Surface Water Information Modeling System (SWIMS)

Declining Summer Streamflow and Weakening PDO Teleconnections in Oregon

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Abstract

Climate change influences on streamflow are globally variable and difficult to quantify due to the confounding effects of climate oscillations and water management activities. Within the Pacific Northwest, Oregon supports extensive irrigated agriculture, globally important aquatic ecosystems, and a high prevalence of snow-dominated watersheds, making the region socioeconomically and ecohydrologically vulnerable to climate change. Using an information-theoretic framework, streamflow stationarity was assessed at 51 low-disturbance reference stations across Oregon. After accounting for Pacific Decadal Oscillation (PDO) and El Niño–Southern Oscillation variability, 24% of stations showed strong evidence of declining annual streamflow. Monthly trends were strongly seasonal, with June–September exhibiting strong evidence of declines at 22–51% of stations, consistent with earlier snowmelt. Power analysis indicated that these percentages may underestimate the actual extent of change. Subperiod analysis of 30 longer-record stations suggested trends were most prevalent before ~1980, aligning with documented global regime shifts. Consistent with this pattern, a step-change model with a breakpoint near 1980 was strongly preferred for precipitation–PDO relationships. PDO–precipitation correlations weakened substantially over time, declining from a median r = -0.32 (40% of stations significant) in early periods to r = -0.09 (2% significant) in recent decades, while precipitation–streamflow correlations remained strong (r > 0.8). These results suggest that Oregon's water resources are experiencing non-stationarity driven by both long-term hydrologic change and evolving teleconnections, challenging reliance on historical conditions to predict future water availability.

Introduction

Streamflow Stationarity

Water resources plans have traditionally assumed that past conditions are representative of future conditions (Galloway 2011). Under a changing climate, the validity of this assumption for streamflow is contested (Milly et al. 2008, Bayazit 2015). While climate change impacts on temperature are broadly characterized, impacts on precipitation and therefore streamflow, which integrates complex and idiosyncratic watershed responses, are more complex and less understood (Hirsch 2011; USACE 2015). Furthermore, streamflow responds to natural climate oscillations, mimicking trends over short records, as well as non-climate factors such as water management practices and watershed alterations (Hirsch 2011). Accordingly, streamflow stationarity results have varied widely by flow metric, method, degree of anthropogenic disturbance, and region (Rice et al. 2015, Ryberg et al. 2020, Yang et al. 2021, Wang and Yang 2024).

However, the hydrology of snow-dominated watersheds shows clear vulnerability to climate change: earlier snowmelt and lower proportions of precipitation as snowfall can shift streamflow timing and even magnitude (Berghuijs et al. 2014, Han et al. 2024, Berghuijs et al. 2025). In much of western North America, stream hydrology is driven by snow dynamics (Li et al. 2017). Indeed, in this region, warming temperatures are reducing the proportion of precipitation falling as snow and driving earlier snowmelt (Mote et al. 2005, Barnett et al. 2008, Hamlet 2011, Fleishman 2025). In the Pacific Northwest, these changes may be altering seasonal distributions of streamflow (Stewart et al. 2005, Luce and Holden 2009, Gangopadhyay and McGuire 2021). This streamflow supports extensive irrigated agriculture and globally important aquatic ecosystems, making the region socioeconomically and ecohydrologically vulnerable to climate change (Fleishman 2025).

Oregon Streamflow and Teleconnections

Within the Pacific Northwest, the Oregon Water Resources Department (OWRD) has a mission to address Oregon's water supply needs, which are directly impacted by changing streamflow. To better understand water supply, OWRD is currently completing an update to its statewide water availability model. As part of this effort, OWRD conducted a streamflow stationarity assessment using 51 relatively low-disturbance reference stations, representing one of the most spatially extensive evaluations of its kind for the state (Cameron 2025). The work assessed trends in the 20th, 50th, and 80th percentiles at annual and monthly time scales using quantile regression with a 10-year moving window approach. Results generally indicated stationary mean annual streamflow at most stations. However, summer monthly flows showed significant declines at many stations. Qualitatively, clusters of significant stations were noted around the Cascades. The results were generally consistent with expected climate change impacts on snow-dominated systems.

However, Cameron's (2025) moving window approach introduced temporal autocorrelation and did not account for key climate oscillations, such as the Pacific Decadal Oscillation (PDO) and El Niño–Southern Oscillation (ENSO). These multi-year to multi-decade climate cycles influence regional precipitation and streamflow, superimposed upon any long-term monotonic trends (Cayan et al. 1999, Mantua and Hare 2002, Fleming and Weber 2012, Fleming and Dahkle 2014, Fleming and Sauchyn 2013). A teleconnection is a statistical relationship between climate phenomena that are geographically distant from each other, such as between Pacific sea surface temperatures and Oregon precipitation. Failure to account for climate oscillations when detecting trends can thus produce misleading conclusions (Hirsch 2011, Woo et al. 2018, Georgiadis and Baker 2023). However, the PDO teleconnection itself may be nonstationary (Wu et al. 2019, Litzow et al. 2020, Cluett et al. 2025). Finally, record length and timing can substantially change results (Yue et al. 2002, Dixon et al. 2006, Hirsch 2011). Therefore, a panel of scientific experts reviewing the work suggested alternative analytical approaches to better isolate trends from oscillations, account for record timing, and address inherent weaknesses with hypothesis test approaches (Andrews 2026).

Study Approach and Aims

The Akaike Information Criterion (AIC) and its small-sample correction (AICc) provide an information-theoretic framework for model selection that balances goodness-of-fit with model parsimony (Akaike 1974, Burnham and Anderson 2002, Fleming and Dahlke 2014). Rather than relying on binary hypothesis tests, AICc-based approaches provide probabilities that candidate models are the best approximating given the data, allowing comparison of the relative support for competing explanations. AICc accommodates nested model structures where the null (no trend), oscillation-only, and oscillation-plus-trend models can be simultaneously evaluated. Evidence ratios derived from AICc weights quantify the strength of collective support for trend versus non-trend models.

This study reexamines streamflow trends at Oregon reference stations using AICc-based model selection to address three primary questions: (1) What is the evidence for trends in streamflow mean and variance after accounting for PDO and ENSO variability? (2) How do record length, record timing, and streamflow characteristics influence trend detection? (3) Has the strength of PDO teleconnections to precipitation and streamflow changed over time? By explicitly separating cyclical climate variability from trends and evaluating the stability of climate–streamflow relationships, this work provides a refined assessment of streamflow stationarity to inform Oregon's water resource planning.

Methods

Data

Streamflow

Mean daily streamflow data were acquired from OWRD, including provisional and published data, for 51 reference stations through water year (WY) 2025 (Fig. 1). These 51 stations have active monitoring, ≥30 water years of data, an irrigation withdrawal ratio of ≤0.10, and a storage ratio ≤0.05 (Andrews and Huang 2024). Reference stations are assumed unaffected or negligibly impacted by groundwater withdrawals; however, 13 stations have at least one groundwater right point of diversion somewhere in their basins (Ryan Andrews, pers. comm., 16 Dec 2025).

Data gaps of up to seven consecutive days were linearly interpolated. Daily flows were aggregated to annual and monthly metrics, including mean flow and flow variance. Only months and years with complete daily coverage following interpolation were retained for analysis.

Two analysis periods were considered. The "long-term" period represents the longest consecutive sequence of water years with complete flow data available at each station and varies among stations. The "base period" was defined uniformly as WY1991–2020. Long-term records ranged from 35 to 115 years (median: 84 years). After merging with climate indices, the most temporally limiting of which begin in 1950, usable long-term records ranged from 35 to 75 years (median: 73 years).

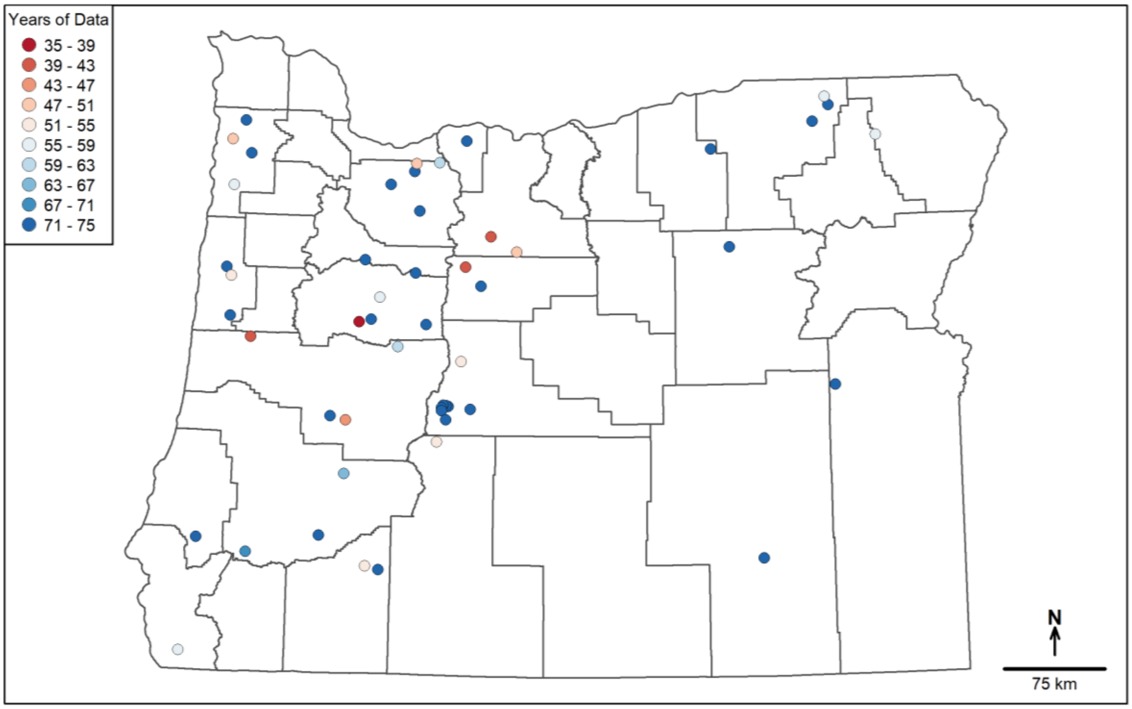

Figure 1. Map of Oregon reference streamflow stations assessed for trends.

Precipitation

Monthly 4-km precipitation data were acquired from PRISM (2025) covering calendar years 1895-2025. Watershed geospatial data for the stations were acquired from Andrews and Stratton-Garvin (2025). Precipitation time series were developed for each watershed using the average of all PRISM grid cells intersecting the watershed.

Climate Oscillations

Indices representing the El Niño–Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) were obtained from NOAA (2026a, b). The ENSO index was available from 1950 onward, and the PDO index from 1870 onward. ENSO values are provided as three-month seasons. PDO monthly values were aggregated into seasonal indices.

To avoid station-specific tuning, a single seasonal definition for each climate index was applied uniformly to all stations. Optimal seasons were selected empirically by computing Pearson correlations between annual mean flow and season across all stations and selecting the season that maximized the median absolute correlation. This procedure was conducted separately for PDO and ENSO and resulted in the use of December-January-February (DJF) for PDO and November-December-January (NDJ) for

ENSO indices for all subsequent analyses. Correspondence between flow and winter PDO and ENSO indices is consistent with previous work (e.g., Fleming and Weber 2012, Fleming and Dahlke 2014).

Streamflow Trends

AICc Models

Trends in streamflow were evaluated after accounting for climate oscillations using a model selection framework based on the corrected Akaike Information Criterion (AICc; Burnham and Anderson, 2002). Analyses were conducted separately for mean flow and flow variance, and independently for annual flows and monthly flows (e.g., all Januaries were evaluated separately from all Februaries), resulting in 13 model sets per station, variable, and time period. Flow data were log10-transformed prior to analysis to improve residual normality based on preliminary analysis. For each condition, six models were evaluated:

- Model 1 (Null): Flow ~ $\beta_0 + \varepsilon$
- Model 2 (Linear Oscillation): Flow ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{ENSO}) + \varepsilon$
- Model 3 (Parabolic Oscillation): Flow ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{ENSO}) + \beta_3(\text{PDO}^2) + \beta_4(\text{ENSO}^2) + \varepsilon$
- Model 4 (Linear Trend): Flow ~ $\beta_0 + \beta_1(\text{Year}) + \varepsilon$
- Model 5 (Linear Oscillation + Trend): Flow ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{ENSO}) + \beta_3(\text{Year}) + \varepsilon$
- Model 6 (Parabolic Oscillation + Trend): Flow ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{ENSO}) + \beta_3(\text{PDO}^2) + \beta_4(\text{ENSO}^2) + \beta_5(\text{Year}) + \varepsilon$

where Flow is log10-transformed discharge, PDO is the DJF index, ENSO is the NDJ index, and year represents water year as a continuous variable. This six-model structure tests whether trends persist after accounting for variability explained by PDO and ENSO.

Although ENSO cycles are shorter and less likely to mimic trends over multidecadal record lengths compared to the PDO, they were included after preliminary analysis showed they improved model fit. Parabolic models were included following previous work (Fleming and Dahlke 2014). Oscillation-year interaction terms were not included for parsimony, and preliminary analysis suggested that these models were not favored. If PDO or ENSO relationships with streamflow change over time, this would also manifest as a trend in this approach, but for water management purposes, this mechanism also represents departure from stationarity.

Model fit was evaluated using AICc, which penalizes model complexity and is appropriate for moderate sample sizes. AICc values were converted to Akaike weights, representing the probability that a given model is the best approximation among the candidate set. To quantify evidence for trends independent of climate variability, an evidence ratio (ER) was calculated as:

ER = [w(Trend) + w(Linear Oscillation + Trend) + w(Parabolic Oscillation + Trend)] / [w(Null) + w(Linear Oscillation) + w(Parabolic Oscillation)]

where w denotes the Akaike weight. This ratio compares support for the trend models against non-trend explanations. For example, an ER of 3 indicates that the models including a trend is three times better supported by the data than all non-trend models combined. ER > 3 was interpreted as moderate evidence and ER > 10 as strong evidence for trends.

Trend direction was determined by averaging time coefficients, weighted by each model's Akaike weight, with non-trend models assigned a coefficient of 0.

ER vs Record Length

To evaluate whether evidence for streamflow trends was influenced by record length, Spearman correlations were computed between station-specific evidence ratios (ER) and the number of years with complete flow, PDO, and ENSO data. This analysis was conducted for the long-term period for annual mean flow and annual flow variance. This was further considered as part of power analysis, described below.

Subperiod Analysis

To further assess whether detected trends were influenced by the timing of observations or differences in record length, a fixed subset of stations with ≥70 years (i.e., covering most of WY1951–2025) of complete flow and climate data was selected (n = 30). For these stations, the AICc-based trend analysis was repeated for three non-overlapping 24-year windows: WY1951–1974 (early), WY1975–1998 (middle), and WY1999–2022 (late). Results from these subperiods were compared to full-record results for the same stations. This analysis isolates the effect of record timing on inferred trends.

Power Analysis

Detectability of streamflow trends was evaluated using Monte Carlo simulation for the 30 stations with ≥70 years of data in WY1951–2025. For each station, 500 synthetic time series were generated across a range of record lengths (30–70 years) and trend magnitudes (-50% to 0% per decade).

Synthetic data were constructed using station-specific characteristics extracted from Model 6 (residual standard deviation, lag-1 autocorrelation coefficient, PDO and ENSO response coefficients) combined with block-resampled observed PDO and ENSO values. To generate autocorrelated errors, the first error term was randomly drawn from the long-run variance of the AR1 process, then subsequent errors were generated recursively as a weighted combination of the previous error and new random noise. Model 6 was selected as the plurality best-performing model and to avoid overfitting. Sensitivity analyses testing alternative models (null, linear oscillation, and station-specific best models) showed power estimates at observed trends were nearly identical across approaches ($r \geq 0.99$; median difference ≤0.2 percentage points), confirming robustness to this modeling choice.

Each synthetic series was analyzed using the six-model AICc framework. For simulated trend series, detectability was defined as the proportion of simulations yielding ER > 3 in favor of trend models. False positive rates were calculated as proportion where ER > 3 for no-trend simulations. Comparisons primarily focused on 70-year simulations to match the calibration dataset record length.

For mean and variance, generalized additive models (GAMs) were fitted to predict power as a smooth function of trend magnitude, noise level, autocorrelation, record length, and time scale (annual or specific month) and their interactions using beta regression with a logit link. (Time scale, as in annual or month, was not included after preliminary analysis showed it did not substantially improve fit relative to the introduced complexity.) These GAMs enable power estimation for arbitrary combinations of station characteristics, including stations outside the calibration set.

To test whether simulation-based power estimates accurately predict real-world detection, GAM-predicted power at each station was compared with actual detection outcomes (ER > 3 in observed data) using logistic regression for annual trends.

PDO Teleconnection

To evaluate changes in PDO influence over time, three approaches were used: rolling correlations, formal model comparison, and breakpoint analyses. Analyses were restricted to the 30 stations with ≥70 years of data in WY1951–2025. Only annual (water year) values were assessed.

Rolling Corrrelations

Rolling 30-year Pearson correlations were computed between PDO and precipitation, PDO and log10 streamflow, and precipitation and log10 streamflow for each station. Paired Wilcoxon signed-rank tests were used to assess whether changes between early (windows ending before 1985) and late (windows ending after 2005) periods were systematic across stations.

AICc Models

To formally test whether PDO effects changed over time, station-level linear models were compared using AICc. For PDO effects on precipitation, seven models were evaluated:

- Model 1 (Null): Precip ~ $\beta_0 + \varepsilon$
- Model 2 (Linear, Constant): Precip ~ $\beta_0 + \beta_1(\text{PDO}) + \varepsilon$
- Model 3 (Parabolic, Constant): Precipitation ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{PDO}^2) + \varepsilon$
- Model 4 (Linear, Time-varying): Precipitation ~ $\beta_0 + \beta_1(\text{PDO}) + \gamma_1(\text{PDO} \times \text{Year}) + \varepsilon$
- Model 5 (Linear, Step): Precipitation ~ $\beta_0 + \beta_1(\text{PDO}) + \delta_1(\text{PDO} \times \text{I[Year} > 1980]) + \varepsilon$
- Model 6 (Parabolic, Time-varying): Precipitation ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{PDO}^2) + \gamma_1(\text{PDO} \times \text{Year}) + \gamma_2(\text{PDO}^2 \times \text{year}) + \varepsilon$
- Model 7 (Parabolic, Step): Precipitation ~ $\beta_0 + \beta_1(\text{PDO}) + \beta_2(\text{PDO}^2) + \delta_1(\text{PDO} \times \text{I[Year} > 1980]) + \delta_2(\text{PDO}^2 \times \text{I[Year} > 1980]) + \varepsilon$

where Precipitation represents the water year sum, PDO is the DJF index, and Year is water year as a continuous variable. Post-breakpoint is a binary indicator for years after 1980. This year was selected a priori based on 1970s-1980s regime shifts (Reid et al. 2016, Giamalaki et al. 2018). Models 3 and 4 allow the PDO effect to vary over time: gradually (linear) or abruptly (step).

To quantify evidence for nonstationary PDO effects, an evidence ratio was calculated as:

ER = [w(Linear, Time-varying) + w(Linear, Step) + w(Parabolic, Step) + w(Parabolic, Time-varying)] / [w(Null) + w(Linear, Constant) + w(Parabolic, Constant)].

This ratio compares support for time-varying models against stationary models. ER strength was interpreted as done for streamflow trend models. PDO effect change was assessed by comparing PDO coefficients at the start versus end of each station's record using the best-supported model selected via AICc; stations where the null model was best-supported were excluded from change analysis.

Breakpoint Analysis

Pettitt's breakpoint tests were conducted for mean annual flow, annual precipitation, and PDO-streamflow regression residuals. This nonparametric test detects abrupt shifts in the mean of a time series and identifies the most likely breakpoint year, including significance. An alpha of 0.05 was used.

Results

Streamflow Trends

The parabolic trend model was the best-approximating at 43% of the 51 stations, followed by linear and parabolic non-trend models each at 16%, then the null model at 14% (Fig. 2a). Trend coefficients were negative at 84% of stations.

At least moderate evidence for trends was detected at a large minority of stations during the long-term record, while evidence favored the absence of trends during the recent base period (Fig. 3). For annual mean flow, 41% of stations exhibited moderate evidence for trends and 24% exhibited strong evidence, all declining. Patterns for flow variance were broadly similar but fewer stations showed evidence.

Monthly trends were strongly seasonal (Fig. 3 and Fig. 4). Summer and early autumn months exhibited the highest prevalence of trends, with June, July, August and September showing strong evidence of trends at, respectively, 22%, 45%, 51%, and 35% of stations. Across all months, downward trends predominated. Patterns for flow variance were broadly similar but fewer stations showed evidence.

ER vs Record Length

ER and record length significantly correlated for annual flow mean ($\rho = 0.48$, $p < 0.001$) and variance ($\rho = 0.43$, $p < 0.001$) at the 51 stations. For monthly flows, the correlation between ER and record length was significant for 6 months for mean ($\rho \geq 0.33$, $p < 0.02$) and 3 months for variance ($\rho \geq 0.28$, $p < 0.04$).

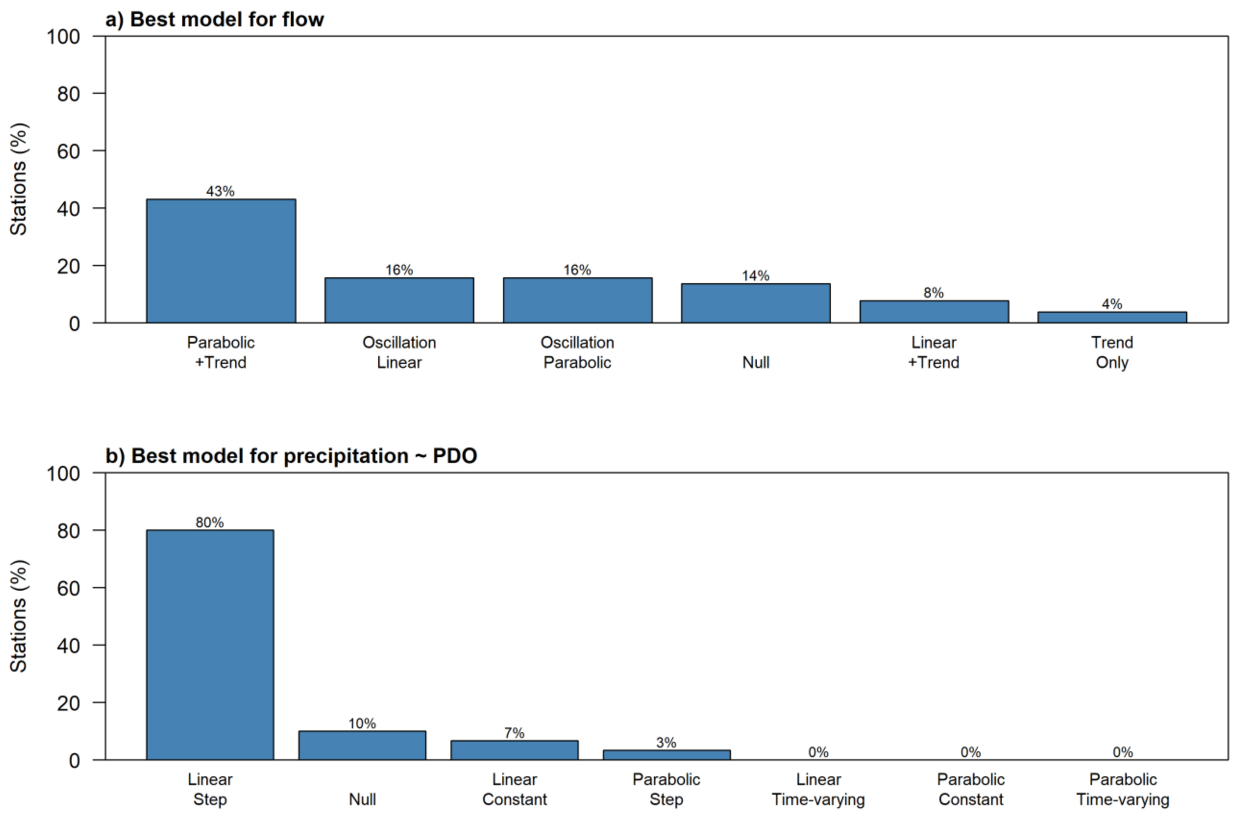

Figure 2. Best model for annual values for (a) flow (n=51) and (b) precipitation (n=30).

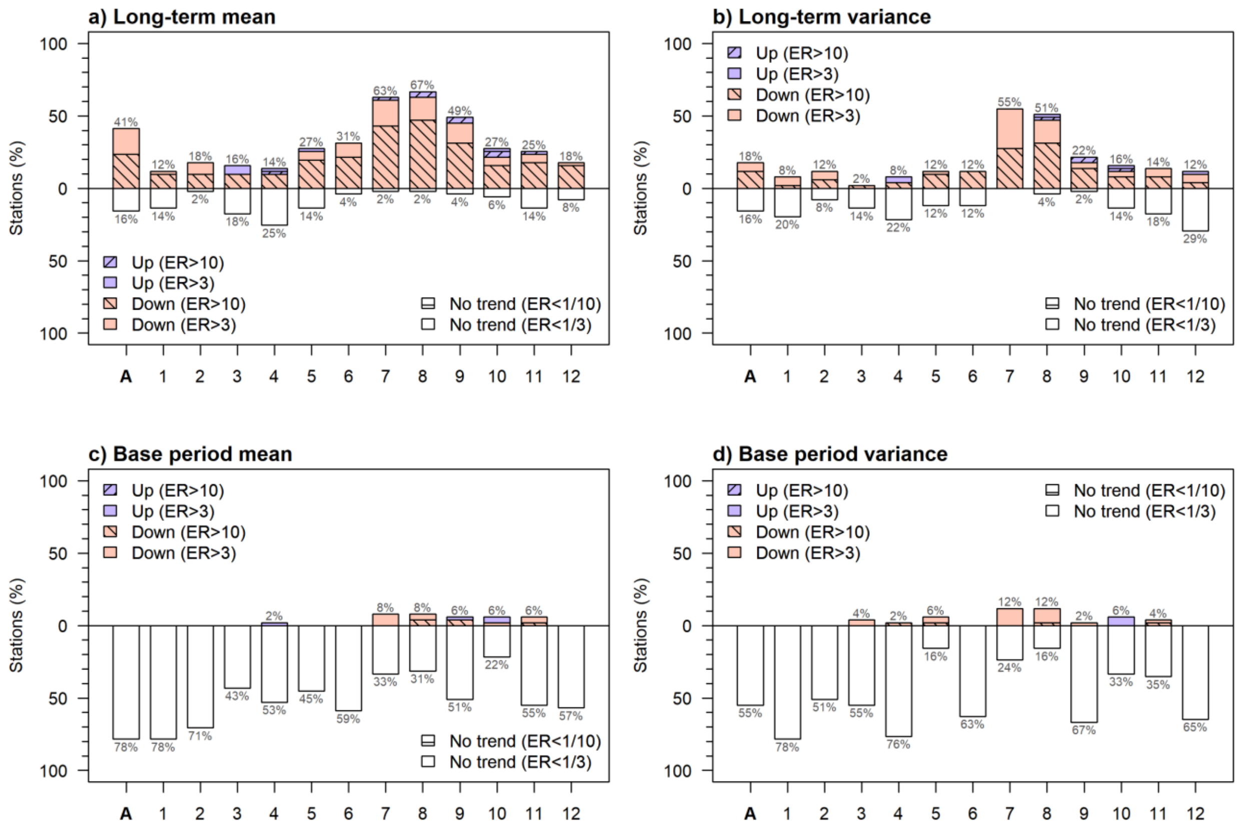

Figure 3. Percentage of 51 Oregon reference stations with moderate (ER>3) and strong (ER>10) evidence for or against trends in annual (A) or monthly flow after accounting for climate oscillations. Results for (a) long-term mean flows, (b) long-term mean variance, (c) base period mean flow, and (d) base period variance. The long-term period represents the longest available consecutive record (varies among stations), while the base period (bottom) represents WY1991–2020 (identical among stations). Trend direction from weighted average of models.

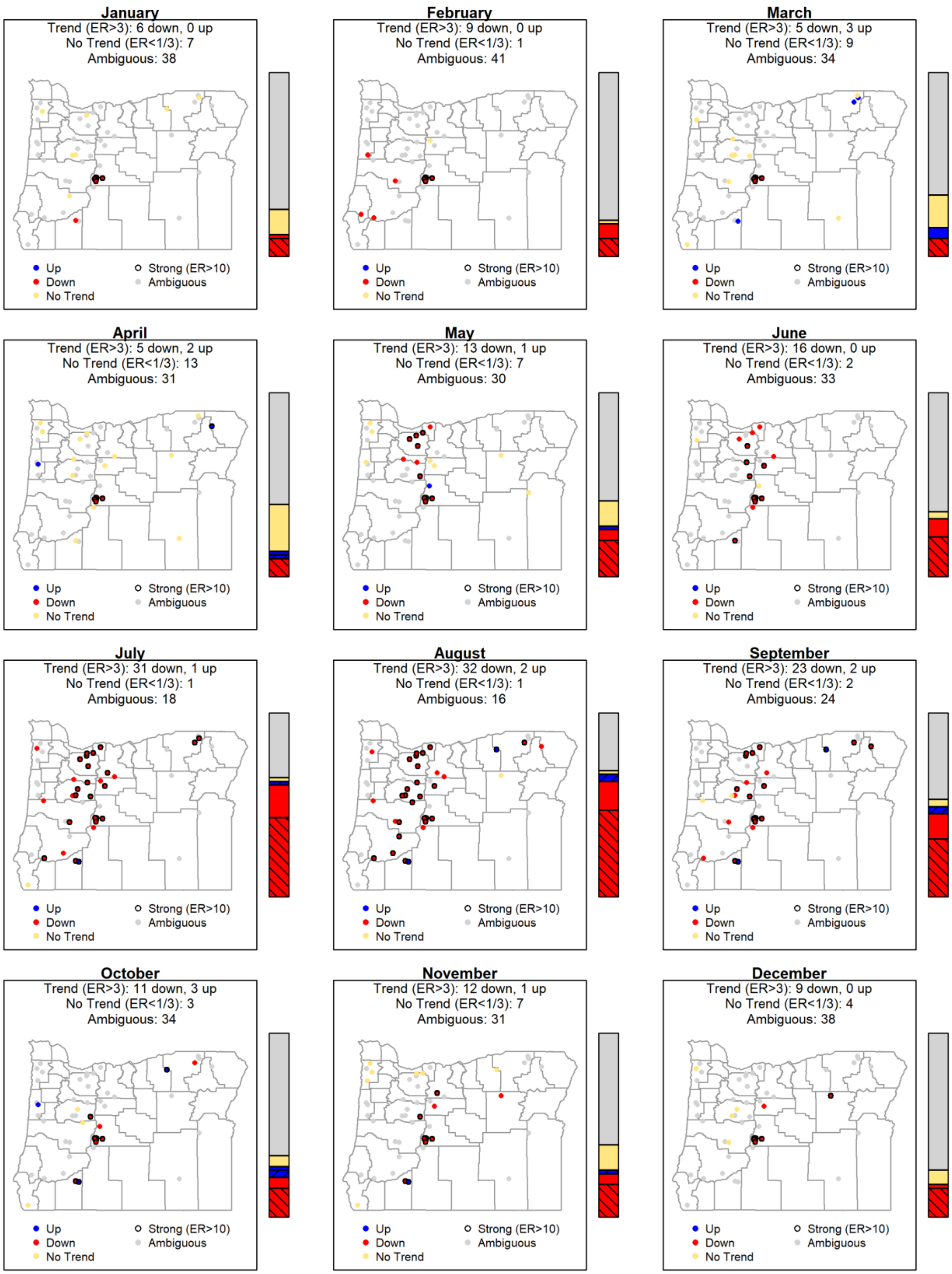

Figure 4. Maps of monthly mean trend results for 51 Oregon reference stations using each station’s longest available consecutive record.

Subperiod Analysis

For the 30 stations with at least 70 years of complete data, splitting the record into thirds, all subperiods generally favored moderate evidence for no trends (Fig. 5). Detected trends are most prevalent during the early portion; for the WY1951–1974 early subperiod, 17% of stations exhibited at least moderate evidence of annual trends, whereas 0% showed trends for WY1975-1998 and 3% for WY1999-2022. However, as noted in the following section, power is low.

Monthly results followed a similar pattern, with more evidence of trends in the early subperiod and few found in the middle and late subperiods. However, for the full (long-term) record, a majority of stations exhibited at least moderate evidence for annual, July, August, and September trends, mostly downward. Few stations showed evidence of no trends.

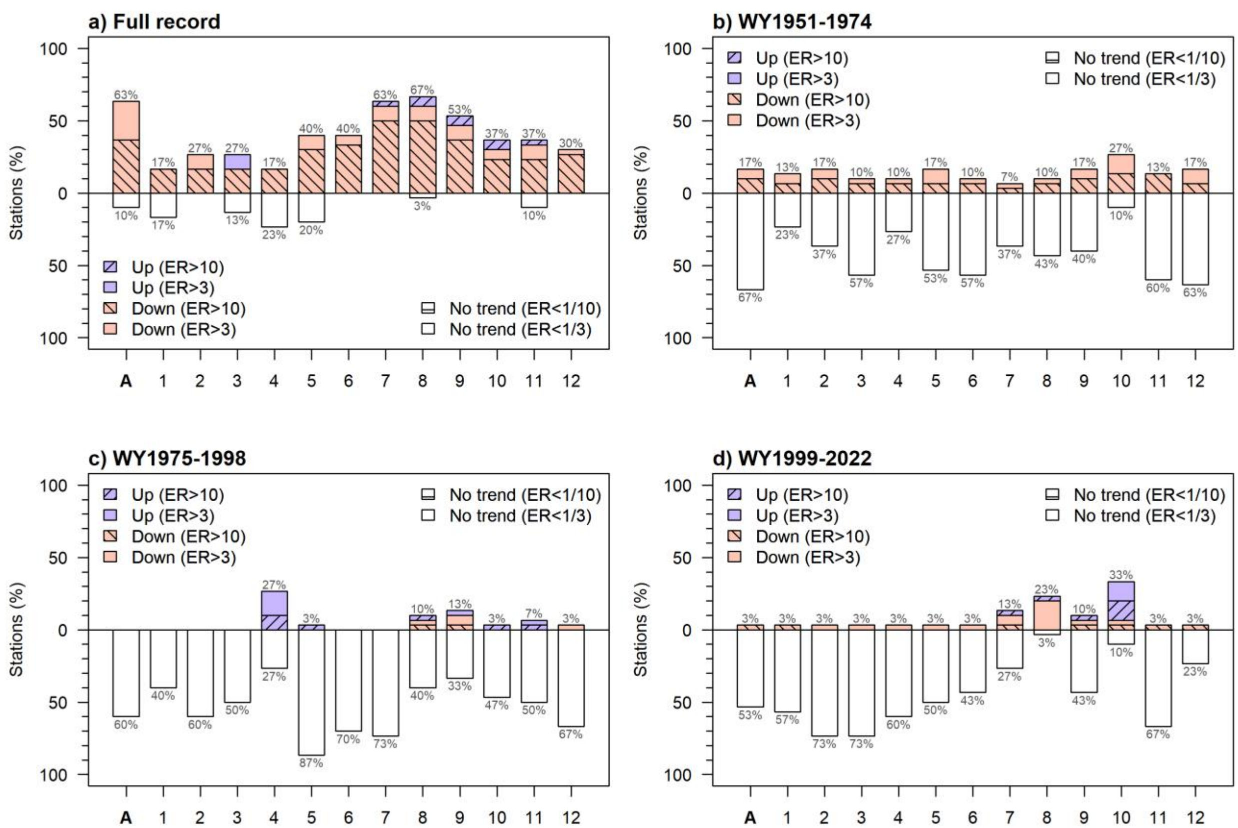

Figure 5. Percentage of stations with moderate (ER>3) and strong (ER>10) evidence for or against trends in annual (A) or monthly flow after accounting for climate oscillations

using data for (a) period of record, (b) WY 1951-1974, (c) WY1975-1998, and (d) 1999-2022. Includes 30 Oregon references stations with ≥70 years of data in WY1951–2025. Trend direction from weighted average of models.

Power Analysis

For mean annual flows at long-record stations, median observed trends (IQR: -3.4%/decade to 0.6%/decade) were typically above minimum detectable trends (IQR: -6.7%/decade to -4.5%/decade) (Fig. 6a). Only 17% of stations achieved ≥80% power (Fig. 6b). Monthly detectability peaked in summer, with July and August showing, respectively, 33% and 40% of stations with ≥80% power, compared to ≤20% for most other months (Fig. 6b).

For annual flow variance, median observed trends (IQR: -6.6%/decade to -0.7%/decade) were typically above minimum detectable trends (IQR: -16.8%/decade to -10.9%/decade) (Fig. 6c). Only 7% of stations achieved ≥80% power (Fig. 6d).

False positive rates were generally low (mean IQR: 2.8%–8.8%; variance IQR: 3.8%, IQR: 2.2%–5.5%) but ranged as high as 39.4%. False positive rates were strongly correlated with residual autocorrelation for mean ($r = 0.93$, $p < 0.001$) and variance ($r = 0.90$, $p < 0.001$).

GAMs explained 98% of variance in simulation-based power estimates (Fig. 7a and 7c). All predictors (trend magnitude, residual standard deviation, lag-1 autocorrelation, and record length) and their interactions significantly influenced power (all $p < 0.001$).

Logistic regression suggested that estimated power predicted actual trend detection (Fig. 7b and 7d). For long-record calibration stations, each 10 percentage point increase in predicted power increased detection odds 4.1-fold for mean ($\beta = 0.140$, $p < 0.001$; 74% deviance explained) and 8.7-fold for variance ($\beta = 0.216$, $p < 0.001$; 80% deviance explained). When extended to all station, the relationships weakened but remained strong, with each 10 percentage point increase in predicted power increasing detection odds 3.5-fold for mean flow ($\beta = 0.124$, $p < 0.001$; 72% deviance explained) and 4.2-fold for variance ($\beta = 0.143$, $p < 0.001$; 74% deviance explained), indicating generalizability beyond the long-record calibration set. Using a 0.5 probability cutoff, logistic models correctly predicted 97% of actual station–period trend results for mean and variance.

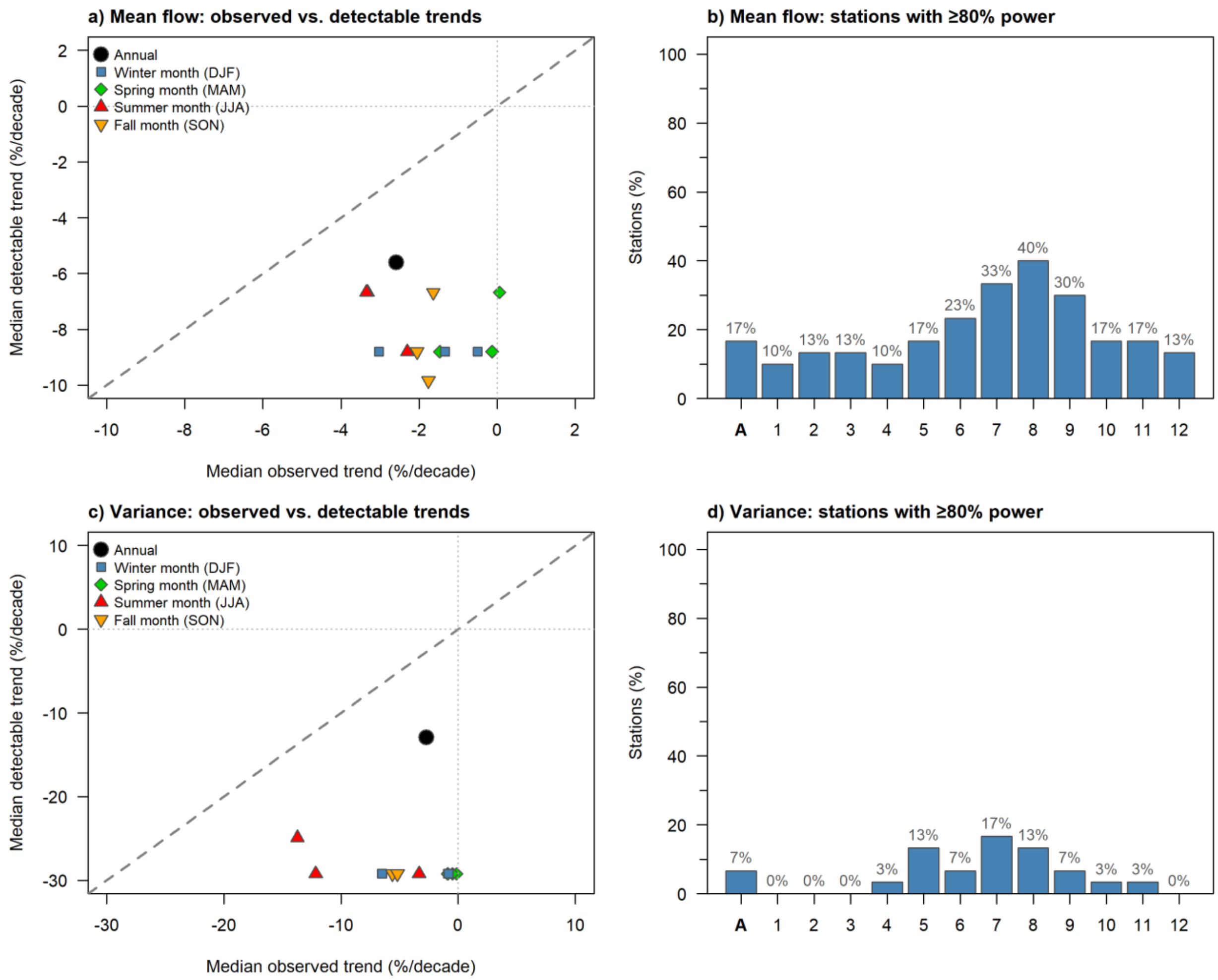

Figure 6. (a) Median minimum detectable trend versus median observed trend versus. (b) Percentage of stations with ≥80% power for annual (A) and monthly flows. (c–d) Same as (a–b) but for flow variance. Includes 30 Oregon references stations with ≥70 years of data in WY1951–2025.

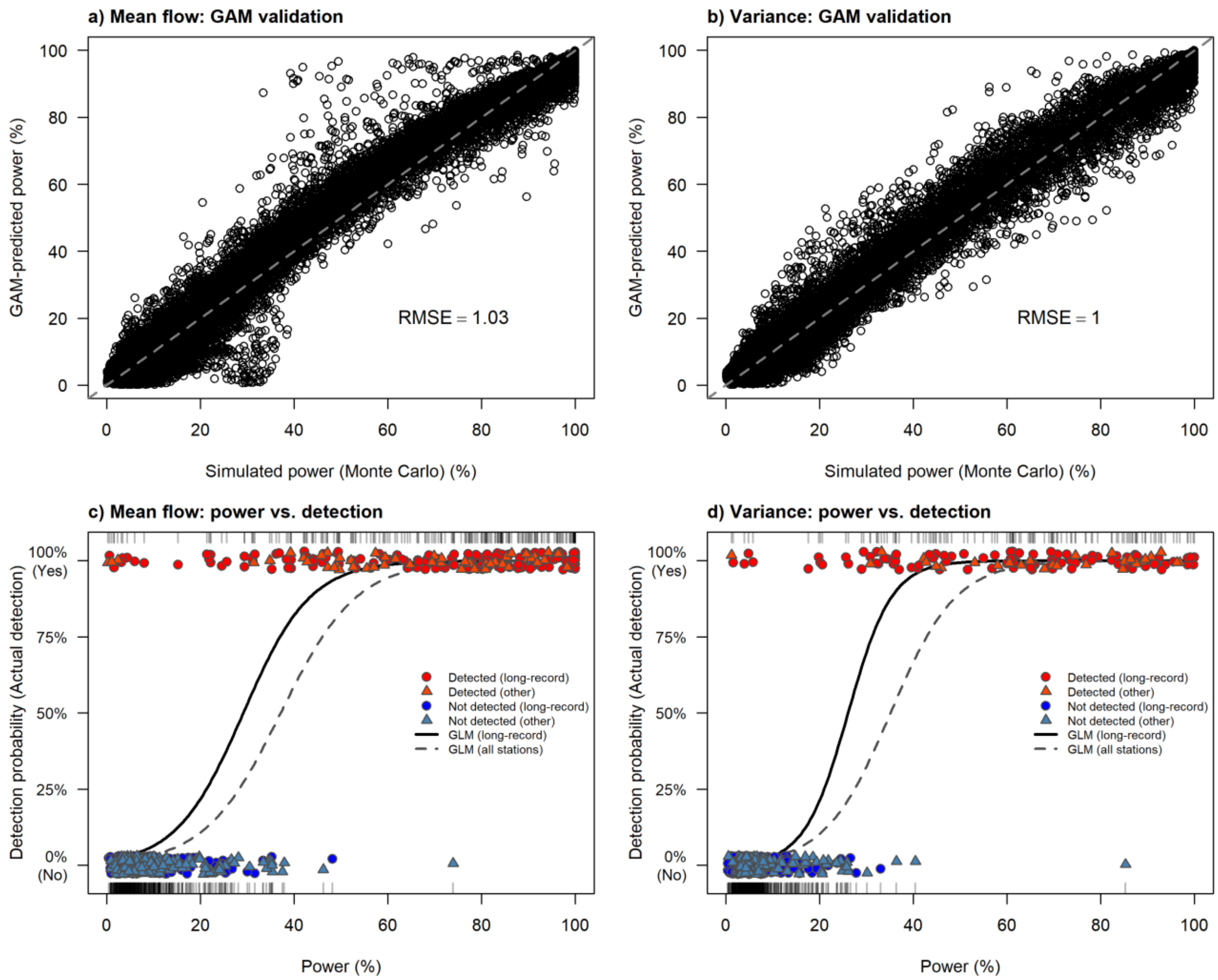

Figure 7. (a) GAM-predicted versus simulated (Monte Carlo) power. (b) Logistic models of trend detection (ER>3 for observed data) versus simulated power. (c–d) Same as (a–b) but for flow variance. GAMs and long-record logistic models use 30 Oregon references stations with ≥70 years of data in WY1951–2025; all stations use 51 Oregon reference stations with ≥35 years of data in WY1951–2025.

PDO Teleconnection

The PDO–precipitation correlation weakened substantially over time. Averaging full 30-year windows ending before WY1980 (the first third), the mean correlation was r = -0.32, and 49% of individual station-window correlations were significant at α = 0.05 (Fig. 8a). For windows ending after WY2013 (the last third), the mean correlation had weakened to r = -0.09, and only 2% of individual station-windows were significant. PDO–flow correlations showed similar collapse, declining from r = −0.36 (67% of stations significant) before 1995 to r = -0.16 (6% significant) after 2005 (Fig. 8b). Paired

Wilcoxon tests confirmed systematic weakening across stations for both PDO–precipitation ($p < 0.001$) and PDO–flow ($p < 0.001$) correlations.

Conversely, precipitation–flow correlations remained strong throughout the analysis period, with median values $r \geq 0.83$ (Fig. 8c) and ≥97% individual station-windows significant at $\alpha = 0.05$. Paired Wilcoxon tests did not detect a significant change in precipitation–flow correlations between early and late subperiods ($p = 0.70$).

AICc model comparisons generally corroborated weakening of the PDO–precipitation relationship. The linear step-change model was the best approximating model for PDO–precipitation relationships at 80% of stations, followed by the null model at 10%, linear constant model at 7%, and parabolic step model at 3% of stations (Fig. 2b). Among best linear models, 92% of stations showed a weakening relationship w¬ith PDO (decreasing $|\beta|$ over time). However, while 60% of stations showed moderate evidence of change, only 3% showed strong evidence.

Of Pettit tests, 4 (13%) were significant for annual precipitation with a median breakpoint of 1945 (IQR: 1945-1954), 6 (20%) were significant for annual flow with a median breakpoint year of 1976 (IQR: 1976-1984), and 11 (37%) were significant for flow-PDO residuals with a median breakpoint year of 1986 (IQR: 1986-1987).

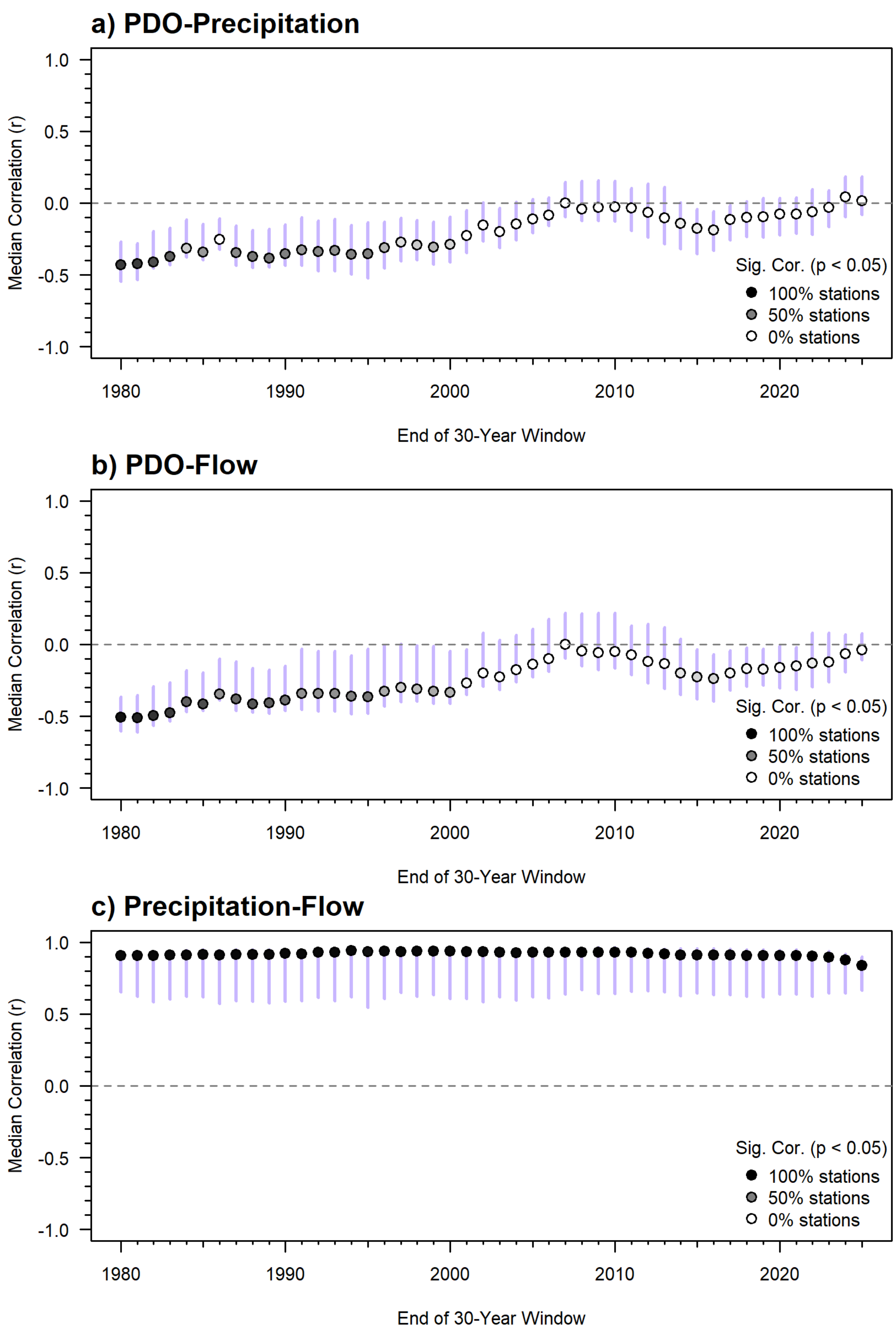

Figure 8. Correlations between climate oscillations, precipitation, and flow. Color intensity (circle fill) indicates percentage of stations with statistically significant correlations ($p < 0.05$). Purple vertical bars capture the middle 90% (interdecile range)

of station correlations. Includes 30 Oregon references stations with ≥70 years of data in WY1951–2025.

Discussion

Streamflow Trends

After accounting for cyclical PDO and ENSO variability, evidence emerged for widespread trends in Oregon streamflow that were not explained by known climate oscillations (Fig. 3-5). A majority of stations showed at least moderate evidence of downward trends in July and August over their periods of record. A large minority of stations also showed at least moderate evidence of downward trends for annual flows and late spring and autumn months. Fewer trends were detected for variance, reflecting lower power (Fig. 5d), which is typical for variance (Yang et al. 2021). As in earlier work, stations with trends tended to visually cluster along the Cascades, although this region also has higher station density (Fig. 4) (Cameron 2025).

Power analysis generally suggested a low ability to detect trends (Fig. 6-7). Detectability was influenced by trend magnitude, residual autocorrelation, residual variability, and record length. Interestingly, observed detection rates typically greatly exceeded estimated percentages of stations with estimated power ≥80%. Many stations exhibited intermediate power, which may be sufficient for detection in a substantial fraction of cases. The simulation parameterization may also be poorly representative of processes driving interannual streamflow variation. Trends were rarely detected at stations with estimated low power, most high-power stations had detected trends, simulated false positives were low, and moderate evidence for non-trends was typically low across periods of record (Fig. 3a-b). This suggests that some "ambiguous" stations (lacking at least moderate evidence for either trends or stationarity) may be experiencing non-stationarity below detection thresholds.

Downward summer trends are consistent with earlier snowmelt, reduced snowpack accumulation, and increased evapotranspiration. The potential time-varying strength of climate teleconnections itself constitutes a form of non-stationarity. Both monotonic trends and weakening climate teleconnections represent departures from stationarity relevant to water management. The preference for parabolic PDO–flow models matches previous work showing polynomial teleconnections in western North America (Fleming and Dahkle 2014, Georgiadis and Baker 2023).

Timing of Changes

Among longer-record stations, the early period exhibited more streamflow trends than the middle or late periods, but all three periods actively favored no trends. This contrasts with results for the full record, where annual and some monthly flows favored trends for a majority of stations. Detected changes could reflect an abrupt regime shift concentrated around the 1980s (Reid et al. 2016, Litzow et al. 2020). For PDO–precipitation relationships, AICc model comparison favored step-change models. The early subperiod may capture regime transitions, and stronger PDO relationships could enhance trend detection. Later subperiods may be limited to post-transition states. However, all subperiods were underpowered. The full record captures both the abrupt transition and benefits from maximum sample size, yielding the strongest evidence.

Changing Influence of PDO

Over the span of the observational record, the PDO–precipitation correlation weakened at majority of stations from strong and highly significant to essentially zero and nonsignificant (Fig. 8). The PDO reflects the integration of multiple physical processes, including the Kuroshio oceanic current, oceanic thermal inertia, and low atmospheric pressure near the Aleutian Islands (Newman et al. 2016). Recent work has shown that basin-wide anthropogenic warming has created a nonstationary background against which the PDO, while still present, appears increasingly faint (Cluett et al. 2025). Additionally, the association of PDO with the Kuroshio Current has decreased since the late 1990s (Wu et al. 2019). However, the linkage between precipitation and streamflow remained strong. While water managers can still rely on precipitation as a strong predictor of runoff, the PDO may be less reliable as a predictor of precipitation.

Limitations

Stations included are not evenly distributed spatially, with higher density near the Cascades and western Oregon and sparser coverage in southeastern regions, and spatial autocorrelation was not evaluated. Not all potentially relevant climate indices were evaluated; for example, the Trans-Niño Index has been shown to influence Pacific Northwest hydroclimate (Kennedy et al. 2009), and higher modes of the PDO can be predictive of streamflow in western North America (Duan et al. 2024). Finally, while stations were screened for low irrigation and storage ratios, whether some stations experience depletion from groundwater withdrawals is uncertain.

Temporal autocorrelation was not addressed; while this may inflate detection rates, correction methods can remove real hydroclimatic signals that operate across multiple years or basins (Fleming and Sauchyn 2013). The power analysis used parabolic oscillation models with time-invariant climate coefficients, which may not accurately represent processes driving interannual variability at all locations. Furthermore, this parameterization assumes stationarity in climate relationships, but teleconnection analyses suggest these relationships are changing, which may bias power estimates. All evaluated models represent simplified approximations of complex physical watershed processes and may not adequately capture basin-specific responses to climate forcing. The uniform application of DJF PDO and NDJ ENSO indices across all stations, while avoiding overfitting, may miss station-specific seasonal sensitivities that could improve model performance. Step changes in streamflow were not assessed. For teleconnections, the step change year was selected a priori to approximately align with documented global regime shifts; results may differ if alternative breakpoints are assumed, and sensitivity to this choice was not formally evaluated.

Finally, the analysis focused on detecting whether trends exist rather than quantifying their magnitudes or identifying causes. Trend direction and evidence were prioritized over effect sizes. Only linear trends were assessed. Furthermore, changing teleconnection relationships could manifest as apparent trends; from a water management perspective, both trends and time-varying climate relationships constitute departures from stationarity, though they have different implications for forecasting approaches. Most stations showed limited statistical power, meaning the absence of detected trends cannot be confidently interpreted as evidence of stationarity, particularly at shorter time scales.

Conclusion

After accounting for climate oscillations, the majority of reference stations in Oregon show declines in monthly summer streamflow. This is consistent with climate change–driven increases in evapotranspiration and reductions in snowfall and snowpack longevity. The PDO–precipitation teleconnection may be weakening as anthropogenic warming overwhelms the PDO signal, making the PDO less useful for predicting precipitation and therefore streamflow. Water resource systems designed and operated under the premise that historical patterns provide reliable predictions of future conditions must confront a more complex reality. Models that rely on past streamflow conditions to model present and future streamflow will benefit from more frequent updates. Trend evidence supports construction of policy statements that can guide decisions for water allocation as the climate changes. Future work should expand analyses beyond Oregon, explore other climate oscillations, compare trends to snow dominance and other watershed factors, and further evaluate potential changes in climate teleconnections.

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References

Akaike, Hirotugu. 1974. “A New Look at the Statistical Model Identification.” IEEE Transactions on Automatic Control 19 (6): 716–23. https://doi.org/10.1109/TAC.1974.1100705.

Andrews, Ryan, and Huang, Cheng-Wei. 2024. “WARS Update: Streamgage Network Expansion Documentation”. Oregon Water Resources Department.

Andrews, Ryan. 2026. “TAG Meeting #2 – Feedback Summary”. Oregon Water Resources Department.

Andrews, Ryan, and Stratton-Garvin, Laurel. 2025. “Development of a Flow Management Index for Gaged Watersheds in Oregon.” Oregon Water Resources Department. Accessed January 13, 2026. https://www.oregon.gov/owrd/WRDPublications1/Andrews&StrattonGarvin_OFR2025-01.zip.

Barnett, Tim P., David W. Pierce, Hugo G. Hidalgo, Celine Bonfils, Benjamin D. Santer, Tapash Das, Govindasamy Bala, et al. 2008. “Human-Induced Changes in the Hydrology of the Western United States.” Science 319 (5866): 1080–83. https://doi.org/10.1126/science.1152538.

Bayazit, M. 2015. Nonstationarity of Hydrological Records and Recent Trends in Trend

Analysis: A State-of-the-art Review. Environmental Processes 2 (3): 527–542. https://doi.org/10.1007/s40710-015-0081-7.

Berghuijs, Wouter R., Ross Woods, and Markus Hrachowitz. 2014. “A Precipitation Shift From Snow Towards Rain Leads to a Decrease in Streamflow.” Nature Climate Change 4 (7): 583–86. https://doi.org/10.1038/nclimate2246.

Berghuijs, Wouter R., and Kate Hale. 2025. “Streamflow Shifts With Declining Snowfall.” Nature 638: E35–37. https://doi.org/10.1038/s41586-024-07299-y.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: A practical information-theoretic approach. 2nd ed. Springer.

Cameron, C. 2025. “Streamflow Stationarity Assessment for the Surface Water Information Modeling System” (September 2025 draft). Oregon Water Resources Department.

Cayan, Daniel R., Kelly T. Redmond, and Laurence G. Riddle. 1999. “ENSO and Hydrologic Extremes in the Western United States.” Journal of Climate 12 (9): 2881–93. https://doi.org/10.1175/1520-0442(1999)012<2881:EAHEIT>2.0.CO;2.

Cluett, A. A., S. J. Bograd, M. G. Jacox, et al. 2025. “Pan-Basin Warming Now Overshadows Robust Pacific Decadal Oscillation.” Nature Climate Change 15: 1340–47. https://doi.org/10.1038/s41558-025-02482-z.

Cooper, R.M. 2002. “Determining Surface Water Availability in Oregon.” Oregon Water Resources Department.

Duan, Shiheng, Giuliana Pallotta, and Céline Bonfils. 2024. “Higher-Order Internal Modes of Variability Imprinted in Year-to-Year California Streamflow Changes.” Communications Earth & Environment 5: 448. https://doi.org/10.1038/s43247-024-01594-2.

Dixon, H., D. M. Lawler, A. Y. Shamseldin, and P. Webster. 2006. “The Effect of Record Length on the Analysis of River Flow Trends in Wales and Central England.” In Climate Variability and Change—Hydrological Impacts, IAHS Publication No. 308, 358–64. Wallingford, UK: International Association of Hydrological Sciences.

Fleishman, E. 2025. Seventh Oregon Climate Assessment. Oregon Climate Change

Research Institute, Oregon State University. https://doi.org/10.5299/osu/1181.

Fleming, Sean W., and Frank A. Weber. 2012. "Detection of Long-Term Change in Hydroelectric Reservoir Inflows: Bridging Theory and Practise." Journal of Hydrology 470–471: 36–54. https://doi.org/10.1016/j.jhydrol.2012.08.008.

Fleming, Sean W., and David J. Sauchyn. 2013. "Availability, Volatility, Stability, and Teleconnectivity Changes in Prairie Water Supply From Canadian Rocky Mountain Sources Over the Last Millennium." Water Resources Research 49 (1): 64–74. https://doi.org/10.1029/2012WR012831.

Fleming, Sean W., and Helen E. Dahlke. 2014. "Modulation of Linear and Nonlinear Hydroclimatic Dynamics by Mountain Glaciers in Canada and Norway: Results From Information-Theoretic Polynomial Selection." Canadian Water Resources Journal / Revue Canadienne des Ressources Hydriques 39 (3): 324–41. https://doi.org/10.1080/07011784.2014.942164.

Fleming, Sean W., and Helen E. Dahlke. 2014. "Parabolic Northern-Hemisphere River Flow Teleconnections to El Niño-Southern Oscillation and the Arctic Oscillation." Environmental Research Letters 9 (10): 104007. https://doi.org/10.1088/1748-9326/9/10/104007.

Fleming, Sean W., and M. Barton. 2015. "Climate Trends but Little Net Water Supply Shift in One of Canada's Most Water-Stressed Regions Over the Last Century." Journal of the American Water Resources Association 51 (3): 833–41. https://doi.org/10.1111/jawr.12281.

Gangopadhyay, S., and McGuire, M. 2021. West-Wide Climate and Hydrology Assessment. Technical Memorandum No. ENV-2021-001. U.S. Bureau of Reclamation.

Georgiadis, Nicholas J., and Joel E. Baker. 2023. "A Multidecadal Oscillation in Precipitation and Temperature Series Is Pronounced in Low Flow Series From Puget Sound Streams." Journal of the American Water Resources Association 59 (5): 970–83. https://doi.org/10.1111/1752-1688.13129.

Giamalaki, K., C. Beaulieu, D. Faranda, S. A. Henson, S. A. Josey, and A. P. Martin. 2018. "Signatures of the 1976–1977 Regime Shift in the North Pacific Revealed by Statistical Analysis." Journal of Geophysical Research: Oceans 123 (6): 4388–97.

https://doi.org/10.1029/2017JC013718.

Han, Juntai, Ziwei Liu, Ross Woods, Tim R. McVicar, Dawen Yang, Taihua Wang, Ying Hou, Yuhan Guo, Changming Li, and Yuting Yang. 2024. “Streamflow Seasonality in a Snow-Dwindling World.” Nature 629: 1075–81. https://doi.org/10.1038/s41586-024-07299-y.

Hamlet, Alan F. “Assessing water resources adaptive capacity to climate change impacts in the Pacific Northwest Region of North America.” 2011. Hydrology and Earth System Sciences 15 (5): 1427–43.

Hirsch, Robert M. 2011. “A Perspective on Nonstationarity and Water Management.” Journal of the American Water Resources Association 47 (3): 436–46. https://doi.org/10.1111/j.1752-1688.2011.00539.x.

Kennedy, Adam M., David C. Garen, and Roy W. Koch. 2009. “The Association Between Climate Teleconnection Indices and Upper Klamath Seasonal Streamflow: Trans-Niño Index.” Hydrological Processes 23 (7): 973–84. https://doi.org/10.1002/hyp.7200.

Li, Dongyue, Melissa L. Wrzesien, Michael Durand, Jennifer Adam, and Dennis P. Lettenmaier. 2017. “How Much Runoff Originates as Snow in the Western United States, and How Will That Change in the Future?” Geophysical Research Letters 44 (12): 6163–72. https://doi.org/10.1002/2017GL073551.

Litzow, Michael A., Michael J. Malick, Nicholas A. Bond, Curry J. Cunningham, Jennifer L. Gosselin, and Eric J. Ward. 2020. “Quantifying a Novel Climate Through Changes in PDO-Climate and PDO-Salmon Relationships.” Geophysical Research Letters 47 (16): e2020GL087972. https://doi.org/10.1029/2020GL087972.

Litzow, Michael A., M. E. Hunsicker, Nicholas A. Bond, et al. 2020. “The Changing Physical and Ecological Meanings of North Pacific Ocean Climate Indices.” Proceedings of the National Academy of Sciences 117 (14): 7665–71. https://doi.org/10.1073/pnas.1921266117.

Luce, C.H., and Holden, Z.A. 2009. Declining annual streamflow distributions in the Pacific Northwest United States, 1948–2006. Geophysical Research Letters 36 (16): 2009GL039407. https://doi.org/10.1029/2009GL039407.

Newman, Matthew, Alexander, Michael A., Ault, Toby R., Cobb, Kim M., Deser, Clara, Di Lorenzo, Emanuele, Mantua, Nathan J., Miller, Arthur J., Minobe, Shoshiro, Nakamura, Hisashi, Schneider, Niklas, Vimont, Daniel J., Phillips, Adam S., Scott, James D., and Smith, Catherine A. (2016). The Pacific Decadal Oscillation, Revisited: Journal of Climate, 29(12), 4399–4427. https://doi.org/10.1175/JCLI-D-15-0508.1

Milly, P.C., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., and"Stouffer, R.J. 2008. “Stationarity is dead: Whither water management?” Science 319(5863): 573-574. https://doi.org/10.1126/science.1151915.

Mantua, Nathan J., and Steven R. Hare. 2002. “The Pacific Decadal Oscillation.” Journal of Oceanography 58 (1): 35–44. https://doi.org/10.1023/A:1015820616384.

Mote, Philip W., Alan F. Hamlet, Martyn P. Clark, and Dennis P. Lettenmaier. 2005. “Declining Mountain Snowpack in Western North America.” Bulletin of the American Meteorological Society 86 (1): 39–49. https://doi.org/10.1175/BAMS-86-1-39.

National Oceanic and Atmospheric Administration (NOAA). 2026a. “Cold & Warm Episodes by Season.” Accessed January 8, 2026. https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php.

National Oceanic and Atmospheric Administration (NOAA). 2026b. “Pacific Decadal Oscillation (PDO).” Accessed January 8, 2026. https://psl.noaa.gov/data/timeseries/month/PDO/.

PRISM. 2026. PRISM Climate Group, Oregon State University. Accessed January 13, 2026. https://prism.oregonstate.edu.

Reid, Philip C., Renata E. Hari, Grégory Beaugrand, David M. Livingstone, Christoph Marty, Dietmar Straile, Jonathan Barichivich, et al. 2016. “Global Impacts of the 1980s Regime Shift.” Global Change Biology 22 (2): 682–703. https://doi.org/10.1111/gcb.13106.

Rice, Joshua S., Ryan E. Emanuel, James M. Vose, and Stacy A. C. Nelson. 2015. “Continental U.S. Streamflow Trends From 1940 to 2009 and Their Relationships With Watershed Spatial Characteristics.” Water Resources Research 51 (8): 6262–75. https://doi.org/10.1002/2014WR016367.

Ryberg, Karen R., Glenn A. Hodgkins, and Robert W. Dudley. 2020. “Change Points in Annual Peak Streamflows: Method Comparisons and Historical Change Points in the United States.” Journal of Hydrology 583: 124307. https://doi.org/10.1016/j.jhydrol.2019.124307.

Stewart, Iris T., Daniel R. Cayan, and Michael D. Dettinger. 2005. “Changes Toward Earlier Streamflow Timing Across Western North America.” Journal of Climate 18 (8): 1136–55. https://doi.org/10.1175/JCLI3321.1.

[USACE] U.S. Army Corps of Engineers. 2015. “Recent US Climate Change and Hydrology Literature Applicable to US Army Corps of Engineers Missions – Water Resources Region 17, Pacific Northwest.” Civil Works Technical Report, CWTS 2015-23. USACE, Washington, DC.

Wang, Zhengrong, and Yuting Yang. 2024. “Stationarity of High- and Low-Flows Under Climate Change and Human Interventions Across Global Catchments.” Earth and Space Science 11 (1): e2023EA003456. https://doi.org/10.1029/2023EA003456.

Woo, M., and Robin T. 2008. “Analysis of cold season streamflow response to variability of climate in north-western North America.” Hydrology Research 39(4): 257-265.

Wu, Chau-Ron, Wang, You-Lin, and Chao, Shenn-Yu. (2019). Disassociation of the Kuroshio Current with the Pacific Decadal Oscillation Since 1999: Remote Sensing, 11(3), 276. https://doi.org/10.3390/rs11030276

Yang, Yuting, Michael L. Roderick, Dawen Yang, Zhengrong Wang, Fangzheng Ruan, Tim R. McVicar, Shulei Zhang, et al. 2021. “Streamflow Stationarity in a Changing World.” Environmental Research Letters 16 (6): 064096. https://doi.org/10.1088/1748-9326/ac08c1.

Yue, Sheng, Pierre Pilon, and Georges Cavadias. 2002. “Power of the Mann–Kendall and Spearman’s Rho Tests for Detecting Monotonic Trends in Hydrological Series.” Journal of Hydrology 259 (1–4): 254–71. https://doi.org/10.1016/S0022-1694(01)00594-7.