Hydrological Processes

WILEY

RESEARCH ARTICLE OPEN ACCESS

The Great Catchment Hysteresis Challenge

Keith J. Beven | David Mindham | Nick A. Chappell

Lancaster Environment Centre, Lancaster University, Lancaster, UK

Correspondence: Keith J. Beven (k.beven@lancaster.ac.uk)

Received: 14 August 2025 | **Revised:** 29 January 2026 | **Accepted:** 2 February 2026

Keywords: CAPTAIN toolbox | catchment scale hysteresis | data-based mechanistic model identification

ABSTRACT

This paper makes the argument for treating the response of small catchments as an exercise in the identification of hysteretic functions as a way of overcoming the impossibility of knowing all the small-scale detail of time variable and spatial heterogeneous catchment processes. An initial form of analysis is proposed based on the Data-Based Mechanistic (DBM) transfer function methodology to define functions for classes of events based on rainfall input volumes and antecedent flow as an index of catchment wetness. From the resulting transfer functions, event-scale storage-discharge plots can be derived if within-event evapotranspiration is neglected as small relative to event inputs. The great hysteresis challenge is to find a way of identifying a more continuous mechanistic function that allows for the change in input–output gains and transfer function state variables directly from the observed data without invoking a particular conceptual storage model structure (or structures) or a difficult-to-interpret machine-learning framework.

1 | Introduction

One of the most interesting yet rarely explicitly studied aspects of catchment hydrology is the hysteretic nature of the streamflow response to rain-event inputs. Hysteresis is evident in the common asymmetric nature of hydrographs, where the flow at a given storage level in a catchment is different for rising and falling limbs. We expect hysteresis to be dynamic in the same way that runoff generation is dynamic, varying with patterns of antecedent wetness and event rainfall characteristics. Hysteretic behaviour has long been observed in hydrology and been the subject of theorising at the detailed level of local soil physics at least since the experimental work of W. B. Haines (1930) and Lorenzo K. Richards in 1931. But in the responses at the catchment scale it has been largely left implicit. It is implicit in the asymmetric form of unit hydrographs; it is implicit in the multiple storage elements of conceptual models; it is implicit in analyses of transit time and residence time distributions of tracers relative to the timing and shape of hydrographs; it is implicit in the performance of deep learning models used to predict discharges (e.g., Kratzert et al. 2018; Frame et al. 2022; K. J. Beven 2020a). It can be made more explicit in, for example, in solutions of the kinematic wave analogy for hillslope responses (e.g., K. J. Beven 1982, 2012).

Although a number of indices of hysteresis have been suggested (e.g., Zuecco et al. 2016) only rarely has hysteresis been treated in any direct way, as for example in the papers of J. Philip O'Kane and Denis Flynn in the early 2000s (O'Kane and Flynn 2007), although this also originated in the evidence of local soil physics hysteresis (O'Kane 2005, 2006). At much the same time, K. J. Beven (2006), following the Representative Elementary Watershed (REW) work of Reggiani et al. (1999, 2000), was suggesting that hysteresis would be important in providing a proper closure scheme for the catchment scale control volume and, in particular, that the hysteresis in the flow response would reflect the celerities in the system, while hysteresis in the tracer response would also reflect the changing velocity distribution of water particles in the system (see also McDonnell and Beven 2014; Davies and Beven 2015; K. J. Beven 2020b). This, it was suggested, implied a length scale dependence would be needed in any closure scheme and provided one explanation for the double paradox of Kirchner (2003) of fast old-water responses at the catchment scale.

These discussions have, however, had little impact on modelling practice in hydrology (but see the Richards equation-based model of Camporese et al. 2014; the lumped storage-flow hysteresis model of Ewen and Birkinshaw 2007, and the FEST (*Fully vEgetated slab of Soil with Transpiring plants*) model of Appelbe et al. 2009, for exceptions). In the review of model structures of Gupta et al. (2012) hysteresis is mentioned only in relation to soil physics. In some recent discussions of physically informed machine learning hydrological models of Razavi (2021), Herath et al. (2021), Liu et al. (2021), and Razavi et al. (2022) it is not mentioned at all. This is really rather surprising because of how the difference in celerities and velocities will result in a length scale dependence in the timing of the hydrograph and transit time responses (e.g., Davies and Beven 2015; Beven 2021). Hysteresis thereby provides a potential approach to deal with scale issues, albeit that catchment scale differences will depend on the joint effect of hillslope responses and routing in the channel network (e.g., Beven and Wood 1993; Robinson et al. 1995; D'Odorico and Rigon 2003; Zoccatelli et al. 2015).

Perhaps the reason why the representation of hysteresis at catchment scales does not get the open recognition it deserves is because it is clearly a complex problem. Under simplifying assumptions it is perfectly possible to provide a theoretical analysis of the difference between celerities and velocities, such as in the many applications of kinematic wave theory to simple hillslope geometries (e.g., K. J. Beven 1981, 1982; Troch et al. 2002; Norbiato and Borga 2008), while solutions to the St. Venant routing equations based on the method of characteristics implicitly use celerities (even though such solutions have largely now been forgotten in favour of finite difference, element or volume schemes). However, it is clear that even the most detailed distributed hydrological model will have difficulty in predicting the correct patterns of celerities and velocities within hillslopes, especially given the generally unknown heterogeneity of soil and regolith properties. This will be true even for small research catchments ($<10\,\mathrm{km}^2$) where a complex network of flow pathways is present even at this small scale.

Thus, rather than trying to address the complex spatially-distributed details of the response processes, it would seem to be better to consider the functionality and temporal evolution of hysteresis at the catchment scale, something that was described as the 'Holy Grail' for hydrological theory by K. J. Beven (2006). This was explored in part with a hypothetical dataset for both flow and tracer data at three different scales of a small catchment by Davies and Beven (2015) using the MIPs particle tracking model under kinematic assumptions. The conclusions of that study were that the storage–discharge hysteresis was dependent on antecedent wetness, input rate, and scale in rather complex (and site-specific) ways at both the catchment scale and at individual local grid element scales. They also showed how the different forms of residence time distributions were scale dependent and non-stationary in time.

But the Davies and Beven study used virtual catchment simulations, albeit calibrated to catchment scale flow and travel time data at small catchment scales, so was not based on actual observations and did not include any effects of the channel network. For real catchments, with heterogeneous soil properties and more complex surface and bedrock geometries (e.g., Freer et al. 2002), and channel networks that expand/contract with time (e.g., Blyth and Rodda 1973 and more recently Godsey and Kirchner 2014; van Meerveld et al. 2019; Durighetto et al. 2022), then celerities will vary in both space and time, and velocities will be dependent on the hydraulic gradients that arise from the nonstationary and nonlinear patterns of celerity.

As an example of such complexity we can cite the recognition of 'groundwater ridging' as a mechanism for the fast subsurface response on hillslopes dating back to Ragan (1968), though there were earlier expressions of 'groundwater throttling' dating back at least to the 1930s (see K. J. Beven 2004). Ridging implies an increase in effective hydraulic gradient of the saturated zone towards the stream, but also (if truly a ridge) away from the stream. There will then be a local celerity away from the stream as a result of the gradient induced flow in that direction. At larger catchment scales ($>100\,\mathrm{km}^2$), the representation is then complicated further by the difference in controls of celerities and velocities in the hillslope and in the channel network, when the hydrograph and transit time distributions will be an integral of both.

Any perceptual model of the physical processes that underly hysteresis in catchment response and lead to larger scale behaviours will be complex. It will include local infiltration excess runoff generation, the dynamics of surface and subsurface contributing areas, connectivity of hillslope fluxes with stream channels and fill-and-spill thresholds in storage-discharge relationships (e.g., McDonnell et al. 2021, and references therein). The changing nature of hysteresis is evidenced by coherent changes in the transfer function (or unit hydrograph) between inputs and outputs, such as the input dependence recognised by Minshall (1960) and, for example, Reed et al. (1975). While there might still be advances in understanding in the future, we already appreciate that the perceptual model will include nonlinear interactions between surface and subsurface processes, and processing of the inputs by vegetation and the soil surface, local soil water hysteresis, preferential flow pathways, storage in the regolith and the role of convergence and divergence of the topography. Other complexities, such as local controls on groundwater-streamwater interactions or bedrock topography controls on downslope storage and flows can be perceived but will be very difficult to quantify. This means that it will be very difficult to specify all the mass, energy and momentum fluxes required for closure of the balance equations in the REW theory of catchment response or more recent theoretical process formulations (e.g., Singh and Vimal 2022).

And yet, we do not expect nonlinear chaotic and bifurcating process responses (though this is one area where understanding might change in future), in part because hydrological responses are constrained by the inputs on an event-by-event basis (even if some event data might be disinformative in trying to evaluate model adequacy, Beven and Smith 2015; Beven 2019). There should perhaps be some consistent and coherent hysteretic behaviour that could be identified from catchment scale data, ideally from both hydrograph (celerity controlled) and tracer (velocity controlled) data. A data-based catchment scale approach makes no assumptions (prior to application) about hydrological processes; it seeks only some functional representation of the nature of the response.

There have been many recent applications of data-based machine learning at catchment scales. These have mostly been applied to large databases of many catchments at daily time steps, even in small catchments where times to hydrograph peaks might be less than a day. There have been fewer studies of small catchments with higher temporal frequency data that would allow hysteretic storage-discharge relationships to be identified. However, machine learning approaches have shown that such models can provide greater predictive capability than conceptual hydrological models even if not in all catchments or for the most extreme events. Here we apply the Data-based Mechanistic (DBM) methodology to data from small catchments with a view to capturing the dominant modes of the hysteretic behavior.

The DBM modelling methodology was first applied to rainfall-streamflow modelling by Young and Beven (1991, 1994). They showed how linear transfer functions could be used to model streamflow without hydrograph separation and allowing for nonlinearity in event runoff coefficients using state dependent parameter estimation (see also Chappell et al. 1999, 2017, 2006; Beven et al. 2011; Mindham et al. 2018, 2023). The methodology has evolved to use continuous-time model identification (e.g., P. Young 2003, 2013; Young and Garnier 2006) with applications for forecasting and control in a wide range of domains. In hydrology it has been used for adaptive forecasting of river discharges and levels for a range of different catchment scales (Lees et al. 1994; P. C. Young 2002; Romanowicz et al. 2006; Leedal et al. 2013; Smith et al. 2014) and in predictions of water quality (Beven and Young 1988; Wallis et al. 1989; Green et al. 1994; Jones and Chappell 2014; Jones et al. 2014). The DBM methodology has been used before to explore the representation of catchment responses under different antecedent conditions and rainfall inputs (e.g., Beven et al. 2008; Chappell et al. 2017).

The DBM approach has some advantages over more general machine learning algorithms in that the identified transfer functions have to be physically meaningful (in the final step of the approach), while requiring only a small number of parameters, but consequently with somewhat less flexibility. The parametric parsimony of DBM models also means that relative to high dimensional pattern recognition machine learning, the uncertainty in estimated parameter values should be considerably more constrained, albeit still subject to uncertainties and errors in the observed data available.

As its name implies, the DBM methodology attempts to find functional representations of input–output data that have a mechanistic (e.g., hydrological) interpretation. For the present purpose, there are two key characteristics that need to be considered for each event investigated: the input–output gain for that event (analogous to a runoff coefficient but without baseflow separation) and the shape of the transfer function that will embody the hysteresis in response for that event. Here we will consider the responses in different classes of event, classified by depths of rainfall input and wetness prior to an event, where antecedent observed flow per unit basin area at the catchment outlet is used as an index of wetness. This allows the changing nature of the hysteresis to be assessed for each catchment.

2 | Experimental Data

The analysis focuses on rainfall-streamflow responses for four micro-catchments in the Cumbrian uplands of the United Kingdom (Figure 1). These data were collected as part of the UK Natural Environment Research Council (NERC) funded Q-NFM project. Two of these (Eggerslack and Whale) drain permeable karstic limestone of the Dinantian epoch of the Lower Carboniferous period (British Geological Survey 1977, 2025). However, the later has a surficial geology of glacial till that is less permeable, while it is absent at Eggerslack. The other two micro-catchments are on lower permeability rocks comprising sandstone, siltstone, and mudstone of the Coniston Group of the Silurian period (British Geological Survey 2025). One of these micro-catchments (Tebay Gill) is covered in both glacial till and peat that further limits percolation. The other micro-catchment (Sedbergh), while comprising the Coniston Group solid geology in its headwater, has a lower catchment comprising permeable argillaceous rocks of the Screes Gill Formation (British Geological Survey 1977, 2025). Extensive fracturing of the solid geology is present below the Sedbergh micro-catchment (Thomas and Woodcock 2015). Defined by surface topography, the Eggerslack, Whale, Tebay Gill, and Sedbergh micro-catchments are 0.305, 1.143, 0.116 and 0.173 km^2 in area, respectively.

Rainfall (mm/5 min) and unit area stream discharge (mm/5 min) measurements began on July 28 2018, June 5 2020, January 15 2019, and September 29 2019, respectively, and continue to date. Over this period, annual rainfall totals have ranged from 861 to 3088 mm in 2021–22 and 2019–20, respectively. The monitoring setup at each micro-catchment was the same, with stream level being measured using a pressure transmitter (SLS-A-DC-A010-BV-0250G-00, Stork Solutions, UK) in a trapezoidal flume (maximum capacity of 430 L/s) with a known rating curve and a known catchment size and so could be converted to streamflow per unit catchment area (mm/5 min). Rainfall (mm/5 min) is measured with a tipping bucket raingauge (S-RGB-M002, LICOR, USA) situated on a 1.5 m mast next to the flume. The stage-discharge rating for the flumes was checked with dilution gauging. Data are captured from all gauging stations using mobile (cell) phone telemetry (RX3000, LICOR, USA). For the analysis presented here, flows were aggregated to 15 min time steps.

To derive classifications from multi-year, high frequency time-series of rainfall and streamflow the following steps were undertaken:

1. Break the time-series into individual storm events (detailed below),
2. Apply DBM model identification to each event, and remove events with a poorly identified rainfall-streamflow relationship ($R_t^2 < 0.75$),
3. Use the modelled recession from the immediate prior event to allow for a baseflow contribution for the event of interest, as if the rainfall for that event had not occurred before refitting the model for each event,

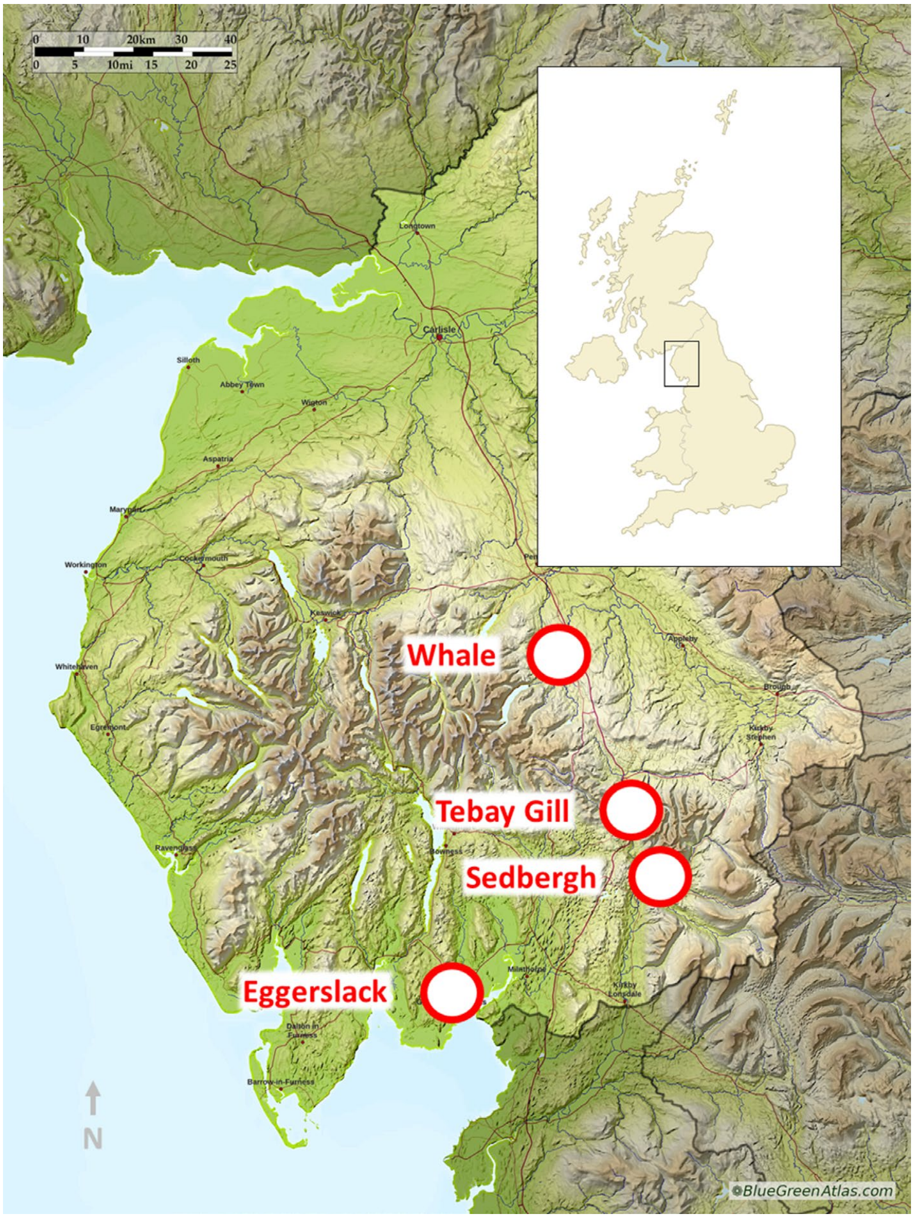


FIGURE 1 | Location of the four headwater micro basins used in this study. All lie in the Cumbrian mountains in the centre of the United Kingdom.

4. Classify each event into 1 of 16 classifications, based on total event rainfall and antecedent observed streamflow,
5. Superimpose the rainfalls and flows for all events in each class, taking the average at each time step and identifying a linear transfer function for each class.
6. Infer the hysteretic storage-discharge function for each class of event by mass balance relative to a baseline of zero storage at the start of the event and neglecting any evapotranspiration effects within the event. Thus at each time step:

$$S_t = \left(\sum_{i=1}^{t} P_i - \sum_{i=1}^{t} Q_i \right) \Delta t \qquad (1)$$

where S is storage in mm per unit area at time t, P is the precipitation per unit area, and Q is flow at the catchment outlet in depth per unit time, and Δt is the time step for the calculations (here 15 min).

2.1 | Single Event Time-Series

The following criteria were used to break the time-series of rainfall and streamflow into single event time-series:

- At least 5 mm of rainfall in the period from event start to peak streamflow.
- Peak streamflow was at least 0.0075 mm/15 min and not greater than flume capacity.
- Rise to peak height of at least 0.005 mm/15 min.
- At least 90% of the recession tail occurred before the start of the next rain-event.

2.2 | Event Classification

How a catchment responds to a storm event is dependent on the shape of the storm hyetograph (Chappell et al. 2017) and the hydrological state of that catchment at the time of the storm (Young and Beven 1994). Two simple metrics were used to represent event magnitude and antecedent state of the catchment:

- Event magnitude: total rainfall from the beginning of the rain-storm to peak streamflow, termed here 'Total Rainfall' (mm/event) and had the following classifications:
  - < 10 mm (Very low)
  - 10–20 mm (Low)
  - 20–40 mm (Medium)
  - > 40 mm (High)
- State of the catchment immediately pre-event: streamflow at the beginning of the rain-storm, termed 'Antecedent Streamflow' (mm/15 min) and had the following classifications:
  - < 0.015 mm/15 min (Very dry)
  - 0.015–0.03 mm/15 min (Dry)
  - 0.03–0.05 mm/15 min (Wet)
  - > 0.05 mm/15 min (Very wet)

Cross-classification then occurred to place each event into 1 of 16 classes (i.e., 4 total rainfall classes × 4 antecedent condition classes).

2.3 | DBM Rainfall-Streamflow Modelling

2.3.1 | Rainfall-Streamflow Modelling

To establish the strength of the causal relationship between rainfall and streamflow, a first-order DBM model was identified for each event. In continuous time, the model is described by

$$\dot{Q}_t = -\frac{1}{\alpha} Q_t + \beta P_{t-\delta} \tag{2}$$

where Q_t is the flow output at time t, P_t is the rainfall input, δ is the pure time delay, α and β are constant real parameters and $\dot{Q}_t$ is the time derivative of the output Q_t. For the first-order continuous-time model used here, the Laplace operator s and ignoring initial conditions (2) becomes:

$$\underline{Q} = \frac{SSGe^{-sTD}}{TCs + 1} \underline{P} \tag{3}$$

where $\underline{Q}$ is a vector of flow outputs, $\underline{P}$ is a vector of rainfall inputs, s is the Laplace operator, TD is the pure time delay, TC is the time constant (3a) that is the time it takes for the system to respond to a step change in the input, and SSG is the steady state system gain (3b), determining the scale of magnitude of the output in relation to the input.

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

$$\mathrm{SSG} = \frac{\beta}{\alpha} \tag{3b}$$

This model structure utilises only three parameters: a steady state gain (SSG), a pure time delay (TD) and a time scale (celerity) for the transfer function (TC). This latter parameter has often been called the mean residence time in the past but this could be confusing when used for hydrographs because it will reflect celerities rather than water particle velocities, that is, it is not the same as a mean residence time derived from tracer velocities.

The identification of the parameters within the DBM framework uses the Refined Instrument Variable (RIV) parameter estimation method (Young and Jakeman 1979) for transfer functions within the CAPTAIN toolbox for Matlab (Taylor et al. 2007). RIV is essentially a maximum likelihood optimisation algorithm that returns the model parameters representing the input–output relationship of the observed data (for other examples of use see: Ockenden and Chappell 2011; Magliano et al. 2019).

Since this study was concerned with identifying the dominant hysteretic modes of response and their changes with antecedent wetness and event rainfall depths, any event with a model efficiency < 75% was deemed to have an inadequate representation of the dynamics and was discarded. The remaining events were then superimposed and averaged to produce a single representative event time series in each class. The input series was then smoothed using an integrated random walk (IRW) smoother (Taylor et al. 2007), and any input that occurred significantly after the superimposed output peak was removed.

Fitting a DBM model to the resulting time series then provided the TD, TC and SSG characteristics for the events in that class. While first-order models gave high efficiency models for the data from Eggerslack, Whale and Tebay Gill, high efficiency models for the Sedbergh micro-catchment required second-order models. A second-order model is described by:

$$\underline{Q} = \frac{\left(\mathrm{SSG}_1 + \mathrm{SSG}_2\right)e^{-s\delta}}{\left(TC_1 s + 1\right)\left(TC_2 s + 1\right)} \underline{P} \tag{4}$$

where one physical interpretation of this model is to view it as a parallel connection of two first-order models (5), where one describes the combination of fast (subscript 1 in 5) flow processes or pathways and the other describes the group of slower (subscript 2 in 5) processes (P. C. Young 1992)

$$\underline{Q} = \left(\frac{\mathrm{SSG}_1 e^{-s\delta}}{\mathrm{TC}_1 s + 1} + \frac{\mathrm{SSG}_2 e^{-s\delta - 1}}{\mathrm{TC}_2 s + 1}\right) \underline{P} \tag{5}$$

2.4 | Defining Hysteresis for the Classes

The resulting DBM models were then used to produce a characteristic hysteretic storage-discharge curve for each class applying the identified steady state gain to the superimposed rainfall inputs over all events in the class, assuming that all losses were represented by the identified SSG gain parameter. In addition, a normalised Hysteresis Index was calculated for each class as defined by Zuecco et al. (2016). This involves a normalisation of the inputs and outputs as follows:

$$u(t) = \frac{Q(t) - Q_{\min}}{Q_{\max} - Q_{\min}} \tag{6a}$$

$$v(t) = \frac{S(t) - S_{\text{min}}}{S_{\text{max}} - S_{\text{min}}} \tag{6b}$$

The function $v(t)$ is then integrated over the rising and falling limbs of the hydrograph to give the areas under each part of the curve.

$$A_{\text{rising}} = \int_i^j v_{\text{rising}}(u)du \tag{7a}$$

$$A_{\text{falling}} = \int_i^j v_{\text{falling}}(u)du \tag{7b}$$

where the limits of integration can take on any values between 0 and 1. The hysteresis index (HI) is then defined by:

$$\text{HI} = \sum_{k=1}^{N} \Delta A_{i,j} \tag{8}$$

where $\Delta A_{i,j}$ is defined for each of the $k = 1$ to N increments of the normalised scale of u as:

$$\Delta A_{i,j} = \left(A_{\text{rising}} - A_{\text{falling}}\right)_{i,j} \tag{9}$$

Here we used 19 increments to define HI from 0.05 to 1 in 0.05 steps.

3 | Results

After classifying events according to the criteria set out above, not all classes in all the catchments had sufficient events for analysis. In general, the model fits to the superposed events for each class were good. All the calibrated parameters and fits for each of the classes are given in the Supporting Information file for this paper (Tables S1–S4). An example of the hydrograph fits for the Eggerslack micro-catchment using a first-order model is shown in Figure 2, and for the Sedbergh micro-catchment using a 2nd order model is shown in Figure 3 (see Figures S1 and S2 for the Tebay Gill and Whale results).

Here we are primarily concerned with the hysteresis loops for each of the catchments. Figure 4 shows the resulting storage-flow hysteresis loops for each class for the Eggerslack micro-catchment. These are calculated following the normalisation of storage to zero

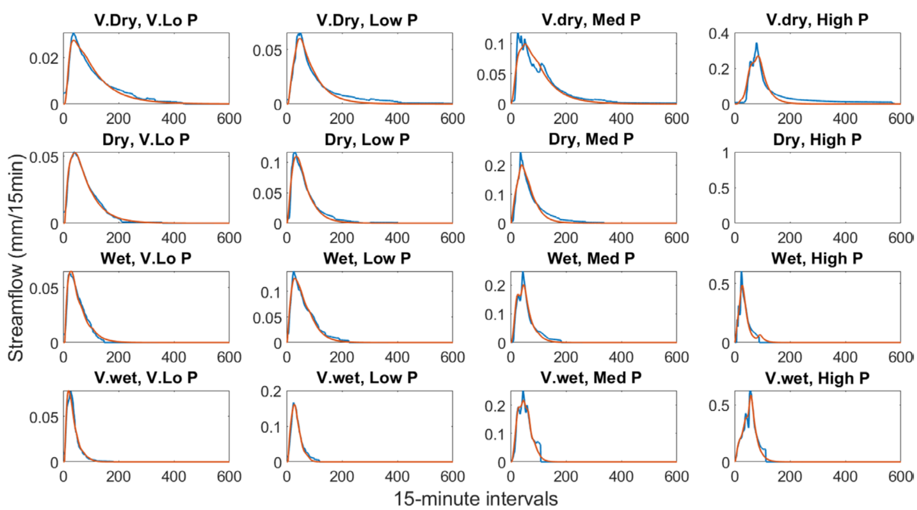


FIGURE 2 | Modelled (red) and superposed observed (blue) discharges for each class of events for the Eggerslack micro-catchment.

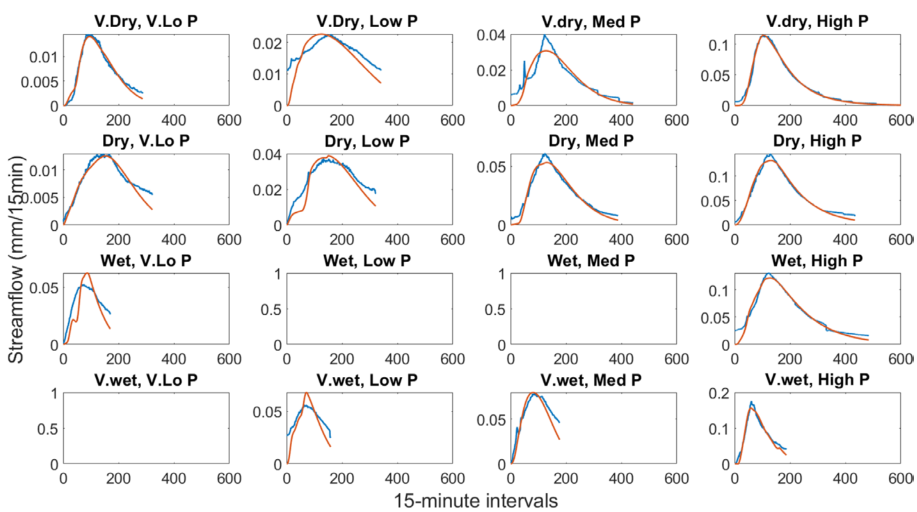
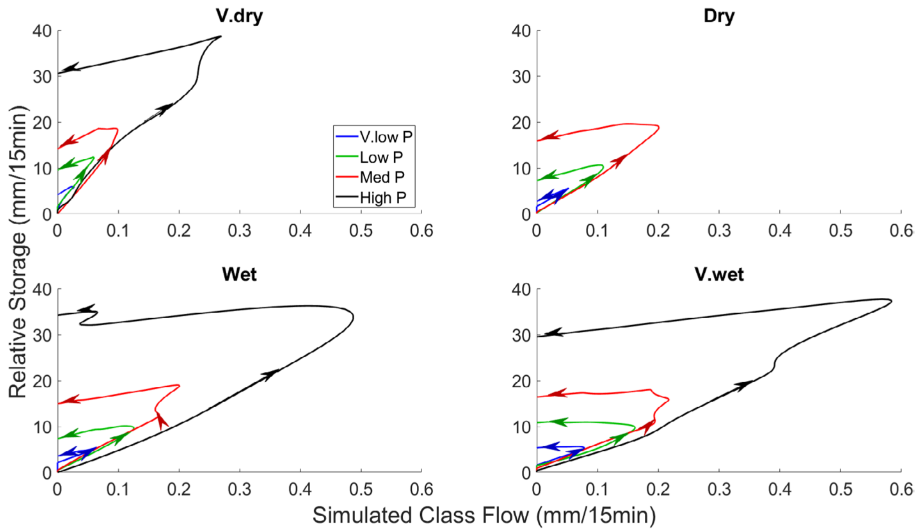


FIGURE 3 | Modelled (red) and superposed observed (blue) discharges for each class of events for the Sedbergh micro-catchment.



h index		Antecedent condition			
		Very dry	Dry	Wet	Very wet
Rainfall profile	Very low	-0.36	-0.48	-0.69	-0.50
	low	-0.20	-0.50	-0.61	
	Medium	-0.23	-0.57	-0.57	-0.71
	High	-0.57	-0.73	-0.74	-0.57

FIGURE 4 | Storage-discharge hysteresis and Hysteretic Index values for each class of events for the Eggerslack micro-catchment. Smaller loops without arrows are all anti-clockwise.

at the start of each event. For each micro-catchment, the Hysteresis Index for each class is also shown. Nearly all the hysteresis loops are anti-clockwise (with a negative Hysteresis Index), as is expected from the initial increase in storage following the start of the rainfall inputs and the asymmetric form of the transfer functions. The calculated storage changes reflect both the depth of rainfall inputs and the steady state gains for the DBM models for each class. The higher falling limb, which gives rise to such strongly negative values of the Hysteresis Index, reflects the greater retention of water in the catchment over the event (which will then evolve via other loss processes before the next event). This type of behaviour was evident in the original analysis of K. J. Beven (2006) where hysteresis loops for different events were superimposed on a form of linear recession attractor (see also the recession study of Kim et al. 2023).

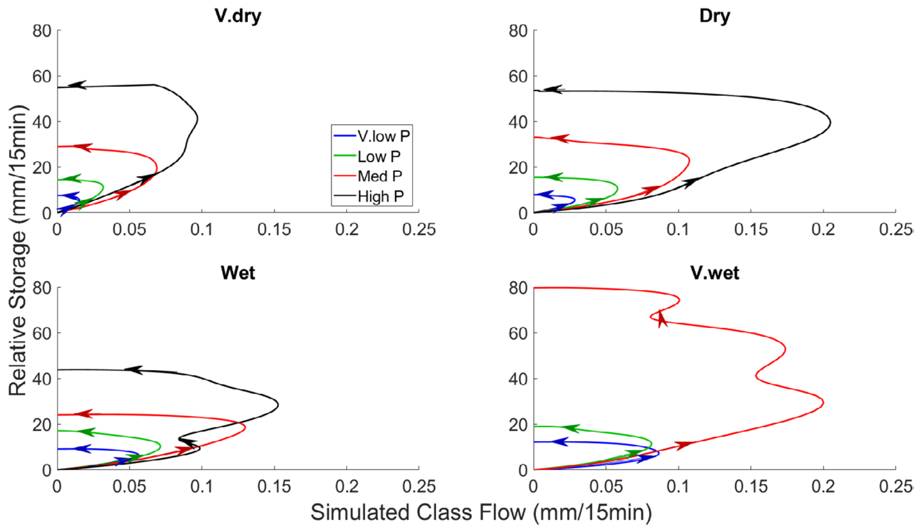
The response of the Tebay Gill micro-catchment is notable in that all event classes exhibit strong negative hysteresis loops (HI >0.5; Figure 5). Eggerslack exhibits 11/16 (69%) of event classes with an HI >0.5, while Whale has only 6/16 (38%) and none for Sedbergh. Indeed, the Sedbergh micro-catchment has 2/16 event classes with weak positive hysteresis loops (Figure 6). These differences between the hysteretic responses of the micro-catchments seem to be associated with the median time constants for the micro-catchments, where Tebay has the fastest TC time constant, then Eggerslack, Whale, and then Sedbergh (Tables S1–S4; see also Mindham et al. 2023).

Strong hysteresis was exhibited in the Eggerslack responses for most classes except for those for the driest antecedent catchment conditions (Figure 4). The highest rainfall class of >40 mm/event consistently produced strong negative hysteresis (HI of -0.50 to -0.75) in the Whale data (Figure 7).

Hysteresis loops for Sedbergh are also notable in that some classes, particularly very wet antecedent conditions, show a marked delay before discharge responds significantly, as shown in the modelling of Mindham et al. (2023). Further, the storage-discharge curves for this micro-catchment often contain minor loops, where discharge continues to rise after storage starts to be depleted.

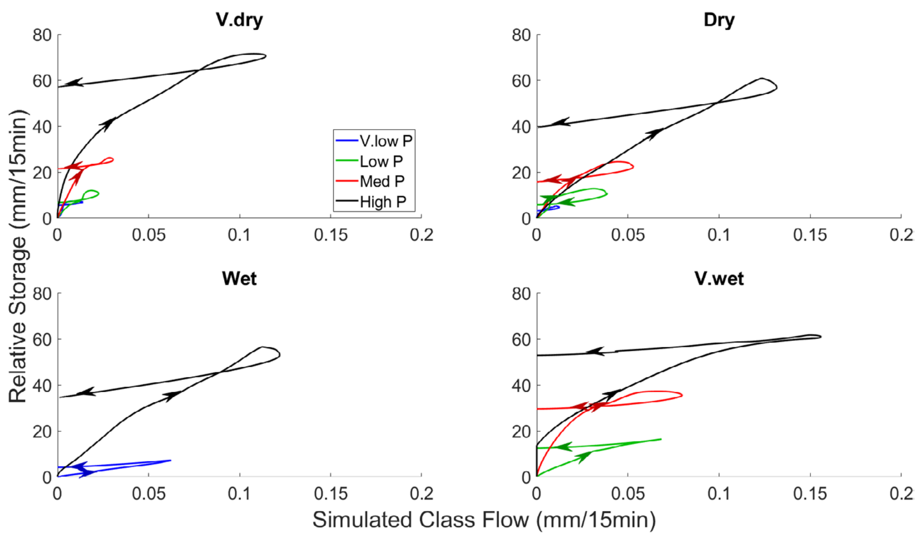
4 | Discussion

By investigating the simple gain and transfer function characteristics within different classes of events it has been shown how there is some consistency and coherence in the nature of micro-catchment (ca. 1 km^2) rainfall-streamflow responses where we expect the channel routing to have only a small impact on the response. The strength of the hysteresis has been shown to vary significantly between the evaluated micro-catchments and seems associated with other dynamic response characteristics such as time constant. The strength of the hysteresis in the storage-discharge curves is seen to be relatively stationary in some micro-catchments (e.g., the flashy low permeability Tebay Gill basin), but varying considerably with rain-event size and antecedent wetness in others (e.g., Whale). Combination of the methodology applied with the selection of micro-catchments (with differing hydrogeological conditions and derived response characteristics) has therefore been shown to capture potentially



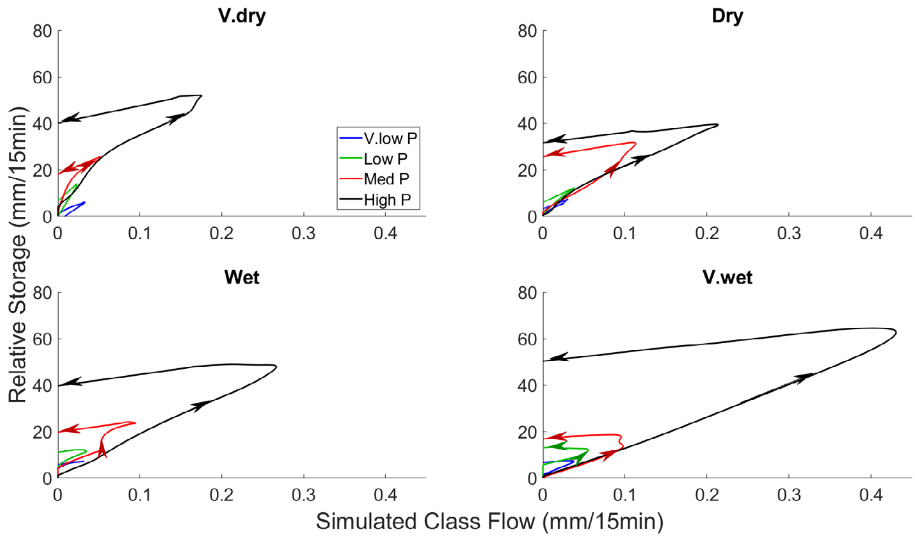
h index		Antecedent condition			
		Very dry	Dry	Wet	Very wet
Rainfall profile	Very low	-0.75	-0.76	-0.70	-0.73
	low	-0.69	-0.75	-0.71	-0.76
	Medium	-0.76	-0.69	-0.78	-0.74
	High	-0.74	-0.69	-0.67	

FIGURE 5 | Storage-discharge hysteresis and Hysteretic Index values for each class of events for the Tebay Gill micro-catchment.



h index		Antecedent condition			
		Very dry	Dry	Wet	Very wet
Rainfall profile	Very low	-0.01	0.15	-0.31	-0.23
	low	-0.24	0.13	-0.16	-0.43
	Medium	-0.26			-0.31
	High		-0.35	-0.02	-0.31

FIGURE 6 | Storage-discharge hysteresis and Hysteretic Index values for each class of events for the Sedbergh micro-catchment. Smaller loops without arrows are all anti-clockwise.



h index		Antecedent condition			
		Very dry	Dry	Wet	Very wet
Rainfall profile	Very low	0.22	-0.30	-0.29	-0.41
	low	-0.21	-0.25	-0.55	-0.44
	Medium	-0.09	-0.43	-0.44	-0.56
	High	-0.55	-0.50	-0.75	-0.54

FIGURE 7 | Storage-discharge hysteresis and Hysteretic Index values for each class of events for the Whale micro-catchment. Smaller loops without arrows are all anti-clockwise.

interpretable differences in the storage-discharge hysteresis. The way the events in each class have been defined and superimposed, however, certainly has obscured a lot of the detailed variation in responses to individual rainfall events under different antecedent conditions (when we have not, for example, taken any account of seasonality, only of antecedent flow as an index of wetness).

Nearly all the classes of events presented here have shown anti-clockwise (negative) hysteresis loops for relative storage in relation to discharge, in part because the loops show retention of water in the system at the end of events. There have been cases reported for clockwise loops in discharge to riparian water table responses in a very small 2.5 ha catchment by Gelmini et al. (2022). This implies a faster response of the stream discharge relative to the response of the water table (as also observed elsewhere by Cheng et al. 2023). These were for dry antecedent conditions with a peak in discharge before the peak in water table. In their study, anti-clockwise hysteresis loops did however appear under wet antecedent conditions and long duration events (they also describe more complex loops). Such clockwise loops may be a result of using local water table information rather than changes in total storage, which in general will increase before any water table response. Such local effects have been suggested as contributing to changes in hysteresis behaviour in other cases, such as the hillslope to streamflow relations in McGuire and McDonnell (2010). Other studies, such as Pavlin et al. (2020) and Nanda and Safeeq (2024) indicate that hysteresis in soil moisture content or water table to discharge responses may be a function of the spatial structure within a catchment. This would therefore be one reason for treating the catchment response as a whole so as to integrate out the complex heterogeneity of local responses. Indeed, the dual-loop hysteretic responses found here for the Sedbergh micro-catchment are a result of the delayed initial response (extended pure time delay) whereby discharge continues to rise after the calculated relative storage starts to fall.

However, the big question and Great Challenge that then arises is whether these varying responses can be integrated into a single continuous and mechanistic functional representation of gain and hysteresis that might then be fitted in some form of data-based model to time-series observations from other catchments. This could be an alternative approach to determining catchment response functions than, for example, the nonlinear scaling of unit hydrographs (e.g., Dooge 2005). The DBM methodology has been applied to continuous data series from small catchments in the past, assuming a constant linear transfer function but with a nonlinear gain (e.g., Young and Beven 1994; P. Young 2003, 2013). However, the constant transfer function implies a constant time scale for the hysteresis, something that is not supported by the transfer function approach applied to different classes of event described above (as reflected in the time-variable '*a*' parameters of Tables S1–S4 in the Supporting Informations).

Thus, as suggested by K. J. Beven (2020a) it is important to explore other data-based or machine learning methodologies to investigate if a functional form for the hysteresis might be identifiable, related to other dynamic response characteristics and to independently measured catchment properties with a credible mechanistic interpretation. Some investigations of this type have already been made for the small-scale hysteresis in soil moisture characteristic curves (e.g., Beriozkin et al. 2024) and to discharge-concentration curves (e.g., Hamshaw et al. 2018; Liu et al. 2021) but not, to our knowledge, directly to any catchment-scale storage-discharge relationship, since catchment storage is not itself easily derived from mass balance or readily observed even at small catchment scales (at least as yet, observations of storage by gravity anomaly methods at small scales still seem to have limitations, see, for example, Güntner et al. 2017; Creutzfeldt et al. 2014; Chaffaut et al. 2022). Some catchments, such as those with doubled peaked hydrographs, with initial peaks generated on dynamic saturated areas, might be particularly challenging to describe in this way, but given enough reliable data it might well be possible using direct data-based methods applied at the catchment scale rather than postulating ever more complex conceptual model structures. And if the resulting functions can have a mechanistic interpretation then perhaps we will be able to directly address the dynamics of effective celerities for rising limbs and recession limbs of the hydrograph at catchment scales and relate these to catchment processes.

5 | Conclusions

We have demonstrated the types of hysteresis that might be found in some micro-catchments ranging in size from 0.1 to 1.1 sq. km when the storage-discharge relationship is considered under different antecedent flow and rainstorm magnitude conditions. The type of event classification we have used to be able to parameterise a simple model of the response in different classes does, however, have some limits to its general applicability. Notably, it does not provide a complete description of the changes in hysteretic behaviour across even the small set of classes examined.

The Great Hysteresis Challenge is then really quite simple. It is to find a parsimonious and physically interpretable set of nonlinear functions to represent in a single framework the nonlinear hysteresis in catchment response across the types of classes used in the analysis here, and beyond. This needs to include the effects of evapotranspiration on the seasonality of responses and a representation of the hysteretic departures of single event responses from a longer term storage-discharge attractor as demonstrated by K. J. Beven (2006) and Kim et al. (2023). We do not expect, of course, that such functions would be easily interpretable, for example to differentiate surface and subsurface processes, but rather that the parameters of the functions might be interpreted as changing time constants and gains (or other dynamic response characteristics) that reflect the effective storage behaviour of a catchment. Such parameters might then provide useful signatures for catchment behaviour, perhaps in terms of scaling and in relation to perceptual models of the processes of catchment response (Beven and Chappell 2021; Wagener et al. 2021; McMillan et al. 2023, 2025) or the physical characteristics over a set of catchment applications (Tarasova et al. 2024). Parameter parsimony in such functions would be valuable in terms of integrating over the variability, uncertainty and errors in the rainfall and discharge observations (Beven and Chappell 2021).

A real challenge to achieve such an aim is illustrated by the complex forms of storage-discharge relationships that have been demonstrated in this paper. It is also a challenge that is made greater by knowing that some observational data might introduce disinformation into a model calibration process (see for example K. J. Beven 2024 and references therein) and by the seasonal effects of evapotranspiration, which were only treated here as implicit in the antecedent conditions for an event.

Recent work with machine learning models, however, has suggested that there may be more information to be extracted from input data than has been achieved using conceptual hydrological models. Many such models do not fit the requirements of the Great Hysteresis Challenge directly since, while the catchment hysteresis may be implicit in their function, many are not easily interpreted and are not parametrically parsimonious (though see, for example, Lees et al. 2022 for an argument to interpret a machine learning model in terms of hydrological processes). Such an approach would, however, provide a way of encapsulating the hysteretic behaviour of a catchment across the different cases. Forcing such models with defined sequences of inputs might then provide information for the identification of the simpler functional form that would meet the challenge.

In time it might also be possible to extend the Challenge further to combine both hydrological and tracer data in a related way, so that effective values of both celerities and velocities can be addressed. This, however, would require the availability of high resolution tracer data over a sufficient range of events to allow the data-based analyses of a sufficient number of events. As yet, such data are still lacking in most catchments but hopefully will be available in future.

Acknowledgements

The data used in this paper were collected as part of the NERC funded project NE/R004722/1 called 'Quantifying the likely magnitude of nature-based flood mitigation effects across large catchments' or 'Q-NFM'. Additional funding for monitoring was provided by the Environment Agency funded C-NFM project (ENV0000826C) of the Defra Natural Flood Management programme and CiFR-Lancaster project (EAA7861) of the Defra Flood and Coastal Resilience Innovation Programme (FCRIP). All projects were supervised by NAC.

Funding

This work was supported by the Environment Agency; Natural Environment Research Council; Department for Environment, Food and Rural Affairs, UK Government.

Data Availability Statement

The data presented in all the Figures are available from the corresponding author upon request.

References

Appelbe, B., D. Flynn, H. Mcnamara, et al. 2009. "Rate-Independent Hysteresis in Terrestrial Hydrology." *IEEE Control Systems Magazine* 29, no. 1: 44–69.

Beriozkin, A., O. H. Anidjar, A. Azaria, and N. Hazon. 2024. "Machine Learning Approach to Predicting the Hysteresis of Water Retention Curves of Porous Media." *Expert Systems With Applications* 237: 121469.

Beven, K. J. 1981. "Kinematic Subsurface Stormflow." *Water Resources Research* 17, no. 5: 1419–1424.

Beven, K. J. 1982. "On Subsurface Stormflow: Predictions With Simple Kinematic Theory for Saturated and Unsaturated Flows." *Water Resources Research* 18, no. 6: 1627–1633.

Beven, K. J. 2004. "Robert Horton and Abrupt Rises of Groundwater." *Hydrological Processes* 18: 3687–3696.

Beven, K. J. 2006. "The Holy Grail of Scientific Hydrology: Q = H(SR)A as Closure." *Hydrology and Earth Systems Science* 10: 609–618.

Beven, K. J. 2020a. "Deep Learning, Hydrological Processes and the Uniqueness of Place." *Hydrological Processes* 34, no. 16: 3608–3613. https://doi.org/10.1002/hyp.13805.

Beven, K. J. 2020b. "A History of the Concept of Time of Concentration." *Hydrology and Earth System Sciences* 24: 2655–2670. https://doi.org/10.5194/hess-24-2655-2020.

Beven, K. J. 2024. "A Brief History of Information and Disinformation in Hydrological Data and the Impact on the Evaluation of Hydrological Models." *Hydrological Sciences Journal* 69, no. 5: 519–527. https://doi.org/10.1080/02626667.2024.2332616.

Beven, K. J., and N. A. Chappell. 2021. "Perceptual Perplexity and Parameter Parsimony." *WIREs Water* 8, no. 4: e1530. https://doi.org/10.1002/wat2.1530.

Beven, K. J., D. T. Leedal, P. J. Smith, and P. C. Young. 2011. "Identification and Representation of State Dependent Non-Linearities in Flood Forecasting Using the DBM Methodology." In *System Identification, Environmetric Modelling and Control*, edited by L. Wang and H. Garnier, 341–366. Springer-Verlag.

Beven, K. J., R. Romanowicz, P. Young, et al. 2008. "An Event Classification Approach to the Identification of Hydrological Change." In *43rd Defra Flood & Coastal Management Conference 2008*. Manchester University.

Beven, K. J., and E. F. Wood. 1993. "Flow Routing and the Hydrological Response of Channel Networks." In *Channel Network Hydrology*, edited by K. J. Beven and M. J. Kirkby, 99–128. Wiley.

Beven, K. J., and P. C. Young. 1988. "An Aggregated Mixing Zone Model of Solute Transport Through Porous Media." *Journal of Contaminant Hydrology* 3: 129–143.

Beven, K. J. 2012. *Rainfall-Runoff Modelling-The Primer*. 2nd ed. Wiley-Blackwell.

Beven, K. J. 2019. "Towards a Methodology for Testing Models as Hypotheses in the Inexact Sciences." *Proceedings Royal Society A* 475, no. 2224: 20180862. https://doi.org/10.1098/rspa.2018.0862.

Beven, K. J. 2021. "The Era of Infiltration." *Hydrology and Earth System Sciences* 25: 851–866. https://doi.org/10.5194/hess-25-851-2021.

Beven, K. J., and P. J. Smith. 2015. "Concepts of Information Content and Likelihood in Parameter Calibration for Hydrological Simulation Models." *Journal of Hydrologic Engineering* 20, no. 1: A4014010. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000991.

Blyth, K., and J. C. Rodda. 1973. "A Stream Length Study." *Water Resources Research* 9, no. 5: 1454–1461.

British Geological Survey. 1977. *Hydrogeological Map of England and Wales*. Vol. 1, 625. Ordnance Survey.

British Geological Survey. 2025. "User Guide: BGS Geology 50k v9. OR/24/041." Nottingham, UK, British Geological Survey. 38.

Camporese, M., D. Penna, M. Borga, and C. Paniconi. 2014. "A Field and Modeling Study of Nonlinear Storage-Discharge Dynamics for an Alpine Headwater Catchment, Water Resour." *Resource* 50: 806–822. https://doi.org/10.1002/2013WR013604.

Chaffaut, Q., J. Hinderer, F. Masson, et al. 2022. "New Insights on Water Storage Dynamics in a Mountainous Catchment From Superconducting Gravimetry." *Geophysical Journal International* 228, no. 1: 432–446.

Chappell, N. A., T. D. Jones, W. Tych, and J. Krishnaswamy. 2017. "Role of Rainstorm Intensity Underestimated by Data-Derived Flood Models: Emerging Global Evidence From Subsurface-Dominated Watersheds." *Environmental Modelling & Software* 88: 1–9.

Chappell, N. A., P. McKenna, K. Bidin, I. Douglas, and R. P. D. Walsh. 1999. "Parsimonious Modelling of Water and Suspended Sediment Flux From Nested Catchments Affected by Selective Tropical Forestry." *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences* 354, no. 1391: 1831–1846.

Chappell, N. A., W. Tych, A. Chotai, K. Bidin, W. Sinun, and H. C. Thang. 2006. "BARUMODEL: Combined Data Based Mechanistic Models of Runoff Response in a Managed Rainforest Catchment." *Forest Ecology and Management* 224: 58–80.

Cheng, Z., J. Zhang, B. Yu, et al. 2023. "Stormflow Response and 'effective' Hydraulic Conductivity of a Degraded Tropical *Imperata* Grassland Catchment as Evaluated With Two Infiltration Models." *Water Resources Research* 59: e2022WR033625.

Creutzfeldt, B., P. A. Troch, A. Güntner, T. P. Ferré, T. Graeff, and B. Merz. 2014. "Storage-Discharge Relationships at Different Catchment Scales Based on Local High-Precision Gravimetry." *Hydrological Processes* 28, no. 3: 1465–1475.

Davies, J., and K. J. Beven. 2015. "Hysteresis and Scale in Catchment Storage, Flow, and Transport." *Hydrological Processes* 29, no. 16: 3604–3615. https://doi.org/10.1002/hyp.10511.

D'Odorico, P., and R. Rigon. 2003. "Hillslope and Channel Contributions to the Hydrologic Response." *Water Resources Research* 39, no. 5: 1113. https://doi.org/10.1029/2002WR001708.

Dooge, J. C. I. 2005. "Bringing It All Together." *Hydrology and Earth System Sciences* 9, no. 1/2: 3–14.

Durighetto, N., L. E. Bertassello, and G. Botter. 2022. "Eco-Hydrological Modelling of Channel Network Dynamics—Part 1: Stochastic Simulation of Active Stream Expansion and Retraction." *Royal Society Open Science* 9, no. 11: 220944.

Ewen, J., and S. J. Birkinshaw. 2007. "Lumped Hysteretic Model for Subsurface Stormflow Developed Using Downward Approach." *Hydrological Processes* 21, no. 11: 1496–1505.

Frame, J. M., F. Kratzert, D. Klotz, et al. 2022. "Deep Learning Rainfall–Runoff Predictions of Extreme Events." *Hydrology and Earth System Sciences* 26, no. 13: 3377–3392.

Freer, J., J. McDonnell, K. J. Beven, et al. 2002. "The Role of Bedrock Topography on Subsurface Stormflow." *Water Resources Research* 38, no. 12: W01269. https://doi.org/10.1029/2001WR000872.

Gelmini, Y., G. Zuecco, M. Zaramella, D. Penna, and M. Borga. 2022. "Hysteresis in Streamflow-Water Table Relation Provides a New Classification System of Rainfall-Runoff Events." *Hydrological Processes* 36, no. 9: e14685.

Godsey, S. E., and J. W. Kirchner. 2014. "Dynamic, Discontinuous Stream Networks: Hydrologically Driven Variations in Active Drainage Density, Flowing Channels and Stream Order." *Hydrological Processes* 28: 5791–5803. https://doi.org/10.1002/hyp.10310.

Green, H. M., K. J. Beven, K. Buckley, and P. C. Young. 1994. "Pollution Incident Prediction With Uncertainty." In *Mixing and Transport in the Environment*, edited by K. J. Beven, P. C. Chatwin, and J. H. Millbank, 113–140. Wiley.

Güntner, A., M. Reich, M. Mikolaj, B. Creutzfeldt, S. Schroeder, and H. Wziontek. 2017. "Landscape-Scale Water Balance Monitoring With an iGrav Superconducting Gravimeter in a Field Enclosure." *Hydrology and Earth System Sciences* 21, no. 6: 3167–3182. https://doi.org/10.5194/hess-21-3167-2017.

Gupta, H. V., M. P. Clark, J. A. Vrugt, G. Abramowitz, and M. Ye. 2012. "Towards a Comprehensive Assessment of Model Structural Adequacy." *Water Resources Research* 48, no. 8: W08301. https://doi.org/10.1029/2011WR011044.

Haines, W. B. 1930. "Studies in the Physical Properties of Soil. V. The Hysteresis Effect in Capillary Properties, and the Modes of Moisture Distribution Associated Therewith." *Journal of Agricultural Science* 20, no. 1: 97–116.

Hamshaw, S. D., M. M. Dewoolkar, A. W. Schroth, B. C. Wemple, and D. M. Rizzo. 2018. "A New Machine-Learning Approach for Classifying Hysteresis in Suspended-Sediment Discharge Relationships Using High-Frequency Monitoring Data." *Water Resources Research* 54, no. 6: 4040–4058.

Herath, H. M. V. V., J. Chadalawada, and V. Babovic. 2021. "Hydrologically Informed Machine Learning for Rainfall–Runoff Modelling: Towards Distributed Modelling." *Hydrology and Earth System Sciences* 25, no. 8: 4373–4401.

Jones, T. D., and N. A. Chappell. 2014. "Streamflow and Hydrogen Ion Interrelationships Identified Using Data-Based Mechanistic Modelling of High Frequency Obser- Vations Through Contiguous Storms." *Hydrology Research* 45: 868–892.

Jones, T. D., N. A. Chappell, and W. Tych. 2014. "First Dynamic Model of Dissolved Organic Carbon Derived Directly From High Frequency Observations Through Contiguous Storms." *Environmental Science & Technology* 48: 13289–13297.

Kim, M., H. H. Bauser, K. Beven, and P. A. Troch. 2023. "Time-Variability of Flow Recession Dynamics: Application of Machine Learning and Learning From the Machine." *Water Resources Research* 59: e2022WR032690. https://doi.org/10.1029/2022WR032690.

Kirchner, J. W. 2003. "A Double Paradox in Catchment Hydrology and Geochemistry." *Hydrological Processes* 17, no. 4: 871–874.

Kratzert, F., D. Klotz, C. Brenner, K. Schulz, and M. Herrnegger. 2018. "Rainfall–Runoff Modelling Using Long Short-Term Memory (LSTM) Networks." *Hydrology and Earth System Sciences* 22, no. 11: 6005–6022.

Leedal, D. T., A. Weerts, P. J. Smith, and K. J. Beven. 2013. "Application of Data Based Mechanistic Modelling for Flood Forecasting at Multiple Locations in the Eden Catchment in the National Flood Forecasting System (England and Wales)." *Hydrology and Earth System Sciences* 17: 177–185.

Lees, M., P. C. Young, S. Ferguson, K. J. Beven, and J. Burns. 1994. "An Adaptive Flood Warning Scheme for the River Nith at Dumfries." In *River Flood Hydraulics*, edited by W. R. White and J. Watts, 65–75. Wiley.

Lees, T., S. Reece, F. Kratzert, et al. 2022. "Hydrological Concept Formation Inside Long Short-Term Memory (LSTM) Networks." *Hydrology and Earth System Sciences* 26: 3079–3101. https://doi.org/10.5194/hess-26-3079-202.

Liu, W., F. Birgand, S. Tian, and C. Chen. 2021. "Event-Scale Hysteresis Metrics to Reveal Processes and Mechanisms Controlling Constituent Export From Watersheds: A Review." *Water Research* 200: 117254.

Magliano, P. N., D. Mindham, W. Tych, et al. 2019. "Hydrological Functioning of Cattle Ranching Impoundments in the Dry Chaco Rangelands of Argentina." *Hydrology Research* 50, no. 6: 1596–1608.

McDonnell, J. J., and K. J. Beven. 2014. "Debates—The Future of Hydrological Sciences: A (Common) Path Forward? A Call to Action Aimed at Understanding Velocities, Celerities, and Residence Time Distributions of the Headwater Hydrograph." *Water Resources Research* 50, no. 6: 5342–5350.

McDonnell, J. J., C. Spence, D. J. Karran, H. J. Van Meerveld, and C. J. Harman. 2021. "Fill-and-Spill: A Process Description of Runoff Generation at the Scale of the Beholder." *Water Resources Research* 57, no. 5: e2020WR027514.

McGuire, K. J., and J. J. McDonnell. 2010. "Hydrological Connectivity of Hillslopes and Streams: Characteristic Time Scales and Nonlinearities." *Water Resources Research* 46, no. 10: W10543. https://doi.org/10.1029/2010WR009341.

McMillan, H., R. Araki, L. Bolotin, et al. 2025. "Global Patterns in Observed Hydrologic Processes." *Nature Water* 3: 497–506.

McMillan, H., R. Araki, S. Gnann, R. Woods, and T. Wagener. 2023. "How Do Hydrologists Perceive Watersheds? A Survey and Analysis of Perceptual Model Figures for Experimental Watersheds." *Hydrological Processes* 37, no. 3: e14845.

Mindham, D., K. Beven, and N. Chappell. 2023. "Rainfall–Streamflow Response Times for Diverse Upland UK Micro-Basins: Quantifying Hydrographs to Identify the Nonlinearity of Storm Response." *Hydrology Research* 54, no. 2: 233–244.

Mindham, D. A., W. Tych, and N. A. Chappell. 2018. "Extended State Dependent Parameter Modelling With a Data-Based Mechanistic Approach to Nonlinear Model Structure Identification." *Environmental Modelling & Software* 104: 81–93.

Minshall, N. E. 1960. "Predicting Storm Runoff on Small Experimental Watersheds." *Journal of the Hydraulics Division* 86, no. HYB: 17–38.

Nanda, A., and M. Safeeq. 2024. "Nonlinear Storage–Discharge Dynamics of Forested Headwater Catchment: A Hysteresis Index Approach." *Hydrological Processes* 38, no. 6: e15201.

Norbiato, D., and M. Borga. 2008. "Analysis of Hysteretic Behaviour of a Hillslope-Storage Kinematic Wave Model for Subsurface Flow." *Advances in Water Resources* 31, no. 1: 118–131.

Ockenden, M. C., and N. A. Chappell. 2011. "Identification of the Dominant Runoff Pathways From Data-Based Mechanistic Modelling of Nested Catchments in Temperate UK." *Journal of Hydrology* 402, no. 1–2: 71–79.

O'Kane, J. P. 2005. "Hysteresis in Hydrology." *Acta Geophysica Polonica* 53, no. 4: 373–383.

O'Kane, J. P. 2006. "The Hysteretic Linear Reservoir—A New Preisach Model." *Physica B: Condensed Matter* 372, no. 1–2: 388–392.

O'Kane, J. P., and D. Flynn. 2007. "Thresholds, Switches and Hysteresis in Hydrology From the Pedon to the Catchment Scale: A Non-Linear Systems Theory." *Hydrology and Earth System Sciences* 11, no. 1: 443–459.

Pavlin, L., B. Széles, P. Strauss, A. P. Blaschke, and G. Blöschl. 2020. "Event and Seasonal Hydrologic Connectivity Patterns in an Agricultural Headwater Catchment." *Hydrology and Earth System Sciences Discussions* 25, no. 4: 2327–2352. https://doi.org/10.5194/hess-25-2327-2021.

Ragan, R. M. 1968. "An Experimental Investigation of Partial Area Contributions." *International Association of Scientific Hydrology Publication* 76: 241–249.

Razavi, S. 2021. "Deep Learning, Explained: Fundamentals, Explainability, and Bridgeability to Process-Based Modelling." *Environmental Modelling & Software* 144: 105159.

Razavi, S., D. M. Hannah, A. Elshorbagy, et al. 2022. "Coevolution of Machine Learning and Process-Based Modelling to Revolutionize Earth and Environmental Sciences: A Perspective." *Hydrological Processes* 36, no. 6: e14596.

Reed, D. W., P. Johnson, and J. M. Firth. 1975. "A Non-Linear Rainfall-Runoff Model, Providing for Variable Lag Time." *Journal of Hydrology* 25, no. 3-4: 295–305.

Reggiani, P., S. M. Hassanizadeh, M. Sivapalan, and W. G. Gray. 1999. "A Unifying Framework for Watershed Thermodynamics: Constitutive Relationships." *Advances in Water Resources* 23, no. 1: 15–39.

Reggiani, P., M. Sivapalan, and S. M. Hassanizadeh. 2000. "Conservation Equations Governing Hillslope Responses: Exploring the Physical Basis of Water Balance." *Water Resources Research* 36, no. 7: 1845–1863.

Robinson, J. S., M. Sivapalan, and J. D. Snell. 1995. "On the Relative Roles of Hillslope Processes, Channel Routing, and Network Geomorphology in the Hydrologic Response of Natural Catchments." *Water Resources Research* 31, no. 12: 3089–3101.

Romanowicz, R., P. C. Young, and K. J. Beven. 2006. "Data Assimilation and Adaptive Forecasting of Water Levels in the River Severn Catchment, UK." *Water Resources Research* 42: W06407. https://doi.org/10.1029/2005WR004373.

Singh, V. P., and S. Vimal. 2022. "A Unified Framework for Governing Equations of Hydrologic Flows." *Journal of Hydrologic Engineering* 27, no. 1: 04021044.

Smith, P. J., K. J. Beven, D. Leedal, A. H. Weerts, and P. C. Young. 2014. "Testing Probabilistic Adaptive Real-Time Flood Forecasting Models." *Journal of Flood Risk Management* 7, no. 3: 265–279.

Tarasova, L., S. Gnann, S. Yang, A. Hartmann, and T. Wagener. 2024. "Catchment Characterization: Current Descriptors, Knowledge Gaps and Future Opportunities." *Earth-Science Reviews* 252: 104739.

Taylor, C. J., D. J. Pedregal, P. C. Young, and W. Tych. 2007. "Environmental Time Series Analysis and Forecasting With the Captain Toolbox." *Environmental Modelling and Software* 22: 797–814.

Thomas, C. W., and N. H. Woodcock. 2015. "The Kinematic Linkage of the Dent, Craven and Related Faults of Northern England." *Proceedings of the Yorkshire Geological Society* 358, no. 60: 258–274. https://doi.org/10.1144/pygs2015-358.

Troch, P., E. Van Loon, and A. Hilberts. 2002. "Analytical Solutions to a Hillslope-Storage Kinematic Wave Equation for Subsurface Flow." *Advances in Water Resources* 25, no. 6: 637–649.

van Meerveld, H. J. I., J. W. Kirchner, M. J. P. Vis, R. S. Assendelft, and J. Seibert. 2019. "Expansion and Contraction of the Flowing Stream Network Alter Hillslope Flowpath Lengths and the Shape of the Travel Time Distribution." *Hydrology and Earth System Sciences* 23: 4825–4834. https://doi.org/10.5194/hess-23-4825-2019.

Wagener, T., S. J. Dadson, D. M. Hannah, et al. 2021. "Knowledge Gaps in Our Perceptual Model of Great Britain's Hydrology." *Hydrological Processes* 35, no. 7: e14288.

Wallis, S. G., P. C. Young, and K. J. Beven. 1989. "Experimental Investigation of the Aggregated Dead Zone Model for Longitudinal Solute Transport in Stream Channels." *Proc. Inst. Civ. Eng., Part 2* 87: 1–22.

Young, P. 2003. "Top-Down and Data-Based Mechanistic Modelling of Rainfall–Flow Dynamics at the Catchment Scale." *Hydrological Processes* 17, no. 11: 2195–2217.

Young, P. C. 1992. "Parallel Processes in Hydrology and Water Quality: A Unified Time-Series Approach." *Water Environment Journal* 6, no. 6: 598–612.

Young, P. C. 2002. "Advances in Real–Time Flood Forecasting." *Philosophical Transactions of the Royal Society of London, Series A: Mathematical, Physical and Engineering Sciences* 360, no. 1796: 1433–1450.

Young, P. C. 2013. "Hypothetico-Inductive Data-Based Mechanistic Modeling of Hydrological Systems." *Water Resources Research* 49, no. 2: 915–935.

Young, P. C., and K. J. Beven. 1991. "Computation of the Instantaneous Unit Hydrograph and Identifiable Component Flows With Applications to Two Small Upland Catchments - a Comment." *Journal of Hydrology* 129: 389–396.

Young, P. C., and K. J. Beven. 1994. "Data-Based Mechanistic Modelling and the Rainfall-Flow Non-Linearity." *Environmetrics* 5: 335–363.

Young, P. C., and H. Garnier. 2006. "Identification and Estimation of Continuous-Time, Data-Based Mechanistic (DBM) Models for Environmental Systems." *Environmental Modelling & Software* 21, no. 8: 1055–1072.

Young, P. C., and A. J. Jakeman. 1979. "Refined Instrumental Variable Methods of Recursive Time-Series Analysis Part I. Single Input, Single Output Systems." *International Journal of Control* 29, no. 1: 1–30.

Zoccatelli, D., M. Borga, G. B. Chirico, and E. I. Nikolopoulos. 2015. "The Relative Role of Hillslope and River Network Routing in the Hydrologic Response to Spatially Variable Rainfall Fields." *Journal of Hydrology* 531: 349–359.

Zuecco, G., D. Penna, M. Borga, and H. J. van Meerveld. 2016. "A Versatile Index to Characterize Hysteresis Between Hydrological Variables at the Runoff Event Timescale." *Hydrological Processes* 30, no. 9: 1449–1466.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** hyp70438-sup-0001-Supinfo.docx.