CORRECTING FOR SYSTEMATIC BIASES IN GCM SIMULATIONS IN THE FREQUENCY DOMAIN

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Abstract

Bias correction is considered as a critical post-processing step to remove systematic errors and improve the quality of General Circulation Model (GCM) simulations before their use in climate change impact assessment applications. A majority of the bias correction approaches correct for biases either at a single time scale or at multiple pre-specified time scales. An inappropriate or insufficient selection of time scales may lead to improper or sub-optimal bias corrected outputs, especially when persistence attributes across a range of scales are of interest. In this paper, we present a new bias correction approach that works in the frequency space and is independent of specific time scales. The approach is named as frequency-based bias correction (FBC). The usefulness of the approach is demonstrated by applying it to the monthly rainfall simulations of MIROC5 GCM over Australia and comparing the results with two other approaches, namely, empirical quantile mapping and recursive nesting bias correction, in cross validation. The comparison is based on the reproduction of various observed distribution and persistence attributes. Cross-validation results indicate that the proposed approach shows similar

performance in terms of reproducing the first- and second- order moments of observed precipitation time series, however, outperforms with regard to persistence attributes. The approach shows high potential for use in downscaling and other climate change impact assessment studies, especially for the planning and design of hydrologic systems that are sensitive to the characterisation of persistence in the hydrologic time series.

Key words: General circulation models; downscaling; biases in atmospheric variables; recursive nesting bias correction; empirical quantile mapping; frequency-based bias correction.

1. Introduction

Quantifying climate change impacts on water resources systems at regional or catchment scales is very important in water resources planning and management of hydrological extremes (floods and droughts) (Chen et al., 2013; Haerter et al., 2011; Johnson and Sharma, 2011; Johnson and Sharma, 2012; Mehrotra and Sharma, 2010; Mehrotra and Sharma, 2012). General circulation models (GCMs) are regarded as the primary tool available to achieve the above purpose (Chen et al., 2013; Johnson and Sharma, 2009; Maraun et al., 2010). However, there are a number of key limitations that restrict the direct use of GCM outputs. The first important limitation relates to the spatial scale mismatch between the coarse resolutions of GCMs and the finer scale requirement of the hydrological models (Wood et al., 2004). Spatial downscaling techniques are available to bridge this gap and transfer the coarser scale GCM outputs to the finer scale (Fowler et al., 2007). The second core limitation relates to the presence of systematic biases in the GCM outputs. Despite much advancement in our understanding of the science and computing resources, various assumptions and limitations in processes parameterizations often lead to systematic biases in GCM simulations (Bennett et al., 2014; Chen et al., 2013; Muerth et

al., 2013; Teutschbein and Seibert, 2012). Statistical bias correction is routinely applied to remove these systematic biases in GCM simulated variables before their use in either downscaling or other impact assessment models (Chen et al., 2013; Haerter et al., 2011; Johnson and Sharma, 2012; Mehrotra and Sharma, 2012). A number of bias correction approaches have been proposed in the recent past, and a detailed review of them can be found in Johnson and Sharma (2012); Watanabe et al. (2012); Lafon et al. (2013) and; Chen et al. (2013). These bias correction approaches can be broadly grouped into three main groups: mean-based, distribution-based, and distribution- and persistence-based bias correction approaches (Chen et al., 2013; Johnson and Sharma, 2012). A mean-based bias correct approach, also commonly known as delta change (Hay et al., 2000), is simple to apply; however, it cannot take into account the biases in the variability of time series which forms one of the most important attributes in any climate change impact assessment study. Distribution properties of input meteorological variables, described by the first moment (mean) and second moment (variance) or even third moment (skewness), significantly affect the hydrological process. For example, extreme hydrological events are often associated with unusual variability of rainfall and temperature. Hence, the use of a mean-based approach is not recommended if extreme values of variables are important in the impact studies, such as flood and drought (Fowler et al., 2007; Haerter et al., 2011; Mehrotra and Sharma, 2012). Consequently, more sophisticated approaches are required to take into account for the biases in various distribution attributes of GCM simulated variables (Pegram and Bárdossy, 2013).

Distribution-based bias correction approaches such as quantile mapping (Wood et al., 2004) or an improved version named equidistance quantile-matching (Li et al., 2010) can overcome this problem to some extent. Chen et al. (2013) evaluated different bias correction techniques including those belonging to the mean-based approach and those

pertaining to the distribution-based approach; and concluded that distribution-based approaches are consistently better than mean-based approaches. However, as the name suggests, the commonly used distribution-based approaches only allow for the biases in the distribution of the variables to be corrected at a single specified time scale (daily, monthly or annual) overlooking the biases in the persistence of the time series. Recognising this, Johnson and Sharma (2012) proposed a nesting bias correction (NBC) approach that allows to simultaneously correct for the biases at multiple time scales. NBC is based on the assumption of a linear autoregressive model; it focuses on correcting biases in mean, standard deviation and lag-1 autocorrelation (a measure of persistence) at pre-specified time scales. As both distribution and persistence related attributes are considered in the NBC's structure, the approach falls into the category of distribution and persistence-based bias correction approaches. Johnson and Sharma (2012) tested the approach using raw GCM rainfall over Australia and concluded that NBC performed better than other bias correction approaches including the quantile mapping in correcting means, variances and lag 1 autocorrelations at pre-determined time scales if the biases were not too large. NBC was also used to bias correct the monthly GCM rainfall over India, and similar conclusions were obtained (Ojha et al., 2013). Additionally, an assessment of the implications of using NBC and other bias correction approaches for simulating future droughts over Australia was recently presented in Johnson and Sharma (2015). They concluded that in comparison to the raw GCM projections, the bias correction tends to moderate increases of the future drought frequencies, and provides smaller ranges of future changes across a large set of GCMs in many parts of Australia.

Mehrotra and Sharma (2012) extended the NBC by including more time scales and multiple recursions and called it as Recursive Nested Bias Correction (RNBC) approach. The RNBC approach included five specified time scales, namely daily, monthly, seasonal,

99 annual and tri-annual; in addition, three to five iterations were carried out to further
100 improve the bias corrected results. The RNBC approach was tested on atmospheric
101 variables and was found to be more effective in correcting distribution and persistence
102 attributes at multiple time scales than the original NBC.

103 Recognising the importance of the low frequency variability in climate time series, bias
104 correction approaches such as NBC or RNBC are considered highly efficient as they
105 consider the biases in both distribution and persistence characteristics (lag-1 correlation) of
106 the time series at multiple selected time scales. However, the prior specification of bias
107 correction time scales and limiting to only lag-1 persistence somewhat limit their use in all
108 kind of applications.

109 These limitations of the nesting approach prompted us to look for alternatives that are
110 independent of time scales and are not limited to only lag-1 persistence. One such
111 possibility is the representation of the time series in the frequency domain. The analysis of
112 the time series in the frequency space makes it more suitable for studying the variability
113 across different time scales without the need of specifying the time scale (Bloomfield,
114 2004). In the past, Fourier transform based spectral analysis has been widely employed in
115 the fields of meteorology and hydroclimatology to examine the seasonal, annual and multi-
116 annual cycles in the time series (see Hegge and Masselink (1996); Leite and Peixoto
117 (1995); Fleming et al. (2002)). Besides, the Fourier transform technique is also applied to
118 generate surrogate time series in which linear properties of the original data are preserved
119 in the synthetic time series. More details on the application of Fourier transform technique
120 for the generation of synthetic climate time series are found in Prichard and Theiler
121 (1994); Keylock (2012); Chen et al. (2010). Following this, we propose a bias correction
122 approach that operates in the frequency space and thus negates the requirement of time

scale specification as needed by the NBC and its variants. This approach is hereafter referred to as the frequency-based bias correction (FBC).

The remainder of the paper is organised as follows. In the next section, we provide theoretical and technical details of our proposed bias correction approach. In section 3, we present the results of the application of FBC to GCM rainfall simulations and compare the results with other bias correction approaches. In section 4, we discuss the limitations and assumptions of the approach. Finally, in section 5, we summarise the results and draw the conclusions.

2. Methodology

The idea of FBC stems from the concept that when a time series is converted in the frequency domain, the variance of the time series is expressed as a function of frequency, making it more suitable for studying variability at different time scales (Bloomfield, 2004). Recognizing this, if a bias correction procedure is performed in the frequency domain, it is expected to provide an improved representation of the observed variability across different time scales including the low frequency variability, while avoiding the need for specification of time scale(s) of interest. The discrete Fourier transform is one of the approaches that allow the time series to be expressed in the frequency domain. Transforming the time series into the frequency domain using the forward Fourier transform provides information on the amplitudes and phases at different frequencies. The amplitudes are used to estimate the power spectrum, also called a periodogram or Fourier spectrum. As the power spectrum represents the variance of the time series as a function of frequency, in FBC the power spectrum of the biased time series is modified to map that of the reference time series across their respective frequencies. The bias corrected Fourier spectrum is then transformed back (using an inverse Fourier transform) to the time domain

to obtain bias corrected time series. This concept is explained in detail using a synthetic example.

2.1. The FBC logic

The philosophy behind FBC is now explained by using two synthetic time series, X and Y. The 240 data points of these two series are obtained by adding three different sinusoidal waveforms. In addition, Gaussian noise signals are added to both X and Y series. As such, the total variability of X and Y is largely contributed by the three frequency components with their respective amplitudes which are different for the two series. For simplicity, let us assume that X represents the observed time series while Y represents the GCM simulated time series; their time scales and units are arbitrary. It may be noted that the mixing of variations at different time scales within one single time series makes it difficult to distinguish and thus perhaps correct for biases in magnitudes of different cycles. Nevertheless, it perhaps matches well with the many hydrological observations, for example, rainfall which shows strong seasonal, annual and multiannual cycles.

These two time series are shown in the first plot of Figure 1 (plot a). An autocorrelation plot provides a simple measure to examine persistence at varying time lags in a time series. The other two plots of the first row of Figure 1 presents the autocorrelation plots of Y (plot b) and X (plot c). Their mean and standard deviation are also shown in these plots. As can be seen, the two series have different means, standard deviations and persistence statistics.

Plotting X and Y together as shown in Figure 1a does not tell much about the complex underlying fluctuations contributing to their overall variability. Performing a routine bias correction procedure on Y in the time domain might miss some parts of the observed (in X series) high- and low-frequency variability and persistence in the corrected time series (as shown later). To emphasize this point further, we bias correct Y in both time and

frequency domain. In the time domain, we apply two commonly used bias correction approaches. In the first approach (TBC1) we correct for the biases in the mean and standard deviation of Y to get a bias corrected time series, Y_{tbc1} . In the second approach (TBC2), in addition to mean and standard deviation, we also correct the Y series for the bias in lag-1 autocorrelation coefficient (Johnson and Sharma, 2012) and obtain a bias corrected time series, Y_{tbc2} . In the frequency domain, we bias correct the Y time series using FBC (explained later in detail) and match the spectrum of Y to that of the X to capture the magnitudes of different cycles in the observed series X . The corrected spectrum of Y together with its original phase spectrum is used for the inverse Fourier transform back to the time domain to derive the corrected Y , Y_{fbc} . The phase spectrum is kept untouched because the locations of peaks or troughs with respect to the time origin of Y are not expected to shift. As both time series based bias correction approaches are designed to capture first and second order moments of the observed series, it would be of interest to examine how well these approaches perform in correcting for the biases in the persistence attributes. Plots d, e and f of Figure 1 (bottom row) present autocorrelation plots of the bias corrected time series Y_{tbc1} , Y_{tbc2} and Y_{fbc} , respectively. As TBC1 corrects for the biases in mean and standard deviation, the autocorrelation structure remains unaffected owing to the fact that correcting for means and standard deviation does not change the temporal autocorrelation structure of the time series (plot d, Figure 1). TBC2, in addition to mean and standard deviation also removes the biases in the lag-1 correlation (built in the model structure), although biases at other lags are still present (plot e, Figure 1). The FBC reproduces the exact observed autocorrelation plot (plot f, Figure 1). Although it is possible to correct for the biases in the higher order lags in the time domain by using a more complex bias correction procedure, it will introduce added mathematical complexity and would correct for the specified lags only. Converting the time cycles in

frequencies allows one to apply a simple addition/subtraction procedure to correct for the biases in these frequencies and therefore, provides a simple yet powerful tool to correct for the biases in all dominant cycles present in the time domain without involving additional complexities in the bias correction procedure.

2.2. FBC Formulation

The formulation of FBC is based on the discrete Fourier transform technique. Appendix A provides the mathematical basis for the discrete Fourier transform technique and estimation of power spectrum based on the Fourier components. For clarity, the parameters of the FBC bias-correction approach are estimated using observed and calibration period data sets and these are applied to an independent data set (validation period or future period) not used in the calibration process. The following describes the step-wise procedure used to implement the FBC algorithm.

- (i) Preprocess the raw data before the actual application of the bias correction approach by removing seasonality or trends, if any, present in the data. A majority of hydrology-relevant variables, such as precipitation, exhibit strong seasonal variations. Removing seasonality is necessary when data exhibit multiple seasonal patterns (i.e. winter and summer patterns). These differing seasonal variations are removed by using monthly statistics (i.e. means, standard deviations and lag-1 correlations) derived from the observed and calibrated period datasets (Johnson and Sharma, 2012; Sharma et al., 2013). Furthermore, de-trending is necessary for atmospheric variables, which are known to exhibit significant systematic trends, for example, temperature (Brooks, 2011; Johnson and Sharma, 2012). The de-seasonalising and de-trending of time series transform the data to be closer to the stationarity conditions assumed, a prerequisite for the application of Fourier

transform. These pre-processed data sets are called as the observed, calibration and validation residuals.

(ii) Transform observed, calibration and validation residuals into the frequency domain using the discrete Fourier transform technique as presented in the Appendix A. Calculate amplitudes and phases across different frequencies of the observed, calibration and validation residuals using equation A5 and A6. Let $A^{obs}(f)$, $A^{mc}(f)$, and $A^{mf}(f)$ represent the amplitudes of the observed, calibration and validation residuals at frequency f , respectively. Likewise, $\phi^{obs}(f)$, $\phi^{mc}(f)$, and $\phi^{mf}(f)$ represent the phases of the observed, calibration and validation residuals at frequency f , respectively.

(iii) Derive the (Fourier) power spectra of the observed, calibration and validation residuals from their respective amplitude spectra using equation A9a and A9b. Denote FP^{oc} , FP^{mc} , and FP^{mf} as the power spectra of the observed, calibration and validation residuals, respectively.

(iv) Map the power spectrum of the calibration residuals onto that of the observed residuals of the same control period in the frequency domain. This is implemented by taking the difference of the periodogram ordinates of FP^{oc} and those of FP^{mc} at the corresponding frequencies. This difference is the so-called spectral fit-coefficients. Add the spectral fit-coefficients to the periodogram ordinates of FP^{mc} at the corresponding frequencies to yield the corrected Fourier spectrum of the calibration residuals ($\widetilde{FP}^{mc}$) to match exactly with the Fourier spectrum of the observed residuals.

(v) Apply spectral fit-coefficients obtained in step (iv) to bias correct for the power spectrum of the validation residuals. Specifically, add the spectral fit-coefficients to

244 FP^{mf} at the corresponding frequencies to produce the bias corrected power
 245 spectrum of the validation residuals ($\widetilde{FP}^{mf}$).

246 (vi) Once $\widetilde{FP}^{mc}$ and $\widetilde{FP}^{mf}$ are obtained, rearrange equations A9a and A9b to calculate
 247 amplitudes across the different frequencies. Denote $\tilde{A}^{mc}(f)$ and $\tilde{A}^{mf}(f)$ as the
 248 amplitudes at frequency f derived from the corresponding $\widetilde{FP}^{mc}$ and $\widetilde{FP}^{mf}$.

249 (vii) Construct the modified Fourier components using $\tilde{A}^{mc}(f)$ and $\phi^{mc}(f)$ for the
 250 calibration residuals, and $\tilde{A}^{mf}(f)$ and $\phi^{mf}(f)$ for the validation residuals (equation
 251 A7) up to the Nyquist frequency (f_c). Recall that the Fourier components at the
 252 frequencies greater than f_c are just the complex conjugate of those at the
 253 frequencies less than f_c (Hegge and Masselink, 1996).

254 (viii) Once the modified complex Fourier components of the calibration and validation
 255 residuals are derived, transformed back them to the time domain using the inverse
 256 Fourier transform (equation A8) to yield the bias corrected calibration and
 257 validation residuals.

258 (ix) In the last step, rescale back the bias corrected calibration and validation residuals
 259 following a reversed deseasonalising procedure adopted in the step (i) using the
 260 observed statistics (i.e. observed means, standard deviations and/or lag-1
 261 correlations) as described in Sharma et al. (2013) to obtain the bias corrected time
 262 series for calibration and validation periods.

263 **3. Application of FBC on Raw GCM Precipitation**

264 **3.1 Data**

265 The observed and GCM simulated monthly rainfall time series are used to assess the
 266 performance of FBC. The observed rainfall series used in this study is monthly gridded
 267 rainfall on a 0.5° latitude – longitude resolutions for the period from 1901 to 2000,

provided by the Australian Bureau of Meteorology (BOM). This dataset covers the whole land mass of Australia, from 10°S to 45°S latitude and from 115°E to 165°E longitude.

Simulated monthly raw precipitation of MIROC5 GCM is extracted from the Coupled Model Intercomparison Project phase 5 (CMIP5), archived by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) website: <http://pcmdi9.llnl.gov/esgf-web-fe/live>. The MIROC5 is maintained by the Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology. It is noteworthy that we use MIROC5 to illustrate the proposed approach; however, the proposed bias corrected approach here is generic and can be applied (and has been applied though results are not presented for conciseness) to other GCMs as well.

MIROC5 simulated rainfall has a grid resolution of approximately 1.4° latitude and longitude; therefore, a common 1.0° rectangular grid is chosen, and the MIROC simulated and observed rainfall time series is re-gridded into the same spatial resolution using bilinear interpolation. As a result, there are 772 grid points (1.0° latitude and longitude resolutions) covering the Australian land surface. Each grid point has single monthly time series from the observed and simulated monthly precipitation over the period from 1901 to 2000. Like most of the bias correction approaches, the proposed bias correction procedure is also performed independently at each grid cell assuming spatial independence (Johnson and Sharma, 2012).

3.2. Methodology Assessment

The performance of FBC is assessed in cross validation by dividing the available 100 years of record into five 20 years long non-overlapping subsets. Each subset is then used as a validation set (20-year period), with the remaining data (80-year period) used as a

calibration set. It is important to note that unequal length of the calibration and validation datasets also results in dissimilar frequencies while deriving the Fourier spectra. To deal with this issue, in the step (ii) of the FBC procedure, we construct averaged periodogram estimates for the observed and current GCM residuals having the same frequencies as those defined by the validation dataset (more information is presented in the discussion section).

In order to have a proper assessment of the performance of FBC, we also apply the empirical quantile mapping (EQM) and the recursive nesting bias correction (RNBC) approaches and compare the results. Going by the model structure, we know that EQM corrects for the distribution biases only at a specified time scale and does not correct for the biases in the temporal persistence. The bias correction formulation for EQM is based on equation 1 following Li et al. (2010) with the approach applied separately for each month.

$$\tilde{x}_{mf} = x_{mf} + \left\{ F_{oc}^{-1} \left(F_{mf}(x_{mf}) \right) - F_{mc}^{-1} \left(F_{mf}(x_{mf}) \right) \right\} \quad (1)$$

In which, x is a climate variable, $F(\cdot)$ is the empirical cumulative distribution of either observation (o) or model (m) for the calibration period (c) or future period (f).

The RNBC as described in Mehrotra and Sharma (2012), corrects for distribution as well as lag-1 persistence attributes at the predefined time scales. In the present study, RNBC is applied at monthly and annual time scales.

The performance of these approaches is assessed on the basis of reproduction of various distribution- and persistence-based attributes. For the distribution-based properties, we use means and standard deviations at monthly, seasonal and annual time scales. For the persistence-based attributes, we measure the persistence of oscillations within the time series using the autocorrelation function (ACF). We use the Root-Mean-Squared Error

(RMSE) statistic (Equation 2) as an error measure between the ACF of the monthly observed time series and that of the monthly simulated time series.

$$RMSE_{ACF} = \sqrt{\frac{\sum_{l=1}^L (\rho_{o,\tau} - \rho_{m,\tau})^2}{L}} \quad (2)$$

Where, L is the number of autocorrelation lags used and $\rho_{o,\tau}$ and $\rho_{m,\tau}$, respectively, are the sample autocorrelation functions at lag τ for the observed and simulated time series. It is known that when L increases, the significance of $\rho_{o,\tau}$ and $\rho_{m,\tau}$ decreases; therefore, following Caiado et al. (2009), we adopt $L = N_{data}/10$, where N_{data} is the number of data points.

To measure how well the bias-corrected GCM precipitation time series capture observed low-frequency variability, we use aggregated persistence score (APS), proposed by Rocheta et al. (2014). In general, the APS score is an alternative metric of persistence, related to the Hurst exponent; however, it measures the magnitude of differences between the GCM and observed standard deviations scaled by no-persistence confidence interval of the standard deviations over all aggregation periods (Rocheta et al., 2014). The procedure for calculating APS involves two steps: (i) obtain the scaled deviations at different aggregated periods (denotes as SD_i) by dividing the differences in standard deviations of the observed and simulated time series at each aggregated period by a scaling factor (equation 3) and (ii) average SD_i over all the aggregated periods (equation 4).

$$SD_i = \frac{A_i}{B_i} = \frac{S(i)_m - S(i)_o}{B_i} \quad (3)$$

$$APS = \frac{1}{i} \sum_i SD_i \quad (4)$$

Where SD_i is the scaled deviance at aggregation period i ; $S(i)$ is the standard deviation of the i^{th} aggregation period for the GCM simulations (m) or the observations (o); and B_i is

the reference no-persistence confidence interval of the standard deviation for the same aggregation period i .

For spatial averaging of the APS values over all grid cells, Rocheta et al. (2014) defined three kinds of spatially averaged APS metrics: (1) APS_{abs} measuring the overall performance across the land mass in term of reproducing the persistence without considering over- or under-simulations of the persistence (equation 5); (2) APS_{pos} measuring an over-simulation of the persistence over the land mass (equation 6); and (3) APS_{neg} measuring the persistence under-simulation over the study area (equation 7).

$$APS_{abs} = \frac{1}{n} \sum_n \frac{1}{i} \sum_i |SD_i| \quad (5)$$

$$APS_{pos} = \frac{1}{n} \sum_n \frac{1}{i} \sum_i SD_i^+ \quad (6)$$

$$APS_{neg} = \frac{1}{n} \sum_n \frac{1}{i} \sum_i SD_i^- \quad (7)$$

Where $|SD_i|$, SD_i^+ , SD_i^- the absolute, positive and negative values of the scaled deviance at aggregation period i and n is the number of grid cells.

In addition, the 3 year and 5-year minimum rainfall totals are also considered in order to assess the performance of the approaches in capturing runs of low rainfall years.

3.3 Results

The performance of EQM, RNBC and FBC approaches is evaluated in terms of reproduction of observed distribution and persistence attributes in the cross validation period across a range of time scales of interests. The seasonal time series is formed by accumulating monthly rainfall values for the four seasons, namely; autumn (March, April and May), winter (June, July and August), spring (September, October, and November) and summer (December, January, and February). The annual rainfall time series is formed by summing up the twelve monthly rainfall values of each calendar year. We first look at

how well the three bias correction approaches perform in reproducing the mean and standard deviation, which to a large extent are representative of the distributional attributes. Figure 2 presents the scatter plots of observed, raw and bias corrected monthly, seasonal and annual means and standard deviations at individual grid points. In Figure 2, each panel contains three plots showing monthly, seasonal and annual statistics. Dots in these plots indicate grid points. It can be seen that the GCM raw simulations misrepresent the observed means and standard deviations (column 1 of Figure 2). The model overpredicts means and standard deviations for most of the grid cells over Australia across the three time scales. As, after performing the bias correction at monthly time scale, mean biases at all other time scales are automatically taken care of; results for the mean at annual time scale only are presented (the three last columns in the top row in Figure 2). For the second-order moment, represented here by the standard deviation (SD), all the approaches perform well at the monthly time scale (bottom row of Figure 2). However, at seasonal and annual time scales, EQM shows some scatter in comparison to RNBC and FBC. As EQM corrects for the biases in the distribution attributes at monthly time scales only, the biases in the variations at other time scales are not accounted for (Haerter et al., 2011). For RNBC, the annual standard deviation is an explicitly defined parameter while in FBC corrects separately for each variation components associated with each frequency in the frequency domain.

It is recalled that the main strength of our proposed approach lies in its capability to correct for the biases in persistence attributes. We present next the performance evaluation of bias correction approaches in terms of their ability to correct for the biases in persistence based attributes.

Box plots in Figure 3 present the distribution of the prediction error for $RMSE_{ACF}$ (equation 2) across all grid cells over Australia. It can be seen that FBC outperforms

RNBC and EQM with the lowest mean error and the least spatial variation for $RMSE_{ACF}$ (Figure 3). This is due to the fact that the FBC technique corrects for magnitudes of the various kinds of oscillations associated with different frequencies separately in the frequency domain so that the magnitudes of oscillations in the observed time series are well reproduced. Although RNBC corrects for the biases in lag-1 autocorrelation at monthly and annual time scales, both RNBC and EQM perform similarly in the $RMSE_{ACF}$ statistic (Figure 3). It appears that the $RMSE_{ACF}$ statistic is influenced by the correlations at higher lags used in the calculation of ACF .

We now specifically look at the RMSE of autocorrelations at some significant lags (normally linked to stronger persistence), for example, lag-1, lag-2 and lag-3 autocorrelations of the monthly and annual time series averaged over all grid points (Table 1). While RNBC approach has the least RMSE for lag-1 autocorrelations at monthly and annual time scales (an integral part of the model structure), FBC does for other lags and time scales (Table 1). These results are quite encouraging as FBC corrects for the biases at multiple lags and time scales.

Figure 4 presents the APS scores, calculated using temporal aggregations from 24 to 60 months with a time step of one month at each grid cell over Australia. We consider the APS value within the range of -0.25 to 0.25 to be close to zero to calculate the percentage of grid cells showing the over-simulation or under-simulation of rainfall persistence (Rocheta et al., 2014). It can be seen that the raw model simulations over-estimate the persistence over most of the Australian landmass, with 89% of grid cells showing the over-simulation and 6% of grid cells showing the under-simulation (Figure 4a). The bias corrected simulations from EQM, RNBC and FBC show improvements over raw GCM simulations in capturing the persistence with a significant reduction of over-simulation of persistence as shown in Figures 4b, c, and d. Considering the overall performance in terms

of reproduction of observed persistence and ignoring the over-simulation or under-simulation (APS_{abs}), FBC provides the best performance with APS_{abs} of 0.41 as opposed to 0.62 and 0.59 for the EQM and RNBC approaches, respectively.

We finally compare the performance of the three approaches in representing the interannual variability expressed in terms of the runs of low rainfall years by considering the 3 and 5 year minimum total rainfalls rescaled by the observed annual standard deviations (Johnson and Sharma, 2012) (Figure 5). Although all the approaches provide a good simulation of these statistics, FBC provides the lowest RMSE over Australia for both the 3-year and 5-year minimum total rainfalls (Figure 5).

4. Discussion

Bias correction approaches are routinely applied to remove the systematic biases in GCM outputs. Proper reproduction of observed year-to-year or low frequency variability in GCM output of climate variables has received considerable attention in the recent past with quite a few studies concentrating on the issue of appropriate bias correction approaches for use in hydrological impact studies (Chen et al., 2013; Johnson and Sharma, 2011; Li et al., 2010; Rocheta et al., 2014). Use of a proper bias correction approach assumes more importance for countries like Australia, where the climate is frequently characterized by cycles of below and above average rainfall leading to severe droughts and widespread flooding (Westra and Sharma, 2006). The strength of FBC approach lies in its capability of working in the frequency domain and correcting for the magnitudes of different fluctuations across multiple frequencies (they are independent of time origin and time scale).

Like any other bias correction approaches, there are some limitations and assumptions associated with the FBC approach as well. For example, the selection of data length might

affect the ability of representing oscillation components in the frequency domain. Fourier frequencies including the lowest frequency (fundamental frequency), harmonic frequencies and the highest frequency (Nyquist frequency) depends on the time period of data (Appendix A). Therefore, the amplitudes of oscillations obtained by the Fourier transform, which are gauged at the harmonic frequencies up to the Nyquist frequency, also depend on the data length. The FBC approach cannot precisely correct for biases in the amplitudes at frequencies other than the harmonic frequencies defined by the data length.

When the calibration and validation (or future) time series have unequal lengths, Fourier frequencies at which periodogram ordinates are gauged are not the same (Caiado et al., 2009). Therefore, before applying the bias correction procedure in the frequency domain, either one has to drop the extra data points and make both series to be of the same length or somehow calculate the periodogram ordinates at common frequencies. If time series of the calibration period is long enough to be divided into multiple segments of data length equal to the future time series, one of the solutions is to calculate the periodogram of each segment separately and construct an averaged periodogram to have the same frequencies as that of the validation (or future) time series (this procedure is also implemented in section 3). It is noteworthy that the averaged periodogram also provides statistically reliable and stable Fourier spectral estimates in comparison to single time series periodogram (Hegge and Masselink, 1996; Thomson and Emery, 2014). If the data length is not long enough to be divided into multiple segments, an alternative solution is to use the interpolation periodogram technique proposed by Caiado et al. (2009). In this approach, the periodogram ordinates at common frequencies are obtained by interpolation. In order to get a better idea of the implication of these alternatives on the final bias corrected time series, in Appendix B, we present a few common statistics of interest

459 obtained by using the averaged and interpolated periodogram alternatives of the FBC
460 approach.

461 In line with the other commonly used bias correction approaches, the FBC approach also
462 assumes that biases in the magnitudes of different variations of the control period are same
463 as those of the future period. Although this assumption simplifies the bias correction
464 procedure, it may not necessarily be hold true if biases in the amplitudes of oscillations
465 evolve over time. This limitation can be overcome by investigating the spectral behaviour
466 of time series evolving over time using a time-frequency analysis such as dynamic Fourier
467 analysis or Wavelet analysis (Shumway and Stoffer, 2005). Future work could investigate
468 the utility of the time-frequency analysis for this purpose.

469 The FBC approach, being univariate, does not account for the dependence biases across
470 climate variables. We know that many climate variables have strong physical relationships
471 leading to strong cross-dependence structure, for example, temperature and rainfall. A
472 univariate bias correction approach may alter the physical consistency of multiple climate
473 variables, of importance in applications such as downscaling or other hydrological
474 applications (Mehrotra and Sharma, 2010; Mehrotra and Sharma, 2015). An extension of
475 the univariate FBC to the multivariate case is an interesting research problem which we
476 intend to take up in the near future.

477 The FBC approach as presented here operates independently at individual grid cells; this
478 means the approach does not take into account the observed spatial dependence - a
479 common practice followed in the most bias correction approaches. In many applications,
480 preserving the spatial correlation structure is very important (for example see Johnson and
481 Sharma (2012)). Some ideas for correcting for the biases in spatial dependence are

discussed in Johnson and Sharma (2012); Mehrotra and Sharma (2015). It is possible to extend the FBC following these ideas.

The paper illustrates the utility of the FBC approach using monthly data. Monthly records are useful in some applications such as drought or water resources planning and assessment whereas daily records are required for other applications such as flood studies and streamflow modelling (Johnson and Sharma, 2012). In order to apply the FBC approach to daily data, the pre-processing step (step 1 of section 2.2., FBC Formulation) has to be suitably modified to accommodate the daily variations. For example, a treatment for seasonality for daily data can be found in Rajagopalan and Lall (1999) and Mehrotra and Sharma (2015). In addition, some kinds of smoothing techniques would also be needed to filter out the noise from the signals, if daily data spectra are too noisy (Chatfield, 2003). Future work will address these issues.

The applicability of the proposed approach is demonstrated using a single GCM (MIROC) and variable (rainfall). The methodology presented here, however, is generic and can be applied to any GCMs or other climate variables commonly used in statistical/dynamical downscaling and hydrology. We have successfully applied the proposed approach to the precipitation output of 37 GCMs (results available upon request) and have found improved performance of the FBC approach over other two approaches used.

5. Conclusions

This work presents a new bias correction procedure that operates in the frequency domain. The FBC utilises the Fourier transform technique to convert the series from time to the frequency domain and then corrects for the biases in magnitudes of different fluctuations separately, which is not possible using a routine bias correction approach in the time

domain. We believe that this research provides a new direction for conducting further research in improving the quality of raw GCM outputs.

The performance of the approach is compared and assessed using raw GCM monthly rainfall simulations in cross validation and the two existing bias correction approaches, namely an empirical quantile mapping (EQM) and a recursive nesting bias correction (RNBC). The results suggest that while the performance of FBC is comparable with other two approaches in terms of reproduction of the observed first- and second- moment statistics, it outperforms in reproducing various persistence based attributes at multiple time scales. As a result, it offers a great promise for use in various impact assessment applications, particularly in hydrological impact studies where year to year variability plays an important role.

Appendix A: Discrete Fourier Transform and Fourier Spectrum Estimation

The discrete Fourier transform of a finite time series $x(n)$ of N data points taken at regular intervals of time Δt (the forward transform) can be expressed as follows (Hegge and Masselink, 1996):

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-jn\omega_k} \quad (A1)$$

in which:

k = number of cycles (per time period $P = N\Delta t$) or so-called harmonic numbers, $k = 0, 1, \dots, N-1$. Harmonic 1 ($k = 1$) corresponds to one cycle over the time period, and higher harmonics are integer multiples of one cycle over the time period.

$X(k)$ = Fourier components or coefficients at the frequencies f_k or ω_k

$$\omega_k = 2\pi f_k = \frac{2\pi k}{N\Delta t} \quad (A2)$$

ω_k = frequency of the k^{th} Fourier coefficient in radians per unit time

528 f_k = frequency of the k^{th} Fourier coefficient in cycles per unit time, it is also called
529 harmonic frequency.

$$530 \quad f_k = \frac{k}{N\Delta t} \quad (A3)$$

531 The Fourier coefficients are complex, each having a real (X_{real}) and imaginary part (X_{imag});
532 therefore, we can represent equation A1 in the below form (Fleming et al., 2002):

$$533 \quad X(k) = X_{real}(k) + j X_{imag}(k) \quad (A4)$$

534 These complex Fourier coefficients $X(k)$ are then used to calculate the amplitude $A(k)$ and
535 phase $\phi(k)$ (with respect to the beginning the series) for each k^{th} component as follows
536 (Fleming et al., 2002):

$$537 \quad A(k) = \left(X_{real}^2(k) + X_{imag}^2(k) \right)^{1/2} \quad (A5)$$

$$538 \quad \theta(k) = \tan^{-1} [X_{imag}(k)/X_{real}(k)] \quad (A6)$$

539 Equation A1 may be redefined in terms of the amplitude $A(k)$ and phase $\phi(k)$ as follows
540 (Fleming et al., 2002):

$$541 \quad X(k) = A(k)e^{j\theta(k)} \quad (A7)$$

542 In summary, the forward discrete Fourier transform allows the time series to be
543 represented in the frequency domain by the Fourier components whose frequencies are
544 integer multiples of $(N\Delta t)^{-1}$ (fundamental frequency), ranged from a frequency of zero (f_0)
545 to Nyquist frequency (f_c). The Fourier component at the frequency of zero (f_0) is equal to
546 the mean of the time series (Fleming et al., 2002). The fundamental frequency $(N\Delta t)^{-1}$ is
547 the lowest frequency which can be detected by the data series using the discrete Fourier
548 transform, also defined as the frequency bandwidth (Hegge and Masselink, 1996). The
549 Nyquist frequency ($f_c = f_{N/2} = 1/2\Delta t$) is the highest frequency which the Fourier transform

can resolve by the given time series (Hegge and Masselink, 1996). The Fourier components at the frequencies greater than f_c are just the complex conjugate of those at the frequencies less than f_c (Hegge and Masselink, 1996).

The inverse discrete Fourier transform, which allows the Fourier components from the frequency domain back to the time domain, is defined using equation A8 (Thomson and Emery, 2014) :

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{jn\omega_k} \quad (A8)$$

In practice, the implementation of the forward and inverse discrete Fourier transforms can be achieved by fast Fourier transform (FFT) and inverse fast Fourier transform (IFFT) algorithms of the programming language, Matlab (Hegge and Masselink, 1996).

After obtaining the Fourier components, the one-sided Fourier spectrum or power spectrum (also called periodogram) can be calculated as follows (Hegge and Masselink, 1996):

$$FP(k) = \frac{A(k)^2}{N} \quad \text{for } k = 0, \frac{N}{2} \quad (A9a)$$

$$FP(k) = \frac{2A(k)^2}{N} \quad \text{for } k = 1, \dots, \frac{N}{2} - 1 \quad (A9b)$$

To improve the statistical reliability of the periodogram estimate, it is recommended to combine periodograms estimates obtained from different segments of the long time series using segment-averaging technique (referred to Hegge and Masselink (1996); Thomson and Emery (2014)). The periodogram estimate obtained from the segment-averaging technique are called the average periodogram.

Appendix B: Compares a few common statistics of the bias corrected results obtained by using averaged periodogram (called FBCa) and interpolation periodogram techniques (called FBCi).

573 Table B.1. RMSE of statistics of interest and the APS metric over Australia based on the
574 raw GCM time series and bias corrected time series using FBCa and FBCi*

Statistics	Raw GCM	FBCa	FBCi
Monthly Standard Deviation (mm)	28.26	1.57	2.98
Annual Mean (mm)	420.18	31.09	41.18
Annual SD (mm)	72.34	12.80	18.80
3 Year Minimum Total Rainfall (mm)	1004.	0.8	0.88
5 Year Minimum Total Rainfall (mm)	1743	1.34	1.5
Mean of RMSE for ACF*	0.062	0.028	0.033
Standard Deviation of RMSE for ACF*	0.027	0.006	0.006
Monthly Lag-1 Autocorrelation	0.075	0.032	0.033
Monthly Lag-2 Autocorrelation	0.061	0.027	0.038
Monthly Lag-3 Autocorrelation	0.070	0.029	0.039
Annual Lag-1 Autocorrelation	0.139	0.115	0.130
Annual Lag-2 Autocorrelation	0.140	0.107	0.131
Annual Lag-3 Autocorrelation	0.171	0.128	0.140
APS _{abs}	1.92	0.41	0.47

* RMSE for ACF is calculated using equation 2. The best results are highlighted in bold.

575 The results presented in Table B.1 suggest that although both the techniques reduce the
576 biases in various statistical attributes, the results of averaging periodogram technique
577 (FBCa) are better in comparison to the interpolation periodogram technique. These results

confirm the earlier findings that the averaged periodogram provides statistically reliable and stable Fourier spectral estimates in comparison to single time series periodogram (Hegge and Masselink, 1996; Thomson and Emery, 2014). However, in most practical situations, the data length is not long enough to calculate the average periodogram and the interpolation periodogram technique provides an easy workable solution to deal with unequal data length situations.

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718

719 Table 1. RMSE for Autocorrelation Statistics^{*}

Statistics	Raw GCM	EQM	RNBC	FBC
Monthly Lag-1 Autocorrelation	0.075	0.059	0.020	0.032
Monthly Lag-2 Autocorrelation	0.061	0.049	0.041	0.027
Monthly Lag-3 Autocorrelation	0.070	0.044	0.039	0.029
Annual Lag-1 Autocorrelation	0.139	0.142	0.093	0.115
Annual Lag-2 Autocorrelation	0.140	0.144	0.149	0.107
Annual Lag-3 Autocorrelation	0.171	0.175	0.175	0.128

^{*} The bias correction approach with the lowest RMSE across Australia is highlighted in bold

Figure Captions

Figure 1. Illustration of the FBC approach (a) two signals, X and Y plotted in the time domain; (b and c) autocorrelation plots of Y and X; (d, e and f), autocorrelation plots for the bias corrected time series obtained using TBC1, TBC2 and FBC approaches. The units and time scales for X and Y are arbitrary.

Figure 2. Scatter plots of mean (first row) and standard deviation denoted as SD (second row) at monthly, seasonal and annual time scales of raw GCM (first column), EQM (second column), RNBC (third column) and FBC (four column) bias corrected rainfall in the cross-validation. Means and SD are divided by 100 for the presentation purpose. Plot with letter M denotes monthly, letter S is for seasonal and letter A is for annual statistics. The horizontal axis represents the observed, while the vertical axis represents the model simulated. Points on these plots denote each grid cell across Australia.

Figure 3. Boxplots of the RMSE for the autocorrelation function (ACF) based on the raw GCM, EQM, RNBC and FBC bias corrected monthly time series across Australia in the cross-validation. Outliers exceeding the length of the whiskers are shown as crosses.

Figure 4. The results for the APS metric from 24 to 60 months based on the raw GCM, EQM, RNBC and FBC bias corrected monthly time series across Australia in the cross validation. The bottom of each plot also shows the results for APS_{abs} , APS_{pos} and APS_{neg} . Yellow to red areas indicate oversimulation of persistence while light blue to dark blue areas indicate undersimulation of persistence. Colour intensities reflect the magnitudes of oversimulation or undersimulation. Values in parentheses show the percentages of grid cells with the over- or under-simulation of rainfall persistence.

Figure 5. Three year and five year minimum total rainfalls of raw GCM (first column) and bias corrected rainfall using EQM (second column), RNBC (third column), and FBC (four

column) in the cross-validation.. Three year and five year minimum total rainfalls are rescaled by the annual observed standard deviations. First row shows 3-year minimum total rainfall, second row presents 5-year minimum total rainfall. The horizontal axis represents the observed, while the vertical axis represents the model simulated. Points on these plots denote each grid cell across Australia. The top left corner of each plot shows RMSE for the raw GCM and bias corrected results using EQM, RNBC and FBC across the grid cells.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5