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Research papers

Rainfall intensity and catchment size control storm runoff in a gullied blanket peatland

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ABSTRACT

Upland blanket peat is widespread in the headwaters of UK catchments, but much of it has been degraded through atmospheric pollution, vegetation change and erosion. Runoff generation in these headwaters is an important element of downstream flood risk and these areas are increasingly the focus of interventions to restore the peat ecosystem and to potentially mitigate downstream flooding. Here we use a series of multivariate analysis techniques to examine controls on storm runoff behavior within and between ten blanket peat catchments all within 5 km of one another and ranging in size from 0.2 to 3.9 ha. We find that: 1) for all 10 catchments, rainfall intensity is the dominant driver for both magnitude and timing of peak discharge, and that total and antecedent rainfall is important for peak discharge only in small storms; 2) there is considerable inter-catchment variability in: runoff coefficient, lag time, peak runoff, and their predictability from rainfall; however, 3) a significant fraction of the inter-catchment variability can be explained by catchment characteristics, particularly catchment area; and 4) catchment controls on peak discharge and runoff coefficient for small storms highlight the importance of storage and connectivity while those for large events suggest that surface flow attenuation dominates. Together these results suggest a switching rainfall-runoff behavior where catchment storage, connectivity and antecedent conditions control small discharge peaks but become increasingly irrelevant for larger storms. Our results suggest that, in the context of Natural Flood Management potential, expanding depression storage (e.g. distributed shallow water pools) in addition to existing restoration methods could increase the range of storms within which connectivity and storage remain important and that for larger storms measures which target surface runoff velocities are likely to be important.

1. Introduction

Headwater streams are key features of upland landscapes connecting hillslope runoff to downstream river systems (Nadeau and Rains, 2007). In the UK, many upland headwaters drain areas of blanket peat degraded due to climatic and anthropogenic pressures such as high atmospheric deposition of pollutants since the Industrial Revolution, grazing, prescribed burning, wildfire, peat extraction and artificial drainage (Joosten, 2016; Holden et al., 2012; Limpens et al., 2008; Ellis and Tallis, 2001; Evans et al., 1999). This has resulted in widespread vegetation loss, which on sloping blanket peatlands has exacerbated gully erosion and increased sediment export (Shuttleworth et al., 2015; Evans and Lindsay, 2010a, Allott et al., 2009; Daniels et al., 2008). These degradation effects increase the velocity of overland flow (Holden et al., 2008) and the flashiness of storm hydrographs at the headwater catchment scale (Grayson et al., 2010; Gao et al., 2016; Holden et al, 2015). There is concern that the enhanced flashiness of storm runoff may propagate downstream through river systems and exacerbate downstream flooding. Under current climate change projections, the severity of extreme rainfall events in the UK and thus flood risk is expected to rise in the coming decades (Met Office, 2019; Committee on Climate Change, 2017).

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Considerable investment has been made towards restoring the ecological integrity of upland peatlands in the UK to regain some of the multiple-benefits lost through degradation including biodiversity, carbon sequestration, climate and water regulation (Pilkington et al., 2015; Bonn et al., 2014; 2009). Recent work suggests that such restoration activities also have the potential to reduce flood peak discharge from headwater catchments (Goudarzi et al., 2021; Shuttleworth et al., 2019). The growing interest in runoff generation processes in upland peat systems has been motivated in part by a desire to harness natural hydrological and morphological processes to mitigate downstream flood risk (Wingfield et al., 2019; Dadson et al., 2017). However, attributing changes in hydrological function to restoration activities requires a good understanding of the hydrological processes at work in degraded peatlands prior to intervention. It also requires understanding of the variability in hydrological response due to catchment morphometry or the scale of investigation.

Water movement over and through peatlands is influenced by the physical properties of the peat including compaction and vegetation composition (Labadz et al., 2010; Daniels et al., 2008; Holden, 2005; Evans et al., 1999). Structurally, peat has been considered to consist of an 'active' upper layer (acrotelm) of relatively high hydraulic conductivity and a permanently saturated lower layer (catotelm) of low hydraulic conductivity (Hilbert et al., 2000; Egglesmann et al., 1993; Ingram and Bragg, 1984; Ivanov, 1981). This idealized diplotelmic model of water movement in peat has, however, been criticized for its shortcomings (Holden and Burt, 2003a; Morris et al., 2011) in: i) promoting one indicator - minimum water-table depth - as a key threshold point between two 'distinct' layers and ii) failing to facilitate spatial conceptualizations of peatland systems which more appropriately characterise spatially variable water flow paths within the peat profile and across the landscape.

On peatland hillslopes, runoff production most commonly occurs via saturation-excess overland flow, subsurface pipe flow, macropore flow and shallow saturated subsurface flow (Daniels et al., 2008; Holden and Burt, 2003a; Evans et al., 1999). The dominant runoff mechanism will, however, vary with storm characteristics, antecedent moisture conditions, hillslope configuration and local variability in peat properties (Daniels et al., 2008; Holden and Burt, 2003a). Hydrological studies in a range of environments have shown that heterogeneity in material properties generates heterogeneous flow pathways, and storage distributions within hillslopes (James and Roulet, 2009; Gomi et al., 2008; Blume et al., 2007; Lehmann et al., 2007) and thus subsurface and overland flows that are patchy in space and time across a catchment (Bromley et al., 2004; Holden and Burt, 2003b).

Many runoff studies in UK peatlands are based on measurements conducted at plot or single catchment scales (e.g. Daniels et al., 2008; Holden and Burt, 2002, Evans et al., 1999), with some exceptions (e.g. Howson et al., 2021; Holden et al., 2015; Holden et al., 2006). This, limits our understanding of: 1) the variability in process controls on hydrological response in upland peat catchments; and 2) how this variability influences response across a range of spatial scales. Studies have shown that the complex interactions between processes operating at different spatial–temporal scales tend to produce strong nonlinearity in event-based hydrological response (Hopp and McDonnell, 2009; Lehmann et al., 2007; Kusumastuti et al., 2007; Cammeraat, 2002). This makes the extrapolation of fine-scale measurements to larger areas a major challenge (Parsons et al., 2006; Kim et al., 2004). A better understanding of the spatial linkages between the processes of runoff generation and catchment-scale hydrological behavior is necessary to more accurately parameterize fine-scale heterogeneity at large spatial scales.

Here, we assemble a robust observational dataset from high temporal resolution monitoring of 10 replicate headwater micro-catchments of comparable but varying scales which lie above communities at risk of flooding along the western fringe of the Pennines in northern England (Allott et al., 2019). We aim to examine the controls on storm runoff magnitude and timing in these blanket peat systems focusing on: 1) whether there are consistent storm properties that drive response; 2) variability in both runoff response and its drivers across replicate catchments; 3) the role of scale in runoff generation processes. The results will provide a baseline that accounts for variability against which impacts of landscape scale changes could be examined, whether these are deliberate interventions (e.g. peatland restoration) or wider environmental changes (e.g. climate change).

2. Materials and method

2.1. Study area

This study was conducted in 10 comparable small headwater catchments of varying sizes ranging between 0.24 and 3.93 ha at a mean elevation of 480 m in the western Pennines, draining towards Greater Manchester, UK (Fig. 1; Table 1). The catchments have a blanket peat cover underlain by sandstones and millstones grit interspersed by shale. The landscape is dissected by erosion gullies that are variable in form; either branching or running parallel to each other (Bower, 1961). The mean annual rainfall was 2071 mm and mean temperature was 8.98 °C with a maximum of 24.3 °C and a minimum of −0.87 °C recorded in July and December, respectively (April 2019–March 2020 data obtained from 4 HOBO RG3 data logging rain gauges (0.2 mm resolution) installed at the monitoring sites). Although high summer rainfalls are associated with convective storms, long winter frontal events also generate flood relevant discharges in the catchments. The vegetation of the area consists of a mix of *Eriophorum vaginatum*, *Eriophorum angustifolium and Calluna vulgaris*, with *Empetrum nigrum* ssp. *Hermaphroditum*, *Rubus chamaemorus*, and *Vaccinium* ssp. (Elkington et al., 2001). The catchments are labelled A-J from west to east (Fig. 1) but do not systematically vary in their characteristics along this transect.

The study area was impacted by a moorland wildfire in 2018. A burn severity analysis (Key and Benson, 2006) using Sentinel-2A satellite imagery acquired on 24 June 2018 (pre-fire) and 04 July 2018 (post-fire) showed that our study catchments fall within the unburned and low-moderately low burn severity classes (Millin-Chalabi, *unpublished data*). The vegetation cover of the low-severity burn areas had mostly recovered prior to the start of hydrological monitoring in April 2019. Comparative within-catchment analysis of the hydrological data show no fire impact on the hydrological behavior of the catchments.

2.2. Hydro-meteorological monitoring

The monitoring period spans April 2019 to March 2020. Similar to the field monitoring of hydrograph behavior described in Shuttleworth et al. (2019), stream water level was monitored using pressure transducers (HOBO U20 series) in stilling wells installed at 90° V-notch weirs located at the outlet of the respective micro-catchments (Table 1). Pressure transducers continuously recorded the depth of water (d) flowing over the V-notch at 5-min intervals. The recorded water depth was subsequently converted to discharge and normalized to the catchment area to allow for comparative analysis. To check for logger performance, a calibrated measuring board was attached to the stilling wells and manually read off during monthly logger downloads.

Four rain gauges logging at 5-min intervals were installed in catchments B, E, G and I. Their locations were chosen to represent the nearest catchment or approximate geometric centre of catchment clusters. Specifically, rainfall data from the rain gauge at catchment B was used for catchments A, B and C; rain gauge at E was used for catchments D, E and F; rain gauge at G for catchments G and H, and rain gauge at I for catchments I and J. Examination of the residuals between the rain gauges reveals no significant spatial bias. However, there was less error observed between rain gauges closer to each other and on relatively similar catchment elevation than between more distant gauges (Figure SI 1 and Table 1).

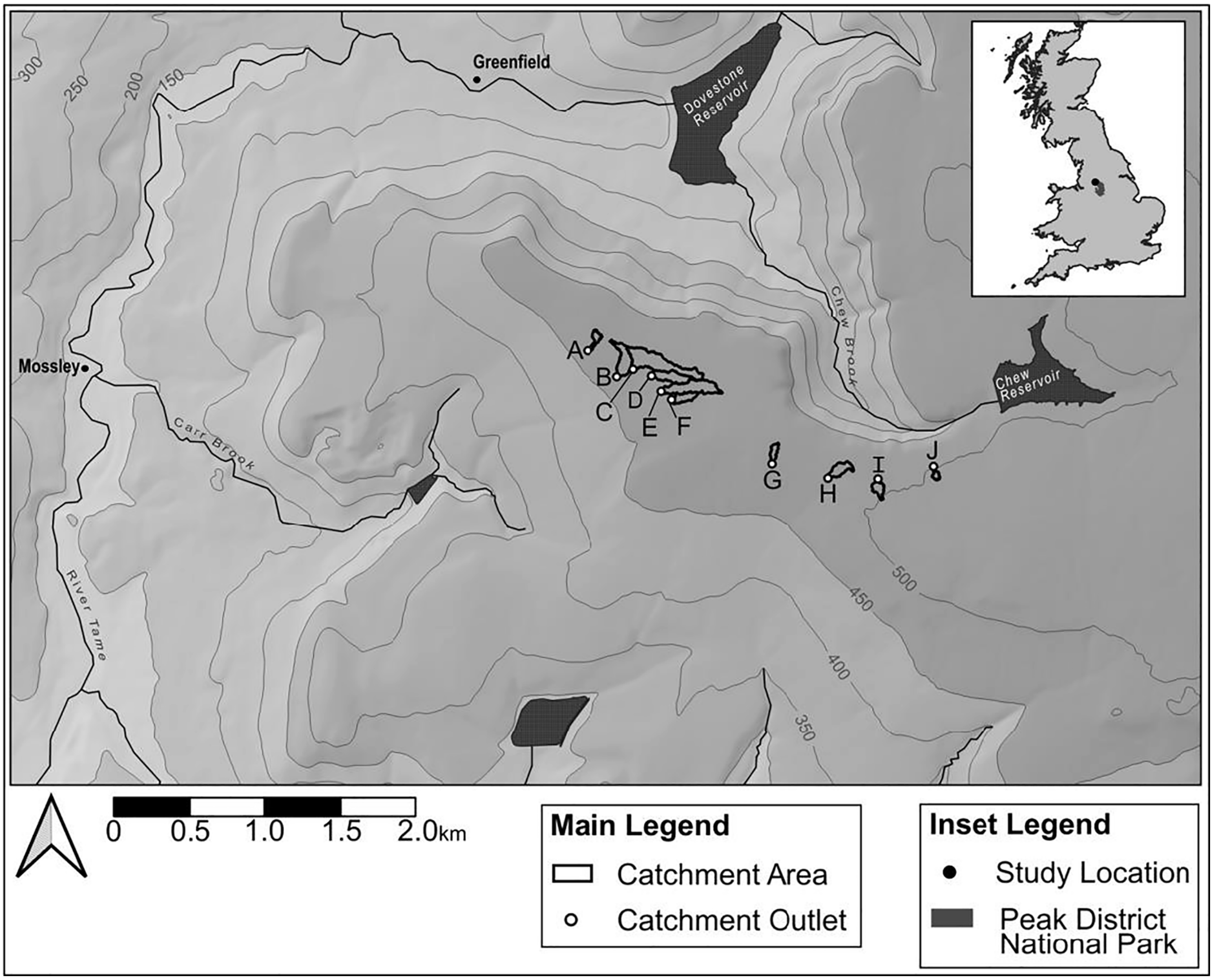

Fig. 1. Study catchments.

2.3. Storm hydrograph extraction

Hydrographs were extracted for each of the catchments for all storm events that met the following criteria: 1) a discrete event without ice/snowmelt; 2) having a total rainfall of at least 4 mm; and 3) resulting in discernible changes in streamflow characteristics. Storms were identified as potentially at risk of meltwater-influence if temperatures fell below 0 °C within 2 days of the discharge response and/or if there was no rainfall within 2 hrs of a discharge response. These storms were not included in the storm set. The start of an event was determined as the timestep after which discharge consistently increased for >4 timesteps (20 min). The end of an event flow was determined as the point of inflection on the recession limb of the hydrograph (Beighley et al., 2002; Bedient and Huber, 1992; Singh, 1992). There were a total of 900 extracted hydrographs covering 102 storm events. The number of extracted event hydrographs differed between catchments (ranging from 68 to 102) due to gaps in discharge data resulting from occasional logger failure. For each of the extracted hydrographs, five hydrological response metrics were calculated: total storm discharge (Qtot), peak storm discharge (Qpeak), runoff coefficient (the ratio of area-normalised total storm discharge to total storm rainfall), lag time (the time between peak rainfall and peak discharge following a storm event) and time to peak Q (the time from the start of the hydrograph rising limb to peak discharge). The Qtot, Qpeak and runoff coefficients were used to represent the magnitude of stormflow to the streams while lag time and time to peak Q were taken as indicators of catchment runoff timings.

2.4. Potential predictor variables

The potential predictor variables consisted of catchment characteristics and hydro-meteorological variables (Table 2). The catchment characteristics variables included several physical characteristics hypothesized to affect processes of hydrological response to rainfall input (Holden et al., 2006; Holden and Burt, 2003c). These characteristics include catchment area, relief, slope, flow path length, topographic depressions and gully area extent. The catchments were delineated using Bluesky lidar DSMs with 0.25 m resolution. Catchment relief was calculated as change in elevation between the highest and lowest elevation in the catchment scaled by the square root of the catchment area (Ali et al., 2015). The average slope for each catchment was computed as the difference between the maximum elevation and outlet elevation over the distance of the longest drainage path length. Maximum flow path length (Lmax) was identified using D8 single direction flow algorithm (Hogg et al., 1997) after filling the DSM depressions. Topographic depression storage (Sd) for each catchment was derived as the residual of depression filled DSM and the original DSM converted to storage volume and normalised to catchment area. Estimates of gully extent for the catchments were derived following methods described in Evans and Lindsay (2010b).

Flowpath length distributions or 'width functions' express the area of the catchment within a particular flow length band from the outlet (i.e. area/length = width) and have been widely used in unit hydrograph rainfall-runoff models (Diaz-Granados et al., 1984). Runoff generated at a given location has a particular flow path length and thus travel time to

Table 1
Catchment characteristics and locational information of V-notch weirs.

Catchment	TotalArea (ha)	Mean Elevation (m)	Mean Slope (°)	Topographic Depression storage (m^3 ha^{-1})	Weir location (Latitude & Longitude)
A	0.46	470	2.48	11	53° 30′ 58.92′' −1° 59′ 20.34′'
B	1.63	466	1.23	25	53° 30′ 21.26′' −1° 59′ 9.71′'
C	3.93	468	0.91	42	53° 30′ 54.94′' −1° 59′ 3.89′'
D	1.47	470	1.20	22	53° 30′ 53.52′' −1° 58′ 57.32′'
E	2.52	474	1.79	22	53° 30′ 50.25′' −1° 58′ 53.90′'
F	0.82	472	1.26	28	53° 30′ 48.53′' −1° 58′ 50.10′'
G	0.45	493	2.56	17	53° 30′ 34.84′' −1° 58′ 14.23′'
H	0.96	491	2.23	23	53° 30′ 31.76′' −1° 57′ 54.09′'
I	0.60	499	1.56	24	53° 30′ 31.62′' −1° 57′ 36.29′'
J	0.24	502	2.26	21	53° 30′ 34.30′' −1° 57′ 16.42′'

Table 2
Response and predictor variables included in the analysis.

Variable	Units	Abbreviation
Hydrological/response variables		
Total storm discharge	m^3	Qtot
Peak storm discharge	$L\ s^{-1}$	Qpeak
Runoff coefficient	%	
Lag time	min	
Time to peak discharge	min	
Predictor variables		
Catchment characteristics		
Area	ha	
Relief	m/m	
Slope	°	
Flow path length	m	
Topographic depression storage	$m^3\ ha^{-1}$	
Gully area extent	m^2/m^2	
Maximum width	m^{-1}	
Hydro-meteorological variables		
Total event rainfall	mm	TOTPPN
Event-averaged rainfall intensity	$mm\ h^{-1}$	PPTINT
5-day antecedent rainfall	mm	API5

reach the catchment outlet. By expressing the spatially variable flow path lengths as a probability distribution and assuming spatially uniform runoff amount and velocity we can hypothesise that: peak discharge should have a positive linear correlation with peak probability density (i.e. maximum width, Wmax); and lag time should be positively correlated with modal flow path length. We used kernel density estimation to calculate flowpath length distributions, avoiding the problem of sensitivity to binning but introducing a (weaker) sensitivity to kernel bandwidth. We chose an Epanechnikov kernel (Epanechnikov, 1969), because we did not expect the distributions to have a particular form *a priori,* and accounted for bandwidth sensitivity by taking median values of our metrics from a range of kernel bandwidths (range 0.05–0.5 m n = 10, chosen to capture a reasonable range of smoothing).

For the hydro-meteorological variables (Table 2), total event rainfall (TOTPPN – the sum of rainfall for the duration of a storm hydrograph) and event-averaged rainfall intensity (PPTINT – the ratio of total event rainfall to event duration) were used to represent the storm characteristics while the sum of the 5-day antecedent rainfall (API5) was used as a surrogate for the antecedent moisture condition of the catchments. We did not examine higher order measures of hyetograph shape for example the degree or orientation of asymmetry in rainfall intensity within a storm.

3. Data analyses

3.1. Classification and regression trees

The non-parametric classification and regression trees (CART) modelling approach was used to assess the relative influence of the hydro-meteorological predictors (Table 2) on the hydrological behavior of each catchment. The model allows for detection of thresholds in hydro-meteorological variables associated with each hydrological response metric. This technique has been widely used to analyze complex hydro-ecological datasets composed of a response variable and any number of explanatory variables (Ali et al., 2010; Rothwell et al., 2008; Lawler et al., 2006; Spruill et al., 2002; DeAth and Fabricius, 2000; Rejwan et al., 1999; Breiman et al., 1984). The CART analysis was performed in JMP statistical software package (e.g. Rothwell, et al., 2008; Lougheed and Chow-Fraser, 2002). The model predicts a single response variable by building a nested sequence of reasonably homogenous groups defined by a simple rule applied to predictor variables that can be scanned more than once in a stochastic recursive search of dissimilar subsets. It begins from a 'root node' containing all observations in the dataset. The algorithm then partitions the 'root node' by applying a logical operator to predictor variables to split the data into two mutually exclusive and reasonably internally homogeneous 'child nodes' (Rothwell et al., 2008; Yohannes and Hoddinott, 1999). Both the predictor variable and the logical operation are optimised to minimise the sums of squares within each child node. These child nodes become the new parent nodes for the next partitioning. The splitting process can be stopped using a range of rules: we chose to minimise the sum of squares errors in cross validation. A five-fold cross-validation procedure was used to assess how the results of our model will generalize to an independent dataset. This technique randomly partitions the dataset into five equally sized subsample groups with a single group retained as the validation data for testing the model. Each group of the subsamples is sequentially used as a test set for the model derived from the combined set of the remaining groups five times. This procedure was used to obtain estimates of the true prediction errors for trees of a given size to avoid over-sized or over-fitted trees with few data in the terminal nodes (Breiman et al, 1984). Given the stochastic path-dependent nature of our CART analysis we performed multiple runs for each analysis using the Akaike Information Criteria (AICc) (Akaike, 1974) to quantify model goodness-of-fit. We chose the model that minimised AICc and stopped our analysis when subsequent runs resulted in no significant improvement in AICc ($p \leq 0.05$).

3.2. Catchment characteristics and hydrological response

Due to the multi-variate character of the dataset, principal component analysis (PCA) was used to identify combinations of response variables (Table 2) that best explain the within-catchment variability in their hydrological response. PCA is a data reduction method that simplifies high-dimensional data by transforming the original data into fewer dimensions (principal component – PCs), enabling the identification of gradients, trends and influential variables in the summarized dataset (Lever et al., 2017; Legendre and Legendre, 1983). In this study only the first two PC axes are retained so that events are classified into four hydrological response quadrants based on their main characteristics and location in reduced space (e.g. Ali et al., 2010). For each of the identified hydrological response types or quadrants, Spearman rank correlation coefficient was subsequently used to measure the strength and direction of the relationships between the metrics of hydrograph response and a suite of catchment and hydro-meteorological predictor variables (Table 2).

4. Results

4.1. Thresholds in hydro-meteorological variables

Figure 2 shows the structure of an optimally pruned CART model for Qpeak for catchment C, the largest catchment (3.93 ha) in the dataset. Each split in the CART structure is labeled with the threshold value responsible for the split, the distribution and the decision variable. The structure of all other CART models for each hydrological response variable and catchment are available as Supplementary Information (Figure SI 2 – 6). The summary statistics of the CART analysis for all catchments are shown in Table 3. The CART models explain 77–90% variance in Qpeak across the catchments with PPTINT identified as the most significant hydro-meteorological control, contributing 86 – 98% of the variation explained by the models. TOTPPN played only a minor role and antecedent precipitation was less significant still in its control on Qpeak in the catchments, both were important only in small low intensity storms (≤14 mm) at PPTINT < 3 mm h^{-1}.

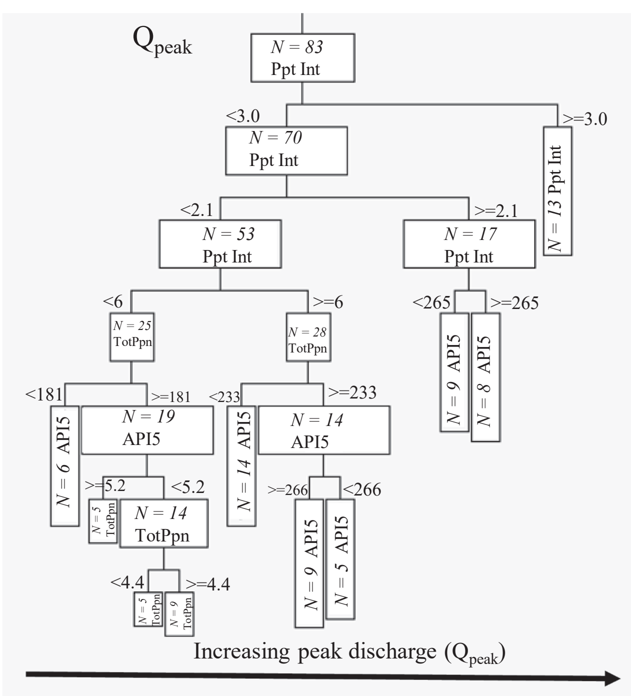

Fig. 2. Classification and regression trees analysis of peak storm discharge for catchment C. Each split in the CART structure is labeled with the threshold value responsible for the split, the distribution and the decision variable.

The CART models explain <50% variance in the runoff coefficient dataset for all but catchments H, I and J where it explains 51–63% variance in the dataset. Unlike Qpeak, identifying the main hydro-meteorological driver of runoff coefficient was more complicated and varied across the catchments. With the exception of catchments H and J, TOTPPN was the dominant control on runoff coefficients whilst API5 was only important when TOTPPN was below 12 mm. In catchments H and J, API5 was identified as the most important control on runoff coefficient, contributing 40–45% of the variance explained by the models. API5 was also identified as the second most important control on runoff coefficient in catchments A, D, E, F, G and I.

TOTPPN was identified as the most significant control on Qtot, contributing 97–100% of the 59–82% variance explained by the CART models. The influence of PPTINT on Qtot is only important when TOTPPN is <22 mm, while API5 as a control is only relevant in small rainfall events of low average intensity (<1.4 mm h^{-1}). This suggests that in large storms Qtot is dominated by TOTPPN, while intensity and API only become important for smaller storms.

For lag time, the CART models explain 49–65% variance in the dataset, with PPTINT identified as the most important explanatory variable of lag in the catchments, contributing 49 – 73% of the variance explained by the models. TOTPPN was the second most important control and contributed 15–50% of the explained variance. The influence of API5 on lag is important when TOTPPN is <20 mm and event-averaged rainfall intensity is in the range of 1–4 mm h^{-1}. The CART models for time to peak Q in the catchments explain 57–75% variance in the dataset and TOTPPN was identified as the most important control, contributing 51–77% of the explained variance in all but catchment A where PPTINT was slightly more important. The influence of API5 on time to peak Q is important when TOTPPN is <24 mm and PPTINT is in the range of 1–4 mm h^{-1}.

In general the hydro-meteorological variables that best predict a given discharge response (e.g. Qpeak) are consistent in terms of the share of the variance that they explain across the catchments. For Qpeak, Qtot and lag the same predictor (PPTINT) is best for all catchments and for Qpeak and Qtot, the other predictors have only a small share of the variance (<10%) across all catchments. For lag, across all catchments, TOTPPN is always as important as or more important than API but all three predictors explain a non-trivial share (>11%) of the variance in half the catchments. For time to peak the behaviour is broadly consistent across catchments: PPTINT and TOTPPN are both important predictors at all catchments, TOTPPN is best in 9/10 catchments but the variance share in these nine varies widely (51–77%). In the one catchment where PPTINT is best, its variance share is only 2% higher than that of TOTPPN. For runoff coefficient, all three predictors have a non-trivial share of the variance in most catchments (8/10). The order of the predictors in terms of their variance share varies across catchments. TOTPPN is best in 8/10 and API in the other two; however, API is second best in 6/10 and PPTINT in the other four.

The CART models using hydro-meteorological variables are consistently good predictors of Qpeak across all catchments and are good predictors of Qtot but with more inter-catchment variability. Timing is less well predicted (both lag and time to peak) but performance is relatively consistent across catchments. Runoff coefficients are generally not well predicted by the CART models but there is considerable variability between catchments such that they can explain >43% of the variance in the two best performing catchments but <15% in the worst two.

There do not appear to be consistent ‘outlier’ catchments that always differ from the majority whether in terms of the roles of the predictor variables or the models’ performances. Instead, different catchments appear as outliers for the different discharge properties that are being predicted.

Table 3
Summary statistics of CART models for each catchment.

	A	B	C	D	E	F	G	H	I	J	Median	IQR
Sample size	70	68	83	97	97	95	98	102	102	88		
Qpeak (L s^{-1})												
CV (k-fold = 5) R^2	0.84	0.81	0.77	0.78	0.74	0.72	0.73	0.73	0.85	0.80	0.78	0.08
Overall Model R^2	0.90	0.86	0.83	0.84	0.82	0.77	0.81	0.82	0.87	0.85	0.84	0.04
Contribution to fit (%)												
PPTINT	0.89	0.99	0.86	0.98	0.94	0.99	0.98	0.96	0.98	0.94		
TOTPPN	*0.10*	0.00	0.06	0.02	*0.06*	0.00	*0.02*	*0.03*	0.00	*0.04*		
API 5	0.01	*0.01*	*0.08*	0.00	0.01	*0.01*	0.00	0.01	*0.02*	0.02		
Runoff coefficient (%)												
CV(k-fold = 5) R^2	0.15	0.17	0.22	0.16	0.33	0.11	0.34	0.43	0.46	0.36	0.28	0.19
Overall Model R^2	0.22	0.33	0.41	0.43	0.47	0.42	0.48	0.62	0.63	0.51	0.45	0.09
Contribution to fit (%)												
PPTINT	0.00	*0.28*	*0.28*	0.20	0.18	0.11	0.06	*0.33*	0.27	*0.41*		
TOTPPN	0.86	0.72	0.49	0.51	0.60	0.47	0.49	0.27	0.41	0.14		
API 5	*0.14*	0.00	0.23	*0.29*	*0.22*	*0.42*	*0.45*	0.40	*0.32*	0.45		
Qtot (m^3)												
CV(k-fold = 5) R^2	0.60	0.64	0.52	0.75	0.78	0.73	0.70	0.66	0.61	0.76	0.68	0.13
Overall Model R^2	0.69	0.72	0.59	0.81	0.82	0.78	0.75	0.72	0.73	0.76	0.74	0.06
Contribution to fit (%)												
PPTINT	0.00	0.00	0.00	*0.01*	0.00	0.00	0.00	*0.01*	*0.02*	0.00		
TOTPPN	0.99	1.00	1.00	0.99	1.00	1.00	1.00	0.99	0.97	0.99		
API 5	*0.01*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	*0.01*		
Lag (min)												
CV(k-fold = 5) R^2	0.37	0.32	0.40	0.48	0.41	0.37	0.48	0.57	0.46	0.32	0.41	0.11
Overall Model R^2	0.59	0.49	0.64	0.61	0.54	0.61	0.63	0.65	0.61	0.54	0.61	0.07
Contribution to fit (%)												
PPTINT	0.63	0.49	0.65	0.66	0.66	0.73	0.50	0.72	0.73	0.50		
TOTPPN	*0.23*	*0.43*	*0.35*	*0.19*	*0.27*	*0.15*	*0.25*	*0.21*	*0.15*	0.50		
API 5	0.14	0.08	0.00	0.15	0.07	0.12	*0.25*	0.07	0.11	0.00		
Time to peak Q (min)												
CV(k-fold = 5) R^2	0.55	0.49	0.46	0.56	0.61	0.50	0.62	0.61	0.55	0.60	0.56	0.10
Overall Model R^2	0.69	0.57	0.63	0.63	0.69	0.60	0.72	0.69	0.63	0.67	0.65	0.06
Contribution to fit (%)												
PPTINT	0.48	*0.28*	*0.46*	*0.39*	*0.44*	*0.46*	*0.33*	*0.34*	*0.23*	*0.41*		
TOTPPN	*0.46*	0.67	0.51	0.61	0.56	0.54	0.62	0.66	0.77	0.59		
API 5	0.06	0.05	0.03	0.00	0.00	0.00	0.06	0.00	0.00	0.00		

Note: PPTINT = Event-averaged rainfall intensity, TOTPPN = Total rainfall, API5 = 5-day antecedent rainfall, CV = cross validation, IQR = Interquartile range, bold values indicate the variable with the highest % contribution to the variance explained by the model, italics indicate second highest contribution, contributions <0.1 are in grey.

4.2. Characterization of hydrological response

Figure 3 shows the PCA correlation biplot for catchment C. The PCA biplots for all other catchments are available as Supplementary Information (Figure SI 7). Across all catchments, PCA revealed two dominant axes which together explained 73 – 80% of the variance in the hydrological dataset (Table 4). Thus, subsequent PCA axes were not considered further. The first component (PC 1) is associated with Qtot, Qpeak and runoff coefficient, while the second (PC2) is associated with lag and time to peak Q (Table 4) suggesting that PC 1 is a gradient of runoff magnitude and PC 2 is a gradient of runoff timing. Based on the positioning of individual events in the reduced PCA space and the correlation between descriptor and PC axes, the hydrological response types in the four PCA quadrants can be partitioned into high/low magnitude and quick(i.e. short lag time and time to peak)/slow(i.e. long lag time and time to peak) response types (Fig. 3). The medians and interquartile ranges of response and hydro-meteorological variables in each PCA segmentation quadrant are shown in Table 5. Across the range of catchment scales, storm events associated with the high magnitude/quick timing (HQ), high magnitude/slow timing (HS), low magnitude/quick timing (LQ) and low magnitude/slow timing (LS) quadrants of the PCA space have median Qpeak of 5.6–15.6 L s^{-1} ha^{-1}, 2.9–9.1 L s^{-1} ha^{-1}, 1.9–6.2 L s^{-1} ha^{-1} and 1.0–2.9 L s^{-1} ha^{-1}, respectively. Median Qtot ranges between 18 – 170 m^3 in high magnitude event type and 6–64 m^3 in low magnitude events. Runoff coefficients range between 27 and 73% for high magnitude events and 14–48% for low magnitude events.

The example storm hydrographs for different PCA quadrants in Fig. 3 demonstrate that rainfall in slow timing events can occur over an extended period but still produce peak Q similar in magnitude to quick timing events (storm #50). For quick timing events, median lag and time to peak Q ranged from 23 to 82 min and 40–125 min, respectively with

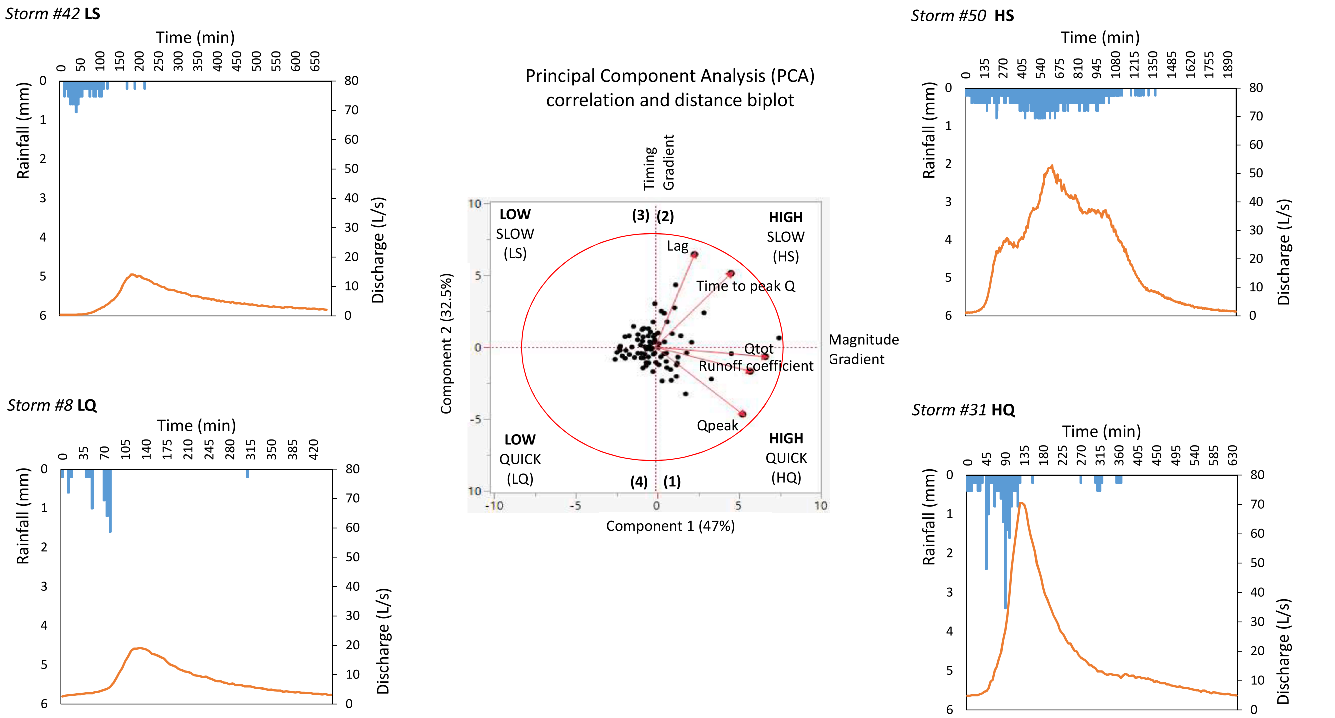

Fig. 3. Principal component analysis (PCA) correlation and distance biplot of the storm hydrology dataset for catchment C. Arrows represent the descriptor or hydrological variables and data points represent individual events. The red equilibrium circle of descriptors indicates the contribution of each response variable to the formation of the PCA space. The closer the projected length of a variable to the equilibrium circle, the higher their importance in explaining the structure of the reduced PCA space. Magnitude and timing quadrants of the PCA space characterised based on arrow orientation and the correlation between descriptor and PC axes. The hydrographs are example storms in the magnitude/timing quadrants of the biplot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Correlation between PC axes and descriptor axes for each catchment, with best predictor in bold, second best in italics, and predictors with correlation < 0.3 in grey text.

Descriptors		Catchment A	B	C	D	E	F	G	H	I	J
	PCA axis 1										
	% of Variance explained	41.4	44.3	47.0	44.0	47.8	44.8	44.7	42.4	48.6	48.2
Qtot (m^3)		0.90	0.91	0.89	0.88	0.91	0.71	0.91	0.89	0.89	0.88
Qpeak ($L\ s^{-1}$)		0.73	0.67	0.71	*0.86*	0.70	0.89	0.76	*0.80*	0.85	0.58
Runoff coefficient (%)		*0.75*	*0.77*	*0.77*	0.77	*0.79*	*0.75*	*0.78*	0.75	*0.88*	*0.77*
Lag (min)		0.02	0.20	0.32	−0.30	0.27	−0.57	0.14	−0.06	−0.13	0.44
Time to peak Q (min)		0.39	0.55	0.61	0.14	0.61	−0.26	0.44	0.36	0.35	0.71
	PCA axis 2										
	% of Variance explained	36.9	31.8	32.5	34.2	32.5	33.5	31.4	30.2	31.4	28.9
Qtot (m^3)		0.10	0.00	−0.09	0.27	−0.08	0.60	0.08	0.16	0.20	−0.14
Qpeak ($L\ s^{-1}$)		−0.47	−0.60	−0.62	−0.26	−0.59	0.06	−0.51	−0.45	−0.35	*−0.73*
Runoff coefficient (%)		−0.14	−0.18	−0.22	0.14	−0.21	0.20	−0.17	−0.04	−0.07	−0.22
Lag (min)		0.92	0.84	0.85	*0.84*	0.87	0.70	0.82	0.81	0.84	0.75
Time to peak Q (min)		*0.86*	*0.69*	*0.68*	0.91	*0.69*	0.89	*0.77*	*0.79*	*0.83*	0.54

median PPTINT in the range of 2–6 mm h^{-1}. For slow timing events, the median lag and time to peak Q ranged from 80 to 175 min and 115–273 min, respectively, with median PPTINT of 1–3 mm h^{-1}. Median time to peak Q is consistently longer than lag across catchments and storm types, reflecting the near instantaneous response times of these small catchments. Time to peak primarily reflects the duration of the storm while lag time reflects the response time over which a rainfall signal propagates through the catchment. There was high variability in TOTPPN producing high magnitude response, with medians of 10–20 mm and interquartile ranges (IQR) of 6–43 mm, compared to TOTPPN medians of 5–7 mm and IQRs of 2–7 mm for low magnitude events (Table 5).

There is appreciable inter-catchment variability in peak discharge (normalized by area) despite the close proximity of the catchments (<3 km span) and similar conditions (all gullied blanket peat). For all storm types the cross-catchment IQR in Qpeak is close to half the cross-catchment median (Table 5). This also suggests that inter-catchment variability in peak discharge is retained across storm types rather than emerging only for quick, slow, large or small storms.

High flow events have consistently higher runoff coefficients than low flow events with median values across the catchments of 54–56% for large and 28–30% for small events. There is considerable variability

Table 5
Medians of response and hydro-meteorological variables in the magnitude/timing segmentation of the PCA space for each catchment. Interquartile range (IQR) is shown in brackets.

Response type		A	B	C	D	E	F	G	H	I	J
HQ	Qpeak (L s^{-1} ha^{-1})	14.5 (27.1)	14.7 (13.0)	5.6 (4.3)	9.7 (14.8)	6.8 (8.0)	7.4 (8.1)	15.6 (16.5)	12.3 (18.4)	14.4 (20.1)	12.9 (8.9)
	Qtot (m^3)	31 (24)	84 (56)	183 (86)	97 (89)	123 (77)	43 (43)	36 (32)	63 (40)	45 (39)	23 (10)
	Runoff coefficient (%)	63 (28)	36 (14)	36 (10)	59 (17)	35 (12)	51 (13)	67 (14)	54 (15)	58 (18)	73 (13)
	Lag (min)	23 (43)	33 (48)	55 (45)	35 (35)	33 (39)	50 (39)	33 (24)	40 (20)	30 (30)	60 (45)
	Time to Peak Q (min)	80 (106)	60 (81)	125 (82)	83 (105)	110 (120)	80 (65)	73 (64)	80 (85)	65 (50)	90 (58)
	TotPpn (mm)	12 (9)	16 (13)	11 (6)	13 (9)	14 (6)	10 (10)	12 (11)	12 (10)	13 (9)	13 (7)
	Ppt Int (mm h^{-1})	5 (6)	6 (4)	3 (2)	3 (4)	3 (4)	2 (3)	4 (4)	4 (5)	4 (3)	3 (2)
	API5	343 (135)	237 (187)	271 (124)	300 (141)	251 (130)	293 (156)	324 (166)	333 (173)	302 (143)	278 (155)
	Sample size	16	10	17	22	18	32	24	23	23	17
HS	Qpeak (L s^{-1} ha^{-1})	7.5 (5.1)	3.9 (3.6)	3.0 (3.5)	9.1 (7.0)	2.9 (2.5)	9.1 (6.5)	7.6 (5.3)	6.2 (2.8)	8.3 (4.8)	7.9 (8.7)
	Qtot Q (m^3)	40 (47)	83 (115)	159 (268)	170 (147)	89 (114)	80 (214)	31 (36)	60 (56)	41 (140)	18 (30)
	Runoff coefficient (%)	55 (13)	30 (4)	36 (14)	58 (32)	27 (12)	53 (16)	56 (16)	56 (17)	48 (12)	71 (18)
	Lag (min)	130 (40)	125 (55)	168 (52)	100 (81)	170 (92)	125 (100)	100 (72)	90 (32)	80 (70)	175 (83)
	Time to Peak Q (min)	210 (285)	220 (185)	273 (185)	165 (258)	248 (199)	165 (110)	205 (108)	120 (88)	195 (360)	250 (158)
	TotPpn (mm)	18 (18)	17 (16)	13 (12)	19 (14)	14 (11)	20 (43)	13 (15)	12 (18)	16 (18)	16 (15)
	Ppt Int (mm h^{-1})	3 (2)	2 (2)	1 (1)	2 (1)	2 (2)	3 (2)	2 (1)	2 (1)	3 (1)	2 (2)
	API5	295 (71)	268 (141)	241 (107)	268 (90)	228 (109)	289 (83)	251 (84)	252 (96)	301 (117)	255 (103)
	Sample size	09	11	16	08	16	07	17	17	11	17
LQ	Qpeak (L s^{-1} ha^{-1})	3.3 (3.3)	2.7 (1.8)	2.4 (2.2)	3.1 (2.1)	1.9 (1.5)	2.7 (1.9)	5.1 (3.8)	3.8 (2.7)	4.2 (4.0)	6.2 (3.7)
	Qtot (m^3)	6 (7)	19 (10)	64 (57)	25 (24)	32 (19)	10 (11)	9 (8)	18 (16)	11 (12)	8 (6)
	Runoff coefficient (%)	26 (20)	19 (7)	20 (18)	30 (17)	19 (12)	24 (20)	41 (22)	32 (25)	32 (30)	48 (22)
	Lag (min)	30 (20)	35 (20)	65 (24)	60 (34)	40 (35)	82 (38)	40 (30)	45 (23)	45 (25)	48 (35)
	Time to Peak Q (min)	40 (35)	70 (58)	70 (45)	80 (39)	65 (50)	103 (38)	55 (31)	60 (32)	55 (50)	70 (36)
	TotPpn (mm)	6 (2)	6 (2)	7 (3)	6 (3)	7 (3)	6 (3)	5 (3)	7 (3)	6 (4)	7 (3)
	Ppt Int (mm h^{-1})	2 (2)	2 (2)	2 (1)	2 (1)	2 (2)	2 (1)	2 (1)	2 (1)	2 (1)	2 (1)
	API5	344 (229)	255 (156)	202 (100)	278 (196)	276 (174)	271 (208)	287 (156)	282 (133)	297 (169)	235 (127)
	Sample size	27	33	28	40	43	26	46	41	47	34
LS	Qpeak (L s^{-1} ha^{-1})	1.6 (2.5)	1.0 (1.5)	1.2 (0.8)	1.9 (1.8)	1.2 (0.7)	1.6 (1.1)	2.9 (2.4)	1.9 (1.9)	2.0 (2.5)	2.7 (2.6)
	Qtot (m^3)	9 (16)	14 (25)	51 (38)	35 (39)	22 (24)	14 (16)	7 (5)	17 (11)	10 (10)	5 (6)
	Runoff coefficient (%)	26 (20)	14 (11)	21 (13)	30 (22)	17 (11)	30 (20)	36 (34)	33 (20)	34 (32)	39 (31)
	Lag (min)	143 (116)	98 (30)	138 (60)	150 (70)	105 (55)	155 (50)	100 (50)	120 (55)	125 (75)	103 (38.8)
	Time to Peak Q (min)	185 (126)	118 (84)	160 (83)	180 (125)	115 (54)	183 (111)	115 (50)	125 (70)	125 (90)	118 (53)
	TotPpn (mm)	7 (7)	7 (4)	5 (4)	7 (5)	6 (3)	6 (4)	5 (2)	5 (4)	5 (3)	6 (4)
	Ppt Int (mm h^{-1})	1 (1)	1 (1)	1 (0)	1 (0)	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)
	API5	314 (173)	239 (139)	200 (146)	217 (110)	254 (198)	245 (138)	246 (223)	237 (213)	236 (160)	213 (111)
	Sample size	18	14	22	27	20	30	11	21	21	20

in runoff coefficient for all catchments and storm types but variability is most extreme for small events where the median IQR across catchments is 20% compared with 14–15% for large events. Large events have higher and less variable runoff coefficients while small events have lower more variable runoff coefficients. The IQR in median runoff coefficient across the 10 catchments is a little less than half the median for QH storm types and this pattern is repeated across the other storm types. For large events this between catchment variability (IQR of medians = 17–22%) is larger than the average between storm variability (median of the IQRs = 14–15%), while the opposite is true for small events. Large events have runoff coefficients that are more consistent across catchments than they are between storms - i.e. the storm drives the response, small events are more consistent between storms than they are across catchments - i.e. the catchment drives the response.

For HQ events, median lag times vary by a factor of three between catchments from 23 to 60 min but half the catchments have median lags in the range 30–35 min. Median time to peak is less variable in relative terms (a factor of two) but more variable in absolute terms with half the medians in the range 73–83 min. There is limited inter-catchment agreement between the two metrics (i.e. the catchment with the longest or shortest lag is not also the catchment with longest or shortest time to peak). Across all storm types, there is more variability in lag within catchments (on average) than the variability in average behaviour between catchments. This is true for all storm types and is reflected in lower median IQR (28–39 for quick and 55–71 min for slow) than IQR of the medians (15–17 for quick and 38–58 min for slow). Inter-catchment variability in median lag is considerable relative to the lag times themselves but is less remarkable relative to lag variability within a given catchment over time. Time to peak Q follows a similar pattern with median IQR always greater than IQR of the medians. Both metrics highlight considerable variability in discharge timing both within and between catchments.

4.3. Controls on hydrological response types

The Spearman rank correlation coefficients between the hydrological response types and hydro-meteorological variables are shown in Table 6. There were strong positive relationships ($p < 0.01$) between Qpeak and the hydro-meteorological variables PPTINT and TOTPPN in the majority of catchments in all but LS events. Qpeak is significantly related to TOTPPN in the majority of the catchments where it is related to intensity, but it is rare for TOTPPN to be related in a catchment where intensity is not related (3/21 cases) and almost as rare for TOTPPN to be a stronger predictor than intensity in cases where both are significant (5/18 cases). With the exception of low magnitude events in catchment I, there was no statistically significant ($p < 0.01$) relationship between Qpeak and API5 for all hydrological response types.

Strong positive relationships were observed between Qtot and TOTPPN in the catchments. However, the strength and significance of these relationships varied with storm type. For high magnitude events, the relationship was significant for 9/10 catchments, with R^2 always > 0.66; for low magnitude events there were fewer significant relationships (8/10 catchments for LQ but only 2/10 for LS); and where significant relationships did exist these were weaker, with $R^2 < 0.69$ in all but one case. Qtot was positively correlated ($p < 0.01$) with PPTINT in high magnitude events. No correlation was found between Qtot and API5 except for LQ events in catchment I.

Runoff coefficient was not well predicted by precipitation properties for high magnitude events, other than for C where HQ runoff coefficient was positively correlated with PPTINT and TOTPPN. For low magnitude events, runoff coefficients were strongly influenced by precipitation properties with negative correlations with PPTINT for LQ events in D, E and J; with TOTPPN for LQ in A; and with API5 for both LQ and LS in catchment I.

The discharge timing (i.e. lag and time to peak) for quick timing events was more predictable from rainfall properties than slow timing events. Lag was generally well predicted by PPINT in HQ events (7/10 events) but rarely in LQ events (2/10) and almost never in those with slow timing (1/20). For HQ events, where significant relationships exist they were always negative and were not only more common but also stronger for HQ events than for any other event type. Correlation of lag with TOTPPN was rarer but stronger than with PPINT, while API5 was rarely (3/40) and inconsistently correlated with lag (positive in one case negative in two others).

PPINT is consistently the best predictor of timing metrics (10/40 for lag, 10/40 for ttp) but the metric that it predicts changes depending on the magnitude of the discharge: lag for high magnitude (7/10) but time to peak for low magnitude (7/10). None of the predictors are well correlated with either of the timing metrics for slow timing storms (significant correlations in only 8/40 events). Slow storm timings were more predictable for time to peak than for lag, for HS than LS and from TOTPPN ahead of any other predictor. The correlation between TOTPPN and time to peak Q is positive indicating that larger storms result in longer time to peak. There was only one statistically significant relationship between time to peak Q and API5 (LQ events in catchment B).

€Correlation shown at $p < 0.01$ and * at $p < 0.05$. Note that exactly equal correlation coefficients are relatively common in rank based correlation when the sample size is small. Bold entries indicate the most skillful predictor for each response variable.

In spite of the small sample size (10 catchments), some strong statistically significant relationships ($p < 0.05$) were observed between the response and catchment predictor variables. Table 7 shows the significant Spearman rank correlation coefficients between the hydrological variables and catchment characteristics variables.

Catchment area is strongly and positively related to Qtot explaining >90% of its variance for all storm types. This is consistent with our expectation from mass conservation. Slope, flowpath length metrics and gully area are also well correlated with Qtot but these relationships are always weaker than that with area and are likely the result of covariance in predictor variables.

To account for the influence of precipitation amount and catchment area on total discharge we examine runoff coefficients, which normalise for both catchment area and input rainfall. Catchment area is the best predictor of runoff coefficient for HQ storms and second best for small storms; it is always negatively correlated. Maximum catchment width is the best predictor of runoff coefficient for small storms and is always positively correlated. Runoff coefficient is also significantly negatively correlated with both maximum and modal flowpath length (for HQ and LQ) and depression storage (for HQ storms); and positively correlated with gully extent (for HQ and LQ).

The relationship between peak discharge and catchment characteristics differs between storm types. Inter-catchment differences in quick timing storms are generally more predictable from catchment characteristics, with up to 79% and 93% of the variance explained for HQ and LQ storms respectively. Peak discharge for quick timing storms whether high or low magnitude are well correlated (negatively) with modal flow path length and (positively) with maximum width and gully extent. Peak discharge for small storms (LQ and LS) is well correlated with catchment area and maximum flow path length (negatively), and maximum width (positively). Inter-catchment differences in high magnitude storms are generally more difficult to predict from catchment characteristics, with at most 79% of the variance explained for HQ storms and no significant relationships for HS storms. Maximum width is the most consistent predictor of peak discharge across all storm types, with significant relationships for three of the four types, though the best predictor differs for each storm type. Lag and time to peak Q were negatively correlated with catchment relief and slope in quick timing events. In all cases the relationships are negative such that steeper slope or relief results in faster response times. Lag is correlated only with relief but for both high and low magnitude events. Time to peak is correlated with slope and relief but only for low magnitude events (i.e. LQ) and with modal flow path length but only for high magnitude events (i.e. HQ). Inter-catchment variability in lag and time to peak are not predicted by any catchment characteristics for slow timing events.

5. Discussion

5.1. Hydro-meteorological controls on hydrological behavior

Both Spearman's rank and CART analyses indicate that total storm discharge for upland blanket peat catchments is primarily predicted by total rainfall (Tables 3 and 6). The storm type analysis shows strong positive relationships between Qtot and TOTPPN in general with strongest relationships for high magnitude events, weaker for low magnitude events and particularly weak for low magnitude slow timing events (Table 6). In large storms total discharge is dominated by TOTPPN, while intensity and API only become important for smaller storms (Table 3 and Figure SI 2). Some storm rainfall is stored within the catchment but the amount does not scale with rainfall amount, it is a function of intensity and API. In large storms the fraction lost to storage is smaller and total rainfall can explain most of the variance. In smaller storms storage becomes increasingly important. In these storms, storage losses are driven by: intensity because shorter more intense storms offer less time for losses (e.g. through evapotranspiration, deep groundwater infiltration); and API because a wetter catchment has less available storage to fill.

Table 6
Spearman rank correlation coefficients between response and hydro-meteorological variables. Bold entries indicate the most skillful predictor for each response variable. Correlation shown at $p < 0.01$.

Response type	Catchment	Qpeak vs. TOTPPN	Qpeak vs. PPTINT	Qpeak vs. API5	Qtot vs. TOTPPN	Qtot vs. PPTINT	Qtot vs. API5	Runoff coefficient vs. TOTPPN	Runoff coefficient vs. PPTINT	Runoff coefficient vs. API5	Lag vs. TOTPPN	Lag vs. PPTINT	Lag vs. API5	Time to Peak Q vs. TOTPPN	Time to Peak Q vs. PPTINT	Time to Peak Q vs. API5
HQ	A	0.79	0.91		0.74							−0.72				
	B		0.83		0.75							−0.84				
	C		0.77					−0.61	−0.63		−0.61	−0.65				
	D	0.71	0.94		0.83	0.58					−0.67	−0.64				
	E	0.64	0.90		0.66							−0.65				
	F	0.82	0.87		0.83	0.62					−0.65	−0.54	−0.42			
	G		0.91		0.96	0.58										
	H	0.50	0.87		0.90	0.64						−0.52			−0.51	
	I	0.52	0.92		0.89	0.62										
	J		0.90		0.66											
HS	A	0.85	0.92		0.98											
	B		0.95		0.87	0.76										
	C	0.89	0.97		0.98	0.96										
	D												0.86	0.95		
	E	0.84	0.79		0.94	0.76										
	F	0.86	0.86		0.93	0.89										
	G	0.61	0.87		0.93	0.75								0.58		
	H		0.74		0.97	0.85								0.79	0.64	
	I		0.78		0.87											
	J	0.85	0.87		0.90	0.79										
LQ	A		0.55													
	B		0.49		0.66										−0.51	−0.46
	C	0.58			0.62										−0.53	
	D	0.51	0.44		0.56				−0.44			−0.51			−0.73	
	E		0.43		0.48				−0.52						−0.52	
	F															
	G	0.46	0.52		0.63										−0.52	
	H	0.39	0.42		0.58										−0.52	
	I	0.39	0.44	0.41	0.51		0.40			0.48		−0.39		0.42		
	J	0.66	0.43		0.69				−0.56						−0.55	
LS	A	0.75	0.61		0.84			0.58								
	B															
	C															
	D	0.56			0.60											
	E															
	F	0.43			0.54											
	G												−0.72			
	H															
	I		0.56	0.54						0.70		−0.54			−0.60	
	J															

Table 7
Spearman rank correlation coefficients between response and catchment characteristics variables.

	Area	Relief	Slope	Max flow path length	Modal flow path length	Max width	Topographic depression storage	Gully area extent
High Magnitude Quick-timing (HQ)								
Qpeak (L s^{-1} ha^{-1})					−0.79*	0.65*		0.67*
Qtot (m^3)	0.96		−0.76*	0.90	0.72*	−0.88		−0.73*
Runoff coefficient (%)	−0.88			−0.78	−0.64*	0.81	−0.65*	0.78
Lag (min)		−0.90						
Time to Peak Q (min)					0.67*			
High Magnitude Slow-timing (HS)								
Qpeak (L s^{-1} ha^{-1})								
Qtot (m^3)	0.92		−0.86	0.90	0.79*	−0.92		−0.67*
Runoff coefficient (%)	−0.70*							
Lag (min)								
Time to Peak Q (min)								
Low Magnitude Quick-timing (LQ)								
Qpeak (L s^{-1} ha^{-1})	−0.87		0.64*	−0.88	−0.84	0.94		0.81
Qtot (m^3)	0.94		−0.77	0.87	0.69*	−0.84		−0.72*
Runoff coefficient (%)	−0.83			−0.83	−0.66*	0.84		0.73*
Lag (min)		−0.80						
Time to Peak Q (min)		−0.91	−0.69*					
Low Magnitude Slow-timing (LS)								
Qpeak (L s^{-1} ha^{-1})	−0.78			−0.76*		0.78		
Qtot (m^3)	0.90		−0.77	0.89	0.84	−0.89		−0.77
Runoff coefficient (%)	−0.82			−0.82		0.82		
Lag (min)								
Time to Peak Q (min)								

Peak storm discharge is predicted by rainfall intensity for the majority of catchments in all but the low magnitude slow timing storms (Tables 3 and 6). An intensity control on runoff response has been identified by Daniels et al. (2008) and Evans et al. (1999), and is likely due to rapid saturation of the peat leading to saturation-excess overland flow which may have a strong component of fresh rainfall within it combined with return flow. In these circumstances, the hydrograph becomes a transformed function of the hyetograph (e.g. Kirchner, 2009; Nash, 1960) thus more kurtotic hyetographs characteristic of more intense storms will generate more kurtotic hydrographs. More intense rain implies shorter duration of runoff for the same total precipitation and thus more water to exit the catchment in a given timestep even if water velocity or flood wave celerity is independent of flow depth. This effect will be increasingly dominant as catchment size decreases because smaller catchments translate the rainfall signals more directly into discharge (e.g. Post and Jakeman, 1996; Heerdegen and Reich, 1974).

For our storm dataset there is evidence of weak positive correlation between TOTPPN and PPTINT albeit with considerable scatter. This correlation implies that more intense storms are also more likely to deliver more rainfall in total, so that intensity and amount compound one another. However, 1) intensity has been identified as the dominant predictor relative to total precipitation by two separate statistical approaches (Tables 3 and 6); and 2) the mechanism described above suggests that for two storms with the same total rainfall the more intense storm, where the rain is delivered over a shorter period, will generate a larger peak flow. Gao et al. (2018) suggested from their modelling of a UK blanket peatland that the shape of the hyetograph altered the discharge response even for the same total rainfall, though in their case they altered the skew of the hyetograph rather than its average intensity.

Both of the statistical methods applied here indicate that antecedent conditions continue to play a role for less intense or smaller (LQ, LS) storms. Though small storms are less productive of catchment runoff they may have the effect of wetting up the catchments and filling up subsurface stores and topographic depressions enabling the next storm to quickly connect to the catchment outlet even if it is of only low intensity. However, our results show that while the same may be true in more intense storms this antecedent rainfall and associated storm sequencing has little impact on peak discharge. It is possible that the relative roles of total precipitation, antecedent precipitation and intensity might change for larger catchments with longer response times. However, there is little evidence of this for the range of (small) catchment areas examined here. These results together suggest that rainfall intensity is the dominant driver of peak discharge, perhaps due to storage dynamics in the upper peat and vegetation but likely also due to simple mass accounting where in the absence of significant or variable storage losses the same volumetric input over a shorter time drives a larger output discharge.

Runoff coefficients vary considerably between storms for any given catchment (Table 5) but are not well predicted by the hydrometeorological properties examined here (whether in CART, Table 3, Figure SI 4; or in Spearman's Rank correlation, Table 6). This differs from the inter-catchment analysis where runoff coefficient is relatively well predicted by catchment characteristics, perhaps reflecting a stronger dependence on catchment properties than rainfall properties. Table 5 shows that high magnitude storms consistently have higher median runoff coefficients than low magnitude storms. This is true both on average (cross-catchment median runoff coefficient 54–56% for high and 28–30% for low magnitude storms) and for individual catchments, where catchment median runoff coefficient is never higher for a low magnitude storm set (i.e. QL, SL) than a high magnitude storm set (QH, SH).

Unlike other metrics examined here, runoff coefficients are sensitive to rain gauge uncertainty, particularly undercatch, since these are aboveground mounted rain gauges on exposed upland sites where wind speeds can be high (Pollock et al., 2018). However, given the similarity in elevation, and surface roughness at gauging sites we expect undercatch errors to primarily affect absolute values of runoff coefficient rather than relative differences between catchments or storms.

Our results suggest that storm rainfall characteristics (intensity and amount) are the primary driver of discharge timing with antecedent rainfall having little effect in these peatland systems. For lag, rainfall intensity is the primary driver, with more intense storms resulting in shorter lag times (Tables 3 and 6). Lag times for large storms with quick response times are most predictable (Table 6); and antecedent conditions are only relevant in small storms (Figure SI 5). For time to peak, total rainfall rather than intensity is almost always the most important predictor, though both play a significant (and sometimes comparable) role in all catchments (Table 3; Figure SI 6). Spearman's rank suggests that rainfall intensity is only a consistently significant predictor of time to peak for low magnitude but quick timing storms (Table 6).

The different controls on lag and time to peak are initially surprising. However, they reflect the different reference frames within which hydrograph response is being examined. For lag, which frames timing with respect to peak rainfall, rainfall intensity dominates over the amount of rain or the antecedent conditions. The shape of the hyetograph (i.e. its peakiness) is the primary control on lag, the influence of rainfall amount (before or during the event) on the transmission of flood waves through the catchment is of secondary importance. For time to peak, which captures the length of the rising limb, larger storms (in terms of total rainfall) result in longer time to peak particularly for high magnitude slow timing storms, and this storm size control can be as strong or stronger than that of rainfall intensity. This suggests that rainfall duration has a stronger influence on time to peak than it does on lag, and is particularly detectable for slow timing events. If larger storms are also longer duration (i.e. HS type) we expect longer time to peak Q but where larger storms are also more intense storms, the primary driver is rainfall intensity and lag times are reduced. In both cases our results suggest that storm to storm variation in timing of peak discharge, whether measured with respect to rainfall or with respect to discharge itself is primarily influenced by the shape of the hyetograph and is dominated by the input signal rather than changes to the system that propagates that signal into discharge. As with peak discharge, this is consistent with the idea, introduced above, that small catchments result in only modest transformation from hyetograph to hydrograph.

5.2. Catchment controls on hydrological behaviour

Despite the prevalence of detailed experimental and field investigations of rainfall-induced runoff production in blanket peat systems of the UK (Shuttleworth et al., 2019; Daniels et al., 2008; Holden and Burt, 2003a; b; c; Evans et al., 1999), studies exploring the relationships between hydrological behavior and physical catchment morphometry or characteristics are scarce because these studies tend either to focus on a single catchment or to examine multiple catchments but with varying land cover or drainage conditions (Howson et al., 2021; Holden et al., 2015; Holden et al., 2006). Findings in this study based on the ten study catchments with the same land cover and drainage regime show that runoff production and transmission across a range of scales (0.2–4 ha) in peatland catchments is influenced by a combination of rainfall and catchment characteristics (Tables 6 and 7).

Runoff coefficient was strongly negatively correlated with catchment area (Table 7). Negative scaling between catchment area and runoff coefficient has been widely reported (e.g. Joel et al., 2002; Cerdan et al., 2004) but to our knowledge only in contexts where runoff is generated by infiltration-excess overland flow. Our result suggests that the same is true for our peat systems, where runoff is dominated by saturation-excess overland flow. Runoff transmission is less efficient in these peat systems as catchment area increases with more water lost either to storage, groundwater or evaporation. Logically, flow path length scales to catchment area, and for our catchments they are related with correlation coefficients of 0.58 for modal flow path length and 0.90 for maximum length. This implies that larger catchments that necessitate flow over longer distances and durations will be less hydrologically connected because they contain more opportunities for disconnection and reinforces the importance of thinking spatially outside of the 1D diplotelmic model of peatlands (Holden and Burt, 2003a). As a result, the magnitude of runoff coefficient is reduced with increasing catchment area (Table 7).

The significant positive relationship between runoff coefficient and gully area for quick timing events suggests that gully systems transmit water more efficiently to the catchment outlet during flood relevant events. The significant negative relationship between runoff coefficient and topographic depression storage per unit area (Table 7) suggests that one mechanism for disconnection may be ponding of surface water in micro-topographic depressions within these catchments (a process which favours storage, evaporation and losses to groundwater). Although this relationship is significant only at 95% confidence and only in HQ storms, it does suggest that depression storage can influence runoff coefficients. Depression storage within the catchments (11–42 m^3/ha), can make up a considerable fraction of their median total discharge even for the HQ events considered here (16–90%). This storage estimate is derived from analysis of the DSM, which includes the (low, <0.5 m) vegetation canopy in the catchments and thus is an upper bound on macro-scale depression storage. However, its resolution (0.25 m) likely also leads to an underestimation of surface water storage behind micro-scale (i.e. mm-cm) roughness elements and temporary storage cavities formed by pipe networks (Smart et al, 2013, Regensburg et al., 2021). Subsurface piping may form important temporary storage areas in blanket peatlands but the volume and proportion of pipe networks that remain full or drain between events remains largely unknown. Given these uncertainties, our depression storage estimates are best interpreted as an indicator of relative differences in macroscale storage between catchments. Depression storage is well correlated with catchment slope, which is expected from the geometry of variably tilted roughness elements. However, catchment slope is never a good predictor of runoff coefficients.

The role of catchment width in predicting runoff coefficients (best for LQ and LS, second best for HQ) suggests that the flowpath network structure plays an important role not only in defining the opportunities for disconnection but also in concentrating storm discharge with tighter more peaky flowpath length distributions resulting in higher runoff coefficients. This, in turn, suggests that our runoff coefficients reflect in-storm conditions rather than those of the full multi-storm hydrograph. Strong relationships between network structure and runoff coefficient would be expected if runoff routing plays an important role in defining the volume of runoff leaving the catchment over the study period (i.e. the time window over which the coefficient is calculated). Instead, coefficients calculated over longer periods (e.g. encompassing long periods of hydrograph recession and even multiple storms) should not display this relationship because routing delays become negligible relative to the duration of the study period. Since our coefficients reflect in-storm rather than full-hydrograph conditions, they should be interpreted as a metric for rapid storm discharge response rather than for the relative role of streamflow vs non-streamflow losses from the catchment.

These results suggest that catchment area controls runoff coefficient by increasing opportunities for water to be disconnected (i.e. stored within the catchment for the duration of the storm or lost from the system). This disconnection is more likely where topographic depression storage is larger or more extensive and less likely where gullies are more extensive; both are correlated with catchment area (0.76 and −0.38, respectively) in directions that would amplify their effect, perhaps explaining the stronger correlation with area than maximum or modal flow path length. The negative correlation between runoff coefficient and topographic depression storage (Table 7) suggests, in line with the idea presented by Holden et al. (2018), that the deliberate artificial creation of storage through distributed shallow water pools targeted in the extreme peatland headwaters (sub hectare scale) could increase the range of storms within which connectivity and storage remain important and provide additional natural flood management benefits when combined with the current standard restoration measures (e.g. Goudarzi et al., 2021; Shuttleworth et al., 2019). However, peak discharge appears to be primarily controlled by attenuation, particularly in the largest storms. This is consistent with the findings of Goudarzi et al. (2021) and Shuttleworth et al. (2019) and suggests that restoration interventions on hillslopes will be particularly effective in reducing peak discharge where they increase surface roughness and therefore mobile storage (in the sense of Goudarzi et al., 2021).

The considerable overlap between significant predictors of runoff coefficient and peak discharge suggest similar underlying hydrological processes: 1) reduced connectivity and increased storage in larger catchments with longer associated flow path lengths; but also 2) increased floodwave attenuation for wider flow path length distributions, since surface flows typically attenuate as they propagate. In addition, maximum width is the most consistent predictor of peak discharge suggesting that network structure plays an important role, through its control on flood wave arrival times. Peak discharge for low magnitude storms (LQ and LS) is well correlated (negatively) with catchment area, flowpath length and maximum width consistent with both connectivity and attenuation explanations. Inter-catchment differences in high magnitude storms are generally more difficult to predict from catchment characteristics. Good predictors for runoff coefficient are no longer significant with respect to peak discharge (area, maximum flowpath length, depression storage). Instead, only gully extent, modal flow path length and maximum width are significant predictors and only for quick travel time events. These metrics all point towards an increased role of attenuation and topographic concentration (due to network structure) of surface flow for the high magnitude storms. In addition, runoff coefficients for high magnitude events are consistently higher than for low magnitude events (Table 5), indicating a more efficient runoff response. Taken together these results suggest a minor role for connectivity and a dominant role for attenuation in these high magnitude events. High magnitude slow timing events are not well predicted by any catchment variables. This suggests that peak discharge in longer more complex storms may reflect the finer detail of the flow path length (and thus travel time) distribution and its interaction with a particular rainfall time series rather than being a simple function of maximum or modal flow path length.

Inter-catchment variability in peak discharge timing (i.e. lag and time to peak) is only predictable from catchment characteristics for quick timing events and is best predicted by catchment relief and/or slope. The relationships are always negative, with quicker response times in more steeply sloping catchments (Table 7). This is consistent with a strong surface gradient control on water velocity/celerity (e.g. McDonnell and Beven, 2014; Manning, 1891) though the strength of the influence is somewhat surprising given the modest range of slopes across our study catchments. Modal flow path length, which might be expected to correlate well with timing variables, is a significant predictor but only for time to peak and only for HQ storms. This likely reflects spatially complex floodwave propagation speeds in smaller storms, perhaps related to disconnection, storage and the time delays associated with filling that storage. For slow timing events, lag and time to peak are not significantly related to any of the catchment characteristics examined here. As with peak discharge, this may reflect the more complex rainfall time series associated with slower events and the importance of the detail of each catchment's travel time distribution in these storms.

This inter-catchment comparison highlights the importance of catchment scale not only for total discharge which scales with area as expected but also for both peak discharge and runoff coefficient. This is important for our understanding of how catchments function because it suggests that runoff processes even in saturation-excess overland flow landscapes, and over a relatively small range of catchment areas, are very sensitive to scale, particularly in small storms and for the partitioning between discharge, storage and other losses. It has important implications for our research methods because it implies that the scale of catchment under consideration has a first order effect on the measurements themselves even for catchments that vary by less than two orders of magnitude in area. This scale dependence could perhaps be mitigated through statistical or process modelling but with considerable care. Alternatively, while process understanding gained at a particular scale is likely to be more easily transferable, absolute values (e.g. runoff coefficients, lag times or peak discharges) should be handled with care and linear upscaling is likely impossible (Camerat, 2002).

Hydro-meteorological thresholds as controls on peak discharge.

There is a switch in the drivers of peak discharge for storms above a threshold intensity, with rainfall intensity the dominant control on discharge in intense storms (>5 mm h^{-1} on average, Figure SI 3), but total and antecedent precipitation becoming important for low magnitude and less intense events. The peak discharge response to low intensity storms is consistent with runoff production dominated by saturation-excess overland flow since it suggests runoff generation even at very low intensities as long as there is sufficient water input to the system (Holden and Burt, 2002; Evans et al., 1999; Burt, 1996). The dominant control of rainfall intensity (and apparent irrelevance of API) on peak discharge for high intensity storms implies that the catchment plays only a very minor role in filtering the rainfall signal in these storms. This is surprising for a saturation-excess overland flow dominated system because it implies that catchment storage either does not change or that the change does not affect the extent of the critical (runoff generating) source area. We propose the latter. In the gullied peat catchments examined here, the gullies are relatively linear in a downslope direction and closely spaced. The gully sides are steep and the interfluves (small ridges) between gullies have ~ 0.5–1 m relief over a distance of 5–10 m. Gully edges have relatively deep water tables and steep hydraulic gradients and are relatively 'difficult' to saturate (Daniels et al., 2008; Allott et al., 2009). The gully floors and gully heads, which are extensive and low gradient with large upslope areas, are almost permanently saturated. The interfluves between gullies are low gradient with water tables close to the surface and low specific yield such that they saturate after only small amounts of rainfall. We suggest that there are two zones (1, gully floors and interfluves; and 2, gully edges) which define the extent of the critical source areas that expand only by a small amount in response to antecedent rainfall or storm rainfall. Rainfall amount remains important for example in filling depression storage along flowpaths in order for the floodwave to propagate but the total rainfall necessary to achieve this connectivity is small and delivered early on in intense storms. We define this hydrological connectivity as the ability of flood waves to move from one location to another (typically the outlet) within the catchment and to do so within the timescale of a single storm (i.e. minutes to hours).

Inter-catchment comparison also suggests that the controls on peak discharge change with storm size and that connectivity is particularly important for small storms. The strong relationship between catchment area and runoff coefficient is difficult to explain without connectivity, disconnectivity and an increased likelihood of catchment quickflow losses in larger catchments. The same is true for peak discharge in small magnitude events (LQ and LS) but is not the case for high magnitude events, which are well predicted only by gully area and modal flowpath length and maximum catchment width (for HQ), all variables that we interpret as indicators that concentration and attenuation of surface flow is the key control.

Both spatial inter-catchment and time varying within-catchment results point to a switching in rainfall-runoff behavior as storm size increases. We suggest that this is related to storage within the catchment and the intensity/storm size at which this storage is overwhelmed. Low magnitude events are small enough that disconnection and losses strongly influence peak discharge, the system must use a significant fraction of the total rainfall inputs to fill stores and generate connectivity. High magnitude events are large enough that they can fill stores and generate connectivity with relatively little impact on peak discharge. As a result antecedent conditions are of little importance for these events, catchment characteristics that capture connectivity become less skillful predictors of discharge and the catchment begins to function as a relatively simple system (delivering runoff with limited thresholds or feedbacks). The identification of this threshold behavior has implications for stormflow response to predicted climate change. Warmer summers are likely to trigger greater convective instability and so there is a risk of increasing frequency of destructive storms associated with high intensity rainfall (Met Office, 2019; Committee on Climate Change, 2017). Since large storm character is influenced primarily by rainfall type, catchment based interventions need to be at landscape scale.

6. Conclusions

Our examination of rainfall-runoff response in ten comparable upland peat micro-catchments show that hydrological responses to rainfall vary across small spatial scales. The findings reveal that optimal runoff production and transmission in these peat catchments is influenced by a combination of rainfall and catchment characteristics:

The catchments are heterogeneous and scale dependent in their runoff responses, even across the relatively small catchment scale gradient examined here (0.24–3.93 ha).

Rainfall intensity is the dominant hydro-meteorological driver for the runoff response of large magnitude storms, and antecedent conditions are only relevant for small storms.

Storm to storm variation in timing of peak discharge, whether measured with respect to rainfall or with respect to discharge itself is primarily influenced by the shape of the hyetograph and is dominated by the input signal rather than changes to the system that propagates that signal into discharge.

For peak discharge in high magnitude storms there is a dominant role for attenuation processes in terms of travel times, which are controlled by flow path structure and catchment size.

Hydrograph responses in smaller storms are also related to catchment size and we interpret this as a function of decreasing hydrological connectivity as scale increases (i.e. above ~ hectare scale). From our data we hypothesise that depression storage is the most likely process control on this (dis)connectivity.

Our results suggest that the creation of storage through distributed shallow water pools in small scale (0.24–3.93 ha) peatland headwater catchments may provide additional natural flood management benefits beyond existing restoration methods. Further work is however needed to quantify the impact of micro-topographic depression storage on runoff delivery in these upland peat catchments.

Peak discharge in longer, more complex storms is less predictable from catchment variables and may reflect the finer detail of the travel time distribution and its interaction with a particular rainfall time series.

Both spatial inter-catchment and time varying within-catchment results point to a switching in rainfall-runoff behavior within these catchments where catchment storage, connectivity and antecedent conditions are relevant to peak discharge in small storms but become increasingly irrelevant as rainfall intensity increases.

Runoff processes even in saturation-excess overland flow landscapes, and over a relatively small range of catchment areas, are very sensitive to scale, particularly in small storms and for the partitioning between discharge, storage and other losses.

The role of scale and heterogeneity has implications for the interpretation of catchment process response from micro-catchment data: responses inferred from single-scale studies do not fully represent those at cognate scales, even within what seems a relatively homogenous peatland.

The dominant role of attenuation in the scaling of runoff generation suggests that efforts to manipulate peatland runoff as a flood risk control measure should pay attention to the potential to manipulate surface roughness and runoff velocities.

CRediT authorship contribution statement

Donald Edokpa: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **David Milledge:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Tim Allott:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Joseph Holden:** Funding acquisition, Methodology, Writing – review & editing. **Emma Shuttleworth:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Martin Kay:** Data curation, Investigation, Methodology. **Adam Johnston:** Resources, Investigation, Methodology. **Gail Millin-Chalabi:** Methodology. **Matt Scott-Campbell:** Methodology, Funding acquisition. **David Chandler:** Methodology. **Jamie Freestone:** Methodology. **Martin Evans:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

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