Headwaters of the Western US: Base-flow Analyses and Projections

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Abstract

Headwater streams make up nearly 88% of the stream network in the western United States and supply most of the region’s surface water. These systems are highly sensitive to climate change, as warming, snowpack loss, and drought alter groundwater recharge and the timing of streamflow. As surface-water inputs decline, streams increasingly depend on groundwater to sustain base flow, underscoring the need to understand long-term trends and climate controls on these flows. We analyzed 75 years of streamflow records (1950–2024) from 115 headwater basins across the western United States to quantify historical patterns, climatic drivers, and projected changes in base flow. Statistical analyses (base-flow separation, Mann–Kendall, mixed-effects modeling) and cluster-specific Long Short-Term Memory (LSTM) models trained on dynamically downscaled climate data (WUS-D3, CESM2) were used to assess both historical and future conditions. Historical results show widespread base-flow declines, especially in early summer, linked to warming, reduced snowmelt, and declining antecedent moisture. Antecedent moisture is the dominant positive driver across all regions, while snow and temperature exert regime-dependent negative effects. Future projections under SSP2-4.5 and SSP5-8.5 indicate continued base-flow declines of 45–65% by late century, with earlier seasonal peaks and shorter summer flow duration. Snowmelt-dominated and arid basins show the largest relative declines, while mixed-regime basins contribute the greatest volumetric losses. These results highlight the vulnerability of groundwater-supported streamflow to warming and drying trends and demonstrate the value of combining statistical and machine-learning approaches to assess regional-scale climate sensitivity.

## Introduction

Increasing water demand, land-use change, and climate-driven shifts in precipitation are intensifying water scarcity across the western United States (Taylor et al. 2013; Diffenbaugh, Swain, and Touma 2015). Headwater catchments are the primary sources of streamflow, sustaining downstream ecosystems, agriculture, and communities. Globally, headwater systems make up approximately 80% of river networks (Golden et al. 2025) and contribute disproportionately to total streamflow, particularly in mountainous and semi-arid regions (Viviroli, Weingartner, and Messerli 2003). These catchments are critical zones of groundwater–surface water interaction, where recharge, storage, and discharge processes regulate the timing and persistence of streamflow (Thomas C Winter et al. 1998).

Base flow is the sustained portion of streamflow that is derived from groundwater discharge or other delayed sources (U. S. Geological Survey 2018). It provides a surface-water view of the groundater system, maintaining perennial reaches, buffering flow during drought, supporting aquatic habitats, and sustaining downstream water supply. Base flow reflects the integrated response of the watershed to precipitation, snow accumulation and melt, evapotranspiration, and subsurface storage (Smakhtin 2001). As such, base-flow magnitude and timing provide key indicators of groundwater availability and watershed resilience under changing climate conditions (Tague and Grant 2009; Diffenbaugh, Swain, and Touma 2015).

Groundwater recharge, the source of base flow, is highly sensitive to shifts in temperature, snowpack, and precipitation. Warming across the western United States has already reduced snow accumulation, shifted precipitation regimes from snow to rain, and increased evaporative demand (Barnett, Adam, and Lettenmaier 2005; Mote et al. 2018). These changes alter groundwater recharge, advance seasonal streamflow peaks, and diminish late-season flows. However, the magnitude and timing of these effects differ across hydroclimatic regimes. Quantifying regime-specific climatic controls is essential for anticipating water availability under continued warming.

Previous studies have advanced understanding of base-flow variability (Beck et al. 2013; Santhi et al. 2008) and its relationship to climate drivers (Ayers et al. 2022; Tan, Liu, and Tan 2020) in different settings. Extending these analyses to incorporate climate projections is critical for anticipating how groundwater-supported flows, especially in headwater systems, will respond to future climate change. As noted by Golden et al. (2025), a key opportunity in headwater research is to move beyond isolated studies toward an integrative understanding of headwater flow regimes across space and time. This integrated approach is limited by the scarcity of adequately gauged headwater sites and by large-scale analyses that generalize hydrologic behavior across diverse climatic and physiographic settings.

Addressing these challenges requires an approach that captures both the historical evolution and the future trajectory of base flow. While headwater systems responds on the basin scale, the overarching effects of climate change on hydrologic systems is best understood on a regional scale (Gorelick and Zheng 2015). To integrate streamflow–climate relationships across diverse settings, we grouped study sites into distinct hydroclimatic clusters that share similar climatic and physiographic controls on base flow.This clustering links local headwater processes to broader regional patterns, allowing comparison of regime-specific responses to climate forcing. Within this framework, we integrate long-term streamflow observations with climate-driven modeling to examine how base flow has changed, what drives those changes, and how it is likely to evolve under future conditions.

Statistical analyses, including Mann–Kendall trend test, Thiel-Sen slope, and mixed-effects modeling, provide the historical understanding of long-term patterns and are used to quantify climate sensitivity. However, these approaches cannot fully represent nonlinear and time-dependent systems, which are inherent in groundwater–surface water systems (Sivakumar 2009). To shore these gaps, we use cluster-specific Long Short-Term Memory (LSTM) neural networks, which excel at capturing time series dependencies and have been shown to capture complex climate–hydrology interactions (Kratzert, Klotz, et al. 2019). Our cluster-based framework groups basins by shared hydroclimatic characteristics, allowing the LSTM models to resolve regime-specific dynamics and improve regional interpretability.

Our approach forms a regional modelling framework to quantify base-flow changes and identify the climatic drivers shaping long-term trends. Specifically, this study aims to:

1. Quantify seasonal and long-term changes in historic base flow across western U.S. headwater catchments (1950–2024);
2. Identify dominant climate drivers of base-flow variability (1980-2014); and
3. Project future base-flow trajectories using Long Short-term Memory (LSTM) models under both SSP2-4.5 (“Business as usual”) and SSP5-8.5 (“Fossil-fueled Development”) scenarios.

## Data & Methods

### Data

Daily mean discharge data were obtained for 115 U.S. Geological Survey (USGS) streamgages located across the eleven western states [Figure 1](#fig-cluster-map). Streamflow records were downloaded from the USGS National Water Information System for the period of water years 1950–2024 (Geological Survey (U.S.) 2025). Sites were selected to have > 90% daily data completeness, with no gaps exceeding three consecutive years, and to have catchments located entirely within U.S. borders to avoid data restrictions. This period of record provides sufficient length to detect long-term trends and hydrologic regime shifts and encompasses three phases of the Pacific Decadal Oscillation (Newman et al. 2016), reducing the likelihood that results are biased by decadal climate variability. Sites with a dam on the main stem, as reported in the National Inventory of Dams (US Army Corps of Engineers, n.d.), were excluded to reduce the influence of direct flow regulation. Drainage areas ranged from 4 to 21,167 km², with a mean of 1,524 km² and a median of 558 km²

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| Figure 1: Study region and analysis timeline. (a) Study basins across the western United States grouped into four clusters representing distinct hydroclimatic regimes as defined in Section. (b) Study timeline showing observed streamflow (1950–2024) and historical (1980–2013) and projected (2014–2099) climate periods under SSP2-4.5 and SSP5-8.5 scenarios. |

Headwaters have been operational defined as streams with Strahler stream order 1 or 2 (Golden et al. 2025; Freeman, Pringle, and Jackson 2007; Imberger et al. 2023). It’s been found that large-scale stream network datasets may underestimate the extent of localized headwater reaches (Brinkerhoff 2024), indicating that these delineated headwater streams likely represent a minimum bound on actual headwater extent. To overcome this deficiency, in this study, streamgages located on streams of order 1 to 3 were included to capture the cumulative processes of headwater systems. By focusing on headwater systems, we overcome issues of scale that arise from the coarse resolution of national and global models and from the limited availability of catchments with adequate monitoring for both streamflow and climate variables.

Basin boundaries were delineated using the Hydro Network-Linked Data Index from the National Hydrography Dataset (Geological Survey (U.S.) 2025). Across the western United States, headwater systems, as defined above, constitute 88.15% of total river length. To assess the representativeness of study sites, their distribution was compared to the full headwater network across the western United States using Köppen climate classifications and the U.S. Forest Service Watershed Condition Framework. All seven major (two-letter) Köppen climate classes present in the region are represented in the study dataset (Peel, Finlayson, and McMahon 2007). Approximately 90 percent of study basins contained U.S. Forest Service lands, consistent with findings that most western water originates in forested areas (Brown, Hobbins, and Ramirez, n.d.). Across the region, 49.1 percent of forested headwater catchments are considered at risk, defined as Functioning at Risk or Impaired Function, the study basins represent this well with 48.5 percent of forested catchment areas falling into these categories.

Climate data were obtained from the Western United States Dynamically Downscaled Dataset (WUS-D3) (Rahimi et al. 2024), a dynamically downscaled product specifically developed for climate applications in the western United States. WUS-D3 contains simulations from multiple GCMs, including the Community Earth System Model v2 (CESM2) global climate model, downscaled with the Weather Research and Forecasting (WRF) model to a spatial resolution of 9 km (Danabasoglu et al. 2020). Climate forcings from CESM2 were selected because it is the only GCM within the WUS-D3 archive that provides simulations for both the SSP2-4.5 and SSP5-8.5 scenarios, allowing direct comparison of both moderate- and high-emissions futures within the modeling framework. The dataset includes a historical period from 1980 to 2013 and extends through 2099 for future projections. Variables used in this study included daily precipitation, daily mean temperature, daily minimum temperature, and daily maximum temperature. Snow precipitation was calculated by summing daily precipitation on days when maximum temperature was below 0 °C. Antecedent moisture was calculated as the cumulative precipitation over the previous three months, following the approach of Ayers et al. (2022) , and serves as a proxy for short-term water storage within the basin. Monthly, area-weighted climate summaries were calculated for each basin to align with the temporal resolution of the base-flow dataset and support climate–base flow relationship analyses.

### Base-flow Separation

Directly estimating base flow from streamflow records presents unique challenges because it cannot be measured directly at the gauge and must be inferred from the total hydrograph (Eckhardt 2008). Numerous approaches have been developed for separating base flow from total streamflow, including tracer studies (Gonzales et al. 2009), graphical interpolation methods (Institute of Hydrology 1980; Sloto and Crouse 1996) , and digital filtering techniques (Arnold et al. 1995; Eckhardt 2005; Nathan and McMahon 1990). The suitability of these approaches depends on factors such as spatial scale, record length, and study objectives. While the choice of method and parameterization can introduce subjectivity, prior work has shown that digital filters provide reliable and repeatable estimates when applied consistently within a study domain (Chapman 1999; Eckhardt 2005; Institute of Hydrology 1980; Ayers et al. 2022).

In this study we used the Eckhardt (2005) digital filter to estimate base flow from daily streamflow records using this equation:

where is the filtered base-flow response at time step , is the observed streamflow at time step , is the base-flow response at the previous time step, is the recession constant, and is the maximum possible base-flow index for the catchment. The recession constant was estimated for each site through hydrograph recession analysis. was determined for each site using the backwards filter method proposed by Collischonn and Fan (2013), which allows to be estimated from without requiring site-specific hydrogeologic field data. The Eckhardt filter was selected because it has shown strong performance in diverse hydrologic settings across the contiguous United States and has been recommended as a preferred base-flow separation method in large-sample studies (Xie et al. 2020).

### Hydroclimate Clustering

To classify study basins into groups with similar hydroclimatic regimes, we applied k-means clustering to basin-averaged climate and hydrologic variables. Clustering was conducted on long-term records of base flow magnitude and variability, precipitation, snow-derived precipitation, mean temperature, antecedent moisture, and static physiographic attributes including drainage area, relief, and elevation. To compare across watersheds with different areas, precipitation, and discharge, we normalized variables (z-scores) prior to clustering to ensure equal weighting. The optimal number of clusters was selected based on a combination of the elbow method and interpretability of known hydrologic regimes in the western United States. K-means was chosen because it is an efficient method for partitioning basins into internally cohesive groups which minimize within-group variance and enhances the detection of coherent regional trends in streamflow across diverse hydroclimatic settings (Dethier et al. 2020). This approach is well suited for large-sample hydrology applications where hydroclimatic gradients are continuous rather than categorical (Ikotun et al. 2023). The resulting clusters were used to stratify subsequent statistical and machine learning analyses, allowing for the identification of climate–base flow relationships and projected changes within distinct hydrologic response regimes.

### Statistical Models

We used the Mann-Kendall (MK) trend test to determine the presence of trends in the base-flow data at a monthly time-step. The MK test is a nonparametric test that detects monotonic trends in non-normally distributed data. The MK test is widely used in hydrologic studies (Murray, Ayers, and Brookfield 2023; Ayers et al. 2022; Woodhouse and Udall 2022; Chen and Teegavarapu 2021), and was used here to establish statistically significant trends ( < 0.05). Autocorrelation was present in many of the streamflow records used here, as such we employed the modified MK test proposed by Hamed and Ramachandra Rao (1998) . The trend magnitude was estimated using the Thiel-Sen slope, a non-parametric technique widely used in hydrologic studies (Rice et al. 2015; Tillman et al. 2022; Murray, Ayers, and Brookfield 2023).

We used a linear mixed-effects modeling framework to quantify relationships between monthly base flow and climate variables. Fixed effects included precipitation, snow, temperature, and antecedent moisture; which capture broad regional-scale climate drivers. A random intercept for each catchment accounts for site-level variability in base flow that is not explained by the fixed predictors. All models were fit using log-transformed monthly base flow as the response variable to reduce skewness, stabilize variance, and improve model performance. To address strong multicollinearity among the temperature variables (mean, minimum, and maximum daily temperature), we retained only mean temperature in the mixed-effects model to ensure interpretability of parameter estimates. This constraint was applied only in the mixed-effects framework; the LSTM modeling framework retained all three temperature variables, as deep learning approaches do not require independence among predictors and are capable of capturing nonlinear relationships and interactions (Razavi 2021).

### LSTM Neural Network Modeling

#### Model Framework

This model is designed to predict monthly stream base flow using both climate history and watershed characteristics. It combines two types of input data: (1) a sequence of monthly climate variables over the past 24-months, and (2) static basin attributes like latitude, elevation, and area.

To capture monthly flow dynamics, the model was trained using overlapping 24-month climate input sequences (e.g., months 1–24, 2–25, 3–26, etc.), where each sequence was used to predict base flow in the subsequent month ([Figure 2](#fig-lstm_diagram)). This sliding-window approach increases the number of training samples and enables the model to learn temporal dependencies and incremental changes in base flow across consecutive months. The climate sequence is combined with the static features and passed through two fully connected layers (also called dense layers) (Hochreiter and Schmidhuber 1997), with dropout included to reduce overfitting (Srivastava et al. 2014). The final output is a single number: the predicted log-transformed base flow for the subsequent month. The model is trained to minimize the difference between its predictions and observed log(base flow), using a loss function based on mean absolute error (MAE). This hybrid architecture allows the model to learn both temporal patterns and site-specific differences in hydrologic behavior.

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| Figure 2: Structure of the Long Short-term Memory (LSTM) model used to predict monthly base flow. (a) Conceptual layout of the LSTM-based recurrent neural network. (b) Model configuration showing 24-month climate inputs and static basin attributes processed through LSTM, dense, and output layers to predict next-month base flow. |

#### Model Training and Testing

Model training and hyperparameter selection were conducted separately for each hydroclimatic cluster. We tested a range of LSTM configurations varying the number of hidden units, dropout rates, learning rates, and batch sizes. The final hyperparameters were chosen based on minimizing cross-validated mean absolute error (MAE) during the 2006–2013 period (Table S1). Each model used a 24-month input sequence of climate predictors (precipitation, temperature, antecedent moisture indices, snow fraction, and seasonal harmonics) along with static basin characteristics (elevation, relief, drainage area, latitude, longitude). Inputs were standardized using the mean and standard deviation from the training period (1980–2005).

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| Table 1: Predictors used in the LSTM models, grouped by general data type. Variables include raw climate inputs, lagged terms, derived precipitation metrics, static basin attributes, and seasonal harmonics.   | **Data Type** | **Predictor** | **Description** | | --- | --- | --- | | **Temperature** | t2 | Mean monthly near-surface (2 m) air temperature (°C) | |  | t2max | Monthly maximum temperature (°C) | |  | t2min | Monthly minimum temperature (°C) | |  | t2\_lag1 | Mean temperature, 1-month lag | |  | t2\_lag3 | Mean temperature, 3-month lag | | **Precipitation** | prec | Monthly precipitation (mm) | |  | prec\_lag1 | Precipitation, 1-month lag | |  | prec\_lag2 | Precipitation, 2-month lag | |  | prec\_lag3 | Precipitation, 3-month lag | |  | prec\_lag6 | Precipitation, 6-month lag | |  | rolling\_prec3 | 3-month rolling precipitation mean (mm) | |  | ppt\_change | Monthly precipitation change (current minus prior month) | | **Snow / Moisture** | snow | Precipitation falling when t2max < 0 °C (mm) | |  | prec\_mois | Antecedent moisture (3-month precipitation sum) | |  | prec\_mois\_lag1 | Antecedent moisture, 1-month lag | | **Seasonality** | month\_sin | Cyclical encoding of month (sine transform) | |  | month\_cos | Cyclical encoding of month (cosine transform) | | **Basin Attributes** | Area\_km | Watershed area (km²) | |  | Elev\_mean\_m | Mean basin elevation (m) | |  | Elev\_min\_m | Minimum basin elevation (m) | |  | Elev\_max\_m | Maximum basin elevation (m) | |  | Relief\_m | Basin relief (elev. max – elev. min, m) | |

For model evaluation, we validated each cluster-specific LSTM model against climate forcing from the WUS-D3 SSP2-4.5 and SSP5-8.5 datasets and observed base flow (2014–2024). Models were trained on data from 1980–2005 and cross-validated on 2006–2013, then applied to the scenario data to assess predictive skill outside the training period. To reduce sensitivity to initialization, we trained five models per cluster with different random seeds and combined them into a ensemble using the median prediction across seeds. Model skill was quantified using MAE, root mean square error (RMSE), and the Nash–Sutcliffe efficiency (NSE). The ensembled predictions showed improved performance over single-model predictions across clusters and scenarios.

## Results

### Hydroclimate Clustering

The k-means clustering identified four distinct hydroclimatic groups among the 115 study basins, reflecting differences in elevation, relief, basin size, climate regime, and base-flow response characteristics. These clusters capture gradients in snow influence, seasonal precipitation patterns, and base-flow variability across the western United States. Two clusters (1 and 3) are primarily high-elevation, snow-influenced headwaters but differ in their sensitivity to temperature and snowpack persistence. Cluster 2 contains the largest, mixed-regime basins with relatively stable base flow and Cluster 4 represents low-elevation, arid to monsoon-influenced basins with the lowest base flow and highest interannual variability. Descriptive statistics for each cluster, including key climate, physiographic, and base-flow metrics, are provided in [Table 2](#tbl-cluster-summary), and the spatial distribution of clusters across the study area is shown in [Figure 1](#fig-cluster-map).

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| Table 2: Summary of physical, climatic, and base-flow characteristics for each hydroclimatic cluster. Values represent mean conditions for basins within each cluster; base-flow statistics are derived from the full 1950–2024 record. Base flow CV indicates the coefficient of variation ()).   | Cluster | n | Area (km²) | Elev. Mean (m) | Relief (m) | Prec. Mean (mm) | Temp. Mean (°C) | Monthly Base Flow Mean (cfs) | Base Flow CV | | --- | --- | --- | --- | --- | --- | --- | --- | --- | | 1 | 10 | 1193.3 | 2106 | 1930 | 107.48 | 5.51 | 4765 | 1.37 | | 2 | 17 | 4452.2 | 1266 | 2825 | 200.78 | 5.74 | 51840 | 0.74 | | 3 | 50 | 1124.8 | 2330 | 1772 | 85.69 | 3.97 | 4357 | 1.30 | | 4 | 38 | 865.1 | 735 | 1263 | 141.28 | 11.06 | 8071 | 1.77 | |

Cluster 1 (Snowmelt-Dominated Mountain Catchments) occupies steep, high-relief mountain terrain where winter precipitation is primarily stored as snowpack and released during a concentrated late-spring melt period. These basins are located across the study area in high-elevation mountains. Base flow peaks in June, approximately six months after the precipitation maximum, and inter-annual variability is high due to differences in snow accumulation and melt timing.

Cluster 2 (Mixed-Regime Large Catchments) represents moderate-elevation, high-relief basins with the largest drainage areas in the dataset. Most of these basins are found along the Cascade Range in the north west of the study area along CA, OR, and WA, including basins with perennial snow and glaciers (Pelto 2008). Base flow peaks earlier, in May, about five months after the precipitation maximum. Snowmelt remains important, but basin size and integrated flow paths buffer short-term variability, resulting in lower inter-annual variability during peak months.

Cluster 3 (Snowy, Responsive Headwaters) also peaks in June but differs from Cluster 1 in showing a stronger positive association between temperature and base flow, consistent with more immediate snowmelt responses during warm periods. These basins are found throughout the Intermountain West where they may experience earlier onset of melt or mid-winter melt events, leading to sustained base flow through early summer and moderate-to-high interannual variability in late spring.

Cluster 4 (Arid/Monsoon or Ephemeral Basins) occurs at the lowest elevations with minimal snow influence. Base flow peaks in March, only about three months after the precipitation maximum, reflecting rapid winter-to-spring runoff and limited storage. These basins are mostly located along the Pacific coast. Flows recede quickly, and summer base flow is minimal due to high evapotranspiration and low infiltration from monsoon rains.

Across all clusters, precipitation peaks in December, contributing roughly 15–18% of the annual total, and remains elevated through February ([Figure 3](#fig-bf-precip-contrib)). Snowmelt-dominated clusters (1 and 3) exhibit the largest variability in late-spring base flow, whereas Cluster 4 shows the strongest temperature-driven suppression of base flow in the dry season. These distinct seasonal signatures and sensitivities highlight the potential for divergent base-flow responses to future climate change across hydroclimatic regimes.

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| Figure 3: Monthly distribution of base flow and precipitation as a percentage of the annual total, stratified by hydroclimatic cluster. Base-flow boxes are colored by cluster (Cluster 1: green, Cluster 2: red, Cluster 3: yellow, Cluster 4: blue), precipitation is shown in gray. |

### Historical Base-flow Analysis

#### Climate-Base Flow Relationship

When the mixed-effects model was analyzed across all sites [Table 3](#tbl-mixed-effect_all-site), it revealed that antecedent moisture was the most consistently positive and influential driver of base flow across the study region. This supports the role of cumulative recharge and basin memory in sustaining flows, particularly during dry-season months. In contrast, snow precipitation had a strong negative contemporaneous effect in all clusters, consistent with winter accumulation storing water in the snowpack and delaying its release to streams. Mean temperature showed an overall negative association with base flow, suggesting that warmer conditions correspond to seasonal drying, likely through enhanced evapotranspiration or reduced soil moisture. Monthly precipitation had a generally weak to negative effect, with the strongest suppression in arid or monsoon-influenced basins.

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| Table 3: Mixed-effects model results for climate and static predictors of monthly base flow across all study basins. Estimates represent fixed effects on log-transformed base flow, with positive coefficients indicating a positive association and negative coefficients indicating a negative association. Significance codes: \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05; ns = not significant.   | Predictor | Estimate | Std. Error | t-value | Significance | | --- | --- | --- | --- | --- | | Precipitation | -0.085 | 0.009 | -8.99 | \*\*\* | | Snow Precipitation | -0.316 | 0.007 | -42.51 | \*\*\* | | Mean Temperature | -0.079 | 0.009 | -9.03 | \*\*\* | | Antecedent Moisture | 0.477 | 0.009 | 52.50 | \*\*\* | | Mean Elevation | -0.420 | 0.206 | -2.03 | \* | | Relief | 1.059 | 0.225 | 4.70 | \*\*\* | | Area | -0.012 | 0.223 | -0.06 | ns | |

When the model was evaluated by hydroclimatic cluster ([Table 4](#tbl-mixed-effect_cluster)), key differences in climate–base flow relationships emerged. Antecedent moisture remained strongly positive in all groups, with the largest effect in Cluster 4, indicating its particular importance in sustaining flows in water-limited environments. Snow suppression of base flow was strongest in Cluster 1, reflecting the storage-dominated snowmelt regime of steep mountain catchments. Temperature effects varied markedly: Cluster 3, comprising snow-responsive headwaters, was the only group with a positive temperature effect, consistent with warming-induced snowmelt boosting base flow during the transitional period between accumulation and melt. In contrast, Cluster 4 exhibited a strong negative temperature effect, suggesting enhanced evaporative losses or soil moisture depletion during warm periods. Terrain metrics were also important in certain regimes; elevation and relief had the strongest positive effects in Cluster 1, indicating that steep, high-relief basins may enhance routing of melt-water into groundwater and streams. Basin area had limited influence in most clusters but was strongly negative in Cluster 4, potentially reflecting inefficient runoff generation or storage losses in large, low-relief arid basins.

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| Table 4: Mixed-effects model estimates for climate and static predictors of monthly base flow, stratified by hydroclimatic cluster. Estimates represent fixed-effects on log-transformed base flow; positive values indicate a positive association and negative values indicate a negative association.   | Variable | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | | --- | --- | --- | --- | --- | | Precipitation | -0.075 | -0.139 | -0.015 | -0.227 | | Snow Precipitation | -0.369 | -0.124 | -0.286 | -0.125 | | Mean Temperature | -0.064 | -0.104 | 0.325 | -0.568 | | Antecedent Moisture | 0.417 | 0.354 | 0.412 | 0.548 | | Mean Elevation | 0.474 | -0.402 | 0.031 | -0.268 | | Relief | 1.153 | 0.059 | 0.657 | -0.168 | | Area | 0.219 | -0.172 | 0.325 | -0.480 | |

These results highlight that while antecedent moisture is a dominant control on base flow in all regimes, the influence of snow, temperature, and terrain varies systematically across hydroclimatic clusters. These distinctions underscore the value of classification-informed modeling for understanding and projecting base-flow responses to climate variability and change.

#### Base-Flow Trends and Seasonality

Across the four hydroclimatic clusters, long-term, historical base-flow trends (1950-2024) varied in both magnitude and seasonal timing ([Table 5](#tbl-bf-trend_cluster); [Figure 4](#fig-hist_trends_monthly)). The most widespread declines occurred in early summer, especially in June and July, consistent with reductions in snowmelt-driven base flow. Historical rates in [Table 5](#tbl-bf-trend_cluster) are continuous Theil-Sen slopes (trend per decade) rather than baseline-referenced anomalies, and are thus not expressed in the same units as projected annual change (Section 3.3). Modest increases were observed in winter and early spring months, particularly January and March in Cluster 1 and March–April in Cluster 3. Cluster 1 showed a mix of increases in colder months and decreases in summer, resulting in a small overall positive annual trend. Cluster 2 exhibited consistent and large negative trends across nearly all months, with the strongest declines in February, June, and December. Clusters 3 and 4 showed modest negative trends overall, with variability in both direction and timing depending on the month. These patterns highlight seasonal shifts in base flow that differ across hydroclimatic regimes.

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| Table 5: Median monthly base-flow trends by hydroclimatic cluster for 1950–2024, shown as percent change **per decade** from Theil–Sen slope estimates. Positive values indicate increasing base flow; negative values indicate decreasing base flow. “Pct. Sig. Up” and “Pct. Sig. Down” show the percentage of sites with statistically significant (p < 0.05) positive or negative trends.   | Cluster | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Median Trend | Pct. Sig. Up | Pct. Sig. Down | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | 1 | 1.22 | 0.38 | 5.60 | 3.92 | 0.50 | -1.31 | -1.71 | 0.08 | -3.22 | -0.64 | 3.14 | 1.10 | 0.44 | 20.69 | 16.38 | | 2 | -0.39 | -3.75 | -0.24 | -1.28 | -1.63 | -3.54 | -3.71 | -2.79 | -3.04 | -2.59 | -1.10 | -2.31 | -2.45 | 1.47 | 30.39 | | 3 | -0.61 | -0.95 | 1.12 | 1.12 | 0.04 | -2.33 | -3.10 | -3.26 | -2.25 | -0.92 | -0.77 | -1.81 | -0.94 | 8.60 | 17.37 | | 4 | -0.13 | -4.27 | 0.32 | 0.00 | -0.11 | -0.37 | -1.92 | -2.75 | -3.54 | -3.28 | -0.88 | -2.35 | -1.40 | 12.79 | 18.84 | |

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| Figure 4: Historic monthly base-flow trends across western U.S. headwater basins (1950-2024), colored by Theil–Sen slope and shaped by statistical significance. Upward- and downward-pointing triangles indicate significant increasing or decreasing trends (p < 0.05), respectively, while circles denote non-significant trends. Colors correspond to slope magnitude and direction, with warmer tones indicating negative trends and cooler tones indicating positive trends. |

### Projected Base-flow Analysis

#### Model Validation

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| Figure 5: Observed vs. predicted monthly log-transformed base flow for the ensemble LSTM models across four hydroclimatic clusters under two climate scenarios (SSP2-4.5 and SSP5-8.5). Each panel shows one cluster and scenario combination. The 1:1 dashed line indicates perfect prediction. Performance metrics (MAE, RMSE, NSE) are shown within each facet, demonstrating consistent model skill across clusters and scenarios, with strongest performance in Clusters 2 and 3 and higher variance in Cluster 4. |

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| Table 6: Ensemble LSTM evaluation metrics (MAE, RMSE, NSE) for each hydroclimatic cluster under SSP2-4.5 and SSP5-8.5 (2014–2024).   | Cluster | Scenario | MAE | RMSE | NSE | | --- | --- | --- | --- | --- | | 1 | SSP2-4.5 | 0.72 | 1.16 | 0.79 | |  | SSP5-8.5 | 0.69 | 1.10 | 0.81 | | 2 | SSP2-4.5 | 0.42 | 0.54 | 0.77 | |  | SSP5-8.5 | 0.42 | 0.54 | 0.77 | | 3 | SSP2-4.5 | 0.68 | 1.06 | 0.80 | |  | SSP5-8.5 | 0.65 | 1.00 | 0.82 | | 4 | SSP2-4.5 | 1.14 | 1.76 | 0.79 | |  | SSP5-8.5 | 1.13 | 1.73 | 0.80 | |

Model performance was evaluated using observed versus predicted monthly log-transformed base flow for each hydroclimatic cluster and future climate scenario ([Figure 5](#fig-obs_pred); [Table 6](#tbl-model_eval)). The ensemble LSTM models demonstrated strong predictive skill across all clusters and both climate scenarios during the validation period (2014–2024). Performance was highest for Clusters 2 and 3, with low MAE (0.42–0.68), low RMSE (<1.1), and high NSE (0.77–0.82), indicating accurate prediction of both magnitude and variability in monthly base flow. Cluster 1 showed moderate skill (MAE ≈ 0.7, NSE ≈ 0.8), while Cluster 4 had the largest errors (MAE ≈ 1.1–1.2, RMSE ≈ 1.7, NSE ≈ 0.8), reflecting the difficulty of modeling base flow in arid and monsoon-influenced basins. While Cluster 4 had higher errors, it retained good NSE due to stronger performance at higher flows, while low-flow values were more weakly predicted. Model skill was consistent between SSP2-4.5 and SSP5-8.5, indicating robustness across climate forcings.

In [Figure 5](#fig-obs_pred), the vertical alignment of points at very low observed values arises from two factors. First, a minimum threshold applied before log-transformation set all flows ≤0.01 cfs to the same log value, creating an artificial “fence” effect. Secondly, because the models were trained using MAE on log(base flow), errors at very low flows were weighted less by the loss function, reducing accuracy at low values, where observations are inherently noisy. Residual distributions are shown in Figures S1 and S2.

#### Magnitude and Scenario Dependence

Projections indicate persistent declines in base flow across western U.S. headwater systems throughout the 21st century, with the magnitude of reductions varying between emission scenarios ([Figure 6](#fig-annualized_anomaly) a). Relative to the 1980–2013 baseline, projected base flow under both SSP2-4.5 and SSP5-8.5 shows similar early-century (2025–2049) anomalies, followed by continued declines through the mid- (2050–2074) and late-century (2075–2099) periods. Trajectories remain comparable through mid-century in both scenarios, but, by late-century, SSP5-8.5 produces substantially larger reductions and greater inter-site variability ([Figure 6](#fig-annualized_anomaly) a).

Early-century base-flow anomalies are projected to range from –30 to –40 %, corresponding to basin-averaged losses of 3.0–3.4 million AF yr⁻¹. Mid-century reductions deepen to –40 to –50 % (3.6–4.1 million AF yr⁻¹), and by late-century, annual anomalies reach –45 to –65 %, or roughly 3.7–5.8 million AF yr⁻¹, relative to the 1980–2013 baseline ([Figure 6](#fig-annualized_anomaly) b). These patterns indicate that while early-century changes are similar across scenarios, the high-emission SSP5-8.5 pathway drives markedly greater declines in the late-century.

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| Figure 6: Projected magnitude of base-flow change across western U.S. headwaters under SSP2-4.5 and SSP5-8.5 scenarios. (a) Regional annual base-flow anomalies (percent difference from the 1980–2013 mean) with shaded 25–75 % ranges across basins. Both scenarios project sustained declines through the 21st century, with greater divergence after ~2050. Median losses are ~30–40 % by mid-century and ~45–65 % by late century. (b) Cluster-balanced mean annual volumetric change (million acre-feet yr⁻¹) summarized by period and scenario. Region-wide average losses equal approximately –3.7 million AF yr⁻¹ for SSP2-4.5 and –5.7 million AF yr⁻¹ for SSP5-8.5 by end-of-century, emphasizing the greater depletion expected under higher-emission conditions. |

#### Relative and Absolute Cluster Change

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| Figure 7: Monthly base-flow anomalies by hydroclimatic cluster, period, and emissions scenario. (a) Percent anomalies show the relative change in base-flow volume compared to the 1980–2013 baseline, summarized by cluster medians. Snow- and monsoon-influenced clusters (1 and 4) exhibit the largest relative declines, while Cluster 2 experiences smaller proportional reductions. (b) Corresponding volumetric anomalies (million acre-feet per month) highlight the absolute magnitude of change. Despite modest percent reductions, Cluster 2 contributes the greatest total volume loss across all future periods. |

Cluster-level projections reveal clear heterogeneity in base-flow responses between hydroclimatic clusters ([Figure 7](#fig-monthly-anomaly_period)). Snowy, responsive Cluster 3 and arid/monsoon-influenced Cluster 4 exhibit the largest relative declines, with median reductions of ~80–90 % by late-century under SSP5-8.5 ([Figure 7](#fig-monthly-anomaly_period) a). Cluster 1, snow-dominated mountainous catchments, showed less declines in the summer and fall. In contrast, mixed-regime Cluster 2 shows more moderate, but variable, relative declines of ~20–70% throughout the year, likely due to its larger size and integrated flow paths buffering against extreme variability. When considering absolute volumetric changes ([Figure 7](#fig-monthly-anomaly_period) b), Cluster 2 contributes the greatest monthly losses (≈0.5-3 million AF mo⁻¹) across all future periods, despite its smaller relative declines. This reflects its’ larger base-flow volumes and highlights the importance of considering both relative sensitivity (percent) and hydrologic significance (volume) when assessing climate impacts on streamflow.

#### Changes in Base-flow Timing

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| Figure 8: Monthly change in base-flow contribution by hydroclimatic cluster for end-of-century projections relative to the 1980–2013 baseline. Colored lines show SSP2-4.5 (blue) and SSP5-8.5 (red). Clusters 1–3 exhibit modest winter–spring increases and strong summer declines (up to ~5 %), while Cluster 4 shows earlier winter peaks and sustained reductions through summer. These shifts indicate earlier groundwater discharge and reduced summer base-flow persistence under warmer futures. |

Projected base-flow anomalies show clear shifts in seasonal timing ([Figure 8](#fig-monthly-contrib)). Relative to the 1980–2013 baseline, future projections indicate earlier contributions in spring and pronounced reductions in late-summer base flow, particularly under SSP5-8.5. The greatest reductions in base-flow contribution are seen in June across all clusters. Clusters 1, 2, and 3 exhibit modest winter–spring increases of approximately 1–5 %, followed by strong summer declines reaching −4 to −5 % of annual base flow. Cluster 4, the most water-limited regime, displays an earlier winter peak (~5 %) and sustained reductions through summer and fall. These patterns suggest earlier groundwater release and diminished late-season persistence, consistent with warming-driven snowpack loss, reduced recharge, and earlier runoff timing in snowmelt-dominated basins.

## Discussion

### Overview of main findings

The results of this study reveal consistent regional patterns of declining base flow across western U.S. headwaters, with the strongest reductions occurring in snow- and mixed-regime basins and more moderate declines in arid and transitional systems. These trends reflect both a long-term downward trajectory in annual base flow and a shift toward earlier seasonal contributions, which is consistent with observed warming and snowpack loss throughout the region (Barnett, Adam, and Lettenmaier 2005; Carroll et al. 2024). Relative base-flow reductions in Cluster 2 align with previous findings from the Pacific Northwest, where declining low-flow quantiles have been attributed to temperature-driven decreases in snowpack and late-season recharge (Luce and Holden 2009). Across clusters, base flow is most sensitive to antecedent moisture and snow contributions, echoing nationwide patterns identified by Ayers et al. (2022). Looking forward, LSTM projections indicate continued annual declines culminating in 45–65% reductions by late century under both SSP2-4.5 and SSP5-8.5 scenarios. Together, these findings provide a regionally consistent, climate–based synthesis of base-flow behavior across western U.S. headwaters, building on recent calls to integrate diverse headwater systems into coherent regional frameworks (Golden et al. 2025; Beck et al. 2013).

### Historical base-flow changes and climate drivers

Observed historical declines in base flow across western U.S. headwaters reflect a combination of warming-driven snowpack loss, earlier snowmelt, and increasing evaporative demand. Our results show reductions in late-summer and early-autumn base flow ([Figure 4](#fig-hist_trends_monthly)), consistent with widespread evidence of hydrologic timing shifts over the past half century. These patterns are consistent with observed and projected trends toward warmer winters, rain-on-snow events, and earlier peak flows in snow-dominated basins (Musselman et al. 2018). Stewart, Cayan, and Dettinger (2005) documented regional advances of spring snowmelt and streamflow by 1–4 weeks across western North America, driven primarily by rising winter and spring temperatures. Similarly, Mote et al. (2018) found that over 90% of long-term snow monitoring sites in the western U.S. show declining snow water equivalent, with the greatest losses occurring in transitional snow regimes typical of the PNW. These findings align with the patterns we observe in snow-dominated and mixed-regime clusters (Clusters 1-3), where reduced snowpack storage and earlier melt have translated into diminished groundwater recharge and shortened base-flow duration.

The link between reduced snow storage and declining summer flow has been widely recognized in mountain systems (Tague and Grant 2009; Safeeq et al. 2013). In our analysis, the strongest base-flow declines occurred in clusters with large snowmelt contributions and steep topographic gradients ([Table 5](#tbl-bf-trend_cluster)), regions where snow loss directly limits recharge. Tague and Grant (2009) found that in the Cascades range in Oregon, summer streamflow declines were four times greater that in fast-draining basins, emphasizing how subsurface storage capacity controls the sensitivity of base flow to warming. Our results echo this relationship: catchments with greater storage or higher antecedent moisture exhibit smaller declines, suggesting that storage buffers can offset some climatic drying.

Antecedent moisture emerged as the dominant positive predictor of base flow in our mixed-effects models, highlighting the importance of soil–groundwater storage in sustaining streamflow between storm events. Similar results were reported by Ayers et al. (2021) and Ayers et al. (2022), which identified antecedent moisture as the most consistent driver of base-flow variability across the conterminous U.S. These findings emphasize that even in warming climates, multiseasonal storage integration can maintain low flows when recharge is insufficient. In some regions, this effect may counterbalance drying trends. For example, Douglas, Vogel, and Kroll (2000) suggests that increased rainfall, in place of snow, can enhance shallow groundwater storage, potentially raising low flows even as high flows decline. This mechanism may explain the modest increases we observed in winter base flow in some transitional basins.

Conversely, the combined effects of warming and rising evapotranspiration (ET) are likely accelerating groundwater depletion and constraining recharge, particularly in non-snowmelt-dominated systems. Condon, Atchley, and Maxwell (2020) demonstrated that increased ET under warming leads to net groundwater loss across the contiguous U.S., even in regions with stable precipitation. In our study, these dynamics are evident in Cluster 4, where elevated temperatures coincide with persistently low base-flow fractions. These responses emphasize the role of water balance partitioning to determine the direction, magnitude, and leading caue of base-flow change across regimes.

In all, these results illustrate the regime-dependent nature of base-flow responses to climate forcing. Snow-dominated systems show the largest relative declines, consistent with reduced snowpack and earlier melt (Stewart, Cayan, and Dettinger 2005; Mote et al. 2018). Mixed regimes exhibit middling declines, reflecting both snow loss and modest recharge from rainfall. Non-snowmelt-dominated basins remain most limited by storage and precipitation frequency, with warming-driven ET likely outweighing the potential of rainfall gains. These findings align with the broader understanding of hydrologic partitioning in the critical zone where catchments with greater subsurface permeability and snow-derived recharge maintain higher base-flow indices and reduced sensitivity to seasonal drying (Wlostowski et al. 2021). Our regional synthesis thus reinforces that the sensitivity of base flow to climate is mediated by both the magnitude and timing of water inputs and by the storage characteristics that regulate basin streamflow.

### Spatial heterogeneity and cluster-based insights

We developed a set of base-flow-specific clusters following the principles outlined by Olden, Kennard, and Pusey (2012), classifying basins based on data-driven hydrologic and climate attributes tailored to groundwater-surface water interactions rather than pre-defined regions. Regional hydroclimatic clustering provides a powerful framework for interpreting base-flow variability across diverse headwater systems. This method minimizes within-group variability (including differences in elevation, snowmelt timing, and precipitation regime) while maximizing between-group contrast. Similar to the hydro-region framework of Dethier et al. (2020), our cluster-based method allows for the identification of regionally consistent signals in base-flow behavior and climate response. This methodology supports the idea that hydrologic similarity can be identified empirically through shared climatic and physiographic attributes, as emphasized by Wagener et al. (2007) and Beck et al. (2020).

Differences among clusters reveal distinct climate–base-flow relationships driven by regional water balance controls. In snow-dominated systems (Cluster 1, 3), snow precipitation and melt timing govern interannual variability, while in transitional and mixed regimes (Cluster 2), the balance between rainfall and antecedent moisture determines the persistence of base flow. Arid clusters (Cluster 4) are most sensitive to temperature-driven evapotranspiration and storage limitation, showing weak climatic elasticity and minimal recovery following droughts. These contrasting responses mirror the spatial structure of recharge and storage capacity across the western U.S. and show how hydrologic regimes operate along a spectrum from energy- to water-limited systems. Importantly, the clustering approach offers a scalable framework for regional hydrologic modeling, enabling data-driven models, such as LSTMs, to learn regime-specific dynamics more effectively [Kratzert, Herrnegger, et al. (2019); Lees et al. (2022). This framework strengthens the integrative understanding of headwater behavior across space and time suggested by Golden et al. (2025) and provides a path towards multi-regime hydrologic synthesis.

### Future baseflow trajectories and implications for water resources

Our projections indicate substantial, continued base-flow declines of roughly 45–65% by late century depending on SSP2-4.5 and SSP5-8.5 scenarios, along with earlier seasonal peaks and shorter summer flow duration. The greatest relative declines occur in snow-dominated basins and monsoon-influenced basins (Clusters 3, 4), while mixed regimes experience the largest total losses (Cluster 2). These trends align with broader projections of warming, drying, and increased drought frequency across the western United States (Diffenbaugh, Swain, and Touma 2015).

Earlier base-flow timing and reduced late-season flow may have important consequences for aquatic ecosystems and downstream water supply reliability. For water management, these shifts suggest that existing reservoir operations and drought plans, which are often based on historical flow timing, may become less effective. Increasingly variable and intermittent flow regimes could make it more difficult to meet environmental flow needs and sustain base-flow-dependent systems (Hammond et al. 2021).

Direct comparisons between SSP2-4.5 and SSP5-8.5 emphasize how emissions pathways amplify base-flow declines. Although anomalies under both scenarios overlap through mid-century, divergence becomes more evident after ~2060. By late-century, basins under SSP5-8.5 are projected to experience 10–20% larger declines relative to SSP2-4.5 ([Figure 6](#fig-annualized_anomaly)), with the gap particularly pronounced in snowmelt-dominated regions ([Figure 7](#fig-monthly-anomaly_period)). These contrasts underscore the long-term importance of emissions mitigation in reducing the magnitude of base-flow losses across western headwaters.

While some uncertainty remains due to model structure, climate forcing, and the nonstationary nature of hydrologic systems (Milly et al. 2008), the direction of change is consistent across scenarios and clusters. The integration of statistical trend analysis with cluster-specific LSTM models captures both linear sensitivities and nonlinear climate–hydrology interactions (Kratzert, Herrnegger, et al. 2019), providing a more complete picture of how groundwater-supported flow may evolve under future warming. Continued efforts to couple machine learning with process-based understanding and to expand headwater monitoring networks will be essential for improving projections and supporting climate-resilient water management.

### Methodological advances and integration of statistical + machine learning approaches

By combining statistical and machine learning approaches, this study bridges historical interpretation with predictive modeling to better understand base-flow dynamics across diverse hydroclimatic regimes. Statistical models provide interpretable estimates of long-term change and quantify the strength of climatic drivers, aligning with similar approaches in previous studies linking base flow to precipitation, temperature, and snow metrics (Ayers et al. 2022; Murray, Ayers, and Brookfield 2023). However, these linear models are limited in their ability to capture the nonlinear, lagged feedbacks that characterize groundwater–surface water interactions. Integrating LSTM neural networks addressed this gap, allowing the detection of complex, time-dependent relationships between climate inputs and base-flow responses that vary seasonally and across clusters.

Across hydroclimatic clusters, the LSTM models successfully captured both the magnitude and variability headwater base flow. In particular, the models accurately reproduced seasonal lags between climate forcings and streamflow response. Model performance was strongest in snow- and mixed-regime basins where long-term climate signals are more coherent, while arid clusters exhibited higher uncertainty due to more variation in low-flows and weaker climate–base-flow relationships. These factors highlight the importance of dataset length, cluster representativeness, and model transferability when applying deep learning to hydrologic prediction. Even so, the hybrid framework demonstrated how process-informed statistical analyses and data-driven models can complement one another with statistical methods identifying dominant drivers and LSTMs modeling their nonlinear integration. This approach attempts to answer recent calls for *process-based machine learning* (Shen et al. 2023; Nearing et al. 2021) and contributes to emerging efforts to combine empirical studies, physical understanding, and regional synthesis in hydrologic science (Kratzert, Herrnegger, et al. 2019; Golden et al. 2025).

### Implications and future directions

Our projections rely on CESM2 from the WUS-D3 dataset, as it is the only GCM with full coverage for both SSP2-4.5 and SSP5-8.5 in this region-specific dataset. Using a single model ensures internal consistency between scenarios but narrows the range of climate uncertainty represented. Future work should incorporate multi-GCM ensembles to assess the robustness of projected declines and to quantify scenario and model spread.

Our results point to heightened vulnerability of groundwater-supported flow under continued aridification, with the greatest risks during late summer and early autumn when ecological needs and human demands converge. Protecting and managing headwaters, where groundwater–surface water exchange sustains downstream supply, will require strategies that prioritize aquatic refugia, riparian and meadow restoration, and recharge-enhancing practices. This is in line with recent calls to elevate headwaters in conservation and policy frameworks (Golden et al. 2025; McDonnell et al. 2007; Creed et al. 2017). Growing non-perennial segments and increased intermitent flow emphasize the need to integrate headwater systems into regional water-management planning, including environmental flow targets that explicitly account for declining base flow and earlier seasonal timing (Datry, Larned, and Tockner 2014).

Future work should prioritize reducing uncertainty and improving the decision-making relevance of base-flow projections. Expanding monitoring in data-sparse regions, especially in non-perennial reaches and headwater catchments, will be critical for capturing emerging hydrologic change. The hybrid modeling framework used here, which couples LSTM models (to capture nonlinear, lagged responses) with process-based or statistical models, can improve model transferability across regimes and can help bridge knowledge gaps in the near term. To better constrain possible climate futures, future analyses should draw on multi-model climate ensembles that capture a broader range of warming and precipitation trajectories. The cluster-based framework presented in this study provides a scalable way to generalize climate–streamflow relationships and to translate insights between site-level and regional scales. Together, these steps can strengthen the connection between scientific knowledge and water management, by putting forth a headwater-focused approach to climate resilience that recognizes base flow as a key indicator of groundwater-surface water connectivity, watershed health, and water-supply reliability.

## Conclusions

This study analyzed base-flow trends and seasonality across western U.S. headwaters to understand both historical patterns and future changes under different climate scenarios. We found persistent regional declines in base-flow volume that are projected to continue and intensify through the 21st century, regardless of emissions pathway. Along with these volumetric reductions, base-flow contributions are expected to shift earlier in the year, with earlier spring peaks and lower summer flows. Using cluster-wise LSTM models, which captured both temporal and spatial heterogeneity, we modeled distinct hydroclimatic responses that reflect the diversity of western headwater systems.

The four hydroclimatic clusters highlight meaningful contrasts in both historical base-flow behavior and climate sensitivity. Clusters 1 and 3 are both snowmelt-dominated but differ in how temperature affects flow. Cluster 1 shows pronounced snow suppression and a weakly negative temperature effect, reflecting delayed melt and storage-dominated runoff. In contrast, Cluster 3 exhibits a positive temperature effect, consistent with enhanced snowmelt contributions to base flow during transitional warming periods. Cluster 2 exhibits the smallest projected declines, likely reflecting the buffering influence of perennial snow and glacier melt in the Cascade Range. In contrast, Cluster 4 is characterized by low and highly variable base flow, dominated by short recharge events and strong evaporative losses typical of arid and monsoon-driven systems. These distinctions highlight how physiographic and climatic setting shape base-flow resilience and provide a meaningful framework for interpreting spatial and cluster-wise hydrologic change.

Antecedent moisture was consistently the most positive driver of base flow, emphasizing that cumulative recharge is key in sustaining groundwater-supported streamflow. Snow precipitation had strong negative effects, while temperature and precipitation effects varied by regime with positive effects in snow-responsive basins and negative effects in arid basins. Future projections indicate continued declines in base flow across all clusters, with regional reductions of between 45–65% by late century depending on climate scenario. Although early-century changes are similar across scenarios, stronger declines and greater variability emerge after mid-century under higher emissions.

Overall, our results show that base flow in western headwaters is highly sensitive to both temperature-driven hydrologic shifts and long-term wetness conditions. Earlier runoff timing and reduced summer flows will likely worsen late-season water scarcity, ecosystem stress, and wildfire risk. By combining statistical and machine-learning approaches, this work offers a framework for identifying climate-sensitive hydrologic regimes and improving regional water management under a warming climate.

## Acknowledgments

## Open research

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