf96-2ab-6668. The major area is covered by I-Ne-3729 (37.31%), Nd50-2b-3819 (34.71%), Vc21-3b-3860 (24.61%) in the river basin.

The river basin is generally influenced by the south-west monsoon, which begins in the month of June and extends up to October. According to Indian Meteorological Data (IMD), the average annual rainfall in the basin is about 1800 mm. The Subarnarekha river is mostly a rainfed peninsular river. During the dry period, the river flow is almost no flow situation in the upper and middle reaches. The climate in the river basin is tropical with hot summer and mild winters. The mean monthly temperature varies from 40.5°C in the month of May to 9.00°C in the month of December. The annual average maximum and minimum temperatures vary from 32.40°C to 18.00°C in the study region. In recent years, the frequency of extreme climates has been increased in the study area. Consequently, the availability of surface water and groundwater has been reduced in the study region. Therefore, a comprehensive study is imperative to assess the impact of climate change on the hydrology of the Subarnarekha river basin.

3. Data sources and Methodology

3.1 Data sources

The observed streamflow data at the Ghatsila gauging station for the period 2000-2013 (14 years) was obtained from central water commission (CWC), New Delhi, India. The major inputs, viz.

digital elevation model (DEM) to represent the topography, Land use/land cover (LU/LC), soil maps to demonstrate the soil layers in the study region and hydro-meteorological data like daily rainfall in mm, minimum and maximum daily temperature in ^{o}C, relative humidity, solar radiation and wind speed are collected from different sources. Table 1 shows the summary of the different sources of major inputs i.e., spatial data with meteorological variables, grid resolutions and time periods.

3.2 Methodology

The present study evaluates the hydrological response to the anticipated climate change scenarios in the Subarnarekha river basin using two climate models: 1) general circulation model (GCM) datasets driven by bias-corrected results of four different climate models under the representative concentration pathways (RCPs) 4.5 and 8.5 scenarios, 2) hypothetical climate change scenarios using the perturbed temperatures $\Delta T = 0$ to $4^{o}C$ with an interval of $0.5^{o}C$ and perturbed precipitations $\Delta P = 0$, ± 10, ± 20 and ± 30% as input to hydrologic model. These two model performances were verified individually on the same river basin. A comparative performance of the models was evaluated to relate the two models for the near (2014-2040) period climate.

The downscaled GCM and bias-corrected datasets and the hypothetical climate change scenarios have used as inputs to the ArcSWAT model for prediction of streamflows in the river basin. The ArcSWAT model was calibrated using SUFI-2 optimization technique to evaluate the impact of climate change on streamflows and water balance components of Subarnarekha river basin up to Ghatsila gauging station. The ArcSWAT model was simulated for a period of 14 years, i.e., from 2000 to 2013. The first two years from 2000 to 2001 are considered as warmup period. The warmup period minimizes the effect of simulated initial state variables such as soil water content and surface residue. The next 8 years from 2002 to 2009 were considered as calibration period and the remaining 4 years from 2010 to 2013 were considered as validation period in the model.

Monthly calibration and validation were performed using the daily observed streamflow data of the Ghatsila gauging station in the Subarnarekha river basin. Further, the SCS (Soil Conservation Service) curve number method USDA-SCS (USDA, 1972) for estimating surface runoff, the Hargreaves method (Hargreaves *et al.*, 1985) for estimation of evapotranspiration, the Muskingum-Cunge method (Cunge, 1969) for flow routing and the SUFI-2 algorithm for sensitivity and uncertainty analysis linked to SWAT-CUP (Abbaspour *et al.*, 2007) were used in the study.

3.2.1 GCM

The GCM preferably embedded in so-called earth system models that account for variety of processes interactions in the climate systems. GCM produce their projections at relatively coarse spatial scales and they are unable to resolve sub-grid scale features such as topography, clouds and land use. The scale mismatch between the GCM outputs and the hydro-climatic information needed at the catchment level is a major obstacle in catchment climate impact assessment studies of hydrology and water resources (Willems and Vrac, 2011). Downscaling to the catchment scale can be accomplished through regional climate model (RCM) that uses the GCM as boundary conditions for the simulated regions.

In this study, four (ACCESS1-0, CNRM-CM5, MPI-ESM-LR, and NorESM1-M) historical (1976-2005) period and near (2014-2040) period simulated high-resolution GCM datasets for the representative concentration pathways (RCPs) 4.5 and 8.5 scenarios were used from high resolution Coordinated Regional Climate Downscaling Experiment (CORDEX)-South Asia of Indian Institute of Tropical Meteorology, Pune (IITM 2016). The list of CORDEX South Asia Climate Projections used in the study is given in Table 2. The GCM datasets were downscaled through CORDEX, and taken them to a high-resolution of 0.5^o x 0.5^o (~50 x 50 km), with a bias-corrected performed through R- software.

3.2.2 Hypothetical climate change scenarios

Several researchers (e.g., Arnell *et al.*, 1992; Clinton, 1994; Xu, 2000; Jiang *et al.*, 2007; Rehana and Mujumdar, 2011; Ramadan *et al.*, 2013; Uniyal *et al.*, 2015) have used hypothetical climate change scenarios for initial stage of climate change impact studies in river basins. These hypothetical scenarios can easily be generated to provide useful information on the response of hydrologic systems to plausible levels of climate change and variability (Clinton, 1994).

In the present study, these scenarios were performed by perturbing the baseline simulation (the validated simulation forced with observed station data) as input. A total of 63 (9 perturbed temperatures and 7 precipitations) anticipated hypothetical climate change scenarios such as combinations of temperature change ΔT = 0 to 4°C with an interval of 0.5°C (adding the prescribed change to the baseline simulation temperatures) and precipitation change ΔP = 0, ± 10, ± 20 and ± 30% (multiplied with a given factor) were considered in this study to assess the hydrologic response of the Subarnarekha river basin. But, other climatic variables such as relative humidity, wind speed, and solar radiation were considered to be unchanged (e.g., Mengistu and Sorteberg, 2012). Every scenario was then run for the same simulation period as the baseline simulation. The 12 year period from 2002 to 2013 is considered as baseline. Varied incremental climate scenarios are being applied to the daily temperatures and precipitation baseline datasets. The response of the Subarnarekha river basins streamflow and the water balance components under combinations of temperature and precipitation changes i.e., warming climate scenarios are examined.

3.3 ArcSWAT model

ArcSWAT is the most widely used watershed simulation model in geographic information system (GIS). In the present study, the ArcGIS10.2.2 interface for SWAT (ver. 2012) was used for water cycle simulation based on water balance. The water balance equation which governs the water balance components of SWAT model is given as:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \quad (1)$$

where, SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), t is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} 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).

The ArcSWAT model calculates hydrological processes occurring in a watershed such as runoff, streamflow, sediment transport and nutrients transport at the hydrological response units (HRUs) level. The HRUs are unique blend of a specific soil type, land cover type and slope within a sub-basin. The study area consists of 21 sub-basins which were divided into 251 HRUs that satisfactorily represent the watershed's heterogeneity. The present study did not employ any threshold refinement for HRU definition.

3.4 SUFI-2 Algorithm

In this study, the SUFI-2 algorithm was used to investigate sensitivity and uncertainty in streamflow prediction. The SUFI-2 algorithm is based on Latin Hypercube Sampling (LHS) which is used to find the model output uncertainty by 95% Probable Prediction Uncertainty (95PPU) evaluated at 2.5% and 97.5% levels of cumulative distribution of output variables (Abbaspour et al., 2007). The SUFI-2 starts with large parameter uncertainty so that the measured data should be within the 95PPU band. One-factor-At-a-time (OAT) sensitivity of LHS is used to select the sensitive parameters and its sensitiveness with its probable range like parameters value range should be higher or lower (Van Griensven, 2005). The SUFI-2 technique needs a minimum number of model simulations to attain a high-quality calibration and uncertainty results (Yang et al. 2008).

3.5 Sensitivity Analysis

In this study, monthly calibration and validation was performed using daily observed streamflow data of the Ghatsila gauging station in Subarnarekha river basin. The Latin Hypercube One-factor-At-a-Time (LH-OAT) sensitivity analysis was used to identify the most sensitive input parameters.

The ArcSWAT model was calibrated using SUFI-2 algorithm. The most likely sensitive SWAT parameters were included in the final calibration to perform the global sensitivity analysis for monthly time step. The most sensitive parameters were identified with respect to their sensitivity ranking done on the basis of t-stat value and p-value obtained at monthly time step for the study area.

The model performance during calibration and validation periods was evaluated by the use of selected performance statistics such as R^2, NSE, PBIAS, RSR, p-factor and r-factor. Further, the parameters t-stat and p-value are also estimated for global sensitivity analysis. In order to know the effects of different climatic parameters on the streamflows and major water balance components of Subarnarekha river basin, the climate change sensitivity analysis is performed. The calibrated ArcSWAT model is used as the base platform for this purpose. The climate changing scenarios (perturbed temperatures and precipitations) have been used to perform the sensitivity analysis of major water balance components namely evapotranspiration, surface runoff, soil water, ground water contribution, percolation and water yield. The other weather components were not included in the present sensitivity analysis because of their less impact on major changes in climate (Mishra and Lilhare, 2016).

Further, the I_{CCWI} (climate change water impact index) value is estimated to detect the degree of the temporal and spatial sensitivity of the basin. I_{CCWI} be able to evaluate the sensitivity of any component of the water budget equation to all applied scenarios correctly (Ramadan *et al.*, 2013). The I_{CCWI} value represents the state of the baseline and the streamflow response to climate change. The equation for I_{CCWI} as proposed by Ramadan *et al.*, 2013 is:

$$I_{CCWI} = \sqrt{\frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{U_{i.j}}{U_b}*100-100\right)^2} \qquad (2)$$

where, $U_{i.j}$ is the streamflow for the i^{th} precipitation and j^{th} temperature scenario, U_b is the streamflow baseline value, *m* and *n* are the total number of modelled precipitation and temperature scenarios, respectively. The value of I_{CCWI} ranges from zero to positive value. The higher value of I_{CCWI} indicates the more sensitivity in the streamflow due to changes in precipitation and/or temperature.

4. Results and Discussion

4.1 Model calibration, validation and sensitivity analysis

The hydrological model calibration and validation results were acceptable, when the performance statistics reach the desired limits between the observed and the final simulated data. The widely used performance statistics are p-factor, r-factor, coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), percentage bias (PBIAS), and root mean square error to the standard deviation of measured data (RSR). The performance statistics value and the performance rating as adopted from Moriasi *et al.,* (2007) is being followed by many researchers for systematic quantification of accuracy in the river basin simulations.

Table 3 demonstrates the summary of performance statistics of the ArcSWAT model efficiency in estimating the streamflows for monthly time step both in calibration and validation periods. For the results during the calibration period, the values of R^2, NSE, PBIAS, and RSR obtained were 0.98, 0.97, 7.30 and 0.17, respectively, while during the validation the R^2, NSE, PBIAS, and RSR obtained were 0.94, 0.94, 3.50, and 0.25, respectively, which indicates that the model performed very good for monthly time step both in calibration and validation periods.

Further, the desired value for p-factor, very close to 1 and the value of r-factor nearly to zero signifies excellent model performance with higher probability and lower uncertainty (Abbaspour *et al.,* 2007; Uniyal *et al.,* 2015). During the calibration period, the value for p-factor was 0.85 and the r-factor was 0.81, and during the validation period they were obtained as 0.44 and 0.62, respectively. It is revealed from the obtained p-factor value showing the model performance was very good. It also realized from the obtained r-value that the model was unable to capture the uncertainty exactly in the parameter estimates. The uncertainty may be due to discrepancy in the input rainfall as it was affected by climate change impacts in the study region. However, as the obtained PBIAS value is positive indicating that the model performance shows tendency to slightly underestimation.

The sensitive SWAT parameters included in the final calibration, t-stat and p-values for monthly streamflow simulations are presented in Table 4. About 14 sensitive SWAT parameters (Table 4) were included in the final calibration to perform the global sensitivity analysis for monthly time step. Out of these 14 parameters, the first 5 parameters such as V__CH_K2.rte; V__ALPHA_BF.gw; V__CH_N2.rte; R__SOL_AWC(..).sol; and R__CN2.mgt were identified as the most sensitive parameters with respect to their sensitivity ranking done on the t-stat values ranging from -35.96 to 3.33 and p-value shows zero in all 5 parameters assessed at monthly time step in the study area. The fitted value and the parameter range (minimum and maximum) for all the 14 sensitive parameters included in the final calibration are given in Table 5. The results of sensitivity analysis have confirmed that all these sensitive parameters are considered to be applicable to base flow, surface runoff, groundwater, channel routing, and soil properties. This final calibration model was used to assess the water balance components such as streamflows, evapotranspiration (ET), surface runoff (SURQ), groundwater contribution (GW_Q), percolation (PERC), water yield (WYLD) and soil water (SW) in the study area.

4.2 GCM model results

4.2.1 Projected changes and uncertainty in hydrologic variables

The projected changes in the streamflows and water balance components of the Subarnarekha river basin were estimated for the near (2014-2040) period climate under the RCP 4.5 and 8.5 scenarios with reference to the historic (1976-2005) period. The near (2014-2040) period climate includes the recent past (2014-2020) period as the model simulation is ending in the year 2013 as per the available data. The staring year of the near period may be assumed immediately after the end of simulation period. This type of procedure is in practice (e.g. Mishra and Lilhare, 2016; Kumar *et al.,* 2017). In order to meet the present and near period water requirements in the Subarnarekha river basin only near period climate changes were assessed and their results are demonstrated herein. The mid and end period climate changes were not presented in this study.

Table 6 shows the values of projected changes in the streamflow and water balance components with their percentage change in parenthesis computed using four GCM models under the RCPs 4.5 and 8.5 scenarios. Figures 2 depicts the pictorial views of projected changes in the water balance component ET of the Subarnarekha river basin for ACCESS1-0 historical and near period simulated GCM dataset under the RCPs 4.5 and 8.5 given as a sample case of the obtained results. Table 7 reveals the overall projected percentage change in the water balance components of Subarnarekha river basin computed using GCM model under the RCPs 4.5 and 8.5.

Other than the CNRM-CM5 and MPI-ESM-LR models of GCM, the remaining two GCM model results show the increase in the streamflows of the Subarnarekha river basin in the near (2014-2040) period climate under the RCP 4.5 and 8.5 scenarios (Table 6). The CNRM-CM5 model shows decrease in streamflow at near period by an annual average of 16.15% and 16.98% (Table 6) under both RCP 4.5 and 8.5 scenarios, respectively. Whereas, MPI-ESM-LR model shows a decrease of 0.93% only in RCP 4.5 scenario but not in RCP 8.5 indicating that there is a larger intermodal uncertainty. Further, the overall streamflows is projected to increase by 0.73% and 8.59% (Table 7) in the Subarnarekha river basin in the near period climate under the RCP 4.5 and 8.5 scenarios, respectively.

The overall evapotranspiration (ET) is projected to increase by 3.46% and 4.24% under both RCP 4.5 and 8.5 scenarios, respectively for the near period (Table 7). The similar observation i.e., increase of ET is also seen in all the four GCM models (Table 6). The increase in ET can be attributed to significant increase in precipitation while a substantial rise in air temperature.

The surface runoff (SURQ) in the river basin is going to decrease by 2.53% under the RCP 4.5 scenario, whereas it is going to increase by 8.86% under the RCP 8.5 scenario (Table 7). Similarly, the other water balance components such as groundwater contribution (GW_Q), percolation (PERC), water yield (WYLD) shows increasing trend, whereas the soil water (SW) shows decreasing trend under the RCP 4.5 and 8.5 scenarios (Tables 6, Table 7). The SW is projected to decrease by 2.14% and 0.50% under the RCP 4.5 and 8.5 scenarios. This indicate the initial and final soil water contents on monthly time steps are undergoing significant changes due to large variations in all other water balance components for near period climate change in the river basin (Equation 1). It is observed from the GCM model results that the RCP 8.5 is more suitable than RCP 4.5 in assessing the hydrological response in the river basin for near period climate change scenarios as there is less intermodel uncertainty in the water balance component projections.

4.3 Hypothetical scenarios model results

Table 8 to Table 14 demonstrates the percentage change in streamflows and water balance components such as ET, SURQ, GW_Q, PERC, WYLD, and SW, respectively, estimated on monthly time step under the considered hypothetical climate change scenarios. Note that in all the tables from Table 8 to Table 14, the alphabet T denotes temperature in ^{o}C and P denotes percentage change of precipitation. The value zero given to T and P in the first column of all the tables indicates no change in precipitation and temperature. The positive/negative value indicates the percentage increase/reduction in precipitation.

Figure 3a and Figure 3b shows the pictorial views of subbasin wise spatial variations of water balance components of Subarnarekha river basin presented herein as the sample cases for the selected hypothetical climate change scenarios. Figure 3a demonstrates the sensitivity of water balance components ET, SURQ and GW_Q of Subarnarekha river basin under the impact of climate change by 1^{o}C in future with a variable rate of change in precipitation (-10 % and +10%). Figure 3b demonstrates the same as in the case of Figure 3a but for PERC, WYLD and SW of Subarnarekha river basin.

The results of hypothetical sensitivity analysis show a warming of 4°C without any change in precipitation will lead to 5.57% reduction in streamflow in Subarnarekha river basin (Table 8). On the other hand, a 10, 20 and 30% increase in precipitation under the projected future climate with a rise of 4°C or less will not cause any reduction streamflow in Subarnarekha river basin. However, reduction of 10, 20, 30% precipitation with 4°C warming will lead to reduction in streamflow by 25.78%, 45.25%, and 63.01%, respectively. Further, the reduction of 10% in precipitation without warm climate condition will lead to reduction in streamflow by 20.61% (Table 8). Therefore, from the results of hypothetical analysis it is revealed that the annual streamflows of Subarnarekha river basin are very sensitive to variations in precipitation changes and less sensitive to temperature changes in the river basin.

It is seen again from Table 9 and Figure 3a that, evapotranspiration (ET) in the Subarnarekha river basin show less sensitivity as compared to other components. The warm climate condition of increase in temperature up to 4°C without any change in precipitation led to increase the ET by around 4.65%. The reduction of 10% in precipitation without warm climate condition shows 2.04% decrease in ET; whereas considering the same condition of precipitation with warm climate of increase in temperature up to 4^{o}C show increase in ET by around 2.16%. In all 7 different precipitation scenarios, with increase in temperature, the ET has increased. This happens due to proportionality of ET with temperature. Therefore, this analysis shows that any increase in precipitation along with climate warming will lead to increase in ET. On the other hand, a decrease in precipitation with climate warming in the basin will lead to reduction in ET in the Subarnarekha river basin.

The surface runoff (SURQ) in the Subarnarekha river basin is high sensitive as compared to the other components after streamflow (Table 10, Figure 3a). In warm climate condition of increase in temperature up to 4^0C with 10% reduction in precipitation led to decrease in SURQ by 19.92%; whereas with 10% increase in precipitation with warm climate condition of increase in temperature up to 4^0C, the surface runoff increased by 16.63% which indicates that the SURQ is highly sensitive even for modest change in precipitation. Similar to the streamflow a warming without any change in precipitation will cause a reduction in SURQ in the Subarnarekha river basin. On the other hand, a 30% increase/reduction in precipitation with 4°C warming will lead to an increase/decrease of 56.16/52.57% in SURQ.

The sensitivity results of groundwater contribution (GW_Q) are given in Table 11. In warm climate condition of increase in temperature up to 4^0C without any change in precipitation led to decrease of GW_Q by 9.34%. With modest warm climatic conditions, increase in temperature increases up to 0.5^oC and 1^oC without any change in precipitation led to decrease in GW_Q by 1.28% and 2.61% respectively. This shows that the GW_Q is moderate sensitive to the climate change in the river basin. The ground water contributions in the Subarnarekha river basin are declining due to climate change.

The percentage change in percolation (PERC) values obtained for varied precipitations and temperatures scenarios are presented in Table 12 and their pictorial representations are demonstrated in Figure 3b. The PERC shows moderate sensitiveness with respect to hypothetical climate change scenarios in the Subarnarekha river basin.

As depicted in Table 13 and Figure 3b, the water yield (WYLD) show high sensitiveness with respect to hypothetical climate change scenarios in the Subarnarekha river basin. In case of warm climate condition of increase in temperature up to 4^oC without any change in precipitation led to a decrease of WYLD by around 4.41%. Under modest warm climatic scenario like increase in temperature to 1^oC with an increase in precipitation up to 10% led to an increase of WYLD by

16.12%; whereas for temperature increase up to 1^0C along with 10% reduction in precipitation led to a decrease of WYLD by 18.11% in the river basin.

The Soil Water (SW) content shows unique behaviour compared to the other water balance components (Table 14, Figure 3b). This is expected due to the initial soil water (SW_0) and final soil water (SW_t) contents available along with the other water balance components as mentioned in Equation (1) at a particular time step. In warm climate condition of increase in temperature up to 4^0C without any change in precipitation led to a decrease of SW to around 2.14% and with 30% reduction in precipitation led to a decrease of soil water by around 7.15%; whereas for 30% increase in precipitation along with an increase in temperature up to 4^oC led to an increase of soil water by around 0.35%.

Further, Table 15 demonstrates the I_{CCWI} calculated for monthly streamflows for Subarnarekha river basin, and Table 16 demonstrates the I_{CCWI} values obtained for water balance components and streamflows of Subarnarekha river basin. The results of I_{CCWI} values revealed that the monthly streamflows and the water balance components of Subarnarekha river basin are more responsive to climate change as their I_{CCWI} values show higher values.

5. Conclusions

The ArcSWAT model was applied in the Subarnarekha river basin to simulate the monthly streamflows for the period 2000-2013 by following the calibration and validation analysis using the SUFI-2 algorithm. The outcomes of the sensitivity and uncertainty analysis using ArcSWAT and SUFI-2 indicate that the model is appropriate for streamflow prediction in the Subarnarekha river basin. The ArcSWAT model has closely simulated the observed streamflows in both the calibration and validation. This calibrated model can be used in further assessment of climate change using uncertainty techniques in the model calibration.

The hydrological response under the anticipated climate change in the Subarnarekha river basin is well assessed by GCM under the RCP 8.5 scenarios compared to the RCPs 4.5. Results indicate

GCM model is best suitable over the hypothetical climate change scenarios as GCM has established their potential in accurately reproducing the past observed climatic changes. It can be seen from the GCM results that the monthly streamflows and the water balance components of Subarnarekha river basin are more responsive in the near (2014-2040) period climate. The mid and end period climate effects on the water resources of the river basin are under consideration in the future scope of this work.

The hypothetical climate change scenario model results show that the combined change in precipitation and temperature are likely to affect the streamflows of Subarnarekha river basin in addition to the decline of water availability in the river basin. The streamflows have tendency to be reduced with temperature increase and precipitation decrease. However, precipitation variation has a substantial weight on the river basin's streamflows behaviour. This may cause uncertainties in the future streamflows of the river basin. The I_{CCWI} values of the Subarnarekha river basin demonstrate more distinct sensitivity to climate change indicting that the monthly streamflows and the water balance components of the river basin are more responsive to climate change due to uncertainties and nonstationarity effects.

Therefore, it is suggested in future studies, to use the probabilistic analysis using probability density functions (PDFs) and cumulative distribution functions (CDFs) curves in quantifying the uncertainties in the future streamflows of the river basin. Further, the high and low flow statistics are to be assessed under nonstationarity assumptions as they are very important for flood estimation and drought determination in the river basin. This work would be useful for the effective management of soil and water resources for sustainable agriculture in the river basin.

Acknowledgement

The authors would like to express sincere gratitude to the editor and reviewers for their valuable and constructive comments which improved the quality of the present work.

References

Abbaspour K.C., Vejdani, M. and Haghighat S. (2007), SWAT-CUP: Calibration and uncertainty programs for SWAT. Proceedings of the International Congress on Modelling and Simulation (MODSIM 2007), Modelling and Simulation Society of Australia and New Zealand, New Zealand, 1596-1602.

Abbaspour K.C. (2011), SWAT Calibration and Uncertainty Programs: A User Manual. Swiss Federal Institute of Aquatic Science and Technology. Eawag, Dubendorf.

Arnell N.W. (1992), Factors controlling the effects of climate change on river flow regimes in a humid temperate environment, *J. of Hydrol.*, **132**, 321–342, https://doi.org/10.1016/0022-1694(92)90184-W.

Arnold J.G., Srinivasan R., Muttiah R.S. and Williams J.R. (1998), Large area hydrologic modeling and assessment, Part I: Model development, *J. Am. Water Resour. Assoc.*, **34**, 73–89.

Baltas E.A. and Mimikou M.A. (2007), Climate change impacts on the water supply of Thessaloniki, *International Journal of Water Resources Development*, **21(2)**, 341-353.

Bobba A.G., Jeffries D.S. and Singh V.P. (1999), Sensitivity of hydrological variables in the Northeast Pond River watershed, New found land, Canada, due to climate change, *Water Resources Management*, **13**, 171–188.

Clinton M.R. (1994), Sensitivity of streamflow to climate change: A case study for Nebraska, *Great Plains Research*, 27-49.

Cunge J.A. (1969), On the subject of a flood propagation method (Muskingum Method), *J. Hydraul. Res.*, IAHR, **7(2)**, 205–230. https://doi.org/10.1080/00221686909500264.

FAO. (2009), Harmonized World Soil Database (Version 1.1), In Global Environmental Change-Human and Policy Dimensions, FAO: Rome, Italy and IIASA, Laxenburg, Austria.

Fiseha 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.

Gleick P. H. (1986), Methods for evaluating the regional hydrologic impacts of global climatic changes, *J. of Hydrology*, **88(1-2)**, 97-116.

Gosain A.K., Rao S. and Basuray D. (2006), Climate change impact assessment on hydrology of Indian river basins, *Curr. Sci.*, **90(3)**, 346-353.

Goyal M.K., Burn D.H. and Ojha C.S.P. (2012), Evaluation of machine learning tools as a statistical downscaling tool: temperatures projections for multi-stations for Thames River Basin, Canada, *Theor. Appl. Climatol.*, **108**, 519–534, https://doi.org/10.1007/s00704-011-0546-1.

Hargreaves G.L., Hargreaves G.H. and Riley J.P. (1985), Irrigation Water Requirements for Senegal River Basin, *Journal of Irrigation and Drainage Engineering-ASCE*, **111(3)**, 265–275. https://doi.org/10.1061/(ASCE)0733-9437(1985)111:3(265).

Hassan H., Aramaki T., Hanaki K., Matsuo T. and Wilby R. (1998), Lake stratification and temperature profiles simulated using downscaled gcm output, *Water Science and Technology*, **38(11)**, 217-226.

Hay L.E. and Clark M.P. (2003), Use of statistically and dynamically downscaled atmospheric model output for hydrologic simulations in three mountainous basins in the western United States, *J. of Hydrol.*, **282**, 56–75.

IPCC. (2014), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Jiang T., Chen Y.D., Xu. C.Y., Chen X., Chen X. and Singh V.P. (2007), Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China, *J. of Hydrol.*, **336**, 316–333, doi:10.1016/j.jhydrol.2007.01.010.

Kumar N., Tischbein B., Kusche J., Laux P., Beg M.K. and Bogardi J. J. (2017), Impact of climate change on water resources of upper Kharun catchment in Chhattisgarh, India, *J. Hydrol. Reg. Std.*, **13**, 189-207, doi: 10.1016/j.ejrh.2017.07.008.

Mengistu D.T. and Sorteberg A. (2012), Sensitivity of SWAT simulated streamflow to climate changes within the Eastern Nile River basin, *Hydrol. Earth Syst. Sci.*, **16**, 391–407, doi: 10.5194/hess-16-391-2012.

Mimikou M.A., Baltas E., Varanou E. and Pantazis K. (2000), Regional impacts of climate change on water resources quantity and quality indicators, *J. of Hydrol.*, **234**, 95-109.

Mishra V. and Lilhare R. (2016), Hydrologic sensitivity of Indian sub-continental river basins to climate change, *Global and Planetary Change*, doi: 10.1016/j.gloplacha.2016.01.003.

Moriasi D.N., Arnold J.G., Van Liew M.W., Bingner R.L., Harmel R.D. and Veith T.L. (2007), Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Transactions of the ASABE*, **50(3)**, 885-900.

Narsimlu B., Gosain A.K., Chahar B.R., Singh S.K. and Srivastava P.K. (2015), SWAT Model Calibration and Uncertainty Analysis for Streamflow Prediction in the Kunwari River Basin, India, Using Sequential Uncertainty Fitting, *Environ. Process*, **2**, 79–95, DOI 10.1007/s40710-015-0064-8.

Nemec J. and Schaake J. (1982), Sensitivity of water resource systems to climate variation, *Hydrological Sciences Journal*, **27(3)**, 327-343, DOI: 10.1080/02626668209491113.

Ramadan H.H., Beighley R.E. & Ramamurthy A.S. (2013), Sensitivity analysis of climate change impact on the hydrology of the Litani Basin in Lebanon, *Int. J. Environment and Pollution*, **52(1/2)**, 65-81, doi: 10.1504/IJEP.2013.056359.

Rehana S. and Mujumdar P.P. (2011), River water quality response under hypothetical climate change scenarios in Tunga-Bhadrariver, India, *Hydrol. Process.*, **25**, 3373–3386, doi: 10.1002/hyp.8057.

Sachindra, D. A., Huang, F., Barton, A., and Perera, B. J. C. (2014). Statistical downscaling of general circulation model outputs to precipitation – part 1: calibration and validation. Int. *J. of Climatol.*, **34**, 3264–3281 (2014), DOI: 10.1002/joc.3914.

Uniyal B., Jha M.K. and Verma A.K. (2015), Assessing climate change impact on water balance components of a river basin using SWAT model, *Water Resour. Manage.*, **29**, 4767-4785, doi 10.1007/s11269-015-1089-5.

Uniyal B., Jha M.K. and Verma A.K. (2015), Parameter identification and uncertainty analysis for simulating streamflow in a river basin of eastern India, *Hydrol. Process.*, **29(17)**, 3744–3766, https://doi.org/10.1002/hyp.10446.

USDA-SCS. (1972), USDA Soil Conservation Services National Engineering Handbook, Section 4: Hydrology. U.S. Government printing office, 1972.

Van Griensven A. (2005), Sensitivity, auto-calibration, uncertainty and model evaluation in SWAT 2005. UNESCO-IHE, 48.

Wilby R.L. and Wigley T.M.L. (1997), Downscaling general circulation model output: a review of methods and limitations, *Progress in Physical Geography: Earth and Environment*, **21(4)**, 530–548.

Willems P. and Vrac M. (2011), Statistical precipitation downscaling for small- scale hydrological impact investigations of climate change, *J. of Hydrology*, **402(3-4)**, 193-205.

Xu C.Y. (2000), Modeling the effects of climate change on water resources in Central Sweden, *Water Resources Management*, **14**, 177–189.

Yang J, Reichert P, Abbaspour K, Xia J, Yang H (2008) Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China, *J. of Hydrol.*, **358**,1–23.

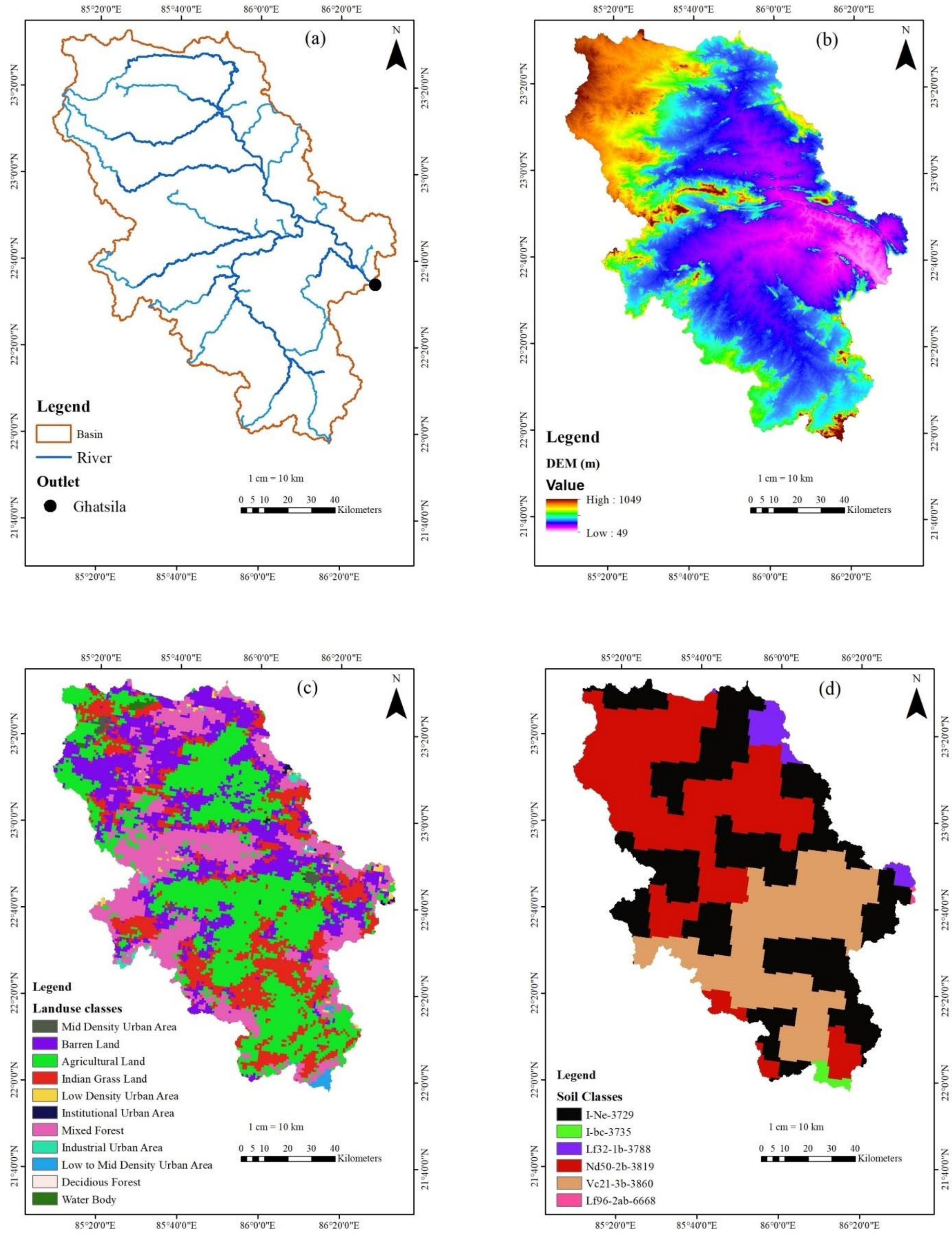


Figure 1. (a), (b), (c) and (d) Showing the location map with Ghatsila gauging station, Digital Elevation Model (DEM) map, land use class map and soil map of Subernarekha river basin, respectively.

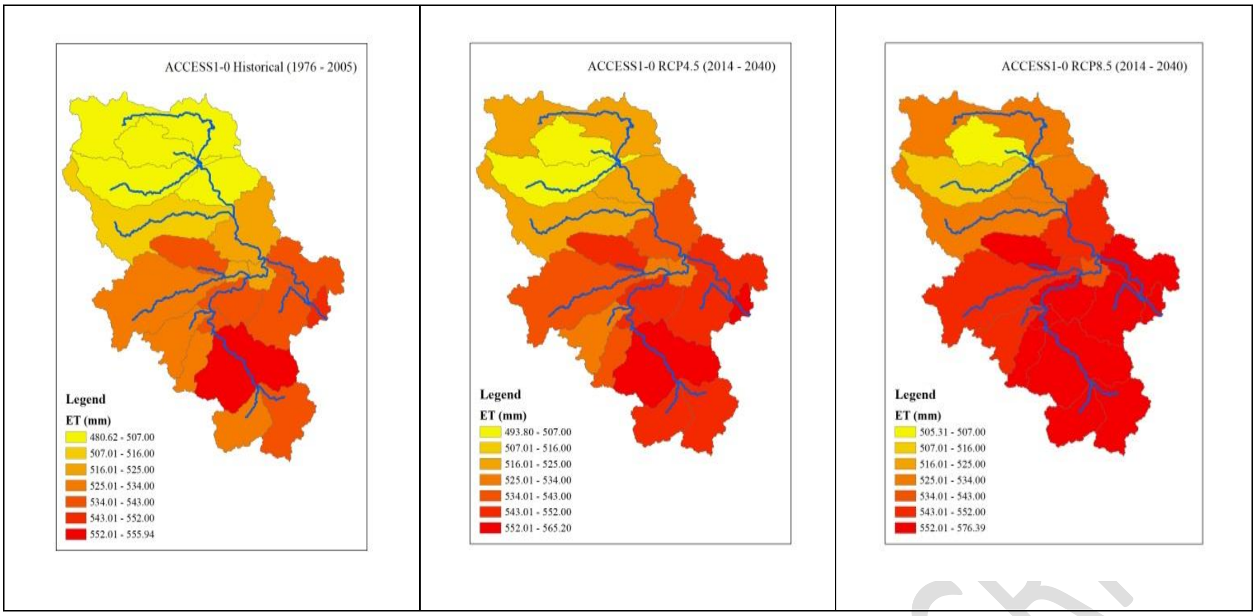


Figure 2. Depicts the pictorial views of projected changes in the water balance component ET of the Subarnarekha river basin for ACCESS1-0 historical and near period simulated GCM dataset under the RCPs 4.5 and 8.5.

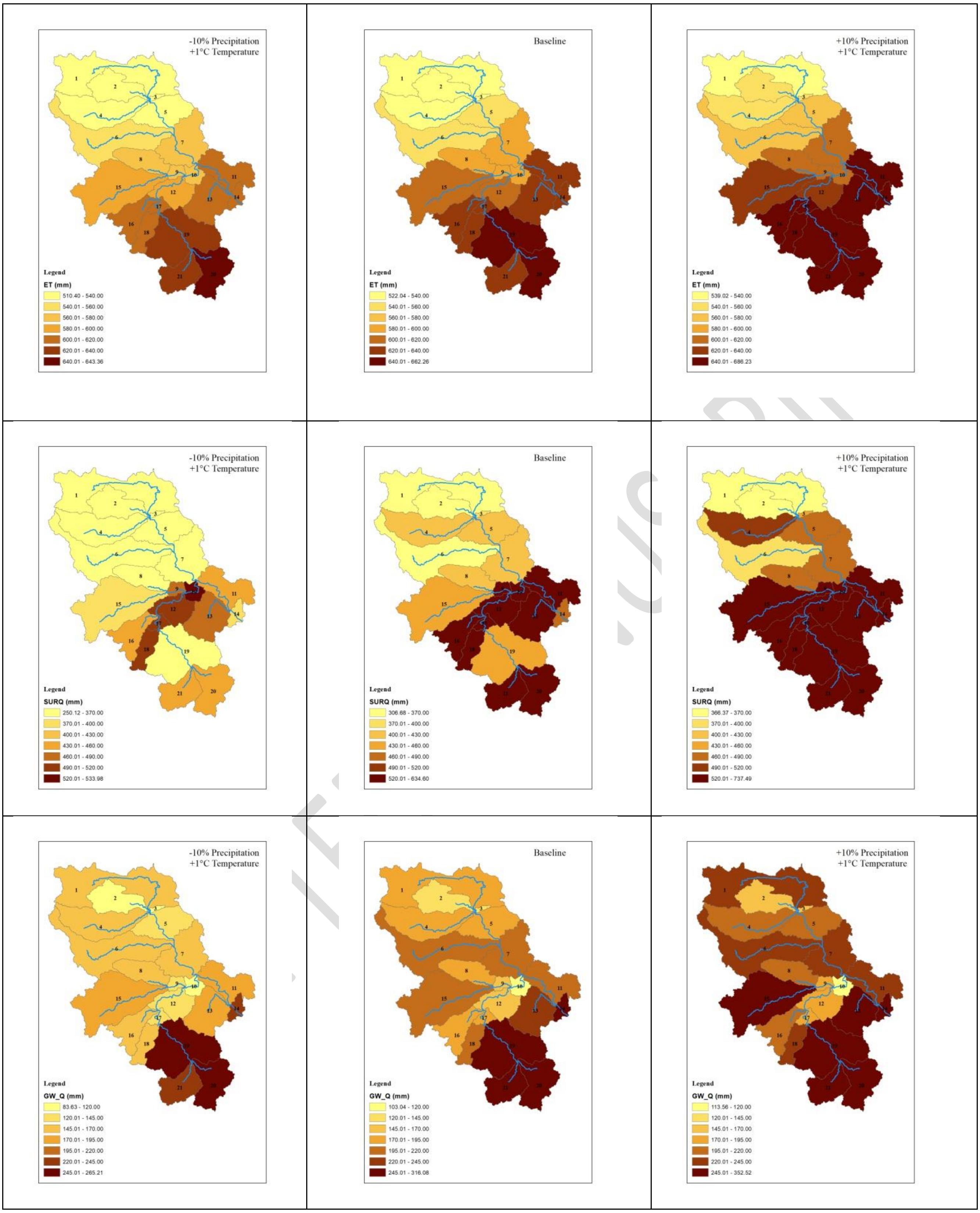


Figure 3a. Showing the pictorial views of sensitivity of water balance components ET, SURQ and GW_Q of Subarnarekha river basin under the impact of climate change by 1°C in future with a variable rate of change in precipitation (-10 % and +10%).

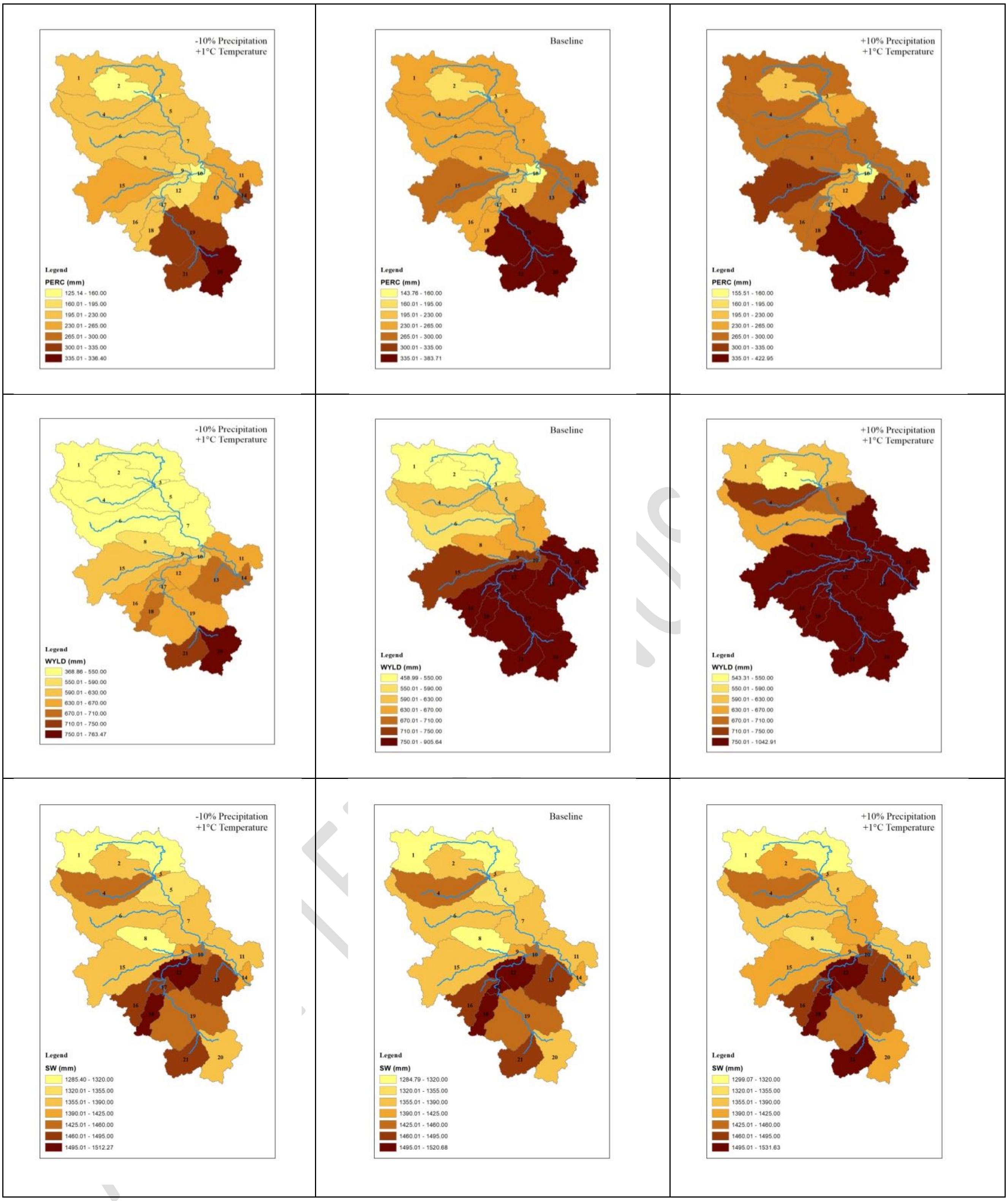


Figure 3b. Same as Figure 3a but for the water balance components PERC, WYLD and SW.

Table 1. Summarized spatial data descriptions and their sources.

Sl. No.	Spatial data	Description / resolution	Duration / Time period	Source
1.	Digital Elevation Model	30 m x 30 m grid resolution DEM to represent the topography	Collected on December 2015	Shuttle Radar Topography Mission (SRTM) of USGS
2.	Land use and land cover	1 km x 1 km grid resolution LU/LC map to represent the crops and urban specific digital layers	2005 Map	Nation Remote Sensing Centre, India / Water Resources information System (http://www.india-wris.nrsc.gov.in) and Texas A & M University (http://swat.tamu.edu/)
3.	Soil	1 km x 1 km grid resolution soil map to demonstrate the soil layer	2009 FAO soil Map	Food and Agriculture Organization (FAO)
4.	Hydrological data	Gauged daily discharge data at Ghatsila gauging station of Subarnarekha river	2000 – 2013	Central Water Commission (CWC), New Delhi, India
5.	Weather inputs (for model simulation)	0.25° x 0.25° grid resolution daily precipitation data and 0.5° X 0.5° grid resolution data of weather inputs such as maximum and minimum temperature, relative humidity, solar radiation and wind speed daily data	2000 – 2013	Indian Meteorological Department (IMD), Pune, India
6.	Climate change data	0.5° x 0.5° grid resolution precipitation and temperature (maximum and minimum) data on daily time step	Historic (1976 – 2005) period and Near (2014 – 2040) period	CORDEX-South Asia data set from IITM

Table 2. List of CORDEX South Asia Climate Projections used in the study.

Institute	Contributing Modelling Centre	GCM	Related RCM	Resolution (degree)
CSIRO	CSIRO, Australia	ACCESS1-0	CCAM-1391M	0.5
CSIRO	Centre National de Recherches Météorologiques (CNRM), France	CNRM-CM5	CCAM-1391M	0.5
CSIRO	MPI-M, Germany	MPI-ESM-LR	CCAM-1391M	0.5
CSIRO	Norwegian Climate Centre (NCC), Norway	NorESM1-M	CCAM-1391M	0.5

Note: CSIRO = Commonwealth Scientific and Industrial Research Organization; GCM = Global Climate Modal; RCM = Regional Climate Model

Table 3. Summary of performance statistics showing the ArcSWAT model efficiency in estimating the streamflows for monthly time step both in calibration and validation periods.

Sl. No.	Statistics	value	Monthly time step		Performance rating (adopted from Moriasi *et al.*, (2007)
			Calibration period	Validation period	
1.	$R^2 = \frac{\left[\sum_i \left(Q_{o,i} - \overline{Q}_o\right)\left(Q_{s,i} - \overline{Q}_s\right)\right]^2}{\sum_i \left(Q_{o,i} - \overline{Q}_o\right)^2 \sum_i \left(Q_{s,i} - \overline{Q}_s\right)^2}$	Closer the value of R^2 to 1, the simulated and observed values are very close.	0.98	0.94	Very good
2.	$NSE = 1 - \frac{\sum_i \left(Q_o - Q_s\right)_i^2}{\sum_i \left(Q_{o,i} - \overline{Q}_o\right)^2}$	Ranges between -∞ to 1, with optimal value of 1.	0.97	0.94	Very good
3.	$PBIAS = 100 \times \frac{\sum_{i=1}^{n} \left(Q_o - Q_s\right)_i}{\sum_{i=1}^{n} Q_{o,i}}$	Optimum value is zero, positive value indicates a tendency to underestimation and negative value indicates a tendency to overestimation.	7.30	3.50	Very good for <±10
4.	$RSR = \frac{\sqrt{\sum_{i=1}^{n} \left(Q_m - Q_s\right)^2{}_i}}{\sqrt{\sum_{i=1}^{n} \left(Q_{m,i} - \overline{Q_m}\right)^2}}$	Value varies from 0 to positive value. The optimal value of RSR is 0 "which indicates best model performance. The lower value RSR indicates the performance of the model is better.	0.17	0.25	Very good

Table 4. Sensitive SWAT parameters included in the final calibration, t-stat and p-values for monthly streamflow simulations.

Sl. No.	Parameter name	Parameters description	Rank	t-stat	p-value
1	V__CH_K2.rte	Effective hydraulic conductivity in main channelalluvium (mm/hr)	1	-35.96	0.00
2	V__ALPHA_BF.gw	Baseflow alpha factor (days)	2	35.44	0.00
3	V__CH_N2.rte	Manning's "n" value for the main channel	3	8.40	0.00
4	R__SOL_AWC(..).sol	Available water capacity of the soil layer soil layers (mm/mm)	4	-3.36	0.00
5	R__CN2.mgt	SCS runoff curve number	5	3.33	0.00
6	R__ESCO.hru	Soil evaporation compensation factor	6	-1.28	0.20
7	R__MSK_X.bsn	Weighting factor controlling relative importance of inflow rate and outflow rate in determining water storage in reach segment	7	-1.15	0.25
8	R__GW_DELAY.gw	Groundwater delay (days)	8	-1.09	0.28
9	R__GWQMN.gw	Threshold depth of water in the shallow	9	-1.01	0.31
10	R__SOL_K(..).sol	Saturated hydraulic conductivity soil layers (mm/hr)	10	-0.92	0.36
11	R__MSK_CO2.bsn	Calibration coefficient used to control impact of the storage time constant for low flow	11	0.85	0.40
12	V__SURLAG.bsn	Surface runoff lag time	12	0.61	0.54
13	R__OV_N.hru	Manning's "n" value for overland flow	13	-0.53	0.59
14	R__MSK_CO1.bsn	Calibration coefficient used to control impact of the storage time constant for normal flow	14	0.03	0.97

Table 5. Fitted values and the parameter range used for calibration.

Sl. No.	Parameter name	Fitted value	Parameter range	
			Min value	Max value
1	V__CH_K2.rte	21.84	0.01	38.17
2	V__ALPHA_BF.gw	0.28	-0.09	0.34
3	V__CH_N2.rte	0.12	0.01	0.13
4	R__SOL_AWC(..).sol	0.45	0.17	0.54
5	R__CN2.mgt	0.01	-0.02	0.04
6	R__ESCO.hru	-0.12	-0.13	-0.02
7	R__MSK_X.bsn	0.34	0.12	0.41
8	R__GW_DELAY.gw	0.06	0.01	0.21
9	R__GWQMN.gw	0.05	-0.20	0.21
10	R__SOL_K(..).sol	-0.13	-0.13	0.02
11	R__MSK_CO2.bsn	0.03	-0.05	0.08
12	V__SURLAG.bsn	11.51	8.56	20.63
13	R__OV_N.hru	0.20	0.11	0.35
14	R__MSK_CO1.bsn	-0.08	-0.10	0.03

Table 6. Showing the values of projected changes in the streamflow and water balance components with their percentage change in parenthesis computed using four GCM models under the RCPs 4.5 and 8.5 scenarios.

GCM Model/ Water balance component	RCP4.5	RCP8.5
Streamflow		
ACCESS1-0	11.03 (13.65)	20.43 (25.28)
CNRM-CM5	-17.58 (16.15)	-18.49 (16.98)
MPI-ESM-LR	-0.89 (0.93)	11.78 (12.26)
NorESM1-M	5.83 (6.36)	12.64 (13.79)
ET		
ACCESS1-0	13.11 (2.55)	26.20 (5.10)
CNRM-CM5	23.87 (4.79)	20.18 (4.05)
MPI-ESM-LR	19.02 (3.74)	20.11 (3.95)
NorESM1-M	14.00 (2.74)	19.65 (3.84)
SURQ		
ACCESS1-0	15.23 (11.08)	39.97 (29.07)
CNRM-CM5	-21.40 (12.12)	-23.51 (13.31)
MPI-ESM-LR	-14.46 (8.70)	12.21 (7.35)
NorESM1-M	-0.57 (0.36)	19.33 (12.33)
GW_Q		
ACCESS1-0	8.26 (8.69)	9.52 (10.01)
CNRM-CM5	-16.29 (13.99)	-15.00 (12.89)
MPI-ESM-LR	12.32 (12.33)	18.92 (18.94)
NorESM1-M	13.50 (13.39)	11.33 (11.24)
PERC		
ACCESS1-0	8.67 (6.99)	9.97 (8.04)
CNRM-CM5	-18.02 (12.25)	-15.39 (10.46)
MPI-ESM-LR	12.75 (9.88)	20.05 (15.54)
NorESM1-M	14.57 (11.26)	12.02 (9.28)
WYLD		
ACCESS1-0	24.30 (9.85)	50.47 (20.45)
CNRM-CM5	-38.99 (12.62)	-39.65 (12.83)
MPI-ESM-LR	-1.24 (0.44)	32.73 (11.66)
NorESM1-M	14.08 (5.17)	31.71 (11.64)
SW		
ACCESS1-0	-2.66 (3.00)	2.48 (2.80)
CNRM-CM5	-2.13 (2.31)	-1.36 (1.47)
MPI-ESM-LR	0.34 (0.37)	0.01 (0.01)
NorESM1-M	-3.32 (3.62)	-3.07 (3.34)

Table 7. Overall projected percentage change in the water balance components of Subarnarekha river basin computed using GCM models under the RCPs 4.5 and 8.5.

Water balance components	RCP 4.5	RCP 8.5
Streamflow	0.73	8.59
ET	3.46	4.24
SURQ	-2.53	8.86
GW_Q	5.10	6.82
PERC	3.97	5.60
WYLD	0.49	7.73
SW	-2.14	-0.50

Table 8. Percentage change in streamflows.

T ºC / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-59.32	-59.83	-60.33	-60.82	-61.26	-61.71	-62.14	-62.62	-63.01
p-20%	-40.68	-41.29	-41.88	-42.45	-43.05	-43.61	-44.15	-44.73	-45.25
p-10%	-20.61	-21.33	-21.98	-22.62	-23.32	-23.94	-24.55	-25.21	-25.78
p	0.00	-0.76	-1.47	-2.14	-2.87	-3.56	-4.25	-4.96	-5.57
p+10%	21.33	20.53	19.80	19.09	18.32	17.61	16.89	16.14	15.52
p+20%	42.85	42.06	41.30	40.55	39.75	39.05	38.29	37.51	36.85
p+30%	65.18	64.33	63.58	62.79	61.98	61.21	60.44	59.61	58.91

Table 9. Percentage change in evapotranspiration (ET).

T ºC / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-8.44	-7.92	-7.20	-6.95	-6.52	-6.13	-5.55	-5.00	-4.55
p-20%	-5.03	-4.68	-4.16	-3.52	-2.50	-2.45	-2.08	-1.40	-0.97
p-10%	-2.04	-1.78	-1.23	-0.66	-0.05	0.50	1.10	1.54	2.16
p	0.00	0.63	1.49	1.71	2.34	2.92	3.49	4.13	4.65
p+10%	2.23	2.88	3.59	4.05	4.89	5.37	5.96	6.63	7.18
p+20%	4.25	4.92	5.58	6.29	6.74	7.59	7.96	8.78	9.35
p+30%	6.19	6.88	7.62	8.12	9.00	9.38	10.26	10.71	11.41

Table 10. Percentage change in surface runoff (SURQ).

T ºC / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-50.90	-51.11	-51.41	-51.53	-51.71	-51.87	-52.13	-52.36	-52.57
p-20%	-34.00	-35.27	-35.50	-35.76	-36.21	-36.23	-36.40	-36.68	-36.89
p-10%	-15.69	-18.18	-18.43	-18.68	-18.95	-19.19	-19.46	-19.65	-19.92
p	0.00	-0.27	-0.63	-0.76	-1.04	-1.30	-1.56	-1.83	-2.07
p+10%	18.88	18.59	18.28	18.06	17.69	17.46	17.18	16.89	16.63
p+20%	38.35	38.06	37.77	37.46	37.24	36.87	36.67	36.30	36.04
p+30%	58.55	58.24	57.91	57.68	57.29	57.10	56.71	56.48	56.16

Table 11. Percentage change in ground water contribution (GW_Q).

T ºC / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-51.19	-52.23	-53.18	-54.11	-55.04	-55.91	-56.73	-57.67	-58.42
p-20%	-33.10	-34.53	-35.59	-36.67	-38.74	-38.75	-39.68	-40.76	-41.64
p-10%	-14.97	-17.39	-18.53	-19.67	-20.83	-21.93	-22.98	-24.11	-25.13
p	0.00	-1.28	-2.61	-3.59	-4.82	-5.96	-7.06	-8.30	-9.34
p+10%	15.43	14.13	12.85	11.75	10.36	9.29	8.16	6.89	5.81
p+20%	29.81	28.48	27.20	25.89	24.79	23.42	22.46	21.05	19.97
p+30%	43.74	42.38	41.02	39.91	38.40	37.46	36.03	34.96	33.74

Table 12. Percentage change in percolation (PERC).

T °C / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-42.85	-43.65	-44.64	-45.10	-45.74	-46.34	-47.12	-47.90	-48.51
p-20%	-26.68	-28.66	-29.43	-30.34	-31.80	-31.86	-32.41	-33.35	-33.95
p-10%	-11.33	-14.36	-15.18	-16.01	-16.85	-17.64	-18.45	-19.14	-19.96
p	0.00	-0.94	-2.13	-2.54	-3.44	-4.25	-5.03	-5.95	-6.67
p+10%	12.85	11.89	10.88	10.18	9.06	8.36	7.55	6.62	5.86
p+20%	24.83	23.84	22.87	21.86	21.19	20.05	19.50	18.41	17.64
p+30%	36.44	35.42	34.36	33.62	32.43	31.85	30.70	30.03	29.10

Table 13. Percentage change in water yield (WYLD).

T °C / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-50.14	-50.62	-51.13	-51.51	-51.94	-52.33	-52.77	-53.23	-53.62
p-20%	-33.07	-34.39	-34.89	-35.42	-36.39	-36.40	-36.82	-37.37	-37.79
p-10%	-15.14	-17.57	-18.11	-18.65	-19.21	-19.72	-20.24	-20.74	-21.25
p	0.00	-0.60	-1.27	-1.67	-2.26	-2.80	-3.33	-3.92	-4.41
p+10%	17.36	16.74	16.12	15.62	14.92	14.42	13.87	13.26	12.74
p+20%	34.73	34.10	33.49	32.86	32.35	31.66	31.22	30.52	29.99
p+30%	52.40	51.75	51.10	50.58	49.83	49.40	48.68	48.17	47.57

Table 14. Percentage change in soil water (SW).

T °C / P%	*0*	*0.5*	*1*	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*
p-30%	-4.91	-4.42	-4.56	-4.59	-4.93	-5.25	-5.85	-6.52	-7.15
p-20%	-2.73	-2.32	-2.21	-2.58	-3.36	-3.42	-3.80	-4.55	-5.12
p-10%	-1.09	-0.75	-0.62	-0.90	-1.32	-1.71	-2.29	-2.76	-3.48
p	0.00	0.46	0.34	0.36	-0.04	-0.40	-0.92	-1.53	-2.14
p+10%	1.00	1.45	1.49	1.32	0.76	0.48	-0.05	-0.65	-1.26
p+20%	1.85	2.28	2.37	2.02	1.79	1.21	0.90	0.20	-0.42
p+30%	2.62	3.05	3.09	2.93	2.37	2.17	1.45	1.07	0.35

Table 15. Monthly I_{CCWI} values for Subarnarekha river basin.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
I_{CCWI}	69.35	79.17	49.54	44.47	66.28	54.00	48.97	39.84	36.40	36.85	50.53	80.88

Table 16. I_{CCWI} values for water balance components and streamflow of Subarnarekha river basin.

Water Balance Components	WYLD	PERC	GW_Q	SURQ	ET	SW	Streamflow
I_{CCWI}	34.07	26.65	32.00	36.46	5.60	2.81	41.29