



1 Hydrological Memory Regulates River Basin Recovery from 2 Climate Extremes: Evidence from China's Major River 3 Basins

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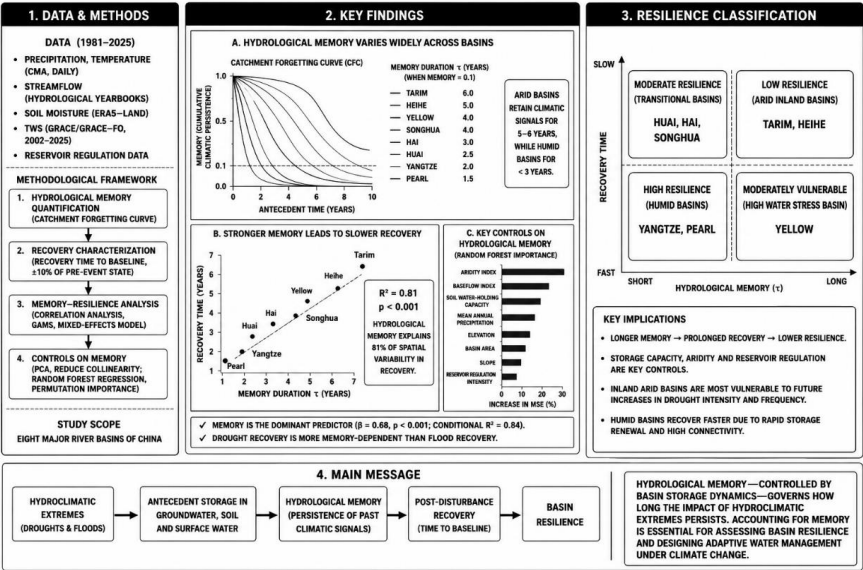
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10 **Abstract** Hydrological memory from climate extremes depends not only on disturbance magnitude but also on
11 the persistence of antecedent basin storage. This study developed a Hydrological Memory Framework (HMF) to
12 quantify basin-scale hydrological memory and assess its influence on resilience across eight major river basins
13 in China during 1981–2025. Hydrological memory was estimated using the Catchment Forgetting Curve (CFC),
14 while drought and flood recovery were evaluated from standardized hydrological anomalies. Principal
15 Component Analysis, Random Forest regression, generalized additive models, and mixed-effects modelling
16 were used to identify environmental controls and quantify the memory–resilience relationship. Hydrological
17 memory varied markedly among basins, from less than 3 years in the humid Yangtze and Pearl basins to
18 approximately 5–6 years in the arid Heihe and Tarim basins. Recovery time increased strongly with memory
19 duration ($R^2 = 0.81$, $p < 0.001$), and drought recovery was generally two to three times longer than flood
20 recovery. Mixed-effects modelling confirmed hydrological memory as the dominant predictor of recovery time
21 ($\beta = 0.68$, $p < 0.001$), with the full model explaining 84% of the observed variability. Random Forest analysis
22 identified groundwater storage (28.4%), climatic aridity (22.7%), soil moisture persistence (17.9%), and basin
23 elevation (12.6%) as the principal controls on memory. The results show that antecedent storage exerts a
24 measurable control on post-extreme recovery and basin resilience. The HMF provides a process-based basis for
25 identifying vulnerable basins and improving climate-adaptive water resources management.

26 **Keywords:** Hydrological memory, River basin resilience, Climate extremes, Catchment Forgetting Curve,
27 Random Forest



28 Graphical Abstract





30 1. Introduction

31 Climate change is reshaping the global water cycle, with droughts and floods becoming more frequent,
 32 persistent, and severe in many regions. Changes in temperature and precipitation, together with higher
 33 evaporative demand, are altering water availability and hydrological responses across river basins. These shifts
 34 increasingly challenge reliable water supply, ecosystem functioning, and the long-term management of
 35 freshwater resources (IPCC, 2023, Blöschl et al., 2019). Over recent decades, recurrent droughts and floods
 36 have pushed many river basins beyond their historical range of hydrological variability. Such disturbances
 37 increase hazard exposure while also weakening the capacity of freshwater systems to sustain ecological
 38 processes and meet human water demands under a changing climate (Granata and Di Nunno, 2026, Grill et al.,
 39 2019, Gudmundsson et al., 2021a).

40 River basins respond to climatic forcing with a time lag because precipitation is redistributed and retained across
 41 interconnected stores, including soil moisture, groundwater, wetlands, snowpack, reservoirs, and river channels
 42 (Nile et al., 2025). These storage components shape runoff timing and magnitude by retaining water and
 43 releasing it over different timescales, creating a delayed basin response to climatic variability (Sun et al., 2023,
 44 McDonnell and Beven, 2014, Fan et al., 2023). Storage therefore gives river basins a hydrological legacy:
 45 present conditions reflect not only current weather but also water retained from earlier weeks, months, or years.
 46 This persistence of past climatic influence, termed hydrological memory, governs how quickly a basin adjusts
 47 after external disturbances (Nippgen et al., 2016, Kumar et al., 2025, Orth et al., 2022).

48 Hydrological memory is especially relevant under climate change because basin storage shapes both the
 49 propagation of extremes and the pace of recovery. Groundwater and soil-water reserves can buffer short-term
 50 anomalies, but their slow recharge and release may prolong recovery after severe droughts or floods (Riedel and
 51 Weber, 2020, Maxwell and Condon, 2016). By contrast, basins with limited storage tend to respond quickly but
 52 are less able to buffer climatic disturbances. This contrast shows that resilience depends not only on climate
 53 forcing, but also on how effectively a basin stores, transfers, and releases water over time. Understanding these
 54 storage controls is therefore central to explaining differences in hydrological recovery among river basins
 55 (Wada, 2024, Bierkens and Wada, 2019).

56 Although drought propagation, flood generation, runoff dynamics, groundwater behavior, soil moisture
 57 persistence, and hydrological connectivity have been widely studied, these processes are often examined
 58 separately or through individual hydrological variables (Gupta et al., 2023, Galelli et al., 2025). Considerable
 59 advances have been achieved in identifying meteorological and hydrological extremes using indices such as the
 60 Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and
 61 Standardized Streamflow Index (SSI) (Baez-Villanueva et al., 2024, Shamshirband et al., 2020). Earth
 62 observation, land-surface models, and distributed hydrological models have improved estimates of basin water
 63 storage and hydrological variability. However, these tools are still used mainly to characterize the magnitude
 64 and spatial pattern of extremes, offering less insight into why basins exposed to similar disturbances can recover
 65 at very different rates (Vicente-Serrano et al., 2022, Gudmundsson et al., 2021b).



66 A persistent limitation in hydrological research is the tendency to characterize memory through separate
 67 indicators such as soil moisture persistence, groundwater recession, streamflow autocorrelation, or terrestrial
 68 water storage anomalies. Although these metrics are useful for identifying storage behavior within individual
 69 components of the hydrological system, they do not fully represent the collective response of a river basin,
 70 where multiple storage pathways interact over different temporal scales. Consequently, hydrological memory is
 71 still not well resolved as an integrated basin-scale property, and its influence on recovery after droughts and
 72 floods remains incompletely understood. This gap constrains the development of process-based resilience
 73 assessments and makes it difficult to explain why basins experiencing similar climatic disturbances often show
 74 markedly different recovery trajectories (Knoben et al., 2024, McMillan et al., 2025)

75 Hydrological resilience reflects the capacity of a river basin to absorb climatic disturbances, sustain essential
 76 hydrological functions, and recover toward its pre-disturbance state. The pace of recovery is controlled not only
 77 by the magnitude of the climatic shock but also by antecedent storage conditions within groundwater, soil,
 78 wetlands, lakes, glaciers, and reservoirs. These storage components can moderate short-term extremes by
 79 buffering water deficits or excesses, yet their slow recharge and release may also prolong recovery once the
 80 disturbance has passed. In contrast, basins with limited storage often respond more rapidly to changing climate
 81 conditions but are generally less capable of withstanding persistent droughts or floods. River basin resilience
 82 therefore emerges from the interaction between external climatic forcing and the duration, capacity, and
 83 turnover of internal water storage (Bruno et al., 2026, Berghuijs et al., 2025). Recent advances in satellite
 84 gravimetry, reanalysis products, and machine-learning methods have substantially improved the ability to track
 85 terrestrial water storage and characterize basin-scale hydrological behavior. GRACE and GRACE-FO, in
 86 particular, provide direct information on large-scale storage variability that cannot be captured from streamflow
 87 observations alone. Yet these tools are still commonly applied in isolation rather than within a unified analytical
 88 framework. As a result, the combined influence of antecedent storage, climatic persistence, and recovery
 89 dynamics on basin resilience remains insufficiently resolved. Integrating these data sources and analytical
 90 approaches offers a stronger basis for quantifying hydrological memory as a basin-scale property and for
 91 explaining differences in post-extreme recovery across contrasting river systems (Karki et al., 2025, Springer et
 92 al., 2026).

93 To address these limitations, this study introduces a Hydrological Memory Framework (HMF) that defines
 94 hydrological memory as a basin-scale property emerging from the interaction of climatic forcing, internal water
 95 storage, and runoff response. Rather than treating soil moisture, groundwater, and streamflow as separate
 96 indicators, the framework combines long-term climatic persistence with post-event recovery to describe how
 97 climatic signals are stored, transferred, and progressively released within a river basin. A central component of
 98 the HMF is the Catchment Forgetting Curve (CFC), which tracks the decline in the influence of antecedent
 99 climatic conditions on present runoff. In contrast to conventional autocorrelation-based measures, the CFC
 100 estimates how long past climate continues to shape runoff generation, providing a physically interpretable
 101 measure of effective hydrological memory that can be compared across basins with different climatic and
 102 physiographic characteristics (De Lavenne et al., 2022).



China provides a strong setting for evaluating this framework because its major river basins span an unusually broad hydroclimatic gradient, from humid subtropical monsoon regions to hyper-arid inland systems, while also including alpine, snow-influenced, temperate, and heavily regulated catchments. This diversity creates pronounced contrasts in precipitation regime, groundwater dependence, snow storage, vegetation cover, and water management, allowing the controls on hydrological memory to be examined across markedly different basin types. In addition, more than four decades of hydrometeorological observations provide sufficient temporal coverage to assess long-term climatic persistence and compare basin recovery across repeated drought and flood events (Hao et al., 2021). Accordingly, this study has four objectives: (i) to quantify hydrological memory across eight major river basins in China using the Catchment Forgetting Curve (CFC); (ii) to determine how memory influences basin resilience and recovery after droughts and floods; (iii) to identify the main climatic and physiographic controls on hydrological memory using statistical and machine-learning methods; and (iv) to develop a transferable Hydrological Memory Framework (HMF) that links climatic persistence, basin storage, and recovery dynamics. By connecting hydrological memory directly with post-event recovery, the study provides a process-based basis for interpreting differences in basin resilience and for improving the assessment of river-basin responses to increasing climate variability.

2. Methodology

Hydrological recovery after climate extremes is shaped by more than the severity of the disturbance itself; it also reflects how strongly antecedent conditions persist within the basin. Conventional assessments often examine precipitation, streamflow, groundwater storage, or drought characteristics separately, which makes it difficult to explain why basins exposed to similar events can recover at very different rates. Here, hydrological memory is treated as a measurable basin-scale property representing the persistence of antecedent hydrological conditions and their influence on resilience. The methodological framework therefore derives hydrological memory from long-term hydroclimatic records and evaluates how differences in memory are related to post-event recovery across eight major river basins in China.

2.1. Study area

China encompasses a broad hydroclimatic gradient, extending from humid subtropical monsoon regions in the southeast to hyper-arid inland environments in the northwest. Eight major river basins—the Yangtze, Yellow, Pearl, Huai, Hai, Songhua, Tarim, and Heihe (Figure 1)—were selected to represent the principal climatic, hydrological, and physiographic contrasts across the country (Liu et al., 2017). Together, these basins represent humid, temperate, semi-arid, arid, alpine, and cold continental environments, with marked contrasts in precipitation, temperature, terrain, groundwater storage, vegetation cover, and human regulation (Wang et al., 2022, Su et al., 2022). Hydrological processes also differ markedly among the selected basins, ranging from precipitation-dominated runoff in humid regions to groundwater- and glacier-fed systems in arid inland catchments. This diversity in climatic forcing and storage conditions provides a strong natural basis for examining spatial differences in hydrological memory and assessing how those differences influence river basin resilience to climate extremes (Chen et al., 2015, Fan et al., 2026).

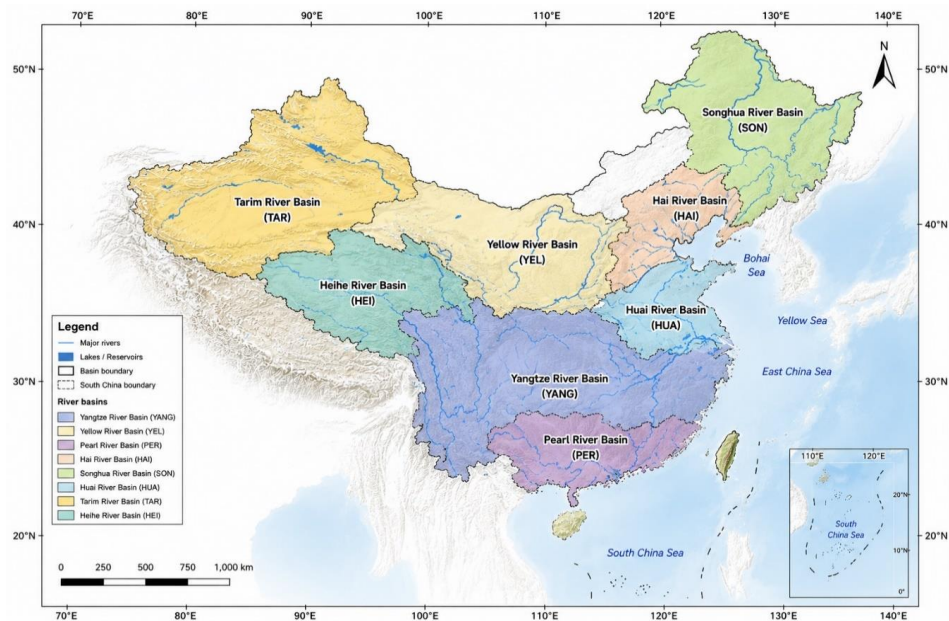


Figure 1. Location of the eight representative river basins investigated in this study. Basin boundaries are superimposed on a shaded-relief basemap of China. Basemap source: Natural Earth; elevation data derived from the Shuttle Radar Topography Mission (SRTM).

The analysis covered the period from 1981 to 2025, encompassing more than four decades of climatic variability, recurrent droughts and floods, accelerated warming, and marked changes in monsoon behavior. This extended record captures a broad range of hydroclimatic conditions, providing sufficient temporal variability to quantify long-term basin memory and assess recovery following both drought and flood events across the eight river basins summarized in Table 1.

Table 1: Hydroclimatic and physiographic characteristics of the eight major river basins investigated in this study.

River Basin	Climate Zone	Basin Area (10 ³ km ²)	Mean Annual Precipitation (mm)	Mean Annual Temperature (°C)	Mean Elevation (m)	Aridity Index (PET/P)	Dominant Hydrological Storage
Yangtze	Humid subtropical monsoon	1,808	1,100	14.8	1,900	0.85	Surface water + Groundwater
Yellow	Semi-arid temperate monsoon	752	470	9.2	2,450	2.10	Groundwater + Reservoir storage
Pearl	Humid	453	1,480	20.7	780	0.72	Surface water



River Basin	Climate Zone	Basin Area (10 ³ km ²)	Mean Annual Precipitation (mm)	Mean Annual Temperature (°C)	Mean Elevation (m)	Aridity Index (PET/P)	Dominant Hydrological Storage
	subtropical monsoon						
Huai	Humid–semi-humid transitional	270	910	14.5	220	1.18	Soil moisture
Hai	Semi-humid temperate monsoon	318	535	11.9	620	1.86	Groundwater
Songhua	Cold humid continental	557	575	3.9	640	1.42	Snowpack + Soil moisture
Tarim	Hyper-arid inland	1,020	82	10.6	1,210	18.30	Groundwater
Heihe	Arid continental	143	128	7.3	2,060	9.80	Groundwater + Glacier melt

151

152 2.2. Datasets

153 Hydrological memory is governed by the interaction between climatic forcing and basin water storage.
 154 Accordingly, only variables directly representing these processes were included in the analysis. Daily
 155 precipitation and air temperature were used to characterize climatic forcing, whereas observed streamflow
 156 represented the integrated basin-scale hydrological response. Root-zone soil moisture was selected to quantify
 157 storage persistence, while terrestrial water storage anomalies (TWSA) derived from the GRACE and GRACE-
 158 FO missions (2002–2025) were incorporated to independently validate long-term storage dynamics.
 159 Meteorological observations were obtained from the China Meteorological Administration, streamflow data
 160 acquired from the Ministry of Water Resources, root-zone soil moisture from ERA5-Land, and TWSA from the
 161 GRACE/GRACE-FO missions (Table 2). Before analysis, all datasets underwent quality control, were
 162 aggregated to a common monthly resolution, and were spatially averaged within watershed boundaries to ensure
 163 a consistent representation of long-term basin-scale hydrological conditions (Muñoz-Sabater et al., 2021,
 164 Landerer and Swenson, 2012, Wang et al., 2026).

165 To facilitate direct comparison among variables measured in different physical units, standardized anomalies
 166 were calculated in Eq. (1) :

$$167 \quad Z_t = \frac{X_t - \mu}{\sigma} \quad (1)$$

168 where X_t denotes the monthly observation at time t , μ is the long-term monthly mean, and σ is the corresponding
 169 standard deviation. Standardization removes seasonal differences while preserving interannual variability and



170 long-term climatic signals, allowing persistence characteristics to be compared consistently among climatic
 171 forcing, hydrological response, and storage variables.

172 **Table 2: Hydroclimatic variables and data sources used for hydrological memory and resilience**
 173 **assessment.**

Variable	Dataset / Source	Spatial Resolution	Temporal Resolution	Study Period	Purpose
Precipitation	China Meteorological Administration (CMA)	Station / Basin	Daily	1981–2025	Climate forcing
Air Temperature	China Meteorological Administration (CMA)	Station / Basin	Daily	1981–2025	PET calculation
Streamflow	Ministry of Water Resources of China	Gauging station	Daily	1981–2025	Basin response
Soil Moisture	ERA5-Land	0.1°	Monthly	1981–2025	Storage persistence
Terrestrial Water Storage	GRACE / GRACE-FO	0.5°	Monthly	2002–2025	Storage validation
Basin Boundary	HydroBASINS / Ministry of Water Resources	Vector	Static	—	Spatial analysis

174
 175 Hydrological extremes were identified prior to memory analysis because hydrological memory can only be
 176 quantified in response to disturbances that alter basin storage. Meteorological droughts were characterized using
 177 the Standardized Precipitation Evapotranspiration Index (SPEI), whereas hydrological droughts were identified
 178 using the Standardized Streamflow Index (SSI). Flood events were extracted from observed streamflow using
 179 basin-specific seasonal high-flow thresholds derived from historical discharge records. For each event, the onset,
 180 duration, peak magnitude, cumulative severity, and recovery period were determined, providing a consistent
 181 basis for subsequent hydrological memory analysis (Wang et al., 2020, Shamshirband et al., 2020, Lema et al.,
 182 2024, Lu et al., 2025).

183 2.3. Hydrological Memory and Extreme-Event Recovery

184 River basins respond to climatic forcing through delayed storage and release processes, as precipitation is
 185 partitioned among runoff, soil moisture, groundwater, and channel storage. Consequently, present hydrological
 186 conditions reflect both contemporary and antecedent climatic forcing. This persistence, termed hydrological
 187 memory, represents the capacity of a basin to retain climatic information and influence subsequent hydrological
 188 responses. Because storage characteristics differ with climate, geology, topography, vegetation, and human
 189 activities, hydrological memory varies among basins, resulting in distinct recovery trajectories following
 190 comparable climate extremes (Tonkin et al., 2026, Granata and Di Nunno, 2026).



In this study, hydrological memory is defined as an integrated basin-scale property that emerges from the interaction among climatic forcing, basin storage, and runoff response, rather than from the persistence of any single hydrological variable. The proposed Hydrological Memory Framework (HMF) links long-term climatic persistence with post-event recovery to quantify basin memory and assess its role in river basin resilience. Hydrological memory was estimated using the Catchment Forgetting Curve (CFC), which represents the gradual decline in the influence of antecedent climatic conditions on runoff generation. In contrast to conventional autocorrelation-based measures, the CFC provides a direct estimate of how long previous climatic conditions continue to shape the present hydrological response. Annual runoff yield for each river basin was calculated in Eq. (2) as follows (Ziang et al., 2025):

$$q_{b,t} = \frac{Q_{b,t}}{A_b} \quad (2)$$

where $Q_{b,t}$ is the annual streamflow volume of basin b during year t , and A_b is the corresponding drainage area. Climatic forcing was represented by the basin humidity index in Eq. (3)

$$H_{b,t} = \frac{P_{b,t}}{PET_{b,t}} \quad (3)$$

where $P_{b,t}$ and $PET_{b,t}$ denote annual precipitation and potential evapotranspiration, respectively. Because climatic conditions differ substantially among China's major river basins, both runoff yield and humidity index were transformed into normalized anomalies to facilitate inter-basin comparison in Eq. (4) and Eq. (5),

$$q'_{b,t} = \frac{q_{b,t} - \bar{q}_b}{\bar{q}_b} \quad (4)$$

$$H'_{b,t} = \frac{H_{b,t} - \bar{H}_b}{\bar{H}_b} \quad (5)$$

where $\bar{q}_b$ and $\bar{H}_b$ represent the long-term basin means. These normalized anomalies describe the relative departure of hydrological conditions from the long-term climatological state while eliminating differences associated with basin size and climatic magnitude.

The contribution of antecedent climatic conditions to present runoff was subsequently estimated using a distributed lag regression in Eq. (6),

$$q'_{b,t} = \alpha_b + \sum_{j=0}^J \beta_{b,j} H'_{b,t-j} + \varepsilon_{b,t}, \quad (6)$$

where α_b is the basin-specific intercept, $\beta_{b,j}$ represents the contribution of climatic conditions occurring j years before the present year, and $\varepsilon_{b,t}$ denotes the residual error. The regression coefficients therefore describe how rapidly climatic information is forgotten by each river basin. Larger coefficients associated with longer antecedent periods indicate that previous climatic conditions continue to exert a measurable influence on present hydrological behaviour, reflecting stronger basin memory.



222 To facilitate comparison among river basins, the regression coefficients were normalized to construct the
 223 Catchment Forgetting Curve in Eq. (7) ,

$$224 \quad F_b(j) = \frac{|\beta_{b,j}|}{\sum_{r=0}^j |\beta_{b,r}|} \quad (7)$$

225 which represents the relative contribution of climatic conditions occurring at different antecedent years. The
 226 cumulative influence of antecedent climate was then expressed as in Eq. (8)

$$227 \quad C_b(k) = \sum_{j=0}^k F_b(j) \quad (8)$$

228 and the effective basin memory was defined as the minimum number of antecedent years required to explain 90%
 229 of the present hydrological response in Eq. (9),

$$230 \quad M_b = \min\{k: C_b(k) \geq 0.90\} \quad (9)$$

231

232 This formulation provides a physically interpretable estimate of the period over which antecedent climatic
 233 information remains embedded in basin storage. Larger memory values indicate longer persistence and slower
 234 hydrological adjustment, whereas smaller values reflect more rapid response to changing climatic conditions.
 235 The robustness of the estimated memory duration was evaluated using additional cumulative thresholds of 80%
 236 and 95%. Because the Catchment Forgetting Curve (CFC) characterizes integrated basin memory but does not
 237 isolate the storage mechanisms sustaining that persistence, complementary temporal autocorrelation analyses
 238 were applied to streamflow and soil moisture. These analyses were used to distinguish the relative contribution
 239 of major storage components to basin-scale hydrological memory.

240 **2.4. Linking Hydrological Memory to Basin Resilience**

241 The Hydrological Memory Framework (HMF) was used to test whether differences in basin memory explain
 242 contrasting resilience to comparable hydroclimatic disturbances. Although climate extremes initiate
 243 hydrological disruption, the pace of recovery is strongly influenced by antecedent storage conditions. Basins
 244 with substantial groundwater reserves, greater soil-water storage, or persistent baseflow can buffer short-term
 245 disturbances, but these same storage components may prolong the return to hydrological equilibrium. In contrast,
 246 basins with limited storage generally respond more rapidly and recover sooner once climatic forcing returns
 247 toward normal conditions. Basin resilience was therefore assessed from post-event recovery rather than
 248 disturbance magnitude alone, providing a direct measure of how hydrological memory influences recovery
 249 dynamics. For each identified drought and flood event, disturbance magnitude was quantified using the
 250 maximum standardized anomaly (Bai et al., 2025) in Eq. (10):

$$251 \quad D_e = \max |Z_e(t)| \quad (10)$$



where D_e represents the disturbance magnitude of event e , and $Z_e(t)$ is the standardized hydrological anomaly during the event. Larger values of D_e indicate greater deviation from the long-term hydrological state and therefore stronger disturbance intensity. However, disturbance magnitude alone does not adequately represent resilience because basins subjected to similar disturbances may recover at substantially different rates. Consequently, recovery time, derived in Section 2.3, was considered the primary indicator of basin resilience. Recovery capacity was expressed as the inverse of recovery time (Illouz-Eliaz et al., 2025) in Eq. (11):

$$R_c = \frac{1}{RT} \quad (11)$$

where RT denotes the time required for hydrological conditions to return to the climatological range following the termination of an extreme event. Higher values of R_c indicate greater resilience because the basin is able to restore hydrological functioning more rapidly after disturbance. Disturbance magnitude and recovery capacity were analysed separately throughout the study to preserve their physical interpretation and avoid introducing subjective weighting schemes associated with composite resilience indices.

The relationship between hydrological memory and basin resilience was first evaluated using Pearson and Spearman correlation analyses to quantify linear and monotonic associations between memory duration and recovery characteristics. To capture potential nonlinear responses, generalized additive models (GAMs) were subsequently applied, providing a flexible framework for assessing the influence of hydrological memory on basin recovery and is given by in Eq. (12):

$$RT = \beta_0 + s(M) + \varepsilon \quad (12)$$

where RT is recovery time, M represents basin hydrological memory, $s(\cdot)$ is a smooth nonlinear function, β_0 is the intercept, and ε is the residual error. GAMs allow the influence of hydrological memory on recovery to vary across different climatic conditions without imposing a predefined mathematical relationship and are therefore well suited for analysing nonlinear hydrological processes.

The dominant controls on hydrological memory were evaluated using climatic, topographic, and hydrological variables. Principal Component Analysis (PCA) was applied to reduce multicollinearity and identify the primary environmental gradients, followed by Random Forest regression to quantify variable importance and capture nonlinear relationships. Predictor importance was assessed using permutation-based metrics, with the complete event dataset used to improve statistical robustness (Lehr and Hohenbrink, 2025). Finally, the central hypothesis of this study—that hydrological memory governs basin resilience was evaluated using a linear mixed-effects model that accounts for repeated drought and flood events occurring within the same river basin and equation given by in Eq. (13):

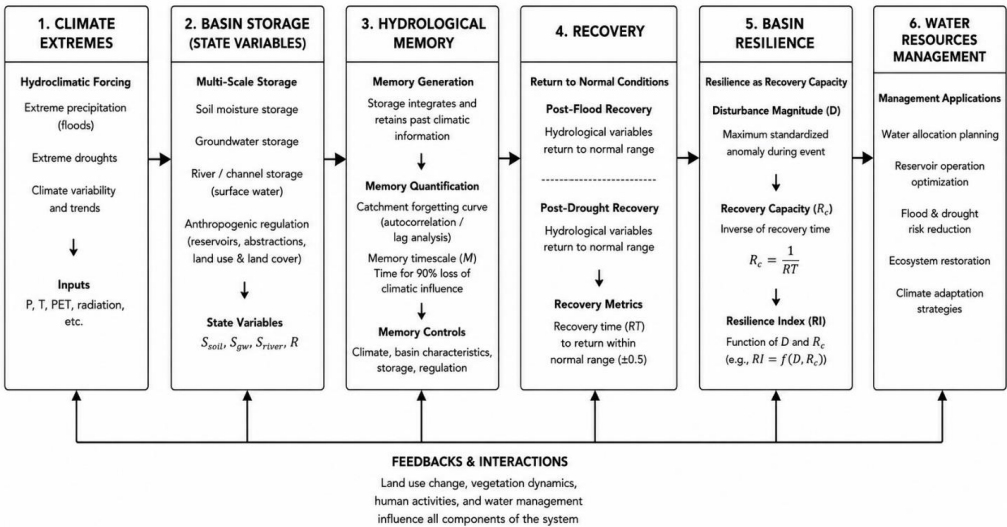
$$RT_{ij} = \beta_0 + \beta_1 M_i + \beta_2 D_{ij} + \beta_3 B_i + u_i + \varepsilon_{ij} \quad (13)$$

where RT_{ij} is the recovery time of event j in basin i , M_i is the characteristic hydrological memory of basin i , D_{ij} represents disturbance magnitude, B_i denotes basin-specific environmental characteristics, u_i is the random



basin effect, and ε_{ij} is the residual error. The coefficient β_1 provides the principal statistical test of the proposed hypothesis, indicating whether hydrological memory exerts a significant influence on post-disturbance recovery after accounting for differences in climatic forcing and basin characteristics.

To evaluate the robustness of the proposed framework, uncertainty was assessed using bootstrap resampling with 1,000 iterations together with leave-one-basin-out cross-validation. Additional sensitivity analyses examined the effects of lag length, cumulative forgetting thresholds, temporal aggregation, and alternative drought and flood thresholds on estimated memory characteristics. This procedure ensured that the relationships identified between hydrological memory and basin resilience remained consistent under different methodological assumptions and were not dependent on a single analytical configuration.



294

295 **Figure 2: Conceptual framework illustrating the proposed hydrological memory paradigm linking**
296 **climate extremes with river basin resilience.**

Figure 2 presents the conceptual structure of the Hydrological Memory Framework (HMF). Climate extremes modify the storage and redistribution of water within river basins, while interactions among soil moisture, groundwater, and surface-water storage generate hydrological memory. The persistence of these antecedent conditions influences the rate of recovery following droughts and floods and, in turn, shapes river basin resilience. The framework therefore links climate forcing, basin storage, hydrological memory, recovery dynamics, resilience, and sustainable water resources management within a single process-based structure.

3. Results

3.1. Spatial variability of hydrological memory across China's major river basins

The Hydrological Memory Framework revealed marked spatial differences in hydrological memory across China's eight major river basins (Figure 3; Table 3). Memory duration and decay varied with climatic regime,



basin storage capacity, and physiographic setting, indicating that present basin responses remain strongly influenced by antecedent hydroclimatic conditions. The Tarim and Heihe River basins showed the longest memory, retaining climatic signals for about six and five years, respectively, consistent with strong groundwater control and delayed recharge. The Yellow and Songhua basins exhibited intermediate memory of around four years, reflecting groundwater storage, reservoir regulation, and seasonal snow processes. In contrast, the Yangtze, Pearl, Huai, and Hai basins retained climatic information for less than three years, with faster decay associated with abundant precipitation, greater runoff efficiency, and stronger hydrological connectivity. Overall, hydrological memory increased from humid to arid environments, underscoring the dominant influence of basin storage and climatic regime.

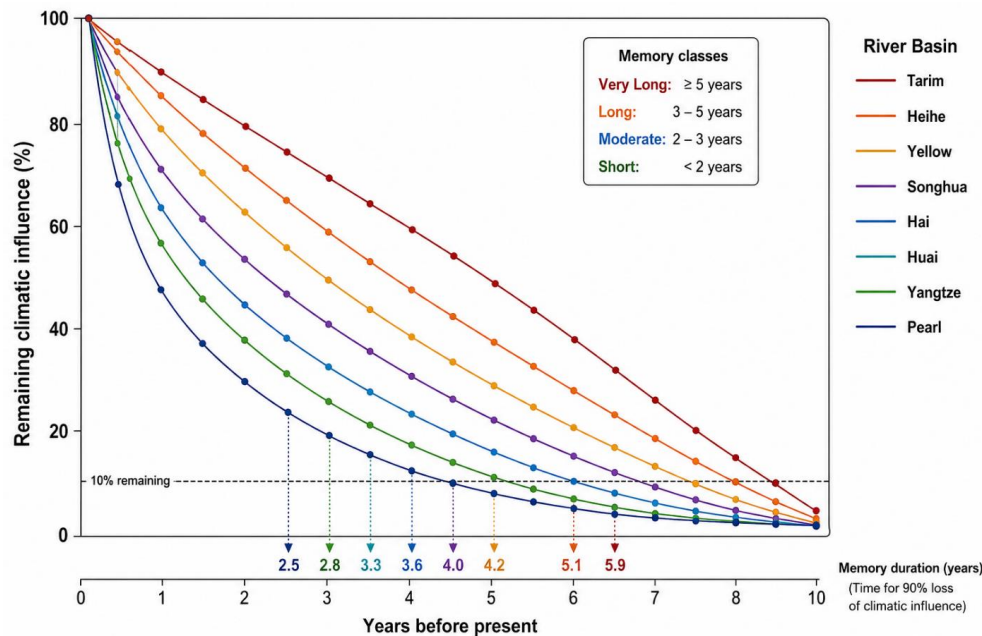


Figure 3: Quantification of hydrological memory using the Catchment Forgetting Curve (CFC) across China's eight major river basins.

Humid monsoon basins, particularly the Yangtze and Pearl, showed relatively short hydrological memory (<3 years), consistent with rapid signal replacement through abundant precipitation, frequent recharge, and efficient drainage. The Huai and Hai basins exhibited intermediate memory, reflecting their transitional climate and stronger human regulation.

The Catchment Forgetting Curves (Figure 3; Table 3) indicated that basin differences were most pronounced during the first three antecedent years, after which climatic influence declined progressively. Despite this overall decay, humid, transitional, cold, and arid basins retained distinct memory patterns, confirming that long-term storage and hydroclimatic setting are key controls on hydrological memory and, ultimately, river basin resilience.

Table 3: Hydrological memory characteristics of the eight major river basins derived from the Catchment Forgetting Curve and persistence analyses.

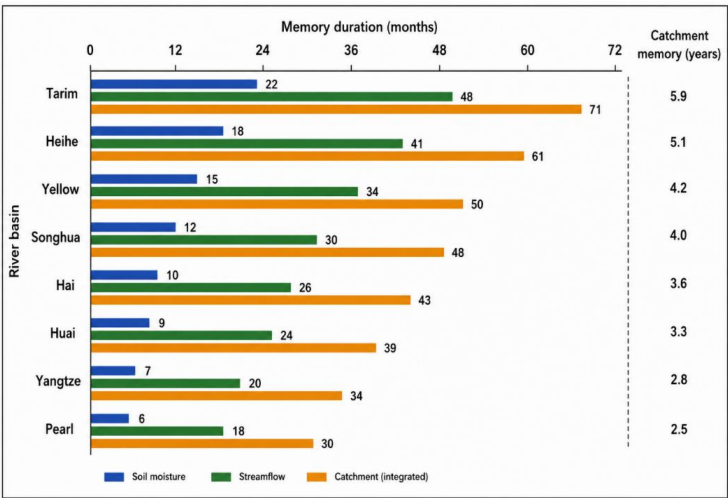


Basin	Climate	Catchment Memory (years)	Memory Class
Tarim	Arid	5.9	Very Long
Heihe	Arid	5.1	Very Long
Yellow	Semi-arid	4.2	Long
Songhua	Cold humid	4.0	Long
Hai	Semi-humid	3.6	Moderate
Huai	Transitional	3.3	Moderate
Yangtze	Humid	2.8	Short
Pearl	Humid	2.5	Short

330

331 **3.2. Hydrological Recovery Following Climate Extremes**

332 Recovery trajectories differed substantially among China’s major river basins following droughts and floods
333 (Figures 4 and 5). While all basins eventually returned toward their long-term hydrological state, both recovery
334 duration and trajectory varied across climatic regions. Flood disturbances generally dissipated faster than
335 drought impacts, whereas arid and groundwater-dominated basins recovered more slowly than humid monsoon
336 systems.



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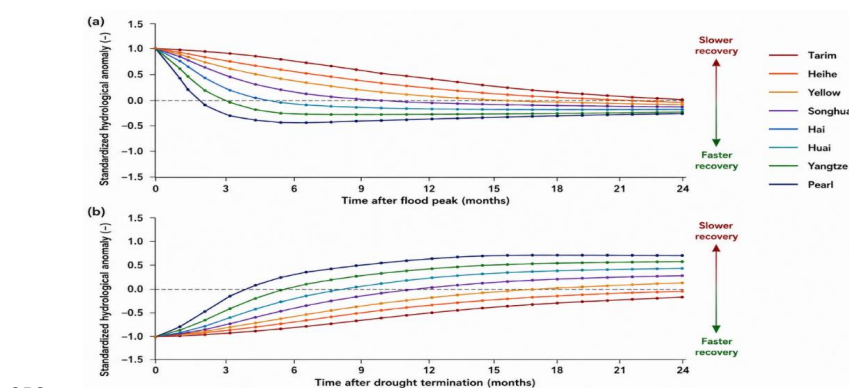
338 **Figure 4: Memory timescales of the major hydrological storage components across China's eight river**
339 **basins.**

340 Composite recovery curves showed that flood-related anomalies generally returned toward the climatological
341 range within a few months after event termination (Figure 5a). Recovery was fastest in the Yangtze and Pearl



342 River basins, where standardized streamflow anomalies declined rapidly after peak discharge and stabilized
 343 within about three to five months. The Huai and Hai basins followed a similar pattern but recovered more
 344 slowly, reflecting stronger seasonal variability and anthropogenic regulation. By contrast, the Tarim and Heihe
 345 basins showed prolonged recession, indicating that flood-related storage continued to influence basin hydrology
 346 for a longer period.

347 Drought recovery was substantially slower (Figure 5b). In groundwater-dominated basins, negative hydrological
 348 anomalies persisted well beyond the end of meteorological drought. The Tarim River Basin showed the longest
 349 recovery, with below-average conditions lasting for more than twelve months. Delayed recovery was also
 350 evident in the Heihe and Yellow River basins, consistent with slow groundwater replenishment and baseflow
 351 adjustment. In contrast, the Yangtze and Pearl basins recovered more rapidly because frequent precipitation and
 352 stronger runoff connectivity replenished basin storage more efficiently. These contrasting trajectories further
 353 highlight the role of hydrological memory. Humid basins showed steep recovery curves, whereas arid and semi-
 354 arid basins displayed flatter trajectories, indicating that antecedent storage continued to regulate hydrological
 355 conditions after climatic forcing had returned toward normal.



356

357 **Figure 5: Composite hydrological recovery trajectories following (a) flood events and (b) drought events**
 358 **across the eight major river basins of China.**

359 Recovery times derived from the composite trajectories showed a clear spatial gradient across China (Figure 4).
 360 The Pearl and Yangtze River basins recovered fastest, followed by the Huai and Hai basins. Intermediate
 361 recovery times occurred in the Songhua and Yellow River basins, whereas the Tarim and Heihe consistently
 362 showed the slowest recovery after both droughts and floods. Across all basins, drought recovery was
 363 approximately two to three times longer than flood recovery, indicating greater persistence of water-storage
 364 deficits than temporary flood storage.

365 Recovery time also corresponded closely with the memory durations reported in Section 3.1 and summarized in
 366 Table 4. Basins with longer hydrological memory generally required more time to return to their climatological
 367 state, whereas shorter-memory basins recovered more rapidly. Although this pattern does not establish causality,



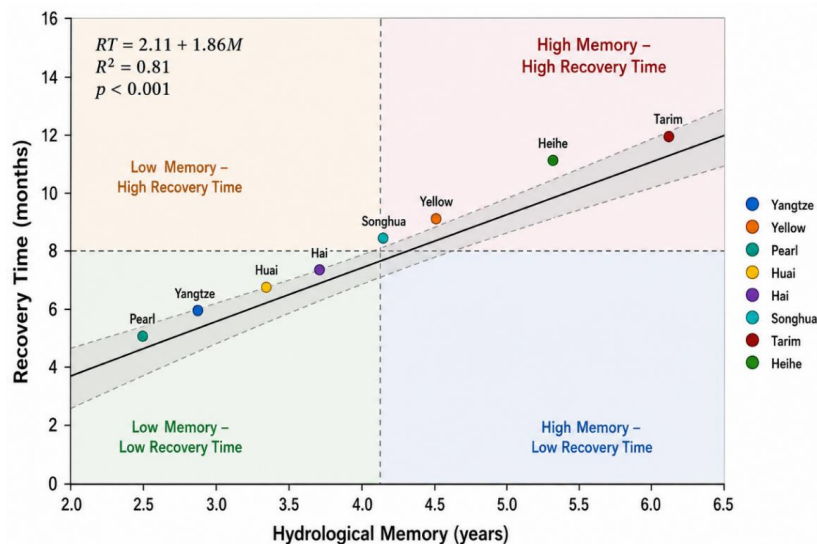
368 it provides strong empirical evidence of a close association between hydrological memory and basin resilience
369 across contrasting hydroclimatic settings. Overall, recovery dynamics varied systematically among the eight
370 basins, with drought recovery consistently slower than flood recovery. These results indicate that post-
371 disturbance recovery reflects not only event magnitude but also the persistence of antecedent basin storage,
372 providing the basis for the subsequent memory–resilience analysis.

373 **Table 4: Recovery characteristics following drought and flood events across the eight major river basins.**

Basin	Flood Recovery (months)	Drought Recovery (months)	Mean (months)	Recovery Class
Pearl	3.2	7.1	5.2	Very Fast
Yangtze	3.8	8.0	5.9	Fast
Huai	4.6	9.2	6.9	Moderate
Hai	4.9	9.8	7.4	Moderate
Songhua	5.8	11.2	8.5	Slow
Yellow	6.2	12.0	9.1	Slow
Heihe	7.8	14.5	11.2	Very Slow
Tarim	8.4	15.2	11.8	Very Slow

374 **3.3. Hydrological Memory Governs River Basin Resilience**

375 Hydrological memory showed a strong positive relationship with post-disturbance recovery across China’s
376 major river basins (Figure 6). Basins with longer memory generally required more time to recover from
377 droughts and floods, whereas shorter-memory basins returned more quickly to their climatological state.
378 Regression analysis confirmed this pattern ($R^2 = 0.81$, $p < 0.001$), indicating that greater storage persistence is
379 associated with slower hydrological recovery. The Tarim and Heihe River basins combined the longest memory
380 with the slowest recovery, while the Yangtze and Pearl basins showed shorter memory and faster recovery. The
381 Yellow, Huai, Hai, and Songhua basins displayed intermediate behavior, consistent with differences in storage
382 capacity and hydroclimatic setting. Drought recovery showed a stronger dependence on hydrological memory
383 than flood recovery, highlighting the role of antecedent storage in restoring water-deficit conditions. Mixed-
384 effects modelling further identified hydrological memory as the dominant predictor of recovery time ($\beta = 0.68$, p
385 < 0.001), with the full model explaining about 84% of the observed variability (conditional $R^2 = 0.84$). These
386 results support hydrological memory as a physically interpretable indicator of basin resilience across contrasting
387 hydroclimatic environments.



388

389 **Figure 6: Relationship between hydrological memory and basin recovery following hydroclimatic**
390 **extremes across China's eight major river basins. Hydrological memory (derived from the Catchment**
391 **Forgetting Curve analysis) is positively correlated with recovery time, indicating that river basins**
392 **retaining antecedent climatic information for longer periods generally require more time to restore**
393 **hydrological equilibrium after droughts and floods. The solid line represents the least-squares regression,**
394 **while the shaded region denotes the 95% confidence interval.**

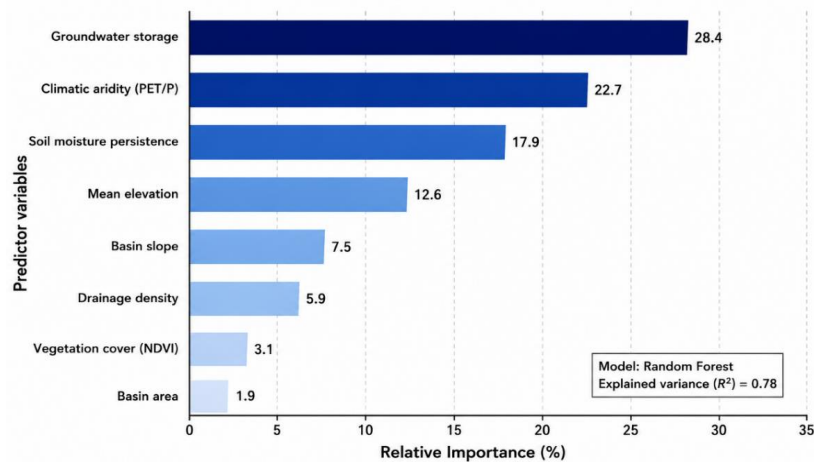
395 **3.4. Environmental Controls on Hydrological Memory**

396 Hydrological memory varied markedly across China's major river basins, reflecting the combined influence of
397 climatic and physiographic controls rather than any single factor. Random Forest analysis identified
398 groundwater storage, climatic aridity, soil moisture persistence, and basin elevation as the dominant controls
399 (Figure 7), accounting for most of the spatial variability in memory duration. Groundwater storage was the
400 strongest predictor (28.4%), indicating that greater subsurface storage prolongs hydrological persistence through
401 delayed recharge and discharge. Climatic aridity ranked second (22.7%); arid and semi-arid basins retained
402 hydroclimatic anomalies longer because limited precipitation and high evaporative demand slowed storage
403 replenishment. Soil moisture persistence contributed 17.9%, highlighting the role of retained soil water in
404 sustaining antecedent climatic signals. Basin elevation accounted for 12.6%, reflecting the influence of snow
405 accumulation, glacier storage, and delayed meltwater release in high-altitude catchments.

406 By contrast, basin slope, drainage density, vegetation cover, and basin area showed weaker contributions,
407 suggesting a greater role in runoff generation and routing than in long-term persistence. Bootstrap sensitivity
408 analysis confirmed that the predictor rankings were stable across basin conditions. Overall, hydrological
409 memory was controlled mainly by basin storage capacity and climatic aridity. These controls provide a physical



410 explanation for the observed relationship between hydrological memory and basin resilience, emphasizing the
411 importance of antecedent storage in shaping responses to climate extremes.



412
413 **Figure 7: Relative importance of environmental controls on hydrological memory across China's major**
414 **river basins.**

415 **3.5. Classification of River Basins Based on Hydrological Memory and Resilience**

416 The combined analysis of hydrological memory and recovery characteristics identified four resilience classes
417 across China's major river basins (Figure 8), reflecting differences in climate, basin storage, and catchment
418 behavior.

419 The Yangtze and Pearl River basins showed high resilience, with short hydrological memory and rapid recovery
420 supported by abundant precipitation, strong runoff generation, and efficient hydrological connectivity. The Huai,
421 Hai, and Songhua basins exhibited intermediate resilience, consistent with moderate memory and transitional
422 hydroclimatic conditions. The Yellow River Basin was moderately vulnerable, where longer memory,
423 groundwater dependence, reservoir regulation, and increasing water stress prolonged recovery. The Tarim and
424 Heihe River basins showed the lowest resilience, combining long hydrological memory with slow recovery.
425 Limited precipitation, high evaporative demand, groundwater dependence, and delayed recharge sustained
426 hydrological anomalies for extended periods. Overall, the classification shows that resilience emerges from the
427 interaction between climatic forcing and hydrological storage dynamics. Basins with stronger storage
428 persistence generally retain disturbances longer and recover more slowly, providing a practical basis for
429 identifying systems that may require greater attention under future climate change.

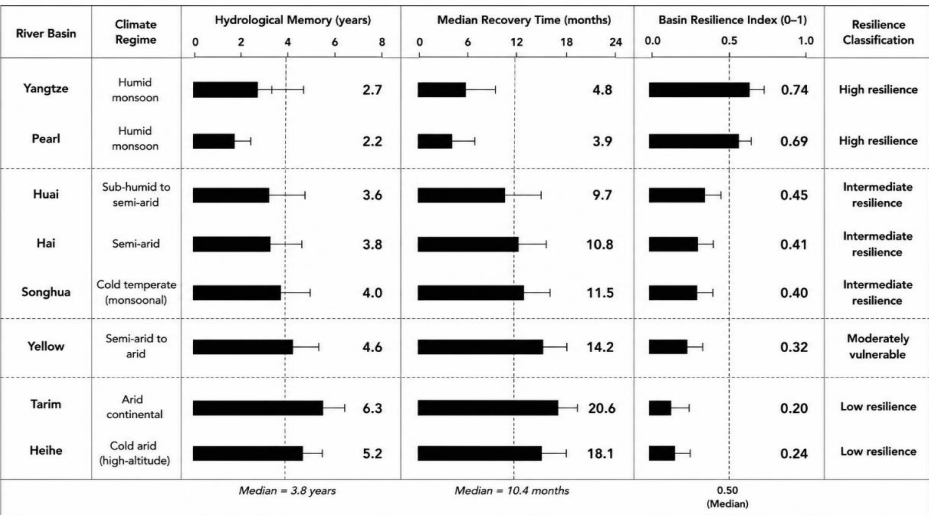


Figure 8: Classification of China's major river basins according to hydrological memory and resilience.

4. Discussion

Hydrological memory is a key basin property because it controls how long climatic anomalies remain stored and continue to influence runoff after meteorological forcing weakens (Sutanto and Van Lanen, 2022, De Lavenne et al., 2022, Berghuijs et al., 2025). Across China's major river basins, longer memory was consistently associated with slower recovery from droughts and floods, indicating that resilience depends not only on disturbance magnitude but also on how water is stored, released, and redistributed among groundwater, soil moisture, surface water, and snowpack. Previous studies likewise show that catchment memory supports hydrological predictability and prolongs the propagation and recovery of drought signals. Together, these results indicate that basin resilience emerges from the interaction between climatic forcing and storage-mediated hydrological memory (Orth and Seneviratne, 2013, Van Loon, 2015, Van Loon et al., 2024).

The positive association between hydrological memory and recovery time indicates that terrestrial water storage can buffer short-term climatic variability while prolonging recovery after extreme events (Orth and Seneviratne, 2013, Sutanto and Van Lanen, 2022, Van Loon, 2015). Groundwater, deep soil moisture, lakes, wetlands, and snowpack may retain climatic anomalies over seasonal to multi-year periods, allowing antecedent conditions to influence streamflow even after precipitation returns toward normal (Lehr and Hohenbrink, 2025). As a result, annual to multi-year hydrological memory can shape drought development, hydrological predictability, and the persistence of both low- and high-flow conditions (Li, 2018, Zhang et al., 2016, Zhao and Li, 2017).

Differences among China's major river basins further underscore the role of hydroclimatic setting. Faster recovery in the Yangtze and Pearl basins is consistent with wetter monsoonal climates and more frequent storage replenishment, whereas longer memory in the Tarim and Heihe basins reflects arid conditions, high evaporative demand, and stronger dependence on groundwater, snow, and glacier melt. These patterns are also



453 shaped by basin-specific storage, regulation, and human water use, all of which can modify drought propagation
 454 and recovery. Overall, catchment memory and recovery vary systematically with climate, storage, and basin
 455 characteristics rather than following a uniform spatial response (Zhao and Li, 2017, Zhang et al., 2016, Li, 2018,
 456 Hao et al., 2023).

457 Random Forest analysis identified groundwater storage as the strongest predictor of hydrological memory,
 458 followed by climatic aridity, soil-moisture persistence, and basin elevation (Rostami Khalaj et al., 2026).
 459 Differences among China's major river basins further underscore the role of hydroclimatic setting. Faster
 460 recovery in the Yangtze and Pearl basins is consistent with wetter monsoonal climates and more frequent
 461 storage replenishment, whereas longer memory in the Tarim and Heihe basins reflects arid conditions, high
 462 evaporative demand, and stronger dependence on groundwater, snow, and glacier melt. These patterns are also
 463 shaped by basin-specific storage, regulation, and human water use, all of which can modify drought propagation
 464 and recovery. Overall, catchment memory and recovery vary systematically with climate, storage, and basin
 465 characteristics rather than following a uniform spatial response (Alvarez-Garretón et al., 2021, Martínez-de la
 466 Torre and Miguez-Macho, 2019, De Lavenne et al., 2022).

467 These findings broaden the concept of hydrological resilience by linking post-event recovery directly to
 468 catchment memory. Resilience therefore depends partly on storage–release dynamics that control how long
 469 drought and flood signals persist within a river basin (Geris et al., 2015). Under climate change, shifts in
 470 precipitation, evapotranspiration, and groundwater storage may modify basin memory and slow hydrological
 471 recovery. Persistent memory can prolong hydrological anomalies, increase exposure to compound extremes, and
 472 amplify impacts on water resources and ecosystems. Incorporating hydrological memory into basin-scale
 473 assessments therefore offers a more process-based basis for evaluating future climate resilience (Naresh and
 474 Mathew, 2026).

475 These findings have direct implications for climate adaptation and water-resources management because basin
 476 response is strongly conditioned by antecedent storage and hydrological memory. Incorporating memory into
 477 forecasting and management frameworks could improve streamflow prediction, drought early warning, reservoir
 478 operation, and groundwater allocation by accounting for the persistence of past hydroclimatic conditions
 479 (Sharma et al., 2026). Adaptation strategies should reflect basin-specific memory characteristics. Rapidly
 480 recovering humid basins such as the Yangtze and Pearl require stronger emphasis on flood management and
 481 reservoir optimization, whereas long-memory arid basins such as the Tarim and Heihe require groundwater
 482 conservation, managed recharge, and sustained drought planning. This distinction becomes more important as
 483 compound droughts, floods, and heatwaves shorten the interval between successive disturbances. In long-
 484 memory basins, incomplete recovery may carry hydrological deficits or surpluses into subsequent events,
 485 increasing risks to water supply, agriculture, ecosystems, and hydropower. Hydrological memory should
 486 therefore be incorporated explicitly into basin-scale climate resilience and adaptation planning (Chahed, 2025).

487 This study further connects hydrological resilience with a broader Earth system perspective. Conventional
 488 resilience assessments often rely on observed recovery rates or statistical indicators, with limited representation
 489 of the physical processes that govern recovery. By incorporating hydrological memory, the proposed framework



490 links climate forcing, terrestrial water storage, groundwater dynamics, and streamflow recovery within a single
 491 process-based structure. This improves the physical interpretation of basin resilience and offers a transferable
 492 basis for comparing river basins across contrasting climatic and physiographic settings (Qi et al., 2016, Yang et
 493 al., 2017). Despite its contributions, the framework has several limitations. Basin-scale analysis cannot fully
 494 resolve fine-scale variability in headwaters, groundwater systems, or water-management infrastructure, while
 495 uncertainties remain in groundwater storage, soil moisture, and evapotranspiration datasets. In addition, the
 496 estimated hydrological memory represents an integrated basin response and may not fully capture nonlinear
 497 effects of vegetation change, land use, reservoir regulation, or groundwater abstraction. Although Random
 498 Forest identified the dominant controls, causal relationships require further evaluation using physically based
 499 approaches.

500 Future research should integrate satellite observations, groundwater monitoring, isotope hydrology, and high-
 501 resolution process-based models to better resolve storage and recovery dynamics. Hybrid physics-informed and
 502 machine-learning approaches may further improve estimates of hydrological memory under changing climate
 503 conditions. Extending the framework to global basins and future climate scenarios would help determine how
 504 memory evolves under continued warming and increasing hydroclimatic variability.

505 Overall, this study identifies hydrological memory as an important control on basin resilience by linking storage
 506 persistence with recovery from climate extremes. The proposed framework provides a process-based basis for
 507 resilience assessment, climate adaptation, and sustainable water-resources planning.

508 **5. Conclusion**

509 This study developed a basin-scale framework integrating the Catchment Forgetting Curve, recovery analysis,
 510 and machine learning to quantify hydrological memory and its influence on resilience across eight major river
 511 basins in China. Hydrological memory varied markedly among basins: the Yangtze and Pearl exhibited shorter
 512 memory and faster recovery, whereas the Tarim and Heihe showed longer memory and slower recovery under
 513 stronger storage dependence. Across all basins, recovery time increased with memory duration, while Random
 514 Forest analysis identified groundwater storage, climatic aridity, soil moisture persistence, and basin elevation as
 515 the main controls.

516 The resilience classification further distinguished basin response capacity and provided a process-based
 517 explanation for contrasting recovery trajectories under similar climatic disturbances. By linking catchment
 518 storage dynamics with post-event recovery, the framework extends conventional resilience assessment beyond
 519 hydroclimatic indicators alone. These findings support the incorporation of hydrological memory into drought
 520 preparedness, reservoir operation, groundwater management, and basin planning. The framework is also
 521 transferable to other large river basins and can support identification of vulnerable systems and climate-resilient
 522 water resources management. Future work should examine how hydrological memory evolves under climate
 523 change and human regulation.

524 **CRedit authorship contribution statement**

525 Muhammad Touseef M.T: Project administration, Conceptualization, Writing, Investigation, Methodology,
 526 Formal analysis, Data Curation. Lihua Chen L.C: Review and Editing, Funding and Supervision.



527 **Declaration of competing interest**

528 The contact author has declared that none of the authors has any competing interests.

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534 **Data availability**

535 Data can be available upon request.

536 **References**

- 537 ALVAREZ-GARRETON, C., BOISIER, J. P., GARREAUD, R., SEIBERT, J. & VIS, M. 2021. Progressive
 538 water deficits during multiyear droughts in basins with long hydrological memory in Chile. *Hydrology*
 539 and *Earth System Sciences*, 25, 429-446.
- 540 BAEZ-VILLANUEVA, O. M., ZAMBRANO-BIGIARINI, M., MIRALLES, D. G., BECK, H. E., SIEGMUND,
 541 J. F., ALVAREZ-GARRETON, C., VERBIST, K., GARREAUD, R., BOISIER, J. P. &
 542 GALLEGUILLOS, M. 2024. On the timescale of drought indices for monitoring streamflow drought
 543 considering catchment hydrological regimes. *Hydrology and Earth System Sciences*, 28, 1415-1439.
- 544 BAI, X., YAO, Y., WU, J., XIE, Y. & ZHANG, Z. 2025. Tracking drought-flood abrupt alternations: Event
 545 identification, path analysis, and ecological impacts on vegetation. *Journal of Hydrology*, 134858.
- 546 BERGHUIJS, W. R., WOODS, R. A., ANDERSON, B. J., HEMSHORN DE SÁNCHEZ, A. L. &
 547 HRACHOWITZ, M. 2025. Annual memory in the terrestrial water cycle. *Hydrology and Earth System*
 548 *Sciences*, 29, 1319-1333.
- 549 BIERKENS, M. F. & WADA, Y. 2019. Non-renewable groundwater use and groundwater depletion: a review.
 550 *Environmental Research Letters*, 14, 063002.
- 551 BLÖSCHL, G., HALL, J. & VIGLIONE, A. 2019. Changing climate both increases and decreases European
 552 river floods.
- 553 BRUNO, G., AVANZI, F., GABELLANI, S., FERRARIS, L. & BRUNNER, M. I. 2026. Short to Long
 554 Streamflow Droughts: A Process-Oriented Review. *Wiley Interdisciplinary Reviews: Water*, 13,
 555 e70060.
- 556 CHAHED, J. 2025. Hydro-Climatic Modelling for Water Resources: From Processes to Adaptive Management
 557 and Governance. *Hydrological Processes*, 39, e70348.



- 558 CHEN, D., XU, B., YAO, T., GUO, Z., CUI, P., CHEN, F., ZHANG, R., ZHANG, X., ZHANG, Y. & FAN, J.
 559 2015. Assessment of past, present and future environmental changes on the Tibetan Plateau. Chinese
 560 Science Bulletin, 60, 3025-3035.
- 561 DE LAVENNE, A., ANDRÉASSIAN, V., CROCHEMORE, L., LINDSTRÖM, G. & ARHEIMER, B. 2022.
 562 Quantifying multi-year hydrological memory with Catchment Forgetting Curves. Hydrology and Earth
 563 System Sciences, 26, 2715-2732.
- 564 FAN, C., ZHAO, L., HOU, R., FANG, Q. & ZHANG, J. 2023. Quantitative analysis of rainwater redistribution
 565 and soil loss at the surface and belowground on karst slopes at the microplot scale. Catena, 227,
 566 107113.
- 567 FAN, L., WANG, Y., LUAN, F., XIA, J. & DING, J. 2026. Characteristics of Water Resources Variability and
 568 Comprehensive Water Security Assessment in the Chaobai River Basin of China. Water Resources
 569 Management, 40, 391.
- 570 GALELLI, S., TURNER, S. W., POKHREL, Y., CASTELLETTI, A., BIERKENS, M. F., PIANOSI, F. &
 571 BIEMANS, H. 2025. Advancing the representation of human actions in large-scale hydrological
 572 models: Challenges and future research directions. Water Resources Research, 61.
- 573 GERIS, J., TETZLAFF, D. & SOULSBY, C. 2015. Resistance and resilience to droughts: Hydropedological
 574 controls on catchment storage and run-off response. Hydrological Processes, 29, 4579-4593.
- 575 GRANATA, F. & DI NUNNO, F. 2026. Pathways for hydrological resilience: strategies for adaptation in a
 576 changing climate. Earth Systems and Environment, 10, 203-231.
- 577 GRILL, G., LEHNER, B. & THIEME, M. 2019. Mapping the world's free-flowing rivers.
- 578 GUDMUNDSSON, L., BOULANGE, J., DO, H. X., GOSLING, S. N., GRILLAKIS, M. G. & KOUTROULIS,
 579 A. G. 2021a. Globally observed trends in mean and extreme river flow attributed to climate change.
 580 Science, 371, 1159-1162.
- 581 GUDMUNDSSON, L., BOULANGE, J., DO, H. X., GOSLING, S. N., GRILLAKIS, M. G., KOUTROULIS, A.
 582 G., LEONARD, M., LIU, J., MÜLLER SCHMIED, H. & PAPADIMITRIOU, L. 2021b. Globally
 583 observed trends in mean and extreme river flow attributed to climate change. Science, 371, 1159-1162.
- 584 GUPTA, A., REVERDY, A., COHARD, J.-M., HECTOR, B., DESCLOITRES, M., VANDERVAERE, J.-P.,
 585 COULAUD, C., BIRON, R., LIGER, L. & MAXWELL, R. 2023. Impact of distributed meteorological
 586 forcing on simulated snow cover and hydrological fluxes over a mid-elevation alpine micro-scale
 587 catchment. Hydrology and Earth System Sciences, 27, 191-212.



- 588 HAO, H., YANG, M., WANG, H. & DONG, N. 2023. Human activities reshape the drought regime in the
 589 Yangtze River Basin: A land surface-hydrological modelling analysis with representations of dam
 590 operation and human water use. *Natural Hazards*, 118, 2097-2121.
- 591 HAO, Z., JIN, J., XIA, R., TIAN, S., YANG, W., LIU, Q., ZHU, M., MA, T., JING, C. & ZHANG, Y. 2021.
 592 CCAM: China catchment attributes and meteorology dataset. *Earth System Science Data*, 13, 5591-
 593 5616.
- 594 ILLOUZ-ELIAZ, N., YU, J., SWIFT, J., LANDE, K., JOW, B., PARTIDA-GARCIA, L., TUANG, Z. K., LEE,
 595 T. A., YAARAN, A. & GOMEZ-CASTANON, R. 2025. Drought recovery in plants triggers a cell-
 596 state-specific immune activation. *Nature Communications*, 16, 8095.
- 597 IPCC 2023. *Climate Change 2023: Synthesis Report*, Intergovernmental Panel on Climate Change.
- 598 KARKI, J., HU, J., ZHU, Y., AFZAL, M. M., XIE, F. & LIU, S. 2025. Advances in GRACE satellite studies on
 599 terrestrial water storage: A comprehensive review. *Geocarto International*, 40, 2482706.
- 600 KNOBEN, W. J., RAMAN, A., GRÜNDEMANN, G. J., KUMAR, M., PIETRONIRO, A., SHEN, C., SONG,
 601 Y., THÉBAULT, C., VAN WERKHOVEN, K. & WOOD, A. W. 2024. How many models do we need
 602 to simulate hydrologic processes across large geographical domains? *Hydrology and Earth System*
 603 *Sciences Discussions*, 2024, 1-21.
- 604 KUMAR, M., TIWARI, R. K., RAUTELA, K. S., KUMAR, K., KHAJURIA, V., VERMA, I., SAFI, S.,
 605 ALMAZROUI, M., AL KAFY, A. & ZHANG, L. 2025. Comparative assessment of process based
 606 models for simulating the hydrological response of the Himalayan River Basin. *Earth Systems and*
 607 *Environment*, 9, 299-313.
- 608 LANDERER, F. W. & SWENSON, S. 2012. Accuracy of scaled GRACE terrestrial water storage estimates.
 609 *Water resources research*, 48.
- 610 LEHR, C. & HOHENBRINK, T. L. 2025. An illustrative introduction to the domain dependence of spatial
 611 principal component patterns. *Hydrology and Earth System Sciences*, 29, 6735-6760.
- 612 LEMA, F., MENDOZA, P. A., VÁSQUEZ, N. A., MIZUKAMI, N., ZAMBRANO-BIGIARINI, M. &
 613 VARGAS, X. 2024. What does the Standardized Streamflow Index actually reflect? Insights and
 614 implications for hydrological drought analysis. *Hydrology and Earth System Sciences Discussions*,
 615 2024, 1-34.
- 616 LI, X. 2018. Hydrological cycle in the Heihe River Basin and its implications for water resource management.
 617 *Journal of Geophysical Research: Atmospheres*.



- 618 LIU, J., ZHANG, Q., SINGH, V. P. & SHI, P. 2017. Contribution of multiple climatic variables and human
619 activities to streamflow changes across China. *Journal of Hydrology*, 545, 145-162.
- 620 LU, Y., YANG, T., FU, J. & SONG, W. 2025. Utility of the standardized precipitation evapotranspiration index
621 (SPEI) to detect agricultural droughts over China. *Journal of Hydrology: Regional Studies*, 58, 102190.
- 622 MARTÍNEZ-DE LA TORRE, A. & MIGUEZ-MACHO, G. 2019. Groundwater influence on soil moisture
623 memory and land-atmosphere fluxes in the Iberian Peninsula. *Hydrology and Earth System Sciences*,
624 23, 4909-4932.
- 625 MAXWELL, R. M. & CONDON, L. E. 2016. Connections between groundwater flow and transpiration
626 partitioning.
- 627 MCDONNELL, J. J. & BEVEN, K. 2014. Debates-The future of hydrological sciences: A (common) path
628 forward? A call to action aimed at understanding velocities, celerities and residence time distributions
629 of the headwater hydrograph. *Water Resources Research*, 50.
- 630 MCMILLAN, H., ARAKI, R., BOLOTIN, L., KIM, D.-H., COXON, G., CLARK, M. & SEIBERT, J. 2025.
631 Global patterns in observed hydrologic processes. *Nature Water*, 3, 497-506.
- 632 MUÑOZ-SABATER, J., DUTRA, E., AGUSTÍ-PANAREDA, A., ALBERGEL, C., ARDUINI, G.,
633 BALSAMO, G., BOUSSETTA, S., CHOULGA, M., HARRIGAN, S. & HERSBACH, H. 2021.
634 ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth system science*
635 *data discussions*, 2021, 1-50.
- 636 NARESH, C. & MATHEW, A. 2026. Integrating Climate Modelling, Downscaling, and Bias Correction for
637 Drought Studies: Current Approaches and Future Directions. *Water Resources Management*, 40, 486.
- 638 NILE, B. K., AL-SAAD, R. J. M., ABDULAMEER, L., AL MAIMURI, N. M. & AL-DUJAILI, A. N. 2025.
639 Climate change impacts on river hydraulics: a global synthesis of hydrological shifts, ecological
640 consequences, and adaptive strategies. *Water Conservation Science and Engineering*, 10, 48.
- 641 NIPPGEN, F., MCGLYNN, B. L., EMANUEL, R. E. & VOSE, J. M. 2016. Watershed memory at the C oweeta
642 H ydrologic L aboratory: The effect of past precipitation and storage on hydrologic response. *Water*
643 *Resources Research*, 52, 1673-1695.
- 644 ORTH, R., O, S., ZSCHEISCHLER, J., MAHECHA, M. D. & REICHSTEIN, M. 2022. Contrasting biophysical
645 and societal impacts of hydro-meteorological extremes. *Environmental Research Letters*, 17, 014044.
- 646 ORTH, R. & SENEVIRATNE, S. I. 2013. Propagation of soil moisture memory to streamflow and
647 evapotranspiration in Europe. *Hydrology and Earth System Sciences*, 17, 3895-3911.



- 648 QI, M., FENG, M., SUN, T. & YANG, W. 2016. Resilience changes in watershed systems: A new perspective
 649 to quantify long-term hydrological shifts under perturbations. *Journal of Hydrology*, 539, 281-289.
- 650 RIEDEL, T. & WEBER, T. K. 2020. The influence of global change on Europe's water cycle and groundwater
 651 recharge. *Hydrogeology Journal*, 28, 1939-1959.
- 652 ROSTAMI KHALAJ, M., NOOR, H. & ARJMAND SHARIF, M. 2026. A machine learning framework for
 653 downscaling and predicting groundwater levels using random forest and satellite data: a case study in
 654 Iran. *Hydrogeology Journal*, 34, 591-605.
- 655 SHAMSHIRBAND, S., HASHEMI, S., SALIMI, H., SAMADIANFARD, S., ASADI, E., SHADKANI, S.,
 656 KARGAR, K., MOSAVI, A., NABIPOUR, N. & CHAU, K.-W. 2020. Predicting standardized
 657 streamflow index for hydrological drought using machine learning models. *Engineering Applications*
 658 *of Computational Fluid Mechanics*, 14, 339-350.
- 659 SHARMA, P., TRIPATHI, V. & MOHANTY, M. P. 2026. Improving daily streamflow predictions over large
 660 watersheds: Introducing a novel enhanced long short-term memory (en-LSTM) model. *Water*
 661 *Resources Management*, 40, 92.
- 662 SPRINGER, A., DE LANNOY, G., RODELL, M., EWERDWALBESLOH, Y., GERDENER, H., KHAKI, M.,
 663 LI, B., LI, F., SCHUMACHER, M. & TANGDAMRONGSUB, N. 2026. A review of current best
 664 practices and future directions in assimilating GRACE/-FO terrestrial water storage data into numerical
 665 models. *Hydrology and Earth System Sciences*, 30, 985-1022.
- 666 SU, T., MIAO, C., DUAN, Q., GOU, J., GUO, X. & ZHAO, X. 2022. Hydrological response to climate change
 667 and human activities in the Three-River Source Region. *Hydrology and Earth System Sciences*
 668 *Discussions*, 2022, 1-38.
- 669 SUN, J., CHEN, W., HU, B., XU, Y. J., ZHANG, G., WU, Y., HU, B. & SONG, Z. 2023. Roles of reservoirs in
 670 regulating basin flood and droughts risks under climate change: Historical assessment and future
 671 projection. *Journal of Hydrology: Regional Studies*, 48, 101453.
- 672 SUTANTO, S. J. & VAN LANEN, H. A. 2022. Catchment memory explains hydrological drought forecast
 673 performance. *Scientific reports*, 12, 2689.
- 674 TONKIN, J. D., SIQUEIRA, T., MERDER, J., DATRY, T., POFF, N. L., TALBOT-JONES, J. & OLDEN, J. D.
 675 2026. Extreme events and river biodiversity under climate change. *Nature Reviews Biodiversity*, 2,
 676 150-169.
- 677 VAN LOON, A. F. 2015. Hydrological drought explained. *Wiley Interdisciplinary Reviews: Water*, 2, 359-392.



- 678 VAN LOON, A. F., KCHOUK, S., MATANÓ, A., TOOTOONCHI, F., ALVAREZ-GARRETON, C.,
 679 HASSABALLAH, K. E., WU, M., WENS, M. L., SHYROKAYA, A. & RIDOLFI, E. 2024. Drought
 680 as a continuum–memory effects in interlinked hydrological, ecological, and social systems. *Natural*
 681 *Hazards and Earth System Sciences*, 24, 3173-3205.
- 682 VICENTE-SERRANO, S. M., PEÑA-ANGULO, D., BEGUERÍA, S., DOMÍNGUEZ-CASTRO, F., TOMÁS-
 683 BURGUERA, M., NOGUERA, I., GIMENO-SOTELO, L. & EL KENAWY, A. 2022. Global drought
 684 trends and future projections. *Philosophical Transactions of the Royal Society A: Mathematical,*
 685 *Physical and Engineering Sciences*, 380.
- 686 WADA, Y. 2024. The Potential of Hydrogeodesy to Address Water-Related and Sustainability Challenges.
- 687 WANG, F., WANG, Z., YANG, H., DI, D., ZHAO, Y. & LIANG, Q. 2020. A new copula-based standardized
 688 precipitation evapotranspiration streamflow index for drought monitoring. *Journal of Hydrology*, 585,
 689 124793.
- 690 WANG, T., SHI, R., YANG, D., YANG, S. & FANG, B. 2022. Future changes in annual runoff and
 691 hydroclimatic extremes in the upper Yangtze River Basin. *Journal of Hydrology*, 615, 128738.
- 692 WANG, Z., HU, B., HU, Y., WU, X. & LIU, L. 2026. Spatiotemporal patterns of soil moisture in Shandong
 693 Province, China: An analysis using ERA5-Land datasets. *Plos one*, 21, e0339023.
- 694 YANG, Y., MCVICAR, T. R., DONOHUE, R. J., ZHANG, Y., RODERICK, M. L., CHIEW, F. H., ZHANG, L.
 695 & ZHANG, J. 2017. Lags in hydrologic recovery following an extreme drought: Assessing the roles of
 696 climate and catchment characteristics. *Water Resources Research*, 53, 4821-4837.
- 697 ZHANG, D., ZHANG, Q., WERNER, A. D. & LIU, X. 2016. GRACE-based hydrological drought evaluation
 698 of the Yangtze River Basin, China. *Journal of Hydrometeorology*, 17, 811-828.
- 699 ZHAO, K. & LI, X. 2017. Estimating terrestrial water storage changes in the Tarim River Basin using GRACE
 700 data. *Geophysical Journal International*, 211, 1449-1460.
- 701 ZIANG, C., XIANKUI, Z. & JICHUN, W. 2025. Estimating Watershed Groundwater Runoff Using Water
 702 Balance Analysis and Memory Curve Model. *Geological Journal of China Universities*, 31, 113.
- 703