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Assessment of Future Hydrological Flow Regime Analysis Under Changing Climate in a Tropical River Basin

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ABSTRACT

Understanding how river flow regimes may evolve under changing climatic conditions is fundamental for sustainable water resources planning, particularly in tropical monsoon river basins where streamflow exhibits strong seasonal variability. This study presents a novel framework for assessing future hydrological flow regimes at a 10-daily timescale under near-future climate scenarios and subsequently examines the associated seasonal variability in streamflow and baseflow components. The framework was implemented in the Brahmani River Basin (39,116 km²) located in eastern India, a region characterized by pronounced monsoonal hydrology. The semi-distributed Soil Water Assessment Tool (SWAT) model was employed to simulate historical streamflow dynamics and demonstrated satisfactory performance in reproducing observed hydrological behaviour. Future climate projections for the basin were obtained from the REMO regional climate model under three Representative Concentration Pathways (RCP2.6, RCP4.5, and RCP8.5). Changes in future flow regimes were analysed using flow duration curves (FDCs) developed at a 10-daily timescale, while long-term trends in streamflow and baseflow were evaluated using the non-parametric Mann-Kendall test and Theil-Sen slope estimator. Baseflow separation was performed using the Recursive Digital Filter (RDF) method based on hydrograph recession characteristics. The results reveal a tendency towards increasing streamflow and baseflow during the near-future period (2021-2045), suggesting enhanced water availability in the basin under projected climatic conditions. By capturing hydrological variability at a finer temporal resolution, the proposed framework provides improved insights into future water availability and seasonal flow characteristics. The methodology is readily transferable to other river basins and offers a practical basis for climate-resilient water resources planning and management in monsoon-dominated regions.

Keywords: Baseflow; Climate Scenarios; Flow duration curve; Hydrologic regime; SWAT

INTRODUCTION

Hydrological flow regimes govern the ecological integrity, water availability, and socio-economic sustainability of river basins. The magnitude, timing, frequency, duration, and rate of change of streamflow collectively determine the functioning of aquatic ecosystems, groundwater recharge processes, agricultural productivity, and the resilience of water resources systems to climatic extremes[1,2]. In tropical monsoon river basins, where a substantial fraction of annual runoff is concentrated within a few months of intense rainfall, even modest alterations in precipitation and temperature patterns can substantially modify the seasonal distribution of river flows. Consequently, understanding the future evolution of hydrological flow regimes under a changing climate[3,4] has become a central challenge in sustainable water resources planning and management.

Climate change is expected to intensify the global hydrological cycle by altering precipitation characteristics, evapotranspiration demands, and catchment-scale runoff generation processes[5] (*Sixth Assessment Report — IPCC*). These changes rarely manifest uniformly across regions, resulting in considerable spatial variability in water availability and hydrological extremes. In many parts of the world, increasing temperatures and changing precipitation regimes have already been linked with shifts in flood frequency, prolonged low-flow conditions, and altered river flow seasonality[7]; [8]. Such hydrological alterations have direct implications for ecosystem functioning, irrigation, hydropower generation, and environmental flow management, particularly in monsoon-dominated river basins. Changes in high flows can increase flood risks and geomorphic disturbances, whereas modifications in low flows may threaten water supply reliability and ecological sustainability [1]. Among the available assessment approaches, the Indicator of Hydrologic Alteration (IHA) framework has become one of the most widely adopted methods for quantifying deviations from natural flow conditions and evaluating their ecological implications[9].

Alongside climate variability, human interventions have emerged as equally important drivers of hydrological change. Reservoir construction, river regulation, groundwater abstraction, urbanization, and land-use modifications can substantially modify downstream flow characteristics by altering the timing and magnitude of streamflow release[10]. In regulated river basins, reservoir operations often dampen flood peaks, augment dry-season flows, and modify the natural seasonality. Although previous studies have shown that reservoir regulation can exert impacts comparable to climate change, its representation in future hydrological impact assessments remains limited, introducing additional uncertainty into projected flow regimes[10]. Baseflow, representing the delayed groundwater contribution that sustains streamflow during dry periods, is another critical component of basin hydrology. Despite the availability of several baseflow separation techniques, future assessments of baseflow under changing climatic conditions remain limited, particularly in tropical monsoon river basins [11]; [12].

Reliable assessment of future hydrological regimes requires realistic climate projections. While Global Climate Models (GCMs) provide valuable information on future climatic conditions, their coarse spatial resolution limits direct application at the river basin scale. Regional Climate Models (RCMs), driven by GCM boundary conditions, provide improved representation of regional climatic processes and have therefore become widely used in hydrological impact assessments [13]; [14]. However, most previous studies have focused on monthly, seasonal, or annual timescales, which are often inadequate for operational water resources management. Sub-monthly assessments are better suited for reservoir operation, irrigation scheduling, and environmental flow allocation, particularly in monsoon river basins where hydrological conditions evolve rapidly. Accordingly, a 10-daily framework provides a practical balance between highly variable daily observations and coarse monthly averages, enabling more realistic assessment of future water availability.

Dependable flow regimes provide valuable insights into hydrological variability and water security[15]. High (Q_{10}), median (Q_{50}), and low (Q_{90}) flows characterize wet, average, and dry hydrological conditions, respectively, and are essential for flood management, reservoir operation, and drought planning. Assessing their future evolution is therefore critical for climate adaptation and sustainable water resources management. Non-parametric methods such as the Mann-Kendall test and Theil-Sen slope estimator are widely used for detecting hydrological trends because of their robustness to non-normal data and outliers[16]; [17]. However, applications of these methods to future 10-daily flow regimes remain extremely limited, despite their considerable relevance for infrastructure planning, reservoir operation, and climate adaptation policies.

In light of the above discussions, three major research gaps can be identified. First, relatively few climate change impact studies explicitly incorporate reservoir regulation effects within their modelling conceptualization framework while assessing downstream hydrological responses. Second, the predominance of monthly and seasonal analyses limits the practical applicability of projected hydrological changes for operational decision-making, highlighting the need for finer temporal resolutions such as 10-daily assessments. Third, the inherent trends associated with future 10-daily flow regimes have received little attention despite their importance for long-term planning and adaptation strategies.

To address these gaps, the present study investigates the impacts of future climate change on hydrological flow regimes in a tropical monsoon river basin using a high-resolution temporal framework. Specifically, this study

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seeks to answer the following research questions: (1) How will future climate change influence the 10-daily high-flow (Q_{10}), median-flow (Q_{50}), and low-flow (Q_{90}) regimes of the basin? (2) To what extent will future hydrological regimes deviate from historical conditions? and (3) What are the implications of climate change for major water balance components, including streamflow and baseflow dynamics? Accordingly, the objectives of this study are: (i) to analyse the spatio-temporal variability of 10-daily flow regimes corresponding to Q_{10}, Q_{50}, and Q_{90} dependable flow conditions using moving climatic windows; and (ii) to evaluate the influence of future climate change on streamflow, baseflow, and associated hydrological components within a tropical monsoon river basin.

Study Area and Pedo-Hydrologic Database

Site Description

The Brahmani River, one of the major east-flowing rivers of India, originates in the eastern plateau region and traverses approximately 799 km before draining into the Bay of Bengal. The Brahmani River Basin (BRB), covering an area of 39,116 km², lies between 20°28′–23°35′ N and 83°52′–87°30′ E in eastern India, shown in the Figure. 1. The basin experiences a typical sub-humid tropical monsoon climate, receiving an average annual rainfall ranging from about 1200 mm in the southern coastal plains to nearly 1700 mm in the northern plateau region,

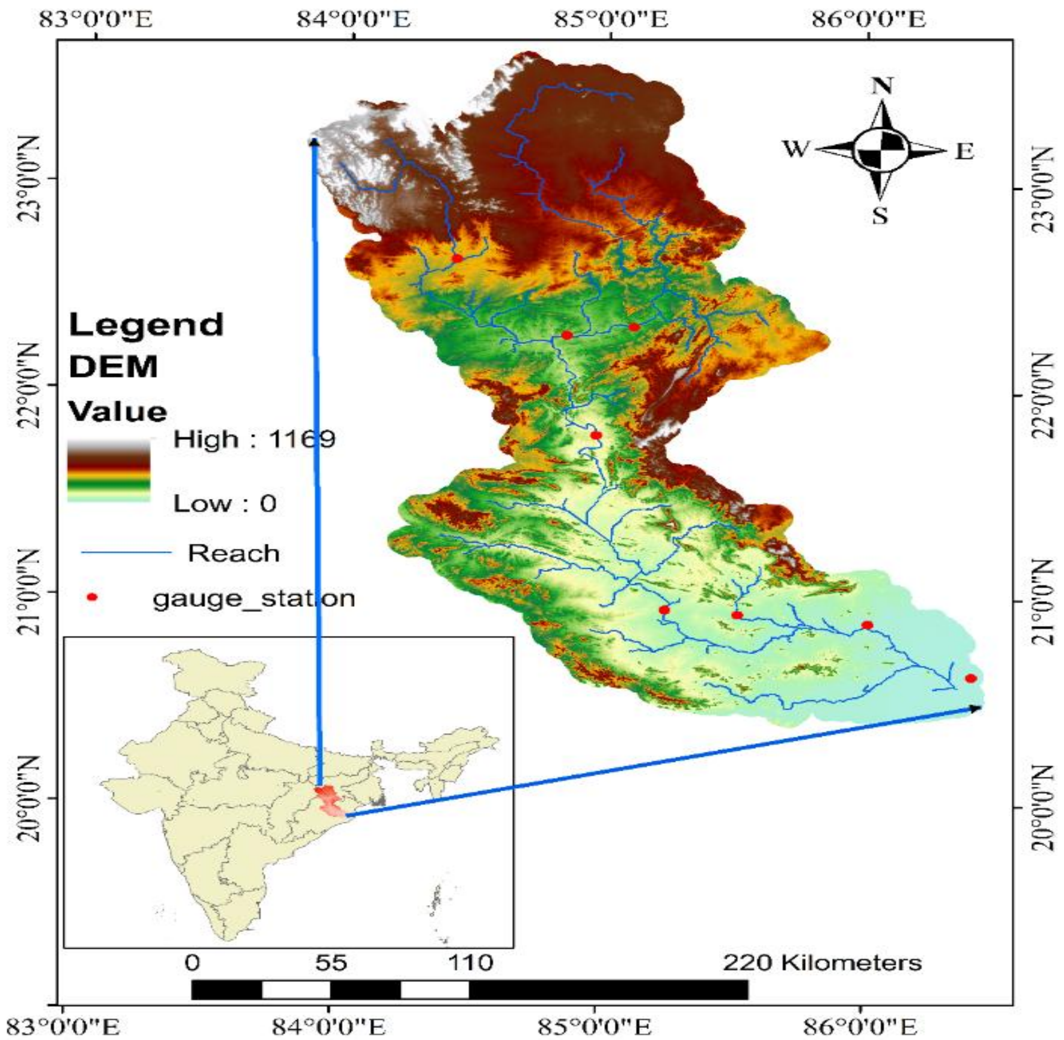

Figure 1. Map of the Brahmani River Basin of the study area.

with nearly 78% of the rainfall occurring during the southwest monsoon season (June–September). Mean temperatures vary considerably across seasons, with winter minima of 10–15°C and summer maxima reaching 34–42°C. The basin is characterized by diverse soil types, including red, yellow, black, sandy loam, and coastal

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sandy soils, supporting a heterogeneous landscape dominated by agriculture (52%) and forests (38%), along with a small fraction of water bodies (~3%). Owing to the abundance of mineral resources such as coal, iron ore, and limestone, the basin has also undergone substantial industrial development. Hydrological conditions in the lower basin are strongly influenced by the Rengali reservoir, the second-largest reservoir in Odisha after the Hirakud reservoir. Constructed primarily for irrigation and hydropower generation, the reservoir plays an important role in regulating downstream flows, particularly during low-flow periods, while also moderating monsoon flood peaks.

Data Sources

The SWAT-reservoir model was developed using a 90 m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM), a 56 m land use/land cover (LULC) map for the year 2007 obtained from the National Remote Sensing Centre (NRSC), and a 1 km soil map derived from the Food and Agriculture Organization (FAO) soil database. A basin slope map was generated using user-defined slope classes. Daily precipitation and minimum and maximum temperature data for the period 2000-2018 were obtained from the India Meteorological Department (IMD), while observed streamflow records at Jaraikela, Gomlai, and Jenapur stations were collected from the Central Water Commission (CWC) for model calibration and validation. Reservoir characteristics, including storage-area relationships and daily reservoir operation data for the Rengali Reservoir, were obtained from the Odisha Watershed Development Mission (OWDM) to represent reservoir regulation effects in the hydrological simulations.

METHODOLOGY

Swat-Reservoir Model: The Hydrological Model Framework

The SWAT was employed to simulate the hydrological processes of the Brahmani River Basin. The basin was delineated into 115 sub-basins and further discretized into 2,561 Hydrologic Response Units (HRUs) based on land use, soil, and slope characteristics. Five slope classes (0-2%, 2-8%, 8-16%, 16-33%, and >33%), 12 land use categories, and seven soil types were used to represent basin heterogeneity. Surface runoff was estimated using the SCS Curve Number method, while streamflow generation followed the standard SWAT water balance approach[18].

Sensitivity And Uncertainty Analysis

The sensitivity and uncertainty analyses were performed using the Sequential Uncertainty Fitting Version 2 (SUFI-2) algorithm implemented in SWAT-CUP[19]. A global sensitivity analysis (GSA) was employed to identify the most influential model parameters governing streamflow simulation. Model uncertainty was evaluated using the 95% prediction uncertainty (95PPU), with the P-factor and R-factor adopted as the performance indicators. Following Dash et al. (2020)[14], P-factor values >0.7 and R-factor values <1.5 were considered acceptable for daily streamflow simulations. A three-year warm-up period (1997-1999) was used to establish the initial hydrological conditions, followed by model calibration (2000-2012) and validation (2013-2018). The optimized parameter values obtained from calibration were subsequently incorporated into the SWAT model for future simulations.

Future Flow Regime Assessment

Climate Scenarios and Bias Correction

Future climate projections were obtained from the REgional MOdel (REMO2009) developed by the Max Planck Institute for Meteorology, Germany. Daily precipitation and minimum and maximum temperature projections under RCP2.6, RCP4.5, and RCP8.5 were extracted for 23 grid locations covering the Brahmani River Basin. The historical period (2006-2018) was used for retrospective evaluation, while future simulations (2021-2100) were analysed for the near-future (2021-2045), mid-future (2046-2070), and far-future (2071-2100) periods. Systematic biases in the climate projections were corrected using the Cumulative Distribution Function

Transform (CDF-t) method, which preserves the statistical characteristics of the projected climate variables while reducing model bias[20].

Future Streamflow Simulation

The bias-corrected climate projections were used to drive the calibrated SWAT-reservoir model for future streamflow simulations. Land use, soil, topography, and reservoir operation were assumed to remain unchanged throughout the simulation period to isolate the impacts of climate change on basin hydrology.

Baseflow Separation

Baseflow was separated from the simulated streamflow using the Recursive Digital Filter (RDF) method[21]. A filter parameter ($\alpha = 0.925$) was selected based on trial simulations and applied consistently to both historical and future streamflow series to derive comparable baseflow estimates.

Future flow regimes analysis using flow-duration curve approach

Future streamflow regimes were evaluated using the Flow Duration Curve (FDC) approach at a 10-daily timescale for the Jaraikela, Gomlai, and Jenapur stations. Daily streamflow was aggregated into three consecutive 10-day periods (I, II, and III) for each month to minimise short-term variability while preserving seasonal flow characteristics. Six overlapping 30-year moving windows with a 10-year interval (2021-2050 to 2071-2100) were constructed to capture the temporal evolution of future hydrological regimes.

Considering the averaged value of consecutive 10-daily streamflow data as one set, each month can be expressed as a set of three individual values. For example, January month can be expressed as Jan-I (averaged of first ten consecutive daily data), Jan-II (averaged of next ten continuous daily data), Jan-III (averaged of remaining data of the month). For understanding, these Jan-I, Jan-II are referred as sub-monthly period throughout the study. Expressing a month in this way will decrease the daily noise in the data due to the effect of averaging during monsoon season. Moreover, it stabilizes the fluctuations in the streamflow data during the lean period, particularly those days having high and un-usually high precipitations.

Then six windows of thirty years of sub-monthly data have been grouped with an interval of ten years. First window contains thirty years of sub-monthly data from 2021 to 2050. The next window is started with an interval of ten years from the starting of the previous window, i.e., 2031 to 2060 and so on. A window containing thirty years represents a standard climatic cycle. Ten years of interval has been taken to capture the decadal variability of streamflow components due to the effect of natural variation in biota in conjunction with the gradual climatic alterations. This approach may stand as unique, since not being explored in any past available literatures.

Using the Weibull's technique, plotting position has been computed for the streamflow time series of same sub-monthly stage within each window. Then flow value for each sub-monthly stage has been computed from the plotted FDC corresponding to 10th percentile, 50th percentile, and 90th percentile of the time, signified as Q_{10}, Q_{50}, and Q_{90}, respectively. Each window's sub-monthly frames of Q_{10}, Q_{50}, and Q_{90} value are subjected to Theil-Sen's slope analysis for the computation of percent of change with respect to base period.

Criteria for model performance evaluation

The performance of the SWAT model was evaluated using the Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2), root mean square error (RMSE), and percent bias (PBIAS), which are widely used to assess the agreement between observed and simulated streamflow. Baseflow simulation was further evaluated using the Kling-Gupta Efficiency (KGE), which simultaneously accounts for correlation, bias, and variability between observed and simulated data[22].

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RESULTS AND DISCUSSION

Calibration and Validation of Daily Scale Streamflow Simulation

The SWAT model was calibrated for the period 2000-2012 and validated for 2013-2018 at the Jaraikela, Gomlai, and Jenapur gauging stations, representing the upper, middle, and lower reaches of the basin, respectively. Prior to calibration, a SWAT-CUP based Latin Hypercube One-factor-At-a-Time (LH-OAT) sensitivity analysis was performed to identify the dominant parameters governing basin-scale runoff generation (Table 1). Based on the

Table 1. Best-fitted value of SWAT model parameters with sensitivity analysis value

No	Variation	Parameter	Definition	Fitted value	Sensitivity Analysis	
					t-statistics	**P-value**
1	Relative	CN2	SCS curve number (condition II)	0.13	-1.57	0.115
2	Absolute	SOL_AWC	Soil layer available water content (mm)	0.33	1.29	0.19
3	Absolute	GW_DELAY	Groundwater delay (days)	66	0.05	0.95
4	Absolute	GWQMN	Threshold water level in shallow aquifer (mm H_2O)	1432	-0.31	0.75
5	Absolute	GW_REVAP	Revap coefficient	0.03	3.25	0.74
6	Absolute	REVAPMN	Threshold water level in shallow aquifer (mm H_2O)	223	1.25	0.36
7	Absolute	RCHRG_DP	Aquifer percolation constant	0.03	-0.51	0.95
8	Absolute	ESCO	Soil evaporation compensation coefficient	0.43	0.05	0.85
9	Absolute	EPCO	Plant uptake consumption factor	0.06	-0.08	0.93
10	Relative	SOL_K	Soil hydraulic conductivity (cm/h)	0.26	-0.29	0.76
11	Absolute	ALPHA_BF	Baseflow recession constant	0.24	0.148	0.88
12	Absolute	CH_K2	Muskingum routing coefficient	236	-0.0001	0.98
13	Absolute	CH_N2	Manning's "n" value for the main channel	0.028	1.5	0.62

significance of the t-statistics and associated p-values (<0.05), ten out of the initially selected eighteen parameters were identified as highly sensitive and subsequently included in the calibration process. Among them, the curve number parameter (CN2) and available soil water capacity (SOL_AWC) emerged as the two

Table 2. Statistics for daily streamflow simulation in calibration and validation phase

Location	Calibration						Validation					
	P-factor (-)	R-factor (-)	NSE (-)	R^2 (-)	RMSE (m^3/s)	PBIAS (%)	P-factor (-)	R-factor (-)	NSE (-)	R^2 (-)	RMSE (m^3/s)	PBIAS (%)
Jaraikela	0.59	0.71	0.63	0.65	172.30	-38.20	0.63	0.69	0.64	0.68	139.07	-29.40
Gomlai	0.71	0.69	0.71	0.76	405.22	-49.10	0.61	0.72	0.67	0.72	404.06	-49.30
Jenapur	0.82	0.67	0.73	0.75	466.23	-24.20	0.89	0.68	0.74	0.74	413.22	-20.70

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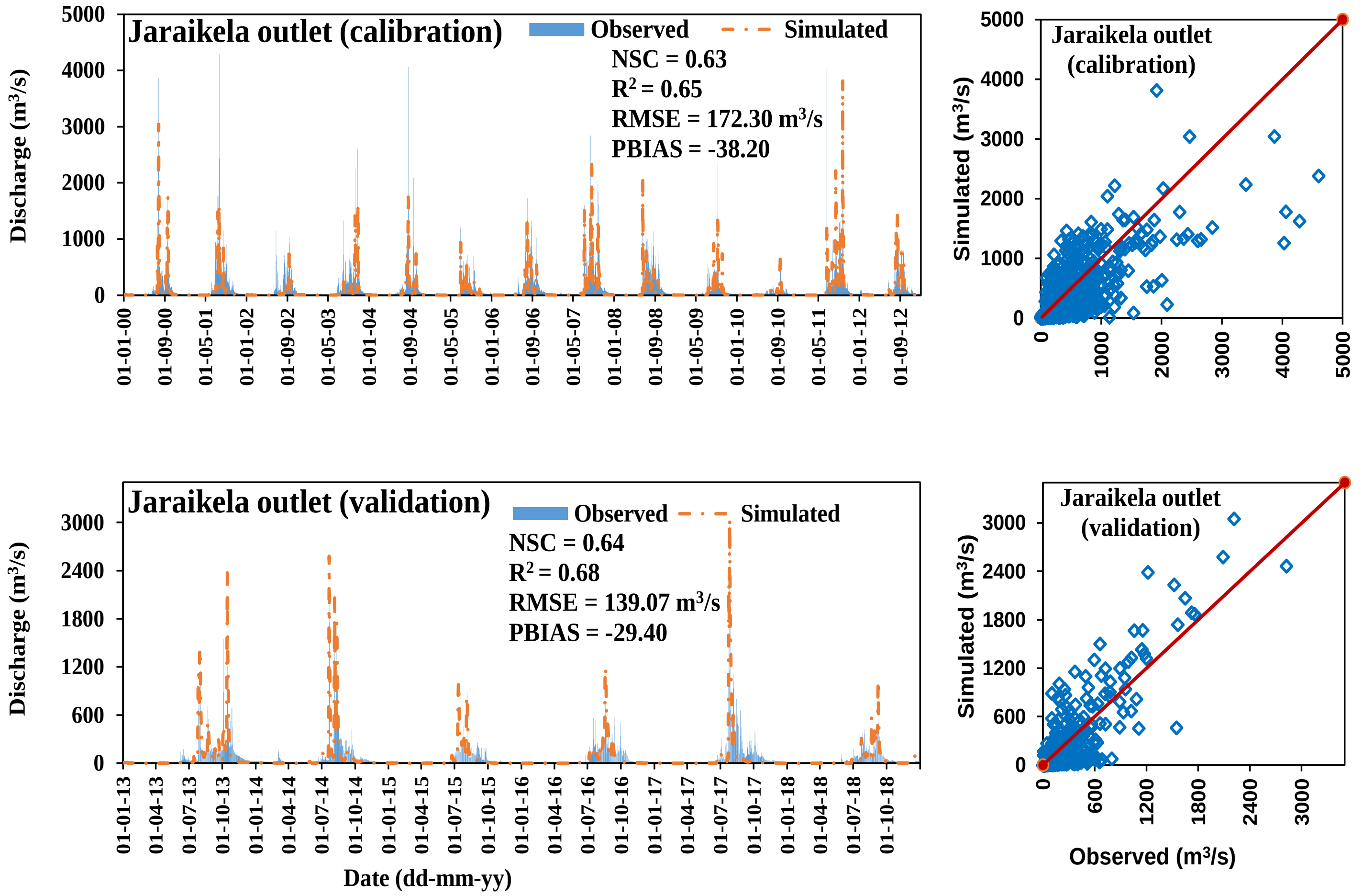

Figure 2. Comparison of observed (CWC) and SWAT-simulated daily streamflow through hydrographs and scatter plots during the calibration (2000–2012) and validation (2013–2018) periods at Jaraikela station.

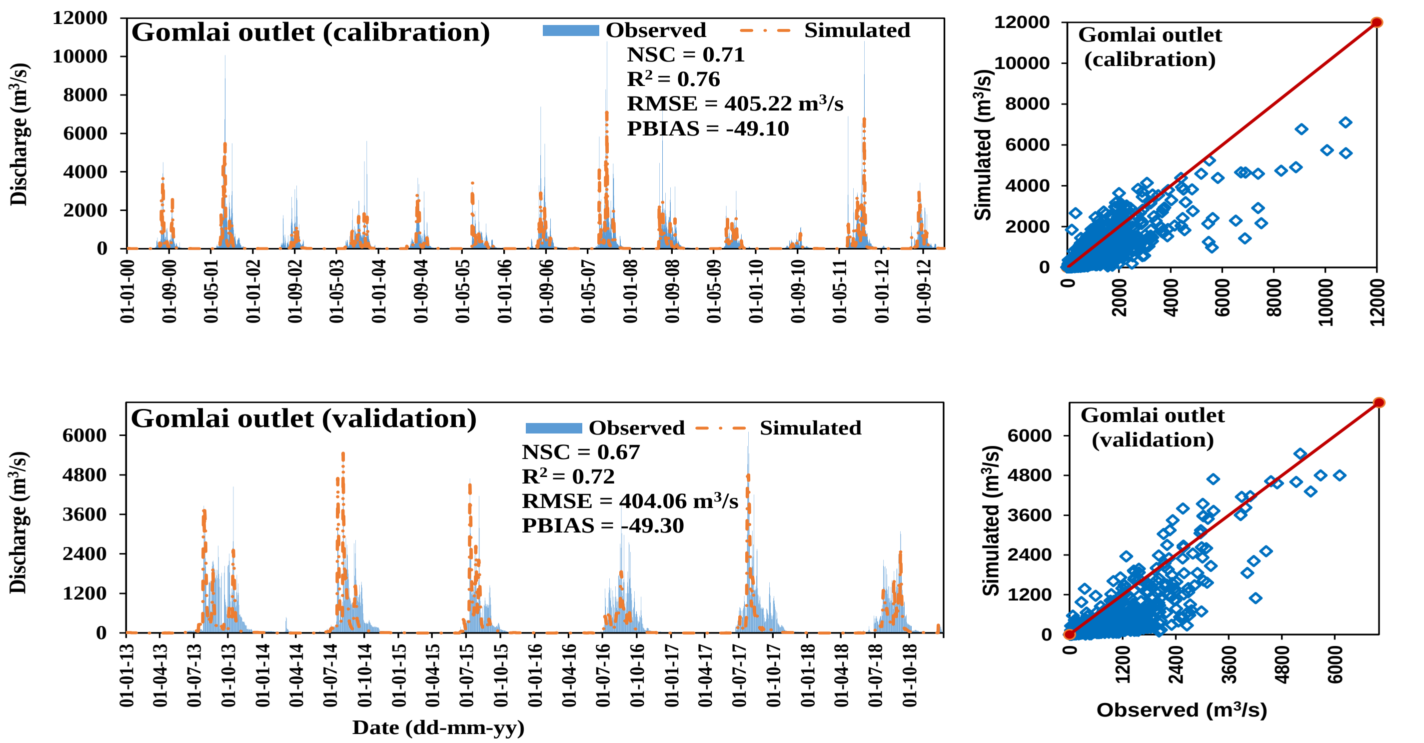

Figure 3. Similar to Figure 2, but for Gomlai station.

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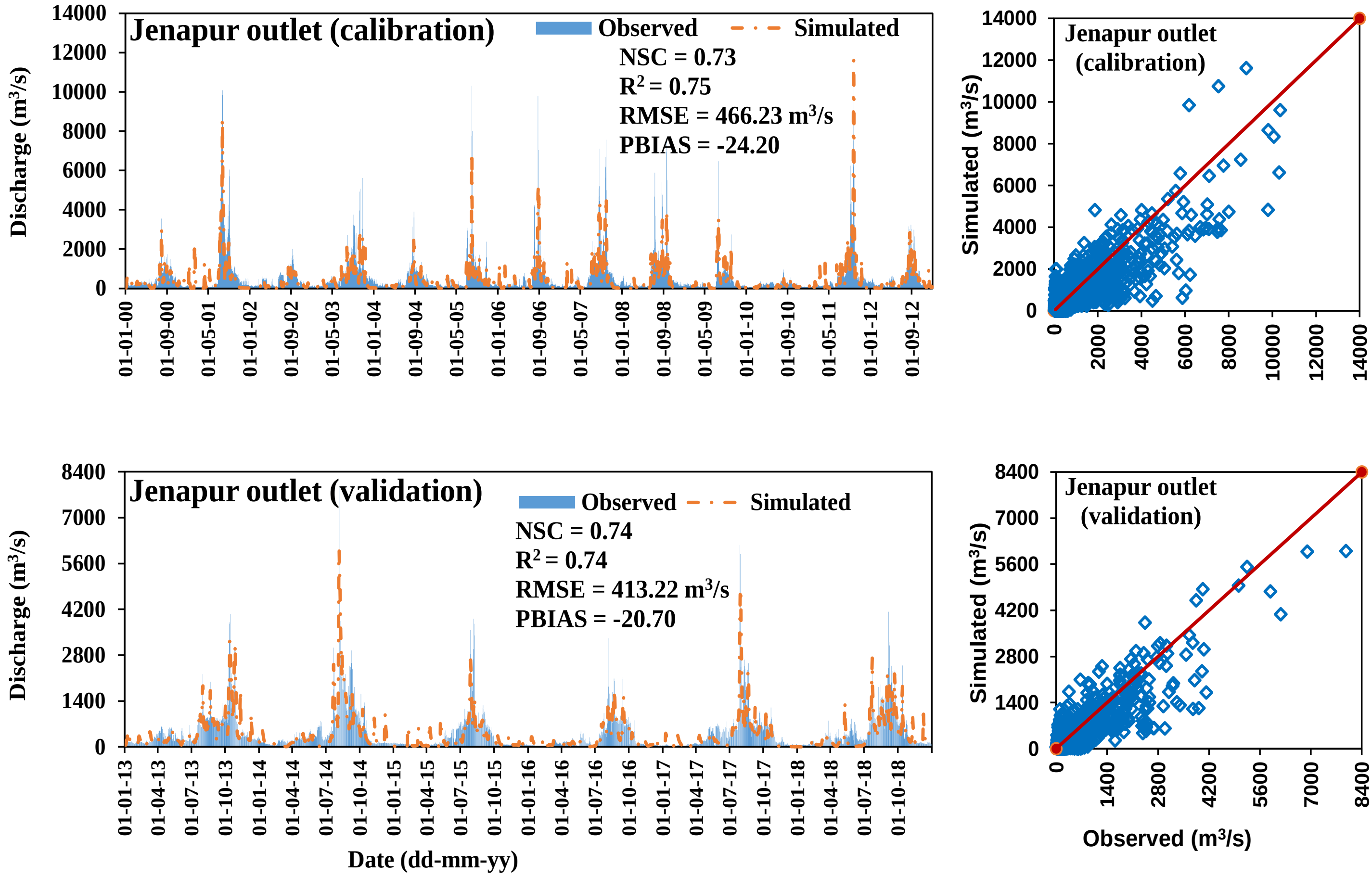

Figure 4. Similar to Figure 2, but for Jenapur station.

most influential parameters, highlighting the combined control of channel routing and soil moisture dynamics on runoff generation in the basin. The relatively higher sensitivity of the curve number parameter (CN2) suggests a comparatively higher influence of surface characteristics on streamflow response. The calibrated parameter values further indicate moderate channel hydraulic conductivity and limited deep aquifer recharge, while the estimated lateral flow travel time reflects a moderately delayed subsurface response. Overall, the results suggest that both surface and subsurface hydrological processes contribute substantially to the runoff generation mechanism in the basin. The performance statistics during calibration and validation are summarized in Table 2, while the corresponding hydrographs are presented in Figure 2-4. The model reproduced the observed daily streamflow satisfactorily across all three stations. During calibration, NSE values ranged from 0.63 at Jaraikela to 0.73 at Jenapur, while the corresponding R^2 values varied between 0.65 and 0.75. Similar performance was observed during the validation period, with NSE values ranging from 0.64 to 0.72 and R^2 values from 0.68 to 0.77. Model performance consistently improved from the upstream station (Jaraikela) towards the basin outlet (Jenapur), indicating enhanced simulation accuracy at larger spatial scales and under regulated flow conditions. The negative PBIAS values obtained at all stations indicate a tendency to underestimate peak flows, a commonly reported limitation in SWAT applications for monsoon-dominated river basins (Dash et al., 2020). Nevertheless, the overall model performance remained within acceptable limits for daily streamflow simulation and was considered adequate for future climate impact assessments. The uncertainty analysis based on the SUFI-2 framework demonstrated satisfactory predictive capability across all stations. The P-factor values indicated that between 59% and 89% of the observed streamflow data were enclosed within the 95% prediction uncertainty (95PPU) band, while the corresponding R-factor values remained within acceptable ranges (Table 2). The best uncertainty performance was observed at the Jenapur station, where 89% of the observed flows were captured with the lowest uncertainty band thickness (R-factor = 0.67). Overall, the uncertainty estimates confirm the robustness of the calibrated model and support its application for investigating future changes in streamflow, baseflow, and other hydrological fluxes.

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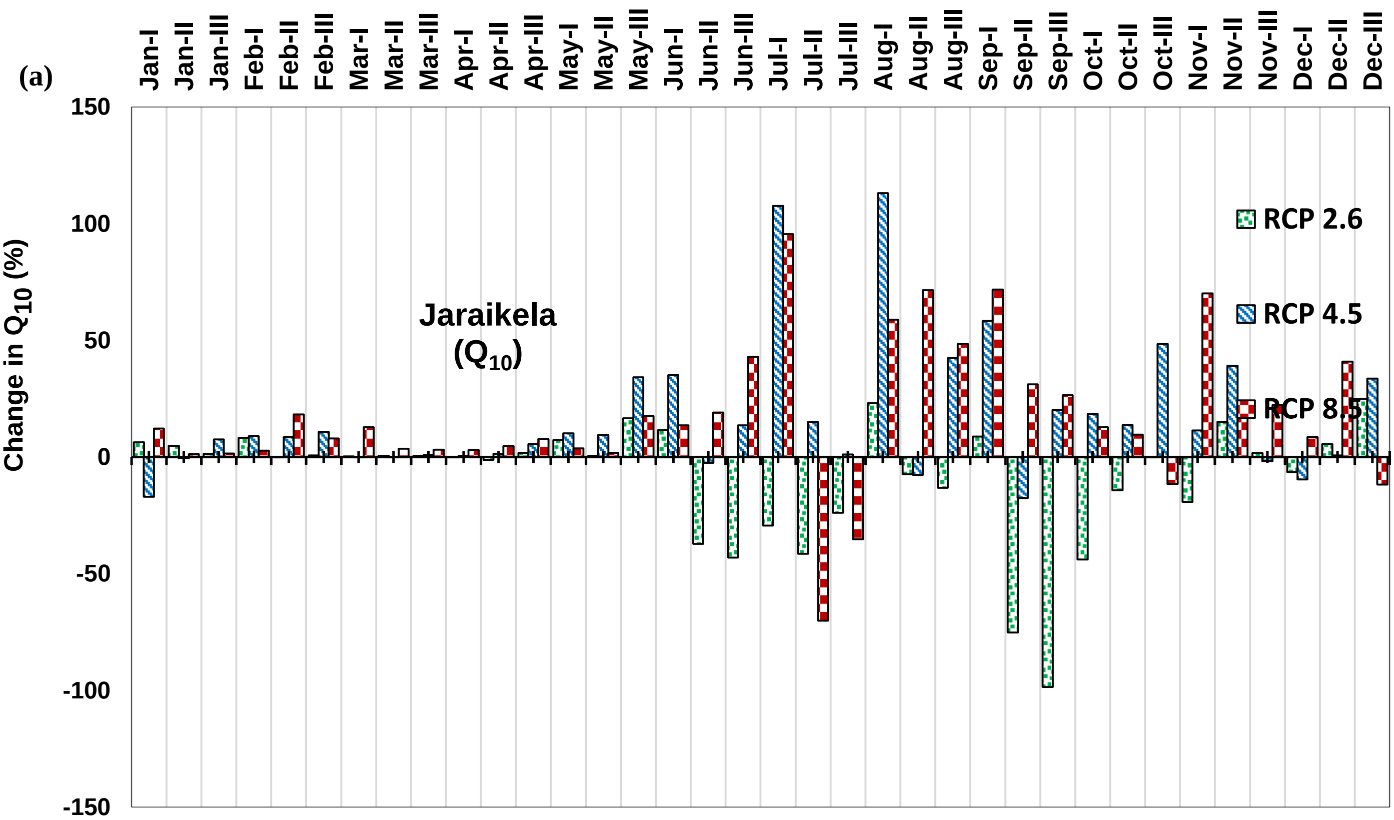
Alteration of Future Streamflow Regimes

The projected changes in high (Q_{10}), median (Q_{50}), and low (Q_{90}) flow regimes relative to the baseline period (2000-2018) at a 10-daily timescale are summarized in Table 4 and illustrated in Figure 5-7. The results reveal substantial intra-seasonal variability in future flow regimes, with the largest deviations occurring during the monsoon season. Here, monsoon and non-monsoon season are indicated as M, Non-M respectively in Table 4. At the upstream Jaraikela station, monsoon flows exhibit considerable sensitivity to future climate forcing. Streamflow changes under RCP2.6 and RCP4.5 range from substantial reductions to pronounced increases, reflecting increased hydrological variability under future climatic conditions. In contrast, RCP8.5 generally exhibits comparatively smaller deviations in low-flow conditions, suggesting a relatively stable dry-season response despite stronger climatic forcing.

Table 4. 10-daily flow regime matrix for future climate scenarios.

RCPs / Stations		RCP 2.6		RCP 4.5		RCP 8.5	
		Non-M(%)	M(%)	Non-M(%)	M(%)	Non-M(%)	M(%)
Jaraikela	High	-19.28 to 24.92	-98.54 to 22.98	-17.08 to 39.12	-17.6 to 113.1	-11.82 to 40.86	-70.15 to 95.45
	Med	-1.15 to 0.11	-12.5 to 18.14	-0.65 to 2.55	-5.31 to 16.6	0.19 to 2.19	-0.36 to 36.37
	Low	-19.28 to 24.92	-98.54 to 22.98	0.12 to 1.5	-3.03 to 7.51	0.34 to 1.34	-8.55 to 2.92
Gomlai	High	-49.03 to 40.88	-239.98 to 43.87	-27.03 to 90.06	-82.85 to 212.35	-3.08 to 117.26	-218.64 to 110.76
	Med	-2.9 to 2.65	-63.4 to 6.91	-0.27 to 7.96	-23.38 to 40.9	2.69 to 8.64	-31.71 to 100.77
	Low	-49.03 to 40.88	-239.97 to 43.88	0.32 to 2.88	-11.34 to 23.79	0.13 to 3.54	-19.16 to 3.63
Jenapur	High	-25.51 to 51.66	-96.32 to 84.67	-22.51 to 87.26	-280.73 to 118.47	-147.12 to 204	-51.17 to 232.14
	Med	-41.16 to 4.96	-64.41 to 32.10	-0.79 to 15.24	-27.64 to 35.5	-6.45 to 32.65	-21.4 to 90.15
	Low	-25.52 to 20.74	-175.95 to 84.67	-2.25 to 22.35	-20.35 to 34.9	-0.001 to 40.09	-27.434 to 46.38



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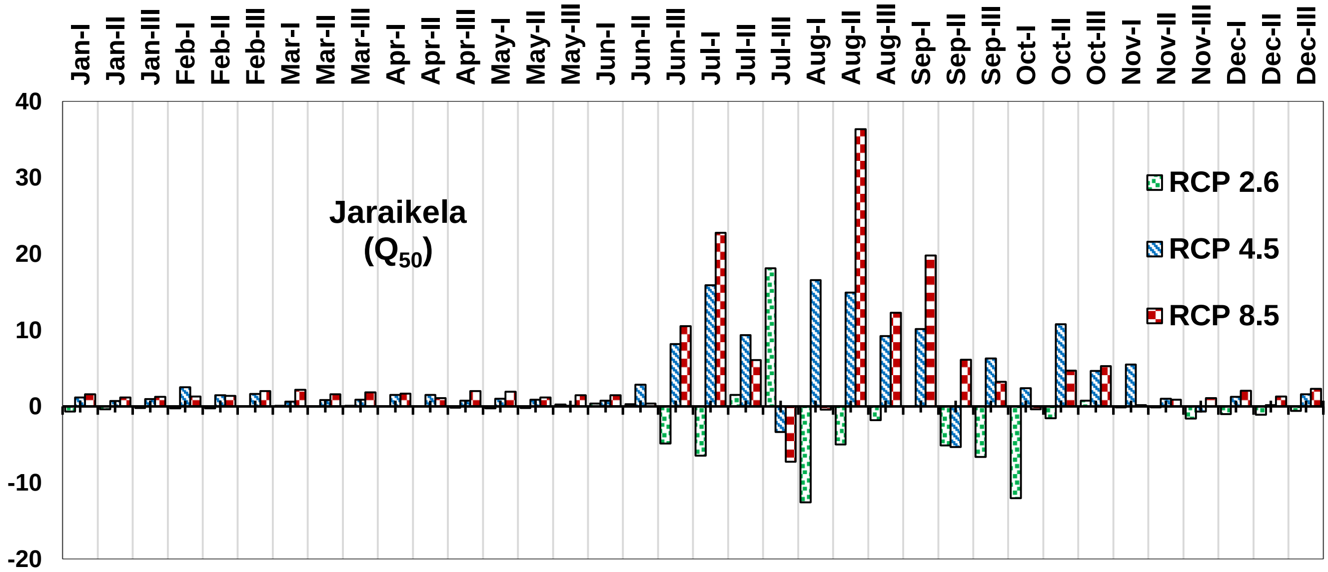
(b)



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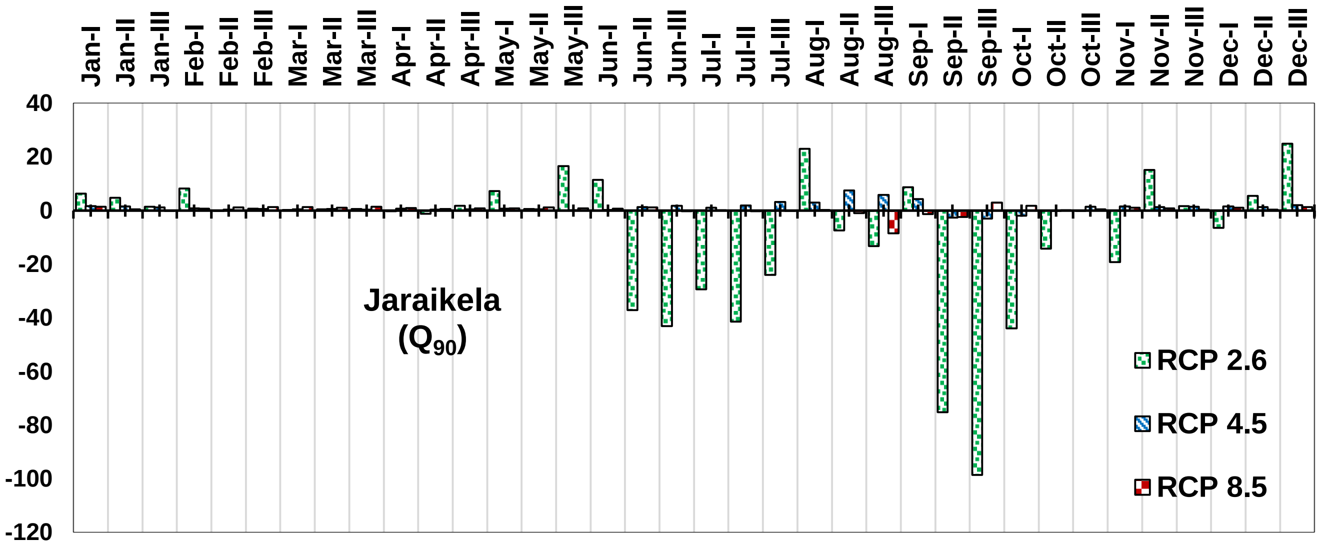
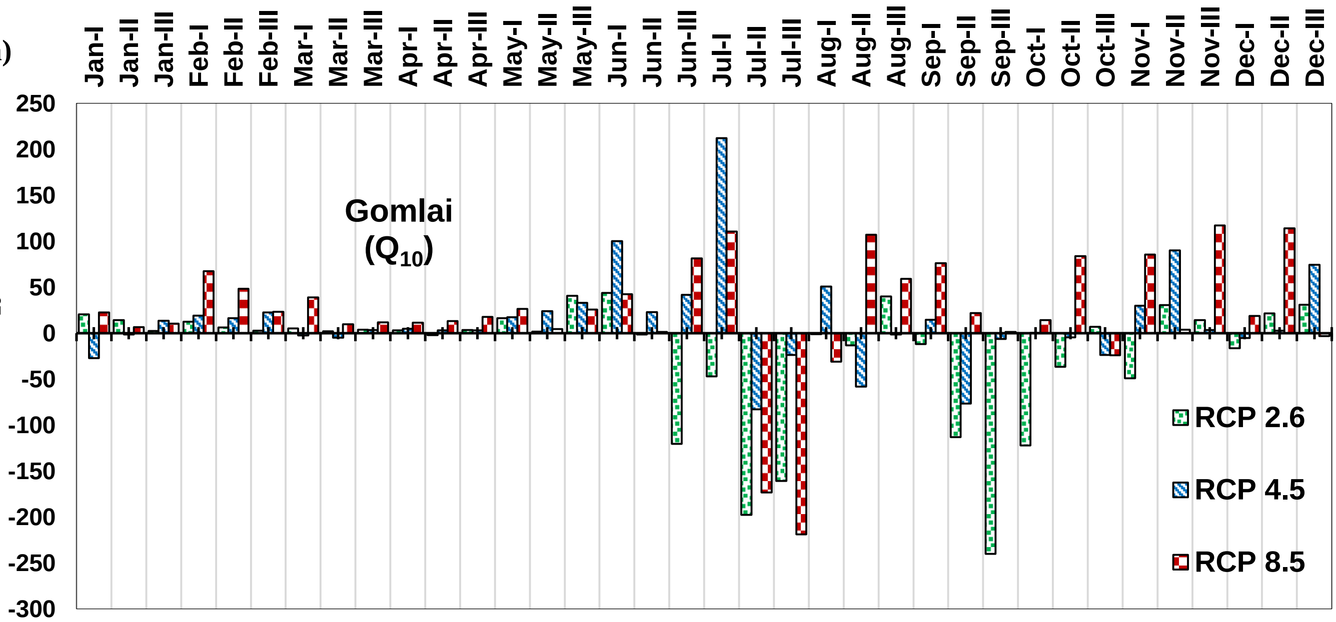


Figure 5. Temporal evolution of (a) Q_{10}, (b) Q_{50}, and (c) Q_{90} flow regimes across successive 30-year moving windows at a 10-daily timescale for the Jaraikela station.

(a)



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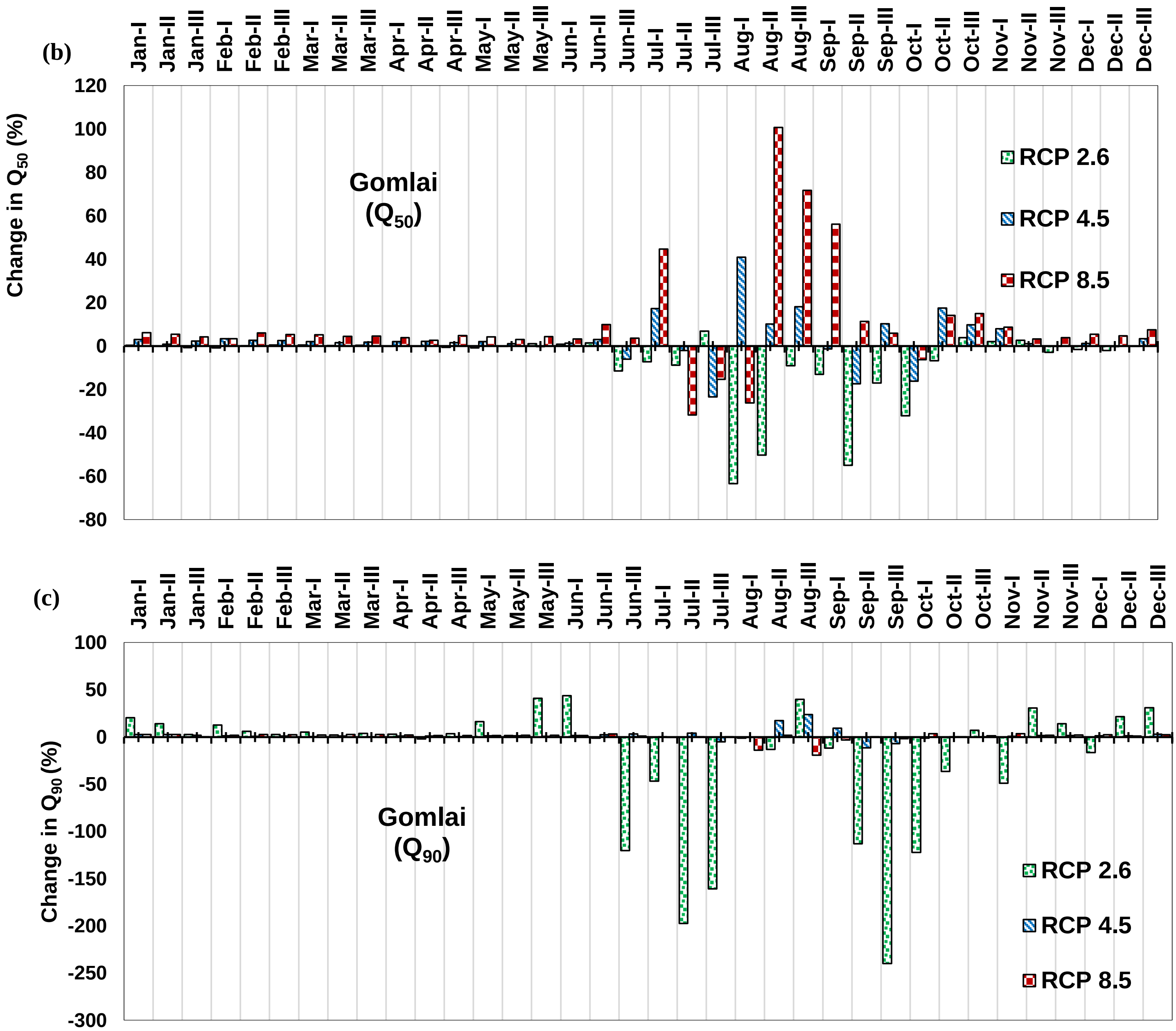
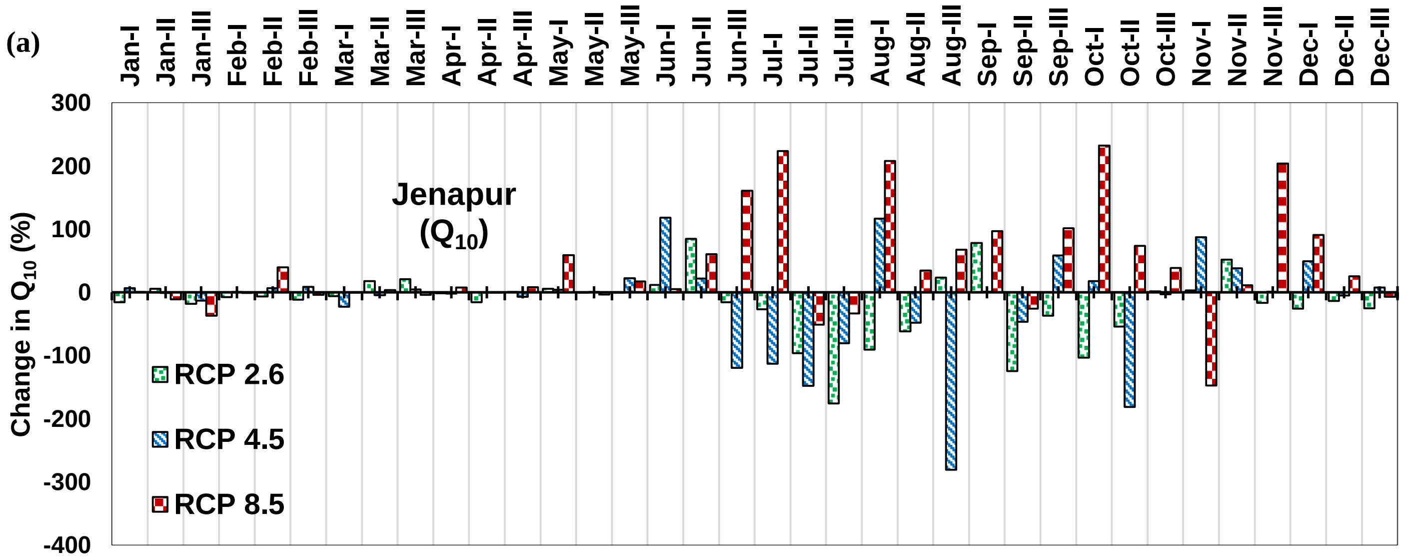


Figure 6. Similar to Figure 5, but for Gomlai station.



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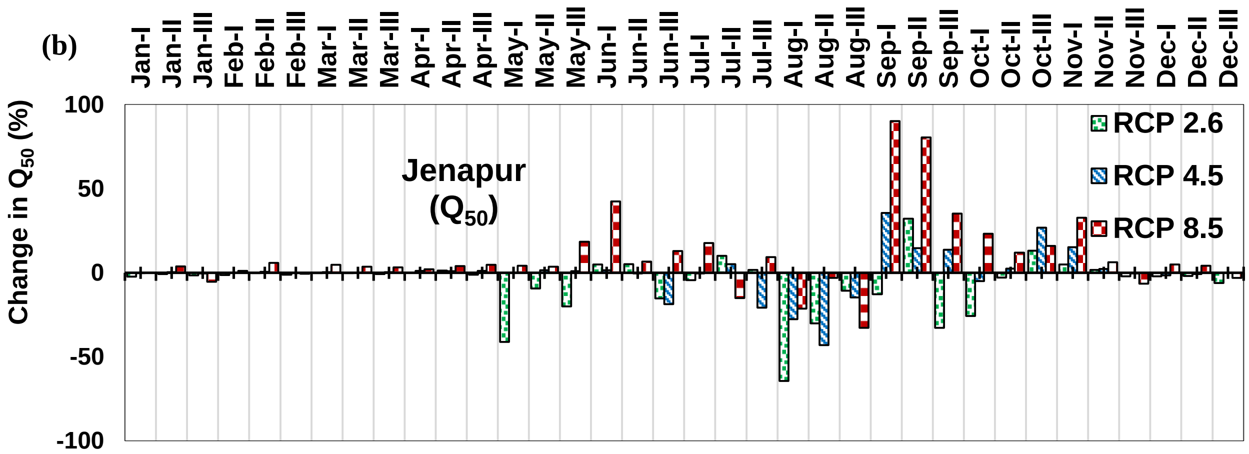

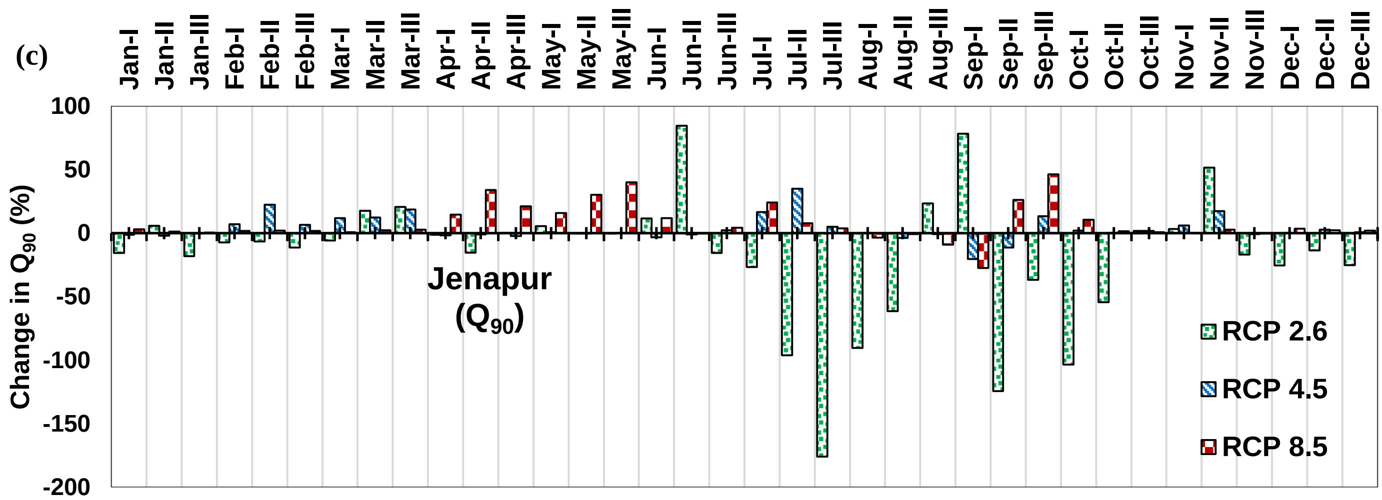

Figure 7. Similar to Figure 5, but for Jenapur station.

The projected alterations are considerably more pronounced for high flows than for median and low flows across all climate scenarios. While August is characterized by enhanced streamflow availability under RCP2.6 and RCP4.5, a noticeable decline in flows is projected during September, indicating a possible shift in the timing and concentration of monsoonal runoff. Such changes may have important implications for reservoir inflows, flood management, and agricultural water availability. At the downstream Jenapur station, future changes in flow regimes become increasingly evident. The substantial increase in Q_{50} during mid-August under certain climate scenarios suggests improved soil moisture conditions and enhanced water availability for downstream irrigation demands. However, the projected amplification of Q_{10} flows under RCP8.5 also indicates an elevated risk of extreme flood events, emphasizing the importance of adaptive reservoir operation strategies for mitigating future hydrological extremes.

Most previous climate change impact assessments have evaluated streamflow at monthly or seasonal timescales, which are adequate for identifying broad hydrological trends but often fail to capture the intra-seasonal variability that governs day-to-day reservoir operation and water allocation. In contrast, the proposed 10-daily moving-window framework resolves short-term variations in dependable flow regimes, enabling the identification of critical shifts within the monsoon season. For instance, the projected increase in streamflow during August followed by a decline in September would have been largely obscured in conventional monthly analyses. Similarly, the pronounced increase in Q_{50} during mid-August and the amplification of Q_{10} under RCP8.5 provide actionable information for irrigation scheduling, reservoir storage optimization, and flood preparedness. By capturing the progressive evolution of flow regimes through overlapping climatic windows, the proposed framework offers a more operationally relevant assessment of future hydrological changes than traditional fixed-period analyses, thereby supporting adaptive reservoir management and climate-resilient water resources planning.

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Overall, the analysis suggests a tendency towards increasing high and median flows, whereas low-flow conditions exhibit comparatively limited changes across the basin. The persistence of relatively stable non-monsoon flows further indicates that future hydrological alterations in the Brahmani River Basin are likely to be dominated by intensified monsoon dynamics rather than substantial changes during the dry season. These findings collectively point towards a future characterized by stronger seasonal contrasts and increased concentration of runoff during the monsoon months.

Relative Changes in Future Baseflow Characteristics

The performance of SWAT in reproducing baseflow dynamics was evaluated using the Kling-Gupta Efficiency (KGE) metric. Model performance improved progressively from the upstream to downstream locations, with KGE values increasing from Gomlai (0.21) and Jaraikela (0.22) to Jenapur (0.52), indicating comparatively complex groundwater-streamflow interactions in the upstream catchments and improved representation of flow regulation effects in the downstream reach. The observed baseflow contribution was highest during September (633.63 m^3/s) and lowest during February (66.49 m^3/s), whereas the simulated baseflow exhibited a slightly earlier seasonal response, with peak and minimum contributions occurring during August and January, respectively. The earlier response was more evident in the upstream stations, while the downstream reach showed a relatively moderated and delayed baseflow behaviour owing to reservoir regulation.

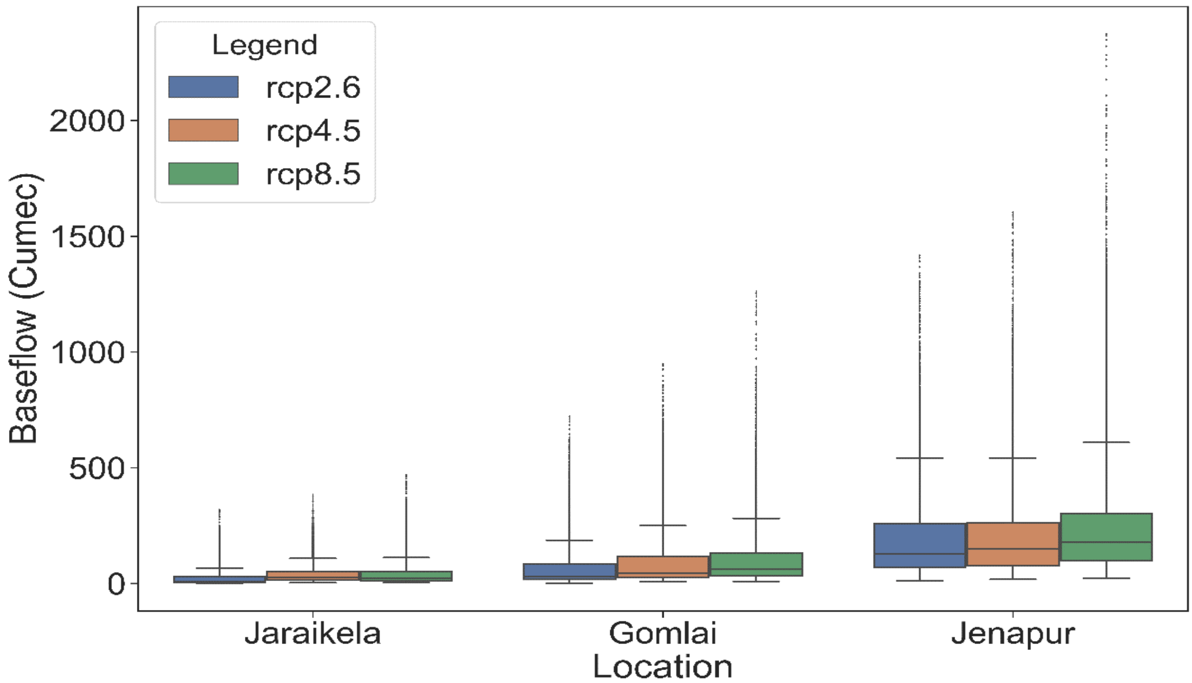

Figure 8. Grouped box plots of projected baseflow variations at the Jaraikela, Gomlai, and Jenapur stations.

Future baseflow projections derived from the SWAT simulations under the three RCP scenarios are presented in Figure 8. At Jaraikela, mean baseflow is projected to increase from 24.42 m^3/s under RCP2.6 to 40.24 m^3/s and 41.43 m^3/s under RCP4.5 and RCP8.5, respectively, corresponding to increases of 66-112% relative to the baseline period. Across the basin, mean annual baseflow remains highest at Jenapur, followed by Gomlai and Jaraikela, reflecting the cumulative contribution of groundwater along the river network. The projected increase in baseflow under future climate scenarios may enhance dry-season water availability and partially support irrigation demands. However, the substantial changes in groundwater contributions also highlight the need for integrated assessments of evapotranspiration and groundwater recharge processes to better understand future water availability and drought resilience in the basin.

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CONCLUSIONS

The effective policy formulation in water resource management can only be achieved by accurate quantification of the hydrological flux components over the planning horizon. In this context, the alteration in the future flow regime of the BRB, and subsequent, impact on streamflow and baseflow variability over the future time-scales was analyzed using the novel 10-daily scale FDC approach. The specific conclusions from this study are enlisted below:

1. The SWAT model satisfactorily reproduced the daily-scale streamflow with NSC and R^2 estimates of 0.73 and 0.75, respectively. The SWAT model performance at the three gauging locations is in the increasing order of: Jaraikela → Gomlai → Jenapur.
2. The predictive uncertainty in the streamflow simulation by the SWAT model is the lowest at the Jenapur outlet. All the three gauging locations experienced considerable underestimation in the peak flows; however, the baseflow and low flows are well represented by the SWAT model.
3. The alteration in the hydrologic flow regime is more prominent during the near and far future periods of the BRB across all the RCP scenarios. Although a substantial reduction in the environmental flow would be expected, the high and medium flows are expected to increase across all the RCP scenarios causing flood hazard in the downstream of Rengali reservoir. The hydrological alterations in the future time scales are more dynamic during the monsoon season at all the three locations.
4. The baseflow dynamics at the reservoir downstream location of Jenapur is well captured by the SWAT model with KGE=0.52. Overall, the baseflow projections revealed an increasing scenario at all the three locations, with highest and lowest increase of 112 and 66 % during the RCP 8.5 and 2.6 scenarios, respectively with reference to the baseline period.

The proposed flow regime analysis approach could have potential implications on water managers while formulating a sustainable water resource policy. The applicability of this integrated hydrological modeling approach could further be explored under varying climate and LULC conditions.

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Data Availability

Data will be made available on request.

Credit Authorship Contribution Statement

Subhadeep Mandal: Conceptualization, Data curation, Software, Formal analysis, Writing - original draft. **Bhabagrahi Sahoo:** Supervision, Investigation, Writing - review & editing. **Ashok Mishra:** Supervision, Resources, Writing - review & editing.

Declaration Of Competing Interest

None.

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