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Title

Evaluating landscape metrics for characterising hydrological response to storm events in urbanised catchments

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Abstract

Hydrological response of an urban catchment to storm events is determined by a number of factors including the degree of urbanisation and distribution and connectivity of urbanised surfaces. Therefore the ability of spatially-averaged catchment descriptors to characterise storm response is limited. Landscape metrics, widely used in ecology to quantify landscape structure, are employed to quantify urban land-cover patterns across a rural-urban gradient of catchments and attribute hydrological response. Attribution of all response metrics response, except peak flow, is improved by combining lumped catchment descriptors with spatially-explicit landscape metrics. Those representing connectedness and shape of suburban and natural greenspace improve characterisation of percentage runoff and storm runoff. Connectivity and location of urban surfaces are more important than impervious area alone for attribution of timing, validating findings from distributed hydrological modelling studies. Findings suggest potential improvements in attribution of storm runoff in ungauged urban catchments by applying landscape metrics.

Keywords (3-6)

Hydrology, Urban, Flood, Hydrograph, Landscape metrics, catchment descriptors,

1 Introduction

The process of urbanisation involves hydrological and hydraulic changes to catchment rainfall-runoff relationships through the progressive loss of pervious surfaces and natural drainage pathways and their replacement with impervious surfaces and artificial drainage. Such changes decrease infiltration and localised soil storage, thereby increasing runoff volume (Yang & Zhang, 2011). Combined with more rapid conveyance of runoff as a result of artificial drainage (Burns et al., 2012) this results in a more flashy response with earlier flood peaks (Graf, 1977), reduced baseflow (Braud et al., 2013) overall increased peak flow (Ogden et al., 2011; Miller et al. 2014) and increased downstream fluvial flooding (Fletcher et al., 2013).

Catchment impervious area is widely recognised and used as an indicator for characterising the impacts of urbanisation on hydrology (Lee & Heaney, 2004; Dams et al., 2013). It is conceptually easy to understand (Lim, 2016) but simplifies the complex urban processes of hydrological response resulting from spatial elements of land cover distribution and connectivity (Shuster et al., 2005; Redfern et al., 2016). Empirical studies are generally constrained to characterising urbanisation with lumped catchment values such as total impervious area (Sillanpää and Koivusalo, 2015) or urban extent (Putro et al., 2016) and disregard spatial variability. Likewise, most statistical flood estimation methods rely on lumped catchment representations that simplify spatial properties into a catchment wide approximation of that system (e.g. Flood Estimation Handbook: IH, 1999; Kjeldsen, 2010). Yet high-resolution monitoring technologies and distributed hydrological models have facilitated research beyond the effects of catchment imperviousness alone, revealing the importance of considering both the connectivity of impervious areas (Roy & Shuster, 2009; Ebrahimian et al., 2016) and the spatial distribution of these surfaces (Gironás et al. 2009; Zhou et al., 2014; Zhang & Shuster, 2014; Du et al., 2015). Such methods certainly benefit from using spatial analysis methods to characterise land cover distribution in order to estimate rainfall-response characteristics (L'homme et al. 2004; Rodriguez et al. 2005; Gironás et al. 2008). Rodriguez et al. (2003) note morphology-based methods potential for evaluating urbanisation impacts. Miller & Brewer (2018) have shown the potential for improved characterisation of storm runoff for attribution methods that rely on lumped catchment representations.

The role of spatial metrics for analysing and modelling urban land use change has long been an area of active research (Herold et al., 2005). Landscape metrics were developed as a means to characterise the composition and spatial configuration of patches of land cover typologies to link to ecological processes (Turner et al., 2001) and thus offer potential improvements over lumped catchment descriptors. These are calculated using software that can process spatial data and derive variable metrics for characterising the distribution, shape and connectivity of land cover. Ecologists have long applied spatially explicit landscape metrics (LMs) to study ecosystem dynamics (Brady et al., 1979) and they are increasingly being used in hydrological studies (Schröder, 2006; Yuan et al., 2015) where combining established landscape metrics alongside hydrologically relevant metrics is an emerging area of investigation for characterisation of catchment properties affecting hydrological response (Van Nieuwenhuyse et al,. 2011; Miller & Brewer, 2018; Oudin et al., 2018).

In this study we aim to evaluate the performance of lumped urban catchment descriptors and spatially-explicit landscape metrics for explaining inter-catchment variation in storm runoff in small urbanised catchments. To achieve this, there are a number of related objectives: i) to quantify differences in inter-catchment rainfall-runoff behaviour across a range of urbanised catchments; ii) to characterise catchment properties using a range of catchment descriptors and landscape metrics; and iii) to identify the relative performance of catchment descriptors and landscape metrics for explaining rainfall-runoff response. The findings will be used to assess what landscape metrics can tell us regarding the role that spatial layout of urban surfaces has on storm runoff response and their potential role in statistical procedures for flood frequency estimation and other lumped catchment hydrological applications.

2 Method

2.1 Study area and hydrological monitoring

FIGURE 1

The study area focuses on two towns of similar climate and geology in the south of the UK (Figure 1) located within the River Thames catchment (Figure 1, inset). Both towns have an Environment Agency (EA) gauging station and rain gauge recording at a 15 min resolution. We additionally monitored flow in 16 locations that represent catchments of varying urbanisation. Flow and rainfall was measured between 2011 and 2016: flow at a 5 min resolution using in-situ ultrasonic instruments, rainfall at a 15 min resolution across eight locations spread over the two towns using tipping bucket raingauges. Miller & Hess (2017) provide a detailed description of equipment and data processing. The total dataset of 18 sites were separated into calibration (11) and validation (7) catchments (Figure 1) - whereby storm responses across the grouped calibration sites were not observed to be directly impacted or materially similar to response observed at other calibration sites.

Both Swindon (population 210,000) and Bracknell (population 77,000) catchments are rapidly urbanising urban centres typical of UK post-World War II development and of progressive peri-urbanisation. In addition to urbanisation, hydrology is affected by hydraulic infrastructure including sewage treatment works (STW) outfalls (Figure 1) and for Bracknell local retention ponds.

2.2 Storm event data

The variable pattern of rainfall-runoff response across the catchments was quantified using storm event data captured and was characterised by a suitable range of hydrological metrics

(Table 1) using the methods outlined by Miller & Hess (2017). This involved first isolating storm events using rainfall depth and intensity thresholds. An automated baseflow separation method was used to isolate the surface runoff hydrograph, based on identifying the starting point of the hydrograph rising limb and applying a linear interpolation to the end of stormflow. Finally, visual analysis was undertaken to filter out erroneous events and ensure only single-peak events were selected.

TABLE 1

2.3 Catchment descriptors and landscape metrics

A number of catchment descriptors and landscape metrics were selected to provide characterisation of catchment properties (Table 2). Both catchment descriptors and landscape metrics were based on 50 m resolution mapping of UK land cover. *Suburban* and *Urban* classes were taken from the UK Land Cover Map updated for 2015 (LCM2015), following Morton et al. (2011), and represent the varying intensity of urban development – *Suburban* areas having a mix of housing and greenspace, while *Urban* is dominated by continuous development and minor greenspace. Likewise, the combined *Grassland/woodland/arable* class is a collation of these broad classes from LCM2015 to represent the non-urban terrestrial areas. Using data and methods outlined by Miller and Brewer (2018), a further class of *Natural Greenspace* was introduced that differentiated from areas of urban greenspace that can be highly compacted. The *Water* class mapped all ponds/wetlands/lakes/reservoirs using high-resolution mapping of elevation and water, downscaled to 50 m.

TABLE 2

The eight catchment descriptors selected are those used for estimating floods in ungauged catchments in the UK (IH, 1999; Kjeldsen, 2007) and provide characterisation of catchment geometry, climate, geology, soil hydrology, and urban extent (Table 2). The 11 selected landscape metrics were identified by Miller & Brewer (2018) as uncorrelated and highly descriptive of urban spatial form and function with regard to catchment hydrological function. These include the proximity index (*PX*), which indexes the hydrological distance of all *Urban/Suburban* patches to the outlet, alongside the one landscape-level metric (CONTAG) and nine other metrics based on four class-level landscape metrics (LPI, CONTIG, CLUMPY, COHESION) (Table 2).

The majority of landscape metrics were derived using the Fragstats software package (McGarigal and Marks, 1994) which is one of a number of tools available for quantifying landscape structure through geo-spatial analysis of land cover (Frazier & Kedron, 2017). Fragstats was selected as it's a relatively accessible tool that works with raster data and contains all required metrics (McGarigal et al. 2009) and has demonstrated performance in urban areas (Grafius et al. 2018). Its inability to deal with non-Euclidean distances (e.g. flow length pathways), required using ArcGIS to quanitfy PX using methods outlined by Miller & Brewer (2018).

2.4 Calibration and validation of linear models

The approach to characterising hydrological response using the various landscape metrics and catchment descriptors follows a standard multivariate linear model optimization method as employed in similar studies (e.g. Oudin et al. 2018) and UK flood estimation methods (IH, 1999). A log-linear regression model (Kjeldsen, 2010) was best suited, as it allowed the attribution of hydrological data to a number of catchment variables.

Using data from the 11 calibration catchments (Figure 1) the best performing model variables were identified using 'leaps' regression subset selection (Lumley, 2017). Leaps identifies the best combination of variables for performing a linear regression of the observed response metric, using an efficient 'branch-and-bound' algorithm that systematically searches for the optimal solution. This algorithm uses a systematic enumeration of solutions that explore branches of a tree that represent possible subsets of the solution, each branch being checked against bounds of the optimal solution. Given the relatively small subset of calibration catchments and variables, the adjusted r-squared (R^2adj) performance criterion, with an associated weighting based on data frequency (events captured), was used to account for the number of predictor variables in the model relative to the number of data points. A further check for consistency, and to ensure no over-fitting, was undertaken by extracting the Akaike information criterion (AIC) scores (Akaike, 1987) for model variants.

Leaps was bounded to selecting the best three subsets of variables at each level of complexity, from one to four variables, in order to identify patterns in model complexity and between catchment descriptors and landscape metrics selected. This first stage involved using only catchment descriptors as a baseline for comparing model performance. The second stage added landscape metrics to see if there was improved performance when landscape metrics are additionally considered. This approach also facilitated identification of which catchment descriptors were supplemented. The model with the highest R^2adj and lowest AIC was then taken forward to fit model parameters.

The second stage of model development involved fitting parameters for the optimal combination of catchment descriptor or landscape metric variables identified for each response metric across the 11 calibration catchments. We employed the weighted least squares regression method (Ruppert & Wand, 1994), applying a weighting factor based on number of events captured for each site, as this was most suitable given the limited number of calibration catchments (11) and variation in monitoring duration between sites (Figure 1). Hydrological metric data normality across the 11 sites was tested using the Shapiro-Wilk statistic test and where non-normal ($p < 0.05$), data were transformed using the natural logarithm. For cases requiring natural log transformation and to maximise performance, optimal transformation of variables were derived using the following transformations: none, logarithmic, inverse (1000/x), and power (c^x). The optimal form of the variable transformation was subsequently used in the final linear model derived for each response metric.

The independence of data among study sites was ensured by selecting only catchments with little or no physical relationship in the event hydrographs while multicollinearity of model variables was reduced by selecting only landscape metrics with little or no significant correlation. Linear model assumptions were further tested using model residuals to ensure that linear regressions conformed to the assumptions of linear regression (Faraway, 2004). The fitted models were subsequently tested on the seven validation catchments (Figure 1) to assess performance and to identify any outliers.

3 Results

3.1 Storm event data

Table 3 details the mean values for all hydrological metrics across the 18 selected catchments for the events captured during the monitoring period. The large variability in size of catchments selected (0.27 km^2 – 82.5km^2) means there is a wide range of all non-normalized metric values. Importantly, for the analysis that follows, the data indicate a wide range of hydrological responses have been captured across the sites, with a balanced proportion of events between the calibration (438) and validation (326) catchments.

TABLE 3

3.2 Catchment characterisation

Land cover mapping of the five main classes is illustrated in Figure 2. Table 4 details the derived catchment descriptor and landscape metric values for each catchment. Urbanisation clearly varies across the selected catchments and reveals Swindon to have much higher *Urban* coverage across the town centre and peripheral industry/business parks than Bracknell, reflected in generally higher *URBEXT* values (Table 4). Bracknell has a much higher number of urban water bodies (*Water*: Figure 2) compared to Swindon, resulting in lower catchment *FARL* values (Table 5). Likewise, mapping of *Natural Greenspace* (Figure 2) shows these areas are clearly present in varying degrees of extent and distribution across the 18 catchments/sub-catchments. In general, individual patches of *Natural Greenspace* are not large but notable exceptions include the urban B2 and S8 and the rural B1 catchments, and EA_39052 which has a large patch located near to the catchment outlet.

The majority of catchment descriptors and landscape metrics (Table 4) have high variability between the selected calibration/validation catchments (e.g. *AREA, URBEXT, PX*) while only two have little variation across catchments (*SAAR, PROPWET*) and three have general low variability but with outlier values (*BFIHOST, CONTAG,* $CLUMPY_{SUB}$). Landscape metrics based on *Suburban* and *Urban* land-cover patches vary considerably compared to the catchment descriptor *URBEXT*.

FIGURE 2

TABLE 4

3.3 Identifying model variables and testing models

The best performing combination of catchment descriptors and landscape metrics for each metric were identified using the ‘regsubsets’ plot (Figure 3) in leaps (Lumley, 2017) and by comparing results with the associated AIC. The use of AIC scores provided a further means of differentiating between model selections and isolating the optimal model variables for both Q_{max}, *PR and* T_{LC}, where more than one combination had resulted in the same recorded R^2adj.

For each hydrological metric the plot lists the catchment descriptors and landscape metrics along the x-axis and the y-axis indicates the model performance using R^2adj to 2 decimal places. Four levels of model complexity are included (each separated by a horizontal dashed line), from 1 variable (M1) to 4 variables (M4), and the plot showing the 3 best performing models for each level of complexity (and associated R^2adj). The shaded rectangles indicate which variables are included in the given model and increasing shading indicates a higher R^2adj. Those of similar value are ranked by subsequent decimal places. Figure 3a plots the results of only using the eight catchment descriptors, while Figure 3b plots the eight catchment descriptors alongside the 11 landscape metrics (separated by a vertical line).

3.3.1 Model development and validation

The fitted model equations for estimating each response metric from selected variables are detailed in Table 5, alongside their respective performance (R^2adj). For those response metrics found to be non-normally distributed (Q_{max}, TP, T_{LPP}) the fitted model equation takes the exponentiated form of the log-transformed model and includes the optimal variable transformations. The linear models on which all equations were based were found to meet linear model assumptions. Table 6 details the observed metric values for each validation site against values derived using the equations in Table 5, alongside comparative predictive performance (MSE) for equations using either calibration or validation data. These results reveal a number of insights:

Q_{max} – Model fit is good and three catchment descriptors were shown to be significant, while the additional landscape metric $CONTIG_{NAT}$ is not. The fitted model performs well across the validation sites compared to calibration with no tendency to over- or under-predict Q_{max}, but certain sites are poorly predicted (B4, B6, S6).

DR and PR – Both models show that a combination of landscape metrics and catchment descriptors provide the optimal model of good fit, with all selected variables being significant. The high significance of $CONTIG_{NAT}$ in both the *DR* and *PR* models highlights the potentially important role of urban greenspace for explaining the amount of runoff generated in the urbanised catchments. Validation performance drops considerably as a result of significant over prediction of runoff volume in S4 and S8 and under predict in S6.

θ – All selected variables are shown to be highly significant but the equation applied to validation data results in a large drop in predictive performance compared to calibration data mainly due to under prediction of flood duration in S6. There is also one result (S5) indicating a negative value.

TP, T_{LPP} and T_{LC} – Fitted models show a similar pattern in variable selection and high model predictive performance but only *DPLBAR* is significant in all three calibrated models, while *PX* is significant in two. For both *TP* and T_{LPP} the fitted model applied to the validation catchments resulted in increased predictive performance over calibration data reflecting generally good predictive ability across all sites. For T_{LC} the performance dropped considerably with poor predictive performance across most sites and one negative value (S5).

TABLE 5

TABLE 6

4 Discussion

4.1 Landscape metrics for characterising storm response

4.1.1 Peak flow and runoff volume

Landscape metrics were found to provide little added value for attribution of peak flows in urbanised catchments, peak flow being primarily a function of catchment area, and to a lesser degree, urbanised area. This suggests spatial layout is not an important factor which contrasts with observations from Miller and Brewer (2018) and modelling results from Mejía and Moglen (2009). While data was limited this warrants further investigation as there is considerable interest in using spatial planning of green infrastructure within a catchment to specifically reduce flood peaks (Jiang et al., 2018).

Variable selection and fitting for hydrograph metrics of runoff volume - *PR* and *DR* - showed the optimal combination included landscape metrics representing the connectedness and shape of *Suburban* and *Natural Greenspace* patches, alongside lumped catchment descriptors indicative of urban extent and climate or soils. This suggests that connectivity and extent of urbanised and pervious surfaces within an urbanised catchment are important variables driving the volume of runoff, and are mediated by location specific catchment hydrological functions. This validates findings from other studies that have found that connectivity is an important determinant of runoff volume (Lee and Heaney, 2004; Krebs et al., 2013) and that pervious surfaces have notable effects on runoff volume (Ellis, 2010; Jarden et al., 2015).

4.1.2 Runoff timing

Combining landscape metrics representing the connectivity and location of urbanised surfaces alongside catchment descriptors greatly improved the attribution of runoff timing. Flood duration (θ) was particularly well characterised by a combination of information on catchment length and connectivity and the hydrological location of the dominant urbanised surface classes within catchments. This shows that the physical connectedness of the predominant suburban class is a driving factor, alongside flow path length, for explaining the flashiness of storm runoff for the selected catchments. A similar finding was reported by Mejía and Moglen (2010) when using a dedicated modelling framework. Time-to-peak (*TP*) was also well characterised using a combination of information on catchment length alongside layout and connectivity of urban patches (*PX*) and percentage of landscape comprised by the largest patch (*LPI*). The optimal combination provided good predictive ability across the range of catchment shapes, sizes and levels of urbanisation. Conversely, the lack of any catchment descriptor or landscape metric that might characterise attenuation of runoff (e.g. *BFIHOST, FARL,* $CONTIG_{NAT}$) was surprising. Features such as retention ponds and greenspace are generally thought to slow down the speed of runoff and delay runoff peaks (Woods Ballard et al., 2015) and are installed across Bracknell for this purpose. The inclusion of PROPWET suggests it's important to consider general patterns of catchment wetness irrespective of urbanised surfaces that are generally considered to reduce this influence (Shuster et al., 2005).

For both lag-time metrics (T_{LC}, T_{LPP}) runoff timing was primarily a function of flow path length (*DPLBAR*) and the location and connectivity of urban patches (*PX*). The higher model fit and significance of selected variables for T_{LC} was expected as we would expect less inter-event variability in centroid-to-centroid values than peaks, which would be highly influenced by the spatial and temporal distribution of rainfall between events (IH, 1999). The tendency to under-predict for Swindon sites, and over-predict across the larger Bracknell catchments suggests that either, *PROPWET* does not enable this model to account for climate/soil differences, or, that the overall greater role of attenuation ponds in Bracknell is not being well characterised, with *FARL* not being a selected variable.

4.1.3 Performance limitations in validation catchments

Poor performance in application of calibrated models to validation sites was observed for Q_{max}, runoff volume (*DR, PR*), and two time-based metrics (θ, T_{LC}). Overall the validation results are indicative that a much larger pool of variably urban catchments is required for calibration, to reduce such catchment specific variability, but also that more indicative features are required to be mapped and further characterised in more urban relevant landscape metrics. Observed performance limitations for the validation is put down to features including storm drainage and artificial transfer of water that have not been represented in the catchment descriptors or landscape metrics used in this study and which are likely catchment specific and not captured in the calibration catchments.

Low predicted Q_{max} values for B6 and S6 could result from there being more runoff than expected due to STW outflows diverting significant storm water flows from other contributing areas, in effect increasing the natural drainage catchment area. STW outfalls have been shown to have a range of impacts on both the quality and quantity of storm runoff (Braud et al., 2013; Hale et al., 2014; McGrane et al., 2016). Conversely the high predicted Q_{max} values for B4 is viewed as resulting from an underestimation of the attenuating effects of waterbodies, with *FARL* not included in fitted models. Studies have pointed to the important role that urban waterbodies play in reducing flood peaks (Meierdiercks et al., 2010) but there is evidence to suggest that the level of control measures in many urban catchments could be insufficient to influence hydrological response (Bell et al., 2016). This contradiction could be why *FARL* was not included in the fitted models as expected.

Volume results from catchments S4 and S8 both suggest the catchments have features that act to significantly reduce the volume of runoff generated compare to what has been predicted. Both contain a large area of greenspace that is viewed as having significant surface water storage potential during floods. This underestimation of this areas effect is likely due to a lack of calibration sites with such a large relative area of *Natural Greenspace*. The role of such spaces is well covered in the literature (Gill et al., 2007) given their perceived role in acting like a sponge for runoff from urban areas (Jiang et al., 2018). However, given that they may not be as effective when soils are wet (Nied et al., 2016) the use of mean metric values across the monitoring period may be masking their potential contribution in drier periods.

The poor prediction and underestimation of flood duration and centroid lag-time in S4, S5 and S6, and in particular the negative values for site S5, suggests the calibrated model was not suitable for these sites. The model formulae for both (Table 5) suggest an overestimation of *PX* effects on reducing response times. The negative value for S5 is further suggestive that the model was not able to deal with a catchment so heavily dominated by large-scale storm drainage and this with such short response times relative to its size. The wider literature suggest form and function of storm drainage networks can accelerate runoff and increase peak flows (Meierdiercks et al., 2010; Ogden et al., 2011).

4.2 Landscape metrics for hydrological applications

The retention and significance of *URBEXT* in all quantity-based models indicates that total coverage of impervious surfaces is a more important factor in runoff generation and peak flows than the distribution and layout of such surfaces, as reflected in the general literature (Krebs et al., 2013; Shuster et al., 2005). Conversely, the replacement of *URBEXT* with *PX*, even in simpler models, clearly indicates that layout, connectivity and location of urban surfaces can be more important than impervious area alone for characterising the timing of runoff. The lack, or unexpected pattern, of variability in runoff timing across a range of urban development found in some studies, when only considering imperviousness or *URBEXT* (e.g. Gallo et al., 2013; Miller & Hess, 2017), could be in part due to such effects. This suggests that proximity index (*PX*) could be an improved measure of urbanisation for characterising the spatial effects on runoff timing in spatially-averaged 'lumped' catchment hydrological applications. In particular, such spatially-explicit and hydrologically-relevant landscape metrics could have a role for calibrating runoff timing parameters in national flood estimation methods that rely on lumped catchment models, such as the UK industry-standard Revitalised Flood Hydrograph (ReFH) model (EA, 2012; Kjeldsen, 2007; Kjeldsen et al, 2013).

While this study has found only limited evidence for applying landscape metrics to better characterise the hydrological effects of natural greenspace in urban areas, the potential for spatially-explicit metrics such as PX is evident to improve poor performance of time-based metrics in certain validation catchments with large areas of such greenspace was indicative. Empirical research is limited and primarily set at local or plot scales (e.g. Jarden et al., 2015) the science at catchment scales is emerging and based primarily on modelling, showing that spatial distribution of green infrastructure affects relative effectiveness in urban areas (Loperfido et al., 2014; Bell et al., 2016) and could be more important than overall coverage (Fry and Maxwell, 2017). Golden & Hoghooghi (2017) find this is an area of fertile research and suggest that novel measurements and big data are required.

4.3 Study limitations and further research

The limited number of sites, and their size and relative levels of urbanisation, means the statistical analyses are not representative of, and cannot be immediately applied to, larger catchments with more dense urban centres or types of development. Further, the lack of any extreme storm events limits any investigation into whether the patterns observed would change with more intense storms. Wider testing of the landscape metrics used here across a range of catchment sizes and levels of urbanisation, alongside additional metrics to represent storm drainage and green infrastructure, is required to determine if landscape metrics could improve the operational methods and is a key area for further research. An additional area would be the potential application for lumped hydrological modelling and performance comparison with distributed methods.

5 Conclusions

This study assessed the potential of spatially explicit landscape metrics compared to lumped catchment descriptors for explaining storm runoff from urbanised catchments. This had not been previously explored and provided an opportunity to empirically test whether findings from the limited modelling studies are reflected in empirical data at catchment scales and whether landscape metrics could lead to improvements in lumped-catchment attribution studies and flood estimation.

The study showed that attribution of the volume and timing of storm runoff using lumped urban catchment descriptors, such imperviousness or urban extent, could be significantly improved in combination with more spatially explicit landscape metrics capable of representing the connectivity, layout and location of urban surfaces. It was also demonstrated that landscape metrics applied to areas of natural greenspace within urban areas can be useful for explaining the volume of runoff generated in storm events. These observations suggest potential improvements in modelling design flood events or water resources in ungauged catchments where models rely on lumped catchment parameters. Landscape metrics pose significant potential for bridging the gap between the spatial limitations of more simple lumped modelling approaches and the more complex but data intensive limitations of distributed modelling approaches. Landscape metrics could also provide a less data-intensive and more repeatable means of investigating how the spatial configuration of green infrastructure and urban land-use interacts with hydrological response.

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7 Declaration of interest

The authors declare no conflicts of interest.

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9 Tables

Table 1: Hydrometerological storm response metrics used in the study to quantify variability in catchment responses to storm events

	Metric	**Description and units**	**Reference application**
Hydrograph shape	DR	Direct Runoff - storm runoff volume expressed as depth over catchment area (mm)	Shaw et al. (2010)
	PR	Percentage runoff - proportion of rainfall converted to direct runoff (%)	Burn and Borman (1993)
	Q_{max}	Peak flow - maximum recorded flow during storm event (cumecs)	Hollis and Ovenden (1998)
	θ	Flood duration - measure of hydrograph shape defined by duration where $Q/Q_{max}= 0.5$ (h)	Braud et al. (2013)
	TP	Time-to-peak - time between onset of storm runoff and peak flow (h)	Gallo et al. (2013)
Rainfall runoff timing	T_{LPP}	Lag-time peak-to-peak - time between peak rainfall and peak flow from storm event (h)	Scheeder et al. (2003)
	T_{LC}	Lag-time centroid-to-centroid - time between centroid of rainfall and centroid of storm flow (h)	Hall (1984)

Table 2: Catchment descriptors and landscape metrics used for characterising catchment properties (full details on derivation provided in Supplementary Material Table 1)

Catchment Descriptors	
AREA	Catchment drainage area (km^2)
SAAR	Standard-period Average Annual Rainfall (mm) rainfall for the period 1961-1990
FARL	Index of flood attenuation from rivers and lakes.
BFIHOST	Base flow index from Hydrology of Soil Types (HOST) Boorman et al. (1995)
URBEXT	FEH index of fractional urban extent
PROPWET	Index of proportion of time that soils are wet (%)
DPLBAR	Mean drainage path length
DPSBAR	Mean drainage path slope
Landscape Metrics	
CONTIG	Contiguity Index assesses spatial connectedness, or contiguity, of cells within a grid-cell patch to provide an index of patch boundary configuration and thus patch shape.
LPI	Largest patch index quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance.
CLUMPY	Clumpiness index quantifies the deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution.
COHESION	Patch cohesion index measures the physical connectedness of the corresponding patch type.
CONTAG	Contagion Index assesses the extent to which patch types are aggregated or clumped as a percentage of the maximum possible; characterised by high dispersion and interspersion.
PX	Proximity Index (PX) accounts for hydrological distance and connectivity of all suburban and urban patches relative to catchment outlet

Table 3: Catchment average values for storm event metrics – subset by Calibration (11) and Validation (6) catchments

Site ID	AREA (km²)	Freq	Q_{max} (m^3s^{-1})	DR (mm)	PR (%)	Θ (h)	TP (h)	L_{TPP} (h)	T_{LCC} (h)
Calibration									
EA_39052	51.96	52	3.45	2.3	18.2	12.4	7.5	3.1	8.4
B1	18.37	50	0.61	1.7	12.4	18.0	14.9	10.5	13.5
B2	12.49	30	1.30	1.8	16.5	4.7	5.2	1.2	5.3
B3	12.55	12	2.50	3.9	34.0	3.5	5.7	1.6	4.1
EA_39087	82.5	72	6.14	3.5	25.6	15.8	15.3	10.7	14.2
S1	28.97	27	2.67	4.4	29.4	11.4	8.4	4.5	8.2
S2	3.24	30	0.14	1.5	10.5	21.8	12.6	8.8	11.0
S3	5.98	53	0.74	3.2	31.4	5.7	6.0	2.2	4.9
S7	0.54	39	0.43	2.4	22.5	0.5	3.6	0.3	1.0
S9	0.27	34	0.15	2.5	21.0	0.8	3.7	0.3	2.5
S10	0.49	39	0.27	1.7	16.1	0.8	3.5	0.3	0.9
Validation									
B4	33.66	34	0.93	1.1	9.8	13.3	10.2	6.4	9.2
B5	37.5	37	1.74	2.2	15.4	14.4	10.6	6.6	10.0
B6	58.24	51	4.26	3.0	21.6	13.3	9.6	5.1	9.5
S4	3.09	74	0.45	3.0	24.9	5.5	6.9	3.4	5.5
S5	2.18	56	1.50	2.9	26.4	0.8	3.8	0.7	1.2
S6	35.2	18	4.49	6.0	43.9	17.7	9.3	5.6	10.5
S8	2.16	56	0.37	2.3	21.3	2.9	4.9	1.4	3.5

Table 4: Catchment descriptor and landscape metric values

	FEH catchment descriptors								Landscape metrics										
Site ID	**AREA (km²)**	**DPLBAR (km)**	***BFIHOST***	**SAAR (mm)**	**FARL**	***URBEXT***	**DPSBAR**	**PROPWET**	**PX**	**CONTAG**	**LPI_{URB}**	**$CONTIG_{URB}$**	**$CLUMPY_{URB}$**	**$COHESION_{URB}$**	**LPI_{SUB}**	**$CONTIG_{SUB}$**	**$CLUMPY_{SUB}$**	**$COHESION_{SUB}$**	**$CONTIG_{NAT}$**
EA_39052	51.96	7.46	0.36	676	0.86	0.19	24.7	0.29	3.55	47.89	3.66	0.40	0.81	93.77	26.88	0.36	0.81	98.42	0.60
B1	18.37	4.77	0.29	679	0.88	0.09	25.3	0.29	1.15	50.96	0.15	0.37	0.54	59.62	11.89	0.39	0.74	93.65	0.53
B2	12.49	3.9	0.51	686	0.94	0.19	21.5	0.29	1.69	58.08	1.44	0.38	0.74	78.94	41.75	0.37	0.85	98.89	0.63
B3	12.55	3.75	0.43	672	0.92	0.37	17.9	0.29	2.76	52.81	13.30	0.48	0.83	95.90	51.63	0.36	0.78	99.24	0.64
B4	33.66	6.22	0.36	680	0.9	0.12	25.8	0.29	2.07	49.96	0.53	0.38	0.68	74.27	17.11	0.39	0.80	96.74	0.64
B5	37.5	6.52	0.34	678	0.87	0.13	22.5	0.29	1.85	50.35	0.63	0.38	0.71	80.54	19.15	0.38	0.80	97.19	0.64
B6	58.24	7.84	0.34	674	0.87	0.17	30.2	0.29	2.84	48.34	3.26	0.37	0.81	93.58	23.95	0.37	0.81	98.20	0.65
EA_39087	82.5	9.31	0.39	698	0.95	0.23	27.4	0.34	3.95	55.55	8.10	0.42	0.83	96.77	11.73	0.40	0.83	97.41	0.55
S1	28.97	5.82	0.38	707	0.97	0.23	35.8	0.34	3.88	57.48	10.96	0.36	0.82	96.23	6.66	0.36	0.76	95.09	0.47
S2	3.24	2.12	0.67	712	0.85	0.03	33.8	0.34	0.2	76.41	0.00	0.00	0.00	0.00	6.26	0.39	0.69	81.36	0.00
S3	5.98	2.84	0.32	683	1	0.57	33.4	0.34	1.68	61.72	31.27	0.34	0.85	97.68	50.79	0.44	0.74	98.38	0.00
S4	3.09	2.11	0.43	688	1	0.33	14	0.34	1.38	68.04	1.05	0.55	0.82	70.68	79.31	0.89	0.66	99.64	0.84
S5	2.18	1.79	0.43	688	1	0.39	33.7	0.34	3.53	52.52	9.91	0.40	0.77	85.53	38.82	0.57	0.70	96.05	0.17
S6	35.2	6.29	0.36	705	0.96	0.29	40.6	0.34	4.28	55.45	13.56	0.40	0.83	97.06	10.43	0.40	0.81	95.98	0.47
S7	0.54	0.95	0.56	692	1	0.4	45.2	0.34	1.54	52.68	3.65	0.44	0.70	66.01	48.86	0.69	0.19	94.72	0.00
S8	2.16	1.79	0.34	684	1	0.31	27.3	0.34	1.07	52.68	1.50	0.60	0.94	74.81	70.47	0.63	0.72	98.88	0.84
S9	0.27	0.69	0.37	685	1	0.51	28.9	0.34	0.66	62.34	0.00	0.00	0.00	0.00	99.08	0.83	0.00	99.95	0.00
S10	0.49	0.6	0.54	686	1	0.37	35	0.34	2	93.82	0.00	0.00	0.00	0.00	6.66	0.36	0.76	95.09	0.00

Table 5: Derived model equations for response metrics based on multivariate regression between selected variables and observed hydrological response metrics for the 11 calibration catchments, with associated model fit to observed data using the adjusted R-squared (R^2adj) criterion: * p value: 0.01 < p < 0.05, **p value: 0.01 < p < 0.001, *** p value: p < 0.001.

Metric	Var 1	Var 2	Var 3	Var 4	Linear model	R^2adj
Q_{max}	AREA***	*URBEXT***	*BFIHOST**	$CONTIG_{NAT}$	$Q_{max} = 2.196\ AREA^{0.705}0.924^{(\frac{1}{URBEXT})}0.520^{(\frac{1}{BFIHOST})}0.613^{CONTIG_{NAT}{}^2}$	0.972
DR	*URBEXT**	PROPWET**	$COHESION_{SUB}$*	$CONTIG_{NAT}$**	$DR = 12.442 + 10.901\ URBEXT + 25.031\ PROPWET - 0.243\ COHESION_{SUB} + 7.039\ CONTIG_{NAT}$	0.84
PR	*URBEXT***	SAAR**	$COHESION_{SUB}$**	$CONTIG_{NAT}$***	$PR = 19.351 + 110.392\ URBEXT + 0.210\ SAAR - 1.974\ COHESION_{SUB} + 48.459\ CONTIG_{NAT}$	0.96
θ	DPLBAR***	*BFIHOST**	$COHESION_{SUB}$***	PX**	$\theta = 128.878 - 19.42\ BFIHOST + 2.287\ DPLBAR - 2.068\ PX - 1.215 COHESION_{SUB}$	0.99
TP	DPLBAR**	PROPWET	PX*	LPI_{SUB}	$TP = 24.606\ DPLBAR^{0.592}PROPWET^{1.482}1.204^{(\frac{1}{PX})}LPI_{SUB}{}^{-0.193}$	0.83
T_{LPP}	DPLBAR**	PROPWET	PX	LPI_{SUB}	$T_{LP} = 150.506\ 0.11^{(\frac{1}{DPLBAR})}PROPWET^{1.482}1.204^{(\frac{1}{PX})}LPI_{SUB}{}^{-0.492}$	0.82
T_{LC}	DPLBAR***	PROPWET	PX***	LPI_{SUB}*	$T_{LC} = -2.905 + 2.369\ DPLBAR + 30.562\ PROPWET - 3.712\ PX - 0.051\ LPI_{SUB}$	0.94

Table 6: Observed ($_{obs}$) and predicted ($_{calc}$) hydrological response metric values for seven independent validation catchments – with model predictive performance (MSE – Mean Square Error) using either calibration or validation data shown (calibration performance – in italics – based on 11 calibration catchments data).

	Site ID							Predictive performance	
	B4	B5	B6	S4	S5	S6	S8	Validation (MSE)	*Calibration (MSE)*
freq	34	37	51	74	56	18	56		
$Q_{max,obs}$ (m^2s^{-1})	0.9	1.7	4.3	0.4	1.5	4.5	0.4		
$Q_{max,calc}$ (m^2s^{-1})	1.8	1.8	2.9	0.6	0.9	3.0	0.3	0.71	*0.12*
$DR_{,obs}$ (mm)	1.1	2.2	3.0	3.0	2.9	6.0	2.3		
$DR_{,calc}$ (mm)	2.1	2.1	2.3	6.3	3.1	4.2	6.3	4.58	*0.88*
$PR_{,obs}$ (%)	9.8	15.4	21.6	24.9	26.4	43.9	21.3		
$PR_{,calc}$ (%)	15.5	15.3	17.2	44.2	25.4	32.8	42.6	143.47	*1.93*
$\theta_{,obs}$ (h)	13.3	14.4	13.3	5.5	0.8	17.7	2.9		
$\theta_{,calc}$ (h)	14.4	15.3	15.0	1.5	-1.7	10.8	4.0	3.94	*0.35*
$TP_{,obs}$ (h)	10.2	10.6	9.6	6.9	3.8	9.3	4.9		
$TP_{,calc}$ (h)	10.0	10.4	9.8	5.2	4.1	10.4	5.2	0.64	*3.56*
$T_{LPP,obs}$ (h)	6.4	6.6	5.1	3.4	0.7	5.6	1.4		
$T_{LPP,calc}$ (h)	4.6	4.4	4.1	1.4	1.5	7.1	1.3	2.25	*5.68*
$T_{LC,obs}$ (h)	9.2	10.0	9.5	5.5	1.2	10.5	3.5		
$T_{LC,calc}$ (h)	12.1	13.6	12.8	3.3	-3.4	6.0	4.2	11.18	*1.19*

10 Figures

Figure 1

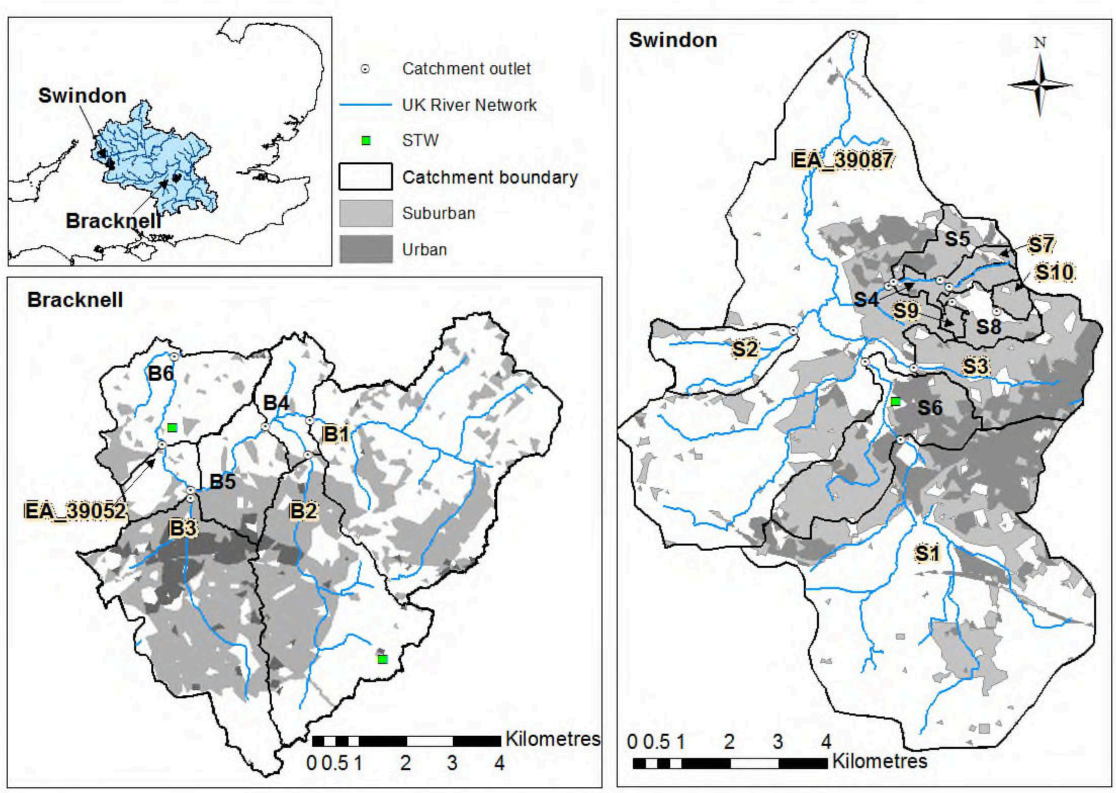
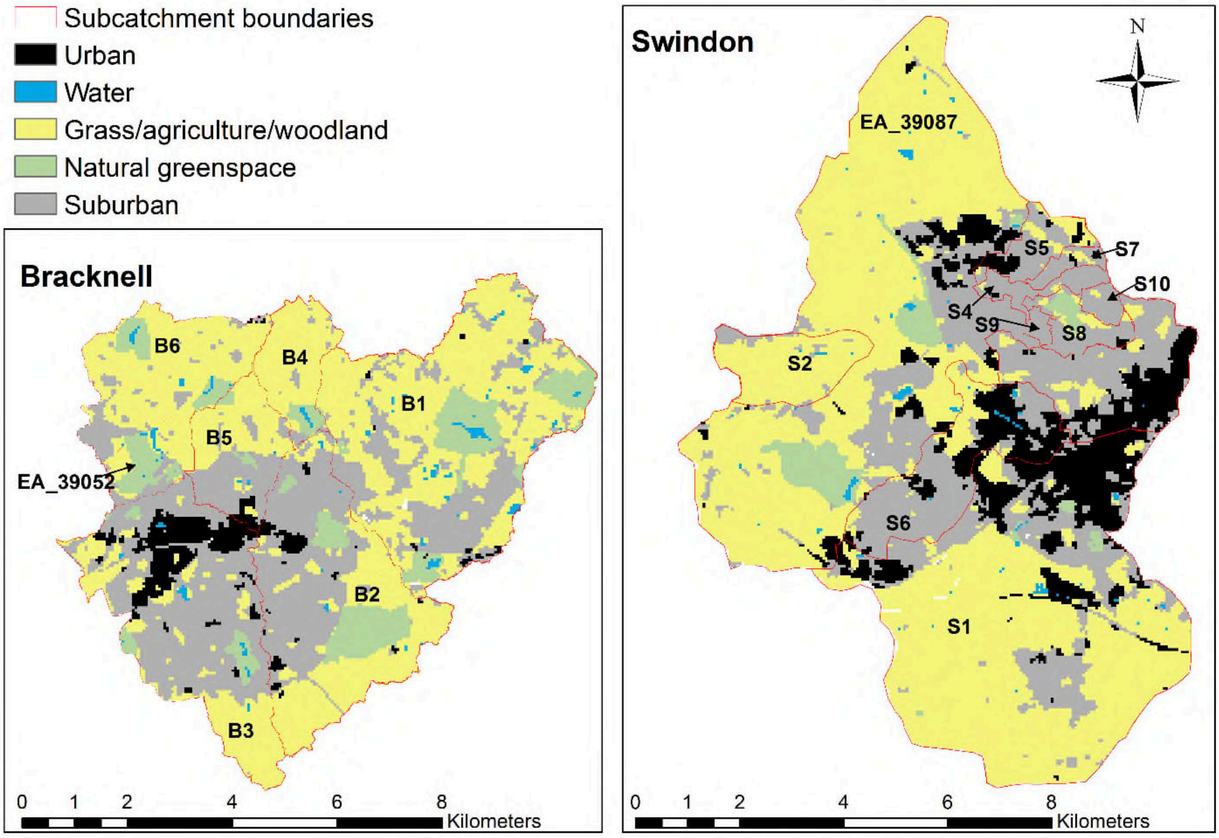
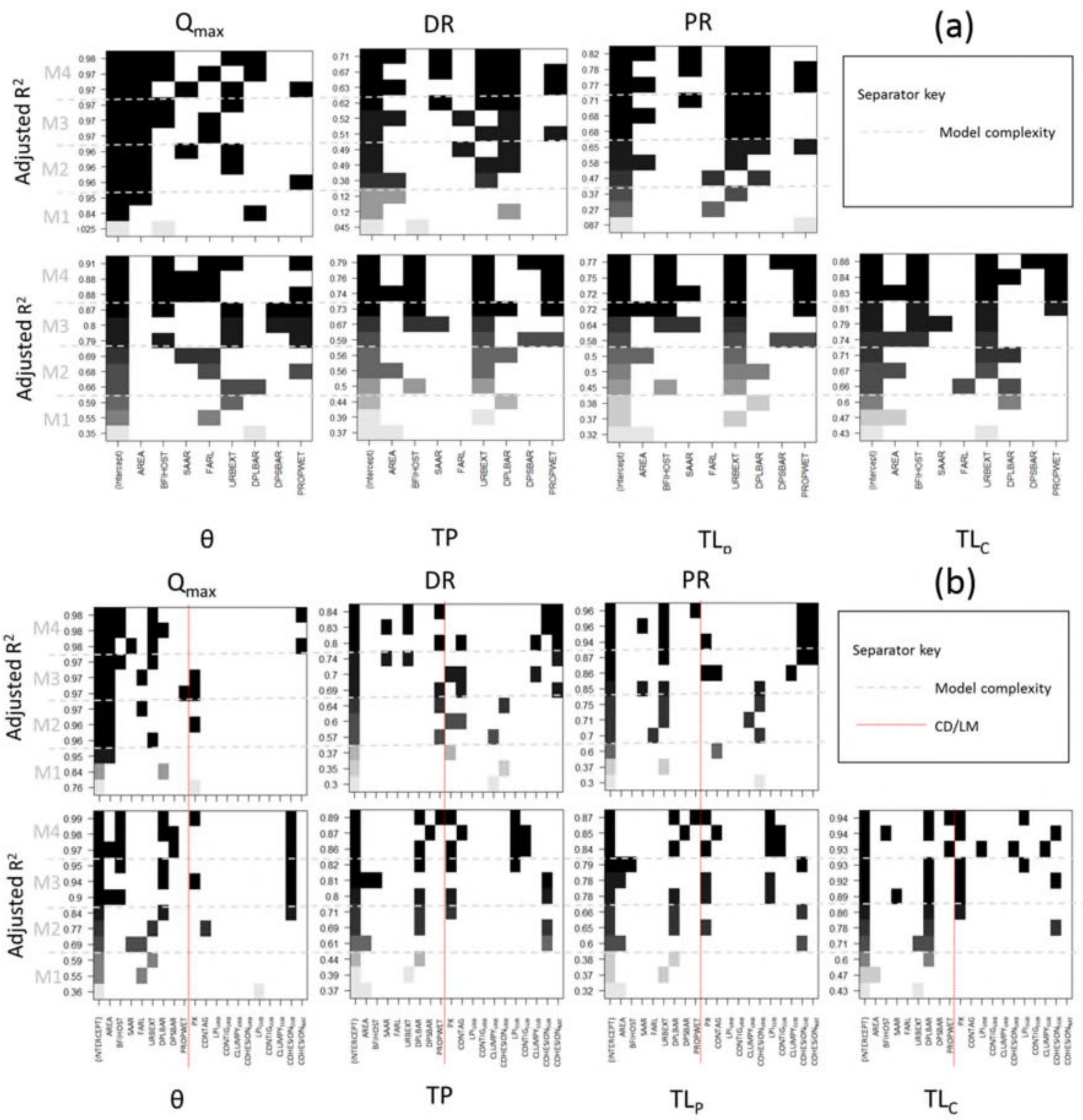


Figure 2



Subcatchment boundaries
Urban
Water
Grass/agriculture/woodland
Natural greenspace
Suburban
Bracknell
B6
B4
B1
B5
EA_39052
B2
B3
0 1 2 4 6 8 Kilometers
Swindon
N
EA_39087
S5
S7
S10
S4
S9
S8
S2
S6
S1
0 1 2 4 6 8 Kilometers

Figure 3



(a)
Qmax
DR
PR
Separator key
Model complexity
Adjusted R²
M4
M3
M2
M1
(Intercept)
AREA
BFIHOST
SAAR
FARL
URBEXT
DPLBAR
DPSBAR
PROPWET
θ
TP
TLp
TLc
(b)
Qmax
DR
PR
Separator key
Model complexity
CD/LM
Adjusted R²
M4
M3
M2
M1
θ
TP
TLp
TLc

11 Figure captions

Figure 1: Study area and location of monitored catchments: calibration catchment labels are highlighted (B1, B2, B3, EA39052, S1, S2, S3, S7, S9, S10, EA39087).

Figure 2: Land cover mapping used in derivation of catchment descriptors and landscape metrics

Figure 3: Subset plots for each hydrological metric: a) Catchment descriptors, b) Catchment descriptors and landscape metrics

Evaluating landscape metrics for characterising hydrological response to storm events in urbanised catchments

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2020-05-12

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