Surface Water Information Modeling System (SWIMS)

Streamflow Stationarity Assessment

Author: Cortney Cameron

Executive Summary

This document describes the results of a stationarity assessment to support base period selection and evaluate future applicability of results for the Surface Water Information and Model System update. Stationarity evaluation helps assess the extent to which past streamflow observations are useful for inferring future water availability.

To aid selection of appropriate statistical tests for stationarity, stationarity concepts and tests as applied in the hydrologic sciences are reviewed. To provide background on the range of expected results, several existing studies that have evaluated streamflow stationarity in Oregon are discussed. Then, stationarity tests are conducted for 51 long-term, low-disturbance streamflow gages operated by the Oregon Water Resources Department, covering most of the state's major ecoregions and hydrologic classes. Use of low-disturbance stations helps to eliminate the impacts of watershed alterations, diversions, and regulation on streamflow changes, thus focusing the assessment on climate influences that would be broadly applicable to stations throughout the state.

The results suggest that annual flows at most long-term, low-disturbance stations in Oregon can be considered stationary over long-term periods of interest. However, for monthly flow metrics, all stations showed at least one significant trend, most frequently during summer. Significant downward trends in summer flows correspond with previously documented shifts in earlier snowmelt timing in snow-dominated watersheds. Non-stationarity of monthly streamflow suggests that, for updating a statistical water availability model, a recent representative period is more appropriate. In alignment with standard climatological practice, the 1991 to 2020 period is proposed.

Introduction

Stationarity determines whether historical patterns can reliably predict future conditions (Cooper 2002, Murphy and Ellis 2014, Bayazit 2015). In a stationary system, statistical properties remain constant over time, allowing past data to inform future projections with confidence. However, with climate change, streamflow in Oregon may be changing, challenging water management approaches that assume stationarity (Milly et al. 2008, Dalton and Fleishman 2021, Gangopadhyay and McGuire 2021). For example, warming temperatures could drive earlier snowmelt and reduce proportions of precipitation falling as snow, shifting seasonal streamflow distributions (Barnett et al. 2008, Luce and Holden 2009). Changes in evapotranspiration, wildfire frequency, and land and water use patterns can also alter streamflow patterns (Holden et al. 2011, Yang et al. 2021, Wampler et al. 2023, Hou and Wei 2024). As diversions and regulation are explicitly addressed in water availability modeling, climate-induced non-stationarity is of particular interest, as climate change occurs throughout the state regardless of water use practices.

During original development of Oregon's existing Water Availability Reporting System, stationarity was assessed using ordinary least squares linear regressions for only mean annual flows at four long-term stations (Cooper 2002); no slopes were significant. Since then, methodological and computational advances have improved options for trend testing in the hydrologic sciences. More importantly, water availability is assessed on a monthly basis for specific percentiles, and it is possible for mean annual flows to be stationary while monthly flows are not (e.g., decreasing summer flows may be masked by increasing winter flows). However, limited literature is available for Oregon addressing monthly streamflow changes. Thus, an updated stationarity assessment of Oregon streamflow is needed.

While findings of non-stationarity are unlikely to substantially change the statistical modelling approach currently envisioned for the project, they are important for understanding model limitations, justifying a base period selection, and providing policy recommendations for future model updates. Following sections review streamflow stationarity concepts and selected studies relevant to Oregon, then a statewide stationarity assessment is completed.

Stationarity Concepts

Statistically, a time series is stationary when its moments are invariant over time (Murphy and Ellis 2014, Bayazit 2015). A time series is strictly stationary when all moments of the probability function are constant and weakly stationary when only the mean and covariance (first and second moments) are constant. In practice, it is generally considered sufficient to test only for weak stationarity (Murphy and Ellis 2014, Bayazit 2015, Sun et al. 2018). Some studies only test for the first moment, depending on research goals (e.g., Asarian and Walker 2016).

Although statistical tests for stationarity in the hydrological sciences have been criticized, they have been and continue to be widely applied as useful, practical tools (Milly et al. 2008, Murphy and Ellis 2014, Bayazit 2015, Serinaldi et al. 2018, Yang et al. 2021). Specifically, stationarity tests have been faulted for assumptions of independence and well-behaved distributions, limited ability to distinguish natural variability from non-stationarity, and climate change undermining stationarity as a hydrologic concept. Conversely, when appropriately applied with understanding of watershed processes and test limitations, these tests provide systematic frameworks for evaluating potential changes in hydrologic systems. Thus, a variety of statistical tests have been used to assess stationarity (Table A1 and Table A2). Tests can either be parametric or nonparametric. Nonparametric tests are needed when the underlying population distribution is unknown or parametric test requirements (e.g., normality) are not met. However, parametric methods are more powerful and therefore preferred when data allow.

Most stationarity tests assess only either the first or second moment. First moment tests typically assess either for changepoints (sudden changes in the mean) or monotonic trends (gradual changes in the mean over time), so first moment tests can be paired (e.g., Miao et al. 2012, Murphy and Ellis 2014, Jiang and Wang 2016, Wang et al. 2021). Similarly, tests for different statistical properties can be used together on a time series (e.g., Murphy and Ellis 2014, Yang et al. 2021). Due to limited ability to detect changes in variance given only a few decades of data, autocorrelation can be assessed as a proxy for temporal dependence of higher-order processes but also often captures hydrologic memory (Sun et al. 2018, Yang et al., 2021, Wang and Yang 2024). However, each additional test increases the probability of false positives (e.g., Asarian and Walker 2016). When all selected tests are non-significant, the time series can be assumed stationary. Hydrologic stationarity studies usually select a significance level (alpha) of 0.05 or 0.10 (e.g., Luce and Holden 2009, Murphy and Ellis 2014, Rice et al. 2015, Asarian and Walker 2016).

Previous Oregon Studies

Climate change impacts on precipitation, evapotranspiration, and wildfire (Holden et al. 2011, Wampler et al. 2023) can affect streamflow. However, precipitation changes are difficult to predict and globally heterogeneous (Dore 2005, Murphy and Ellis 2014, Sun et al. 2018). Additionally, various watershed characteristics can influence streamflow vulnerability (Leibowitz et al. 2014). Thus, results of previous streamflow stationarity studies for Oregon have varied by region, types of streams assessed, and flow metrics of interest. Summaries of climate change impacts on Oregon are available in Dalton and Fleishman (2021) and Gangopadhyay and McGuire (2021).

For mean annual flow, stationarity assessments in Oregon have typically found non-significant trends for low-disturbance watersheds (Table 1). However, in some watersheds, shifts in snowmelt timing and precipitation form may be causing changes to seasonal distributions of streamflow (Barnett et al. 2008, Dalton and Fleishman 2021, Gangopadhyay and McGuire 2021). Selected studies are summarized below.

Using data from 1906 to 2000, Cooper (2002) performed linear trend tests of mean annual flows for four long-term Oregon streamflow stations on the John Day, Rogue, Umpqua, and Willamette Rivers; none were significant.

In the Pacific Northwest, Luce and Holden (2009) assessed changes in lower quartile, mean, median, and upper quartile annual flow from 1948 to 2006 using quantile regression. Forty-three stations representative of natural conditions were used. A majority of stations showed significant declines in lower quartile flow, with less pronounced changes at other percentiles. In Oregon, six stations were evaluated. At the two stations in the eastern third of the state, no significant changes were found (Figure C3). At the four stations in the northwestern quadrant of the state, all generally showed significant declines except for upper quartile flows (Figure C3).

Rice et al. (2015) evaluated streamflow trends across the continental U.S. from 1940 to 2009. Stations were divided into ecoregions, including the Western Mountains and Western Xeric ecoregions that cover Oregon (Figure C4 and Figure C5). Mann-Kendall trend tests were conducted for annual mean, variance, skewness, kurtosis, minimum, maximum, tenth percentile, and ninetieth percentile flows. Additionally, relationships between watershed characteristics, including disturbance, and streamflow trends were assessed. Of all ecoregions, the Western Mountains displayed the largest flow decreases; large clusters of decreasing flows were noted in the Southern Cascades. Conversely, the Western Xeric region experienced a roughly even split of upward and downward trends and relatively small trend magnitudes. Changes in variance were generally downward. Nationally, reference watersheds exhibited significantly smaller trend magnitudes.

In an evaluation of southern Oregon and northern California, Asarian and Walker (2016) found that annual precipitation was stationary from 1953 to 2012; however, precipitation changes were significant for some individual months, such as September (Figure C6). For streamflow, 26 dam-regulated and 41 unregulated stations were assessed, including a total of 29 stations in Oregon; watershed characteristics, such as relative groundwater contribution, were also considered. While significant changes in streamflow were found at many stations, on the basis of limited precipitation changes and findings for least-impacted watersheds, the study concluded that observed streamflow decreases were mainly driven by increased human withdrawals and vegetation changes.

Working at the global scale, Yang et al. (2021) similarly found that stationarity of long-term annual streamflow was largely dependent on human alterations of watersheds; streamflow was stationary at almost 80 percent of minimally disturbed catchments versus about 40 percent of highly disturbed catchments. The assessment included stations with at least 30 years of continuous streamflow record with no more than 5% missing data, selected from a previously compiled global dataset that includes U.S. Geological Survey data. Human disturbances considered were irrigation, impoundment, and urbanization, all derived from global layers. The study classified most of Oregon as stationary for mean annual flow (Figure C7). A follow-up study by Wang and Yang (2024) focusing on minimum and maximum flows found similar results (Figure C8 and Figure C9).

Gangopadhyay and McGuire (2021) evaluated 64 sets of CMIP5-LOCA streamflow projections from 1950 to 2099 for major Western U.S. basins, including the Columbia and Klamath Rivers (Figure C10 and Figure C11). Compared to the 1990s, results for both systems through 2050 generally suggest modest annual flow changes but increasing flows in late winter to early spring (December to March) and decreasing flows in late spring to early summer (April to July).

These studies provide valuable insights into Oregon streamflow stationarity. This work builds on these insights with statewide assessment using low-disturbance stations, often longer periods of record, monthly analyses for three percentiles, and multiple statistical approaches.

TABLE 1. SELECTED STUDIES OF OREGON STREAMFLOW STATIONARITY.

Reference	Number of OR stations	Disturbance degree	Time period	Method(s) used	Findings
Cooper (2002)	4	Varying	1906-2000	Linear regression	No significant trend
Pagano and Garen (2005)	6	Low	1901-2002 (varies by station)	Lag-1 autocorrelation; variance and other statistical metrics	For Oregon stations, varies by assessment period; for 1983-2002, decreasing mean and skewness, but usually not significant
Luce and Holden (2009)	6	Low	1948-2006	Quantile regression (linear)	Significant declining low-to-median flows at northwestern Oregon stations; no significant trends in eastern Oregon stations
Rice et al. (2015)	>10	Varying	1940-2009	Mann-Kendall trend test for mean, variance, skewness, kurtosis	Many significant downward trends in Western Mountains, especially Southern Cascades; mix for Western Xeric; nationally, smaller trends in reference watersheds
Asarian and Walker (2016)	29	Varying	1953-2012	Mann-Kendall trend test	Stationary mean annual precipitation; streamflow dependent on watershed characteristics including disturbance
Ryberg et al. (2020)	>10	Varying	1916-2015	Pettitt test and others	Mixed results for peak flow changes in Oregon
Yang et al. (2021)	>10	Varying	≥30 years through 2018	Mann-Kendall trend; lag-1 autocorrelation	Generally, stationary streamflow in low-disturbance watersheds
Gangopadhyay and McGuire (2021)	4 (2 major basins: Columbia, Klamath)	Varying	1950-2099	CMIP5-LOCA projections, compared to past flows	For Oregon basins, relatively small annual flow changes, but increasing flows in late winter to early spring; decreasing flows in late spring to early summer

Methods

Data Compilation

To conduct an updated, statewide assessment of streamflow stationarity for Oregon, a list of 51 low-disturbance, long-term stations (Figure 1) was acquired from Andrews and Huang (2024), who adapted Falcone et al.'s (2010, 2011) anthropogenic disturbance methodology, with a focus on surface water withdrawals and dam storage. These 51 near-natural "index" stations, also used in Huang (2024), have active monitoring, ≥30 water years of data, an irrigation withdrawal ratio of ≤0.10, and a storage ratio ≤0.05. Use of low-disturbance stations reduces the impacts of watershed alterations, diversions, and regulation on streamflow changes and thus focuses the stationarity assessment on climate influences that would be broadly applicable throughout the state.

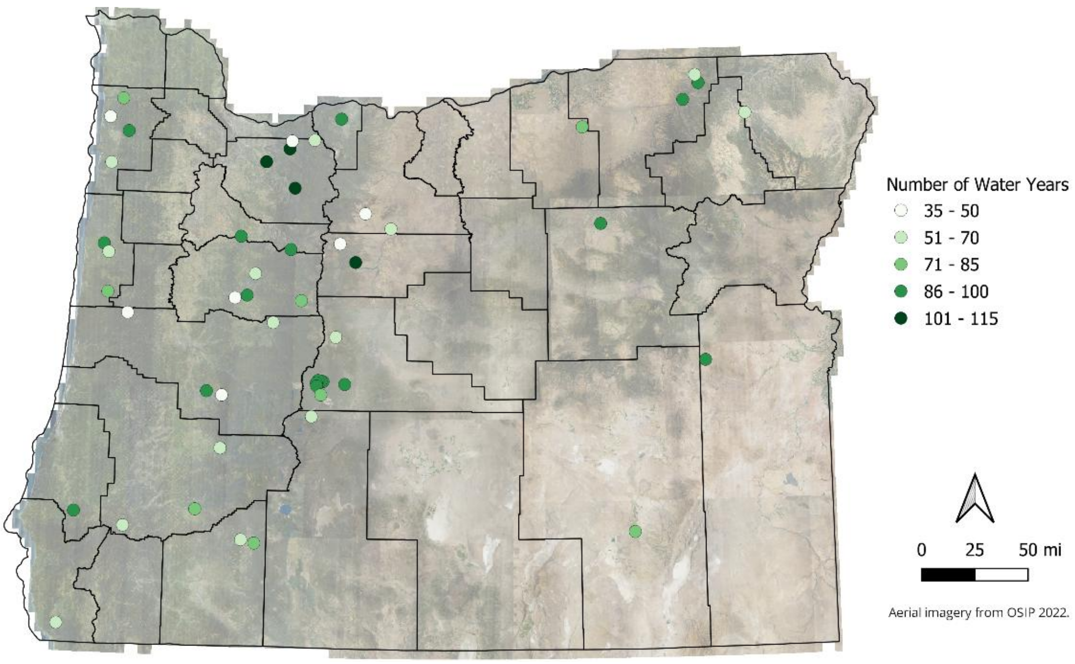

FIGURE 1. CONSECUTIVE YEARS OF DATA AVAILABLE AT LONG-TERM, LOW-DISTURBANCE STATIONS.

Published and provisional mean daily flow data were acquired for the 51 stations from the Oregon Water Resources Department database through water year 2024 (database version 6/3/2025). Gaps of up to 7 days were linearly interpolated. Daily values were aggregated into mean monthly and mean annual (water year) flow values. Consecutive years of data availability ranged from 35 to 115 years, with a median of 84 years (Figure 1).

Stationarity Tests

Two approaches were employed to provide complementary perspectives on streamflow stationarity: quantile regression and a moving window percentile analysis. Quantile regression directly measures trends across the entire period to assess how specific flow quantiles change using a more traditional approach for trend testing. The moving window percentile analysis shows how parts of the flow distribution evolve across overlapping windows, better representing how water managers traditionally leverage flow duration curves. Additionally, due to the high number of tests, false discovery rate correction was performed.

Four groupings of data were assessed for stationarity testing: long-term (longest consecutive number of available) annual flows, proposed base period (1991 to 2020) annual flows, long-term monthly flows, and proposed base period monthly flows. The long-term analysis allows trend assessments to capture the longest period possible without introducing biases from data gaps, while the base period analysis provides a common analysis period such that variable record lengths do not influence inter-station differences. Thirty years is generally considered a sufficient minimum for trend tests of mean flows, but detecting changes in variance typically requires a longer period (Yang et al. 2021). Annual flow assessments provide "big picture" snapshots of potential changes, while monthly assessments are more granular and target seasonal flow changes that are relevant for water availability.

Three non-exceedance flow percentiles (Q) were assessed based on relevance to water availability policy: 20th (Q20, a low flow), 50th (Q50, a median flow), and 80th (Q80, a high flow). A significance level of 0.05 was used for all tests.

Quantile Regression and Autocorrelation

Quantile regression is a semiparametric method that estimates the relationship between a predictor variable and specific percentiles of a dependent variable (Luce and Holden 2009). This method was selected due to interest in specific quintiles. For convenience, although resulting percentiles are "conditional" (on predictor variables; as used here, time), they are not explicitly labeled as such in the remainder of this report.

The quantreg package (v6.0) for R (v4.1) was used (Koenker 2025), implementing options for the modified Barrodale and Roberts algorithm for quantile regression. The quantile regression algorithm begins with an initial solution, then iterates to minimize the weighted sum of absolute errors. Weights are determined by the quantile; for example, for the 20th non-exceedance percentile (Q20), points above the fitted line get a weight of 0.2 and points below get a weight of 0.8. Coefficient significance was assessed using standard errors estimated using pairwise bootstrapping using 200 resamples with replacement; this approach does not assume error independence and is less affected by time series autocorrelation.

Lag-1 autocorrelation was assessed as a proxy for higher order moment stationarity (Yang et al., 2021), evaluating mean annual and monthly flow. Significant autocorrelation suggests non-stationarity. Positive autocorrelation suggests shifts in temporal dependence or processes with long memory, while negative autocorrelation suggests an oscillating pattern. Unequal trends among percentiles also imply changing variance.

Moving Window Percentile Analysis

The moving window percentile analysis was implemented using a 10-year sliding window to calculate how flow percentiles evolved over time. By showing temporal changes in specific portions of a longer-term flow distribution, this method better represents how water managers traditionally work with flow duration curves. The 10-year window balances sufficient window length and sample size. A 30-year window, matching typical base period length, would result in few processed points for many stations, limiting ability to detect trends.

A custom C++ function was used to calculate moving 10-year Q20, Q50, and Q80 flows. Trend significance of resulting 10-year percentile time series was assessed using the Mann-Kendall test, which tests for monotonic trends without assuming normality. To account for the inherent autocorrelation introduced by the moving window, the Hamed-Rao correction (Hamed and Rao, 1998) was applied using the modifiedmk package (v1.6) for R. This correction adjusts the Mann-Kendall test's variance using autocorrelation coefficients at significant lags. Sen's slope estimator was used for trend magnitude. Overlapping windows create autocorrelation that violates trend test independence assumptions, only partially addressed by correction. Results may be interpreted as exploratory rather than definitive hypothesis tests.

False Discovery Rate Correction

To reduce false positives from the large number of statistical tests performed, the Benjamini-Hochberg false discovery rate correction (Benjamini et al. 1995, 2001) was applied. This method creates a "sliding scale" where smaller p-values must meet stricter significant thresholds than larger ones. This correction offers greater statistical power than Bonferroni correction when conducting many simultaneous tests, particularly when tests are not independent (as in the case of spatially correlated streamflow stations).

The correction was applied to 182 hypothesis families, representing each unique combination of method, time period, month (or annual), and percentile (or mean, for autocorrelation). This approach tests for statewide and seasonal patterns by comparing all 51 stations against each other within each family. Rather than correcting for multiple testing across individual stations, this approach places emphasis on detection of statewide trends.

Results

Quantile Regression and Autocorrelation

Individual station results for quantile regression and autocorrelation analyses are shown in Appendices D and E and maps of monthly results in Appendices F and G.

Annual Flows

For long-term (consecutive period-of-record) annual quantile regression and autocorrelation analyses, 1 (2%), 1 (2%), 4 (8%), and 9 (18%) stations showed significant results for Q20, Q50, and Q80, and lag-1 autocorrelation of annual flows, respectively (Figure 2A). These stations were mostly along the eastern foothills of the Cascades, although some western and eastern stations showed significant results (Figure 3). Significant trends were downward and autocorrelation positive (Figure 2A).

For base period (1991-2020) analyses, no stations showed significant results for Q20, Q50, and Q80 annual flows, while 6 (12%) showed significant lag-1 autocorrelation (Figure 2B). Significant stations were clustered along the eastern foothills of the Cascades (Figure 4). Significant lag-1 autocorrelations were positive (Figure 2).

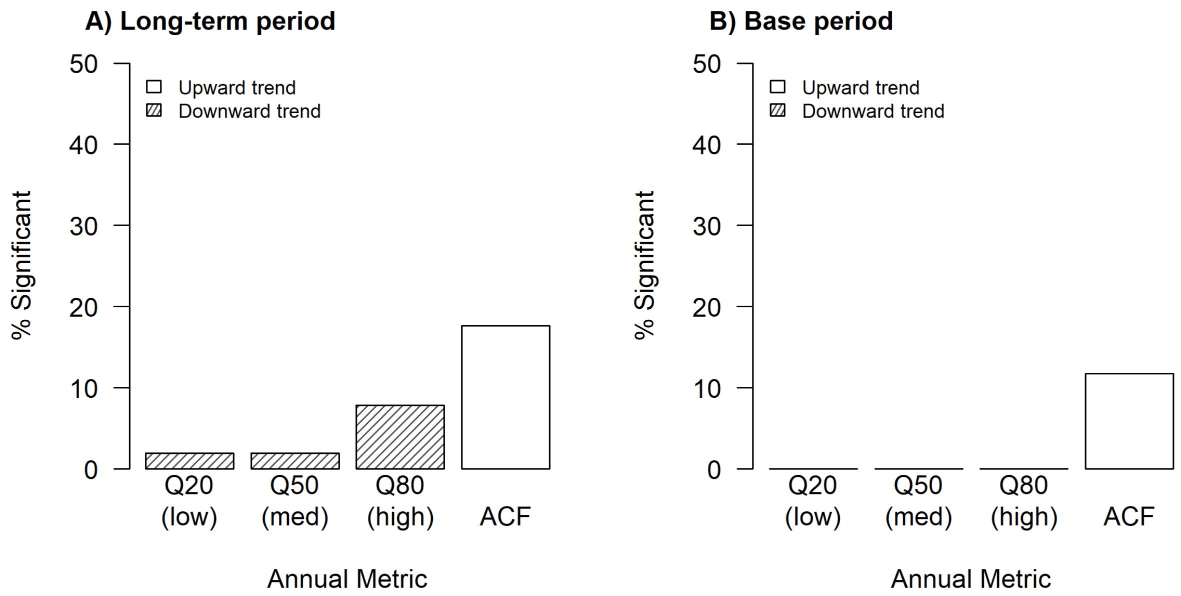

FIGURE 2. PERCENTAGE OF 51 STATIONS WITH SIGNIFICANT RESULTS FOR Q20, Q50, AND Q80 QUANTILE REGRESSIONS AND LAG-1 AUTOCORRELATION (ACF) OF MEAN ANNUAL FLOWS FOR A) LONG-TERM (35-115 YEARS) AND B) BASE (1991-2020) PERIODS.

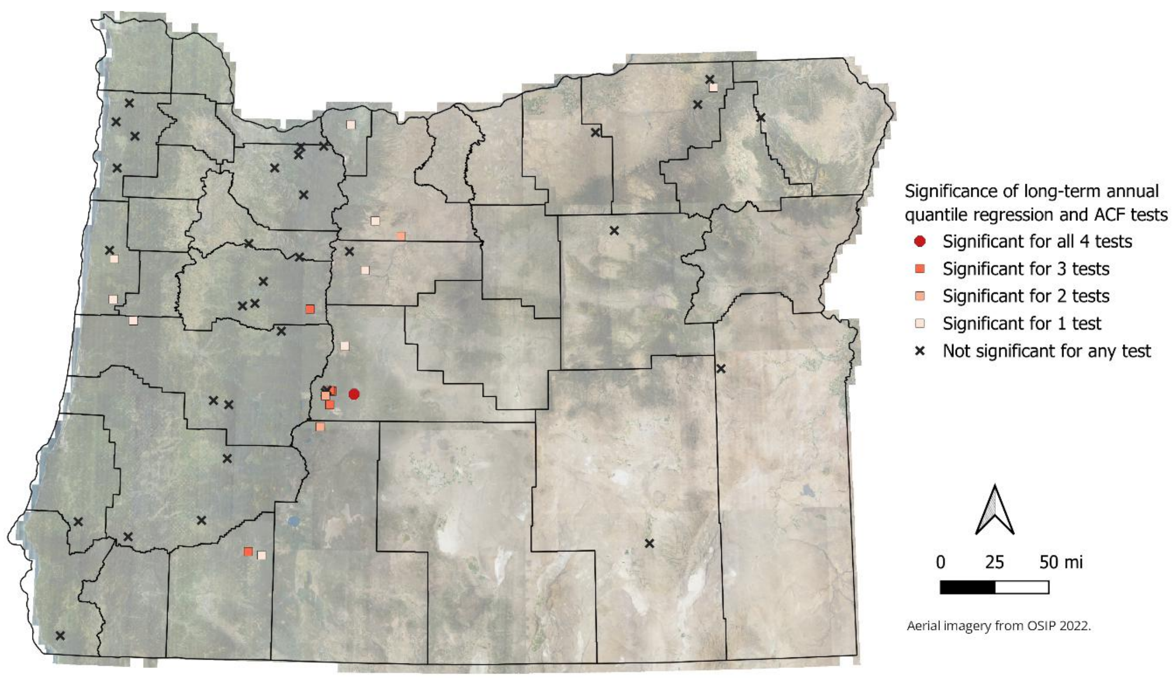

FIGURE 3. MAP SUMMARIZING SIGNIFICANCE OF Q20, Q50, Q80 QUANTILE REGRESSIONS AND LAG-1 AUTOCORRELATION OF MEAN ANNUAL FLOW AT 51 STATIONS. RECORD ASSESSED RANGES FROM 35 TO 115 YEARS.

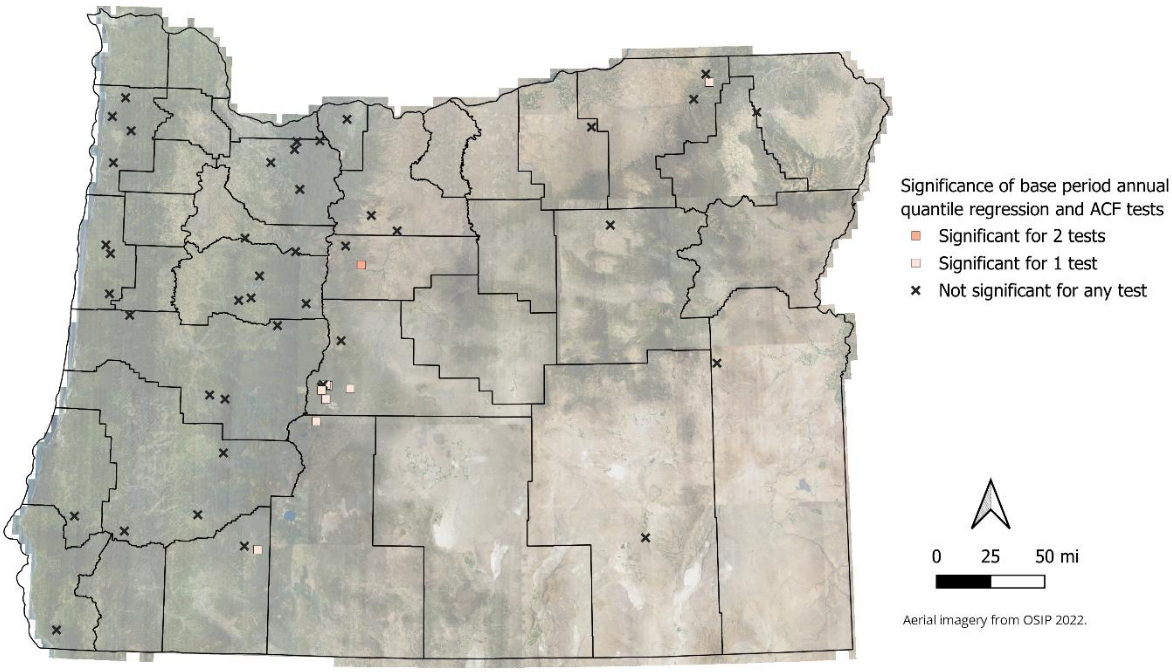

FIGURE 4. MAP SUMMARIZING SIGNIFICANCE OF Q20, Q50, Q80 QUANTILE REGRESSIONS AND LAG-1 AUTOCORRELATION OF MEAN ANNUAL FLOW AT 51 STATIONS. RECORD ASSESSED FOR 30 YEARS (1991-2020).

Monthly Flows

For long-term monthly quantile regression and autocorrelation analyses, depending on the month and percentile, between 0 (0%) and 20 (39%) stations had a significant result (Figure 5). Across all 48 monthly tests per station (4 tests, 12 months), 32 stations (63%) had at least one significant result. For summer months specifically (July to September), 30 (59%) stations had at least one significant result within one or more months. Significant results clustered along the Cascades for most tests (Figure D1 to Figure D4). For nearly all months and metrics, most significant trends were downward, while significant autocorrelations were positive (Figure 5).

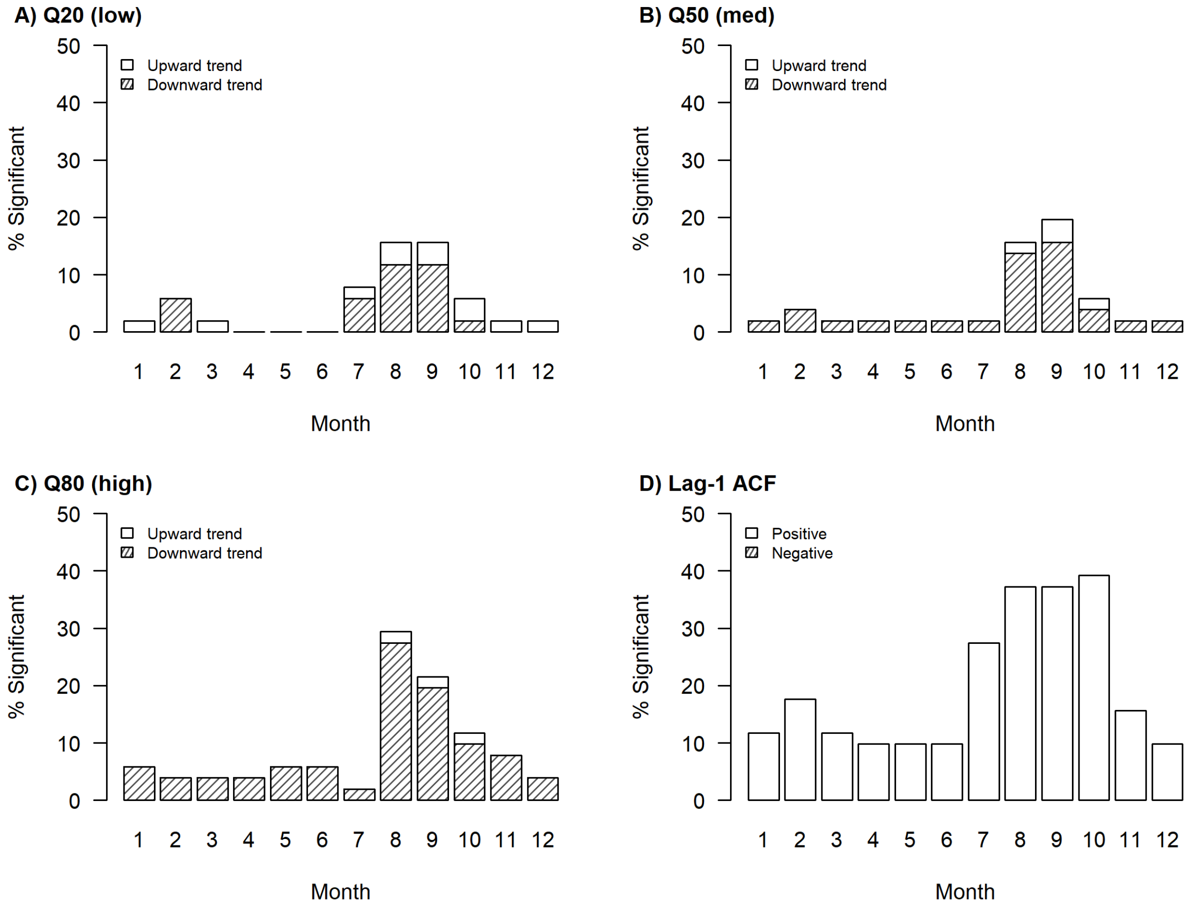

FIGURE 5. PERCENTAGE OF 51 STATIONS WITH SIGNIFICANT RESULTS FOR LONG-TERM (35-115 YEARS) A) Q20, B) Q50, AND C) Q80 QUANTILE REGRESSIONS AND D) LAG-1 AUTOCORRELATION (ACF) OF MEAN MONTHLY FLOW. RECORD ASSESSED RANGES FROM 35 TO 115 YEARS.

For base period monthly tests, almost no stations had significant trends for Q20, Q50, and Q80 mean monthly flows (Figure L1). Relatively few stations showed significant autocorrelation, with September and October showing the greatest number of significant stations at 4 (8%) each (Figure L1).

Moving Window Percentile Analyses

Individual station results for moving window percentile analyses are shown in Appendices H and I and maps of monthly results in Appendices J and K.

Annual Flows

For long-term annual moving window percentile analyses, 22 (43%), 17 (33%), and 8 (16%) stations showed significant results for Q20, Q50, and Q80 annual flows, respectively (Figure 6A). These stations were mostly along the Cascades and coast (Figure 7). Significant trends were predominantly downward (Figure 6A).

For base period tests, 13 (25%), 4 (8%), and 9 (18%) stations showed significant results for Q20, Q50, and Q80 annual flows, respectively (Figure 6B). These stations were mostly along the Cascades and coast (Figure 8). Significant trends were mixed, with a majority of upward trends for Q20 flows but predominantly downward trends for Q50 and Q80 (Figure 6B).

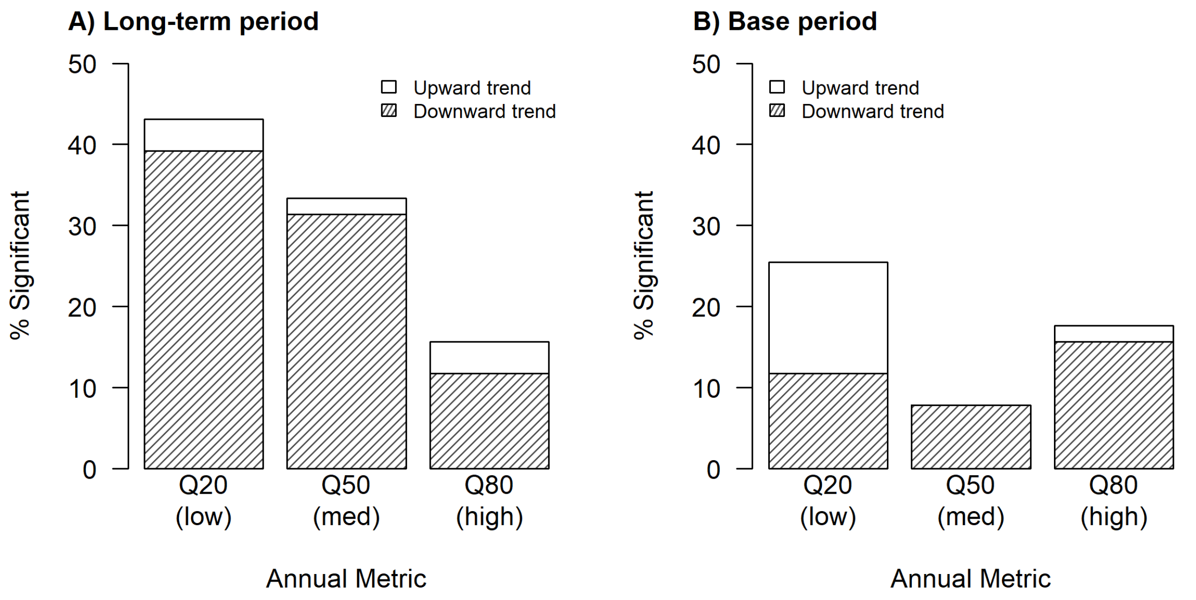

FIGURE 6. PERCENTAGE OF 51 STATIONS WITH SIGNIFICANT RESULTS FOR Q20, Q50, AND Q80 10-YEAR MOVING WINDOW PERCENTILE ANALYSES FOR A) LONG-TERM (35-115 YEARS) AND B) BASE (1991-2020) PERIODS.

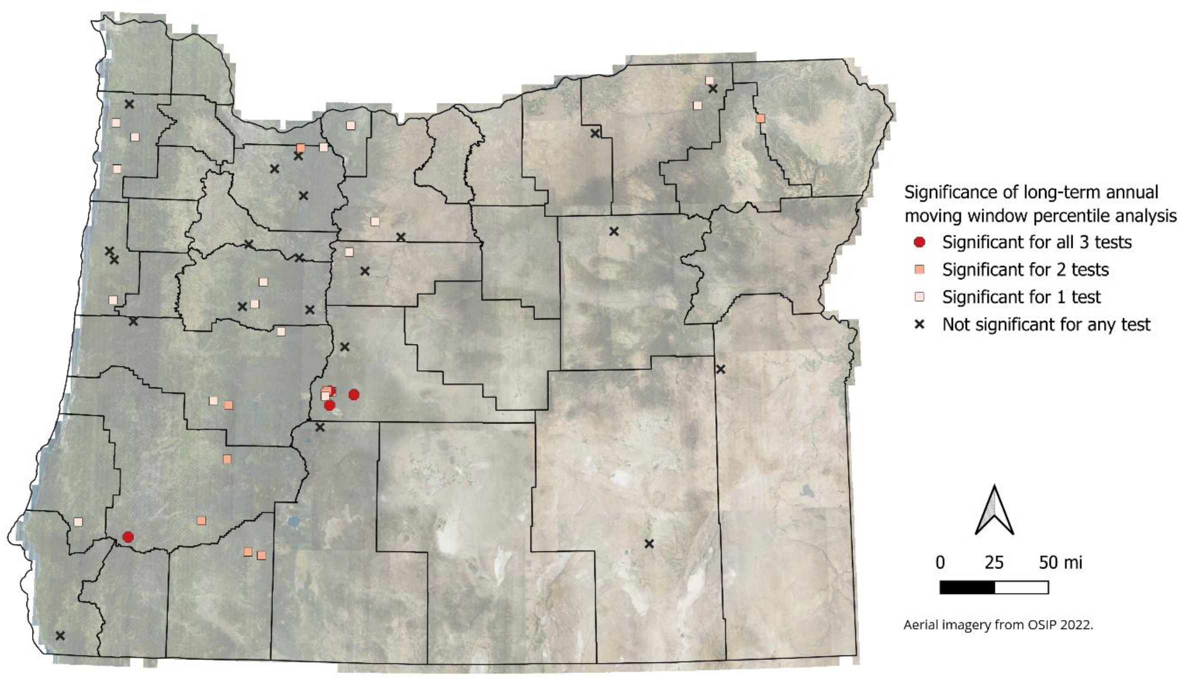

FIGURE 7. MAP SUMMARIZING SIGNIFICANCE OF 10-YEAR MOVING WINDOW PERCENTILE ANALYSES FOR Q20, Q50, AND Q80 ANNUAL FLOW AT 51 STATIONS. RECORD ASSESSED RANGES FROM 35 TO 115 YEARS.

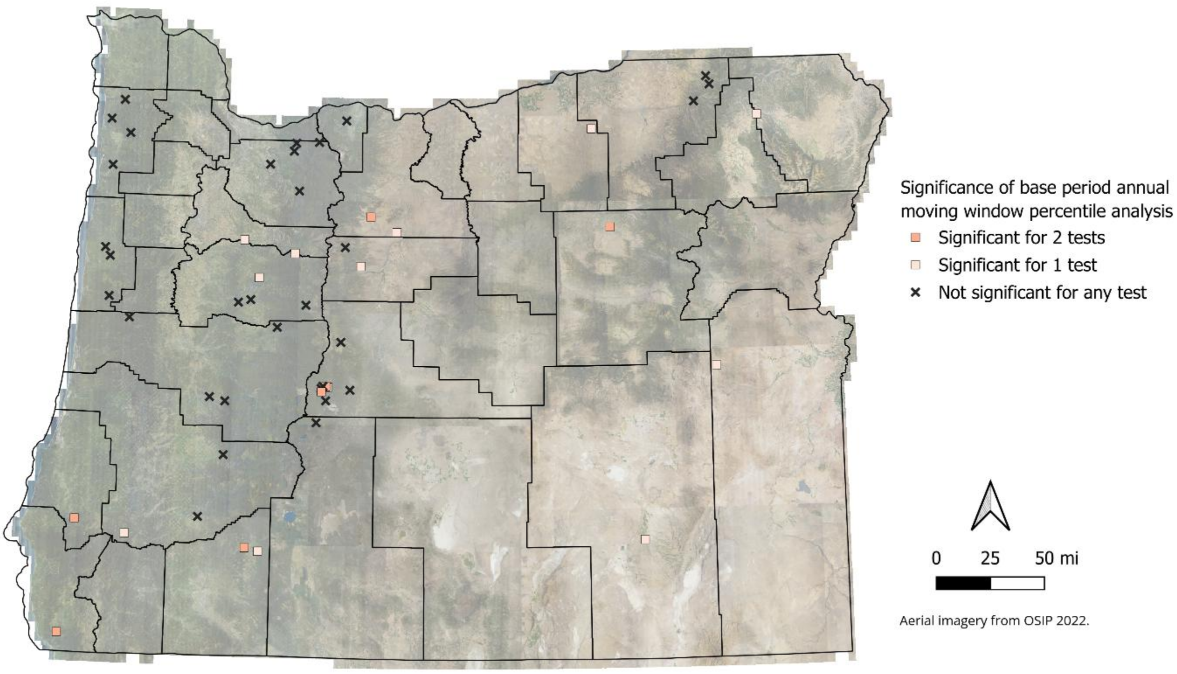

FIGURE 8. MAP SUMMARIZING SIGNIFICANCE OF 10-YEAR MOVING WINDOW PERCENTILE ANALYSES FOR Q20, Q50, AND Q80 ANNUAL FLOW AT 51 STATIONS. RECORD ASSESSED FOR 30 YEARS (1991-2020).

Monthly Flows

For long-term monthly moving window percentile analyses, depending on the month and percentile, between 6 (12%) and 29 (57%) stations had a significant result (Figure 9). Across all 36 monthly tests per station (3 tests, 12 months), 51 stations (100%) had at least one significant result. For summer months specifically (July to September), 41 (80%) stations had at least one significant result within one or more months. Significant results clustered along the Cascades for most tests (Figure D1 to Figure D4). For nearly all months and metrics, most significant trends were downward (Figure 9).

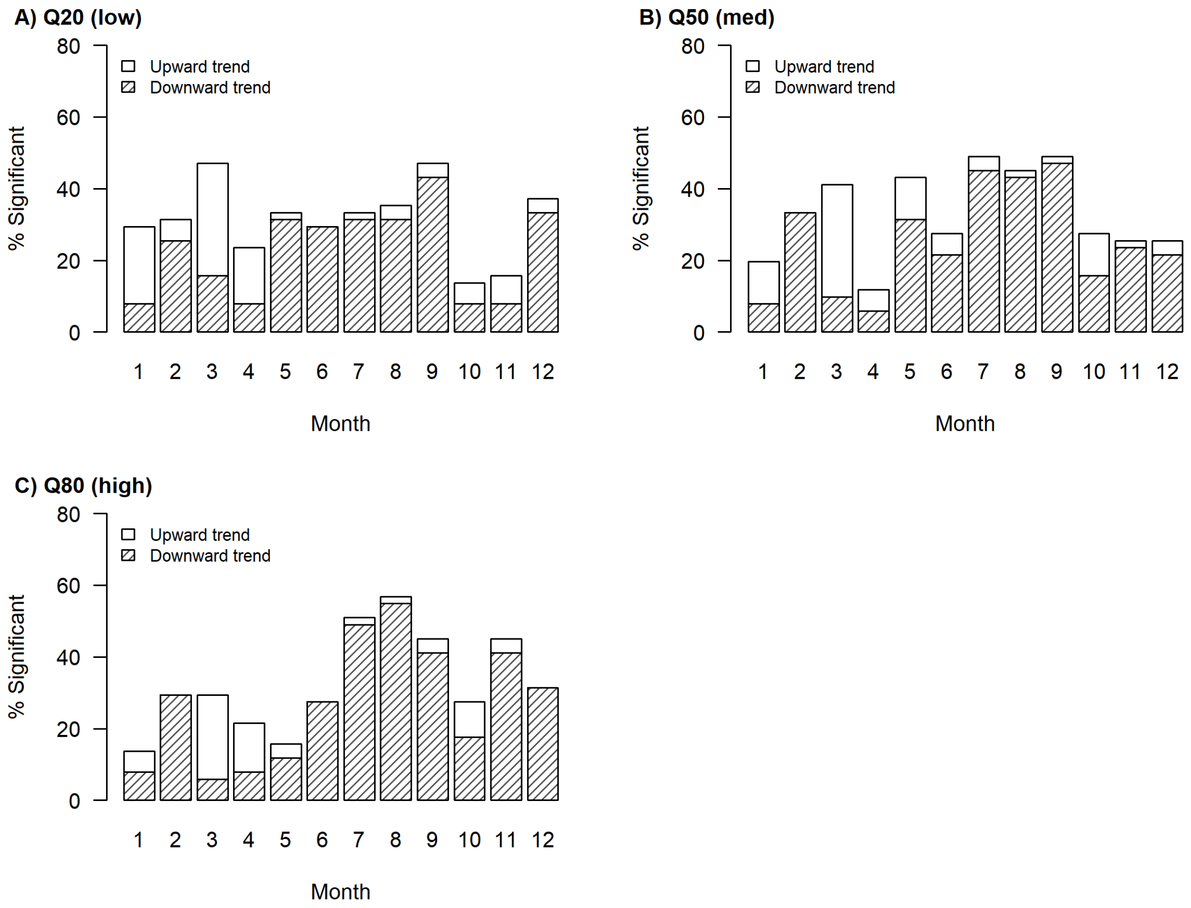

FIGURE 9. PERCENTAGE OF 51 STATIONS WITH SIGNIFICANT RESULTS FOR LONG-TERM (35-115 YEARS) A) Q20, B) Q50, AND C) Q80 10-YEAR MOVING WINDOW PERCENTILE ANALYSES. RECORD ASSESSED RANGES FROM 35 TO 115 YEARS.

For base period analyses, depending on the month and percentile, between 0 (0%) and 34 (67%) stations had a significant result (Figure L1). Across all 36 monthly tests per station (3 tests, 12 months), 50 stations (98%) had at least one significant result. For summer months specifically (July to September), 42 (81%) stations had at least one significant result within one or more months. Trend directions were mixed, but summer directions were predominantly downward (Figure L1).

Discussion

Results Overview

In general, the results of the stationarity assessment are consistent with previous work in Oregon showing that, although annual flows generally do not show significant trends at low-disturbance stations (Cooper 2002, Asarian and Walker 2016, Yang et al. 2021), at many stations, summertime flows may be decreasing in snow-dominated systems due to earlier snowmelt (Barnett et al. 2008; Gangopadhyay and McGuire 2021). For each annual test, a majority of stations had non-significant results. While the same was generally true for each monthly test, across tests, every station had at least one significant monthly result; this was especially pronounced during summer months, which showed frequent downward trends.

Spatially, stations with significant trends tend to occur along the Cascades and eastern foothills. Similar to Luce and Holden (2009), easternmost stations typically showed fewer significant trends; however, in contrast to Luce and Holden (2009), northwestern stations showed mixed results. Although certain portions of the state, such as central Oregon, are underrepresented, most major ecoregions and hydrologic classes (Sanborn and Bledsoe 2005, Andrews and Huang 2024; Figure M1 and Figure M2) are covered, so the dataset can be considered broadly representative of the state.

For all methods, while most stations exhibited no significant annual trends, many showed declining summer flows. However, the approaches produced several notable differences in results. Moving window analyses captured increasing flows in March and April, consistent with earlier melt in snow-dominated watersheds. Autocorrelation and moving window percentile analyses identified more stations with significant trends. Autocorrelation can capture higher-order moments and so is expected to show more significant results than regression. All autocorrelations were positive, suggesting nonstationarity in higher order moments (not necessarily trends) and hydrologic memory. The moving window approach smooths out short-term variability, making persistent trends easier to detect, and inherent autocorrelation of overlapping windows likely inflate significance, despite variance correction. For the quantile regression, almost no significant trends were identified in the shorter base period, likely due to the reduced statistical power; however, the moving window percentile analysis identified similar numbers of non-stationary stations between periods, as 10-year smoothing enhances detection of gradual shifts.

Limitations

The analyses applied in this study have important limitations. Differing results between approaches highlight the sensitivity of stationarity testing to methodological choices such as data aggregation (e.g., monthly, decadal) and statistical methods, emphasizing the need to interpret findings within physical contexts such as changing snowmelt patterns. The disturbance index does not account for groundwater withdrawals, which could affect streamflow stationarity in some areas. Additionally, the implemented tests are designed to identify monotonic trends, so other types of non-stationarity may not be detected. Wildfire represents an important climate change-related factor that may cause abrupt changes in streamflow. Thus, failure to detect a trend does not necessarily mean one does not exist. Statistical power may be too low to consistently detect modest changes, such as increases in winter or spring flow that could be distributed across multiple, high-variability months. Conversely, despite correction efforts, some detected trends may be false positives, particularly in autocorrelated series. Lag-1 autocorrelation, used as a proxy for higher-order moment changes, does not distinguish between natural hydrologic memory processes and true non-stationarity. Finally, this analysis did not evaluate trend magnitudes, only direction and significance, and some significant trends may have small effect sizes that may not be meaningful for medium-term water management purposes.

Notably, longer-term climate cycles, such as the Pacific Decadal Oscillation (PDO), complicate trend detection. With phases typically lasting one to three decades, the PDO significantly influences Oregon's streamflow patterns, with cool phases generally bringing increased winter precipitation and warmer phases are relatively drier (Newman et al. 2016). Phase reversals have occurred around 1920, 1945, 1975, 2000, and 2010 (Hamamoto & Yasuda 2021), with a potential recent reversal around 2020 to a cool phase (TCC 2024). Superimposition of PDO (and other cyclic) phases with climate change–driven trends could mask or amplify trends, especially problematic for shorter time periods.

Despite these limitations, the spatial grouping of significant trends along the Cascades, relatively consistent results across approaches, and general agreement with previous work and changing climate suggests most identified patterns represent genuine hydrological changes rather than statistical artifacts.

Future Work

Future work could employ alternative statistical approaches, such as change-point detection methods to identify abrupt shifts. Coupled with fire history data, this could be useful to identify fire-related hydrologic regime shifts. Spatial interpolation and regression techniques could extend findings to ungaged areas and improve understanding regional patterns of non-stationarity, particularly valuable for underrepresented regions such as central and eastern Oregon. Additionally, incorporating climate teleconnection indices (e.g., Pacific Decadal Oscillation) could help distinguish natural climate variability from trends related to climate change. To explore causative factors driving streamflow change, trend analyses could be conducted for Oregon climate data, such as temperature, precipitation, and snow water equivalent. Finally, systematic analyses of trend magnitudes would help distinguish between statistically detectable changes and effect sizes meaningful for water management purposes.

Water Management Implications

Overall, mean annual flows can be considered as stationary for most of Oregon. At the same time, seasonal distributions of streamflow appear to be changing, which could alter monthly water availability. Non-stationarity of monthly streamflow suggests that, for updating a statistical water availability model, a recent period would be more representative of future conditions. In alignment with standard climatological practice (WMO 2017), the 1991 to 2020 period is proposed.

Many basins are already fully allocated for summer under the existing water availability model, particularly in areas with significant trends; these areas are unlikely to support new allocations of surface water. Changing seasonality of streamflow may necessitate more frequent updates for future assessments.

Conclusion

Stationarity tests were conducted for 51 long-term, low-disturbance streamflow gages to produce one of the most comprehensive assessments of streamflow stationarity in Oregon. Multiple flow percentiles were analyzed at monthly resolution across some of the state's longest available periods of record. The results suggest that most of these stations can be considered stationary for annual flows over available consecutive periods of record and the proposed 1991-2020 base period, generally consistent with previous stationarity studies. At the same time, many stations show changing monthly flows, with summer decreases especially notable. Non-stationarity of monthly streamflow suggests that a recent period would be more representative of future conditions. In alignment with standard climatological practice, the 1991 to 2020 period is proposed. Changing seasonality of streamflow may necessitate more frequent updates for future assessments. Stations with significant trends tended to occur along the Cascades and eastern foothills, also a region of higher station coverage. While station density is not uniform throughout the state, most major ecoregions and hydrologic classes are covered, so the results can be considered broadly representative of the state.

References

Andrews, R., and Huang, C. 2024. WARS Update: Streamgage Network Expansion Documentation. Oregon Water Resources Department.

Asarian, J.E., and Walker, J.D. 2016. Long-Term Trends in Streamflow and Precipitation in Northwest California and Southwest Oregon, 1953-2012. JAWRA Journal of the American Water Resources Association 52 (1): 241–261. https://doi.org/10.1111/1752-1688.12381.

Barnett, T.P. et al. 2008. Human-Induced Changes in the Hydrology of the Western United States. Science 319 (5866): 1080–1083. 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.

Benjamini, Y., & Hochberg, Y. 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. Journal of the Royal statistical society: series B (Methodological) 57 (1): 289-300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Benjamini, Y., & Yekutieli, D. 2001. The control of the false discovery rate in multiple testing under dependency. Annals of Statistics, 29(4): 1165-1188.

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

Dalton, M., and Fleishman, E. 2021. Fifth Oregon Climate Assessment. Oregon Climate Change Research Institute.

Dore, M.H.I. 2005. Climate change and changes in global precipitation patterns: What do we know? Environment International 31 (8): 1167–1181. https://doi.org/10.1016/j.envint.2005.03.004.

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

Hamamoto, M., & Yasuda, I. (2021). Synchronized interdecadal variations behind regime shifts in the Pacific Decadal Oscillation. Journal of Oceanography, 77(3), 383-392. https://doi.org/10.1007/s10872-021-00592-8.

Hamed, K.H. and Rao, A. R. 1998. A modified Mann-Kendall trend test for autocorrelated data. Journal of Hydrology 204 (1-4): 182-196. https://doi.org/10.1016/S0022-1694(97)00125-X

Holden, Z.A., Luce, C.H., Crimmins, M.A., and Morgan, P. 2012. Wildfire extent and severity correlated with annual streamflow distribution and timing in the Pacific Northwest, USA (1984–2005). Ecohydrology 5 (5): 677–684. https://doi.org/10.1002/eco.257.

Huang, C. 2024. Gap tolerance analysis for streamflow data. Oregon Water Resources Department.

Jiang, C., and Wang, F. 2016. Temporal changes of streamflow and its causes in the Liao River Basin over the period of 1953–2011, northeastern China. CATENA 145: 227–238. https://doi.org/10.1016/j.catena.2016.06.015.

Kazemzadeh, M., and Malekian, A. 2018. Homogeneity analysis of streamflow records in arid and semi-arid regions of northwestern Iran. Journal of Arid Land 10 (4): 493–506. https://doi.org/10.1007/s40333-018-0064-4.

Koenker, R. (2025). quantreg: Quantile Regression. R package version 6.00. https://CRAN.R-project.org/package=quantreg.

Leibowitz, S. G., Comeleo, R. L., Wigington Jr, P. J., Weaver, C. P., Morefield, P. E., Sproles, E. A., & Ebersole, J. L. (2014). Hydrologic landscape classification evaluates streamflow vulnerability to climate change in Oregon, USA. Hydrology and Earth System Sciences, 18(9), 3367-3392. https://doi.org/10.5194/hess-18-3367-2014.

Liu, X., Dai, X., Zhong, Y., Li, J., and Wang, P. 2013. Analysis of changes in the relationship between precipitation and streamflow in the Yiluo River, China. Theoretical and Applied Climatology 114 (1–2): 183–191. https://doi.org/10.1007/s00704-013-0833-0.

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.

Miao, C.Y., Shi, W., Chen, X.H., and Yang, L. 2012. Spatio-temporal variability of streamflow in the Yellow River: possible causes and implications. Hydrological Sciences Journal 57 (7): 1355–1367. https://doi.org/10.1080/02626667.2012.718077.

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.

Modarres, R., and Ouarda, T.B.M.J. 2013. Modelling heteroscedasticty of streamflow times series. Hydrological Sciences Journal 58 (1): 54–64. https://doi.org/10.1080/02626667.2012.743662.

Murphy, K.W., and Ellis, A.W. 2014. An assessment of the stationarity of climate and stream flow in watersheds of the Colorado River Basin. Journal of Hydrology 509: 454–473. https://doi.org/10.1016/j.jhydrol.2013.11.056.

Newman, M., Alexander, M. A., Ault, T. R., Cobb, K. M., Deser, C., Di Lorenzo, E., ... & Smith, C. A. (2016). The Pacific decadal oscillation, revisited. Journal of Climate, 29(12), 4399-4427. https://doi.org/10.1175/JCLI-D-15-0508.1.

Pagano, T., and Garen, D. 2005. A Recent Increase in Western U.S. Streamflow Variability and Persistence. Journal of Hydrometeorology 6 (2): 173–179. https://doi.org/10.1175/JHM410.1.

Pandžić, K. et al. 2020. Standard normal homogeneity test as a tool to detect change points in climate-related river discharge variation: case study of the Kupa River Basin. Hydrological Sciences Journal 65 (2): 227–241. https://doi.org/10.1080/02626667.2019.1686507.

Rice, J.S., Emanuel, R.E., Vose, J.M., and Nelson, S.A.C. 2015. Continental U.S. streamflow trends from 1940 to 2009 and their relationships with watershed spatial characteristics. Water Resources Research 51 (8): 6262–6275. https://doi.org/10.1002/2014WR016367.

Andrews, R., and Huang, C. 2024. WARS Update: Streamgage Network Expansion Documentation. Oregon Water Resources Department.

Ryberg, K.R., Hodgkins, G.A., and Dudley, R.W. 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.

Sanborn, S.C., and Bledsoe, B.P. 2006. Predicting streamflow regime metrics for ungauged streams in Colorado, Washington, and Oregon. Journal of Hydrology 325 (1–4): 241–261. https://doi.org/10.1016/j.jhydrol.2005.10.018.

Serinaldi, F., Kilsby, C.G., and Lombardo, F. 2018. Untenable nonstationarity: An assessment of the fitness for purpose of trend tests in hydrology. Advances in Water Resources 111: 132–155. https://doi.org/10.1016/j.advwatres.2017.10.015.

Sun, F., Roderick, M.L., and Farquhar, G.D. 2018. Rainfall statistics, stationarity, and climate change. Proceedings of the National Academy of Sciences 115 (10): 2305–2310. https://doi.org/10.1073/pnas.1705349115.

Tao, H., Gemmer, M., Bai, Y., Su, B., and Mao, W. 2011. Trends of streamflow in the Tarim River Basin during the past 50years: Human impact or climate change? Journal of Hydrology 400 (1–2): 1–9. https://doi.org/10.1016/j.jhydrol.2011.01.016.

Tokyo Climate Center (TCC). 2024. Pacific Decadal Oscillation (PDO) index. Climate Prediction Division, Japan Meteorological Agency. https://ds.data.jma.go.jp/tcc/tcc/products/elnino/decadal/pdo.html (accessed 11 June 2025)

Wampler, K.A., Bladon, K.D., and Faramarzi, M. 2023. Modeling wildfire effects on streamflow in the Cascade Mountains, Oregon, USA. Journal of Hydrology 621: 129585. https://doi.org/10.1016/j.jhydrol.2023.129585.

Wang, F., Huang, G.H., Cheng, G.H., and Li, Y.P. 2021. Impacts of climate variations on non-stationarity of streamflow over Canada. Environmental Research 197: 111118. https://doi.org/10.1016/j.envres.2021.111118.

Wang, W., Chen, X., Shi, P., and Van Gelder, P.H.A.J.M. 2008. Detecting changes in extreme precipitation and extreme streamflow in the Dongjiang River Basin in southern China. Hydrology and Earth System Sciences 12 (1): 207–221. https://doi.org/10.5194/hess-12-207-2008.

Wang, Z., and Yang, Y. 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.

World Meteorological Organization (WMO). 2017. WMO Guidelines on the Calculation of Climate Normals. WMO-No. 1203. Geneva, Switzerland.

Yang, Y. et al. 2021. Streamflow stationarity in a changing world. Environmental Research Letters 16 (6): 064096. https://doi.org/10.1088/1748-9326/ac08c1.