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The contribution of anthropogenic influence to more anomalous extreme precipitation in Europe

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Abstract

Anthropogenic influences can modulate the low-frequency variability of extreme precipitation and increase the likelihood of flooding events. It is not, however, clear how much and in what manner the low-frequency variability has changed in recent decades as global warming has intensified. Here, we investigate the contribution of anthropogenic influences to the time evolution of extreme precipitation anomalies in different seasons using Coupled Model Intercomparison Project Phase 6 (CMIP6) and CMIP5 model simulations and observations over Europe. Our results show a latitudinal dependence of changes in extreme precipitation anomalies for all seasons due to anthropogenic impacts. While the contribution of anthropogenic influences to extreme precipitation anomalies at low latitudes ($<50^\circ$) is less than 8% in all seasons, it goes up to 26% and 41% at mid (50° – 60°) and high ($>60^\circ$) latitudes. Without the offsetting effect of anthropogenic aerosols, anthropogenic emissions of greenhouse gases alone should have produced larger anomalies than observed. For all seasons, the more extreme the precipitation, the larger the anthropogenic influences.

1. Introduction

Climate fluctuations occur on multiple time and spatial scales, which in turn, can influence the spatiotemporal patterns of precipitation, potentially leading to dramatic social and economic consequences. Precipitation variability may increase the likelihood of extreme events such as floods and droughts (Tabari 2020) and endanger the food security through reducing agricultural yield (Rowhani *et al* 2011, Stevens and Madani 2016). In regions affected by strong low-frequency variability such as Europe, water management and planning, including the design and operation of engineering infrastructure have to account for this mode of variability (Rocheta *et al* 2014). A substantial portion of the precipitation variability in Europe can be explained by large-scale ocean-atmosphere circulations such as the North Atlantic Oscillation (Tabari and Willems 2018). Such a linkage triggered the hope to partly identify the driving

forces of the extreme precipitation anomaly and project extreme events.

The low-frequency variability of extreme precipitation can also be modulated by anthropogenic climate change. In other words, human-caused changes are able to alter existing modes of climatic variability and dampen or amplify the natural cycle and move the oscillation outside the range of natural variability (Dong *et al* 2014). In the case of amplifying the oscillation high period, the wet extreme period has the potential to cause flooding. A heuristic argument based on ‘wet gets wetter, dry gets drier’ paradigm suggests that the increase in atmospheric precipitable water in a warmer climate enhances moisture convergence or divergence during wet or dry years, consequently increasing precipitation variability (Liu and Allan 2013, Chou *et al* 2013, Konapala *et al* 2017, Schurer *et al* 2020).

To date, there is still a lack of a quantitative assessment of the response of the amplitude of

low-frequency variability (decadal to multi-decadal timescales) in extreme precipitation to anthropogenic influences. The low-frequency variability of observed monthly precipitation has increased in the interval 1890–1989 (Tsonis 1996); however, it is not clear how much and in what manner the low-frequency variability has changed in recent decades with global warming. A recent study by Pendergrass *et al* (2017) suggested that precipitation variability for time scales ranging from 1 d to 3 years increases in a warmer climate. Yet, how daily extreme precipitation variability over longer time scales (decadal to multi-decadal) responds to anthropogenic influences remains unassessed. Addressing this knowledge gap can provide important information on the physical mechanisms behind the extreme variability for the decadal predictability and the temporal evolution of the drivers (Solomon *et al* 2011), necessary for developing effective climate change adaptation strategies.

One way to examine the impact of anthropogenic influences on the low-frequency extreme precipitation variability is by climate models through which extreme precipitation variability in real world simulations is compared with that in counterfactual natural world simulations (i.e. unaffected by anthropogenic influences). However, climate models are far from perfect, with systematic bias, especially suffering from the underestimation of the observed changes in extreme precipitation and of the noise of natural variability (Allan and Soden 2008, Trenberth 2011, Sarojini *et al* 2016), even though they are able to properly capture the patterns of the forced response (Fischer and Knutti 2015). The systematic bias as well as the structural uncertainties (Sarojini *et al* 2016) of these models can have a large bearing on their results (Allen *et al* 2006, Santer *et al* 1996, Hegerl *et al* 2000).

The results derived from imperfect climate models need to be validated based on observations (Fischer and Knutti 2015). Yet, the scarcity of long, homogeneous, daily ground precipitation records often hinders the validation process (Hosseinizadehtalaei *et al* 2020). Consequently, studies that benefit from both observation and model data are limited. Most of the previous analyses have focused on the recent past events, for which recorded data are much more reliable (more homogeneous) and complete (less gaps and higher spatial resolution) (Stott *et al* 2016, 2018). Early instrumental records, though more challenging to work with, contain a wealth of information (Hegerl *et al* 2019) and may lead to more reliable results on decadal changes (O'Reilly *et al* 2017, Weisheimer *et al* 2017). High quality, long records facilitate a more powerful detection of anthropogenic signals from the background of natural variability (Hegerl *et al* 2006, Dai 2013) and reduces false correlation between forcings that produce misleading results (Hegerl *et al* 2019). In other words, short instrumental records are mostly unable to properly differentiate between trends and low-frequency variations

at local spatial scales and thereby fail to identify anthropogenic forced signals. Thus, they may fail to provide reliable information for developing proper future adaptation planning and disaster risk reduction activities (Li *et al* 2018).

Here, we investigate an important topic which is yet not well understood, namely the contribution of anthropogenic influences to the low-frequency variability of extreme precipitation. This study endeavors to answer some important open questions regarding the seasonality and latitudinal (spatial) pattern of the anthropogenic contributions to extreme precipitation anomalies over Europe. We perform the analyses using the E-OBS (ENSEMBLES OBServation) precipitation dataset along with natural (NAT), greenhouse gas (GHG) and historical (ALL) forcing simulations from 26 Coupled Model Intercomparison Project Phase 6 (CMIP6) and 25 CMIP5 general circulation models (GCMs). The use of such a large multi-model ensemble makes the external forcing response in extreme precipitation more resistant to the random bias of the individual models (Gillett *et al* 2002, Deser *et al* 2010).

2. Materials and methods

2.1. Data

We used model simulations from the CMIP5 (Taylor *et al* 2012) and CMIP6 (Eyring *et al* 2016) to assess the anthropogenic influence on changes in European precipitation extreme events. We analyzed the daily output of historical simulations from CMIP6 and CMIP5 GCMs, representing external natural forcing only ('historicalNat' experiment; NAT), greenhouse gas forcing only ('historicalGHG' experiment; GHG), and historical forcing ('historical' experiment; ALL). The NAT simulations only consider volcanic aerosols and solar forcings, while the ALL simulations include anthropogenic GHG and aerosols in addition to the natural forcings. The ALL simulations from 26 CMIP6 and 25 CMIP5 GCMs were used while the NAT and GHG simulations were available for eight CMIP6 and thirteen CMIP5 GCMs. All the analyses are based on the first ensemble member (r1i1p1) of each CMIP6 and CMIP5 model. The 1861–2005 and 1861–2014 periods, respectively the common periods among the CMIP5 runs and the CMIP6 runs, were selected for this study (table 1). Prior to all the model-based analyses, different spatial resolutions of the CMIP6 (ranging between 0.9° and 2.8°) and CMIP5 (ranging between 0.9° and 3.8°) GCMs were regridded to a common rectangular grid of 2° × 2 using the bilinear interpolation method. Although a conservative interpolation is recommended for precipitation interpolation, it was found that the regridding results are not sensitive to the choice of the interpolation method and of the common grid size (Tabari *et al* 2019).

Table 1. Summary of the 26 CMIP6 and 25 CMIP5 GCMs used in this study.

Ensemble	Model	Available data period		
		ALL	GHG	NAT
CMIP6	ACCESS-CM2	1850–2014	—	—
	ACCESS-ESM1-5	1850–2014	—	—
	BCC-CSM2-MR	1850–2014	1850–2020	1850–2020
	BCC-ESM1	1850–2014	—	—
	CanESM5	1850–2014	1850–2020	1850–2020
	CESM2	1850–2014	1850–2014	1850–2014
	CESM2-FV2	1850–2014	—	—
	CESM2-WACCM	1850–2014	—	—
	CNRM-CM6-1	1850–2014	1850–2020	1850–2020
	CNRM-ESM2-1	1850–2014	—	—
	GFDL-CM4	1850–2014	—	—
	GFDL-ESM4	1850–2014	—	—
	HadGEM3-GC3	1850–2014	1850–2020	1850–2020
	INM-CM4-8	1850–2014	—	—
	INM-CM5-0	1850–2014	—	—
	IPSL-CM6A-LR	1850–2014	1850–2020	1850–2020
	MIROC6	1850–2014	—	—
	MIROC-ES2L	1850–2014	—	—
	MPI-ESM-1-2-HAM	1850–2014	—	—
	MPI-ESM1-2-LR	1850–2014	—	—
	MRI-ESM2	1850–2014	1850–2020	1850–2020
	NorESM2-LM	1850–2014	1850–2020	1850–2020
	NorESM2-MM	1850–2014	—	—
	SAM0-UNICON	1850–2014	—	—
	TaiESM1	1850–2014	—	—
	UKESM1-0-LL	1850–2014	—	—
CMIP5	BCC-CSM1-1	1850–2012	1850–2012	1850–2012
	CanESM2	1850–2005	1850–2012	1850–2012
	CCSM4	1850–2005	1850–2005	1850–2005
	CMCC-CESM	1850–2005	—	—
	CMCC-CMS	1850–2005	—	—
	CNRM-CM5	1850–2012	1850–2012	1850–2012
	CSIRO-Mk3-6-0	1850–2012	1850–2012	1850–2012
	EC-EARTH	1850–2009	—	—
	GFDL-CM3	1860–2005	1860–2005	1860–2005
	GFDL-ESM2G	1861–2005	—	—
	GFDL-ESM2M	1861–2005	1861–2005	1861–2005
	HadGEM2-ES	1859–2005	1859–2099	1859–2019
	INM-CM4	1850–2005	—	—
	IPSL-CM5A-LR	1850–2005	1850–2012	1850–2005
	IPSL-CM5A-MR	1850–2005	—	—
	IPSL-CM5B-LR	1850–2005	—	—
	MIROC5	1850–2012	—	—
	MIROC-ESM	1850–2005	1850–2005	1850–2005
	MIROC-ESM-CHEM	1850–2005	1850–2005	1850–2005
	MPI-ESM-LR	1850–2005	—	—
	MPI-ESM-MR	1850–2005	—	—
	MPI-ESM-P	1850–2005	—	—
	MRI-CGCM3	1850–2005	1850–2005	1850–2005
	MRI-ESM1	1850–2005	—	—
	NorESM1-M	1850–2005	1850–2012	1850–2012

ALL, GHG and NAT represent simulations driven by all forcings, by only greenhouse gas forcing, and by only external natural forcing, respectively.

In addition to model simulations, we used daily precipitation data from the E-OBS v20.0e dataset (Cornes *et al* 2018) with a 0.1° spatial resolution which covers the period from 1950-01-01 to 2019-07-31. The dataset was developed by statistically interpolating about 15 000 ground raingauges. The E-OBS observations were also regridded to the $2^\circ \times 2$ grid.

2.2. Estimation of latitudinal precipitation

Given the large internal variability of extreme precipitation at the local scale (Fischer *et al* 2014, Fischer and Knutti 2016), detection analyses were performed on a larger scale to derive a stronger anthropogenic signal. To detect any possible latitudinal pattern in extreme precipitation changes over the continent,

average precipitation for all grid cells in each latitude over $(-10^{\circ}-(+40^{\circ})$ longitude range was calculated (hereafter referred to as latitudinal precipitation). Because of a high spatial variability of precipitation over Europe, regional precipitation is dominated by areas with large precipitation amounts. To limit this effect on latitudinal precipitation estimates, precipitation amounts were normalized locally for each grid cell into a zero-to-one scale (1 representing the strongest event and 0 indicating no precipitation) before calculating latitudinal precipitation (Min *et al* 2009). This also facilitates the comparison between observations and model simulations and reduces the uncertainty in latitudinal precipitation estimation related to a sparse gauge network to capture high spatial precipitation variability in gridded observations (Min *et al* 2011).

2.3. Examination of trends and nonstationarity in extreme precipitation anomalies

Once latitudinal precipitation was estimated, the decadal anomalies in daily observed and model (ALL simulations) extreme precipitation were computed using the quantile perturbation method (QPM; Ntegeka and Willems 2008, Willems 2013) for winter (DJF), spring (MAM), summer (JJA) and autumn (SON) seasons (figure S1 (available online at stacks.iop.org/ERL/15/104077/mmedia)). In QPM, all quantiles above a given threshold (peaks-over-threshold) in a 20-year sub-series are compared with those in the full time series (reference series) with the same exceedance probability. As our analysis was performed at the European scale with diverse extreme precipitation regimes (Łupikasza 2017), a latitude-specific percentile-based threshold (rather than absolute values) was selected to define extreme precipitation, allowing a spatial (latitudinal) comparison as pointed out by Klein Tank and Können (2003). The thresholds chosen are the 95–99.5th percentiles of all precipitation data rather than wet days to avoid the effects of varying number of wet days in Europe on the percentile level (Fischer and Knutti 2015, Schär *et al* 2016). To compare the extremes between any possible sub-period and the full period, the time slice in the sub-period is moving with a sliding window of one year from the beginning towards the end of the full series. For example, CMIP6 simulations during 1861–2014 include 135 sub-series of 20-year long, with 1861–1880 and 1995–2014 as the first and last sub-series, respectively. The sensitivity of the results to the length of the moving window was investigated by comparing the results with those derived from 10-, 30- and 40-year moving window, indicating a low sensitivity of the results to the moving window length (not shown). The higher quantile values in the sub-period compared to the full period denote a positive anomaly (>1) while lower quantile values in the sub-period lead to a negative anomaly (<1) (figure S1). The larger the extreme precipitation

difference between sub-series and reference series, the larger the anomaly.

The anomaly series of extreme precipitation was tested for presence of trends and nonstationarity using the nonparametric Mann-Kendall test (figure 1). The statistic S of the Mann-Kendall test is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (1)$$

where x_j and x_i are the sequential data values, n is the length of the data set, and $\text{sgn}(\theta)$ is the sign function that is equal to 1, 0, -1 if θ is greater than, equal to, or less than zero, respectively. The variance of S is obtained by:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18} \quad (2)$$

where m is the number of tied groups (a tied group is a set of sample data having the same value) and t_i is the number of data points in the i th group. Finally, the Mann-Kendall statistic, Z_{MK} , is given by:

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (3)$$

The Z_{MK} values are approximately normally distributed, and a positive Z_{MK} value denotes an increasing trend, whereas a negative Z_{MK} value shows a decreasing trend. The null hypothesis, H_0 , of no trend is rejected if $|Z_{MK}| > |Z_{\alpha/2}|$, where Z is taken from the standard normal distribution table and α is the significance level.

It is well documented that serial correlations in time series have a noticeable influence on trend test results, with a positive serial correlation inflating the variance of the Mann-Kendall test and rejecting the null hypothesis of no trend while it is actually true (Tabari and Hosseinzadeh Talaee 2011). Because of using a moving window in the anomaly calculations, significant serial correlations up to a few lags are created in the anomaly series. To remove the effect of serial correlations, the variance of the Mann-Kendall test was modified using the effective sample size (ESS) method (Hamed and Rao 1998) by taking into account all significant serial correlations at the 95% confidence level:

$$\text{Var}^*(S) = \text{Var}(S) \cdot \frac{n}{n^*} \quad (4)$$

where $\text{Var}^*(S)$ is the modified variance, $\text{Var}(S)$ is the variance of the Mann-Kendall statistic before modification, n is the actual sample size of the sample data, and n^* is the effective sample size. The following

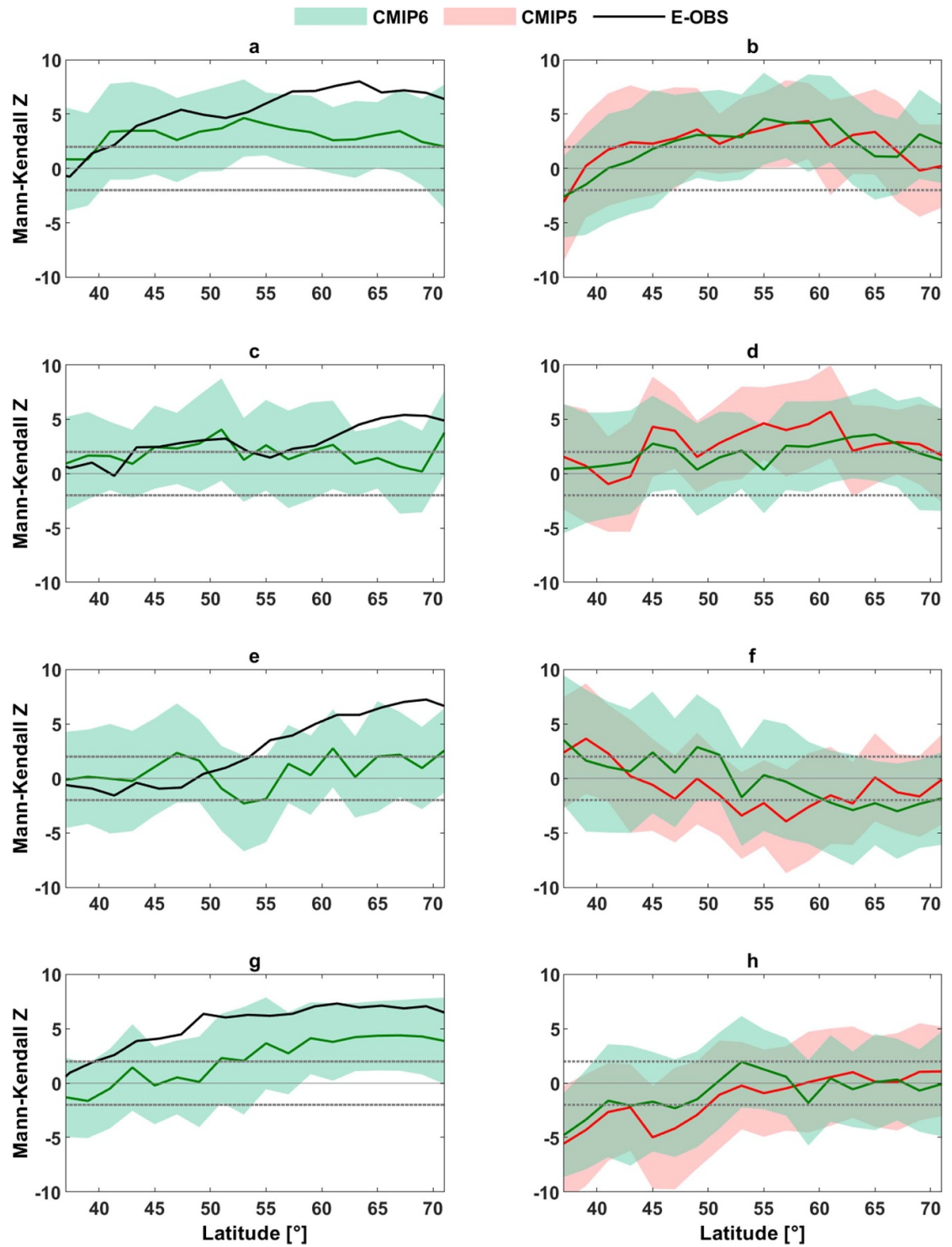


Figure 1. Temporal trends in latitudinal extreme (99th percentile) precipitation anomalies with a 20-year moving window in Europe for different seasons (a, b: winter; c, d: spring; e, f: summer; g, h: autumn) using the ALL simulations of 26 CMIP6 GCMs and 25 CMIP5 GCMs and E-OBS data for the 1950–2014 period (a, c, e, g) and for the full simulations of the GCM ensembles (b, d, f, h). The ensemble medians of the CMIP6 and CMIP5 GCMs are marked with solid green and red lines, respectively, while uncertainty bands represent ± 1 ensemble standard deviation. The 5% significance thresholds for trends (Mann-Kendall $Z = \pm 1.96$) are marked with grey dotted lines. Note that the CMIP5 and CMIP6 results in the right-column panels are not comparable as the models and the simulation periods (1861–2005 for CMIP5 GCMs and 1861–2014 for CMIP6 GCMs) are different; the analysis only shows the latitudinal and seasonal patterns of the anthropogenic contributions.

equation is used for computing n^* based on significant lag- k serial correlation coefficient (r_k):

$$n^* = \frac{n}{1 + 2 \cdot \sum_{k=1}^{n-1} \left(1 - \frac{k}{n}\right) \cdot r_k}. \quad (5)$$

2.4. Contribution of anthropogenic influences to anomaly changes in models

To examine the anthropogenic influences on extreme precipitation anomalies (95–99.5th percentiles), we compared the anomalies under ALL or GHG forcings

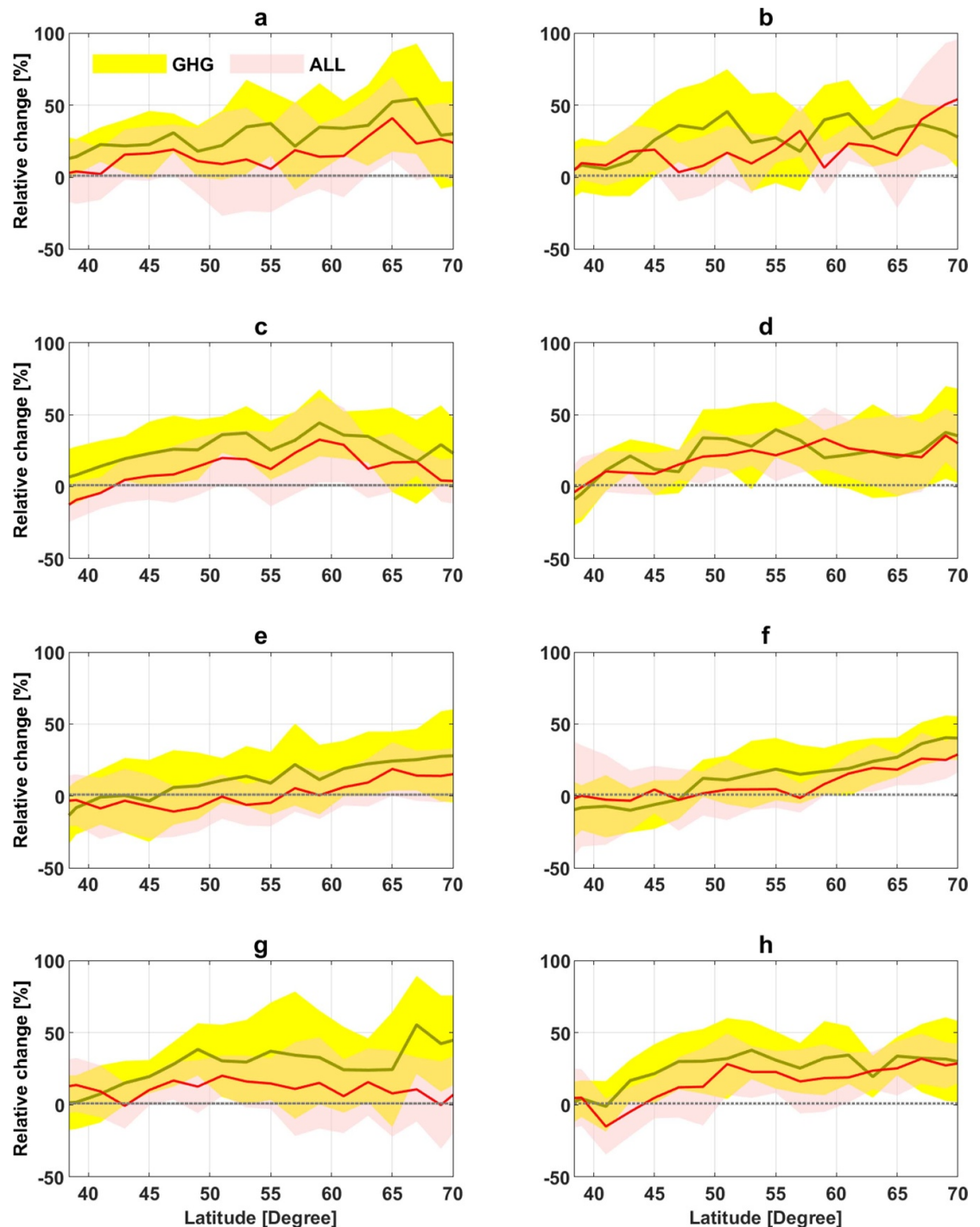


Figure 2. Latitudinal pattern of relative change (RC_{ALL} and RC_{GHG}) for 99th percentile precipitation for the most recent 20-year period (1986–2005 for CMIP5 GCMs and 1995–2014 for CMIP6 GCMs) in different seasons (a, b: winter; c, d: spring, e, f: summer; g, h: autumn) using daily precipitation simulations from 13 CMIP5 (a, c, e, g) and 8 CMIP6 (b, d, f, h) GCMs. Lines and uncertainty bands represent the ensemble median and ± 1 ensemble standard deviation, respectively.

with those under NAT forcing as the reference series (figures 2–5). This is different from the previous analysis on the historical trends in anomalies in which the full time series of each simulation was used as the reference series. The relative changes in extreme precipitation anomalies due to all anthropogenic influences (RC_{ALL}) are computed as a ratio of the quantiles above the threshold in ALL simulations in the first 20-year time slice (1861–1880) with those in the

NAT simulations of the same time-slice with the same exceedance probability. The sub-series was then moved by one year from the beginning to the end of the time period, with 1995–2014 (1986–2005) as the last 20-year time slice for the CMIP6 (CMIP5) GCMs. A similar procedure was followed to calculate the relative changes in extreme precipitation anomalies due to GHG-alone influences (RC_{GHG}), by comparing GHG and NAT simulations-driven extremes.

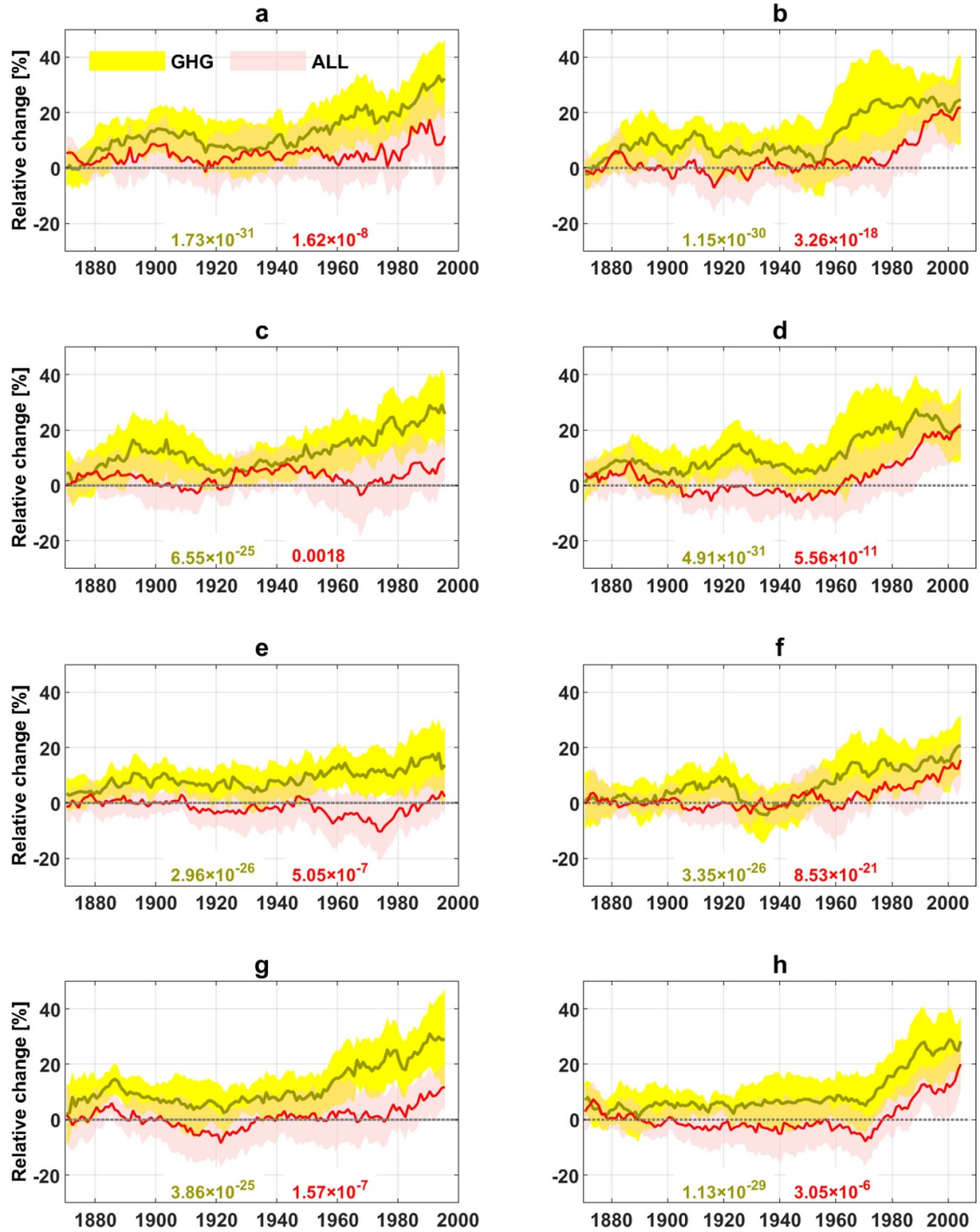
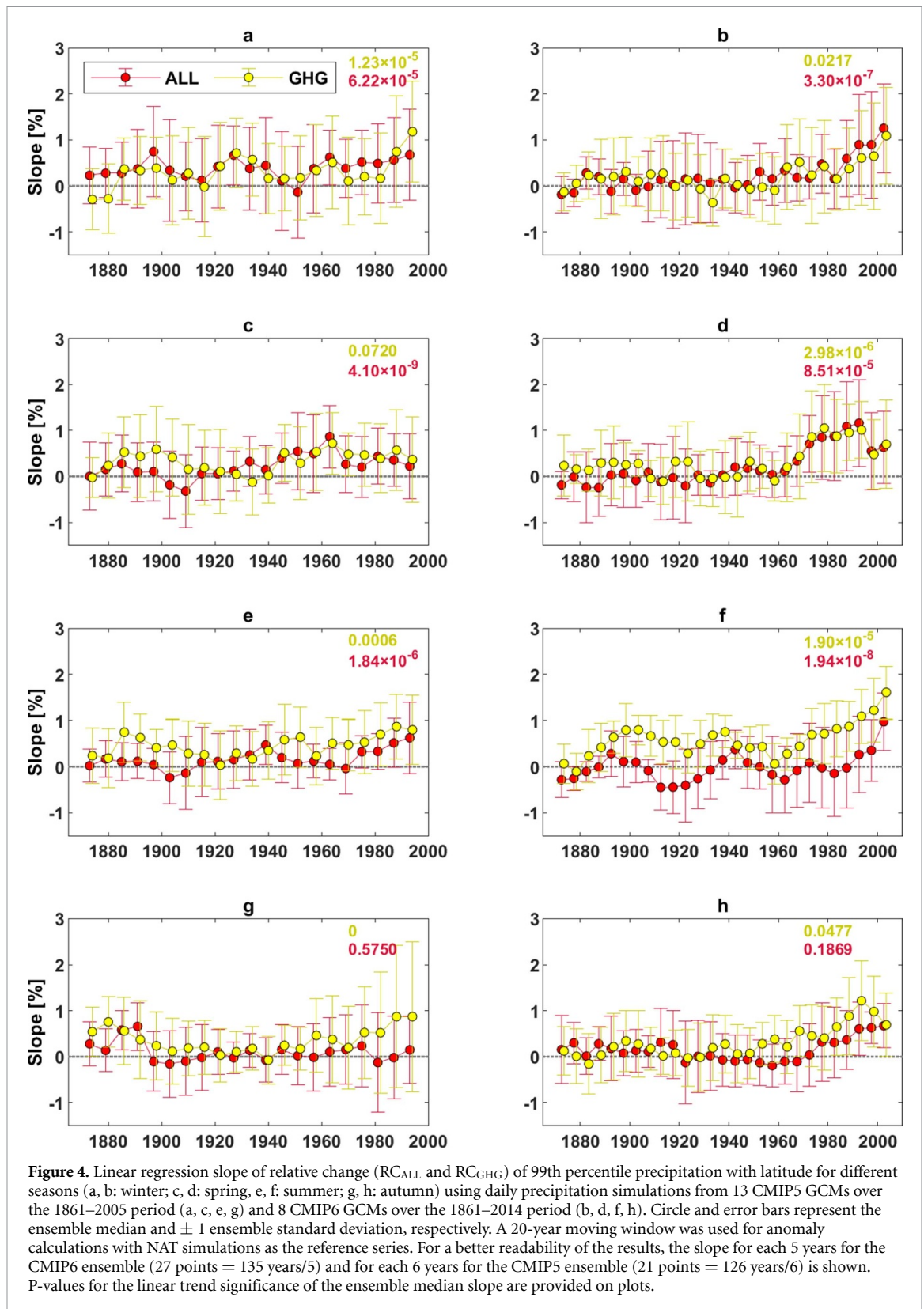


Figure 3. Evolution of continental relative change (RC_{ALL} and RC_{GHG}) of 99th percentile precipitation for different seasons (a, b: winter; c, d: spring; e, f: summer; g, h: autumn) using daily precipitation simulations from 13 CMIP5 GCMs over the 1861–2005 period (a, c, e, g) and 8 CMIP6 GCMs over the 1861–2014 period (b, d, f, h). Lines and uncertainty bands represent the ensemble median and ± 1 ensemble standard deviation, respectively. Continental relative change denotes the median relative change over all grid cells across Europe. A 20-year moving window was used for anomaly calculations with NAT simulations as the reference series. P-values for the linear trend significance of the ensemble median are provided on plots.

The mathematical expression of the method is as follows:

$$RC(p, s, t) = \begin{cases} \left(\frac{P_{ALL}(p, s, t)}{P_{NAT}(p, s, t)} - 1 \right) \times 100 \\ \left(\frac{P_{GHG}(p, s, t)}{P_{NAT}(p, s, t)} - 1 \right) \times 100 \end{cases} \quad (6)$$

where RC is the relative change for extreme precipitation anomaly (%) for exceedance probability p , season s and time slice t , P_{ALL} is the extreme precipitation of ALL simulations and P_{NAT} is the extreme precipitation of NAT simulations. RC is computed for thirteen CMIP5 and eight CMIP6 GCMs as the GHG and NAT simulations are only compared with the ALL simulations of the same models.



The contributions of anthropogenic influences to the changes in extreme precipitation anomalies are determined as robust when at least 70% of the GCMs agree on the direction of change (figure S2). The agreement of at least two-thirds of climate models on the direction of climate change signals has been applied as a common criterion to quantify their robustness (IPCC 2013).

3. Results and discussion

3.1. Detection of trends in extreme precipitation anomalies

Examination of trends in latitudinal extreme precipitation anomalies over Europe shows a latitudinal dependence of the changes for all seasons (figure 1). The trends increase with latitude,

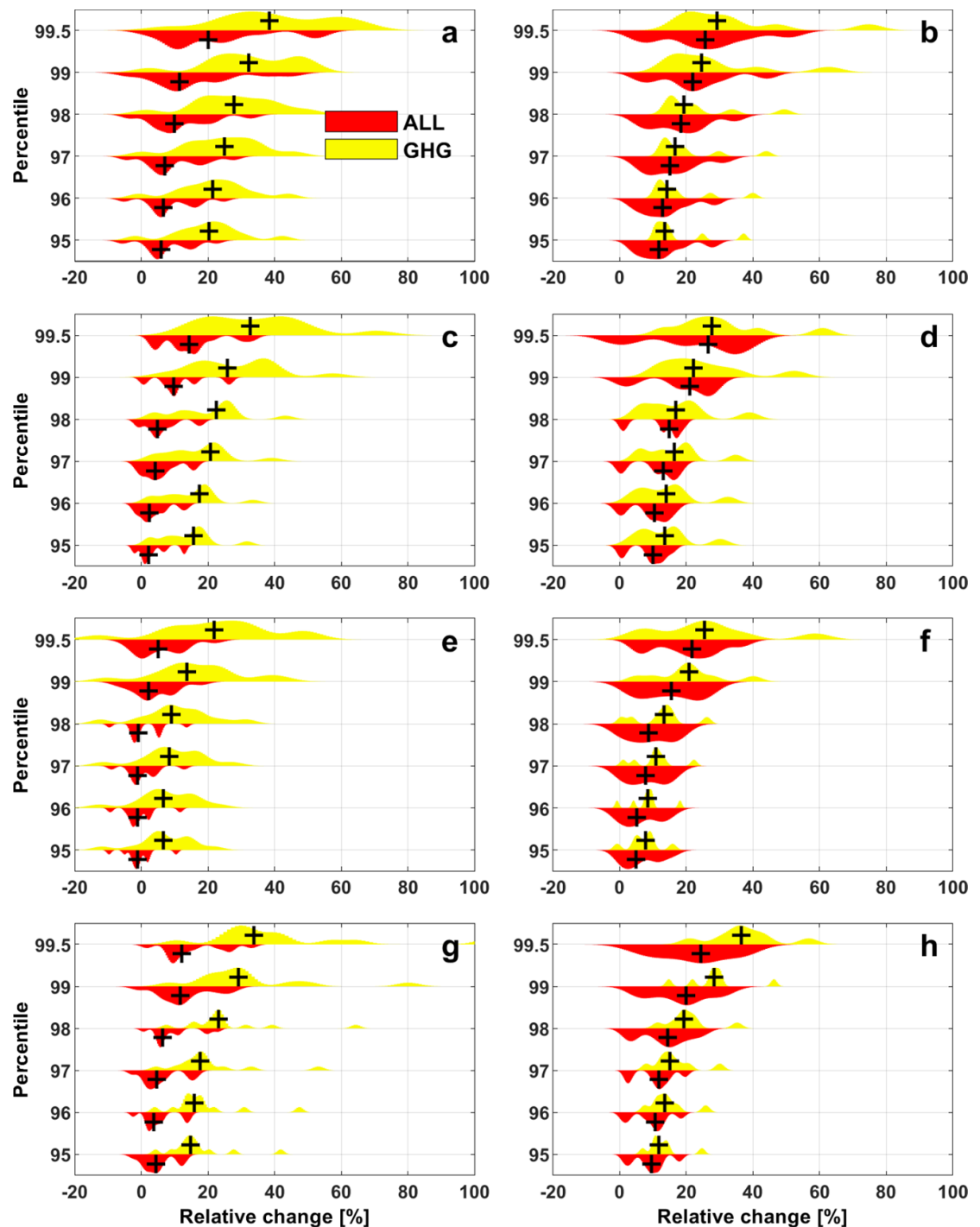


Figure 5. Continental relative change (RC_{ALL} and RC_{GHG}) of extreme precipitation of different percentiles ranging between 95 and 99.5 for the most recent 20-year period (1986–2005 for CMIP5 GCMs and 1995–2014 for CMIP6 GCMs) in different seasons (a, b: winter; c, d: spring; e, f: summer; g, h: autumn) using daily precipitation simulations from 13 CMIP5 (a, c, e, g) and 8 CMIP6 (b, d, f, h) GCMs. Continental relative change denotes the median relative change over all grid cells across Europe. Violin plots depict ensemble probability density, and the ensemble median is shown by black cross. See figure S3 for the results of the CMIP6 ensemble for the period 1986–2005.

particularly in the observed trends whose slope with latitude is significant at the 5% level in December–February, June–August and September–November and at the 10% level in March–May (table s1). For all seasons, the simulated trends are, however, subject to a large uncertainty, ranging from negative to significantly strong positive trends. The results show a significant increasing trend in both observed and

simulated winter extreme precipitation anomalies across all latitudes except for the latitudes equatorward of 45° (figure 1(a)). Longer model simulations also reveal significant increasing trends in winter at mid-latitudes, although there is a large ensemble spread (figure 1(b)). For spring, a significant increasing trend is found in both model and observed anomalies over latitudes 45° – 52°

(figure 1(c)). A significant increasing trend is also seen in observed spring extreme precipitation anomalies at high latitudes ($>57^\circ$), which emerges in the longer model simulations (figure 1(d)). While no significant trends are detected in simulated summer extreme precipitation anomalies, a significant increasing trend is found in observed anomalies at latitudes poleward of 53° (figure 1(e)). In longer simulations, some insignificant simulated trends in summer turn to decreasing trends at higher latitudes (figure 1(f)). Both model simulations and observations show a significant increasing trend in autumn extreme precipitation anomalies at latitudes poleward of 50° (figure 1(g)). A significant increasing trend is also detected in observed autumn anomalies over latitudes 40° – 50° (figure 1(g)). The significant increasing trends disappear in longer model simulations (figure 1(h)).

The latitudinal pattern of changes in extreme precipitation intensity and frequency has also been reported in previous studies (Karagiannidis *et al* 2012, Westra *et al* 2013, Cioffi *et al* 2015). The intensification of extreme precipitation in mid-to-high latitudes is expected to be due to an increase in the atmospheric water-holding capacity under warmer climates dictated by the Clausius–Clapeyron (CC) relation of $\simeq 7\% \text{ }^\circ\text{C}^{-1}$ (Fischer and Knutti 2016, Pfahl *et al* 2017, Norris *et al* 2019, Chen *et al* 2019). In contrast to extreme precipitation changes in the mid-to-high latitudes that are predominantly manipulated by thermodynamics, the wetting tendency in south Europe is offset by the dynamic effects that strongly modifies extreme precipitation intensification and even reverses the direction of the changes (Fischer and Knutti 2016, Pfahl *et al* 2017, Norris *et al* 2019, Chen *et al* 2019). The causes of extreme precipitation changes also depend on the season, owing to different seasonally dominant precipitation formation mechanisms. For summer, formed convective precipitation is more abundant, and hence changes in local thermodynamic state are relevant, while for winter, precipitation is primarily generated by synoptic processes and large-scale ocean to land transport, and hence changes in the large-scale circulation and mean state of the atmosphere must play a central role (Brogli *et al* 2019).

In terms of trend magnitude, observation-based trends are generally larger than model ensemble median trends (figures 1(a), (c), (e) and (g)). Our findings agree with those of Min *et al* (2011), Janssen *et al* (2014) and Asadieh and Krakauer (2015) who found an underestimation of observed increases in extreme precipitation using CMIP3 and CMIP5 GCMs. As underestimation has been found in different generations of GCMs (CMIP3, CMIP5 and CMIP6), one may conclude that this is an ongoing problem with climate models that can lead to further underestimation in their future extreme precipitation projections. Inconsistent trends between model

simulations and observations have also been found for mean precipitation (Zhang *et al* 2007, Wilcox *et al* 2013, Knutson and Zeng 2018) and soil moisture (Jiang *et al* 2019).

The largest discrepancy between models- and observations-based trends in terms of significance is found for summer (figure 1(e)). This can be explained by the convective nature of summer extreme precipitation in the study region (Rossow *et al* 2013), with a smaller spatial and temporal scale (Ye *et al* 2017), which is typically underestimated by coarse-scale climate models (Hirota *et al* 2016). This is also evident from a larger climate model uncertainty in south Europe compared with the north (figure 1(e)). Tropical and subtropical regions were also identified as the global uncertainty hotspots for future projections of extreme precipitation (Tabari *et al* 2019). Climate model uncertainties arise in south Europe from the different treatment of sub-grid scale convection, i.e. convective parameterization schemes, in different models (Fosser *et al* 2015), while in the extratropics, upward velocities are controlled predominantly by large-scale processes (synoptic eddies) and hence extreme precipitation changes are less dependent on convection parameterization details (O’Gorman and Schneider 2009). The inadequate representation of upward velocities by climate models may explain not only the uncertainty, but also the inability of models to reproduce interannual variability in extreme precipitation when compared to observations (Allan and Soden 2008). The discrepancy between model-based and observation-based trends in south Europe may additionally be triggered by a larger observation uncertainty (Zhang *et al* 2007) arising from a sparse station network in the region. Different levels of internal variability (known modes of lower frequency variability in the Atlantic Ocean (Tabari and Willems 2018)) between observations and climate models (Tokarska *et al* 2020) might also have contributed to the discrepancy between simulated and observed trends.

3.2. Contribution of anthropogenic influences to extreme precipitation anomaly changes in models

We estimate the extent to which the historical changes in extreme precipitation anomalies are attributable to ALL and GHG-alone forcings. Relative change is calculated with respect to NAT simulations and it is expected to fluctuate around zero in a stationary climate. The results confirm the anthropogenic influences on extreme precipitation anomalies over Europe, which are varying latitudinally and temporally. The latitudinal pattern of anthropogenic contributions to extreme precipitation anomalies during the last 20-year period reveal that the influences of ALL or GHG-alone forcings for all seasons increase with latitude (figure 2). Based on the CMIP6 simulations which include recent warming, while the contribution of anthropogenic influences to the extreme

precipitation anomalies is less than 8% in all seasons at latitudes below 50°, it can reach to 26% and 41% for latitudes between 50°–60° and higher than 60°, respectively. In other words, while extreme precipitation in ALL simulations is larger than NAT simulations, it is not uniform across all latitudes. Similarly, GHG-alone contributions to the extreme precipitation anomalies are 17%, 33% and 44% for the respective latitude ranges. The latitudinal dependence of anthropogenic climate change impacts on extreme precipitation anomaly in Europe is likely to continue in the future based on the projections of global and regional climate models (Rajczak and Schär 2017, Tabari *et al* 2019). The footprints of ALL and GHG-alone forcings on extreme precipitation anomalies are weaker in summer compared to the other seasons, which can be attributed to a larger internal variability of local summer extremes that masks the anthropogenic signal (Hosseinzadehtalaei *et al* 2019). Considering the robustness of the contributions defined based on the GCM agreement on the direction of change, the contributions of ALL and GHG-alone forcings to winter extreme precipitation anomalies are robust across latitudes (figure S2). The contributions to spring and summer extreme anomalies are also robust over all latitudes except for latitudes below 45°. For summer, a robust contribution is only found for ALL forcing at high latitudes and for GHG-alone forcing at mid and high latitudes. It is worthwhile to note that in all cases, the GCM uncertainty is large and varies with season and latitude.

The GHG forcing-induced climate change has a larger impact on extreme precipitation anomalies compared to ALL forcing induced climate change (figure 2). A plausible physical explanation is that the cooling effect of anthropogenic aerosols (included in ALL simulations) through their influence on the radiative transfer budget and by aerosol-cloud interactions masks the GHG effects on extreme precipitation (Sillmann *et al* 2013, 2019, Samset *et al* 2018, Zhao *et al* 2019). Due to a relatively short lifetime of anthropogenic aerosols, their concentrations and thereby the cooling effects are expected to have been largest over Europe and North America with high industrial activities and/or biomass burning (Huang *et al* 2007). The impact of anthropogenic aerosols has also been observed in other places around the world (Wilcox *et al* 2013, Song *et al* 2014, Hegerl *et al* 2019). The decrease in precipitation over the global land surface between the early to mid-20th century has been attributed to aerosol forcing (Wilcox *et al* 2013).

In order to examine the evolution of the contributions from the all anthropogenic (RC_{ALL}) and GHG-alone (RC_{GHG}) forcings to extreme precipitation anomalies, we calculated the contributions during every possible 20-year period from the pre-industrial time up to present, with reference to NAT simulations (figure 3). The temporal evolution of the contributions shows a general increase in anthropogenic

influence from 1861 to 2014. A significant increasing trend is seen for RC_{ALL} and RC_{GHG} of all seasons for both GCM ensembles excluding summer RC_{ALL} for the CMIP5 ensemble. In all cases, the p-value is smaller for RC_{GHG} compared to RC_{ALL} , pointing to a larger trend in the former. A larger discrepancy between RC_{ALL} and RC_{GHG} values in recent decades reveal a growing concentration of aerosols and their cooling effect on the atmosphere. Specifically, the RC_{ALL} and RC_{GHG} curves diverge after the 1950s when industrial activities picked up following the Second World War and led to the buildup of sulfate aerosols due to the widespread burning of high sulfur coal, and thereby, blocking out sunlight from reaching the surface of the Earth. The RC_{ALL} and RC_{GHG} curves in the CMIP6 GCMs converge again towards the end of the series, which can be attributed to an aerosol decline over Europe in recent years (Schwarz *et al* 2020).

Further investigation of anthropogenic contribution to the latitudinal pattern of changes shows that the latitudinal dependence of extreme precipitation changes was created by anthropogenic influences (figure 4). While the slope of the relative change with latitude was around zero in the pre-industrial era, it has changed to a steep slope in the recent decades. The statistical significance testing of the ensemble median slope evolution from the pre-industrial era to present shows that the slope of the relative change with latitude has significantly increased for both RC_{ALL} and RC_{GHG} in all seasons except for MAM RC_{GHG} in case of the CMIP5 ensemble median and SON RC_{ALL} for both ensembles. The ensemble spread is, however, large in all cases. The spatial heterogeneity of the radiative effect of anthropogenic aerosols is attributed to the geographically variable surface emissions of aerosols and relatively short atmospheric residence times (Hegerl *et al* 2018). Furthermore, the gradient of extreme precipitation changes varies seasonally and between the forcings so that during recent decades, a stronger slope of the relative change with latitude under the influence of GHG-alone forcing is found for June–August and September–November while a mixed pattern is seen for December–February and March–May (figure 4).

The more extreme the precipitation, the larger the anthropogenic influence (figure 5). The increment becomes more obvious for precipitation values of higher than 98th percentile. This supports the previous findings that changes in more extreme precipitation are larger (Allen and Ingram 2002, Allan and Soden 2008). For the most extreme event considered (99.5% percentile), anthropogenic influences have contributed to larger extreme precipitation anomalies by 26%, 26%, 22% and 24%, respectively in winter, spring, summer and autumn during 1995–2014 based on the CMIP6 multi-model ensemble median. The contributions for the CMIP5 ensemble for the last 20-year period (1986–2005) are 20%, 14%, 5% and 12% for the seasons, respectively. The contributions

of anthropogenic influences on extreme precipitation derived from the CMIP6 GCMs which include the intensified global warming in recent years are larger than those derived from the CMIP5 GCMs. For the 1986–2005 period, the anthropogenic influences from the CMIP6 GCMs drop to 24%, 19%, 13% and 15%, respectively for winter, spring, summer and autumn (figure S3). There are still differences between the anthropogenic contributions derived from the CMIP5 and CMIP6 ensembles which are attributed to different climate sensitivities of CMIP5 and CMIP6 GCMs (Tokarska *et al* 2020).

The anthropogenic emissions of GHGs should have produced larger increases in extreme precipitation anomalies than what has been observed (figure 5). The results show a seasonality in the cooling effect of the anthropogenic aerosol with the largest difference between RC_{ALL} and RC_{GHG} in autumn. This largely supports the finding of the earlier studies on the seasonality in the climatic impacts of anthropogenic aerosols (Huang *et al* 2007, Guo *et al* 2013). The potential contribution of GHGs to more anomalous 99.5th percentile extreme precipitation is 29%, 28%, 25% and 37%, respectively in winter, spring, summer and autumn, based on the CMIP6 multi-model ensemble median. The percentages for the CMIP5 ensemble are 38%, 33%, 22% and 34% for these seasons. Over global land, approximately 18% of precipitation extremes was previously found to be attributable to human influences using the CMIP5 GCM simulations (Fischer and Knutti 2015).

4. Conclusions

The temporal trends in European multi-decadal extreme precipitation anomalies in different seasons were first examined using historical simulations (1861–2014) from 26 CMIP6 and 25 CMIP5 GCMs and E-OBS data (1950–2014). The temporal evolution and latitudinal pattern of anthropogenic influences on the 99th percentile of daily precipitation were then estimated. The analysis results showed a latitudinal dependence of changes in extreme precipitation anomalies over Europe for all seasons. The observation-based trends were generally larger than model-based ones with the largest discrepancy in summer for south Europe where/when extreme precipitation is mainly convective which is poorly represented by large-scale climate models. In addition to the well-known deficiencies of climate models for simulations of meso-scale extreme precipitation and a different level of internal variability between models and observations, there are also uncertainties associated with observations arising from inhomogeneous temporal and spatial sampling and measurement errors such as changes in observation technique, instrument relocations and changes in the stations' surrounding environment, e.g. by urbanization (Tabari 2019). This is especially the case for south Europe where a sparse

station network leads to a larger observation uncertainty.

Our results verify the temporally-varying anthropogenic influences on extreme precipitation anomalies over Europe. The temporal evolution of the contribution of the anthropogenic influences to extreme precipitation anomalies reveals that the latitudinal dependence of the extreme precipitation changes must have been created by anthropogenic influences, as the changes had a zero slope with latitude in the pre-industrial era which has grown by few times in the recent decades.

According to the simulations from the newest generation of GCMs (CMIP6), while the contribution of anthropogenic influences to the extreme precipitation anomalies at latitudes below 50° does not exceed 8% in all seasons, it reaches 26% and 41% at latitudes between 50° – 60° and over 60° , respectively. A similar spatial pattern is found for GHG-alone contributions: 17%, 33% and 44% increases in extreme precipitation anomalies for the respective latitude ranges. The anthropogenic contribution to extreme precipitation changes varies seasonally. The seasonality in the anthropogenic contribution to extreme precipitation is a consequence of the inherent seasonal variability in precipitation formation processes (Łupikasza 2017). Due to a stronger fluctuation of extreme precipitation in summer that is often linked to free convection, the anthropogenic signal is masked by the internal variability. Averaged over Europe, anthropogenic influences have contributed to approximately 26%, 26%, 22% and 24% larger increases in extreme precipitation (99.5% percentile) anomalies, respectively in winter, spring, summer and autumn based on the CMIP6 multi-model ensemble median during 1995–2014. The contributions for the CMIP5 ensemble are 20%, 14%, 5% and 12% for the respective seasons during 1986–2005. Without the offsetting effect of anthropogenic aerosols, warming due to anthropogenic emissions of greenhouse gases alone should have produced larger anomalies than observed: 29%, 28%, 25% and 37% for the respective seasons based on the CMIP6 multi-model ensemble median. The contributions for the CMIP5 ensemble are 38%, 33%, 22% and 34% in the winter, spring, summer and autumn seasons, respectively. The difference between the contributions from ALL and GHG-alone forcings gets larger since the 1950s, when industrial activities upraised following the World War II and reached the maximum in recent decades when the concentration of aerosols and its cooling effect on the atmosphere has intensified. The difference gets smaller towards the end of the study period in the CMIP6 GCM simulations, what can possibly be explained by the decline in anthropogenic aerosol emissions over Europe.

The study results showed that anthropogenic influences have altered the present modes of climatic variability and thereby increased the occurrence probability of extreme precipitation with its

potential dramatic natural and socio-economic consequences. The anthropogenic influences are larger for more extreme precipitation events, which are typically used for the design of flood management infrastructure. This calls for accounting for both climate variability and climate change, even under deep uncertainty (Babovic *et al* 2018), when planning for new infrastructure, developing revised operation policies for the existing infrastructure, and making engineering infrastructure removal and rehabilitation decisions (Vahedifard *et al* 2020). Given the lifetime of installed hydraulic structures and water management systems, they have to be able to cope with the intrinsic decadal natural variations in meteorological pressures next to the longer term gradual trends due to climate change, making their design under nonstationary hydrology very challenging (Hui *et al* 2018).

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://esgf-index1.ceda.ac.uk>.

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