Hydrologic risk from consecutive dry and wet extremes at the global scale

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Abstract

Dry and wet extremes (i.e., droughts and floods) are the costliest hydrologic hazards for infrastructure and socio-environmental systems. Being closely interconnected and interdependent extremes of the same hydrological cycle, they often occur in close succession with the potential to exacerbate hydrologic risks. However, traditionally this is ignored and both hazards are considered separately in hydrologic risk assessments; this can lead to an underestimation of critical infrastructure risks (e.g., dams, levees, dikes, and reservoirs). Here, we identify and characterize consecutive dry and wet extreme (CDW) events using the Standardized Precipitation Evapotranspiration Index, assess their multi-hazard hydrologic risks employing copula models, and investigate teleconnections with large-scale climate variability. We identify hotspots of CDW events in North America, Europe, and Australia where the total numbers of CDW events range from 20 to 30 from 1901 to 2015. Decreasing trends in recovery time (i.e., time between termination of dry extreme and onset of wet extreme) and increasing trends in dry and wet extreme severities reveal the intensification of CDW events over time. We quantify that the joint exceedance probabilities of dry and wet extreme severities equivalent to 50-year and 100-year univariate return periods increase by several folds (up to 20 and 54 for 50-year and 100-year return periods, respectively) when CDW events and their associated dependence are considered compared to their independent and isolated counterparts. We find teleconnections between CDW and Niño3.4; at least 80% of the CDW events are causally linked to Niño3.4 at 50% of the grid locations across the hotspot regions. This study advances the understanding of multi-hazard hydrologic risks from CDW events and the presented results can aid more robust planning and decision-making.

1. Introduction

Hydro-meteorological extremes are the drivers of many natural disasters causing devastating loss of life, infrastructure damage, and economic hardship. Among those, dry extremes (i.e., droughts) and wet extremes (i.e., floods) are the most frequent and impactful around the world. Between 2000 and 2017, global drought and flood losses amounted to US$596 billion, which is about a tenfold increase compared to the second half of the last century (EM-DAT 2018). Globally, over the period 1995 to 2015, droughts and floods have affected approximately 1.1 billion and 2.3 billion people, respectively (UNISDR 2015). Climate model projections indicate increases in the frequency and magnitude of droughts and floods due to anthropogenic climate change (e.g., Sheffield and Wood 2008, Rashid et al 2015, Martin 2018, Zhan et al 2020). Furthermore, their adverse impacts are likely to increase due to population growth, ongoing infrastructure development, and economic...
prosperity. Therefore, quantifying hydrological risks of dry and wet extremes is vital for building resilient infrastructure and socio-environmental systems.

While dry and wet extremes belong to the same hydrological cycle and can occur consecutively without leaving adequate time for recovery of infrastructure and socio-environmental systems between subsequent events, they are considered separately in hydrologic risk assessments and water resource management practices (e.g., dam operation rules). Dry and wet extremes are inherently interconnected and changes in the frequency and magnitude of one can influence the other (De Luca et al. 2020, Shi et al. 2020). Even taking measures to reduce the impacts of one can negatively impact the other (Ward et al. 2020). There are many examples of system failures and devastating impacts due to consecutive occurrences of dry and wet extremes. For example, in California, a record-breaking drought (2012–2017) was terminated by an extreme wet event, causing major damage to the spillway of the Oroville dam in 2017 (Vahedifard et al. 2017). The event caused immense environmental losses and evacuation of nearly 200,000 people along the downstream areas of the dam. In Australia, the so called Millennium drought (1997–2010) was ended with floods that caused failure of levees along the Murray riverbank (Van Dijk et al. 2013). Apart from these consecutive events of long duration (multi-year) dry extremes followed by sudden wet extremes, there are consecutive events comprised of relatively shorter duration (e.g., half-yearly to annual) dry and wet extremes. The latter are more frequent and the swing from dry to wet can also cause infrastructure failure (e.g., operation failure of dams and reservoirs, landslides, and structural failure of dikes and levees) and environmental degradation (e.g., loss of crop yield and deterioration of water quality) (Handwerger et al. 2019, Bi et al. 2020). In September 2015, a 6-months long (May to September 2015) drought over South Carolina turned into flooding within a week. A season with extremely dry condition followed by an extreme wet condition can also create a favorable environment for discharging emerging contaminants from land surfaces to water courses (Lehman et al. 2020). Consecutive dry and wet extremes occur across the globe (He and Sheffield 2020) and are expected to become more frequent in the future (Collet et al. 2018, Chen et al. 2020). Therefore, accounting for consecutive occurrences of dry and wet extremes is crucial to ensure that infrastructure (e.g., dams, dikes, levees, and reservoirs) and socio-environmental systems are resilient to the unforeseen impacts from such events.

Despite their devastating impacts and possible modulations of hydrologic risks, the characteristics of consecutive events of dry and wet extremes and their teleconnections to the large-scale climatic drivers are not adequately explored. Most importantly, to the best of our knowledge, impacts of such consecutive events on hydrologic risk assessments have not been explicitly assessed. Few studies have addressed the issue, but they generally concentrate on dry and wet extremes at shorter time scales (e.g., 1 to 3-months) (Li et al. 2017, Chen et al. 2020, He and Sheffield 2020) which are generally related to crop failure and short-term agriculture planning. Hence, these studies overlook the time scales relevant (e.g., >6 months) for water resources management (e.g., reservoir operation rules) and infrastructure failure (e.g., dam and levees) (Sheffield and Wood 2007, Van Dijk et al. 2013). Moreover, these studies are mostly regional and global analyses are rare. He and Sheffield (2020) performed a global analysis to characterize the lag compound occurrence of droughts and pluvial flooding events using Standardized Precipitation Index (SPI) and soil moisture percentiles simulated by the Variable Infiltration Capacity (VIC) model. However, this study considered soil moisture and SPI at 1-month time scale and did not quantify hydrologic risks.

Large-scale climatic teleconnections of dry and wet anomalies were investigated in numerous studies, revealing that they are often linked to large-scale atmospheric circulation patterns; among those El Niño–Southern Oscillation (ENSO) is the most prominent and widespread (e.g., Kingston et al. 2015, Sun et al. 2016, Rashid and Beecham 2019a, Hassan and Nayak 2020a). Combined impacts of ENSO and Pacific Decadal Oscillation (PDO) were also reported (Nguyen et al. 2021). Most of these teleconnection studies investigated the links considering the entire time series of drought indices and climate drivers (e.g., Niño3.4 and PDO). Unlike this, an event-based analysis is required for assessing the connections between consecutive dry and wet extreme events and climate indices. This advances the understanding of how the variability and shifting of dry to wet anomalies within consecutive events are linked to the variability of climate indices. While few regional studies concluded that consecutive occurrences of dry and wet extremes may be related to the shifting of ENSO phases (i.e., El Niño to La Niña or vice versa, depending on the geographical location) (Marengo and Espinoza 2016, Shan et al. 2018), a global analysis is still missing.

Here, we characterize consecutive dry and wet extreme (CDW) events at global scale and explore how they are connected to large-scale climatic variability (i.e., ENSO). We quantify multi-hazard hydrologic risk by estimating the joint exceedance probabilities of dry and wet extreme severities when CDW events and their associated dependence are considered, and we compare our results to those from traditional hydrologic risk assessments where dry and wet extremes are considered independent.
2. Data and methods

2.1. Dry and wet extremes

To define the CDW events, different indices are derived from streamflow, precipitation, or soil moisture data (Li et al. 2017, Chen et al. 2020). Besides, state-of-the-art drought indices (e.g., SPI and Standardized Precipitation Evapotranspiration Index, SPEI) are used for defining dry and wet extremes and identifying their consecutive/ laged occurrences (e.g., Du et al. 2013, Nkiaka et al. 2017, He et al. 2020). The main advantage of the standardized indices is that they can be estimated at different time scales to cover the meteorological, agricultural, and hydrological risk perspectives. Among those, SPEI is the most widely used and considered suitable to account for a changing climate. Hence, we use SPEI as the candidate index to quantify univariate dry and wet extremes as well as multivariate CDW events. The Global SPEI database is used which provides global gridded (at 0.5° spatial resolution) SPEI at different time scales and covers the period from 1901 onwards (Begueria et al. 2010, Vicente-Serrano et al. 2010a, 2010b). To calculate SPEI, they used climate data (precipitation and temperature) from Climate Research Unit (CRU) datasets (available online at http://badc.nerc.ac.uk/data/cru/). The SPEI is derived based on the climatic water balance and estimated by fitting a log-logistic probability distribution to the differences between precipitation and potential evapotranspiration (D), followed by transforming the cumulative distribution functions to standard normal distributions. The calculated D values are aggregated at various time scales (e.g., 1, 3, 6, and 12-month) to estimate SPEI, hence covering both short-term and long-term dry and wet conditions. In general, SPEI values less than −1 and greater than +1 are considered as dry and wet conditions, respectively.

Standardized drought indices (i.e., SPI and SPEI) are used for identifying consecutive dry and wet extreme events (i.e., CDW) because they provide information on both dry and wet extremes (Chen et al. 2020, He and Sheffield 2020). The selection of timescales of standardized indices for identifying CDW events depends on the type of risk one is most interested in (e.g., agricultural, hydraulic structures, etc.). In this study, we use SPEI at 6-month timescale. Relatively longer timescales (>=6 months) are often used to capture hydrologic anomalies (e.g., hydrologic changes in streams, rivers, and reservoirs) (Seiler et al. 2002, Peña-Gallardo et al. 2019). Shorter timescales (1 to 3 months) typically represent meteorological anomalies (e.g., changes in soil moisture) and are useful for monitoring crop failure risks. Hence, the timescale of standardized indices should be selected based on the nature of dry and wet extremes and the type of risk one is interested in. We consider the 6-month SPEI for studying CDW events because we are interested in risks to different types of infrastructure (e.g., reservoirs and flood control structures such as dams and levees) resulting from hydrologic anomalies. Earlier studies considered relatively shorter timescales (1 to 3 months) related to the meteorological changes because the main interest was in agricultural risks (Chen et al. 2020, He and Sheffield 2020). One could even consider longer time scales (e.g., 12-month) but this would lead to a small number of CDW events inappropriate for statistical analysis and multi-hazard risk characterization as conducted here.

In this study, we define the dry (wet) extreme events as the periods when SPEI is consistently negative (positive) at least for 6 months and reaches a threshold value of −1 or less (+1 or higher). The dry and wet extremes we identify are representative of droughts and floods. The event duration is the total number of months below/above the threshold (−1 or +1) and the severity is the cumulative sum of SPEI values below/above the threshold. For further analysis, absolute values of severity of dry extremes are used for calculation convenience, but that does not affect the results.

An event is defined as a consecutive dry and wet extreme (CDW) when both occur consecutively and the time between the termination of the dry extreme and onset of the wet extreme is defined as the recovery time (figure 1). Therefore, any consecutive dry and wet extreme is defined as a CDW event; however, if a dry extreme event is followed by a non-extreme wet event, it is not considered as a CDW event. We did not consider recovery time as a constraint parameter to defining the CDW events, rather we consider CDW events as long as dry and wet extremes occur consecutively irrespective of recovery time. This approach allows us to investigate how the recovery time varies for CDW events and across different regions as well as to estimate the trend to explore potential changes, such as a decrease in recovery time. In CDW events, the recovery time is a crucial parameter which refers to the time available for infrastructure and socio-environmental systems to recover from the impacts of the previous extreme (drought) before the next extreme (flood) takes place. The shorter the recovery time the higher the likelihood of cascading impacts leading to higher hydrological risk compared to a longer recovery time. For any event of dry or wet extreme, onset rate is defined as the ratio of the maximum absolute value of SPEI to the time required to reach that value starting from zero. On the other hand, termination rate is the ratio of the maximum absolute value of SPEI to the time required to reach zero after the peak (see also inset in figure 3(d)). The modified version (accounting for autocorrelation and seasonality) of the Mann-Kendall test (Hamed and Rao 1998) is used to identify the monotonic trends of onset and termination rates by estimating the Mann-Kendall test statistic Z. A positive Z value indicates that there is a positive trend whereas a negative value...
corresponds to a negative trend. A significance level of \( p = 0.1 \) is considered to test the significance of the monotonic trends.

### 2.2. Multi-hazard hydrologic risk

We identify CDW events from the SPEI series; each CDW event includes one dry and one wet extreme event. There are also dry and wet extreme events in the SPEI series that are not consecutive, and hence are not part of the CDW event sample. We also identify these individuals (or univariate) dry or wet extreme events (using the thresholds outlined in the previous section). Thus, we develop data for 3 different event types: (1) CDW events, (2) univariate dry extreme events, and (3) univariate wet extreme events, and estimate their severities (as defined in the earlier section). Traditionally, for infrastructure risk analysis and design purposes severities of univariate dry and wet extreme events are considered separately while ignoring their dependence and consecutive occurrences. It is likely that the joint exceedance of certain dry and wet severities will be higher when CDW events and their associated dependence are considered compared to the condition when dry and wet extremes are analyzed as univariate, isolated, and independent events. Therefore, we introduce the metric Multi-Hazard Hydrologic Risk Ratio (MHRR) that represents the ratio of the joint exceedance probabilities of dry and wet extreme severities (i.e., equivalent to univariate severities with certain return periods) between the two above-mentioned conditions (i.e., one considers CDW events, and their dependence and the other is the univariate case that does not consider dependence). Hence, MHRR is analogous to the likelihood amplification factor used in Zscheischler and Seneviratne (2017). It is leveraged here to quantify how joint exceedances of dry and wet extreme severities amplify when CDW events and their dependence are considered, something that has not been addressed at the global scale before.

The MHRR is derived from the univariate and copula-based bivariate joint probability of dry and wet extreme severities. As mentioned earlier, severity is the cumulative sum of SPEI values above the critical threshold. We identify the best distributions for the univariate dry and wet extreme severities. In the univariate case, the exceedance probability (i.e., reciprocal of return period) of a dry or wet extreme with a given severity \( P_{DS} \) or \( P_{WS} \) can be estimated as:

\[
P_{DS} = \frac{1 - F_{DS}}{\mu_D} \quad \text{or} \quad F_{DS} = 1 - P_{DS} \times \mu_D \tag{1}
\]

\[
P_{WS} = \frac{1 - F_{WS}}{\mu_W} \quad \text{or} \quad F_{WS} = 1 - P_{WS} \times \mu_W \tag{2}
\]

Where \( P_{DS} \) and \( P_{WS} \) (\( F_{DS} \) and \( F_{WS} \)) represent the exceedance probabilities (cumulative probabilities) corresponding to different return periods for the dry and wet extreme severities, respectively. For example, the exceedance probability corresponding to a 100-year return period is 0.01 (i.e., 1% chance to be exceeded in any given year). Therefore, the joint exceedance probability of dry and wet extreme severities (equivalent to 100-year return periods) when they are considered as univariate and isolated events with no dependence is \((0.01 \times 0.01) = 0.0001\), with an interarrival time equal to 1. In equations (1) and (2), \( \mu_D \) and \( \mu_w \) are the interarrival times of the observed univariate dry and wet extreme events, respectively. We considered \( \mu_D \) and \( \mu_w \) in the analysis to factorize the occurrence probability because the total numbers of dry or wet extreme events at the grid locations are different from the total number of years (106 years from 1910 to 2015) of available data. For a given exceedance probability (e.g., \( P_{DS} = P_{WS} = 0.01 \)), the corresponding marginal cumulative probabilities of dry
and wet extremes (i.e., $F_{DS}$ and $F_{WS}$) are estimated using equations (1) and (2). Then the joint exceedance probability considering dependence can be estimated using the concept of copulas (Sklar 1959, Nelsen 2007) as:

$$P_{DS} * P_{WS} = 1 - F_{DS} - F_{WS} + C(F_{DS}, F_{WS})$$

(3)

In the case of statistical independence between dry and wet extreme severities $C(F_{DS}, F_{WS}) = F_{DS}F_{WS}$ which reduces equation (3) to:

$$P_{DS} * P_{WS} = (1 - F_{DS})(1 - F_{WS})$$

(4)

For the CDW case, we first identify the best marginal distributions for the dry and wet extreme severities and then re-calculate the critical severity thresholds of the univariate case (i.e., $F_{DS}$ and $F_{WS}$) corresponding to any return period (e.g., 100-year) by mapping to the identified marginals of CDW events are $F_{DS}^*$ and $F_{WS}^*$ respectively. The joint exceedance probability of critical severity thresholds of univariate dry and wet extremes when CDW events are considered with dependence between dry and wet extremes can be estimated as:

$$P_{DS,WS} = \frac{1 - F_{DS}^* - F_{WS}^* + C(F_{DS}^*, F_{WS}^*)}{\mu_{DW}}$$

(5)

Where $C(F_{DS}^*, F_{WS}^*)$ is the copula that represents the dependence between dry and wet extreme severities. $\mu_{DW}$ is the average interarrival time of the observed CDW events. Finally, MHRR can be defined as:

$$MHRR_{DS,WS} = \frac{P_{DS,WS}}{P_{DS} * P_{WS}}$$

(6)

We identify the best marginal distributions in terms of Kolmogorov—Smirnov (KS) and the Akaike Information Criterion (AIC) from a selected number of univariate distributions: beta, normal, gamma, logistic, lognormal, Weibull, exponential, extreme value, generalized extreme value and generalized pareto. For the bivariate joint exceedance probability, we consider Gaussian, t, Clayton, Gumbel, and Frank copulas (Rashid and Beecham 2019a, 2019b, Fahimird and Shakharami 2021). The best copulas are selected based on the root mean square error (RMSE) and AIC employing the maximum likelihood approach.

We quantify MHRR at each grid point (locations with $\geqslant 20$ CDW events) with the best combination of models (i.e., marginal distributions and copulas) and estimate the uncertainty in MHRR adopting the method discussed in Fan et al (2020). The method is based on a bootstrap-based algorithm where observations of marginal variables (dry and wet extreme severities in our case) are resampled with replacement before the best copulas and corresponding copula parameters are quantified to estimate MHRR. This is repeated 1,000 times. In contrast to Fan et al (2020), we allow the method to integrate uncertainty form both dependence structure (represented by different copulas) and strength (represented by copula parameters). Thus, 1,000 MHRR values are estimated from 1,000 bootstrap samples at each grid location and the 5%—95% range of MHRR values is considered as the uncertainty at the corresponding grid location.

### 2.3. Correlation and granger causality test

For assessing the relationships between CDW events and sea surface temperature (SST) anomalies over the Niño3.4 region ($5^\circ$N$–5^\circ$S, $120^\circ$W–$170^\circ$W), we use the monthly time series of Niño3.4 index, downloaded from the Global Climate Observation System (GCOS) Working Group on Surface Pressure (WG-SP) (http://www.esrl.noaa.gov/psd/gcos wgsp/Timeseries). We filter Niño3.4 employing a 5-months moving average to reflect the El Niño Southern Oscillation (ENSO). To examine the teleconnections of Niño3.4 to the CDW events, we apply correlation and the Granger causality (GC) test between the SPEI values of CDW events and corresponding Niño3.4 at the grid locations where at least 20 CDW events are identified over the analysis period (1901 to 2015). The GC test has been used successfully to study teleconnections (Jiang et al 2015, Sun et al 2016, McGraw and Barnes 2018), while inferring causation in large-scale dynamical systems from time series remains challenging (Runge et al 2019). CDW events with at least 25 SPEI values are considered because a sample size of 25 is often recommended for correlation and GC tests (Jenkins and Quintana-Ascencio 2020). As per the Granger notion of causality, Niño3.4 is causal for CDW events if past information of Niño3.4 is useful for predicting the future state of SPEI in addition to the knowledge of the past history of SPEI. Thus, if the predictions of SPEI are improved by adding Niño3.4 as predictor, then Niño3.4 is considered as Granger causal for the CDW events. Unlike earlier studies (e.g., Sun et al 2016), which considered full SPEI time series for correlation and causality tests, we examine only CDW events using the corresponding SPEI and Niño3.4 values, and identify CDW events that are significantly correlated and/or causally linked to Niño3.4. To obtain the optimum lags in the GC test, we set the maximum lag length to 6 months, and a significance level of $p = 0.1$ is used.
3. Results

We identify CDW events using the 6-month SPEI time series at each grid location across the globe. Figure 2 shows various statistical attributes of the identified CDW events at each grid location such as frequency of CDW events (figure 2(a)), mean duration of dry and wet extremes of the CDW events (averaged over all identified CDW events from 1901 to 2015) (figures 2(b) and (c)), monotonic trends in the recovery time (figure 2(d)), and severity of dry and wet extremes of the CDW events (figures 2(e) and (f)). Results show that the total number of CDW events identified over the century long observations vary significantly across the globe, but prominent clusters of high CDW event frequency (\(\geq 20\)) are spread across North America, Europe, and Australia (termed as hotspot regions hereafter). In the other continents such as South America, Africa, and Asia, fewer grid locations exhibit \(\geq 20\) of CDW events and those are not clustered tightly. The average duration of dry extremes of the CDW events are longer than 10 months a.e. across the globe (including the hotspots and other regions) whereas longer duration (>10 months) wet extremes are found only across the CDW hotspot regions. This reveals that the CDW events across the hotspot regions are often composed of longer duration dry and wet extremes compared to the other regions. In the subsequent analysis, we consider the grid locations across the hotspot regions where the total number of CDW events is higher than 20.

We observed significant negative trends in the recovery time in many grid locations across the hotspot regions (figure 2(d)). Over the century long period the recovery time of the CDW events (i.e., time between consecutive occurrence of dry and wet extremes) is decreasing indicating that the dry and wet extremes are occurring in closer succession. This in turn can lead to infrastructure and socio-environmental systems not having enough time to recover from the impacts of the earlier extreme (i.e., drought) before the next extreme (i.e., flood) (as occurred in Oroville in California, USA in 2017). If these trends continue, the cascading effects of dry and wet extremes would become more devastating in the future. Monotonic increasing trends (figures 2(e) and (f)) are also identified in the dry or wet extreme severities of the CDW events at many grid locations across the hotspot regions.
Onset and termination rates of the dry and wet extremes (defined here as outlined in the inset of figure 3(a)) are useful statistics to understand how they affect the CDW events. Figure 3 represents the differences of mean (averaged over identified CDW events at grid points with \( \geq 20 \) CDW events) onset and termination rates of dry and wet extremes: differences in the onset rates of dry and wet extremes (a), differences in the termination rates of dry and wet extremes (b), and differences in the termination rate of dry extremes and onset rate of wet extremes (c). The stippling represents the grid locations where values are significant (at 10% significance level as per t-test). For clarity, plots of only stipple are shown in figure S5.

Figure 3. Definition of onset and termination rates (inset of (a)); slopes of the dashed lines represent the onset or termination rates of the dry or wet extremes. (a)–(c) Differences of mean (averaged over identified CDW events at grid points with \( \geq 20 \) CDW events) onset and termination rates of dry and wet extremes: differences in the onset rates of dry and wet extremes (a), differences in the termination rates of dry and wet extremes (b), and differences in the termination rate of dry extremes and onset rate of wet extremes (c).

Onset and termination rates of the dry and wet extremes (defined here as outlined in the inset of figure 3(a)) are useful statistics to understand how they affect the CDW events. Figure 3 represents the differences of mean (averaged over identified CDW events) onset and termination rates of the dry and wet extremes (figures 3(a) and (b)) as well as the differences of the mean termination rates of the dry extremes and the onset rates of the wet extremes (figure 3(c)) of the CDW events. At around 60% of the grid locations, the differences in the onset rates are negative indicating that the onset of the wet extremes is relatively quicker than that of the dry extremes. On the other hand, termination of dry extremes is quicker than that of the wet extremes at around 57% of the grid.
locations (positive values in figure 3(b)). While we generally expect slower onset and termination of dry extremes compared to the quicker onset and termination of wet extremes, we also find the opposite at many grid locations (grid points with positive values in figure 3(a) and negative values in figure 3(b)). Results also show that at around 46% of the grid locations dry extremes are terminated relatively quicker than the onset of wet extremes (negative values in figure 3(c)) indicating sudden shifts from longer duration dry extremes to wet extremes in the CDW events, as opposed to the typically expected slower termination of dry extremes and quicker onset of wet extremes.

We identify the most suitable copula at each grid location, capable of capturing the dependence between dry and wet extremes of the CDW events. While no distinct spatial pattern is identified for the best-fitted copulas, the Gaussian and Frank copulas are most often selected, for 29% and 39% of the grid locations, respectively (figure S2). Clayton, Gumbel, and t Copulas are identified at 19%, 13%, and 5% of the grid locations, respectively. Figures S3 and S4 represent the probability density contours and isolines of bivariate joint return levels for selected grid locations across different continents, indicating how they vary depending on geographical location and the selected copula.

The MHRR for the dry and wet extreme severities equivalent to the univariate 50- and 100-year return periods are presented in figure 4. Results show that the joint exceedance probabilities of dry and wet extremes increase by several folds almost at all selected grid locations when CDW events and dependence between dry and wet extremes are considered, compared to the scenario when univariate dry and wet extremes are treated as independent and isolated events. However, there are few locations where joint probabilities obtained from the copula models (i.e., $P_{DS,WS}$ in equation (6)) are lower than the joint probabilities of univariate dry and wet extreme severities estimated without considering dependence (i.e., $P_{DS} P_{WS}$ in equation (6)); in those instances, MHRR values are less than or equal to 1. This suggests that either no or even negative dependence between dry and wet extreme severities (of CDW events) exists. MHRR values are generally higher in the case of severities
Clusters of exceptionally high MHRR values (up to 20 and 54 for 50-year and 100-year return periods, respectively), though smaller in size, are observed across the Gulf of Mexico (particularly Texas) and southeastern Australia, particularly when focusing on the 100-year return period.

We simulate 1,000 MHRR values employing multivariate copula models (see Methods) from resampled observed dry and wet extreme severities (i.e., marginal variables) allowing us to quantify the uncertainty originating from the dependence structure and strength. The uncertainties in MHRR (5%–95% range of simulated MHRR values) are shown in figure 5 (5% and 95% values of MHRR simulations are presented in figures S6 and S7 in the supporting document). Uncertainties in MHRR corresponding to univariate 100-year return periods are higher compared to those of the 50-year return periods. The spatial pattern of MHRR uncertainties is coherent to that of the MHRR values (figure 4), indicating that higher MHRR are associated with larger uncertainties.

Teleconnections between CDW and Niño3.4 in terms of correlation coefficient and GC test at global scale are represented in figure 6. CDW events are significantly correlated to the Niño3.4 across the global hotspots (figure 6(a)) especially North America and southern and western Australia. Teleconnections are also evident in the GC test results (figure 6(b)). The GC test indicates that a comparatively higher percentage of observed CDW events are causally linked to the Niño3.4 than found statistically significant in the correlation analysis. According to the correlation analysis, 60% of CDW events are significantly correlated to Niño3.4 at 50% of the grid locations (figure 5(c)), whereas the GC test indicates that at least 82% of CDW events are causally linked to Niño3.4 at 50% of the grid locations (figure 5(d)). The differences between correlation analysis and GC test results stem from the fact that the GC test considers the lag information of Niño3.4, whereas the correlation coefficient is estimated considering the concurrent Niño3.4 values. Hence, the GC test results also reveal the potential of using lagged information of Niño3.4 to forecast CDW events.

Figure 5. Uncertainty in MHRR (5% - 95% ranges) for dry and wet extreme severities equivalent to univariate 50-year (a) and 100-year (b) return periods.
locations across the hotspot regions are evident in different regions analysis and GC test. Earlier studies conclude that the teleconnections between ENSO and dry We investigate the teleconnections between large-scale climate variability and CDW events using correlation analysis and GC test. Earlier studies conclude that the teleconnections between ENSO and dry

4. Discussion

We investigate the teleconnections between large-scale climate variability and CDW events using correlation analysis and GC test. Earlier studies conclude that the teleconnections between ENSO and dry/wet conditions are evident in different regions (Sun et al. 2016) and ENSO can even trigger dry/wet conditions concurrently across multiple regions (Hassan and Nayak 2020b). This study found significant co-variability between Niño3.4 and SPEI for the CDW events which provides further evidence of the important role of ENSO when assessing CDW events. Other regional studies also concluded that the relationship between ENSO and dry/wet conditions is significant, even during the shift from dry to wet conditions (Shan et al. 2018, Shi et al. 2020). Large-scale sea surface temperature (SST) anomalies influence the intensity of convection which causes changes in the large-scale atmospheric circulations and leads to changes between dry and wet episodes. Intensification of this process due to an increase of ENSO SST variability and frequency over time (Cai et al. 2014) can lead to more frequent termination of extreme dry conditions with extreme wet conditions; such changes are projected to continue in the future (Cai et al. 2022).

An intuitive argument is that the shift from dry to wet extremes might be related to the shift in ENSO phases from cold to warm (or warm to cold, depending on the hemisphere and geographic location). To investigate this further, we identify and quantify the frequency of ENSO shifts (i.e., consecutive events of cold and warm phases or warm and cold phases) and compare those to the frequency of CDW events at each grid location across the globe, including hotspot and non-hotspot regions. The cold (La Niña) and warm (El Niño) phases are defined as the events when 5-month running means of Niño3.4 SSTs exceed −0.4 °C and +0.4 °C for a period of at least six months, respectively (Trenberth 1997). The ratios of frequencies of CDW events and ENSO shifts reveal that the frequencies of CDW events are nearly equivalent to the frequencies of ENSO shifts at the majority of grid locations across the hotspot regions (North America, Europe, and Australia) (figure 7). The relative differences between the frequencies of the CDW events and ENSO shifts are less than 20% at around 85% of the grid locations across the hotspot regions. The ratios are notably lower across the non-hotspot regions, indicating that the CDW events are less frequent than ENSO shifts. Overall, higher frequencies of CDW are identified across the ENSO dominated regions and nearly equivalent to the frequency of ENSO shifts.

The influence of other prominent global atmospheric oscillation patterns may be investigated in a similar way to further improve understanding of the regional variations; for example, the North Atlantic Oscillation (NAO) is linked to the dry/wet conditions across Europe and Russia (e.g., Kingston et al. 2015). Besides, CDW events may be linked to the regional changes of synoptic atmospheric conditions. Earlier studies identified significant correlation between dry/wet conditions and atmospheric variables (e.g., relative humidity, geopotential height, zonal and meridional wind) at various pressure levels (e.g., Rashid et al. 2018). Land-atmospheric feedbacks might be one of the underlying physical processes intensifying the shift from dry extremes to wet extremes because of the continuing increase in temperature causing higher rates of evapotranspiration leading to quicker termination of dry episodes with intense storm events. Furthermore, land-ocean interactions resulting in onshore advection of moist air masses due to relatively higher temperature

Figure 6. Teleconnections of CDW events to sea surface temperature (i.e., Niño3.4). Percentage of CDW events significantly (at 90% significance level) correlated to the Niño3.4 (a) and causally linked to Niño3.4 (b) at grid locations with > 20 CDW events. Empirical probability distribution functions of percent of CDW events significantly correlated to Niño3.4 (c) and causally linked to Niño3.4 (d).
over land areas compared to the ocean can lead to termination of extreme droughts with extreme storms (Kam et al 2014).

5. Conclusion

Dry and wet extremes are often considered separately in hydrologic risk assessments. However, a wet extreme event can occur shortly after a dry extreme event to exacerbate the impacts on infrastructure, society, and the environment. In this study, we perform a comprehensive analysis to characterize CDW events at the global scale, assess the importance of considering CDW events in hydrologic risk assessments, and identify their relationships with large-scale climate variability. We considered relatively longer and intense dry and wet extremes, which are relevant to water resources infrastructure failure and relatively larger scale socio-environmental damage, while shorter and less intense dry and wet extremes are often related to crop failures (short-term agricultural planning). However, the approach used in the study can be employed for identifying CDW events comprised of shorter and less intense dry and wet extremes by considering SPEI at shorter time scales and redefining the CDW events.

Hotspots of CDW events are identified in North America, Europe, and Australia where total numbers of CDW events range from 20 to 30 over the period 1901 to 2015. CDW events across these hotspot regions are also often comprised of longer dry and wet extremes (10 to 20 months). Decreasing trends in the recovery time and increasing trends in the dry and wet extreme severities indicate an intensification of CDW events over time, which could be related to the increase in ENSO variability and frequency over time; these changes are expected to continue into the future due to a warming climate. This highlights the importance to account for such events for planning infrastructure and socio-environmental systems. Our analysis confirms that the multi-hazard hydrologic risks of dry and wet extreme severities are significantly higher than their univariate counterparts. The joint exceedance probabilities of dry and wet extreme severities increase by several folds (up to 20 and 54 for 50-year and 100-year return periods, respectively) when CDW events and their associated dependence are considered. Correlation analysis and the GC test also show that the variability and seesaw of dry and wet extremes of the CDW events are linked to ENSO.

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Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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