



Two sets of bias-corrected regional UK Climate Projections 2018 (UKCP18) of temperature, precipitation and potential evapotranspiration for Great Britain

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Abstract. The United Kingdom Climate Projections 2018 (UKCP18) regional climate model (RCM) 12 km regional perturbed physics ensemble (UKCP18-RCM-PPE) is one of the three strands of the latest set of UK national climate projections produced by the UK Met Office. It has been widely adopted in climate impact assessment. In this study, we report biases in the raw UKCP18-RCM simulations that are significant and are likely to deteriorate impact assessments if they are not adjusted. Two methods were used to bias-correct UKCP18-RCM: non-parametric quantile mapping using empirical quantiles and a variant developed for the third phase of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) designed to preserve the climate change signal. Specifically, daily temperature and precipitation simulations for 1981 to 2080 were adjusted for the 12 ensemble members. Potential evapotranspiration was also estimated over the same period using the Penman–Monteith formulation and then bias-corrected using the latter method. Both methods successfully corrected biases in a range of daily temperature, precipitation, and potential evapotranspiration metrics and reduced biases in multi-day precipitation metrics to a lesser degree. An exploratory analysis of the projected future changes confirms the expectation of wetter, warmer winters and hotter, drier summers and shows uneven changes in different parts of the distributions of both temperature and precipitation. Both bias-correction methods preserved the climate change signal almost equally well, as well as the spread among the projected changes. The change factor method was used as a benchmark for precipitation, and we show that it fails to capture changes in a range of variables, making it inadequate for most impact assessments. By comparing the differences between the two bias-correction methods and within the 12 ensemble members, we show that the uncertainty in future precipitation and temperature changes stemming from the climate model parameterization far outweighs the uncertainty introduced by selecting one of these two bias-correction methods. We conclude by providing guidance on the use of the bias-corrected datasets. The datasets bias-adjusted with ISIMIP3BA are publicly available in the following repositories: <https://doi.org/10.5281/zenodo.6337381> for precipitation and temperature (Reyniers et al., 2022a) and <https://doi.org/10.5281/zenodo.6320707> for potential evapotranspiration (Reyniers et al., 2022b). The datasets, bias-corrected using the quantile mapping method, are available at <https://doi.org/10.5281/zenodo.8223024> (Zha et al., 2023).

1 Introduction

Climate model projections are essential to anticipate and adapt to future climate change impacts. Continuous efforts by the climate modelling community have led to major improvements in the realism of climate model simulations, yet significant discrepancies (biases) between observations and simulations of climatic variables remain (e.g. Kotlarski et al., 2014; Vautard et al., 2021). Biases in climate projections require particular attention when the projections are used to force impact models, for instance, to assess future impacts on river streamflow, ecosystems, or agricultural yields. Capturing the whole distribution of rainfall amounts is an essential prerequisite for hydrological modelling, but is still notoriously challenging for many climate models. The response of impact models to forcing errors can be non-linear and amplify the severity of the biases; hence, biases are typically adjusted before the climate projections are used in impact models.

To this effect, a range of bias-correction (BC) methods have been developed and compared (Wood et al., 2004; Teutschbein and Seibert, 2012; Gutmann et al., 2014; Maraun et al., 2019). Our purpose here is not to provide an extensive review of alternative bias-correction methods, because such reviews are available elsewhere (see the introductory sections of Robertson et al. (2023) and Zhang et al. (2024) and the literature they cite for recent examples). These methods vary in complexity and scope from univariate approaches to more advanced multivariate methods. For example, Cannon (2016) introduced a multivariate BC algorithm designed to correct inter-variable correlations, and later Cannon (2018) developed an n -dimensional multivariate quantile mapping BC method for a more comprehensive correction of multivariate dependence structures. Moreover, for completeness, we note that bias correction is not only used as a processing step between climate model output and impact model but is also sometimes applied to correct the global climate model-derived boundary conditions used for dynamical downscaling with regional climate models (e.g. Bruyère et al., 2014). For example, Kim et al. (2023a) (software from Kim et al., 2023b) improved the simulation of diurnal precipitation cycles using their proposed sub-daily multivariate BC method. Generally speaking, bias-adjustment methods transform the simulations so that some of their statistical properties match those of the observations. This efficiently reduces biases and, as a result, can considerably improve impact simulations (Rojas et al., 2011; Hakala et al., 2018; Pastén-Zapata et al., 2020). We note, however, that residual biases remain after bias correction and can deteriorate the impact simulations (Teng et al., 2015). This highlights that these biases are not corrected and removed but rather adjusted; as such, the term bias adjustment is more accurate and becoming more widely used, but here we use BC to match how these methods are more commonly described in the literature. In addition, the statistical nature of BC methods means

they only address the symptoms and not the origin of model errors; i.e. they do not identify the causes of model biases nor account for them (Addor et al., 2016; Maraun et al., 2017).

Furthermore, the reliability of BC can be questioned because of its reliance on the assumption that climate model biases are stationary in time or in a changing climate state (Maraun, 2012; Ehret et al., 2012; Teutschbein and Seibert, 2012; Chen et al., 2015; Hui et al., 2020). A related issue is that BC can modify the simulated climate change trends. This poses an issue if the origin of model errors in daily variability in an evaluation period (to which BC is often calibrated) differs from the origin of potential errors in the model's climate change response (Maraun et al., 2017). These challenges are difficult to overcome. However, when following the alternative approach of using unadjusted climate model output, propagation of biases through impact models can severely bias the resulting simulations and sometimes render them unusable (Hakala et al., 2020). As such, BC is usually necessary and widely used to assess climate change impacts despite its imperfections.

In the context of the UK, several recent studies have been published on impact assessment using the UK Climate Projections 2018 (UKCP18) regional climate model (RCM) 12 km regional perturbed physics ensemble (UKCP18-RCM-PPE, referred to as UKCP18-RCM hereinafter; Met Office Hadley Centre, 2018; Lowe et al., 2018). The studies span various sectors, including the impact assessment on future river and groundwater flow (Kay et al., 2020; Hanford et al., 2023; Kay et al., 2023), extremes (Hanlon et al., 2021) such as flooding (Griffin et al., 2024; Gudde et al., 2024) and drought (Reyniers et al., 2023), heat stress (Kennedy-Asser et al., 2022), and multi-sectoral analysis (Arnell et al., 2021). Although the UKCP18 data have been widely used, the UKCP18 project itself does not provide bias-corrected climatic variables for impact assessment. The aforementioned studies use different bias-correction methods for their relevant climatic variables, which potentially make the impact assessment less comparable due to methodological differences in bias correction. The recently published CHES-SCAPE dataset (Robinson et al., 2023) also provides UKCP18 bias-corrected data. It contains 11 near-surface meteorological variables, is downscaled to a 1 km spatial resolution, and is provided at several temporal resolutions (from daily to decadal means) for the time period of 1980–2080. For the temperature in the CHES-SCAPE dataset, the seasonal (DJF, MAM, JJA, and SON) offsets were calculated for each season and each 1 km grid cell as the difference between CHES-SCAPE and CHES-met observations (Robinson et al., 2020a). The offsets were then subtracted from the CHES-SCAPE data. For precipitation, the seasonal scaling factors were calculated as the ratio of CHES-SCAPE to CHES-met, and the CHES-SCAPE precipitation was then multiplied by these factors. In the CHES-SCAPE dataset, 4 out of the 12 RCM-PPE members (01, 04, 05, and 15) are provided. The bias-corrected CHES-SCAPE data were

shown to be consistent with the CHES-met observations in the historical period of 1980–2000. However, the simple linear scaling BC method used in CHES-SCAPE does not take into account changes in moments of higher order than the mean.

Several studies have compared different BC methods including linear scaling, delta change, local intensity scaling, variance scaling, and quantile mapping (QM). These studies consistently find that QM outperforms other BC methods in effectively correcting higher-order statistical properties, such as standard deviation and percentiles (Azmat et al., 2018; Teutschbein and Seibert, 2012; Worku et al., 2020). Specifically, Fang et al. (2015) and Enayati et al. (2021) highlighted the strengths of empirical QM for effectively correcting precipitation and temperature biases. The bias-corrected regional UKCP18 data produced as part of the enhanced Future Flows and Groundwater (eFLaG Hannaford et al., 2023) project have also been made available (Lane and Kay, 2022). Unlike CHES-SCAPE, they are based on the full 12-member ensemble, but they only include one variable, available precipitation (the sum of rainfall and snowmelt derived using a snow module). The inclusion of snowmelt means that this is not directly comparable to the bias-corrected rainfall data introduced here even though the raw rainfall data are the same. But it is worth noting that eFLaG relies on bias-correction factors computed from monthly means, i.e. based on the assumption that the whole distribution is affected by the same bias as the mean. We illustrate below that this assumption is often violated; e.g. the bias in the 95th percentile can be quite different from the bias in mean precipitation (Fig. 1). Furthermore, our understanding is that eFLaG only contains bias-corrected precipitation and not temperature or potential evapotranspiration.

In this study, the precipitation and temperature of UKCP18-RCM are evaluated and bias-corrected. The empirical QM method and a change-preserving variant of the QM method were applied to bias-correct the UKCP18-RCM precipitation and temperature variables from all 12 RCM-PPE members over the period of 1980–2080. In addition, potential evapotranspiration (PET) was computed from these UKCP18 simulations and bias-corrected using the trend-preserving BC method. In comparison to some more sophisticated proposed methods in literature (such as the examples discussed earlier in the introduction, which also rely on quantile mapping), the bias-adjustment methods selected for the production of the datasets in this study are relatively straightforward as they are univariate and correct only on the native daily timescale of the regional climate model simulations. However, these established quantile-mapping-based methods provide substantial added benefits over the simplest bias-adjustment methods and strike a good balance for the production of multi-purpose datasets from which the impact modelling community can benefit. The raw precipitation and temperature simulations and derived PET data were evaluated before the two BC methods were applied. The result-

ing bias-corrected datasets are also evaluated and compared, and finally, recommendations are made concerning the use of the datasets. Specifically, the following questions are investigated:

1. How biased are the UKCP18-RCM projections?
2. Can existing bias-correction methods successfully correct errors in simple and more challenging metrics?
3. What climatic changes do the UKCP18-RCM ensemble members broadly project for the UK, and do the chosen bias-correction techniques affect them?

An exploratory analysis of the changes projected by UKCP18-RCM is discussed in Sect. 3.2 using metrics based on daily precipitation and daily average temperature.

2 Data and methods

2.1 Data

2.1.1 The UKCP18 regional climate projections

The UK Climate Projections 2018 (UKCP18) are the current generation of national climate projections for the UK, developed by the Met Office Hadley Centre as part of their Climate Programme (Met Office Hadley Centre, 2018). The research presented in this study makes use of its third strand, an ensemble of the 12km regional climate model projections (UKCP18-RCM; Met Office Hadley Centre, 2018), available from the Centre for Environmental Data Analysis (CEDA). The RCM simulations were run over the EURO-CORDEX rotated pole grid with a horizontal resolution of 0.11° , which results in quasi-uniform 12 km spacing over the European domain (Murphy et al., 2018) and made available for the UK region with these coordinates along with the OSGB36 projection, which was used for the work presented in this paper. Simulations of different variables are available from 1 December 1980 to 30 November 2080 at a daily time step (for practical reasons, December 1980 was left out of our analyses). The UKCP18-RCM simulations are a perturbed physics ensemble (PPE), obtained by running the global climate model (GCM) HadGEM3-GC3.05 with perturbations in 47 parameters from the convection, gravity wave drag, boundary layer, cloud, large-scale precipitation, aerosols, and land surface interaction schemes. The global simulations were then downscaled by one-way nesting with a regional configuration of this model using the same perturbed parameter sets as its driving GCM ensemble member. The HadGEM3-GC3.05 parameter sets chosen for the global and regional UKCP18 PPE ensembles were selected in multiple stages based on different criteria, as summarized briefly below and explained in Murphy et al. (2018) and references therein. The UKCP18-RCM simulations were forced by the RCP8.5 scenario, a very high emission scenario characterized by high population growth and energy demand (Riahi et al., 2011).

2.1.2 Observation data

As an observational reference for the evaluation and bias correction of UKCP18-RCM precipitation and temperature, the Met Office's 1 km HadUK-Grid dataset (Hollis et al., 2019) was used after regridding to the UKCP18-RCM 12 km grid by averaging all 1 km grid points that lay in each UKCP18-RCM grid cell (consistent with Hollis et al., 2019). For the bias correction and evaluation of PET, the CHES-PE dataset provided by the Centre for Ecology and Hydrology was used (Robinson et al., 2020b), also after regridding by averaging to the UKCP18-RCM 12 km grid. Daily data from 1981 to 2010 are used here (December 1980 is omitted for practical reasons).

2.2 Potential evapotranspiration

Potential evapotranspiration (PET) is not provided by UKCP18-RCM, but it is a necessary input variable for some impact models and indicators, so it was calculated offline here. While rising temperatures lead to PET increases, changes in humidity, net radiation, and wind speed can also play a significant role. Therefore, PET was calculated using the Penman–Monteith method, which includes the effect of all these variables and is recommended over simpler temperature-based methods (e.g. Dewes et al., 2017), although it is still subject to significant limitations (Milly and Dunne, 2016; Greve et al., 2019). The calculation of PET for the UKCP18-RCM used here relies on the same variant of the Penman–Monteith method used by Robinson et al. (2017) to ensure consistency with the CHES-PE dataset. Specifically, the following variables simulated by the UKCP18-RCM ensemble were used: specific humidity, pressure at sea level, net downwelling longwave radiation, net downwelling shortwave radiation, wind speed at 10 m, and daily average surface air temperature. PET was set to zero wherever a calculated value was negative (which occurred for less than 1 % of the values overall and, when split by ensemble member and month, also less than 1 % for all cases except December in ensemble member 1 with 1.2 % of negative values). PET was calculated from the uncorrected model variables, and then it was bias-corrected against PET calculated from observed variables (i.e. CHES-PE). This was preferred to the alternative approach of bias-correcting the individual variables and then calculating PET from the bias-corrected individual variables because that PET might still show biases compared with observation-based PET, requiring a further bias-correction step.

2.3 Evaluation and trend analysis

Biases in UKCP18-RCM precipitation and temperature metrics were assessed over the reference period of 1981–2010 (REF) using the 30-year temporal averages of a range of metrics computed for each grid cell. For analysing projected

changes, the final 30-year period of the simulations was chosen as the future period (2051–2080; FUT) for each ensemble member.

Climate model errors are not necessarily homogeneous across the range of the precipitation and temperature distributions. Therefore, the initial model evaluation metrics shown consist of the errors in the mean, lower-tail metric (Q05 for temperature and PET, dry-day frequency for precipitation), and Q95 as an upper-tail metric. This is based on the results of a preliminary analysis.

Changes in temperature and precipitation extremes are generally of greater societal interest than changes in the mean (although extreme impacts do not always need extreme meteorological conditions to arise; van der Wiel et al., 2020). Therefore, a set of moderate and extreme climate indicators was used to further evaluate the model error and analyse projected changes in simulated precipitation and temperature. These metrics were drawn from or inspired by the list of indices compiled by the Expert Team on Climate Change Detection and Indices (ETCCDI; http://etccdi.pacificclimate.org/list_27_indices.shtml, last access: 18 April 2024), which has been extensively used in the literature, including in Intergovernmental Panel on Climate Change (IPCC) reports (IPCC, 2021). Daily-mean temperature was used in this study, so the ETCCDI temperature indicators (which typically use daily minimum and maximum temperatures) were modified to use mean temperature. Table 1 gives an overview of all indices used and their definitions.

2.4 Bias correction

Comparison to observations revealed significant biases in the simulations of precipitation, temperature, and PET, so these variables were statistically post-processed. Two closely related BC methods (quantile mapping and the ISIMIP3BA approach; see below) were used to bias-adjust UKCP18-RCM to allow for exploring the sensitivity of the results to the differences between the BC methods, including but not limited to whether or not the BC method explicitly aims to preserve the changes in the climate. Both BC methods were applied to each grid cell, ensemble member, and calendar month combination separately and were calibrated using simulated and observed data for 1981–2010. For precipitation, we also compared future projections from these BC methods with the change factor method, which is not considered a bias-correction method but consists of applying projected changes in mean climate to observed time series. The change factor method was applied using the same period as the BC methods.

2.4.1 Quantile mapping

Quantile mapping (QM; e.g. Piani et al., 2010) is a statistical transformation of the distribution of a modelled variable such that it matches the distribution of the observed variable.

Table 1. Climatic indices used to evaluate and examine trends in precipitation, temperature, and PET simulated by UKCP18 and derived PET.

Index	Description
Temperature	
yMEAN	Average annual (seasonal) mean daily-mean temperature (°C)
yMIN	Average annual (seasonal) minimum daily-mean temperature (°C)
yMAX	Average annual (seasonal) maximum daily-mean temperature (°C)
Qn	Daily-mean temperature exceeded on average $n\%$ of days in a year (season) (°C)
Precipitation	
prTOT	Average annual (seasonal) total precipitation (mm)
SDII	Simple precipitation intensity index: average annual (seasonal) mean wet-day precipitation intensity (mm)
DF	Average annual (seasonal) dry-day fraction (%)
Qn	Daily precipitation exceeded on average $n\%$ of days in a year (season) (mm)
Rx5day	Average annual (seasonal) maximum 5-day total precipitation (mm)
CDD	Average annual (seasonal) maximum number of consecutive dry days (d)
CWD	Average annual (seasonal) maximum number of consecutive wet days (d)
Potential Evapotranspiration	
Qn	Daily PET exceeded on average $n\%$ of days in a year (season) (mm)
Mean	Mean annual (seasonal) PET (mm)

By construction, the resulting distributions of the reference period simulations and observations match closely, removing deviations from the observed data in the mean, variance, and higher-order moments. The application of the mapping to either the quantiles of an empirical cumulative distribution function (CDF) or an assumed parametric CDF can result in varying performance of the QMs depending on the transformation functions employed (Enayati et al., 2021). Switanek et al. (2017) demonstrated that, where the parametric distribution is known to be a perfect fit to the observed and simulated data (because, for example, it is synthetic data that are drawn from that distribution), parametric QM then reduces the influence of sample size-induced noise that degrades the empirical CDFs of observed and simulated time series. However, Gudmundsson et al. (2012) found that empirical BC methods were more successful at bias-correcting different precipitation quantiles than fitted distributions or simpler parametric methods.

Here, the choice was made to use non-parametric QM with an empirical distribution as a complement to the second BC method which uses a parametric distribution. The resulting dataset will be referred to as BCQM. To implement QM, the R package qmap (Gudmundsson et al., 2012) was used, with QM applied to 1000 empirical quantiles. The type of interpolation used between the fitted transformed values is linear interpolation. It is worth noting that Lafon et al. (2013) demonstrated error reduction for the empirical distribution method increases with the number of quantiles used. They have done a cross-validation test of empirical QM with 25, 50, 75, and 100 quantiles, and 100 quantiles yielded the best results, excluding any cases with over 100 quantiles. Our study ex-

panded the number of quantiles to include 1000 for comparison with the ISIMIP3BA BC method. However, it should be acknowledged that increasing the number of quantiles may potentially compromise the efficiency or lead to overfitting issues. Our analysis shows that the differences between this non-parametric method and the parametric method introduced below are overall minor, implying that, in this case, the climate signal is not particularly sensitive to any overfitting that may have resulted from this, especially when compared to other decisions, such as the climate model selection. QM was not used to bias-adjust PET.

2.4.2 ISIMIP3b bias-correction method

The second method used in this study is the univariate change-preserving bias-correction method developed for phase 3b of the Inter-Sectoral Impact Model Intercomparison Project (BCI3; Lange, 2019). A parametric quantile mapping method which approximately preserves the climate change signal in each quantile was applied to each variable independently, with a different distribution used for each variable. Here, we correct daily average temperature, precipitation, and potential evapotranspiration using the normal, gamma, and Weibull distributions, respectively.

The choices for temperature and precipitation here are motivated by their use in the literature and by Lange (2019) combined with verifying the results. For PET, the Weibull, gamma, and beta distributions were fitted to sample grid cells representative of different climates across the UK. While all three would have been adequate, the Weibull distribution was used in the end due to slightly better performance in the sam-

ple cells, and, using the Kolmogorov–Smirnov test statistic, it showed a better fit than the beta distribution in most regions of the UK in most months.

For precipitation and potential evapotranspiration, the BCI3 option to apply a separate correction to the probability of the occurrence of events beyond thresholds was used to adjust bias and preserve the projected change in the frequency of dry days/no PET ($< 0.1 \text{ mm d}^{-1}$). For each combination of ensemble member, month, and location, the change in the distributions of precipitation, PET, and temperature between present-day (calibration) and future periods was preserved by computing the change for 50 quantiles and applying it to the observed quantiles. This was done multiplicatively (but additively if there are large negative biases in the model data to avoid obtaining unrealistically large values; Lange, 2019) for precipitation and PET and purely additively for temperature. For PET and temperature, the transient trend was preserved by removing it before bias correction and adding it back afterwards, as described in Lange (2019).

The code used for this bias correction is version 2.4.1 of the Python code made available on Zenodo by Lange (2020). Version 2.4.1 differs from the originally published method (version 1.0; Lange, 2019) in the equation used for the correction of the frequency of events beyond thresholds (in this case dry days) and code error fixes. The code was modified for this study in minor ways: to allow it to be used when simulations and observations have different calendars (360-day and Gregorian, respectively) and to suit the format of the data used.

The BCI3 method was applied to, and preserves changes between, two 30-year periods (the 1981–2010 reference period and future application periods). This can introduce artefacts such as step changes between adjacent future 30-year application periods and imperfect preservation of the trend within each 30-year application period. In order to produce a continuous, bias-corrected 100-year sequence (1981–2080), the algorithm was applied to overlapping periods of 30 years (same length as the reference time period), with the starting point of the application period increasing in decadal steps. Then, the central 10 years (as well as the first and last 10 for the first and last 30-year period, respectively) of each run was extracted and concatenated to obtain the final semi-transient bias-corrected time series. Note that the climate change signal in the very first and last decades of the resulting concatenated bias-corrected time series may be slightly stronger or weaker, respectively, because here, the beginning and end of the application periods are used instead of the central decade. To estimate the magnitude of the effect of this strategy, the 10-year overlaps of pairs of 30-year bias-corrected periods separated by 20 years were used to examine differences in the resulting distributions. The decades 2001–2010 and 2051–2060 (i.e. the earliest and latest of the 6 decades that were part of three 30-year chunks, respectively) were chosen for making scatter plots and Q–Q plots for precipitation and temperature in two grid cells representing different UK climates.

For each decade, the three sets of BC data are called tail, middle, and head, depending on whether they are the first, middle, or last decade of the 30-year bias-correction period, respectively.

2.4.3 Change factor method

The change factor method is commonly used in impact studies (e.g. Prudhomme et al., 2012; Kay et al., 2020). It is included here as a benchmark for precipitation only for the purpose of demonstrating the limitations of basing impact studies on an observed time series perturbed only by a change in mean climate and thus shows the added value of assessing changes based instead on the RCM output itself. A multiplicative change factor (CF) was computed and applied to the simulated precipitation time series for each month m as follows:

$$CF_{m,p} = \frac{\overline{P}_{\text{raw,FUT},m,p}}{\overline{P}_{\text{raw,REF},m,p}}, \quad (1)$$

where (\overline{P}) is the mean precipitation from the raw UKCP18-RCM data over the future (FUT) or calibration (REF), i.e. reference) period for month m and ensemble member p . Each monthly CF is then applied to the observed calibration period time series to generate the CF precipitation values for each time step i within month m :

$$P_{\text{CF},i,p} = CF_{m,p} P_{\text{obs},i}. \quad (2)$$

3 Results

3.1 Evaluation

3.1.1 Bias of raw simulations

The maps in Fig. 1 show the ensemble mean errors of the raw UKCP18-RCM projections in the dry-day frequency, mean daily precipitation, and Q95 of precipitation in the reference period, expressed as a percentage of the observed value. In general, the frequency of dry days in UKCP18-RCM is too low (and therefore the wet-day frequency is too high), particularly in the winter and in regions of higher elevation. In summer, the dry-day frequency bias is very small for most of England. The precipitation mean and Q95 are strongly overestimated across the UK in winter, although in highly elevated areas, this bias is smaller or even reversed in sign (especially for Q95). In summer, however, the mean and Q95 biases show a strong spatial variability, with underestimations toward the south and at high elevation levels and a wet bias in the north of the UK. These seasonal bias differences result in an annual bias of too few dry days almost everywhere, too wet of a mean precipitation in most regions, and more mixed wet and dry Q95 relative biases.

The maps in Fig. 2 show the ensemble mean errors of the raw UKCP18-RCM projections in the mean daily tempera-

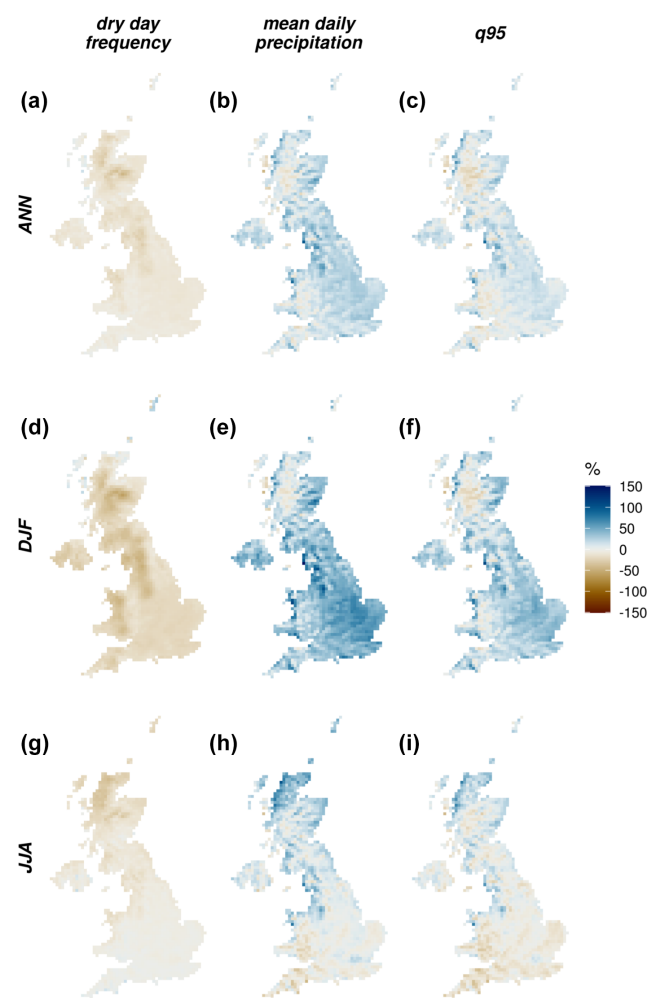


Figure 1. Precipitation biases in UKCP18-RCM for 1981–2010 expressed as a percentage of the observed values. The percentage bias for each ensemble member was computed, and the mean across the ensemble is shown. Dry-day frequency is the percentage of days with $P < 1$ mm, mean daily precipitation is the precipitation averaged over all days, and q95 is the 0.95 quantile of precipitation across all days. Top, middle, and bottom rows are for annual, DJF (December, January, February), and JJA (June, July, August), respectively.

ture as well as the cold (Q05), and hot (Q95) tails of the distribution. At the annual scale, temperature tends to be underestimated in UKCP18 across its distribution, as reflected by the mean, Q05 and Q95. Temperature biases in winter show a gradient from north to south, with generally cold biases in the north and warm in the south. Along the north–south axis, biases are generally colder in the lower tail and warmer in the upper tail of the distribution, indicating an overestimation of temperature variability in winter. In the middle regions along the north–south axis, the biases in the cold and hot tails of the distribution have opposite signs. UKCP18-RCM underestimates temperature on cold days (Q05) in the north especially strongly. In summer, temperature is typically underestimated

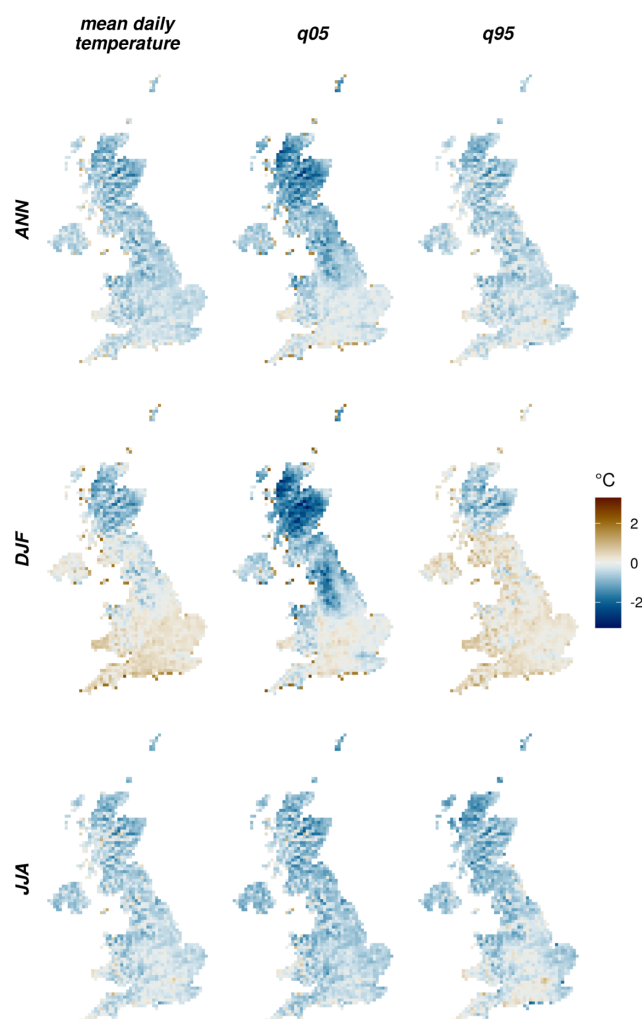


Figure 2. Temperature biases (°C) in UKCP18-RCM for 1981–2010. The bias for each ensemble member was computed, and the mean across the ensemble is shown here. Q05 and Q95 are the 0.05 quantile and the 0.95 quantile across all days, respectively.

across the UK in all three indices considered. One exception is the overestimation (or smaller cold bias) in Q95 in major built up areas (e.g. London in south-east England). Biases in the representation of urban heat islands were previously documented by Lo et al. (2020), who found that UKCP18-RCM tends to overestimate the intensity of urban heat islands in summer, more so for nighttime than daytime.

The maps in Fig. 3 show the absolute UKCP18-derived PET biases in mm. Note that these maps do not show Northern Ireland, as this region is not included in the CHES-PE dataset which served as the observational reference. The predominantly cool bias in the UKCP18-RCM ensemble mean (Fig. 2) contributes to the low PET bias in some regions and seasons (Fig. 3). Interestingly, however, the regional and seasonal variations in the PET biases do not closely follow the

temperature bias patterns, implying that the bias in PET is not solely caused by errors in the daily average temperature.

Note that the strong positive temperature biases shown by some grid cells along the coast in winter come from the use of the regridded 1 km HadUK-Grid, which covers the land only and contrary to UKCP18-RCM does not account for the warmer sea temperature in winter, leading to “observed” grid cell averages that are too low. The opposite but smaller effect occurs in summer, and a similar effect can be observed in the PET bias maps.

Figure 4 shows the UK average seasonal cycle of the raw and bias-corrected precipitation and temperature. For precipitation, the raw UKCP18-RCM ensemble is too wet from November to June, and its range does not encompass the observations during these months. The seasonal timing also appears to be shifted: the driest and wettest months are delayed in the simulations (June and January) compared to the observations (May and October). The ensemble averaged daily-mean temperature generally matches observations far more closely than precipitation (although individual members can contain biases of either sign). The largest mean temperature biases over the UK occur from March to May, a period during which almost all members are too cold.

3.1.2 Evaluation of bias correction

The biases of monthly-mean temperature and precipitation are effectively corrected by both BCQM and BCI3, with observations very closely matching the processed ensemble members (Fig. 4). The remaining error in the statistics shown in the maps in Figs. 1, 2, and 3 is small (and therefore not shown here as it takes up a lot of space for so little information).

Figures 5 and 6 show heatmaps of the spatially averaged errors in precipitation and daily-mean temperature, respectively, before and after bias correction. The value of each metric was calculated for each RCM ensemble member and for the observations at each grid cell for each year and then averaged over 1981–2010. The heatmaps show the spatial average of the absolute values of the difference between observations and simulations (as a percentage of the observed value for precipitation). For the metrics which are also shown in the maps in Figs. 1 and 2, the UK-averaged errors are strongly reduced for the full year as well as winter and summer for all ensemble members, resulting in a large decrease in the ensemble mean errors. The standard deviation (sd; bottom rows) of the errors decreases largely as well as the statistics of the ensemble members converge toward those of the observations for the reference period.

A close look at the figures in Figs. 5 and 6 reveals that biases may be smaller in BCQM than in BCI3, which is not surprising since empirical quantiles were fitted for BCQM, while BCI3 relied on parametric distribution. This should not be interpreted as an advantage of BCQM over BCI3, as the slight edge conferred by the non-parametric fit is likely to be

lost when the bias correction is applied to a period not used for calibration (Chen et al., 2019).

For precipitation, BCQM outperforms BCI3 for reducing the bias in the total precipitation (prTOT) (Fig. 5). Since both methods perform very well for correcting the DF and Q95 bias, the difference in skill for prTOT may be related to the wet end ($> Q95$) of the precipitation distribution: BCQM (with 1000 quantiles) adjusts the simulated extremes more precisely to fit the observed extremes, while the fit of the gamma distribution used in BCI3 can deviate more from the observations for those extremes. Note that this is not necessarily a disadvantage in BCI3. BCQM may be overfitting to the most extreme events occurring in the 30-year observations (Switanek et al., 2017). Due to the strongly skewed nature of precipitation distributions, its extremes (in this case, the upper tail beyond Q95) make a large contribution to the mean (Pendergrass and Knutti, 2018). Evaluation based on the mean may thus be influenced by how well these extreme quantiles are reproduced. In reverse, this reasoning implies that bias correction relying solely on errors and projected changes in the precipitation mean could be sensitive to the variability in observed and projected extreme events, including relatively rare events that might be included or excluded depending on the choice of calibration period.

Although biases in daily precipitation statistics (TOT, DF, and SDII) are largely removed, biases in multi-day metrics (CWD, CDD, and Rx5day) still remain, although reduced. This is expected (Addor and Seibert, 2014), as both BC methods are designed to correct biases in daily values, but not the temporal structure of the time series. For instance, although the dry-day frequency is well corrected by both BC methods, these methods fail to correct errors in the sequences of consecutive wet days in winter and on an annual basis. This is due to an over-correction from mostly overestimated toward the east to mostly underestimated toward the west, where the observed CWD is longer. On the contrary, both methods reduced the summer CWD and the CDD in each time period by about half on average.

For temperature, the biases in the mean are almost entirely removed by both methods (Fig. 6). The ensemble mean, Q05, and Q95 biases are strongly reduced, by a factor 7 to 18 for the year and by a factor 3 to 7 for winter and summer. The most persistent biases are found in the winter (and annual) minimum daily temperature (computed for each season and then averaged over the whole period). The remaining winter maximum temperature bias is also markedly higher using BCI3 (about half the raw bias on average) than using BCQM (less than a quarter).

Importantly, across the metrics in Figs. 5 and 6, the differences between BCQM and BCI3 are generally relatively modest during the reference period. Both methods effectively reduce biases in single-day metrics, and they mostly struggle with the same metrics and, to some extent, with the same ensemble members.

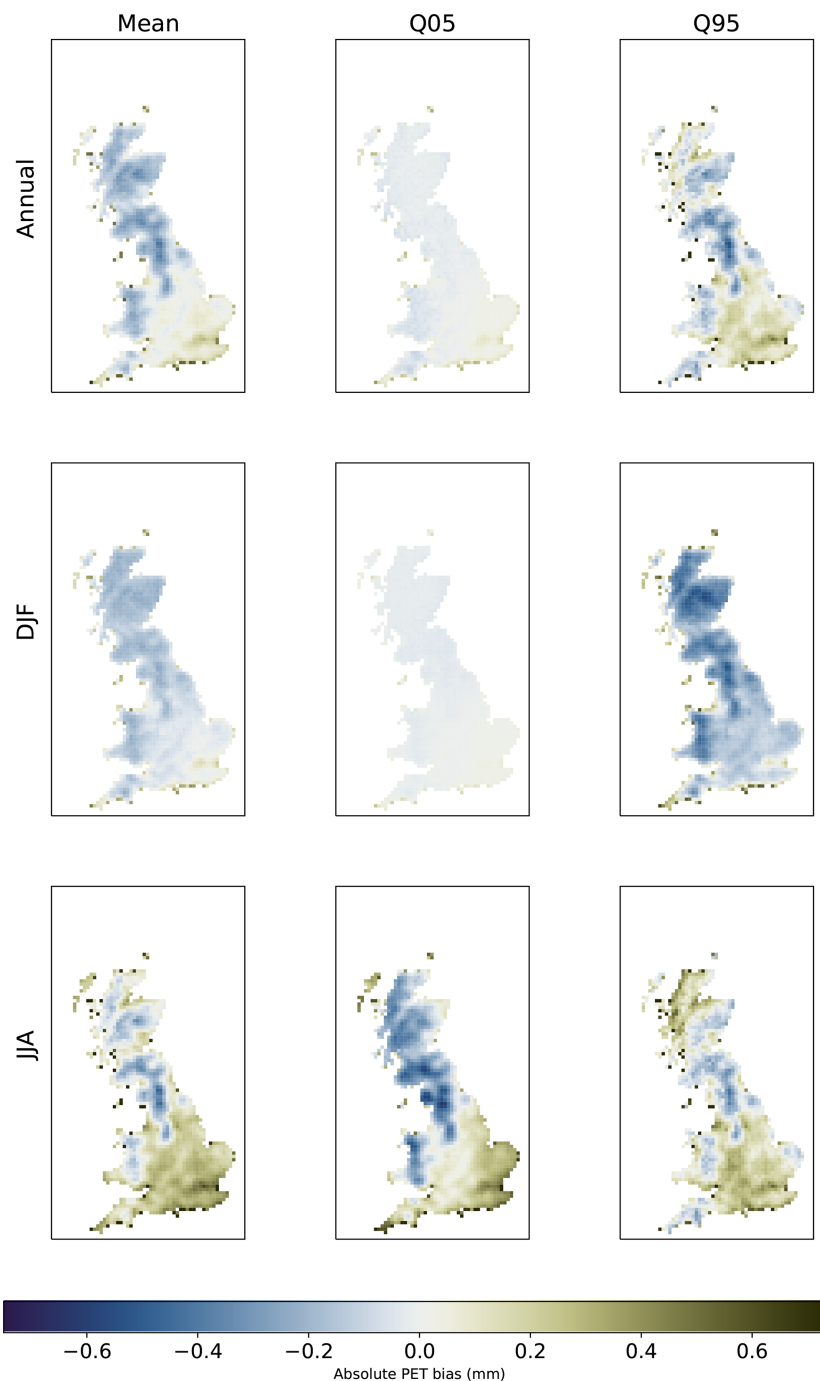


Figure 3. As Fig. 2 but for PET (mm d^{-1}).

To conclude this evaluation, Figs. 7 and 8 assess whether errors were induced by concatenating the centre period of 30-year time series to make BCI3. These figures only show the results for ensemble member 1 as the results were similar across the ensemble. The middle daily values (and quantiles for the Q–Q plots) are plotted on the x axis, and the corresponding tail and head values (quantiles) are plotted on the y axis. For temperature, the uncertainty introduced by differ-

ent periods for change preservation is very small. For precipitation, the match between the quantiles is good (dark circles), although there is some uncertainty introduced for the most intense precipitation events (light circles). The precipitation range covered by these dots in the upper-right corner of the panels highlights the variability within the wettest quantiles, highlighting that when fitting the upper tail of a 30-year period distribution, it is unlikely to perfectly match the upper

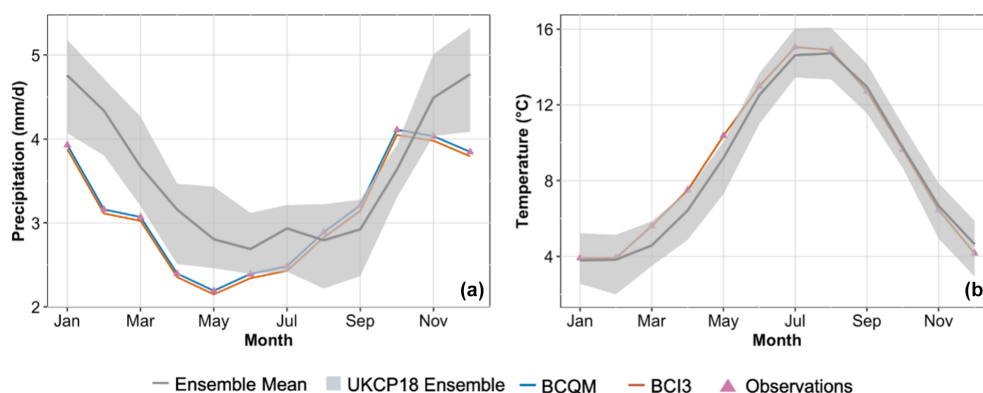


Figure 4. Comparison between observations and UKCP18-RCM simulations before and after bias correction for monthly precipitation (a, mm d^{-1}) and temperature (b, $^{\circ}\text{C}$) averaged over the UK for 1980–2010. The grey shading shows the spread of the 12-member ensemble prior to bias correction. The blue line lies underneath the red line in the temperature panel).

tail from another period, in particular in the presence of climate change. Since some large differences in extreme rainfall can be introduced depending on the period used, the concatenated time series or the data from each 30-year period can be used when the focus is on these events in order to capture the influence of the bias correction. Overall, the differences appear to be small enough to justify concatenation.

3.2 Projected changes before and after bias correction

This section analyses the climate change signal (CCS) projected by UKCP18-RCM in the evaluation metrics used above (Sect. 3.1) and particularly considers whether BCQM and the change-preserving BCI3 alter the CCS compared to the raw simulations. Furthermore, for precipitation, these changes are compared to those simulated using the change factor approach. The CCS is defined as the relative or absolute difference between metrics computed over 1981–2010 and 2051–2080. Maps of projected changes in the mean precipitation and temperature (Figs. 9 and 10) show the spatial variability of the CCS in UKCP18-RCM mean, while the CCS aggregated over the whole domain is summarized for each member and index in heat maps (Figs. 11 and 12).

The CCS of mean precipitation and temperature in the raw projections (left columns in Figs. 9 and 10) confirms the conclusions of the UKCP18 headline findings: warmer, wetter winters and hotter, drier summers. The precipitation CCS shows substantial regional variation in all seasons, influenced by topography. The summer drying signal is the strongest toward south-west England, while the winter wetting signal is the weakest in the north-east of Scotland and strongest along the west and south coasts. The seasonally contrasting changes result in an overall precipitation decrease over most of the UK except along the west coast of north England and Scotland. For temperature, the annual and winter projections are more spatially homogeneous than the sum-

mer projections, which show an increasing gradient from the north-west toward the south and south-east.

Overall, these regional variations in the projected changes in mean annual, winter, and summer precipitation and temperature over the UK are well preserved in both BCQM and BCI3. In BCQM, the summer temperature increase contains more local variation and is somewhat exacerbated over the regions of higher elevation, and the winter precipitation increase is slightly greater than in the original projections. Spatial patterns in the local variations in the BCQM projected summer temperature changes resemble those in the summer temperature errors (Fig. 2). The raw changes are better preserved in BCI3, although the added value of this method in terms of change preservation is limited.

The heatmaps in Figs. 11 and 12 summarize the UK-averaged projected changes in precipitation and temperature metrics and allow for the comparison between the contributions of (i) the different ensemble members and (ii) the two bias-correction techniques to the uncertainty in the projected changes. Before proceeding to a discussion of the effects of the different bias-correction techniques, the projected changes are briefly discussed below (based on the columns labelled RAW in the heatmaps).

More so than the mean, precipitation variability has a profound influence on society, and how it is influenced by climate change is thus of great interest. In general, the wet precipitation metrics show wetter (or less dry) projected changes than the total precipitation. The projected total precipitation decrease for summer is the combined effect of an increasing proportion of dry days (DFs), and slightly decreasing precipitation falling on wet days, marked by greater relative decreases in the Q95 than in the SDII. The longest summer dry spell is projected to lengthen by a third on average (with wide variation across the ensemble). In winter, the relative increases in pTOT can be attributed to similar increases in SDII Q95 and Rx5day rather than changes in the fraction of wet days. Interestingly, this is paired with a slight shorten-

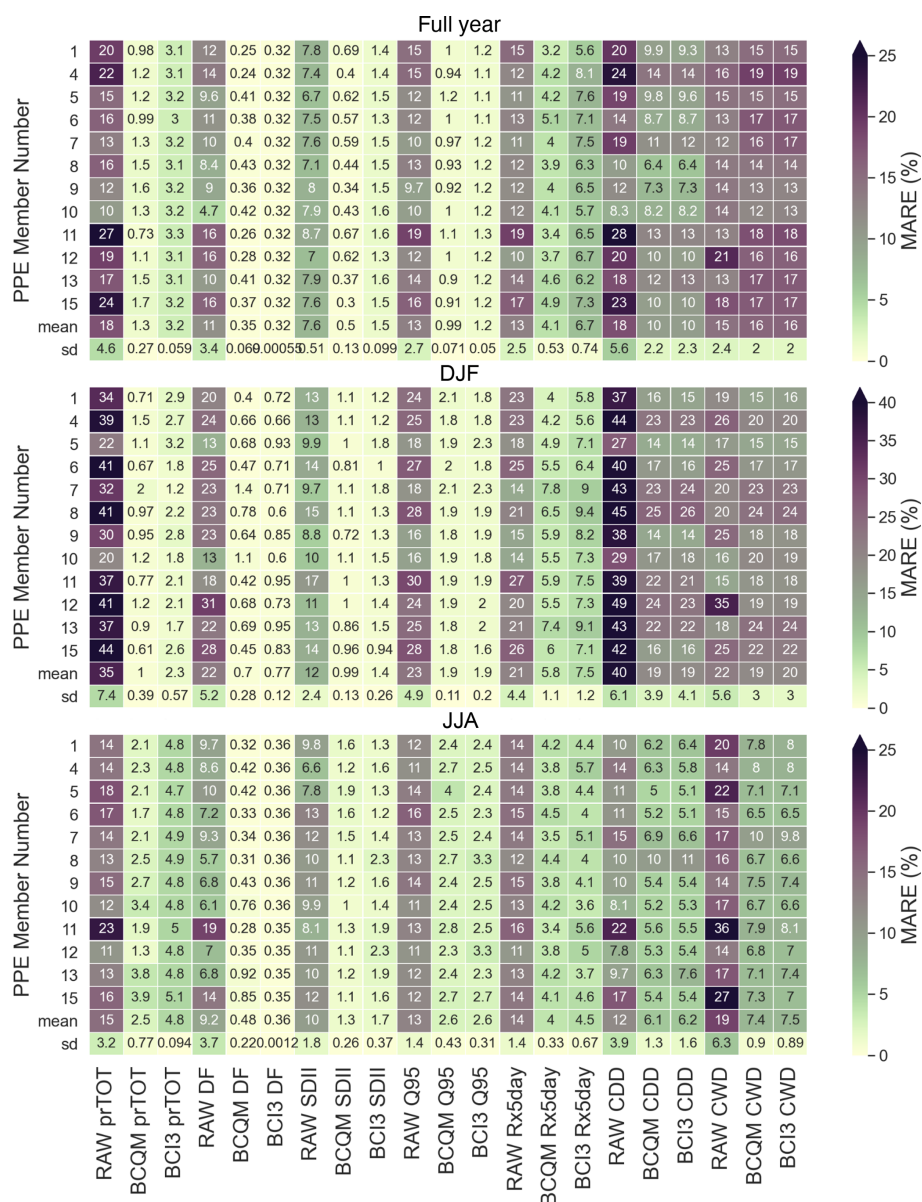


Figure 5. Mean absolute relative error (MARE, %) for calibration period precipitation, for the UKCP18 RCM simulations before (RAW) and after bias correction (BCQM and BC13). Values shown are UK-wide averages for 1981–2010. prTOT: annual total precipitation, DF: fraction of days that are dry ($P < 1$ mm), SDII: mean wet-day precipitation, Q95: 0.95 quantile of daily precipitation, Rx5day: maximum 5-consecutive-day precipitation, CDD (CWD): maximum number of consecutive dry (wet) days. The mean and standard deviation across the 12-member RCM ensemble are included at the bottom of each panel.

ing of the longest wet-day streak on average. Annually, these seasonal changes combine into a slight projected prTOT decrease and a modest increase in the fraction of dry days, combined with wetter wet days, including in the wet end of the precipitation distribution. These findings are in agreement with increases in moderate- and high-impact 1 d rainfall threshold exceedances found by Hanlon et al. (2021).

The projected average temperature increases in the UK are greater in summer than in winter. Projected changes in the range of daily-mean temperatures are opposite between win-

ter and summer: in summer, the Q95 and maximum daily-mean temperatures increase more than the Q05 and minimum daily-mean temperature, whereas in winter, the colder end of the tail is projected to warm more than the warmer end of the tail. There exists a partial overlap between the ensemble members with high summer CDD increases (6, 9, 11, and 13), and the ensemble members with the highest maximum daily-mean temperature increases (5, 8, 9, 11, and 13). In line with the projected increases in minimum temperatures, Hanlon et al. (2021) found a continued decreasing number of

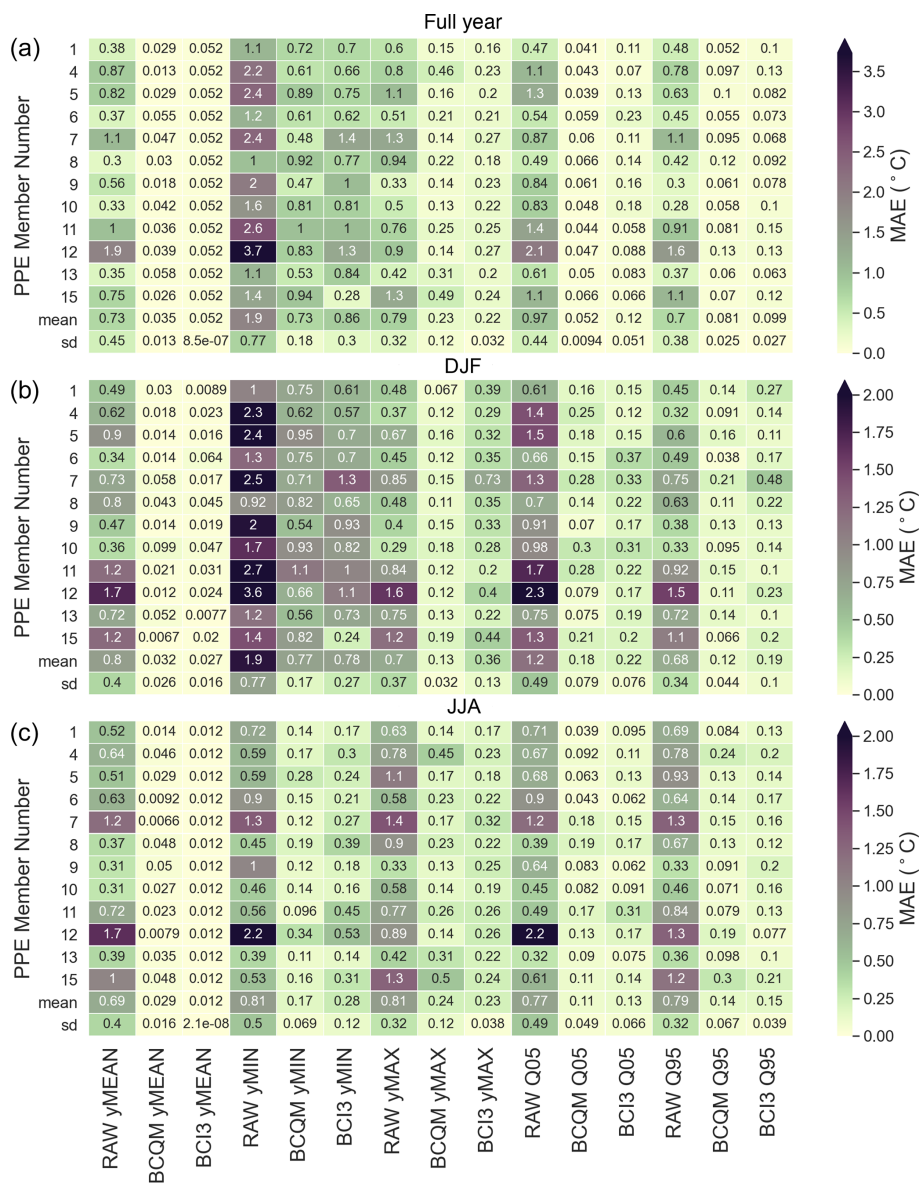


Figure 6. As Fig. 5 but for temperature, showing the bias (mean absolute error, MAE; °C) of the mean (MEAN), minimum (MIN), maximum (MAX), 0.05 quantile (Q05), and 0.95 quantile (Q95) of daily temperatures over each year (a), winter (b), or summer (c).

days with minimum and maximum temperatures below 0 °C (frost and icing days, respectively). On the warm end of the distribution, the larger increases in the expected maximum mean daily temperatures match their findings of increasing days with maximum temperatures exceeding 25 °C and increasing nights with minimum temperatures over 20 °C. Similarly, Arnell et al. (2021) found increases in the annual probability of experiencing at least one heat wave (based on regionally varying thresholds).

The differences between the rows for the different metrics and columns for bias-correction methods in the heatmaps (Figs. 11 and 12) show a wide range of projected changes among the ensemble members, which usually exceeds the

differences from the BC method. In other words, at least when aggregated over the UK, the differences between the ensemble members are much greater than between the two bias-correction methods. This is also summarized well by the two last rows of each heat map panel for each metric: the standard deviation (summarized by the sd row) across the ensemble is typically much larger than the difference between the BC methods in the mean row. While over the reference period the BC significantly reduces the spread of the biases among the ensemble members (see row sd in Figs. 5 and 6), the spread in the projected changes is quite well retained by both BC methods (same row in Figs. 11 and 12).

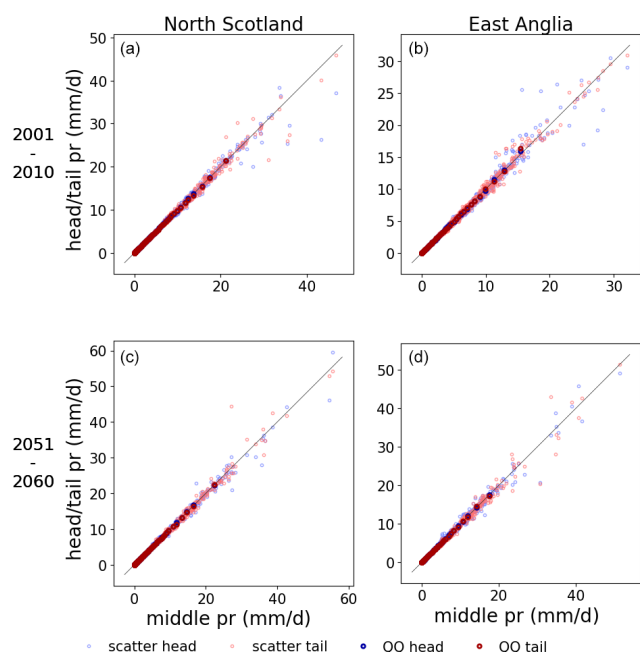


Figure 7. Quantile–quantile plot (dark colours) and scatter plot (light colours) of precipitation (pr) in 2 overlapping decades (**a** and **b** showing 2001–2010, **c** and **d** showing 2051–2060) for UKCP18-RCM ensemble member 1 for two example grid cells (columns). Tail, middle, and head, respectively, refer to the first, middle, and end 10 years of each 30-year period that overlaps in these decades. The line $y = x$ is shown for reference.

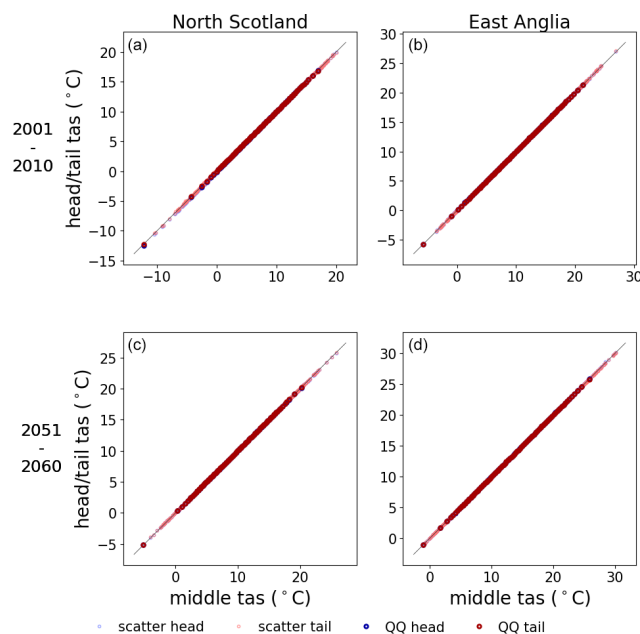


Figure 8. As Fig. 7 but for temperature.

Although the differences in CCS between the two BC methods are relatively minor when compared to the differences between ensemble members for the same metric, there

is a subtle added value of BCI3 over BCQM for preserving the changes, which is generally more visible looking at the individual ensemble members than in the ensemble means. It is worth noting that BCQM already largely preserves the projected changes even though it was not explicitly designed to do so, which limits the potential benefit of even a perfect change preservation over this method. For temperature, the heatmaps in Fig. 12 show a limited added value of BCI3 compared to BCQM. This is in part due to the spatial averaging that took place in order to produce the heatmaps. Results for the climate change signal for each month and ensemble member for different quantiles (not shown) and Fig. 10 show that BCQM modifies the projected temperature climate change signal differently in different regions of the UK, in particular over significant topographical variation; this is not the case for BCI3, which better preserves the raw CCS spatial patterns. Finally, the differences in the climate change signal between both BC methods are the largest for several precipitation indices in winter, where BCI3 slightly improves the preservation of the projected change. Interestingly, for many of the temperature indices and the winter precipitation indices, the spread of projected changes is also better preserved in BCI3 than in BCQM (compare the ensemble sd values). For potential evapotranspiration, similar analyses (figures not included here) show that BCI3 successfully reduced errors and conserved the climate change signal. Lastly, the heatmaps in Fig. 11 highlight the pitfalls of the change factor (CF) approach for UKCP18-RCM. There are large differences between the CF approach and the raw (or bias-corrected) projections when looking at the CCS in precipitation metrics beyond the seasonal or annual totals. The projected lengthening of the longest annual or summer dry-day sequences and shortening of the longest annual, winter, or summer wet-day sequences in all ensemble members, which is well preserved by both BC methods, is largely or almost entirely disregarded using the CF approach. Most of the projected changes in CDD and CWD can thus not simply be attributed to changes in the mean. The smaller projected decrease in the summer maximum 5 d accumulated precipitation (Rx5day) compared to the total precipitation decrease is not captured by the CF approach. What is worse, at the annual scale, the CF approach projects a decrease in the Q95 (similarly to the prTOT changes), whereas the raw UKCP18-RCM projects an increase on average. At the annual scale, the CF approach is unable to capture the simulated change toward fewer (DF increase) but wetter (SDII increase) wet days, the combined effect of which is an overall decrease in total precipitation. This inability of the CF approach to account for changes in the variability in precipitation severely narrows its suitability for climate impact modelling studies on, for example, floods or droughts, for which the temporal variability and changes to the precipitation distribution are highly relevant.

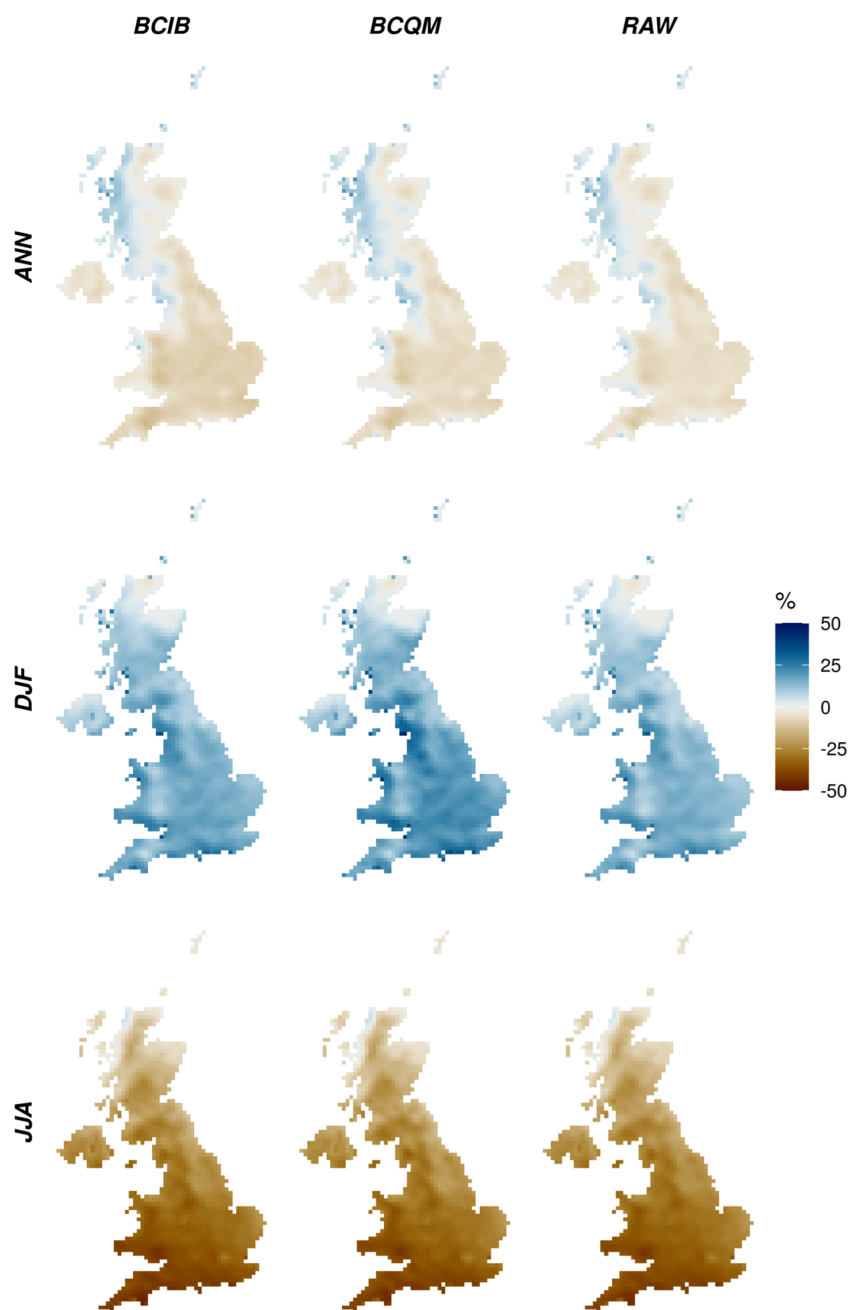


Figure 9. Projected changes in annual or seasonal mean precipitation from the ensemble mean of UKCP18-RCM simulations before (RAW) and after bias correction (BCQM and BCIB). Values shown are the percentage change from 1981–2010 to 2051–2080 under RCP8.5.

4 Code and data availability

This study produces bias-corrected UK Climate Projections 2018 (UKCP18) regional projections of temperature, precipitation, and potential evapotranspiration for 1981–2080. All 12 members of the UKCP18 regional ensemble are bias-corrected using the empirical quantile mapping method and a change-preserving variant of the ISIMIP3BA method. The access links for these datasets are provided below:

- Daily temperature and precipitation data, bias-corrected by the empirical quantile mapping method, are available at <https://doi.org/10.5281/zenodo.8223024> (Zha et al., 2023).
- Daily temperature and precipitation data, bias-corrected using the ISIMIP3BA method, are accessible at version 1 <https://doi.org/10.5281/zenodo.6337381> (Reyniers et al., 2022a).

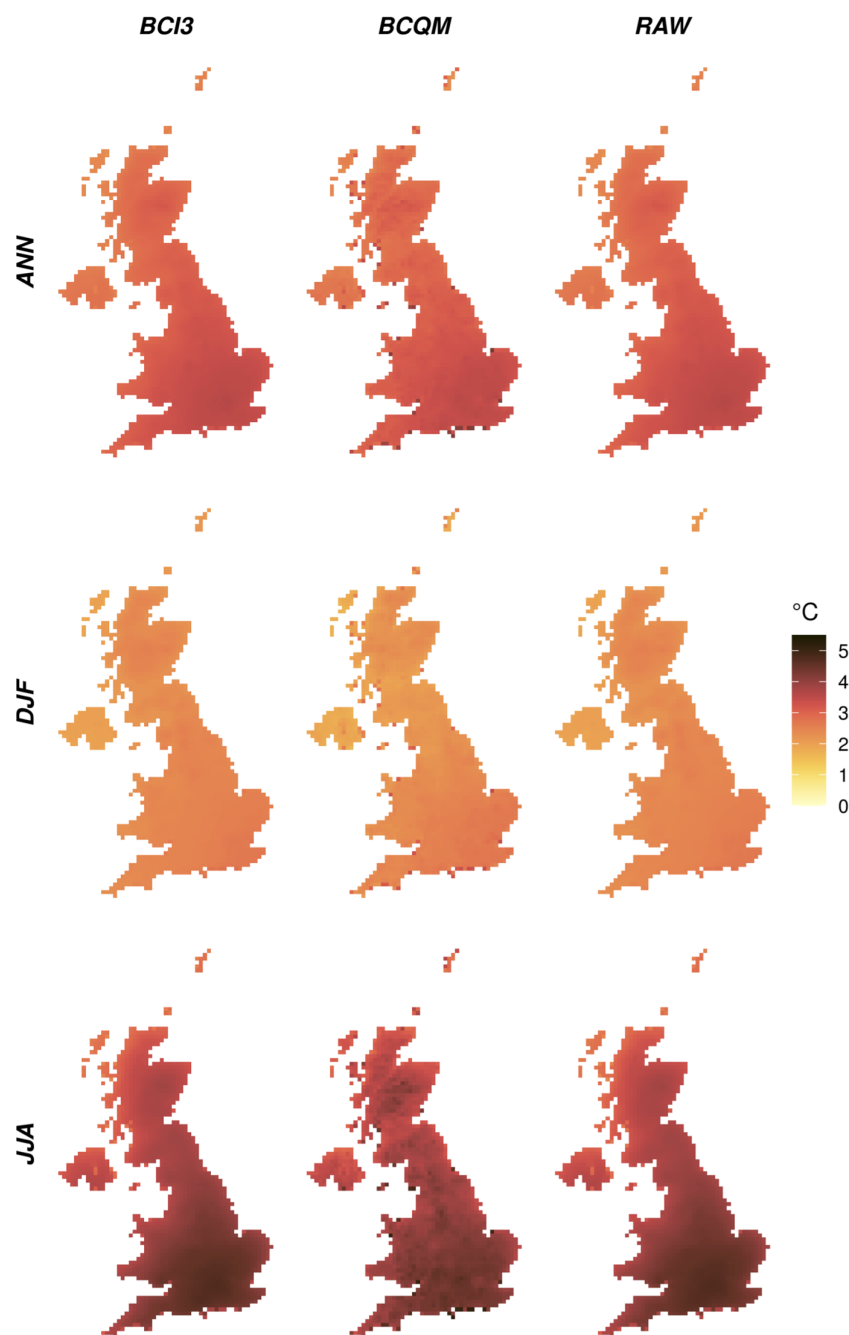


Figure 10. As Fig. 9 but for the change in temperature expressed in °C.

- Bias-corrected daily potential evapotranspiration data can be found at <https://doi.org/10.5281/zenodo.6320707> (Reyniers et al., 2022b).

The sources and links to the datasets used in this study:

- CHES-PE data were obtained from the UK CEH Environmental Information Data Centre (<https://doi.org/10.5285/9116e565-2c0a-455b-9c68-558fdd9179ad>) (Robinson et al., 2020b).
- HadUK-Grid data were obtained from the Centre for Environmental Data Analysis (<https://doi.org/10.5285/d134335808894b2bb249e9f222e2eca8>) (Met Office et al., 2019).
- UKCP18-RCM simulations were acquired from the Centre for Environmental Data

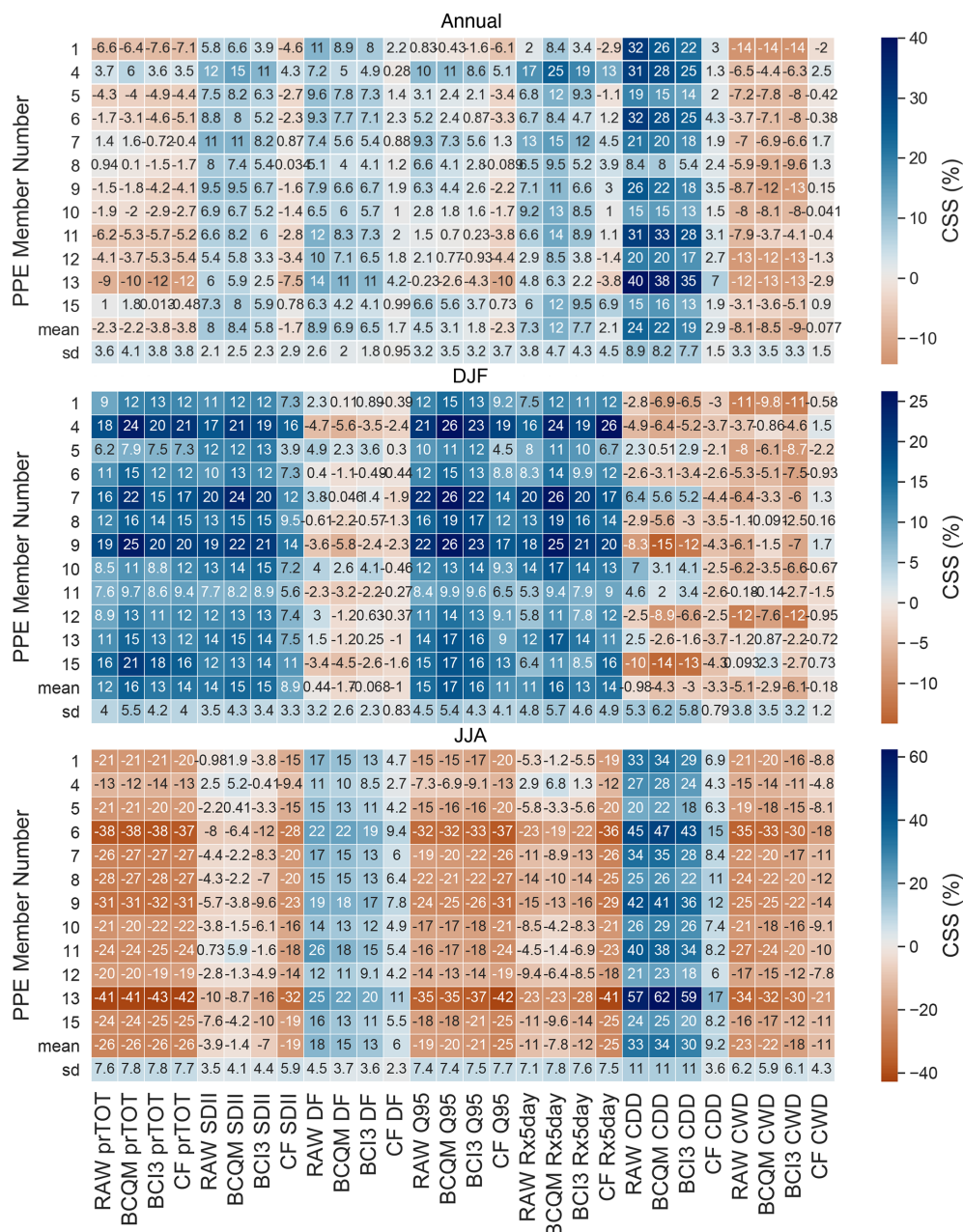


Figure 11. Projected changes (climate change signal, CCS) in precipitation characteristics in the ensemble of UKCP18-RCM simulations before (RAW) and after bias correction (BCQM and BCI3) and after applying a change factor (CF) to the observed time series. Each indicator shows the spatial average (UK-mean) of the changes by 2051–2080 compared to 1981–2010 expressed as a percentage of the observed values for 1981–2010. Statistics shown are the same as in Fig. 5.

Analysis (<https://catalogue.ceda.ac.uk/uuid/589211abeb844070a95d061c8cc7f604>) (Met Office Hadley Centre, 2018).

The ISIMIP3BA code by Lange (2019) used in this study is accessible on Zenodo at <https://doi.org/10.5281/zenodo.3898426> (Lange, 2020).

5 Conclusions

5.1 General conclusions

Significant biases in temperature, potential evapotranspiration, and precipitation statistics were found in the UKCP-RCM simulations. To improve their usability for impact modelling, two bias-correction methods were applied to all ensemble members of the UKCP-RCM perturbed physics

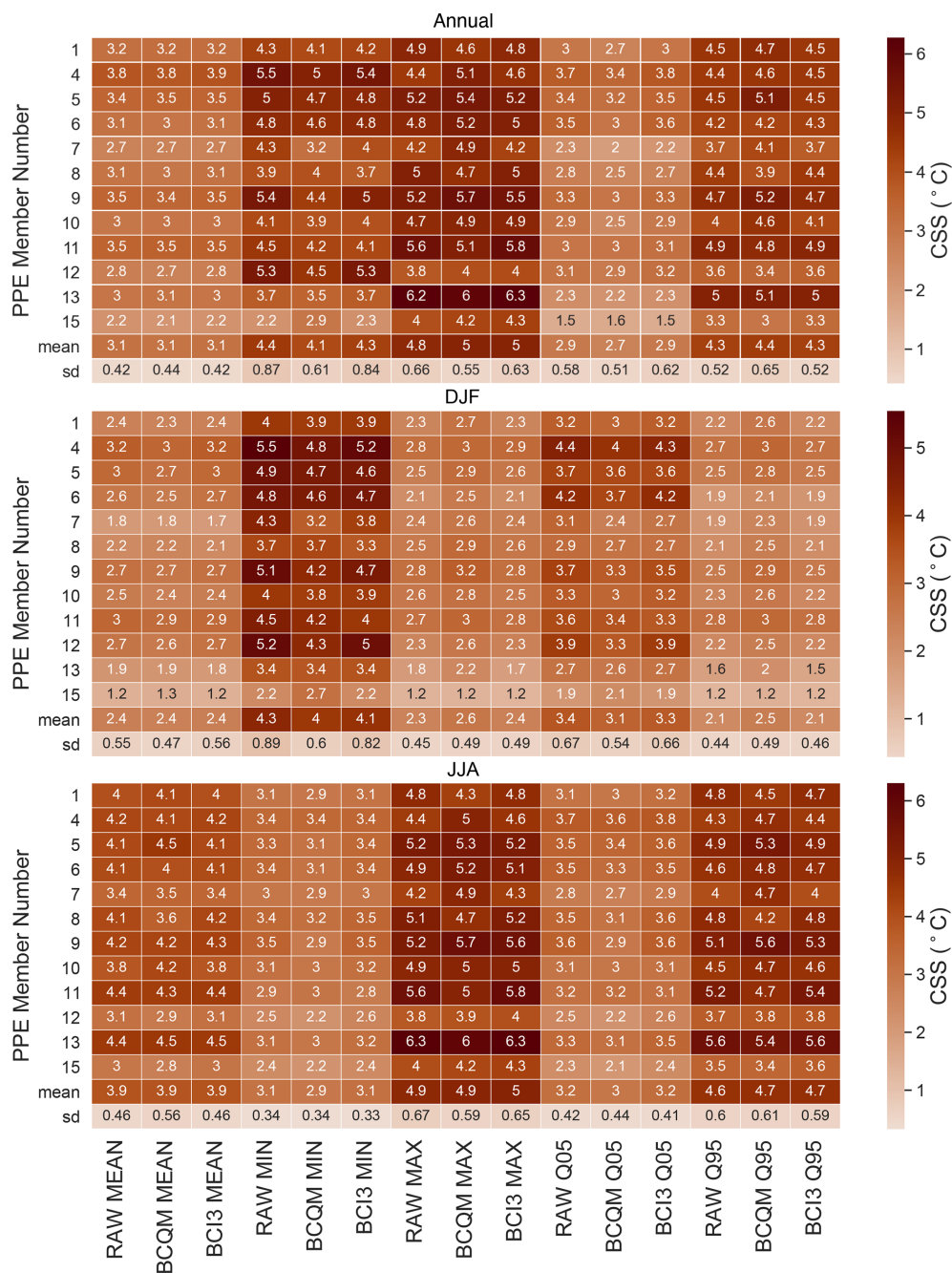


Figure 12. As Fig. 11 but for temperature characteristics, and actual (°C) rather than percentage changes are shown. Statistics shown are the same as in Fig. 6.

ensemble: the widely used empirical quantile mapping (BCQM) and the bias-correction method developed for phase 3 of the ISIMIP project (BCI3), which is designed to preserve the climate change signal. Both methods successfully reduced errors in daily temperature and precipitation metrics, and reduced errors in multi-day precipitation metrics to a lesser degree. Both methods also satisfactorily conserved the climate change signal as well as the spread among the

projections, with a minor improvement in BCI3 compared to BCQM. Analysis of projected changes in temperature and precipitation metrics suggests a higher likelihood of extreme weather (hot, dry, or wet) and confirms the headline findings of projected hotter, drier summers and warmer, wetter winters.

5.2 Recommendations for users of the bias-corrected datasets

Potential users of these bias-corrected simulations are encouraged to consider the following points.

1. Both bias-corrected datasets may be of interest for users whose impact model is affected by the biases in the UKCP18-RCM simulations and whose application requires changes in the precipitation (and/or temperature or potential evapotranspiration) distribution and temporal variability to be captured as well as the mean. Conversely, using the change factor method is discouraged for applications where changes to the temporal variability and full distribution are important.
2. Caution is needed with coastal grid cells as the 1 km dataset used as reference for the bias correction only covers the land, which results in biases in grid cell averages along the coast (especially for temperature and potential evapotranspiration). This should not be an issue for users only interested in land temperature or potential evapotranspiration, but we recommend that users consider the fraction of each grid cell covered by land before using the data.
3. At the regional scale, the climate change signal is slightly better preserved by BCI3 (especially for temperature). Although the differences between BCI3 and BCQM are small, they might grow or shrink after propagation in impact models, so it may be valuable to use both as a limited way of sampling the uncertainty due to statistical post-processing. However, the difference between BCQM and BCI3 is unlikely to be the greatest source of uncertainty.
4. PET time series are only provided for BCI3, so if using them alongside of temperature and/or precipitation time series, using BCI3 data only guarantees a consistent treatment of projected changes across variables.
5. Potential users of these bias-corrected datasets should also consult the UKCP18 user guidance published by the Met Office, in particular guidance on bias correction (e.g. Fung et al., 2018). Since the uncertainty among the UKCP18-RCM ensemble members is large for changes in the precipitation and temperature metrics studied here, it is recommended to employ multiple ensemble members to sample this uncertainty. Users are encouraged to perform their own evaluation of these datasets to ensure that they are adequate for their planned use, for example, if the correction of dependence structures of multiple variables is required (since both of our methods are univariate, and we did not evaluate multivariate metrics).
6. As discussed in the Introduction, all bias-correction methods rely on strong assumptions about climate pro-

jections, which all users of any bias-corrected climate projections should keep in mind when using the data and interpreting the resulting impacts.

Author contributions. NR and QZ applied ISIMIP3BA and QM BC methods for bias correction, respectively. NR, QZ, and NF performed the evaluations and assessment of projected changes. NR, NA, TJO, and YH analysed results and drafted the manuscript. NF assisted with data processing and figure producing. All authors reviewed the resulting inventory and assisted with paper writing.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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