The Role of Climate in Monthly Baseflow Changes across the Continental United States

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Abstract: Baseflow is the portion of streamflow that comes from groundwater and subsurface sources. Although baseflow is essential for sustaining streams during low flow and drought periods, we have little information about how and why it has changed over large regions of the continental United States. The objective of this study was to evaluate how changes in the climate system have affected observed monthly baseflow records at 3,283 USGS gauges over the last 30 years (1989–2019). We developed a statistical modeling framework to determine the relationship between monthly baseflow and monthly climate predictors (i.e., precipitation, temperature, and antecedent wetness). Overall, we found that baseflow trends and the factors influencing them vary by region and month. In the US Northeast, increases were detected earlier in the year (February and March) and in the summer (May and June), and were likely due to increasing precipitation, warmer temperature, and subsequent changes in snowmelt. Increasing baseflow in the US Pacific Northwest and Midwest were associated with increases in precipitation and antecedent wetness throughout the year. Decreasing trends were located in the US Southeast and Southwest. Baseflow trends in the US Southeast were only detected in March, possibly as a result of decreased precipitation during the spring. On the other hand, decreases in baseflow in the Central Southwestern United States occurred throughout the year. These trends were associated with a lack of precipitation and increases in temperature. Finally, we examined the relationship between monthly baseflow trends and changes in total water storage using monthly Gravity Recovery and Climate Experiment mascon products from the Jet Propulsion Laboratory. In this study, trends in total water storage were strongly associated with baseflow trends across the United States. The spatial and temporal variability in baseflow response to climate reported here can aid water managers in adapting to future climate change. **DOI: 10.1061/(ASCE)HE.1943-5584.0002170.**

Introduction

Baseflow is the portion of streamflow that is discharged from groundwater and subsurface sources. Shallow and deep aquifers contribute to baseflow, along with water transmitted through soil layers from precipitation, snowmelt, lakes, riverbanks, floodplains, wetlands, and/or springs (Price 2011; Stoelzle et al. 2013). It is a critical water resource because it maintains streamflow during droughts and dry seasons, and it sustains aquifer and stream ecosystems (Gleeson and Richter 2017). Baseflow is also an important contributor to water quality because it is associated with higher in-stream nitrate (e.g., Ayers et al. 2021; Kang et al. 2008; Schilling and Lutz 2004; Schilling and Zhang 2004) and lower temperatures (Price 2011). While baseflow is especially critical in regions that experience long dry seasons with minimal rainfall, it also supplies the majority of streamflow in wetter, temperate regions (Bosch et al. 2016; Santhi et al. 2008). In recent decades, water-rich regions across the continental United States have experienced water shortages because of droughts and growing demands for water supply during baseflow conditions (Peterson et al. 2020; Stephens and Bledsoe 2020). Baseflow reductions contribute to water stress and are associated with warmer stream temperatures and lower dissolved oxygen (Price 2011). On the other hand, increases in baseflow have been shown to contribute to higher nitrate loads that promote excessive algae growth in agricultural watersheds (e.g., Ayers et al. 2021; Kelly et al. 2015; Richards et al. 2021; Schilling and Lutz 2004). Understanding baseflow changes is essential to inform risk-based management decisions for water quality and counteracting adverse effects of climate change.

Previous studies examining streamflow trends across the United States have tended to focus on extreme events and high flows that cause costly floods (e.g., Archfield et al. 2016; Douglas et al. 2000; Hirsch and Ryberg 2012; Hodgkins and Dudley 2011; Rice et al. 2015; Slater and Villarini 2016). However, because baseflow contributes to a large portion of streamflow in many US watersheds, it is important to understand baseflow changes for human activities (e.g., food production, drinking water, recreation), water

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quality (e.g., nitrate loads and streamflow temperature), ecosystem health (e.g., connectivity of in-stream habitat) and droughts that cause high economic losses (Ahiablame et al. 2013; Hellwig and Stahl 2018; Rumsey et al. 2015; Santhi et al. 2008). Furthermore, streamflow trends have been found to closely follow baseflow trends, indicating that groundwater discharge controls many aspects of streamflow regimes (e.g., Döll et al. 2009; Lucas et al. 2020; Huntington and Niswonger 2012; Kim and Jain 2010; Luce and Holden 2009; Rumsey et al. 2015).

Despite its relevance, our current understanding of baseflow is narrow, and we do not have a clear understanding of how baseflow has changed at the national scale. Studies that investigated baseflow across the continental United States usually focused on estimation methods and the accuracy of measurements rather than baseflow response (e.g., Chen and Teegavarapu 2021; Ficklin et al. 2016; Gnann et al. 2020; Santhi et al. 2008; Xie et al. 2020). For example, Xie et al. (2020) created a criterion to evaluate the accuracy of baseflow separation methods across the United States. Aboelnour et al. (2021) created a regression model to predict the Baseflow Index (BFI) using a watershed's physical and geological properties. These recent studies point to the uncertainty and gaps in our understanding of baseflow for different climate and topographic conditions. In addition, there are discrepancies in the literature as to how low-flow statistics are defined, and many studies narrowly analyze changes in low flow (Smakhtin 2001). For example, it is common for studies to assess the annual minimum 7-day discharge (e.g., Kormos et al. 2016; Smakhtin 2001; Stephens and Bledsoe 2020), which is useful to determine changes in the severity of annual dry spells and to set permit discharge limits. However, these studies lack a comprehensive understanding of the variability in baseflow seasonality and volumes (Dudley et al. 2020; McCabe and Wolock 2002).

While a substantial body of work provides some consensus concerning changes in streamflow, disparities still exist in our understanding of baseflow changes and factors driving trends. The attribution of changes in baseflow is important for distinguishing natural and anthropogenic factors that affect water supply. Attribution studies are often conducted through case studies (e.g., Ahiablame et al. 2017; Bosch et al. 2016; Brutsaert 2008; Chen 2019; Meyer 2005) or at the regional scale (e.g., Ayers et al. 2020; Demaria et al. 2016; Ledford et al. 2020; Luce and Holden 2009; Rumsey et al. 2015; Singh et al. 2015). At these smaller scales, baseflow analyses are spatially dense and can analyze local response at a higher temporal resolution using a multitude of factors. However, we still do not have a clear picture of the patterns or drivers responsible for baseflow changes across large spatial scales. Some existing work focused on the attribution of baseflow changes at the continental scale (e.g., Ayers et al. 2019; Chen and Teegavarapu 2021; Ficklin et al. 2016), but they calculated the correlation between hydrologic factors and baseflow to relate variables rather than developing a multivariate approach to identify the relative and potential concurrent role of different drivers. Although these types of analyses are useful to identify individual relationships, they do not tell us what the most important variables are, nor do they account for the role of multiple variables at once.

To adapt to climate change and secure water resources in the future, we need a comprehensive framework that determines baseflow changes and identifies climatic factors driving trends. As a result, the objective of this study was to analyze the role of climate on baseflow response across the continental United States. First, we detected trends in monthly baseflow from 1989 to 2019 at 3,283 USGS streamflow gauges. We identified the relationship between monthly baseflow and monthly climate variables (precipitation, temperature, and antecedent wetness) at the watershed scale, using a statistical modeling framework. Furthermore, we calculated monthly trends in Gravity Recovery and Climate Experiment (GRACE) mascon products (2002–2017) as a representation of changes in total water storage. We also conducted a sensitivity analysis to understand how the results presented here depend on the baseflow separation method selected. The results of this work provide insights into the role that climate has played in driving the changes in baseflow across the continental United States.

Data and Methodology

Data

Daily discharge data were obtained for 3,283 USGS GAGES-II streamflow gauges (Falcone 2011) across the continental United States. Daily mean discharge was downloaded from the USGS National Water Information System website (USGS 2021). Sites were only included if they had at least 30 years of data from 1989 to 2019 with less than 5% of missing values and if they were currently active sites (as of January 2020). The median record length is 75 years. Sites with long-term records were preferred because they are likely to be more representative of hydrologic conditions, and they are better for statistical analyses (Feaster and Lee 2017). Furthermore, the USGS defines long-term stream gauges as those containing at least 30 years of streamflow records (USGS 2021). Of the selected streamflow gauges, 657 were classified as reference, which Falcone (2011) defined as minimally affected by anthropogenic influences relative to other gauges in that region. On the other hand, 2,626 gauges were considered nonreference (i.e., gauges that have been altered by human activities). Drainage areas for all catchments ranged from 6 to 50,362 km^2 with a mean of 3,473 km^2 and a median of 860 km^2.

Precipitation and temperature data were downloaded from the Parameter-elevation Regression on Independent Slopes Model (PRISM) climate group data (Daly et al. 2002). These data are freely available from 1890 to the present at a spatial resolution of approximately 4 km. At every USGS streamflow gauge, we aggregated the basin-averaged monthly mean temperature and accumulated precipitation using the watershed boundaries (taken from the USGS Streamgage NHDPlus Version 1) (Stewart et al. 2006). Antecedent wetness is defined using the sum of the previous 3 month's precipitation as an approximation for basin wetness. For example, average monthly baseflow in May is related to antecedent wetness using the sum of precipitation in April, March, and February. Defining antecedent wetness in this way is useful because it utilizes available precipitation data when soil moisture data are insufficient over large scales and long record periods. In addition, Ayers et al. (2020) determined that the sum of the previous 3 months' precipitation was a better metric for defining antecedent conditions relative to baseflow compared with other definitions using monthly precipitation data (e.g., different weighted values of the previous months' precipitation).

To assess changes in total water storage, GRACE mission remote-sensing data products were used. GRACE products report terrestrial water storage changes across the globe by measuring gravitational anomaly. Data sets measure changes in the earth's gravitational pull as differences in rates between two satellites, which can be used to infer changes in groundwater. For more details, see Save et al. (2016) and Tapley et al. (2004). Many studies have utilized GRACE data products to assess changes in total water storage, specifically groundwater levels and subsidence (e.g., Brookfield et al. 2018; Kim et al. 2021; Rateb et al. 2020; Tapley et al. 2004). Total terrestrial water storage includes groundwater, soil moisture, vegetation, surface water, snow, and ice.

GRACE products are available at a resolution of 300–400 km (at midlatitudes) from 2002 to 2017. For this study, we used the 3° mascon solutions downscaled to a 0.5° grid (Landerer and Swenson 2012; Swenson and Wahr 2006; Swenson 2012; Watkins et al. 2015), which were downloaded from Save et al. (2016). Although the data set may be too coarse for watershed scale analyses, for the purposes of this study, it provides insight into changes in water storage and basin wetness across a large spatial scale. It also captures changes in water stored in deeper subsurface layers that may not be detected using simple climate predictors (i.e., precipitation and temperature).

Baseflow Separation Methods

Many methods have been developed to separate baseflow from streamflow, including tracer-based methods and hydrograph separation techniques (e.g., Aksoy et al. 2009; Boussinesq 1877; Cartwright et al. 2014; Cey et al. 1998; Chapman 1999; Eckhardt 2008; Lyne and Hollick 1979; Miller et al. 2015; Sloto and Crouse 1996). In the present study, we used the Eckhardt (2005) digital filter method in the following formulation:

$$b_t = \frac{(1 - \mathrm{BFI}_{\mathrm{max}})\alpha b_{t-1} + (1 + \alpha)\mathrm{BFI}_{\mathrm{max}} Q_t}{(1 - \alpha \mathrm{BFI}_{\mathrm{max}})} \tag{1}$$

where b_t = filtered baseflow response at the t time step; b_{t-1} = response at the t-1 time step; Q_t = original streamflow at the t time step; and α = recession constant. In this study, we set $\alpha = 0.925$ as recommended by Nathan and McMahon (1990) and because other studies have shown high correlation between baseflow estimates using $\alpha = 0.925$ and tracer-based observations (e.g., Gonzales et al. 2009; Lott and Stewart 2016; Partington et al. 2012). In addition to the recession constant, the $\mathrm{BFI}_{\mathrm{max}}$ parameter needed to be defined. We used the FlowScreen package in R (Dierauer and Whitfield 2019) to determine the $\mathrm{BFI}_{\mathrm{max}}$ value and to calculate baseflow using the Eckhardt method. The FlowScreen package reports BFI summary statistics for daily discharge over the summary period, and we selected the mean of the daily BFI values (1989–2019) for each watershed. Although there is inherent subjectivity involved in selecting appropriate parameters for the recession constant and BFI, these filters have been found to be reliable methods as long as their use is consistent throughout the study (Chapman 1999; Eckhardt 2005; Institute of Hydrology 1980; Nathan and McMahon 1990). See also Tallaksen (1995), Brodie (2005), and Xie et al. (2020) for a review of the baseflow separation techniques and their performance. It is also worth noting that the use of graphical hydrograph separation methods is challenging in snowmelt dominated systems (e.g., Miller et al. 2015). While digital filters could impact the results of a study of this kind in areas like the Western United States, we aggregated baseflow to monthly resolution for our analysis, which should alleviate some of the potential concerns by decreasing the sensitivity of our results to potential errors in the exact timing of baseflow changes.

Statistical Modeling Framework

To determine the presence of temporal trends, we used the Mann-Kendall (MK) trend test (Kendall 1948; Mann 1945). The MK is a nonparametric trend test that determines the presence of monotonic patterns in the central part of the distribution. We used the period of record from 1989 to 2019 to detect trends in monthly baseflow. GRACE mascon products were analyzed from 2002 to 2017 because the mission was only run for this 15-year period. Trend detection was conducted on a monthly time scale for the baseflow and GRACE time series. We set a significance level to 5% in this analysis. All calculations were performed in R using the modifiedmk package (Patakamuri and O'Brien 2018).

To model the observed average monthly baseflow time series, we used the generalized additive model for location, scale, and shape (GAMLSS) (Rigby and Stasinopoulos 2005; Stasinopoulos and Rigby 2007) because it provides a high degree of flexibility for distributions and their functional relationships in its parameters compared with other statistical models. The gamma distribution was selected because it is a suitable distribution for describing positive continuous values that are skewed, such as baseflow. Furthermore, previous studies have determined that the gamma distribution is well suited for modeling streamflow and low flow across regions of the United States (e.g., Slater and Villarini 2017; Villarini and Strong 2014). In these models, μ and σ are the two parameters of the gamma distribution where the variability in μ over the record period was described by one of seven possible regression models that relate baseflow to the climate predictors: precipitation (x_p), antecedent wetness (x_m), and temperature (x_t). In addition, σ was held constant because it did not significantly depend on the covariates analyzed here. Table 1 shows the four most commonly selected statistical models with their corresponding model formulations. The parameterization of our models is based on the gamlss package in R (Rigby and Stasinopoulos 2005). The monthly models provide a probability distribution for every year, and reflect a range of possible values for the variable of interest. Fig. S1 illustrates two examples of the type of time series that were created for each site and month, comparing a good model fit for Neuse River near Goldsboro, North Carolina (02089000), for June ($R = 0.81$) and a poor model fit for Baron Fork at Eldon, Oklahoma (USGS station 07197000), for April ($R = 0.57$).

To determine the best model formulation that characterized baseflow at each site and month, we used stepwise model selection. We selected the GAMLSS model with the smallest Bayesian information criterion (BIC) (Schwarz 1978) value, which generally results in a more parsimonious model than one obtained with respect to the Akaike information criterion (AIC) (Akaike 1978). Because many streams across the United States have a high degree of intermittency, the analysis was only run for months that contributed greater than 5% of the total annual baseflow.

To evaluate model performance, the Pearson's correlation coefficient was calculated between the observations and the median (50th quantile) of the probabilistic model fit. In this analysis, we did not apply any model validation because of the good model

Table 1. Formulations of the four most common statistical models and their model formulations

Model	Model formulation	Percentage selected (%)
Precipitation + antecedent wetness	$\log(y_1) = \alpha_1 + \beta_1 \cdot x_p + \gamma_1 \cdot x_m$	49
Precipitation + antecedent wetness + temperature	$\log(y_2) = \alpha_2 + \beta_2 \cdot x_p + \gamma_2 \cdot x_m + \delta_2 \cdot x_t$	18
Antecedent wetness	$\log(y_3) = \alpha_3 + \beta_3 \cdot x_m$	11
Precipitation	$\log(y_4) = \alpha_4 + \beta_4 \cdot x_p$	6

Note: Baseflow (y_1) is modeled as a function of precipitation (x_p), antecedent wetness (x_m), and temperature (x_t). "Percentage selected" is the number of models selected out of all models for every month and site.

performance overall, and in similar analyses (i.e., Ayers et al. 2019), we applied leave-one-out cross validation, which showed comparable results to the correlations coefficients obtained when using the full data set. However, we further quantified how well our models perform using the mean square error (MSE) skill score (SS_{MSE}) and its decomposition (Hashino et al. 2006):

$$SS_{MSE} = 1 - \frac{MSE}{\sigma_0^2} \tag{2}$$

where σ_0 = standard deviation of the observations. A skill score of 1 is a perfect score, whereas lower values indicate bias in the model predictions, in which a value of 0 specifies that the performance of the model is the same as the climatology, and negative values indicate worse performance

$$SS_{MSE} = \rho_{ro}^2 - \left[\rho_{ro} - \frac{\sigma_r}{\sigma_0}\right]^2 - \left[\frac{\mu_r - \mu_0}{\sigma_0}\right]^2 \tag{3}$$

where ρ_{ro}^2 represents the potential skill (i.e., the coefficient of determination and quantifies the skill in the absence of biases); and ρ_{ro} is the correlation coefficient. The $[\rho_{ro} - (\sigma_r/\sigma_0)]^2$ is the slope reliability (SREL), which captures the conditional bias, and σ_r indicates the standard deviation of the model predictions. The term $[(\mu_r - \mu_0)/\sigma_0]^2$ represents the unconditional bias (SME), where μ_r and μ_0 are the mean of the modeled and observational data, respectively.

Results and Discussion

Monthly Baseflow Trend Results

The MK trend test was used to evaluate trends in observed monthly baseflow from 1989 to 2019 (Fig. 1). Overall, 28% of stations had a significant trend in at least 1 month (16% increasing and 12.7% decreasing). Across all stations and all months that the analysis was run (i.e., for a given month in which baseflow contributed greater than 5% of the annual total baseflow), a significant increase and decrease were detected 4.2% and 3.6% of the time, respectively. There were regional patterns in the direction and seasonality of trends. In the US Northeast (Maine, Vermont, New Hampshire, New York, Massachusetts, Connecticut, Rhode Island, New Jersey, and Pennsylvania), increasing baseflow trends were detected from January to July. Increases were detected more often in January and February and then again in June and July. Clusters of increasing baseflow trends persisted from March to May, but in smaller numbers along the East Coast. Increasing trends in the US Northeast are consistent with Hodgkins and Dudley (2011), who found that mean summer (May to September) baseflow increased in Maine, New Hampshire, and Vermont from 1950 to 2006. Other studies have also reported increased baseflow during the winter in the US Northeast (e.g., Ficklin et al. 2016; Hodgkins et al. 2005).

Increasing trends were detected in the US Midwest from March to August. Although trends were numerous in May and June, there were temporal differences in trend detection across the region. In the southeast part of this region (Ohio, Indiana, Illinois, and Kentucky), increases were detected earlier (March and April), whereas in the north (North Dakota, South Dakota, and Minnesota) increases persisted later in the summer (July and August). Increasing baseflow trends were consistent with many other studies that have examined baseflow and low flow trends in the US Midwest (e.g., Ayers et al. 2019; Douglas et al. 2000; Lins and Slack 2005; Zhang and Schilling 2006). Increases in baseflow were also located in the US Pacific Northwest (Washington, Oregon, and Northern California) in April and May. Slightly east in Idaho, Montana, and

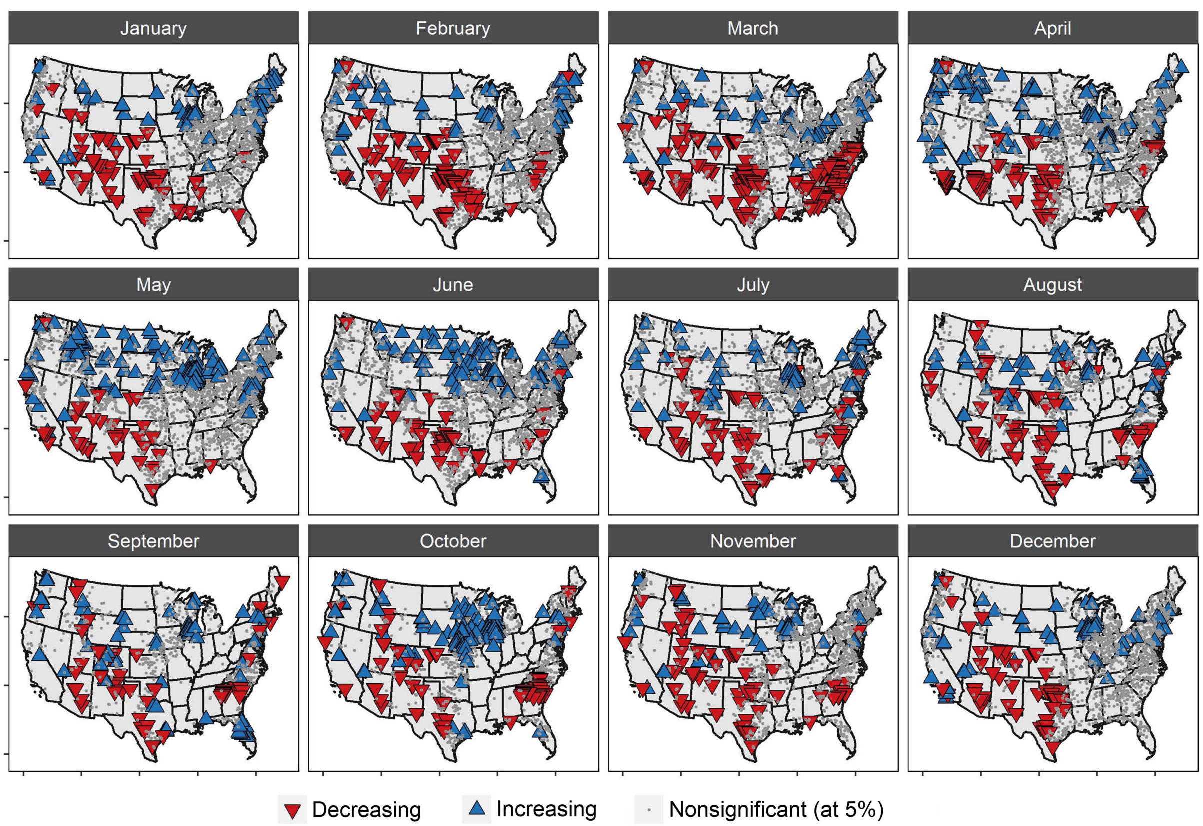

Fig. 1. Results of the MK trend test applied to the observed time series of monthly baseflow from 1989 to 2019.

Wyoming, increases occurred from April to June. Although upward trends were detected more often during the spring, increasing trends persisted throughout the remainder of the year for some gauging stations. These trend results were dissimilar from other studies that found decreased streamflow in the US Pacific Northwest (e.g., Kormos et al. 2016; Luce and Holden 2009). For example, Lins and Slack (2005) found few trends in streamflow, but more decreases than increases in the annual minimum flow over the second half of the twentieth century. However, consistent with these studies, our results detected decreasing baseflow trends at some locations from July to March.

While increasing trends display seasonal differences across the continental United States, decreases in baseflow were consistently located in the US Southwest (Southern California, Arizona, Utah, Colorado, and New Mexico) and in the southern Great Plains (Texas, Oklahoma, Nebraska, and Kansas). Many studies have also reported streamflow declines in the Central and Western United States (e.g., Barnett et al. 2008; Peterson et al. 2020; Rumsey et al. 2015; Stewart et al. 2005). Furthermore, downward trends in baseflow were located in the US Southeast, which stretches from North Carolina south along the East Coast and into Mississippi. Although decreases in baseflow occurred often in March, almost no statistically significant trends are found in all other months. Recently, a few studies reported decreases in baseflow in the US Southeast and the Gulf of Mexico (e.g., Bosch et al. 2016; Rodgers et al. 2020; Singh et al. 2015; Stephens and Bledsoe 2020), but they usually focused on annual baseflow trends. The results from our analysis could indicate that annual low flow trends are driven by lower baseflow during March.

Model Performance

To assess how well models fit at the 3,283 USGS stations, we calculated Pearson's correlation coefficient, R, between the observations and the median (50th quantile) of the probabilistic fit for every month (Fig. 2). Furthermore, we calculated the decomposition of the skill score, which includes conditional and unconditional biases in the model outputs (Fig. S2). The results based on the skill score confirm the results of the correlation coefficient and show that our models work well overall. Across all months and stations, the models performed well with a mean and median correlation coefficients of 0.65 and 0.69, respectively. The models fit slightly better from November to January (monthly mean $R > 0.70$), which is likely because baseflow is more stable during the winter, thus easier to model. The models performed worst during April (mean $R = 0.48$), highlighting that, for many sites, the models had difficultly identifying the relationship of baseflow with snowmelt and spring precipitation. For all other months, mean R values range from 0.61 to 0.68, indicating good overall fit.

Model performance varied based on regional differences in climate. During colder months (December to March), higher correlation coefficients were located in the US Northeast, Southeast and along the Pacific coast. From May to August, the models performed better in the US Midwest, the Great Plains, and in the Western United States. However, the models performed poorly during the fall and winter in the US Southwest. Furthermore, for about 4% of sites, no predictors were selected in the model formulation (Fig. 2). For these sites, climate predictors used in this analysis did not capture baseflow response. Because these predictors are simple, there are inherent limitations associated with our methodology, i.e., we can only identify the factors controlling baseflow

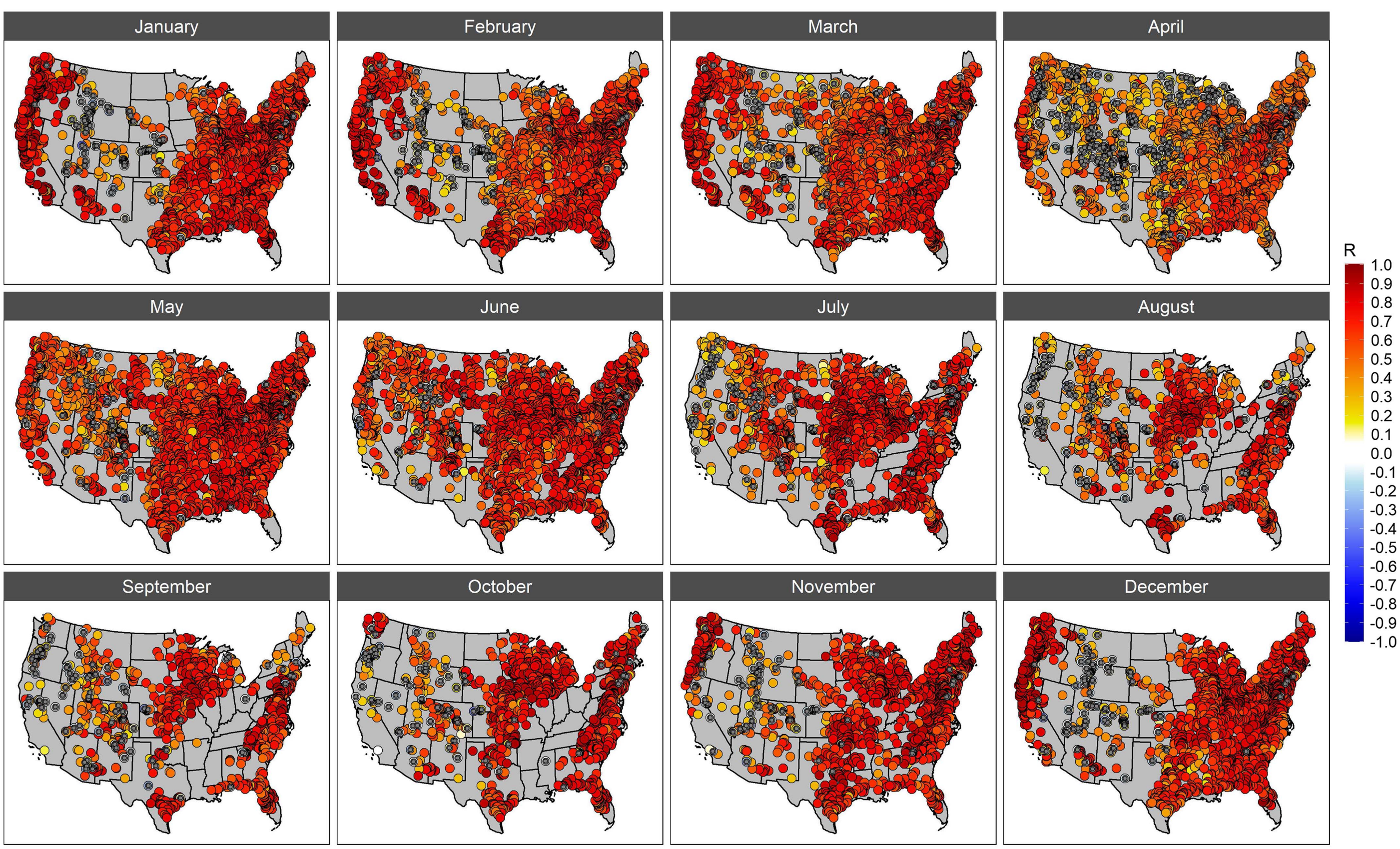

Fig. 2. Map of the Pearson correlation coefficient between the baseflow observations and the median (50th quantile) of the best selected based on BIC for every month. For each site and month, model selection was only run if that month's baseflow contributed more than 5% of total annual baseflow.

and not necessarily capture all the physical mechanisms at play. However, correlation coefficients are high overall (mean of 0.65), which gives evidence that the models are good at capturing variability in monthly baseflow. Albeit simple, this framework identifies the relationship between climate variables and baseflow, providing insight into baseflow trends on a large scale across the continental United States.

Climate Predictors

To understand the factors driving baseflow trends, we modeled monthly baseflow using monthly precipitation, temperature, and antecedent wetness. Fig. 3 shows the results using one month to represent each season (i.e., March, June, September, and December), whereas Figs. S3–S5 show the results for each predictor and month. Overall, precipitation and antecedent wetness were selected most often in the model formulations. For every site and month, precipitation was selected 76% of the time, and antecedent wetness was selected 85% of the time. Furthermore, the model that only considered precipitation and antecedent wetness in its formula was selected most often (49%), which indicates that both predictors are important to determine water availability. While precipitation is more relevant at a shorter temporal scale (i.e., the same month's precipitation), the previous 3 months' precipitation provides information about the memory in the system and baseflow's delayed response to precipitation events. Together, the positive relationships indicate that increases in baseflow over the last 30 years were driven by increased precipitation.

On the other hand, temperature was selected in 29% of all model formulations. Either a positive or negative relationship with baseflow was detected depending on the month and location. Because temperature controls evapotranspiration and snowmelt processes, it likely plays more of an indirect role in our results. Generally, temperature has a positive relationship with baseflow during the winter and spring, pointing to snowmelt processes contributing to baseflow increases. During the summer, a negative relationship indicates that increased temperature and subsequent increases in evapotranspiration have likely caused declines in baseflow. Although the indirect relationship between baseflow and temperature may be muted, we speculate about the physical processes that may be controlling baseflow for different regions.

Across the continental United States, there are differences in climate factors due to weather patterns and watershed characteristics that dominate the response time of baseflow. Some groundwater systems have a greater connection to the surface because of shallow water tables and/or vegetation where a drying or wetting of the soil layer is more quickly observed in baseflow response (Price 2011). For example, there are characteristically shallow water tables and unconfined aquifers across the US Midwest (Fan et al. 2013). As a result, baseflow in this area may respond to precipitation more quickly than in other regions. In this study, precipitation and antecedent wetness were consistently selected as predictors and more often during warmer months (March to August) (Figs. 3, S3, and S4). Other studies have reported increases in heavy and long-lasting precipitation events over the US Midwest as a result of persistent weather types that are tied to moisture transport and low-level jet streams (e.g., Cook et al. 2008; Gao and Schlosser 2019; Harding and Snyder 2015; Villarini et al. 2011; Zhang and Villarini 2019). Increases in heavy precipitation (and antecedent wetness) are likely a contributing factor to increasing baseflow trends observed across the region. Furthermore, during the late spring and summer, temperature is negatively associated with baseflow. Although increased temperature and evapotranspiration inversely affected baseflow, the increasing baseflow trends detected in the US Midwest indicate that their influence over trends is outweighed by increases in precipitation.

During the winter, a positive relationship between baseflow and temperature is detected in higher latitude catchments (Figs. 3 and S5). Temperature influences snow and snowmelt processes that control the timing of winter/spring recharge and baseflow

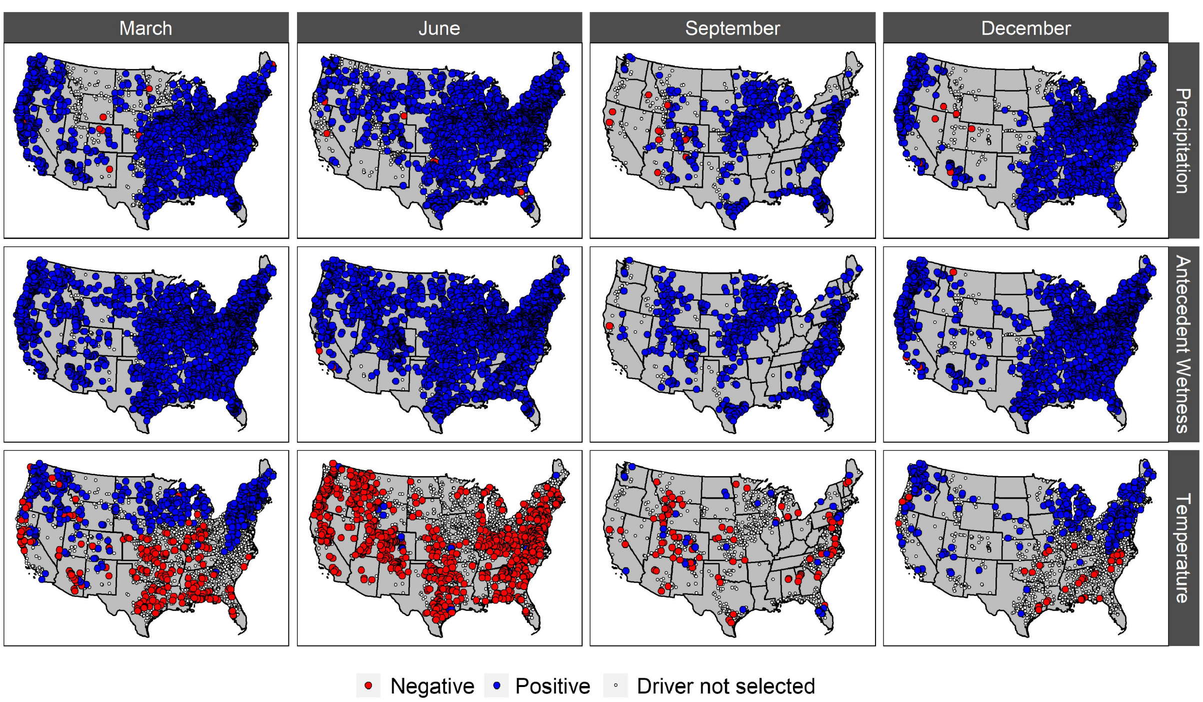

Fig. 3. Relationship between monthly baseflow and monthly precipitation, monthly antecedent wetness, and monthly temperature. Selected months are shown for simplicity.

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discharge. Earlier snowmelt has been shown to affect the seasonality of baseflow. Studies have reported increases in streamflow as a result of increased precipitation, and they have shown that longer recession periods cause more streamflow earlier with less streamflow in the late summer (e.g., Ahiablame et al. 2017; Coleman and Budikova 2013; Demaria et al. 2016; Hayhoe et al. 2008; Hodgkins and Dudley 2011; Hodgkins et al. 2005; Sen Gupta 2010). In the US Northeast, changes to snow and snowmelt are likely causing changes in baseflow. The selected models showed a positive relationship between temperature and baseflow from December to April, contributing to increased baseflow in January and February. Precipitation and antecedent wetness were also selected, which could drive increasing winter baseflow trends as well as increases detected from May to July. The results reported here are consistent with those of Hodgkins and Dudley (2011), who found that summer 7-day low flows (May to September) had a strong positive correlation with summer precipitation, although correlation with air temperature was mostly negative and not significant at the 10% level.

The US Pacific Northwest is characterized by a warm and dry summer with the majority of precipitation falling as mountain snow during the winter. In terms of baseflow trends, there were distinct increases during April and May (Fig. 1). Interestingly, precipitation was selected as a predictor, but antecedent wetness was less important in April (Figs. 3, S3, and S4). Here, stations that selected antecedent wetness were located along the Cascade mountain range, whereas sites closer to the coast indicated no relationship. These results highlight that winter precipitation and spring temperature are likely controlling the magnitude of baseflow in late spring. Over a similar study period (1980–2012), Abatzoglou et al. (2014) noted a regional warming trend paired with decreases in summer and autumn precipitation. Furthermore, other studies have shown that the frequency of heavy precipitation decreased over the region (e.g., Harding and Snyder 2015; Mallakpour and Villarini 2017), which could account for the few decreasing trends detected.

In the US Southwest, a negative relationship between temperature and baseflow was detected for most months (Figs. 3 and S5). As expected, warmer air temperature contributed to higher evapotranspiration and less water available for infiltration and subsequent baseflow discharge. Precipitation and antecedent wetness were also selected, but the interaction between climate factors may be more complex in the Western United States than in other regions. In arid mountainous watersheds (i.e., the Sierra Nevada and Rocky Mountain ranges), snow accounts for the largest component of precipitation received (Carroll et al. 2019; Hammond et al. 2019; Rumsey et al. 2015). As a result, baseflow response may depend heavily on snowmelt processes, which are controlled by temperature. Since the 1990s, climatic oscillations in the Pacific Ocean have caused the US Southwest to be severely dry and warm with a deficit of cold-season precipitation (Cayan et al. 2010; Williams et al. 2020). The recent, long-term trend toward a warmer climate caused decreased snowpack, earlier runoff, increased evapotranspiration, and dryer soils (Rumsey et al. 2015). In our results, it is difficult to identify the physical mechanisms controlling baseflow declines because warmer temperature could also be correlative to a lack of precipitation and decreases in evaporative cooling during drought conditions (Milly et al. 2018; Mueller and Seneviratne 2012). Overall, these large-scale circulation patterns likely contributed to the consistently decreasing trends in baseflow found in this study.

Although the estimated coefficients for antecedent wetness and precipitation were positive at most stations, some watersheds in the Western United States detected a negative relationship with baseflow. This inverse relationship could indicate that other factors are at play. For example, irrigation and groundwater pumping are implemented more frequently when not enough precipitation is available for water supply. Although studies have shown that land use practices in the Western United States decreased groundwater levels and baseflow (e.g., Russo and Lall 2017; Zipper et al. 2019), pumping and irrigation can also increase water inputs at the surface, resulting in more water available for baseflow discharge. Pumped irrigation water coming from deeper aquifers would not normally come to the stream and thus would represent new water available for baseflow.

Groundwater pumping in the High Plains Aquifer (underlying Kansas, Nebraska, and Oklahoma and Texas) is likely contributing to baseflow decreases in the southern Great Plains. Many studies documented streamflow depletion as a result of changes in the High Plains Aquifer water levels (e.g., Peterson et al. 2020; Scanlon et al. 2012; Sophocleous 2005; Zipper et al. 2021). Because crop irrigation demands are highest during dry climate conditions (Butler et al. 2018), baseflow reductions are due to either streamflow depletion or surface water diversions that are indirectly related to climate. Furthermore, increased temperature lengthens the growing season (Jeong et al. 2014), which could increase plant transpiration and water demand causing baseflow declines for some months. However, here we can only speculate about the influence of land use and land management because our models focus on the role of climate only (Figs. 3 and S3–S5). Across the southern Great Plains, precipitation and antecedent wetness were selected as predictors. Temperature was selected throughout the year, but it was more prominent from March to August. Furthermore, a consistent negative relationship was detected between temperature and baseflow. Because baseflow is decreasing throughout the region, temperature and land use practices are likely outweighing precipitation inputs. Similarly, in the US Southeast, decreases in baseflow could be driven by increases in temperature and a lack of precipitation. Previous studies pointed to the role of large-scale circulation patterns and drought conditions in streamflow response in the Eastern United States (e.g., Coleman and Budikova 2013; Rodgers et al. 2020; Singh et al. 2015). For example, Singh et al. (2015) quantified the impact of climate variability cycles on baseflow for the Flint River in Georgia, showing that La Niña patterns were associated with baseflow decreases.

GRACE Trends

To further verify our modeling results and assess baseflow changes, we investigated monthly trends in GRACE mascon products (2002–2017). GRACE products describe changes in wetness or total water storage because they indicate changes in water available in the surface and subsurface. It is important to note that GRACE data products are reported as a gridded data set, and it is much larger than the typical watershed analyzed in this study (i.e., greater than 3,000 km^2). As a result, it does not provide an understanding of changes in basin wetness on an individual watershed scale. Rather, the benefit of reporting changes in GRACE data products (i.e., total water storage trends) is to verify our modeling results across a large, regional scale using an additional data set. Furthermore, there can be substantial changes in baseflow with slight changes in groundwater storage because groundwater discharge to streams is controlled by the hydraulic gradient between the stream and the aquifer (Currell 2016; de Graaf et al. 2019). For this comparison, we ran trend detection for monthly baseflow trends over the same period (2002–2017).

Fig. 4 illustrates strong agreement between monthly trends in total water storage and baseflow for March, June, September,

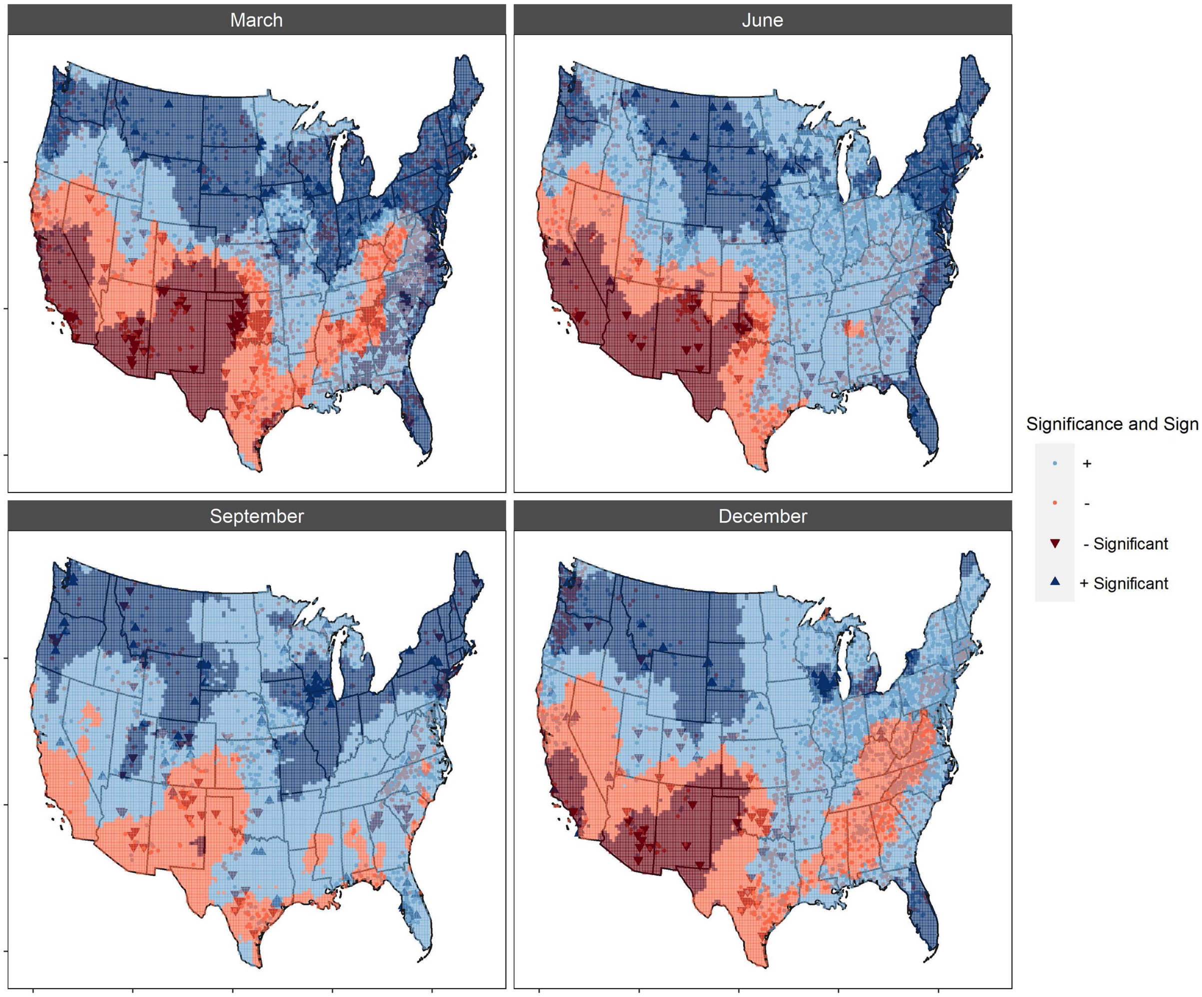

Fig. 4. Total water storage trends (2002–2017) using GRACE data products compared to the monthly baseflow trends (computed for the same time period) for selected months. Trends were computed using the MK trend test applied to monthly total water storage.

and December. See Fig. S6 for the trend results for each month. Generally, increasing total water storage trends were detected across the Northern United States while decreases are located in the South. GRACE trends correspond well to baseflow trends over the same period from December to June in terms of the statistical significance of increasing and decreasing water storage trends. On the other hand, from July to November there is more ambiguity because GRACE trends are nonsignificant, which may indicate that total water storage was relatively stable over the 15-year period. Furthermore, significant trends in baseflow could be a result of a lagged response to precipitation earlier in the year.

In terms of the statistical models developed in this study, the stations that did not select any predictors are located in the Western United States. For this area, decreases in total water storage agreed with decreasing baseflow trends throughout the year. In addition, significant increases in basin wetness were detected in the North Central United States (Montana, Wyoming, and Idaho), where our models did not perform as well. Overall, changes in total water storage agree with the seasonality of baseflow trends in most regions. These results indicate that baseflow trends in the last 30 years were dominated by more recent changes in climatology, highlighting the influence of hydrometeorological processes in the subsurface. Similarly, Brookfield et al. (2018) found that GRACE-derived changes in total water storage in the High Plains Aquifer were representative of changes in shallower alluvial aquifers, but the relationship was weaker for saturated groundwater storage deeper in the High Plains Aquifer.

Conclusions and Future Directions

The objective of this study was to detect changes in monthly baseflow across the continental United States over the last 30 years. We built a statistical modeling framework to determine the role of climate in driving baseflow response. Overall, we found that changes in monthly baseflow and model selection varied with region and month across the United States. Specifically, the results of this study can be summarized as follows:

- Increasing trends in baseflow occurred often but varied depending on the month. Model selection showed a positive relationship with precipitation and antecedent wetness, indicating that increases in precipitation are likely the main driver of increasing baseflow trends. The seasonality of baseflow is controlled by changes in temperature during the late winter and early spring likely through snowmelt processes. This relationship was more prominent in higher latitudes and higher elevations, such as in the US Northeast, upper Midwest, and Pacific Northwest.
- Decreases in baseflow did not vary across months and were found in the US Southwest, southern Great Plains, and US Southeast. Our statistical models showed that decreasing trends

were driven by increases in temperature and subsequent evapotranspiration. However, further research is needed to relate baseflow to physical mechanisms and land management practices because irrigation and groundwater pumping are likely playing a major role in controlling decreasing baseflow trends across arid and semiarid regions of the United States.

- Overall, models performed well with a mean correlation coefficient of 0.65 for all months and sites. For some stations, none of the predictors were selected (4% of sites) in the model formulations. In other words, the climate factors considered here were not informative for describing baseflow response.
- Despite the large spatial resolution of GRACE data products, monthly trends in total water storage were congruent with baseflow trends across the continental United States. Trends agreed well in areas where the models were not able to predict baseflow as well (e.g., in the Western United States). Statistically significant trends in total water storage were also located across the North Central United States, corresponding to baseflow trends that have not been examined in much detail within the literature.
- We found that the selected baseflow separation method did not influence the trend detection or the model selection results reported in this study.

This study provides a critical first step to understand baseflow response under recent changes in the climate system. An interesting next step in this work would be to regionalize the baseflow trends and improve the modeling framework by including watershed characteristics and other predictors. A limitation of this analysis is that we did not include baseflow response to other climate drivers (i.e., evapotranspiration, snowmelt processes, and rainfall intensity and type) and land use change (i.e., vegetation, agriculture, and urbanization). Other climate variables were not included because data were difficult to obtain over large regions of the continental United States. As reported in this study, the influence of snow processes is likely contributing to baseflow changes during the late winter and early spring. However, the indirect relationship between temperature and snow creates uncertainty in the interpretation, and data were not included because they were difficult to obtain (i.e., snow type and amount can be hard to measure). Since warmer global temperatures have may effect changes in snow and snowmelt timing, it is important that future studies examine their influence on baseflow, especially in mountainous watersheds that are more vulnerable. It could also be useful to include interaction terms as potential predictors because of the relationship between climate and subsurface processes.

Future studies assessing in more detail the influence of land use and land cover changes on baseflow could help to better capture complex processes. A next step in this work could be to include agricultural predictors from the US Department of Agriculture's database in model formulations, similar to the approach used in Ayers et al. (2020), where agriculture in the US Midwest was characterized using corn and soybean data. For the purposes this study, we did not include agricultural predictors because it would require that we regionalize the trends and identify predictors accordingly for different time frames. However, including agricultural predictors in model formulations would be useful to understand the interaction between climate and land use on a large scale. Furthermore, groundwater pumping was not included in the analysis. Although pumping is known to influence groundwater levels and baseflow, it is not readily available with sufficient resolution over long periods. Existing data sets have uncertainties about where groundwater pumping is located, and there are often little to no observations to verify results (Foster et al. 2020; Taylor and Alley 2001). Because groundwater supply controls water available for baseflow discharge, future studies could relate land use and land management practices to changes in baseflow.

In this analysis, we assume that the trends are monotonic and the outcome of these test depends on a relatively short 30-year record. Furthermore, our statistical modeling framework assumes that the relationship between baseflow and climate predictors is stationary. We acknowledge that the observed time series may exhibit more complicated behaviors and that there is an ongoing debate about the limitations of nonstationary methods (e.g., Douglas et al. 2000; Serinaldi and Kilsby 2016; Serinaldi et al. 2018). As a result, the results of this study would require additional efforts and refinements in their application for future realizations to water resource management. However, our study provides valuable insight into climate factors driving the direction and magnitude of historic baseflow trends. Our statistical framework can be applied in other regions to understand baseflow trends on a finer scale. This work also highlights limitations and gaps in our current knowledge of baseflow across the continental United States. By examining baseflow over large regions, we can understand groundwater availability and changes in streamflow that are critical for water resources management at the local, regional, and national scales. Predicting baseflow response is essential to understand how a watershed's hydrology will change in the face of climate and land use changes.

Data Availability Statement

All data and models generated or used during the study appear in the published article. Some of data, models, or code that support the findings of this study are available at https://github.com/jessayers20/Baseflow-Continental-US or from the corresponding author upon reasonable request.

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Supplemental Materials

Figs. S1–S6 are available online in the ASCE Library (www.ascelibrary.org).

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