

RESEARCH ARTICLE

A Multi-Model Ensemble Reveals a Diverging Hydrological Cycle in the Upper and Lower Transboundary Brahmaputra River Basin

Priyam Deka¹  | Manabendra Saharia^{1,2}  | Sharad Jain³ | Ved Prakash¹ | Sujay Kumar⁴ | Augusto Getirana^{4,5} | Suneet Bansal⁶ | Kondapalli Niranjan Kumar⁷ | V. S. Prasad⁷ | Mrutyunjay Mohapatra⁸

¹Department of Civil and Environmental Engineering, Indian Institute of Technology Delhi, New Delhi, India | ²Yardi School of Artificial Intelligence, Indian Institute of Technology Delhi, New Delhi, India | ³Department of Civil Engineering, Indian Institute of Technology Gandhinagar, Gandhinagar, Gujarat, India | ⁴Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, Maryland, USA | ⁵Science Applications International Corporation, Greenbelt, Maryland, USA | ⁶Central Water Commission, Ministry of Jal Shakti, New Delhi, India | ⁷National Centre for Medium Range Weather Forecasting, Ministry of Earth Sciences, Noida, India | ⁸Indian Meteorological Department, Ministry of Earth Sciences, New Delhi, India

Correspondence: Manabendra Saharia (msaharia@iitd.ac.in)

Received: 13 November 2025 | **Revised:** 4 June 2026 | **Accepted:** 3 August 2026

Keywords: Brahmaputra basin | hydroclimatology | Indian land data assimilation system | multi-model ensemble

ABSTRACT

The transboundary Brahmaputra basin is a significant component of the Asian Water Tower, housing approximately 66 million people in four countries and experiencing intense floods. However, this data-scarce river has been subject to very few studies related to the long-term assessment of its water budget. In this study, a multi-model ensemble Indian Land Data Assimilation System (ILDAS) is set up to study the trends and variability in the water budget components from 1981 to 2020. The results indicate no significant long-term trend in the annual basin-averaged precipitation, evapotranspiration (ET), and runoff; however, spatial divergence in the hydrological cycle within the basin is observed, with the upper/Himalayan part showing an accelerating hydrologic cycle, contrasted by a decelerating hydrological cycle in the lower/plain part, which gets 70% of the basin rainfall. Our findings show that the winter precipitation in the basin has decreased by 5 mm per decade. The decreasing winter precipitation is confined to the lower part of the basin, which translates into a decrease in winter ET and runoff, whereas the upper part of the basin experienced an increase in precipitation in the pre-monsoon and monsoon periods, resulting in increasing ET and runoff. It is observed that increasing runoff enhances streamflow in the upper basin; however, this signal is nullified by declining runoff towards the downstream region, leading to no significant trend in streamflow in the lower part of the basin. Further, it is observed that the TWSA variability in the basin is significantly dependent on groundwater storage variability and the amount of water stored in rivers and floodplains. These insights enhance our understanding of the complex variability of the hydrology of the Brahmaputra River basin.

1 | Introduction

Changes in water availability in a river basin are a growing concern due to the changing climate and global warming. Water budgeting is the estimation of the movement and storage of water in the surface, sub-surface and atmosphere. A

better understanding of the water budget of a river basin, that is, knowledge about the movement of the water, is required to understand the complex basin behaviour under various hydro-meteorological conditions and to estimate water availability in the basin (Jung et al. 2017; Tekleab et al. 2013). Although conceptually simple, accurately estimating water budget components is

challenging due to natural variability, data scarcity, and significant associated uncertainties.

The Brahmaputra River basin is a sizeable transboundary basin subjected to extreme hydro-climatic conditions, creating challenging conditions for water resource management. The Brahmaputra basin is adversely affected by extreme rainfall and flooding, with major implications for the economy and human life. The Brahmaputra basin is geographically diverse and ecologically rich in natural and crop-related biodiversity, and supports the livelihood of 66 million people (Pervez and Henebry 2015). Due to the complex nature and diverse ecology of the basin, comprehensive studies on the composite hydrological processes are necessary to ensure effective water management. Several researchers have studied individual behaviour of various hydrological processes in the Brahmaputra basin, for example, physiography and channel aggradation (Goswami 1985), precipitation (Jain et al. 2013; Kripalani et al. 2007), rainfall erosivity (Raj et al. 2022), runoff (Ghosh and Dutta 2012; Monirul Qader Mirza 2002), temperature (Immerzeel 2008; Shi et al. 2011), streamflow (Gain et al. 2011; Jian et al. 2009), groundwater (Tiwari et al. 2009) and extreme events (Rajeevan et al. 2008; Webster and Jian 2011). However, very few quantifications are available on comprehensive long-term water budget studies of the basin. Although understanding the water budget is critical for sustainable water management, the reasons for changes in the behaviour of the water budget for large basins remain unclear (Jing et al. 2019; Pan et al. 2012; Posada-Marín and Salazar 2022; Xiong et al. 2022).

This paper attempts to understand the basin hydrology and its long-term behaviour. Several studies on the hydrological behaviour of the Chinese part of the Brahmaputra basin, known as the Yarlung-Zangbo, are available (Chen 2012; Liu et al. 2019; Wang et al. 2021; Xuan et al. 2021; Zhou et al. 2022). However, comprehensive studies of the hydrological behaviour of the lower Brahmaputra and, especially, the characteristics of the transboundary Brahmaputra basin are very few. In the Brahmaputra basin, a data-sparse region, physically based modelling is challenging, as these models can introduce biases and uncertainties (Müller Schmied et al. 2014). The uncertainties in models result from different representations of hydrological processes in different models (Bonan et al. 2011; Koster et al. 2000; Yang et al. 2011). The uncertainties in the model output can also be due to uncertainties in the model forcing data (Gelati et al. 2018; Mockler et al. 2016). To mitigate the impact of uncertainties, we employ a multi-model, multi-forcing ensemble approach for generating water balance estimates, which is more effective than relying on a single model and forcing data. This approach surpasses individual models by mitigating both model and forcing uncertainties (Kumar et al. 2017). The ensemble modelling strategy has been applied in diverse hydro-climatological studies, including examinations of water scarcity (Schewe et al. 2014), floods (Dankers et al. 2014) and water budget assessments (Getirana et al. 2014; Getirana, Boone et al. 2017).

Two Land Surface Models (LSMs) (NoahMP and CLSM) are integrated with a hydrodynamic routing model (HyMAP) and forced with MERRA2, with precipitation replaced by IMD and CHIRPS products, resulting in four experiments. The mean of the four-experiment ensemble is used for the analysis. This study

focuses on (1) understanding the precipitation variability, hydrological cycle, and the representation of water budget variables by an integrated hydrologic-hydrodynamic modelling system, (2) the assessment of the long-term behaviour of the hydrological cycle and related trends and (3) the impact of various water storage components on the terrestrial water stored in the basin. Hence, first, an assessment of the spatiotemporal variation of precipitation from different forcings is carried out, followed by an evaluation of model performance and inter-comparison. Then, the established model outputs are used for various annual water budget attribution assessments, including assessments of whether there have been any changes in the spatial and temporal variations of precipitation, evapotranspiration, runoff and terrestrial water storage anomalies. This is followed by an analysis of how changing hydrology has influenced annual streamflow variability. This paper also examines the contribution of various storage components to the basin's terrestrial water storage. This study aims to understand the long-term hydrological behaviour of the basin focusing on its fluxes and storage components.

This paper is collated as follows: Section 2 describes the study area and its various physical attributes. Section 3 introduces the design of this study, including the meteorological forcing data sets, the multi-model setup, the observation-based precipitation data, the river routing scheme and the model setup. Section 4 describes the theories and methodologies used in the experiments conducted for the study. Section 5 presents results and discussion of the precipitation variability within the basin, model performance assessment, long-term basin hydrological attribution assessment and the impact of various storages on terrestrial water storage. The last section (Section 6) summarizes the findings of this study.

2 | Study Area

The Brahmaputra River originates from the Chema Yundung glacier in the Kailash range in southwest Tibet, at an elevation of 5300 m. Flowing eastward in South Tibet, the river reaches Namcha Barwa, where it takes a U-turn and enters Arunachal Pradesh. Here, the river is known as the Dihang (or Siang) River, and later as the Brahmaputra. In India, the Brahmaputra is joined by many big tributaries: Subansiri, Kameng, Bhareli, Dhansiri, Manas, Champamati, Sankosh, Burhi Dihing, Disang and Kopili. The Brahmaputra River is approximately 2880 km long (Pervez and Henebry 2015) and is the world's fourth-largest in terms of average discharge at the mouth, with a flow of approximately $20,000 \text{ m}^3 \text{ s}^{-1}$ (Jian et al. 2009) and an average annual sediment load of 735 million metric tons.

The Brahmaputra basin is a complex transboundary basin covering parts of India, China, Bhutan, and Bangladesh (Figure 1). The total drainage area basin is $519,500 \text{ km}^2$ (82°E – 98°E , and 23°N – 32°N), of which 50.5% is in China, 33.6% is in India, 8.1% is in Bangladesh, and 7.8% is in Bhutan (Immerzeel 2008). The basin exhibits two distinct climatic zones: (1) the northern (upper) part experiences a mountain climate characterized by cold and dry conditions, while (2) the southern (lower) part is dominated by the monsoon, featuring a warm and humid climate with substantial Indian summer monsoon rainfall (Pervez and Henebry 2015; Singh et al. 2004). From here on, the upper

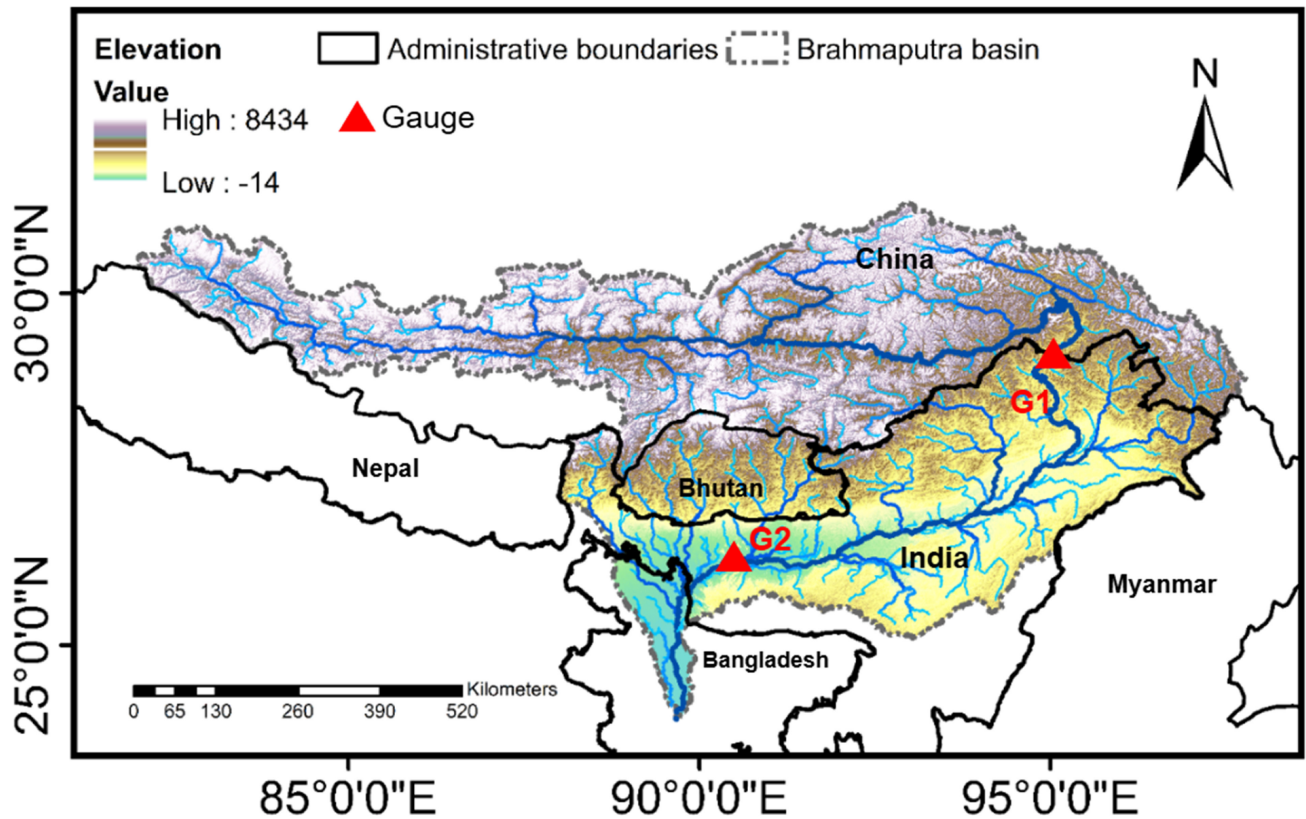


FIGURE 1 | The transboundary Brahmaputra Basin covers parts of China, India, Bhutan, and Bangladesh, covering a catchment area of 519,500 km². G1 and G2 are the two stations considered in the study, where G1 captures the streamflow of UBRB, and G2 captures the streamflow of UBRB and LBRB. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/joc.7049)]

part of the Brahmaputra river basin will be called UBRB, and the lower part will be called LBRB.

3 | Model and Data

3.1 | Model Forcings

Meteorological forcings (e.g., precipitation, wind, temperature, humidity, shortwave and longwave radiation) provide the boundary conditions for land surface models (LSMs). In this study, we have used the two precipitation products from CHIRPS and IMD (Magotra et al. 2024) and MERRA2 for the remaining forcing variables.

The Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) (Gelaro et al. 2017) is an upgraded version of MERRA, which includes the recent advances made in the assimilation systems by NASA's Global Modelling and Assimilation Office (GMAO) that can assimilate microwave observations, hyperspectral radiance, and other data types. The MERRA-2 product is available globally at a spatial resolution of 0.25° × 0.625° and an hourly time step. The product has been available since 1980 and is operationally updated with about 1 week of latency.

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al. 2015) is a quasi-global precipitation

dataset derived from global Cold Cloud Duration (CCD) rainfall estimates calibrated using Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis version 7 (TMPA 3B42 v7). CHIRPS precipitation estimates integrate active radar and satellite systems with in situ gauge station data, with a 3-week lag. From 1981 to the present, CHIRPS data are available at a spatial resolution of 0.05°. While using CHIRPS precipitation data as an input, other required meteorological variables are specified from MERRA-2.

The Indian Meteorological Department (IMD) gridded precipitation data is generated by spatially interpolating data from 6995 gauged stations. The stations, sourced from various sources, include IMD observatory stations, hydro-meteorological observatories, and Agromet observatories (Pai et al. 2014) across India. Based on Shepard (1968), the IMD gridded product is constructed using an inverse-distance weighting system with localized directional effects and barriers. IMD gridded data with a 0.25° spatial resolution is available from 1981 to the present. Similar to CHIRPS, MERRA-2 is also used for other required meteorological variables in IMD gridded precipitation. However, IMD precipitation data is available only for India and covers about 34% of the catchment area. Since the Brahmaputra basin is transboundary, MERRA2 precipitation is used for the part outside the IMD precipitation domain. Choosing MERRA2 precipitation for outside India was deliberate because previous studies have shown that MERRA2 precipitation shows a consistent trend with observed station precipitation over the Tibetan

part (Wang et al. 2020). Across the Indian region, IMD gridded precipitation derived from observation stations is most consistent with the observations (Pai et al. 2014), and discrepancies were observed in MERRA2 precipitation in the Indian part of the Brahmaputra basin (Magotra et al. 2024). Thus, using the hybrid IMD+MERRA2 ensures that precipitation forcing is consistent with observed data in terms of the long-term trend across the entire region. Henceforth, IMD precipitation refers to IMD precipitation data in the Indian region, and MERRA-2 in the part of the Brahmaputra basin not covered by IMD precipitation data.

3.2 | The Indian Land Data Modelling System (ILDAS)

The Indian Land Data Assimilation System (ILDAS) is a trans-boundary multi-model, multi-forcing hydrological-hydrodynamic setup over South Asia (Chakraborty et al. 2024; Magotra et al. 2024). It is developed using the NASA Land Information System (LIS) Framework (Kumar et al. 2006), where multiple LSMs are coupled with a hydrodynamic routing model to simulate the hydrological cycle of the Brahmaputra River basin. Here, we employed two LSMs in conjunction with a river routing model. They are the Noah land surface model with multi-parameterization options (Noah-MP; Niu et al. 2011), the Catchment LSM (CLSM; Koster et al. 2000), and the Hydrological Modelling and Analysis Platform (HyMAP; Getirana, Kumar, et al. 2017; Getirana et al. 2012) river routing scheme. The models are described in Section S1 of the Supporting Information.

3.3 | Satellite Products and Observation Data

This study employs a combination of satellite products and observational data to evaluate model outputs. The subsequent section provides detailed descriptions of the products utilized in the study.

a. MODIS Evapotranspiration

Evapotranspiration from the Moderate Resolution Imaging Spectroradiometer (MODIS) is obtained. MYD16A2GF product (Running et al. 2019), a gap filled at 8-day temporal resolution and 500m spatial resolution, is used to validate the ET results. The Penman–Monteith equation (Monteith et al. 1965) has been used in the ET algorithm.

b. GLEAM Evapotranspiration

Evapotranspiration from Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al. 2017; Miralles et al. 2011) is also used to validate ET results. GLEAM provides evaporation estimates from various land surface components.

c. Grun (Runoff)

The Global Runoff Reconstruction (GRUN) dataset (Ghiggi et al. 2019) is an observationally driven globally reconstructed monthly runoff at 0.5° resolution for 1902–2014. GRUN uses machine learning-based Random Forest to generate the runoff data. The machine learning algorithm was trained on in situ streamflow observations from the GSIM dataset that predicts

monthly runoff rates based on antecedent precipitation and temperature from the Global Soil Wetness. GRUN runoff estimates are used to validate model outputs.

d. GRACE Terrestrial Water Storage Anomalies

TWSA data derived from the Gravity Recovery Climate Experiment ((GRACE; Landerer and Swenson 2012) and GRACE Follow-On (GRACE-FO; Landerer et al. 2020)) are obtained from the Jet Propulsion Laboratory (JPL). TWSA is obtained using the Mass Concentration blocks (mascons) techniques, which implement geophysical constraints referred to as mascons. TWSA is available monthly at 0.5° spatial resolution. The anomalies are calculated relative to the long-term mean of the time series as the time-mean baseline and provided as TWSA.

e. Streamflow Data

The observed streamflow data from 2006 to 2020 were collected from the Central Water Commission (CWC) through official inquiries at two gauges in the basin. The gauges in the Indian part of the basin fall under the jurisdiction of the Central Water Commission (CWC), and the streamflow data are classified, restricting public access and availability.

4 | Methodology

4.1 | Experiment Design

A multi-model, multi-forcing system performs better than a single-model system by negating the model and forcing uncertainties (Kumar et al. 2017). In this study, results from four experiments are analysed to understand the long-term hydrological behaviour of the basin. The four model-generated outputs are validated at a monthly scale with various observed data as described in Section 3.3 to test for the model's ability to simulate the hydrology of the basin. Further, the ensemble of the model outputs is used for the analysis of the hydrological behaviour of the basin in Sections 5.3 and 5.4.

4.2 | Hydrological Variables Used for Model Validation

The water budget equation for a basin can be represented as follows:

$$\frac{dS}{dt} = P - ET - R \quad (1)$$

where $\frac{dS}{dt}$ is the change in water storage (S) with time t. Hence the following variables that represent the water budget of a basin are selected to validate the modelling setup.

Evapotranspiration is a comprehensive process encompassing the vaporization of water from the Earth's surface into the atmosphere. ET is the combination of two processes: (a) evaporation, the process of conversion of liquid water to vapour and directly releasing to the atmosphere, and (b) transpiration, the process of conversion of liquid water to vapour and releasing it to the atmosphere through plants' stomata after utilizing it for the plant's metabolism and growth. Accurate estimation of

the spatial distribution of ET is challenging because the number of monitoring sites is limited compared to precipitation or streamflow. Physical-based modelling proves to be a better alternative for estimating ET's spatial and temporal distribution. This study compares the monthly model-simulated ET with MODIS and GLEAM evapotranspiration datasets. In the past, Kim et al. 2012 and Miranda et al. 2017 attempted to validate MODIS 16 global terrestrial ET products using data from 17 flux tower locations in Asia. Good agreement was observed between MODIS-based ET and flux tower measurements. They concluded that MODIS global terrestrial ET products can provide a reasonably accurate estimate of actual ET.

Precipitation falling on the land can be stored in depression areas, return to the atmosphere through evapotranspiration, and move into the ground surface by infiltration or runoff to areas with lower elevation. A major portion of the precipitation converts into runoff and infiltration. Measuring runoff is expensive and requires a permanent setup, specialized instruments, and skilled personnel. Although the streamflow hydrograph is used in analysing runoff rate and base flow, runoff contributes as one of the components of the total streamflow. Physical-based models are capable of estimating the spatiotemporal variation of runoff rates and can be one of the most viable options for estimating runoff. In this study, the monthly model-simulated runoff is compared with the GRUN runoff dataset (Ghiggi et al. 2019).

Terrestrial water storage comprises a cumulative sum of groundwater storage (GWS), surface water storage (SWS), soil moisture (SM) and snow water equivalent (SWE). It plays a crucial role in climate variability by facilitating water and energy exchange at the land surface (Kim et al. 2009). In this study, SWS encompasses water stored in river channels, floodplains, lakes, reservoirs and wetlands. The spatiotemporal variability of TWSA can be observed from the GRACE data (Jung et al. 2017). Apart from GRACE, Land surface models can provide an estimate of TWSA. Before the GRACE mission, physically based LSMs were the only suitable tools for estimating TWSA (Nie et al. 2016). In this study, the basin-averaged TWSA estimates from the model simulations are compared with GRACE TWSA estimates to check for the model's ability to simulate the TWSA variability of the basin.

4.3 | Validation Statistics

The model simulations are validated with observed data (Section 3.3) based on commonly used statistical indices: Coefficient of Determination, Nash-Sutcliffe Efficiency index, Kling-Gupta Efficiency index, and Root Mean Square Error. The detailed formulation of the statistical indices is mentioned in the Section S2.

4.4 | Mann-Kendall Test (MK Test)

The trends reported in this study are calculated using the Mann-Kendall test. MK test is a non-parametric test, mainly used to detect trends in meteorological and hydrological time series statistically (Burn et al. 2004; Chandole et al. 2019;

Jain et al. 2013; Joshi et al. 2016; Kaur et al. 2017; Meshram et al. 2017). It is a robust technique for trend tests and can handle outliers in the form of extreme values in hydrological time series (Helsel et al. 2020). Formulations are mentioned in Section S3.

4.5 | Impact Index

To understand the impact of various storage components on TWS in the basin and quantify it, the following impact index was formulated by Getirana, Kumar, et al. (2017) is being used. The impact index (I_i) is based on the water storage component (C). In this analysis, the TWS is considered the sum of GWS, SWS, SM and SWE, whereas vegetation water storage is not considered. The impact index is formulated as Equation (2).

$$I_i = \frac{C_i}{\sum_{i=1}^{nc} C_i} \quad (2)$$

where C is the water storage component, the sum of absolute monthly climatology anomaly values.

$$C_i = \sum_{t=1}^{12} |S_{i,t} - \bar{S}_i| \quad (3)$$

where I and t are indexes of the water storage component and time step, respectively, and $nc=4$, corresponding to the four types of water storage (S) considered.

5 | Results and Discussion

5.1 | Precipitation Variability

Precipitation variability governs the variability of a basin's water budget. The Brahmaputra basin receives heavy precipitation, most of which occurs during the Indian Summer Monsoon Rainfall (ISMR). The basin-averaged annual rainfall calculated using IMD precipitation is 1455 mm/year with a standard deviation of 207 mm/year, and CHIRPS is 1405 mm/year with a standard deviation of 119 mm/year (Figure 2a). Figure 2b shows the mean monthly precipitation value from 1981 to 2020. The majority of precipitation occurs during the Indian summer monsoon months (JJAS), with July having the highest precipitation. Both the precipitation products show a similar temporal variation. While ISMR brings large amounts of rainfall, the pre-monsoon months of April and May, as well as the post-monsoon month of October, also experience considerable rainfall. The ensemble mean of both precipitation products is used to analyse seasonal precipitation variation in the basin (Figure 2c-f). During the monsoon season, the basin receives an annual average of 983 ± 100 mm of rainfall; followed by the pre-monsoon season, which receives 318 ± 53 mm; the post-monsoon season, which receives 96 ± 37 mm; and the winter season, which receives the least amount, with 37 ± 14 mm. The trends in the seasonal rainfall are also calculated using the MK-test and Sen's slope. The trends suggest a small increase in precipitation during

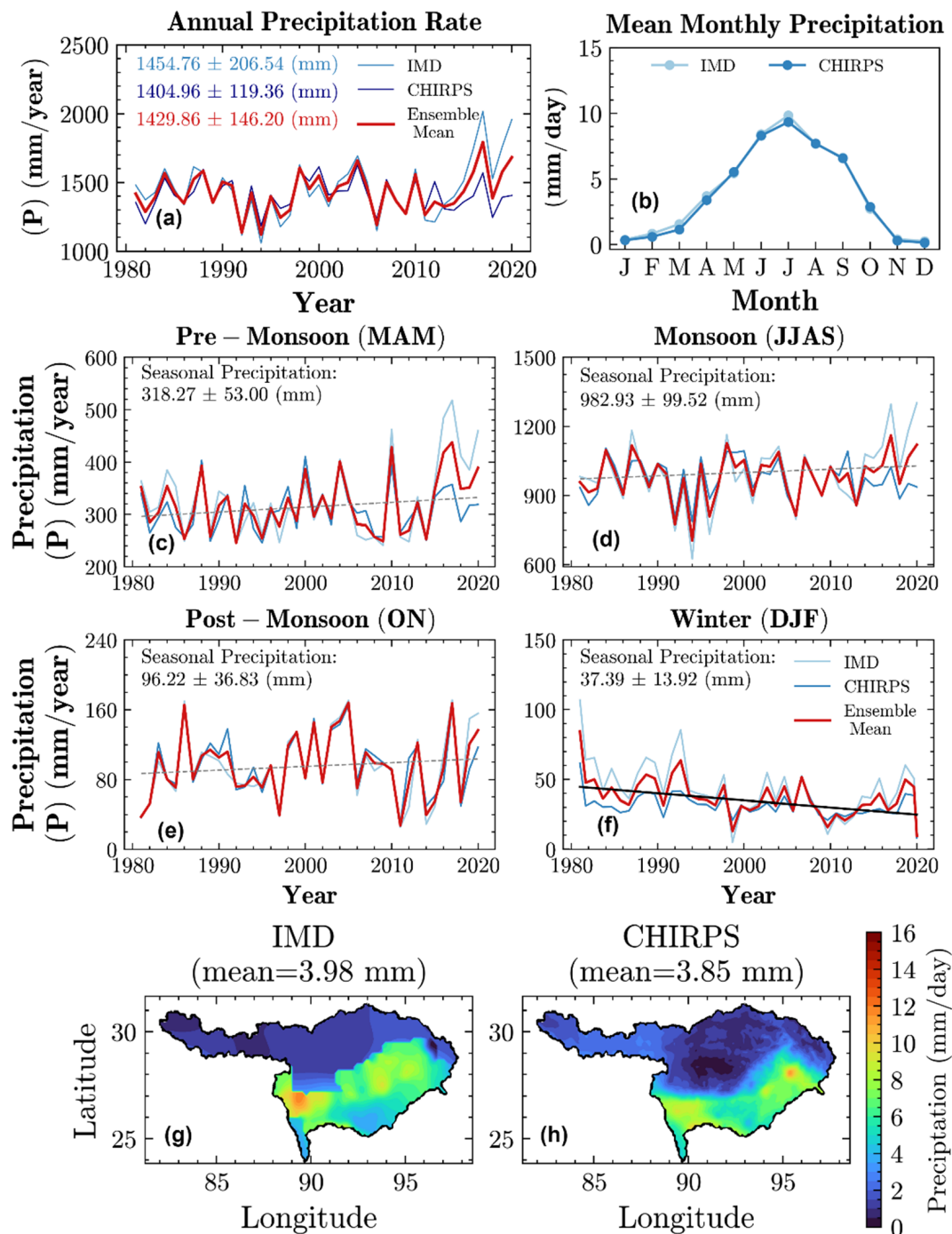


FIGURE 2 | (a) Annual precipitation rate, (b) Mean monthly precipitation rate, (c–f) Seasonal precipitation rate (black solid line is the trend line with $p < 0.05$ and grey dotted line is the trendline with $p < 0.05$), (g, h) Spatial variation of precipitation rate with IMD and CHIRPS precipitation data respectively in the Brahmaputra basin. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

the pre-monsoon, monsoon, and post-monsoon periods, but this increase is not statistically significant (p -value > 0.05) (Figure 2c–e). However, the winter precipitation shows a statistically significant decreasing trend of 5 mm per decade at a 95% confidence level (Figure 2f). Decreasing precipitation can affect winter agriculture and increase water stress in the basin during the lean period. Decreasing precipitation can also have a cascading effect on early pre-monsoon precipitation, reducing it due to reduced terrestrial moisture supply, which contributes to pre-monsoon precipitation in the basin.

Figure 2g,h shows the spatial variation of daily precipitation in the basin temporally averaged from 1981 to 2020. A mean daily precipitation of 3.98 mm/day is observed for IMD, and 3.85 mm/day for CHIRPS. The spatial distribution of precipitation is consistent for both precipitation datasets. The UBRB, which is in the Himalayas of China, India, and Bhutan, receives lower precipitation than the LBRB, which lies in the plains of India and Bangladesh. The lower altitude and the high mountains surrounding it in a horseshoe shape facilitate high precipitation in the LBRB, resulting in the LBRB receiving about 70% of the total rainfall of the basin.

5.2 | Multi-Scale Validation

The monthly basin-averaged ET, runoff, and TWSA obtained from the four experiments were validated with standard satellite observation data (Figure 3). The validation period was taken based on the available length of the standard datasets. However, for GLEAM ET data, the evaluation period is limited to the availability of MODIS ET data, although GLEAM data was available for the entire period to maintain consistency. Table 1 provides insight into the performance of the model simulation in terms of R^2 , NSE and KGE for the model-generated ET, runoff and TWSA compared to MODIS and GLEAM data for ET, GRUN data for runoff and GRACE/GRACE-FO data for TWSA.

All four experiments show reasonably high r^2 values across the variables. For runoff, r^2 ranges from 0.88 to 0.93, indicating that all members capture the temporal variability well. For TWSA, r^2 ranges from 0.62 to 0.73, and for ET, it ranges from 0.72 to 0.80 against MODIS and 0.89–0.93 against GLEAM. While the NSE and KGE values vary more substantially, particularly for CLSM-IMD, which yields negative NSE for ET, these metrics are more sensitive to magnitude and peak errors than to the overall temporal pattern. Hence, we observe that the peaks in ET and runoff are not well captured by some configurations, as reflected in the lower NSE and KGE values. The poor NSE values for CLSM ET reflect CLSM's tendency to misrepresent ET magnitude in this basin, likely due to its simplified catchment-based formulation of soil moisture and evapotranspiration partitioning, which

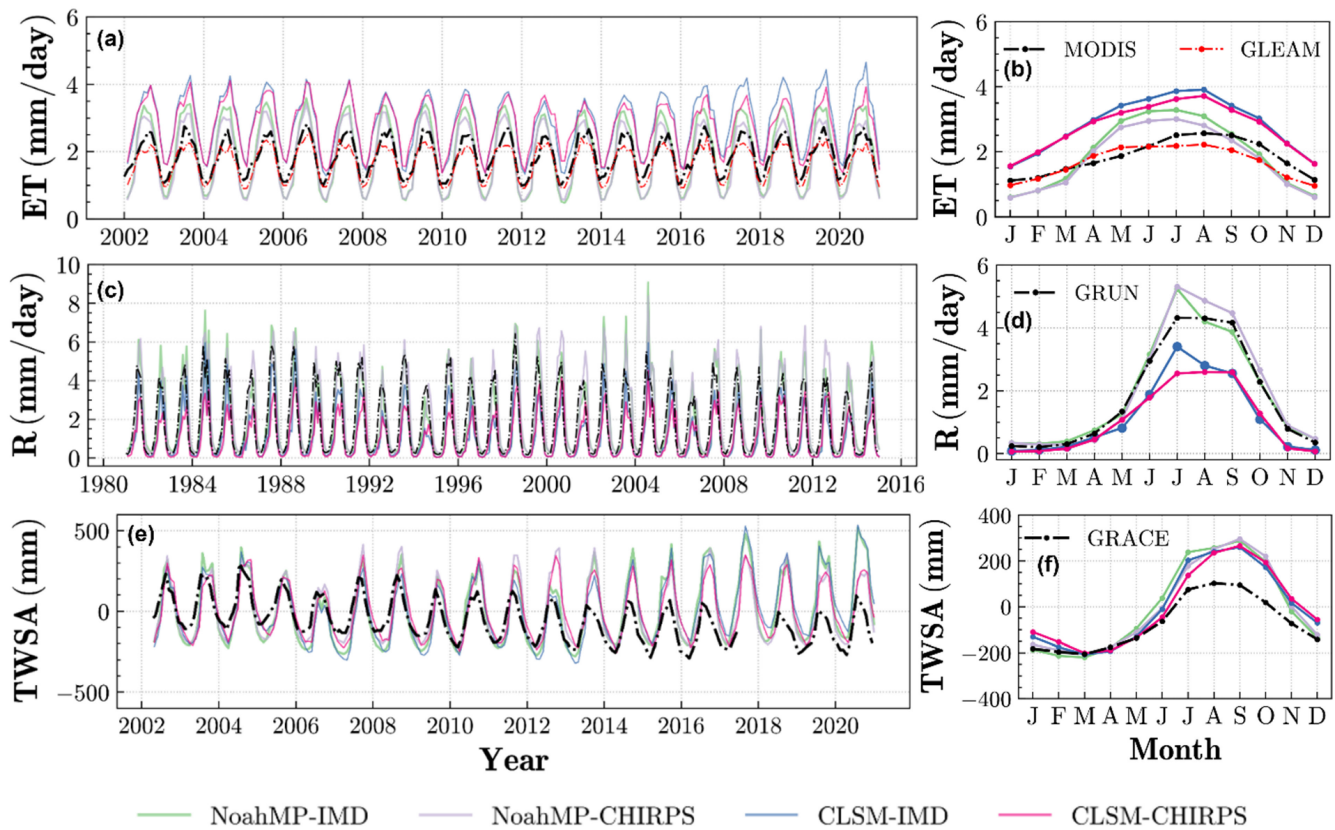


FIGURE 3 | Comparison of simulated results from Noah MP and CLSM. (a) ET estimate and validated with MODIS and GLEAM estimates from 2002 to 2020, (b) ET seasonality from 2002 to 2020. (c) Runoff estimate and validated with GRUN estimates from 1981 to 2014, (d) Runoff seasonality from 1981 to 2014. (e) Monthly TWSA estimate and validated with GRACE/GRACE-FO estimates from April 2002 to December 2020, (f) TWSA seasonality from April 2002 to December 2020. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/joc.7649)]

TABLE 1 | Statistical indices for model performance evaluation for monthly simulations of four experiments. Best figures are mentioned in bold.

LSM	Forcing	ET (MODIS, GLEAM)			Runoff			TWSA		
		r^2	NSE	KGE	r^2	NSE	KGE	r^2	NSE	RMSE
Noah MP	IMD	0.73, 0.92	0.61, 0.61	0.50, 0.45	0.89	0.89	0.88	0.65	0.60	121.30
	CHIRPS	0.72, 0.93	0.65, 0.71	0.56, 0.52	0.93	0.90	0.81	0.73	0.64	110.58
CLSM	IMD	0.80 , 0.89	-0.68, -1.15	0.48, 0.40	0.88	0.48	0.34	0.62	0.55	119.64
	CHIRPS	0.78, 0.90	-0.74, -1.27	0.56 , 0.47	0.92	0.14	0.12	0.71	0.56	110.82

differs substantially from the more explicit soil-layer scheme in Noah-MP. However, CLSM retains acceptable r^2 values for ET, indicating that it still captures the timing and temporal variability of the ET signal even where magnitude is not properly represented. However, since the focus of this study is on long-term trend analysis rather than magnitude estimation, these biases do not undermine the suitability of the simulations for our purpose. Hence, the simulated results should be used with cautious judgement for the magnitude. More description of the model performance is given in the Section S4.

Further analysis of the model's performance in the UBRB and LBRB separately (Tables S1 and S2) showed that ET is better simulated in the UBRB across all configurations in terms of r^2 . In contrast, runoff and TWSA are better simulated in the LBRB. While the TWSA temporal variation is not properly captured in the UBRB with the best r^2 value of 0.51 by the NoahMP-CHIRPS configuration, the ET values in the LBRB show lower r^2 values when compared to MODIS, but GLEAM gives good values. Runoff shows good model performance in both UBRB and LBRB in terms of r^2 . Overall, the r^2 values are largely consistent and within an acceptable range across the basin, except TWSA in the UBRB, where lower values are observed, likely reflecting the limited representation of high-altitude cryosphere and groundwater processes. These reasonably acceptable values indicate that the model adequately captures the temporal variability of the hydrological fluxes in both the upper and lower parts of the basin. Examining the NSE and KGE for both UBRB and LBRB shows that the magnitude-sensitive performance of the model varies more compared to r^2 . For ET, the UBRB shows positive NSE for Noah-MP under both forcings, whereas CLSM yields negative NSE against GLEAM (down to -0.54) and, in the LBRB, strongly negative NSE values (as low as -3.42), indicating that CLSM substantially misrepresents the ET magnitude and seasonal peaks despite reasonable r^2 . Runoff performance in UBRB for IMD-MERRA2 precipitation is better in both models; however, CHIRPS simulated results show a negative NSE. The performance is better in LBRB, with NSE reaching 0.91 (Noah-MP-CHIRPS), confirming that temporal runoff dynamics are well reproduced. For TWSA, NSE values are negative in the UBRB across all configurations with high RMSE, reflecting the difficulty in capturing the magnitude of total water storage in the high-altitude, cryosphere and groundwater-influenced UBRB, whereas LBRB shows clear improvement, with positive NSE (0.61–0.74) and lower RMSE (146–208 mm relative to the much larger storage in the valley). The TWSA results in the UBRB reflect the limited representation of high-altitude cryosphere and groundwater processes in the models. The generally lower KGE and NSE for ET and TWSA, particularly for CLSM, indicate that absolute magnitudes and seasonal peaks should be interpreted with caution. However, since the objective of this study is the analysis of long-term trends rather than the estimation of absolute magnitudes, these magnitude-related biases do not compromise the suitability of the simulations, as the temporal variability is captured well by the consistently acceptable r^2 values.

A multi-model, multi-forcing ensemble is used in this study to counter the uncertainties associated with the models and forcings in further analysis. Henceforth, all results are evaluated using the ensemble mean of the outputs from all experiments.

TABLE 2 | Coefficient of determination of streamflow for all four experiments at the two gauge stations considered for the study. Best figures are mentioned in bold.

LSM	Forcing	Coefficient of determination (r^2)	
		G1	G2
Noah MP	IMD	0.55	0.81
	CHIRPS	0.32	0.90
CLSM	IMD	0.64	0.79
	CHIRPS	0.67	0.90
Ensemble		0.76	0.91

We use the simple arithmetic mean as the ensemble mean. All four configurations exhibit comparable r^2 values across the evaluated variables, indicating that no single member is disproportionately better or worse at capturing the temporal variability. This makes equal weighting a reasonable and unbiased choice.

To infer the impact of hydrological behaviour on streamflow, we routed the runoff with HyMAP to obtain streamflow estimates. We selected two gauge locations to validate the simulated streamflow, one at the downstream end of the UBRB (G1) and the other at the downstream end of the LBRB (G2), where observed data is available between 2006 and 2020. The dataset used in this manuscript is classified and restricted for publication; therefore, it cannot be made publicly available or reproduced. However, the normalized streamflow time series from all four experiments, the ensemble mean, and the observed at both gauges are presented in Supporting Information (Figure S1). We obtain a good coefficient of determination at both gauges with the monthly simulated streamflow (Table 2), with the ensemble mean showing r^2 of 0.76 and 0.91 for G1 and G2, respectively. The high r^2 indicates a good representation of temporal variability between the modelled streamflow and the observed streamflow. However, the magnitude of the streamflow may not be accurately represented, and it is not the focus of this current study.

5.3 | Annual and Seasonal Variability of Trend in Hydrological Fluxes

The ensemble mean of four experiments with two LSMs and two precipitation datasets is considered to understand the trend and variability of the water budget variables. The 40-year annual variability of basin-averaged precipitation. Evapotranspiration, surface runoff, ratio of ET/P, and runoff coefficient (C) from 1981 to 2020 is shown in Figure 3. The following inferences are made from the ensemble mean of the experiments.

Examining Figure 4 reveals a fluctuating pattern in P, ET and R over the years. From 1980 to 1990, there was a decline, followed by an increase from 1990 to 2000, a subsequent decrease until 2015, and a notable rise post-2016. These trends and patterns are consistent across all three variables. Mann–Kendall (MK) test suggests no significant long-term (1980 to 2020) trend in the variables. Jain et al. (2013) reported no significant long-term rainfall trend from 1951 to 2008 in the Indian part of the basin;

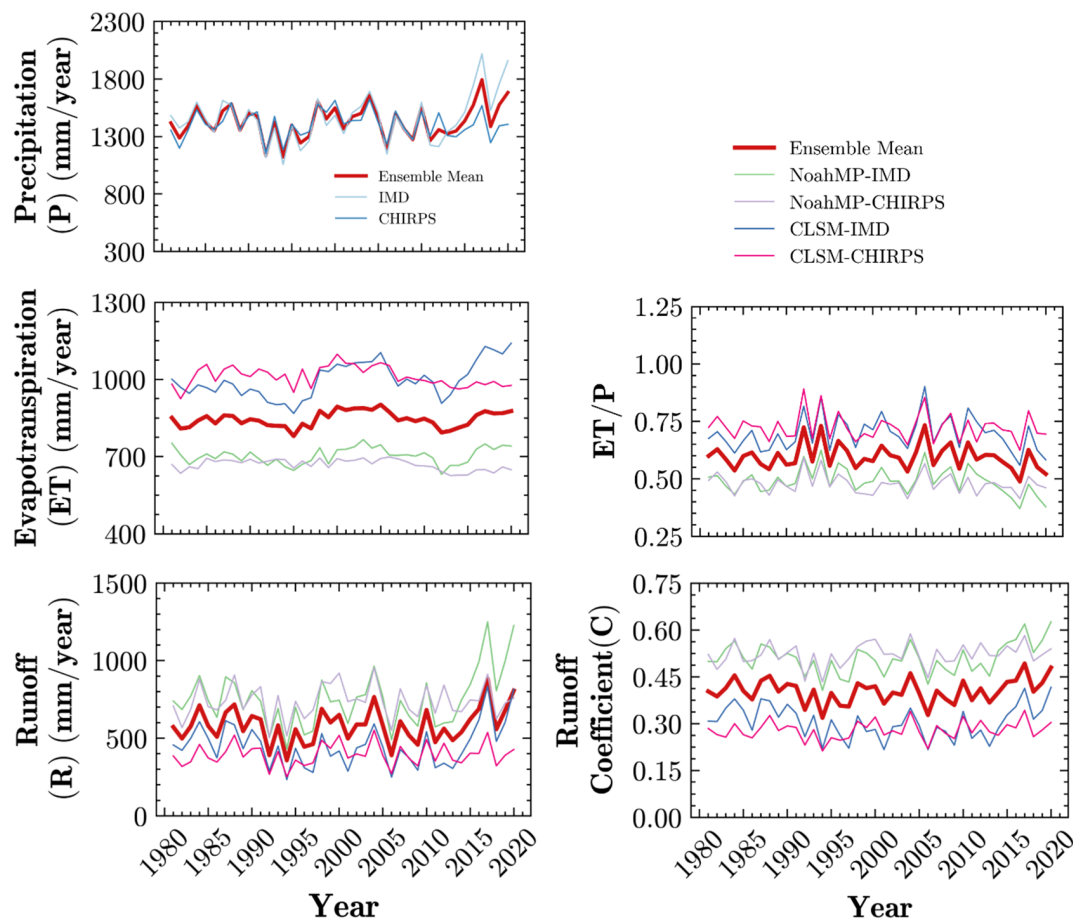


FIGURE 4 | Annual basin-averaged water budget components of the Brahmaputra River Basin during 1981–2020 from the multi-model and 1 model–forcing combinations. Shown are (a) precipitation (P), (b) evapotranspiration (ET), (c) runoff (R), (d) evapotranspiration ratio (ET/P) and (e) runoff coefficient ($C = R/P$). The thick red line represents the ensemble mean, while thin lines indicate individual simulations. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

however, Gogoi et al. (2023) reported a decreasing trend in precipitation from 1998 to 2018. We have observed an increase from 2015 to 2020 in P, ET and R; however, the ET/P ratio is decreasing, whereas Runoff (C) is increasing. The decreasing trend in the ET/P ratio and increasing trend of C suggest that the share of ET from precipitation is decreasing, whereas the share of runoff from precipitation is increasing. The decreasing share of ET results in an increase in soil water content. A higher water content in soil decreases its infiltration capacity, resulting in increased surface runoff. This suggests that the basin is responding to increasing precipitation with higher surface runoff in recent years.

To analyse the hydrology of the UBRB and LBRB, spatially averaged time series of the hydrological fluxes are plotted in Figures S2 and S3. It is observed that precipitation is lower in the upper part of the basin compared to the lower part. Lower precipitation results in lower ET and runoff in the upper part of the basin compared to the lower, as can be observed from the ensemble mean of the model outputs. Higher annual variability of the hydrological fluxes is observed in the lower part of the basin. The standard deviation of the annual precipitation, ET, and runoff in the upper part of the basin as calculated from the ensemble mean of the model outputs are 101.90, 22.82 and 80.98 mm/year, respectively, whereas for the LBRB the standard deviation is more than double that of UBRB with values 228.36, 44.37 and

190.13 mm/year, respectively, for precipitation, ET and runoff. ET has low variability compared to precipitation and runoff. The share of precipitation to ET and runoff are within a similar range in both parts of the basin as can be seen from the runoff coefficient and ET/P ratio. However, the spatially averaged time series shows no significant long-term trends in the hydrological fluxes.

However, the basin-averaged trend is not consistent throughout the basin. The spatial variation in the trends of annual precipitation, evapotranspiration and runoff at a 95% confidence level in the Brahmaputra basin is shown in Figure 5a–c (trends with $p < 0.05$ are set to zero). The trend in the water budget components is calculated from the ensemble means of the simulation resulting from the four independent experiments. The spatial distribution of the trend in annual precipitation shows an increase in the northern part of the basin, whereas patches of decreasing trend are observed in the southern part. Although the spatial extent of the increasing trend is large, its magnitude is lower than the decreasing precipitation trend, which is seen in patches in the southern part of the basin. A decreasing trend is observed in the eastern boundary of the basin in Arunachal Pradesh, India, near the India–Bhutan border, and in Meghalaya, India, where one of the wettest places on earth, Mawsynram, is located. Total

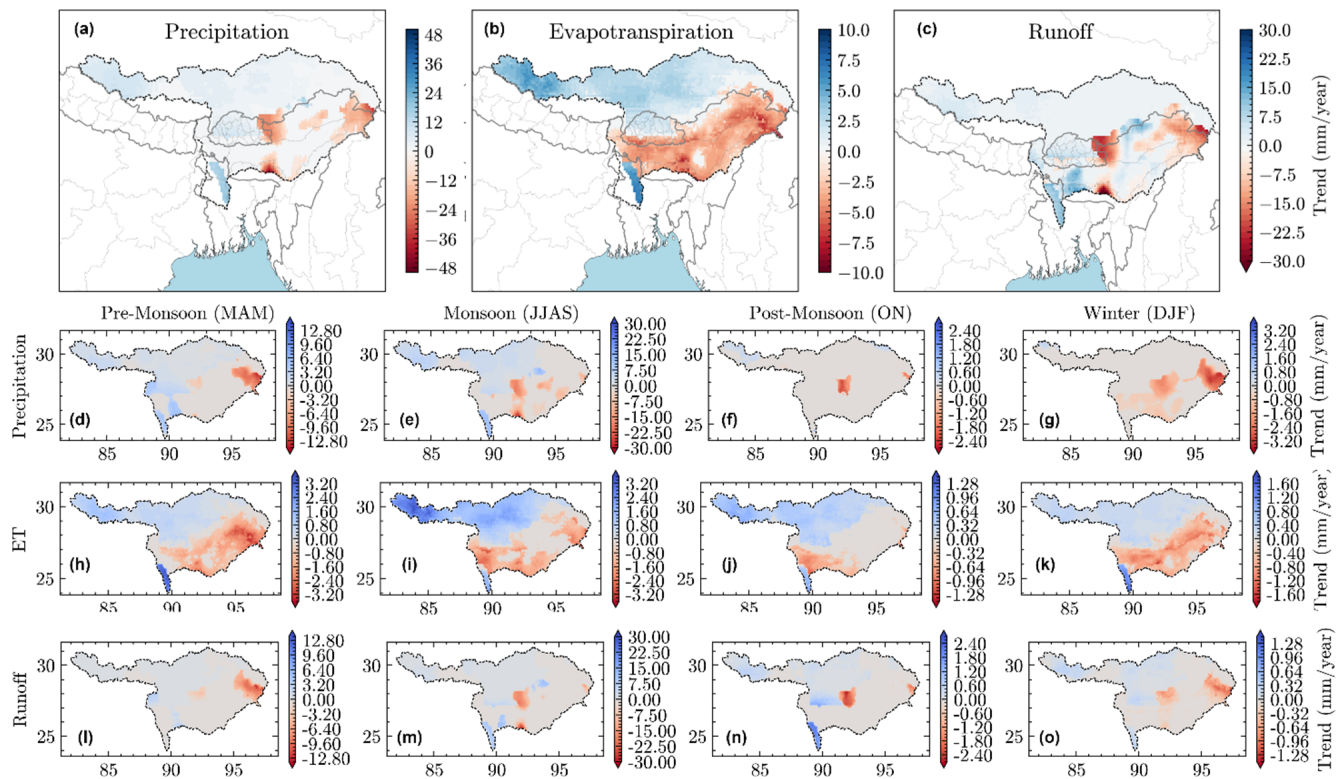


FIGURE 5 | (a–c) Spatial distribution of significant trends ($p < 0.05$) in annual Precipitation, Evapotranspiration, and Runoff. (A bold dashed line depicts the catchment boundary, and a bold grey solid line defines the country boundary), Figures (d–o) Spatial distribution of seasonal trend for all three hydrological fluxes. The components are the ensemble means of the simulation resulting from the four experiments. Trends with p -values greater than 0.05 are set to zero. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

runoff in the basin also exhibits similar diverging spatial variability in the trend as precipitation, with a magnitude that is less than that of precipitation. The increasing trend in the UBRB and decreasing trend in the LBRB of the total runoff will further impact the streamflow variability of the basin. The annual spatial variability of the ET trend shows a clear diverging pattern between UBRB and LBRB, with an increasing trend in ET in UBRB and a decreasing trend in LBRB. The increasing trend in ET in the Himalayan region (UBRB) of the basin is also reported by Ma and Zhang (2022). Precipitation is the dominant driver of ET in the Himalayan part of the basin (Ma and Zhang 2022). Hence, an increasing trend in precipitation in UBRB can be attributed to an increasing trend in ET. However, the decreasing trend in ET in the lower part of the basin does not follow the spatial pattern of precipitation or runoff and shows a consistent decrease throughout the lower part of the basin. Temperature also plays a dominant role in the variability of snow-covered areas (Ban et al. 2021). The increasing trend of ET in UBRB, which is predominantly a snow-covered region, can also be attributed to the rising temperature in the area (Figure 6e–h). The spatial trend variation reflects the influence of precipitation as the primary driver of the water budget variables in the basin.

Furthermore, we also examine the seasonal spatial variability in trends of the basin's fluxes (Figure 5d–o). The decreasing winter precipitation in the basin (Figure 2f) is confined to the LBRB, whereas the UBRB shows no trend. The pre-monsoon and monsoon precipitation show an increasing trend in the upper basin and patches of a decreasing trend in the lower basin.

Post-monsoon precipitation has been mostly consistent over the years in the basin. ET shows a pronounced diverging trend during the winter and pre-monsoon periods, whereas during the monsoon and post-monsoon periods, the upper part of the basin experiences acceleration, and the lower part of the basin shows fewer patches of decrease compared to winter and pre-monsoon. The basin-averaged temperature shows a significant increase in the monsoon, post-monsoon, and winter seasons; the spatial distribution reveals distinct seasonal patterns (Figure 6). During the pre-monsoon and monsoon seasons, the warming is largely confined to the UBRB, whereas in the post-monsoon and winter seasons, both the UBRB and LBRB exhibit increasing temperature trends. This spatial correspondence between warming and enhanced ET in the UBRB, particularly in the pre-monsoon and monsoon seasons, supports temperature as a driver of the evaporative response in this energy-limited upper basin, along with precipitation. The increasing temperature and increasing ET in the UBRB were also reported by Zhang et al. (2020). While the basin-averaged temperature trend shows a significant increase in the monsoon, post-monsoon, and winter seasons, the spatial distribution of the temperature trend reveals that during the pre-monsoon and monsoon seasons, the increasing temperature is mostly confined to the UBRB (Figure 6). In contrast, for the post-monsoon and winter seasons, both the UBRB and LBRB exhibit an increasing trend. Total runoff is primarily governed by precipitation; hence, the seasonal spatial variation in runoff trends in the basin exhibits a similar pattern to precipitation in the LBRB across all seasons. In contrast, the upper part of the basin shows increasing trends across all seasons. Studies have reported the contribution of glacier melt and snow melt

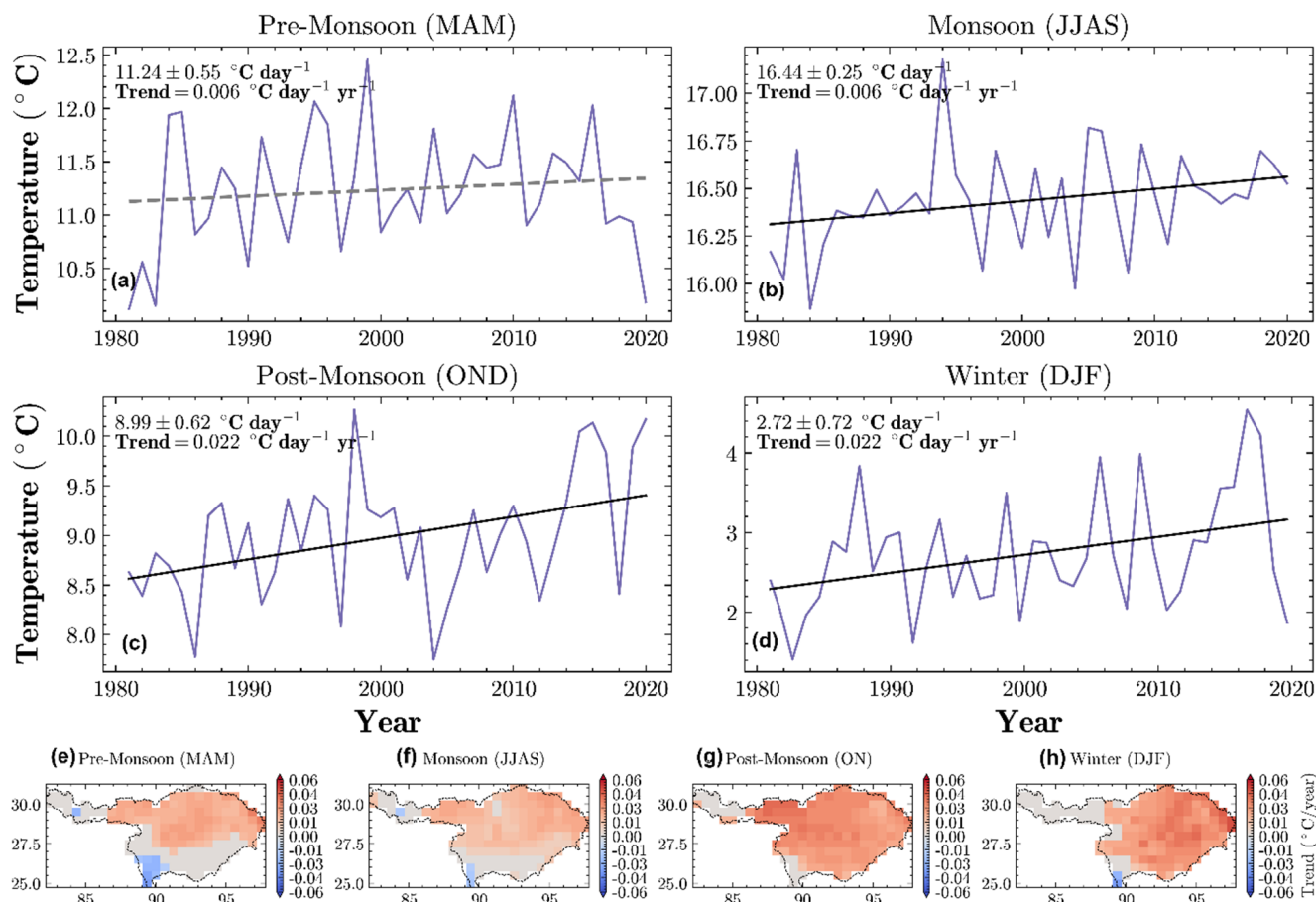


FIGURE 6 | Seasonal variations and trends of daily temperature (°C) over the Brahmaputra basin from 1980 to 2020. Sub-plots (a–d) show the time series of mean seasonal temperatures for the four seasons, with solid lines representing statistically significant trends (p -value < 0.05) and dashed lines representing statistically non-significant trends (p -value > 0.05). The reported values indicate the seasonal mean and standard deviation and the corresponding trend (°C day⁻¹ year⁻¹). Sub-plots (e–h) show the spatial distribution of the trend for each season, highlighting areas of warming and cooling across the region. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

to runoff; however, variations in the quantification have been observed (Wang et al. 2022). We note that glacier melt, not represented in the present land surface models, may provide an additional contribution to the observed UBRB runoff increase and warrants dedicated cryosphere modelling in future work. The overall decreasing trend in the water fluxes in the LBRB can be attributed to the reduced Indian summer monsoon rainfall. The decreasing trend in the lower Himalayas of Arunachal Pradesh, India, may also be attributed to the weakening of water vapour exchange between the Tibetan Plateau and the Asian monsoon (Yang et al. 2014).

An intensified hydrological cycle is observed in the upper part of the basin, whereas a decelerating hydrological cycle is observed in the lower part of the basin, suggesting a diverging hydrological cycle in the basin.

5.4 | Impact of Diverging Hydrology of BRB on Streamflow Variation

While we have observed diverging hydrological fluxes in UBRB and LBRB, we have also evaluated how these diverging hydrological patterns are impacting streamflow variability in

the Brahmaputra River. Annual streamflow at G1 exhibits a significant increasing trend of approximately 9 m³/s. Seasonal analysis further reveals that monsoon (JJAS), post-monsoon (ON), and winter (DJF) flows show positive trends, suggesting intensification of surface water availability in UBRB (Figure 7). These increases can be attributed to enhanced precipitation and runoff in the region. In contrast, G2 does not exhibit a significant annual trend. This muted response of streamflow in G2 is a result of decreases in runoff, which dampens the increasing trend of the UBRB. Seasonally, only the pre-monsoon (MAM) period at G2 exhibits a clear decreasing trend, with no significant trends observed during the monsoon, post-monsoon or winter seasons.

5.5 | Representation of TWSA and Impact of Storage Component on TWSA

While temporal variability of the fluxes is well-represented by LSMs (Table 1), the model-simulated TWSA results diverge from satellite observations (Figure 1). While the model reproduces the seasonal variability and overall dynamics of TWSA reasonably well through approximately 2012 (Figure 3), the simulated and observed trends diverge thereafter, with

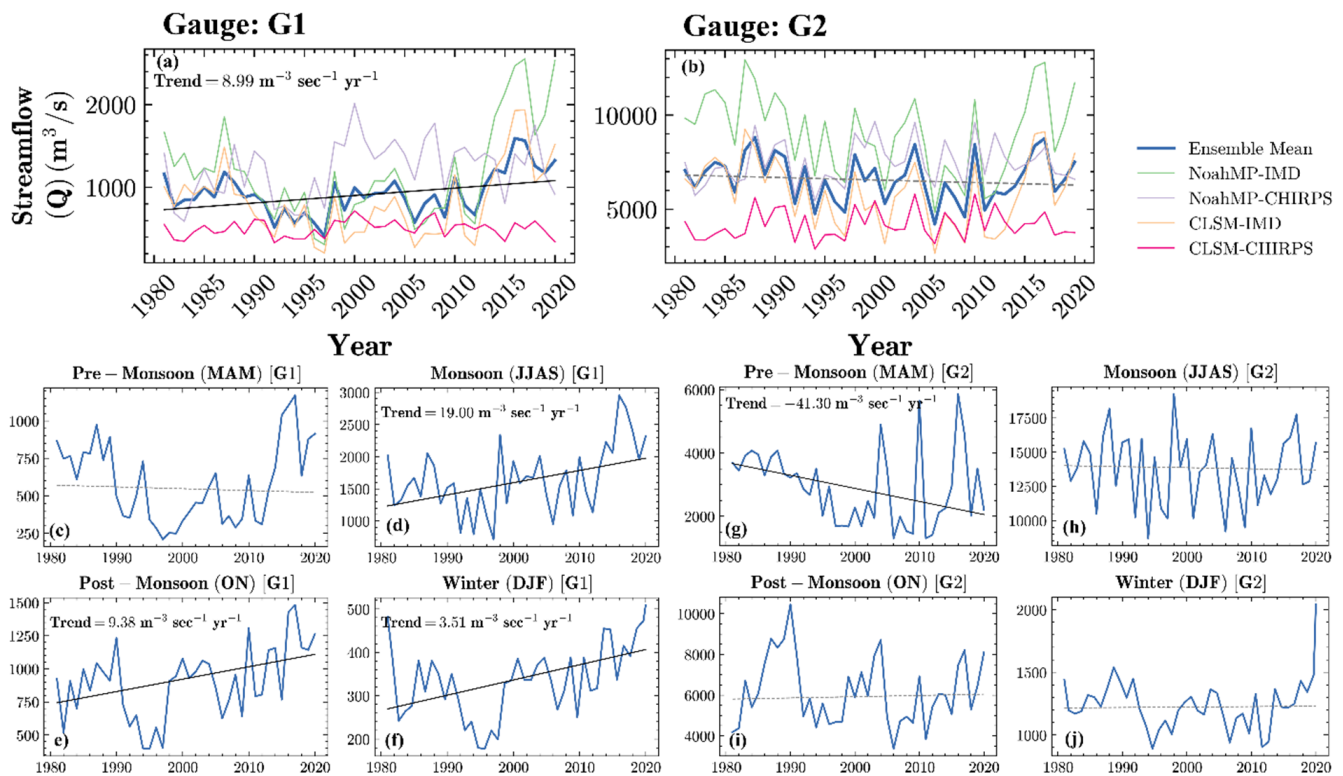


FIGURE 7 | Long-term annual and seasonal streamflow variability and trends at Gauge G1 (left) and Gauge G2 (right) for 1980–2020. Figures (a, b) show annual streamflow time series from individual LSM–forcing combinations along with the ensemble mean. Linear trends are shown with corresponding slope estimates. Figures (c–j) present seasonal streamflow for the pre-monsoon (MAM), monsoon (JJAS), post-monsoon (ON) and winter (DJF) periods at each gauge, with trend lines indicating the seasonal trends. The black solid line indicates a significant trend with p -value < 0.05 , and the grey dashed line indicates trends with p -value > 0.05 . [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

GRACE indicating a continued decline while the model shows an increasing trend. Similar divergence in the LSM-simulated TWSA is also reported in other studies (Loomis et al. 2019; Yoon et al. 2019). This diverging nature can be attributed to limitations in the model structure. The subsurface storage change in both Noah MP and CLSM is represented by the unconfined aquifer storage. However, neither model represents a confined aquifer. Hence, the impact of groundwater is not well represented in the TWSA generated from LSMs. Anthropogenic impacts on water storage, such as surface water diversions and pumping (Maina et al. 2022), are not represented in the LSMs, which may account for the disagreement. Loomis et al. (2019) suggested this divergence can be attributed to the uncertainty in the precipitation products over this region.

This study examines the impact of various storage components on changes in terrestrial water storage within the basin. Although there is a diverging trend in the storage results, the impact index (Section 4.5) is a reliable diagnostic of the relative contribution of the different components. The impact index quantifies the relative contribution of each component by summing the absolute monthly climatology anomalies (Equation 3). It is therefore dependent on the temporal structure of each component's variability, not on its absolute magnitude. Since all four components (GWS, SM, SWS, SWE) are simulated together within the same model, any bias in the total TWSA tends to affect them similarly. As a result, the relative shares of each component in the total variability remain

largely unchanged, even when the TWSA magnitude differs from that of GRACE.

Figure 8 shows the impact of various storage components across the basin. The basin-averaged impact values are listed in Table 3, along with the global storage impact estimates taken from Getirana, Kumar, et al. (2017). From the spatial plots of the impact of water storage components on TWS, soil moisture, and groundwater storage have the most impact on the TWS variability across the basin (Figure 8a–c). Basin-averaged impact values of 39.7% and 37.7%, respectively. However, SWS dominates the TWS variability in the valley portion that lies in Assam, India, and Bangladesh (Figure 8b). SWS has a basin average impact value of 21.5%. SWE has a negligible impact except in small patches in the Himalayan region. The basin-averaged impact value is 1.1% for SWE. Soil moisture and groundwater storage impact the TWS variability across the basin the most. Surface water storage (SWS), that is, water stored in rivers and flood plains, is also a significant component contributing to the TWS variability in the basin. Compared to the global average of the basin, the terrestrial water stored in the basin has a higher dependence on GWS and SWS. Hence, due to the higher contribution of GWS and SWS, a lower dependence on TWS on SM is observed as compared to the global. Being a tropical basin, SWS has a higher impact than the global average (Getirana, Kumar, et al. 2017). In the valley, the higher contribution of SWS can be attributed to the large volume of water carried by the river and the water stored in the floodplains during the monsoon season.

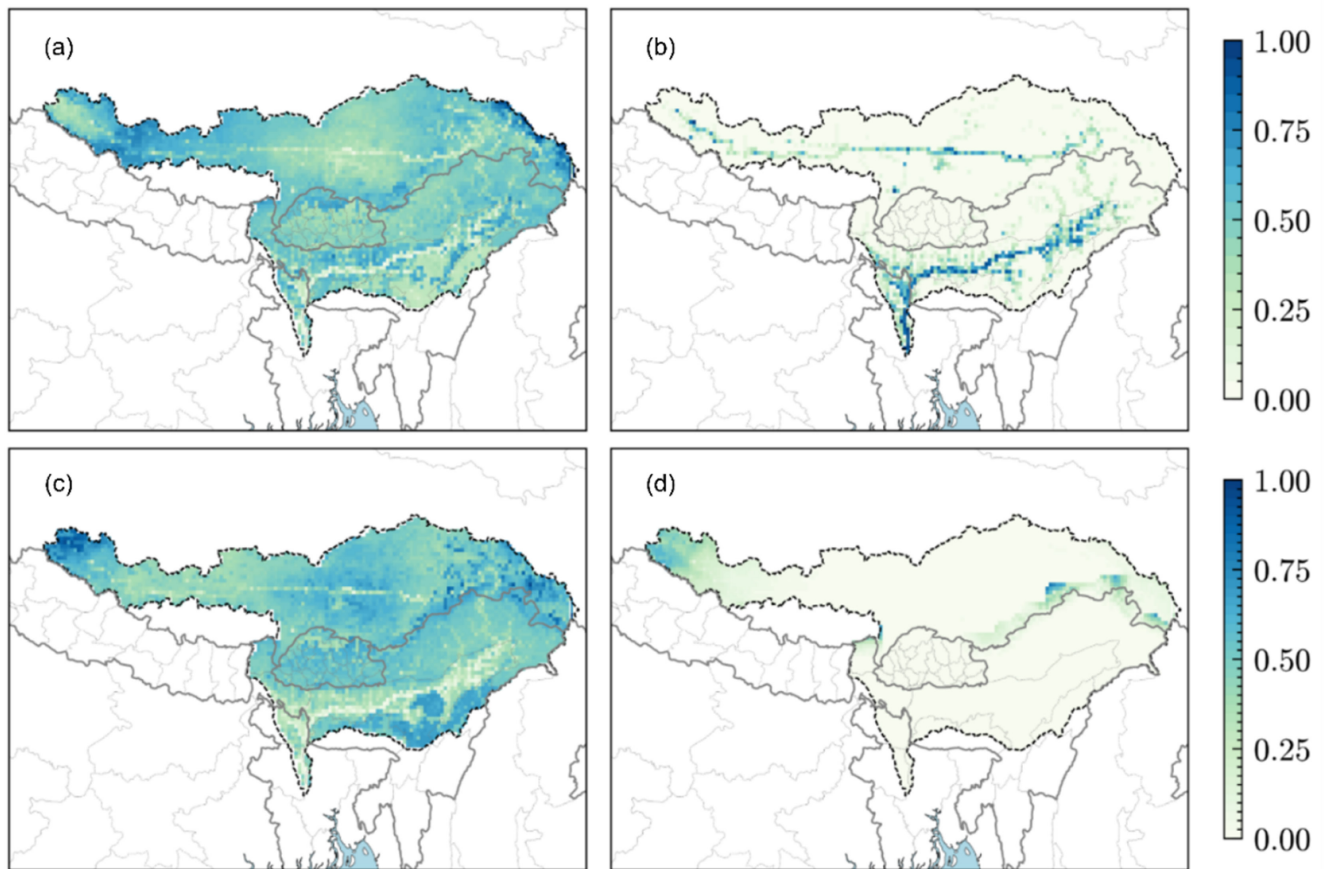


FIGURE 8 | Spatial distribution of the impact index of (a) groundwater storage (GWS), (b) surface water storage (SWS), (c) soil moisture (SM) and (d) snow water equivalent (SWE) on the terrestrial water storage (TWS) variability over the Brahmaputra River Basin. The colour scale represents the Impact index of each storage component on TWS variability. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

TABLE 3 | Average impact of various water storage components in the Brahmaputra basin and globally.

Impact index	GWS	SM	SWS	SWE
Brahmaputra basin	39.7%	37.7%	21.5%	1.1%
Global (Getirana, Kumar, et al. 2017)	17.4%	51.2%	8.3%	23.1%

6 | Conclusions and Future Work

The Brahmaputra basin is a major basin of the world with complex terrain that experiences hydroclimatological extremes. The changing climate has led to challenges in water availability and basin management. A multi-model, multi-forcing hydrologic-hydrodynamic modelling approach is used in this study. Two LSMs (Noah MP and CLSM) coupled with a routing model (HyMAP) are forced with MERRA2, where the precipitation is replaced by CHIRPS (reanalysis product based on satellite and ground-based precipitation) and IMD gridded product (ground observation-based precipitation).

Some of the major conclusions from this study are as follows:

1. A mean annual rainfall of 1455 mm/year with a standard deviation of 207 mm/year is observed with IMD data, and

a 1405 mm/year with a standard deviation of 119 mm/year is observed with CHIRPS. The basin receives most of its rainfall during the monsoon period. The spatial distribution of precipitation suggests a clear demarcation in the basin's annual precipitation rate, with the upper and lower parts accounting for 30% and 70%, respectively. Although no long-term trend (1981–2020) is observed in the basin-averaged annual precipitation, winter precipitation exhibits a significant decreasing trend, affecting winter agriculture and increasing water stress during the lean period.

2. The ensemble mean of basin-averaged precipitation, ET and runoff shows no significant trend. However, increases in P, ET and R have been observed in recent years. A decreasing trend in the ET/P ratio and an increasing trend in C are observed, suggesting that the share of ET from precipitation is decreasing, whereas the share of runoff from precipitation is increasing, leading the basin to respond to increasing precipitation with higher surface runoff. The basin-averaged trend is not consistent throughout the basin.
3. The findings of this study have implications for understanding the diverging hydrological cycle of the basin. The spatial distribution of trends in the water fluxes of the basin suggests an accelerating hydrological process in the upper part of the basin, whereas a decelerating hydrological cycle

in patches in the lower part. The variability of the hydrological variables in the lower part of the basin is double that of the upper part of the basin.

4. Increasing runoff in the UBRB is strengthening streamflow in the region, while opposing runoff signals in the LBRB suppress streamflow variability and thus imply that hydrologic responses in the Brahmaputra Basin are strongly spatially divergent.
5. GWS and SM are the largest contributors to TWS of the basin. However, the contribution of river and floodplain storage is significant compared to global numbers. The contribution of SWS is mostly higher in the valley part of the basin, resulting from the large amount of water carried by the river and stored in the floodplains during the monsoon period.

The spatially divergent hydrological trends identified in this study have significant implications for transboundary water management and climate adaptation in the Brahmaputra basin, which is shared among China, Bhutan, India and Bangladesh. The accelerating hydrological cycle in the UBRB increases the risk of floods, glacial lake outburst events, and sediment transport into downstream regions, underscoring the need for joint flood early warning systems among riparian countries. In contrast, the decelerating hydrology in parts of the LBRB, coupled with declining winter precipitation, raises concerns over dry-season water availability, agriculture and ecosystem health in downstream Assam and Bangladesh. These contrasting trends underscore the need for spatially differentiated adaptation strategies: flood resilience and sediment management in the upper basin, and drought preparedness, groundwater regulation and conjunctive water use in the lower basin.

Certain model limitations related to the aquifer representation in the LSMs and the exclusion of reservoirs and lakes in the routing scheme will be subject to future research. The study provides valuable insights into comprehensively assessing the long-term water budget of the Brahmaputra basin, spanning from 1981 to 2020, and its findings serve as a significant reference for informing sustainable water management practises in the basin. The adopted multi-model, multi-forcing approach effectively accounts for uncertainties in both model and forcing. Nonetheless, enhancing the robustness of such studies could involve incorporating data assimilation of satellite products, thereby improving the Indian Land Data Assimilation System (ILDAS).

Author Contributions

Priyam Deka: conceptualization, methodology, software, formal analysis, writing – original draft, visualization, data curation, validation. **Manabendra Saharia:** conceptualization, methodology, supervision, writing – review and editing. **Sharad Jain:** writing – review and editing. **Ved Prakash:** software, writing – review and editing, data curation. **Sujay Kumar:** writing – review and editing. **Augusto Getirana:** writing – review and editing. **Suneet Bansal:** writing – review and editing. **Kondapalli Niranjan Kumar:** writing – review and editing. **V. S. Prasad:** writing – review and editing. **Mrutyunjay Mohapatra:** writing – review and editing.

Acknowledgements

This research was conducted in the HydroSense lab (<https://hydrosense.iitd.ac.in/>) of IIT Delhi and the authors acknowledge the IIT Delhi High

Performance Computing facility for providing computational and storage resources. Dr. Manabendra Saharia gratefully acknowledges financial support for this work through grants from MoES Monsoon Mission III (RP04574). The authors gratefully acknowledge the Central Water Commission (CWC), National Water Informatics Centre (NWIC), and the Ministry of Jal Shakti (MoJS) for providing the streamflow datasets used in this study. The authors also acknowledge ISRO NRSC for providing access to the 1:50000 LU/LC dataset.

Funding

Dr. Manabendra Saharia gratefully acknowledges financial support for this work through grants from MoES Monsoon Mission III (RP04574).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets used in this research are IMD precipitation (Pai et al. 2014): https://www.imdpune.gov.in/Clim_Pred_LRF_New/. MERRA-2: GMAO, NASA Goddard Space Flight Centre (Gelaro et al. 2017) <https://disc.gsfc.nasa.gov/datasets?project=MERRA-2>. CHIRPS: Climate Hazards Centre, UC Santa Barbara, (Funk et al. 2015) <https://data.chc.ucs.edu/products/CHIRPS-2.0/>. GRUN Runoff: Institute for Atmospheric and Climate Science, ETH Zurich, (Ghiggi et al. 2019) https://figshare.com/articles/dataset/GRUN_Global_Runoff_Reconstruction/9228176. MODIS Evapotranspiration: GSFC, NASA, (Running et al. 2019) <https://modis.gsfc.nasa.gov/data/dataproduct/mod16.php>. GLEAM Evapotranspiration: (Martens et al. 2017; Miralles et al. 2011) <https://www.gleam.eu/>. GRACE and GRACE-FO: Center for Space Research (CSR), The University of Texas, (Landerer et al. 2020; Landerer and Swenson 2012) <https://podaac.jpl.nasa.gov/GRACE>.

References

- Ban, C., Z. Xu, D. Zuo, X. Liu, R. Zhang, and J. Wang. 2021. "Vertical Influence of Temperature and Precipitation on Snow Cover Variability in the Yarlung Zangbo River Basin, China." *International Journal of Climatology* 41, no. 2: 1148–1161. <https://doi.org/10.1002/joc.6776>.
- Bonan, G. B., P. J. Lawrence, K. W. Oleson, et al. 2011. "Improving Canopy Processes in the Community Land Model Version 4 (CLM4) Using Global Flux Fields Empirically Inferred From FLUXNET Data." *Journal of Geophysical Research* 116, no. G2: G02014. <https://doi.org/10.1029/2010JG001593>.
- Burn, D. H., J. M. Cunderlik, and A. Pietroniro. 2004. "Hydrological Trends and Variability in the Liard River Basin/Tendances Hydrologiques et variabilité dans le bassin de la rivière Liard." *Hydrological Sciences Journal* 49, no. 1: 53–67. <https://doi.org/10.1623/hysj.49.1.53.53994>.
- Chakraborty, A., M. Saharia, S. Chakma, et al. 2024. "Improved Soil Moisture Estimation and Detection of Irrigation Signal by Incorporating SMAP Soil Moisture Into the Indian Land Data Assimilation System (ILDAS)." *Journal of Hydrology* 638: 131581. <https://doi.org/10.1016/j.jhydrol.2024.131581>.
- Chandole, V., G. S. Joshi, and S. C. Rana. 2019. "Spatio-Temporal Trend Detection of Hydro-Meteorological Parameters for Climate Change Assessment in Lower Tapi River Basin of Gujarat State, India." *Journal of Atmospheric and Solar-Terrestrial Physics* 195: 105130. <https://doi.org/10.1016/j.jastp.2019.105130>.
- Chen, H. 2012. "Assessment of Hydrological Alterations From 1961 to 2000 in the Yarlung Zangbo River, Tibet." *Ecohydrology & Hydrobiology* 12, no. 2: 93–103. <https://doi.org/10.2478/v10104-012-0009-z>.
- Dankers, R., N. W. Arnell, D. B. Clark, et al. 2014. "First Look at Changes in Flood Hazard in the Inter-Sectoral Impact Model Intercomparison

- Project Ensemble." *Proceedings National Academy of Sciences United States of America* 111, no. 9: 3257–3261. <https://doi.org/10.1073/pnas.1302078110>.
- Funk, C., P. Peterson, M. Landsfeld, et al. 2015. "The Climate Hazards Infrared Precipitation With Stations—A New Environmental Record for Monitoring Extremes." *Scientific Data* 2, no. 1: 150066. <https://doi.org/10.1038/sdata.2015.66>.
- Gain, A. K., W. W. Immerzeel, F. C. Serna Weiland, and M. F. P. Bierkens. 2011. "Impact of Climate Change on the Stream Flow of the Lower Brahmaputra: Trends in High and Low Flows Based on Discharge-Weighted Ensemble Modelling." *Hydrology and Earth System Sciences* 15, no. 5: 1537–1545. <https://doi.org/10.5194/hess-15-1537-2011>.
- Gelaro, R., W. McCarty, M. J. Suárez, et al. 2017. "The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2)." *Journal of Climate* 30, no. 14: 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>.
- Gelati, E., B. Decharme, J.-C. Calvet, et al. 2018. "Hydrological Assessment of Atmospheric Forcing Uncertainty in the Euro-Mediterranean Area Using a Land Surface Model." *Hydrology and Earth System Sciences* 22, no. 4: 2091–2115. <https://doi.org/10.5194/hess-22-2091-2018>.
- Getirana, A., A. Boone, C. Peugeot, and ALMIP2 Working Group. 2017. "Streamflows Over a West African Basin From the ALMIP2 Model Ensemble." *Journal of Hydrometeorology* 18, no. 7: 1831–1845. <https://doi.org/10.1175/JHM-D-16-0233.1>.
- Getirana, A., S. Kumar, M. Girotto, and M. Rodell. 2017. "Rivers and Floodplains as Key Components of Global Terrestrial Water Storage Variability: Water Storage in Rivers and Floodplains." *Geophysical Research Letters* 44, no. 20: 10359–10368. <https://doi.org/10.1002/2017GL074684>.
- Getirana, A. C. V., A. Boone, D. Yamazaki, B. Decharme, F. Papa, and N. Mognard. 2012. "The Hydrological Modeling and Analysis Platform (HyMAP): Evaluation in the Amazon Basin." *Journal of Hydrometeorology* 13, no. 6: 1641–1665. <https://doi.org/10.1175/JHM-D-12-021.1>.
- Getirana, A. C. V., E. Dutra, M. Guimberteau, et al. 2014. "Water Balance in the Amazon Basin From a Land Surface Model Ensemble." *Journal of Hydrometeorology* 15, no. 6: 2586–2614. <https://doi.org/10.1175/JHM-D-14-0068.1>.
- Ghiggi, G., V. Humphrey, S. I. Seneviratne, and L. Gudmundsson. 2019. "GRUN: An Observation-Based Global Gridded Runoff Dataset From 1902 to 2014." *Earth System Science Data* 11, no. 4: 1655–1674. <https://doi.org/10.5194/essd-11-1655-2019>.
- Ghosh, S., and S. Dutta. 2012. "Impact of Climate Change on Flood Characteristics in Brahmaputra Basin Using a Macro-Scale Distributed Hydrological Model." *Journal of Earth System Science* 121, no. 3: 637–657. <https://doi.org/10.1007/s12040-012-0181-y>.
- Gogoi, P. P., V. Vinoj, K. Landu, and P. Phukon. 2023. "The Changing Characteristics of Rainfall Over the Brahmaputra Basin During 1998–2018." *Quarterly Journal of the Royal Meteorological Society* 149, no. 751: 608–620. <https://doi.org/10.1002/qj.4427>.
- Goswami, D. C. 1985. "Brahmaputra River, Assam, India: Physiography, Basin Denudation, and Channel Aggradation." *Water Resources Research* 21, no. 7: 959–978. <https://doi.org/10.1029/WR021i007p00959>.
- Helsel, D. R., R. M. Hirsch, K. R. Ryberg, S. A. Archfield, and E. J. Gilroy. 2020. *Statistical Methods in Water Resources: U.S. Geological Survey Techniques and Methods*, book 4, chap. A3, 458. <https://doi.org/10.3133/tm4a3>.
- Immerzeel, W. 2008. "Historical Trends and Future Predictions of Climate Variability in the Brahmaputra Basin." *International Journal of Climatology* 28, no. 2: 243–254. <https://doi.org/10.1002/joc.1528>.
- Jain, S. K., V. Kumar, and M. Saharia. 2013. "Analysis of Rainfall and Temperature Trends in Northeast India." *International Journal of Climatology* 33, no. 4: 968–978. <https://doi.org/10.1002/joc.3483>.
- Jian, J., P. J. Webster, and C. D. Hoyos. 2009. "Large-Scale Controls on Ganges and Brahmaputra River Discharge on Intraseasonal and Seasonal Time-Scales." *Quarterly Journal of the Royal Meteorological Society* 135, no. 639: 353–370. <https://doi.org/10.1002/qj.384>.
- Jing, W., P. Zhang, and X. Zhao. 2019. "A Comparison of Different GRACE Solutions in Terrestrial Water Storage Trend Estimation Over Tibetan Plateau." *Scientific Reports* 9, no. 1: 1765. <https://doi.org/10.1038/s41598-018-38337-1>.
- Joshi, N., D. Gupta, S. Suryavanshi, J. Adamowski, and C. A. Madramootoo. 2016. "Analysis of Trends and Dominant Periodicities in Drought Variables in India: A Wavelet Transform Based Approach." *Atmospheric Research* 182: 200–220. <https://doi.org/10.1016/j.atmosres.2016.07.030>.
- Jung, H. C., A. Getirana, F. Policelli, et al. 2017. "Upper Blue Nile Basin Water Budget From a Multi-Model Perspective." *Journal of Hydrology* 555: 535–546. <https://doi.org/10.1016/j.jhydrol.2017.10.040>.
- Kaur, S., S. K. Diwakar, and A. K. Das. 2017. "Long Term Rainfall Trend Over Meteorological Sub Divisions and Districts of India." *Mausam* 68, no. 3: 439–450. <https://doi.org/10.54302/mausam.v68i3.676>.
- Kim, H., P. J.-F. Yeh, T. Oki, and S. Kanae. 2009. "Role of Rivers in the Seasonal Variations of Terrestrial Water Storage Over Global Basins." *Geophysical Research Letters* 36, no. 17: L17402. <https://doi.org/10.1029/2009GL039006>.
- Kim, H. W., K. Hwang, Q. Mu, S. O. Lee, and M. Choi. 2012. "Validation of MODIS 16 Global Terrestrial Evapotranspiration Products in Various Climates and Land Cover Types in Asia." *KSCE Journal of Civil Engineering* 16, no. 2: 229–238. <https://doi.org/10.1007/s12205-012-0006-1>.
- Koster, R. D., M. J. Suarez, A. Ducharme, M. Stieglitz, and P. Kumar. 2000. "A Catchment-Based Approach to Modeling Land Surface Processes in a General Circulation Model: 1. Model Structure." *Journal of Geophysical Research: Atmospheres* 105, no. D20: 24809–24822. <https://doi.org/10.1029/2000JD900327>.
- Kripalani, R. H., J. H. Oh, A. Kulkarni, S. S. Sabade, and H. S. Chaudhari. 2007. "South Asian Summer Monsoon Precipitation Variability: Coupled Climate Model Simulations and Projections Under IPCC AR4." *Theoretical and Applied Climatology* 90, no. 3–4: 133–159. <https://doi.org/10.1007/s00704-006-0282-0>.
- Kumar, S., C. Peterslidard, Y. Tian, et al. 2006. "Land Information System: An Interoperable Framework for High Resolution Land Surface Modeling." *Environmental Modelling & Software* 21, no. 10: 1402–1415. <https://doi.org/10.1016/j.envsoft.2005.07.004>.
- Kumar, S. V., S. Wang, D. M. Mocko, C. D. Peters-Lidard, and Y. Xia. 2017. "Similarity Assessment of Land Surface Model Outputs in the North American Land Data Assimilation System." *Water Resources Research* 53, no. 11: 8941–8965. <https://doi.org/10.1002/2017WR020635>.
- Landerer, F. W., F. M. Flechtner, H. Save, et al. 2020. "Extending the Global Mass Change Data Record: GRACE Follow-On Instrument and Science Data Performance." *Geophysical Research Letters* 47, no. 12: e2020GL088306. <https://doi.org/10.1029/2020GL088306>.
- Landerer, F. W., and S. C. Swenson. 2012. "Accuracy of Scaled GRACE Terrestrial Water Storage Estimates." *Water Resources Research* 48, no. 4: 2011WR011453. <https://doi.org/10.1029/2011WR011453>.
- Liu, X., Z. Xu, W. Liu, and L. Liu. 2019. "Responses of Hydrological Processes to Climate Change in the Yarlung Zangbo River Basin." *Hydrological Sciences Journal* 64, no. 16: 2057–2067. <https://doi.org/10.1080/02626667.2019.1662908>.

- Loomis, B. D., A. S. Richey, A. A. Arendt, et al. 2019. "Water Storage Trends in High Mountain Asia." *Frontiers in Earth Science* 7: 235. <https://doi.org/10.3389/feart.2019.00235>.
- Ma, N., and Y. Zhang. 2022. "Increasing Tibetan Plateau Terrestrial Evapotranspiration Primarily Driven by Precipitation." *Agricultural and Forest Meteorology* 317: 108887. <https://doi.org/10.1016/j.agrformet.2022.108887>.
- Magotra, B., V. Prakash, M. Saharia, et al. 2024. "Towards an Indian Land Data Assimilation System (ILDAS): A Coupled Hydrologic-Hydraulic System for Water Balance Assessments." *Journal of Hydrology* 629: 130604. <https://doi.org/10.1016/j.jhydrol.2023.130604>.
- Maina, F. Z., S. V. Kumar, C. Albergel, and S. P. Mahanama. 2022. "Warming, Increase in Precipitation, and Irrigation Enhance Greening in High Mountain Asia." *Communications Earth & Environment* 3, no. 1: 43. <https://doi.org/10.1038/s43247-022-00374-0>.
- Martens, B., D. G. Miralles, H. Lievens, et al. 2017. "GLEAM v3: Satellite-Based Land Evaporation and Root-Zone Soil Moisture." *Geoscientific Model Development* 10, no. 5: 1903–1925. <https://doi.org/10.5194/gmd-10-1903-2017>.
- Meshram, S. G., V. P. Singh, and C. Meshram. 2017. "Long-Term Trend and Variability of Precipitation in Chhattisgarh State, India." *Theoretical and Applied Climatology* 129, no. 3: 729–744. <https://doi.org/10.1007/s00704-016-1804-z>.
- Miralles, D. G., T. R. H. Holmes, R. A. M. De Jeu, J. H. Gash, A. G. C. A. Meesters, and A. J. Dolman. 2011. "Global Land-Surface Evaporation Estimated From Satellite-Based Observations." *Hydrology and Earth System Sciences* 15, no. 2: 453–469. <https://doi.org/10.5194/hess-15-453-2011>.
- Miranda, R. D. Q., J. D. Galvncio, M. S. B. D. Moura, C. A. Jones, and R. Srinivasan. 2017. "Reliability of MODIS Evapotranspiration Products for Heterogeneous Dry Forest: A Study Case of Caatinga." *Advances in Meteorology* 2017: 1–14. <https://doi.org/10.1155/2017/9314801>.
- Mockler, E. M., K. P. Chun, G. Sapriza-Azuri, M. Bruen, and H. S. Wheeler. 2016. "Assessing the Relative Importance of Parameter and Forcing Uncertainty and Their Interactions in Conceptual Hydrological Model Simulations." *Advances in Water Resources* 97: 299–313. <https://doi.org/10.1016/j.advwatres.2016.10.008>.
- Monirul Qader Mirza, M. 2002. "Global Warming and Changes in the Probability of Occurrence of Floods in Bangladesh and Implications." *Global Environmental Change* 12, no. 2: 127–138. [https://doi.org/10.1016/S0959-3780\(02\)00002-X](https://doi.org/10.1016/S0959-3780(02)00002-X).
- Monteith, J. L., G. Szeicz, and P. E. Waggoner. 1965. "The Measurement and Control of Stomatal Resistance in the Field." *Journal of Applied Ecology* 2, no. 2: 345. <https://doi.org/10.2307/2401484>.
- Muller Schmied, H., S. Eisner, D. Franz, et al. 2014. "Sensitivity of Simulated Global-Scale Freshwater Fluxes and Storages to Input Data, Hydrological Model Structure, Human Water Use and Calibration." *Hydrology and Earth System Sciences* 18, no. 9: 3511–3538. <https://doi.org/10.5194/hess-18-3511-2014>.
- Nie, N., W. Zhang, Z. Zhang, H. Guo, and N. Ishwaran. 2016. "Reconstructed Terrestrial Water Storage Change (Δ TWS) From 1948 to 2012 Over the Amazon Basin With the Latest GRACE and GLDAS Products." *Water Resources Management* 30, no. 1: 279–294. <https://doi.org/10.1007/s11269-015-1161-1>.
- Niu, G.-Y., Z.-L. Yang, K. E. Mitchell, et al. 2011. "The Community Noah Land Surface Model With Multiparameterization Options (Noah-MP): 1. Model Description and Evaluation With Local-Scale Measurements." *Journal of Geophysical Research* 116, no. D12: D12109. <https://doi.org/10.1029/2010JD015139>.
- Pai, D. S., M. Rajeevan, O. P. Sreejith, B. Mukhopadhyay, and N. S. Satbha. 2014. "Development of a New High Spatial Resolution ($0.25^\circ \times 0.25^\circ$) Long Period (1901–2010) Daily Gridded Rainfall Data Set Over India and Its Comparison With Existing Data Sets Over the Region." *Mausam* 65, no. 1: 1–18. <https://doi.org/10.54302/mausam.v65i1.851>.
- Pan, M., A. K. Sahoo, T. J. Troy, R. K. Vinukollu, J. Sheffield, and E. F. Wood. 2012. "Multisource Estimation of Long-Term Terrestrial Water Budget for Major Global River Basins." *Journal of Climate* 25, no. 9: 3191–3206. <https://doi.org/10.1175/JCLI-D-11-00300.1>.
- Pervez, M. S., and G. M. Henebry. 2015. "Assessing the Impacts of Climate and Land Use and Land Cover Change on the Freshwater Availability in the Brahmaputra River Basin." *Journal of Hydrology: Regional Studies* 3: 285–311. <https://doi.org/10.1016/j.ejrh.2014.09.003>.
- Posada-Marın, J. A., and J. F. Salazar. 2022. "River Flow Response to Deforestation: Contrasting Results From Different Models." *Water Security* 15: 100115. <https://doi.org/10.1016/j.wasec.2022.100115>.
- Raj, R., M. Saharia, S. Chakma, and A. Rafieinasab. 2022. "Mapping Rainfall Erosivity Over India Using Multiple Precipitation Datasets." *Catena* 214: 106256. <https://doi.org/10.1016/j.catena.2022.106256>.
- Rajeevan, M., J. Bhate, and A. K. Jaswal. 2008. "Analysis of Variability and Trends of Extreme Rainfall Events Over India Using 104 Years of Gridded Daily Rainfall Data." *Geophysical Research Letters* 35, no. 18: 2008GL035143. <https://doi.org/10.1029/2008GL035143>.
- Running, S. W., Q. Mu, M. Zhao, and A. Moreno. 2019. "MODIS Global Terrestrial Evapotranspiration (ET) Product (MOD16A2/A3 and Year-End Gap-Filled MOD16A2GF/A3GF)." In *NASA Earth Observing System MODIS Land Algorithm (For Collection 6)*. National Aeronautics and Space Administration, 6, 735. <https://doi.org/10.5067/MODIS/MOD16A2>.
- Schewe, J., J. Heinke, D. Gerten, et al. 2014. "Multimodel Assessment of Water Scarcity Under Climate Change." *Proceedings National Academy of Sciences United States of America* 111, no. 9: 3245–3250. <https://doi.org/10.1073/pnas.1222460110>.
- Shepard, D. 1968. "A Two-Dimensional Interpolation Function for Irregularly-Spaced Data." *Proceedings of the 1968 23rd ACM National Conference*, 517–524. <https://doi.org/10.1145/800186.810616>.
- Shi, Y., X. Gao, D. Zhang, and F. Giorgi. 2011. "Climate Change Over the Yarlung Zangbo–Brahmaputra River Basin in the 21st Century as Simulated by a High Resolution Regional Climate Model." *Quaternary International* 244, no. 2: 159–168. <https://doi.org/10.1016/j.quaint.2011.01.041>.
- Singh, V. P., N. Sharma, and C. S. P. Ojha, eds. 2004. *The Brahmaputra Basin Water Resources*. Vol. 47. Springer Netherlands. <https://doi.org/10.1007/978-94-017-0540-0>.
- Tekleab, S., Y. Mohamed, and S. Uhlenbrook. 2013. "Hydro-Climatic Trends in the Abay/Upper Blue Nile Basin, Ethiopia." *Physics and Chemistry of the Earth, Parts A/B/C* 61, no. 62: 32–42. <https://doi.org/10.1016/j.pce.2013.04.017>.
- Tiwari, V. M., J. Wahr, and S. Swenson. 2009. "Dwindling Groundwater Resources in Northern India, From Satellite Gravity Observations." *Geophysical Research Letters* 36, no. 18: L18401. <https://doi.org/10.1029/2009GL039401>.
- Wang, L., L. Cuo, D. Luo, et al. 2022. "Observing Multisphere Hydrological Changes in the Largest River Basin of the Tibetan Plateau." *Bulletin of the American Meteorological Society* 103, no. 6: E1595–E1620. <https://doi.org/10.1175/BAMS-D-21-0217.1>.
- Wang, Y., L. Wang, X. Li, J. Zhou, and Z. Hu. 2020. "An Integration of Gauge, Satellite, and Reanalysis Precipitation Datasets for the Largest River Basin of the Tibetan Plateau." *Earth System Science Data* 12, no. 3: 1789–1803. <https://doi.org/10.5194/essd-12-1789-2020>.
- Wang, Y., L. Wang, J. Zhou, et al. 2021. "Vanishing Glaciers at Southeast Tibetan Plateau Have Not Offset the Declining Runoff at Yarlung Zangbo." *Geophysical Research Letters* 48, no. 21: e2021GL094651. <https://doi.org/10.1029/2021GL094651>.

Webster, P. J., and J. Jian. 2011. "Environmental Prediction, Risk Assessment and Extreme Events: Adaptation Strategies for the Developing World." *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 369: 4768–4797. <https://doi.org/10.1098/rsta.2011.0160>.

Xiong, J., S. Guo, Abhishek, J. Chen, and J. Yin. 2022. "Global Evaluation of the "Dry Gets Drier, and Wet Gets Wetter" Paradigm From a Terrestrial Water Storage Change Perspective." *Hydrology and Earth System Sciences* 26, no. 24: 6457–6476. <https://doi.org/10.5194/hess-26-6457-2022>.

Xuan, W., Y.-P. Xu, Q. Fu, M. J. Booij, X. Zhang, and S. Pan. 2021. "Hydrological Responses to Climate Change in Yarlung Zangbo River Basin, Southwest China." *Journal of Hydrology* 597: 125761. <https://doi.org/10.1016/j.jhydrol.2020.125761>.

Yang, K., H. Wu, J. Qin, C. Lin, W. Tang, and Y. Chen. 2014. "Recent Climate Changes Over the Tibetan Plateau and Their Impacts on Energy and Water Cycle: A Review." *Global and Planetary Change* 112: 79–91. <https://doi.org/10.1016/j.gloplacha.2013.12.001>.

Yang, Z.-L., G.-Y. Niu, K. E. Mitchell, et al. 2011. "The Community Noah Land Surface Model With Multiparameterization Options (Noah-MP): 2. Evaluation Over Global River Basins." *Journal of Geophysical Research* 116, no. D12: D12110. <https://doi.org/10.1029/2010JD015140>.

Yoon, Y., S. V. Kumar, B. A. Forman, et al. 2019. "Evaluating the Uncertainty of Terrestrial Water Budget Components Over High Mountain Asia." *Frontiers in Earth Science* 7: 120. <https://doi.org/10.3389/feart.2019.00120>.

Zhang, R., Z. Xu, D. Zuo, and C. Ban. 2020. "Hydro-Meteorological Trends in the Yarlung Zangbo River Basin and Possible Associations With Large-Scale Circulation." *Water* 12, no. 1: 144. <https://doi.org/10.3390/w12010144>.

Zhou, Z., Y. Tuo, J. Li, et al. 2022. "Effects of Hydrology and River Characteristics on Riverine Wetland Morphology Variation in the Middle Reaches of the Yarlung Zangbo–Brahmaputra River Based on Remote Sensing." *Journal of Hydrology* 607: 127497. <https://doi.org/10.1016/j.jhydrol.2022.127497>.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Statistical indices for model performance evaluation for monthly simulations of four experiments in UBRB. **Table S2:** Statistical indices for model performance evaluation for monthly simulations of 4 experiments at LBRB. **Figure S1:** Comparison of the normalized streamflow [(Obs-mean)/Standard-deviation] for the two gauges selected for the study, where Gauge 1 is at the downstream of UBRB and Gauge 2 is at the downstream of LBRB. **Figure S2:** Variation of spatially averaged annual precipitation, evapotranspiration, runoff, ET-P ratio, and runoff coefficient in the upper Brahmaputra basin. **Figure S3:** Variation of spatially averaged annual precipitation, evapotranspiration, runoff, ET-P ratio, and runoff coefficient in the lower Brahmaputra basin.