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Key Points:

- Tradition alternatives for bias correction distort continuity in corrected series
- A discrete wavelet transform based signal processing alternative for correcting trend and variability bias is proposed
- The approach is demonstrated to correct trends in global mean sea level and Arctic sea ice extent simulations for the future

Supporting Information:

Supporting Information may be found in the online version of this article.

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A Signal Processing Approach to Correct Systematic Bias in Trend and Variability in Climate Model Simulations

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Abstract Bias correction of General Circulation Model (GCM) is now an essential part of climate change studies. However, the climate change trend has been overlooked in majority of bias correction approaches. Here, a novel signal processing-based approach for correcting systematic biases in the time-varying trend of GCM simulations is proposed. The approach corrects for systematic deviations in spectral attributes of raw GCM simulations using discrete wavelet transforms. The order one and two moments of the underlying trend represented by the lowest frequency of wavelet component are corrected to ensure continuity in the corrected time series from the current to the future simulation period. The approach is applied to correct two data sets that exhibit opposite time-varying trends representing the global mean sea level (GMSL) and the Arctic sea-ice extent. Results indicate that bias in trend is corrected, while continuity in time and observed variability at all frequencies in current climate simulations are maintained.

Plain Language Summary GCMs are an essential tool to assess climate change impacts. However, they exhibit systematic biases which restrict their direct use. A wide range of alternatives for correcting biases has been proposed. Most such approaches are unable to correct biases in trend and variability attributes together. When a variability correction is applied, it reduces biases in trend, however, introduces a discontinuity in trend between current and future climate bias-corrected simulations. We present an approach for correcting systematic biases in trend and variability to ensure continuity of GCM simulations from the current to the future. The application of our approach to two data sets exhibiting opposite trends - the GMSL and the Arctic sea ice extent - shows a remarkable improvement that maintains continuity overtime, corrects bias in trends, and preserves observed variability across the frequency spectrum in current period GCM simulations.

1. Introduction

General Circulation Model (GCM) simulations are an important tool to assess the impacts of climate change on our society and the environment. However, raw GCM simulations exhibit systematic biases which restrict their direct use in impact studies (Bollasina & Nigam, 2008; Johnson & Sharma, 2011; Lhotka & Farda, 2018; Mehrotra et al., 2014; Randall et al., 2007). Bias correction procedures are, therefore, routinely applied to improve raw GCM simulations (Haerter et al., 2011; Johnson & Sharma, 2012; Mehrotra & Sharma, 2012) by correcting systematic biases with respect to observational records.

The purpose of performing bias correction in climate change studies is to achieve a high degree of similarity between simulations and observations (Maraun, 2016). This objective can be attained by adjusting the statistical attributes of the simulations, such as the mean, variance, and persistence as represented in the observations (Johnson & Sharma, 2012; Mehrotra & Sharma, 2015; Nguyen et al., 2016). Another alternative often used is to match associated probability distributions (Haerter et al., 2011; Li et al., 2010; Teutschbein & Seibert, 2013; Wood et al., 2004), such alternatives being broadly referred to as quantile matching (QM) in the literature. Although bias correction approaches are popular, these are not free from limitations and can modify the climate change signals for the future by altering spatiotemporal relationship across variables and possibly violating conservation principles (Ehret et al., 2012; Muerth et al., 2013) a problem that especially impacts the distribution-based approaches referred to as QM above (Cannon et al., 2015; Maraun, 2016; Maurer & Pierce, 2014).

The QM algorithm has been shown to cause large deviation of the long-term trend of projected modeled temperature (Maraun, 2016) and precipitation (Cannon et al., 2015) mainly due to the application of the same transfer function to both current and projected climate models. To address this issue, modifications in the QM transfer function have been proposed (Cannon et al., 2015; Grillakis et al., 2017; Hempel et al., 2013; Lange, 2019; Maraun, 2016).

Daily or monthly QM bias correction and its variants are popular and have been used in many climate change impact studies (Boé et al., 2007; Haerter et al., 2011; Wood et al., 2004). However, where low-frequency variability and persistence attributes assume importance, a standard application of QM shows limited advantage as it corrects for biases at a given time scale, and does not specifically correct for the biases at higher aggregated time scales (Haerter et al., 2011; Mehrotra & Sharma, 2016). One possible solution to this is a nesting of corrections for selected attributes at multiple predefined time scales (Haerter et al., 2011; Johnson & Sharma, 2012; Mehrotra & Sharma, 2016). However, biases at other timescales, not included in the bias correction procedure, may not be corrected. Another solution is to apply a suitable spectral disaggregation procedures to extract the underlying frequency components of the time series thereby making the bias correction independent of time (Maheswaran & Khosa, 2012). A similar motivation forms the basis for bias correction procedures in the frequency domain (Nguyen et al., 2016, 2017; Pierce et al., 2015) where a Fast Fourier Transform (FFT) is used and the variability associated with each frequency corrected. Similar to FFT, wavelet analysis localizes the signal in the frequency domain. In addition, it also localizes the spectral representation as a function of time, making wavelet analysis more powerful than FFT. Both discrete and continuous wavelet transform have been used for a range of applications in climatology (Farge, 1992; Jiang et al., 2020; Torrence & Compo, 1998). DWT disaggregates the time series (signals) into multiple high- and low-frequency components (Percival & Walden, 2000). Therefore, the slow-moving component of a time series which represents the underlying low-frequency behavior, can be extracted and separately modeled (Belayneh, Adamowski, Khalil, & Quilty, 2016; Maheswaran & Khosa, 2012; Sang et al., 2016). Additionally, the lowest-frequency component can be used to represent the predominant underlying trend of the original time series (Adarsh & Janga Reddy, 2015).

In this paper, we demonstrate that the most bias correction alternatives currently in use create a temporal discontinuity following the correction between the current and the future climate. This discontinuity accentuates the mismatch in the trend simulations before and after correction. The present study proposes a novel way of treating trend-biases by addressing this discontinuity between the current and future climate simulations. The observed and GCM climate simulations are disaggregated by performing DWT and the lowest-frequency component is bias corrected to remove trend-related biases. To ensure the continuity of bias-corrected time series of current and future climate simulations, a modification of the well-studied mean and standard deviation bias correction is proposed. In addition, a similar modification is also performed across the spectrum to correct systematic bias in variability at all frequency bands. The theoretical basis and algorithms for the wavelet-based bias correction (WBC) procedure are presented in Section 2. Section 3 discusses the performance of WBC based on application to simulations of two rigorously studied climate variables, that is, Global Mean Sea Level (GMSL) and Sea-ice extent. Finally, conclusions are presented in Section 4.

2. Materials and Methods

2.1. Correcting Systematic Bias in Variable Trends

To demonstrate the implications of applying routine bias correction alternatives on trend, a numerical experiment consisting of two linear time series with different means and slopes (the underlying trend) is created to represent observed and raw current climate model simulations. The same degree of slope is maintained for the pseudo-observed-future and future climate model simulations to preserve continuity in both time series from the current into the future. Next, a simple mean and standard deviation bias correction (Hawkins et al., 2013) and a variant of QM bias correction, equidistant-quantile matching (EQM) (Li et al., 2010), are applied to correct both current and future raw climate simulations. Both multiplicative and additive variants of EQM are applied. The results from this synthetic experiment are presented in Figure 1.

The mean correction procedure resolves the mismatch between the mean of current climate simulations to observations with notable deviations in the beginning and at the end of the corrected series (Figures 1a and 1b). The deviation at the end of the corrected current climate simulations increases with time when

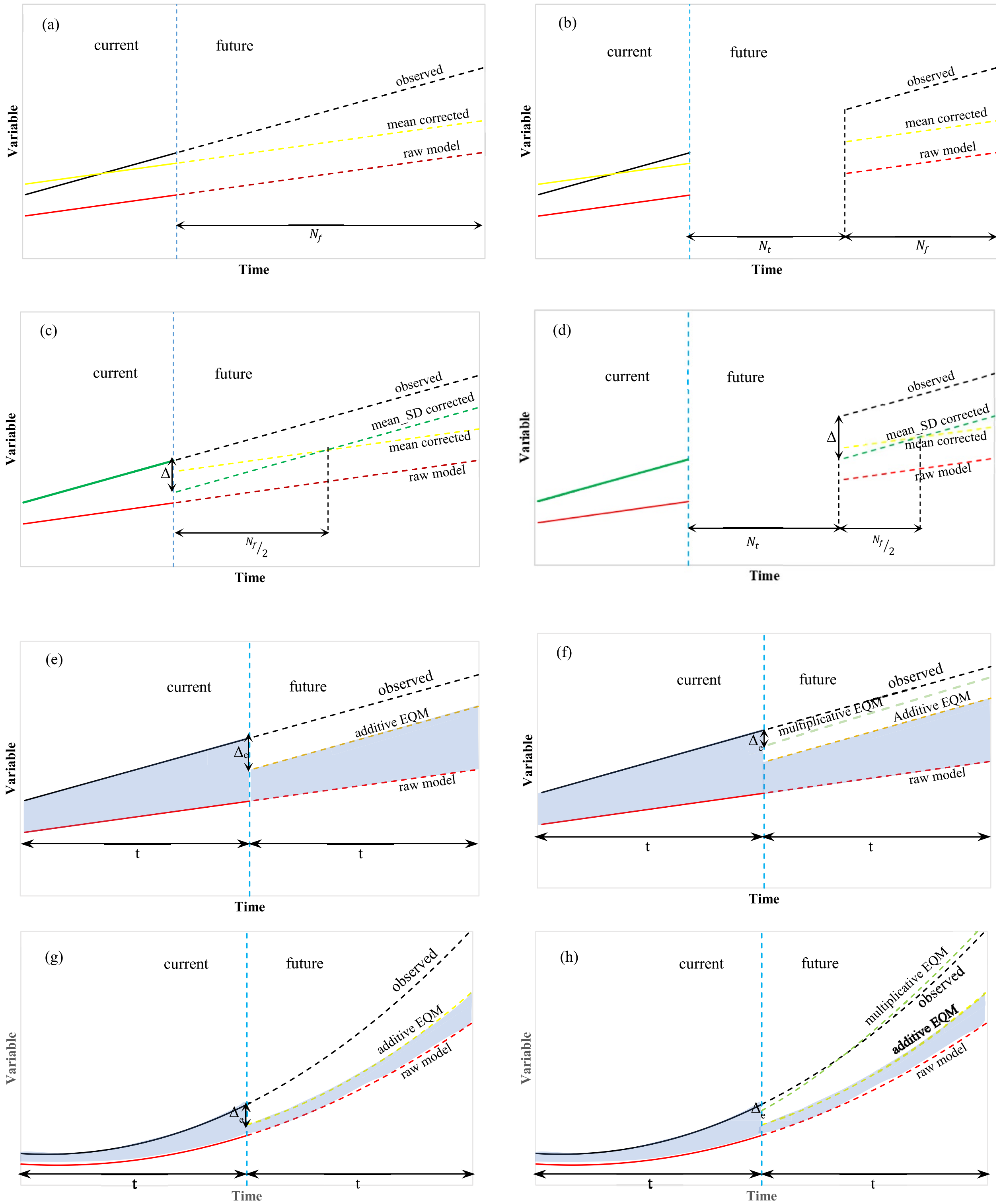

Figure 1. Illustration of the implications of bias correction on variable trend in simplistic linear and nonlinear settings: (a) mean-corrected continuous time-series, (b) mean-corrected future time-series with N_t-gap from the current time-series, (c) mean- and standard deviation-corrected continuous time-series, (d) mean- and standard deviation-corrected future series with N_t-gap from the current time-series (e) corrected raw current and future linear time-series using additive-EQM, (f) corrected raw current and future linear time-series using multiplicative-EQM, (g) corrected raw current and future nonlinear time-series using additive-EQM, (h) corrected raw current and future nonlinear time-series using multiplicative-EQM.

the same mean correction factor is applied to future climate simulations. Following the mean correction, a variance bias correction using the ratio between the standard deviation of observations and mean corrected raw climate simulations is implemented. In addition to removing variance biases, the correction also rotates the current climate simulations at their centroid to create the same gradient as observations (Figure 1c). When the same correction is applied to the future climate simulations, the deviation at the beginning of the corrected series becomes larger compared to the post mean bias-corrected case. The procedure shifts the corrected climate future simulation to become parallel to the pseudo-observed future climate (Figures 1c and 1d) although now exhibiting a discontinuity between corrected current and future climate simulations and a constant deviation of Δ overtime.

A slightly more complex bias correction procedure, that is, EQM with additive correction, provides similar results as mean and standard deviation bias correction (Figure 1e). The procedure creates the same extent of discontinuity when it is applied to a linear time series. When EQM with a multiplicative correction is applied, the deviation between the corrected future climate simulations and pseudo-observed future climate is reduced (Figure 1f). With further increase in the complexity of the time series structure, such as introduction of a nonlinear trend (Figures 1g and 1h), the degree of discontinuity between the corrected current and future climate simulations, Δ_e, also increases. The discontinuity in time after mean and standard deviation or EQM bias correction is notable and represents an issue that needs addressing before the post-processed simulations are used for further applications.

2.2. Wavelet Based Bias Correction (WBC)

In the following, we denote $\boldsymbol{t}_{oc}$ as observations, $\boldsymbol{t}_{rc}$ as current climate, and $\boldsymbol{t}_{rf}$ as the future climate time series of wavelet decomposed components (details or approximations), with statistics mean denoted $\boldsymbol{\mu}$, and standard deviation, $\boldsymbol{\sigma}$. Our approach aims to transform the current and future climate series to create a mean and variance corrected times series for the current $\boldsymbol{t}''_{rc}$ and future $\boldsymbol{t}''_{rf}$ climate. In general, any bias correction procedure implemented over the current climate simulations can be expressed as

$$\boldsymbol{t}''_{rc} = \boldsymbol{g}\left(\boldsymbol{t}_{rc} \middle| \boldsymbol{\theta}\right) \tag{1}$$

where $\boldsymbol{g}\left(\cdot\right)$ is the bias correction function and $\boldsymbol{\theta}$ represents parameters that have been estimated based on the observed and current climate series. After bias correction, $\boldsymbol{t}''_{rc}$ ideally exhibits similar statistical attributes and trend to $\boldsymbol{t}_{oc}$. The statistical attributes of the future climate series, $\boldsymbol{t}_{rf}$ are then bias corrected based on the correction model applied to $\boldsymbol{t}_{rc}$.

While the above explanation applies to any correction procedure, the WBC is implemented on a wavelet decomposition of the variable time series of interest. This decomposition enables the representation of the underlying time series as a summation of multiple decomposed time series, each representing different frequency bands (also referred to as "detail"), with the last such series representing the residual (called "approximation") and containing the trend. Correction of the detail time series entails ensuring an accurate representation of variability associated with each frequency band, while correction of trend builds on the discontinuity illustration presented earlier in Figure 1. More information on the decomposition and the correction is presented next.

2.3. DWT for Time Series Disaggregation

Climatic variables exhibit variability as a function of the temporal scale they are assessed at, whether it is daily, monthly, seasonal, annual, or longer. The DWT enables a disaggregation of the variable time series into different discrete frequency bands, along with a residual series that represents the underlying trend. A DWT of a time series $\boldsymbol{t}$ is an orthonormal transform (Percival & Walden, 2000) which can be written as per Equation 2. In the equation, $\boldsymbol{W}$ is column vector of length, $N = 2^J$ (DWT follows a dyadic scale); $\mathcal{W}$ is the wavelet coefficient consist of two sets of filter banks having a length of $N / 2$ for each set. Using each set of filter banks, the various frequency components of the time series can be identified (Percival &

Walden, 2000; Strang & Nguyen, 1996). By construction, $\mathcal{W}$ is a $N \times N$ real-valued matrix defining the DWT and satisfying $\mathcal{W}^T\mathcal{W} = \boldsymbol{I}_N$ where $\boldsymbol{I}_N$ is the $N \times N$ identity matrix.

$$\boldsymbol{W} = \mathcal{W}\boldsymbol{t} \tag{2}$$

The orthonormality property of wavelet implies that $\mathcal{W}^{\boldsymbol{T}}\boldsymbol{W} = \mathcal{W}^{\boldsymbol{T}}\mathcal{W}\boldsymbol{t} = \boldsymbol{t}$. Therefore, the reconstruction of the time series can be done based on the following (Percival & Walden, 2000):

$$\boldsymbol{t} = \mathcal{W}^{\boldsymbol{T}}\boldsymbol{W} = \sum_{j=1}^{J}\boldsymbol{D}_j + \boldsymbol{A}_J \tag{3}$$

where $\boldsymbol{D}_j$ are the detail wavelets (representing the level j frequency component) and $\boldsymbol{A}_J$ is the approximation wavelets which represents the lowest frequency component at the last level of decomposition $\boldsymbol{J}$. In the presence of a trend in the variable time series, the approximation can be used to represent the underlying trend in the data. The reconstruction of the decomposed time series using Equation 3 is referred to as multiresolution analysis (Percival & Walden, 2000) in the remainder of this paper.

In DWT, two essential steps are needed to be performed. The first is the selection of a wavelet mother function and the second is the determination of the maximum level of decomposition. There is no universal method to help select the right wavelet mother function (Sang et al., 2016) though the Daubechies wavelets family (Adarsh & Janga Reddy, 2015), are commonly adopted in statistical and hydrological studies for trend analysis (Craigmile et al., 2004; Maheswaran & Khosa, 2012; Nourani et al., 2014). In our presentation, the db2 wavelet is adopted to decompose the time series, in consideration of low order of polynomial the trend represents in the time series. Additional details regarding DWT and the merits and demerits of alternate wavelet mother functions are presented in Jiang et al. (2020), Maheswaran and Khosa (2012), Sang et al. (2016), and Torrence and Compo (1998).

The number of disaggregated discrete frequency levels using DWT is a function of the data length. Following previous studies using wavelet transforms, the maximum level of decomposition can be determined using Equation 4 (Belayneh, Adamowski, Khalil, & Ozga-Zielinski, 2014; Jiang et al., 2020).

$$\boldsymbol{J} = \frac{\log\left[\frac{\boldsymbol{N}}{(2\boldsymbol{v}-1)}\right]}{\log 2} \tag{4}$$

where $\boldsymbol{J}$ is the maximum level of decomposition, $\boldsymbol{N}$ is the size of the time series and $\boldsymbol{v}$ is the vanishing moment of the wavelet mother function.

2.4. Correcting Systematic Bias in Simulated Trend

The simple mean bias correction of current ($\boldsymbol{t}_{rc}$) and future ($\boldsymbol{t}_{rf}$) climate simulations with respect to observations, $\boldsymbol{t}_{oc}$ can be performed using Equations 5 and 6.

$$\boldsymbol{t}'_{rc} = \boldsymbol{t}_{rc} - \boldsymbol{\mu}_{rc} + \boldsymbol{\mu}_{oc} \tag{5}$$

$$\boldsymbol{t}'_{rf} = \boldsymbol{t}_{rf} - \boldsymbol{\mu}_{rc} + \boldsymbol{\mu}_{oc} \tag{6}$$

The mean of mean-corrected current climate simulation ($\boldsymbol{t}'_{rc}$), $\boldsymbol{\mu}'_{rc}$, now equals $\boldsymbol{\mu}_{oc}$. Equations 7 and 8 are then used to bias correct the standard deviations of current and future climate simulations. After bias correction, the statistical attributes, that is, mean, standard deviation, and trend of the corrected current climate simulation, $\boldsymbol{t}''_{rc}$, are similar to observations.

$$\boldsymbol{t}''_{rc} = \left(\boldsymbol{t}'_{rc} - \boldsymbol{\mu}'_{rc}\right) \times \frac{\boldsymbol{\sigma}_{oc}}{\boldsymbol{\sigma}_{rc}} + \boldsymbol{\mu}'_{rc} \tag{7}$$

$$t''_{rf} = \left(t'_{rf} - \mu'_{rf}\right) \times \frac{\sigma_{oc}}{\sigma_{rc}} + \mu'_{rf} \tag{8}$$

As noted in Section 1, while mean and standard deviation bias correction corrects the trend bias in the current climate variable series, the bias correction of future climate simulations (using Equation 8) introduces a discontinuity (Figures 1a–1d) at the commencement of the future climate series. As a result, bias-corrected future climate simulations, t'_{rf}, require a modulation to correct the discontinuity that results. For the case of simple linear trend, t'_{rf} will translate higher (or lower) for the underestimated (or overestimated) simulations with an increasing (or decreasing) trend. This translation is represented as Δ in Equation 9 which is obtained by considering the observed and current climate trends. In Equation 10, N_t represents the time delay between the last point of current climate simulations $t(N)$ and the start point of future climate simulations; N_f is the length of future climate simulations; and m refers to the slope of the associated time series. It should be noted that when observations and current climate simulations have the same trend, $\mu'_{rf} = \mu_{rf} + \left(t(N)''_{rc} - t(N)_{rc}\right)$, Δ will be equal to zero and Equation 9 collapses to Equation 8. For a majority of climate simulations that exhibit minimal or no-trend, $\Delta = 0$ and Equation 8 would instead be used.

$$t''_{rf} = \left(t'_{rf} - \mu'_{rf}\right) \times \frac{\sigma_{oc}}{\sigma_{rc}} + \mu'_{rf} + \Delta \tag{9}$$

$$\Delta = \left(N_t + \frac{N_f}{2}\right) \times \left(m'_{rc} - m_{rc}\right) \tag{10}$$

Finally, the mean, μ''_{rf}, and standard deviation, σ''_{rf}, of the corrected future climate simulations can be estimated using Equations 11 and 12, respectively. As our main objective is to bias correct the mean, standard deviation, and trend of climate simulations under the assumption that the future climate simulations will have the same systematic bias as current climate simulations, the derived equations satisfy all the necessary conditions of statistical correction and ensure the continuity of current and future climate simulations.

$$\mu''_{rf} = \mu_{rf} + \left(t(N)''_{rc} - t(N)_{rc}\right) + \Delta \tag{11}$$

$$\sigma''_{rf} = \frac{\sigma_{oc}}{\sigma_{rc}} \times \sigma_{rf} \tag{12}$$

2.5. WBC Algorithm

With the understanding that the underlying trend of a time-series can be predominantly represented in the lowest frequency, the following stepwise procedure is used to implement WBC:

1. Obtain maximal decomposition using Equation 4. Perform DWT to form decomposed series at all levels for t_{oc}, t_{rc}, and t_{rf}, separately. Through this step, the constituent approximation (A) and detail (D) wavelet components time series are obtained.
2. Perform bias correction by replacing the current and future simulations of t_{rc} and t_{rf} in Equations 5–10 by their constituent wavelets A_{Jrc}, D_{jrc}, A_{Jrf}, and D_{jrf}. For the current series,
   i. Bias correct the mean using Equation 5 and standard deviation using Equation 7 for the last level of approximation wavelets (A_{Jrc}) and all detail wavelets (D_{jrc}) to obtain (A''_{Jrc}) and (D''_{jrc}).
   ii. Perform multiresolution analysis with (A''_{Jrc}) and all (D''_{jrc}) using Equation 3 to obtain the corrected raw-current series, t''_{rc}.
3. For the future series,
   i. Bias correct the mean using Equation 6 of the last level of approximation wavelets (A_{Jrf}) and detail wavelets (D_{jrf}) to obtain (A'_{Jrf}) and (D'_{jrf}).

ii. Ascertain the linear trend of A_{Jrc} of A''_{Jrc} using weighted least squares fitting to obtain the slope of current climate simulation, m_{rc}, and the slope of the bias-corrected current climate simulation, m''_{rc}, which the latter is already equal to the slope of observations.

iii. Bias correct the standard deviation of A'_{Jrf} using Equations 9 and 10 and the derived slope obtained from step 3 ii and using Equation 8 of (D'_{jrf}) to obtain A''_{Jrf} and D''_{jrf}.

iv. Perform the multiresolution analysis with (A''_{Jrf}) and (D''_{jrf}) using Equation 3. In this step, the bias-corrected future time series, t''_{rf}, is obtained.

v. The final step is to verify the mean and standard deviation of t''_{rf} using Equations 11 and 12.

3. Application of WBC

3.1. Data

The observed and GCM simulations for current and future periods for the GMSL and Arctic sea-ice extent variables are used to assess the robustness of the WBC algorithm. The annual GMSL values from 1900 to 2010 used in this paper are based on the reconstructed GMSL time series published in Figure 5 of Church and White (2011). While the current period GCM simulation for GMSL is based on the published figure (Figure 13.7) of the mean of Atmosphere-Ocean General Circulation Model (AOGCM) of Coupled Model Intercomparison Project Phase 5 (CMIP5) GMSL (Church et al., 2013), the future period is based on the published time series of the median of 21 CMIP5 AOGCMs GMSL projection (Figure 13.11, Church et al., 2013). The reconstructed GMSL exhibits a mild increasing trend over the last two centuries and is estimated to have significant increase of four degrees in the form of an increasing trend into the future under the four representative concentration pathway (RCP) scenarios evaluated (Church et al., 2013).

The data for the second variable, Arctic sea-ice extent in September, is collected from the National Snow and Ice Data Center, National Aeronautics and Space Administration of the USA for the observed time series and from the fifth assessment report (AR5) of Intergovernmental Panel on Climate Change, IPCC (Flato et al., 2014), for the GCM simulations for current and future periods. The simulated Arctic sea-ice extent from 1900 to 2010 is presented as the ensemble mean of 37-CMIP5 models in Figure 9.24 of AR5, IPCC (Flato et al., 2014) and is given as 5 yr running mean of projected Arctic sea-ice extent from 2010 to 2100 (Figure TS.17, Stocker et al., 2013).

It should be noted that the proposed approach is applied to the above univariate time series, and no attempt is made to correct spatial biases (Nahar et al., 2017, 2018) that may exist in the above data sets.

3.2. Global Mean Sea Level Simulations

The reconstructed historical GMSL is presented in Figure 2 (solid-black line) and the ensemble medians of CMIP5 GMSL-current climate time raw series (solid-red line) shows a good agreement with the historical nonlinear increasing trend from 1900 to 2010. However, the simulated raw GMSL exhibits an underestimation of nonlinearity increment with milder fluctuation which reflects the limitations of the GCMs to represent the variability in time.

Following the stepwise WBC procedure, the ensemble median of CMIP5-GMSL current period is statistically bias corrected at the lowest level of approximation wavelet and across multiple frequency bands represented by detail wavelets for correction of variability. The bias correction leads to a correction of the statistical attributes (details presented in Table S1), the trend, and the variability of the time series as can be observed in Figure 2 (solid-green line).

It should be noted that our approach has been derived assuming a linear trend in the climate simulations and the observations, whereas a future time series containing a nonlinear trend may exhibit a residual bias even though the discontinuity noted is minimized by giving more weight to recent data points of the current climate simulations to adjust the trend of future climate simulations. This aspect is explored by implementing this logic to the near future GMSL simulation (Figure 2, dashed-red line). Although WBC has been applied to all four RCP scenarios, RCP 8.5 represents the scenario with the steepest nonlinear

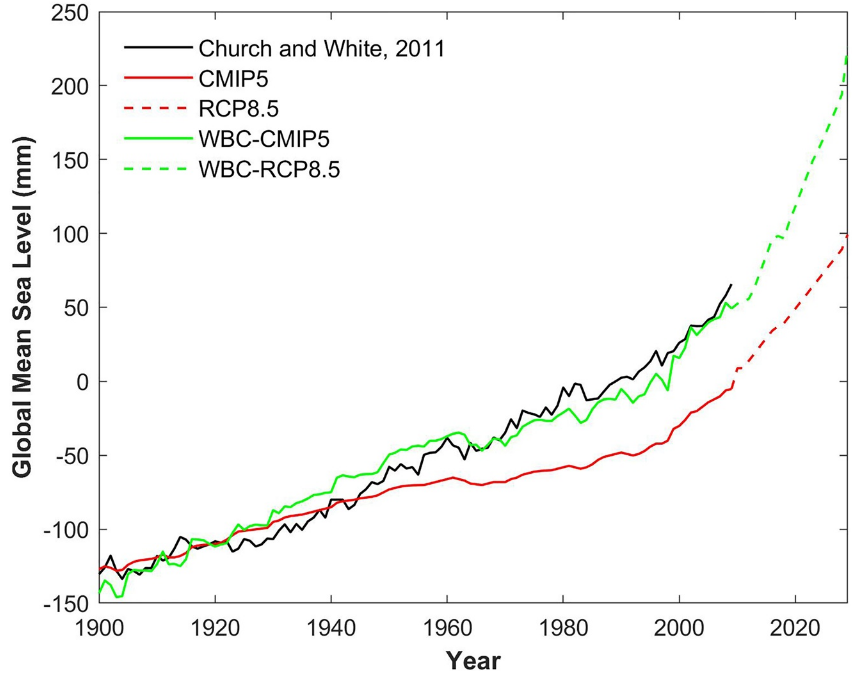

Figure 2. Reconstructed historical GMSL (Church & White, 2011), simulated GMSL-current series, WBC-GMSL-current series, WBC near future simulated GMSL under RCP8.5.

projection (Church et al., 2013), and has been chosen to illustrate the robustness of the proposed approach. WBC provides a better fit to the CMIP5 bias corrected time series, introduces variability, and matches the overall trend (Figure 2, solid-black and -green lines). The corrected series for the GMSL-future simulation (Figure 2, dashed-green line) confirms that WBC also ensures continuity in time. However, the correction for variability (Table S3) appears to be less significant due mainly to the significant nonlinear trend present. On the contrary, the Linear Scaling bias correction creates a discontinuity from the current to future series (Figure S1) with a lower value in 2011 than in 2010 and leads to a lower mean for the corrected future series (Table S1).

3.3. Sea-Ice Extent Simulations

Similar to GMSL simulations, the ensemble means of Arctic sea-ice extent (Figure 3, solid-red line) underestimates the observations but follows the overall decreasing trend of observations which becomes steeper from 1980 onwards. The application of WBC bias-corrects the series, shifts it up, fixes the trend, and introduces variability equivalent to the observed Arctic sea-ice extent (Figure 3, solid-black and -green lines).

In this second demonstration, a single Arctic sea-ice extent future simulation with the mildest projected-nonlinear decreasing trend of RCP 2.6 scenario (Figure 3, dashed-red line) starting 2011–2100 has been selected to illustrate the effectiveness of the WBC algorithm. The robustness of WBC is better emphasized in this case by accurately ensuring the continuity of the corrected future simulation with a steep trend in the beginning which becomes milder beyond 2040 onwards (Figure 3, green line). The correction of the variability across the low frequencies (Table S4) can be better observed in the future period (Figure 3, dashed-green line) which follows the correction for variability in the current period. This application, again, emphasizes that WBC maintains the continuity of current and future period which cannot be achieved by simple linear scaling (Figure S2) as it shows a large deviation in the beginning of the corrected future series. In addition, WBC adjusts the mean of the corrected future series to be higher than the linear scaling mean bias-corrected (Table S2).

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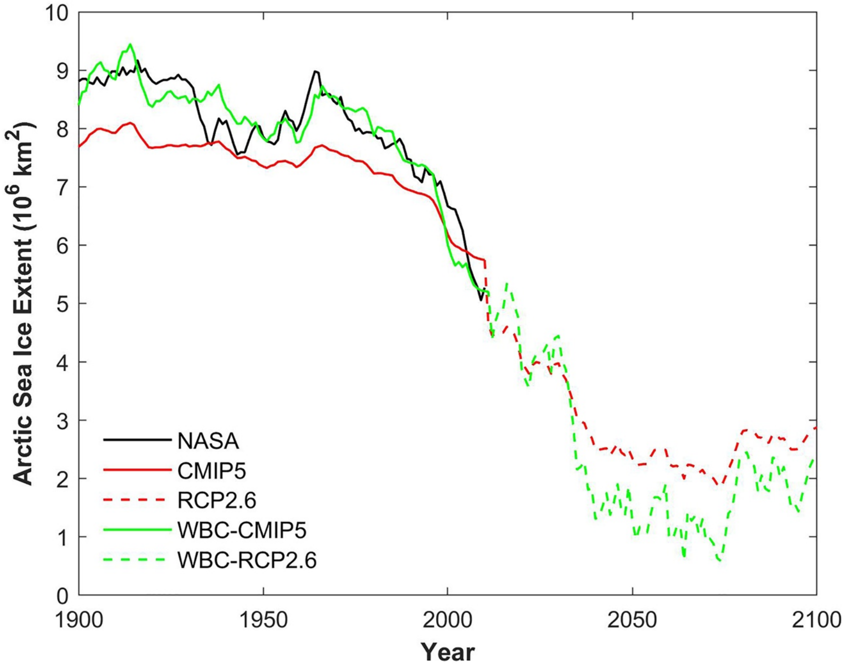

Figure 3. Five year running mean of observed, raw, and bias-corrected Arctic sea ice extent in September for current and future climate for CMIP5 RCP2.6 projections.

4. Conclusions

This paper proposes a signal processing based bias correction approach using wavelets (WBC) for bias correction of variability and trends in climate model simulations. In addition, the paper also addresses an often-overlooked aspect of discontinuity in the climate simulations, which develops as a result of variance correction for the future period simulation. A set of synthetic time series representing the observations, current, and future simulations are used to illustrate the mismatch of trends after the application of a simple linear scaling and QM bias correction. A simple modification in the bias correction procedure is suggested to patch the discontinuity in time.

The robustness of WBC has been demonstrated by applying it to the GCM simulations of GMSL and Arctic sea-ice extent variables. The WBC enables the representation of continuity in the corrected simulations exhibiting linear or nonlinear trends. The method here uses wavelets to ensure that the correction is across the entire frequency spectrum as well as the trend of the variable being corrected, and the rationale behind the trend correction is generic and can be embedded in other more commonly used bias correction alternatives.

Finally, our presentation is incomplete without a discussion of possible limitations our proposed approach may have. First, the use of wavelets necessitates a long time series of observations and model simulations, the absence of which will reduce the number of levels (frequencies) that can be considered with stability. This in turn can compromise the spectral corrections that are imparted. Next, an underlying linear trend is assumed to characterize the lowest level wavelets approximation time series. The wavelets methodology allows for a nonlinear trend being present, which suggests that users should assess the nature of the trend in the approximation time series and choose the best polynomial option that justifies the pattern visible. If this is used, modifications need to be incorporated into the equations that formed the WBC algorithm or alternate wavelet mother functions adopted. It should be noted that the use of a weighted linear fit in our illustrations reduced the need for adopting a nonlinear model, as the nonlinearity was mildly present. A proper higher-order polynomial or other suitable fits should be considered if this is not the case.

Data Availability Statement

The authors acknowledge the National Snow and Ice Data Center, National Aeronautics and Space Administration (NASA) of the U.S. through https://sos.noaa.gov/datasets/sea-ice-extent-arctic-only-1850-present/ to make the Arctic sea-ice extent data is available and the Commonwealth Scientific and Industrial Research Organization (CSIRO) of Australia for the reconstructed global mean sea level data is available (Church & White, 2011).

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References

Adarsh, S., & Janga Reddy, M. (2015). Trend analysis of rainfall in four meteorological subdivisions of southern India using nonparametric methods and discrete wavelet transforms. *International Journal of Climatology*, *35*(6), 1107–1124. https://doi.org/10.1002/joc.4042

Belayneh, A., Adamowski, J., Khalil, B., & Ozga-Zielinski, B. (2014). Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models. *Journal of Hydrology*, *508*, 418–429. https://doi.org/10.1016/j.jhydrol.2013.10.052

Belayneh, A., Adamowski, J., Khalil, B., & Quilty, J. (2016). Coupling machine learning methods with wavelet transforms and the bootstrap and boosting ensemble approaches for drought prediction. *Atmospheric Research*, *172–173*, 37–47. https://doi.org/10.1016/j.atmosres.2015.12.017

Boé, J., Terray, L., Habets, F., & Martin, E. (2007). Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies. *International Journal of Climatology*, *27*(12), 1643–1655. https://doi.org/10.1002/joc.1602

Bollasina, M., & Nigam, S. (2008). Indian Ocean SST, evaporation, and precipitation during the South Asian summer monsoon in IPCC-AR4 coupled simulations. *Climate Dynamics*, *33*(7), 1017–1032. https://doi.org/10.1007/s00382-008-0477-4

Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, *28*(17), 6938–6959. https://doi.org/10.1175/jcli-d-14-00754.1

Church, J. A., Clark, P. U., Cazenave, A., Gregory, J. M., Jevrejeva, S., Levermann, A., et al. (2013). Sea level change. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, et al. (Eds.), *Climate change 2013: The physical science basis. Contribution of Working group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Church, J. A., & White, N. J. (2011). Sea-level rise from the late 19th to the early 21st century. *Surveys in Geophysics*, *32*(4), 585–602. https://doi.org/10.1007/s10712-011-9119-1

Craigmile, P. F., Guttorp, P., & Percival, D. B. (2004). Trend assessment in a long memory dependence model using the discrete wavelet transform. *Environmetrics*, *15*(4), 313–335. https://doi.org/10.1002/env.642

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., & Liebert, J. (2012). HESS Opinions "Should we apply bias correction to global and regional climate model data? *Hydrology and Earth System Sciences*, *16*(9), 3391–3404. https://doi.org/10.5194/hess-16-3391-2012

Farge, M. (1992). Wavelet transforms and their applications to turbulence. *Annual Review of Fluid Mechanics*, *24*(1), 395–458. https://doi.org/10.1146/annurev.fl.24.010192.002143

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., et al. (2014). Evaluation of climate models. In Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 741–866). Cambridge University Press.

Grillakis, M. G., Koutroulis, A. G., Daliakopoulos, I. N., & Tsanis, I. K. (2017). A method to preserve trends in quantile mapping bias correction of climate modeled temperature. *Earth System Dynamics*, *8*(3), 889–900. https://doi.org/10.5194/esd-8-889-2017

Haerter, J. O., Hagemann, S., Moseley, C., & Piani, C. (2011). Climate model bias correction and the role of timescales. *Hydrology and Earth System Sciences*, *15*(3), 1065–1079. https://doi.org/10.5194/hess-15-1065-2011

Hawkins, E., Osborne, T. M., Ho, C. K., & Challinor, A. J. (2013). Calibration and bias correction of climate projections for crop modeling: An idealized case study over Europe. *Agricultural and Forest Meteorology*, *170*, 19–31. https://doi.org/10.1016/j.agrformet.2012.04.007

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., & Piontek, F. (2013). A trend-preserving bias correction—The ISI-MIP approach. *Earth System Dynamics*, *4*(2), 219–236. https://doi.org/10.5194/esd-4-219-2013

Jiang, Z., Sharma, A., & Johnson, F. (2020). Refining predictor spectral representation using wavelet theory for improved natural system modeling. *Water Resources Research*, *56*(3), e2019WR026962. https://doi.org/10.1029/2019wr026962

Johnson, F., & Sharma, A. (2011). Accounting for interannual variability: A comparison of options for water resources climate change impact assessments. *Water Resources Research*, *47*(4). https://doi.org/10.1029/2010wr009272

Johnson, F., & Sharma, A. (2012). A nesting model for bias correction of variability at multiple time scales in general circulation model precipitation simulations. *Water Resources Research*, *48*(1). https://doi.org/10.1029/2011wr010464

Lange, S. (2019). Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1.0). *Geoscientific Model Development*, *12*(7), 3055–3070. https://doi.org/10.5194/gmd-12-3055-2019

Lhotka, O., & Farda, A. (2018). Links between temperature biases and flow anomalies in an ensemble of CNRM-CM5.1 global climate model historical simulations. *Advances in Meteorology*, *2018*, 4984827. https://doi.org/10.1155/2018/4984827

Li, H., Sheffield, J., & Wood, E. F. (2010). Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *Journal of Geophysical Research*, *115*(D10). https://doi.org/10.1029/2009jd012882

Maheswaran, R., & Khosa, R. (2012). Comparative study of different wavelets for hydrologic forecasting. *Computers & Geosciences*, *46*, 284–295. https://doi.org/10.1016/j.cageo.2011.12.015

Maraun, D. (2016). Bias correcting climate change simulations—A critical review. *Current Climate Change Reports*, *2*(4), 211–220. https://doi.org/10.1007/s40641-016-0050-x

Maurer, E. P., & Pierce, D. W. (2014). *Bias correction can modify climate model simulated precipitation changes without adverse effect on the ensemble mean*.

Mehrotra, R., & Sharma, A. (2012). An improved standardization procedure to remove systematic low frequency variability biases in GCM simulations. *Water Resources Research*, *48*(12). https://doi.org/10.1029/2012wr012446

Mehrotra, R., & Sharma, A. (2015). Correcting for systematic biases in multiple raw GCM variables across a range of timescales. *Journal of Hydrology*, *520*, 214–223. https://doi.org/10.1016/j.jhydrol.2014.11.037

Mehrotra, R., & Sharma, A. (2016). A multivariate quantile-matching bias correction approach with auto- and cross-dependence across multiple time scales: Implications for downscaling. *Journal of Climate*, *29*(10), 3519–3539. https://doi.org/10.1175/jcli-d-15-0356.1

Mehrotra, R., Sharma, A., Bari, M., Tuteja, N., & Amirthanathan, G. (2014). An assessment of CMIP5 multi-model decadal hindcasts over Australia from a hydrological viewpoint. *Journal of Hydrology*, *519*, 2932–2951. https://doi.org/10.1016/j.jhydrol.2014.07.053

Muerth, M. J., Gauvin St-Denis, B., Ricard, S., Velázquez, J. A., Schmid, J., Minville, M., et al. (2013). On the need for bias correction in regional climate scenarios to assess climate change impacts on river runoff. *Hydrology and Earth System Sciences*, *17*(3), 1189–1204. https://doi.org/10.5194/hess-17-1189-2013

Nahar, J., Johnson, F., & Sharma, A. (2017). Assessing the extent of non-stationary biases in GCMs. *Journal of Hydrology*, *549*, 148–162. https://doi.org/10.1016/j.jhydrol.2017.03.045

Nahar, J., Johnson, F., & Sharma, A. (2018). Addressing spatial dependence bias in climate model simulations—An independent component analysis approach. *Water Resources Research*, *54*(2), 827–841. https://doi.org/10.1002/2017wr021293

Nguyen, H., Mehrotra, R., & Sharma, A. (2016). Correcting for systematic biases in GCM simulations in the frequency domain. *Journal of Hydrology*, *538*, 117–126. https://doi.org/10.1016/j.jhydrol.2016.04.018

Nguyen, H., Mehrotra, R., & Sharma, A. (2017). Can the variability in precipitation simulations across GCMs be reduced through sensible bias correction? *Climate Dynamics*, *49*(9–10), 3257–3275. https://doi.org/10.1007/s00382-016-3510-z

Nourani, V., Hosseini Baghanam, A., Adamowski, J., & Kisi, O. (2014). Applications of hybrid wavelet–Artificial intelligence models in hydrology: A review. *Journal of Hydrology*, *514*, 358–377. https://doi.org/10.1016/j.jhydrol.2014.03.057

Percival, D. B., & Walden, A. T. (2000). *Wavelet methods for time series analysis*. Cambridge University Press.

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved bias correction techniques for hydrological simulations of climate change. *Journal of Hydrometeorology*, *16*(6), 2421–2442. https://doi.org/10.1175/jhm-d-14-0236.1

Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., et al. (2007). Climate models and their evaluation. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, et al. (Eds.), *Climate change 2007: The physical science basis. Contribution of working group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 589–662). Cambridge University Press.

Sang, Y.-F., Singh, V. P., Sun, F., Chen, Y., Liu, Y., & Yang, M. (2016). Wavelet-based hydrological time series forecasting. *Journal of Hydrologic Engineering*, *21*(5), 06016001. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001347

Stocker, T. F., Qin, D., Plattner, G.-K., Alexander, L. V., Allen, S. K., Bindoff, N. L., et al. (2013). Technical summary. In *Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 33–115). Cambridge University Press.

Strang, G., & Nguyen, T. (1996). *Wavelets and filter banks*. SIAM.

Teutschbein, C., & Seibert, J. (2013). Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions? *Hydrology and Earth System Sciences*, *17*(12), 5061–5077. https://doi.org/10.5194/hess-17-5061-2013

Torrence, C., & Compo, G. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, *79*, 18. https://doi.org/10.1175/1520-0477(1998)079<0061:apgtwa>2.0.co;2

Wood, A. W., Leung, L. R., Sridhar, V., & Lettenmaier, D. P. (2004). Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic Change*, *62*(1), 189–216. https://doi.org/10.1023/B:CLIM.0000013685.99609.9e