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Author:
Mehrotra, R; Johnson, F; Sharma, A

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A software toolkit for correcting systematic biases in climate model simulations

R. Mehrotra*, F. Johnson, A. Sharma

School of Civil and Environmental Engineering, University of New South Wales, Australia

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A B S T R A C T

Simulations from climate models require bias correction prior to use in impact assessments or for statistical or dynamic downscaling to finer scales. There are a number of different approaches to bias correction, although most of these focus on a single variable for a particular location. Another limitation is that often corrections are only applied for one time scale of interest, for example daily or monthly aggregated simulations despite evidence of different bias structures existing at different time scales. Recent works have sought to address each of these limitations and have led to the development of the Multivariate Recursive Nesting Bias Correction (MRNBC) and Multivariate Recursive Quantile-matching Nested Bias Correction (MRQNBC) methods. An open-source software toolkit in the R statistical computing environment has been developed to provide access to these methods. Several applications of the software are demonstrated in this paper along with information about the capabilities of the software.

1. Introduction

General circulation models (GCMs) are becoming increasingly sophisticated with improvements in resolution and the range of processes that are represented. As a result, in many cases GCMs are now more accurately referred to as Earth System Models (ESMs) because of the number of processes that can be simulated. Despite these improvements and overall confidence in the representation of large scale responses such as the global temperature sensitivity, there remain a number of biases in GCM simulations, particularly with respect to the hydrological cycle. Dynamic downscaling using regional climate models (RCMs) can improve some of these biases because their finer resolutions allow topography to be more accurately represented and at the finest resolutions, these models are now considered convection-permitting. However in many cases significant biases can persist either from the driving GCM or the RCM itself. When GCM or RCM simulations are used in statistical downscaling approaches or directly for impact assessments, bias correction of the variables of interest is required (Mehrotra and Sharma, 2006, 2010). There is also an increasing interest in the need to correct GCM biases in the lateral boundary conditions used to downscale to finer resolutions using appropriately chosen RCMs (Rocheta et al., 2017).

Traditionally bias correction has focussed on correcting the representation of individual variables over a single time-scale of interest (e.g., daily or monthly data). The underlying idea behind any bias correction approach is to identify the bias (in a statistic or quantile) for the current climate and correct the future climate under the assumption that the bias does not change over time. Daily or monthly standardization forms the most basic bias correction and is used to correct for systematic biases in the mean and variances of GCM simulations (Wilby et al., 2004). Nonparametric bias correction approaches include quantile matching, correction factors and transfer functions based approaches (e.g., Arnell and Reynard, 1996; Chen et al., 2013; Chiew and McMahon, 2002; Teutschbein and Seibert, 2013; Mpelasoka and Chiew, 2009; Ines and Hansen, 2006; Li et al., 2010; Piani et al., 2010; Wood et al., 2004). These approaches address biases in the overall distribution of GCM simulations (e.g., Cayan et al., 2008; Li et al., 2010; Teutschbein and Seibert, 2013; Maurer and Hidalgo 2008). A variation of quantile matching, named equidistant quantile matching (EQM), has been proposed by Li et al. (2010). Analogous approaches have also been proposed to correct biases in the frequency

* Corresponding author. Water Research Centre, School of Civil and Environmental Engineering, University of New South Wales, Sydney, 2052, Australia.
E-mail address: raj.mehrotra@unsw.edu.au (R. Mehrotra).

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spectrum of variables of interest (Nguyen et al., 2016, 2017).

Commonly used bias correction approaches generally consider a single time scale (e.g. day, month or year) and do not consider the biases in persistence attributes. When the bias corrected variables are aggregated/averaged to longer time scales (for example, daily to monthly/seasonal or annual), observed and bias corrected statistics can be quite different. Johnson and Sharma (2012) proposed the idea of nesting multiple time scales including a persistence correction in the standard bias correction procedure. This was named Nested Bias Correction (NBC). As the nesting was found to create artifacts in some of the statistics of the bias corrected series, Mehrotra and Sharma (2012) proposed multiple repeats of the nested bias correction procedure to minimise the biases at all time scales. This modification was termed Recursive Nested Bias Correction (RNBC).

One of the criticisms of bias correction is that it is generally applied to each variable separately (Mehrotra and Sharma, 2015, 2016; Vrac and Friederichs, 2015; Li et al., 2014). As a result, although it improves the statistics of each variable, the physical dependencies between different variables are overlooked (Colette et al., 2012; Maraun, 2013). For water resources impact assessments, bias corrected time series of a number of different variables is often needed in catchment modelling (for example precipitation and temperature, potential evapotranspiration etc.) and statistical downscaling (requires a number of bias corrected upper air variables). A related problem can arise with poor representation of spatial correlations if variables are corrected separately for different locations (Hnilica et al., 2016; Hanel et al., 2017).

To address these problems, multivariate bias correction approaches have been proposed. Piani and Haerter (2012) proposed a bias correction approach to simultaneously correct temperature and precipitation. This was achieved by correcting one time series (e.g., precipitation) conditionally to the bias-corrected values of the other variable's time series (e.g., temperature). Copula-based methods have also been proposed to consider the joint dependence between variables or the spatial dependence across grids (Mao et al., 2015; Vrac and Friederichs, 2015). Mehrotra and Sharma (2015) proposed a parametric multivariate extension, whilst a multivariate and multi-timescale extension of quantile matching based nonparametric bias correction alternatives was suggested by Mehrotra and Sharma (2016). The latter approach corrects biases in probability space as well as the more routine distribution corrections. The bias corrected simulations are shown to have the correct dependence between variables or locations as well as improved persistence structures and distributions over multiple time-scales.

The mathematical relationships used in bias correction are developed based on historical and current climate observations and are applied in a future climate under the assumption of stationarity over time (Salvi et al., 2016). The stationary bias assumption is questionable (Nahar et al., 2017; Buser et al., 2009; Ehret et al., 2012) but efforts to improve on the assumption still need further development. Different researchers have recognised this issue and have suggested possible solutions. Grillakis et al. (2016) provide a review of a few of these approaches in the context of bias correction.

While multivariate bias correction approach is attractive, the multivariate setup requires estimation of additional parameters, extremely large matrices and complex mathematical formulations, making it inaccessible to practitioners wishing to use such methods for climate change impact assessments. Keeping in view these aspects, a Multivariate Bias Correction (MBC) software package has been developed in the R statistical computing environment. The package includes both Multivariate Recursive Nesting Bias Correction (MRNBC) and Multivariate Quantile-matching Recursive Nesting Bias Correction (MRQNBC) approaches (Mehrotra and Sharma, 2015, 2016) and makes it simple to implement both these approaches in a fairly simple manner. This paper describes the software package and provides simple examples of its applications.

2. Multivariate bias correction

The multivariate modelling of Mehrotra and Sharma (2015, 2016) corrects the raw GCM simulations at pre-defined time-scales to match the observed distributional and persistence attributes at each of these time-scales. While we do not claim that the proposed multivariate modelling will keep the physical relationship among the climate variable intact, it is certainly a better choice than the univariate bias correction option, especially when dependence biases (between the multiple variables of interest) are present. Future GCM simulations have the same corrections applied, which allows for changes in the statistical properties over time but corrects for biases, assuming that the biases are stationary and smaller than the magnitude of changes that are projected (Chen et al., 2015). The approach first applies a univariate bias correction at each time-scale to match the observed statistical/distributional attributes. These univariate bias corrected time series are subsequently adjusted to reproduce the observed auto and cross dependence attributes at each time-scale. More details on the structure of the multivariate bias correction models are discussed in Salas (1980) and Mehrotra and Sharma (2015, 2016) and only a few key points related to multivariate and multi-timescale aspects

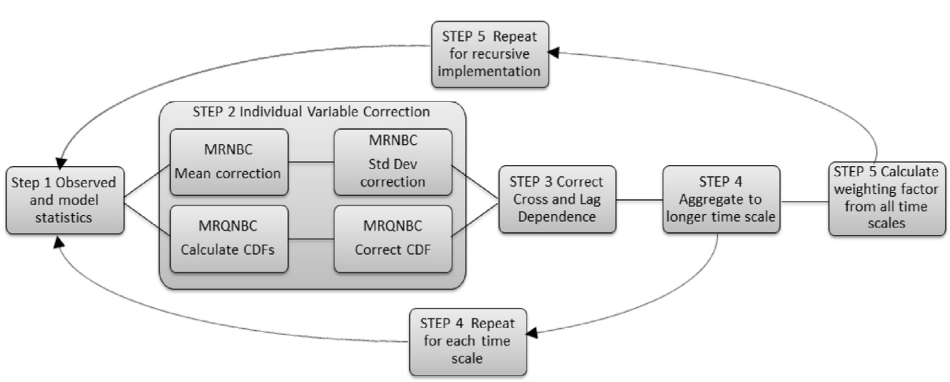

Fig. 1. Correction flow chart of MBC.

Table 1
Structure of 'Basic.dat' file used for dataset 1.

```
Information about observed data for calibration
        No of years of data     Start Year
                66                1881
Observed data file name along with directory path for calibration (if not in the directory where executable is located)
        obsC.dat
Information about observed data for validation
        No of years of data     Start Year
                70                1947
Observed data file name along with directory path for validation (if not in the directory where executable is located)
        obsF.dat
Information about raw data used in calibration
        No of years of data     Start Year
                63                1891
Data file name with directory path (if not in the directory where executable is located)
        rawC.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
        stat_rawc.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
        bcc.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
        stat_bcc.dat
Information about data used for bias correction - validation
        No of years of data          Start Year
                61                      1954
Data file name with directory path (if not in the directory where executable is located)
        rawF.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
        stat_rawf.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
        bcf.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
        stat_bcf.dat
Number of variables
        7
Specify time scale of data used 0-daily; 1-monthly
        0
Number of iterations
        3
Missing number identifier (any number equal to or slightly higher than the defined value is ok)
        -9000.0
Bias correction model (1 - multivariate NBC (MRNBC); 2 - multivariate CDM (MRQNBC))
        1
Width of one side of moving window for daily data (in days)
        15
Option whether data (gcm_cali gcm_vali obs_cali obs_vali) follows a usual leap year (0), or fixed days in a month format (1)
        0   0   0   0
Nesting levels and bias correction options:  1-included   and  0-excluded
        Time          MEAN    SD/Dist   LAG1 Auto   LAG0 CROSS   LAG1 CROSS
        Daily           1       1         1           1            1
        Monthly         1       1         1           1            1
        Quarterly       1       1         1           1            1
        Annual          1       1         1           1            1
        Triannual       0       0         0           0            0
Number of seasons in a year
        3
Number of months in each season
        4   4   4
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	Time scale aggr 0-av, >0 sum	Threshold indicator	Threshold
1	500	1000	0	0	0
2	2500	4000	0	0	0
3	-100	100	0	0	0
4	-100	100	0	0	0
5	-100	100	0	0	0
6	-100	100	0	0	0
7	0	500	1	1	0.30

Information about no of days in a month for

Obs_cali	Obs_vali	GCM_cali	GCM_vali
31	31	31	31
28	28	28	28
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

of MRNBC and MRQNBC approaches are discussed here.

In MBC, we describe the main statistical attributes by mean and standard deviation or distribution and, the dependence attributes by the lag-0 and lag-1 auto and cross correlations at four selected bias correction time scales - daily, monthly, quarterly and annual. The statistical attributes and time scales selected are arbitrary, and the approach presented here could accommodate more generic representations of statistical attributes, as well as time scales (Johnson and Sharma, 2012; Mehrotra and Sharma, 2012, 2015). The bias correction approach works in stages, from univariate to multivariate and from one time-scale to another. At each time step, it first corrects for the biases in statistics/distribution of the individual variables. Once all variables are corrected for the distributional biases, these are further corrected for the time and across-variables dependence biases using a multivariate autoregressive model. Bias corrected time series is aggregated/averaged to the next time scale and same procedure is repeated. The multivariate component includes two auto-regressive models — the first has constant parameters over time and is used to represent the daily and annual time series, whilst the second model uses periodic parameters to represent the monthly and seasonal characteristics (Salas, 1980).

3. Multivariate bias correction package

The Multivariate Bias Correction (MBC) package for the R statistical software includes both multivariate bias correction approaches, namely, MRNBC and MRQNBC. This section provides the general details of the implementation of the bias correction methods in the R package, data requirements and form of the outputs from the package.

3.1. General modelling philosophy

MBC provides bias corrected climate model simulations which match observed statistics and then uses the correction factors for future simulations. To demonstrate the fidelity of any bias correction method, it is optimal to test the method using a split sample approach with data from the historical period used to estimate the bias properties and then test the bias corrections on a second sample of historical data. Borrowing from hydrological literature, these two periods are referred to as calibration and verification here. The general idea then is to divide the historical data into two (or more) periods to test and compare bias correction method performance. Once the best bias correction approach has been determined then the full historical record can be used to estimate the bias properties which are then applied to future simulations. The verification stage can be thought as of pseudo-future data and thus in the following section, “future” is used as a generic term to refer to the simulations that are being corrected using bias statistics from another period of time.

There is often a mismatch between the spatial scale of climate model simulations and traditional meteorological observations (e.g. rain gauge or temperature measurements). Therefore it is generally recommended that gridded data products are used to calculate the bias in climate model simulations. Alternatively reanalysis data may also be taken as the observation data set; this is particularly relevant when upper-air variables require bias correction prior to use in a downscaling scheme. In what follows, observations thus refer to a gridded data product derived either from station data or reanalysis. Raw simulations are those taken directly from a climate model and the corrected simulations are the products/outputs of the bias correction.

Although in the previous discussions, the MRNBC and MRQNBC were motivated by the requirements for multiple climate variables, the cross dependence that is corrected in both methods can also refer to spatial correlations of a single climate variable or some combination of both multi-variate and spatial dependence. The mathematical formulations are the same in either case so the methods are sufficiently flexible to address the important

Table 2
A few statistics of raw and bias corrected time series for calibration period: dataset 1.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	799.2	805.57	10.448	7.3822	6.29E-02	−0.12856	−1.18E-02	−2.23E-02	−0.67703	−0.54338
2	3084.5	3073.6	13.129	8.3843	0.11065	5.09E-02	3.93E-02	−0.14447	−0.85143	−0.24484
3	14.759	16.19	1.7092	0.48531	0.76638	8.25E-02	0.61275	−4.76E-02	−0.13596	0.12686
4	3.7496	13.797	0.86558	1.1113	−4.90E-02	−0.23689	6.35E-02	4.04E-02	−0.41173	0.17588
5	−0.10001	1.7554	6.67E-02	0.32202	−0.13885	−0.1242	0.23474	−0.17528	0.44325	0.11812
6	−6.8031	−9.1646	0.49192	0.40722	0.42392	4.75E-02	0.3041	−0.41958	−0.15264	−0.7137
7	890.3	982.82	201.3	82.466	0.21671	0.34836	8.03E-02	−1.65E-03	0.66521	0.21706
Statistics at Seasonal Level										
1	799.37	805.68	17.426	12.745	3.22E-02	4.23E-02	−0.12479	−6.53E-02	−2.54E-02	−0.15631
2	3084.8	3073.8	30.423	36.691	−0.22758	−0.41603	−0.30329	−0.4227	−0.1002	−0.19421
3	14.783	16.179	2.0931	0.838	0.46685	−4.12E-02	0.45662	9.93E-03	0.16403	0.32333
4	3.7208	13.759	1.816	3.3506	−0.16286	−0.3251	−0.23692	−0.34362	−0.40158	−3.20E-02
5	−9.77E-02	1.7453	0.19015	2.0889	−0.33866	−0.46739	−0.36098	−0.44312	−0.20454	0.29945
6	−6.7913	−9.1456	1.7953	2.3018	−0.39417	−0.44114	−0.38031	−0.4456	−0.20933	−0.53134
7	294.56	328.35	140	56.678	−0.14266	−7.13E-02	−6.04E-02	−0.17794	0.96754	0.2844
Statistics at Monthly Level										
1	799.47	805.74	26.794	24.581	0.42444	0.39698	0.23919	7.26E-02	−2.80E-02	−0.16702
2	3085	3074	39.297	45.254	0.55487	0.71759	0.32193	0.37707	−0.36822	−0.59163
3	14.799	16.193	2.691	1.698	0.48683	1.29E-02	0.33766	4.19E-02	0.28141	7.16E-02
4	3.7083	13.741	2.6835	4.5097	0.40958	0.51489	0.21201	0.23403	0.14113	0.27599
5	−9.71E-02	1.7365	0.26001	2.6065	0.55018	0.71749	0.3084	0.37586	−0.45568	0.34304
6	−6.7859	−9.153	2.4329	3.1767	0.62997	0.68014	0.34904	0.36054	0.44128	0.28678
7	73.864	82.065	65.711	24.007	9.74E-02	0.21816	−1.55E-03	7.29E-02	2.0688	0.54542
Statistics at Daily Level										
1	799.44	805.73	53.656	50.349	0.80069	0.72517	0.51084	0.37852	−0.26637	−0.32211
2	3084.8	3073.8	66.002	64.532	0.84538	0.83991	0.61416	0.62907	−0.57223	−0.67303
3	14.796	16.188	7.8462	7.1408	0.36527	0.31681	0.12926	3.64E-02	0.64827	0.23459
4	3.725	13.766	5.9557	8.7608	0.66244	0.69139	0.37796	0.39625	0.19452	0.41635
5	−9.85E-02	1.7506	0.54697	4.1443	0.65919	0.67424	0.3627	0.46985	−0.4166	0.2612
6	−6.7993	−9.1586	4.8967	5.7433	0.62385	0.64094	0.34523	0.36707	0.14528	0.20862
7	2.4301	2.6971	6.9737	2.7322	0.43823	0.32295	0.16405	0.11627	6.6146	2.225

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	799.2	799.43	10.448	10.635	6.29E-02	8.14E-02	−1.18E-02	0.24946	−0.67703	0.22288
2	3084.5	3084.9	13.129	13.294	0.11065	0.11773	3.93E-02	0.21788	−0.85143	0.20766
3	14.759	14.817	1.7092	1.7263	0.76638	0.77538	0.61275	0.72393	−0.13596	0.23182
4	3.7496	3.7478	0.86558	0.89467	−4.90E-02	−5.14E-02	6.35E-02	7.75E-02	−0.41173	0.40343
5	−0.10001	−0.10062	6.67E-02	5.20E-02	−0.13885	−7.92E-02	0.23474	−6.05E-03	0.44325	−0.85179
6	−6.8031	−6.7924	0.49192	0.49353	0.42392	0.41223	0.3041	0.23695	−0.15264	−0.13285
7	925.04	944.34	198.88	195.57	0.2143	0.18759	8.00E-02	0.16401	0.65994	−4.69E-03
Statistics at Seasonal Level										
1	799.37	799.31	17.426	17.443	3.22E-02	2.43E-02	−0.12479	−0.13361	−2.54E-02	0.25641
2	3084.8	3084.7	30.423	30.309	−0.22758	−0.22793	−0.30329	−0.30005	−0.1002	1.90E-02
3	14.783	14.77	2.0931	2.0743	0.46685	0.50132	0.45662	0.42284	0.16403	0.29685
4	3.7208	3.7132	1.816	1.8293	−0.16286	−0.14092	−0.23692	−0.23566	−0.40158	−0.18427
5	−9.77E-02	−9.86E-02	0.19015	0.18566	−0.33866	−0.38797	−0.36098	−0.40095	−0.20454	−0.32784
6	−6.7913	−6.7943	1.7953	1.7984	−0.39417	−0.38369	−0.38031	−0.39944	−0.20933	−0.21778
7	306.17	317.11	138.81	141.35	−0.14573	−0.1276	−6.04E-02	−1.69E-02	0.97353	0.23065
Statistics at Monthly Level										
1	799.47	799.41	26.794	26.924	0.42444	0.43306	0.23919	0.25193	−2.80E-02	0.21545
2	3085	3084.9	39.297	39.399	0.55487	0.56385	0.32193	0.32532	−0.36822	−0.27262
3	14.799	14.803	2.691	2.7454	0.48683	0.56558	0.33766	0.34055	0.28141	0.33964
4	3.7083	3.7135	2.6835	2.6833	0.40958	0.40133	0.21201	0.1867	0.14113	0.27874
5	−9.71E-02	−9.83E-02	0.26001	0.25964	0.55018	0.51822	0.3084	0.28566	−0.45568	−0.38639
6	−6.7859	−6.7882	2.4329	2.4331	0.62997	0.63638	0.34904	0.33559	0.44128	0.39904
7	76.764	79.241	65.269	65.445	9.54E-02	0.10091	−2.69E-03	−1.61E-02	2.0832	1.2038
Statistics at Daily Level										
1	799.44	799.43	53.656	53.84	0.80069	0.80531	0.51084	0.55086	−0.26637	−2.64E-02
2	3084.8	3084.8	66.002	65.979	0.84538	0.84758	0.61416	0.63369	−0.57223	−0.35677
3	14.796	14.796	7.8462	7.8097	0.36527	0.37268	0.12926	0.15041	0.64827	0.37522
4	3.725	3.7341	5.9557	6.8117	0.66244	0.64963	0.37796	0.33916	0.19452	0.62231
5	−9.85E-02	−1.00E-01	0.54697	0.73117	0.65919	0.55383	0.3627	0.2651	−0.4166	−0.18684
6	−6.7993	−6.8	4.8967	4.8995	0.62385	0.63086	0.34523	0.35212	0.14528	6.95E-03
7	2.5253	2.6028	6.9419	6.0008	0.43638	0.39386	0.16258	0.19995	6.6717	4.0517

Table 3
A few statistics of raw and bias corrected time series for verification period: dataset 1.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	801.82	806.04	10.083	6.9476	1.11E-01	−1.40E-01	−6.53E-03	−0.064736	−0.6954	−0.65354
2	3086.9	3074.1	12.865	7.9435	0.17649	0.0058495	6.41E-02	−0.18061	−0.86638	−0.29524
3	17.221	16.196	1.8551	0.46233	0.78197	0.083988	0.59588	−0.047471	−0.097257	0.15775
4	5.5251	13.809	0.87693	1.0751	−8.93E-02	−2.43E-01	−3.27E-02	−9.28E-03	−0.48678	0.11914
5	0.0072851	1.768	6.72E-02	3.17E-01	−0.15099	−1.39E-01	0.139	−2.12E-01	0.61316	−0.03166
6	−6.5359	−9.1325	0.48334	0.4035	0.4618	−0.012868	0.30361	−0.35267	−0.15479	−0.71788
7	1029.4	965.29	281.19	77.627	0.15706	0.32043	5.44E-02	0.090364	0.41021	−4.67E-02
Statistics at Seasonal Level										
1	801.45	805.94	16.925	12.41	5.19E-02	1.61E-02	−0.11423	−0.072367	−2.13E-02	−0.14879
2	3086.5	3074.2	30.643	36.497	−0.22729	−0.42115	−0.30495	−0.43186	−0.0722	−1.87E-01
3	17.168	16.194	2.251	0.84498	0.51509	−0.073796	0.50499	−0.03973	0.2906	0.29664
4	5.5431	13.825	1.8173	3.3713	−0.14495	−0.33003	−0.23686	−0.33839	−0.41845	−0.012333
5	6.82E-03	1.77E+00	0.19146	2.091	−0.33338	−0.46307	−0.36605	−0.44241	−0.18635	0.29924
6	−6.5294	−9.1307	1.84	2.3011	−0.40062	−0.44513	−0.3833	−0.44317	−0.16383	−0.5209
7	344.82	321.7	156.27	62.335	0.063775	−0.18648	−7.08E-02	−2.20E-01	0.89084	0.34467
Statistics at Monthly Level										
1	801.53	806	26.499	24.294	0.41757	0.38805	0.22792	0.063787	−2.48E-02	−0.085212
2	3086.7	3074.3	39.338	44.841	0.56321	0.7148	0.31908	0.3763	−0.31272	−0.58567
3	17.179	16.194	2.7979	1.6763	0.52305	−0.0023815	0.38124	0.060226	0.39952	0.049156
4	5.5276	13.799	2.6863	4.547	0.41863	0.51732	0.22372	0.23025	0.20236	0.26496
5	7.89E-03	1.76E+00	0.26454	2.6075	0.54483	0.71583	0.30429	0.37496	−0.50771	0.33287
6	−6.5197	−9.1254	2.4789	3.171	0.641	0.68654	0.35253	0.36307	0.42072	0.28071
7	86.268	80.461	72.287	24.58	8.24E-02	0.25561	8.60E-02	1.19E-01	1.7117	0.62554
Statistics at Daily Level										
1	801.54	805.96	53.422	50.292	0.80206	0.72396	0.51171	0.37665	−0.26489	−3.23E-01
2	3086.5	3074.1	65.85	64.418	0.84729	0.83821	0.61718	0.62504	−0.56517	−0.68181
3	17.175	16.194	7.6451	7.1433	0.38717	0.31694	0.14717	0.033556	0.70504	0.22337
4	5.5414	13.827	5.8321	8.7871	0.69733	0.69417	0.39974	0.40021	0.19833	0.42556
5	6.70E-03	1.77E+00	0.546	4.1436	0.67625	0.67705	0.37616	0.47405	−0.41558	0.26704
6	−6.5326	−9.1301	4.917	5.7241	0.62697	0.64248	0.35066	0.36814	0.16968	2.11E-01
7	2.8319	2.6439	8.2525	2.6774	0.43571	0.31402	0.14635	0.11767	6.6261	2.0999
Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	801.82	797.88	10.083	16.499	0.11099	4.39E-02	−6.53E-03	1.06E-02	−0.6954	0.27535
2	3086.9	3082.7	12.865	20.178	0.17649	0.17107	6.41E-02	0.14375	−0.86638	0.15392
3	17.221	14.174	1.8551	2.7506	0.78197	0.75409	0.59588	0.6588	−9.73E-02	−0.17874
4	5.5251	3.6012	0.87693	1.1731	−8.93E-02	−0.11637	−3.27E-02	3.84E-02	−0.48678	−0.32479
5	7.29E-03	−0.12518	6.72E-02	7.59E-02	−0.15099	−0.30397	0.139	−5.63E-02	0.61316	0.10396
6	−6.5359	−6.736	0.48334	0.83645	0.4618	0.22028	0.30361	−0.10401	−0.15479	0.20617
7	1029.4	1153.7	281.19	612.02	0.15706	0.25011	5.44E-02	2.76E-02	0.41021	0.63243
Statistics at Seasonal Level										
1	801.45	797.63	16.925	23.115	5.19E-02	0.21561	−0.11423	−2.57E-02	−2.13E-02	−4.51E-02
2	3086.5	3082.7	30.643	35.845	−0.22729	−4.28E-02	−0.30495	−0.1806	−7.22E-02	−0.45548
3	17.168	14.213	2.251	3.088	0.51509	0.65316	0.50499	0.56497	0.2906	−0.10237
4	5.5431	3.6498	1.8173	2.2981	−0.14495	−6.45E-02	−0.23686	−0.25418	−0.41845	−5.92E-02
5	6.82E-03	−0.1265	0.19146	0.19813	−0.33338	−0.30188	−0.36605	−0.25324	−0.18635	−1.0672
6	−6.5294	−6.7065	1.84	2.01	−0.40062	−0.24038	−0.3833	−0.30826	−0.16383	0.14126
7	344.82	391.13	156.27	358.05	6.38E-02	−3.47E-02	−7.08E-02	0.16302	0.89084	1.3546
Statistics at Monthly Level										
1	801.53	797.67	26.499	32.829	0.41757	0.43973	0.22792	0.32727	−2.48E-02	−2.55E-02
2	3086.7	3082.7	39.338	45.659	0.56321	0.53985	0.31908	0.37495	−0.31272	−0.43219
3	17.179	14.196	2.7979	3.6997	0.52305	0.66203	0.38124	0.52924	0.39952	6.01E-02
4	5.5276	3.633	2.6863	3.257	0.41863	0.34891	0.22372	0.20967	0.20236	0.33435
5	7.89E-03	−0.1258	0.26454	0.34365	0.54483	0.16867	0.30429	8.32E-02	−0.50771	−0.23969
6	−6.5197	−6.7158	2.4789	2.7002	0.641	0.60047	0.35253	0.32764	0.42072	0.41992
7	86.268	97.613	72.287	137.78	8.24E-02	0.25944	8.60E-02	0.12097	1.7117	2.5459
Statistics at Daily Level										
1	801.54	797.58	53.422	57.502	0.80206	0.82427	0.51171	0.59534	−0.26489	−2.29E-02
2	3086.5	3082.5	65.85	70.784	0.84729	0.86214	0.61718	0.66807	−0.56517	−0.35377
3	17.175	14.182	7.6451	8.0904	0.38717	0.43926	0.14717	0.23534	0.70504	0.5663
4	5.5414	3.6468	5.8321	8.5728	0.69733	0.63745	0.39974	0.34613	0.19833	0.53635
5	6.70E-03	−0.12716	0.546	1.0895	0.67625	0.51989	0.37616	0.2337	−0.41558	−4.38E-02
6	−6.5326	−6.7286	4.917	5.3531	0.62697	0.63754	0.35066	0.37005	0.16968	0.11416
7	2.8319	3.2031	8.2525	9.379	0.43571	0.49439	0.14635	0.29516	6.6261	4.6994

dependence structures for any particular problem.

For the treatment of zero values in the observed and modelled time series, a very small value (uniform random values between 0 and one, multiplied by a small value 0.0001 and the value itself) is added to the time series before the implementation of MBC (Cannon et al., 2015, Vrac et al., 2016, Cannon, 2017). This procedure while practically has no effect on the actual values, overcomes the problem of zeros in the time series.

3.2. Bias correction framework

This section describes the general process that is required for bias correction using the MRNBC and MRQNBC approaches. Full details and relevant equations are available in Mehrotra and Sharma (2012, 2015 and 2016). The univariate corrections for both methods are applied first with the multivariate corrections applied as the second step. There are some differences in the

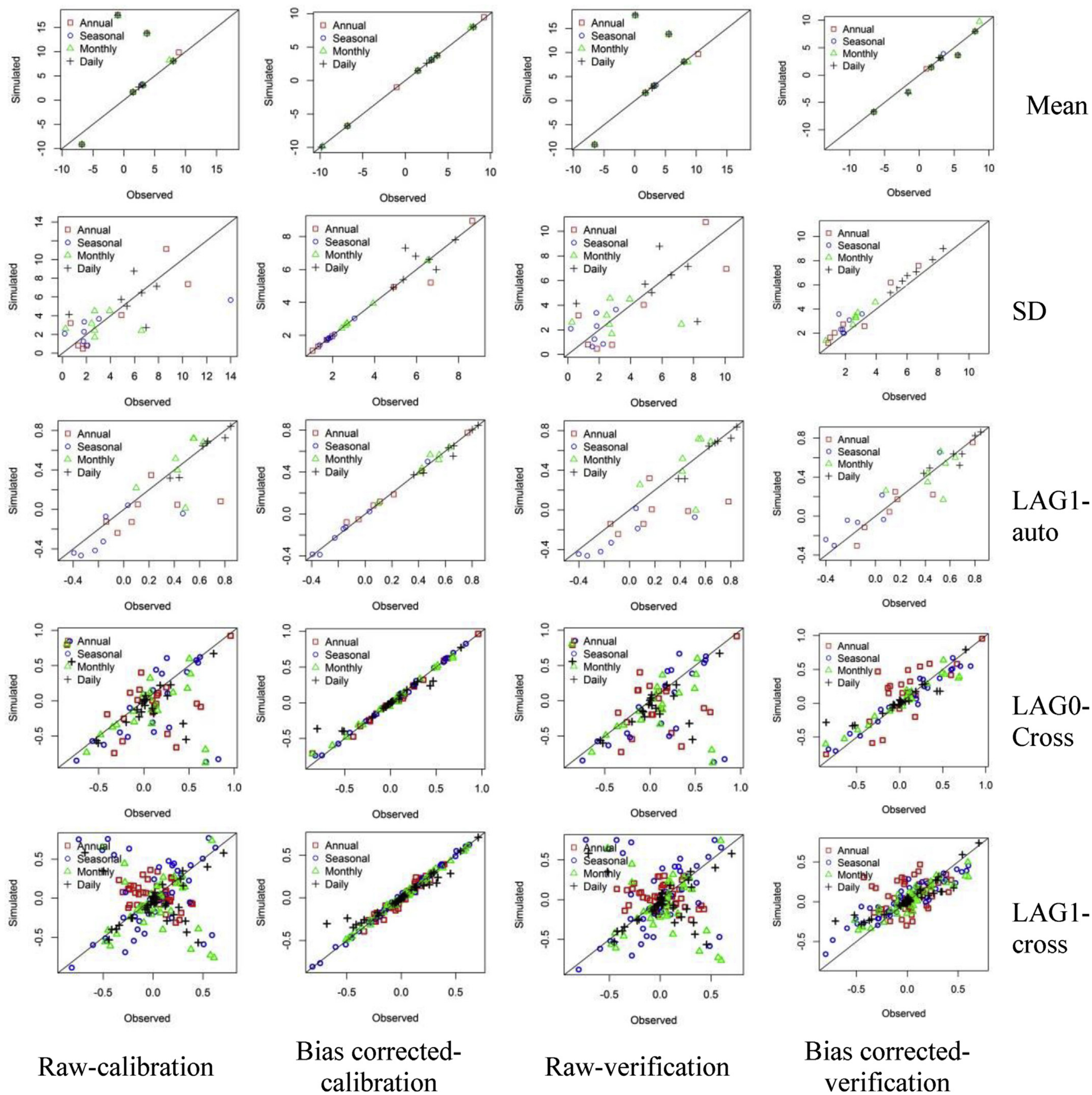

Fig. 2. Scatter plots of daily, monthly, seasonal and annual means, standard deviations and LAG0 and LAG1 auto and cross correlations of reanalysis and raw and bias corrected GCM data for calibration and verification periods using MRQNBC bias correction approach and dataset 1. Points on the plots denote variables. Mean and standard deviation (SD) values of all variables are rescaled to lie between −100 and 100.

univariate corrections for the MRNBC and MRQNBC due to the differences in the underlying correction philosophies (parametric vs non parametric respectively). Fig. 1 shows the correction flow chart.

3.2.1. Step 1: calculate observed and model statistics

The required bias corrections statistics are calculated for the observed and GCM current and future climates for all variables and all locations using the daily time series. This is done using the data falling within a moving window of pre-specified width (for example, 31 days) centred on the current day of interest (Rajagopalan and Lall, 1999; Sharma and Lall, 1999). The required statistics are: daily mean and standard deviation as well as the lag-0 and lag-1 auto and cross correlations matrices across the variables.

3.2.2. Step 2: correct current and future climate model statistics for individual variables

For the MRNBC approach, the biases in the raw current and future GCM simulations are corrected first for the mean by subtracting the current climate GCM mean and adding the observed mean. This time series is then centred and the standard deviation of the residuals is corrected by dividing by the current climate GCM standard deviation and multiplying by the observed standard

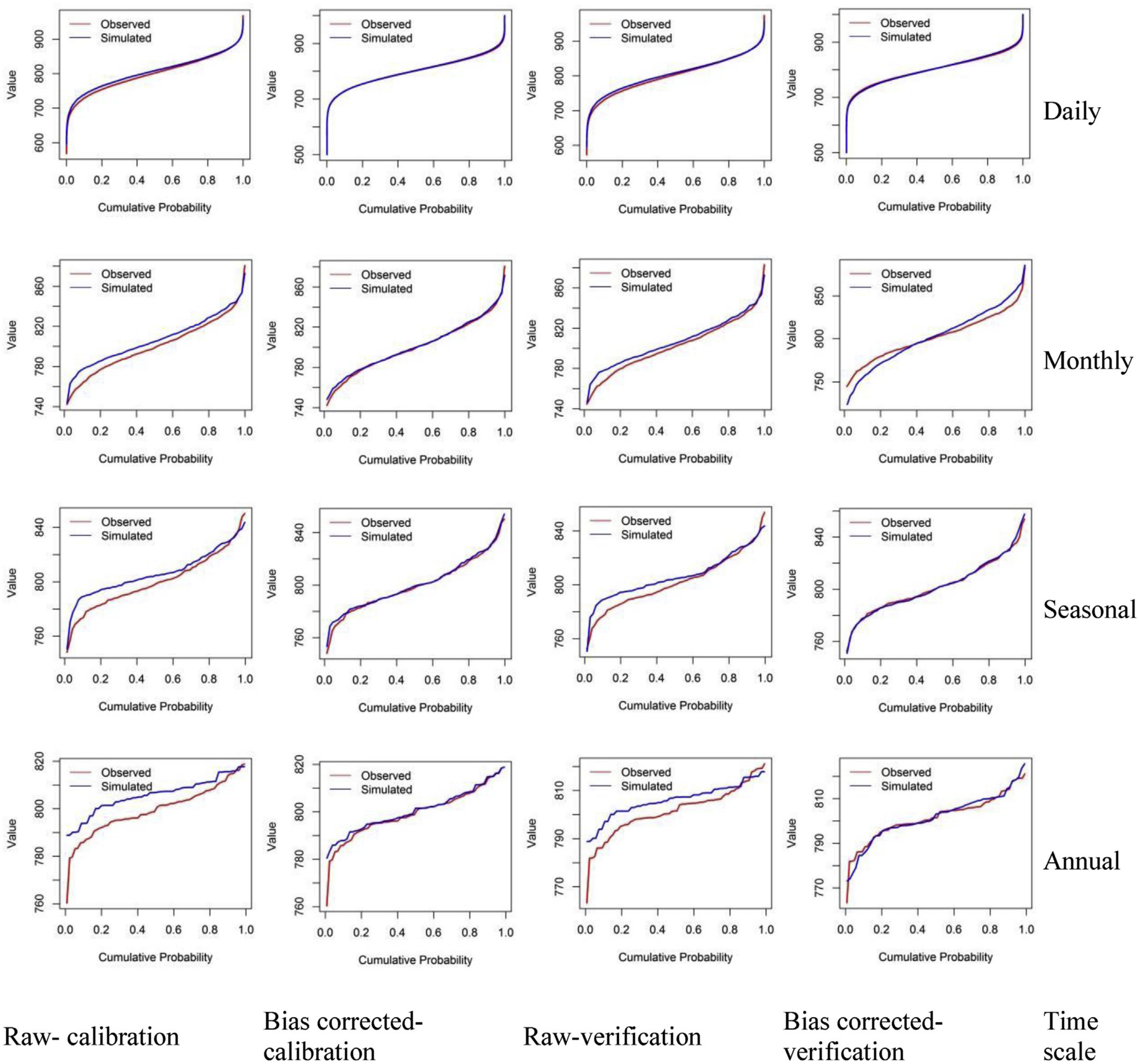

Fig. 3. Distribution plots of daily, monthly, seasonal and annual time series of reanalysis and raw and bias corrected GCM data for calibration and verification time periods for a selected variable-1 and dataset 1.

Table 4
Structure of 'Basic.dat' file for dataset 2.

```
Information about observed data for calibration
          No of years of data     Start Year
                    30                1950
Observed data file name along with directory path for calibration (if not in the directory where executable is located)
          obs_cali.dat
Information about observed data for validation
          No of years of data     Start Year
                    30                1980
Observed data file name along with directory path for validation (if not in the directory where executable is located)
          obs_vali.dat
Information about raw data used in calibration
          No of years of data     Start Year
                    30                1950
Data file name with directory path (if not in the directory where executable is located)
          gcm_raw_cali.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
          stat_raw_cali.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
          gcm_bc_cali.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
          stat_bc_cali.dat
Information about data used for bias correction - validation
          No of years of data          Start Year
                    30                      1980
Data file name with directory path (if not in the directory where executable is located)
          gcm_raw_vali.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
          stat_raw_vali.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
          gcm_bc_vali.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
          stat_bc_vali.dat
Number of variables
          7
Specify time scale of data used 0-daily; 1-monthly
          0
Number of iterations
          3
Missing number identifier (any number equal to or slightly higher than the defined value is ok)
          -9000.0
Bias correction model (1 - Multivariate NBC (MRNBC); 2 - Multivariate CDM (MRQNBC))
          1
Width of one side of moving window for daily data (in days)
          15
Option whether data (gcm_cali gcm_vali obs_cali obs_vali) follows a usual leap year (0), or fixed days in a month format (1)
          1   1   0   0
Nesting levels and bias correction options:  1-included   and  0-excluded
          Time           MEAN    SD/Dist   LAG1 Auto   LAG0 CROSS   LAG1 CROSS
          Daily            1        1         1            1              0
          Monthly          1        1         1            1              0
          Quarterly        1        1         1            1              0
          Annual           1        1         1            1              0
          Triannual        0        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)
```

2

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	500	1000	0	0	0
2	-100	100	0	0	0
3	-100	100	0	0	0
4	200	500	0	0	0
5	-100	100	0	0	0
6	-100	100	0	0	0
7	-100	100	0	0	0

Information about no of days in a month for Obs_cali	Obs_vali	GCM_cali	GCM_vali
31	31	31	31
28	28	28	28
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

deviation. The time series is then rescaled by adding back the mean (which was removed when the time series was centred).

For the MRQNBC approach, the commonly used quantile matching method is implemented. Empirical Cumulative Distribution Functions (CDFs) are calculated for the observed data as well as the current and future GCM simulations. For a given value in the future climate GCM simulations, its cumulative probability is found from the CDF. The difference in the values from the observed CDF and GCM current climate CDF for this cumulative probability is also calculated. This difference is used to correct the future GCM value. The process is repeated for the full future time series.

3.2.3. Step 3: correcting for auto and cross dependence

The corrected time series from Step 2 are standardised. This residual time series is then bias corrected for a day t lag-1 and lag-0 auto and cross correlations. The correction is based on a standard multivariate autoregressive model as discussed in Mehrotra and Sharma (2015, 2016). The corrected residual time series is then rescaled by the mean and standard deviation.

3.2.4. Step 4: aggregate and correct longer time scales

After correction at the daily time scale, the time series is aggregated to longer time scales and Steps 1 to 3 are repeated at each time scale. Note that for monthly and seasonal time scales, the parameter estimation procedure is slightly different from what is used at daily and annual time scales. For some variables the transformation to longer time scales is a simple averaging process whilst for other variables, for example precipitation and evapotranspiration, aggregation to a longer time scale involves summation.

3.2.5. Step 5: final bias correction steps

A weighting factor can be derived to summarise the correction required at each time scale. The raw GCM daily time series is multiplied by the weighting factor from each time scale to obtain the final bias corrected time series. If the recursive scheme of Mehrotra and Sharma (2012) is required, then the bias corrected time series is again treated as a raw GCM input and the process from Step 1 to Step 5 is repeated multiple times.

3.3. MBC details

MBC is implemented in a R shell and allows variants of MRNBC and MRQNBC bias correction approaches to be applied in a fairly simple manner.

3.3.1. Input data

The package requires all general information on the modelling choices to be provided in the 'basic.dat' file. In addition, four data files need to be prepared. These include observed and raw data files for calibration as well as verification period. It is not necessary to have equal length of data or start date for raw and observed file either for calibration or verification periods. The package also allows having different number of days in a month. For example, GCM simulations can have 28 days in February while observed data follows a leap year format. As discussed above, spatial dependence across multiple locations can be corrected instead of the cross dependence of multiple climate variables. It is also fairly straightforward to use the package with three files (observed and GCM/RCM current and future climates raw data files) which is the usual case with GCM/RCM output. In this case, the observed verification period file will be same as observed calibration period file. In this set up, the observations can be used to compare the change in each variable in the future/verification period compared to the historical climate (i.e. by comparing observations with bias corrected future simulations).

The user is first required to pick either the MRNBC or MRQNBC correction options. The user then has a choice of which statistics and time scales should be corrected. Choices for the bias statistics include:

- mean,

Table 5
A few statistics of raw and bias corrected time series for calibration period: dataset 2.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	794.81	801.84	11.076	6.4839	−0.009916	0.0067381	−0.11382	−0.11245	−0.96319	−0.16135
2	11.858	19.596	0.92815	1.5756	0.33265	−0.08367	0.19667	−0.077789	−0.009815	0.31725
3	13.171	28.015	0.8791	1.9957	0.54293	0.11067	0.29168	−0.29451	−0.66259	−0.23645
4	314.49	318.78	0.59721	0.55375	−0.036338	−0.16019	−0.10199	0.088898	0.62391	0.15436
5	10.836	12.306	1.48	1.7264	−0.27599	−0.20838	0.11715	0.18376	0.10133	0.25361
6	1.3672	2.7184	0.84796	0.68789	0.0096441	−0.12843	0.29021	0.33886	−0.090254	−0.42544
7	−0.075738	0.44321	0.077589	0.041766	−0.32606	0.029743	0.20014	−0.1495	0.06629	−0.057448
Statistics at Seasonal Level										
1	795.31	802.34	20.396	26.764	0.16185	0.025187	−0.20461	−0.84656	−0.097332	−0.13649
2	11.945	19.611	1.4406	3.0571	0.26435	0.14366	0.081481	−0.24	0.065764	0.52498
3	13.199	28.029	1.4436	4.6663	0.15866	0.042361	0.17951	−0.38803	0.1139	0.45566
4	314.47	318.8	5.4101	3.1225	0.0013153	−0.016323	−0.95212	−0.84833	0.15662	0.49632
5	10.866	12.303	3.3071	6.2787	0.04932	0.035324	−0.25427	−0.80165	0.047173	0.069979
6	1.3899	2.7218	1.3382	1.2839	0.22178	0.17434	0.021637	−0.18992	0.20634	−0.054398
7	−0.078321	0.44159	0.22043	0.1096	0.049168	0.10328	−0.66237	−0.56597	−0.10211	−0.17218
Statistics at Monthly Level										
1	795.3	802.06	25.937	30.329	0.39917	0.74986	0.25618	0.42914	0.0070548	−0.26332
2	11.921	19.571	2.0405	5.1066	0.2718	0.1383	0.15533	0.0072709	0.25562	0.38357
3	13.205	27.988	2.0149	6.5857	0.33338	0.34664	0.11978	0.10914	0.31916	0.27284
4	314.53	318.83	5.9568	3.5271	0.81329	0.75277	0.46613	0.39677	0.076766	0.3454
5	10.843	12.265	4.3094	7.304	0.35642	0.66165	0.1721	0.38297	0.18946	0.20633
6	1.3712	2.7077	2.1102	2.0881	0.13949	0.1819	0.12983	−0.014968	−0.10573	0.21797
7	−0.075689	0.44231	0.26207	0.14563	0.54396	0.35159	0.31928	0.18359	−0.36481	−0.23272
Statistics at Daily Level										
1	795.17	802.09	52.988	39.463	0.80411	0.90689	0.51485	0.76014	−0.20804	−0.36652
2	11.914	19.574	6.5913	15.241	0.45394	0.59802	0.15635	0.23365	0.91426	0.9294
3	13.189	27.994	6.7716	15.496	0.37049	0.60734	0.10879	0.3146	0.78014	−0.12217
4	314.51	318.81	7.0939	4.5642	0.8854	0.85902	0.78182	0.70978	0.033976	−0.015037
5	10.872	12.296	9.0483	10.583	0.74194	0.83019	0.46237	0.65287	0.20257	0.24834
6	1.3706	2.7183	7.4519	6.3134	0.49701	0.54555	0.11775	0.20068	−0.054628	−0.032854
7	−0.07706	0.44196	0.53425	0.42664	0.68808	0.60479	0.3961	0.28059	−0.37952	−0.12086
Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	794.81	794.68	11.076	10.965	−0.009916	−0.059853	−0.11382	0.10717	−0.96319	0.42436
2	11.858	11.865	0.92815	0.94293	0.33265	0.379	0.19667	0.043969	−0.009815	0.14025
3	13.171	13.124	0.8791	0.81465	0.54293	0.51468	0.29168	0.11501	−0.66259	0.1552
4	314.49	314.49	0.59721	0.60232	−0.036338	−0.2104	−0.10199	−0.26219	0.62391	−0.2822
5	10.836	10.882	1.48	1.4948	−0.27599	−0.26554	0.11715	0.15242	0.10133	−0.20707
6	1.3672	1.3507	0.84796	0.8841	0.0096441	−0.04421	0.29021	−0.03125	−0.090254	−0.37206
7	−0.075738	−0.088157	0.077589	0.043706	−0.32606	−0.34862	0.20014	−0.098948	0.06629	1.3065
Statistics at Seasonal Level										
1	795.31	795.3	20.396	20.631	0.16185	0.22112	−0.20461	−0.27882	−0.097332	0.10069
2	11.945	11.926	1.4406	1.4836	0.26435	0.34585	0.081481	0.092086	0.065764	0.12414
3	13.199	13.195	1.4436	1.4865	0.15866	0.14559	0.17951	0.060253	0.1139	0.22533
4	314.47	314.46	5.4101	5.4056	0.0013153	−0.000197	−0.95212	−0.95425	0.15662	0.15693
5	10.866	10.859	3.3071	3.3247	0.04932	0.032887	−0.25427	−0.40561	0.047173	0.0046635
6	1.3899	1.3417	1.3382	1.4455	0.22178	0.31869	0.021637	0.033713	0.20634	−0.026625
7	−0.078321	−0.08214	0.22043	0.22108	0.049168	0.0075264	−0.66237	−0.7409	−0.10211	−0.008865
Statistics at Monthly Level										
1	795.3	795.32	25.937	26.804	0.39917	0.38401	0.25618	0.30273	0.0070548	0.12274
2	11.921	11.914	2.0405	2.1373	0.2718	0.24227	0.15533	0.19913	0.25562	0.11205
3	13.205	13.2	2.0149	2.0595	0.33338	0.36166	0.11978	0.21087	0.31916	0.18752
4	314.53	314.52	5.9568	5.9607	0.81329	0.80998	0.46613	0.46254	0.076766	0.08854
5	10.843	10.833	4.3094	4.3393	0.35642	0.34462	0.1721	0.14065	0.18946	0.12566
6	1.3712	1.3326	2.1102	2.9028	0.13949	0.068926	0.12983	−0.084108	−0.10573	0.35121
7	−0.075689	−0.080003	0.26207	0.32615	0.54396	0.34368	0.31928	0.075188	−0.36481	−0.084017
Statistics at Daily Level										
1	795.17	795.17	52.988	52.402	0.80411	0.81432	0.51485	0.55517	−0.20804	−0.19136
2	11.914	11.914	6.5913	6.5337	0.45394	0.46573	0.15635	0.07994	0.91426	0.99368
3	13.189	13.187	6.7716	6.7431	0.37049	0.37603	0.10879	0.058458	0.78014	0.067118
4	314.51	314.5	7.0939	7.0294	0.8854	0.89831	0.78182	0.79923	0.033976	−0.047037
5	10.872	10.876	9.0483	9.0795	0.74194	0.74103	0.46237	0.48555	0.20257	0.14657
6	1.3706	1.3337	7.4519	13.714	0.49701	0.47688	0.11775	0.15911	−0.054628	−0.2814
7	−0.07706	−0.081148	0.53425	0.76449	0.68808	0.642	0.3961	0.40277	−0.37952	−0.31996

Table 6
A few statistics of raw and bias corrected time series for verification period: dataset 2.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	802.54	804.9	8.2407	5.5514	0.0006185	0.058713	−0.3108	−0.38406	0.45871	0.50201
2	14.556	19.808	0.83537	1.3725	0.41963	0.067747	0.3452	0.0020699	−0.027828	−0.13106
3	16.164	27.967	0.97117	1.9298	0.56657	0.32919	0.16865	0.30263	−0.20598	−0.24847
4	315.15	319.94	0.72181	0.53343	0.35424	0.43284	0.29409	0.38337	−0.17428	−0.76439
5	10.96	12.432	1.2125	1.0884	0.11899	−0.16125	−0.007394	0.031728	−0.18692	−0.58607
6	1.5228	2.5571	0.52059	0.66569	0.064273	−0.20993	0.1153	−0.055782	−0.23976	0.11596
7	−0.11541	0.41088	0.047959	0.035319	0.020074	0.15538	0.11886	0.13269	0.54829	0.35152
Statistics at Seasonal Level										
1	802.6	804.85	20.05	27.341	0.078186	0.035607	−0.46944	−0.8364	0.15219	−0.075176
2	14.535	19.786	1.4495	3.2023	0.10807	−0.085523	0.13201	−0.23641	−0.21674	0.28984
3	16.164	27.971	1.6998	5.3378	0.04073	−0.004932	0.15855	−0.48008	0.20454	−0.021649
4	315.13	319.93	5.103	3.0915	0.0020615	−0.034957	−0.93845	−0.7678	0.14859	0.5791
5	10.933	12.473	2.9905	5.8105	0.047331	−0.002756	−0.48093	−0.85581	0.28448	0.09785
6	1.4919	2.5142	1.0843	1.3288	−0.008111	0.16333	−0.019403	0.1265	−0.35661	−0.081298
7	−0.1158	0.40888	0.21283	0.11491	−0.028647	−0.078904	−0.79011	−0.45558	−0.52749	−0.37559
Statistics at Monthly Level										
1	802.5	804.61	26.732	31.776	0.41975	0.70947	0.1944	0.39788	−0.095755	−0.3489
2	14.54	19.781	2.3738	5.2195	0.10715	0.19133	0.044919	−0.01693	0.084526	0.25352
3	16.162	27.952	2.4047	6.9941	0.24609	0.41429	0.05646	0.21151	0.20854	0.038747
4	315.19	319.97	5.7191	3.5889	0.78996	0.72495	0.44904	0.37152	0.087425	0.50613
5	10.94	12.41	4.0537	7.0549	0.36997	0.61064	0.17676	0.31748	0.4395	0.22788
6	1.5022	2.5241	1.9873	2.1223	−0.023569	0.093865	0.02616	0.13214	−0.067153	−0.067647
7	−0.11443	0.40959	0.258	0.16636	0.56403	0.25632	0.30329	0.15966	−0.56034	−0.26391
Statistics at Daily Level										
1	802.37	804.74	53.754	40.216	0.79841	0.91246	0.50453	0.7762	−0.3085	−0.36312
2	14.533	19.8	8.4802	15.716	0.42558	0.61166	0.10318	0.25092	0.77109	0.91409
3	16.141	27.989	8.0306	15.697	0.35078	0.61536	0.10014	0.32766	0.55773	−0.091917
4	315.16	319.95	6.9678	4.7174	0.86444	0.8623	0.75042	0.71093	0.075651	−0.041852
5	10.975	12.44	9.1289	10.614	0.70597	0.82688	0.39794	0.6386	0.25012	0.25401
6	1.5028	2.5227	7.7697	6.5574	0.4495	0.56019	0.078288	0.19736	−0.11677	−0.02074
7	−0.11551	0.40915	0.54737	0.4431	0.65908	0.62103	0.34904	0.29215	−0.46302	−0.097697
Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	802.54	798.42	8.2407	13.586	0.0006185	−0.046354	−0.3108	0.10439	0.45871	0.58993
2	14.556	12.186	0.83537	1.6823	0.41963	0.56904	0.3452	0.29697	−0.027828	−0.50239
3	16.164	13.389	0.97117	1.814	0.56657	0.74698	0.16865	0.39573	−0.20598	−0.34458
4	315.15	315.5	0.72181	0.83253	0.35424	0.028032	0.29409	0.18692	−0.17428	−0.13462
5	10.96	10.959	1.2125	2.2591	0.11899	−0.31203	−0.007394	0.23187	−0.18692	−1.349
6	1.5228	2.2068	0.52059	2.2524	0.064273	0.098042	0.1153	−0.32715	−0.23976	−0.41529
7	−0.11541	−0.041989	0.047959	0.076971	0.020074	−0.14932	0.11886	−0.02562	0.54829	−0.29008
Statistics at Seasonal Level										
1	802.6	798.08	20.05	24.012	0.078186	0.16273	−0.46944	−0.22747	0.15219	−0.077314
2	14.535	12.186	1.4495	2.6818	0.10807	0.37936	0.13201	0.055916	−0.21674	−0.21871
3	16.164	13.412	1.6998	2.5637	0.04073	0.29107	0.15855	0.498	0.20454	0.16212
4	315.13	315.5	5.103	5.349	0.0020615	0.0026433	−0.93845	−0.91074	0.14859	0.15745
5	10.933	10.914	2.9905	4.7318	0.047331	0.13808	−0.48093	−0.16327	0.28448	−0.45523
6	1.4919	2.1488	1.0843	4.6552	−0.008111	0.10472	−0.019403	−0.035937	−0.35661	0.34058
7	−0.1158	−0.048511	0.21283	0.24297	−0.028647	−0.002035	−0.79011	−0.4891	−0.52749	−0.37237
Statistics at Monthly Level										
1	802.5	798	26.732	34.689	0.41975	0.22935	0.1944	0.21902	−0.095755	0.295
2	14.54	12.202	2.3738	3.7695	0.10715	0.30788	0.044919	0.24538	0.084526	0.34041
3	16.162	13.427	2.4047	3.2567	0.24609	0.37273	0.05646	0.27781	0.20854	0.19932
4	315.19	315.57	5.7191	6.1893	0.78996	0.75493	0.44904	0.43099	0.087425	0.21654
5	10.94	10.88	4.0537	6.3633	0.36997	0.2963	0.17676	0.17332	0.4395	−0.53974
6	1.5022	2.1858	1.9873	8.7365	−0.023569	−0.012084	0.02616	0.0044606	−0.067153	0.56772
7	−0.11443	−0.046977	0.258	0.41355	0.56403	0.096982	0.30329	−0.013455	−0.56034	−1.6358
Statistics at Daily Level										
1	802.37	797.96	53.754	57.417	0.79841	0.84414	0.50453	0.6305	−0.3085	−0.066228
2	14.533	12.215	8.4802	7.6381	0.42558	0.55433	0.10318	0.23067	0.77109	1.2268
3	16.141	13.438	8.0306	7.3835	0.35078	0.45022	0.10014	0.17262	0.55773	0.34153
4	315.16	315.53	6.9678	7.3215	0.86444	0.89991	0.75042	0.79497	0.075651	−0.000117
5	10.975	10.905	9.1289	11.532	0.70597	0.74326	0.39794	0.50181	0.25012	−0.17587
6	1.5028	2.1315	7.7697	24.181	0.4495	0.47282	0.078288	0.16542	−0.11677	−0.11961
7	−0.11551	−0.047782	0.54737	1.064	0.65908	0.63318	0.34904	0.34914	−0.46302	−0.08824

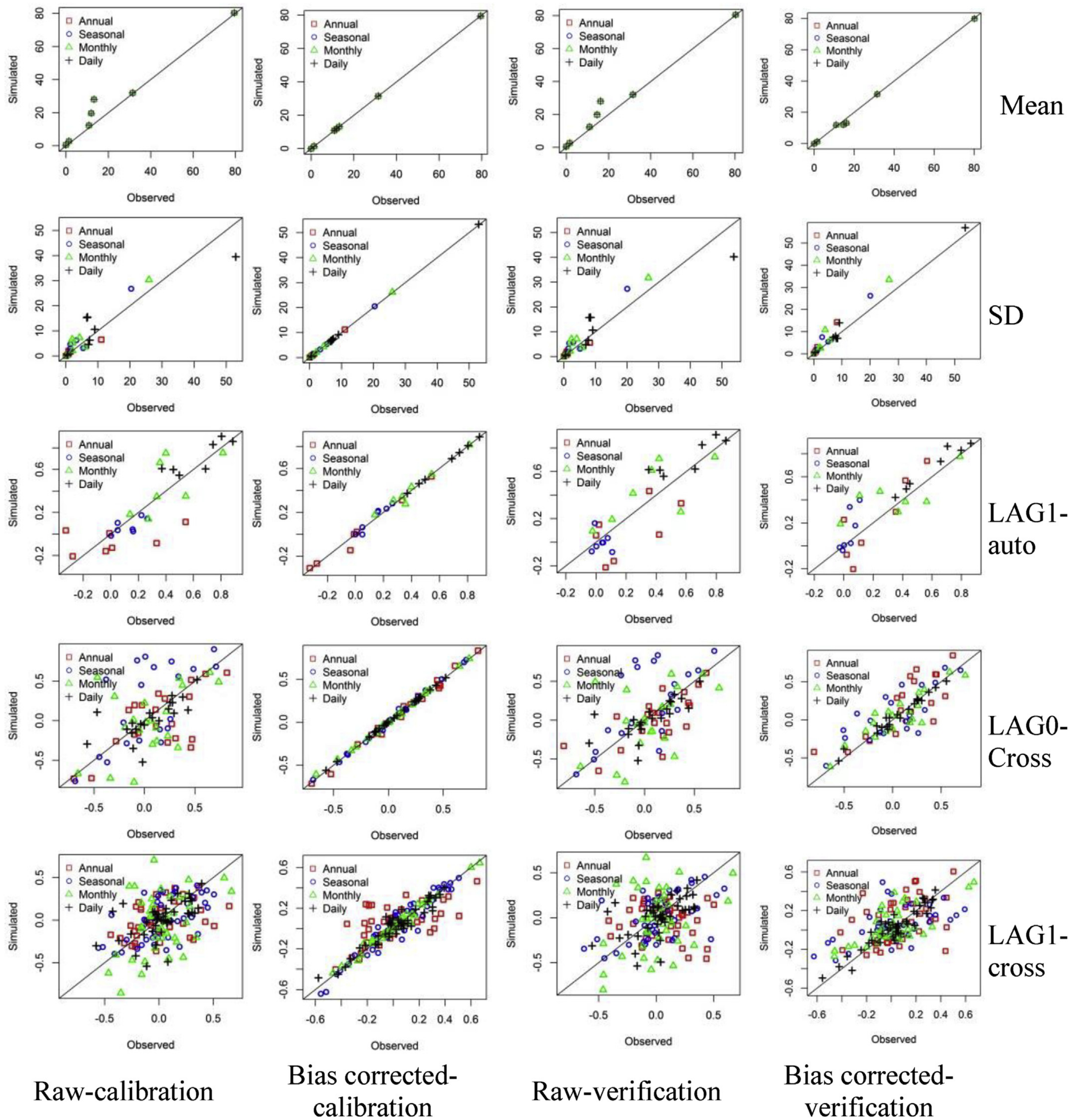

Fig. 4. For dataset 2. Details are same as Fig. 1 except that the Lag1 cross correlations are not modelled.

- mean and SD (or full distribution for MRQNBC),
- LAG1 auto correlation
- LAG0 and LAG1 cross correlation.

The options for time nesting include, daily, monthly, seasonal, annual and tri-annual. The package also allows flexibility of applying bias correction either to daily or to monthly time series. Users are allowed to define their own seasons.

In addition to the names of the four data files, the 'basic.dat' file also requires information about the number of years of data, number of variables, width of the moving window used to correct the daily data, the number of repeats in the recursive procedure, physical lower and upper limits on the variables, whether data consider leap years or not and the split of calendar months across

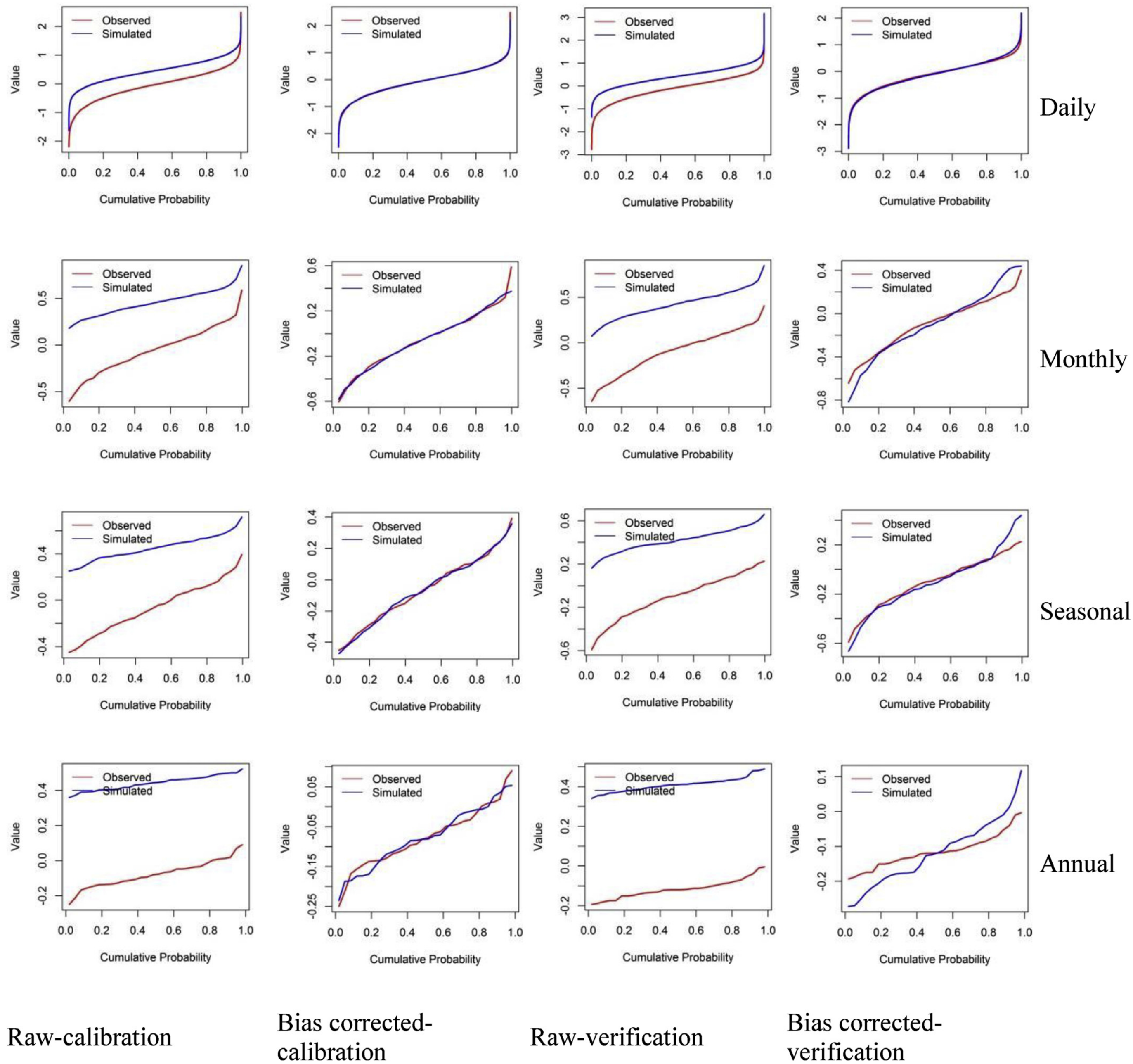

Fig. 5. For dataset 2 and variable 7. Other details are same as Fig. 2.

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.

3.3.2. *Package outputs*

Upon successful completion of the program, 6 output files are generated. Two files provide the bias corrected time series for the current and future periods. There are four summary results files which provide relevant statistics on the observed, raw and bias corrected data for the current and future climates containing important statistics of 1) observed and raw data for calibration; 2) observed and raw data for verification; 3) observed and bias corrected data for calibration; and 4) observed and bias corrected data for verification time periods. As mentioned above, for GCM/RCM future climate data corrections, the observed verification file would be same as the observed calibration file. Summary statistics include the 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.

Table 7
Structure of Basic.dat file used for dataset 3.

```
Information about observed data for calibration
   No of years of data      Start Year
           70                  1921
Observed data file name along with directory path for calibration (if not in the directory where executable is located)
           data_obsc.dat
Information about observed data for validation
   No of years of data      Start Year
           70                  1921
Observed data file name along with directory path for validation (if not in the directory where executable is located)
           data_obsc.dat
Information about raw data used in calibration
   No of years of data      Start Year
           70                  1921
Data file name with directory path (if not in the directory where executable is located)
           data_rawc.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
           stat_rawc.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
           data_bcc.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
           stat_bcc.dat
Information about data used for bias correction - validation
   No of years of data      Start Year
            70                 1921
Data file name with directory path (if not in the directory where executable is located)
           data_rawf.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
           stat_rawf.dat
Bias corrected data file name with directory path (if not in the directory where executable is located)
           data_bcf.dat
Statistics (to be computed and stored) file name with directory path (if not in the directory where executable is located)
           stat_bcf.dat
Number of variables
           15
Specify time scale of data used 0-daily; 1-monthly
           1
Number of iterations
           3
Missing number identifier (any number equal to or slightly higher than the defined value is ok)
     -9000.0
Bias correction model (1 - multivariate NBC (MRNBC); 2 - Multivariate CDM (MRQNBC))
           1
Nesting levels and bias correction options:  1-included   and  0-excluded
           Time           MEAN   SD/Dist   LAG1 Auto    LAG0 CROSS   LAG1 CROSS
           Monthly          1      1          1            1             0
           Quarterly        1      1          1            1             0
           Annual           1      1          1            1             0
           Triannual        0      0          0            0             0
Number of seasons in a year
           2
Number of months in each season
           6   6
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)
     2
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           1500            1                                       1          0.3
           2     0           1500            1                                       1          0.3
           3     0           1500            1                                       1          0.3
           4     0           1500            1                                       1          0.3
```

5	0	1500	1	1	0.3
6	0	1500	1	1	0.3
7	0	1500	1	1	0.3
8	0	1500	1	1	0.3
9	0	1500	1	1	0.3
10	0	1500	1	1	0.3
11	0	1500	1	1	0.3
12	0	1500	1	1	0.3
13	0	1500	1	1	0.3
14	0	1500	1	1	0.3
15	0	1500	1	1	0.3

4. Presentation of results

Three sample data sets have been included with the package to provide guidance to users on the different options in the package. The first dataset has synthetically generated daily time series for 7 variables that could represent typical atmospheric variables used in downscaling. It also includes daily rainfall as one of the variable in order to show the capability of the packages in reproducing the number of wet/dry days. In the application demonstrated here the MRNBC bias correction approach has been used. This example also demonstrates the use of unequal lengths of time series for calibration and verification periods.

The second dataset demonstrates an application with equal lengths of observed and GCM data for calibration (current) and verification time periods. It uses 7 atmospheric variables and MRNBC as the bias correction approach. The third datasets uses observed and AR1 model simulated monthly rainfall at 15 locations over Sydney region. For this final example the MRQNBC approach is used to correct spatio-temporal dependence in the rainfall simulations.

4.1. First dataset

The first dataset consists of 7 synthetic daily time series that are representative of reanalysis data and raw GCM simulations. These include geopotential heights at 925 and 700 hPa, temperature depression at 500 hPa, U wind at 850 hPa, north-south gradient of mean sea level pressure, thickness of equivalent potential temperature at 500-850 hPa and precipitation. The important feature of the 7th variable of the dataset (precipitation) is that it demonstrates the features of the bias correction for a time series that is highly skewed with many zero values. The time series have been divided into two parts with unequal data lengths and different data lengths have been used to represent the availability of reanalysis and GCM simulations. The dates for the years are arbitrary and used for illustration purposes and to demonstrate the ability of the software to handle leap years or fixed number of days in a month. 66 years of daily data (from 1881 to 1946) is used for model calibration whereas another subset of 70 years (from 1947 to 2016) is used for model verification. Likewise, a subset of 63 years of raw GCM data (from 1891 to 1953) is used for model calibration and of 61 years (from 1954 to 2014) is used for model verification.

The nested multivariate bias correction model has been used with the bias correction applied for daily, monthly, seasonal and annual time scales. For all atmospheric variables average, while for rainfall summation, option at aggregated time scales is selected. Three seasons in a year have been chosen as shown in the information provided in the 'basic.dat' input file (Table 1). The number of seasons and their definition is arbitrary in this example and used for illustration purpose only. For this example, the LAG0 cross and LAG1 auto dependence options are selected. Table 1 presents the details of 'basic.dat' file used for this dataset.

The statistics for the calibration and verification periods are presented in Tables 2 and 3. The scatter plots of statistics and distribution plots of time series of raw and bias corrected data for calibration and verification periods are presented in Figs. 2 and 3, respectively. The bias correction approach performs well in reproducing the statistics of the reanalysis data in the GCM simulations at all time scales during calibration period (Table 2 and Fig. 2). It also reproduces the time distribution of variable at all selected time scales (Fig. 3). Some biases in the statistics during verification period are noted. Although, LAG1-cross correlations and skewness are not modelled explicitly, the bias correction improves their representation in the corrected time series (Table 2 and Fig. 3). The observed rainfall time series exhibits very different number of wet days (34%) as against the raw time series (76%) for both calibration and verification time periods. After bias correction, these are matched with the observations.

4.2. Second dataset

The second dataset includes four files of equal lengths with daily records of 7 atmospheric variables averaged over Sydney, Australia, obtained from the National Center for Environmental Prediction (NCEP) reanalysis2 data provided by the NOAA-CIRES Climate Diagnostics Center, Boulder, Colorado, USA, from their web site at http://www.cdc.noaa.gov/. These variables include geopotential height at 925 hPa, temperature depression at 700 and 500 hPa, equivalent potential temperature at 500 hPa, U and V winds at 500 hPa and north-south gradient of mean sea level pressure. Likewise, daily output of CSIRO's Mk3.0 A2 GCM for these variables for the same time period is obtained from the Atmospheric Research Division of the CSIRO, Australia. A subset of 30 years of data from 1950 to 1979 is considered for model calibration while the remaining 30 years from 1980 to 2009 is used for the model verification. The GCM data has fixed 28 days in February for all years, whilst the reanalysis data follows the usual leap year format. The basic information about the data start and end years, number of years of data, file names, number of variables and type of bias

Table 8
A few statistics of raw and bias corrected time series for calibration period: dataset 3.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	1014.9	1024.2	276.99	289.79	0.20078	−0.007277	0.11882	−0.14028	0.41272	0.68209
2	1222.3	1206.5	336.85	366.12	0.12894	−0.068625	0.097368	−0.20475	0.58218	0.26037
3	770.82	824.01	260.94	245.54	0.16415	0.038867	0.15104	−0.10877	0.79906	0.52426
4	1485.3	1543.6	494.17	372.63	0.20772	0.22107	0.16392	0.29684	0.68392	0.70558
5	998.5	1021	281.74	351.92	0.061185	−0.033309	0.10916	0.094892	0.46197	1.28
6	843.77	798.47	279.72	238.56	0.11363	−0.096652	0.17029	−0.087969	0.59495	0.33969
7	1721.7	1722.6	574.67	644.19	0.092873	0.043655	0.077811	0.095534	0.75477	0.6964
8	1286.8	1177.3	419.3	428.06	0.23546	0.23313	0.26223	0.1217	0.69044	1.0031
9	759.54	743.83	248.9	234.06	0.10013	0.21105	−0.006959	0.087064	0.64455	0.58042
10	849.86	864.66	235.18	222.11	0.10367	0.14455	0.083192	0.10028	0.75813	0.29947
11	660.41	689.02	185.79	226.16	0.13378	0.37698	0.10124	0.29106	0.39915	0.40045
12	1026.5	993.32	328.81	297.63	0.12129	0.14271	−0.019797	0.16268	0.55826	0.39022
13	723.19	760.36	230.43	199.04	0.20123	0.011782	0.099234	−0.15049	0.65003	0.47358
14	847.45	836.21	228.78	222.34	−0.009265	0.10773	0.062107	−0.071532	0.37807	0.13083
15	1168.9	1241.7	315.87	400.9	0.095609	0.1426	0.11504	0.0073666	0.54859	0.21068
Statistics at Seasonal Level										
1	509.68	511.35	185.41	183.29	0.080553	0.14575	0.24326	−0.043463	0.94651	0.66807
2	617.09	599.62	278.01	252.07	−0.24395	−0.034837	0.37353	0.096741	0.82174	0.64315
3	388.39	412.61	195.1	177.35	−0.084859	−0.14252	0.31414	0.17733	1.4665	1.1023
4	746.17	762.45	389	294.95	−0.20983	−0.16445	0.413	0.30582	1.1228	0.79173
5	500.43	508.18	211.38	253.68	−0.18875	−0.032606	0.28589	0.0474	1.0218	2.4356
6	423.14	400.82	207.48	174.35	−0.10512	−0.088835	0.26796	0.1436	1.2901	1.02
7	858.12	863.3	433.95	443.05	−0.19661	0.048758	0.3426	0.12112	1.1469	1.2948
8	648.46	588.97	326.94	301.22	−0.19245	0.073088	0.40733	0.30502	0.97957	1.2712
9	380.36	369.19	169.45	156.55	0.0081074	0.19119	0.1811	0.12515	1.0965	0.85006
10	423.81	433.85	153.43	152.08	0.076582	0.15049	0.13811	−0.027265	1.0456	0.8417
11	329.94	342.62	119.99	138.13	0.11768	0.3161	0.094466	0.25288	0.5162	0.66487
12	512.88	497.23	237.99	195.84	−0.1266	0.16604	0.29012	0.046919	1.054	0.66134
13	362.16	379.6	158.32	135.48	0.009791	0.065096	0.24026	−0.057383	1.2587	0.7055
14	426.23	417.14	151.52	137.22	0.032197	0.23076	0.059567	0.069761	0.85885	0.58081
15	589.57	622.09	263.1	274.48	−0.24958	0.039088	0.35374	0.18354	0.84178	0.80628
Statistics at Monthly Level										
1	84.953	85.039	64.026	61.133	0.11608	0.13843	0.092567	0.11446	1.8015	1.7707
2	102.78	100.39	93.969	82.978	0.068764	0.068338	0.040008	0.10208	1.9586	1.6782
3	64.796	68.841	64.962	66.56	0.11085	0.050597	0.10407	0.029114	1.9747	2.4499
4	124.3	128.05	128.47	115.55	0.085876	0.016255	0.043492	−0.002874	2.2036	2.1561
5	83.521	84.54	74.296	90.832	0.059826	0.083832	−0.007514	0.070943	2.1116	6.5284
6	70.644	66.891	70.277	62.562	0.11805	0.11473	0.082829	0.050974	1.9376	2.2506
7	143.12	143.33	144.16	152.45	0.068133	0.12671	0.041331	0.073403	2.1536	3.2247
8	107.99	98.142	107.56	97.383	0.12874	0.13538	0.067131	0.13661	2.0011	2.2046
9	63.483	61.657	59.3	54.795	0.10462	0.053852	0.025115	0.01758	2.9013	2.0252
10	70.844	72.105	54.536	53.369	0.13535	0.067353	0.028737	0.074362	1.7081	1.7009
11	55.147	57.037	42.124	44.476	0.12365	0.088833	0.04126	0.10798	1.4474	1.4725
12	85.595	82.743	82.921	74.375	0.073004	0.074605	0.023471	0.054047	2.6154	2.2324
13	60.562	63.21	53.284	50.063	0.10551	0.16056	0.052594	0.025339	1.9695	1.5994
14	71.035	69.526	52.602	48.425	0.11733	0.042623	0.068041	0.013794	1.706	1.5669
15	98.232	103.71	89.485	87.351	0.060895	0.12032	0.040198	0.06352	1.9854	1.8573
Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	1014.9	1024.9	276.98	277.48	0.20079	0.20546	0.11882	0.06105	0.41272	0.053972
2	1222.3	1237	336.85	347.29	0.12894	0.15112	0.097368	0.13817	0.58218	0.42652
3	770.85	780.75	260.93	266.08	0.16417	0.18563	0.15107	0.30329	0.79906	0.36701
4	1485.3	1497.1	494.17	495.81	0.20772	0.22133	0.16392	0.24198	0.68391	0.39762
5	998.5	1008.7	281.74	281.16	0.061186	0.094065	0.10916	0.18626	0.46193	0.41313
6	843.78	850.4	279.71	281.5	0.11368	0.13462	0.17031	0.23164	0.59504	0.49324
7	1721.7	1719.6	574.67	575.21	0.092878	0.11763	0.077803	0.23137	0.75476	0.36622
8	1286.9	1303.3	419.3	422.6	0.23547	0.33057	0.26222	0.35024	0.69045	0.59313
9	759.54	764.12	248.9	248.65	0.10012	0.10287	−0.006983	0.13275	0.64453	0.39526

Table 8 (*continued*)

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
10	849.87	852.31	235.17	235.04	0.10367	0.12856	0.083232	0.073581	0.75838	−0.08729
11	660.43	664.32	185.78	185.43	0.13373	0.14544	0.1013	0.11903	0.39935	0.24128
12	1026.5	1029.7	328.81	328.02	0.12135	0.14275	−0.01979	0.11381	0.55832	0.27629
13	723.2	730.63	230.43	230.54	0.20128	0.21244	0.09924	0.16689	0.65004	0.1185
14	847.45	855.9	228.77	230.55	−0.009286	0.032697	0.062175	0.084177	0.37815	0.14407
15	1168.9	1181.6	315.87	324.92	0.095609	0.10258	0.11504	0.21947	0.54859	0.37036
Statistics at Seasonal Level										
1	509.68	511.14	185.41	185.27	0.080552	0.14528	0.24325	0.12403	0.94653	0.26315
2	617.09	616.14	278.01	277.54	−0.24395	−0.21171	0.37353	0.33811	0.82174	0.70357
3	388.41	389.1	195.09	193.32	−0.084875	−0.030363	0.31411	0.2722	1.4666	0.78167
4	746.17	744.45	389	388.23	−0.20983	−0.17641	0.413	0.3451	1.1228	0.59086
5	500.43	501.77	211.38	211.89	−0.18875	−0.14086	0.28589	0.24909	1.0218	0.42357
6	423.15	424.1	207.48	207.45	−0.10514	−0.04753	0.26798	0.19293	1.2902	0.75051
7	858.12	859.8	433.95	432.34	−0.19661	−0.15972	0.34259	0.27877	1.1469	0.42888
8	648.46	647.2	326.94	326.05	−0.19246	−0.15225	0.40733	0.40849	0.97958	0.75023
9	380.37	380.75	169.45	172.42	0.0081049	0.027148	0.18109	0.10058	1.0965	0.47981
10	423.81	426.12	153.43	155.39	0.076563	0.11567	0.1381	0.075404	1.0457	0.30235
11	329.95	331.74	119.99	120.75	0.11759	0.13126	0.094425	0.047567	0.51641	0.47521
12	512.89	513.63	237.99	239.44	−0.12657	−0.056165	0.29014	0.14834	1.0541	0.45597
13	362.17	364.35	158.31	157.98	0.0097893	0.065265	0.24027	0.1589	1.2588	0.37283
14	426.23	426.73	151.52	152.88	0.032167	0.05241	0.059569	0.044164	0.85892	0.50968
15	589.57	588.73	263.1	263.07	−0.24958	−0.24014	0.35374	0.33676	0.84178	0.70471
Statistics at Monthly Level										
1	84.953	84.99	64.026	61.462	0.11608	0.061704	0.092566	0.14501	1.8015	0.81525
2	102.78	102.82	93.969	88.814	0.068764	0.044712	0.040008	0.08788	1.9586	0.99453
3	64.799	64.83	64.959	61.226	0.11085	0.13371	0.10405	0.10454	1.9749	1.1721
4	124.3	124.32	128.47	119.57	0.085877	0.072461	0.043492	0.11956	2.2036	1.109
5	83.521	83.521	74.296	71.105	0.059821	0.01005	−0.007515	0.079591	2.1117	1.1678
6	70.645	70.603	70.276	65.948	0.11803	0.12223	0.082817	0.080957	1.9377	1.195
7	143.12	143.12	144.16	135.45	0.068131	0.045076	0.041329	0.11933	2.1536	1.1972
8	107.99	108	107.56	99.968	0.12874	0.11534	0.067128	0.10089	2.0012	1.0908
9	63.484	63.436	59.3	56.09	0.10462	0.07652	0.025116	0.0644	2.9014	1.2189
10	70.845	70.839	54.535	52.661	0.13536	0.062969	0.028732	0.055397	1.7082	0.75978
11	55.15	55.101	42.121	41.217	0.12369	0.057379	0.041239	0.01608	1.4478	0.86316
12	85.596	85.519	82.92	78.534	0.073017	0.029034	0.02347	0.082655	2.6156	1.2174
13	60.563	60.575	53.283	51.059	0.10551	0.067705	0.052585	0.063418	1.9696	0.91791
14	71.036	71.003	52.601	51.21	0.11734	0.060128	0.06803	0.058416	1.7061	0.78029
15	98.232	98.238	89.485	84.721	0.060895	0.039839	0.040198	0.082096	1.9854	1.0401

correction model are given in 'basic.dat' file in a simple text format. The bias correction model selected is a multivariate recursive nested bias correction (MRNBC) model with the option of bias correction in mean, standard deviation, LAG1 auto and LAG0 cross correlations at daily, monthly and annual time scales. Four seasons in a year are considered. More details on the information included in the 'basic.dat' file are provided in Table 4.

Upon successful completion of the bias correction procedure, four result files containing a few important statistics of the raw and bias corrected data are created. Tables 5 and 6 provide the snapshots of a part of these files for raw and bias corrected data for mean, standard deviation and auto correlation statistics for calibration and verification periods, respectively. Raw data (Tables 5a and 6a) exhibits some biases in these statistics. The bias correction model provides a near perfect fit for the calibration period and a reasonably good fit for the verification period. Similarly, Fig. 4 provides scatter plots of scaled means, standard deviations, LAG1 autocorrelation, LAG0 cross correlations and LAG1 cross correlations of raw and bias corrected time series for these two periods. For a good match all points should lie close to diagonal. The model does a good job in reproducing these statistics during the verification period albeit with some scatter for some variables.

Fig. 5 presents empirical distribution plots of daily, monthly, seasonal and annual time series of reanalysis and raw and bias corrected GCM data for calibration and verification time periods for a selected variable, specifically temperature depression at 700 hPa. Temperature depression is the difference of dewpoint and air temperature at that particular pressure level. Here again, the model performs well at all time scales during calibration, however, exhibits some biases at longer time scales during verification.

The biases noted during verification period are a function of the differences in the behaviour of the observed and raw time series during calibration and verification time periods. MRNBC like any other bias correction model works on the assumption that the biases are stationary and corrects the verification time series for the biases observed in the calibration time period. As seen in these results, the stationary bias assumption is questionable (Nahar et al., 2017; Buser et al., 2009; Ehret et al., 2012) but efforts to improve on the assumption still need further development.

4.3. Third dataset

The third dataset consists of observed and model simulated monthly rainfall time series. 70 years of observed rainfall records from 1921 to 1990 at 15 locations around Sydney is used to generate synthetic rainfall time series using an AR1 model. This dataset does not directly relate to climate model simulations but is provided to demonstrate the capability of the bias correction model to correct

Table 9
A few statistics of raw and bias corrected time series for verification period: dataset3.

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(a) Raw data										
Statistics at Annual Level										
1	1014.9	998.69	276.99	213.57	0.20078	−0.06654	0.11882	−0.11346	0.41272	0.43369
2	1222.3	1273.2	336.85	356.42	0.12894	0.16291	0.097368	0.14804	0.58218	0.74283
3	770.82	785.36	260.94	284.29	0.16415	0.0016455	0.15104	0.16045	0.79906	1.3386
4	1485.3	1450.9	494.17	467.86	0.20772	−0.035183	0.16392	0.058029	0.68392	0.57882
5	998.5	1012.9	281.74	259.37	0.061185	0.19398	0.10916	0.15209	0.46197	0.66826
6	843.77	818.83	279.72	240.84	0.11363	0.15808	0.17029	0.061923	0.59495	0.48861
7	1721.7	1772.7	574.67	635.37	0.092873	0.27919	0.077811	−0.023144	0.75477	0.75706
8	1286.8	1239.3	419.3	332.33	0.23546	0.14295	0.26223	−0.0962	0.69044	0.78949
9	759.54	738.6	248.9	213.67	0.10013	0.18019	−0.006959	−0.18179	0.64455	0.59869
10	849.86	867.71	235.18	200.65	0.10367	0.27373	0.083192	0.093826	0.75813	0.18647
11	660.41	644.13	185.79	190.91	0.13378	0.070319	0.10124	−0.1509	0.39915	0.80709
12	1026.5	914.54	328.81	230.13	0.12129	0.020066	−0.019797	−0.18458	0.55826	0.64622
13	723.19	788.04	230.43	240.24	0.20123	0.32659	0.099234	−0.024078	0.65003	0.31927
14	847.45	851.34	228.78	229.99	−0.009265	0.17852	0.062107	−0.02065	0.37807	0.23765
15	1168.9	1206.3	315.87	460.32	0.095609	0.32721	0.11504	0.15553	0.54859	0.4134
Statistics at Seasonal Level										
1	509.68	504.79	185.41	148.34	0.080553	0.1481	0.24326	−0.056639	0.94651	0.59455
2	617.09	631.66	278.01	242.42	−0.24395	0.075573	0.37353	0.20527	0.82174	0.68641
3	388.39	390.98	195.1	188.65	−0.084859	0.13032	0.31414	0.094472	1.4666	1.0285
4	746.17	726.65	389	347.78	−0.20983	−0.14669	0.413	0.26356	1.1228	1.0142
5	500.43	508.31	211.38	188.06	−0.18875	0.010286	0.28589	0.16019	1.0218	0.92644
6	423.14	409.6	207.48	161.42	−0.10512	0.08514	0.26796	0.14416	1.2901	0.44551
7	858.12	888.7	433.95	424.23	−0.19661	0.069976	0.3426	0.21112	1.1469	1.0265
8	648.46	622.85	326.94	259.14	−0.19245	−0.082149	0.40733	0.2167	0.97957	0.77818
9	380.36	370.44	169.45	141.37	0.0081075	0.12603	0.1811	0.11362	1.0965	0.91293
10	423.81	432.51	153.43	140.54	0.076582	0.061318	0.13811	0.2154	1.0456	0.52666
11	329.94	322.53	119.99	129.88	0.11768	0.058417	0.094466	−0.03476	0.5162	0.80956
12	512.88	458.3	237.99	170.82	−0.1266	0.042106	0.29012	−0.07753	1.054	0.5622
13	362.16	391.69	158.32	149.55	0.0097909	0.21922	0.24026	0.20729	1.2587	0.58326
14	426.23	425.08	151.52	149.74	0.032197	0.17943	0.059567	0.12176	0.85885	0.42771
15	589.57	600.38	263.1	305.59	−0.24958	0.029107	0.35374	0.47106	0.84178	0.91288
Statistics at Monthly Level										
1	84.953	83.824	64.026	59.709	0.11608	0.051161	0.092568	0.074498	1.8015	1.5093
2	102.78	105.59	93.969	84.562	0.068764	0.12824	0.040008	0.0007778	1.9586	1.5339
3	64.796	65.078	64.962	67.491	0.11085	0.10255	0.10407	0.084085	1.9747	2.4281
4	124.3	120.74	128.47	110.07	0.085876	0.11189	0.043492	0.039962	2.2036	2.0995
5	83.521	84.662	74.296	67.369	0.059826	0.046649	−0.007514	0.00574	2.1116	1.97
6	70.644	68.419	70.277	63.892	0.11805	0.040187	0.082829	0.052712	1.9376	1.8965
7	143.12	147.63	144.17	146.36	0.068133	0.076831	0.041331	0.049835	2.1536	2.4304
8	107.99	103.84	107.56	91.603	0.12874	0.096673	0.067131	0.060813	2.0011	1.7166
9	63.483	61.597	59.3	51.454	0.10462	0.041876	0.025115	0.050073	2.9013	1.614
10	70.844	72.002	54.536	50.499	0.13535	0.03547	0.028737	0.038403	1.7081	1.3845
11	55.147	53.76	42.124	42.737	0.12365	0.1283	0.04126	0.10348	1.4474	1.6967
12	85.595	76.347	82.921	65.982	0.073004	0.027347	0.023471	0.021926	2.6154	1.8343
13	60.562	65.69	53.284	56.167	0.10551	0.062668	0.052594	0.083017	1.9695	1.9355
14	71.035	70.901	52.602	50.079	0.11733	0.14219	0.068041	0.025942	1.706	1.2594
15	98.232	100.43	89.485	91.614	0.060895	0.21205	0.040198	0.11656	1.9854	2.3029

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
(b) Bias corrected										
Statistics at Annual Level										
1	1014.9	1002.2	276.99	246.65	0.20078	0.086056	0.11882	−0.01186	0.41272	0.42117
2	1222.3	1311.9	336.85	400.27	0.12894	0.31571	0.097368	0.17588	0.58218	0.5712
3	770.82	756.04	260.94	227.81	0.16415	0.18691	0.15104	0.10738	0.79906	0.55567
4	1485.3	1423.7	494.17	507.35	0.20772	0.37971	0.16392	0.17294	0.68392	0.43814
5	998.5	995.39	281.74	274.91	0.061185	0.098056	0.10916	0.062105	0.46197	0.43801
6	843.77	893.19	279.72	280.66	0.11363	0.17557	0.17029	0.18049	0.59495	0.22904
7	1721.7	1869.8	574.67	627.44	0.092873	0.30485	0.077811	0.22918	0.75477	0.46634
8	1286.8	1344.1	419.3	384.6	0.23546	0.29375	0.26223	0.20317	0.69044	0.25543
9	759.54	778.54	248.9	280.51	0.10013	0.068539	−0.006959	0.019884	0.64455	0.30339
10	849.86	858.03	235.18	236.53	0.10367	0.18378	0.083192	0.019856	0.75813	−0.097315

Table 9 (*continued*)

Variable	Mean		SD		LAG1 Correl		LAG2 Correl		Skewness	
	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled	Observed	Modelled
11	660.41	624.62	185.79	197.17	0.13378	−0.088194	0.10124	−0.059923	0.39915	0.78646
12	1026.5	951.46	328.81	310.11	0.12129	0.09329	−0.019797	−0.001884	0.55826	0.39047
13	723.19	774.8	230.43	236.32	0.20123	0.20517	0.099234	0.17376	0.65003	0.51261
14	847.45	882.68	228.78	265.36	−0.009265	−0.087708	0.062107	−0.039479	0.37807	0.45085
15	1168.9	1162.6	315.87	380.03	0.095609	0.28718	0.11504	0.17079	0.54859	0.64414
Statistics at Seasonal Level										
1	509.68	503.85	185.41	185.47	0.080553	0.0026395	0.24326	0.037113	0.94651	0.39766
2	617.09	653.98	278.01	311.87	−0.24395	−0.19812	0.37353	0.41478	0.82174	0.69115
3	388.39	378.35	195.1	182.96	−0.084859	−0.13065	0.31414	0.19155	1.4666	0.39102
4	746.17	711.31	389	443.22	−0.20983	−0.34317	0.413	0.49884	1.1228	0.94453
5	500.43	498.32	211.38	204	−0.18875	−0.15951	0.28589	0.14913	1.0218	0.16637
6	423.14	447.5	207.48	214.42	−0.10512	−0.10697	0.26796	0.13417	1.2901	0.38666
7	858.12	934.23	433.95	501.82	−0.19661	−0.15324	0.3426	0.19408	1.1469	0.53335
8	648.46	673.31	326.94	337.59	−0.19245	−0.31512	0.40733	0.40542	0.97957	0.30791
9	380.36	389.69	169.45	191.14	0.0081075	−0.061824	0.1811	0.12948	1.0965	0.49239
10	423.81	428.67	153.43	171.36	0.076582	−0.046069	0.13811	0.14416	1.0456	0.34919
11	329.94	312.98	119.99	140.36	0.11768	−0.10732	0.094466	−0.035846	0.5162	0.43938
12	512.88	476.34	237.99	231.48	−0.1266	−0.21924	0.29012	0.18588	1.054	0.39278
13	362.16	387.72	158.32	179.23	0.0097909	−0.12922	0.24026	0.28113	1.2587	0.6197
14	426.23	442.37	151.52	186.11	0.032197	−0.14732	0.059567	0.0092072	0.85885	0.36011
15	589.57	579.84	263.1	328.79	−0.24958	−0.34749	0.35374	0.54924	0.84178	1.0047
Statistics at Monthly Level										
1	84.953	83.886	64.026	67.934	0.11608	0.080358	0.092568	0.099141	1.8015	1.2025
2	102.78	109.34	93.969	106.4	0.068764	0.043743	0.040008	0.0073063	1.9586	1.4794
3	64.796	63.037	64.962	66.393	0.11085	0.075233	0.10407	0.084651	1.9747	1.4372
4	124.3	118.77	128.47	138.25	0.085876	0.066562	0.043492	0.074581	2.2036	2.4033
5	83.521	83.014	74.296	69.05	0.059826	0.099968	−0.007514	0.045223	2.1116	0.99147
6	70.644	74.57	70.277	74.057	0.11805	0.061462	0.082829	0.091337	1.9376	1.3267
7	143.12	155.81	144.17	171.55	0.068133	0.023047	0.041331	0.060373	2.1536	1.8976
8	107.99	112.42	107.56	107.6	0.12874	0.076452	0.067131	0.020728	2.0011	1.18
9	63.483	64.901	59.3	65.518	0.10462	0.14818	0.025115	0.025245	2.9013	2.433
10	70.844	71.475	54.536	56.999	0.13535	0.15808	0.028737	0.056355	1.7081	0.9369
11	55.147	52.19	42.124	44.736	0.12365	0.19721	0.04126	0.095128	1.4474	1.2149
12	85.595	79.402	82.921	79.494	0.073004	0.12106	0.023471	0.031506	2.6154	1.7934
13	60.562	64.687	53.284	62.263	0.10551	0.10475	0.052594	0.045678	1.9695	1.4199
14	71.035	73.701	52.602	59.93	0.11733	0.17283	0.068041	0.051715	1.706	0.975
15	98.232	96.893	89.485	100.89	0.060895	0.083595	0.040198	0.050446	1.9854	1.7254

for biases in any model data set. As the generated rainfall comes from a univariate model with order-one temporal dependence, it is not expected to reproduce the observed spatio-temporal dependence in the simulations. Two sample realisations of monthly rainfall, each 70 years in length, are generated. These synthetic rainfall sequences are then corrected using the MRQNBC model, with one realisation used to calibration of the bias correction model compared to the observed rainfall data. The second synthetic series is then corrected in the verification time period. The observed rainfall is used both for calibration as well as to assess the skill of the bias correction over the verification period. Bias correction is applied at monthly, seasonal and annual time scale. Two seasons in a year are considered and since the variable being considered is rainfall, the time aggregation option is also activated. The structure of 'basic.dat' file used in this example is presented in Table 7 while a few basic statistics of the observed, raw and bias corrected data for the calibration and verification periods are presented in Tables 8 and 9. A few scatter plots of statistics of raw and bias corrected data for calibration and verification periods are presented in Fig. 6 whereas empirical distribution plots of monthly, seasonal and annual rainfall are presented in Fig. 7. As raw data comes from a model which is calibrated using the observed data, there is a good match between means and standard deviations of observed and simulated raw data for calibration and verification time periods (Tables 8a and 9a and Fig. 6) and empirical distributions (Fig. 7). However, as expected, auto and cross dependence attributes are not simulated well by the univariate rainfall generation model. The bias correction model improves the representation of these observed attributes in the bias corrected time series.

5. Conclusion

The majority of existing bias correction approaches focus on a single variable and consider corrections only over a single time scale of interest, for example daily or monthly. To address this gap, open-source software in R statistical computing environment has been developed to provide simple access to multivariate and multi-timescale bias correction alternatives. The software includes the option of running multivariate recursive NBC and two multivariate and timescale nested distribution function based approaches. The package also allows the user to run these approaches as univariate alternatives with varying degree of complexities depending upon the requirement. Applications of the software along with information about the capabilities of the software are demonstrated using three sample datasets. It is anticipated that the ease of running the software and the flexibility of exercising a wide variety of options will make it popular for practitioners carrying out impact assessments and researchers investigating downscaling methods.

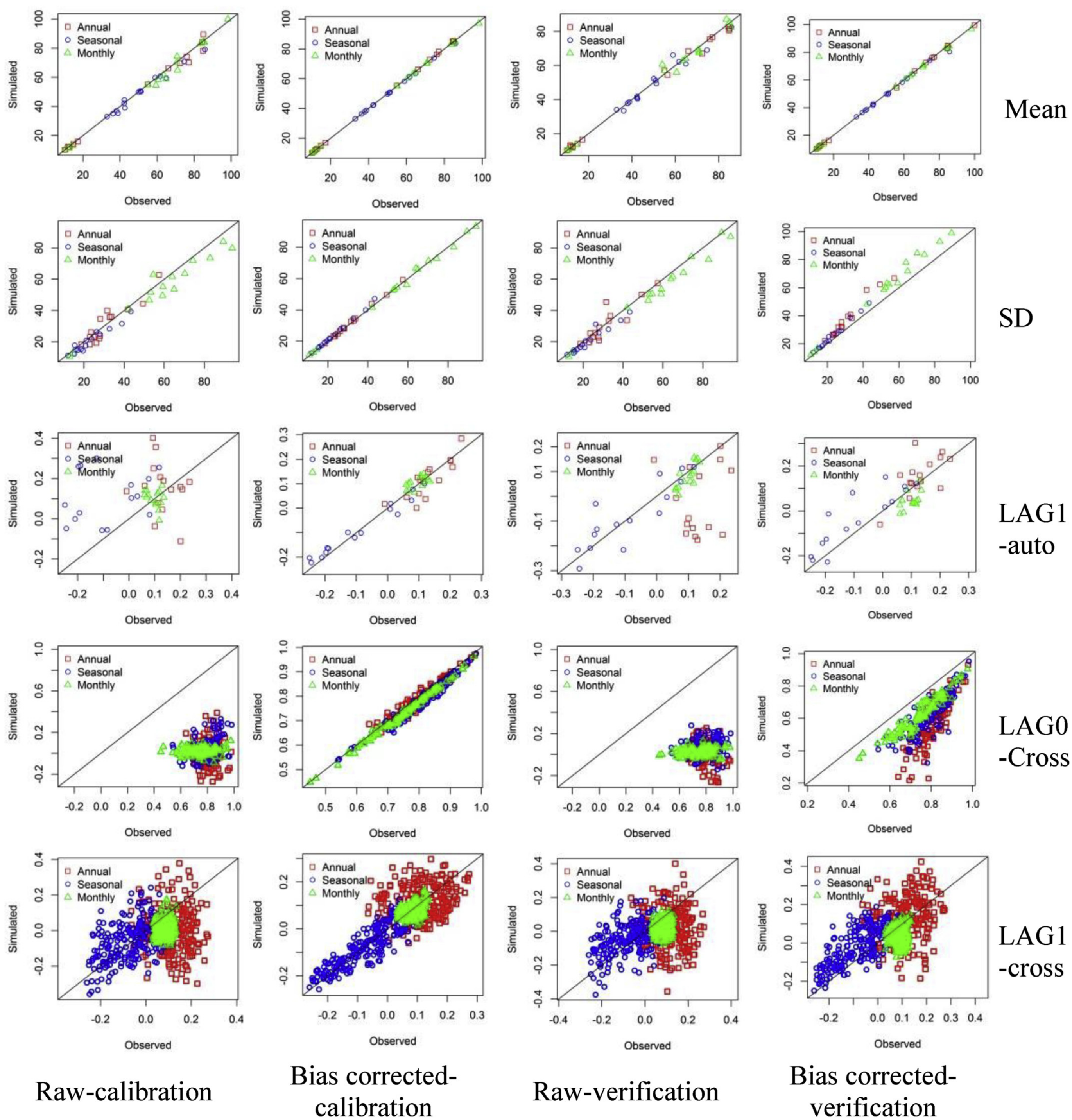

Fig. 6. For dataset 3. Other details are similar to Fig. 1.

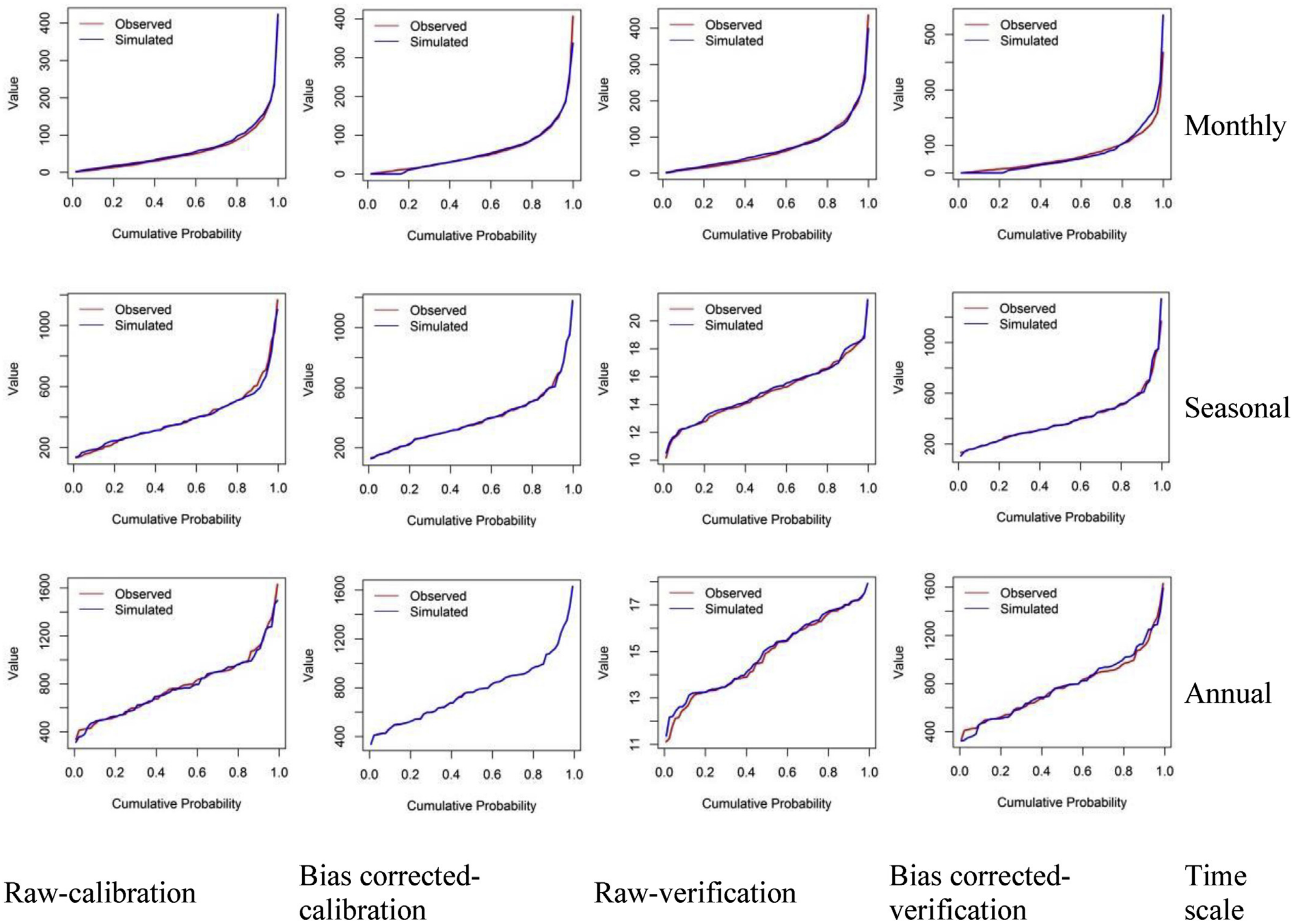

Fig. 7. For dataset 3 and station 3. Other details are similar to Fig. 2.

Software availability

Name of software package MBC
Developers Raj Mehrotra, WRC, Civil and Env. Engg., UNSW Sydney
E-mail address raj.mehrotra@unsw.edu.au
Fiona Johnson, WRC, Civil and Env. Engg., UNSW Sydney
E-mail address f.johnson@unsw.edu.au
Ashish Sharma, WRC, Civil and Env. Engg., UNSW Sydney
E-mail address a.sharma@unsw.edu.au
Year first available 2018
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

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envsoft.2018.02.010.

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