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An Objective Time-Series-Analysis Method for Rainfall-Runoff Event Identification

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Key Points:

- The proposed methodology compares well with a more traditional baseflow-based event identification approach
- The proposed method does not require any a priori baseflow separation and allows to produce a baseflow separation a posteriori
- The proposed method can be consistently applied to different time resolutions of the data

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Methodologies for rainfall-runoff event identification from continuous time series suffer from significant subjectivity. In particular, whether they initiate the identification from rainfall or from the streamflow timeseries, they usually require baseflow separation and they need substantial modifications and parameters' recalibration when changing temporal resolution of the data. Therefore, here we propose a novel objective methodology for event identification that is easily transferable across sites and temporal resolutions, without having to make subjective choices and adjust multiple parameters. The proposed method to identify rainfall-runoff events is based on a time series analysis technique that simultaneously considers rainfall and streamflow time series and does not make any a priori assumptions about baseflow separation. The novel method allows also to produce a baseflow separation a posteriori by connecting the delimiters of identified streamflow events. Moreover, the proposed method can be applied at any time resolution as long as the resolution is high enough to capture the time delay between precipitation and runoff response. When comparing the results between the proposed and the traditional baseflow-based event identification approach, we observe a good agreement in terms of event properties both at hourly and daily scale (correlation of runoff ratios between the two methods equal to 0.78 [daily data] and 0.84 [hourly data]). The analysis comparing hourly and daily event identifications with the proposed method reveals also that the novel method produces coherent events across different temporal resolutions (correlation of runoff ratios between daily and hourly data equal to 0.71).

1. Introduction

Precipitation and streamflow characteristics can be described using hydrological signatures based on continuous time series (e.g., Addor et al., 2018; Sawicz et al., 2011; Troch et al., 2009) or statistics of individual events (e.g., Merz et al., 2006; Rodríguez-Blanco et al., 2012; Tarasova et al., 2018). In the first case, hydrological procedures seem to be more standardized, relying mainly on averaging and aggregating over certain periods, while statistics of individual events are largely dependent on the spectrum of different criteria used for event identification. This problem applies to rainfall-runoff events and hydrograph recessions (e.g., Dunkerley, 2008; Stoelzle et al., 2013).

Rainfall-runoff event identification is essential to study for example flood generating mechanisms or changes in magnitude of flood events (e.g., Bertola et al., 2020; Tarasova et al., 2020). When looking at catchment-averaged rainfall and streamflow at the catchment outlet, the event selection routine aims to split the time series into separated realizations of rainfall-runoff processes. However, defining which rainfall or runoff contributions should be grouped together and which ones are instead part of another event is a quite subjective task and the importance and impact of the choices made to perform the event identification is largely underestimated (Dunkerley, 2008).

A widely accepted methodology to select individual rainfall-runoff events is missing and different studies develop their *ad hoc* methods (e.g., Graeff et al., 2012; Koskelo et al., 2012; Mei & Anagnostou, 2015; Merz et al., 2006; Rodríguez-Blanco et al., 2012; Seibert et al., 2016; Tang & Carey, 2017; Tarasova et al., 2018), sometimes even requiring manual inspection (Bieroza & Heathwaite, 2015; Dupas et al., 2016; Von Freyberg et al., 2018). The choice of the parameters for event identification is often not clearly stated and it is often left to the hydrologist experience and knowledge to adjust the parameters when changing study area. This hampers direct comparison of findings from independent research initiatives. Depending on the perspective the hydrologist is taking, focusing first on separating the rainfall into different events (e.g., Koskelo et al., 2012; Seibert et al., 2016) or first on separating the streamflow into different events (e.g., Fischer et al., 2021; Graeff et al., 2012; Merz et al., 2006; Oppel & Mewes, 2020), the chosen routine and corresponding assumptions can be quite different.

When focusing on catchment-averaged rainfall event selection first, a widely applied strategy is to use dry spells as delimiters. The minimum duration of the dry spell can range from few minutes to a day (Dunkerley, 2008; Graeff et al., 2012; Rodríguez-Blanco et al., 2012; Seibert et al., 2016). In addition, a combination of the following criteria can be eventually considered: minimum rain depth (e.g., Balme et al., 2006; Ziegler et al., 2006), minimum rain event duration (e.g., Fornis et al., 2005), minimum rain rate for a period of the event (Fornis et al., 2005; Loukas & Quick, 1996), minimum rain rate to identify the starting point of the event (Kerr et al., 1974). What remains unclear is whether independent rainfall events in turn produce independent runoff events.

On the other hand, the identification of runoff events traditionally requires implementation of a baseflow separation method. The large spectrum of baseflow separation methods (e.g., Blume et al., 2007; Chapman & Maxwell, 1996; Eckhardt, 2005; Institute of Hydrology, 1980) make this step highly subjective and dependent on the chosen routine and parameter estimation. On top of this, a peak-over-threshold criteria can be applied to consider only larger events (Norbiato et al., 2009; Tang & Carey, 2017). Recently, different studies have developed methodologies to avoid the baseflow separation (Fischer et al., 2021; Oppel & Mewes, 2020; Thiesen et al., 2019; Towler & McCreight, 2021). However, these methodologies still require the calibration of parameters or to manually train machine learning algorithms. Moreover, if these methods identify separate runoff peaks, are these peaks caused by different rainfall events?

Whether the event selection routine starts from rainfall or from streamflow, the problem of the attribution of the independent events of one record to the corresponding ones on the other highlights the fact that the selection of events in hydrology is not seen as the extraction of “system” realizations (i.e., considering event rainfall-runoff processes as a whole at once). To our knowledge, the modified Sliding Average with Rain Record (SARR) methodology proposed by Koskelo et al. (2012) is the only method to select events which intersects the information coming from the two timeseries in the baseflow separation step, although a post-attribution of rainfall events to the identified runoff events is still needed.

Moreover, even if in different studies the principles upon which the routine is based are very similar, finer temporal resolution of the timeseries can make necessary the use of different criteria and parameters. If we visually compare hourly and daily rainfall timeseries, we can clearly see how finer resolutions can make the identification of events more complicated. This translates into more complex procedures for event extraction which have to cope with more variability and noise (e.g., see comparison by Mei & Anagnostou, 2015 [hourly] and Tarasova et al., 2018 [daily] for the attribution of rainfall events).

Therefore, a flexible but coherent methodology for event selection is clearly missing: different perspectives, criteria and data resolution bring hydrologists to use a wide range of different strategies which produce a reasonable selection of events but do not allow a direct comparison between independent studies. Moreover, bringing together conclusions reached on precipitation studies with those reached on runoff response studies becomes difficult if different perspectives lead to different event concepts and definitions.

For this reason, we propose a novel methodology which, by looking at the simultaneous evolution in time of rainfall and streamflow time series, is able to identify events as “system” realizations. The proposed methodology builds upon the Detrending Moving-average Cross-correlation Analysis (DMCA)-based method to estimate catchment response time (see Giani et al., 2021) and hence is named DMCA-Event Separation Routine (DMCA-ESR). The aim is to build a time-series analysis approach which identifies the events using the information contained in the signals, minimizing conceptual hypothesis and hence not requiring major adjustments for the application at coarser/finer temporal resolutions.

After a detailed explanation of how the DMCA-ESR performs the event identification (Section 2.1), in this work we will present a comparison of the DMCA-ESR with a more traditional approach supported by baseflow separation (Section 2.2) both at hourly and daily scales. The comparison will be presented first when running the DMCA-ESR with rainfall and total streamflow time series (Sections 4.1 and 5.1) and then when running the novel method with rainfall and quick flow (Sections 4.2 and 5.2), with the aim of testing if difference between the DMCA-ESR and the more traditional method are to be attributed mainly to how the rainfall-quick flow series is converted to events or mainly due to the baseflow separation. Furthermore, we will present a direct comparison of event properties extracted from daily and hourly timeseries (Sections 4.3 and 5.3), to test if the DMCA-ESR is able to provide a coherent event identification across different temporal resolutions. Limitations of the presented method (Section 6) and conclusions (Section 7) will follow.

2. Methodology

2.1. DMCA-Based Rainfall-Streamflow Event Separation Routine (DMCA-ESR)

The DMCA-ESR builds upon the DMCA-based method to estimate catchment response time (Tr) (Giani et al., 2021). Since events at the catchment scale are of particular interest in hydrological science and practice, we use the catchment response time for a hydrologically meaningful selection of rainfall-streamflow events or, in simpler words, to group together all the rainfall contributions which build the same streamflow event.

According to the DMCA-based method, Tr is defined as the average lag between center of mass of rainfall and center of mass of streamflow across all the events. The DMCA-based method is able to provide an estimate of Tr by identifying the time scale for which two time series are most strongly correlated. Because of the different frequency spectra of rainfall and streamflow time series, a simple cross-correlation would not be as effective as the DMCA-based method (Giani et al., 2021).

However, the DMCA-ESR we are presenting here not only takes into account the output from the DMCA-based method to estimate Tr, but it also makes use of the time series analysis technique itself to detect the events. Unlike the other methodologies of event identification, the DMCA-ESR looks simultaneously at the evolution in time of rainfall and streamflow, allowing a "system" definition of the event.

Moreover, the methodology we are presenting can be applied to different time resolutions by adjusting only one parameter. Its definition is physically based as it is linked to the minimum rainfall intensity which we can consider significant at a given resolution of the data. As a general guidance, we assume the minimum rainfall intensity considered significant at the given resolution comparable with the uncertainties in the tipping bucket and radar rainfall intensity estimates (Fabry, 2015; Villarini et al., 2008). Some guidance on how to define this tolerance is provided in the relevant section.

A detailed list of the steps through which the DMCA-ESR performs the event extraction from continuous time series is provided below and the code to perform the event identification with the DMCA-ESR is freely available from https://github.com/giuliagiani/DMCA-ESR, last access 04.08.2021. In Figure 1 we present a schematic summary of the DMCA-ESR steps together with some explanatory figures. However, the explanation of the DMCA-ESR builds upon the understanding of the DMCA-based method for which we provide a reminder in Text S1 in Supporting Information S1.

Step 1: Search of typical catchment response time

The first step is to find the characteristic Tr for the examined catchment using the DMCA-based method (see Text S1 in Supporting Information S1). It is important to note that this estimate is dependent on the temporal resolution of the data (e.g., using hourly data catchment response time can be 29 hr, but using daily data in the same catchment this becomes 1 day). Nevertheless, it is essential that the resolution of the data is fine enough to capture the delay between rainfall and runoff response (e.g., peak of rainfall and peak of related streamflow event cannot be recorded at the same time step).

The Tr supports identification of the events. It is not used just to set a distance backward or forward for the attribution of the correspondent events among timeseries, but also to evaluate rainfall-streamflow interactions when contributions in the two timeseries are grouped at the window scale associated to Tr, $L_{\min}$. In fact, once we have produced an estimate of Tr, we re-apply the steps of the DMCA-based method using only the window $L_{\min}$ to obtain timeseries of rainfall fluctuations and streamflow fluctuations. These timeseries, together with the original ones, contain all information needed to identify the rainfall and streamflow events.

Step 2: Setting a rainfall fluctuation tolerance

With this step we aim to adjust the time series analysis technique for the long dry or steady period required to break down rainfall and streamflow contributions into different events (i.e., larger than $L_{\min}$, which is equal to 2Tr+1, see Text S1 in Supporting Information S1 for more details).

When the fluctuation between cumulative timeseries and averaged-cumulative timeseries (see Equations S3 and S4 and Text S1 in Supporting Information S1) are zero it means that the original record is steady (or zero) and hence no event is occurring. We intend to use those periods of zero fluctuations as break points to identify events,

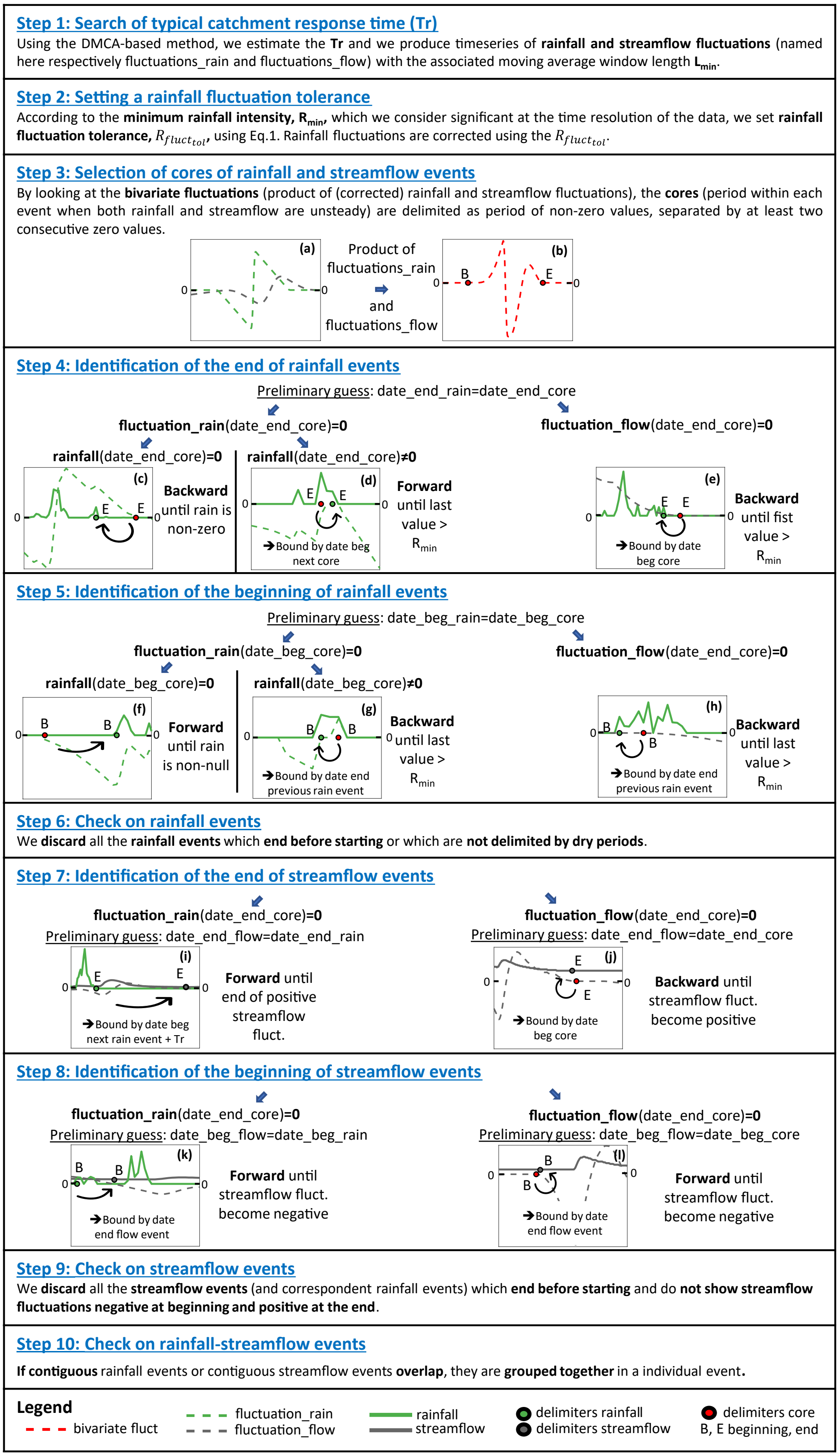

Figure 1. Summary of DMCA-ESR. The legend applies to all the individual subfigures (1a–1l).

but for this to happen a dry or steady period of minimum duration equal to $L_{\min}$ is required (see Section 2.1.2, step IV in Giani et al., 2021 for more details). Any rainfall contribution within any time window equal to $L_{\min}$, however small, would make the rainfall fluctuations different from zero and hence would prevent from discretizing the timeseries into different events resulting in excessively long events. Although these unusually long events might not affect estimates of runoff ratio substantially, they might not exactly comply with the length of events expected by most hydrologists.

For this reason, we introduce a tolerance for rainfall fluctuations so that small and isolated rainfall contributions do not prevent from breaking down the timeseries in different events. Any rainfall fluctuation smaller in absolute value than the rainfall fluctuation tolerance is set to zero so it can contribute to discretize the timeseries into different events. To define the rainfall fluctuation tolerance, $R_{\mathrm{fluct}_{\mathrm{tol}}}$, we looked at the maximum absolute rainfall fluctuation between cumulative rainfall and averaged-cumulative rainfall generated by a given rainfall intensity, $R_{\min}$, which is geometrically defined as follows:

$$R_{\mathrm{fluct}_{\mathrm{tol}}} = \frac{R_{\min}}{L_{\min}} * \frac{(L_{\min} - 1)}{2} \tag{1}$$

where $\frac{R_{\min}}{L_{\min}}$ is the absolute increment in fluctuation per time step and $\frac{(L_{\min}-1)}{2}$ corresponds to the maximum number of time steps for which there is an increase in fluctuation (i.e., roughly half of the window). In the equation above, the only unknown variable is the rainfall intensity, $R_{\min}$, which needs to be set equal to the smallest rainfall intensity considered significant at the resolution of the data. Although this is subjectively defined, at hourly scale we tested a range of values finding that between 0.1 and 1 mm/hour there is no significant difference in the resulting event selection (Text S3 and Figure S1b in Supporting Information S1). In order to coherently convert the $R_{\min}$ values at daily resolution we suggest to use an Intensity-Duration-Frequency approach considering the same return period (i.e., finding on the same exponential curve the intensity associated to the 24 hr duration, see Text S2 in Supporting Information S1). Using this approach, the range 0.1–1 mm/h converts to 0.02–0.2 mm/hr and again the event identification does not seem to be very sensitive to the value of $R_{\min}$, unless larger than 0.2 mm/hr (see Text S3 and Figure S1a in Supporting Information S1). For this study we chose a value of $R_{\min}$ equal to 0.2 mm/hr at hourly scale, which converts to 0.04 mm/hr at daily scale (see Text S2 in Supporting Information S1). The above ranges are valid for the study area under consideration, but application of the DMCA-ESR in other regions would require to re-run the sensitivity analysis as these ranges might vary depending on the main runoff generating mechanism.

Even if a similar thought process could be developed for streamflow timeseries, we avoid the introduction of a streamflow fluctuation tolerance as it is very hard to define a streamflow rate associated to the termination of the event. In fact, during the recession of the event or the baseflow only, the streamflow rate can be very different depending on the antecedent conditions (Basso et al., 2021; Patnaik et al., 2015). Nevertheless, our testing indicates that acting on the forcing variable, the rainfall, is sufficient to break down the two timeseries in different events as we assume a one-to-one correspondence.

Step 3: Selection of cores of rainfall and streamflow events

We define the core of an event as the time interval within each event when both rainfall and streamflow are unsteady. Rainfall and streamflow events are associated to each other if they share the same core. To find the core of the rainfall-streamflow event we look at bivariate fluctuations (Figure 1b, Equation 7 in Text S1 in Supporting Information S1), the product of rainfall fluctuations (corrected using the rainfall fluctuation tolerance) and streamflow fluctuations (Figure 1a). This step allows to find events as "system" realizations, as bivariate fluctuations contain information both on rainfall and streamflow. When bivariate fluctuations are different from zero it means both rainfall and streamflow fluctuations are different from zero and therefore an event is already happening. Instead, when bivariate fluctuations are equal to zero, it means that either rainfall fluctuation or streamflow fluctuations (or both) are zero. The method therefore excludes a priori from the list of events all those small isolated rainfall contributions which do not generate any response because their bivariate fluctuations are zero (streamflow is steady hence streamflow fluctuations are zero as well as the bivariate fluctuations).

Regarding zero bivariate fluctuations, we consider them as a break point for identifying the cores only if two consecutive time steps show zero values. This is to prevent that a change of fluctuations' sign can be interpreted as break point (e.g., the change from negative to positive fluctuations in the center of mass). The search for the cores of the events is therefore performed by identifying periods of non-zero bivariate fluctuations separated by at least two time steps of zero bivariate fluctuations. Once we have identified the beginning and end of the event core, we can make use of this information to isolate rainfall and streamflow events. The delimiters of the core are in fact the starting point to set the delimiters of rainfall and streamflow events, depending on the individual fluctuation signs.

Step 4: Identification of the end of rainfall events

As initial guess we assume the end of the rainfall event to coincide with the end of the core. Then we adjust the position of the end of the rainfall event considering three following cases:

1. The core has ended because rainfall fluctuations are zero and the rain at that point in time is already zero. This is the most common case and has to do with the moving average process which leads to fluctuations different from zero for a duration equal to $L_{\min}$ after the rainfall ends. In this case, we move backward in time until we find the first time step of non-zero rainfall, where we place the end of the rainfall event (Figure 1c).
2. The core has ended because rainfall fluctuations are zero and the rain at that point in time is different from zero. This is the case generated by the introduction of the rainfall fluctuation tolerance, because, as explained before, the rainfall should be zero if the rainfall fluctuations are zero. In this case we move forward in time until the rainfall becomes lower than $R_{\min}$. The search in this case is bounded by the beginning of the following core (Figure 1d).
3. The core has ended because streamflow fluctuations are zero: the streamflow appears steady and hence we want to make use of this information to break the time series. We move backward in time until the rainfall becomes lower than $R_{\min}$ and then backward again to the first time step of rainfall larger than $R_{\min}$. The search in this case is bounded by the beginning of the core associated to the examined event (Figure 1e).

It is important to note that $R_{\min}$ here is used just to move to the previous/next dry period but does not have any role in breaking the timeseries at this stage. $R_{\min}$ is involved in record breaking through the $R_{\mathrm{fluct}_{\mathrm{tol}}}$, which is applied to the rainfall fluctuations.

As the rainfall is the forcing variable, in the case when both rainfall and streamflow fluctuations are zero at the end of the core, we will delimit the end of the rainfall event following the procedure indicated for cores which ended because of zero rainfall fluctuations.

Step 5: Identification of the beginning of rainfall events

As initial guess we assume the beginning of the rainfall event to coincide with the beginning of the core. Then we adjust the position of the beginning of the rainfall event by considering the following three cases:

1. At the time step just before the core started, rainfall fluctuations are zero and the rain at that point in time is also zero. This is the most common case and has to do with the moving average process which leads to non-zero fluctuations for a duration equal to $L_{\min}$ before the rainfall starts. In this case, we move forward in time until we find the first time step of non-zero rainfall, where we place the beginning of the rainfall event (Figure 1f).
2. At the time step just before the core started, rainfall fluctuations are zero but the rain at that point in time is non-zero. This is the case generated by the introduction of the rainfall fluctuation tolerance, because as explained before the rainfall should be zero if the rainfall fluctuations are zero. In this case we move backward in time until the rainfall becomes lower than $R_{\min}$. The search in this case is bounded by the end of the previous rainfall event (Figure 1g).
3. At the time step before the core started the streamflow fluctuations are zero: the streamflow appears steady and hence we want to make use of this information to break the time series. We move backward in time until the rainfall becomes lower than the $R_{\min}$. The search in this case is bounded by the end of the previous rain event (Figure 1h).

Again, here $R_{\min}$ is used just to move to the previous/next dry period and if both rainfall and streamflow fluctuations are zero, we process the event considering the zero rainfall fluctuations.

Step 6: Check on rainfall events

During the definition of the rainfall events we move backward and forward in time from the delimiters of the core, so we can sometimes get unrealistic rainfall events which end even before starting (example: the event is short and shows condition 1 for Step 4 and condition 1 for Step 5). For this reason, all the rainfall events which show their beginning after their end are discarded at this stage. Moreover, we also discard all the events which are not delimited by dry periods or periods of rainfall lower than $R_{\min}$.

The information about the valid rainfall events together with that for their cores is used in the next steps to identify the streamflow events. Theoretically, as the methodology assumes a "system" event approach, the identification could also start from the streamflow events and then define the rainfall events. However, here we provide the detailed instruction only for the event identification which first defines rainfall events and then the streamflow ones, as the other way around would produce similar results.

Step 7: Identification of the end of streamflow events

1. If the core has ended because the rainfall fluctuations were zero, as a preliminary guess we assume the end of the streamflow event to coincide with the end of the rainfall event. As we expect the streamflow event to end after the rainfall event, we move forward in time until the positive streamflow fluctuations end (this is the expected fluctuation sign after the center of mass). In the case when at the end of the rainfall event the streamflow fluctuations are still negative (because the center of mass of the streamflow event has still to come) we first move forward in time until the end of negative fluctuations and then forward again until the end of the positive ones. The search of the end of the streamflow event is bounded by the time defined by the beginning of the following rainfall event plus one catchment response time, Tr (Figure 1i).
2. If the core has ended because the streamflow fluctuations were zero, as a preliminary guess we assume the end of the streamflow event to coincide with the end of the core. As we expect the streamflow fluctuations to be positive at the end of the event we move backward in time until we find the streamflow fluctuations to be positive. This search is bounded by the beginning of the core of the examined event (Figure 1j).

Again, in the case when both rainfall and streamflow fluctuations are zero, we follow the procedure indicated for zero rainfall fluctuations.

Step 8: Identification of the beginning of streamflow events

1. If at the timestep just before the core started the rainfall fluctuations were zero, as a preliminary guess we assume the beginning of the streamflow event to coincide with the beginning of the rainfall event. As we expect the streamflow event to start after the rainfall event, we move forward in time until the streamflow fluctuations become negative. The search of the beginning of the streamflow event is bounded by the end of the streamflow event (Figure 1k).
2. If at the timestep just before the core has started the streamflow fluctuations were zero, as a preliminary guess we assume the beginning of the streamflow event to coincide with the beginning of the core. In this case we move forward in time until the streamflow fluctuations become negative. The search of the beginning of the streamflow event is bounded by the end of the streamflow event (Figure 1l).

Again, in the case when both rainfall and streamflow fluctuations are zero, we follow the procedure indicated for zero rainfall fluctuations.

Step 9: Check on streamflow events

During the definition of the streamflow events we move backward and forward in time from the delimiters of the core or from the delimiters of the rainfall events, so we can sometimes get unrealistic streamflow events which end even before starting (example: the event is short and we observe condition 2 for Step 7 and condition 1 for Step 8). For this reason, all the streamflow events which show their beginning after their end are discarded at this stage, together with their corresponding rainfall events. We also discard events if the beginning (or end) delimiter of the streamflow event occur earlier in time than the beginning (or end) delimiter of the rain event.

Moreover, we discard also all the streamflow events (and correspondent rainfall events) if they do not start with negative streamflow fluctuations and they do not end with positive ones. In fact, as explained in Giani et al. (2021), fluctuations should be negative before the center of mass and positive after it. This check was not applied to rainfall events, as the rainfall timeseries evolves in a much more variable way and hence changes of sign in the rainfall fluctuations are very frequent. Instead, for the streamflow, which shows higher autocorrelation compared to the rainfall (Oliveira & Maia, 2018), the sign of the fluctuations tends to be more stable and hence can be used at this stage to check on the selection of streamflow events.

Step 10: Check on rainfall-streamflow events

Given that when we start defining the ending delimiters of rainfall and streamflow events we use the core information and then we can move backward and forward in time, there might be some overlaps between contiguous rainfall events or between contiguous streamflow events. Overlapping events are lumped together into one single event.

2.2. Traditional Rainfall-Streamflow Event Separation Routine (Trad-ESR)

Although in the literature we found a few different methodologies to select events from continuous rainfall and streamflow timeseries, the following procedure appears to be commonly used: first separating the hydrograph into quick and slow flow (with the latter named baseflow), then identifying runoff events with the help of a set of separation thresholds and finally attributing the corresponding rainfall event. This conceptual framework is then applied by making a series of subjective choices (e.g., algorithm used for baseflow separation), which can potentially result in considerable differences in the event identification. This conceptual framework can be applied at different time resolution as well, but it requires consistent adjustments to re-estimate the parameters (see for comparison Tarasova et al., 2018 and Mei & Anagnostou, 2015).

Among all the similar conceptual workflows, in this study we considered the one by Tarasova et al. (2018), as when subjective choices occur, it considers a wide range of options and picks the most appropriate one making use of an iterative procedure. Moreover, the methodology introduces a further step to identify multi-peak events which are merely artifacts created by the baseflow separation. In summary the methodology to select events by Tarasova et al. (2018) involves the following steps (for further details we refer to the original paper):

1. Baseflow separation: Four different algorithms (Chapman & Maxwell, 1996; Eckhardt, 2005; Institute of Hydrology, 1980; Wittenberg, 1999) are tested and the one that provides an optimal trade-off between the number of identified troughs and cross-correlation with the total streamflow is selected.
2. Runoff events identification: they are identified by periods of non-zero quick flow separated by periods of zero quick flow. A further condition is applied: a runoff event is taken into account only if the peak runoff is higher than 10% of the baseflow.
3. Attribution of rainfall event: using a median basin lag time (the delay between rainfall and runoff generation) the rainfall event is identified by setting a distance backward in time from the delimiters of the runoff event.
4. Refinement of multi-peak events: further separation thresholds are introduced and iteratively adjusted to avoid the selection of multi-peak events which are just the result of the artifacts created by the baseflow separation.

The methodology has been developed originally to process time series at daily resolution but in this work, after re-adapting the parameters (Text S4 in Supporting Information S1 for more details), it is also applied at hourly resolution. In this paper, we will refer to the methodology by Tarasova et al. (2018) as Traditional Event Separation Routine (Trad-ESR).

2.3. ESRs Evaluation

The evaluation is performed as follow:

1. Comparison between DMCA-ESR with a posteriori baseflow separation and Trad-ESR at daily and hourly scale.
2. Comparison between DMCA-ESR with a priori baseflow separation and Trad-ESR at daily and hourly scale.
3. Comparison between daily DMCA-ESR and hourly DMCA-ESR with a posteriori baseflow separation.

In order to evaluate the ESRs, we characterize the identified events using 6 descriptors: duration of rainfall events, duration of runoff (quick flow) events, volume of rainfall events, volume of runoff (quick flow) events, runoff ratios (ratio between volume of quick flow and volume of rainfall) and the number of identified events. These descriptors are chosen because they are widely used to characterize rainfall-runoff events. Similarity between events characteristics coming from different distributions are evaluated visually and with the help of Spearman Rank correlation (named simply "Corr" in Figures 3 and 5) and median relative bias (named simply "Bias" in Figures 3 and 5) :

$$\text{Median relative bias} = \text{median}\left(\frac{X1_i - X2_i}{X2_i}\right) \quad i = 1, \ldots, N \text{ with } N = \text{number of events} \tag{2}$$

where $X1$ is the estimate from one distribution and $X2$ is the correspondent estimate from another distribution. Traditionally it is assumed that the estimate used at the denominator, $X2$, is the "correct" one but in this work we do not make this assumption instead we simply use it as a baseline for the comparison. When comparing DMCA-ESR with Trad-ESR, $X1$ is the estimate using DMCA-ESR and $X2$ is the estimate using Trad-ESR (see Figure 3), while when comparing daily and hourly event identification from the DMCA-ESR, $X1$ is the hourly estimate and $X2$ the daily estimate (see Figure 5).

3. Data

The evaluation of the DMCA-ESR is performed on nine catchments in Great Britain. These nine catchments are selected as they present the following characteristics: (a) an average catchment response time of at least 1 day (or slightly less), to be able to capture a delay between new rainfall input and runoff response even at daily scale (the DMCA-ESR can also be applied in catchments with shorter responses, as long as the resolution of the data is able to capture the delay between rainfall and runoff response); (b) a Base Flow Index (BFI- ratio between volume of baseflow and volume of total streamflow) lower than 0.85, to guarantee a significant response to new rainfall inputs; (c) surface and groundwater abstraction respectively lower than 5% and 10% of the mean streamflow value, and no reservoirs, to avoid significant changes in the streamflow rate due to human disturbance. The catchment descriptors to identify the catchments that fulfill the above characteristics are used and these are taken from the CAMELS-GB data set (Coxon et al., 2020). A summary of the characteristics of the selected catchments is presented in Table 1.

In each catchment, the mean areal hourly rainfall has been derived from the continuous CEH-GEAR 1hr data set (Lewis et al., 2018). Streamflow data at 15-min step were provided by the Environment Agency (EA), Natural Resources Wales (NWR) and Scottish Environmental Protection Agency (SEPA) and then processed to obtain hourly streamflow time series. The record length is of 24 years, from 1990 to 2014, but in some catchments the streamflow records are discontinued (maximum percentage of missing values 8%). Nevertheless, both the DMCA-ESR and Trad-ESR are able to ignore missing values, especially if in large gaps so the discontinuity in the records has not been an issue for this analysis. The hourly timeseries are subsequently aggregated to obtain daily rainfall and streamflow timeseries.

4. Results

4.1. Comparison Between DMCA-ESR and Trad-ESR at Daily and Hourly Scale

As a first step we tested the DMCA-ESR when run using rainfall and total streamflow in each catchment. After, the events are identified using the DMCA-ESR, we estimate the baseflow by connecting the delimiters of the identified streamflow events and consequently we compute the runoff volumes for each event in each catchment. When connecting the delimiters of the streamflow events, if at any point in time the baseflow is above the streamflow curve, we set the baseflow equal to the streamflow. In Text S5 and Figure S2 in Supporting Information S1 we present the comparison between the BFIs (total volume of baseflow divided by total volume of streamflow) computed using the baseflow from the Trad-ESR and the baseflow retrieved using the DMCA-ESR.

Characteristics of the events selected with the DMCA-ESR, run with daily rainfall and total streamflow and computing the baseflow a posteriori, are compared to the ones of the events selected by the Trad-ESR both at daily (Figure 2) and hourly (Figure S3 in Supporting Information S1) resolution. To assure comparability of two methods here we remove all events smaller than 10% of baseflow as required and estimated by the Trad-ESR from the analysis, but at this stage a priori separated baseflow is not considered in the DMCA-ESR procedure.

The numbers of events identified in each catchment over the same record length by the DMCA-ESR and the Trad-ESR are comparable (Figure 2a and Figure S3a in Supporting Information S1), with slightly larger numbers

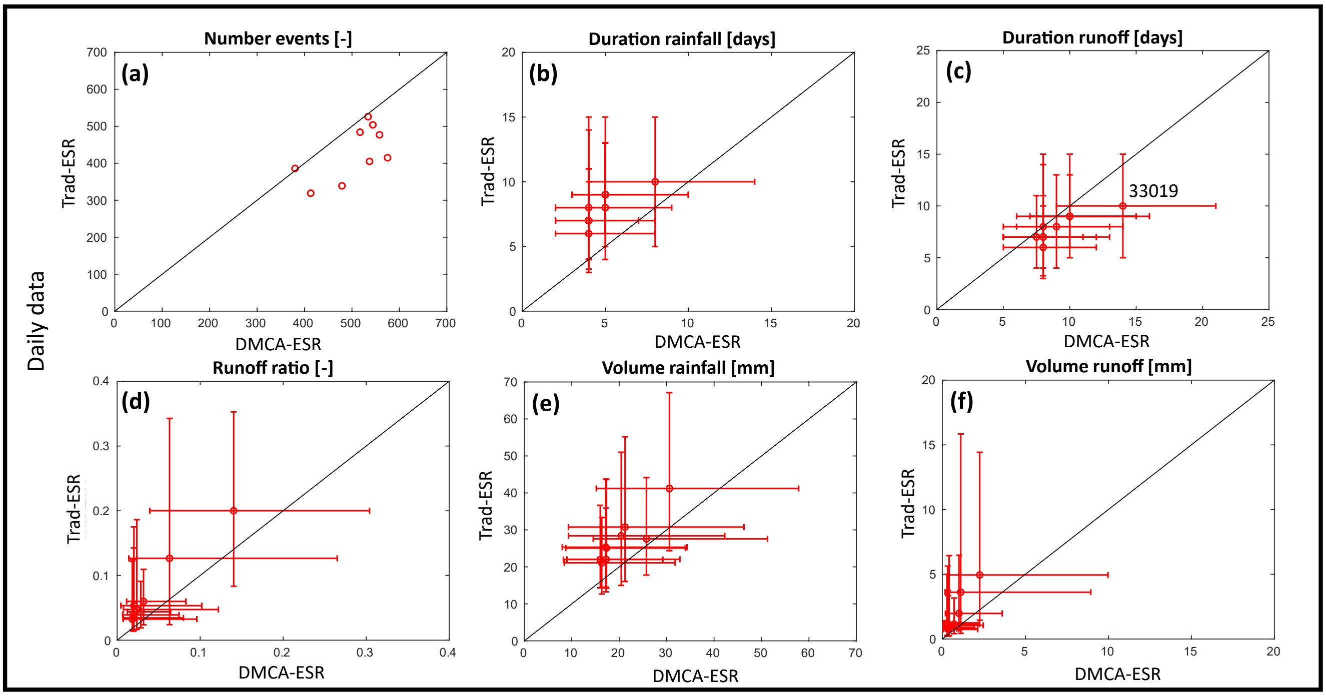

Figure 2. Comparison between DMCA-ESR without a priori baseflow separation (run with rainfall and total streamflow timeseries) and Trad-ESR at daily scale. The considered events for each of the methods are the ones which have runoff peak at least 10% higher than the baseflow value. Each dot (median) with the 25th and 75th bars represent one catchment.

for the DMCA-ESR. Volume of rainfall and runoff events appear slightly larger for the Trad-ESR (Figure 2e and Figure S3e in Supporting Information S1, Figure 2f and Figure S3f in Supporting Information S1). While for rainfall this is probably due to the longer durations (Figure 2b and Figure S3b in Supporting Information S1), we do not observe a similar pattern in the runoff durations (Figure 2c and Figure S3c in Supporting Information S1). Durations of runoff events are in fact very similar, with the exception of one catchment (ID: 33019), strongly baseflow dominated. Overall, differences are minor and considering the very different approaches adopted by the two methods, there is a good agreement especially in case of runoff ratios (Figure 2d and Figure S3d in Supporting Information S1).

As larger events are generally of greater interest for the analysis of flood events, we considered in each of the 9 catchments the 50 highest peaks separated by at least 10 days and we compared the properties of the events identified by the DMCA-ESR and by the Trad-ESR to which they belong. This analysis is repeated both daily and hourly scale. Out of the 450 events (50*9 = 450), the DMCA-ESR is able to identify events for 390 at daily and 431 at hourly scale while the Trad-ESR identifies 433 at daily scale and 430 at hourly scale. The top row of Figure 3 shows results for the analysis at daily scale, while the bottom one for hourly scale. We present in each subplot in Figure 3 the Spearman Rank correlation values and the relative bias normalized against the Trad-ESR distributions. Overall, we can see that for the majority of the events there seem to be a good agreement between the two methodologies in terms of volume of rainfall (Figures 3b and 3e) and runoff events (Figures 3c and 3f), but there is a number of events which show larger volumes when extracted with the DMCA-ESR. However, for the vast majority of the events the runoff ratios (Figures 3a and 3d) are very similar using the two methods, meaning that despite the different approach the transformation rate is very similar.

4.2. Are the Disagreements Between DMCA-ESR and Trad-ESR Due Mainly to Baseflow Separation, or Mainly Due to How the Rainfall-Quick Flow Series is Converted to Events?

As a second test we aim to understand if differences in event identification between the DMCA-ESR and Trad-ESR are caused mainly by the baseflow separation or mainly due to how the rainfall-quick flow series is converted to events. Therefore, the DMCA-ESR was run using the rainfall and quick flow time series in each

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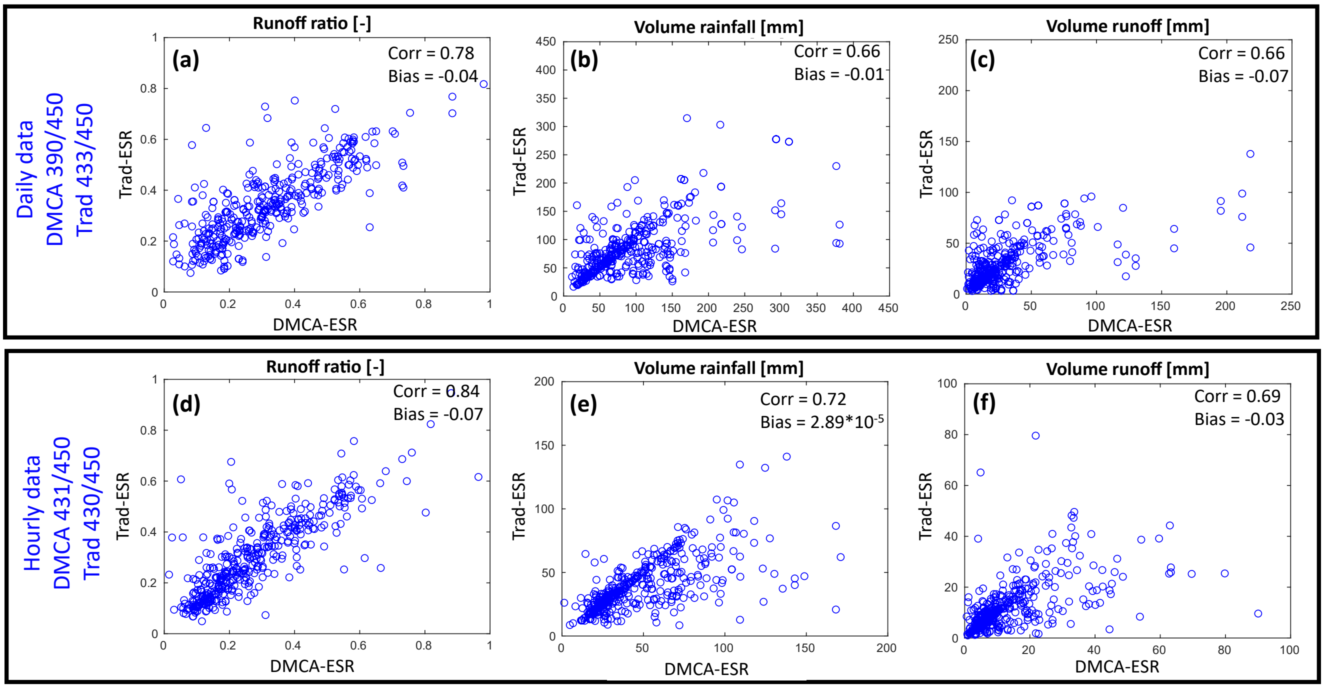

Figure 3. Comparison between DMCA-ESR (with rainfall and runoff timeseries) and Trad-ESR at daily (top row) and hourly (bottom row) scale. Among the 50 highest peaks in each catchment, the considered events are the ones which have been identified by both methods (378 at daily, 414 events at hourly scale).

catchment, where the quick flow is obtained by subtracting the baseflow from the total streamflow. The baseflow has been calculated according to the Trad-ESR. Although possible, we do recognize that the application of the DMCA-ESR following the *a priori* baseflow would not be common practice, as hydrologists would probably complete the event identification using Trad-ESR or a similar approach, but it is used here to better understand differences between the two methodologies.

Characteristics of the identified events using the DMCA-ESR with rainfall and quick flow timeseries are compared with those of the events identified by the Trad-ESR, both at daily (Figure S4 in Supporting Information S1) and hourly (Figure S5 in Supporting Information S1) resolution. To coherently compare the results from the two methodologies, we consider only events with peak runoff higher than the 10% of the baseflow as suggested for the Trad-ESR.

The number of events identified by the two methods are shown in Figures S4a and S5a in Supporting Information S1 and they are very similar compared to Figure 2a and Figure S3a in Supporting Information S1 respectively. Similarly, the rainfall volumes and durations show almost identical distribution compared to the analysis using rainfall and total streamflow timeseries (Figures 2b and 2e vs. Figures S4b and S4e in Supporting Information S1; Figures S3b and S3e vs. Figures S5b and S5e in Supporting Information S1). Despite this time the DMCA-ESR was run using the quick flow, there is still a very good match between durations of runoff events identified by the DMCA-ESR and by the Trad-ESR (Figures S4c and S5c in Supporting Information S1) and the distribution is very similar to one generated by the analysis using rainfall and total streamflow timeseries (Figure 2c and Figure S3c in Supporting Information S1). Similar results are shown for runoff ratios (Figure 2d vs. Figure S4d in Supporting Information S1, Figure S3d vs. Figure S5d in Supporting Information S1). Overall, results seems to be very similar to the previous analysis using rainfall and total streamflow, meaning that the difference are mainly to be attributed to how the rainfall-quick flow series is converted to events and not to the baseflow separation process. Moreover, this demonstrate that a baseflow separation *a priori* for the DMCA-ESR is not essential as the method is able to provide very similar results using the baseflow a posteriori retrieved by connecting delimiters of events.

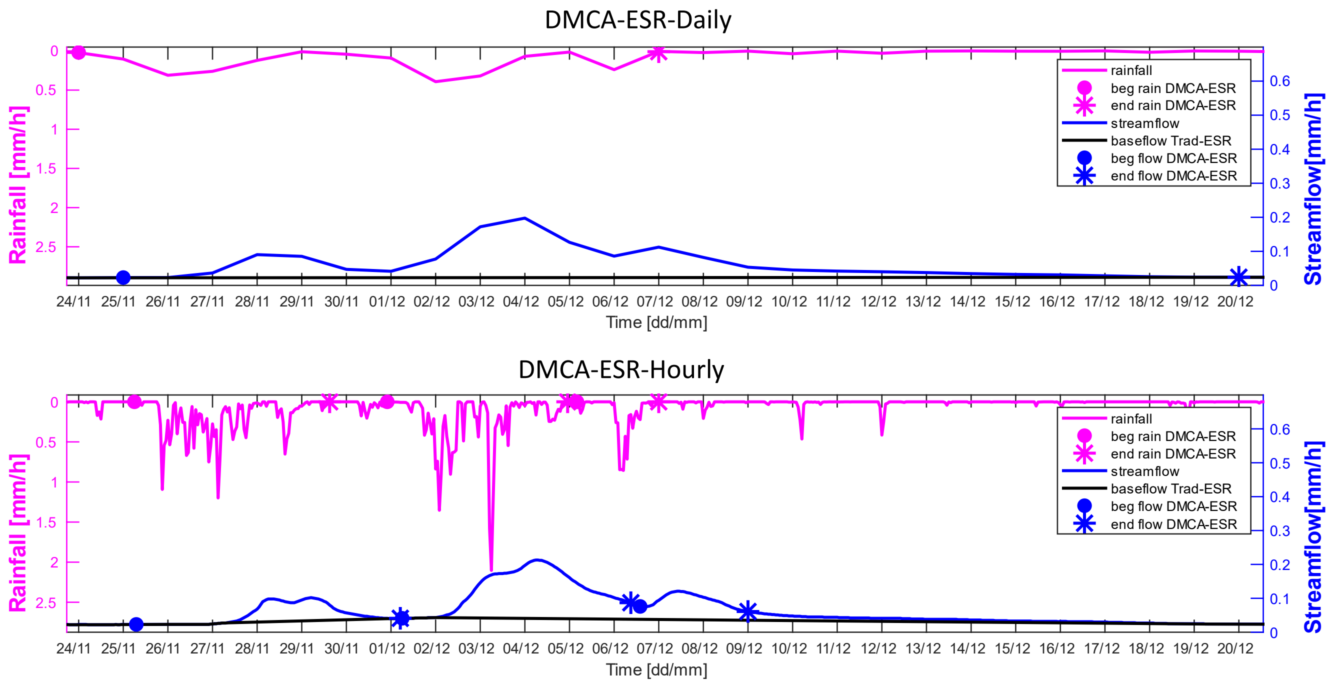

Figure 4. Example of event identification using the DMCA-ESR at daily (top) and hourly (bottom) resolution. The black line is the baseflow computed according to Trad-ESR to show that at hourly scale the last two peaks are grouped together by the Trad-ESR, while the rest of the events both at hourly and daily scale are identified in a similar way by the two methods.

4.3. Comparison Between Daily DMCA-ESR and Hourly DMCA-ESR

At hourly scale the temporal dynamics of the timeseries is more pronounced than at daily scale, therefore at finer resolutions it is possible to separate the series into more events than at coarser (i.e., aggregated) resolutions over the same time period (see comparison Figure 2a and Figure S3a in Supporting Information S1 for number of events, and Figure 4 identification of events with DMCA-ESR at daily [top] and hourly [bottom] scale). For reference in Figure 4 we also draw the baseflow (in black) according to the Trad-ESR, to show that at daily scale the identification of the events with DMCA-ESR would be very similar to Trad-ESR while for the hourly scale using the Trad-ESR the last two peaks are part of the same event. Although there is no objective way to identify which situation is correct, we consider these are acceptable differences between the two methods.

Considering the different number of identified events by DMCA-ESR at different resolutions, we compare the identification at hourly and daily resolution we consider the 50 highest streamflow peaks separated by at least 10 days in each of the 9 catchments. After running the DMCA-ESR at hourly and daily scale using rainfall and streamflow timeseries, we extract the events in which these 50 highest peaks fall. Volumes of runoff are computed using the baseflow drawn by connecting the delimiters of the streamflow events.

Out of the 450 expected peaks (50*9 = 450), the daily event selection is able to find events only for 390 of them and the hourly selection for 431 of them. The comparison is therefore performed on the intersection of the two sets of events. For each of the event descriptors in Figure 5 we present the Spearman Rank correlation and the relative bias normalized against the daily distributions. When looking at the event durations we expectedly see that daily data tend to produce longer events (Figures 5a and 5b) which in turn results in larger volumes (Figures 5d and 5e). However, the runoff ratios show strong similarity at both scales (Figure 5c) proving that the DMCA-ESR is able to produce a coherent selection across different time resolutions, but coarser data will always produce longer and bigger events due to the lack of information. Note that running the DMCA-ESR at different temporal resolutions requires very minimal effort compared to the Trad-ESR, where an intensive recalibration of parameters is required (see Text S4 in Supporting Information S1).

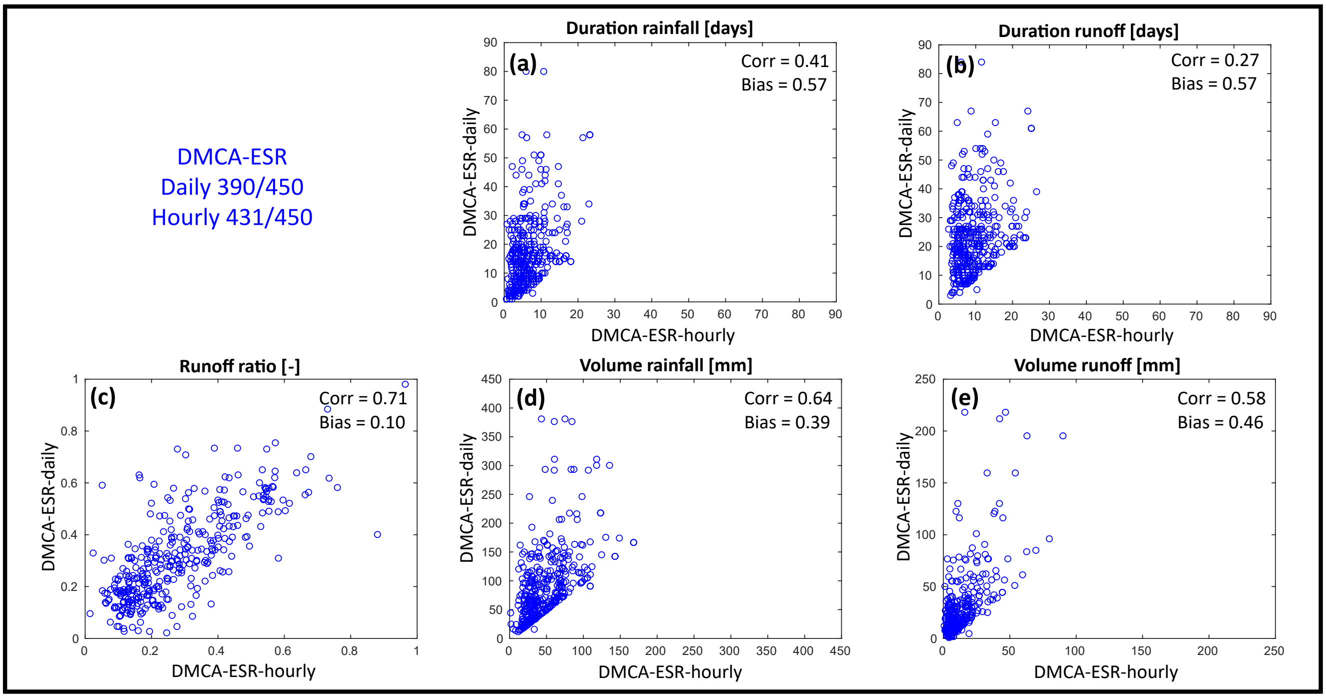

Figure 5. Comparison between DMCA-ESR at daily and hourly scale. Among the 50 highest peaks in each catchment, the considered events are the ones which have been identified at both resolutions (375 events).

5. Discussion

5.1. The DMCA-ESR Corresponds Well to Trad-ESR

Considering the very different approaches adopted by the two methods for event identification, we observe a good agreement in terms of event properties at both temporal scales. Nevertheless, we observe several differences. Volume of runoff events appear systematically slightly smaller for the DMCA-ESR, due to the larger number of smaller events identified by this method compared to the Trad-ESR. The correlation between the difference in total number of identified events by the two methods and the difference in number of runoff events smaller than 2 mm identified by the two methods is equal to 0.92 both at daily and hourly scale. This indicates that a large part of the difference between the distributions can be explained by the DMCA-ESR identifying more of smaller events. In fact, Trad-ESR tends to discard some of the very small events because their runoff ratios are larger

Table 1
Characteristics of the Study Catchments.

Catchment ID	Catchment name	Catchment response time Tr (hours)	Area (km^2)	Qmean (mm/d)	Pmean (mm/d)	BFI (-)
27071	Swale at Crakehill	29	1354.43	1.32	2.34	0.54
33019	Thet at Melford Bridge	59	311.37	0.53	1.76	0.75
34002	Tas at Shotesham	27	153.19	0.41	1.73	0.64
34006	Waveney at Needham Mill	27	376.07	0.40	1.67	0.52
37008	Chelmer at Springfield	29	189.62	0.49	1.65	0.61
39081	Ock at Abingdon	33	233.6	0.60	1.77	0.66
39105	Thame at Wheatley	44	531.53	0.62	1.78	0.59
43006	Nadder at Wilton	22	215.63	1.15	2.48	0.76
43009	Stour at Hammoon	20	518.75	1.11	2.41	0.43

Note. Catchment response time is computed according to the DMCA-based method (Giani et al., 2021), while area, Qmean (mean daily discharge), Pmean (mean daily precipitation) and BFI (Base Flow Index) are from Coxon et al., 2020.

than 1. This is caused by the fact that the Trad-ESR uses the median lag (time between rainfall and flow peaks), to attribute the rainfall to the identified runoff event. However, often smaller events tend to show longer response times and hence the median lag might be too short to include all the rainfall contributions which generate the related runoff event. Instead, the DMCA-ESR has a more flexible approach to differences in response times due to the use of bivariate fluctuation for the identification of the event cores. As mentioned before the window length associated to Tr, L_{min}, is equal to 2Tr+1 and cores are identified as periods of non-zero bivariate fluctuations. Hence, the response time of an event needs to be longer than 2Tr+1 for the bivariate fluctuations to be zero between the rainfall contribution and the runoff response and hence generate an incorrect event identification. Compared to the Trad-ESR, this gives certainly more flexibility to the differences in responses and show how a "system" approach can be beneficial. The larger number of small events identified by the DMCA-ESR explains not only the smaller median volume of runoff but also the smaller rainfall volumes and durations.

However, it initially seems surprising that runoff volumes are smaller for the DMCA-ESR but we do not observe the same pattern in the duration of runoff events. The reason of this result is in how the delimiters of the runoff events are placed by the DMCA-ESR. As a reminder, we place the beginning marker of the runoff event when streamflow fluctuation start becoming negative (this occurs slightly before the trough, due to the moving average process). The end marker is set at the last time step of positive streamflow fluctuations (this generally occurs right before the following trough). Especially the way the end delimiter is placed produces longer durations, which however do not result in a detectable increase in volume because the delimiter is just pushed forward in time on the tail of the event when flows are relatively low. This behavior is particularly enhanced for the catchment ID 33019 (Figure 2c and Figure S3c in Supporting Information S1), which shows a strong baseflow component and long recessions. Overall, the median durations should be shorter because the DMCA-ESR identifies more of smaller events but it is balanced by the fact that delimiters are allocated on steady parts of the hydrographs, resulting in a similar duration distribution with the traditional method (Trad-ESR).

When looking at 50 highest peaks in each catchment (Figure 3), we can see how the DMCA-ESR identify slightly fewer events compared to the Trad-ESR at daily scale. This is caused by the coarse resolution of the data that hampers verification of required checks for the DCMA-ESR method (step 6 and 9 of Section 2.1). At hourly scale, instead, the two methodologies are comparable in the number of identified events. At both scales, we can see that there is a group of events which show larger volumes when identified with the DMCA-ESR. This is caused by the fact that the DMCA-ESR requires both the streamflow to be steady and the rainfall to be zero for a duration equal to L_{min} to delimit the event. The introduction of R_{min} allows to reduce the identification of long events but only if the rainfall contributions between events are very small. Instead, the Trad-ESR by just stepping back in time with a fixed step equal to the lag to identify the rainfall event does not require any minimum length of dry period, hence being advantaged in breaking down the record. However, as it only performs rainfall attribution and does not adopt a "system" approach, the resulting rainfall-runoff events might be biased. Nevertheless, from the runoff ratios we can deduce that in most of the cases of mismatch the DMCA-ESR is identifying longer runoff events as well as longer rainfall events, hence generating very similar runoff ratios (Figures 3a and 3d).

5.2. Differences Between DMCA-ESR and Trad-ESR are not to be Attributed to the Baseflow Separation

When comparing Figure 2 with Figure S4 and Figure S3 with Figure S5 in Supporting Information S1 we observe very minor differences. In particular, durations of runoff events (Figure 2c and Figure S4c in Supporting Information S1, Figures S3c and S5c in Supporting Information S1) appear almost unchanged meaning that the differences between the DMCA-ESR and Trad-ESR are to be attributed mainly to how the rainfall-quick flow series is converted to events and not to the baseflow separation process. Moreover, results confirm that an a priori baseflow separation does not improve the event identification when using the DMCA-ESR. By avoiding the *a priori* baseflow separation step, the DMCA-ESR offers the chance to make the whole procedure of event identification more objective. Baseflow separation is generally a quite subjective procedure that is difficult to evaluate in an objective manner (Tarasova et al., 2018). Unless tracer studies or groundwater measurements have been conducted in the catchment, the absence of a benchmark makes impossible to evaluate which method is more representative of the actual baseflow. In this work we suggest an alternative *a posteriori* method to produce the baseflow curve in case runoff volumes are required, but for the reasons mentioned above it is impossible to assess if it provides more realistic results compared to traditional methods. However, the differences in BFIs using the baseflow separation from the DMCA-ESR and from the Trad-ESR are rather small (Figure S2 in

Supporting Information S1) if compared with how different the BFIs can be using different algorithms as shown by Eckhardt (2008). This means that the novel method produce baseflow volumes which are at least in line with the more traditional digital filters.

5.3. DMCA-ESR Produces Coherent Event Identification Across Different Temporal Resolutions

The DMCA-ESR requires the rainfall to be zero (or nearly zero) to delimit an event. This condition generates certainly longer events at daily scale as even if it is raining only for one hour throughout the day, the daily precipitation will be different from zero, preventing from discretizing the rainfall contributions into different events. Longer durations of events at daily time scale make also the volumes larger. However, it is important to note that there is a strong similarity in terms of runoff ratios (Figure 5c), meaning that despite the different resolutions the DMCA-ESR produces a coherent "system" event identification. Moreover, for specific purposes, such as for example sediment transport (e.g., Hamshaw et al., 2018) longer events might be better suited as they allow to study complete hysteresis patterns.

Being able to apply the DMCA-ESR method at finer temporal resolutions with very minor changes (only the rainfall fluctuation tolerance) is certainly a very important advantage of the proposed method. In fact, because of the large amount of information contained in the data at finer resolutions, the event identification methodologies generally require a high number of steps, often subjective, to be able to overcome the complexity and automate the procedure (e.g., Mei & Anagnostou, 2015 and modification from Tarasova et al., 2018 to run Trad-ESR at hourly scale—Text S4 in Supporting Information S1).

Although many studies avoid the sub-daily complexity by looking at rainfall-runoff process at daily scale, from the timeseries in Figure 4, one can get an impression how much information is going missing when looking at daily records compared to the hourly ones. Hourly rainfall data tends to produce higher correlations to streamflow compared to coarser data (Dougherty et al., 2021) highlighting how higher resolution data can help better explaining relationship between rainfall and runoff. As in the recent years more data become available at higher resolutions (both temporal and spatial), there is certainly a need of handling the additional information in a more straightforward and reproducible way. This is what DCMA-ESR can offer. Moreover, the higher the data resolution the higher are the probabilities that all the checks (see step 6 and 9 in Section 2.1) are reliably verified reducing the number of discarded events (Figure 5, see number of identified events at hourly and daily scale).

6. Limitations of the DMCA-ESR

Despite the generally good performance of the DMCA-ESR, there are certainly a number of limitations which should be recognized. First of all, as pointed out in Section 2.1, this method as well as the DMCA-method to estimate catchment response time cannot be applied where the resolution of the data is not high enough to capture the delay between new rainfall input and runoff response. This means that where only daily data are available and the average catchment response time is effectively only a few hours, the DCMA-based method cannot be applied, and an alternative method such as the one proposed by Tarasova et al. (2018) might be used instead.

Moreover, as mentioned in Section 5.1, the allocation of the runoff events' delimiters generates slightly longer events compared to what hydrologists are used to: the markers are generally placed in the steady part of the record just preceding and following the actual runoff event. Although this allows us to produce a baseflow separation by just connecting the delimiters, the durations of the runoff events result slightly bigger than those durations estimated according to the Trad-ESR. However, this does not have any significant impact on the volumes because time markers are just shifted in time to periods of steady streamflow. Moreover, this can be even desirable in cases when the focus is on the event-driven dynamics of water quality parameters (e.g., suspended solids) that might have more rapid or more lagged response than streamflow itself (e.g., Hamshaw et al., 2018).

When manually inspecting the events identified by the DMCA-ESR sometimes we observe incorrect identification for some of the multi-peak events and some of those small runoff events happening in the tail of a bigger one. The variability of the time series, especially for the rainfall, can make the fluctuation signs highly variable and hence it can become difficult to place the delimiters. In cases when the response time of an event is much longer than the average one, the guidance provided by the catchment response time estimate by the DMCA method is not sufficient and might also result in unreliable event identification. Finally, we observe some weaknesses in the method when constant rainfall or streamflow rates occur for a duration equal at least to L_{min} (most likely happening at coarser time resolution). In fact, in these cases constant values either of rainfall or streamflow can produce zero fluctuations which can be interpreted as break points.

Regarding the application of the proposed method in different climates and environments, particularly karst environment and arid conditions might pose considerable challenges. In fact, in karst regions the streamflow peaks tend to be attenuated (Charlier et al., 2019) -sometimes hard to identify even with visual inspection-, ultimately undermining the characteristic step shape of streamflow response when converted in cumulative timeseries (see Figure 1b gray solid line in Giani et al., 2021). As the DMCA-ESR relies on this concept, the application of the DMCA-ESR might produce outputs that are not necessarily in line with the hydrologists' expectation in these cases.

The challenge in arid conditions, instead, emerges through the variability in the timing of the response. Even in humid environment the response time is quite variable due many different factors, in arid conditions reliable identification of the characteristic catchment response time might be more challenging. Although the DMCA-ESR shows a considerable flexibility in detecting events with different response times, this flexibility goes only up to about twice the typical catchment response time (i.e., 2Tr+1) and relies on a meaningful estimate of the catchment response time. Therefore, as well as for karst region, the application in arid climates of the DMCA-ESR might produce events which do not reflect our expectations. Although this is certainly a limitation, it is important to note that the identification of events in these climates and environments is often very difficult even with visual inspection.

On the contrary, we believe there might be potential in the application of the DMCA-ESR in snow dominated catchments by using as input the catchment-scale liquid water input time series (rainfall plus snowmelt) and as output the streamflow time series. Although this application has not been tested yet, we believe that by modifying the input time series, the proposed method could help in the event identification in snow dominated catchments. Concluding, the current version of DMCA-ESR (https://github.com/giuliagiani/DMCA-ESR, last access 04.08.2021) represents an effort to automate and standardize the event identification across different time resolutions and sites. However, we recognize its limitations and we are open to modifications which allow to overcome those issues. Therefore, we always recommend to carefully check the events identified by the DMCA-ESR method. Suggested checks might include but not limited to reviewing the runoff ratio and event duration. Eventually tailored filters can be applied to exclude specific group of events (e.g., consider only events with peak flow larger than the mean flow). However, the current version of the code does not include post-processing tools, as this filtering is likely to be specific to the application.

7. Summary

A recognised methodology for rainfall-runoff event identification is missing. Methodologies found in the literature differ in perspective (focusing first on separating input or output), involve a number of subjective steps (e.g., *a priori* baseflow separation) and need to be substantially modified when applied to different temporal resolution of the data.

For this reason, we identified the need of a new methodology for rainfall-runoff event extraction from continuous timeseries. The main advantages of the proposed method are: (a) it identifies rainfall-runoff events by simultaneously looking at rainfall and streamflow records, (b) it does not require *a priori* baseflow separation, and indeed can produce a simple baseflow separation by connecting the delimiters of the identified streamflow events *a posteriori* and (c) can be used with different time resolution of the data by only modifying one parameter.

When tested both methods on nine UK catchments, the DMCA-ESR, which was implemented using rainfall and total streamflow time series, shows a good agreement with the traditional baseflow-based approach (Trad-ESR). Differences between the Trad-ESR and DMCA-ESR are to be attributed to how the rainfall-quick flow timeseries are converted into events and not the baseflow separation process. When running the DMCA-ESR an *a priori* baseflow separation is not essential to perform a sensible event identification, allowing to avoid such a subjective procedure. If quick flow volumes are required, the baseflow can be deduced a posteriori and proved to produce very similar estimates compared to more traditional event separation approaches. Moreover, we also showed that the DMCA-ESR performs a coherent event identification at different temporal scales and allows effortless switch between temporal resolutions.

We provide freely available DMCA-ESR code, hoping that our first effort to standardize the event identification can be improved by other members of the hydrology community, especially for the groups of events (e.g., multi-peak event, smaller events on the falling limb of much larger events) that are still very challenging to identify correctly.

Data Availability Statement

Information about the U.K. Catchments can be obtained from the website https://nrfa.ceh.ac.uk/data/search. Hourly streamflow timeseries are available on request from Environmental Agency (EA), Natural Resources Wales (NWR) and Scottish Environmental Protection Agency (SEPA). CEH-GEAR1hr precipitation data are available from the website https://doi.org/10.5285/d4ddc781-25f3-423a-bba0-747cc82dc6fa. Catchment descriptors are available from the website https://catalogue.ceh.ac.uk/documents/8344e4f3-d2ea-44f5-8afa-86d2987543a9. The code for the proposed novel method is available at https://github.com/giuliagiani/DMCA-ESR.

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