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RESEARCH ARTICLE
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Key Points:

- A non-stationary regional regression is used to estimate variability in annual elasticity estimates for the USA
- Annual streamflow elasticity to precipitation is more sensitive to interannual climate variability in dry regions
- Statistically significant temporal trends in elasticity exist in some regions but are generally small

Supporting Information:

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

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Stationarity Assumptions in Streamflow Sensitivity to Precipitation May Bias Future Projections

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Abstract Streamflow elasticity to precipitation is a metric which is used to estimate how responsive rivers are to changes in precipitation. It is commonly used to anticipate future impacts of climate change on streamflow and is assumed to be constant in time, despite evidence that this relationship varies with climatological and landscape changes. To assess the need for a more flexible definition, we present a large-sample non-stationary regional regression approach to estimate long-term trends and variability in interannual streamflow elasticity to precipitation in the USA. We find that elasticity is highly variable in water-limited catchments year-to-year, indicating high sensitivity to climate variability in arid regions. Statistically significant long-term trends in elasticity exist in some regions, but trend magnitude is generally small. We demonstrate that a single average estimate of elasticity may be a poor indicator of streamflow sensitivity to climate change. Consideration of the variability of response is essential for elasticity to be a useful hydrologic signature.

Plain Language Summary Streamflow elasticity to precipitation is a simple metric used to estimate how much river flow changes in response to shifts in precipitation, on average, over long timescales. This understanding is important for predicting how climate change might affect water availability. Often researchers implicitly assume that this relationship stays the same over time, but in reality, it can change due to shifts in climate and landscape conditions. In our study, we analyzed data from many rivers and used a regional regression model to estimate long-term trends and year-to-year changes in streamflow response to precipitation. We found that in dry areas, river flow can be very sensitive to climate variations, meaning that changes in rainfall have a relatively large impact on water in rivers. Some regions exhibit long-term trends in the response of streamflow to rainfall, but these trends are generally small. Our findings suggest that using a single estimate for elasticity oversimplifies the problem. To better understand how rivers will respond to climate change, it is important to account for variations in how streamflow reacts to precipitation over time.

1. Introduction

Some of the most fundamental questions in the environmental sciences deal with how changes in one environmental variable influence another. This is especially true as we deal with anthropogenic climate and environmental changes. In hydrology, we are particularly concerned with how the environment influences the water cycle, and especially how climate change may be expressed through, and increase the threat of, hydrologic hazards (Douville et al., 2021). Understanding the sensitivity of the hydrologic cycle to changes in climatic factors is essential for continued water security.

Evidence suggests that climatological shifts might result in more extreme floods and droughts as well as elevated risks associated with water availability (Abbott et al., 2019). However, there is rarely a one-to-one relationship between climatological changes and changes in the volume of water in rivers (Ivancic & Shaw, 2015; Sharma et al., 2018). Instead, the rainfall-runoff relationship is controlled by the combined effects of the climatological and landscape properties of a river catchment, which modulate the partitioning of precipitation between storage, runoff, and evaporative processes. Water storage capacity, both short- and long-term, plays a key role in modulating how streamflow responds to precipitation—acting as a buffer, thereby dampening and delaying runoff (Anderson et al., 2024; Staudinger et al., 2017). Changes in water storage availability, as a result of landscape or

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climatological shifts, may result in substantial variation in the rainfall-runoff relationship in the future (Anderson et al., 2022; Bassiouni et al., 2016; Blum et al., 2020; Davenport et al., 2020; Neri et al., 2019; Slater & Villarini, 2017; Vicente-Serrano et al., 2019). Regardless of the direction of change, if not considered, this issue could dramatically bias projections of future changes in water resources, with potentially serious implications for infrastructure, health, and quality of life.

Much like climate, river basins are complex natural systems, meaning that, with few exceptions, it is difficult to study changes in a controlled or experimental way. Instead, hydrologists often rely on modeling, statistical analysis, and proxies such as hydrologic signatures, to decipher physical processes and study the response of river basins to changes in climate, land cover, and water demand. Hydrologic signatures are widely used numerical metrics that describe the properties or characteristics of streamflow (McMillan, 2021). These metrics function as a set of tools which aid in understanding the underlying physical processes which control streamflow. They are frequently used to reveal weaknesses in hydrological models, for model calibration, and as tool to learn about hydrologic systems in empirical analyses (Addor et al., 2018; McMillan, 2021).

"Streamflow elasticity" is one such signature which describes how responsive streamflow is to precipitation or other environmental variables such as land cover change (Schaake, 1990) at the seasonal, annual, or multi-annual (Zhang et al., 2023) timescale. It is frequently used to estimate future climate change impacts on streamflow (Addor et al., 2018; Awasthi et al., 2024). Streamflow elasticity, henceforth referred to as "elasticity," is most often estimated as a single number calculated for a given period of record (e.g., decades) representing the average relationship between precipitation and streamflow over time.

While the *average* sensitivity of streamflow to changes in mean precipitation in a catchment or region is potentially useful information, the metric is limited in several ways. For instance, streamflow elasticity to precipitation is poorly predicted by climate indices (such as snow fraction, aridity, and precipitation seasonality) as well as the physical and landscape characteristics of a catchment (Addor et al., 2018). Physical reasons for spatial variability in elasticity can be difficult to pinpoint (Andréassian et al., 2016), suggesting that the metric is not well understood, and therefore may not be very informative. Further, some have recognized the limitations of elasticity regarding its ability to capture potential non-linearities in the precipitation-streamflow relationship (Fu et al., 2007; Tang et al., 2019).

Finally, typical elasticity estimates fail to acknowledge or address the potential for substantial variation in these estimates from year to year, or in response to persistent physical or climatological changes within a catchment over time (Bassiouni et al., 2016; Harman et al., 2011). This is problematic, given that a large body of research demonstrates that streamflow is influenced by, for example, changes in land cover (Anderson et al., 2022; Blum et al., 2020; Han et al., 2022; Slater & Villarini, 2017), antecedent moisture conditions (Bennett et al., 2018; Han et al., 2022; Wasko et al., 2020), and groundwater influxes (Berghuijs & Slater, 2023; Tague & Grant, 2009), among others. Thus, a stationary estimate of elasticity seems physically implausible.

Recent work has aimed to address the problem by incorporating a storage component, represented by a proxy such as baseflow or the residuals of the water balance closure, into elasticity estimation approaches (Cooper et al., 2018; Konapala & Mishra, 2016; Tang et al., 2020; Zhang et al., 2023). The inclusion of these parameters has led authors to claim that "elasticity changes little over time since it already represents the adaptation of catchment response to changes in its drivers" (Zhang et al., 2023). This approach relies on the assumption that the baseflow index fully captures the effect of water storage within the same year, as well as the effect of water storage brought forward from previous years. Baseflow is associated with storage contributions to streamflow, for groundwater and other stores, but it is unlikely to fully capture these storage components (Kalbus et al., 2006) or the variability which catchments experience on an interannual basis. Thus, it is possible that the inclusion of this component does not fully account for variation in streamflow response over time.

Broadly speaking, a large body of literature exists that investigates the ways in which the relationship between precipitation and streamflow response varies over time. For instance, as far back as Horton (1933), discussed the properties of soil, water content and how these relate to event runoff. Recently, research has investigated how streamflow response to precipitation might change, for example following prolonged drought (Fowler et al., 2022; Saft et al., 2016), and how changes in precipitation phase, for instance, can have an effect on response intensity and timing (Berghuijs et al., 2014). Given the long history of research into how what drives this relationship, it is surprising that streamflow elasticity is generally accepted as a stationary metric. To our knowledge,

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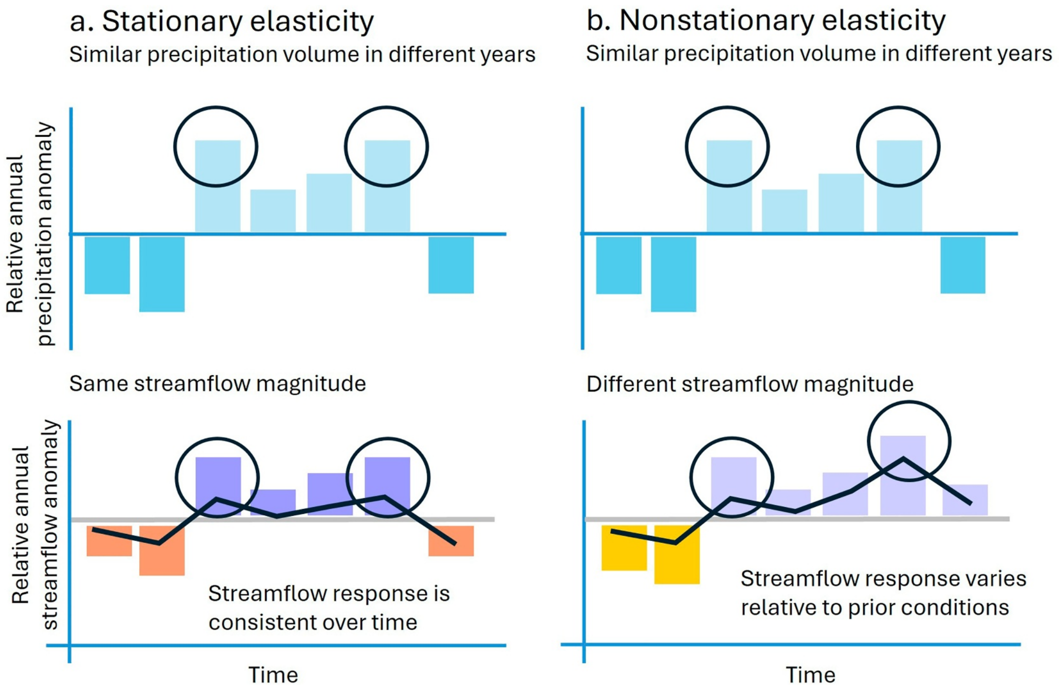

Figure 1. Conceptual diagram. Shows "elasticity" as (a) a single average value representing streamflow response across time (black horizontal line), and (b) the hypothesized temporally variant values (black time-varying line). In (a), elasticity is constant, and streamflow response to the same amount of precipitation input is consistent. In (b) streamflow elasticity varies relative to, as an example, antecedent wetness in previous years, resulting in a different streamflow response to the same precipitation volume falling in different years.

only one publication has explicitly quantified variability in streamflow elasticity to precipitation over time. Tang et al. (2020) investigated the elasticity of streamflow to interannual climate variability directly using an analytical approach based on the Budyko hypothesis (Tang et al., 2020). The authors assessed how sensitive streamflow elasticity to precipitation and potential evaporation is on average from year to year in the United States. They accounted for the storage component of the water balance more explicitly, by estimating the difference in the residuals of the annual water balance closure. With respect to streamflow elasticity to precipitation, they argued that the coefficients of variation are "small" and thus that variability is not of great importance. However, the coefficients range as high as 0.6, which not particularly small. Further, the relatively large variability which they do find is generally in arid regions. These catchments were few and the attribution to irrigation posited by the authors is not empirically supported.

Therefore, there remains much more to be learned about the variable nature of hydrologic sensitivity to streamflow. In particular, to address this research gap, we assess how climate variability influences elasticity over time and in regions with different climatological norms. Figure 1 shows a conceptual representation of elasticity estimated using a typical approach in which it is represented as a single value over time (a), and a hypothetical representation of elasticity varying over time (b).

In this manuscript, we aim to quantify climate-driven variability in interannual streamflow elasticity and question the extent to which streamflow elasticity, as a hydrologic signature, may be biased by assumptions of temporal stationarity. More specifically, we address the following questions: "Is streamflow sensitivity to precipitation robust to interannual climate variability and well represented by a mean long-term estimate of elasticity?," "Do the regional interannual elasticity estimates exhibit long-term trends in elasticity which can be attributed to climate or anthropogenic drivers?." Capturing these aspects of nonstationarity in streamflow sensitivity carries implications for the use of elasticity as a hydrologic signature and for future streamflow projection. Additionally, it may provide evidence of the need to investigate variability in the response of similar metrics within the earth and environmental sciences. Our primary focus in this manuscript is on the median annual streamflow, and some additional results for low and high flows are included in the Supporting Information S1.

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2. Materials and Methods

2.1. Methodological Justification

The approach used in this paper relies on a regional panel regression model to develop interannual elasticity estimates. To isolate climate effects and be able to capture interannual variability in the sensitivity of streamflow using observed data, the elasticities are calculated for climatologically similar regions. The use of the regions is essential for calculating interannual elasticities when using an observed, empirical approach, because it increases the degrees of freedom, allowing sufficient annual-scale data for estimations to be made with a reasonable degree of confidence. The regional approach also offers several advantages in that it allows us to capture the influence of climate, a characteristic which largely exhibits regional-scale behavior, on streamflow sensitivity to temporal changes in precipitation, while data pooling allows for more robust estimates of elasticity in each year. Within the regions, catchment-scale hydrological behavior may also be influenced by the physiographic characteristics of a catchment. We rely on the model design to isolate interannual and long-term variability which is the result of processes that occur at the regional scale, namely, climate, and to control for catchment characteristics (Anderson et al., 2022; Blum et al., 2020).

The panel regression approach which we use has been shown to adequately control for time invariant differences at the catchment scale and to facilitate the isolation of regional-scale effects (Anderson et al., 2022; Bassiouni et al., 2016; Blum et al., 2020; Steinschneider et al., 2013). Similar regional regression approaches have been popular in work related to predictions in ungauged basins (Cutore et al., 2007; Hailegeorgis & Alfredsen, 2017; Vogel et al., 1999). The primary disadvantage of the methodology is that the data aggregation used to strengthen statistical robustness also results in a reduction in the specificity of results; we estimate temporally variable, but *spatially averaged* elasticity values for each hydro-climatic region. This means that the results are best interpreted relative to one another (i.e., as a representation of change over time) rather than as individual elasticity estimates. While it is well known that elasticity varies substantially across space (Addor et al., 2018; Anderson et al., 2024; Sankarasubramanian et al., 2001), climatology has a more persistent spatial pattern. Thus, it is assumed that interannual variability in elasticity resulting from the regionalized model can be attributed to climate. In other words, the results can be interpreted as regional averages, and variability in elasticity as an approximation of the relative sensitivity experienced in each region, rather than precise estimates of elasticity at individual locations. Further, spatial variation in elasticity is frequently attributed to long-term climate, or at least described in terms of climate zones, and there is a strong connection between elasticity and the runoff ratio, lending further credibility to the approach (Ho et al., 2022).

2.2. Observed Hydrologic and Climate Data

The daily streamflow time series were obtained for the period 1981–2020 from the USGS website (https://waterdata.usgs.gov/nwis) using the R package dataRetrieval (DeCicco et al., 2024) and were selected from the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES II) catchments (Falcone, 2011). These catchments were filtered so that streamflow records used in the analysis had at least 30 years of 95% complete consecutive daily streamflow data between 1 January 1981 and 31 December 2021. Daily streamflow records were converted to water years, defined here as October through September, so that snowfall seasons occurred within the same water year. Since timeseries based on water years require data from the previous calendar year, water years 1981 and 2021 were excluded from the final analysis because they are incomplete. The 10th, 50th, and 90th percentiles of daily streamflow were calculated for each water year.

Ephemeral streams, defined as records including zero flow days were removed from the data set because we rely on a log-log linear regression approach for this analysis. This resulted in a total sample size of 2967 catchments. Separately, a subsample of 830 catchments meeting the same criteria but with minimal regulation (Anderson et al., 2022; Blum et al., 2020) was selected. We perform the same analysis with this subsample to confirm that dam storage had little influence on the overall detected relationships. Data used to estimate upstream dam storage was taken from GAGES II data set, as were watershed boundaries (Falcone, 2017). Upstream dam storage was calculated by dividing total upstream dam storage by annual average inflow (Falcone, 2011) resulting in a value with units in days. Stream gages with more than one day of upstream dam storage were eliminated (Blum et al., 2020; Hodgkins et al., 2019).

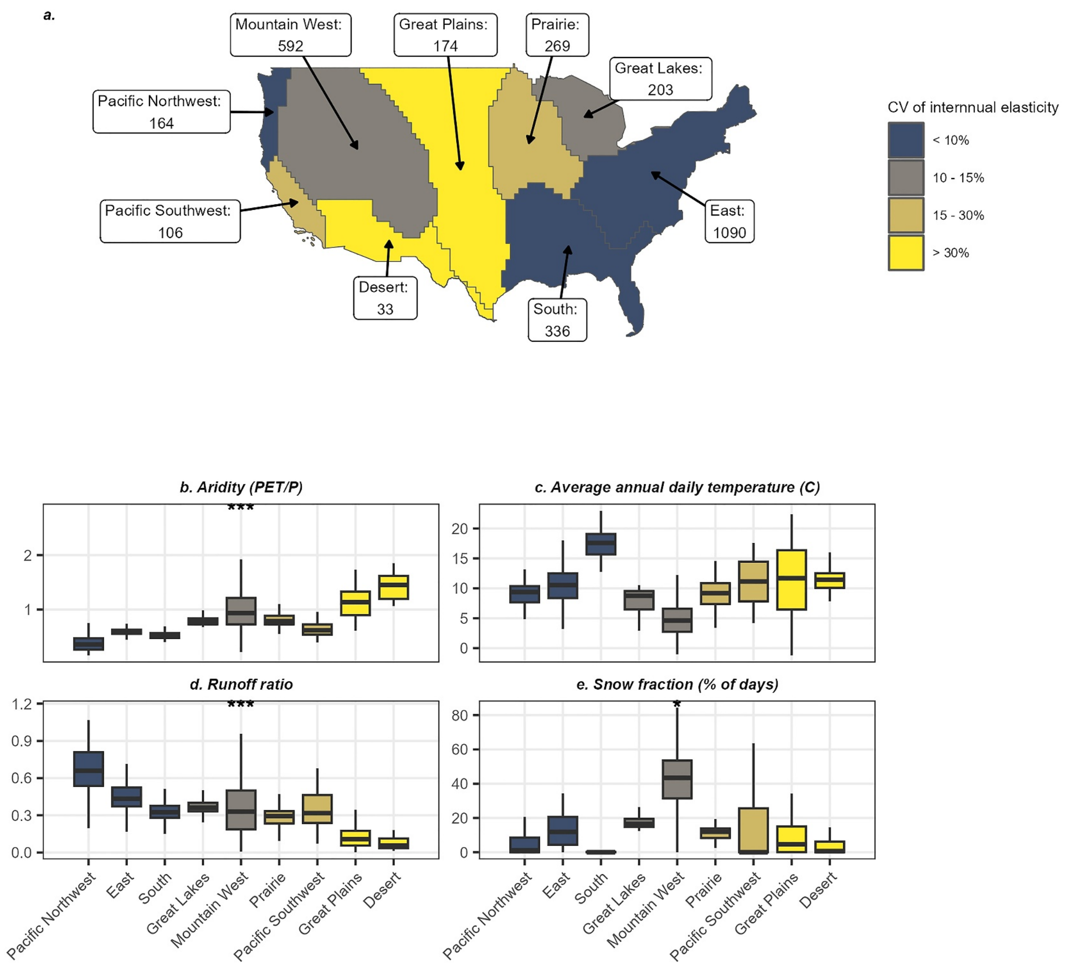

Figure 2. Average interannual variability of elasticity and catchment attributes by region. (a) Map of hydro-climatologic regions used for grouping catchments in the model, colored according to the coefficient of variation (CV) of the interannual elasticity to precipitation. Numbers are the total number of catchments within each region in the study. (b–e) Box plots showing the distribution of the (b) aridity index (dimensionless), (c) average temperature (degrees Celsius), (d) the runoff ratio (dimensionless), and (e) the snow fraction (in percent of day/year) for individual catchments in each region. Center line is the median, boxes show the 25th and 75th percentiles, and whiskers represent the interquartile range multiplied by ± 1.5 from the 25th and 75th percentiles. Regions are ordered on the x-axis from least to most variable based on coefficient of variation and colored as in sub-plot a. Stars indicate a significant difference in the median of each variable of interest between the groups with the least variable (average CV < 10%) and most variable interannual elasticity (average CV > 30%): $p < 0.001$ (***); $p < 0.01$ (**); $p < 0.05$ (*).

Gridded monthly precipitation and temperature (4 km resolution) were extracted from the Oregon State PRISM project data set (https://prism.nacse.org/recent/) using the R package prism (Edmund & Bell, 2015). We estimated average daily precipitation (mm/day) for each year from the monthly raster grid within each catchment boundary. We calculated average daily potential evaporation (mm/day) for each year in R using the Hamon equation (Hamon, 1963; Lu et al., 2007) with monthly temperature as previously described, and solar radiation estimated from latitude and Julian date (Equations S5–S7 in Supporting Information S1). The Hamon equation was used to retain consistency with the GAGES II data set and because this method has been shown to perform well relative to other approaches, despite its simple formulation (Lu et al., 2007). Annual values for climatological variables were calculated for water years, to coincide with streamflow data and snowfall seasons.

The Bukovsky regions (Bukovsky, 2011) were used to define the nine hydro-climatic regions used in this analysis (Figure 2a). These were selected because they offer a `middle ground' between climatological and hydrologically relevant regions (Brunner & Dougherty, 2022). We also tested the regionalization approach (Figure S1 in Supporting Information S1) presented in Knoben et al. (2018) which aims to address the shortcomings of

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climatological regions for hydrological research and compares a classification approach based on hydrologic signatures to the Köppen-Geiger climate zones, in which they find that their index based approach is better. We replicated their methodology and found that the Bukovsky regions perform as well or better than the approach used in Knoben et al., 2018 (Figure S1 in Supporting Information S1 while maintaining a much higher degree of spatial contiguity, and therefore climatological similarity.

2.3. Panel Model Setup

We estimate average interannual elasticity using a fixed effects panel regression model. These models resemble those which have been used for similar problems in hydrology (Anderson et al., 2022, 2024; Bassiouni et al., 2016; Blum et al., 2020). They allow for consideration of double indexed data, while controlling for time-invariant confounding variables at the catchment level, making them more robust than a typical cross sectional or time series regression model. The model is designed so that time-invariant confounding variables which exist at the catchment scale are controlled for by the fixed effects. Thus the captured variability in streamflow elasticity to precipitation is attributable to drivers which exist at the scale of the hydroclimatic regions. We assume that regional-scale changes predominantly relate to climate.

The regional average interannual elasticity estimates were calculated for three percentiles of streamflow: the 10th, 50th, and 90th using the following model:

$$\ln(Q_{\text{it}}) = \alpha_i + \sum_{r,y} \varepsilon_{P(r,y)} \cdot \ln(P_{\text{it}}) \cdot 1_{\text{region}_{i=r}} \cdot 1_{\text{year}_{t=y}} + \sum_{r} \varepsilon_{E(r)} \cdot \ln(E_{\text{it}}) \cdot 1_{\text{region}_{i=r}} + \sum_{r} \varepsilon_{\text{BFI}(r)} \cdot \text{BFI}_{\text{it}} \cdot 1_{\text{region}_{i=r}} + \eta_{\text{it}} \tag{1}$$

where $\ln(Q_{\text{it}})$ represents the natural logarithm of the streamflow percentile (Q10, Q50, or Q90) for catchment i in year t. The percentile streamflow values are calculated annually, with Q10 representing low flows, Q50 median flows, and Q90 high flows. The term α_i is a streamgage-specific intercept that accounts for time-invariant, catchment-specific confounding variables through the inclusion of individual fixed effects. The variable $\ln(P_{\text{it}})$ is the natural logarithm of the annual daily mean precipitation averaged over each catchment i in year t, $\ln(E_{\text{it}})$ is the natural logarithm of the annual daily mean potential evaporation for each catchment and year. BFI_{it} denotes the annual baseflow index, calculated using the UK Institute of Hydrology's "smoothed minima" approach (Gustard et al., 1992) and a standard 5 days block size (Stoelzle et al., 2020) and the R package *lfstat* (Gauster et al., 2022).

Although the streamflow percentile response variable varies across models (Q10, Q50, Q90), the same set of predictors—namely precipitation, potential evaporation, and BFI—is used to estimate each. This allows us to evaluate the sensitivity of low, median, and high flows to changes in total annual precipitation and associated hydrometeorological drivers. The main text focuses on median flows (Q50), with additional results for Q10 and Q90 presented in the Supporting Information S1.

The interaction terms between precipitation, potential evaporation, BFI, and region indicators are used to allow these predictors to have region-specific effects. Specifically, the precipitation elasticity varies by both year and region and is captured by the coefficient $\varepsilon_{P_{r,y}}$. The coefficients for potential evaporation and BFI are assumed constant over time but vary across regions and are denoted $\varepsilon_{E(r)}$ and $\varepsilon_{\text{BFI}(r)}$ respectively. This modeling structure is equivalent to fitting separate regression models by region, however, it does influence the model adjusted R^2 and AIC. Therefore, we additionally calculated the models for the regions individually to estimate the model adjusted R^2 values.

The error term η_{it} represents the residual unexplained variation for catchment i in year t. BFI is included as a covariate due to its use in previous elasticity studies as a proxy for hydrologic storage. While the coefficient on BFI reflects a regionally averaged relationship between baseflow and streamflow, we acknowledge that its effect likely varies at the catchment scale. This is due to spatial heterogeneity in groundwater contributions, geology, and other physical catchment characteristics. Despite this, we include BFI to facilitate comparisons with related published models.

Equation 1 can be rearranged to solve for interannual precipitation elasticity in each region so that:

$$\varepsilon_{P_{\mathrm{it}}} = \frac{\ln(Q_{\mathrm{it}}) - \alpha_i - \varepsilon_{E(r)} \cdot \ln(E_{\mathrm{it}}) - \varepsilon_{\mathrm{BFI}(r)} \cdot \mathrm{BFI}_{\mathrm{it}} - \eta_{\mathrm{it}}}{\ln(P_{\mathrm{it}}) \cdot 1_{\mathrm{region}_{i=r}} \cdot 1_{\mathrm{year}_{t=y}}} \tag{2}$$

The model is estimated in *R* using the *plm* package (Croissant & Millo, 2008) and the "within" estimator is used to define fixed effects. The catchment level fixed effects control for time-invariant confounding variables at the catchment level, for example the physical characteristics of individual catchments, such as soil type and geology. By controlling for time-invariant confounders at the catchment level, we isolate changes in $\varepsilon_{P(\mathrm{it})}$ which occur at the regional scale on a year-to-year basis, effectively limiting these effects to climatic changes. Thus, the interannual coefficients represent the effect of climate on the elasticity of streamflow to precipitation.

Autocorrelation in fixed effects panel models can lead to the underestimation of standard errors. We address this concern by clustering standard errors at the streamgage level (Anderson et al., 2022, 2024; Bertrand et al., 2004; Blum et al., 2020). A generalized R script for the application of these approaches is available in the Supporting Information S1 (Text S1).

2.4. Model Comparison

We fit two additional forms of this model for comparison. The first is a fixed effects panel regression model which excludes the interaction term for "year" as below:

$$\ln(Q_{\mathrm{it}}) = \alpha_i + \sum_r \varepsilon_{P(r)} \cdot \ln(P_{\mathrm{it}}) \cdot\ 1_{\mathrm{region}_{i=r}} + \sum_r \varepsilon_{E(r)} \cdot \ln(E_{\mathrm{it}}) \cdot\ 1_{\mathrm{region}_{i=r}} + \sum_r \varepsilon_{\mathrm{BFI}(r)} \cdot\ \mathrm{BFI}_{\mathrm{it}} \cdot\ 1_{\mathrm{region}_{i=r}} + \eta_{\mathrm{it}} \tag{3}$$

where all terms are the same as in Equation 1. This model estimates the average elasticity across the period of record without considering the effects of temporal change in precipitation on streamflow.

The second model form is a version of Equation 1 which excludes the annual baseflow index (BFI), as in Equation 4 below.

$$\ln(Q_{\mathrm{it}}) = \alpha_i + \sum_{r,y} \varepsilon_{P(r,y)} \cdot \ln(P_{\mathrm{it}}) \cdot\ 1_{\mathrm{region}_{i=r}} \cdot\ 1_{\mathrm{year}_{t=y}} + \sum_r \varepsilon_{E(r)} \cdot \ln(E_{\mathrm{it}}) \cdot\ 1_{\mathrm{region}_{i=r}} + \eta_{\mathrm{it}} \tag{4}$$

where all terms are the same as in Equation 1. This model is estimated to determine if the inclusion of BFI substantially reduces the effect of interannual variability on the model.

The results of these two models are compared with the results of the time variant model in Equation 1 using the Akaike information criterion (AIC; Equation S8 in Supporting Information S1), and indicate that the model which accommodates temporal variation in the precipitation elasticity of streamflow as well as annual BFI as in Equations 1 and 2 outperforms the long-term average model (Equation 3) and the temporally variant model which excludes BFI (Equation 4) for every flow percentile tested (Table S1 in Supporting Information S1).

Trends in the interannual elasticity estimates were calculated using a trend-free pre-whitened version (Bayazit & Önöz, 2007) of the widely applied Mann Kendall trend test (Hamed, 2008; Kendall, 1948; Mann, 1945). This test was applied using R package modifiedmk (Jassby et al., 2022).

The standardized precipitation index (SPI; Equation S1 in Supporting Information S1) and the standardized temperature anomaly (STA; Equation S2 in Supporting Information S1) are used to assess the relationship between streamflow and climate anomalies. These were calculated from annual regional average precipitation and temperature using a 12-month aggregation window, by taking the mean of the catchment averaged values in each region. The runoff ratio was calculated as the average total annual streamflow in mm divided by the average total annual precipitation (mm). Note that our primary focus in this manuscript is on the median annual streamflow (Q50). Additional results for low and high flows are included in the Supporting Information S1.

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Table 1
Mean Absolute and Relative Difference in the Regional Interannual Elasticity Estimates As Well As the Long-Term Trends in Elasticity

	a. Pacific northwest	b. East	c. South	d. Great lakes	e. Mountain west	f. Prairie	g. Pacific southwest	h. Great plains	i. Desert
Long-term estimate	1.42	1.74	2.22	1.41	1.14	2.66	1.34	1.35	0.63
Interannual range	1.29–1.55	1.26–1.92	1.77–2.43	0.95–1.57	0.79–1.24	1.41–2.87	0.23–1.36	0.24–2.03	−0.07–1.44
Mean relative diff.	4%	6%	6%	11%	13%	18%	31%	23%	48%
Mean absolute diff.	0.05	0.11	0.14	0.15	0.15	0.48	0.42	0.31	0.30

Note. Values are estimated using the whole period of record (39-year) and the full interannual range for median streamflow. "Mean absolute difference" is the average difference between streamflow elasticity estimated as a single value and the individual annual elasticity estimates in percentage points—meaning that they correspond to an absolute difference in elasticity. "Mean relative difference" is calculated by dividing the average difference in interannual elasticity from the long-term estimate and then normalizing by the long-term estimate (mean absolute diff. divided by long-term estimate).

3. Results

3.1. Justification of a Temporally Variable Model

We test and compare three different model formulations using the Akaike information Criterion (AIC; Equation S8 in Supporting Information S1). The results of this comparison indicate that the model which incorporates both temporal variability, and annual BFI in the precipitation elasticity of streamflow (Equations 1 and 2) outperforms the long-term average model (Equation 3) and the temporally variant model which excludes BFI (Equation 4) for every flow percentile tested (Table S1 in Supporting Information S1). These results indicate that allowing for temporal variability improves model performance and that the inclusion of a storage component (BFI) alone is insufficient to capture variability in its entirety (e.g., Equation 3).

3.2. Regional Scale Interannual Variability

We use the temporally variable model to estimate regional average long-term and interannual elasticity for nine hydro-climatic regions in the United States. Long-term elasticity estimates here are calculated using an approach akin to those typical to the discipline, as a single value representing the average across the complete timeseries. In this study, these are averages for an entire hydroclimatic region rather than a single catchment.

We find long-term elasticity estimates ranging from approximately 0.63 in the Desert region to 2.66 in the Prairie region (Table 1). These values are interpreted as the corresponding proportional change in the median annual streamflow for a 1% change in total annual precipitation. In other words, an elasticity of 0.63 suggests that median streamflow in the Desert region increases by about 6.3% when precipitation increases by 10%. Meanwhile, an elasticity of 2.66 indicates that precipitation changes are magnified in streamflow, pointing to a streamflow increase of approximately 26.6% if precipitation increases by 10%.

However, the interannual elasticity can deviate greatly from these long-term elasticity estimates (Table 1). For instance, the mean absolute difference between the long-term elasticity estimates and the interannual estimates for median streamflow in the Prairie region is approximately 0.5. This means that on average across the 39-year period, the elasticity in each year deviates from the long-term mean by half a percentage point. Thus, elasticity estimates in each year range between about 1.4 and 2.9. This corresponds to a mean relative difference of 18% between elasticity estimated as a single long-term value and the mean interannual estimate (Table 1). In other words, a 10% change in precipitation could result in anywhere from a 14%–29% change in streamflow, assuming changes magnify linearly. In other words, while the coefficient of variation (Table 2) in the Prairie region is relatively small (0.17), these values represent a substantial difference in the context of streamflow projection. Similarly, in the Desert region, where the long-term elasticity is 0.63, the interannual estimates range from approximately 0 to 1.4, meaning that there could be anywhere from no response to a response in which precipitation is magnified in flow.

The range of interannual elasticity estimates varies substantially between regions, with some regions, like the Desert, Great Plains, and Pacific Southwest, showing large fluctuations in responsiveness, and others, like the Pacific Northwest and the East showing limited variability. These differences are clear and statistically significant between the nine Bukovsky regions (Bukovsky, 2011) (Figure 2).

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Table 2
Results of the Mann Kendall Trend Test on Interannual Elasticity and the Coefficient of Variation of Interannual Elasticity for the 50th Percentile of Flow

		a. Pacific northwest	b. East	c. South	d. Great lakes	e. Mountain west	f. Prairie	g. Pacific southwest	h. Great plains	i. Desert
Mann Kendall trend test	Total change	0.06	−0.04	**−0.28**	−0.07	0.04	0.05	**0.33**	−0.37	**−0.58**
	p value	0.145	0.669	**0.003**	0.513	0.706	0.88	**0.013**	0.066	**0.01**
Coefficient of variation		0.04	0.08	0.08	0.12	0.13	0.17	0.27	0.33	0.58
Model adjusted R^2		0.62	0.58	0.57	0.5	0.32	0.58	0.51	0.31	0.36

Note. Statistically significant trends ($p < 0.05$) are presented in bold font. Total change is the Sen's slope rate of change multiplied by 39 years. This is a unitless value representing the linearly estimated difference in streamflow elasticity to precipitation in water year 1982 versus water year 2020. The coefficient of variation in each region over each time period is presented as a percentage. Model performance is represented by the model adjusted R^2 presented for each region.

The regions with the highest variability tend to be more water-limited (higher aridity index and lower runoff ratio) and receive the majority of precipitation as rain rather than snow, although not exclusively (Figures 2b–2e). The most variable regions also have the lowest runoff ratios, in line with existing literature (Chiew et al., 2006). Meanwhile the regions which experience the least interannual variability in streamflow elasticity to precipitation (e.g., the East and South) are also warm and rain-dominated, but climatic conditions in these regions are far more humid on average (Figure 2). The precise estimates of elasticity in each year are included in Figure 3, demonstrating how the range of hydrological responses can vary widely from year to year.

3.3. Long-Term Trends in Interannual Elasticity

In addition to interannual variability due to climate fluctuations, it is possible that elasticity could exhibit long term changes due to shifts in typical climate patterns. For example, recent evidence has suggested that prolonged drought can have a lasting influence on streamflow sensitivity to precipitation (Fowler et al., 2022; Saft et al., 2016) and changes in precipitation phase, for instance, can have an effect on response intensity and timing (Berghuijs et al., 2014). Therefore, we investigate the influence of climate on average streamflow elasticity to precipitation over time by examining the presence of trends in the interannual estimates.

Results show that strongly statistically significant monotonic trends (Mann-Kendall $p < 0.01$) are present in the Desert, South, and Pacific Southwest regions (Figure 3; Table 2; c, g, i). This indicates that elasticity could be changing, on average, in these regions over time. Here, in addition to interannual variability, the relationship between streamflow and precipitation may be non-stationary even as an average. The Desert and South regions show negative trends, indicating that streamflow has become less responsive to precipitation change over the study period, while elasticity in the Pacific Southwest has increased. For the most part, however, the magnitude of the trends is small (less than 0.6; Table 2). Therefore, while statistically significant, these trends may not represent a substantial change in average streamflow sensitivity to precipitation over the 39-year study period. Regardless, this demonstrates the possibility of long-term trends in elasticity, which may influence the appropriateness of the metric for future streamflow projection.

We reran the analysis with a sub-sample of data (Table S3 in Supporting Information S1) from which sites with substantial dam storage had been removed. Trends in the South and the Desert region (c, i) persisted in this smaller sub-sample. These results suggest that long-term trends in these regions may be due to climate or land cover changes, rather than regulation, with the caveat that this change resulted in substantially reduced sample sizes (Table S3 in Supporting Information S1) and therefore confidence in the estimates. Interannual variability remained relatively consistent in the models resulting from this subsample.

3.4. Comparison of Interannual Variability to Climate

To assess how year-to-year climate variability influences streamflow sensitivity to precipitation, we compare region-scale annual standardized anomalies of precipitation and temperature to interannual elasticity. This simplified approach does not pretend to capture the complete effects of changes in antecedent conditions or memory effects on hydrologic response but is representative of a general climatological pattern.

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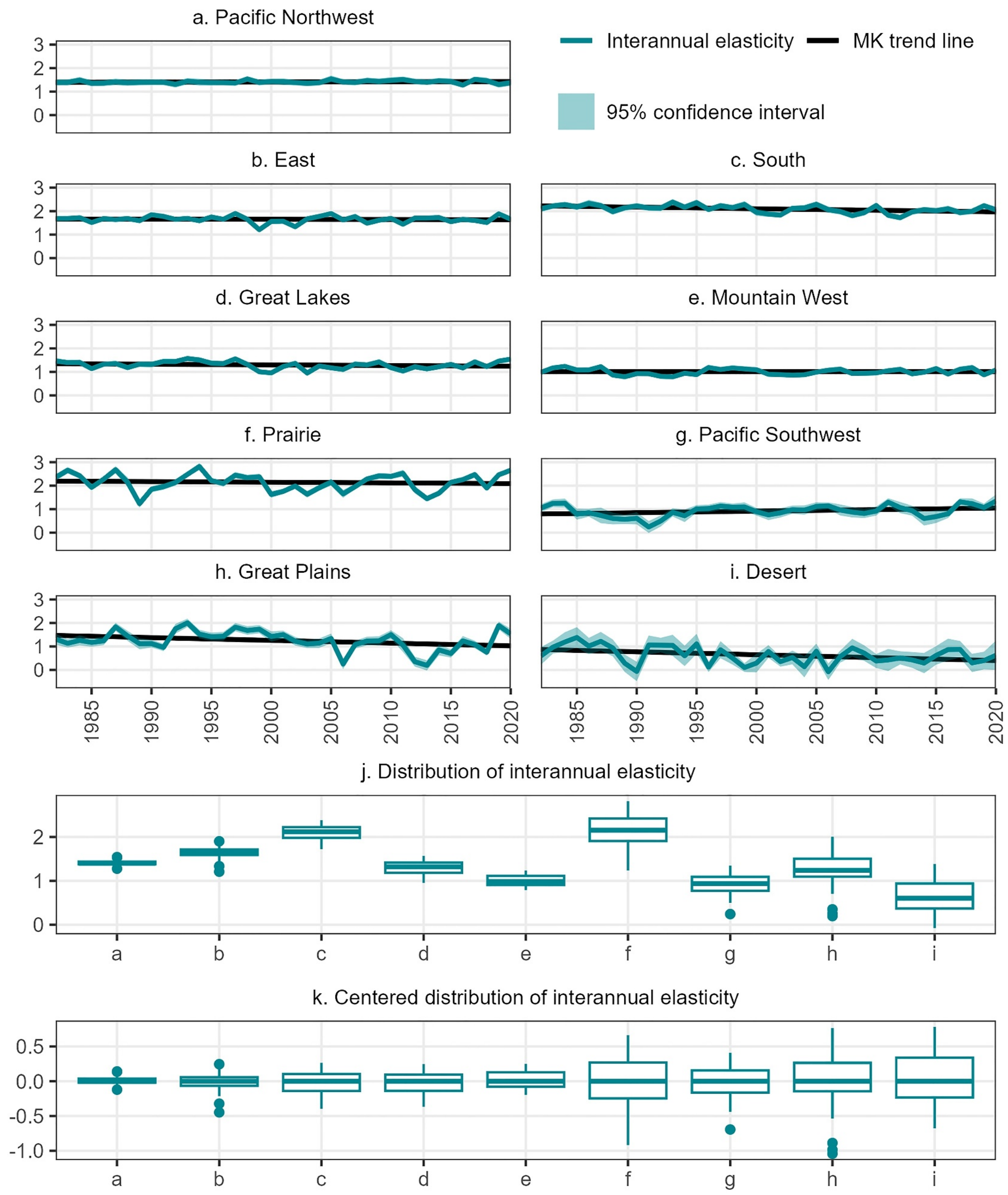

Figure 3. Interannual variability and long-term trends in interannual elasticity estimates for the 50th percentile of streamflow by hydro-climatologic region. Linear trend lines are presented in black on panels (a–i), with significance test results in Table 2. Subplots (a–i) show individual regions, and subplot k. shows the distributions of elasticity for each region as boxplots, where the upper and lower hinges are the 25th and 75th quantiles, and the whiskers include all values ±1.5 times the interquartile range. The boxplots in sub-plots (j, k) show the distribution of elasticity estimates per region across all years. The box plots in sub-plot k are normalized by the median that the range of values can be easily compared without considering the magnitude.

Comparing the interannual elasticity estimates to contemporary and lagged climatic variables reveals that the regional standardized precipitation index (SPI) is highly ($R > 0.5$ and $p < 0.05$) or moderately ($0.5 > R > 0.3$ and $p < 0.05$) positively correlated with interannual variability in elasticity in the previous, present, or both years in a majority of regions (89% for median flows). The five regions with the most variable interannual elasticity (e–i) were correlated with SPI in the same year or first lag for all examined flow percentiles (Figures 4e–4i). In the five regions with the most variable interannual elasticity (e–i in Figure 4), we show correlation with SPI values.

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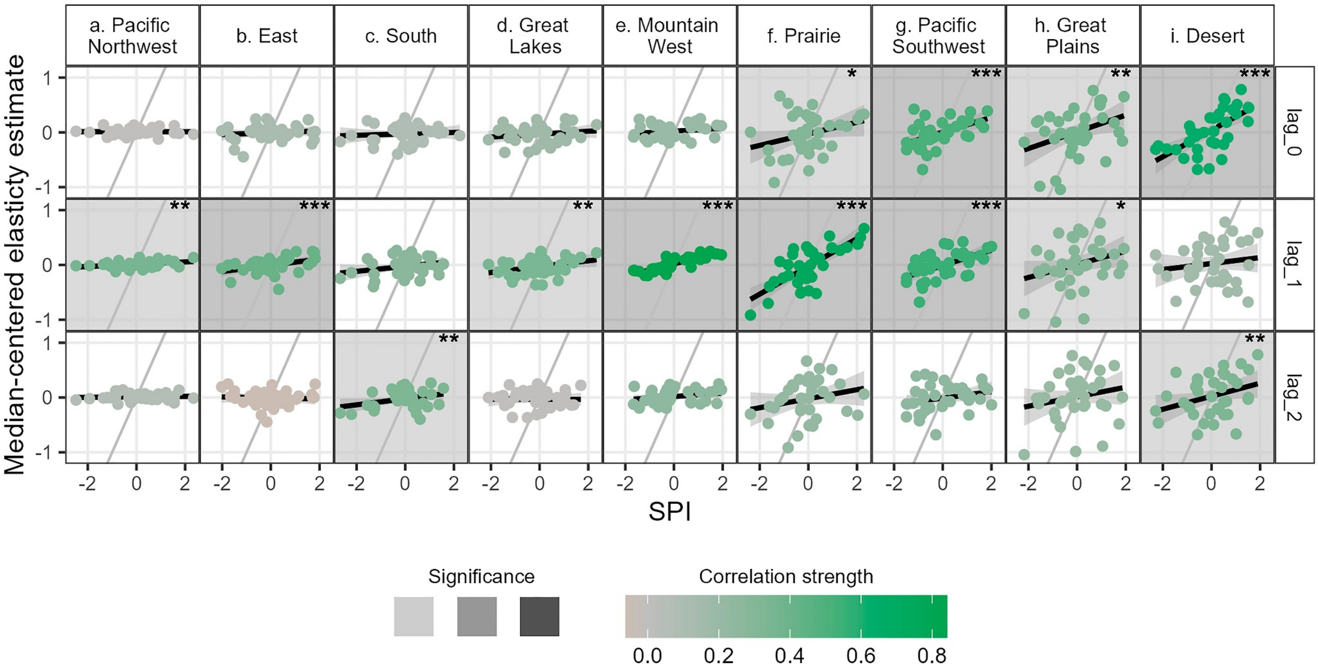

Figure 4. Pearson correlation between streamflow elasticity to precipitation and the regional average SPI. Shown for the same (lag_0), the previous (lag_1), or two water years prior (lag_2) for the 50th percentile of streamflow. Significance is rounded to two digits and indicated by stars where $p < 0.1$ is represented by *, $p < 0.05$ is represented by ** and $p < 0.01$ is represented by ***. The linear trend line is shown in black and the one-to-one trend line is shown in gray. SPI and Elasticity are unitless metrics and elasticity is normalized by the median to facilitate comparison between the regions.

Streamflow responsiveness depends on conditions in previous years; namely streamflow is more responsive to average annual precipitation if that year, the previous year, or both are wetter than average, while the opposite is true for drier years.

SPI is most frequently correlated with elasticity in the first lagged water year. The correlation between delayed SPI and elasticity is likely due in part to the seasonality of precipitation and streamflow (Table S2 in Supporting Information S1). For example, the low flow season for most catchments in the desert region is summer, thus occurring within the same water year as the high precipitation season (typically winter or summer). In many catchments in the Pacific Southwest region, the low flow season is autumn while the largest proportion of precipitation falls in winter which occurs after autumn in the water year (October–September). Thus, it follows that antecedent precipitation in the previous year could have a larger effect on low flows than precipitation events in the same year. Further, while the October through September water year is widely used in the United States, it may not correctly capture the complete hydrologic cycle in all locations.

Baseflow, the proportion of streamflow originating from delayed sources, also represents more than 10% of median streamflow in the Pacific Southwest, Mountain West, Pacific Northwest, East, and Great Lakes regions (a, b, d, e, g), based on the regional median ratio of annual average daily baseflow to the annual median streamflow (Table S4 in Supporting Information S1). This contribution may explain some of the pattern of delayed responses in median streamflow. The proportion is even larger in catchments without substantial dam storage (Table S4 in Supporting Information S1). Precipitation elasticity of high streamflow magnitude shows fewer correlations with SPI overall. Results indicate a correlation only in the five most variable regions.

Correlations between interannual elasticity and temperature, characterized using the regional standardized temperature anomaly (STA; Figure 5), are weaker and less consistent overall than those with SPI. However, STA is moderately negatively correlated ($p < 0.05$) with elasticity in the same year for median flows in the most arid regions, the Desert and Great Plains (h, i). At the lag-1 timestep (previous water year), STA is negatively correlated with interannual elasticity in the Great Plains, Prairie, and Great Lakes regions (d, f, h) for median flows. These results indicate that increased temperatures exert some negative influence on

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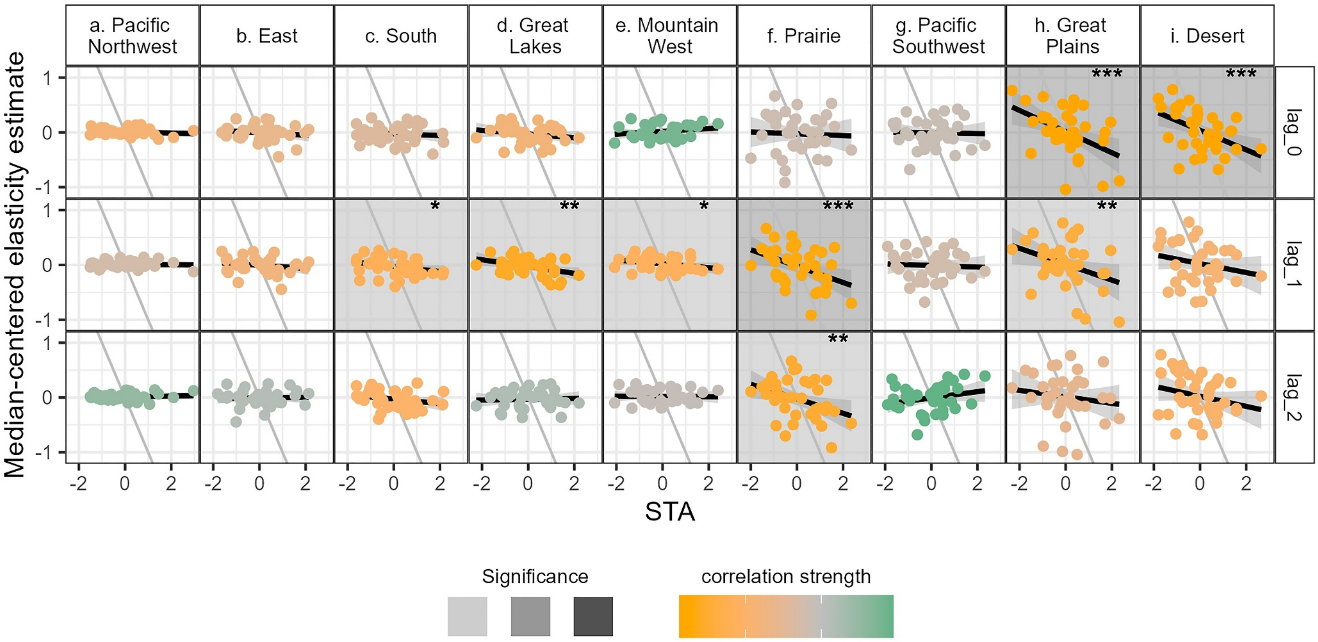

Figure 5. Pearson correlation between streamflow elasticity to precipitation and the regional average STA. Shown for the same (lag_0), the previous (lag_1), or two water years prior (lag_2) for the 50th percentile of streamflow. Significance is rounded to two digits and indicated by stars where $p < 0.1$ is represented by *, $p < 0.05$ is represented by ** and $p < 0.01$ is represented by ***. The linear trend line is shown in black, and the negative one-to-one trend line is shown in gray. STA and Elasticity are unitless metrics and elasticity is normalized by the median to facilitate comparison between the regions.

streamflow elasticity on a year-to-year basis, likely as a result of increased potential evaporation and drying soils (Sharma et al., 2018), or in response to a reduction in rain days with increased temperatures (Wasko & Nathan, 2019).

4. Discussion

Building on our foundational hypothesis that *streamflow elasticity is unlikely to be stationary in time*, the objective of this paper is to examine the extent to which an average estimate of streamflow response to precipitation at the annual time scale, as characterized by elasticity, may fail to capture changes in hydrologic response over time. Our results demonstrate that elasticity does, in fact, vary over time at a regional scale. This variation occurs over multiple timescales—both interannually and, in some regions, as a long-term average—over the 39-year study period.

We find similar spatial patterns to previous research on interannual streamflow elasticity (Tang et al., 2020). For example, large variability generally occurs in more arid regions. However, in contrast to Tang et al. (2020) we do not consider interannual elasticity to precipitation to be small. Interannual elasticity estimates in some regions deviate widely from the long-term average estimate. Coefficients of variation show a mean relative difference in response to annual precipitation of over 20% in some regions, and up to almost 50% in the most extreme case (Desert). Future streamflow projections that assume stationary elasticity could be substantially over- or under-estimated, and elasticity estimates may poorly describe hydrologic behavior if used as a regime descriptor. For instance, a projected median streamflow which is 50% higher than is realistic, would result in failure to capture potentially severe drought conditions, and may result in severe overestimation of groundwater recharge and availability. These concerns are further demonstrated in the results for low and high flows as presented in the Supporting Information S1 (Table S5 and S6).

Our results show that dry catchments are more susceptible to fluctuations in precipitation than catchments in humid regions. These findings generally align with prior literature regarding the variability of flow in arid and semi-arid catchments (Farquharson et al., 1992) and the importance of antecedent moisture conditions for generating flow in these regions (Ivancic & Shaw, 2015). For example, a recent analysis presented the concept of an "antecedent effect ratio" (AER) which quantifies the difference in catchment response to heavy precipitation dependent on antecedent moisture conditions (Bennett et al., 2018). They found that more arid catchments had high AER values, indicating that antecedent conditions were more important for flood flow generation in drier catchments than wetter ones. The authors speculated that the difference in response was related to the range of antecedent moisture conditions in drier catchments (i.e., arid catchments become much drier than humid ones, so relative moisture has a larger impact) (Bennett et al., 2018). In other words, as we demonstrate, antecedent precipitation conditions have a larger influence on streamflow response to precipitation in these regions because the role of hydrologic memory is more clearly expressed (Berghuijs et al., 2025; de Lavenne et al., 2022).

Another recent study demonstrated that the water balance in arid regions is dominated by extreme rainfall events (Dykman et al., 2023), thus streamflow response is susceptible to shorter term storage components, that is precipitation in the recent past, rather than contributions from long-delayed sources. Rivers in the Great Plains, Prairie, and Desert regions of our analysis likely have a weaker seasonality and flows are dominated by the occurrence of short precipitation events such as storms (Brunner et al., 2020). The fast and slow flow thresholds, two parameters that indicate the amount of precipitation required to generate storm runoff and baseflow respectively, are likely to consume a large proportion of annual precipitation in arid catchments (Harman et al., 2011; Sivapalan et al., 2011). In other words, streamflow which is driven predominantly by weather events, rather than longer-term storage, may be more sensitive at short timescales to both antecedent and present climate conditions. It is therefore unsurprising that drier regions experience larger shifts in elasticity on an interannual basis, a fact which is further supported in some previous research.

Previous research has also suggested that drier regions experience higher, and more spatially variable elasticity (Harman et al., 2011; Sankarasubramanian et al., 2001). Many of these studies have relied on the MOPEX data set, which is geographically limited in the especially arid Desert and southern portion of the Great Plains. Contrary to the results of these studies, we find relatively low long-term average elasticities in the arid Desert region. However, highly variable interannual elasticities here indicate that previously identified high spatial variability in dry regions may also be reflected in temporal variability, and years which are highly responsive will be interspersed with those that are not. Streamflow sensitivity may be better represented in these cases by an index which takes into consideration the importance of individual precipitation events on longer-term streamflow. For instance, it is possible that some version of an event dependence index, for example similar to the event flow distributions assessed in Dykman et al. (2023), may provide a suitable proxy for variability in elasticity over time. This concept could be explored in future research.

We detect some significant long-term trends in the regional interannual elasticity estimates, indicating that overall streamflow sensitivity to precipitation may be changing in some regions and for some parts of the flow distribution. Previous research has indicated that elasticity is correlated with the Horton index, a water-balance-based indicator of catchment humidity which relates evaporation to catchment wetting (precipitation-surface runoff) (Harman et al., 2011). Shifts in this index at long timescales may cause changes in catchment wetting and vaporization thresholds, eventually leading to changes in elasticity as a new climatic equilibrium is achieved (Harman et al., 2011). Further, it is possible that prolonged drought conditions may influence the long-term relationship between precipitation and streamflow (Fowler et al., 2022; Saft et al., 2015), and it is the case that significant increasing trends in drought (Ficklin et al., 2015), as well as large scale decreases in terrestrial water storage (Slater & Villarini, 2016) have been detected in the Desert region and in large parts of the South. These patterns may carry some responsibility for the decreasing trends in elasticity in these regions, providing another avenue for future research.

We find that long-term trends in elasticity due to climate may be occurring in some places, but that the geographic extent and magnitude of these changes is, so far, limited. The statistically significant trends which we detect are small in magnitude, showing a total absolute estimated linear change over the 39-year period of between 0.28 and 0.58. Due to the regional design of our study, we focus here on climate impacts, however, other anthropogenic activities such as land cover changes are also likely to influence elasticity at smaller spatial scales—potentially outsizing the average climate-driven patterns we find here in some places (Auerswald et al., 2025).

Long-term trends in several regions appear to be explained by dam regulation, as removal of these catchments from the data sample eliminated trends in several regions. In these cases, it may be reasonable to assume that long-term trends are due to management of hydrological resources rather than changes in climatology. Regardless of the magnitude and extent of long-term trends in elasticity, we demonstrate here that they are possible, suggesting

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that changes in climatology over the long term could lead to differences in the typical streamflow response to precipitation.

4.1. Limitations

We focus on a first-order precipitation elasticity of streamflow, and do not consider the explicit interactions and subsequent non-linear nature of streamflow elasticity as precipitation and temperature (potential evaporation) vary simultaneously (Fu et al., 2007). The elasticity estimates presented in the study represent within-group averages for entire regions, and therefore are not likely accurate estimates of streamflow elasticity at individual locations. The fixed effects in the panel regression model control for time-invariant confounders at the catchment scale (ex. topography), and thus it is assumed that the interannual and long-term variability detected here is the result of processes occurring at the regional scale, principally climate.

These results can be interpreted as regional averages, and variability in elasticity as an approximation of the relative sensitivity experienced in each region. The variations in elasticity which are presented in this study are robust at the regional level, with some caveats. The sample sizes in each region influence the statistical significance of the annual estimates. This is most relevant to the estimates for the Desert region which contains fewer catchments than the others, the implications of which are visible in the breadth of the associated confidence intervals (Figure 3). Regardless, the majority (∼80%) of interannual elasticity estimates are statistically significant ($p < 0.05$) in the Desert region.

Further, the model adjusted R^2 is generally low to moderate (Table 2), especially for low flows, while the model adjusted R^2 for high flows shows better performance (Table S6 in Supporting Information S1). Low model adjusted R^2 for low flows is expected because this section of the annual streamflow hydrograph is typically by delayed sources and is difficult to predict especially with a simple model formulation. The models used here were designed to capture the effect of temporally variant factors and were not focused on prediction but rather explanation. Given the careful construction of the model, this highlights the importance of delayed sources of runoff in explaining low flow behavior, while still capturing the role of precipitation in driving this streamflow. It is worth noting that the sample size within each region influences the precision and accuracy of regression coefficient estimation in the panel regression model. As noted in Figure 2a, the Desert region contains substantially fewer catchments than other regions in the analysis, which may partially explain the relatively wider confidence intervals and reduced significance of interannual elasticity.

5. Conclusions

In this paper, we have used a series of straightforward regional regression models to assess the degree to which streamflow elasticity to precipitation might vary over time. The model design isolates the effects of regional-scale processes which vary in time and helps control for processes at the catchment scale.

We have demonstrated that elasticity can sometimes vary substantially from year to year. We have also shown that this variation corresponds, to a high degree, to climate conditions in the previous year(s). Further, the difference in model performance indicates that inclusion of storage processes via a baseflow index metric does not adequately correct this shortcoming, as has been assumed in some previous work. Interannual variability is largest in dry regions, highlighting the importance of hydrologic memory for determining streamflow response. Lastly, we have shown that, while small, statistically significant long-term trends in elasticity are present in some regions. This suggests that climate change could, over time, shift catchment response to precipitation, further complicating the predictability of future streamflow.

Our results carry several implications. First, in catchments which experience high degrees of variability in streamflow elasticity to precipitation, future streamflow projections which rely on a single average estimate of elasticity are likely to over- or under-estimate flow. Biases could be as high as 50% in some cases, according to our results. Second, when elasticity is used as a hydrologic signature, for example for catchment classification, process exploration, or model calibration, a long-term average value may be a poor proxy for streamflow responsiveness. For this reason, it may not be a useful metric, especially in dry regions. Finally, if for some reason, a single long-term average estimate of elasticity is sought, our results indicate that, in catchments which experience high variability or long-term trends in elasticity, the time period used to estimate this metric could have a substantial effect on the resulting value. In other words, a short period of record may distort elasticity estimates in

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dry regions, while in regions where interannual variability in elasticity is marginal, a short period of record may still yield a reasonable representative estimate.

Thus, our results, combined with those presented in previous work (Addor et al., 2018), suggest that as it is currently estimated and understood, elasticity is a poorly informative hydrologic signature. So long as elasticity is poorly explainable by climate and catchment characteristics, shows limited predictability in space, as indicated in previous work (Addor et al., 2018), and is sometimes highly temporally variable, as demonstrated here, its usefulness may be quite restricted. Future research should investigate methods for estimation of the degree of variability in elasticity at individual catchments, or more generally, other approaches to understand rainfall-runoff responses (Kirchner, 2024).

Improving knowledge of why elasticity varies, both spatially and temporally, is an important step toward understanding how, and if, elasticity can be used to project streamflow changes into the future, or to validate simulations. These questions lend themselves to larger considerations which are not addressed here regarding how to manage hydrological non-stationarity, and the lengths of time series necessary to adequately estimate streamflow sensitivity from the observed record.

Conflict of Interest

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

Data Availability Statement

The calculated data used to produce the main results (Anderson, 2023) is available here: https://doi.org/10.5281/zenodo.8370039. All original data used in this analysis is publicly available from the following webpages: total upstream dam storage, average annual runoff, drainage area, mean catchment elevation, latitude and average catchment slope are available through GAGES II (Falcone, 2011) at https://doi.org/10.3133/70046617 watershed boundaries are also available through GAGES II (Falcone, 2017) at https://doi.org/10.5066/F7HQ3XS4; climate data is available from PRISM at https://www.prism.oregonstate.edu/recent/ and can be downloaded using the prism R package (Edmund & Bell, 2015). Streamflow data can be downloaded from the National Water Information System (NWIS) using the R package dataRetrieval (DeCicco et al., 2024). Bukovsky regions are accessible through the North American Regional Climate Change Assessment Program at https://www.narccap.ucar.edu/data/access.html.

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