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RESEARCH ARTICLE

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Process-Based Hydrologic Model Representations of Non-Perennial Streamflow in the Pacific Northwest, USA

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Key Points:

- Large-scale process-based models perform poorly when simulating non-perennial rivers and streams
- Model performance is inversely related to hydrologic landscape classification aridity
- Understanding models of non-perennial systems, outlines the usefulness for management, regulation needs, and climate studies

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract There is a global abundance of non-perennial rivers and streams, of which are predicted to increase due to environmental change and anthropogenic influences. However, most modeled representations of streamflow have been constructed with perennial systems in mind, leaving a gap in our understanding and representation of non-perennial systems. To adapt to future challenges, there is a need to determine what modeled representations of low- and no-flow in non-perennial rivers and streams do well and where uncertainties may lie in the internal representations of hydrologic processes. Here we compare four publicly available process-based hydrologic models: Variable Infiltration Capacity, Precipitation Runoff Modeling System, and National Water Model versions 2.1 and 3.0, in their ability to represent non-perennial streamflow regimes across 156 streamgages that experience non-perennial streamflow behavior in the Pacific Northwest. Our results show that process-based models are largely unable to capture non-perennial streamflow behavior, and that simulation skill decreases as a function of increasing aridity of a streamgage location. Most simulations underestimate the number of no- and low-flow days a streamgage experiences and overestimates the magnitude of low-flows. The ability to accurately model non-perennial systems is paramount to draw inferences about the connections between hydrologic characteristics of low- and no-flow and the potential ecological, biogeochemical, and societal implications of these important systems. Our findings suggest that improving our predictive understanding of non-perennial streamflow of rivers and streams within the Pacific Northwest will fill critical gaps and better target the timing and location of future research, management, and conservation efforts as well as improve the usability of these models for a wider audience of practitioners across fields.

1. Introduction

Non-perennial rivers and streams are globally pervasive systems that cease to flow, either spatially and/or temporally, and make up the majority of river and stream miles globally and in the Pacific Northwest (Figure 1; Messager et al., 2021). Non-perennial systems are important mediators of water quality and quantity and provide important ecosystem services and across landscapes (Datry et al., 2023; Price et al., 2024; Zimmer et al., 2022). In the Pacific Northwest, tribal governments, land managers, and community members depend on non-perennial systems as sources of drinking and irrigation water as well as refugia for first foods and other aquatic species. However, there is a paucity of streamflow data in non-perennial systems that give us insights into flow regimes (*sensu* Poff et al., 1997) and other relevant streamflow proxies important to managers and rights-holders. Therefore, there is a need to explore how publicly available hydrologic models represent non-perennial behavior in these systems.

Process-based hydrologic models (henceforth referred to as PBM) are mathematical models that use empirically derived equations to represent physical hydrologic processes across time and space. In this study, we use PBMs that are publicly accessible and cover a large spatial and temporal extents for use by a wide berth of researchers, practitioners, stakeholders, and water managers. PBMs, especially those with retrospective data, are particularly useful for managers that need long-term records of flow regimes to make management decisions in locations where no observational data exist. To date, relatively few studies have focused on the applicability or usability of PBMs for decision-making with even fewer focusing on non-perennial systems (*sensu* Hafen et al., 2022). Given the variability in drivers of stream permanence from one region to another (Jaeger et al., 2019; Zipper et al., 2021), and the variability in process representation from PBM to PBM, there is a need to examine which tools are most appropriate in ecosystem and management scenarios under continued climate change.

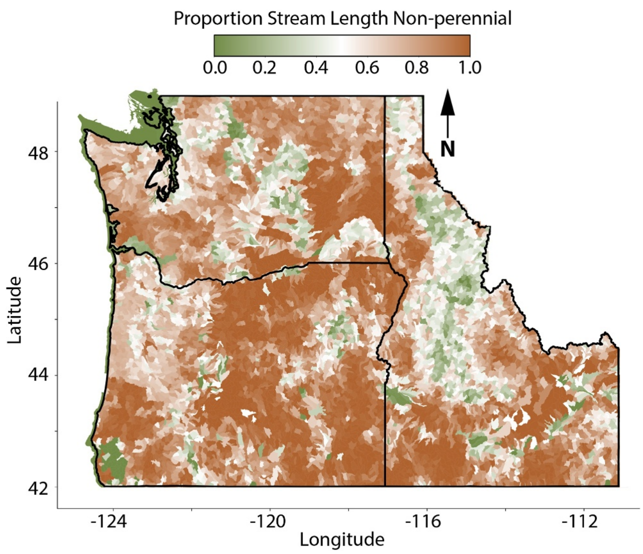

Figure 1. Spatial distribution of the proportion of non-perennial stream lengths in hydrologic unit code subwatersheds (HUC12) in Pacific Northwest.

Recent modeling efforts that use data driven approaches at large spatial scales have focused on how to characterize non-perennial systems (Figure 2). Statistical and machine learning models have been used to advance our understanding of the drivers of streamflow (or lack thereof) in non-perennial systems and describe the degree of streamflow permanence and/or the drying and wetting regimes of these systems (Dralle et al., 2023; Hammond et al., 2021; Jaeger et al., 2019; Price et al., 2021; Reynolds et al., 2015; Sando & Blasch, 2015; Zipper et al., 2021). Data driven approaches are useful for describing the range and variability of streamflow behavior observed in non-perennial systems but are limited by the quality and quantity of data, the latter of which is known to be biased toward perennial systems (Krabbenhoft et al., 2022).

PBMs that simulate non-perennial systems, either explicitly or implicitly, have largely focused on the catchment scale (Gutiérrez-Jurado et al., 2019; Gutierrez-Jurado et al., 2021; Hafen et al., 2023; Mimeau et al., 2024; Ward et al., 2018). These models are invaluable in describing the dominant physical mechanisms that drive non-perennial streamflow; however they simulate temporal or spatial scales below what may be important for regional or national management or regulatory determinations (*sensu* Hafen et al., 2022). Yet, managers rely on models like these to make decisions about local watershed management activities and prioritization (*sensu* Mauger et al., 2021). There are PBMs that are capable of accurately representing non-perennial systems (e.g., emergent water table, coupled groundwater/surface-water) (Gutiérrez-Jurado et al., 2019; Hafen et al., 2023; Mahoney et al., 2023; Ward et al., 2018) but yet are unable to resolve non-perennial streamflow phenomena at scales needed to inform management and regulatory decision makers. Additionally, the difficulty of accessing and querying these products makes them difficult to apply outside highly parameterized catchment scale simulations. The diversity of approaches and representation of time and space, presents an additional challenge for managers and stakeholders who are actively seeking to adaptively manage aquatic ecosystems (Fausch et al., 2002).

In this study, we compare the ability of four publicly available, large-scale PBMs to represent low- and no-flow in non-perennial rivers and streams in the Pacific Northwest. We use a commonly applied goodness-of-fit metric in combination with duration, frequency, and timing of low- and no-flow streamflow metrics to compare PBM simulation output to streamflow observations across dominant hydrologic landscape classifications. We then investigate hydrologic process representation within the PBM to identify which internal model processes could be responsible for model performance, with a focus on processes important in non-perennial systems. The ability to accurately model non-perennial systems is paramount to understanding the connections between hydrologic characteristics of low- and no-flow and the potential ecological, biogeochemical, and societal implications of these important systems. Improving our predictive understanding of low- and no-flow periods in non-perennial systems will fill critical knowledge gaps and better target the timing and location of future research, management, and conservation efforts.

2. Methods

2.1. Process-Based Model Selection and Processing

This study uses distributed process-based models that cover spatially and temporally extensive time periods (Table 1). Application of PBMs to management of low- and no-flows is a key question of this study; therefore, only PBMs that are easily accessible and publicly available are used for analysis. National Water Model (NWM) version 3.0 and 2.1 is a PBM that utilizes the Weather Research and Forecasting Hydrologic model (WRF-hydro) framework, and simulates hydrologic processes, including streamflow across the United States (NOAA NWM et al., 2024). For comparison to PBMs more commonly used in hydrologic studies focusing on ecohydrology and climate adaptation, we analyzed both the Variable Infiltration Capacity (VIC) and Precipitation Runoff Modeling System (PRMS). Both VIC and PRMS simulations used in this study were run with identical forcings and discretization over the Columbia Basin for a study on climate change impacts under future climate scenarios (Chegwidden et al., 2017). We acknowledge that there are many different instances of these PBMs (VIC, PRMS,

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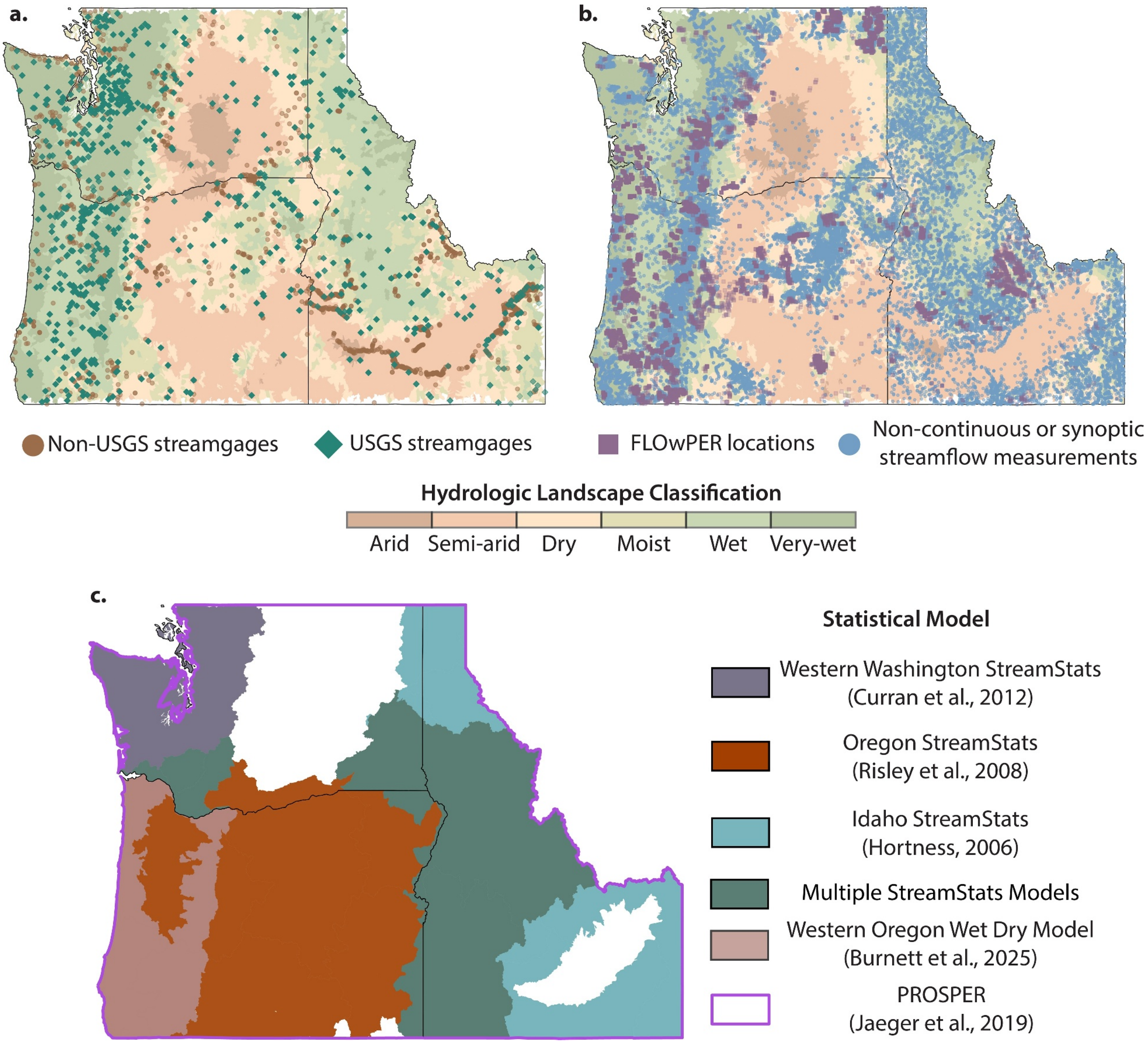

Figure 2. Spatial distribution of (a) continuous streamgages, (b) synoptic streamflow measurements and non-continuous streamgages, and (c) statistical models available in the Pacific Northwest. (Burnett et al., 2025; Curran et al., 2012; Hortness, 2006; Jaeger et al., 2019; Risley et al., 2008).

WRF-hydro) that have been applied across the landscape, but we used these instances for the ease of access to simulation outputs that are time varying and spatially discretized across the PNW. The four PBMs were extracted using publicly available tools (Castronova, 2024) and sampled to a mean daily time series for comparison to US Geological Survey National Water Information Service (United States Geological Survey, 1994) streamgages.

2.2. Streamgage Selection

To analyze the utility of PBMs for simulating low- and no-streamflows, we extracted USGS National Water Information System (NWIS) streamflow time series data from streamgages in the Columbia Basin (HUC02-17) (United States Geological Survey, 1994). Using the "dataretrieval" Python package (Hodson & Hariharan, 2023), we isolated both perennial and non-perennial streamgages in the Columbia Basin (both active and inactive) over the time period 1950 to 2023. We filtered the streamgages to select for two conditions (a). Those that had daily mean streamflow values for greater than or equal to 2 years; and (b) those that had less than or equal to 1 cubic feet per second of flow for 7 or more non-consecutive days. This process allowed that identification of both perennial and non-perennial streams that had the lowest observed flows in the period of record.

Table 1
Table of Process-Based Model Details for Simulations Used and Compared in This Study

Model	Spatial extent	Spatial resolution	Simulation period	Temporal resolution	Climate forcing
NWM 3.0	CONUS	1 km × 1 km	February 1979–December 2023	Hourly	NLDAS (Xia et al., 2012)
NWM 2.1			February 1979–December 2020		
VIC	HUC02–17	6 km × 6 km	January 1950–December 2011	Daily	Livneh (Livneh et al., 2013)
PRMS			January 1950–December 2011		

2.3. Model Fit Statistics

We used the Kling-Gupta Efficiency (KGE; Equation 1; Gupta et al., 2009; Hallouin, 2021) as our goodness-of-fit metric to analyze how PBM simulations represented low- and no-streamflow in the Pacific Northwest. Kling-Gupta efficiency is known to be sensitive to extreme high values and to focus goodness-of-fit toward low-streamflow values, we calculated KGE on inverse streamflow values (*sensu* Knoben et al., 2019; Yang et al., 2022).

$$\mathrm{KGE}(1/Q) = 1 - \sqrt{(\mathrm{KGE}_\alpha - 1)^2 + (\mathrm{KGE}_\beta - 1)^2 + (\mathrm{KGE}_r - 1)^2} \tag{1}$$

Where:

$$\mathrm{KGE}_\alpha = \frac{\sigma_{\text{simulation}}}{\sigma_{\text{observation}}}\ ;\ \mathrm{KGE}_\beta = \frac{\mu_{\text{simulation}}}{\mu_{\text{observation}}}\ ;\ \mathrm{KGE}_r = \frac{\mathrm{cov}\ (\text{observation}, \text{simulation})}{\sigma_{\text{observation}} * \sigma_{\text{simulation}}}$$

where KGE_r is the linear correlation of the simulation and the observation of the daily mean streamflow, KGE_α (or variability ratio) is the ratio of the standard deviation of the simulation and observation, and KGE_β (or bias ratio) is the ratio of the mean of the simulation to the observational data. The decomposition of the KGE in this way can lend insights into the impacts of streamflow timing, magnitude, and frequency on overall goodness-of-fit (Knoben et al., 2019). Using the KGE as a filter, we compared and calculated streamflow statistics for streamgages that have a KGE value for all four PBMs of $\mathrm{KGE} \geq -1$ to remove the poorest performing simulations.

2.4. Streamflow Statistics

To evaluate the ability of PBMs to represent low- and no-flows and applicability to management, we calculated metrics capture characteristics of non-perennial streamflow regimes (*sensu* Hammond et al., 2021; Price et al., 2021; Zipper et al., 2021), and that are relevant in streamflow management for water quality or quantity and have relevant for aquatic ecology.

2.4.1. Calculation of Low- and No-Flow Days

The total number of no-flow days was calculated from streamflow measurements by using commonly used techniques in non-perennial streamflow studies, where no-flow days are identified by rounding streamflow to the nearest 0.1 $\mathrm{ft^3s^{-1}}$ and identifying discharge equal to zero (*sensu* Busch et al., 2024; Hammond et al., 2021; Price et al., 2021; Zipper et al., 2021). Therefore, any streamflow <0.05 $\mathrm{ft^3s^{-1}}$ is considered no-flow for streamflow observations (i.e., USGS NWIS gages). Many of the PBMs in this study are mathematically unable to reach zero flow, as a result we delineated no-flow for simulated streamflow as any values below 10% of the mean annual flow (*sensu* Wenger et al., 2010). We performed a sensitivity analysis for the no-flow threshold and determined this threshold identifies no-flow values most similar to the USGS NWIS distribution (Figure 1 in Supporting Information S1). The number of low-flow days for the subset of gages was calculated the same for both observational and modeled data by counting the total number of days ≤25th percentile of streamflow for the respective data set (Hammond et al., 2021, 2022; Price et al., 2021; Zipper et al., 2021). The number of low- and no-flow days is a critical indicator for community ecology composition and drives the spatial and temporal distribution of habitat for aquatic species.

Low-flow statistics were calculated for lowest annual 7-mean-daily period of streamflow for a recurrence interval of 10 years (7Q10) and 2 years (7Q2) using a log-Pearson Type III flow estimation technique (Helsel et al., 2020; Novak et al., 2016). The frequency of low-flow is critical for hydrological and ecological indicators alike. Specifically, 7Q10 is used to evaluate the impact of water withdrawals or other flow alterations on species in systems that experience these low-flow periods (Smakhtin, 2001). Low-flow indices with shorter periods of flow and a higher frequency return intervals are used in EPA designations for water quality standards and toxic wasteload allocation and impacts to aquatic life (Novak et al., 2016; Rossman, 1990).

2.4.2. Definition of Seasons

Low- and no-flow metrics calculated above were also grouped based on seasons to compare annual and inter-annual variability and to evaluate the timing of simulated low and no-flows. For this study, we define seasons as meteorological seasons defined as: spring is March, April, May, summer is June, July, August, fall is September, October, November, and winter is December, January, February. An additional seasonal break defined as "late-summer" includes the months of August and September. This late-summer period is a commonly used temporal period to calculate low-flows and stream temperatures for salmonid habitat in the Pacific Northwest (Ebersole et al., 2009; May & Lee, 2004).

2.4.3. Spatial Grouping

In order to observe spatial bias as a driver of model performance, results were grouped by Strahler order and Hydrologic Landscape Classification (HLC; Leibowitz et al., 2016). PBMs use both climatic and geologic data for parametrization data, given that these characteristics differentiate the dominant hydrologic processes across landscapes, we use Hydrologic Land Classification (HLC) for spatial groupings because of its ability to delineate between wet and arid regions and the incorporation of subsurface hydrologic characteristics (e.g., soils, aquifer permeability) and climate (e.g., seasonality, ET). Furthermore, HLC relies on spatial groupings of areas that may have similar drivers of hydrologic processes, allowing a framework to better interpret simulation results.

3. Results

3.1. Data Description and Spatial Distribution

We identified 156 streamgages across the Pacific Northwest that displayed low-flow and/or non-perennial characteristics and met our filtering criterion (e.g., KGE and flow; Figure 3a). Streamgages are somewhat evenly distributed across regions with 58%, or 89 streamgages in wetter regions and 42%, or 67 streamgages in arid regions (Figures 3a and 3c). The streamgages in wetter regions tend to represent lower-Strahler order streams with the opposite being true in arid regions (Figure 3c). However, the majority of streamgages (155 out of 156) represent basin areas of $\leq$100 km^2 (Figure 2 in Supporting Information S1).

3.2. Goodness-of-Fit (KGE)

Kling-Gupta efficiency results show that simulations perform poorly when representing streamflow in non-perennial systems (Figure 4). Out of the 156 streamgages used in this analysis, only 33% of simulations performed better than KGE = −0.41 (Knoben et al., 2019). This KGE threshold delineates the value at which the mean of the observed streamflow time series is a better predictor of the observed time series than simulated streamflow. Kling-Gupta efficiency decomposition shows that all PBMs have positive correlations to observed streamflow but with a very low magnitude of correlation with mean values equal to 0.25 for KGE_r (Figure 4). Both the variability (KGE_α) and bias (KGE_β) ratios are different between PBMs. Both NWM versions have very similar but low magnitude bias and variability ratios, where the mean for bias ratio is to $\beta = \sim 0$ and $\alpha = \sim 0.1$, but have a higher range with 75th percentile value above ~0.25 for both components. For VIC and PRMS, KGE_β and KGE_α have similar mean values to NWM but the ranges are much smaller and have a tighter distribution around the mean value (Figure 4).

Spatially discretizing KGE by HLC shows very clear trends between model performance and aridity. Our results highlight that KGE decreases with increased aridity with the mean of all simulations in arid HLC (e.g., dry, semiarid, and arid) all below KGE = −0.41 (Figures 5a–5d). This behavior is observed across all PBMs. Results of KGE decomposition show similar trends for correlation with VIC having a negative correlation for arid HLC

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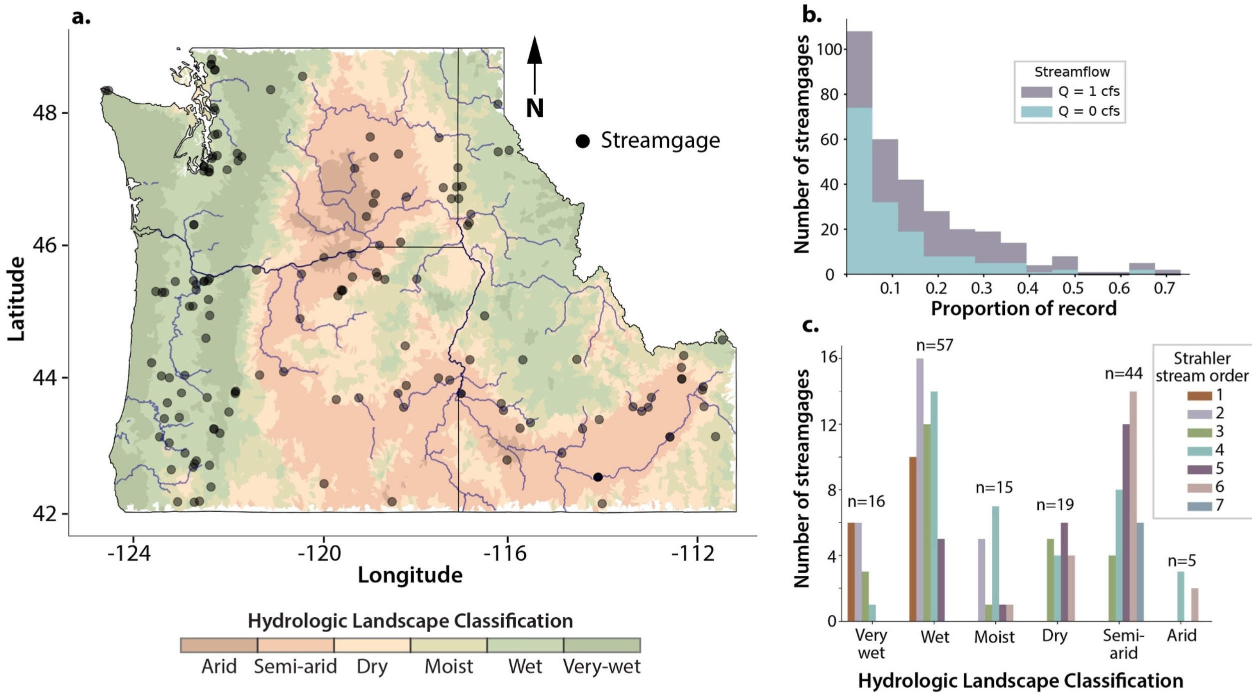

Figure 3. Spatial distribution of (a) subset of streamgages used for analysis ($Q < 1$ for at least 7 non-consecutive days, $n = 156$) overlaid on hydrologic landscape classification. Distribution of streamgages by (b) proportion of zero streamflow (blue) and streamflow $0 \leq Q \leq 1$ cfs (purple); and (c) as a function of hydrologic landscape classification and each bar represents the number of streamgages in that Strahler stream order classification with the total number of streamgages denoted by the number above the bars.

(Figures 5e–5h). This behavior is more nuanced for KGE_α and KGE_β, with similar trends (e.g., decreasing with aridity) as for VIC and PRMS and no distinct trends in NWM (Figures 5i–5p).

3.3. Non-Perennial Streamflow Regimes

3.3.1. No-Flow

PBMs were not able to accurately represent no-flow in streamflow simulations. The observational data show a clear increase in mean number of no-flow days with increasing aridity where the most arid streamgage sites have a mean number of no-flow days of ∼200 days (Figure 6a). It is likely that the sites in the most arid regions experience short seasonal flow events, owing to the increased number of no-flow days. However, the relationship between aridity and number of no-flow days is not apparent in any of the streamflow simulations, and furthermore there are notable differences between PBMs (Figures 6b–6e). For no-flow, both NWM versions are able to match the magnitude for number of no-flow days for humid regions, but not for arid regions. VIC and PRMS are unable to match the relationship or magnitude of no-flow days regardless of region. NWM3.0 underestimates the number of no-flow days, while NWM2.1 has a varied response, except for at the most arid streamgages where no-flow days do not occur in the simulation. PRMS and VIC greatly overestimate the number of low-flow days across regions with no clear trend related to aridity.

3.3.2. Low-Flow

PBMs underestimate the total number of low-flow days at both annual and seasonal scales, with a few caveats. Observations of annual number of low-flow days show no clear pattern related to HLC or aridity, unlike no-flows above (Figure 6f). Instead, annual number of low-flow days are relatively consistent across HLC with a mean value of between 80 and 90 days, with the exception of the most arid sites with a mean of ∼92 days (Figures 6g–6j). PBMs are not able to match the relationship (or lack thereof) to aridity or magnitudes of annual number of low-flow days. Overall, PBMs simulate streamflow that is more variable across HLCs, with mean magnitudes lower than observed (with an exception being VIC at more arid sites). NWM 3.0 and 2.1 show variable number of

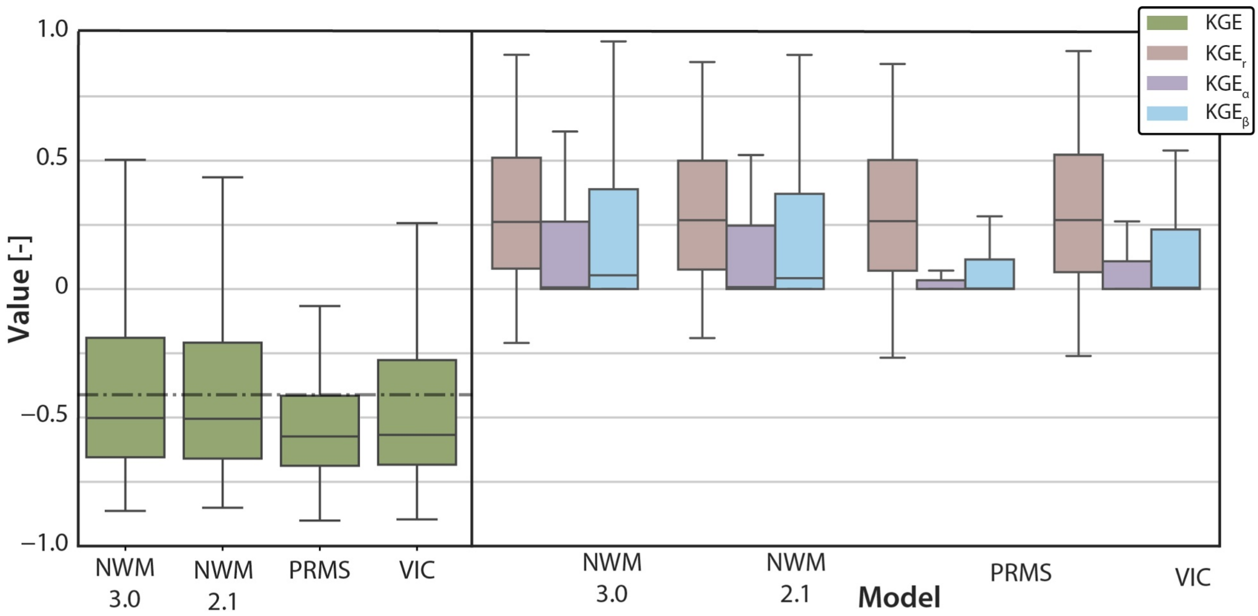

Figure 4. Boxplot of Kling-Gupta efficiency (KGE) decomposition function of process-based model simulation, KGE values above the dashed line (KGE = −0.41) denote where the models perform better than the mean of the observations.

low-flow days across HLCs with magnitudes ≥50 days. VIC shows a clear trend of increasing days of low-flow with increasing aridity, but only matches the magnitudes of days of low-flows in the most arid sites. PRMS also has a trend of increasing low-flow days with aridity, albeit much less variable than other PBMs and more in line with observations. However, the magnitude of low-flow days simulated by PRMS, ~20–60 days, is well below the observed magnitude.

3.3.3. Late-Summer Low-Flow

The distribution of late-summer low-flow days observed across HLCs is similar to the annual number of no-flow days observed with no clear trend related to aridity (Figure 7). The mean number of late-summer low-flow days is similar for all landscape classifications (~40 days) with the exception of semi-arid which has a mean of ~20 days. PBM simulation of late-summer low-flows is highly variable across models and HLCs (Figures 7b–7e). There are no clear trends related to aridity and magnitudes of late-summer low-flow days disagree between PBMs. NWM 3.0 and 2.0 underestimate late-summer low-flow days across all HLCs but in particular at more arid locations. VIC is the only simulation that comes close in matching the magnitude of late-summer low-flow days observed for humid regions but underestimates the number of days for arid regions. PRMS also underestimates the number of low-flow days but has the opposite pattern where humid regions have a greater degree of underestimation than arid regions. Simulations also predict a later timing of minimum annual low-flow (Figures 7f) and 7-day low-flow (Figure 7g) compared to observations.

3.3.4. Low-Flow Frequency

Both observations of 7Q2 and 7Q10 exhibited similar patterns with a steady mean value that slightly decreased as a function of aridity (Figure 8). The mean values for observed 7Q2 are all between 10^{-1} and 10^{-2} m^3s^{-1} (Figure 8a) whereas 7Q10 mean values have higher variability and are between 10^{-1} and 10^{-3} m^3s^{-1} (Figure 8b), with lower values at the more arid sites. Similar to low- and no-flows above, PBMs overestimate magnitudes of low-flow frequencies across models and in particular at more arid sites. All PBMs show a clear trend of increasing magnitude of low-flow frequency with increasing aridity that is not seen in the observations. For 7Q2 simulations, PBMs provide a fair match to magnitudes of low-flow frequency (Figures 8b–8e) but at 7Q10 all models greatly overestimate the magnitude of low-flows (Figures 8g–8j). Low-flow frequency is an integrator of both low- and no-flow using these periods of the lowest flows for calculation. Therefore, this relationship between PBMs and

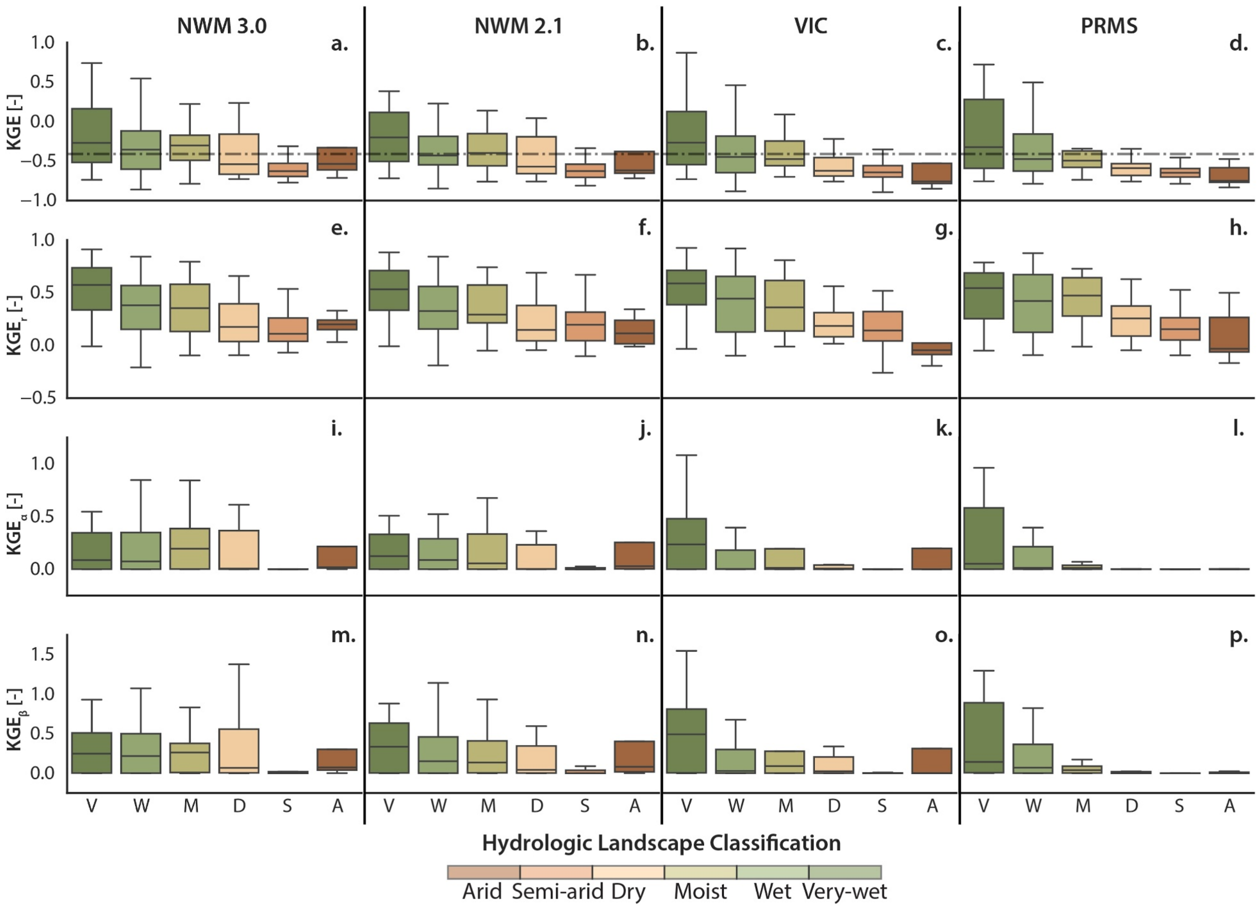

Figure 5. Boxplots of Kling-Gupta efficiency (KGE) and KGE decomposition as a function of aridity and process-based model. Panels (a–d) plot total KGE, panels (e–h) plot linear correlation (KGE$_r$), panels (i–l) plot variability ratio (KGE$_\alpha$), and panel (m–p) plot bias ratio (KGE$_\beta$).

observations, as well as the trends observed, are a combination of behavior observed in low- and no-flow simulations.

4. Discussion

4.1. Process-Based Models Overrepresent Low- and No-Streamflow

Process-based models are unable to accurately represent streamflow regimes associated with non-perennial systems. Our results highlight that PBMs overestimate low- and no-flow duration (Figures 6 and 7), magnitudes (Figure 8), and model performance is related to the degree of aridity of a location (Figure 5). Previous studies have described the poor performance of PBMs when representing low-flows, particularly in the western US (Abdelkader et al., 2023; Simeone et al., 2024; Towler et al., 2023), but where and why this overestimation occurs has not been further explored. For example, in Towler et al., 2023, the western US is grouped into one spatial unit for comparison to the entire US, when the geographic and hydrologic conditions are quite diverse, just not in a simple regional grouping. PBMs have the ability to represent events that act like non-perennial streamflow regimes but do not seem to be able to resolve the magnitude, duration, timing, or frequency, associated with observed streamflow in non-perennial systems (Figure 9; *sensu* Hammond et al., 2021; Kar et al., 2024; Price et al., 2021; Zipper et al., 2021). Poor model performance and the inability to simulate both drying and wetting regimes is manifestation of the misrepresentation of hydrologic processes in PBMs. This behavior is not unique to a single PBM used in this study, instead all PBMs perform poorly but in differing ways. For example, all PBMs were able to match seasonal trends, but were unable to simulate no-flow in some locations in humid regions of the PNW (Figures 6a–6e; Figure 9a). However, in arid and semiarid areas, PBMs poorly

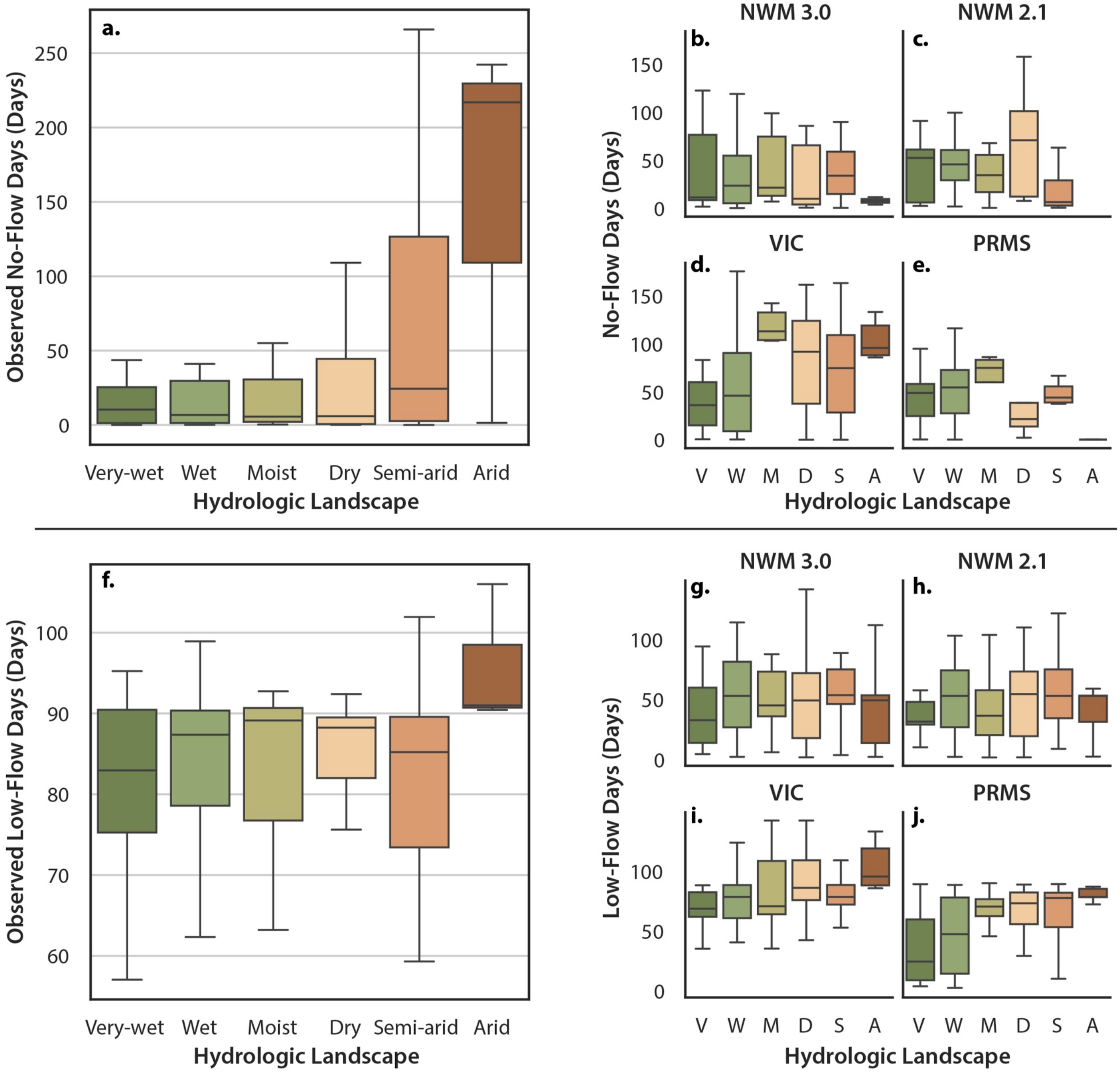

Figure 6. Box plots of observed and simulated no-flow days (a–e) and low-flow days (f–j) as a function of aridity. Observations are plotted in panels (a, f), and simulations are plotted in panels (b–e and g–j). Simulation output panels are faceted by model type.

captured both timing and no-flows in general (Figures 5e–5h; Figure 7), elucidating trends observed in goodness-of-fit metrics (Figure 4).

Many studies have shown that the majority of headwater rivers and streams are non-perennial and are poorly represented in data collection efforts and streamgage locations, which could be one component contributing to poor model performance (Figures 2a and 2b; Krabbenhoft et al., 2022). In this study, observations are distributed across low- and high-Strahler order streams, specifically where humid locations represent lower orders and arid areas higher order streams (Figure 3c). We find that model performance is inversely correlated with stream order showing performance is better in the lower order streams (Figure 2 in Supporting Information S1). The poorest performing simulations (i.e., KGE < -1) shows a similar spatial distribution across HLCs (Figure 3 in Supporting Information S1). Therefore, the performance of PBMs is not specifically linked to spatially biased collection of data in arid versus humid regions or headwater versus non-headwater systems (*sensu* Beven, 2024). Rather, the

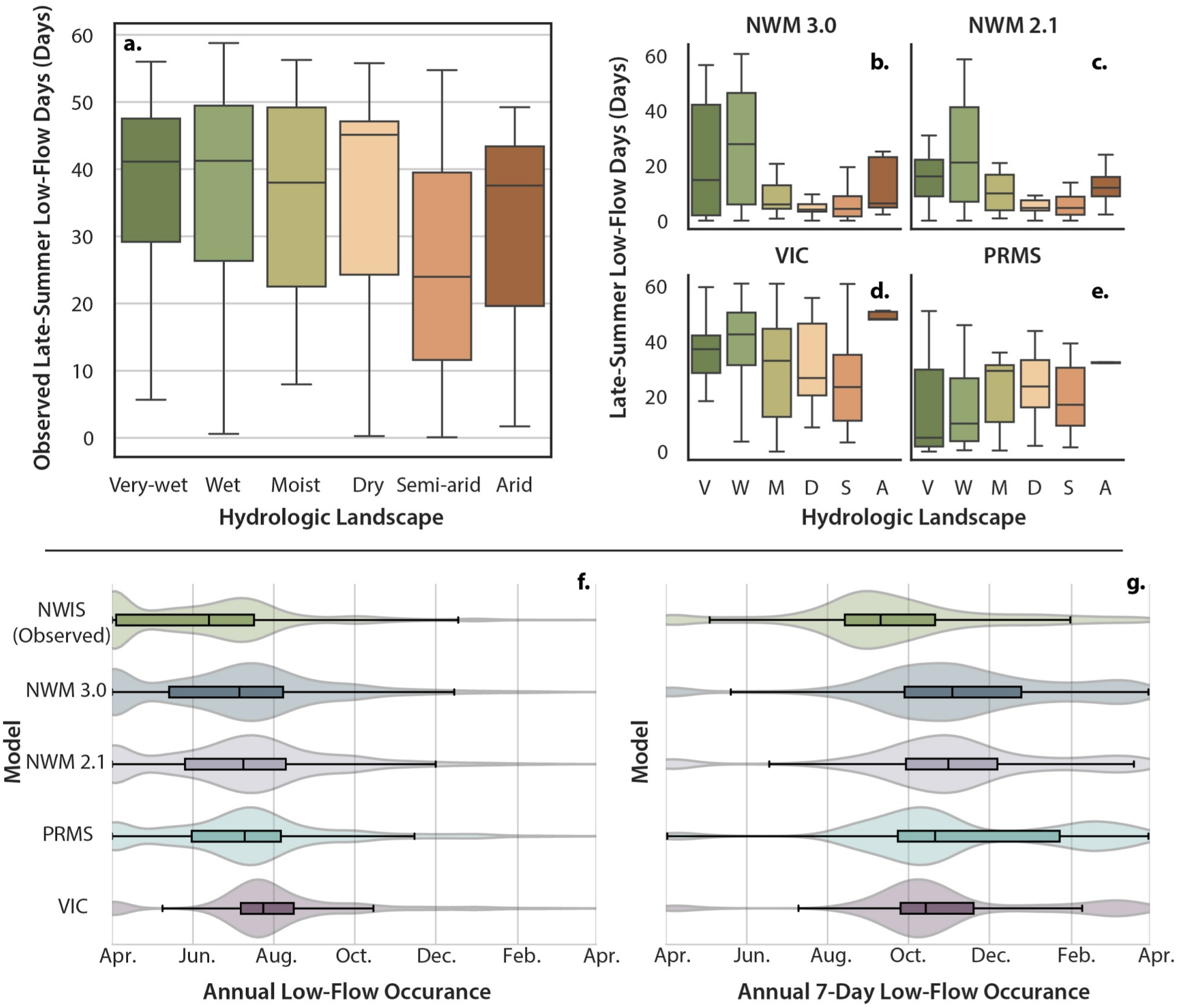

Figure 7. Box plots of late-summer low-flow days and violin plots of low-flow occurrence. Observations of late-summer low-flow days is plotted in panel a and simulated late-summer low-flow days are plotted in panels (b–e). Annual (panel f) and 7-day low-flow (panel g) occurrence are shown in violin plots overlain with box blots that report descriptive statistics.

problem could relate to the fact that the basins that PBMs are calibrated on in the PNW are primarily humid regions and streamflow out of those basins is majority perennial (Figure 4 in Supporting Information S1).

PBMs inaccurately represent non-perennial processes for multiple reasons that stem from being fundamentally biased toward representation of perennial rivers and streams, largely due to the prioritization of predicting flood events (Cosgrove et al., 2024). The majority of our conceptual models of streamflow and channel processes have been built around perennial systems which can limit their usefulness to non-perennial systems and poses an immediate bias in our construction, derivation, and calibration of quantitative models (e.g., Allen et al., 2020; Clark et al., 2016). Consequently, the principles that underpin most hydrologic models (i.e., conservation of mass) are focused on in-channel flow at all times, while processes that result in losses from the stream to groundwater are either simplified or not represented at all. The resulting simulated streamflow signatures fundamentally misrepresent important hydrologic processes such as hillslope-channel connectivity, subsurface fluxes, or the ability to resolve nonlinear behavior associated with hydrologic state transitions in non-perennial streams. Model agnostic inability to represent low- and no-flows highlights a pervasive challenge of PBMs to represent non-perennial systems across landscapes and their usefulness for management, advocacy, or rights-holder needs.

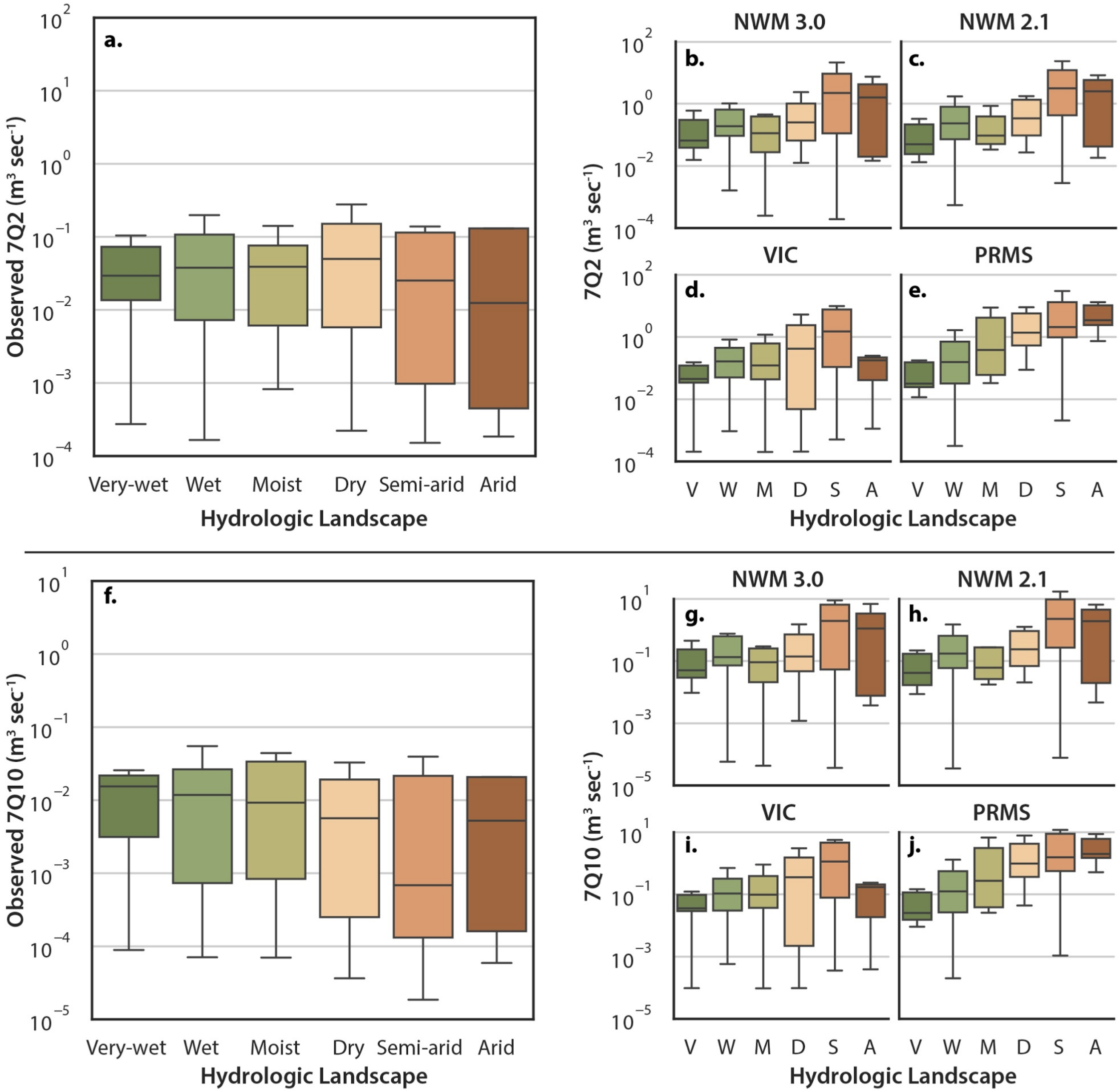

Figure 8. Box plots of observed and simulated lowest 7-day flow with 2-yr recurrence interval (a–e) and lowest 7-day flow with 10-yr recurrence interval (f–j) as a function of aridity. Observations are plotted in panels (a, f), and simulations are plotted in panels (b–e and g–j). Simulation output panels are faceted by model type.

4.2. PBM Accuracy a Function of Aridity

PBM performance decreased as a function of aridity across all models used in this study (Figure 5). The relationship of NWM 2.1 and 3.0 KGE performance to aridity is primarily driven by the linear correlation term KGE_r, which is the only decomposed value that has a signal matching KGE (Figures 5e and 5f), suggesting that this poor performance is related to the timing of streamflow in these systems, but NWM still exhibits relative skill at estimating overall magnitudes and variance in the streamflow time series. For VIC and PRMS, the errors associated with KGE are spread out in all components of the KGE decomposition signaling that errors in timing, magnitude, and variance have similar impacts as on the goodness-of-fit metric (Figure 5). These results highlight that the PBMs are not accurately representing inputs into the system or the connection of the system as a whole. The inability of PBMs to represent non-perennial streamflow behavior during periods of low- or no-flow, compound to impact the behavior of the goodness-of-fit metric (Figures 3 and 4).

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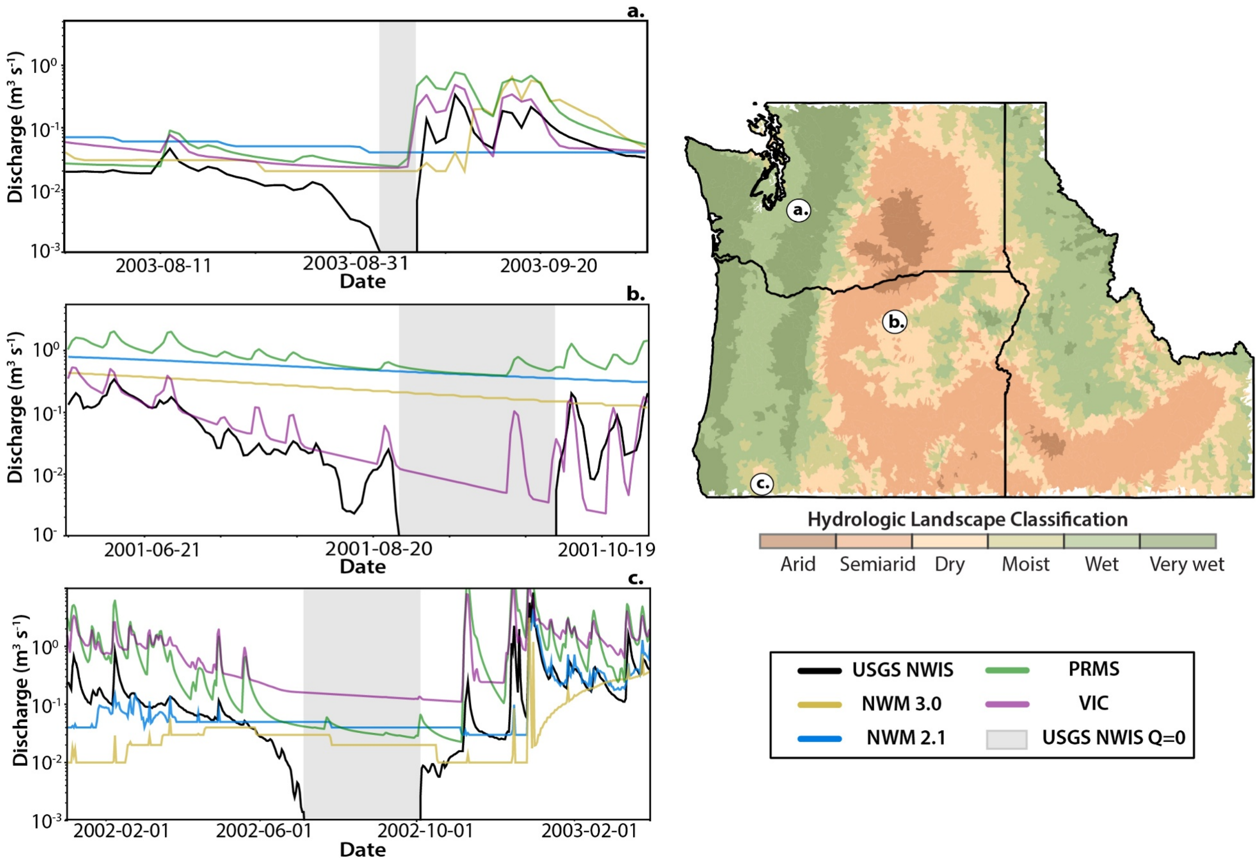

Figure 9. Hydrographs from three non-perennial streams (a). USGS National Water Information System (NWIS) 12115700 Boulder Creek near Cedar Falls, Washington; (b). USGS NWIS 14034470 Willow Creek above Willow Creek Lake, near Heppner, Oregon; (c). USGS NWIS 14362250 Star Gulch near Ruch, Oregon; showing observed streamflow (black line) and four simulation outputs for National Water Model (NWM) 3.0 (yellow line), NWM 2.1 (blue line), Precipitation Runoff Modeling System (green line), and Variable Infiltration Capacity (purple line). Shaded gray represents observed no-flow periods at the respective USGS streamgage. Inset map on right shows the locations of the streamgages where background in shaded by hydrologic landscape classification.

The climate of the PNW is mediterranean with the majority of precipitation accumulating in late-Fall through early-Summer *or* is snowmelt dominated, with very few summer precipitation events, which impacts the timing of streamflow in systems regardless of location. The low amount of precipitation in arid systems contributes less water to drive streamflow throughout the year and puts an increased reliance on streamflow generation from subsurface storage (Carroll et al., 2024; Gannett et al., 2017; Rumsey et al., 2015). Our results show that PBMs are capable of capturing the precipitation signal in streamflow in humid regions with some skill but fail to capture that signal in arid regions. Hydrologic processes that drive streamflow, such as soil moisture, are not aptly represented across PBMs and HLCs. For example, representation of soil moisture has proven to be a significant driver of performance (and usability) of PBMs in arid systems (Hughes et al., 2024; Husic et al., 2024; Simeone et al., 2024; Towler et al., 2023). Focusing PBM improvements on the specific processes that drive non-perennial streamflow, such as soil moisture regimes, would improve the usability and relevance of these models, in the face of continued climate change, particularly in arid systems.

4.3. Influence of Process-Based Model Architecture on Representation of Hydrologic Processes Important For Low- and No-Flow Prediction

Non-perennial streams have distinct characteristics of wetting and drying not only in comparison to their perennial counterparts, but also across intermittent and ephemeral behaviors (Busch et al., 2020; Price et al., 2021, 2024; Shanafield et al., 2021; Warix et al., 2021; Zimmer et al., 2020). PBMs differ from one another through their representation of physical processes, numerical solution schemes, spatial representation of hydrologic systems, climatic forcings used and a myriad of other modeling choices, all of which place a high value on model selection for modeling flows across hydrologic signatures (Table 2). Studies that have focused on the interaction

Table 2
Descriptions of Process-Based Model Subsurface Representations and Capabilities

Feature	Precipitation-Runoff Modeling System (PRMS)	National Water Model (NWM)	Variable Infiltration Capacity model (VIC)
Groundwater storage	Two conceptual groundwater reservoirs per HRU: shallow (fast drainage/interflow) and deep (slow baseflow)	Single conceptual groundwater bucket per catchment that provides baseflow to streams	One conceptual linear baseflow reservoir per grid cell to represent groundwater storage and release
Baseflow/streamflow generation	From shallow (linear response) and deep groundwater reservoirs (non-linear response) using storage–discharge functions	From groundwater bucket using an exponential storage–release function	From a linear reservoir with recession constant; mimics delayed baseflow contribution to streams
Groundwater–surface water connectivity	Can represent gaining streams, but not losing streams from both reservoirs	Can represent gaining streams, but not losing streams	Can represent gaining streams, but not losing streams
Lateral flow/underflow	Supports routing outflow to downslope groundwater reservoirs (inter-HRU flow)	No lateral groundwater exchange	No explicit lateral groundwater movement; groundwater flow is treated as vertical recharge and delayed baseflow
Technical citation	Markstrom et al. (2015)	Gochis et al. (2018)	Liang et al. (1994)

of forcing, model structure, and inputs have found model structure, in particular, has the greatest impact on correctly simulating low- and no-flows (Chegwidden et al., 2019; Mendoza et al., 2015; Vidal et al., 2016). Our results build on prior studies and highlight that the combination of PBM architecture and process representation impacts the simulation and predictability of components of non-perennial streamflow regimes.

4.3.1. Subsurface Processes

Groundwater and soil moisture dynamics are key hydrologic processes that contribute a significant portion of streamflow to non-perennial systems (Costigan et al., 2016; DelVecchia et al., 2022; Shanafield et al., 2021; Warix et al., 2021; Zipper et al., 2022). PBMs represent these processes in differing ways and the relative skill of each model has been discussed extensively in the literature. For example, VIC does not explicitly simulate groundwater flux, but instead assumes that vertical fluxes of groundwater are much greater than horizontal fluxes, and that groundwater fluxes are much less than surface and near-surface fluxes. Studies that have focused on differences in groundwater versus surface water dominated watersheds using VIC have observed under estimation of low-flow in groundwater-dominated systems (Safeeq et al., 2014; Wenger et al., 2010) and that coupling VIC with groundwater models resulted in much better model performance (e.g., Liang et al., 2003; Sridhar et al., 2018). Studies that have focused on using NWM for understanding groundwater impacted flows (i.e., baseflows, irrigation return flows) showed that the "exponential bucket model" used by NWM for groundwater flows (Table 2), have resulted in missing important stream-groundwater interactions when used for these applications (Jachens et al., 2021; Karki et al., 2021; Putman et al., 2024). Of the PBMs used in this study, PRMS has the most sophisticated representation of groundwater using two coupled groundwater reservoirs for shallow, linear fast subsurface flow, and deep groundwater, for slow, non-linear baseflow (Table 2; Markstrom et al., 2015). Additionally, PRMS can be coupled with the U.S. Geological Survey's Modular Finite-Difference Flow Model (MODFLOW). However, most large-scale applications of PRMS lack the input data to fully parameterized MODFLOW and usually rely on the standard modules within the PRMS modeling system.

Non-perennial streamflow is highly correlated with bedforms and other geologic features that facilitate surface water–groundwater connection (Costigan et al., 2016; Peterson et al., 2024); Yet many spatially extensive PBMs simulate hydrologic fluxes with at resolutions and grid cells that are much larger than the spatial scales that streamflow processes operate as well as can poorly represent heterogeneity of subsurface properties. For example, VIC discretizes the near-surface soil zone in simulations as a continuous 2-m-thick layer across the landscape, a parameterization that is highly idealized. Simplification of subsurface and groundwater fluxes is not unique to VIC, many PBMs do not specifically solve for or couple groundwater models and land surface models (Table 2). Our results highlight that without representation of groundwater contributions or simulating subsurface hydrologic processes, PBMs have limited success in simulating non-perennial flow regimes.

4.3.2. Stream Channel Processes

Streamflow in non-perennial systems is highly dependent on the connection of the stream channel to groundwater. Surface water–groundwater connections can represent the majority of streamflow loss or generation in a non-perennial system (Brackins et al., 2021; Jachens et al., 2021; Lahmers et al., 2021). Many PBMs do not represent surface water groundwater connections, when coupled with idealized subsurface structure and channel geometry, the applicability of these models in groundwater dominated and extractive areas are severely limited. For example, in all PBMs in this study, when water reaches a channel network, it is assumed to stay in the channel (i.e., it cannot flow back into the soil or subsurface) preventing the gaining and losing behavior commonly seen in non-perennial systems (Table 2; Gochis et al., 2018; Lahmers et al., 2019; Liang et al., 1994). PBM underestimation of low- and no-flow days (Figure 6), highlights the inability of PBMs to represent important groundwater connections (e.g., gains and losses) that could generate streamflow in these systems. We expect that PBMs that can represent surface water–groundwater connections would show that significant portions of late-summer flow are generated from these sources, increasing the number of low- and no-flow days simulated in arid areas where these processes generate a significant portion of streamflow. However, to date, these simulations do not exist at scale. Previous studies have highlighted that not accurately representing subsurface sources and sinks of water, is a limitation in both our conceptual and quantitative representation of non-perennial systems (DelVecchia et al., 2022; Shanafield et al., 2021).

Furthermore, equations that represent in-channel groundwater–surface water interaction in the form of baseflow, are highly sensitive across both high- and low-flows. VIC uses a baseflow term that is linear at low soil moisture and non-linear at high soil moisture (Franchini & Pacciani, 1991). This representation of baseflow allows for greater responsiveness of baseflow at higher soil moisture levels or during precipitation events (Franchini & Pacciani, 1991; Hughes et al., 2024; Karki et al., 2021) and very low sensitivity at low soil moisture levels. The combination of the lack of sensitivity at low-flows and poor parameterization (*sensu* Lahmers et al., 2021) lead to poor model performance in areas that utilized the linear portions of the baseflow curve to simulate streamflow (Abdulla et al., 1999).

Finally, an additional source of simulation error of low- and no-flows could stem from the routing schema used in PBMs. The fundamental formulation of stream routing schema is conceptualized as a propagation of a flood wave, which requires the presence of flow in a channel. These schemas are based upon assumptions of channel geometry, geomorphology, topology, and other channel conditions. While our study doesn't specifically examine the impact of channel routing schema on non-perennial flow regimes, the mismatch between simulated and observed streamflow in our study could stem from violated assumptions in a routing schema (i.e., geometry, topology). The mismatch of the KGE_r (Figures 4 and 5) and timing of streamflow (Figures 7 and 9) could be influenced by idealized routing schema or incorrect parameterization of channel characteristics that impacts the timing of flow (both high and low in this case). Studies that have focused on the impacts of routing schema found that low- and medium-flows are highly impacted by parametrization of channel geometry and properties as well as the conceptualization of baseflow (Cortés-Salazar et al., 2023). Any combination of routing processes and processes highlighted above, interact to impact the performance of PBMs in non-perennial systems.

4.4. Physical Underpinnings and Conceptual Understanding of Low- and No-Flow Conditions in Non-Perennial Systems (Point to Studies Across Scales)

As the focus on non-perennial systems has increased over the past decade (Brinkerhoff et al., 2024; Busch et al., 2020; Messager et al., 2021; Zimmer et al., 2020), particular attention has been brought to the fact that the physical drivers of streamflow generation. Studies have found that losses to groundwater in non-perennial systems can be fundamentally different than in perennial systems, in addition to having much higher spatial variability in flow through a given network, or even reach (Datry et al., 2023; Shanafield et al., 2021). Studies of non-perennial systems at reach scales produce highly non-linear relationships that are variable across the landscape, which are difficult to capture in large-scale hydrologic models, in part due to data limitations and physical representation discussed above. Below we highlight observational studies that describe non-perennial phenomena and describe spatial and temporal relationships that may be important to incorporate into PBMs.

In arid to semi-arid environments, substantial portions of the subsurface may be unsaturated during low-flow periods. During this time, the lack of hydrologic connectivity between hillslopes, the riparian area and streams dampens the movement of water from the uplands to the stream. In semi-arid environments, portions of a given watershed may only be connected during the wettest periods of the year or in response to major precipitation events (Jencso et al., 2009). As such, streamflow response to precipitation events in these systems is non-linear, and riparian areas are a major control on streamflow (Jencso et al., 2010; Newcomb & Godsey, 2023), particularly given the vegetation density and productivity in the near stream environment compared to the uplands. Development of a hydrologic connection, from the pore to hillslope scale, and associated response times, are a function of hillslope-controlled runoff dynamics that dominate in headwater streams (McNamara et al., 2005; Nippgen et al., 2011, 2015; Zimmer & McGlynn, 2017).

It appears that these models don't effectively capture the non-linear dynamics of wetting and drying that we observe in arid, intermittent, and headwater systems. For example, PBM simulations in this study have linear groundwater drainage, which is an oversimplification of groundwater reservoirs and groundwater–surface water connectivity. Zipper et al. (2022) shows that there is a hysteretic response of stream intermittency to climate drivers in the Arkansas river, and that groundwater levels in the alluvial aquifer are the primary driver of reach-scale streamflows. Therefore, there exists a non-linear decline in the sensitivity of streamflow to these changes from wet to dry landscapes and seasons, yet the parameterization that reflects the influence of flow on storage are relatively consistent across the same region when using PBMs (Ghimire et al., 2023). This highlights that representing hydrologic connectivity across scales and the associated non-linear behavior, is an important factor to include in PBMs to match our observational data sets and correctly represent non-perennial streamflow.

4.5. Implications for PBM Performance and Future Recommendations

Characterizing streamflow conditions under future climates is one of the values of using PBMs, particularly as more extreme hydrologic conditions occur. While modifications of some models have resulted in the ability to represent relevant characteristics of hydrologic regimes in small streams (*sensu* Wenger et al., 2010), we expect that more streams will experience increased non-perennality in locations where the frequency and magnitude of drought increases (Hammond et al., 2022; Simeone et al., 2024). Our results highlight that PBMs might not be well equipped to elucidate the true low- and no-flow conditions of non-perennial rivers and streams, both past, present, and future. This is of concern because PBMs are often used in ungauged basins, the results of which may be used to identify and prioritize management actions and data collection efforts (*sensu* Farmer et al., 2019). For example, there is significant regional interest in restoration activities that support fisheries where low-flow presents critical thresholds in temperature, water quality, and habitat (Beechie & Bolton, 1999; Flitcroft et al., 2022; Justice et al., 2017). When ecologic metrics are coupled with hydrologic models, the uncertainty is compounded and percent bias is often highest in non-perennial streams (Eddy et al., 2022). Model comparison studies are particularly useful for highlighting coherence across models and identifying the scales at which low-flow statistics are no longer accurate (Caldwell et al., 2015). Furthermore, prior studies have focused on which flow metrics and regimes of perennial and non-perennial systems that are important for ecosystem function and resilience (McMillan, 2021, 2022; Poff et al., 1997). Formulating and calibrating our models around a holistic set of performance metrics and calibration points, such as flow regimes, could greatly improve the accuracy and interdisciplinary usability of these models. We recommend that modelers (a) document the best use cases in addition to assumptions and limitations for these models, (b) quantify the variability in model uncertainty as a function of hydroclimate and stream size/classification, and (c) establish relationships with decision makers and resource managers to ensure that model results are being used properly. Furthermore, we suggest a set of model improvements specifically focused on non-perennial systems. While PBM's exist that simulate groundwater-surface water interactions (e.g., Gutiérrez-Jurado et al., 2019; Hafen et al., 2023; Mahoney et al., 2023; Ward et al., 2018), operationalizing these models and/or improving routines in the operational models presented in this study, specifically focused on processes presented above, is the first step making models more useful for non-perennial systems. Additionally, improving data streams associated with soil moisture, degree of groundwater-surface water losses, and additional stream gaging locations in non-perennial systems would greatly improve the parameterization and validation of these models. Finally, we suggest that calibration of these models find parity between humid and arid basins, specifically in regions like the Pacific Northwest that are predominantly arid or that draw a significant volume of flow from non-perennial systems. Iteratively improving frameworks, model structure and input data, as well as building relationships with resource managers could generate use cases that inform how we improve and increase usability of PBMs across landscapes and stream networks.

5. Conclusion

In this study, we highlighted that process-based models showed limited skill in simulating non-perennial streamflow. PBMs overestimated the amount of streamflow in non-perennial rivers and streams while simultaneously underestimating the duration and frequency of low- and no-flow in these systems. Goodness-of-fit metrics associated with PBM performance were related to the degree of aridity of the HLCs, where PBMs performed better in humid regions and model skill decreased with increased aridity. Our results highlight that hydrologic processes that are important in non-perennial streams, such as representation of the subsurface, groundwater–surface water connectivity, and baseflow, are not adequately represented or parameterized in PBMs. These results highlight a need for PBM to better align with our empirical understanding of these systems that has been outlined in many studies. Better formulation, calibration, and increased accessibility of PBMs has important impacts on the usability of these models to managers and stakeholders to inform decision-making. Utilizing an iterative approach that is highly interdisciplinary and includes managers, stakeholders, and researchers, to develop and better parametrize PBMs, will ultimately increase the impact and application of these models for water resource management, ecology, and continued climate change impacts.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All code and associated data files can be found at http://www.hydroshare.org/resource/7226ffe6eb26401e94558d337a25b7ac.

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