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Does comprehensive evaluation of hydrological models influence projected changes of mean and high flows in the Godavari River basin?

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Abstract
Understanding the projected changes in the mean and high flows remains a significant challenge due to uncertainty arising from global climate models (GCMs) and hydrological models. Moreover, the calibration approaches used for hydrological models can influence the climate change impact assessment. We use the combination of three hydrological models, four global climate models, and two RCPs (2.6 and 8.5) to analyze the projected changes in mean flow, high flow, and the frequency of high flow under the projected future climate in the Godavari River basin (GRB) until the gauge Tekra. The two evaluation approaches: a simple approach (TASK A) based on the calibration and validation at a single streamflow gauge station and a comprehensive approach (TASK B) based on multi-variable and multisite calibration and validation and trend analysis were employed to evaluate the hydrological models. The differences between the projected changes in mean and high flows calculated using models after TASK A and TASK B were estimated. Our results show that the differences can be up to 10–13% in mean annual flow and high flow, and up to 40% in high flow frequency. The comprehensively evaluated hydrological models were chosen for impact assessment, and they project increases in mean and high flows, and the frequency of high flow at all four gauge stations in the GRB. The projected increases are higher under RCP 8.5 and in the End century (2071–2100). Our results demonstrate the importance of the comprehensive evaluation of hydrological models in advance of climate change impact assessment.

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1 Introduction

Climate change poses an enormous risk to water availability and water management (Barnett et al. 2005; Immerzeel et al. 2010). Freshwater availability under climate change can affect the water requirements for irrigation and area under irrigation (Elliott et al. 2014). For instance, Elliott et al. (2014) reported that limited freshwater under climate change could force about 20–60 Mha of irrigated cropland to rainfed globally. Climate change also has simultaneous impacts on multisectors (e.g., water, agriculture, and ecosystems). For instance, Piontek et al. (2014) reported that warming above 3 °C above 1980–2010 mean can affect about 11% population with multisectoral impacts. Also, Wada and Bierkens (2014) argued that unsustainable water consumption would rise under climate change, which could lead to a decline in water availability despite the projected increase in precipitation.

Despite the extensive evaluation of climate change impacts on water resources at the global and regional scales, Indian River basins are relatively less studied (Mall et al. 2006). Gosain et al. (2006) based on Soil and Water Assessment Tool (SWAT) reported a decline in available runoff under the warming climate in Indian River basins. Moreover, Gosain et al. (2011) estimated climate change impacts on water yield in different river basins and reported both increase and decline in water yield under the projected future climate. Ali et al. (2018) studied the impacts of climate change on hydropower production in India. They reported that hydropower production is projected to rise in the future climate due to the projected increase in streamflow. Meenu et al. (2013) conducted a river basin (Tungabhadra River basin) study and reported an increase in runoff and decline in evapotranspiration under the warming climate. Similarly, Pechlivanidis et al. (2016) used multibasin modeling to show the changes in hydrological fluxes in the Indian sub-continental river basins. Indian sub-continental river basins are projected to experience a warmer and wetter climate (Mishra and Lilhare 2016), which can have implications for water availability.

One of the adverse impacts of climate change is the increased frequency of extreme hydroclimatic events (floods, extreme precipitation). The frequency and intensity of extreme precipitation are projected to rise under the warming climate (Allan and Soden 2008; Prein et al. 2017), which is directly related to the water holding capacity of the atmosphere (Pall et al. 2007; Mukherjee et al. 2018; Zhang et al. 2018), which is projected to increase under the warming climate (Mukherjee et al. 2018; Ali et al. 2018). Increased frequency and intensity of extreme precipitation can lead to frequent high flow events and flooding (Dottori et al. 2018; Ali et al. 2019). River floods are among the costliest natural disasters that can have profound socio-economic impacts under the warming climate. For instance, Dottori et al. (2018) reported that human losses could rise by 70–83%, and direct flood damage can increase by 160–240% if the global mean temperature increases by 1.5 °C. Notwithstanding the implications of climate change on flooding, studies on understanding the flood and high-flow risk in India under climate change are somewhat limited (Guhathakurta et al. 2011). Ali et al. (2019) reported a significant increase in multiday flood events under climate change in India. They (Ali et al. 2019) found that the risk of flooding in India is half under the lower (RCP 2.6) emission scenario than that under the higher (RCP 8.5) emission scenario.

Climate change impact assessment of hydrological processes is performed using hydrological models. While considering multiple global climate models (GCMs) for impact assessment is common, most of the hydrological impact assessments are limited to a single hydrological model. Multiple GCMs for the climate change impacts assessment provide a better estimate of uncertainty arising from the GCMs. However, the quantification of uncertainty in climate change impact assessment due to hydrological models is often ignored or underestimated (Mishra et al. 2017). The intersectoral impact model intercomparison project (ISIMIP) is a unique effort to evaluate the climate change impacts considering multiple GCMs and hydrological models (Warszawski et al. 2014). Eisner et al. (2017) and Vetter et al. (2017) used nine regional hydrological models and five GCMs to study climate change impacts on streamflow seasonality in 12 large river basins worldwide, and the latter reported that hydrological models account for 16% of the total uncertainty. These studies underscored the need for climate change impacts assessment based on multiple hydrological models.

The combination of multiple hydrological and climate models helps in quantifying the uncertainty of projections under climate change. However, the role of calibration and evaluation of hydrological models on the projected changes is often ignored in the climate impact assessment. Hydrological models intended for impact studies are often calibrated only to discharge at the outlet gauge, i.e., not comprehensively or not calibrated at all (e.g., most of the global hydrological models). The performance of individual models in the historical period and their robustness can be attributed to the credibility of climate impact projections of hydrological variables. According to Krysanova et al. (2018), a comprehensive evaluation of hydrological models could provide more trustworthy projections with lower uncertainty for climate change adaptation. Therefore, the scientific questions that we address here are—*to what extent do climate impact projections based on the simple and comprehensive model evaluation approaches differ in the Godavari River basin in India? Which model evaluation approach should be applied to enable more credible impact assessment results and why? And what are the projected changes in streamflow and high flow in the Godavari River basin?*

To respond on these questions, we aim to systematically examine the influence of the comprehensive and simple model evaluation approaches on climate change impact results. First, we apply two approaches for calibration and evaluation of hydrological models. The simple approach is based on the calibration/evaluation of hydrological models against the observed flow at the single gauge station (outlet of the river basin). On the other hand, the comprehensive approach is based on calibration and evaluation of hydrological models at multisites and for multiple hydrological variables (e.g., streamflow, evapotranspiration (ET), high flow) and analysis of trends. Second, we apply hydrological models evaluated using both approaches for impact assessment and compare the projections to examine the influence of two approaches. Third, we hypothesize that the differences due to the two approaches in climate change impact results are not negligible. If the differences are negligible, the hydrological projections based on both approaches can be equally meaningful. However, if the differences in projections based on the two approaches are substantial, then we consider the comprehensively evaluated models more robust under the changed climate conditions. In the latter case, the comprehensively evaluated hydrological models should be used for climate change impact assessment in the GRB. Notwithstanding the number of previous impact studies (Gosain et al. 2011; Mishra and Lilhare 2016; Pechlivanidis et al. 2016; Shah and Mishra 2016), the role of calibration and evaluation of hydrological models on climate change impacts assessment remains unexplored in India.

2 Study area

The Godavari River basin (GRB) is located within geographical coordinates of 73 to 84° E and 16 to 23° N, as shown in Fig. 1. The Godavari is the second longest (1465 km) river in India, which passes through the states of Maharashtra, Telangana, Andhra Pradesh, Chhattisgarh, Madhya Pradesh, Odisha, and Karnataka. GRB has a tropical climate, and the annual maximum temperature varies between 26 and 44 °C (1969–2004). The basin experiences cold weather from mid-October to mid-February, and the western and the northeastern parts are colder than the other parts. The maximum rainfall occurs during the southwest monsoon (June to September). Annual rainfall in the basin varies from 755 to 1531 mm while average annual rainfall (1971–2005) is 1097 mm. Average water resources potential of the basin is 110,540 million cubic meters (MCM). Utilizable surface water resources in the basin are about 76,300 MCM. The basin has about 18 flood forecasting stations that are being monitored by the Central Water Commission (CWC). The Godavari River basin experiences flooding in the downstream regions while the coastal areas are cyclone prone. A large part of the Marathwada region is drought prone. There are a number of places that are important for the socio-economic perspective in the Godavari basin (Babar and Kaplay 2018).

We selected a sub-basin in the Godavari River basin with four gauge stations (Ghugus, Pauni, Bamini and Tekra) (see Fig. 1) to minimize the impact of reservoir operation on streamflow (Shah and Mishra 2016), because the part downstream of Tekra is largely affected by the presence of major reservoirs. The selected area covers mainly Wardha (15.31% of GRB), Weinganga (16.45% of GRB), and Pranhita (only a very small part) sub-catchments of

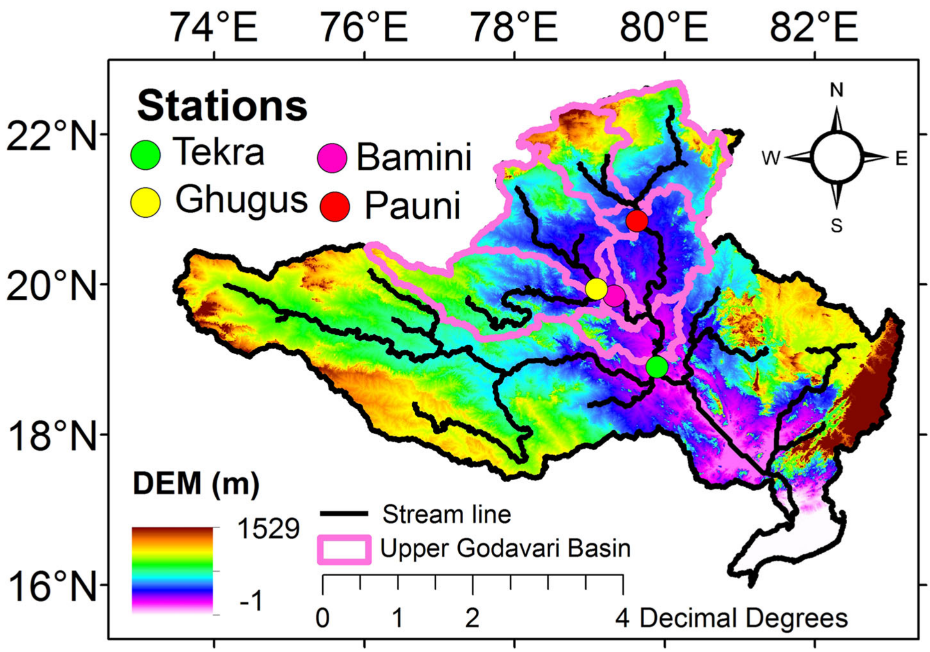

Fig. 1 Base map of the Upper Godavari River Basin (GRB) and location on the gauge stations. The GRB has a total 113664.4 km^2 catchment area till Tekra gauge station, while the catchment area till Pauni, Bamini, and Ghugus gauge stations is 37905.5 km^2, 48953.9 km^2, 21048.6 km^2, respectively

GRB. The major reservoirs in the chosen sub-basin are Isarpur, Totladoh, and Upper Wardha with approximate volumes of 1254, 1241.1, and 786.5 MCM, respectively. The three reservoirs have been operational since 1982, 1989, and 1993, respectively. The major part of the sub-basin (59.6%) is covered with agricultural land. Forest area is about 29.8% while water bodies occupy 2.06% of the total basin area.

3 Data and methods

3.1 Data

We used WATer and global CHange (WATCH) Forcing Data Era Interim (WFDEI) meteorological forcing (precipitation, mean, maximum and minimum surface air temperature, relative humidity, surface downwelling shortwave radiation, and wind) data as the observed forcing to drive the hydrological models. The WFDEI dataset was developed using the ERA-Interim reanalysis product (Weedon et al. 2011). With the global coverage, WFDEI daily data is available from 1979 to 2016 at 0.5° resolution from the phase 2a of the ISIMIP project (https://www.isimip.org). ISIMIP provides a framework for the intercomparison of global and regional-scale models within and across multiple sectors to assess projected risks (Rosenzweig et al. 2017), and our study was done in this framework. ISIMIP phase 2a serves for the evaluation of impact models using reanalysis climate data, and the evaluated models are used afterwards for impact assessment, driven by climate forcing provided from ISIMIP, phase 2b (Frieler et al. 2017). Using WFDEI forcing data, we calibrated hydrological models against observed discharge and satellite-derived evapotranspiration (ET) datasets.

We obtained observed discharge data from 1964 onwards for four gauges from the Indian Central Water Commission (http://www.india-wris.nrsc.gov.in). Data have been measured by area–velocity or slope–area methods. We checked discharge data quality by calculating the coefficient of correlation (r) between annual mean discharge and total precipitation and found a reasonable agreement with a correlation coefficient of 0.78. In addition, we checked the observed flow data for the inconsistencies and abrupt shifts, which were not found.

We used the Global Land Evaporation Amsterdam Model (GLEAM) and the Moderate Resolution Imaging Spectroradiometer (MODIS) global datasets for the evaluation of the actual evapotranspiration simulated by the hydrological models. GLEAM is a set of algorithms that estimate the components of terrestrial evaporation and root zone soil moisture. GLEAM v3 is used to produce three new datasets, including GLEAM v3a, a global dataset based on satellite-observed soil moisture, vegetation optical depth, snow water equivalent, reanalysis air temperature, net radiation, and a multisource precipitation product (Miralles et al. 2011a, b; Martens et al. 2017). As GLEAM v3.2a spans 38 years (1980–2017), we selected it for this study. It is available under http://www.gleam.eu at the daily time step and 0.25° spatial resolution.

MODIS latest global ET products are the first regular 1-km^2 land surface ET datasets for the global vegetated land areas at 8-day, monthly, and annual intervals. MODIS global ET is estimated using Mu et al.'s (2011) improved ET algorithm based on the Penman–Monteith equation (Monteith 1965), which uses daily meteorological reanalysis data and 8-day remotely sensed vegetation dynamics from MODIS as inputs. We obtained MODIS ET dataset from the University of Montana (http://files.ntsg.umt.edu/data/NTSG_Products/MOD16) for our analysis.

We obtained four bias-corrected GCM forcing data: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5 GCMs that participated in the Coupled Model Intercomparison Project 5 (CMIP5) for two extreme RCPs (RCP2.6 and RCP8.5) for the 1970–2099 period from ISIMIP2b to analyze the projected changes in discharge under a warming climate. The GCM data was bias-corrected using the method described in Hempel et al. (2013) and Frieler et al. (2017) using EWEMBI data (Lange 2018). The EWEMBI dataset was compiled to support the bias correction of climate input data for the impact assessments carried out in ISIMIP2b. The EWEMBI data covers the entire globe at 0.5° horizontal and daily temporal resolution from 1979 to 2016, and it is based on ERA-Interim reanalysis data (ERAI; Dee et al. 2011), WFDEI data (Weedon et al. 2011), Earth2Observe forcing data (E2OBS; Calton et al. 2016), and NASA/GEWEX Surface Radiation Budget data (SRB; Stackhouse et al. (2011). The CMIP5 data availability constrained the selection of four GCMs for the required daily atmospheric variables and period (Frieler et al. 2017). However, the selected four GCMs provide a fractional range coverage (FRC; McSweeney and Jones 2016) that was close to FRC of any four randomly selected GCMs from CMIP5. Further details on bias correction methods and the selection of GCMs can be obtained from Frieler et al. (2017).

3.2 Hydrological models

We used three hydrological models (HMs) to assess the projected changes in mean and extreme flows in the GRB.

The Soil and Water Assessment Tool (SWAT) is a watershed-scale hydrological model developed by the United States Department of Agriculture, Agriculture Research Service (USDA-ARS) (Arnold et al. 1998). The SWAT divides a watershed into sub-watersheds and hydrological response units (HRUs) using land use, soil, and topography information to simulate hydrological fluxes for each HRU at a daily time step. SWAT uses curve numbers to determine runoff while evapotranspiration is derived from the Penman–Monteith equation. We calibrated SWAT model manually by changing some soil, curve number (CN), groundwater, and management parameters as described in Neitsch et al. (2002).

The Soil and Water Integrated Model (SWIM) is a continuous-time semi-distributed model (Krysanova et al. 2000), which is based on the previously developed models SWAT (Arnold et al. 1993) and MATSALU (Krysanova et al. 1989). The SWIM works at a daily time step and uses a 3-level disaggregation scheme: basin–sub-basins–hydrotopes. Hydrotope is defined as a set of units that belong to the same sub-basin, characterized by the same soil and land use types, and therefore having the same hydrological behavior. In the SWIM, surface runoff is a nonlinear function of precipitation and a retention coefficient, whereas sub-surface flow occurs once the storage in the soil layer exceeds field capacity after percolation. The Priestley–Taylor method is used to estimate evapotranspiration. The SWIM uses Muskingum flow routing model (Maidment 1993) to simulate streamflow. We manually adjusted groundwater parameters, two routing coefficients, factor affecting saturated conductivity, baseflow, and evapotranspiration to calibrate the SWIM.

The variable infiltration capacity (VIC) model is a process-based macroscale hydrological model (Liang et al. 1994, 1996). It simulates daily/sub-daily water and energy fluxes at each grid cell. The VIC model estimates runoff and baseflow using the Arno model (Franchini and Pacciani 1991). Sub-grid variability of vegetation, soil, and topography are represented within grid cell. The Penman–Monteith equation is used to estimate evapotranspiration. A stand-alone routing model (Lohmann et al. 1996) based on the linearized Saint–Venant equation is used to route runoff and baseflow to the selected gauge locations. We manually calibrated the simulated discharge by modifying soil parameters as described in Shah and Mishra (2016).

We used the same meteorological forcings to drive three hydrological models for the historical and future periods. Elevation, soil, and vegetation parameters were obtained from Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), Harmonized World Soil Database (HWSD), and Advanced Very High-Resolution Radiometer (AVHRR), respectively.

3.3 Simple and comprehensive evaluation approaches

We used the simple and comprehensive approaches to evaluate the performance of the hydrological models. All three hydrological models were calibrated manually. Therefore, the model evaluation was done twice, firstly using the simple calibration/validation approach (TASK A) and secondly applying a more comprehensive approach (TASK B) suggested as guidelines for model evaluation by Krysanova et al. (2018). TASK A was performed by calibrating and validating models only for discharge at the catchment outlet (Tekra) with the monthly time step. In TASK B, we evaluated the model performance using more indicators: monthly discharge at four gauge stations, long-term mean monthly evapotranspiration over the basin, and three (90th, 95th, and 99th) high flow percentiles. In addition, we compared trends in the observed and simulated time series of discharge at four gauge stations in the GRB. Here, we assume that the application of TASK B for model evaluation, in case of success, would increase the confidence in the simulated hydrological variables and in the projections based on that under the warming climate. After evaluation, the models could be weighted for impact assessment, or a model could be rejected from the ensemble for a certain indicator in case its performance for this indicator is poor (as suggested in Krysanova et al. 2018).

We evaluated the performance of three hydrological models for the monthly discharge in the calibration (1980–1989) and validation (1990–1999) periods and for the high flows (daily discharge exceeding the 90th, 95th, and 99th percentiles) over the period of 1980–1999. We evaluated the model performance using the following: Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970), Kling–Gupta efficiency (KGE; Ghosh et al. 2009 and Kling et al. 2012), and percent bias (PBIAS). Since we did not calibrate models for high flow conditions, only PBIAS was used for evaluation of high flow percentiles while all three performance measures were used to evaluate the monthly discharge. The model performance was evaluated as good if the following levels were reached: NSE $\geq$ 0.7, KGE $\geq$ 0.7, and |PBIAS| $\leq$ 15, and as satisfactory if 0—5 $\leq$ NSE < 0.7, 0. 5 $\leq$ KGE < 0.7, and 15 < |PBIAS| $\leq$ 25. Using Mann–Kendall trend test (Mann 1945) at the 5% significance level, we estimated low flow (10th), mean flow (50th), and high flow (90th) trend directions for the observed and simulated flows using simulations obtained in TASK B.

Further, to understand the influence of the simple and comprehensive evaluation approaches on simulated impacts, we estimated the differences in projected changes in mean monthly and mean annual discharge using model parameterizations after the TASK A and TASK B model evaluations for the Near (N: 2010–2039), Mid (M: 2040–2069), and End (E: 2070–2099) periods against the historical reference (H: 1970–1999) period.

Monthly change ΔQ for a month i between future (F) and historical (H) periods based on model parametrizations after tasks A and B (in $m^3\ s^{-1}$):

$$\Delta Q_i(F,A) = Q_i\ (F,A) - Q_i\ (H,A)$$

$$\Delta Q_i\ (F,B) = Q_i\ (F,B) - Q_i\ (H,B)$$

Monthly difference in ΔQ for a month i between future (F) and historical (H) periods based on model parametrizations after tasks B and A (in $m^3\ s^{-1}$):

$$\text{Difference in } \Delta Q_i\ (F) = (Q_i\ (F,B) - Q_i\ (H,B)) - (Q_i\ (F,A) - Q_i\ (H,A))$$

Relative annual difference in ΔQ between future (F) and historical (H) periods based on model parametrizations after tasks B and A (in %):

$$\text{Relative annual difference in } \Delta Q(F) = \left(\frac{Q_i(F,B) - Q_i(H,B)}{Q_i(H,B)} \times 100\right) - \left(\frac{Q_i(F,A) - Q_i(H,A)}{Q_i(H,A)} \times 100\right)$$

Here, F (Near, Mid, and End) and H are the future and historic reference periods, respectively.

We analyzed the uncertainty among the three hydrological models and four GCMs by estimating one standard deviation (of 12 simulations) using TASK B simulation results. In addition, we assigned weighting coefficients (WCOs) to each hydrological model to estimate impacts based on their performance for the mean monthly and 99th percentile flows (Table 1).

The long-term mean monthly and annual discharge changes for three hydrological models and associated uncertainties were estimated under the RCP 2.6 and RCP 8.5 scenarios. Moreover, we calculated the changes in flow duration curve (Vogel and Fennessey 1994, 1995) for the Near, Mid, and End periods under RCP 2.6 and RCP 8.5. We also evaluated uncertainty among datasets and the impact of climate change on high flow by considering 90th, 95th, and 99th percentiles of discharge.

4 Results

First, we compared precipitation, maximum, and minimum temperatures from WFDEI and India Meteorological Department (IMD) at daily and monthly time scales and found that they are in good agreement (see more details in Supplementary, part X1 and Fig. S1), Therefore, WFDEI data can be used to evaluate model performance and to study hydrological impacts.

4.1 Performance of the hydrological models

We performed manual calibration and validation of the hydrological models using the two methods referred to as TASK A and TASK B, and results are presented in Table 1. In TASK A, all three hydrological models were calibrated and validated at only one gauge (Tekra) for discharge. We found a “good” performance of all three hydrological models (Table 1).

Regarding the evaluation of monthly dynamics in TASK B and considering the whole set of criteria at four gauge stations (Table 1), we note that all the models show good performance (17 out of 18 values are “good”) for the outlet station Tekra. Slightly lower performance can be seen for Bamini with 15 out of 18 values being in the “good” range. Results for Pauni and especially for Ghugus are weaker as about 33% of criteria values correspond to “satisfactory” or even “poor” (three values for Ghugus). The reason for the relatively weaker performance of models at Ghugus, Bamini, and Pauni is probably the difference between WFDEI and IMD

Table 1 Results of simple (TASK A) and comprehensive (TASK B) evaluation (calibration: 1980–1989 and validation: 1990–1999) approaches for the three hydrological models at gauge locations for monthly and high flow performance. Here, NSE is Nash–Sutcliffe efficiency, KGE is Kling and Gupta efficiency, Pbias is percentage bias, and 90th, 95th, and 99th percentiles flow are estimated as high flow

Evaluation of monthly dynamics											
Task	**Station**	**Criteria**	**SWAT**			**SWIM**			**VIC**		
			Calibration	**Validation**		**Calibration**	**Validation**		**Calibration**	**Validation**	
A	Tekra	NSE	0.94	0.9		0.92	0.89		0.83	0.81	
		KGE	0.92	0.86		0.89	0.85		0.71	0.78	
		PBIAS	7	12		5.2	13.6		− 14	− 7	
B	Pauni	NSE	0.82	0.91		0.91	0.88		0.78	0.7	
		KGE	0.67	0.84		0.82	0.83		0.77	0.64	
		PBIAS	23	10		17.4	15.8		− 12	− 24	
	Ghugus	NSE	0.74	0.78		0.75	0.78		0.72	0.64	
		KGE	0.84	0.63		0.74	0.79		0.76	0.48	
		PBIAS	0.9	28		− 3.3	18		19	46	
	Bamini	NSE	0.83	0.71		0.82	0.76		0.78	0.74	
		KGE	0.87	0.61		0.84	0.77		0.76	0.79	
		PBIAS	10	32		4.3	18.4		− 3	10	
	Tekra	NSE	0.91	0.86		0.93	0.89		0.81	0.76	
		KGE	0.83	0.77		0.9	0.87		0.81	0.85	
		PBIAS	15	21		5.4	12		− 6	− 1	
Evaluation of high flows (1980–1999)											
Task			**SWAT**			**SWIM**			**VIC**		
	Station	**Criteria**	**90th**	**95th**	**99th**	**90th**	**95th**	**99th**	**90th**	**95th**	**99th**
B	Pauni	PBIAS	20	31	13	− 19.5	− 17.6	13.4	− 5	− 12	− 27
	Ghugus		47	47	0	− 38.3	− 17.2	33.9	91	49	− 17
	Bamini		76	47	− 13	− 42.4	− 22.2	33.6	45	9	− 34
	Tekra		31	19	3	− 23.5	− 7.8	25	11	− 1	− 22

daily precipitation in these smaller sub-catchments. Also, as we calibrated and evaluated the models without considering water management (reservoirs, water abstraction for agriculture), it may affect the performance in these sub-catchments as well.

Comparing performances of the three hydrological models for monthly dynamics, we find that the SWIM shows the best performance, with 83% of criteria values corresponding to a good performance, according to the accepted thresholds. The SWAT performed slightly weaker with 71% of the values in the "good" ranges and the rest corresponding to the "satisfactory" (21%) or "poor" (8%). The VIC model shows a good performance for all three criteria at two gauges: Bamini and Tekra, however, weaker performance at the other two stations. Considering the thresholds for satisfactory performance, all the results are above 0.5 for NSE and KGE in all the cases except one (VIC at Ghugus, one period) and |PBIAS| below 25% in all cases except three (SWAT and VIC at Ghugus, one period and SWAT at Bamini, one period). Therefore, in general, the results of all hydrological models can be accepted as being good or satisfactory (with a few exclusions) and thus suitable for climate impact assessment.

In addition, we analyzed trends in the observed and simulated data. We found the positive trends in the observed and simulated 50th flow at the four locations in the GRB for the 1980–1999 period (Table S1). On the other hand, negative trends were observed for 10th flow in most cases based on observed data and simulations from three models. If to consider all trends, the trend directions were successfully captured by the SWIM and VIC. However, except for the observed 50th flow at Pauni, all other trends were not statistically significant at 5% level, meaning that there are practically no trends. Thus, we can conclude that trend analysis revealed identical results based on the observed and simulated time series, with one exception.

Regarding the evaluation of high flows and looking at the whole set of criteria values for three percentiles at four gauge stations (Table 1), we can see that performance for the Tekra station is the best, with eight of nine values (89%) in the good or satisfactory categories. The performance is slightly weaker for Pauni, with seven of nine values belonging to "good" or "satisfactory." The performance for Ghugus and Bamini is rather low, with six criteria values out of nine showing |PBIAS| above 25%. Comparing the three hydrological models, we find that the SWAT was successful in simulating 99th flow at all gauge stations (all four |PBIAS| values below 15%), but weaker in reproducing two other percentiles (90th and 95th). The SWIM shows satisfactory performance for 95th in terms of |PBIAS| (all four values below 25%). Moreover, the VIC model demonstrated better results for 95th and 90th (5 of 8 values below 15%) compared with 99th. Overall, our results indicate that the impact assessment considering high flows can be done for three percentiles with all three hydrological models at Tekra and with the SWAT for 99th flow at all the four stations.

In addition to discharge, we evaluated the model performance for the second variable, actual evapotranspiration, and compared the long-term mean monthly ET simulated by the three hydrological models against ET from GLEAMv3.2 and MODIS (Fig. S2). We found that ET simulated by the SWIM is closer to ET from GLEAM with a correlation of 0.89 (0.77 for SWAT, 0.86 for VIC). ET simulated by the SWAT and VIC models is closer to that of MODIS, with a correlation of 0.89 and 0.87, respectively (0.7 for SWIM). Although GLEAM and MODIS datasets are based on observation data, they include other sources (e.g., reanalysis). According to Miralles et al. (2011a), GLEAM underestimates ET during the monsoon season by 15–20% which might be attributed to considering only three land surface classes for land evaporation estimation. Moreover, the bias in simulated ET can be attributed to different schemes and input parameters used by hydrological models (Shah et al. 2019). Overall, we can conclude that the hydrological models successfully captured the seasonal cycle of ET over the Godavari basin.

4.2 Analysis of climate scenarios

We analyzed the projected changes in surface air mean temperature and precipitation over the upper Godavari River basin using scenarios from the four GCMs and two RCPs (Figs. S3–S4). The projected increase in the long-term mean annual temperature ranges from 1.1 °C in the Near future to 1.4 °C in the Mid century and to 1.3 °C in the End period for RCP 2.6. On the other hand, under the RCP 8.5, the temperature is projected to rise by 1.1 °C in the Near future to 4.4 °C in the End period, according to medians of the climate models ensemble. A slight decrease by the end of the century under RCP 2.6 is due to stabilization of the CO_2 level assumed in this scenario. Comparing projections from different GCMs, we can see that IPSL-CM5A-LR shows the highest increase while MIROC5 shows the lowest in all three periods under both RCPs. The long-term mean monthly temperature shows an increase by all GCMs in both RCP scenarios, three periods and all months, with a few exceptions (e.g., HadGEM2-ES showing a minor decrease in November in the near future). Difference between the projected temperatures under RCP 2.6 and 8.5 becomes notable in the middle of the century and raises further in the far future period. Another observation is that the seasonal anomalies of temperature projected by the GCMs fluctuate during the year, being lower in the monsoon season (August–September) when usually the temperature is lower than in summer.

All GCMs show an increase in the long-term mean annual precipitation in the GRB agreed by most of the models for all three periods under both RCPs. The mean increase ranges from 13 mm in the near period to 138 mm in the mid and to 124 mm at the end century for RCP 2.6. Under RCP 8.5, mean annual precipitation is projected to increase by 138 mm in the near period, 207 mm in the mid, and 239 mm in the far future period, according to the medians of the climate models ensemble. Some stabilization of changes in precipitation is observed for RCP 2.6, similar as for temperature. However, IPSL-CM5A-LR does not show a stabilization but a very strong decrease by the end century (opposite to its increasing trend in temperature). HadGEM2 shows the highest increase in precipitation.

The highest seasonal precipitation increase is projected in the rainy season (June–September/October) in all three periods for both RCPs, with a few exceptions: decrease of precipitation in June (minor) and July (− 30 mm) under RCP 2.6 in the near future, the latter would mean a delay in the onset of the rainy season (Fig. S4). The magnitude of increase for the ensemble median reaches its maxima of ~ 50 mm in August under RCP 2.6 (second period) and 88 mm in June under RCP 8.5 (end of the century). Rather, small projected changes are observed in the rest of the season: from November to May in all the three periods, ranging from − 6.5 mm (in January, second period, RCP 8.5) to 5 mm (in April, second period, RCP2.6). The GCM precipitation projections show a higher uncertainty in the rainy season (June–September/October) compared with that in the dry months (October/November–May).

Based on results of models performance for monthly discharge (Table 1), we assigned (qualitatively) weighting coefficients of 0.4, 0.3, and 0.3 to the SWIM, SWAT, and VIC outputs, respectively, as SWIM performed better than other two models. Other WCOs were assigned for 99th percentile based on Table 1: 0.3, 0.5, and 0.2 to the SWIM, SWAT and VIC, respectively, as SWAT showed the best performance and VIC the weakest. These WCOs are used for evaluation of impacts based on the WCOs in Sections 4.3–4.4.

4.3 Projected changes in discharge

Our aim was to evaluate the influence of two calibration/evaluation approaches on the hydrological projections in the Godavari River basin. Therefore, we analyzed the effect of the two calibration methods (TASK A and TASK B) on monthly and annual discharge projections at four gauge stations (Fig. 2, left and right). In addition, we also analyzed the influence of calibration methods on projections of high flow (99th percentile) and the frequency of high flows (Fig. 2, right part). For that, we used the ensemble mean of HMs and GCMs for RCP2.6 and RCP8.5 to calculate the projected changes in discharge during three future periods based on TASK A and TASK B, and then, the differences between (TASK B and TASK A) projected changes in mean monthly (in m^3/s) and mean annual (in %) discharge were estimated.

We find that differences in projected mean monthly discharge changes at Bamini and Tekra are high (reaching 150 m^3/s) during the monsoon season (June–September). Moreover, the mean monthly differences increase over time (from Near to End) and warming scenarios (from RCP2.6 to RCP8.5). The projected change in mean monthly discharge under TASK B is greater (150 m^3/s) than under TASK A at Tekra station.

The differences in mean annual discharge are not exceeding 3% at Ghugus, Pauni, and Tekra stations. However, about 10% difference in the projected changes in mean annual flows was found at Bamini. Similar, but slightly higher differences (about 14% at Bamini) were found for the projected high flows, and quite considerable differences could be noticed for the frequency of high flow: up to 35–40% at three gauge stations in the GRB. Overall, we can see that the calibration approaches of the hydrological models do influence the projected changes in discharge and high flow under the warming climate. Since TASK B is based on a more rigorous evaluation of hydrological models, and models after TASK B are more robust, further we used models after the comprehensive evaluation for assessment of climate change impacts in GRB under the warming climate.

Next, we estimated the projected changes and associated uncertainties in mean monthly flow using ensemble mean of hydrological models (Fig. 3), and results for every of three models can be seen in Supplementary (Figs. S5–S7). Uncertainty (based on one standard

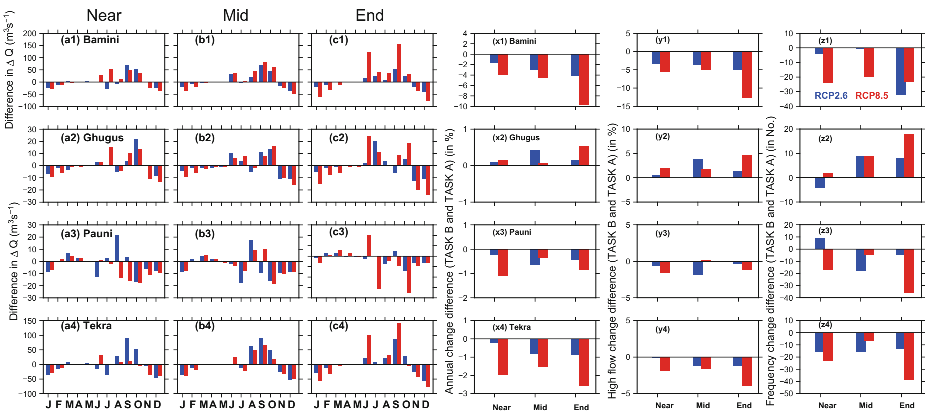

Fig. 2 Differences between the projected changes in mean monthly discharge (in m^3/s, left part) and between the projected changes in mean annual discharge, high flow magnitude, and high flow frequency (in %, right part) based on two model evaluation methods in three future periods for RCP 2.6 and RCP 8.5 at four gauge stations

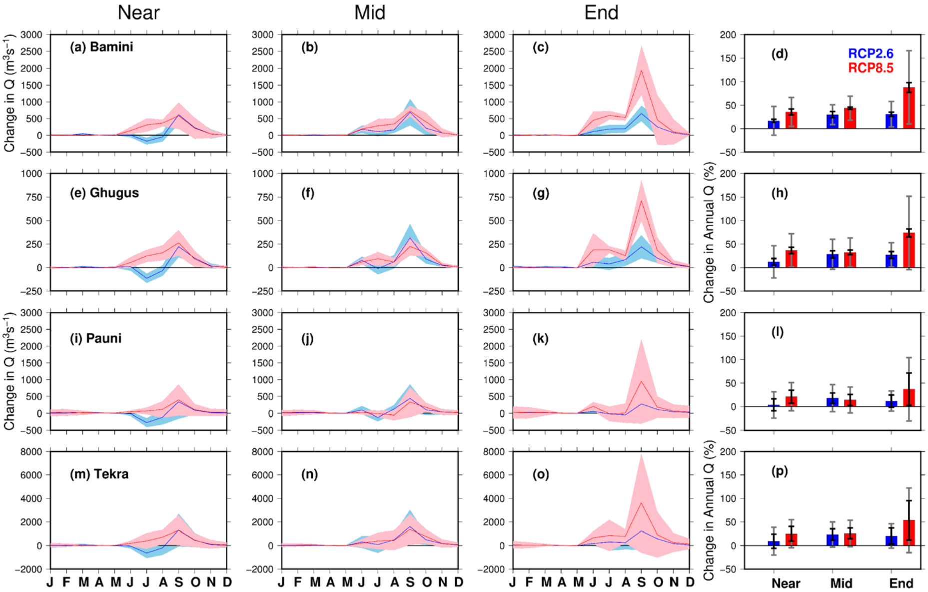

Fig. 3 Projected change in mean monthly and mean annual discharge (*Q*) under RCP 2.6 and RCP8.5 scenarios, calculated using ensemble mean of hydrological models (VIC, SWAT, and SWIM) simulations based on the comprehensive (TASK B) approach for the Near, Mid, and End terms at four gauge locations in the Godavari River basin. Spread and error bars in (*d*), (*h*), (*l*), and (*p*) show overall and HM-related uncertainty in the results with gray and black colors, respectively

deviation) in the projected changes and influence of the ensemble mean and WCO methods were evaluated. A negligible difference between results based on the WCOs and ensemble mean methods was found for the mean monthly discharge, which could be attributed to similar WCOs of the models. Further, we estimated uncertainty in annual discharge due to three hydrological models by considering the largest standard deviation in the projected change for a single GCM. To do so, we compared the standard deviations of the projected change from the combination of three models with each GCM for each period. Then, we selected the HM and GCM combination with the largest uncertainty to represent uncertainty arising from the hydrological models. The overall uncertainty due to hydrological models and GCMs was estimated using a standard deviation of 12 simulations (3 hydrological models and 4 GCMs) (Fig. 3).

Our results in Fig. 3 show that mean monthly discharge is projected to increase (except June–August of RCP 2.6 in Near future) under the warming climate during the monsoon season under both RCPs. Mean annual discharge is projected to increase by 25–75% at the end of the twenty-first century at four gauge stations under RCP 8.5. Uncertainty in the projected discharge due to GCMs is substantially higher than that due to three hydrological models (Fig. 3(d, h, l, p)). All hydrological models project a higher increase in discharge during the monsoon season, which can be attributed to the projected increase in precipitation in this season.

Besides, we estimated changes in flow duration curves that describe the relationships between flow and probability of exceedance of time (Ali et al. 2018) at four gauge stations in the GRB (see in Supplementary, part X2 and Fig. S8).

Mishra and Lilhare (2016) reported that streamflow in the Godavari River basin is more sensitive to change in the monsoon season precipitation in comparison with the warming.

Therefore, the projected changes in the flow are largely driven by the increase in the monsoon precipitation under the warming climate. In contrast to our findings, Gosain et al. (2011) reported a decline of about 30% in water yield in the Godavari River basin by the end of the twenty-first century. However, their findings were based on only one climate model. We also note that the uncertainty due to hydrological models is substantially lower than the uncertainty in the projected discharge due to GCMs. Therefore, reducing the precipitation uncertainty in the GCMs would enhance the decision making at the river basin scale.

4.4 Projected changes in high flows

Finally, we estimated the projected changes in high flow (90th, 95th, and 99th percentiles of daily flow) and the frequency of high-flow events (number of days exceeding high flow threshold) at the four gauge stations in the GRB using hydrological models after TASK B. The projected changes in high flow were estimated against the historical period for three periods under two RCPs (Fig. 4). We can see that the multimodel ensemble means of high flows are projected to increase at all four gauge stations. Moreover, the projected rise in high flows under RCP 8.5 is considerably higher than under RCP 2.6, which indicates the implications of climate change mitigation. Our results show that the uncertainty in the projected high flows is lower in the Near and Mid periods than at the end of century (Fig. 4). We did not find considerable differences in the projected changes in high flows based on the ensemble mean

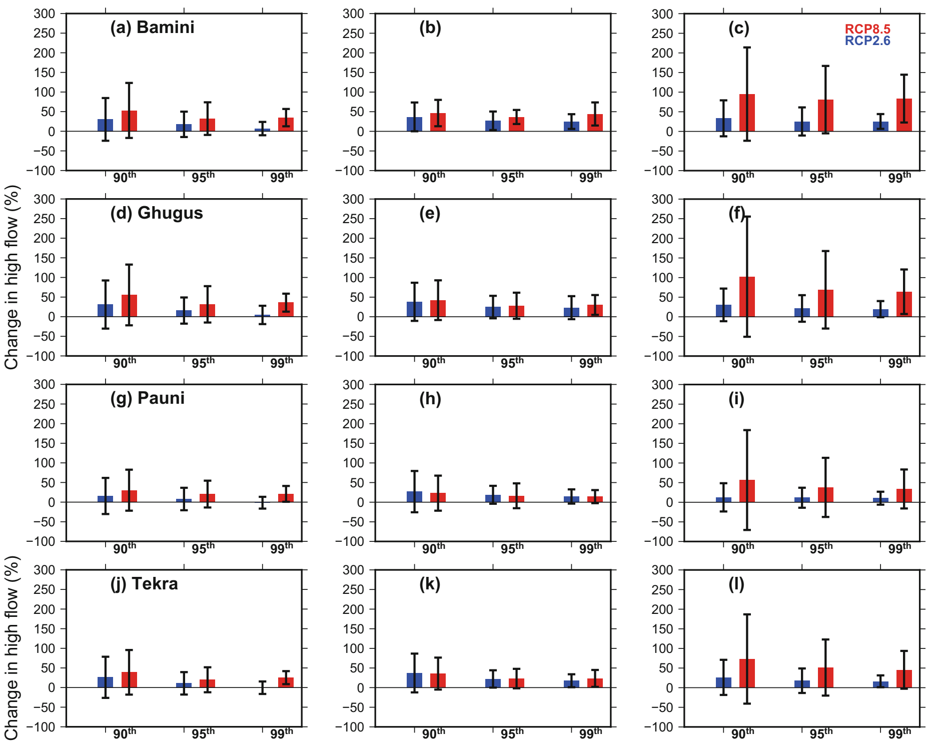

Fig. 4 Changes in high flows (90th, 95th, and 99th percentiles of daily flow) magnitude during the Near, Mid, and End periods calculated against the historical reference period (1971–2000). Error bars show overall uncertainty arising from the four GCM and three HM combinations

and with model weighting. The maximum difference of 5% for 99th percentile was found (Fig. S9), which further indicates that the projected changes are largely driven by the precipitation projections in GCMs. Notwithstanding the uncertainty arising from GCMs, the frequency of high flows based on 90th, 95th, and 99th percentiles is projected to increase at all four stations of the GRB (Fig. S10). The projected increase is higher for the End period in comparison with the Near or Mid periods. Moreover, the projected increase in high flow frequency is higher under RCP 8.5 compared with RCP 2.6.

A majority of GCMs under CMIP5 show an increase in the monsoon season precipitation (Chaturvedi et al. 2012; Menon et al. 2013). In addition, a consistent increase in the frequency of extreme precipitation is projected (Goswami et al. 2006; Mishra et al. 2014). The projected rise in the intensity of extreme precipitation is associated with the water holding capacity of the atmosphere that is projected to rise in the warming climate (Mukherjee et al. 2018; Zhang et al. 2018). The projected rise in high flows and the frequency of high flows can be attributed to the projected increase in extreme precipitation. However, previous studies reported that high flows are not only affected by extreme precipitation, but antecedent moisture conditions can also play a significant role (Sharma et al. 2018). For instance, Sharma et al. (2018) reported that an increase in extreme precipitation might not necessarily translate in the increased floods. Similarly, Garg and Mishra (2019) analyzed the role of initial moisture conditions and extreme precipitation in the GRB and found that the combination of the wet initial condition and extreme precipitation can produce high flows in the observed and projected climates. Therefore, changes in the antecedent moisture condition, land cover, and extreme precipitation all can influence the projected changes in high flows in the GRB.

5 Discussion and conclusions

The Godavari is one of the major river basins in India, which is affected by climate conditions and topography. Understanding of the projected changes in streamflow under the future climate is essential for climate change adaptation. Hydrological assessments under climate change are often performed using the bias-corrected and downscaled projections that are appropriate at regional scale (Wood et al. 2004; Frieler et al. 2017). However, global assessments are generally based on the global hydrological models that are not calibrated (Schewe et al. 2014; Warszawski et al. 2014). The use of hydrological models in climate change impact assessment depends on model parameters that are either calibrated or based on empirical knowledge (Merz et al. 2011). Hydrological models applied at the river basin scale are often calibrated using observed discharge data at the outlet (Mishra and Lilhare 2016). The calibration parameters are considered static throughout the time period for which a hydrological model is applied. However, there are uncertainties associated with climate change projections due to the choice of the calibration period and method (Wilby 2005). Moreover, the calibration parameters can vary from upstream to downstream of the catchment (Merz et al. 2011), which highlights the need for multisite model evaluation.

Our results showed that the comprehensive evaluation of hydrological models based on streamflow, ET, high flow, and trends in streamflow is more robust for climate change impact assessment in the Godavari River basin, and differences in impacts based on two calibration methods (Section 4.3) are notable. Depending on the combination of catchment and climate characteristics (Brown et al. 2014), the differences in impacts based on simple and comprehensive calibration approaches can be significant and influence the climate change impact assessment in the basin. Therefore, taking into account the higher robustness of the models after the comprehensive evaluation, we find them more reliable for climate change impact assessment and results based on them more trustworthy.

Climate change impact assessment at the regional scale is often influenced by different uncertainties. The primary source of uncertainty is the climate change projections from global climate models (Kay et al. 2009). However, hydrological models can also contribute substantial uncertainty due to differences in their process representation and parameterization (Poulin et al. 2011; Mishra et al. 2017). We used three hydrological models, which were calibrated and evaluated using two approaches. As expected, three models showed differences in their performance to simulate streamflow, ET, and high flows. However, all the hydrological models projected an increase in streamflow in the Godavari River basin under the future climate. The projected increase in mean and high flows can be attributed to the projected increase in the monsoon season precipitation. Moreover, consistent with the previous studies (Teng et al. 2012; Thompson et al. 2013; Clark et al. 2016; Vetter et al. 2017), uncertainty in mean annual streamflow from the GCMs is higher than that from hydrological models. Therefore, there is a need to account for the uncertainty in the climate change adaptation at the river basin scale.

Based on our findings, the following conclusions can be made:

1. The climate in the Godavari River basin is projected to become warmer and wetter in future for both RCP 2.6 and RCP 8.5 scenarios. Projected increase in temperature varies from about 1 °C in the Near period to 4.5 °C in the End period under the high emission scenario RCP 8.5. In addition, precipitation is also projected to increase considerably under RCP 8.5 in the End period.
2. The combination of three hydrological models and four GCMs was used to study the impacts of climate change on mean annual discharge, high flows, and the frequency of high flows under the warming climate. The hydrological models were calibrated and validated using the simple and more comprehensive approaches. The hydrological models performed well or satisfactory against discharge, ET, and high flows at the four gauge stations in the GRB.
3. The previous study (Krysanova et al. 2018) suggested to use the comprehensive evaluation of hydrological models as more trustworthy for climate change impact assessment and climate change adaptation. We estimated differences between the projected changes in mean and high flows based on two calibration methods. Our results show that two calibration and validation approaches lead to considerable differences in the projected changes that can have implications for climate change adaptation. Since models after the comprehensive evaluation are more robust, these model versions were used for the assessment of climate change impacts.
4. The comprehensively evaluated hydrological models projected increased discharge, high flows, and frequency of high flows under the future climate at all gauge stations. The projected rise in discharge, high flow magnitude, and frequency increases with time (End period) and emission scenario (RCP 8.5). In addition, models project substantial changes in the flow duration curves, which can have implications for hydropower production, water management, and ecology of the basin.
5. The uncertainty arising from hydrological models is substantially lower than the uncertainty from GCMs, indicating the need for improving GCMs projections and their

resolution (Aadhar and Mishra 2019) for use in climate change impact assessment. However, applying multiple hydrological models that are comprehensively evaluated can provide better confidence in the projected changes.

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References

Aadhar S, Mishra V (2019) A substantial rise in the area and population affected by dryness in South Asia under 1.5, 2.0 and 2.5°C warmer worlds. Environ Res Lett. https://doi.org/10.1088/1748-9326/ab4862

Ali SA et al (2018) Projected increase in hydropower production in India under climate change. Sci Rep 8:12450. https://doi.org/10.1038/s41598-018-30489-4

Ali H et al (2019) Increased flood risk in Indian sub-continent under the warming climate. Weather Clim Extrem 25:100212. https://doi.org/10.1016/J.WACE.2019.100212

Allan RP, Soden BJ (2008) Atmospheric warming and the amplification of precipitation extremes. Science (80-). https://doi.org/10.1126/science.1160787

Arnold JG, Engel BA, Srinivasan R (1993) Continuous time, grid cell watershed model, application of advanced information technologies. Effective management of natural resources. ASAE Publication, 04–93. American Society of Agricultural Engineers 267–278

Arnold JG et al (1998) Large area hydrologic modeling and assessment part I: model development. J Am Water Resour Assoc. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x

Babar M, Kaplay RD (2018) Godavari River: geomorphology and socio-economic characteristics. In: The Indian Rivers. Springer Hydrogeology, Singapore, pp 319–337

Barnett TP et al (2005) Potential impacts of a warming climate on water availability in snow-dominated regions. Nature 438:303–309. https://doi.org/10.1038/nature04141

Brown C et al (2014) Analysing uncertainties in climate change impact assessment across sectors and scenarios. Clim Chang. https://doi.org/10.1007/s10584-014-1133-0

Calton B et al (2016) Water resource reanalysis v1: data access and model verification results. https://doi.org/10.5281/ZENODO.57760

Chaturvedi RK et al (2012) Multi-model climate change projections for India under representative concentration pathways. Curr Sci. https://doi.org/10.2307/24088836

Clark MP et al (2016) Characterizing uncertainty of the hydrologic impacts of climate change. Curr Clim Chang Rep 2:55–64. https://doi.org/10.1007/s40641-016-0034-x

Dee DP et al (2011) The ERA-interim reanalysis: configuration and performance of the data assimilation system. Q J R Meteorol Soc. https://doi.org/10.1002/qj.828

Dottori F et al (2018) Increased human and economic losses from river flooding with anthropogenic warming. Nat Clim Chang 8:781–786. https://doi.org/10.1038/s41558-018-0257-z

Eisner S et al (2017) An ensemble analysis of climate change impacts on streamflow seasonality across 11 large river basins. Clim Chang. https://doi.org/10.1007/s10584-016-1844-5

Elliott J et al (2014) Constraints and potentials of future irrigation water availability on agricultural production under climate change. Proc Natl Acad Sci U S A. https://doi.org/10.1073/pnas.1222474110

Franchini M, Pacciani M (1991) Comparative analysis of several conceptual rainfall-runoff models. J Hydrol. https://doi.org/10.1016/0022-1694(91)90178-K

Frieler K et al (2017) Assessing the impacts of 1.5 °C global warming - simulation protocol of the inter-sectoral impact model Intercomparison project (ISIMIP2b). Geosci Model Dev. https://doi.org/10.5194/gmd-10-4321-2017

Garg S, Mishra V (2019) Role of extreme precipitation and initial hydrologic conditions on floods in Godavari river basin, India. Water Resour Res. https://doi.org/10.1029/2019WR025863
Ghosh S et al (2009) Trend analysis of Indian summer monsoon rainfall at different spatial scales. Atmos Sci Lett. https://doi.org/10.1002/asl
Gosain AK et al (2006) Climate change impact assessment on hydrology of Indian river basins. Curr Sci 90:346–353
Gosain AK et al (2011) Climate change impact assessment of water resources of India. Curr Sci 101:16
Goswami BN et al (2006) Increasing trend of extreme rain events over India in a warming environment. Science (80-). https://doi.org/10.1126/science.1132027
Guhathakurta P et al (2011) Impact of climate change on extreme rainfall events and flood risk in India. J Earth Syst Sci. https://doi.org/10.1007/s12040-011-0082-5
Hempel S et al (2013) A trend-preserving bias correction – the ISI-MIP approach. Earth Syst Dyn. https://doi.org/10.5194/esd-4-219-2013
Immerzeel WW et al (2010) Climate change will affect the Asian water towers. Science (80-). https://doi.org/10.1126/science.1183188
Kay AL et al (2009) Comparison of uncertainty sources for climate change impacts: flood frequency in England. Clim Chang. https://doi.org/10.1007/s10584-008-9471-4
Kling H et al (2012) Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. J Hydrol. https://doi.org/10.1016/j.jhydrol.2012.01.011
Krysanova V et al (1989) Simulation modelling of the coastal waters pollution from agricultural watershed. Ecol Model. https://doi.org/10.1016/0304-3800(89)90041-0
Krysanova V, Wechsung F, Arnold J, Srinivasan R, Williams J (2000) PIK Report Nr. 69 "SWIM (Soil and Water Integrated Model), User Manual", Potsdam, p. 239
Krysanova V et al (2018) How the performance of hydrological models relates to credibility of projections under climate change. Hydrol Sci J. https://doi.org/10.1080/02626667.2018.1446214
Lange S (2018) Bias correction of surface downwelling longwave and shortwave radiation for the EWEMBI dataset. Earth Syst Dyn. https://doi.org/10.5194/esd-9-627-2018
Liang X et al (1994) A simple hydrologically based model of land surface water and energy fluxes for general circulation models. J Geophys Res. https://doi.org/10.1029/94JD00483
Liang X et al (1996) Surface soil moisture parameterization of the VIC-2L model: evaluation and modification. Glob Planet Chang. https://doi.org/10.1016/0921-8181(95)00046-1
Lohmann D et al (1996) A large-scale horizontal routing model to be coupled to land surface parameterization schemes. Tellus Ser A-Dyn Meteorol Oceanogr. https://doi.org/10.1034/j.1600-0870.1996.t01-3-00009.x
Maidment D (1993) GIS and hydrological modeling. In: Goodchild M, Parks B, Steyaert L (eds) Environmental Modeling within CIS. : University Press, Oxford, pp 147–167
Mall RK et al (2006) Impact of climate change on Indian agriculture: a review. Clim Chang 78:445–478
Mann HB (1945) Nonparametric tests against trend. Econometrica. https://doi.org/10.2307/1907187
Martens B et al (2017) GLEAM v3: satellite-based land evaporation and root-zone soil moisture. Geosci Model Dev. https://doi.org/10.5194/gmd-10-1903-2017
McSweeney CF, Jones RG (2016) How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? Clim Serv. https://doi.org/10.1016/j.cliser.2016.02.001
Meenu R et al (2013) Assessment of hydrologic impacts of climate change in Tunga-Bhadra river basin, India with HEC-HMS and SDSM. Hydrol Process. https://doi.org/10.1002/hyp.9220
Menon A et al (2013) Consistent increase in Indian monsoon rainfall and its variability across CMIP-5 models. Earth Syst Dyn. https://doi.org/10.5194/esd-4-287-2013
Merz R et al (2011) Time stability of catchment model parameters: implications for climate impact analyses. Water Resour Res. https://doi.org/10.1029/2010WR009505
Miralles DG et al (2011a) Magnitude and variability of land evaporation and its components at the global scale. Hydrol Earth Syst Sci. https://doi.org/10.5194/hess-15-967-2011
Miralles DG et al (2011b) Global land-surface evaporation estimated from satellite-based observations. Hydrol Earth Syst Sci. https://doi.org/10.5194/hess-15-453-2011
Mishra V, Lilhare R (2016) Hydrologic sensitivity of Indian sub-continental river basins to climate change. Glob Planet Chang. https://doi.org/10.1016/j.gloplacha.2016.01.003
Mishra V et al (2014) Reliability of regional and global climate models to simulate precipitation extremes over India. J Geophys Res. https://doi.org/10.1002/2014JD021636
Mishra V et al (2017) Multimodel assessment of sensitivity and uncertainty of evapotranspiration and a proxy for available water resources under climate change. Clim Chang 141:451–465. https://doi.org/10.1007/s10584-016-1886-8
Monteith JL (1965) Evaporation and environment. Symp Soc Exp Biol 19:205–224
Mu Q et al (2011) Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sens Environ. https://doi.org/10.1016/j.rse.2011.02.019

Mukherjee S et al (2018) Increase in extreme precipitation events under anthropogenic warming in India. Weather Clim Extrem. https://doi.org/10.1016/j.wace.2018.03.005
Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I - a discussion of principles. J Hydrol. https://doi.org/10.1016/0022-1694(70)90255-6
Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2002) Soil and water assessment tool —theoretical documentation (ver. 2000). Texas Water Resour Inst:College Station, TX 458
Pall P et al (2007) Testing the Clausius-Clapeyron constraint on changes in extreme precipitation under CO2 warming. Clim Dyn. https://doi.org/10.1007/s00382-006-0180-2
Pechlivanidis IG et al (2016) Multi-basin modelling of future hydrological fluxes in the Indian subcontinent. Water (Switzerland). https://doi.org/10.3390/w8050177
Piontek F et al (2014) Multisectoral climate impact hotspots in a warming world. Proc Natl Acad Sci U S A. https://doi.org/10.1073/pnas.1222471110
Poulin A et al (2011) Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin. J Hydrol. https://doi.org/10.1016/j.jhydrol.2011.08.057
Prein AF et al (2017) The future intensification of hourly precipitation extremes. Nat Clim Chang. https://doi.org/10.1038/nclimate3168
Rosenzweig C, Arnell NW, Ebi KL, Otze-Campen H, Raes F, Rapley C, Stafford Smith M, Cramer W, Frieler K, Reyer CPO, et al (2017) Assessing inter-sectoral climate change risks: The role of ISIMIP Assessing inter-sectoral climate change risks: The role of ISIMIP. Environ Res Lett 12
Schewe J et al (2014) Multimodel assessment of water scarcity under climate change. Proc Natl Acad Sci. https://doi.org/10.1073/pnas.1222460110
Shah HL, Mishra V (2016) Hydrologic changes in Indian Subcontinental River basins (1901–2012). J Hydrometeorol 17:2667–2687. https://doi.org/10.1175/JHM-D-15-0231.1
Shah HL et al (2019) Roles of irrigation and reservoir operations in modulating terrestrial water and energy budgets in the Indian Subcontinental River basins. J Geophys Res Atmos 124:12915–12936. https://doi.org/10.1029/2019JD031059
Sharma A, Wasko C, Lettenmaier DP (2018) If precipitation extremes are increasing, why aren't floods? Water Resour Res 54(11):8545–8551. https://doi.org/10.1029/2018WR023749
Stackhouse PW, Jr., Gupta SK, Cox SJ, Zhang T, Mikovitz JC, Hinkelman LM (2011) The NASA/GEWEX surface radiation budget release 3.0: 24.5-year dataset. GEWEX News, No. 21 (1), International GEWEX Project Office, Silver Spring, MD, 10–12
Teng J et al (2012) Estimating the relative uncertainties sourced from GCMs and hydrological models in modeling climate change impact on runoff. J Hydrometeorol. https://doi.org/10.1175/JHM-D-11-058.1
Thompson JR et al (2013) Assessment of uncertainty in river flow projections for the Mekong River using multiple GCMs and hydrological models. J Hydrol. https://doi.org/10.1016/j.jhydrol.2013.01.029
Vetter T et al (2017) Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins. Clim Chang. https://doi.org/10.1007/s10584-016-1794-y
Vogel RM, Fennessey NM (1994) Flow-duration curves. I: New interpretation and confidence intervals. J Water Resour Plan Manag 120:485–504. https://doi.org/10.1061/(ASCE)0733-9496(1994)120:4(485)
Vogel RM, Fennessey NM (1995) Flow duration curves ii: a review of applications in water resources planning. J Am Water Resour Assoc 31:1029–1039. https://doi.org/10.1111/j.1752-1688.1995.tb03419.x
Wada Y, Bierkens MFP (2014) Sustainability of global water use: past reconstruction and future projections. Environ Res Lett. https://doi.org/10.1088/1748-9326/9/10/104003
Warszawski L, Frieler K, Huber V, Piontek F, Serdeczny O, Schewe J (2014) The inter-sectoral impact model intercomparison project (ISI-MIP): project framework. P Natl Acad Sci USA 111:3228–3232. https://doi.org/10.1073/pnas.1312330110
Weedon GP et al (2011) Creation of the WATCH forcing data and its use to assess global and regional reference crop evaporation over land during the twentieth century. J Hydrometeorol. https://doi.org/10.1175/2011JHM1369.1
Wilby RL (2005) Uncertainty in water resource model parameters used for climate change impact assessment. Hydrol Process. https://doi.org/10.1002/hyp.5819
Wood AW et al (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Clim Chang. https://doi.org/10.1023/B:CLIM.0000013685.99609.9e
Zhang W et al (2018) Reduced exposure to extreme precipitation from 0.5 °C less warming in global land monsoon regions. Nat Commun. https://doi.org/10.1038/s41467-018-05633-3