



# Climate change impact assessment on the water resources of the Upper Yamuna River Basin in India

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## Abstract

Climate change has ability to intensify the magnitude of flood and drought episodes, as well as their amplitude; also it has the potential to exacerbate hydrological extremes. It is crucial to forecast changes to hydrological regimes and determine the level of uncertainty around them to increase resilience and prepare for future changes. In order to enlighten long-term estimates, an attempt has been made to sustain the available water resources through Calibration and Validation of river discharge data using SWAT model for Upper Yamuna River Basin. Spatial climatic data were further crystallized to forecast climatic projection scenarios for Base line period, Mid-Century and End Century considering RCPs 2.6, 4.5 and 8.5. Result reveals that the average annual minimum temperature is estimated to be increased 1.4 °C in Mid-Century and 2.2 °C in End Century from the Base line Scenario while the average annual maximum temperature is found to be increased 1.5 °C in Mid-Century and 2.1 °C in End Century from the Base line Scenario. Further, while analyzing the hydrological components, Soil water percentage is expected to be increased in Mid-Century, whereas Percolation rate is found to be increased for all scenarios other than BL-MC (4.5) which is an indication of rise in Ground water. In addition to it, Surface flow is observed as a considerable increase from 4.33 to 72.69% in all scenarios. Also the Surface flow is more in case of End Century as compared to the Mid-Century. The estimated Ground water flow is found to be increased except BL-MC (4.5 & 8.5). Overall water yield has been estimated as a relative change from 7.06 to 18.70% based upon the specified conditions. The prediction for Evapotranspiration values is found as decreased in all scenarios except BL-MC (4.5 & 8.5). The outcome of the present study is very useful for planning of development strategies in the project area.

**Keywords** Climate change · Hydrology · River basin · SWAT · Watershed

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## 1 Introduction

Climate change has direct impact on natural available resources, ecosystem and baseline services of the water supply chain (Aghion et al., 2019). Change in global and regional water presence will be impacted due to the long-term impact of changing climatic conditions and anthropogenic forces (IPCC, 2007). It will also affect the socio-economic growth of the rural as well as urban societies (Radhakrishnan et al., 2018). Additionally, rapid urbanization leads to emission of greenhouse gases and thus affects the environment (Gudmundsson et al., 2012).

The effects of climate change on catchment hydrology are likely to exhibit significant regionalism, given the spatially varied climate change and the frequently distinct physiographic characteristics of different catchments. Numerous studies have been conducted to estimate the hydrological response of the catchment area to a scenario of climate change under various climate zones while taking into account physiographic parameters as topography, geology, geomorphology, land cover/use, etc., which shows that climate change and land use have adverse impact on hydrological cycle (Ma et al., 2009; Wang et al., 2008). In recent years, various studies have shown that climate change is likely to impact on natural water resources considering different factors viz. precipitation pattern, increased surface temperature, runoff variation, changes in soil characteristics due to de-silting and erosion, groundwater recharge, surface runoff and rise in evaporation etc. (Ficklin et al., 2018). It will create a need of fresh water availability and related ecosystem which consequently create a pressure on the sustainability of natural resources (Pham et al., 2019). The water availability mainly depends upon the climatic condition like monsoon in the project area.

In India, there is a variability in the distribution of the precipitation with respect to the location and time (Diwan, 2002). The effect of global change on available water resources is a serious issue (Githui et al., 2009). With a view toward sustainability of natural water resources and sustainable ecosystem, it is important to estimate the climate change future scenarios (Kumar et al., 2016).

Since climate change has impacts on the hydrology of the region and water resources, changes in the hydrological process such as evapotranspiration, surface runoff, etc. can be quantified and understood with a SWAT model (Zhang et al., 2002; Arnold et al., 1998; Neitsch et al., 2002). SWAT is a hydrological model which can be used to analyze the impact of climate change on the sensitivity of crop yield (Xie & Eheart, 2003) and crop market scenarios (Mishra, 2013). Basically SWAT is a semi-distributed hydrological model which is used for the flow simulation, sediment and crop yield estimation in a river basin (Arnold et al., 2012). Garg et al. (2012) used the SWAT model in their study for characterizing irrigation water requirements in the Upper Bhima Catchment in India. Nowadays, terrifying with the limited availability of freshwater, almost all the countries over the world are using the SWAT model for future predictions of water and soil conservations (Patel et al., 2015; Spruill et al., 2000). In another study, the SWAT model is used for predicting the changes in land use because of the Land Change Modeler and attribution of changes in the water equilibrium of the Ganga basin to land-use change (Anand et al., 2018).

Climate Forecast System Reanalysis (CFSR) datasets have been used widely for hydrological simulation through SWAT Modeling (Globalweather.Tamu.Edu—CFSR, n.d.). The least inputs of SWAT Model involve precipitations data and minimum–maximum temperature datasets for the particular location. Multi-objective Calibration is the next recommended step to simulation of data in SWAT which is a remedy for equifinality of the parameters (an accuracy issue occurs during Calibration) (Odusanya, 2019). Moreover, in

order to assess the impact of agricultural production trends on crop yield, erosion (soil and water) and nutrient losses under future climatic circumstances, Global Circulation Model (GCM) forecasts can be used in combination with the SWAT model (Panagopoulos et al., 2014).

Climate indices and estimates depend upon the analysis of experimental readings, monitoring methods and used climate models. All these factors are overlaid using statistical and dynamical downscaling techniques to develop the climate projections at accurate spatial and temporal scales. Further, a comparative analysis of historical data as well as the projected data for few coming years is examined to reach out the conclusions.

The Upper Yamuna River Basin is one of the most critical basins under climate change in Northern India, and from the best of knowledge of the authors, it is understood that several studies with limited scope of work have been conducted in and around the Upper Yamuna River Basin; however, the objective and area of concerns are different for the respective authors/researchers (Khan et al., 2020; Misra & Misra, 2010; Sarkar & Shekhar, 2018). Moreover, the spatio-temporal impact up to the extent of sub-basin level has not been explored yet which can help the policy makers for better management of water resources and their conservation on subbasin scale. The outcomes of this study are expected to come up with value added informative inputs on spatio – temporal heterogeneity to the water resource planners at a fine scale for future water management, conservation and sustainable development of water resources along with the identified critical sub basins of the watershed.

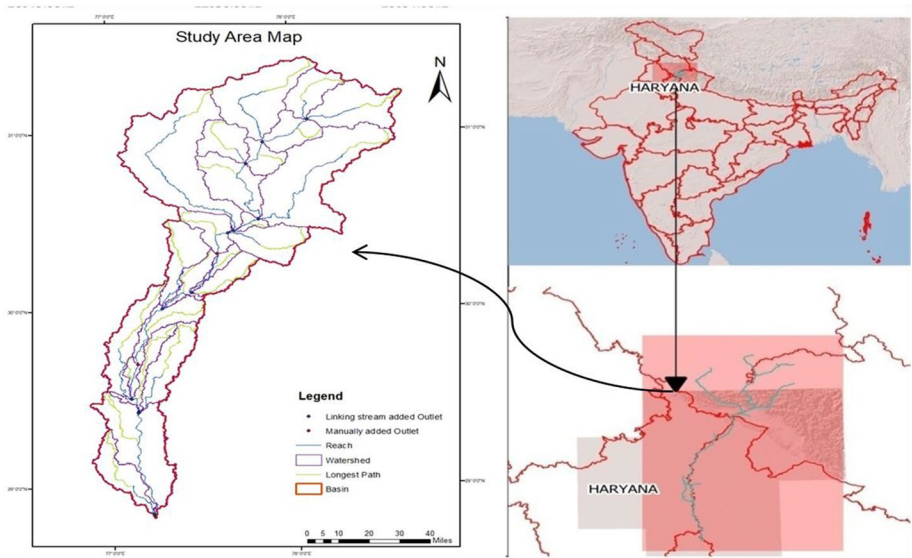
*Objective of the study* The main objective of the present study is to predict the spatio-temporal impact along with climate change scenarios through natural climatic conditions (temperature and precipitation) based upon hydrological components within the project area, i.e., Upper Yamuna River Basin in India. In this connection, this study consists of following objectives:

- (a) To perform Calibration, Validation and sensitivity analysis of the SWAT model for UYRB.
- (b) To predict the Climate change Scenarios for Water Balance components and assessing its spatio temporal impacts on sub basin scale.

## 2 Material and methods

### 2.1 Study area

The Upper Yamuna Basin has been taken as a study area to understand a spatio-temporal climate change using the SWAT model. The area under study is located between the latitudes  $28^{\circ}48'00''$  N to  $31^{\circ}12'00''$  N and longitudes  $76^{\circ}48'00''$  E to  $78^{\circ}24'00''$  E. The total basin (watershed) area was 17,591.65 Sq.km. consisting of 25 sub-basins as shown in Fig. 1. The river Yamuna originates from the Yamunotri glacier in the Mussorie range of lower Himalayas above 6300 m and then flows through the Indo-Gangetic Plains. The Upper Yamuna River flows through multiple valleys carved by snow masses during the previous snow-age. Most of the Upper Yamuna River is contained in the Himalayan and Upper segments of the basin which is upto Delhi (Basin Details: | Yamuna Basin Organisation, 2021).



**Fig. 1** Study area map of Upper Yamuna Basin and major streams

## 2.2 Data used

The geo-spatial information used for the analysis includes Digital Elevation Model (DEM), Soil data, Land use land cover (LULC), stream network, etc. The delineation of catchment area and sub-basin area was done using DEM through SWAT Model. Thereafter HRUs were created by overlaying LULC map (Pasture 3%, Range grass 11%, Agriculture land 36%, Urban area 2.98%, Water bodies & snow 0.02%, Forest 47%); Soil information (Loam, Clay loam, Sandy loam, Clay and Sandy loam clay); and Topographic elevation (1–3%, 3–10%, 10–15% and > 15%) of the study area. Climatic variables such as precipitation and temperature (minimum and maximum) were further used to predict the future climate change scenarios (Table 1).

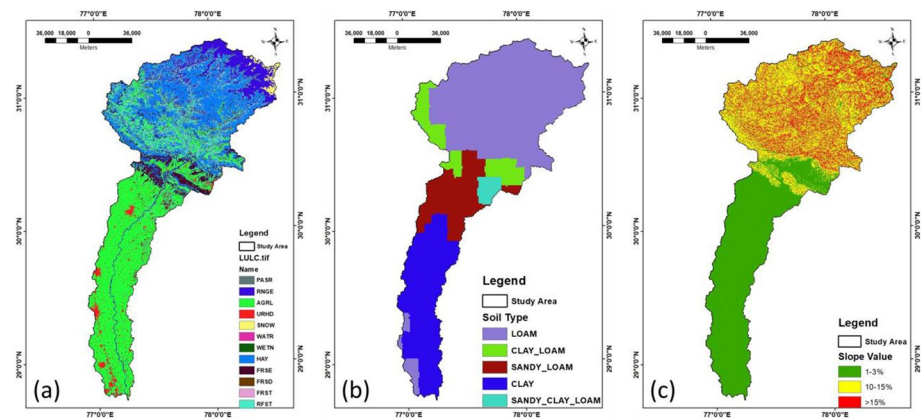
The LULC map, Soil classification map and the Slope classification maps are shown in Fig. 2.

## 2.3 SWAT model

The SWAT model (Arnold et al., 1998) is a river basin-scale model created to evaluate the effects of land management techniques in substantial, intricate watersheds. This semi-conveyed catchment (stream bowl) model is created to measure effects of land on surface waters by mimicking evapotranspiration, plant development, penetration, permeation, spill over and supplement burdens, and disintegration (Neitsch et al., 2011). Catchment measures in SWAT are demonstrated in two stages—the land stage covering the loadings of water, dregs, supplements and pesticides from all sub-bowls to a principle channel; and the water steering stage covering measures in the primary channel to the catchment outlet (Neitsch et al., 2011). The model is used to analyze the spatial-temporal heterogeneity

**Table 1** Spatial data input into the SWAT model for the Upper Yamuna Basin

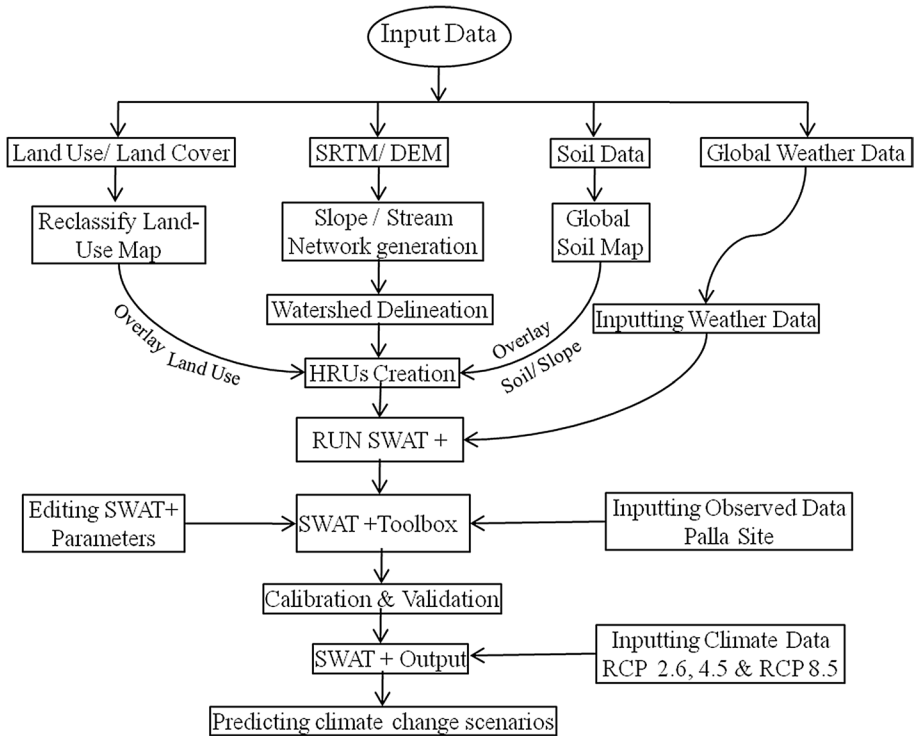
S. N	Data used	Specification	Source of data
1	DEM	30 m × 30 m	<a href="https://earthexplorer.usgs.gov/">https://earthexplorer.usgs.gov/</a>
2	Land use/Land cover	Landsat 8–15 m panchromatic and 30 m multi-spectral spatial reso	<a href="https://earthexplorer.usgs.gov/">https://earthexplorer.usgs.gov/</a>
3	Soil Map	30 m × 30 m	<a href="https://swat.tamu.edu/data/india-datas-et/">https://swat.tamu.edu/data/india-datas-et/</a>
4	Slope	30 m × 30 m	<a href="https://swat.tamu.edu/data/india-datas-et/">https://swat.tamu.edu/data/india-datas-et/</a>
5	Precipitation	Annual	<a href="https://globalweather.tamu.edu/">https://globalweather.tamu.edu/</a>
6	Temperature	Minimum & Maximum	<a href="https://globalweather.tamu.edu/">https://globalweather.tamu.edu/</a>
7	Stream flow data for calibration & validation	2001 to 2020 for Palla, Delhi, gauge station	Central Water Commission (CWC)

**Fig. 2** a LULC map, b soil classification map, c slope classification map

considering different scenarios of the watershed (Mishra, 2013). In SWAT, a "catchment" is additionally separated into sub-basins and Hydrologic Response Units (HRUs), of which the last are interesting mixes of land use, soil and slope. The SWAT model principally requires five sorts of information, namely a Digital Elevation Model (DEM), land use/land cover data, soil data, environmental data and other yield data. The SWAT model development and runoff simulation process is shown in Fig. 3.

## 2.4 Calibration, validation, sensitivity and uncertainty analysis

Calibration and Validation processes were performed using the available discharge data which were divided into two predefined sets. Calibration process is very challenging as it involves various uncertainties. The source of uncertainty may be a part of model process, input dataset or operational portion (Uniyal et al., 2015). Also sensitivity is a reflection of any minor change in any one parameter keeping other values as constant. All four tasks, namely Calibration, Validation, sensitivity and uncertainty, were performed using the algorithm in Sequential Uncertainty Fitting (SUFI-2) which is an in-build component under



**Fig. 3** Methodology of the model development: calibration and validation

the SWAT Cup model (Abbaspour et al., 2007). Further,  $P$  and  $R$ -factor values were used to explain the model performance, wherein  $P$  factor may be described as percentage of the available data and  $R$  factor is average thickness of 95 PPU divided by standard deviation of available dataset (Abbaspour et al., 2007; Kumar et al., 2017a). The definition of satisfactory output is  $P$  factor close to 1 while  $R$  value  $< 1$  or close to zero (Kumar et al., 2017a).

The Calibration of Upper Yamuna River Basin model through SWAT is a challenging task because of few uncertainties such as input variability, model uncertainty and common parameter (Abbaspour, 2010; Schuol & Abbaspour, 2006). In case of model Calibration, the SUFI-2 process using SWAT-CUP has been used, which was developed by Abbaspour (Schuol & Abbaspour, 2006). Further, in case of SUFI-2, the uncertainty of each parameter takes into consideration all the uncertainties. These uncertainties can be expressed as a percentage of observed data lying inside the 95% prediction uncertainty (95PPU) band, which is measured by the  $p$ -factor. Additionally, the  $r$ -factor is crucial in describing the 95PPU range. The  $p$ -factor number should be as high as feasible, and the  $r$ -factor value should be as low as possible, in order to achieve better outcomes (Schuol & Abbaspour, 2006).

The  $R^2$  is a metric for the goodness of fit of a linear regression model that shows how much of the variance in the dependent variable each independent variable individually and collectively accounts for. On a practical scale (0–100%), it quantifies the strength of the association between our model and the dependent variable. It is a statistical measurement to know that how close the data's are to the fitted regression line. Further,  $R^2$  ranges from the 0 to 1 with higher values indicating the less error variance. The  $R^2$  value should be

more than 0.5 (Van Liew et al., 2003). The output values of other factors such as NSE, PBIAS, KGE and  $bR^2$  (Knoben et al., 2019) showed that for a good simulation NSE value should be greater than 0.75, whereas it is more than 0.36 for satisfactory.

Further, Calibration and Validation procedure required the bifurcation of the whole time in to Calibration and Validation epochs (Bouslihim et al., 2016). In the Calibration phase, the stream flow (output) was adjusted using SWAT-CUP so that the observed inflow data matched the stream flow. Additionally, the Validation period enables us to determine whether the model setup has been appropriately designed utilizing certain time frames (other than Calibration period). Here the epochs have been decided, considering the availability of inputs for following major input parameters such as Stream flow, Rainfall data, Max and Min Temperature. The SWAT model has been calibrated using the time period from 2002 to 2013. By comparing observed and simulated values, the Calibration technique steps involved optimizing the model performances. These parameters are still used for Calibration following the sensitivity analysis. For Calibration, statistical criteria of goodness (fit curve) have been calculated; thereafter, the prepared model is tested to check its performances through Validation procedure for 7 years (2014–2020).

## 2.5 Climate change projections

Climate change is considered to be the biggest threat of the twenty-first century and sustainable development in the entire world (IPCC, 2014; Lema & Majule, 2009). Despite numerous climate change adaptation strategies, these efforts have been deemed insufficient for long-term climate change (IPCC, 2014). Future precipitation is anticipated to be more variable, according to IPCC (2014). Literature review showed that the SDSM daily precipitation data at weather station are almost problematic predicted along with the variable used for the downscaling. Reason behind it is because values at individual sites are comparatively poorly resolved by the regional-scale predictors (Wilby & Dawson, 2004; Wilby, 2007; Gachon et al., n.d.; Hassan et al., 2011). This problem occurs due to low predictability of the daily precipitation data at local scale by the regional forcing factors. Moreover, the other factors highlighting the complexity of modeling precipitation are related to some characteristics such as intermittency, rain extreme events, rain intensity variability and the multiple scaling regimes.

In the present study, data interpolation method was used for monthly climatic dataset gathered from weather stations. Monthly precipitation and temperature (minimum and maximum values) variables were used for the study. A set of future data were obtained for each CFSR grid (Fuka et al., 2014), (Dile & Srinivasan, 2014). Delta change approach (Hipt et al., 2019) was used to derive monthly bias coefficient value which was obtained from the CCAFS projected month-wise data. The following formula applies:

$$(\beta_{\text{CCAF}})_j = \frac{(V_{\text{CCAF}})_j}{(V_{\text{BASE}})_j}$$

$\beta_{\text{CCAF}}$  = Bias coefficient of CCAF weather datasets

$V$  denotes climatic variables such as precipitation and temperature;  $j$  = Monthly values as 1, 2, 3...up to 12.

$V_{\text{CCAF}}$  = Monthly data set variable of CCAF weather datasets.

$V_{\text{BASE}}$  = Base period.



The crop yield is indirectly affected by the temperature. Warmer regions yield less as compared to the colder areas due to climate change in warm regions; the negative effect of precipitation is on higher side. Higher mean temperature will lead to the increase in evapotranspiration (ET) as well as accumulated Growth degree day's. Further, faster crop yield growth will be there along with early ripening stage. It will also decrease soil moisture by rising water demand in the atmosphere with increased stress and lower yield (Hipt et al., 2019). Evapotranspiration and yield of crop are inversely correlated with crop ET; however, ET depends upon precipitation and temperature; therefore, climatic factors will affect the crop yield. The SWAT model uses the same idea to determine the change in crop yield dependent on meteorological parameters.

## 2.6 Downscaling the climate model (GCM)

The Global Climate Model (GCM) is an accurate tool for forecasting information on ranges of about 1000 by 1000 km that encompass a diverse range of landscapes and have different potential for extreme events including floods, droughts and other occurrences. Regional climate models (RCM) and empirical statistical downscaling (ESD), both powered by global climate models (GCMs), are used across a specific area and provide information at lower scales with supporting details for planning and assessing adaptation. Further, GCM provides projections of climate change scenarios for the future which helps in decision making on the climate change mitigation strategies. Further, Regional Climate Downscaling (RCD) provides projections with more accurate representation of the localized extreme events. The downscaling process is explained through Fig. 4.

The IPCC has chosen a trajectory for greenhouse gas concentrations (not emissions), known as the Representative Concentration Pathway (RCP). Various climate scenarios are

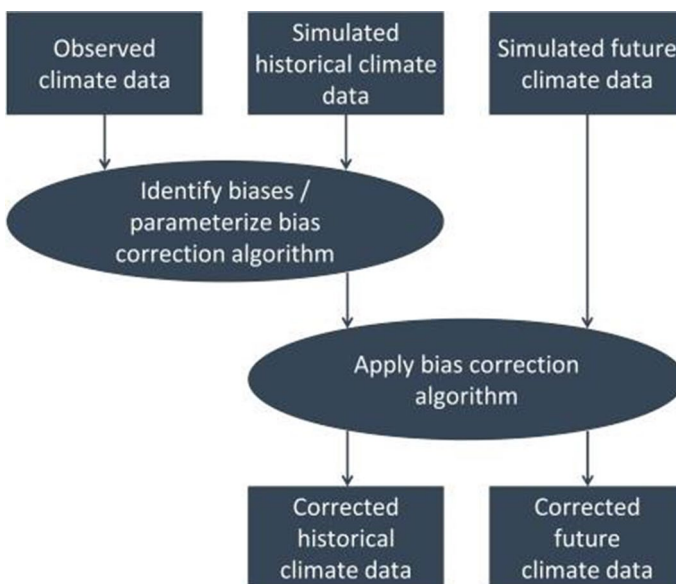


Fig. 4 Climate change projections flow chart



depicted in the pathways, all of which are thought to be feasible given the level of greenhouse gas (GHG) emissions in the years to come. Here, in this research RCP 2.6, RCP 4.5 & RCP 8.5 have been used to quantify the future climate change.

A program called CMhyd (Climate Model data for hydrological modeling) is available for extracting and bias-correcting data from regional and global climate models. In order to make hydrological simulations powered by corrected simulated climate data reasonably match simulations utilizing observed climate data, bias correction processes are utilized to reduce the difference between observed and simulated climate variables on a daily time step. According to (Teutschbein & Seibert, 2012), the use of simulated climate data as direct input data for hydrological models is hampered by simulations of temperature and precipitation frequently exhibiting significant biases caused by systematic model errors or discretization and spatial averaging within grid cells.

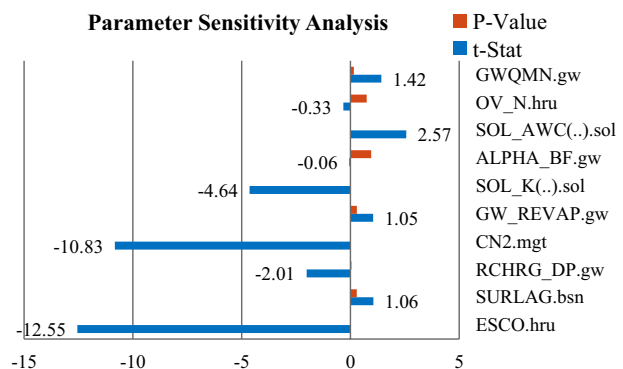
The underlying physics can be translated to finer spatial and temporal scales by downscaling GCM results. GCM projections are useful for both short-term seasonal forecasts and long-term climate projects when downscaled spatially using either statistical or dynamical methods (Robertson et al., 2020; Vitart & Stockdale, 2001). In order to analyze the future climate and assess its effects, downscaled GCM forecasts are frequently utilized in estimating droughts, floods, etc.

### 3 Results

#### 3.1 Sensitivity and uncertainty analysis

Based upon the analysis, it is found that some of the sensitive parameters (Jha et al., 2006; Narsimlu Boini et al., 2013; van Griensven et al., 2006) affect the simulation more commonly such as base flow recession factor, percolation coefficient values, aquifer storage range which allow return flow, water capacity, Soil moisture, Soil evaporation constant, Groundwater revamp factor, etc. In this connection, the considered factors under the study are termed as CN2, ALPHA BF, GW REVAMP, ESCO, GWQMN, SOL\_K, SOL\_AWC, OV\_N and RCHRG\_DP in the model. Results indicate that among all factors taken into consideration for the analysis, ESCO, CN2, SOL K, SOL AWC and RCHRG DP are the most sensitive parameters (Fig. 5).

**Fig. 5** Parameters sensitivity analysis



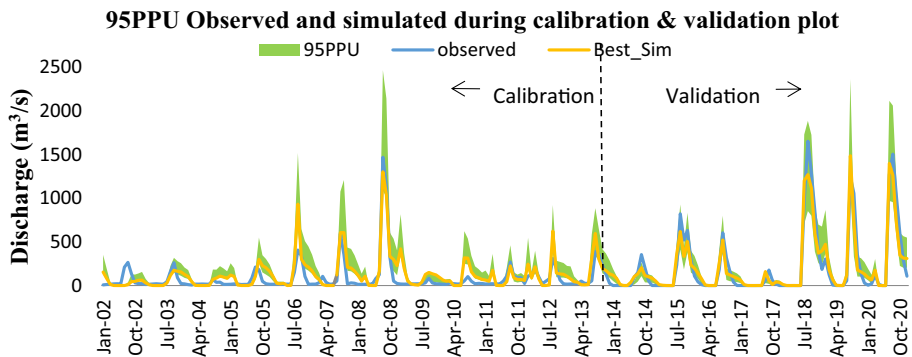


Fig. 6 95 Percentage prediction uncertainty band

Table 2 Model input parameters for the SWAT model for calibration and validation

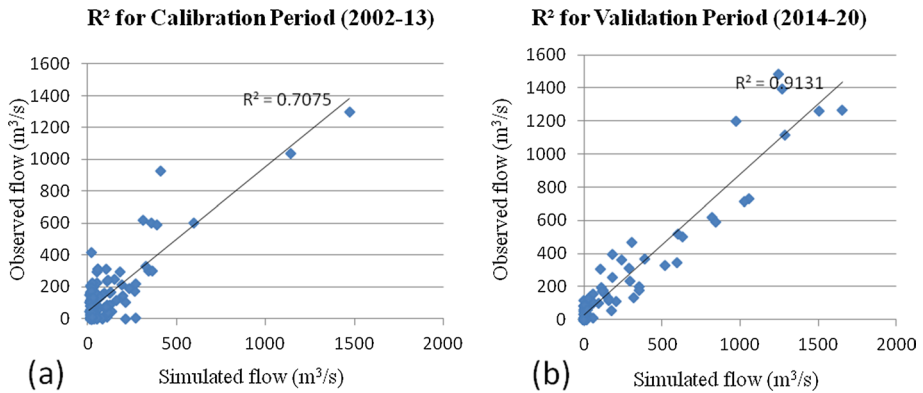
Sl. no	Parameter name	Description	Fitted value	Min value	Max value
1	V_ESCO.hru	Soil evaporation compensation factor	0.25	0.00	1.00
2	V_RCHRG_DP.gw	Deep aquifer percolation fraction	3.96	2.00	10.00
3	R_CN2.mgt	SCS Curve number for soil moisture	-1.99	-2.00	0.20
4	V_GW_REVAP.gw	Groundwater evaporation coefficient	0.17	0.02	0.20
5	R_SOL_K.sol	Saturated hydraulic conductivity	10.26	10.00	40.00
6	V_ALPHA_BF.gw	Alpha base flow factor	0.30	0.00	1.00
7	R_SOL_AWC.sol	Available water capacity of the soil layer	0.48	-0.50	0.50
8	V_OV_N.hru	Manning's 'n' value for the channel	0.08	0.01	1.00
9	V_GWQMN.gw	Threshold water depth in shallow aquifer for return flow to occur	3193	0.00	5000
10	V_SURLAG.bsn	Surface runoff lags time, days	7.41	1.00	24.00

Based upon the specified interrelationship as per hydrological model, it is considered that among all parameters, uncertainty is an important component. In this study, data from simulations and observations are limited to 95PPU; also it is found medium discharge flow for medium uncertainty estimation and details are shown in Fig. 6 as the best fit values.

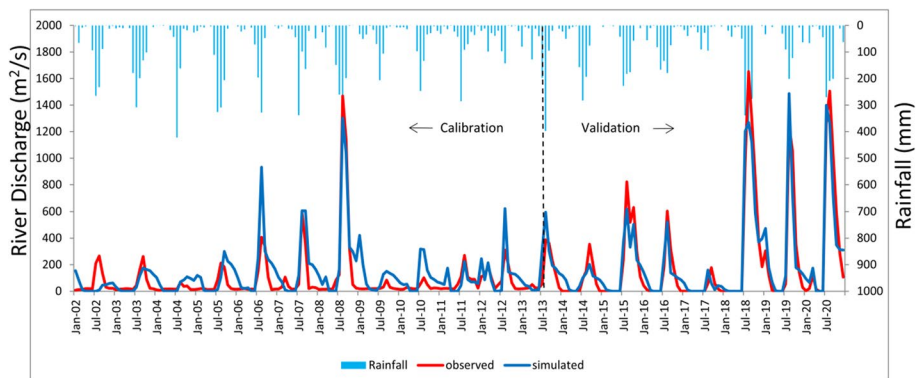
In this connection, 95PPU band was calculated for the study using SUFI-2 model of SWAT-CUP wherein it is observed that the outcomes of the Calibration and Validation of observed and simulated flow for 95% prediction uncertainty (95PPU band) are within the permissible limit as shown in Fig. 6.

### 3.2 Model calibration and validation

The monthly discharge data from 2001 to 2020 for Palla, Delhi, gauge station were used for Calibration and Validation purpose. During the Calibration, 2000 simulations were run using the final optimized values of the 10-parameters as shown in Table 2 and the same no. of simulations was catered for the Validation period. The result shows all positive values



**Fig. 7** Scatter plot of the observed versus simulated flow **a** calibration, **b** validation



**Fig. 8** Observed and simulated discharge, rainfall during calibration and validation

except CN2 (fitted values, minimum and maximum values) and minimum values under Available water capacity of the soil layer.

The fitted value of all the parameters shows good performance within the permissible limits as notified by the SWAT document. The results during Validation phase showed a remarkable enhancement as compared with the Calibration phase results.

Further, the observed and simulated flow of Yamuna River Basin was compared at Pala Delhi site and the value of  $R^2$  has come out as 0.71 for Calibration period (2002–2013) and 0.91 for Validation period (2014–2020) which showed a good performance of the SWAT model regarding water balance of the project area during Calibration and Validation as presented in Fig. 7. Moreover, the flow was under-estimated during the years 2002–2004 and 2015–2020 and was over-estimated during the years 2005–2014.

Figure 8 represents the observed and simulated discharge plotted against river discharge data and rainfall. It shows the highest peak in July–September 2008 (simulated) followed by peak obtained in July–September 2008 (observed data) during Calibration. In case of Validation period, the peak was highest during July–September 2018 followed by July–October 2020 under (observed data). Further, the underestimation of few peaks could be identified due to non-uniform metrological data values and model limitation to analyze

**Table 3** Model statistics for accuracy assessment of the SWAT model for calibration and validation period

Site	Period	Year	<i>p</i> -factor	<i>r</i> -factor	$R^2$	NSE	PBIAS	KG E	$bR^2$
Palla Delhi	Calibration	2002–2013	0.16	0.3	0.71	0.6	−4.3	0.49	0.64
	Validation	2014–2020	0.23	0.33	0.91	0.91	2.2	0.88	0.78

the complex climatic scenarios. Additionally, there could be a chance of error in the geomorphologic data entered in the model for the project area (Table 3).

### 3.2.1 Model statistics for accuracy assessment

The *r*-factor is 0.3 for Calibration (2002–2013) and 0.33 for Validation (2014–2020), whereas *p*-factor was obtained 0.16 and 0.23 for Calibration and Validation, respectively. As per (Moriassi et al., 2015), if  $NSE > 0.75$  and PBIAS is  $< \pm 10\%$ , the stream flow simulation is considered as very good on monthly basis; however, PBIAS ( $> 25\%$ ), unsatisfactory performance can be observed due to some bias input which creates wrong peak flow simulation events based upon the rainfall data.

### 3.3 Projected change in climate for different periods (baseline, mid-century and end century)

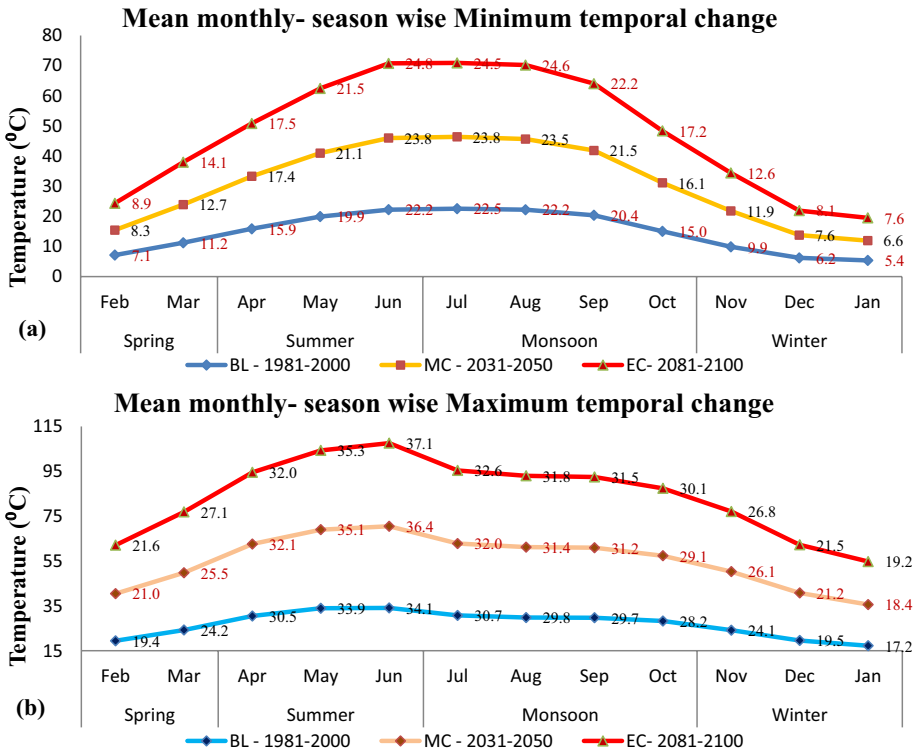
This section focuses over the prediction of climate change scenarios for Mid-Century (2031–2050) and End Century (2081–2100) along with corresponding Baseline period (1980–2000) considering parameters such as Temperature, Precipitation and Watershed Hydrology. The other factors considered for analyzing the Watershed Hydrology are Ground water, Evapotranspiration, Soil Water, Percolation and Surface water under RCP 2.6, 4.5 & 8.5.

#### 3.3.1 Future climate change—temperature change

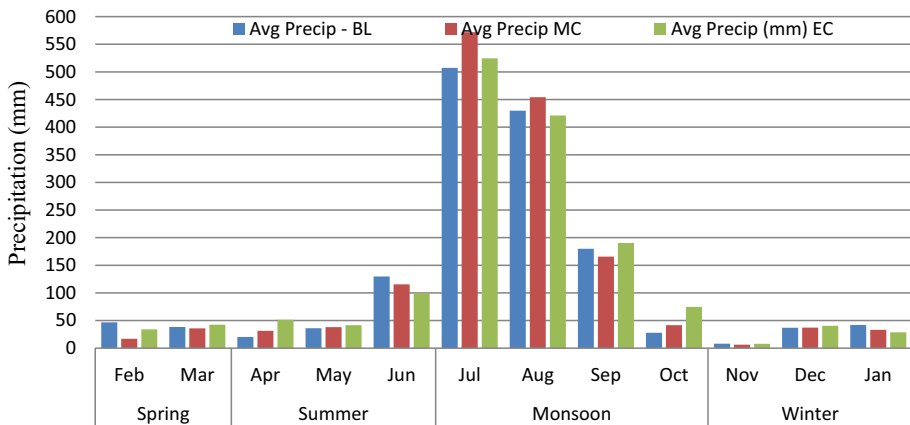
The scenarios have been estimated considering mean monthly temperature (minimum and maximum) for two future centuries, namely Mid-Century (2031–2050) and End Century (2081–2100), along with one Base line period (1981–2000). As mentioned in Fig. 9, the Baseline minimum temperature varied from 5.4 to 22.4 °C; however, in Mid-Century it is between 6.6 and 23.8 °C and in End Century it is found to be ranging from 7.6 to 24.8 °C. Similarly, the maximum temperature during Base line period is found to be ranging from 17.2 to 34.1 °C and in the Mid-Century it is 18.4–36.4 °C, whereas in the End Century it became 19.2–37.1 °C. It can be seen from Fig. 9a, b that the trend in rise in temperature is almost uniform for all month with respect to the considered period.

#### 3.3.2 Future climate change—precipitation change

The average monthly precipitation is shown in Fig. 10, wherein the maximum rise has been observed in the month of July followed by August and September for Mid-Century among all three considered periods. The average precipitation in the month of November has been observed as the lowest values which could be probably due to change in climatic



**Fig. 9** Comparison of the mean monthly **a** minimum and **b** maximum temperatures of the RCPs 2.6, 4.5 & 8.5 with the Base line



**Fig. 10** Monthly average precipitation of RCPs 2.6, 4.5 & 8.5 with respect to Base line scenario

conditions. In order to prevent water from percolating through the soil to the aquifer and increasing surface runoff, the expected increase in urbanization will lead to more impermeable surfaces. It will result in to reduced Ground water recharge affecting the water table

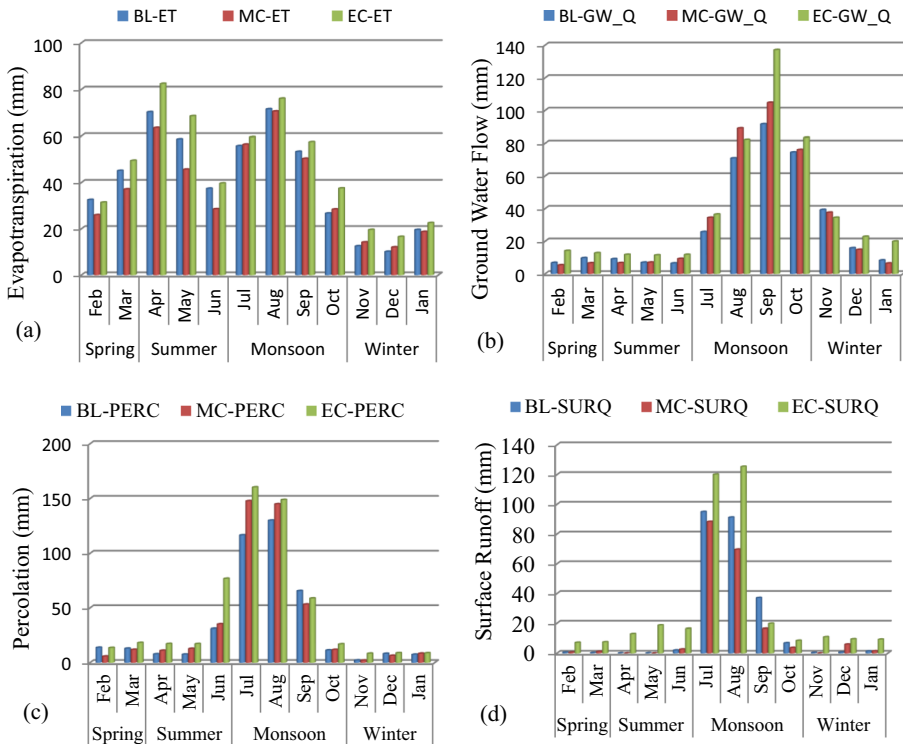
level. A similar trend in surface runoff has been observed in different Indian researches using SWAT Model (Kumar et al., 2017b; Uniyal et al., 2015). In the month of June, precipitation is decreased in both the Mid- and End Centuries which might be the result of climate change in delaying the onset monsoon.

### 3.3.3 Future impact on watershed hydrology

Many researchers have used the SWAT model (Gosain et al., 2011; Mishra & Lilhare, 2016; Abeysingha et al., 2017) to determine the impact of climate change on the hydrology aspect and the availability of water resources in the Indian River basins using different projected climate change scenarios from GCMs.

Maximum values of Groundwater flow are obtained in End Century RCP 8.5 followed by EC RCP 2.6 and EC RCP 4.5. Further, Evapotranspiration is observed highest in Mid-Century 4.5 followed by MC RCP 8.5 and Base line historical data. On the same lines, the Soil water is projected as higher in Mid-Century 8.5 followed by MC RCP 4.5 and MC RCP 2.6. Percolation factor shows high projection under End Century RCP 2.6 followed by EC RCP 8.5, whereas the lowest case is in Mid-Century RCP 8.5. Similarly, Surface flow is higher in EC RCP 8.5 and lowest for Base line historical data (Figs. 11 and 12).

As shown in Table 4, the precipitation is found to be increased in the mid-century by 0.72% while in case of End Century, decreased value has been estimated with respect to



**Fig. 11** Average monthly—season-wise **a** ET, **b** GW\_Q, **c** PERC, **d** SURQ for base line, mid-century and end century

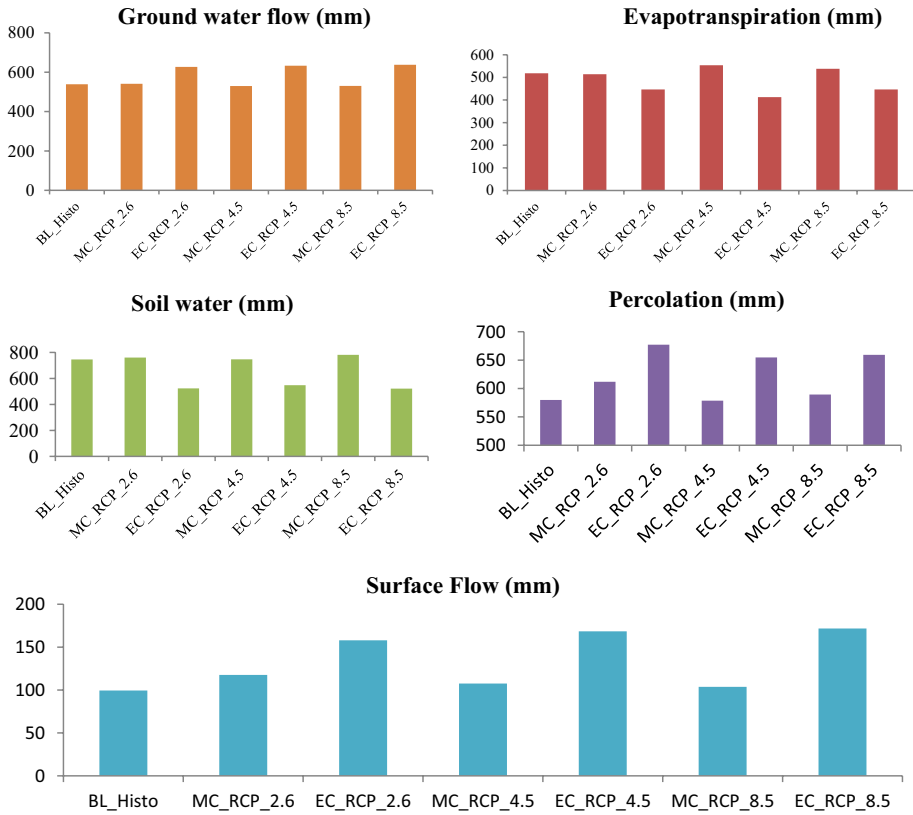


Fig. 12 Water budget components (GW, ET, SW, percolation and surface flow)

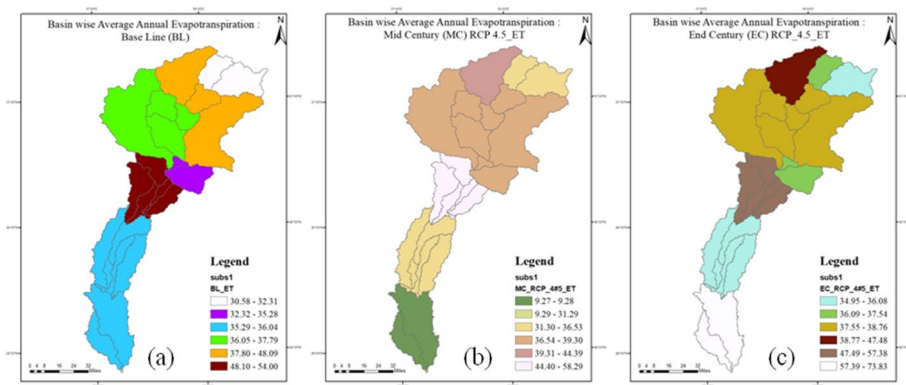
Table 4 Relative percentage change in the hydrological components

Period	PRECIP (%)	ET (%)	SW (%)	PERC (%)	SURQ (%)	GW_Q (%)	WYLD (%)
BL-MC (2.6)	0.72	-0.86	2.02	5.53	18.26	0.45	7.06
BL-EC (2.6)	-22.14	-13.80	-29.83	16.80	58.85	16.39	18.34
BL-MC (4.5)	2.51	6.86	0.13	-0.21	8.23	-1.68	8.61
BL-EC (4.5)	-20.57	-20.33	-26.50	12.93	69.35	17.55	16.76
BL-MC (8.5)	0.91	3.77	4.73	1.66	4.33	-1.53	14.68
BL-EC (8.5)	-22.95	-13.79	-30.03	13.71	72.69	18.43	18.70

the Base line period in all considered RCPs. Further, while predicting the Evapotranspiration values (Fig. 13), the ET is decreasing in all scenarios except BL-MC (4.5 & 8.5).

Results of Mid-Century and End Century were compared to Baseline values which showed an increase in annual average precipitation of 0.72% (RCP 2.6), 2.51% (RCP 4.5) and 0.91% (RCP 8.5) for Mid-Century; however, in End Century the same is expected to be decreased by of 22.14% (RCP 2.6), 20.57% (RCP 4.5) and 22.95% (RCP 8.5). The decreased value is an indication for drought situation due to climate change.

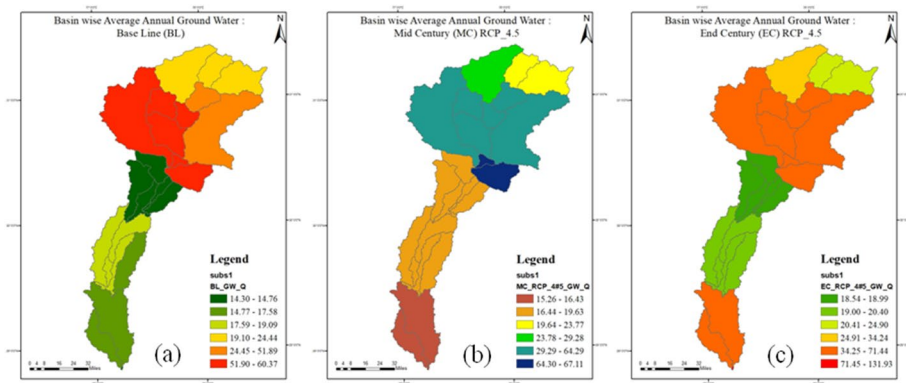




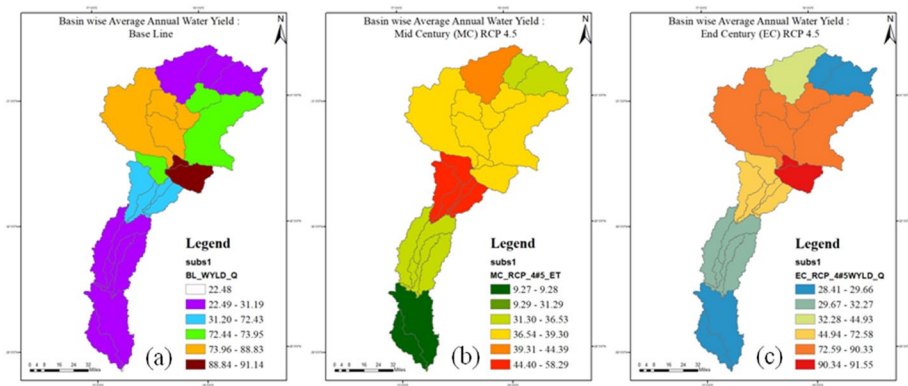
**Fig. 13** Basin-wise average annual evapotranspiration in mm for **a** base line, **b** mid-century (MC) & **c** end century (EC)

Soil water percentage has been increased in MC (2.6, 4.5 & 8.5), whereas Percolation rate is increasing in scenarios other than BL-MC (4.5) which is an indication of rise in Ground water. The corresponding rise in Surface flow is observed from 4.33 to 72.69% in all scenarios. The rise is more in case of End Century as compared to the Mid-Century. Also Ground water flow (Fig. 14) estimation is in positive except BL-MC (4.5 & 8.5).

Basin-wise spatial analysis showed a variation in average annual Ground water (Base line) from 14.30 to 60.37 mm while in case of Mid-Century considering Scenarios 2.6, 4.5 and 8.5, the values range from 16.17 to 65.95 mm, 15.26 to 67.11 mm and 14.35 to 68.26 mm, respectively. The variation is considerable due to the topography, Land use land cover and other geographical parameters. Further, the water yield parameter reflects a wide range of data observed basin-wise. The minimum 22.48 mm and maximum value is 91.14 mm for Base line considered scenario; however, in case of Mid-line century, the data vary from 14.35 to 68.26 mm for all three RCPs. Furthermore, the values calculated for End Century have a variation from minimum 27.53–91.55 mm. Overall water yield (Fig. 15) has been estimated as a relative change from 7.06 to 18.70%



**Fig. 14** Basin-wise average annual ground water flow in mm for **a** base line, **b** mid-century (MC) & **c** end century (EC)



**Fig. 15** Basin-wise average annual water yield in mm mm for **a** base line, **b** mid-century (MC), **c** end century (EC)

due to hydrological water balance. The results of the research implied that changes in the climatic parameters, i.e., Precipitation and Temperature, affect the ET, Water Yield and Ground water significantly.

As a result, the projected climate change will significantly alter the Upper Yamuna River Basin's water balance, which would therefore have an impact on future water available resources and river discharge patterns.

## 4 Discussion

In the present study, climate change scenarios have been predicted through spatio-temporal analysis, wherein SWAT model and SUFI-2 algorithm in SWAT-CUP have been used. Further water balance components have been predicted for the twenty-first century considering different parameters such as Temperature, Precipitation and Watershed Hydrology. Result showed that, the trend of rise in monthly temperature is almost uniform for all months with respect to the Base line, Mid-Century and End Century. Any unusual change or rise in temperature could result stress conditions which may lead to crop yield reduction. As mentioned by Anandhi et al., (2009), rise in surface temperature may increase the rate of evaporation leading to rise in precipitation. The results of a prior study in India provide evidence for the predicted loss in agricultural yields in the watershed as a result of the impacts of global warming and the rise in temperature (Gosain et al., 2011). The effects of temperature increase will be significant. Globally, a rise in temperature of 1 degree Celsius in developing nations will slow the expansion of agricultural output by 2.66% (Dell et al., 2012).

The main threats of the climate changing scenarios stemming from rising temperature include rising sea level, collapsed ecosystem, frequent severe weather. The prediction could be helpful in managing such aspect including exploring the potential regarding adaptation of the climate to reduce the risks and also to quantify the development costs associated with the adaptive actions.

Moreover, the predicted growth in urbanization will result in more impermeable surfaces, such as roads and buildings, which will prevent water from percolating through the soil to the aquifer, increasing surface runoff. In addition, the higher runoff will result in less

groundwater recharge, which will decrease the water table and exacerbate drought conditions. Farmers and other marginal growers who depend on water for their livelihood would be impacted by this. A similar trend in surface runoff has also been observed in India, according to various other studies using the SWAT model (Kumar et al., 2017b; Uniyal et al., 2015).

In case of water yield parameter, the projection shows a rise for the Mid-Century and End Century, which will be beneficial to other water users and agricultural operations. It would be practical and efficient to store water in the additional reservoir built to make up for the reduced flow and water supply. This will benefit agriculture and raise the catchment's hydropower generation potential. These findings support (Luhunga et al., 2018) finding that an increase in water yield is influenced by precipitation levels.

Also, when the amount of precipitation rises, the intense downpour of rain will saturate the soil, increasing surface runoff. As a result, water will start pouring into the river channel, raising the discharge level. Several researchers have noted a similar pattern of flow and surface runoff for the Indian River Basin (Pandey et al., 2017; Raneesh & Santosh, 2011).

Since the depleting groundwater is one of the major issues for the increasing population, development of a strategic planning to conserve the surface runoff, minimize the use of Ground water and recharge the Ground water could be initiated on the basis of the estimated water balance components. It will be useful to reducing the wet spell, controlling water pollution, adaptation to climate change, early warning to the communities, manage agriculture farms in a better way. As the climate change scenarios have direct impact on agriculture production, such outcomes could be used to plan a cropping system accordingly. Additionally, it will be helpful to lower the energy cost, controlling flood and drought conditions, richer biodiversity, better opportunities for climate resilience, conservation of natural water resources, etc. However, the study has the following limitations which impact the interpretations of the findings:

- (a) The results of the climate model may also be impacted by its coarser resolution. Although "downscaling" is a way to reduce the gap between temporal and geographical resolution, the procedures used are still a source of uncertainty.
- (b) The SWAT model makes use of a number of empirical and quasi-physical variables that were created based on the climate in the USA and may not be suitable for all watersheds. It has become a generally recognized model, nonetheless, as a result of numerous modifications added throughout time.
- (c) The scenarios have been considered by using hydrological parameters based upon the specified land use land cover and other properties. Also, future development projects are not considered under the study which may change the water balance of the study area. Therefore, the study outcomes may please be viewed keeping the above-mentioned facts in consideration.

## 5 Conclusions

The present study assessed the change in climate by considering different scenarios for Yamuna River Basin using SWAT model. During the Calibration and Validation, 2000 simulations were run using the final optimized values of the specified parameters. The findings of the observed and simulated Calibration and Validation periods, as well as the 95% prediction uncertainty, fall within the 95PPU band. The fitted value of all the parameters

shows good performance within the permissible limits as notified by the SWAT document. The results during Validation phase show remarkable enhancement as compared with the Calibration phase results. The scenarios have been estimated considering mean monthly temperature (minimum and maximum) for two future centuries namely Mid-Century (2031–2050) and End Century (2081–2100) along with one Base line period (1981–2000). The average annual minimum temperature is found to be increased 1.4 °C in Mid-Century and 2.2 °C in End Century from the Base line Scenario while the average annual maximum temperature is found to be increased 1.5 °C in Mid-Century and 2.1 °C in End Century from the Base line Scenario. Various components for hydrologic budget are simulated such as Ground water, Evapotranspiration, Soil Water, Percolation and Surface flow for Base line period along with Mid-Century and End Century considering different scenarios, i.e., 2.6, 4.5 and 8.5. The result shows a considerable rise in Surface flow from 4.33 to 72.69% in Mid-Century and End Century which may lead to flush floods. Overall water yield has been estimated as a relative change from 7.06 to 18.70% due to hydrological water balance based upon the specified conditions. The hydrologic budget of the study area may alter substantially because of projected climate change. Introduction of appropriate operations is very important to address the problems that may rise due to climate change. Further, the output of the present study is useful to introduce the climate change adaption strategies, Soil and Water Conservation Measures, Agriculture conservation, Crop rotation, etc.

**Data availability** The authors declare that [the/all other] data supporting the findings of this study are available within the article.

## Declarations

**Conflict of interest** The authors have no conflict of interest in relation to this work.

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