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climQMBC: A package with multiple bias correction methods of GCM climatic variables at daily, monthly and annual scale, developed in Python, R and MATLAB

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Abstract. Climate change projections are studied using General Circulation Models (GCMs). GCMs are models that simulate climate on a broad scale, hence they cannot be directly used in local impact studies, such as, for example, hydrological studies. GCMs must go through a process of downscaling, to adjust their results in terms of spatial scale and reduce their bias before being used at the local scale. Quantile Mapping is one of the most widely used approaches for bias correcting GCM climate outputs. However, in its conventional formulation QM assumes a time-invariant correction function, which potentially results in additional biases. This has motivated the development of trend-preserving variations, accounting for a non-stationary correction function and aiming to preserve the raw GCM signal. Unfortunately, choosing which variation to use is not straight-forward. We present the climQMBC package (https://github.com/saedoquililongo/climQMBC or https://doi.org/10.5281/zenodo.18392900) as an easy-to-use tool to compare quantile mapping approaches. climQMBC is available in Python, R and MATLAB, and contains the classic QM method and four trend-preserving variations: Detrended Quantile Mapping (DQM), Quantile Delta Mapping (QDM), Unbiased Quantile Mapping (UQM) and Scaled Distribution Mapping (SDM). This package has a built-in summary report that allows comparing methods in terms of their capability of preserving raw GCM trends. A synthetic exercise showed that the most reliable methods are the UQM and DQM.

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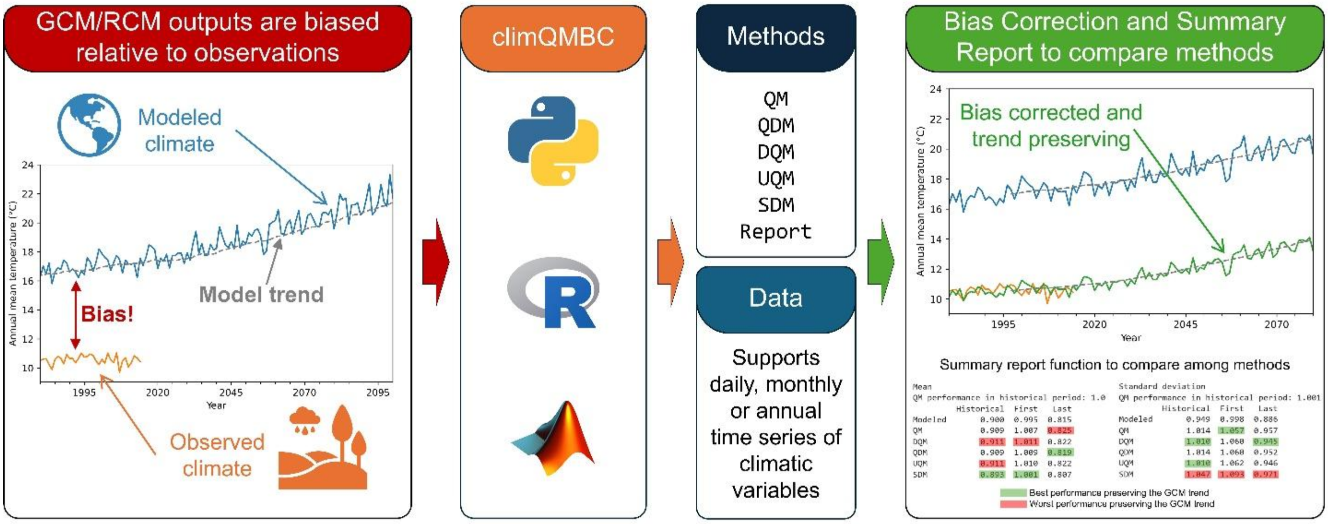

1 Introduction

Results from General Circulation Models (GCMs) or Regional Climate Models (RCMs) are often used to assess climate change impacts on water resources, crop productivity, heat waves, among others climate risks (Fowler et al., 2007; Cannon, 2017; Portalanza et al., 2024). However, GCMs spatial resolution is not suitable for local-scale analysis as these models have biases associated with the parametrization of sub-processes, and their results correspond to mean values over large area (~ hundreds of km) (Mauritsen et al., 2012; Yuval and O'Gorman, 2020). On the other hand, RCMs are climate models with higher spatial resolution, driven by GCMs results, allowing for a higher topography detail and sub-processes representation; however, RCMs results are also biased with respect to observations at the local scale (Christensen et al., 2008; Hakala et al., 2019; Bayissa et al., 2021; Petrovic et al., 2024). Several bias correction (or bias adjustment) methods have been developed to fulfill the limitations of climate models and allow the assessment of climate change impacts at the local scale (e.g. Maraun et al., 2010; Teutschbein and Seibert, 2012; Gutiérrez et al., 2013; Maraun, 2016, Bedia et al., 2020). One approach that stands out is that of quantile mapping, given its easy implementation, low need of calibration parameters, low computational cost, and applicability to several climate variables (e.g., temperature and precipitation) (Andres et al., 2014; Kim et al., 2016).

The classical Quantile Mapping method (QM; Wood et al., 2002) removes the climate model bias by matching the historical model distribution to that of the observed climate. Then the same correction is applied to the projected period. This implies a time-invariant assumption where the transfer function obtained with information from the historical or reference period is valid for the projected periods (Christensen et al., 2008; Maraun, 2012; Themeßl et al., 2012; Brekke et al., 2013; Chen et al., 2013). Several studies have raised concerns towards this stationarity assumption of the QM method and its capability to preserve the climate models signal (Hageman, 2011; Ehret et al., 2012; Maurer et al. 2013; Maurer and Pierce, 2014; Cannon et al., 2015; Pierce et al., 2015; Hnilica et al., 2017; Chadwick et al., 2018; Chadwick et al, 2023). As a response to this issue, several authors have developed trend-preserving versions of the quantile mapping approach focusing on preserving the raw changes or signals of the climate models (e.g. Bürger et al., 2013; Cannon et al., 2015; Switanek et al., 2017; Chadwick et al., 2023).

Some of the trend-preserving methods are: the Detrended Quantile Mapping (DQM; Bürger et al., 2013), developed to preserve the projected changes in the mean; the Quantile Delta Mapping (QDM; Cannon et al., 2015), developed to preserve the projected changes in the quantiles; the Scaled Distribution Mapping (SDM; Switanek et al., 2017), developed to preserve the likelihood of events and changes in quantiles; and the Unbiased Quantile Mapping (UQM; Chadwick et al., 2023), developed to preserve the changes in statistical moments: mean and standard deviation. Several studies have shown that these modified versions outperform the classical QM method (e.g. Cannon et al., 2015; Switanek et al., 2017; Chadwick et al., 2023). Currently, the QM method and its trend-preserving variants are widely used in several areas of analysis (Fowler et al., 2007; Cannon, 2017; Portalanza et al., 2024).

It is worth noting that there is no consensus regarding the quantile mapping method that is the most adequate for each specific condition. However, as Hakala et al. (2019) detail, the climate change impacts assessment is surrounded by uncertainties in each of the assessment steps, including the GCMs drivers and construction, the downscaling process (RCMs and/or bias correction), and the tool to assess the specific risk (e.g. hydrological models). Thus, choosing a bias correction method should not be a simple decision as it could add additional uncertainty or bias to the related assessment (Hanel et al., 2017; Aedo-Quililongo, 2024; Aedo-Quililongo and Chong, 2024). Hence, there is the need for tools to implement several quantile mapping methods to compare their results and discern the most appropriate for each specific condition (Polasky et al., 2023).

Several efforts have been made to provide users with different versions of the quantile mapping approach for their climate change impacts assessment workflow. The publicly available coding packages for bias correction of climatic variables based on the approach have the following characteristics: 1) the existing coding packages are available mainly in R (MBC, https://github.com/cran/MBC; downscaleR, https://doi.org/10.5281/zenodo.5070432; snowQM, https://doi.org/10.5281/zenodo.10257951), Python (pyCAT, https://github.com/wegener-center/pyCAT; xclim, https://doi.org/10.5281/zenodo.18352200; ibicus, https://doi.org/10.5281/zenodo.8101842) and MATLAB (GCD, https://github.com/thomasmosier/GCD), and a few in Julia (ClimateTools.jl, https://doi.org/10.5281/zenodo.8047681), NCAR programming language (QQmap, https://doi.org/10.5281/zenodo.4009101), Excel (ClimateScenarioAnalysisToolbox, https://github.com/mxgiuliani00/ClimateScenarioAnalysisToolbox), among others; 2) there used to be a research lab with a package available in two programming languages, but one of these is no longer available; hence, at this moment, none of the explored tools is available in more than one programming language with the exact structure and functionality to allow a unique framework for different user needs or capabilities; 3) the more sophisticated packages are usually frameworks, like the xclim (Bourgault et al., 2023) and downscaleR (Iturbide et al., 2019), that aim for a more complete tool that escapes from the scope of users that only require the downscaling process in their workflow; thus, a deep understanding of the workflow

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and more structured inputs are needed, which could lead to avoid using that package; and 4) except for the MBC package, which includes several multivariate versions of quantile mapping, but not several trend-preserving bias correction methods, to the best of our knowledge, no package includes more than three contrasting trend preserving bias correction methods to systematically compare their performance in a simple and user-friendly framework. Thus, there is the need for comprehensive coding packages that implement and allow comparing a wide range of quantile mapping methods to facilitate the obtention of local climatic projections and discern the most appropriate one for specific applications.

This paper presents and assesses the climQMBC coding package (Aedo-Quililongo et al., 2026), an easy-to-use tool written in Python, R and MATLAB to perform bias correction of climatic variables with the QM, DQM, QDM, UQM and SDM methods for daily, monthly and annual time series. This package aims to make available the QM and several trend-preserving QM methods to facilitate the performance assessment of these methods, making it easier to incorporate the bias correction process as a standard part of climate change impact assessment of final users of local climatic projections that might not be directly related to climate sciences. The climQMBC package also includes a summary report utility to easily compare the performance of the implemented methods at the monthly temporal scale, allowing the user to identify the most appropriate method for their specific situation.

For demonstration purposes, we present a synthetic example to show the capabilities of the climQMBC package to systematically bias correct climatic variables and to show the general performance of the implemented methods. Additionally, we show with a few lines of code how to bias correct real data with the climQMBC package and compare the performance of the implemented methods with the summary report utility.

2 Climate change impact assessment

Climate change assessment at local scales based on projections from climate models (GCMs or RCMs) requires a downscaling and/or bias adjustment/correction process to overcome the differences in resolution and biases of climate models and local climate. The bias corrected climatic variables are then used to assess climate change impacts on water availability, crop productivity, wildfire, or heat waves occurrence, among many others. Figure 1 presents a general workflow of a typical assessment study of climate change impacts, highlighting in grey where the climQMBC package is involved.

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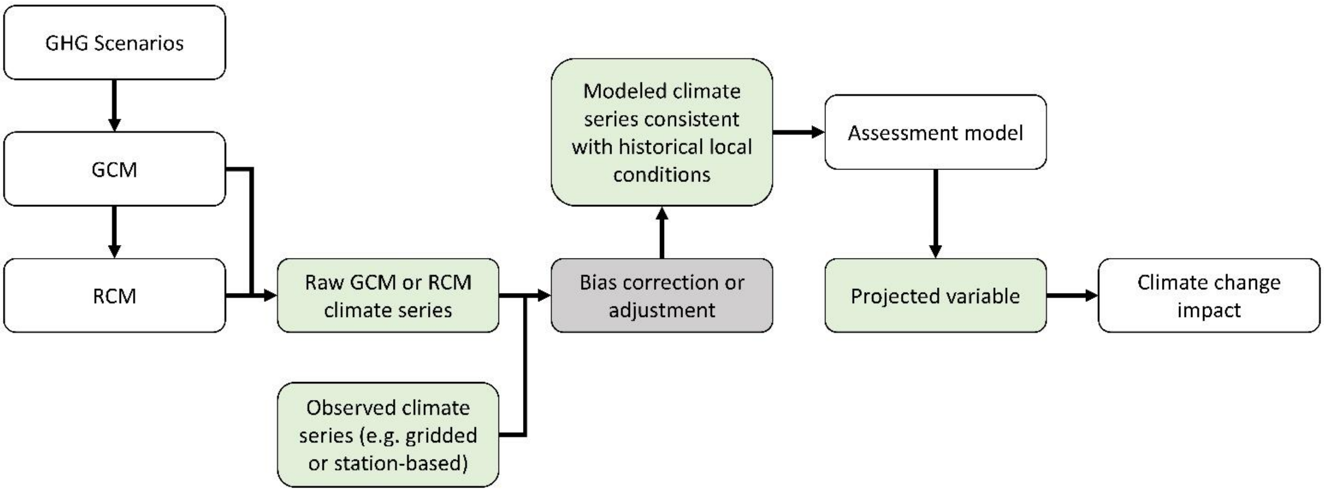

Figure 1: General workflow of a typical assessment study of climate change impacts. Green boxes indicate data or time series. Grey box shows where the climQMBC package is involved in the workflow.

3 climQMBC package

3.1 Package characteristics and functionalities

The climQMBC package is a coding package available for Python, R and MATLAB that contains five bias correction methods: QM, DQM, QDM, UQM, and SDM. These methods were implemented for variables associated to both relative (or multiplicative) and absolute (or additive) changes (e.g., precipitations and temperature, respectively). The package supports point or station-based data at daily, monthly or annual time step. The bias correction process and a unified description of methods implemented in the climQMBC package are summarized in the following subsections.

3.1.1 Bias correction process in the climQMBC package

The climQMBC package takes as input (1) an observed and modeled series at one specific point, (2) a flag indicating if the variable allows negative values, (3) a flag indicating if the variable is related to relative or absolute changes (does not apply for the QM method), and (4) a flag indicating if the series frequency is daily, monthly or annual. In the SDM method, a single flag is used to indicate if the variable allows negative values and is related to absolute changes or if the variable does not allow negative values and is related to relative changes, as this method was built explicitly for temperature and precipitation. On the other hand, the modeled series is a single series that merges the historical and future projected periods starting on the same date as the observed series. In the climQMBC package, the trend-preserving bias correction methods capture the transient model changes by a continuum approach using moving windows, as recommended by Chadwick et al. (2018), to capture the non-stationary signals of the GCM. Hence, for each value x of the modeled future period, the climQMBC package considers moving windows with length equal to the number of observed years, ending in the value to be

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corrected (Fig. 2). The moving window strategy is an improvement implemented in Chadwick et al. (2023), as the original DQM, QDM and SDM consider future data as a single window.

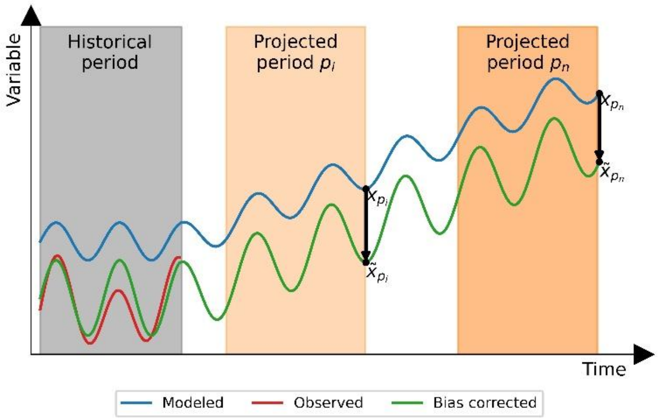

Figure 2: Schematic illustration of the trend-preserving bias correction (i.e., all but the QM) continuum approach considered in the climQMBC package. Each projected period p ends in the value x which is corrected to a value $\tilde{x}$, considering the change rates between the projected and historical period of the modeled series.

As an example of the moving window, if the observed period is 1985-2014, then the moving window will consider 30 years, and when correcting a future year, e.g., 2030, the moving window will cover 2001-2030. Each moving window is used to compute the change rates of the modeled series and the probability distribution function (if applies), and to modify the modeled value x to a corrected value $\tilde{x}$. Periods of 20 to 40 years are recommended. Shorter periods might not capture correctly the variable statistics, while longer ones might dampen the signal of the variable or induce a "pseudo-stationary bias" of the transient changes (Chadwick et al., 2023). Note that during the historical period, DQM, QDM and UQM methods become the standard QM method as the change rates are 0 for additive changes and 1 for relative changes (Chadwick et al., 2023).

When the frequency is set to monthly, the bias correction process is performed for each month of the year independently (e.g., each January is corrected based on the information of January in the historical and projected period). If the frequency is set to daily, the bias correction process is performed for each day of the year considering a centered moving window of length defined by the user (e.g., if the window is of 31 days, then the 16th of July uses the days between July 1st to July 31st to compute the required statistics for the bias correction).

The values of the historical period and each projected period are used to fit a probability distribution function. Furthermore, changes in the mean (δ_μ), standard deviation (δ_σ) or quantiles (Δ), depending on each method, between the projected and historical period of the modeled series are computed with the following equations:

$$\delta_\mu = \begin{cases} \dfrac{\overline{x_{m,p}}}{\overline{x_{m,h}}}, & \text{relative change variable} \\ \overline{x_{m,p}} - \overline{x_{m,h}}, & \text{absolute change variable} \end{cases}, \tag{1}$$

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$$\delta_{\sigma} = \begin{cases} \dfrac{\widetilde{x_{m,p}}}{\widetilde{x_{m,h}}} & \text{, relative change variable} \\ \widetilde{x_{m,p}} - \widetilde{x_{m,h}}, & \text{absolute change variable} \end{cases}, \tag{2}$$

$$\Delta = \begin{cases} \dfrac{F_{m,p}^{-1}(\tau_p)}{F_{m,h}^{-1}(\tau_p)} & \text{, relative change variable} \\ F_{m,p}^{-1}(\tau_p) - F_{m,h}^{-1}(\tau_p) & \text{, absolute change variable (all but SDM),} \\ \dfrac{\widetilde{x_{o,h}}}{\widetilde{x_{m,h}}}\left(F_{m,p}^{-1}(\tau_p) - F_{m,h}^{-1}(\tau_p)\right) & \text{, absolute change variable (SDM)} \end{cases} \tag{3}$$

with

$$\tau_p = F_{m,p}(x), \tag{4}$$

Subindexes o and m refer to the observed and modeled series, respectively, whereas subindexes h and p refer to the historical and projected period, respectively. Accents $\bar{}$ and $\tilde{}$ denote mean and standard deviation, respectively. F and F^{-1} are the cumulative distribution function (CDFs) and its inverse CDF (invCDFs), respectively; and τ is the non-exceedance probability.

The climQMBC package assigns a probability distribution function for each day or month and period based on the method of moments and by default chooses the distribution considering the one with the lowest error in the Kolmogorov-Smirnov test. The exception is the SDM method in which a gamma or normal distribution is fitted by the maximum likelihood method for variables associated with precipitation and temperature, respectively (Switanek et al., 2017). The available distribution functions in the climQMBC package are the Normal, Log-normal, Two-parameter Gamma, Three-parameter Gamma, Log-Gamma, Gumbel, and Exponential.

For variables that do not allow negative values, the climQMBC package internally filters those distributions that allow negative values (Normal, Three-parameter Gamma, Gumbel and Exponential distributions). On the other hand, if the series has negative values, the climQMBC package discards those distributions that are strictly positive (Log-normal, Two-parameter Gamma and Log-Gamma distributions).

To ensure stability when computing the invCDFs, τ values are constrained to $0.001<\tau<0.999$. Additionally, to improve the management of non-precipitation days, values below a threshold representing physically zero precipitation value (1 mm as default) are replaced with random numbers that are barely positive. This procedure, referred to as "random near zero replacement" (Chadwick et al., 2023) allows fitting distributions and performing bias correction to avoid numerical problems in periods with large number of physically zero precipitation values, or periods with only zero values. Nevertheless, the threshold and the magnitude of the random values should be analyzed to enhance the methods performance depending on the specific conditions. For daily data, the number of wet days is corrected as most models have a drizzling bias that generates rainy days but with intensity lower than observed (Chen et al., 2021). To correct the number of rainy days, in all methods but SDM, an internal threshold representing physically zero precipitation value for the modeled series is fitted to match the

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175 number of rainy days of the observed series in the reference period. The SDM has its own method of correcting rainy days, as described in Switanek et al. (2017).

3.1.2 Description of the bias correction methods implemented in the climQMBC package

The bias correction methods available in the climQMBC package are now briefly described using a unified mathematical notation. Their main objectives and corresponding considerations are summarized in Table 1, while Fig. 3 shows a schematic
180 illustration of the procedure performed in the projected periods and the CDF involved, highlighting the main differences among methods.

Table 1: Summary of the bias correction methods available in the climQMBC package

Method	Abbreviation	Summary	Reference
Quantile Mapping	QM	Considers a transfer function built with information from the observed and modeled historical period and applies it to the modeled series. Corrected series values will match its CDF with the observed series, maintaining the model occurrence of the events and limiting future scenarios exceeding this range.	Wood et al. (2002)
Detrended Quantile Mapping	DQM	Considers the same transfer function as in the QM method but applies it to a detrended modeled series, to then reimpose the trends. Corrected series tends to preserve changes in the mean of the modeled series.	Bürger et al. (2013)
Quantile Delta Mapping	QDM	The QM method is applied to the modeled future to detrend the modeled values. Then, the change between the future value and its respective quantile in the modeled historical period is used to rescale the series. Corrected series tends to preserve changes in the quantiles of the modeled series.	Cannon et al. (2015)
Unbiased Quantile Mapping	UQM	The QM method is applied to the modeled future, and the changes of the moments (e.g. mean and standard deviation) are imposed in the observed CFD to scale the transfer function. Corrected series tends to preserve changes in the moments of the modeled series.	Chadwick et al. (2023)
Scaled Distribution Mapping	SDM	Scales the observed CDF by the ratio between the future and historical modeled CDFs to correct the recurrence interval. A scaling factor like in the QDM method is then applied to the scaled probability distribution. Finally, the corrected values are allocated accordingly to likelihood of events. For precipitation, the SDM method additionally adjusts rain-day frequency. Corrected series tends to preserve changes in quantiles (as in the QDM method) and likelihood of events.	Switanek et al. (2017)

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Note: In the DQM, QDM, UQM and SDM methods the future period is divided in moving windows as an improvement implemented in Chadwick et al. (2023) to prevent pseudo-stationary biases.

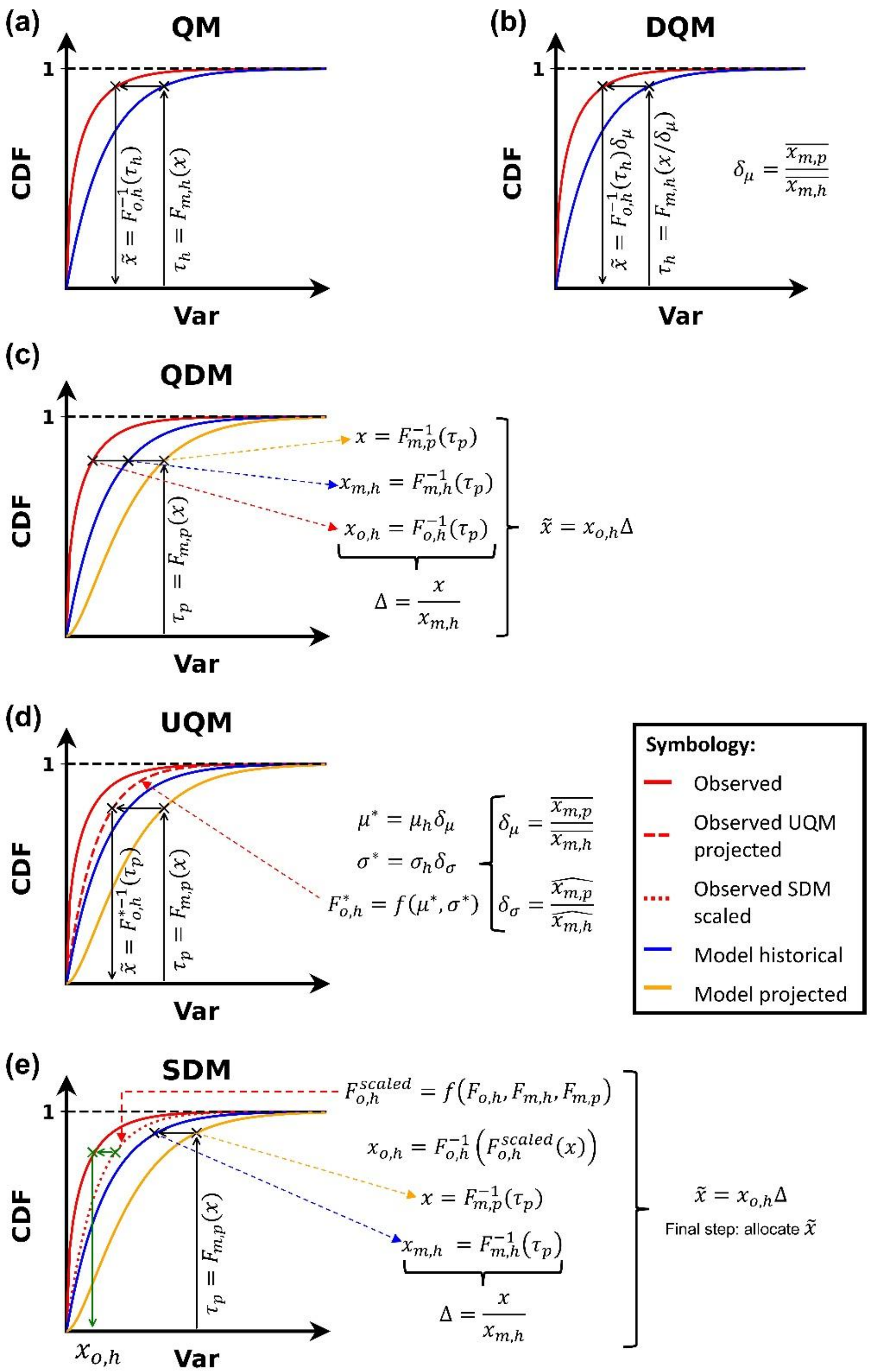

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Figure 3: Schematic illustration of the main processes computed in the (a) QM, (b) DQM, (c) QDM, (d) UQM and (e) SDM methods available in the climQMBC package, at each projected period for variables related to relative changes (e.g. precipitation). For variables related to absolute changes (e.g. temperatures) the deltas (δ and Δ) are computed and applied additively, rather than multiplicatively.

Quantile Mapping (QM):

The QM method (Fig. 3a) bias corrects the modeled series by evaluating the modeled values (x) in the CDF of the modeled historical period ($F_{m,h}$) to get the associated probabilities of each value and then evaluates them in the invCDF of the observed historical period ($F_{o,h}^{-1}$) to obtain a vector of corrected values ($\tilde{x}$). This method aims to correct each value of the modeled series by matching its quantile computed on its historical period with the quantile of the observed values, and is formulated as:

$$\tilde{x} = F_{o,h}^{-1}\big(F_{m,h}(x)\big), \qquad (5)$$

The QM method assumes that the correction process is time-invariant and in some cases may result in distortion of the raw model projected change rates. In most cases distortions are caused by projected climate being outside the range of historical modeled climate.

Detrended Quantile Mapping (DQM):

The DQM method (Fig. 3b) detrends the modeled series by computing the projected change in the mean of the modeled series for each rolling window (δ_μ, Eq. 1) and scaling the last value of each rolling window (x) to a range within the historical values. Then, the same transfer function described in the QM method is applied to the detrended values. Finally, the bias corrected values are rescaled multiplicatively or additively to obtain the corrected value ($\tilde{x}$). The procedure for each projected period is formulated as follows:

$$\tilde{x} = \begin{cases} F_{o,h}^{-1}\left(F_{m,h}(x/\delta_\mu)\right)\delta_\mu \,, & \text{relative change variable} \\ F_{o,h}^{-1}\left(F_{m,h}(x-\delta_\mu)\right)+\delta_\mu \,, & \text{absolute change variable} \end{cases}, \qquad (6)$$

Quantile Delta Mapping (QDM):

In the QDM method (Fig. 3c) the non-exceedance probability τ_p (Eq. 4) of each value x to be corrected is calculated based on its associated moving window. Then, τ_p is evaluated in the observed invCDF to obtain the modeled projected values after correction, $x_{m,p\rightarrow o,h}$, as follows:

$$x_{m,p\rightarrow o,h} = F_{o,h}^{-1}(\tau_p), \qquad (7)$$

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given that τ_p depends on a moving window, $x_{m,p\rightarrow o,h}$ does not have the model trend. Finally, the percentile change Δ (Eq. 3) of the projections is estimated as the ratio between the projected climate and its respective quantile in the historical modeled period. Then, Δ is applied to $x_{m,p\rightarrow o,h}$ to obtain the corrected value $\tilde{x}$ as follows:

$$\tilde{x} = \begin{cases} x_{m,p\rightarrow o,h}\Delta\,, & \text{relative change variable} \\ x_{m,p\rightarrow o,h} + \Delta\,, & \text{absolute change variable'} \end{cases} \tag{8}$$

When Δ is estimated for relative changes, it can get indetermined as a result of a division by a near-zero value. To avoid this, the climQMBC package considers an upper limit for Δ when dividing by a physically no-precipitation value. This strategy mimics the implementation of the QDM method in the MBC package (Multivariate Bias Correction of Climate Model Outputs; Cannon, 2017), available in CRAN.

Unbiased Quantile Mapping (UQM):

In the UQM method (Fig. 3d) the projected change in the moments (i.e., mean and standard deviation) of the modeled series is first computed for each moving window (δ_μ and δ_σ, respectively; Eq. 2 and Eq. 3, respectively). Then, these change rates are used to project the observed historical mean (μ_h) and standard deviation (σ_h) into the future to obtain future values μ^* and σ^* as follows:

$$\mu^* = \begin{cases} \mu_h\delta_\mu, & \text{relative change variable} \\ \mu_h + \delta_\mu, & \text{absolute change variable'} \end{cases} \tag{9}$$

$$\sigma^* = \begin{cases} \sigma_h\delta_\sigma, & \text{relative change variable} \\ \sigma_h + \delta_\sigma, & \text{absolute change variable'} \end{cases} \tag{10}$$

Subsequently, μ^* and σ^* are used to produce future projections of the selected distribution for the historical observed values, $F^*_{o,h}$, as follows:

$$F^*_{o,h} = f(\mu^*, \sigma^*), \tag{11}$$

Finally, the non-exceedance probability of the modeled values x in each moving window (τ_p, Eq. 4) are evaluated in the inverse projected distribution invCDF, $F^{*-1}_{o,h}$, to obtain the bias corrected value $\tilde{x}$ as follows:

$$\tilde{x} = F^{*-1}_{o,h}(\tau_p), \tag{12}$$

Scaled Distribution Mapping (SDM):

The SDM method (Fig. 3e) considers several steps (Switanek et al., 2017; Chadwick et al., 2023). Note that they are presented in a sequence different than the originally depicted by Switanek et al. (2017), with the intention of better illustrate the implications and structure of the method.

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For temperatures, the first step is to linearly detrend both the observed and modeled series for each period. For precipitation, the first step is to remove all non-precipitation values (< 1 mm/day as default) to account only for the rain values in each period. Then, the expected number of rain events for the corrected series (RD^{scaled}) is calculated by scaling multiplicatively (linear scaling) the number of rain events of each moving window ($RD_{m,p}$) with the ratio between the frequency of rainy days in the observed historical period ($RD_{o,h}/TD_{o,h}$) and in the modeled historical period ($RD_{mh}/TD_{m,h}$) as follows:

$$RD^{scaled} = RD_{m,p} \times \frac{RD_{o,h}/TD_{o,h}}{RD_{mh}/TD_{m,h}}, \tag{13}$$

where TD represents the total number of days, including rain and non-rain days. Hereafter, the SDM method is applied to a vector (bold notation) of sorted detrended temperature or non-zero precipitation values, to which the normal and gamma probability distribution functions are fitted by the maximum likelihood method, respectively.

In the second step the sorted vectors of the observed historical ($\boldsymbol{x}_{o,h}$), modeled historical ($\boldsymbol{x}_{m,h}$) and modeled projected period or moving window ($\boldsymbol{x}_{m,p}$) series are evaluated in their respective fitted CDF to obtain their associated probability vectors ($F_{o,h}(\boldsymbol{x}_{o,h})$, $F_{m,h}(\boldsymbol{x}_{m,h})$, $F_{m,p}(\boldsymbol{x}_{m,p})$). In the climQMBC package, each CDF is fitted considering a gamma distribution for positive precipitation and normal distribution for detrended temperature, using the maximum likelihood, following the SDM implementation in the pyCAT package. These probability vectors are used to estimate each recurrence intervals $\boldsymbol{RI}_{i,j}$ as follows:

$$\boldsymbol{RI}_{i,j} = \begin{cases} \frac{1}{1-F_{i,j}(x_{i,j})}, & \text{for precipitation} \\ \frac{1}{0.5-|0.5-F_{i,j}(x_{i,j})|}, & \text{for temperature} \end{cases} \quad ; \quad i = \{m, o\}, j = \{h, p\}\,, \tag{14}$$

In the third step, the recurrence interval of the observed historical series is linearly scaled by the ratio of the recurrence intervals of the model projected period and the model historical period (i.e., capturing the changes in recurrence intervals in the model) to build a scaled recurrence interval $\boldsymbol{RI}^{scaled}$ as follows:

$$\boldsymbol{RI}^{scaled} = \max\left(1, \boldsymbol{RI}_{o,h} \circ \boldsymbol{RI}_{m,p} \circ \frac{1}{\boldsymbol{RI}_{m,h}}\right)\,, \tag{15}$$

$\boldsymbol{RI}^{scaled}$ is built using the Hadamard product for vectors (i.e., multiplying element by element in a vector and preserving their dimensions), which requires equally sized vectors. Hence, prior to computing the precipitation recurrence intervals, the probability vectors are linearly interpolated to match the number of rain day events of the modeled projected period. The linear interpolation stretches or contracts the series to match the number of values in the modeled vector, keeping the original range and distribution of values.

In the fourth step, $\boldsymbol{RI}^{scaled}$ is used to go back into a scaled probability vector $\boldsymbol{F}_{o,h}^{scaled}$, which represents the scaled distribution function vector of the observed historical period as follows:

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$$\boldsymbol{F}_{o,h}^{scaled} = \begin{cases} 1 - \frac{1}{\boldsymbol{RI}^{scaled}} & , \text{ for precipitation} \\ \left(1 - \frac{1}{\boldsymbol{RI}^{scaled}}\right) \times sgn\left(F_{o,h}(\boldsymbol{x}_{o,h}) - 0.5\right), & \text{ for temperature} \end{cases}, \tag{16}$$

In the fifth step, $\boldsymbol{F}_{o,h}^{scaled}$ is sorted in descending order for precipitation, then, for both precipitation and temperature, it is evaluated in the invCDF of the observed historical period to get the associated value in the historical observed series domain $\boldsymbol{x}_{scaled\rightarrow o,h}$ as follows:

$$\boldsymbol{x}_{scaled\rightarrow o,h} = F_{o,h}^{-1}\left(\boldsymbol{F}_{o,h}^{scaled}\right), \tag{17}$$

In the sixth step, the vector with the projected change in the quantiles $\boldsymbol{\Delta}$ (Eq. 3. for SDM; similar to that of the QDM) is computed for all the values of the projected series and it is used to scale the vector computed in the previous step as follows:

$$\tilde{\boldsymbol{x}}_{temp} = \begin{cases} \boldsymbol{x}_{scaled\rightarrow o,h}\boldsymbol{\Delta}, & \text{for precipitation} \\ \boldsymbol{x}_{scaled\rightarrow o,h} + \boldsymbol{\Delta}, & \text{for temperature} \end{cases}, \tag{18}$$

For precipitation, if the number of rainy days of the projected period ($RD_{m,p}$) is greater than the expected number of rain events (RD^{scaled}), the frequency of rain events is adjusted by linearly interpolating $\tilde{\boldsymbol{x}}_{temp}$ to a length equal to RD^{scaled}. As a final step for precipitation, each value of the $\tilde{\boldsymbol{x}}_{temp}$ is placed in the location of the rainy values of the modeled projected temporal series, from the highest to the lowest. In case where RD^{scaled} is greater than $RD_{m,p}$, the remaining values are replaced with zeros. For temperatures the final step is to place back the $\tilde{\boldsymbol{x}}_{temp}$ values in the correct temporal location based on the modeled time series, process that is done in descending order. Then, the linear trend of the modeled projected temporal series is added back. Because the climQMBC package considers a continuum approach to capture transient changes from the models, the corrected value $\tilde{x}$ of the projected period corresponds to the value of the last year of the corrected series; then, the complete procedure is repeated for the following year.

3.2 climQMBC package example and report function

As an easy-to-use tool, the climQMBC package requires familiarity with importing and processing arrays, matrices, or vectors. Four steps are needed for its use: (1) Import the climQMBC package and its functions; (2) load the observed and modeled series; (3) define the type of variable (i.e. negative or strictly non-negative, and variable associated with additive or multiplicative changes) and data frequency (daily, monthly or annually); and (4) apply the selected bias correction method or methods. These steps can be applied to multiple locations or grids cells to systematically downscale a region of interest. Also, different bias correction methods can be used and compared to identify the better ones in preserving the changes from raw GCM/RCMs for the specific conditions under study. Figure 4 illustrates a simple Python code with an example, and the corresponding plotted results, based on the sample data available in the package repository (https://github.com/saedoquililongo/climQMBC/tree/main/Sample_data). Detailed demonstration of the capabilities of the

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package is provided in an example notebook available in its repository (https://github.com/saedoquililongo/climQMBC/blob/main/Example_notebook.ipynb).

(a)

```
# 1. Import the climQMBC package and its functions
from climQMBC.methods import QM, DQM, QDM, UQM, SDM

# 2. Load the observed and modeled series
import pandas as pd
obs = pd.read_csv('sample_data/obs_tas_M.csv')[['tas']].values
mod = pd.read_csv('sample_data/mod_tas_M.csv')[['tas']].values

# 3. Define the type of variable
frq = 'M'                # Monthly data
mult_change = 0          # Additive changes
allow_negatives = 1      # Allow negative values
SDM_var = 0              # Temperature variable for SDM

#4. Apply the selected bias correction method or methods
qm_series = QM(obs, mod, allow_negatives=allow_negatives, frq=frq)
dqm_series = DQM(obs, mod, mult_change=mult_change, allow_negatives=allow_negatives, frq=frq)
qdm_series = QDM(obs, mod, mult_change=mult_change, allow_negatives=allow_negatives, frq=frq)
uqm_series = UQM(obs, mod, mult_change=mult_change, allow_negatives=allow_negatives, frq=frq)
sdm_series = SDM(obs, mod, SDM_var=SDM_var, frq=frq)

# Quick plot
import matplotlib.pylab as plt
plt.figure()
plt.title('Example plot of the time series')
plt.plot(mod, label='Modeled')
plt.plot(qm_series, label='QM')
plt.plot(dqm_series, label='DQM')
plt.plot(obs, label='Observed')
plt.xlabel('Months since starting date')
plt.ylabel('°C')
plt.legend(loc='upper left')
plt.grid()
plt.show()
```

(b)

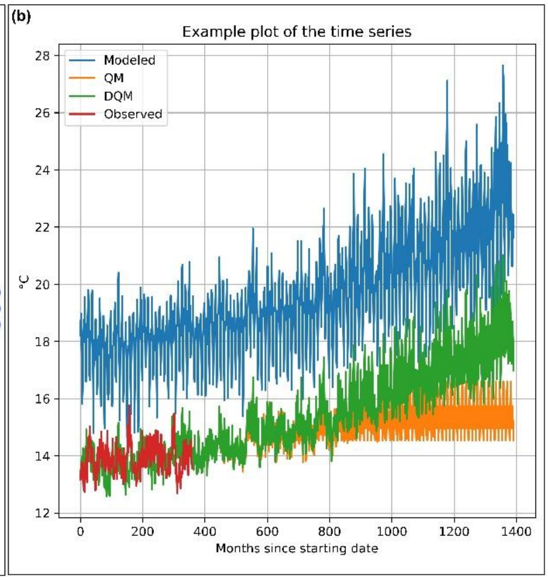

Figure 4: Python script showing the usage of the climQMBC package (a) and plotted results (b).

For monthly values, the climQMBC package has a summary report function to compare the performance or assess trade-offs between bias correction methods based on the preservation of the changes in the mean and standard deviation of the modeled series. This function outputs two reports: (1) a summary table with the overall performance of the bias correction methods in the historical period and in future periods for the mean and standard deviation (Fig. 5), and (2) a set of figures to visualize the main differences among methods in terms of monthly values and quantiles (Fig. 6). The report function requires the same inputs as the bias correction methods functions. Additional inputs of the report functions are the bias correction methods and future periods to be displayed in the summary tables and figures.

The structure of the summary tables for the mean and standard deviation generated by the report function of the climQMBC package are the same (Fig. 5). The first row of the summary tables shows the ratio or difference in the mean value (or standard deviation) between the QM bias corrected and observed historical series. A perfect match between the corrected and observed value would result in a value of 1 for multiplicative change variables and 0 for the additive change variables. In the example shown in Fig. 5a (Mean Table) for precipitation, the ratio between the annual mean values of the QM method and the modeled series in the historical period is 1.002, showing an overestimation of the mean in 0.2 %.

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Mean Table:

Ratio between the future and historical period

Ratio between QM and Observed

Modeled (GCM)

Quantile mapping methods

Ratio between the projected periods and the historical period

QM performance in historical period: 1.002				
	Future	2035	2065	2080
Modeled	0.761	0.893	0.749	0.657
QM	0.697	0.862	0.686	0.568
DQM	0.753	0.887	0.741	0.655
QDM	0.753	0.885	0.741	0.658
UQM	0.745	0.882	0.728	0.645
SDM	0.750	0.880	0.747	0.647

Standard deviation Table:

QM performance in historical period: 0.989				
	Future	2035	2065	2080
Modeled	0.843	0.945	0.830	0.737
QM	0.836	0.948	0.841	0.708
DQM	0.871	0.965	0.874	0.775
QDM	0.858	0.957	0.857	0.756
UQM	0.866	0.960	0.865	0.770
SDM	0.878	0.975	0.887	0.773

Figure 5: Example of the summary tables generated by the report function of the climQMBC package, applied to a precipitation case. The Mean and Standard Deviation Tables show the summary report for the annual mean and standard deviation, respectively. First row presents the performance based on the ratio between the annual mean of the bias corrected and modeled series in the historical period. Second row presents headers for different periods. Third row and below presents the ratio between the periods and the historical period for each series presented in the first column.

The second row of the summary table shows the header of the periods that are compared with the historical period. This comparison considers information exclusively of each series (e.g. projected period and historical information of the UQM corrected series). The third row and below shows the ratio or difference between the future period, based on the header, and the historical period. In these rows the first column indicates the series considered (modeled series, QM corrected series, DQM corrected series, …), the second column, under the header 'Future, shows the ratio or difference between the complete future period and the historical period, the third and following columns show the ratio or difference between the projected period, centered in the year of the corresponding header (defined by the user), and the historical period. For a bias correction model to be good, its value (ratio or difference) should be close to the value of the "Modeled" row in each period, both for the mean and standard deviation. For the example shown in Fig. 5b (Standard deviation Table), the model ratio between the future 2065 and historical is 0.830 (a change of -17 %) whereas the corresponding values for QM, DQM, QDM, UQM and SDM are 0.841, 0.874, 0.857, 0.865 and 0.887, respectively. Hence, all the methods show underestimate the decrease in the standard deviation, being the QM method the closest one to the modeled series. However, for the same future period, the ratio corresponding to changes in the mean for the QM method is the largest as compared to the modeled (0.686 compared to 0.749, Mean Table).

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The report function also provides a second report with three different figures illustrated in Fig. 6. The first figure (Fig. 6a) shows the cumulative distribution of the modeled and corrected series in the historical and future periods, and the cumulative distribution of the observed series (left side). This figure also shows the observed, modeled, and corrected time series (right side). The second figure (Fig. 6b) shows the seasonal monthly mean of each series in the historical and future projected periods (the same projected periods as in the summary tables). Finally, the third figure (Fig. 6c) shows the same monthly seasonality, but for the standard deviation. In the second and third figures, the objective series is the observed monthly mean or standard deviation, scaled by the raw projected change (scaling factor based on the projected and the historical period) of the uncorrected model. Note that, ideally, the corrected value should capture the projected changes; hence, match the objective value.

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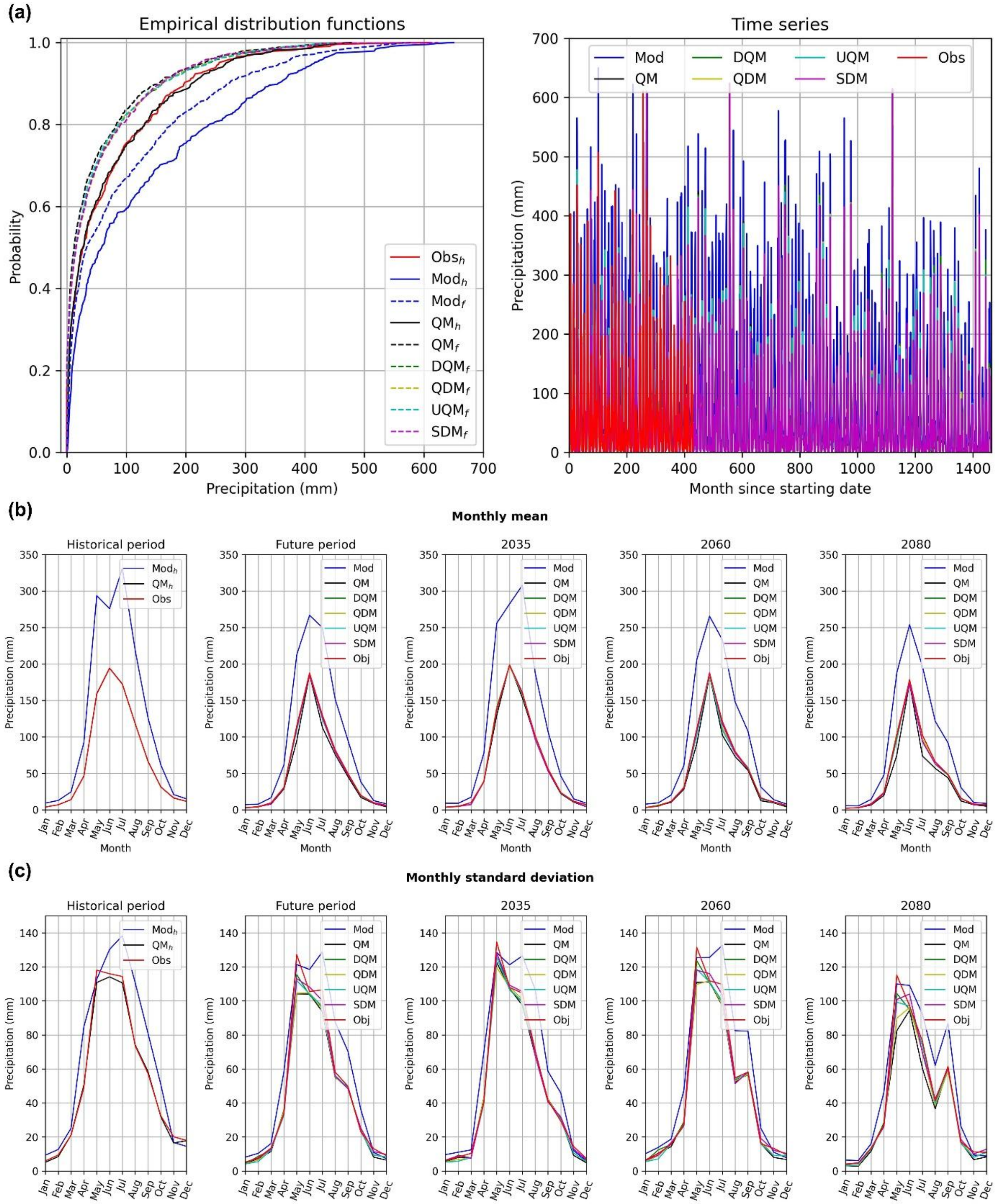

Figure 6: Example of the summary figures generated by the report function of the climQMBC package. (a) cumulative distribution functions in the historical and future periods (left side), and time series (right side); (b) summary plots of the seasonal monthly mean, (c) summary plots of the seasonal monthly standard deviation.

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4 Application examples with synthetic series

In this section we assess the capabilities of the climQMBC package to systematically bias correct climatic variables of GCMs or RCMs. We compared the performance of the implemented bias correction methods in both the historical and projected periods based on a synthetic example. A controlled bias was introduced into a synthetic time series, enabling a clear evaluation of each method-s ability to correct it. This example is designed to demonstrate the performance of bias correction methods under varying conditions, offering insights into their optimal use. Nevertheless, determining the most suitable method for each specific case lies beyond the scope of this study. The example highlights the importance of having an easy-to-use tool, such as the climQMBC package, to implement bias correction methods and discern the most adequate one to a specific case.

4.1 Description of the synthetic example and evaluation

Extending the synthetic example presented by Maurer and Pierce (2014), Cannon et al. (2015), and Chadwick et al. (2023), gamma distributions were used to generate multiple synthetic precipitation time series. The gamma probability density function with shape parameter k and scale parameter θ is given by:

$$f(x;k,\theta) = \frac{x^{k-1}\exp(-x/\theta)}{\theta^k\Gamma(k)}, \quad x>0, \quad k>0, \quad \theta>0, \tag{19}$$

where $\Gamma(\cdot)$ is the gamma function. Using the method of moments the mean (μ) and standard deviation (σ) can be used to estimate the parameters with $\mu = k\theta$ and $\sigma = \sqrt{k}\theta$.

Each generated series has an observed historical and future projected period. The future or projected period considers a multiplicative change compared to the historical period. Then we added bias to both period (historical and future or projected) to obtain a model synthetic series, which allows testing if the bias correction methods can remove the added bias. In this synthetic exercise the projected bias corrected climate should be the same as the synthetic observed projected climate.

We defined observed scenarios with a mean of μ_h=1,000 and coefficients of variation (CV) ranging from 0.25 to 1.00 (Table 2). For each observed scenario we generated several objective future scenarios with combinations of changes in the mean and standard deviation ($\Delta\mu$ and $\Delta\sigma$, respectively) ranging from -50 % to +50 % (Table 2). Note that the projected or future mean is obtained from $\mu^* = \mu\Delta\mu$, while an analogous process is used to obtain the future standard deviation. For each scenario 10,000 values were generated.

To each value x_i^o of the generated observed or objective future series, we added bias Δ_{bias}, with components both in the mean ($\Delta\mu_{bias}$) and in the standard deviation ($\Delta\sigma_{bias}$), to get biased values x_i^b by the following procedure, which shifts the mean and variability of the series:

$$\Delta_{bias}(x_i^o) = (1+\Delta\mu_{bias}) + \frac{(x_i^o-\mu^o)(\Delta\sigma_{bias}-\Delta\mu_{bias})}{x_i^o}, \tag{20}$$

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$$x_i^b = x_i^o \cdot \Delta_{bias}(x_i^o), \quad (21)$$

where μ^o is the mean of the observed or objective future series. This methodology ensures adding the desired bias in the mean ($\Delta\mu_{bias}$)) and standard deviation ($\Delta\sigma_{bias}$). We considered several combinations of bias in the mean and standard deviation with values ranging from -50 % to +50 % (Table 2).

Table 2: Coefficient of variation, projected changes in the mean and standard deviation, and bias in the mean and standard deviation considered in the synthetic example.

Variable	Values
Coefficient of Variation (CV)	0.25, 0.50, 0.75, 1.00
Projected change in mean ($\Delta\mu$)	-50 %, -25 %, -10 %, 0 %, 10 %, 25 %, 50 %
Projected change in standard deviation ($\Delta\sigma$)	-50 %, -25 %, -10 %, 0 %, 10 %, 25 %, 50 %
Bias in mean ($\Delta\mu_{bias}$)	-50 %, -25 %, -10 %, 0 %, 10 %, 25 %, 50 %
Bias in standard deviation ($\Delta\sigma_{bias}$)	-50 %, -25 %, -10 %, 0 %, 10 %, 25 %, 50 %

For the bias correction process, we evaluated all the implemented bias correction methods in the climQMBC package considering each original synthetic series as observed and those with added bias as the modeled series. There are four sets of synthetic series: historical observed, projected observed, historical modeled and projected modeled. The bias correction uses three of the four set of series, both modeled series (projected and historical) and the historical observed, while the projected observed is kept for verification purposes, given that it is the "true series". To assess the performance of each method, we considered (1) performance metrics based on statistical properties, measured as the ratio between statistics of the bias corrected series and those of the expected series, for which a value of 1 means a perfect agreement, and 2) goodness-of-fit metrics (i.e. Nash-Sutcliffe efficiency (NSE) proposed by Nash and Sutcliffe (1970), and Kling-Gupta efficiency (KGE) proposed by Gupta et al., 2009) to evaluate the point-by-point agreement between the bias corrected and expected series. Values of 1 for NSE and KGE indicate perfect agreement. These metrics, their range and possible values are summarized in Table 3.

Table 3: Performance metrics considered.

Variable	Range	Values
Ratio between the corrected and expected mean, standard deviation and percentiles[1]	[0, ∞)	<1: Underestimation =1: Perfect agreement >1: Overestimation
Ratio between the corrected and expected skewness[2]	(-∞, ∞)	<1: Underestimation =1: Perfect agreement >1: Overestimation
Nash-Sutcliffe efficiency (NSE;	(-∞, 1]	<1: Bias among values

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Nash and Sutcliffe, 1970)		=1: Perfect agreement among values <0: Worse than the mean
Kling-Gupta efficiency (KGE; Gupta et al., 2009)	(-∞, 1]	<1: Bias among values, mean or standard deviation =1: Perfect correlation between values and perfect fit among mean and standard deviation <1- $\sqrt{2}$: Worse than the mean (Knoben et al, 2019)

1 Percentiles 5 %, 10 %, 50 %, 90 %, and 95 % are considered

2 Negative values indicate change in the direction of the distribution asymmetry

4.2 Bias correction comparison in the historical period

Regarding the performance of the bias correction methods in the historical period, Fig. 7 shows the NSE values for each combination of coefficient of variation (CV), bias in mean ($\Delta\mu_{bias}$) and bias in standard deviation ($\Delta\sigma_{bias}$). The numbers in the grid of Fig. 7 indicate the percentage of synthetic time series that have some negative values and were replaced with with random values below 0.01, according to the implementation of the climQMBC package. Figure 7 shows only values for the QM and SDM methods because the DQM, QDM and UQM methods are equivalent to the QM method in the historical period (Chadwick et al., 2023).

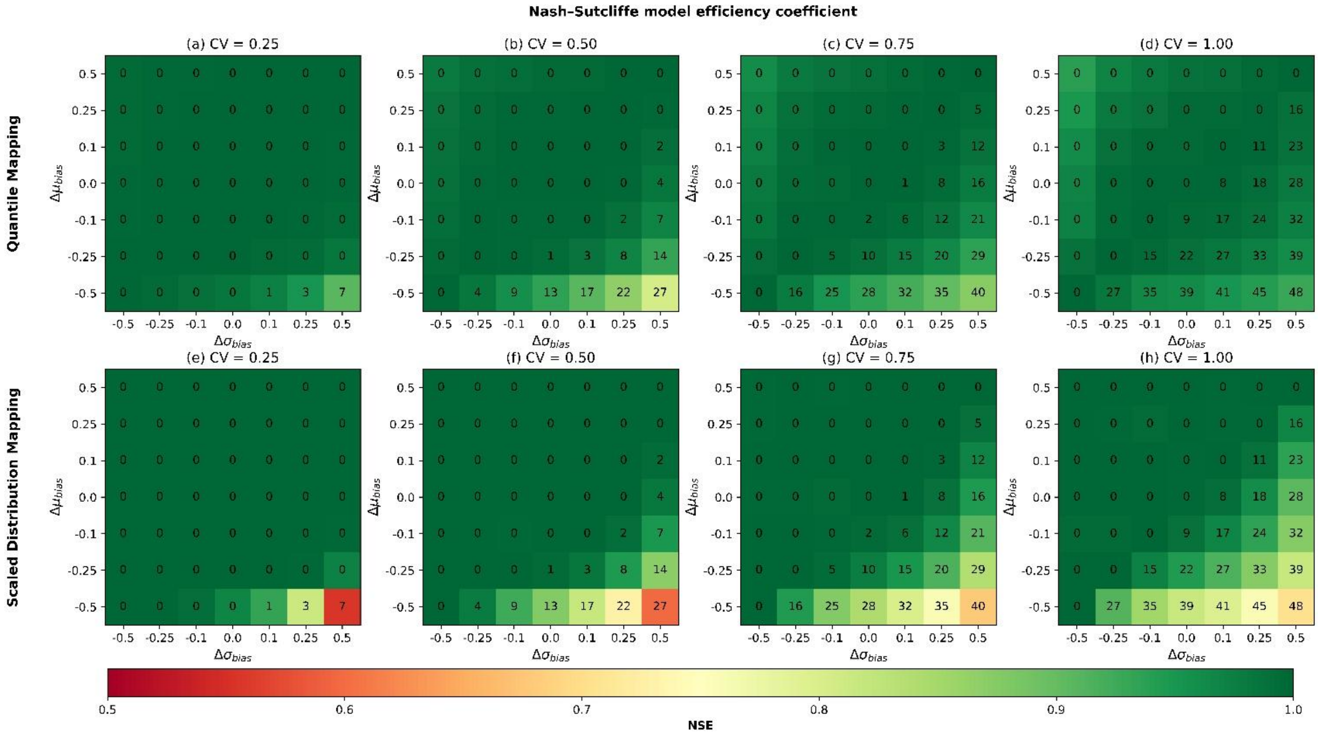

Figure 7: NSE values of the QM and SDM methods in the historical period for different combinations of the observations' CV, $\Delta\mu_{bias}$ and $\Delta\sigma_{bias}$. Green color indicates a perfect fit between the corrected and observed values (NSE ~ 1), and red tones indicate a lower quality fit (NSE < 1). The numbers in the grid indicate the percentage of synthetic time series that have some negative values (that were replaced with random values below 0.01).

Based on the NSE values (Fig. 7), the QM and SDM methods may fit differently to the observed values under different circumstances, with the QM method being the one with better fit when the bias in the standard deviation increases and the bias in the mean decreases to negative values (bottom right corner of each grid). On the other hand, when the bias in the mean increases and the bias in the standard deviation decreases to negative values (top left corner of each grid), NSE values for the QM method tend to slightly decrease for high values of CV, tendency not observed for the SDM. Both methods perform well in terms of NSE values when the bias in the mean and standard deviation are similar. When performance is analyzed based on the mean, standard deviation, skewness, and percentiles, or based on the KGE values, results showed similar patterns (results not shown).

Figure 8 presents boxplots of the performance metrics shown in Table 3 for the ratio between the corrected and observed mean, standard deviation, skewness, percentiles 5th, 10th, 50th, 90th and 95th, alongside the NSE and KGE values in the historical period. The boxplots consider the results after adopting all the CV and bias conditions depicted in Table 2. For all plots in Fig. 8, a value of 1 indicates a perfect agreement between the corrected and observed statistics. Figure 8 shows only values for the QM and SDM methods because the DQM, QDM and UQM methods are equivalent to the QM method in the historical period (Chadwick et al., 2023).

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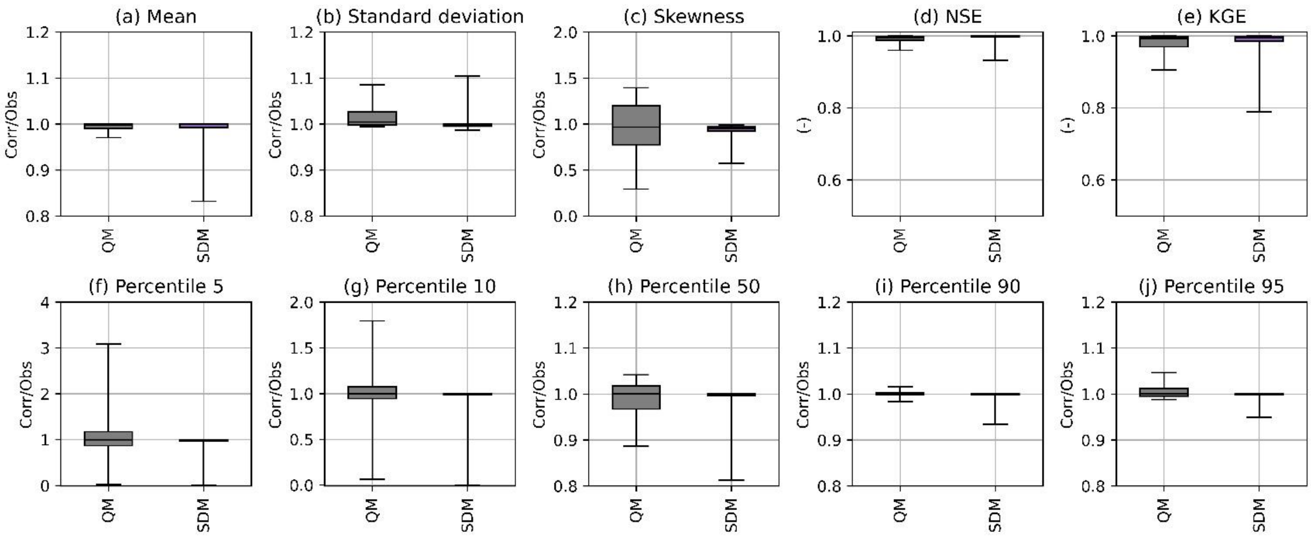

Figure 8: Performance comparison of QM and SDM in the historical period using the ratio between the bias corrected and observed mean (a), standard deviation (b), skewness (c), and percentiles (f to j), in addition to the NSE (d) and KGE (e) values. For all metrics, a value of 1.0 indicates a perfect agreement between the corrected and observed values, as depicted in Table 3.

In all cases, both the QM and SDM have boxes centered in a value of 1.0. Although more stable in terms of a more constrain box (representing the middle 50 % of the data) than the QM method, the SDM method resulted also in more outliers. For the mean, standard deviation, NSE, KGE, percentiles 50 %, 90 % and 95 %, the SDM shows a smaller box than the QM, but the SDM have larger whiskers. For the skewness, the SDM shows a smaller box and whiskers than the QM, and for percentiles 5 % and 10 %, the SDM shows a smaller box than the QM, and the QM shows whiskers for over and underestimation, while SDM only for underestimation. Hence, if the results of the SDM method are not properly analyzed, they may result in larger biases than QM. Having a tool to easily compute and compare among bias correction methods allows the analysis and facilitate the selection of the most adequate method depending on the case study under analysis.

4.3 Projected scenarios

Regarding the performance of the bias correction methods in the future, Fig. 9 shows the cumulative probability of the NSE and KGE values, resulting from the synthetic exercise considering all the combinations of CV, added biases and projected changes shown in Table 2. The desired result, indicating that almost all cases have a perfect agreement with the expected values, is to have cumulative probabilities as close as possible to the value of 1.0; hence the closer to the right the curve is, the better.

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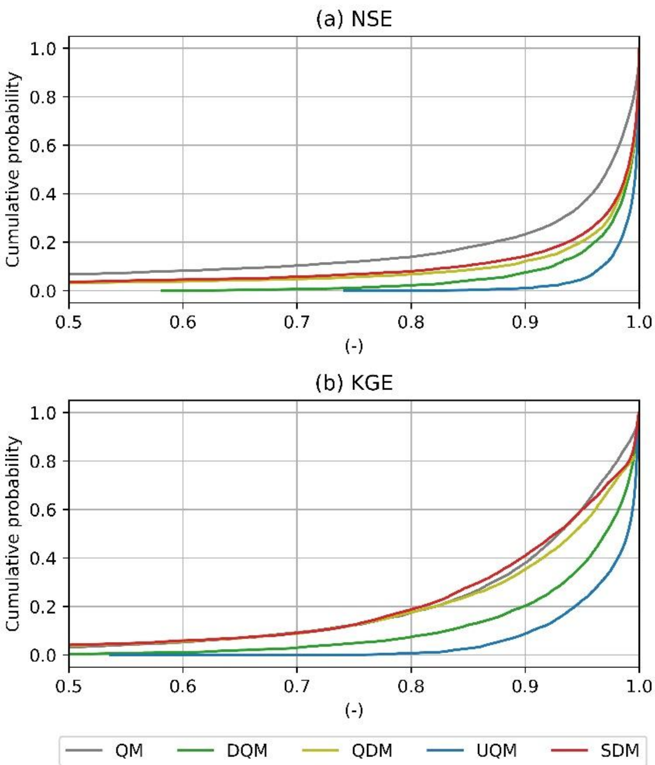

Figure 9: Cumulative probability of the NSE (a), and KGE (b) values of the synthetic example for each implemented method in the climQMBC package.

Based on the NSE and KGE values, the QM, DQM, QDM, UQM and SDM methods result in different series which may differ in their performance. Results of the synthetic example show that the UQM method performs best in eliminating the bias from the modeled series, followed by the DQM method, being the QM method the one with the lowest performance quality. The SDM and QDM methods perform similarly in terms of the NSE values, but the SDM performs worse when evaluated with the KGE. The NSE and KGE indexes give an overall goodness-of-fit; nevertheless, other performance metrics commonly used to assess a bias correction method in terms of how certain statistics are preserved (e.g. mean, standard deviation, skewness, and percentiles) might be adopted. The performance of a method may differ based on the performance metric and the objectives of the user. Figure 10 presents boxplots of the performance metrics depicted in Table 3 representing the ratio between the corrected and expected mean, standard deviation, skewness, and percentiles 5, 10, 50, 90 and 95, and as well as the NSE and KGE values in the future scenario. Again, a value of 1 indicates a perfect fit between the corrected and expected statistics.

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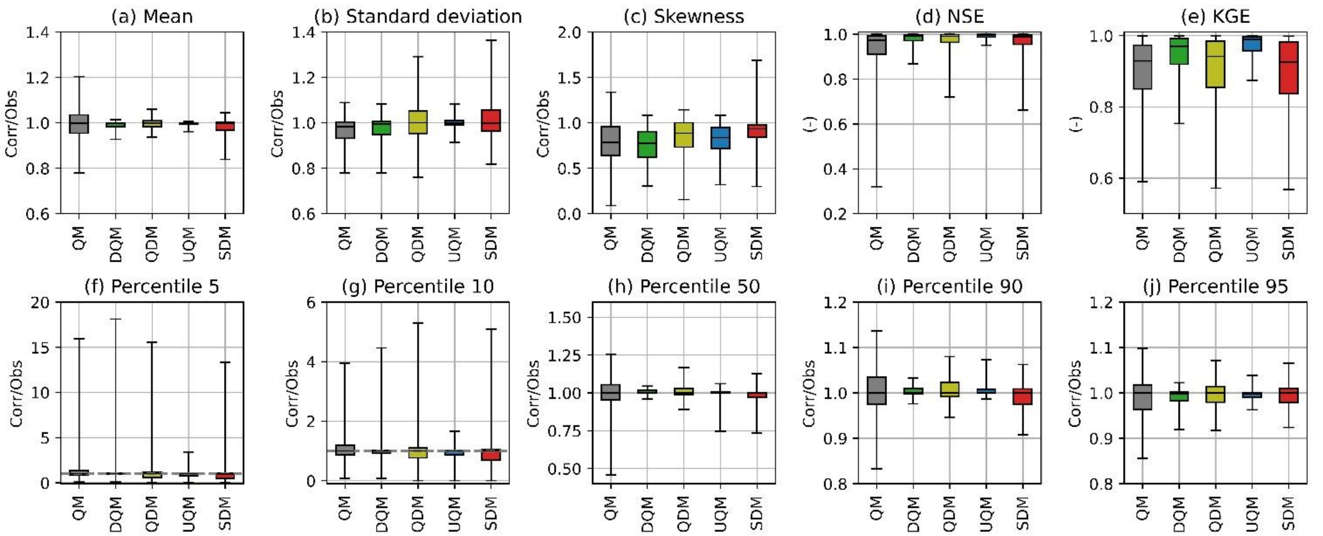

Figure 10: Performance comparison of the QM, DQM, QDM, UQM and SDM in the future period evaluated by means of the ratio between the bias corrected and objective future mean (a), standard deviation (b), skewness (c), and percentiles (f to j), in addition to the NSE (d) and KGE (e) fitness metrics. For all metrics, a value of 1.0 indicates a perfect agreement between the corrected and expected values, as depicted in Table 3.

Figure 10 shows that all the implemented methods might relate to the expected series based on different statistics; however, some methods are more stable in some statistics than others (e.g., UQM and DQM in the mean, UQM in the standard deviation or the SDM, QDM and UQM in the skewness). Overall, UQM tends to be more stable than the other methods. Among the implemented methods in the climQMBC package there is always a trend preserving method that is more stable than the QM method. This does not mean that the QM method should not be used. In fact, as mentioned above, all methods might perform well under certain circumstances, including the QM method. This is why an evaluation of the method for each specific situation is encouraged.

5 Conclusions

Quantile Mapping (QM) is one of the most widely used bias correction methods for climate change impacts, although it might distort raw GCM changes when future climate goes out of the range of the historical climate. Trend-preserving methods such as DQM, QDM, UQM, and SDM aim to address this limitation, each with its own advantages and disadvantages, although the QM method is still widely used because of its simplicity and ease of implementation. This paper presents the climQMBC package, a coding package written in Python, MATLAB and R that makes available all these bias correction methods for daily, monthly and annual data. As such, the package enables incorporating several bias correction methods as a standard component of climate change impact assessment, as well as the identification of the most adequate method for a specific case. Being available in several programming languages avoids users having to change between languages and include the bias correction analysis in their existing workflow.

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Using a synthetic example, we demonstrate that all the methods implemented in the climQMBC package can successfully correct the modeled series in both the historical period and future scenarios; however, this performance cannot be guaranteed as a general rule. In general, among the methods, there is always one whose performance is more robust than the QM method, being UQM and DQM the more stable ones. Nonetheless, in some cases the QM method should not be discarded because it is simple, computationally faster than the trend preserving methods, and might perform well enough under certain conditions. Overall, we emphasize the need to assess the performance of the bias correction methods to avoid unwanted bias in the corrected series. However, there are cases where the best option among the available methods will not perform perfectly, and thus a tool like the climQMBC package will be useful to identify the most adequate method for each specific case.

Code availability

The source code of the climQMBC package for Python, R and MATLAB are openly available at GitHub (https://github.com/saedoquililongo/climQMBC) and has been archived in Zenodo with the DOI https://doi.org/10.5281/zenodo.18392900 (Aedo-Quililongo et al., 2026). Instructions to import the library can be found at https://github.com/saedoquililongo/climQMBC/blob/main/Python/README.md for Python, https://github.com/saedoquililongo/climQMBC/blob/main/R/README.md for R and https://github.com/saedoquililongo/climQMBC/blob/main/Matlab/README.md for MATLAB. Examples for testing the package can be found at https://github.com/saedoquililongo/climQMBC/blob/main/Python/climQMBC_tester_Python.py for Python, https://github.com/saedoquililongo/climQMBC/blob/main/R/climQMBC_tester_R.R for R and https://github.com/saedoquililongo/climQMBC/blob/main/Matlab/climQMBC_tester_Matlab.m for MATLAB. Data for the tester codes can be found at https://github.com/saedoquililongo/climQMBC/tree/main/Sample_data.

Author contributions

Sebastián Aedo-Quililongo: Conceptualization, Formal Analysis, Software, Writing – original draft. Cristián Chadwick: Conceptualization, Formal Analysis, Funding Acquisition, Software, Supervision, Writing – original draft. Fernando González-Leiva: Software, Writing – review & editing. Jorge Gironás: Funding Acquisition, Writing – review & editing

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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