Impact of climate change on European winter and summer flood losses

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Abstract

Climate change is expected to alter European floods and associated economic losses in various ways. Here we investigate the impact of precipitation change on European average winter and summer financial losses due to flooding under a 1.5°C warming scenario (reflecting a projected climate in the year 2115 according to RCP2.6) and for a counterfactual current-climate scenario where the climate has evolved without anthropogenic influence (reflecting a climate corresponding to pre-industrial conditions). Climate scenarios were generated with the Community Atmospheric Model (CAM) version 5. For each scenario, we derive a set of weights that when applied to the current climate's precipitation results in a climatology that approximates that of the scenario. We apply the weights to annual losses from a well-calibrated (to the current climate) flood loss model that spans 50,000 years and re-compute the average annual loss to assess the impact of precipitation changes induced by anthropogenic climate change. The method relies on a large stochastic set of physically based flood model simulations and allows quick assessment of potential loss changes due to change in precipitation based on two statistics, namely total precipitation, and total precipitation of very wet days (here defined as the total precipitation of days above the 95th percentile of daily precipitation). We compute the statistics with the raw CAM precipitation and bias-corrected precipitation. Our results show that for both raw and bias-corrected statistics i) average flood loss in Europe generally tend to increase in winter and decrease in summer for the future scenario, and consistent with that change we also show that ii) average flood loss have increased (decreased) for winter (summer) from pre-industrial conditions to the current day. The magnitude of the change varies among scenarios and statistics chosen.

Keywords: climate change, Paris agreement, flood risk, economic loss, anthropogenic climate change, stochastic precipitation, average flood loss, RCP2.6

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1. Introduction

Inland flooding in Europe and worldwide affects the life of millions and causes large economic losses (Guha-Sapir et al., 2017). The number of severe flood events in Europe has increased over the last 35 years and more than 1500 flood events have been registered in Europe since 1980, half of which occurred after the year 2000 (EEA, 2017). In the future this trend is expected to continue because of changes in land use, socio-economic factors and the potential impacts of climatic changes induced by anthropogenic greenhouse gas emissions (Winsemius et al., 2015). Changes in precipitation patterns and their extremes under global warming are expected to be one of the major drivers in future flood risk; the impact of temperature changes on precipitation has been the subject of many scientific contributions over the last decade leading to a deeper understanding of the mechanisms through which a warmer atmosphere can lead to changes in the rainfall distribution (Pfahl et al., 2017; O'Gorman and Schneider, 2009; Allan, 2011; Haerter et al., 2010). Specifically, Pfahl et al. (2017) have shown how the response of extreme rainfall in the presence of temperature changes shows strong spatial variability due to energy availability in the atmosphere. Although it is widely accepted that precipitation and its extremes are likely to increase in a warmer world, the same is not true for flood frequency and magnitude. Several studies have explored long term river flow data sets to identify potential climate change trends showing how the inhomogeneity of available time series, human influence in shaping the streamflow distributions and statistical uncertainty do not allow a confident statement on present-day trends in flood peak frequency and magnitude over time (Mangini et al., 2018; Hodgkins et al., 2017; Bloschl et al., 2017). Therefore, there is significant uncertainty on the potential impacts of climatic changes on the economic damages associated with flood risk and there is no consensus yet around the magnitude and spatial distribution of change of average annual loss (an indicator of flood risk).

Projections of future annual precipitation indicate wetting tendencies for Scandinavia and central-eastern Europe and drying tendencies for the southern parts of Europe (Maraun, 2013). This pattern has been observed in records of winter extreme precipitation (Donat et al., 2013). A strong increase in winter heavy precipitation (defined as precipitation above the 99th percentile for months December to February) over Scandinavia and eastern Europe has been reproduced with global climate models (Giorgi et al., 2014) and regional climate models (Rajczak et al., 2013). In southern parts of Europe, even though mean precipitation is projected to decrease, heavy precipitation is projected to increase (Sillmann et al., 2013). These studies generally quantify changes at relatively high levels of global warming (3 °C and more). At 1.5 and 2 °C, King and Karoly (2017) showed increased intensity of extreme wet days (day with highest one day precipitation total within the season) in both summer and winter, in contrast to a weaker signal for mean changes over most of the continent. Vautard et al (2014) also found robust increases in mean winter precipitation in northern Europe, with extreme precipitation increase over eastern Europe and Scandinavia in summer and over southern Europe in winter. Dosio and Fischer (2018) found that locally the change in mean precipitation due to further warming is not significant but is accompanied by a robust change in extreme precipitation.

Climate change is expected to alter European flood risk and, specifically, average annual losses in various ways. Rojas et al. (2013) conducted an ensemble-based pan-European flood hazard assessment for present and future conditions and found that with no adaptation to climate change the average annual loss by 2080 with 3 °C global warming (SRES A1B emission scenario) would be about 17 times greater than in the present; with adaptation the increase would be ten-fold. In earlier studies, Kundzewicz et al. (2010) showed projected annual losses for the countries in Europe to be between 2 to 10 times greater by 2080 compared to 1970 (again for the SRES A1B scenario), and Ciscar et al. (2011) found the increase in annual loss from river floods in Europe more than doubles for the same period and employing similar scenarios. In a recent study which considers natural correlation between events, Jongman et al. (2014)

found an almost five-fold increase in annual loss by 2050 for a 3 °C global warming, whereas Alfieri et al. (2015) found for the same period an increase of 4 to 8 times for a 4 °C global warming scenario. More recently, Alfieri et al. (2018) reported changes in annual loss for three warming levels (1.5, 2 and 3 °C) and three independent studies to be roughly in a range between 2 to 4 times of the present. The latter three studies do not include the effect of future socio-economic changes on population, economy, and land use, so flood risk was estimated assuming present-day exposure and vulnerability. Because flood risk is a non-linear function of hazard, exposure, and vulnerability (e.g. de Moel et al., 2015), relative changes in average annual loss including future adaptation measures and socio-economic impacts due to climate change can vastly differ. Here we focus on average annual losses that would occur in a world where only the climatic (i.e. hazard) variables have changed, and particularly the precipitation.

Flood risk assessments at pan-European scale under different degrees of warming typically rely on multi-model ensembles encompassing several climate and hydrological models (e.g. Rojas et al., 2012; Alfieri et al., 2015; Gosling et al., 2016). Donnelly et al. (2017) compared runoff, discharge, and snowpack in Europe for climate change at 1.5, 2 and 3 °C global warming above pre-industrial level. They employed five hydrological models forced with multi-model ensembles of climate projections to calculate changes in hydrological indicators. They found robust increases in runoff over the Scandinavian mountains and robust decreases in Portugal at 1.5 °C, with extents further increasing over Norway and Poland and the Iberian coast, Balkan coast, and parts of the French coast at 3 °C. A robust increase of discharge with warming level was found only in Scandinavia. Thober et al. (2018) also assessed the impacts of climate change employing a multi-model ensemble of three hydrological models forced by five Coupled Model Intercomparison Project Phase 5 (CMIP5) general circulation models (GCMs) under three Representative Concentration Pathways (RCPs 2.6, 6.0, and 8.5). They found decreases for high flows and annual maxima in the Mediterranean and Eastern Europe, mostly related to decreases in total annual precipitation. They also found increases in high flows in Northern regions due to increasing precipitation, but with annual maxima decreasing due to less snowmelt. Alfieri et al. (2018) compared three studies of flood hazard and risk projections based on ensemble projections of expected damage and population affected at country level. They found a substantial increase in flood risk over most of Central and Western Europe at all warming levels. In this study, we do not attempt to simulate flood risk under climate change scenarios. Instead, we employ annual losses from a fully calibrated flood model of the current climate and translate these losses to the future or counterfactual world by reweighting the annual losses. Even though this approach is simple by design, it relies on a long stochastic set of physically based simulations produced with a stochastic rainfall generator, which is not the case in the other studies as they normally use only a hundred years of simulation and extreme value theory for extrapolation to higher return levels.

The objective of this study is to present a simple approach to assess potential changes in European flood risk due to relative changes in precipitation driven by climate change. The proposed approach combines the potential change in flood risk from river and pluvial flooding due to relative changes in precipitation. We apply this approach to assess the impact of relative changes in precipitation on European flood damages for two climate change scenarios produced with the Community Atmospheric Model version 5 (CAM). Precipitation fields are obtained from ensembles generated with CAM for two climate change scenarios. Scenarios include future global warming at 1.5 °C above pre-industrial conditions, and a hypothetical present-day counterfactual scenario where the climate has evolved without anthropogenic influence. The flood risk response to changes in precipitation relies on the RMS European Flood Model: A Monte Carlo model for the simulation of flood risk in Europe for the insurance market. This model has been calibrated and validated in its hazard and damage components with the goal to reproduce economic and insured flood damages and is employed here to evaluate changes in this variable under current climate. The model uses a probabilistic set of flood events to model flood risk, and the approach adopted in this study involves the creation of an alternative probabilistic set, by reweighting the stochastic model precipitation to mimic the precipitation statistics of the climate scenarios produced by the GCM. This paper is organized as follows: Section 2 describes the methods including the model runs, reweighting method, stochastic precipitation, loss tables and bias-correction methodology; Section 3 describes the relative changes in two precipitation statistics for the scenarios using raw input and bias-corrected input, along with the loss changes; Section 4 discusses the results; Section 5 concludes this paper.

2. Methods

In the present work we assess the impact of climate change on flood risk by incorporating a climate change signal, derived from state-of-the-art climate model simulations (Section 2.1) into a European probabilistic flood loss model (Section 2.2). The coupling of the models is done by means of a methodology devised to apply the spatially variable climate change signal to the stochastic flood losses produced by the RMS European Flood Model for the present climate (Section 2.3). Given the large uncertainties involved in climate model outputs and in modelling the hydrologic response in a changing climate (highlighted in the wide literature review discussed above) this paper focuses on the impact of precipitation changes and applies these to a time series of modelled European flood losses. This simplified approach, whilst not targeting changes in the frequency and magnitude of extreme events and their effect on the tail of the economic loss distribution, allows to represent the potential effect of changes in wetness condition over the continent which are reflected on the average annual loss (ie. the mean of the flood loss distribution).

2.1. Climate model runs

Simulations were carried out with CAM version 5.3 (Neale et al. 2010), a dynamical model of the atmosphere run at approximately quarter degree spatial resolution (Wehner et al. 2018) under the protocols of the Half a Degree Additional warming, Prognosis, and Projected Impacts (HAPPI) experiment (Mitchell et al. 2017) and of the C20C+Detection and Attribution Project (Stone et al. in preparation). (Note the model is listed as “CAM5.1.2-0.25degree” under the archive portal for both projects. See http://portal.nersc.gov/c20c/). The HAPPI project was designed to provide model output data describing climate and weather changes under stabilized 1.5 and 2.0°C levels of global warming, as compared to preindustrial conditions (1861-1880). CAM was run under three time-slice experiments to generate five 10-year simulations for the present climate (2006-2015) and six simulations each for potential future climate under stabilized 1.5°C and 2°C levels of global warming (nominally 2106-2115). We use daily resolution output in this paper.

Present climate simulations include observed forcing conditions for sea surface temperatures (SSTs) and sea-ice cover. Each simulation differs from the others in the initial weather state, and they are limited to 10 years in length to avoid long-term trends dominating the variability. The 2006-2015 runs use realistic observation-based time-varying conditions for all climate drivers during that time. These drivers are atmospheric greenhouse gas concentrations, tropospheric aerosol concentrations, atmospheric ozone concentrations, solar luminosity, SSTs, and sea-ice cover. SSTs in scenarios of the future are prescribed by summation of the observed 2006-2015 SSTs and an offset, estimated between decadal-averages of the 2006-2015 period and the projected warmer global conditions for the 2091-2100 period (Mitchell et al. 2017). The 1.5°C scenario was constructed following SST warming according to the response to the RCP2.6 in CMIP5 model simulations (which results in a global warming of approximately 1.5°C), with sea ice concentration modified accordingly. Greenhouse gas, aerosol, and ozone concentrations are set according to RCP2.6. More implementation details can be found in Mitchell et al. (2017) and Wehner et al. (2018).

An additional set of four 10-year simulations corresponds to the counterfactual historical scenario of the C20C+ Detection and Attribution project (Stone et al. in preparation). This 'naturalised' climate scenario represents hypothetical counterfactual time-varying conditions for climate drivers during the 2006-2015 period whereby industrial anthropogenic emissions had not occurred over the course of history. It is constructed by setting the Present-scenario greenhouses gases, aerosols, and ozone to pre-industrial (year 1855) values and adjusting SSTs and sea ice accordingly. The SST adjustment is based on the difference of temperatures from CMIP5 climate models run with and without anthropogenic influence (Stone and Pall in preparation). Here we will make use of the natural scenario simulations as well as those for present climate and future climate at 1.5°C global warming, we will refer to these simulations as NAT, Present and Plus15, respectively.

Modelled precipitation is bias-corrected with respect to observations (E-OBS, Haylock et al, 2008) for the period 1961-2011, using quantile mapping. Specifically, we adopt a non-parametric approach, termed quantile delta mapping (Cannon et al., 2015). First, future (or natural) climate model outputs are bias corrected to observations by quantile mapping. Second, model-projected relative changes in quantiles are superimposed on the bias-corrected model outputs. The method preserves model-projected relative changes in quantiles, while at the same time correcting systematic biases in quantiles of a modeled series with respect to observed values – one of the reasons for discrepancy in flood risk assessments, as pointed out by Thober et al. (2018).

2.2. The RMS European Flood Model

The RMS European Inland Flood Model is a probabilistic, high resolution, flood catastrophe model that is widely used in the insurance industry to estimate flood risk for a given portfolio of insured exposures. The model currently covers 15 countries: Austria, Belgium, Czech Republic, France, Germany, Hungary, Ireland, Italy, Liechtenstein, Luxembourg, Monaco, Poland, Slovakia, Switzerland, and the United Kingdom. In this study we exclude the Republic of Ireland, Italy, and Northern Ireland, which were under development while doing this analysis, and we also exclude Liechtenstein, Luxemburg, and Monaco because of their small size relative to the model domain. The model includes three main components: a hazard module, a damage module, and a financial module. The hazard module simulates precipitation-driven flood risk and risk from major river flooding with a physically based approach. The damage module relies on detailed building inventories and a comprehensive catalogue of damage functions to describe the vulnerability of buildings to flood risk. The financial model quantifies the economic loss of exposure to flooding.

Here we focus on the hazard module and the methodology used to simulate probabilistic flood risk maps from a stochastic rainfall simulation. The flood hazard model relies on a continuous 50,000-year Europe-wide stochastic precipitation dataset which has been generated with a stochastic rainfall generator based on the main modes of variability of gridded precipitation data through Principal Component Analysis (Bouvier et al., 2003; Westra et al., 2007). Observed gridded precipitation (E-OBS, Haylock et al., 2008) was available for the period 1961-2011 (daily resolution at quarter-degree spatial resolution) while the other atmospheric variables relevant for runoff generation were obtained from the GLDAS dataset (https://ldas.gsfc.nasa.gov/gldas/) for the same period (3 hourly resolution at one-degree spatial resolution).

Stochastic monthly rainfall fields, obtained as a linear combination of stochastic Principal Components (PCs) and main modes of variability of the monthly rainfall anomalies (EOFs), were subsequently disaggregated in space and time to 3-hourly, 6km resolution grids. Spatial disaggregation was performed through the scaling properties of standardized rainfall fluctuations with statistical scaling parameters related to elevation and convective available potential energy (CAPE) (Perica and Foufoula-Georgiou, 1996). Temporal disaggregation is performed through a bootstrapping methodology. The stochastic rainfall generator considers the relationship between rainfall and the state of the atmosphere by incorporating the correlation between the rainfall principal components and the North Atlantic Oscillation (NAO), which is simulated in the stochastic model as an AR (1) process calibrated on monthly NAO data in the available observation period (data from National Weather Service http://www.cpc.ncep.noaa.gov/).

The modelling domain is subdivided into 8546 catchments, based on standard catchment delineation routines (Metz et al., 2011); catchment size varies between 50 and 500 km^2. Rainfall-runoff processes are modelled with a semi-distributed rainfall-runoff approach based on TOPMODEL (Beven and Freer, 2001), with a runoff generation module that accounts for evapotranspiration, canopy interception, snow accumulation and melting, formulated by 15 parameters. The hydrological model is calibrated to observations for approximately 2000 gauges employing time series of up to 30 years in length (minimum 10 years) using a genetic algorithm to appropriately cover the parameter space (Deb et al., 2002). We employ two cost functions in the optimization, one for the overall bias and another for the discharge peaks. After performance assessment we retain about 1400 gauges. Parameters are redistributed to upstream catchments when gauges are not available. Discharge at the outlet of the catchments is obtained through the Muskingum-Cunge routing technique. Again, we perform calibration of the routing model for the same gauges. The model is therefore designed to capture the temporal evolution (e.g. antecedent conditions and clustering of events) and the spatial correlation of inland flood risk within and between countries.

We employ a 50 m resolution digital terrain model (DTM) for computing flood depths on major rivers as well as surface flooding induced by precipitation. Manning coefficients are obtained from land use land cover data (https://land.copernicus.eu/pan-european/corine-land-cover). We compute fluvial and pluvial inundation maps for several return periods using the river discharge and surface runoff, respectively. Inundation maps are obtained by solving the shallow water equations. More details about model implementation and validation can be found in Zanardo et al. (2019).

The time sequence of flood damages is obtained in the form of a Monte Carlo set of stochastic flood events resulting from the estimation of economic damages to buildings, for a given portfolio of exposed assets. The damage simulation is performed at the building level by leveraging the high-resolution flood maps and a detailed model of the building stock and their vulnerabilities to a given level of flood depth. The results of the Monte Carlo simulation are outputted to a year-loss table (YLT), where each simulated year has a uniform probability of occurrence equal to the inverse of the length of the simulation. The model contains an average of about 30 damage producing flood events per year over the 50,000 years of simulation. The 30 events are domain wide and a single event can affect multiple countries. For example, the UK has 4.2 events per year. Each event is identified with time and date, duration, and location. We compute the annual loss by aggregating the loss of events occurring in each year. The average annual loss (normally referred as AAL) is obtained by computing the mean of the annual losses over the length of the simulation. Note that in this paper we make the distinction of winter and summer losses, in which case the annual loss is based on winter and summer events separately.

2.3. Reweighting method

We present a method to derive a set of weights that, when applied to a given statistic of the stochastic precipitation dataset, produces a climatology that approximates the statistic of an imposed climate change scenario. We then apply the weights to the YLT and re-compute the AAL to assess the loss change due to precipitation under climate change. Here we introduce the method in terms of yearly calculations whereas in the results section we will adopt a seasonal approach, in which case, the statistics are computed separately for each season of each year and similarly, for the losses. We compute two statistics: total precipitation (SUM) is the sum of all days that belong to the year; and the contribution of very wet days to the total precipitation (R95pTOT), here defined as the sum of all days with precipitation greater than the 95th percentile of the daily precipitation.

In the following, p_{cy} is the stochastic precipitation statistic for catchment c and year y and p_c is the reference climatological mean of the statistic for catchment c. If the mean precipitation statistic varies linearly with time, the expected value N years from the reference period is given by

(Equation 1)

with k_c the annual rate of change in the statistic for catchment c. We derive a set of annual weights ω_y, such that when the mean precipitation statistic is calculated using the weighted $\omega_y p_{cy}$, the latter approximates the expected value given by the above equation. The p_c quantities are computed for each year in the stochastic precipitation dataset whereas the rate of change k_c is computed as the long-term of lumped climate model simulations.

The approach to obtain the weights involves two steps: first, for each year in the stochastic precipitation we calculate a climate change index λ_y. This index gives the year relative to the reference period for which the chosen climate change scenario most closely resembles a given year in the stochastic precipitation. The reference period here is 1961-2011 and corresponds to the observation period over which measured rainfall data were available for the creation of the European Flood HD model's stochastic precipitation set. The minimization is performed across all catchments:

(Equation 2)

where A_c is the catchment area and σ_c is the standard deviation of the precipitation statistic of catchment c. We normalize with the standard deviation to avoid high-precipitation catchments dominating the terms in the summation. Because λ_y does not depend on c, the value that minimizes the expression can be found analytically and is given by:

(Equation 3)

Second, we find the weights ω_y that minimize the following expression:

(Equation 4)

where N_Y is the number of years (or individual seasons) in the stochastic precipitation. We use the climate change index λ_y to inform the weight function ω_y. The expression above is optimized numerically to allow for weight functions of different types.

Here, we employ a two-parameter function such that for positive λ_y and for negative λ_y , with α_1 and α_2 two positive scalars. The two-parameter function allows for different weights in the two regions of the frequency domain above and below unity; this means that weighting towards drier years can have a different scale coefficient than weighting towards wetter years.

3. Results

To compare results between the different climate scenarios, simulations within the respective ensembles are first concatenated. This results in 50-year time series in the case of the future to present comparison (5 simulations of 10 years each for Plus15 and Present), and 40-year time series in the case of the natural to present comparison (4 simulations of 10 years each for NAT and Present). We compute all quantities for winter (DJF) and summer (JJA) seasons.

3.1.1. Mean seasonal precipitation

When compared with E-OBS precipitation, the CAM generally tends to overestimate precipitation in winter months and underestimate precipitation in summer months (Figure 1). The winter bias can be seen mainly in mountainous areas; Barcikowska et al. (2018) argues that these differences can be due to both model and observational biases because observations are less representative in orographic conditions and because topography is too smooth in the comparatively lower resolution model. However, the general large-scale wet bias particularly over western Europe could also be indicative of stronger zonal winds in the model, suggesting more storminess and moisture brought particularly into the UK, Benelux, and Germany. The summer bias may be explained by insufficient resolution in the model to capture heavy convective storms, particularly in inland and mountainous regions.

At 1.5 °C global warming winter precipitation is generally greater throughout Europe compared to the present; summer precipitation shows slightly wetter conditions in Eastern Europe and drier in Northern Europe. These results agree with a consensus towards wetter winters in most parts of Europe. The present to natural comparison mostly shows wetter conditions in winter and drier in summer, which is akin to the future to present comparison since in the present the climate is generally warmer than in the naturalised scenario.

3.2. Relative changes in precipitation statistics

Relative changes are computed with respect to present climate simulations. Figure 2 shows the spatial distribution of the relative changes of the two winter statistics for the two climate change scenarios. The Plus15 scenario generally shows positive changes throughout Europe and with the largest magnitudes of the two scenarios. The NAT scenario shows mostly negative changes for eastern Europe and some small areas with positive changes in western Europe, particularly for R95pTOT. Each scenario shows a smooth spatial pattern for the total precipitation and a slight increase in patchiness and spikiness for the total precipitation from very wet days. This could be attributed to sampling uncertainty because given the same amount of underlying data, extreme metrics are less well sampled than the total. Additionally, since patchiness is concentrated toward southern Europe, we hypothesize that there may be an increased influence of convective cells producing patchy extreme precipitation embedded within large-scale southerly flow due to a warmer Mediterranean under climate warming. In general, patterns are spatially coherent for the different statistics and do not change sign, however, magnitudes generally tend to decrease when looking at the more extreme statistics.

Figure 3 shows the spatial distribution of the relative changes of the two summer statistics for the two climate change scenarios. Gray areas indicate areas with too few rainy days to compute a meaningful change. Relative changes can easily be greater than 100% because summer precipitation is generally noisier than winter precipitation (we have capped these to avoid extending the limits in the color bar plots). Patchiness is much more characteristic in the summer spatial patterns too. Like winter, spatial patterns are generally coherent when looking at the different statistics. The 1.5°C scenario generally shows a tendency for drier conditions in northern Europe and parts of Italy, whereas both statistics seem to agree on wetter conditions over southern and Eastern Europe. These results are not in full agreement with previously published results. Reasons for discrepancy could have to do with scenario design and model resolution. In terms of scenario design, most of the studies mentioned in the introduction concern about +1% CO2 per year emissions scenarios, where CO2 increases dominate any aerosol changes. The Plus15 scenario exhibits an aggressive CO2 ramp-down and aerosol ramp-down, where the effects of any aerosol ramp-down rival that of any further CO2 increase. The NAT scenario also shows drier conditions over northern Europe, and wetter conditions over eastern Europe, France, and parts of the UK.

We bias-correct the CAM simulations by preserving the relative change in precipitation quantiles of modelled precipitation (i.e. trend in modelled projections, see Figure 4). The bias correction is performed for winter and for summer separately, and for days with precipitation greater than 1 mm/day only to avoid changing the wet/dry sequence of the underlying precipitation. Figure 5 shows spatial plots of the mean seasonal precipitation difference between scenarios, after bias-correction. Spatial patterns are comparable to those before bias-correction and differences between scenarios tend to be smaller. Some areas of high precipitation in Plus15 (e.g. France), particularly for winter, are missing after bias-correction. Summer changes for Plus15 indicate drier conditions in GB and Benelux. Winter spatial patterns in the relative change of both statistics after bias-correction (Figure 6) are very similar to the ones computed with the raw precipitation. In the summer (Figure 10), spatial patterns before and after bias correction also compare well.

3.3. Relative changes in average annual loss

In what follows we present the negated results for the NAT scenario so that both Plus15 and NAT scenarios appear with the same sign in the plot. Figure 8 shows the relative change in winter AAL obtained with the raw and bias-corrected (BC) winter precipitation statistics and both climate change scenarios, for the EUFL domain and split by country. The Plus15 scenario results in a positive loss change with both statistics; R95pTOT generally yields a lower magnitude, which is a direct consequence of the smaller relative change of R95pTOT compared to the total precipitation (Figure 6). The NAT scenario shows reduced magnitudes in the relative change of the AAL by country and for the entire domain when compared to the Plus15 scenario. This is because the relative changes of both statistics in the NAT scenario are milder than in the Plus15 scenario. Discrepancies in AAL change arising from both statistics are minor in the NAT scenario, generally showing a slightly higher magnitude with R95pTOT.

Summer changes in AAL (Figure 7) generally show an opposing trend for the two climate change scenarios, except for France in the Plus15 scenario that shows a positive trend with the bias-corrected total precipitation. Magnitudes of the summer AAL change in the Plus15 scenario can be compared with winter; however, summer AAL changes are generally more sensitive to R95pTOT than in winter, showing greater changes in AAL. The NAT scenario shows greater magnitudes of loss change when compared to winter. These observations stem from the fact that in general winter changes are spatially smooth compared to summer changes (Figures 6 and 7); for summer we observe positive and negative changes within the domain, and even within countries. Furthermore, summer changes in statistics show greater magnitudes and more patchy features. It is important to note that for winter differences between SUM and R95pTOT are less prominent than for summer.

4. Discussion

The method we presented assumes that the precipitation statistic varies linearly with time from the present to the time where the climate change scenario applies (either future or pre-industrial). This may limit the application of the method if we consider a hypothetical timeline where global warming, and the precipitation response to that warming, displays a non-linear trajectory. For instance, this is the case of the 2°C global warming (Plus20) simulations of the HAPPI project (Barcikowska et al., 2018; Li et al., 2018). One way of circumventing this limitation would be to compute the changes in AAL by splitting the timeline into two (or more) parts: first compute the changes from Present to Plus15, then apply the weights to Present conditions to obtain a stochastic precipitation for Plus15 climate, and finally compute the changes from Plus15 to Plus20. This results in double-weighing the reference loss estimate. The limitation of this method is that the intermediate stochastic precipitation results from an approximation of the projected climate and further iterations would necessarily imply an accumulation of errors that may render subsequent loss estimates less accurate.

Our methodology relies on the assumption that precipitation alone is a good indicator of changes in the flood loss distribution. This is certainly a simplifying assumption considering that other climatological drivers are likely to have an impact as well (Kay et al. 2011; Schaller et al. 2016), and that feedback mechanisms may exist that are unaccounted for (e.g., increasing mean temperatures leading to increasing evapotranspiration). However, because precipitation acts as a first-order control on flood losses, we believe the approximations made in this paper still provide useful insights. Although at event level, changes in precipitation cannot directly be translated to changes in inundation patterns and flood losses, we believe that the methodology proposed is suitable to capture changes in wetness conditions that translate into an increased/decreased propensity to flooding. Given the non-linearities involved we suggest that these insights should be translated into an average annual loss change rather than impacts on the full probability distribution of flood losses.

Furthermore, the assumptions made need to be evaluated in the context of other approximations in similar research. The observation that a full-fledged impact assessment of climate change on flood risk can carry significant uncertainty due to factors such as climate model choice (Deser et al., 2012), downscaling and bias-correction procedures, hydrological model choice and parameter estimation (Donnely et al., 2017) are examples of such approximations. Moreover, Alfieri et al. (2018) concluded that climate projections are the main driver influencing future trends of flood risk under global warming because model error is small than the difference between different scenarios of future climate change. These factors are further complicated by a small number of flood events, as they correspond to climate simulations that typically span no more than 100 years, similarly to the observed record. Because flood loss time series have a large natural variability, the estimation of an AAL based on a relatively short record (e.g., less than 100 samples) of annualised losses also introduces considerable sampling error. In our case, a fully-fledged approach would require bias-correcting the precipitation and the other atmospheric variables to generate a stochastic dataset that is consistent with the one employed in the RMS European Flood HD Model.

In addition to the already mentioned unmodelled feedbacks, the AAL estimates presented here do not consider the effects of adaptation and other indirect socio-economic impacts and are based on the potential change in the flood hazard only. Population projections suggest that EU population has a mild decreasing trend (UN report, 2017). Jongman et al. (2012) suggest a constant or decreasing exposed population but an increase in exposed assets. The assumptions in this study allow for a reduction of the uncertainty involved in the modelling exercise (eg. bias correction of multiple meteorological variables from the climate model output, uncertainties in simulating the hydrologic response under varying climate, uncertainties in the estimate of socio-economic changes) and therefore to investigate the connection between projected changes in precipitation and projected changes in loss. On the other hand they do not allow us to investigate the full probability distribution of financial losses and the effect of potential changes in the frequency of extremes and the effect of future changes of population and/or economic assets which would likely have a positive effect on AAL. In a recent study on paired flood events, Kreibich et al. (2017) showed that the lower damage caused by a second event was mainly due to significant reductions in vulnerability via raised risk awareness, preparedness, and improvements of organizational emergency management. Furthermore, the observed increase in flood damage in many regions of the world is generally dominated by exposure increase (e.g. Bouwer, 2011), so it is possible a balance between the effects of exposure and vulnerability that could eventually cancel each other out in the future.

We conducted a sensitivity analysis into the effect of raising defences, based on current adaptation literature (Alfieri et al., 2016). The AAL for winter and summer together is reduced by about 2, 12 and 20% for an increase in the defence return period standard of protection of 5, 25 and 50% respectively. If we assume these adaptation measures occur within the coming 50-100 years, the values obtained here are comparable to the changes in AAL that we estimate are due to climate change only. Although it is unlikely all countries in Europe would have raised their standard of protection at the same rate, more complicated adaptation scenarios could be easily assessed under the proposed evaluation setup.

5. Conclusions

Climate change threatens to increase the frequency and magnitude of high precipitation events with an associated risk for flood insurance. This has the potential to lead to year-on-year increase in the cost of flood insurance. In this contribution we assess the potential impact of climate change on Average Annual Loss (AAL) due to floods. We consider two climate change scenarios: one corresponding to a 1.5 °C global warming above pre-industrial level, and one corresponding to a naturalised world where climate has evolved without anthropogenic effects. We introduce a framework to reweight the current precipitation patterns such that the resulting climatology matches with the future or naturalised precipitation climatology. Climatology is understood here as the long-term mean of any precipitation statistic (here the total precipitation and the total precipitation of wet days, for raw and bias-corrected climate model simulations). The weights were determined by minimization of the squared root differences at catchment level and apply to the entire model domain and for each simulated year. We employed the weights to scale the annual loss of events simulated with an in-house European Flood HD model, which is a fully calibrated (to current climate) flood loss model which consists of a 50,000 year-long stochastic simulation. Based on derived weights, the annualized losses were weighted and a corresponding AAL was calculated, to assess the impacts of climate change on flood losses. AAL estimates vary with scenario and precipitation statistic used, with magnitudes typically within 5% per decade for winter and 10% for summer. AAL for the future scenario generally tends to increase in winter and decrease in summer, although the latter shows a magnitude differences when considering the different precipitation statistics. For the naturalised scenario, flood losses in winter are lower than for current-day conditions, and for summer they are larger; magnitudes of change are comparable to the magnitude of change between current-day losses and those for the future scenario. These results are consistent for both raw and bias-corrected precipitation statistics. Moreover, our results show that adaptation measures (included here as updates to the current standard of protection of the flood defences) in an idealised scenario that does not require a cost benefit analysis, could potentially play a role in reducing climate change impacts on European flood risk.

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References

Alfieri L, Burek P, Feyen L, and Forzieri G, 2015. Global warming increases the frequency of river floods in Europe, Hydrol. Earth Syst. Sci., 19:2247–60, 10.5194/hess-19-2247-2015

Alfieri L, Feyen L, and Di Baldassarre G, 2016. Increasing flood risk under climate change: a pan-European assessment of the benefits of four adaptation strategies, Climatic Change, 136:507–521, 10.1007/s10584-016-1641-1

Alfieri L, Dottori F, Betts R, Salamon P, and Feyen L, 2018. Multi-Model Projections of River Flood Risk in Europe under Global Warming, Climate, 6, 16, 10.3390/cli6010016

Allan R, 2011. Climate change: Human influence on rainfall, Nature, 470:344–345, 10.1038/470344a

Barcikowska M, Weaver S, Feser F, Russo S, Schenk F, Stone D, Wehner M, and Zahn M, 2018. Euro-Atlantic winter storminess and precipitation extremes under 1.5°C versus 2°C warming scenarios, Earth Syst. Dynam., 9:679-699, 10.5194/esd-9-679-2018

Beven K, and Freer J, 2001. A dynamic TOPMODEL, Hydrological Processes, 10.1002/hyp.252

Bloschl G, Hall J et al., 2017. Changing climate shifts timing of European floods, Science, 357:588-590, 10.1126/science.aan2506

Bouvier C., Cisneros L., Dominguez R., Laborde J-P., Lebel T, 2003. Generating rainfall fields using principal components (PC) decomposition of the covariance matrix: a case study in Mexico City, Journal of Hydrology, 278(1-4): 107-120, 10.1016/S0022-1694(03)00122-7

Bouwer L, 2011. Have disaster losses increased due to anthropogenic climate change? Bull. Am. Meterol. Soc., 92(1), 39–46, 10.1175/2010BAMS3092.1

Cannon A, Sobie S, and Murdock T, 2015. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? Journal of Climate, 28(17), 10.1175/JCLI-D-14-00754.1

Ciscar J, Iglesias A, Feyen L, Szabó L, van Regemorter D, Amelung B, Nicholls R, Watkiss P, Christensen O, Dankers O, Garrote L, Goodess C, Hunt A, Moreno A, Richards J, and Soria A, 2011. Physical and economic consequences of climate change in Europe, Proceedings of the National Academy of Sciences, 108(7):2678-2683; 10.1073/pnas.1011612108

Deb K, Pratap A, Agarwal S, and Meyarivan T, 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation, 6(2):182-197; 10.1109/4235.996017

Deser C, Phillips A, Bourdette V, and Teng H, 2012. Uncertainty in climate change projections: the role of internal variability, Clim. Dynam., 38:527–546, 10.1007/s00382-010-0977-x

de Moel H, Jongman B, Kreibich H, Merz B, Penning-Rowsell E, and Ward P, 2015. Flood risk assessments at different spatial scales, Mitig Adapt Strateg Glob Change, 20(865), 10.1007/s11027-015-9654-z

Donat M, and Coauthors, 2013. Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The HadEX2 dataset, J. Geophys. Res. Atmos., 118:2098–2118, 10.1002/jgrd.50150

Donnelly C, Greuell W, Andersson J, Gerten D, Pisacane G, Roudier P, and Ludwig F, 2017. Impacts of climate change on European hydrology at 1.5, 2 and 3 degrees mean global warming above preindustrial level, Climatic Change, 143:13–26, 10.1007/s10584-017-1971-7

Dosio A, and Fischer E, 2018. Will Half a Degree Make a Difference? Robust Projections of Indices of Mean and Extreme Climate in Europe Under 1.5°C, 2°C, and 3°C Global Warming, Geophysical Research Letters, 45, 10.1002/2017GL076222

European Environment Agency, 2017. Climate change, impacts and vulnerability in Europe 2016 – An indicator-based report, EEA Report N.1/2017, ISSN: 1977-8449

Giorgi F, Coppola E, and Raffaele F, 2014. A consistent picture of the hydroclimatic response to global warming from multiple indices: Models and observations, Journal of Geophysical Research: Atmospheres, 119(20), 11:695–708, 10.1002/2014JD022238

Gosling S, and coauthors, 2016. A comparison of changes in river runoff from multiple global and catchment-scale hydrological models under global warming scenarios of 1 °C, 2 °C and 3 °C, Clim. Change, 141:577–95, 10.1007/s10584-016-1773-3

Guha-Sapir D, Below R, and Hoyois P, 2017. EM-DAT: The Emergency Events Database (www.emdat.be)

Haerter J, Berg P, and Hagemann S, 2010. Heavy rain intensity distributions on varying time scales and at different temperatures, Journal of Geophysical Research, 115, D17102, 10.1029/2009JD013384

Haylock M, Hofstra N, Klein Tank A, Klok A, Jones P, and New M, 2008. A European daily high- resolution gridded data set of surface temperature and precipitation for 1950–2006, J. Geophys. Res., 113, D20119, 10.1029/2008JD010201

Hodgkins G, and coauthors, 2017. Climate-driven variability in the occurrence of major floods across North America and Europe, Journal of Hydrology, 552, 10.1016/j.jhydrol.2017.07.027

Jongman B., Ward P.J. and Aerts J, 2012. Global exposure to river and coastal flooding: Long term trends and changes, Global Environmental Change, Volume 22, Issue 4

Jongman B, Hochrainer-Stigler S, Feyen L, Aerts J, Mechler R, Wouter Botzen W, Bouwer L, Pflug G, Rojas R, Ward P, 2014. Increasing stress on disaster-risk finance due to large floods, Nature Climate Change, 4:264–268, 10.1038/nclimate2124

Kay, A. L., S. M. Crooks, P. Pall, and D. A. Stone. 2011. Attribution of Autumn/Winter 2000 flood risk in England to anthropogenic climate change: a catchment-based study. Journal of Hydrology, 406, 97-112, 10.1016/j.jhydrol.2011.06.006

King A, and Karoly D, 2017. Climate extremes in Europe at 1.5 and 2 degrees of global warming, Environ. Res. Lett., 12, 114031, 10.1088/1748-9326

Kreibich H, and coauthors, 2017. Adaptation to flood risk: Results of international paired flood event studies, Earth's Future, 5:953–965, 10.1002/2017EF000606

Kundzewicz Z, Lugeri N, Dankers R, Hirabayashi Y, Döll P, Pińskwar I, Dysarz T, Hochrainer S, and Matczak P, 2010. Assessing river flood risk and adaptation in Europe — review of projections for the future, Mitig Adapt Strateg Glob Change, 15: 641, 10.1007/s11027-010-9213-6

Li C, Michel C, Seland Graff L, Bethke I, Zappa G, Bracegirdle T, Fischer E, Harvey B, Iversen T, King M, Krishnan H, Lierhammer L, Mitchell D, Scinocca J, Shiogama H, Stone D, and Wettstein J, 2018. Midlatitude atmospheric circulation responses under 1.5 and 2.0 °C warming and implications for regional impacts, Earth Syst. Dynam., 9:359-382, 10.5194/esd-9-359-2018

Mangini W, Viglione A, Hall J, Hundecha Y, Ceola S, Montanari A, Rogger M, Salinas J, Borzì I, and Parajka J, 2018. Detection of trends in magnitude and frequency of flood peaks across Europe, Hydrological Sciences Journal, 63:4, 493-512, 10.1080/02626667.2018.1444766

Maraun D, 2013. When will trends in European mean and heavy daily precipitation emerge? Environmental Research Letters, 8(1), 14004, 10.1088/1748-9326/8/1/014004

Metz M, Mitasova H, and Harmon R, 2011. Efficient extraction of drainage networks from massive, radar-based elevation models with least cost path search, Hydrol. Earth Syst. Sci., 15:667-678, 10.5194/hess-15-667-2011

Mitchell et al., 2017. Half a degree additional warming, prognosis, and projected impacts (HAPPI): background an experimental design, Geosci. Model Dev., 10:571-583, 10.5194/gmd-10-571-2017

Neale, R, 2010. Description of the NCAR Community Atmosphere Model (CAM 4.0), NCAR TECHNICAL NOTE, http://www.cesm.ucar.edu/models/ccsm4.0/cam/docs/description/cam4_desc.pdf

O'Gorman P, and Schneider T, 2009. The physical basis for increases in precipitation extremes in simulations of 21st-century climate change, Proceedings of the National Academy of Sciences, 106(35):14773-14777, 10.1073/pnas.0907610106

O’Gorman P, Allan R, Byrne M, and Previdi M, 2012. Energetic Constraints on Precipitation Under Climate Change, Surv Geophys, 33:585–608, 10.1007/s10712-011-9159-6

Perica, S. and E. Foufoula-Georgiou, 1996. Model for multiscale disaggregation of spatial rainfall based on coupling meteorological and scaling descriptions, J. Geophysical Research, 101(D21), 26:347-361, 10.1029/96JD01870

Pfahl S, O’Gorman P, and Fisher E, Understanding the regional pattern of projected future changes in extreme precipitation, Nature Climate Change, 7(6), 10.1038/nclimate3287

Rajczak J and Schär C, 2017. Projections of future precipitation extremes over Europe. A multimodel assessment of climate simulations, J. Geophys. Res. Atmos., 122:10773-10800, 10.1002/2017JD027176

Rajczak J, Pall P, and Schär C, 2013. Projections of extreme precipitation events in regional climate simulations for Europe and the Alpine Region, J. Geophys. Res. Atmos., 118:3610–3626, 10.1002/jgrd.50297

Rojas R, Feyen L, Bianchi A, and Dosio A, 2012. Assessment of future flood hazard in Europe using a large ensemble of bias-corrected regional climate simulations J. Geophys. Res.: Atmos., 117, D17109, 10.1029/2012JD017461

Rojas R, Feyen L and Watkiss P, 2013. Climate change and river floods in the European Union: Socio-economic consequences and the costs and benefits of adaptation. Glob. Environ. Change 23:1737–1751, 10.1016/j.gloenvcha.2013.08.006

Sillmann J, Kharin B, Zwiers F, Zhang X, and Bronaugh D, 2013. Climate extreme indices in the CMIP5 multi-model ensemble. Part 2: Future projections, J. Geophys. Res., 10.1002/jgrd.50188

Scoccimarro E, Gualdi S, Bellucci A, Zampieri M, Navarra A, 2016. Heavy precipitation events over the Euro-Mediterranean region in a warmer climate: results from CMIP5 models. Reg Environ Change, 16: 595, 10.1007/s10113-014-0712-y

Schaller et al., 2016. Human influence on climate in the 2014 southern England winter floods and their impacts, Nature Climate Change, DOI:10.1038/nclimate2927

Stone D and Pall P, in preparation, A benchmark estimate of the effect of anthropogenic emissions on the ocean surface

Thober S, Kumar R, Wanders N, Marx A, Pan M, Rakovec O, Samaniego L, Sheffield J, Wood E, and Zink M, 2018. Multi-model ensemble projections of European river floods and high flows at 1.5, 2, and 3 degrees global warming, Environ. Res. Lett., 13,014003, 10.1088/1748-9326/aa9e35

Wehner M, Reed K, Loring B, Stone D, and Krishnan H, 2018. Changes in tropical cyclones under stabilized 1.5°C and 2.0°C global warming scenarios as simulated by the Community Atmospheric Model under the HAPPI protocols. Earth System Dynamics, 9:187-195, 10.5194/esd-9-187-2018

Westra S., Brown C., Lall U., Sharma A, 2007. Modeling multivariable hydrological series: Princpal component analysis or independent component analysis?, Water Resources Research, 43(6), 10.1029/2006WR005617

Winsemius H, Aerts J, van Beek L, Bierkens M, Bouwman A, Jongman B, Kwadijk J, Ligtvoet W, Lucas P, van Vuuren D, and Ward P, 2016. Global drivers of future river flood risk, Nature Climate Change, 6:381-385, 10.1038/nclimate2893

Vautard R, Gobiet A, Sobolowski S, Kjellström E, Stegehuis A, Watkiss P, Mendlik T, Landgren O, Nikulin G, Teichmann C, and Jacob D, 2014. The European climate under a 2 C global warming, Environ. Res. Lett., 9,034006, 10.1088/1748-9326/9/3/034006

UNFCC, 2015. Adoption of the Paris agreement, Proposal by the President Technical report (Geneva: United Nations) (http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf)

UN, 2017. World Population Prospects, The 2017 Revision, Key Findings and Advance Tables. https://esa.un.org/unpd/wpp/publications/files/wpp2017_keyfindings.pdf

Zanardo, S., Nicotina, L., Hilberts, A. G. J., & Jewson, S. P. (2019). Modulation of economic losses from European floods by the North Atlantic Oscillation. Geophysical Research Letters, 46. 10.1029/2019GL08195

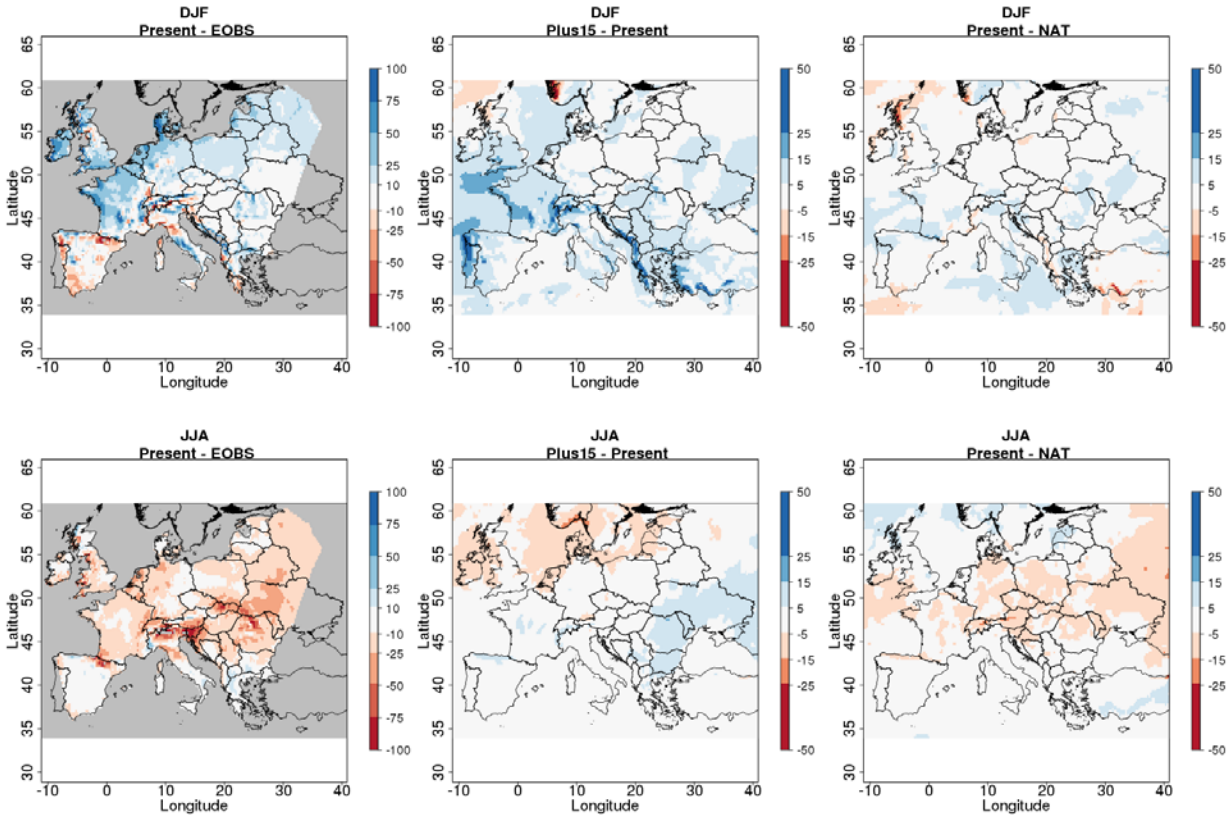

Figure 1. Difference of mean winter precipitation (top) and mean summer precipitation (bottom) for Present minus E-OBS (period 1961-2011), Plus15 minus Present and Present minus NAT scenarios; units are in mm.

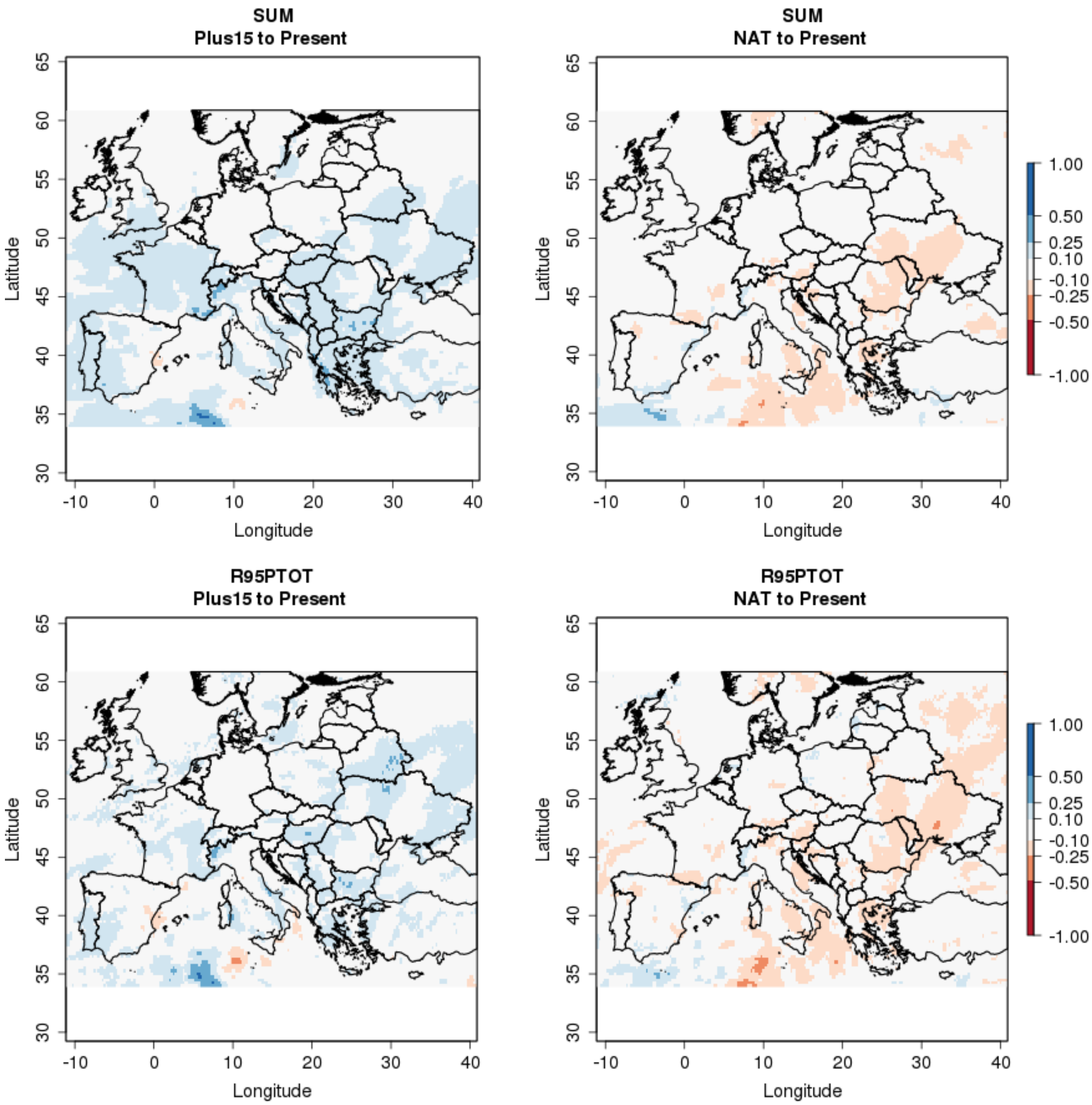

Figure 2. Relative change of winter total precipitation and R95pTOT for future climate (Plus15) and natural climate (NAT).

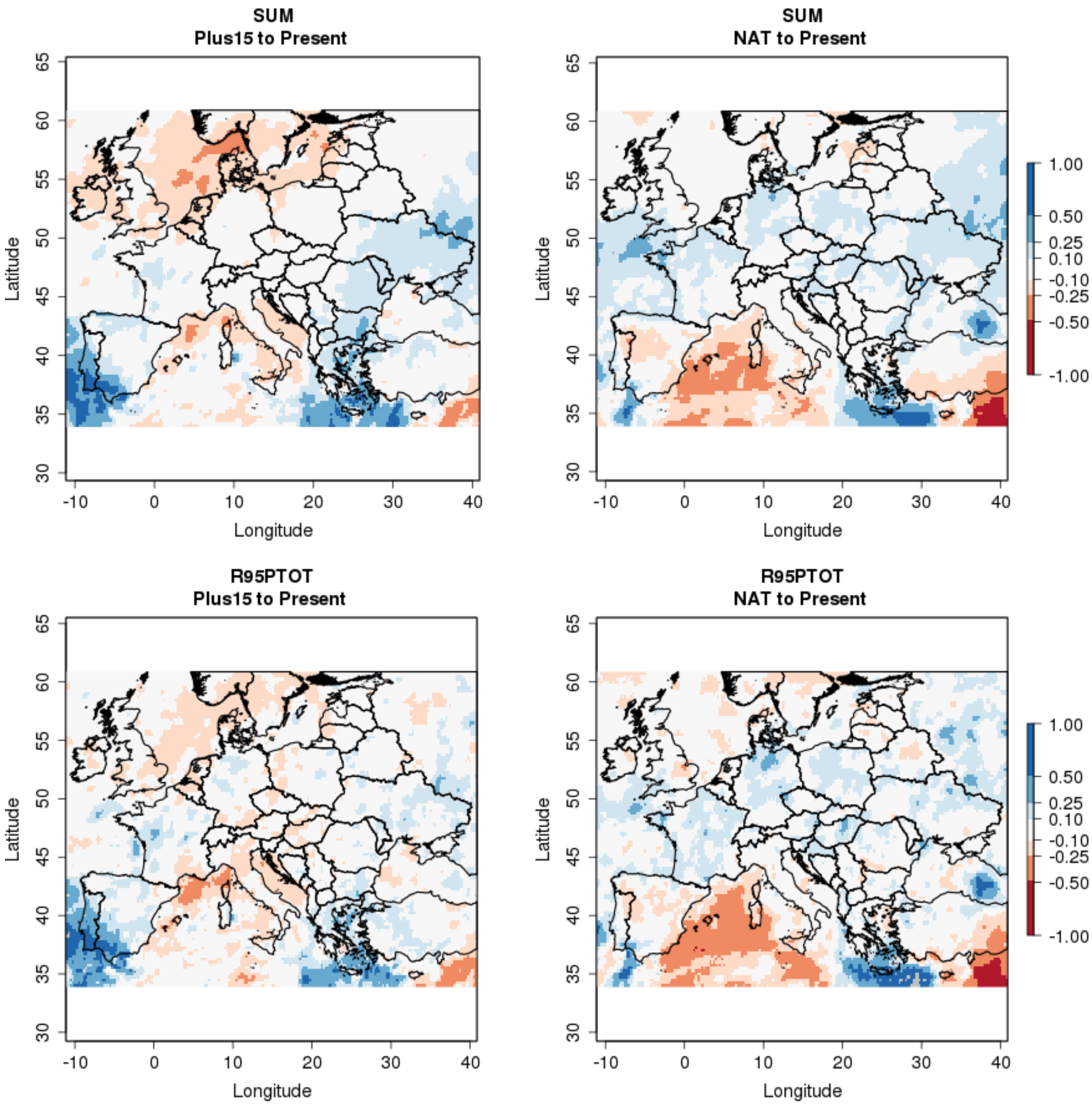

Figure 3. Relative change of summer total precipitation and R95pTOT for future climate (Plus15) and natural climate (NAT).

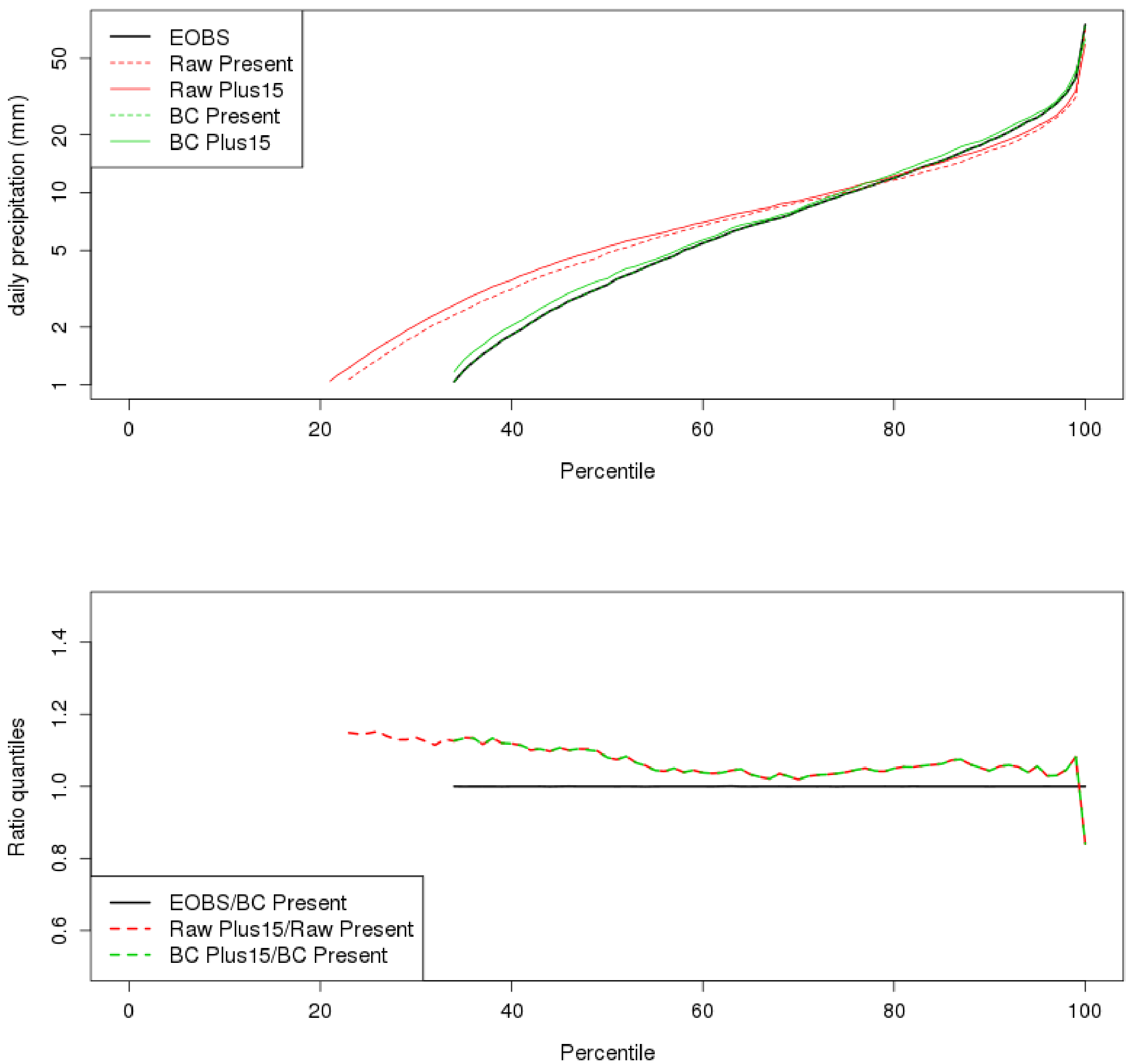

Figure 4. Example of cumulative distributions of winter daily precipitation for E-OBS (period 1961-2011), raw simulations and bias-corrected simulations.

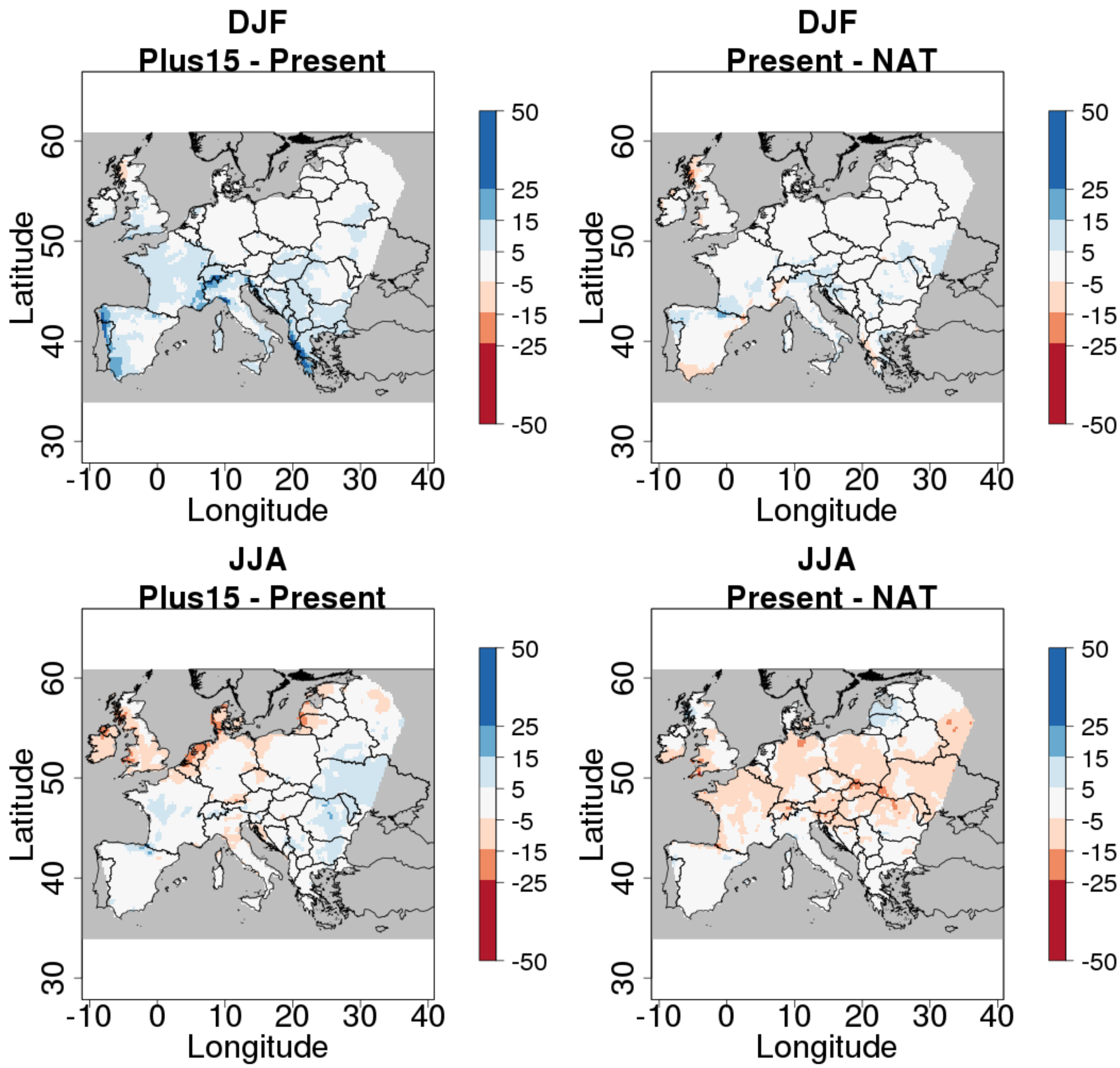

Figure 5. Difference of mean winter precipitation (top) and mean summer precipitation (bottom) for Plus15 minus Present and Present minus NAT scenarios, after bias-correction; units are in mm.

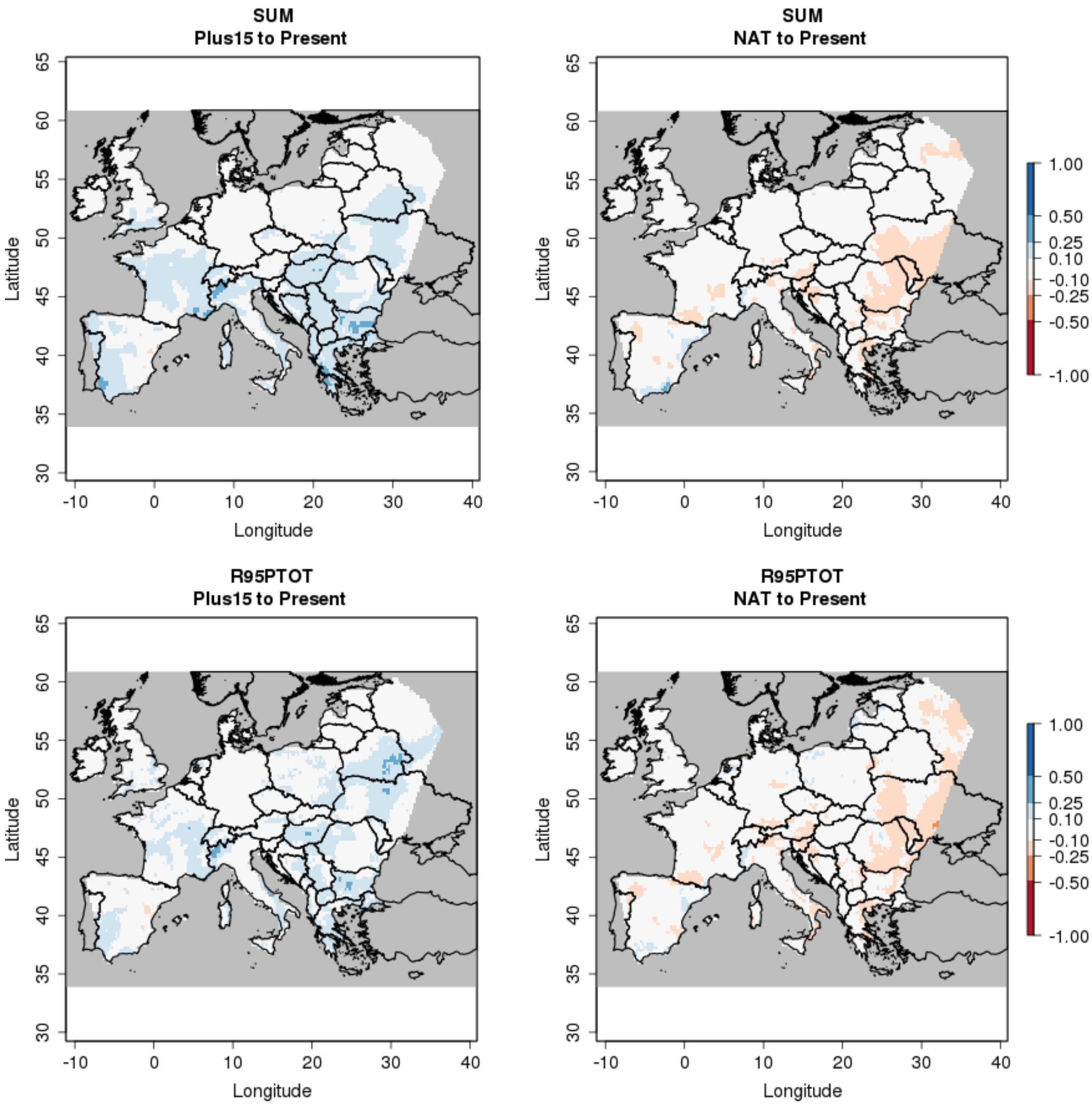

Figure 6. Relative change of winter total precipitation (SUM) and R95pTOT for future climate (Plus15) and natural climate (NAT) after bias-correction.

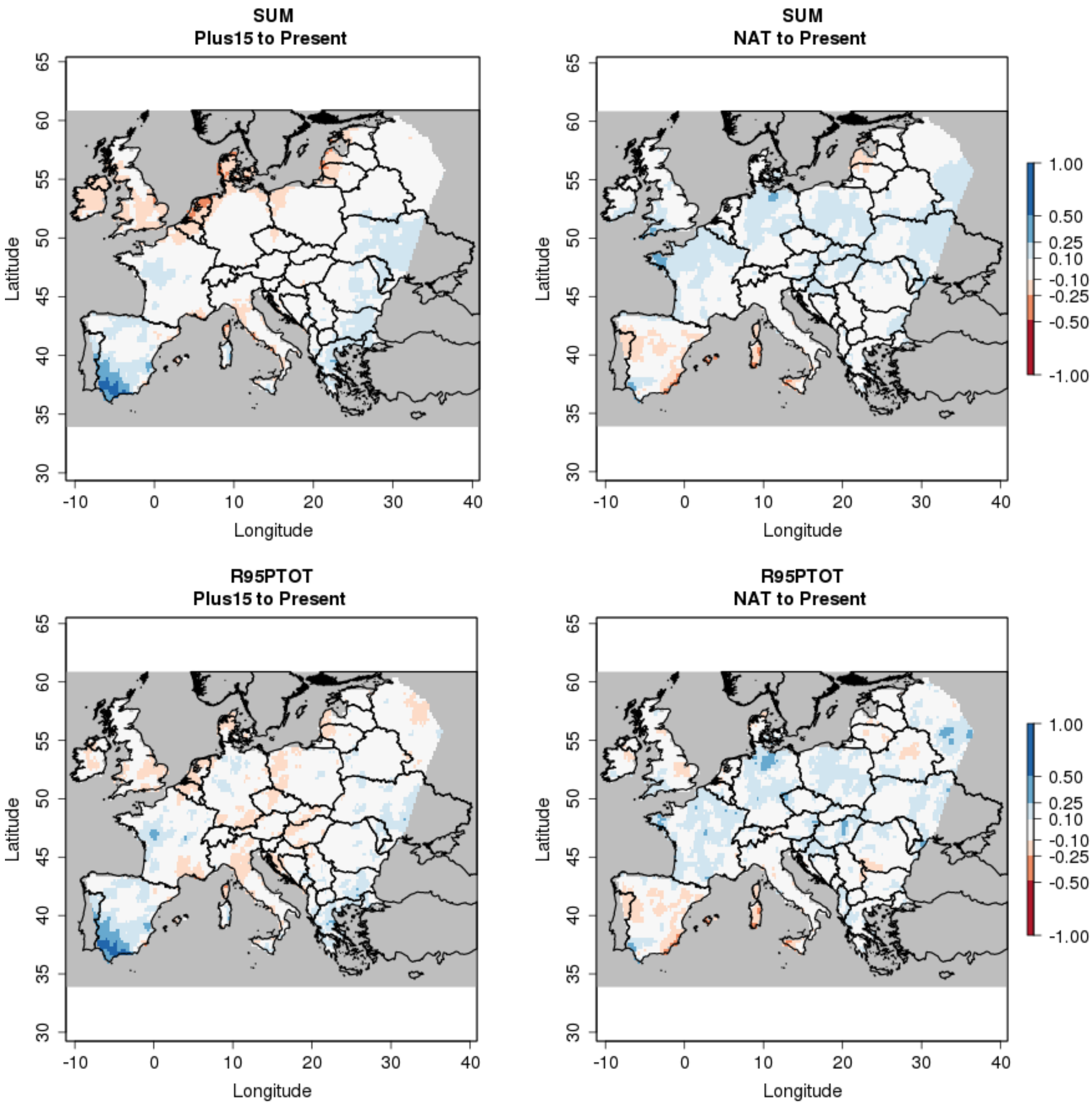

Figure 7. Relative change of summer total precipitation (SUM) and R95pTOT for future climate (Plus15) and pre-industrial climate (NAT) after bias-correction.

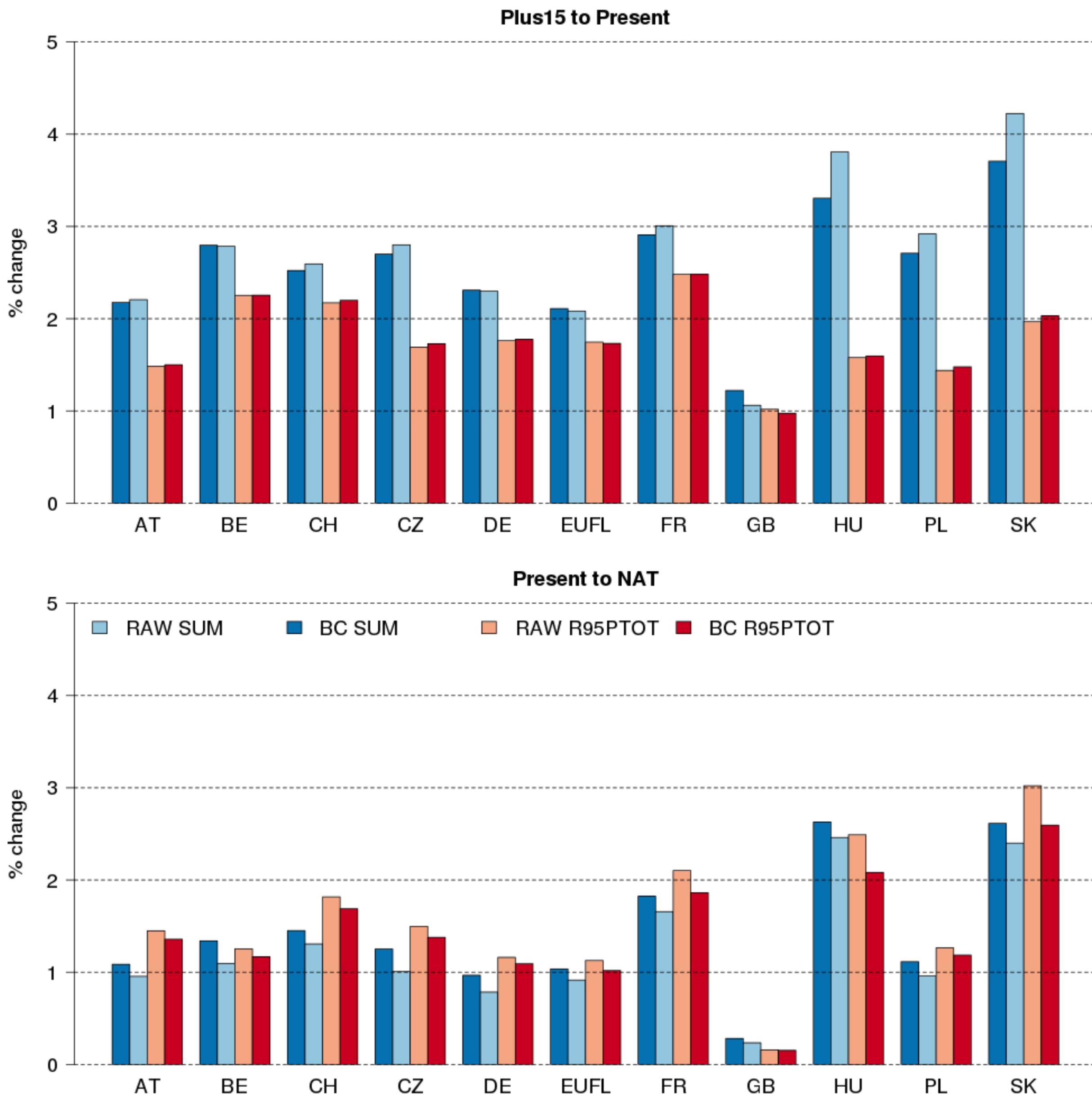

Figure 8. Relative change in winter losses expressed as percentage change per decade by country and for the entire domain (denoted with EUFL), based on the relative change in the raw and bias-corrected precipitation statistics for the Plus15 and NAT scenarios.

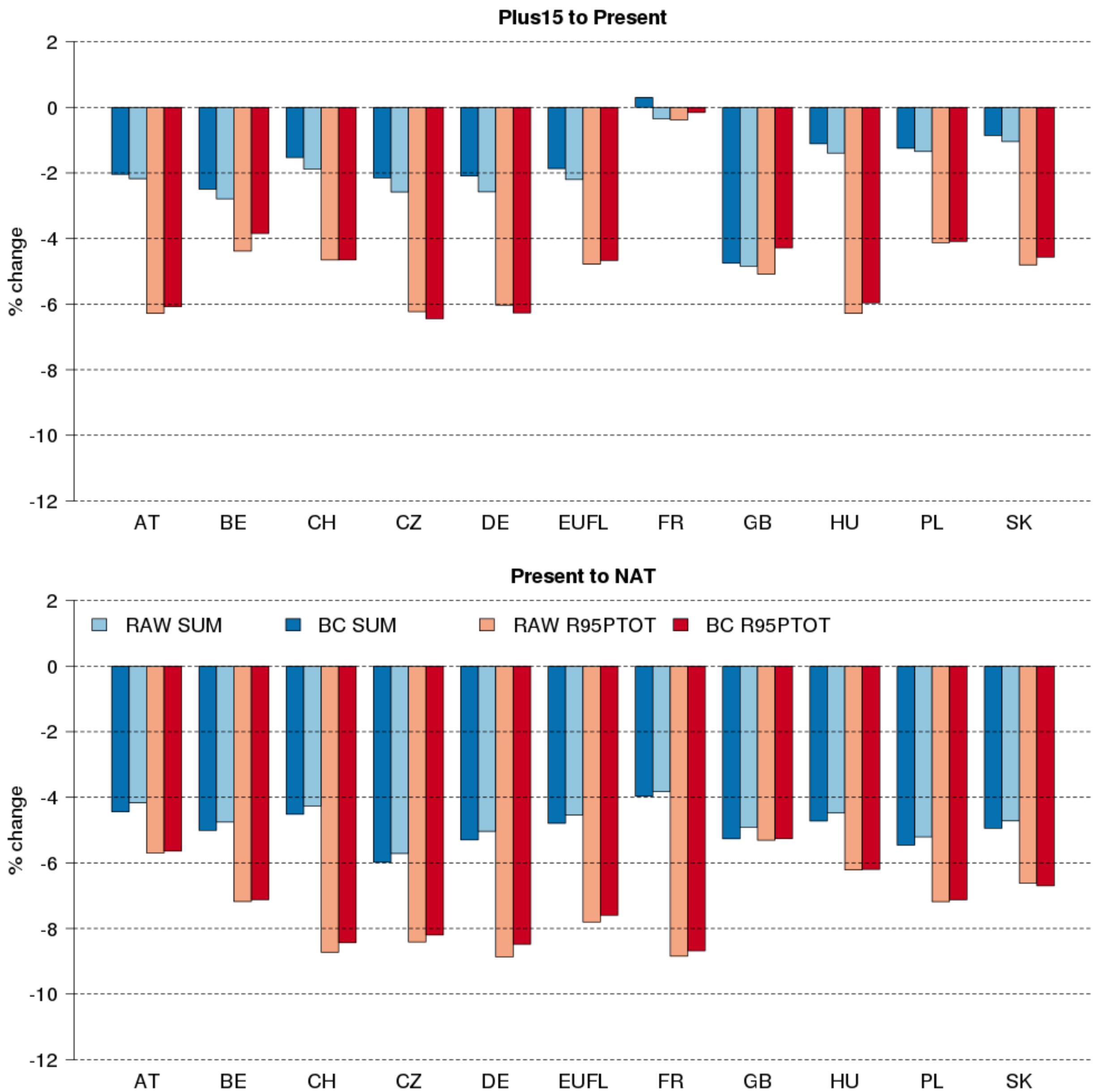

Figure 9. Relative change in summer losses expressed as percentage change per decade by country and for the entire domain (denoted with EUFL), based on the relative change in the raw and bias-corrected precipitation statistics for the Plus15 and NAT scenarios.