

# The significance of spatial variability of rainfall on simulated runoff: an evaluation based on the Upper Lee catchment, UK

I. G. Pechlivanidis, N. McIntyre and H. S. Wheater

## ABSTRACT

The significance of spatial variability of rainfall on runoff is explored as a function of catchment scale and type, and antecedent conditions via the continuous time, semi-distributed probability distributed model (PDM) hydrological model applied to the Upper Lee catchment, UK. The impact of catchment scale and type is assessed using 11 nested catchments, and further assessed by artificially changing the catchment characteristics and translating these to model parameters (MPs) with uncertainty using model regionalisation. Dry and wet antecedent conditions are represented by 'warming up' the model under different rainfall time series. Synthetic rainfall events are introduced to directly relate the change in simulated runoff to the spatial variability of rainfall. Results show that runoff volume and peak are more sensitive to the spatial rainfall for more impermeable catchments; however, this sensitivity is significantly undermined under wet antecedent conditions. Although there is indication that the impact of spatial rainfall on runoff varies as a function of catchment scale, the variability of antecedent conditions between the synthetic catchments seems to mask this significance. Parameter uncertainty analysis highlights the importance of accurately representing the spatial variability of the catchment properties and their translation to MPs when investigating the effects of spatial properties of rainfall on runoff.

**Key words** | antecedent conditions, catchment type, PDM model, semi-distributed modelling, spatial rainfall, uncertainty

**I. G. Pechlivanidis** (corresponding author)  
Swedish Meteorological and Hydrological Institute,  
Folkborgsvägen 1,  
Norrköping S-601 76,  
Sweden  
E-mail: [ilias.pechlivanidis@smhi.se](mailto:ilias.pechlivanidis@smhi.se)

**N. McIntyre**  
Centre for Water in the Minerals Industry,  
Sustainable Minerals Institute, University of  
Queensland,  
Brisbane,  
4072 QLD,  
Australia

**H. S. Wheater**  
School of Environment and Sustainability,  
University of Saskatchewan,  
Saskatoon,  
Canada S7N 5C8  
and  
Department of Civil and Environmental  
Engineering,  
Imperial College London,  
London SW7 2AZ,  
UK

## INTRODUCTION

Rainfall is a highly heterogeneous process over a wide range of scales in space, and lack of its spatial information can affect understanding of catchment-scale hydrological response and affect accuracy of hydrological model predictions (Singh 1997). For hydrological operational purposes, e.g., flood forecasting (in particular, model state initialisation and short lead-time forecasts) and management (catchment water balance), and design (e.g., flood frequency curves), a good knowledge of rainfall is essential (Lamb *et al.* 2000).

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Consequently, one question that arises in rainfall–runoff studies is: '*where and when is the spatial nature of rainfall important to runoff response?*' The rainfall–runoff relationship can be expected to depend on complex interactions between rainfall dynamics, physical properties and the spatial scale (i.e., catchment area) of the problem. Common methods to assess the effects of spatial rainfall are sought through comparison of rainfall–runoff responses between events within a catchment (e.g., Bell & Moore 2000; Cole & Moore 2008) or between catchments covering different hydrological regimes (Smith *et al.* 2012). Other studies have investigated these effects by running realisations of synthetic rainfall patterns through a calibrated hydrological model or running observed

rainfall data through models representing idealised catchments (e.g., [Arnaud \*et al.\* 2002](#)). Overall, despite the extensive literature on the relationship between spatial rainfall and runoff, the picture is still complex in terms of the tools adopted, studied catchments and conclusions drawn from the analyses, with several studies concluding that spatial rainfall distribution is significant for runoff ([Gabellani \*et al.\* 2007](#); [Patil \*et al.\* 2014](#)) and others not ([Brath \*et al.\* 2004](#); [Lobligeois \*et al.\* 2014](#)).

The spatial rainfall–runoff relationship has been investigated for different climatic regimes, in which the spatiotemporal properties of rainfall significantly vary. Studies in arid and semi-arid regions have highlighted the sensitivity of runoff to the spatial–temporal characteristics of the rainfall event at various catchment scales ([Syed \*et al.\* 2003](#)), with the sensitivity being increased for convective compared to frontal events ([Koren \*et al.\* 1999](#); [Vischel & Lebel 2007](#)). The effect of spatial rainfall on runoff is likely to be less clear-cut when humid temperate catchments are investigated due to the dampening effects of soils and vegetation ([Arnaud \*et al.\* 2002](#); [Brath \*et al.\* 2004](#)).

Results regarding the potential impact of catchment scale are contrasting with studies showing that, as the scale increases, the importance of spatial variability of rainfall decreases and catchment response time distribution becomes the dominant factor governing the runoff generation ([Dodov & Foufoula-Georgiou 2005](#)), and others highlighting the role of hillslope versus channel travel time distributions in determining the sensitivity of the hydrological response to rainfall spatial variability ([Nicolina \*et al.\* 2008](#); [Lobligeois \*et al.\* 2014](#)). Yet other studies (based on simulated and observed rainfall–runoff events) did not identify any clear pattern of sensitivity to rainfall variability as a function of catchment scale ([Segond \*et al.\* 2007](#); [Pechlivanidis \*et al.\* 2008](#)).

In addition, catchment perviousness and antecedent catchment conditions can affect the spatial rainfall–runoff relationship. Permeability can substantially control the impact of spatial rainfall on runoff, e.g., noting the high importance of spatial rainfall in urban areas ([Tetzlaff & Uhlenbrook 2005](#)). Moreover, the runoff prediction errors are generally considerably higher for dry than for wet conditions ([Zehe \*et al.\* 2005](#)); however, the spatial variability of soil moisture can also exert a strong control on runoff,

with the dominant flow path varying according to the soil moisture conditions and consequently affecting the runoff peak and response time ([Penna \*et al.\* 2011](#); [Patil \*et al.\* 2014](#)).

Most numerical studies are based on (semi-)distributed hydrological models, since this type of model has the potential to represent the effects of spatially variable inputs. However, (semi-)distributed models can easily become over-parameterised and subsequently ill-posed with respect to the information content of available input–output data ([Pechlivanidis \*et al.\* 2011](#)), resulting in large uncertainties in the parameters and simulated runoff ([Younger \*et al.\* 2009](#)). Regionalisation may be used to spatially generalise parameter estimates from well-gauged areas; however, this introduces new sources of uncertainty ([Wagener & Wheater 2006](#)). Therefore, investigation of the influence of spatial rainfall on simulated runoff should include testing the sensitivity of conclusions to uncertainty in spatial distributions of model parameters (MPs).

This paper uses a semi-distributed rainfall–runoff model to explore the significance of spatial variability of rainfall on runoff properties (hydrograph shape, peak and volume) as a function of catchment scale, catchment type, degree of spatial rainfall variability and antecedent catchment conditions. We also address how uncertainty arising from MP regionalisation affects the results. This investigation is based on the spatial characteristics (i.e., shape, size) of the Upper Lee system, to the north of London, UK, consisting of 11 nested catchments (varying between 26 and 1,040 km<sup>2</sup>), while the synthesis of physical properties is based on the regional relationships developed by [Pechlivanidis \*et al.\* \(2010\)](#). The hydrological variability of the catchment, and availability of extensive data sets, semi-distributed models and regionalisation results make the Upper Lee a suitable case study.

## THE STUDY CATCHMENT

The Upper Lee catchment is located to the north of London, UK, and classified as relatively large, draining an area of 1,040 km<sup>2</sup> (at Feildes Weir) to the River Thames within Greater London. The catchment's location, its physical and hydro-climatic characteristics, and the available data sets (i.e., hourly rainfall, runoff and potential evaporation (PE)) can be found in Figure 1 and Table 1 in the paper by

Pechlivanidis *et al.* (2010); to avoid redundant information we do not repeat them here. In brief, the catchment is divided based on the available river gauge network. Thus, 11 sub-catchments are identified varying in area from 26 to 1,040 km<sup>2</sup>: Gypsy Lane (26 km<sup>2</sup>), Stevenage (31), Griggs Bridge (50), Sheering (55), Mardock (79), Wadesmill (136), Water Hall (150), Hertford (176), Glen Faba (278), Rye Bridge (752) and Feildes Weir (1040). Observed rainfall time series are available from 17 raingauges over the entire Upper Lee catchment (see Figure 1 in Pechlivanidis *et al.* (2010)). These rainfall data are spatially interpolated on a 1 × 1 km<sup>2</sup> grid using the inverse distance weighting method. The arithmetic average of the subunit rainfall provides the subcatchment and catchment mean areal precipitation. A subdivision of the subcatchments into subunits of about 15–25 km<sup>2</sup> is applied, a scale which is judged to represent reasonably homogeneous units (with respect to geology and land cover) while remaining computationally tractable. Additionally, this catchment discretisation is preferable to avoid loss of rainfall information due to averaging over too large a scale. Thus, there are three basic scales considered: the Upper Lee catchment scale, the subcatchment scale and the subunit scale.

## MODEL AND METHODOLOGY

### Rainfall–runoff model structure and parameter identification

The probability distributed model (PDM) is a conceptual model, which uses a distribution of soil moisture storage capacities for soil moisture accounting and (in this application) two linear reservoirs in parallel for the hillslope routing component (Moore 2007). Two parameters control the generation of effective rainfall: the  $C_{\max}$  (mm) parameter, which is the maximum storage capacity across all points in the catchment, and the parameter  $b$  (–), which controls the spatial variability of storage capacity over the catchment. The effective rainfall produced is split into ‘quick’ and ‘slow’ pathways, which are routed via parallel linear storage components (Lamb *et al.* 2000; Orellana *et al.* 2008). The parameter  $q$  defines the proportion of the total effective rainfall going to the fast response reservoir. The simulated runoff is

determined by the combination of the two pathways. This model component has three parameters: a residence time for each reservoir,  $K_q$  and  $K_s$  (hours), and  $q$  (–). Finally, the time delay in the channel ( $TP$  parameter is the average travel time (s) of the subunit) assumes that any hydrograph attenuation at subunit scale is effectively represented within the storage components of the PDM.

We chose this model structure because its simplicity has allowed successful regionalisation via parameter regression against physical characteristics (Wagener & Wheater 2006). In this study, in order to investigate the significance of spatial rainfall on runoff, we use the semi-distributed version of the PDM model (Pechlivanidis *et al.* 2010), in which the PDM model is applied to every subunit and subunit outflows are integrated by a channel network model. The PDM model identification involves a priori parameter estimation for each subunit based on the regional relationships developed by Pechlivanidis *et al.* (2010) and further ‘tuned’ using adjustment factors (AFs). The AFs are seen as downscaling parameters which compensate for the scaling effects of applying the (sub)catchment scale regionalisation to subunit parameter estimation. The value of AF for each parameter is assumed to be homogeneous over the catchment. The equations (see Table 4 in Pechlivanidis *et al.* (2010)) were produced using a stepwise regression procedure and relate the  $C_{\max}$ ,  $K_q$ ,  $q$  and  $TP$  parameters of the PDM model with a set of physical catchment descriptors (CDs) taken from the UK’s *Flood Estimation Handbook*, including drainage area, land use, geology, elevation, soil characteristics as well as climate variables (see Table 1). Based on parameter identification analysis, the  $b$  and  $K_s$  parameter values are fixed for all subunits equal to 0.065 and 4,900 (hours), respectively (see Pechlivanidis *et al.* 2010). Note that due to the distinct nature of the porosity of the chalk, which is not straightforward to represent, the identified  $b$  and  $K_s$  values may not be transferable at the Upper Lee chalk rivers (i.e., the river Mimram in Hertfordshire) and hence this parsimonious model structure could perform poorly.

### Generation of synthetic physical characteristics

The physical properties of the Upper Lee at the subunit scale are artificially modified to represent two simplified catchment types (impermeable and permeable). The geology

**Table 1** | CDs derived from the Flood Estimation Handbook

Abbreviation	Range, theoretical units	Parameter
AREA	[0, ∞] (km <sup>2</sup> )	Catchment drainage area
BFIHOST	[0, 1] (–)	Base flow index using the HOST classification
SPRHOST	[0, 100] (%)	Standard percentage runoff using the HOST classification
SAAR	[0, ∞] (mm)	Standard period (1961–1990) average annual rainfall
DPLBAR	[0, ∞] (km)	Mean distance between each node (on a 50 m grid) and catchment outlet
DPSBAR	[0, ∞] (m/km)	Mean of all inter-nodal slopes in catchment
URBEXT	[0, 1] (–)	Extent of urban and suburban land cover in 1990

and land cover properties of the catchment, as described by URBEXT, BFIHOST and SPRHOST CDs, are controlled and are uniform across the whole catchment (yet their values depend on the synthetic catchment type), while the other descriptors (i.e., AREA, DPSBAR, DPLBAR and SAAR as defined in Table 1) are allowed to remain at the real values, since they represent geomorphological characteristics of the Upper Lee system. AREA, and hence DPLBAR, due to their high correlation (correlation coefficient is equal to 0.82) do not vary much among subunits (subunit areas vary between 15 and 25 km<sup>2</sup>). This approach will allow parameters to vary in space; hence the catchments could be assumed semi-synthetic (based on artificially uniform soil, geology and land cover properties but maintaining the geomorphological characteristics). This allows a more controlled experiment than trying to interpret differences between complex real catchments.

The relationships between MPs and CDs are physically explicable. For instance,  $C_{\max}$  has positive correlation with BFIHOST, which indicates that permeable chalk catchments (high BFIHOST) have high moisture storage capacity.  $C_{\max}$  is negatively correlated with URBEXT; more urbanised catchments tend to have low  $C_{\max}$  values while the more rural catchments have a higher range of values. As expected, BFIHOST has a positive correlation with  $K_q$  (fast routing residence time), while  $TP$  has negative correlation with URBEXT. More details can be found in Pechlivanidis *et al.*

**Table 2** | Range of physical CDs and selected values

Descriptors	Real catchments Range	Synthetic catchments	
		Permeable	Impermeable
URBEXT <sup>a</sup>	0.01–0.2	0.01	0.2
BFIHOST	0.36–0.87	0.87	0.36
SPRHOST	13.2–45.6	13.2	45.6

<sup>a</sup>In general, URBEXT values are less than 0.025 for rural catchments,  $0.025 < \text{URBEXT} < 0.125$  for slightly urbanised, and  $0.125 < \text{URBEXT} < 0.25$  for urbanised catchments.

(2010). The ranges of values of URBEXT, BFIHOST and SPRHOST for the Upper Lee catchments are presented in Table 2. These are the same ranges used to develop the parameter regionalisation and hence parameter estimates are assumed to be reasonable within these ranges. Here we distinguish between the effects of two types of catchment – ‘permeable’ and ‘impermeable’ within the context of the Upper Lee, whose properties are defined by the extremes of the ranges. In other words, the experiment assumes that impermeable catchments are heavily urbanised and with high percentage runoff (and hence low baseflow index); whereas the permeable catchments are mainly rural with high baseflow index and with the potential to infiltrate most of the effective rainfall (low percentage runoff).

### Synthetic rainfall events and spatial deviation index

The analysis introduces a numerical experiment in which the rainfall–runoff model runs under synthetic rainfall events. Synthetic rainfall analyses have the potential to investigate events with high range of spatial variability, aiming to unambiguously relate the change in simulated discharge to the spatial variability of rainfall (assuming that the antecedent catchment conditions and time variability of rainfall are adequately controlled – see the section ‘Representing the effect of antecedent conditions on the results’). To address the latter, during the generation of the synthetic events, rainfall volume, location and duration are preserved at the (sub)catchment scale.

In total, three synthetic rainfall events are generated at a  $1 \times 1$  km<sup>2</sup> grid for the catchment and each gauged subcatchment. A rainfall core (defining the area in which rainfall occurs) is generated covering an area of three different diameters (see a schematic example in Figure A1(a), available

with the online version of this paper), centred on the centroid of the (sub)catchment (to fix the location of the events). In cases where the rainfall core covers areas outside the (sub)catchment boundaries, this amount of rainfall is estimated and equally distributed over the catchment; hence, rainfall volume is preserved. The diameters are sub-catchment dependent with, for instance, in Gypsy Lane varying between 3 and 6 km, while in Feildes Weir varying between 20 and 50 km. All the synthetic events have a 10-hour duration and 26 mm depth, have the same temporal profile, and are spatially uniform. An investigation of 30 observed rainfall events in the Upper Lee catchment showed that these properties – median rainfall duration and volume of about 10 hours and 26 mm, respectively – are typical for the Lee catchment; see details in Pechlivanidis et al. (2008). The consistent time profile means that differences between runoff events can be more easily interpreted in terms of spatial rainfall properties. For this experimental analysis, the synthesised events, derived by different diameters in the rainfall core, are named *high*, *medium* and *low* to denote high, medium and low spatial variability, respectively. The spatial variability of the synthetic low, medium and high spatially variable events over the entire Upper Lee catchment (as represented by the semi-distributed model) is illustrated in Figure A1(b)–1(d) (available with the online version of this paper).

A spatial deviation index (SDI) was defined for each rainfall event and each (sub)catchment as a measure of spatial variability (Segond et al. 2007). The deviation between the  $1 \times 1 \text{ km}^2$  gridded rainfall and the subunit averaged areal rainfall ( $\text{SDI}_G$ ) is defined by:

$$\text{SDI}_G = \frac{1}{N} \sum_{i=1}^N \frac{|r_i - r_k|}{r_k} \quad (1)$$

where  $r_i$  represents the precipitation in the  $i$ th grid,  $r_k$  is the subunit averaged areal precipitation, and  $N$  the number of grids for a given subunit. The catchment's SDI over the entire rainfall event can be estimated as a weighted value (high SDI values indicate high spatial variability) according to:

$$\text{SDI} = \frac{\sum_{k=1}^K \text{SDI}_G \times r_k}{\sum_{k=1}^K r_k} \quad (2)$$

where  $K$  is the number of subunits for a given catchment.

## Representing the effect of antecedent conditions on the results

Here, we investigate the impact of antecedent conditions (wet and dry) on the spatial rainfall–runoff relationship. Both long-term (during a wet or dry season) and short-term (during a single rainfall event) effects are investigated allowing the assessment of the potential impact on runoff when antecedent conditions are spatially smoothed or variable. Two observed rainfall and PE time-series are used to generate antecedent conditions, that are reasonable for this region, for each identified parameter set; the periods from 01/01/1991 to 02/01/1993 and from 01/01/1991 to 07/06/1993 are used to represent wet (winter) and dry (summer) antecedent catchment conditions, respectively. As well as simulating the antecedent conditions in the soil moisture store, the long warm-up period is needed to represent the antecedent conditions in the slow-flow routing store adequately (residence time equals 4,900 hours). Rainfall during the warm-up periods is homogeneously distributed over the catchments.

In addition, we look at the effect of increased variability in antecedent conditions. To do so, the synthetic rainfall events are repeated after a synthetic event has already been run to generate the antecedent soil moisture conditions. An event of *low* spatial variability is applied prior to the synthetic rainfall event of interest to generate almost homogeneous antecedent soil moisture conditions (named *uniform*), whereas a *high* spatially variable event is applied to represent high spatial variability of antecedent soil moisture conditions (named *variable*). The spatial variability of the antecedent conditions is presented in Figure A2 (available with the online version of this paper). This requires that a single event significantly affects the simulated soil moisture. To achieve this, dry conditions were created using the warm-up period 01/01/1991 to 07/06/1993 for all conditions, and then the event was applied (whereas in wet conditions the simulated soil would remain saturated irrespective of the nature of a subsequent event). Consequently, we achieve spatial smoothing of the dry antecedent conditions by considering their long-term history prior to any further investigation. Thus, the following four combinations can be identified: (i) warm-up + *low* + *low*, (ii) warm-up + *low* + *high*, (iii) warm-up + *high* + *low* and (iv) warm-up + *high* + *high*.



## Analysis of simulated hydrological response

The simulated hydrological response is analysed for each sub-catchment and each synthetic rainfall event. This is evaluated measuring the percentage change in the peak runoff and runoff volume of a hydrological response relative to the ‘reference’ simulated runoff, and also a modified definition of the Nash–Sutcliffe efficiency ( $NSE_{ref}$ ; Nash & Sutcliffe 1970) that compares simulated runoff to the reference:

$$NSE_{ref} = 1 - \frac{\sum_{i=1}^n (Q_{Ci} - Q_{Ri})^2}{\sum_{i=1}^n (Q_{Ri} - \overline{Q_{Ri}})^2} \quad (3)$$

where  $Q_{Ci}$  and  $Q_{Ri}$  are the calculated and ‘reference’ discharge at hour  $i$ , and  $n$  is the length (time-steps) of the time series. The hydrograph simulated from the *high* spatially variable event is the ‘reference’ runoff.

The percentage change in peak and volume is estimated for the quick-flow component (quick routing store), which describes the runoff entering the stream channels promptly after rainfall and further forms the bulk of the flood hydrograph; hence, results are independent of the groundwater (slow routing store), including its antecedent conditions, while the effects of the antecedent catchment conditions are represented by the soil moisture status. The start of the event is defined as the start of the simulated hydrograph rise; and the end of the event is defined as the point prior to the following rainfall–runoff event where flow and baseflow intersect.

## Representing the effects of uncertainty in parameters and regional relationships on results

Here, we investigate the relationship between spatial rainfall and runoff within an uncertainty framework allowing a more robust analysis. Pechlivanidis *et al.* (2010) derived different regional relationships to spatially parameterise the PDM model in the Upper Lee catchment; hence, affecting the synthetically generated (given specific physical properties) MPs. In addition, parameter AFs are required to generally improve the model performance and compensate for other uncertainties in the modelling process. These AFs downscale the parameter estimates to the subunit scale from the gauged subcatchments, however they

maintain the prior spatial variability of the parameter values; in other words, they compensate for the uncertainty of regional relationships under the constraint that the spatial pattern must not change. We therefore investigate two sources of uncertainty: (a) parameter uncertainty due to the presence of equifinal AFs and (b) uncertainty in the generation of the regional relationships.

The experimental analysis evaluates the simulated hydrographs generated from the behavioural parameter sets derived from the product of regional estimates and AFs. The calibration of the AFs is based on a uniform random search, whereby 100,000 sets of the AFs are randomly sampled from pre-defined ranges and the ‘optimum’ 100 sets based on the Nash–Sutcliffe efficiency for each (sub)catchment individually are adopted; these behavioural sets correspond to Nash–Sutcliffe greater than 0.7 on average for all catchments.

Finally, two sets of MP–CD relationships are applied to assess uncertainty in the regionalisation models (see Table 3). The first set of MP–CD relationships considers that there may be many equally optimal sets of regression coefficients arising from MP equifinality. Therefore, here the original CDs are maintained but their coefficients are allowed to vary; hence this set is consistent with the physically meaningful relationships of Table 4 in Pechlivanidis *et al.* (2010). These relationships were generated using randomly selected equifinal MP sets (in here the 10th optimum parameter set). The second set omits the constraint of generating physically meaningful relationships and is solely based on statistical significance. Therefore, the empirical regression model aimed at maximising its performance (i.e., coefficient

**Table 3** | Alternative MP–CD relationships to assess the effect of regional relationships on results

### Equation

#### Set 1

$$\begin{aligned} C_{max} &= 117.6 + 56.7 \log(\text{AREA}) - 1140.7 \text{URBEXT} + 4.14 \text{DPSBAR} \\ K_q &= -43.6 + 126.4 \text{BFIHOST} + 156.6 \text{URBEXT} \\ TP &= 233.2 - 32.2 \text{URBEXT} + 0.175 \text{DPLBAR} - 81.7 \log(\text{SAAR}) \end{aligned}$$

#### Set 2

$$\begin{aligned} C_{max} &= 211 - 1168.1 \text{URBEXT} + 0.12 \text{AREA} + 259.3 \text{BFIHOST} \\ K_q &= -812.5 + 1.56 \text{SAAR} - 3.26 \text{DPSBAR} + 12.01 \log(\text{URBEXT}) \\ TP &= 4.26 - 34.69 \text{URBEXT} + 1.78 \log(\text{AREA}) \end{aligned}$$

of determination) without any constraint upon combinations of CDs for each MP. Hence, inter-dependency between CDs could exist, so that the inclusion of different CDs may be giving essentially the same relationship.

## RESULTS

### Impact of regionalisation on reproducing runoff

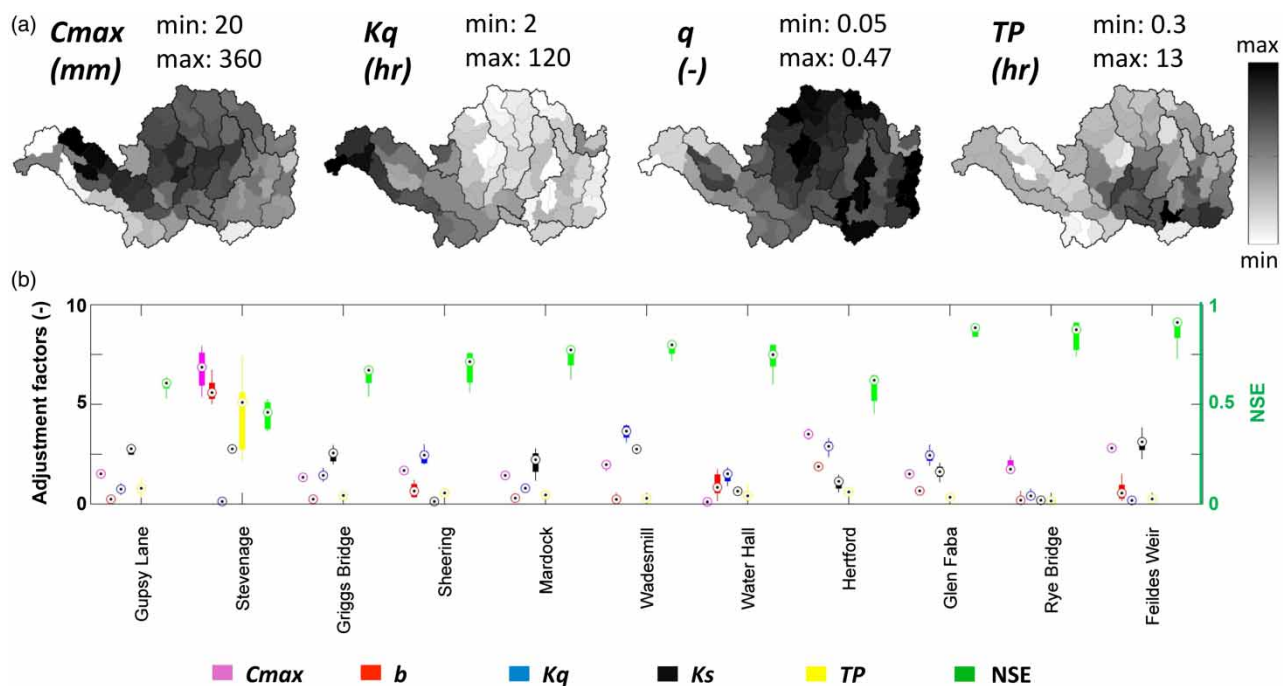
We first summarise the model's ability to represent the spatial heterogeneity of physical properties (as described by the parameters) and reproduce the observed runoff at different locations; note that here the hydrological model is forced with observed rainfall time-series (see the section 'The study catchment'). Figure 1(a) shows the spatial variability of  $C_{max}$ ,  $K_q$ ,  $q$  and  $TP$  parameters derived from regional relationships in Table 4 in Pechlivanidis et al. (2010). Parameter estimates are variable and within their reasonable ranges.

AFs were next calibrated using the NSE objective function and applied to parameters  $C_{max}$ ,  $b$ ,  $K_q$ ,  $K_s$  and  $TP$ , while the  $q$  parameter is kept equal to SPRHOST due to its

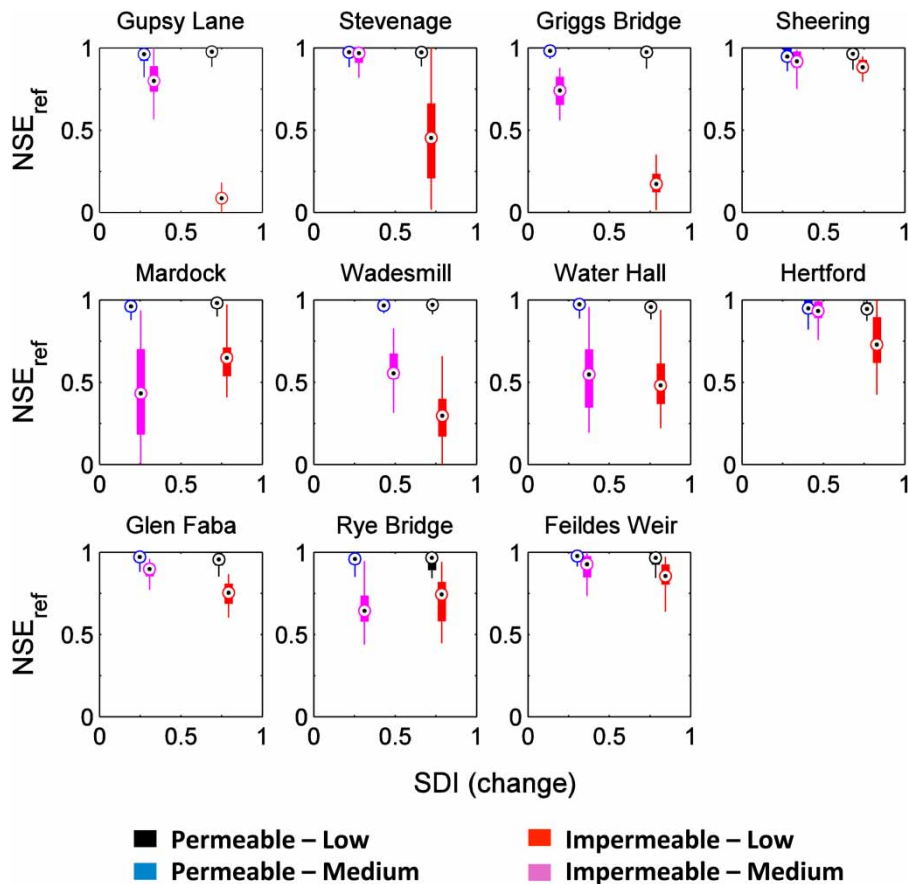
assumed direct physical correspondence (Figure 1(b)). Whereas the parameter estimates vary spatially, the AFs do not. Results show that the model can be calibrated to give high values of NSE (median value greater than 0.7) whereas in most subcatchments parameters are highly identifiable. The Stevenage subcatchment showed limited MP identifiability and poor NSE performance. A possible reason could be the abstractions from their rivers for irrigation purposes (Pechlivanidis 2009); however, no data were available to quantify this. Overall, results justify the need to consider uncertainty in optimum MP sets and regression equations in the sensitivity analysis.

### Impact of spatial variability of rainfall on runoff characteristics

Moving on to the synthetic experiments, we first investigate the relationship between  $NSE_{ref}$  and SDI. In all of the following figures coloured boxplots (derived from 100 parameter sets) are used to show the results obtained using the *low* and *medium* spatially variable rainfall events for the permeable and impermeable catchments. Figure 2 presents the



**Figure 1** | (a) Spatial distribution of a priori MPs and (b) variation of AFs and NSE model performance. The full colour version of this figure is available online at <http://dx.doi.org/10.2166/nh.2016.038> (open access).



**Figure 2** | Impact of spatial variability of rainfall on  $NSE_{ref}$  performance for each (sub)catchment type and scale under dry antecedent conditions. Simulated runoff based on the *high* spatially variable rainfall is used as reference. The full colour version of this figure is available online at <http://dx.doi.org/10.2166/nh.2016.038> (open access).

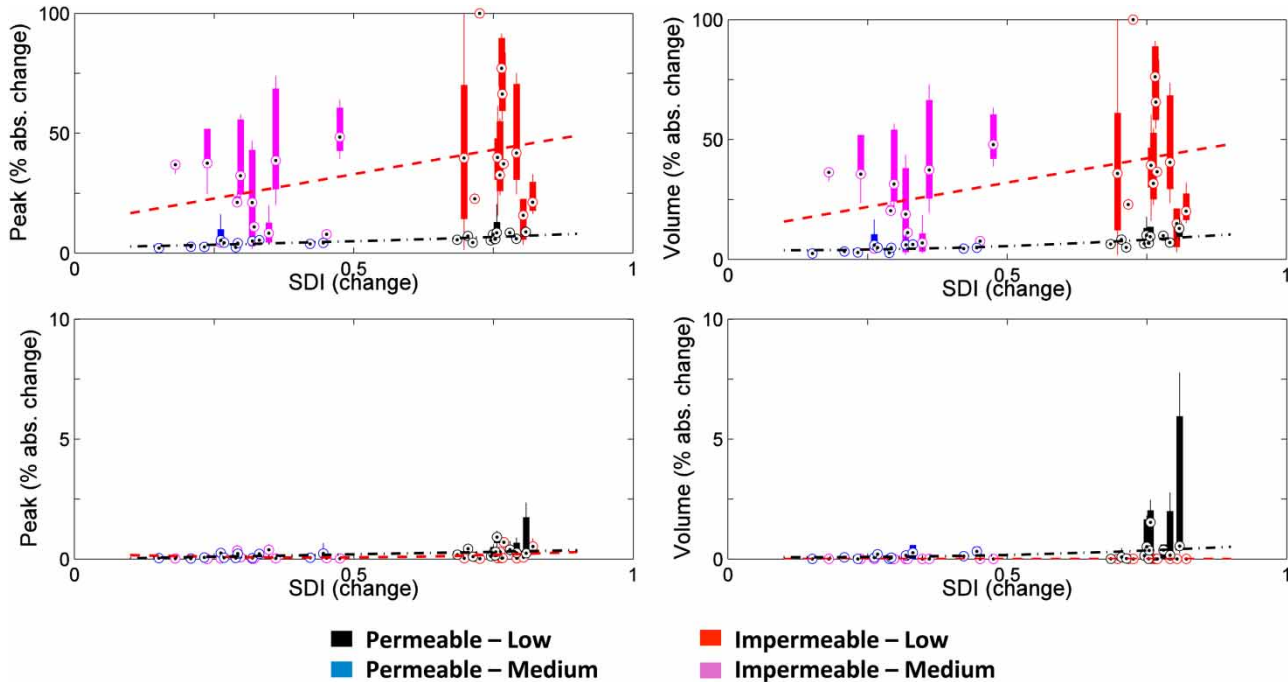
$NSE_{ref}$  values against SDI for the *low* and *medium* events for each permeable and impermeable subcatchment under dry antecedent conditions. The normalised SDI change is used to provide a common scale for comparison of the effect of SDI over different catchment scales. Overall, results show that the  $NSE_{ref}$  value for all subcatchment scales under dry antecedent conditions is sensitive to the spatial rainfall variability. However, the impermeable Rye Bridge and Feildes Weir catchments under dry antecedent conditions show less sensitivity to spatial rainfall compared to the other subcatchments, due to the dampening effect of the catchment at this relatively large scale ( $>750 \text{ km}^2$ ). On average,  $NSE_{ref}$  decreased by up to 0.2 and 0.05 for the medium (100–750  $\text{km}^2$ ) and relatively large-scale ( $>750 \text{ km}^2$ ) impermeable catchments, respectively.

The  $NSE_{ref}$  measure showed much less sensitivity to spatial rainfall ( $NSE_{ref}$  was reduced by 0.01 on average)

under wet antecedent conditions for both permeable and impermeable catchments. This is related to the existence of fully saturated areas in the catchment, and hence the generation of the same amount of effective rainfall for all the three events. It would have been expected that the routing, in particular different distributions of the channel travel times ( $TP$  varies between 0–2 and 0–4 hours for the impermeable and permeable subunits, respectively) between the three rainfall events, would have an impact on the results. However, the sensitivity of runoff to spatial rainfall (as described by the  $NSE_{ref}$  measure) seems to be dominated by the relative role of hillslope routing ( $Kq$  is equal to 20 and 68 hours for impermeable and permeable subunits, respectively) rather than channel travel time distributions.

Figure 3 presents the percentage change of peak runoff (Figure 3(a) and 3(c)) and runoff volume (Figure 3(b) and





**Figure 3** | Impact of spatial rainfall on hydrological response (peak and volume) for each (sub)catchment type and antecedent conditions: (a) peak – dry, (b) volume – dry, (c) peak – wet and (d) volume – wet. Black and red dashed lines are, respectively, the regression fits using quadratic equations for permeable and impermeable catchments. The full colour version of this figure is available online at <http://dx.doi.org/10.2166/nh.2016.038> (open access).

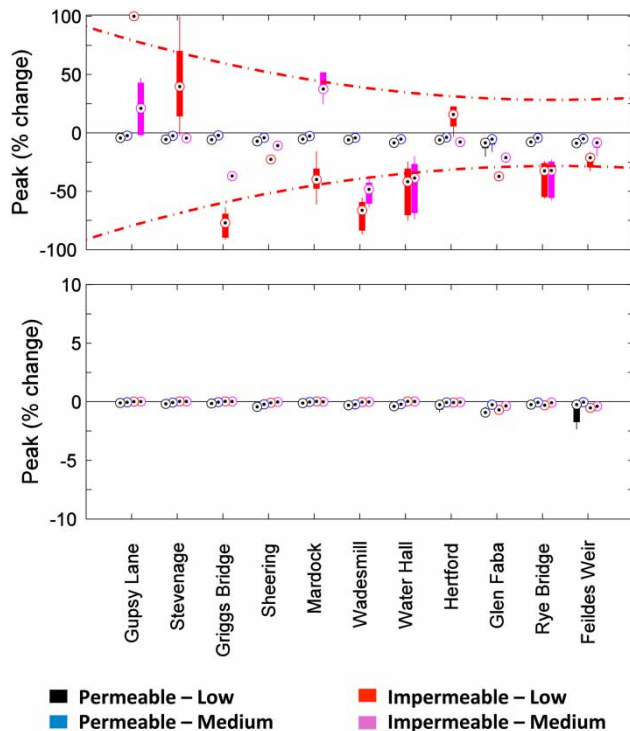
3(d)) relative to the ‘reference’ runoff, in terms of change in SDI for both *low* and *medium* events and all subcatchments (both permeable and impermeable). Both hydrograph characteristics seem to be related to SDI. A trend (5% significance level) exists between percentage change of peak and volume, and SDI for permeable and impermeable catchments under dry antecedent conditions. Results illustrate the increase in the absolute percentage change of peak runoff and volume when spatially variable events occur under dry and wet antecedent conditions. However, the influence (interpreted from the slope of the quadratic equations) is weaker under wet conditions (Figure 3(c) and 3(d)). The relationship between the hydrograph characteristics and spatial properties of rainfall for the impermeable catchments under dry antecedent conditions is more sensitive to the optimum MP set.

### Effect of scale

Results in Figure 4 are similar to those presented in Figure 3, but with the subcatchments ordered along the x-axis from

smallest to largest area. Similar patterns were observed for runoff peak and volume and therefore we only focus on peak runoff. For each catchment there are four boxplots corresponding to the percentage change of a hydrograph characteristic based on the 100 optimum MP sets for each of the two events (*low* and *medium*) and the two catchment types (permeable and impermeable).

Peak runoff and volume were sensitive to spatial rainfall at small-size impermeable catchments (up to 80 km<sup>2</sup>) under dry antecedent conditions. However, results show that Sheering does not follow the trend, possibly due to the spatial variability of  $C_{\max}$ ; the spatial  $C_{\max}$  pattern (and hence the spatial pattern of saturated areas) can affect the effective rainfall generated at each time step. The significance seems to slightly decrease at medium and large catchment scales. Here, this result is not due to the channel routing dampening effect which occurs at the large scales, since it was found that results were relatively insensitive to the channel routing; the simplistic channel model being used is not capable of representing the smoothing effect due, for example, to over-bank flow



**Figure 4** | Impact of spatial variability of rainfall on peak runoff for each (sub)catchment type listed in order of scale and under different antecedent conditions: (a) dry and (b) wet. The red dashed line is the regression fit using quadratic equation for impermeable catchments under dry conditions. The full colour version of this figure is available online at <http://dx.doi.org/10.2166/nh.2016.038> (open access).

and diffusive behaviour of waves. A possible reason is the greater averaging of the spatial variability of  $C_{\max}$  at large scales.

Figure 4 does not show any clear pattern between peak runoff and spatial rainfall under wet antecedent conditions. As explained earlier, the uniform catchment wetness and hillslope routing parameters seem to undermine the relationship between hydrograph characteristics and spatial rainfall. However, it is interesting to note that peak runoff slightly changes (5% change on peak runoff on average) at the large catchment scale (i.e., Feildes Weir). It seems that for large catchments, the residence time in the channel increases significantly and tends to be closer to the hillslope travel time; and hence the spatial distribution of rainfall becomes a main controlling factor. Results based on runoff volume also showed a relationship to spatial rainfall variability. Overall, runoff volume results mirrored peak runoff results.

### Impact of spatial variability of antecedent catchment conditions

Here, we assess the impact of spatial variability of antecedent catchment conditions (*uniform* and *variable*) for each (sub)catchment. *Uniform* is used to represent less spatially variable antecedent conditions, as generated from a prior *low* spatially variable synthetic rainfall event, whereas *variable* is used to represent more spatially variable antecedent conditions as generated from a prior *high* spatially variable synthetic rainfall event. We present the  $NSE_{\text{ref}}$  measure of simulated runoff (simulations from the *low* event) to the ‘reference’ runoff for *uniform* and *variable* antecedent conditions, respectively.

Results show that the spatial antecedent conditions play a significant role on the impact of spatial rainfall on the  $NSE_{\text{ref}}$  measure (see Figure A3, available with the online version of this paper). Although results for both permeable and impermeable scenarios are sensitive to the spatial variability of antecedent conditions, results show that this sensitivity is higher for permeable catchments, probably due to higher  $C_{\max}$  values and hence more scope for variability in initial wetness. Overall, it is interesting to note the variability of the results based on the MP set used, particularly for the permeable catchments, due to variability in initial conditions. This is related to the existence of fully or partially saturated areas over the catchments. Results based on peak runoff and volume also showed the same relationship to spatial rainfall under the two spatially variable antecedent catchment conditions.

### Impact of uncertainty in regional relationships on the significance of results

Results based on the first set of MP-CD relationships (developed using equifinal parameter sets; however, the relationships maintained their physical meaning but allowed CD coefficients to vary) again highlighted the significance of spatial variability of rainfall on peak runoff and volume. Trends and conclusions were similar to those derived in the previous sections.

Results based on the second set of relationships (regression equations were not constrained to link MP with CDs which are expected to be hydrologically related,

but were optimised to maximise the performance of the regional model) showed that the spatial variability of rainfall can influence the hydrograph properties (peak runoff and volume). The same was found for impermeable catchment types under dry antecedent conditions. However, unlike the previous analysis, results did not show any clear relationship with catchment scale. In addition, the uncertainty of the results, as described by the variability of the results using the behavioural parameter sets, was higher than before. It should be noted that results were influenced by the introduction of different CDs, resulting in different spatial variability of MPs over the catchment (i.e.,  $Kq$  was allowed to vary in space using the second set of relationships in Table 3). This highlights the sensitivity of the results to the structure of the MP-CD relationships; the more physically sensible CDs used in Table 4 in Pechlivanidis *et al.* (2010) produce more reliable results.

## DISCUSSION

In this paper, we build upon previous studies on the effects of spatial variability of rainfall on runoff generation, and in several parts we contradict and/or complement previous findings. Analysis of hydrological response using synthetic catchment types and events allowed isolation of the factors that control the spatial rainfall-runoff relationship. Woods & Sivapalan (1999) and Segond *et al.* (2007) concluded that for large catchments, spatial variability of rainfall has less influence compared to small catchments due to the dampening effect. Our analysis verifies that the degree of this effect depends on the antecedent catchment conditions and the catchment's permeability (see Patil *et al.* 2014). Antecedent catchment wetness plays an important role as it can undermine the significance of spatial rainfall, affecting the spatial distribution of effective rainfall. Under wet conditions (fully saturated catchments), the sensitivity to spatial rainfall seems to increase slightly at large catchment scales, because the residence time in the channel is higher compared to small catchments and closer to the hillslope travel time; hence, the runoff response is affected by the channel routing time scale (see also Nicótina *et al.* 2008).

Caution is required when the spatial rainfall-runoff relationship is investigated numerically via rainfall-runoff

models; simulated runoff variability does not only depend on spatial rainfall variability but also on the rainfall-runoff model itself and its spatial heterogeneity, and hence sources of error/uncertainty should be addressed (Younger *et al.* 2009). Lack of parameter identifiability could generate errors in the model response that are not consistent under different rainfall inputs (Pechlivanidis *et al.* 2010). Runoff generation depends on the joint spatial distribution of rainfall and catchment properties and conditions; therefore, prior to any analysis, models should be able to represent the catchment's spatial heterogeneity.

Regression equations, which relate physical CDs with the PDM MPs, are used to generate MP values in the current experiment. Pechlivanidis *et al.* (2010) justified the applicability of the developed relationships on the Upper Lee catchment and assessed the sensitivity of the results to these relationships. In addition, in this paper we propagate the uncertainty associated with the regional relationships (repeating the analysis using different plausible regional relationships) to the results, concluding that conclusions are not always the same when alternative plausible regression equations are applied. Different realisations of regression equations can combine different optimum sets of CDs, produce further different spatial variations in MPs, and hence different responses to spatial patterns in rainfall. This result highlights the importance of considering model uncertainty when investigating the significance of spatial rainfall on runoff.

## SUMMARY AND CONCLUSIONS

The motivation of this study is the need to improve understanding about the significance of spatial properties of rainfall on the hydrological response as a function of catchment scale and type, and antecedent catchment conditions. We investigate three synthetic rainfall-runoff events at 11 (sub)catchments ranging in scale from 25 to 1,040 km<sup>2</sup> through the semi-distributed PDM model. Overall, results show that the antecedent catchment wetness and catchment type play an important role in controlling the significance of the spatial distribution of rainfall on runoff. Results show a relationship between hydrograph characteristics (peak runoff and runoff volume) and the degree of spatial variability of rainfall for the impermeable catchments under dry

antecedent conditions, although this decreases at larger scales. No relationships are identified under wet antecedent conditions for both impermeable and permeable catchments, except at the large catchment scale.

The spatial discretisation of the rainfall–runoff model affects the results particularly at small catchments. Results show that the spatial variability of antecedent catchment conditions has a significant effect on runoff response. Highly spatially variable antecedent conditions can significantly affect the hydrological response due to the existence of fully or partially fully saturated areas over the catchment during the event. Finally, hydrograph responses to different spatial patterns in rainfall depend on assumptions used for MP estimation and also the spatial variation in MPs indicating the need of an uncertainty framework in such investigation.

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