Impact of bias nonstationarity on the performance of uni- and multivariate bias-adjusting methods

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Abstract.

Climate change is one of the biggest challenges currently faced by society, with an impact on many systems, such as the hydrological cycle. To assess this impact in a local context, Regional Climate Model (RCM) simulations are often used as input for rainfall-runoff models. However, RCM results are still biased with respect to the observations. Many methods have been developed to adjust these biases, but only during the last few years, methods to adjust biases that account for the correlation between the variables have been proposed. This correlation adjustment is especially important for compound event impact analysis. As an illustration, a hydrological impact assessment exercise is used here, as hydrological models often need multiple locally unbiased input variables to ensure an unbiased output. However, it has been suggested that multivariate bias-adjusting methods may perform poorly under climate change conditions because of bias nonstationarity. In this study, two univariate and four multivariate bias-adjusting methods are compared with respect to their performance under climate change conditions. To this end, the methods are calibrated in the late 20th century (1970-1989) and validated in the early 21st century (1998-2017), in which the effect of climate change is already visible. The variables adjusted are precipitation, evaporation and temperature, of which the former two are used as input for a rainfall-runoff model, to allow for the validation of the methods on discharge. Although not used for discharge modelling, temperature is a commonly-adjusted variable in both uni- and multivariate settings and we therefore also included this variable in our research. The methods are also evaluated using indices based on the adjusted variables, the temporal structure, and the multivariate correlation. The Perkins Skill Score is used to evaluate the full PDF. The results show a clear impact of nonstationarity on the bias adjustment. However, the impact varies depending on season and variable: the impact is most visible for precipitation in winter and summer. This should be accounted for in both multivariate bias-adjusting methods and impact models. In the former because these do not always include seasonality; in the latter because incorrectly adjusted inputs or forcings will lead to predicted discharges that are biased.

1 Introduction

The influence of climate change is felt throughout many regions of the world, as becomes evident from the higher frequency or intensity of natural hazards, such as floods, droughts, heatwaves and forest fires (IPCC, 2012). As these intensified natural hazards threaten society, it is essential to be prepared for them. Knowledge on future climate change is obtained by running Global Climate Models (GCMs), creating large ensemble outputs such as in the Climate Model Intercomparison Project 6 (CMIP6) (Eyring et al., 2016). Although they are informative on a global scale, the generated data are too coarse for local climate change impact assessments. To bridge the gap from the global to the local scale, Regional Climate Models have become a standard application (Jacob et al., 2014), using the output from GCMs as input or boundary conditions.

Although the information provided by both GCMs and RCMs is valuable, both are biased w.r.t. the observations, especially for precipitation (Kotlarski et al., 2014). The biases can occur in any statistic and are commonly defined as *"a systematic difference between a simulated climate statistic and the corresponding real-world climate statistic"* (Maraun, 2016). These biases are caused by temporal or spatial discretisation and unresolved or unrepresented physical processes (Teutschbein and Seibert, 2012; Cannon, 2016). An important example of the latter is convective precipitation, which can only be resolved by very high resolution models. Although the further improvement of models is an important area of research (Prein et al., 2015; Kendon et al., 2017; Helsen et al., 2019; Fosser et al., 2020), such improved models are computationally expensive. As such, it is still necessary practice to statistically adapt the climate model output to adjust the biases (Christensen et al., 2008; Teutschbein and Seibert, 2012; Maraun, 2016).

Many different bias-adjusting methods exist (Teutschbein and Seibert, 2012; Gutiérrez et al., 2019). They all calibrate a transfer function using the historical simulations and historical observations and apply this transfer function to the future simulations to generate future 'observed values' or an adjusted future. Of all the different methods, the quantile mapping method (Panofsky et al., 1958) was shown to be the generally best performing method (Rojas et al., 2011; Gudmundsson et al., 2012). Quantile mapping adjusts biases in the full distribution, whereas most other methods only adjust biases in the mean and/or variance.

An important problem with quantile mapping and most other commonly used methods is that they are univariate and do not adjust biases in the multivariate correlation. Although quantile mapping can retain climate model multivariate correlation (Wilcke et al., 2013), the ability of univariate methods to improve the climate model's multivariate correlation has been questioned (Hagemann et al., 2011; Ehret et al., 2012; Hewitson et al., 2014). This is important for impact assessment, as local impact models often need multiple input variables and many high-impact events are caused by the co-occurrence of multiple phenomena, the so-called 'compound events' (Zscheischler et al., 2018, 2020). For example, flood magnitude can be projected by a rainfall-runoff model using evaporation and precipitation time series as an input. If the correlation between these variables is biased w.r.t. the observations, then it can be expected that the model output is biased as well, which can further propagate in the impact models. During the past decade, multiple methods have been developed to counter this problem. The first methods focused on the adjustment of two jointly occurring variables, most often precipitation and temperature, such as those by Piani and Haerter (2012) and Li et al. (2014). However, it became clear that adjusting only two variables would not suffice, hence many more methods have been developed that jointly adjust multiple variables, including those by Vrac and Friederichs (2015); Cannon (2016); Mehrotra and Sharma (2016); Dekens et al. (2017); Cannon (2018); Vrac (2018); Nguyen et al. (2018); Robin et al. (2019). Yet, the recent growth in availability of such methods comes along with a gap in the knowledge on their performance. In some studies, these methods have been compared with one or two older multivariate methods to reveal the improvements (Vrac and Friederichs, 2015; Cannon, 2018) or with univariate methods (Räty et al., 2018; Zscheischler et al., 2019; Meyer et al., 2019). Each of the latter three studies comparing uni- and multivariate bias adjusting methods indicates that these lead to different results, yet it is difficult to conclude whether uni- or multivariate methods perform best. According to Zscheischler et al. (2019) multivariate methods have an added value. Räty et al. (2018) conclude that the multivariate methods and univariate methods perform similarly, while Meyer et al. (2019) could not draw definitive conclusions. These studies vary in set-up, adjusted variables and study area, which all could have caused the difference in added value. In all three studies, the same method, namely the Multivariate Bias Correction in n dimensions (MBCn) (Cannon, 2018) was the basis for comparison. Only recently, the first studies comparing multiple multivariate bias-adjusting methods were published (François et al., 2020; Guo et al., 2020). The study by François et al. (2020) focused on the different principles underlying the multivariate bias-adjusting methods and concluded that the choice of method should be based on the end user's goal. Besides, they also noticed that all multivariate methods studied fail in adjusting the temporal structure of a time series. In contrast to the focus of François et al. (2020), Guo et al. (2020) studied the performance of multivariate bias-adjusting methods for climate change impact assessment and concluded that multivariate methods could be interesting in this context. However, they also noticed that the performance of the multivariate methods was lower in the validation period and suggested that this could be caused by bias nonstationarity. As the use of multivariate bias-adjusting methods could be an important tool for climate change impact assessment, this deserves more attention.

The bias stationarity - or bias time invariance - assumption is the most important assumption for bias correction. It implies that the bias is the same in the calibration and validation or future periods and that the transfer function based on the calibration period can thus be used in the future period. However, this assumption does not hold due to different types of nonstationarity induced by climate change, which may cause problems (Milly et al., 2008; Derbyshire, 2017). In the context of bias adjustment, this problem has been known for several years (Christensen et al., 2008; Ehret et al., 2012), but has not received a lot of attention. A few authors have tried to propose new types of bias relationships (Buser et al., 2009; Ho et al., 2012; Sunyer et al., 2014; Kerkhoff et al., 2014). Recently, it has been suggested that it is best to assume a non-monotonic bias change (Van Schaeybroeck and Vannitsem, 2016). Some authors suggested that bias nonstationarity could be an important source of uncertainty (Chen et al., 2015; Velázquez et al., 2015; Wang et al., 2018; Hui et al., 2019), but not all found clear indications of bias nonstationarity (Maraun, 2012; Piani et al., 2010; Maurer et al., 2013).

The availability of new methods and more data enables a more coherent assessment of the bias (non)stationarity issue. By comparing four bias-adjusting methods in a climate change context with possible bias nonstationarity, some of the remaining questions in François et al. (2020) and Guo et al. (2020) can be answered. The four multivariate bias-adjusting methods compared in this study are 'Multivariate Recursive Quantile Nesting Bias Correction' (MRQNBC, Mehrotra and Sharma (2016)), MBCn (Cannon, 2018), 'dynamical Optimal Transport Correction' (dOTC, Robin et al. (2019)) and 'Rank Resampling for Distributions and Dependences' (R^2D^2, Vrac (2018); Vrac and Thao (2020b)). These four methods give a broad view of the different multivariate bias adjustment principles, which we will elaborate on in Section 3.3. As a baseline, two univariate bias-adjusting methods will be used: Quantile Delta Mapping (QDM, Cannon et al. (2015)) and modified Quantile Delta Mapping (mQDM, Pham (2016). QDM is a classical univariate bias-adjusting method and is chosen for this analysis as it is a robust and relatively common quantile mapping method, especially as one of the subroutines in the multivariate bias-adjusting methods (Mehrotra and Sharma, 2016; Nguyen et al., 2016; Cannon, 2018). mQDM, on the other hand, is one of the so-called 'delta change' methods, which are based on an adjustment of the historical time series. Using these univariate bias-adjusting methods, we can assess whether multivariate and univariate bias-adjusting methods differ in their response to possible bias nonstationarity.

The methods will be compared by applying them for the bias adjustment of precipitation, potential evaporation and temperature. The bias-adjusted time series will be used as inputs for a hydrological model in order to simulate the discharge. Discharge time series are the basis for flood hazard calculation, but can also be considered as an interesting source of validation themselves (Hakala et al., 2018). The bias adjustment and discharge simulation are both assessed at one grid cell/location only. Although this does not allow for investigating the spatial extent and impact of nonstationarity, the focus on one location gives information on the influence of possible bias nonstationarity on local impact models and may hence be a starting point for broader assessments. We will also not account for the differences between models, as we only investigate a single GCM-RCM model chain. This allows for a precise investigation of the possible effects of bias nonstationarity, although it does not allow for assessing other types of uncertainty. The change of some biases from calibration to validation time series will be calculated, to indicate the extent of the bias nonstationarity. Maurer et al. (2013) proposed the R index for this purpose. Calculating the bias nonstationarity between both periods will give an indication of the impact of a changing bias on climate impact studies for the end of the 21st century. As Chen et al. (2015) mentioned: *"If biases are not constant over two very close time periods, there is little hope they will be stationary for periods separated by 50 to 100 years"*

2 Data and validation

2.1 Data

The observational data used were obtained from the Belgian Royal Meteorological Institute (RMI) Uccle observatory. The most important time series used is the 10-min precipitation amount, gauged with a Hellmann-Fuess pluviograph, from 1898 to 2018. An earlier version of this precipitation dataset was described by Demarée (2003) and analyzed in De Jongh et al. (2006). Multiple other studies have used this time series (Verhoest et al., 1997; Verstraeten et al., 2006; Vandenberghe et al., 2011; Willems, 2013). The 10-min precipitation time series was aggregated to daily level to be comparable with the other time series used.

For the multivariate methods, the precipitation time series was combined with a 2 meter air temperature and potential evaporation time series. The daily potential evaporation was calculated by the RMI from 1901 to 2019, using the Penman formula for a grass reference surface (Penman, 1948) with variables measured at the Uccle observatory. Daily average temperatures were obtained using measurements from 1901 to 2019. As the last complete year for precipitation was 2017, the data were used from 1901 to 2017, amounting to 117 years of daily data. As Uccle (near Brussels) is situated in a region with small topographic differences, it is assumed that the precipitation statistics within the grid cell are uniform. Hence, the Uccle data can be used for comparison with the gridded climate simulation data discussed below.

For the simulations, data from the EURO-CORDEX project (Jacob et al., 2014) were used. The Rossby Centre regional climate model RCA4 was used (Strandberg et al., 2015) as it is one of the few RCMs with potential evaporation as an output variable. This RCM was forced with boundary conditions from the MPI-ESM-LR GCM (Popke et al., 2013) and has a spatial resolution of 0.11°, or 12.5 km. Historical data and scenario data for the grid cell comprising Uccle were respectively obtained for 1970-2005 and 2006-2100. The former time frame is limited by the earliest available data from the RCM. The latter time frame was only used until 2017, in accordance with the observational data. As climate change scenario, an RCP4.5 forcing was used in this paper (van Vuuren et al., 2011). Since only 'near future' (from the model point of view) data were used, the choice of forcing does not have a large impact. However, when studying scenarios in a time frame further away from the present, using an ensemble of forcings is more relevant to be aware of the uncertainty regarding future climate change impact. evaluations of the RCA4 model have shown that there is a bias in precipitation, especially in winter (Strandberg et al., 2015), but this bias is in line with the biases from other EURO-CORDEX models (Kotlarski et al., 2014).

2.2 Time frames

As mentioned in the introduction, it is important to assess bias-adjusting methods in a context they will be used in, i.e. under climate change conditions. The time series used in this study were chosen accordingly: 1970-1989 was chosen as the 'historical' or calibration time period and 1998-2017 was chosen as the 'future' or validation time period. In this time frame, effects of climate change are already visible (IPCC, 2013). Time series of 20 years were chosen here, although it is advised to use 30 years of data to have robust calculations (Berg et al., 2012; Reiter et al., 2018). However, as no climate model data prior to 1970 are available, using 30 years of data would have led to overlapping time series.

2.3 Validation framework

An important aspect in bias adjustment is the validation of the methods. Different methods are available, of which a pseudo-reality experiment (Maraun, 2012) is one of the most-used ones. In this method, each member of a model ensemble is in turn used as the reference in a cross-validation. However, while such a set-up is useful when comparing bias-adjustment methods, it only mimics a real application context. When sufficient observations are available, a 'pseudo-projection' set-up (Li et al., 2010) can be used. This set-up resembles a 'differential split-sample testing' (Klemeš, 1986) and is more in agreement with a practical application of bias-adjusting methods. Differential split-sample testing has been used in a bias adjustment context by Teutschbein and Seibert (2013), by constructing two time series with respectively the driest and wettest years. In our case study, it is assumed that the two time series differ enough because of climate change. Consequently, the approach is simple, and as the validation is not set in the future, it is considered a 'pseudo-projection'.

Besides the choice of time frames and data, also the choice of validation indices is of key importance. Maraun and Widmann (2018a) stress that these indices should only be indirectly affected by the bias adjustment, as only validating on adjusted indices can be misleading. Such adjusted indices are the precipitation intensity, temperature and evaporation, which are used to build the transfer function in the historical setting and should be corrected by construction. Under bias stationarity, this correction will be carried over to the future, possibly hiding small inconsistencies that may arise for extreme values. If the bias is not stationary, the effect might be different between adjusted and indirectly affected indices. As such, besides the three adjusted variables (indices 1 to 3 in Table 1) and their correlations (indices 4 to 12, which are directly adjusted by some of the methods), also indices based on the precipitation occurrence and on the discharge Q are used. The occurrence-based indices (13 to 16) allow for assessing how the methods influence the precipitation time series structure. The discharge-based indices (17 and 18) allow for the assessment of the impact of the different bias-adjusting methods on simulated river flow. The discharge-based indices combine the information of the other indices by routing through the rainfall-runoff model. They are the most important aspect of the assessment, as they indicate the natural hazard. As the percentiles focus mostly on the extremes, the Perkins Skill Score (PSS) (Perkins et al., 2007) is used to assess the adjustment of the full PDF of the variables. All indices are calculated taking all days into account, instead of only calculating them on wet days, as some of the multivariate bias-adjusting methods do not discriminate between wet or dry days in their adjustment.

The indices are all calculated on a seasonal basis for both the calibration and validation period. By comparing over these periods, we can relate the performance to either the method itself or bias (non)stationarity, on a seasonal basis. Besides, not all methods adjust on a seasonal basis. As such, methods performing poorly in both periods might need a seasonal component for bias adjustment. The seasons were defined as follows: winter (DJF), spring (MAM), summer (JJA) and autumn (SON).

2.4 Bias nonstationarity

In a study on possible changes in bias, Maurer et al. (2013) proposed the R index:

$$\mathrm{R} = 2\frac{\mid \mathrm{bias_f} - \mathrm{bias_h} \mid}{\mid \mathrm{bias_f} \mid + \mid \mathrm{bias_h} \mid}, \tag{1}$$

where $\mathrm{bias_f}$ and $\mathrm{bias_h}$ are the biases in respectively the future and historical time series, calculated on the basis of the observations and raw climate simulations. The R index takes a value between 0 and 2. If the index is greater than one, the difference in bias between the two sets is larger than the average bias of the model and it is likely that the bias adjustment would degrade the RCM output rather than improve it. The index is calculated for the indices used for validation in order to have an indication of the influence of bias nonstationarity on these indices. Besides for the indices, the R index is also calculated for the average and standard deviation of each variable, in order to be able to more easily visualise the changes in distribution.

2.5 Hydrological model

Similar to Pham et al. (2018), we use the Probability Distributed Model (PDM, Moore (2007); Cabus (2008)), a lumped conceptual rainfall-runoff model to calculate the discharge for the Grote Nete watershed in Belgium. This model uses precipitation and evaporation time series as inputs to generate a discharge time series. The PDM as used here was calibrated (RMSE = 0.9

Table 1. Overview of the indices used

Nr	Index	Name
1	P_x	Precipitation amount percentile values, with x the percentile considered
2	T_x	Temperature percentile values, with x the percentile considered
3	E_x	Evaporation percentile values, with x the percentile considered
4	$\mathrm{corr}_{\mathrm{P,E}}$	Spearman correlation between the time series of *P* and *E*
5	$\mathrm{corr}_{\mathrm{P,T}}$	Spearman correlation between the time series of *P* and *T*
6	$\mathrm{corr}_{\mathrm{E,T}}$	Spearman correlation between the time series of *E* and *T*
7	$\mathrm{crosscorr}_{\mathrm{P,E,0}}$	Lag-0 crosscorrelation between the time series of *P* and *E*
8	$\mathrm{crosscorr}_{\mathrm{P,T,0}}$	Lag-0 crosscorrelation between the time series of *P* and *T*
9	$\mathrm{crosscorr}_{\mathrm{E,T,0}}$	Lag-0 crosscorrelation between the time series of *E* and *T*
10	$\mathrm{crosscorr}_{\mathrm{P,E,1}}$	Lag-1 crosscorrelation between the time series of *P* and *E*
11	$\mathrm{crosscorr}_{\mathrm{P,T,1}}$	Lag-1 crosscorrelation between the time series of *P* and *T*
12	$\mathrm{crosscorr}_{\mathrm{E,T,1}}$	Lag-1 crosscorrelation between the time series of *E* and *T*
13	$\mathrm{P}_{\mathrm{P00}}$	Precipitation transition probability from a dry to a dry day
14	$\mathrm{P}_{\mathrm{P10}}$	Precipitation transition probability from a wet to a dry day
15	$\mathrm{N}_{\mathrm{dry}}$	Number of dry days
16	$\mathrm{P}_{\mathrm{lag1}}$	Precipitation lag-1 auto-correlation
17	Q_x	Discharge percentiles, with x the percentile considered
18	$\mathrm{Q}_{\mathrm{T20}}$	20-year return period value of discharge

m^3/h, see Pham et al. (2018) for more details) using the Particle Swarm Optimization algorithm (PSO, Eberhart and Kennedy (1995)). As in Pham et al. (2018), it was assumed that the differences between meteorological conditions in the Grote Nete-watershed and Uccle are negligible, and that thus the adjusted data for the Uccle grid cell can be used as a forcing for the PDM. This assumption is based on the limited distance of 50 km between the gauging stations used for the observations in Uccle and the gauging station used for the PDM calibration. As mentioned before, the region has a flat topography and, hence, the climatology can be considered similar. Furthermore, the goal is not to make predictions, but to assess the impact of different bias adjustment methods on the discharge values. To calculate the bias on the indices, observed, raw and adjusted RCM time series were used as forcing for this model. The discharge time series generated by the observations is considered to be the 'observed' discharge, and biases are calculated in comparison with this time series.

2.6 Validation metrics

The residual biases relative to the observations and to the model bias are often used in this paper to graphically present and interpret the results. These residual biases are based on the 'added value' concept (Di Luca et al., 2015) and enable a comparison based on two aspects. The first aspect is the performance in removing the bias, the second is the extent of the bias removal in comparison with the original value for the corresponding index for the observation time series. The use of the residual biases allows for a detailed study and comparison of the effect of bias adjustment on the different indices.

The residual bias relative to the observations $\mathrm{RB_O}$ for an index k is calculated as follows:

$$\mathrm{RB_O}\,(k) = 1 - \frac{\mid \mathrm{bias}_{\mathrm{raw}(k)} \mid - \mid \mathrm{bias}_{\mathrm{adj}(k)} \mid}{\mid \mathrm{obs}\,(k) \mid}, \tag{2}$$

with raw(k) the raw climate model simulations, adj(k) the adjusted climate model simulations and obs(k) the observed values for index k.

The residual bias relative to the model bias $\mathrm{RB_{MB}}$ for an index k is calculated as follows:

$$\mathrm{RB_{MB}}\,(k) = 1 - \frac{\mid \mathrm{bias}_{\mathrm{raw}(k)} \mid - \mid \mathrm{bias}_{\mathrm{adj}(k)} \mid}{\mid \mathrm{bias}_{\mathrm{raw}(k)} \mid}. \tag{3}$$

Absolute values are used in Eqs. (2) and (3) to compute the absolute difference between the raw and adjusted values, thus neglecting a possible change of sign of the bias. If the values of these residual biases are lower than 1 for an index, the method performs better than the raw RCM for this index. The best methods have low scores on both residual biases for as many indices as possible.

3 Bias-adjusting methods

3.1 Occurrence-bias adjustment: Thresholding

One of the deficiencies of RCMs, especially in Northwest Europe, are the so-called ‘drizzle days’ (Gutowski et al., 2003; Themeßl et al., 2012; Argüeso et al., 2013), during which small amounts of precipitation are simulated while these days should have been dry. This has an influence on the temporal structure of the simulated time series and should thus be adjusted (Ines and Hansen, 2006). This is commonly done in an occurrence-bias-adjusting step before the main step, the intensity-bias adjustment. In this study, we use the thresholding occurrence-bias-adjusting method, which is one of the most common occurrence-bias-adjusting methods (e.g. Hay and Clark (2003); Schmidli et al. (2006); Ines and Hansen (2006)). This method is only applicable in regions where the assumption holds that the simulated time series has more wet days than the observed time series. This is the case for Northwest Europe (Themeßl et al., 2012) and Belgium in particular. An advanced version of the thresholding method is used here. To adjust the number of wet days, the total number of dry days in the observations and in the simulations are calculated. The difference in dry days between the two periods, ΔN, is the number of days of the simulated time series that have to be adapted. If ΔN days have to be converted to dry days, then the ΔN days with the lowest amounts of precipitation are changed to dry days. ΔN is computed for the past and applied in the future and consequently relies on the bias stationarity assumption. However, as thresholding is used prior to all methods, the influence of possible bias nonstationarity on ΔN is assumed to be negligible. Besides, as is shown in Section 4.1, the number of dry days is stationary for the time frames studied in this paper.

In this advanced version of thresholding, some considerations are made. First, a day is considered wet if its simulated precipitation amount is above 0.1 mm, to account for measurement errors in the observations. Second, the adjustment is done on a monthly basis, to account for the temporal structure in the observed time series. Third, both historical and future simulations are adjusted, to ensure that the bias can be transferred from the historical to the future time period would be impaired.

3.2 Univariate intensity-bias-adjusting methods

3.2.1 Quantile Delta Mapping

The Quantile Delta Mapping (QDM) method was first proposed by Li et al. (2010). Its main idea is to preserve the climate simulation trends: it takes trend nonstationarity (changes in the simulated distribution) into account to a certain degree. Although it handles temperature adjustments well, it gives unrealistic values for precipitation and was therefore extended by Wang and Chen (2014) for precipitation adjustment. By combining the methods by Li et al. (2010) (*Equidistant CDF-matching*) and Wang and Chen (2014) (*Equiratio CDF-matching*), Cannon et al. (2015) developed the *Quantile Delta Mapping* method.

Mathematically, this method can be written as

$$x_i^{\mathrm{fa}} = x_i^{\mathrm{fs}} + F_{x^{\mathrm{ho}}}^{-1}\left(F_{x^{\mathrm{fs}}}\left(x^{\mathrm{fs}}\right)\right) - F_{x^{\mathrm{hs}}}^{-1}\left(F_{x^{\mathrm{fs}}}\left(x^{\mathrm{fs}}\right)\right) \tag{4}$$

in the additive case, and

$$x_i^{\mathrm{fa}} = x_i^{\mathrm{fs}} \frac{F_{x^{\mathrm{ho}}}^{-1}\left(F_{x^{\mathrm{fs}}}\left(x^{\mathrm{fs}}\right)\right)}{F_{x^{\mathrm{hs}}}^{-1}\left(F_{x^{\mathrm{fs}}}\left(x^{\mathrm{fs}}\right)\right)} \tag{5}$$

in the ratio or multiplicative case. The superscripts hs, ho, fs and fa indicate respectively the historical simulations, the historical observations, the future simulations and the adjusted future. In this paper, the additive version is used for temperature time series and the multiplicative one for precipitation and evaporation time series. This choice is based on the work of Wang and Chen (2014), who have shown that using the additive adjustment for precipitation results in unrealistic precipitation values and introduced a multiplicative adjustment. For evaporation, we follow the few available studies (e.g. Lenderink et al. (2007)) in using the same adjustment as for precipitation.

To ensure the consistency of the time series, a 91-day moving window is opted for, as suggested by Rajczak et al. (2016) and Reiter et al. (2018). This enables the adjustment of each day based on $91\,\text{days/year} \cdot 20\,\text{years} = 1820$ days. These days were used to build an empirical CDF (as in Gudmundsson et al. (2012); Gutjahr and Heinemann (2013), among others). It is also important to note that for precipitation, Eq. (5) was applied only on the days considered wet, i.e. with a precipitation higher than 0.1 mm. For consistency, a threshold of 0.1 mm was also used for evaporation. It is important to note that although QDM is only applied on wet days, it can still transform low-precipitation wet days into days that are considered to be dry (e.g. with a precipitation amount < 0.1 mm) if the ratio in Eq. (5) is small enough.

3.2.2 Modified Quantile Delta Mapping

Pham (2016) proposed another version of QDM, following the delta change philosophy (Olsson et al., 2009; Willems and Vrac, 2011): the trend established by the RCM is assumed to be more thrust-worthy than the absolute value itself. When applying this type of methods, the simulated change between the historical and the future is applied to the observations. Thus, instead of the future simulations, the historical observations are adjusted to the future ‘observations’. As Johnson and Sharma (2011) mention, this workflow could be problematic for future impact assessment, as it inherits the temporal structure of the historical observations. This method is mathematically very similar to the QDM method, exchanging the roles of x^{fs} and x^{ho}. Thus, it is named ‘modified Quantile Delta Mapping’ (mQDM), and can for the additive case be written as

$$x_i^{\mathrm{fa}} = x_i^{\mathrm{ho}} + F^{-1}_{x^{\mathrm{fs}}}\left(F_{x^{\mathrm{ho}}}\left(x^{\mathrm{ho}}\right)\right) - F^{-1}_{x^{\mathrm{hs}}}\left(F_{x^{\mathrm{ho}}}\left(x^{\mathrm{ho}}\right)\right). \tag{6}$$

The ratio version is given by

$$x_i^{\mathrm{fa}} = x_i^{\mathrm{ho}} \frac{F^{-1}_{x^{\mathrm{fs}}}\left(F_{x^{\mathrm{ho}}}\left(x^{\mathrm{ho}}\right)\right)}{F^{-1}_{x^{\mathrm{hs}}}\left(F_{x^{\mathrm{ho}}}\left(x^{\mathrm{ho}}\right)\right)}. \tag{7}$$

For the implementation, the same principles were used as for the QDM method: a 91-day moving window, empirical CDFs and a minimum value of 0.1 mm/day to be considered as a wet day.

3.3 Multivariate intensity-bias-adjusting methods

The increasing number of multivariate bias-adjusting methods throughout the 2010s urges the need to classify them according to their properties. One possible classification was done by Vrac (2018), who proposed the ‘marginal/dependence’ versus the ‘successive conditional’ approach. The former approach separately adjusts the 1D-marginal distributions and the dependence structure and is applied in e.g. Vrac and Friederichs (2015), Cannon (2018) and Vrac (2018). These two components are then recombined to obtain data that are close to the observations for both marginal and multivariate aspects. The latter approach consists of adjusting a variable conditionally on the variables already adjusted. This procedure is applied successively to each variable. Examples can be found in e.g. Piani and Haerter (2012), Li et al. (2014) and Dekens et al. (2017). Vrac (2018) discusses the limitations of the ‘successive conditional’ approach and advocates for the use of the more robust and coherent ‘marginal/dependence’ approach. Hence, ‘successive conditional’ methods are not included in the present paper. Robin et al. (2019) and François et al. (2020) extended the classification by introducing the ‘all-in-one’ approach, which adjusts the marginal variables and the correlations simultaneously, ‘dynamical Optimal Transport Correction’ (dOTC) (Robin et al., 2019) being such a method.

Another perspective on the multivariate bias-adjusting methods is to consider the amount of temporal adjustment that is allowed or applied by the method. This is important, as the amount of temporal adjustment is intrinsically linked with the main goal, the adjustment of the multivariate distribution of the variables. This distribution, in which the dependence is characterised by the underlying copula (Nelsen, 2006; Schölzel and Friederichs, 2008), can be estimated using the ranks. Thus, to adjust the multivariate distribution, the ranks of the climate model are replaced by those of the observations, using methods such as the ‘Schaake Shuffle’ (Clark et al., 2004; Vrac and Friederichs, 2015). This implies that the temporal structure and trends of the climate model will be altered, which may have a considerable impact (François et al., 2020). This impact is especially large when multiday characteristics strongly matter, such as in applications as the hydrological example we use in this study (Addor and Seibert, 2014). Vrac (2018) mentions this necessity to modify the temporal structure and rank chronology of the simulations. Yet, he also mentions that the extent of this modification is still a matter of debate. Cannon (2016) describes this as the ‘knobs’ that control whether marginal distributions, inter-variable or spatial dependence structure and temporal structure are more informed by the climate model or the observations. Thus, the choice between the temporal structure of the climate model and unbiased dependence structures is a trade-off that has to be made. Some methods, such as those by Vrac and Friederichs (2015), Mehrotra and Sharma (2016) and Nguyen et al. (2018) rely on the observations for their temporal properties, while other methods try to find the middle ground (e.g. Vrac (2018) and Cannon (2018)). A last perspective, which is not limited to multivariate methods, is that of trend preservation, i.e., the capacity of methods to preserve the changes simulated by the climate model, such as changes in mean, extremes and temporal structure. Although the amount of trend preservation or adjustment has been a matter of debate (Ivanov et al., 2018), Maraun (2016) argues that it is sensible to preserve the simulated changes and hence the climate change signal, if the model simulation is credible. As such, trend preservation interacts with bias nonstationarity: non-stationarity can be seen as the divergence between the observed and simulated trends. Hence, in a nonstationary context, trend-preserving methods may be disadvantaged, as they will assume that the simulated trend is trustworthy. In the univariate setting, QDM is an example of a trend-preserving method, as is ’Scaled Distribution Mapping’ by Switanek et al. (2017).

Our choice of multivariate bias-adjusting methods takes the above classification into account. The oldest method in the comparison is ‘Multivariate Recursive Quantile Nesting Bias Correction’ (MRQNBC) (Mehrotra and Sharma, 2016). This method replaces the simulated correlations by those of the observations and is a ‘marginal/dependence’ method according to François et al. (2020). As QDM is used for the marginal distributions, the latter are preserved. However, MRQNBC does not preserve the changes in dependence. ‘Multivariate Bias Correction in n dimensions’ (Cannon, 2018) is both a ‘marginal/dependence’ method and a method that tries to combine information from the climate model and the observations. Similar to MRQNBC, it explicitly preserves the simulated changes in the marginal distributions by applying QDM for the marginal distributions. As the simulated dependence structure is the basis for the adjustment, it will be slightly preserved. The ‘Rank Resampling for Distributions and Dependences’ (R^2D^2, Vrac (2018); Vrac and Thao (2020b)) method preserves the rank correlation of the observations, but allows the climate model to have some influence on the temporal properties. It is also a ‘marginal/dependence’ method: in the present paper, QDM is used as its univariate routine and thus the changes in marginal distributions are preserved by R^2D^2. The most recent method, ‘dynamical Optimal Transport Correction’ (Robin et al., 2019) differs considerably from the other two methods: it generalises the ‘transfer function’-principle using the ‘optimal transport’ paradigm (Villani, 2008), thereby defining a new category of multivariate bias-adjusting methods: the above-mentioned all-in-one approach. It is the only method that explicitly preserves the simulated changes in both the marginal distributions and the dependence structure. Although far from complete, by comparing these four methods, a broad view of the different approaches in multivariate bias adjustment can be obtained. The main principles of the bias-adjusting methods are summarized in Table 2.

3.3.1 Multivariate Recursive Quantile Nesting Bias Correction

In 2016, Mehrotra and Sharma proposed a new multivariate bias adjustment method, named ‘Multivariate Recursive Quantile Nesting Bias Correction’ (MRQNBC), based on a combination of several older methods by Johnson and Sharma (2012), Mehrotra and Sharma (2012) and Mehrotra and Sharma (2015) and by incorporating QDM as the univariate routine for adjust-

Table 2. Overview of the multivariate bias-adjusting methods

	MBCn	MRQNBC	$\mathbf{R^2D^2}$	dOTC
Category	Marginal/dependence	Marginal/dependence	Marginal/dependence	All-in-one
Temporal properties	Shuffle based on observations	Observed	Shuffle based on observations	Future, adjusted
Dependence structure	Future, adjusted based on observations	Observed	Observed	Future, adjusted
Trend preservation	Marginal properties by the application of QDM, dependence structure partly	Marginal properties by the application of QDM	Marginal properties by the application of QDM	Marginal properties and dependence structure
Statistical technique	Iterative partial matrix recorrelation	Autoregressive modeling	Conditional resampling	Optimal transport
Timescale	Daily adjustment by QDM + full time series shuffle	Combination of daily, monthly, seasonal and yearly adjustment	Daily adjustment by QDM + full time series resampling	Full time series

ing the marginals. The underlying idea of this method is to adjust on more than one timescale, and to nest the results of the different timescales within each other. The adjustment on multiple timescales is almost never incorporated in bias-adjusting methods (Haerter et al., 2011). On each timescale, the biases in lag-0- and lag-1-auto and the cross-correlation coefficients, i.e. the persistence attributes, are adjusted, instead of focusing on the mean or the distribution. The biases are adjusted by replacing the modeled persistence attributes with observed persistence attributes, on the basis of autoregressive expressions. Besides replacing the simulated temporal properties with the observed ones, this implies that the simulated dependence structure is also replaced by the observed structure. As QDM is applied on each timescale, the marginal properties are preserved.

After adjusting all timescales, the final daily result is calculated by weighing all timescales. However, as the nesting method cannot fully remove biases at all time scales, Mehrotra and Sharma (2016) suggested to repeat the entire procedure multiple times. Yet, in our case multiple repetitions exacerbated the results. Non-realistic outliers created by the first repetition influenced the subsequent repetitions, creating even more non-realistic values. This was most clearly seen for precipitation. As a bounded variable, precipitation is most sensitive for non-realistic values. Nonetheless, running the method just once yielded satisfactory results. A full mathematical description of the method can be found in Mehrotra and Sharma (2016).

3.3.2 Multivariate Bias Correction in n dimensions

In 2018, Cannon (2018) proposed the 'Multivariate Bias correction in n dimensions' (MBCn) method as a flexible multivariate bias-adjusting method. The method's flexibility has attracted some attention, and it has already been used in multiple studies (Räty et al., 2018; Zscheischler et al., 2019; Meyer et al., 2019; François et al., 2020). This method consists of three steps. First, the multivariate data are rotated using a randomly generated orthogonal rotation matrix, adjusted with the additive form of QDM, and rotated back until the calibration period model simulations converge to the observations. This convergence is verified on the basis of the energy distance (Rizzo and Székely, 2016). Second, the validation period simulations are adjusted using QDM, as this method preserves the simulated trends. As the last step, these adjusted time series are shuffled using the Schaake Shuffle (Clark et al., 2004) based on the rank order of the rotated dataset. A full mathematical description of the method can be found in Cannon (2018).

3.3.3 Rank Resampling for Distributions and Dependences

One of the most recent methods studied in this paper is the 'Rank Resampling for Distributions and Dependences' (R^2D^2) method, which was designed by Vrac (2018) as an improvement of the older EC-BC method (Vrac and Friederichs, 2015). Recently, R^2D^2 was further extended for better multisite and temporal representation by Vrac and Thao (2020b) (R^2D^2 v2.0). This method is a marginal/dependence multivariate bias-adjusting method, which adjusts the simulated climate dependence by resampling from the observed dependence. The resampling is applied through the search for an analogue for the ranks of a simulated reference dimension in the observed time series, which makes this an application of the analogue principle (Lorenz, 1969; Zorita and Von Storch, 1999) in bias adjustment. A detailed mathematical description can be found in Vrac (2018) and Vrac and Thao (2020b).

In the present application of R^2D^2, QDM was used as the univariate bias-adjusting method to ensure consistency with the other multivariate bias-adjusting methods. This ensures the preservation of the changes in the marginal distribution, besides the preservation of some temporal properties, which is inherent to the method. Each variable (precipitation, evaporation and temperature) was in turn used as the reference dimension. No other information was included, as the present study was limited to one grid cell.

3.3.4 Dynamical Optimal Transport Correction

Recently, Robin et al. (2019) indicated that the notion of a transfer function in quantile mapping can be generalised to the theory of optimal transport. Optimal transport is a way to measure the dissimilarity between two probability distributions and to use this as a means for transforming the distributions in the most optimal way (Villani, 2008; Peyré and Cuturi, 2019).

Optimal transport was used by Robin et al. (2019) to adjust the bias of a multivariate data set in the 'dynamical Optimal Transport Correction' method (dOTC), which extends the 'CDF-transform' (CDF-t) bias-adjusting method (Michelangeli et al., 2009) to the multivariate case. dOTC calculates the optimal transport plans from $\mathbf{X}^{\mathrm{ho}}$ to $\mathbf{X}^{\mathrm{hs}}$ (the bias between the model and the simulations) and from $\mathbf{X}^{\mathrm{hs}}$ to $\mathbf{X}^{\mathrm{fs}}$ (the evolution of the model). The combination of both optimal transport plans allows for bias adjustment while preserving the simulated changes in both marginal properties and the dependence structure. A full mathematical description of the method can be found in Robin et al. (2019).

3.4 Experimental design

Prior to all intensity-bias-adjusting methods, the thresholding occurrence-adjusting method was applied. In the intensity-bias-adjustment step, a balance was sought between randomness and computational power for the calculation of the intensity-bias-adjusting methods. Methods with randomised steps were repeated. As such, 10 calculations were made for dOTC. The resulting values of each index were averaged for further comparison. Biases on the indices were always calculated as raw or adjusted simulations minus observations, indicating a positive bias if the raw or adjusted simulations are larger than the observations and a negative bias if the simulations are smaller.

4 Results

In this section, the results will be shown first for the R index calculations for bias change, and then for the validation indices. For the validation indices, first the indices based on the adjusted variables are discussed, followed by an elaboration on the indices based on the derived variables. As the effect on discharge is the overarching goal of this paper and the discharge indices are affected by all other indices, those will be discussed last.

4.1 Bias change

The results for the R index vary considerably depending on the season: bias nonstationarity (R index values > 1) is present for all variables, but the extent varies. For precipitation, bias nonstationarity is most clear in winter and summer for the highest percentiles (P_{99} and $P_{99.5}$). For temperature, winter, spring and summer all show some high R index values, but while winter has high R index values for all percentiles, the nonstationarity is restricted to the lower to middle percentiles (T_5, T_{25}, T_{50} and T_{75}) for spring and the lower percentiles (T_5 and T_{25}) for summer. This is reflected in the mean and standard deviation: both are nonstationary for winter, whereas only the mean is nonstationary for spring and neither mean nor standard deviation is nonstationary for summer. In autumn, the behavior is less clear: two percentiles (P_{50} and P_{95}) have an R index value of 2, but unlike the other seasons, there is no apparent pattern as these values are far apart. However, the standard deviation has an R index value higher than 1 for autumn temperatures, indicating that some bias nonstationarity could be present. For evaporation, spring has the clearest bias nonstationarity: almost all percentiles have an R index value higher than 1. For the other seasons, the nonstationarity is less striking, although present. For winter and autumn, E_{75} has an R index value of 1 or higher and a clearly nonstationary standard deviation, while in summer, E_{25} and E_{50} have an R index value higher than 1, although neither mean nor standard deviation is clearly nonstationary. For occurrence the bias nonstationarity seems limited: only in spring and autumn, the R index value for precipitation lag-1 autocorrelation is higher than 1. For correlation, the bias nonstationarity is also limited, although some of the correlations of evaporation and either temperature or precipitation have an R index value higher than 1, but this depends on the season ($\text{crosscorr}_{E,T,0}$ and $\text{crosscorr}_{E,T,1}$ in spring, $\text{crosscorr}_{E,T,1}$ in winter, $\text{corr}_{E,T}$ in summer and $\text{corr}_{P,E}$ in autumn).

Many of the R index values thus indicate that the bias changes between the two periods considered here (1970-1989 versus 1998-2017) might already be large enough to have an effect on the bias adjustment. As these periods are only separated by 10 years, this is an important indicator for the bias adjustment of late 21st century data, just as Chen et al. (2015) mentioned. The results vary substantially among seasons, variables and distributions of the variables. Although this could give an indication of the reason for poor performance for some of these indices, it is impossible to state exactly what causes the bias nonstationarities purely based on these results. Possible causes could be that recent trends such as those in precipitation extremes (Papalexiou and Montanari, 2019) are poorly captured by the models, that limiting mechanisms such as soil moisture depletion (Bellprat et al., 2013) are poorly modelled or that natural variability (Addor and Fischer, 2015) influences the biases. However, discussing this in depth is out of the scope of the present study and deserves a separate study. In what follows, we will focus on the performance of the bias-adjusting methods and whether or not there is a link with these nonstationarities.

4.2 Precipitation amount

The Perkins Skill Score (PSS) for precipitation (Table 3) indicates that the PDFs of the observations and adjusted simulations agree rather well. These scores are very similar in the calibration and validation period. Only QDM and mQDM perform worse in every season, whereas the change performance of the multivariate methods depends on the season. For dOTC, the result is better in the validation period than in the calibration period.

Table 3. PSS values for precipitation in the calibration (Cal) and validation (Val) periods (%).

	Winter		**Spring**		**Summer**		**Autumn**	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val
QDM	96.5	94.1	97.2	95.0	97.9	96.7	96.8	94.3
mQDM	100.0	92.1	100.0	93.4	100.0	96.5	100.0	94.8
MBCn	94.1	89.9	95.6	95.5	92.6	97.3	97.2	96.8
MRQNBC	93.2	92.8	84.7	81.0	96.1	95.6	93.5	91.0
dOTC	64.6	73.8	66.6	70.0	62.2	91.6	62.8	72.0
R^2D^2	93.3	90.1	94.0	93.1	93.2	92.6	94.1	93.8

The good performance for the full PDF contrasts with the bias adjustment of the extreme values. Figure 1 presents the RB_O and RB_{MB} values for the highest P percentiles in the validation period. The lower percentiles (P_5 to P_{50}) are adjusted very well by all methods, but the performance of the methods for the higher percentiles differs considerably between the seasons. For winter (blue) and summer (yellow), only P_{75} and P_{90} can be plotted in the validation period, whereas for spring and autumn all percentiles, from P_{75} to $P_{99.5}$ can be plotted for all methods. The poor adjustment of the high percentiles in winter and summer could be caused by bias nonstationarity: the R index values for these percentiles are higher than 1, in contrast with the low and well-adjusted higher percentiles for spring and autumn precipitation. However, although P_{95} has an R index value lower than 1 for both winter and summer, it is poorly adjusted. This illustrates that the R index gives an indication of the nonstationarity, but also hides information on the size of the biases. For summer, the bias for P_{95} changes from 5.09 mm in the calibration period to 1.89 mm in the validation period, a change of over 3 mm. For winter, the bias changes from 1.44 mm in the calibration period to 0.52 mm in the validation period, a change of almost 1 mm. Yet, these differences have a very similar R index value. A comparison with the $\mathrm{RB}_{\mathrm{MB}}$ and RB_{O} values of the calibration period (Fig. 2) illustrates that all methods perform well for every season, indicating that the nonstationarity could be a cause of the diverging performances in the validation period between the winter/summer and spring/autumn pairs. However, this nonstationarity is not apparent from the PSS, as it only occurs in the tail of the distribution. This also follows from the R index values for the mean and standard deviation in winter and summer. Only for standard deviation, the R index value indicates nonstationarity in winter and summer: the values are respectively 1.79 and 1.56. Thus, the nonstationarity of the extremes and the standard deviation seem to be linked.

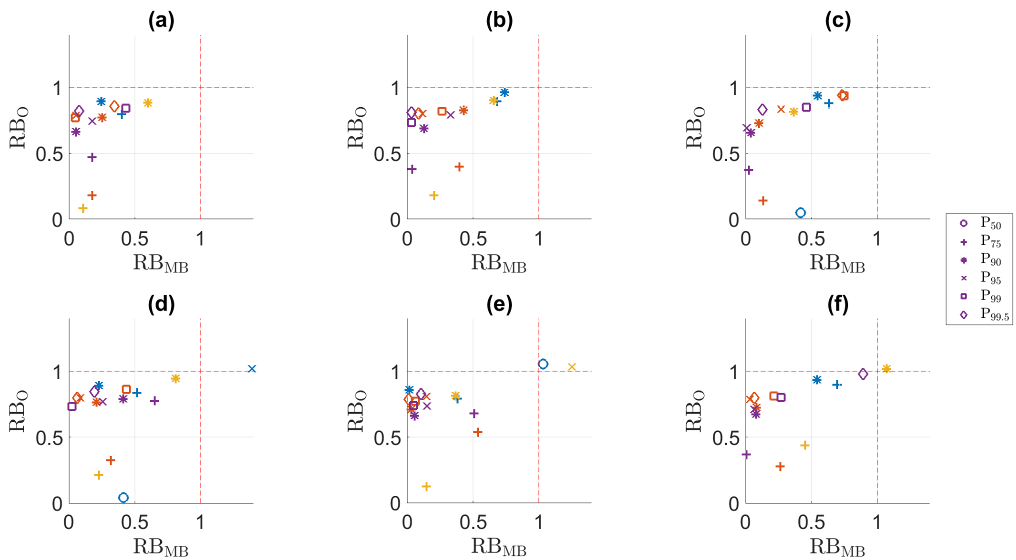

Figure 1. $\mathrm{RB}_{\mathrm{MB}}$ versus RB_0 for the precipitation in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) $\mathrm{R}^2\mathrm{D}^2$. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

The methods seem to perform rather similarly in every season. Although the $\mathrm{RB}_{\mathrm{MB}}$ values vary, indicating that for some methods the bias is removed to a larger extent, the RB_{O} values are similar, indicating that relative to the observations, the influence of the difference in removed bias is low. However, there is a difference that should be acknowledged. For example, on a yearly basis, the mean number of heavy precipitation days (R10, one of the ETCCDI indices (Zhang et al., 2011)) is well presented by all adjusted simulations (Fig. 3), but the yearly variance clearly depends on the method: MRQNBC overestimates the variance, whereas the other methods slightly underestimate it.

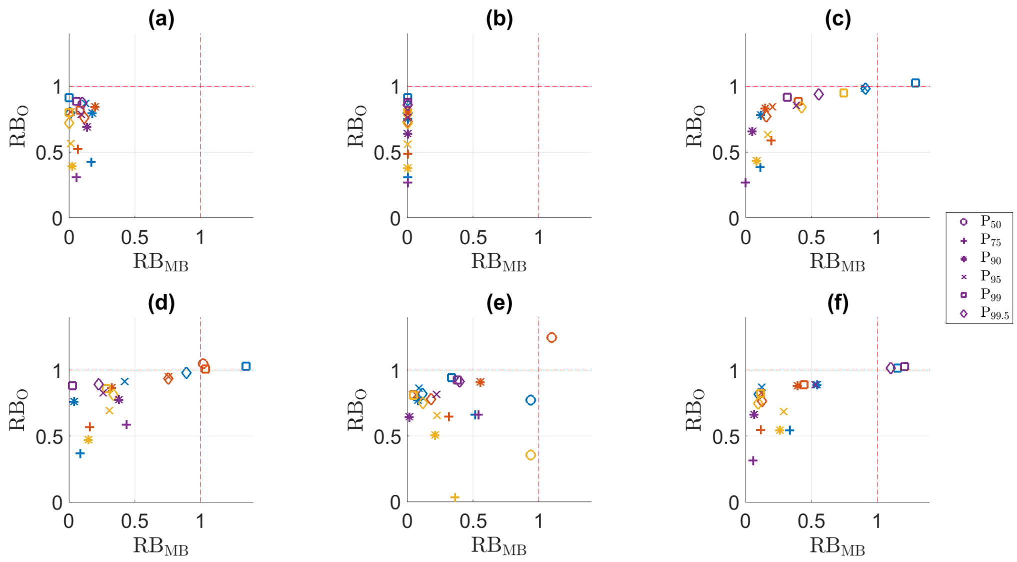

Figure 2. RB$_{MB}$ versus RB$_0$ for the precipitation indices in the calibration period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^{2}D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

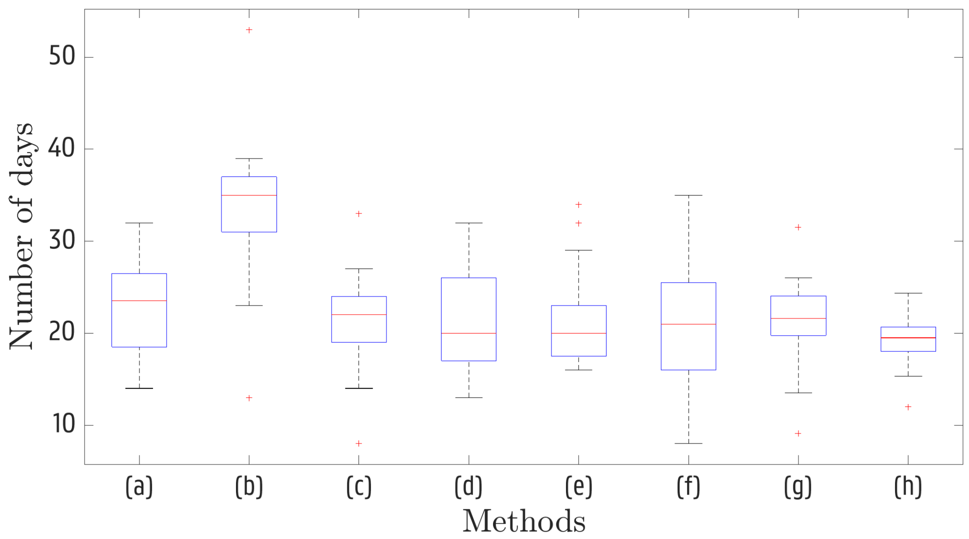

Figure 3. Box plot of the Annual number of days with precipitation higher than 10 mm (ETCCDI 'Heavy precipitation' days, see Zhang et al. (2011)) in the validation period. (a) observations, (b) raw simulations, (c) QDM, (d) mQDM, (e) MBCn, (f) MRQNBC, (g) dOTC, (h) R^{2}D^2.

4.3 Temperature

Table 4 displays the PSS values for temperature. It can be seen that the univariate bias-adjusting methods have higher values than the multivariate methods for all seasons. Among the multivariate methods, the performance also varies: dOTC performs best, whereas the performance for the other multivariate bias-adjusting methods depends strongly on the season. However, the multivariate methods are much more robust between the calibration and validation period: the performance of the univariate methods is worse in all seasons. Nonetheless, the univariate methods still perform better.

Table 4. PSS values for temperature in the calibration (Cal) and validation (Val) periods (%).

	Winter		**Spring**		**Summer**		**Autumn**	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val
QDM	97.1	93.4	95.8	86.8	96.8	88.7	96.5	91.4
mQDM	99.3	94.0	98.8	87.0	99.1	89.8	98.7	91.8
MBCn	52.7	52.5	78.6	77.1	44.8	39.2	77.9	79.3
MRQNBC	78.7	76.6	90.6	75.3	58.9	61.7	87.1	80.7
dOTC	81.6	82.0	81.8	83.0	79.2	77.5	80.3	83.3
R^2D^2	71.7	69.7	75.5	72.2	63.6	59.22	73.4	73.2

Although the PDF of the adjusted simulations matches the observed PDF relatively well, the RB_{MB} and RB_O values (Figure 4) show some clear differences between the seasonal bias adjustment: for winter (blue) all methods perform poorly, whereas for the other seasons, at least some methods are able to adjust the raw simulations. For winter, the R index values are high for all percentiles, which indicates that nonstationarity could be the cause for the poor performance. However, this is not clear-cut. When comparing the winter RB_{MB} and RB_O values of the validation period with those of the calibration period (Fig. 5; blue), it can be seen that only QDM (panel (a)) performs much better and that mQDM, MRQNBC and dOTC (respectively panels (b), (d) and (e)) perform slightly better in the calibration period. The better performance of these methods is clearest for the lower percentiles (T_5, T_{25} and T_{50}). MBCn (panel (c)) and R^2D^2 (panel (f)) seem to perform equally poor in both calibration and validation period. The poor performance of these two methods could be caused by the seasonal evaluation: both apply a shuffling algorithm over the full time period. However, for the other methods, this is harder to explain: QDM, mQDM and MRQNBC all use seasonal time windows, while dOTC does not. However, for QDM and mQDM, the moving time window used in the adjustment and the fixed seasonal window in the evaluation might cause a small mismatch. For MRQNBC, there is also the influence of the monthly and yearly adjustment. For dOTC, the optimal transport and, hence, stochastic element might be better suited for seasonal differences than the shuffling used by MBCn and R^2D^2, but still does not seem optimal. Besides, the seasonal variance is larger for temperature than for precipitation, which increases the susceptibility of the methods to differences in seasonal adjustment and evaluation. As a last reason, it should be considered that the RB_{MB} and RB_O values always depend on respectively the original biases and the observations.

At first sight, in spring (ochre), most methods, with the exception of MBCn (panel (c)) and MRQNBC (panel (d)), seem to perform relatively well. However, when comparing the biases of the validation period with those of the calibration period, the adjustment of T_5 by QDM, mQDM, MRQNBC and dOTC (respectively panels (a), (b), (d) and (e)) is clearly poorer, whereas the highest percentiles (T_{99} and $T_{99.5}$) perform similar to the calibration period or better. For MBCn and R^2D^2, the performance is similarly. The poor performance corresponds to the high R index value for T_5. For summer, this is also observed, although to a smaller extent: only QDM and mQDM were able to properly adjust T_5 in the calibration period. In general, QDM, MRQNBC and dOTC all perform slightly worse in the validation period in comparison with the calibration period for summer. mQDM performs similarly, whereas MBCn and R^2D^2 perform poorly in both periods. In autumn, the performance is poor for all methods in the validation period. However, except for QDM, the performance is poor in the calibration period as well, and, hence, conclusions are hard to draw. However, based on the R index values, which indicate limited nonstationarity, it could be assumed that the influence of the seasonality is larger than that of the nonstationarity.

Based on the results for winter and the lowest percentiles in spring and summer, it seems that the lower temperature values are more susceptible nonstationarity. This should certainly be accounted for when estimating extremes such as cold spells.

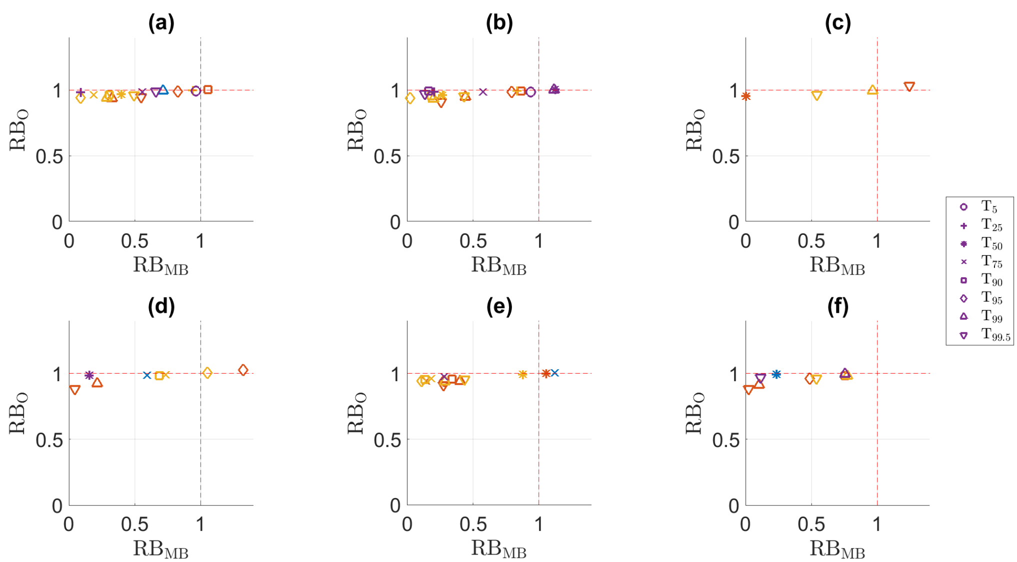

Figure 4. RB_{MB} versus RB_0 for the temperature indices in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^2D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple..

4.4 Potential evaporation

The PSS values for potential evaporation (Table 5) show that the univariate bias-adjusting methods perform better than the multivariate bias-adjusting methods, when considering the full PDF. Similarly to temperature (Table 4) the skill scores differ among the multivariate methods. However, in contrast to temperature, dOTC performs much worse for potential evaporation;

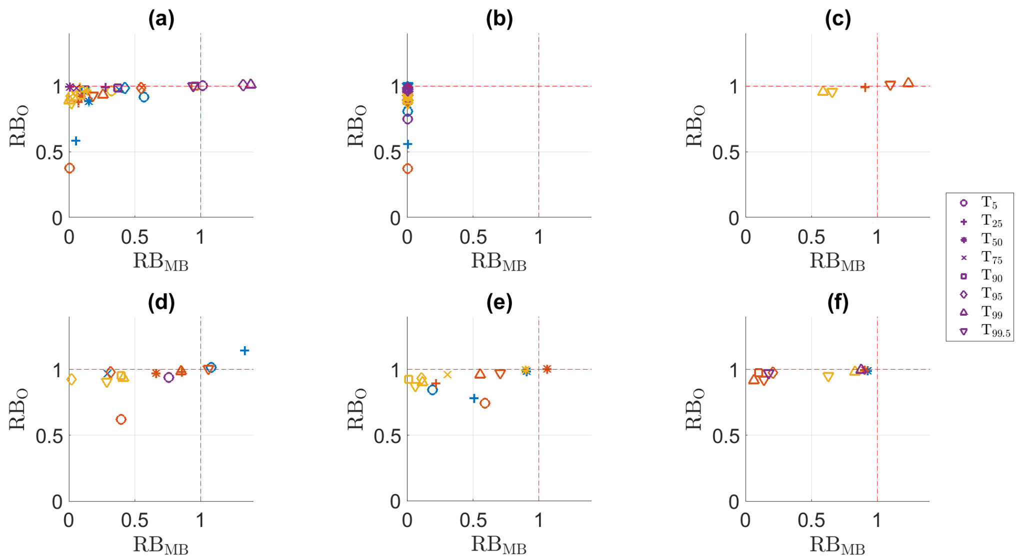

Figure 5. RB_{MB} versus RB_0 for the temperature indices in the calibration period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^2D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

MRQNBC performs best. Similarly to temperature, MBCn and R^2D^2 vary depending on the season. In comparison with the calibration period, the univariate methods perform worse in the validation period in every season, whereas this varies for the multivariate methods: only in spring and summer, all multivariate methods perform worse. For spring, the difference is large, which could be related to the clear nonstationarity for this season. For summer, the R index values are generally lower, which indicates less nonstationarity, but the difference in PSS between calibration and validation period is also smaller. The large difference for spring between both periods is striking, as this was not as apparent for winter temperatures, despite the high R index values. This could be explained by the R index values for the mean and standard deviation: for potential evaporation in spring, only the bias in the mean changed a lot, whereas for temperature in winter, both the biases in mean and standard deviation changed a lot. The combination of these bias changes could offset each other in the calculation of the PSS.

The RB_{MB} and RB_O results for potential evaporation in the validation period are displayed in Figure 6. For every season, all methods perform rather poorly, although there are differences between the method's performances and in the extent of nonstationarity. Based on the R index values and Table 5, it would seem that spring is most influenced by bias nonstationarity, as many percentiles have an R index value higher than 1 and the PSS values differ considerably for spring. Figure 6 shows that only E_5 (for QDM, mQDM, MRQNBC and R^2D^2, respectively panels (a), (b), (d) and (f)), E_{99} (for mQDM and MBCn, panels (b) and (c)) and $E_{99.5}$ (for mQDM and MBCn, panels (b) and (c)) have RB_{MB} and RB_O values lower than 1. Except for $E_{99.5}$, this corresponds to the percentiles that have an R index value lower than 1. For mQDM and MBCn, it cannot be ruled out that the good performance for $E_{99.5}$ is by accident. However, bias nonstationarity alone does not explain the poor performance: when comparing the biases in the calibration (Fig. 7) and validation periods, it can be seen that, except for

Table 5. PSS values for evaporation in the calibration (Cal) and validation (Val) periods (%).

	Winter		Spring		Summer		Autumn	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val
QDM	94.8	86.1	93.3	82.5	97.3	88.6	94.1	91.0
mQDM	100.0	90.5	100.0	83.4	100.0	87.7	100.0	92.4
MBCn	48.5	52.0	78.6	70.8	52.7	48.4	79.5	83.6
MRQNBC	89.1	84.5	91.4	74.1	80.2	78.0	85.1	88.6
dOTC	58.7	52.4	67.4	57.5	63.9	56.0	60.5	57.0
R^2D^2	80.4	79.3	69.1	59.5	66.5	63.9	78.6	76.5

mQDM, all methods perform poorly in the calibration period. For MBCn, dOTC and R^2D^2, which perform the worst in the calibration period, this could be related to the absence of a seasonal component, whereas this is less clear for QDM, mQDM and MRQNBC, as discussed in Section 4.3. Nonetheless, the latter three methods are all able to adjust E_{25} and E_{50}, two percentiles that cannot be adjusted by any method in the validation period.

In the other seasons, the methods behave similarly to spring: most of the multivariate methods perform as poorly in the calibration period as in the validation period (except MRQNBC, to some extent). The poor performance of the multivariate methods in the calibration period indicates that the absence of a seasonal component might have a large impact, as was also discussed in Section 4.3. This is confirmed by the results for the full year (not shown), which show that all methods perform well in the calibration period.

Despite the poor performance of some methods in the calibration period, even for these seasons some differences between the calibration and validation period are worth discussing. In winter (blue), where nonstationarity mostly affected the standard deviation, the performance of all methods for all indices is slightly worse in comparison with the calibration period. Only the lower percentiles (E_5 and E_{25}) can be adjusted well by almost every method. In summer (yellow), where the R index values indicated some nonstationarity for the lower E percentiles, the performance is poorer in the validation period for all percentiles except E_{99} and $E_{99.5}$ (and E_{90} for dOTC). However, the impact seems to be smaller for MBCn, dOTC and R^2D^2. In autumn (purple), the R index values indicated the largest impact on the standard deviation. As in winter, the best performance is obtained for the lowest percentiles and, for the univariate methods, for the highest percentiles (E_{99} and $E_{99.5}$). Despite the seemingly larger impact on the univariate methods in these three seasons, their adjustment is still better than the adjustment by the multivariate methods.

The results for potential evaporation have to be considered in comparison to the effective bias values for the original simulations and the adjusted simulations: the original biases were relatively small (not shown). Hence, even a small change in bias will have a large impact. Nonetheless, even these small changes and relatively small biases have an impact, which is reflected by the RB_O values. On the other hand, when considering the PSS values, which reflect the full PDF instead of focusing on the extremes, the impact is limited, although this depends on the method and season, as was shown for spring.

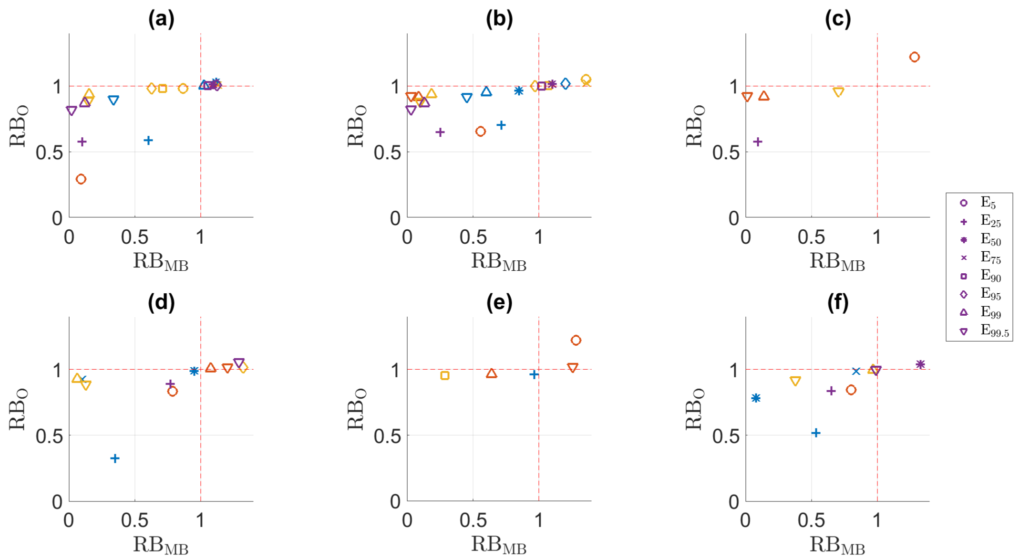

Figure 6. RB$_{MB}$ versus RB$_0$ for the potential evaporation indices in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^{2}D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

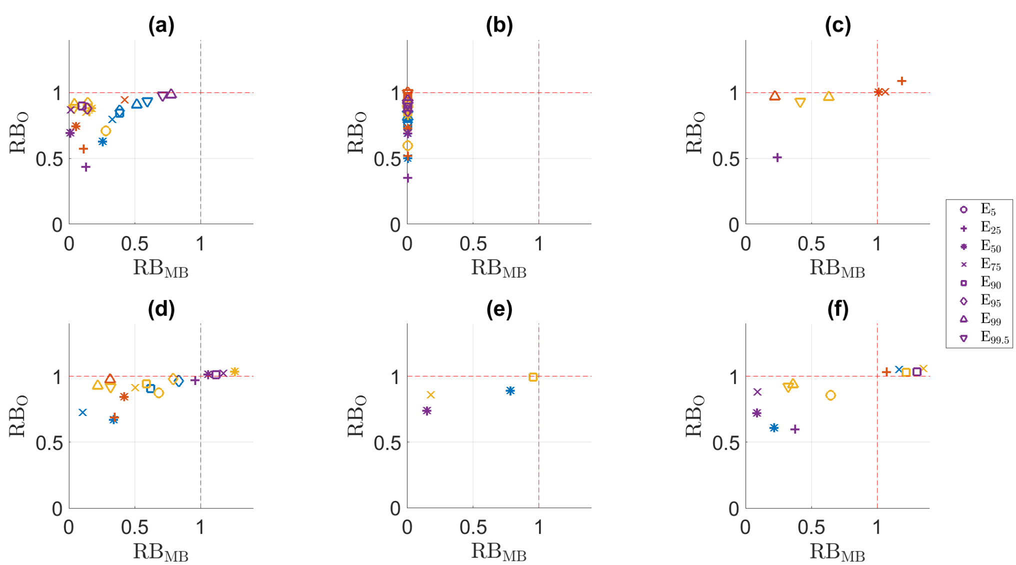

Figure 7. RB$_{MB}$ versus RB$_0$ for the potential evaporation indices in the calibration period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) Winter: blue, spring: ochre, summer: yellow, autumn: purple.

4.5 Correlation

For correlation (Fig. 8), all methods perform relatively well in the validation period. Both the univariate and the multivariate bias-adjusting methods can adjust the simulated biases well. The univariate methods will adopt the dependence structure of the raw simulations, whereas the multivariate methods are specifically designed to adjust the dependence structure, and both strategies seem to work well. However, it should be noted that some of the biases in correlation are very small in the raw simulations (not shown) and that for those correlations, the good adjustment by univariate methods is trivial: they will adopt the correlation of the simulations and only slightly adjust this by adjusting the marginals. This is linked with an issue raised by Zscheischler et al. (2019): in situations with low biases in the correlation, the univariate methods will almost always outperform the multivariate bias-adjusting methods, as specifically adjusting the dependence structure sometimes results in an increase of the bias.

The good performance for the validation period indicates that the impact of nonstationarity is limited, as was also shown by the small R index values (Section 4.1). This is confirmed by the biases in the calibration period (not shown), which are similar to those in the validation period. However, for some values, the R index value was higher than 1, thus it is important to know what caused this. For $\mathrm{corr}_{\mathrm{E,T}}$ in summer, the difference between the validation and calibration period is negligible, although only for QDM this value is well adjusted in both periods. However, the bias for the original simulations is lower than 0.10% in both the calibration and validation period, and switches in sign, which inflates the R index value. For $\mathrm{crosscorr}_{\mathrm{E,T,0}}$ and $\mathrm{crosscorr}_{\mathrm{E,T,1}}$, the same effect occurs. Besides, it seems that the bias of these three correlations is too small to be corrected by any method and that trying to adjust this automatically inflates the results. As discussed earlier, this shows that while the R index can be a valuable tool for some variables, it does not always tell the full story.

4.6 Precipitation occurrence

Figure 9 shows that the bias-adjusting methods are able to adjust the precipitation occurrence well in most seasons. Especially the univariate bias-adjusting methods perform well. Although the multivariate bias-adjustment always results in at least one index that is better than the raw climate simulations (except for MRQNBC in spring: panel (d), ochre), most indices are not, or only slightly better than the raw climate simulations. This is a disadvantage inherent to the current generation of multivariate bias-adjusting methods: as discussed in Section 3.3, the dependence adjustment will always influence the temporal structure (François et al., 2020; Vrac and Thao, 2020b). Nonetheless, on a seasonal level, the temporal structure is sometimes remarkably well adjusted, such as in summer (yellow) and autumn (purple).

The R index values indicated that there might be some nonstationarity in spring and autumn (Section 4.1): the value for P_{lag1} is 2, and for the other indices the values are clearly higher than those in winter and summer. In contrast to other situations of bias nonstationarity, this does not result in a poorer, but actually a better performance for these two seasons (calibration period not shown). Winter and summer, for which no nonstationarity could be detected, perform similarly in both the calibration and validation period. However, in all seasons mQDM (panel (b)) performs worse in the validation than in the calibration period. As this method uses the observed structure, the temporal structure is by construction perfect in the calibration period. The poorer

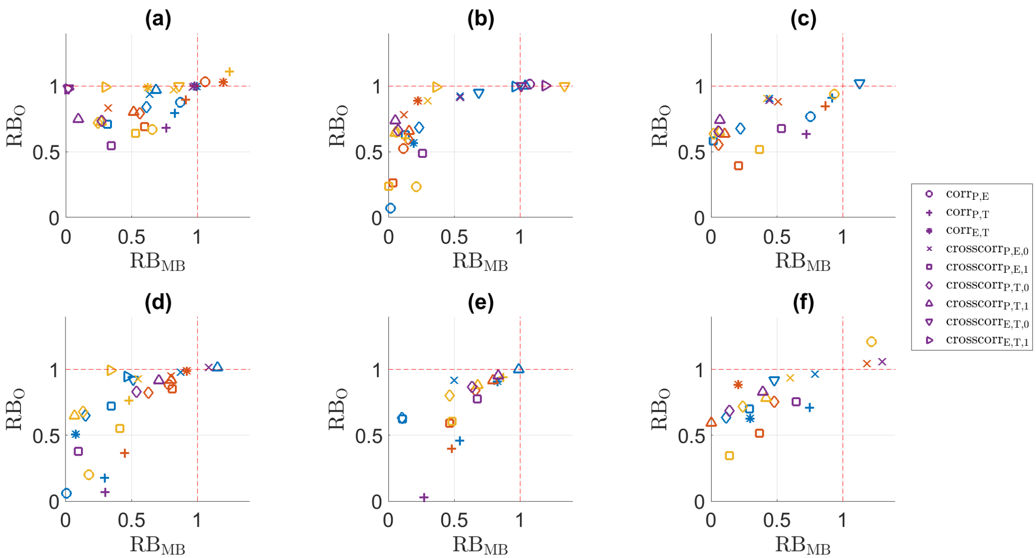

Figure 8. RB_{MB} versus RB_0 for the correlation indices in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^2D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

result in the validation period might imply that using the observed temporal structure does not suffice for future impacts, which might be important when using delta methods for impact assessment.

When comparing the methods, some differences related to their structure can be noticed. In general, QDM (panel (a) in Fig. 9) has the best performance of all methods for the occurrence, indicating once more the impact of the shuffling and similar algorithms of the multivariate bias-adjusting methods. Only in autumn (purple), MRQNBC (panel (d)) and R^2D^2 (panel (f)) perform as well as QDM. However, mQDM (panel (b) also performs well in all seasons, despite the poorer fit. There are also differences among the different multivariate bias-adjusting methods. In all seasons, MBCn (panel (c)) and R^2D^2 (panel (f)) are able to reduce the bias of the number of dry days, whereas this varies for MRQNBC and dOTC (panel (e)). The good performance for this index for MBCn and R^2D^2 is based on the use of thresholding and QDM for the marginal adjustment: these methods are able to perfectly adjust the number of dry days, and any remaining bias can be related to the combination of temporal shuffling and seasonal evaluation. However, dOTC adjusts P_{lag1} and P_{P10} well in every season. This implies that it is able to differentiate in the adjustment between zero and non-zero values, whereas longer series of zeros are harder to adjust. The incorrect series of zeros is probably also linked with one of the deficiencies of dOTC: it sometimes creates nonphysical precipitation values, which have to be corrected by thresholding.

4.7 Discharge

The Perkins Skill Score values for discharge (Table 6) show that the univariate bias-adjusting methods generally perform best, whereas the performance of the multivariate bias-adjusting methods depends on the season. However, all methods perform

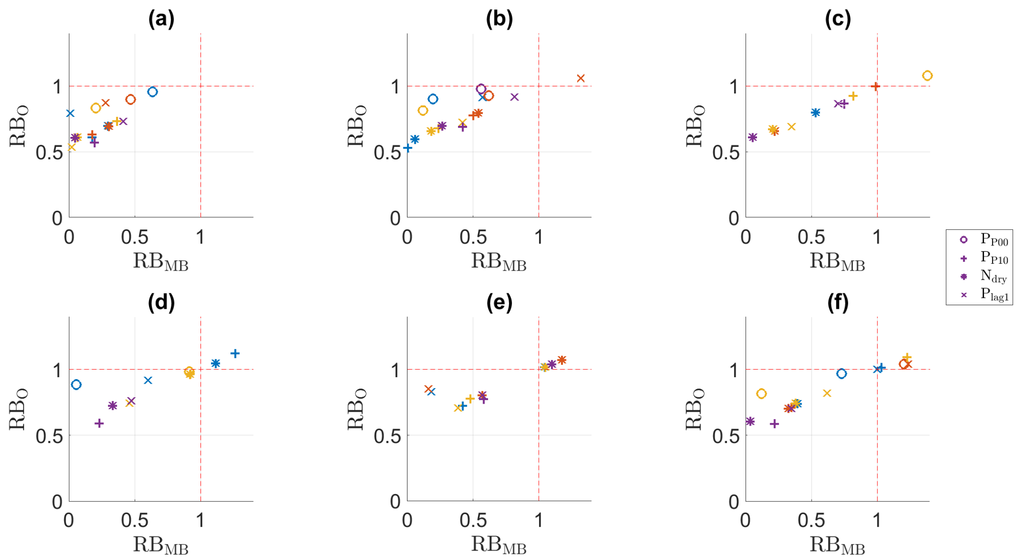

Figure 9. RB$_{MB}$ versus RB$_0$ for the precipitation occurrence indices in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^{2}D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

poorly for spring. The PSS values for evaporation clearly show the impact of nonstationarity, which seems to be propagating to the discharge PDF. This is illustrated when comparing with the PSS values for the calibration period: only in spring, all methods perform worse in the validation period than in the calibration period. For the other seasons, the impact is much more mixed.

Table 6. PSS values for discharge in the calibration (Cal) and validation (Val) periods (%).

	Winter		**Spring**		**Summer**		**Autumn**	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val
QDM	85.9	90.0	87.4	67.0	90.8	81.5	92.4	86.6
mQDM	99.6	85.3	100.0	60.8	100.0	76.8	100.0	86.2
MBCn	49.5	50.7	87.4	51.0	41.8	64.3	74.3	80.0
MRQNBC	92.2	86.4	67.3	38.6	89.1	85.1	57.7	49.8
dOTC	70.0	85.4	48.2	25.0	42.3	58.3	68.5	72.4
R^{2}D^2	75.0	78.0	73.1	42.8	43.2	40.0	69.3	63.8

The impact on the PDF for spring discharge does not clearly appear when comparing the RB$_{MB}$ and RB$_0$ values: for all methods and seasons, the bias adjustment seems to result in an agreeable representation of the discharge in the validation period (Fig. 10). However, when comparing these results with the residual biases in the calibration period (Fig. 11), it becomes clear that the results for winter and summer are much worse in the validation period. This corresponds with the poor performance for precipitation adjustment in these seasons, which was probably linked with bias nonstationarity.

The bias-adjusting methods seem to respond similarly to the nonstationarity. In winter (blue), QDM (panel (a)) performs slightly better, whereas in summer (yellow), R^2D^2 (panel (f)) performs relatively good. In spring (ochre), the methods also perform similarly, although QDM performs slightly better for Q_{99} and dOTC (panel (e)) performs worse than the other methods. As such, whether or not the methods take seasonality explicitly into account does not seem to matter for the impact on discharge. This also follows from the structure of the hydrological model: precipitation is a more important driver than potential evaporation. Seasonality in the bias adjustment had a larger impact on potential evaporation, but this impact disappears when using these variables as inputs to the hydrological model. Besides, it can also be seen that if an important forcing variable for an impact model shows large nonstationarity, this nonstationarity will propagate through the model. This helps explaining the differences between the PSS and the RB values: the impact of nonstationarity on potential evaporation propagates as an influence on the PDF structure, but is less visible in the final bias, as the amount of precipitation has a much larger impact in the hydrological model. Hence, the final bias is more influenced by precipitation nonstationarity.

The impact of bias nonstationarity varies between winter (blue) and summer (Fig. 10, yellow). In winter, the impact is more clearly visible on the higher percentiles: Q_{99}, $Q_{99.5}$ and Q_{T20} are all well adjusted in the calibration period by QDM, mQDM, dOTC and R^2D^2, but are much worse adjusted in the validation period. In summer, the impact seems to be similar for all the percentiles.

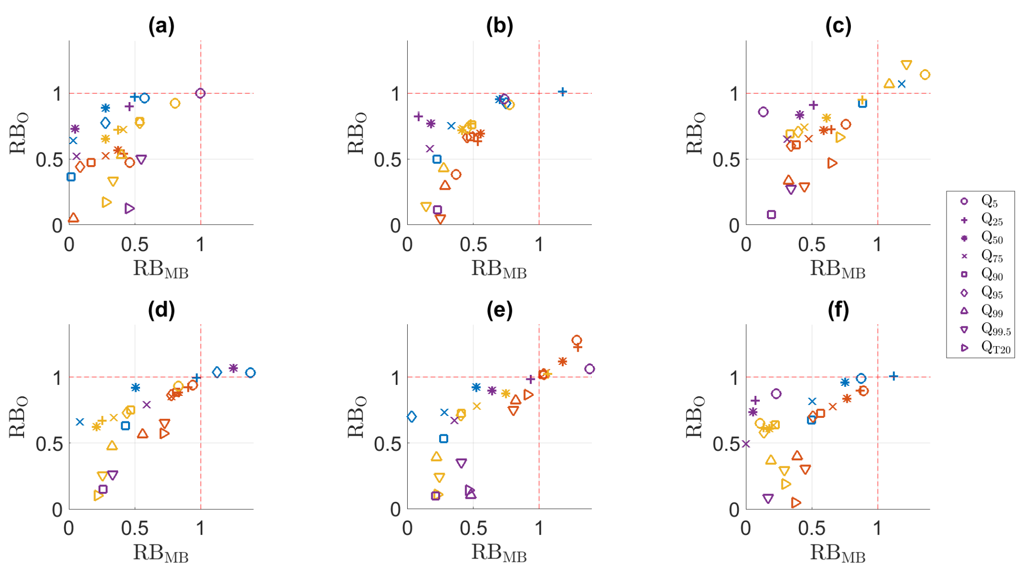

Figure 10. RB_{MB} versus RB_0 for the discharge percentiles and the 20-year return period value in the validation period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) R^2D^2. Winter: blue, spring: ochre, summer: yellow, autumn: purple.

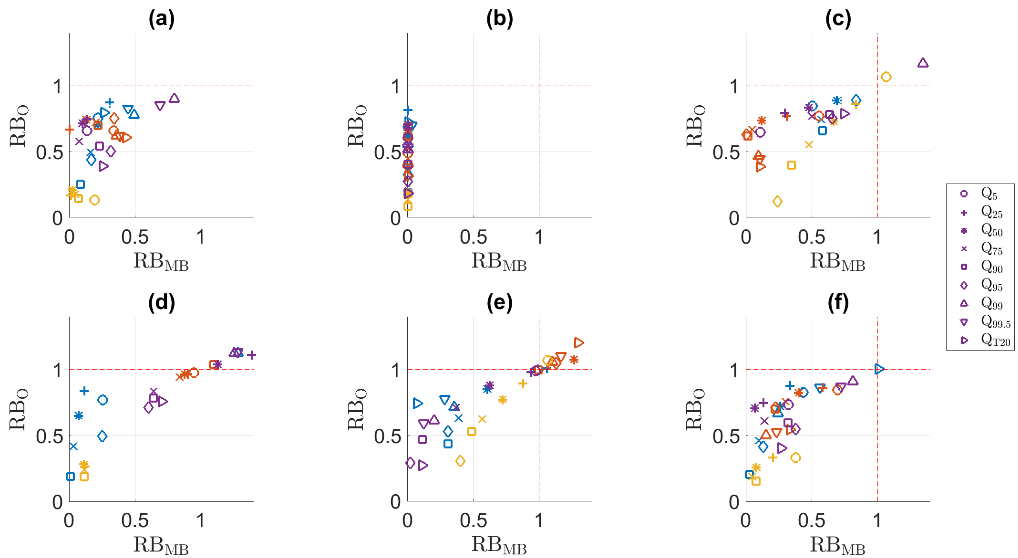

Figure 11. $\mathrm{RB_{MB}}$ versus $\mathrm{RB_0}$ for the discharge percentiles and the 20-year return period value in the calibration period. (a) QDM, (b) mQDM, (c) MBCn, (d) MRQNBC, (e) dOTC, (f) $\mathrm{R^2D^2}$. Winter: blue, spring: ochre, summer: yellow, autumn: purple.dr

5 Discussion and conclusions

The goal of this paper was to assess how six bias-adjusting methods handle a climate change context with possible bias nonstationarity. Four of the methods were multivariate bias-adjusting methods: MRQNBC, MBCn, dOTC and $\mathrm{R^2D^2}$. The two other ones were univariate: one was a traditional bias-adjusting method (QDM), while the other was almost the same method, but modified according to the delta change paradigm (mQDM). These univariate methods were used as a baseline for comparison. The climate change context, using 1970-1989 as calibration time period and 1998-2017 as validation time period, allowed us to calculate the change in bias between the periods, or the extent of bias nonstationarity, using the R index. The results of all methods were compared using different indices, for which the residual biases relative to the observations and model bias were calculated. Although the study was limited in spatial scale and climate models used, this yielded some results that could be valuable starting points for future research.

The calculated R index values generally demonstrated that the bias of some of these indices is not stationary under climate change conditions, although the extent of bias nonstationarity depended on the variable and index under consideration. The bias nonstationarity could be clearly linked to the poor performance of bias-adjusting methods for precipitation, and to some extent for temperature and potential evaporation. For both precipitation and evaporation, it could be observed that the nonstationarity propagated through the rainfall-runoff model used for impact assessment, and that the propagation was different for these variables.

In the context of nonstationarity, it is important to discuss how well the methods performed. Some observations could be made. First, the univariate bias-adjusting methods are relatively robust. Although there always is an impact when bias nonstationarity is present, the univariate bias-adjusting methods still perform best when considering the PSS values, i.e. the full PDF. However, the methods are specifically designed to alter the marginal distributions. As already discussed in Section 4.5, it was pointed out by Zscheischler et al. (2019) that the multivariate bias-adjusting methods were made with other principal goals, such as spatial and dependence adjustment. As it is not assessed in this study, we cannot comment on the spatial adjustment. Nonetheless, the study by François et al. (2020) illustrated that the multivariate bias-adjusting methods can be very informative and robust for spatial adjustment. Concerning the dependence adjustment, it was shown in Section 4.5 that the multivariate methods all perform well for the area and model chain studied here. Second, while QDM and mQDM seem to respond similarly, it should be taken into account that mQDM is designed to have a perfect fit in the calibration period. However, the poorer performance of mQDM for the precipitation occurrence indices is an indication that assuming that the temporal structure of the past can be used for the future might be dangerous, as Johnson and Sharma (2011) and Kerkhoff et al. (2014) already mentioned. Given that mQDM performed worse for two time periods separated by 10 years only, it is unlikely that it is safe to use this method, or other delta change-based methods, for impact assessments targeting the end of the 21st century that depend on the temporal structure of time series. Yet, for some other indices, especially the correlation, mQDM performed better. Consequently, the exact choice should depend on the goals of the end user. Third, the methods with seasonal components do not always perform similarly. MRQNBC is able to address seasonal effects, but its performance varies strongly depending on the variable. Even in the situation where the univariate methods perform well, MRQNBC sometimes performed much worse, such as for temperature in autumn or in winter (Fig 4, panel (d), respectively purple and blue). Although these three observations can be made, it is impossible to fully discuss the method performance based on the set-up considered. The most important cause is the seasonality of the bias nonstationarity: while the bias nonstationarity shows clear differences between the seasons, some of the multivariate bias-adjusting methods are not yet equipped to handle seasonality. When there are large seasonal differences for the variables, for example for E and T, this causes a relatively poor performance in the calibration period, and a similar poor performance in the validation period. It is thus unclear whether the poor seasonal performance obfuscates the effect of nonstationarity, or if the similar performance is a sign of robustness. An earlier study (Guo et al., 2020) indicates the former, but this could also be location- and method-dependent. Hence, the set-up does not allow to clearly discern between the various categories of multivariate bias-adjustment, such as the ‘marginal/dependence’ or ‘all-in-one’ categories. To fully address the question on performance under bias nonstationarity, a better seasonal performance for the multivariate bias-adjusting methods seems crucial. However, not only seasonal differences in bias nonstationarity should be acknowledged: for variables other than P, T or E, or for other regions, bias nonstationarity might be better discernible on a monthly timescale, on a yearly timescale, or even on longer timescales. Only a few multivariate bias-adjusting methods specifically address multiple timescales, such as MRQNBC (Mehrotra and Sharma, 2016), or more recently, ‘Multivariate Frequency Bias Correction’ (MFBC) (Nguyen et al., 2018) or ‘3DBC’ (Mehrotra and Sharma, 2019). Yet, the varying performance of MRQNBC shows that the implementation of the seasonality can have a large impact. As such, the question about seasonality is not easy to answer.

The validation results could only be obtained by analysing and comparing a broad combination of indices. Considering only the mean or other standard statistics would have hidden many of the results seen. For example, in contrast to the results for the mean, the inclusion of both high and low extremes highlighted some problems with bias nonstationarity for some variables. As such, this study does not contradict earlier studies such as Maraun (2012), where the mean-based biases were found to be rather stable. Thus, we repeat the advice by Maraun and Widmann (2018a) to use indices not directly affected by bias-adjusting methods and to analyse the user needs before deciding upon the bias adjustment validation method. An important limitation is that we only used one GCM-RCM-combination. Using a model ensemble would be more informative, but could hide a single model's poor performance. On the other hand, similar assessments could also be used to discard poor-performing models, based on the R index (also suggested by Maurer et al. (2013)) or the remaining bias after adjustment. However, the used indices can still be improved. Although the R index provides a lot of insight into the bias nonstationarity, it has been shown to over- or underestimate the effect of bias nonstationarity depending on the size and sometimes even the sign of the original bias. Other criteria also exist, such as the 'signal-to-noise ratio' (SNR) used by Hui et al. (2020). The different criteria or indices should be compared and maybe new tools are needed, so that the issue of bias nonstationarity can be more thoroughly explored.

To have a better view of how these results should be interpreted for impacts and compound events, the perspective of the end user should be considered (Maraun et al., 2015; Maraun and Widmann, 2018b). We used discharge as an example, using the relatively simple PDM. Even for this model, it could be observed that bias nonstationarity can propagate in multiple ways. The influence of the nonstationarity in precipitation was most clear in summer and winter. As precipitation is the driving variable for the PDM, even the limited nonstationarity, mostly in the precipitation extremes, had an influence on the discharge simulation, as could be seen for the discharge in winter and summer (Fig. 11, respectively blue and yellow). In contrast, the nonstationarity in evaporation propagated much less. However, it had an effect on the full PDF in spring, as could be observed from the PSS value for discharge (Table 6). In spring, no nonstationarity could be observed for precipitation, which allowed the influence of evaporation to be larger, although it theoretically has a smaller influence than precipitation on the discharge. The different propagation of bias nonstationarity, observed here for the extremes versus the full PDF, can be important considering that bias adjustment can be applied for many different types of impact assessment. However, the assessment in this study is relatively simple. For other impact studies, the results may vary considerably. For example, forest fires (a typical compound event, discussed in a bias adjustment context in e.g. Yang et al. (2015), Cannon (2018), Zscheischler et al. (2019)) depend more heavily on T and E to simulate fire weather conditions. Besides such compound events, other types of application can use a wide variety of variables and, hence, the bias nonstationarity may differ. In all of these studies, the propagation of bias nonstationarity will depend on the timescales considered in the impact assessment, the timescales on which nonstationarity is present, the variables considered and the spatial scale. Although this last aspect is limited in this study, it can be assumed that if bias nonstationarity is present in one grid cell, it will also be present in neighbouring grid cells with similar climatic conditions.

To conclude, the results discussed in this paper indicate that bias nonstationarity can have an important influence on the bias adjustment and the propagation of biases in impact models. Depending on the extent of nonstationarity (spatial, temporal and the variables affected), such propagation should be taken into account far more when studying future impacts. As authors have mentioned before (Ehret et al., 2012; Maraun, 2016; Nahar et al., 2017), this foremost implies that climate models have to become better at modelling the future: we need to be able to trust them as fully as possible. As long as this is not the case, bias adjustment methods have to be developed that are more robust and that are able to help us assessing the future correctly. As such, the issue of seasonality as raised here is very important. Yet, impact assessment cannot wait for new methods to be developed and/or tested: we need to prepare ourselves for the future as soon as possible. For now, we can state that for a robust bias adjustment under bias-nonstationary conditions, accounting for seasonality is crucial. Given this statement, we advise to use univariate bias-adjusting methods, until it becomes more clear how it can be ensured that multivariate methods certainly perform well under bias nonstationarity.

Code and data availability. The code for the computations is publicly available at https://doi.org/10.5281/zenodo.4247518 (Hydro-Climate Extremes Lab – Ghent University, 2020). All methods were implemented in Matlab, except R2D2, for which the R package "R2D2" was used (Vrac and Thao, 2020a). The RCA4 data are downloaded and are available from the Earth System Grid Federation data repository. The local observations were obtained from RMI in Belgium, and cannot be shared with third parties.

Author contributions. JVDV, BDB and NV designed the experiments. JVDV developed the code and performed the calculations. JVDV prepared the manuscript with contributions from MD, BDB and NV. All co-authors contributed to the interpretation of the results.

Competing interests. The authors declare that they have no conflict of interests.

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