

Beyond Runoff Coefficient: Revealing Global Patterns of Process Connectivity in Runoff Generation through Intensity Integration

Hanxu Liang¹, Dedi Liu^{1*}, Jiayu Zhang¹, Feng Yue¹, Yuling Zhang¹

¹ State Key Laboratory of Water Resources Engineering and Management, Wuhan University, Wuhan, China

Correspondence to: Dedi Liu (dediliu@whu.edu.cn)

Abstract. Climate change has profoundly altered the connectivity of runoff generation (i.e., the transformation process from precipitation to runoff). It is critical to understand this connectivity for climate change adaptation and water-related risk management. However, the runoff coefficient (RC), as the most common connectivity indicator, only describes the ratio of precipitation transformed into runoff, failing to characterize the rate of the transformation. Here we develop a novel framework to assess process connectivity in runoff generation through intensity integration. The RC and runoff intensity (RI) are adopted to represent the transformation ratio and rate from precipitation to runoff, respectively, and a composite metric runoff efficiency (RE), calculated as the product of RC and RI , is proposed to capture both dimensions. Applying this framework to 6,603 catchments globally over 1950–2020, we quantify the spatial patterns of process connectivity, diagnose their influencing factors, and examine their long-term trends and event-scale responses to precipitation intensity. According to their multi-year average values, we find a relatively high RC and RI in wet and dry areas, respectively. Interpretable machine learning further reveals that climatic attributes primarily control the process connectivity globally. The results of long-term trends show that the hotspots of increasing process connectivity are South America and central North America, which are typically associated with a higher potential for flood generation. Event-scale results indicate a high sensitivity of precipitation intensity on RE in dry climate zones. These findings not only enhance our understanding of runoff generation processes under the changing climate but also offer valuable insights into adaptive water resources management.

1 Introduction

The global hydrological cycle is an integrated system of interconnected components, including evapotranspiration, precipitation, snowmelt, runoff, groundwater, etc. (Yang et al., 2021; Oki and Kanae, 2006). Hydrological connectivity, defined as the water transfer within or between components of the hydrologic cycle, is characterised by both the ratio and rate of the transfer process (Bracken et al., 2013). This broad concept manifests across various hydrological processes such as runoff generation, channel routing, and groundwater recharge (Van Tiel et al., 2024; Wang et al., 2025; Gou et al., 2025; Phillips et al., 2011). Among these, the process connectivity of runoff generation—the transformation from precipitation to runoff—is of particular importance because it determines what fraction of precipitation actually becomes available for streamflow (rather than being lost to evaporation or infiltration) and how rapidly this transformation occurs before the

31 subsequent routing process (Bronstert et al., 2002; Shen et al., 2020). Over the past decades, climate change has profoundly
32 altered this connectivity by modifying both rainfall characteristics and snow-related processes (Richter and Marty, 2026;
33 Zhang et al., 2024). For example, warming has intensified precipitation extremes, leading to more frequent and intense heavy
34 rainfall events (Yin et al., 2018; Zhang et al., 2023). Such changes can generate flash floods with higher peaks and larger
35 volumes, thereby increasing flood hazards and socioeconomic risks (Blöschl, 2022; Miller and Hess, 2017). Moreover,
36 global warming significantly reshapes snowpack dynamics by decreasing the proportion of precipitation being stored as
37 snowpack, along with a faster melting rate (Li and Fan, 2025; Guan et al., 2022). This shifts the seasonal runoff pattern,
38 triggering earlier and more pronounced spring flow peaks followed by the diminished summer baseflow, which exacerbates
39 agricultural drought and water scarcity in downstream regions (Han et al., 2024). Therefore, a comprehensive understanding
40 of the process connectivity in runoff generation is critical to enhancing climate adaptation and mitigating water-related
41 hazards.

42 For quantifying the process connectivity in runoff generation, the most common indicator is the runoff coefficient (RC),
43 defined as the volume ratio of precipitation to runoff (Viglione et al., 2009). While the concept of RC originates from
44 Sherman (1932), investigations into controls on its spatiotemporal variability are still active in hydrology (Massari et al.,
45 2023; Viglione et al., 2009). Many previous studies concentrate on small scales, such as agricultural irrigation plots (Badoux
46 et al., 2006; Taye et al., 2013; Sumner et al., 1996; Nyssen et al., 2010) and hillslopes (Kinnell, 2014; Gomi et al., 2008b;
47 Penna et al., 2011; Gomi et al., 2008a), partly due to the advantages of dense instrumentation and process experiments (e.g.,
48 soil moisture networks, tracers) that are often infeasible at larger scales, thereby supporting hypothesis testing and
49 mechanistic understanding of thresholds and connectivity (Bishop et al., 2024; Wu et al., 2025). These investigations reveal
50 that the spatial variability of RC could be attributed to the spatial pattern of saturated conductivity (Bush et al., 2020;
51 Sheldon and Fiedler, 2008), land degradation (Bush et al., 2020; Sadeghi et al., 2020), land use and cover (Bush et al., 2020;
52 Ziegler et al., 2007), within-plot heterogeneity in soil characteristics (Herbst et al., 2006; Kuhn and Yair, 2004), and
53 interactions among these factors (Li et al., 2025; Xiao et al., 2025). Several studies further investigated the temporal
54 dynamics of the spatial pattern for RC across events and found that the spatial pattern may not persist over time (Jiang et al.,
55 2023; Chen et al., 2019; López-Vicente et al., 2016). However, partly owing to the scale dependency of hydrological laws
56 (Oda et al., 2024; Hunt et al., 2025), the heterogeneity and coupled climate-landscape gradients may increase with scale, and
57 it is often problematic to extrapolate the discoveries derived from small-scale investigations to larger catchments. Scientific
58 endeavours analysing the RC at the catchment scale are therefore necessary and crucial.

59 At the catchment scale, several studies have explored the spatial-temporal variability and influencing factors of RC
60 across diverse climates and catchments. These studies indicate a wide range of factors, and their effects differ across various
61 locations. A classical regional analysis of more than 400 Austrian catchments showed that climatic attributes, particularly
62 mean annual precipitation, exert a dominant control on the spatial distribution of RC (Merz and Blöschl, 2009). These
63 findings have also been confirmed by other further studies in Australia and Italy (Norbiato et al., 2009; Wasko and Guo,

2022). In contrast, other large-sample studies conducted in the United Kingdom and Germany revealed that geological conditions and soil properties are key driving factors for the spatial variability of RC (Zheng et al., 2023b; Tarasova et al., 2018a). Regarding temporal variability, studies reveal that event rainfall or snowmelt volume, and antecedent soil moisture are the dominant influencing factors (Merz et al., 2006; Tarasova et al., 2018b; Wu et al., 2021). Despite these valuable regional findings, existing studies are inherently limited in their spatial scope and covariate diversity. Within constrained hydroclimatic and physiographic domains, the limited variability among controlling factors gives rise to significant multicollinearity, posing a substantial challenge to disentangling their independent contributions and quantifying their relative importance at broader spatial scales (Do Nascimento et al., 2025; Clerc-Schwarzenbach et al., 2024). Consequently, the extrapolation of region-specific findings to ungauged or hydroclimatically divergent catchments is inherently associated with high levels of uncertainty. A global-scale analysis encompassing a more diverse covariate space is therefore essential to disentangle these confounding controls and advance toward a more generalized understanding of runoff generation. More importantly, RC only describes the fraction of precipitation that is transformed into runoff, without reflecting how fast this transformation proceeds. This limitation hinders our comprehensive understanding of the process connectivity in runoff generation.

To address this limitation, we propose a systematic analytical framework for assessing process connectivity in runoff generation through intensity integration. The aim is to understand spatiotemporal variations in the runoff generation process from the perspective of two-dimensional connectivity (i.e., transformation ratio and rate). Specifically, the RC reflects the transformation ratio of precipitation into runoff. The runoff intensity (RI), defined as the ratio of runoff depth to net rainfall duration, can directly indicate the transformation rate. This indicator is closely related to the surface runoff generation rate and the magnitude of peak discharge (Bronstert et al., 2023; Léonard et al., 2006), providing critical insights into the dynamic response of catchments to precipitation events. To achieve a more holistic characterization of the runoff generation process connectivity, runoff efficiency (RE) is further developed to encapsulate both the volumetric ratio of precipitation transformed into runoff (captured by RC) and the temporal rate of this transformation process (reflected by RI). Applying this framework in 6,603 catchments worldwide over 1950–2020, we answer the following critical questions: (a) What are the global spatial patterns of the process connectivity indicators, and to what extent do climate and landscape attributes drive their spatial heterogeneity? (b) What are the temporal dynamics of process connectivity indicators across multiple temporal scales, including long-term trends and event-to-event variability?

2 Methods

To quantify the runoff generation connectivity indicators, the quickflow is first derived from the in situ streamflow observations. Subsequently, a conceptual hydrological model is developed to simulate the quickflow generation process forced by other hydro-meteorological data, and the rainfall-runoff events are further identified. Finally, the spatio-temporal

variability of these connectivity indicators is investigated by interpretable machine learning, Sen's slope analysis, and function fitting approaches. The workflow of this study is illustrated in Fig. 1.

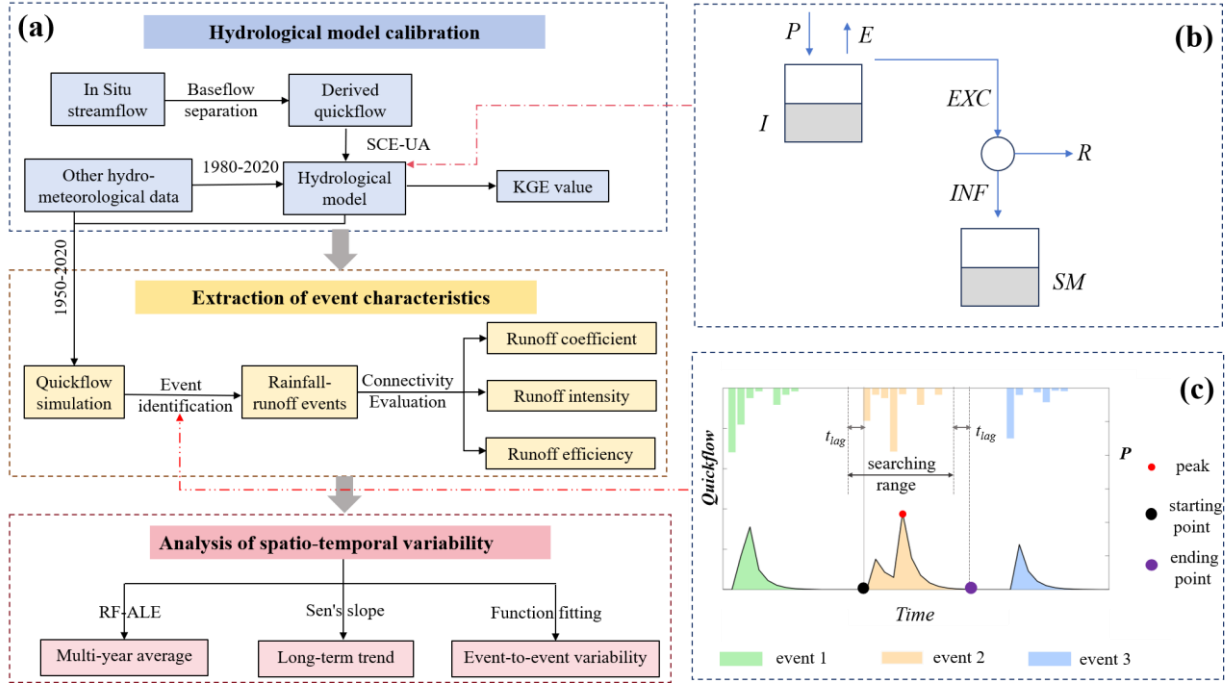


Figure 1. The workflow of this study. (a) General framework. (b) Structure of the conceptual hydrological model. (c) Identification of rainfall-runoff event.

2.1 Quantification of the Process Connectivity in Runoff Generation

2.1.1 Hydrological modeling

As the event runoff-generation process relates to direct runoff (i.e., quickflow), we first separate the baseflow from the observed daily streamflow and then derive the direct-runoff component before running the hydrological modeling (Merz et al., 2006). The baseflow separation is conducted using the one-parameter filter approach (Lyne and Hollick, 1979), a widely employed method in hydrological research (Mei et al., 2024; Xie et al., 2024; Zhang et al., 2022). **To simulate the direct runoff generation process, we develop a conceptual rainfall-runoff model based on the initial-loss and the continuing-loss framework (O'shea et al., 2021), which conceptually captures the effects of interception and infiltration losses in a simplified manner (Fig. 1b). The interception part by vegetation in the hydrological modeling can be described as:**

$$\frac{dI}{dt} = P - E_i - EXC \quad (1)$$

112 where P (mm/day) represents the liquid-water input, that is, the sum of daily rainfall and snowmelt; I (mm) refers to the
 113 current interception storage; E (mm/day) and EXC (mm/day) correspond to the evaporation from the interception store and
 114 the excess rainfall, respectively. Evaporation is assumed to occur at the potential rate E_p (mm/day) when possible. Once I
 115 surpasses the maximum interception capacity I_{max} , the surplus water is routed into the remainder of the model as excess input
 116 EXC .

$$117 \quad E = \begin{cases} E_p, & \text{if } I > 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$118 \quad EXC = \begin{cases} P, & \text{if } I = I_{max} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

119 The subsequent infiltration processes can be described as:

$$120 \quad INF = f_{max} * SM^{-b} \quad (4)$$

121 where INF (mm/day) represents the infiltration rate, determined by the maximum infiltration rate f_{max} , soil moisture SM (%),
 122 and the infiltration exponent b . The surface runoff (R ; mm/day) occurs once the excess rainfall intensity surpasses the
 123 infiltration rate of the soil:

$$124 \quad R = \max (EXC - INF, 0) \quad (5)$$

125 The runoff routing is simulated through the classical Nash instantaneous unit hydrograph (Nash, 1957), with two
 126 parameters n and K . The parameters n and K are the number of linear reservoirs and the routing time, respectively. All five
 127 parameters of the hydrological model (as listed in Table 1) are optimized by the Shuffled Complex Evolution algorithm
 128 (SCE-UA), which is a widely adopted stochastic optimization technique for model calibration and parameter tuning (Duan et
 129 al., 1992). To ensure a global search of the parameter space for the hydrological model, multiple simplexes are utilized to
 130 explore potential solutions concurrently (Kang et al., 2023). The Kling–Gupta Efficiency (KGE) is employed as the
 131 objective function:

$$132 \quad KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (6)$$

133 where r represents the correlation coefficient between the simulated and observed values; α denotes the ratio of the standard
 134 deviation of simulated results to that of observations; and β indicates the ratio of the mean value of simulated to that of
 135 observed streamflow. The calibration and validation of the hydrological model follow the cross-validation technique
 136 recommended by Arsenault et al. (2017) and Yin et al. (2021), in which odd-numbered years are chosen for calibration and
 137 even-numbered years for validation, with the first two years serving as the model warm-up period. Catchments with KGE

values higher than 0.5 during the validation period are retained for further analysis, and their hydrological processes are subsequently simulated over the full 1950–2020 period.

Table 1. Parameters of the hydrological model.

Parameter	Unit	Description
$I_{\max}$	mm	Maximum interception capacity
$f_{\max}$	mm/day	Maximum infiltration rate
b	—	Infiltration exponent
n	—	Number of the linear reservoirs in series
K	day	Routing time parameter

2.1.2 Identification of Rainfall-Runoff Events

We first identify runoff events using the simulated quickflow time series, and then match them to their corresponding rainfall (snowmelt) events. To identify runoff events, following the procedure described by Wu et al. (2021), each quickflow time series is examined starting from the highest peak and then moving to the second-highest peak. The onset of a runoff event is defined as the closest time prior to the peak when quickflow is equal to zero, and the termination is the first time thereafter when quickflow returns to zero, as shown in Fig. 1c. This definition allows multiple peaks to occur within a single runoff event. We then match each identified runoff event with contributing rainfall (including snowmelt) events. Rainfall (or snowmelt) events are defined as periods of rainfall that are separated by no-rainfall periods, with a distinguished threshold of 0.1 mm d⁻¹ for all catchments to remove trace or inconsequential events (Wu et al., 2021). For each runoff event in the time series, the total rainfall (or snowmelt) from all events whose centroids lie within a specified range is assigned as the corresponding event rainfall, as illustrated in Fig. 1c. The range refers to the lag time of catchments in event runoff generation, and is determined by a detrending moving-average cross-correlation method (Giani et al., 2021), which has been extensively utilized in hydrology due to its independence from event selection and parameter estimation (Zheng et al., 2023b; Costabile et al., 2024; Zhang et al., 2022).

2.1.3 Evaluation of process connectivity for runoff generation

We evaluate the process connectivity for runoff generation from the transformation ratio of rainfall to runoff (i.e., runoff coefficient, RC) and the transformation rate (i.e., runoff intensity, RI), respectively, as follows:

$$RC = \frac{R}{P} \quad (7)$$

$$RI = \frac{R}{\Delta t_R} \quad (8)$$

where R denotes the event runoff depth, and P refers to the event rainfall (including the snowmelt) depth. Δt_R is the runoff generation duration of an event and is named as the net-rainfall duration, specifically referring to the time during which $R > 0$ within the event, distinct from the event rainfall period of the event. Thus, Δt_R is expected to be shorter than the rainfall duration as interception, infiltration, and other hydrological losses delay or prevent rainfall from transforming directly into runoff (Gyasi-Agyei and Melching, 2012; Hashino et al., 2002). The higher the RC , the higher the transformation ratio in runoff generation. The greater the RI , the faster the transformation rate.

To comprehensively characterize the process connectivity of the two aspects, we further define a new metric, runoff efficiency (RE), as the product of RC and RI :

$$RE = RC * RI \quad (9)$$

The higher RE value may imply a larger proportion of precipitation is transformed into runoff at a faster rate within an event. It is typically associated with a larger event runoff volume and higher peak discharge, and thus a greater potential for flood generation.

2.2 Analysis of spatio-temporal variability for process connectivity

2.2.1 Analysis of multi-year average

Random Forest (RF)-accumulated local effects (ALE) are employed as an interpretable machine learning approach to explore the spatial patterns of RC s. The Random Forest (RF) is a traditional machine learning approach constructing an ensemble of regression trees (Breiman, 2001). Compared with single regression tree algorithms, RF offers notable strengths, such as the ability to handle highly correlated input variables, capture nonlinear interactions, and improve predictive stability via ensemble aggregation. The RF approach has been widely adopted across a broad spectrum of hydrological applications (Zheng et al., 2023a; Brown et al., 2023; Stein et al., 2021). The input features incorporated into RF encompass four categories of catchment characteristics: climate, topography, soil, and land cover (Zheng et al., 2023a; Kemter et al., 2023). To avoid the redundancy of the input features, following the approach outlined by Brêda et al. (2024) and Liang et al. (2026), catchment attributes are removed if their Pearson correlation coefficient exceeds 0.75 across different attribute groups or 0.9 within the same group (Fig. S1). Ultimately, a total of 21 catchment variables covering all four predefined categories are retained, with detailed descriptions provided in Table. S1. To eliminate overfitting in RF, a 10-fold cross-validation strategy is employed to evaluate its predictive performance (Stein et al., 2021). The dataset is partitioned into ten subsets of equal

size. Nine of these subsets are adopted to train the RF, while the remaining one reserved for testing purpose. The coefficient of determination (R^2) is employed as a metric to evaluate the performance of RF. Model robustness is evaluated by conducting 100 independent training iterations of RF training with varying random seeds. The overall performance of the RF model is quantified by the average R^2 obtained across all 100 independent iterations.

To quantify the average effects of the inputs on the performance of the RF, the ALE is adopted (Apley and Zhu, 2020). As a model-agnostic interpretability technique, ALE extends the concept of partial dependence plots, and provides enhanced computational efficiency and reliability, particularly when dealing with correlated predictors or data with complex structures (Shelef et al., 2022; Kemter et al., 2023). Its robustness stems from focusing on localized variations around observed values rather than the entire predictor range. By concentrating on the empirical distribution of the data, ALE estimates the causal influence of inputs on predictions while reducing extrapolation errors, thereby improving interpretability. To quantify the primary effect of a predictor, the uncentred effect $\hat{g}_{j,ALE}(x)$ is determined by the accumulating differences in the predictions across the quantiles of the predictor as indicated in Equation (10) (Apley and Zhu, 2020).

$$\hat{g}_{j,ALE}(x) = \sum_{m=1}^M \frac{1}{n_j(m)} \sum_{\{i: x_{i,j} \in N_j(m)\}} \{g(z_{m,j}, \mathbf{x}_{i,\setminus j}) - g(z_{m-1,j}, \mathbf{x}_{i,\setminus j})\} \quad (10)$$

where x refers to a given value of predictor j used to generate the ALE plot; m corresponds to a specific quantile within the set of M quantiles ($M = 10$) that subdivide the range of x . The range is partitioned into ten equal intervals for a balance between result robustness and low computational cost. The term $n_j(m)$ refers to the number of values of x that lie in the m th interval $N_j(m)$ ranging from $i = 1, 2, \dots, n$, and n represents the total sample size; $z_{m,j}$ refers to the boundary value of x for the given quantile; $g(\cdot)$ denotes the prediction model output, and $\mathbf{x}_{i,\setminus j}$ corresponds to the values of all other predictors for instance i except predictor j . The primary effect estimator $\hat{f}_{j,ALE}(x)$ of the ALE can be further estimated through deducting the average for uncentred effect value of all quantiles:

$$\hat{f}_{j,ALE}(x) = \hat{g}_{j,ALE}(x) - \frac{1}{M_j} \sum_{m=1}^M \hat{g}_{j,ALE}(x_m). \quad (11)$$

To quantify the contribution of each predictor, the average absolute values of ALE are obtained and normalized into the range [0,1] through maximum-minimum normalization, ensuring comparability across all predictors (Stein et al., 2021).

2.2.2 Analysis of long-term trend

To investigate the long-term evolution of process connectivity indicators, we employ Sen's slope, a robust and nonparametric method, to detect temporal trends, which is commonly used in hydro-meteorological research to estimate linear trends (Bloeschl et al., 2019; Kemter et al., 2023; Wang et al., 2024).

$$k = \text{median}\left(\frac{Y_j - Y_i}{j - i}\right) \quad (12)$$

where k is the slope; Y denotes the process connectivity indicator; i and j (where $i < j$) represent all possible year pairs within the time series.

2.2.3 Analysis of event-to-event variability

To analyze the event-to-event variability of process connectivity indicators, we first examine the variations of the indicators across events that are grouped by distinct discharge quantile intervals (0-20th, 20-40th, 40-60th, 60-80th, and 80-100th percentiles) for each catchment. Besides, we analyse the impact of precipitation intensity on runoff efficiency across events by fitting a power function using the least squares method. The power function is selected due to its universality in numerous hydrological formulas (Ijjaszvasquez et al., 1992; Schwemmler and Weiler, 2024; Li and Sivapalan, 2011).

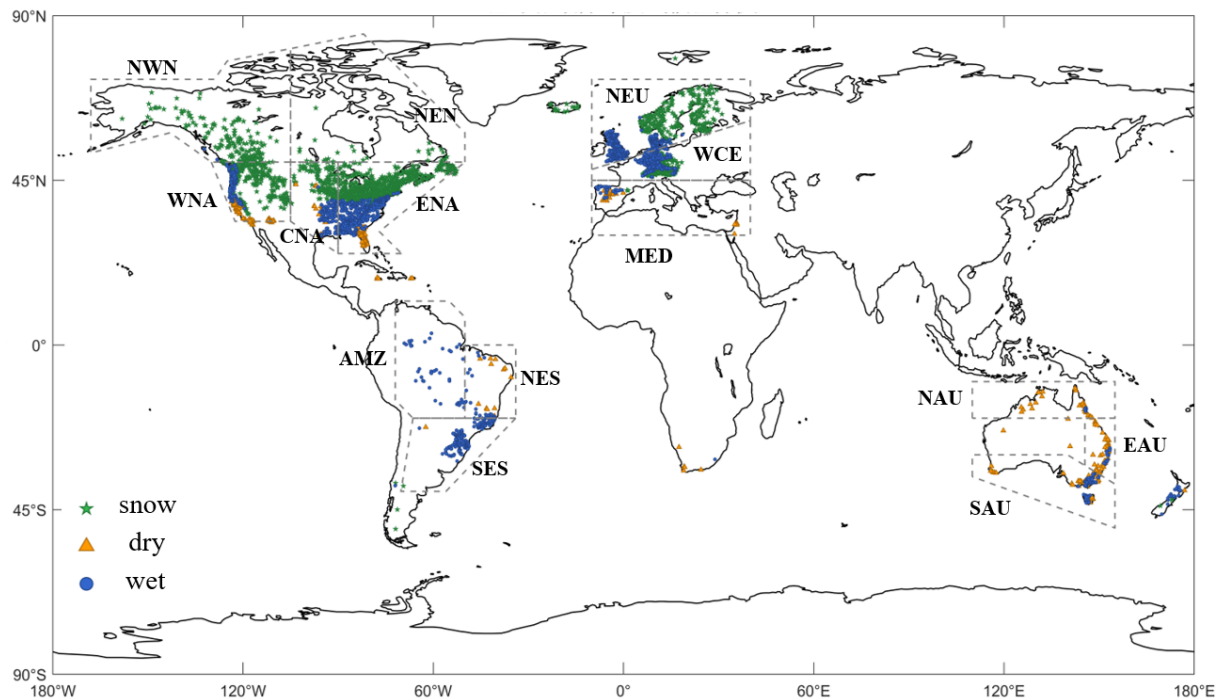
$$RE = RE_{10} * \left(\frac{PI}{10}\right)^m \quad (13)$$

where PI represents the precipitation intensity. RE_{10} and m are the fitted model parameters. The former denotes the runoff efficiency at a unit precipitation intensity of 10mm/day, while the latter denotes the sensitivity of runoff efficiency to changes in precipitation intensity. In alignment with standard engineering hydrology practice, where unit hydrographs are universally defined using 10 mm of effective rainfall, a unit precipitation of 10 mm is adopted (Lu et al., 2015; Singh et al., 2014).

3 Data

The hydrological and meteorological data come from the Caravan large sample dataset (Färber et al., 2025; Kratzert et al., 2023), a comprehensive repository that systematically compiles daily time series and key catchment attribute information for more than 20,000 catchments across the globe. Specifically, daily observed discharge (Q) is sourced from gauge stations, while daily precipitation (P), temperature (T), soil moisture (SM), and snow water equivalent (SWE) are sourced from the ERA5-Land reanalysis dataset. The potential evapotranspiration (PET) is estimated by the FAO Penman–Monteith equation. All meteorological data have been spatially aggregated to the catchment scale to ensure consistency with the hydrological response unit of interest. To guarantee the data quality, only those with at least 20 consecutive years of daily observed Q records between 1980 and 2020, and no single gap in the discharge time series exceeding 10 days are selected in the study (Han et al., 2020); any remaining missing values are imputed using linear interpolation (Jiang et al., 2024). Subsequently, catchments exhibiting unsatisfactory hydrological simulation performance (See section 2.1), indicated by a Kling-Gupta efficiency (KGE) value below 0.5, are filtered out (Kang et al., 2025). Application of these criteria results in the selection of a total of 6603 catchments for subsequent analysis.

241 To investigate the differences across climates, catchments are classified into three climatic categories: wet, dry, and snow.
 242 Wet catchments are characterized by an aridity index below 1, where mean potential evapotranspiration is lower than
 243 precipitation, indicating energy-limited conditions. Dry catchments correspond to an aridity index exceeding 1, in which
 244 mean potential evapotranspiration surpasses precipitation, reflecting water-limited conditions. Snow-dominated catchments
 245 are identified by a snow fraction greater than 0.2, independent of the aridity index (Wang et al., 2024; Stein et al., 2021). To
 246 further highlight regional hydrological characteristics, the catchments are additionally grouped into 14 reference regions
 247 defined by the Intergovernmental Panel on Climate Change (IPCC), with each region encompassing over 30 catchments to
 248 ensure a robust sample size for analysis (Iturbide et al., 2020). The spatial distribution of all the sampled catchments is
 249 illustrated in Fig. 2.



250 **Figure 2. Spatial distribution of 6603 sample catchments for analysis.** Green stars, orange triangles, and blue circles indicate the
 251 catchments in snow, dry, and wet climate zones, respectively. AMZ, Amazon; CNA, central North America; EAU, eastern Australia; ENA,
 252 eastern North America; MED, Mediterranean; NAU, northern Australia; NEN, north-eastern North America; NEU, northern Europe; NES,
 253 northeastern South America; NWN, northwestern North America; SAU, southern Australia; SES, southeastern South America; WCE,
 254 western and central Europe; WNA, western North America.

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260 **4.1 Spatial Patterns of Process Connectivity and Influencing Factors**

261 A total of 2,553,834 rainfall-runoff events occurring between 1950 and 2020 across 6603 catchments have been
262 identified through the simulation conducted with a conceptual hydrological model. **The mean value of each connectivity**
263 **indicator across all events is determined**, and its spatial pattern of the multi-year average is illustrated in Fig. 3. **Given the**
264 **uneven spatial distribution of catchments across regions and climate zones, median values are adopted for group-level**
265 **comparisons to mitigate the influence of unequal sample sizes and outliers**. For the runoff coefficient (Figs. 3a-c), the dry
266 climates are found to exhibit the lowest value, with a median of 0.15, indicating minimal loss in this hydrological
267 transformation process. In contrast, the wet and snow climate zones show notably higher median values of 0.25 and 0.33,
268 respectively, indicating a lower loss in the transformation process. It is also interesting that the highest values are found in
269 western North America (WNA) and northwestern North America (NWN), with a median higher than 0.3, while the lowest
270 values are found in eastern Australia (EAU), northeastern South America (NES), and southern Australia (SAU), with a
271 median lower than 0.15.

272 However, in terms of the runoff intensity as shown in Figs.3d-f, the highest value can be found in the dry climate zones,
273 with a median of 11.3mm/day, signifying a rapid transformation rate from precipitation to runoff. In contrast, the wet and
274 snow climate zones are found to have relatively lower median values of 8.6mm/day and 8.5mm/day, respectively, indicating
275 a slower transformation rate. From the spatial distribution, the highest median runoff intensity (exceeding 12mm/day) are
276 found in the eastern Australia (EAU), northeastern South America (NES), and northern Australia (NAU) In contrast, the
277 lowest median values (below 6.5mm/day) are concentrated in northern Europe (NEU), northwestern North America (NWN),
278 and Mediterranean (MED). It should be noted that the spatial pattern of the runoff coefficient is inconsistent with that of the
279 runoff intensity. For instance, NWN exhibits a relatively high runoff coefficient of 0.3, yet its runoff intensity is
280 comparatively low at 6.5 mm/day.

281 In terms of the runoff efficiency as shown in Figs. 3g-i, which is the product of the runoff coefficient and runoff
282 intensity, its relatively high values are found in snow climates with a median of 2.41 mm/day, while lower values are found
283 in both wet (median=1.75mm/day) and dry (median=1.51mm/day) climates, indicating a balance between runoff coefficient
284 and runoff intensity. Besides, its spatial distribution differs from that of the runoff coefficient and the runoff intensity. The
285 highest median runoff efficiency values (exceeding 2.5 mm/day) are found in western North America (WNA), eastern North
286 America (ENA), and southeastern South America (SES), indicating a higher level of comprehensive connectivity for runoff
287 generation, and consequently, a greater potential for flood generation. In contrast, the lowest median runoff efficiency values
288 (below 1.35 mm/day) are found in southern Australia (SAU), northern Europe (NEU), and northeastern South America
289 (NES), indicating a lower level of comprehensive connectivity for runoff generation.

290 An interpretable machine-learning framework combining RF and ALE is subsequently employed to systematically
291 investigate the key drivers governing the spatial heterogeneity of the process connectivity indicators. A total of 21 catchment
292 attributes serve as input variables into the RF model to predict each of the process connectivity metrics. The cross-validated
293 R^2 values for the RF models are presented in Figs. S3-S5. Generally, the RF model demonstrates robust predictive
294 performance, achieving a mean R^2 over 0.8 for all process connectivity indicators under 10-fold cross-validation. Figure 4
295 illustrates the ALE interpretable results of each indicator. For the runoff coefficient as shown in Fig. 4a, the aridity shows the
296 greatest impact, followed by mean annual precipitation, organic carbon content in soil, **fraction of snow, and seasonality of**
297 **precipitation**. For the runoff intensity as shown in Fig. 4b, the mean annual precipitation has the greatest impact, followed by
298 the mean actual evapotranspiration, the average duration of high precipitation, and the frequency of high precipitation days.
299 For the runoff efficiency as shown in Fig. 4c, the mean annual precipitation shows the greatest impact, followed by the
300 frequency of high precipitation days, seasonality of precipitation, fraction of snow, and pasture extent. It can be noted that
301 climate attributes dominate the impacts on all connectivity metrics, contributing **63.2%, 89.6%, and 79.3%** to the runoff
302 coefficient, runoff intensity, and runoff efficiency, respectively.

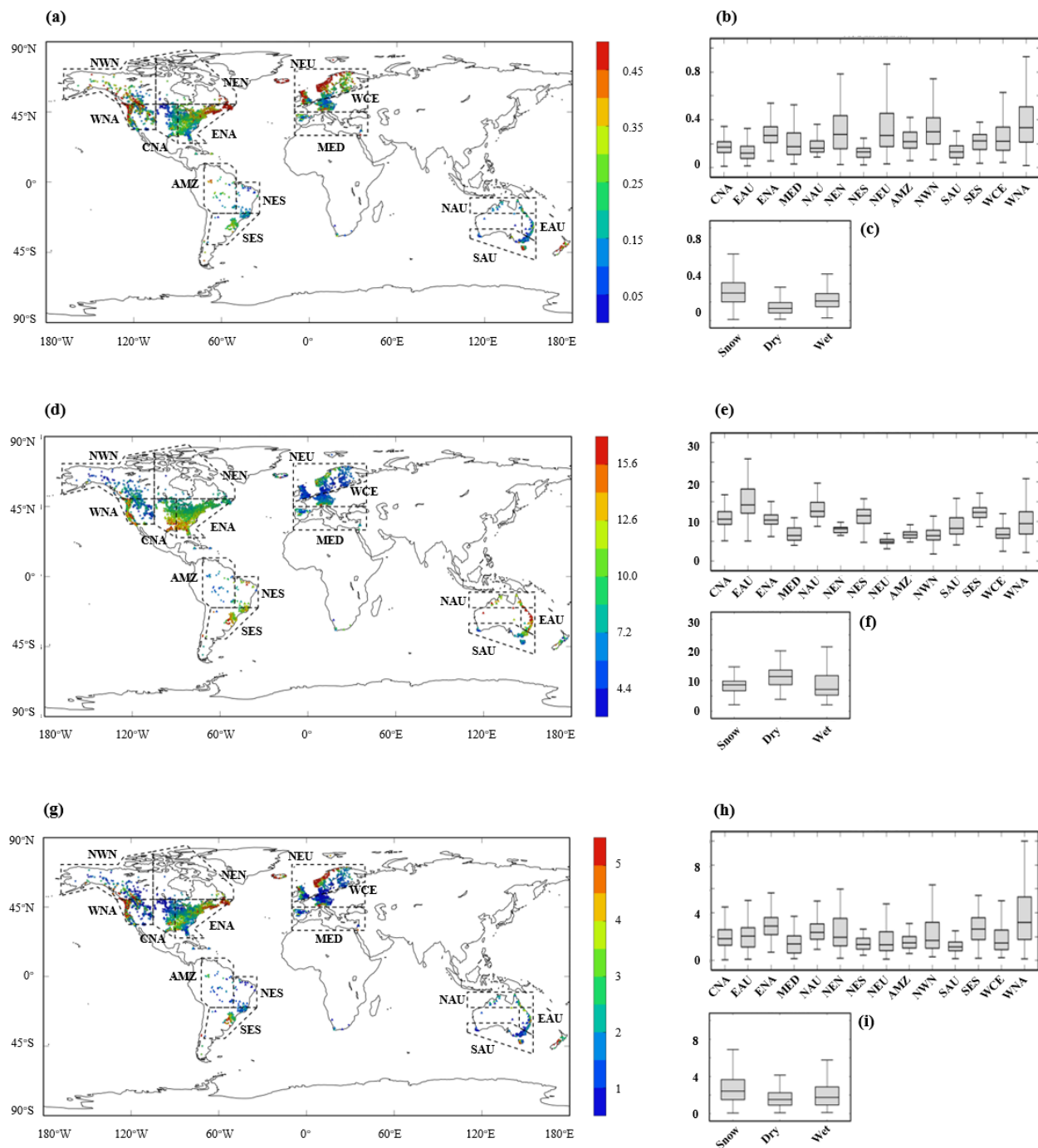


Figure 3. The spatial pattern for the multi-year average values for the process connectivity indicators across the globe. (a-c) for the runoff coefficient. (d-f) for the runoff intensity. (g-i) for the runoff efficiency.

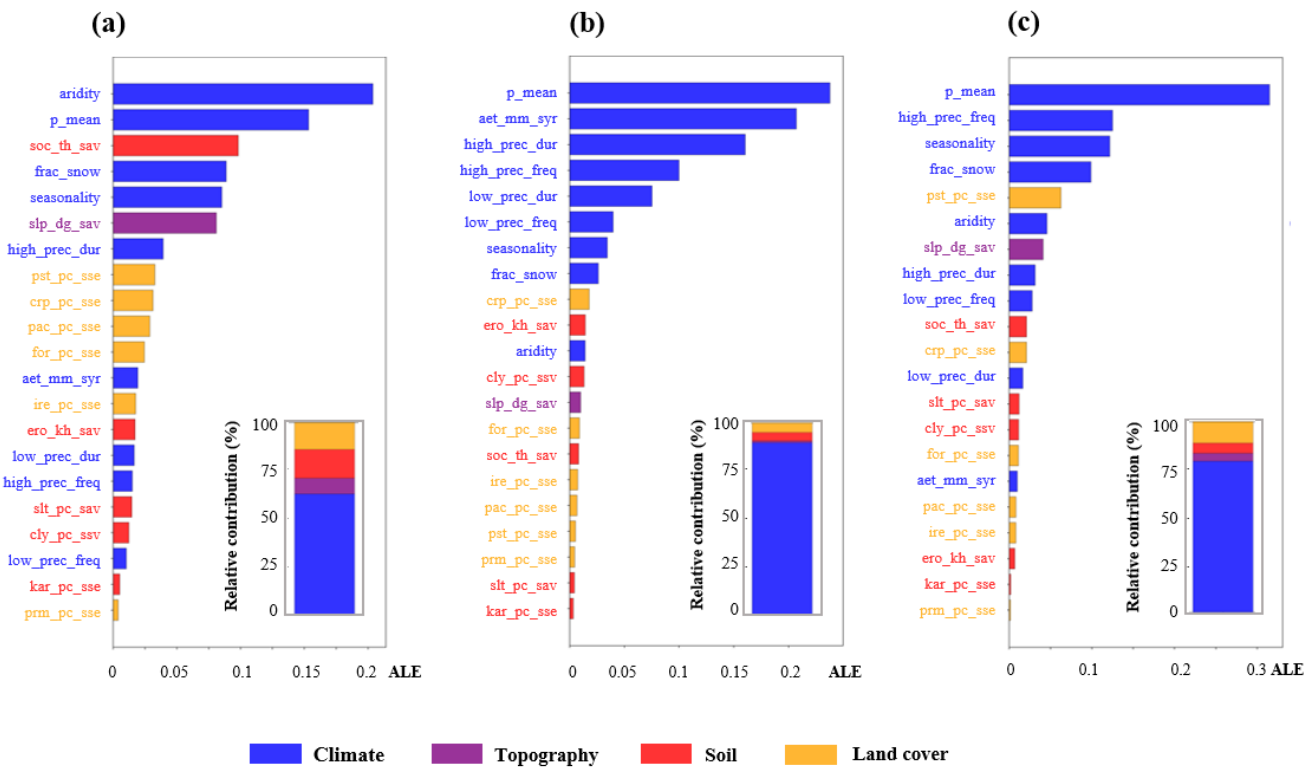


Figure 4. The Influence of catchment attributes on process connectivity indicators based on the interpretable machine learning approach (RF-ALE). (a) runoff coefficient. (b) runoff intensity. (c) runoff efficiency. Blue, purple, red, and yellow correspond to the categories of catchment attributes related to climate, topography, soil properties, and land cover, respectively. The proportional contribution of each category is illustrated by the bar height in the lower-right corner.

4.2 Long-Term Trends of Process Connectivity

Figure 5 depicts the long-term trends of process connectivity spanning from 1950 to 2020. For the runoff coefficient as shown in Figs.5a-c, the increasing trends are observed across the majority of catchments in both dry and wet climate zones, with a median relative Sen's slope of 0.6% per decade and 0.3% per decade, respectively. In contrast, the majority of catchments in snow climates exhibit declining trends, with a median relative Sen's slope of -0.2% per decade. The high increasing trends are mainly located in the Amazon (AMZ; 1.6% per decade), northern Australia (NAU, 1.2% per decade), central North America (CNA; 1.2% per decade), southeastern South America (SES, 1.1% per decade), and northeastern South America (NES, 1.0% per decade). Meanwhile, significant decreasing trends are mainly observed in the Mediterranean (MED, -1.0%/ per decade) and western North America (WNA, -0.6% per decade). For the runoff intensity (Figs. 5e-f), the spatial distribution of long-term trends matches that of the runoff coefficient, with the high increasing trends in the AMZ

323 (2.6% per decade), SES (2.0% per decade), NES (1.9% per decade), NAU (1.8% per decade) and CNA (1.4 % per decade),
324 and the high decreasing trends in WNA (-0.9% per decade) and MED (-0.7% per decade). This indicates that long-term
325 trends of the transformation ratio (i.e., runoff coefficient) and the transformation rate (i.e., runoff intensity) from
326 precipitation to runoff show great synergy, meaning that regions with a higher transformation ratio may simultaneously
327 experience a faster transformation rate under climate change. For runoff efficiency as shown in Figs.5g-i, the high increasing
328 trends also lie in the AMZ (3.4% per decade), SES (2.5% per decade), CNA (2.3% per decade), NAU (1.8% per decade),
329 and NES (3.0% per decade), and the high decreasing trends are also in the WNA (-1.5 % per decade) and MED (-0.9 % per
330 decade), with the magnitude of change exceeding that of both runoff coefficient and runoff intensity.

331 Overall, the hotspots of increasing process connectivity for runoff generation under climate change are the Amazon,
332 southeastern South America, central North America, northern Australia, and northeastern South America. In these regions, a
333 larger proportion of rainfall is transformed to runoff at a faster rate, typically accompanied by greater event runoff volumes
334 and higher peak discharges, thereby elevating the potential for flood generation. By contrast, the hotspots of decreasing
335 process connectivity are western North America and the Mediterranean, with relatively lower potential for flood generation.

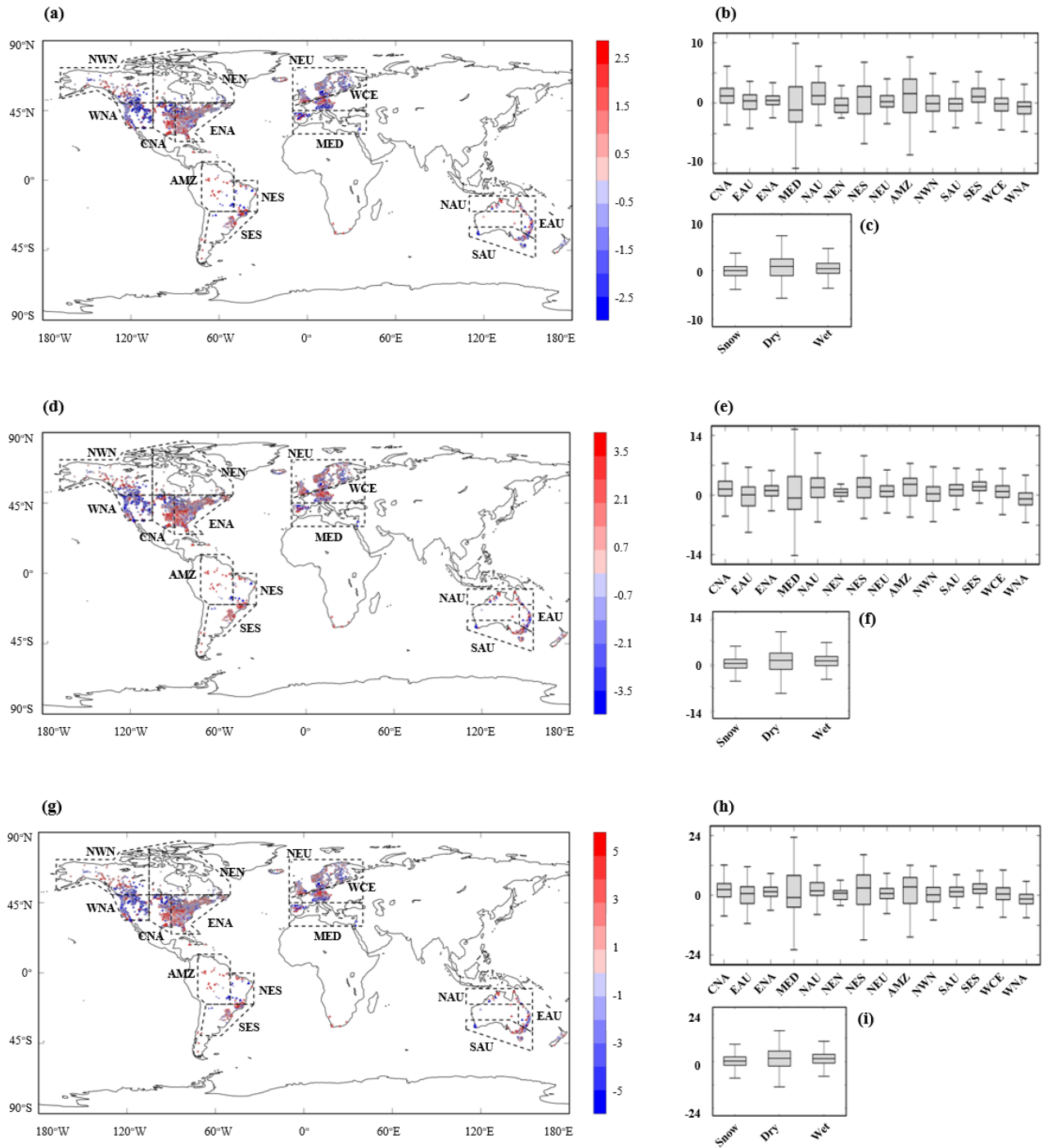
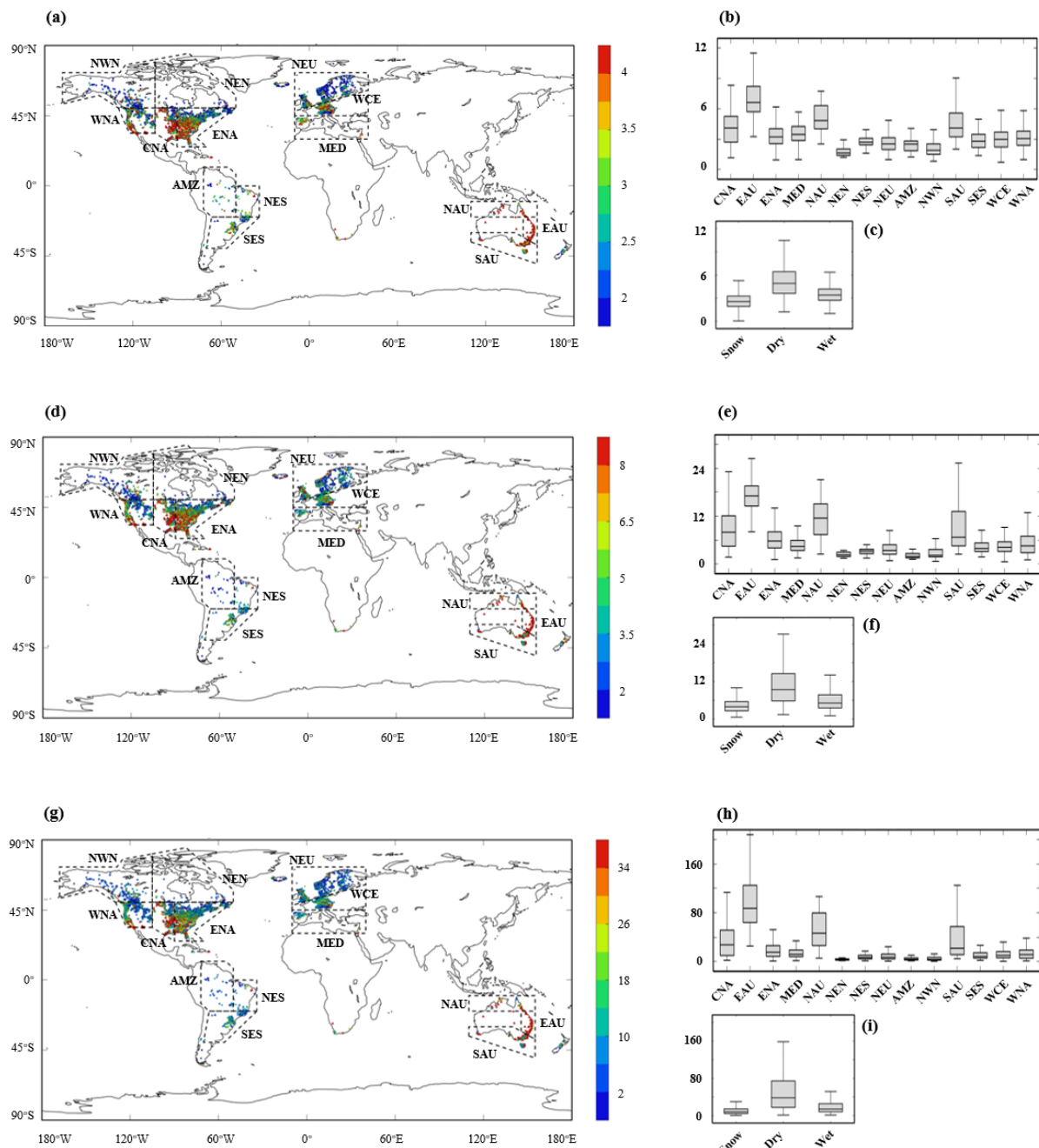


Figure 5. The long-term trends of the process connectivity indicators over 1950-2020. (a-c) for the runoff coefficient. (d-f) for the runoff intensity. (g-i) for the runoff efficiency.

339 4.3 Event-To-Event Variability of Process Connectivity

340 By examining the variations in process connectivity indicators across events grouped by peak discharge quantile ranges
341 (Figs. S6-S8), we find that these connectivity indicators increase consistently with increasing discharge quantiles,
342 demonstrating a robust positive association between the runoff generation process connectivity and the event peak
343 discharges. To highlight the contrast between the extreme conditions, we further quantified the fold-change in the
344 connectivity indicators across peak-discharge quantile ranges, specifically the ratios of values in the highest range (i.e., 80–
345 100th percentile) to those in the lowest range (i.e., 0–20th percentile), as shown in Fig. 6. Across all catchments, the runoff
346 coefficient, runoff intensity, and runoff efficiency associated with events in the high peak discharge quantiles range are 3, 4,
347 and 11 times those for low peak discharge quantile range, respectively. For the runoff coefficient (Figs. 6a-c), the highest
348 fold-change ratios are found in the dry climate zones, with a median value of 5.4. In contrast, wet and snow climate zones
349 exhibit relatively lower values, with a median value of 3.5 and 2.7, respectively. Spatially, the high values are found in EAU,
350 NAU, CNA, and SAU, with a median value of 6.6, 4.8, 4.1, and 4.1, respectively, while the low values are found in NEN,
351 NWN, and AMZ, with a median value of 1.6, 1.9, and 2.5. For the runoff intensity and runoff efficiency as shown in Figs.
352 6d-i, the spatial distribution is similar to that of the runoff coefficient, with the high values in EAU(17.1 for runoff intensity;
353 87.3 for runoff efficiency), NAU(11.5; 46.5), CNA(8.0;27.5), and SAU(6.7;21.9), and low values in NEN (2.3;2.9), NWN
354 (2.2;3.6), and AMZ (1.9;3.6) for both indicators. Furthermore, the highest fold-change ratios are found in the dry climate
355 zones, where runoff intensity and runoff efficiency reach 10.7 and 54.4 folds, respectively, suggesting the significant
356 nonlinear response of runoff processes to peak discharge.

357 To investigate how precipitation intensity influences runoff efficiency, we adopt a power function to fit event-based
358 data for each individual catchment, with model parameters calibrated by the least squares method. A representative fitting
359 example is illustrated in Fig. S9, while the overall fitting performance across all catchments is summarized in Fig. S10, with
360 a mean R^2 of 0.37. The spatial distributions of the two fitted parameters RE_{10} , defined as the runoff efficiency under a unit
361 precipitation intensity of 10mm/day, and m , representing the sensitivity of runoff efficiency to changes in precipitation
362 intensity, are illustrated in Fig. 7. The regional statistical summaries for these parameters are provided in Table 2. For the
363 parameter RE_{10} (Figs. 7a-c), its spatial distribution closely aligns well with that of multi-year average runoff efficiency (Fig.
364 4c). Dry climate zones exhibit relatively lower values, with a median of 1.9mm/day, whereas wet and snow climate zones
365 show higher median values of 2.8mm/day and 3.8mm/day, respectively. Regionally, the highest values (i.e., 3.9mm/day) are
366 found in NEN and WNA, whereas the lowest values (0.9mm/day) are found in EAU. For the parameter m (Figs. 7d-f), the
367 highest median value of 1.65 is found in the dry climate zones, while wet and snow climate zones exhibit relatively lower
368 median values of 1.17 and 1.05, respectively. Thus, dry climate zones exhibit relatively high RE_{10} values that are associated
369 with high sensitivity, whereas wet and snow climate zones show relatively low RE_{10} values that are associated with low
370 sensitivity. Regionally, the highest sensitivity values are found in EAU (1.88) and NAU (1.70), while the lowest are found in
371 MED (0.67) and NEN (0.72).



372

373 **Figure 6. The fold-change in the connectivity indicators from the highest to the lowest peak-discharge quantile ranges, i.e., (80–**
 374 **100th percentile)/ (0–20th percentile). (a–c) for the runoff coefficient. (d–f) for the runoff intensity. (g–i) for the runoff efficiency.**

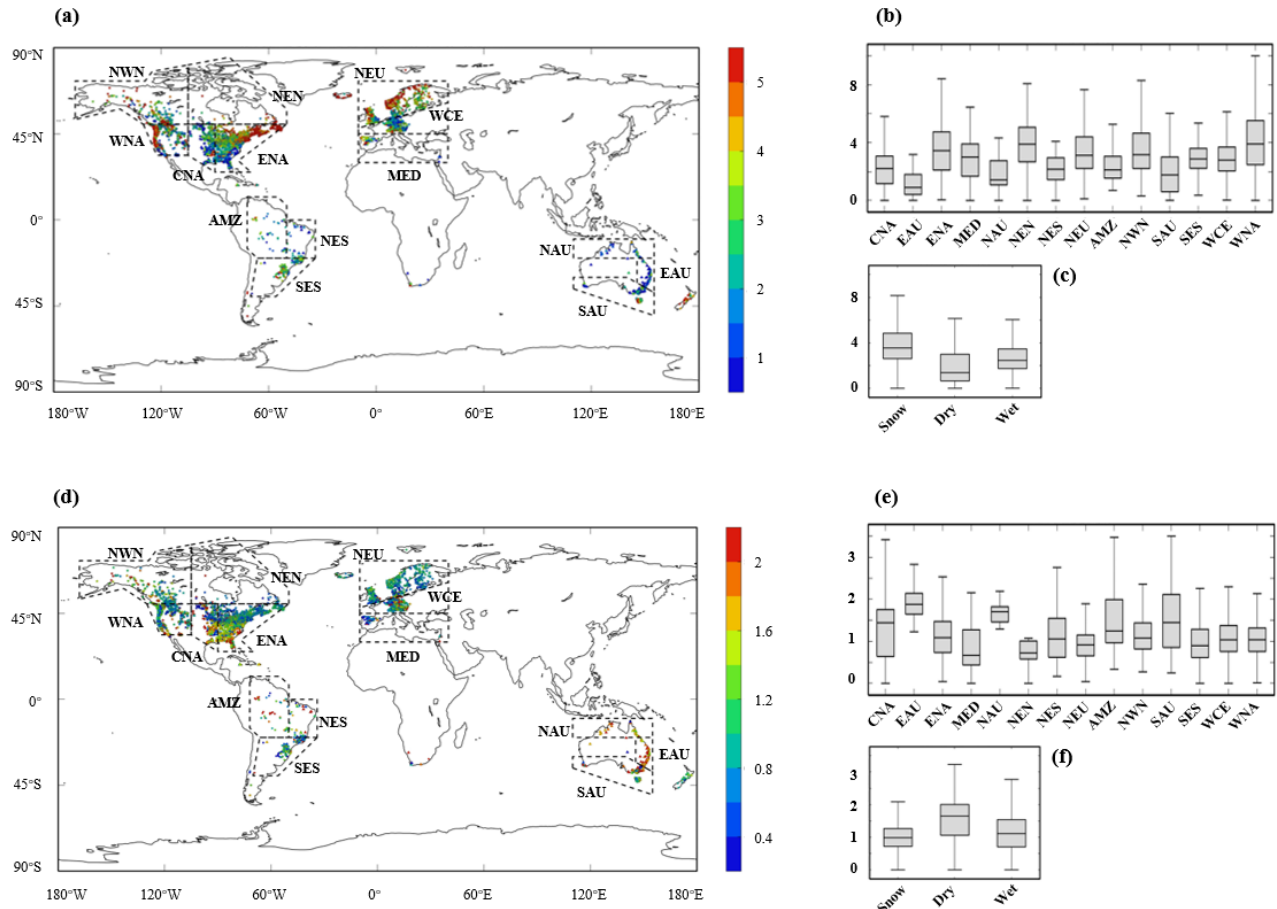


Figure 7. The spatial pattern of parameters of the power-law relationships between precipitation intensity and runoff efficiency. (a-c) for the parameter RE_{10} . (d-f) for the parameter m .

Table 2. Parameters and determination coefficients (R^2) of the power-law relationships between precipitation intensity and runoff efficiency across regions.

Region	CNA	EAU	ENA	MED	NAU	NEN	NES	NEU	AMZ	NWN	SAU	SES	WCE	WNA
RE_{10}	2.21	0.90	3.45	3.00	1.43	3.90	2.16	3.12	2.12	3.17	1.77	2.88	2.80	3.91
m	1.44	1.88	1.09	0.67	1.70	0.72	1.06	0.92	1.25	1.08	1.45	0.90	1.04	1.04
R^2	0.36	0.69	0.36	0.22	0.67	0.38	0.34	0.37	0.37	0.44	0.37	0.25	0.34	0.44

383 Through an interpretable machine learning approach, we revealed the factors driving the spatial variability of the
 384 process connectivity indicators across the globe (Fig. 4). For the runoff coefficient (RC), the dominant factors are aridity and
 385 mean annual precipitation. This finding aligns with previous regional investigations, which demonstrated that mean runoff
 386 coefficients are primarily governed by climatic factors, particularly the multi-year average of precipitation and the ratio of
 387 evapotranspiration to precipitation (Merz and Blöschl, 2009; Merz et al., 2006). Thus the climatic water–energy balance
 388 largely determines the average fraction of precipitation that transforms into runoff, consistent with the classical Budyko
 389 framework that a higher climatic aridity index increases the evaporative fraction (E/P) and reduces the runoff coefficient,
 390 leading to low runoff coefficients in dry areas and higher runoff coefficients in wet areas (Liang et al., 2015; Cheng et al.,
 391 2025; Cavalcante et al., 2019). **It is worth highlighting that snow-dominated catchments exhibit the highest multi-year mean**
 392 **RC , which is likely attributed to the generally lower evaporative losses and the reduced infiltration capacity in frozen or**
 393 **near-saturated soils (Lundberg et al., 2016). This finding is further supported by the importance of snow fraction in**
 394 **explaining spatial RC variations (Fig. 4a).** For the runoff intensity (RI), the dominant factors are the average duration and
 395 frequency of high-precipitation events, **suggesting that shorter and/or more frequent intense precipitation events tend to**
 396 **generate more temporally concentrated runoff events with shorter Δt_R and consequently higher RI values.** For the runoff
 397 efficiency (RE), the dominant factors are the multi-year average of precipitation, frequency of high-precipitation events, and
 398 seasonality of precipitation, indicating the rationality of this integrated connectivity metric that can capture both quantity and
 399 speed dimensions of runoff generation processes. **In terms of categorical attributions, the explainable machine learning**
 400 **reveals that climate-related attributes account for a substantial portion of the cross-catchment variability in RC , RI and RE ,**
 401 **suggesting that climatic water–energy availability acts as a first-order constraint on long-term runoff-generation connectivity**
 402 **at the global scale, while landscape characteristics (e.g., topography, soils and land cover) exert potentially region-specific**
 403 **regulatory effects. This finding is consistent with previous large-sample research on the dominant role of climate attributes in**
 404 **runoff generation processes (Jehn et al., 2020). It is also important to note that the strong climate gradients inherent in global**
 405 **datasets may mask subtler (yet process-relevant) controls from soils and geology characteristics that are frequently**
 406 **emphasized in field-based studies on the connectivity of the runoff generation process (Tromp-Van Meerveld and McDonnell,**
 407 **2006).**

408 By analysing long-term trends of the runoff generation connectivity indicators for runoff generation over 1950–2020,
 409 we identified several hotspots (Fig. 5). In general, trends in the RC and RI are highly coherent across most catchments
 410 worldwide, with regions experiencing increases in runoff transformation ratios tending to exhibit simultaneous increases in
 411 transformation intensity, and vice versa. Under the changing climate, the Amazon, southeastern and northeastern South
 412 America, central North America, and northern Australia exhibit pronounced increases in runoff generation connectivity. This
 413 might be attributed to the increases in occurrence frequency and magnitude of extreme precipitation events, which result in a
 414 greater fraction of precipitation being rapidly transformed into runoff (Donat et al., 2016; Harp and Horton, 2022). The

415 increasing connectivity brings larger event runoff volumes and higher peak discharges, and thus causes a greater **potential for**
416 **flood generation**. In contrast, the decreasing trends in runoff generation connectivity are found in western North America and
417 the Mediterranean, which might be attributed to the reduction of total precipitation and enhanced evaporation. Thus, there
418 are drier soils, lower runoff coefficients, and weaker runoff intensity, and consequently a reduction in average **potential for**
419 **flood generation** (Zhan et al., 2019). It is important to note that a lower connectivity does not guarantee complete safety, as
420 extreme events can still occur unexpectedly (Yan et al., 2025). Overall, the trends of the runoff generation connectivity offer
421 a process-based perspective on acceleration or deceleration of the global hydrological cycle and reveal how the spatial
422 pattern of **potential for flood generation** evolves in response to climate change.

423 At the event scale, we developed an empirical power-law model that quantifies the linkage between precipitation
424 intensity and runoff efficiency. Characterized by its simplicity and flexibility, this two-parameter model effectively captures
425 how runoff-generation connectivity evolves in response to precipitation intensity from weak to strong events. Across all
426 catchments, the mean coefficient of determination is around 0.37, indicating that precipitation intensity alone can explain a
427 substantial portion of the variability in runoff efficiency. Cross-climate analyses reveal that dry catchments exhibit a low
428 baseline runoff efficiency per unit precipitation intensity (RE_{10}), while exhibiting the highest sensitivity parameter m (Figs.
429 7c,f). This pattern implies that strong evaporation and infiltration losses keep low runoff-generation connectivity under
430 ordinary storms, whereas sufficiently intense events can temporarily exceed the soil infiltration capacity, causing the amount
431 and intensity of runoff to increase sharply and leading to an amplification effect to precipitation intensity ($m > 1$). In contrast,
432 wet catchments exhibit high baseline RE_{10} but low values for the sensitivity parameter m . Even small to moderate storm
433 events in these hydrologically saturated regions generate a relatively large fraction of runoff, and further increases in
434 precipitation intensity might not translate into proportional gains in runoff efficiency. This contrast reflects the fundamental
435 differences in runoff-generation mechanisms: runoff generation in dry catchments is typically dominated by the infiltration-
436 excess runoff with clear intensity thresholds, whereas it is more prone to saturation-excess runoff in wet catchments, where
437 near-saturated soils allow even modest storms to produce runoff, leading to high baseline efficiency but much smoother
438 changes with intensity. As the precipitation regime is projected to change under future climates (Song et al., 2024; Liu et al.,
439 2024), regional empirical relationships between precipitation intensity and runoff efficiency provide a practical way for
440 assessing shifts in runoff-generation connectivity, with potential applicability across the globe.

441 Our results show that **at the multi-year mean scale**, RE predominantly reflects a trade-off between RC and RI spatially.
442 Specifically, under long-term average hydrological conditions, catchments with high RC tend to exhibit relatively low RI ,
443 and vice versa (Fig. 3). This contrast highlights the long-term regulatory role of climatic conditions in shaping the process
444 connectivity for runoff generation, that is, water-abundant conditions tend to “win by quantity”, whereas water-limited
445 conditions “win by rate”, **revealing a fundamental compensatory balance between RC and RI . Besides, at the event scale, RE**
446 **exhibits a strongly nonlinear response to meteorological forcing within a given catchment, particularly marked by a**

pronounced amplification with increasing precipitation intensity. Specifically, our analysis reveals that *RE* increases nonlinearly with the intensity of individual precipitation events, where high-intensity storms produce substantially greater *RE* values compared with low-intensity events (Fig. 7). Such behaviour is difficult to detect in long-term averages, where the effects of individual events with varying intensities are smoothed out over time. This nonlinear amplification indicates that, during heavy storms, both the ratio and the rate of precipitation to runoff transformation increase simultaneously and substantially. This nonlinear amplification is likely attributed to the threshold effect inherent in the precipitation–runoff process. When precipitation intensity surpasses the soil’s infiltration capacity or storage thresholds of the underlying surface, excess precipitation rapidly produces overland flow, and the runoff connectivity is activated (Zhang et al., 2021). More precipitation could be transformed into runoff at a faster rate, causing a sharp increase in *RE*. Such threshold-triggered nonlinear responses in runoff generation have been reported in many previous studies (Detty and McGuire, 2010; Mahmood and Vivoni, 2011; Willgoose and Perera, 2001). Moreover, it should be noted that the *RE* is an integrated connectivity indicator for runoff generation, and a given *RE* value can result from different combinations of *RC* and *RI*. For instance, a high *RE* may stem from a scenario of high *RC* and low *RI*, or, conversely, from a scenario of low *RC* paired with exceptionally high *RI*. This multiplicity of pathways highlights that *RE* is not determined by a single factor but emerges from the nonlinear integration of catchment-specific connectivity and infiltration processes. It is necessary to comprehensively use these indicators for characterising the connectivity of the runoff generation to improve our understanding of how the water cycle responds to the changing climate from a process perspective.

It is also important to acknowledge the limitations of our study. First, our analysis only relies on a single conceptual rainfall–runoff model with its own assumptions and simplifications, which may not be universally applicable across the diverse range of global catchments and introduces structural uncertainty (Parasuraman and Elshorbagy, 2008). Although parameter calibration and performance screening have already secured a reasonable level of accuracy, future work could be done for ensembling hydrological models to better capture runoff-generation processes and to enhance the robustness of the results (Solanki et al., 2025). Second, the selected catchments exhibit uneven spatial distribution across regions and climate zones, a limitation that could undermine the representativeness of data-sparse areas. Although median-based summaries can reduce the effects of uneven spatial distribution, interpretation of the regional results from these underrepresented areas should be cautious. More data from the available hydrological stations would enable more refined and robust regional analyses. Third, uncertainties also exist in the identification and matching of rainfall–runoff events. Runoff events are currently defined to end when simulated quickflow returns to zero, yet in humid catchments, slow recession and structural biases from baseflow separation and model simulation may prevent strict zero-flow conditions, potentially causing event splitting or merging. In addition, the 0.1 mm d⁻¹ threshold employed to delineate rainfall events is an empirical truncation criterion that may alter event boundaries, especially under hydroclimatic extremes. Moreover, rainfall–runoff matching relies on the DCMA-based lag window and the assumption that the rainfall-event centroid falls within that window; this assumption may be violated by nonlinear responses, particularly for long-duration and low-intensity events, thereby

introducing matching errors. These uncertainties potentially affect event-scale identification and matching to some degree, but are expected to be partially mitigated in our analysis of multi-event averages and large-scale spatial patterns. Finally, the empirical power-law relationship developed here does not exactly account for event total precipitation depth and antecedent soil moisture, which can influence runoff-generation connectivity by governing storage filling and the expansion of saturated contributing areas, particularly in wet catchments where saturation-excess runoff is more prevalent (Zhang et al., 2021). Two storms with similar precipitation intensities can produce significantly different runoff efficiencies. For instance, a storm following a prolonged dry period generally tends to produce lower efficiency compared to one occurring under wet antecedent conditions. Since future climate change is projected to alter both the distribution of precipitation characteristics and soil moisture conditions (Yao et al., 2025), the empirical relationship calibrated under current conditions is likely to become invalid under future climate scenarios. These acknowledged limitations and uncertainties will be addressed and mitigated in future work.

6 Conclusions

A novel framework has been developed for assessing process connectivity in runoff generation through intensity integration. The *RC* and *RI* are adopted to represent the transformation ratio and rate from precipitation to runoff, respectively, and a composite metric *RE* is proposed to characterise process connectivity in runoff generation across both dimensions. Applying this developed framework to 6,603 catchments globally over 1950–2020, we quantify the spatial patterns of process connectivity, figure out their climatic and landscape controls using interpretable machine learning, and examine their long-term trends and event-scale responses to precipitation intensity. According to the long-term average values of the metrics, we find a relatively high *RC* and *RI* in wet and dry areas, respectively, highlighting a compensatory balance between the transformation ratio and rate across climates. Interpretable machine learning further reveals that climatic attributes, especially aridity, mean annual precipitation, average duration and frequency of high-precipitation events, and the seasonality of precipitation, primarily control the process connectivity indicators at the global scale. The analysis of long-term trends reveals a synergy of transformation ratio and rate, with the hotspots of increasing process connectivity are Amazon, southeastern South America, central North America, northern Australia, and northeastern South America, suggesting a larger event runoff volume and higher peak discharge, and thus a higher potential for flood generation, while hotspots of decreasing process connectivity are found in western North America and the Mediterranean, with relatively lower potential for flood generation. Event-scale analysis reveals that across all selected catchments, the *RC*, *RI*, and *RE* for events with the highest peak discharge quantiles are three times, four times, and 11 times higher than corresponding values for events with the lowest peak discharge quantiles, respectively. We further establish an empirical power-law relationship between precipitation intensity and *RE* and find a high sensitivity under dry climates, indicating the nonlinear amplification effect of runoff generation in water-limited regions during intense storm events. Overall, our proposed process-connectivity framework, integrated both the transformation ratio and rate from precipitation to runoff, offers a novel and multi-dimensional perspective to understand spatiotemporal variations in the runoff generation process. And the framework allows

513 for extension to other critical processes in the global hydrological cycle, including precipitation recycling and runoff routing
514 dynamic processes.
515

516 **Code and data availability**

517 The Caravan dataset (Kratzert et al., 2023) can be accessed publicly via <https://zenodo.org/records/7540792>. The Random
518 Forest algorithm was implemented using the Python scikit-learn library, which is available at <https://scikit-learn.org/stable/>.
519 The code for computing accumulated local effects (ALE) can be obtained from <https://github.com/DanaJomar/PyALE>.

520 **Author contributions**

521 HL designed the model architecture, performed the computations, conducted the statistical analysis, and drafted the
522 manuscript. DL acquired funding, contributed to the study design, provided research data, supervised the project, and guided
523 the manuscript revision. JZ contributed to manuscript revision discussions and provided advice on submission procedures.
524 FY and YZ participated in revision discussions and contributed to figure and chart preparation. All authors reviewed and
525 approved the final version of the manuscript for submission.
526

527 **Competing interests**

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

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