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Key Points:

- Stream drying behavior clustered into four drying regimes with minimal spatial coherence, reflecting key differences in drying signatures
- Cluster regime membership varied temporally and 77% of gages experienced events belonging to more than one drying regime
- Land cover was more significant than climate in explaining event drying regime membership

Supporting Information:

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

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The Drying Regimes of Non-Perennial Rivers and Streams

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Abstract The flow regime paradigm is central to the aquatic sciences, where flow drives critical functions in lotic systems. Non-perennial streams comprise the majority of global river length, thus we extended this paradigm to stream drying. Using 894 USGS gages, we isolated 25,207 drying events from 1979 to 2018, represented by a streamflow peak followed by no flow. We calculated hydrologic signatures for each drying event and using multivariate statistics, grouped events into drying regimes characterized by: (a) fast drying, (b) long no-flow duration, (c) prolonged drying following low antecedent flows, (d) drying without a distinctive hydrologic signature. 77% of gages had more than one drying regime at different times within the study period. Random forests revealed land cover/use are more important to how a river dries than climate or physiographic characteristics. Clustering stream drying behavior may allow practitioners to more systematically adapt water resource management practices to specific drying regimes or rivers.

Plain Language Summary How, when, and where streams and rivers dry are important variables that influence ecosystem functions, such as regulating downstream water quality, supporting fisheries, and promoting carbon storage. Non-perennial streams, which flow only part of the year, comprise the majority of the global river length and are understudied. Specifically, we do not understand similarities and differences in how these streams dry down. Here, we propose a novel drying regime concept to characterize stream drying that complements the flow regime paradigm employed in aquatic ecology. We characterize the timing, duration, magnitude, and rate of drying for 25,207 drying events observed at 894 stream gages across the Contiguous United States (CONUS). Our results highlight that there is considerable variability in stream drying both through time at individual stream gage locations and through space across CONUS. Our machine learning analyses suggest that land cover/use is more important overall than climate or physical characteristics in driving how individual drying events are grouped together by similar drying patterns. Grouping stream drying behavior may allow practitioners to adapt water resource or ecosystem management practices to specific drying regimes or river systems.

1. Introduction

Variability in streamflow is the template for physical, chemical, and biological functions in aquatic systems (Bernhardt et al., 2018; Covino, 2017; Harvey & Gooseff, 2015; Stanford & Ward, 1993; Stanley et al., 1997; Wohl et al., 2019). The aquatic sciences have a long tradition of connecting hydrologic variability to ecosystem function by characterizing ecologically important components of the flow regime, such as the timing, duration, frequency, magnitude, and rate of change of flow (Poff et al., 1997). While the flow regime paradigm continues to be important for advancing the understanding and management of lotic ecosystems (Palmer & Ruhi, 2019), there is a need to extend this perspective to aquatic systems that dry, referred to as non-perennial rivers (Busch et al., 2020). Non-perennial rivers comprise the majority of global river networks (Datry, Larned, & Tockner, 2014; Goodrich et al., 2018; Yu et al., 2020) and are predicted to increase in extent due to further human alterations and climate change (Jaeger et al., 2014; Ward et al., 2020). From local to global scales, non-perennial rivers play an important role in material storage and downstream transport (Jaeger et al., 2017), habitat partitioning for riparian plants and aquatic organisms (Schilling et al., 2020), and biogeochemical processing of carbon (Shumilova et al., 2019; von Schiller et al., 2019).

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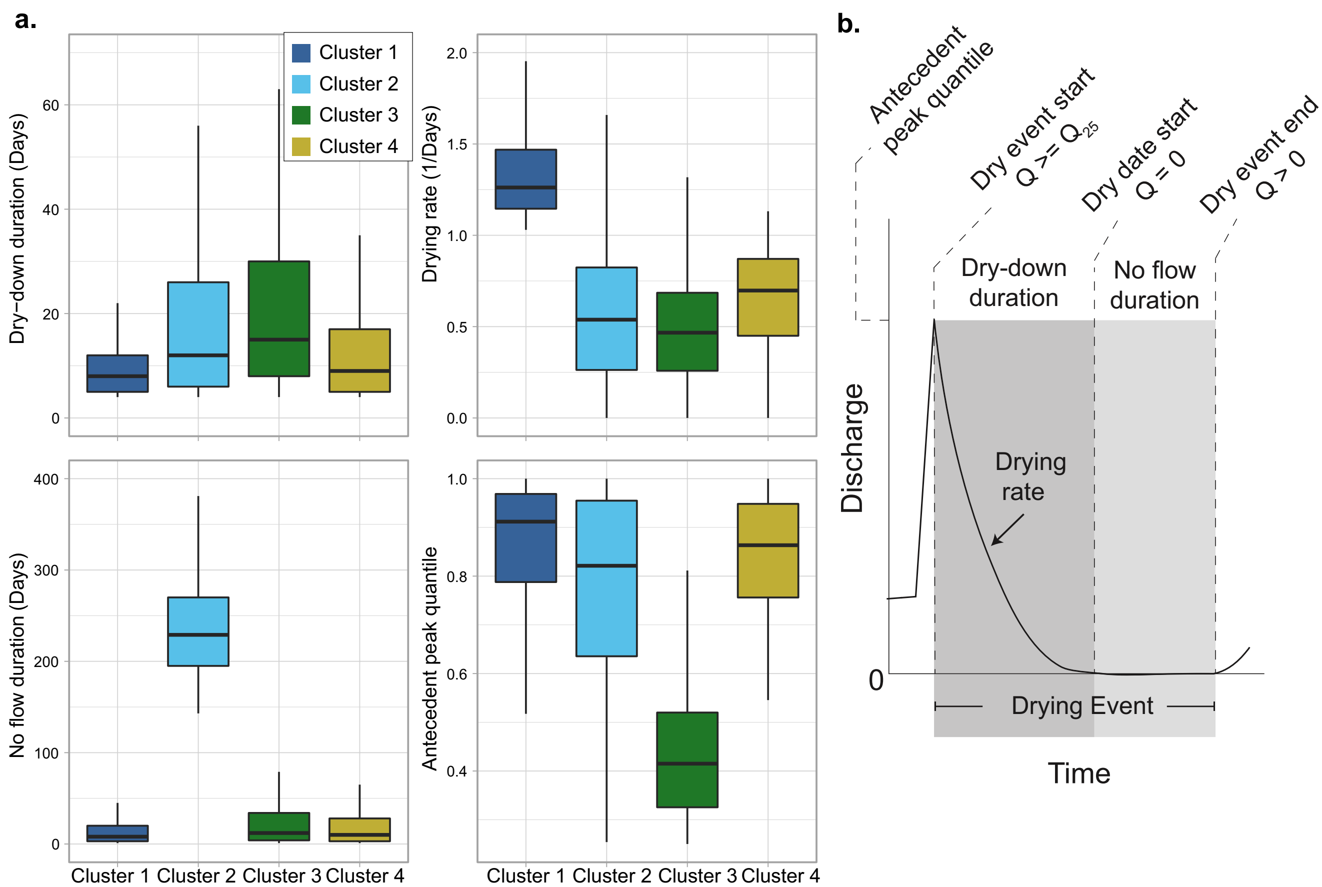

Figure 1. (a) Boxplots showing the distribution of the four hydrologic signatures used in K-means cluster analysis calculated for 25,207 drying events with at least five or more no-flow days over the period of record (1979–2018), over 894 USGS stream gages for each of the four calculated clusters; (b) Conceptual hydrograph illustrating a drying event with associated hydrologic signatures.

These unique functions are due to the occurrence of flowing and dry states, yet most of our scientific and management frameworks are built around perennial streamflow (Allen et al., 2020). To connect river drying to the physical, chemical, and biological functioning of streams, there is a need to understand not just whether a river dries, but the characteristics of how it dries, in terms of the timing, duration, frequency, magnitude, and rate of drying (Fritz & Dodds, 2005). There is limited understanding of how distinct or similar the characteristics of drying are across watersheds with different climates, physiography, or land cover/uses. Without this information, our ability to directly compare ecosystem conditions and functions as well as management strategies between river networks is limited.

Here, we complement the "flow regime" conceptual paradigm (Poff et al., 1997) by presenting a conceptual hydrological framework for the river "drying regime." Focusing on drying characteristics extends the flow regimes paradigm into relatively uncharted waters of non-perennial rivers and their ecosystem functions. Moreover, it recognizes that drying is a complex hydrologic process that impacts ecological, chemical, and physical characteristics of river systems across the Contiguous United States (CONUS). Our analysis addresses the following research questions:

1. Are there continental-scale patterns in stream drying that indicate the presence of distinct drying regimes?
2. If so, how does the occurrence of these drying regimes vary through space and time?
3. What watershed and climate drivers are most important in determining a drying regime?

Specifically, we use gaged rivers and streams across CONUS to quantify common drying regimes defined with a suite of hydrologic signatures that describe drying behavior (Figure 1). Individually these hydrologic signatures mirror the event-specific components of the flow regime, and together can be derived from a streamflow hydrograph to provide a parsimonious description of stream drying.

2. Methods

2.1. Site Selection

We used daily streamflow data from 894 GAGES-II US Geological Survey gages (Falcone, 2011) with at least 10 years of complete data and an average of five or more days with no flow each year from 1979 to 2018, a period selected to overlap with high spatial resolution daily climate data. We analyzed all available data from 1979 to 2018 and rounded streamflow to the nearest 0.1 cfs to reduce noise near zero flow. We identified the extent of discrete drying events for when streamflow declined from a local peak in flow to zero, and ended the event when flow resumed. Following Hammond et al. (2021) and to eliminate non-input related streamflow fluctuations that could have been identified as drying events, we removed events without a local peak in antecedent streamflow above the 25th percentile of long-term daily flows (Text S1). The resulting sample contains a total of 25,207 distinct drying events with an average of 28 events per gage.

2.2. Hydrologic Signature Calculation

Through an initial analysis of metric redundancy (Text S1 and Hammond et al., 2021) and hydrological and ecological relevance (Olden & Poff, 2003), we identified five hydrologic signatures that capture critical functions of the event-scale drying of rivers.

1. Dry-down duration—Number of days from a local streamflow peak to the first occurrence of no flow.
2. Drying rate—The streamflow recession rate defined as the slope in log-log space of −dQ/dt plotted against Q.
3. No-flow duration—The length of consecutive no flow days.
4. Antecedent peak quantile—The long-term streamflow quantile value associated with the local peak in daily flow prior to no flow.
5. No-flow start date—Date (Julian day) of first no flow occurrence.

These five hydrologic signatures have been directly or indirectly linked to a stream's ecological, biological, and chemical patterns and processes (Costigan et al., 2015, 2017; Naiman et al., 2008; Poff et al., 1997). For example, dry-down duration, drying rate, and no-flow start date have ecological consequences for mobile aquatic species that may relocate in drying periods (Rosset et al., 2017), no flow duration is critical for the survivability of species that have certain streambed moisture saturation thresholds (Vorste et al., 2021), and antecedent peak quantile may influence pre-drying hydrologic connectivity conditions such as floodplain connectivity that may provide cascading ecological implications (Penha et al., 2017).

2.3. Analyses on Hydrologic Signatures

We used cluster analysis to identify distinct event-scale drying regimes at all gages. Drying events were clustered based on four event-scale signatures listed above (dry-down duration, drying rate, no flow duration, and antecedent peak quantile). We selected K-means and Hierarchical Ward's Distance algorithms and used the NbClust R package (Charrad et al., 2014) to determine the optimal number of clusters based on the optimal cluster chosen across 30 indices. Ultimately, we present only the clusters from the K-means analysis because of agreement between both clustering analyses (Text S3). In our analysis, drying events occurring at the same gage can belong to different drying regime clusters though time.

We then used a random forest model to assess how watershed-scale variables influence event assignment to drying regime clusters (described in detail in SI). These variables included day-of and 90-days-antecedent climate characteristics, time varying land cover/use, static topography, geology, and soil metrics (Table S1). Prior to the random forest analysis, we removed predictor variables with Pearson correlations greater than 0.7 with other variables in combination with recursive feature selection using the R caret package (Kuhn, 2008), thus retaining 23 predictor variables hypothesized to have greatest influence on stream drying. We generated classification random forest models to examine the variable importance in explaining cluster membership for each drying event. We optimized each model through hyper-parameter tuning using the tidy models R package (Kuhn & Wickham, 2020) and executed using the randomForest R package (Liaw & Wiener, 2002) and calculated variable importance using permutation importance.

3. Results and Discussion

3.1. Clustering of Streamflow Drying Event Signatures Produce Four Dominant Drying Regimes

Clustering analysis of hydrologic signatures from 25,207 distinct drying events resulted in four clusters that represented distinct drying regimes. Clusters 1, 2, 3, and 4 contained 4,428, 1,127, 9,878, and 9,774 events, respectively. Combined, clusters 3 and 4 represented 78% of all drying events, but 77% of gages experienced events that belonged to multiple clusters: 27% of gages had events in two clusters, 34% of gages in three clusters, and 15% of gages had events in all four clusters. A prior analysis that classified gages with non-perennial flow at the mean annual time scale similarly identified a small number of clusters, with five clusters representing distinct regions with similar longer term no-flow behavior (Eng et al., 2016). Further, in an analysis of hydrological drought regime classification, Konapala and Mishra (2020) found three distinct clusters representing drought duration, intensity, and frequency across CONUS. Both of these studies used clusters that represented long-term seasonal timing and frequency of no and low-flow, and clustered at the resolution of each stream gage. In contrast, the clusters developed here reflect event-scale drying behavior with the possibility for different events from the same gage to fall into different clusters, allowing us to explore both spatial and temporal variability in drying regimes.

Cluster 1 (18% of all drying events) represented flashy drying events with short dry-down duration intervals (Figure 1). Short no-flow and dry-down duration coupled with high variability in peak quantile compared to other clusters suggests a rapid driver of flow generation. For example, this cluster may represent drying events occurring in ephemeral streams that experience flashy flow events caused by thunderstorms or monsoonal rains, and also implies that there are limited groundwater contributions to flow.

Cluster 2 was rare (4% of all drying events) and events were characterized by the longest no-flow periods and relatively extended dry-down durations (Figure 1). As such, this cluster may represent drying events that occur in intermittent streams that experience strong seasonality in precipitation inputs (and/or strong seasonality in the ratio of precipitation to evapotranspiration, Figure S1) where subsurface storage tends to fill during the wet months and deplete during the dry months (sensu Dralle et al., 2016).

Cluster 3 was common (39% of all events) and 91% of gages had at least one event in cluster 3. These events characteristically followed smaller relative peak flows and had less rapid drying rates and longer periods of drying (Figure 1). This cluster may represent drying events that occur in intermittent streams where temporary groundwater connectivity slows stream drying.

Cluster 4 was also common (39% of all events) and 75% of gages had at least one event in cluster 4. This cluster did not have a specific hydrologic signature that defined its behavior to distinguish it from the other clusters (Figure 1). Instead, this cluster showed slightly flashier behavior, higher mean peak flow quantile values, and shorter dry down duration, all of which align closely with the median values of the other clusters (except where a cluster is distinguished by that hydrologic signature). This drying regime may represent drying events occurring in intermittent streams that receive frequent precipitation that still results in flashy behavior, indicating contributing flowpaths that dry down or disconnect quickly.

3.2. Variability in Drying Regime Clustering Across Space and Time

There was relatively little spatial coherence in the observed drying regimes (Figure 2). Across CONUS, cluster 3 and 4 events were the most prevalent and were found nationwide. Cluster 1 events primarily occurred at gages in the central and southwestern United States, with pockets in the eastern United States, most notably in the drainages in Illinois and Indiana and the Piedmont Region. Cluster 2 events were the most spatially coherent, primarily occurring west of the Mississippi River. These visual patterns are confirmed by Kolmogorov-Smirnov and rank correlation tests comparing distributions across regions (Text S3; Table S4–S7).

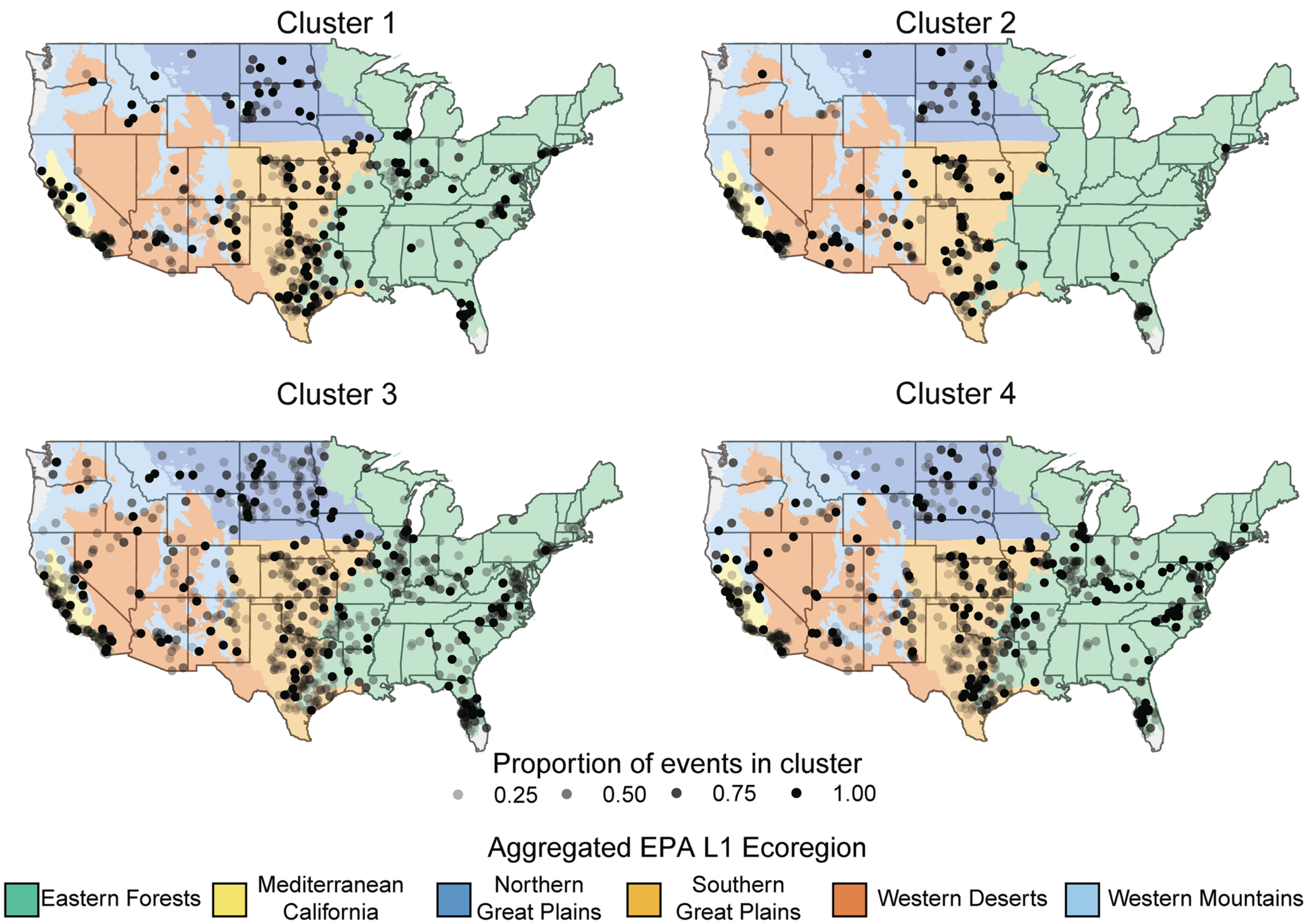

Figure 2. Maps of Contiguous United States showing the spatial distribution of drying regime clusters by GAGES-2 (Falcone, 2011) stream gage location. The background of the map is the aggregate EPA level 1 ecoregions and the transparency of each point is determined by the proportion of drying events that make up that cluster (i.e., less transparent = more events in cluster, more transparent = fewer events in cluster).

The general lack of regional coherence in event-scale drying regimes is a novel finding, contrasting with previous no-flow studies that found strong regional patterns in the mean annual timing of no-flow (Eng et al., 2016) and the annual fraction of no-flow (Hammond et al., 2021). Climate is a primary driver of ecoregion classification (Bailey, 2004), though our spatial results highlight that localized conditions appear to impact drying characteristics at event scales. Limited regional coherence indicates a larger role of local physiographic and land cover/use characteristics in influencing drying characteristics than previously expected. Prior work has found numerous local characteristics influencing stream intermittency, including watershed storage (McDonnell et al., 2018; Nippgen et al., 2016; Tashie et al., 2020), subsurface heterogeneity (Herzog et al., 2019; Klaus & Jackson, 2018; Zimmer & McGlynn, 2017), land use change (Julian et al., 2015), and water withdrawals (Fuchs et al., 2019; Perkin et al., 2017). Potential drivers are explored in Section 3.3.

The clusters exhibited substantial temporal variability, highlighting the seasonality of stream drying (Eng et al., 2016; Hammond et al., 2021). We observed variation in the relative proportion of each cluster within the year (Figure 3), with the greatest fraction of drying events occurring during summer months (i.e., 44% of drying events started between June and August). For example, 40% of Cluster 1 events started between June and August. Cluster 2 displayed a slightly later peak in occurrence (October/November) than the other three clusters, which might reflect drying after summer and fall monsoonal rains, thunderstorms, or late-fall and winter freezing events. Cluster 3 had pronounced seasonality in event occurrence, with a clustering of events in summer months, supporting our interpretation that this cluster may represent intermittent streams where no flow occurs following low antecedent flows during summer months. Cluster 4 displayed the earliest event proportion peak, supporting our interpretation of this cluster representing intermittent

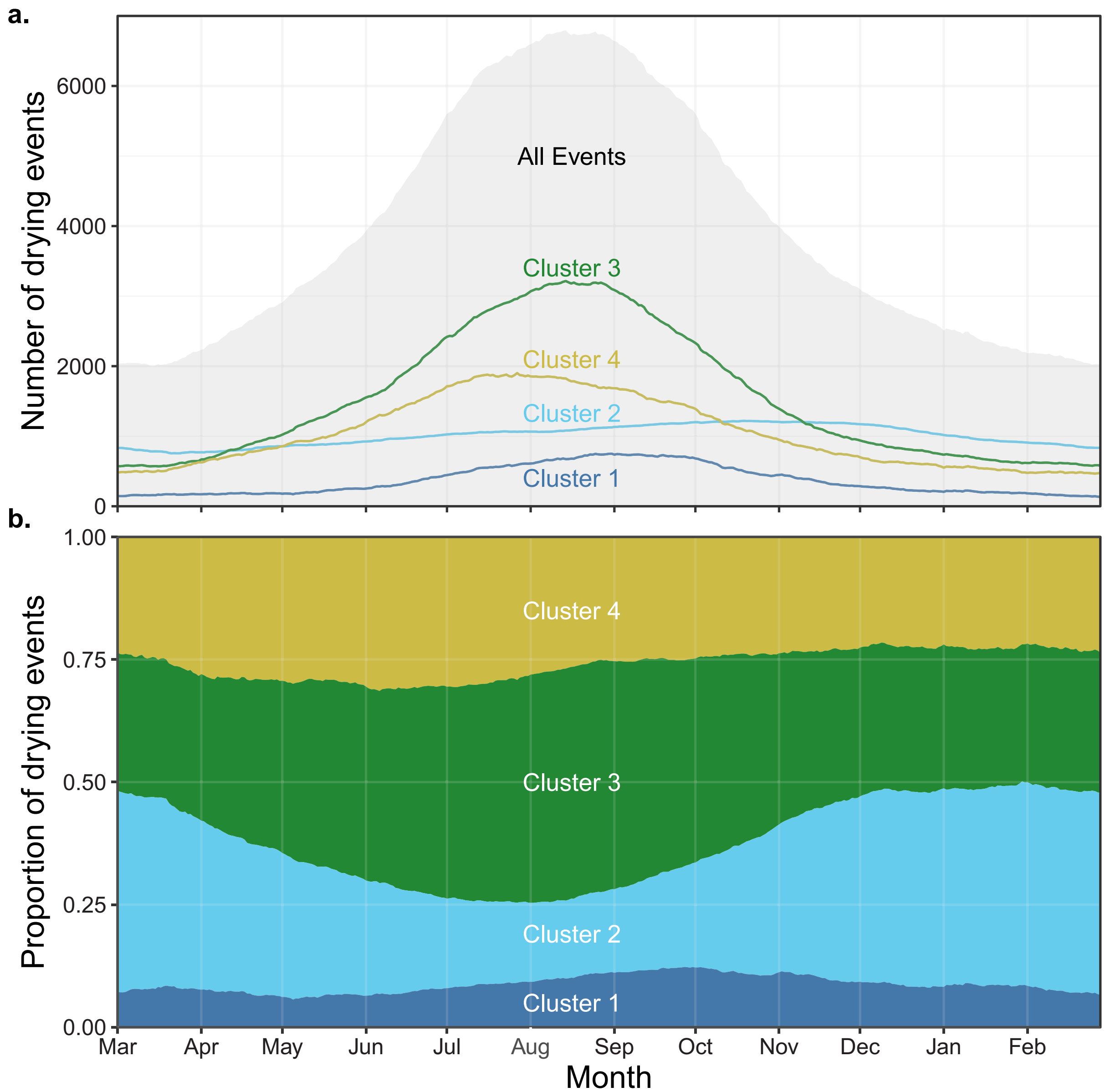

Figure 3. (a) Total number of drying event occurrences in each drying regime cluster by annual occurrence and total number of events; and (b) proportion of drying events occurring at each clustered drying regime relative to the total number of drying events occurring on that calendar day. Occurrence and length of drying event is defined as drying duration plus the no flow duration.

streams that experience rapid seasonal disconnect with contributing flowpaths, such as groundwater (Figures 1 and S3). These seasonal similarities and differences in cluster membership undoubtedly reflect the unique influence that each drying regime may impart on ecosystem processes, such as habitat partitioning (Crabot et al., 2020), organic matter processing (Harjung et al., 2019), and community structure (Vorste et al., 2021).

3.3. Dominant Watershed Properties and Climate Drivers of Drying Regime Clusters

We developed a random forest model, described in detail in Text S3, to evaluate the relative importance of climate, land cover/use, and physiographic predictor variables in determining the drying event cluster classification (response variable), following Konapala and Mishra (2020). The random forest models were effective at drying event classification, with an overall accuracy of 61% on the independent data set of

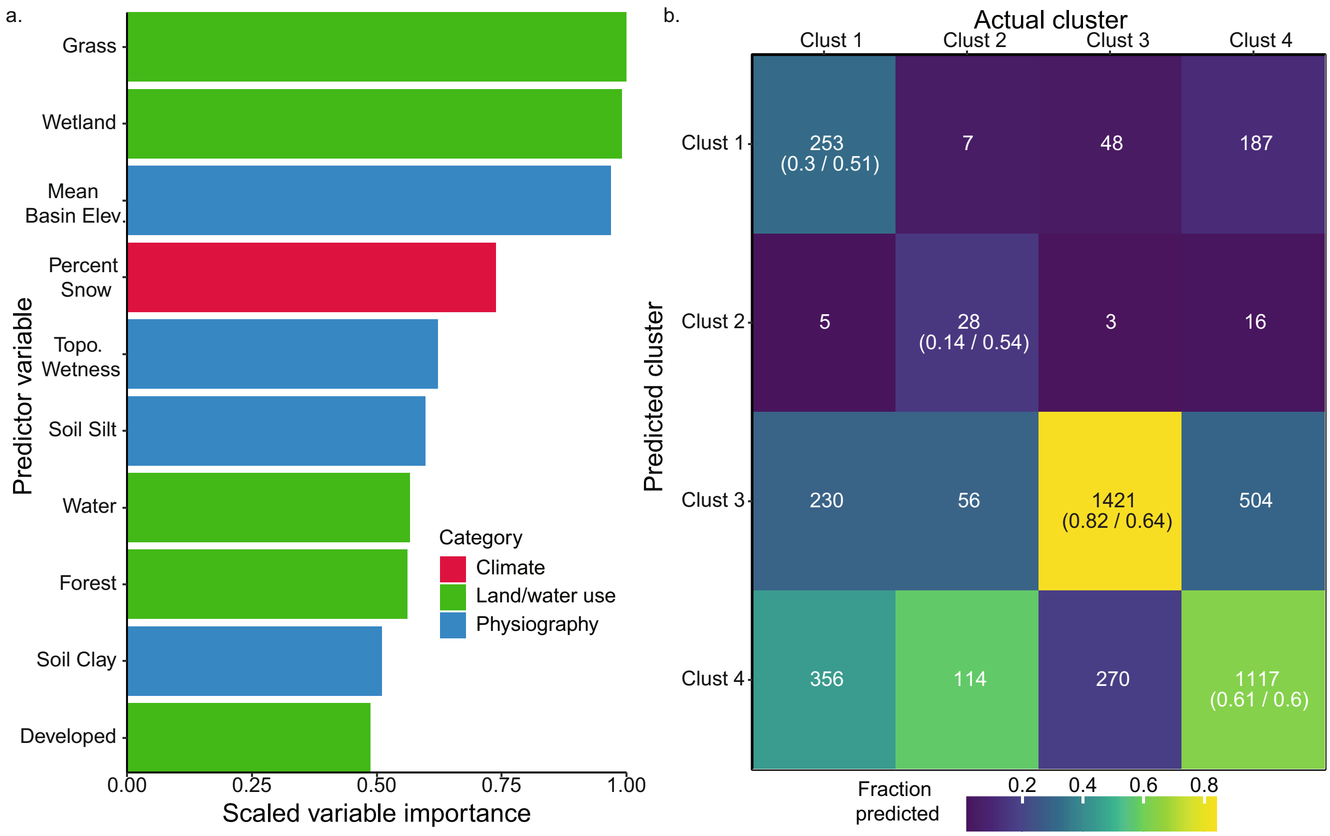

Figure 4. Variable importance plot (a) and confusion matrix (b) from the results of random forest analysis. Variable importance is scaled relative to the predictor variable with the highest importance. All blocks within the confusion matrix have the total number of the predicted cluster relative to the true cluster. The diagonal of the confusion matrix also contains the values for precision and recall, respectively.

events reserved for model testing (Figure 4). To confirm that the random forest model was accurate at the drying event-level, rather than just the gage-level, we also confirmed that the model accurately predicted the relative proportion of events in the different clusters at each gage (Figure S9). Three of the four clusters were classified accurately, with an F1 score (Text S4) of 38%, 22%, 72%, and 61% for clusters 1–4, respectively (Figure 4b; Table S8). This level of accuracy is comparable and sometimes outperforms studies focusing on hydrological regime classification at the reach scale (Dhungel et al., 2016; McManamay & DeRolph, 2019; Merritt et al., 2021). The random forest model struggled to accurately classify cluster 2, which was only correctly identified for 14% of events (Figure 4b). This may be driven by the small number of events in this cluster (only 4% of all drying events) spread out over a relatively large spatial area (Figure 2). Typically, cluster 2 events were misclassified as cluster 4 events (57% of events), which had a similarly widespread spatial distribution across CONUS (Figure 2). This indicates that this unique type of drying event, which occurs infrequently but has a long duration (Figure 1), may be particularly hard to predict based on climate, physiography, and land cover/use. The model's high overall classification accuracy (61%), ability to accurately differentiate cluster memberships among different events at the same gage (Figure S9), and high-class specific accuracy signal its effectiveness as a tool to identify watershed and climatic characteristics associated with each cluster.

We found that land cover/use and physiographic characteristics had the strongest influence over cluster classification, with the top two most influential predictor variables belonging to the land cover/use category (Figures 4 and S7). Of the top 10 predictors, 5 were land cover/use variables, 4 were physiographic, and only 1 was a climate variable (Figure 4a). To confirm our results, random forests using conditional inference trees as well as random forests using hydrologic signatures as the response variable were constructed and resulted in similar behavior (Figures S12 and S13). The dominant importance of land cover/use and physiography relative to climate is surprising, given that land cover/use and physiography change relatively slowly through time compared to climate, we observed seasonal patterns in drying event type (Figure 3), and previous studies have shown that climate is the most important factor in predicting mean annual no flow occurrence (Hammond et al., 2021; Tyralis et al., 2021).

Our results illustrate that characteristics defining a drying regime are more strongly influenced by watershed characteristics such as land cover/use, subsurface storage, and topography, with a decreased dependence on the climatic gradients that typically distinguish ecoregions. Furthermore, the drivers of drying regimes are not only linked to the occurrence of these specific land cover/use categories but also to the resulting mechanism responsible for altering flow behavior associated with these land cover/use types, the combination of which define the template upon which climate acts to determine the eventual stream drying response. While this result is surprising and cannot easily be explained given typical conceptual models of stream drying, it demonstrates the power of data-driven approaches to uncover novel and surprising relationships among variables (Nearing et al., 2021), and suggests an avenue for future exploration. Subsequent analysis of the large dataset compiled for this study using structural equation modeling (e.g., Allen et al., 2020) could allow for enhanced understanding of the interplay between the various drivers and categories of drivers determining drying variability.

3.4. The Implications of Understanding Drying Event Characteristics for Physical, Chemical, and Biological Function and Management in Non-Perennial Rivers

By extending the widely applied flow regime concept (Poff et al., 1997) to non-perennial streams, the conceptual drying regime framework presented here could be used to develop holistic management strategies for the >50% of global river length that dries. While recent work has found that mean annual hydrologic characteristics of non-perennial streams have spatial coherence (Hammond et al., 2021) and are undergoing widespread change (Tramblay et al., 2021), limited focus has been on characterizing event-scale stream drying behavior. As a result, it is unclear both how components of stream drying (duration, rate, frequency, and magnitude; Table S1) vary through space and time, and how different aspects of stream drying may cascade to impact ecological and biogeochemical processes both locally and in downstream waters. While most gages experience different drying regimes across the year, the importance of specific characteristics of individual drying events on the dominant physical, chemical, and biological processes may vary.

The duration, rate, frequency, and magnitude of stream drying have been extensively linked to ecological and biogeochemical processes; we argue that combining these drying regime components together similar to the flow regime paradigm may lead to greater understanding of these processes. That is, the interaction between both flow and drying characteristics is essential to understanding hydrologic impacts on non-perennial streams. For example, previous work has found that a "harshness" index integrating multiple aspects of stream intermittency is a reliable predictor of macroinvertebrate communities (Fritz & Dodds, 2005). As a result, we anticipate that our clustering approach to develop distinct drying regimes may allow us to identify similarities in the drying components of non-perennial streams across CONUS. From this, we may be able to apply similar water resources or ecosystem management strategies to specific streams or at certain times of year. For example, it has been shown that the duration of drying is a key variable influencing biodiversity in non-perennial streams (Datry, Larned, Fritz, et al., 2014) and the rate at which drying occurs also affects the degree to which aquatic taxa are able to migrate elsewhere and persist during no-flow conditions (Vorste et al., 2021). Therefore, we anticipate aquatic taxa maybe more diverse and have higher survival rates in the cluster 3 drying regime with longer drying duration, and may require less conservation interventions during periods that are dominated by cluster 1 events, which display rapid drying. From a biogeochemical perspective, leaf litter often builds up in dry streambeds and is mobilized upon rewetting (Datry et al., 2018), indicating that the no-flow duration may impact nutrient loading and downstream transport. Elsewhere, the frequency of stream drying has been shown to influence patterns in carbon export (Hale & Godsey, 2019) and carbon emissions (Datry et al., 2018). Together, this may suggest that cluster 1 drying regimes may see high carbon and nitrogen processing rates and may explain differences in spatiotemporal patterns in material export from watersheds, which is critical for management of downstream water quality.

While 894 gages and 25,207 drying events used in this study is a substantial sample size, it is important to note that the USGS gaging network is skewed toward perennial flow measurement and has disproportionately less gaging in dry regions (Kiang et al., 2013). In particular, the gage network does not adequately represent gages measuring flow in smaller drainage basins, which correspond to smaller stream orders and in many cases more intermittent flow, as well as in the wetter regions of CONUS. Additionally, less than half of the long-term non-perennial USGS gages drain watersheds dominated by natural flow conditions (Hammond et al., 2021). Despite these limitations, this data set offers unique, high-quality and long-term gaging records useful for the development of the drying regime concept with the possibility for future refinements using additional data. Specifically, this data set provides a novel glimpse into widespread drying event behavior, which our community can use to better understand intra-annual variability, predictability, and controls on stream drying. This, in turn, has the potential to be leveraged for regional to CONUS scale water resource or watershed management practices that focus on maintaining particular flow regimes.

4. Conclusions

We developed a novel conceptual drying regime framework, which characterizes the magnitude, timing, duration, rate, and frequency of river drying as a complement to the widely used flow regime concept. Application of this conceptual framework across CONUS highlights the complex interplay between event-scale characteristics and watershed properties that together control the drying patterns of non-perennial streams. Despite the wide variability of drying behavior observed across drying events identified in this study, this complexity coherently groups into four overall drying regimes.

We found that most USGS gages in this study experience drying events belonging to multiple drying regimes throughout their record, suggesting the dominant drying mechanisms and drivers within a watershed change through time. It must be noted that gages are point-scale measurements that integrate watershed-scale hydrologic conditions. Thus, variation in drying event types at individual gages is likely due to spatial and temporal heterogeneity in upstream watershed storage and hydrologic connectivity (Kleine et al., 2021; Pavlin et al., 2021; Zimmer & McGlynn, 2018). Increased sub-watershed gaging may help decipher what intra-watershed changes drive variability in streamflow at the watershed outlet. Similarly, we suggest the four drying regime clusters may represent differences in the hydrologic connectivity between streams and subsurface flow paths that lead to ephemeral or intermittent flow. Further work is needed to fully characterize how variation in upstream storage and connectivity impact patterns of drying including measures of vertical connectivity along the stream bed (Shanafield & Cook, 2014), horizontal connectivity with the hillslope (Zimmer & McGlynn, 2018), and longitudinal connectivity along river networks (Jensen et al., 2019).

This conceptual drying regime framework can be employed to: (a) understand how drying characteristics of a particular site or event compare to the range of drying conditions in time or space, (b) examine how drying characteristics at individual sites have changed through time in response to climatic and land cover/use changes, (c) enhance our understanding of how internal watershed properties store and release water to drive intra-annual variability in stream drying, (d) link observed ecological and biological parameters with dominant drying regimes to extend estimates of ecological understanding to unobserved sites, (e) and fine tune ecosystem and water resource management practices.

Data Availability Statement

Datasets for this research are available through CUASHI Hydroshare at https://doi.org/10.4211/hs.5f974604766a4c03a2e24b9d1ba720d4 (Price et al., 2021).

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