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Research papers

Contribution of urbanisation to non-stationary river flow in the UK

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ABSTRACT

Urbanisation is a recognized driver of changes in catchment river flow. However, quantifying the urban influence remains a major challenge, due to the brevity of land cover records and the challenge of isolating this signal from other drivers. This study assesses the contribution of urbanisation to changes in river discharge across different seasons and quantiles (low, median, high, mean, and peak flows). Twelve catchments (21–1660 km^2) are selected after screening all gauged UK catchments for minimal human influences other than significant changes in urban land cover. Generalized Additive Models for Location, Scale and Shape (GAMLSS) are developed using long (40–63 years) historical records of precipitation, temperature, urban land cover, and daily river discharge (m^3/s). Model coefficients reveal that increased urban area is associated with a rise in discharge across all flow quantiles and seasons, on average, and the contribution of urbanisation to non-stationarity is stronger for low flows and average flows than it is for high flows. For every 1 % increase in urban land cover there is an associated increase in the median of 1.9 % ±2.8 % (1 s.d.) for low flow, 0.9 % ±2.3 % (1 s.d.) for median flow, 0.9 % ±1.9 % (1 s.d.) for mean flow, 1.1 % ±2.0 % (1 s.d.) for high flow, and 0.5 % ±2.2 % (1 s.d.) for seasonal maximum flow across seasons. The urbanisation-flow signal tends to be greatest in catchments with less initial urban extent and low bedrock permeability.

1. Introduction

Historical trends in both mean and peak river flow in the UK broadly reveal increases in the northwest and a mix of increases and decreases in the southeast (Hannaford et al., 2021; Hannaford and Buys, 2012; Hannaford and Marsh, 2006; Hannaford and Marsh, 2008; Harrigan et al., 2018; Prosdocimi et al., 2014). These regional variations differ from river flow projections of mean and peak flow for coming decades based on the latest UK climate projections (UKCP). Outlooks suggest increases for western Britain with some decreases in central and eastern England and eastern Scotland (Kay, 2021; Lane et al., 2021). Yet, historical and projected climate show similar trends. Since 1960, the UK has warmed by about 0.2 °C per decade and with ∼6 % increase in annual average precipitation (McSweeney et al, 2009; Kendon et al., 2020). By the 2060s, the country is expected to witness 1.2–1.8 °C further warming and 1.8–7.2 % increase in annual precipitation depending on the emission scenario (Lowe et al., 2018; McSweeney et al, 2009). Thus, the spatial discrepancy in observed and projected river flow trends as well as the heterogeneity of local trends raises the question of whether future climate-driven river flow projection should be taken at face value or whether we may be ‘missing’ some key drivers of non-stationary river flow (Slater et al., 2021; Wilby et al., 2008)? Local catchment-specific drivers may also play an important role, such as urbanisation (Dawson et al., 2006; Faulkner et al., 2020; Hannaford et al., 2021).

Quantifying the effect of urbanisation on river flow is not straightforward. Some authors have found that urbanisation increases flows, as impervious land cover leads to reduced infiltration, increased runoff volume, as well as shortened runoff response time (Blum et al., 2020; Cuo, 2016; De Niel and Willems, 2019; Prosdocimi et al., 2015; Teuling et al., 2019; Anderson et al., 2022). Various modelling approaches have been applied. For example, Prosdocimi et al. (2015) employed point process models in a paired catchment study, that included one urbanised catchment and a nearby rural catchment with similar hydrological characteristics, and detected an increase in high flows due to urbanisation, especially in summer. Blum et al. (2020) employed panel regression models with a large sample of US catchments, and estimated that a 1 % increase in urban cover leads to on average 3.3 % increase in

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annual maximum floods. De Niel and Willems (2019) fitted statistical regression models to 29 catchments in Belgium, and found the land cover effect on peak flows varies signicantly across catchments depending on soil textures and slopes. They estimated that a 1 % increase in urban area could cause up to a 5 % increase in peak flows in steep catchments with a high percentage of loamic soils. By applying conceptual rainfall-runoff models to 95 catchments in the Rhine basin, Hundecha and Bárdossy (2004) found that urbanisation increased summer peak flows and also caused a modest rise in winter peak flows. Using distributional regression models in 290 catchments in the US Midwest, Slater and Villarini (2017) found that a 10 % increase in population density (a proxy for urbanisation) was associated with more than a 20 % increase in median streamflow in summer.

Some studies report contrary responses in catchments with specific characteristics. Using linear mixed effects modelling of 19 watersheds in central Arizona, USA, McPhillips et al. (2019) found that, in arid catchments, urbanisation decreases flood flashiness, flow variability, and hydrograph rise and fall rates. The decreasing effects were explained in terms of increased retention (by engineered basins) of water during storm events, instead of flowing directly to the river.

Others suggest that urbanisation effects on river flow or hydrologic response are inconsistent or difficult to detect. This could reflect differences in the methods applied (e.g. Anderson et al., 2022), or the difficulty in quantifying urbanisation (typically quantified as the catchment 'urban area fraction' or the 'mean areal imperviousness'). Such urbanisation metrics may not sufficiently explain the location, distribution, and character of impervious cover within a given catchment (Salavati et al., 2016). Like Tolstoy's unhappy families, every urban catchment is urbanised in its own way. For example, impervious areas that drain runoff to pervious surfaces may have less effect on river flow than impervious areas that are directly connected to the drainage system (Jacobson, 2011). Vesuviano and Miller (2019) found that in an urban catchment in Swindon, UK, the effect of draining to pervious surfaces could even reduce the peak flows to below what would be expected for a rural catchment. Other reasons may be that it is difficult to isolate the signal of urbanisation from other drivers (e.g., climate change and other headwater land cover changes) or from background hydrologic noise (e.g., the imports and exports of sewage water across catchment boundaries, upstream river regulation, and ground and surface water abstraction). Beyond uncertainties in the underlying river flow observations (Wilby et al., 2017), the river flow response can differ significantly between catchments due to poorly observed confounding factors such as variable soil composition, subsurface geology, infrastructure systems, and water resources management strategies (Steinschneider et al., 2013). Furthermore, absence of an urban signal may be due to the offsetting influence of other factors. For instance, the positive effects of urbanisation on runoff may become insignificant due to flood reduction measures such as sustainable urban drainage systems and flood attenuation features.

Although various studies have shown that urbanisation may alter river flow distributions, the role of catchment properties combined with rates of urbanisation are poorly understood. This paper is the first to quantify and compare the contribution of urbanisation to trends in river discharge using carefully selected catchments across the UK, with long (median 58 years) observed records, under different flow quantiles and seasons. We ask to what extent do urbanisation signatures manifest differentially by 1) river flow quantiles (low to high flows); 2) season; 3) underlying geology and flow regime? In summary, we explore the sensitivity of the urban signature to flow quantile, season, and catchment properties.

2. Study catchments and data

2.1. Selection of study catchments

The study catchments were selected from the National River Flow Archive (NRFA, https://nrfa.ceh.ac.uk/) – the primary source of hydrometric information in the UK. The total number of NRFA stations available is 1598. After applying strict filtering criteria (see Fig. 1), a sub-set of 12 eligible sites were retained for detailed investigation. Filtering was applied to identify only sites where an urban influence might be objectively detectable by excluding sites with:

1) ***Less than 90 % of daily discharge values*** in each year during the period 1985–2015 (coinciding with the initial period with satellite observations of urbanisation);
2) ***Upstream storage or impounding reservoirs*** as denoted by NRFA Factors Affecting Runoff (FAR) codes (which indicate artificial influences within the catchment that might alter the natural runoff);
3) ***Stationary flood series***, on the basis that it only makes sense to detect a non-stationary driver if there is non-stationarity in the underlying time series (based on the change point and expert assessment compiled by Faulkner et al. (2021). Sites identified as suitable by Faulkner et al. (2021) are those with non-stationary annual maximum flow (AMAX) and where the data quality is sufficient to detect non-stationarity. Sufficient data quality means the length of flow data, the percentage of missing data, and the consistency of the data are good enough to be used in statistical tests. It is worth noting that although the flood series are non-stationary, other flow quantiles may not be);
4) ***Less than 5 % urban cover change*** during the study period (40–63 years depending on the length of the observed river discharge record), the rationale being that a minimum amount of change in the predictor variable is necessary for robust statistical detection;
5) ***Suspect values for urban data***, which had a 30 % discrepancy between extracted satellite-based urban percent from Liu et al (2020) compared with the urban extent from NRFA (for the year 1990) and CAMELS-GB (for the year 2015), as well as one site with an unrealistic decrease in the reconstructed urban extent time series using household-based estimates.

We retained only the sites with non-stationary streamflow to objectively **quantify the contribution of urbanisation to observed streamflow trends** across all the flow quantiles (from low to high). If instead, the aim was to assess whether urbanization has a detectable effect on streamflow, we might have included sites with stationary flood series. However, there are only 4 additional stationary sites that meet the criteria (good flow record, absence of major human influence such as reservoirs, presence of significant urban land change, and reliable urban data): sites 17003, 19001, 27030 and 28026. Sites that have experienced significant urbanisation but show stationary flow are very likely have other drivers or other artificial influences that affect river flow. For instance, the 4 additional stationary sites all reported either public water supply abstraction, industrial and/or agricultural abstraction, or groundwater abstraction (NRFA, 2022). Stationary sites were therefore excluded, to focus on the contribution of urbanisation to flow non-stationarity.

This catchment selection workflow is also theoretically applicable to other global catchments through adapting each criterion based on available datasets, for example, by employing alternative data sources. As a comparison, an equal number of non-urbanising catchments (12) which have less than 2.5 % urban change over the study period were also selected, using the same site selection procedure as described above, but changing only the urban change criterion from more than 5 % to less than 2.5 %. After applying all the filtering steps, the locations of the short-listed 12 urbanising catchments and 12 non-urbanising catchments are presented in Fig. 2, and the summary of urbanising catchments is in Table 1. Most of the urban sites are near large cities that have experienced rapid urbanisation over recent decades, including London and Birmingham. Drainage areas range between 21 km^2 and 1660 km^2, mean annual precipitation from 604 mm to 868 mm, and mean daily discharge varies between 0.17 m^3/s to 11.53 m^3/s. Land cover

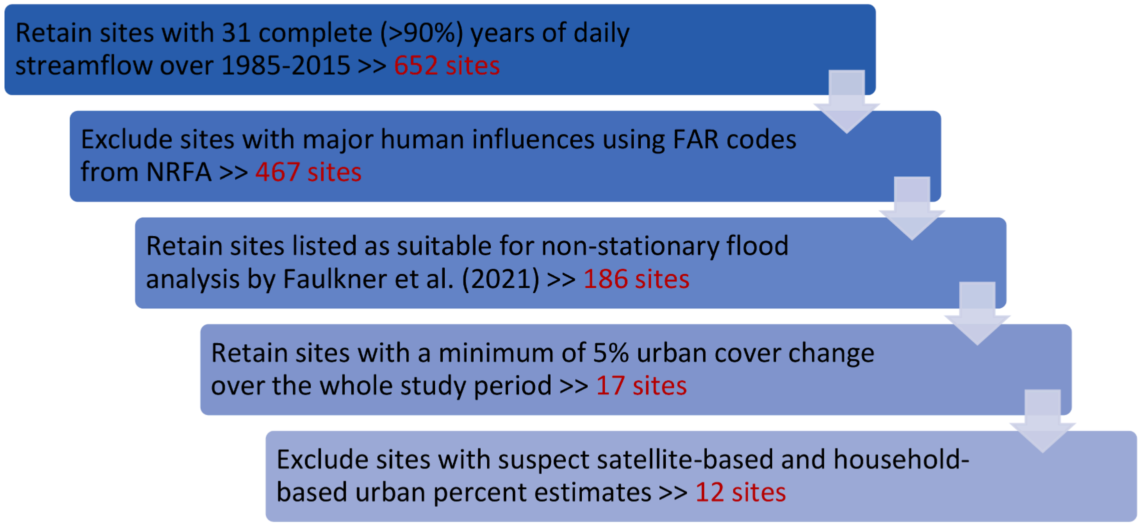

Fig. 1. Catchment selection workflow.

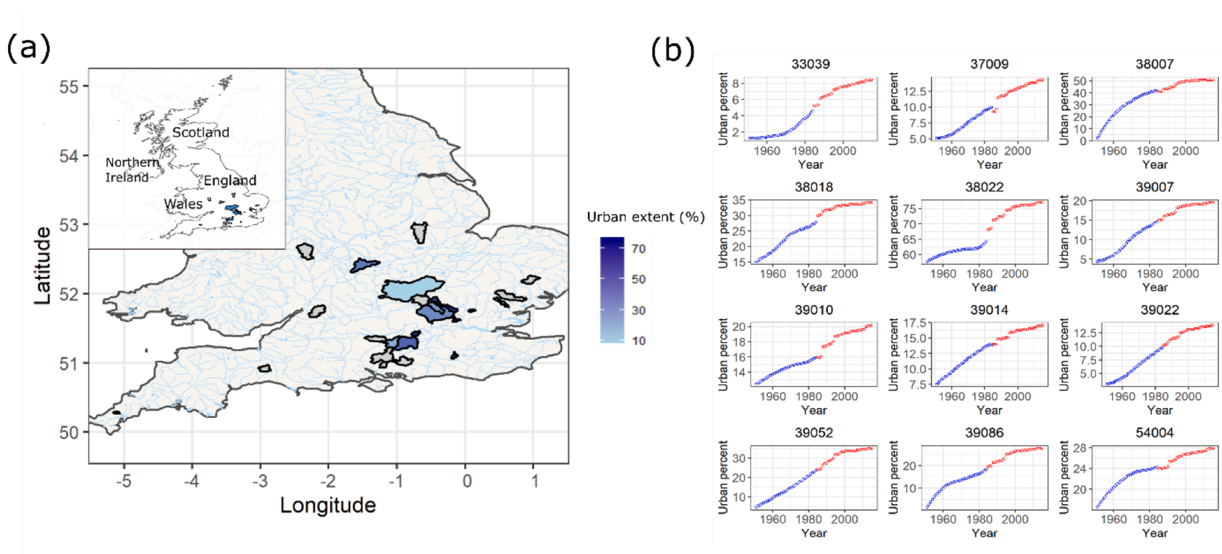

Fig. 2. (a): Location of the 12 selected urbanising catchments (in blue) and the 12 non-urbanising catchments (in grey). The blue gradient for the urban catchments shows the percentage of urban land cover in the year 2015. (b): Urban area percent time series for all the 12 urban catchments; blue circles indicate converted households data, and red circles are extracted satellite urban percent. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(according to the NRFA) includes woodland (3.9 % to 41.7 % of catchment area), arable/horticultural (3.7 % to 69 %), grassland (13.7 % to 29.7 %), heath/bog (0 % to 2.8 %), and urban extent (8.2 % to 72.5 %). The catchments are underlain by various geological and superficial deposits. The strata span high (e.g., fissured aquifer for bedrock, sand and gravel for superficial deposits), low (e.g., impermeable rock for bedrock, clay and peat for superficial deposits), and mixed permeability (e.g., confined aquifer for bedrock, brickearth and alluvium for superficial deposits) (NRFA, 2022).

2.2. Data collection and processing

Daily flow data were retrieved for the selected catchments using the 'rnrfa' R package (Vitolo et al., 2016). Catchment shapefiles were automatically extracted from CAMELS-GB (Coxon et al., 2020) or downloaded from the NRFA if the catchment was not included in CAMELS-GB. Catchment averaged daily precipitation (1950 to 2020) and monthly mean temperature (1884 to 2020) were extracted from the Met Office Hadley Centre for Climate Science and Services HadUK-Grid with 5 km resolution (Hollis et al., 2019).

Annual urban land cover percent during 1985 to 2015 was based on satellite-derived 30 m resolution global urban maps (Liu et al., 2020). Urban extent for the year 1990 from the NRFA (weighted sum of urban and suburban land cover map classes) and urban extent for the year 2015 from CAMELS-GB (Coxon et al., 2020) (percentage of urban and suburban extent based on the land cover map 2015) were also obtained as references to assess the extracted urban time series. To reconstruct urban extent prior to 1985, time series of "total households" from census data (available from 1951 to 2011) were downloaded and employed as a proxy for urban percent (Great Britain Historical GIS Project, 2017). Since census data are collected based on administrative units, the total households from the local authority covering the main course of the river were used for each catchment. A linear scaling method (Shrestha et al., 2017) was used to relate household data to the satellite urban area series. We computed the conversion factor (as shown in Table 1) between the extracted 30 m resolution urban percent time series (red line

Table 1
Summary of study catchments. 'Urban percent change' is the total change of urban cover (%) over the study period for each site, derived from the extended urban percent time series (urban percent in the end year from satellite maps minus the urban percent in the start year from converted households data). The study period varies by catchment depending on the available daily discharge record. 'Conversion factor' is the ratio between the satellite-derived urban percent and households data over 1985–2011. All the other variables are obtained from the NRFA data catalogue; land cover data including urban extent are for the year 1990 (NRFA, 2022).

Site number	River	Location	Period of record (flow)	Total years of record used in the model	Urban percent change (%)	Urban percent at start year (%)	Urban percent at end year (%)	Drainage area (km2)	BFI	Woodland (%)	Arable/ horticultural (%)	Grassland (%)	Mountain/ heath/bog (%)	Urban extent (%)	Conversion factor for households (*10–4)	Catchment description
33,039	Bedford Ouse	Roxton	1973–2018	43	6.19	2.26	8.45	1660	0.57	10.10	51.33	29.66	0.02	8.23	0.96	Mixed geology, including significant clay and greensand fractions. Predominantly agricultural with substantial urban development
37,009	Brain	Guithavon Valley	1963–2018	53	8.33	5.97	14.30	61	0.67	3.92	68.77	14.06	0.00	12.61	2.46	London clay with superficial deposits, mainly boulder clay and some sands and gravels. Predominantly rural, but some built-up areas
38,007	Canons Brook	Elizabeth Way	1954–2018	62	41.74	9.24	50.98	21	0.40	10.38	22.23	22.24	0.00	41.83	15.15	Impervious catchment dominated by London clay. Rural headwaters but heavily urbanised downstream
38,018	Upper Lee	Water Hall	1960–2018	56	16.07	18.08	34.15	150	0.82	12.32	31.86	20.97	0.00	34.38	4.90	Mainly pervious (chalk) but with glacial drift in the headwaters. Principally agricultural with some expanding urban centres
38,022	Pymmes Brook	Edmonton Silver Street	1955–2018	61	18.33	58.66	76.99	43	0.48	9.67	3.68	13.66	0.39	72.51	6.19	Impervious (London clay) and highly urban catchment
39,007	Blackwater	Swallowfield	1953–2018	63	14.91	4.60	19.51	355	0.67	22.54	18.09	25.38	2.82	29.70	5.78	Permeable chalk in the headwaters; clay, sands and

(*continued on next page*)

Table 1 (*continued*)

Site number	River	Location	Period of record (flow)	Total years of record used in the model	Urban percent change (%)	Urban percent at start year (%)	Urban percent at end year (%)	Drainage area (km2)	BFI	Woodland (%)	Arable/ horticultural (%)	Grassland (%)	Mountain/ heath/bog (%)	Urban extent (%)	Conversion factor for households (*10–4)	Catchment description
																alluvium in the valley. Substantial urban development in the eastern Blackwater Valley, but some large rural tracts of arable and pasture remain
39,010	Colne	Denham	1953–2018	63	7.42	12.72	20.14	743	0.87	14.46	36.15	25.59	0.01	23.08	5.95	Largely chalk catchment with drift cover. Clays in the valleys supplemented by extensive gravel tracts. Chilterns scarp is largely rural in the headwaters but considerable suburban development in the middle and lower reaches
39,014	Ver	Hansteads	1957–2018	59	8.17	8.86	17.03	132	0.88	9.49	51.29	19.93	0.00	18.74	3.10	Permeable chalk catchment, with significant drift cover. Mostly rural headwaters but with significant urban development in the lower valley
39,022	Loddon	Sheepbridge	1966–2018	50	8.34	5.51	13.85	165	0.76	14.71	38.77	28.59	0.00	16.54	2.13	Headwaters are in the chalk of the North Downs but the catchment is largely impervious. Predominantly rural catchment, containing some growing urban centres

(*continued on next page*)

Table 1 (*continued*)

Site number	River	Location	Period of record (flow)	Total years of record used in the model	Urban percent change (%)	Urban percent at start year (%)	Urban percent at end year (%)	Drainage area (km2)	BFI	Woodland (%)	Arable/ horticultural (%)	Grassland (%)	Mountain/ heath/bog (%)	Urban extent (%)	Conversion factor for households (*10–4)	Catchment description
39,052	The Cut	Binfield	1958–2018	58	26.57	8.40	34.97	50	0.46	23.28	5.96	29.09	0.90	40.30	7.86	Impermeable catchment (London clay). Rural headwaters, including considerable woodland, but major new town development built upstream. Downstream the land use is almost a third urban overall
39,086	Gatwick Stream	Gatwick Link	1976–2018	40	12.40	15.26	27.66	34	0.61	41.71	9.40	16.26	0.32	31.55	6.62	Mixed geology but mainly impervious (weald clay). Mixed land use with significant urban and forested areas
54,004	Sowe	Stoneleigh	1953–2018	63	10.33	17.54	27.87	262	0.61	10.24	34.06	26.63	0.00	27.54	2.16	Substantially urbanised catchment. Western half on outcrop Coal Measures; Eastern half Mercia Mudstone Group overlain by Boulder clay and glacial sand and gravel

in Fig. 3) and the household data, over the period 1985–2011. We applied the same conversion factor to the raw household data, then employed the converted household data (blue line in Fig. 3) to reconstruct the urban percent time series back to 1951, under the assumption that pre-1985 and post-1985 periods have the same developed area associated with each household. The final extended urban percent time series is a blend of the household-based estimates for 1951–1984 with the satellite-based urban percent for 1985–2015 (Figs. 2-3).

To investigate whether other factors may modulate the contribution of urbanization to observed non-stationarity on river discharge, catchment attributes such as drainage area, base flow index (BFI), factors affecting runoff (FAR), urban extent, land cover and geology data were obtained from the NRFA catalogue (NRFA, 2022). Detailed water import/export information at the catchment level, including the fully licenced quantity of surface water abstraction, groundwater abstraction, and discharge, were obtained from Environment Agency (Environment Agency, 2021).

3. Methodology

3.1. Model development and performance evaluation

Generalized Additive Models for Location, Scale and Shape (GAMLSS) were used to quantify the contribution of urbanisation to trends in river discharge. GAMLSS were introduced by Rigby and Stasinopoulos (2005) and are flexible semiparametric regression models. They allow any parametric distribution for the response variable and allow a variety of additive terms for the distribution parameters, which can be modelled as linear, non-linear, or non-parametric smooth functions of the explanatory variables (Stasinopoulos and Rigby, 2007).

We implemented GAMLSS using the 'gamlss' R package (Stasinopoulos et al., 2017). Two GAMLSS models were developed at each site to estimate relationships between the river flow and the predictors precipitation (x_p), temperature (x_t), antecedent precipitation (x_{ap}), and urbanisation area (x_u) for different seasons and flow quantiles. Variable x_p is the seasonal precipitation total (mm) computed as catchment averages from daily precipitation observations; x_{ap} is the accumulated catchment average precipitation (mm) for the previous season, employed as an indicator of soil moisture initial conditions. For example, if the predictand is summer low flow, then x_p is the sum of precipitation from June to August every year, and x_{ap} is the sum of precipitation for the previous season (March to May). Variable x_t is seasonal catchment average temperature (°C), and x_u is urban land cover (%) for the catchments on an annual basis.

The gamma distribution, which has been frequently employed for streamflow modelling in previous studies (Prekopa and Szantai, 1978; Yue, 2001; Yue et al., 2001), was used for the response variable river flow with two parameters (i.e., the location parameter μ which defines the location of the distribution and the scale parameter σ which defines its statistical dispersion). For simplicity, μ is linearly dependent on the predictors through a logarithmic function whereas σ is held constant following Slater and Villarini (2018) since varying this parameter over time does not systematically improve the fits of the GAMLSS models for river discharge (Villarini and Strong, 2014).

The model formulations are shown in Table 2. Model 1 (M1) is without urbanisation, whereas model 2 (M2) includes urbanisation. Notations a, b, c, d, and e are regression coefficients. For brevity, M1 is referred as Q ~ P + T + AP, and M2 is referred as Q ~ P + T + AP + U, where Q stands for river discharge, and P, T, AP, and U correspond to the predictors x_p, x_t, x_{ap} and x_u, respectively. The seasons are spring (March, April, May), summer (June, July, August), autumn (September, October, November), and winter (December, January, February). The analysed river discharge quantiles are low flow (10th percentile; denoted by Q_0.1), median flow (50th percentile; denoted by Q_0.5), high flow (90th percentile; denoted by Q_0.9), mean flow (denoted by Q_mean), and seasonal maximum flow (denoted by Q_max), calculated from daily discharge records for every season and year.

The Akaike information criterion (AIC) and worm plots were used to assess the goodness-of-fit of the GAMLSS models. The formula of AIC is defined as Eq. (1), where K is the number of model parameters and L is

Table 2
Formulations of the GAMLSS models.

Model abbreviation	Model acronym	Model formulation
M1	Q ~ P + T + AP	$\begin{cases} \ln(\mu_1) = a_1 + b_1 \bullet x_p + c_1 \bullet x_t + d_1 \bullet x_{ap} \\ \ln(\sigma_1) = \kappa_1 \end{cases}$
M2	Q ~ P + T + AP + U	$\begin{cases} \ln(\mu_2) = a_2 + b_2 \bullet x_p + c_2 \bullet x_t + d_2 \bullet x_{ap} + e_2 \bullet x_u \\ \ln(\sigma_2) = \kappa_2 \end{cases}$

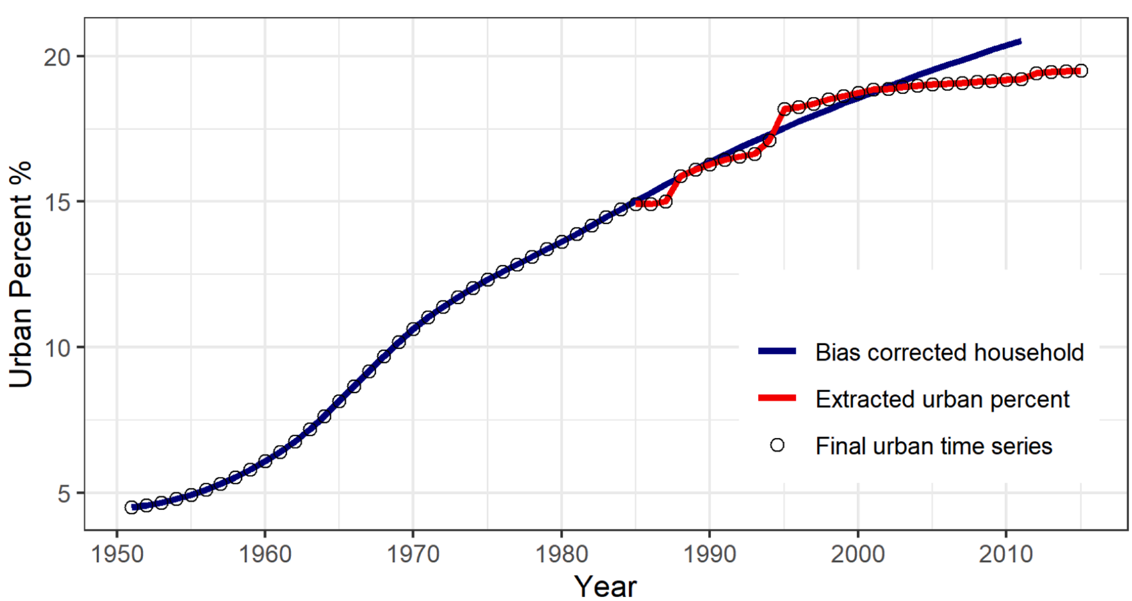

Fig. 3. An example reconstruction of the annual urban area percent using the Blackwater at Swallowfield (39007). The red line is data extracted from satellite-derived maps; the blue line is from household data. The complete urbanisation time series is a blend of the blue line (1951–1984) and red line (1985–2015), as indicated by the black circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the maximum value of the log-likelihood estimate (Akaike, 1974). Lower AIC indicates a better model fit. Worm plots are detrended QQ-plots of the model residuals (see Fig. S1 and Fig. S2 in Supplementary material). For a well-fitted model, the dots should be close to the central horizontal line, and 95 % of them distributed between the upper and lower curve (Stasinopoulos et al., 2017).

$$AIC = 2K - 2\ln(L) \tag{1}$$

3.2. Analysis of urbanisation coefficients

The coefficients for urbanisation (e_2 from M2 in Table 2), which describe the change in discharge for every unit change in urban area, were extracted for further analysis. Using the regression model we assess the effect of a unit increase in the predictor (in this case, urban land cover) on the predictand (streamflow). This approach allows a straightforward comparison of the effect of a unit (1 %) increase in urbanisation on streamflow across different locations. Given that our model is a logarithm model (as shown in Table 2), the urbanisation coefficients were then transformed to be expressed as percentage values using $[\exp(e_2) - 1] \times 100\%$, to give the percentage change in discharge for every-one percent change in urbanisation. The p-values associated with the urbanisation coefficients were also analysed to assess their statistical significance. If the p-value is less than the significance level ($p < 0.05$), then it implies that the urban covariate has a statistically significant relationship with river discharge in the model, and the urbanisation coefficient is significantly different from zero.

Effects of catchment properties (e.g., urban extent, drainage area, and bedrock permeability) were analysed by fitting a linear regression between the extracted urbanisation coefficients and each catchment property across different flow quantiles and seasons. The regression p-value and coefficient of determination (R^2) show the significance of these relationships.

3.3. Effects of other model predictors

Additionally, we assessed the effect of adding other predictors – such as 1-day maximum rainfall and antecedent day maximum – on the model fit and coefficients. We do so because such predictors may better describe high flows (Q_max) than seasonal precipitation total (x_p) or accumulated catchment average precipitation for the previous season (x_{ap}). Changes in AIC and urban coefficients were analysed after including 1-day maximum rainfall and antecedent day maximum as additional predictors in the urban models (M2).

Previous work has highlighted that beyond proving evidence of the *consistency* of specific drivers (e.g., discharge change consistent with urbanisation change), robust hydrological attribution also requires testing of *inconsistency* (i.e., when flow change is inconsistent with changes in other drivers) (Merz et al., 2012). Such evidence is particularly important in the case of statistical modelling, where a monotonically increasing variable, such as urbanisation or time, may inadvertently track other monotonically increasing catchment drivers of river flows, such as greenhouse gas concentrations or storm intensity. Therefore, to assess the consistency/inconsistency of an urban effect on river flow, we also tested the effects of adding time as an additional covariate (representative of any monotonically-increasing driver) at non-urbanising sites. Two models ($Q \sim P + T + AP$; $Q \sim P + T + AP +$ time) were fitted for both 12 urbanising and 12 non-urbanising catchments (for each season), where the 'time' covariate is simply the year of record. The AIC values for models with and without time covariate were compared to assess the effect of including a monotonically-increasing covariate on model performance.

4. Results and discussions

4.1. Performance of the urban models

Model fits for an exemplar catchment (Blackwater at Swallowfield) are shown in Fig. 4 (low flow across all the seasons) and Fig. 5 (autumn season across different flow quantiles). For the Blackwater, AIC values for urban models (M2) are much lower than for models without urbanisation (M1) for low flow across all seasons (e.g., spring low flow: AIC M2 = 5.87 < AIC M1 = 55.36). The model fits are also much better in autumn across low flow, median flow, and mean flow (Fig. 5). This indicates that urban models perform significantly better in simulating historical flow for these quantiles. The fits are satisfactory since the observations closely follow the fitted distribution and are mostly well within the 5th-95th percentiles. The goodness-of-fit is also indicated by worm plots (see Figs. S1 and S2). Comparison between M1 and M2 for this catchment indicates that urbanisation is associated with river discharge increase (Figs. 4 and 5). Extracted coefficients indicate that a 1 % increase in urban extent increases the low, median, high, mean, and seasonal maximum discharge by 3.5 %, 2.6 %, 1.6 %, 2.0 %, and 1.0 %, respectively in autumn (Fig. 5). The strongest effect is seen for the low flows, whereby a 1 % increase in urban extent increases discharge by 3.5 %, 3.4 %, 4.3 %, and 2.5 % in autumn, spring, summer, and winter seasons, respectively (Fig. 4). The increasing effect tends to be more significant for low flow and for the summer season. One possible explanation for the greater contribution of urbanisation to low flow (versus high flow) may be that the absolute effect (i.e. the magnitude of change in streamflow caused by urbanization) is proportionately larger relative to the total streamflow when flows are low. Low flow tends to occur during the summer months when there is less rain and more evapotranspiration due to the higher temperature (Burn et al., 2008). However, we cannot discount that there may be another explanation: sewer systems and hard drainage networks are usually developed as part of the urbanisation process, thus discharge from sewage works may also play a role in increasing low flows (Smakhtin, 2001). In other words, it is not impossible that urbanisation may be acting as a proxy for more sewage discharge and/or water imports across catchment boundaries, which would have a proportionately larger effect on low flow volumes.

Comparisons of AIC values between the two models (M1: model without urbanisation and M2: model with urbanisation) across different seasons and flow quantiles for all the sites are shown in Fig. 6. The majority of M2 AIC values are lower than M1. In some cases, M1 shows a better AIC, but the AIC differences between M1 and M2 are very low (less than 2). Differences of less than 2 imply that neither model is significantly better than the other (Burnham and Anderson, 1998). Overall, the AIC comparisons indicate that the urban model M2 performs better; the model fits are improved when urban percent is included as a covariate, and the colour gradient shows the improvement is more significant for low flow, median flow, and mean flow across different seasons. The worm plots indicate the M2 fits for the 12 sites are adequate as the dots are all near the red horizontal line and lie between the upper and lower dotted curves which denote 95 % confidence intervals. We show example worm plots for the Blackwater at Swallowfield (39007) in Fig. S1 and Fig. S2, but not all sites (4 seasons × 5 flow quantiles × 13 sites).

4.2. Assessment of the contribution of urbanisation to non-stationarity

Distributions of the transformed urban coefficients (expressed as percentages) for different seasons and flow quantiles are presented in Fig. 7. We find that the magnitude of the contribution of urbanisation to river discharge non-stationarity varies considerably by catchment, depending on season, flow quantile, and geology. As indicated in Fig. 7, the urbanisation contribution is typically positive (increasing river discharge), since all the urban coefficient medians (as shown above each boxplot for all the seasons and flow quantiles) are greater than zero.

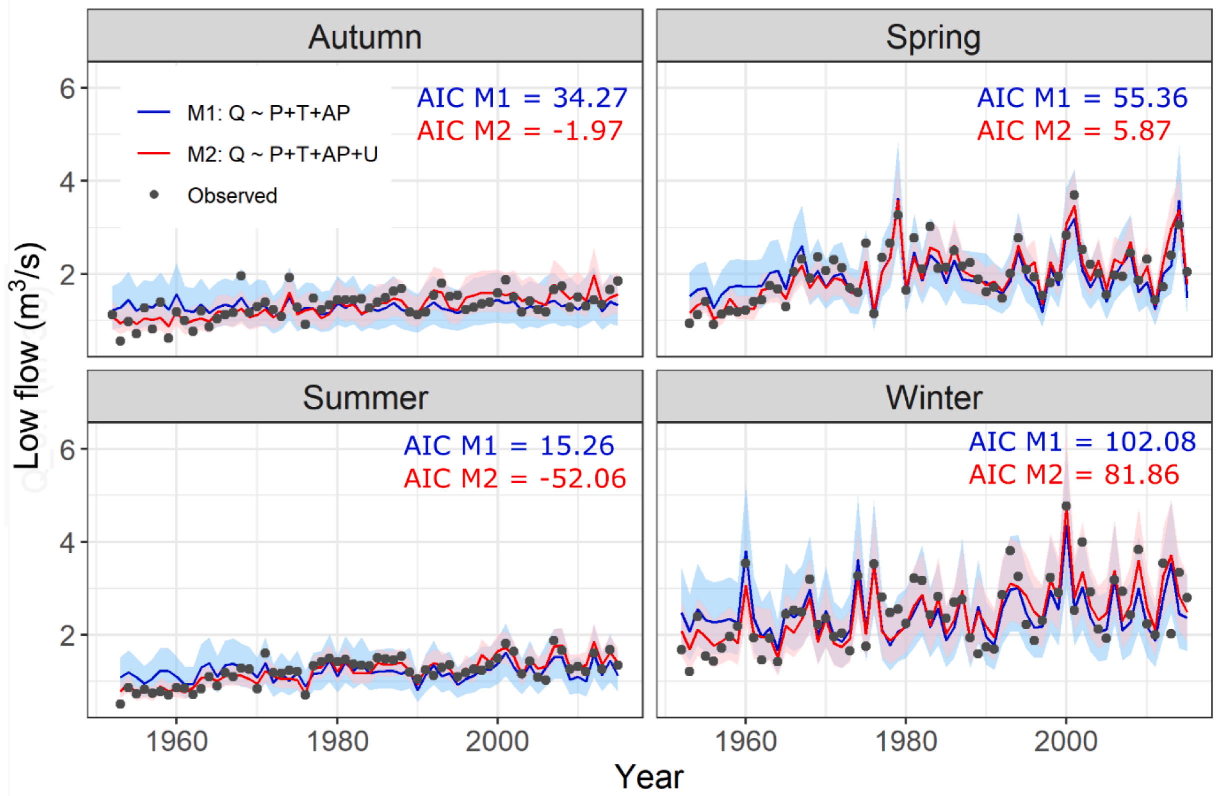

Fig. 4. Seasonal low flows in the Blackwater at Swallowfield (39007) estimated by models without (M1, blue) and with urbanisation (M2, red). The shaded colour ribbons represent the 5th to 95th percentiles of the probabilistic model fit, and the dark blue/red lines indicate the median. Black circles indicate observed seasonal river flow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

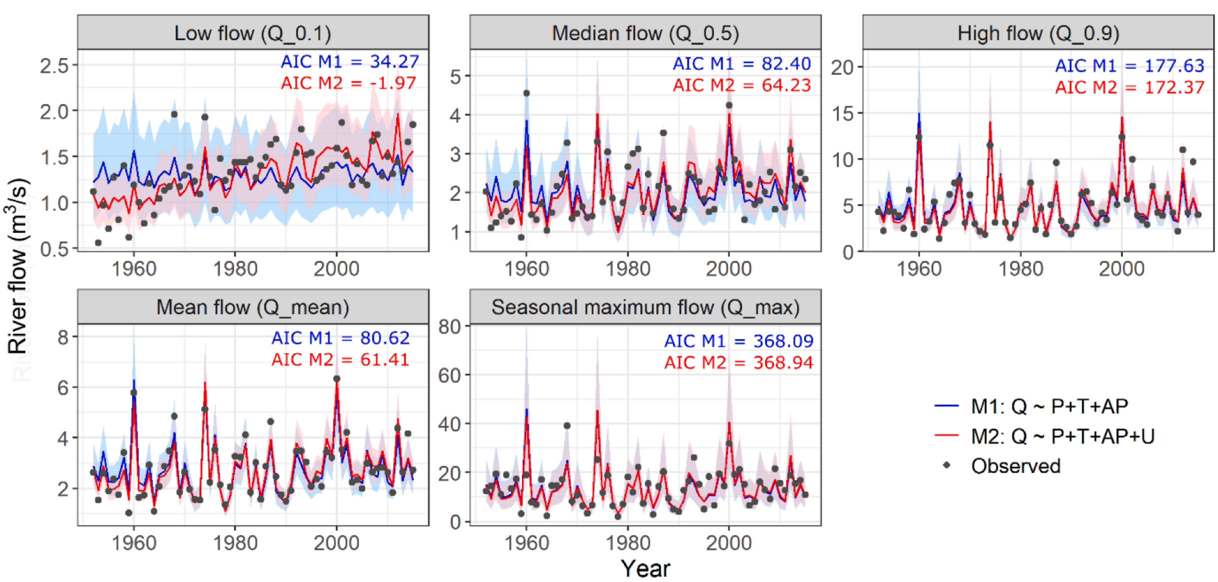

Fig. 5. As in Fig. 4 but for autumn river flow quantiles.

Among all the 20 boxplots (4 seasons × 5 flow quantiles), there are 16 in which about 75 % or more of the cases show positive effects. But for seasonal maximum flow, approximately 50 % of the cases show a positive effect and about 50 % show a negative effect in winter, spring, and summer. This suggests that the contribution of urbanisation is significantly stronger for changes in low flows and average flows than it is for seasonal maximum flows. The positive urbanisation effect is likely driven by the creation of impervious surfaces (e.g. streets and pavements) and constructed drainage systems, which result in losses of infiltration and faster runoff response to rainfall, thus increasing runoff rate and volume (e.g. Fletcher et al. 2013). Decreasing effects were also detected in a much smaller number of catchments, namely the Pymmes Brook at Edmonton Silver Street (site 38022) and the Ver at Hansteads (site 39014). These decreases may be due to the offsetting effect of groundwater use in these two catchments as documented by British Geological Survey (2022), who note that sometimes river water may

Autumn

	Q_0.1	Q_0.5	Q_0.9	Q_mean	Q_max
33039	-7	-2	-2	-3	-1
37009	-1	-5	0	-2	1
38007	1	2	-9	-2	-1
38018	2	2	2	2	2
38022	-6	-5	1	-5	0
39007	-36	-18	-5	-19	1
39010	0	2	1	1	1
39014	1	0	0	0	-3
39022	-4	2	2	2	2
39052	-1	-9	-9	-10	1
39086	-15	1	1	-1	0
54004	-23	-18	-1	-22	-4

Spring

	Q_0.1	Q_0.5	Q_0.9	Q_mean	Q_max
33039	-1	2	2	2	2
37009	-1	0	1	1	2
38007	2	2	0	1	2
38018	2	2	1	2	-1
38022	-8	-9	-5	-8	2
39007	-50	-25	-7	-21	0
39010	2	2	2	2	2
39014	2	1	-1	1	-1
39022	-1	-3	-1	-1	2
39052	-26	-16	-8	-13	2
39086	-15	-1	0	-4	2
54004	-33	-15	1	-5	2

Summer

	Q_0.1	Q_0.5	Q_0.9	Q_mean	Q_max
33039	-22	-17	-1	-6	1
37009	-2	-4	-15	-6	2
38007	1	1	-17	-3	-2
38018	2	1	-1	1	1
38022	-7	-9	0	-9	-2
39007	-67	-64	-17	-39	-1
39010	2	2	2	2	2
39014	1	1	2	1	0
39022	-8	-9	-2	-4	1
39052	-14	-19	-19	-18	1
39086	-18	-17	0	-7	-3
54004	-25	-17	-14	-16	0

Winter

	Q_0.1	Q_0.5	Q_0.9	Q_mean	Q_max
33039	1	1	2	2	2
37009	-3	2	1	0	0
38007	2	1	1	0	2
38018	1	0	1	0	1
38022	-3	-4	1	-5	-3
39007	-20	-15	1	-10	1
39010	1	1	2	1	2
39014	2	2	0	2	-2
39022	-1	1	2	1	2
39052	-15	-8	1	-3	1
39086	0	-1	-3	-1	2
54004	-18	-8	0	-4	2

Fig. 6. Differences in AIC values at each site between models with (M2) and without (M1) urbanisation ($AIC_{M2} - AIC_{M1}$). Negative values show when M2 fits better than M1, with the darker red shades indicates a better model fit at the same site. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

seep down to recharge groundwater. It is however impossible to document all the water uses in every catchment, so here we provide suggestions rather than definitive explanations.

The median and standard deviation of the urban coefficients across the 12 sites for each flow quantile and season are presented in Table 3. Our results show that a 1 % increase in urban land cover is associated with 1.7–2.2 % increase in low flow, 0.8–2.5 % increase in median flow, 0.8–1.9 % increase in mean flow, 0.5–2.0 % increase in high flow, and 0–0.9 % increase in seasonal maximum flow depending on season. The increasing effect of urbanisation on streamflow non-stationarity is stronger in the summer rather than in the winter, and is stronger for low flow rather than high flow. As mentioned earlier, this may be due to the relatively lower flow volume in summer or at low flow conditions, which leads to a proportionately larger effect. Additionally, one potential explanation for the greater contribution of urbanisation to streamflow in the summer may be the greater likelihood of intense convective storms over urban land during the summer months, which may amplify urban runoff (Li et al., 2020). Areas with fast urban expansion rates may exhibit stronger increases in heavy precipitation (Yu et al. 2022), and in the UK, intense convective rainfall tends to occur in the summer months. The greater contribution of urbanisation to low flow may also be due to the development of sewer systems and hard drainages associated with urbanisation, which potentially cause more sewage discharge and/or water imports and thus increase low flows. Our detected percentage change in flow quantiles is consistent with unit changes reported by Anderson et al. (2022), who found a 0.6–0.7 % increase in mean and high flows for 1 % increase in urban area using panel regression for 729 US catchments. Some studies have reported a higher value, for example, Blum et al. (2020) found a 3.3 % increase in annual maximum flood for a 1 % increase in impervious basin cover using 280 US catchments; Yang et al. (2021) found a 3.9 % increase in annual maximum discharge for a 1 % increase in urban area using 757 catchments in China. The variations in the magnitude may be due to the different statistical approaches (Anderson et al., 2022; Salavati et al., 2016), as well as the sampling sizes and methods (Blum et al. 2020).

For low to high flows, the urban signal (signs of changes in river discharge that are linked to urbanisation) is greatest in summer, with a median increase of 2.2 % ±4.0 % (1 s.d.) for low flow, 2.5 % ±3.3 % (1 s.d.) for median flow, 1.9 % ±2.6 % (1 s.d.) for mean flow, and 2.0 % ±2.2 % (1 s.d.) for high flow, respectively. For seasonal maximum flow, the urban signal is greatest in autumn, with a median increase of 0.9 % ±2.7 % (1 s.d.) for 1 % urban increase. When pooling all seasons, a 1 % increase in urban extent yields an increase of 1.9 % ±2.8 % (1 s.d.) for low flow, 0.9 % ±2.3 % (1 s.d.) for median flow, 0.9 % ±1.9 % (1 s.d.) for mean flow, 1.1 % ±2.0 % (1 s.d.) for high flow, and 0.5 % ±2.2 % (1 s.d.) for seasonal maximum flow. Our results indicate that changes in low flows due to urbanisation tend to be proportionately larger than those for higher flows. Although distributions of urban coefficients vary somewhat between seasons and flow quantiles, these differences are not statistically significant according to the Kruskal-Wallis and pairwise Wilcoxon rank sum test (Table S1 and Table S2 in the Supplementary material).

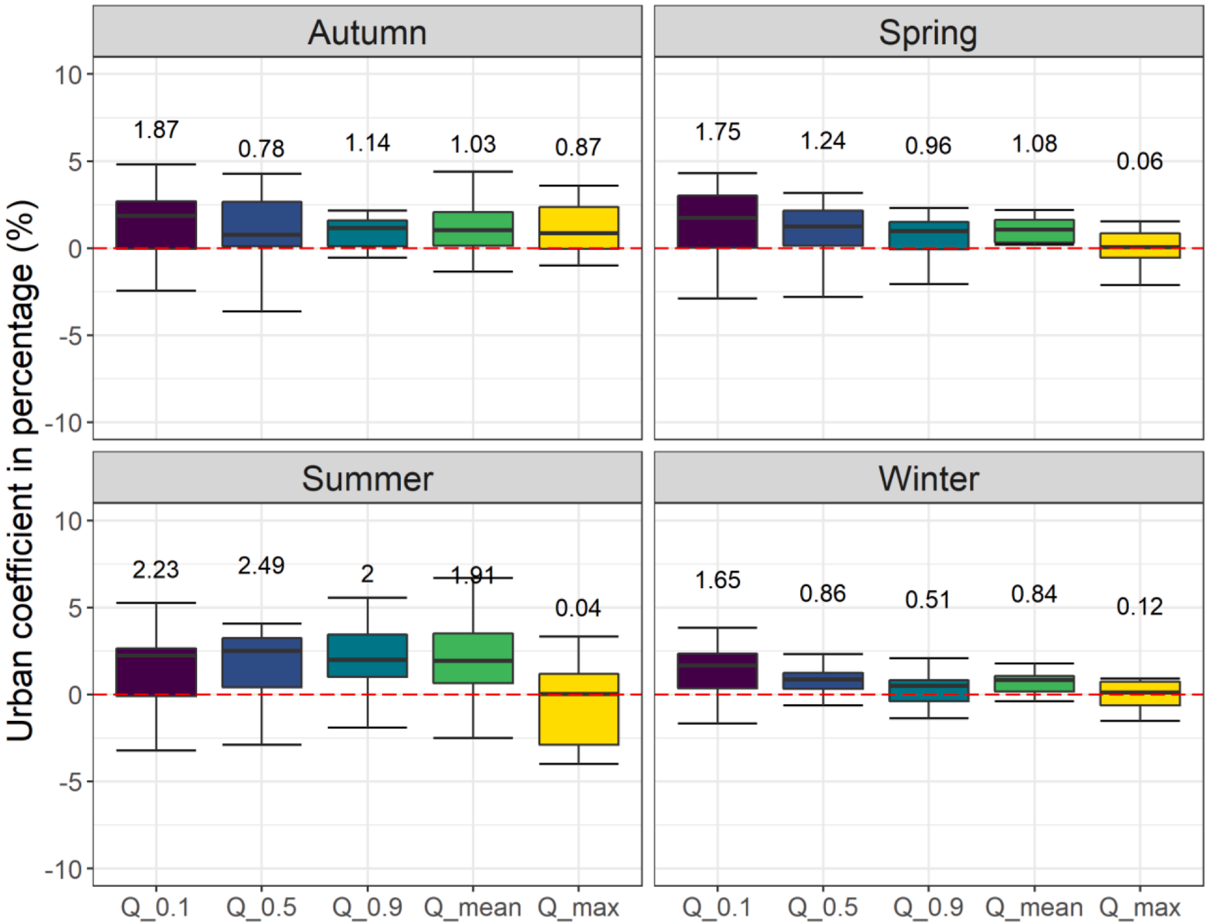

Fig. 7. Distribution of model coefficients in percentages for urban area, by season, and flow quantile, across the 12 catchments. The vertical axis is set to −10:10 on all figures for comparability. The horizontal red dashed line represents zero urban effect. The median of the distribution is shown above each boxplot in black font. Box colours denote different flow quantiles – here and throughout the paper. Outliers are not shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Median and standard deviation of the urban coefficients expressed as percentages across the 12 sites for each flow quantile and season.

Season	Q_0.1		Q_0.5		Q_0.9		Q_mean		Q_max	
	Median	S.D.	Median	S.D.	Median	S.D.	Median	S.D.	Median	S.D.
Autumn	1.9 %	2.8 %	0.8 %	2.4 %	1.1 %	2.3 %	1.0 %	2.1 %	0.9 %	2.7 %
Spring	1.8 %	2.3 %	1.2 %	2.0 %	1.0 %	1.9 %	1.1 %	1.6 %	0.1 %	1.5 %
Summer	2.2 %	4.0 %	2.5 %	3.3 %	2.0 %	2.2 %	1.9 %	2.6 %	0.0 %	2.5 %
Winter	1.7 %	1.6 %	0.9 %	1.1 %	0.5 %	1.3 %	0.8 %	1.0 %	0.1 %	1.9 %

S.D. indicates the standard deviation.

Given that urban percent change varies across catchments for the study time period, besides the effect of a 1 % increase in urbanisation as reflected by the extracted urban coefficient, we also checked the total urbanisation effect on river flow changes during the entire interval in all 12 catchments. The 30 year period from 1985 to 2015 (based on satellite-based urban percent) was considered, and the percentage change in discharge which is associated with urbanisation over the period was calculated using $[\exp(e_2{}^*\Delta x_u) - 1] \times 100\%$, where Δx_u is the urban percent increase over these fixed 30 years. Distributions of the urbanisation effect over the 30 year period for all study catchments are expressed as percentage changes in discharge in Fig. 8. This includes all the seasons and all flow quantiles. The same findings emerge: urbanisation in recent decades is highly likely associated with an increase in discharge, as indicated by the positive medians for all the distributions. The increase in urban land cover over 1985 to 2015 is associated with a median increase of 5.3–10.0 % in low flow, 4.1–10.0 % in median flow, 3.9–11.4 % in mean flow, 2.3–9.3 % in high flow, and 0.2–7.6 % in seasonal maximum flow across the four seasons.

4.3. Evaluation of the consistency and inconsistency of other drivers

The changes in AIC and urban coefficients in each catchment, when including 1-day maximum rainfall and antecedent day maximum in the urban models (M2), are shown in Fig. S3 and Table S3. Including 1-day maximum rainfall and antecedent day maximum improves the AIC for seasonal maximum flow, but the urban coefficients do not change significantly (only a few changes are larger than 0.01).

The comparisons of AIC for models with (Q ~ P + T + AP + time) and without (Q ~ P + T + AP) a time covariate are presented in Fig. S4 and Fig. S5. Adding a time covariate for non-urbanising catchments does not significantly improve model performance (Fig. S4; only one or two catchments show a consistent effect of including a monotonically-

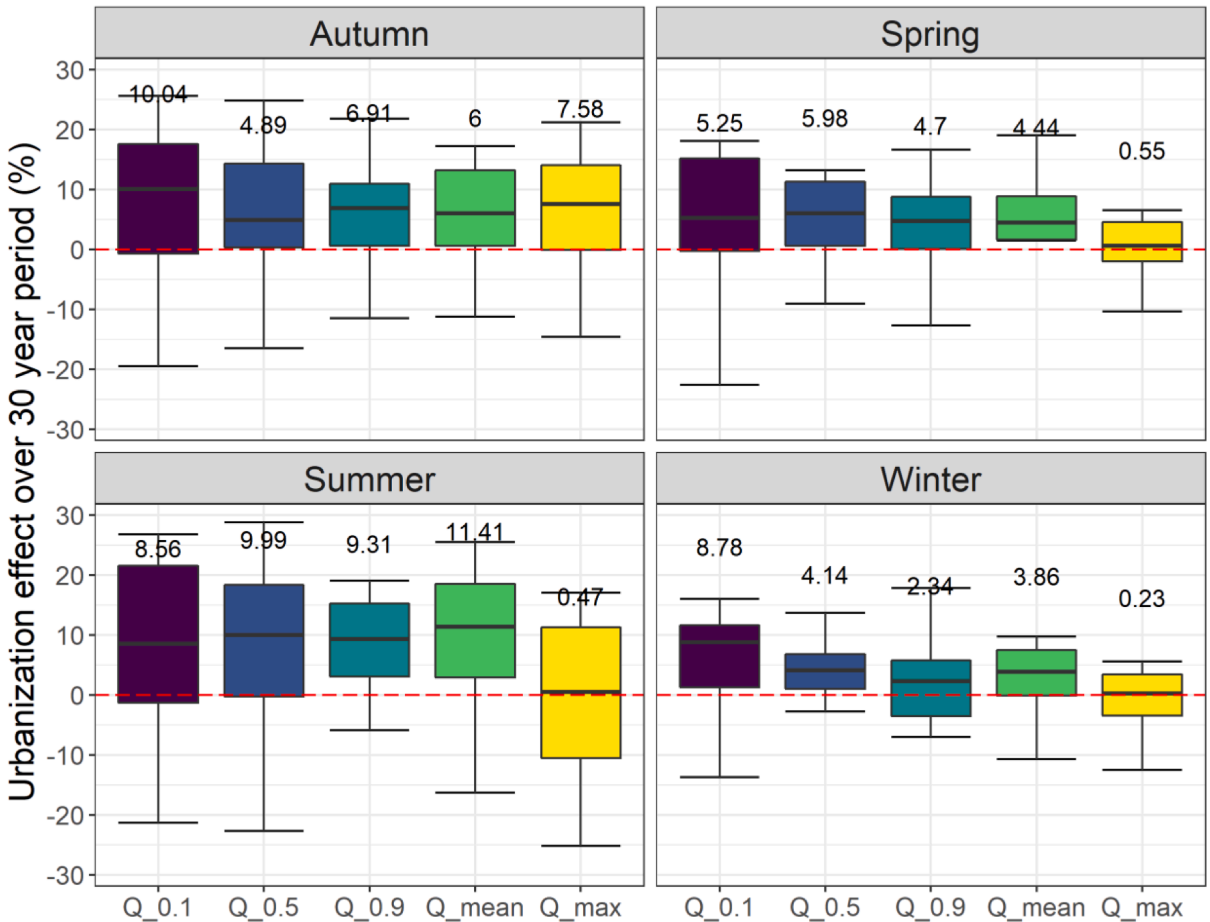

Fig. 8. Total contribution of urbanisation to river discharge non-stationarity (expressed as percentage changes in discharge) over the 30 year period (1985–2015), disaggregated by season and flow quantile, across the 12 catchments. The total urbanisation differs in each catchment. The vertical axis is the same on all figures for comparability. The horizontal red dashed line represents zero urban effect. The median change (%) of the distribution is shown above each boxplot in black font. Box colours denote different flow quantiles and the colour is consistent throughout the paper. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increasing variable), but for urbanising catchments, the proportion of catchments showing improvement is greatly increased (Fig. S5; eight catchments show a consistent effect). This evaluation confirms that in our urbanising catchments there is a monotonic time-varying variable affecting flow (i.e., urbanisation) whereas in our non-urbanising catchment there is not (i.e., increasing urbanisation, rainfall intensity, or some other unspecified drivers).

4.4. Assessment of catchment variation

We also investigated various factors that could be modulating the contribution of urbanisation to river discharge non-stationarity, including baseflow (BFI), drainage area (km^2), total urban change (%), urban extent (%), bedrock permeability (%), and water abstraction (m^3). Linear regressions between the urban coefficients and each factor as well as the corresponding R^2 and p-value were used to assess the significance of contributions. We first consider all 12 sites pooled together, irrespective of the statistical significance of the individual urbanisation coefficients within each GAMLSS model. We find no clear association between urban coefficients versus BFI, urban change, or water abstraction, and the associations with these three factors remain statistically insignificant if we only consider the sites with significant coefficients.

In contrast, results indicate a typically negative association between the urban regression coefficients and the urban extent in each catchment, in all seasons (Fig. 9). The regressions are significant only for some seasons and flow quantiles based on the p-values. This finding suggests that catchments that are less urbanised to begin with might be proportionately more sensitive to urbanisation effects on river discharge changes. The high sensitivity in less urbanised catchments suggests that the contribution of urbanisation to streamflow non-stationarity may be non-linear, i.e. as the degree of urbanisation increases, its impacts on runoff generation processes may potentially slow down. The reason for nonlinearity are not known, but it could be that other effects (e.g. greater urban heat island effect, or greater evaporation) are more prominent beyond certain levels of urbanisation. For example, the Bedford Ouse at Roxton (site 33039) is a less urbanised catchment (8.2 % in 1990), and yields increases to low flow of 6.7 %, median flow of 4.3 %, high flow of 1.8 %, mean flow of 3.1 %, and seasonal maximum flow by 0.7 % per 1 % increase in urban area (all seasons combined). In contrast, Pymmes Brook at Edmonton Silver Street (site 38022) is a heavily urbanised catchment (72.5 % in 1990), where urbanisation is estimated to decrease low flow by 2.4 %, median flow by 2.3 %, high flow by 0.8 %, mean flow by 1.7 %, and seasonal maximum flow by 1 % for a 1 % increase in urban area. Hence, the magnitude of the urban contribution tends to be large in the less urbanised catchment (33039) compared with highly urbanised catchment (38022). Another possible reason for the differences in urban contributions may be the location and distribution of the urbanised areas. In the less urbanised Bedford Ouse catchment where the contribution is large, for instance, urban area are mainly located in upstream and middle stream areas of the catchment, which may be hydrologically more sensitive to land use change impacts

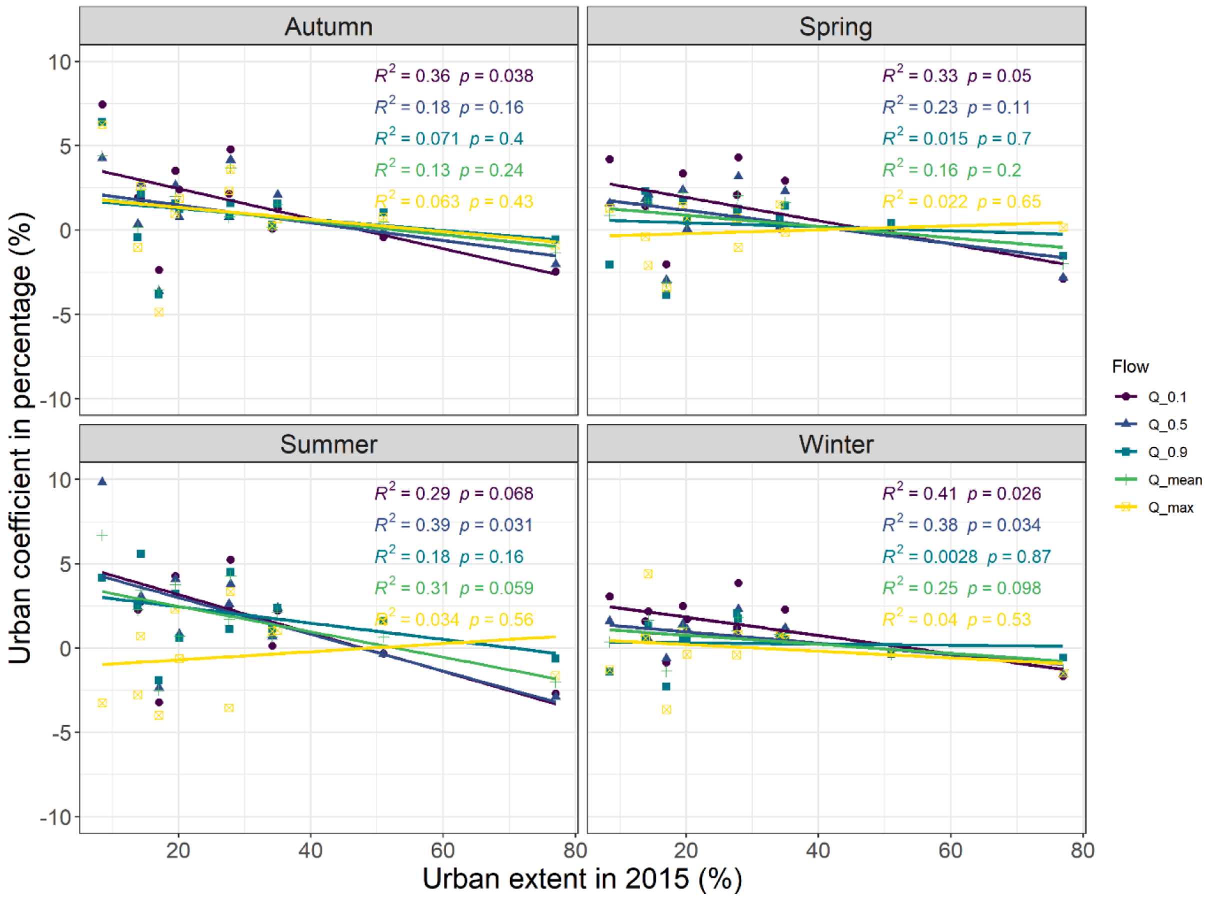

Fig. 9. Urban coefficient in percentage (effect of each percent increase in urbanisation on river flow) versus urban extent in 2015 (taken from Liu et al., 2020) for the 12 catchments (one dot per site). Linear regressions are fit for each season and flow quantile, with corresponding R^2 and p-value shown. Vertical axes are set to −10:10 for comparability.

as receiving and routing water flows. In contrast, in the highly urbanised Pymmes Brook catchment, where the urban contribution is less, urban land extends almost everywhere in the catchment, including both the upstream and downstream areas. If we consider only catchments with significant urban coefficients at $p < 0.05$ (significantly different from zero; Fig. S6), the relationship between urban extent and urban coefficients becomes even stronger (as indicated by the improved R^2 and p-values), although the sample size is evidently much smaller.

We also find a negative association between the urban coefficients and the percentage of high permeability bedrock (Fig. 10). The link is highly significant for low and median flows ($p < 0.05$) across all seasons but becomes less significant for high flows. This finding suggests that urbanisation tends to increase flow most in catchments with low bedrock permeability, likely because such strata slow the infiltration process and thus increase runoff. For instance, we compare the Bedford Ouse at Roxton (site 33039, high permeability bedrock = 6.7 %) – see above paragraph – with the Upper Lee at Water Hall (site 38018, high permeability bedrock = 88.4 %). For the Upper Lee, a 1 % increase in urban extent is estimated to increase low flow by 0.2 %, median flow by 0.5 %, high flow by 0.7 %, mean flow by 0.5 %, and seasonal maximum flow by 0.9 % on average. Hence, the increases in discharge in the highly permeable Upper Lee are much smaller than in the Bedford Ouse, across all quantiles. Overall, the effect of bedrock permeability is stronger in summer rather than in winter.

Similarly, we find positive associations between the urban coefficients and drainage area (Fig. S7), but these are significant only for some flow quantiles in autumn and summer. The significance of the association remains similar if we include only the sites with statistically significant ($p < 0.05$) urban coefficients (Fig. S8). This suggests that greater urban contributions to changes in river discharge are found in larger catchments, albeit influenced by a few outliers. It is possible that the contribution of urbanisation becomes more noticeable once an absolute threshold of surface area or urbanised land is reached. We take the Bedford Ouse at Roxton (site 33039) again as an example since it is the largest among our study catchments (drainage area = 1660 km^2), and compare it with a small catchment, Canons Brook at Elizabeth Way (site 38007; drainage area = 21 km^2). In the Canons Brook, a 1 % increase in urban area on average leads to 0.3 % decrease in low flow, 0.1 % decrease in median flow, 0.7 % increase in high flow, 0.2 % increase in mean flow, and 0.5 % increase in seasonal maximum flow across different seasons. In other words, the magnitude of change is smaller than in the larger Bedford Ouse catchment.

5. Study limitations

Here, we employ daily discharge records to assess the contribution of urbanisation to non-stationary river flows. For high flows, the impacts may differ if we use instantaneous maximum flow rather than mean daily flow, but we employ daily flow for consistency across quantiles. We also employ a statistical approach, in which monotonically increasing predictors (such as urbanisation) may inadvertently reflect the impact of other drivers within a catchment (such as changes in rainfall intensity, or gradual monotonic increases in flow abstraction/augmentation over time). For instance, it is possible that increases in low flows in a catchment may be driven by imported effluent flows. It is important to recognise that although statistical methods are powerful tools for detecting signals in observational data, one can never be entirely sure of the drivers, as with a physics-based model. To counter

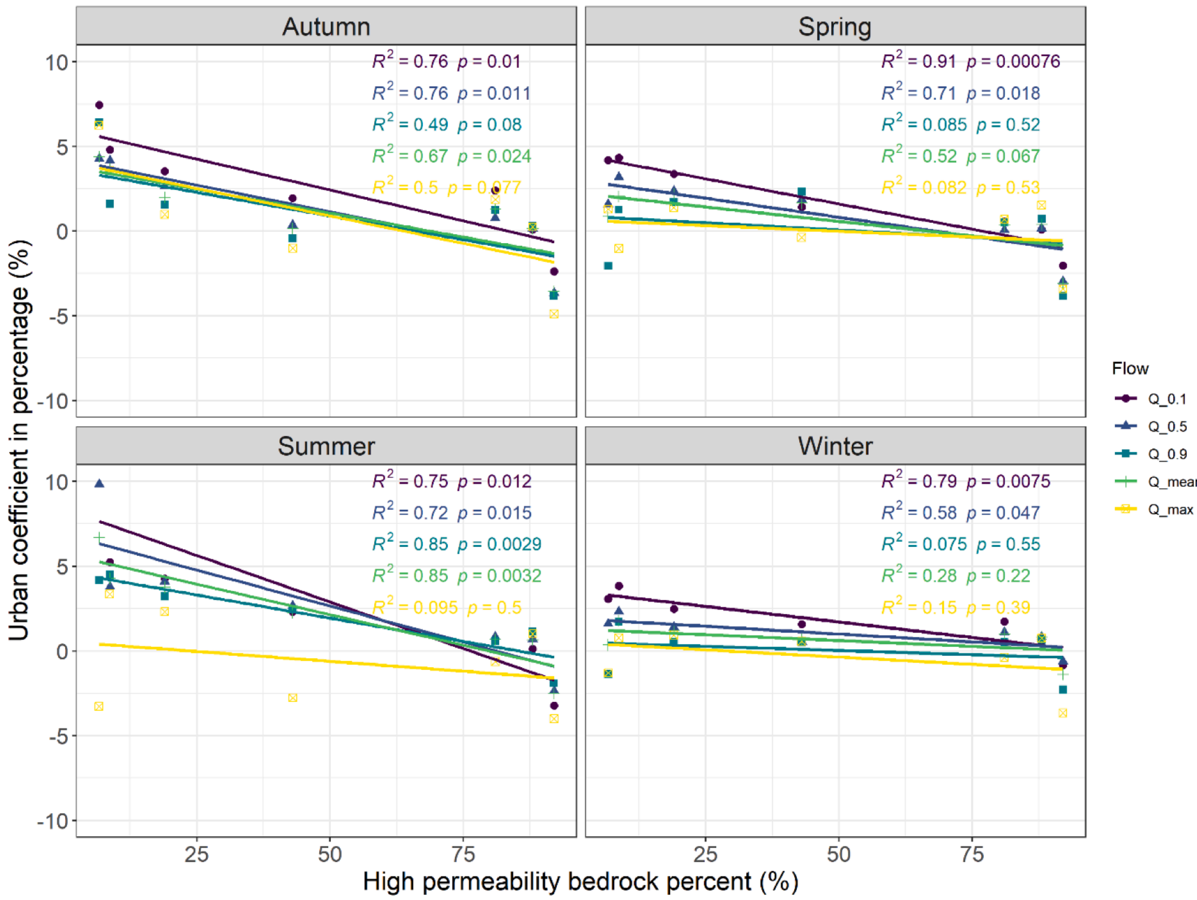

Fig. 10. As in Fig. 9 but for urban coefficient (%) versus percentage of high permeability bedrock. There are 7 catchments after removing those without high permeability bedrock.

such weaknesses, we developed a procedure for assessing the consistency/inconsistency of predictors. Further, recent and future urbanisation might have different effects on discharge than historic urbanisation (for instance due to greater uptake of sustainable drainage systems or higher-density urban development). Also, other factors such as river management (e.g., channelization, river bed paving), geomorphological differences among the catchments (e.g. basin shape, channel network density), and temporal changes in transport and deposition of sediment leading to changes in channel width, depth, and slope (e.g. Slater et al., 2019), may have certain impacts on river discharge as well as our ability to reliably measure discharge.

6. Conclusions

In this study, we investigated the contribution of changes in urban area to river discharge trends for a representative sample of UK catchments, covering different flow quantiles and seasons. Using a stringent set of criteria, 12 catchments were selected based on the completeness of their observed data records, absence of major human influences, significant changes in flow, and changes in urban land cover. Two statistical models were developed at each site to estimate relationships between river flow, precipitation, temperature, and antecedent rainfall, for specified flow quantiles and seasons – one model without and one with urbanisation, as a predictor variable. Model coefficients for urbanisation were then extracted from urban models to quantify river flow quantile sensitivity to urban area.

Results show that the model performance is generally improved in urban catchments when urbanisation is included as a covariate, suggesting that non-stationary river discharge is partly driven by growing urban areas. The improvement is more significant for low, median, and mean flow relative to high flow, and there are no significant differences between seasons. We find urbanisation is more likely to be associated with increases than decreases of river discharge across flow quantiles and seasons. However, the magnitude of the association varies considerably across catchments depending on season, flow quantiles, and geology. A unit (1 %) increase in urban land cover is associated with 1.9 % ±2.8 % (1 s.d.) increase in low flow, 0.9 % ±2.3 % (1 s.d.) increase in median flow, 0.9 % ±1.9 % (1 s.d.) increase in mean flow, 1.1 % ±2.0 % (1 s.d.) increase in high flow, and 0.5 % ±2.2 % (1 s.d.) increase in seasonal maximum flow across different seasons, on average. The contribution of urbanisation tends to be proportionately larger for low flows than the highest flows, which implies that urbanisation has most significant impacts on changes in non-flood flows. Results also indicate a greater sensitivity of river flow to urbanisation in those catchments with low initial urban extent and in catchments with less area underlain by high permeability bedrock.

Overall, our results suggest that for urbanising catchments, historical river flow models and future river flow projections are unlikely to be robust if they are only driven by meteorological inputs. Our findings also highlight that one must be particularly cautious when estimating or projecting future river flow in catchments that are less urbanised and likely to witness rapid urbanisation, and in catchments with low bedrock permeability. Future research will investigate the relative impact on river discharge of projected changes in climate and urbanisation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2022.128417.

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