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Characterising runoff processes for Australia: Insights from a parsimonious rainfall-runoff event identification method

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Abstract. Rainfall-runoff events are widely used in hydrological applications, from flood estimation and flood forecasting, to understanding catchment responses in a climate/anthropogenic affected world. The majority of methods used to identify rainfall-runoff events are statistical in nature, relying on subjective, user-defined 'rules' (i.e., parameters) that define a rainfall-runoff event. Since no ground-truth information is available to confirm the exact beginning and end of rainfall-runoff events, there is noticeable inconsistency (i.e. uncertainty) within the results. In this study, we propose the Robust Variance-based Event Identification Method (RVEIM), a new parsimonious rainfall-runoff event identification method which uses fewer parameters and better mimics the natural runoff generation process; decreasing the uncertainty in rainfall-runoff event identification. RVEIM detects runoff events by focusing on changes of streamflow variance and pairs to the corresponding rainfall event(s) simultaneously. RVEIM was compared to a benchmarking event identification method in 8 representative catchments in Australia. A sensitivity analysis was performed using a comprehensive set of plausible event identification parameter values for both methods. Results revealed that the variation of rainfall-runoff events characteristics – including annual number, length of runoff events, and the mean volume of runoff events – showed limited uncertainty from the RVEIM (standard deviation within ±15% of the mean across 8 representative Australian catchments). This demonstrates robustness of RVEIM, while the benchmarking method exhibited considerably greater uncertainty in the event characteristics, with coefficients of variation exceeding 23% and more than an order of magnitude difference across catchments. Using RVEIM, we present the first comprehensive summary of rainfall-runoff event characteristics across 467 Australian catchments. The distribution of event-scale runoff coefficients for individual catchments shows a strong climate gradient. Such systematic shifts in the distribution of runoff coefficient across climate regions indicate that climate variables play an important role in catchment response and point to potential contrasts in dominating runoff generation mechanisms across climate zones.

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1 Introduction

Event-based rainfall-runoff analyses provide insights into the catchment response and promote the understanding of streamflow processes (Fischer & Schumann, 2024); Tang and Carey (2017); (Tarasova et al., 2020; Tarasova, Basso, Zink, et al., 2018; Wasko & Guo, 2022). Streamflow and rainfall timeseries are analysed to identify independent events, which are then paired to characterize rainfall-runoff events. Characteristics such as the number, duration, volume, Runoff Coefficient (RC, the ratio of rainfall contributing in runoff) are commonly assessed to understand rainfall-runoff relationships and the dynamics of catchment responses. Event-based rainfall-runoff analyses have hence been widely used to explore hydrological processes and to assess the impact of both anthropogenic and climatic change (Chen et al., 2020; Ho et al., 2022; Hu et al., 2021; Merz & Blöschl, 2009; Sillanpää & Koivusalo, 2015; Sriwongsitanon & Taesombat, 2011; Wang et al., 2012; Wu et al., 2025).

For example, Tarasova, Basso, Poncelet, et al. (2018) used rainfall-runoff event identification methods to recognize regional patterns of rainfall-runoff events in Germany. Their results showed that subsurface properties significantly contribute to runoff response. Merz et al. (2006) identified rainfall-runoff events and analysed RCs across Austria. They showed that the RC is spatially correlated with mean annual precipitation, soil type, and land use. By analysing rainfall-runoff events characteristics, Merz et al. (2006) also reported that the RC is a function of current and previous rainfall event. Similarly, Rahi et al. (2023) studied the trends of RCs and its drivers in Upper Tiber basin, Italy. They showed that RC has experienced a decreasing trend from 1927-2020 while the air temperature has increased. They also noted that, among hydroclimate variables, RC showed the strongest correlations with soil water storage. In China, Chen et al. (2007) reported that annual RC is positively correlated with precipitation and negatively correlated with temperature in the Huanghe River basin. Ho et al. (2022) further showed that the RC of flood events in Australia exhibit regionally varying trends under climate change. Together, these studies highlight the utility of event-based analysis in identifying regional hydroclimatic patterns, catchment runoff drivers, as well as detecting long-term changes in rainfall–runoff dynamics.

Several rainfall-runoff event identification methods have been proposed in the literature (Fischer et al., 2021; Giani et al., 2022; Kaur et al., 2017; Koskelo et al., 2012; Merz et al., 2006; Tang & Carey, 2017; Tarasova, Basso, Zink, et al., 2018). Table 1 shows a summary of developed method for identifying rainfall-runoff events. Rainfall-runoff event identification often involves separating baseflow, detecting rainfall and runoff events, and then pairing the corresponding rainfall events to runoff. In some cases, methods simultaneously detect and pair rainfall-runoff events (Giani et al., 2022). Rainfall-runoff event identification methods generally follow a pre-defined statistical framework, which relies on using parameters to specify rules to define individual events. Using statistical techniques with predefined parameters automates rainfall-runoff event identification which is beneficial when dealing with long records as well as large-scale analysis. For example, when detecting runoff events, a threshold parameter is typically used to filter out small runoff events in runoff event detection methods (Kaur et al., 2017; Tang & Carey, 2017). Or in some runoff event detection methods, a time interval parameter is used to ensure the independency of two consecutive peaks (Merz et al., 2006; Wasko & Guo, 2022). Pairing rainfall and runoff events also incorporates parameters. Pairing procedures are usually performed by applying a search window with the start of search, the

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search window length, and the searching direction (e.g., whether events are matched from runoff to rainfall or vice versa) all act as parameters (Wasko & Guo, 2022). Selecting appropriate parameter values for rainfall-runoff event identification is complicated because of the absence of direct measurements for baseflow and quickflow (i.e. runoff). The lack of reliable 'ground truth' data makes the choice of parameter value subjective, relying on expert judgment or site-specific calibration (Tang & Carey, 2017; Wasko & Guo, 2022). Although tracer studies can facilitate the estimation of baseflow values, they are expensive and not applicable for large scale analysis (Mei et al., 2024). There are usually some recommendations proposing a suitable range for parameter values (Nathan & McMahon, 1990), however, sensitivity analysis show that changes in the parameter value (i.e. 'rules'), even in valid parameter range, can significantly affect the rainfall-runoff events characteristics (Giani et al., 2022). For example, Wasko and Guo (2022) found that changes in pairing rules, pairing from runoff to rainfall and vice versa, can affect the selection of rainfall and runoff events to be paired. Therefore, changing pairing rules affects characteristics of resulted rainfall-runoff events and significantly impacts RCs in a catchment. Current rainfall-runoff event identification methods usually use multiple parameters with no standard guideline on selecting parameter values resulting in large uncertainties in the events identified magnitudes (Mohammadpour Khoie et al., 2025). From here on in, we refer to the differing rainfall-runoff event identification due to differing parameter values as the 'uncertainty' of rainfall-runoff identification.

Table 1. A summary of literature of developed methods for identifying rainfall-runoff events

Developer	Method description		Application area
	Runoff detection	Rainfall-runoff pairing	
Merz et al. (2006)	Runoff events identified on direct runoff using peak ratio.	Linear-reservoir model fitted to estimate runoff coefficient.	337 catchments in Austria
Metcalfe and Schmidt, 2016	Runoff events are detected based on peaks over a specific threshold. The difference between a peak and the neighboring valley is used to ensure about the independency.	-	-
Tang and Carey, 2017	Local minima values are firstly recognized as valleys. The absolute difference between valleys is used to confirm termination of runoff events. The time difference between valleys is used to ensure independence of runoff events.	Pairing is optional using a backward search window.	Scotland (1 catchment) United Kingdom (1 catchment) Canada (1 catchment)
Kaur et al., 2017	Runoff events are detected based on the falling of baseflow index bellow a threshold.	-	Yarra River, Australia
Tarasova et al. (2018)	A modified baseflow filter is used to separate baseflow from streamflow. Streamflow and baseflow end points are considered as starts and ends of runoff events.	Rainfalls occurring with specific distance before the identified runoff event are considered as the contributing rainfall.	185 catchments in Germany

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	Ratio of peak to baseflow		
Fischer et al. (2021)	A variance-based method is used to detect sudden streamflow movements.	A search window is used to search backward from the start of detected runoff event.	7 catchments in Germany
Giani et al. (2022)	Detrending Moving-average Cross-correlation Analysis (DMCA) Detects runoff events based on rainfall events		9 catchments in Great Britain

For a single catchment, a given parameter value used for event identification may bias towards a limited range of event magnitudes (Mohammadpour Khoie et al., 2025). For example, selecting larger threshold leads to detecting large runoff events only (Leenman et al., 2023). The limited representation of rainfall-runoff events over their full range of magnitudes prevents comprehensiveness in understanding catchment response. Appropriate parameter values vary across climatic regions, limiting transferability (Giani et al., 2022; Merz & Blöschl, 2009). For instance, when using a time parameter to separate independent runoff events, users may need to specify lower values for regions with shorter runoff events, and a purely statistical runoff event detection method may split a multi-peak runoff event into two independent runoff events under some settings. Runoff event detection and rainfall–runoff pairing are also usually performed as two separate steps, which increases the likelihood of mismatched events leading making unrealistic results, leading to rainfall-runoff events with RCs ≥ 1 which are physically implausible (Mohammadpour Khoie et al., 2025). Moreover, pairing is often conducted using a time-invariant search window, a simplification that does not reflect the underlying physical processes. To address the challenges in rainfall–runoff event identification, a transferable method that integrates conceptual understanding of rainfall–runoff processes with statistical techniques is needed. Such a method should provide consistent event detection across parameter choices and enable large-scale event-based streamflow analysis.

This study presents a novel, robust and transferable rainfall-runoff event identification method building on the runoff event definition proposed by Fischer et al. (2021). We extend the definition proposed Fischer et al. (2021) which uses streamflow variance to detect sudden streamflow movements to pairing runoff events to rainfall in a parsimonious way. The novelty of our methods lies in 1) the method only relying on two parameters; 2) the method simultaneously detecting independent rainfall events and pairing them to runoff events, and 3) using a time-variant search window for pairing, which together improves robustness and transferability of rainfall-runoff event identification. We test the proposed rainfall-runoff event identification method with a benchmarking method across catchments with diverse hydro-climate condition in Australia. We demonstrated that the proposed rainfall-runoff event identification method leads to noticeably lower percentage of RCs better reflecting physical processes. Finally we apply our proposed method across Australia to characterise rainfall-runoff processes across natural catchments.

2 Data

Here we use 467 Australian catchments which encompass a diverse set of hydrologic and climate conditions. These catchments were identified by the Australian Bureau of Meteorology's as Hydrologic Reference Stations (HRS) (Bureau of Meteorology,

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2025c) as unregulated with minimal water resources development and land use change (Fig. 1). Located across the Australian continent the HRS catchments provide us with comprehensive data to compare rainfall-runoff relationships and test our proposed method for a wide range of hydro-climatic conditions. Daily recorded streamflow data at the outlet of each of the 467 catchments (in megalitre per day) were obtained for each of the HRS. The streamflow record at each station span at least 30 years extended through February 2024 (Bureau of Meteorology, 2025c). This dataset presents the highest quality long-term streamflow records in Australia which are widely used for large-sample hydrologic studies and assessing climate change-driven variability in streamflow (Amirthanathan et al., 2023; Guo et al., 2020; Wasko & Guo, 2022). Missing data accounts for less than 5% and were infilled using GR4J model (Bureau of Meteorology, 2025c). Infilled flows make up < 10% of the total volume at each location, and < 25% of the total flow volume are flows produced using extrapolated rating curves (Bureau of Meteorology, 2025c). Here we divide the recorded streamflow by the catchment area to have units of mm/day, consistent with the rainfall data.

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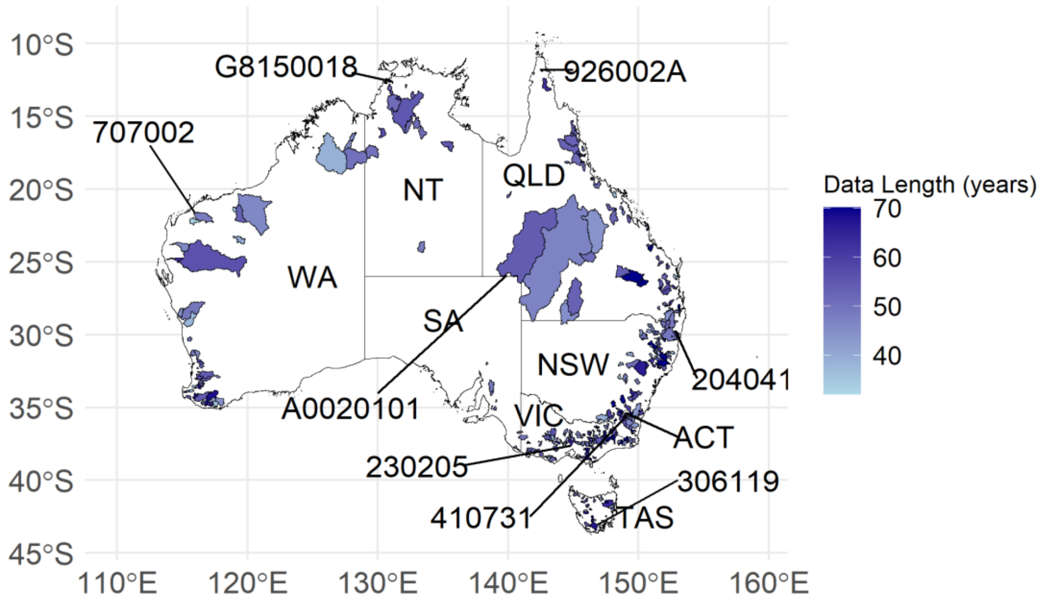
(a)



(b)

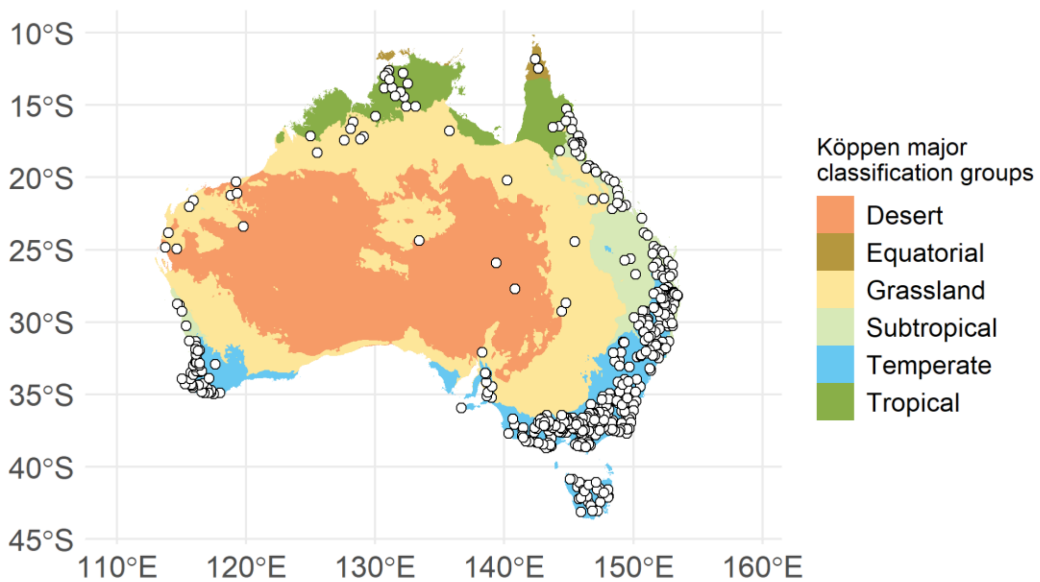


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Figure 1. a) Location and streamflow record length for the 467 HRS catchments over Australia within different states and territories (WA: Western Australia, NT: Northern Territory, QLD: Queensland, NSW: New South Wales, ACT: Australian Capital Territory, VIC: Victoria, TAS: Tasmania, SA: South Australia) b) location of the 467 catchment outlets within various climates as defined by the Australian Köppen classification in (Stern et al., 2000). There are 7 sites in desert, 2 sites in equatorial, 23 sites in grassland, 58 sites in subtropical, 345 sites in temperate, and 32 sites in tropical regions. The 8 site IDs and arrows label the representative catchments selected across Australia for more detailed analyses.

Daily rainfall records (mm) were sourced from Australian Water Availability Project (AWAP), which provides a high-quality gridded rainfall product at a resolution of 0.05°x0.05° (approximately 5km x 5km) (Jones et al., 2009). AWAP has been extensively applied in Australian studies examining long-term, climate-driven trends (Jones et al., 2009) and is largely unbiased for calculating catchment average rainfall (Nathan et al., 2016; Nathan & McMahon, 2017; Wasko et al., 2023). Catchment averaged rainfall values were computed using the "AWAPer" R package (Peterson et al., 2020). In this study, rainfall represents the total accumulated precipitation (including rain, snow, hail, and dew) because rainfall dominates total precipitation in the study region, in line with the terminology used in the development of the AWAP (Jones et al., 2009).

From the 467 HRS catchments we selected 8 representative catchments across the continent to represent different climatic zones and geographic regions (represented by states). There are more selected catchments within the temperate climate zone because most HRS catchments are within this zone. The information for the selected catchments is presented in Table 2. The selected catchments are intended to spread across the continent as well as representing contrasting hydroclimatic and catchment-specific characteristics for testing the robustness of the proposed rainfall-runoff event identification methodology.

Table 2. Hydroclimate and catchment-specific characteristics of selected catchments

State/Territory	Station ID	Climate	Catchment area (km^2)	Mean annual temperature (°C)	Mean annual rainfall (mm)	Mean annual streamflow (mm)
SA	A0020101	Desert	119034.0	24.2	289.1	0.0
WA	707002	Grassland	7263.0	26.1	389.5	0.0
VIC	230205	Temperate	858.7	12.9	699.1	0.2
ACT	410731	Temperate	671.6	9.9	869.9	0.2
NSW	204041	Subtropic	1807.0	18.3	1366.2	1.2
TAS	306119	Temperate	1824.0	9.2	1625.0	3.9
QLD	926002A	Equatorial	333.3	26.5	1628.0	1.9
NT	G8150018	Tropical	95.6	27.5	1637.4	1.8

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3 Methodology

3.1 The Robust Variance-based Event Identification Method (RVEIM)

We have named the proposed rainfall-runoff event dentification method the Robust Variance-based Event Identification Method (RVEIM). RVEIM adopts the definition of runoff event from Fischer et al. (2021) who defined runoff event as “a temporally limited exceedance of normal discharges”. Similar to Fischer et al. (2021), we used a moving window to estimate streamflow variance, which is used to identify sudden movement of streamflow. However, RVEIM adopts a different approach to detect runoff events beyond Fischer et al. (2021) by detection and pairing rainfall-runoff events while only using two parameters. Figure 2 present a flowchart of the developed method. Each major and minor step is explained in detailed in the following sections.

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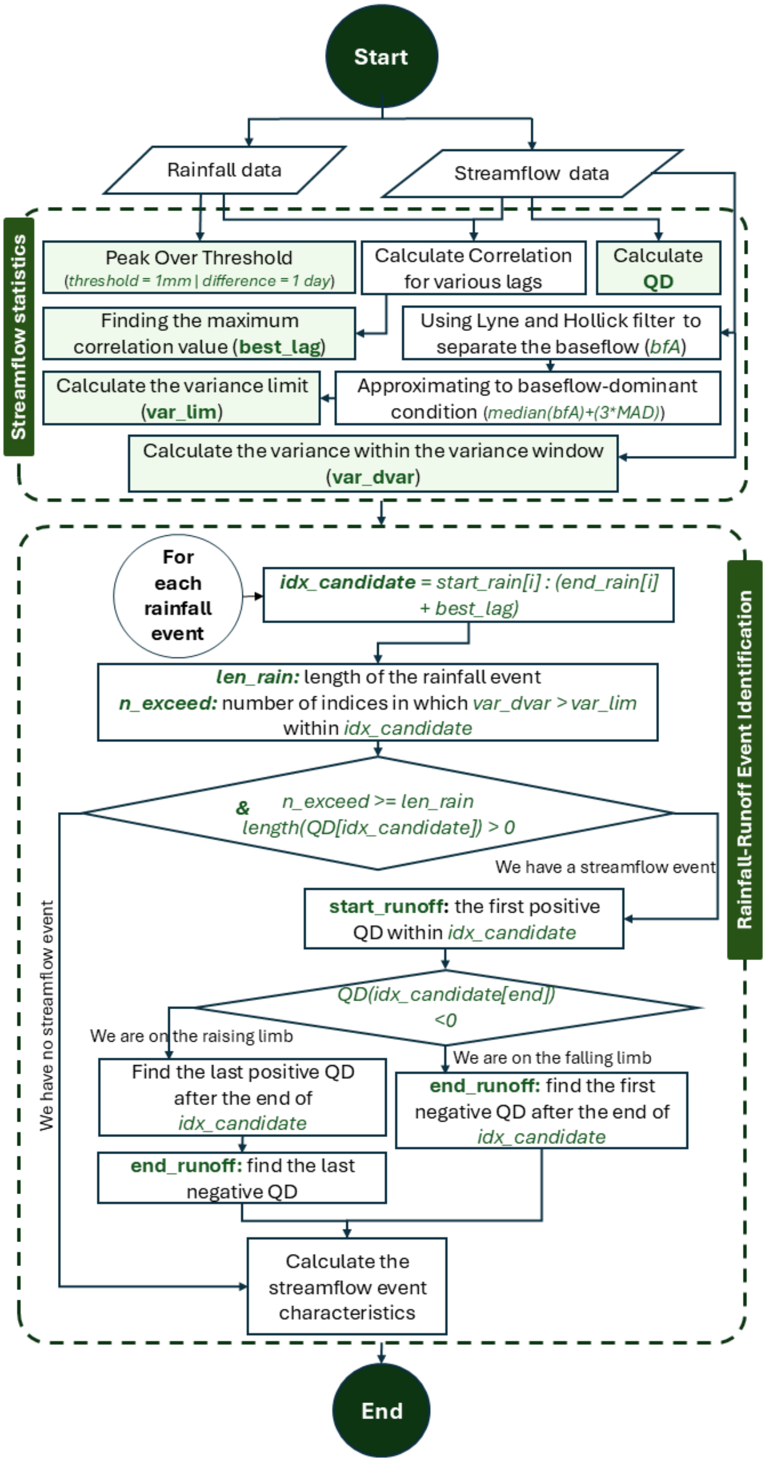

145 **Figure 2. Flowchart of the RVEIM for identifying rainfall-runoff events**

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3.1.1 Streamflow statistics calculations

RVEIM detects runoff events when the streamflow time-series shows sudden short-term variation that clearly exceeds "normal" conditions. We defined "normal" conditions as the condition when baseflow is mostly contributing to streamflow (negligible runoff contribution). As such, prior to detecting runoff events and pairing them to corresponding rainfall, some statistics of the streamflow should be calculated. These RVEIM statistics include calculating the moving variance, flow deviation and variance threshold of streamflow, and cross-correlation between rainfall and streamflow. The first three statistics are needed for runoff event detection, and the last is necessary for the subsequent rainfall-runoff event pairing.

1. *Moving variance window.* A moving variance window is employed to estimate the short-term variance of streamflow over time (Fischer et al., 2021). By doing so, it captures temporal fluctuations in streamflow variance, providing a dynamic assessment of variability. The length of the moving variance window is controlled by the parameter *d_var* (as the first parameter of RVEIM) which determines the number of observations included in each calculation.

2. *Streamflow gradient.* (QD) plays a role in defining the start and the end of runoff events. Therefore, before runoff event detection and pairing, the QD is needed to be calculated by simply subtracting the streamflow in the current time step from the previous time step as shown in Eq. (1).

$$QD_i = Q_i - Q_{i-1} \tag{1}$$

where Q indicates on daily streamflow value, and i and $i\text{-}1$ indicate on the current and the previous timesteps. Note that QD_1 cannot be defined as there is no streamflow record before the first time-step.

3. *Cross-Correlation*. A runoff event is paired to the corresponding rainfall event based on a time-varying search window which is controlled by the maximum cross-correlation between the rainfall and streamflow timeseries and the length of the rainfall event (Eq. 2). The *best_lag* physically represents the average time needed for rainfall to reach at the main channel, thus the average time between the start of a rainfall event (as shown in a hyetograph) and the start of a runoff event (as shown in a hydrograph).

$$length(search\_window_j) = best\_lag + l\_rainfall_j \tag{2}$$

where j is the counter of rainfall events and *l_rainfall* is the length of rainfall event.

4. *Variance threshold.* We defined a threshold for moving variance (*var_lim*), to consider any short-term variance of streamflow below as "normal" streamflow (i.e. exceedance as a runoff event). We propose an approach that is easy transferable to other catchments. To find the variance of baseflow-dominated condition, we firstly used V. Lyne and M. Hollick (1979) baseflow filter to extract the baseflow timeseries from the total streamflow timeseries. This baseflow filter is widely used in the literature (Wasko & Guo, 2022) and has a parameter called filter parameter (*alpha* – the second parameter of RVEIM). Since baseflow increases during a runoff event, the separated baseflow should be processed to identify the non-event portion of baseflow. To exclude event-influenced high-flow parts, we removed parts of baseflow that are larger than

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limit which was estimated to the upper bound of baseflow under normal conditions. Specifically, the Median Absolute Deviation (MAD) of baseflow (Eq. 3 and 4) was used:

$$MAD = median\big(abs(baseflow - median(baseflow))\big) \tag{3}$$

$$limit = median(baseflow) + 3 * MAD \tag{4}$$

Then, the variance of baseflow values below limit is considered as the threshold below which the local variance of streamflow is considered as "normal" flow.

$$var\_lim = variance(baseflow < limit) \tag{5}$$

Although this process in Eq. 3 and 4 is known as "outlier" removal, we use it for approximating to baseflow-dominant condition. The variance of baseflow values below *limit*, which we considered as representative of baseflow-dominated condition, is considered as the threshold. Figure 3 shows the process of obtaining *limit* for catchment "230205" in the subtropical region from the streamflow timeseries.

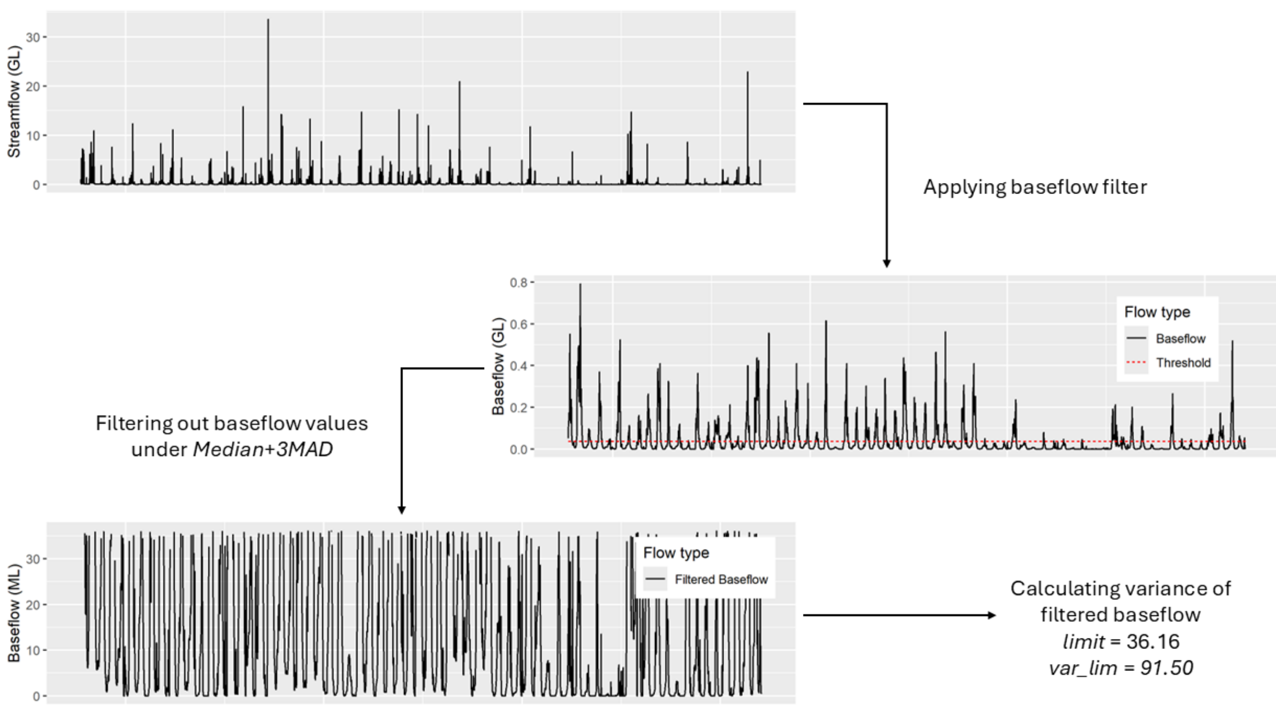

Figure 3. The process of obtaining the *var_lim*

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3.1.2 Runoff event detection and pairing

Runoff event detection and pairing start after detecting rainfall events. We apply the widely used Peak Over Threshold (POT) approach for detecting independent rainfall events. Two parameters are associated in POT including the threshold above which a rainfall amount is meaningful and the minimum time difference between two successive events (Wasko & Guo, 2022). Numerous studies have confirmed that POT with 1 mm threshold and 1 day minimum difference is appropriate to identify rainfall events with daily data (Ashcroft et al., 2019; Wasko & Guo, 2022; Zhang et al., 2011). In contrast to most rainfall-runoff event identification methods, RVEIM detects and pairs runoff events simultaneously. For each rainfall event, a search window is specified to search for a probable corresponding runoff event. The search window is the summation of *best_lag* and the length of rainfall *l_rainfall* (i.e., *best_lag* + *l_rainfall*) and starts from the beginning of the rainfall event (see dashed vertical lines in Fig. 4). After defining the length of the search window, for the current rainfall event, the method searches for any sign of streamflow movement. So, unlike most pairing strategies, the strategy here does not search for the peak of runoff event within the search window. In the search window, if the length of streamflow records which exceed *var_lim* is greater or equal to the length of rainfall, the first positive *QD* represents the start of the runoff event (see the start of bold line of streamflow for both events in Fig. 4). Otherwise, there is no runoff event in the search window. For any rainfall event, if the search window overlaps with a previously detected and paired runoff event, the start of the search window will be modified to the end of the runoff event without any modification of the end of the search window (compare shaded area and dashed vertical lines in second runoff event in Fig. 4). To specify the end of the runoff event, the last streamflow record of the search window should be checked. If the *QD* of the last streamflow record is negative (first runoff event in Fig. 4), theRVEIM moves forward to find the last negative *QD* (it assumes being on the falling limb, so continues to find the end of falling limb). Otherwise (see the second runoff event in Fig. 4), it continues to find the peak and then the last negative *QD*. After finding the start and the end of the runoff event, the volume of runoff is calculated by subtracting the volume of baseflow from streamflow in the event duration.

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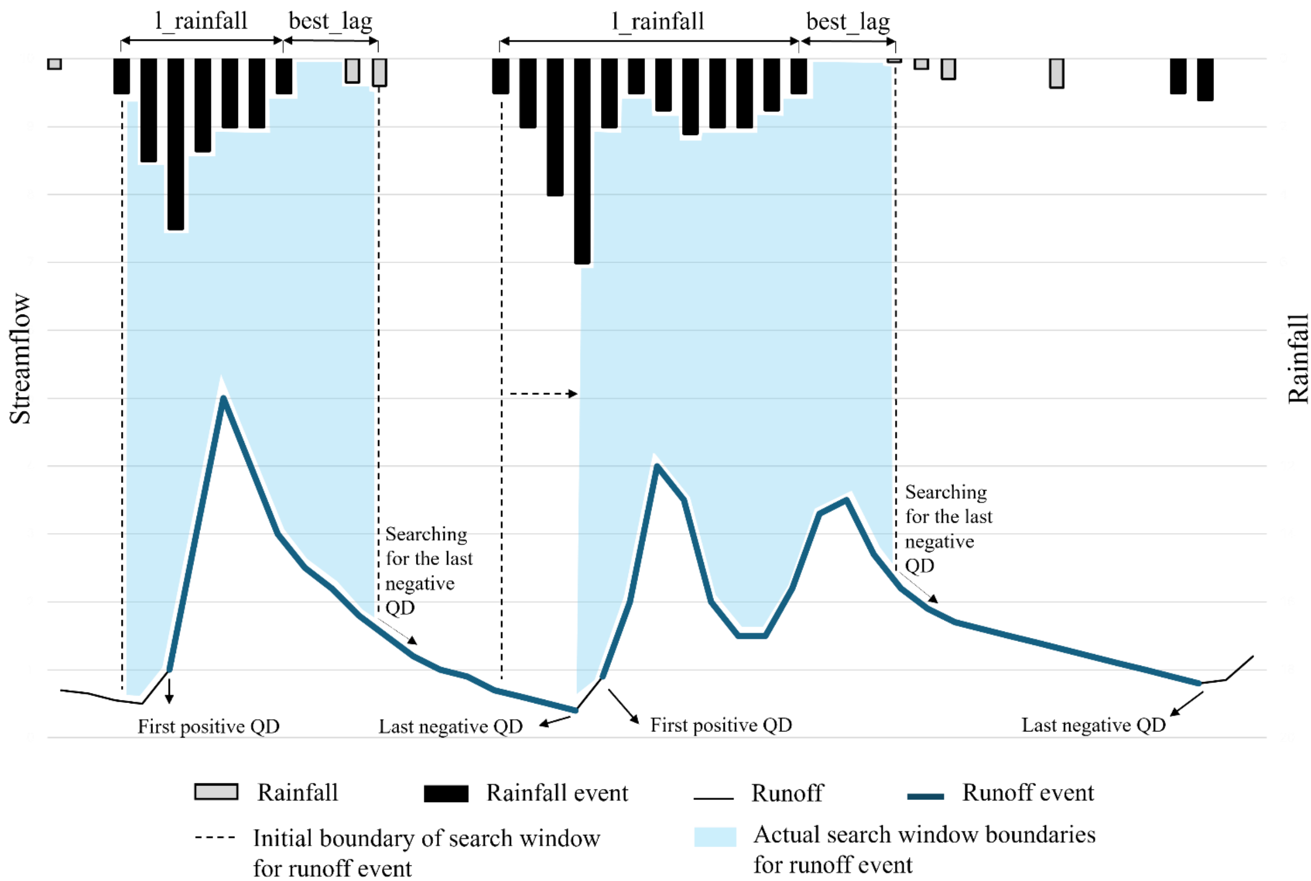

215 **Figure 4. Schematic of the event identification and pairing procedure**

3.2 Benchmarking the rainfall-runoff event identification

To demonstrate the advantages of the RVEIM, we compare our results with an existing method. Since there are numerous rainfall-runoff event identification methods we benchmark against a most commonly used method which uses local maxima to identify events before pairing the streamflow to the driving rainfall. Following the recommendation by Mohammadpour Khoie et al. (2025) which compared event identification methods, the “local maxima” method generally had less uncertainty in its outputs; and as such, we benchmark our new method with the local maxima method. To detect runoff events, the local maxima method firstly detects local maximum values in streamflow/runoff timeseries. Then, by comparing each peak with the next valley it decides about a new runoff event: if the difference between a peak with the next valley is higher than a user-defined value (*delta.y*), a new runoff event is detected. Otherwise, the peak is part of a multi-peak runoff event. To filter out small runoff, the local maxima method considers a minimum t*hreshold* above which runoff is considered. A minimum spacing between two consecutive runoff events (*delta.x*) is considered to ensure independency of runoff events.

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Baseflow separation is usually used before detecting runoff events to separate runoff (i.e. quickflow – the part of streamflow which directly comes from rainfall) and baseflow. In this regard, the V. Lyne and M. Hollick (1979) baseflow filter is widely used in the literature (Ho et al., 2022; Kemp & Alankarage, 2023; Ladson et al., 2013; Miao et al., 2020; Wasko & Guo, 2022). The filter separates baseflow with the help of a parameter called the "filter parameter". The filter parameter varies between 0 and 1 and defines how the digital filter should respond to streamflow variation. Lower values of the filter parameter indicate on a quicker response to streamflow changes. Nathan and McMahon (1990) investigated the best choice of filter parameter. They showed the range of 0.9-0.95 for filter parameter works better and recommended the value of 0.925 for the better performance of the filter.

The benchmarking approach performs rainfall-runoff event pairing after both rainfall and runoff events are detected. The pairing uses a search window to pair each rainfall to a corresponding runoff event. The benchmarking approach included five pairing strategies which are different in their directions and start points used for searching. Pairing type 1 searches from the start of rainfall event to the peak of runoff event. Pairing type 2- searches from the start of rainfall event to the end of runoff event. Pairing type 3 searches from the peak of runoff event to the peak of rainfall event. Pairing type 4 searches from the start of runoff event to the start of rainfall event. Pairing type 5 searches from the peak of rainfall event for the peak of runoff event both forwards and backwards. The pairing type and length of search window (*lag*) are both user-specified.

3.3 Evaluation

To assess the uncertainty associated with parameter value selection in both the RVEIM and local maxima event identification methods, a sensitivity analysis is performed for the sites representing different climates and regions listed in Table 1. A plausible range is specified for each parameter for each rainfall-runoff event identification method. Then, random samples within the parameter range are drawn and used for identifying rainfall-runoff events. The changes in characteristics of rainfall-runoff events are then analyzed to understand the uncertainty in event detection due to parameter change. The characteristics here are the volume of paired runoff events, the number of rainfall-runoff events, and the RCs. We compare the percentage of RCs ≥1 since this implies physically implausible rainfall-runoff events. We also estimate the ECDF of RCs for each sampled parameter set and then across each catchment considering the 95% confidence interval (between 2.5th percentile and 97.5th percentile).

Two parameters are associated with the development of RVEIM: the length of the moving variance window, *d_var* (Section 3.1.1) and the filter parameter of the baseflow digital filter, *alpha*. For the benchmarking local maxima event identification method five parameters were varied, the *Threshold*, *delta.x*, *delta.y*, pairing type, and pairing *lag*. Here the sensitivity of the local maxima event identification to the baseflow separation parameter *alpha* is not assessed since baseflow separation is performed in a prior step to event identification. However, baseflow separation is embedded in the event detection and pairing process for RVEIM. Nathan and McMahon (1990) investigated the appropriate range for the filter parameter used in Vincent Lyne and M. Hollick (1979) baseflow separation method. They found that values within 0.9 to 0.95 work better for this

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baseflow separation method. Hence, we used this range when assessing uncertainty of RVEIM (Table 3). They recommended the value of 0.925 within the mentioned range which is used when separating baseflow in the local maxima method.

To specify a plausible range for the length of moving variance window (Section 3.1.1) we used the range of 3-10 days. The maximum 10 days was chosen to capture the temporal variability of runoff events without excessively smoothing the data. This range is was informed by the range specified by Fischer et al. (2021) which proposed another variance-based runoff event detection method. Parameter ranges presented in Table 1 for local maxima are informed by Mohammadpour Khoie et al. (2025) based on the dynamics of streamflow in different climate zones. We used 300 samples (i.e., parameter sets) for RVEIM and 600 samples for local maxima to properly cover the parameter space for each method.

Table 3. Ranges considered for parameters in each method for selected catchments

Station ID	RVEIM		Local maxima				
	alpha	*d_var*	*threshold* (ML)	*delta.y* (ML)	*delta.x* (days)	pairing type	*lag* (days)
A0020101	0.9 to 0.95	3 to 10	0 to 5	0 to 30	1 to 10	1 to 5	1 to 7
707002	0.9 to 0.95	3 to 10	0 to 5	0 to 30	1 to 10	1 to 5	1 to 7
230205	0.9 to 0.95	3 to 10	0 to 250	0 to 30	1 to 10	1 to 5	1 to 7
410731	0.9 to 0.95	3 to 10	0 to 250	0 to 30	1 to 10	1 to 5	1 to 7
204041	0.9 to 0.95	3 to 10	0 to 5	0 to 30	1 to 10	1 to 5	1 to 7
306119	0.9 to 0.95	3 to 10	0 to 250	0 to 30	1 to 10	1 to 5	1 to 7
926002A	0.9 to 0.95	3 to 10	0 to 250	0 to 30	1 to 10	1 to 5	1 to 7
G8150018	0.9 to 0.95	3 to 10	0 to 250	0 to 30	1 to 10	1 to 5	1 to 7

Rainfall event detection is considered a deterministic process common to both methods meaning uncertainty is not investigated. Here, both the POT method with 1 mm threshold is appropriate to identify rainfall events (Ashcroft et al., 2019; Wasko & Guo, 2022; Zhang et al., 2011).

4 Results

The results are presented in multiple parts. We firstly present detailed time-series of identified rainfall-runoff events for a single catchment to demonstrate the application of RVEIM (Section 4.1). Then, we compare the uncertainty and reliability of the RVEIM with the benchmarking method for 8 representative catchments with diverse climatic conditions (Sections 4.2). And finally, the variation of rainfall-runoff relationship across Australia derived using the RVEIM are investigated across various climates (Section 4.3).

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4.1 Demonstrating rainfall-runoff event identification for a single catchment

To demonstrate the performance of the proposed rainfall-runoff event identification method, we chose catchment 306119 in Tasmania. Within the eight representative catchments, 306119 has the third highest annual rainfall and the largest annual streamflow (Table 1). As one of the wetter catchments, identifying rainfall-runoff events is more challenging as there are higher number of rainfall-runoff events and usually a higher baseflow contribution to streamflow through year which makes it harder for statistical rainfall-runoff event identification methods to identify events precisely. Consequently, adequate performance of a rainfall-runoff event identification method in such a catchment means it will likely obtain satisfactory performance in other catchments. Here an example event identification with RVEIM with *alpha* 0.904 and *d_var* 3 (one random sample of the 300 random parameter sample sets drawn, as detailed in Section 3.3) is presented. Figure 5 shows identified rainfall-runoff events from 1973-06-01 to 1973-09-01, with each pair of identified rainfall and runoff events highlighted in the same color on top of the original time-series in black. Within the selected period, 11 rainfall events are recognized with 8 runoff events detected and paired with rainfall. Although some rainfall events have suitable volume for generating runoff, they did not lead to runoff events because the variance does not exceed the *var_lim* (Section 3.1). Both small and large runoff events including single-peak and multi-peak runoff events are detected and paired demonstrating the power and flexibility of RVEIM. Some streamflow peaks (for example, the small peak after the first runoff event toward mid-June) are not detected since the variance is lower than *var_lim*. Note that such events have minor effects on streamflow analysis even if they are detected and paired, and the key point demonstrated here is that the pairing appears plausible and consistent with our physical understanding.

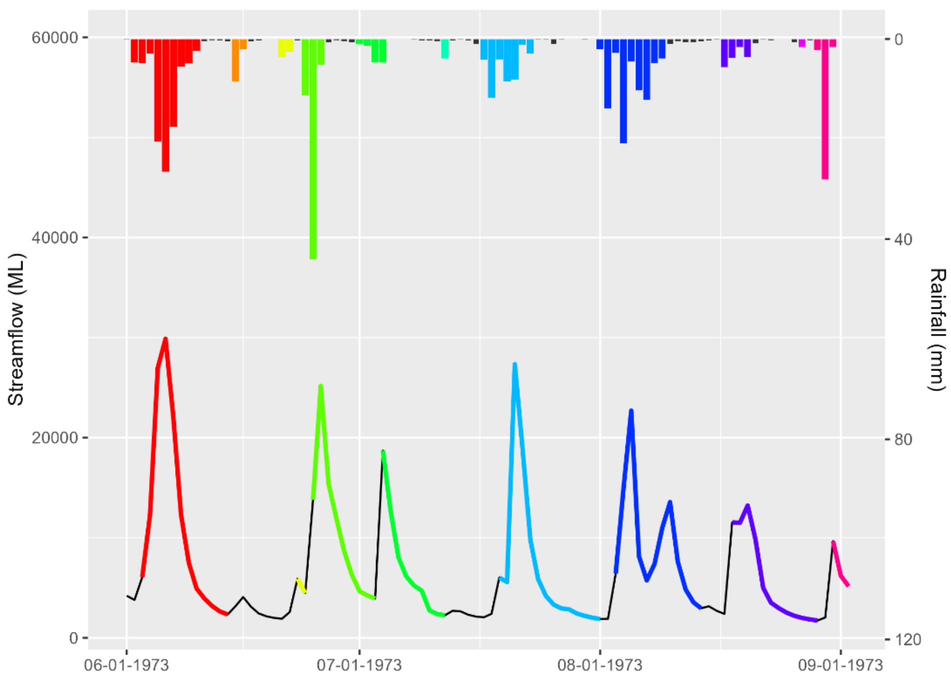

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Figure 5. Identified rainfall-runoff events from 1973-06-01 to 1973-09-01 in catchment 306119. Rainfall is shown as a reversed barchart and streamflow is shown as a line. Each pair of identified rainfall and runoff events is highlighted in the same color on top of the original time-series

4.2 Comparing the RVEIM with the benchmarking method

Mean annual characteristics of paired runoff events are extracted from both the RVEIM and local maxima method over all samples. Figure 6 demonstrates that the uncertainty of paired runoff events' characteristics detected by RVEIM is much lower than that from local maxima, highlighting higher robustness of the proposed method against parameter value change. Boxplot of paired runoff event characteristics detected by the local maxima method includes many outliers, with much fewer when using the RVEIM. Noticeably there are fewer outliers in the average annual number rainfall-runoff events identified by RVEIM providing more confidence on number of paired runoff events. Considering the mean length and volume of paired runoff events, it can be concluded that local maxima generally finds shorter but larger runoff events meaning local maxima probably biases towards large runoff events while RVEIM performs better in identifying a broader range of runoff events.

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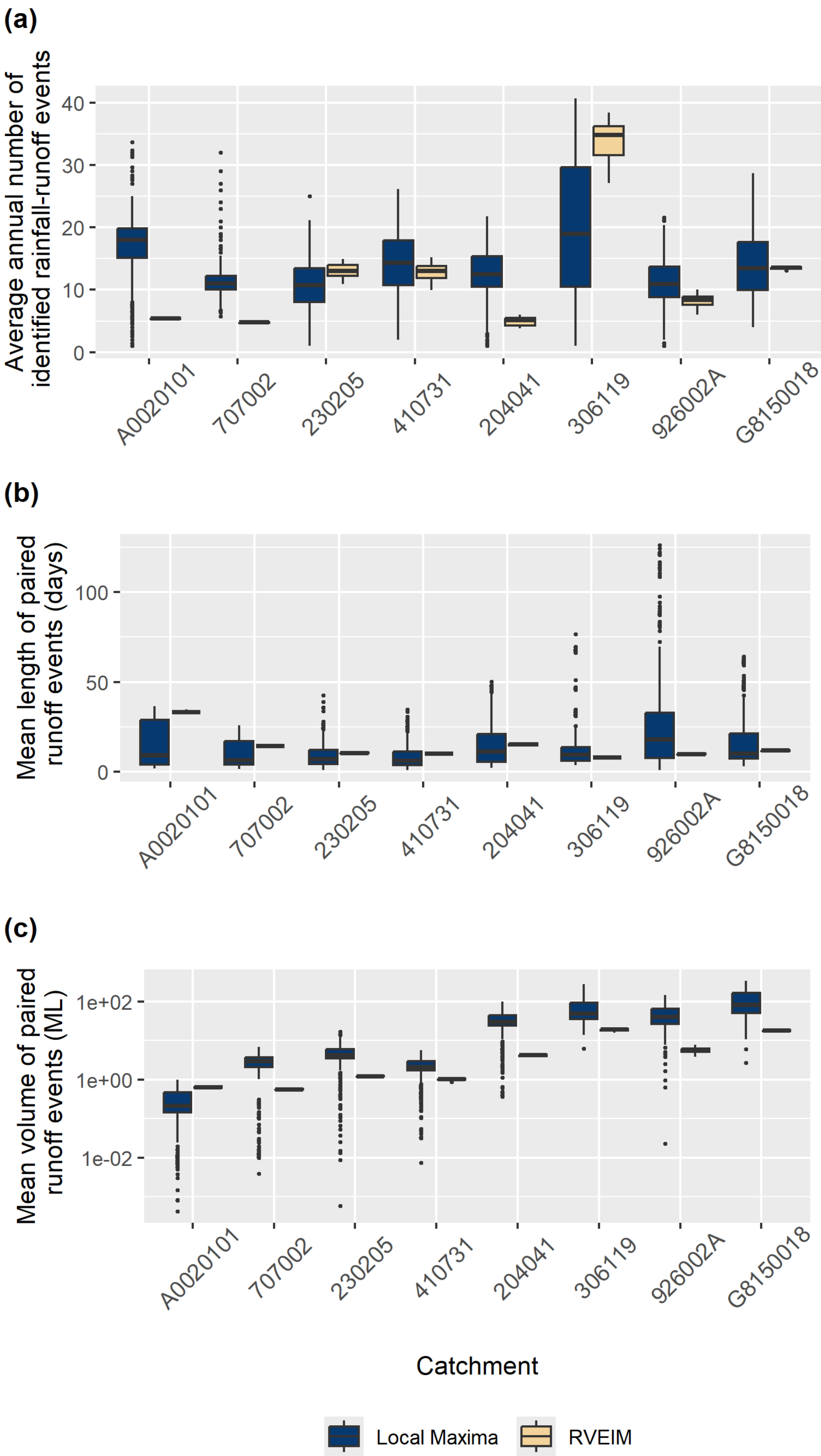

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Figure 6. Boxplots of annual characteristics of paired runoff events identified by the proposed method and the local maxima method. a) average annual number of rainfall-runoff events b) mean length of paired runoff events c) mean volume of paired runoff events (log-scale). The outliers in each panel are identified with the first quartile (Q1), third qurtile (Q3) and interquartile range (IQR), as points lower than (Q1) - 1.5 * IQR or higher than (Q3) + 1.5 * IQR.

Assuming the measured rainfall and runoff are accurate, errors in rainfall-runoff event identification can come during detecting the start and end of rainfall and runoff events, and pairing runoff events to rainfall, which leads to uncertainties in estimating the runoff events' volume. Here, to examine the reliability of RVEIM with local maxima, we compare the percentage of RCs > 1. A higher percentage of RCs > 1 means there are more physically implausible rainfall-runoff events and hence a lower reliability in the identified events.

Figure 7 shows the percentage of RCs > 1 for rainfall-runoff events identified by the RVEIM and the local maxima method for the 8 representative catchments. Each boxplot presents the variability of percentage of RCs > 1 over the full sample of plausible parameter sets. The percentage of RCs > 1 is substantially lower for RVEIM. All catchments (except for catchment 306119) have a less than 4% events with RCs > 1, which also does not change substantially when the parameter values change (shown by the width of the boxplot). However, the percentage of RCs > 1 in local maxima is consistently higher and vary across a wider range for all catchments with changing parameter values. Among all catchments, the three wettest catchments (306119, 926002A and G8150018) have obtained both higher percentages of RCs > 1 and higher variability in the percentages when using local maxima to identify events. The percentages of RCs > 1 obtained from RVEIM for these wetter catchments are still under 4% except for 306119 (median around 17%). This highlights the challenge for rainfall-runoff event identification in wetter catchments, which is further discussed in Section 5.

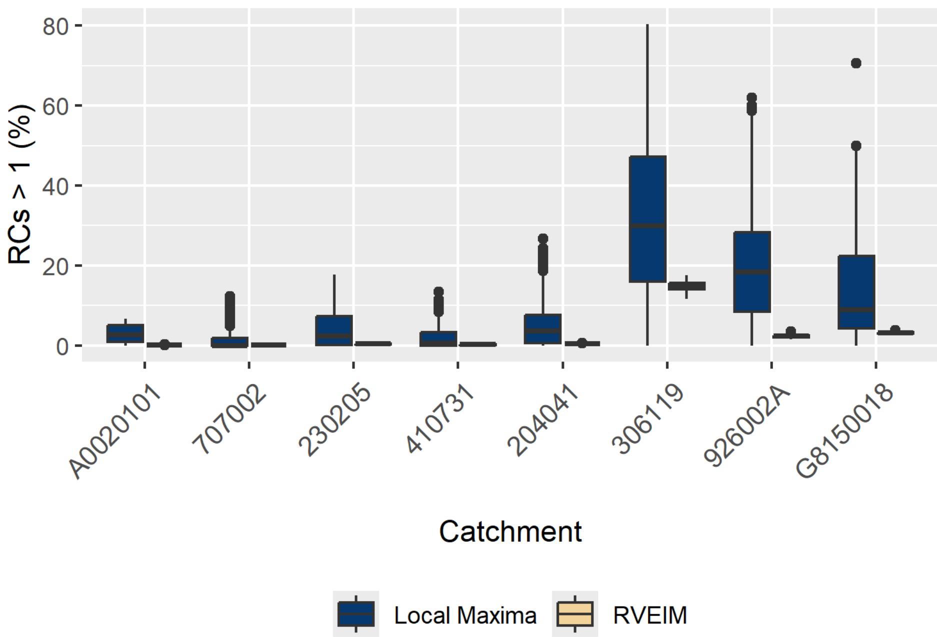

Figure 7. Percentage of RCs > 1 across representative catchments

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As a signature of catchment response, the Empirical Cumulative Distribution Function (ECDF) of all RCs informs the event-scale rainfall-runoff relationship. Here we compare the uncertainties in the ECDFs of RCs obtained using the local maxima method and the RVEIM, over all parameter samples used (Fig. 8). Since rainfall-runoff events with RCs > 1 are physically implausible, we have estimated the ECDFs of RCs with rainfall-runoff events with RCs < 1. As demonstrated in Fig. 7, with the RVEIM there is generally only a small number of identified events with RCs > 1 (less than 4% for most catchments), there omitting rainfall-runoff events with RCs > 1 is not expected to greatly impact the ECDF of RCs for an individual catchment.

The RVEIM has a significantly narrower uncertainty band in the ECDFs compared to using local maxima for event identification across all representative catchments. For example, the probability identifying a rainfall-runoff event with RC < 0.25 in catchment 926002A is roughly between 0.3-1 when the local maxima method is used (Fig. 8g). However, when the RVEIM is used, the probability of rainfall-runoff events with RC < 0.25 is approximately 0.48-0.65 indicating greater confidence. This uncertainty reduction in the ECDF of RCs offered by the RVEIM varies between catchments. For example, the uncertainty in catchment A0020101 is much lower than catchment G8150018 for both the local maxima method and the RVEIM (Fig. 8a and h). The change of uncertainty across catchments is likely due to differing catchment responses and climatic conditions. Rainfall-runoff events are identified with greater certainty for drier catchments, where there are fewer number of rainfall/runoff events and a steady contribution of baseflow throughout a year (e.g. catchment A0020101 in Fig. 8a).

The shape of the ECDF of RCs contains important information regarding the rainfall-runoff events in a catchment. A steeper ECDF emphasizes that there is a mass of rainfall-runoff events with a limited range of RCs. A more gradually increasing ECDF represents a wider range of RCs with a more uniform distribution. For example, in catchment A0020101 (Fig. 8a), there is a sharp increase in the slope of the ECDFs around RC between 0-0.125 up to around 70th percentile, meaning that most rainfall-runoff events (around 70% of rainfall-runoff events) have the RC between 0-0.125. However, in catchment G8150018 (Fig. 8h), the ECDF increases smoothly between RC = 0 to 0.25 up to around 50th percentile meaning a more uniform distribution of rainfall-runoff events with RCs between 0 and 0.25.

The median of ECDFs for both local maxima and RVEIM are quite close for some catchments, like catchment 707002 (Fig. 8b). Although the median ECDF obtained from the two methods seem similar across catchments, RVEIM offers clear reduction in the uncertainty around the shape of ECDF too, giving higher confidence of the rainfall-runoff relationship for individual catchments. The ECDF of RCs differ significantly for some other cases, like 204041 (Fig. 8e) emphasizing a disagreement between results of the two methods, where local maxima shows around 27% of rainfall-runoff events with RC ≤ 0.05. However, the ECDF of RCs found using the RVEIM suggests only around 2% of rainfall-runoff events with RCs ≤ 0.05. In other words, RVEIM suggests a higher potential of runoff generation in catchment 204041. The disagreement between two methods arises when moving towards wetter catchments (i.e. catchments presented in later panels, as they are ordered by annual rainfall as per Table 1) can be explained by the challenges in rainfall-runoff event identification in wetter catchments mentioned in Section 4.1.

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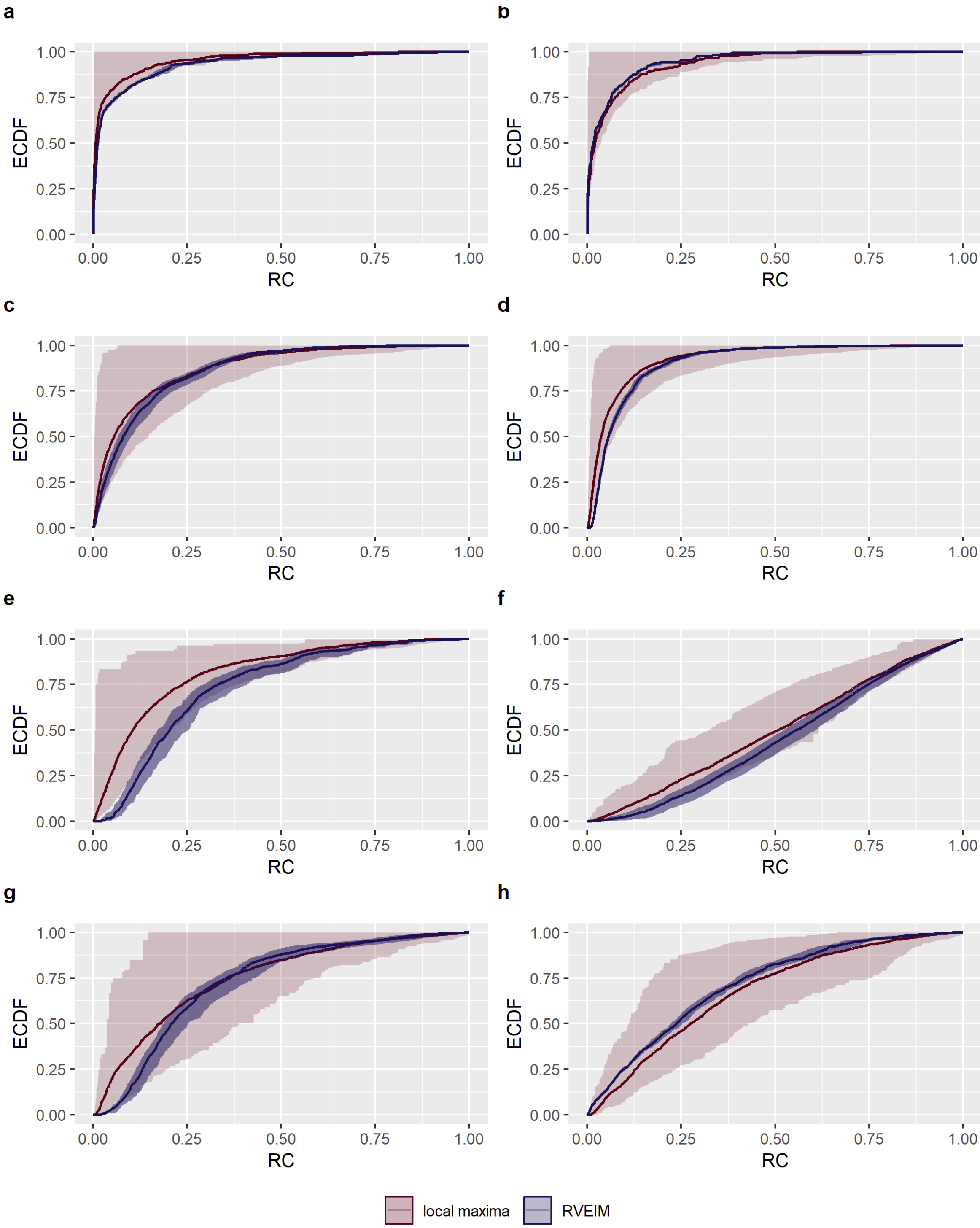

365 **Figure 8. The ECDF of RCs using the local maxima method and RVEIM (rainfall-runoff events with RCs > 1 are omitted a) catchment A0020101 b) catchment 707002c) catchment 230205 d) catchment 410731 e) catchment 204041 f) catchment 306119 g)**

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catchment 926002A h) catchment G8150018. In all panels, the 95% uncertainty band and the median across samples for each rainfall-runoff event identification method are shown in shades and a continuous line, respectively.

4.3 Characterising Australian catchment responses

The RVEIM is applied to all 467 HRS catchments in Australia. The characteristics of rainfall and runoff events are extracted and the mean value over 300 parameter samples are plotted in Fig. 9. There is a clear increase of the average annual number of rainfall events from northwestern to southeastern Australia (Fig. 9a). There is a positive correlation between the average annual number of rainfall and runoff events except for catchments in the north and south-west of Australia. For these regions, although the average annual number of rainfall events is lower (Fig. 9a), the average annual number of runoff events is similar to other catchments in southern Australia (Fig. 9b). A positive correlation between mean length of rainfall and runoff events is also seen except for western Tasmania (see Fig. A1 in Appendix A). Although catchments in western Tasmania have longer rainfall events than other catchments (Fig. 9c), their corresponding runoff events are shorter compared to other catchments (Fig. 9d). The shorter duration of runoff events in Tasmania can be explained by the steeper slopes of catchments in Tasmania which develop quick flow paths (Douinot et al., 2022). A high positive correlation between the mean volume of runoff and rainfall events is also detected (Fig. A2) with some inconsistencies for catchments in northern WA. Catchments in northern WA have the lowest mean volume of rainfall (Fig. 9e), however they have relatively larger mean annual volume of runoff (Fig. 9f) pointing to lower losses in these catchments compared to others. This can be explained by the relatively lower evapotranspiration (Fig. A3) and higher soil moisture (Fig. A4) in northern WA (Bureau of Meteorology, 2025a) meaning lower rainfall losses (Bureau of Meteorology, 2025b) and higher potential of runoff generation. Figure 9g presents mean RC values of identified rainfall-runoff events across Australia. Higher RC values are concentrated around coasts pointing out that catchments around coasts have higher potential of runoff generation. Among all catchments, catchments in Tasmania obtained highest RCs which can be a combined effect of the lower evapotranspiration and significantly higher soil moisture in Tasmania (Bureau of Meteorology, 2025a, 2025b). The percentage of RCs > 1 within all events identified for each catchment is shown in Fig. 9h. The mean percentage of RCs > 1 is below 6% for almost all catchments (around 90% of catchments). However, the ~10% of catchments that have 6%-25% of RCs > 1 are mostly concentrated in the east of Australia and Tasmania. Catchments in east coast of Australia and Tasmania which generally have higher soil moisture (highest in Tasmania). Higher soil moisture increases the runoff volume and the RC as well (Schoener & Stone, 2019; Song & Wang, 2019). The increase in RC, on the other hand, increases the potential of estimating RCs > 1 because of errors in runoff volume estimation (Mohammadpour Khoie et al., 2025). The potential errors leading to RCs > 1 are further discussion in Section 5.3.

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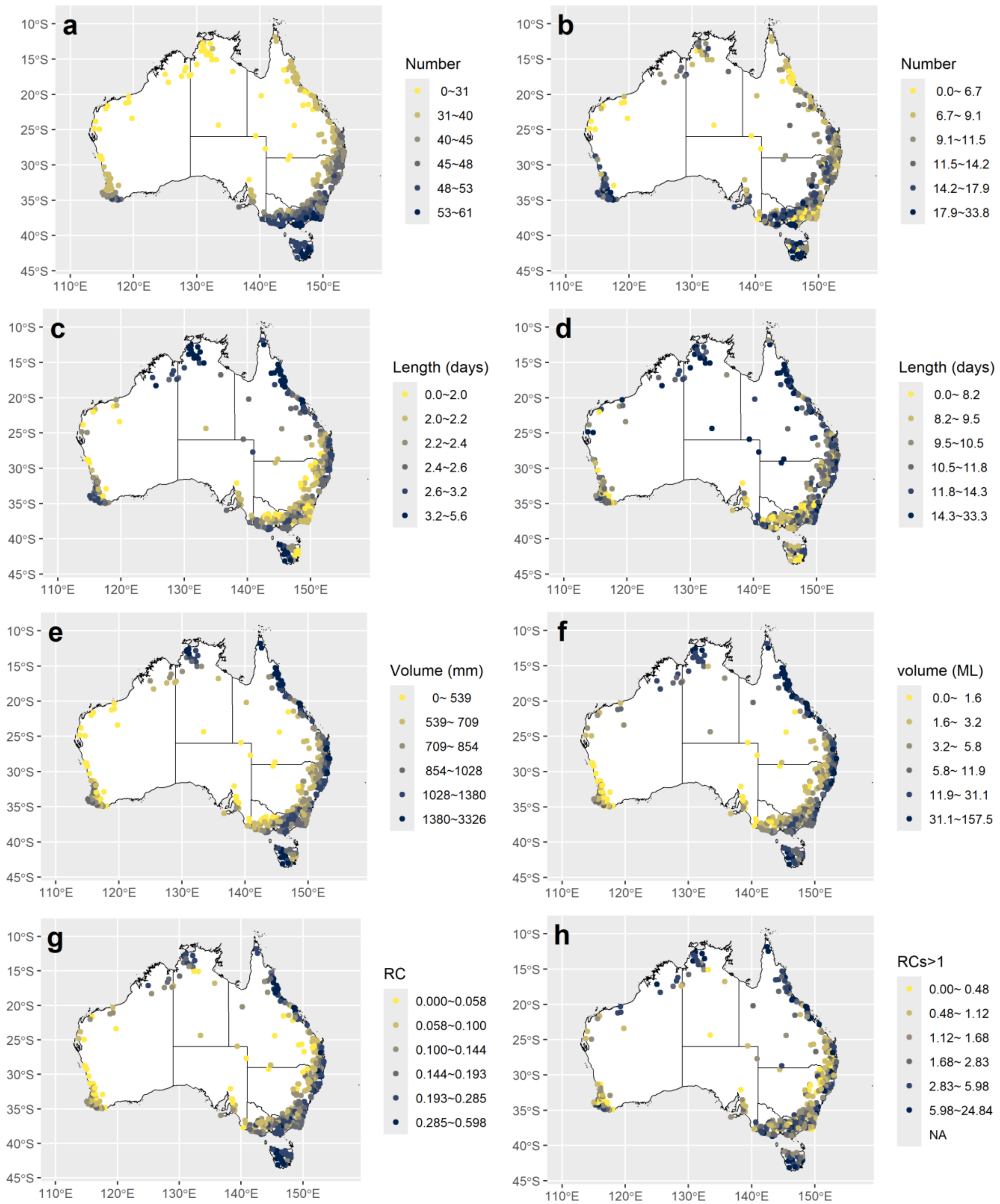

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Figure 9. Characteristics of rainfall-runoff event across Australia. a) mean annual number of rainfall events b) mean annual number of runoff events c) mean annual length of rainfall events d) mean annual length of runoff events e) mean annual volume of rainfall events f) mean annual volume of runoff events g) mean runoff coefficient of all rainfall-runoff events h) mean percentage of rainfall-runoff events with RCs > 1

Figure 10 compares the ECDF of RCs in each climate region by presenting the median of ECDFs of RCs across the 300 parameter samples of individual catchments within each climate region. This provides the first Australia-wide summary of the distribution of event RCs. Where the ECDF of RCs has a sharp increase at the beginning it means that there is a mass of rainfall-runoff events with low RC values. According to Fig. 10, there is a clear gradient of the shapes of ECDFs of RCs from dryer to wetter climate regions. For example, at RC = 0.02, the ECDF of desert climate is around 50% meaning 50% of rainfall-runoff events in desert climate region have RC < 0.02. In grassland climate (wetter than desert), the ECDF of RC = 0.02 is roughly 40%. The ECDF at RC = 0.02 for temperate, subtropical, and equatorial climate regions is around 10% while in decreases to 2% in equatorial. The similar relationship between RC distribution and climate is observed for other RC values. Although we acknowledge that the number of catchments in equatorial regions are much fewer than others with just 2 catchments, a clear large-scale pattern across Australia emerges: in wetter catchments, during each event rainfall contributes more to runoff, highlighting increasing potential for runoff generation. Studies in other places around the world have shown that the spatial distribution of RCs is strongly correlated with precipitation and aligns with our findings (Merz & Blöschl, 2009; Merz et al., 2006; Norbiato et al., 2009a).

Figure 10 exhibits a climatic signature that can be used to categorize Australian catchments in three different groups across climates based on their dominant runoff generation mechanism. In desert and grassland regions, the ECDF rises sharply at RC ≈ 0, indicating that high proportion of rainfall-runoff events produce negligible runoff, meaning rainfall is largely lost due to infiltration and evaporation. This points to less potential for rainfall to produce runoff via saturation excess, and thus suggests the potential dominance of infiltration-excess runoff generation mechanism in these regions. In subtropical, temperate, and equatorial regions, however, the ECDFs rise most gradually towards higher RCs, suggesting a high proportional rainfall becoming runoff in general. This pattern is often seen in regions with greater antecedent soil moisture and the predominance of saturation-excess processes. Tropical catchments show an intermediate pattern: the ECDF increases smoothly from RC = 0 and is right-shifted relative to arid zones, indicating a mixed regime of runoff generation. Saturation-excess may dominate during wet periods, while infiltration-excess can occur under high-intensity rainfall (Johnson et al., 2016; Kidron, 2021; Mirus & Loague, 2013; Trancoso et al., 2016). Moreover, runoff events in desert and grassland regions have longer duration than runoff events in temperate, subtropical, and equatorial regions (Fig. 9d) confirming this categorization.

Moving from dryer towards wetter catchments, the ECDF of RCs become less skewed (Fig. 10). This is consistent with (Merz & Blöschl, 2009) who reported that RC in dryer catchments is more skewed. RCs between 0 to 0.25 become more evenly distributed moving from dryer to wetter climates. In equatorial climate region, the ECDF of RCs between 0 to 0.25 resemble to follow a uniform distribution. For RCs more than 0.5, the ECDF of RCs almost follows a linear relationship with steeper slope for wetter catchments. The steeper slope of ECDF of RCs in wetter catchments reveals that there is a higher probability

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of occurrence of hydrologic extremes in wetter catchments which is align with what reported in Norbiato et al. (2009b) and Breinl et al. (2021).

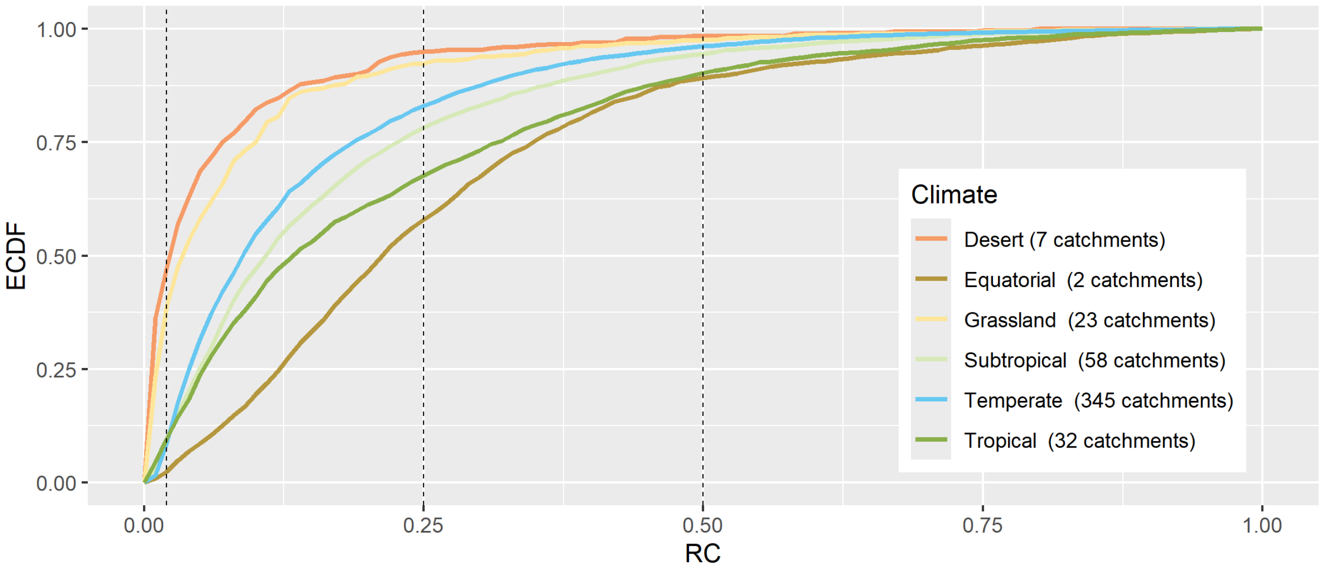

Figure 10. The ECDF of RCs across climate region

5 Discussion

5.1 On the use of the RVEIM

In the process of identifying rainfall-runoff events, the use of parameters to specify 'rules' to define events is usually unavoidable, however, decreasing the number of parameters is beneficial for reducing uncertainty (Mohammadpour Khoie et al., 2025). In this study, we presented the RVEIM which attempts to address the challenges with conventional rainfall-runoff identification methods while using a fewer number of parameters. RVEIM's key benefit is incorporating a physical understanding of runoff-generation processes into statistical event identification with the fewest parameters within known methods, which are unlikely to differ across different hydro-climatic conditions, making the method less uncertain and more transferable across different hydro-climatic conditions.

Independence of runoff events is always an important consideration in identifying rainfall-runoff events with parameters used to define periods of time without an event usually used to define independence (Tang & Carey, 2017). Although such parameters might be useful, they increase the uncertainty, as there is no standard to select such a time period, as it may vary between catchments and the events themselves. To address this, the RVEIM identifies runoff events based on independent rainfall events; hence it ensures the independence of corresponding runoff events while minimizing the number of parameters. A threshold value is usually necessary to detect/delineate a runoff event. The threshold, in some cases, is applied directly to the streamflow records (Tang & Carey, 2017; Wasko & Guo, 2022), sometimes to the variance of streamflow data (Fischer et

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al., 2021), or in other cases, to the rainfall records (Giani et al., 2022). This also adds uncertainty and reduces transferability. For example, in the method developed by Giani et al. (2022), a threshold is considered for detecting rainfall events (distinct from the peak-over-threshold approach). They showed that change in the threshold value can significantly change the characteristics of identified rainfall-runoff events. They showed that lower values of the threshold lead to fewer but longer and larger rainfall-runoff events, while larger values lead to more but shorter and smaller ones. The variability introduced by threshold value change leads to substantial uncertainty, complicating subsequent analyses.

Compared with the existing approaches, the proposed approach to specify the variance threshold of streamflow is more robust across different climates while relying on less parameters. The proposed approach tries to find the variance of baseflow-dominated streamflow. In RVEIM, there is only one *alpha* parameter which affects the estimation of baseflow, and hence, the variance threshold *var_lim*. To show the robustness of variance threshold against parameter value change, we tested the changes of the average annual number of rainfall-runoff events against changing *alpha* value (*d_var* is fixed). Figure 11 shows the variability of average annual number of rainfall-runoff events across *alpha* values for 8 representative catchments. In all catchments, the variability of average annual number of rainfall-runoff events is low (where the standard deviation for each catchment is within ±3.48% of the corresponding mean). This approach to threshold selection enhances the transferability of the RVEIM while reducing uncertainty.

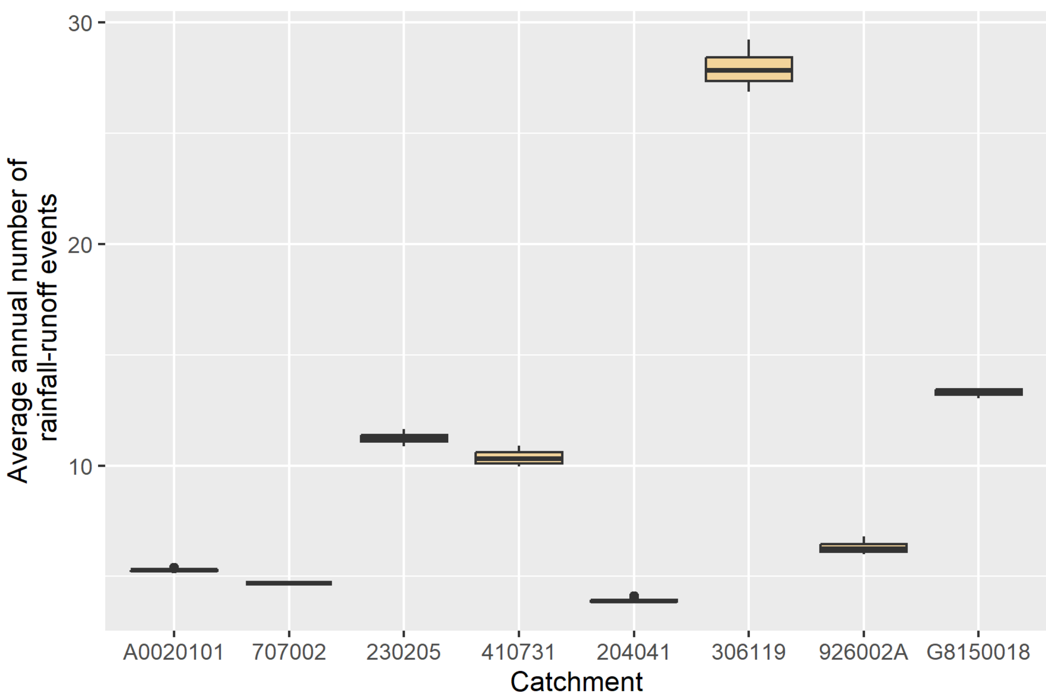

Figure 11. Boxplot of the average annual number of rainfall-runoff events

The RVEIM simultaneously detects and pairs runoff events on the basis of detected rainfall events. The dynamic detection and pairing of rainfall and runoff events has several advantages. By detecting runoff events from rainfall events, RVEIM mirrors

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the natural hydrologic process. In RVEIM, each rainfall event is matched with its corresponding runoff event (if one can be identified) before moving to the next rainfall event reducing the risk of mispairing. Existing methods vary the direction of pairing (many studies pairing from runoff to rainfall), and they may also vary the statistics used to pair (peak of rainfall/runoff, start/end of rainfall/runoff) (Wasko & Guo, 2022). However, RVEIM considers the temporal runoff generation casualty and searches for runoff from the start of each rainfall event.

RVEIM also enhances the way of determining the length of search window and the way of finding corresponding runoff for each rainfall. Conventional methods usually use a time-invariant search window should be defined by the user. Using a time invariant search window may force rainfall-runoff event identification to identify specific types of events, such as shorter runoff events (Mohammadpour Khoie et al., 2025), which may bias towards specific runoff generation mechanism. However, in RVEIM, the length of search window is not user-defined and changes across rainfall events. This allows RVEIM to capture runoff events with various lengths which has higher potential of capturing a fuller range of mechanisms of runoff generation.. Moreover, including the length of rainfall in the search window can maximize the probability of correctly capturing multi-peak runoff events. The number of peaks in a runoff event is usually dependent on number of peaks in the corresponding rainfall event and wetness conditions during the runoff event (Gao et al., 2025; Tarasova, Basso, Zink, et al., 2018); hence, incorporating rainfall length as well as *best_lag* in the search window implicitly considers the temporal pattern of the rainfall and helps ensure that the associated runoff is accurately captured. This also eliminates the parameter usually considered to ensure the independency of two consecutive runoff peaks (Wasko & Guo, 2022).

5.2 Limitations

The use of the RVEIM is still associated with some errors. Although it is challenging to identify errors due to a lack of 'ground truth' data, analyzing RC values may help as RCs > 1 indicate physically implausible events. We must acknowledge that there might be some rainfall-runoff events with valid RC values that are still incorrectly identified or paired, however, a high percentage of rainfall-runoff events with RCs > 1 generally indicates greater errors in rainfall-runoff event identification.

Values of RC ≥ 1can occur because of various reasons. The first reason is overestimation of runoff volume. For some *alpha* values, the baseflow filter may estimate lower baseflow locally/generally which causes an overestimation of runoff volume leading to RCs > 1. This situation is more probable in wet catchments. Wet catchments usually have lower rainfall losses (higher RC values) which increases the probability of RC values exceeding 1. Secondly, in some cases, the rainfall-runoff event identification method may pair a runoff event with the incorrect runoff leading to identifying a rainfall-runoff event with RC > 1. This is, again, more probable in wetter catchments where there is higher number of rainfall and runoff events. When the number of rainfall/runoff events increases, there can be less clear separation of rainfall-runoff events which confuses rainfall-runoff event identification.

Underestimation of rainfall volume is the third potential reason for RCs > 1, most likely due to disinformation in the observations (Beven, 2019). In some cases (especially regions where rainfall is highly spatially variable, such as mountainous regions) not all rainfall events may be captured by the rainfall gauges. In this case, a large volume of runoff might be correctly

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paired to a small recorded rainfall event, which is actually an underestimate of a larger rainfall event, causing RC to exceed. Here we have assumed rainfall events to be deterministic. However, it may be that two consecutive rainfall events are both part of a single multi-peak event but are separated by a rainfall amount below the 1 mm threshold. In this case the POT detects two smaller rainfall events, and it is probable that one rainfall event is paired to the runoff with the other one left unpaired. However, this can be accommodated through post processing of unpaired rainfall events. Finally, errors in streamflow gauging, rating curve extrapolation, and the use of daily data (which may not accurately capture the timing or dynamics of rainfall-runoff events) can also contribute to RC values exceeding 1 (Beven, 2012) but the impacts of such errors are beyond the scope here.

Considering Fig. 9, catchments which are in regions with more rainfall/runoff events do indeed have higher uncertainty and percentage of RCs > 1. For example, catchment G8150118 has relatively higher percentage of RCs > 1 according to Fig. 7. Tasmanian catchments are usually the worst cases with the highest percentages of RCs > 1, and they satisfy all above-mentioned contributing conditions. For example, catchment 306119 located in western Tasmania where there is high number of rainfall/runoff events, the soil moisture is the highest (Fig A4), and the elevation is high. In such catchments, improving the temporal resolution of data (i.e. sub-daily data) may enhance the correct identification of rainfall-runoff events but will also likely introduce more noise in the measurements.

5.3 Implications

We used the RVEIM to generate a first Australia-wide summary of rainfall-runoff event characteristics, as well as the distribution of event RCs (Section 4.3). Catchments showing a gradual/slow increase of ECDF of RCs at RC = 0 suggest dominance of the saturation-excess runoff process, distinguishing them from those governed by infiltration-excess runoff (sharp increase of ECDF at RC = 0). The results closely align with hydrologic understanding of climate variations in Australia. In northern Australia (tropical and equatorial climates) catchment responses highly vary based on rainfall intensity and soil moisture during wet seasons. So, it is expected to see a wider variety of rainfall-runoff events with various RCs comparing to other regions (Duvert et al., 2022). In the desert climate in Australia, the rainfall losses are high, meaning there is lower potential for catchments in arid climate to generate runoff (Zaman et al., 2012). Therefore, it is expected to see rainfall-runoff events have lower RCs (i.e., ECDF of RCs shifts to left) in Fig. 7. Comparing catchments in different climates, catchments with higher soil moisture and lower actual evapotranspiration are expected to have less rainfall losses and thus higher RCs. ECDFs of RCs obtained from both local maxima and RVEIM indicate that RVEIM better presents rainfall-runoff relationships (Fig. 7). For example, catchment 306119 in western Tasmania, where soil moisture is extremely high, should generate rainfall-runoff events with relatively high RCs. While the ECDF extracted from local maxima suggests some rainfall-runoff events in Tasmania have low RCs (0–0.04) (Fig. 7f), the RVEIM results show that events with very low RCs are rare, which is more consistent with the expected hydrological behavior (Fig. 7f). Results are broadly consistent with (Merz et al., 2006) demonstrating that the shape of ECDF of RCs can relate to climatic conditions (such as mean annual rainfall or soil moisture).

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More broadly, accurate identification of rainfall–runoff events across the full spectrum of event magnitudes and climates is crucial for characterizing catchment responses at large/national scale. Australia has a highly diverse runoff patterns, ranging from water-limited regions in central Australia to regions with frequent rainfall/runoff events such as Tasmania. Existing rainfall-runoff event identification methods are often highly sensitive to parameter values, which can lead to biased identifying of event characteristics. For example, some settings may capture only very large events (Leenman et al., 2023), while others may force the identification of only short-duration runoff responses (Mohammadpour Khoie et al., 2025) and identification of only a limited number of runoff processes that exist in a catchment (Merz et al., 2006). These biases reduce comparability across regions and may obscure the climatic gradients that shape runoff response. However, the RVEIM provides a more consistent basis for comparing runoff processes across contrasting climates, thus offering a systematic classification of runoff response.

Many regions worldwide face the challenge of understanding hydrological response under changing conditions, whether due to droughts, land-use change, or climate change. As the RVEIM reduces uncertainty and captures both small and large runoff events, it provides a transferable framework for exploring how catchments respond to rainfall in different hydroclimatic settings. Future studies can further investigate the key climatic and catchment-scale drivers of rainfall-runoff event characteristics identified by RVEIM. Linking event-scale characteristics (RC, for example) to such drivers would help explain regional variations in runoff generation. The RVEIM can be also used to classify rainfall–runoff events based on dominant runoff mechanisms (e.g., infiltration- versus saturation-excess) and to explore how these behaviors evolve under different hydroclimatic conditions (such as climate change). Such analyses would facilitate systematic understanding of catchment response and enhance predictive rainfall-runoff models at large spatial scales. Using RVEIM, therefore, improves confidence in runoff characteristics used for infrastructure design and flood risk assessment, and allows researchers to better assess how event-scale processes shift under climate change in large sample studies.

6 Conclusion

Various rainfall-runoff event identification methods have been developed using different frameworks to help better characterize rainfall-runoff events. These methods are largely statistical in nature, with the use of parameters inevitable in their use to identify rainfall-runoff events. However, deciding about which parameters values to adopt can be challenging, as not only is there an absence of ground-parameters' for calibration of these methods, changing the parameter values, in most cases, significantly alters the rainfall-runoff events characteristics and hence our understanding of the catchment response.

In this study, we proposed the RVEIM, a novel rainfall-runoff event identification method which better mimics the runoff generation process and offers greater robustness compared to current methods. Current rainfall-runoff event identification methods usually detect runoff events and pair them to detected rainfall events. The RVEIM, however, detects independent rainfall events, and pairs them to runoff events one by one. On this basis, the number of parameters, as a source of uncertainty, is decreased while ensuring independence of runoff events and detection of multi-peak events. Additionally, the one-by-one

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pairing of rainfall and runoff events decreases the potential of wrong pairing which is responsible for identifying physically implausible rainfall-runoff events (e.g., generating RCs > 1) and disturbing our understanding about hydrologic regime in a catchment.

We applied the RVEIM to 467 unimpacted catchments across Australia meaning a mostly natural runoff generation is observed. Results of the RVEIM demonstrated that the method generally performs well across different climate regions in Australia. Assessing uncertainty of parameter value change showed that the use of RVEIM results in a more confident characterization of rainfall-runoff events in all catchments. For example, for 90% of catchments in Australia, the maximum percentage of RCs > 1 was 6%, much lower than the baseline rainfall-runoff event identification method. The ECDFs of RCs obtained from RVEIM and the benchmarking rainfall-runoff event identification method in various catchments demonstrated that the results of the proposed rainfall-runoff event identification method are more aligned with the hydrologic understandings in catchment.

Using the RVEIM, we compiled a first, comprehensive summary of rainfall-runoff event characteristics across Australian catchments. Results showed that the distribution of RCs gradually differs moving across climates – moving from drier to wetter catchments the ECDF of RCs shift from sharper to more gradual curves – highlighting a systematic increase in the RCs across rainfall-runoff events and thus higher potential of runoff generation. Moreover, it is also shown that the distribution of RCs become more uniform when moving towards wetter catchments. Results of this study lead to better understanding of rainfall-runoff relationships in Australian catchments and with the method performing well across the diverse range of climate, RVEIM is likely transferable to catchments in other regions globally.

7 Acknowledgements

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Appendix A

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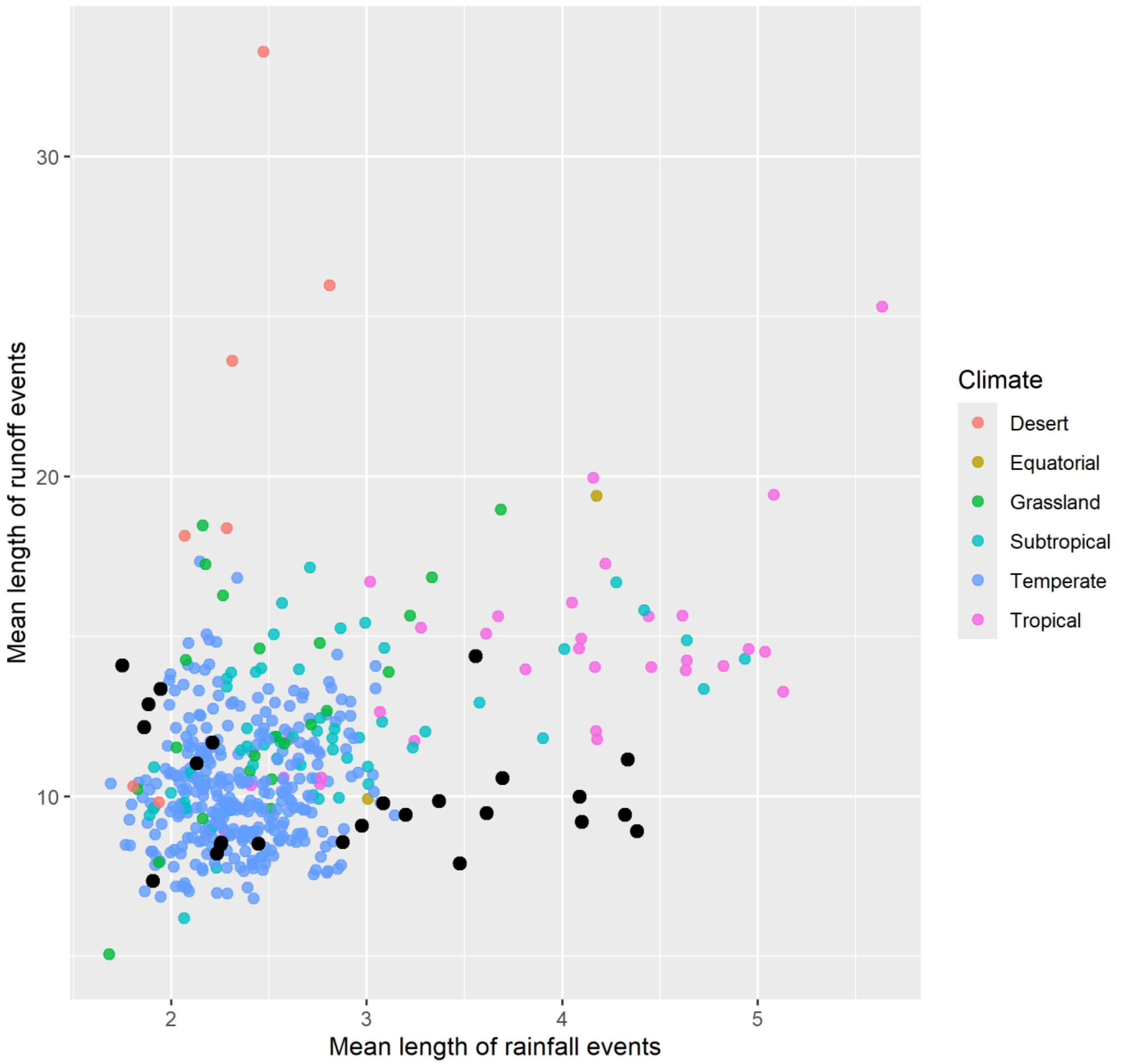

590 **Figure A1. Mean length of rainfall versus runoff events for each catchment. Black dots show catchments in Tasmania.**

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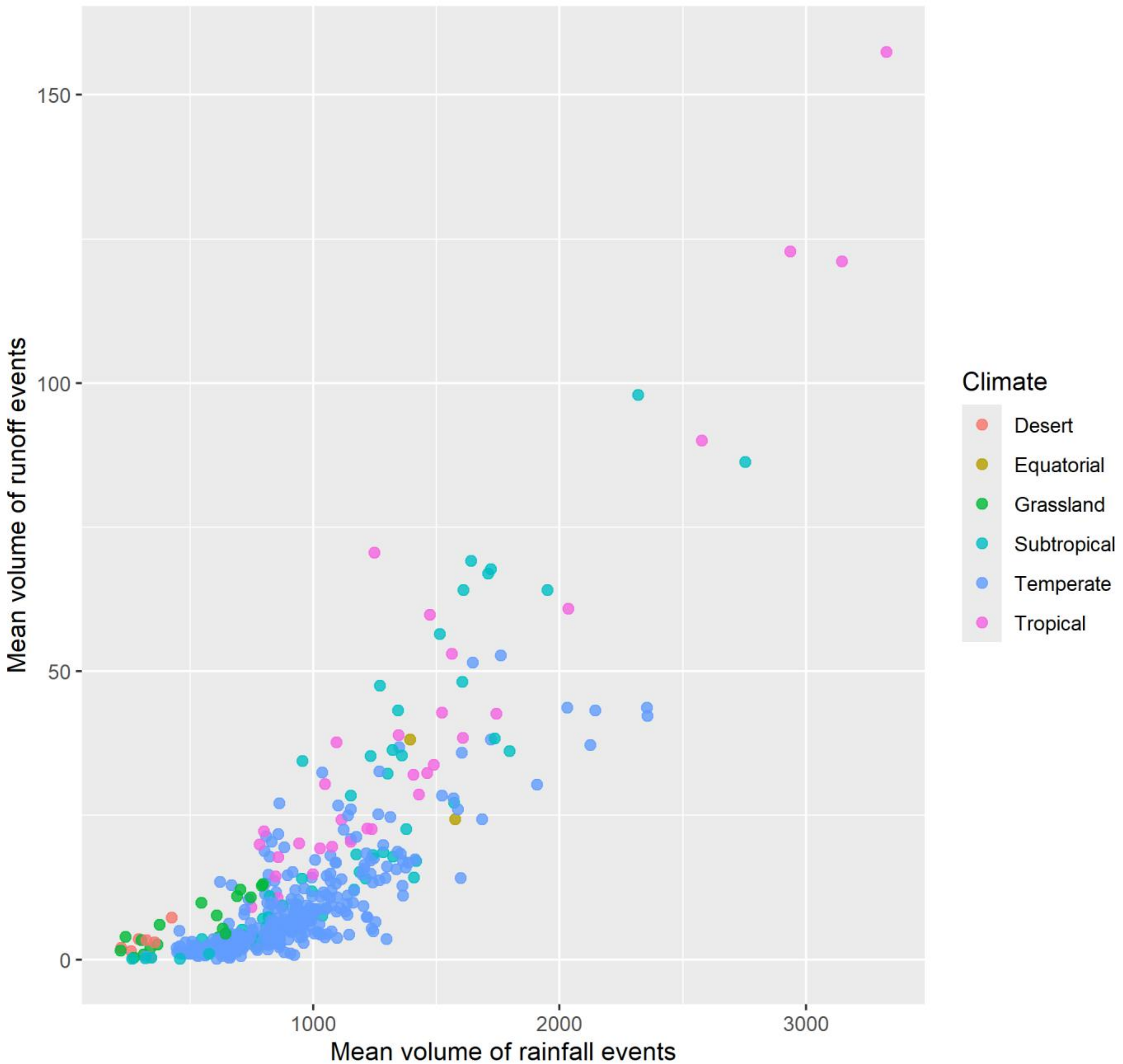

Figure A2. Mean volume of rainfall versus runoff events for each catchment.

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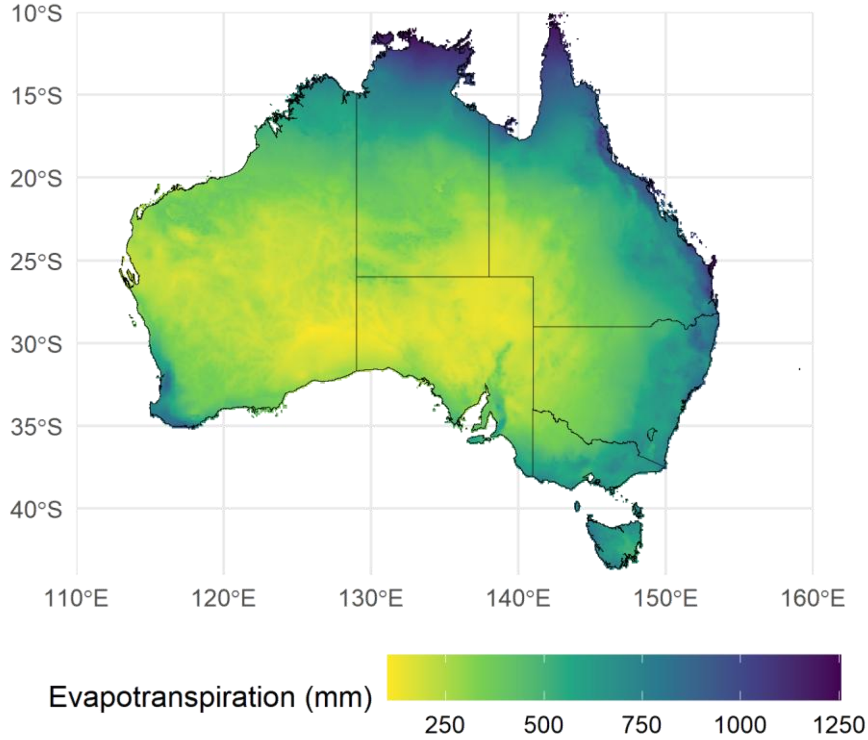
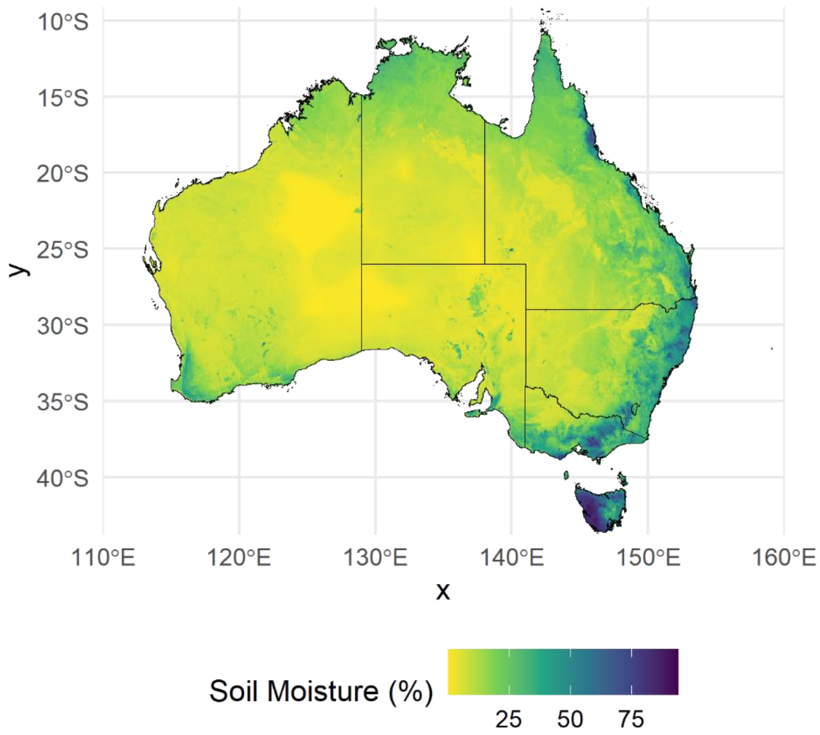


Figure A3. Spatial distribution of mean annual evapotranspiration across Australia.



595 **Figure A4. Spatial distribution of mean soil moisture across Australia.**

Data availability

All data used in this study were sourced from public repositories as detailed in Section 2. Streamflow from the Bureau of
600 Meteorology's Hydrologic Reference Stations (Bureau of Meteorology, 2025c), and rainfall, evapotranspiration, and soil moisture from the Bureau of Meteorology's Australian Water Availability Project (AWAP) (Jones et al., 2009) available at http://www.bom.gov.au/jsp/awap/.

Code availability

605 The new event identification and pairing method developed is published as a function named *eventRVEIM* within the R package *hydroEvents* (ver. 0.13.0), accessible via CRAN: https://cran.r-project.org/web/packages/hydroEvents/index.html.

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Author contribution

Mohammad Masoud Mohammadpour Khoie: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Danlu Guo:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Conrad Wasko:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization.

Competing interests

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

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