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A method to preserve trends in quantile mapping bias correction of climate modeled temperature

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Abstract

Bias correction of climate variables is a standard practice in Climate Change Impact (CCI) studies. Various methodologies have been developed within the framework of quantile mapping. However, it is well known that quantile mapping may significantly modify the long term statistics due to the time dependency that the temperature bias. Here, a method to overcome this issue without compromising the day to day correction statistics is presented. The methodology separates the model temperature signal into a normalized and a residual component relatively to the molded reference period climatology, in order to adjust the biases only for the former and preserve intact the signal of the later. The results show that the adoption of this method allows for the preservation of the originally modeled long-term signal in the mean, the standard deviation and higher and lower percentiles of temperature. The methodology is tested on daily time series obtained from five Euro CORDEX RCM models, to illustrate the improvements of this method.

Keywords: temperature, trend preservation, moment preservation, statistical bias correction,

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1 Introduction

Climate model output consist the primary source of information used to quantify the effect of the foreseen anthropogenic climate change on natural systems. One of the most common and technically sound practices in Climate Change Impact (CCI) studies is to calibrate impact models using the most suitable observational data and then to replace them with the climate model data in order to assess the effect of potential changes in the climate regime. Often, raw climate model data cannot be used in CCI models due to the presence of biases in the representation of regional climate (Christensen et al., 2008; Haerter et al., 2011). In fact, hydrological CCI studies outcome have been reported to become unrealistic without a prior adjustment of climate forcing biases (Hansen et al., 2006; Harding et al., 2014; Sharma et al., 2007). These biases may be attributed to a number of sources such as the imperfect representation of the physical processes within the model code and the coarse spatial resolution that do not permit the accurate representation of small-scale processes. Furthermore, in some cases, climate model tuning for global projections focuses on the adequate representation of feedbacks between processes and hence the realistic depiction of a variable, such as temperature, against observations is sidelined (Hawkins et al., 2016).

A number of statistical bias correction methods have been developed and successfully applied in CCI studies (e.g. Grillakis et al., 2013; Haerter et al., 2011; Ines and Hansen, 2006; Teutschbein and Seibert, 2012). Their main task is to adjust the statistical properties of climate simulations to resemble those of observations, in a common climatological period. A commonly used type of procedure to accomplish this is using a Transfer Function (TF) which minimizes the difference between the cumulative density function (CDF) of the climate model output and that of the observations, a process also referred to as quantile mapping. As a result of quantile mapping, the reference (calibration) period's adjusted data are statistically closer, and sometimes near-identical to the observations. Hence the statistical outcome of an impact model run using observational data is likely to be reproduced by the adjusted data. The good performance of statistical bias correction methods in the reference period is well documented (Grillakis et al., 2011; Grillakis et al., 2013; Ines and Hansen, 2006; Papadimitriou et al., 2015). The procedure however overlooks the time dependency of the biases, i.e the unequal effect of the TF to the varying over time CDF. An indicative example is presented in Figure 1 where modeled temperature data have a mean bias of 2.49 ºC in the reference period (Figure 1a) relatively to the observations. This mean bias is expressed by the average horizontal distance between the TF and the bisector of the central plot. The left histogram illustrates the reference period modeled data for 1981-2010. The histogram at the bottom is derived from observational data. The histogram on the right is derived

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from a moving 30-year period between 1981 and 2098. Finally the rightmost histogram shows the difference between the reference period and the moving 30-year period. The red mark shows the theoretical change in the average correction applied by the TF, due to the changes in the projected temperature histogram. Hence, the average correction applied for the 2068-2097 period reaches 3.85 ^{o}C, significantly higher than the reference period's bias (Figure 1b). The time-dependency of the correction magnitude introduces a long term signal distortion in the corrected data. In the quantile mapping based correction methodologies in which the TF distance from the bisector is variable, this effect is unavoidable. Nevertheless, in cases where the TF retains a relatively constant distance to the bisector (i.e. parallel to the bisector), the trend of the corrected data remains similar to the raw model data regardless of the temporal change in the model data histogram.

Based on the previous example, the time extrapolation of the TF use is regarded as a leap of faith that may lead to a false certainty about the robustness of the adjusted projection. This may significantly change the original model derived long-term trend or other higher moments of the climate variable statistics that eventually change the long-term signal of the climate variable. In their work on distribution based scaling (DBS) bias correction, Olsson et al. (2015) showed that their methodology might alter the long-term temperature trends, attributing the phenomenon in the severity of the biases in the mean or the standard deviation between the uncorrected temperatures and the observations. Maraun, (2016) discuss on whether the change in the trend is a desired feature of bias correction, concluding that it is case specific, depending on the skillfulness of a model to simulate the correct long term signal. In the case of CCI studies this implies that climate model data is assessed for its skill to well represent the trend, which does not consist a common practice. A possible but indirect solution to this is described in Maurer and Pierce, (2014) who study the change in precipitation trend over an ensemble of atmospheric general circulation model (AGCM). They concluded that, while individual quantile mapping corrected AGCM data may significantly modify the signal of change, a relatively large ensemble estimation diminished the problem due to the cancel out of the individual model trend changes. Li et al. (2010) present a quantile mapping method to adjust temperature biases taking into account the differences of the future and reference period distributions. A drawback of the method is that the difference between the two periods' distributions depends on the future period length. In their work, Hempel et al. (2013) propose a methodology to resolve the trend changing issue,

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by preserving the absolute changes in monthly temperature, and relative changes in monthly values of precipitation. A conceptual drawback of this approach that it maps anomalies instead of absolute values, indicating that specific correction values are attached to each temperature anomaly. A similar additive for temperature and multiplicative for precipitation approach was also followed by (Pierce et al., 2015).

In this study, we present a methodology to conserve the long term statistics of the climate model data in quantile mapping. The methodology considers the separation of the temperature signal relatively to the raw data reference period, producing a normalized and a residuals data stream. The residuals include the gradual changes in the signal and potential non-stationary changes. The quantile mapping bias correction is then applied to the normalized time series. Finally, the residual components are again merged to the bias corrected time series to form the finally corrected time series. The methodology is tested along with a generalized version of the Multi-segment Statistical Bias Correction (MSBC) quantile mapping methodology (Grillakis et al., 2013). The methodology takes the form of a pre- and post-processing module that can be applied along with different statistical bias correction methodologies.

2 Methods

2.1 Residual separation

The statistical difference of each individual year's simulated data, comparing to the average reference period simulated data is identified as residuals. These are estimated between the CDF of each year's modeled climate data and the CDF of the entire reference period of the model data. Let S_R be the reference period model data and S_i the climate data for year i, then the normalized data S_i^N for year i are estimated by transferring each year's data onto the average reference period CDF through a transfer function TF_{S_i} estimated annually. This can be formulated as Eq.(1).

$$S_i^n = TF_{S_R}^{-1}\left(TF_{S_i}(S_i)\right) \qquad \text{Eq. (1)}$$

The difference between the original model data S_i and the normalized data S_i^N are the residual components S_i^D of the time series (Eq. (2)).

$$S_i^D = S_i - S_i^n \qquad \text{Eq. (2)}$$

The original model data S_i can be reproduced by adding back the residuals S_i^D to the normalized data S_i^n. After the separation, the normalized climate model data are statistically bias corrected following a suitable methodology. The residuals are preserved in order later to be added again to the bias corrected time series. We refer to the described method as Normalization Module (NM) to hereafter lighten the nomenclature of the paper. The normalization procedure is performed in annual basis, as it consists an obvious periodicity to use in the case of temperature, even if it is not so well defined in tropics. The underlying assumption of the NM procedure is that it assumes that there are no major changes in the reference period data, an assumption that can hardly fall short due to the usually short length of the reference period.

2.2 Bias correction

Here, the NM is applied along with a modification of the MSBC algorithm that is presented in Grillakis et al. (2013). This methodology follows the principles of quantile mapping correction techniques and was originally designed and tested for GCM precipitation adjustment. The method partitions the CDF data into discrete segments and an individual quantile mapping correction is applied to each segment, achieving a better fitted transfer function. Here the methodology is modified to use linear functions instead of the gamma functions used in the original methodology, in order to facilitate potential negative temperature values but also as a known technique in quantile mapping, as it has also been used elsewhere (Themeßl et al., 2011). An indicative example is shown in Figure 2, where the CDFs are split into discrete segments and linear functions are fit to each of them. In Figure 2, p symbolizes the cumulative probability and s is the slope of the linear function. Then the corrected temperature for each temperature value of the specific segment is estimated as in Eq. (3).

$$T_{corr}^{n} = s_{obs}^{n} * \left(\frac{T_{raw}^{n} - b_{raw}^{n}}{s_{raw}^{n}}\right) + b_{obs}^{n} \qquad \text{Eq. (3)}$$

The optimal number of the segments is estimated by Schwarz Bayesian Information Criterion (SBIC) to balance between complexity and performance. Additionally, the upper and lower edge segments are explicitly corrected using the average difference between the reference period of the raw model data and the observations (Figure 2 ΔT). This provides robustness, avoiding unrealistic temperature values at the edges of the model CDF. The bias correction methodology modification has been already used in the Bias Correction Intercomparison Project (BCIP) (Nikulin

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et al., 2015), while produced adjusted data have been used in a number of CCI studies (Daliakopoulos et al., 2016; Grillakis et al., 2016; Koutroulis et al., 2016; Papadimitriou et al., 2016). As the MSBC methodology belongs to the parametric quantile mapping techniques, it shares their advantages and drawbacks. A comprehensive shakedown of advantages and disadvantages of quantile mapping in comparison to other methods can be found in Maraun et al. (2010) and Themeßl et al. (2011). A step by step example of the multisegment correction procedure is provided in Appendix A of (Grillakis et al., 2013).

3 Case study area and data

To examine the effect of NM on the bias correction on a timeseries, the Hadley Center Central England Temperature (HadCET - Parker et al., 1992) observational dataset was considered to adjust the simulated output from the earth system model MIROC-ESM-CHEM (Hasumi and Emori, 2004) historical emissions run between 1850 and 2005 for Central England. This particular case study was chosen due to the large observational record (the longest instrumental record of temperature in the world) that is available for central England, i.e. the triangular area of the United Kingdom enclosed by Lancashire, London and Bristol. Discussion about dataset related uncertainties can be found in Parker et al., (1992) and Parker and Horton (2005). The Klemes (1986) split sample test methodology was adopted for verification. Split sample is the most common type of test used for the validation of model efficiency. The methodology considers two periods of calibration and validation, between the observed and modeled data. The first period is used for the calibration, while the second period is used as a pseudo-future period in which the adjusted data are assessed against the observations. A drawback of the split sample test in bias correction validation operations is that the remaining bias of the validation period is a function of the bias correction methodology deficiency and the model deficiency itself to describe the validation period's climate, in aspects that are not intended to be bias corrected. That said, a skillful bias correction method should deal well in that context, as model "democracy" (Knutti, 2010), i.e. the assumption that all model projections are equally possible, is common in CCI studies with little attention to be given to the model selection. In the specific application and in order to resemble a typical CCI study, data between 1850 and 1899 serve as calibration period, while the rest of the data between 1900 and 2005 is used as pseudo-future period for the validation. Finally, the bias correction results of the two procedures, with (BC-NM) and without (BC) the normalization module, were compared against the validation period observations.
Furthermore, to expand the methodology assessment in regional scale, the split sample test is adopted to assess the efficiency of the two procedures in a pan European scale. In order to scale

up the split sample test, the k-fold cross validation test (Geisser, 1993) is employed. The procedure has been proposed for evaluating the performance of bias correction procedures in (Maraun, 2016). In k-fold cross validation test, the data is partitioned into k equal sized folds. Of the k folds, one subsample is retained each time as the validation data for testing the model, and the remaining k-1 subsamples are used as calibration data. In a final test, the procedures are applied on a long-term transcend climate projection experiment to assess their effect in the long-term attributes of the temperature in a European scale application.

Temperature data from the European division of Coordinated Regional Downscaling Experiment (CORDEX), openly available through the Earth System Grid Federation (ESGF), are considered. Additional information about the Euro - CORDEX domain can be found on the CORDEX web page (http://wcrp-cordex.ipsl.jussieu.fr/). Data from five RCM models (Table 1) with 0.44° spatial resolution and daily time step between 1951-2100 are used. The projection data are considered under the Representative Concentration Pathway (RCP) 8.5, which projects an 8.5 W m^{-2} average increase in the radiative forcing until 2100. The European domain CORDEX simulations have been evaluated for their performance in previous studies (Kotlarski et al., 2014; Prein et al., 2015). The EOBSv12 temperature data was used (Haylock et al., 2008). Discussion about the applicability of EOBS to compare temperature of RCMs control climate simulations can be found in Kyselý and Plavcová (2010). Figure 3 shows the 1951-2005 daily temperature average and standard deviation for the five RCMs of Table 1. The RCMs' mean bias ranges between about -2 ºC and 1 ºC relatively to the EOBS dataset. The positive mean bias in all RCMs is mainly seen in Eastern Europe, while the same areas exhibit negative bias in standard deviation. Some of the bias is however attributed to the ability of the observational dataset to represent the true temperature.

For the k-fold cross validation, the RCM data between 1951-2010 are split into 6 ten-year sections, comprising a 6-fold, 5 RCM ensemble experiment of Figure 4. Each section is validated once by using the rest five sections for the calibration. A total number of 30 tests are conducted using each procedure.

For the transient experiment, the RCM data between 1951 and 2100 are considered, using the 1951-2010 as calibration to correct the 1951-2100 data.

4 Results and discussion

The results of the split sample test on the central England example are presented in Figure 5. In Figure 5a the separation of the raw data performed by the NM into residuals and normalized raw data in annual aggregates is shown. The normalized time series do not exhibit any trend or

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significant fluctuation in the annual aggregates, since the normalization is performed at annual basis, while the long-term trend and the variability is contained in the residual time series. In Figure 5b, annual aggregates obtained via the above two procedures are compared to the raw data and the observations. Results show that both procedures adjust the raw data to better fit the observations in the calibration period 1850-1899. In the validation period, both procedures produce similar results, but the BC-NM long-term linear trend is slightly lower than that of the BC results. While the latter slope is closer to the observations' linear trend, the former is closer to the raw data trend (Table 2). The persistence of the long-term trend is a desirable characteristic of the NM procedure as the GCM long-term moments were not distorted by the correction. However, the wider deviation of the BC-NM trend relatively to the BC depicts the skill of the GCM to simulate the observations' respective trend. Figure 5c shows that the BC-NM output resemble the raw data histograms in shape, but are shifted in their mean towards the observations. A small decrease in the variability can also be observed in the BC-NM but consists a substantially smaller disturbance relatively to the BC. The transfer of the mean with a simultaneous preservation of the larger part of the variability consists a nearly idealized behavior for the adjusted data, as the distribution of the annual temperature averages are retained after the correction. Similar results generated on daily data (Figure 5d) show that both procedures adjust the calibration and validation histograms in the same degree towards the observations. This can also be verified by the mean, the standard deviation and the 10th and 90th percentile of the daily data (Table 2). An early concluding remark about the NM is that it improved the long-term statistics of the adjusted data towards the climate model signal, without sacrificing the daily scale quality of the correction.

In Figure 6, the results of the cross validation test of the bias correction on the Euro – CORDEX data with and without the use of NM are shown, in terms of mean temperature. The mean of the raw temperature data and the observations are respectively equal for their calibration and the validation periods due to the design of the experiment. The bias correction results show that both correction procedures with and without the NM, appropriately meet the needs in terms of the mean value. The differences between the calibration and validation averages with the corresponding observations show consistently low residuals. A significant difference between the two tests is that the use of the NM increases the residuals due to the exclusion of the potentially non-stationary components from the correction process. Nonetheless, the scale of the residuals is considered below significance in the context of CCI studies, as it ranges only up to 0.035 ºC. The increased residuals of the NM are the trade off to the preservation of the model long-term climate change signal, in the transient experiment. Figure 7 shows the long-term change in the signal of the mean temperature, for the 10th and 90th percentiles (estimated on annual basis). The

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trends are estimated by linear least square regression and are expressed in °C per century. The use of the NM profoundly better preserved the long-term trend relatively to the raw model data in all three cases. Without using the NM module, the distortion in the mean annual temperature trend lies between -0.5 and 0.5 degrees per century, while the distortion in the 10^{th} and 90^{th} percentiles are apparently more profound. Additionally, the northeastern Europe's 10^{th} and 90^{th} percentiles reveal a widening of the temperature distribution when NM is not used. The widening is attributed to the considerable negative trend in the p10 and the considerable positive p90 trend in the same areas. The magnitude of the distortion is considerable and can potentially lead to CCI overestimation. In contrast, with the use of NM the change in the trend is reduced in most of the Europe's area.

The impact of NM on the standard deviation is also significant. Figure 8 shows the evolution of the standard deviation of the daily data for each model, in the cases of raw data and the bias corrected data using the BC and the BC_{NM}. The standard deviation is estimated for each grid point and calendar year, and is averaged across the study domain. The results show that the standard deviation of the adjusted data differ from the respective standard deviations of the raw data, in both adjustment approaches. This is an expected outcome, as raw model data standard deviations differ from the respective observed data standard deviation (Figure 8 d, e). However, the standard deviation differences between BC_{NM} and the raw data (Figure 8 f) is significantly more stable than that the respective differences from BC (Figure 8 g), meaning that the signal of standard deviation is better preserved and does not inflate with time in the former case. Additionally, the variation of the standard deviations time series exhibits lower fluctuations.

5 Conclusions

This study elaborates with the issue of the distortion of the long term statistics in quantile mapping statistical bias correction relatively to the raw model data. An extra processing step is presented, that can be applied along with quantile mapping statistical bias correction techniques. This step, namely NM, splits the original data into two parts, a normalized one that is bias adjusted using quantile mapping, and the residuals part that is added to the former after the bias correction. The methodology is tested and validated from several points of view, leading to some key remarks about its added value. First, it is shown that the use of the NM module results in the long-term temperature trend preservation of the mean temperature change, but also of the trend in the higher and lower percentiles. Furthermore, the examination of the standard deviation temporal evolution show that is better retained relatively to the raw data, as the exclusion of the residuals form the correction minimizes the inflation of the variance. Additionally, the inter-annual variability of the raw data is preserved relatively to the simple quantile mapping, which consists an important feature for climate impact studies that involve carbon cycle simulations (Rubino et al., 2016). As a drawback, the corrected temperature using the NM is found to retain small portions of the biases, which however is shown that is rather low to virtually affect an CCI study results.

The main advantage of the proposed method compared to other trend preserving methods is that the preservation of the long-term mean trend is not the objective but rather an ineluctable consequence of normalization before the bias correction process. Additionally the normalization is performed in annual basis, hence the projection period results are not affected by the length of the projection period. Nevertheless, it has to be stressed that a range of issues, such as the disruption of the physical consistency of climate variables, the mass/energy balance and the omission of correction feedback mechanisms to other climate variables (Ehret et al., 2012) have not been addressed in this work despite the existence of methods that preserve consistency between specific variables (Sippel et al., 2016). Finally, one should bare in mind that climate data quality prime driver is the climate model skillfulness itself. Statistical post processing methods like bias correction cannot add new information to the data but rather add usefulness to it, depending on the needs of each application.

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Figure 7: Ensemble long-term linear trend of the 5 RCM models' data. The trend is estimated on the mean temperature (top) and the 10th (mid) and 90th (bottom) percentiles in annual basis. The change in the corrected data trend relatively to the raw data trend is provided for the BC (middle panels) and the BCNM data (right panels). All values are expressed as degrees per century [^{o}C/100 y].

Figure 8: Average of standard deviations for the study domain, for the raw data (a), the BC (b) and the BCNM (c) for the different models and the observations, in annual basis. Differences between the raw and the bias corrected standard deviations are shown in (d) and (e). Plots (f) and (g) correspond to the same data as (d) and (e), but normalized for their 1951-2005 mean.

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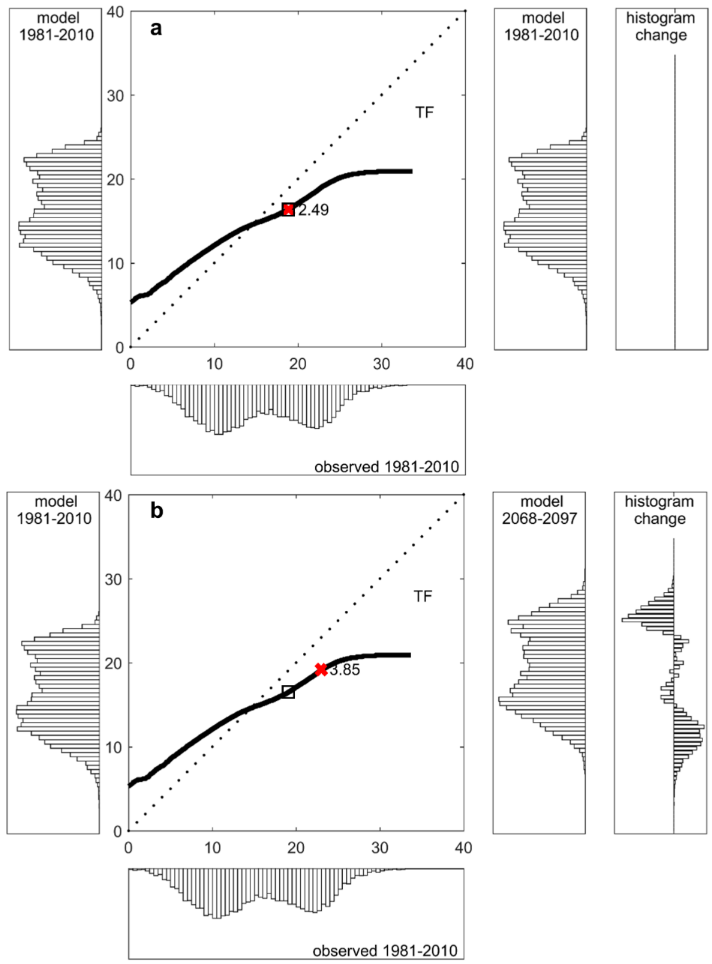

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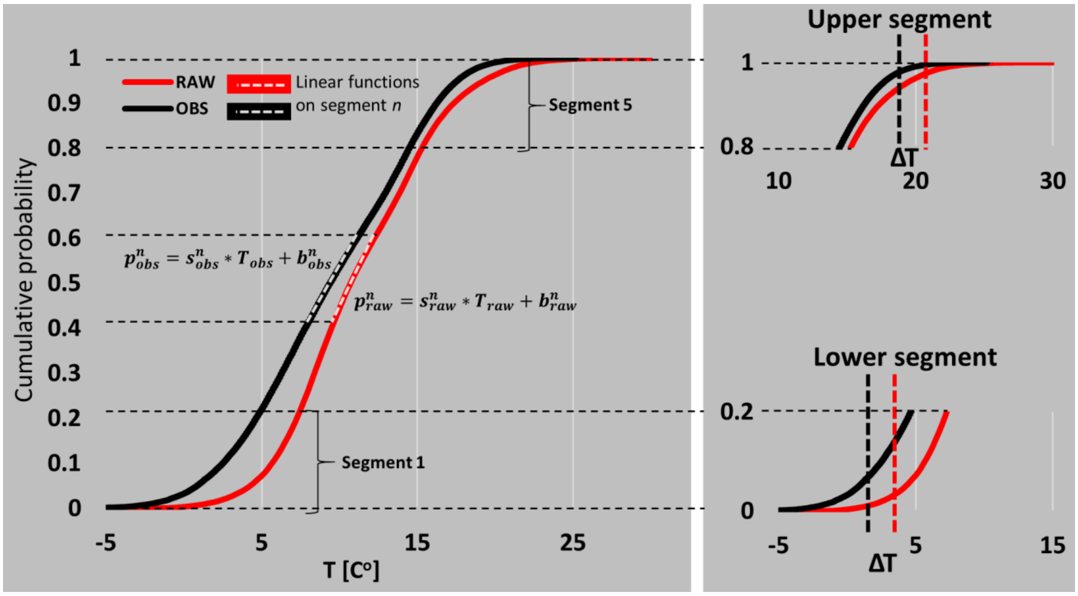

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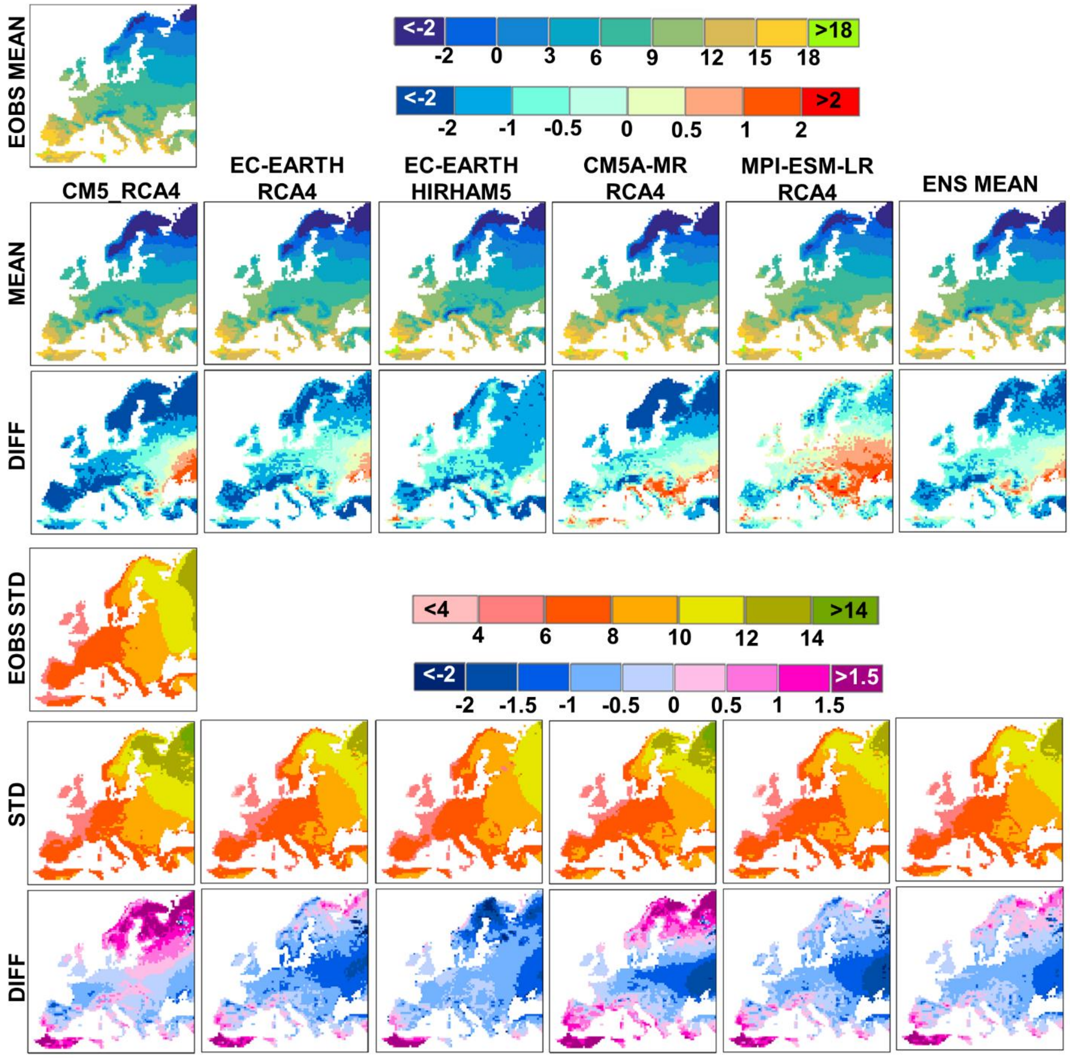

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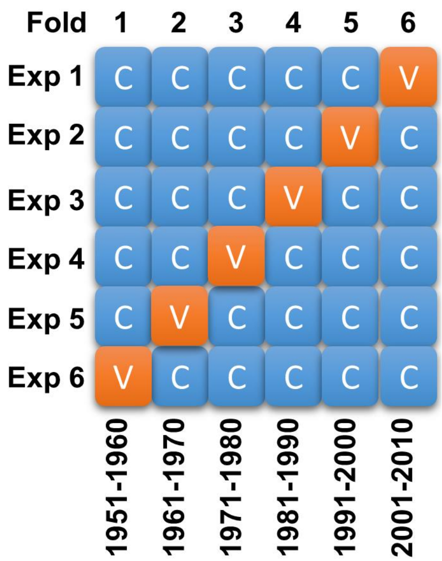

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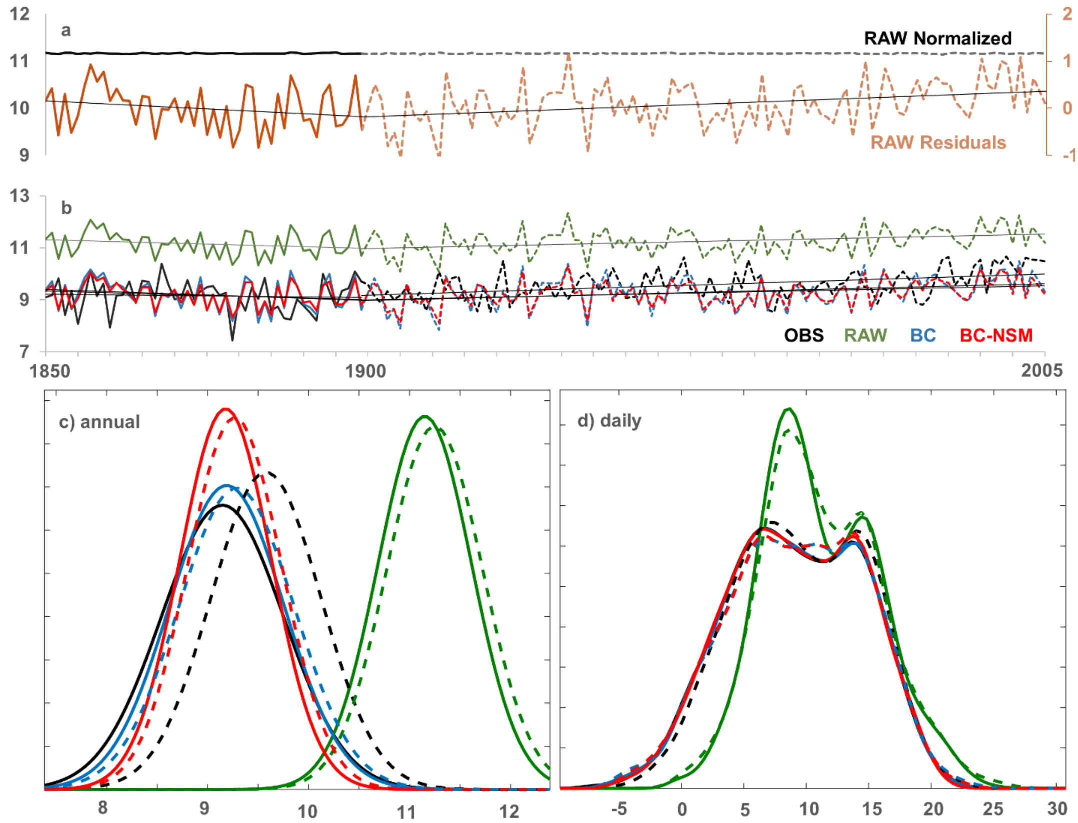

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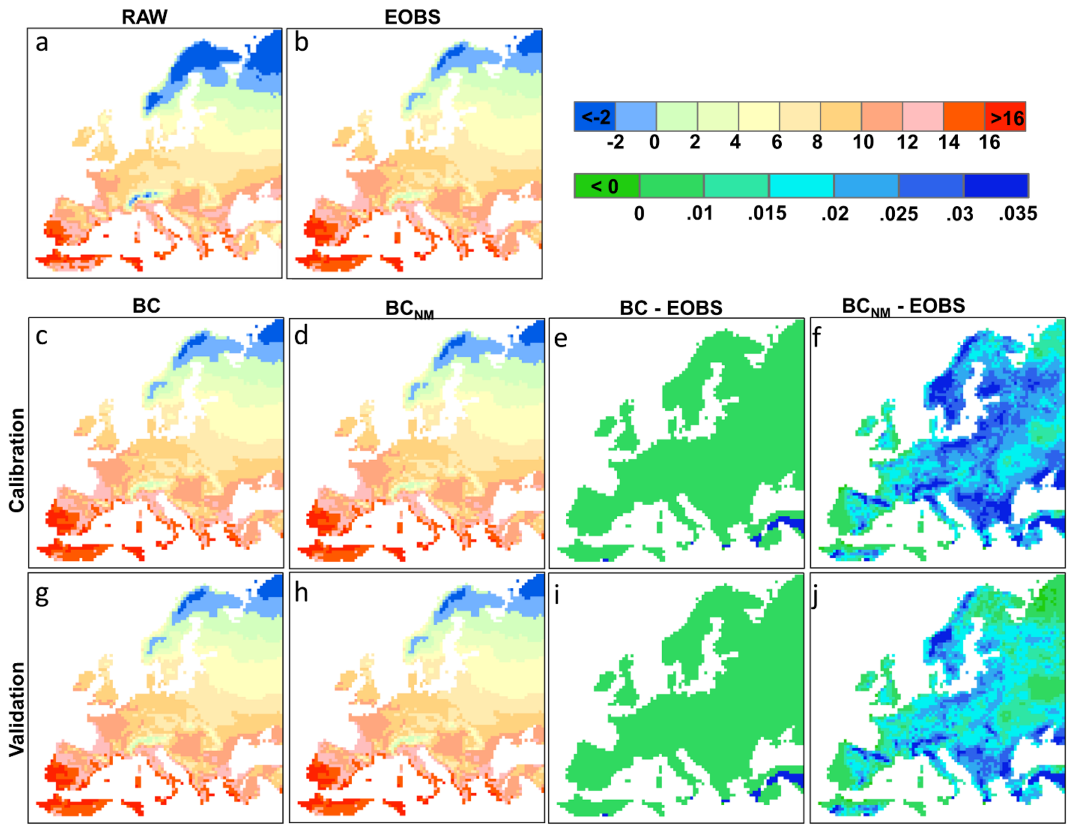

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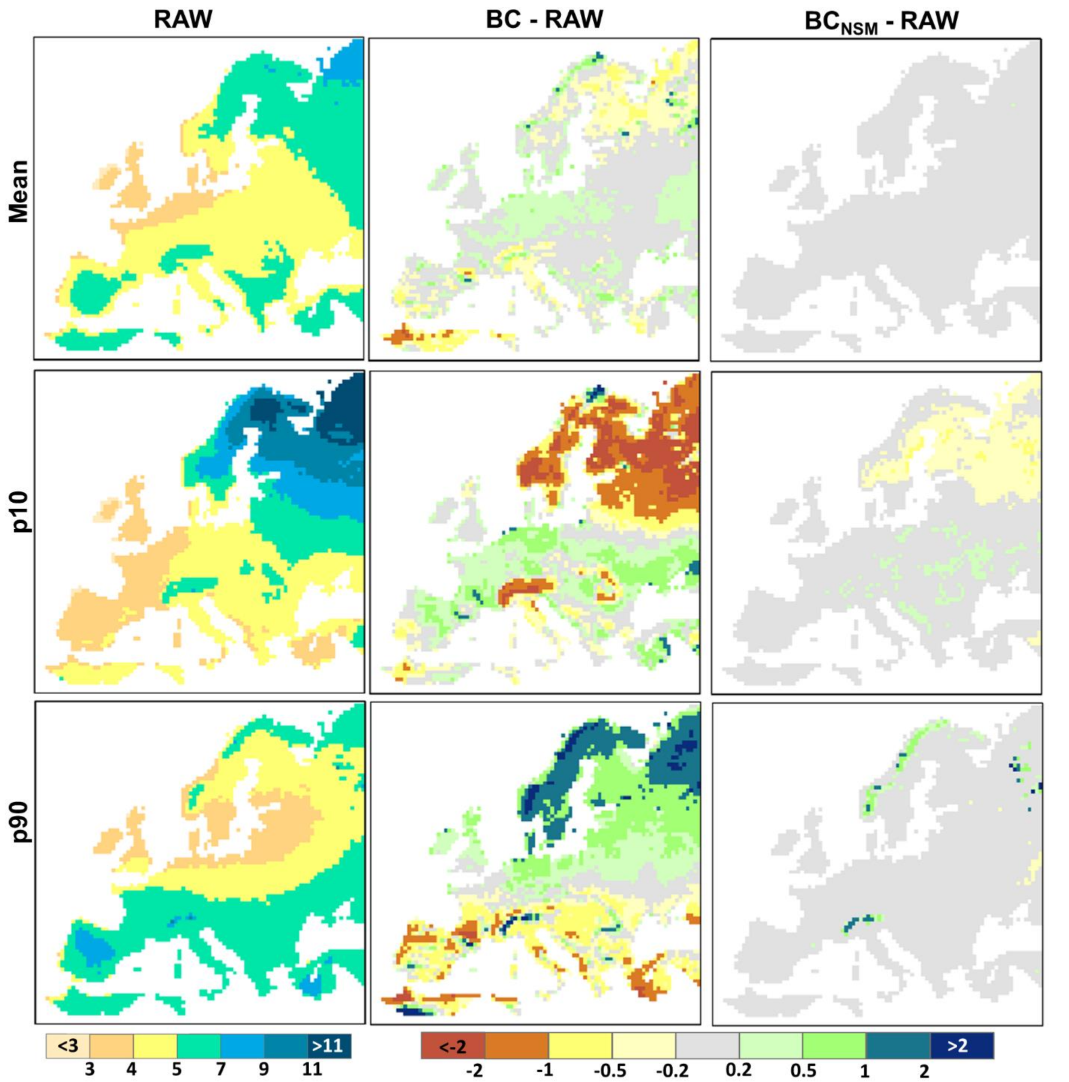

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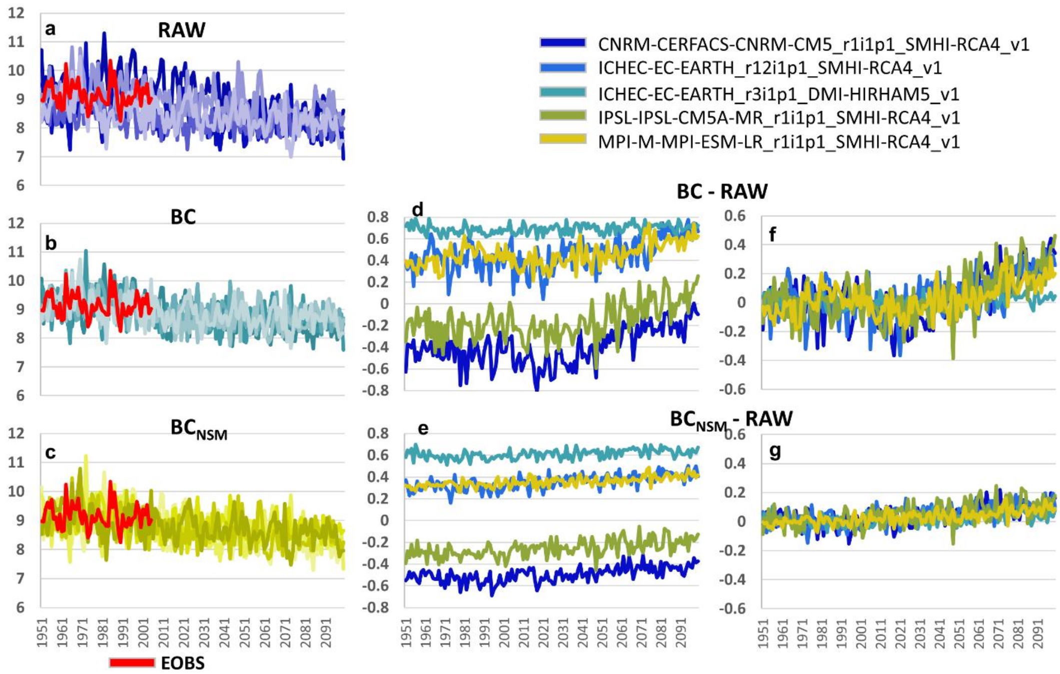

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578 ***Table 1: RCM models used in this experiment.***

#	{GCM}_{realization}_{RCM}
1	CNRM-CM5_r1i1p1_SMHI-RCA4_v1
2	EC-EARTH_r12i1p1_SMHI-RCA4_v1
3	EC-EARTH_r3i1p1_DMI-HIRHAM5_v1
4	IPSL-CM5A-MR_r1i1p1_SMHI-RCA4_v1
5	MPI-ESM-LR_r1i1p1_SMHI-RCA4_v1

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Table 2: Statistical properties of the calibration and the validation periods for the two bias correction procedures. Variables denoted with * are estimated on annual aggregates. SD stands for standard deviation and p*n *for the* nth *quantile.

	Parameter	RAW	Normalized	Residuals	OBS	BC	BC$_{NM}$
Calibration	Slope [ºC/10yr]*	-0.067	0.000	-0.067	-0.026	-0.086	-0.065
	Mean [ºC]	11.2	11.2	0.0	9.1	9.2	9.2
	SD [ºC]	4.5	4.6	0.9	5.3	5.3	5.3
	p10 [ºC]	5.7	5.7	-0.9	2.1	2.2	2.2
	p90 [ºCº]	17.4	17.2	1.0	16.3	16.3	16.2
Validation	Slope [ºC/10yr]*	0.052	0.000	0.051	0.076	0.062	0.051
	Mean [ºC]	11.3	11.2	0.1	9.6	9.3	9.3
	SD [ºC]	4.7	4.6	0.9	5.2	5.5	5.4
	p10 [ºC]	5.6	5.7	-0.9	2.7	2.0	2.0
	p90 [ºC]	17.4	17.2	1.0	16.3	16.3	16.2