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Rainfall–streamflow response times for diverse upland UK micro-basins: quantifying hydrographs to identify the nonlinearity of storm response

David Mindham *, Keith Beven and Nick Chappell
Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK
*Corresponding author. E-mail: d.mindham@lancaster.ac.uk

DM, 0000-0002-9818-1465; KB, 0000-0001-7465-3934; NC, 0000-0001-6683-951X

ABSTRACT

While it is known that antecedent conditions and rainfall profiles contribute to the nonlinearity of streamflow response and that hydrograph shape can be dependent on the nature of rainfall inputs, how antecedent conditions (with similar rainfall inputs) impact hydrograph shape is less known. Here, a data-based mechanistic (DBM) approach is applied to quantify hydrograph shape, in terms of timing and volume, for the purposes of comparing hydrographs across 17 micro-basins at selected localities in upland UK over a 4-year period. The analysis demonstrates the nonlinearity of storm response for small catchments and revealed that with low antecedent conditions and/or small rainfall inputs there was a high variance in hydrograph shape quantifiers and that these variances decrease (at rates micro-basin dependent) as the micro-basins became wetter or as the storms increased in size, potentially converging to a more stable response.

Key words: hydrographs, micro-basins, nonlinearity, quantification, streamflow

HIGHLIGHTS

- Quantification of hydrograph shape in terms of timing and volume.
- Comparison of hydrograph quantifiers across time and space (17 micro-basins, 4 years).
- Observation of reduction in timing as antecedent conditions or storm size increase.
- Observation of reduction in quantifier variance as antecedent conditions or storm size increase – convergence to more stable response.
- Rate of convergence/stabilisation micro-basin dependent.

1. INTRODUCTION

Antecedent (or pre-storm) conditions of a catchment may affect the magnitude (Black 1972) and shape (Minshall 1960) of a storm hydrograph to a unit input of rainfall. This may be partly responsible for the nonlinearity in rainfall to streamflow response seen within many catchment datasets (such as Mathias *et al.* 2016 and Kokkonen *et al.* 2004). The traditional approach to this problem has been to assume that a single hydrograph shape can be fitted to the data from a catchment as the Unit Hydrograph, which represents a flexible form of linear transfer function under the assumptions of superposition and linear proportionality. The effects of nonlinearity (partly caused by variations in antecedent conditions) are removed by the joint use of baseflow separation and the calculation of an 'effective rainfall' input ensuring that the inputs equal the predicted outputs. In recent years, however, there has been a move towards modelling the whole of the outflow using linear transfer functions, with the effects of nonlinearity reduced by pre-processing the input signal through for example DBM (e.g., Young 1986; Young & Beven 1994; Beven *et al.* 2011; Chappell *et al.* 2017) or IHACRES (e.g., Jakeman *et al.* 1990; Littlewood 2021). For a comparative discussion of the two approaches, see Littlewood *et al.* (2010). For more background to the philosophy of the DBM approach, see Young (2013). Little research has, however, focused on how the shape of derived transfer functions might vary with rainfall amounts and intensities and antecedent conditions. Past research has shown how different rainfall volume and intensity inputs may produce different hydrograph shapes (starting with Childs 1958 and Minshall 1960; see also Caroni *et al.* 1986; Rodriguez-Blanco *et al.* 2012), while spatial rainfall variability and storm direction might also affect derived unit hydrographs (Singh 1997; Paschalis *et al.* 2014).

However, the question as to whether hydrographs are more damped or flashier in response to similar rainfall events occurring at times of low-flow vs high-flow (i.e., relatively dry vs wet catchment states) has been less studied (Beven *et al.* 2008). Since the earliest days of the unit hydrograph (Sherman 1932), this was considered more of a problem of the volume of effective rainfall than of unit hydrograph shape. The flashiness of a catchment (e.g., the time constant (TC) of a rainfall–streamflow transfer function) may be important to informing our perceptual model of a catchment's response, for subsequent physics-based modelling (Beven & Chappell 2021). Equally, a better understanding of how parameters of the hydrograph shape (to a unit input of rainfall) vary over time (e.g., Mindham *et al.* 2018) may lead to improved models for flood forecasting.

Within the UK NERC funded Q-NFM project, the focus is on quantifying the behaviour of large storm hydrographs generated at micro-basin scales of around 1 km^2. Many of these basins include nature-based interventions which *should be* designed to mitigate storm hydrograph peaks during large rainfall events. The within-storm dynamic behaviour of these interventions (e.g., change of storage per unit time, m^3/s) may be linked directly to observed stream discharges (m^3/s) at this micro-basin scale. The significance of these interventions, sometimes called 'natural flood management' (NFM), at reducing hydrograph peaks (for local streams) may differ depending on whether the catchment is naturally flashy (e.g., headwater peatland with slowly permeable subsoil dominated by near-surface pathways) or damped (e.g., a micro-basin on a deep permeable aquifer with no impeding surficial deposits). This study focuses on small and large storms to gain some understanding of the flashiness of these micro-basins.

Ongoing studies of micro-basins in upland UK have noted the importance of antecedent conditions on hydrograph response (e.g., Monger *et al.* 2021; Norbury *et al.* 2021) and as many of these recent studies are associated with evaluating the benefits of so-called nature-based interventions (e.g., Shuttleworth *et al.* 2019; Monger *et al.* 2022), it is necessary to understand hydrograph sensitivity to antecedent conditions in understanding the processes involved in nature-based solutions.

If the flashiness of these micro-basins to a unit input of rainfall (i.e., hydrograph shape) differs with event size, then there may be benefits from quantifying the shape characteristics for different event sizes. For NFM studies focused on larger event sizes, this could become critical where smaller hydrographs are more difficult to characterise due to confounding effects of varying antecedent (pre-storm) conditions.

1.1. Quantification

The shape of a unit hydrograph or unit transfer function should be quantifiable in terms of speed of response, the flashier the response, the narrower the peak. One method for estimating this speed of response is through the objective identification of the parameters of a first-order transfer function model and calculating the TC from those parameters. The interpretation of the TC depends on the particular application of the transfer function and observed data used. In this study, rainfall and streamflow time-series data are used (at 15-min intervals), where 'streamflow' is here defined as specific discharge ('discharge per unit catchment area') and has the same units as rainfall (mm/15 min). A transfer function represents the dominant modes of response that converts the input (rainfall) to output (streamflow). When derived from single event rainfall–streamflow data, then the TC (hours) may be interpreted as the speed of response for that hydrograph, and here is referred to as response time (RT). It is important to clarify that RT is the measure of the pattern of water celerities in space and time and not the velocities of water particles (Eagleson 1970; Beven 2012, 2020; McDonnell & Beven 2014). It is the speed of propagation of the integrated effects of the inputs that cause the stream response from a rainfall event.

In addition to the TC, the parameters of the transfer function can be used to calculate the gain of the system and when the input and output have the same units, as they are here, the gain can be interpreted as the simulated runoff coefficient (SRC), i.e., simulated streamflow divided by observed rainfall. This gives another method of quantifying hydrograph shape, in terms of relative volumes.

A further important parameter of the transfer function is the pure time delay (TD), the time taken for the input to influence the output.

1.2. Objectives

The specific research objectives for this component study are therefore as follows:

- To develop an objective method for quantifying individual rainfall–streamflow events.
- To apply the method to 17 micro-basins in upland UK (mostly located in the Cumbrian mountains) to quantify each individual storm event.
- To compare and contrast these quantified events:

- across time and space – between other events at the same micro-basin and events at other micro-basins.
- against metrics for the drivers of stream response.

1.3. Study sites

In this study, 15 micro-basins in the Cumbrian mountains and 2 micro-basins in the Peak District massif in the UK (Figure 1 and Table 1) are used with sizes ranging from 0.0071 to 2.7329 km^2, with rainfall (mm/5 min) and stream level (mm) measured at 5-min intervals for approximately 4 years (see Supplementary Material A1 for first and last event dates of each micro-basin, and Supplementary Material B for full time-series of each micro-basin).

The sites are dominated by three principal land covers of pasture, moorland and woodland, and most of the sites have natural flood management (NFM) features, with others acting as reference or control basins (details found in Supplementary Material A1). While there is a range of land covers, water pathways and NFM features, these contrasting characteristics are not the focus of this initial study.

The monitoring system for each micro-basin was standardised, with the stream level being measured in an FRPB trapezoidal flume (maximum capacity of 430 l/s) with a known rating curve and a known basin size and so could be converted to streamflow (mm/5 min), while rainfall (mm/5 min) was measured with a tipping-bucket raingauge located next to the flume. Data from all flumes and raingauges were delivered via telemetry. Basic micro-basin details are found in Table 1, for more details, including dominant geology and soils, see Supplementary Material A.

2. METHODOLOGY

The methodology followed this procedure:

1. To break whole time-series into single event time-series, discarding those that do not meet the described criteria (Section 2.1).

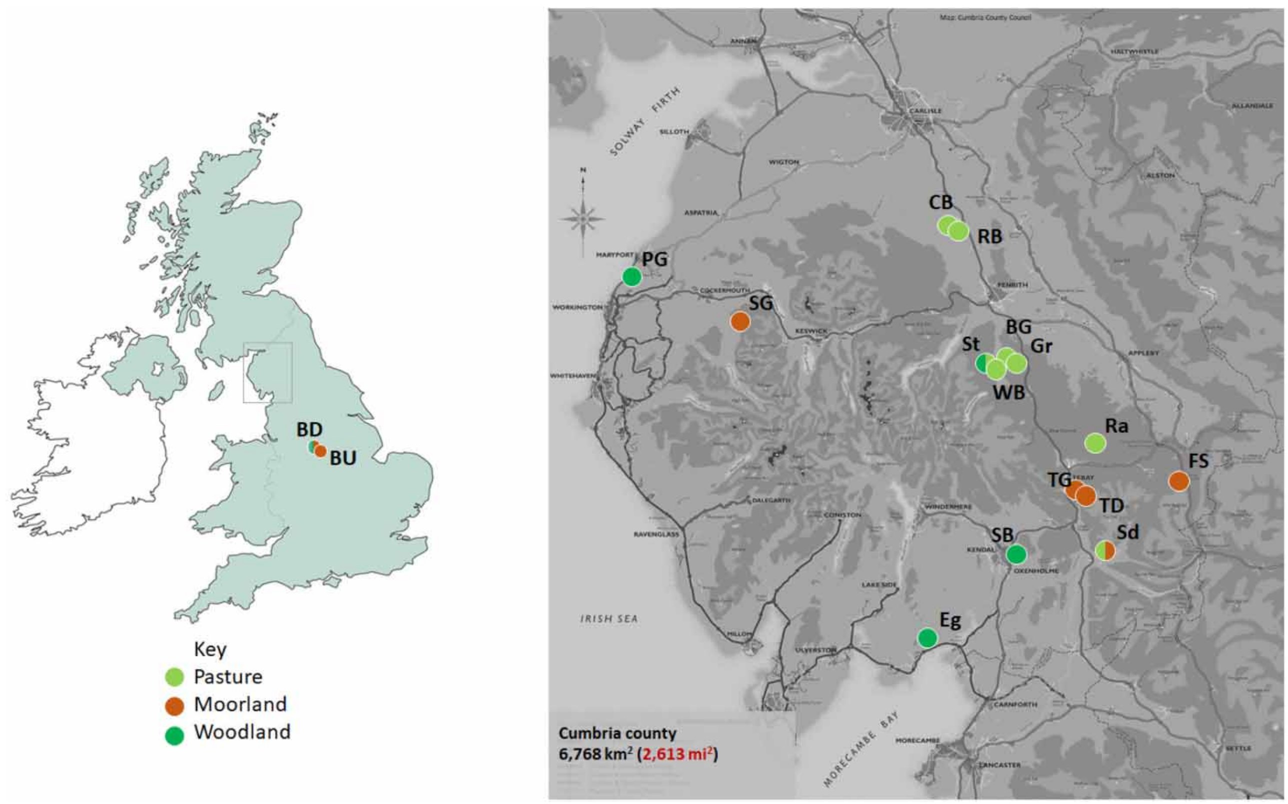

Figure 1 | Map of micro-basin locations (see Table 1 for site code) colour-coded base on the dominant land-cover. Source of right-hand base map: Cumbria Country Council.

Table 1 | Micro-basin information

Basin	Symbol	Area (km^2)	Number of accepted events
Tebay Dams	Td	0.0071	78
Bareleg Upstream	BU	0.1097	74
Tebay Gill	TG	0.1163	209
Fallgill Syke	FS	0.1439	180
Bareleg Downstream	BD	0.1540	76
Sedbergh	Sd	0.1732	23
Penny Gill	PG	0.2118	56
Sware Gill	SG	0.2356	43
Eggerslack	Eg	0.3054	87
Setterah	St	0.3749	36
Stock Beck East	SB	0.4725	21
Ravensgill Beck	RB	0.5870	43
Whale Beck	WB	1.1432	31
Calthwaite Beck	CB	1.2248	42
Back Greenriggs	Gr	1.9474	80
Bessy Gill	BG	2.5371	74
Rais Beck	Ra	2.7329	71

Number of 'accepted events' is the number of rainfall–streamflow events that meet the description in Section 2.1 and the model evaluation requirements in Section 2.3.

2. To identify transfer function parameters for each event and calculate their response times, simulated runoff coefficients, and time delays (Section 2.2).
3. To discard events if model outputs do not meet described criteria (Section 2.3).
4. To compare modelling outputs with response drivers (Section 2.4).

2.1. Creating the single event time-series

Here, a rainfall–streamflow event is defined as 2 h prior to the lowest streamflow before the hydrograph rise to when recession approaches the initial streamflow (Figure 2). In some cases, a complete recession was not possible due to the closeness of the next event (bottom right, Figure 2), so events, where streamflow did not drop by at least 75% of the rise during recession, were discarded (e.g., if the rising limb was from 0.05 to 0.15 mm/15 min, then the recession had to continue to below 0.075 mm/15 min to avoid being discarded). In addition, the event had to meet the following criteria:

- At least 10 mm of rainfall in the period from event start to peak streamflow.
- Peak streamflow was at least 0.015 mm/15 min and not greater than flume capacity.
- Rise to peak height of at least 0.01 mm/15 min.

The above criteria were chosen by trial and error to maximise the number of events while maintaining modelling efficiency. Very small events were excluded due to high rating curve error for very low flows with the flumes used.

Streamflow was calculated from flume level (1):

$$Q_t = c_1 \cdot L_t^3 + c_2 \cdot L_t^2 + c_3 \cdot L_t \tag{1a}$$

$$\text{Streamflow}_t = Q_t/A \times 1,000 \times 60 \times 5 \tag{1b}$$

where Q is the volumetric discharge (m^3/s), $c_{(1:3)}$ are flume rating coefficients (fixed for all sites), L is the water level at point of critical flow within the flume (mm), A is the micro-basin area (m^2), t is the time (5-min intervals), and integers are conversion to mm/5 min.

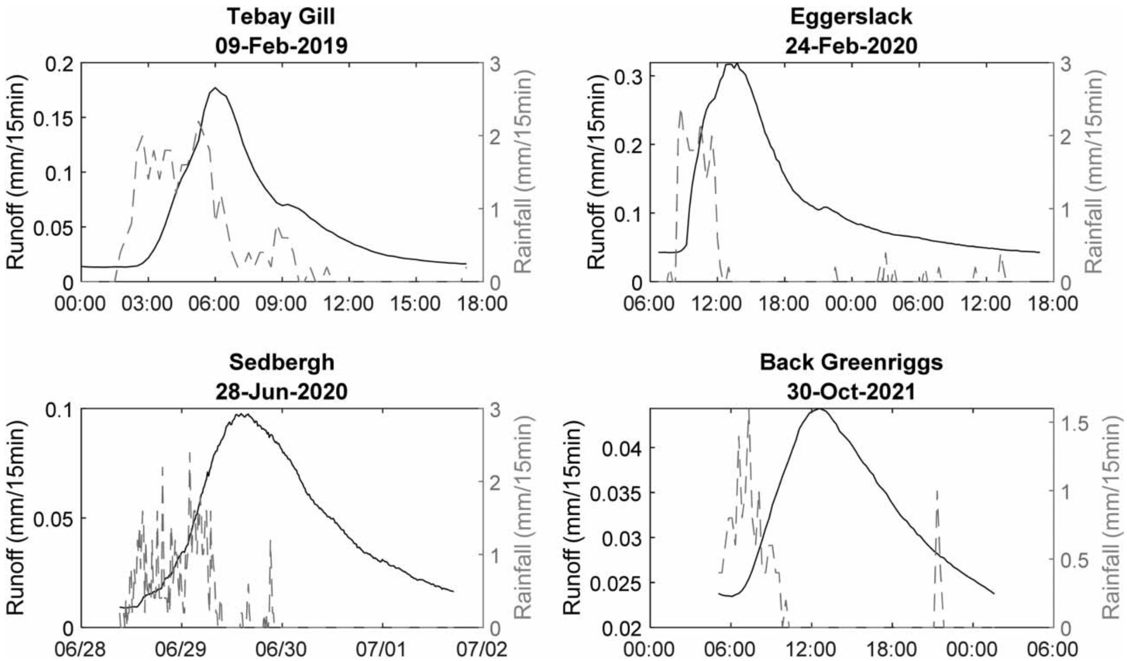

Figure 2 | Examples of rainfall and streamflow events from four of the micro-basins. The broken grey line is rainfall (mm/15 min) and the solid black line is streamflow (mm/15 min).

Prior to modelling, the time-series were converted to mm/15 min (sum of mm/5 min per each 15 min) and for each event, the antecedent streamflow (a measure of 'baseflow') for that event was removed ($\widehat{\text{Streamflow}}_t = \text{Streamflow}_t - \text{Streamflow}_{\text{min}}$) to improve modelling efficiency.

2.2. Model identification and estimation

A well-established linear dynamic model is described by (2):

$$\dot{y}_t = -\frac{1}{\alpha} y_t + \beta u_{t-\delta} \tag{2}$$

where y_t is the output at time t, u_t is the input, δ is the pure time delay, also called TD (between input and output), α and β are constant real parameters, and $\dot{y}_t$ is the time derivative of the output y_t.

For the continuous-time model used here, using the Laplace operator s and ignoring initial conditions (2) becomes:

$$\text{Streamflow} = \frac{g e^{-s\delta}}{\text{TC}s + 1} \text{Rainfall} \tag{3}$$

where s is the Laplace operator, TC is the time constant (3a), which is the time it takes for the system to respond to a step change in the input, and g is the system gain (3b), determining the scale of magnitude of the output in relation to the input (and is also referred here as SRC).

$$\text{TC} = \frac{1}{\alpha} \tag{3a}$$

$$g = \frac{\beta}{\alpha} \tag{3b}$$

As the TC and TD are calculated at 15-min intervals, a conversion to hourly values ($\text{RT} = T/4$ and $\text{TD} = \delta/4$) was undertaken for easier interpretation. Model structure identification was conducted by fitting the first-order model coefficients, α and β, for a range of time delays, δ, retaining the model that returns the best model fit in terms of sum of squared errors.

The calculation of RT, TD, and SRC was undertaken within a DBM framework (Young 1999, 2013) utilising the refined instrument variable (RIV) parameter estimation method (Young & Jakeman 1979) for transfer functions within the CAPTAIN toolbox for MATLAB (Taylor *et al.* 2007). RIV is designed to improve the consistency and efficiency of transfer function parameter estimates (Young 1984) and here the continuous-time RIV (Young & Jakeman 1980) is used (for a simulated example, see Young 2002). RIV is essentially a maximum-likelihood optimisation algorithm that returns the statistically most likely model parameters that represent the input–output relationship of the observed data (for examples of use, see Ockenden & Chappell 2011; Patricio *et al.* 2019).

The DBM approach involves the creation from the observed data of simple low-order models that represent the dominant mode(s) of a system, in this case rainfall and streamflow, and are evaluated in terms of their hydrological credibility before being accepted. Given the flashy nature of the small catchments in this study, a single first-order transfer function is able to capture the dominant mode of the rainfall–streamflow system.

2.3. Model acceptance

In the DBM methodology, models are evaluated not just in terms of model fit, as a model that gives a good fit to the observations does not necessarily mean a hydrologically feasible mode, i.e., a model can fit the data well, but the estimated parameters could have poor physical interpretations meaning the model may not be fit-for-purpose. So, in addition to rejecting poor fitting models, events were also rejected if their modelled outputs were deemed unrealistic in terms of how these 17 micro-basins behave. Events were only accepted if:

- Model fit $\geq$80%. Of the 1,379 events, only 10% (144) were rejected (52% (75) from TD).
- RT $<$ 50 h, or if RT $>$ 50, then acceptance depended on the model fit of the recession tail. Fifty hours were chosen from the observation of all models for all sites. Only one event was rejected.
- SRC $<$ 1.2, as $>$1.0 implies more streamflow than rainfall and while plausible in some cases, anything greater than 1.2 was considered unrealistic for these micro-basins. A total of 11 events were rejected.

Examples of models are shown in Figure 3.

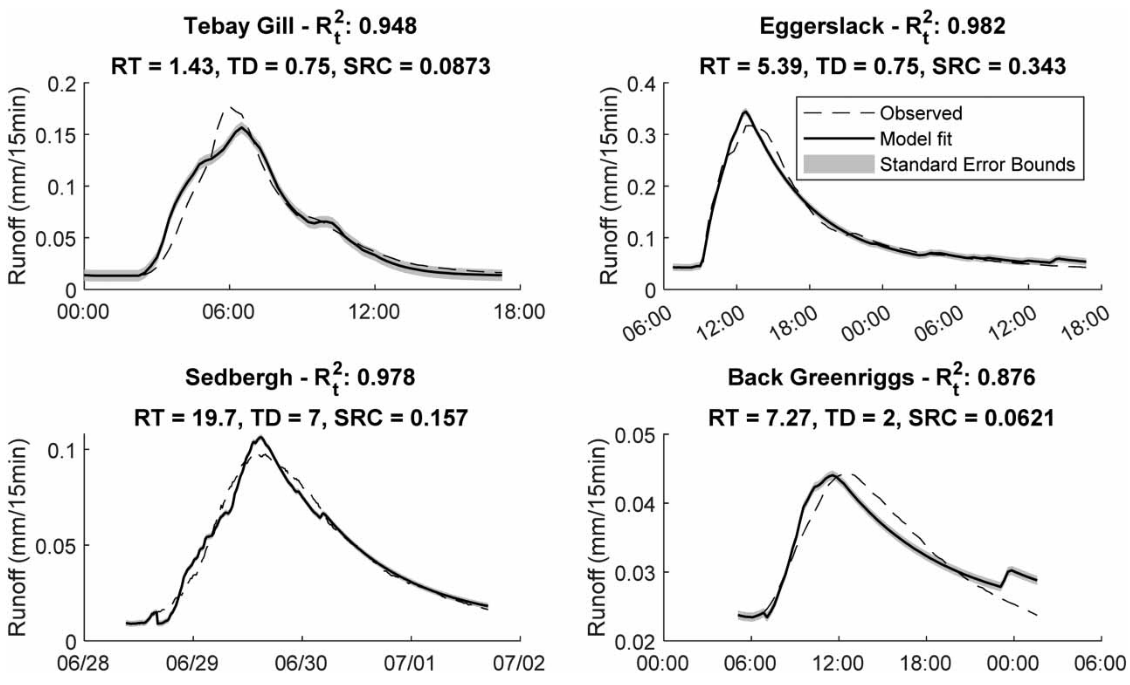

Figure 3 | Examples of model fits for an event from four micro-basins. The black broken line is the observed streamflow. The black solid line is the modelled streamflow. Grey shading is the uncertainty bounds from parameter variance.

2.4. Model analysis

Antecedent conditions are considered to play an important role in how streams respond to rainfall events with a general expectation that, the wetter the catchment the larger the response. Initial streamflow (the streamflow just prior to stream response to an input of rainfall) can be used as a metric for antecedent conditions (e.g., Beven *et al.* 2008; Beven 2019), here termed antecedent flow (AF) and is the first value of streamflow for that event.

Rainfall characteristics are important in driving stream response as the volume, intensity, and direction of the storm will affect how the stream responds with a general expectation that, the greater the volume and intensity of the storm, the quicker and larger the response. Here, the metrics for storm size/intensity are volume (RV, mm, total rainfall for the event duration) and intensity (RI, mm/hour, rainfall total from the beginning of storm to peak streamflow, divided by time).

3. RESULTS AND DISCUSSION

Over the 4-year period, each of the 17 upland micro-basins display a wide range of RT and SRC values, indicating changing hydrograph shapes associated with the dynamic nature of catchment response (Figure 4).

One striking contrast is between Tebay Gill (TG) and Stock Beck East (SB), TG micro-basin has a very low SRC and low RT (flashy response), whereas SB micro-basin has a very low SRC but high RT (damped response). SB is underlain by sandstone, with deep groundwater (and so high storage) pathways leading to more damped responses. TG micro-basin is covered by peat soils in its middle and upper basins. The fast response is likely associated with pathways above a slowly permeable peat sub-soil. The very low SRC is likely associated with the small size of the basin (0.116 km^2), giving insufficient distance for the subsurface flows to return to the surface before the flume is reached.

Tebay Dams (Td) micro-basin is located in the headwater of the TG micro-basin and is completely covered by peat soil. The greater extent of peat soil (see Goudarzi *et al.* 2021) and even smaller basin size (0.0071 km^2) explain why the Td micro-basin has the shortest RT.

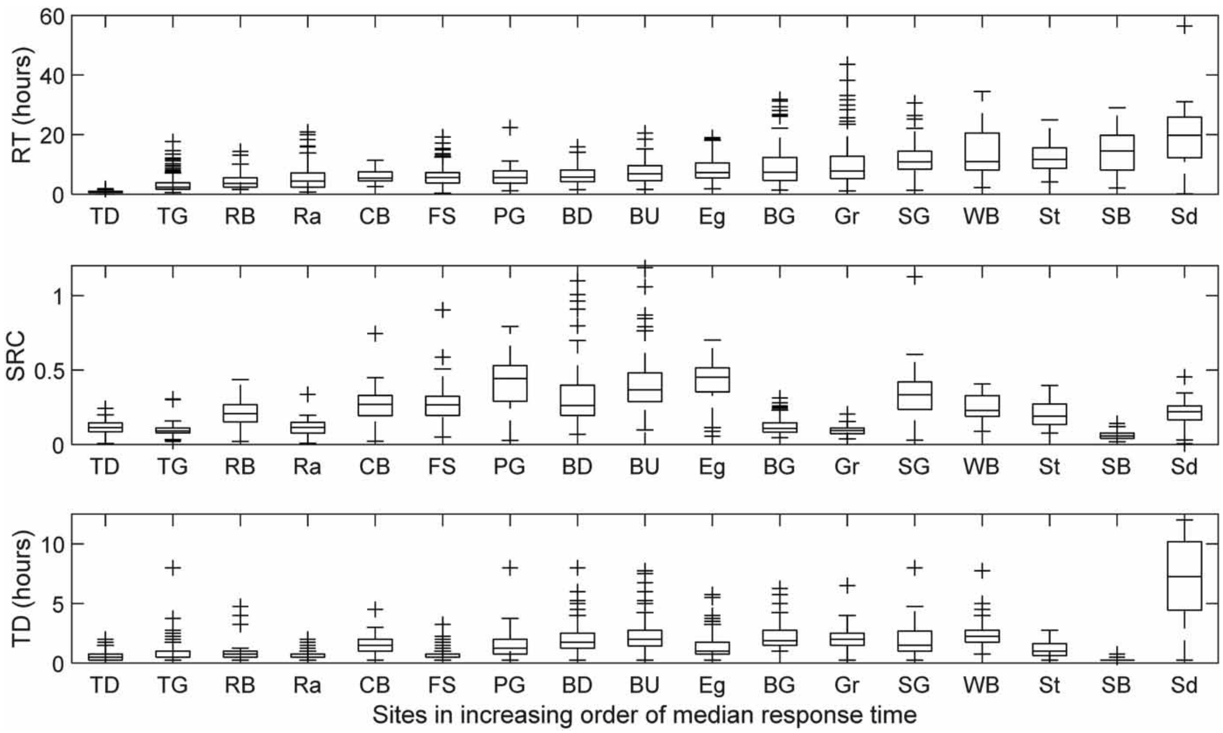

Figure 4 | Distributions of response times for 'acceptable events' (upper plot), simulated runoff coefficients (middle plot), and pure time delays (lower plot).

3.1. Drivers of storm response

When event amplitude (peak streamflow) is plotted against corresponding drivers (Figure 5), a trend is observed. Generally, as the metrics of AF, RI, and RV increase, peak streamflow increases. Only 4 of the 17 sites will be displayed in the figures, the rest can be found in Supplementary Material C.

When RT (Figure 6), SRC (Figure 7) or TD (Figure 8) are plotted against the same response drivers, a different pattern emerges. As the metric for response drivers increase, the timing (RT and TD) decreases, with the variance in all response quantifiers (RT, SRC, and TD) decreasing, converging to a more stable response. These observations reinforce the idea of non-linearity in stream response, particularly at lower antecedent flows, rainfall intensities and rainfall totals.

The rate of decrease in response variance (or rate of stabilisation of response) varies between micro-basins and may be linked to intrinsic catchment characteristics. For example, a high response variance is maintained over a wider range of flows for the groundwater-dominated Rais Beck (Ra) micro-basin, in comparison to the near-surface dominated peatland TG micro-basin.

The scatter in the data for some of the micro-basins could be a result of the event selection criteria (both pre- and post-modelling), which was generalised for all micro-basins for the purposes of comparing across the micro-basin network. A more refined selection criteria based on each individual micro-basin might yield clearer trends.

3.2. Trade-offs in response drivers

If the events with greatest peak streamflow are highlighted within the plots of response quantifier and their driving/moderating metric, it becomes apparent (Figure 9) that there must be trade-offs between the drivers to account for that amplitude of peak streamflow. For example, a lower AF could be offset by higher storm volumes/intensities to produce a higher streamflow, whereas a higher AF might allow a lower storm volume/intensity to produce a higher peak flow.

These trade-offs may be important for designing NFM interventions at certain sites, particularly for micro-basins with significantly different behaviours like SB. The largest events at SB micro-basin tended to occur during times of high AF, and this

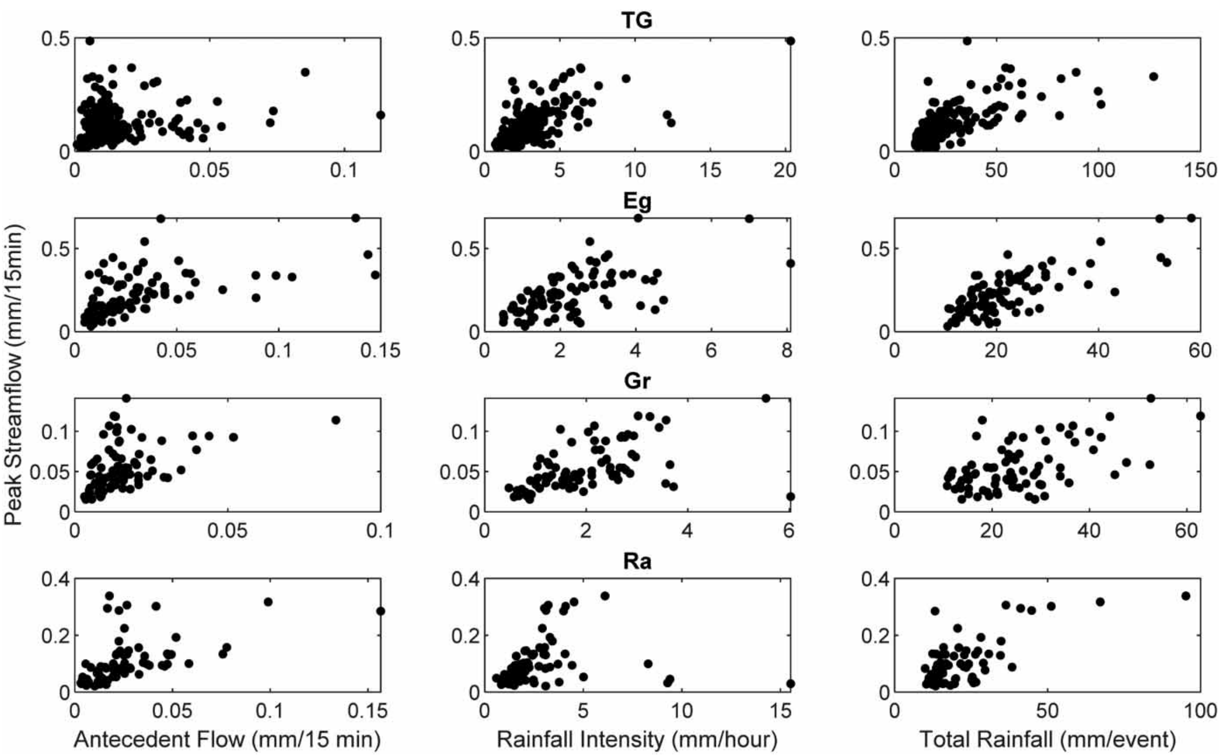

Figure 5 | Peak streamflow vs driver metrics of antecedent flow, event rainfall intensity, and total event rainfall for Tebay Gill (top), Eggerslack (2nd down), Back Greenriggs (3rd down), and Rais Beck (bottom).

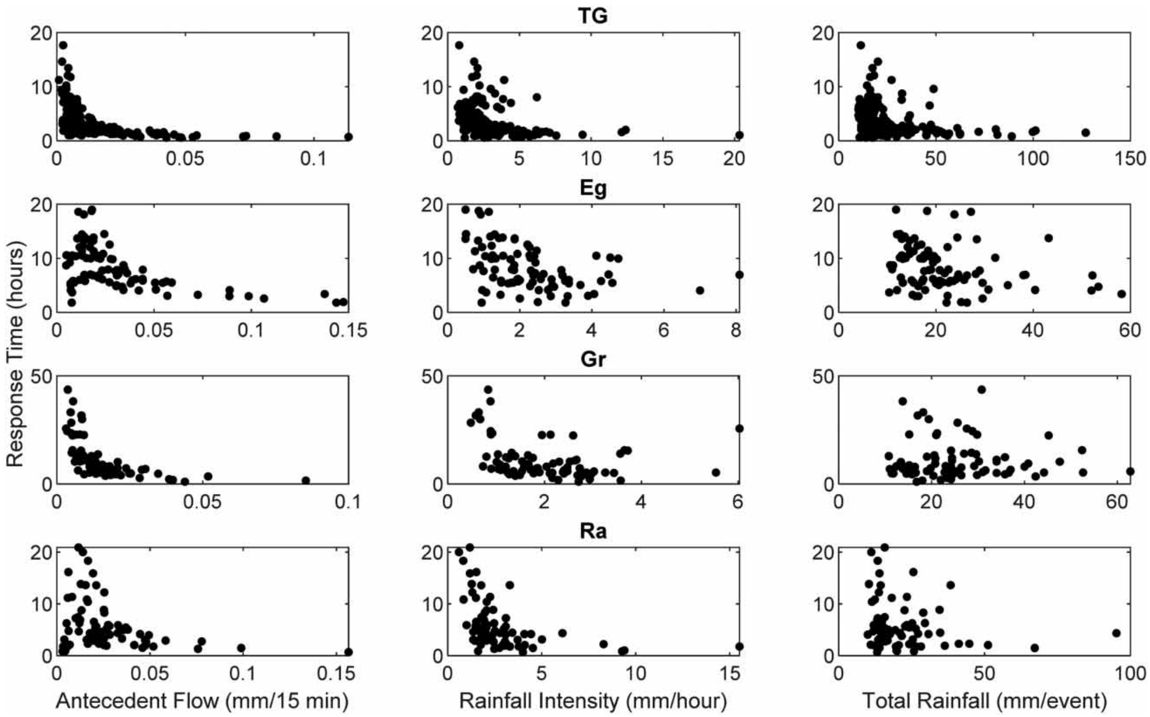

Figure 6 | Response time vs driver metrics of antecedent flow, event rainfall intensity, and total event rainfall for Tebay Gill (top), Eggerslack (2nd down), Back Greenriggs (3rd down), and Rais Beck (bottom).

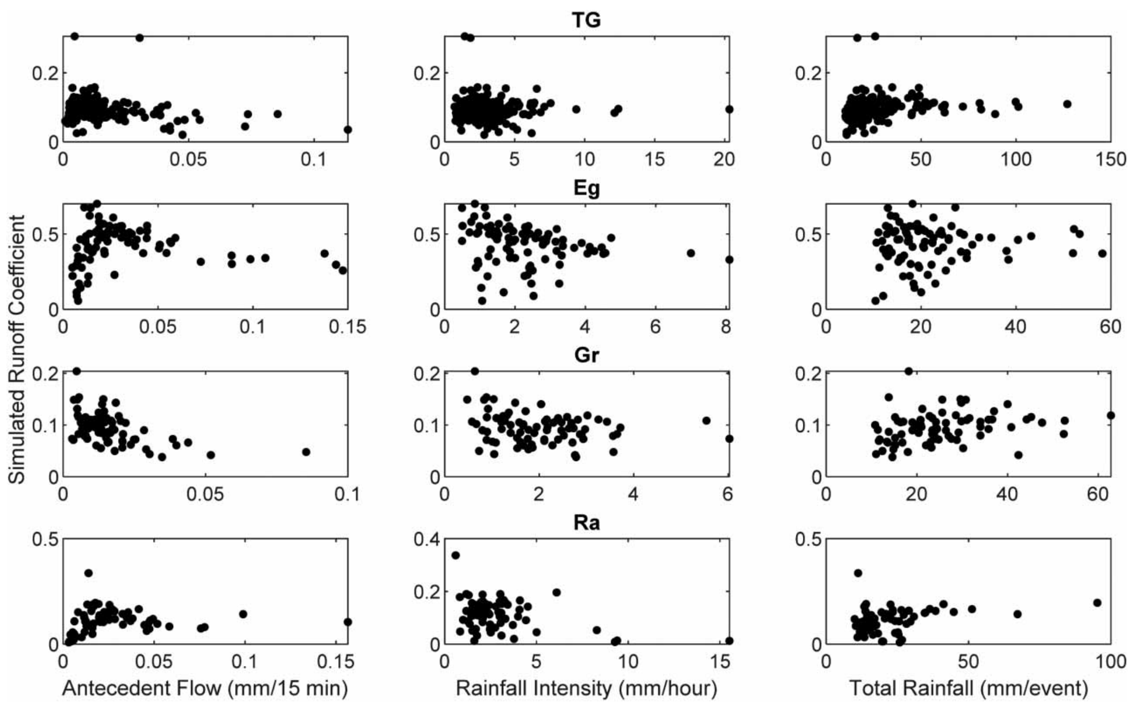

Figure 7 | Simulated runoff coefficient vs driver metrics of antecedent flow, event rainfall intensity, and total event rainfall for Tebay Gill (top), Eggerslack (2nd down), Back Greenriggs (3rd down), and Rais Beck (bottom).

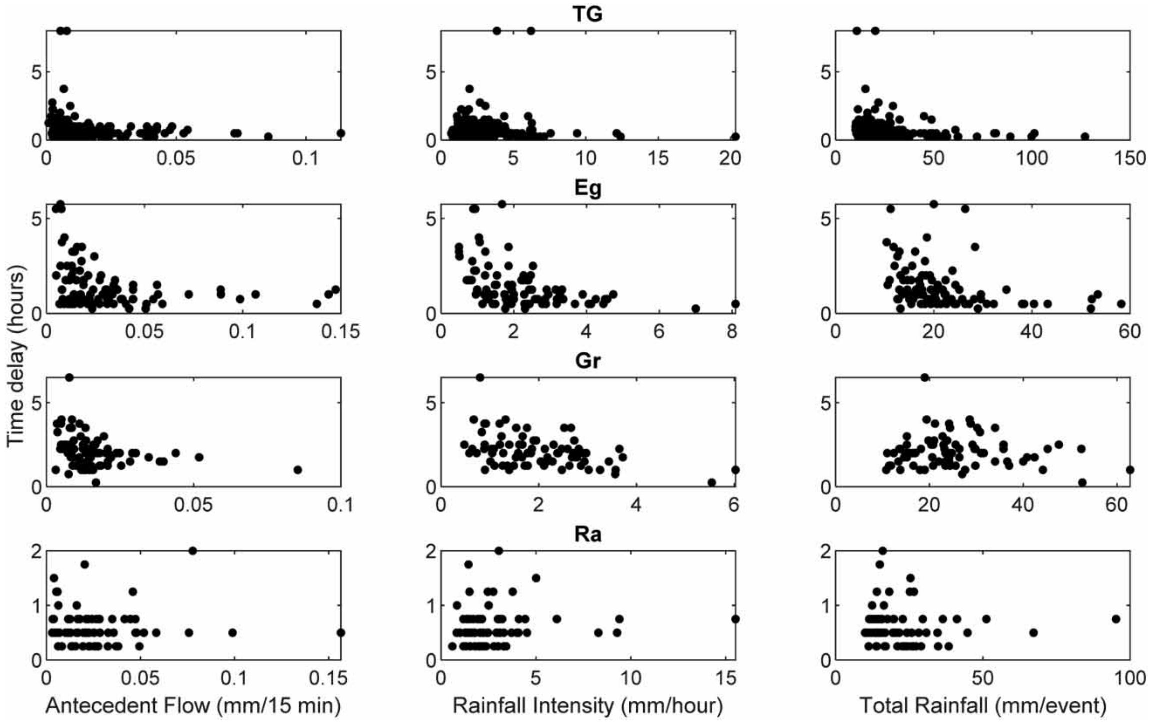

Figure 8 | Time delay vs driver metrics of antecedent flow, event rainfall intensity, and total event rainfall for Tebay Gill (top), Eggerslack (2nd down), Back Greenriggs (3rd down), and Rais Beck (bottom).

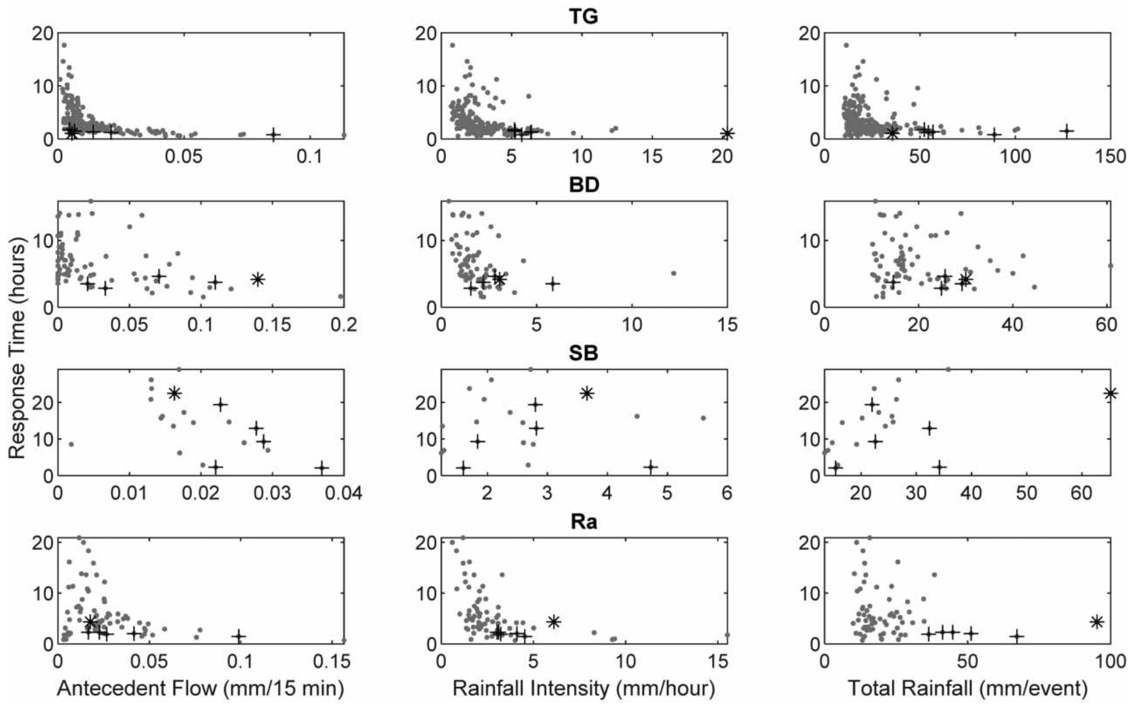

Figure 9 | Response time vs driver metrics (grey dots) for Tebay Gill (top), Eggerslack (2nd down), Stock Beck East (3rd down), and Rais Beck (bottom). Asterisk, largest peak streamflow event; plus, next five largest peak streamflow events.

could indicate that for such micro-basins with significant groundwater involvement there is a greater dependency on antecedent conditions to produce higher streamflows.

RT may be important for the design of NFM interventions as it indicates how long a storage feature should retain storm rainfall for. If a micro-basin has a very short RT (such as TG), then the intervention should not hold onto the storm water for very long. However, if the micro-basin has a typically very long RT (such as Sedbergh), then the intervention should hold onto the storm water for a much longer time.

4. CONCLUSION

An objective method for quantifying hydrograph shape (in both timing and volume) has been demonstrated and used to compare stream responses from upland micro-basins in time and space. This revealed a high variance in stream response during low antecedent conditions or during smaller storms. Variance in response tended to decrease as the micro-basins became wetter or storms increased in size, converging towards a more stable response with very wet micro-basins or large storms. The rate of decrease in response variance was seen to be micro-basin dependent, highlighting the spatial variance of stream response at scales of 1 km^2 or less.

The methodology can be applied to larger catchments, but would require rainfall to be measured over a spatial distribution of raingauges.

SOFTWARE AVAILABILITY

The CAPTAIN toolbox is available from Lancaster University at the below link: http://www.lancaster.ac.uk/staff/taylorcj/tdc/download.php.

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DATA AVAILABILITY STATEMENT

The data plotted in Figures 1–9 are available from the corresponding author upon request.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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