

Supplementary Information for

**Changing snowmelt and glacier-melt contributions reshape hydrological
dynamics and flood generation in a high-mountain headwater basin**

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Text S1 Hydrological process representation in SPHY

The model differentiates rainfall from snowfall using temperature thresholds and dynamically simulates precipitation interception, snow accumulation and ablation, glacier melt, and infiltration-driven recharge. Its modular architecture allows the selective activation of components such as glacier, reservoir, or vegetation modules according to the characteristics of a given study area. In the SPHY model, each runoff component is computed independently during the simulation of hydrological processes. The potential runoff from glacier melt and snowmelt is estimated using the degree-day approach, which relates melt rates to positive air temperatures (Rango & Martinec, 1995):

$$Melt_{pot} = \begin{cases} DDF \times T_t & T_{max,t} \geq 0 \\ 0 & T_{max,t} < 0 \end{cases} \quad (S1)$$

where $Melt_{pot}$ represents the potential meltwater from glaciers or snow, and DDF is the degree-day factor, which takes different values for snow, clean ice, and debris-covered ice. $T_{max,t}$ denotes the daily maximum temperature.

When calculating potential snowmelt ($Melt_{pot}$), T_t refers to the daily effective temperature for snowmelt, representing the melt potential integrated over the full diurnal temperature cycle. For glaciers, T_t corresponds to the daily mean temperature. Based on potential melt, the model applies a set of constraints to derive actual meltwater runoff. Actual snowmelt runoff (SRO) is limited by the available snow water equivalent and occurs only when air temperature remains above freezing. For glaciers, the total meltwater is partitioned into glacier runoff and percolation recharge according to a calibrated parameter (GlacROF). After all runoff components are computed, the model aggregates them using the following equation:

$$QTot = RRo + SRO + GRO + BF \quad (S2)$$

Where $QTot$ (mm) represents the total runoff from each grid cell, RRo (mm) is rainfall runoff, SRO (mm) is snowmelt runoff, GRO (mm) is glacier runoff, and BF (mm) denotes baseflow from the third soil layer or lateral flow from the second layer (Terink et al., 2015). To obtain streamflow, $QTot$ is routed through a flow direction network. Here, to separately assess the contributions of rainfall, snowmelt, glacier melt, and baseflow to streamflow, the model was configured to route each of the four runoff components independently.

To reduce data dependency, the SPHY model employs the modified Hargreaves equation to compute daily reference evapotranspiration (ET_r), a formulation that relies solely on temperature data (Hargreaves & Samani, 1985):

$$ET_r = 0.0023 \times 0.408 \times Ra(T_{avg} + 17.8) \times TD^{0.5} \quad (S3)$$

Where Ra denotes extraterrestrial radiation, T_{avg} is the daily average air temperature, and, and TD represents the difference between daily maximum and minimum temperatures, which serves as an indicator of diurnal thermal variation. The resulting ET_r is subsequently used to calculate potential evapotranspiration (ET_{pot}):

$$ET_{pot} = ET_r \times Kc \quad (S4)$$

Where Kc represents the crop coefficient, which adjusts for variations in transpiration and soil evaporation among different vegetation types. In this study, the dynamic vegetation module was enabled, allowing Kc , to be dynamically computed for each grid cell based on remotely sensed NDVI data from MODIS, according to the following equation:

$$Kc = Kc_{min} + (Kc_{max} - Kc_{min}) \times \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \quad (S5)$$

Where Kc_{max} , Kc_{min} , $NDVI_{max}$ and $NDVI_{min}$ are parameter values specified in the model configuration file.

Text S2 Detailed formulation of meteorological and radiation terms governing sublimation

Prior to applying the combination equation (Eq. 1), several diagnostic variables are derived from meteorological forcing to represent snow-surface conditions.

Wind speed at 10 m is standardized to 2 m using the FAO-56 wind-height conversion:

$$u_2 = 0.748 u_{10} \quad (S6)$$

where u_{10} and u_2 are wind speeds (m s^{-1}) at 10 m and 2 m height, respectively.

Actual vapor pressure (e_a) is calculated as:

$$e_a = \frac{qP}{0.622+0.378q} \quad (S7)$$

where q is specific humidity of moist air (kg kg^{-1}) and P is atmospheric pressure (kPa).

Saturation vapor pressure over ice ($e_{s,ice}$) and its slope (Δ_{ice}) are given by:

$$e_{s,ice} = 0.6108 \exp\left(\frac{21.875 T_a}{T_a + 265.5}\right) \quad (S8)$$

$$\Delta_{ice} = \frac{5808 e_{s,ice}}{(T_a + 265.5)^2} \quad (S9)$$

where $e_{s,ice}$ is saturation vapor pressure over ice (kPa) and Δ_{ice} is the slope of the saturation vapor pressure curve over ice ($\text{kPa } ^\circ\text{C}^{-1}$).

The psychrometric constant for sublimation is calculated as:

$$\gamma_s = \frac{c_p P}{\varepsilon L_s} \quad (S10)$$

where γ_s is the psychrometric constant for sublimation ($\text{kPa } ^\circ\text{C}^{-1}$). c_p is the specific heat of dry air at constant pressure ($1.013 \times 10^{-3} \text{ MJ kg}^{-1} ^\circ\text{C}^{-1}$); P is atmospheric pressure (kPa); ε is the ratio of the molecular weight of water vapor to dry air (0.622); and L_s is the latent heat of sublimation, taken as 2.838 MJ kg^{-1} (Stigter et al., 2018). This formulation uses the latent heat of sublimation rather than the latent heat of vaporization employed in the standard FAO-56 formulation, consistent with the direct phase transition from ice to water vapor. Accordingly, γ_s can be approximated as $5.74 \times 10^{-4} P$.

Snow-surface net radiation ($R_{n,snow}$) is calculated as:

$$R_{n,snow} = (1 - \alpha_{snow})R_s + \epsilon_{snow}(R_l - \sigma T_k^4) \quad (S11)$$

where R_s and R_l are incoming shortwave and longwave radiation ($\text{MJ m}^{-2} \text{ d}^{-1}$), respectively; α_{snow} is snow albedo; ϵ_{snow} is snow emissivity; T_k is surface temperature in Kelvin; and σ is the Stefan-Boltzmann constant.

Text S3 Data processing

The SPHY model was executed at a spatial resolution of 250 m × 250 m with a daily temporal step. Meteorological forcing was derived from CMFD V2.0, which has a native spatial resolution of 0.1° × 0.1° and a temporal resolution of 3 h. The 3-hourly meteorological variables were first aggregated to daily values consistent with the model time step and then spatially resampled to the 250-m model grid. All spatial input datasets were processed into PCRaster raster files comprising 860 × 720 grid cells. A fully automated preprocessing pipeline was developed in Python to generate both single-layer and time-series raster files compatible with the SPHY framework, based on the project template (clone.map) and the variable-specific NetCDF files from CMFD V2.0. Bilinear interpolation was used to resample the CMFD forcing fields to the model grid. To account for the pronounced topographic variability of the basin and the elevation mismatch between the coarse CMFD grid and the 250-m model grid, near-surface air temperature was further corrected using a temperature lapse-rate adjustment based on the elevation difference between the CMFD grid-cell elevation and the corresponding 250-m DEM elevation. Land-use, glacier-thickness, and DEM data were likewise converted to PCRaster raster files with consistent spatial extent, resolution, projection, and grid alignment. The overall data preparation procedure followed the workflow described by Khanal et al. (2024).

Text S4 Flood identification

Flood events were identified following an event-based framework adapted from previous studies (Guo et al., 2025). Specifically, flood detection was based on a peak-over-threshold approach applied to the daily streamflow series. The 95th-percentile discharge during the reference period (P1: 1980-1999) was used as the threshold for peak identification, and all local maximum exceeding this threshold were considered potential flood events. The start and end of each flood event were determined using stable valley points in the hydrograph. For multi-peak events with overlapping valley points, adjacent peaks were merged into a single flood event according to two criteria. First, events sharing identical start and end valley points were directly combined. Second, when the end valley of one event overlapped with or was close to the start valley of another, the ratio of their peak discharges was evaluated; events were merged if this ratio exceeded 2.5. After merging, the start and end points of the combined events were redefined. Following event identification, the dominant runoff component of each flood was determined based on its relative contribution to total event discharge. The runoff component with the largest contribution to the total event volume was defined as the dominant driver of the flood event.

Text S5 Estimation of Irrigation Water Demand

In this arid environment, where annual precipitation is less than 50 mm, agricultural production in the Hotan Oasis depends almost entirely on irrigation water supplied by the Yulong Kashi and Karakashi rivers. To assess the influence of climate warming on agricultural irrigation, we calculated irrigation water demand based on methodologies established in earlier studies from the arid regions of northwestern China (Shen et al., 2013; Guo & Shen, 2016). In the first step, daily reference evapotranspiration (ET_0) in the Hotan Oasis was derived from CMFD V2.0 meteorological forcing using the Penman–Monteith method (Eq. 6). Subsequently, potential evapotranspiration (ET_{pot}) for croplands was calculated with Eq. (4), employing crop coefficients (K_c) provided by the Food and Agriculture Organization of the United Nations (FAO) together with crop planting area data obtained from the Xinjiang Statistical Yearbook. Finally, by accounting for irrigation water use efficiency, the irrigation water demand (IWD) was determined:

$$IWD = \frac{S \times (ET_{pot} - P_e)}{1000 \times IWUEC} \quad (S6)$$

where S refers to the planting area of each crop type, $IWUEC$ denotes the irrigation water use efficiency coefficient, as determined by earlier studies on agricultural irrigation in the arid regions of Xinjiang (Zhou et al., 2013), while

P_e represents the effective precipitation, which was estimated using the procedure described by Döll and Siebert (2002).

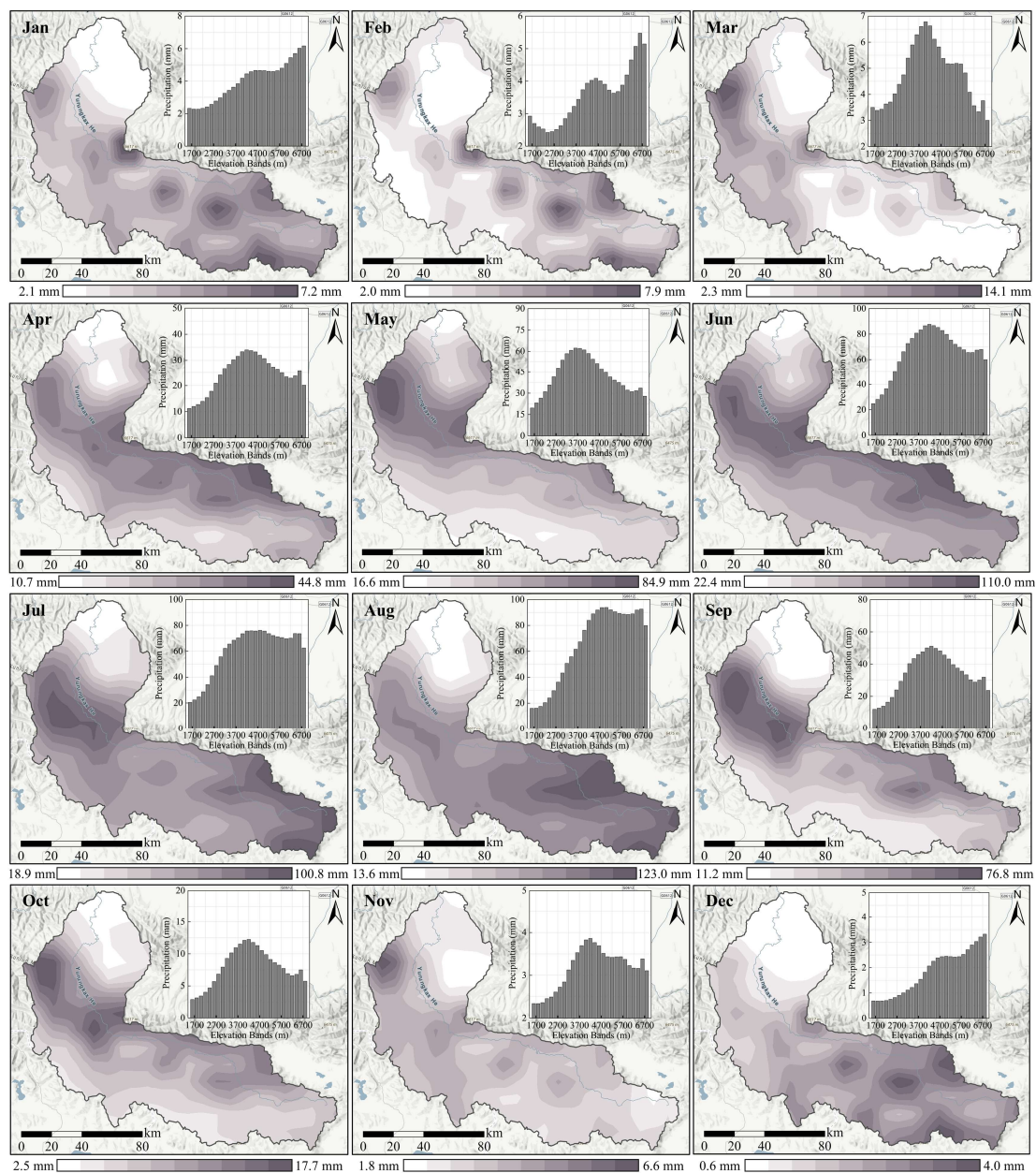


Fig.S1 Monthly distribution of precipitation across the source region of the YRB during 2000-2020. Each panel illustrates the spatial pattern of mean monthly precipitation, with darker shades indicating higher precipitation intensity. Insets depict the vertical distribution of precipitation. The insets overall show an increase of precipitation with elevation up to a mid-altitude maximum, followed by a decrease at higher elevations from March to December.

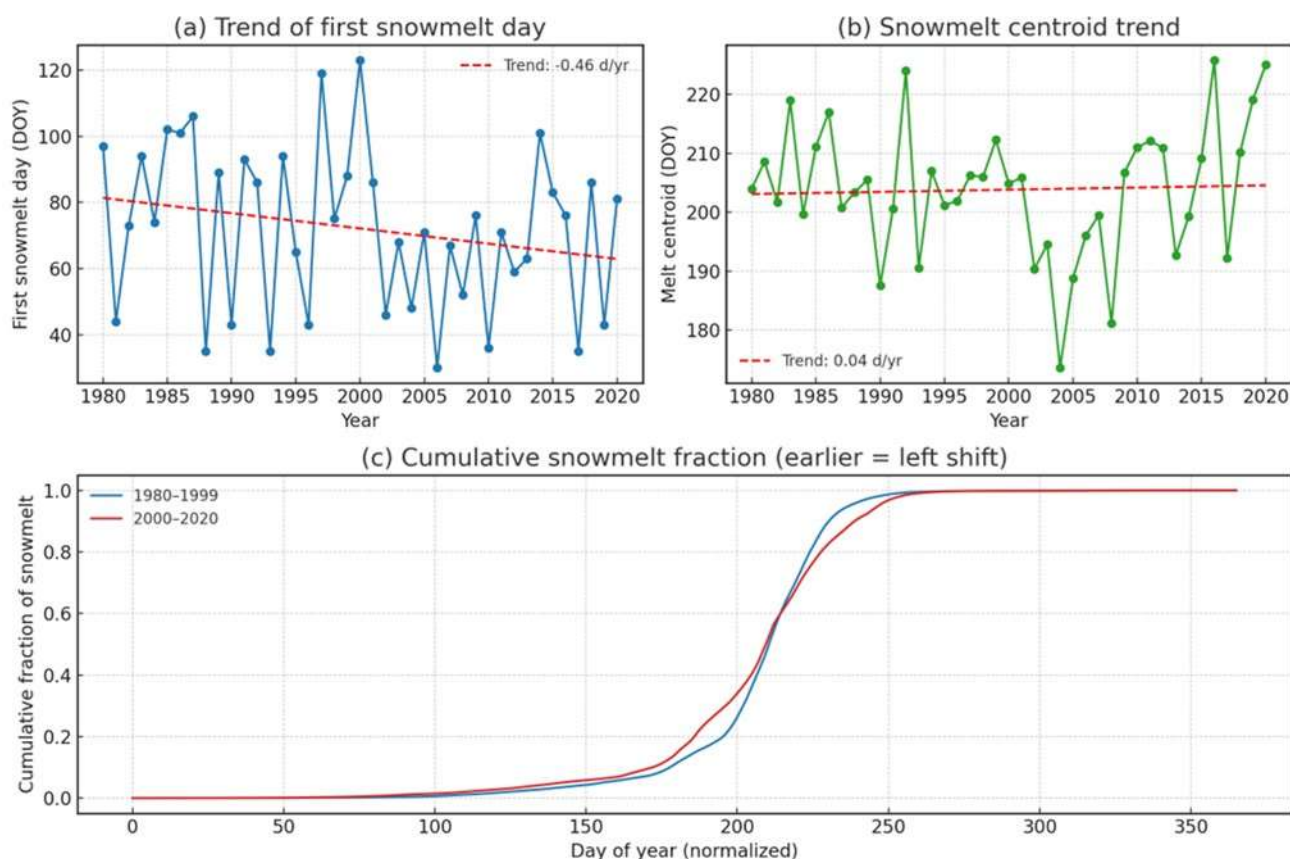


Fig.S2 Earlier onset and prolongation of the snowmelt process across the source region of the YRB during 1980-2020. (a) Temporal trend of the onset day of snowmelt. The onset of snowmelt was identified as the first day of the year when the simulated daily streamflow from snowmelt exceeded $1 \text{ m}^3/\text{s}$ and persisted for at least three consecutive days. A significant advancement trend of $-0.46 \text{ days yr}^{-1}$ indicates progressively earlier onset of snowmelt. (b) Temporal trend of the snowmelt centroid. The snowmelt centroid was determined as the day of year (DOY) corresponding to the weighted mean timing of daily melt flux. A slight increasing trend of $0.04 \text{ days yr}^{-1}$ indicates a little delay in the center timing of snowmelt. (c) Cumulative snowmelt fractions for 1980-1999 and 2000-2020, with blue and red lines representing the two periods, respectively. The cumulative fraction was derived by normalizing and integrating the daily snowmelt flux over the year to represent the progressive contribution of melt through time. The curves exhibit opposite shifts at different stages: the early portion (lower DOY) moves leftward, indicating an earlier onset of snowmelt, whereas the later portion (higher DOY) shifts rightward, suggesting prolonged late-season melting.

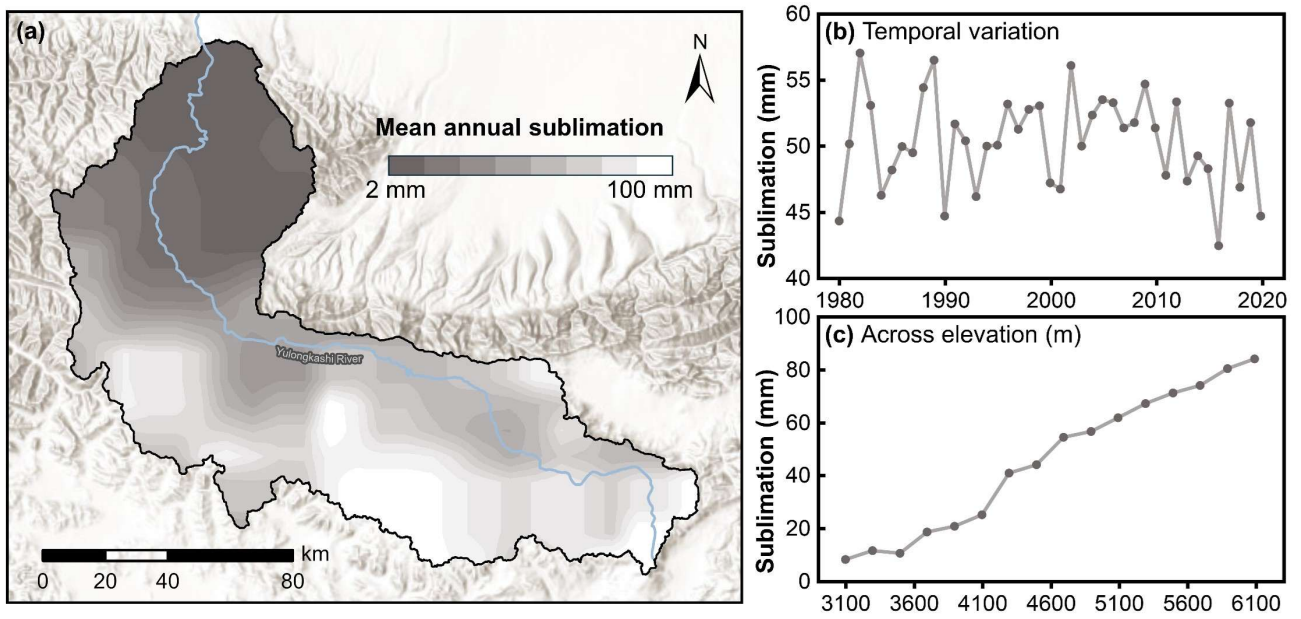


Fig.S3 Spatiotemporal characteristics of snow sublimation in the source region of the Yulongkashi River Basin during 1980-2020. (a) Spatial distribution of mean annual snow sublimation. (b) Interannual variability of basin-averaged annual sublimation over 1980-2020. (c) Elevation-dependent pattern of mean annual sublimation, showing a systematic increase with altitude.

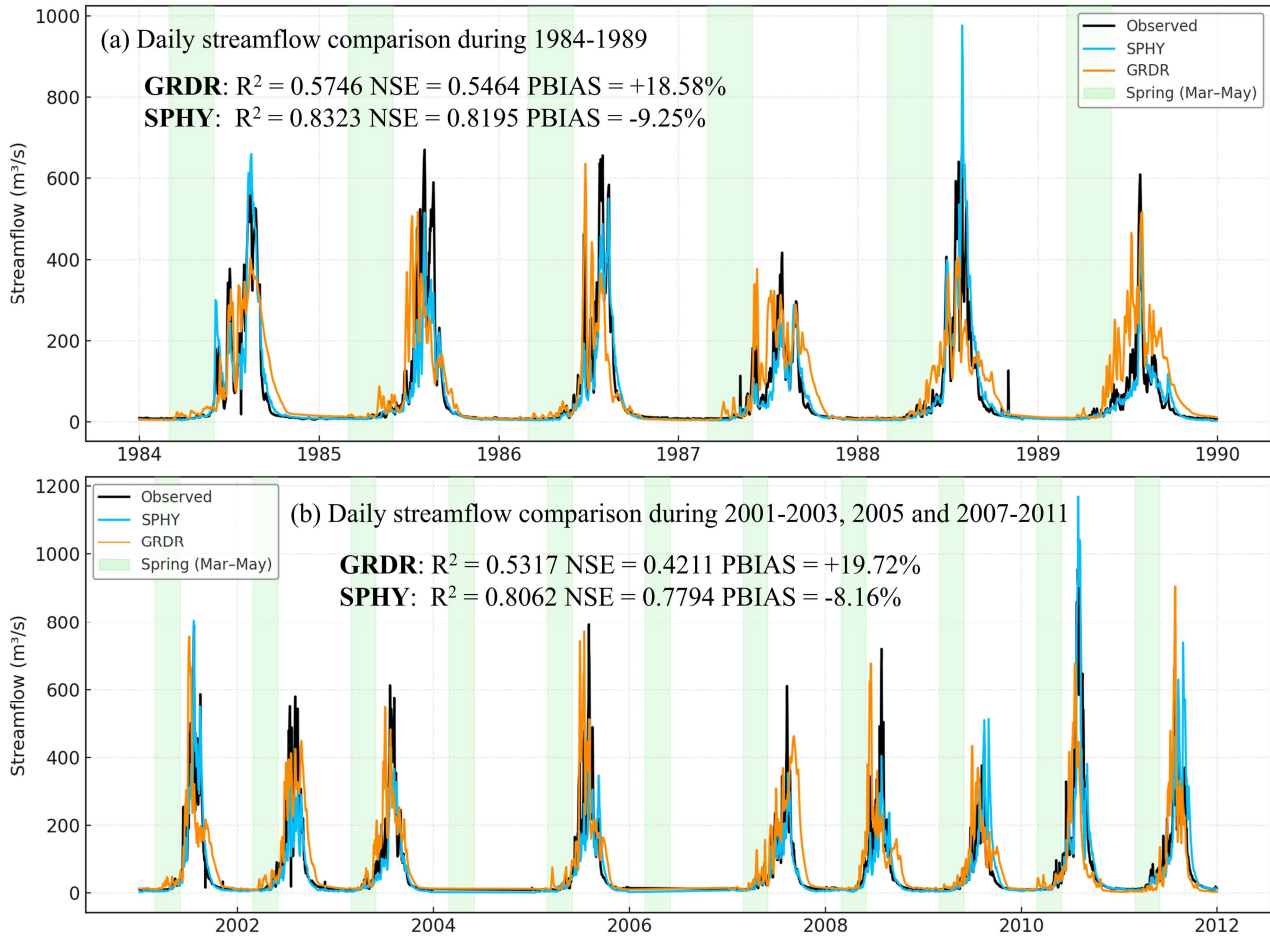


Fig.S4 Daily streamflow comparison between observations, the GRDR dataset, and the modified SPHY model for (a)1984-1989 and (b) 2001-2011. Data for 1990-2000, 2004, and 2006 are not shown due to missing observations. The shaded green bands indicate the March-May (spring), corresponding to the early snowmelt and irrigation during a critical crop growth stage. The coefficients of determination (R^2), Nash-Sutcliffe efficiencies (NSE), and percent biases (PBIAS) of the SPHY simulations and the GRDR dataset are presented. By enhancing snowmelt and snowpack simulating schemes, the modified SPHY model outperform the GRDR runoff simulation by nearly 30%, yielding more accurate spring streamflow and offering a promising model to capture snowmelt evolution in cold high-mountain basins.

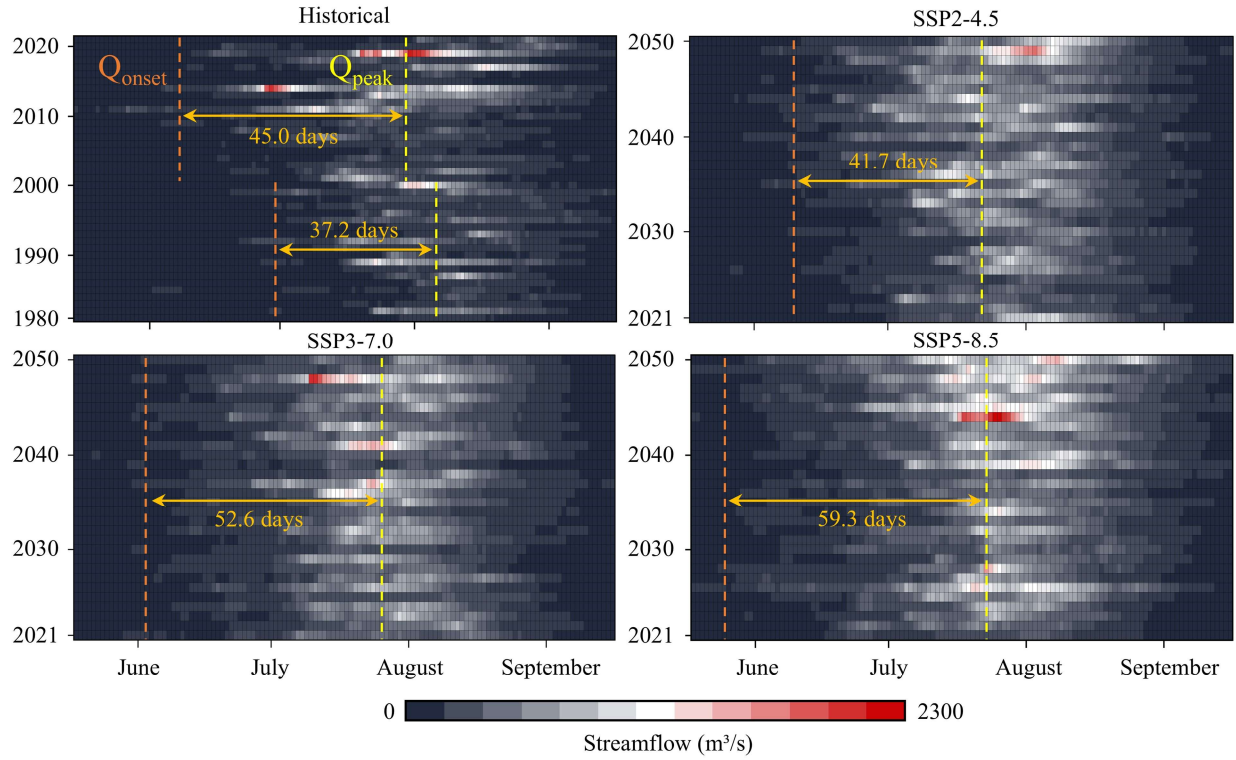


Fig.S5 Daily streamflow heatmaps for the source region of the YRB during (a) the historical period (1980-2020) and (b-d) the future period (2021-2050) under three CMIP6 scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5). The orange and yellow dashed lines mark the onset (Q_{onset}) and discharge peak (Q_{peak}) of the flood season, respectively, with horizontal arrows denoting the duration between these two phases. The threshold for Q_{onset} was determined as the 80th percentile of daily streamflow during 1980-1999, and for each year, the first day when the 7-day moving average exceeded this threshold was defined as Q_{onset} . Q_{peak} corresponds to the day of annual maximum discharge. The results reveal that both Q_{onset} and Q_{peak} have shifted earlier, accompanied by a growing frequency of high-magnitude discharge events and a pronounced extension of the flood season under future warming scenarios.

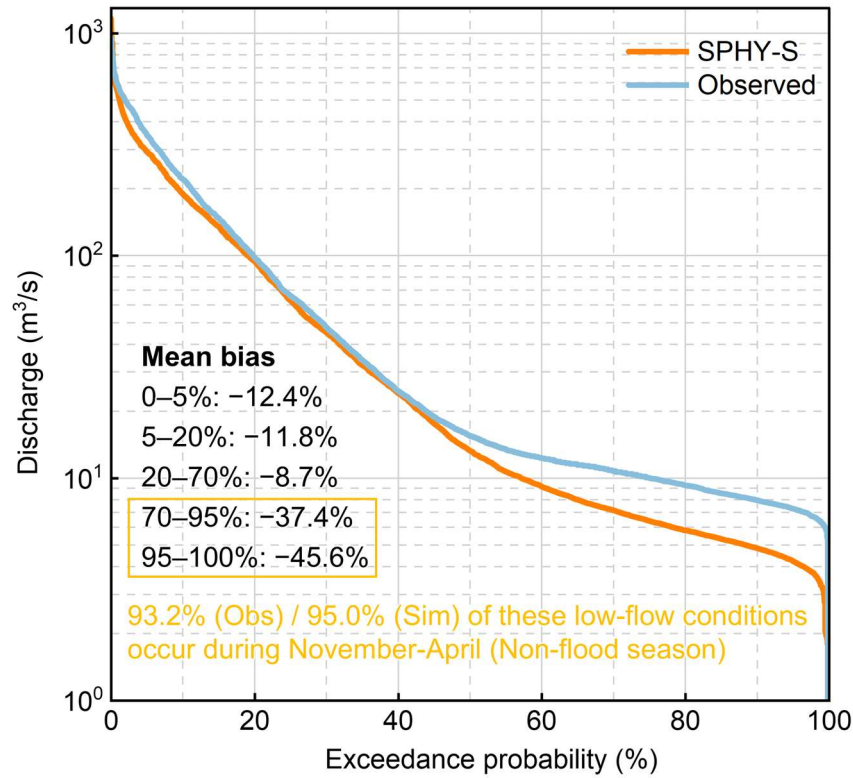


Fig. S6 Flow duration curves (FDCs) of observed and simulated (SPHY-S) daily discharge in the upstream Yulongkashi River Basin, based on all periods with available observations during 1980–2020. The model reproduces the overall flow regime well, with moderate negative biases in high- and mid-flow conditions (0–70% exceedance), while larger underestimation occurs in the low-flow range (70–100%). The low-flow regime is predominantly associated with the cold season (November–April), during which 93.2% (observed) and 95.0% (simulated) of low-flow conditions occur. As this period is characterized by limited meltwater contribution and corresponds to the non-flood season, biases in this range have limited implications for flood-generation processes, which are the primary focus of this study.

Table S1. Overview of CMIP6 climate models used in this study.

Model	Institution	Country	Resolution
CNRM-CM6-1	CNRM/CERFACS modelling group	France	$1.3^{\circ} \times 1.3^{\circ}$
EC-Earth3-Veg	The EC-Earth consortium	Europe	$0.7^{\circ} \times 0.7^{\circ}$
MPI-ESM1-2-HR	Max-Planck-Institute for Meteorology	Germany	$0.938^{\circ} \times 0.938^{\circ}$
MRI-ESM2-0	Meteorological Research Institute	Japan	$1.125^{\circ} \times 1.125^{\circ}$
NorESM2-MM	Norwegian Climate Centre	Norway	$1.250^{\circ} \times 0.938^{\circ}$

*The table presents the native spatial resolutions of each model. In this study, we employ the HiCPC (High-resolution CMIP6 downscaled daily Climate Projections over China), a newly developed dataset specifically designed for China's climatic applications. HiCPC integrates outputs from 22 global climate models (GCMs) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6). To correct systematic biases inherent in daily GCM simulations, an advanced Bias Correction and Spatial Disaggregation (BCSD) method is applied, using the China Meteorological Forcing Dataset (CMFD) as the reference. HiCPC provides high-resolution ($0.1^{\circ} \times 0.1^{\circ}$) daily forcing data across China, covering both the historical period (1979–2014) and future projections (2015–2100) under four CMIP6 Shared Socioeconomic Pathways (SSPs: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Validation results indicate that HiCPC performs robustly and exhibits markedly improved accuracy relative to the original CMIP6 GCMs during the historical period (Yuan et al., 2024). Model evaluations suggest that the five models listed in the table capture the hydro-climatic characteristics of the Yulongkashi River Basin (western Kunlun Mountains region) with higher fidelity than other models, particularly in reproducing temperature and precipitation variations (Cui et al., 2021; Yang et al., 2021; Wang et al., 2023).

Table S2. Summary of calibrated parameters for the SPHY model.

Parameter	Description	Fitted value	Unit
DDFS	Degree-day factor for snowmelt	1.521806	mm/°C/d
T_{crit}	Critical temperature for distinguishing between snowfall and rainfall	-2.78832	°C
SnowSC	Water storage capacity of snowpack	0.170199	mm/mm
DDFG	Degree-day factor for debris-free ice	0.640067	mm/°C/d
DDFDG	Degree-day factor for debris-covered ice	1.04	mm/°C/d
Rootfieldfrac	Scaling factor for field capacity	0.839161	-
Rootsatfrac	Scaling factor for saturated soil water content	0.948192	-
Rootdryfrac	Scaling factor for wilting point	0.816417	-
Rootwiltfrac	Scaling factor for permanent wilting point	1.048583	-
Rootsatfrac	Scaling factor for saturated hydraulic conductivity	1.156862	-
δ_{gw}	Groundwater recharge delay time	326.5155	day
Basethresh	Threshold for baseflow to occur	166.9856	mm
α_{gw}	Baseflow recession coefficient	0.325705	day ⁻¹
Glacf	Fraction of glacier melt that becomes glacier runoff	0.738226	-
Rootdepthflat	Rootlayer thickness	566.1867	mm
Subdepthflat	Sublayer thickness	1842.512	mm
K_x	Flow recession coefficient	0.902945	-
k_a	Aerodynamic resistance adjustment factor	0.193641	-

Table S3. Monthly increase in total streamflow and the percentage contribution of each component to the increase for Period 2 (2000-2020) relative to Period 1 (1980-1999).

Month	Δ Streamflow (million m ³)	Contribution to the increase in streamflow (%)			
		Snowmelt	Glacier-melt	Rainfall	Baseflow
January	+7.1	0.6	0.0	0.0	99.4
February	+6.9	15.3	0.0	0.0	84.7
March	+12.0	51.3	0.3	0.1	48.3
April	+13.1	53.0	3.6	4.4	39.0
May	+25.8	45.2	2.1	33.5	19.1
June	+68.2	60.5	4.1	28.1	7.3
July	+161.9	71.5	11.5	13.7	3.3
August	+214.5	32.7	52.1	13.0	2.2
September	+118.7	40.7	34.8	19.7	4.8
October	+12.3	6.1	28.0	14.9	51.0
November	+5.8	3.9	0.8	0.0	95.3
December	+5.0	0.6	0.0	0.0	99.4

Table S4. Mann-Kendall trend test, Sen's slope, and Pettitt change-point analysis for climatic variables and runoff components over three periods (1980-1999, 2000-2020, and 1980-2020).

Variable	1980-1999 (P1)		2000-2020 (P2)		1980-2020				P1 vs. P2
	Sen's slope	MK p-value	Sen's slope	MK p-value	Sen's slope	MK p-value	Pettitt change point (year)	Pettitt p-value	Mann-Whitney U test p-value
Qall	1.6981	0.0125	0.5228	0.4503	0.9360	0.0003	1997	0.0045	0.0047
Qsnow	0.4435	0.2300	0.5782	0.2157	0.4201	0.0023	1997	0.0206	0.0127
Qglacier	0.5575	0.0980	-0.0108	0.9759	0.3234	0.0167	1996	0.0408	0.0335
Qrain	0.1228	0.0252	0.0638	0.5661	0.1358	0.0000	1997	0.0001	0.0000
Qbaseflow	0.5890	0.0005	0.1236	0.4503	0.1433	0.0123	1987	0.0990	0.2460
Precipitaion	0.0381	0.9741	1.7380	0.0852	1.5635	0.0007	2000	0.0003	0.0000
Temperature	0.0554	0.0212	0.0372	0.0967	0.0442	0.0000	1997	0.0099	0.0015

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