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

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Abstract

Headwater streams comprise approximately 88% of the stream network in the western United States and serve as critical sources of the nation’s water supply. In the 11 western states, nearly 66% of the water originates on federal lands, with forested lands alone providing over half of this contribution. These headwaters yield disproportionately high volumes of water and are vital for sustaining downstream ecosystems and communities. Yet many of these forests are already degraded or at risk, underscoring the vulnerability of these systems. Headwater systems are especially sensitive to drought and climate change, which alter stream water balance, chemistry, and ecological function. As droughts intensify, streams increasingly rely on groundwater to maintain flow, especially during low-flow periods when base flow can become the primary source of discharge. This dependence is expected to grow under future climate scenarios. Understanding long-term trends in base flow and its drivers is essential for anticipating climate impacts and guiding restoration and protection efforts. This study addresses these challenges by analyzing 75 years of streamflow records to quantify historical patterns and trends in base flow across western U.S. headwaters. Using base-flow separation techniques, the Mann-Kendall trend test, and the Theil-Sen estimator, we identify regional shifts in base-flow magnitude, timing, and variability, and link these patterns to key climatic drivers such as precipitation and temperature. Regional climate projections (SSP2-4.5 and SSP5-8.5) are used to estimate future base-flow responses under low- and high-emission scenarios. Our results will provide critical insight into the past and future of groundwater-supported flows in sensitive headwater systems. By bridging the gap between regional-scale hydrologic projections and fine-scale headwater dynamics, this work aids efforts to monitor and manage headwater systems for long-term ecosystem and community resilience in an era of increasing aridity.

## Introduction

### Importance of base flow in headwater systems

* Headwaters contribute disproportionately to total streamflow in the western US
* Base flow maintains perennial reaches, supports aquatic ecosystems, and buffers downstream water supply during drought
* Critical zones of groundwater–surface water interaction where recharge, storage, and release occur

### Sensitivity to climate variability and change

* Base flow reflects integrated watershed response to precipitation, snowpack dynamics, evapotranspiration, and groundwater storage
* Climate warming drives earlier snowmelt, reduced snowpack, and phase shifts from snow to rain - expected shifts, shifts in streamflow (CITE?)
  + Anticipated changes include greater variability, altered seasonality, and diminished summer/early-fall flows

### Knowledge gap

* Prior work has focused on either long-term streamflow trends or site-specific base flow studies, but regional synthesis are less common
  + Limited understanding of how seasonality shifts across diverse settings
* Uncertainty remains about how climate change will reshape base flow across temporal and spatial scales

### Motivation

* Integrate observational and modeling approaches to address both historical patterns and future projections
  + Bridge statistical analysis (trends, sensitivity) with machine learning models capable of handling nonlinear climate–hydrology relationships
* Provide insights into regional water resource vulnerability under climate change

### Objectives

1. Quantify seasonal and long-term changes in base flow across western U.S. headwater catchments (1950–2024)
2. Identify dominant climate drivers of base-flow variability
3. Project future base-flow trajectories using LSTM models under both SSP2-4.5 and SSP5-8.5 scenarios

## Data & Methods

### Data

Daily mean discharge data were obtained for 115 U.S. Geological Survey (USGS) streamgages located across the eleven western United States (FIG - STUDY AREA). 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. 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. 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.

FIG - STUDY AREA

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). 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. In this analysis, streamgages located on streams of order 1 to 3 were included to capture cumulative processes in 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 streams, 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) . CESM2 was 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 2014 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 some subjectivity, prior work has shown that digital filters can 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 mean values of base flow magnitude and variability, precipitation, snow-derived precipitation, mean temperature, antecedent wetness, and static physiographic attributes including drainage area, relief, and elevation. Variables were standardized (z-scores) prior to clustering to ensure equal weighting across metrics with different units and magnitudes. 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 provides a transparent, reproducible, and computationally efficient method for partitioning basins into internally cohesive and externally distinct groups. 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 baseflow 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 12-months, and (2) static basin attributes like latitude, elevation, and area.

The climate sequence is passed through a Long Short-Term Memory (LSTM) layer, which learns patterns and memory from time series data. The output of this LSTM is combined with the static features and passed through two fully connected layers (also called dense layers) (Hochreiter and Schmidhuber 1997). Dropout layers are included to reduce overfitting. The final output is a single number: the predicted log-transformed base flow. 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.

??FIGURE??

#### 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 cross-validated mean absolute error (MAE) during the 2006–2013 period. Each model used a 12-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).

??Hyperparams and residuals in SI??

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.

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| Table 1: 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 | 0.852 | 1.70 | 0.708 | |  | SSP5-8.5 | 0.811 | 1.64 | 0.730 | | 2 | SSP2-4.5 | 0.438 | 0.558 | 0.750 | |  | SSP5-8.5 | 0.432 | 0.552 | 0.755 | | 3 | SSP2-4.5 | 0.699 | 1.19 | 0.804 | |  | SSP5-8.5 | 0.668 | 1.13 | 0.823 | | 4 | SSP2-4.5 | 1.43 | 2.55 | 0.714 | |  | SSP5-8.5 | 1.40 | 2.49 | 0.727 | |

## 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 key 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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| Figure 1: Spatial distribution of study streamgages across the western United States, colored by hydroclimatic cluster. Clusters reflect differences in elevation, snow influence, base-flow magnitude, and seasonality. Basins were grouped using k-means clustering on long-term climate and physiographic attributes. |

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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. 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 (Snow-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 2](#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 2: Monthly distribution of baseflow and precipitation as a percentage of the annual total, stratified by hydroclimatic cluster. Baseflow 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 wetness 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 Code | | --- | --- | --- | --- | --- | | 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 wetness 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 accumulation–melt transition period. 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 enhance routing of meltwater 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 | |

Together, 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 base-flow trends (1950-2024) varied in both magnitude and seasonal timing [Table 5](#tbl-bf-trend_cluster). The largest decreases in these groups occurred in early summer, particularly June and July, consistent with reduced snowmelt contributions. Modest increases were observed in midwinter months such as January and March in Cluster 1, and April in Cluster 3, though these gains were outweighed by summer declines. Clusters 1, 3, and 4 generally showed small to moderate changes, with a mix of positive and negative trends. In contrast, Cluster 2 exhibited large, widespread negative trends across nearly all months, with the most severe decreases in February, June, and December, and a median annual decline exceeding 50% per decade. These pronounced decreases may reflect reduced snowpack and a shift in precipitation phase from snow to rain, increasing the frequency of rain-on-snow events and accelerating seasonal runoff (Musselman et al. 2018).

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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 Annual Trend | Pct. Sig. Up | Pct. Sig. Down | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | 1 | 1.03 | 0.33 | 2.13 | 1.67 | 0.97 | -5.08 | -2.45 | 0.02 | -0.82 | -0.16 | 0.32 | 0.42 | 0.33 | 50.00 | 50.00 | | 2 | -7.62 | -150.49 | -19.86 | -59.72 | -80.37 | -235.58 | -85.41 | -53.45 | -44.44 | -50.54 | -29.95 | -115.73 | -74.55 | 17.65 | 88.24 | | 3 | -0.18 | -0.23 | 0.14 | 0.73 | 0.01 | -6.38 | -4.08 | -2.12 | -0.76 | -0.22 | -0.37 | -0.59 | -0.41 | 44.00 | 44.00 | | 4 | -0.04 | -9.92 | 0.04 | 0.00 | 0.00 | -0.02 | -0.10 | -0.88 | -1.02 | -1.30 | 0.00 | -6.59 | -3.58 | 31.58 | 63.16 | |

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| Figure 3: 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 4: 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. |

In [Figure 4](#fig-obs_pred), the vertical alignment of points at very low observed values reflects two interacting factors. First, a minimum threshold was imposed on base-flow values prior to log-transformation which made all flows ≤0.001 equal to the same log value. This creates an artificial “fence” of points along the lower bound of the observed axis. Secondly, the LSTM models themselves show weaker skill in reproducing extremely low flows. Because the model was trained using MAE on log(base flow), errors at very low flows contribute less to the loss, and these flows are also noisier and harder to predict. As a result, predictions scatter around the imposed minimum threshold instead of following the 1:1 line.

#### Base-Flow Projections

* predictions produced by scenario (SSP245 vs 585) and future time period
  + time periods: early (2025-2049), mid (2050-2074), late (2075-2099)
* Look at seasonality shifts (contribution shift), monthly anomalies from baseline (1980-2013),

##### Temporal Variability of Projected Base Flow

##### Spatial Variability

## Discussion

* Summary of key findings
* Historical trends + Climate sensitivity
* Model Performance and Validation
* Projected changes in vase flow (future periods)
* Spatial and cluster-wise differences
* Ecological/Water resource implications
* Comparison with Prior Work
* Limitations, Uncertainty, Future Directions

## Conclusions

## Acknowledgments

## Open research

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