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Which catchment characteristics control the temporal dependence structure of daily river flows?

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Abstract:

Hydrological classification systems seek to provide information about the dominant processes in the catchment to enable information to be transferred between catchments. Currently, there is no widely agreed-upon system for classifying river catchments. This paper develops a novel approach to classifying catchments based on the temporal dependence structure of daily mean river flow time series, applied to 116 near-natural 'benchmark' catchments in the UK. The classification system is validated using 49 independent catchments. Temporal dependence in river flow data is driven by the flow pathways, connectivity and storage within the catchment and can thus be used to assess the influence catchment characteristics have on moderating the precipitation-to-flow relationship. Semi-variograms were computed for the 116 benchmark catchments to provide a robust and efficient way of characterising temporal dependence. Cluster analysis was performed on the semi-variograms, resulting in four distinct clusters. The influence of a wide range of catchment characteristics on the semi-variogram shape was investigated, including: elevation, land cover, physiographic characteristics, soil type and geology. Geology, depth to gleyed layer in soils, slope of the catchment and the percentage of arable land were significantly different between the clusters. These characteristics drive the temporal dependence structure by influencing the rate at which water moves through the catchment and/or the storage in the catchment. Quadratic discriminant analysis was used to show that a model with five catchment characteristics is able to predict the temporal dependence structure for un-gauged catchments. This method could form the basis for future regionalisation strategies, as a way of transferring information on the precipitation-to-flow relationship between gauged and un-gauged catchments. © 2014 The Authors. *Hydrological Processes* by published by John Wiley & Sons, Ltd.

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INTRODUCTION

Hydrology has yet to achieve a widely agreed-upon system which classifies catchments based on the movement and storage of water within the catchment (Wagener *et al.*, 2007; Ley *et al.*, 2011). Even though internal complexity will remain within each class as every catchment is unique (Beven, 2000), a broad classification process should be possible. This is based on the general assumption that some level of organisation and therefore predictability in catchment 'function' (i.e. the translation of catchment input into river flow) exists (Dooge, 1986; Bloschl *et al.*, 2013). A broad classification process should cluster together similar catchments, thus limiting the variability within classes and maximising the variability between them. The between-catchment similarities may be a result of natural self-organisation or the co-evolution of climate, soils, vegetation and topography (Sivapalan, 2006).

Classification is a means to identify the dominant processes and mechanisms operating in a given catchment type, as well as the most important controls on water fluxes and pathways (McDonnell and Woods, 2004). Identifying the dominant processes which transform precipitation into runoff will enhance understanding about the similarity or dissimilarity between catchments (Gottschalk, 1985). Being able to classify catchments has a range of benefits (Grigg, 1965, 1967):

1. *To give names to things* (enable grouping as seen in other disciplines).
2. *To permit transfer of information* (from gauged to un-gauged catchments as well as enabling comparison between studies in different catchments).
3. *To permit development of generalisations* (improve knowledge about the drivers behind the precipitation-to-flow relationship).

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As the impacts of a non-stationary climate are becoming of greater concern (Wagener *et al.*, 2010), Sawicz *et al.* (2011) added a fourth:

4. *To provide a first-order environmental change impact assessment* (identify the impacts from land management and climate change).

Hydrological science has developed descriptive classifications categorising catchments in terms of, e.g. land cover (forested, urban, arable, etc); climate (humid, arid, semi-arid, etc); flow pathways (fast, slow); storage (groundwater dominated, surface water catchments); etc (Wagener *et al.*, 2007). These groupings do not provide a comprehensive classification system as they do not enable understanding about the partitioning of water nor the importance of different water stores (McDonnell and Woods, 2004). A further drawback with the aforementioned groupings is that no information is provided about the impact of the interaction between different descriptors. Previous classification studies have either focused on physical catchment characteristics (e.g. Acreman and Sinclair (1986) and Burn and Boorman (1993)) or on indicators derived from specific aspects of the flow record (e.g. floods—Robson and Reed (1999); low flows and flow duration curves—Holmes *et al.* (2005); seasonally averaged flows—Laizé and Hannah (2010); long term average annual regimes and long term annual flow average—Bower *et al.* (2004)). Bower *et al.* (2004) differentiated between first and second-order controls (precipitation and catchment characteristics, respectively) on flow. Ali *et al.* (2012) and Ley *et al.* (2011) showed a lack of correlation between flow-derived indicators and catchment characteristics. The difference is likely to be caused by the catchment characteristics not adequately capturing the climatic effects (first-order control of flow).

Temporal dependence represents the similarity between the river flow on a given day and river flow on the preceding days. As temporal dependence is likely to be driven by catchment characteristics (Szolgayova *et al.*, 2013), classification based on the temporal dependence has some key advantages: (1) raw flow data can be used, rather than having to calculate indicators from discharge data (e.g. annual or seasonal averages, minimum or maximum flows). (2) The method can handle missing data. (3) The classification is based on catchment function (i.e. the degree to which catchment characteristics filter rainfall into runoff) and not a specific part of the flow regime. This confers significant benefits for advancing our understanding of the drivers behind the precipitation-to-flow relationship in a much more generalised way (benefit 3) rather than for a specific process (e.g. flooding or low flows).

Szolgayova *et al.* (2013) suggested that catchment properties can influence the temporal dependence of river flow. Such properties are likely to include those governing the predominant catchment second-order controls (i.e. catchment characteristics which modify the precipitation-to-flow relationship (Bower *et al.*, 2004). These will influence: partitioning between vertical and lateral pathways (e.g. interception, overland flow, infiltration and percolation); connectivity of the drainage network and hydraulic gradients (Buttle, 2006) and storage (e.g. soil moisture storage, lakes and storage in the saturated zone (Black, 1997)).

This paper develops a new catchment classification system based on the temporal dependence of river flow; an integration of water input, storage and flow pathways within a catchment. A hydrological classification method becomes more powerful if catchments can be classified without the use of river flow data; enabling un-gauged catchments to be classified and hence allowing data transfer between gauged and un-gauged catchments. Therefore, the second part of this paper will demonstrate how un-gauged catchments could be clustered into the same classification using their catchment characteristics thereby facilitating data transfer (benefit 2).

The methodology used in this paper is designed to capture differences in the precipitation to channel-flow relationship (benefit 3). This novel approach of assessing the temporal dependence in a catchment based on semi-variograms, created using daily river flow data, will be applied to a range of catchments throughout the UK. The term semi-variogram refers to the semi-variance calculated from the data without fitting model (also known as the experimental or empirical variogram) (Chandler and Scott, 2011).

DATA

Catchment selection

A sample of catchments was needed to represent the population of UK catchments in terms of spatial location and catchment characteristics. The choice of catchments selected was constrained: (1) to remove the influence of weather, the time series is averaged over a long time period. Therefore, only catchments with a record length of 30 years or more with less than 5% missing data were considered. (2) As controls from climate and land use change through time (Wagener *et al.*, 2007), a common time period (1970 to 2010) was used to enable comparisons between catchments. (3) Artificial influences on river flows (such as reservoirs or sewage discharges) could affect the dependence structure of the data series, so near-natural UK benchmark catchments, with only modest net impacts from artificial influences were chosen

(Bradford and Marsh, 2003). (4) Nested catchments with similar flow regimes were removed.

Any study using observed hydrometric data faces an inevitable degree of uncertainty due to limitations with the measurement techniques (McMillan *et al*., 2012). The amount of uncertainty will depend on the gauging station to a great degree. In this study, the impacts of data error were minimised insofar as possible through judicious selection of catchments. One of the criteria Bradford and Marsh (2003) used to develop the benchmark network was hydrometric performance, with the gauging stations in the network generally producing good quality data. Furthermore, the data used in this study has undergone validation by the National River Flow Archive (NRFA) as outlined in Dixon *et al*. (2013); Muchan and Dixon (2014) demonstrated that NRFA data is generally of high quality thanks to these quality control procedures.

The 116 catchments used in this paper provide good spatial coverage of the UK (Figure 1) and a wide variety of catchment types with varying characteristics (Table I). However, catchments in the South East are smaller, as artificial influences are more pervasive in this densely populated region. In addition, a further 49 catchments were selected for validation purposes (Figure 1). These were selected using the approach outlined above, except the requirement to be a benchmark catchment was removed; instead, they were screened for artificial influences using the metadata records from the NRFA. The hydrometric data were collected by the measuring authorities (Environment Agency in England, Natural Resources Wales in Wales, Scottish Environment Protection Agency in Scotland, and the Rivers Agency in Northern Ireland) and stored on the NRFA (http://www.ceh.ac.uk/data/nrfa/). Daily rainfall data for each catchment were also calculated from 1 km by 1 km gridded rainfall data using the method outlined in Keller *et al.* (2006).

Catchment characteristics

In order to investigate the drivers behind the different shapes of semi-variogram, 29 catchment characteristics were analysed, grouped into categories: elevation$_{(e)}$, land cover$_{(Lc)}$, physiographic and hydrological descriptors from the FEH$_{(FEH)}$ (Flood Estimation Handbook, the UK's principal methodology for flood estimation at ungauged sites; (Robson and Reed, 1999)), geology$_{(g)}$, storage$_{(St)}$ and soil classification$_{(s)}$ (Table I).

Five elevation characteristics were considered to assess how topography varies between the clusters, all derived from the Integrated Hydrological Digital Terrain Model (Morris and Flavin, 1990), as published in the UK Hydrometric Register (Marsh and Hannaford, 2008). Land cover was derived from the Land Cover Map 2000 (Fuller *et al.*, 2002), grouped into four categories from the 26 LCM2000 subclasses, to ensure the representation in the 116 catchments and preservation of the four major land covers. Nine characteristics from the FEH were included, incorporating the important characteristics of the catchment and excluding discharge features (e.g. return periods). Four different Hydrology of Soils Types (HOST) (Boorman *et al.,* 1995) soil types based on the depth to gleyed layer (reduced from 29 HOST classes) and seven different hydrologically important rock types calculated from the 1:625 000 scale digital hydrogeological map of the UK were identified. As with land cover these categories were defined to capture the main hydrological differences whilst being represented throughout the 116 catchments. In addition to the HOST soil classes, BFIHOST and BFI are included as indicators of catchment storage. Base flow index is not a catchment characteristic *per se* as it is calculated from the flow data. However, it is frequently used as an indication of storage and is included here to compliment the BFIHOST values, which are BFI values predicted from HOST classes.

METHOD

An overview of the methods used in this paper is provided here, before more detail is provided in the following sections. Firstly, the daily flow data are transformed to make them suitable for (semi-)variogram analysis. Second, a semi-variogram is created for each catchment. Third, the semi-variogram for all sites is categorised into groups using cluster analysis. Finally, the influence catchment characteristics have on the temporal dependence of each of these clusters is analysed in two ways: through box plots, to investigate the distribution of catchment characteristics for each cluster; and by using Quadratic Discriminant Analysis (QDA) to independently predict membership of the clusters using catchment characteristics rather than the semi-variogram.

River flow data transformation

To calculate a semi-variogram, the data should first be transformed into a normally distributed, deseasonalised time series (Skøien *et al*., 2003). Therefore, a number of transformation steps were implemented, each one using the data from the previous, starting with raw daily discharge data:

1. As some hydrological time series had periods of no data and all sites had a good analogue station, the time series were in-filled to improve the fit of the periodic function used for deseasonalisation (step 3). Infilling was carried out using the equipercentile linking method (Hughes and Smakhtin, 1996) where the flows from one gauging station are linked to another through percentile ranks. Harvey *et al.* (2012) showed that the equipercentile method outperforms other methods such as scaling factors for infilling mean daily river flow data.

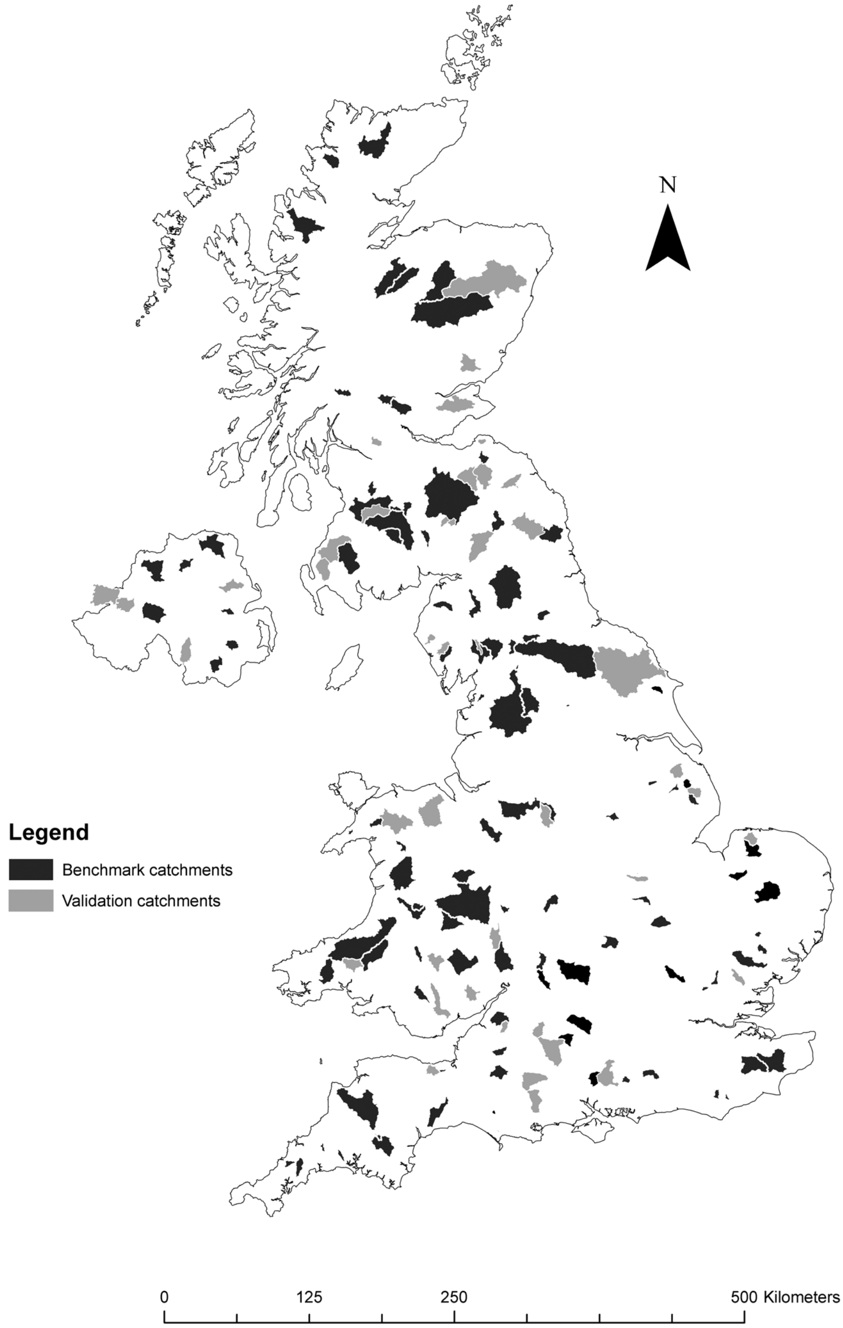

Figure 1. Location of the 116 benchmark (black) and 49 validation catchments (grey) used in this study

2. Logarithms were taken, to create a near normal distribution. Zero values were replaced by 0.001 $m^3 s^{-1}$.
3. Seasonality was removed (to avoid exaggerating the temporal dependence) using Fourier representation; a periodic function was fitted to the data using a sum of sine and cosine waves, at frequencies which are integer multiples of the annual cycle. For each catchment, the number of covariates was set to six to enable a good fit to the data (more covariates increases the flexibility of the function, enabling a better fit to the data). While it is acknowledged that using six covariates might over fit the model, this is deemed appropriate to model the seasonal effects (and not to extrapolate). Akaike's Information Criterion, a relative goodness of fit measure, was used to select the best parameters for the periodic function. The effect of seasonality was removed by deducting the magnitude and dividing by standard deviation caused by seasonality (both calculated from the periodic function) for each day in a year. Although infilling the data enhanced the ability to fit a

Table I. Summary of the catchment characteristics investigated

Catchment characteristic	Abbreviation	Units	Description	Min	Max	Mean	Median
Altitude$_{(e)}$	N/A	m	Altitude of the gauging station to the nearest datum[a] (derived using IHDTM[b])	3	356	60	35
Elevation 10$_{(e)}$	Elv-10	m	Height above datum[a] below which 10% of the catchment lies (derived using IHDTM[b]).	9	408	114	92
Elevation 50$_{(e)}$	Elv-50	m	As above but for 50%	20	604	198	164
Elevation 90$_{(e)}$	Elv-90	m	As above but for 90%	52	889	316	279
Elevation max$_{(e)}$	Elv-M	m	As above but for the maximum value	68	1309	484	470
Woodland$_{(Lc)}$	Wood	%	Amount of the catchment covered by woodland Calculated from CEH land cover maps 2000. This is an aggregation of: broad-leaved/mixed woodland and coniferous woodland	0	49	12	10
Arable land$_{(Lc)}$	Arable	%	As above but using an aggregation of: arable cereals, arable horticulture and arable non-rotational	0	86	23	12
Grassland$_{(Lc)}$	Grass	%	As above but using an aggregation of: improved grassland, neutral grassland, set-aside grassland, bracken, calcareous grassland, acid grassland and fen, marsh and swamp	6	96	47	45
Urban$_{(Lc)}$	N/A	%	As above but using an aggregation of: suburban, urban and inland bare ground	0	40	2	1
Area$_{(FEH)}$	N/A	Km^2	Area of the catchment calculated using the CEH's Digital Terrain Model (IHDTM[b])	3.1	1500.0	227.6	108.5
Drainage path slope$_{(FEH)}$	DPS	m km^{-1}	Mean drainage path slope calculated from the mean of all inter-nodal slopes (derived using IHDTM[b])	12	309	100	91
PROPWET$_{(FEH)}$	P-WET	%	Proportion of the time soils are wet (defined as a soil moisture deficit of less than 6 mm)	23	83	48	46
Flood plain extent$_{(FEH)}$	FPext	Ratio	Proportion of the floodplain which would be covered by the 1 in a 100-year flood event	0.010	0.226	0.064	0.052
Longest drainage path$_{(FEH)}$	LDP	Km	Longest drainage path from a catchment node to the defined outlet	4.01	116.09	33.49	27.76
Drainage path length$_{(FEH)}$	DPL	Km	Mean drainage path length from the distances between all nodes and the catchment outlet	2.04	60.39	17.78	14.96
FARL$_{(FEH)}$	N/A	Ratio	Flood attenuation attributed to reservoirs and lakes	0.67	1.00	0.98	0.99
BFIHOST$_{(St)}$	BFI-H	ratio	Area-weighted base flow index derived using the Hydrology Of Soil Types (HOST) classification	0.24	0.95	0.50	0.48
BFI$_{(St)}$	N/A	ratio	Calculated from mean daily flow data using the method outlined in Gustard *et al.* (1992)	0.16	0.96	0.50	0.48
HOST no gleying$_{(s)}$	S-no	%	Percentage of the catchment made up of classes: 1 to 8, 16 and 17	0	98	34	29
HOST gleyed between 40 and 100 cm$_{(s)}$	S-deep	%	Percentage of the catchment made up of classes: 13 and 18 to 23	0	99	19	13
HOST gleyed within 40 cm $_{(s)}$	S-shal	%	Percentage of the catchment made up of classes: 9, 10, 14, 24 and 25	0	93	22	15
HOST peat$_{(s)}$	peat	%	Percentage of the catchment made up of classes: 11, 12, 15 and 26 to 29	0	90	24	11
Fracture high$_{(g)}$	F-High	%	Percentage of the catchment underlain by highly productive fractured rocks	0	100	13	0
Fracture medium$_{(g)}$	F-Med	%	Percentage of the catchment underlain by moderately productive fractured rocks	0	100	23	0

(Continues)

Table I. (Continued)

Catchment characteristic	Abbreviation	Units	Description	Min	Max	Mean	Median
Fracture low$_{(g)}$	F-Low	%	Percentage of the catchment underlain by low productivity fractured rocks	0	100	45	31
Intergranular high$_{(g)}$	I-High	%	Percentage of the catchment underlain by highly productive intergranular rocks	0	42	2	0
Intergranular medium$_{(g)}$	I-Med	%	Percentage of the catchment underlain by moderately productive intergranular rocks	0	71	5	0
Intergranular low$_{(g)}$	I-Low	%	Percentage of the catchment underlain by low productivity intergranular rocks	0	11	0	0
No groundwater $_{(g)}$	No-G	%	Percentage of the catchment underlain by rocks classed as having essentially no groundwater	0	100	11	0

[a] Datum refers to Ordnance Datum or, in Northern Ireland, Malin Head Datum.
[b] IHDTM refers to the Integrated Hydrological Digital Terrain Model (Morris and Flavin, 1990).

periodic function to the data and improved the removal of seasonality, the in-filled data were considered less accurate than measured data, so were removed after the seasonality had been taken out.

4. The flow data for each catchment were standardised by deducting the mean and dividing by the standard deviation of the time series; standardising enables comparison of catchments with different magnitudes of flow.

Semi-variograms

The temporal dependence structure can be represented by a one dimensional temporally averaged (semi-) variogram (see Chandler and Scott (2011) or Webster and Oliver (2007) for detailed background about the (semi-)variogram). A (semi-)variogram has several components (displayed in Figure 2): throughout this paper the 'sill' is defined as the (semi-)variance where the gradient of the (semi-)variogram is zero. A zero gradient indicates the limit of temporal dependence and is an indicator for the total amount of variance in the time series. The 'range' is the time it takes to reach the zero gradient. If the lag time between water landing in the catchment and reaching the gauging station is small and the catchment has little storage, then the resulting semi-variogram would be expected to have a short range.

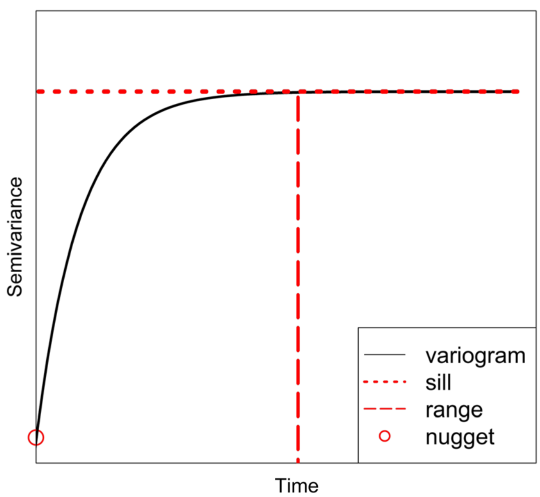

Figure 2. Range and sill for a theoretical (semi-)variogram

For second-order stationary processes, the (semi-) variogram and autocorrelation graph are symmetrical. However, (semi-)variograms are defined for a wider class of processes and therefore enable temporal dependence to be analysed even if there is missing data or a trend. The nugget, which is the y intercept on the modelled semi-variogram, represents a combination of measurement error and sub daily variability. The partial-sill is the range minus the nugget and shows the temporally dependent component. A semi-variogram was calculated for each catchment using the average squared difference between all pairs of values which are separated by the corresponding time lag (Equation 1):

$$\hat{v}(h) = \frac{1}{2(\mathbf{N}-\mathbf{h})} \sum_{i=1}^{\mathbf{N}-\mathbf{h}} \left[\left(Y(t_{i+h}) - Y(t_i) \right)^2 \right] \qquad (1)$$

where $\mathbf{h}$ is the lag time, $Y(t_i)$ is the value of the transformed data at time t_i and $(\mathbf{N}-\mathbf{h})$ is the number of pairs with time lag $\mathbf{h}$. A maximum lag distance over which to calculate the semi-variogram was defined to enable the clustering to capture differences in the temporal dependence structure.

In order to quantify the differences between the mean values in each cluster, variogram models were fitted to the average semi-variogram for each cluster (see below for details of clustering). These were fitted using the variofit function from the geoR package in the R statistical software. Ten different model shapes (Matern, exponential, gaussian, spherical, circular, cubic, wave, powered exponential, Cauchy and gneiting) were fitted to the semi-variogram using the Cressie method (Cressie, 1985). The Matern shape produced the best fit for each cluster average.

Clustering

Catchments were clustered using a Euclidean squared distance matrix, calculated using the whole of the semi-variogram to maximise the information going into the clustering algorithm (Wagener *et al.*, 2007). There are many clustering methods available, with none universally outperforming the others (Hannah *et al.*, 2005). Hierarchical clustering was undertaken using seven methods (Ward, single, complete, average, McQuitty, median and centroid), resulting in dendrograms, agglomeration schedules and maps. These were used to assess the spread of catchments across the clusters (i.e. how many catchments there are within each cluster) and physical explanation of clusters. Ward's method gave the best results for clustering based on the semi-variogram shape, with relatively well-defined evenly sized clusters. Ward's method has been found to be robust for clustering catchments in terms of hydrological response in a wide range of other studies (e.g. Laizé and Hannah (2010); Köplin *et al.* (2012) and Bower *et al.* (2004)). Hierarchical clustering based on Ward's minimum variance method was applied to the distance matrix. The algorithm starts with n clusters (i.e. the number of catchments), at each step the joining of every cluster pair is considered, and the two clusters which result in the minimum increase in the sum of squared differences are combined. The final number of clusters is subjective, based on assessing the structure of the dendrogram and changes in gradient of the agglomeration.

Quadratic discriminant analysis

Discriminant analysis was used to determine which catchment characteristics can be used to attribute a catchment to a cluster. The analysis identifies whether the mean of the catchment characteristic differs between clusters. Once the variables (characteristics) have been selected, discriminant analysis creates an equation with the aim of minimising the possibility of misclassifying catchments. The equation will be in the form:

$$D = v_1X_1 + v_2X_2 + v_3X_3 + \ldots + v_nX_n + \mathrm{C} \quad (2)$$

where D is the discriminant function; v is the coefficient for the variable; X is the transformed value for the variable; C is a constant and n is the number of variables. The v*'s* are selected to maximise the difference between clusters. There is one less discriminant equation than the number of clusters. Each equation explains as much of the between-cluster variability as possible with the first equation explaining the most. Quadratic discriminant analysis was used (as opposed to linear discriminant analysis) because it allows a different covariance matrix for each cluster, increasing the model's flexibility. This is deemed acceptable due to the number of catchments being investigated.

To meet the assumptions associated with discriminant analysis, the catchment characteristics were transformed to be normally distributed. The Shapiro–Wilks value was used to select the best transformation.

To avoid making prior assumptions about the characteristics which best discriminated between the different clusters, a backwards stepwise variable selection was used. A matrix containing total variance and covariance and a matrix containing pooled within-group variance and covariance were compared using a multivariate F test. This indicates the extent to which a variable makes a unique contribution to the prediction of cluster membership. The F value was used to select the variables to be removed at each step. Further to this, to avoid redundant variables, characteristics which were highly correlated (>0.8 or ≤ 0.8 Spearman's rank) were removed.

Finally, the 49 independent catchments were used in a separate 'validation' analysis to evaluate the discriminant expressions fitted to the 116 original catchments. In order to determine whether the validation catchments were successfully clustered from their catchment characteristics, the validation catchments were fitted into the clusters derived from the 116 benchmark catchments. The validation catchments were placed into the cluster for which the semi-variogram was closest to the mean semi-variogram of the cluster.

RESULTS

Clustering

Four clusters were selected because analysis of the agglomeration showed that the benefit of increasing the number of clusters to more than four was small. Analysis of the semi-variograms showed that 87% (101 catchments) had a range of ~90 days or less, and the maximum lag was set to 90 days to maximise the difference of the catchments with semi-variogram ranges of less than 90 days. It is acknowledged that differences between the remaining 13% (15 catchments) which have a range much greater than 90 days are unlikely to be identified during the clustering process.

Distinction between clusters

The clustering analysis (Figures 3 and 4) gave 32 catchments in cluster 1, 34 catchments in cluster 2, 35 catchments in cluster 3 and 15 catchments in cluster 4. There is a spatial difference between clusters 1 and 2 which are predominantly in the north and west and clusters 3 and 4 which are predominantly in the Midlands and south east.

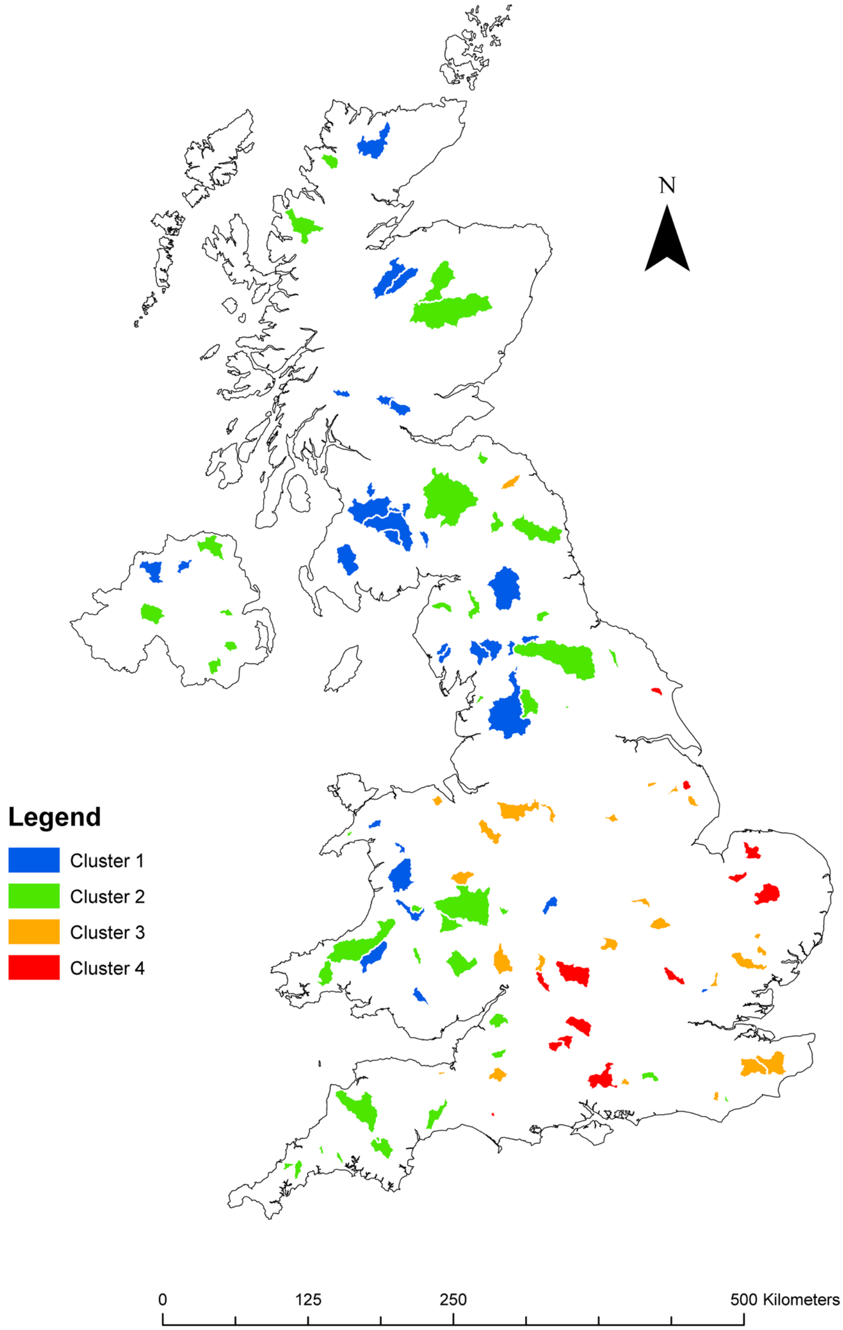

Figure 3. Location of the catchments in the four clusters

The difference in the temporal dependence structure between the clusters is illustrated in Figure 4 and Table II, with increases in range, and decreases in the sill and nugget from clusters 1 to 4. An increasing range indicates less short-term (less than 90 days) variability in the daily mean river flow, while a decreasing sill is caused by less temporally autocorrelated variability throughout the 30 year record. Figure 4 also shows that the clusters are reasonably well defined; there is an overlap between all four clusters for the short time lags due to similarity in the temporal dependence of the first few days. At longer lags (after ~30 days), there is only an overlap between clusters 1 and 2 due to the different shapes of the semi-variograms and no overlap at the 95% confidence interval.

In order to investigate how much rainfall influenced the temporal dependence of river flow, the same method of temporal dependence analysis was applied to catchment averaged daily precipitation from 1980 to 2008 for all catchments. Results showed no significant difference (at the 95% confidence interval) in the temporal dependence

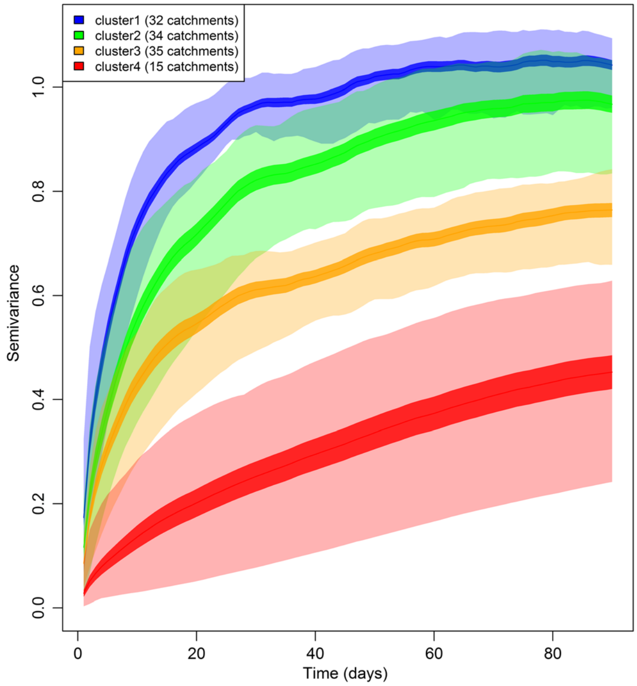

Figure 4. Semi-variograms from daily river flow for the four identified clusters with the 95% confidence intervals (dark shaded area) and the upper and lower bounds of each cluster (light shaded area)

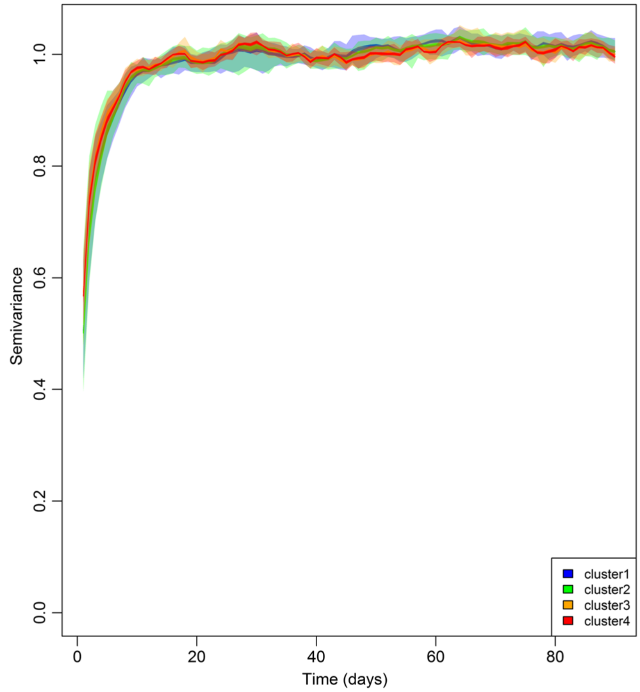

Figure 5. Semi-variograms from daily precipitation data for the four identified clusters with the mean of each cluster (line) and the 95% confidence intervals (shaded area)

Table II. Characteristics of the variogram models fitted to the mean of each cluster

Cluster number	Nugget	Partial sill	Range (days)
1	0.0186	0.67	29
2	0.0099	0.54	40
3	0.0088	0.48	45
4	0.0075	0.32	172

of rainfall between catchments in different clusters (Figure 5). Compared with discharge, the temporal dependence is much shorter in rainfall, only lasting around 10 days.

Catchment characteristics differentiating between the clusters

Initially, box plots were used to investigate the possible catchment characteristics driving the differences between the four identified clusters. All the characteristics in Table I are shown except for the percentage of urban land cover, FARL and elevation 90 which were removed because the majority of the catchments had little or no urban area or FARL, and elevation 90 was almost identical to elevation max. The characteristics that differ most between all four clusters are shown in Figure 6. Figure 7 identifies characteristics which distinguish between two or more clusters, whilst Figure 8 shows characteristics for which the median does not change between clusters. BFIHOST represents the distribution of BFI between clusters (Figure 6) agreeing with Marechal and Holman (2005) who showed that BFIHOST is a robust way to calculate BFI, low flow statistics and the percentage of runoff. As BFI is not a catchment characteristic (being calculated from flow data) it is removed from subsequent analysis.

Figure 9 shows the correlation between all the characteristics which differentiate between clusters (Figures 6 and 7). The physical catchment characteristics in Table I are not independent from each other, as shown in Figure 9 by scatter plots and (Spearman's rank) correlation. The correlation between different catchment characteristics highlights the influence elevation (elevation max and elevation 90) has on the value of PROPWET, DPSBAR, percentage of peat soils and percentage of arable land, all of which have correlations greater than |0.7|. Characteristics describing the pathway and storage are also highly (>0.7) correlated (e.g. BFI HOST and the percentage of highly productive fractured rock).

Quadratic discriminant analysis

Due to the statistical distribution of: peat soils, PROPWET and all the rock descriptors (Figure 9), a transformation to a normal distribution was not possible, and these were excluded from the discriminant analysis. In addition, elevation characteristics were highly corre-

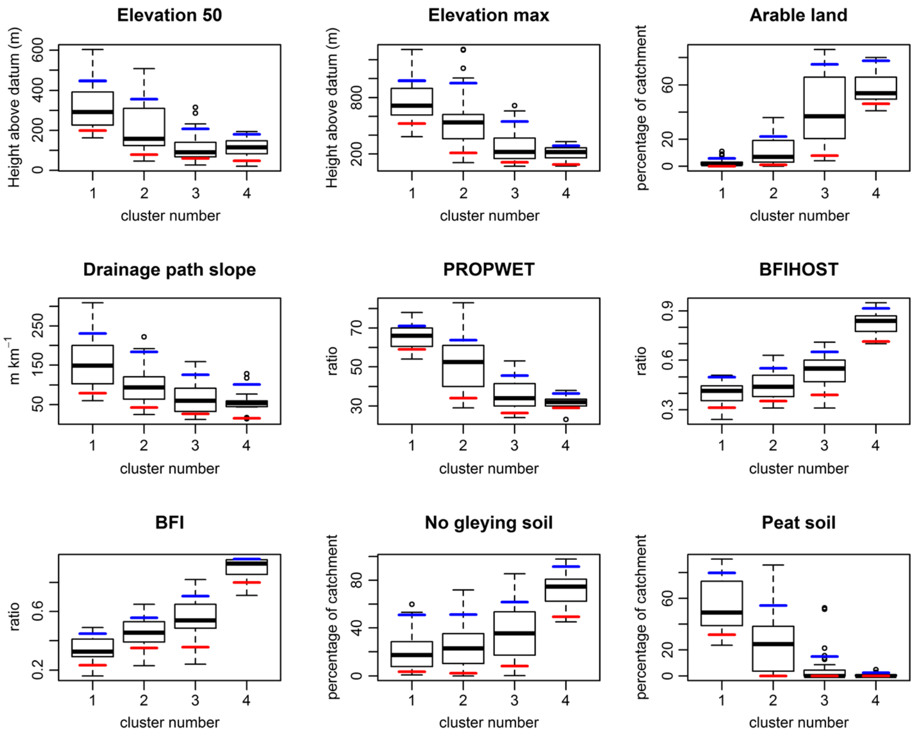

Figure 6. Box plots of characteristics which differ between all four clusters. Thick black line is the median value. Box shows the inter-quartile range. Black whiskers represent 1.5 times the inter-quartile range. Blue and red lines show the upper and lower 90% confidence intervals, respectively, and the circles show outliers

lated (>0.8 or ≤0.8 Spearman's rank; Spearman, 1904) with one another and drainage path slope. Highly correlated variables invalidate the assumption of independence. Therefore, elevation 10, elevation 50, elevation 90 and elevation max (elevation characteristics with the lowest F values) were also removed from the discriminant analysis. Further to this, BFIHOST and no gleying soils were also highly correlated; the percentage of no gleying soils correctly clustered slightly more catchments; therefore, BFIHOST was also omitted. The transformations applied to the characteristics included in the QDA are shown in Table III.

For each variable combination, a set of three equations (in the format of Equation 2) which maximise the difference between clusters were created. The first two equations were found to explain 85 to 88% and 7 to 10% of the between cluster variability respectively, with the information added significant at the 99.9% confidence interval. The third equation explained the remaining (2 to 5%), with a significance of between 94 and 99%. The values resulting from these equations were used to cluster the catchments based on the probability of the catchment being in each of the four clusters (Table IV).

The more catchment characteristics there are in the model, the higher the percentage of correctly classified benchmark catchments (89.7% with 12 characteristics and 54.3% with 1 characteristic). In addition, Table IV identifies that the percentage of arable land discriminates best between the clusters. A relatively accurate model can be made using only a few variables (arable land, depth to gleying in soils and slope).

VALIDATION

The 49 validation catchments were clustered based on the distance of their semi-variogram to the centre of the already generated clusters (Figure 4); this resulted in 14 from cluster 1, 12 from cluster 2, 14 from cluster 3 and 9 from cluster 4. To test the quadratic discriminant models, these were then clustered using their catchment characteristics and the same equations generated for the 116 catchments; the percentage clustered correctly is shown in Table IV.

The validation of the discriminant analysis on the 49 independent catchments (Table IV) shows that models with fewer explanatory variables are more robust. Although a model using 12 catchment characteristics correctly classified 104 out of 116 benchmark catchments, the percentage of correctly clustered validation catchments (Table IV) highlighted that models with a lot of parameters were over-fitted to the data. Based on the percentage of catchments correctly classified in both the benchmark and validation catchments, Model 5 (Table V) is deemed to have the best performance as both the benchmark and validation catchments are clustered well (>70% are correctly clustered).

The values are calculated for each catchment by multiplying the adjusted values for the catchment characteristics (i.e. the values obtained after transforming the data as outlined in Table III which correspond to the X's in Equation 2) by the coefficient (i.e. the v's in Equation 2), e.g. for model 5 (Equation 1):

$$
\begin{aligned}
D = \; & ((\text{arable}(X_1) * 1.12(V_1)) \\
& + (\text{no gley}(X_2) * 0.25(V_2)) \\
& + (\text{gleyed 40-100}(X_3) * \text{-}0.44(V_3)) \\
& + (\text{gleyed} < 40\ (X_4) * \text{-}0.37\ (V_4) \\
& + (\text{DPS}\ (X_5) * \text{-}0.60(V_5))
\end{aligned}
$$

Although Model 5 does not classify all the catchments correctly, all but one of the misclassified catchments is predicted to be in an adjacent cluster (Table VI). If a catchment is predicted to be in a higher numbered cluster than the actual cluster, the catchment characteristics indicate larger storage and/or slower response than is indicated by the discharge. Catchments predicted to be less than their actual class demonstrate the opposite.

Results (Table IV) highlight that arable land is the catchment characteristic which best discriminates between the temporal dependence-based clusters for the 116 benchmark catchments. However, unlike the rest of the characteristics, land cover is dynamic and will change through time, thereby potentially leading to a change in the cluster allocation. In order to investigate this issue, the discriminant analysis was redone without land cover characteristics (Table VII), which showed a deterioration of less than 2% for the model with 5 variables.

DISCUSSION

This paper identified four distinct clusters of catchment based on the temporal dependence structure of 116 catchments throughout the UK. The mapping of these clusters (Figure 3) highlighted a spatial pattern between clusters 1 and 2 against clusters 3 and 4. This spatial pattern is indicative of a broad NW–SE gradient in several inter-related variables in the UK (e.g. precipitation, temperature, elevation, soil type, land use and to a certain extent rock type) as found in previous clustering (Bower *et al.*, 2004). The temporal dependence of rainfall (Figure 5) showed no difference between the clusters, indicating that precipitation is not influencing the river flow′s temporal dependence structure. The homogeneity of the rainfall dependence structure is caused by the high temporal variability (Chang *et al.*, 1984) and lack of

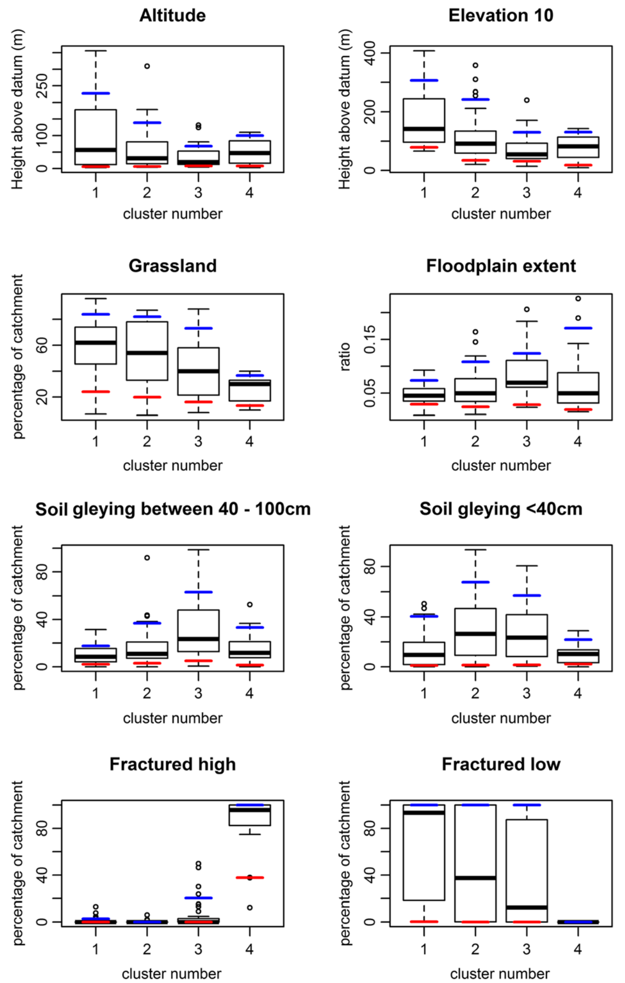

Figure 7. Box plots of characteristics which differ between two or three clusters, as in Figure 6

precipitation attenuation features (i.e. characteristics which influence lag time).

The characteristics which differentiated best between the clusters (benefit 3) were those that drive (or are highly correlated with characteristics which drive) the precipitation-to-flow relationship, by influencing either the pathway from precipitation to discharge and/or the amount of storage in a catchment (Ali *et al.*, 2012). Values describing the highest parts of the catchment (i.e. elevation 50 and above) have bigger variations between the clusters than lowland elevation values (Figure 7). Topography controls the strength of the forces acting on surface and groundwater flows as well as influencing the evolution of soils and vegetation (Bloschl *et al.*, 2013) which in turn alter the macropores in the soil, hence the travel time of the water through the catchment. This is seen with the higher elevations being correlated with drainage path slope, PROPWET and the percentage of peat soils (Figure 9) which all influence infiltration and hence lag time. PROPWET and peat soils provide information about how

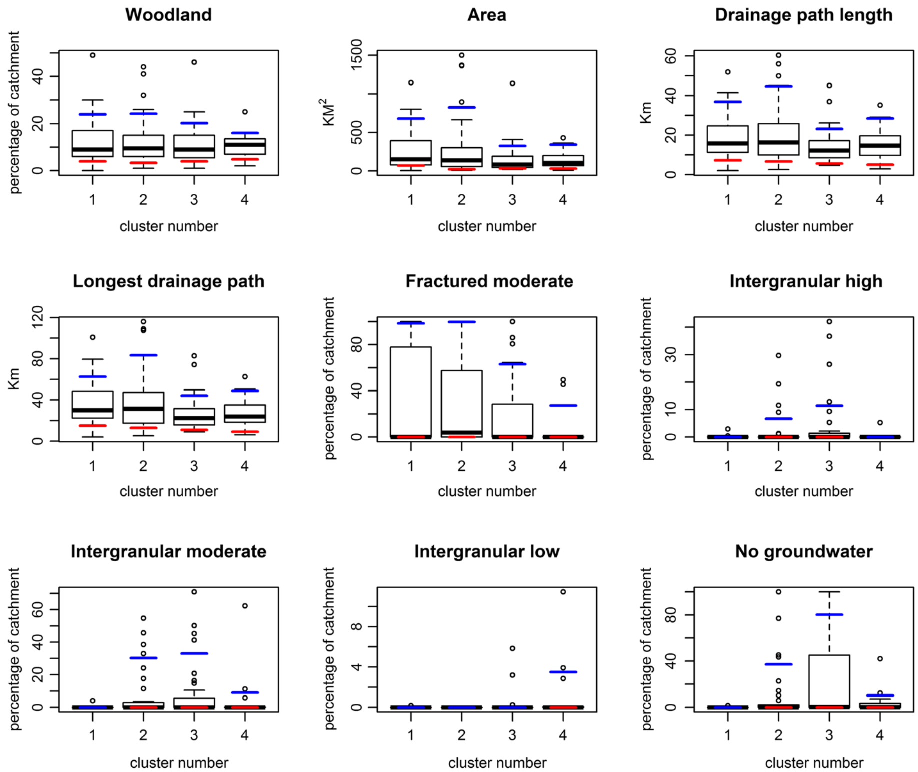

Figure 8. Box plots of characteristics which do not differ between clusters, as in Figure 6

waterlogged the soil is and hence drive the partitioning of water between surface and subsurface flow paths as well as the depth to which water can percolate before horizontal flow occurs. High elevation and low infiltration will result in water travelling via a fast pathway where less attenuation of the precipitation will occur; hence, the variability in the river flow will be greater (higher maximum semi-variance) and the range shorter (e.g. cluster 1 in Figure 4 and Table II). This is consistent with Ley *et al.* (2011) who highlighted a relationship between flow characteristics and the steepness and infiltration capacity of the catchment. Laizé and Hannah (2010) also identified that upland catchments were more impermeable and thus had a stronger relationship with the regional climate drivers than lowland permeable catchments.

BFIHOST and the percentage of no gleying soils are highly correlated (≥0.79, Figure 9) and are an indication of infiltration and storage. No gleying soils do not become waterlogged, and hence water can percolate through the soil, and BFIHOST is an indication of storage and is correlated (>0.7) with highly productive fractured rock. Sawicz *et al.* (2011) also showed that the precipitation-to-discharge relationship is influenced by soil characteristics. High infiltration and storage (exhibited in cluster 4) result in semi-variograms with a long range due to the attenuation resulting from the slow transformation from precipitation to discharge.

Figure 6 shows that BFIHOST differentiates cluster 4 from the other clusters. However, there is considerable overlap between clusters 1 to 3. It appears that BFIHOST does not adequately capture the differences between catchments with fast precipitation-to-flow relationships (Dunn and Lilly, 2001) as other characteristics (e.g. topography) have a large influence.

Cluster 4 has a median BFIHOST of around 0.84. With a median proportion of soils without gleying of 75%, cluster 4 is dominated by HOST class 1 (median proportion of 46% and an inter-quartile range (IQR) of between 34% and 67%) and HOST class 18 (median of 7% and IQR of 1%–18%). HOST class 1 are free draining soils which overlay chalk aquifers (Figure 6), whilst HOST class 18 is characterised by soils with a high soil water storage capacity but which are developed in low permeability superficial deposits.

In contrast, Cluster 1 has a median BFIHOST of 0.42 and is characterised by a high proportion of peat soils (median percentage of 50%) and only 16% of soils without gleying. The soils are dominated by HOST classes 15 (median of 14% with an IQR of 6%–30%) and 29 (median of 18%, IQR of 10%–25%) with large proportions of 17 (median of 6%, and IQR of 1%–18%), 24 (median of 7%, IQR of 1%–16%) and 26 (median of 6%, IQR of 1%–12%). HOST classes 15, 26 and 29 are peat soils. HOST classes 17 and 24 have a range of

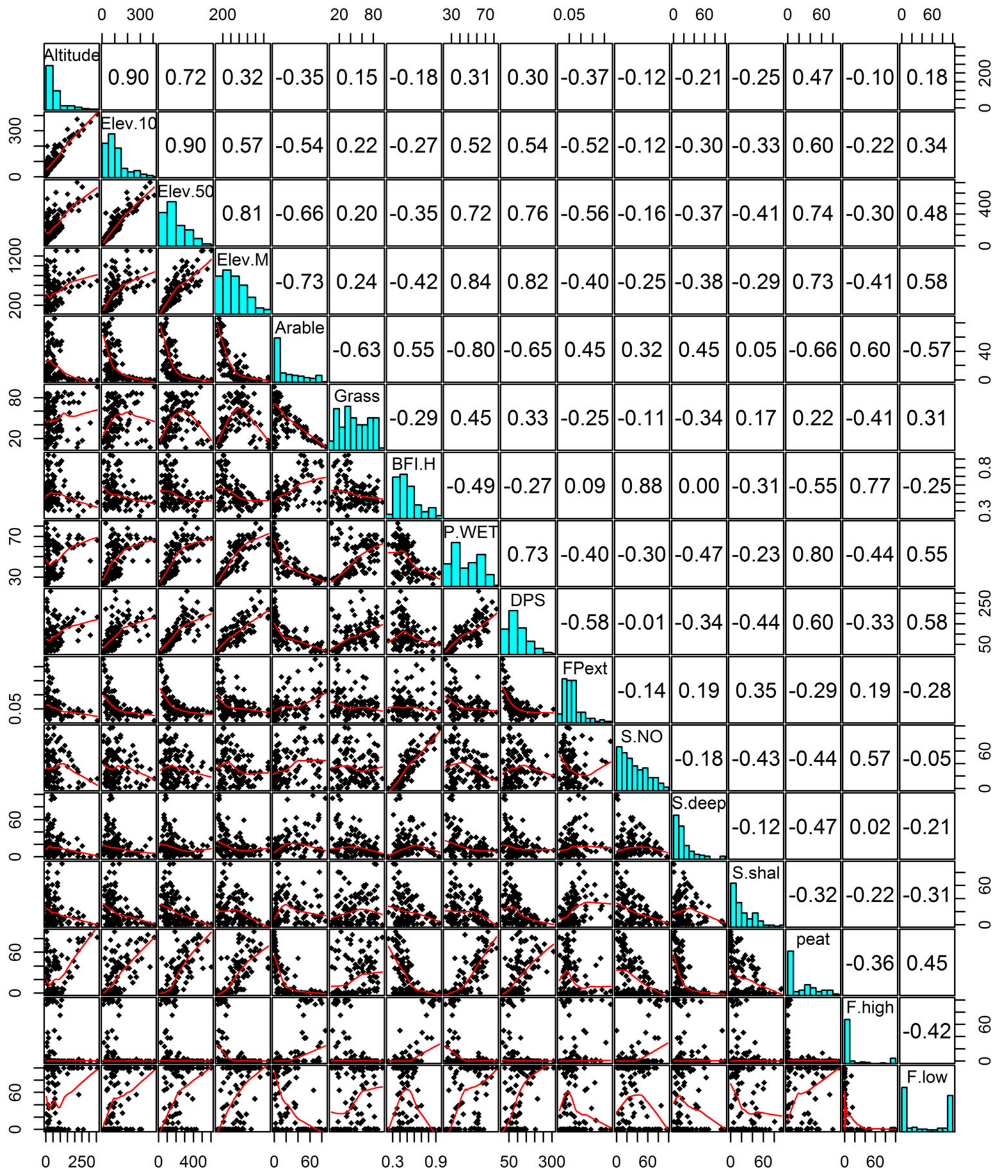

Figure 9. Correlations between the different catchment characteristics shown as scatter plots with locally weighted smoothed red line and histograms showing the distribution of the catchment characteristics. Correlation values are calculated using Spearman's rank ranging from negative one to positive one

permeability but overlay superficial or solid geological deposits with no significant groundwater.

Clusters 2 and 3, with their intermediate BFIHOST, differentiate on the seasonal duration of soil waterlogging, with Cluster 2 having lower proportions of soils in HOST classes with no gleying or gleying 40–100 cm; and higher proportions of peat soils (HOST classes 15, 26, 29) and soils with gleying at <40 cm. The seasonally waterlogged soils of HOST class 24 are the most common class in both Clusters 2 and 3 with median proportions of 22% and 8% and IQRs of 6–34% and 2–28%, respectively.

The final characteristic in Figure 6 is the percentage of arable land. Although Ragab and Cooper (1993) show that arable land has a significantly lower hydraulic conductivity value than grassland, the difference is unlikely to be seen at catchment scale. It is likely that the differences in the percentage of arable land between the clusters are caused by the negative correlation (<-0.7) with high elevations, PROPWET and to a lesser extent peat soils which have a large affect on infiltration (Masicek *et al.*, 2012). This agrees with Yadav *et al.* (2007) who identified that land cover (woodland and grassland) characterises some of the river flow response, although the influence was secondary to climate and other catchment characteristics. Grassland does not differentiate between the clusters as well as arable land, likely to be because of the lower correlation with characteristics which drive changes in temporal dependence.

Table III. Transformations applied to each catchment characteristic in order to create a normal distribution

Characteristic	Transformation
Elev 10	$\sqrt[5]{x}$
Woodland	$\sqrt[3]{x}$
Arable land	$\sqrt[3]{x}$
Grassland	$\sqrt[3]{x}$
Area	$\ln(x)$
DPS	$\sqrt[3]{x}$
FPext	$\ln(x)$
LDP	$\ln(x)$
DPL	$\sqrt[5]{x}$
No gleying soils	$\sqrt[2]{x}$
Gleying 40–100 cm	$\sqrt[3]{x}$
Gleying <40 cm	$\sqrt[3]{x}$

The distribution of high and low productivity fractured rocks between the clusters (Figure 7) shows that the majority of catchments in cluster 4 have a larger percentage of highly productive fractured rock (predominantly Chalk); river flow in catchments in cluster 4 thus has a greater contribution from groundwater than the other three clusters, which will have the effect of moderating higher frequency variability in precipitation and is consistent with the relatively large range and small semi-variance exhibited in catchments in cluster 4 (Figure 4 and Table II). The converse is seen in the box plot for catchments underlain by low productivity fractured rock where cluster 1 has a larger median value. For catchments in this cluster, there will be negligible groundwater to river flow, and river flows will be characterised by much shorter temporal dependence (Figure 4 and Table II). These observations are consistent with the findings of Bloomfield and Marchant (2013) who showed that differences in temporal dependence in groundwater are correlated with hydraulic diffusivity (the product of transmissivity and storage). The similarity between the box plots for BFIHOST (Figure 9) and that for the highly productive fractured aquifer type is also consistent with the above conceptualisation of controls on

Table IV. Different discriminant models and the percentage of catchments which were correctly classified by using the catchment characteristics. Shaded cells show the catchment characteristics included in the model

Model number (number of variables)	**% classified correctly (benchmark)**	**% validated correctly**	Wood	DPL	Area	Grass	Elev-10	LDP	FPext	DPS	Gleyed less than 40cm	Gleyed between 40 and 100cm	No gleyed soil	Arable
12	**89.7**	**32.7**	■	■	■	■	■	■	■	■	■	■	■	■
11	**89.7**	**30.6**		■	■	■	■	■	■	■	■	■	■	■
10	**87.9**	**57.1**			■	■	■	■	■	■	■	■	■	■
9	**86.2**	**63.3**				■	■	■	■	■	■	■	■	■
8	**81.9**	**53.1**					■	■	■	■	■	■	■	■
7	**80.1**	**57.1**						■	■	■	■	■	■	■
6	**75.9**	**63.2**							■	■	■	■	■	■
5	**72.4**	**71.4**								■	■	■	■	■
4	**70.7**	**71.4**									■	■	■	■
3	**68.1**	**73.4**										■	■	■
2	**67.2**	**75.5**											■	■
1	**54.3**	**55.1**												■

Table V. Variables and associated coefficients used in Model 5 to classify the catchments based on their catchment characteristics

	Arable land	No gleying	Gleyed 40–100 cm	Gleyed <40	DPS
Model 5 (Equation 1)	1.12	0.25	−0.44	−0.37	−0.60
Model 5 (Equation 2)	0.09	−0.19	0.83	0.51	0.05
Model 5 (Equation 3)	−0.91	0.51	0.46	1.02	−0.29

Table VI. Confusion matrix showing benchmark and validation (in brackets) catchments in each cluster after clustering using the catchment characteristics in model 5

		Actual class			
		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Predicted class	Cluster 1	27 (11)	10 (2)	0 (0)	0 (0)
	Cluster 2	6 (3)	23 (6)	4 (3)	0 (0)
	Cluster 3	1 (0)	8 (6)	19 (10)	0 (0)
	Cluster 4	0 (0)	0 (0)	1 (1)	15 (9)
	% correctly clustered	79 (79)	55 (50)	76 (71)	100 (100)

Table VII. Discriminant models and the percentage of catchments which were correctly classified; shaded cells show the catchment characteristics which were included in the model

Model number (number of variables)	**% classified correctly**	**% validated correctly**	Area	DPL	Elev-10	LDP	FPext	Gleyed less than 40cm	Gleyed between 40 and 100cm	No gleyed soil	DPS
9	**79.3**	**20.6**	■	■	■	■	■	■	■	■	■
8	**80.1**	**20.6**		■	■	■	■	■	■	■	■
7	**78.4**	**55.1**			■	■	■	■	■	■	■
6	**76.7**	**55.1**				■	■	■	■	■	■
5	**70.7**	**69.4**					■	■	■	■	■
4	**69.8**	**69.4**						■	■	■	■
3	**66.4**	**63.2**							■	■	■
2	**66.4**	**67.3**								■	■
1	**38.7**	**40.8**									■

surface water flows and the results of Bloomfield *et al.* (2009) who demonstrated the correlation between aquifer type and BFI for 44 sub-catchments in the Thames, UK.

The intergranular aquifer types do not show the same variations between clusters as the fractured rocks (Figure 8). This could be caused by: (1) the catchments are mainly situated on fractured rock, hence do not adequately represent the impact of intergranular aquifer types. (2) The seven classes of rock used are too simplistic and do not capture the difference in sub-surface processes occurring in different catchments. (3) The velocity of the water through the consolidated intergranular aquifers is relatively low (Gehlin and Hellström, 2003) and not captured in the timescales being investigated for gauged flow in this paper. Area, longest drainage path and drainage path length showed no significant difference between the clusters due to the flow data being standardised. Woodland also does not distinguish between the clusters and is not correlated with any of the driving characteristics (Figure 6). Therefore, these characteristics are not expected to influence the shape of a semi-variogram (Figure 4).

The IQRs of all the catchment characteristics in Figure 6 overlap, suggesting that no single catchment characteristic fully describes the temporal dependence structure, which underlines the importance of a multivariate approach. As such, quadratic discriminant analysis was used to investigate how accurately the catchment characteristics could be used to cluster the catchments into the clusters derived from the semi-variograms. Assessing new (validation) catchments, based on the catchment characteristics provided an indication of how accurately these models could be applied to un-gauged catchments (benefit 2). Model 5 was deemed to be the best model and successfully clustered most (>70%) of the benchmark and validation catchments. All but one of the misclassified catchments were predicted to be in an adjacent cluster (Table VI); this could be caused by an overlap between the clusters (Figure 4).

As previously discussed arable land is not likely to be the driver behind the different dependence structures exhibited by the catchments. Arable land is highly correlated with high elevation (−0.73) and peat soils (−0.66) which drive PROPWET (−0.8 correlation with arable land) and is correlated with F-high (0.6) which indicates a large amount of storage in rocks. Therefore, arable land (in the UK) is characterising low, well-drained land (particularly separating clusters 1 and 2 from 3 and 4). The percentage of no gleying soil is the second best characteristic at differentiating between the clusters and is highly correlated (0.88) with BFIHOST indicating that it is representing the storage in the catchment, particularly separating cluster 4 from the rest. Other key catchment characteristics included soil type and slope which describe the residuals left after the percentage of arable land and the percentage of no gleying soils have been used to discriminate between the clusters and mainly help to discriminate between clusters 1 and 3.

Models which excluded land use characteristics were developed (as the percentage of arable land is not temporally stable). Except for models 4 and 5, there was a large decrease between the percentage of correctly clustered catchments for both the validation and benchmark data sets (Tables IV and VII). In the models, arable land was replaced with drainage path slope (the variable used in the discriminant analysis which is most correlated with arable land). However, drainage path slope is less correlated with BFIHOST than arable land, indicating that storage is not as well characterised.

CONCLUSION

This study has developed a novel technique to classify catchments into clusters based on the temporal dependence structure of daily flow data using semi-variograms. The clusters were investigated in the context of identifying the catchment characteristics which moderate the precipitation-to-flow relationship implicit in the semi-variogram structure. Semi-variograms have the advantage over other techniques for indexing dependence of being able to handle missing data and being calculated from raw data, rather than having to calculate indicators from the discharge data (e.g. annual or seasonal averages, minimum/maximum flows). Therefore, this technique could be applied to any set of catchments for which daily flow data are available, including sites with incomplete data coverage. The results show that clustering the catchments based on the semi-variogram is an effective way to obtain separate groups of catchments based on their catchment function and not a specific aspect of the flow regime; this method could provide a useful basis for future catchment typologies.

Four clusters best represented the range of temporal dependence structures found in the UK. Catchments with characteristics indicative of fast flow paths and low storage (i.e. upland catchments) resulted in semi-variograms with a large gradient, levelling off after a few weeks. In contrast, catchments with characteristics which enable water to infiltrate deep into the soil/rock have a small gradient and do not level off within 90 days (benefit 3, improving knowledge about drivers). The key catchment characteristics able to discriminate between catchments with different controls on the precipitation-to-flow relationship (pathways and storage) were found to be: percentage of arable land, depth to gleyed layer in soils, slope, PROPWET, BFI, percentage of highly productive fractured rock and elevation. It is likely that arable land is not a driver behind the different clusters *per se*, but a surrogate for a combination of other characteristics (elevation, PROPWET and peat soils) which drive infiltration and hence the precipitation-to-flow relationship.

This paper also demonstrated that using a combination of catchment characteristics enables un-gauged catchments to be classified into clusters; consequently, the shape of the (semi-) variogram can be estimated. The preferred model (Model 5) with five variables (arable land, depth to gleyed layer (×3) and drainage path slope) correctly clustered 70.7–72.4% and 69.4–71.4% of the benchmark and validation catchments, respectively, depending on whether land cover parameters were excluded. This study found the amount of arable land in a catchment to be a useful characteristic for distinguishing between the clusters. However, as arable land is not temporally stable, values from different time periods could provide different results.

This method is valuable for transferring information about the precipitation-to-flow relationship from gauged to un-gauged catchments (benefit 2). This could be expanded upon in future work to enable predictions of regime characteristics at un-gauged sites to be made. In addition, ongoing work by the authors will use this temporal dependence approach to assess the impact catchment characteristics have on moderating the non-stationary of hydrological regimes (benefit 4); catchment properties will likely have a major influence on the response of river flow regimes to climate variability (e.g. Laizé and Hannah (2010)) and future anthropogenic climate change (Prudhomme *et al.*, 2013).

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