Zhang, J., & Han, D. (2017). Assessment of rainfall spatial variability and its influence on runoff modelling: A case study in the Brue catchment, UK. *Hydrological Processes*, *31*(16), 2972-2981. https://doi.org/10.1002/hyp.11250

Title:

Assessment of rainfall spatial variability and its influence on runoff modelling - A case study in the Brue catchment, UK

Running head:

Rainfall spatial variability and its influence on runoff modelling

Jun Zhang[1*], Dawei Han[1]

[1] Department of Civil Engineering, University of Bristol, Bristol BS8 1TR, UK

*Corresponding author: Jun Zhang,

E-mail: jun.zhang@bristol.ac.uk, Catherine.zjun@gmail.com

Tel: (+44)7502275527

Postal address: 93 Woodland Road, Bristol, BS8 1US, UK

Abstract

This study explores rainfall spatial variability and its influence on runoff modelling. A novel assessment scheme integrated with coefficients of variance (CV) and Moran's I is introduced to describe effective rainfall spatial variability. CV is widely accepted to identify rainfall variability through rainfall intensity, whereas Moran's I reflects rainfall spatial autocorrelation. This new assessment framework combines these two indicators to assess the spatial variability derived from both rainfall intensity and distribution, which are crucial in determining the time and magnitude of runoff generation. Four model structures embedded in the Variable Infiltration Capacity (VIC) model are adopted for hydrological modelling in the Brue catchment of England. The models are assigned with 1, 3, 8 and 27 hydrological response units (HRUs) respectively and diverse rainfall spatial information for 236 events are extracted from 1995. This study investigates the model performance of different partitioning based on rainfall spatial variability through peak volume (Q_p) and time to peak (T_p), along with the rainfall event process. The results show that models associated with dense spatial partitioning are broadly capable of capturing more spatial information with better performance. It is unnecessary to utilize models with high spatial density for simple rainfall events, though they show distinct advantages on complex events. With additional spatial information, Q_p experiences a notable improvement over T_p. Moreover, seasonal patterns signified by the assessment scheme implies the feasibility of seasonal models.

Keywords: rainfall spatial variability, runoff modelling, CV, Moran's I

1 Introduction

Rainfall is one of the most important inputs for hydrological modelling, but it is rarely evenly distributed over the whole catchment. This is known as rainfall spatial variability and is mainly caused by the synoptic regime and catchment morphology (McMillan, Krueger, & Freer, 2012). Rainfall depth and routing paths in multiple locations over the catchment may result in dispersed runoff distribution over a spatial scale. Rises in runoff variability correspond to the increase in rainfall spatial variability (E. F. Wood, Sivapalan, Beven, & Band, 1988). Previous studies note that runoff modelling performance is significantly affected by rainfall spatial variability; for instance, a large uncertainty existed in estimated model parameters without consideration of detailed variation in the input rainfall (Chaubey, Haan, Grunwald, & Salisbury, 1999). Moreover, peak flow and runoff volume were influenced by spatially distributed rainfall (Arnaud, Bouvier, Cisneros, & Dominguez, 2002; Singh, 1997); this finding was supported by Younger *et al.*(2009), who found that perturbation of rainfall in upstream and downstream areas led to distinct impact on peak time and runoff volume in the Brue catchment.

A number of studies have looked into the relationship between rainfall spatial variability and model output as well as possible impact factors. Segond *et al.* (2007) found that model performance decreased with the increase of rainfall spatial variability after investigating spatial rainfall resolution for runoff estimation in a 1400 km^2 catchment with 28 events. Convective storms were found to have greater runoff variability than stratiform rainfall (V. A. Bell & Moore, 2000). Moreover, variability in the storm core beyond the rainfall overall spatial variability could be more influential in runoff generation (Syed, Goodrich, Myers, & Sorooshian, 2003). Shah *et al.* (1996a) discovered that rainfall spatial distribution contributed significantly to runoff modelling when the catchment antecedent soil water condition was dry, in an investigation in the Wye catchment of a 10.55 km^2 drainage area in the UK. On the other hand, Nicótina *et al.* (2008) revealed that for catchments with a rainfall spatial variability scale larger than the hillslope scale, flood response was more sensitive to the average rainfall. Additionally, for large-scale catchments, runoff generation depended more on the spatial distribution of rainfall because of the heterogeneous transport paths.

In contrast, a number of researchers have argued that rainfall spatial variability could be smoothed out by the rainfall-runoff process because of damping within the catchments. Obled *et al.* (1994) noted that rainfall spatial variability was not sufficiently organized to overcome damping in a rural medium-sized catchment. Skøien (2003) suggested that the decrease of spatial characteristic scale from catchment rainfall to runoff was a result from the superposition of small-scale variability of catchment and aquifer properties. Moreover, Zoccatelli *et al.* (2011) showed that the catchment acted as a space-time filter by quantifying the effect with a function of rainfall organization and catchment geomorphic information. Smith *et al.* (2004) indicated that all basins presented a damping effect on input rainfall signals. A catchment with high complexity suggested the use of a distributed model, while sometimes average rainfall was enough for other catchments due to the smoothing fact. A study by Bell and Moore (2000) showed that lower rainfall resolution outperformed higher resolution input in the Brue catchment. Moreover, model calibration obscured the importance of rainfall spatial information by detecting a slight improvement from a lumped model to a distributed model (Shah, O'Connell, & Hosking, 1996b). Lobligeois *et al.* (2014) noted that the model performance was catchment scale–dependent and event–characteristic–dependent. Despite many previous studies, it is significant not only to identify how rainfall spatial characteristics affect runoff modelling but also to link the input spatial variability with model spatial resolution.

In this study, an assessment approach is required to provide insight into the potential impact of rainfall spatial variability on runoff modelling based on the analysis of observed rainfall spatial variability and corresponding model performance. Many indicators to describe rainfall spatial characteristics have been introduced in the last decades. Coefficient of variance (CV), because of its simplicity and the ability to describe the rainfall measurement variation, has been widely used in hydrological research (Arnaud et al., 2002; Chaubey et al., 1999; Pedersen, Jensen, Christensen, & Madsen, 2010). Additionally, the inter-gauge correlations (Ciach & Krajewski, 2006; Pedersen et al., 2010) and spatial deviation index (SDI) (Segond et al., 2007) have been investigated based on gauge measurements. However, the practice of seeking for a relationship between existing gauges with the aforementioned indicators is limited in terms of mapping the overall spatial correlation across the whole catchment. Some practical procedures have been implemented based upon the semi-variogram to provide the decorrelation distance of rain gauges (Bacchi & Kottegoda, 1995; Baigorria, Jones, & O'Brien, 2007); the distance was examined around 80 km based on daily rainfall in Belgium (Ly, Charles, & Degré, 2011). The drawback of this approach is the varied decorrelation distances in different locations. Due to the risk of obtaining a decorrelation distance larger than the scale of a catchment, constraints exist in applying semi-variograms to small catchments where inner rainfall gauges are in close proximity. In addition, spatial moments of catchment rainfall, as defined by Zoccatelli *et al.* (2011), depicted spatial rainfall organization in terms of concentration as a function of distance measured along the flow routing without considering the variation of rainfall intensities among gauges. Although there are different assessment methods already in use, most of them are not well defined and therefore difficult to apply in a consistent manner.

Therefore, more research is still expected in this field to add new knowledge and evidence to find clearer patterns for rainfall variability and its relationship with rainfall-runoff modelling. In this study, we were interested in how models with various spatial resolutions respond to varied rainfall spatial variabilities, which is expected to provide a guidance for how to choose an appropriate model structure. Firstly, an assessment framework integrated with CV and Moran's I is introduced for the first time so that we could evaluate rainfall spatial variability attributed to both spatial dispersion and intensity variation. Models based on the Variable Infiltration Capacity (VIC) model were assigned four spatial resolutions to examine the performance on an event-based scale using hourly data from 1995 of 49 gauges in the Brue catchment, UK. Simple, medium and complex events were defined based on the results of assessing the rainfall spatial variability. Model performance, including the goodness of fit as well as the errors in peak volume (Q_p) and time to peak (T_p) were evaluated for detailed analysis.

2 Study area and dataset

The Brue catchment is located in the southwest of England as shown in Figure 1, draining an area of 132 km^2 to its river gauge at Lovington (Dai et al., 2015). The elevation of the catchment is higher in the North and East where the river rises. There is a specially designed HYdrological Radar Experiment (HYREX) dense rainfall network with 49 tipping bucket rain gauges distributed in the whole catchment, as shown in Figure 1 (Moore, Jones, Cox, & Isham, 2000). The project produced an extensive data set including data from 49 rain gauges, one runoff gauge at the outlet and climate data from 1994 to 1999 for the catchment. Data from 1995 were chosen for the study.

The rainfall record in 1995 ranged from 748 mm to 957 mm as shown in the contour map plotted in Figure 1. Rainfall decayed from the east to the west, which is also identified from upstream to downstream. Due to the problems such as blockage and damage of rainfall measurement instruments, a data quality check was performed before analysis using a cumulative hyetograph to detect faulty data (S. J. Wood, Jones, & Moore, 2000). When a gauge was considered to have provided faulty data, a kriging interpolating rainfall (Borga & Vizzaccaro, 1997) using measurements from nearby gauges was used as a substitution.

A total of 236 events originating from hourly data in 1995 were extracted for detailed study. The basic assumption was that the events are independent with each other when sequences of zero-rain rates between rainfall events lasted beyond 5 hours (Güntner, Olsson, Calver, & Gannon, 2001). The starting point of a rainfall event was defined as the point when total flow started to surpass base flow, while the event ended at the point when the total flow decayed to the amount of base flow.

Rainfall events from 1994 to 1999 in seasonal groups were analysed to obtain a preliminary knowledge of rainfall spatial variability in the Brue catchment. Four natural seasons are defined by Lamb (1950) on the basis of climate conditions in England, i.e., spring (30th March to 17th June), summer (18th June to 9th September), autumn (10th September to 19th November), winter (20th November to 29th March in the next year). We used the standard deviation (SD) to compare the average rainfall derived from fewer gauges with that from the 49 gauges. The number of gauges ranged from 1 to 48 and there were 49 sets for groups that contain 1 and 48 gauges respectively. Apart from that, 100 combination sets were randomly chosen for the other groups. By comparing the average rainfall from all groups with that from the 49 gauges, the seasonal SD was generated against the number of gauges as shown in Figure 2 and Table 1. As shown in Figure 2, SD decreased with the increase of gauges, which is verified in Table 1 that one gauge occupied the largest SD. Moreover, the decreasing trend of SD plateaued when the number of gauges was beyond 10.

Figure 3 illustrates that summer presented the largest standard deviation followed by autumn, while winter displayed the smallest standard deviation. The difference among seasons was more distinct when adopting only one gauge, as SD was smallest, 2.87 mm in winter and largest, 4.96 mm, in summer. The average value dropped from 3.57 mm to 1.01 mm as the number of gauges rose from 1 to 10; this discrepancy is larger than the drop from 1.01 mm to 0.41 mm when the number of gauges increased from 10 to 30. Moreover, there is a slight difference between 48 and 49 gauges as the average standard deviation was as low as 0.07 mm due to the extremely high density of the rainfall network. Based on these results, increasing the number of rainfall gauges is prone to mitigate its standard deviation. Thus, the natural spatial variability in storms is observed in the catchment, which is the main subject in this study.

3 Methodology

3.1 Rainfall spatial variability assessment framework

Three main indicators (CV, Moran's I and semi-variogram) were separately applied at the beginning of the study to understand the rainfall spatial characteristics. We believe that an assessment approach, to be widely adopted, should provide a diagnostic metric for model application. Due to the drawbacks of existing assessment indicators, a framework integrated with CV and Moran's I is newly presented in this study. CV describes the variation among values, which is broadly used in rainfall variability assessment. Moran's I, which is well-known in many geological research areas as a tool to evaluate spatial autocorrelation (Li, Calder, & Cressie, 2007; Tiefelsdorf, 1998), is introduced and specified in detail hereafter.

3.1.1 CV

The rainfall spatial variability expressed by the spatial coefficient of variance (CV) calculates the ratio of SD to the mean rainfall depth (Arnaud et al., 2002; Pedersen et al., 2010). The formula for CV shown in Equation 1 aims to provide the rainfall variability caused by the variation of relevant rainfall intensities; a large CV indicates the increase of rainfall variability. It is defined as

$$CV = \frac{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}{\bar{P}} \qquad (1)$$

in which P_i is the rainfall value at the ith gauge, in mm; $\bar{P}$ is the average rainfall of all gauges, in mm; n is the number of gauges.

3.1.2 Moran's I

Spatial autocorrelation is the co-variation of properties within geographic space: characteristics at proximal locations appear to be correlated, either positively or negatively (Legendre, 1993). Moran (1950) proposed a statistic (Moran's I) to assess the spatial autocorrelation by characterising the correlation among nearby locations in space, which is defined as

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(P_i - \bar{P})(P_j - \bar{P})}{\sum_{i=1}^{n}\sum_{i}(P_i - \bar{P})^2} \qquad (2)$$

in which P_i, P_j are the rainfall at the ith, jth gauge, respectively, in mm; W_{ij} specified in Equation 3 is an element in a matrix of spatial weight:

$$W = \frac{W^*}{W_0} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{n1} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \qquad (3)$$

The weight matrix W is derived by normalizing the contiguity matrix $W^* = [w_{ij}^*]$ with a normalization factor $W_0 = \sum_{i=0}^{n}\sum_{j=0}^{n} w_{ij}^*$. Values of the matrix w_{ij}^* can be calculated in several ways, and are originally defined as $w_{ij}^* = 1$ if ith and jth are adjacent, and $w_{ij}^* = 0$ otherwise, most commonly. Since 0/1 weighting is used for discrete rather than continuous and geographic data, w_{ij} is calculated by the inverse distance method in this study, which is defined as

$$w_{ij}^* = {r_{ij}}^{-b} \qquad (4)$$

in which r_{ij} is the distance between ith gauge and jth gauge, in m; b is a distance parameter ($b = 1$ in this study).

The Moran's I formula outputs a value for the spatial correlation at proximal locations, i.e. rainfall measurements in this study, that varies from -1 to 1 (Stephens, Bates, Freer, & Mason, 2012). A zero value means a random spatial pattern, and negative values indicate a dispersed spatial distribution while positive values demonstrate correlated spatial characteristics.

Moran's I close to 1 indicates a strong level of positive spatial autocorrelation exists, and it can be explained as high/low values are collocated with high/low ones (Tiefelsdorf, 1998).

3.1.3 Assessment framework of rainfall spatial variability

The objective of this study was to depict rainfall spatial variability on the basis of events to provide a guidance on choosing appropriate models. Pros and cons can be found for both CV and Moran's I, as described in Section 3.1.1and 3.1.2 above. CV describes the variance between values in the rainfall field, while a large CV shows higher variance and vice versa, the spatial distribution is neglected. On the other hand, Moran's I represents the spatial autocorrelation among gauges without considering their values. To effectively describe variability derived from spatial distribution and rainfall intensities, we propose an assessment scheme integrated with CV and Moran's I, as shown in Table 2. By combining CV and Moran's I, the variability caused by both rainfall magnitude and spatial distribution is taken into consideration. With a high CV and low Moran's I, the variability is complex, whereas a decline of CV (and growth of Moran's I) indicates lower variability.

Three groups with different levels of rainfall spatial variability were extracted for further investigation, as seen in Section 4.2. An F-test was carried out to determine whether the groups were considerably different from each other by comparing the sample variances. The hypothesis is that if the test statistic p-value is lower than 0.05, the two groups being compared are independent from each other (Lomax & Hahs-Vaughn, 2013).

3.2 Hydrological model setup

The Variable Infiltration Capacity (VIC) model was first developed by Wood *et al.* (1992) and then extended to the widely spread VIC-2L (two-layer) and VIC-3L (three-layer) by Liang *et al.* (1994). VIC model introduces a variable infiltration capacity in different catchment areas, which allows for heterogeneity of fast runoff production (Beven, 2011). VIC-3L, which was adopted in this study, adds a thin soil layer above the upper soil layer (Liang et al., 1994). The model allows a spatially variable soil moisture capacity, which has been proved to have a good performance with spatially distributed input information (V. a. Bell, Kay, Jones, Moore, & Reynard, 2009).

3.2.1 Model spatial partitioning

The catchment was partitioned into different numbers of hydrological response units (HRUs) in the four models as shown in Figure 3. An average rainfall intensity was derived using the Theissen Polygon method with gauges inside the HRU and selected as the rainfall input of the corresponding HRU. To avoid the influence of spatial parameters on modelling performance, all parameters were assumed to be the same for all HRUs in a model. Since the Brue catchment is relatively homogenous, such an assumption is not far from reality.

3.2.2 Assessment indicators

All models were calibrated separately for the whole year of 1995 with 49 gauges and optimized with the runoff data at the catchment outlet. Event-based modelled runoff was extracted from the entire year of modelling instead of simulating runoff for each event individually.

Firstly, the goodness of fit was evaluated by the Nash-Sutcliffe efficiency (NSE) as

$$NSE = 1 - \frac{\sum_{i=1}^{m}(Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^{m}(Q_{obs,i} - \overline{Q_{obs}})^2} \qquad (5)$$

in which, $Q_{sim,i}$ is the simulated runoff at time i, in m^3/s; $Q_{obs,i}$ is the observed runoff at time i, in m^3/s; $\overline{\mathrm{Q_{obs}}}$ is the mean observed runoff over the modelling span, in m^3/s; m is the total number of time intervals.

With more sensitivity to large values, the NSE values of relatively small events are sometimes negative, which fails to evaluate the performance. NSE was only used for assessing the full runoff record in this study, and relative root mean square error (RRMSE), which reflects the simulation error but eliminates the influence of rainfall magnitude, was used for selected rainfall events. RRMSE is calculated as shown in the following equation:

$$RRMSE = \frac{1}{\overline{Q_{obs}}}\sqrt{\frac{\sum_{i=1}^{m}(Q_{sim,i}-Q_{obs,i})^2}{m}} \qquad (6)$$

In addition, the Q_p and T_p of each event were taken into consideration to evaluate any possible improvement in hydrograph shape by relative absolute error (RAE) as shown in Equation 7,

$$\mathrm{RAE} = \frac{|Q_{p,sim}-Q_{p,obs}|}{Q_{p,obs}} \times 100\% \quad (7)$$

4 Results and discussion

4.1 General performance

The performance of a lumped model (1 HRU) was evaluated to obtain a general idea of how the rainfall spatial information would affect the model performance. The average rainfall of different numbers of gauges was assigned as input for the lumped model. We used the same method to choose the combinations and permutations of gauge groups as described in Section 2. The goodness of fit was evaluated using NSE by comparing the modelled runoff with the observed runoff at the outlet for the whole year and is displayed in Figure 4. The boxplot was derived from all the combinations for each number of gauges. The tops and bottoms of each blue box are the 25th and the 75th percentiles and the red line in the box is the sample median. The black dash lines are the 5th and the 95th percentiles of the sample while the observations beyond the black lines are outliers.

Figure 4 shows NSEs derived from different numbers of gauges from 1 to 49 for the whole year, and it displays a sharp increase from 1 to 5 gauges, followed by a relatively slow rise from 6 to 10 gauges. It is worth noting that NSE gradually plateaued around 0.810 with more than 10 gauges. There was a tendency for the model performance to move forwards higher values with the increase of rainfall information, which also eliminated the model uncertainty (blue boxes). A large uncertainty appeared in the model with fewer gauges, while models were more stable with more gauges. However, it was also possible to find some combinations with less spatial information that outperformed those with more gauges estimated when referring to the upper boundary of the boxes in Figure 4.

All four models were calibrated for the whole year with NSE increasing steadily from 0.813 (1 HRU) to 0.867 (27 HRUs), while the NSEs of two intermediate models were 0.834 (3 HRUs) and 0.862 (8 HRUs).

4.2 Event-based analysis

4.2.1 Rainfall spatial variability analysis

CV and Moran's I were assessed for 236 events in 1995 by comparing the accumulative rainfall of all gauges for each event separately. As shown in Figure 5, CV ranged from 0.064 to 7.000 and Moran's I ranged from 0.003 to 0.292 with a slight decreasing trend between CV and Moran's I. In 1995, summer rainfall events were located mostly in the upper part and winter events were more prevalent in the lower part. A lot of 29 of 51 summer events were present where their CV was greater than 4, while 42 events had Moran's I smaller than 0.15, which indicates a high variability in both spatial distribution and rainfall intensity variation. In contrast, CV values were less than 2 in 62 of 79 events in the winter, while Moran's I had 41 events greater than 0.15, showing low spatial variability. Moreover, relatively low CV and Moran's I in autumn indicated that spatial variability was mainly the consequence of dispersed spatial distribution. Spring events were distributed in a relatively scattered pattern, as seen in Figure 5 which implies that these events did not have a consistent spatial pattern.

With the framework integrating CV and Moran's I, rainfall events could be categorized into three groups based on different spatial variability levels. To explicitly distinguish rainfall events in groups, not all the events were taken into account for further analysis. Three rectangles are plotted to define groups these in Figure 5. Events in the complex groups are defined as $\mathrm{CV} > 4$ and $\mathrm{Moran's\,I} \leq 0.1$, while events with $2 < \mathrm{CV} \leq 4$ and $0.05 < \mathrm{Moran's\,I} \leq 0.15$ are assigned into the medium group. Finally, events with $\mathrm{CV} \leq 2$ and $\mathrm{Moran's\,I} > 0.2$ are considered as simple events.

According to the results of the F-test, the p-value between the simple and medium groups was 0.0036, between the simple and complex groups was 0.0011, and between the medium and complex groups was 0.012. All p-values were lower than 0.05, indicating that the three groups are significantly different with each other, which verifies that it is rational to compare the model performance within the chosen groups.

4.2.2 Overall performance of events

Three rainfall event groups were derived from the assessment framework described in Section 4.2.1. The simulations of the events were extracted from the whole year simulation by four model structures and assessed with RRMSE respectively. Therefore, the samples in each group were RRMSEs of rainfall events within the group. Figure 6 depicts the RRMSEs of events in different groups derived from four model structures. The explanation of the boxplot is the same with the boxplot described in Section 4.1. In Figure 6, one column represents the performance in one group with one model, e.g., Sim_27 represents the performance of rainfall events in the simple group simulated by the model with 27 HRUs.

The model with 1 HRU presented the worst performance in all three groups. Model performance with 27 HRUs was stable without an apparent difference in RRMSE of rainfall events among three groups. However, the other three models all displayed larger RRMSE with larger spatial variability as well as an increasing instability, as revealed by the wider ranges of error.

A decline in error appeared from 27 HRUs to 8 HRUs, followed by a rise to 1 HRU in the simple groups, which identifies the model with 8 HRUs performed best. The models with 27 HRUs and 8 HRUs came up with an equally low median error in the medium group, albeit the more stable performance made the model with 27 HRUs outperform the 8 HRUs model with a narrower uncertainty, when considering the 25^{th} and the 75^{th} percentiles. In the complex group, it is more marked that the model with 27 HRUs defeated all the other models with a notably smaller error along with a more stable model performance.

4.2.3 Assessment of event-based Q_p and T_p

Event-based Q_p and T_p are assessed in terms of RAE and displayed in Table 3. The increase of model HRUs shows the ability to improve Q_p significantly in all events as RAE drops vastly from 64.50% (1 HRU) to 16.14% (27 HRUs) in the complex group. A similar tendency with event overall performance happened in that models with a lower density of HRUs produced a much larger error of Q_p in complex events than simple ones, whereas the model with 27 HRUs experienced less fluctuation. T_p was simulated better in medium and complex events when adding more partitioning in the model but not in the simple group. However, all models performed poorly in capturing T_p with RAE greater than 50% and model with finer spatial resolution did not improve the fit.

5 Discussion

In the results section, we looked at the overall model performance, and the timing and magnitudes of the peaks responding to different levels of rainfall spatial variability. Rainfall events with larger spatial variability were more difficult to simulate. In general, the model with a higher density of partitioning showed an improved and more stable modelling ability than one with lower density. However, models with finer resolution did not always result in a better simulation for simple events, which still even took a high computational load. Using a model with a lower density such as 8 HRUs was sufficient to simulate simple events. However, a model with higher resolution is highly recommended when dealing with a rainfall event with large spatial variability due to its ability in capturing more detailed spatial information.

Only the variation of rainfall gauge values is considered in CV without considering the spatial distribution of rainfall events, although it is one of the widely accepted indicators for spatial variability assessment. Nevertheless, the rainfall distribution, especially for the location of the rainfall core, matters significantly for runoff generation (Syed et al., 2003). An upstream rainfall centre would result in a delay and lower magnitude in peak runoff occurrence, whereas the peak would appear earlier followed by a longer recession period when rainfall centre is positioned downstream. Therefore, only considering the values of different gauges is inadequate to predict the potential errors for runoff modelling attributed to the rainfall spatial variability. On the other hand, the spatial autocorrelation in the study area is revealed by Moran's I. Provided there is a positive Moran's I, the more uniform the rainfall event leads to a larger Moran's I. However, Moran's I remains constant when detecting the same distribution of a rainfall event disregarding the rainfall values. Nevertheless, the runoff volume relies on rainfall volume more than rainfall spatial distribution.

The rainfall spatial variability is prone to be over/under-estimated by CV/Moran's I when rainfall fields are clustered together but with varying intensities, and vice versa. To overcome the limits of simply adopting either CV or Moran's I, a framework which accounts both rainfall intensity and spatial distribution by incorporating these two elements is proposed and it quantifies the spatial variability along with identifying its source. Three groups with different rainfall spatial variability are analysed and the results prove that it is reasonable to define rainfall spatial variability based on this framework. The high CV and low Moran's I events are defined as complex while the reverse relationship implies simple variability. Moreover, different sources of spatial variability can induce timings and magnitudes errors in hydrographs.

T_p is more liable to be affected by simple CV and complex Moran's I, whereas Q_p is more sensitive to high CV and low Moran's I.

A lumped model tends to ignore spatial information by taking an assumption of homogeneous rainfall over the whole catchment. The same average values accompanied by different spatial distributions could result in totally dissimilar peak times and peak volumes. However, it is not always true that models with a higher density of partitioning perform better than the ones with fewer HRUs. The advantage of a model with higher spatial resolution is distinct when dealing with complex spatial variability because of its ability to capture the spatial information. It is not worthwhile to carry out a model with an excessive spatial resolution for simple events, which is time-consuming and onerous for computation. A model with lower resolution is adequate for simple event simulation based on the aforementioned results. Moreover, storm patterns, including how a storm approaches a catchment like moving direction, moving velocity, etc., can be included in future studies to examine their influence on choosing a suitable model structure. An optimal model based on a more comprehensive assessment framework of storm spatial fields will benefit efficiency and accuracy in real-time flood forecasting.

The framework reveals seasonal patterns in rainfall spatial variability. Convective storms mostly happen in summer, which are likely to bring unevenly distributed rainfall, while stratiform storms are relatively even over the catchment. Seasonal models with varied spatial resolutions are possible, allowing more optimal utilization of spatial information.

However, it should be pointed out that there are still several limitations in this study that can be improved and further explored. 1) The grouping principle based on CV and Moran's I is not entirely distinctive, which means information overlap exists between them. It may be possible to introduce another indicator to increase their severability (e.g., rainfall centre distance to the outlet). 2) Only one hydrological model at one catchment is explored which provides narrow insight inside the study. Meanwhile, the effect of the heterogeneity of the catchment is worthwhile to be explored on the corresponding runoff variability. More studies are desired to provide a comprehensive view to point out where the proposed scheme works well, and where it fails. 3) Homogenous parameters for the catchment are adopted, which is proper in this study to eliminate the model heterogeneity and emphasize rainfall spatial variability, but it will be useful to explore the case where the HRUs are allowed to vary.

6 Conclusion

The aim of this study is to explore how to match model spatial partitioning with rainfall spatial variability. Drawbacks exist in currently used approaches to describe rainfall spatial variability. As acknowledged, CV calculates the variation between rainfall intensity of gauges, and Moran's I reflects the autocorrelation in space. This study proposes a novel framework taking advantage of CV and Moran's I by combining them to classify rainfall variabilities into groups. As a result, both rainfall values and distribution are taken into account with a more comprehensive indication than their individual representations.

It is found that model performance decreases with the increase of rainfall spatial variability by studying groups based on the new rainfall variability classification scheme. Additional rainfall spatial information contributes an improvement in the model performance even for a lumped model. In general, the model with higher spatial resolution outperforms the lower ones. A model with lower density is sufficient for simple events although the model with higher spatial resolution shows the most noticeable advantage when dealing with the events with the highest rainfall spatial variability. Apparently, seasonal patterns in spatial variability strongly imply seasonal models. The results are meaningful to provide a reference on configuring an optimal spatial resolution model. It is clear that the proposed scheme is still in its very early stage (as a proof of concept) and there are several weaknesses as described in the discussion section.

Nevertheless, it is important for the hydrological community to put more effort into such a key issue. We hope this research will stimulate the community to carry out more case studies using different hydrological models at different geographical locations to further evaluate and improve the proposed rainfall variability assessment scheme.

Acknowledgement

The authors would like to thank Professor Jim Freer and Professor Thorsten Wagener in the University of Bristol for the helpful discussions in this study. The first author would like to thank the University of Bristol and China Scholarship Council for providing the necessary support and funding for this research. The authors acknowledge the British Atmospheric Data Centre for providing the dataset used in this study.

Reference

Arnaud, P., Bouvier, C., Cisneros, L., & Dominguez, R. (2002). Influence of rainfall spatial variability on flood prediction. *Journal of Hydrology*, *260*(1-4), 216–230. https://doi.org/10.1016/S0022-1694(01)00611-4

Bacchi, B., & Kottegoda, N. T. (1995). Identification and calibration of spatial correlation patterns of rainfall. *Journal of Hydrology*, *165*(1-4), 311–348. https://doi.org/10.1016/0022-1694(95)92778-C

Baigorria, G. A., Jones, J. W., & O'Brien, J. J. (2007). Understanding rainfall spatial variability in southeast USA at different timescales. *International Journal of Climatology*, *27*(6), 749–760. https://doi.org/10.1002/joc.1435

Bell, V. a., Kay, a. L., Jones, R. G., Moore, R. J., & Reynard, N. S. (2009). Use of soil data in a grid-based hydrological model to estimate spatial variation in changing flood risk across the UK. *Journal of Hydrology*, *377*(3), 335–350. https://doi.org/10.1016/j.jhydrol.2009.08.031

Bell, V. A., & Moore, R. J. (2000). The sensitivity of catchment runoff models to rainfall data at different spatial scales. *Hydrology and Earth System Sciences*, *4*(4), 653–667. https://doi.org/10.5194/hess-4-653-2000

Beven, K. J. (2011). *Rainfall-runoff modelling: the primer*. John Wiley & Sons.

Borga, M., & Vizzaccaro, A. (1997). On the interpolation of hydrologic variables: Formal equivalence of multiquadratic surface fitting and kriging. *Journal of Hydrology*, *195*(1-4), 160–171. https://doi.org/10.1016/S0022-1694(96)03250-7

Chaubey, I., Haan, C. T., Grunwald, S., & Salisbury, J. M. (1999). Uncertainty in the model parameters due to spatial variability of rainfall. *Journal of Hydrology*, *220*(1), 48–61. https://doi.org/10.1016/S0022-1694(99)00063-3

Ciach, G. J., & Krajewski, W. F. (2006). Analysis and modeling of spatial correlation structure in small-scale rainfall in Central Oklahoma. *Advances in Water Resources*, *29*(10), 1450–1463. https://doi.org/10.1016/j.advwatres.2005.11.003

Dai, Q., Han, D., Rico-Ramirez, M. a., Zhuo, L., Nanding, N., & Islam, T. (2015). Radar rainfall uncertainty modelling influenced by wind. *Hydrological Processes*, *29*(7), 1704–1716. https://doi.org/10.1002/hyp.10292

Güntner, A., Olsson, J., Calver, A., & Gannon, B. (2001). Cascade-based disaggregation of continuous rainfall time series: the influence of climate. *Hydrology and Earth System Sciences*, *5*(2), 145–164. https://doi.org/10.5194/hess-5-145-2001

Lamb, H. H. (1950). Types and spells of weather around the year in the British Isles : Annual trends, seasonal structure of the year, singularities. *Quarterly Journal of the Royal Meteorological Society*, *76*(330), 393–429. https://doi.org/10.1002/qj.49707633005

Legendre, P. (1993). Spatial autocorrelation: trouble or new paradigm? *Ecology*, *74*(6), 1659–1673. https://doi.org/10.2307/1939924

Li, H., Calder, C. a., & Cressie, N. (2007). Beyond Moran's I: Testing for spatial dependence based on the spatial autoregressive model. *Geographical Analysis*, *39*(4), 357–375. https://doi.org/10.1111/j.1538-4632.2007.00708.x

Liang, X., Lettenmaier, D. P., Wood, E. F., & Burges, S. J. (1994). A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, *99*(D7), 14415. https://doi.org/10.1029/94JD00483

Lobligeois, F., Andréassian, V., Perrin, C., Tabary, P., & Loumagne, C. (2014). When does higher spatial resolution rainfall information improve streamflow simulation? An evaluation using 3620 flood events. *Hydrology and Earth System Sciences*, *18*(2), 575–594. https://doi.org/10.5194/hess-18-575-2014

Lomax, R. G., & Hahs-Vaughn, D. L. (2013). *Statistical concepts: A Second Course*. Routledge.

Ly, S., Charles, C., & Degré, a. (2011). Geostatistical interpolation of daily rainfall at catchment scale: The use of several variogram models in the Ourthe and Ambleve catchments, Belgium. *Hydrology and Earth System Sciences*, *15*(7), 2259–2274. https://doi.org/10.5194/hess-15-2259-2011

McMillan, H., Krueger, T., & Freer, J. (2012). Benchmarking observational uncertainties for hydrology: Rainfall, river discharge and water quality. *Hydrological Processes*, *26*(26), 4078–4111. https://doi.org/10.1002/hyp.9384

Moore, R., Jones, D., Cox, D., & Isham, V. (2000). Design of the HYREX raingauge network. *Hydrology and Earth System Sciences*, *4*(4), 523–530. https://doi.org/10.5194/hess-4-521-2000

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*(1/2), 17–23. https://doi.org/10.2307/2332142

Nicótina, L., Alessi Celegon, E., Rinaldo, A., & Marani, M. (2008). On the impact of rainfall patterns on the hydrologic response. *Water Resources Research*, *44*(12). https://doi.org/10.1029/2007WR006654

Obled, C., Wendling, J., & Beven, K. J. (1994). The sensitivity of hydrological models to spatial rainfall patterns: an evaluation using observed data. *Journal of Hydrology*, *159*(1-4), 305–333. https://doi.org/10.1016/0022-1694(94)90263-1

Pedersen, L., Jensen, N. E., Christensen, L. E., & Madsen, H. (2010). Quantification of the spatial variability of rainfall based on a dense network of rain gauges. *Atmospheric Research*, *95*(4), 441–454. https://doi.org/10.1016/j.atmosres.2009.11.007

Segond, M. L., Wheater, H. S., & Onof, C. (2007). The significance of spatial rainfall representation for flood runoff estimation: A numerical evaluation based on the Lee catchment, UK. *Journal of Hydrology*, *347*(1-2), 116–131. https://doi.org/10.1016/j.jhydrol.2007.09.040

Shah, S. M. S., O'Connell, P. E., & Hosking, J. R. M. (1996a). Modelling the effects of spatial variability in rainfall on catchment response. 1. Formulation and calibration of a stochastic rainfall field model. *Journal of Hydrology*, *175*(1-4), 67–88. https://doi.org/10.1016/S0022-1694(96)80006-0

Shah, S. M. S., O'Connell, P. E., & Hosking, J. R. M. (1996b). Modelling the effects of spatial variability in rainfall on catchment response. 2. Experiments with distributed and lumped models. *Journal of Hydrology*, *175*(1-4), 89–111. https://doi.org/10.1016/S0022-1694(96)80007-2

Singh, V. P. (1997). Effect of spatial and temporal variability in rainfall and watershed characteristics on stream flow hydrograph. *Hydrological Processes*, *11*(12), 1649–1669. https://doi.org/10.1002/(SICI)1099-1085(19971015)11:12<1649::AID-HYP495>3.0.CO;2-1

Skøien, J. O. (2003). Characteristic space scales and timescales in hydrology. *Water Resources Research*, *39*(10). https://doi.org/10.1029/2002WR001736

Smith, M. B., Koren, V. I., Zhang, Z., Reed, S. M., Pan, J. J., & Moreda, F. (2004). Runoff response to spatial variability in precipitation: An analysis of observed data. *Journal of Hydrology*, *298*(1-4), 267–286. https://doi.org/10.1016/j.jhydrol.2004.03.039

Stephens, E. M., Bates, P. D., Freer, J. E., & Mason, D. C. (2012). The impact of uncertainty in satellite data on the assessment of flood inundation models. *Journal of Hydrology*, *414*, 162–173. https://doi.org/10.1016/j.jhydrol.2011.10.040

Syed, K. H., Goodrich, D. C., Myers, D. E., & Sorooshian, S. (2003). Spatial characteristics of thunderstorm rainfall fields and their relation to runoff. *Journal of Hydrology*, *271*(1-4), 1–21. https://doi.org/10.1016/S0022-1694(02)00311-6

Tiefelsdorf, M. (1998). Some practical applications of Moran’s i's exact conditional distribution. *Papers in Regional Science*.

Wood, E. F., Lettenmaier, D. P., & Zartarian, V. G. (1992). A land-surface hydrology parameterization with subgrid variability for general circulation models. *Journal of Geophysical Research*, *97*(D3), 2717–2728. https://doi.org/10.1029/91JD01786

Wood, E. F., Sivapalan, M., Beven, K., & Band, L. (1988). Effects of spatial variablity and scale with implications to hydrologic modeling. *Journal of Hydrology*, *102*(1-4), 29–47. https://doi.org/10.1016/0022-1694(88)90090-X

Wood, S. J., Jones, D. A., & Moore, R. J. (2000). Accuracy of rainfall measurement for scales of hydrological interest. *Hydrology and Earth System Sciences*. https://doi.org/10.5194/hess-4-531-2000

Younger, P. M., Freer, J. E., & Beven, K. J. (2009). Detecting the effects of spatial variability of rainfall on hydrological modelling within an uncertainty analysis framework. *Hydrological Processes*, *23*(14), 1988–2003. https://doi.org/10.1002/hyp.7341

Zoccatelli, D., Borga, M., Viglione, a., Chirico, G. B., & Blöschl, G. (2011). Spatial moments of catchment rainfall: Rainfall spatial organisation, basin morphology, and flood response. *Hydrology and Earth System Sciences*, *15*(12), 3767–3783. https://doi.org/10.5194/hess-15-3767-2011