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RESEARCH ARTICLE

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Precipitation trends in the island of Ireland using a dense, homogenized, observational dataset

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Abstract

A dense monthly precipitation dataset of Ireland and Northern Ireland was homogenized with several modern homogenization methods. The efficiency of these homogenizations was tested by examining the similarity of homogenization results both in the real data homogenization and in the homogenization of a simulated dataset. The analysis of homogenization results shows that the real dataset is characterized by a large number of, but mostly small, non-climatic biases, and a moderate reduction of such biases can be achieved with homogenization. Finally, a combination of the ACMANT and Climatol homogenization results was applied to improve the data accuracy before the trend calculations. These two methods were selected for their proven high accuracy, missing data tolerance and ability to complete time series via the infilling of missing values before the trend calculations. Metadata were used within the Climatol method. To facilitate this analysis the study area was split into smaller climatic regions by using the Ward clustering method. Five climatic zones consistent with the known spatial patterns of precipitation in Ireland were established. Linear regression fitting and the Mann-Kendall test were applied. Low frequency fluctuations were also examined by applying a Gaussian filter. The results show that the precipitation amount generally increases in the study area, particularly in the northwestern region. The most significant increasing trends for the whole study period (1941–2010) are found for late winter and spring precipitation, as well as for the annual totals. In the period from the early 1970s the increase of precipitation is general in all seasons of the year except in winter, but the statistical significance of this increase is weak.

KEYWORDS

ACMANT, Climatol, homogenization, Ireland, precipitation, trend, Ward clustering

1 | INTRODUCTION

The quantity of precipitation is of high importance for theoretical and applied research and also directly impacts the lifestyle of people. Long series of precipitation observations have been produced in many parts of the world to monitor both the spatial and temporal variation of this essential climate variable. Trend and temporal variability of observed precipitation have been examined recently for various European countries, for example, for

Ireland (Murphy *et al.*, 2018), England (de Leeuw *et al.*, 2016), Germany (Duan *et al.*, 2019) and Switzerland (Isotta *et al.*, 2019), and also for countries outside of Europe (Vincent *et al.*, 2015; Hu *et al.*, 2017; Abahous *et al.*, 2018, etc.). Precipitation trends are also examined on continental and global scales (Allan and Zveryaev, 2011; Li *et al.*, 2016). Station rain gauge series are used most frequently, followed by gridded data (González-Hidalgo *et al.*, 2011; Wang *et al.*, 2014; Jones *et al.*, 2016; Iqbal *et al.*, 2019). By contrast, for data sparse land regions and overseas and oceans satellite data are frequently used (e.g., Hatzianastassiou *et al.*, 2016; Zhang *et al.*, 2017; Qin *et al.*, 2019). However, it should be noted that rain gauge data are generally more accurate (Tong *et al.*, 2014), therefore their use is preferred where they are available with sufficient temporal coverage and spatial density. The analysis of the temporal variability of observed precipitation data is often accompanied by (a) careful quality control (QC) procedures and time series homogenization, that is, filtering of non-climatic impacts from the observed data (e.g., González-Hid*algo et* al., 2011; Irannezhad *et al.*, 2014; Pérez-Zanón *et al.*, 2017); (b) analysis of the relationship with large scale circulation patterns (Gutiérrez-Ruacho *et al.*, 2010; Romano and Preziosi, 2013; Duan *et al.*, 2017), and with other climatic elements (Yasunaga and Tomochika, 2017; Beranová and Kyselý, 2018); (c) analysis of extreme precipitation indices based on data of daily resolution (Murawski *et al.*, 2016; Valdes-Abellan, 2017; Maheras *et al.*, 2018).

In this study the trend and variability of precipitation in the island of Ireland will be examined for the period 1941–2010 with a QC-ed and homogenized rain gauge observation dataset of monthly resolution. It is a high density dataset including 703 station series for Ireland and further 207 station series for Northern Ireland. Note, however, that in most of the analysis a subset of 299 series including long and complete series of observed data will be used. Henceforth the whole dataset of 910 series will be referred to as whole IENet and the subset of 299 series as sub-IENet, respectively, while the study area is referred to as either as the island of Ireland or the IENet area.

The study has two main aims: Firstly, the calculation of accurate precipitation trends for the IENet area, and secondly, examining the usefulness of some up-to-date statistical homogenization methods used for the homogenization of the IENet dataset.

The homogenization is based on the use of four homogenization methods: HOMER (Mestre *et al.*, 2013), ACMANT (Domonkos and Coll, 2017), AHOPS (Rustemeier *et al.*, 2017) and Climatol (Guijarro, 2018). In a previous study, the operation and the break detection statistics of these methods have been studied (Coll *et al.*, 2020, hereafter: C2020) with the same precipitation dataset. Here, and as an extension of the previous study, the similarities and differences of the homogenization results will be analysed further before the final homogenization method for application to the climate variability analyses will be selected. The similarity of homogenization results will be evaluated with the calculation of root mean square differences between synchronous monthly and annual values, as well as with the mean absolute difference between the linear trends for the whole study period (1941–2010). A section of the MULTITEST experiments (Guijarro *et al.*, 2017) will be incorporated, since as part of this the Irish precipitation dataset was used for building a homogeneous benchmark. The comparison of the similarities of homogenization results using the real observational dataset on the one hand, and using an artificially developed benchmark dataset on the other side will serve to elucidate more clearly the role of real datasets and benchmark datasets in the assessment of homogenization efficiency.

Trend and variability analyses are often performed for regions with little spatial variability of climate within a region. Such regionalization can be done by principal component analysis (e.g., Brienen *et al.*, 2013), cluster analysis (e.g., Scherrer *et al.*, 2016) or with subjective analysis of varied geographical factors (e.g., Daniels *et al.*, 2014). In this study, the Ward clustering algorithm will be used, and the trend and variability of precipitation will be evaluated for five climatic regions of the island of Ireland. The linear trend of precipitation will be examined for both annual and 3-month seasonal values across the whole study period and for some selected shorter periods.

The organization of the paper is as follows. The data and methods are described in the next section. In Section 3, the similarity of the homogenization results is shown and the results are discussed. In Section 4 the trend and variability of the Irish precipitation data are shown and discussed. The study ends with a discussion and conclusions presented in Section 5.

2 | DATA AND METHODS

2.1 | Observed data

Time series of monthly precipitation totals are collected from stations with rain gauge observations across the island of Ireland. The whole dataset (whole IENet) includes 703 time series of Ireland and 207 time series of Northern Ireland (Figure 1). The datasets have already been subjected to rigorous QC as part of Met Éireann and

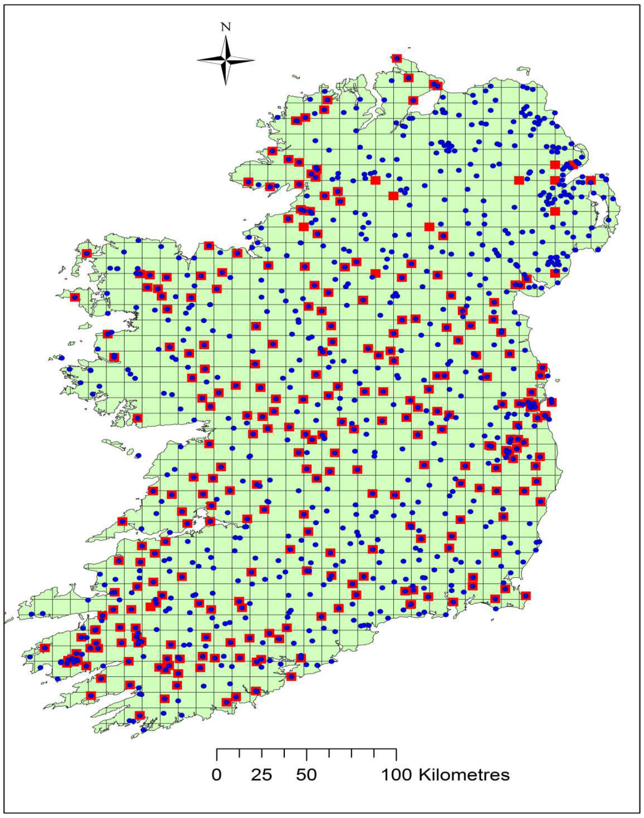

FIGURE 1 Annotated map of the island of Ireland showing the selected met Éireann and met Office, United Kingdom station locations for the network of: (a) 299 stations (sub-IENet) denoted by squares; (b) 910 stations (whole-IENet) denoted by circles. Station details marks are overlain on a regular 10 × 10 km grid to give an indication of density [Colour figure can be viewed at wileyonlinelibrary.com]

the UK Met Office data screening protocols and further QC procedures (C2020). The study period is of 1941–2010, but most of the series do not have fully intact data for this period. In most calculations only the 299 time series with greater than 30 years intact observational records are used, and this subset is referred to as sub-IENet. The mean missing data ratio of the sub-IENet is 24.2%.

The relatively small extent of the IENet area (84,421 km^2), the high station density and the relatively small geographical variation, that is, all station heights are between 5–701 m above sea level, provide high spatial correlations between the precipitation totals. The mean spatial correlation for each of the 10 best neighbours of a candidate series is above 0.9 even in the sub-IENet (not shown).

2.2 | Surrogate data

Within the framework of the MULTITEST project (Guijarro *et al.*, 2017) a surrogate dataset of the IENet precipitation dataset was constructed. The first step was to homogenize and complete the real series with Climatol 3.0 and use these series to calculate variograms, gamma probability distribution coefficients and frequencies of zeros. These parameters were then used to generate 100 homogeneous series of 60 years length by means of the R package "gstat", which allowed the preservation of a realistic spatial correlation structure (López *et al.*, 2016).

Breaks (i.e., sudden shifts in the means) were then inserted into the inhomogeneous part of the dataset to randomly selected positions with 1 per 20 years mean frequency. The values of inhomogeneous periods are biased by multiplying the unbiased values by a factor drawn from a Gaussian distribution of 1.0 mean and 0.2 standard deviation (equivalent to a 20% variation in precipitation).

2.3 | Homogenization methods

Four homogenization methods are applied in this study, although finally one method will be selected to prepare the analysis of precipitation trends on homogenized IENet data. Three from the four methods, that is, HOMER (Mestre *et al.*, 2013), ACMANT (Domonkos and Coll, 2017) and AHOPS (Rustemeier *et al.*, 2017) are developed from the method PRODIGE (Caussinus and Mestre, 2004). PRODIGE is known to be one of the best homogenization methods of the 00s, this evaluation has both theoretical reasoning (Domonkos, 2017; Lindau and Venema, 2018) and justification by tests (Venema *et al.*, 2012). All of HOMER, ACMANT and AHOPS preserve the best theoretical properties of PRODIGE, while also including added favourable features. By contrast, Climatol (Guijarro, 2018) is a more conservative homogenization method based on a stepwise approximation with the single break detection method of Alexandersson (1986), cutting algorithm (Easterling and Peterson, 1995) and spatial interpolation for adjusting inhomogeneities. However, efficiency tests (Guijarro, 2018) prove that the accuracy of Climatol homogenization results is close to that of the modern multiple break methods. See more details about these homogenization methods and their break detection skills in C2020. Note that in this study a newer version of ACMANT is used, that is, the ACMANTv4 (https://github.com/dpeterfree/ACMANT). In this version, the adjustments for inhomogeneities are derived from ensemble scenarios of break populations, and the adjustments are calculated with the weighted ANOVA model of spatially changing climate (Domonkos, 2017).

In applying HOMER and AHOPS only the data of the sub-IENet network are used due to the limited missing data tolerance of these methods. ACMANT and Climatol are used both for the whole IENet and sub-IENet, although it should be noted that only the sub-IENet data are used in the calculation of climatic trends. Additionally, Climatol is used in a third way, that is, with the consideration of metadata confirmed by two different homogenization methods, from which at least one method is Climatol or HOMER. Note that in the validation of metadata a larger role is given to Climatol and HOMER, since both ACMANT and AHOPS are characterized by relatively high false alarm rates (C2020). The validation of metadata with statistical break detection methods is presented in C2020. We have found 50 cases in which Climatol or HOMER detected a break close to the timing of a validated metadata. From 45 of these 50 cases Climatol detected the event within 2 years distance from the date of the metadata. In the preparation of the Climatol homogenization with metadata use, the break position of Climatol detection was shifted to the timing of the nearby metadata if the time lapse was shorter than 2 years, while new breaks were added in the remaining five cases.

Before the calculation of climatic trends, a combination of two methods, namely the results of Climatol with metadata use and the results of ACMANTv4 were averaged. Both these participating methods used the data of the whole IENet in this final homogenization, and the use of this denser network improved their accuracy. Within the homogenization procedure, all the time series are completed to extend across the entire study period. In the data completion, spatial interpolation is applied to infilling gaps of the observed series with the help of the intrinsic routines of ACMANT and Climatol. It has been found in previous work that the infilling of data gaps with spatial interpolation does not have adverse effects on the accuracy of climatic trends (Domonkos and Coll, 2019).

2.4 | Similarity of homogenization results

Precipitation amounts are expressed in mm / monthly total unit in the analysis of similarities and differences. Root mean square difference (D_r) and mean absolute difference of linear trends (D_t) are used to characterize the similarities of and differences between homogenization products of different homogenization methods. Mean absolute trend differences are expressed by the 70-year mean changes of monthly totals. Beyond the use of D_r and D_t, similarity indices are constructed whose values do not depend on the frequency and magnitude of the adjustments applied in the homogenization methods. For these indices (S_r and S_t), products with random adjustments are generated (D_{r0} and D_{t0}), in which the signs and magnitudes of adjustments randomly vary, but the mean adjustments are the same as in the real homogenization products. The purpose of these random adjustments is to set $S = 0$ for the case of random adjustments, set $S = 1$ for the case of whole similarity (identity), and create with the use of these two fixed points a scale of similarity indices.

Let two homogenization products of the same precipitation series be denoted by **A** and **B**.

$$\mathbf{A} = a_1, a_2, \ldots, a_n$$

$$\mathbf{B} = b_1, b_2, \ldots, b_n \quad (1)$$

Where n is the number of the elements in the time series. Then their root mean square difference ($D_r[\mathbf{A},\mathbf{B}]$) is defined by (2).

$$D_r = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(a_i - b_i)^2} \quad (2)$$

Equation (2) can be applied with any time unit, and in the study it is used for the calculation of monthly and annual root mean square differences.

The mean absolute trend difference is shown by (3).

$$D_t = |t(\mathbf{A}) - t(\mathbf{B})| \quad (3)$$

In (3), t stands for the linear trends of the study period (1941–2010).

The root mean square difference with random adjustments (D_{r0}) is defined by the help of raw time series (**Q**) and random variable x (4), (5).

$$D_{r0} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(x_a(a_i - q_i) - x_b(b_i - q_i)\right)^2} \quad (4)$$

$$\{x_a, x_b\} \in \mathrm{U}\left[-\sqrt{2}, \sqrt{2}\right] \quad (5)$$

In (5), U represents uniform probability distribution. With the same logic, the mean absolute trend bias with random adjustments (D_{t0}) is defined by (6) and (7), with the help of random variable y.

$$D_{t0} = |y_a(t(\mathbf{A}) - t(\mathbf{Q})) - y_b(t(\mathbf{B}) - t(\mathbf{Q}))| \quad (6)$$

$$\{y_a, y_b\} \in \mathrm{U}[-2, 2] \quad (7)$$

The similarity indices for root mean square differences (S_r) and mean absolute trend differences (S_r) are described by (8) and (9).

$$S_r = \frac{D_{r0} - D_r}{D_{r0}} \cdot 100\% \tag{8}$$

$$S_t = \frac{D_{t0} - D_t}{D_{t0}} \cdot 100\% \tag{9}$$

To reduce random effects from D_{r0} and D_{t0}, the means of 1,000 repetitions of Equations (4)–(7) are applied in Equations (8) and (9).

A working hypothesis: Higher similarity of homogenization results tends to indicate higher accuracy of the results.

2.5 | Division to regions

The Ward clustering algorithm (Ward, 1963) was applied to the stations of sub-IENet by means of the hclust R function with method "ward.D2", which follows the original description by Ward. Before this step, time series were homogenized by the finally selected homogenization method (Section 2.3).

The Ward method has been widely used and generalized in various ways since Ward's first description (e.g., Murtagh and Legendre, 2014). At the beginning, the number of clusters (K) equals the number of stations. Then, one-by-one, a pair of clusters are merged, whereby K decreases with 1 at each step. The criterion of selecting a pair of clusters at a particular step is based on the minimization of overall within cluster variance (Murtagh and Legendre, 2014). This procedure generates an optimal clustering for all possible K. Finally a K is selected, for which all the clusters represent regions with common climatic – geographic properties. In our case K = 5. The clustering results of seven stations (2.3%) were modified manually based on geographic – climatic knowledge. Figure 2 shows the spatial distribution of the finally selected clusters.

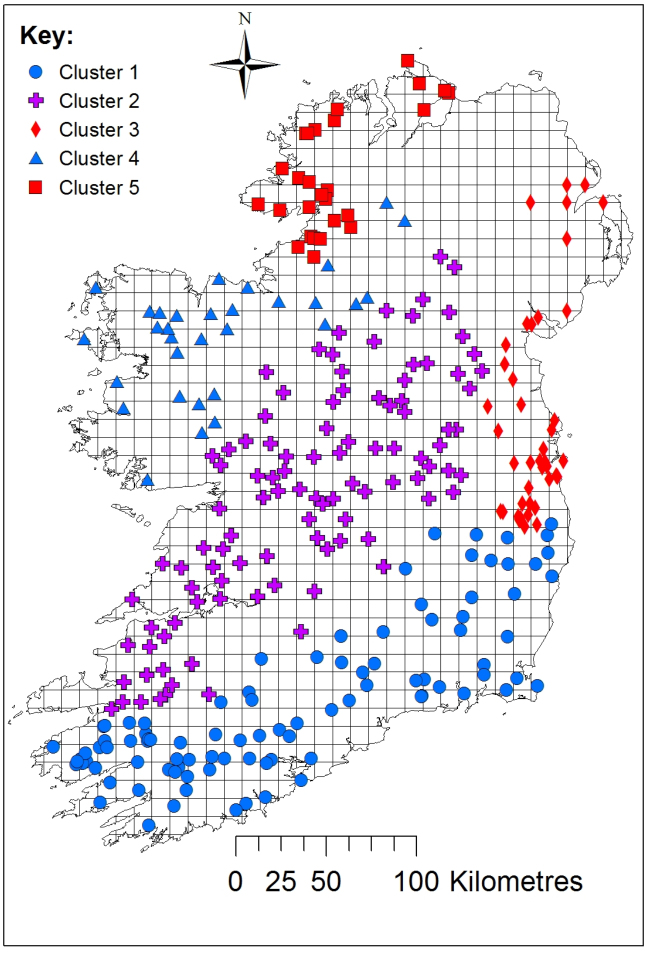

FIGURE 2 Regional classification of sub-IENet stations [Colour figure can be viewed at wileyonlinelibrary.com]

This choice of K and the subsequent regional split obtained is in accordance with earlier knowledge regarding the spatial variation of precipitation in Ireland. Ireland's northeast Atlantic location in the path of the main depression tracks results in a strong west to east decline in precipitation totals. To illustrate the magnitude of this variation, isolated mountain locations in the west and southwest receive over 3,000 mm annually, while areas around Dublin receive less than 750 mm (Sweeney, 1985). Superimposed on this are local spatial contrasts due to the interaction between relief and the prevailing Atlantic air streams; orographic effects can be particularly marked since all the land above 750 m lies within 56 km of the coastline (Sweeney, 1985). Consequently, there are significant rain-shadow effects to the east of the mountains, and there are also cyclonic and convective processes active in introducing further temporal and spatial variability in the mix (Sweeney, 2014).

Due to the surrounding coastal mountains a coast-versus-interior geography is also a principal characteristic of the Irish climate (Sweeney, 2014), and the Central Plain pattern of the precipitation climate is well captured in Cluster 2 of our analysis. Other features of the spatial variation of the precipitation climate are also well captured in the clusters, although there are small overlaps between some of the cluster groups in places. Cluster 1 is capturing the drier south-east and east in the lee of the Cork-Kerry mountains and some of the other eastern hills; while Cluster 3 is capturing the somewhat drier again central eastern and north-eastern pattern. By contrast, Cluster 4 is capturing the wetter western pattern, and Cluster 5 is able to distinguish some of the wettest parts of the country in the north-west.

2.6 | Linear trends and their statistical significance

Linear trend slopes are determined by the calculation of linear regression. The statistical significance is controlled by the Mann – Kendall test (Mann, 1945; Kendall, 1948). The linear trends often strongly depend on the period examined (e.g., de Leeuw *et al*., 2016), therefore we apply a variety of starting and ending dates as has been done similarly in other studies (e.g., Turco and Llasat, 2011; Murphy *et al*., 2020).

The trends are calculated for annual values and for 12 overlapping 3-month seasons (JFM, FMA, etc.). Series of 3-month seasons are examined instead of series of fixed individual calendar months in order to improve the signal-to-noise ratio.

3 | SIMILARITIES AND DIFFERENCES OF HOMOGENIZATION RESULTS

Table 1 presents the root mean square differences and mean absolute trend differences of homogenization methods both for the real sub-IENet and for the surrogate dataset. All the homogenization exercises performed for the real data homogenization and presented in Table 1 are using only the data of sub-IENet. The differences by comparison with the raw dataset are also presented. AHOPS is omitted from Table 1, as AHOPS has not been tested by MULTITEST.

Table 1 shows that the differences between the homogenized and raw time series are much larger in the surrogate dataset than in the real dataset. This finding allows a number of conclusions: (a) In spite of the large number of breaks detected in the real IENet (C2020), the number of large inhomogeneities is much lower there than in the surrogate dataset. (b) Comparing the D_r and D_t values of Table 1 with the climatic mean monthly totals in IENet (~100 mm, Walsh, 2012), this shows that the inaccuracy for inhomogeneities is generally low in the sub-IENet, both for the raw and homogenized data. (c) The results obtained with the use of the surrogate dataset must be treated with caution due to the big difference in the frequency and magnitude of inhomogeneieties between the real and surrogate datasets.

The differences between homogenization results are very similar for the real dataset to those of the surrogate dataset. However, while such differences are much

TABLE 1 Mean differences between the homogenization results in the real sub-IENet dataset and in its surrogate dataset

Monthly root mean square difference (mm/month)								
	Observed data				Surrogated data			
	Raw	HOMER	ACMANT	Climatol	Raw	HOMER	ACMANT	Climatol
Raw	—	3.72	6.24	4.96	—	15.29	15.10	14.81
HOMER	3.72	—	6.48	5.97	15.29	—	6.26	5.88
ACMANT	6.24	6.48	—	5.41	15.10	6.26	—	5.45
Climatol	4.96	5.97	5.41	—	14.81	5.88	5.45	—
Annual root mean square difference (mm/month)								
	Observed data				Surrogated data			
	Raw	HOMER	ACMANT	Climatol	Raw	HOMER	ACMANT	Climatol
Raw	—	2.34	5.38	4.25	—	13.54	13.24	12.96
HOMER	2.34	—	4.83	4.43	13.54	—	5.08	4.79
ACMANT	5.38	4.83	—	4.49	13.24	5.08	—	4.37
Climatol	4.25	4.43	4.49	—	12.96	4.79	4.37	—
Mean absolute trend difference (mm/month for 1941–2010)								
	Observed data				Surrogated data			
	Raw	HOMER	ACMANT	Climatol	Raw	HOMER	ACMANT	Climatol
Raw	—	3.14	7.17	5.55	—	19.73	19.62	19.71
HOMER	3.14	—	5.40	5.01	19.73	—	5.86	5.08
ACMANT	7.17	5.40	—	4.26	19.62	5.86	—	5.14
Climatol	5.55	5.01	4.26	—	19.71	5.08	5.14	—

smaller than the differences from the raw data in the surrogate dataset, these are of the same order as the differences from the raw data in the real dataset. This finding might give the impression that the homogenization of real IENet was unsuccessful or unnecessary. However, the similarity indices will be used subsequently to examine in more detail the similarity of the homogenization results (Table 2).

In Table 2, the similarity indexes are presented for all the executed homogenizations of the real dataset. The similarity between different versions of the same method applications is generally much higher than the similarity between different methods, as might be expected. Comparisons with the raw data are not shown in Table 2, as the similarity with the raw data is 0, it follows from the definitions.

The similarity of the homogenized monthly values is generally low at mostly 9–18%, except between ACMANT and Climatol where it is 35–40%. The similarity of the homogenized annual values is slightly higher, although the improvement relative to the monthly index is not

TABLE 2 Similarity indices of the homogenization results

Similarity index (%) for monthly root mean square differences								
	HOMER	**AC-299**	**AC-910**	**AHOPS**	**Cl-299**	**Cl-910**	**Cl-meta**	**Final**
HOMER	—	16	17	9	16	12	13	16
AC-299	16	—	57	18	40+	35+	35+	50
AC-910	17	57	—	17	40+	37+	37+	66
AHOPS	9	18	17	—	15	13	14	17
Cl-299	16	40+	40+	15	—	66	65	56
Cl-910	12	35+	37+	13	66	—	95	64
Cl-meta	13	35+	37+	14	65	95	—	65
Final	16	50	66	17	56	64	65	—
Similarity index (%) for annual root mean square differences								
	HOMER	**AC-299**	**AC-910**	**AHOPS**	**Cl-299**	**Cl-910**	**Cl-meta**	**Final**
HOMER	—	19	20	13	19	15	15	19
AC-299	19	—	58	24	41+	36+	36+	51
AC-910	20	58	—	22	42+	39+	39+	67
AHOPS	13	24	22	—	19	17	17	23
Cl-299	19	41+	42+	19	—	67	66	57
Cl-910	15	36+	39+	17	67	—	95	65
Cl-meta	15	36+	39+	17	66	95	—	66
Final	19	51	67	23	57	65	66	—
Similarity index (%) for mean absolute trend differences								
	HOMER	**AC-299**	**AC-910**	**AHOPS**	**Cl-299**	**Cl-910**	**Cl-meta**	**Final**
HOMER	—	30	31	28	31	28	29	31
AC-299	30	—	68	57*	52*	50+	50+	62
AC-910	31	68	—	54*	53*	50+	51*	74
AHOPS	28	57*	54*	—	47+	48+	48+	56*
Cl-299	31	52*	53*	47+	—	73	72	64
Cl-910	28	50+	50+	48+	73	—	96	71
Cl-meta	29	50+	51*	48+	72	96	—	72
Final	31	62	74	56*	64	71	72	—

Note: AC-299, ACMANT with the use of the sub-IENet; AC-910, ACMANT with the use of the whole IENet; Cl-299, Climatol with the use of the sub-IENet; Cl-910, Climatol with the use of the whole IENet; Cl-meta, Climatol with the use of the whole IENet + metadata; Final, the finally selected homogenization method (Section 2.4). "*" indicates higher than 50% similarity (S) of independent methods, "+" indicates 33% < S < 51% similarity of independent methods.

significant. The similarity of annual values is mostly between 13–24%, and for the pair of ACMANT and Climatol it is 36–42%. The similarity of homogenized trends is much higher than the similarity of individual annual or monthly values. The similarity between any two of ACMANT, AHOPS and Climatol trend results is between 47–57%, while the similarity between HOMER trends and the trends of any other method is only 28–31%.

The relatively high similarity between ACMANT and Climatol (for linear trends between any two of ACMANT, AHOPS and Climatol) suggests that these methods, in spite of their underlying different methodologies, provide the most accurate results among the methods examined here. It is interesting to note that the 47–57% similarity of trend results is only slightly lower than the 57–73% similarity for the different versions of the same methods, from which only the similarity between homogenizing with metadata or without metadata is higher. On the other hand, it must be noted that high similarity does not necessarily assure high accuracy or high efficiency. Relying only on the similarity results, it could not be excluded that the HOMER homogenized trends are the most accurate and all the other methods fail partly in the same way. However, we can add that HOMER failed to detect 15 breaks which were concordantly detected with the other 3 homogenization methods and were justified also with metadata (C2020), and also, that in MULTITEST experiments ACMANT and Climatol gave better results than some automated versions of HOMER.

Another observation is that the Climatol version using the whole IENet has lower similarity with the other methods (except the trend results with AHOPS) than the version using only the sub-IENet, while the opposite should be expected in line with the denser data in the whole IENet. Note that the capacity of Climatol to incorporate short and fragmented time series has been tested on large benchmark datasets (Guijarro, 2011), hence we assess that the slight decrease of similarity observed here is accidental.

The use of metadata made very little difference in the Climatol homogenization results. The likely reasons for this are that (a) only metadata confirmed by statistical break detection methods were involved, which were in 40 time series (13% of the series in sub-IENet); (b) 85% of the confirmed breaks are detected with Climatol also without the help of metadata and at the same or nearby position as the metadata date; (c) the metadata are used only in the last phase of the Climatol procedure, and this excludes any impact of metadata on the detection of other, non-documented breaks of the dataset. The first two factors show that the incorporation of metadata use in automated homogenization methods tends to be redundant when the station density and spatial correlations are high, as in our case. Note, however, that in certain coincidences of data quality and inhomogeneity issues, metadata can help a lot in clarifying such issues, even in dense datasets (not demonstrated). Factor (c) is related to the restricted use of metadata in Climatol, and it is due to the ambiguity of the incorporation of generally incomplete and non-quantitative pieces of information in an automated statistical procedure. Undesired effects of pre-setting metadata based break positions in time series before statistical homogenization were also reported by Gubler *et al.* (2017).

Considering the low differences between the raw and homogenized data, and the likely minor improvement of accuracy by homogenization, the question remains as to whether it is necessary or not to homogenize precipitation total time series. In contemporary studies of precipitation climate, data are often subjected only to quality control, but not to homogenization (e.g., Anderson *et al.*, 2015), or only inhomogeneities known from metadata are considered (Mekis and Vincent, 2011). In studies related to precipitation observations, low frequency of significant inhomogeneities were found in several other studies (Domonkos, 2015 and references therein). Spinoni *et al.* (2015) reported that series of precipitation amount are less affected by inhomogeneities than the time series of several other climatic elements. However, the situation can be very different when early observations or series of mixed forms of precipitation (i.e., rain and snow) are examined (Auer *et al.*, 2005).

In spite of the doubts discussed here, we recommend the statistical homogenization of precipitation datasets when the station density is sufficient for doing that. Firstly, in spite of most time series not having important non-climatic biases, a few of them may have large and non-documented inhomogeneities, as those were found also in the IENet series (C2020). Secondly, because the non-climatic impacts on observed data depend both on the history of instrumentation and the strictness of following observation rules, and these vary according to countries and the period of data record analysed. Thirdly, because some modern and thoroughly tested homogenization methods, particularly ACMANT and Climatol, almost always improve the mean accuracy of the data (Guijarro *et al.*, 2017), and when large inhomogeneities occur in the raw data, there is a substantial improvement in the affected time series.

4 | TRENDS AND VARIABILITY

Precipitation trends have been calculated using the homogenized sub-IENet dataset (1941–2010). Table 3 summaries the trends for the whole study period,

TABLE 3 Mean seasonal trends of five 66-year periods of 1941–45 to 2006–10, in percentage per decade

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Whole area
DJF	0.6	1.0	−0.4	2.2	2.0	0.9
JFM	1.8	3.5***	0.9	4.6***	5.1***	2.8**
FMA	2.9**	4.3***	2.4**	5.1***	5.4***	3.7***
MAM	2.1***	3.5***	2.4***	4.2***	4.4***	3.0***
AMJ	2.2	1.7	1.7	1.2	0.7	1.7
MJJ	0.7	−0.4	−0.7	−0.8	−1.1	−0.2
JJA	0.2	−1.3	−1.8*	−1.6*	−1.3	−0.9*
JAS	−1.6	−3.2**	−3.5**	−2.6**	−2.1*	−2.5*
ASO	0.6	−0.8	−0.4	−0.1	0.2	0.0
SON	1.8	0.6	1.3*	1.3**	1.1*	1.3
OND	2.1	1.5	2.0	2.3**	1.7	1.9*
NDJ	0.8	0.8	0.3	1.8*	1.4	0.9
Annual	1.2	0.9	0.3	1.5***	1.4***	1.0*

Note: Asterisks indicate statistical significance, 1 (2) [3] asterisks indicate that at least 1 tenth (1 third) [2 thirds] of the station series have significant trends.

obtained with averaging slightly varying starting and ending years near to the endpoints of the study period. The trends show large seasonal variation, but relatively little spatial variation. The most significant trends are found for the late winter and spring seasons where significant increasing trends are detected across the entire IENet area. By contrast, somewhat smaller, but still statistically significant decreasing trends appear in late summer. The annual totals are generally increasing, but the increasing trend is significant only in the NW part of the island of Ireland (Cluster 4 and Cluster 5), while the increase is the smallest near to the east coast (Cluster 3). The regional data reveal that the largest seasonal increasing trend slopes occur also in the NW regions (Cluster 4 and Cluster 5).

Figure 3 and Figure 4 help to analyse in more detail the area-average trends by presenting moving-window Mann-Kendall statistics. These figures show the Mann-Kendall statistics for all possible starting year – ending year pair combinations for periods of at least 10-years.

Figure 3 shows the results for the 4 main seasons (MAM, JJA, SON and DJF). The long-term trends are significant only for spring, and even for this season, only when the starting date is earlier than 1950. Note, however, that the precipitation increases also in autumn, and although with a mild slope, this trend is consistently present with any starting date before 1990.

Figure 4 shows that even in early spring (FMA), which is the season with the largest increasing trends, the trends are significant only for periods starting near to the earliest date of the study period, and this feature only differs slightly for the NW region relative to the average of the whole island of Ireland. Moreover, a significant decreasing trend appears for the last 15 years (from around 1995 to 2010) both for the NW region and for the IENet area. Regarding the annual totals, their increase is slightly significant for the IENet area and more highly significant for the NW region when any starting date before 1970 is chosen.

Figure 5. shows the low frequency changes for the 4 main seasons of the year and for the annual totals, for the IENet area. It can be seen that irregular fluctuations are more characteristic of precipitation changes in the island of Ireland than long-standing systematic trends.

A general increase of precipitation appears from the early 1970s in spring, summer and autumn, as well as in the annual totals, but the statistical significance of the increasing trend in the annual totals is weak (Figure 4c).

5 | DISCUSSION AND CONCLUSIONS

The comparative analysis of homogenization results of various homogenization methods, as well as the comparison between the results of real data homogenization and the homogenization of simulated data proved the high quality of the IENet precipitation dataset, with a large number of, but mostly small, non-climatic biases.

The comparison of differences between the results of the real data homogenization and those of the simulated data homogenization indicates that the magnitude of residual non-climatic biases is partly independent from that of the non-climatic biases in the raw data. Our

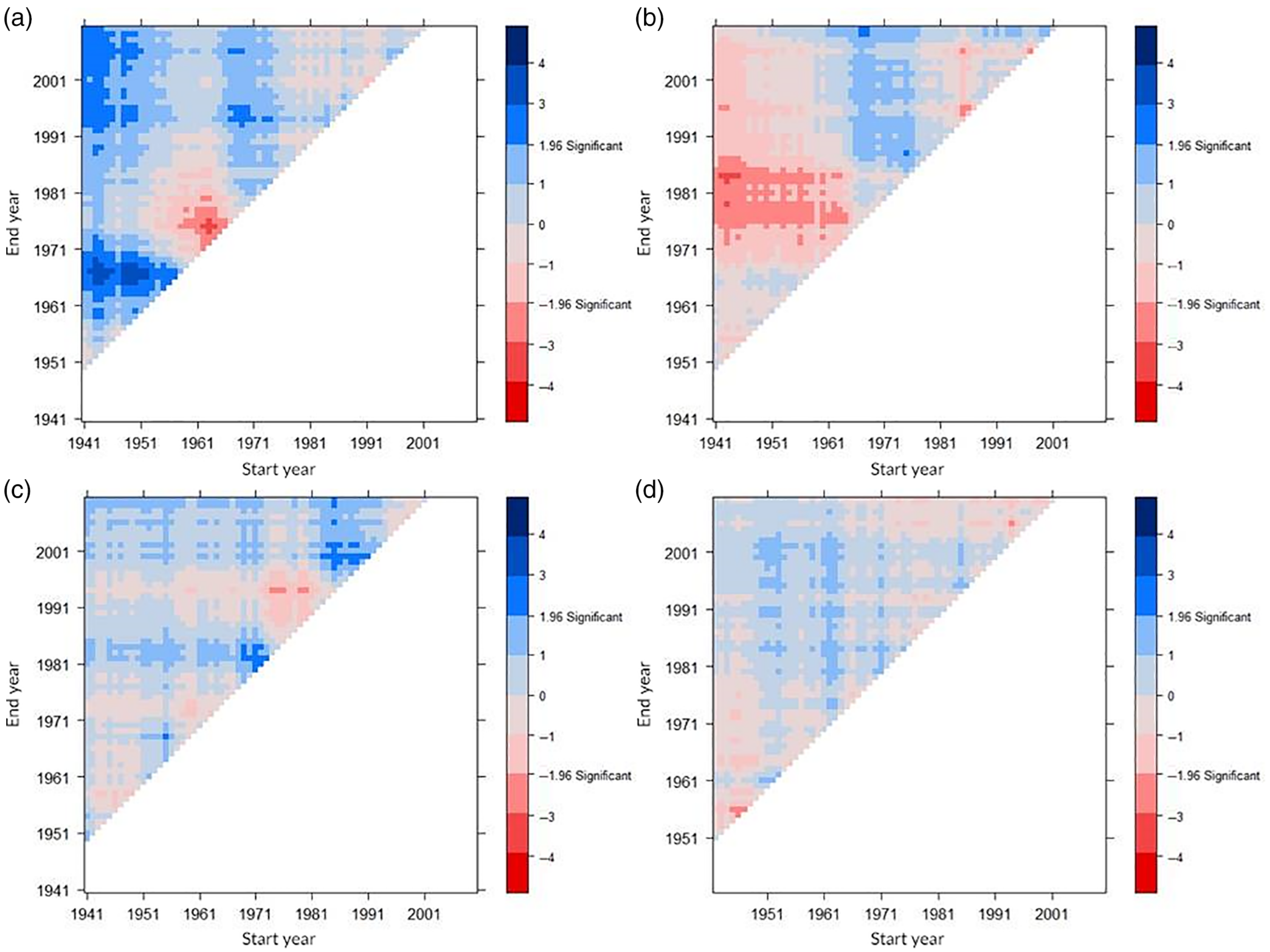

FIGURE 3 Moving window Mann-Kendall statistics in the four main seasons of the year, for the entire island of Ireland. (a) MAM, (b) JJA, (c) SON, (d) DJF

results indicate that a moderate reduction of non-climatic biases can be achieved in dense precipitation datasets with small magnitude non-climatic biases like the IENet dataset. We have applied a combination of ACMANT and Climatol homogenization results to further improve data quality. We selected these two methods for their proven high accuracy, missing data tolerance and ability to complete time series by infilling data gaps before the trend calculations. The Climatol homogenization included metadata use.

Precipitation totals have a general increasing trend over the island of Ireland, but the trends vary substantially according to the season of the year and the period selected for analysis, in addition they also show more moderate, but still substantial variation according to geographical regions. If the entire study period (1941–2010) is considered, the most sharply increasing trends occur in late winter and spring, while for the period from the early 1970s the increasing trends are general in all seasons except in winter. When the seasonal differences of trends for the entire study period are examined (Figure 6), symmetric (opposite) trends are found for the late summer and late winter – early spring seasons, although with milder slopes and weaker statistical significance in late summer than in late winter.

In Figure 6 the same pieces of the results appear as in Table 3. However, this illustration makes for an easier comparison with the results of Daniels *et al.* (2014) about the seasonal curve of precipitation trends in the Netherlands over the period 1951–2009. In the Netherlands, the highest positive trend was found for February and a secondary peak for November, while the smallest (although still non-negative) trends are for July, August and September, so the similarity with Figure 6 of this study is striking. A further similarity to the precipitation trends of the Netherlands is, that the largest positive trends were found in regions close to north-western coasts, in both of the island of Ireland and the Netherlands.

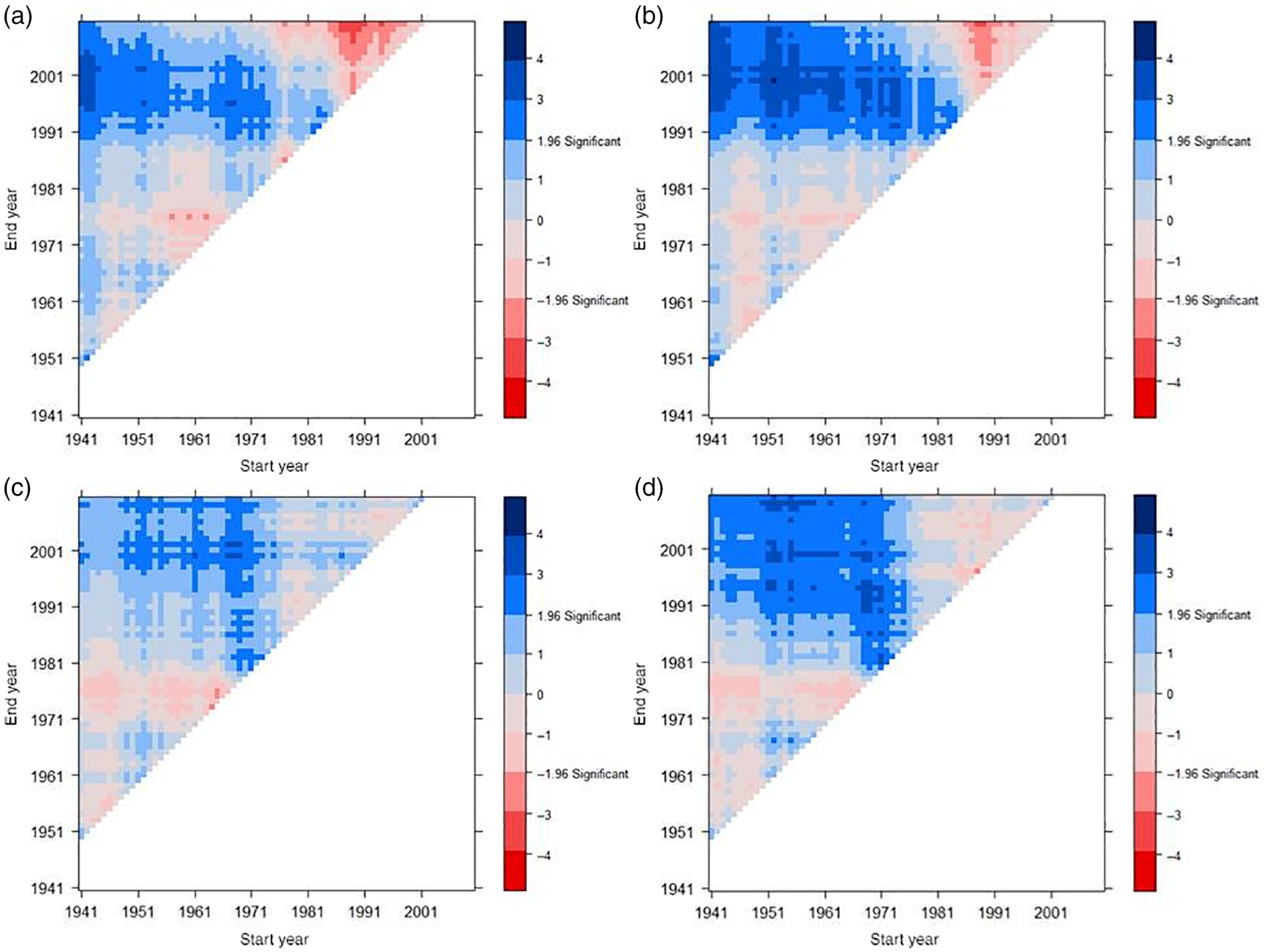

FIGURE 4 Moving window Mann-Kendall statistics for the early spring season and for the annual totals. (a) FMA, whole IENet area, (b) FMA, NW region (Cluster 4 and Cluster 5), (c) annual total, whole IENet area, (d) annual total, NW region

The increase of late winter – early spring precipitation over the IENet area is likely linked to the intensification of westerlies in the region in that season. The increase of winter precipitation over the British Islands in the last decades of the 20th century in connection with the intensification of westerlies, was reported first in the 90's (Wilby *et al*., 1997). More recently, an in-depth analysis of the winter precipitation – macro-circulation relationship for the entire Euro-Atlantic region (Ummenhofer *et al*., 2017) found that the domination of a circulation pattern characterized by stronger than average meridional sea level pressure gradients over most part of the Euro-Atlantic region has become more frequent after 1980.

The North Atlantic Oscillation (NAO) is a primary mode of seasonal variability in the North Atlantic region, affecting numerous climate parameters. For example, the NAO is related to the severity and track of storms and depressions across the North Atlantic region and into Europe, and also influences the strengths of the prevailing westerly winds (Osborn, 2006; Vallis and Gerber, 2008). However, while the winter North Atlantic Oscillation Index (NAOI, https://climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-station-based) has also shown a tendency towards a more positive phase in recent decades, its correlation with the intensity of westerlies is moderated and depends upon how the NAOI is defined (Allan *et al*., 2009; Coll *et al*., 2013). A study by Matthews *et al*. (2016) reported that regional cyclone frequency over and around the British Isles does not have significant connection with the winter – spring precipitation anomalies of that region, rather it suggests that the lifting air in fronts of remote northern cyclones and orographic uplifting are responsible for the positive precipitation anomalies over Scotland and the NW part of the island of Ireland.

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FIGURE 5 Low frequency changes of precipitation totals in the island of Ireland for the four main seasons of the year and for the annual values. The curves are smoothed with a 15-point Gaussian filter [Colour figure can be viewed at wileyonlinelibrary.com]

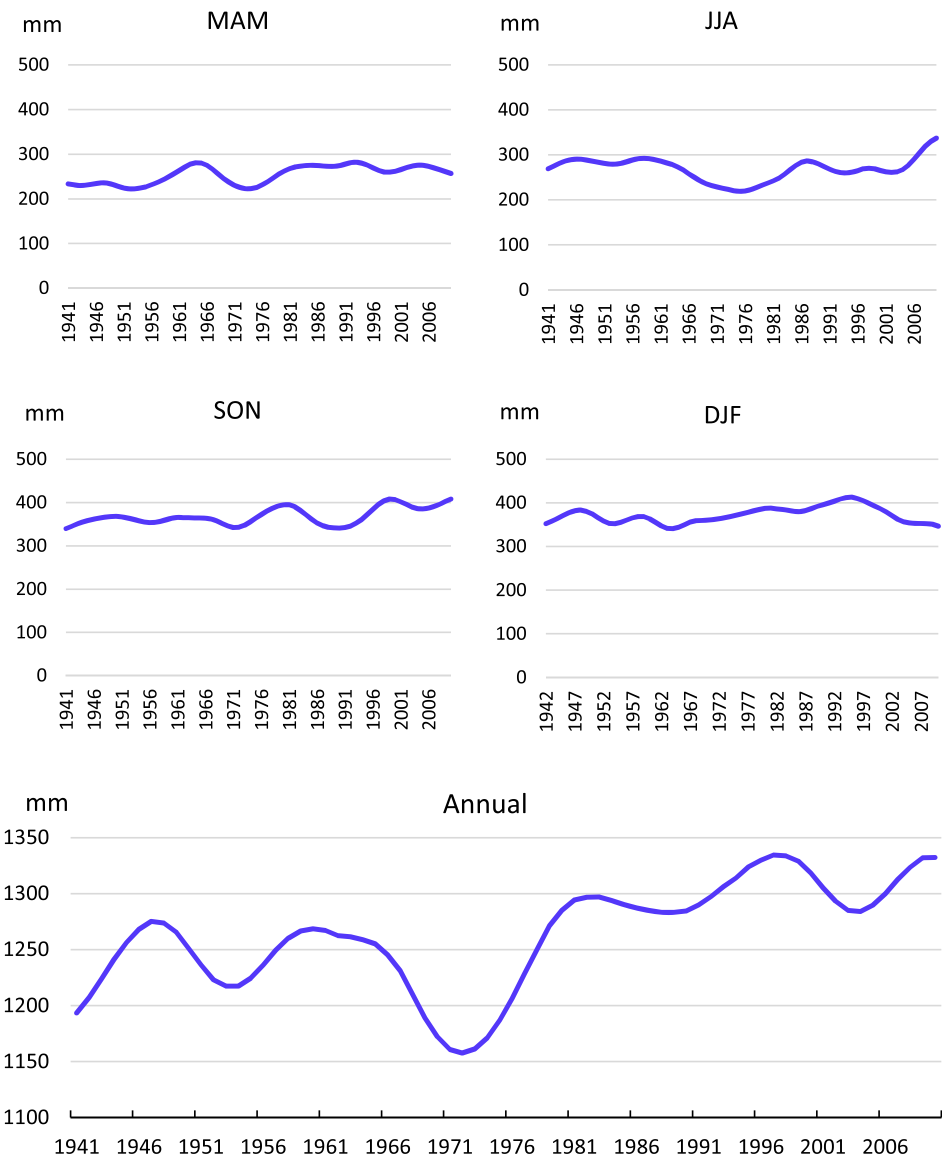
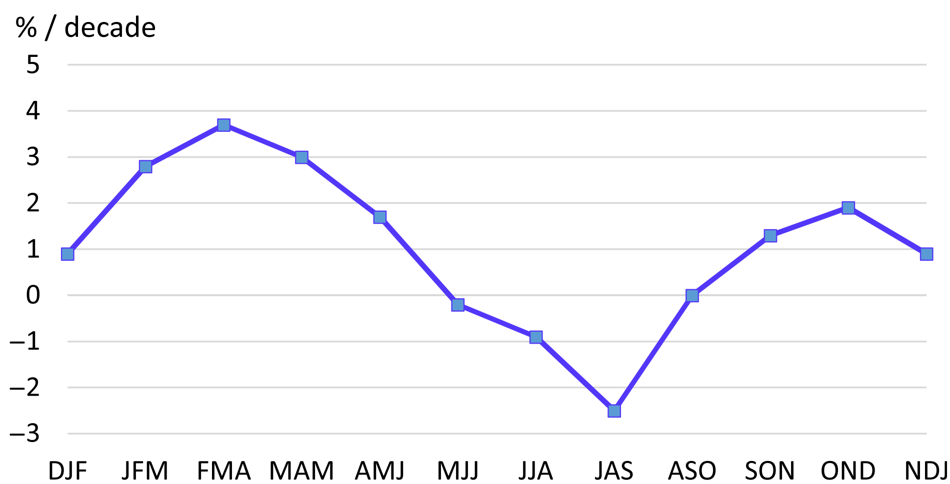


FIGURE 6 Seasonal curve of precipitation trends for the island of Ireland. Averages of the trends for five 66-year long periods (1941–2006, 1942–2007...1945–2010) [Colour figure can be viewed at wileyonlinelibrary.com]



In this study we used a large and dense dataset whose quality and homogeneity have been meticulously developed, hence there is a reasonable expectation that the calculated trends will be highly accurate. This improved accuracy of the description of the observed climatic trends aims to better serve the overall understanding of large-scale climatic processes in the era of global warming.

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REFERENCES

Abahous, H., Ronchail, J., Sifeddine, A., Kenny, L. and Bouchaou, L. (2018) Trend and change point analyses of annual precipitation in the Souss-Massa region in Morocco during 1932–2010. *Theoretical and Applied Climatology*, 134, 1153–1163. http://doi.org/10.1007/s00704-017-2325-0.

Alexandersson, H. (1986) A homogeneity test applied to precipitation data. *Journal of Climatology*, 6, 661–675.

Allan, R., Tett, S. and Alexander, L. (2009) Fluctuations in autumn-winter severe storms over the British Isles: 1920 to present. *International Journal of Climatology*, 29, 357–371. http://doi.org/10.1002/joc.1765.

Allan, R.P. and Zveryaev, I.I. (2011) Variability in the summer season hydrological cycle over the Atlantic-Europe region 1979–2007. *International Journal of Climatology*, 31, 337–348. http://doi.org/10.1002/joc.2070.

Anderson, B.T., Gianotti, D.J. and Salvucci, G.D. (2015) Detectability of historical trends in station-based precipitation characteristics over the continental United States. *Journal of Geophysical Research-Atmospheres*, 120, 4842–4859. http://doi.org/10.1002/2014JD022960.

Auer, I., Böhm, R., Jurkovic, A., Orlik, A., Potzmann, R., Schöner, W., Ungersböck, M., Brunetti, M., Nanni, T., Maugeri, M., Briffa, K., Jones, P., Efthymiadis, D., Mestre, O., Moisselin, J.-M., Begert, M., Brazdil, R., Bochnicek, O., Cegnar, T., Gajic-Capka, M., Zaninovic, K., Majstorovicp, Z., Szalai, S., Szentimrey, T. and Mercalli, L. (2005) A new instrumental precipitation dataset for the greater alpine region for the period 1800–2002. *International Journal of Climatology*, 25, 139–166. http://doi.org/10.1002/joc.1135.

Beranová, R. and Kyselý, J. (2018) Trends of precipitation characteristics in The Czech Republic over 1961–2012, their spatial patterns and links to temperature and the North Atlantic oscillation. *International Journal of Climatology*, 38(S1), e596–e606. http://doi.org/10.1002/joc.5392.

Brienen, S., Kapala, A., Mächel, H. and Simmera, C. (2013) Regional centennial precipitation variability over Germany from extended observation records. *International Journal of Climatology*, 33, 2167–2184. http://doi.org/10.1002/joc.3581.

Caussinus, H. and Mestre, O. (2004) Detection and correction of artificial shifts in climate series. *Journal of the Royal Statistical Society: Series C*, 53, 405–425. http://doi.org/10.1111/j.1467-9876.2004.05155.x.

Coll, J., Domonkos, P., Guijarro, J., Curley, M., Rustemeier, E., Aguilar, E., Walsh, S. and Sweeney, J. (2020) Application of homogenization methods for Ireland's monthly precipitation records: comparison of break detection results. *International Journal of Climatology*. http://doi.org/10.1002/joc.6575.

Coll, J., Woolf, D.K., Gibb, S.W. and Challenor, P.G. (2013) Sensitivity of ferry services to the western isles of Scotland to changes in wave and wind climate. *Journal of Applied Meteorology and Climatology*, 52, 1069–1084. http://doi.org/10.1175/JAMC-D-12-0138.1.

Daniels EE, G. Lenderink G, Hutjes RWA, Holtslag AAM (2014) Spatial precipitation patterns and trends in The Netherlands during 1951–2009. *International Journal of Climatology* 34: 1773–1784. http://doi.org/10.1002/joc.3800

Domonkos, P. (2015) Homogenization of precipitation time series with ACMANT. *Theoretical and Applied Climatology*, 122, 303–314. http://doi.org/10.1007/s00704-014-1298-5.

Domonkos, P. (2017) Time series homogenisation with optimal segmentation and ANOVA correction: past, present and future. In: Szentimrey, T., Lakatos, M. and Hoffmann, L. (Eds.) *Ninth Seminar for Homogenization and Quality Control in Climatological Databases and Fourth Conference on Spatial Interpolation Techniques In Climatology and Meteorology*. Geneva, Switzerland: WMO, pp. 29–45.

Domonkos, P. and Coll, J. (2017) Homogenization of temperature and precipitation time series with ACMANT3: method description and efficiency tests. *International Journal of Climatology*, 37, 1910–1921. http://doi.org/10.1002/joc.4822.

Domonkos P, Coll J (2019) Impact of missing data on the efficiency of homogenization: experiments with ACMANTv3. *Theoretical and Applied Climatology* 136:287-299. http://doi.org/10.1007/s00704 018-2488-3

Duan, W., He, B., Sahu, N., Luo, P., Nover, D., Hu, M. and Takara, K. (2017) Spatiotemporal variability of Hokkaido's seasonal precipitation in recent decades and connection to water vapour flux. *International Journal of Climatology*, 37, 3660–3673. http://doi.org/10.1002/joc.4946.

Duan, Z., Chen, Q., Chen, C., Liu, J., Gao, H., Song, X. and Wei, M. (2019) Spatiotemporal analysis of nonlinear trends in precipitation over Germany during 1951–2013 from multiple observation-based gridded products. *International Journal of Climatology*, 39, 2120–2135. http://doi.org/10.1002/joc.5939.

Easterling, D.R. and Peterson, T.C. (1995) A new method for detecting undocumented discontinuities in climatological time series. *International Journal of Climatology*, 15, 369–377.

González-Hidalgo, J.C., Brunetti, M. and de Luisa, M. (2011) A new tool for monthly precipitation analysis in Spain: MOPREDAS database (monthly precipitation trends (December 1945–November 2005)). *International Journal of Climatology*, 31, 715–731. http://doi.org/10.1002/joc.2115.

Gubler, S., Hunziker, S., Begert, M., Croci-Maspoli, M., Konzelmann, T., Brönnimann, S., Schwierz, C., Oria, C. and Rosas, G. (2017) The influence of station density on climate data homogenization. *International Journal of Climatology*, 37, 4670–4683. http://doi.org/10.1002/joc.5114.

Guijarro, J.A. (2011) Influence of network density on homogenization performance. In: Lakatos, M., Szentimrey, T. and Vincze, E. (Eds.) *Seventh Seminar for Homogenization and Quality Control in Climatological Databases*. Geneva, Switzerland: WMO, pp. 11–18.

Guijarro JA (2018) Homogenization of climatic series with Climatol. http://www.Climatol.eu/homog_Climatol-en.pdf.

Guijarro, J.A., López, J.A., Aguilar, E., Domonkos, P., Venema, V., Sigró, J. and Brunet, M. (2017) Comparison of homogenization packages applied to monthly series of temperature and precipitation: the MULTITEST project. In: Szentimrey, T., Lakatos, M. and Hoffmann, L. (Eds.) *Ninth Seminar for Homogenization and Quality Control in Climatological Databases*. Geneva, Switzerland: WMO, pp. 46–62.

Gutiérrez-Ruacho, O.G., Luis Brito-Castillo, L., Díaz-Castro, S.C. and Watts, C.J. (2010) Trends in rainfall and extreme temperatures in northwestern Mexico. *Climate Research*, 42, 133–142. http://doi.org/10.3354/cr00874.

Hatzianastassiou, N., Papadimas, C.D., Lolis, C.J., Bartzokas, A., Levizzani, V., Pnevmatikos, J.D. and Katsoulis, B.D. (2016) Spatial and temporal variability of precipitation over the Mediterranean Basin based on 32-year satellite global precipitation climatology project data. Part-II: inter-annual variability and trends. *International Journal of Climatology*, 36, 4755–4766. http://doi.org/10.1002/joc.4666.

Hu, Z., Zhou, Q., Chen, X., Qian, C., Wang, S. and Li, J. (2017) Variations and changes of annual precipitation in Central Asia over the last century. *International Journal of Climatology*, 37(S1), 157–170. http://doi.org/10.1002/joc.4988.

Iqbal, Z., Shahid, S., Ahmed, K., Ismail, T. and Nawaz, N. (2019) Spatial distribution of the trends in precipitation and precipitation extremes in the sub-Himalayan region of Pakistan. *Theoretical and Applied Climatology*, 137, 2755–2769. http://doi.org/10.1007/s00704-019-02773-4.

Irannezhad, M., Marttila, H. and Kløve, B. (2014) Long-term variations and trends in precipitation in Finland. *International Journal of Climatology*, 34, 3139–3153. http://doi.org/10.1002/joc.3902.

Isotta, F.A., Begert, M. and Frei, C. (2019) Long-term consistent monthly temperature and precipitation grid data sets for Switzerland over the past 150 years. *Journal of Geophysical Research-Atmospheres*, 124, 3783–3799. http://doi.org/10.1029/2018JD029910.

Jones, P.D., Harpham, C., Harris, I., Goodess, C.M., Burton, A., Centella-Artola, A., Taylor, M.A., Bezanilla-Morlot, A., Campbell, J.D., Stephenson, T.S., Joslyn, O., Nicholls, K. and Baur, T. (2016) Long-term trends in precipitation and temperature across the Caribbean. *International Journal of Climatology*, 36, 3314–3333. http://doi.org/10.1002/joc.4557.

Kendall, M.G. (1948) *Rank Correlation Methods*. New York: Hafner.

de Leeuw, J., Methven, J. and Blackburn, M. (2016) Variability and trends in England and Wales precipitation. *International Journal of Climatology*, 36, 2823–2836. http://doi.org/10.1002/joc.4521.

Li, X., Hu, Z.-Z., Jiang, X., Li, Y., Gao, Z., Yang, S., Zhu, J. and Jha, B. (2016) Trend and seasonality of land precipitation in observations and CMIP5 model simulations. *International Journal of Climatology*, 36, 3781–3793. http://doi.org/10.1002/joc.4592.

Lindau, R. and Venema, V. (2018) On the reduction of trend errors by the ANOVA joint correction scheme used in homogenization of climate station records. *International Journal of Climatology*, 38, 5255–5271. http://doi.org/10.1002/joc.5728.

López, J.A., Guijarro, J.A., Aguilar, E., Domonkos, P. and Brunet, M. (2016) Una propuesta metodológica para la generación de redes de precipitación simuladas a partir de redes de precipitación observadas en el marco del proyecto MULTITEST. In: Olcina, J., Rico, A.M. and Moltó, E. (Eds.) *Clima, sociedad, riesgos y ordenación del territorio*. Spain: University of Alicante, Asociación Española de Climatología, pp. 183–194 (In Spanish with an English abstract).

Maheras, P., Tolika, K., Anagnostopoulou, C., Makra, L., Szpirosz, K. and Cs, K. (2018) Relationship between mean and extreme precipitation and circulation types over Hungary. *International Journal of Climatology*, 38, 4518–4532. http://doi.org/10.1002/joc.5684.

Mann, H.B. (1945) Nonparametric tests against trend. *Econometrika*, 13, 245–259.

Matthews, T., Murphy, C., Wilby, R.L. and Harrigan, S. (2016) A cyclone climatology of the British-Irish isles 1871–2012. *International Journal of Climatology*, 36, 1299–1312. http://doi.org/10.1002/joc.4425.

Mekis, É. and Vincent, L.A. (2011) An overview of the second generation adjusted daily precipitation dataset for trend analysis in Canada. *Atmosphere-Ocean*, 49, 163–177. http://doi.org/10.1080/07055900.2011.583910.

Mestre, O., Domonkos, P., Picard, F., Auer, I., Robin, S., Lebarbier, E., Böhm, R., Aguilar, E., Guijarro, J.A., Vertacnik, G., Klancar, M., Dubuisson, B. and Štěpánek, P. (2013) HOMER: homogenization software in R – methods and applications. *Időjárás (Quart J Hungarian Met Serv)*, 117, 47–67.

Murawski, A., Zimmer, J. and Merz, B. (2016) High spatial and temporal organization of changes in precipitation over Germany for 1951–2006. *International Journal of Climatology*, 36, 2582–2597. http://doi.org/10.1002/joc.4514.

Murphy, C., Broderick, C., Burt, T.P., Curley, M., Duffy, C., Hall, J., Harrigan, S., Matthews, T.K.R., Macdonald, N., McCarthy, G., McCarthy, M.P., Mullan, D., Noone, S., Osborn, T.J., Ryan, C., Sweeney, J., Thorne, P.W., Walsh, S. and Wilby, R.L. (2018) A 305-year continuous monthly rainfall series for the Island of Ireland (1711-2016). *Climate of the Past*, 14, 413–440. http://doi.org/10.5194/cp-14-413-2018.

Murphy, C., Wilby, R.L., Matthews, T.K.R., Thorne, P., Broderick, C., Fealy, R., Julia Hall, J., Harrigan, S., Jones, P., McCarthy, G., MacDonald, N., Noone, S. and Ryan, C. (2020) Multi-century trends to wetter winters and drier summers in the England and Wales precipitation series explained by observational and sampling bias in early records. *International Journal of Climatology*, 40, 610–619. http://doi.org/10.1002/joc.6208.

Murtagh, F. and Legendre, P. (2014) Ward's hierarchical agglomerative clustering method: which algorithms implement Ward's criterion? *Journal of Classification*, 31, 274–295. http://doi.org/10.1007/s00357-014-9161-z.

Osborn, T.J. (2006) Recent variations in the winter North Atlantic oscillation. *Weather*, 61, 353–355. https://doi.org/10.1256/wea.190.06.

Pérez-Zanón, N., Sigró, J., Domonkos, P. and Ashcroft, L. (2017) Temperature and precipitation regional climate series over the Central Pyrenees during 1910–2013. *International Journal of Climatology*, 37, 1922–1937. http://doi.org/10.1002/joc.4823.

Qin, F., Jia, G., Yang, J., Na, Y. and Bao, Y. (2019) Decadal decline of summer precipitation fraction observed in the field and from TRMM satellite data across the Mongolian plateau. *Theoretical and Applied Climatology*, 137, 1105–1115. http://doi.org/10.1007/s00704-018-2655-6.

Romano, E. and Preziosi, E. (2013) Precipitation pattern analysis in the Tiber River basin (Central Italy) using standardized indices. *International Journal of Climatology*, 33, 1781–1792. http://doi.org/10.1002/joc.3549.

Rustemeier, E., Kapala, A., Meyer-Christoffer, A., Finger, P., Schneider, U., Venema, V., Ziese, M., Simmer, C. and Becker, A. (2017) AHOPS Europe – a gridded precipitation data set from European homogenized time series. In: *9th Seminar for Homogenization and Quality Control in Climatological Databases*. Geneva, Switzerland: WMO, pp. 88–101.

Scherrer, S.C., Begert, M., Croci-Maspoli, M. and Appenzeller, C. (2016) Long series of Swiss seasonal precipitation: regionalization, trends and influence of large-scale flow. *International Journal of Climatology*, 36, 3673–3689. http://doi.org/10.1002/joc.4584.

Spinoni, J., Szalai, S., Szentimrey, T., Lakatos, M., Bihari, Z., Andrea Nagy, A., Németh, Á., Kovács, T., Mihic, D., Dacic, M., Petrovic, P., Kržič, A., Hiebl, J., Auer, I., Milkovic, J., Štěpánek, P., Zahradníček, P., Kilar, P., Limanowka, D., Pyrc, R., Cheval, S., Birsan, M.-V., Dumitrescu, A., Gy, D., Matei, M., Antolovic, I., Nejedlík, P., Štastný, P., Kajaba, P., Bochnícek, O., Galo, D., Mikulová, K., Nabyvanets, Y., Skrynyk, O., Krakovska, S., Gnatiuk, N., Tolasz, R., Antofie, T. and Vogt, J. (2015) Climate of the Carpathian region in the period 1961–2010: climatologies and trends of 10 variables. *International Journal of Climatology*, 35, 1322–1341. http://doi.org/10.1002/joc.4059.

Sweeney, J. (1985) The changing synoptic climatology of Irish rainfall. *Transactions of the Institute of British Geographers*, 10, 467–480.

Sweeney, J. (2014) Regional weather and climates of the British Isles – part 6: Ireland. *Weather*, 69(1), 20–27. http://doi.org/10.1002/wea.2230.

Tong, K., Su, F., Yang, D., Leilei Zhang, L. and Hao, Z. (2014) Tibetan plateau precipitation as depicted by gauge observations, reanalyses and satellite retrievals. *International Journal of Climatology*, 34, 265–285. http://doi.org/10.1002/joc.3682.

Turco, M. and Llasat, M.C. (2011) Trends in indices of daily precipitation extremes in Catalonia (NE Spain), 1951–2003. *Natural Hazards and Earth System Sciences*, 11, 3213–3226. http://doi.org/10.5194/nhess-11-3213-2011.

Ummenhofer, C.C., Seo, H., Kwon, Y.-O., Parfitt, R., Brands, S. and Joyce, T.M. (2017) Emerging European winter precipitation pattern linked to atmospheric circulation changes over the North Atlantic region in recent decades. *Geophysical Research Letters*, 44, 8557–8566. http://doi.org/10.1002/2017GL074188.

Valdes-Abellan J, Pardo MA. Tenza-Abril AJ (2017) Observed precipitation trend changes in the western Mediterranean region. *International Journal of Climatology* 37/S1:1285–1296. http://doi.org/10.1002/joc.4984

Vallis, G.K. and Gerber, E.P. (2008) Local and hemispheric dynamics of the North Atlantic oscillation, annular patterns and the zonal index. *Dynamics of Atmospheres and Oceans*, 44, 184–212. http://doi.org/10.1016/j.dynatmoce.2007.04.003.

Venema, V., Mestre, O., Aguilar, E., Auer, I., Guijarro, J.A., Domonkos, P., Vertacnik, G., Szentimrey, T., Štěpánek, P., Zahradnicek, P., Viarre, J., Müller-Westermeier, G., Lakatos, M., Williams, C.N., Menne, M., Lindau, R., Rasol, D., Rustemeier, E., Kolokythas, K., Marinova, T., Andresen, L., Acquaotta, F., Fratianni, S., Cheval, S., Klancar, M., Brunetti, M., Gruber, C., Duran, M.P., Likso, T., Esteban, P. and Brandsma, T. (2012) Benchmarking monthly homogenization algorithms. *Climate of the Past*, 8, 89–115. http://doi.org/10.5194/cp-8-89-2012.

Vincent, L.A., Zhang, X., Brown, R.D., Feng, Y., Mekis, E., Milewska, E.J., Wan, H. and Wang, X.L. (2015) Observed trends in Canada's climate and influence of low-frequency variability modes. *Journal of Climate*, 28, 4545–4560. http://doi.org/10.1175/JCLI-D-14-00697.1.

Walsh, S. (2012) A summary of climate averages for Ireland 1981-2010. In: *Met Éireann Climatological Note 14*. Dublin: Met Éireann, p. 16.

Wang, F., Yang, S., Higgins, W., Lia, Q. and Zuod, Z. (2014) Long-term changes in total and extreme precipitation over China and the United States and their links to oceanic–atmospheric features. *International Journal of Climatology*, 34, 286–302. http://doi.org/10.1002/joc.3685.

Ward, J.H. (1963) Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association*, 58, 236–244.

Wilby, R.L., O'Hare, G. and Barnsley, N. (1997) The North Atlantic oscillation and British Isles climate variability, 1865-1996. *Weather*, 52, 266–276.

Yasunaga, K. and Tomochika, M. (2017) An increasing trend in the early winter precipitation during recent decades along the coastal areas of the sea of Japan. *Journal of Hydrometeorology*, 18, 2893–2906. http://doi.org/10.1175/JHM-D-17-0105.1.

Zhang, W., Zhou, T. and Zhang, L. (2017) Wetting and greening Tibetan plateau in early summer in recent decades. *Journal of Geophysical Research-Atmospheres*, 122, 5808–5822. http://doi.org/10.1002/2017JD026468.

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