



Linking European droughts to year-round weather regimes

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Abstract. European droughts have far-reaching socio-economic and ecological impacts, yet their prediction remains challenging due to the complex interplay between regional climate variability and large-scale atmospheric circulation. This study investigates how persistent North Atlantic weather regimes influence the occurrence and spatial distribution of seasonal meteorological droughts across Europe throughout the year. Using reanalysis datasets and a tailored regionalization based on drought synchronicity, we identify six coherent European sub-regions and relate drought events, defined by the standardized precipitation index (SPI3), to year-round weather regimes derived from 500 hPa geopotential height anomalies. Our analysis shows that while each weather regime exhibits distinctive and seasonally consistent precipitation patterns, only a fraction of droughts—primarily in western Europe and during winter—can be directly attributed to anomalies in regime frequency. The findings underline the partial but regionally significant role of North Atlantic circulation patterns in shaping European drought risk, highlighting opportunities and limitations for improving drought forecasts on sub-seasonal to seasonal timescales. This study emphasizes the added value of using year-round weather regimes as a unifying framework for understanding drought drivers, overcoming the constraints of purely seasonal classifications. Improved understanding of these links could help refine climate models and support more robust early-warning systems for drought management across diverse European climates.

1 Introduction

Droughts are complex climate events (Dracup et al., 1980; Kallis, 2008) with potentially disastrous consequences on society and ecosystems. They are classically classified into four categories: meteorological, hydrological, agricultural, and economical droughts (Yevjevich, 1967; Wilhite and Glantz, 1985), depending on the physical variables that they affect. These different types of droughts have various causes, consequences, and time scales, typically from a few weeks to several months. All of them start with a meteorological drought, i.e. a precipitation deficit which can affect surface reservoirs and rivers. Droughts can occur at any time of year, with different impacts depending on the season. For instance a winter drought will prevent groundwater recharge, while a summer drought will have a more direct impact on agriculture and ecosystems.

Recent years have been remarkably warm in Europe, and some heat episodes were associated with strong precipitation deficits, as in summer 2022 (Lentze, 2023). The Mediterranean area is particularly sensitive to the issue of water resources, since it is expected to receive less precipitation in a warmer climate, which should increase the probability of meteorological droughts in the basin (see Fig.8.14 from (Intergovernmental Panel On Climate Change (Ipcc), 2023)). Rainfall has been



decreasing in recent years, although this has been argued to result from natural variability rather than climate change (Vicente-Serrano et al., 2025). At the time of writing, the year 2025 is marked by a significant drought event in Northern Europe, which began during the period March–April–May period and has continued into June. This drought stretches from the north of France to the Netherlands, descending across the whole of Germany and affecting part of the Scandinavian region. This drought is likely to cause problems for vegetation as the summer season approaches (European Commission. Joint Research Centre., 2025).

Understanding the underlying conditions that precede droughts in Europe thus appears crucial. In this region, seasonal and sub-seasonal climatic variations are less dependent on tropical connections than in other regions of the world (Van Oldenborgh et al., 2000; Fraedrich, 1994; Shaman and Tziperman, 2011). Surface climate in this region is rather driven by more regional phenomena (Casanueva et al., 2014; Wibig, 1999; Boé et al., 2009), particularly the North Atlantic atmospheric circulation (Vicente-Serrano and López-Moreno, 2008; Bladé et al., 2012). The influence of atmospheric patterns on sub-seasonal to seasonal anomalies in European rainfall has been evidenced by various methods, such as the weather regimes (WRs) approach (Michelangeli et al., 1995; Boé, 2013; Lavaysse et al., 2018), which provide a useful framework for interpreting the circulation (Pasquier et al., 2019; Madonna et al., 2017; Cassou, 2008). However, because of the strong seasonality in atmospheric circulation, WRs are often defined differently for each season (Kimoto and Ghil, 1993), which hinders a systematic analysis of the drought-circulation relationship throughout the entire year. Droughts can indeed occur any time of the year, including during transitional seasons between winter and summer.

To overcome this limitation, a few recent studies have proposed the use of weather regimes defined over the whole year, also known as year-round weather regimes (Grams et al., 2017; Lee et al., 2023). In this study, we aim to investigate the causal relationship between large-scale atmospheric circulation and droughts in Europe, using such year-round weather regimes (WRs) as a proxy for atmospheric circulation. In particular, we want to evaluate the extent to which droughts development can be explained by anomalous WRs frequencies, and assess this relationship across different regions of Europe.

To do so, we first regionalize Europe based on a drought concurrency index, and we assess the precipitation pattern of WRs throughout the year. Then, for each region, we weight these precipitation patterns by the frequency anomalies of WRs occurring over the period preceding the droughts. Our focus is on meteorological droughts, defined as precipitation deficits over a seasonal time scale (3 months).

The following section presents the data and methodology employed in this study, while the main results are presented in the Sect.3. In particular, Sect.3 presents the results concerning the proportion of droughts attributable to weather patterns. Elements of discussions relative to our results are provided in Sect.4, followed by concluding remarks.



60 2 Data and methodology

2.1 Data

Daily precipitation and 500 hPa geopotential height fields (z_{500}) at the 0.5×0.5 degrees spatial resolution are computed over the period 1960–2022 from hourly ERA5 reanalysis data (Hersbach et al., 2020). We initially considered the period 1940–2022 before restricting the analysis to the period 1960–2022 due to a spurious trend over the period 1940–1960 in the precipita-
65 tion data (Soci et al., 2024), leading to a bias when studying droughts. The period 1991–2020 is taken as the reference for computing precipitation anomalies and for the WR definition.

Precipitation data cover a wide European region corresponding to the union of the zones defined in AR6 North Europe (NEU), Western and Central Europe (WCE), Eastern Europe (EEU), and Mediterranean (MED) (Iturbide et al., 2020). The
70 total area is therefore comprised between 10° W and 60° E, and 30° N and 72° N.

Geopotential height data at 500 hPa are determined over the North Atlantic domain from 75° W to 64° E and from 28° N to 75° N. The width of this spatial domain enables to capture the relevant characteristics of the North Atlantic circulation (e.g. Azores high, Icelandic low, and the variability associated with synoptic-scale transient eddies) and compute weather regimes
75 adequately.

2.2 Methodology

2.2.1 Drought index

Numerous drought indices exist, each of them highlighting a different aspect of drought (Heim Jr, 2002; Keyantash and Dracup, 2002). Here we use the Standardized Precipitation Index (SPI), as defined by (McKee et al., 1993) and recommended by the
80 World Meteorological Organisation (Hayes et al., 2011). The SPI has the advantage of being extensively documented (Guttman, 1999; Lloyd-Hughes and Saunders, 2002), requiring only the precipitation dataset to be calculated. This index characterizes the intensity of a precipitation anomaly in terms of its probability of occurrence over a given period of time. The underlying idea is that the impact of a drought in a given part of the world depends on the recurrence of this type of drought on a large time scale.

Specifically, for a given day, the SPI calculates the cumulative precipitation over a given duration (integration period), comparing it with the long-term median cumulative precipitation for that same duration. Here, we focus on a 3-month integration period (hereafter SPI3), which corresponds to droughts prolonged enough to impact farming practices (McKee et al., 1995; Wu et al., 2005), but short enough to understand their link with the atmospheric circulation at synoptic to subseasonal timescales.
90 The SPI is a mathematical tool that converts the non-normal precipitation distribution into a normal one. This can be used to define droughts according to their intensity, which is linked to their probability of occurrence. This link is done by setting a



threshold on the SPI3 value. The more negative the threshold, the lower the probability of a drought exceeding it, and therefore the greater its impact. A more comprehensive overview of the SPI is provided by (Cheval et al., 2014).

95 Here, we consider moderate droughts defined by a 5-year return period, which corresponds to an SPI3 threshold of -0.84, according to the classification system of (Agnew, 2000). The identification of drought periods is detailed in Sect.2.2.4.

2.2.2 Validity of the SPI across the region

The SPI3 has been used to forecast droughts with a high level of confidence (Cancelliere et al., 2007), and to establish a climatology of drought for the European region (Gudmundsson and Seneviratne, 2015; Caloiero et al., 2018; Spinoni et al., 2017).
100 As mentioned earlier, the SPI allows to transform the generally non-Gaussian probability density function of precipitation climatology into an index exhibiting normal/gaussian distribution properties and centered on the 0 value. However, it assumes that the probability of having a dry event with a certain intensity is the same as that of having a wet event with the same intensity. This symmetry assumption in the cumulative precipitation distribution, although generally valid, is questionable for arid regions, according to the study of (Wu et al., 2007). Yet, to our knowledge, there is no off-the-shelf method to assess the
105 validity of this index. We thus propose two distinct methods to assess its applicability.

The first method consists in fitting a gamma distribution on 3-month precipitation and estimating the skewness parameter that characterizes its asymmetry. Since the problem of validity of the SPI arises from the asymmetric shape of the precipitation distribution, the higher the skewness the less valid the SPI. In the context of a random variable (in this case, daily precipitation),
110 if it is observed to follow a Gamma distribution with parameters k and θ , the probability density is expressed as follows:

$$f(x, k, \theta) = \frac{x^{k-1} e^{-\frac{x}{\theta}}}{\Gamma(k) \theta^k}$$

for all $x > 0$ where k is the shape parameter and θ is the scale parameter, and Γ is Euler's Gamma function. The skewness coefficient of the distribution is $\frac{2}{\sqrt{k}}$. For each season (DJF, MAM, JJA, SON) of the period, we averaged over the years all cumulative precipitation, then performed a Gamma regression on this resulting distribution, and calculated the skewness coefficient. The results are shown in the right-hand panel of Fig.1 for the winter and summer seasons.
115

The second method relies on the variance of the SPI that should be close to 1 by construction (Sonmez et al., 2005). When the asymmetry of the precipitation distribution is too skewed, the normalization leads to a SPI with a variance different from 1. We thus compute at each grid point and for every season of each year the variance of the SPI3 timeserie. This variance
120 was then averaged over all years, to obtain a mean value for each season. The results are displayed in Fig.1 on the right for the winter and summer seasons. The statistical significance of the result was computed by means of a bootstrap algorithm processing 1000 resampling draws with replacement

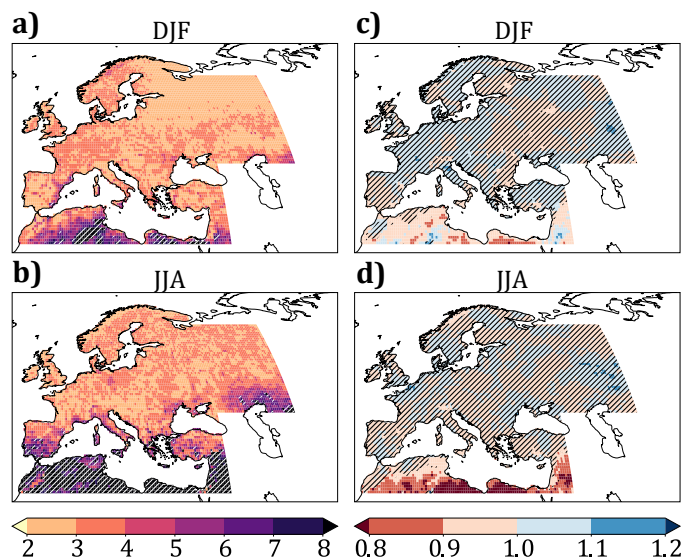


Figure 1. (a) and (b) Skewness coefficient of the Γ distribution fitted on precipitation data for winter (DJF) and summer (JJA). Hatching indicates a skewness coefficient significantly greater than 7 (p-value < 0.05). (c) and (d) Variance of SPI3 in winter (DJF) and summer (JJA). Hatching indicates values not significantly different from 1 (p-value < 0.05).

We find that the SPI3 variance is close to 1 (i.e. not statistically different) over most of the domain except for its southernmost part. This is confirmed by the skewness coefficient that is significantly larger than 7 in the North African and Middle East regions in summer. This questions the validity of the SPI over such regions. We thus exclude this region in the subsequent analysis and focus on a reduced domain extending from 34° N to 72.6° N (see Sect.2.2.3).

There is a significant similarity between the skewness coefficient and the variance. The skewness coefficient, which is calculated before the SPI is obtained, is therefore an acceptable proxy for the validity of the SPI. However, there is no quantifiable criterion for the value of this skewness coefficient. In the context of our study, a threshold of 7 for the skewness coefficient seems appropriate.

2.2.3 Regionalization of Europe

To study large-scale droughts in Europe and their link with North Atlantic circulation, we must identify coherent dry periods across broad regions. A grid point is considered dry when its SPI3 is below -0.84 (see Sect.on SPI definition above); but since we focus on droughts with significant spatial extent, point-by-point analysis is not sufficient. Rather than relying on predefined regions (e.g., AR6), which may average out inconsistent SPI3 signals, we employ a data-driven regionalization approach. This also ensures that the regionally-aggregated SPI3 preserves its near-1 variance property. A region will then be considered in drought if its spatially-averaged SPI3 falls below -0.84 (see Sect.2.2.3).



We build on the method described by (Pappert et al., 2024) to perform a regionalization of the domain based on the temporal concurrence of adjacent droughts. This method uses the UPGMA (Unweighted Pair Group Method with Arithmetic Mean), see (Sokal et al., 1958)) algorithm to perform clustering and take into account the simultaneity of droughts. At each grid point, the SPI3 is binarized, taking the value 1 when below the drought threshold (i.e. -0.84 , see Sect.2.2.1), or 0 otherwise. The similarity between binarized time series is then computed with the Jaccard distance index (Jaccard, 1912). This index, expressed in Eq. 1, quantifies the distance between two time series, $x_1(t)$ and $x_2(t)$, by determining the ratio of time units when both series are simultaneously 1 to the total time.

$$D(x_1, x_2) = 1 - J(x_1, x_2) = 1 - \frac{|x_1(t) \cap x_2(t)|}{|x_1(t) \cup x_2(t)|} \quad (1)$$

In this study, the term $|x_1(t) \cap x_2(t)|$ expresses the number of time steps where both timeseries are equal to 1, while the term $|x_1(t) \cup x_2(t)|$ denotes the total number of time steps. The distance coefficient can be rewritten using the Jaccard coefficient, as defined by (Jaccard, 1912), denoted by $J(x_1, x_2)$. This metric highlights the synchronicity of time series and is therefore particularly appropriate to create regions with similar drought behavior. The UPGMA algorithm is initialized by taking the total region, which it then subdivides into two regions for which the metrics are similar. At each iteration, it increases the number of clusters by one, by optimally subdividing one of the regions defined at the previous iteration. The algorithm stops when the set of defined regions corresponds to the grid points. A compromise must therefore be found between the number of regions, their sizes, and the synchronicity of the time series within these regions. To judge the relevance of this division, we check that the seasonal variance of SPI3 (as defined in the previous section) averaged over all regions remains within the interval $[0.95, 1.05]$.

After applying this algorithm and studying the proposed regional breakdowns, we have decided to retain six regions. The regionalization is illustrated in Fig.2. The variance of the SPI3 averaged over each region is not different from 1 at the 95%

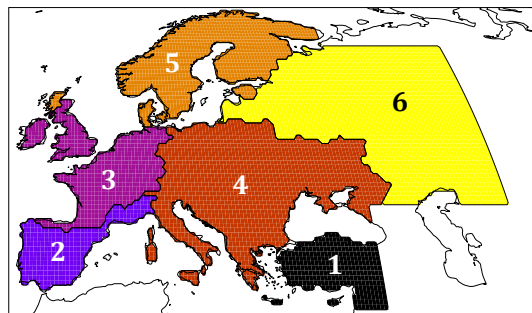


Figure 2. Regionalization of Europe derived from seasonal drought concurrence (see text for details).

confidence level, which confirms the suitability of the regionalization for the purpose of this study. The names of these regions and their variance are presented in the table 1. The seasonal variance of the SPI3 (calculated over the previous 3 months) averaged over the year is also presented. For each of these six regions, the average SPI3 variance is significantly equal to 1. These regions are therefore relevant when using the SPI.



Table 1. Region names and mean SPI3 variances

Region	Name	3-month variance
1	Eastern Mediterranean (EMed)	0.98
2	Western Mediterranean (WMed)	0.99
3	Western Europe (WEur)	1.01
4	Central Europe (CEur)	0.99
5	Scandinavia (Scand)	1.00
6	Eastern Europe (EEur)	1.00

2.2.4 Identifying drought events

165 Having defined these new regions, we then consider a region to be dry if its spatially-averaged SPI3 falls below the value
 –0.84. Further, droughts lasting ten days or less have been excluded in order to retain relatively severe events only. If two
 droughts are separated by less than 3 months, then we consider that it is the same event, consistently with the use of the SPI3.
 Each drought is associated with a characteristic date corresponding to the minimum SPI3 over the drought period. The Fig.3
 presents the spatially averaged timeseries of SPI3 over one of the previously defined regions (see Sect.2.2.3). Dry spells (SPI3
 170 less than –0.84) are shown in dark red. For each drought period, the red dotted vertical line indicates the local minimum SPI3
 corresponding to its reference date. For each region, we identified a number of droughts presented in the Table 2.

Table 2. Number of detected droughts, for each region

Region	Number of detected droughts
EMed	28
WMed	38
WEur	30
CEur	21
Scand	24
EEur	23

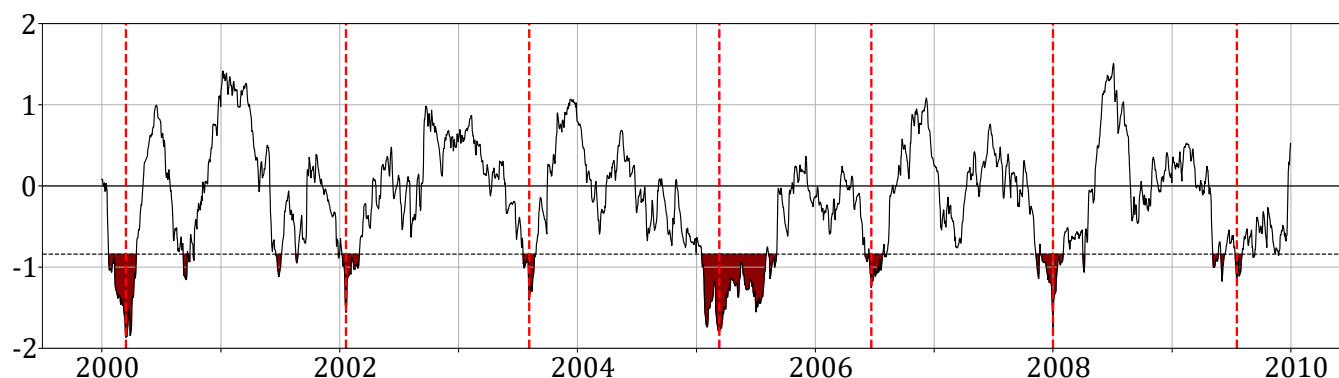


Figure 3. Drought characterization principle: The SPI3 time series (here for the Western Mediterranean region) is used to detect droughts by selecting periods for which the SPI3 is less than -0.84 . The vertical red line shows the minimum of the SPI for the detected drought, corresponding to the day where the maximum intensity of the drought is reached.

2.2.5 Weather regimes

The year-round weather regimes are computed from daily 500 hPa geopotential height ($z500$) over the 1991 – 2020 period. The pre-processing and clustering steps are described hereafter. The climatology of daily $z500$ is calculated and smoothed by
175 interpolating a periodic spline at each grid point. This climatology is then removed from the raw signal to obtain the $z500$ anomalies. A linear regression is also used to remove the temporal trend (computed over the spatially-averaged signal) over the 1991 – 2020 period. This is to remove the effect of thermal expansion of the lower troposphere, which can distort the distance metrics used by the classification even though it does not reflect a circulation effect. We then apply a low-pass filter to the anomalies, in the form of a 5-day moving average. The variance of $z500$ at mid-latitudes being larger in winter than in summer,
180 the normalization of $z500$ anomalies requires to remove this seasonality. Disregarding this seasonal difference in variability may result in a spurious predominance of winter weather patterns. Normalization is obtained by dividing the daily filtered anomalies at each grid point by the same calendar scalar index. This index is calculated by computing the standard deviation of the $z500$ signal over a sliding window of 30 days, for each day of the year and at each grid point, and then spatially averaging over the domain.

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We then reduce the dimensionality by determining the first empirical orthogonal functions (EOF) of the previously computed $z500$ anomaly time series (Wilks, 2019) and their associated principal components (PC). We retain a minimum of 90% of the total variance, which leads to keep the first 13 components of the signal. The time-averaged spatial correlation coefficient between the reconstructed daily $z500$ anomaly maps (sum of all the retained EOFs multiplied by their respective principal



190 components) and the initial signal is 0.95, which also validates our choice.

Finally, the weather regimes are obtained by clustering the principal components using the k-means algorithm. The number of clusters is arbitrary, but can be oriented using several metrics (Lee et al., 2023). We applied these metrics to our case study (see discussions in appendix A1), but we found that there is no optimal number of weather regimes. Our choice to retain 7
195 weather regimes is thus arbitrary but aligns with the existing literature (Grams et al., 2017; Büeler et al., 2021).

The centroids are calculated over the reference period (1991 – 2020) and subsequently assigned to each day of the study period (1960 – 2022). To reassign WRs to each day of this longer period, we project the daily z500 anomaly in the principal components space and then compute the euclidean distance to each of the WR. The attributed WR is the one presenting the
200 minimum distance. If the distance is too high for each WR (distance superior to 4.5, chosen to retain approximately 20% of WR0), we attribute the "no regime" WR to this day (or "Weather regime 0"). Further, we apply a persistence criterion to retain sequences of at least 4 days in the same regime. Leftover days are assigned to the additional regime "WR0", accounting for transition between canonical regimes. The resulting weather regimes, expressed as z500 anomaly composites, are illustrated in Fig.4. The analysis yields two cyclonic weather regimes, designated as the Zonal Regime (ZO) and the Atlantic Trough (AT),

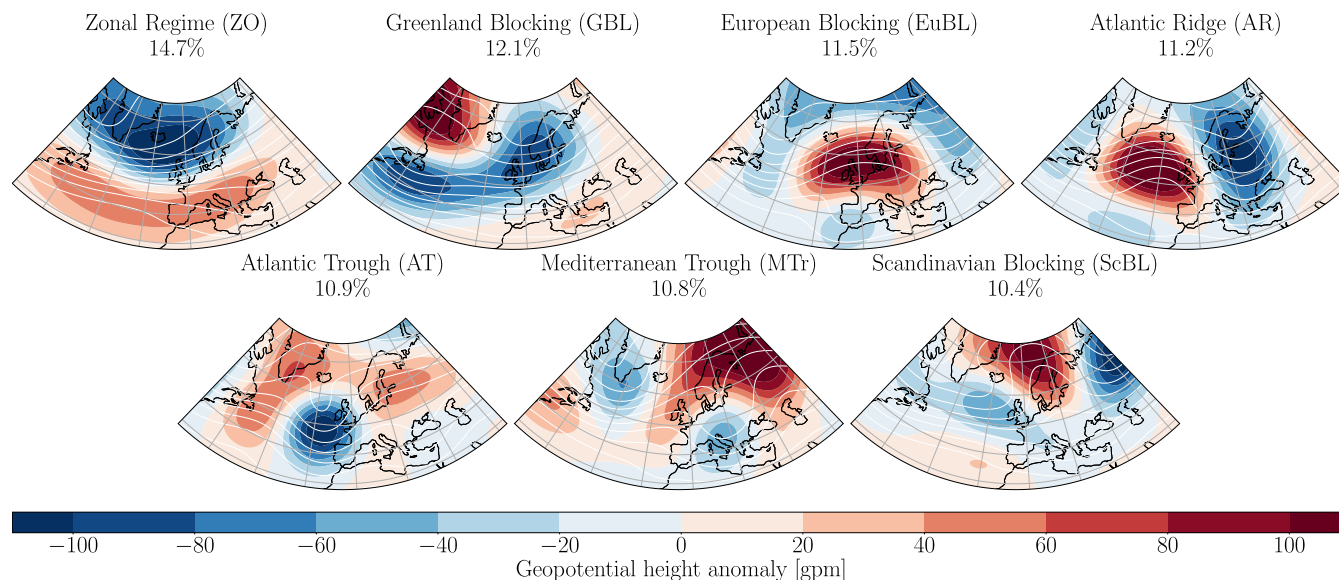


Figure 4. Composite z500 (contours) and z500 anomalies (color shades) for each weather regime, and their associated frequency (in %), calculated over the reference period (1960 – 2022). Isolines are shown every 65 gpm.

205 and five blocking weather regimes, namely the Mediterranean Trough (MTr), the European Blocking (EuBL), the Greenland Blocking (GL), the Atlantic Ridge (AR), and the Scandinavian Blocking (ScBL). These results are mostly consistent with WR obtained by (Büeler et al., 2021) and (Grams et al., 2017). We can attribute discrepancies with these studies to the use of ERA5



instead of Era Interim, and by a slightly different spatial domain (75° W to 64° E and 28° N to 75° N as opposed to 80° W to 40° E and 30° N to 90° N), and time period (1991 – 2020 vs. 1979 – 2015 for (Grams et al., 2017) and 1997 – 2017 for (Büeler et al., 2021)).

The weather patterns presented here are ranked in descending order of frequency over the entire period, irrespective of season. The Fig.B1 shows, for each day of the year, the mean frequency of each WR. This frequency has been calculated over the period 1960 – 2022. The seasonal predominance of these weather regimes is consistent with the findings of (Büeler et al., 2021). There is a more homogeneous frequency distribution of weather regimes in winter than in summer, but a winter predominance of cyclonic weather regimes and a summer predominance of blocking weather regimes. The zonal regime is found to be the most frequent, with an occurrence frequency of 14.7%. These averaged frequencies mask multi-decadal variations affecting large-scale circulation. We discussed this point in Sect.4.1

The precipitation anomaly pattern associated to a given weather regime is obtained by averaging the precipitation anomalies of all the days assigned to that weather regime. The resulting composite patterns are shown in Fig.5. Precipitation composites show strong and coherent signals, thereby justifying the use of year-round regimes in our analysis. Large-scale patterns of precipitation anomalies were expected, in association with large-scale regimes. Overall, anti-cyclonic weather regimes are associated with negative precipitation anomalies, while low-pressure regimes induce positive precipitation anomalies.

As demonstrated in Fig.C1 in the appendix, the precipitation signature associated to year-round weather regimes is relatively stable across seasons. This demonstrates the relevance of using the average composite over the whole period, regardless of the time of year. Yet, a few noticeable differences are worth mentioning: The most striking differences are the shifts between dry winter (DJF) and wet summer (JJA) anomaly over southwestern Europe for EuBL and conversely for AT. Another seasonal change is the dampening of the wet-north dry-south contrast (resp. wet-southeast dry-southwest) between winter and summer for ZO (resp. AR). Finally, MTr and ScBL wet patterns show a stronger amplitude in Autumn, possibly due to seasonal heavy precipitation events affecting the Mediterranean and surrounding regions.

The ZO and EuBL regimes exhibit a more pronounced precipitation contrast during winter months compared to summer months, particularly in the December-January-February (DJF) season. Similarly, the AT regime yields much drier anomalies in summer than in winter over Southwestern Europe, while the same phenomenon is observed for the AR regime over the JJA and SON periods. These differences require to quantify the error made when considering a single precipitation pattern per regime, rather than four per regime (one per season). This question is discussed in Sect.4.2

2.2.6 Drought reconstruction informed by weather regimes

In order to quantify the contribution of weather patterns to the precipitation deficit leading to droughts, we calculate for each region the average frequency of each weather pattern during the 91 days preceding the droughts. We can then compute the part

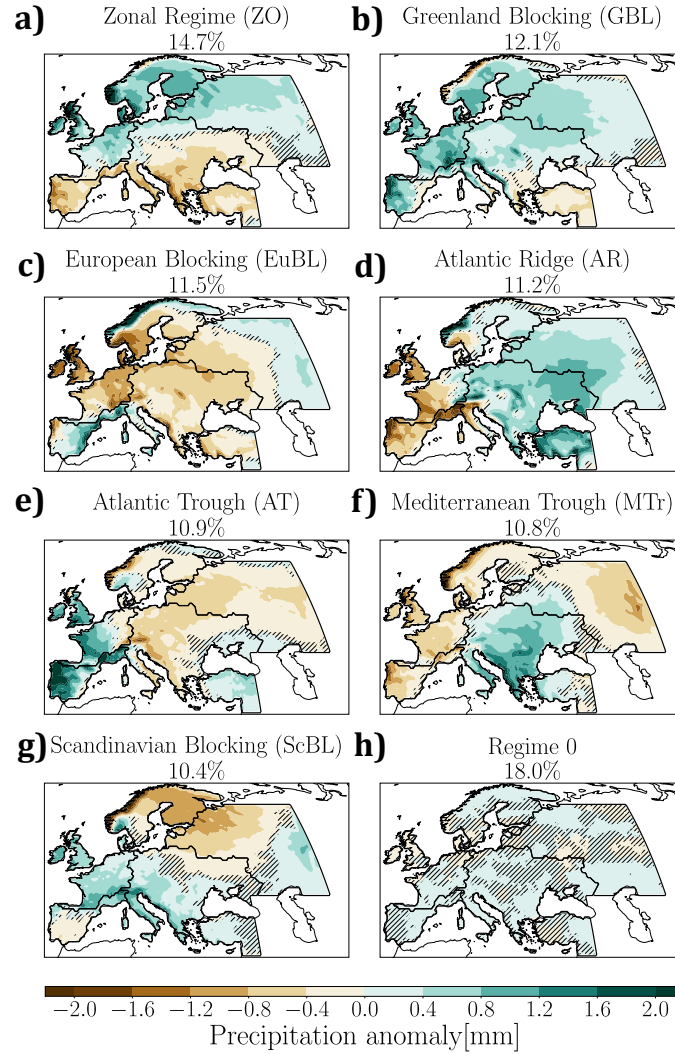


Figure 5. Average precipitation field (composite) for each weather regime. Non-significant results (p-value > 0.05) are hatched.

of the precipitation anomaly that can be explained by an anomaly in the frequency of occurrence of each weather pattern.

For each region, we aim to reconstruct the averaged precipitation anomaly $\overline{p_s}$, computed over all periods of 91 days that precede droughts. One can get the mathematical expression of $\overline{p_s}$ using the following decomposition. We first categorize the ensemble of days Ω , into 8 weather regimes k (counting the regime 0) so that $\Omega = \bigcup_k \Omega_k$. On the entire period we have :

- The climatological frequency of the weather regime k :

$$f_k = \frac{n_k}{N}$$



where n_k is the number of days in the WR k , and N the total number of days in Ω , so that $\sum_k n_k = N$ and $\sum_k f_k = 1$.

250 – The canonical precipitation anomaly pattern of the WR k :

$$C_k = \frac{1}{n_k} \sum_{d \in \Omega_k} p_d \quad (2)$$

which are the mean precipitation anomaly pattern when in WR k (shown in 5), with p_d the daily precipitation anomaly.

On the subset of N^S days that precede droughts (here, $N^S = 91 \times N_{\text{droughts}}$ days), we have

– The frequency of the WR k :

255
$$f_k^S = \frac{n_k^S}{N^S}$$

where n_k^S is the number of days in the WR k throughout the 91-day periods that precede droughts, with $\sum_k n_k^S = N^S$.

– The precipitation anomaly pattern of the WR k during this period:

$$C_k^S = \frac{1}{n_k^S} \sum_{d \in \Omega_k^S} p_d \quad (3)$$

with $\Omega_k^S = \Omega^S \cap \Omega_k$.

260 By construction, precipitation anomalies $\bar{p}$ verify $\bar{p} = 0$ and write as follows:

$$\begin{aligned} \bar{p} &= \frac{1}{N} \sum_{d \in \Omega} p_d \\ &= \sum_k \sum_{d \in \Omega_k} \frac{1}{n_k} \frac{n_k}{N} p_d \\ &= \sum_k f_k C_k \end{aligned} \quad (4)$$

Similarly, on shorter periods S :

$$\bar{p}^S = \sum_k f_k^S C_k^S \quad (5)$$

Hence, the difference between the precipitation anomalies preceding droughts and climatological precipitation anomalies is
265 (using Eq.4 and Eq.5):

$$\bar{p}^S - \bar{p} = \sum_k f_k^S C_k^S - \sum_k f_k C_k \quad (6)$$

So, by using

$$\Delta f_k = f_k^S - f_k \quad (7)$$



and

$$\Delta C_k = C_k^S - C_k \quad (8)$$

we can rewrite Eq.6 such that

$$\bar{p}^S = \sum_k (f_k + \Delta f_k) (C_k + \Delta C_k) - f_k C_k \quad (9)$$

Ultimately we obtain the expression of the precipitation anomalies preceding droughts as a function of the variation of frequency anomalies and variation of precipitation patterns :

$$\bar{p}^S = \sum_k \Delta f_k C_k + \sum_k f_k \Delta C_k + \sum_k \Delta f_k \Delta C_k \quad (10)$$

The term $\sum_k \Delta f_k C_k$ reflect the contribution of the anomalous WR frequencies to influence the precipitation. The $\sum_k f_k \Delta C_k$ term characterize the departure from the canonical precipitation patterns in periods preceding droughts. The third term can be interpreted as the interaction between patterns departure and anomalous WR frequencies. Hence, we can see this method as a way to use these frequencies to weight and cumulate each of the precipitation maps associated with the weather patterns. This entire process is illustrated in 6. Please note that the WR0 is not taken into account in the reconstruction but whose days are nevertheless taken into account when calculating the average precipitation anomalies.

In the following sections, we quantify the suitability of WRs to reconstruct precipitation anomalies by computing spatial average of these terms. In order to assess their relative contribution to the original precipitation anomalies, we normalize these terms by the precipitation anomalies computed over the 91 days preceding droughts :

$$1 = \underbrace{\frac{\langle \sum_k \Delta f_k C_k \rangle}{\langle \bar{p}^S \rangle}}_{\alpha_1} + \underbrace{\frac{\langle \sum_k f_k \Delta C_k \rangle}{\langle \bar{p}^S \rangle}}_{\alpha_2} + \underbrace{\frac{\langle \sum_k \Delta f_k \Delta C_k \rangle}{\langle \bar{p}^S \rangle}}_{\alpha_3} \quad (11)$$

where $\langle \cdot \rangle$ denotes spatial averaging. However, the sum of the terms is always 1. Taking the equation 11, we can rewrite it as a sum of three scalars:

$$1 = \alpha_1 + \alpha_2 + \alpha_3 \quad (12)$$

Therefore, for the first term to predominate over the other two, we can arbitrarily set the criterion that the weather patterns explain a satisfactory part of the drought when

$$\alpha_1 > 0.33 \quad (13)$$

In those case, we can verify that $\alpha_1 > \alpha_2$ and $\alpha_1 > \alpha_3$ for most of the droughts. We can therefore consider that the frequency anomalies of WRs influences droughts when $\alpha > 0.33$.

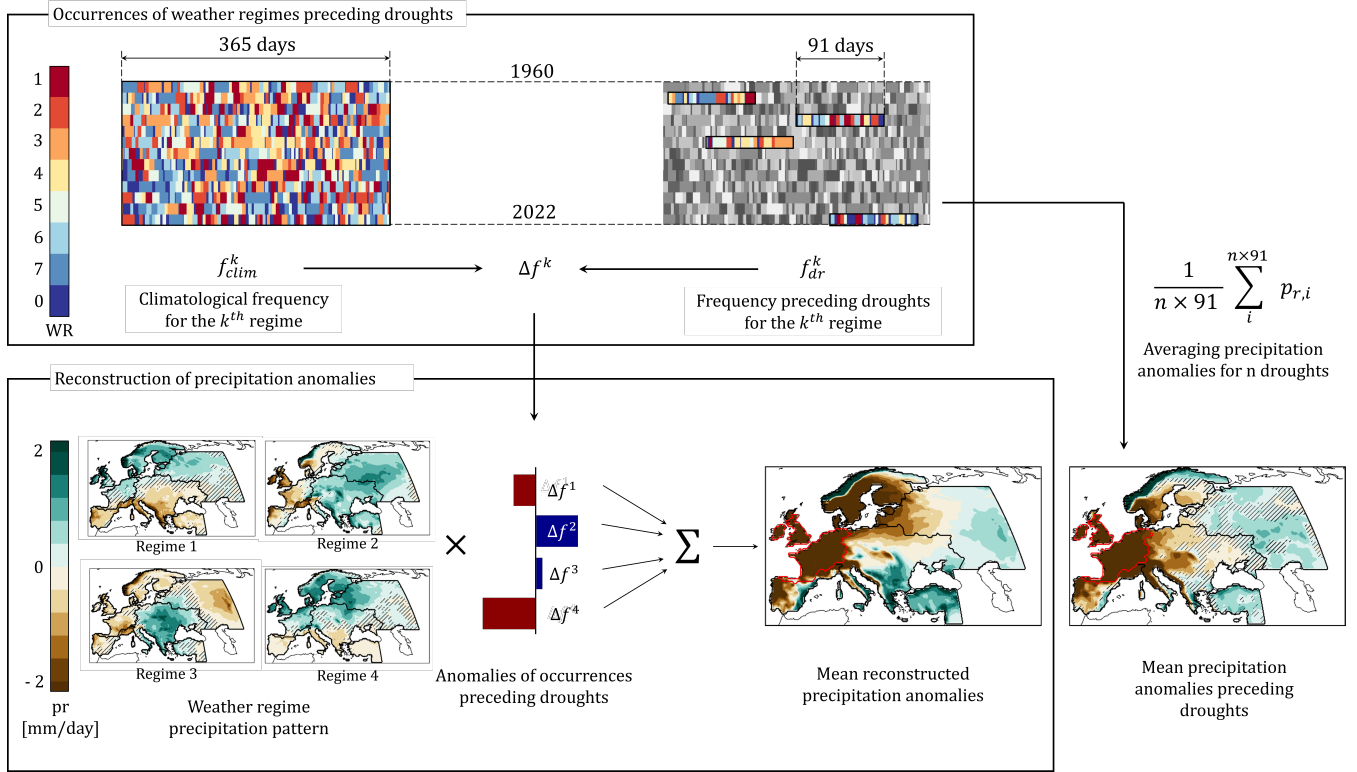


Figure 6. Flowchart showcasing the methodology to reconstruct meteorological droughts over the Western Europe region (highlighted with red contours) derived from frequency anomalies of weather regimes. The bottom-right maps illustrate the comparison between the reconstructed and actual mean precipitation anomaly associated to Western Europe droughts. For simplicity, this illustration displays only four weather regimes out of the seven regimes used for the reconstruction.

295 3 Results

3.1 Average precipitation anomalies reconstructed from WRs

For each region, we analyse the sequences of WRs during the 91-day period before the peak day of the 50 identified droughts, as detailed in Sect.2.2.6. The occurrence anomalies of each regime, for each region, are presented in Table 3. The same information but with uncertainties is presented in the appendix D1.

300 The droughts in each of these regions are therefore characterized by a significant frequency anomaly for at least four weather regimes out of seven. EMed, which is furthest region from the Atlantic Ocean and therefore potentially the least influenced by weather patterns, is the region exhibiting the largest number of WRs without any significant change in frequency. Overall, the confidence interval associated with each frequency anomaly is of the order of 4%. The presence of a clear frequency anomaly signal confirms the influence of weather patterns on droughts in these regions. In addition, the differences between
305 regions suggest that this influence is diverse across Europe, which further justifies our spatial breakdown of the continent (see



Table 3. Frequency anomalies (in %) averaged over all the 91-days period preceding droughts, for each weather regime. A non-significant frequency anomaly is marked with 'NS'.

	ZO	GBL	EuBL	AR	AT	MTr	ScBL
EMed	12	NS	6	−4	2	NS	NS
WMed	8	NS	2	12	−4	1	NS
WEur	−1	−4	12	11	−3	5	−2
CEur	12	−3	10	−3	2	NS	NS
Scand	−8	4	NS	−1	4	6	12
EEur	−4	NS	2	−4	10	12	4

Sect.2.2.3) For each region, the decomposition of the precip anomalies associated with droughts into the three terms of Eq. 11 is shown in Fig. 7. The right column (column V) is presenting the normalized spatial average of each of the three terms.

On average, the $f_k \Delta C_k$ term dominates (Fig. 7III). For all the regions, this term reproduces a large fraction of the dry anomaly over the region of interest, then the amplitude of the signal decreases with the distance. This term shows the departure of the precipitation pattern associated to WRs ahead of drought events compared with the canonical situations shown in Fig. 5. The strength of the signal over the dry region and its attenuation elsewhere shows that precipitation during droughts is abnormally dry compared with canonical precipitation.

The $\Delta f_k C_k$ term (Fig. 7II) is relatively small in all the regions, on average. The signal distribution (Fig. 7V) shows that the contribution of the $\Delta f_k C_k$ term is slightly larger for the three regions bordering the Atlantic Ocean (WEur, WMed, Scand). Conversely, the regions the most distant from the coast EEur and EMed exhibit the lowest contribution of this term to the precipitation anomaly. Despite the low amplitude of the reconstructed signal, the precipitation pattern for this term is relatively accurate. For example, in the case of the WEur region (panel 3.II of Fig. 7), the East-West gradient of precipitation is well reconstructed with a maximum signal amplitude over the region of interest. Although the weather regimes have large-scale canonical precipitation patterns, in some particular cases the reconstruction of the precipitation anomaly can nevertheless capture small-scale features: for the WEur region, the reconstruction easily captures the wet zone over eastern Spain with a maximum of dry intensity over the province of La Coruña. A special case is the reconstruction over the EEur region, which proposes a dry anomaly over the region of interest, but extends it to the rest of northern Europe. In this way, the reconstructed pattern resembles the reconstructed pattern for the Scand region. This stems from similarities in the frequency anomalies of WRs preceding droughts in these regions, with the AT, MTr and ScBL regimes being overrepresented.

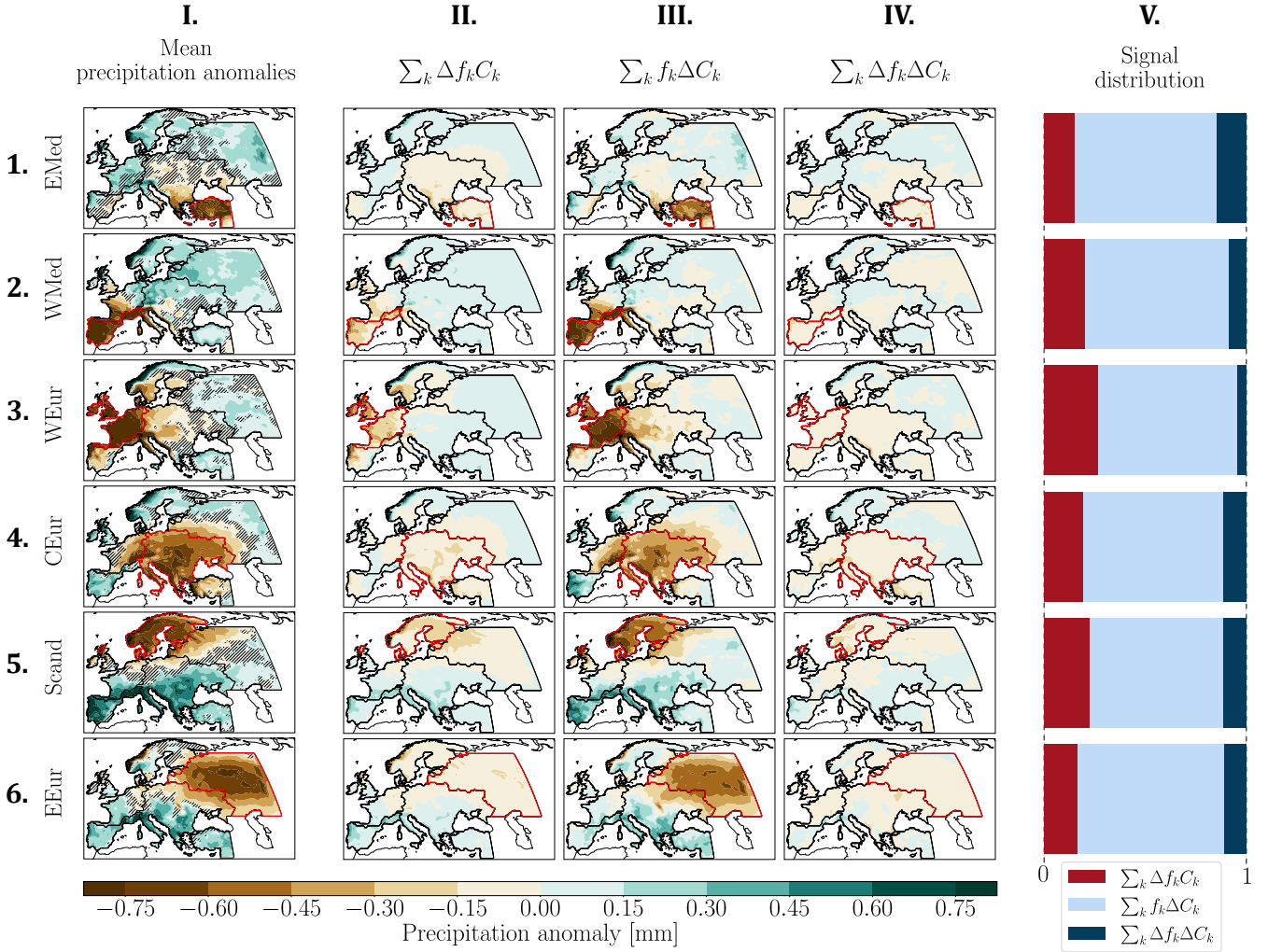


Figure 7. (I) Composite precipitation anomaly over the 3 months preceding the droughts for each region. Non-significant results (p -value > 0.05) are hatched. (II to IV) Precipitation anomaly reconstructed by each term of Eq. 10 and (V) relative contribution of each term to the total precipitation anomaly.

The $\Delta f_k \Delta C_k$ term (see column IV of 7) is weak whatever the region. While less straightforward to interpret, this term can be understood as the departure of the canonical precipitation pattern occurring when the associated WR is abnormally frequent. Thus, the weak amplitude of this term can be explained by considering that this is a 2nd order term, expected to be less powerful than the other one. The sum of the three terms is not exactly equal to the composite precipitation anomalies over the three months (see Fig.7-I).



Therefore, when averaging out over all the drought events, most of the precipitation deficit signal comes from a departure from of the canonical pattern of the WRs, and conversely, a reduced fraction can be attributed to the change in their frequency . However, for the latter contribution, we have shown that the shape of the original signal is reproduced despite a weak amplitude. This might be a consequence of averaging out over many drought events, which could conceal a variety of situations. In the next section (see Sect.3.2), we analyse the relative contributions of the three terms for each individual drought event, rather than on average over all droughts.

While this analysis has been carried for all six regions, the following section only shows the results for the WEur region for the sake of brevity. However, the studies presented below were carried out for all regions. The results can be found in the supplementary material.

3.2 WR contribution to individual droughts

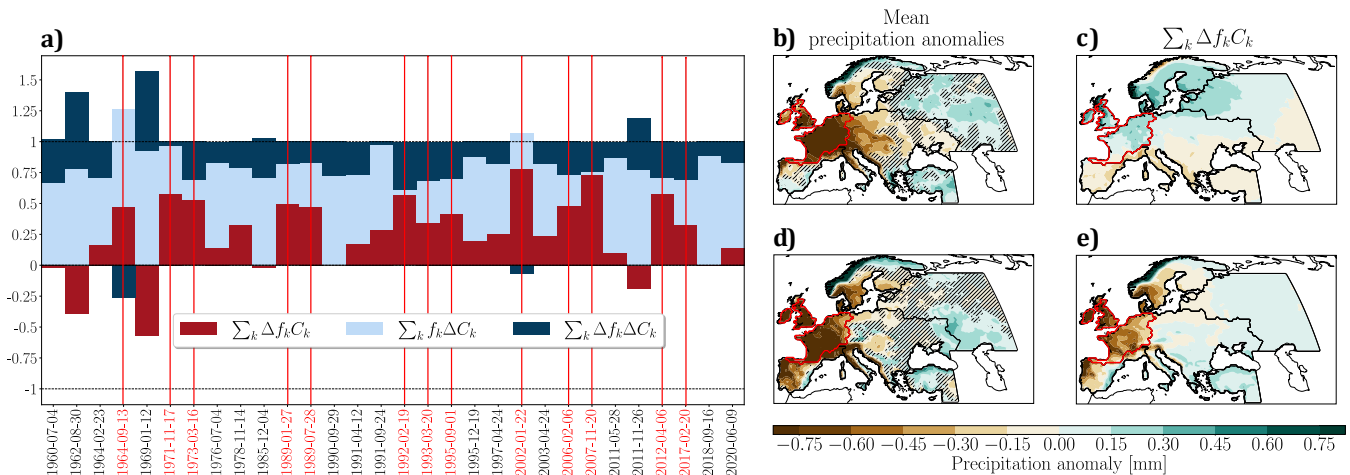


Figure 8. (a) Precipitation anomalies averaged over the 91 days preceding droughts, for all cases where droughts cannot be explained with year-round weather-regimes. (b) Mean reconstruction's first term. (c) and (d) Same for all cases where droughts can be explained with year-round weather-regimes. (e) Precipitation anomalie signal distribution for each droughts of the region WEur, red vertical lines highlighting well reconstructed droughts

Fig.8 shows the distribution of the signal between the three terms for each of the droughts detected over the example of the WEur region. Negative values indicate that the contribution of the concerned term is of opposite sign to the actual precipitation anomaly (e.g. a wet contribution to a dry anomaly). The table 4 shows, for each region, the percentage of droughts for which the contribution of anomalous WR frequencies is relatively high, i.e. that fulfill the criterion $\alpha_1 > 0.33$ (see Methods). The right column shows the number of droughts that fulfill this criterion over the number of detected droughts in this region. The regions with the higher percentage of droughts that can be explained by the WR frequencies are WEur, WMed and Scand.



Reg. name		
EMed	17.8	5/28
WMed	36.8	14/38
WEur	46.7	14/30
CEur	23.8	5/21
Scand	37.5	9/24
EEur	13.0	3/23

Table 4. Percentage of drought for which $\alpha_1 > 0.33$.

350 Those western regions are the ones that are the most influenced by the North-Atlantic circulation. The EMed region and EEur are the two regions the least influenced by the large-scale atmospheric circulation, since only 17.8% and 13.0% of their respective droughts are substantially explained by anomalous WR frequencies.

355 Panels a) and b) in Fig.8 show the mean of the precipitation anomalies and the mean of the reconstructed signal, in cases explained by anomalous WR frequencies. Figures c) and d) show the cases that are explained by anomalous WR frequencies.

For these two categories of droughts, the dry pattern is very similar, but with a slight eastward extension in the case of droughts that cannot be explained by WR. About 50% of droughts in the WEur region can be explained by anomalies in WR frequency, in the sense of $\alpha_1 > 0.33$. In these cases, the average dry pattern is well reconstructed and is characterised by a dry
360 anomaly extending southwards to a large part of the Iberian Peninsula. The reconstructed pattern faithfully captures medium-scale details, such as the rainfall anomaly over eastern Spain and eastern Italy. The explanation provided by the weather patterns therefore provides a satisfactory understanding of the dry anomaly.

For cases poorly captured by the anomalies of WR frequencies, the reconstruction shows a north-south gradient of reconstructed precipitation, which does not correspond to the actual dry anomalies. The region of interest is even reconstructed with a slightly wet anomaly. This can be seen in sub-Fig.e) of Fig.8, by observing that the α_1 signal is either very weak or negative
365 in such cases.

3.3 Frequency anomalies

We have just shown that nearly 50% of the WEur droughts can be satisfactorily reconstructed through the frequency anomaly
370 of WRs (fig. 8e). Fig.E1 shows these frequency anomalies for each of the WRs, calculated for the droughts for which the WE contribution is substantial (right) or not substantial (left).

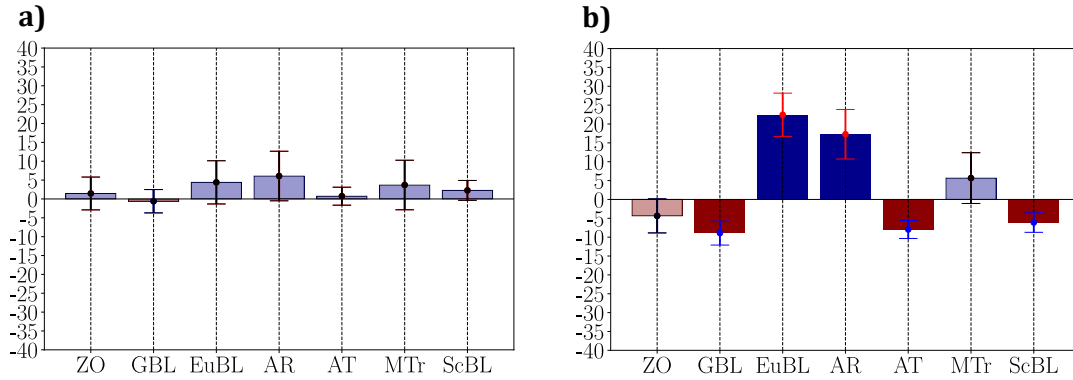


Figure 9. (a) Frequency anomaly of WRs in the 90 days preceding WEur droughts where the α_2 or α_3 terms are predominant ($\alpha_1 \leq 0.33$). (b) Same as (a) for droughts where $\alpha_1 > 0.33$.

This figure illustrates the fact that the droughts for which the Δf_k signal is predominant are also the droughts for which the weather regimes have a well-marked frequency anomaly. The confidence interval associated with droughts where the ΔC_k term dominates does not allow us to conclude on any significant WR frequency anomaly. Therefore, these droughts are not
 375 mainly triggered by the anomalous occurrence of WRs. Appendix E1 shows similar results for all the other regions. All of the regions shows no significant frequency anomaly for droughts for which the Δf_k signal is not predominant. Some of them are significant but with a very low amplitude. The Scandinavian region, for instance, shows significant anomalies but with a maximum amplitude of 10%, and with an uncertainty of $\pm 7\%$.

380 Signs of the frequency anomalies shown in Fig.9b are the same as the average frequency anomalies over all the droughts, but with a stronger signal. This suggests that regime frequency anomalies are informative, but only really contribute to drought (i.e. precipitation deficit) when they are sufficiently strong. Averaging over all the events (cf. previous section) leads to an attenuation of the precipitation anomaly signal. However, the shape of the signal is still there.

385 Seasonality can also come into play when we look at the distribution between droughts substantially explained by anomalous WR frequency. Fig.10 shows the percentage by season of well-reconstructed droughts for all regions, without taking into account the above-mentioned differences concerning the heterogeneity of the reconstruction quality. We find that a higher fraction of winter droughts, and autumn droughts to a lesser extent can be reproduced using our weather pattern approach, with respect to spring and summer. As the large-scale atmospheric circulation is more variable in winter, the classical weather
 390 patterns have a stronger signal in winter. The fact that the link between these new patterns and European seasonal climatology is stronger in winter is consistent.

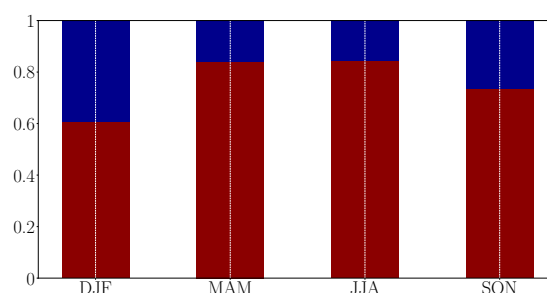


Figure 10. Average fraction of all-regions droughts explained (not explained) by large-scale atmospheric circulation through an analysis of WR frequency in blue (red)

4 Discussion

4.1 Representativity

During this study, we considered that the anomaly in frequency for each WR could be computed relatively to the same climatic frequency. Since this frequency is an averaged frequency over the entire period, this leads to mask variation in WR occurrence. If a regime varies too widely over the period and some periods are more prone to droughts than others, the climatological frequency of the regime during these droughts will no longer be representative of the neutral state of the system.

To verify this, we calculated linear regressions over the entire period on the occurrences of WRs (see Appendix F1 and G1) and obtained that WRs occurrence exhibit no strong trend, excepting the Zonal Regime (significant correlation coefficient of 0.12) which present a positive slope of approximately $+0.5$ per year.

To verify the hypothesis of equidistribution of droughts over the study period, we calculated the change in the number of days separating two consecutive droughts, for all regions (not shown). There was no significant trend (p-value between 0.1 and 0.7 for all regions). Thus, it is consistent to consider droughts to be equally distributed throughout the period, and therefore to take an average climatological frequency to study them.

4.2 Seasonality of reconstruction

The mean precipitation over 91 day periods is reconstructed using precipitation patterns that are assumed to be annually invariant. However, in reality, year-round WRs are associated with a precipitation signature that slightly varies throughout the year, possibly inducing a little bias in our results. We discuss here the implication of these slight variations.



When reconstructed precipitation pattern for a given region, we assumed that the droughts were equally distributed along the year for this region. Hence, if this hypothesis is not perfectly verified, the reconstruction will slightly miss the seasonal component of the precipitation signature associated with the predominant season. For instance, locally, a WR can correspond to precipitation anomalies of opposite sign in winter and summer, which can cancel out when annually averaged. Hence, all reconstructions of precipitation with this weather regime will lead to a near-zero anomaly. With this example, if the studied droughts are not evenly distributed throughout the year, the reconstructed precipitation anomaly based on yearly averaged precipitation patterns will be underestimated.

We thus compute the seasonally-averaged precipitation signature of each WR (Fig. C1). By comparison with the annually-averaged signature (Fig. 5), we can compute for each region and each WR the bias induced by the seasonality of droughts. The results are presented Fig.H1. In these maps displaying the difference annual average - seasonal average, negative precipitation anomaly values (red shades) indicate an underestimation of the real precipitation anomaly with our method of reconstruction, and conversely.

Three striking points emerge : the row corresponding to the ScBL WR, the one corresponding to the AT WR, and the column for CEur. The AT WR shows a systematic underestimation of the precipitation anomaly over the Western Mediterranean region. When looking at the seasonal precipitation anomaly pattern Fig.C1, we can see that the precipitation signature during MAM and JJA is less pronounced than during the other seasons. The WR is equally distributed along the year, but the annually-averaged precipitation pattern will underestimate the precipitation anomaly if droughts occur during the SON or DJF seasons. The same conclusion also concerns the ScBL weather regime: the systematic under-representation of the precipitation anomalies over the western part of Europe, corresponds to a substantial variability in the precipitation pattern along the year for the ScBL WR (Fig. C1-7). The same explanation can be made for the ScBL WR.

The analysis of Fig.H1 by column reveals that CEur exhibits larger bias than other regions when reconstructing precipitation anomalies. This probably means that the droughts are not equally distributed along the year for this region. The seasonally-averaged precipitation pattern for the EuBL are drier for the SON and DJF seasons, while the annually-averaged pattern presents a diminished negative anomaly. This is also a consequence of our regionalization method that led to define a very large CEur region. Hence, we can expect from this region to present the more heterogeneous pattern of droughts, thereby exhibiting a limitation of the choices to keep only 6 regions during the regionalization method.

Although the error due to seasonality is small in the majority of cases, we find that the quality of the reconstruction can however be reduced in cases where the AT or the ScBL regimes are highly predominant.



5 Conclusions

445 The aim of this study is to quantify the strength of the relationship between large-scale North-Atlantic atmospheric circulation and 3-month meteorological droughts over Europe. Droughts are here defined relatively to the seasonal cycle of precipitation, and can thus occur anytime within the year. We use year-round weather regimes (WRs) to assess the link between atmospheric patterns and droughts over regions obtained with an original regionalization method, regardless of the season. We quantify the contribution of WR frequency anomalies in the 3 month preceding the drought to the resulting precipitation deficit. We find
450 that the WR approach to characterize the atmospheric circulation explains only partly the development of European droughts. The strength of the signal depends strongly on the region considered, with a stronger (weaker) influence of the circulation for western (eastern) regions.

The contribution of WRs frequency anomaly is important for around 50% of drought events, since its able to define a frame-
455 work of precipitation patterns that are mostly invariants along the year. The contribution of WRs frequency anomaly is more important for winter and autumn droughts than for summer droughts.

Our findings could have substantial implications in the field of sub-seasonal to seasonal drought predictions, provided forecast models manage to capture and anticipate anomalous WR frequency (Osman et al., 2023; Ferranti et al., 2018). In our future
460 work, we will then assess the capacity of state-of-the-art ESMs to capture the appropriate amount of WR variability and their relation to seasonal precipitation anomalies across Europe. We will also evaluate the stability of this relationship in a context of climate change.



Appendix A: Choosing the optimal number of weather regimes

Building on the methodology proposed by (Lee et al., 2023), we use four metrics to determine the optimal number of weather regimes. These four metrics are chosen according to the following criteria :

- Limiting the number of weather regimes for the sake of simplicity and robustness
- Minimizing the distance of each points of a given cluster to the centroid of this cluster
- Maximizing the distance between each centroids

For each number of cluster, we compute the following indices :

– Intercluster correlation : we compute the Pearson correlation coefficient between the centroid coordinates in PC space, for each pair of centroids. We aim to get the maximal number of cluster such that the pearson correlation coefficient is negative, hence all clusters are anticorrelated. This method leads to $k = 7$.

– Davies Bouldin index : proposed by (Davies and Bouldin, 1979), the Davies-Bouldin index is computed as follows

$$DB(k) = \frac{1}{k} \sum_{i=1}^k \max_{i \neq j} \left(\frac{s_i + s_j}{d_{ij}} \right) \quad (A1)$$

where s_i is the average distance between members of cluster i and the centroid of that cluster, and d_{ij} is the distance between the centroids of cluster i and j . This metric is to be minimized. The computation of this metrics doesn't leads to a clear choice of a number of cluster, but using the elbow method we can see that the optimal number seems to be around 7.

– Intercluster spatial correlation : the Pearson correlation coefficient computed in (a) doesn't take into account the spatial pattern of the weather regimes obtained after clustering. We compute the anomaly correlation coefficient (ACC) between each pair of weather regimes, computed for each number of cluster. Once again we have to keep a negative ACC coefficient to ensure that all pattern are anticorrelated. This metric is not optimized for $k = 7$, and demonstrate that the optimal number seems to be around 4.

– Calinski Harabasz index : expressed as the ratio of intercluster variance over the intracluster variance, we aim to maximize this index. Here, no optimal solution appears as the CH index seams to be strictly decreasing with the number of cluster.

In conclusion, the answer to the question of the optimal number of weather regime is less evident than for the seasonal weather regimes ($k = 4$). The metrics used here do not rule out the $k = 7$ option, which seems to be the best compromise between the maximum number of clusters and the criteria defined above.

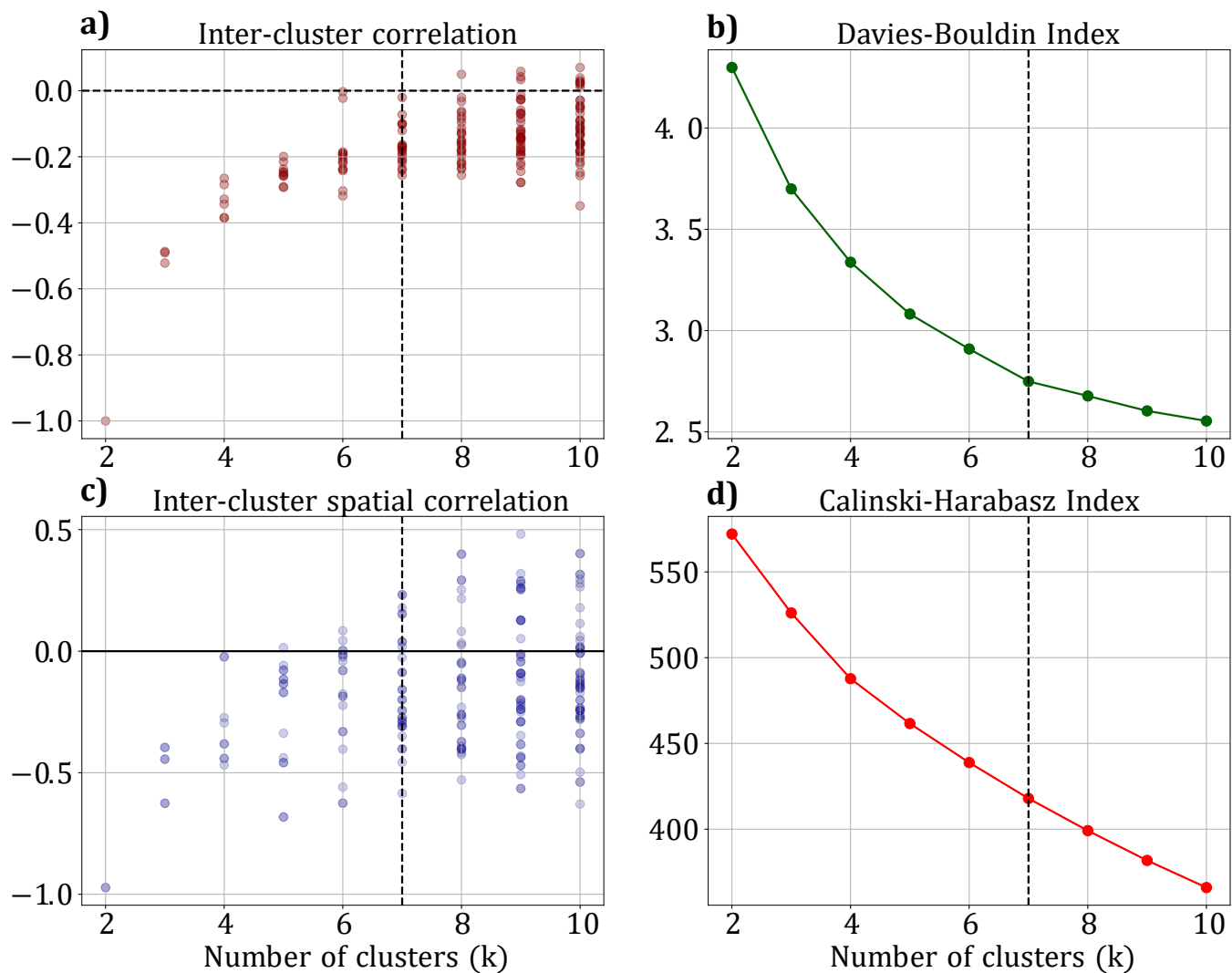


Figure A1. (a) Intercluster correlation : arithmetic distance between the centroids of each cluster, calculated in the Principal Components space. (b) Davies-Bouldin index, expressing the ratio of a point from a cluster to the centroids of this cluster, over the distance of this centroids to other centroids. This metric is averaged for all clusters. (c) Intercluster spatial correlation : anomaly correlation coefficient between all centroids, calculated in the EOF space. (d) Calinski-Harabasz index : ratio between intercluster variance and intracluster variance.



490 Appendix B

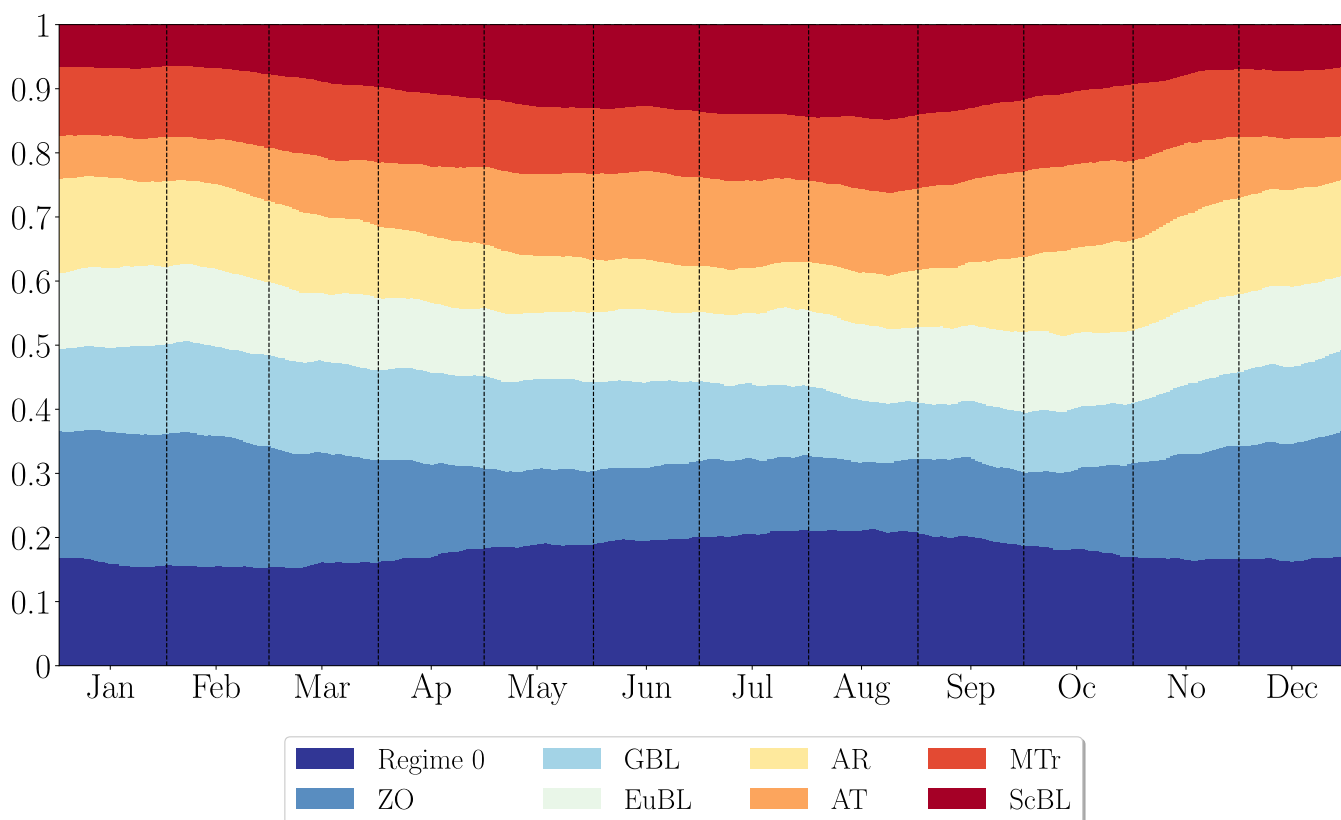


Figure B1. For each day of the year, average frequency of WRs computed over the period 1960 – 2022.



Appendix C

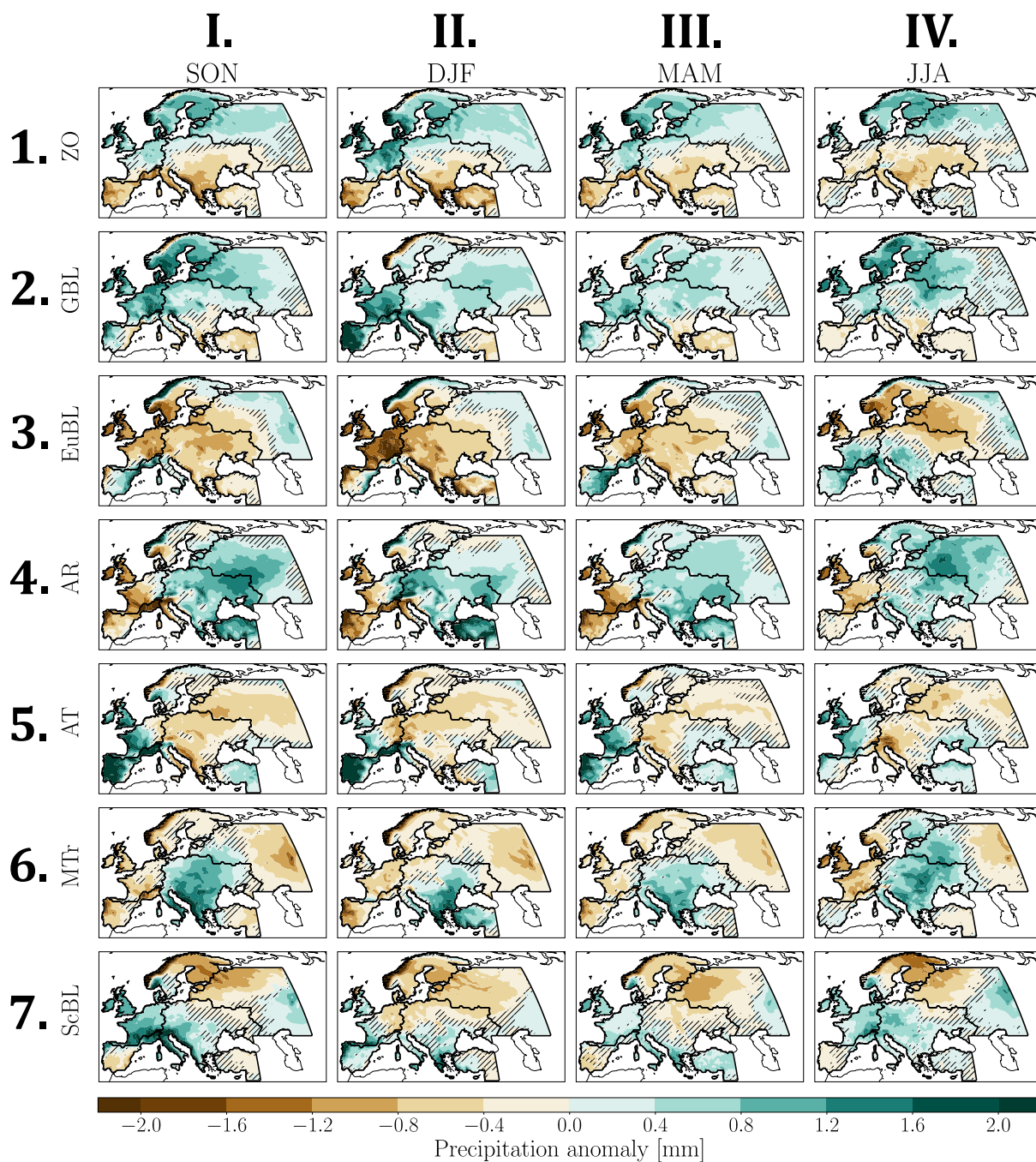


Figure C1. Seasonal precipitation anomalies (in mm) obtained for each weather regime. Non-significant values ($p\text{-value} > 0.05$) are hatched



Appendix D

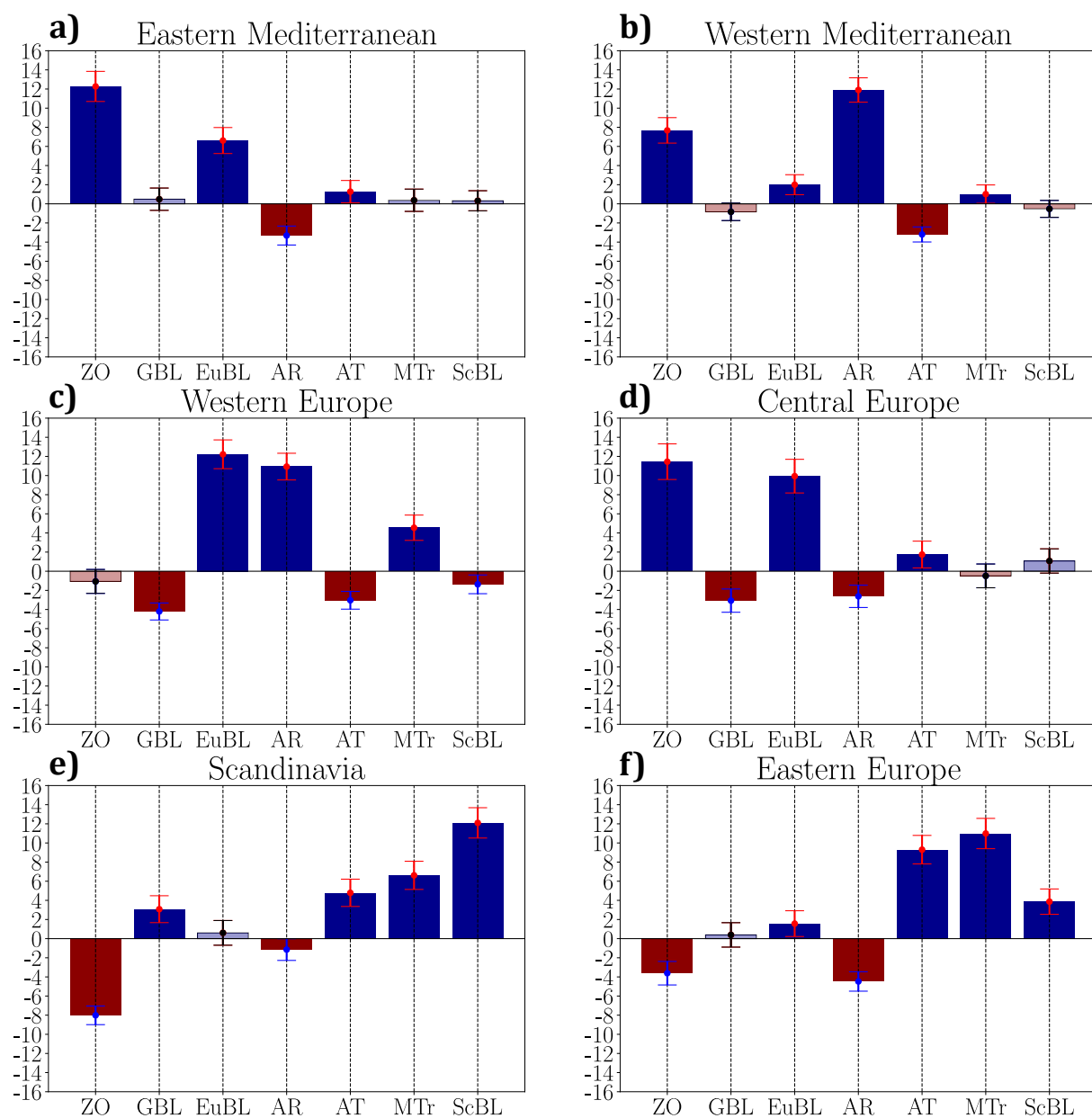


Figure D1. Difference in frequency of occurrence of each regime between the period of 91 days preceding the droughts in each region and the frequency of occurrence.



Appendix E

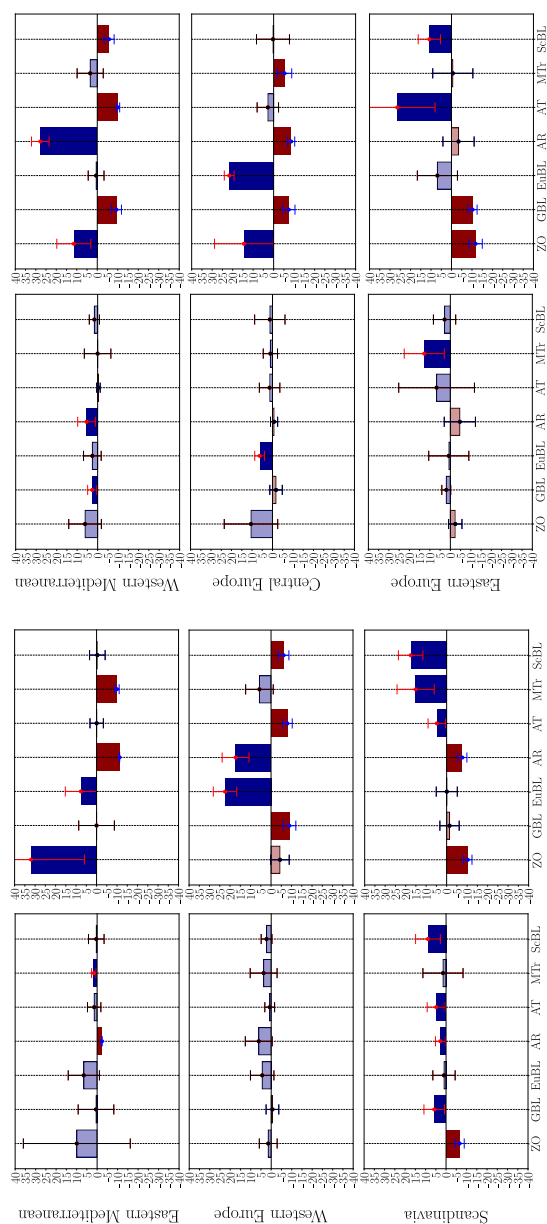


Figure E1. Frequency anomalies for droughts unsuccessfully reconstructed with the WR approach (left) and successfully reconstructed (right)



Appendix F

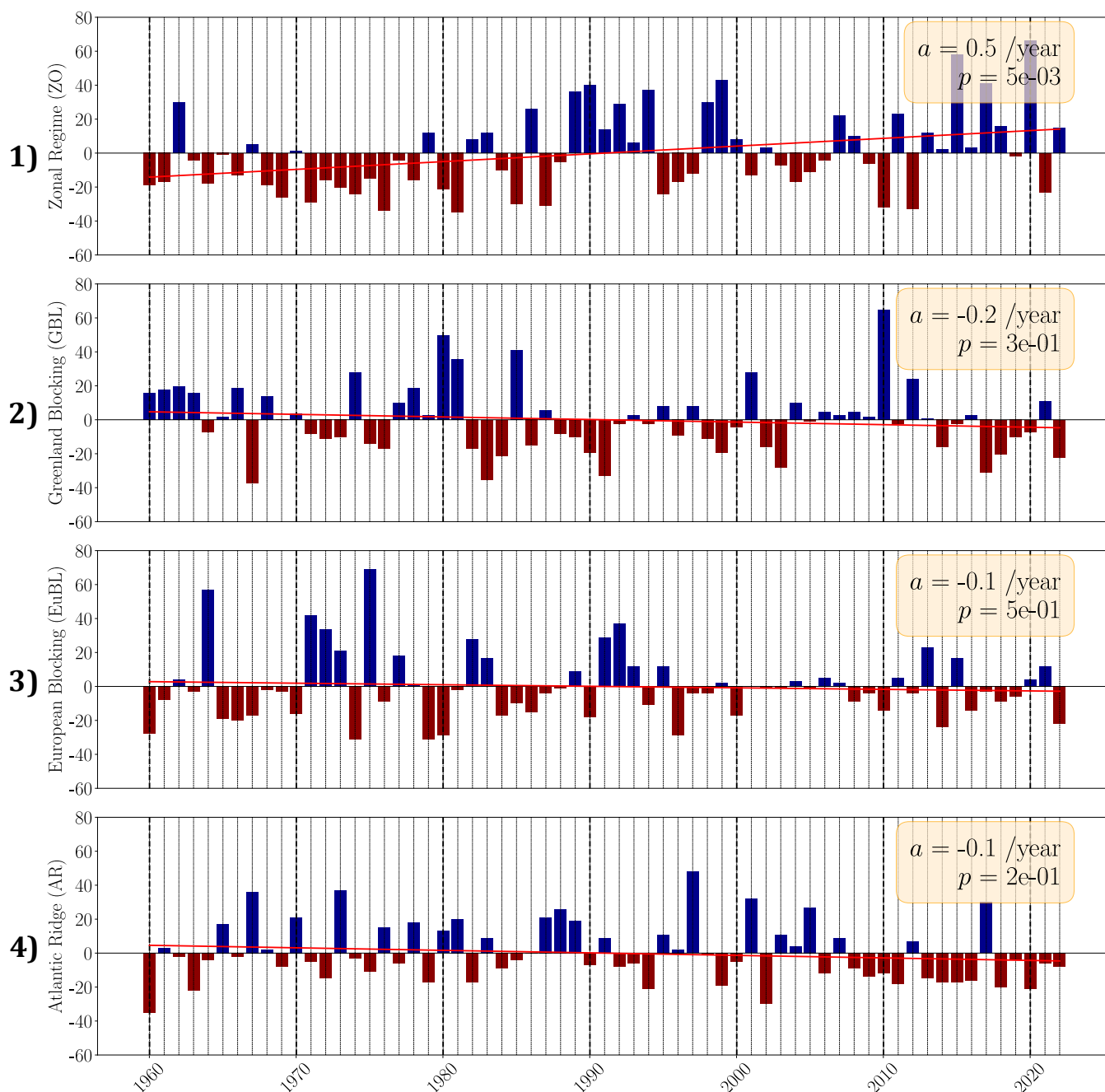


Figure F1. Annual number of days spent in the regimes, relatively to the average number of days calculated over the period 1960 – 2020. Linear trend obtained by regression (in red).

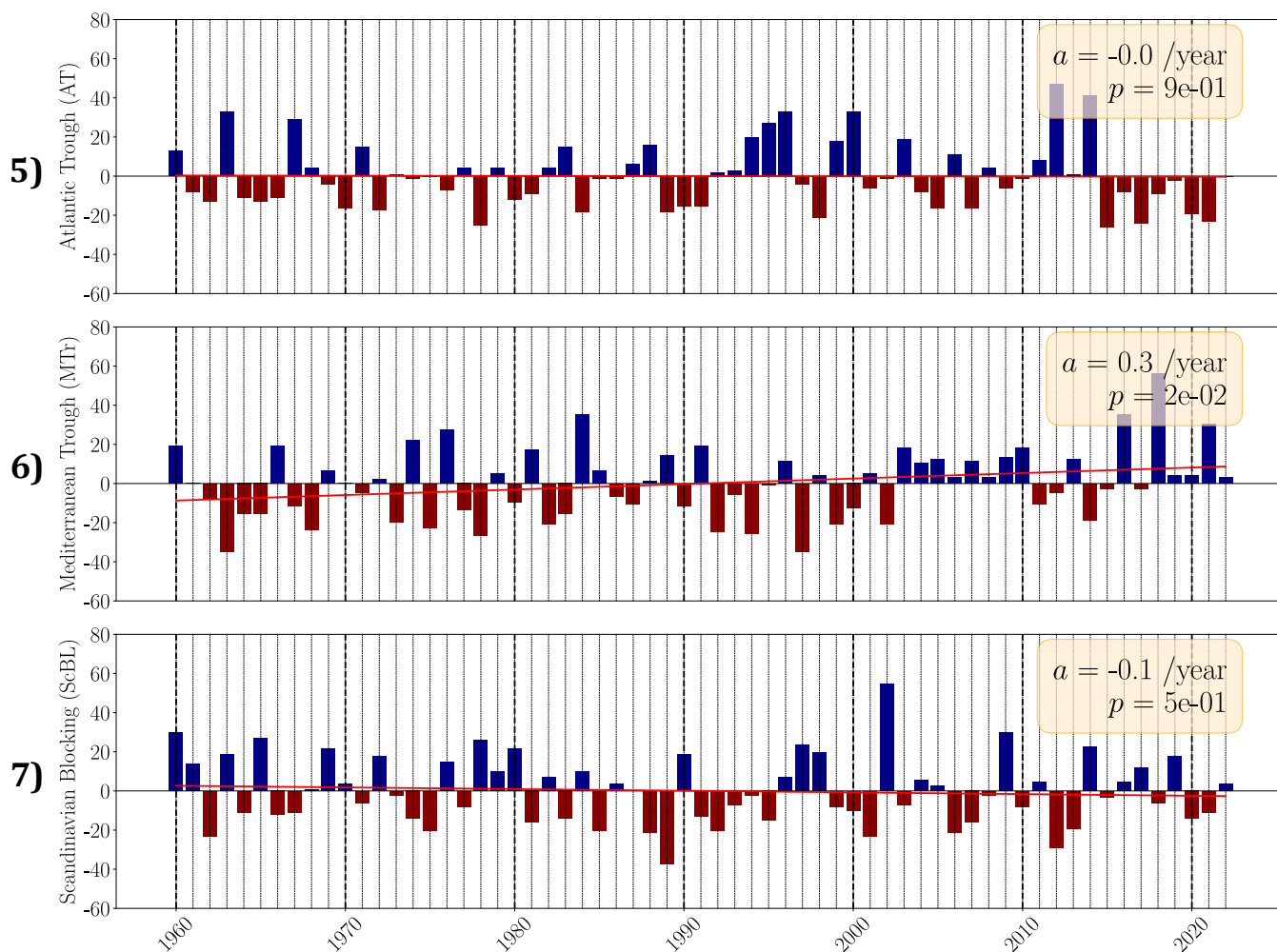


Figure F2. Annual number of days spent in the regimes, relatively to the average number of days calculated over the period 1960 – 2020. Linear trend obtained by regression (in red).



495 Appendix G

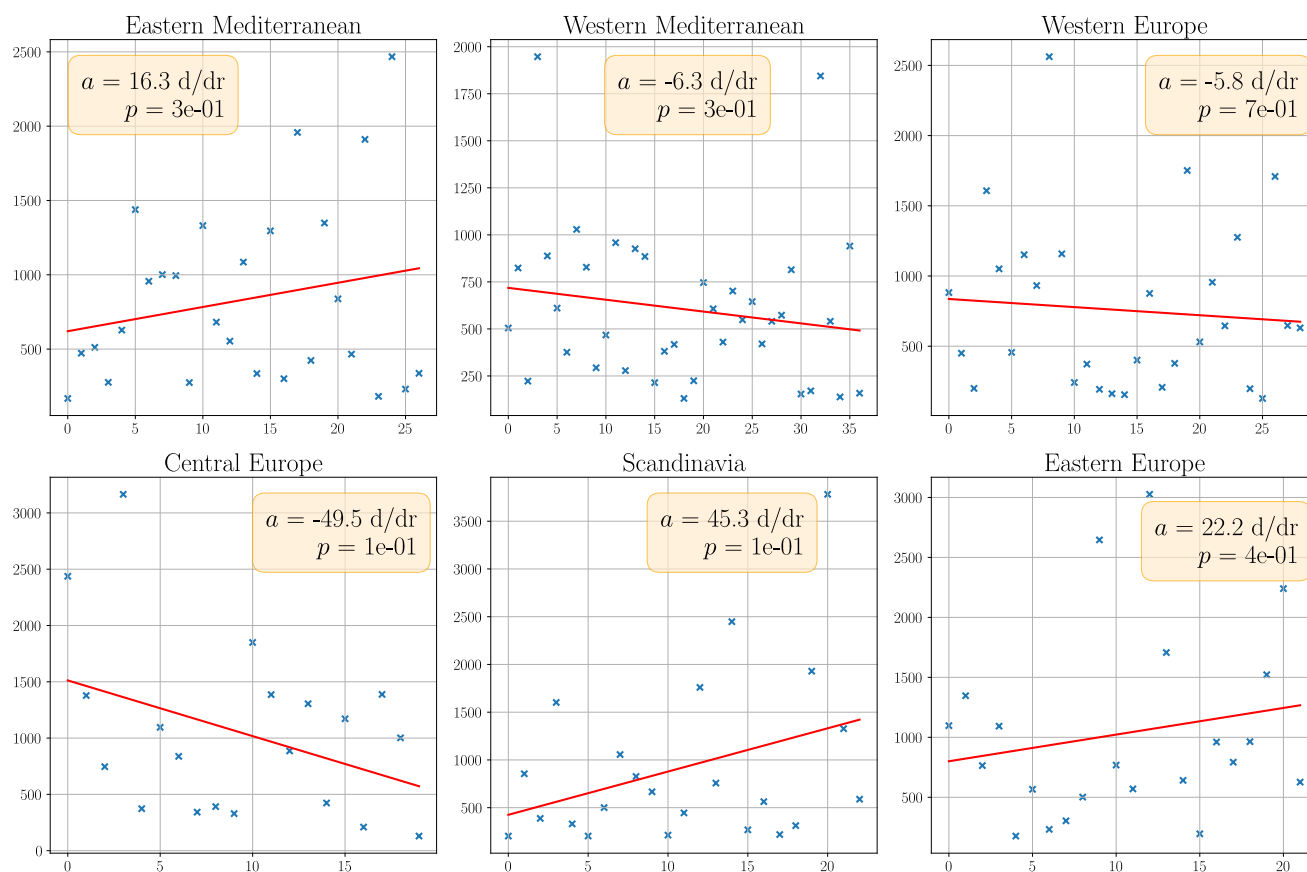


Figure G1. Evolution of the number of days between two successive droughts, for each regions. Linear trend obtained by regression (in red).



Appendix H

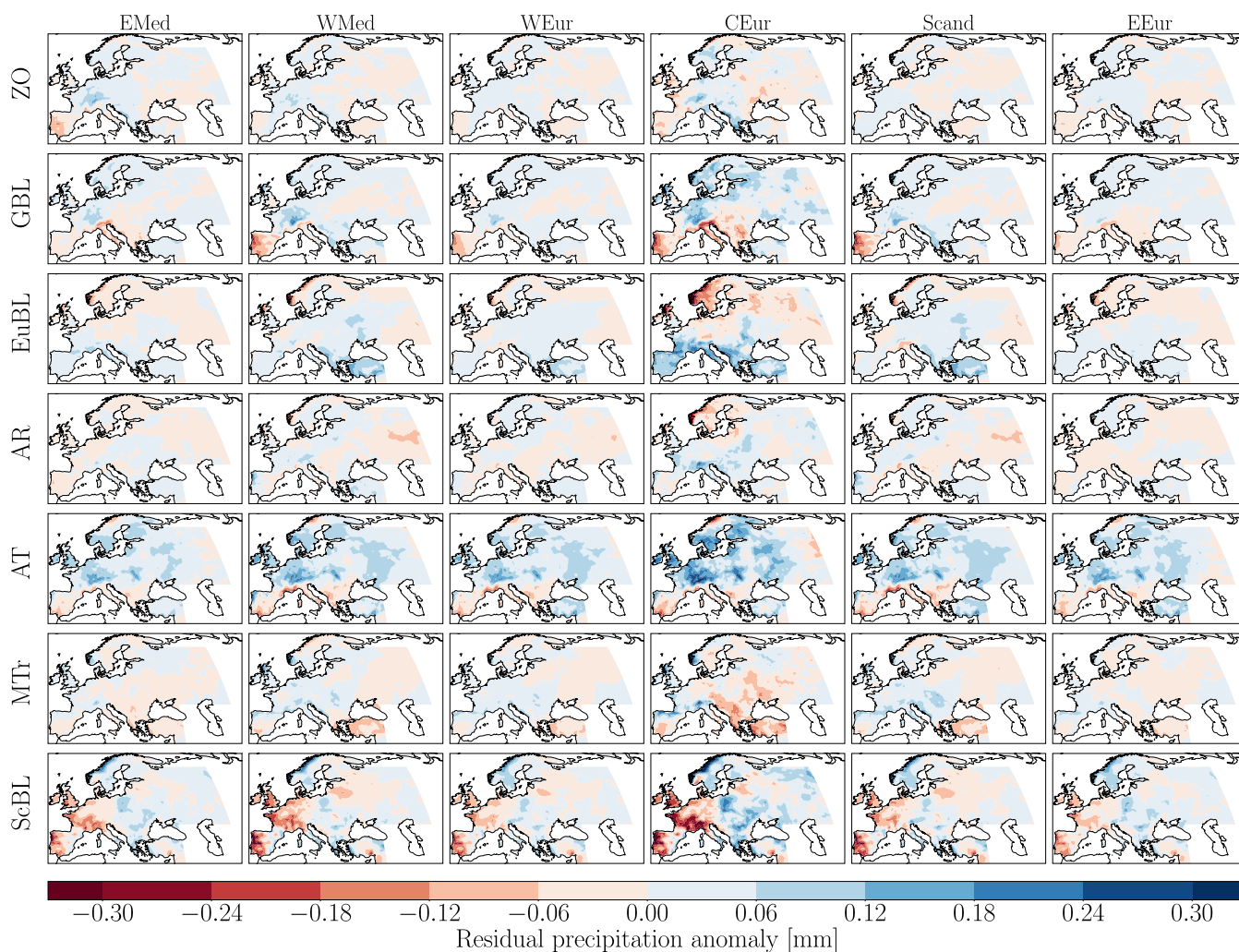


Figure H1. For each WR, difference between the composite obtained by considering an equirepartition of droughts along the year for this region, and the real composite obtained by taking into account the variation of number of droughts from one season to another.

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Author contributions. O. Savary prepared the manuscript with contributions from all co-authors.

Competing interests. The authors declare that they have no conflict of interest.



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