

Temporal hydrological drought clustering varies with climate and land-surface processes

Journal Article**Author(s):**

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Publication date:

2023-03

Permanent link:

<https://doi.org/10.3929/ethz-b-000601521>

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Originally published in:

Environmental Research Letters 18(3), <https://doi.org/10.1088/1748-9326/acb8ca>

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

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OPEN ACCESS

RECEIVED

24 November 2022

REVISED

17 January 2023

ACCEPTED FOR PUBLICATION


3 February 2023

PUBLISHED

14 February 2023

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E-mail: manuela.brunner@slf.ch**Keywords:** streamflow drought, hydrological drought, temporal clustering, successive droughts, large-sample datasets, multi-year droughtsSupplementary material for this article is available [online](#)**Abstract**

Recurrent hydrological droughts (streamflow deficits) are highly impactful and challenge water management. Regional studies have provided some evidence of drought-rich periods at specific time scales. However, it is yet unclear where and when droughts cluster in time. Here, we test for significant temporal hydrological drought clustering at subseasonal to multi-year time scales in different climate zones around the world using two different clustering metrics, i.e. the dispersion index and Ripley's K . We find that (1) only 10% of the catchments show temporal hydrological drought clustering, (2) hydrological droughts cluster from seasonal to 3-year time scales with clustering being strongest at an annual time scale; (3) arid catchments with a low snow fraction are most prone to temporal drought clustering; and (4) temporal clustering is more pronounced for hydrological than for meteorological droughts. These results suggest that besides climatic drivers, land-surface processes importantly influence the temporal clustering behavior of hydrological droughts.

1. Introduction

Consecutive droughts can have more severe impacts than droughts occurring in isolation. For example, consecutive droughts severely impact tree growth (Mijnsbrugge *et al* 2016), reduce forest productivity (DeSoto *et al* 2020), and increase tree mortality (Caldeira *et al* 2015, Anderegg *et al* 2020, Schuldt *et al* 2020, Obladen *et al* 2021, Sánchez-Pinillos *et al* 2022). Similarly, they can severely impact crop yields (Yu *et al* 2018) and impede vegetation recovery (Hari *et al* 2020). In addition, recurrent hydrological droughts, i.e. streamflow deficits, also substantially challenge water management by increasing pressure on water resources (Tramblay *et al* 2020) as illustrated by the consecutive 2018 and 2019 summer droughts in Central Europe (Boergens *et al* 2020, Hari *et al* 2020).

For meteorological drought, alternations between drought-rich and drought-poor periods have been documented at multi-year (Moreira *et al* 2015, Noone

et al 2017, Yue *et al* 2021), decadal (Ionita *et al* 2012, Tong *et al* 2018), and multi-decadal time scales (Tanguy *et al* 2021). However, the existence of meteorological drought clustering is not unequivocal as some studies also provide evidence for a lack of cyclicity in precipitation deficits (Pelletier and Turcotte 1997, Bunde *et al* 2013). In addition, drought periodicity has been documented for hydrological droughts at decadal time scales (Hannaford 2015, Barker *et al* 2019). While these previous studies suggest that drought periodicity exists in certain regions and at certain time scales, they have a rather narrow geographical scope and focus mostly on meteorological droughts. Therefore, it is yet unclear which catchments are prone to the occurrence of drought-rich periods, i.e. show significant temporal clustering in terms of hydrological droughts, and how this clustering behavior relates to the temporal clustering of meteorological droughts.

Temporal clustering can be quantified using different types of metrics, including the dispersion

index, which quantifies the departure from a homogeneous Poisson process (Vitolo *et al* 2009, Mediero *et al* 2015, Merz *et al* 2016); kernel estimation (Cowling *et al* 1996, Mudelsee *et al* 2003), which estimates the time variation of extreme event counts as smooth functions of time; or Ripley's K function (Ripley 1981, Dixon 2014, Tuel and Martius 2021a), which measures the average number of extreme events in the temporal neighborhood of extreme events. Such measures have been successfully used to demonstrate the existence of precipitation-rich (Tuel and Martius 2021a, 2021b) or flood-rich periods (Villarini *et al* 2013, Mediero *et al* 2015, Gu *et al* 2016, Merz *et al* 2016, Liu and Zhang 2017, Wang *et al* 2020). Here, we apply the concept to droughts and use two of these temporal clustering metrics to test whether and at which temporal scales hydrological droughts cluster in time. Our analysis focuses on drought clustering as opposed to drought persistence. That is, we study the occurrence of multiple drought events in close temporal succession, rather than the occurrence of individual, long, and persistent drought events. Specifically, we investigate (1) whether and how hydrological droughts cluster temporally in different hydro-climatic regions across the globe, (2) whether and how the temporal clustering of hydrological droughts varies between natural and regulated catchments, and (3) how the temporal clustering of hydrological drought relates to the clustering behavior of meteorological drought. We expect that hydrological droughts show substantially more temporal clustering than meteorological droughts because of memory introduced through different storage and land-surface processes (Alvarez-Garreton *et al* 2021, Ho *et al* 2021).

To address these questions, we compile a large-sample dataset of catchments in different climate zones of the world. We combine data available through different hydrological large sample datasets providing not just streamflow observations but also catchment boundaries and characteristics. We use this 'quasi-global' dataset to identify catchments showing significant temporal hydrological drought clustering at different time scales ranging from sub-seasonal, seasonal, annual, to multi-year scales. Then, we investigate how the physiographical and climatic characteristics of the catchments with significant temporal clustering differ from those without clustering. Finally, we investigate the relationship between meteorological and hydrological drought clustering to assess the relative importance of meteorological and land-surface processes for hydrological drought clustering.

2. Methods

2.1. Dataset

To identify catchments with significant temporal clustering at different time scales across climate zones, we

compile a quasi-global dataset consisting of different large-scale and -sample datasets providing streamflow and catchment characteristics. We include nearly natural and regulated catchments with continuous daily streamflow time series of at least 30 years in the period 1981–2018 with <10% of missing data (missing data were omitted for drought identification). The selection consists of 5015 catchments, more specifically, 720 gauges in Central Europe from the LamaH dataset (Klingler *et al* 2021), 2683 gauges in the United States from the streamflow and basin characteristics dataset by Dudley *et al* (2018) (Dudley18), 208 gauges in Australia from the CAMELS-AUS dataset (Fowler *et al* 2021), 109 gauges in Chile from the CAMELS-CL dataset (Alvarez-Garreton *et al* 2018), 576 catchments in Great Britain from the CAMELS-GB dataset (Coxon *et al* 2020), and 733 catchments in Brazil from the Catchments Attributes for Brazil (CABra) dataset (Almagro *et al* 2021).

For the selected catchments, we retrieve a set of different catchment characteristics available in all datasets including catchment area (km²), mean elevation (m.a.s.l), catchment slope (°), mean annual precipitation (mm), aridity (mean potential evaporation/mean precipitation), fraction of snow (0–1), and reservoir regulation (yes/no). In addition, we derive precipitation and potential evaporation (E_p) time series for the period 1981–2018 for which streamflow data are available from the different large-sample datasets cited above. For the US catchments, we derived precipitation and potential evaporation time series from gridded ERA5-Land reanalysis data (ECMWF 2019, Muñoz-Sabater *et al* 2021) because the Dudley18 dataset used to obtain streamflow and regulation information does not provide hydro-climatic time series.

2.2. Drought event identification

For each catchment in the dataset, we identify a set of independent hydrological drought events using a variable threshold-level approach (Van Loon and Laaha 2015). To minimize the number of dependent events, we smooth the daily time series over a time window of 30 days prior to event extraction (Fleig *et al* 2006). We compute the variable threshold using the 20th flow percentile for each day of the year derived within a moving window ± 15 days before and after the day of interest (Brunner *et al* 2021a, 2021b). Only drought events longer than 30 days are retained to limit the selection to important events. This event identification procedure resulted in a median number of 27 extracted events per catchment (1st quartile: 22 events, 3rd quartile: 31 events). For each of the selected drought events, we determine a set of characteristics including its day of occurrence (day of year), duration (i.e. time elapsing between the time when streamflow falls below the drought threshold and the time when it again exceeds this threshold, days),

deficit (sum of streamflow drought intensities, i.e. differences between the threshold and actual streamflow, accumulated during an event, mm/event), and intensity (i.e. minimum flow, mm, the smaller the value the more intense). Using these event characteristics, we compute the mean drought seasonality using circular statistics (which are suitable for describing variables measured on a cyclical timescale; Burn (1997)), mean duration, deficit, and intensity for each catchment. We assess the sensitivity of our results toward threshold and minimum duration choice by running the temporal clustering analysis for different thresholds (15th, 20th, 30th percentile) and minimum durations (10 and 30 days). Choosing alternative lower (15th percentile) or higher (30th percentile) thresholds, results in the selection of fewer (<25 events) or more events (40 events) per catchment, respectively. Including shorter events with durations longer than 10 days would increase the number of events to around or above 50 events per catchment depending on the threshold. In addition to hydrological droughts, we identify meteorological droughts in a similar way as hydrological droughts by applying the variable threshold-level approach to precipitation time series and precipitation-potential evaporation ($P-E_p$) time series, i.e. by defining negative anomalies in precipitation and $P-E_p$.

2.3. Temporal clustering quantification

To identify catchments with significant temporal hydrological and meteorological drought clustering at different time scales, we use two different metrics, i.e. the dispersion index and Ripley's K . The dispersion index is defined as the ratio of the variance of drought event counts and mean drought counts within a specific time window similarly to the approaches used by Vitolo *et al* (2009) for storms and by Merz *et al* (2016) for floods. To compute this index, we first create a binary time series of drought event occurrences where the days of maximum drought intensity are indicated with 1's and all other days with 0's. That is, each drought event is counted only once, independent of its duration. Second, we count the number of droughts (c) within non-overlapping time windows of t days, where the time window t corresponds to subseasonal to seasonal time scales of 1, 30, 90, and 180 days and annual to decadal time scales of 1, 3, and 5 years. Third, the dispersion index is computed as

$$I_D = \text{var}(c)/\text{mean}(c) - 1. \quad (1)$$

Finally, we test for clustering significance by running a bootstrap experiment (Merz *et al* 2016). That is, we simulate $n = 1000$ binary time series from a homogeneous Poisson process, in which events occur at random time points, with an occurrence rate corresponding to the mean occurrence rate of drought

events in the observed time series. For each simulated drought count time series, we compute the dispersion index according to equation (1). Using the n indices, we derive the sampling distribution of the dispersion index and a critical value for a significance level of 5%, i.e. the 95th quantile of the sampling distribution. A time series is said to exhibit significant temporal clustering, if the observed dispersion index is larger than this critical value. If the observed drought occurrence time series shows no temporal clustering, it should show a similar behavior as a homogeneous Poisson process in which events are randomly distributed in time. In contrast, drought occurrence time series showing temporal drought clustering would deviate from a homogeneous Poisson process. An illustration of this procedure is provided for four example catchments in figure A1 in the supporting information.

Ripley's K is a cumulative function that has been traditionally used to study the spatial or spatio-temporal clustering behavior of point processes at different spatial scales (Ripley 1981). More recently, it has also been used to study the temporal clustering behavior of extreme events (Dixon 2014, Barton *et al* 2016, Tuel and Martius 2021a) and is defined as the average number $E(t)$ of events within a time window t around a randomly chosen drought event

$$K(t) = E(t). \quad (2)$$

We again vary the time window t between subseasonal to seasonal time scales of 1, 30, 90, and 180 days and annual to decadal time scales of 1, 3, and 5 years. Finally, we also run a bootstrap experiment to test for clustering significance. That is, we simulate $n = 1000$ samples from a homogeneous Poisson process with the same event occurrence rate as the observations and compute $K_b(t)$ for each of these samples to derive a sampling distribution and critical value. For any given t , the data are significantly temporally clustered if the estimated $K(t)$ from the observed data is greater than the 95th percentile of the simulated $K_b(t)$ values. An illustration of this procedure is provided for four example catchments in figure A2 in the supporting information. We test for significant temporal drought clustering at different time scales for hydrological and meteorological droughts by applying the dispersion index and Ripley's K to streamflow, precipitation, and $P-E_p$ time series, respectively. To quantify the degree of clustering for different time scales, we determine the percentage (0–1) of catchments showing significant temporal clustering at a specific time scale.

To assess the differences between catchments with and without significant clustering, we focus on a specific time scale, e.g. one year. We divide the catchments into two groups, those catchments which show significant temporal clustering at that time scale and those catchments that do not show any clustering at that time scale. Then, we summarize the catchment

and drought characteristics of each group of catchments using boxplots to highlight the differences in characteristics between catchments with and without temporal hydrological drought clustering.

3. Results

3.1. Spatio-temporal drought variability

The catchments included in the quasi-global dataset are hydro-climatologically diverse, with drought seasonality (figure A3 in the supporting information) and drought characteristics varying across different climate zones (figures A4–A6).

Hydrological drought events in the Northern Hemisphere, i.e. in the US, GB, and Central Europe, mainly occur during the warm season (summer and fall) except in mountain regions where hydrological droughts are observed mainly in the cold season (figure A3). In the Southern Hemisphere, hydrological droughts in coastal regions mainly occur during the cold season, while hydrological droughts in the Amazon and Central Australia occur in fall and summer, respectively. These findings regarding hydrological drought seasonality are in line with previous studies which have shown similar spatial patterns when using a variable drought threshold e.g. for Europe (Sutanto and Van Lanen 2021). These diverse catchments, with respect to climate and hydrological drought seasonality, can have different behaviors in terms of the occurrence of drought events and their temporal clustering, as illustrated for two catchments in figures 1(b) and (c). The first catchment shows temporal clustering at seasonal time scales (figure 1(b)), meaning that hydrological droughts are likely to occur in subsequent seasons. The second catchment shows temporal clustering at longer, i.e. multi-annual time scales (1(c)), meaning that the catchment is affected by hydrological droughts in regular multi-annual intervals.

3.2. Temporal drought clustering

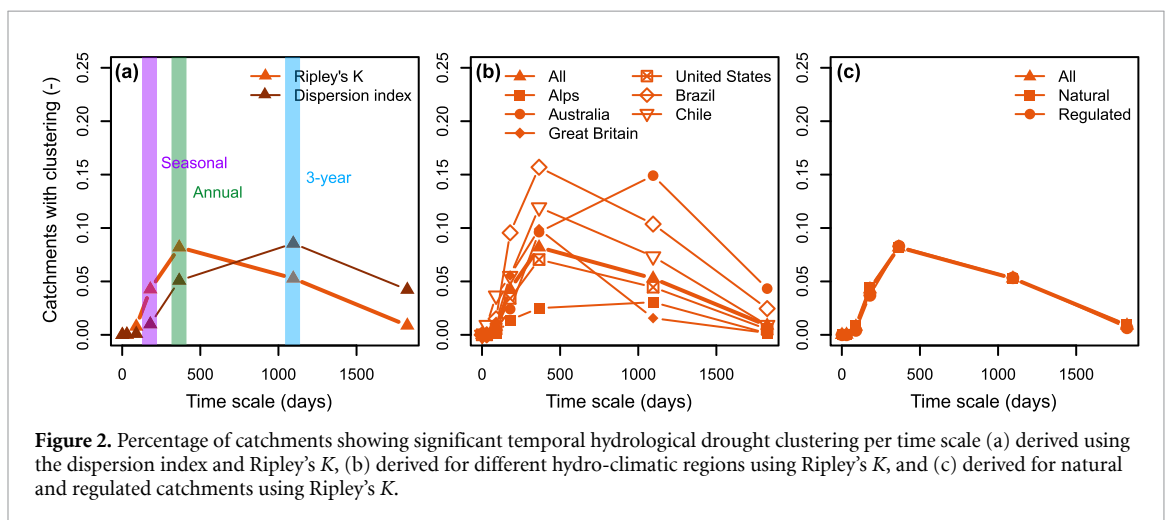
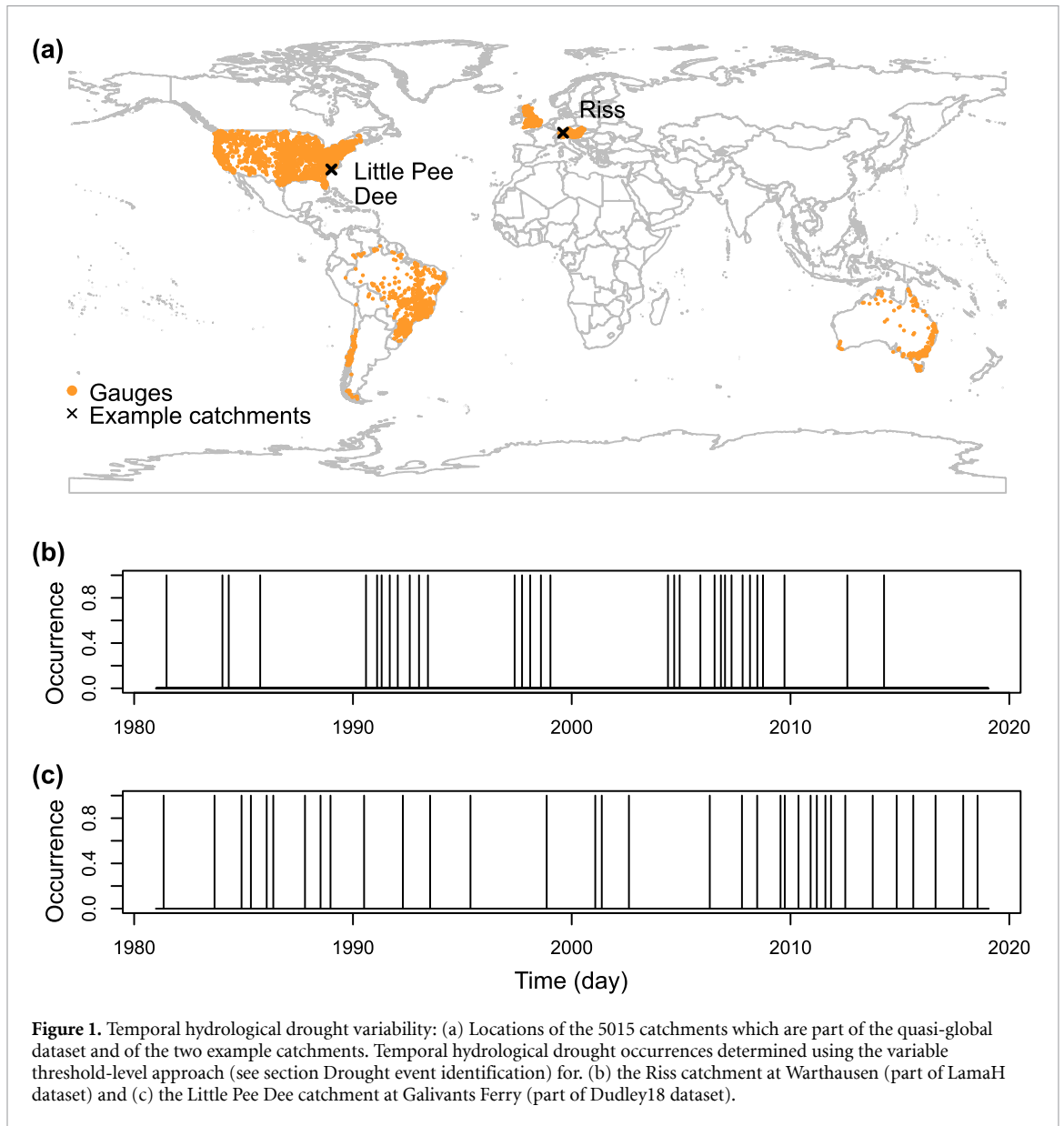
Only a small part of the catchments analyzed (<10%) show significant temporal hydrological drought clustering with the percentage of catchments varying by time scale (figure 2(a)).

Temporal hydrological drought clustering is most common at seasonal (180 days), annual (365 days), and multi-year time scales of up to 5 years independent of the clustering metric chosen. At a seasonal timescale, around 5% of the catchments show significant temporal clustering according to Ripley's K , at an annual scale, 10%, and at a 3-year time scale, 5% of the catchments. Hardly any significant temporal clustering is observed at sub-seasonal scales (<180 days) and at longer time scales exceeding 5 years. These findings are robust with respect to the choice of the clustering metric, except for longer time scales where the dispersion index still indicates some

significant temporal clustering while Ripley's K does not. Because the results derived with the two metrics are very similar, the subsequent analyses will mostly focus on one of the metrics, i.e. Ripley's K , which has been used to study the temporal clustering behavior of a range of other extreme phenomena. The results are also robust with respect to the choice of the dataset as illustrated by the comparison of the results obtained for the quasi-global dataset and the results obtained for a different dataset containing 421 catchments in Europe part of the Global Run-off Data Center database (GRDC 2019) (figure A7 in the supporting information). Furthermore, these findings are independent of the exact hydrological drought definition (i.e. the exact drought threshold and minimum duration) chosen to identify drought events, with temporal clustering being strongest at seasonal, annual, and 3-year time scales independent of the drought threshold and minimum duration chosen (figure A8 in the supporting information).

In addition, the finding that temporal hydrological drought clustering is most common at seasonal, annual, and 3-year time scales applies to all six regions in our dataset (figure 2(b)). In most regions, temporal hydrological drought clustering is most common at an annual time scale (Brazil, Chile, Great Britain, United States), while in Australia and the Alps temporal hydrological drought clustering is most common at a 3-yearly time scale. However, the regions considered slightly differ in terms of the percentage of catchments that show significant clustering. Temporal hydrological drought clustering is most common in Brazil and Australia at an annual time scale and at a 3-year time scale, respectively, and least common in the Alps. While the percentage of catchments showing temporal hydrological drought clustering to some degree depends on the region, it is independent of whether catchments are natural or regulated (figure 2(c)). Catchments showing significant temporal hydrological drought clustering share some common characteristics as shown by our comparison of physiographical and drought characteristics for catchments with significant and non-significant temporal clustering (figure 3). Catchments with significant temporal clustering at an annual time scale (figure 3) have a small fraction of snow and/or are characterized by an arid climate with little precipitation input. They also show comparably long hydrological drought events, low minimum flows but small deficits. In contrast, wetter catchments and catchments influenced by snow are less likely to show significant temporal clustering at an annual time scale.

Temporal clustering is even less common for meteorological droughts (P deficits and $P-E_p$ deficits) than for hydrological droughts but follows the same pattern with respect to time scale (figure 4(a)). Hardly any catchments show temporal clustering for meteorological droughts (both derived based on P and



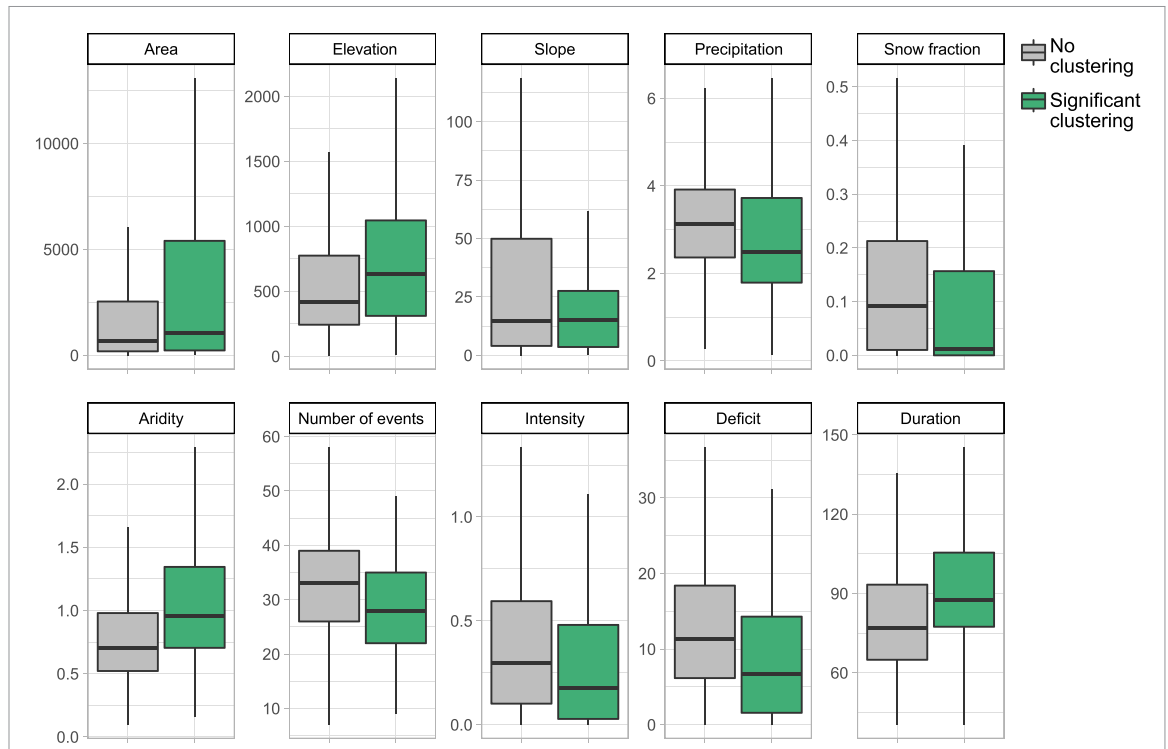


Figure 3. Catchment and hydrological drought characteristics of catchments with and without significant temporal hydrological drought clustering at an annual time scale according to Ripley’s K : catchment area (km^2), mean elevation (m.a.s.l), catchment slope ($^\circ$), mean annual precipitation (mm), fraction of snow (0–1), and aridity (mean potential ET/mean precipitation), number of drought events, drought intensity (i.e. minimum flow; mm/day), drought deficit (mm/event), and drought duration (number of days the streamflow is below the threshold). All differences between catchments with and without significant temporal clustering are statistically significant according to the Kolmogorov–Smirnov test.

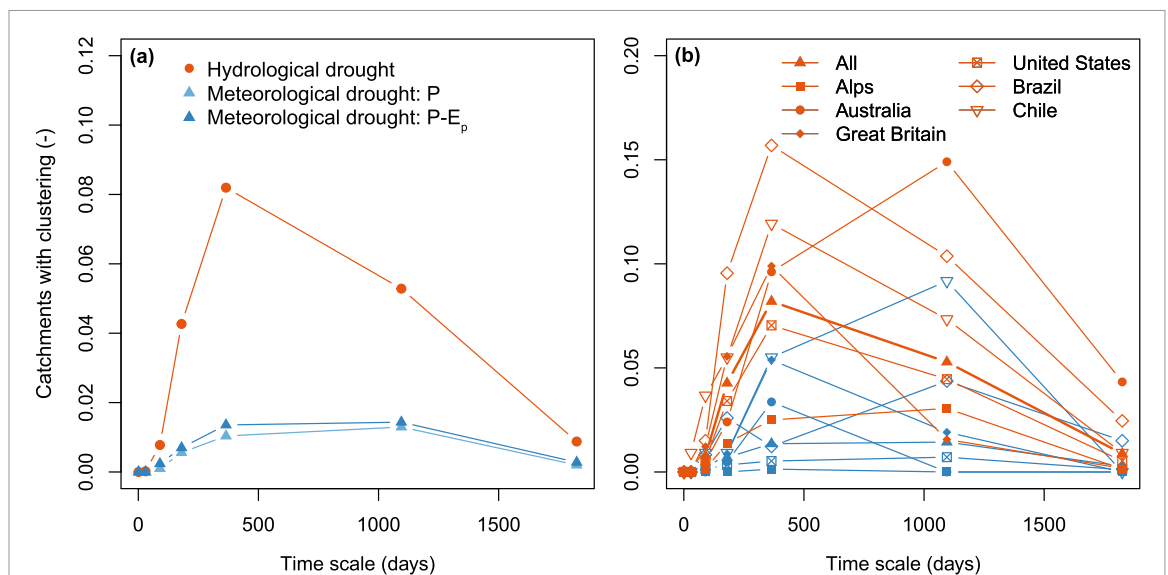


Figure 4. Fraction of catchments with significant drought clustering at different time scales for Ripley’s K for (a) hydrological vs. meteorological drought (defined using precipitation (P) and P -potential evaporation (E_p) deficits) and (b) for hydrological and meteorological droughts (defined using E_p deficits) for all regions.

P - E_p deficits) when looking at Ripley’s K , while up to 10% of the catchments show significant clustering at seasonal, annual, and multi-annual (up to 5 years) time scales for hydrological drought. However, similar to hydrological droughts, temporal clustering of meteorological droughts is strongest at seasonal, annual, and 3-yearly time scales independent of the

clustering metric chosen. In case of the dispersion index, there is still some temporal clustering at shorter time scales (up to 3%) but it is also much less common than for hydrological droughts. The finding that temporal clustering is more common for hydrological than for meteorological droughts applies to all regions (figure 4(b)) but the difference between the

meteorological and hydrological temporal drought clustering is stronger for some than for other regions. For example, the difference between temporal meteorological and hydrological drought clustering is particularly large in Brazil, while it is relatively small in Chile.

4. Discussion

Our analysis included different methodological choices, i.e. the choice of the dataset, the drought definition and threshold applied, and the clustering metric, which influence the results to a certain degree. However, our sensitivity analysis shows that the results and conclusions are relatively robust toward the choice of dataset (figure A7 in the supporting information), drought threshold and minimum drought duration (figure A8 in the supporting information), and clustering metric (figure 2).

Our detection of significant hydrological drought clustering at different time scales, ranging from seasonal, over annual, to multi-annual time scales, expands findings of previous studies suggesting hydrological drought clustering at decadal time scales in the UK (Hannaford 2015, Barker *et al* 2019). While these regional studies have highlighted drought periodicity at longer time scales, we here show that temporal hydrological drought clustering is most common at seasonal to 3-year time scales using a dataset spanning different climate zones (figure 2). Our findings indicate temporal hydrological clustering in 5%–10% of the catchments considered, depending on time scale and region (figure 2(b)). Temporal hydrological drought clustering is in most regions more common at an annual than at a 3-yearly time scale, in particular in wet regions such as Brazil or Great Britain, while it is more common at a 3-yearly time scale in dry regions such as Australia. These regional differences in the importance of different time scales for temporal hydrological drought clustering, are on the one hand related to differences in the temporal clustering behavior of meteorological droughts (figure 4(b), meteorological drought clustering varies by region) and on the other hand to the memory of the system (figure 4(b), differences between meteorological and hydrological drought clustering vary by region), which is shorter in wetter than in drier regions (De Lavenne *et al* 2022). Short memories in wetter regions imply that droughts happening in any given year may influence the likelihood of drought occurrence in the next year but not in 3-years, while longer memories may result in drought influences on future droughts at longer than annual time scales. The relationship between meteorological and hydrological drought clustering varies by region (figure 4(b)) suggesting that the relative importance of climatic and land-surface effects for temporal hydrological drought clustering varies for

regions characterized by different climate and catchment properties.

While up to 10% of the catchment show temporal clustering of hydrological droughts, only up to 2% of the catchments show significant temporal clustering of meteorological droughts (figure 4). Such relatively weak clustering of meteorological droughts is in contrast to findings of previous studies which documented meteorological drought variations at multi-year to multi-decadal time scales by assessing inter-annual and decadal drought variability (Ionita *et al* 2012, Yue *et al* 2021). These differences in the temporal clustering behavior of meteorological drought may be explained by the different methods and datasets used for the analyses. We focused on event occurrences independent of drought duration, while these previous studies focused either on very long events or on fluctuations in meteorological drought magnitude rather than occurrence.

Our finding that temporal hydrological drought clustering is substantially more common than the temporal clustering of meteorological droughts suggests that only looking at the temporal clustering of meteorological droughts does not provide a comprehensive picture of temporal clustering in the hydrological domain. There, additional land-surface processes appear to enhance temporal clustering, particularly in arid catchments and catchments without snow storage (figure 3). In addition, it supports our hypothesis that storage or the lack thereof importantly influence the temporal clustering behavior of hydrological droughts. That is, the less storage a catchment has, the higher is the likelihood that it shows temporal hydrological drought clustering. In a snow-dominated catchment, for example, regular streamflow contributions from snowmelt might prevent the development of recurrent hydrological droughts. In contrast, in an arid, precipitation-driven regime, subsequent hydrological droughts might develop if streamflow deficits develop as a result of low precipitation inputs in combination with low baseflow contributions related to persistently low groundwater levels. Similarly, recurrent hydrological droughts can also evolve if soil moisture is consistently low and remains unreplenished for a long time. The importance of land-surface processes for temporal hydrological drought clustering corroborates findings of earlier studies highlighting the important role of catchment memory for drought propagation (Van Loon and Laaha 2015, Alvarez-Garreton *et al* 2021).

Various local and regional studies provide evidence for the occurrence of drought persistence in the form of multi-year droughts both from a meteorological and hydrological perspective. The occurrence of multi-year meteorological droughts has for example been documented for France (Vidal *et al* 2010), Central Europe (Moravec *et al* 2021), and

the United States (Goodrich 2007, Diffenbaugh *et al* 2015, Abatan *et al* 2018, Bales *et al* 2018) and the occurrence of multi-year hydrological droughts for different parts of Europe (Parry *et al* 2012, Folland *et al* 2015, Hanel *et al* 2018, Brunner and Tallaksen 2019) and Chile (Alvarez-Garreton *et al* 2021). The phenomenon of multi-year droughts is distinct from the temporal clustering behavior investigated in this study because it focuses on individual, long droughts compared to the multiple subsequent droughts studied here. However, the two phenomena—multi-year and temporally clustered droughts—might to some degree be related, as indicated by our finding that catchments with significant temporal hydrological drought clustering tend to be characterized by longer droughts than catchments without significant clustering (figure 3). For example, a long drought with slow recovery might prompt further subsequent droughts because the hydrological system might take a long time to fully recover from depleted groundwater storage. How exactly the two concepts of multi-year and temporally clustered droughts are related, remains to be investigated.

Our findings show that climate and the land-surface are important modulators of the temporal clustering behavior of hydrological droughts. In contrast, the degree of reservoir regulation does not affect the temporal clustering of hydrological drought (figure 2(c)). While the impact of reservoir regulation does not influence the temporal clustering of hydrological drought, it has been shown to affect local (e.g. duration or deficit) and regional drought characteristics (e.g. spatial extent) or drought propagation (López-Moreno *et al* 2009, Wen *et al* 2011, Mix *et al* 2016, Wan *et al* 2017, van Oel *et al* 2017, Tu *et al* 2018, Brunner 2021, Ribeiro Neto *et al* 2022). These findings suggest that while reservoirs are able to alleviate drought magnitude, they may not necessarily prevent the occurrence of drought altogether, which results in small impacts on the temporal clustering behavior of hydrological drought as defined in this study. How other types of regulation such as groundwater abstraction affect the temporal clustering behavior of hydrological droughts remains to be investigated (Tijdeman *et al* 2018, Van Loon *et al* 2022). Overall, our finding that the temporal clustering behavior of hydrological droughts varies with climate and catchment characteristics stresses that the influence of climate and catchment characteristics influence a range of drought characteristics not limited to magnitude and frequency (Van Loon and Laaha 2015, Barker *et al* 2016, Parry *et al* 2016, Apurv and Cai 2020, Konapala and Mishra 2020, Ganguli *et al* 2022).

The existence of temporal hydrological drought clustering has considerable implications for hazard assessments, trend analyses, climate impact assessments, and risk analyses. Hazard estimates derived

using a short record might not be representative in catchments with significant temporal drought clustering, as estimates derived on a drought-poor or drought-rich period can under- or overestimate drought risk, respectively. This issue highlights the importance of using a sufficiently long time series for drought frequency analysis. In addition, temporal drought clustering should be considered in trend analyses where drought-rich periods at the beginning or end of a time series might lead to the detection of artificial decreasing or increasing trends, respectively. This problem highlights the importance of choosing a sufficiently long time window for a trend analysis. Furthermore, temporal drought clustering needs to be considered in climate impact assessments, which is challenging because of various uncertainties introduced along different parts of the modeling chain. For example, it has been shown that global circulation models underestimate persistence in precipitation deficits (Kumar *et al* 2013, Ault *et al* 2014, Moon *et al* 2018). Such misestimation might become more pronounced when coupling climate models with hydrological models, i.e. when including storage processes that also need to accurately represent clustering behavior. While modeling the temporal clustering behavior of hydrological droughts might be challenging, it is also crucial to understand how temporal drought clustering might change in a warming world.

Our results suggest that temporal hydrological drought clustering might become more common with increasing temperatures as aridity increases and snow storage decreases (figure 3). For example, temporally clustered events may become more common in regions with increasing aridity such as central North America, central South America, southern Europe and southern Africa (Chai *et al* 2021). Furthermore, more catchments in snow-influenced regions such as the Alps and other mountain regions of the world, where currently only few catchments show temporal hydrological drought clustering (figure 2(b)), may become more affected by this phenomenon as snow cover decreases (Beaumont *et al* 2021, Matiu *et al* 2021). How exactly climate change affects temporal drought clustering needs to be assessed in targeted modeling experiments by e.g. using large ensembles of climate model output in combination with a hydrological model (Deser *et al* 2012). We might also improve our understanding of changes in drought clustering by identifying reasons/drivers for clustering at different time scales.

5. Conclusions

We tested for significant temporal hydrological drought clustering at subseasonal to multi-year time scales in different climate zones ranging from tropical

regions in the Amazon, over snow-influenced regions in the Alps, to arid regions in Australia and the United States using two different clustering metrics, i.e. Ripley's K and the dispersion index. We find that temporal hydrological drought clustering is not very common, as only roughly 10% of the catchments show such clustering behavior. In catchments with temporal clustering, hydrological droughts cluster in time at seasonal, annual, and multi-year time scales and less at subseasonal and longer time scales. Temporal clustering is most common at annual time scales where roughly 10% of the catchments show such clustering behavior and at seasonal and 3-year time scales where roughly 5% show significant temporal clustering. Catchments most prone to significant temporal clustering are arid catchments and catchments with a low snow fraction, i.e. precipitation-driven catchments. Finally, we demonstrate that the temporal clustering of hydrological droughts is substantially more common than the clustering of meteorological droughts. That is, climatic drivers are insufficient to explain the temporal clustering of hydrological droughts, suggesting that additional land-surface processes are needed to explain this behavior. Such processes include snow storage or the absence thereof, seasonal and inter-annual groundwater level variations, temporal soil moisture variability, or fluctuations in glacier-melt contributions but not reservoir storage. We conclude that the risk of recurrent hydrological droughts is substantial in arid catchments without substantial snow storage, which should be considered in hazard, risk, and climate impact assessments.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://doi.org/10.4211/hs.31b56632213345db889a9eee981619f6>.

Acknowledgment

The authors declare no competing interests. We thank the German Research Foundation for funding this project (Grant 2100371301). We also thank the two anonymous reviewers for their constructive comments, which helped to improve the presentation of the paper. The data on which this article is based are available in Alvarez-Garreton *et al* (2018), Dudley *et al* (2018), Coxon *et al* (2020), Fowler *et al* (2021), Klingler *et al* (2021), and Almagro *et al* (2021). The quasi-global dataset (i.e. streamflow, precipitation, evaporation, and catchment characteristics) compiled from these open-access data sources will be made available through HydroShare upon acceptance of this manuscript. Data archiving is underway on HydroShare and the data will be available upon acceptance of this manuscript.

Author contributions

M I B designed the study, performed all analyses, and wrote the first draft of the manuscript, which was revised and edited by K S.

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References

- Abatan A A, Gutowski W J, Ammann C M, Kaatz L, Brown B G, Buja L, Bullock R, Fowler T, Gilleland E and Halley Gotway J 2018 Statistics of multi-year droughts from the method for object-based diagnostic evaluation *Int. J. Climatol.* **38** 3405–20
- Almagro A, Oliveira P T S, Meira Neto A A, Roy T and Troch P 2021 CABra: a novel large-sample dataset for Brazilian catchments *Hydrol. Earth Syst. Sci.* **25** 3105–35
- Alvarez-Garreton C *et al* 2018 The CAMELS-CL dataset: catchment attributes and meteorology for large sample studies-Chile dataset *Hydrol. Earth Syst. Sci.* **22** 5817–46
- Alvarez-Garreton C, Pablo Boisier J, Garreaud R, Seibert J and Vis M 2021 Progressive water deficits during multiyear droughts in basins with long hydrological memory in Chile *Hydrol. Earth Syst. Sci.* **25** 429–46
- Anderegg W R, Trugman A T, Badgley G, Konings A G and Shaw J 2020 Divergent forest sensitivity to repeated extreme droughts *Nat. Clim. Change* **10** 1091–5
- Apurv T and Cai X 2020 Drought propagation in contiguous U.S. watersheds: a process-based understanding of the role of climate and watershed properties *Water Resour. Res.* **56** 9
- Ault T R, Cole J E, Overpeck J T, Pederson G T and Meko D M 2014 Assessing the risk of persistent drought using climate model simulations and paleoclimate data *J. Clim.* **27** 7529–49
- Bales R C, Goulden M L, Hunsaker C T, Conklin M H, Hartsough P C, O'Geen A T, Hopmans J W and Safeeq M 2018 Mechanisms controlling the impact of multi-year drought on mountain hydrology *Sci. Rep.* **8** 1–8
- Barker L J, Hannaford J, Chiverton A and Svensson C 2016 From meteorological to hydrological drought using standardised indicators *Hydrol. Earth Syst. Sci.* **20** 2483–505
- Barker L J, Hannaford J, Parry S, Smith K A, Tanguy M and Prudhomme C 2019 Historic hydrological droughts 1891–2015: systematic characterisation for a diverse set of catchments across the UK *Hydrol. Earth Syst. Sci.* **23** 4583–602
- Barton Y, Giannakaki P, von Waldow H, Chevalier C, Pfahl S and Martius O 2016 Clustering of regional-scale extreme precipitation events in southern Switzerland *Mon. Weather Rev.* **144** 347–69
- Beaumont J *et al* 2021 Twentieth century temperature and snow cover changes in the French Alps *Reg. Environ. Change* **21** 114
- Boergens E, Güntner A, Dobslaw H and Dahle C 2020 Quantifying the central European droughts in 2018 and 2019 with GRACE follow-on *Geophys. Res. Lett.* **47** 14
- Brunner M I 2021 Reservoir regulation affects droughts and floods at local and regional scales *Environ. Res. Lett.* **16** 124016
- Brunner M I, Slater L, Tallaksen L M and Clark M 2021a Challenges in modeling and predicting floods and droughts: a review *WIREs Water* **8** e1520
- Brunner M I, Swain D L, Gilleland E and Wood A 2021b Increasing importance of temperature as a driver of streamflow drought spatial extent *Environ. Res. Lett.* **16** 024038

- Brunner M I and Tallaksen L M 2019 Proneness of European catchments to multiyear streamflow droughts *Water Resour. Res.* **55** 8881–94
- Bunde A, Büntgen U, Ludescher J, Luterbacher J and Von Storch H 2013 Is there memory in precipitation? *Nat. Clim. Change* **3** 174–5
- Burn D H 1997 Catchment similarity for regional flood frequency analysis using seasonality measures *J. Hydrol.* **202** 212–30
- Caldeira M C, Lecomte X, David T S, Pinto J G, Bugalho M N and Werner C 2015 Synergy of extreme drought and shrub invasion reduce ecosystem functioning and resilience in water-limited climates *Sci. Rep.* **5** 15110
- Chai R *et al* 2021 Human-caused long-term changes in global aridity *npj Clim. Atmos. Sci.* **4** 65
- Cowling A, Hall P and Phillips M J 1996 Bootstrap confidence regions for the intensity of a Poisson point process *J. Am. Stat. Assoc.* **91** 1516–24
- Coxon G *et al* 2020 CAMELS-GB: hydrometeorological time series and landscape attributes for 671 catchments in Great Britain *Earth Syst. Sci. Data* **12** 2459–83
- De Lavenne A, Andréassian V, Crochemore L, Lindström G and Arheimer B 2022 Quantifying multi-year hydrological memory with catchment forgetting curves *Hydrol. Earth Syst. Sci.* **26** 2715–32
- Deser C, Phillips A, Bourdette V and Teng H 2012 Uncertainty in climate change projections: the role of internal variability *Clim. Dyn.* **38** 527–46
- DeSoto L *et al* 2020 Low growth resilience to drought is related to future mortality risk in trees *Nat. Commun.* **11** 545
- Diffenbaugh N S, Swain D L, Touma D and Lubchenco J 2015 Anthropogenic warming has increased drought risk in California *Proc. Natl Acad. Sci. USA* **112** 3931–6
- Dixon P M 2014 Ripley's K function *Wiley Statsref: Statistics Reference Online* ed Balakrishnan N, Colton T, Everitt B, Piegorch W, Ruggeri F and Teugels J L (<https://doi.org/10.1002/9781118445112.stat07751>)
- Dudley R, Archfield S, Hodgkins G, Renard B and Ryberg K 2018 Peak-streamflow trends and change-points and basin characteristics for 2,683 U.S. Geological Survey streamgages in the conterminous U.S. (available at: www.sciencebase.gov/catalog/item/5b183960e4b092d965219d62)
- ECMWF 2019 ERA5-Land hourly data from 1981 to present [Dataset] Copernicus (available at: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview>)
- Fleig A K, Tallaksen L M, Hisdal H and Demuth S 2006 A global evaluation of streamflow drought characteristics *Hydrol. Earth Syst. Sci.* **10** 535–52
- Folland C K *et al* 2015 Multi-annual droughts in the English lowlands: a review of their characteristics and climate drivers in the winter half-year *Hydrol. Earth Syst. Sci.* **19** 2353–75
- Fowler K J, Acharya S C, Addor N, Chou C and Peel M C 2021 CAMELS-AUS: hydrometeorological time series and landscape attributes for 222 catchments in Australia *Earth Syst. Sci. Data* **13** 3847–67
- Ganguli P, Singh B, Reddy N N, Raut A, Mishra D and Das B S 2022 Climate-catchment-soil control on hydrological droughts in peninsular India *Sci. Rep.* **12** 8014
- Goodrich G B 2007 Multidecadal climate variability and drought in the United States *Geogr. Compass* **1** 713–38
- GRDC 2019 Global runoff data centre (available at: www.bafg.de/GRDC/EN/02_srvcs/21_tmsrs/riverdischarge_node.html)
- Gu X, Zhang Q, Singh V P, Chen Y D and Shi P 2016 Temporal clustering of floods and impacts of climate indices in the Tarim River basin, China *Glob. Planet. Change* **147** 12–24
- Hanel M, Rakovec O, Markonis Y, Máca P, Samaniego L, Kyselý J and Kumar R 2018 Revisiting the recent European droughts from a long-term perspective *Sci. Rep.* **8** 1–11
- Hannaford J 2015 Climate-driven changes in UK river flows: a review of the evidence *Prog. Phys. Geogr.* **39** 29–48
- Hari V, Rakovec O, Markonis Y, Hanel M and Kumar R 2020 Increased future occurrences of the exceptional 2018–2019 Central European drought under global warming *Sci. Rep.* **10** 1–10
- Ho S, Tian L, Disse M and Tuo Y 2021 A new approach to quantify propagation time from meteorological to hydrological drought *J. Hydrol.* **603** 127056
- Ionita M, Lohmann G, Rimbu N, Chelcea S and Dima M 2012 Interannual to decadal summer drought variability over Europe and its relationship to global sea surface temperature *Clim. Dyn.* **38** 363–77
- Klingler C, Schulz K and Herrnegger M 2021 LamaH-CE: LARge-SaMple DATA for hydrology and environmental sciences for Central Europe *Earth Syst. Sci. Data* **13** 4529–65
- Konapala G and Mishra A 2020 Quantifying climate and catchment control on hydrological drought in the continental United States *Water Resour. Res.* **56** 1
- Kumar S, Merwade V, Kinter J L and Niyogi D 2013 Evaluation of temperature and precipitation trends and long-term persistence in CMIP5 twentieth-century climate simulations *J. Clim.* **26** 4168–85
- Liu J and Zhang Y 2017 Multi-temporal clustering of continental floods and associated atmospheric circulations *J. Hydrol.* **555** 744–59
- López-Moreno J I, Vicente-Serrano S M, Begueria S, Garcia-Ruiz J M, Portela M M and Almeida A B 2009 Dam effects on droughts magnitude and duration in a transboundary basin: the lower River Tagus, Spain and Portugal *Water Resour. Res.* **45** W02405
- Matiu M *et al* 2021 Observed snow depth trends in the European Alps: 1971 to 2019 *Cryosphere* **15** 1343–82
- Mediero L *et al* 2015 Identification of coherent flood regions across Europe by using the longest streamflow records *J. Hydrol.* **528** 341–60
- Merz B, Nguyen V D and Vorogushyn S 2016 Temporal clustering of floods in Germany: do flood-rich and flood-poor periods exist? *J. Hydrol.* **541** 824–38
- Mijnsbrugge K V, Turcsán A, Maes J, Duchêne N, Meeus S, Steppe K and Steenackers M 2016 Repeated summer drought and re-watering during the first growing year of oak (*quercus petraea*) delay autumn senescence and bud burst in the following spring *Front. Plant Sci.* **7** 419
- Mix K, Groeger A W and Lopes V L 2016 Impacts of dam construction on streamflows during drought periods in the Upper Colorado River Basin, Texas *Lakes Reserv.: Res. Manage.* **21** 329–37
- Moon H, Gudmundsson L and Seneviratne S I 2018 Drought persistence errors in global climate models *J. Geophys. Res. Atmos.* **123** 3483–96
- Moravec V, Markonis Y, Rakovec O, Svoboda M, Trnka M, Kumar R and Hanel M 2021 Europe under multi-year droughts: how severe was the 2014–2018 drought period? *Environ. Res. Lett.* **16** 034062
- Moreira E E, Martins D S and Pereira I S 2015 Assessing drought cycles in SPI time series using a Fourier analysis *Nat. Hazards Earth Syst. Sci.* **15** 571–85
- Mudelsee M, Börngen M, Tetzlaff G and Grünwald U 2003 No upward trends in the occurrence of extreme floods in central Europe *Nature* **425** 166–9
- Muñoz-Sabater J *et al* 2021 ERA5-Land: a state-of-the-art global reanalysis dataset for land applications *Earth Syst. Sci. Data* **13** 4349–83
- Noone S, Broderick C, Duffy C, Matthews T, Wilby R L and Murphy C 2017 A 250-year drought catalogue for the island of Ireland (1765–2015) *Int. J. Climatol.* **37** 239–54
- Obladen N *et al* 2021 Tree mortality of European beech and Norway spruce induced by 2018–2019 hot droughts in central Germany *Agric. Forest Meteorol.* **307** 108482
- Parry S, Hannaford J, Lloyd-Hughes B and Prudhomme C 2012 Multi-year droughts in Europe: analysis of development and causes *Hydrol. Res.* **43** 689
- Parry S, Wilby R L, Prudhomme C and Wood P J 2016 A systematic assessment of drought termination in the United Kingdom *Hydrol. Earth Syst. Sci.* **20** 4265–81

- Pelletier J D and Turcotte D L 1997 Long-range persistence in climatological and hydrological time series: analysis, modeling and application to drought hazard assessment *J. Hydrol.* **203** 198–208
- Ribeiro Neto G G, Melsen L A, Martins E S P R, Walker D W and Oel P R 2022 Drought cycle analysis to evaluate the influence of a dense network of small reservoirs on drought evolution *Water Resour. Res.* **58** e2021WR030799
- Ripley B D 1981 *Spatial Statistics* (Hoboken, NJ: Wiley)
- Sánchez-Pinillos M, D'Orangeville L, Boulanger Y, Comeau P, Wang J, Taylor A R and Kneeshaw D 2022 Sequential droughts: a silent trigger of boreal forest mortality *Glob. Change Biol.* **28** 542–56
- Schuldt B *et al* 2020 A first assessment of the impact of the extreme 2018 summer drought on Central European forests *Basic Appl. Ecol.* **45** 86–103
- Sutanto S J and Van Lanen H A 2021 Streamflow drought: implication of drought definitions and its application for drought forecasting *Hydrol. Earth Syst. Sci.* **25** 3991–4023
- Tanguy M, Haslinger K, Svensson C, Parry S, Barker L J, Hannaford J and Prudhomme C 2021 Regional differences in spatiotemporal drought characteristics in Great Britain *Front. Environ. Sci.* **9** 1–20
- Tijdeman E, Hannaford J and Stahl K 2018 Human influences on streamflow drought characteristics in England and Wales *Hydrol. Earth Syst. Sci.* **22** 1051–64
- Tong S, Lai Q, Zhang J, Bao Y, Lusi A, Ma Q, Li X and Zhang F 2018 Spatiotemporal drought variability on the Mongolian Plateau from 1980–2014 based on the SPEI-PM, intensity analysis and Hurst exponent *Sci. Total Environ.* **615** 1557–65
- Tramblay Y *et al* 2020 Challenges for drought assessment in the Mediterranean region under future climate scenarios *Earth-Sci. Rev.* **210** 103348
- Tu X, Wu H, Singh V P, Chen X, Lin K and Xie Y 2018 Multivariate design of socioeconomic drought and impact of water reservoirs *J. Hydrol.* **566** 192–204
- Tuel A and Martius O 2021a A climatology of sub-seasonal temporal clustering of extreme precipitation in Switzerland and its links to extreme discharge *Nat. Hazards Earth Syst. Sci.* **21** 2949–72
- Tuel A and Martius O 2021b A global perspective on the sub-seasonal clustering of precipitation extremes *Weather Clim. Extremes* **33** 100348
- Van Loon A F *et al* 2022 Streamflow droughts aggravated by human activities despite management *Environ. Res. Lett.* **17** 044059
- Van Loon A F and Laaha G 2015 Hydrological drought severity explained by climate and catchment characteristics *J. Hydrol.* **526** 3–14
- van Oel P R, Martins E and Costa A 2017 The effect of reservoir networks on drought propagation *Eur. Water* **60** 287–92
- Vidal J P, Martin E, Franchistéguy L, Habets F, Soubeyroux J M, Blanchard M and Baillon M 2010 Multilevel and multiscale drought reanalysis over France with the Safran-Isba-Modcou hydrometeorological suite *Hydrol. Earth Syst. Sci.* **14** 459–78
- Villarini G, Smith J A, Vitolo R and Stephenson D B 2013 On the temporal clustering of US floods and its relationship to climate teleconnection patterns *Int. J. Climatol.* **33** 629–40
- Vitolo R, Stephenson D B, Cook I M and Mitchell-Wallace K 2009 Serial clustering of intense European storms *Meteorol. Z.* **18** 411–24
- Wan W *et al* 2017 Hydrological drought in the anthropocene: impacts of local water extraction and reservoir regulation in the U.S. *J. Geophys. Res.: Atmos.* **122** 11313–28
- Wang N, Lombardo L, Tonini M, Cheng W, Guo L and Xiong J 2020 Space-time clustering of flash floods in a changing climate (China, 1950–2015) *Nat. Hazards Earth Syst. Sci.* **21** 2109–24
- Wen L, Rogers K, Ling J and Saintilan N 2011 The impacts of river regulation and water diversion on the hydrological drought characteristics in the Lower Murrumbidgee River, Australia *J. Hydrol.* **405** 382–91
- Yu H, Zhang Q, Sun P and Song C 2018 Impact of droughts on winter wheat yield in different growth stages during 2001–2016 in Eastern China *Int. J. Disaster Risk Sci.* **9** 376–91
- Yue Y, Liu H F, Mu X X, Qin M S, Wang T T, Wang Q and Yan Y Q 2021 Spatial and temporal characteristics of drought and its correlation with climate indices in Northeast China *PLoS One* **16** e0259774