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## RESEARCH ARTICLE

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### Key Points:

- We compare two common statistical attribution methods to contrast model assessments of the influence of land cover changes on streamflow
- Panel regression shows that mean and high streamflow increase due to urbanization, while a GLMs show no average association
- Neither the panel nor the single catchment regression approach revealed a significant average effect of tree cover changes on streamflow

### Supporting Information:

Supporting Information may be found in the online version of this article.

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## Statistical Attribution of the Influence of Urban and Tree Cover Change on Streamflow: A Comparison of Large Sample Statistical Approaches

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**Abstract** The strengths and weaknesses of different statistical methodologies for attributing changes in streamflow to land cover are still poorly understood. We examine the relationships between high ( $Q_{99}$ ), mean ( $Q_{\text{mean}}$ ), and low ( $Q_{01}$ ) streamflow and urbanization or tree cover change in 729 catchments in the United States between 1992 and 2018. We apply two statistical modeling approaches and compare their performance. Panel regression models estimate the average effect of land cover changes on streamflow across all sites, and show that on average, a 1%-point increase in catchment urban area results in a small (0.6%–0.7%), but highly significant increase in mean and high flows. Meanwhile, a 1%-point increase in tree cover does not correspond to strongly significant changes in flow. We also fit a generalized linear model to each individual site, which results in highly varied model coefficients. The medians of the single-site coefficients show no significant relationships between either urbanization or tree cover change and any streamflow quantile (although at individual sites, the coefficients may be statistically significant and positive or negative). On the other hand, the GLM coefficients may provide greater nuance in catchments with specific attributes. This variation is not well represented through the panel model estimates of average effect, unless moderators are carefully considered. We highlight the value of statistical approaches for large-sample attribution of hydrological change, while cautioning that considerable variability exists.

## 1. Introduction

### 1.1. Land Cover Effects on Streamflow

Significant trends have been detected in historical streamflow records across the United States (e.g., Archfield et al., 2016; Douglas et al., 2000; Lins & Slack, 1999, 2005; Rice et al., 2015; Sadri et al., 2016; Slater & Villarini, 2016; Tamaddun et al., 2016; Y.-K. Zhang & Schilling, 2006). Shifts in climate characteristics, such as precipitation totals, phase, and timing are widely considered to be the dominant drivers of hydrologic change, but land cover changes, consisting of changes in the biological or physical features present in a landscape (e.g., forested or urban area), also have the potential to drive changes in streamflow, potentially even offsetting the influence of climate (Slater, Anderson, et al., 2021). The effects of land cover changes on hydrological extremes, such as worsening flood risk (e.g., Bradshaw et al., 2007; van Dijk et al., 2009), or as potential mechanisms by which hydrological and climatic risks may be managed or offset (e.g., Dadson et al., 2017; Dixon et al., 2016) remain poorly understood. It is clear that land cover changes can alter hydrological response to precipitation events by influencing the degree and rate at which water is intercepted and evaporated, stored, or allowed to run off into a river channel (Filoso et al., 2017; Jacobson, 2011; Shuster et al., 2005), however, the extent to which they do so lacks clear definition.

There are a number of ways in which land cover change might be expected to influence the magnitude of high, mean, and low daily streamflows. Widely discussed in the literature, urbanization is typically expected to increase high flows and flood risk (Blum et al., 2020; Hodgkins et al., 2019; Hollis, 1975; Prosdocimi et al., 2015; Salavati et al., 2016; Yang et al., 2021) and to a lesser extent, water balance or mean annual flows (Oudin et al., 2018; Salavati et al., 2016). Urbanization has been associated with a wide range of changes in low or base flows in general, including significant decreases and increases in flow, likely dependent on the specific activities associated with urbanization in a given catchment (Dudley et al., 2020; Jacobson, 2011; O'Driscoll et al., 2010).

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The relationship between streamflow and tree cover change is less well defined in the literature. Typically, one might expect tree loss or deforestation to be associated with increases in streamflow, and afforestation to be associated with decreases in streamflow. This expectation remains consistent in the literature for low, mean and high flows generally (Ahn & Merwade, 2017; Bladon et al., 2019), although the relationship appears particularly well defined for mean flows (Brown et al., 2005; Hibbert, 1965; Swank et al., 2001) and low flows (Smakhtin, 2001) with evidence suggesting pronounced decreases in flow following afforestation (Farley et al., 2005) and vice versa. While there is generally agreement regarding the ways in which changes in each of these land cover types affect streamflow, there exists a range of research which reports contrasting or even non-existent associations between these variables (e.g., Biederman et al., 2014, 2015; Bart et al., 2016; Goeking & Tarboton, 2020; Guar-diola-Claramonte et al., 2011; Slinski et al., 2016).

Understanding the role that both tree cover change and urbanization play in the hydrologic cycle is increasingly important in light of growing discussion around natural flood management, which focuses on the use of land management strategies for mitigating flood risk (Dadson et al., 2017), and nature-based solutions to climate change (Cohen-Shacham et al., 2016). This discussion centers the potential for afforestation to sequester carbon (e.g., Bastin et al., 2019), and in a hydrological context, begs the questions: What effects would large-scale afforestation have on water availability and risk? Conversely, to what extent is urbanization altering our susceptibility to water related risks?

While many have attempted to understand the influence of land cover changes on streamflow, the breadth of knowledge that we have about those relationships is deep, but incomplete. Most of these studies have used small sample sizes and employed methods such as paired catchment analysis (e.g., Brown et al., 2005; Prosdocimi et al., 2015; Seibert & McDonnell, 2010; L. Zhang et al., 2012), or simulation and modeling-based approaches (e.g., Hejazi & Markus, 2009; Hidalgo et al., 2009; Schilling et al., 2014). Small sample analyses are useful for understanding physical relationships within a single catchment or a limited number of catchments. They are not, however, particularly well-suited to extrapolating findings across larger regions and making generalized statements about hydrological behavior.

Much large sample research has relied on regression techniques to develop our understanding of the potential effects of land cover changes on streamflow. There are some definitive benefits to these approaches. For example, statistical approaches may allow for the quantification of relationships between flow characteristics and catchment descriptors for which data are available (e.g., potential for differing effect sizes based on soil type or air temperature), as well as the ability to state a level of confidence in results (Gupta et al., 2014). There are two dominant statistical approaches to attribute the drivers of large-sample hydrological change in the literature. First, a single-catchment approach involves fitting distinct regression models to often “lumped” time-series data for individual catchments, then assessing the fit of these models and signs of their coefficients (e.g., Neri et al., 2019; Prosdocimi et al., 2015; Slater, Anderson, et al., 2021; Villarini et al., 2009). Alternatively, a combined multi-catchment approach involves fitting panel regression models to estimate average causal effects across many sites (recent examples in hydrology include: Bassiouni et al., 2016; Blum et al., 2020; Brady et al., 2019; De Niel & Willems, 2019; Lombard & Holtschlag, 2018; Steinschneider et al., 2013; Yang et al., 2021). The deceptively simple nature of regression approaches means that they have been widely applied, however, while both single-catchment and multi-catchment approaches have their unique benefits, they are best suited to slightly different questions.

## 1.2. Study Scope

The aims of this work are twofold. We first seek to improve understanding of the relationships between land cover changes, specifically tree cover and urban area, and low, mean, and high annual streamflows. Then, we compare the results from two different statistical techniques, a multi-catchment panel regression approach, and a single-catchment regression approach applied to the same sites. Specifically, we address the following research questions and hypotheses:

1. How are urbanization and tree cover change associated with or affecting streamflow across the conterminous United States?

In accordance with prior research, we hypothesize that urbanization may result in increased mean and high flows, and that low flow relationships will be more varied (e.g., Blum et al., 2020; Prosdocimi et al., 2015; Villarini et al., 2009), while afforestation (deforestation) may decrease (increase) streamflow for all parts of the hydrograph.

2. How do the results of single-catchment and multi-catchment (panel) regression methods differ?

We expect that our panel regression model coefficients will roughly correspond with the central summary of the distribution of the combined single-catchment regression coefficients; however, the panel model estimates will exhibit less variability, demonstrating that they are a more reliable metric for estimating the typical effect of different drivers on flow across a wide scale.

## 2. Data

We use the Geospatial Attributes of Gages for Evaluating Streamflow version II (GAGES II) dataset (Falcone, 2011) as a basis for selecting catchments to include in the analysis. GAGES II contains geospatial characteristics and catchment descriptors for 9,322 gaged river basins in the United States which had a long flow record at the time of its creation in 2011 (Falcone, 2011). We downloaded the daily streamflow data between 1992 and 2018 for all catchments in the GAGES II dataset from the United States Geological Survey using the R package “*dataRetrieval*” (DeCicco et al., 2018; United States Geological Survey, 2020) and calculated the annual 0.99 ( $Q_{99}$ ), mean ( $Q_{\text{mean}}$ ), and 0.01 ( $Q_{01}$ ) quantiles of the daily streamflow to represent high, mean, and low flows, respectively, for each calendar year. We then used the catchment boundaries associated with each of these gage sites from the National Hydrography Dataset version 1 (NHDv1) Watershed Boundary Dataset (WBD; United States Geological Survey and United States Department of Agriculture, 2020) to quantify the annual average percentage of tree cover and urban area in each catchment from the European Space Agency (ESA) Climate Change Initiative (CCI) Global Land Cover dataset (300 m resolution; 1992–2018). The dataset is described in more detail later in this section (ESA CCI, 2017).

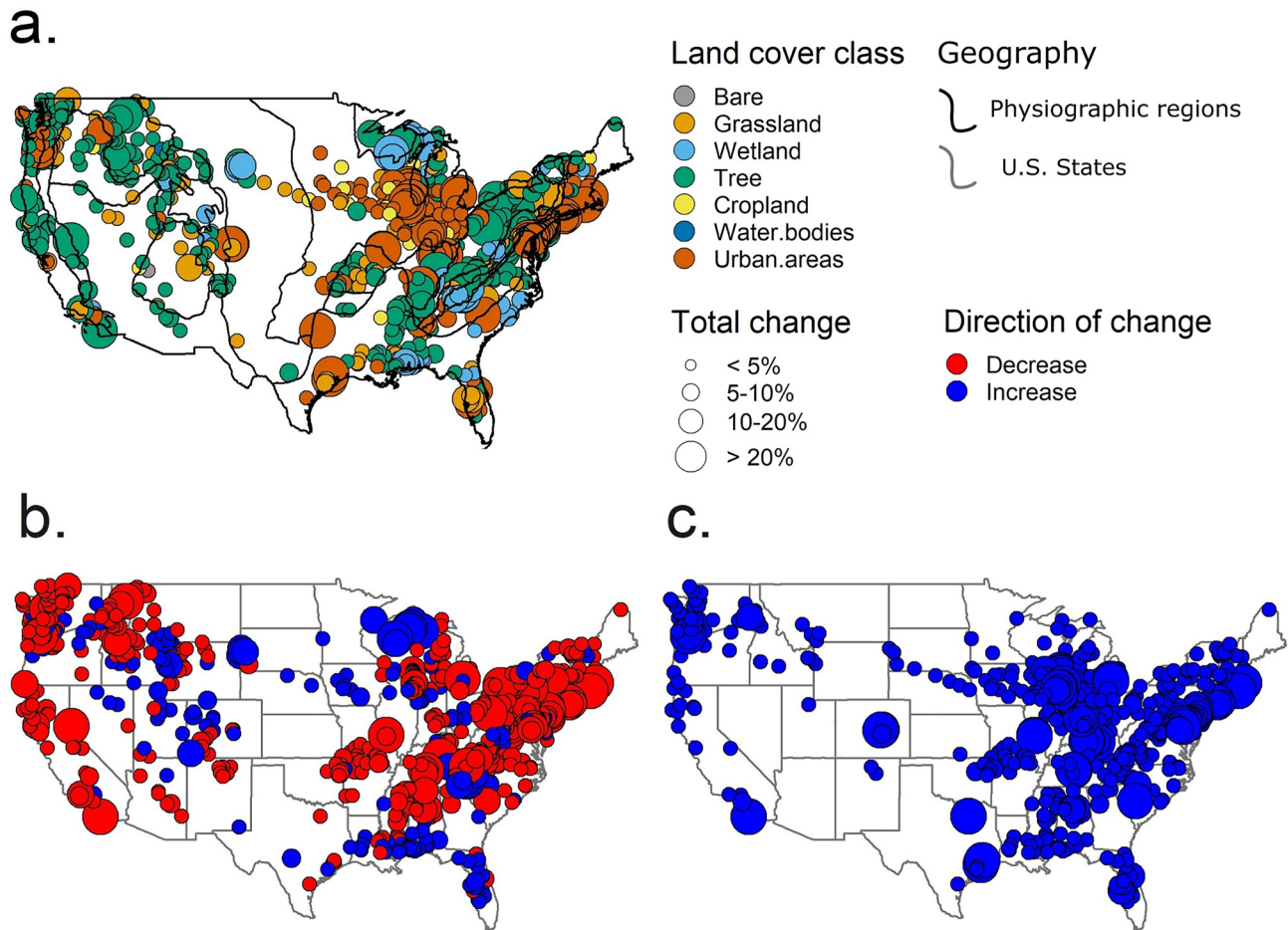
We then assessed the daily streamflow data from all catchments to ensure that they had:

1. At least 20 yr of 95% complete daily streamflow records (more than 347 days/yr) in the years for which land cover data are available.
2. No zero flow values in the annual flow quantiles.
3. Not experienced more than 1 day of upstream dam storage, calculated by dividing the total upstream dam storage by the estimated catchment annual runoff, both taken from GAGES II (Blum et al., 2020; Falcone, 2017; Hodgkins et al., 2019).
4. A minimum of four distinct values in the land cover time series being assessed (i.e., experienced land cover change over time).

We require the presence of some land cover change to have occurred in each catchment because this is necessary to be able to fit the single site models, no zero flow values because the low flow behavior of these catchments may be too complex to model well with a regression-based approach, and removed catchments with greater than 1 day of dam storage because we expect that dam storage may be used to counter high runoff relevant to flood events.

The final dataset included the high, mean, and low annual quantiles of the daily streamflow data for 729 catchments. On average, sites used in the analysis had 26.5 yr of complete daily streamflow data. We organized the discharge data according to calendar years (January–December) rather than water years (October–September) to maintain consistency between the climate and land cover datasets. Calendar years are also better suited to studying low flows, which occur in the autumn in many US catchments (Sadri et al., 2016).

While the ESA-CCI land cover dataset is based in large part on the medium resolution imaging spectrometer surface reflectance (MERIS SR) time series, the urban area class is supplemented by two external sources (ESA, 2017): The Global Human Settlement dataset, created using Landsat imagery and validated using population, among other sources (Pesaresi et al., 2016) and the Global Urban Footprint dataset, derived using high-resolution information from the synthetic aperture radar satellites, TerraSAR-X and TanDEM-X (Esch et al., 2013). The ESA-CCI dataset has an estimated overall accuracy of around 71% (ESA, 2017) and the user accuracy



**Figure 1.** (a) Total absolute change (1992–2018) in the land cover class which in 2018 occupied the largest percentage of the catchment area in the 729 catchments used in this analysis. Land cover classes represent aggregated groups (Table S1 in Supporting Information S1) based on the ESA CCI Global Land Cover dataset. (b and c) Show total changes in tree cover (b) and urban areas (c), respectively, in the 729 catchments used in this analysis.

estimates for the land cover classes which we use in this work are generally higher, for example, for four of the tree cover classes (ranging from 75% to 90% accuracy) and urban area (75%). It is worth noting that these accuracy estimates are global averages based on the 2015 land cover data. Actual accuracy is likely to be much higher over the study area because the number of valid observations is high for the USA (ESA, 2017). It is also possible that accuracy varies from year-to-year.

We aggregated the original land cover classification categories into seven broad groups (Table S1 in Supporting Information S1) based on the recommendations of the United Nations Convention to Combat Desertification (UNCCD) good practice guidance for SDG Indicator 15.3.1 (Sims et al., 2017), prior to calculating the catchment percentages of land cover area. We then retain the data for urbanization and tree cover change for analysis (Figure 1). In referring to tree cover change, we use the term “afforestation” as the equivalent of a net increase in tree cover, and “deforestation” to refer to a net decrease in tree cover, but we do not consider the mechanisms by which tree cover change has occurred (e.g., reforestation). Evidence suggests that effects are similar regardless of the mechanism by which change occurred (Filoso et al., 2017). Urban area did not decrease in any catchment. On the other hand, tree cover change was not unidirectional; a given catchment may have experienced relative gains and losses in tree cover in different years, over the period of record.

We compute catchment-averaged annual precipitation and mean annual temperature from 44 km × 4 km resolution annual Parameter-elevation Regressions on Independent Slopes Model (PRISM) data (Daly et al., 2008; Di Luzio et al., 2008; PRISM Climate Group, 2019) accessed using the R package “prism” (Hart & Bell, 2015). The PRISM dataset is the most widely used spatial climate dataset in the United States, and is the official climate



dataset for the United States Department of Agriculture (Daly & Bryant, 2013). Finally, we use the United States Geological Survey Physiographic divisions of the United States (Figure 1) to represent geomorphic and geologic characteristics in our multi-catchment models (Fenneman & Johnson, 1946).

### 3. Methods

#### 3.1. Causal Diagrams

We construct causal diagrams to outline the potential relationships within the hydrological system (Blum et al., 2020), and inform the design of our regression models. The mechanisms by which tree cover change and urbanization might influence streamflow are outlined in the causal diagrams in Figure 2. The arrows in these diagrams denote causal relationships and not physical pathways. Confounders are variables which could potentially influence both the land cover variable in question as well as streamflow. Moderators are catchment characteristics which are likely to influence the degree to which different land cover changes influence streamflow, but not whether or not there is a relationship between the two. The diagrams are used to help construct the models outlined in the remainder of this section.

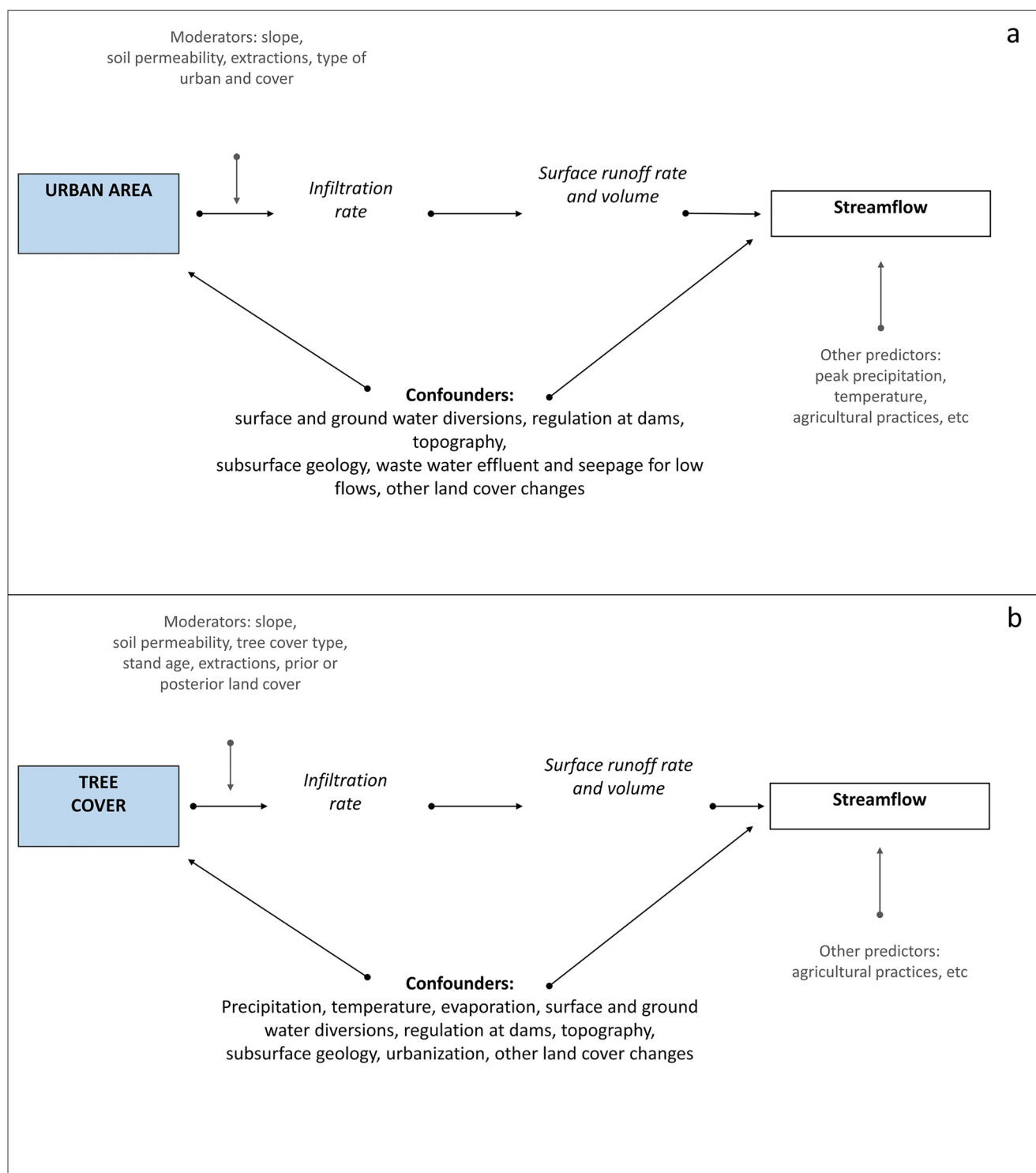
#### 3.2. Single-Catchment Models

Next, we fit generalized linear models (GLMs) using the R package *gamlss* (Rigby & Stasinopoulos, 2005) to each individual streamflow quantile time series (Table 1). The *gamlss* framework is highly flexible, however, the use of more complex models was attempted but did not result in increased goodness of fit. For more detailed discussion on the GAMLSS framework the reader is directed to Rigby and Stasinopoulos (2005) and Stasinopoulos and Rigby (2007).

We fit GLMs using the lognormal distribution (LOGNO in the *gamlss* package) for the response variable  $Y$  (Tables 1 and 2b), so that the coefficients would be directly comparable across both modeling approaches. The lognormal distribution is parametrized by  $\mu$  and  $\sigma$ , which, in the GAMLSS framework, can both be modeled as a function of explanatory variables. The  $\mu$  parameter models the location of the distribution while the  $\sigma$  parameter (scale) relates to the dispersion of the distribution. Here, we are concerned with the typical behavior of the flow variables, and so focus on  $\mu$  parameter modeled as a function of explanatory variables (Table 2b.). We hold the  $\sigma$  parameter constant in our GLMs (Table 2b) meaning that its estimation does not vary with time or any other variables. In effect, a GLM based on a log-normal distribution with constant  $\sigma$  is equivalent to the traditional multiple linear regression based on the ordinary least squares estimator, in which the original response variable is log-transformed: the  $\sigma$  parameter is estimated using the residual sum of squares of the OLS fit.

In some instances, tree cover and urban area changes will be correlated with one another. Urbanization is a confounder for tree cover because changes in tree cover are potentially caused by urbanization and, urbanization is also likely to have an effect on streamflow. We therefore introduce a variable selection procedure to select the data incorporated into the models for each catchment. We prioritize reducing collinearity between land cover variables to improve our coefficient estimations because when two or more variables in the model are highly correlated they are more likely to provide redundant information about the response, and reduce our ability to interpret the results in a meaningful way (James et al., 2013).

In catchments where only tree cover or urban area change was present in the study period, we are not concerned about collinearity between the land cover variables. In those catchments, we use the land cover change variable which was present and do not apply the variable selection procedure. In catchments where both tree cover change and urbanization occurred, we examine the collinearity between the land cover variables by fitting a log-normal GLM (Table 1) for which the  $\mu^{i,t}$  parameter includes both tree cover and urbanization variables, as defined in Equation 1 (Tables 1, 2a, and 2b). We then estimate the variance inflation factor (VIF) for Equation 1 (with  $Q_{\text{mean}}$  as the predictand) using the R package *car* (Fox & Weisberg, 2011) to determine the impact of collinearity on the precision of the model parameter estimation. VIF has a minimum possible score of 1 (no collinearity), and as a rule of thumb, a VIF of greater than either 5 or 10 can be considered to have a potentially dangerous level of collinearity (James et al., 2013). Since our intention is to interpret the regression coefficients as a form of attribution, we adopt a conservative VIF threshold of 2.5. Then if VIF is  $>2.5$  we retain only urban area in the model, and if VIF  $<2.5$  for a catchment, we retain the land cover variable which experienced the largest absolute



**Figure 2.** Causal diagrams depicting the relationships between urban area and streamflow in (a) and tree cover and streamflow in (b) adapted from Blum et al. (2020). Arrows denote causal relationships, not physical pathways.

change between 1992 and 2018 and exclude the other, using Equations 2 and 3 as our final single site regression models for the analysis (Tables 1, 2a, and 2b). Our approach prioritizes urbanization when the two variables are collinear because it makes intuitive sense that urbanization is a likely driver of changes in tree cover, rather than the reverse.

**Table 1**  
*Equations for GLMs and Panel Models*

Types	#	Models	Equations	Description
GLM	1	Both	$Y_{i,t} \sim \ln(\mu_{i,t}, \sigma_i^2) \mu^{i,t} = \alpha^i + \beta_1^i urban_{i,t} + \beta_2^i tree_{i,t} + \varepsilon_{i,t}$	Model fit exclusively to estimate VIF
GLM	2	Tree cover	$y_{i,t} \sim \ln(\mu_{i,t}, \sigma_i^2) \mu^{i,t} = \alpha^i + \beta_2^i tree_{i,t} + \theta_1^i \ln(P_{i,t}) + \theta_2^i Tmean_{i,t} + \varepsilon_{i,t}$	Single catchment model for tree cover only
GLM	3	Urbanization	$y_{i,t} \sim \ln(\mu_{i,t}, \sigma_i^2) \mu^{i,t} = \alpha^i + \beta_1^i urban_{i,t} + \theta_1^i \ln(P_{i,t}) + \theta_2^i Tmean_{i,t} + \varepsilon_{i,t}$	Single catchment model for urban area only
Panel	4	Tree cover	$\ln(Y_{r(i),t}) = \alpha_i + \beta_2 tree_{i,t} + \theta_1 \ln(P_{i,t}) + \theta_2 Tmean_{i,t} + \delta_i D_t + \gamma_{i,r} D_r D_t + \varepsilon_{i,t}$	Panel model for tree cover only
Panel	5	Urbanization	$\ln(Y_{r(i),t}) = \alpha_i + \beta_1 urban_{i,t} + \theta_1 \ln(P_{i,t}) + \theta_2 Tmean_{i,t} + \delta_i D_t + \gamma_{i,r} D_r D_t + \varepsilon_{i,t}$	Panel model for urban area only

*Note.* VIF is the variance inflation factor used to select catchments where tree cover and urbanization are strongly correlated. The variables used and terms estimated by these equations are described in Table 2.

While temperature and precipitation are not confounding variables for urbanization, they are important predictors of flow and are therefore included in our models. We use the natural log of the precipitation variable in order to make the coefficients interpretable as equivalent to associated percentage change in the original flow scale. We apply an exponential transformation to the land cover and temperature coefficients so that they are interpretable relative to the non-log transformed streamflow quantiles as described in Text S1 in Supporting Information S1.

### 3.3. Multi-Catchment (Panel) Regression Design

Panel regression models have recently been applied in hydrological research (Blum et al., 2020; Davenport et al., 2020; De Niel & Willems, 2019; Ferreira & Ghimire, 2012; Levy et al., 2018; Müller & Levy, 2019; Yang et al., 2021). The approach allows consideration of the data across both time and space; here we quantify the average effects of individual drivers (changes in tree cover and urban area) across all sites while controlling for the influence of a wide range of confounding variables (Figure 2). Through careful consideration of the data and the aid of the causal diagrams, we attempt to isolate a causal effect (Ferraro et al., 2019; Pearl, 2009). Therefore, when discussing the results of the panel models, we refer to an “effect” size and not merely an association between variables. We formulate our panel regression models based on the design proposed in Blum et al. (2020) with some modifications, and fit them using the R package “plm” (Croissant & Millo, 2008).

The panel models in Equations 4 and 5 test the effects of change in tree cover and urban area on streamflow, respectively (Tables 1, 2a, and 2c). These models replicate the Blum et al. (2020) model with some changes. While precipitation and temperature are unlikely to be significant confounders for the effect of urban area on streamflow, they are confounding variables in the tree cover model because, in addition to streamflow, they each might influence tree growth directly. As an example, an event such as prolonged drought might affect both tree cover and streamflow, and if we failed to include precipitation in the tree cover model, these effects might not be captured in the annual dummy variable. For this reason, we equally tested the urban area model in Equation 5 (Tables 1, 2a, and 2c) without the climatological variables (Text S3 in Supporting Information S1). Results showed that the inclusion of total annual precipitation and mean annual daily temperature had a small influence on the urbanization coefficient (Table S2 in Supporting Information S1) resulting in slightly higher and more significant coefficients. While there was substantial overlap in the confidence intervals of these two models, the difference in significance suggests that climatological confounders might not be fully controlled for in the model design if these variables are not explicitly defined. Therefore, we include climatological variables in both models so that all of the models are comparable, and so that climatological coefficients may be considered across models. We apply the same transformation to the land cover and temperature coefficients as we do to the GLM coefficients (Text S1 in Supporting Information S1).

The “fixed effects” ( $\alpha_i$ ) are intercepts specific to each stream gage (Table 2c). These account for possible confounding variables which are constant over time. Similar to Blum et al. (2020), we use an annual dummy variable to control for time-varying national scale confounders, an interaction term for the United States Geological Survey Physiographic divisions of the United States (Fenneman & Johnson, 1946), with the annual dummy variables to control for regionally time-varying confounders (Figure 2; Table 2c). The physiographic regions

**Table 2**

*Description of Variables Used and Terms Estimated by the GLMs and Panel Models Described by the Equations in Table 2*

Name	Models	Description	Purpose
(a) All independent variables			
$urban_{i,t}$	1–5	Annual catchment averaged urbanization in %	
$tree_{i,t}$	1–5	Annual catchment averaged tree cover in %	
$\ln(P_{i,t})$	1–5	Natural logarithm of catchment averaged total annual precipitation in mm	
$Tmean_{i,t}$	1–5	Mean annual catchment averaged temperature in °C	
$D_t$	4–5	Dummy variable for year	
$D_t D_r$	4–5	Interaction between annual dummy variables and physiographic regions	
(b) GLM terms			
$Y_{i,t}$	1–3	One of three annual streamflow quantiles (0.1, mean, and 0.99) representing low, mean, and high flows, estimated from daily streamflow data, for each streamgauge ( $i$ ) and each annual timestep ( $t$ ) in m <sup>3</sup> /s	Response variable
$\mu^{i,t}$	1–3	Median of the GLM for each site ( $i$ ) at time step ( $t$ ) using the maximum likelihood estimator	Represents the predicted value of $Y$ for each site and year
$\sigma_i$	1–3	Scale parameter for the GLM model estimation	
$\alpha_i$	1–5	Stream gage specific intercept of the fitted model	
$\beta_1^i$	1 and 2	Estimated influence of a 1%-point increase in urban area on streamflow for a single site	Association estimated by this model
$\beta_2^i$	1 and 3	Estimated influence of a 1%-point increase in tree cover on streamflow for a single site	Association estimated by this model
$\theta_1^i$	1–3	Estimated influence of a 1% change in total annual precipitation on streamflow for a single site	Controls for association between precipitation and streamflow
$\theta_2^i$	1–3	Estimated influence of a 1°C change in mean annual temperature on streamflow for a single site	Controls for association between temperature and streamflow
(c) Panel terms			
$Y_{r(i),t}$	4–5	One of three annual streamflow quantiles (0.1, mean, and 0.99) representing low, mean, and high flows, estimated from daily streamflow data, for each stream gage ( $i$ ), in region ( $r$ ), and annual timestep ( $t$ )	Response variable
$\alpha_i$	4–5	Stream gage specific intercept of the fitted model	Controls for time invariant confounders at the basin level
$\beta_1$	4	Average effect of a 1%-point increase in urban area on streamflow	Causal effect estimated by this model
$\beta_2$	5	Average effect of a 1%-point increase in tree cover on streamflow	Causal effect estimated by this model
$\theta_1$	4–5	Estimated average influence of a 1% change in total annual precipitation on streamflow; not considered causal	Controls for confounding effect of precipitation on tree cover; allows estimation of precipitation elasticity
$\theta_2$	4–5	Estimated average influence of a 1°C change mean annual temperature on streamflow; not considered causal	Controls for confounding effect of temperature on tree cover; allows estimation of temperature elasticity
$\delta_t$	4–5	Overall effect of annual flow magnitude on year ( $t$ )	Controls for time-varying confounders at the national level
$\gamma_{t,r}$	4–5	Overall effect of annual flow magnitude on year ( $t$ ) in region ( $r$ )	Controls for time varying confounders at the physiographic region level

represent broadscale geomorphic regions based on similar terrain texture, rock type, geologic structure, and history (Fenneman & Johnson, 1946). These models provide a minimally biased estimate of effect size assuming that there are no sub-regional time-varying factors impacting both streamflow and urban area.

Autocorrelation in fixed effects panel models can lead to the underestimation of standard errors. We address this concern by clustering standard errors at the streamgauge level (Arellano, 1987; Bertrand et al., 2004;



**Table 3**  
*Threshold of Minimum Land Cover Change Used in Sensitivity Analysis*

Threshold (%)	Model	Total
0	Tree cover	388
0	Urbanization	341
1	Tree cover	333
1	Urbanization	168
5	Tree cover	122
5	Urbanization	109

*Note.* “Total” is the number of sites included in the model for each of the sub-datasets tested in the sensitivity and robustness analysis.

## 4. Results and Discussion

### 4.1. Land Cover Coefficients

Our first question addresses the expectation that urbanization would, on average, increase streamflow and that afforestation and deforestation would decrease or increase streamflow respectively. In Sections 4.1.1. and 4.1.2., we focus on the models which were fit to all catchments which experienced any total absolute change in land cover ( $>0\%$ ) between 1992 and 2018.

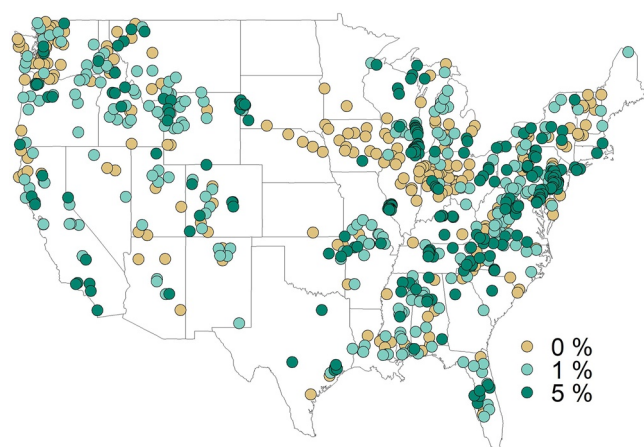
#### 4.1.1. Multi-Catchment Approach: 0% Land Cover Change Threshold

The effect of urbanization on mean and high flows is positive ( $\sim 0.6\%$ ) and highly statistically significant according to the panel model results (Table 4). The estimated effect sizes are small compared to those of Blum et al. (2020) who looked at the effect of urbanization on the instantaneous annual peak flood, using a similar methodology and estimated an average 3.3% effect of a 1%-point increase in impervious surface area on annual floods, from a sample of 280 catchments for which sites which did not experience substantial dam storage. It is possible that the difference in our results when compared to Blum et al. (2020) relate to the urbanization data, which was created from a different origin. However, Yang et al. (2021), also use the ESA CCI land cover data for a similar application in China, and estimate an approximately 3.9% effect of a 1%-point increase in urban area on annual floods in a sample of 757 catchments. It is more likely then, that the difference in results relates to the segment of the streamflow hydrograph which is being examined. The mean daily peak streamflow averages out the instantaneous maximum peak flow, meaning that

the maximum daily streamflow could be substantially smaller than the instantaneous maximum peak flow. This difference in flow is further magnified because we consider the 95th quantile of annual daily flow, rather than the maximum. Results for low flows in our urbanization model are not statistically significant.

The estimated panel effects of tree cover change are not statistically significant (Table 4). The weaker statistical significance may be indicative of unidentified confounding which dampens the estimated effect, may reflect the complex relationship between tree cover change and streamflow, or the challenges and limitations of the data used. However, strictly in terms of  $p$ -values, the model results indicate that tree cover change does not have a statistically significant average effect on any examined streamflow quantile. The low flow model also differs from the other tree cover panel models in that the resulting coefficient is positive (the inverse of those for mean and high flows), although not statistically significant.

While the insignificance of the effect of urbanization on low flows and of tree cover overall indicates that these land cover changes have no effect in an average sense, it does not necessarily mean that these land cover changes have no effect in particular circumstances. Rather, it may speak to the wider range of possible effects. For low flows, smaller overall differences in runoff



**Figure 3.** Location of catchments which met each land cover change threshold in the sensitivity analysis. Thresholds are cumulative, so that sites in each category are also included in samples with lower thresholds for land cover change.

**Table 4**  
*Model Results for Land Cover Coefficients: 0% Land Cover Change Threshold*

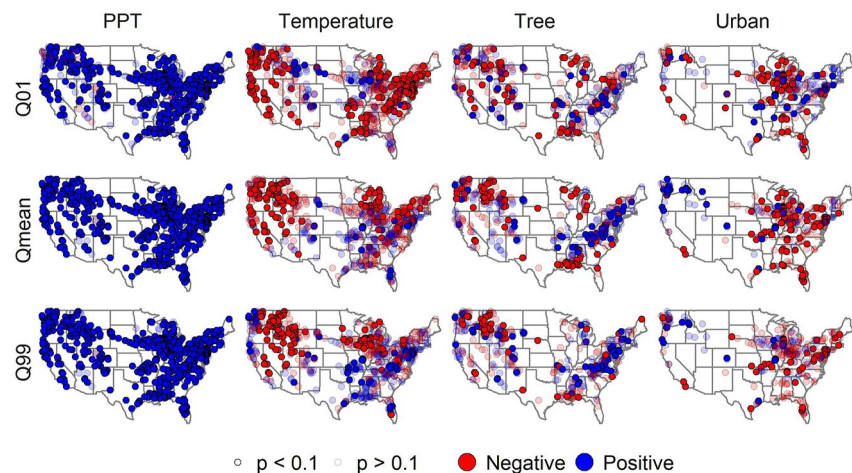
$Q$	Model	Variables	Estimate	$p$ -Value	Lower bound	Upper bound
$Q_{01}$	Urban GLM	Urban	−1.686		−98.045	80.679
$Q_{\text{mean}}$	Urban GLM	Urban	−2.099		−85.091	17.349
$Q_{99}$	Urban GLM	Urban	−2.704		−89.332	27.933
$Q_{01}$	Urban panel	Urban	0.34	0.4276	−0.363	1.048
$Q_{\text{mean}}$	Urban panel	Urban	0.623	<0.0001**	0.397	0.85
$Q_{99}$	Urban panel	Urban	0.675	0.0002**	0.374	0.977
$Q_{01}$	Tree GLM	Tree	−1.053		−20.271	21.946
$Q_{\text{mean}}$	Tree GLM	Tree	0.241		−18.252	20.188
$Q_{99}$	Tree GLM	Tree	1.223		−20.274	32.641
$Q_{01}$	Tree panel	Tree	0.275	0.209	−0.085	0.636
$Q_{\text{mean}}$	Tree panel	Tree	−0.261	0.1505	−0.559	0.038
$Q_{99}$	Tree panel	Tree	−0.384	0.1057	−0.773	0.006

*Note.* The  $p$ -values <0.01 are indicated with \*\*. Lower and upper bounds indicate the middle 90% of the distribution of GLM coefficients and the 90% confidence intervals of the panel models. Coefficients represent the % change in streamflow expected for a 1 %-point change in the land cover variable. Coefficients have been transformed using  $100(e^{\theta_2} - 1)$  where  $\theta_2$  is the relevant temperature coefficient.

and the intricacies of land cover change may have a proportionally larger influence on streamflow than they do for higher flows. For instance, the location of waste water treatment plants in urban areas (Oudin et al., 2018), landscape irrigation and water withdrawals and returns, as well as forest life stage (age) or the mechanisms by which deforestation occurs (Biederman et al., 2014, 2015; Slinski et al., 2016), or the aridity of a region (Goeking & Tarboton, 2020) may play an important role in determining the directionality of the effects of land cover change on low flows, depending on the particular characteristics of what comprises “urbanization” or “tree cover change” (Smakhtin, 2001). In other words, if many outcomes are possible, developing a meaningful average across sites is far more difficult.

#### 4.1.2. Single-Catchment Approach: 0% Land Cover Change Threshold

We address the same question using the single-catchment regression approach and expect that the land cover coefficients might vary more widely for streamflow in relation to tree cover change and for low flows than for higher flows in relation to urbanization, based on the previous literature.



**Figure 4.** Sign of the coefficients for the land cover and climatological variables in the single-catchment models at the 0% land cover change threshold. Red points represent a negative coefficient while blue represent a positive coefficient. Coefficients which are not significant at the  $p < 0.1$  level are presented in a transparent shade.

The expectation that urbanization would, on average, increase streamflow and that afforestation and deforestation would decrease or increase streamflow, is not clearly supported by the single-catchment regression models (Figure 4; Table 4). In fact, the median coefficients for both land cover variables are indistinguishable from zero relative to the width of the middle 90% of the distribution. In other words, in an average sense neither has an effect on streamflow. These results are contrary to expectations.

The distribution of coefficients is not dramatically different than the results of similar studies, however. For instance, Salavati et al. (2016) which, when using a paired catchment and a simulation driven residual analysis approach for 24 paired US catchments all with more than 9% urbanization, found a range of different associated changes in streamflow. The estimated changes in their study often widely overlapped 0 and the medians were small (median change adjusted for a 1%-point change in urban area for paired catchment models:  $Q_{95} = 0.5\%$ ,  $Q_{\text{mean}} = 0.36\%$ ,  $Q_{05} = 0.36\%$ ; median change adjusted for a 1%-point change in urban area for regression-based models:  $Q_{0.95} = -0.03\%$ ,  $Q_{\text{mean}} = -0.06\%$ ,  $Q_{0.05} = -0.06\%$ ). Oudin et al. (2018) used the same residual analysis approach to examine the effects of urbanization on flow change in 142 catchments in the United States. They find that the median of these single catchment models for mean and high flows were negative and the middle 90% of the distribution overlapped 0 until a minimum urbanization change threshold of 10% was used. Even then, the distribution was wide, and error bars crossed zero.

We do notice some geographical patterns in the direction of the land cover coefficient resulting from the single site models (Figure 4). Most noticeably, there is a predominantly positive association between tree cover and streamflow in the eastern United States, and a predominantly negative or insignificant association in the western portion of the country. The insignificance of the tree cover coefficients in the southwestern United States is in line with the conclusions of Goeking and Tarboton (2020) who suggest that deforestation may often fail to increase water yield in semi-arid western watersheds. There is no immediately apparent explanation for the largely negative urbanization coefficients which do not appear to follow a clear regional pattern, although, estimated coefficients may be more reliable in catchments with greater land cover change or better-fitting models.

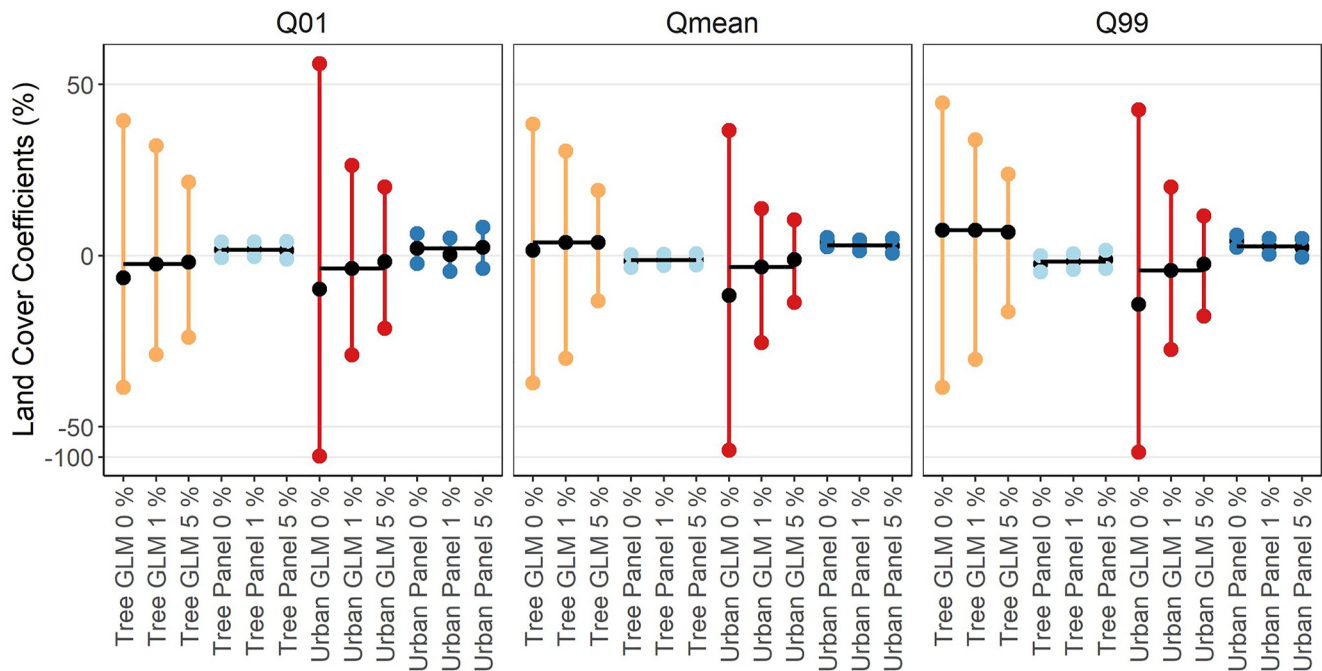
#### 4.1.3. A Multi-Catchment Versus Single-Catchment Approach

In the previous subsections, results for two statistical modeling strategies have been presented. We next consider how the results of single-catchment and multi-catchment (panel) regression methods differ. In principle, the multi-catchment, panel regression approach is substantially more robust than the single-catchment models.

We conducted a sensitivity analysis to examine the robustness of each modeling approach to changes in the data sample, refitting the panel models or adjusting the GLM sample three times each. In the first instance, we fit each model to all sites with any percentage change in the land cover variable; then only to sites with more than 1%-point change; then, finally, to sites with more than a 5%-point change in land cover.

We first consider the land cover coefficients resulting from both the GLMs and the panel regression models fit for each of the data samples selected according to the sensitivity analysis (Table 3). The variation in resulting GLM coefficients is dramatically reduced as the threshold for land cover change is increased (Figure 5). Similarly, the standard errors of the coefficients decrease as the absolute values of catchment averaged land cover change increase (Figure 6). This improvement in the reliability of the estimated GLM coefficients is especially apparent for the urbanization coefficients, and suggests that implementing a minimum threshold for land cover change may remove some catchments with spurious results.

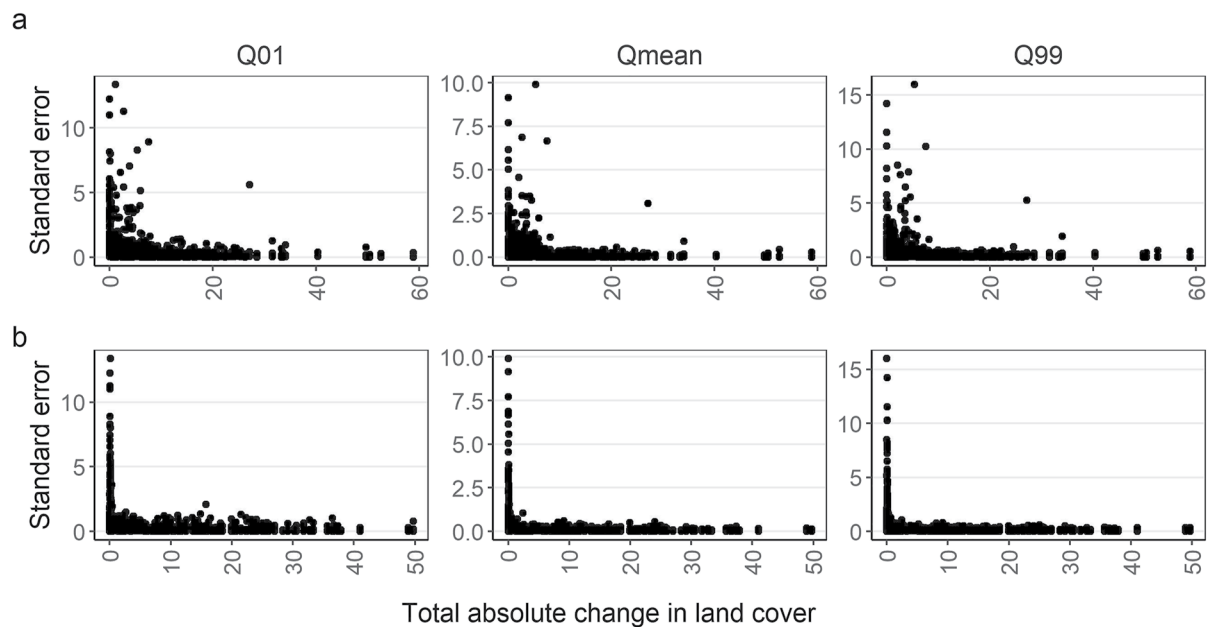
Despite this shift, the middle 90% of the distribution of GLM coefficients always overlap 0, even with increasing land cover change thresholds. This behavior differs from that of temperature, for which the distributions of GLM coefficients continue to vary widely even with reduced sample sizes, and from the precipitation coefficients, for which the distributions are narrow, but consistent over time (Figure 7, Section 4.2). Meanwhile, the effects of land cover change on streamflow may occur inconsistently or be too small to be reliably detected at the catchment scale, unless substantial land cover change has taken place (Figure 6). On the other hand, the estimated effects of urbanization and tree cover change in the panel models are relatively consistent, even in instances where the effects are not statistically significant, speaking to the robustness of the modeling approach—and its potential to isolate relatively marginal effects.



**Figure 5.** Sensitivity analysis and comparison of the land cover variables in the GLMs and panel models. Colored bars represent the middle 90% of the distribution of GLM coefficients, and the 90% confidence intervals of the panel models. The medians of each group are represented by a black horizontal line. The y-axis is presented on a pseudo-log scale which maps numbers to a signed logarithmic scale with a smooth transition to linear scale around 0.

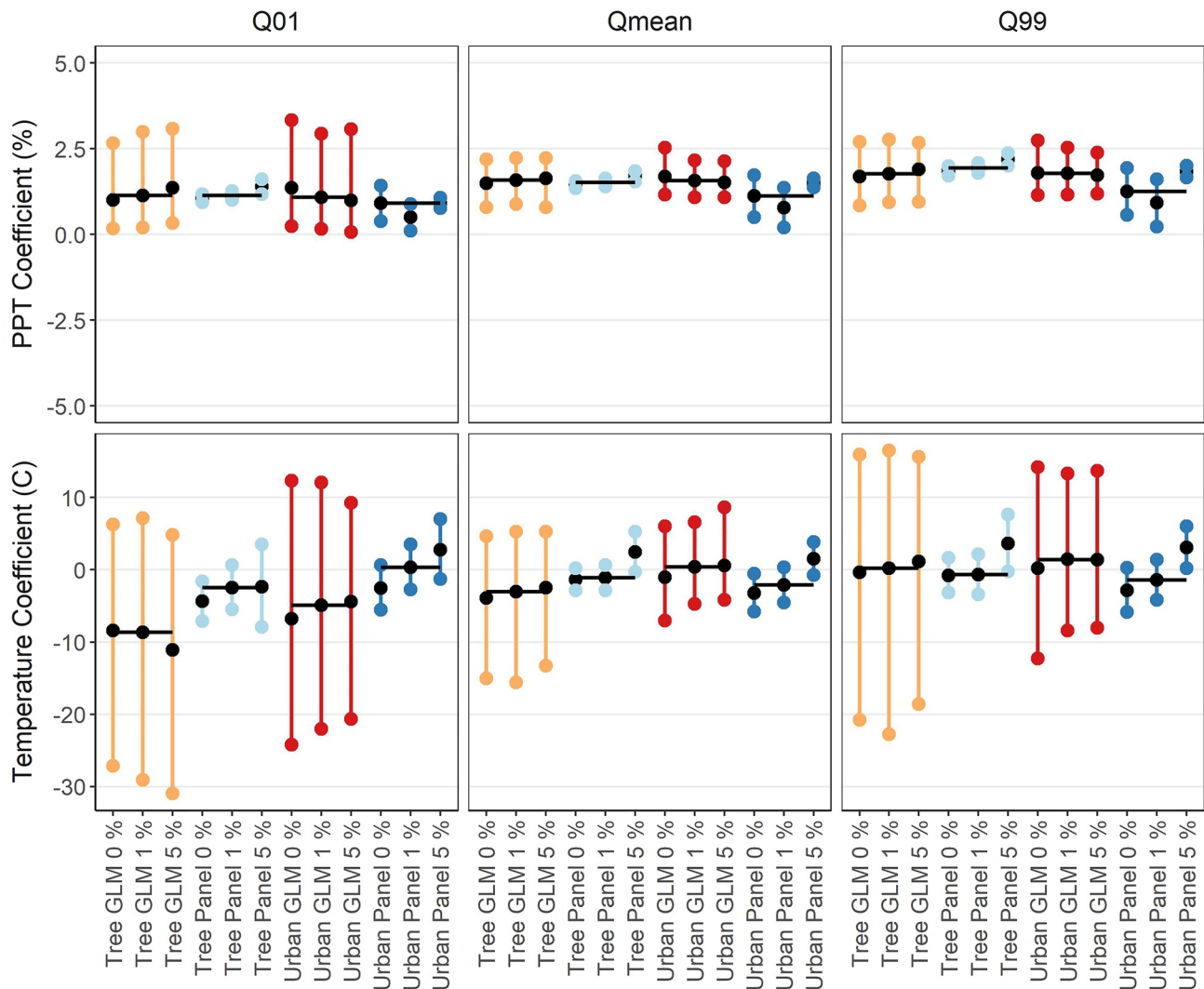
#### 4.2. Climatological Coefficients

While the focus of this study is not to quantify the relative importance of land cover change when compared to climatological variables, or to quantify the climatological elasticity of streamflow, we consider the coefficients for mean annual temperature (% change in streamflow per 1°C change in temperature) and total annual precipitation (% change in streamflow per 1% change in precipitation) and compare them between models as one mechanism by which we validate model performance.



**Figure 6.** Scatterplot of the standard errors of the land cover coefficients (y) versus the absolute change in (a) tree cover and (b) urban area between 1992 and 2018.





**Figure 7.** Sensitivity analysis and comparison of the climatological variables in the GLMs and panel models. Colored bars represent the middle 90% of the distribution of GLM coefficients, and the 90% confidence intervals of the panel models. The medians of each group are represented by a black horizontal line. Coefficients for temperature represent the expected % change in streamflow for each 1°C change in mean annual temperature, and coefficients for precipitation represent the expected % change in streamflow for a 1% change in annual total precipitation.

When comparing the coefficients from the GLM and panel models across all thresholds, the relationship between precipitation and high, mean, and low flows is clear. The median precipitation coefficients from the GLMs closely align with the coefficients from the panel models (Figure 7; Table 5), for the most part. The coefficients are positive, strongly significant (panel models), and the 90% confidence intervals of the panel models consistently overlap with the middle 90% of the distribution of GLM coefficients (Figure 7). The precipitation coefficients in the panel models are smallest for low flows (Table 5). Similarly, the range of resulting GLM coefficients is widest for low flows and narrowest for mean flows, indicating wider ranging possible relationships between more extreme flows and precipitation change depending on catchment specific characteristics (Figure 7; Table 5).

The precipitation coefficients are larger in the tree cover panel models relative to urbanization models, while the reverse is generally true for the GLMs. However, the confidence intervals overlap, indicating that this difference is not substantial. Finally, as expected, the middle 90% of the distribution of the GLM precipitation coefficients generally exhibits more variability than the corresponding confidence intervals of the panel regression models. However, the 90% confidence interval of precipitation in the mean and high flow urbanization panel models are wider (lower statistical significance), rivaling those of the GLMs.



**Table 5**  
*Model Results for Climatological Coefficients: 0% Land Cover Change Threshold*

$Q$	Model	Variables	Estimate	$p$ -Value	Lower bound	Upper bound
$Q_{01}$	Urban GLM	Total annual PPT (%)	1.365		0.235	3.334
$Q_{\text{mean}}$	Urban GLM	Total annual PPT (%)	1.683		1.161	2.535
$Q_{99}$	Urban GLM	Total annual PPT (%)	1.796		1.151	2.746
$Q_{01}$	Urban panel	Total annual PPT (%)	0.908	0.004**	0.39	1.427
$Q_{\text{mean}}$	Urban panel	Total annual PPT (%)	1.12	0.0027**	0.506	1.733
$Q_{99}$	Urban panel	Total annual PPT (%)	1.256	0.0026**	0.57	1.943
$Q_{01}$	Tree GLM	Total annual PPT (%)	1.001		0.178	2.656
$Q_{\text{mean}}$	Tree GLM	Total annual PPT (%)	1.487		0.793	2.184
$Q_{99}$	Tree GLM	Total annual PPT (%)	1.687		0.844	2.696
$Q_{01}$	Tree panel	Total annual PPT (%)	1.058	<0.0001**	0.94	1.175
$Q_{\text{mean}}$	Tree panel	Total annual PPT (%)	1.452	<0.0001**	1.344	1.56
$Q_{99}$	Tree panel	Total annual PPT (%)	1.853	<0.0001**	1.719	1.986
$Q_{01}$	Urban GLM	Mean annual temperature (°C)	−6.802		−24.212	12.305
$Q_{\text{mean}}$	Urban GLM	Mean annual temperature (°C)	−1.057		−7.006	5.992
$Q_{99}$	Urban GLM	Mean annual temperature (°C)	0.197		−12.267	14.224
$Q_{01}$	Urban panel	Mean annual temperature (°C)	−2.512	0.1876	−5.559	0.634
$Q_{\text{mean}}$	Urban panel	Mean annual temperature (°C)	−3.196	0.0496*	−5.794	−0.526
$Q_{99}$	Urban panel	Mean annual temperature (°C)	−2.857	0.1293	−5.863	0.245
$Q_{01}$	Tree GLM	Mean annual temperature (°C)	−8.419		−27.1	6.276
$Q_{\text{mean}}$	Tree GLM	Mean annual temperature (°C)	−3.929		−15.009	4.644
$Q_{99}$	Tree GLM	Mean annual temperature (°C)	−0.338		−20.779	15.957
$Q_{01}$	Tree panel	Mean annual temperature (°C)	−4.366	0.0108*	−7.082	−1.571
$Q_{\text{mean}}$	Tree panel	Mean annual temperature (°C)	−1.321	0.1585	−2.839	0.222
$Q_{99}$	Tree panel	Mean annual temperature (°C)	−0.793	0.5881	−3.165	1.636

*Note.* The  $p$ -values <0.5 are indicated with \* and <0.01 with \*\*, as are GLM coefficients for which the confidence intervals do not cross zero. Lower and upper bounds indicate the middle 90% of the distribution of GLM coefficients and the 90% confidence intervals of the panel models. Coefficients represent the % change in streamflow expected for a 1% increase in total annual precipitation or a 1°C increase in mean annual temperature. The temperature coefficients have been transformed using  $100(e^{\beta} - 1)$  where  $\beta$  is the land cover coefficient of interest.

Across all land cover change thresholds tested, the precipitation coefficients from the two models remain fairly consistent, always with overlapping distributions, speaking to a generally robust relationship between precipitation change and flow change (Figure 7; Table 5). The most notable change is a narrowing of the panel model confidence intervals and an increase in the estimated effects for all flow quantiles when the threshold for urbanization was increased from 1% to 5%. It is possible that this hints at a nonlinear relationship between precipitation and streamflow, that is, more urbanized catchments experience higher precipitation elasticity of streamflow than less urbanized ones. However, because we do not explicitly test interaction terms between precipitation and urbanization, we cannot say for certain. It is also possible that the change in the estimation is due to the shift in sample size. Furthermore, exploration of the potentially varying effects of precipitation on streamflow under different land cover scenarios is needed in the future, particularly as the spatial distribution of catchments across the study area remains relatively consistent even with the increased thresholds (Figure 3).

The temperature coefficients vary more widely for different land cover sensitivity thresholds (Figure 7; Table 5). While the coefficients resulting from the panel models with 0% change threshold are statistically significant for mean flows in the urbanization model ( $p < 0.10$ ) and for low flows in the tree cover model ( $p < 0.05$ ), the statistical significance of these coefficients is inconsistent as the land cover coefficient threshold increases. Further,

the estimated coefficients from the panel models shift from negative to positive. While the median temperature coefficients of the GLMs are similar to the panel models in that they are all negative, the middle 90% of the distribution is wider and overlapping zero. GLM temperature coefficients follow a similar pattern as the precipitation coefficients in that the range is narrower for mean flows, and more variable for the extremes.

In many ways the variation in temperature coefficients and statistical significance, as compared to the precipitation coefficients, is important for contextualizing the land cover coefficients. We would expect the influence of temperature on streamflow to be more varied than precipitation and therefore less likely to be significant across all catchments because it is reasonable to expect temperature to have differing effects on streamflow depending on the other characteristics of the watersheds in question. These differences can be seen, to some extent, in the regional variation in GLM temperature coefficients (Figure 4).

For the most part, the climatological coefficients are not particularly surprising. We expect the changes in precipitation to be the most important driver of changes in streamflow magnitude in our models (e.g., Slater & Villarini, 2017; Slater, Villarini, et al., 2021). Contrary to our results, there is some evidence in the literature that lower flows may be more sensitive to changes in annual precipitation than are mean and high flows respectively (Allaire et al., 2015; Lins & Cohn, 2002), however, studies which explore this relationship at the annual timescale are limited. We might also expect changes in temperature, which affects streamflow by modifying evaporation, and may be serving as a proxy for snowfall, to be important for low flows which already occur in drier periods, but not for higher flows, when precipitation could be expected to be the primary influencer. Milly et al. (2018a), published a global dataset of regression based and theoretical precipitation and temperature sensitivities of the annual water balance between 1901 and 2013, the central summaries of which closely resemble our single catchment and the urbanization panel model coefficients for temperature (median regression and theoretical coefficients:  $\sim -0.02$ ) and the coefficients of all models for precipitation (median regression and theoretical coefficients:  $\sim 1.6$ ; Milly et al., 2018b). The authors acknowledge that the models are subject to errors and that ignored processes may carry regional importance.

#### 4.3. Model Context and Assumptions

We build on the question of comparability between methodological approaches posed in Salavati et al. (2016) by comparing single-catchment attribution approaches with the multi-catchment panel methods. These two general modeling approaches were selected due to their relative prevalence in the literature.

The GLMs used in our analysis are applied to time series data from individual sites. GLMs are models in which the response variable is expected to follow an exponential family distribution, in our case, the log normal distribution, and in which there is a linear relationship between the transformed response in terms of the link function and the explanatory variables. The single site models are susceptible to issues caused by time series length, influential cases—points in the time series which would significantly alter the regression coefficients if removed, and an inability to control for omitted variable bias. The specific formulation of our GLMs was selected so that the models would be approximately comparable to the panel regressions.

In a broad sense, panel regression models combine the data from the time series observations of multiple individuals, resulting in an increase in the degrees of freedom and model variability, and therefore improve the inference accuracy of model parameters (Hsiao, 1995). A key problem in single site regression on observed data is that of omitted variable bias which gives rise to endogeneity, meaning that a regressor is correlated with the error term. While endogeneity can arise from a number of sources, most important are omitted variable bias, error in the explanatory variable, and simultaneity, instances in which there is an explanatory variable, that is, jointly determined with the response variable (Croissant & Millo, 2018). Fixed effects panel regression models address the majority of omitted variable bias, enabling a causal interpretation, by requiring that confounding variables either be directly measured or be invariant along at least one dimension of the data, for instance, time (Nichols, 2007). This bias remains unaddressed in single site regression models. Additional sources of endogeneity, in particular, time-variant error in the explanatory variables, and omitted variable bias due to time-varying sub-regional variables may not be fully controlled for by the panel regression method either.

While we know that each catchment has unique and unmeasured characteristics which may affect streamflow, a panel regression approach allows us to explicitly define time variant attributes which affect multiple catchments, while minimizing the signal of catchment attributes which are constant in time, to isolate an average effect of

a specific driver of change, in this instance, land cover change (Croissant & Millo, 2018). In essence, the panel regression approach does not consider every point in every time series as uniquely and specifically important, instead relying on inter-individual differences. It is therefore better equipped to formulate a robust average estimation by controlling for cross-sectional heterogeneity. This robustness is exhibited by the relative consistency in the estimated effects of land cover changes across the sensitivity test thresholds, even when considering only sites where minimal land cover change occurred. That being said, pooling sites in this way may not be the best approach if we anticipate that land cover changes will affect streamflow in opposite ways (increasing or decreasing flow) depending on the specific attributes of the sites examined.

In contrast, the single-catchment regression models are more susceptible to bias arising from the limited length of the time series, quality of the data used in fitting, and our inability to control for all confounding variables at individual sites. As such, in an average sense, the results can be misleading, especially if expected effects are marginal. On the other hand, the methods perform similarly when the effects are consistent, as is true for precipitation (Figure 7), and panel regression models require data from a large number of sites in order to perform well.

With longer time series, we might discover more land cover change and more certain associated streamflow responses, which may improve the performance of the single site models, however, it is also possible that because the effects are so small, the differences in catchment moderators may continue to render the land cover effects indistinguishable. For instance, if one is interested in a particular catchment for which a long, reliable, time series is available, the national or even regional average deliverable by a multi-catchment regression may not provide the most accurate description of the land cover-streamflow relationship. However, due to the dearth of long, consistent, time series, particularly for land cover, averaging across space and time in a multi-catchment regression may provide the best available estimates of the effects of land cover on streamflow.

## 5. Limitations

It is possible that there are other, unidentified, time-varying factors which have been omitted from our models, and which may bias the coefficients of the single site models. For instance, it is imaginable that water management practices, especially the presence of wastewater treatment facilities as they relate to urbanization (Oudin et al., 2018), flood alleviation schemes, or other land cover changes may affect the influence of land cover change on streamflow to a high degree, particularly for low flows. Both the type and age of trees (Brown et al., 2005), and the land cover types which tree cover or urban area replace are likely to alter how these land cover types influence streamflow. The location of the land cover change within a catchment is also likely to influence how streamflow responds to land cover change, and fragmentation of urban area can have a key influence on flow response, particularly for low flows (Oudin et al., 2018). We also do not consider the potential effects of allowing nested catchments to exist within the dataset, a factor which might positively bias the panel model significance if the same relationship exists as catchment size increases.

While the regional dummy variable in the urbanization panel regression models controls for national and regional scale changes, it is possible that sub-regional trends that vary over time may be overlooked by this approach. Some examples of possibly influential omitted variables include antecedent moisture, and water management practices which may be specific to a city or subregion. Similarly, it is possible that average annual precipitation may not be the ideal metric for predicting low or high streamflow, so the inclusion of different precipitation quantiles could potentially affect the research outcomes. Removal of sites which are ephemeral at the annual timescale may have unintentionally excluded sites with strong signals from the analysis, particularly as there is some evidence that large-scale land cover changes can lead to 0 flows in formerly perennial rivers (e.g., Brown et al., 2013). A land cover dataset with a higher spatial resolution, or improved accuracy and longer time period might also result in different land cover classifications and results. Similarly, error in the land cover time series may vary year-to-year, which could potentially cause coefficient attenuation. While these data improvements could hypothetically increase confidence in the results, it is unlikely that the influence of small changes in land cover will be easily detected in the single site models.

Future work should include more detailed consideration of confounding variables, as well as the numerous potential moderators which determine the effect of land cover changes on flow at different sites. Improved observational data, and consideration of other land cover types or classifications would likely also prove useful.

## 6. Conclusions

In order to effectively manage water resources and their associated risks it is important to understand where and to what extent streamflow distributions are being modified by anthropogenic drivers, such as land cover change. Regression modeling approaches are popular for the purpose of attempting to attribute such changes to different drivers. Here, we use two statistical approaches to explore land cover changes in a large-sample dataset and compare the outcomes of the models. Using both single-catchment and multi-catchment (panel) regression methods, we address the following questions: (a) How do urbanization and tree cover change associate with or affect streamflow across the conterminous United States; (b) How do the results of single-catchment and multi-catchment regression methods differ?

The panel regression models generally conform with our expectations regarding the direction of expected changes in streamflow in response to land cover change. According to our panel models, a 1 percentage point increase in catchment urban area leads to an average increase of  $\sim 0.6\%$  to  $0.7\%$  in both mean and high flows ( $p < 0.0001$ ). Meanwhile, the effects of tree cover changes are generally not significant. The panel models indicate that there is not a statistically significant causal relationship between either land cover class or low flows. Interestingly, the panel models also indicate that streamflow response to changes in annual precipitation is less certain (wider confidence intervals) and relatively smaller in catchments where urbanization is also considered. We also demonstrate that at the annual timescale, low flows appear to be less sensitive to changes in precipitation than mean and high flows, respectively.

The single-catchment GLM approach reveals an impressively wide range of coefficients, the median of which is largely close to zero in any case. However, due to the limitations of the data, and of the single catchment models for explaining bias, much of the variability is also related to confounding variables and omitted variable bias which are overlooked by the single-catchment models. The panel regression approach provides an immense increase in statistical robustness, and is capable of detecting the essentially marginal effects on flow consistently.

The panel regression approach may be inappropriate in instances where an average effect is not a helpful metric and at-site estimates are needed, or where we are unable to control for the influence of catchment specific attributes in a meaningful way. This is further characterized by the climatological coefficients, which are consistent and significant for precipitation in both approaches, but which vary more widely, and are frequently statistically insignificant for temperature. The systematic failure of the GLMs to detect a meaningful “average” association between either tree cover change or urbanization, and streamflow, despite increasing the minimum land cover change threshold required for analysis, suggests that the relationship is, in an average sense, so small at the individual site level, that the effects of these land cover changes on flow are canceled out by other intra-catchment processes. When using a longitudinal approach, as we do with the panel regression models, we are better able to tease out the small changes which are consistent over many individual catchments, over time.

This analysis therefore serves as a word of caution against the over-interpretation of single-catchment approaches as an optimal strategy for hydrologic attribution, at least with short time series. Conversely, while panel regression approaches provide a more robust estimation of average land cover effects on streamflow, the complicated nature of these relationships means that an average estimated effect may be not be a useful metric to capture the complexity of different climates and physical environments.

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Data Availability Statement

All data used in this study are openly available. The land cover data are available through ESA-CCI at <http://maps.elie.ucl.ac.be/CCI/viewer/download.php> (ESA CCI, 2017); climatological data are available through PRISM at <https://prism.oregonstate.edu/recent/> (PRISM Climate Group, 2019) where both mean annual precipitation and temperature can be downloaded; Stream flow data is available from the USGS at <http://waterdata.usgs.gov/nwis/> (United States Geological Survey, 2020), and is easily bulk downloaded using the R package dataRetrieval. More information on the package is available at: <https://code.usgs.gov/water/dataRetrieval/>; catchment boundaries are

available from the USGS and USDA at <https://prd-tnm.s3.amazonaws.com/index.html?prefix=StagedProducts/Hydrography/WBD/National/GDB/> (United States Geological Survey and United States Department of Agriculture, 2020); GAGES II data are available from USGS at <https://doi.org/10.3133/70046617> (Falcone, 2011) by selecting “metadata” and then “Distribution\_Information”; information regarding dam storage is available at <https://doi.org/10.5066/F7HQ3XS4> (Falcone, 2017); finally, physiographic regions used in the panel regression models are available at <https://water.usgs.gov/lookup/getspatial?physio> (Fenneman & Johnson, 1946), under the “Distribution\_Information” header.

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