

# A robust alternative for correcting systematic biases in multi-variable climate model simulations

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## ABSTRACT

The existing bias correction (BC) methods used in impact studies are routinely based on a fixed model structure and often ignore the nature and magnitude of biases, and their variations into the future. As a calibrated model is applied to bias correct the future time series, there is no feedback mechanism to assess the impact of model complexity on the model performance in the future. In this paper we propose a flexible modelling strategy to create a robust bias correction procedure, in the form of an open-source toolkit in the R statistical computing environment. The approach allows the user to apply a multi-dimensional bias correction model that is self-evolving and grows in complexity on the basis of the requirement of the raw data. The theoretical background and the capabilities of the software along with a sample application and results discussions are demonstrated in this paper.

## 1. Introduction

Quantification of the effects of climate change is currently one of the most debatable and challenging topics in science. Global Circulation Models (GCMs) are considered as the best tools to understand Earth's climate dynamics and evolution (Randall et al., 2007). At regional or local scales, Regional Climate Models (RCMs) or statistical downscaling models are often used to provide future projections of climate variables and to assess the impacts of climate change on regional water resources (Mehrotra and Sharma, 2006, 2010; Vrac and Naveau, 2007; Fowler et al., 2007; Graham et al., 2007; Forzieri et al., 2014; Reshmidevi et al., 2017; Steinfeld et al., 2020; Woldemeskel et al., 2016; Wood et al., 2004; Hu et al., 2020; Nguyen et al., 2020). With the improvement in computing and data storage resources, the climate models can now operate at finer resolution, and with the advancement of our knowledge and better understanding of science and nature they offer a better representation of the physical processes embodied. Thus, the recent past has witnessed improved capability and sophistication in GCMs and RCMs. Notwithstanding these improvements, the climate model simulations still show biases, particularly for variables dealing with the hydrological cycle (Navarro-Racines et al., 2020; Koutroulis et al., 2016; Papadimitriou et al., 2017; Maraun, 2012). Such biases come from varied sources; the most obvious reasons are imperfect model representations of atmospheric physics (Maraun, 2012) and incorrect initialization of the

model or errors in the parameterization chain with respect to GCMs (Nguyen et al., 2016). Theoretically, finer resolution of Regional climate models (RCMs) should improve some of the physical processes and reduce biases as it allows topography, land type and land use distribution to be more accurately represented in climate models. However, as GCMs provide the forcing/driving boundary conditions for the RCMs, significant biases can persist either from the driving GCM or from the RCM itself (Rocheta et al., 2017; Sippel et al., 2016; Troin et al., 2015; Nahar et al., 2017; Eden et al., 2012). As a result, it is important to bias-correct the raw climate model outputs before their use in impact assessments studies (Piani et al., 2010; Mehrotra and Sharma, 2010; Nguyen et al., 2016; Sarhadi et al., 2016). Bias correction can reduce GCM/RCM biases and forms a necessary post-processing step in almost all impact assessment studies that rely on the outputs of climate models. According to Murphy (1993), a proper BC should improve quality (matching of model output and observations), consistency (matching of model dynamics/output and our judgement), and value (meaningful model output for the benefit of the users) of the raw model output.

Bias correction algorithms vary from equalization of statistical characteristics between modelled and observed precipitation, for example, simple correction for means and variance (Wilby et al., 2004; Ghosh and Mujumdar, 2008; Hay et al., 2000; Lenderink et al., 2007), to more complex approaches designed to correct for quantiles, popularly known as Quantile Mapping (QM) approaches (Li et al., 2014; Wood

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et al., 2004; Piani et al., 2010; Boé et al., 2007), or variability and persistence attributes at multiple time scales (Haerter et al., 2011; Johnson and Sharma, 2011) and in space as well as across variables (Mehrotra and Sharma, 2015, 2016, 2019; Vrac and Friederichs, 2015). The complexity of BC models increases with an increase in the type of attributes to be bias corrected, time scales, number of variables and locations included. In general, the model complexity increases if the intention is to look beyond a) distribution biases i.e. dependence biases, b) single variable i.e. multivariate, c) single location i.e. multiple locations, d) single time scale i.e. time nesting and, e) their combinations. The size of matrices grows exponentially with an increase in the number of variables, locations and time nesting considered.

So, ‘How complex should a BC model be?’ Should a basic QM or mean and SD correction model be enough, or a comprehensive BC model be selected? How much complexity can be allowed before there is a risk of overfitting (an excessive number of model parameters) and the danger of altering the physical credibility of GCMs? Model complexity is traditionally evaluated by splitting the data into two parts, using one to develop the model while using the other to evaluate the model performance and to compare how the model performs during the evaluation phase as model complexity is increased. This procedure is popularly known as a split sample test and the two parts are known as calibration and validation samples or time periods. A more complex model, in general, is expected to perform better in calibration than a simpler model as it has got more parameters that can be fine-tuned to obtain a good fit to the data used. It might struggle in validation as multiple parameters will force the model to behave like the calibration period. A simpler model, on the other hand, is expected to produce similar performances both in calibration and validation. This idea is presented in Fig. 1 where a general relationship between model performance and model complexity is shown. As can be seen, there is a small window that defines a “reasonable” model performance in both calibration and validation along with an optimal level of complexity (a function of the number of parameters) of a model.

While dealing with the systematic biases in climate model simulations, the consideration of a number of variables, multiple locations, time scales and attributes of interest further complicates the selection and assessment of a BC model structure. Like any other model, increasing BC model complexity also increases overall agreement of bias corrected climate model output with observations during calibration (current climate). However, as the calibrated model is applied to future climate simulations, it cannot be validated and an overfit can easily provide escalated results. It is of more concern when dealing with multivariate data sets or a single variable at multiple locations. There is

no simple feedback mechanism to assess the impact of model complexity on model performance in the future. Even, performing the split sample test on the current climate data is of little help as real validation lies in assessing the model performance when it is applied to the future climate data that can exhibit significantly larger changes compared to what the historical record exhibits (Mehrotra and Sharma 2019). As the climate system evolves with time, the distribution of climate variables is also likely to change with time and along with the model biases (Maraun, 2013). Although, almost all existing BC modelling approaches assume time-invariant biases and there seems to be no simple way forward to account for non-stationary bias in BC models (Nahar et al., 2017).

In majority of climate change impact studies, the spatial, temporal and multi-variable attributes are often misrepresented by climate models. The univariate approaches modify marginal distributions and leave other multi-dimensional aspects largely unchanged (Mehrotra and Sharma, 2016). Many derived hydrological variables such as flow, soil moisture and groundwater levels are often a result of accumulated precipitation and/or temperature anomalies over several days, weeks or months covering the large areas. Therefore, for hydrological impact studies, a univariate bias correction approach is of limited use and the use of more comprehensive bias correction approaches is warranted.

In recent past, many multi-dimensional BC approaches aimed at correcting bias in time, space and across variables have been proposed (Piani and Haerter, 2012; Vrac and Friederichs, 2015; Mehrotra and Sharma, 2015, 2016, 2019). Parametric multivariate bias correction approaches and multivariate variants of QM, for example, N-dimensional probability density function transform (MBCn) (Cannon, 2018) and MRNBC or MRQNBC of Mehrotra and Sharma (2015; 2016) and Mehrotra et al. (2018) are based on complex mathematical formulations and require estimation of many parameters with large matrices. The intricacy of these approaches increases with an increase in the number of variables, timescales and statistics to be corrected and to some extent, draw a limitation on their use.

Keeping these aspects in mind, we propose here a self-evolving robust BC model formulation that relies on the data itself and defines an optimal configuration within the MRQNBC modelling strategy (Mehrotra et al., 2018), optimality being defined here in terms of model robustness in current and future model projections. In the approach, we start with a simple BC model and gradually bring in model complexity by testing, validating and adding additional BC components for each biased statistic, time scale, location and variable in a stepwise manner following the response we obtain from the data used for current (“calibration”) and future (“validation”) climate. The approach ensures that we have tested the need and usefulness of individual BC components to

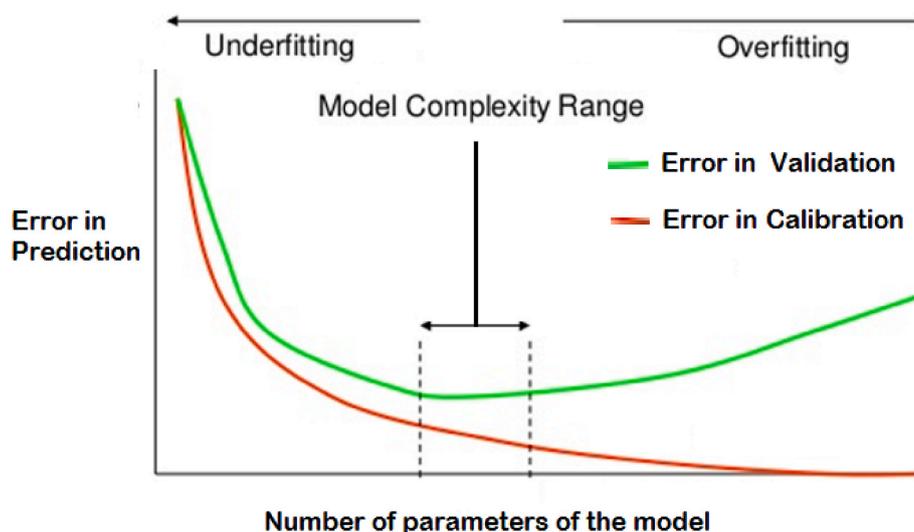


Fig. 1. Model complexity and performance.

be applied for that statistic, variable, time scale and location and not just applying a BC following a pre-fixed model structure selected. The stepwise procedure checks the evolved model structure for stability and allows model structure complexity to grow only if it is required and justified by the data. At each step, we check the utility of BC in validation (future climate), another important principle of model development. The final objective of this stepwise model building procedure is to have a final BC structure that performs well both on the data that is used to calibrate (e.g. the observed and current climate) and on the data that is used to validate the model (bias correction of future climate projections).

Following this, the Robust Multivariate Bias Correction (RoMBC) software package has been developed in the R statistical computing environment. It broadly follows the modelling strategy adopted in our earlier multivariate rigid bias correction approaches, for example, Multivariate Nested Bias Correction approach as described in Mehrotra and Sharma (2015; 2016) and Mehrotra et al. (2018). The flexibility introduced avoids the need of specifying the timescales and statistics to be included at each time step of bias correction for calibration and validation, thereby making it easier for the users to implement the approach in a fairly simple manner. This paper describes the software package and provides a simple example of its applications.

## 2. Data used

CSIRO and Bureau of Meteorology (2015) (hereafter referred to as CB 2015) have prepared a technical report, ‘Climate Change in Australia’ to help capture the range of projection results arising from the CMIP5 database. Considering a large number of GCM simulations available under the CMIP5 archive, a proper selection of a sub-set of models for use in impact assessment studies becomes important. The selected model should be able to reproduce the major climatic features and modes of variability, for example, seasonal and annual cycles of rainfall and temperature. Although, the ability of individual CMIP5 models to simulate Australian climate varies depending on the climatic variable, region and season under consideration. Model selection is also influenced by the availability of relevant data, since some climate variables were not archived for some models or emission scenarios. Considering model skill, model genealogy and other relevant factors, a subset of eight CMIP5 models, from a total of 40, was selected by CB2015 for use in climate change impact assessments. The method used for selection of these models is described in Chapter 9 of the Technical Report (CB 2015). At the time of data collection, out of these eight models, data of six models was readily available on the CMIP5 archive and has been used in the present research. Table 1 provides details of these six GCMs.

The Greater Sydney Region contains 18 sub-catchments. The daily time series of catchment averaged rainfall was formed using gridded

**Table 1**  
Details of models used in the study (from CB15).

MODEL	INSTITUTE	OCEAN RESOLUTION (°)	ATMOSPHERE RESOLUTION (°) [km at Equator]
ACCESS1.0	CSIRO-BOM, Australia	1.0 × 1.0	1.9 × 1.2 [210 × 130]
CanESM2	CCCMA, Canada	1.4 × 0.9	2.8 × 2.8 [310 × 310]
CNRM-CM5	CNRM-GERFACS, France	1.0 × 0.8	1.4 × 1.4 [155 × 155]
GFDL-ESM2M	NOAA, GFDL, USA	1.0 × 1.0	2.5 × 2.0 [275 × 220]
HadGEM2-CC	MOHC, UK	1.0 × 1.0	1.9 × 1.2 [210 × 130]
MIROC5 (for non-commercial use only)	JAMSTEC, Japan	1.6 × 1.4	1.4 × 1.4 [155 × 155]

data from the Bureau of Meteorology while daily time series of evaporation at three operational meteorological stations located within the region was provided by WaterNSW for the 1900–2013 time period (114 years). In addition to observed data, daily time series of GCM rainfall and temperature data for 30 years each for current (1976–2005) and future (2069–2099) climates, for 6 GCMs for RCP8.5 scenario over the study region is obtained and interpolated over the 18 sub-catchments. As evaporation was not directly available from these GCMs, a conditional model was developed using observed evaporation and temperature, and daily time series of GCM evaporation was simulated conditional on the GCM temperature for current and future time periods. Observed gridded temperature was obtained from Bureau of Meteorology, The Australian Climate Observations Reference Network – Surface Air Temperature (ACORN-SAT) dataset which has been developed to monitor climate variability and change in Australia. The dataset provides a daily record of Australian temperatures since 1910 (Trewin, 2018).

## 3. Methodology

Among the different univariate bias correction methods that have been suggested, quantile mapping has been found to provide particularly stable results (Themeßl et al., 2012; Teutschbein and Seibert, 2012) and is increasingly used to bias correct the RCM/GCM climate data all over the world (e.g. Finger et al., 2012; Forzieri et al., 2014). The approach is capable of correcting for the biases in the daily distribution (mean and in variance) of the raw time series. Similarly, multivariate nested bias correction (MNBC) approaches of Mehrotra and Sharma (2015; 2016) and Mehrotra et al. (2018) are quite effective in correcting for dependence biases (Zhu and Zhao, 2018). Following this, we adopt daily QM as our base BC model and apply it at each location and to each variable separately. More complex BC alternatives are added subsequently to this base model in a stepwise manner until the optimally robust configuration is reached. More details on the approach are presented later. The general structure of both QM and MNBC approaches is discussed in brief here.

### 3.1. Quantile mapping (QM)

The bias correction formulation of QM is based on equation (1) following Li et al. (2010).

$$Z'_{m,f} = \check{Z}_{m,f} + \left\{ F_o^{-1} \left( F_{mf} \left( \check{Z}_{m,f} \right) \right) - F_{mc}^{-1} \left( F_{mf} \left( \check{Z}_{m,f} \right) \right) \right\} \quad (1)$$

In which  $F(\cdot)$  is the empirical cumulative distribution of either observations ( $o$ ) or model ( $m$ ) for a historical training period or calibration or current climate ( $c$ ) or future projection or validation period ( $f$ ). ( $\check{Z}$ ) is the raw and  $Z'$  is the bias corrected time series. The same notation is used hereafter to define pre BC or raw ( $\check{Z}$ ) and post BC or bias corrected ( $Z'$ ) series. Also, multivariate matrices and variables are expressed as bold while univariate and scalars are expressed as non bold characters.

### 3.2. Multivariate nested bias correction (MNBC)

A full multivariate BC that maintains the observed LAG1 and LAG0 cross dependence in the bias corrected time series  $Z_t^g$ , is given by (Mehrotra and Sharma, 2015, 2016):

$$Z_t^g = \mathbf{C}Z_{t-1}^g + \mathbf{D}\mathbf{F}^{-1}\check{Z}_t^g - \mathbf{D}\mathbf{F}^{-1}\mathbf{E}Z_{t-1}^g \quad (2)$$

where,  $\check{Z}$  and  $Z'$  are raw and bias corrected time series of climate variables and matrices  $\mathbf{C}$ ,  $\mathbf{E}$ ,  $\mathbf{D}$  and  $\mathbf{F}$  are the LAG0 and LAG1 cross correlations of observed and raw current climate GCM series of variables. Expressions for the matrices  $\mathbf{C}$  and  $\mathbf{E}$  or  $\mathbf{D}$  and  $\mathbf{F}$  are obtained following Matalas (1967) as follows:

$$\mathbf{C} \text{ or } \mathbf{E} = \mathbf{M}_1 \mathbf{M}_0^{-1} \text{ and } \mathbf{D} \mathbf{D}^T \text{ or } \mathbf{F} \mathbf{F}^T = \mathbf{M}_0 - \mathbf{M}_1 \mathbf{M}_0^{-1} \mathbf{M}_1^T \quad (3)$$

where,  $\mathbf{M}_0$  and  $\mathbf{M}_1$  are, respectively, the LAG0 and LAG1 cross-correlation matrices of observed/raw current climate GCM daily time series of variables as appropriate.  $\mathbf{D}$  or  $\mathbf{F}$  is found by singular value decomposition. The elements of  $\mathbf{M}_0$  and  $\mathbf{M}_1$ , corresponding to variables  $i$  and  $j$ , are obtained from the observed/raw current climate GCM time series  $\mathbf{Z}$  using equation (4).

$$m_{0,ij}^{ij} = \sum_{t=1}^N \frac{Z_t^i Z_t^j}{N} \quad (4a)$$

$$m_{1,ij}^{ij} = \sum_{t=1}^N \frac{Z_t^i Z_{t-1}^j}{(N-1)} \quad (4b)$$

Similarly, for monthly or seasonal periodic time series, different matrices for each month/season are used. Parameters of these periodic matrices are obtained using equation (5) following Salas (1980).

$$\mathbf{C}_\tau \text{ or } \mathbf{E}_\tau = \mathbf{M}_{1,\tau} \mathbf{M}_{0,\tau}^{-1} \text{ and } \mathbf{D}_\tau \mathbf{D}_\tau^T \text{ or } \mathbf{F}_\tau \mathbf{F}_\tau^T = \mathbf{M}_{0,\tau} - \mathbf{M}_{1,\tau} \mathbf{M}_{0,\tau}^{-1} \mathbf{M}_{1,\tau}^T \quad (5)$$

where,  $\tau$  represents month or season,  $\mathbf{M}_{0,\tau}$  and  $\mathbf{M}_{1,\tau}$  are, respectively, the LAG0 and LAG1 cross-correlation matrices of observed/raw GCM monthly/seasonal time series of variables as appropriate. The elements of  $\mathbf{M}_{0,\tau}$  and  $\mathbf{M}_{1,\tau}$  are obtained using equation (4) in a manner similar to the case with constant parameters.

Models of multivariate time series at multiple levels usually involve a large number of parameters to account for the cross and auto and lagged time dependences. In situations where lagged cross correlations are either not important or significant, a contemporaneous model with reduced number of parameters can be formed by considering matrices  $\mathbf{C}$  and  $\mathbf{E}$  as diagonal matrices and ignoring the LAG1 cross correlations (Salas 1980; Salas et al., 1985). The diagonalisation of the parameter matrices  $\mathbf{C}$  and  $\mathbf{E}$  allows applying a univariate procedure for parameter estimation of these matrices. The elements of  $\mathbf{C}$  and  $\mathbf{E}$  corresponding to variables  $i$  and  $j$  are expressed as:

$$\mathbf{C}_{ij} \text{ or } \mathbf{E}_{ij} = \mathbf{M}_{1(ij)} \text{ , if } i = j; \mathbf{C}_{ij} \text{ or } \mathbf{E}_{ij} = 0 \text{ , otherwise} \quad (6a)$$

$$\mathbf{D} \mathbf{D}_{ij}^T \text{ or } \mathbf{F} \mathbf{F}_{ij}^T = \mathbf{M}_{0(ij)} \left( 1 - \mathbf{M}_{1(ij)} \mathbf{M}_{1(jj)} \right) \quad (6b)$$

$$\mathbf{C}_{\tau(ij)} \text{ or } \mathbf{E}_{\tau(ij)} = \mathbf{M}_{1,\tau(ij)} \text{ , if } i = j; \mathbf{C}_{\tau(ij)} \text{ or } \mathbf{E}_{\tau(ij)} = 0 \text{ , otherwise} \quad (6c)$$

$$\mathbf{D} \mathbf{D}_{\tau(ij)}^T \text{ or } \mathbf{F} \mathbf{F}_{\tau(ij)}^T = \mathbf{M}_{0,\tau(ij)} - \mathbf{M}_{1,\tau(ij)} \mathbf{M}_{0,\tau-1(ij)} \mathbf{M}_{1,\tau(jj)} \quad (6d)$$

Similar to MNBC variants (Mehrotra and Sharma 2012, 2015), two different auto-regressive multivariate models are considered – the one with constant parameters for the daily and annual time series and, another with periodic parameters for the monthly and seasonal time series (Salas, 1980).

If only LAG0 cross correlations are of interest then the above equations are simplified as:

$$\mathbf{Z}'_t = \mathbf{D} \mathbf{F}^{-1} \mathbf{Z}_t \quad (7)$$

where,  $\mathbf{Z}$  and  $\mathbf{Z}'$  are pre and post bias corrected series and matrices  $\mathbf{D}$  and  $\mathbf{F}$  are the LAG0 cross correlations of observed and GCM series. The elements of  $\mathbf{D}$  and  $\mathbf{F}$  are obtained by using equation (4a). Similarly, if only LAG1 correlations are of interest then the multivariate correction is not required and a standard univariate autoregressive LAG1 model for individual variable is considered (Johnson and Sharma, 2012):

$$\mathbf{Z}'_t = r^h \mathbf{Z}'_{t-1} + \sqrt{1 - (r^h)^2} \left( \frac{\tilde{\mathbf{Z}}_t - r^m \tilde{\mathbf{Z}}_{t-1}}{\sqrt{1 - (r^m)^2}} \right), \quad (8)$$

where,  $\tilde{\mathbf{Z}}_t^g$  is the bias corrected time series for time step  $t$ ,  $r^h$  is the observed and  $r^m$  is the GCM time series LAG1 correlations.

### 3.3. Robust Multivariate Bias Correction (RoMBC)

The modelling strategy proposed here is termed as Robust MBC (RoMBC). We describe the primary statistical attributes using distribution/statistics, and dependence attributes using the LAG0 and LAG1 auto and cross correlations. Similar to other variants of a Multivariate BC model, the RoMBC bias correction considers four popular bias correction time scales - daily, monthly, quarterly and annual. The model structure evolution procedure operates in stages, from univariate to multivariate and from one time-scale to the next. At each time scale, the approach evaluates the reparations of bias correction application in stages, first in LAG1 auto dependence of the individual variables and thereafter for LAG0 cross dependence across variables for both calibration and validation (current and future) time periods.

As mentioned before, the first stage of the approach is to apply univariate QM at a daily time scale and univariate variance correction at higher aggregated time scales, individually to all variables and locations. This forms the base bias corrected time series to be used as a reference to assess the need for the more complex BC alternatives that are assessed next.

The next stage is to examine the necessity and the applicability of BC in dependence attributes at daily, monthly, seasonal and annual time scales. The dependence attributes are defined in terms of LAG1 auto-correlation and LAG0 cross correlation attributes at all four time scales. The aim here is to specify a BC model structure that is appropriate at that time scale. The assessment of dependence attributes in bias correction is conducted in a stage-wise manner at each time scale. The sequence of these BC stages includes, LAG1, LAG0, a contemporaneous (L1C) and finally a full model (L1F). For LAG1 only dependence, being a univariate correction, the procedure is conducted separately at each location and for each variable and the BC model varies across variables, while for cross dependence, joint collective assessment is undertaken. At each time scale, the final BC is applied only when the assessment at all four stages is completed.

At each BC stage, the assessment is performed in two steps that are designed to be intuitive and straightforward. In the first step, called hereafter as 'Necessity Check', the base time series is evaluated to assess if the BC procedure being considered is necessary by comparing the current climate dependence statistics with those representing the observed record. If this difference is found statistically unimportant, there is no need of applying the bias correction in the dependence attribute considered and we proceed on to the next stage. The second step of checking the applicability of BC in validation/future is called the 'Applicability Check' and is initiated only if the difference is found significant at the first step. In the second step the BC is applied to the future climate time series and the bias corrected time series is assessed to see if the application of BC brings in significant changes in extreme values or designated statistics in comparison to those obtained using the base case simulation. If these changes are found statistically significant, the BC procedure is ignored and the correction at the next stage is considered. The following describes in brief the two step criteria adopted.

#### 3.3.1. Necessity check

The structure of the necessity check procedure remains the same for all BC stages. For LAG1, this involves assessing LAG1 correlations of individual variables while for LAG0 these represent cross correlations across variables. For brevity, both are simply denoted as correlations here. For a given location (and variable) let the correlations of observed and GCM current climate series be denoted as ( $r_o$ ) and ( $r_g$ ), respectively. For daily series, these are calculated for each day of the year using a moving window of 31 days centred on the day of interest. The user is

allowed to change the length of the moving window through a parameter in the data file. The significance of difference of observed and current climate correlations is assessed using Fisher Z test statistic as shown in equation (9) at 5% level of significance (significant if Fisher Z value > 1.96). In the equation  $N_o$  and  $N_g$ , respectively, are the number of observed and GCM data points used to calculate correlations.

$$F_z = \frac{|z_o - z_g|}{\sqrt{\frac{1}{(N_o-3)} + \frac{1}{(N_g-3)}}} \quad \text{and} \quad z_o = \frac{1}{2} \ln\left(\frac{1+r_o}{1-r_o}\right) \quad \text{and} \quad z_g = \frac{1}{2} \ln\left(\frac{1+r_g}{1-r_g}\right) \quad (9)$$

with daily data the process is repeated for all 365 calendar days while for monthly and seasonal data for each month/season. If out of 365 days/12 months/4 seasons, this difference is found statistically significant for more than 1% of time, bias correction of correlation is assumed to be needed. This is denoted as the necessity check. Note that the ‘5% level of significance’ is a common choice in hydrology while threshold of ‘1% of time’ was picked following a sensitivity analysis by varying it from 0.05 to 5% and 1% was found to provide satisfactory performance on the data used. The second step is applicability check and is explained next.

### 3.3.2. Applicability check

If the necessity check suggests that a dependence correction is needed, the next step is to check the impact of the dependence correction on the future climate time series. The dependence correction is applied to the base future climate series and the percent of time the bias corrected values cross designated lower or upper practical limits, is noted. Also, the means (AVs) and standard deviations (SDs) of the pre and post bias corrected series are calculated and compared to check if the correction has made any significant changes in the AV or SD of the time series by using equation (10), again at 5% level of significance:

$$|AV_{Post} - AV_{Pre}| > 1.96 \sqrt{(SD_{Pre}^2 + SD_{Post}^2) / N} \quad (10a)$$

$$\text{if } SD_{Pre} > SD_{Post} \quad SD_{Pre}^2 / SD_{Post}^2 > 1.96 \quad (10b)$$

$$\text{if } SD_{Post} > SD_{Pre} \quad SD_{Post}^2 / SD_{Pre}^2 > 1.96$$

Here  $N$  is number of data points and *pre* and *post* subscripts represent the statistics before and after the application of bias correction. These equations check the significance of the differences of statistics at the 5% significance level. If upper and lower limits are crossed more than 1% of time or the difference of the statistics (equation (10)) exceeds the specified threshold by more than 1%, this BC model is not considered. Our aim here is to make sure that we do not allow the BC to change the future irrationally and end up having few very high/low values. As mentioned before, the thresholds at 95% level of confidence is a commonly used choice while the ‘1% of time’ is used to define a check on the BC procedure as it would not be violated under normal conditions. The 1% threshold chosen was found to perform well based on sensitivity assessments across GCMs and a range of variables being corrected.

Once all the correction stages at a given time scale are assessed, the final selected bias correction model is applied at that time scale. The bias corrected time series is then aggregated/averaged to the next time scale and the same procedure is repeated. The time scales adopted and statistical attributes considered represent common choices the developers and other researchers have found important for water resources applications. The approach is quite flexible and allows users to accommodate alternate representations of time scales as well as other statistical attributes (Johnson and Sharma 2012; Mehrotra and Sharma 2012, 2015).

The following describes the stepwise procedure adopted in the implementation of RoMBC.

### 3.4. Stepwise RoMBC procedure

The complete bias correction procedure is divided into three parts. Part A deals with the formulation of base series in the form of a univariate primary bias correction. Part B is core of RoMBC and deals with the checking and application of complex bias correction procedures at each time scale. Part C aggregates the time series to higher time scale and repeats the part B. Steps involved in these parts are discussed next.

#### 3.6.1. Part A – defining the primary base BC series

1. Calculate monthly, seasonal and annual means and standard deviations of all the variables of the observed ( $Z_t^h$ ) time series. Also, calculate daily, monthly seasonal and annual LAG1 auto and LAG0 and LAG1 cross correlations of variables. Use a moving window of 31 days (or the number of days as specified by the user) centred on the current day of interest while calculating the statistics for the daily data (Rajagopalan and Lall, 1999; Sharma and Lall, 1999).
2. Consider a variable at a location/grid point. Apply QM to the daily data by fitting an empirical Cumulative Distribution Functions (CDFs) to the observed ( $Z_t^h$ ) and raw GCM series ( $\tilde{Z}_t$ ) for current and future climate. For a given value in the future climate GCM series, calculate the cumulative probability and obtain the difference of observed and GCM current climate values for this cumulative probability from the corresponding CDFs (Bias). Obtain the corresponding value for this cumulative probability from the future climate CDF. Apply the difference to the value to obtain the bias corrected value for the future climate. Repeat the same procedure for every data point and obtain the bias-corrected daily time series for current and future climates. Note these form univariate corrections for each variable with no consideration is given to cross-dependence biases that may be present.
3. Aggregate the daily QM corrected time series to monthly time scale. For standard deviation (SD) correction, assess the difference of observed and current climate monthly SDs using equation (10b). If this difference is found statistically significant for more than 1% of time, bias correction of SD is needed. This is denoted as the necessity check.
4. For the applicability check, apply SD bias correction to future monthly time series. Check the significance of the SD corrections by noting the percent of time the corrected monthly values cross the theoretical lower and upper limits. Also, count the percent of times AVs and SDs of post BC series are different from pre BC (Raw aggregated monthly series) using equation (10). If series passes the applicability check, apply SD correction to both current (c) and future (f) daily time series.

$$Y'_{j,i,k}{}^{g,c} = \left( \hat{Y}_{j,i,k}{}^{g,c} - \mu_{j,k}^{g,c} \right) \left( \frac{\sigma_{j,k}^h}{\sigma_{j,k}^{g,c}} \right) + \mu_{j,k}^{g,c} \quad (11a)$$

$$Y'_{j,i,k}{}^{g,f} = \left( \hat{Y}_{j,i,k}{}^{g,f} - \mu_{j,k}^{g,f} \right) \left( \frac{\sigma_{j,k}^h}{\sigma_{j,k}^{g,f}} \right) + \mu_{j,k}^{g,f} \quad (11b)$$

where,  $\mu_{j,k}^{g,c}$  is mean of current,  $\mu_{j,k}^{g,f}$  is mean of future,  $\sigma_{j,k}^h$  is SD of observed and  $\sigma_{j,k}^{g,c}$  is SD of current climate time series for  $j$ th month and  $k$ th variable. Similarly,  $\hat{Y}_{j,i}{}^{g,c}$  and  $Y'_{j,i,k}{}^{g,c}$  and,  $\hat{Y}_{j,i}{}^{g,f}$  and  $Y'_{j,i,k}{}^{g,f}$  are monthly time series before and after SD correction, for current and future climate for  $k$ th variable,  $j$ th month and  $i$ th year.

5. Aggregate both current and future climate time series monthly bias corrected time series to seasonal and annual time scales and check for the applicability of SD correction.
6. Finally, incorporate the changes at all time scales by modifying the daily time series as follows:

$$\hat{Z}_{t,j,s,i,k}^g = \left( \frac{Y'_{j,s,i,k}^g}{\hat{Y}_{j,s,i,k}^g} \right) \times \left( \frac{X'_{s,i,k}^g}{\hat{X}_{s,i,k}^g} \right) \times \left( \frac{A'_{i,k}^g}{\hat{A}_{i,k}^g} \right) \times \hat{Z}_{t,j,s,i,k}^g \quad (12)$$

where  $Y'_{j,s,i,k}^g$  is the monthly corrected value,  $\hat{Y}_{j,s,i,k}^g$  the aggregated monthly value,  $X'_{s,i,k}^g$  the seasonal corrected value,  $\hat{X}_{s,i,k}^g$  the aggregated seasonal value,  $A'_{i,k}^g$  the yearly corrected value and  $\hat{A}_{i,k}^g$  the aggregated yearly value. In equation (12), subscript  $k$  stands for variable,  $t$  for day,  $j$  for month,  $s$  for season and  $i$  for year. Do it for both current and future climate time series.

7. Store the daily distribution and higher time scales SD corrected time series of individual variables ( $Y'_{j,s,i,k}^g$ ) for current and future climate.
8. Repeat steps 1–7 for other variables and locations.

The above steps form the base or reference bias corrected time series which is corrected for essential biases in daily distribution and variability at monthly, seasonal and annual time scales. The base series is now used to define the practical lower and upper limits on the data and forms the starting step to test and apply more complex dependence attributes based BC models (4 in all, LAG1, LAG0, contemporaneous and full). It should be noted that if a more complex BC model is accepted to be valid, the base bias corrected time series at that time scale is updated only at the end of the fourth stage to define a new reference. The practical lower and upper limits are used to additionally validate the advanced bias correction stages. The daily, monthly, seasonal and annual upper and lower limits on individual variables at all locations for both current and future climates are formed by calculating the standard deviations (SDs) and maximum and minimum values of the entire time series at all four time scales. The maximum limit is defined as the maximum value in the entire time series plus SD and minimum limit as minimum value in the entire time series minus SD as per the following:

$$\text{Maximum limit} = \max(Y'^g + \text{SD}(Y'^g)) \quad (13a)$$

$$\text{Minimum limit} = \min(Y'^g - \text{SD}(Y'^g)) \quad (13b)$$

for current and future climate, at each time scale, location and for all variables. The daily limits are further checked against the physical lower and upper limits specified by the user. For example, with rainfall as a variable, the lower physical limit is zero and if the practical limit given by equation (13b) is less than zero, it is set as zero.

The next stage is to examine the necessity and applicability of BC in dependence attributes at daily, monthly, seasonal and annual time scales. The aim here is to identify a suitable BC model structure that is appropriate at that time scale. A flow chart presented in Fig. 2, highlights the procedure adopted in part B. The steps involved are as follows.

### 3.6.2. Part B – assessing checking and applicability of dependence BC model structure at each time scale

9. Start with daily data. Consider GCM current and future climates daily base time series as obtained from step 8. Consider each variable and calculate LAG1 auto correlations of observed and GCM current climate series.
10. For each day of the year assess the difference of observed and current climate LAG1 auto correlations using equation (9). If this difference is found statistically significant for more than 1% of time, bias correction of Lag 1 auto correlation is needed. This is denoted as the necessity check.
11. For the applicability check, apply LAG1 auto bias correction to future daily time series using equation 8 and check the significance of the bias correction (applicability check) by noting the percent of time the corrected daily values have crossed the lower

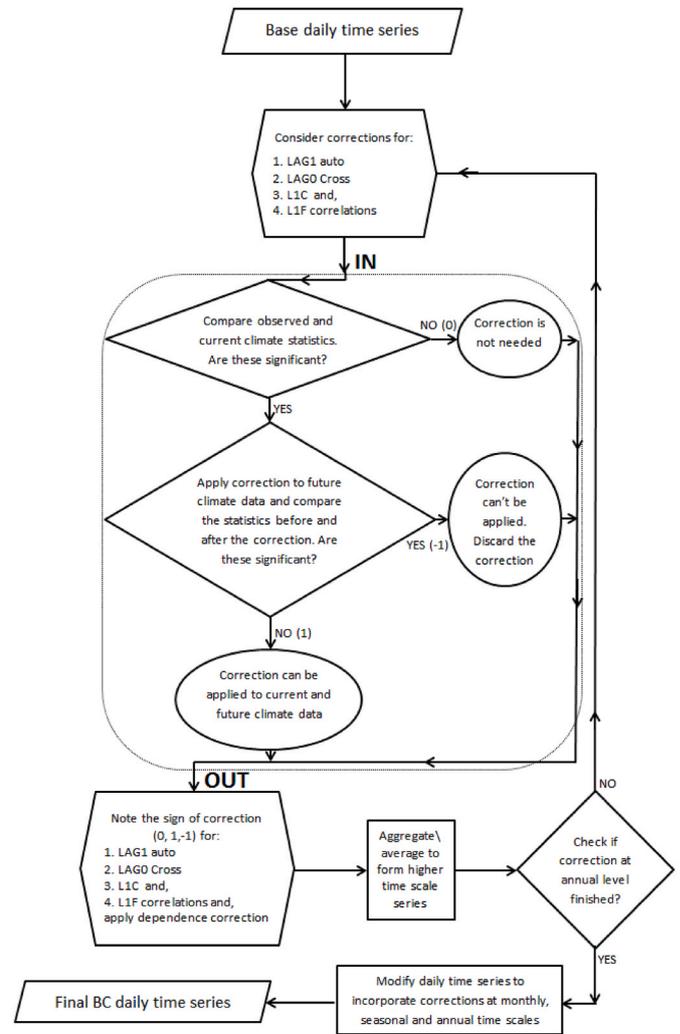


Fig. 2. Flow chart of modelling philosophy used. Base time series refers to daily QM corrected and variance corrections checked and applied at higher time scales. There are two loops in the whole procedure, one for four dependence statistics (LAG1, LAG0, L1C and L1F) and another for time nesting at monthly, seasonal and annual time scales.

and upper limits. Also, count the percent of times means and SDs of post BC series are different from pre BC (base) series using equation (10). If series passes the applicability check, the LAG1 bias correction forms as our plausible BC model for this variable and time scale.

12. Repeat the above steps for other variables. Store the results of all variables.
13. Next, assess the need for LAG0 cross-dependence correction. Calculate observed and current climate LAG0 cross correlation matrices of base model corrected daily time series considering all variables. Repeat step 10 and assess the need of bias correction.
14. If BC is needed then form future climate LAG0 bias corrected series by using equation (7). Repeat step 11 to check for the statistical significance of the changes. Note if the changes are statistically significant or not. Move to the next stage.
15. Check the need of a contemporaneous BC model (L1C). Calculate LAG0 and LAG1 cross correlations of observed and daily current climate base time series considering all variables/locations. Repeat step 10 and assess the need of bias correction considering LAG0 and LAG1 auto correlations. If test suggests the need of a bias correction, go to next step otherwise move to next stage.

16. Calculate LAG0 and LAG1 correlation matrices of observed and daily current climate base time series considering all variables/locations using equations (4) and (6). Apply bias correction to future climate series using equation (2).
17. Repeat step 11 to check for the statistical significance of the changes. Note if the changes are statistically significant or not.
18. Check the need of a full BC model (L1F) by repeating the procedure mentioned in steps 15–17.
19. Now assessment of all 4 BCE models at daily time scale is finished. If no model is suggested, do not apply any correction and move to the next time scale. If a full (L1F) or contemporaneous model (L1C) is picked, just apply that model to both current and future climate time series and move to the next time scale. If a LAG0 model is suggested, apply LAG0 model and see for the applicability of LAG1 model for individual variables.

3.6.3. Part C – aggregating series and assessing optimal BC model structure for the next aggregated time scale

20. Aggregate the time series to higher time scale(s) and check for the necessity and applicability of all the four BC model structures by following the procedure specified in steps 9 to 19.
21. Incorporate the corrections at all time scales into the daily series by using the aggregated and bias corrected time series at monthly, seasonal and annual time scales and equation (12).

It should be noted that if there are no significant biases in auto or cross-dependence attributes at the original (daily) time scale, or if the correction results in significant changes to the future climate simulation, the base model would be retained and will be used to form the time series at the aggregated time scale (Part C). If similar outcomes result at aggregated time scales, the end model will be the base model defined in Part A. Also note that the auto-correlation corrections can differ from variable to variable, creating corrected time series that have been processed using the minimal complexity model that is applicable.

4. Results

We apply univariate QM, multivariate quantile based NBC (hereafter called as MBC) and RoMBC to the daily rainfall and evaporation time series of 6 GCMs at 21 locations, including 18 rainfall and 3 evaporation points/stations, over the Greater Sydney region. For MBC, single iteration with QM correction at daily and SD and L1C bias corrections at daily, monthly, seasonal and annual time scales, was chosen. For GCM current climate, a 30 year time window spanning over 1976–2005, and for the future climate, three 30 year time windows from 2010 to 2039, 2040–2069 and 2070–2099, are considered. For space limitation, before presenting the overall results of all GCMs, we present and discuss detailed results for one representative GCM, ACCESS, only for one time window, 2070–2099, centred around 2085.

Table 2 presents the finalised structure of the flexible bias correction model. In the table, correction criteria are shown by zeros and ones. A ‘one’ with a star, ‘1\*’, implies that the statistic is directly applied or is ‘built in’ as a part of model structure. A zero (0) implies bias correction for that statistic is not needed while one (1) implies correction is needed as per the current climate. Negative one (–1) implies that while the correction is necessary, application of bias correction to the future climate time series makes the changes significant and therefore the correction is not applied.

Some specific findings can be drawn from Table 1. For all locations and variables, daily LAG0 and LAG1 dependence attributes are significantly different in the raw GCM series for the current climate and hence require corrections. However, as bias correction changes the statistics of the future time series quite significantly, the correction is ignored. LAG1 correction to evaporation time series was needed and applied. Monthly and seasonal LAG0 and L1C statistics require corrections and correction

Table 2  
RoMBC model structure adopted for the Greater Sydney rainfall and evaporation time series.

Catchments/EVP Stations	Daily				Monthly				Seasonal				Annual			
	QM	LAG0	LAG1	L1C	L1F	SD	LAG0	LAG1	L1C	L1F	SD	LAG0	LAG1	L1C	L1F	
1	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
2	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
3	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
4	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
5	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
6	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
7	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
8	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
9	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
10	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
11	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
12	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
13	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
14	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
15	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
16	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
17	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
18	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
19	1*	-1	-1	-1	-1	1	1	0	1	-1	-1	1	0	1	0	
20	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	
21	1*	-1	-1	-1	-1	1	1	0	1	-1	0	1	0	1	0	

Note: 1\*: Compulsory correction applied; 0: Correction not needed; 1: Correction required and applied; -1: Correction required but can't be applied.

for L1C is applied as it also includes correction for LAG0. Statistics at annual time scale does not require any corrections. Thus, the flexible model suggests a BC structure which is more complex than a traditional QM, however, is much simplified than a rigid multivariate BC (MBC)

although it does involve a complex full model (L1F) structure in the model identification exercise.

Figs. 3 and 4 present a comparison of the three approaches in the form of scatter plots of selected observed and bias corrected statistics of

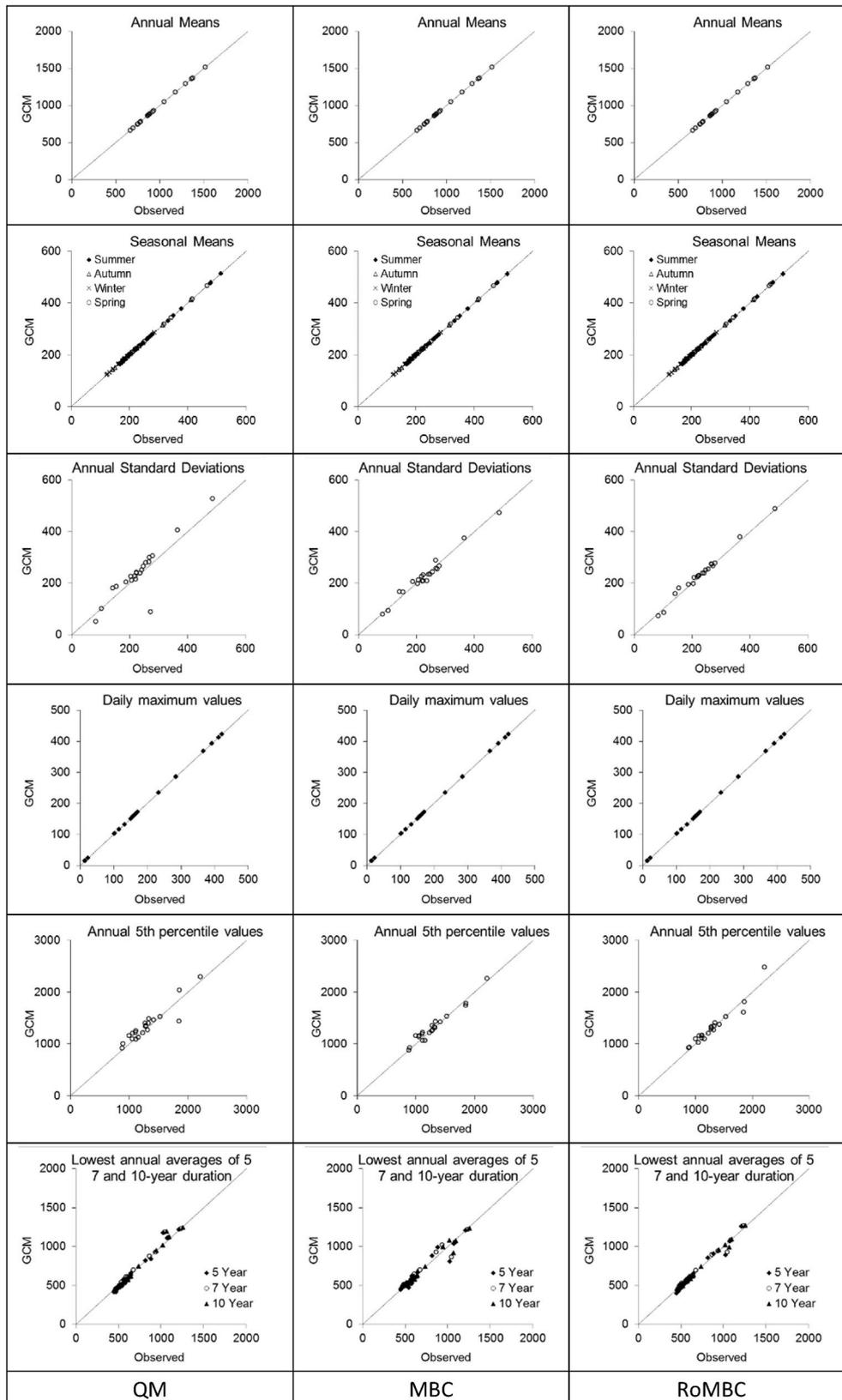


Fig. 3A. A few distributional statistics of the observed and GCM bias corrected data for the current climate.

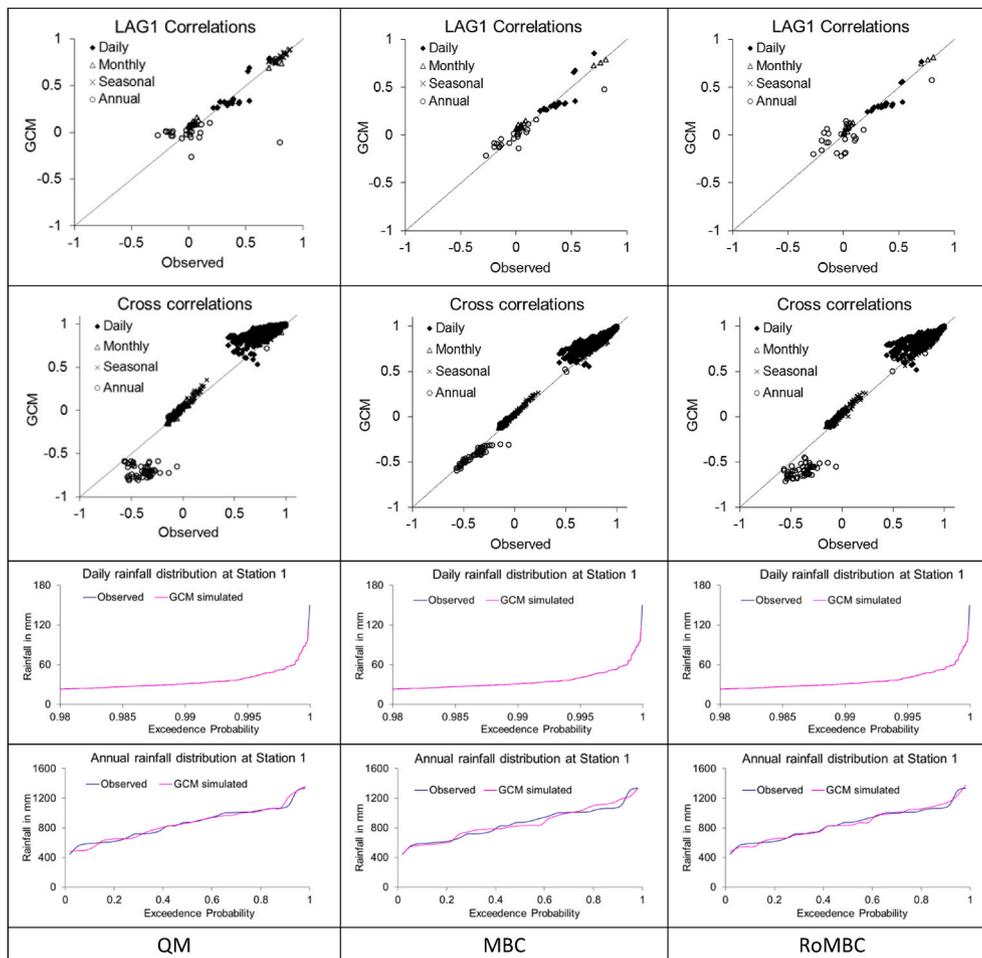


Fig. 3B. A few dependence statistics of the observed and GCM bias corrected data for the current climate.

general interest for current and future climates, respectively, for ACCESS GCM. Considering current climate results (Fig. 3a), the mean is reproduced well by all the models (top two rows, Fig. 2a). Annual SDs are also well reproduced by all the models except for the SD at one location by QM (row 3, Fig. 3a). Other statistics of interest, for example, daily maxima and annual 5th percentile values and lowest annual 3, 5 and 7 years totals are also well reproduced by all the three models considered (rows 4–6, Fig. 3a). Fig. 3b presents a few distribution and dependence statistics of observed and BC results. Lag1 and LAG0 cross correlations are better reproduced by MBC. As expected, RoMBC results are better than QM but not as good as MBC, more specifically for annual statistics. Considering results for the current climate, selecting MBC would be a reasonable choice. Bottom two rows of Fig. 3b present daily and annual rainfall distribution of observed and models simulated time series. All models are able to reproduce daily and annual distribution behaviour of observed rainfall. As QM is applied to daily data only, reproduction of observed annual distribution in the BC series indicates relatively good quality of raw GCM data over the study region for this statistic.

Now consider results for future climate as presented in Fig. 4 for ACCESS GCM for the time window, 2070–2099. Mean changes are shown in the top two rows of Fig. 4a. Annual rainfall shows almost no change while the three evaporation stations (top circles in the plots) show increases in annual evaporation. Seasonal rainfall shows increases in spring and summer while slight decreases in autumn and winter seasons. All BC models project similar increases in the annual and seasonal means. Annual SDs show some scatter with QM projecting slight under estimation of the statistic (3rd row, Fig. 4a). Daily maxima and annual 5th percentiles and lowest annual averages show no changes for

rainfall and increases for evaporation values. All models project similar results (4th - 6th rows, Fig. 4a). Top two rows of Fig. 4b present scatter plots of LAG1 and LAG0 cross correlations. All models show some scatter for these statistics, more specifically at the annual time scale. Daily and annual distribution of rainfall at a representative station 1 shows no notable changes albeit a few extreme daily values by MBC (bottom two rows, Fig. 4b). These results indicate no substantial loss of information if we selectively apply bias correction using RoMBC.

We now look at the projected changes in the average and extreme rainfall statistics in the future considering all GCMs. It may be noted that the climate models exhibit high variations across them in the projected changes with MIROC projecting increases in rainfall and CNRM and GFDL projecting decreases in rainfall in the future over the study area. Table 3 presents the percent changes in annual rainfall and evaporation, averaged across all GCMs, for all catchments and for three time windows. Similarly, Fig. 5 presents changes in annual rainfall, annual wet days, lowest 7 years totals and daily maximum rainfall as projected by all six GCMs by 2085 over all catchments using all BC models. Percent changes are derived by comparing the changes in the future with respect to current climate. In the figure, X axis shows all 18 catchments considered whereas on Y axis, percent changes are plotted. Similarly, statistics of individual GCMs are shown as thin lines, of no changes as black dotted lines and GCMs averaged values as thick black lines. Lines across catchments are joined for the sake of presentation only. Considering the models averaged results as presented in Table 3 and Fig. 5, all BC models project around 1–4 percent decrease in rainfall during 2010–2039, a similar percent increase during 2040–2069 and again a similar percent decrease during 2070–2099 time periods over the study

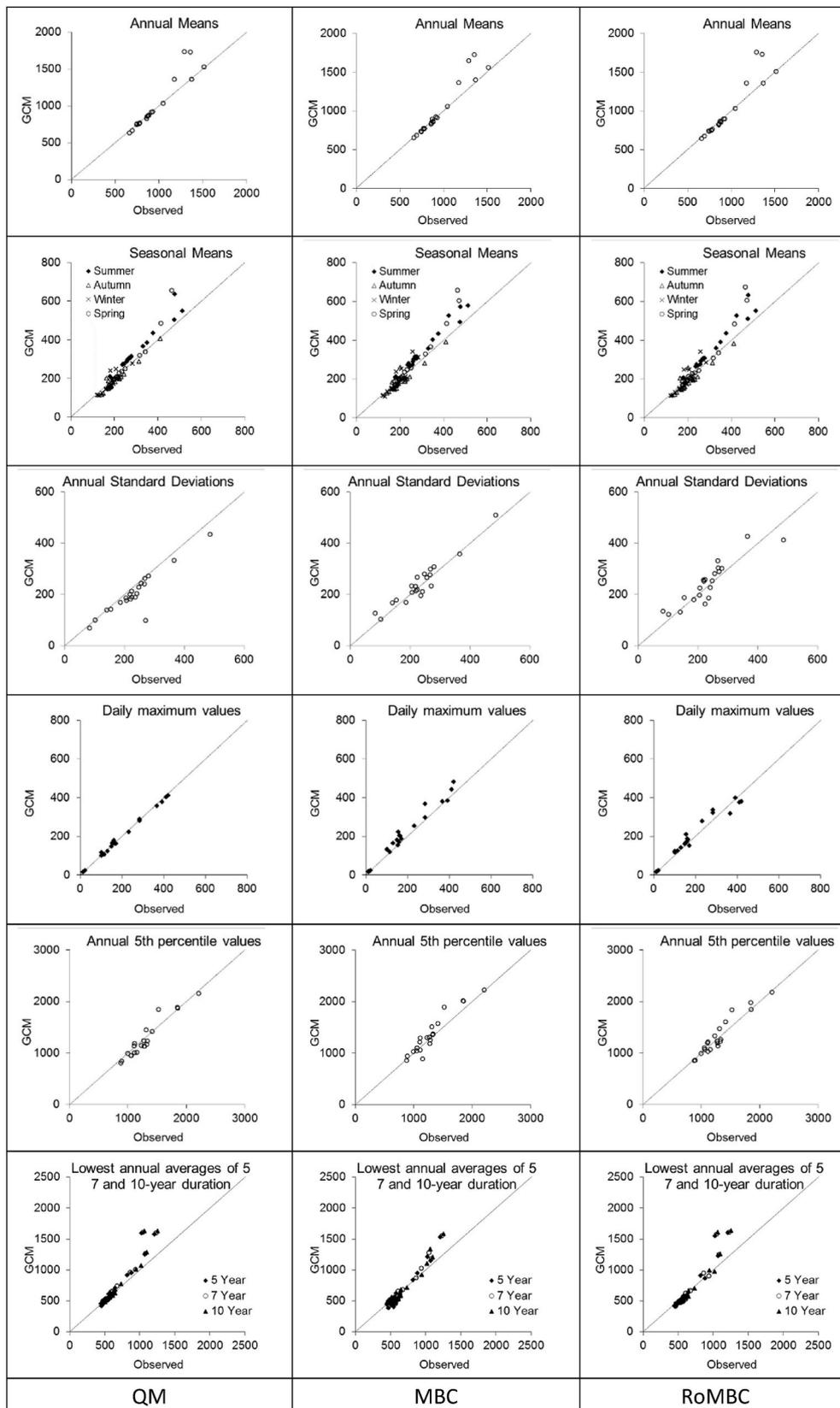


Fig. 4A. Same as Fig. 2A for future climate (2070–99).

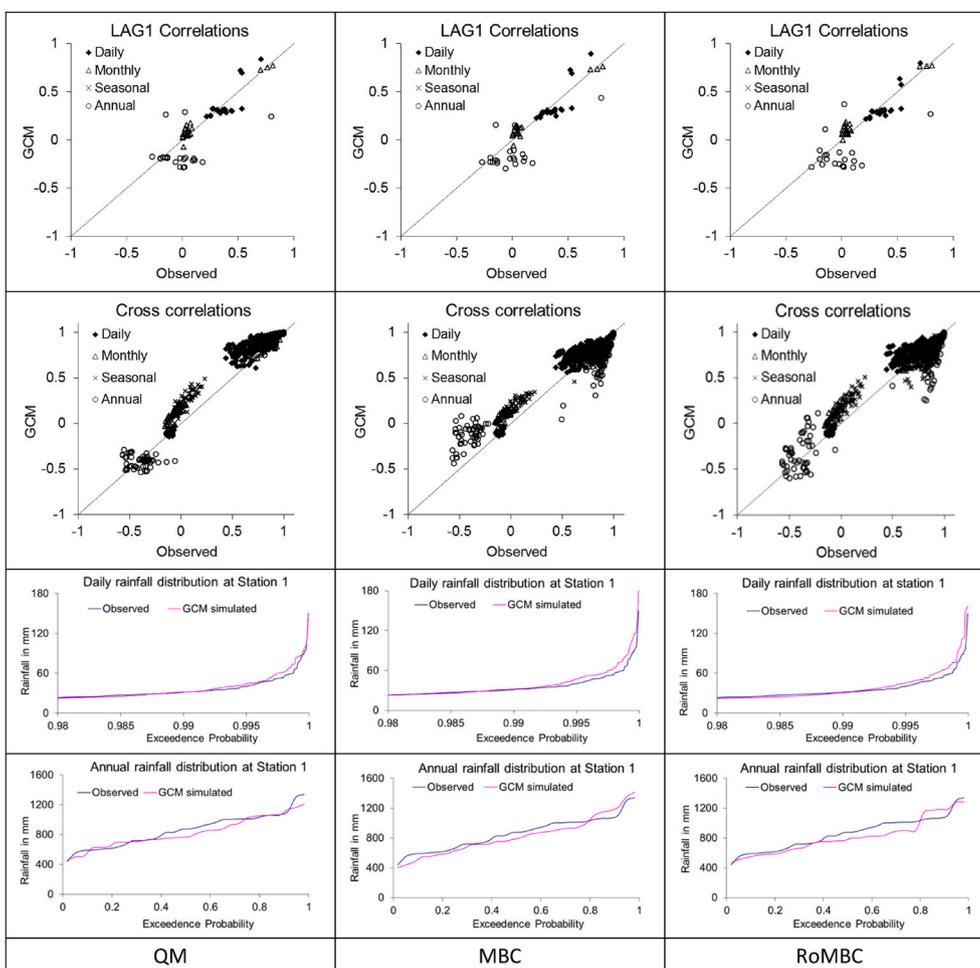


Fig. 4B. Same as Fig. 2B for future climate (2070–99).

Table 3  
Percent changes in annual rainfall and evaporation averaged across GCMs.

Rain/EVP Locations	Time periods – RAW data			Time periods – QM data			Time periods – MBC data			Time periods – RoMBC data		
	2010–39	2040–69	2070–99	2010–39	2040–69	2070–99	2010–39	2040–69	2070–99	2010–39	2040–69	2070–99
1	-5	3	-5	-4	2	-4	-4	2	-4	-4	2	-5
2	-5	3	-5	-4	2	-4	-4	1	-4	-4	0	-5
3	-5	4	-2	-3	2	-1	-3	7	2	-3	-2	-1
4	-5	4	-2	-3	3	-2	-1	5	1	-4	1	-2
5	-5	5	-1	-4	4	-1	-1	8	1	-5	2	-2
6	-5	5	-2	-4	4	-1	-1	7	2	-5	5	-1
7	-5	5	0	-5	5	0	-5	5	-3	-5	4	-2
8	-4	5	-2	-4	4	-2	-2	4	0	-4	4	-3
9	-5	5	0	-5	5	0	-4	9	-1	-4	2	-1
10	-4	5	-3	-3	4	-2	-2	5	-1	-4	5	-3
11	-3	5	-3	-3	4	-2	-2	3	-3	-4	1	-4
12	-3	5	-3	-3	4	-2	-3	1	-3	-4	3	-3
13	-3	5	-3	-2	4	-2	-2	4	-2	-4	2	-4
14	-3	5	-2	-2	4	-2	-2	3	-2	-4	3	-3
15	-2	5	-3	-2	4	-2	-1	3	-2	-3	11	-3
16	-2	5	-4	-2	4	-4	0	6	-1	-2	5	-4
17	-2	5	-5	-1	4	-5	2	7	-2	-1	4	-3
18	-4	5	1	-2	2	0	1	5	3	-5	-1	-1
1	7	18	28	8	20	32	3	11	27	6	19	34
2	2	8	15	2	8	15	3	7	15	3	9	15
3	5	13	23	6	15	26	7	15	25	7	15	26

region (top row of Fig. 5). Evaporation stations show around 5% increase during 2010–39, 11–12% during 2040–69 and 22–25% increase during 2070–99 time periods. Percent changes in bias corrected rainfall and evaporation results are in line with those projected by the raw GCMs

(Table 3). Changes are, in general consistent across catchments and GCMs with MIROC being the wet model and GFDL and CNRM being the dry ones (Fig. 5). All BC models project around 5% increase in the number of wet days in a year over the study catchments by 2085 (second

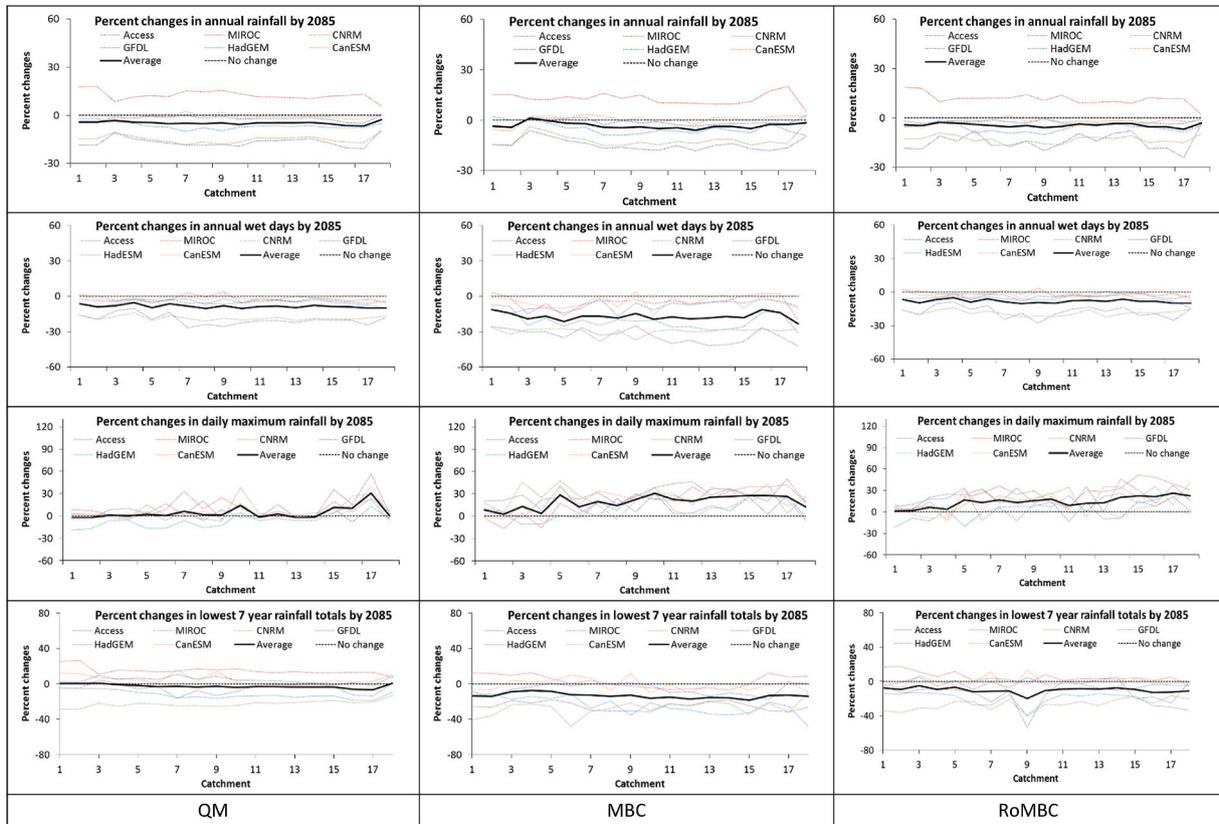


Fig. 5. Percent changes in a few rainfall statistics by 2085 as projected by six GCMs and three BC models over the catchments.

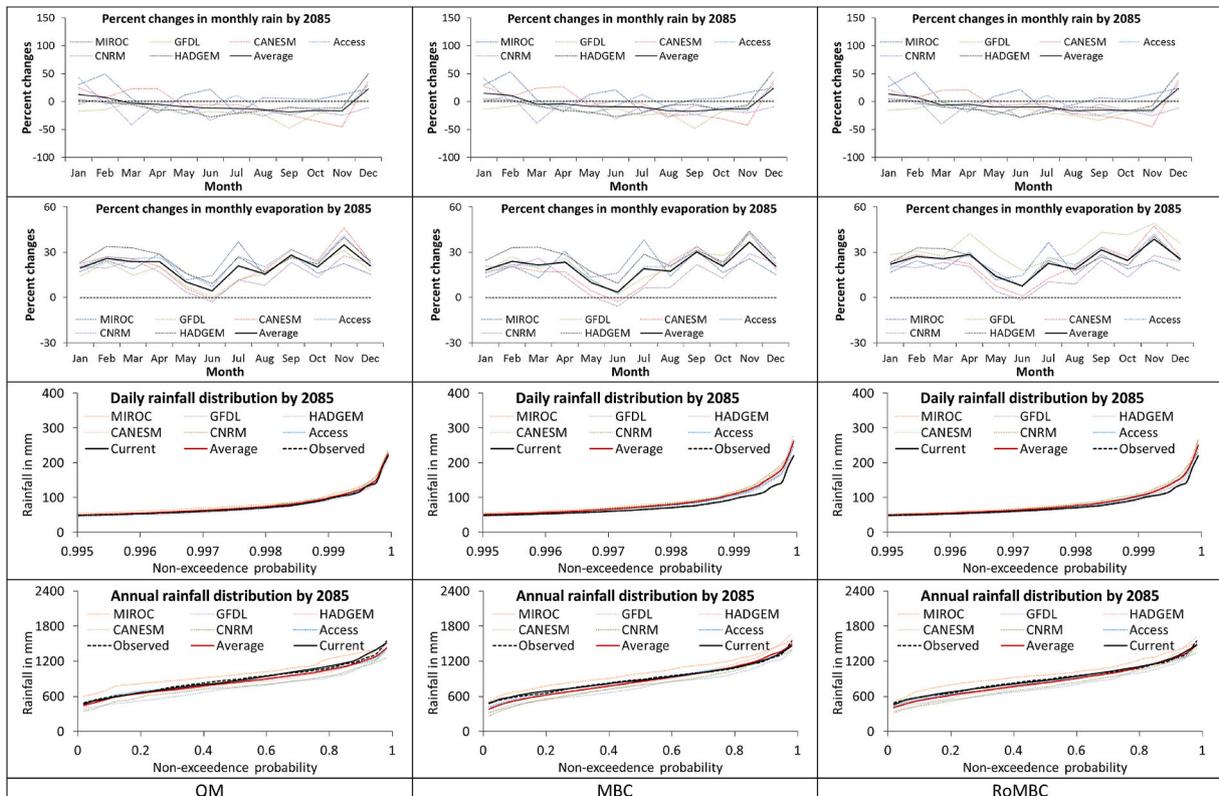


Fig. 6. Distributional changes in the catchment-averaged daily and annual rainfall by 2085 as projected by six GCMs and three BC models.

row, Fig. 5). Fig. 5 also includes the changes in daily maximum rainfall by 2085 (third row, Fig. 5). QM projects no appreciable changes in the catchment averaged daily maximum rainfall over the study region. MBC Projects 15% while RoMBC projects about 10% increase in the daily extreme rainfall in the future over the study catchments. As mentioned before, the rigid application of BC in MBC might force a few data points to take high or low values in order to match the observed dependence characteristics. RoMBC checks for this possibility at each time scale before applying BC and possibly avoids such instances. Percent changes in the lowest 7 year rainfall are presented in the last row of Fig. 5. QM shows no changes, MBC around 10–15% while RoMBC projects around 10% decreases in the statistic by 2085 over the study region. This statistic kind of represents the low frequency behaviour of the time series and is important for water resources management and water availability related applications. As QM is applied only at daily time scale, it is insensitive to the biases in the low frequency variability.

Fig. 5 presents the distributional changes of the catchments averaged time series formed by taking the average of catchment rainfall and evaporation over the region. Top two rows present the temporal distribution of monthly rainfall and evaporation while the changes in the probability distribution of area averaged daily and annual rainfall are presented in the bottom two rows. All BC models projects rainfall to increase in summer and decrease in spring. No shift of season is noted. Monthly evaporation shows lowest increase in June and maximum increase in November. Surprisingly, this increase does not occur during summer months. Perhaps, increase in summer rainfall (and more rainy days) causes the evaporation to be lower on the rainy days. Distribution of area averaged daily rainfall (only extreme values) is shown in the third row of Fig. 6. QM does not show any significant changes in the extreme daily values in relation to the observed values. RoMBC results are in between QM and MBC with a mild increase in very extreme daily values by 2085. Considering distribution of area averaged annual rainfall (last row of Fig. 6), QM projects negligible changes in the shape of the annual rainfall distribution, with a slight reduction in the higher quantile rainfall by 2085. MBC and RoMBC project a few more dry years with minor changes in the shape of the distribution at both lower and higher ends.

#### 4.1. RoMBC details

RoMBC is implemented in a R shell and allows the bias correction approach to be applied in a fairly simple manner.

##### 4.1.1. Input data

The software requires information about data in the form of four files in a specific format. These include observed and raw data files for calibration (current climate) as well as verification (future climate) time periods. When dealing with GCM current and future climates data, the package uses three files (observed and GCM/RCM current and future climates raw data files. In this case, the observed verification period file will be same as observed calibration period file. In this set up, the observed data is used to compare the changes in each variable in the future. It is not necessary to have equal length of data for raw and observed file either for calibration or verification periods. Users are allowed to define their own seasons.

In addition to the names of the four data files, all other general information is provided through the 'basic.dat' file (Table 4). It includes the information about the number of years of data, number of variables, width of moving window used to correct the daily data, physical lower and upper limits on the variables, whether data consider leap years or not and the split of calendar months across the seasons being modelled. All the information is provided in a free format, separated by spaces. At present, the package allows for a maximum of 150 years of daily data, 30 variables, 12 seasons and 31 day moving window.

##### 4.1.2. Package outputs

Upon successful completion of the program, 6 output files are generated. Two files contain the bias corrected time series for the current and future time periods. Remaining four files contain a few common statistics of the observed, raw and bias corrected data for the current and future climate as per the followings: 1) observed and raw data for current climate; 2) observed and raw data for future climate; 3) observed and bias corrected data for current climate; and 4) observed and bias corrected data for future climate time periods. As for GCM/RCM future climate data corrections, the observed file would be same as the observed file for current climate; the observed statistics would not change while we move from current to future climate. Statistics considered include, means, standard deviations, skewness, LAG1 and LAG2 auto correlations. When multiple variables or locations are corrected then auto and LAG1 cross correlations are also computed. The package allows the users to look at raw and bias corrected statistics either in the form of a table or as plots at multiple time scales of interest. Finally the package also provides plots of the empirical cumulative probability distributions of the observed and raw and observed and bias corrected time series.

## 5. Discussion and conclusions

Bias correction has now become a standard post-processing procedure to correct systematic biases and convert climate model raw output to one that is suitable for use in climate change impact assessment studies. The majority of existing multivariate bias correction approaches work on a pre-defined rigid bias correction model structure without looking into the magnitude and nature of biases and their behaviour in the future. This study presented a novel approach for specifying the optimal structure of a multivariate bias correction model based on the premise that a pre-defined fixed bias correction structure does not apply when biases are being assessed across time scales, variables and dependence attributes, and if imposed, such a bias correction model can provide unstable and physically incompatible projections for the future where the impact of unneeded structural complexity will be most evident. Given this, the approach adopted resided on specifying a base or reference bias correction model, and updating this reference to a new model only if (a) systematic biases are noted in the simulations representing the observed period using the reference model, and (b) an updated bias correction model that addresses the systematic biases in (a) does not, in turn, lead to projections of the future that are untenable. Only if these conditions are satisfied is the bias correction model updated, and the process repeated to extend to all time scales and variables being modelled.

While models have long been formulated with limited data for application in scenarios that have not been observed, in most cases these models are developed assuming the observational record used in their testing and validation exhibits stationarity. As our situation is one where the future can be expected to change significantly (at least for temperature and hence for evaporation), forming a robust model requires an added means for identifying one that will exhibit stability into the future. What is different in our approach here is the use of statistics to quantify instability, which is performed by defining a base case and discarding model formulations that deviate significantly from this reference. While the statistics we have chosen here are relevant in the water resources context, the choice of attributes that define stability is one that should reside with the user based on the applications the climate model simulations are intended for.

An open-source software in R statistical computing environment is presented here. It provides an easy means to apply an in-built flexible multivariate and multi-timescale bias correction alternative that is self-evolving and grows in complexity following the requirement of the raw data. Applications of the software along with information about the capabilities of the software are demonstrated using a sample dataset. It is anticipated that the ease of running the software and the flexibility of

**Table 4**  
Structure of 'Basic.dat' file used in the example.

```

Information about observed data used in calibration
  No of years of data      Start Year
    30                    1976
Observed data file name along with directory path for calibration (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_obs.dat
Information about observed data used in validation
  No of years of data      Start Year
    30                    1976
Observed data file name along with directory path for validation (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_obs.dat
Information about raw data used in calibration
  No of years of data      Start Year
    30                    1976
Data file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_access_hist.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\stat_access_RAW_1976_05.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_access_BCC_1976_05.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\stat_access_bcc_1976_05.dat
Information about data used for bias correction - validation
  No of years of data      Start Year
    30                    2070
Data file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_access_rcp85.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\stat_access_RAW_2070_99.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\rain_access_BCF_2070_99.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
  h:\FMBC_software\Example\stat_access_BCF_2070_99.dat
Number of variables
  21
Specify time scale of data used 0-daily; 1-monthly
  0
Missing number identifier (any number equal to or slightly higher than the defined value is ok)
  -9000.0
Width of one side of moving window for daily data (in days)
  15
Option whether data follows a usual leap year format (0), or fixed days in a month format (1)
  0 0 0 0
Number of seasons in a year
  4
Number of months in each season
  3 3 3 3
Month numbering assigned to each season (1-Jan, 2-Feb....., 12-Dec)
  1 2 3
  4 5 6
  7 8 9
  10 11 12
Option for creation of plots (0: no plots, 1: plots of statistics, 2: plots of empirical distribution as well)
  1
Specify physical lower and upper limits on the variables/locations and aggregation criteria
  Variable  Lower limit  Upper limit  higher time scale aggr 0-av, >0 sum  Threshold indicator  Threshold
  1 0 800 1 1 1.0
  2 0 800 1 1 1.0
  3 0 800 1 1 1.0
  4 0 800 1 1 1.0
  5 0 800 1 1 1.0
  6 0 800 1 1 1.0
  7 0 800 1 1 1.0
  8 0 800 1 1 1.0
  9 0 800 1 1 1.0
  10 0 800 1 1 1.0
  11 0 800 1 1 1.0
  12 0 800 1 1 1.0
  13 0 800 1 1 1.0
  14 0 800 1 1 1.0
  15 0 800 1 1 1.0
  16 0 800 1 1 1.0
  17 0 800 1 1 1.0
  18 0 800 1 1 1.0
  19 0 50 1 0 5.0
  20 0 50 1 0 5.0
  21 0 50 1 0 5.0
Information about no of days in a month for Obs_cali  Obs_vali  GCM_cali  GCM_vali
  31 31 31 31
  29 29 29 29
  31 31 31 31
  30 30 30 30
  31 31 31 31
  30 30 30 30
  31 31 31 31
  31 31 31 31
  30 30 30 30
  31 31 31 31
  30 30 30 30
  31 31 31 31
  30 30 30 30
  31 31 31 31
  30 30 30 30
  31 31 31 31
  
```

exercising a wide variety of options will make it popular for practitioners carrying out impact assessments and researchers investigating downscaling methods.

### Software Availability

Name of software package RoMBC.  
 Developers: Raj Mehrotra, WRC, Civil and Env. Engg., UNSW Sydney  
 E-mail address: [raj.mehrotra@unsw.edu.au](mailto:raj.mehrotra@unsw.edu.au).  
 Ashish Sharma, WRC, Civil and Env. Engg UNSW Sydney E-mail address [a.sharma@unsw.edu.au](mailto:a.sharma@unsw.edu.au).  
 Year first available 2021.  
 Hardware required standard PC for Windows.  
 Software required RGUI or R-Studio.  
 Availability and cost: Available free of charge. Software along with sample data and help file can be downloaded from the following website <http://www.hydrology.unsw.edu.au/download/software>.  
 Programme language Written in R and Fortran.

### Declaration of competing interest

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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### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envsoft.2021.105019>.

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