

Research papers

Quantifying hydrological responses to climate change and associated canopy variability using an integrated LSTM-SWAT modeling framework

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ABSTRACT

Climate change and climate-driven canopy variability jointly influence terrestrial hydrological processes, while their combined effects on individual water-balance components across complex terrains remain insufficiently quantified. This study integrated a modeling framework by coupling a Long Short-Term Memory (LSTM) network with the Soil and Water Assessment Tool (SWAT) to assess scenario-based hydrological responses in the Weihe River Basin (WRB) through 2100. The LSTM model was employed to predict grid-level Normalized Difference Vegetation Index (NDVI) trajectories under Coupled Model Intercomparison Project Phase 6 scenarios, including Shared Socioeconomic Pathway 2–4.5 (SSP245) and Shared Socioeconomic Pathway 5–8.5 (SSP585). The predicted NDVI trajectories were then converted into Leaf Area Index (LAI) and incorporated into SWAT as seasonal canopy constraints. The LSTM-based approach reasonably represented climate-driven canopy variability ($R^2 > 0.90$), projecting increasing canopy density under future climate scenarios, particularly under SSP585. Climate change was projected to intensify simulated hydrological fluxes. In the diagnostic climate-change perturbation scenarios, mean streamflow increased by 12.0% under SSP245 and 21.2% under SSP585, whereas the integrated climate-canopy scenarios moderated these increases to 10.7% and 19.4%, respectively, through enhanced evapotranspiration (ET). Terrain-dependent variations in hydrological sensitivity were identified. Specifically, plain regions exhibited stronger responses in surface runoff (SURQ) and groundwater flow (GWQ), plateau regions (PLT) demonstrated larger changes in water yield (WYLD), and mountainous regions (MTN) displayed more pronounced responses in lateral subsurface flow (LATQ). These findings provide scenario-based diagnostic evidence for assessing how climate-driven canopy variability may moderate hydrological responses in topographically diverse watersheds.

1. Introduction

Climate change has induced significant non-stationarity in the terrestrial hydrological cycle, altering water availability through shifts in precipitation regimes and temperature patterns across global watersheds (Arantes et al., 2021; Li et al., 2010). In semi-arid regions, where ecosystems are inherently water-limited, hydrological processes exhibit heightened sensitivity to climatic forcing. Beyond the direct impacts on streamflow generation and groundwater recharge, climate change may also influence hydrological partitioning indirectly via climate-driven changes in canopy conditions. As terrestrial ecosystems exhibit greening responses to warming, changing precipitation regimes, and

CO₂ fertilization, the resulting changes in canopy condition—typically quantified by the Leaf Area Index (LAI) or Normalized Difference Vegetation Index (NDVI)—can modify water flux partitioning through enhanced transpiration and interception (Lei et al., 2014; Hwang et al., 2018; Peng et al., 2024).

This hierarchical dependence between climatic forcing, climate-driven canopy variability, and hydrological response necessitates integrated modeling approaches. The Soil and Water Assessment Tool (SWAT) has emerged as a cornerstone in process-based hydrological research due to its robust physical representation of watershed processes (Arnold et al., 1998). However, a persistent limitation in conventional SWAT applications is the reliance on static vegetation parameters or

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simplified phenological representations, which fail to capture the climate-sensitive variability in canopy density (Strauch and Volk, 2013). While recent studies have integrated satellite-derived products into hydrological models (Ma et al., 2019; Chen et al., 2023), the predictive capacity to assess how future climate-driven canopy variability may influence hydrological partitioning remains limited.

The rapid advancement of machine learning offers a promising bridge to close this gap. Long Short-Term Memory (LSTM) networks are particularly effective in capturing the complex nonlinear temporal relationships between climatic variables and climate-driven canopy variability (Cho and Kim, 2022). By coupling LSTM-based predictive modeling with distributed process-based hydrological models, it is possible to represent indirect canopy-mediated hydrological responses within a process-based watershed simulation framework.

Despite this potential, critical knowledge gaps remain. Existing

studies primarily focus on total basin-scale streamflow, leaving the response of individual hydrological components—such as surface runoff (SURQ), GWQ, lateral flow (LATQ), ET, and water yield (WYLD)—insufficiently explored. Moreover, climate change and climate-driven canopy variability are frequently analyzed separately, limiting understanding of how climate-driven canopy responses propagate through hydrological systems across heterogeneous landscapes (Zhao et al., 2016; Ji and Duan, 2019; Wu et al., 2023). In addition, the spatio-topographic heterogeneity of these responses is often overlooked; it remains unclear how complex terrains modulate the propagation of climate and canopy-related signals. In the Weihe River Basin (WRB), a region characterized by diverse geomorphology and increasing water scarcity, understanding these nuanced interactions is vital for sustainable water management.

To address these issues, this study develops a coupled LSTM-SWAT

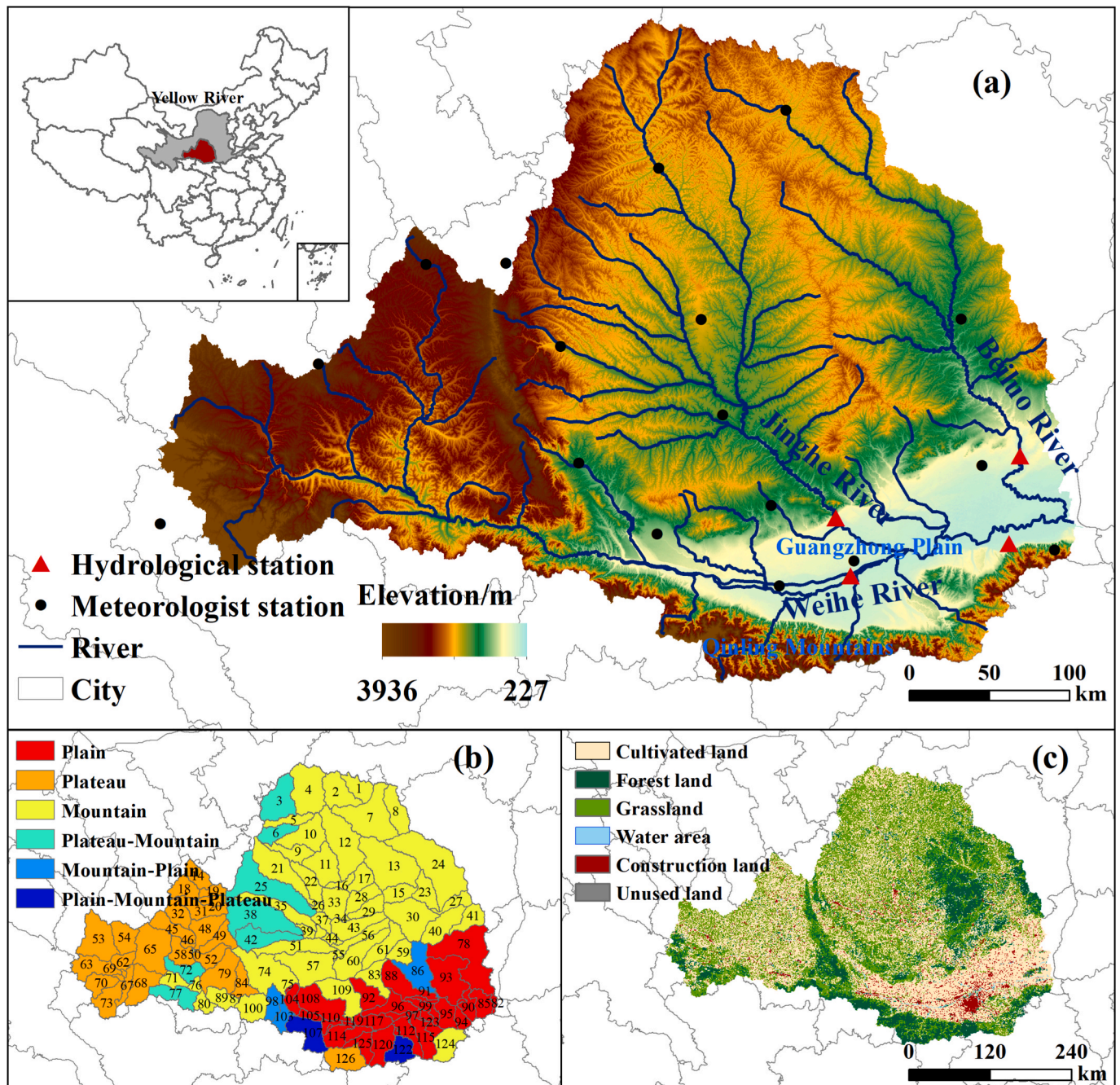


Fig. 1. Geographical location map (a), topography (b), and land use map (c) of the Weihe River Basin in China.

framework to investigate the partitioned hydrological responses of the WRB under both historical and future CMIP6 scenarios (SSP245 and SSP585). Accordingly, the coupled framework enables an assessment of both the direct hydrological response to climate change and the indirect canopy-mediated hydrological regulation driven by climate change. Distinct from studies focusing on land-use change, our approach diagnoses canopy-mediated hydrological responses by simulating climate-driven canopy variability while maintaining fixed land-cover types, vegetation types, rooting-depth parameters, soil properties, and land-surface configurations. The specific objectives are to: (1) integrate an applied climate-canopy-hydrology modeling framework linking LSTM-based NDVI prediction with SWAT simulations; (2) evaluate historical and future variations in hydrological balance components under CMIP6 SSP scenarios; (3) diagnose scenario-based hydrological sensitivity to climatic forcing and canopy-mediated responses using controlled perturbation experiments; and (4) examine geomorphological controls on hydrological sensitivity across plains (PLN), plateau (PLT), and mountainous (MTN) units. The results aim to improve understanding of climate-canopy-hydrology interactions and provide scientific support for adaptive water resource management under future environmental change.

2. Materials and methods

2.1. Study area

The Weihe River, located in the northwestern region of China, is the largest tributary of the Yellow River (Fig. 1). The river begins in the northern part of Niushou Mountain, passes through Tongguan County in Weinan City, Shaanxi Province, and ultimately reaches the Yellow River. The system is 818 km long and drains a drainage area of $1.35 \times 10^5 \text{ km}^2$. The Jinghe River is the primary tributary of the Weihe River, spanning a total distance of 455.1 km and covering a basin area of $4.54 \times 10^4 \text{ km}^2$. This basin area accounts for 33.7% of the Weihe River basin. The Beiluo River is the second largest tributary of the Weihe River. It spans a total length of 680 km and has a drainage area of $2.69 \times 10^4 \text{ km}^2$. This area accounts for 20% of the Weihe River basin. The WRB is characterised by diverse geomorphological features, with the Qinling Mountains in the south, the Loess Plateau in the north, and the Guanzhong Plain in the central and southern regions. These geographical and climatic characteristics make the WRB a suitable case for examining terrain-dependent hydrological responses to climate change and climate-driven canopy variability.

2.2. Data collection

This study used multi-source data to analyze the linkages among climate change, NDVI-derived canopy conditions, and hydrological responses in the WRB (Table 1). Meteorological data include historical observations (1982–2021) and CMIP6 future scenario data (Table S1). Land-use distribution characteristics are shown in Fig. 1(c). NDVI was used as a remotely sensed proxy for canopy density, with spatiotemporal variation characteristics illustrated in Fig. S1. All datasets were quality-controlled, spatially harmonized, and temporally matched to provide consistent inputs for LSTM-based NDVI prediction and SWAT hydrological simulations.

2.3. Methods

This study used a hierarchical modeling workflow to diagnose watershed hydrological responses to climate change and climate-driven canopy variability (Fig. 2). The workflow linked climate-driven prediction of canopy density with process-based hydrological simulation. Specifically, NDVI variability was first reconstructed using a grid-level LSTM model driven by precipitation and temperature. The predicted NDVI was then converted into LAI and incorporated into the SWAT

Table 1
Information on multi-source datasets.

Data Category	Description	Source
Basic geographic information data of the study area	Boundary, river, and elevation data.	National Data Center for Glaciology and Permafrost Desert Science (https://www.ncdc.ac.cn).
Meteorological data	Daily measurements of cumulative precipitation, solar radiation, relative humidity, maximum temperatures ($T_{\max}$), and minimum temperatures ($T_{\min}$). Future projections of the same variables were obtained from 27 CMIP6 GCMs.	Historical Data: the China Meteorological Data Service Center (http://data.cma.cn/). Future Data: the World Climate Research Programme (WCRP).
Soil data	Harmonized World Soil Database version 2.0 (HWSD v2.0) with 1 km $\times$ 1 km spatial resolution.	Harmonized World Soil Database (HWSD v2.0) (https://gaaz.fao.org/p ages/hwsd).
Land use data	The 2020 land use maps with a spatial resolution of 1 km $\times$ 1 km, consisting of six categories: grassland, cultivated land, forest land, construction land, water areas, and unused land. (The basin is dominated by grassland, cultivated land, and forest, accounting for over 90% of the total area).	Data Center for Resource and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn)
NDVI data	Monthly GIMMS3G+ NDVI dataset.	The GIMMS3G+ NDVI dataset released by NASA (https://ecocast.arc.nasa.gov)
Hydrological data	Monthly flow data from four hydrological stations (Xianyang, Huaxian, Zhangjiashan, Zhuangtuo)	Yellow River Conservancy Commission (https://www.yrcc.gov.cn)

vegetation-growth parameter database as seasonal canopy constraints, thereby representing climate-driven canopy-density variability under fixed land-use configurations. Hydrological responses were subsequently simulated using the calibrated SWAT model, while sub-basins were classified into geomorphological units to examine terrain-dependent differences in water-balance dynamics. Finally, scenario-based diagnostic perturbation experiments were conducted to distinguish the direct hydrological response to climatic forcing from additional canopy-mediated responses associated with prescribed climate-driven canopy variability.

Within this modeling chain, the canopy representation refers specifically to climate-driven variations in NDVI-derived LAI, rather than structural vegetation transitions, land-cover conversion, rooting-depth adjustment, or soil-property changes. Land-use distribution, vegetation types, rooting-depth parameters, and soil hydraulic properties were held constant across all simulations. Consequently, the canopy-related effects quantified in this study should be interpreted as indirect hydrological responses transmitted through climate-driven canopy variability, rather than as effects of broader ecological or land-cover change. Hydrological responses were evaluated using key SWAT-simulated water-balance components, including ET, percolation (PERC), SURQ, GWQ, LATQ, and WYLD.

2.3.1. Climate-driven NDVI prediction using LSTM

Climate-driven NDVI variability was predicted using an LSTM neural network, which is widely used for modeling nonlinear temporal dependencies in environmental time-series data (Hochreiter and Schmidhuber, 1997; Chen et al., 2021; Guo et al., 2024). In this study, the LSTM model was used to predict climate-sensitive NDVI variability. The

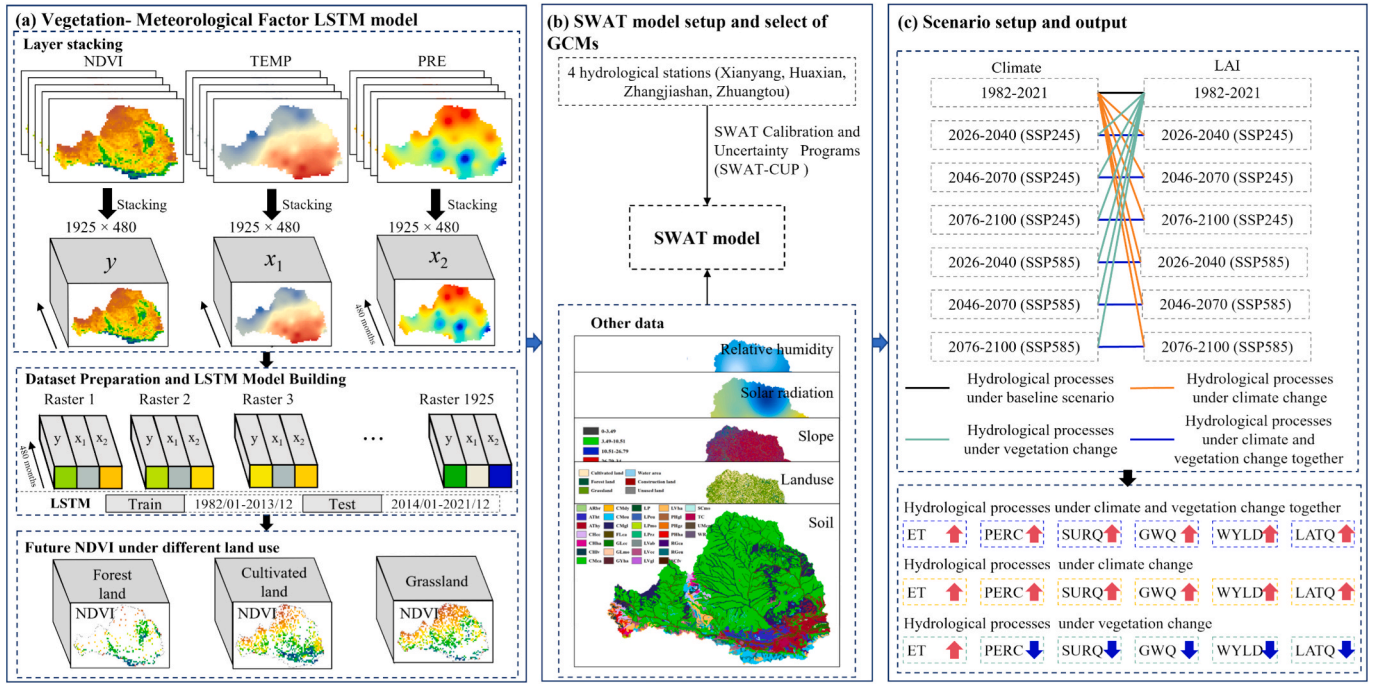


Fig. 2. The technical flowchart of this study.

predicted NDVI was subsequently converted into LAI and used to constrain SWAT-simulated canopy development. Monthly NDVI derived from the GIMMS3G+ dataset was adopted as the target variable (Pinzon et al., 2023). The original NDVI product has a spatial resolution of approximately $1/12^\circ$ and a 15-day compositing interval. Monthly NDVI values were generated using the maximum value composite (MVC) method to reduce the effects of clouds and atmospheric contamination. Fig. S1 shows a south-high and north-low spatial pattern, with 69.2% of grid cells exhibiting positive trends.

Meteorological observations from 18 stations were spatially interpolated using inverse distance weighting (IDW) to generate basin-wide gridded datasets, yielding 1925 grid cells with continuous monthly records from 1982 to 2021. To account for spatial heterogeneity in climate-NDVI relationships, a separate LSTM model was trained for each grid cell, with no parameter sharing across grids.

A fixed three-layer multivariate LSTM architecture was adopted across all grids. Each LSTM layer contained 128 hidden units, followed by a rectified linear unit (ReLU) activation layer and a fully connected regression output layer. This macro-architecture was held constant to ensure structural consistency across the basin and to avoid introducing structural variability unrelated to environmental differences. Model training employed the Adam optimizer. To improve convergence stability, selected optimizer hyperparameters were tuned using a grid search. Specifically, the initial learning rate was evaluated within the range of 1×10^{-4} to 1×10^{-3} (1×10^{-4} , 5×10^{-4} , and 1×10^{-3}), the learning-rate decay factor was tested at 0.1 and 0.5, and the learning-rate drop period was examined at 50, 100, and 150 epochs. A piecewise learning-rate schedule was adopted. The dataset was divided chronologically, with the period 1982–2013 used for model training and 2014–2021 used for validation. All model training and prediction procedures were implemented in MATLAB R2022b, and a fixed random seed was used during training to improve computational reproducibility. Pearson correlation coefficients (r) were also calculated to quantify the statistical relationships between NDVI variability and meteorological drivers:

$$r = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2} \sqrt{n \sum y_i^2 - (\sum y_i)^2}} \quad (1)$$

where x_i represents the observed value of the i meteorological factor, y_i represents the observed value of the i NDVI, and n represents the sample size.

2.3.2. NDVI-LAI conversion and temporal integration

Predicted NDVI values were converted to LAI using an empirical relationship proposed by Hou et al. (2022):

$$LAI = 12.274 \times NDVI - 3.917 \quad (2)$$

LAI values were estimated for the main growing season from June to August (Hou et al., 2022), corresponding to peak canopy development. Because SWAT internally simulates daily vegetation growth through heat-unit accumulation and does not directly accept externally prescribed daily LAI trajectories, NDVI-derived LAI information was incorporated by adjusting the maximum potential leaf area index parameter (BLAI) in the SWAT vegetation-growth database (Neitsch et al., 2011). BLAI controls the upper limit of canopy development and influences canopy interception and transpiration processes. Monthly canopy information was therefore translated into seasonally representative constraints on SWAT-simulated canopy development, thereby ensuring temporal consistency between monthly LSTM-based NDVI predictions and daily hydrological simulations. In this framework, the imposed LAI signal represents a seasonal canopy constraint used for hydrological modeling.

2.3.3. Hydrological simulation using SWAT

The SWAT, developed by the United States Department of Agriculture-Agricultural Research Service (USDA-ARS), is a process-based, semi-distributed hydrological model designed explicitly for basin-scale applications. It is widely used to simulate hydrological processes, sediment transport, and nutrient and agrochemical dynamics in complex watershed systems. The model accounts for the combined influences of climate change, land surface characteristics, soil properties, and water resource management practices, enabling assessments of watershed-scale water balance components under varying environmental and management conditions (Arnold et al., 2012). This model aims to simulate the hydrological cycle based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^t (Precipitation_i - SURQ_i - ET_i - W_{seep,i} - GWQ_i) \quad (3)$$

where SW_t represents the final soil water content (mm), SW_0 represents the initial soil water content (mm) on given day i , t represents time in days, $Precipitation_i$ represents the amount of precipitation on day i (mm), $SURQ_i$ represents the amount of surface flow on day i (mm), ET_i represents the amount of ET on day i (mm), $W_{seep,i}$ represents percolation and bypass flow leaving the soil profile on day i (mm), GWQ_i represents the amount of return flow on day i (mm).

WYLD is a core output variable in the SWAT model for simulating watershed hydrological cycles, calculated based on the following water balance equation:

$$WYLD_i = SURQ_i + LATQ_i + GWQ_i - TLOSS_i - pond\ abstractions_i \quad (4)$$

where $WYLD_i$ represents the WYLD on day i (mm), $TLOSS_i$ represents the transmission losses on day i , and $pond\ abstractions_i$ represents the pond abstractions on day i .

For each soil layer, the daily water balance can be expressed as:

$$\Delta SW_{ly} = PERC_{ly-1} - PERC_{ly} - LATQ - ET_{ly} \quad (5)$$

where ΔSW_{ly} is the change in soil water content in soil layer ly , $PERC_{ly-1}$ represents the $PERC$ received from layer $ly-1$, and $PERC_{ly}$ represents the $PERC$ in layer ly .

The WRB was divided into 126 sub-basins and 2304 hydrological response units (HRUs) based on land-use, soil type, and slope class. Model calibration was conducted using the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm implemented in SWAT-CUP. Twelve key hydrological parameters were adjusted within predefined uncertainty ranges (Table S2).

Calibration and validation were performed using monthly streamflow observations from four hydrological stations. Due to differences in data availability and record continuity, calibration and validation periods varied among stations. At the Xianyang station, calibration was conducted from January 1982 to December 2012, and validation was conducted for January 2013–December 2021. At the Huaxian station, calibration covered January 1982–December 2005, whereas validation was performed for January 2008–December 2012. For the Zhangjiashan and Zhuangtuo stations, calibration was conducted for June 2000–December 2014, followed by validation for January 2015–December 2021. Due to data gaps in the observed streamflow records, model calibration and validation were conducted using all available observation periods rather than strictly continuous time segments.

Model performance was evaluated using the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS) (Nash and Sutcliffe, 1970; Parajuli et al., 2009). Simulation performance was considered acceptable when R^2 and NSE exceeded 0.50 and |PBIAS| remained within 15–20%.

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}} \right)^2 \quad (6)$$

$$NSE = \frac{\sum_{i=1}^n (O_i - \bar{O})^2 - \sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (7)$$

$$PBIAS = \frac{\sum_{i=1}^n O_i - \sum_{i=1}^n S_i}{\sum_{i=1}^n O_i} \times 100 \quad (8)$$

where O_i and S_i represent the observed and SWAT-simulated streamflow values at time i , respectively; $\bar{O}$ and $\bar{S}$ denote their corresponding mean values; and n is the number of paired observations.

Accordingly, the calibration primarily constrained streamflow dynamics, whereas internal water-balance components were further interpreted with caution in the uncertainty analysis.

2.3.4. Future climate projection

Global Climate Models (GCMs) generally operate at coarse spatial resolutions, which limits their direct applicability for regional- and watershed-scale hydrological assessments. To overcome this limitation, we applied the NWAI-WG statistical downscaling method to process monthly gridded outputs from 27 CMIP6 GCMs under multiple Shared Socioeconomic Pathway (SSP) scenarios. This downscaling procedure was used to generate station-scale daily meteorological series, including precipitation, T_{max} , T_{min} , solar radiation, and relative humidity. These datasets were prepared for 18 meteorological stations across the WRB, covering the period 1961–2100, thereby providing climate-forcing inputs for LSTM-based NDVI prediction and SWAT-driven hydrological modeling (Liu and Zuo, 2012).

To select GCMs for subsequent analyses, we evaluated the performance of the 27 models during the historical period (1961–2010) using the Taylor skill score (Taylor, 2001), focusing on the four core meteorological variables: precipitation, solar radiation, T_{max} , and T_{min} . Observations from the 18 meteorological stations across the Weihe River Basin were used as reference data (Fig. S2). For each meteorological variable, the 27 GCMs were ranked according to their Taylor skill scores. Only models that ranked within the top 50% for all four evaluated variables were retained. Based on this multi-variable screening criterion, four GCMs, including CNR3, GFD2, MRIE, and UKES, were selected for subsequent climate forcing, LSTM-based NDVI prediction, and SWAT hydrological simulations.

The calculation formula for the Taylor skill score is as follows:

$$\sigma_s = \sqrt{\frac{1}{N} \sum_{i=1}^N (S_i - \bar{S})^2} \quad (10)$$

$$R_T = \frac{\frac{1}{N} \sum_{i=1}^N (O_i - \bar{O})(S_i - \bar{S})}{\sigma_O \sigma_S} \quad (11)$$

$$CRMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N [(O_i - \bar{O}) - (S_i - \bar{S})]^2} \quad (12)$$

$$S_T = \frac{4(1 + R_T)^2}{\left(\frac{\sigma_S}{\sigma_O} + \frac{\sigma_O}{\sigma_S} \right)^2 (1 + R_0)^2} \quad (13)$$

where N is the number of paired samples; O_i and S_i denote the observed and GCM-simulated values of a given meteorological variable, respectively; $\bar{O}$ and $\bar{S}$ are their corresponding mean values; σ_O and σ_S are the standard deviations of the observed and simulated values, respectively; R_T is the Pearson correlation coefficient; CRMSE is the centered root-mean-square error; R_0 is the reference correlation coefficient, set to 0.999; and S_T is the Taylor skill score. A larger S_T indicates better agreement between the GCM simulations and the observed climate records.

2.3.5. Terrain classification of sub-basins

Terrain-dependent hydrological responses were examined by classifying sub-basins into geomorphological units based on topographic characteristics. A terrain classification raster was first generated using elevation and slope derived from a digital elevation model (DEM). The natural breaks classification method was applied to delineate three primary terrain categories: plains (PLN), plateaus (PLT), and mountainous regions (MTN). This classification captures inherent discontinuities in topographic gradients and reflects major geomorphological contrasts across the basin. The terrain classification raster was

subsequently overlaid with sub-basin boundaries, and the areal proportion of each terrain category within each sub-basin was calculated using zonal statistics. A dominant terrain type was assigned when one terrain class occupied at least 80% of the sub-basin area. Transitional terrain units were defined when two terrain classes each exceeded 40% of the area, while sub-basins lacking a dominant terrain signal were classified as mixed terrain units. This rule-based aggregation enabled consistent assignment of terrain attributes to hydrological response units at the sub-basin scale and facilitated spatial comparison of hydrological responses along major geomorphological gradients (Iwahashi and Pike, 2007).

2.3.6. Scenario design and pathway attribution

To disentangle the direct climate change pathway and the indirect canopy-mediated pathway of hydrological responses, an experimental framework consisting of six scenario groups (S1–S6) was established (Table 2). It should be emphasized that this complete set of diagnostic perturbation scenarios, which incorporates both climate change and canopy variability perturbations, is specifically designed for attribution analysis. The framework does not constitute a physical manipulation experiment, nor does it aim to represent physically realistic or internally consistent future environmental states.

The direct climate-change pathway was represented by S1–S2, in which future climate projections under SSP245 and SSP585 were imposed while LAI was held at the historical baseline level. These scenarios diagnose the hydrological response to future climate change in the absence of prescribed climate-driven canopy changes. The indirect canopy-mediated pathway was represented by S3–S4, in which future climate-driven LAI changes were imposed under baseline climate

Table 2

Design of diagnostic scenario experiments for assessing hydrological responses to climate change and climate-driven canopy variability.

Scenario	Climate Period	LAI Period	Definition
Baseline	1982–2021	1982–2021	Baseline scenario
S1	2026–2040 (SSP245)	1982–2021	Climate change only
	2046–2070 (SSP245)	1982–2021	
	2076–2100 (SSP245)	1982–2021	
S2	2026–2040 (SSP585)	1982–2021	Climate change only
	2046–2070 (SSP585)	1982–2021	
	2076–2100 (SSP585)	1982–2021	
S3	1982–2021	2026–2040 (SSP245)	Climate-driven canopy variability
	1982–2021	2046–2070 (SSP245)	
	1982–2021	2076–2100 (SSP245)	
S4	1982–2021	2026–2040 (SSP585)	Climate-driven canopy variability
	1982–2021	2046–2070 (SSP585)	
	1982–2021	2076–2100 (SSP585)	
S5	2026–2040 (SSP245)	2026–2040 (SSP245)	Integrated response
	2046–2070 (SSP245)	2046–2070 (SSP245)	
	2076–2100 (SSP245)	2076–2100 (SSP245)	
S6	2026–2040 (SSP585)	2026–2040 (SSP585)	Integrated response
	2046–2070 (SSP585)	2046–2070 (SSP585)	
	2076–2100 (SSP585)	2076–2100 (SSP585)	

conditions. This configuration is hypothetical and should not be interpreted as a physically realistic future condition; instead, it was used to evaluate the sensitivity of hydrological partitioning to canopy-density changes alone. The integrated response was represented by S5–S6, in which future climate change and the corresponding climate-driven LAI changes were imposed simultaneously. These integrated scenarios provide a more internally consistent representation of future climate-canopy-hydrology responses within the assumptions of this modeling framework.

3. Results

3.1. Simulation performance of the SWAT model

The performance of the SWAT model was evaluated against observed monthly streamflow at four hydrological stations with different record lengths and calibration-validation periods (Fig. 3). Model skill varied among stations but reasonably reproduced the seasonal variability and magnitude of monthly streamflow.

During calibration, R^2 ranged from 0.54 to 0.87, while NSE values ranged from 0.53 to 0.87. PBIAS ranged between -6.74% and -3.84% , indicating limited systematic deviation between simulated and observed discharge. Validation performance showed comparable or slightly improved agreement at most stations, with R^2 values between 0.80 and 0.95 and NSE values between 0.68 and 0.89, while PBIAS ranged from -14.82% to -0.25% .

Station-specific differences were evident. At Xianyang, calibration yielded $R^2 = 0.82$, $NSE = 0.81$, and $PBIAS = -6.74\%$, while validation produced $R^2 = 0.85$, $NSE = 0.84$, and $PBIAS = -0.41\%$. Huaxian showed higher calibration skill ($R^2 = 0.87$, $NSE = 0.87$, $PBIAS = -6.05\%$) but lower validation efficiency ($R^2 = 0.95$, $NSE = 0.68$, $PBIAS = -14.82\%$), indicating increased variability in streamflow simulation during the validation period. At Zhangjiashan, calibration performance was lower ($R^2 = 0.54$, $NSE = 0.53$, $PBIAS = -3.84\%$), whereas validation statistics improved ($R^2 = 0.80$, $NSE = 0.76$, $PBIAS = -0.25\%$). Zhuangtuo exhibited relatively stable performance, with calibration $R^2 = 0.66$, $NSE = 0.65$, $PBIAS = -6.99\%$, and validation $R^2 = 0.90$, $NSE = 0.89$, $PBIAS = -13.08\%$. Across stations, simulated hydrographs reproduced the timing of seasonal streamflow fluctuations but showed reduced agreement during high-flow months, with peak discharge events generally underestimated.

3.2. Assessment and trends of future climate change

Projected changes in climatic variables relative to the historical baseline period (1982–2021) indicate an overall warming and wetting tendency across the WRB under both emission scenarios. Under SSP245, mean annual precipitation is projected to increase by 2.7% during 2026–2040, 8.3% during 2046–2070, and 15.2% during 2076–2100. Corresponding increases in mean annual temperature are estimated at 1.1 °C, 1.9 °C, and 2.7 °C, respectively. Under SSP585, projected precipitation increases reached 9.3%, 11.7%, and 19.5% across the same three future periods. Mean annual temperature increases are estimated at 1.2 °C, 2.7 °C, and 4.8 °C, respectively. Multi-model ensemble averages derived from 4 GCMs (Table S3) show generally positive changes in both precipitation and temperature across future time slices. In addition, solar radiation and relative humidity show increasing trends in most models, although the magnitudes of projected changes vary across time periods (Fig. S3).

3.3. NDVI prediction based on the LSTM method

Partial correlation analysis indicated that NDVI variability is significantly associated with both temperature and precipitation across most grid cells in the WRB ($p < 0.05$; Fig. S4). Correlation coefficients between NDVI and temperature reached values of up to 0.95, while basin-

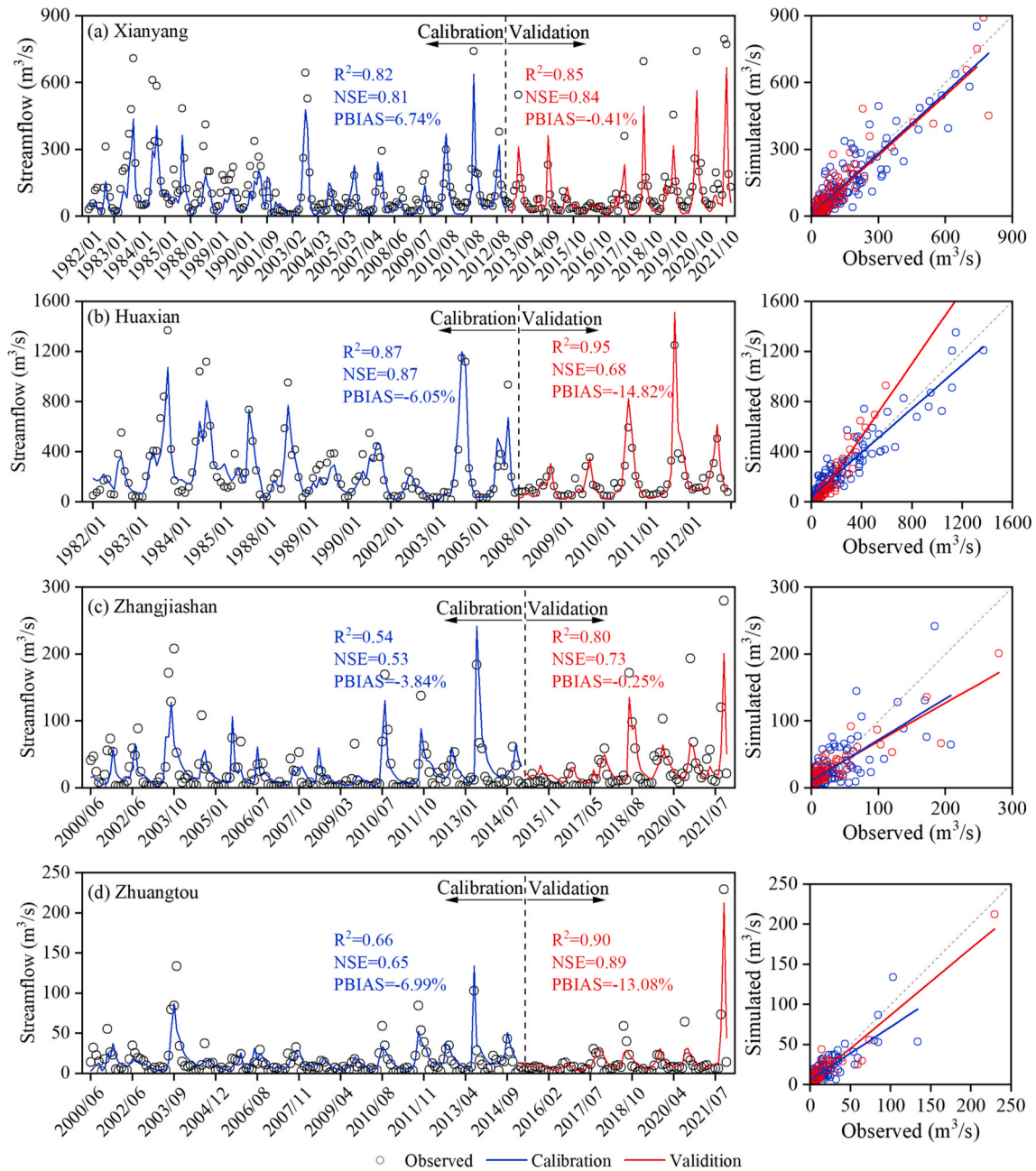


Fig. 3. Calibration and validation of monthly streamflow at four hydrological stations.

mean correlations exceed 0.60. In contrast, only two grid cells exhibited non-significant correlations between NDVI and precipitation. Grassland regions showed comparatively higher correlation magnitudes, with typical values reaching 0.70 (Table S4).

Using monthly NDVI as the response variable and monthly cumulative precipitation and mean temperature as predictors, grid-specific three-layer multivariate LSTM models were trained on 1982–2013 and validated on 2014–2021. Basin-scale performance metrics indicate coefficients of determination exceeding 0.90 for aggregated land-cover classes, with RMSE values below 0.06 (Fig. S5). Time-series comparisons show that simulated NDVI captures the amplitude and phase of the seasonal cycle across grassland, cropland, and forest land-cover types.

Spatial evaluation further reveals heterogeneity in model skill. Training-period grid-level R^2 values range approximately between 0.20 and 1.00, with lower values concentrated in southern cropland areas. RMSE distributions remain comparatively uniform, typically below 0.10

(Fig. S6). During validation, grid-level R^2 patterns shift, with several northern regions exhibiting reduced performance relative to the training period. In cropland regions, lower R^2 values are occasionally observed despite maintaining low RMSE. This pattern reflects the relatively low interannual variance of NDVI in intensively managed agricultural systems, where small absolute prediction deviations reduce explained variance while maintaining limited absolute error.

Future NDVI projections were generated by forcing the trained LSTM models with bias-corrected monthly climate inputs from the four selected CMIP6 GCMs. Growing-season NDVI exhibited increasing tendencies under both emission scenarios (Fig. 4). The projected NDVI values were then converted into LAI according to the empirical NDVI-LAI relationship described in Section 2.3.2, and the derived growing-season LAI values are summarized in Table S5. Ensemble-mean LAI values generally increased more under SSP585 than under SSP245, with relatively larger changes observed in grassland areas. For example,

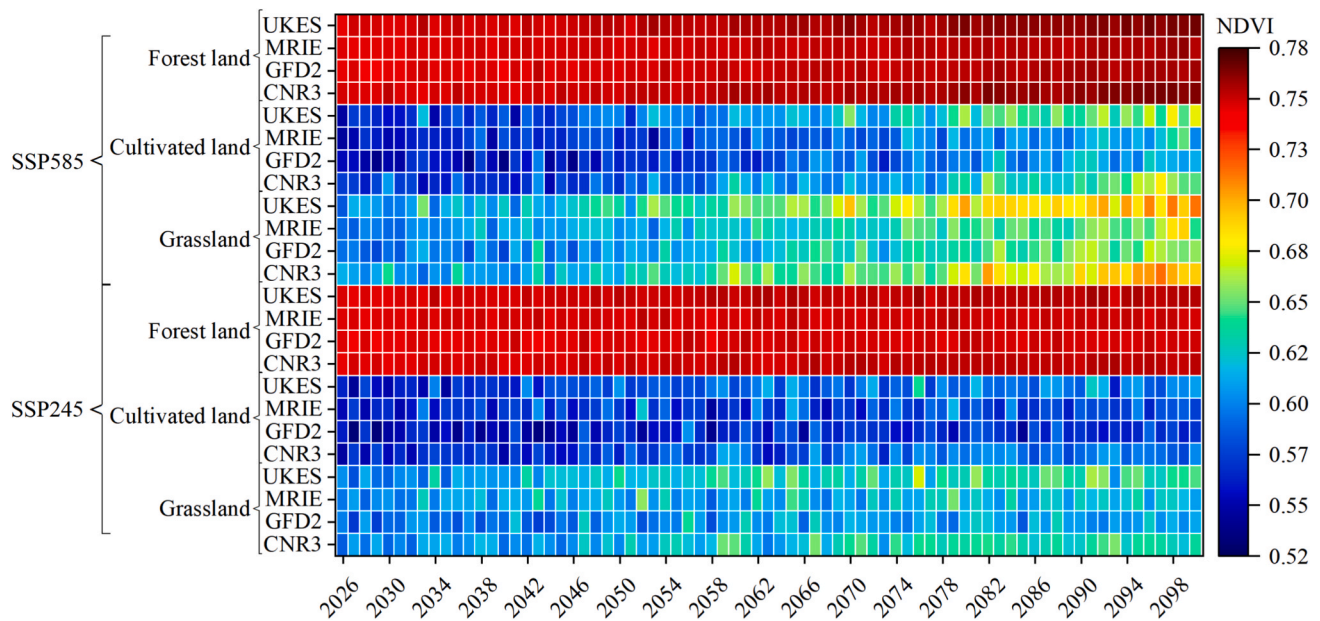


Fig. 4. Predicted growing season NDVI for different periods under different climate scenarios.

grassland LAI increased from approximately 3.3–3.5 in the near term to 3.9–4.5 in the long term under SSP585, whereas the corresponding values under SSP245 increased more moderately to 3.5–3.9. Forest LAI remained comparatively stable, increasing slightly from about 5.28–5.31 in the near term to 5.32–5.49 in the long term across scenarios. Cropland LAI showed moderate increases, rising from approximately 2.8–3.0 in the near term to 3.0–3.4 under SSP245 and up to about 3.5–4.0 under SSP585. These NDVI-derived LAI trajectories were used as seasonal canopy constraints for subsequent SWAT simulations.

3.4. Effects of climate change and climate-driven canopy variability on hydrological processes

Projected streamflow responses under future scenarios show consistent increases relative to the historical baseline across both emission pathways (Fig. 5a). In the climate-change scenarios, mean streamflow increased by approximately 12.0% under SSP245 and 21.2% under SSP585. In the integrated climate canopy scenarios, where climate-driven LAI variability was incorporated, the corresponding increases were moderated to 10.7% and 19.4%, respectively.

Time-slice analysis indicated progressive increases in streamflow across future periods. Under SSP245, the climate-change scenarios produced mean increases of approximately $1.47 \text{ m}^3 \cdot \text{s}^{-1}$, $4.87 \text{ m}^3 \cdot \text{s}^{-1}$, and $8.11 \text{ m}^3 \cdot \text{s}^{-1}$ during the short-term (2026–2040), medium-term (2046–2070), and long-term (2076–2100) periods (Fig. 5b1). The corresponding integrated climate-canopy scenarios produced smaller increases of $1.40 \text{ m}^3 \cdot \text{s}^{-1}$, $4.41 \text{ m}^3 \cdot \text{s}^{-1}$, and $7.06 \text{ m}^3 \cdot \text{s}^{-1}$ across the same periods (Fig. 5f1).

Under SSP585, the climate-change scenarios produced larger increases of $7.83 \text{ m}^3 \cdot \text{s}^{-1}$, $8.53 \text{ m}^3 \cdot \text{s}^{-1}$, and $9.04 \text{ m}^3 \cdot \text{s}^{-1}$ for the three future periods (Fig. 5c1). Incorporating climate-driven canopy variability moderated these increases by approximately 0.07 – $1.30 \text{ m}^3 \cdot \text{s}^{-1}$, depending on time slice (Fig. 5g1).

Spatial patterns indicate heterogeneous responses among sub-basins. The largest absolute increases are concentrated in downstream areas near the basin outlet, where projected changes reached approximately $76.8 \text{ m}^3 \cdot \text{s}^{-1}$ under SSP585. In contrast, several upstream PLT sub-basins show smaller increases or near-neutral changes.

Terrain-aggregated analysis further indicated that PLN exhibit larger absolute streamflow changes compared with PLT, while mountain-plain transition zones show intermediate responses (Fig. 5b1–g1). Differences

among terrain classes become more pronounced under SSP585, particularly during the long-term period.

Model-diagnostic changes in hydrological components varied across scenarios, periods, and terrain units (Fig. 6; Figs. S7–S14). In the climate-change scenarios, all major components increase relative to the historical baseline (1982–2021). Basin-scale mean increases under SSP245 reached +37.44 mm (9.24%) for ET, +4.11 mm (5.56%) for PERC, +2.34 mm (26.82%) for SURQ, +3.23 mm (17.38%) for GWQ, +5.03 mm (7.60%) for LATQ, and +10.45 mm (10.78%) for WYLD (Fig. S8). Larger increases are projected under SSP585, with mean ET increases of +51.41 mm and WYLD increases of +19.77 mm, together with increases of +9.02 mm for PERC, +3.50 mm for SURQ, +6.12 mm for GWQ, and +9.51 mm for LATQ (Fig. S11). The magnitude of change increases toward the late-century period (2076–2100), with wider simulation envelopes under SSP585.

Terrain-based aggregation under climate change reveals substantial spatial variability. Under SSP245, the interquartile range (IQR) reached 20.57 mm for PERC and 17.31 mm for ET in PLN, while WYLD variability is largest over PLT (IQR = 14.77 mm) and LATQ variability is highest in MTN (IQR = 5.50 mm) (Fig. 6). Under SSP585, IQRs expand for all components, particularly for GWQ in terrain transition zones (Fig. S10). Basin-scale mean changes under SSP245 further indicate terrain-dependent responses. Mean ET increases across most sub-basins, with the largest increases in PLT (38.63 mm), followed by PLN (35.77 mm) and MTN (34.75 mm). Transition zones show comparable increases, including 38.54 mm in MTN-PLN and 37.88 mm in PLT-MTN. Other components exhibit stronger terrain contrasts. PERC increases most in PLT (mean 9.22 mm), whereas PLN shows smaller mean changes (2.52 mm) with a wide IQR (−12.06 to 6.57 mm). SURQ increases primarily in PLN (mean 5.26 mm) but remains small in PLT (0.36 mm). GWQ shows the largest mean increase in PLN (6.14 mm) with substantial variability (−12.22 to 56.56 mm). LATQ increases most in MTN (6.52 mm), while WYLD increases are highest in PLN (15.16 mm) compared with 12.74 mm in MTN and 8.70 mm in PLT. In contrast, some transition zones show opposite responses. For example, PERC and GWQ decrease in the MTN-PLN transition zone (mean −0.47 mm and −1.86 mm), indicating nonlinear responses across terrain boundaries.

The diagnostic canopy-variability perturbation scenarios suggested that prescribed climate-driven LAI increases tended to enhance ET while reducing several water-balance components (Fig. 6; Figs. S9 and S12). Under SSP245, the basin-wide median ET increase is 1.45 mm,

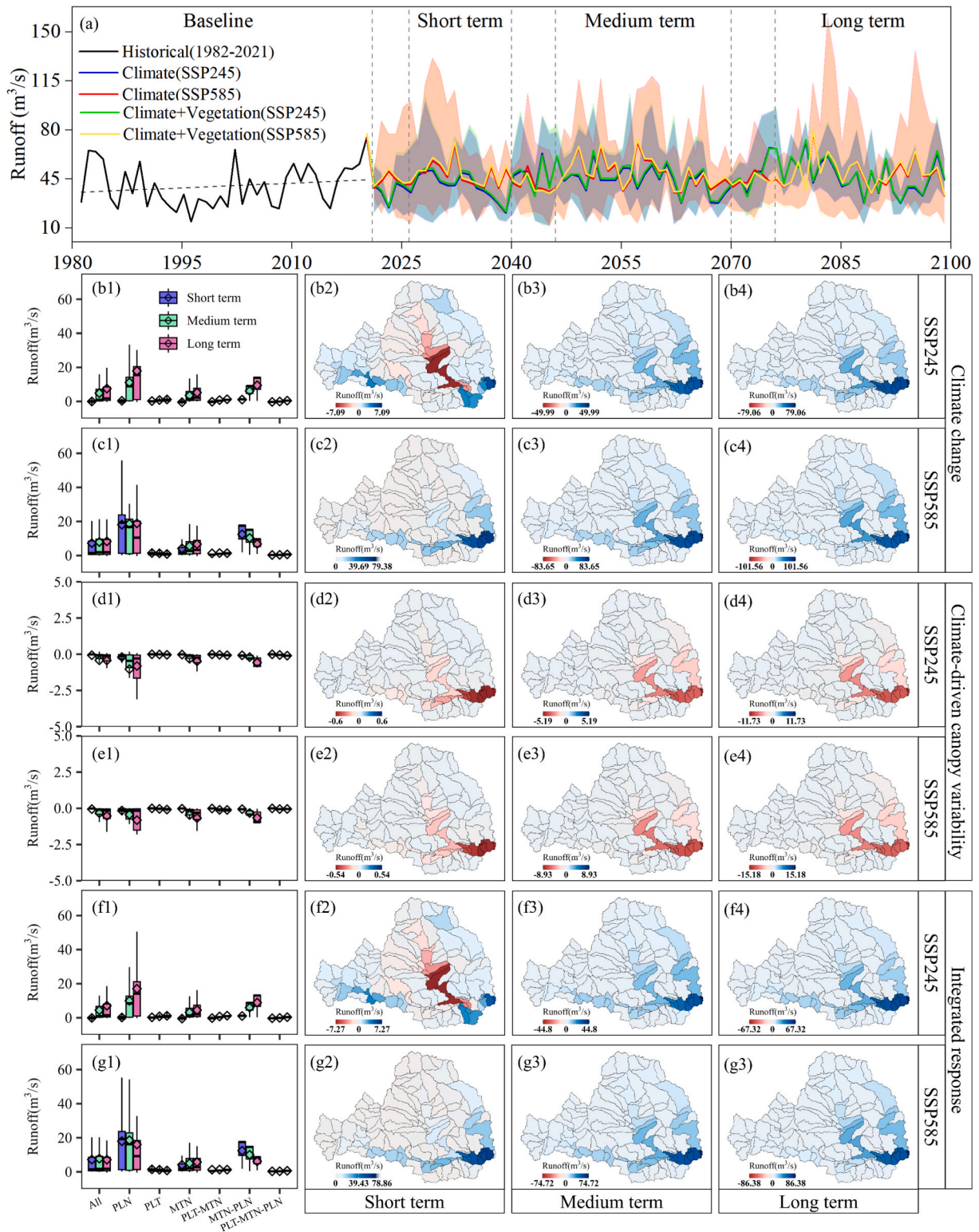


Fig. 5. Absolute changes in streamflow across different terrain types attributable to climate-change effects, canopy-variability effects, and integrated climate-canopy effects. Panel (a) shows the simulated annual streamflow series from 1982 to 2100, with shaded areas indicating the simulation range of the four GCMs. Panels (b), (d), and (f) present the absolute changes in annual streamflow under SSP245, while panels (c), (e), and (g) show the corresponding changes under SSP585.

accompanied by a median WYLD reduction of 0.64 mm. Median decreases also occur in PERC (1.13 mm), SURQ (0.15 mm), and LATQ (0.24 mm), while GWQ shows a near-zero median change. Under SSP585, the canopy-related diagnostic response was slightly stronger, with a median ET increase of 1.69 mm and a median WYLD reduction of 0.67 mm. Median reductions reached 1.35 mm for PERC, 0.15 mm for

SURQ, 0.18 mm for LATQ, and 0.18 mm for GWQ.

Terrain contrasts are also evident for canopy-mediated changes. Under SSP245, the median WYLD reduction reached 1.44 mm in MTN, compared with 0.18 mm in PLN and 0.28 mm in PLT. Under SSP585, the median WYLD reduction increases to 2.29 mm in MTN, whereas changes remain smaller in PLN (−0.25 mm) and PLT (−0.51 mm). Transition

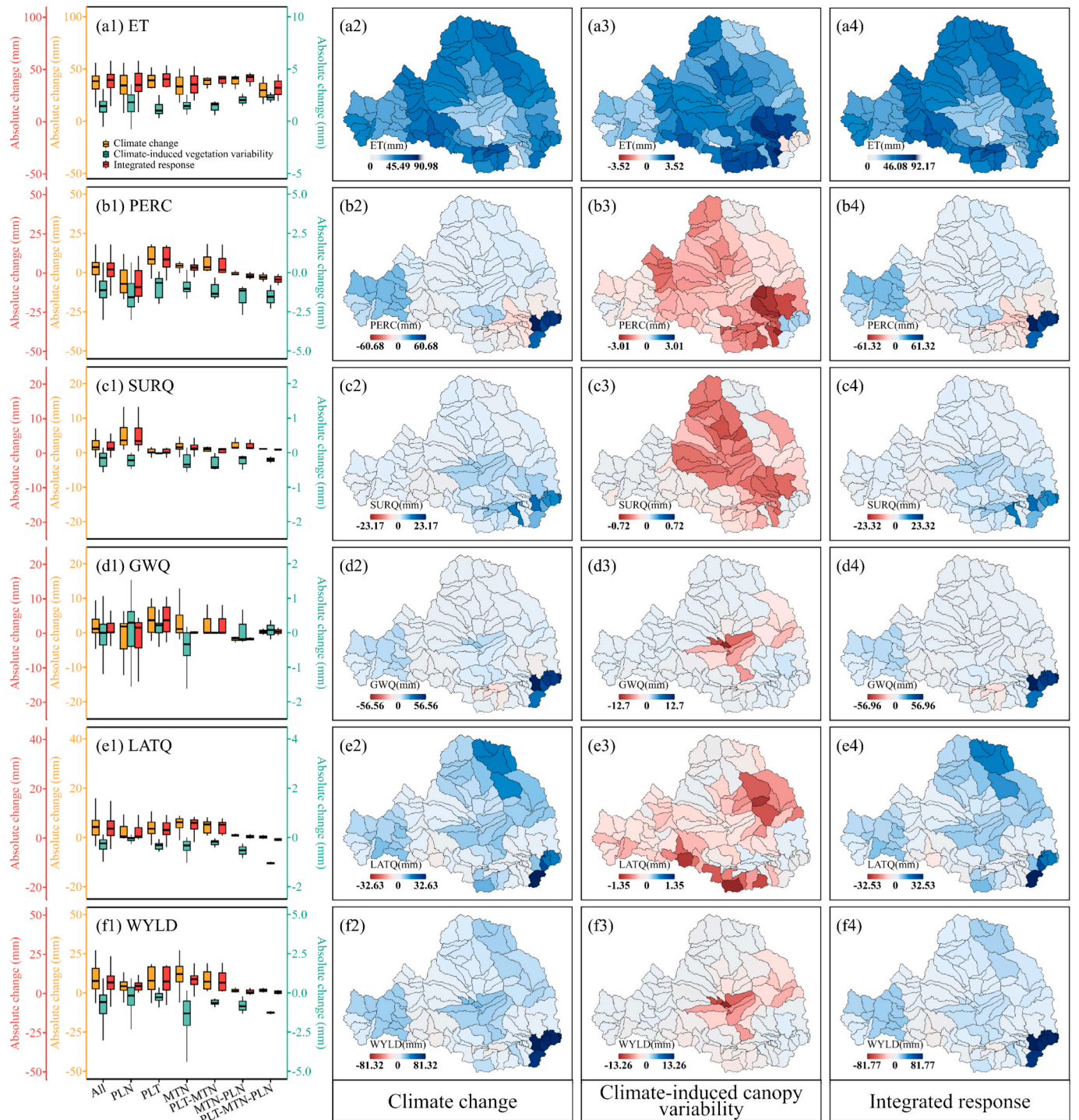


Fig. 6. Absolute changes in hydrological variables under different terrain conditions under the SSP245 scenario, attributable to climate-change effects, canopy-variability effects, and integrated climate-canopy effects. Panels (a)–(f) represent evapotranspiration (ET), percolation (PERC), surface runoff (SURQ), ground-water flow (GWQ), lateral flow (LATQ), and water yield (WYLD), respectively. Columns 1–4 represent the terrain-aggregated results, climate-change effect, canopy-variability effect, and integrated climate-canopy effect, respectively.

zones show intermediate responses, with median WYLD reductions of 0.65 mm under SSP245 and 0.79 mm under SSP585 in PLT-MTN regions.

In the integrated climate-canopy scenarios, climate-change effects generally dominated the direction of hydrological change, while climate-driven canopy variability partially moderated water-balance components through enhanced ET and canopy interception (Figs. S10 and S13). Across scenarios, terrain transition zones consistently

exhibited larger variability than individual terrain units.

3.5. Correlations between environmental variables and simulated hydrological components

Basin-scale correlation analysis indicated that precipitation had the strongest statistical association with simulated hydrological variability in the WRB under the SSP245 and SSP585 scenarios (Fig. 7, Fig. S15).

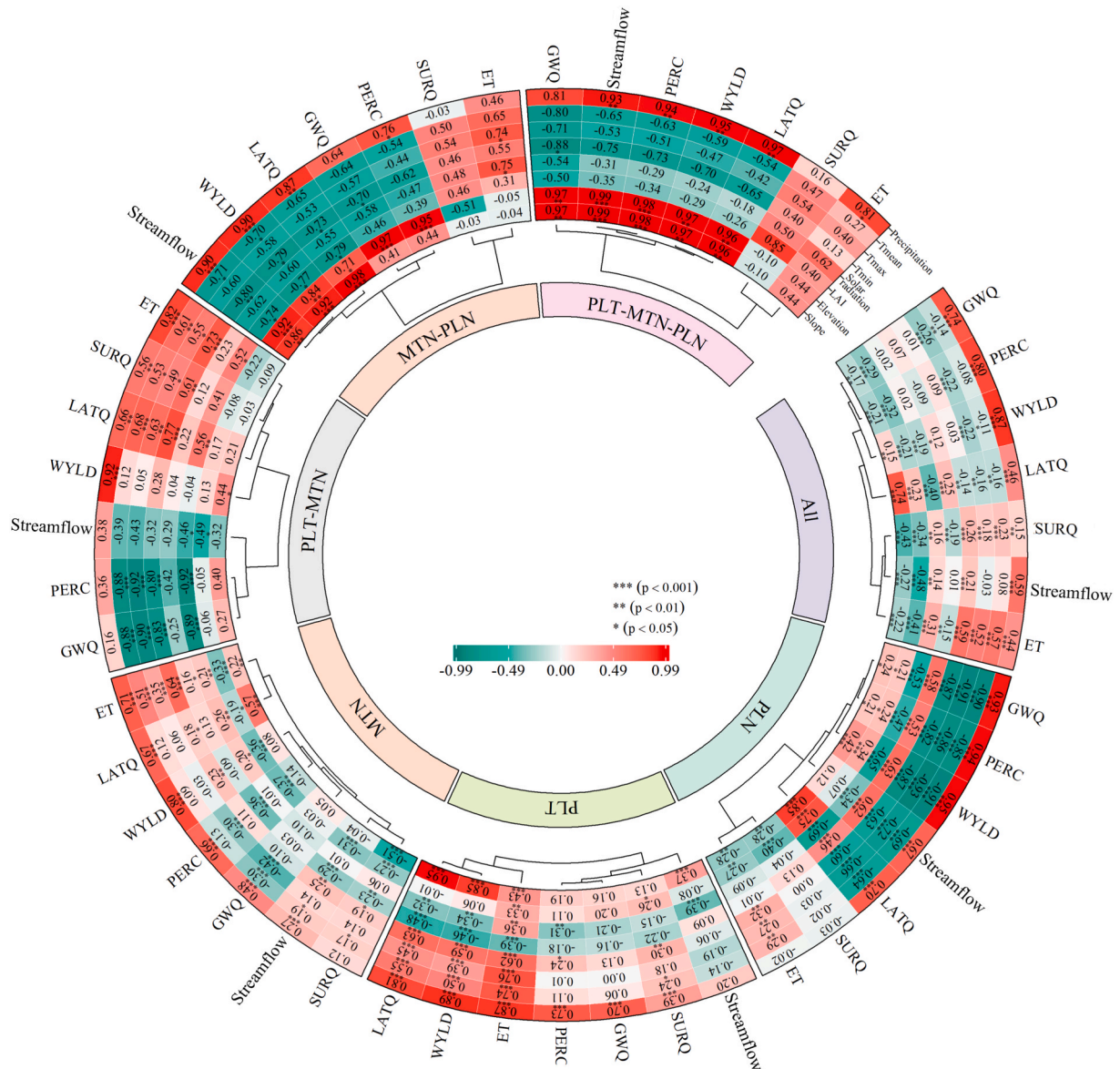


Fig. 7. Correlations between environmental variables and water-balance components under different terrain conditions in the Shared Socioeconomic Pathway 2–4.5 (SSP245) scenario.

Precipitation shows a strong positive correlation with total WYLD ($r = 0.87, p < 0.001$) and significant positive relationships with PERC, SURQ, and GWQ. In contrast, its association with ET is comparatively weaker ($r = 0.44$).

Temperature variables exhibited consistent positive correlations with ET ($r = 0.52$ – 0.59) but weak negative correlations with most water-balance components, including WYLD, PERC, and GWQ. This pattern suggests that increasing temperatures are associated with greater evaporative demand and reduced effective water availability for streamflow generation.

Topographic factors also demonstrate significant relationships with several hydrological components. Slope shows a strong positive correlation with LATQ at the basin scale ($r = 0.74, p < 0.001$), whereas its correlations with SURQ and WYLD are generally weaker and vary spatially.

Marked spatial heterogeneity was observed among geomorphological units. In PLN, precipitation was the variable most strongly associated with WYLD, with correlation coefficients exceeding 0.93. Temperature shows strong negative correlations with GWQ, PERC, and WYLD ($r = -0.82$ to -0.91), suggesting lower simulated water-balance

fluxes under warmer conditions.

In PLT, precipitation maintains significant positive correlations with WYLD, LATQ, and ET, while slope exhibited particularly strong associations with LATQ and WYLD ($r > 0.85$). In MTN, precipitation remained strongly associated with WYLD variability ($r = 0.80$), whereas slope is negatively correlated with SURQ ($r = -0.51$) and positively correlated with LATQ ($r = 0.57$), reflecting terrain-dependent redistribution of streamflow pathways.

In transitional geomorphological zones (e.g., PLT-MTN and MTN-PLN), correlation patterns became more complex. For instance, temperature exhibited a strong negative correlation with GWQ in PLT-MTN ($r = -0.88$), whereas slope shows a very high positive correlation with LATQ in MTN-PLN ($r = 0.98$).

LAI-based canopy variability, rather than full vegetation structural change, also shows terrain-dependent correlations with hydrological components. In PLN, LAI is negatively correlated with LATQ and GWQ ($r = -0.34$ to -0.69). In PLT, LAI shows a positive association with ET ($r = 0.36$) but generally negative correlations with several water-balance components. In MTN, correlations between LAI and hydrological variables are comparatively weaker.

These results highlight the strong statistical association between precipitation and basin-scale hydrological variability, while also revealing terrain-dependent differences in the associations of temperature, slope, and LAI-based canopy variability with hydrological partitioning.

4. Discussion

4.1. Model performance and representation of climate-driven canopy variability

The coupled LSTM-SWAT modeling framework showed acceptable performance in reproducing observed streamflow dynamics and climate-driven canopy variability across the WRB. The SWAT model achieved acceptable performance during both calibration and validation periods, with NSE and R^2 values exceeding commonly recommended thresholds for watershed-scale applications. The close alignment between simulated and observed streamflow indicates that the model reasonably captured the dominant seasonal rainfall-streamflow dynamics in this semi-arid environment. However, peak flows were occasionally underestimated and recession flows slightly overestimated, which are typical limitations of semi-distributed hydrological models. These performance patterns are consistent with findings from other SWAT-based studies in semi-arid basins, where model skill is generally stronger in reproducing seasonal variability than extreme hydrological events (Arnold et al., 2012). These discrepancies are likely due to uncertainties in precipitation forcing, spatial parameter aggregation, and the representation of rapid streamflow processes in complex terrains (Guan et al., 2023; Rodell and Li, 2023).

The LSTM model, on the other hand, showed strong predictive skill for monthly NDVI dynamics ($R^2 > 0.90$), captured the main nonlinear and lagged statistical relationships between NDVI and climatic predictors. By dynamically linking these LSTM-derived LAI trajectories with the SWAT model, the framework improves the representation of climate-sensitive canopy density relative to a fully static vegetation parameterization, rather than introducing a fundamentally new ecohydrological process formulation. This coupling helped represent the hydrological influence of climate-sensitive canopy-density variability.

It is important to note that LSTM predictions are primarily driven by meteorological factors, focusing on climate-driven canopy variability but excluding localized human influences, such as agricultural management or specific ecological restoration projects (Xu et al., 2023). While this approach is consistent with the study's focus on climate-canopy-hydrology interactions, it may underestimate the complexity of canopy development in highly managed landscapes. Similar limitations have been identified in recent machine-learning vegetation modeling studies, which note that climate-only predictors can reproduce large-scale canopy-condition trends but may underestimate localized anthropogenic disturbances (Li et al., 2021; Ahmad et al., 2023).

4.2. Climate-driven hydrological intensification and canopy-mediated moderation

Future climate projections consistently indicate a warming and wetting tendency across the WRB, which translates into systematic intensification of basin-scale hydrological fluxes. Increased precipitation directly enhances water availability for streamflow generation, PERC, and GWQ recharge, while rising air temperature elevates atmospheric evaporative demand and promotes higher ET rates. Such climate-driven hydrological intensification has been widely documented in semi-arid and monsoon-influenced river basins, where streamflow variability is primarily controlled by precipitation inputs but increasingly modulated by temperature-driven energy constraints (Bajracharya et al., 2018; Gudmundsson et al., 2017; Huntington, 2006).

However, our diagnostic simulations suggest that climate-driven canopy variability may act as a secondary moderating pathway for

runoff-related responses within the diagnostic framework. Increased LAI enhances canopy interception storage and transpiration demand, thereby redistributing a greater fraction of precipitation inputs toward atmospheric return flows and reducing effective streamflow generation (Peng et al., 2022). This buffering effect is particularly evident in water-limited environments, where increases in canopy density have been shown to significantly reduce SURQ and WYLD by intensifying ET and altering rainfall partitioning processes (Feng et al., 2016; Zhang et al., 2016; Zhou et al., 2021). This interpretation is supported by the correlation analysis, which showed that grasslands exhibited the strongest response to precipitation variations ($r = 0.70$) among all evaluated land cover types. While closely coupled with temperature as well ($r = 0.85$), this dominant sensitivity to rainfall further suggests that these ecosystems are heavily reliant on, and rapidly respond to, short-term moisture inputs (Teuling et al., 2010). As a result, variations in precipitation and temperature can induce more pronounced changes in canopy development.

Critically, the LAI-based canopy effect quantified in this study is not an independent ecological forcing but rather a component of a hierarchical climate-canopy-hydrology pathway. In this framework, climate change alters precipitation regimes and energy conditions, which are associated with climate-driven canopy changes. These canopy changes partially mitigate climate-driven increases in streamflow through enhanced ET and interception losses. This interpretation is consistent with recent attribution studies, which suggest that vegetation feedbacks typically operate as secondary modifiers within climate-dominated hydrological systems (Yang et al., 2023; Zhuang et al., 2024).

Moreover, our results indicate that the combined effects of climate change and canopy variability were not strictly additive (Fig. 6; Fig. S11), reflecting complex nonlinear interactions within the system. Because the scenario combinations are diagnostic, this non-additivity should be interpreted as sensitivity evidence rather than as a fully realistic future pathway. For example, increased vegetation density may reduce streamflow sensitivity to precipitation variability by enhancing soil water uptake and delaying saturation thresholds, thereby altering the efficiency with which additional rainfall is converted into streamflow (Jiang et al., 2022). In contrast, under high-emission scenarios with substantial precipitation increases, vegetation-mediated ET may transition from water-limited to energy-limited, thereby weakening its capacity to offset streamflow gains. These non-linear interaction effects imply that future hydrological responses are shaped by interacting climate and canopy processes rather than by a simple linear sum of separate effects (Alkama et al., 2022; Betts et al., 2006; Chang et al., 2023).

4.3. Geomorphological controls on hydrological responses and sensitivity

Hydrological responses exhibited pronounced spatial heterogeneity across geomorphological units of the WRB, reflecting the role of terrain in modulating runoff generation and flow partitioning (Fig. 6; Figs. S7–S14). Our results indicate a distinct terrain signature in the water balance components: Plain regions show the largest variability in SURQ and PERC. Owing to relatively limited storage capacity and weaker drainage gradients, these areas may be more sensitive to precipitation variability. In contrast, PLT display stronger variability in WYLD. The moderate slopes and soil depth gradients regulate the efficiency with which precipitation inputs are converted into basin outflow. MTN are characterized by more pronounced changes in LATQ, highlighting the important role of slope-controlled subsurface redistribution processes in steep terrain.

These patterns are consistent with terrain-based hydrological theory, which emphasizes that topographic gradients regulate both hydraulic connectivity and soil moisture redistribution at hillslope and basin scales (Anderson and Goulden, 2011; Ivanov et al., 2008; McDonnell, 2013). In steeper environments, increased hydraulic gradients enhance downslope subsurface flow and reduce the persistence of surface

saturation zones, thereby limiting direct runoff generation while promoting interflow pathways. Conversely, flatter landscapes tend to favor infiltration-excess or saturation-excess runoff mechanisms due to reduced gravitational drainage efficiency and higher potential for surface water accumulation.

A key applied insight of this study is that terrain also influences the effectiveness of canopy-mediated regulation. In plain regions, climate-driven increases in LAI were more strongly associated with reductions in water-balance components, suggesting that canopy interception and transpiration may have a stronger influence on water-balance partitioning under conditions of limited subsurface storage. Because shallow soils and weaker hydraulic gradients constrain vertical and lateral redistribution, canopy-induced ET losses can more effectively reduce effective runoff generation. Similar patterns have been reported in semi-arid lowland basins where increased canopy density can reduce streamflow sensitivity to precipitation variability (Feng et al., 2016; Li et al., 2022).

In contrast, topographic controls may dominate over canopy effects in MTN (Fig. 7; Fig. S15). Steep slopes promote rapid subsurface drainage and strong hydraulic connectivity, allowing precipitation inputs to be redistributed downslope before substantial canopy-mediated water losses can accumulate. Consequently, hydrological variability in such environments is governed more strongly by terrain structure than by canopy density fluctuations. This terrain dominance has been widely observed in ecohydrological studies showing that topographic gradients may exert stronger influence than vegetation effects in controlling runoff partitioning and soil moisture dynamics in complex MTN catchments (Fan et al., 2019).

4.4. Uncertainties and limitations

Several uncertainties should be considered when interpreting the projected hydrological responses. These uncertainties mainly arise from hydrological calibration constraints, future climate forcing, climate-driven canopy prediction, and the assumption of fixed land-surface conditions. They do not invalidate the coupled LSTM-SWAT framework, but they define the appropriate interpretation of the results as scenario-dependent and model-diagnostic estimates rather than deterministic predictions. The first source of uncertainty arises from hydrological calibration constraints. Although the SWAT model reproduced observed monthly streamflow reasonably well during the calibration and validation periods, internal water-balance components such as ET, PERC, GWQ, and LATQ were not independently constrained by field observations, remotely sensed ET products, groundwater-level records, or baseflow separation estimates. Therefore, streamflow calibration alone may not uniquely determine internal hydrological partitioning. Parameter equifinality can allow different combinations of soil, groundwater, vegetation, and routing parameters to produce comparable streamflow simulations while generating different estimates of ET, percolation, groundwater contribution, and lateral subsurface flow (Yang et al., 2019; Luan and Ma, 2025). Consequently, the simulated absolute changes in these internal components should be interpreted with caution. Greater confidence should be placed on their direction of change, spatial pattern, terrain-dependent contrast, and inter-scenario differences than on their exact magnitudes as independently validated quantities. Future studies could reduce this uncertainty by incorporating additional observational constraints, such as remote-sensing-based ET products, groundwater-level measurements, soil moisture observations, and baseflow separation indices (Murray et al., 2013).

A second uncertainty is associated with future climate forcing and canopy prediction. Although a multi-model GCM ensemble was used to reduce the influence of individual model biases, differences among climate models in precipitation intensity, seasonal distribution, temperature increase, radiation, and humidity can propagate through both LSTM-based canopy prediction and SWAT hydrological simulations (Knutti and Sedláček, 2013; Tokarska et al., 2020). In semi-arid basins

such as the WRB, hydrological responses are particularly sensitive to precipitation variability, and relatively small differences in projected rainfall may lead to larger changes in streamflow, percolation, and water yield. In addition, canopy-related changes in this study were represented by LSTM-predicted NDVI and subsequent NDVI-LAI conversion driven primarily by precipitation and temperature. This design is consistent with the objective of isolating climate-driven canopy variability, but it does not represent full vegetation dynamics in an ecological sense. The framework does not explicitly simulate vegetation-type shifts, rooting-depth adjustment, carbon allocation, nutrient limitation, disturbance regimes, species composition, or anthropogenic land-management practices (Chen et al., 2019; Forzieri et al., 2020). In highly managed landscapes, especially cropland areas, canopy development and phenology may be partly decoupled from meteorological forcing because of irrigation, fertilization, cultivar selection, harvest timing, and other management interventions. As a result, climate-based NDVI prediction may overestimate canopy sensitivity to climate change in some agricultural areas, while underestimating localized disturbances or management-driven vegetation changes (Dierauer et al., 2018; Gu et al., 2024; Guan et al., 2015). Accordingly, the canopy-related effects quantified in this study should be interpreted as hydrological responses to prescribed NDVI-derived LAI variability, rather than as responses to broader ecological vegetation dynamics. Future work could improve the ecological realism of canopy prediction by incorporating additional predictors such as soil moisture, groundwater availability, irrigation intensity, land-management indicators, vegetation functional type, and remotely sensed phenological metrics (Guan et al., 2016; Zhu et al., 2015).

A third uncertainty arises from the fixed land-surface configuration used in future simulations. All future hydrological simulations were conducted using the 2020 land-use map, while potential land-cover transitions, vegetation-type conversion, rooting-depth changes, soil-property evolution, and management shifts under different SSP pathways were not explicitly represented (Hurtt et al., 2020). In reality, urban expansion, agricultural intensification, ecological restoration, forest management, and changes in irrigation infrastructure may alter infiltration capacity, evapotranspiration, groundwater recharge, and subsurface-flow connectivity (Mengistu et al., 2022; Sterling et al., 2013). Therefore, the projected hydrological responses should be understood as conditional on the assumption of relatively stable land use, soil properties, and vegetation structural parameters.

Overall, these uncertainties clarify the interpretation boundary of the present study rather than undermine its main findings. The coupled LSTM-SWAT framework is most useful for diagnosing the direction, spatial heterogeneity, terrain-dependent contrasts, and scenario differences of climate-canopy-hydrology interactions, rather than for providing precise absolute estimates of each internal water-balance component. The main conclusions regarding climate-driven hydrological intensification, canopy-mediated moderation of water-balance components, and terrain-dependent hydrological sensitivity should therefore be viewed as scenario-based diagnostic evidence. Future work should further improve the framework by integrating multi-source observational constraints, broader climate-model ensembles, dynamic land-use or management scenarios, and hybrid modelling approaches that combine machine-learning canopy prediction with process-based ecohydrological or vegetation modules.

5. Conclusions

This study integrated LSTM-SWAT modeling framework to assess how climate change and climate-driven canopy variability may jointly influence hydrological responses in the WRB. Future NDVI was predicted using climate-sensitive LSTM models, converted into LAI, and incorporated into SWAT as a seasonal canopy constraint. The results indicate that climate change is the primary factor shaping future hydrological changes in the WRB, leading to an overall intensification of

simulated water-cycle components under both SSP245 and SSP585. Projected increases in precipitation and temperature enhance water availability and atmospheric evaporative demand, resulting in simulated increases in streamflow and major water-balance components, including ET, PERC, SURQ, GWQ, LATQ, and WYLD in the climate-change scenarios.

The scenario experiments further suggest that climate-driven canopy variability can partially moderate climate-driven increases in streamflow and water-balance components. Increased LAI enhances canopy interception and evapotranspiration, thereby redistributing part of the additional water input toward atmospheric return flow. Consequently, the integrated climate-canopy scenarios produce smaller streamflow increases than the climate-change-only perturbation scenarios. This indicates that canopy variability acts as a secondary moderating pathway within a climate-dominated hydrological response, rather than as an independent ecological forcing.

Hydrological responses also exhibited pronounced terrain-dependent heterogeneity. Plain regions generally showed larger simulated changes in water-balance components, reflecting stronger sensitivity to precipitation variability and surface-water accumulation processes. Plateau regions display marked changes in water yield and subsurface partitioning, while mountainous regions show stronger variations in lateral flow, consistent with the influence of slope-controlled hydraulic gradients and hillslope connectivity. These results suggest that future hydrological changes in the WRB are unlikely to be spatially uniform and should be evaluated according to geomorphological conditions.

From a water-resource management perspective, the projected intensification of hydrological fluxes and their spatial heterogeneity highlight the need for terrain-specific adaptation strategies. In lowland and plain areas, improving soil-water retention, streamflow regulation, and flood-buffering capacity may help reduce the risks associated with increasing streamflow variability. In PLT and MTN, maintaining vegetation cover, soil conservation capacity, and subsurface-flow connectivity may be important for sustaining downstream water supply and basin-scale hydrological stability. Overall, the proposed LSTM-SWAT framework provides scenario-based diagnostic evidence for understanding climate-canopy-hydrology interactions and supports spatially differentiated watershed management under future climate change.

CRedit authorship contribution statement

Kunhao Jiang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Hui Ran:** Supervision, Conceptualization, Writing – review & editing. **Xinyi Chen:** Software, Formal analysis. **Yingnan Wei:** Software, Resources. **Yuanxin Dai:** Validation. **Qiang Yu:** Writing – review & editing. **Hao Feng:** Resources. **Xiaotao Hu:** Resources. **Ning Yao:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhydrol.2026.135998>.

Data availability

Data will be made available on request.

References

- Ahmad, R., Yang, B., Ettlin, G., Berger, A., Rodríguez-Bocca, P., 2023. A machine-learning based ConvLSTM architecture for NDVI forecasting. *Int. Trans. Oper. Res.* 30, 2025–2048. <https://doi.org/10.1111/itor.12887>.
- Alkama, R., Forzieri, G., Duveiller, G., Grassi, G., Liang, S., Cescatti, A., 2022. Vegetation-based climate mitigation in a warmer and greener world. *Nat. Commun.* 13, 606. <https://doi.org/10.1038/s41467-022-28305-9>.
- Anderson, R.G., Goulden, M.L., 2011. Relationships between climate, vegetation, and energy exchange across a montane gradient. *J. Geophys. Res. G: Biogeosci.* 116. <https://doi.org/10.1029/2010JG001476>.
- Arantes, L.T., Carvalho, A.C.P., Carvalho, A.P.P., Lorandi, R., Moschini, L.E., Di Lollo, J. A., 2021. Surface runoff associated with climate change and land use and land cover in southeast region of Brazil. *Environ. Challenges* 3, 100054. <https://doi.org/10.1016/j.envc.2021.100054>.
- Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., van Griensven, A., Van Liew, M.W., Kannan, N., Jha, M.K., 2012. SWAT: model use, calibration, and validation. *Trans. ASABE* 55, 1491–1508. <https://doi.org/10.13031/2013.42256>.
- Arnold, J.G., Srinivasan, R., Mutiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. *J. Am. Water Resour. Assoc.* 34, 73–89. <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>.
- Bajracharya, A.R., Bajracharya, S.R., Shrestha, A.B., Maharjan, S.B., 2018. Climate change impact assessment on the hydrological regime of the Kaligandaki Basin, Nepal. *Sci. Total Environ.* 625, 837–848. <https://doi.org/10.1016/j.scitotenv.2017.12.332>.
- Betts, R.A., Falloon, P.D., Klein, G.K., Navin, R., 2006. Biogeophysical effects of land use on climate: model simulations of radiative forcing and large-scale temperature change[J]. *Agric. For. Meteorol.* 142 (2–4), 216–233. <https://doi.org/10.1016/j.agrformet.2006.08.021>.
- Chang, D., Li, S., Lai, Z., Fu, F., Qi, X., 2023. Integrated effects of co-evolutions among climate, land use and vegetation growing dynamics to changes of runoff quantity and quality. *J. Environ. Manage.* 331, 117195. <https://doi.org/10.1016/j.jenvman.2022.117195>.
- Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R.R., Myneni, R.B., 2019. China and India lead in greening of the world through land-use management. *Nat. Sustain.* 2, 122–129. <https://doi.org/10.1038/s41893-019-0220-7>.
- Chen, S., Fu, Y.H., Wu, Z., Hao, F., Hao, Z., Guo, Y., Geng, X., Li, X., Zhang, X., Tang, J., Singh, V.P., Zhang, X., 2023. Informing the SWAT model with remote sensing detected vegetation phenology for improved modeling of ecohydrological processes. *J. Hydrol.* 616, 128817. <https://doi.org/10.1016/j.jhydrol.2022.128817>.
- Chen, Y., He, Y., Zhang, L., Chen, Y., Pu, H., Chen, B., Gao, L., 2021. Prediction of InSAR deformation time-series using a long short-term memory neural network. *Int. J. Remote Sens.* 42, 6919–6942. <https://doi.org/10.1080/01431161.2021.1947540>.
- Choi, K., Kim, Y., 2022. Improving streamflow prediction in the WRF-Hydro model with LSTM networks. *J. Hydrol.* 605, 127297. <https://doi.org/10.1016/j.jhydrol.2021.127297>.
- Dierauer, J.R., Whitfield, P.H., Allen, D.M., 2018. Climate controls on runoff and low flows in mountain catchments of Western North America. *Water Resour. Res.* 54, 7495–7510. <https://doi.org/10.1029/2018WR023087>.
- Fan, Y., Clark, M., Lawrence, D.M., Swenson, S., Band, L.E., Brantley, S.L., Brooks, P.D., Dietrich, W.E., Flores, A., Grant, G., Kirchner, J.W., Mackay, D.S., McDonnell, J.J., Milly, P.C.D., Sullivan, P.L., Tague, C., Ajami, H., Chaney, N., Hartmann, A., Hazenberg, P., McNamara, J., Pelletier, J., Perket, J., Rouholahnejad-Freund, E., Wagoner, T., Zeng, X., Beighley, E., Buzan, J., Huang, M., Livneh, B., Mohanty, B.P., Nijssen, B., Safeeq, M., Shen, C., Verseveld, W., Volk, J., Yamazaki, D., 2019. Hillslope hydrology in global change research and Earth system modeling. *Water Resour. Res.* 55 (2), 1737–1772. <https://doi.org/10.1029/2018WR023903>.
- Feng, X., Fu, B., Piao, S., Wang, S., Ciais, P., Zeng, Z., Lü, Y., Zeng, Y., Li, Y., Jiang, X., Wu, B., 2016. Revegetation in China's Loess Plateau is approaching sustainable water resource limits. *Nat. Clim. Change* 6, 1019–1022. <https://doi.org/10.1038/nclimate3092>.
- Forzieri, G., Miralles, D.G., Ciais, P., Alkama, R., Ryu, Y., Duveiller, G., Zhang, K., Robertson, E., Kautz, M., Martens, B., Jiang, C., Arneeth, A., Georgievski, G., Li, W., Ceccherini, G., Anthoni, P., Lawrence, P., Wiltshire, A., Pongratz, J., Piao, S., Sitch, S., Goll, D.S., Arora, V.K., Lienert, S., Lombardozzi, D., Kato, E., Nabel, J.E.M. S., Tian, H., Friedlingstein, P., Cescatti, A., 2020. Increased control of vegetation on global terrestrial energy fluxes. *Nat. Clim. Change* 10, 356–362. <https://doi.org/10.1038/s41558-020-0717-0>.
- Gu, Z., Chen, X., Ruan, W., Zheng, M., Gen, K., Li, X., Deng, H., Chen, Y., Liu, M., 2024. Quantifying the direct and indirect effects of terrain, climate and human activity on the spatial pattern of KNDVI-based vegetation growth: a case study from the

- Minjiang River Basin, Southeast China. *Ecol. Inform.* 80, 102493. <https://doi.org/10.1016/j.ecoinf.2024.102493>.
- Guan, K., Berry, J.A., Zhang, Y., Joiner, J., Guanter, L., Badgley, G., Lobell, D.B., 2016. Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence. *Glob. Change Biol.* 22, 716–726. <https://doi.org/10.1111/gcb.13136>.
- Guan, R., Huang, W., Li, Y., Zhu, D., Liu, X., Wang, Z., Song, J., 2023. Can land use/land cover optimization improve the environmental flow guarantee in regulated basins? *J. Hydrol.* 626, 130309. <https://doi.org/10.1016/j.jhydrol.2023.130309>.
- Guan, K., Sultan, B., Biasutti, M., Baron, C., Lobell, D.B., 2015. What aspects of future rainfall changes matter for crop yields in West Africa? *Geophys. Res. Lett.* 42, 8001–8010. <https://doi.org/10.1002/2015GL063877>.
- Gudmundsson, L., Seneviratne, S.I., Zhang, X., 2017. Anthropogenic climate change detected in European renewable freshwater resources. *Nat. Clim. Change* 7, 813–816. <https://doi.org/10.1038/nclimate3416>.
- Guo, Y., Zhang, L., He, Y., Cao, S., Li, H., Ran, L., Ding, Y., Filonchik, M., 2024. LSTM time series NDVI prediction method incorporating climate elements: a case study of Yellow River Basin, China. *J. Hydrol.* 629, 130518. <https://doi.org/10.1016/j.jhydrol.2023.130518>.
- Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. *Neural Comput.* 9, 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735>.
- Hou, X., Zhang, S., Ruan, Q., Tang, C., 2022. Synergetic impact of climate and vegetation cover on runoff, sediment, and nitrogen and phosphorus losses in the Jialing River Basin, China. *J. Clean. Prod.* 361, 132141. <https://doi.org/10.1016/j.jclepro.2022.132141>.
- Huntington, T.G., 2006. Evidence for intensification of the global water cycle: review and synthesis. *J. Hydrol.* 319, 83–95. <https://doi.org/10.1016/j.jhydrol.2005.07.003>.
- Hurttt, G.C., Chini, L., Sahajpal, R., Frokling, S., Bodirsky, B.L., Calvin, K., Doelman, J.C., Fisk, J., Fujimori, S., Klein Goldewijk, K., Hasegawa, T., Havlik, P., Heinemann, A., Humpenöder, F., Jungclaus, J., Kaplan, J.O., Kennedy, J., Krisztin, T., Lawrence, D., Lawrence, P., Ma, L., Mertz, O., Pongratz, J., Popp, A., Poulter, B., Riahi, K., Shevliakova, E., Stehfest, E., Thornton, P., Tubiello, F.N., van Vuuren, D.P., Zhang, X., 2020. Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6. *Geosci. Model Dev.* 13, 5425–5464. <https://doi.org/10.5194/gmd-13-5425-2020>.
- Hwang, T., Martin, K.L., Vose, J.M., Wear, D., Miles, B., Kim, Y., Band, L.E., 2018. Nonstationary hydrologic behavior in forested watersheds is mediated by climate-induced changes in growing season length and subsequent vegetation growth. *Water Resour. Res.* 54, 5359–5375. <https://doi.org/10.1029/2017WR022279>.
- Ivanov, V.Y., Bras, R.L., Vivoni, E.R., 2008. Vegetation-hydrology dynamics in complex terrain of semiarid areas: 2. Energy-water controls of vegetation spatiotemporal dynamics and topographic niches of favorability[J]. *Water Resour. Res.* 44 (3), W03430. <https://doi.org/10.1029/2006WR005595>.
- Iwahashi, J., Pike, R.J., 2007. Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature. *Geomorphology* 86, 409–440. <https://doi.org/10.1016/j.geomorph.2006.09.012>.
- Ji, L., Duan, K., 2019. What is the main driving force of hydrological cycle variations in the semi-arid and semi-humid Weihe River Basin, China? *Sci. Total Environ.* 684, 254–264. <https://doi.org/10.1016/j.scitotenv.2019.05.333>.
- Jiang, F., Xie, X., Wang, Y., Liang, S., Zhu, B., Meng, S., Zhang, X., Chen, Y., Liu, Y., 2022. Vegetation greening intensified transpiration but constrained soil evaporation on the Loess Plateau. *J. Hydrol.* 614, 128514. <https://doi.org/10.1016/j.jhydrol.2022.128514>.
- Knutti, R., Sedláček, J., 2013. Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Clim. Change* 3 (4), 369–373. <https://doi.org/10.1038/nclimate1716>.
- Lei, H., Yang, D., Huang, M., 2014. Impacts of climate change and vegetation dynamics on runoff in the mountainous region of the Haihe River basin in the past five decades. *J. Hydrol.* 511, 786–799. <https://doi.org/10.1016/j.jhydrol.2014.02.029>.
- Li Zhi, Zheng Fen-li, Liu Wen-zhao, Flanagan Dennis C. Spatial distribution and temporal trends of extreme temperature and precipitation events on the Loess Plateau of China during 1961–2007[J]. *Quat. Int.*, 2010, 226(1-2): 92-100. DOI:10.1016/j.quaint.2010.03.003.
- Li, P., Wang, J., Liu, M., Xue, Z., Bagherzadeh, A., Liu, M., 2021. Spatio-temporal variation characteristics of NDVI and its response to climate on the Loess Plateau from 1985 to 2015. *Catena* 203, 105331. <https://doi.org/10.1016/j.catena.2021.105331>.
- Li, Z., Li, X., Zhou, S., Yang, X., Fu, Y., Miao, C., Wang, S., Zhang, G., Wu, X., Yang, C., Deng, Y., 2022. A comprehensive review on coupled processes and mechanisms of soil-vegetation-hydrology, and recent research advances. *Sci. China-Earth Sci.* 65, 2083–2114. <https://doi.org/10.1007/s11430-021-9990-5>.
- Liu, D.L., Zuo, H., 2012. Statistical downscaling of daily climate variables for climate change impact assessment over New South Wales, Australia. *Clim. Change* 115, 629–666. <https://doi.org/10.1007/s10584-012-0464-y>.
- Luan, J., Ma, N., 2025. Responses of seasonal hydrological processes to vegetation change in the Yellow River basin. *J. Hydrol.* 660, 133449. <https://doi.org/10.1016/j.jhydrol.2025.133449>.
- Ma, T., Duan, Z., Li, R., Song, X., 2019. Enhancing SWAT with remotely sensed LAI for improved modelling of ecohydrological process in subtropics. *J. Hydrol.* 570, 802–815. <https://doi.org/10.1016/j.jhydrol.2019.01.024>.
- McDonnell, J.J., 2013. Are all runoff processes the same?[J]. *J. Hydrol. Process.* 27 (26), 4103–4111. <https://doi.org/10.1002/hyp.10076>.
- Mengistu, T.D., Chung, I.-M., Kim, M.-G., Chang, S.W., Lee, J.E., 2022. Impacts and implications of land use land cover dynamics on groundwater recharge and surface runoff in East African Watershed. *Water* 14, 2068. <https://doi.org/10.3390/w14132068>.
- Murray, S.J., Watson, I.M., Prentice, I.C., 2013. The use of dynamic global vegetation models for simulating hydrology and the potential integration of satellite observations. *Prog. Phys. Geogr.* 37, 63–97. <https://doi.org/10.1177/0309133312460072>.
- Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I - a discussion of principles. *J. Hydrol.* 10, 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6).
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and Water Assessment Tool Theoretical Documentation: Version 2009. Texas Water Resources Institute Technical Report No. 406, Texas A&M University System, College Station, TX, USA.
- Parajuli, P.B., Nelson, N.O., Frees, L.D., Mankin, K.R., 2009. Comparison of AnnAGNPS and SWAT model simulation results in USDA-CEAP agricultural watersheds in south-central Kansas. *Hydrol. Process.* 23, 748–763. <https://doi.org/10.1002/hyp.7174>.
- Peng, S., Mihara, K., Xu, X., Kuramochi, K., Toma, Y., Hatano, R., 2024. Modeling hydrological processes under multi-model projections of climate change in a cold region of Hokkaido, Japan. *Catena* 234, 107605. <https://doi.org/10.1016/j.catena.2023.107605>.
- Peng, D., Zhou, Q., Tang, X., Yan, W., Chen, M., 2022. Changes in soil moisture caused solely by vegetation restoration in the karst region of southwest China. *J. Hydrol.* 613, 128460. <https://doi.org/10.1016/j.jhydrol.2022.128460>.
- Pinzon, J.E., Pak, E.W., Tucker, C.J., Bhatt, U.S., Frost, G.V., Macander, M.J., 2023. Global vegetation greenness (NDVI) from AVHRR GIMMS-3G+, 1981–2022. ORNL DAAC, Oak Ridge, Tennessee, USA. <https://doi.org/10.3334/ORNLDAAAC/2187>.
- Rodell, M., Li, B., 2023. Changing intensity of hydroclimatic extreme events revealed by GRACE and GRACE-FO. *Nat. Water* 1, 241–248. <https://doi.org/10.1038/s44221-023-00040-5>.
- Sterling, M., Ducharme, A., Polcher, J., 2013. The impact of global land-cover change on the terrestrial water cycle[J]. *Nat. Clim. Change* 3 (4), 385–390. <https://doi.org/10.1038/nclimate1690>.
- Strauch, M., Volk, M., 2013. SWAT plant growth modification for improved modeling of perennial vegetation in the tropics. *Ecol. Model.* 269, 98–112. <https://doi.org/10.1016/j.ecolmodel.2013.08.013>.
- Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. *J. Geophys. Res. D: Atmos.* 106, 7183–7192. <https://doi.org/10.1029/2000JD900719>.
- Tokarska, K.B., Stolpe, M.B., Sippel, S., Fischer, E.M., Smith, C.J., Lehner, F., Knutti, R., 2020. Past warming trend constrains future warming in CMIP6 models. *Sci. Adv.* 6, eaaz9549. <https://doi.org/10.1126/sciadv.aaz9549>.
- Teuling, A.J., Seneviratne, S.I., Stöckli, R., Reichstein, M., Moors, E., Ciais, P., Luyssaert, S., van den Hurk, B., Ammann, C., Bernhofer, C., Dellwik, E., Ganielle, D., Gielen, B., Grünwald, T., Klumpp, K., Montagnani, L., Moureaux, C., Sottocornola, M., Wohlfahrt, G., 2010. Contrasting response of European forest and grassland energy exchange to heatwaves. *Nat. Geosci.* 3, 722–727. <https://doi.org/10.1038/ngeo950>.
- Wu, C., Xie, J., Qiu, D., Xie, Z., Gao, P., Mu, X., 2023. Effects of climate change and anthropogenic activities on runoff change of the Weihe River basin, Northwest China. *River Res. Appl.* 39, 648–660. <https://doi.org/10.1002/rra.4102>.
- Xu, Y., Dai, Q.-Y., Zou, B., Xu, M., Feng, Y.-X., 2023. Tracing climatic and human disturbance in diverse vegetation zones in China: over 20 years of NDVI observations. *Ecol. Ind.* 156, 111170. <https://doi.org/10.1016/j.ecolind.2023.111170>.
- Yang, W., Long, D., Bai, P., 2019. Impacts of future land cover and climate changes on runoff in the mostly afforested river basin in North China. *J. Hydrol.* 570, 201–219. <https://doi.org/10.1016/j.jhydrol.2018.12.055>.
- Yang, Y., Roderick, M.L., Guo, H., Miralles, D.G., Zhang, L., Faticchi, S., Luo, X., Zhang, Y., McVicar, T.R., Tu, Z., Keenan, T.F., Fisher, J.B., Gan, R., Zhang, X., Piao, S., Zhang, B., Yang, D., 2023. Evapotranspiration on a greening Earth. *Nat. Rev. Earth Environ.* 4, 626–641. <https://doi.org/10.1038/s43017-023-00464-3>.
- Zhang, S., Yang, H., Yang, D., Jayawardena, A.W., 2016. Quantifying the effect of vegetation change on the regional water balance within the Budyko framework. *Geophys. Res. Lett.* 43, 1140–1148. <https://doi.org/10.1002/2015GL066952>.
- Zhao, A., Zhu, X., Liu, X., Pan, Y., Zuo, D., 2016. Impacts of land use change and climate variability on green and blue water resources in the Weihe River Basin of northwest China. *Catena* 137, 318–327. <https://doi.org/10.1016/j.catena.2015.09.018>.
- Zhou, X., Zhang, Y., Beck, H.E., Yang, Y., 2021. Divergent negative spring vegetation and summer runoff patterns and their driving mechanisms in natural ecosystems of northern latitudes. *J. Hydrol.* 592, 125848. <https://doi.org/10.1016/j.jhydrol.2020.125848>.
- Zhu, L., Gong, H., Dai, Z., et al., 2015. An integrated assessment of the impact of precipitation and groundwater on vegetation growth in arid and semiarid areas[J]. *Environ. Earth Sci.* 74 (6), 5009–5021. <https://doi.org/10.1007/s12665-015-4513-5>.
- Zhuang, J., Li, Y., Bai, P., Chen, L., Guo, X., Xing, Y., Feng, A., Yu, W., Huang, M., 2024. Changed evapotranspiration and its components induced by greening vegetation in the Three Rivers Source of the Tibetan Plateau. *J. Hydrol.* 633, 130970. <https://doi.org/10.1016/j.jhydrol.2024.130970>.