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Abstract

Flood estimation methods in ungauged basins rely upon generalized relationships between flows and catchment properties. Generally such catchment properties are based on low-resolution national datasets from low density urbanized basins and do not consider location, connectivity and patch size. Such factors are more routinely represented in landscape metrics employed in ecology, and could be particularly useful for representing the diversity of urban land-use. Here, hydrologically relevant landscape metrics are brought together with refined land-use classes and catchment descriptors routinely applied in UK flood estimation methods to estimate the median annual flood (QMED) in order to evaluate the potential role of such metrics. The results show that using higher resolution geospatial data can improve the representation of the urban environment, having particular effects on the delineation of urban water features and catchment area, but not urban extent. Refinement of landscape metrics based on correlations resulted in 12 metrics and 5 catchment descriptors being tested against observed QMED at 18 sites using a weighted least squares regression. The revised equation showed that certain landscape metrics can better represent the hydrological complexity of an urban catchment in a single distributed numerical form, leading to improved estimates of QMED over non-distributed descriptors, for the selected case-study sites. The ability of landscape metrics to express connectivity and relative size and location of urban development promises significant potential for application in urban flood estimation and catchment-scale hydrological modelling.

1 Introduction

The process of urbanization entails a progressive loss of agriculture and natural habitat, converting pervious soil surfaces and natural drainage into impervious surfaces serviced by artificial drainage. These changes have a particular effect upon the storm runoff response of catchments, whereby impervious surfaces act to reduce soil infiltration and increase surface runoff (Jacobson, 2011), and artificial drainage speeds up the conveyance of runoff and the connectivity of urban surfaces to drainage channels (Shuster et al., 2005). This can increase the risk of flooding through higher peak flows (Hawley and Bledsoe, 2011) greater volumes (Packman, 1980) and more frequent flooding (Braud et al., 2013).

In order to quantify the impacts of urbanization on the environment some form of classification or quantification of the urban fabric is required, for example, both the UK Countryside Survey (http://www.countrysidesurvey.org.uk/) and UK Flood Estimation Handbook (FEH) methods (Institute of Hydrology, 1999) rely upon a temporal range of UK wide Land Cover Mapping (LCM) products (Morton et al., 2011). Hydrological quantification of the urban environment can be derived from land use classes with variations based on density, for example, low-high density residential (Gallo et al., 2013) or using classes to derive an index of urbanization, for example, the catchment index of urban extent (*URBEXT*: Bayliss et al., 2006). These both provide an index of catchment imperviousness, or total impervious area (TIA), which is increasingly being directly measured using remotely sensed data to faciliate an enhanced representation of the urban environment (Weng, 2012), often for use in high-resolution hydrological modelling (Salvadore et al., 2015). Combining remote sensing imagery with other spatial data has proven particularly effective at determining how connected urban surfaces are to storm drainage, producing indicators such as directly connected impervious area (DCIA) (Roy and Shuster, 2009) or effective impervious area (EIA) (Janke et al., 2011). However such detail is not always required at catchment scales (>0.25 ha) where TIA is sufficiently accurate for estimating DCIA across multiple developed parcels in certain applications (Roy and Shuster, 2009) and URBEXT can be a direct index of imperviousness (Miller & Grebby, 2014). At national scales class based mapping remains more readily available and routinely used, particularly as it can offer historical picture of change. Progress is however being made across the globe in national mapping of imperviousness and temporal change, from Europe (EEA, 2016) to India (Wang et al., 2017) and USA (US Geological Survey, 2013).

For national methods of flood estimation at ungauged sites, there remains in many countries a reliance on the simplicity of empirical formulae relating the index flood to catchment characteristics (Bocchiloa et al., 2003) that include land class data to inform upon levels of imperviousness for more urbanized locations (Formetta et al., 2017). National agencies across Europe continue to employ such methods (Castellarin et al., 2012), based on regressions of index flood data to catchment characteristics in gauged basins. When considering more urbanized catchments, research has additionally highlighted the need to consider connectivity and location relative to the catchment outlet and scale considered (Kjeldsen et al., 2013; Miller et al., 2014; Sillanpää and Koivusalo, 2015). For example, in the UK, where such descriptors are routinely used to estimate the median annual flood (*QMED*), both Vesuviano et al (2016) and Faulkner et al. (2012) find that existing descriptors and equations perform with less certainty in small urbanized catchments compared to rural catchments. Further, Miller and Hess (2017) find a non-distributed measure such as imperviousness does not mirror the variation in peak flows between urban catchments potentially driven by spatial layout. Thus, while imperviousness is important, class data remain employed for its estimation, and as Mejía and Moglen (2009) show, it is equally important to consider the spatial distribution of impervious land cover, as this can have consequences for the resulting flood peaks.

Spatial or landscape metrics are a tool for quantifying structure and pattern in thematic data, and have been highlighted by Herold et al. (2005) and Ogden et al. (2011) as valuable for improving representations of urban hydrological dynamics. The use of landscape metrics in hydrology has however been limited, despite showing promise in predicting urban land-use change impacts through representation of form and function (Lin et al., 2007; Van de Voorde et al., 2016). Comparatively, urban ecological research, which has long been using ecological typologies to study ecosystem dynamics (Brady et al., 1979), has evolved into many detailed landscape metrics of landscape structure in dedicated spatial statistical software (Kupfer, 2012) with diverse applications (e.g. Alberti, 2005; Jiao, 2015; Muhs et al., 2016). Within ecological landscape metrics, distance is often considered as Euclidean and thus is not calculated according to a hydrological network. The importance of hydrological distance to catchment outlet is demonstrated by Van Nieuwenhuyse et al. (2011), yet while aggregation based landscapes metrics have been tested for hydrological applications, and shown to be effective at providing an estimate for connectivity (Yang et al., 2011), there have been few efforts to consider hydrological distance. Wan Jaafar and Han (2012) have shown the potential for improving *QMED* using more hydrologically relevant descriptors to be derived from catchment form and information on land cover.

Local scale hydraulic features are increasingly being installed within the urban environment to control runoff, such as sustainable urban drainage systems (SuDS) (Woods Ballard et al., 2015). Studies suggest features such as green roofs (Vesuviano et al., 2014), offline storage (Wilkinson et al., 2010) and plot-scale bio-retention features (Hood et al., 2007) reduce and attenuate runoff, but such features are not routinely mapped. Additionally, attenuation of runoff as baseflow (Rivett et al., 2011) can be altered by soil management (Holman et al., 2011) and evidence suggests that soils in urban areas can be so degraded through compaction and decreased hydraulic conductivity (Chen et al., 2014) that infiltration potential approaches that of impervious surfaces (Gregory et al., 2006) and increases runoff (Yang and Zhang, 2011). There are, however, currently no distinctions made in Land Cover Map (LCM) grassland classes between such surfaces (Morton et al., 2011). Conversely there is evidence that improving soil condition will improve infiltration (Chen et al., 2014) and better management of the urban landscape can provide green infrastructure (GI) and ecosystem services (Tratalos et al., 2007) that reduce runoff volumes (Shuster et al., 2014). Infiltration and local storage is also much improved in areas of preserved or managed nature and woodland (Nisbet and Thomas, 2006). Again, given the potential role of SuDS and GI for flood attenuation, there is surprisingly little attention paid to mapping such land-use and testing its effect on urban runoff. There is however a growing body of research mapping GI, based on using remote sensing data (Liquete et al., 2015; Vatseva et al., 2016) and developing a comprehensive classification of GI (Koc et al., 2017). Given these recent advances, and recent GI interest in both the UK (Kelly, 2016; POST, 2016) and internationally (Jarden et al., 2015), the lack of consideration regarding the functionality of SuDS and green space as GI, is clearly an area that should be expanded upon (Gill et al., 2007).

This study aims to use high-resolution spatial data alongside refined urban land cover classes from a UK case study to derive spatial landscape metrics and assess the potential application of landscape metrics for estimating the index flood in urbanized catchments. For this, three objectives are set: i) develop a set of hydrologically relevant urban land-use classes that can be mapped using readily available geo-spatial information, ii) derive enhanced urbanized catchment descriptors and identify suitable landscape metrics for use in flood estimation within the United Kingdom, and iii) test the performance of updated catchment descriptors and landscape metrics for estimating *QMED* for selected study catchments compared with existing flood estimation methods. This will inform the potential for developing a wider method using spatial metrics and remote sensing data in attribution and modelling of floods.

2 Method

2.1 Study area

The selected catchments are located within and surrounding the urbanized towns of Swindon and Bracknell and include two national river flow gauging stations used by the UK Environment Agency (EA) (National River Flow Archive stations 39052 and 39087) (Figure 1). All catchments are tributaries within the Thames basin and have a similar climate, with the Standard Annual Average Rainfall (SAAR) of between 676mm and 712mm. Thames basin soils and geology are highly variable, but the selected catchments are generally similar, with shallow clay or loam soils, with neither dominated by groundwater inputs from Jurassic limestones. The similarity in soil hydrology, low slope, and overall topography was a basis for catchment selection (Miller & Hess, 2017). Alongside the two EA gauged catchments (herein labelled EA_39052 and EA_39087), data from a hydro-meteorological monitoring network spanning 16 variable urban catchments, of record length between 2 and 5 years between 2011 and 2016 (Miller et al., 2014; McGrane et al., 2016; Putro et al., 2016) were additionally used (Figure 1). These employed ultrasonic streamflow gauging technologies to monitor streamflow at high resolution and capture stormflow events and peak flows. These delineate a range of catchment types from rural to highly urbanized and contain a diversity of land cover and hydraulic infrastructure that influence the hydrological response (Miller and Hess, 2017).

Swindon has grown from a small 19th century industrial town into an area of mixed urbanized and peri-urban development and commerce with a population now exceeding 215,000 (2015). Bracknell was previously a small village but after being designated a new town in 1949 has grown rapidly to a population of 120,000 (2015). Bracknell was designed with consideration of water management, utilizing a number of flood storage tanks and ponds within urbanized areas to attenuate floods and store sediment (Packman and Hewitt, 1998). Swindon has less flood storage infrastructure, but with increased development in recent years has had to adapt to increased flooding in certain dense areas of housing through flood protection measures.

Figure 1

2.2 Reclassification of land cover classes

The standard LCM groups of 50m gridded land cover classes used for flood estimation applications (Environment Agency, 2017) in urbanized areas of the UK (Table 1 - *Urban*; *Suburban*; *Water*; *Rural*: composed of Agricultural/managed and Woodland/scrub) were refined into more hydrologically relevant classes using a number of nationally available ancillary datasets (Table 1), illustrated in Figure 2. In order to identify key areas of 'natural' surfaces that might exist within the urban area and its fringes, relevant Natural England datasets were merged to provide a single dataset on natural areas.

Table 1

Figure 2

Reclassification of LCM classes, outlined in Table 2 and illustrated in Figure 2, was based on a hydrological perspective and consideration of features across the study areas that could significantly alter the rainfall-runoff response of catchments. The justification for the reclassifications and the additional SuDS sub-class, along with method used to map each typology, are outlined here:

Urban: Urban was not reclassified - agreeing with other studies assessing varying land use responses which have similarly used only one ‘Urban’ class, such as the ‘commercial’ class used by Gallo et al. (2013), and Van de Voorde et al. (2011) who reported classes of commercial and industrial areas had broadly similar levels of impervious cover (82% and 73%, respectively).

Table 2

Suburban: Suburban has been noted as a highly generalized class for hydrological applications (Kjeldsen et al., 2013; Miller et al., 2014) and the refined classification used in this study followed a classification according to density: low, medium and high, which has been shown to be effective in other studies (Sjöman and Gill, 2014; Gallo et al., 2013). Reclassification of *Suburban* grids was undertaken using Ordnance Survey MasterMap (OSMM) (Appendix: Table 2).

Water: LCM areas of water were not found to cover many of the smaller and more fragmented water bodies evident in OSMM mapping in urban areas. Such features, despite their size, could play an active role in flood attenuation if receiving runoff from urban surfaces (Smith et al., 2013). The high level of water feature detail in OSMM mapping was used to develop a refined water raster and to identify any grids with a certain coverage of water features (Appendix: Table 3).

Urban greenspace: Greenspaces in urbanized areas have been shown to be hydrologically impacted compared to grassland and agriculture (Chen et al., 2014) with explict effects evident as increases in runoff (Yang and Zhang, 2011). Existing approaches for semi-automated mapping of urban greenspace (e.g. Troy and Wilson, 2006; Gill et al., 2007; Vatseva et al., 2016) were not found to be suitable so patch size and location were utilized, whereby the size and location of the greenspace relative to urban areas were concurrently assessed (Appendix: Table 4), to isolate urban greenspaces ($Green_{URB}$) such as recreation areas, roadside verges, and large gardens, from those larger, less altered, and more continuous areas of grassland and agriculture within or surrounding areas of development (*Green*) (Figure 2).

Natural urban greenspace: Natural areas of vegetation, either managed or conserved, can potentially reduce runoff (Gill et al., 2007), thus reducing the index flood. Natural areas of greenspace within or surrounding urban areas were classified as areas managed to preserve natural vegetation and soils, improving soil condition and permeability, leading to an enhanced capacity for abstraction and mitigation of runoff formation processes. These were identified from Natural England ancillary datasets (Table 1) and subsequently merged and gridded to a 50m scale to subsequently reclassify such areas (except water) as natural Greenspace ($Green_{NAT}$) (Appendix: Table 5).

SuDS: An additional sub-class was added to the Urban and Suburban classes to account for the presence of localized SuDS designed to reduce runoff and frequent flooding (Defra, 2014). The locations of SuDS were identified using a combination of geo-spatial information on age and suitability for SuDS (Appendix: Table 6). Age indicates developments designed and built after regulations required SuDS measures to be put in place (Flood and Water Management Act 2010). Sites built post 2000 were identified as having SUDS potential, here comparing all

Suburban and Urban surfaces in 2010 with 2000 (Miller and Grebby, 2014: Table 1). However, as not all sites are suitable for SuDS, due to lack of soil infiltration or issues with groundwater, the SuDS Infiltration Map (SIM: Dearden, 2016) was used to locate sites that should have SuDS in place. Sites built post 2000 where SIM indicated SuDS suitability, were subsequently re-classed as *SuDS*.

2.3 Identifying suitable catchment descriptors and landscape metrics

The second stage refined existing catchment descriptors using the refined land cover data, and calculated and identified a number of potentially relevant landscape metrics. In the UK, the index flood *QMED* is the flood exceeded in half of all years and forms the basis of subsequent derivation of flood estimates for rarer events, such as the 1 in 100 year flood. *QMED* can be accurately derived from hydrological observations of peak flows using the methods outlined in volume 3 of the FEH (Institute of Hydrology, 1999: Chapter 12) – herein termed $QMED_{obs}$. For ungauged sites, *QMED* is estimated from a number of FEH catchment descriptors (Eq. 1) that are derived from a regression between catchment descriptors and $QMED_{obs}$ (Kjeldsen, Jones and Bayliss, 2008) – herein termed $QMED_{FEH}$

Eq. 1)

$$QMED_{FEH} = 8.3062\ AREA^{0.851}\ 0.1536^{\frac{1000}{SAAR}}\ FARL^{3.4451} 0.0460^{BFIHOST^2}$$

In urban catchments, this is subsequently adjusted to account for the level of urbanization using an Urban Adjustment Factor (UAF) based on the catchment urbanisation index *URBEXT* (Table 3).

2.3.1 Catchment descriptors

The catchment descriptors used in the FEH statistical procedures for flood frequency estimation were refined for use in this study, being calculated using the methods (Table 3) outlined by

Bayliss (1999) but with a higher resolution 10m DEM and the refined LCM classes (Table 2). Here we outline the method and improvements gained over existing FEH descriptors used in Eq. 1.

Catchment area – AREA: Catchment areas were calculated using 10m resolution DEM data (Table 1) in combination with storm drainage maps following the method of Rodriguez et al. (2013) (Appendix: Table 3). The combination of DEM and drainage data is often necessary in urban environments as artificial drainage can alter catchment area from natural conditions (Braud et al., 2013). Finer scale resolution DEM data (5m) was not suitable as it captured manmade interventions in the urban landscape that significantly altered the natural elevation surface and thus drainage area, while lower resolution (50m) data did not capture small catchment areas and was not suitable for the urban scale.

Urban extent – URBEXT: The index of urban extent provides a weighted index value for Suburban and Urban land cover (Table 3) to provide a proxy measurement for imperviousness within a catchment (Bayliss, 1999). This has been shown to be a robust method for estimating imperviousness from land class data at catchment scales (Miller and Grebby, 2014). With the refined Suburban classes (Table 2) the *URBEXT* calculation has been reclassified here ($URBEXT_{rc}$) using weightings (Eq. 2) that account for the variation in impervious/pervious surfaces between the new classes. Additionally, *Urban* or *Suburban* class areas re-classified as *SuDS* were not included in this revised calculation, as SuDS are designed to effectively remove the hydrological impact of impervious surfaces for all but extreme events (POST, 2007; Ballard et al., 2015; Environment Agency, 2013).

Eq. 2) $$URBEXT_{rc} = URBAN + 0.75\, SUBURBAN_{HD} + 0.5\, SUBURBAN_{MD} + 0.25\, SUBURBAN_{LD}$$

Flood attenuation – FARL: The method used to calculate an index of attenuation from rivers and lakes - *FARL* - follows the FEH method outlined by Bayliss (1999: Table 3). The basis of this method is that the storage of high flows in lakes and reservoirs will attenuate the flood hydrograph, and that large lakes with large drainage areas have a high storage potential, and can modify flood response to a greater extent than small lakes with small drainage areas. Bayliss (1999) utilized a 50m gridded reservoir/lakes dataset developed as part of the Institute of Hydrology Digital Terrain Model (IHDTM) which was found to be broadly similar to the lakes and reservoirs mapped in the LCM data and OS 1:50,000 Landranger map series (Morris and Flavin, 1990). Here, we recalculate a refined flood attenuation index $FARL_{rc}$ using the refined Water class detailed in 2.2 that captures much smaller local water bodies in urbanized areas.

Catchment slope and drainage path length – DPSBAR and *DPLBAR*: Mean catchment slope and mean drainage path length were calculated using the methods outlined by Bayliss (1999: Table 3) but using the 10m DEM and associated flow accumulation network utilized in this study. This is more accurate in urban areas, capturing artificial drainage and associated alterations to natural pathways.

Hydrological soil type – BFIHOST: Soil hydrology type is defined by the base flow index (*BFI*) for the dominant hydrology of soil type (*HOST*) class (Boorman et al., 1995) within each catchment (*BFIHOST*).

2.3.2 Landscape metrics for connectivity and location

Landscape metrics suitable for connectivity representation were selected and calculated using the FRAGSTATS software (McGarigal and Marks, 1994). Both the class-based and landscape metrics selected are detailed in Table 3, along with details on the calculation method, parameters, and source.

Table 3

While landscape metrics used in ecological applications have shown some effectiveness for attributing hydrological response through measuring general shape (Lin et al., 2007), other metrics using hydrological distance, rather than Euclidian distance, have been shown to be more effective at representing hydrological connectivity. Van Nieuwenhuyse et al. (2011) found that landscape metrics can be particularly useful for expressing connectivity of hydrological systems, and that hydrological connectivity is determined by the spatial organisation of heterogeneity. They took the Proximity Index (*PX*) metric developed by Gustafson and Parker (1992) to account for Euclidean distance and connectivity and adapted this to capture the effects of both hydrological distance and connectivity of urbanized patches to the catchment outlet (Eq. 3):

Eq. 3) $$PX = \sum A_k / mdo_k$$

where, A_k is the area of patch k, and mdo_k is the mean distance to the outlet (*mdo*: Table 3) of patch k, and *PX* is the product of these ratios for all *Urban* and *Suburban* land use patches.

While the *PX* metric used by Van Nieuwenhuyse et al. (2011) did incorporate hydrological distance, the application was for a stochastic drainage network within a triangular conceptual catchment. Thus we have additionally normalized both patch area A_k and patch flow path length d_k by catchment area (*AREA*) and mean catchment drainage path length (*DPLBAR*), respectively, to additionally derive a normalized unit-less PX_N index (Eq. 4);

Eq. 4)

$$PX_N = \sum \frac{A_k/AREA}{mdo_k/DPLBAR}$$

In total, 30 separate landscape and class-based metrics were computed (Appendix: Table 8) by using the metrics in Table 3 and in Eqs 2-4 across the variable classes considered. This included 10 *Urban* and 10 *Suburban* class metrics, 3 landscape metrics, 5 hydrological metrics, and 2 $Green_{NAT}$ class metrics. To determine which catchment descriptors (2.3.1) and potentially suitable landscape metrics (2.3.2: Table 3; Appendix Table 8) should be used in the development of a revised index flood equation ($QMED_{rev}$), we assessed correlations between descriptors/metrics against the observed index flood $QMED_{obs}$ using Spearman's rank correlation coefficient (Spearman, 1904). $\mathrm{QMED_{obs}}$ was calculated for each catchment from the monitored data using the methods outlined in FEH (Institute of Hydrology, 1999).

Catchment descriptors are routinely used for deriving flood estimates for ungauged catchments based on derived relationships between peak flows and various catchment descriptors in both the UK (Environment Agency, 2012) and internationally (Feaster et al., 2014). The third stage introduced the refined descriptors and metrics into a regression model for estimating the index flood (*QMED*) for the selected catchments to assess the potential for using landscape metrics in flood estimation. Here this was done using three steps: i) identifying the best performing variables in a step-wise regression against $QMED_{obs}$; ii) deriving $QMED_{rev}$ for all sites using the regression variables, and; iii) comparing the performance of $QMED_{rev}$ and $QMED_{FEH}$ against $QMED_{obs}$ for all sites.

QMED was derived for the 18 sites across both study sites using both the observation-based ($QMED_{obs}$) and catchment descriptor-based ($QMED_{FEH}$) methods to provide baseline estimates with which to compare the performance of the refined catchment descriptor equation ($QMED_{rev}$) that utilizes the refined descriptors and landscape metrics (Section 2.3). In order to identify the best performing descriptors/metrics as variables for $QMED_{rev}$ we employed the weighted least squares (WLS) approach to linear regression modelling (Ruppert and Wand, 1994). The WLS approach was the most suitable regression given that the limited number of catchments and limited quantity of annual maxima at 16 of the 18 sites precluded accounting for covariance in estimating *QMED*. The WLS approach involved iterative testing of potential variables for estimating *QMED* and applying a weighting factor based on record length. For each iteration all metrics were compared using the following transformations: none, logarithmic, inverse (1000/x), and power (c^x) and the best performing combination of metrics was retained based on the adjusted r^2.

3 Results and discussion

3.1 Refining urban land cover classes

Mapping of the refined urban land use classes (Table 2) formed the first step in deriving enhanced catchment descriptors and landscape metrics. The results of refining the existing basic LCM classes for Swindon and Bracknell are illustrated in Figure 3 and summarized in Table 4.

Figure 3

Table 4

The most evident and expected change observed in Figure 3 between the standard and refined classification is the significant change in the Suburban class. Table 4 reveals the majority becomes reclassified as either low-density Suburban$_{LD}$ (peripheral, isolated, satellite or rural) developments or medium-density Suburban$_{MD}$ (cores of large suburban) developments. A much lower portion becomes reclassified as high-density Suburban$_{HD}$ areas close to central urban development. This suggests that impervious cover, relative to development density, may be overestimated when using a less detailed index of urban extent such as *URBEXT* or taking an assumed impervious cover and applying it to a single urban land use class that is in reality highly variable, as identified by Redfern et al. (2016). Additionally, the form this takes differs between the two catchments, mainly due to historical development patterns. The higher relative coverage of low-density development in Bracknell (Table 4) further indicating variability in impervious cover not well represented by a single suburban class applied over a range of different catchment development types. Further, while Miller and Grebby (2014) found that *URBEXT* was indicative of impervious cover in small urban catchments, that study only considered a limited area with very similar development types. This points to the potential for significantly improving estimates of urbanisation impacts in catchment descriptor-based flood estimation methods for urbanized catchments by directly using impervious estimates derived from remote sensing imagery (Weng, 2012).

The high proportion of low-density suburban housing identified in this study poses significant potential for contributing large areas of domestic garden as green infrastructure (Cameron et al., 2012), which have been shown to have a role in runoff regulation (Warhurst et al., 2014). Such variability could be important for explaining the fact that generalized estimates of impervious cover based on *URBEXT* do not explain hydrological response in urbanized catchments (Miller and Hess, 2017). Further, while impervious estimates may be ultimately refined, the refined classes based on density may in fact offer additional information on the variability of water management and transfer, and therefore GI potential, not quantified by imperviousness alone.

In both catchments the Water class in standard LCM mapping is not high (0.1-0.3%: Table 4), however the inclusion of OSMM water has significantly increased water cover in both catchments, by 400% in Swindon, and nearly 300% in Bracknell. Although the relative areas are not high compared to total catchment area (0.5% and 1.1% for Swindon and Bracknell, respectively), it must be considered that it is the area serviced by these water bodies that's important (*FARL* – Table 3) and thus these changes should affect *FARL*. Additionally much of this increased cover is within urban areas, so could be providing localized flood attenuation, with the higher value in Bracknell reflecting the deliberate design of flood attenuation features (Packman and Hewitt, 1998). The availability of high resolution OSMM data provides the user with up to date and accurate data from which to delineate such features. Given that new small waterbodies are increasingly being used in mitigating runoff in urban catchments (Jarden et al., 2015; Wilkinson et al., 2010) these results highlight the importance of using contemporary high-resolution imagery to map such features. One shortcoming however is that such methods do not facilitate identification of temporary storage features, such as swales or offline temporary storage. Subsurface retention areas are also not identified. Both have been identified as having flood storage capacity (CIRIA, 2014) but would be difficult to map from remote imagery.

The overall coverage of completely pervious classes (Grassland/Agriculture, Woodland) between the two towns and surrounding catchment is a combined 60.3% in Swindon, and 59.3% in Bracknell (Table 4), reflecting the urbanized nature of both catchments. The distribution within classes is different however, reflective of geographical location and planning controls: Bracknell being located near to London but having a large area of protected woodland to the south, and Swindon being more remote and surrounded by farmland. Urban reclassification of greenspaces indicates that urban greenspace ($Green_{URB}$) can make up significant areas within the urban fringes (2.3 – 4.4%). While less than 10% of overall pervious cover (31.1-49.3%), if such areas are fundamentally so altered or compacted as to behave like impervious surfaces (Chen et al., 2014) then the effect on runoff within the urban areas is likely to be significant at local scales. These effects could however be balanced by the areas of natural greenspace ($Green_{NAT}$) that have been shown to reduce runoff through enhanced infiltration (Zhang et al., 2015). Certainly such areas could play a role in localized runoff reduction, and given their location in these towns, this reveals the importance of considering types of urban greenspace and of using high accuracy datasets for estimating local runoff in urban areas (Verbeiren et al., 2013).

Further refinement by identification of likely areas of SuDS did not reveal any significant areas, with total areas of 0.3% and 0.4% in Swindon and Bracknell, respectively (Table 4). These are likely to be conservative values, reflecting that while much of Swindon is not hydro-geologically suitable for infiltration based SuDS, being composed of clay soils, retention based SuDS could be prevalent. Similarly, in Bracknell retention SuDS design is in fact integrated into the overall hydraulic design of the town, rather than having localized implementation or infiltration-based measures. Even so, the low values do not indicate these sub-classes will have a significant impact on refining *URBEXT* or explaining *QMED* in this study. However, with new developments required to implement such features where possible (Defra, 2011), such areas will increasingly become important. Going forward, accurately delineating areas serviced by SuDS is a clear priority for urban land cover mapping. This will enable better modelling of SuDs impacts and more accurate representation in a suitable catchment scale index for index flood methods.

3.2 Identifying suitable catchment descriptors and landscape metrics

A comparison between FEH catchment descriptors and those derived from refined classes across the 18 sites revealed there to be a high degree of correlation (>0.95), with associated minor improvements (<0.05) to the correlations with $QMED_{obs}$ for all except $FARL_{rc}$ (-0.22 → -0.38) which improved significantly. Regression model analysis (Table 5) further indicated the significant relationships between both standard and reclassified descriptors across the 18 sites, with the lowest fit observed for $FARL_{rc}$ (r^2 = 0.894) while both $AREA_{rc}$ and $URBEXT_{rc}$ exceed an r^2 of 0.99. Taken together these results suggest the use of the reclassified $FARL_{rc}$ catchment descriptor will improve estimates of catchment flood attenuation from water bodies in small urbanized catchments, and subsequently replaces *FARL* in this study.

Table 5

For $URBEXT_{rc}$ the correlation with $QMED_{obs}$ actually decreased (-0.05), indicating that the refined suburban classes and inclusion of SuDS areas provides no evident improvement in providing a descriptor of urban extent for use in *QMED* estimation across the 18 sites. Combined with the high model r^2 in Table 5 this further suggests that detailed efforts to map variation in suburban land cover classes under current conditions has no real benefit for estimating *QMED,* and as such we retained the standard *URBEXT* and Urban/Suburban land cover classes for subsequent steps. Other studies have shown that such variation only becomes important at local scales (Shuster et al., 2005) or between distinct development types (Valtanen et al., 2013). Going forward however, as SuDS are increasingly adopted and more attention is paid to urban design to reduce runoff generation, such a refined approach could well become much more important.

$AREA_{rc}$ showed minor improvements over standard values but importantly did not consider those four small urban catchments (S4, S7, S9, S10) in which it was not possible to automatically determine catchment area, as no natural catchment existed at these artificial drainage points. This is a limiting factor in using FEH catchment descriptors for small highly altered urban catchments (Miller et al., 2014). This highlights the need for a high resolution DEM to be used in conjunction with ancillary datasets on stormwater infrastructure and impervious areas to delineate artificial urban catchment boundaries (Braud et al., 2013). $AREA_{rc}$ values were used henceforth in place of *AREA*.

From the 30 catchment descriptors and landscape metrics computed (Appendix: Table 8), this was reduced down in four iterations to 17 descriptors/metrics (Table 6) that are subsequently used. This includes 12 landscape metrics that were not significantly (>0.8) correlated with at least three other metrics, alongside four catchment descriptors used in estimating *QMED* (Eq. 1) and one (*URBEXT*) used to adjust for urbanization (Kjeldsen, Jones and Bayliss, 2008). Table 6 reveals that $AREA_{rc}$, as expected, was the most highly correlated descriptor to $QMED_{obs}$ (0.95). For the landscape metrics, *PX* correlates surprisingly well with $QMED_{obs}$ (0.82), as does $COHESION_{URB}$ (0.61). Interestingly, many of the metrics applied to Urban or Suburban classes prove more correlated with $QMED_{obs}$ than *URBEXT*. Additionally, the normalised PX_N does not correlate as well with $QMED_{obs}$ (-0.52), but performs better than *URBEXT* (-0.36) with which it is highly correlated (0.83). This suggests that efforts to normalize the *PX* metric reduces its descriptive ability and renders it more like *URBEXT,* further illustrating the relatively weak performance of this catchment descriptor at such local urban scales compared to more spatially orientated landscape metrics. The results detailed in Table 6 suggest that some metrics could be important variables in the final *QMED* regression, thus reinforcing what Van Nieuwenhuyse et al. (2011) and others have found (e.g. Lin et al. 2007; Yuan et al. 2015) in that landscape metrics are a useful tool for comparing hydrological basins with significant potential for application in lumped hydrological studies and modelling.

Table 6

3.3 Catchment descriptors and landscape metrics for flood estimation

The optimal configuration for refining the *QMED* equation was to follow the FEH $QMED_{FEH}$ equation (Eq. 1) and iteratively select four catchment descriptors and/or landscape metrics as variables based on forward step-wise maximisation of the adjusted r^2 using the weighted least squares (WLS) function (Ruppert and Wand, 1994) against $QMED_{obs}$ for the 18 sites. The four variables identified were catchment areas ($AREA_{rc}$), and three landscape metrics: *PX*, $COHESION_{SUB}$, and *CONTAG*.

The final derived equation of the maximised WLS regression for $QMED_{rev}$ across the 18 sites using the variables selected is shown in Eq.5. Table 7 details the catchment values for the selected variables along with the model fit and differences in estimated index flood values for both $QMED_{rev}$ and $QMED_{FEH}$ compared with $QMED_{obs}$ (catchment FARL and URBEXT values are also included for reference). Importantly, the addition of *PX* proved highly effective at explaining the variability in $QMED_{obs}$ not covered by $AREA_{rc}$ alone from an adjusted r^2 of 0.848 to 0.972, and the inclusion of the final two metrics only improved the overall fit to r^2=0.984. The range of values for both these additional metrics is generally low across the sites but a very high *CONTAG* value at S10 (93.8: Table 7) and low $COHESION_{SUB}$ value for S2 (81.4: Table 7) could explain their inclusion in the final equation, given both sites have the same $QMED_{obs}$ (0.64 m^3s^{-1}: Table 7) but are significantly different in area (S2 - 3.24 km^2; S10 - 0.49 km^2). The high *CONTAG* value at S10 is indicative of the fact that the area is almost entirely Suburban and has high storm drainage connectivity, while the low $COHESION_{SUB}$ value at S2 is clearly indicative of a rural catchment with patchy areas of housing and low drainage connectivity.

Eq. 5) $$QMED_{rev} = 357.0943\, {AREA_{rc}}^{0.4007}\, PX^{0.8195}\, 1.0595^{COHESION_{SUB}} 1.0115^{CONTAG}$$

Table 7

Overall $QMED_{rev}$ was shown to have an r^2 of 0.984 across the 18 sites, an improvement over the r^2 of 0.907 estimated by using $QMED_{FEH}$. Assessing the performance across the 18 sites and between each method for estimating *QMED* it is clear from Table 7 that $QMED_{rev}$ performs well against the observed values, with an average difference of only -3.5%, and exceeding 25% in only two cases (B5 and B6) where it significantly underestimates *QMED*. The FEH equation performed well considering these are small highly-urban catchments and the $QMED_{FEH}$ is derived from national data across a wide range of catchment types and scales, but still had a mean difference to $QMED_{obs}$ of -27.5% and a majority of sites (12) exceeding 25%. There are no discernible patterns to explain why certain catchments performed better or worse, either relative to size or potential flood attenuation ($AREA_{rc}$ and $FARL_{rc}$: Table 7), level of urbanization (*URBEXT*), location (Swindon or Bracknell), monitoring source (EA gauging or local monitoring) or between methods. This would indicate that the revised equation based on landscape metrics performs well across a range of catchments from predominantly rural, e.g. B1 and S2, to highly urbanized e.g. S9 and B3.

While $FARL_{rc}$ was not included in the step-wise variable selection it should be noted that it may well pose a greater significance across a broader selection of study catchments as in certain Bracknell catchments (B1, B5, B6, EA_39052: Table 7). $FARL_{rc}$ falls below the threshold value 0.9 below which the EA do not recommend using the catchment descriptor method for estimating *QMED* (Environment Agency, 2012). This demonstrates the value of using high-resolution imagery for identifying such small but potentially hydrologically important features.

Considering urbanization, the lack of a significant relationship between *URBEXT* and $QMED_{obs}$ (r^2=0.09) compared to the stronger relationship with *PX* (r^2=0.634), would indicate that urbanization is not a good indicator of high flow variability in urbanized catchments without explicit consideration of spatial layout. This unexpected pattern was similarly observed by Miller and Hess (2017) and highlights the value of considering both the relative coverage and hydrological distance to outlet of each urban patch. This study demonstrates that such a landscape metric could improve flood estimation in urban catchments and should be considered at a more national scale in flood estimation, particularly in the light of growing urbanization, and poor performance of existing methods in small urban catchments (Faulkner et al., 2012). Further, both *TIA* and distribution of impervious area, will certainly be improved by using detailed mapping of imperviousness from remote sensing imagery, as shown in numerous detailed hydrological studies (Dams et al., 2013; Verbeiren et al., 2013). Further, the inclusion of both the class-based *COHESION* metric applied to suburban areas and the landscape-based *CONTAG* metric, demonstrates that such metrics could be useful at capturing variability in between catchments not covered by explicit representation of area or urbanisation.

The omission of both variables *FARL* and *URBEXT* from the revised index flood equation $QMED_{rc}$, and the performance of landscape metrics compared to such routinely used descriptors, was surprising and indicates such metrics, could have significant potential in improving flood estimates in ungauged small urban catchments. Similarly, other studies have shown that alternative catchment descriptors can be derived from readily available geo-spatial data, and prove both more heterogeneous and perform better at estimating *QMED* (Wan Jaafar and Han, 2012). Overall, this study has demonstrated the potential of ecological landscape metrics (Yang et al., 2011) and hydrologically relevant metrics (Van Nieuwenhuyse et al., 2011) for estimating QMED in urbanized catchments.

4 Conclusions

This study has sought to assess the potential for refined land cover information and landscape metrics in flood estimation. The results of refining catchment descriptors using higher-resolution data suggest that using such data alongside emerging datasets can alter the representation of the urban environment, having particular impacts on how urban water features are accounted for and where the catchment boundaries exist. Additionally, they suggest that class based approaches can be limited by nationally available data, indicating the need to test the application of more detailed global remotely sensed data. The results of employing landscape metrics alongside catchment descriptors has shown that index flood estimation in urbanized catchments could be improved by employing landscape metrics that represent hydrological distance relative to patch size and connectivity of urbanized areas. These provide a means of representing the hydrological complexity of an urban catchment in a single but spatially-explicit distributed numeric form, suitable for design flood methods and lumped hydrological modelling. We conclude the evidence indicates that a ‘one-size-fits-all’ national approach to flood estimation in urbanized areas could be improved by having more spatially explicit catchment descriptors and QMED equations, and that this should be the focus of further research to upscale and validate the application of such metrics and refined index flood equations.

The ability of landscape metrics to express hydrological connectivity and relative size and location of urban development to the location of interest has been clearly shown and promises significant urban planning improvements for flood management. This suggests such metrics could further be useful in the design and testing of green infrastructure for natural flood management, given their respective role in mitigation of floods and clear links between runoff and catchment properties.

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5 Tables

Table 1: Source geo-spatial data and derived geo-spatial data

Dataset	Data type	Description
OS Master Map Topography Layer	Polygon	OS MasterMap Topography Layer is a large-scale digital database of detailed surface features in the landscape of Great Britain. (www.ordnancesurvey.co.uk)
Land Cover Map (LCM) (2015)	Raster (50m)	LCM is a national mapping product derived from satellite images and digital cartography and gives land cover information for the entire UK. LCM used in this study is an updated version of the most recent national dataset LCM 2007 (Morton et al., 2011)
Natural Areas	Polygon	Mapping of Local Nature Reserves, Country Parks, and Woodpasture and Parkland sites – from Natural England. http://magic.defra.gov.uk/
SuDS Infiltration Map	Polygon	Mapping of SuDS potential – based on derived substrate infiltration properties. (Dearden, 2016)
Urban/Suburban Land Use Change (1960 – 2010)	Raster (50m) aggregated from 1m raster	Mapping of Urban and Suburban LCM classes using historical topographical mapping (1960 – 2010) published by Ordnance Survey.
NEXTMap Digital Elevation Model (DEM)	10m DEM	Used to determine surface-water catchment boundaries and flow pathways/accumulation.

Table 2: Refined Land Cover Mapping urban hydro-typologies. Suburban sub-classes were based on typical development density ranges (Appendix: Table 1) for 9 selected training areas selected from visual analysis of aerial photography.

LCM classes	**Refined typology**	**Sub-class (SuDS)**	**Description**
Urban	Urban	Urban$_{SUDS}$	Town centre/ industry/commercial/office/large infrastructure
Suburban	Suburban$_{HD}$ (High-Density)	Suburban$_{SUDS}$	High-density building (> 19% per 50 x 50m^2 grid) e.g. urban fringe and terraced
	Suburban$_{MD}$ (Medium-Density)	Suburban$_{SUDS}$	Medium density building (13% - 19% per 50 x 50m^2 grid) e.g. peri-urban housing developments
	Suburban$_{LD}$ (Low-Density)	Suburban$_{SUDS}$	Low density building (<13% per 50 x 50m^2 grid) e.g. rural and isolated developments
Woodland	Woodland		Areas of continuous woodland and shrub
Agricultural/ managed	Greenspace (Green)		Land with agricultural or managed land use not in an urban area
	Greenspace – urban (Green$_{URB}$)		Highly managed green space within urban areas (e.g. parks, recreation areas)
	Greenspace – natural (Green$_{NAT}$)		Natural/ low-management greenspaces such as nature reserves and conservation woodland
Water	Lake/Pond/Wetland		Natural water body identified on LCM and with additional water bodies from OSMM

Table 3: FEH catchment descriptors used for estimating QMED and selected hydrologically suitable landscape metrics

Descriptor/ Metric	**Formula**	**Explanation**	**Parameters**
FEH catchment descriptors			
Area		Catchment drainage area (km^2)	A = Area of catchment
SAAR	$\frac{\sum_{i=1961}^{1990} P_i}{30}$	Standard-period Average Annual Rainfall (mm) rainfall for the period 1961-1990 in Great Britain and Northern Ireland	P = Precipitation (annual total)
FARL	$FARL = \prod_{i\in} \alpha_i$ where: $\alpha = (1-\sqrt{r})^w$ $r = \frac{water\ surface\ area}{subcatchment\ area}$ $w = \frac{subcatchment\ area}{catchment\ area}$	Index of flood attenuation from rivers and lakes. The overall *FARL* index has a value close to one when a catchment has low attenuation from water bodies, and as attenuation effects become more important the index decreases.	α = effect of individual water body r = relative size of water body to upstream catchment w = weighting reflecting importance of water body
BFIHOST	Area weighted base flow index (BFI) assigned from catchment 1km gridded dominant HOST class	Base flow index from Hydrology of Soil Types (HOST) Boorman et al. (1995)	
URBEXT	$URBEXT = Urban + 0.5\ Suburban$	FEH index of fractional urban extent	Urban and Suburban are Land Cover Mapping (LCM) classes for urbanized surfaces
Class based landscape metrics			

Percentage of Landscape	$PLAND = A_C/A_T$	Equals the percentage of the landscape comprised of the corresponding patch type.	A_C = Class area A_T = Total catchment area
Perimeter-Area Ratio	$PARA = \frac{P_{ij}}{a_{ij}}$	*Perimeter-area ratio* is a simple measure of shape complexity, but without standardization to a simple Euclidean shape	p_{ij} = perimeter (m) of patch ij. a_{ij} = area (m^2) of patch ij.
Total Edge	$TE = \sum_{k=1}^{m} e_{ik}$	*Total edge* at the class level is an absolute measure of total edge length of a particular patch type.	e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.
Edge Density	$ED = \frac{E}{A}(10{,}000)$	*Edge density* reports edge length on a per unit area basis that facilitates comparison among landscapes of varying size	E = total length (m) of edge in the landscape. A = total landscape area (m^2).
Contiguity Index	$CONTIG = \frac{\left[\frac{\sum_{r=1}^{z} c_{ijr}}{a_{ij}}\right]}{v-1}$	Assesses the spatial connectedness, or contiguity, of cells within a grid-cell patch to provide an index of patch boundary configuration and thus patch shape	c_{ijr} = contiguity value for pixel r in patch ij. V = sum of the values in a 3-by-3 cell template (13 in this case). A_{ij} = area of patch ij in terms of number of cells.
Largest Patch Index	$LPI = \frac{\underset{j=1}{\overset{a}{max}}(a_{ij})}{A}(100)$	*Largest patch index* at the class level quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance.	a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2).

Clumpiness index	Given: $$G_i = \left(\frac{g_{ii}}{(\sum_{i=1}^{m} g_{ii}) - mine_i}\right)$$ $$CLUMPY = \left[\frac{G_i - P_i}{P_i}\ for\ G_i < P_i \& P_i < 5, e; else\ \frac{G_i - P_i}{1 - P_i}\right]$$	The proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution.	g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) I based on the *double-count* method. G_{ik} = number of adjacencies (joins) between pixels of patch types (classes) I and k based on the *double-count* method. Min-e_i = minimum perimeter (in number of cell surfaces) of patch type (class) I for a maximally clumped class. P_i = proportion of the landscape occupied by patch type (class) i.
Cohesion	$$COHESION = \left[1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p\,ij\sqrt{a_{ij}}}\right]\left[1 - \frac{1}{\sqrt{A}}\right]^{1}(100)$$	*Patch cohesion index* measures the physical connectedness of the corresponding patch type.	p_{ij} = perimeter of patch ij in terms of number of cell surfaces a_{ij} = area of patch ij in terms of number of cells. A = total number of cells in the landscape.
Landscape metrics			
Contagion Index	$$CONTAG = 1 + \sum\sum\left[q_{ij}ln\left(q_{ij}\right)\right]/2ln(2)$$	Assesses the extent to which patch types are aggregated or clumped as a percentage of the maximum possible; characterized by high dispersion and interspersion.	P_i =proportion of the landscape occupied by patch type (class) i. g_{ik} =number of adjacencies (joins) between pixels of patch types (classes) i and k based on the *double-count* method. m =number of patch types (classes) present in the landscape, including the landscape border if present.
Landscape Shape Index	$$LSI = \frac{e_i}{\min e_i}$$	*Landscape shape index* provides a simple measure of class aggregation	e_i = total length of edge (or perimeter) of class i in terms of number of cell surfaces;

		or clumpiness and, as such, is very similar to the aggregation index.	includes all landscape boundary and background edge segments class i. min e_i = minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces
Effective Mesh Size	$MESH\,\frac{\sum_{j=1}^{n} {a_{ij}}^{2}}{A}\left(\frac{1}{10000}\right)$	MESH provides a relative measure of patch structure	a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2).

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Table 4: Percentage coverage of standard and reclassified (rc) Land Cover mapping (LCM) classes, with distribution by catchment, and overall areas of Suburban and Urban areas serviced by Sustainable Urban Drainage Systems (SuDS).

		Swindon			Bracknell		
LCM classes	**LCM_{rc} classes**	**LCM**	**LCM_{rc}**	**SuDS**	**LCM**	**LCM_{rc}**	**SuDS**
Urban	Urban	12.9%	12.8%	0.1%	4.7%	4.7%	0.1%
	$Suburban_{LD}$		11.9%			19.3%	
Suburban	$Suburban_{MD}$	26.8%	12.6%	0.2%	35.7%	13.8%	0.3%
	$Suburban_{HD}$		1.9%			1.3%	
Water	Water	0.1%	0.5%		0.3%	1.1%	
	Green		49.3%			31.1%	
Grassland/ Agriculture	$Green_{URB}$	56.2%	4.4%		38.8%	2.3%	
	$Green_{NAT}$		3.2%			10.7%	
Woodland	Woodland	4.1%	3.4%		20.5%	15.8%	

Table 5: Linear regression model results for FEH and revised (rc) catchment descriptors. Values were normalized using the natural logarithm (ln) to normalize data.

	Coefficient (Θ_p)	**Standard error**	**t-value**	**p-value**
lnURBEXT$_{rc}$ (r^2 = 0.9968, rse = 0.02661 , df = 16)				
Intercept	-0.03637	0.01526	-2.384	0.0299
lnURBEXT	0.96616	0.04339	22.266	1.82E-13
lnAREA$_{rc}$ (r^2 = 0.9965, rse = 1.426, df = 12)				
Intercept	-0.41	0.59442	-0.691	0.503
lnAREA	1.02826	0.01681	61.182	2.41E-16
lnFARL$_{rc}$ (r^2 =0.8943, rse = 0.1872, df = 16)				
Intercept	-0.9723	0.1592	-6.108	1.514E-05
lnFARL	1.9626	0.1631	12.035	1.97E-09

Table 6: Refined list of potential QMED catchment descriptors and metrics. QMED and each descriptor across all sites are transformed using natural logarithm. Correlations greater than 0.8 are highlighted in bold. Correlations between 0.6 and 0.8 are shown in italics and underlined.

	QMED	AREA	BFIHOST	SAAR	FARL	URBEXT	PX	PXN	CONTAG	LPI_{URB}	$CONTIG_{URB}$	$CLUMPY_{URB}$	$COHESION_{URB}$	LPI_{SUB}	$CONTIG_{SUB}$	$CLUMPY_{SUB}$	$COHESION_{SUB}$	$COHESION_{NAT}$
QMED	1	**0.95**	-0.38	0.08	-0.38	-0.36	**0.82**	-0.52	-0.46	0.14	0.28	0.46	0.61	-0.51	-0.5	0.47	0.18	0.42
AREA	**0.95**	**1**	-0.41	-0.05	-0.5	-0.53	0.59	*-0.7*	-0.38	-0.13	-0.35	0.02	0.48	*-0.7*	-0.56	0.48	0	0.27
BFIHOST	-0.38	-0.41	**1**	0.48	0.04	-0.08	-0.31	0.11	*0.6*	-0.27	-0.44	-0.51	-0.54	-0.11	0.04	-0.18	*-0.6*	-0.47
SAAR	0.08	-0.05	0.48	**1**	0.19	-0.12	0.12	-0.02	0.36	0.08	-0.28	-0.22	-0.21	-0.32	0.02	-0.06	*-0.6*	-0.34
FARL	-0.38	-0.5	0.04	0.19	**1**	**0.82**	0	**0.88**	0.3	0.3	0.08	0.05	-0.07	0.53	*0.6*	-0.42	0.38	-0.3
URBEXT	-0.36	-0.53	-0.08	-0.12	**0.82**	**1**	-0.04	**0.83**	0.5	*0.75*	0.22	0.51	0.27	0.59	0.43	-0.41	0.22	*-0.6*
PX	**0.82**	0.59	-0.31	0.12	0	-0.04	**1**	-0.18	-0.17	0.29	-0.33	0.29	*0.77*	-0.57	-0.43	0.34	-0.14	-0.1
PXN_{URBEXT}	-0.52	*-0.7*	0.11	-0.02	**0.88**	**0.83**	-0.18	**1**	0.53	0.33	0.49	0.42	-0.12	*0.73*	**0.8**	-0.59	0.14	-0.41

CONTAG	-0.46	-0.38	*0.6*	0.36	0.3	0.5	-0.17	0.53	**1**	0.35	0.25	0.31	0.01	0.48	0.52	-0.06	0.3	-0.04
LPI$_{URB}$	0.14	-0.13	-0.27	0.08	0.3	*0.75*	0.29	0.33	0.35	**1**	-0.3	0.4	*0.65*	0.04	-0.18	0.08	0.08	*-0.6*
CONTIG$_{URB}$	0.28	-0.35	-0.44	-0.28	0.08	0.22	-0.33	0.49	0.25	-0.3	**1**	0.5	-0.29	*0.75*	*0.68*	-0.22	0.48	0.49
CLUMPY$_{URB}$	0.46	0.02	-0.51	-0.22	0.05	0.51	0.29	0.42	0.31	0.4	0.5	**1**	*0.61*	0.43	0.2	0.16	*0.64*	0.16
COHESION$_{URB}$	*0.61*	0.48	-0.54	-0.21	-0.07	0.27	*0.77*	-0.12	0.01	*0.65*	-0.29	*0.61*	**1**	-0.28	-0.5	0.49	0.31	-0.11
LPI$_{SUB}$	-0.51	*-0.7*	-0.11	-0.32	0.53	0.59	-0.57	*0.73*	0.48	0.04	*0.75*	0.43	-0.28	**1**	*0.76*	-0.36	*0.6*	0.08
CONTIG$_{SUB}$	-0.5	-0.56	0.04	0.02	*0.6*	0.43	-0.43	**0.8**	0.52	-0.18	*0.68*	0.2	-0.5	*0.76*	**1**	*-0.6*	0.15	-0.02
CLUMPY$_{SUB}$	0.47	0.48	-0.18	-0.06	-0.42	-0.41	0.34	-0.59	-0.06	0.08	-0.22	0.16	0.49	-0.36	*-0.6*	**1**	0.37	0.53
COHESION$_{SUB}$	0.18	0	*-0.6*	*-0.6*	0.38	0.22	-0.14	0.14	0.3	0.08	0.48	*0.64*	0.31	*0.6*	0.15	0.37	**1**	0.47
COHESION$_{NAT}$	0.42	0.27	-0.47	-0.34	-0.3	*-0.6*	-0.1	-0.41	-0.04	*-0.6*	0.49	0.16	-0.11	0.08	-0.02	0.53	0.47	**1**

Table 7: $QMED_{rev}$ and $QMED_{FEH}$ estimates with linear model performance and differences to observed QMED (light grey denotes a difference exceeding 10%, medium grey 25%, and dark grey exceeding 50%)

Site_ID	$AREA_{rc}$ (km^2)	PX	CONTAG	$COHESION_{SUB}$	$QMED_{obs}$ (m^3/s)	$QMED_{rev}$ (m^3/s) (r^2=0.984)	Diff (($QMED_{rev}$-$QMED_{obs}$s)/ $QMED_{obs}$)	$QMED_{FEH}$ (m^3/s) (r^2=0.907)	Diff (($QMED_{FEH}$-$QMED_{obs}$) / $QMED_{obs}$)	$FARL_{rc}$	URBEXT
S1	28.97	3.88	57.5	95.1	8.84	8.04	-9.1%	6.28	-28.9%	0.97	0.23
S2	3.24	0.2	76.4	81.4	0.64	0.63	-1.6%	0.24	-62.0%	0.85	0.03
S3	5.98	1.68	61.7	98.4	1.38	1.55	12.9%	2.01	46.1%	1	0.57
S4	3.09	1.38	68.0	99.6	1.17	1.10	-5.3%	0.91	-21.9%	1	0.33
S5	2.18	3.53	52.5	96.0	2.94	3.32	12.7%	0.69	-76.6%	1	0.39
S6	35.2	4.28	55.5	96.0	9.37	10.83	15.6%	7.56	-19.4%	0.96	0.29
S7	0.54	1.54	52.7	94.7	0.97	0.82	-15.6%	0.16	-83.9%	1	0.4
S8	2.16	1.07	52.7	98.9	0.80	0.87	9.6%	0.78	-2.3%	1	0.31
S9	0.27	0.66	62.3	100.0	0.25	0.26	4.2%	0.13	-47.5%	1	0.51
S10	0.49	2	93.8	95.1	0.64	0.61	-4.2%	0.15	-77.1%	1	0.37
EA_39087	82.5	3.95	55.5	97.4	13.41	11.35	-15.3%	13.72	2.3%	0.95	0.23
B1	18.37	1.15	51.0	93.6	2.31	2.26	-1.9%	3.19	38.2%	0.88	0.09
B2	12.49	1.69	58.1	98.9	2.97	2.28	-23.1%	1.84	-38.1%	0.94	0.19
B3	12.55	2.76	52.8	99.2	3.90	4.50	15.3%	2.11	-45.9%	0.92	0.37
B4	33.66	2.07	50.0	96.7	5.35	4.02	-24.8%	5.11	-4.4%	0.9	0.12
B5	37.5	1.85	50.4	97.2	5.61	4.14	-26.2%	5.12	-8.6%	0.87	0.13
B6	58.24	2.84	48.3	98.2	10.63	7.88	-25.9%	7.35	-30.8%	0.87	0.17
EA_39052	51.96	3.55	47.9	98.4	9.70	11.67	20.3%	6.35	-34.6%	0.86	0.19
Mean	21.6	2.2	58.2	96.4	4.5	4.2	-3.5%	3.5	-27.5%	0.9	0.3

6 Figures

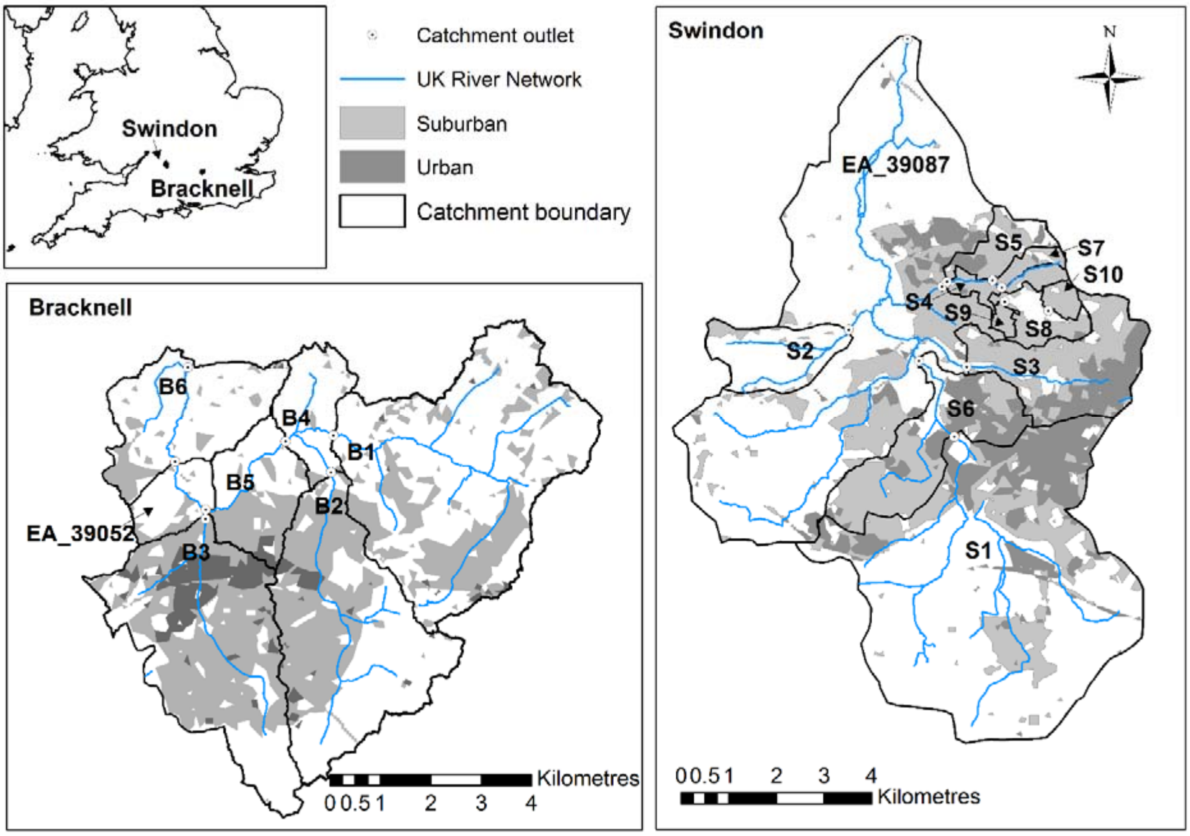
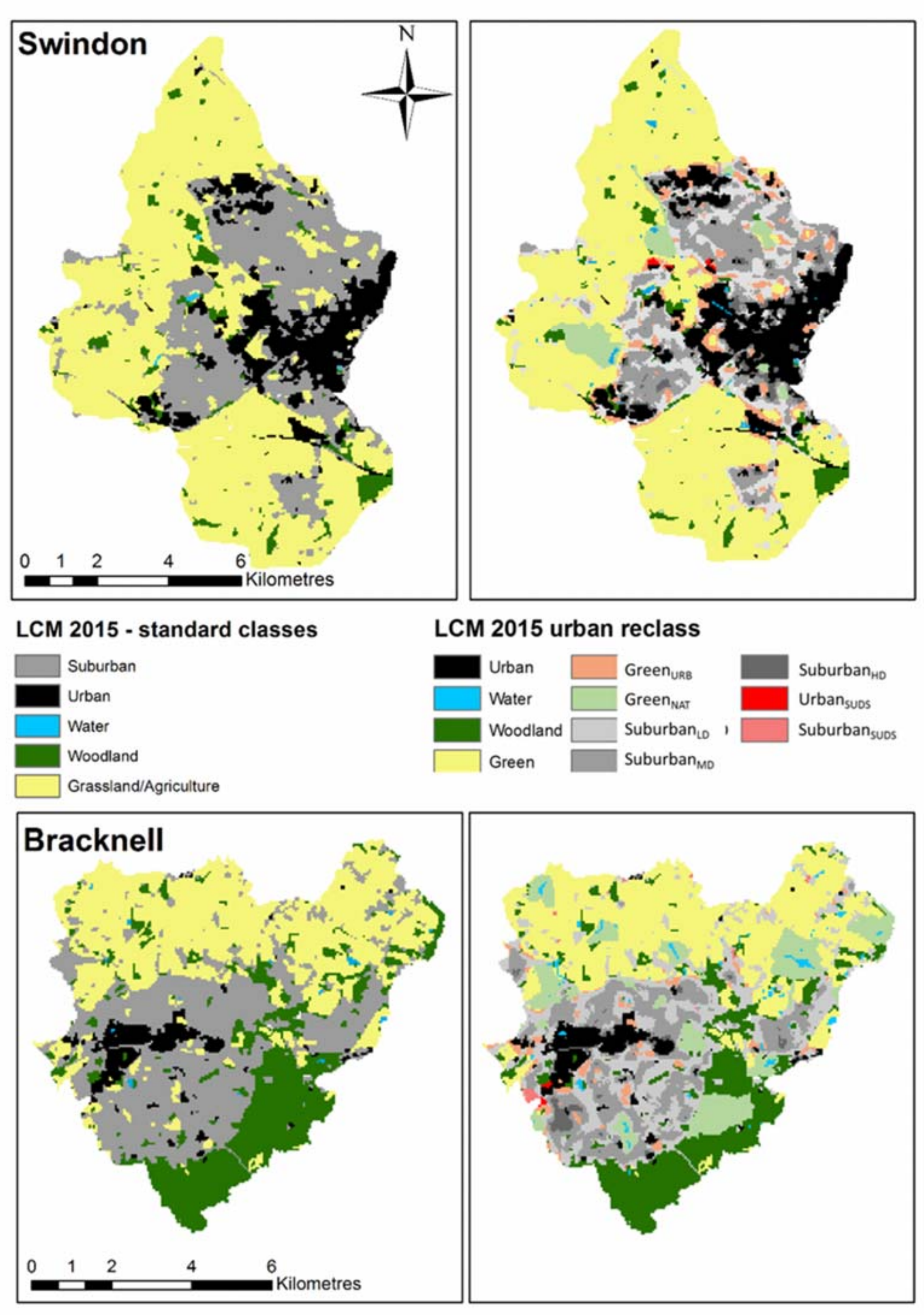


Figure 1: Study locations identifying Environment Agency (EA) gauging stations and selected sub-catchments for Bracknell (B) and Swindon (S), and showing Urban and Suburban extent: labels demote study catchments names (note some catchments are nested)

Figure 2: Refined urban land cover classes (scale 1:800): LD = Low Density, MD = Medium density, HD = High Density, URB = Urban, NAT = Natural.



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782 *Figure 3: Comparison of land cover classes using standard and refined urban reclassification for both Swindon and Bracknell*
783 *town (2015)*

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Appendix

Table 1: Class names and numbers for the vector data– the vector data set is the master data set from which the other products are derived. Note the table contains class numbers for some classes not found in the Thames Basin area – this is to allow the classifications to be extended to wider areas if required in the future.

Class number	Class name	Reclass number	Reclass name
1	Broadleaved / mixed woodland	4	Natural
2	Coniferous woodland	4	Natural
3	Arable	5	Agricultural/managed
4	Improved grassland	5	Agricultural/managed
~~5~~	~~Neutral grassland~~	~~na~~	
6	Calcareous grassland	4	Natural
~~7~~	~~Acid grassland~~	~~na~~	
~~8~~	~~Fen, marsh, swamp~~	~~na~~	
9	Dense dwarf shrub heath (heather)	4	Natural

10	Open dwarf shrub heath (heather grassland)	4	Natural
~~11~~	~~Bog (deep peat)~~		
12	Inland rock	4	Natural
~~13~~	~~Sea / Estuary~~		
14	Water (inland)	3	Water
~~15~~	~~Coastal~~		
~~16~~	~~Saltmarsh~~		
17	Suburban	1	Suburban
18	Urban	2	Urban

Table 2: ArcGIS method for deriving refined Suburban classes (LCM_RC1) based on density information from OSMM. Input data LCM2015 (Suburban), OSMM (buildings).

Step	**Tool and data**	**Description**
1	Select ‘buildings’ from OSMM attribute table and make new polygon layer	

2	**Polygon to raster** (Step1) (5m)	
3	**Reclassify** (no data 0, building 1)	
4	**Aggregate** to 50m (mean)	
5	Identify suitable breaks – test 10 selected areas of different development type and density using 3 classes.	0.13, 0.19 identified as breaks.
6	**Reclassify** using breaks (Step 5)	Set grids as 11, 12, 13
7	**Clip** LCM 2015 to catchment	1 = Suburban
8	**Clip** (5) to catchment	
9	**Raster Calculator**: Con(Step7==1,Step8,Step7)	Re-classes Suburban grids as 11 (LD), 12 (MD), or 13 (HD)
10	**Data export**	LCM_RC1

Table 3: ArcGIS method for deriving refined Water classes (LCM_RC2) based on water features indicated on OSMM. Input data: LCM_RC1 (3), OSMM (water).

Step	**Tool and data**	**Description**

1	Select ‘water’ from OSMM attribute table and save as new layer	
2	**Polygon to raster** (Step1) (1m)	
3	**Reclassify** (no data 0, water 3)	
4	**Aggregate** to 50m (mean)	
5	Identify suitable breaks – test 10 selected areas of water feature (river-lake) using 2 classes.	0.23 identified as suitable break – not encompassing very small features or rivers.
6	**Reclassify**	0 no water, 3 water.
7	**Clip** (Step 6) to catchment	
8	**Raster Calculator**: Con((Step6==3) & (LCM_RC1 != 3),3,LCM_RC1)	Converts non LCM_RC1 water grids to 3.
9	**Data export**	LCM_RC2

Table 4: ArcGIS method for deriving refined greenspace classes (LCM_RC3) based on spatial statistics of LCM_RC2 greenspace (5). Input data: LCM_RC1 (5). Method rationale is to identify small greenspaces in urban areas and separate from larger greenspaces in urban areas or outside urban areas. Key method refinement was altering step 2 Focal Statistics size until smaller greenspaces in urban areas could be separated from larger less-urban greenspaces at the fringes

or in areas of ingress. This took some 10 iterations – from 100m to 1km. 250m was an ideal patch size below which urban greenspaces such as parks and playing fields could be separated from less managed surfaces such as parks and fields.

Step	Tool and data	Description
1	**Reclassify** LCM_RC2	Urban and Suburban HD = 3, Suburban M D & LD = 2, Greenspace and Natural =1, Water = 0.
2	**Focal Statistics:** circle, mean, 5.	Mean value (0-3) in 250m circle around each grid
3	**Reclassify** (5 classes – values 0-3)	1 (1), 2 (1.5), 3 (2), 4 (2.5), 5 (3)
4	**Clip** (step 3 to catchment)	
8	**Raster Calculator**: Con((LCM_RC2==5) & (Step4>2),6, LCM_RC2)	Converts selected LCM_RC2 Greenspace to Green$_{URB}$ (6)
9	**Data export**	LCM_RC3

Table 5: ArcGIS method for deriving 'Green$_{NAT}$' class (RC4) based on Natural England mapping of Local Nature Reserves, Country Parks, and Woodland and Pasture. Input data: LCM_RC3, Local Nature Reserves, Country Parks, and Woodland and Pasture.

Step	Tool and data	Description
1	**Merge** Natural England datasets	
2	**Clip** merged dataset (Step2) to catchment	
3	**Add Field**: Nature (7)	
4	**Polygon to Raster** (5m), Step3 (7)	
8	**Aggregate** (50m) Mean	
9	**Reclassify: No data 0, Nature 7**	Set extent to catchment + Snap
10	**Raster Calculator:** Con((LCM_RC3=!3) & (Step9==7),7,LCM_RC3)	Convert non-water features to Greenspace natural - $Green_{NAT}$
	Data export	LCM_RC4

Table 6: Geoprocessing to determine areas of $Urban_{SUDS}$ or $Suburban_{SUDS}$– post 2010 developments only

Step	Tool and data	Description
1	**Stage 1: Process SuDS maps**	Using the British Geological Survey (BGS) – SuDS

	The following features were selected from each layer as being indicative of features that would negate the possibility of SuDS installation: Drainage summary – identified areas with 'Very significant constraints are indicated' Ground stability summary – identified areas with 'Significant potential for geohazard' and 'Very significant constraints are indicated' Groundwater protection summary – identified areas with 'Considerable susceptibility' and 'Very significant constraints are indicated'	infiltration map (SIM: Dearden, 2016) - that accounts for such factors has been used to locate sites, indicating SuDS suitability
2	Merge the SuDS layers in step 1 to one polygon dataset.	Single layer showing areas of SuDS not being suitable.
3	Clip SuDS layer to catchment – and add field SuDS with value 55.	
4	Polygon to Raster, 50m, snap LCM2015	Convert to raster (50m)
	Reclassify RC5 as SuDS raster with 1=Suds potential, 44=no potential, and clip to catchment > RC5	Reclassify and clip to final SuDS raster RC5

8	**Stage 2: Identify areas of new (post 2010) development** Raster calculator: Con((RC4==2) & (LCM2010>2),14,RC4) >RC4 Raster calculator: Con((RC4==11)|(RC4==12)|(RC4==13) & (LCM2010>2),15,RC4) > RC4 Data export : SuDS	Identify new areas of development – and reclass as either Urban post 2010 (14) or Suburban post 2010 (15) (SuDS)
9	**Stage 3: Identify areas likely to have SuDS** Convert Urban post-2010 to Urban$_{SUDS}$ (141): Con((RC5==14)&(SuDS<44),141,RC5) Convert Suburban post-2010 to Suburban$_{SUDS}$ (151): Con((RC5==15)&(SuDS<44),151,RC5) Convert back areas that were not suitable to their previous classes – removes class 14,15: Con((RC5==14)|(RC5==15),RC4,RC5) Export data>RC6	Identify areas that are post 2010 and have SuDS potential.

Table 7: Method for reclassifying catchment area – $AREA_{rc}$ - manipulated using the ArcGIS 10.3 Hydrology toolset in combination with manual delineation of artificial drainage areas

Step	**Tool and data**	**Description**
1	**Hydrology** tools were used to delineate natural drainage areas to manually mark pour points that identify monitoring locations.	
2	For locations where there was no natural drainage, the contributing drainage area was manually delineated using a combination of drainage map and topographical mapping from OSMM	
3	For catchments where there was a visual discrepancy between the natural drainage area and artificial drainage (B3, S1, S3 - S10), the natural drainage polygon was manually altered to encompass areas where artificial drainage crosses natural boundaries derived from the DEM.	

Table 8: Initial list of landscape metrics and associated values: including 5 hydrological metrics, 3 landscape metrics, 10 Urban class metrics, 10 Suburban class metrics, and 2 Green$_{NAT}$ class metrics. Blank values for certain sites indicate catchments with none of this class present.

	Hydro_Metrics					Landscape metrics			Urban class metrics										Suburban class metrics										Green$_{NAT}$ class metrics	
Site_ID	mdo	PX	PX$_N$	PX$_{URBEXT}$	PX$_{N_URBEXT}$	LSI	CONTAG	MESH	PLAND$_{URB}$	LPI$_{URB}$	TE$_{URB}$	ED$_{URB}$	PARA_MN$_{URB}$	PARA_AM$_{URB}$	CONTIG_MN$_{URB}$	CONTIG_AM$_{URB}$	CLUMPY$_{URB}$	COHESION$_{URB}$	PLAND$_{SUB}$	LPI$_{SUB}$	TE$_{SUB}$	ED$_{SUB}$	PARA_MN$_{SUB}$	PARA_AM$_{SUB}$	CONTIG_MN$_{SUB}$	CONTIG_AM$_{SUB}$	CLUMPY$_{SUB}$	COHESION$_{SUB}$	PLAND$_{NAT}$	COHESION$_{NAT}$
S1	4.42	3.88	0.59	3.88	0.30	8.09	57.48	889	16.03	10.96	53450	18.59	477	135	0.36	0.81	0.82	96.23	18.03	6.66	78650	27.36	480	171	0.36	0.76	0.76	95.09	0.76	0.47
S2	1.87	0.20	0.12	0.20	0.06	2.97	76.41	238											10.51	6.26	6100	18.86	417	271	0.39	0.61	0.69	81.36	0.00	0.00
S3	3.16	1.68	0.89	1.68	0.72	4.77	61.72	214	32.57	31.27	15800	26.42	484	108	0.34	0.85	0.85	97.68	55.77	50.79	26150	43.73	407	111	0.44	0.84	0.74	98.38	0.00	0.00
S4	1.94	1.38	0.87	1.38	0.85	3.25	68.04	199	1.53	1.05	1150	3.70	305	295	0.55	0.57	0.82	70.68	79.31	79.31	8850	28.50	80	80	0.89	0.89	0.66	99.64	9.66	0.84
S5	0.59	3.53	0.96	3.53	0.81	4.02	52.52	45	15.32	9.91	5900	27.19	440	214	0.40	0.70	0.77	85.53	62.10	38.82	10050	46.31	333	121	0.57	0.83	0.70	96.05	0.46	0.17
S6	6.00	4.28	0.73	4.28	0.59	8.79	55.45	804	18.61	13.56	75100	21.48	446	126	0.40	0.82	0.83	97.06	24.27	10.43	100400	28.72	449	129	0.40	0.82	0.81	95.98	0.62	0.47
S7	0.31	1.54	0.88	1.54	0.85	2.77	52.68	19	5.94	3.65	1250	22.83	400	400	0.44	0.44	0.70	66.01	81.74	48.86	2650	48.40	220	170	0.69	0.76	0.19	94.72	0.00	0.00
S8	1.42	1.07	0.70	1.07	0.70	2.77	52.68	19	1.50	1.50	650	3.00	277	277	0.60	0.60	0.94	74.81	72.55	70.47	7100	32.76	271	92	0.63	0.87	0.72	98.88	13.84	0.84
S9	0.41	0.66	1.00	0.66	1.00	3.10	62.34	112											99.08	99.08	100	3.67	122	122	0.83	0.83	0.00	99.95	0.00	0.00
S10	0.24	2.00	0.97	2.00	0.97	1.62	93.82	27											18.03	6.66	78650	27.36	480	171	0.36	0.76	0.76	95.09	0.00	0.00
EA_39087	10.30	3.95	0.49	1.97	0.25	11.92	55.55	1232	4.56	3.26	43500	7.47	467	168	0.37	0.77	0.81	93.58	34.05	23.95	209000	35.89	467	110	0.37	0.85	0.81	98.20	3.24	0.55
B1	4.59	1.15	0.29	0.57	0.14	8.81	50.96	360	0.71	0.15	5200	2.83	468	431	0.37	0.41	0.54	59.62	26.01	11.89	74900	40.80	456	170	0.39	0.76	0.74	93.65	12.75	0.53
B2	4.94	1.69	0.67	0.84	0.33	5.26	58.08	366	3.42	1.44	9750	7.80	465	248	0.38	0.66	0.74	78.94	43.09	41.75	37050	29.65	476	86	0.37	0.88	0.85	98.89	13.50	0.63
B3	3.83	2.76	0.84	1.38	0.42	6.56	52.81	385	15.35	13.30	25150	20.06	374	139	0.48	0.81	0.83	95.90	53.11	51.63	54000	43.06	494	96	0.36	0.87	0.78	99.24	3.87	0.64
B4	5.66	2.07	0.35	1.04	0.17	9.89	49.96	470	1.66	0.53	15000	4.46	466	291	0.38	0.60	0.68	74.27	30.68	17.11	117400	34.88	450	124	0.39	0.83	0.80	96.74	12.75	0.64
B5	7.60	1.85	0.37	0.92	0.19	10.23	50.35	571	1.91	0.63	17200	4.59	465	263	0.38	0.64	0.71	80.54	31.78	19.15	130750	34.88	456	119	0.38	0.84	0.80	97.19	11.80	0.64
B6	9.24	2.84	0.45	1.42	0.23	12.44	48.34	876	4.56	3.26	43500	7.47	467	168	0.37	0.77	0.81	93.58	34.05	23.95	209000	35.89	467	110	0.37	0.85	0.81	98.20	10.65	0.65
EA_39052	7.70	3.55	0.53	1.78	0.26	11.80	47.89	753	4.56	3.26	43500	7.47	467	168	0.37	0.77	0.81	93.58	34.05	23.95	209000	35.89	467	110	0.37	0.85	0.81	98.20	10.73	0.60