

1 **High-end climate change impact on European runoff and**
2 **low flows. Exploring the effects of forcing biases.**

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11 **Abstract**

12 Climate models project a much more substantial warming than the 2°C target under the more
13 probable emission scenarios, making higher end scenarios increasingly plausible. Freshwater
14 availability under such conditions is a key issue of concern. In this study, an ensemble of
15 Euro-CORDEX projections under RCP8.5 is used to assess the mean and low hydrological
16 states under +4 °C of global warming for the European region. Five major European
17 catchments were analyzed in terms of future drought climatology and the impact of +2 °C
18 versus +4 °C global warming was investigated. The effect of bias correction of the climate
19 model outputs and the observations used for this adjustment was also quantified. Projections
20 indicate an intensification of the water cycle at higher levels of warming. Even for areas
21 where the average state may not considerably be affected, low flows are expected to reduce
22 leading to changes in the number of dry days and thus drought climatology. The identified
23 increasing or decreasing runoff trends are substantially intensified when moving from the +2
24 to the +4 degrees of global warming. Bias correction resulted in an improved representation
25 of the historical hydrology. It is also found that the selection of the observational dataset for
26 the application of the bias correction has an impact on the projected signal that could be of the
27 same order of magnitude to the selection of the GCM.

1 **1 Introduction**

2 Global CO₂ emission rates have been following high-end climate change pathways leading to
3 a future global temperature that is likely to surpass the target limit of 2°C, despite the recent
4 hiatus (England et al., 2015), and reach levels of +4 °C and higher at the end of the 21st
5 century. By that time, the seasonality of river discharge is expected to get more pronounced
6 for one-third of the global land surface, which translates to increased high flows and
7 decreased low flows (Van Vliet et al., 2013). By the mid-century, the hydrological regime is
8 projected to change considerably for a significant part of the global land surface (Arnell and
9 Gosling, 2013). The effect that global warming can have on water resources raises serious
10 concerns on future water availability, especially under the pressure of the growing global
11 population and the consequent increased food production needs. It is projected that the
12 number of people coping with significantly reduced water availability will increase by 15%
13 globally due to climate change, while the percentage of the global population living under
14 conditions of absolute water scarcity is also projected to increase (Schewe et al., 2014).

15 In this framework, the future hydrological state needs to be assessed. The runoff production is
16 the component of the hydrological cycle most representative to describe freshwater
17 availability, as it expresses the amount of available water after the evapotranspiration and
18 infiltration losses and before any stream formation process intervenes. Furthermore,
19 ensembles of mean annual and seasonal runoff can provide information about the climate
20 change impact on river flows (Döll and Schmied, 2012). Studies have shown that changes in
21 runoff are not linearly correlated with changes in global mean temperature (Arnell and
22 Gosling, 2013), neither are meteorological with hydrological droughts (van Huijgevoort et al.,
23 2013), concluding that for climate change impact assessments it is fundamental to use an
24 impact model to translate the precipitation derived signal into runoff.

25 A substantial number of large scale climate change impact studies that have been performed
26 recently examine the future hydrological state analyzing projections of runoff or river flow.
27 Fung et al. (2011) compared the projected future water availability under +2 °C and +4 °C of
28 global warming, forcing the MacPDM Global Hydrological Model (GHM) with 22 GCMs
29 from the CMIP3 experiment. Arnell & Gosling (2013) performed a global assessment of the
30 climate driven changes in runoff based hydrologic indicators in mid-21st century, using
31 multiple scenarios derived from the CMIP3 experiment. Schneider et al. (2013) focused on
32 the impacts of climate change for the European river flows, using data from three bias

1 corrected GCM scenarios. Van Vliet et al. (2013) performed a global assessment of future
2 river discharge and temperature under two climate change scenarios, forcing a GHM with an
3 ensemble of bias corrected GCM output. They found that the combination of lower low flows
4 with increased river water temperature can lead to water quality and ecosystem degradation in
5 south-eastern United States, Europe, eastern China, southern Africa and southern Australia.
6 An investigation of the future trends in flood risk at the global scale was performed by
7 Dankers et al. (2014) and for the European region by Alfieri et al. (2015). Betts et al. (2015)
8 performed a global assessment of the impact posed on river flows and terrestrial ecosystems
9 by climate and land use changes described by four RCPs. Various multi-model hydrological
10 simulations have been also performed, in an attempt to quantify the climate change analysis'
11 uncertainty resulting from the impact model (Hagemann et al., 2013; van Huijgevoort et al.,
12 2013; Dankers et al., 2014).

13 Currently, global mean temperature has increased 0.85 °C relative to pre-industrial and
14 already 18% of the moderate daily precipitation extremes is attributed to this warming. At +2
15 °C the fraction of the global warming driven precipitation extremes is projected to rise up to
16 40% (Fischer and Knutti, 2015). The effect of a 2 °C global warming for the European climate
17 was examined by Vautard et al. (2014). The study revealed that warming in Europe is
18 projected to be higher than the global average of 2 °C. Temperature increases of up to 3 °C
19 were found for the winter season over north-western Europe and for the summer months over
20 southern Europe. Heavy precipitation was found to increase over the whole continent for all
21 seasons, with the exception of southern Europe during summer. Prospects of limiting the
22 warming to the +2 °C target have become vanishingly small (Sanford et al., 2014) at the same
23 time that many experts believe that we are on the +4°C path (Betts et al., 2011, 2015). The +4
24 °C global warming scenario is also translated in more intense temperature increases in Europe,
25 especially for the summer season (World Bank, 2014).

26 Significant climate change induced alterations are projected for the flow regime in Europe,
27 with the most pronounced changes in magnitude projected for the Mediterranean region and
28 the northern part of the continent (Schneider et al., 2013). Moreover, considering that southern
29 Europe is identified as a possible hotspot where the fraction of land under drought will
30 increase substantially (Prudhomme et al., 2014), along with global temperature rise exceeding
31 +2 °C, concerns for future water availability in Europe are raising. Prolonged water deficits
32 during long-term droughts surpass the resilience of the hydrological systems and are a

1 significant threat to water resources security in Europe (Parry et al., 2012). In the Euro-
2 Mediterranean regions the severity of droughts has increased during the past 50 years, as a
3 consequence of greater atmospheric evaporative demand resulting from temperature rise
4 (Vicente-Serrano et al., 2014). Besides southern European areas, north-western and central-
5 eastern regions appear more drought prone than the rest of Europe (Bonaccorso et al., 2013).
6 Streamflow projections indicate more severe and persistent droughts in many parts of Europe
7 due to climate change, except for northern and north-eastern parts of the continent. The
8 opposite is projected for the middle and northern parts with a highly significant signal of
9 reduced droughts that may be reversed due to intensive water use (Forzieri et al., 2014).
10 Consequently European cropland affected by droughts is projected to increase 7-fold (up to
11 700,000 km²/year) at about +3°C of global warming (Ciscar et al., 2014) compared to the
12 situation of the last decades. Similarly, under the same warming level, European population
13 affected by droughts is expected to increase by a factor of seven, overcoming the 150
14 million/year.

15 GCM outputs, used as input in impact models to assess the effects of climate change, feature
16 systematic errors and biases. To deal with these, several bias correction techniques have been
17 developed to statistically adjust the GCM output against observations. This process adds
18 another level of uncertainty in the chain of climate to impact modelling that has to be
19 investigated and communicated to the impact research communities. Ehret et al. (2012)
20 acknowledge the fact that inherent climate models' biases render them unsuitable for direct
21 use in climate change impact assessments but express scepticism towards adopting bias
22 correction as a standard undisputed procedure. They argue that bias adjustment hides rather
23 than reduces the uncertainty, as the narrowing of the uncertainty range is not supported by any
24 physical explanation. Teutschbein & Seibert (2012) also accept the need for bias correction
25 but raise awareness towards the increased uncertainty derived from adding this step to the
26 modelling chain. Ehret et al. (2012) introduce the issue of how "correct" is the dataset used as
27 baseline for the bias adjustment. Haerter et al. (2011) underline that the statistical adjustments
28 applied to GCM data with bias correction are bounded to the timescale selected for the
29 adjustment and might have adverse effects on the statistics of another timescale. Haerter et al.
30 (2011) also accentuate that one significant assumption is made when present day based bias
31 correction methods are applied to climate scenario simulations; that of the bias stationarity
32 throughout the future decades. Teng et al. (2015) argue that errors in bias corrected
33 precipitation are inherited and augmented in modelled runoff.

1 The major tools for the investigation of large scale hydrological changes due to climate
2 change are Global Hydrological Models (GHMs) and/or Land Surface Models (LSMs).
3 According to the classification proposed by Haddeland et al. (2011), the models that solve the
4 water balance are considered as GHMs and the models that solve both the water and energy
5 balance are categorized as LSMs. The LSM JULES (Joint UK Land Environment Simulator-
6 Best et al., 2011) has been implemented for many recent climate change impact and model
7 inter-comparison studies (Hagemann et al. 2013; Davie et al. 2013; Dankers et al. 2014;
8 Prudhomme et al. 2014; Harding et al. 2014).

9 The scope of this work is to assess future water availability and identify drought conditions in
10 the European region under high-end scenarios of climate change. Transient hydrological
11 simulations for the period 1971 to 2100 were performed by forcing the JULES model with
12 five Euro-CORDEX (Coordinated Downscaling Experiment over Europe) climate projections.
13 Water availability is described by the output of runoff production. In our analysis the model
14 results are mainly interpreted statistically, aiming to express the changes found in the
15 projected future periods with respect to the historical baseline state rather than describing
16 future regimes with absolute numbers. The research objectives set by this study are the
17 following:

- 18 i) To identify changes posed on the hydrological cycle (mean state and lower extremes) at
19 +4 °C global warming compared to a baseline situation, and relative to the target of 2 °C
20 warming.
- 21 ii) To analyse the effect of bias correction on projected hydrological simulations. To achieve
22 this, both raw and bias corrected Euro-CORDEX data were used as input forcing in the
23 impact model.
- 24 iii) To assess the effect of the observational dataset used for bias correction.
- 25 iv) To identify climate change induced changes in drought climatology at the basin scale.

26

27 **2 Data & Methods**

28 Hydrological simulations were performed with the JULES Land Surface Model driven by
29 Euro-CORDEX climate scenarios. To warm-up the model, 10 spin-up cycles from 1955 to
30 1960 were run. A daily time-step was employed for all the model runs. JULES was setup at

1 the spatial resolution of the forcing Euro-CORDEX data which was 0.44 degrees. The model
2 output was regridded to match a 0.5x0.5 degree grid.

3 Brief descriptions of the climate data and the impact model are included in the following
4 sections.

5

6 **2.1 Climate data**

7 Projections from five Euro-CORDEX experiments under Representative Concentration
8 Pathway RCP8.5 scenario were used as input to JULES. The climate models were selected so
9 as to cover the range of model sensitivity, as expressed by the index of Equilibrium climate
10 sensitivity (ECS) which spans from 2.1 to 4.7 K for the CMIP5 ensemble (Andrews et al.,
11 2012). ECS is a useful metric of the response of a climate model, in terms of air temperature
12 change, to a doubling of the atmospheric CO₂ concentration (Andrews et al., 2012). Another
13 factor for selecting the participating climate models was the availability of GCM downscaled
14 at the spatial resolution of 0.44 degrees.

15 Historical and projected time-slices comprise of 30-years of simulations, for which one time-
16 slice average is extracted. The historical or baseline time-slice covers the period from 1976 to
17 2005. The projected time-slice varies between the models. The definition for determining the
18 projected time-slice here is to take the 30-year average of the slice centered on the year where
19 the +4 (or +2) Specific Warming Level (SWL) is exceeded. The reference period for the
20 calculation of the SWL is the pre-industrial state and specifically the period from 1861 to
21 1880. For three of the selected scenarios the +4 SWL is achieved outside the temporal extend
22 of this study, thus the last 30 year period available is considered instead (2071-2100). The
23 SWL exceeded during that period for the models that reach +4 after 2100 is shown in Table 1.
24 For reasons of consistency in terminology the time-slice of all models describing the greater
25 SWL achieved will be referred to as +4 SWL time-slice.

26 Using the SWL concept constitutes the results independent of the timing that the warming
27 occurs. Although by definition of the SWL, the models reach the same level of warming in
28 their time-slices, the different model sensitivity reflects on the evolution of temperature in the
29 time-slice, as more sensitive models are expected to have higher rates of changes in the period
30 before and after a specific SWL is achieved compared to the less sensitive models. Moreover,

1 considering models of different ECS is important to express the range of other than
2 temperature forcing variables produced by the GCMs (eg. radiation).

3 The five scenarios along with information on the time-slices extracted for our analysis and the
4 corresponding exceeded warming levels and ECS indices are shown in Table 1. Two widely
5 used observational datasets were used to adjust the biases of the RCMs precipitation and
6 temperature data. The first dataset was a hybrid dataset created by the Inter-Sectoral Impact
7 Model Integration and Intercomparison Project ISI-MIP (Warszawski et al., 2014) that
8 consists of the WFD (Weedon et al., 2010) and WFDEI.GPCC. (Weedon et al., 2014)
9 datasets. Additionally, the station data based European Climate Assessment & Dataset
10 (ECA&D) and the ENSEMBLES Observations gridded dataset (E-OBS v10; Haylock et al.
11 2008) was also used for the bias adjustment of the aforementioned climate variables.

12 **2.2 Bias correction method**

13 In the present study the multi-segment bias correction (MSBC) method is used to correct the
14 precipitation and temperature data for their biases. A detailed description of the method can be
15 found in Grillakis et al. (2013). This bias correction methodology has the ability to better
16 transfer the observed precipitation statistics to the raw GCM data. The method utilizes
17 multiple discrete segments on the cumulative density function (CDF) to fit multiple
18 theoretical distributions, as opposed to the commonly used single transfer function at the
19 entire CDF space. Pragmatically, the method eliminates to a large extent the bias in mean
20 precipitation, while significantly reducing the bias of the higher quantile of the precipitation
21 CDF associated with extreme precipitation events.

22 **2.3 The JULES land surface model**

23 JULES is a physically based land surface model that was established in 2006. It is comprised
24 of two parts: the Met Office Surface Exchange Scheme (MOSES; Cox et al. 1998) and the
25 Top-down Representation of Interactive Foliage and Flora Including Dynamics (TRIFFID;
26 Cox 2001) component. MOSES is an energy and water balance model which is JULES'
27 forerunner, and TRIFFID is a dynamic global vegetation model (Best et al., 2011; Clark et al.,
28 2011; Cox, 2001). In our model application for this study we do not examine vegetation
29 dynamics thus we are focusing on the MOSES component of JULES.

1 The meteorological forcing data required for running JULES are: downward shortwave and
2 longwave radiation, precipitation rate, air temperature, wind-speed, air pressure and specific
3 humidity (Best et al., 2011).

4 JULES has a modular structure, which makes it a flexible modelling platform, as there is the
5 potential of replacing modules or introducing new modules within the model. The physics
6 modules that comprise JULES include the following themes: surface exchange of energy
7 fluxes, snow cover, surface hydrology, soil moisture and temperature, plant physiology, soil
8 carbon and dynamic vegetation (Best et al., 2011), with the latter being disabled for this
9 application.

10 In JULES, each gridbox is represented with a number of surface types, each one represented
11 by a tile. JULES recognises nine surface types (Best et al., 2011), of which five are vegetation
12 surface types (broadleaf trees, needleleaf trees, C3 (temperate) grasses, C4 (tropical) grasses
13 and shrubs) and four are non-vegetated surface types (urban, inland water, bare soil and ice).
14 A full energy balance equation including constituents of radiation, sensible heat, latent heat,
15 canopy heat and ground surface heat fluxes is calculated separately for each tile and the
16 average energy balance for the gridbox is found by weighting the values from each tile (Pryor
17 et al., 2012).

18 In JULES the default soil configuration consists of four soil layers of thicknesses 0.1 m, 0.25
19 m, 0.65 m and 2.0 m. This configuration however can be altered by the user. The fluxes of
20 soil moisture between each soil layer are described by Darcy's law and a form of Richards'
21 equation (Richards, 1931) governs the soil hydrology. Runoff production is governed by two
22 processes: infiltration excess surface runoff and drainage through the bottom of the soil
23 column, a process calculated as a Darcian flux assuming zero gradient of matric potential
24 (Best et al., 2011). There is also the option of representing soil moisture heterogeneity. In that
25 case total surface runoff also includes saturation excess runoff. The model allows for two
26 approaches to introduce sub-grid scale heterogeneity into the soil moisture: 1) use of
27 TOPMODEL (Beven and Kirkby, 1979), where heterogeneity is taken into account
28 throughout the soil column, or 2) use of PDM (Moore, 1985), which represents heterogeneity
29 in the top soil layer only (Best et al., 2011). Calculation of potential evaporation follows the
30 Penman-Monteith approach (Penman, 1948). Water held at the plant canopy evaporates at the
31 potential rate while restrictions of canopy resistance and soil moisture are applied for the
32 simulation of evaporation from soil and plant transpiration from potential evaporation.

1 JULES simulates fluxes at the vertical direction only. For hydrological applications this
2 means that the model calculates runoff production in each gridbox which needs to be routed to
3 estimate streamflow. The standard version of the JULES model until very recently (February
4 2015) did not account for a routing mechanism. To overcome this model limitation, we use a
5 conceptual lumped routing approach based on triangular filtering in order to delay runoff
6 response. This is applied after discriminating the gridboxes that contribute to runoff
7 production of a specific basin from the gridded model output. Determination of gridboxes
8 upstream of the gauging station location is implemented using the TRIP river routing scheme
9 (Oki and Sud, 1998).

10 JULES has been used in many recent studies as a tool for evaluating the exchange of water,
11 energy and carbon fluxes between the land surface and the atmosphere. Van den Hoof et al.
12 (2013) assessed JULES' performance in simulating evaporative flux (and its partitions) and
13 carbon flux in temperate Europe. Marthews et al. (2012) implemented JULES in tropical
14 forests of Andes-Amazon to simulate all components of carbon balance and study possible
15 flux variations between sites of different altitude. Zulkafli et al. (2013) implemented JULES
16 in a humid tropical mountain basin of the Peruvian Andes-Amazon. MacKellar et al. (2013)
17 evaluated JULES, implemented in a region of Southern Africa, concerning its ability to
18 simulate the catchment streamflow. In the study of Bakopoulou et al. (2012), the sensitivity of
19 the JULES outputs to the soil parameters of the model at a point scale was estimated. Dadson
20 et al. (2010) sought to quantify the feedback between wetland inundation and heat and
21 moisture fluxes in the Niger inland delta by adding an overbank flow parameterization into
22 JULES. Burke et al. (2013) used JULES to simulate retrospectively the pan-arctic changes in
23 permafrost and Dankers et al. (2011) assessed JULES' performance in simulating the
24 distribution of surface permafrost in large scale catchments. In a study by Jiménez et al.
25 (2013) soil moisture modelled with JULES is evaluated against satellite soil moisture
26 observations.

27 Other studies give insight into the hydrological performance of JULES specifically. Blyth et
28 al. (2011) extensively evaluated the JULES model for its ability to capture observed fluxes of
29 water and carbon. Concerning discharge, their findings suggest that for the European region
30 seasonality is captured well by the model. For temperate regions (like most of central Europe)
31 to model exhibited a tendency towards underestimating river flows due to overestimation of
32 evapotranspiration. Prudhomme et al. (2011) assessed JULES' ability in simulating past

1 hydrological events over Europe. In general terms the model was found to capture the timing
2 of major drought events and periods with no large-scale droughts present were also well
3 reproduced. The model showed a positive drought duration bias, more profoundly present in
4 northwest Spain and East Germany-Czech Republic. Prudhomme et al. (2011) argue that this
5 feature is related to overestimation of evaporation by the model. For regions where droughts
6 tend to last longer, JULES exhibited a better ability of reproducing the drought events'
7 characteristics. Gudmundsson et al. (2012) compared nine large scale hydrological models,
8 and their ensemble mean, based on their skill in simulating the interannual variability of
9 observed runoff percentiles in Europe. According to the overall performance (accounting for
10 all examined percentiles and evaluation metrics), JULES was ranked third best out of the 10
11 models, after the multi-model ensemble mean and the GWAVA model. For low and
12 moderately low flows, expressed as 5th and 25th percentile respectively, JULES is also in the
13 top three models regarding the representation of interannual variability in runoff. In the study
14 of Gudmundsson et al. (2012b), where an ensemble of hydrological models is evaluated for
15 their ability to capture seasonal runoff climatology in three different hydroclimatic regime
16 classes in Europe, JULES exhibits a good performance, comparable to that of the best
17 performing multi-model ensemble mean. In other studies employing multi-model ensembles,
18 focusing on the whole European region (Gudmundsson and Seneviratne, 2015) or a single
19 basin in Europe (Harding et al., 2014; Weedon et al., 2015) JULES' simulations also
20 correspond with these of the other models.

21 **2.4 Identifying changing climate trends**

22 For the assessment of the impact of the +4 °C warming relative to pre-industrial, the projected
23 time-slices are compared to the baseline period in terms of both absolute and percent change.
24 This is done for each ensemble member individually in order to check the variability of the
25 projected changes and also for the ensemble mean. Two hydrologic indicators are tested, the
26 average and the 10th percentile of runoff production.

27 Average runoff production is a good and widely used indicator of mean hydrological state of a
28 region. The 10th percentile runoff is considered as a representative indicator of the low flow
29 regime (Prudhomme et al., 2011). Consistent low flows (relative to the mean state) are
30 connected with the formation of hydrological drought conditions. Thus the assessment of the
31 changes in low flows could reveal trends towards more intense or/and often extreme lows in
32 the future hydrological cycle. The impact of high-end climate scenarios on average and 10th

1 percentile runoff is presented both as gridded results at the pan-European scale and aggregated
2 at the basin scale for five major European river basins.

3 The two hydrological indicators were deduced from monthly runoff data. For the analysis of
4 the gridded results at pan-European scale with the SWL time-slice approach, each indicator
5 was computed from the monthly values of all years in the time-slice. For the analysis of basin
6 aggregated runoff regime, the two hydrologic indicators were calculated per year, for all the
7 years of the simulation. This resulted in time-series of basin aggregated average and 10th
8 percentile runoff production, spanning from 1971 to 2100. The trend of the annual time-series
9 was investigated employing a linear regression analysis to estimate the sign and the average
10 rate of the trend. The significance of the trend was tested at the 95% confidence interval via a
11 Student-t test.

12 The Europe study domain along with information on the catchments tested and their
13 corresponding gauging stations are shown in Figure 1.

14 **2.5 Examination of drought climatology**

15 Another aspect of our low flow analysis is to assess changes in drought climatology, i.e. the
16 number of days per year that particular lows in flow occur. This is here done at the basin
17 scale, following the threshold level method to identify days of discharge deficiencies. The
18 threshold level method is a widely used tool for drought identification applications (Fleig et
19 al., 2006; Vrochidou et al., 2013). According to this method, drought conditions are
20 characterized as the periods during which discharge falls below a pre-defined threshold level.
21 In our application, the threshold is varying daily and is established as in Prudhomme et al.
22 (2011): for each Julian day k , the 10th percentile of a 31-day window discharge centering at
23 day k is derived, from data of all the years of the baseline period (1976-2005). The daily
24 modelled time-series for the whole period simulated (1971-2100) is compared to the daily
25 varying drought limit, and the number of days that fall below the threshold is summed up on
26 an annual basis. The drought threshold is derived from the flows of the baseline period and is
27 applied to both historical and projected flows, in order to capture the climate change induced
28 changes in drought climatology. The regression analysis described in section 2.4 was also
29 applied to the time-series of total drought days per year.

30

1 **3 Results**

2 **3.1 Hydrological simulation at Pan-European scale with raw Euro-CORDEX** 3 **forcing data**

4 Figure 2 shows the average runoff production estimated by JULES forced with the five
5 participating dynamical downscaled GCMs, for each model separately and for the ensemble
6 mean. Measures of model agreement (coefficient of variation between the ensemble members
7 and model agreement on a wetter change in the projected time-slice) are also shown in Figure
8 2. The change in runoff in the +4 SWL projected time-slice with respect to the baseline period
9 is expressed as both absolute and percent relative difference. It is interesting to observe the
10 variations between the models for the historical time-slice, with the low climate sensitivity
11 GFDL and NorESM1 exhibiting generally wetter patterns for northern Europe and
12 Scandinavian Peninsula, and with IPSL describing drier patterns, especially for southern
13 Europe. Concerning the overall agreement of the ensemble members in the baseline period the
14 coefficient of variation is below 0.5 for most of the European region (Figure 2, bottom),
15 indicating a good agreement of the models. In more detail, the coefficient of variation is lower
16 for the Scandinavian region and is reduced towards the lower latitudes.

17 For the projected time-slice, all models agree in a general pattern of increased runoff
18 production in northern Europe and a small part in central Europe and decreased runoff
19 production in Spain, Greece and parts of Italy. Especially for the negative trends shown in
20 southern Europe it is important that though small in absolute terms they increase in magnitude
21 when expressed as a percentage, meaning that small negative changes can pose severe stress
22 in regions where water availability is already an issue.

23 Concerning the ensemble mean, smoothing of the projected changes due to averaging has
24 revealed clear patterns of change, which however have to be interpreted considering the full
25 spread of the GCM-forced outcomes and the agreement between them in order to avoid
26 misguided conclusions. Less extreme values are encountered in the ensemble mean of
27 projected changes in runoff, compared to the change projected by each ensemble member
28 individually (Figure 2). Especially for percent change a clear trend of runoff increase is
29 revealed in northern Europe and decrease in southern Europe, with a mixed pattern for central
30 Europe. Four or five out of the five ensemble members agree on the wetter response in the
31 northern regions and the drier response in the southern part of Europe. The smaller cv value

1 (cv<0.1) for the southern regions indicates that the models agree more on the value of the
2 change compared to the changes in the Scandinavian region (0.11<cv<0.75). For central
3 Europe there are areas of reduced agreement, with two models showing a change different in
4 sign than the other three of the ensemble. For the same areas cv has values greater than 1,
5 marking a large spread between the values of the five ensemble members.

6 Figure 3 has the same features as Figure 2 but concerns the 10th percentile runoff production
7 instead of the average. The 10th percentile limit is used to describe low flows that are related
8 to the creation of hydrological drought conditions. For 10th percentile runoff, model
9 agreement in the baseline period is notably reduced compared to agreement for average
10 runoff, with the coefficient of variation for most regions exceeding 0.5 while it exceeds the
11 unity for a large part of Europe. For the +4 SWL projected time-slice, according to Figure 3,
12 all models agree in relative decreases in runoff production in western and southern Europe
13 which are specifically pronounced in the western Iberian and Balkan Peninsulas. Another
14 common trend between the models is the significant increase in runoff production in the
15 Scandinavian Peninsula, with MIROC5 and HadGEM2 being the two ensemble member that
16 expand this wetter climate down to central Europe.

17 Regarding the ensemble mean changes, percent change in 10th percentile runoff (Figure 3)
18 shows more significant reductions (up to 100%) compared to average runoff (for which
19 changes range between -50% and 50%). It is thus deduced that the changes in low flows are
20 more pronounced than the changes in the mean, a conclusion that points towards the overall
21 intensification of the water cycle. The decreasing trend in 10th percentile runoff covers most
22 of the west and south European area (with 80% to 100% agreement on the sign of the change)
23 while all models agree in an increase in 10th percentile runoff in the Scandinavian region.

24 **3.2 Hydrological simulation at Pan-European scale with bias adjusted Euro-** 25 **CORDEX forcing data**

26 The ensemble mean of average runoff derived from the five participating downscaled GCMs,
27 whose temperature and precipitation were bias adjusted according to the WFDEI dataset is
28 presented in Figure 4. Bias adjustment of the forcing data resulted in a drier ensemble mean
29 runoff for the baseline period for 70.40% of the pan-European land surface, in comparison to
30 26.01% of the land area that had a wetter response after bias adjustment. The remaining
31 3.59% of the European area had changes that were classified as insignificant (see ESM for

1 details). Projected changes from bias adjusted data exhibit very similar patterns and
2 magnitudes with the raw data derived changes. For some regions in central Europe, where a
3 small negative change is reported by the raw data run, a sign change of the projected
4 difference is documented after bias correction. Lastly, bias correction has a strong positive
5 effect on model agreement as it can be documented from the low values of the coefficient of
6 determination all over Europe, with the exception of the Scandinavian Peninsula where model
7 disagreement appears increased after bias correction.

8 In Figure 5, the effect of bias correction on the representation of the 10th percentile runoff is
9 shown. Some hotspots of pronounced negative changes in western Europe have been
10 eliminated and replaced with milder projected absolute changes. There are areas where sign
11 change is observed (central and central-west Europe) however it is difficult to interpret this
12 result and correlate it with bias correction as these are also the areas where models show the
13 lowest agreement (coefficient of variation exceeding one and agreement towards wetter
14 change 40%-60%). Although the coefficient of variation for the baseline period is
15 considerably reduced compared to the raw data runs, there are still areas of high model
16 uncertainty in the representation of lower flows.

17 **3.3 Basin averaged runoff regime**

18 In Figure 6, annual time-series of basin averaged runoff production (average and 10th
19 percentile) for five European basins are shown. These cover the whole length of historical and
20 projected years simulated (1971-2100) in an attempt to identify general trends in average and
21 low runoff, calculating 10-year moving averages from the ensemble mean. Results in Figure 6
22 include both raw and bias adjusted output, thus an assessment of the effect of the bias
23 correction on the basin scale hydrology can be made. A common observation for all the basins
24 is that runoff decreases considerably for bias adjusted input forcing.

25 For Danube and Guadiana, significantly important negative trends are identified for average
26 runoff (-0.24 mm/year and -0.35 mm/year respectively for raw output, -0.11 mm/year and -
27 0.31 mm/year respectively for bias adjusted output) which are more pronounced for the 10th
28 percentile runoff. For Rhine, the identified trends in average runoff production of both raw
29 and bias corrected forcing are not statistically significant. In contrast, the 10th percentile
30 runoff production in Rhine exhibits statistically significant decreasing trends, for both raw (-
31 0.74 mm/year) and bias corrected (-0.50 mm/year) outputs. For Elbe, raw output gives an

1 insignificant trend in average runoff and a slight decreasing trend for 10th percentile runoff.
2 Bias corrected data result in a small but statistically significant increasing trend (0.18
3 mm/year) in annual average runoff while for 10th percentile runoff the trend is decreasing (-
4 0.06 mm/year, statistically significant). For Kemijoki average and low flows, of raw and bias
5 adjusted forcing, are all exhibiting statistically significant increasing trends.

6 Basin scale average annual runoff production for raw and bias adjusted Euro-CORDEX data
7 as well as the +4°C absolute and percent change for each ensemble member and ensemble
8 mean is included in Table 2. Similar information but for low flows (10th percentile) are
9 presented in Table 3. In Tables S1 and S2 of the ESM, the results of the linear regression
10 applied to the average and 10th percentile runoff time-series for the estimation of the trend and
11 its significance can be found.

12

13 **3.4 Drought climatology at basin scale**

14 Figure 7 shows the results of the drought threshold level method analysis for the five study
15 basins, for raw and bias corrected output. For each year, the number of days under the
16 historical drought threshold has been counted. This allows a comparison of the tendency
17 towards the formation of drought conditions between the historical period and the projected
18 period. As this is a statistically oriented interpretation of our data, we can see that the
19 differences between raw and bias corrected time-series are very small, especially compared to
20 the difference in the magnitude of their absolute values. For Danube, Rhine and Guadiana
21 strong rising trends (all statistically significant) were identified in the time-series of ensemble
22 mean of days under threshold per year. Before bias correction these were 0.43, 0.37 and 0.52
23 days/year for the three basins respectively and changed to 0.39, 0.39 and 0.38 days/year
24 respectively after bias correction. For Elbe, non-bias corrected data give a slight but
25 statistically significant increasing trend (0.14 days/year) in contrast to bias corrected output
26 that shows a statistically insignificant trend. For Kemijoki strong decreasing (statistically
27 significant) trends are found for both for raw (-0.20 days/year) and bias corrected (-0.18
28 days/year) data. Table S3 of the ESM, tabulates the results of the linear regression applied to
29 time-series of ensemble mean of days under threshold per year for the estimation of the time-
30 series' trend and its significance.

31

1 **3.5 Impacts of 4°C warming relative to 2°C warming**

2 Figure 8 shows the basin average runoff production for raw and bias corrected Euro-
3 CORDEX data with respect to the corresponding SWL in degrees Celsius. This analysis
4 considers the runoff values corresponding to the +2 °C and +4 °C SWLs, the latter ranging
5 from 3.2 to 4 between the GCMs, and also the SWL achieved by each participating GCM in
6 the baseline period (0.3-0.5 °C). It is thus allowing us to examine the changes in basin runoff
7 as temperature increases and to compare the effect of different SWLs.

8 Comparing the annual average runoff production for raw and bias corrected input forcing it is
9 clear that bias corrected output exhibits a considerably reduced range, which translates in
10 increased model agreement for the basins of Danube, Rhine, Elbe and Guadiana. In Kemijoki
11 basin the bias adjusted output has a greater range than the raw output. Concerning the range of
12 the low flows, an increase in model agreement for the bias corrected forcing is observed for
13 all basins.

14 Examining the changes in annual average runoff, a slight decreasing trend can be identified
15 for Danube and a slight increasing trend for Elbe while for Rhine there is not a clear trend
16 present. In contrast, Guadiana and Kemijoki exhibit strong decreasing and increasing trends
17 respectively. The falling trend in Guadiana is marginally intensified between +2 and +4 SWL
18 compared to 0 to +2 SWL. The rising trend in Kemijoki does not have evident differences
19 between +2 and +4 °C.

20 According to the results in Figure 8 the 10th percentile runoff in Danube and Rhine decreases
21 as SWLs increase while the opposite trend is observed for the low flows in Kemijoki. For
22 Elbe the raw results show an intense decreasing trend up to +2 SWL which continues more
23 moderately until +4 SWL, in contrast with the bias corrected output that shows milder
24 changes with temperature increase . For Guadiana it is difficult to observe a trend in the bias
25 corrected low percentile runoff as the values are already very low. For the raw output however
26 there is an abrupt decrease from 0 to +2 °C which continues with a milder trend up to +4 °C.

27 Figure 9 illustrates the correlation between the percent projected change in annual average and
28 10th percentile runoff production from bias corrected and raw forcing, for the +2 and +4
29 SWLs.

30 Concerning the effect of bias adjustment it can be observed that regardless the significant
31 differences in magnitude between runoff from raw and bias corrected data discussed before,

1 the projected change in average flow by the two forcings almost coincide for the +2 SWL. For
2 the +4 SWL the GCM range has increased for Kemijoki after bias adjustment while for the
3 rest of the basins raw and bias corrected data result in very similar levels of same percent
4 change. For the projected change in 10th percentile runoff, the larger spreading of the values in
5 Figure 9 (right column) shows that the GCM uncertainty on this field is higher. Guadiana is
6 the only basin where bias corrected data result in an improvement in GCM agreement,
7 probably due to its very low values of 10th percentile runoff. Kemijoki is not included in the
8 10th percentile scatterplots as its projected increase far exceeds the 100% limit selected. For
9 the rest of the basins, the effect of the bias correction on the change of the 10th percentile
10 runoff is not constant. For Guadiana and Elbe bias adjustment mostly increases percent
11 change while for Rhine and Danube percent change is in general terms decreased after bias
12 correction.

13 Comparing the difference on percent projected change in average annual runoff from +2 to +4
14 SWL it can be observed that temperature increase results in a slight decline in percent change
15 for basins with small absolute values of change, causing sign changes for Danube and Rhine,
16 and it intensifies the negative and positive changes of Guadiana and Kemijoki respectively.
17 For the 10th percentile runoff there is a similar response to temperature increase. For Elbe
18 there is positive percent change at +2 SWL which falls below zero at +4 SWL while for
19 Danube, Rhine and Guadiana the already declining projected changes present are further
20 intensified.

21

22 **3.6 Effect of observational datasets for bias correction on the output of the** 23 **hydrological model**

24 The aspect of the impact posed by the observational dataset used for bias correction to the
25 results of the hydrological simulations is introduced in this part of our analysis. Additional
26 model runs performed with bias adjusted Euro-CORDEX precipitation and temperature,
27 corrected against the E-OBS (instead of the WFDEI) dataset participate in a comprehensive
28 comparison between all the outputs used in this study. The results are illustrated in Figure 10.
29 Three different sets of outputs are compared: one driven by raw downscaled and two driven
30 by Euro-CORDEX data bias corrected against two different datasets. The comparison
31 considers both the mean and range of the ensembles and results are presented as basin

1 aggregates. The first part of the comparison concerns the long-term annual average for the
2 period 1976 to 2005 (Figure 10, top row) and apart from the model results includes values
3 corresponding to observations, derived from GRDC discharge measurements. Observations
4 can serve as a baseline for this comparison, allowing us to evaluate which configuration can
5 better simulate “true” water budget numbers and the effect of bias correction with respect to
6 this baseline.

7 For all basins the raw data result in overestimates of runoff production which is though
8 significantly reduced after bias correction. E-OBS corrected data however produce values
9 lower than the observations (with the exception of Guadiana) while the WFDEI-corrected data
10 produce the best simulation in terms of approximating the observed values. From Figures S1
11 and S2 of the ESM (showing the effect of bias correction on the forcing variables of
12 precipitation and temperature) it can be deduced that that E-OBS corrected precipitation has
13 lower values than precipitation adjusted against the WFDEI dataset. This explains the lower
14 runoff produced by the E-OBS bias adjusted dataset, as it is reasonable for the differences in
15 precipitation to reflect on the output of the hydrological model. As already has been revealed
16 in previous stages of this analysis, it is again clear the positive impact that bias adjustment has
17 on the increase of model agreement. The only exception is Kemijoki basin due to its high
18 latitude position (coefficient of variation was increased after bias correction for the high
19 latitude areas).

20 Changes in annual average runoff production at the +4 SWL appear to be more intensified
21 compared to the +2 SWL (Figure 10, middle and bottom). Although for percent change the
22 differences of the distinctive configurations are less pronounced, variations can be observed
23 between the two bias corrected data driven simulations. It is also interesting that the effect of
24 bias correction on reducing the uncertainty is not that strong when looking the results from the
25 more statistical perspective of percent projected change. The improvements in model
26 agreement after bias adjustment however are still pronounced for all basins except for Rhine.

27 From the application of the same analysis on 10th percentile runoff production (Figure S6 of
28 the ESM), it is deduced that for the low flows the E-OBS corrected data again produce lower
29 values of runoff compared to WFDEI. In this case, however, even the raw forced output
30 (which is wetter than the bias corrected) underestimates the observed 10th percentile runoff
31 values. Regarding the percent projected changes, results from bias corrected data produce

1 smaller values compared to the raw data while E-OBS adjusted data result in decreased
2 changes compared to output from WFDEI adjusted forcing.

3

4 **4 Discussion**

5 **4.1 Hydrological response to +4 °C global warming**

6 In our analysis we investigated the effects of climate change on the European hydrological
7 resources, extracting time periods that correspond to an increase of 4 °C of the global
8 temperature, rather than using pre-defined time-slices. The same approach was followed by
9 Vautard et al. (2013), stating that reduced GCM induced uncertainty is achieved with this
10 method and thus the regional patterns of change in the variables of study are strengthened.

11 In our study only one impact model (JULES) was used. Hagemann et al. (2013) argue that
12 impact model induced uncertainty in future hydrological simulations is larger than that of the
13 GCMS for some regions of the land surface and suggest using multi-impact model ensembles
14 to deal with this issue. However useful conclusions can be drawn also from studies employing
15 a single GHM/LSM. Examples of such single model climate change impact assessments
16 performed recently are the studies of Schneider et al. (2013) and Laizé et al. (2013) with the
17 WaterGAP GHM, the studies of Arnell and Gosling (2013), Gosling and Arnell (2013) and
18 Arnell et al. (2013) with the GHM MacPDM and of Hanasaki et al. (2010) using the H08
19 LSM.

20 The findings of the study regarding the climate changed induced alterations of the mean
21 hydrological state in Europe show decreasing trends for southern Europe, including the
22 Mediterranean region, and strong increasing trends for northern and north-eastern Europe.
23 These follow the same patterns as identified by previous studies. Schneider et al. (2013) found
24 that the most pronounced changes in the magnitude of European river flows are projected for
25 the Mediterranean region and the northern part of the continent. Hagemann et al. (2013)
26 reported positive changes in projected runoff for the high latitudes and negative changes for
27 southern Europe. For central Europe the projected changes are smaller (mostly in the range of
28 -25% to 25%) and thus more easily obscured by GCM and bias correction uncertainty. Arnell
29 & Lloyd-Hughes (2014) report that the main source of uncertainty in the projected climate
30 impact stems from the GCMs, with a range of uncertainty for the CMIP5 ensemble that is
31 similar to that of older climate model experiments.

1 The projected relative changes found for 10th percentile runoff are far more pronounced than
2 the changes in average, even for the regions where changes in average-state annual runoff
3 were negligible. This finding implies that seasonality in runoff is likely to intensify under
4 climate change and is in accordance with the results of Fung et al. (2011) and Van Vliet et al.
5 (2013) who also reported pronounced seasonality in their projected simulations. This may
6 translate to increased dry spells and thus elevated drought risks in the future. Under the light
7 of these findings (mean-state runoff changing slightly and low-state changing significantly),
8 more extreme hydrological droughts are expected in the future. It should be noted however
9 that projections of low flow bear higher uncertainty compared to average-state, as indicated
10 by the higher values of the coefficient of variation. Similar results of increased model spread
11 expressed as cv for low flows compared to average state flows were found by Koirala et al.,
12 (2014).

13 Specifically for the Guadiana River, the close to zero values of 10th percentile runoff
14 encountered even in the historical period indicate that the river exhibits intermittent flow
15 regime. This is relevant for this particular river, as it is located in a semi-arid region and
16 intermittent flows typically characterize its hydrological regime (Collares-Pereira et al., 2000;
17 Filipe et al., 2002; Pires et al., 1999). Given the changes that are projected for the Iberian
18 Peninsula at +4 SWL, it is expected that the intermittent flow regime in Guadiana might
19 intensify.

20 Concerning the effects of a +4 °C temperature increase on the European hydrological regime
21 compared to a +2 °C increase, significant alterations posed by the +2 degrees of global
22 warming are identified for south Europe and northern and north-eastern Europe, where the
23 respective decreasing and rising trends are intensified. Fung et al. (2011) also found that
24 changes in mean annual runoff identified at +2 are intensified at +4. More specifically, their
25 study reports that regions where decreasing runoff trends have been found become even drier
26 and, in contrast, areas where runoff is projected to increase are getting wetter. For most of the
27 river basins examined by Fung et al. (2011), water stress is increased at +4 compared to +2,
28 with the exception of a few basins where an increase in rainfall is projected thus decreasing
29 water stress. In our study, the basins located at central Europe (Danube, Rhine and Elbe) do
30 not exhibit significant changes in their annual average runoff values due to temperature
31 increase from +2 to +4. For 10th percentile runoff, however, a temperature increase of +4 °C

1 from the pre-industrial baseline results in an aggravation of the lowering trends that are
2 already significantly affecting the low runoff regime at +2 °C.

3 Our analysis of drought climatology at the basin scale was based on the total number of days
4 under a predefined daily varying drought threshold. We did not employ any buffering
5 criterion for the days under threshold to be accounted for in the total sum (as discussed for
6 example by Sung and Chung (2014) and Tallaksen et al. (1997)). The use of such a criterion
7 would have decreased the calculated dry days. However, as the interpretation of the results of
8 this study is mostly oriented in identifying trends of change rather than absolute numbers
9 describing the future regime, the lack of a buffering criterion is not supposed to notably affect
10 the extracted conclusions. Wanders et al. (2015) employed a transient variable threshold for
11 the assessment of the drought conditions under climate change, considering a gradual
12 adaptation of the ecosystem on the altered hydrological regime. This is an interesting
13 alternative, especially for climate change mitigation and adaptation studies. In our study we
14 aimed to identify global warming induced changes in the future hydrological state without
15 considering adaptation, thus the same historically derived threshold was applied to the whole
16 length of the simulated runoff time-series.

17 From the analysis performed on drought climatology, increased number of days per year
18 under the historically defined drought threshold are found for the basins of Danube, Rhine and
19 Guadiana. Our results correspond with the findings of previous studies about drought regime
20 under climate change. Giuntoli et al. (2015), investigating future high and low flow regimes at
21 the global scale, using multiple impact models and climate scenarios, found increased number
22 of low flow days in Southern Europe. In the study of Wanders & Van Lanen (2015) the
23 impact of climate change on the hydrological drought regime of different climate regions was
24 assessed, using a conceptual hydrological model forced with 3 GCMs. The study findings
25 describe a decrease in the frequency of drought events in the future, which however does not
26 point towards drought alleviation. In contrast, it relates to increased drought event duration
27 and deficit volume. These effects are more pronounced for the arid climates that already face
28 problems of water availability.

29

1 **4.2 The effect of bias correction**

2 As proposed by Ehret et al. (2012), both raw and bias corrected data driven simulations are
3 presented in our study, in order to comprehensively assess the effect of bias correction on our
4 results. In four of the five study basins, raw data driven simulated runoff overestimates the
5 corresponding observed values. After bias correction, the modelled results represent more
6 accurately the past hydrological regime. Similar improvements in the bias corrected output
7 have been reported by Hagemann et al. (2011), Muerth et al. (2013) and Harding et al. (2014).

8 For some regions, the sign of the projected change in runoff shifted after bias correction. This
9 finding was also encountered in the study of Hagemann et al. (2011). Hagemann et al. (2011)
10 underline that these changes in the climate signal reveal another uncertainty aspect of the
11 GCM to GHM modelling procedure, that is inherent to the GCM but becomes apparent after
12 the bias adjustment of the climate model output. Teng et al. (2015) argue that signal changes
13 are produced by bias correction errors in higher percentiles' precipitation, thus adding another
14 factor to the uncertainty of the runoff projections.

15 Although the absolute values of raw and bias corrected simulations differ significantly, this
16 does not apply to the projected relative changes. Liu et al. (2014) also found that raw and bias
17 corrected data resulted in similar estimations of relative changes for a series a variables,
18 including ET and runoff. The study of Muerth et al. (2013) investigates the effect of bias
19 adjustment on hydrological simulations and their climate change induced alterations.
20 Concerning the relative changes between baseline and future time-slices, it is reported that
21 bias correction does not influence notably the hydrologic indicators, apart from the one
22 describing flow seasonality.

23 Chen et al. (2011) identify three uncertainty components in bias correction applications: the
24 uncertainty of: the different GCM, the variable emission scenarios and that of the decade used
25 for bias adjustment. From a comparison of the latter uncertainty source with the two former,
26 concluded that the choice of correction decade has the smallest contribution to total
27 uncertainty. In this paper we address another uncertainty source; that of the dataset used for
28 correction. It was found that the WFDEI-bias corrected simulation captured better the past
29 hydrological regime compared to the E-OBS-bias corrected configuration. The differences
30 between the two simulations abate when results are expressed as percent change but still their
31 variation are of the same magnitude as that between raw and bias corrected data. This implies
32 that the selection of the observational dataset used for bias correction is not a trivial step of the

1 modelling procedure and it should be treated as an extra factor that causes the uncertainty
2 window of the projected hydrologic conditions to further open

3

4 **5 Conclusions**

5 In this paper, the future mean- and low- hydrological states under +4 °C of global warming
6 were assessed for the European region, using the novel dataset of the Euro-CORDEX climate
7 projections. An analysis of the changes in future drought climatology was performed for five
8 major European basins and the impact of +2 °C versus +4 °C global warming was estimated.
9 Concurrently, the effect of bias correction of the climate model outputs on the projected
10 climate was also evaluated.

11 The concluding remarks of this study are summarised below:

12 Projections show an intensification of the water cycle at +4 SWL, as even for areas where the
13 average state is not considerably affected, there are remarkable projected decreases of low
14 flows. With the exception of the Scandinavian Peninsula and some small areas in central
15 Europe, 10th percentile runoff production is projected to reduce all over Europe. This favours
16 the formation of extreme hydrological events, thus more droughts compared to the current
17 state could be expected in the future due to the warming climate.

18 Drought climatology is projected to change to more dry days per year for the Danube, Rhine
19 and Guadiana basins. Thus these areas are projected to experience more usual and more
20 intense drought events in the future.

21 For the areas where clear decreasing or increasing runoff trends are identified in the
22 projections, these changes are considerably intensified when moving from the +2 SWL to the
23 +4 SWL. Decreasing trends apply to southern Europe, including the Mediterranean region,
24 while strong increasing trends are projected for northern and north-eastern Europe. For the
25 rest of the European region where trends are not clear or ensemble members do not agree
26 towards the change, the effect of the further warming from +2 SWL to +4SWL, does not seem
27 to severely affect the hydrological state, which is however already significantly altered at +2
28 SWL compared to pre-industrial.

29 Bias correction results in an improved representation of the historical hydrological conditions.
30 However, raw and bias corrected simulations exhibit minor variations for results of statistical
31 interpretation (in our study: percent change, number of days under drought threshold).

1 The dataset used for bias correction can affect the quality of the projections in absolute terms
2 to a great extent. The comparison performed here showed that the WFDEI-corrected dataset
3 produces simulations that capture better the past observed hydrologic state compared to the E-
4 OBS-corrected dataset and should thus be preferred for bias correction applications over
5 Europe. The selection of the “correct” dataset is an added uncertainty to the climate impact
6 modelling chain, with magnitude similar to that of the bias correction procedure itself.

7

8

9

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1 Table 1. Euro-CORDEX climate scenarios used to force JULES.

	GCM	+2 SWL time-slice	Exceeded warming level (°C) in the +2 SWL time-slice	+4 SWL time-slice	Exceeded warming level (°C) in the +4 SWL time-slice	Equilibrium Climate Sensitivity (K)
1	GFDL-ESM2M	2040-2069	2	2071-2100	3.2	2.44
2	NorESM1	2036-2065	2	2071-2100	3.75	2.80
3	MIROC5	2037-2066	2	2071-2100	3.76	2.72
4	IPSL-CM5A	2018-2047	2	2055-2084	4	4.13
5	HadGEM2-ES	2024-2053	2	2060-2089	4	4.59

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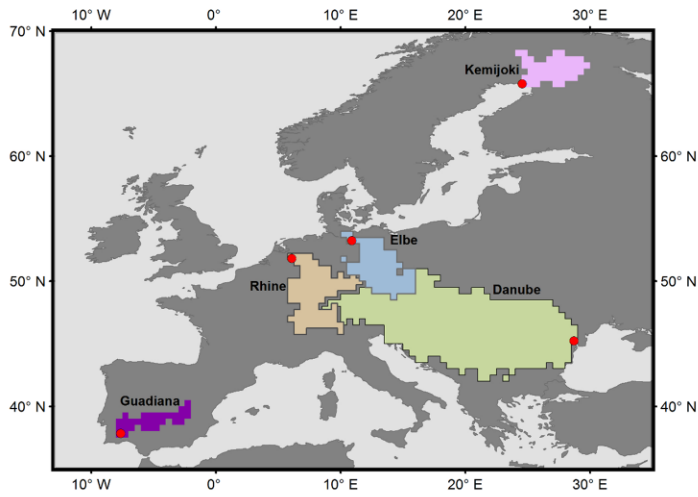
1 Table 2. Basin's annual average runoff production for raw and bias adjusted Euro-CORDEX data.

Basin's Annual Average Runoff Production [mm/year]												
	Raw						Bias Corrected					
	Historical average 1976-2005						Historical average 1976-2005					
Danube	462.05	362.35	383.78	304.02	266.21	355.68	219.37	249.80	201.95	226.70	229.00	225.36
Rhine	794.21	845.83	616.94	710.16	495.99	692.63	426.67	503.68	415.00	439.11	470.29	450.95
Elbe	371.88	356.72	219.68	337.42	174.41	292.02	148.70	203.39	135.98	174.79	202.12	173.00
Guadiana	166.13	71.44	116.14	46.60	81.51	96.36	93.14	96.42	90.06	79.22	89.82	89.73
Kemijoki	428.17	482.28	427.95	418.03	507.48	452.78	174.68	327.78	197.30	238.28	450.70	277.75
RCM-GCM	RCA4-GFDL-ESM2M +3.2 (2071-2100)	RCA4-NorESM1 +3.75 (2071-2100)	RCA4-MIROC5 +3.76 (2071-2100)	RCA4-IPSL-CM5A +4 (2055-2084)	RCA4-HadGEM2-ES +4 (2060-2089)	MEAN	RCA4-GFDL-ESM2M +3.2 (2071-2100)	RCA4-NorESM1 +3.75 (2071-2100)	RCA4-MIROC5 +3.76 (2071-2100)	RCA4-IPSL-CM5A +4 (2055-2084)	RCA4-HadGEM2-ES +4 (2060-2089)	MEAN
	Absolute change from baseline in the projected time-slice						Absolute change from baseline in the projected time-slice					
Danube	-54.57	3.36	-13.20	-42.04	-14.96	-24.28	-11.83	-1.38	3.61	-30.04	-11.48	-10.22
Rhine	59.95	-19.81	-13.23	-39.31	-20.14	-6.51	53.83	-5.91	6.09	-44.17	-21.73	-2.37
Elbe	2.05	33.91	30.00	-28.39	19.05	11.32	22.81	33.28	31.55	-5.57	25.71	21.55
Guadiana	-55.70	-37.02	-17.16	-14.09	-46.16	-34.03	-26.23	-48.81	-10.37	-28.52	-45.23	-31.83
Kemijoki	146.86	67.46	67.48	174.94	108.26	113.00	149.69	97.38	89.71	179.15	119.97	127.18
	Percent change from baseline in the projected time-slice						Percent change from baseline in the projected time-slice					
Danube	-11.81	0.93	-3.44	-13.83	-5.62	-6.83	-5.39	-0.55	1.79	-13.25	-5.01	-4.54
Rhine	7.55	-2.34	-2.14	-5.54	-4.06	-0.94	12.62	-1.17	1.47	-10.06	-4.62	-0.53
Elbe	0.55	9.51	13.66	-8.42	10.92	3.88	15.34	16.36	23.20	-3.19	12.72	12.46
Guadiana	-33.53	-51.82	-14.78	-30.24	-56.63	-35.31	-28.16	-50.63	-11.51	-36.00	-50.35	-35.47
Kemijoki	34.30	13.99	15.77	41.85	21.33	24.96	85.69	29.71	45.47	75.19	26.62	45.79

1 Table 3. Basin's 10th percentile of runoff production, derived on an annual basis, for raw and bias adjusted Euro-CORDEX data.

Basin's 10th percentile on annual basis [mm/year]												
	Raw						Bias Corrected					
	Historical average 1976-2005						Historical average 1976-2005					
Danube	146.63	96.81	80.55	79.71	58.69	92.48	31.49	41.73	28.54	30.32	37.94	34.00
Rhine	250.22	258.37	162.58	200.59	109.23	196.20	98.23	120.41	93.24	101.58	107.68	104.23
Elbe	118.79	99.15	29.98	98.30	28.95	75.04	10.22	20.08	11.23	16.75	22.14	16.08
Guadiana	0.74	0.00	0.12	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00
Kemijoki	0.80	4.50	1.10	1.47	10.79	3.73	0.25	5.91	0.53	1.00	11.60	3.86
RCM-GCM	RCA4-GFDL-ESM2M +3.2 (2071-2100)	RCA4-NorESM1 +3.75 (2071-2100)	RCA4-MIROC5 +3.76 (2071-2100)	RCA4-IPSL-CM5A +4 (2055-2084)	RCA4-HadGEM2-ES +4 (2060-2089)	MEAN	RCA4-GFDL-ESM2M +3.2 (2071-2100)	RCA4-NorESM1 +3.75 (2071-2100)	RCA4-MIROC5 +3.76 (2071-2100)	RCA4-IPSL-CM5A +4 (2055-2084)	RCA4-HadGEM2-ES +4 (2060-2089)	MEAN
	Absolute change from baseline in the projected time-slice						Absolute change from baseline in the projected time-slice					
Danube	-53.89	-23.89	-18.83	-38.22	-27.41	-32.45	-18.03	-15.89	-9.68	-22.28	-24.37	-18.05
Rhine	-89.38	-87.03	-20.39	-103.94	-43.25	-68.80	-31.43	-49.93	-19.49	-69.92	-52.57	-44.67
Elbe	-29.14	-21.01	1.21	-44.80	-9.96	-20.74	-2.03	-2.73	-0.91	-8.90	-8.52	-4.62
Guadiana	-0.73	0.00	-0.11	0.00	0.00	-0.17	0.00	0.00	0.00	0.00	0.00	0.00
Kemijoki	16.77	53.16	36.71	56.80	72.44	47.18	3.24	3.12	5.05	22.55	16.79	10.15
	Percent change from baseline in the projected time-slice						Percent change from baseline in the projected time-slice					
Danube	-36.75	-24.68	-23.38	-47.95	-46.71	-35.09	-57.26	-38.07	-33.90	-73.50	-64.22	-53.08
Rhine	-35.72	-33.68	-12.54	-51.82	-39.59	-35.07	-32.00	-41.46	-20.91	-68.83	-48.82	-42.86
Elbe	-24.53	-21.19	4.04	-45.57	-34.41	-27.64	-19.86	-13.58	-8.11	-53.15	-38.47	-28.71
Guadiana	-98.67	-73.37	-96.24	-26.22	-76.38	-98.01	-48.53	-50.67	-65.42	-32.31	-56.63	-53.36
Kemijoki	2088.40	1181.25	3328.72	3877.01	671.51	1264.16	1283.66	52.88	946.08	2265.11	144.71	263.09

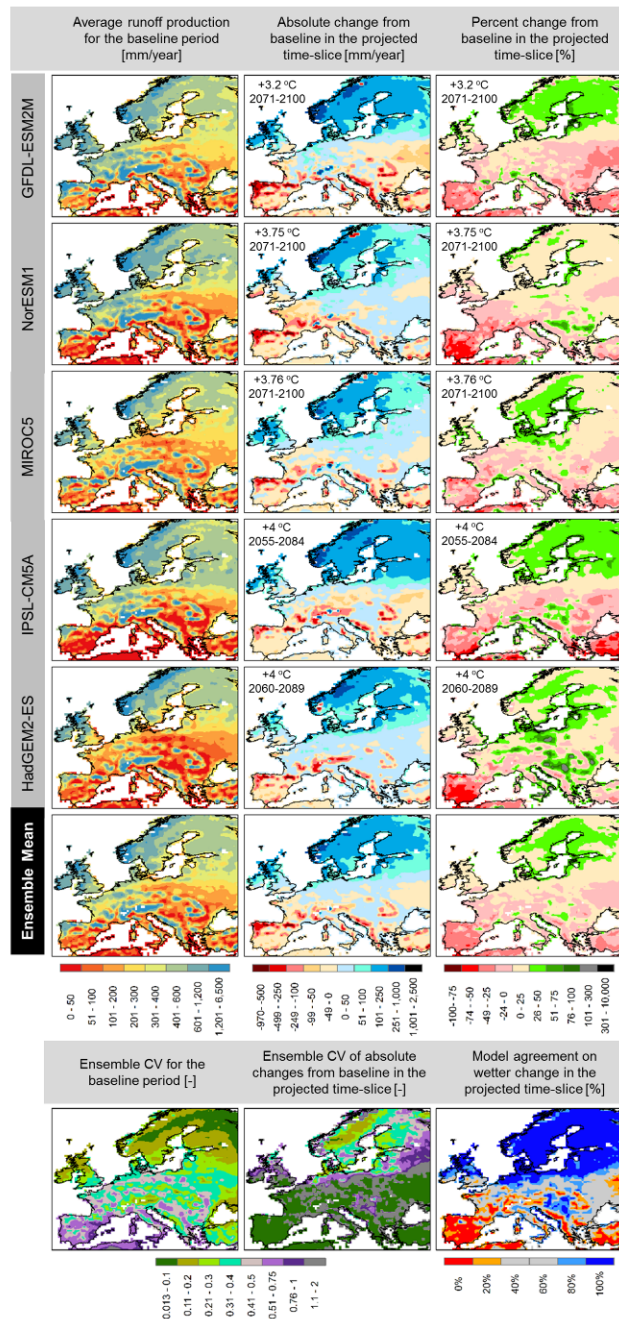
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Station Info						
River	Station	GRDC Station No	Latitude (dec. degrees)	Longitude (dec. degrees)	Observed catchment area [km ²]	Modelled catchment area [km ²]
Danube	Ceatal Izmail	6742900	45.22	28.72	807000	815063
Rhine	Rees	6335020	51.75	6.40	159300	177339
Elbe	Neu-Darchau	6340110	53.23	10.89	131950	133886
Guadiana	Pulo do Lovo	6116200	37.82	-7.63	60883	72215
Kemijoki	Isohaara	6854700	65.78	24.55	50686	55628

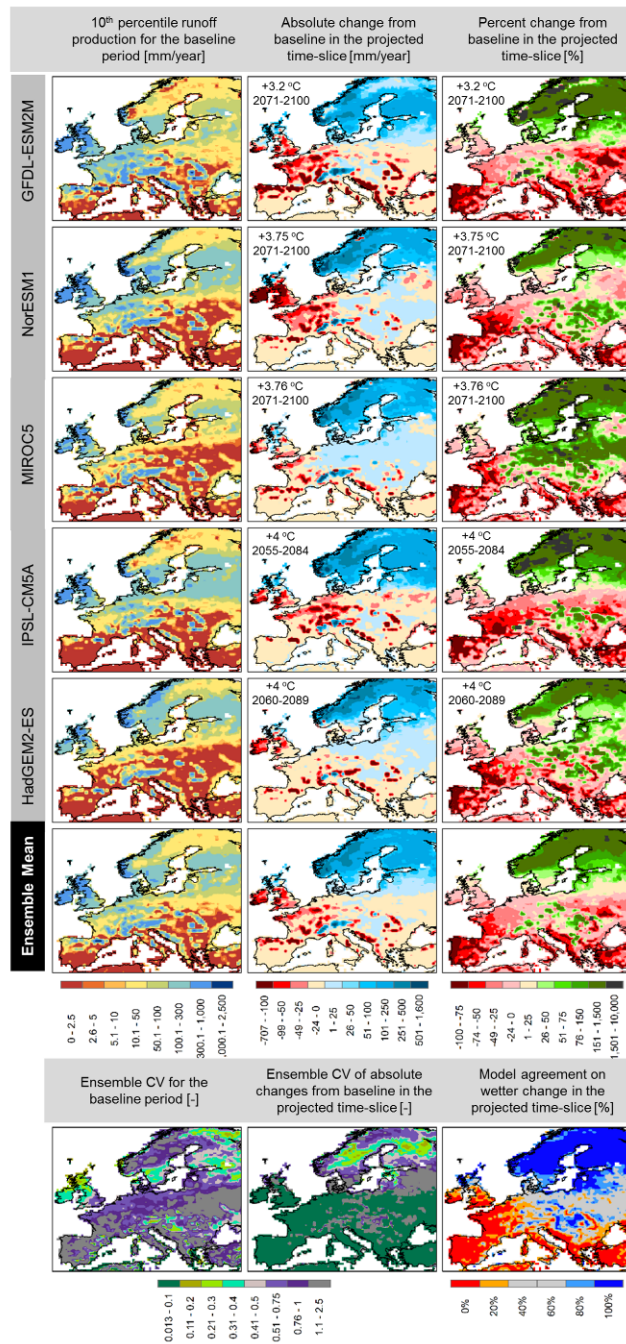
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2 Figure 1. European study domain, tested basins as defined by the model's 0.5 degree
 3 resolution, gauging stations and general information on the stations.

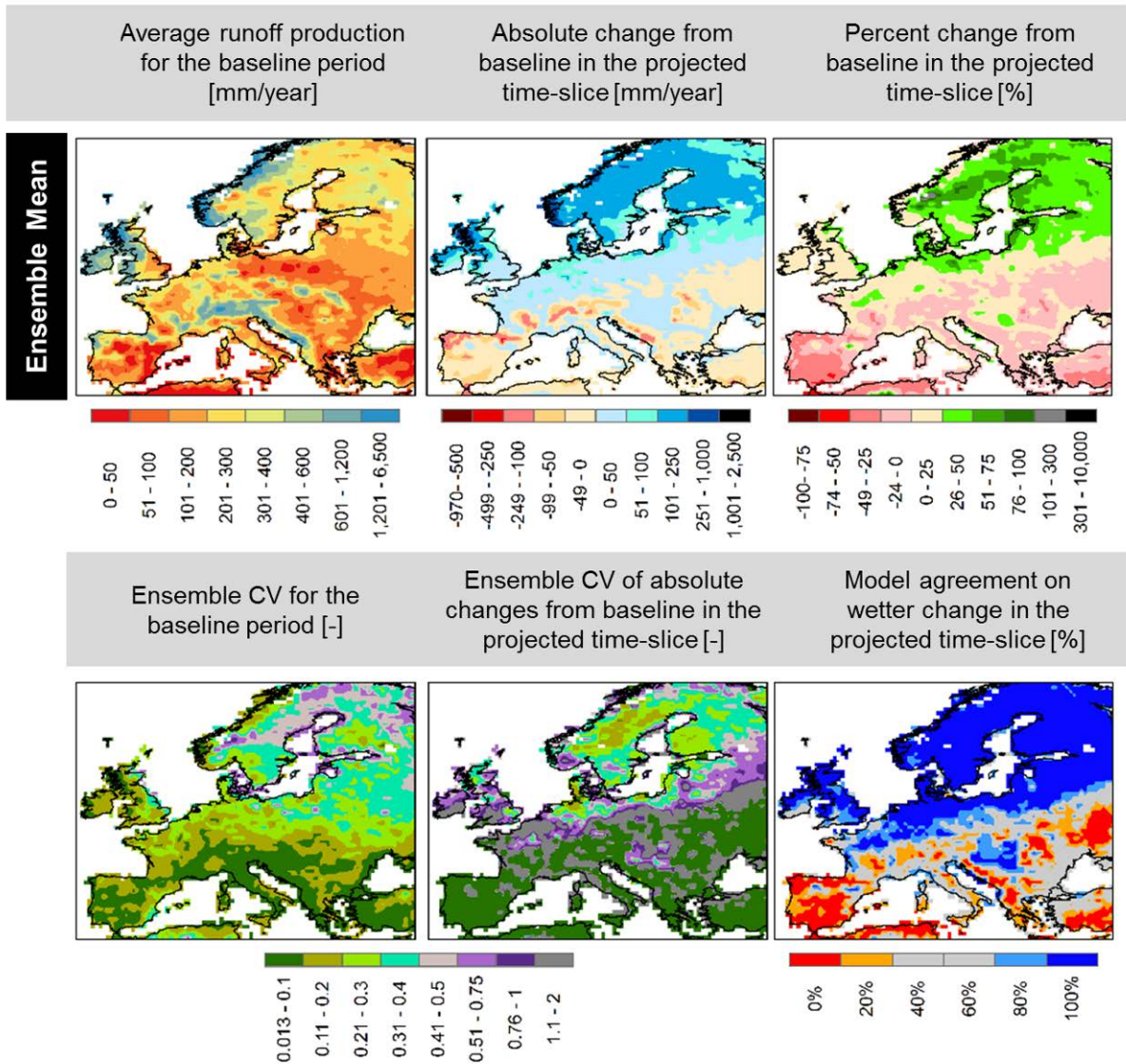


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Figure 2. Average runoff production from raw Euro-CORDEX data for all dynamical downscaled GCMs and their ensemble mean. Runoff production averaged over the baseline period (1976-2005) (left column), absolute change in runoff in the +4 SWL projected time-slice (middle column) and percent change in the +4 SWL projected time-slice (right column). Bottom row: coefficient of variation of the ensemble members for the baseline period (left column), coefficient of variation of the projected absolute changes in the +4SWL projected time-slice (middle column) and model agreement towards a wetter change in the +4 SWL projected time-slice.

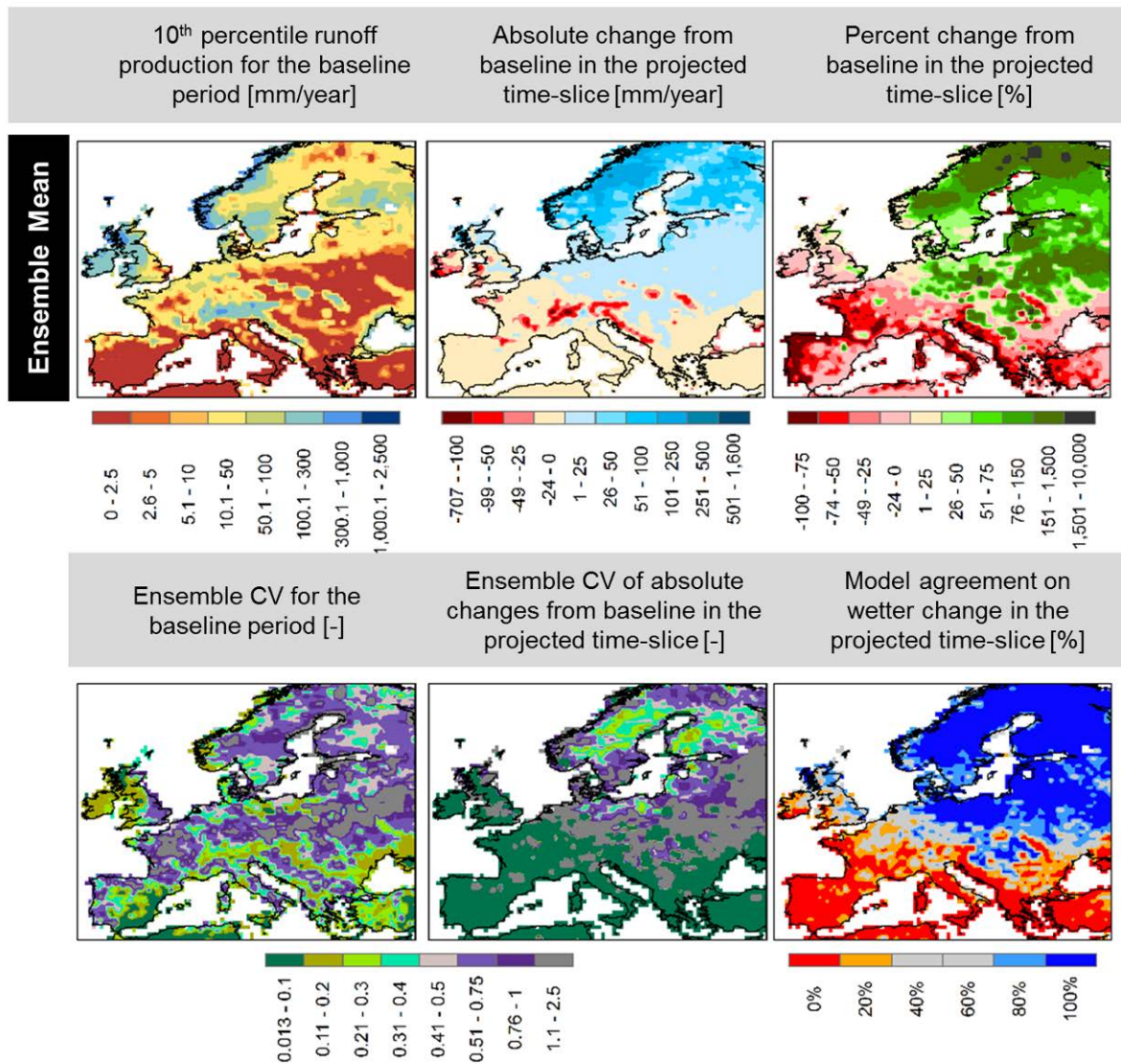


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2 Figure 3. 10th percentile of runoff production from raw Euro-CORDEX data for all
3 dynamical downscaled GCMs and their ensemble mean. 10th percentile runoff production
4 derived on an annual basis and averaged over the baseline period (1976–2005), absolute
5 change in 10th percentile runoff in the +4 SWL projected time-slice (middle column) and
6 percent change in the +4 SWL projected time-slice (right column). Bottom row: coefficient of
7 variation of the ensemble members for the baseline period (left column), coefficient of
8 variation of the projected absolute changes in the +4SWL projected time-slice (middle
9 column) and model agreement towards a wetter change in the +4 SWL projected time-slice.



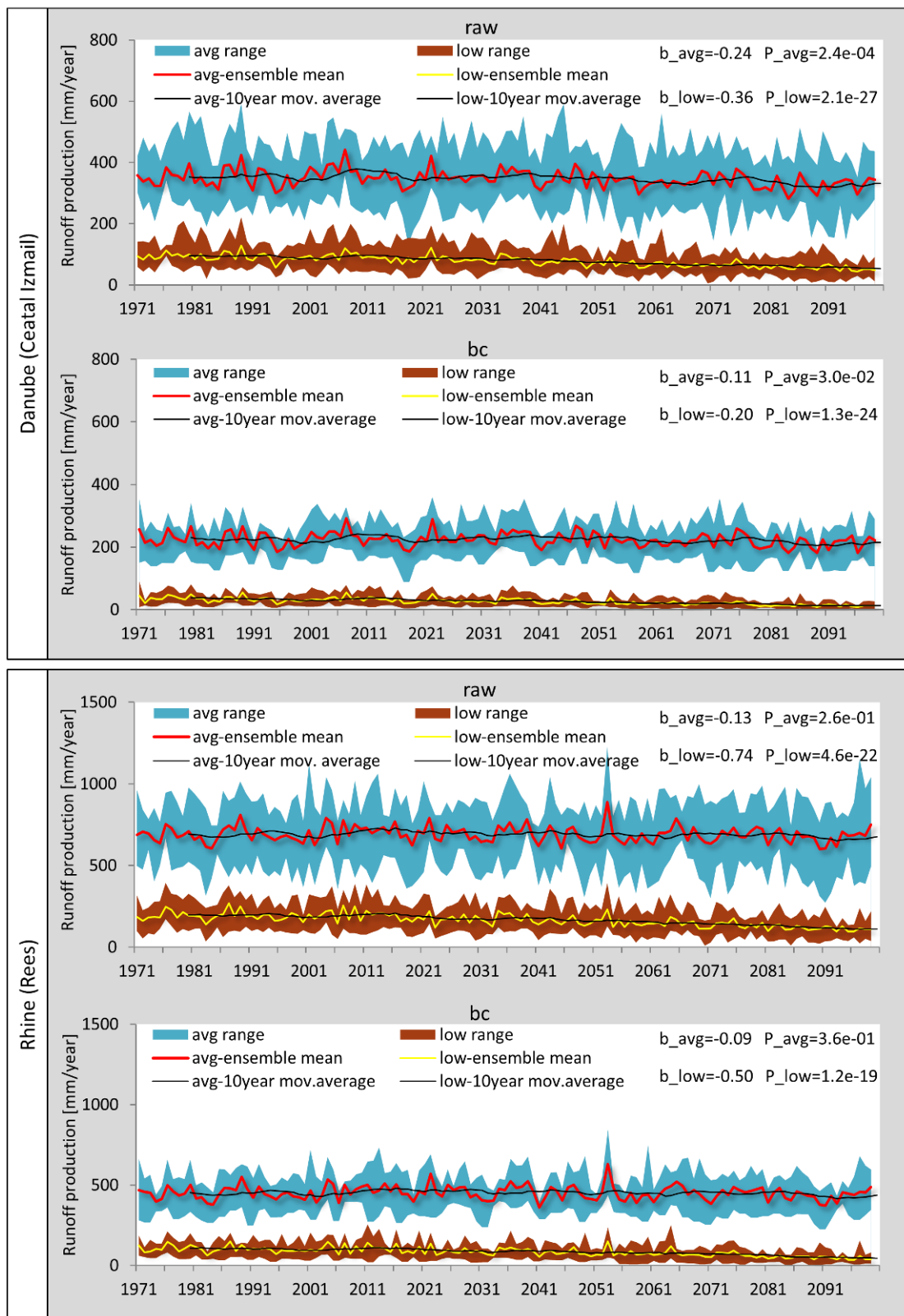
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2 Figure 4. Ensemble mean of average runoff production from Euro-CORDEX data bias
3 adjusted against the WFDEI dataset. Top row: Runoff production averaged over the baseline
4 period (1976-2005) (top row), absolute (middle row) and percent change (bottom row) in
5 ensemble mean runoff in the +4 SWL projected time-slice. Bottom row: coefficient of
6 variation of the ensemble members for the baseline period (left column), coefficient of
7 variation of the projected absolute changes in the +4 SWL projected time-slice (middle
8 column) and model agreement towards a wetter change in the +4 SWL projected time-slice.

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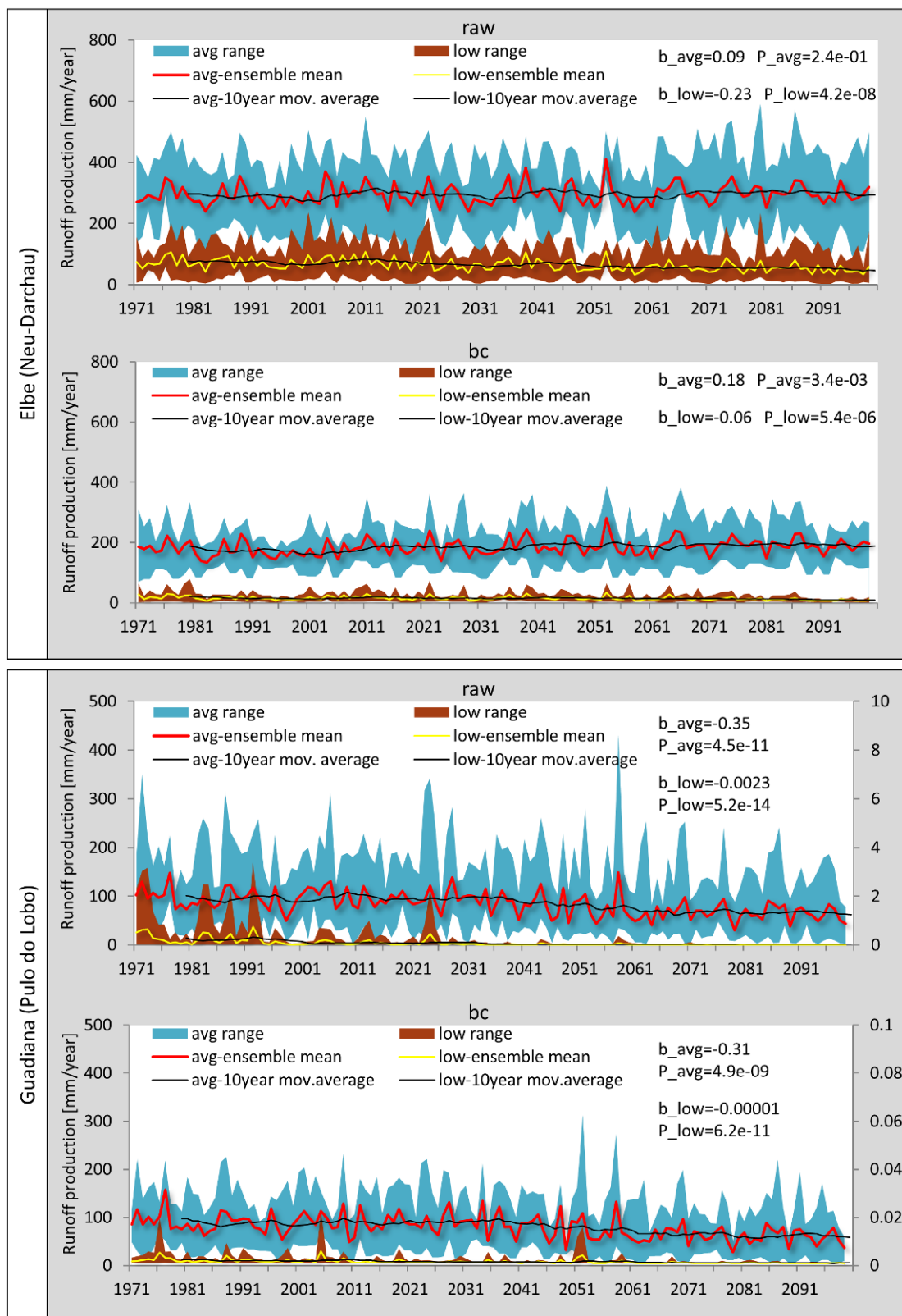


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 2 Figure 5. Ensemble mean of 10th percentile runoff production from Euro-CORDEX data bias
 3 adjusted against the WFDEI dataset. Top row: 10th percentile runoff production derived on an
 4 annual basis averaged over the baseline period (1976-2005) (top row), absolute (middle row)
 5 and percent change (bottom row) in ensemble mean runoff in the +4 SWL projected time-
 6 slice. Bottom row: coefficient of variation of the ensemble members for the baseline period
 7 (left column), coefficient of variation of the projected absolute changes in the +4 SWL
 8 projected time-slice (middle column) and model agreement towards a wetter change in the +4
 9 SWL projected time-slice.

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 2 Figure 6. Annual time-series of basin averaged runoff production (average and 10th
 3 of annual runoff) for raw and bias adjusted Euro-CORDEX data. For both average and 10th
 4 percentile time-series, the ensemble range, mean and 10-year moving average is shown.

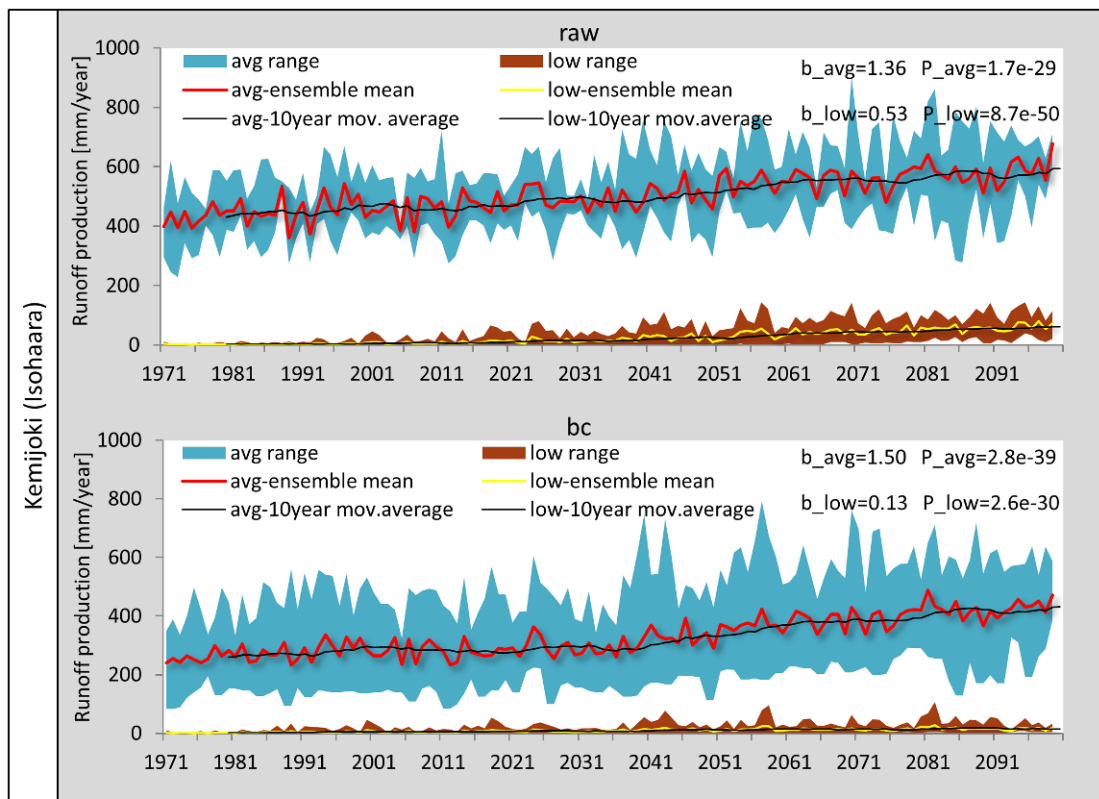


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2 Figure 6 (continued)

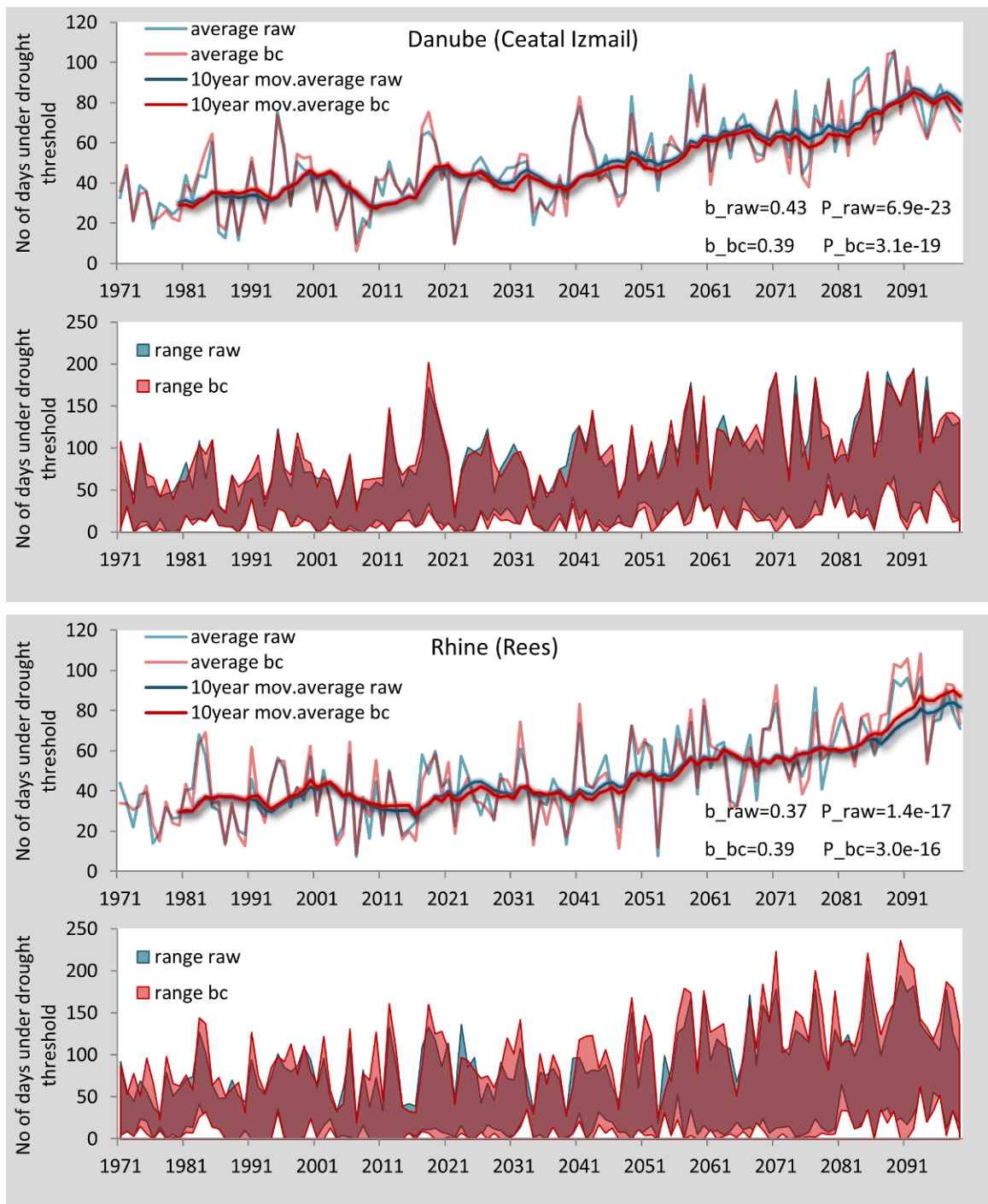
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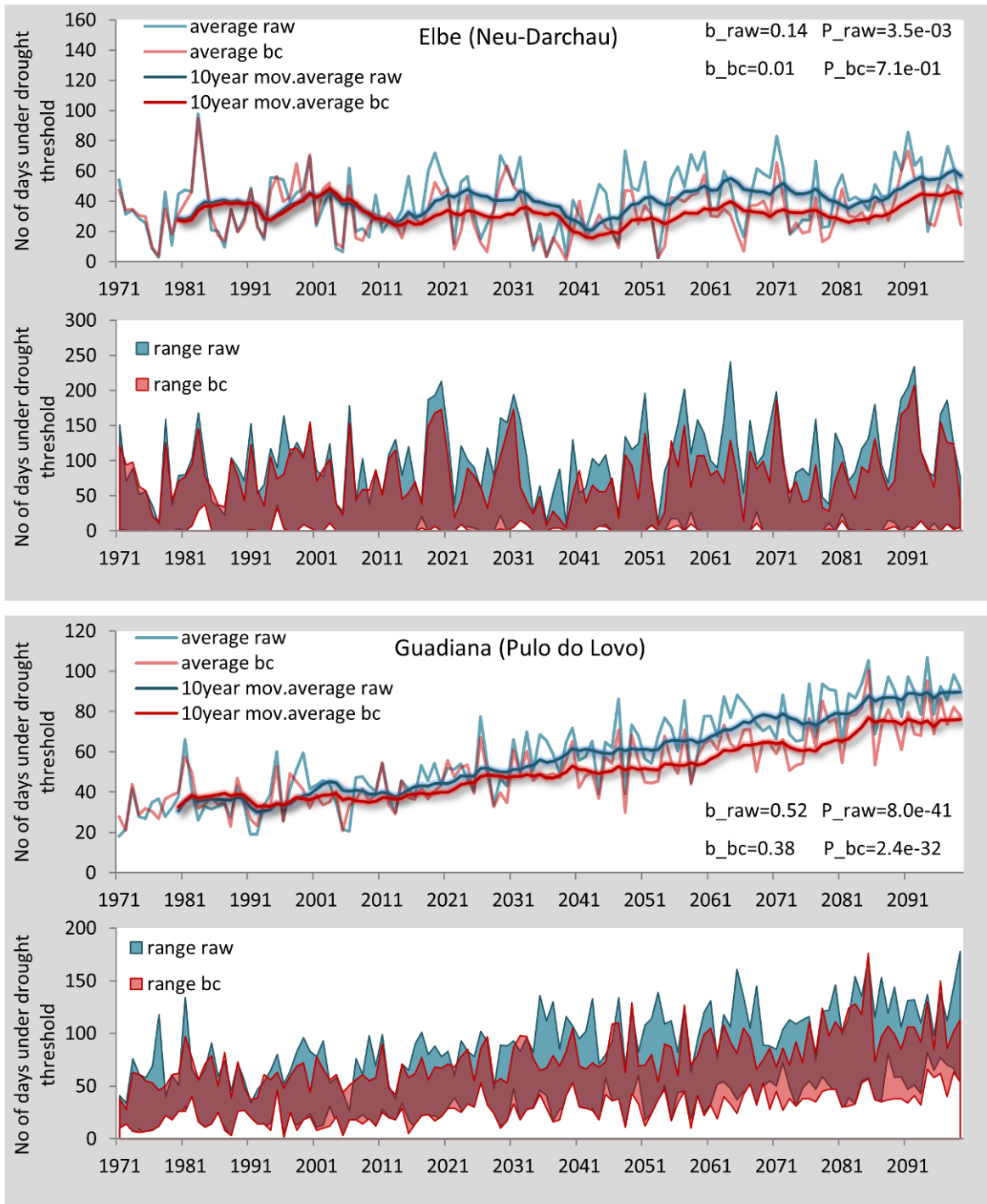


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2 Figure 6 (continued)



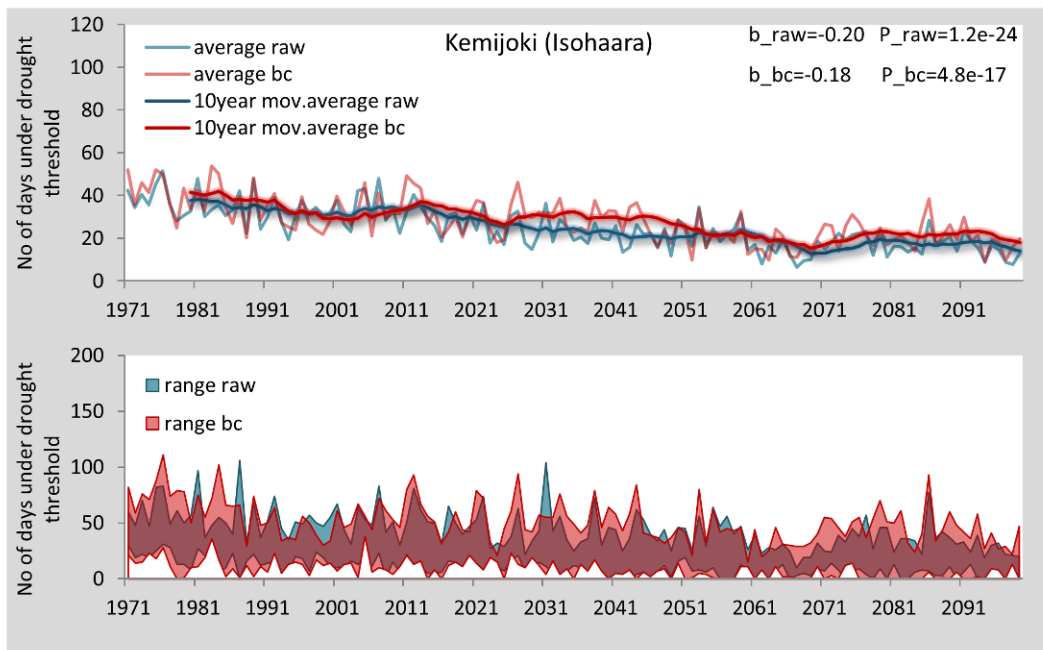
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 2 Figure 7. Number of days under drought threshold per year for raw and bias adjusted Euro-
 3 CORDEX data. Ensemble mean and 10-year moving average of the ensemble mean (top),
 4 ensemble range (bottom).



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2 Figure 7 (continued)

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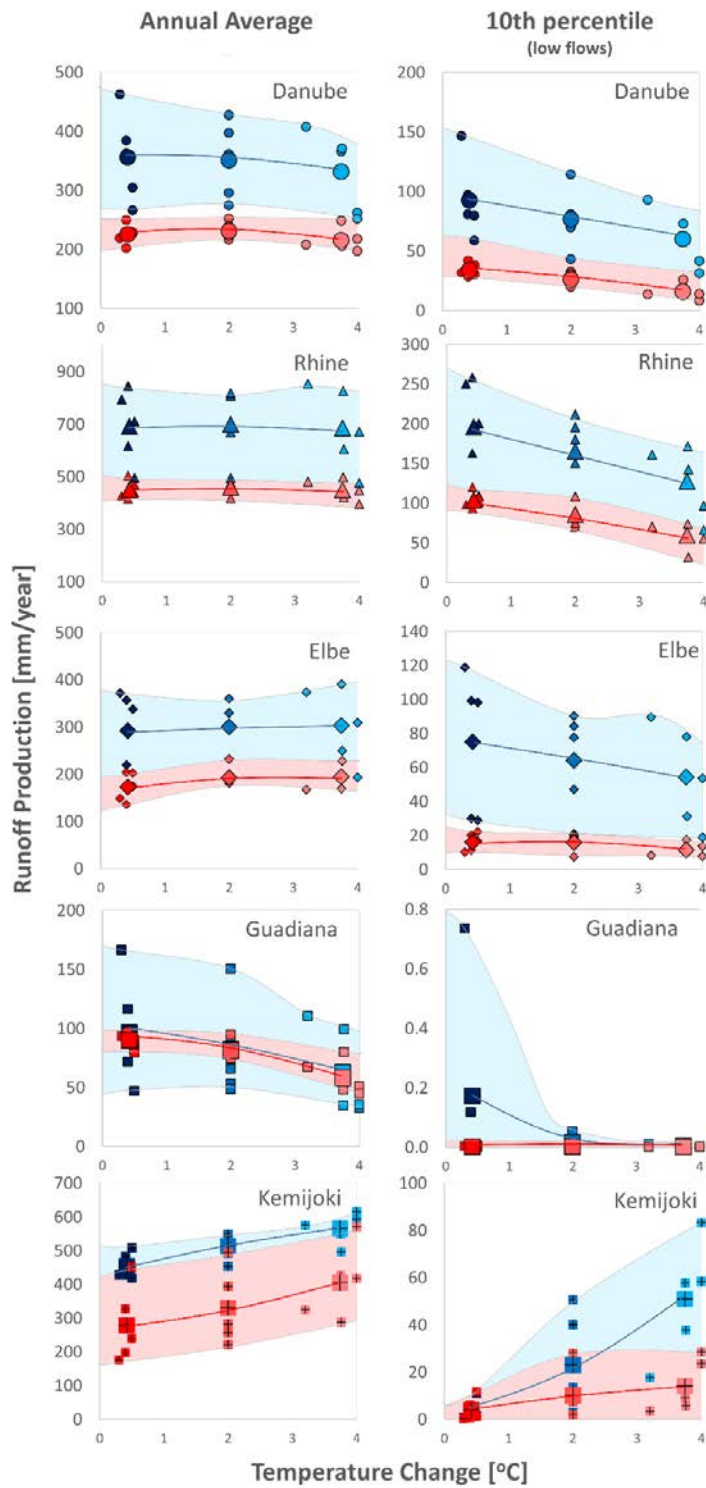


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2 Figure 7 (continued)

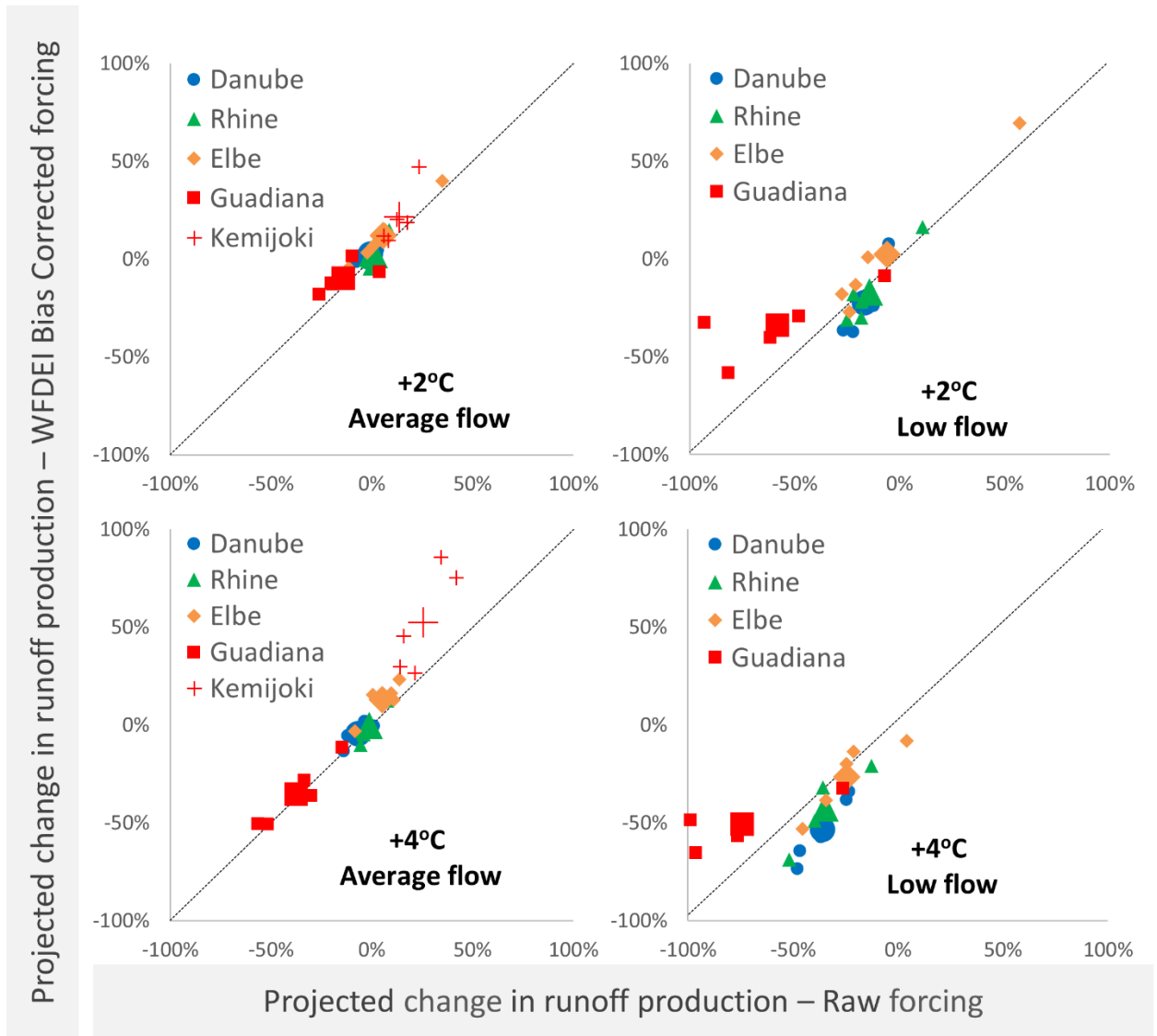
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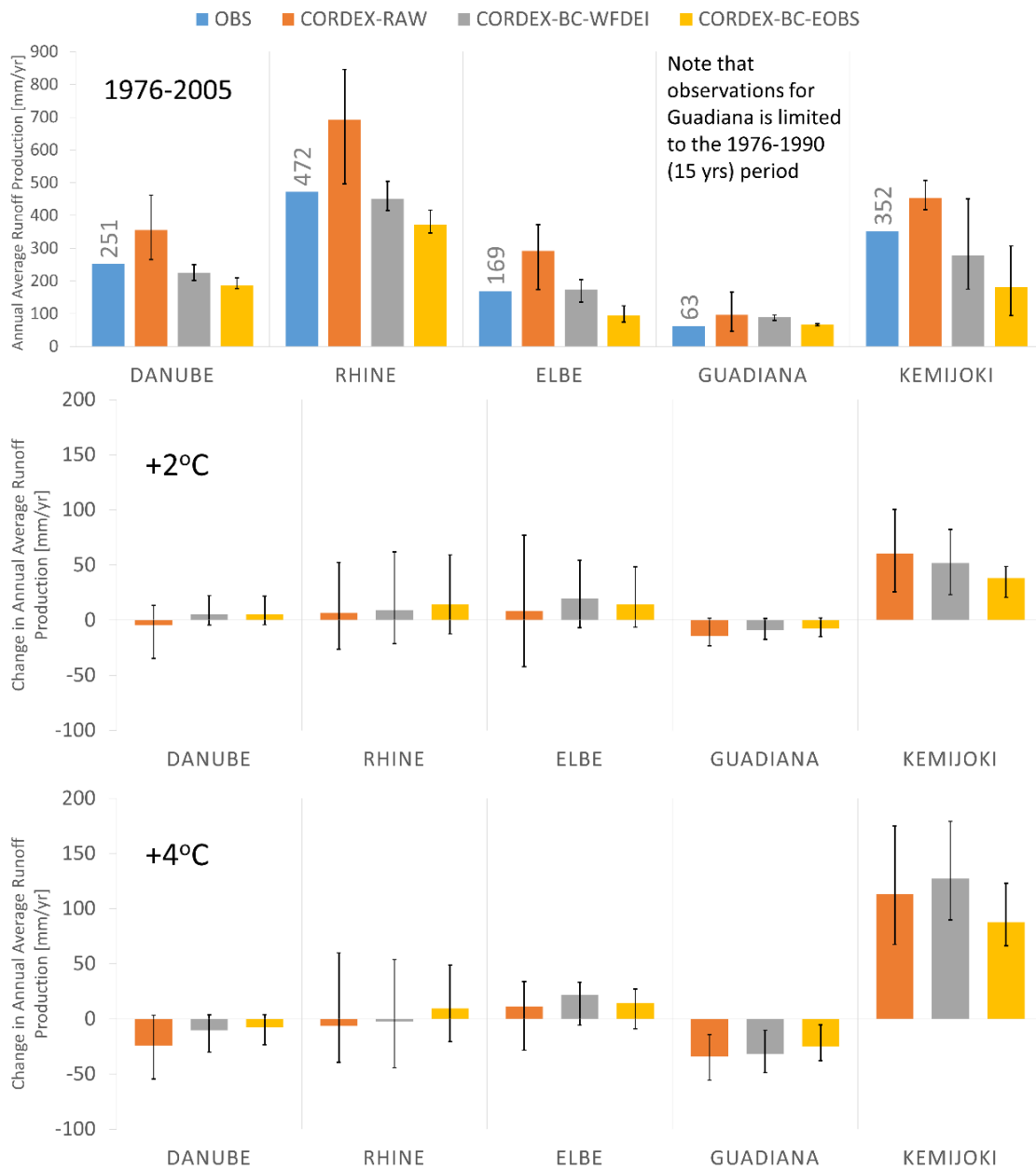
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2 Figure 8. Variation of runoff production with respect to temperature change (+2 and +4
 3 SWLs) for raw (light blue) and bias adjusted (light red) Euro-CORDEX data, for both annual
 4 average (left column) and 10th percentile (right column) runoff production. Small markers
 5 represent the value of each individual model and bigger markers correspond to ensemble
 6 mean value.



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Figure 9. Correlation between projected change in basin averaged runoff production derived from WFDEI-bias adjusted and raw Euro-CORDEX data, for both annual average (left) and 10th percentile (right) runoff production. Correlation is examined at +2°C SWL (top) and at +4°C SWL (bottom). Small markers represent the value of each individual model and bigger markers correspond to ensemble mean value.



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Figure 10. Comparison between the simulations of raw Euro-CORDEX data and bias adjusted against two different datasets (WFDEI and E-OBS) for five study basins. Bars show the ensemble means and error bars the minimum and maximum ensemble member values. (Top row) Annual average runoff production for the period 1976 to 2005. OBS values are derived from GRDC discharge measurements converted to basin averages at the annual time-scale. (Middle row) Percent change in annual average runoff production at the +2 SWL and (bottom row) at the +4 SWL.