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Nonlinear trends in signatures characterizing non-perennial US streams

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ABSTRACT

Stream drying patterns – including duration, timing, and dry-down rates – affect aquatic ecosystems and nutrient exports in non-perennial streams. Because hydrologic processes are often nonlinear, changes in drying may also be nonlinear, but analyses of historical changes in stream drying to date have not characterized the frequency or functional forms of nonlinear change. Understanding the extent of nonlinear change in non-perennial streams is essential for advancing our fundamental knowledge of hydrological processes, aquatic ecosystems, and watershed functioning under a warming climate. This paper uses a polynomial-based trend detection technique (PolyTrend) to analyze the linear and nonlinear trend behaviors of three intermittency signatures (*annual no-flow days* specifying longer or shorter drying duration, *day of first no-flow occurrence* specifying timing of stream drying, and *days from peak to no-flow* specifying dry-down rates) at 540 non-perennial gage stations over 38 years (1980–2017) across the continental United States (CONUS). Additionally, we carried out a breakpoint analysis to characterize the discontinuities in the time series of each intermittency signature. Analysis of *annual no-flow days* shows that about 37 % of the total streamflow stations are drying for longer each year, whereas about 22 % are wetter for longer than in the past. The *day of first no-flow occurrence* analysis shows that 10 % of the streams are drying earlier, and 19 % are drying later. On the other hand, analysis of *days from peak to no-flow* shows that 14 % of streams are drying faster, and 17 % are drying more slowly. For all these metrics, among the significant trends, at least half of the relationships were nonlinear. For *annual no-flow days*, the breakpoint analysis shows more discontinuities in the second half of the analysis period (1999 to 2017) than in the first half, with more discontinuities in the Southern Great Plains than in other regions. The other two signatures demonstrate less frequent discontinuities in the second half of the analysis period, suggesting decreased nonlinear dynamics in recent years. Nonlinear no-flow duration trends are common in Mediterranean California, and the dry-down rate has increased in recent decades. Our findings indicate that nonlinear change in stream drying is widespread and must be accounted for in watershed planning and management.

1. Introduction

Most global waterways (e.g., rivers and streams) are *non-perennial*, meaning continuous surface flows do not occur year-round (Messager et al., 2021; Busch et al., 2020). In recent years, non-perennial streams have been gaining attention due to their importance to ecosystems and society through groundwater recharge for agriculture (Steward et al., 2012; Leigh and Datry, 2017; Datry et al., 2018), debris material storage and downstream sediment transport (Jaeger et al., 2017), habitat segregation as riparian vegetation and biotic components (Schilling et al., 2021), downstream dam management (Smakhtin, 2001; Zimmer et al., 2020), and biogeochemical cycles (Gómez-Gener et al., 2016; Shumilova et al., 2019; Von Schiller et al., 2019). Previously, several studies considered climatic, physiographic, and anthropogenic drivers of the spatial patterns of non-perennial streams (Hammond et al., 2021; Kampf et al., 2021). Since relationships between aridity and stream drying trends have been found in many regions, including the U.S.A., Europe, and Australia (Datry et al., 2023; Zipper et al., 2021; Sauquet et al., 2021), changes in aridity due to climate change threaten to alter stream drying dynamics.

Streamflow trend analyses have been conducted for both perennial (e.g., Rice et al., 2015; Sagarika et al., 2014; Dollan et al., 2022; Dixon

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et al., 2006; Zhang et al., 2001; Birsan et al., 2005) and non-perennial (e.g., Zipper et al., 2021; Sauquet et al., 2021; Tramblay et al., 2021) streams at local, regional, and global scales. Understanding stream processes can be enhanced by investigating hydrologic signatures, which describe streamflow characteristics and hydrograph properties and can effectively indicate hydrological processes (Olden and Poff, 2003; McMillan, 2020). Here we focus on hydrological signatures related to stream drying, referred to as “intermittency signatures”, to represent the streamflow and stream drying response of multiple interacting processes and the presence of streamflow thresholds. For example, *no-flow* is a commonly used hydrological signature for classifying non-perennial streams because it affects hydrological drought and in-stream biogeochemistry and ecosystem processes (Ludlam and Magoulick, 2009). Trend analyses of different intermittency signatures have been conducted across the United States (e.g., Zipper et al., 2021), Europe (Rutkowska et al., 2023; Tramblay et al., 2021; Snelder et al., 2013), and Australia (Morden et al., 2023; Sauquet et al., 2021). However, these past studies have focused only on linear and/or monotonic trends and are not well suited to characterize potential nonlinear hydrologic changes. Several studies implemented nonlinear trend analysis in streamflow (Shao and Li, 2011; Nalley et al., 2012; Zhang et al., 2014), rainfall (Falayi et al., 2023; Kazemzadeh et al., 2021), and vegetation cover (Jamali et al., 2015; Jamali et al., 2014) time series data. Nonlinear hydrologic changes can include threshold-type responses to changing drivers in a complex system or responses to nonlinear changes in driver variables. Applying linear models to nonlinear behavior can negatively affect the prediction accuracy and the depth of our understanding of the system drivers. Nonlinear behavior can create unexpected changes in streamflow and occur at different magnitudes across spatiotemporal scales (Shao and Li, 2011; Nalley et al., 2012; Zhang et al., 2014), and abrupt shifts in stream drying dynamics have been observed in site-based studies (Zipper et al., 2022), suggesting the potential for breakpoints and nonlinear changes at larger spatial scales. However, the extent and types of nonlinear changes in non-perennial streamflow have not previously been characterized at large spatial scales. Furthermore, nonlinear changes observed for low flows may have different characteristics in perennial versus non-perennial streams. Therefore, this research aims to characterize nonlinear changes in non-perennial streamflow across the continental United States (CONUS). First, we use a polynomial fitting-based trend detection technique (PolyTrend) on the time series of the annual intermittency signatures to detect the presence and types of linear and nonlinear trends. We then implement breakpoint analysis on the same time series to detect discontinuities in the streamflow signatures.

2. Data and methods

2.1. Selection of study sites and data

Data used in this study was collected from the United States Geological Survey (USGS) GAGES-II dataset (Falcone, 2011) and contains 540 non-perennial streams with at least 30 climate years (April 1 to March 31) of daily streamflow data from 1980 to 2017. Moreover, the selected gages have an average of at least five days and at most 360 days of no-flow reported yearly. These gages are categorized into six ecoregions based on the United States Environmental Protection Agency (EPA) Level 1 ecoregion (Fig. 1): (1) Eastern Forests (136 gages), (2) Mediterranean California (87 gages), (3) North Great Plains (56 gages), (4) South Great Plains (157 gages), (5) Western Deserts (40 gages), and (6) Western Mountains (64 gages).

Prior research (e.g., Hammond et al., 2021; Price et al., 2021; Zipper et al., 2021) used three intermittency signatures that characterize no-flow regimes for each year and each gage:

a. **Annual no-flow days:** The number of days measuring no streamflow, indicating the overall duration of no-flow conditions at a stream gage.
b. **Day of first no-flow occurrence:** The first day without any surface flow in a climate year, which indicates the timing of dry conditions within the year.
c. **Days from peak to no-flow:** The number of days from a local peak in daily flow to the immediate next occurrence of no-flow, indicating the dry-down rate. Here, the local peak indicates a streamflow value exceeding the 25th percentile, and any secondary peaks during a recession that are below the 25th percentile flow are ignored. Peak to no-flow calculations were able to span climate years, with the drying event classified based on the year in which the peak occurred (Price et al., 2021).

For each gage station, these three signatures were calculated annually for each climate year (April 1 to March 31). When multiple drying events occurred within a climate year, the days from peak to no-flow were averaged to produce a single mean number for this signature for that climate year. The climate year was used to minimize the number of stations with zero flow at the beginning of the calendar year, which could have biased the *day of first no-flow* metric. For details on these calculations, please see the supplemental information of Price et al. (2021).

2.2. Trend type classification

Trend analysis of intermittency signatures is essential because it

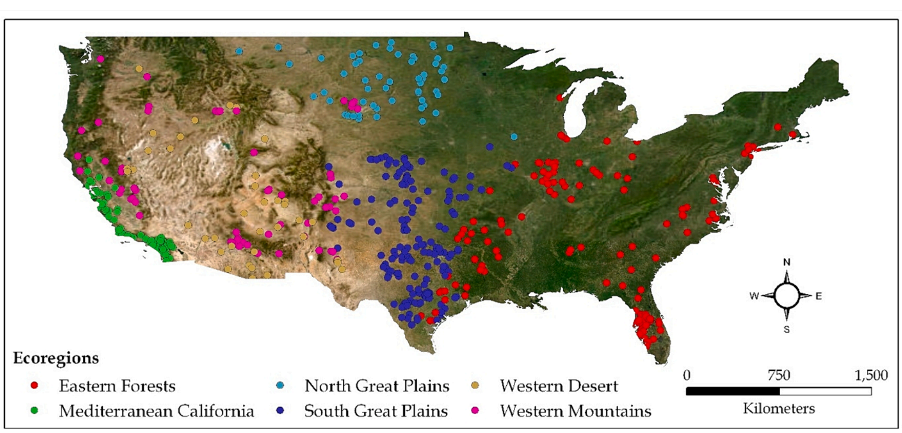

Fig. 1. Gage locations of 540 non-perennial stream gages from six ecoregions across CONUS.

provides a holistic picture of the watershed's vulnerability to climate change, but different trend detection approaches can provide different insights into the hydrological behavior. Zipper et al. (2021) used non-parametric Mann-Kendall tests (Mann, 1945; Kendall, 1948) for trend detection in the intermittency signatures. Although the Mann-Kendall test is robust and sensitive to outliers or data distribution, it can only detect monotonic trends (increasing or decreasing). Due to the influence of variables, such as land use, water use, and climate variability, stream intermittency can change non-monotonically, but it is unknown how common nonlinear changes are in stream intermittency. Therefore, we employ an automated trend classification approach developed by Jamali et al. (2014, 2015), known as "PolyTrend", which detects linear and nonlinear trends on our intermittency signatures. Even though other methods, such as wavelet-based (Partal, 2010; Nalley et al., 2012), polynomial-based (Korup et al., 2021), and Breaks For Additive Seasonal and Trend (BFAST) (Verbesselt et al., 2010), etc., exist for nonlinear trend analyses, we chose PolyTrend for its more straightforward polynomial functions to analyze long-term time series data, computational efficiency, and accuracy (Jamali et al., 2014, 2015).

PolyTrend classifies the time series data using linear and nonlinear (quadratic and cubic) trends. We evaluate three potential functional forms (linear, quadratic, and cubic; Table 1) for each intermittent signature to evaluate which best fits each time series. We also consider two additional trend categories: 1) concealed trend and 2) no-trend. If there is no net change in the streamflow signature time series over the study period within a nonlinear trend (quadratic or cubic), they are considered concealed trends. In simpler terms, concealed trends demonstrate statistically significant nonlinear trends accompanied by statistically insignificant linear trends (Jamali et al., 2014). If the time series shows no significant trends over any timescales, it represents a no-trend scenario.

Trend analysis follows a consistent procedure (Fig. 2) that begins with fitting a cubic polynomial and determining its statistical significance level (i.e., whether the cubic equation fits the data). If the model is significant, then the model confirms the existence of both local maxima (upward and then downward change) and local minima (downward and then upward change) in the polynomial (Fig. 3a). After that, the model is fitted with a linear model, and if the linear coefficient is significant, the time series has a cubic trend; otherwise, it has a concealed (cubic) trend. If the fit parameters are not significant or if PolyTrend fails to detect both the local maxima and minima, a lower-order polynomial is considered (i.e., the quadratic model). In the next step, the significance of the quadratic coefficient is estimated, and PolyTrend again assesses whether the model coefficients are significant and whether the model has captured the local maxima or minima points. If this model can capture the maxima or minima and has a statistically significant linear trend, then it is categorized as a quadratic trend; otherwise, if the linear trend is not statistically significant, it follows the concealed (quadratic) trend type. Finally, if both high-order polynomial criteria are not met, but the regression coefficient is significant (that is, it fits the linear model) it is classified as a linear trend; otherwise, it is classified as a no-trend. On a related note, if a large linear trend is present on top of a quadratic or cubic trend, the algorithm detects the linear trend instead of quadratic or cubic (see Fig. S1 in Supplementary Materials). In this study, we will present slope results from this analysis which will consistently show the linear slope value (a_1) and the slope direction, which can be either increasing (+1) or decreasing (-1).

Table 1
Functions that are applied to describe the trend in the signatures.

Functions	Mathematical Expressions	Parameters
Linear	$Y = a_1x + a_0$	a_1, a_0
Quadratic	$Y = a_2x^2 + a_1x + a_0$	a_2, a_1, a_0
Cubic	$Y = a_3x^3 + a_2x^2 + a_1x + a_0$	a_3, a_2, a_1, a_0

2.3. Detecting the locations of discontinuities

Identifying significant shifts or changes in the time series of intermittency signatures is crucial to understanding the behavior of stream drying characteristics. These shifts can encompass transitions from wet to dry conditions, affecting the timing, duration, and rate of low-flow or no-flow events. We are not aware of past studies characterizing breakpoints for intermittency signatures of streamflow. A few studies have investigated this problem from the context of low-flow. For example, Raczyński and Dyer (2022) applied breakpoint analysis for low-flow identification using the Fisher-Jenks algorithm, which identifies one breakpoint in a time series. For non-perennial streams, this is a limitation since these streams are characterized by periodic shifts between wet and dry states. In this study, we use the High Order Polynomial Segmenter (HOPS) algorithm (Duan et al., 2021), which overcomes the abovementioned issue and can detect multiple discontinuities in time series data. HOPS simplifies linearity and nonlinearity in the trend components by segmentation and curve fitting (Fig. 3b). Thus, sudden structural shifts can be identified by the location of the discontinuities.

The algorithm uses l_0-penalized least-square regression (Duan et al., 2019; Duan et al., 2021), where breakpoint analysis follows the segmentation and curve fitting, as per Eq. (1). This equation can be viewed as a least-square regression penalized by a l_0 norm, whose value is influenced by the penalty (λ) of each piece (non-negative scalar) and segmentation (K), where K-1 is defined by the number of discontinuities. The HOPS algorithm uses dynamic programming to find the segmentation pattern (Bellman, 1961; Jackson et al., 2005), pruning strategy (Killick et al., 2012), and matrix factorization to accelerate the execution speed.

The polynomial segmentation is expressed as:

$$\min_{\mathfrak{T}}\left\{\sum_{k=1}^{K}\varepsilon(v_{k-1}+1,\, v_k)+\lambda K\right\} \tag{1}$$

Here $\mathfrak{T}$ is the segmentation pattern. A larger penalty will identify fewer segmentations/breakpoints, and a smaller penalty will allow more segmentation. We selected the penalty value of 10,000 in our study, which set the maximum limit of segmentations to six (i.e., five breakpoints) across all basins. The penalty value was chosen based on the time series length since we are interested in understanding the significant change patterns in the data. $\varepsilon(v_{k-1}+1, v_k)$ is the least-squares fitting error at the k-th segmentation, which fits error from the data point v_{k-1} to v_k with the selected ***P***-th order polynomial (e.g., 1: linear, 2: quadratic, 3: cubic, etc.) based on the process outlined in Section 2.2.

After quantifying the number and location of discontinuities, we also calculated two more metrics to provide additional information on temporal patterns in changes to the intermittency signatures: (1) *most recent discontinuity occurrence*, which provided information on how recently (which year) the last discontinuity was identified; and (2) *temporal proximity of the three most recent discontinuities*, calculated as the average of the distances of the three most recent discontinuity events from the end of the data record (i.e., 2017 in our case).

3. Results

3.1. Nonlinear changes in intermittency signatures across all ecoregions

Overall, our findings indicate that significant trends in *no-flow duration* signatures are common (39 %) across our study gages; however, significant trends are less common for the *dry-down duration* (17 %) and *no-flow timing* (16 %) signatures. Of those gages with significant trends, we find that nonlinear changes are widespread across our study sites: over half of those gages are best described by a nonlinear functional form for each of the three intermittency signatures (Fig. 4). The nonlinear trend proportion varies among intermittency signatures and ecoregions, with 71 % of the significant trends in *annual no-flow duration*

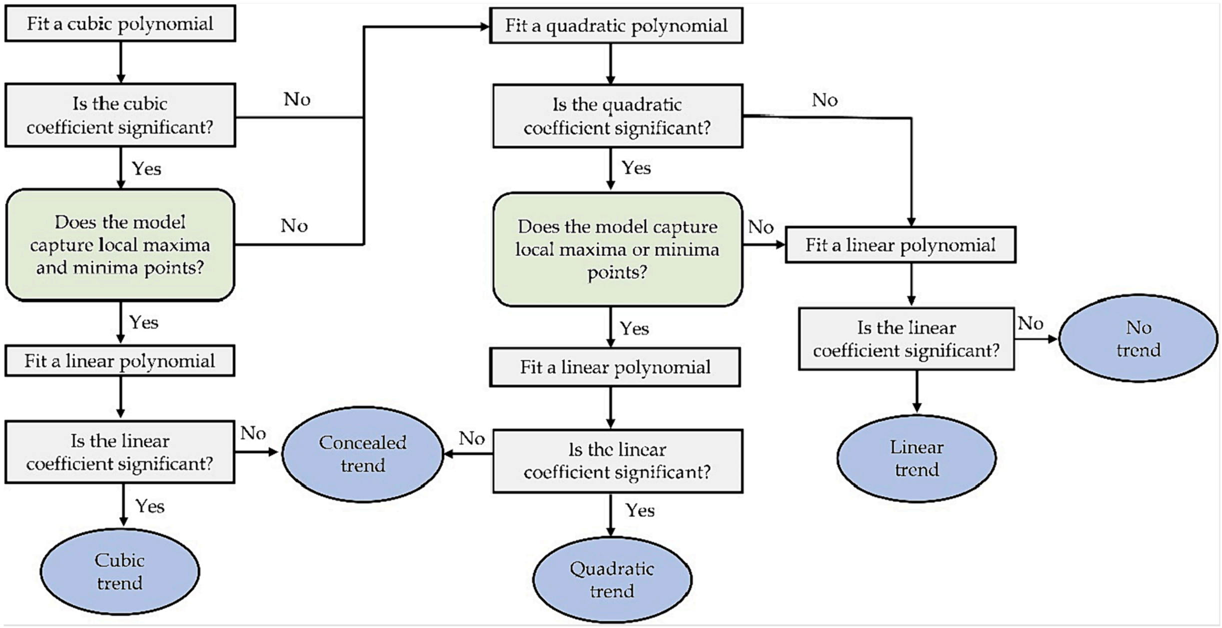

Fig. 2. Flowchart of the PolyTrend classification ().
adapted from Jamali et al., 2014

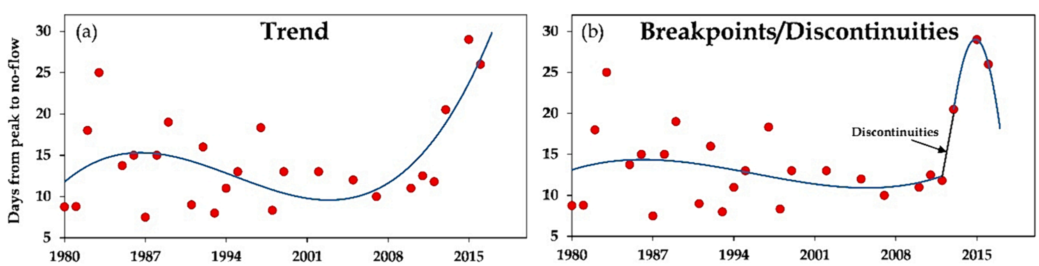

Fig. 3. Time series of the number of *days from peak to no-flow* intermittency signature (red circles) at an example site in New Mexico (USGS station ID: 09386900) showing (a) a nonlinear (cubic) trend and (b) the identification of one discontinuity based on the HOPS algorithm. The best-fit segments are blue for the cubic polynomial fit, and discontinuities are shown with a *black* line. Other examples are illustrated in Fig. S2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

being nonlinear in the Mediterranean California ecoregion. In comparison, 60 % of the trends on the *day of first no-flow occurrence* in the Northern Great Plains are nonlinear, and 68 % of the trends in *days from peak to no-flow* in Mediterranean California are nonlinear.

Among the nonlinear trend types, the cubic and concealed cubic trends dominate the *no-flow duration* signature, while two other signatures (i.e., *day of first no-flow* and *days from peak to no-flow*) are dominated by the concealed quadratic and concealed cubic trends, respectively (Fig. 4). Note that the patterns of trend (positive or negative) in the intermittency signatures found in Zipper et al. (2021) generally support our results from linear trend analysis, suggesting that the large-scale patterns are robust. Some variations were evident, primarily attributable to the difference in the methods used (Mann-Kendall vs PolyTrend).

Regardless of whether the trends are linear or not, nearly all reveal drier conditions, with a few notable exceptions. The *annual no-flow days (duration)* signature shows more prolonged drying in the Western Desert, Mediterranean California, Western Mountain, and South Great Plains regions (Fig. 5a). In contrast, the Northern Great Plains region shows a shorter no-flow pattern at all gage stations. Indeed, the *day of first no-flow occurrence (timing)* occurs earlier across all regions except the Northern Great Plains, consistent with widespread drying conditions (Fig. 5b). Finally, the number of *days from peak to no-flow (dry-down rate)* shows a slower drying rate in the Northern Great Plains and Eastern Forests regions and a faster drying rate in the other regions, although there are some individual exceptions (Fig. 5c).

3.2. Evaluation of trend direction

Nonlinear drying trends were as common or more common than linear drying trends across all regions and signatures. Table 2 summarizes the trends (increasing or decreasing) for the linear and nonlinear polynomials for all three intermittency signatures. Comparing linear and nonlinear trends for the annual no-flow days signature reveals that assessing only linear trends may underestimate the number of sites that are experiencing both longer and shorter dry conditions (Table 2). For example, only the Western Deserts and Western Mountains ecoregions have more sites that exhibit a linear drying trend than those that exhibit a nonlinear drying trend. Similarly, only the North Great Plains region exhibits more linear than nonlinear wetting trends. For the regions with more nonlinear trends, the differences range from a 4 % (Eastern Forests drying trends) to a 16 % increase (Mediterranean California wetting trends) in the number of gages with nonlinear trends relative to linear trends.

The second intermittency signature (day of first no-flow occurrence) shows a significant nonlinear trend that follows the earlier and delayed drying pattern. Only the Eastern Forests, Mediterranean California, and Western Mountains region have sites with more linear earlier drying

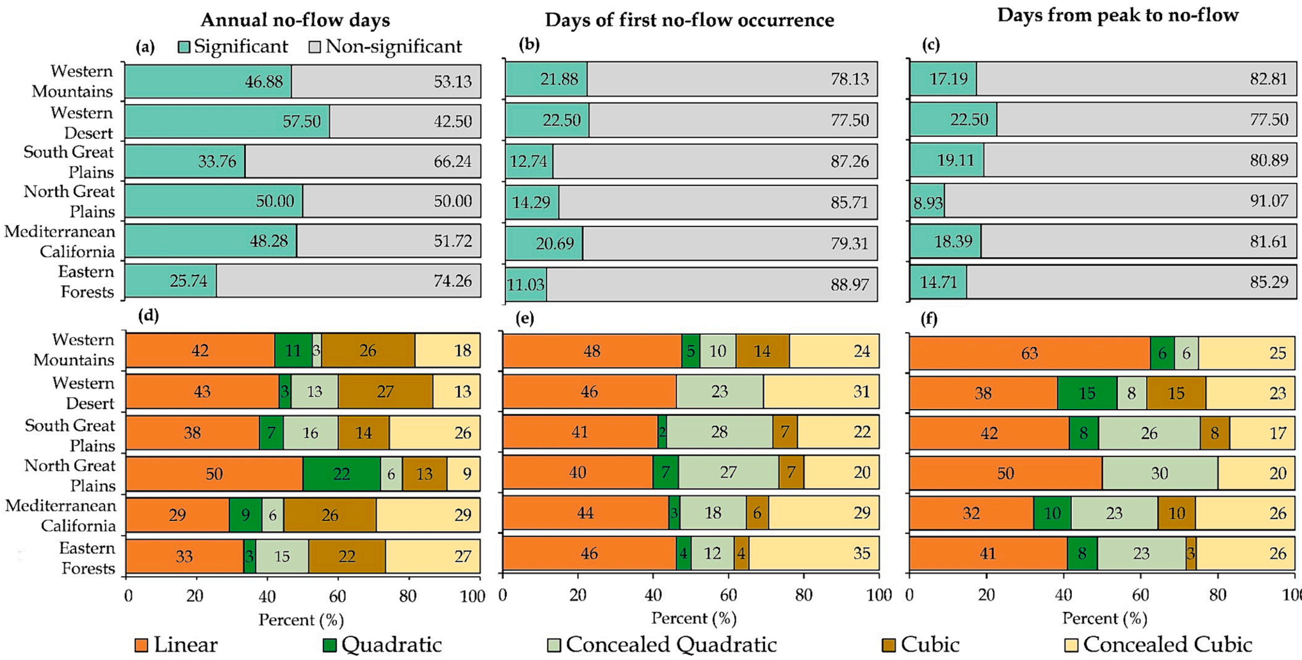

Fig. 4. Number of statistically significant and non-significant trends by ecoregion (a-c). All significant trends are then categorized into linear and nonlinear trend patterns (d-f).

trends than a nonlinear earlier no-flow trend. The North Great Plains region exhibits no differences in later drying trends. For the regions with more nonlinear trends, the differences range from a 1 % (South Great Plains later drying trends) to a 10 % increase (Western Deserts earlier drying trends) in the number of gages with nonlinear trends relative to linear trends.

The third intermittency signature (*days from peak to no-flow)* also reveals that nonlinear trends are widespread, particularly for sites trending towards a faster dry-down rate (i.e., a decreasing trend). For decreasing trends, all ecoregions in CONUS have a greater proportion of sites that exhibit nonlinear trends than linear trends, with the largest difference (-10 %) in the Western Deserts ecoregion. A few sites exhibit slower dry-down; among those, only the South Great Plains and Mediterranean California regions have more sites with nonlinear increasing trends, while other ecoregions have a slightly greater proportion of linear trends than nonlinear trends (from 1 % to 4 %). Overall, no-flow days, no-flow timing, and dry-down rate all have more gages with a nonlinear trend pattern than linear (37 %, 17 %, and 18 % more, respectively).

3.3. Spatial patterns of trends

Trends in each intermittency signature vary among locations in CONUS (Fig. 6). In particular, there are differences in trend classification (left column), trend direction (center column), and magnitude of each trend as measured by the slope (right column). Gages throughout CONUS demonstrate changes in no-flow duration (Fig. 6a–c). Linear and concealed trends are slightly more common in the southern US, where they are the dominant significant trends. There are fewer significant trends in shorter no-flow duration than in longer no-flow duration (Fig. 6b).

The largest magnitudes of change (i.e., steepest slopes) for the no-flow duration signature were detected in the Eastern Forests region with an increasing magnitude of 0.36 days/year with a median increasing magnitude of 0.01 days/year. The lowest negative magnitude was seen in the Western Mountains at 0.28 days/year with a median magnitude of 0.04 days/year (Fig. 6 and Fig. S3). More than 55 % or more streamflow stations are drying in each ecoregion for longer each year, except in the North Great Plains where 91 % (33 stations) of stations in the North Great Plains exhibited decreasing and negative trends. Similarly, ten stations in this region exhibit later no-flow timing. Western Mountains had the largest range of no-flow timing trends, with the highest increasing (0.24 days/year) and decreasing (0.38 days/year) trends for no-flow timing, and a median trend of 0.03 days/year. For dry-down rate signature, 27 stations of the South Great Plains region (of a total of 53 stations) showed an increasing magnitude of change, and the highest slope value was 0.24 days/year. On the other hand, the Mediterranean California region showed the lowest decreasing magnitude of change (0.09 days/year) within the 31 significant trend stations.

Fig. S3 shows the distribution of trend slopes for each signature and ecoregion. A positive slope suggests an increase in the signature over time, while a negative slope indicates a decrease. For no-flow duration, apart from the North Great Plains region, the median value for all regions was positive, indicating increasing no-flow duration through time. Mediterranean California showed a positive slope for no-flow timing, indicating later drying within the year, while other regions showed a negative slope, indicating earlier drying. For dry-down duration, the strongest positive slopes were in the Mediterranean California and Western Desert regions, indicating a longer period of time from peaks to no-flow conditions. There was also a variety of distributions across the signatures and ecoregions, with the widest distributions for no-flow duration in the Eastern Forests and Western Mountains; for no-flow timing in the South Great Plains; and for dry-down rate in Mediterranean California. All signatures and ecoregions, however, have both positive and negative trends, indicating that stream intermittency is not changing homogeneously in these ecoregions, and there is substantial local variability in both the direction and magnitude of change.

The *day of first no-flow occurrence* shows that most stations with later no-flow timing trends are in the northern and eastern US. In contrast, the southern and western US trend towards drying stream patterns, though most (71 %) streams exhibit no trend at all. Our analysis of the *days from peak to no-flow* signature exhibits a similar pattern, with a significant trend in only 30 % of gages and even less spatial clustering in sites exhibiting longer or shorter no-flow timing trends.

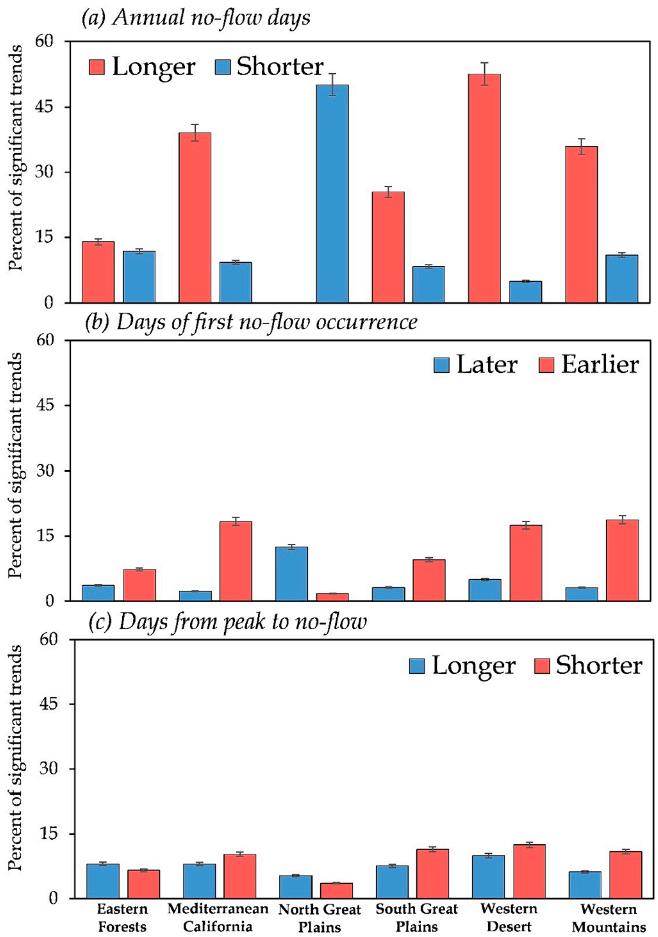

Fig. 5. Direction of trends for all statistically significant trends in each ecoregion (see Fig. 4). Trend directions indicate (a) whether the no-flow duration is getting longer or shorter, (b) if the first day of no-flow is occurring earlier or later, and (c) whether the peak-to-no-flow period is getting longer or shorter, revealing a slower or faster dry-down rate, respectively. The bars and vertical lines represent the mean and 95% confidence interval.

3.4. Spatial patterns of trend discontinuities

Our breakpoint analysis shows variability in the timing of discontinuities in the different intermittency signature trends of stream gages within the 38-year time series (Fig. 7). Discontinuities are most common in the *annual no-flow duration* signature (51 % of gages) and less common for the *no-flow timing* (26 % of gages) and *dry-down duration* (19 % gages) signatures. In general, discontinuities were less common for all intermittency signatures during the first half of the record (1980–1998) and more frequent during the study period's second half (1999–2017). From 1999 to 2017, discontinuities in the Western Mountains and Mediterranean California ecoregions increased by one or two for the no-flow duration and dry-down rate signatures (Fig. 7 and Fig. S4). On the other hand, discontinuities for no-flow timing remained relatively stable between the two periods. Only 26 gage station discontinuities increased while 73 stations decreased, and 51 station discontinuities remained the same on those time differences.

Clear spatial patterns exist in the timing of changes in trends throughout CONUS. For example, the *most recent discontinuity occurrence*, showing how recently a discontinuity occurred for a given intermittency signature at each gage, shows that changes have occurred more recently in the southern US than in the northern US, especially for the *annual no-flow duration* metric (Fig. 8). That same pattern is not clearly evident for the other two intermittency signatures. The results show that for the *annual no-flow duration*, 29 % of streams had significant discontinuities between 2008 and 2015 (Fig. 8). During that time, only 16 % of streams showed discontinuities for the *no-flow timing* and 13 % for the *dry-down rate*.

The *average temporal proximity of the three most recent discontinuities* reveals whether shifts in intermittency trends have been clustered recently or have occurred throughout the record. For the *no-flow duration*, only about nine gage stations show tightly clustered discontinuities (average temporal distance), while 119 gage stations have an average temporal distance between 6 and 15 years. Likewise, the average temporal distance is less than five years for only eight stations for the *no-flow timing* signature. In contrast, the *dry-down rate* discontinuities are most common in the most recent five years (Fig. 8). Not only did *no-flow duration* exhibit discontinuities early during the period of record in the Northern Great Plains (top left Fig. 8), but its average temporal distance was also high, while the Southern Great Plains was predominantly more recent with a range of average temporal distance.

4. Discussion

4.1. Implications for water quality and stream ecosystems

This study explored the spatial patterns and functional forms of non-perennial streamflow change throughout CONUS and found that nonlinear changes in streamflow are more common in non-perennial streams than linear change. We observed that more than half of the significant no-flow duration signature trends were nonlinear over the last four decades, primarily increasing quadratically. Nonlinear drying trends were more prevalent than linear ones in most ecoregions, except the Western Deserts and Western Mountains, while nonlinear wetting trends dominated, except in the Northern Great Plains. These nonlinear changes in streamflow may have significant consequences on water quality by reducing dilution capacity (Binkley and Brown, 1993), altering stream morphology by sedimentation (Deemy and Rasmussen, 2017), and changing microbial communities through changes in habitat and resource availability (Boulton and Lake, 2008). Similarly, nonlinear changes in stream intermittency can significantly affect stream ecosystems and associated ecosystem services, for example, by triggering shifts in groundwater recharge dynamics (Zipper et al., 2022) or aquatic ecosystem composition (Perkin et al., 2017).

The *no-flow duration* trends toward shorter no-flow duration drying in the Northern Great Plains and longer drying elsewhere, consistent with previous regional drought observations (Hoerling et al., 2014). A longer dry period in a stream can have cascading effects on the surrounding ecosystem, including land use, vegetation, and human migration (Shanafield et al., 2021). For instance, an extended period of no-flow in the stream can result in diminished habitat availability for aquatic species, potentially leading to food chain disruption, and affecting the ecosystem services that local populations derive from these streams (Stubbington et al., 2020). Additionally, where surface water supplies become less common, irrigation from streamflow is less reliable, potentially leading to a reduction in irrigated agriculture in the surrounding area. Furthermore, depending upon conditions during the drying period (e.g., shade and brief rainfall events that change moisture content, but do not lead to full rewetting), microbial community response can strongly affect water quality. For example, during the summer months of 2018, longer drying duration led to increasing CO_2 fluxes to the atmosphere in a non-perennial stream (Schreckinger et al., 2021) due to drastic changes in microbial community and CO_2 fluxes that started with drying durations as short as 10 days, but changed further when drying extended past 30 days.

Nonlinear trends for the *dry-down rate* signature were somewhat common in all ecoregions except the Western Mountains and the Northern Great Plains. Especially in the Western Deserts and Mediterranean California, we observed frequent cubic trend patterns and shorter dry-down rates. Both regions also show a decreasing discontinuity pattern. However, discontinuity variability showed a drastic

Table 2
For each intermittency signature, a summary of the increasing and decreasing trends for each ecoregion and the percentage of gages (%) categorized as linear, nonlinear, no-trend, as well as the impact of non-linear trend detection (Δ = linear – nonlinear). Gray shading indicates where nonlinear trends occur more often than linear trends. The "total" row for each signature indicates the overall trend change for all regions, collectively.

Signature	Ecological zone	Increasing trend		Δ (%)	Decreasing trend		Δ (%)	No-trend (%)
		Linear (%)	Nonlinear (%)		Linear (%)	Nonlinear (%)		
(a) Annual no-flow days	Eastern Forests	10	14	−4	5	15	−10	56
	Mediterranean California	21	36	−15	1	17	−16	25
	North Great Plains	0	5	−5	29	23	6	43
	South Great Plains	17	23	−6	4	13	−9	43
	Western Deserts	33	30	1	0	13	−13	24
	Western Mountains	22	20	2	3	14	−11	41
	Total	**16**	**21**	**−5**	**6**	**16**	**−10**	**41**
(b) Day of first no-flow occurrence	Eastern Forests	3	5	−2	6	5	1	81
	Mediterranean California	1	9	−8	16	13	3	61
	North Great Plains	9	9	0	2	7	−5	73
	South Great Plains	3	4	−1	9	11	−2	73
	Western Deserts	5	8	−3	10	20	−10	57
	Western Mountains	2	6	−4	14	11	3	67
	Total	**4**	**6**	**−2**	**9**	**10**	**−1**	**71**
(c) Days from peak to no-flow	Eastern Forests	8	8	0	4	10	−6	70
	Mediterranean California	5	14	−9	7	10	−3	64
	North Great Plains	5	4	1	4	5	−1	82
	South Great Plains	6	9	−3	8	11	−3	66
	Western Deserts	8	5	3	5	15	−10	67
	Western Mountains	6	2	4	9	11	−2	72
	Total	**6**	**7**	**−1**	**7**	**10**	**−3**	**70**

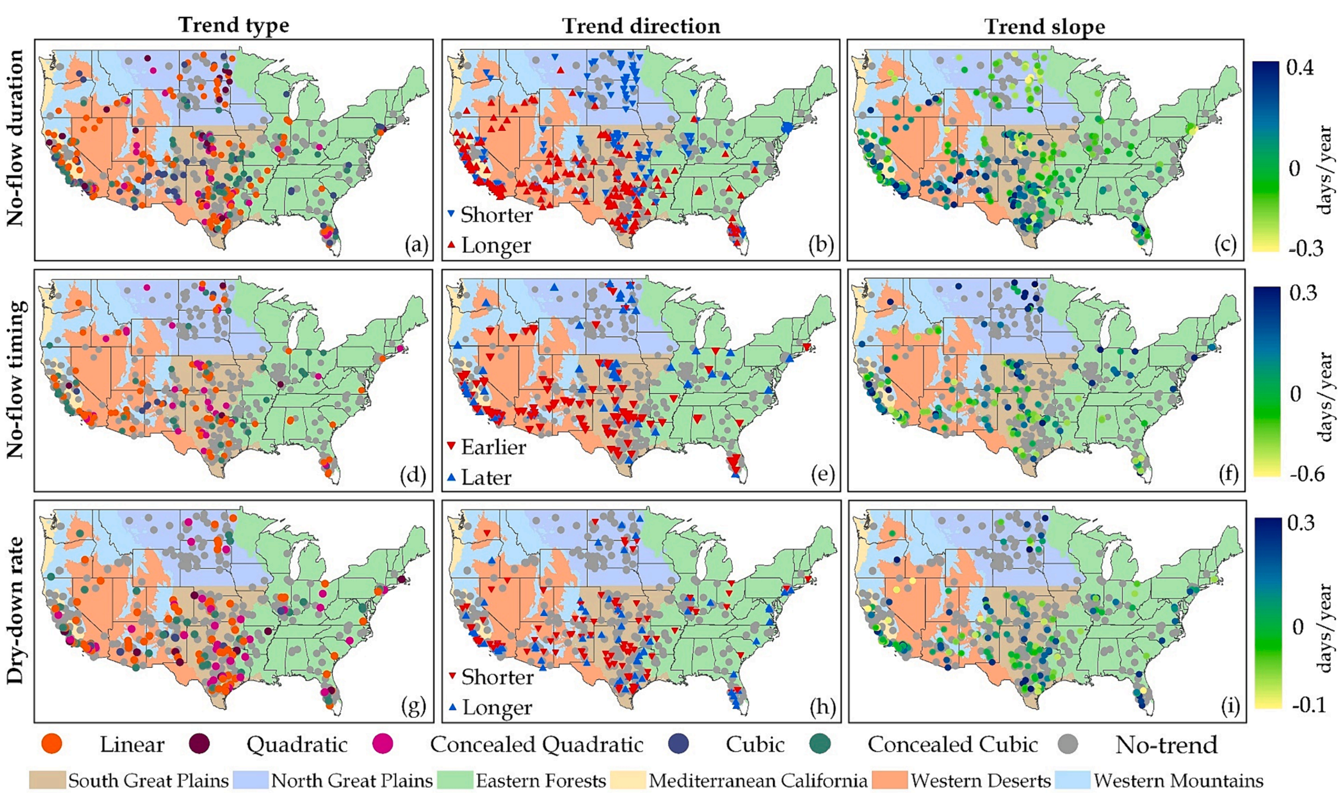

Fig. 6. Trend type, trend direction, and trend slope (magnitude) at (a-c) for annual no-flow days (no-flow duration), (d-f) for days of first no-flow occurrence (no-flow timing), and (g-i) for days from peak to no-flow (dry-down rate) signature.

change after 2000 in the Southern Great Plains (e.g., Texas), with 11 % of gages experiencing more rapid dry-down (Fig. 6(h)), potentially caused by more intense precipitation (Trenberth, 2005). Shorter *dry-down rates* potentially indicate shorter flushing times after a high volume of precipitation. Decreased precipitation inputs can cause declining connectivity between the watershed landscape and the stream channels, decreasing streamflow permanence (Ward et al., 2020). Therefore, enhancing our understanding of changing dry-down rates can provide valuable insights into various hydrological processes in a catchment. For example, during a dry season, a stream like Rio Grande (USGS station ID: 08332010) may be completely dry, but a short burst of intense rainfall could trigger a flash flood that interrupts the dry period. Predicting how long this rewetting persists requires understanding both changes in precipitation intensity and dry-down rates, and the nonlinear shifts in

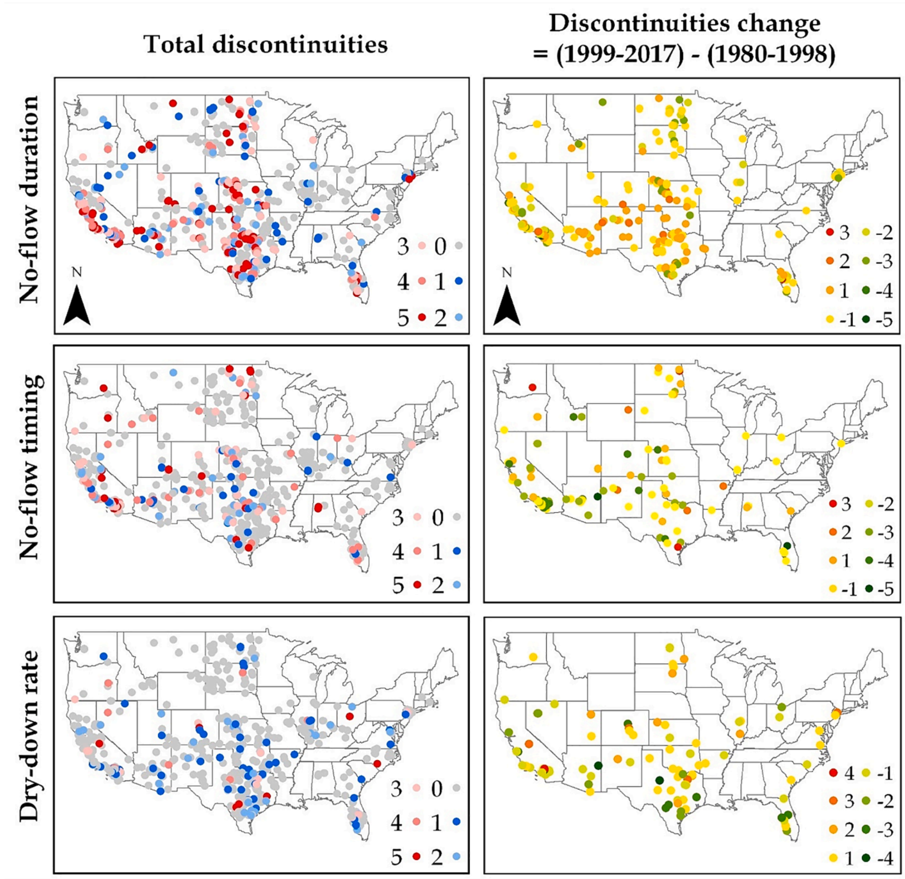

Fig. 7. The total number of discontinuities (left column) and change in the number of discontinuities between the two periods (right column) for the annual no-flow duration (no-flow duration), days of first no-flow occurrence (no-flow timing), and days from peak to no-flow (dry-down rate).

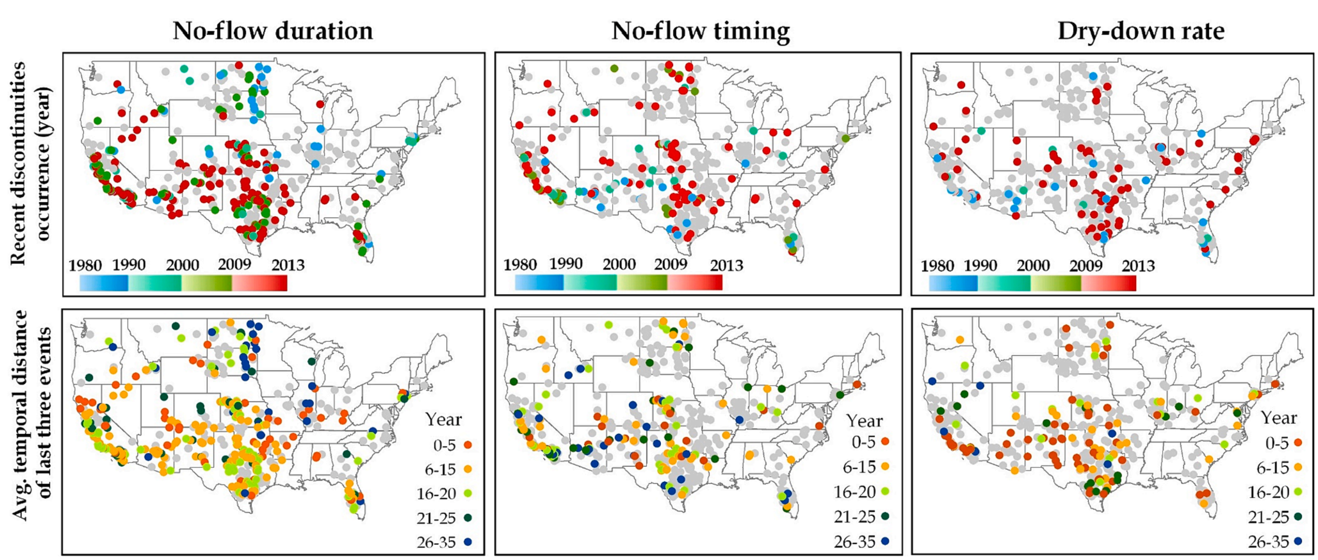

Fig. 8. Recent occurrences of the discontinuities (years) and average temporal distance of the last three events (years) for the no-flow duration, no-flow timing, and dry-down rate.

each.

The widespread nonlinear stream drying dynamics we observe may challenge present and future water management efforts. Nonlinear stream responses to stressors such as climate change or water withdrawals could, for instance, cause hard-to-reverse state shifts (Zipper et al., 2022) with potentially devastating effects on ecological communities (Rosenfeld, 2017; Perkin et al., 2019). As water permitting decisions are often carried out by agencies with limited resources (Lapides et al., 2022), addressing nonlinearities in management plans will require developing clear relationships between management actions, streamflow change, and ecosystem services of interest. Further work characterizing the drivers of nonlinear change in stream drying will be particularly valuable for helping guide these efforts.

4.2. Nonlinear changes in stream drying signature can impact stream connectivity

Nonlinear trends are common, comprising over half of the significant trends within the CONUS database of intermittent streams. Furthermore, most of these trends are towards drying conditions, with the exception of the Northern Great Plains ecoregion. Not only is this ecoregion unusual in trending towards wetter conditions, but it also stands out because its nonlinear behavior occurred relatively early in the period of record over the last four decades. This region may be experiencing wetting conditions due to changing winter freeze-ups, which may have been more sensitive to climate warming than other regions (Archambault et al., 2023). In contrast, nearly all other regions are drying with early no-flow timing, and past work has found that – at least at the CONUS scale - spatial and temporal variability in stream intermittency is strongly influenced by aridity, or the balance between precipitation and potential evapotranspiration (Zipper et al., 2021; Hammond et al., 2021; example in Fig. S5).

However, the balance between these drivers may be distinct in each region, potentially leading to a variety of dominant nonlinear functional forms of drying. Concealed quadratic and cubic patterns, which show substantial variation over short periods without a long-term linear trend, comprise approximately a third or more of all significant trends, suggesting that short-term variations should not be ignored when considering shifting patterns in intermittency. Hydrological processes are multiscale, where variation in one scale (e.g., short term) can manifest their impact on another scale (e.g., long term). Therefore, it is vital to consider short-term variations from the water management standpoint. For example, Fovet et al. (2021) and McDonough et al. (2011) addressed the short-term fluctuations in water distribution, which significantly change stream velocity and flow paths, particularly in intermittent streams. These rapid changes can trigger a multiscale interaction, e.g., mobilization of stream bed particles and biofilms that increase the turbidity, color, and odor in the water as short-term variation. Over time, mobilized stream bed particles can be transported downstream and contribute to a sandbar formation as a part of long-term low water variation that can alter the intermittent flow and create barriers to fish migration.

4.3. Future stream connectivity may be difficult to predict, especially where controls on dry-down rate differ from other drying signatures

Nonlinear trends in all of these drying signatures suggest that connectivity changes may also be less predictable than previously thought. Because relatively small changes in the timing, duration, and rate of drying can drastically affect connectivity in intermittent stream ecosystems (Malish et al., 2023), nonlinear changes in drying that were previously thought to be linear may lead to greater uncertainty in connectivity changes. Furthermore, the abundance of recent discontinuities or breakpoints in trends — regardless of whether they are linear or nonlinear — suggests that past behavior may be a particularly poor predictor of future drying. Because of these discontinuities in the time series, predictions of drying and connectivity across CONUS must consider nonlinear patterns and threshold behavior.

Although most sites outside the Northern Great Plains ecoregion exhibit earlier no-flow timing and longer duration of drying, all ecoregions and signatures have a mixture of positive and negative trends, and the stream drying rate has less clear regional patterns. Instead, some sites are drying faster, whereas others are drying slower, suggesting diverging streamflow recession dynamics across sites. This same variability was observed in past linear analyses (Zipper et al., 2021), and although some sites exhibited nonlinear trends, many sites were simply too variable to exhibit a clear trend. Nonetheless, quite a few sites, especially in the Southern Great Plains, have experienced recent discontinuities in trends, suggesting past dry-down rates would be poor predictors of future recession behavior. These shifts in dry-down rates can occur at a site when different portions of the landscape contribute differently during the streamflow recession (e.g., Shaw et al., 2013). Since past work has found that linear trends in dry-down rate may be more responsive to land cover than no-flow duration or timing (Zipper et al., 2021), it is possible that the nonlinear changes in dry-down rate that we observe may also be more closely linked to changes in land or water use than climate or physiographic factors. Given that the rate of stream drying is hypothesized to have a major effect on ecosystem function (Allen et al., 2020) and hyporheic dynamics (DelVecchia et al., 2022), untangling potential drivers of nonlinear change in drying dynamics is a particularly important area for future characterization of stream drying regimes.

5. Conclusions

Most streamflow trend analyses have focused either on perennial flow trends or have detected only linear trend direction (increase or decrease) and slope of non-perennial drying signatures. These approaches implicitly assume that streamflow changes linearly and monotonically, even at the lowest of flows and during the transition to dry conditions, which may not always be valid. We tested for nonlinear trends in streamflow-based intermittency signatures, using the PolyTrend algorithm to detect both linear and nonlinear trends in the duration, timing, and rate of stream drying across CONUS. Additionally, we identified discontinuities in those signatures through breakpoint analysis.

We found that nonlinear trends in intermittency signatures were common (50 % or more of the significant trends) with varying degrees of nonlinearity depending on the intermittency signature and ecoregion. Regionally, the dominant nonlinear changes occurred in Mediterranean California for *annual no-flow days*, Northern Great Plains for *days of first no-flow occurrence,* and Mediterranean California for *days from peak to no-flow* signature. All signatures suggested drying is common at many sites: *annual no-flow days* lengthened and *days from peak to no-flow* shortened while *the day of first no-flow occurrence* arrived earlier each year.

More discontinuities were detected in the second half of the time series than earlier in the record, especially in the Southern Great Plains, Western Mountains, and Mediterranean California. The streams' dry-down rate (peak to no-flow period) has increased in the southern US in the last two decades (1999–2017). Additionally, the study reveals that discontinuities in no-flow duration have reduced in the second half of the time series and Mediterranean California and North Great Plains. The no-flow timing shows that the discontinuities are reduced in the South Great Plains, while the dry-down rate shows a higher level of discontinuity in the South Great Plains.

Overall, our results indicate that it is vital to consider nonlinear trends and abrupt changes in streamflow drying signatures. In particular, it is essential to recognize that nonlinear trends in drying characteristics may mean that streams dry more rapidly than otherwise predicted, emphasizing the need for long-term data collection and process-based studies to understand how non-perennial streams may respond to climate and land-use changes.

CRediT authorship contribution statement

Kanak Kanti Kar: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Tirthankar Roy:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sam Zipper:** Writing – review & editing, Methodology, Conceptualization. **Sarah E Godsey:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data link is provided in the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.131131.

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