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Investigating Dependence Between Wet And Dry Event Characteristics: Case Study Of Geul River Basin

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Abstract

Consecutive hydrological extremes, i.e., wet and dry extreme events are a common occurrence around the world and are expected to become more frequent in the future due to a changing climate. This raises the question of whether the two events should be jointly accounted for to guarantee water availability and water safety. As a first step, we analyze hydrological extremes from a climate perspective in the case study region of the Geul River basin in the Netherlands. We define the wet and dry extreme events based on precipitation and temperature and analyze the dependence between their climate characteristics. Our results show a tendency for compound warm-wet events and warm-dry in the Geul River basin, which could increase the potential impacts of the corresponding wet and dry hydrological extremes in the region. Moreover, we see the opposite events occurring in a water year to be either water-rich or water-deficient showing that a year consistently has more or less water throughout, information which could be helpful for water resource allocation.

Keywords: Hydrological extremes, compound events, warm-wet, warm-dry, copulas

1. Introduction

Hydrological extremes, particularly wet extremes (floods) and dry extremes (droughts) cause devastating loss of life and socio-economic impacts around the world (Rashid and Wahl, 2022). Consecutive hydrological extremes are a common occurrence (He and Sheffield, 2020). Examples include flooding in the wake of the 1997-2009 Millennium Drought in Australia, heavy rainfall after the 2012-2017 California drought, and flooding following the dry years of 2018-2020 in the Meuse basin in Europe. Additionally, such occurrences are expected to become more frequent in the future (Chen et al., 2020; Collet et al., 2018). Therefore, accounting for both wet and dry extremes in risk assessment can help increase resilience to both hydrological extremes (Rashid and Wahl, 2022).

The estimation of the combined risk of multiple extremes depends on the identification of hazard characteristics and their interactions (Gill and Malamud, 2014). This in-turn is sensitive to the definition adopted for the hazard itself and the hydroclimatic variables considered drivers of the event (Beevers et al., 2022; De Michele et al., 2020). The (meteorological) drivers influencing wet/dry extremes are interconnected which can alter the impact of such events on the environment (Hao et al., 2018; Zscheischler and Seneviratne, 2017). For example, persistent lack of precipitation and extreme temperature over Central Europe in 2018 caused widespread damage to forest and agricultural areas (Suarez-Gutierrez et al., 2023).

The main objective of this study is to investigate the dependence between wet/dry events characteristics and characteristics of opposite events via probabilistic dependence models, i.e., copula functions. Through this assessment, we can gain a better insight into the frequency of dry/wet events and the need to jointly consider opposite hydroclimatic extremes when assessing water availability and safety.

2. Region of interest

The Netherlands has faced an increasing number of drought events in recent years (between 2018 and 2022), which has brought attention to drought management along with traditional flood management. Within the Netherlands, the Geul River basin is a rain-fed basin with one of the few steeply inclined rivers in the Netherlands (Tsiokanos et al., 2023). This makes the Geul River basin a suitable case study for exploring meteorological wet and dry events. The Geul River basin is situated in the southernmost part of the Netherlands, intersecting its border with Belgium and Germany (see Fig. 1). The Geul river originates in eastern Belgium and convergences with the transboundary Meuse River north of the city of Maastricht. The river is 56 km long and the catchment has an area of about 343 km^2 (Tsiokanos et al., 2023). The landscape of the Geul River basin is made up of flat plateaus and deeply incised, asymmetrical river valleys with altitudes varying from 50 m to 400 m AMSL (de Moor, 2007). The basin experienced a mean daily temperature of 9.9 °C between 1950 and 2022. The annual average precipitation received during this period was 886.1 mm/year, which was uniformly distributed over the year (Tsiokanos et al., 2023).

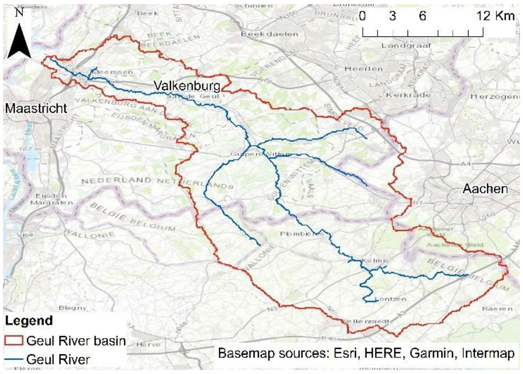

Fig. 1. Map of the region of interest showing the Geul River basin in Southern Netherlands.

3. Methods

In this section, we first discuss the methodology used to define extreme wet and dry events in the region (Section 3.1) and then analyze the relationship between their event characteristics. The analysis of the correlation between event characteristics is described in Section 3.2. The pairs that show a statistically significant correlation are modelled via copula functions. First, theoretical univariate distributions of selected event characteristics are selected based on Goodness of Fit (GoF) tests as discussed in Section 3.3. Then, the concept of copulas is introduced and the GoF tests used to select the best theoretical copula is presented in Section 3.4. Finally, conditional probability distributions are introduced in Section 3.5 to evaluate the effect of one characteristic on the other.

3.1. Data collection and Event definition

In this paper, we are interested in wet and dry events. We define them based on two climate variables: temperature and precipitation. For this purpose, we used climate data from the E-OBS daily observational dataset (https://surfobs.climate.copernicus.eu/, Cornes et al., 2018) available for Europe at 0.1-degree grid resolution. We adopted version 26.0e of the dataset available for the water years 1950 to 2022 (October 1950 to September 2022) for the Geul river basin. We obtained the daily time series of precipitation (P) and temperature (T) over this region by calculating the weighted average of these variables each day using the relative area of the E-OBS grids within the Geul catchment as weights.

To define the wet and dry meteorological events, we implemented precipitation-based thresholds to classify each day as wet or dry. With this method, wet/dry events are consecutive days with more/less precipitation than the corresponding wet/dry threshold level (see Fig. 2). The threshold levels for defining these events were derived from the widely used climate indices developed by the Expert Team on Climate Change Detection and Indices, ETCCDI (https://www.ecad.eu/indicesextremes/index.php). Specifically, the ETCCDI indices categorize days with more than 10 mm of rain as 'heavy precipitation' days and days with less than 1 mm of rain as 'dry' days. Hence, we adopted 10 mm/day as the wet event threshold and 1 mm/day as the dry event threshold in this study (see Fig. 2).

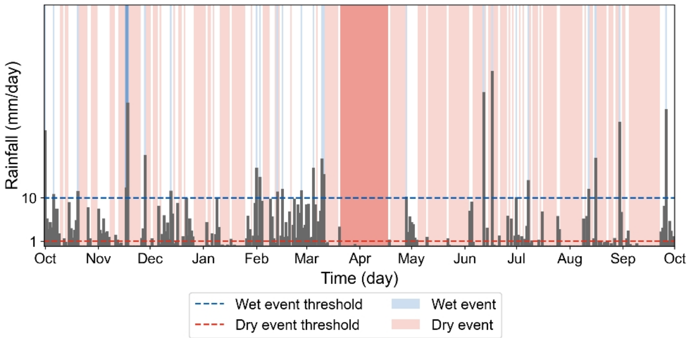

Fig. 2. Illustration of the definition of wet and dry events.
The darker wet and dry event are selected as the extreme wet/dry event of the water year.

Table 1. Wet and dry event characteristics defined in this study along with the notation adopted for each characteristic.

Characteristic	Wet events	Dry events
Duration	Consecutive days above threshold (D_w)	Consecutive days below threshold (D_d)
Magnitude	Total accumulated precipitation ($P_{t,w}$)	Maximum daily temperature ($T_{x,d}$)
Precipitation	Average daily precipitation ($P_{g,w}$)	-
Temperature	Average daily temperature ($T_{g,w}$)	Average daily temperature ($T_{g,d}$)

For each wet/dry event, we obtained the event duration, magnitude, and average precipitation and temperature during the event as event characteristics as summarized in Table 1. Since dry events have, by definition, negligible rain (less than 1 mm/day), average daily precipitation was not calculated for dry events. Instead, the duration of dry events is used to represent precipitation or its lack thereof during the event.

For each water year, we selected only the 'extreme' wet and dry event based on their events characteristics to obtain the same number of opposite events as well as events with comparable severity. To obtain the yearly extreme events, the wet event with the highest accumulated precipitation ($P_{t,w}$) was selected as the extreme wet event of the year and the dry event with the longest duration(D_d) was selected as the extreme dry event of that year (see Fig. 2). The database of yearly extreme wet and dry events thereby obtained was used for the remainder of the study.

3.2. Correlation analysis

The correlation amongst the different wet and dry event characteristics was explored as the starting point to the dependence analysis. To do this, the Kendall rank correlation coefficient (τ) was calculated which assesses the ordinal association between two variables (Kendall, 1938). The value of $\tau \in [-1, 1]$ where $\tau = 1$ represents concordance (observations have similar rank) and $\tau = -1$ represents discordance (observations have dissimilar rank) between the variables. The Kendall's τ correlation is given by

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_i - x_j)\, sgn(y_i - y_j) \quad (1)$$

where $(x_1, y_1), \dots, (x_n, y_n)$ are sets of observations of the variables X and Y and n is the total number of observations for each variable. The correlations were calculated using the Kendall's τ function of the *SciPy Statistics* package on Python.

For wet/dry events, the correlation was calculated for all pairs of wet/dry event characteristics (refer Table 1). In addition, the p-value of Kendall's τ was calculated to determine the significance of the observed correlations. A significance level of 5% was used to determine whether the observed correlation is statistically significant. For analyzing the relationship between the characteristics of opposite extremes, the correlation between all pairs of wet and dry event characteristics was measured via the Kendall's τ correlation coefficient and its statistical significance was checked. In all three cases (wet/dry events and between opposite events), the pairs of event characteristics that show a statistically significant correlation were then selected for further analysis using copulas.

3.3. Univariate distribution

Each wet/dry event characteristic that was selected for further analysis (Section 3.2), was modelled via a theoretical univariate distribution, which is then used in the copula approach. This is because, when dealing with extremes (here, wet, and dry extreme events), extrapolation is often required to analyze events beyond the range of observations. We fit a selected list of common distribution functions to each event characteristic, namely, generalized extreme value, exponential, generalized pareto, normal, gamma, beta, logistic and lognormal distributions (Rashid and Wahl, 2022; Shi et al., 2020). All distributions were fitted using the corresponding functions available on the ***SciPy Statistics*** package of Python. The distribution with the better GoF was then chosen as the best fit distribution for the event characteristic. Kolmogorov-Smirnov (KS) test and root mean square error (RMSE) were used for testing the goodness of fit of the distributions (Rashid and Wahl, 2022; Shi et al., 2020).

The KS test checks the equality of the probability distribution of the observations with the theoretical distribution to test the null hypothesis that the observation is a sample drawn from the theoretical distribution (Massey, 1951). The test was performed using the KS test function of the ***SciPy Statistics*** package on Python. To select best fit distribution, we first performed the KS test at a 5% significance level and distributions that passed the test were then compared based on their RMSE value to select the distribution with the best GoF. RMSE measures the difference between the observed (x_i) and the theoretical ($\hat{x}_i$) probability density function for n samples with

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{x}_i - x_i)^2}{n}} \tag{2}$$

where a lower RMSE value indicates better fit (Hodson, 2022).

3.4. Joint distribution

We fit bivariate copulas to model the dependence between the selected event characteristics pairs as represented by their theoretical marginals (Section 3.3). Following the Sklar Theorem (Sklar. M, 1959), the joint probability distribution $F_{XY}(X,Y)$ of two random variables X and Y can be expressed via a copula function (C) defined in $[0,1]\ x\ [0,1]$ domain as

$$F_{XY}(X,Y) = C\big(F_X(X), F_Y(Y)\big) \tag{3}$$

where $F_X(X)$ and $F_Y(Y)$ are the continuous cumulative distribution function of X and Y respectively. This allows us to model the dependence structure separately from the marginal distributions. (Shi et al., 2020). We considered the Gaussian, Frank, Gumbel, Clayton, Joe, and Student's t copulas here, which are commonly used to determine joint distributions of hydrometeorological variables (Ragno et al., 2022; Rashid and Wahl, 2022; Shi et al., 2020; Zscheischler and Seneviratne, 2017). The copulas were fitted using the ***pyvinecopulib*** package version 0.6.1 on Python (https://vinecopulib.github.io/pyvinecopulib/).

The best fit copula was selected based on two GoF measures, namely, the Akaike Information Criteria (AIC) and the Cramér–von Mises (CvM) test (Ragno et al., 2022; Rashid & Wahl, 2022; Zscheischler & Seneviratne, 2017). The AIC is a relative measure used to select the best model among a number of competing models by penalizing models for their complexity (number of parameters) (Akaike, 1985). The best model is the one with the lowest AIC value. The AIC was also evaluated with the ***pyvinecopulib*** package version 0.6.1 on Python.

CvM statistic (S) evaluates how close a theoretical model is to an empirical model (Genest and Favre, 2007) by

$$S = n\sum_{i=1}^{n}\left\{C_n\left(\frac{R_{1,i}}{n+1}, \frac{R_{2,i}}{n+1}\right) - C_\theta\left(\frac{R_{1,i}}{n+1}, \frac{R_{2,i}}{n+1}\right)\right\}^2 \tag{4}$$

where C_n is the empirical copula, C_θ is theoretical copula, and $R_{1,i}$ and $R_{2,i}$ are the ith ranks of the n observations for the two modelled variables X and Y. The lower the value of the CvM statistic the better the fit of the copula. The copula function with the better goodness of fit according to these two tests was chosen as the best fit distribution for the pairs of event characteristics.

3.5. Conditional probabilities

The dependence between event characteristics modelled by the best fit joint distributions (see Section 3.4) can be used to calculate the conditional probability of exceedance of one variable exceeding a threshold when the value of the other variable is fixed as

$$P[Y > y \mid X = x] = 1 - \frac{\partial C(F_X(x), F_Y(y))}{\partial F_X(x)} \tag{5}$$

$$P[X > x \mid Y = y] = 1 - \frac{\partial C(F_X(x), F_Y(y))}{\partial F_Y(y)} \tag{6}$$

The derivatives of the copula function $\frac{\partial C(F_X(x), F_Y(y))}{\partial F_X(x)}$ and $\frac{\partial C(F_X(x), F_Y(y))}{\partial F_Y(y)}$ were calculated with the *pyvinecopulib* package version 0.6.1 on Python.

4. Results

4.1. Wet event characteristics

The analysis of the Kendall's τ correlations between pairs of wet event characteristics (Table 2) shows a statistically significant correlation of 0.24 between the average precipitation intensity ($P_{g,w}$) and temperature ($T_{g,w}$) experienced during extreme wet events. This shows a tendency for heavy precipitation events to be associated with high temperatures, i.e., compound warm-wet events. We also see a statistically significant negative correlation of -0.19 between the length of wet events (D_w) and the average temperature experience during that period ($T_{g,w}$) which could be a consequence of evaporative cooling caused by persistent precipitation events (You et al., 2023).

We further model the dependence between $P_{g,w}$ and $T_{g,w}$ experienced during the extreme wet events (see scatter plot in Fig. 3 (a)) using bivariate copulas. However, we do not model the dependence between D_w and $T_{g,w}$ further because the duration of wet events cannot be considered a continuous variable since it ranges between 1-4 days only. The best fit distributions for the wet event characteristics $P_{g,w}$ and $T_{g,w}$ are the gamma distribution and the beta distributions respectively (see Fig. 3 (a) and Table 3). The best fit copula to the $P_{g,w}$-$T_{g,w}$ event characteristics pair is the Clayton copula (see Table 4, Fig. 3 (b) and (c)) which is suitable for modelling variables with a stronger association at the lower tail, denoting stronger dependence between lower values of $P_{g,w}$ and $T_{g,w}$.

Table 2. Kendall's τ correlations between the different wet event characteristics where * denotes correlation coefficient statistically significant at 5% significance level.

τ	D_w	$P_{t,w}$	$P_{g,w}$	$T_{g,w}$
D_w		0.24*	-0.47*	-0.19*
$P_{t,w}$			0.44*	0.09
$P_{g,w}$				0.24*
$T_{g,w}$				

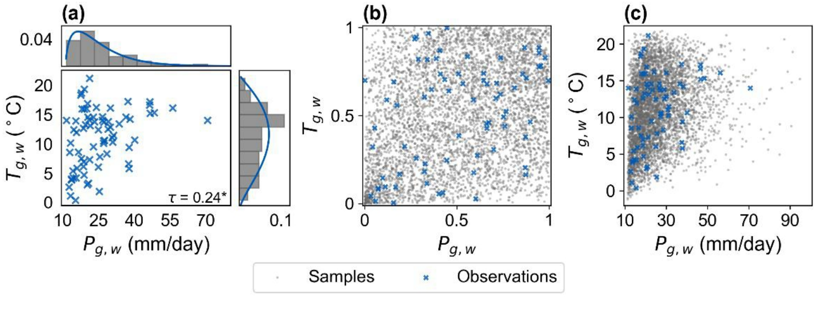

Fig. 3. Analysis of dependence between the wet event characteristics $P_{g,w}$ and $T_{g,w}$. Scatter plot, Kendall's τ correlation (* denotes p-value < 0.05), univariate distributions of the variables and best fit theoretical distributions are shown in (a). 5000 samples from the best fit copula compared to observations in unit space (b) and original space (c).

Table 3. Summary of selected event characteristics, their fitted univariate distributions and the corresponding GoF.

Characteristic	Event type	Distribution	Parameters			KS test	RMSE
			Shape	Location	Scale	p-value	
$P_{t,w}$	Wet event	GEV	-0.27	42.61	10.61	0.111	0.010
$P_{g,w}$		Gamma	1.58	11.32	8.94	0.078	0.021
$T_{g,w}$		Beta	2.52, 2.18	-1.47	23.33	0.968	0.059
D_d	Dry event	Gamma	3.68	7.50	3.20	0.155	0.079
$T_{x,d}$		Beta	2.09, 2.13	1.76	28.10	0.994	0.047

Table 4. Overview of the best fit bivariate copulas, the copula parameters and their corresponding CvM statistic.

Characteristic pair	Event type	Copula	Parameter	CvM Statistic
$P_{g,w} - T_{g,w}$	Wet event	Clayton	0.51	3.59
$D_d - T_{x,d}$	Dry event	Gaussian	0.29	6.23
$P_{t,w} - D_d$	Opposite events	Gaussian	-0.20	3.48

The conditional probability density function (PDF) of precipitation intensity ($P_{g,w}$) of wet events conditioned on the mean temperature ($T_{g,w}$) during the event shows that a change in temperature of 1°C has little effect on precipitation intensity (Fig. 4). For example, the probability for a wet event to have more than 20 mm/day precipitation when the average temperature during the event is 11°C is 65.5% (Table 5). With an increase in $T_{g,w}$ of just 1°C, from 11°C to 12°C, the probability of $P_{g,w}$ > 20mm/day changes only around 2% (Table 5). However, the change in precipitation intensity for a change in temperature (of 1°C) is greater when the temperature is on the lower range of values (Fig. 4, Table 5). For example, a change in $T_{g,w}$ from 20°C to 21°C changes the probability of $P_{g,w}$ > 20mm/day by 0.2% only (from 76%) as opposed to the change of 2% when $T_{g,w}$ changes from 11°C to 12°C. These results suggest that increases in wet event mean temperature of 1°C (due to future climate warming) in the Geul River basin could have relatively little impact on the precipitation intensity of the wet event, especially during warmer seasons.

Table 5. Conditional probability of precipitation intensity ($P_{g,w}$) during wet events exceeding a threshold (p) given the average temperature ($T_{g,w}$) is fixed at a selected value (t).

$P[P_{g,w} > p \mid T_{g,w} = t]$ (%)		$T_{g,w}$ (°C)			
		11	12	20	21
$P_{g,w}$ (mm/day)	20	65.5	67.6	76.0	76.2
	30	28.0	29.6	36.8	37.0
	50	4.1	4.4	5.8	5.8
	60	1.5	1.6	2.1	2.1

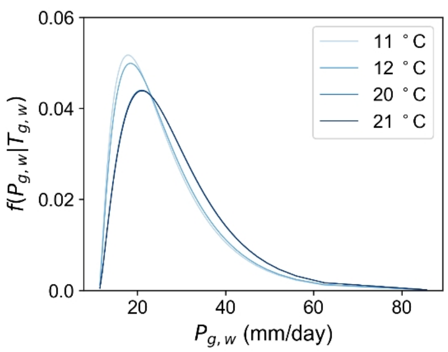

Fig. 4. Conditional probability density functions for $P_{g,w}$ given the values of $T_{g,w}$ is fixed at selected values.

4.2. Dry event characteristics

Analysis of the Kendall's τ correlations between pairs of dry event characteristics (Table 6) shows a statistically significant correlation of 0.20 between the duration of an extreme dry event (D_d) and maximum daily temperature ($T_{x,d}$) experienced during that event. This shows a tendency for persistent rain-free periods to experience high daily temperatures i.e., compound warm-dry events. The best fit distributions for the dry event characteristics D_d and $T_{x,d}$ are the gamma distribution and the beta distribution respectively (see Fig. 5 (a) and Table 3). The best fit copula to the D_d- $T_{x,d}$ event characteristics pair is the Gaussian copula (see Table 4), which is a suitable model for variables which do not have a strong association at the lower or upper tails (i.e., low or high values of D_d and $T_{x,d}$ as visible in Fig. 5 (b)).

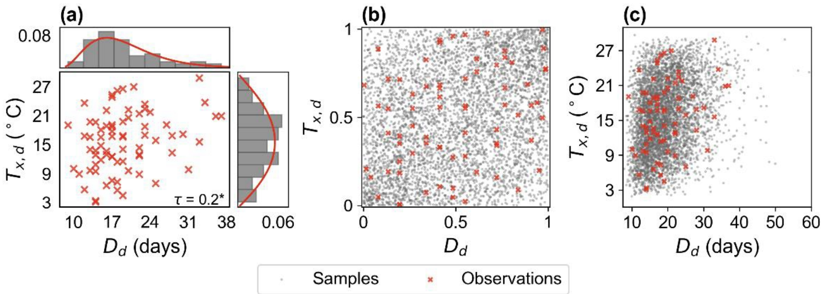

Fig. 5. Analysis of dependence between the dry event characteristics D_d and $T_{x,d}$. Scatter plot, Kendall's τ correlation (* denotes p-value < 0.05), univariate distributions of the variables and best fit theoretical distributions are shown in (a). 5000 samples from the best fit copula compared to observations in unit space (b) and original space (c).

Table 6. Kendall's τ correlations between the different dry event characteristics where * denotes p-value below 5% significance level.

τ	D_d	$T_{x,d}$	$T_{g,d}$
D_d		0.20*	0.10
$T_{x,d}$			0.82*
$T_{g,d}$			

The probability of experiencing dry events (D_d) longer than a chosen threshold does not change much with a change in the maximum temperature ($T_{x,d}$) recorded during the event by 1°C (Fig 6). For example, an increase in $T_{x,d}$ from 28°C to 29°C changes the probability of experiencing dry events longer than a month (D_d > 30 days) from 17.7% to 22.2%, i.e., a change of 4.5% only (Table 7). However, the change in length of the dry events is more sensitive to a 1°C change in the event maximum temperature for its higher range of values (Fig 6, Table 7). For example, an increase in $T_{x,d}$ from 15°C to 16°C changes the probability of D_d > 30 days by 0.5% only (from 4.9%) compared to the 4.5% for a change from 28°C to 29°C. This suggest that the impact of future temperature changes, specifically an increase in the maximum temperature of a dry event by 1°C on the length of the event (rain-free period) could be relatively trivial, especially during colder seasons.

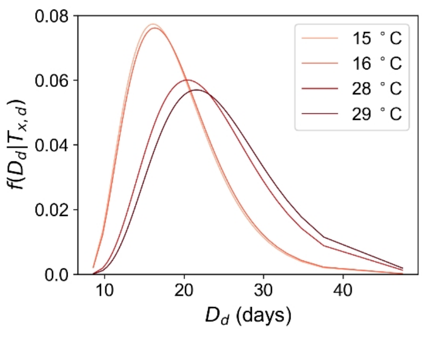

Fig 6. Conditional probability density functions for D_d given the values of $T_{x,d}$ is fixed at selected values.

Table 7. Conditional probability of dry event duration (D_d) exceeding a threshold (d) given the event maximum temperature ($T_{x,d}$) is fixed at a selected value (t).

$P[D_d > d \mid T_{x,d} = t]$ (%)		$T_{x,d}$ (°C)			
		15	16	28	29
D_d (days)	18	50.6	52.2	76.9	81.6
	20	37.1	38.7	65.3	71.1
	30	4.9	5.4	17.7	22.2
	32	3.1	3.4	12.6	16.4

4.3. Opposite extreme characteristics

We investigate the correlation between the characteristics of wet and dry events of each water year as we are interested in exploring the relationship between opposite hydrological extremes and their potential influence on their joint probability of occurrence. We see a statistically significant correlation of -0.18 between the total precipitation recorded during the wet event ($P_{t,w}$) and the duration of the dry event (D_d) of the same water year (Table 8). This negative dependence implies a tendency for wet events with heavy rainfall to occur in the same year as short dry events and for wet events with less rainfall to occur in the same year as long dry events. The best fit distribution for $P_{t,w}$ is the GEV distribution (Table 3) and for D_d is the gamma distribution as discussed previously in Section 0 and the best fit copula to the $P_{t,w}$-D_d pair is the Gaussian copula (Table 4).

The conditional probability of total precipitation received during a wet event ($P_{t,w}$) does not change much when the duration of the dry event (D_d) of the same water year changes by 2 days (Table 9). For example, when D_d increases from 30 days to 32 days, the probability of $P_{t,w}$ > 50mm decreases only by 1.4% (from 28.8%). Also, a decrease of 2.6% (from 41.1%) is observed in the probability of $P_{t,w}$ > 50mm when D_d increases from 18 days to 20 days, showing that the sensitivity of changes in total precipitation of wet events to changes in duration of dry events of the same water year is low for all range of values of D_d. This shows that increase in duration of the extreme dry event of a water year (rain-free periods) by 2 days, a possible scenario in the future for the Geul basin due to climate warming (especially in Summer as per Van Dorland et al., 2023), is only weakly associated with the amount of precipitation received during the extreme wet event of that year.

Table 8. Kendall's τ correlations between the different wet and dry event characteristics where * denotes p-value below 5% significance level. The rows list the wet event characteristics, and the columns list the dry event characteristics.

τ	D_d	$T_{x,d}$	$T_{g,d}$
D_w	-0.06	0.07	0.06
$P_{t,w}$	-0.18*	-0.04	-0.03
$P_{g,w}$	-0.10	-0.08	-0.07
$T_{g,w}$	0.04	-0.05	-0.05

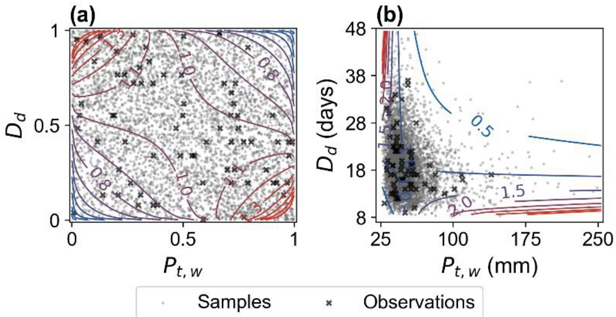

Fig. 7. Analysis of dependence between the opposite event characteristics $P_{t,w}$ and D_d. 5000 samples from the best fit copula compared to observations in unit space (a) and original space (b). Isolines of the joint probability density function modelled using the copula are shown with a gradient from blue to red for increasing values of density.

Table 9. Conditional probability of wet event total precipitation ($P_{t,w}$) exceeding a threshold (p) given the duration of the dry event (D_d) of the same water year is fixed at a selected value (d).

$P[P_{t,w} > p \mid D_d = d]$ (%)		D_d (days)			
		18	20	30	32
$P_{t,w}$ (mm)	50	41.1	38.5	28.8	27.4
	60	22.4	20.4	13.7	12.8
	75	9.8	8.7	5.2	4.8
	100	3.2	2.8	1.4	1.3

The discordance of $P_{t,w}$-D_d shows the tendency for a water year to experience heavy rainfall throughout, i.e., experience consistently wet water year (with high $P_{t,w}$ and short D_d) or for the year to experience less heavy rainfall resulting in a consistently dry water year (with low $P_{t,w}$ and long D_d). To verify this, we checked the relationship between total annual rainfall received in a water year (P_{ann}) to the wet and dry event characteristic ($P_{t,w}$ and D_d). P_{ann} has a Kendall's τ correlation of 0.21 with $P_{t,w}$ and a correlation of -0.29 with D_d, both statistically significant at 5% significance level. The positive dependence between wet event total precipitation and total annual rainfall and the negative dependence between dry event duration and total annual rainfall verify the presence of a consistency in the wetness/dryness of a water year.

5. Conclusion

In this study, we investigate the dependence among event characteristics of wet/dry extremes and event characteristics of opposite extremes in the Geul River basin. We define the extremes as wet/dry events based on the climate drivers: precipitation and temperature for this analysis. Our results show a tendency for compound warm-wet and warm-dry events. Specifically, we found statistically significant correlation between the average precipitation intensity ($P_{g,w}$) and temperature ($T_{g,w}$) during wet events (τ = 0.24) and the duration (D_d) and maximum temperature ($T_{x,d}$) of dry events (τ = 0.20). Compound warm-wet event can have impacts on flood safety, agricultural productivity, and human health (Meng et al., 2022; Wu et al., 2021). For example, the unusually warm and wet winter in 2018 across the Western Alps led to flood induced by rain-on-snow events as well as shallow landslides and debris flows (Stoffel and Corona, 2018). On the other hand, compound warm-dry events can affect water scarcity, agriculture losses, vegetation decline, and fire risk (Meng et al., 2022; Wu et al., 2021). For example, the drought during the 2010 summer heatwaves in eastern Europe and Russia caused massive decrease in crop harvest and forest cover (Barriopedro et al., 2011).

We further analyzed the dependencies between event characteristics identified above ($P_{g,w} - T_{g,w}$ and $D_d - T_{x,d}$) using bivariate copulas to estimate their potential effect on the risk of extreme wet and dry events. A change in $T_{g,w}$ from 11°C to 12°C increases the probability of $P_{g,w}$ > 20mm/day by 2% (from 65.5%) and a change from 20°C to 21°C increases the probability of $P_{g,w}$ > 20mm/day by only 0.2% (from 76%). That is, daily precipitation intensity of wet events are not impacted much by a 1°C increase in the event average temperature, especially for warmer events. For dry events, a change in $T_{x,d}$ from 28°C to 29°C increases the probability of D_d > 30 days by 4.5% (from 17.7%) and a change from 15°C to 16°C increases the probability of D_d > 30 days by only 0.5% (from 4.9%). That is, duration of dry events are less sensitive to an increase in the event maximum temperature by 1°C, especially for colder events. Therefore, future changes in event temperatures in the Geul basin could have little impact on precipitation based event characteristics.

We also see the tendency for a water year to be consistently wet or dry in the Geul River basin. Specifically, we see a negative correlation between the total precipitation during the wet event ($P_{t,w}$) and the duration of the dry event (D_d) occurring in the same water year (τ = -0.18). This resonates with the concept of classifying a water year as wet or dry compared to a 'normal year' used in water planning and management (Null and Viers, 2013). This classification is used to simplify complex hydrology into a single, numerical metric that can be used in rule-based decision making. Through the copula approach proposed here, we were able to proving more information on the specific wet and dry events that could cause more impacts during the water year, providing additional information for efficient water management.

As discussed in Section 1, the wet and dry meteorological extremes analyzed in this study is the first step towards a combined risk assessment of floods and droughts. The agreement of the relationship seen between similar/opposite event characteristics (compound warm-wet events, compound warm-dry events and consistently wet/dry water year) with literature as discussed here provide confidence in the definition of wet and dry events adopted in this study. This analysis was also helpful in understanding the dependence of climate drivers during hydrological extremes and their potential effect on the risk of these events.

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References

Akaike, H. 1985. Prediction and Entropy, Atkinson Anthony, C. and Fienberg, S.E. (Ed.), A Celebration of Statistics. Springer New York, New York, 1–24.

Barriopedro, D., Fischer, E.M., Luterbacher, J., Trigo, R.M., García-Herrera, R. 2011. The Hot Summer of 2010: Redrawing the Temperature Record Map of Europe. Science 332(6026), 220–224.

Beevers, L., Popescu, I., Pregnolato, M., Liu, Y., Wright, N. 2022. Identifying hotspots of hydro-hazards under global change: A worldwide review. Frontiers in Water 4.

Chen, H., Wang, S., Zhu, J., Zhang, B. 2020. Projected Changes in Abrupt Shifts Between Dry and Wet Extremes Over China Through an Ensemble of Regional Climate Model Simulations. Journal of Geophysical Research: Atmospheres 125(23).

Collet, L., Harrigan, S., Prudhomme, C., Formetta, G., Beevers, L. 2018. Future hot-spots for hydro-hazards in Great Britain: A probabilistic assessment. Hydrology and Earth System Sciences 22(10), 5387–5401.

Cornes, R.C., van der Schrier, G., van den Besselaar, E.J.M., Jones, P.D. 2018. An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets. Journal of Geophysical Research: Atmospheres 123(17), 9391–9409.

De Michele, C., Meroni, V., Rahimi, L., Deidda, C., Ghezzi, A. 2020. Dependence Types in a Binarized Precipitation Network. Geophysical Research Letters 47(23).

Genest, C., Favre, A.-C. 2007. Everything You Always Wanted to Know about Copula Modeling but Were Afraid to Ask. Journal of Hydrologic Engineering 12(4), 1155–1167.

Gill, J.C., Malamud, B.D. 2014. Reviewing and visualizing the interactions of natural hazards. Reviews of Geophysics 52(4), 680-722.

Hao, Z., Singh, V.P., Hao, F. 2018. Compound extremes in hydroclimatology: A review. Water 10(6).

He, X., Sheffield, J. 2020. Lagged Compound Occurrence of Droughts and Pluvials Globally Over the Past Seven Decades. Geophysical Research Letters 47(14).

Hodson, T.O. 2022. Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. Geoscientific Model Development 15(14), 5481-5487.

Kendall, M.G. 1938. A new measure of rank correlation. Biometrika 30(1-2), 81–93.

Massey, F.J. 1951. The Kolmogorov-Smirnov Test for Goodness of Fit. Journal of the American Statistical Association 46(253), 68–78.

Meng, Y., Hao, Z., Feng, S., Zhang, X., Hao, F. 2022. Increase in compound dry-warm and wet-warm events under global warming in CMIP6 models. Global and Planetary Change 210.

de Moor, J.J.W. 2007. Human impact on Holocene catchment development and fluvial processes - the Geul River catchment, SE Netherlands. PhD Thesis, Vrije Universiteit Amsterdam.

Null, S.E., Viers, J.H. 2013. In bad waters: Water year classification in nonstationary climates. Water Resources Research 49(2), 1137–1148.

Ragno, E., Hrachowitz, M., Morales-Nápoles, O. 2022. Applying non-parametric Bayesian networks to estimate maximum daily river discharge: potential and challenges. Hydrology and Earth System Sciences 26(6), 1695–1711.

Rashid, M.M., Wahl, T. 2022. Hydrologic risk from consecutive dry and wet extremes at the global scale. Environmental Research Communications 4(7).

Shi, W., Huang, S., Liu, D., Huang, Q., Leng, G., Wang, H., Fang, W., Han, Z. 2020. Dry and wet combination dynamics and their possible driving forces in a changing environment. Journal of Hydrology 589.

Sklar, M. 1959. Fonctions de répartition à N dimensions et leurs marges. Annales de l'ISUP VIII(3), 229–231.

Stoffel, M., Corona, C. 2018. Future winters glimpsed in the Alps. Nature Geoscience 11(7), 458-460.

Suarez-Gutierrez, L., Müller, W.A., Marotzke, J. 2023. Extreme heat and drought typical of an end-of-century climate could occur over Europe soon and repeatedly. Communications Earth and Environment 4(1).

Tsiokanos, A., Rutten, M., van der Ent, R.J., Uijlenhoet, R. 2023. Flood drivers and trends: a case study of the Geul River Catchment (the Netherlands) over the past half century (preprint). Hydrology and Earth System Sciences Discussions 2023, 1–24.

Van Dorland, R., Beersma, J., Bessembinder, J., Bloemendaal, N., Van Den Brink, H., Brotons Blanes, M., Drijfhout, S., Groenland, R., Haarsma, R., Homan, C., Keizer, I., Krikken, F., Le Bars, D., Lenderink, G., Van Meijgaard, E., Meirink, J.F., Overbeek, B., Reerink, T., Selten, F., Severijns, C., Siegmund, P., Sterl, A., De Valk, C., Van Velthoven, P., De Vries, H., Van Weele, M., Wichers Schreur, B., Van Der Wiel, K. 2023. KNMI National Climate Scenarios 2023 for the Netherlands. Scientific report.

Wu, Y., Miao, C., Sun, Y., AghaKouchak, A., Shen, C., Fan, X. 2021. Global Observations and CMIP6 Simulations of Compound Extremes of Monthly Temperature and Precipitation. GeoHealth 5(5).

You, J., Wang, S., Zhang, B., Raymond, C., Matthews, T. 2023. Growing Threats From Swings Between Hot and Wet Extremes in a Warmer World. Geophysical Research Letters 50(14).

Zscheischler, J., Seneviratne, S.I. 2017. Dependence of drivers affects risks associated with compound events. Science Advances 3(6).