



1 **Spatiotemporal variability and hydrological interactions**
2 **of inter-basin groundwater flow in 36 major river basins**
3 **worldwide**

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11 **Abstract**

12 Inter-basin groundwater flow (IGF) transfers water across watershed boundaries
13 and interacts with surface hydrological processes. However, the spatiotemporal
14 characteristics of IGF in major river basins worldwide and its key role in the
15 hydrological cycle remain unclear. Here, we reconstructed IGF time series for 36 major
16 global basins. The results show that the absolute magnitude of the multi-year mean IGF
17 exceeded 20 % of precipitation in nearly half of the basins. Neighboring basins show
18 similar seasonal patterns of IGF, reflecting the response of lateral groundwater flow to
19 climatic seasonality. More importantly, in almost all basins, the rapid response of IGF
20 to precipitation is consistent with pressure propagation through groundwater systems.
21 In half of the basins, IGF could serve as an external water source supporting
22 evapotranspiration. These findings demonstrate that IGF is a critical link in the
23 hydrological cycle. Neglecting IGF may introduce structural biases into the
24 representation of hydrological processes and thus reduce the reliability of climate-
25 change projections based on Earth system models.

26 **Keywords:** Inter-basin groundwater flow; Water balance; Surface water–groundwater
27 interactions

28



29 **1 Introduction**

30 Groundwater flow is an essential component of the hydrological cycle, recharged
31 by precipitation, depleted through evapotranspiration (ET), and dynamically interacting
32 with streamflow (Scanlon et al., 2023; Xie et al., 2024; Kuang et al., 2024; Maxwell
33 and Condon, 2016). Unlike surface runoff, which is generated and transported within
34 the watershed boundaries, groundwater is stored and moves through widespread
35 aquifers. The groundwater flow system (or aquifer distribution) often does not align
36 with the surface watershed boundary, leading to groundwater flow between watersheds,
37 defined as inter-basin groundwater flow (IGF) (Genereux et al., 2005; Eakin, 1966; Fan,
38 2019). Existing studies of IGF have primarily focused on local or regional scales,
39 emphasizing its role in sustaining baseflow (Genereux et al., 2005; Yang et al., 2025;
40 Han et al., 2024; Ockenden et al., 2014), whereas the global spatiotemporal patterns of
41 IGF and its critical role in the hydrological cycle remain poorly understood.

42 IGF contributes to streamflow and transports solutes between watersheds,
43 influencing watershed water quantity and quality (Fan, 2019; Genereux and Jordan,
44 2006; Le Moine et al., 2008). It not only sustains baseflow during dry seasons but also
45 plays a significant role in shaping vegetation distribution and influencing soil and rock
46 weathering (Fan et al., 2019; Frisbee et al., 2016). Furthermore, accounting for IGF can
47 enhance the sensitivity of hydrological processes to climate change by as much as 20 %



48 to 70 % (Han et al., 2021). Because groundwater-flow boundaries commonly diverge
49 from topographic watershed divides, IGF is widespread across global basins (Liu et al.,
50 2020). Several studies have shown that neglecting IGF under the closed basin
51 assumption can introduce biases of approximately 10 % to 50 % in watershed water
52 balance analyses (Le Mesnil et al., 2021; Egusa et al., 2021; Bouaziz et al., 2018).
53 Therefore, quantifying IGF is critical for hydrological cycle studies and water resource
54 protection.

55 Current researches using hydrological modeling and hydrochemical methods have
56 quantified long-term mean IGF at local or regional scales, while its spatiotemporal
57 variability at the global scale remains poorly constrained. Physically based hydrological
58 models estimate IGF based on the groundwater flow field and groundwater dynamics,
59 such as TOPMODEL (Zanon et al., 2014) and MODFLOW (Han et al., 2024; Arce et
60 al., 2023). Nevertheless, constructing hydrological models requires extensive input and
61 calibration data (e.g., streamflow, aquifer structure, groundwater levels).
62 Hydrochemical methods estimate IGF by exploiting differences in water chemistry
63 among basins and applying end-member mixing models, using tracers such as chloride
64 concentration (Genereux et al., 2005), stable isotopes (e.g., $\delta^{18}\text{O}$) (Hagedorn, 2015), or
65 trace elements like $^{87}\text{Sr}/^{86}\text{Sr}$ (Stewart-Maddox et al., 2018). However, hydrochemical
66 methods necessitate spatially distributed observations within watersheds. Therefore,



67 constrained by data availability and accessibility, these two approaches are challenging
68 to apply for estimating IGF at large spatial scales.

69 The water budget method is simple and efficient for IGF estimation, making full
70 use of hydrometeorological remote sensing data and thus well suited for application at
71 the large scale. The reliability of the input data is key to accurately estimating IGF, with
72 ET products carrying the largest uncertainty (Zhang et al., 2016; Long et al., 2014;
73 Khan et al., 2018). Additionally, the water balance method typically represents IGF as
74 the residual of precipitation minus the sum of ET and streamflow (Fan, 2019; Egusa et
75 al., 2021; Gordon et al., 2022), causing IGF to be entangled with data errors, making
76 IGF estimation difficult to quantify. Therefore, it is necessary to explicitly disentangle
77 IGF from data errors.

78 Moreover, as a component of the hydrological cycle, IGF not only responds to
79 precipitation and contributes to stream baseflow but may also influence ET through
80 groundwater-table dynamics. However, current studies have largely focused on
81 evaluating the contribution of IGF to streamflow (Genereux et al., 2005; Yang et al.,
82 2025; Han et al., 2024; Ockenden et al., 2014), with insufficient attention paid to the
83 interactions with precipitation and ET. This limits a deeper understanding of basin-scale
84 hydrological-cycle processes.



85 Based on 36 major basins worldwide, this study investigates the spatiotemporal
86 variability of IGF and identifies the interactions with surface hydrological processes.
87 First, we evaluated input-data uncertainties in the water balance method and reduced
88 basin-scale ET uncertainty using a Penman-Monteith equation-based
89 evapotranspiration model and multi-source ensemble ET products. We then separated
90 the IGF signal from confounding data errors using a machine-learning approach with
91 an additive kernel function. Finally, we identified the mutual driving relationships
92 between IGF and key hydrological processes using causal inference for time series.

93 **2 Data and methods**

94 **2.1 Water balance equation**

95 The boundaries of groundwater flow systems often differ from surface watershed
96 divides. By considering lateral groundwater migration across basin boundaries, the
97 basin-scale water balance equation can be expressed as follows (Fan, 2019):

$$98 \qquad \qquad \qquad TWSC = P - ET - Q - IGF \qquad \qquad \qquad (1)$$

99 where TWSC is the total water storage change within the basin (mm month^{-1}), P is total
100 precipitation (mm month^{-1}), ET is actual evapotranspiration (mm month^{-1}), Q is
101 streamflow at the basin outlet (mm month^{-1}), and IGF is the net inter-basin groundwater
102 flow (mm month^{-1}). A positive IGF indicates groundwater outflow exceeding inflow,
103 whereas a negative IGF indicates the opposite.



104 **2.2 MOD16-based ET model**

105 The MOD16 model is based on the Penman-Monteith (PM) equation and
106 calculates total evaporation as the sum of canopy evaporation, vegetation transpiration,
107 and soil evaporation (Zhang et al., 2019; Running et al., 2021; Mu et al., 2011). Details
108 of the MOD16 model construction are provided in Sect. S3.1 of the Supplement. The
109 MOD16 model employs different parameter sets for varying land cover types. Given
110 the spatial heterogeneity of soil and plant canopy constraints even within the same land
111 cover type (Zhang et al., 2019), parameters may vary geographically. Thus, considering
112 data availability and regional representativeness, a total of 41 MOD16 models were
113 established across continents based on IGBP classification types. Specifically, eight
114 MOD16 models were developed for Asia (WAT, ENF, EBF, DBF, MF, GRA, WET,
115 CRO); nine for North America (ENF, DBF, MF, CSH, OSH, WSA, GRA, WET, CRO);
116 ten for Europe (WAT, ENF, EBF, DBF, MF, CSH, GRA, WET, CRO, URB); five for
117 South America (EBF, DBF, MF, WSA, GRA); three for Africa (EBF, DBF, SAV); and
118 six for Oceania (WAT, DBF, MF, GRA, WET, CRO).

119 Parameters for each MOD16 model were calibrated using measured latent heat
120 data from 206 eddy-covariance flux towers sourced from the FLUXNET2015 and
121 FLUXNET-CH4 datasets. The number of flux towers used for calibration across
122 continents were as follows: Asia (20 stations), North America (90 stations), Europe (59
123 stations), South America (8 stations), Africa (6 stations), and Oceania (23 stations).



Each MOD16 model contains eight critical parameters to be identified (Zhang et al., 2019): VPD_{close} , representing atmospheric vapor-pressure deficit (VPD) that has nearly complete inhibition of transpiration; VPD_{open} , representing VPD that has no inhibition of transpiration; g_{l_sh} , leaf conductance of sensible heat per unit LAI; $g_{l_e_wv}$, leaf conductance of evaporated water vapor per unit LAI; Cl , mean potential stomatal conductance per unit leaf area; r_{bl_min} and r_{bl_max} , the minimum and maximum values for total aerodynamic resistance of soil; and β , a sensitivity index for the soil constraint on VPD.

The DREAMzs-based Markov Chain Monte Carlo (MCMC) method (Laloy and Vrugt, 2012) was used to calibrate these parameters for each of the 41 MOD16 models. Eddy covariance-measured latent heat flux was converted to actual ET using the following formula:

$$ET = \frac{LE \times T}{\lambda \rho} \quad (2)$$

where LE is latent heat flux ($W\ m^{-2}$), T is time (s), λ is latent heat of vaporization for water ($J\ kg^{-1}$, typically 2.45×10^6), and ρ is water density ($kg\ m^{-3}$, typically 1000).

Basin-scale ET was estimated by combining the calibrated MOD16 models with CAMELE. First, each basin was divided into two parts based on the land-cover types. For the part with land-cover types represented by corresponding FLUXNET sites, ET and its uncertainty were estimated using the calibrated MOD16 models. For the other



part whose land-cover types were not represented by FLUXNET sites, ET was estimated using CAMELE. The uncertainty of CAMELE ET was estimated using an error-weighted merging method based on the random errors and error correlations of ERA5-Land, GLEAMv3.7a, and GLDAS2.1 estimated by the Extended Double Instrumental Variable algorithm (EIVD) (Li et al., 2024). Finally, the MOD16- and CAMELE-based ET estimates were area-weighted to obtain total basin ET. Assuming that the ET uncertainties from MOD16 and CAMELE were perfectly positively correlated, the uncertainties of the two components were also area-weighted to provide an upper-bound estimate of total basin ET uncertainty.

2.3 Separating IGF from water-balance errors using additive GPR

Based on Eq. (1), IGF with data errors included can be expressed as

$$IGF + \varepsilon = P - ET - Q - TWSC \quad (3)$$

The standard deviation σ , which represents the uncertainty of IGF with data errors included, was calculated using the error propagation equation:

$$\sigma = \sqrt{\sigma_P^2 + \sigma_{ET}^2 + \sigma_Q^2 + \sigma_{TWSC}^2} \quad (4)$$

where σ_P was obtained from the ERA5 ensemble spread product, which provides an estimate of precipitation uncertainty in ERA5. σ_{ET} was taken from the ET uncertainty estimates derived in this study. σ_Q was estimated by multiplying streamflow by percentile-dependent coefficients. These coefficients were determined according to the



relative percentile of streamflow within its time series (Aerts et al., 2024): 10.20 % when streamflow was below the 25th percentile, 7.65 % when streamflow was between the 25th and 75th percentiles, and 6.12 % when streamflow was above the 75th percentile. σ_{TWSC} was obtained by calculating the standard deviation among the GRACE mascon products (Landerer, 2021; Wiese et al., 2023) from CSR, JPL, and GSFC.

Gaussian Process Regression (GPR) is a flexible non-parametric Bayesian method (Rasmussen and Williams, 2006; Bishop, 2006). To isolate the IGF signal and quantify its uncertainty, we used an additive GPR framework (Duvenaud et al., 2011; Lu et al., 2022) to fit IGF estimates with data errors included (Eqs. (3) and (4)). Specifically, the combined IGF signal and confounding data errors were treated as the observations in the additive GPR model. The uncertainty σ , calculated through error propagation, was treated as Gaussian observational noise. Assuming that IGF and the confounding data errors follow different Gaussian distributions, and are mutually independent, their sum also follows a Gaussian distribution, with prior mean and prior covariance given by the linear sums of the component means and covariances:

$$\mathbf{b} \sim \mathcal{N}(\boldsymbol{\mu}, \mathbf{K} + \sigma^2 \mathbf{I}) \quad (5)$$

where $\mathbf{b}$ is an n -dimensional vector representing the IGF time series with data errors included. $\boldsymbol{\mu}$ is the mean vector of the time series. $\mathbf{K}$ is the $n \times n$ covariance matrix whose



elements reflect covariance between input data $\mathbf{x}_i$ and $\mathbf{x}_j$, computed using a kernel function $k(\mathbf{x}_i, \mathbf{x}_j)$. σ is the standard deviation of the Gaussian observational noise, and $\mathbf{I}$ is the identity matrix.

IGF represents true variations in groundwater flux that are closely associated with the water balance components. The prior mean of IGF was assumed to be the mean of the observations during the calibration period, and its prior covariance matrix was calculated using a smooth squared exponential automatic relevance determination (SE-ARD) kernel, with precipitation, ET, streamflow, and TWSC time series as inputs. The confounding data errors represent systematic deviations of the water balance terms from their true values, with a zero prior mean and a Matérn-kernel covariance defined using the corresponding uncertainty estimates as inputs. Therefore, the prior mean and prior covariance of IGF with data errors included can be expressed as:

$$\boldsymbol{\mu} = \text{Const} \quad (6)$$

$$\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{K}_{IGF}(\mathbf{x}_i, \mathbf{x}_j) + \mathbf{K}_{\varepsilon}(\mathbf{x}_i, \mathbf{x}_j) \quad (7)$$

$$\mathbf{K}_{IGF}(\mathbf{x}_i, \mathbf{x}_j) = \sigma_{IGF}^2 \exp\left(-\frac{1}{2} \sum_{d=1}^4 \frac{(x_{i,d} - x_{j,d})^2}{l_d^2}\right) \quad (8)$$

$$\mathbf{K}_{\varepsilon}(\boldsymbol{\sigma}_i, \boldsymbol{\sigma}_j) = \sum_{d=1}^4 \sigma_{\varepsilon d}^2 \exp\left(-\frac{|\sigma_{d,i} - \sigma_{d,j}|}{\lambda_d}\right) \quad (9)$$



197 where $\mathbf{K}_{IGF}$ is the SE-ARD kernel used to characterize the IGF signal, with $\mathbf{x}_i$ as input.
198 $\mathbf{K}_\varepsilon$ is the Matérn kernel used to characterize the confounding data error ε , with σ_i as
199 input. The GPR hyperparameters $\{\sigma_{\varepsilon 1}, \sigma_{\varepsilon 2}, \sigma_{\varepsilon 3}, \sigma_{\varepsilon 4}\}$ were fixed as the mean standard
200 deviations of precipitation, ET, streamflow, and TWSC uncertainties, respectively,
201 during the calibration period. $\boldsymbol{\phi} = \{\sigma_{IGF}, l_1, l_2, l_3, l_4, \lambda_1, \lambda_2, \lambda_3, \lambda_4\}$ denotes the GPR
202 hyperparameters to be estimated.

203 The first two-thirds of the IGF time series with data errors included were used as
204 the calibration data, and the remaining one-third was used as the validation data. To
205 explicitly incorporate observational uncertainty into the likelihood function, we used a
206 heteroscedastic Gaussian likelihood to represent the month-specific uncertainty of IGF
207 with data errors included. The kernel hyperparameters were then optimized by
208 minimizing the negative log marginal likelihood under prescribed parameter bounds
209 using the nonlinear conjugate gradient method. The negative log marginal likelihood is
210 given by:

$$211 \quad -\log p(\mathbf{y}|\mathbf{X}, \boldsymbol{\phi}) = \frac{1}{2}(\mathbf{y} - \boldsymbol{\mu})^T(\mathbf{K} + \boldsymbol{\Sigma})^{-1}(\mathbf{y} - \boldsymbol{\mu}) + \frac{1}{2}\log|\mathbf{K} + \boldsymbol{\Sigma}| + \frac{n}{2}\log(2\pi) \quad (10)$$

$$212 \quad \boldsymbol{\Sigma} = \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2) \quad (11)$$

213 where $\mathbf{y}$ denotes the calibration data. $\mathbf{X}$ denotes the input data for the GPR model,
214 including precipitation, ET, streamflow, TWSC, and their corresponding uncertainties.

215



2.4 Posterior estimation and uncertainty of IGF

Additive GPR allows the posterior mean of the IGF signal to be analytically derived. The prior joint distribution of the training time series $\mathbf{b}$ and prediction time series $\mathbf{b}^*$ follows a multivariate normal distribution:

$$\begin{bmatrix} \mathbf{b} \\ \mathbf{b}^* \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \boldsymbol{\mu} \\ \boldsymbol{\mu}^* \end{bmatrix}, \begin{bmatrix} \mathbf{K} + \sigma^2 \mathbf{I} & \mathbf{K}^* \\ \mathbf{K}^{*T} & \mathbf{K}^{**} \end{bmatrix} \right) \quad (12)$$

where elements of $\mathbf{K}^*$ and $\mathbf{K}^{**}$ matrices are computed as $K_{ij}^* = k(\mathbf{X}_i, \mathbf{X}_j^*)$ and $K_{ij}^{**} = k(\mathbf{X}_i^*, \mathbf{X}_j^*)$, respectively. $\mathbf{X}$ and $\mathbf{X}^*$ denote the inputs to the additive GPR model during the calibration and validation periods, respectively.

From Eq. (12), the posterior distribution of $\mathbf{b}^*$ given prior distribution assumptions and training data $\mathbf{b}$ can be obtained:

$$\mathbf{b}^* | \mathbf{b} \sim \mathcal{N} \left(\overline{\mathbf{b}^*}, \text{cov}(\mathbf{b}^*) \right) \quad (13)$$

$$\overline{\mathbf{b}^*} = \boldsymbol{\mu}^* + (\mathbf{K}^*)^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} (\mathbf{b} - \boldsymbol{\mu}) \quad (14)$$

$$\text{cov}(\mathbf{b}^*) = \mathbf{K}^{**} - (\mathbf{K}^*)^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{K}^* \quad (15)$$

Furthermore, based on the linear decomposability of additive GPR at the posterior-mean level, the posterior mean of IGF can be expressed as (Duvenaud et al., 2011; Lu et al., 2022):

$$\overline{\mathbf{b}_{IGF}^*} = \boldsymbol{\mu}^* + (\mathbf{K}_{IGF}^*)^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} (\mathbf{b} - \boldsymbol{\mu}) \quad (16)$$

However, because the posterior covariance of additive GPR cannot be exactly decomposed analytically, we used the posterior covariance of $\mathbf{b}^*$ as an approximate



235 representation of IGF signal uncertainty (Eq. (15)). The predictive uncertainty
236 including random observational errors is given by:

$$237 \quad cov(\mathbf{b}_{IGF}^*) = \mathbf{K}^{**} - (\mathbf{K}^*)^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{K}^* + \sigma^{*2} \mathbf{I} \quad (17)$$

238 where σ^* is the standard deviation of observational uncertainty during the validation
239 period.

240 **2.5 Time-series causal discovery using PCMCI+**

241 In this study, we used the Peter-Clark Momentary Conditional Independence Plus
242 (PCMCI+) algorithm within the causal inference for time series framework to perform
243 causal discovery among precipitation, streamflow, ET, and IGF. This method is
244 designed for multivariate time series and can identify significant directed dependencies
245 among variables within a predefined maximum lag, while distinguishing zero-lag from
246 lagged relationships (Runge et al., 2019a; Günther et al., 2023).

247 Specifically, the time-series causal network was constructed in two steps. First,
248 starting from an initial fully connected network, the Peter-Clark condition-selection
249 algorithm (PC) progressively enlarges the conditioning set and removes statistically
250 non-significant links, thereby identifying a set of candidate parents for each variable.
251 The Momentary Conditional Independence (MCI) test is then applied to each candidate
252 link while conditioning on the relevant parents of both the target and driver variables,
253 retaining only significant directed lagged associations. Given the limited length of the
254 time series, the maximum lag was set to 3 months. Conditional independence was

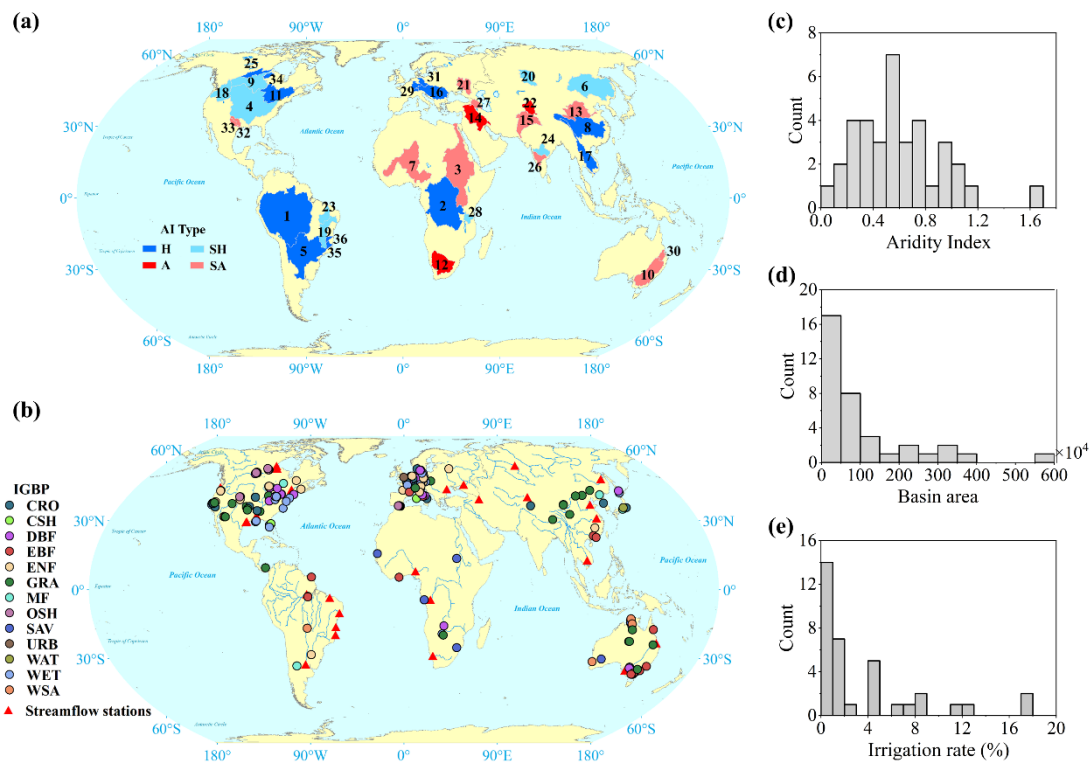


255 assessed using a linear partial correlation test, and links were retained at a significance
256 level of $\alpha = 0.1$.

257 **3 Results**

258 **3.1 Study basins and estimation of ET**

259 We selected 36 major basins worldwide for this study based on their
260 representativeness and the availability of streamflow (Table S1) and other required data.
261 The selected basins represent a diverse range of climate conditions and levels of human
262 activities, with a minimum area of 64 000 km², which was sufficient for reliable
263 application of GRACE data (Vishwakarma et al., 2018) (Fig. 1).



264

265 **Figure 1.** Geographic location and overview of the studied basins. (a) Map showing
266 the locations of the 36 studied basins. Aridity Index (AI) types include Humid (H), Dry
267 Sub-Humid (SH), Arid (A), and Semi-Arid (SA). (b) Map of FLUXNET eddy
268 covariance sites and streamflow stations. The land cover types of sites are identified
269 based on the International Geosphere-Biosphere Programme biome classification
270 (IGBP). CRO, cropland; CSH, closed shrubland; DBF, deciduous broadleaf forest; EBF,
271 evergreen broadleaf forest; ENF, evergreen needleleaf forest; GRA, grassland; MF,
272 mixed forest; OSH, open shrubland; SAV, savanna; URB, urban and built-up lands;
273 WAT, water bodies; WET, permanent wetlands; WSA, woody savanna. (c) Distribution
274 of the aridity index across the 36 basins. (d) Distribution of basin areas across the 36
275 basins. (e) Distribution of the proportion of irrigated area across the 36 basins. Basemap
276 source: Esri World map template | Powered by Esri.

277



278 We developed 41 MOD16 land-surface evapotranspiration models (Zhang et al.,
279 2019; Running et al., 2021; Mu et al., 2011), stratified by the continent and IGBP class
280 of the FLUXNET eddy covariance sites. To reduce uncertainty in ET estimates, the
281 MOD16 models were calibrated using daily ET observations from 206 FLUXNET sites
282 (see Fig. S1 for the calibration results). The reliability of the calibrated MOD16 models
283 was then evaluated by comparison with the widely used Collocation-Analyzed Multi-
284 source Ensembled Land Evapotranspiration Data (CAMELE) product (Figs. S2 and S3).
285 Based on the calibrated MOD16 models, monthly ET and its uncertainty were estimated
286 for the 36 basins during 2003–2016. For land-cover types not represented by
287 FLUXNET sites, the corresponding CAMELE data were used instead (see Sect. 2.2).
288 Compared with ET estimates based solely on CAMELE, the calibrated MOD16 models
289 substantially reduced ET uncertainty (Fig. S4). In addition, precipitation uncertainty
290 was estimated using the ERA5 ensemble spread product, streamflow uncertainty was
291 estimated based on quantile ranges of observed discharge (Aerts et al., 2024), and
292 uncertainty in total water storage change was evaluated using the standard deviation
293 among the CSR, JPL, and GSFC GRACE mascon products (see Sect. 2.3).

294

295 **3.2 IGF estimation and its contribution to the water balance**

296 We first derived IGF from the water balance equation (Eq. (3)), explicitly
297 accounting for input-data errors, and quantified the associated uncertainty using the



298 error propagation equation (Eq. (4)). Additive Gaussian process regression was then
299 applied to the resulting error-contaminated IGF estimates to separate the IGF signal
300 from confounding data errors, with model performance shown in Table S2. The
301 uncertainty of the separated IGF estimates was further evaluated (see Sect. 2.4).

302 Based on the separated monthly IGF estimates for the 36 basins (Fig. S5), we
303 calculated the ratios of IGF, ET, streamflow, and TWSC to precipitation for each basin
304 using multi-year mean values (Fig. 2a). In 47 % of the basins, the absolute value of the
305 ratio of IGF to precipitation exceeded 0.2, underscoring IGF as a critical component in
306 water balance analysis. In contrast, in 17 % of the basins, the absolute IGF-to-
307 precipitation ratios were below 0.05, indicating a relatively limited influence of IGF on
308 their water budgets. We further estimated the 95 % confidence intervals of these ratios
309 using Monte Carlo sampling based on the uncertainties of the corresponding data (Fig.
310 2b). The 95 % confidence intervals of the IGF-to-precipitation ratio for the Murray (No.
311 10), Orange (No. 12), Yellow (No. 13), and Fitzroy (No. 30) basins included both
312 positive and negative values, indicating that it is difficult to determine whether these
313 basins are net IGF importers or exporters. Therefore, the long-term water balance
314 estimates for these basins are subject to substantial uncertainty.

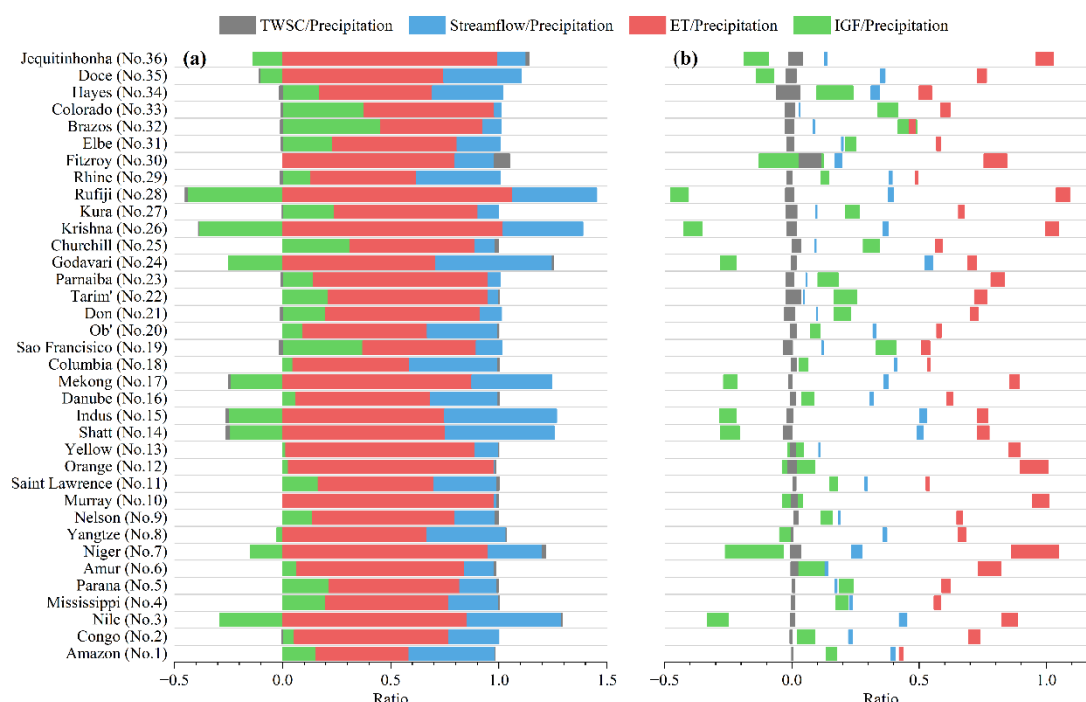


Figure 2. The multi-year average ratio of TWSC, streamflow, ET, and IGF relative to precipitation for the 36 study basins. **(a)** Stacked bar charts. **(b)** 95 % confidence intervals.

3.3 Spatiotemporal patterns of IGF

Based on the multi-year mean IGF values for each basin, we mapped the spatial distribution of IGF (Fig. 3a and 3b). For cross-basin comparison, IGF was expressed as equivalent water depth (mm month^{-1}), with positive values indicating net groundwater export and negative values indicating net groundwater import. The resulting patterns show that North American basins, including those in the central United States and along the southern coast, were generally net groundwater exporters. In South America,



327 eastern coastal basins, such as the Doce (No. 35) and Jequitinhonha (No. 36), were net
328 groundwater importers, whereas basins in the continental interior and along the
329 northeastern coast were net groundwater exporters. These patterns are broadly
330 consistent with groundwater exporter–importer distributions inferred from long-term
331 basin water balance analyses by Schaller and Fan (2009) in the United States and by
332 Liu et al. (2020) at the global scale. In addition, southern Asian basins, including the
333 Mekong (No. 17), Godavari (No. 24), and Krishna basins, were identified as net
334 groundwater importers. This pattern may be related to extensive irrigation and intensive
335 groundwater abstraction in these basins, as multi-year mean IGF was negatively
336 correlated with irrigated area across 36 basins (Pearson’s correlation coefficient is
337 -0.35).

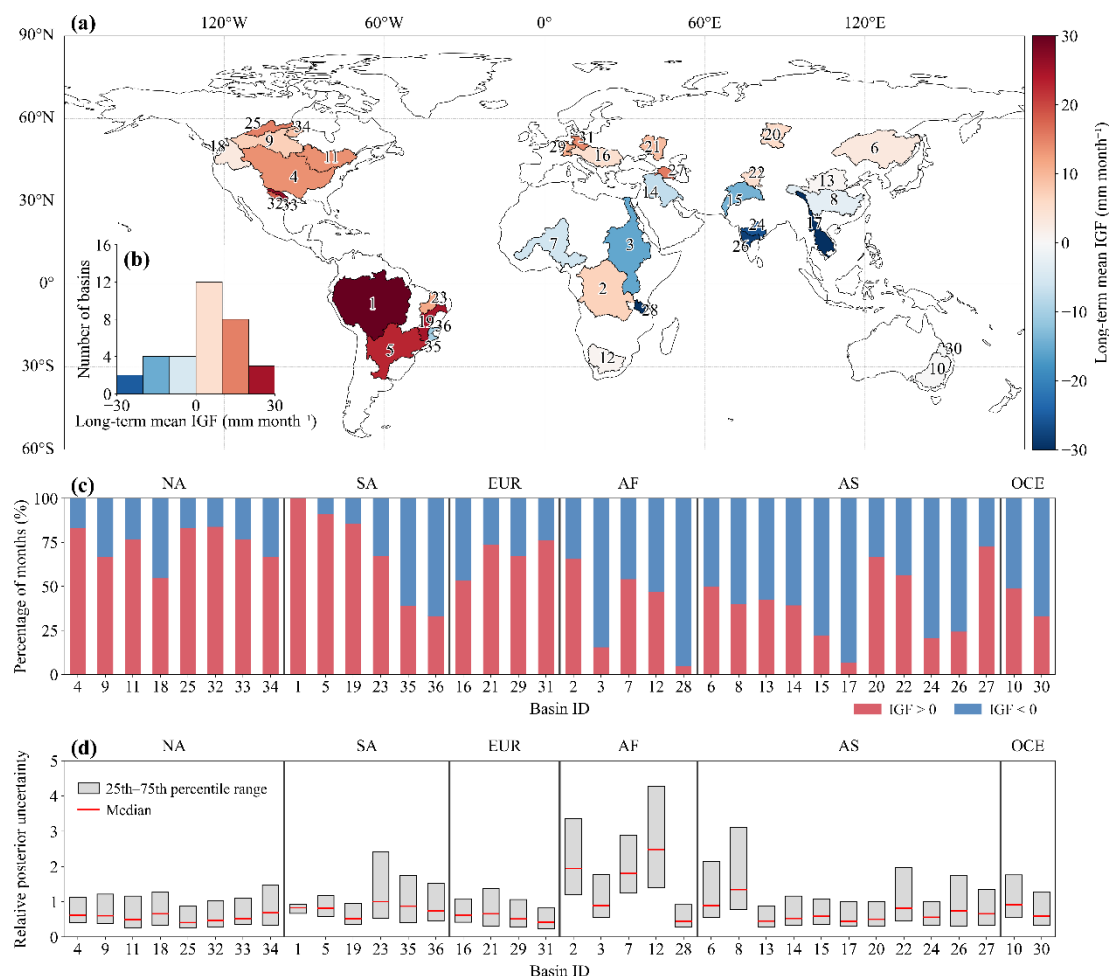


Figure 3. IGF estimates and uncertainty assessment. **(a)** Spatial distribution of multi-year IGF means across the 36 basins, expressed as equivalent water depth in mm month⁻¹. **(b)** Frequency distribution of multi-year mean basin IGF. **(c)** Frequency distribution of the proportion of months with positive IGF for each basin. **(d)** Distribution of relative posterior uncertainty in monthly IGF across basins, calculated as the posterior standard deviation divided by the absolute posterior mean. NA, SA, EUR, AF, AS, and OCE denote North America, South America, Europe, Africa, Asia, and Oceania, respectively. The map in **(a)** was made with Natural Earth.



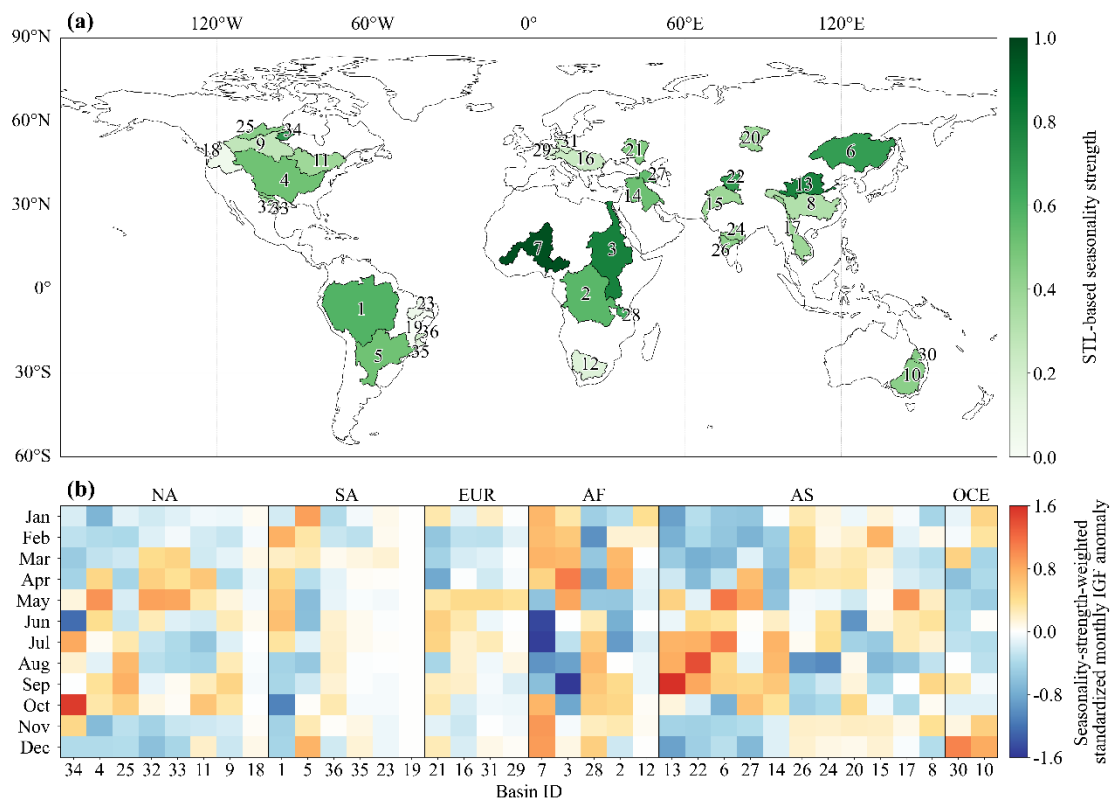
348 According to Fig. 3c and Fig. S5, monthly IGF in most basins fluctuated around
349 zero. In contrast, the Amazon basin (No. 1) showed persistently positive monthly IGF,
350 indicating sustained lateral groundwater export from the basin. We further evaluated
351 the reliability of the monthly IGF estimates using relative uncertainty, defined as the
352 ratio of the standard deviation to the absolute posterior mean. As shown in Fig. 3d,
353 relative uncertainty was relatively low in most basins, generally ranging from 0 to 1.
354 Basins in Africa showed higher IGF uncertainty because the additive GPR-based IGF
355 estimates incorporated input-data uncertainties, while the limited number of FLUXNET
356 eddy covariance sites in this region constrained MOD16 calibration and led to relatively
357 large ET uncertainty.

358 Most basin IGF time series showed clear periodic variability (Fig. S5). To quantify
359 the strength of seasonal variation in IGF for each basin, we calculated a seasonality-
360 strength metric based on STL decomposition (Seasonal-Trend decomposition using
361 LOESS, where LOESS denotes locally estimated scatterplot smoothing) (Wang et al.,
362 2006), as shown in Fig. 4a. In general, larger basins showed stronger IGF seasonality,
363 with STL-based seasonality strength approaching 1.

364 To characterize both the strength and phase of IGF seasonality, we first centered
365 and standardized the multi-year mean monthly IGF values from January to December,
366 and then multiplied them by the STL-based seasonality strength. The resulting



367 seasonality-strength-weighted standardized monthly IGF anomaly was used to compare
368 seasonal IGF cycles among basins. As shown in Fig. 4b, neighboring basins with strong
369 seasonality on each continent generally showed similar intra-annual patterns, including
370 similar timing of peaks, troughs, and transitions between positive and negative
371 anomalies. This suggests that basins under similar climatic and geological conditions
372 tend to exhibit similar seasonal IGF variability.



373

374 **Figure 4.** Seasonal variability of IGF time series. (a) Spatial distribution of STL-based
375 seasonality strength across the 36 basins. (b) Seasonality-strength-weighted
376 standardized monthly IGF anomalies across the 36 basins. The map in (a) was made
377 with Natural Earth.



378 **3.4 Causal time-series links between IGF and surface hydrological processes**

379 Based on the time series of precipitation, streamflow, ET, and IGF, together with
380 prior assumptions regarding their interactions (Fig. S6), we used the Peter-Clark
381 Momentary Conditional Independence Plus (PCMCI+) algorithm within the causal
382 inference for time series framework (Runge et al., 2019b; Günther et al., 2023) to
383 identify causal networks among key hydrological processes in the 36 basins. Each panel
384 in Fig. 5 corresponds to one basin. Node color represents the autocorrelation strength
385 of each hydrological process, edge color represents the association strength between
386 hydrological processes, and arrows indicate the direction of influence. Straight edges
387 represent contemporaneous effects at zero lag, whereas the numbers on curved edges
388 indicate the lag time τ , associated with the strongest lagged association. Here, τ
389 represents the time lag, in months, over which variation in one hydrological process
390 drives a response in another.



Figure 5. Causal relationships derived from the causal inference for time series between precipitation (P), streamflow (Q), evapotranspiration (ET), and inter-basin groundwater flow (IGF).



395 In 94 % of the basins, precipitation showed a significant positive zero-lag effect
396 on IGF, with generally strong conditional associations and a mean conditional partial
397 correlation coefficient of 0.58. Previous studies have mainly focused on the
398 contribution of IGF to streamflow, whereas the time-lagged causal inference revealed
399 a more widespread mechanism through which IGF affects ET. Specifically, in 47 % of
400 the basins, IGF showed a significant negative effect on ET ($\tau = 0, 2, \text{ or } 3$ months), with
401 a mean conditional partial correlation coefficient of -0.31 . This indicates that, in nearly
402 half of the basins, more negative IGF, corresponding to greater groundwater inflow into
403 the basin, was associated with a stronger positive contribution to ET. By comparison,
404 only 14 % of the basins showed a significant negative effect of IGF on streamflow ($\tau =$
405 0 months), with a mean conditional partial correlation coefficient of -0.28 . In a few
406 basins, positive effects of IGF on ET and streamflow were also identified, such as in
407 basin No. 32. These relationships may reflect a common response of IGF, ET, and
408 streamflow to variables not explicitly included in the analysis, such as groundwater
409 storage.

410 In addition, the causal inference for time series identified several unusual causal
411 relationships. In basins No. 14, No. 15, No. 20, No. 28, and No. 36, precipitation
412 showed positive effects on IGF at zero lag but negative effects at nonzero lags. This
413 pattern arises because causal inference identifies directed dependencies after



414 conditioning on other influencing factors. Thus, zero-lag and lagged effects may
415 correspond to two distinct mechanisms by which precipitation affects the groundwater
416 system. The positive zero-lag effect of precipitation on IGF suggests that precipitation
417 inputs can trigger a rapid groundwater-system response through pressure propagation
418 within the aquifer system, leading to an immediate increase in IGF outflow from the
419 basin (Rasmussen et al., 2000; Worthington and Foley, 2021; Guillaumot et al., 2022).
420 By contrast, the negative lagged effect of precipitation on IGF reflects basin storage
421 and slow-release processes. When antecedent precipitation is high, much of the
422 precipitation slowly infiltrates and recharges soil water and groundwater, and is
423 subsequently released to stream baseflow or consumed by evapotranspiration in the
424 following months, thereby reducing IGF outflow from the basin.

425 **4 Discussion**

426 **4.1 Hydrological implications of quantified IGF time series**

427 The spatial patterns of multi-year mean basin IGF estimated in this study are
428 broadly consistent with previous findings (Liu et al., 2020; Schaller and Fan, 2009).
429 Specifically, basins in the central United States and along the southern U.S. coast were
430 identified as net IGF exporters, basins along the eastern coast of South America were
431 identified as net IGF importers, and basins in the continental interior and along the
432 northeastern coast of South America were identified as net IGF exporters.



433 By quantifying IGF's contribution to the hydrological cycle in major river basins
434 worldwide, our study underscores that assuming basin isolation and neglecting lateral
435 groundwater exchange can significantly distort water balance analyses. In nearly half
436 of the major basins worldwide, the absolute value of the ratio of multi-year mean IGF
437 to precipitation exceeded 20 %. Moreover, IGF should not be treated merely as a
438 residual term in basin water balance. Instead, it largely reflects the response of regional
439 groundwater flow to climatic seasonality. Larger basins showed stronger seasonal
440 variability in IGF, and adjacent large basins exhibited similar timing of IGF extrema
441 and similar intra-annual seasonal patterns.

442 More importantly, based on the causal inference for the identified IGF time series,
443 we found that precipitation could rapidly drive IGF within basins through pressure
444 propagation within the aquifer system. In nearly half of the basins, IGF served as an
445 important external water input that replenished ET and supported basin-scale ecological
446 functioning. These findings indicate complex interactions between IGF and surface
447 hydrological processes. Neglecting IGF can therefore introduce structural biases in the
448 quantification of hydrological processes and further reduce the reliability of Earth
449 system model-based assessments of climate change impacts.

450 **4.2 Uncertainties and limitations**

451 Notably, we accounted for uncertainties in the input data used in the water balance
452 method as comprehensively as possible. The additive GPR model developed in this



453 study also fitted the error-contaminated IGF estimates well, with a mean NSE of 0.97
454 during the validation period. Based on the identified additive GPR model, the posterior
455 mean of IGF was analytically decomposed, and the uncertainty of the separated IGF
456 estimates was quantified by accounting for both data errors and statistical estimation
457 uncertainty. However, this decomposition relies on the prior assumption that the IGF
458 signal and confounding data errors differ in their driving inputs and degrees of
459 smoothness (see Sect. 2.3). Moreover, the separated IGF estimates still lack direct
460 validation. Incorporating basin-scale hydrochemical or isotopic evidence, or
461 developing high-resolution coupled hydrological models, would improve the reliability
462 of these findings and represents a key priority for future research.

463 **5 Conclusions**

464 This study reconstructed monthly IGF across 36 major river basins worldwide. An
465 additive Gaussian process framework was used to separate IGF from confounding data
466 errors while accounting for input uncertainties. We further characterized the spatial and
467 seasonal variability of IGF and examined its interactions with precipitation,
468 evapotranspiration, and streamflow.

469 Our results show that IGF represents a substantial component of basin water
470 balance in many regions, with the absolute magnitude of multi-year mean IGF
471 exceeding 20 % of precipitation in 47 % of the studied basins. IGF also exhibited



472 pronounced seasonal variability, and neighboring basins commonly showed similar
473 intra-annual patterns, suggesting a regional response of lateral groundwater flow to
474 climatic seasonality. Causal time-series analysis further indicated a widespread rapid
475 response of IGF to precipitation, with significant positive zero-lag effects in 94 % of
476 the basins. In 47 % of the basins, greater groundwater inflow was associated with
477 enhanced evapotranspiration, highlighting an important pathway through which IGF
478 interacts with surface hydrological processes.

479 Together, these findings show that lateral groundwater exchange is an integral
480 component of the hydrological cycle rather than a negligible term in basin water balance.
481 Explicit representation of IGF may therefore be important for improving basin-scale
482 water-balance analyses and the representation of land–water interactions in Earth
483 system models.

484 **Code and data availability**

485 All code and processed data supporting the findings and calculations are available
486 at <https://www.hydroshare.org/resource/b524ee2f581b4cdd9594be78e6fd7643/> from
487 HydroShare (Ren, 2026).

488 GRACE data are provided by the CSR from NASA's Physical Oceanography
489 Distributed Active Archive Center (PO.DAAC) with the identifier
490 doi:10.5067/TELND-3AC64 (Landerer, 2021), the JPL from PO.DAAC with the



491 identifier doi:10.5067/TEMSC-3JC63 (Wiese et al., 2023), and the GSFC from NASA
492 GSFC (Loomis et al., 2019) at <https://earth.gsfc.nasa.gov/geo/data/grace-mascons>. The
493 ERA5-Land meteorological forcing data (Muñoz Sabater, 2019) are available from the
494 Copernicus Climate Data Store at <https://doi.org/10.24381/cds.e2161bac>. The MODIS
495 MCD43C3 Version 6 broadband albedo data (Schaaf and Wang, 2015) are documented
496 at <https://doi.org/10.5067/MODIS/MCD43C3.006>. The GLASS01J01 and
497 GLASS09J01 data (Liang et al., 2021) can be obtained through the GLASS data portal
498 at <https://glass.hku.hk/download.html>. The MODIS MCD12C1 Version 6 IGBP land-
499 cover classification data (Friedl and Sulla-Menashe, 2015) are documented at
500 <https://doi.org/10.5067/MODIS/MCD12C1.006>. The NCAR Dai and Trenberth Global
501 River Flow and Continental Discharge Dataset (Dai, 2017) is available at
502 <https://doi.org/10.5065/D6V69H1T>. Streamflow observations from the Global Runoff
503 Data Centre can be obtained through <https://portal.grdc.bafg.de/>. The GloFAS
504 streamflow reanalysis v3.0 data (European Commission, Joint Research Centre, 2019)
505 are available at <https://doi.org/10.2905/JRC.75SB12R>.

506 **Author contributions**

507 X.Z. conceptualized the study; L.R. and X.Z. developed the methodology; L.R.,
508 X.Z., J.D., and W.Z. performed the investigation; L.R. and X.Z. prepared the



509 visualizations; X.Z., D.W., and J.W. supervised the research; L.R. wrote the original
510 draft; and X.Z., J.D., and W.Z. reviewed and edited the manuscript.

511 **Competing interests**

512 The authors declare that they have no conflict of interest.

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