Application of the Bias Correction and Spatial Downscaling Algorithm on the Temperature Extremes From CMIP5 Multimodel Ensembles in China

Lianlian Xu1,2 and Aihui Wang1

Key Points:
• The cool bias of the daily maximum temperature would reduce after statistical downscaling
• The BCSD affects the mean value of extreme temperature indices at subregional scales
• The BCSD method would reduce the intermodel spreads of extreme temperature indices

1Nansen-Zhu International Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China, 2College of Earth and Planetary Sciences, University of Chinese Academy of Sciences, Beijing, China

Abstract: The Bias Correction and Spatial Downscaling (BCSD) is a trend-preserving statistical downscaling algorithm, which has been widely used to generate accurate and high-resolution data set. We employ the BCSD technique to statistically downscale projected daily maximum temperature (DMT) over China from 13 general circulation models in Coupled Model Intercomparison Project Phase 5 (CMIP5) project to supplement the National Aeronautics and Space Administration Earth Exchange Global Daily Downscaled Projections data set under the Representative Concentration Pathway 2.6 (RCP2.6) scenario. We then compare the differences of DMT and four DMT-related indices (i.e., summer days (SU), annual maximum value of DMT (TXx), intensity, and frequency of heat wave) between before and after downscaling over eight subregions of China. The results indicate that the BCSD method reduces the cool bias of the DMT over the whole China compared with original CMIP5 simulations, especially over the Qinghai-Tibet plateau. The SU increases after downscaling for both China as a whole and most subregions except for South China. The BCSD also affects the mean value of TXx, intensity, and frequency of heat wave at subregional scales, although it shows little impact on China as a whole. Besides, the BCSD reduces the temporal variability of most indices except for the heat wave frequency. The most striking finding is that the intermodel spreads of DMT, SU, TXx, and heat wave intensity are dramatically reduced after downscaling compared with raw CMIP5 simulations. In summary, the BCSD method shows significant improvements to original CMIP5 climate projections under RCP2.6 scenario.

1. Introduction
Climate extremes induced by anthropogenic emissions of greenhouse gasses influence not only socioeconomic activities but also natural processes and human health (Alexander et al., 2009; Kunkel et al., 1999; Mcguffie et al., 2015; Moberg & Jones, 2005; Santidrián Tomillo et al., 2015; Sun et al., 2016). In recent decades, China has frequently suffered from extreme temperature hazards (Ding et al., 2007; Liu et al., 2005; Shi et al., 2011; Sun et al., 2014; Wang et al., 2011; Wang & Gaffen, 2001; Wang & He, 2015; Xu et al., 2017). Wang and Gaffen (2001) indicated that the number of high-temperature days had largely increased over eastern China since the 1990s. According to the China Meteorological Administration record, extreme high temperatures occurred in 19 provinces during summer 2013, which caused an unprecedented heat waves across central and eastern China (Sun et al., 2014). The Coupled Model Intercomparison Project Phase 5 (CMIP5) multimodel ensembles under different emission scenarios have been widely used to predict future climate change (Dai, 2013; Gao et al., 2015; Monjo et al., 2016; Taylor et al., 2012; Xu et al., 2018; Zhou, 2016). However, the general circulation models (GCMs) in the CMIP5 project have limited ability to capture the spatial details of (extreme) climate characteristics at regional or local scales due to their relatively coarse resolutions (Ines & Hansen, 2006; Xu & Yang, 2015; Xue et al., 2014). Various downscaling methods have been developed to reduce bias in GCM outputs and provide finer resolution climate data sets. Downscaling techniques can be classified into two broad categories: dynamic and statistical downscaling algorithm (Intergovernmental Panel on Climate Change, 2007; Xue et al., 2014). Statistical downscaling methods require less computing resources than dynamic downscaling techniques, and they are subsequently widely used in researches (Cannon et al., 2015; Chen et al., 2017; Li et al., 2010; Maurer & Hidalgo, 2008; Moghim et al., 2017; Xue et al., 2014).
The main idea of statistical downscaling method is to develop a statistical relationship between model simulations and observations in the same period and subsequently apply the constructed relationship to the prospective periods. The inherent assumption is that the statistical relationship is stationary through the time (Fowler et al., 2007; Gobiet et al., 2015; Moghim & Bras, 2017; Wilby & Wigley, 1997). Previous studies demonstrated that the delta change and quantile-based mapping were the two most well-known statistical downscaling approaches (Moghim et al., 2017; Moghim & Bras, 2017). The delta change method adjusts only the first-order moment of the modeled variables to be consistent with the observations. With regard to quantile-based mapping method, an empirical transfer function is derived from the cumulative distribution functions (CDFs) of historical model simulations and the observations, and it outperforms the delta change technique through improving not only the mean but also the higher moments of variables. One important effect of quantile-based mapping is that it can change the variable trend, which might deteriorate the raw climate change signal (Maraun et al., 2017; Maurer & Pierce, 2014). For example, Maurer and Pierce (2014) revealed that trend modifications of seasonal precipitation induced by the quantile-based mapping approach were as large as the original simulated change in some cases. Future climate projections in CMIP5 project are mainly subject to external forcing signals induced by greenhouse gases. Thus, several researches argued that the projected change magnitude (hereafter refer to as “climate trend”) of CMIP5 outputs were believed to be credible, which should be preserved (Hempel et al., 2013; Maurer & Pierce, 2014). Subsequently, numerous trend-preserving quantile-based mapping methods had been developed to correct the biases and downscale the model outputs, among which, the Bias Correction and Spatial Downscaling (BCSD) algorithm had been widely applied to hydrological and meteorological fields (Wood et al., 2002; Wood et al., 2004). The BCSD technique was first proposed by Wood et al. (2002), in which they used this method to generate fine-scale land surface meteorological forcing for hydrological modeling. The result demonstrated that the hydrological model could successfully reproduce surface hydrologic variables (e.g., soil moisture, runoff, or evaporation) and provide hydrologically plausible results under future climate scenarios. The BCSD technique was also used in National Aeronautics and Space Administration Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) to downscale simulations from 21 GCMs in CMIP5 project (Maurer & Hidalgo, 2008; Thrasher et al., 2012; Wood et al., 2002; Wood et al., 2004). Thus, a high-resolution (0.25° × 0.25°) daily data set had been generated for the historical period (1951–2005) and future period (2006–2099) under Representative Concentration Pathway 4.5 (RCP4.5) and RCP8.5 scenarios. The NEX-GDDP data set includes daily precipitation, daily maximum, and minimum temperatures, which had been widely used in changes of mean climate and extreme climate at regional scale (Bao & Wen, 2017; Chen et al., 2017; Raghavan et al., 2018). Comparing with the raw CMIP5 products, Raghavan et al. (2018) indicated that both mean and extreme precipitation over Southeast Asia in the NEX-GDDP data set were better in agreement with the observations on monthly scales. Bao and Wen (2017) also revealed that the NEX-GDDP data set had significantly improved the climatology of three key climatic variables (i.e., daily maximum temperature, daily minimum temperature, and daily precipitation) and reduced their intermodel spreads over China.

The 2015 Paris Agreement proposed two long-term global goals: holding the increase in global mean temperature to well below 2 °C above preindustrial levels and pursuing efforts to limit the temperature increase to 1.5 °C (Schleussner et al., 2016). Numerous researches had been conducted to understand the potential climate impacts of warming both below and above these threshold levels (Schleussner et al., 2016; Wang et al., 2018; Zhang et al., 2018). Schleussner et al. (Schleussner, Rogelj, et al., 2016) revealed that the rate of sea level rise in 2100 would be reduced by about 30% under 1.5 °C of warming compared with 2 °C of warming. Wang et al. (2018) found that the projected reduction in snow area extent under 1.5 °C of warming is lower than that under 2 °C of warming during the second half of the 21st century. Wang et al. (2017) indicated that the RCP2.6 scenario is the only pathway, which is in line with the target of 1.5 °C of warming. Therefore, it is necessary to investigate future climate change by using more accurate and refined data sets under the RCP2.6 scenario. However, the NEX-GDDP data set does not include RCP2.6 projections.

In this study, the BCSD method is employed to bias correct and downscale daily maximum temperature (DMT) over China from 13 GCMs in CMIP5 project to supplement the NEX-GDDP data set under RCP2.6 scenario. We will present a detailed description of BCSD technique, including its computational procedure of each step, assumptions, and limitations, which had not been well addressed in previous studies. In addition, we will also examine the impacts of statistical downscaling method (BCSD) on extreme temperature
through comparing differences of DMT and four DMT-based indices between before and after statistical downscaling. The remainder of this paper is organized as follows: section 2 depicts the BCSD technique, data, and our methods. In section 3, we present our results, and in section 4 we provide a discussion and our conclusions.

2. The BCSD Technique and Data and Methods

2.1. The BCSD Method

As has been described in section 1, the BCSD method is a kind of trend-preserving statistical downscaling technique. It consists of three steps: data preprocessing, bias correction (BC), and spatial disaggregation (SD). The main purpose of the data preprocessing is to detrend the DMTs so that their climate trends would not be affected by the BC step. The detailed procedures are as follows: at each grid cell in each month, 9-year running average of DMTs from both the model and the observations are computed and then removed from their respective original time series, to obtain DMT anomalies for model simulations and observations during 1961–2005 (historical period) and projected simulations during 2006–2065 (future period). It should be noted that these 9-year running averages of DMTs are saved so that they can be added back to the adjusted data after the BC step. Taking monthly DMTs in July at a grid point as an illustrative example, the 9-year running averages exhibit large intermodel spreads during historical period, and the multimodel ensemble mean (24.1 °C) is smaller than the observations (CN05.1; 25.0 °C) during 1961–2005. Since we treat the observations as the true value, the 9-year running average of observations rather than that of individual model would be added back to the adjusted data after BC step in historical period. Considering that the projected DMT change magnitude (“climate trend”) between the future climate projection and the historical simulation is mainly subject to external forcing signals induced by the greenhouse gases, the BCSD method assumes that the “climate trend” in the raw CMIP5 projections would remain unchanged after downscaling.

Figure 1b shows the difference of 9-year running average (climate trend) of the raw CMIP5 simulations between the historical and future period. Subsequently, the projected 9-year running average of DMT includes the nine-year running average of the observations and the climate trend, which would be added to the adjust data after BC step in future climate projections.

The BC step used here follows the method of Maurer and Hidalgo (2008), which corrects the biases in model data using observations. For each grid cell on each day, we select data for the candidate days (day of year ±15 days) from the model anomalies and observational anomalies for 1961–2005 and then generate CDFs based on these candidate days (31×years). A quantile mapping of DMT is constructed between model data and the observations by comparing their CDFs at different probability ranges for the period 1961–2005. Based on this mapping, the DMT anomalies of model can be transformed to the corresponding observational anomalies at the same CDF quantiles. The BCSD method assumes that the quantile mapping is stable through the retrospective and the prospective periods, which are also applied to correct the projected DMT anomalies during 2006–2065. Figure 1c is an illustration of the methodology of BC step. The “X1” and “X2” on the x axis represent DMT values at the twentieth percentile of the CDF for the observation and model during 1961–2005, respectively. During the BC step, the model DMT (X2) in both historical and future period will be replaced with the observation (X1) at the twentieth percentile of the CDF. After the BC step, the previously extracted 9-year running average of observations and projections would be separately added back to the bias-corrected model data for 1961–2005 and 2006–2065.

In the SD step, the adjusted model data (after BC) are interpolated to the observational resolution (0.25° × 0.25°) following a four-step procedure: First, we calculate the daily climatology of observational DMT during 1961–2005 at the resolution of raw CMIP5 model. Second, for each grid cell on each day, a “scale factor” is generated based on the difference between the adjusted DMT and the DMT climatology at the original model resolution. Third, the “scale factor” is interpolated to the observational resolution (0.25° × 0.25°). Finally, we add the daily climatology of observational DMT during 1961–2005 at observational resolution to obtain the desired statistical downscaled DMT. In a word, we compute two climatology of observational DMT during 1961–2005 separately at observational resolution and the original GCM resolution. One is to generate daily DMT anomalies (“scale factor”) at the raw GCM resolution. The other is added back to the interpolated “scale factor” at observational resolution.
2.2. Data and Methods

The DMTs from 13 CMIP5 GCM historical simulations (1961–2005) and future projections (2006–2065) under RCP2.6 scenario in CMIP5 project (Taylor et al., 2012) are adopted to be statistically downscaled. Basic information about these GCMs is provided in Table 1. We focus on the domain covering the whole China. In NEX-GDDP, the Global Meteorological Forcing Data set (GMFD, 0.25° × 0.25°) is used as the observations in the BCSD method, which is derived from merged reanalysis products, remote sensing, and in situ observations (Sheffield et al., 2006). The GMFD was originally developed as the atmospheric forcing data set for of land surface models. In this study, we use gridded station-based DMT data at a horizontal resolution of 0.25° × 0.25° (referred to as CN05.1) as observations (Wu & Gao, 2013). The CN05.1 data set is constructed using daily observations from more than 2,400 meteorological stations in China. The “anomaly approach” was employed to interpolate the station observations to the gridded data. The CN05.1 shows large uncertainty over western China where sparse observation stations are available, especially over regions from northern Qinghai–Tibet Plateau (TP) to Kunlun Mountains and Taklimakan Desert (Wu & Gao, 2013). This data set has been evaluated and widely used in climate change, model validation, and data intercomparison studies over China (Chen et al., 2017; Gao et al., 2013; Guo et al., 2018; Guo & Wang, 2016). Figure 2a shows the spatial distribution of DMT in CN05.1 for 1961–2005. Maximum DMT is found in the south of China, and the minimum occurs over the TP. We compare the differences of DMT between CN05.1 and GMFD for the period of 1961–2005 (Figure 1b). Although the spatial pattern of DMT in GMFD is generally in good agreement with that in CN05.1 (figure not shown), there are discrepancies in some regions. For example, the GMFD underestimates DMT over the Tarim basin and in a small region near the northeast China border but overestimates DMT in the southwest of Sichuan province. Next, we employ CN05.1 as a restriction.
data set to downscale DMT (hereafter referred to as “CN05.1 BCSD”) during 1961–2005. The downscaled DMTs are then compared with the CN5.01, the original CMIP5 simulations, and the NEX-GDDP data set (hereafter referred to as “GMFD BCSD”). Figure 3 depicts the annual cycle of DMT during 1961–2005 over China. The monthly DMT in the observations (CN05.1) shows clearly temporal variations. The relatively large DMT locates in low latitude (20°–25°N) and around 40°N regions during the boreal summer. The DMT in original CMIP5 simulations and in the GMFD BCSD overall reproduces the observed spatial pattern except for some difference in the DMT magnitudes over some latitudes (Figures 3b and 3c). The CN05.1 BCSD is in better agreement with the observations than the former two data sets (Figure 3d). In addition, we compare the mean and standard deviation of DMT during 1961–2005 from raw CMIP5 simulations, GMFD BCSD, and CN05.1 BCSD with the observations (Figure 4). The raw CMIP5 simulations have a cool bias compared with the observations, particularly over the TP, which is coincident with previous studies (Intergovernmental Panel on Climate Change, 2007; Reichler & Kim, 2008; Intergovernmental Panel on Climate Change, 2013). They revealed that the performance of the present GCMs showed systematic improvements compared with their earlier versions, but they still had obviously common cold bias. From above analyses, the downscaled DMTs can well capture the observed spatial distribution. The pattern correlation coefficient between the observations and GMFD BCSD is 0.97, which is 0.99 between the observations and CN05.1 BCSD. The domain averaged DMT is 12.9 °C in both observations and CN05.1 BCSD, which is larger than that in the original CMIP5 products (10.7 °C), but smaller than that in the GMFD BCSD (13.2 °C). It should be noticed that the observations show large uncertainty over the TP. Whether the

Table 1
List of the 13 General Circulation Models (GCMs) From the CMIP5 Archive

| Model name     | Horizontal resolution in degree | Modeling center                                                                 |
|----------------|---------------------------------|--------------------------------------------------------------------------------|
| BNU-ESM        | 2.8° × 2.8°                     | Beijing Normal University                                                      |
| CanESM2        | 2.8° × 2.8°                     | Canadian Centre for Climate Modelling and Analysis                             |
| CNRM-CM5       | 1.4° × 1.4°                     | Centre National de Recherches Meteorologiques/Center Europeen de Recherche et   |
|                |                                 | Formation Avancee en Calcul Scientifique                                      |
| CSIRO-Mk3.6.0  | 1.875° × 1.875°                 | Commonwealth Scientific and Industrial Research Organization in collaboration   |
|                |                                 | with Queensland Climate Change Centre of Excellence                           |
| GFDL-CM3       | 2° × 2.5°                       | NOAA Geophysical Fluid Dynamics Laboratory                                     |
| GFDL-ESM 2G    | 2° × 2.5°                       |                                                                                 |
| GFDL-ESM 2 M   | 2° × 2.5°                       |                                                                                 |
| IPSL-CM5A-MR   | 1.5° × 1.27°                    | Institut Pierre Simon Laplace                                                  |
| MIROC5         | 1.4° × 1.4°                     | Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean      |
|                |                                 | Research Institute (The University of Tokyo), and National Institute for        |
|                |                                 | Environmental Studies                                                          |
| MIROC-ESM      | 2.8° × 2.8°                     | Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)    |
| MPI-ESM-LR     | 1.875° × 1.875°                 |                                                                                 |
| MPI-ESM-MR     | 1.875° × 1.875°                 |                                                                                 |
| MRI-CGCM3      | 1.121° × 1.125°                 | Meteorological Research Institute                                              |

Figure 2. (a) Spatial distribution of DMT during 1961–2005 based on the CN05.1 data set. (b) Spatial distribution of DMT difference between CN05.1 and GMFD for 1961–2005. Unit: °C.
BCSD approach actually improves or deteriorates the DMT over the TP in the raw CMIP5 historical simulations needs further investigation, but one thing is certain that the BCSD method reduces the bias of model outputs as well as produces the high-resolution data set. From Figure 4, northeast China generally shows stronger variabilities than the rest of the areas. Only the CN05.1 BCSD can well represent the observed

**Figure 3.** Annual cycle of DMT during 1961–2005 derived from (a) CN05.1, (b) the raw CMIP5 simulations, (c) in NEX-GDDP data set (GMFD BCSD), and (d) statistical downscaled outputs based on CN05.1 (CN05.1 BCSD). Unit: °C.

**Figure 4.** Mean (top) and standard deviation (bottom) of DMT during 1961–2005. (a and e) For observations (CN05.1). (b and f) For the raw CMIP5 simulations. (c and g) For the NEX-GDDP data set (GMFD BCSD). (d and h) CN05.1 BCSD.
spatial pattern. The pattern correlation coefficient between CN05.1 BCSD and observations is 0.86. However, the GMFD BCSD does not capture the spatial distribution of regions with strong variability, and the original CMIP5 simulations also exhibit less similarity with the observations (Figures 4f and 4g). Considering that the raw CMIP5 simulations produce notable biases in magnitudes and spatial pattern as compared with observations. Therefore, the BCSD is a necessary and useful procedure to produce accurate and refined variables. In addition, there exist some differences in the DMT between GMFD and CN05.1 (Figure 2). The downscaled DMT based on GMFD and CN05.1 (Figures 3c and 3d, and 4g and 4h) is also different. Nevertheless, the CN05.1 is a reliable observational data set in China and has been validated in numerous studies. Therefore, we choose CN05.1 as an observational data set to constrain the BCSD method for 1961–2005 and subsequently downscale the DMT in 13 GCM future projections under RCP2.6 scenario (2006–2065) in CMIP5 project.

To examine the effect of the BCSD on extreme temperature, we investigate the temporal and spatial variations of the DMT and four DMT-related indices before and after statistical downscaling. The raw CMIP5 counterparts are interpolated onto a common global grid to obtain multimodel ensemble mean, and a median resolution of these GCMs (1.875° longitude × 1.875° latitude) is applied. To represent extreme temperature, two DMT-related indices (summer days, SU, and annual maximum value of DMT, TXx) are adopted from the Expert Team on Climate Change Detection and Indices (Karl et al., 1999). The SU is defined as annual count of days when DMT is greater than 25 °C, and the TXx is defined as annual maximum value of DMT. The SU anomaly during 2006–2065 is calculated with respect to the reference period (1961–2005). Since the definition of heat wave is not universal, we identify a heat wave event when the DMT of more than six consecutive days exceeds the threshold, which is defined as the 90th percentile of a 5-day window of DMT for the 1961–2005 (Choi et al., 2009; Karl et al., 1999; Sillmann et al., 2013). The heat wave frequency is annual numbers of heat wave events. The heat wave intensity is defined as the mean temperature during all heat wave events. To quantify the difference between the original CMIP5 simulations and the downscaled outputs, we divide the whole territory of China into eight subregions (Xu et al., 2018), including northeast China (39–54°N, 119–134°E; NEC), north China (36–46°N, 111–119°E; NC), east China (27–36°N, 116–122°E; EC), central China (27–36°N, 106–116°E; CC), south China (20–27°N, 106–120°E; SC), southwest China 1 (27–36°N, 77–106°E; SW1), southwest China 2 (22–27°N, 98–106°E; SW2), and northwest China (36–46°N, 75–111°E; NWC).

3. Results

3.1. The Effect of BCSD on the DMT During 2006–2065 Under RCP2.6 Scenario

We first compare DMT characteristics during 2006–2065 derived from the raw CMIP5 simulations with those from the downscaled products (CN05.1 BCSD) under the RCP2.6 scenario (Figure 5). In general, both products show similarly spatial patterns for the DMT annual cycle. The DMT magnitudes of CN05.1 BCSD are relatively larger than those in the raw CMIP5 simulations at most latitudes during boreal summer (Figures 5a and 5b). The raw CMIP5 products show considerably lower values over the north of the TP than those in CN05.1 BCSD, which is coincident with the model cold bias in historical period (Figures 5c and 5d). Eden et al. (2012) demonstrated that part of systematic errors in GCM outputs can be ascribed to the convective parameterizations and unresolved subgrid orography. The statistical downscaling techniques had approved to be capable of correcting this error. It might be also the reason that the BCSD method can reduce the cold bias of DMT over China, particularly over the TP. With regard to the standard deviation of DMT, these two data sets show significant difference in their spatial patterns, especially over the eastern China and the west of the TP (Figures 5e and 5f). The standard deviations of DMT for the China as a whole and eight subregions in the CN05.1 BCSD all slightly decrease compared with those in the original CMIP5 outputs (Table 2). Box-and-whisker plot of the DMT in the raw CMIP5 simulations and CN05.1 BCSD during 2006–2065 over the whole China and the eight subregions is provided in Figure 5g. General increases in the regional averaged DMT during 2006–2065 are found after downscaling. The most noticeable increases for SWC1 (3.5 °C) occurring in the TP and for NWC (3.1 °C) in Tarim Basin (Figure 5g). The intermodel spreads of DMT in downscaled outputs over these regions are smaller than those in the original CMIP5 simulations. Thus, we believe that the CMIP5 projected DMTs over China are more accurate after
Figure 5. Annual cycle of DMT during 2006–2065 under RCP2.6 scenario derived from (a) the raw CMIP5 simulations and (b) CN05.1 BCSD. Mean (middle) and standard deviation (bottom) of DMT during 2006–2065 under RCP2.6 scenario. (c and e) For the raw CMIP5 outputs. (d and f) For CN05.1 BCSD. (g) Box-and-whisker plots for the mean value of DMT for the whole China and eight subregions. The black boxes indicate the original CMIP5 outputs. The red boxes show the downscaled outputs.
downscaling, particularly at subregional scale. In summary, the BCSD method increases the mean magnitude and reduces the standard deviation and intermodel spread of DMT during 2006–2065 in China.

### 3.2. The Effect of BCSD on the SU and TXx During 2006–2065 Under RCP2.6 Scenario

We also investigate the characteristics of SU in original CMIP5 simulations and downscaled products during 2006–2065 under RCP2.6 scenario, including its mean value, temporal evolution, anomaly, and intermodel spread (Figure 6). The SU in both raw CMIP5 simulations and CN05.1 BCSD depict low value over the TP and high value in the southern China. In some regions of southern China, DMT would exceed 25.0 °C throughout the year during 2006–2065 (SU ≈ 365 days) in both two data sets. The CN05.1 BCSD has smaller SU for most parts of the TP and larger SU over Xinjiang province than those in the original CMIP5 outputs (Figures 6a and 6b). The domain averaged SU for the whole China in raw CMIP5 simulations show a significant increasing trend (0.19 day/year, \( p = 0.01 \) in student \( t \) test and Mann-Kendall test). The SU trend has a slight increase in CN05.1 BCSD (0.22 day/year) compared with the CMIP5 counterpart. This indicates that the BCSD method would not explicitly alter the long-term trend of SU, which is consistent with previous studies in which the BCSD algorithm did not adjust the slope of the trends in GCM projections (Maurer & Hidalgo, 2008; Thrasher et al., 2012; Wood et al., 2004; Wood et al., 2002). The regional averaged SU for the SC region in CN05.1 BCSD is 197.8 days, which is smaller than that in raw CMIP5 simulations (211.3 days) for 2006–2065. As for the other regions and the whole China, the regional averaged SU during 2006–2065 would increase after downscaling. Similarly, the BCSD method also dramatically reduces the intermodel spreads of SU (Figure 6g). Therefore, we believe that the projected SU over China are substantially more robust from CN05.1 BCSD than directly taken from the CMIP5 simulations. Figures 6e and 6f depict the SU anomaly during 2006–2065 with respect to the baseline period (1961–2005). Both data sets show an evidently increased SU over Yunnan province, which might be identified as a hot spot of SU change.

In summary, the BCSD method can affect the spatial distribution of SU and SU anomaly, increase the SU for most of subregions except for SC region, and reduce their intermodel spreads.

Figure 7 describes mean, standard deviation, and annual time series of TXx, as well as the intermodel spreads of TXx for the whole China and eight subregions during 2006–2065 under RCP2.6 scenario. The eastern China and Xinjiang province generally show high TXx while the TP depicts low values in both original and downscaled products (Figures 7a and 7b). The domain averaged TXx for the whole China is 31.5 °C in the raw CMIP5 simulations, which exhibits nearly no change in the downscaled products (31.6 °C). Over eight subregions, the BCSD method increases TXx over EC, SWC1, and SWC2 regions, while it decreases

### Table 2

Regional Averaged Standard Deviation of DMT, TXx, Intensity, and Frequency of Heat Wave for the China as a Whole and Eight Subregions Derived From the Raw CMIP5 Simulations and Statistical Downscaled Outputs

| Region | DMT (°C) | TXx (°C) | SU (°C) | Frequency of heat wave (times) |
|--------|----------|----------|--------|-----------------------------|
| China  | raw      | downscaled| raw     | downscaled                        | raw | downscaled |
| NEC    | 0.7      | 0.6      | 1.7     | 1.4                           | 0.8 | 0.6           |
| NC     | 0.8      | 0.7      | 2.1     | 1.8                           | 0.8 | 0.7           |
| EC     | 0.6      | 0.6      | 1.7     | 1.5                           | 0.6 | 0.6           |
| CC     | 0.9      | 0.7      | 2.0     | 1.6                           | 0.8 | 0.7           |
| SC     | 0.7      | 0.6      | 1.8     | 1.4                           | 0.6 | 0.5           |
| SWC1   | 0.6      | 0.5      | 1.4     | 1.2                           | 0.7 | 0.5           |
| SWC2   | 0.5      | 0.4      | 1.5     | 1.2                           | 0.7 | 0.5           |
| NWC    | 0.6      | 0.5      | 1.6     | 1.4                           | 0.7 | 0.6           |

Note: The eight subregions are northeast China (39–54°N, 119–134°E; NEC), north China (36–46°N, 111–122°E; NC), east China (27–36°N, 116–120°E; EC), central China (27–36°N, 106–116°E; CC), south China (20–27°N, 106–120°E; SC), southwest China 1 (27–36°N, 77–106°E; SW1), southwest China 2 (22–27°N, 98–106°E; SW2), northwest China (36–46°N, 75–111°E; NWC).
Figure 6. Mean (top) of summer days (SU) during 2006–2065 under RCP2.6 scenario for (a) the original CMIP outputs and (b) CN05.1 BCSD. Time series of the domain-averaged SU for the China as a whole during 2006–2065 under RCP2.6 scenario for (c) the raw CMIP5 outputs and (d) CN05.1 BCSD. The SU anomaly during 2006–2065 derived from (e) the raw CMIP5 simulations and (f) CN05.1 BCSD with respect to 1961–2005. (g) Box-and-whisker plots for the mean value of SU for the whole China and eight subregions. The black boxes indicate the original CMIP5 outputs. The red boxes show the downscaled outputs.
Figure 7. Mean (top) and standard deviation (middle) of annual maximum value of DMT (TXx) during 2006–2065 under RCP2.6 scenario for (a) the raw CMIP5 simulations and (b) CN05.1 BCSD. Time series of the domain averaged TXx for the whole China during 2006–2065 under RCP2.6 scenario for (c) the raw CMIP5 simulations and (f) CN05.1 BCSD. (g) Box-and-whisker plots for the mean value of TXx. The black boxes indicate the original CMIP5 outputs. The red boxes show the downscaled outputs.
that over NC and SC regions (Figure 7g). The domain-averaged TXx for the whole China from the original and downscaled outputs shows a slight increasing trend (0.02 °C/year, $p = 0.01$). Similarly, the BCSD method would remarkably reduce intermodel spreads of TXx (Figure 7g). From this perspective, the TXx derived from CN05.1 BCSD is more credible than that from the original CMIP5 counterparts. Besides, the

Figure 8. Same as Figure 7 but for intensity of heat wave.
BCSD method would result in lower variability of TXx than that in the raw CMIP5 simulations, most noticeable over NC, CC, and SC regions, followed by NEC regions (Table 2). In a word, the BCSD can affect the TXx at subregional scale, even though it has little impact on China as a whole. More importantly, the intermodel spreads of TXx would reduce not only for the whole China but also for the eight subregions.

**Figure 9.** Same as Figure 7 but for frequency of heat wave.
3.3. The Effect of BCSD on the Intensity and Frequency of Heat Wave

Both data sets demonstrate that the intense heat wave would likely occur over Yangtze-Huaihe River basin, south of China, Xinjiang province and west part of Inner Mongolia (Figure 8). The spatial distribution of the intensity of heat wave resembles that of TXx. The pattern correlation coefficient between the heat wave intensity and TXx is 0.95 for the raw CMIP5 simulations, which is 0.99 for the statistical downscaled outputs (Figures 7a and 8a, and 7b and 8b). Thus, fierce heat wave is preferred to take place in regions with large TXx. The downscaled intensity of heat wave generally shows lower variability than that in the original CMIP5 simulations, especially over northeast of China (Figures 8c and 8d). The BCSD method has little influence on the intensity of heat wave for the China as a whole but increases that over EC and SWC1 regions and decreases that over NC regions (Figure 8g). The regional averaged standard deviation would slightly decrease after downscaling (Table 2). The domain-averaged intensity of heat wave for the China remains almost unchanged from 2006 to 2065 before and after downsampling under RCP2.6 scenario, but it increases under both RCP4.5 and RCP8.5 scenarios (Sillmann et al., 2013; Sillmann, Kharin, Zhang, et al., 2013). From above results, the RCP2.6 scenario would effectively reduce disaster occurrences induced by heat wave intensity. The BCSD technique would also reduce the intermodel spreads of heat wave intensity (Figure 8g). The CN05.1 BCSD shows high magnitudes of heat wave frequency than that in raw CMIP5 outputs during 2006–2065 under RCP2.6 scenario, which is more obviously in Yunnan province (Figure 9). The domain-averaged frequency of heat wave for the whole China is 3.3 times of that in the original CMIP5 simulations, while it is slightly smaller than that in the downscaled products (3.6 times). Among the eight subregions, the frequency of heat wave increases in NWC and SWC2 regions after downscaling. The strong variability of heat wave frequency happens in the south of China in the raw CMIP5 products, and the center of maximum variability would move westward to Yunnan province in the CN05.1 BCSD (Figures 9c and 9d). The regional averaged standard deviation of heat wave frequency shows little change due to downsampling (Table 2). The BCSD method would slightly increase the intermodel spreads of heat wave frequency over NEC, NC, and SWC2 regions but decrease that over the rest of the regions (Figure 9g). The domain averaged heat wave frequency shows a slight increasing trend (0.02 times/year, p = 0.01) in both data sets.

4. Discussion and Conclusions

In recent years, the GCM outputs in CMIP5 project are commonly used to project changes in extreme climate under the context of global warming. However, several studies revealed that noticeable biases still exist in the GCM products due to their relatively coarse spatial resolution, particularly at regional or local scale (Ines & Hansen, 2006; Xu & Yang, 2015). Numerous statistical downscaling techniques have been developed to reduce biases and bridge the scale gap at relatively less computing expense (Cannon et al., 2015; Chen et al., 2017; Li et al., 2010; Maurer & Hidalgo, 2008; Moghim et al., 2017). One of the fundamental methods is BCSD, which has been widely used in hydrological and meteorological research (Wood et al., 2002; Wood et al., 2004). Based on CMIP5 historical simulations and future projections under RCP4.5 and RCP8.5 scenarios, BCSD technique has been used to generate a high-resolution NEX-GDDP data set (0.25° × 0.25°). However, this data set does not include RCP2.6 projections, which is the only scenario in line with the target of 1.5 °C of warming (Wang et al., 2017). We intend to produce statistically downscaled DMT from 13 CMIP5 GCM future projections under RCP2.6 scenario, to supplement the NEX-GDDP data set over China. In this study, we first present a detailed description of BCSD method for the convenience of future users, which has not been well documented in previous researches. Overall, the BCSD is a trend-preserving statistical downscaling technique with two assumptions. In the preprocessing step, the BCSD method assumes that the climate trend is mainly subject to external forcing signals induced by greenhouse gases and it should be preserved so that the climate signal is not affected by the BC step (Maraun et al., 2017; Maurer & Pierce, 2014). Although such assumption is justifiable, quantifying the climate trend as the difference of 9-year running average of the raw CMIP5 simulations between the historical and future period may not be reasonable because the climate system is nonlinear in nature (Maurer & Hidalgo, 2008; Thrasher et al., 2012; Wood et al., 2004; Wood et al., 2002). The second assumption is that the quantile mapping is stable through the retrospective and the prospective periods in BC step. However, it has been revealed that the CDF of climate variables in future projections would change, especially for the higher-order moments (Yang et al., 2018). Users of the BCSD method should be aware of its limitation induced by these assumptions.
For the historical period, we employ CN05.1 as the observations to bias correct and downscale DMT (“CN05.1 BCSD”) and then we compare the downscaled DMT and its derived indices with those in original CMIP5 simulations and NEX-GDDP data set (“GMFD BCSD”). The statistical downscaled outputs (CN05.1 BCSD and GMFD BCSD) can well capture the observed mean value of DMT, while the raw CMIP5 simulations produce notable biases compared with observations. Hence, the BCSD method is a reliable algorithm and can be used to reproduce accurate and refined variables. The CN05.1 BCSD products derived from current study can well reproduce the observed spatial pattern. Therefore, we choose CN05.1 as an observational data set to constrain the BCSD method for 1961–2005 and subsequently statistical downscale the DMT in 13 GCM future projections under RCP2.6 scenario (2006–2065) in CMIP5 project. In order to examine the impacts of statistical downscaling method (BCSD) on extreme temperature, we simply compare differences of DMT and four DMT-based indices between before and after statistical downscaling. In general, the BCSD method has little influence on the trend of these extreme temperature indices. The regional averaged DMT and SU for the China as a whole and eight subregions would increase after downscaling. As for TXx, intensity, and frequency of heat wave, the BCSD method has impacts on the eight subregions but little impact on the China as a whole. The standard deviations of DMT and four extreme temperature indices are reduced in CN05.1 BCSD compared with those in the raw CMIP5 counterparts, especially over northeast China. More fundamentally, the intermodel spreads for DMT, SU, TXx, and intensity of heat wave are dramatically reduced after applying downscaling algorithm compared with the original CMIP5 simulations. Therefore, we believe that the projected changes in extreme temperature over China are substantially more robust from CN05.1 BCSD than directly taken from the CMIP5 simulations. From this perspective, the BCSD method shows improvements to the original model outputs.

As noted in section 1, there exists numerous statistical downscaling algorithms, such as linear interpolation and SD (Maurer & Hidalgo, 2008; Thrasher et al., 2012; Wood et al., 2002; Wood et al., 2004). In this study, we used just one method (BCSD) to downscale DMT. It is therefore necessary to determine which method is most suitable for downscaling temperatures in China. To build on this research, future work should focus on statistical downscaling of all CMIP5 model predictions of daily precipitation, minimum temperature, and maximum temperature under the RCP2.6 scenario to supplement NEX-GDDP data set.
Ines, A. V. M., & Hansen, J. W. (2006). Bias correction of daily GCM rainfall for crop simulation studies. Agricultural and Forest Meteorology, 138(1), 44–53. https://doi.org/10.1016/j.agrformet.2006.03.009

Intergovernmental Panel on Climate Change (2007). Climate Change 2007: The Physical Science Basis. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, & H. L. Miller (Eds.), Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (Chap. 3, pp. 238–239). Cambridge, UK & New York, NY, USA: Cambridge University Press.

Intergovernmental Panel on Climate Change (2013). Climate Change 2013: The Physical Science Basis. In T. F. Stocker, et al. (Eds.), Contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change (Chap. 8, pp. 1535). Cambridge, United Kingdom and New York: Cambridge University Press. https://doi.org/10.5194/cp-11-539-2015

Karl, T. R., Nicholls, N., & Ghazi, A. (1999). Clivar/GCOS/WMO Workshop on indices and indicators for climate extremes workshop summary. Climatic Change, 42(1), 3–7. https://doi.org/10.1023/a:1005491526870

Kunkel, K. E., Piekarski, R. A. J., & Changnon, S. A. (1999). Temporal fluctuations in weather and climate extremes that cause economic and human health impacts: A review. Bulletin of the American Meteorological Society, 80(6), 1077–1098. https://doi.org/10.1175/1520-0477(1999)080<1077:TFTWAC>2.0.CO;2

Li, H. B., Sheffield, J., & Wood, E. F. (2010). Bias correction of monthly precipitation and temperature fields from the IPCC AR4 models using equidistant quantile matching. Journal of Geophysical Research: Atmospheres, 115(D)10. https://doi.org/10.1029/2009JD012882

Liu, B. H., Xu, M., Henderson, M., & Qi, Y. (2005). Observed trends of precipitation amount, frequency, and intensity in China, 1960–2000. Journal of Geophysical Research: Atmospheres, 110. https://doi.org/10.1029/2004JD004864

Maraun, D., Shepherd, T. G., Widmann, M., Zappa, G., Walton, D., Gutérez, J. M., et al. (2017). Towards process-informed bias correction of climate change simulations. Nature Climate Change, 7(11), 764–773. https://doi.org/10.1038/nclimate3418

Maurer, E. P., & Hidalgo, H. G. (2008). Utility of daily vs. monthly-scale climate data: An intercomparison of two statistical downscaling methods. Hydrology and Earth System Sciences. Discussions, 12(2), 551–563. https://doi.org/10.5194/hessd-4-3413-2007

Maurer, E. P., & Pierce, D. W. (2014). Bias correction can modify climate model simulated precipitation changes without adverse effect on the ensemble mean. Hydrology and Earth System Sciences, 18(3), 915–925. https://doi.org/10.5194/hess-18-915-2014

Moghim, S., & Bras, R. L. (2017). Bias correction of climate modeled temperature and precipitation using artificial neural networks. Journal of Hydrometeorology, 18(7), 1867–1882. https://doi.org/10.1175/JHM-D-16-0247.1

Moghim, S., McKnight, S. L., Zhang, K., Eltahay, A. M., Knox, R. G., Bras, R. L., et al. (2017). Bias corrected data sets of climate model outputs at uniform space–time resolution for land surface modelling over Amazonia. International Journal of Climatology, 37(2), 621–636. https://doi.org/10.1002/joc.4728

Monjo, R., Gaitán Fernández, E., Pórtoles, J., Ribhalgaya, J., & Torres, L. (2016). Changes in extreme precipitation over Spain using statistical downscaling of CMIP5 projections. International Journal of Climatology, 36(2), 757–769. https://doi.org/10.1002/joc.4380

Raghavan, S. V., Huir, J., & Lüong, S. Y. (2018). Evaluations of NASA NEX-GDP data over Southeast Asia: present and future climates. Climatic Change, 144(4), 503–518. https://doi.org/10.1007/s10584-018-2213-3

Reichler, T., & Kim, J. (2008). How well do coupled models simulate today’s climate? Bulletin of the American Meteorological Society, 89(3), 303–311. https://doi.org/10.1175/BAMS-89-3-303

Santidrián Tomillo, P., Saha, S. V., Lombard, C. D., Valulius, J. M., Robinson, N. J., Paladino, F. V., et al. (2015). Global analysis of the effect of local climate on the hatching output of leatherback turtles. Scientific Reports, 5(1), 1–12. https://doi.org/10.1038/srep16789

Schlesinger, C. F., Lisnser, T. K., Fischer, E. M., Wehladian, J., Perrette, M., Gobly, A., et al. (2016). Differential climate impacts for policy-relevant limits to global warming: The case of 1.5 °C and 2 °C. Nature Climate Change, 6(9). https://doi.org/10.1038/nclimate3096

Sheffield, J., Goteti, G., & Wood, E. F. (2006). Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. Journal of Climate, 19(1). https://doi.org/10.1175/jcli3970.1

Shi, X. H., Lu, C. G., & Xu, X. D. (2011). Variability and trends of high temperature, high humidity, and sultry weather in the warm season in China during the period 1961–2004. Journal of Applied Meteorology and Climatology, 50(1), 127–143. https://doi.org/10.1175/2010JAMC2345.1

Stilmann, J., Kharin, V. V., Zhang, X., Zwiers, F. W., & Bronnagha, D. (2013). Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. Journal of Geophysical Research: Atmospheres, 118(4), 1716–1733. https://doi.org/10.1002/jgrd.50203

Stilmann, J., Kharin, V. V., Zwiers, F. W., Zhang, X., & Bronnagha, D. (2013). Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. Journal of Geophysical Research: Atmospheres, 118(6), 2473–2493. https://doi.org/10.1002/jgrd.50188

Sun, Q. H., Miao, C. Y., & Duan, Q. Y. (2016). Extreme climate events and agricultural climate indices in China: CMIP5 model evaluation and projections. International Journal of Climatology, 36(1), 43–61. https://doi.org/10.1002/joc.4328

Sun, Y., Zhang, X., Zwiers, F. W., Song, L., Wan, H., Hu, T., et al. (2014). Rapid increase in the risk of extreme summer heat in Eastern China. Nature Climate Change, 4, 1082–1085. https://doi.org/10.1038/nclimate2410

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society, 93(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00631.1

Thrasher, B., Maurer, E. P., McKellar, C., & Duffy, P. B. (2012). Technical note: Bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrology Earth System Sciences, 16(9), 3309–2214. https://doi.org/10.5194/hess-9-3551-2012

Wang, A. H., Lettenmaier, D. P., & Sheffield, J. (2011). Soil moisture drought in China, 1950–2006. Journal of Climate, 24(13), 3257–3271. https://doi.org/10.1175/2011JCLI3733.1

Wang, A. H., Xu, L. L., & Kong, X. H. (2018). Assessments of the northern hemisphere snow cover response to 1.5 and 2.0 °C warming. Earth System Dynamics, 9(2), 865–877. https://doi.org/10.5194/esd-9-865-2018

Wang, C., Cui, W., Gan, B., Wu, L., Santos, A., Lin, X., et al. (2017). Continued increase of extreme El Niño frequency long after 1.5 °C warming stabilization. Nature Climate Change, 7(8). https://doi.org/10.1038/nclimate3351
Wang, H. J., & He, S. P. (2015). The north China/northeastern Asia severe summer drought in 2014. *Journal of Climate, 28*(17), 6667–6681. https://doi.org/10.1175/JCLI-D-15-0202.1

Wang, J. X. L., & Gaffen, D. J. (2001). Late-twentieth-century climatology and trends of surface humidity and temperature in China. *Journal of Climate, 14*(13), 2833–2845. https://doi.org/10.1175/1520-0442(2001)014<2833:LTCCAT>2.0.CO;2

Wilby, R., & Wigley, T. M. L. (1997). Downscaling general circulation model output: A review of methods and limitations. *Progress in Physical Geography, 21*(4), 530–548. https://doi.org/10.1177/030913339702100403

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*, 189–216. https://doi.org/10.1023/b:clim.0000013685.99609.9e

Wood, A. W., Maurer, E. P., Kumar, A., & Lettenmaier, D. P. (2002). Long-range experimental hydrologic forecasting for the eastern United States. *Journal of Geophysical Research: Atmospheres, 107*(D20). https://doi.org/10.1029/2001JD000659

Wu, J., & Gao, X. J. (2013). A gridded daily observation dataset over China region and comparison with the other datasets. *Chinese Journal of Geophysics, 56*(4), 1102–1111. https://doi.org/10.6038/cjg20130406 (in Chinese)

Xu, L. L., He, S. P., Li, F., Ma, J. H., & Wang, H. J. (2017). Numerical simulation on the southern flood and northern drought in summer 2014 over Eastern China. *Theoretical and Applied Climatology, 134*(3-4), 1267–1299. https://doi.org/10.1007/s00704-017-2341-0

Xu, Y., Gao, X. J., Giorgi, F., Zhou, B. T., Ying, S., Wu, J., & Zhang, Y. X. (2018). Projected changes in temperature and precipitation extremes over China as measured by 50-yr return values and periods based on a CMIP5 ensemble. *Advances in Atmospheric Sciences, 35*(4), 376–388. https://doi.org/10.1007/s00376-017-6269-1

Xu, Z. F., & Yang, Z. L. (2015). A new dynamical downscaling approach with GCM bias corrections and spectral nudging. *Journal of Geophysical Research: Atmospheres, 120*(8), 3063–3084. https://doi.org/10.1002/2014JD022958

Xue, Y. K., Janjic, Z., Dudhia, J., Vasic, R., & De Sales, F. (2014). A review on regional dynamical downscaling in intraseasonal to seasonal simulation/prediction and major factors that affect downscaling ability. *Atmospheric Research, 147–148*, 68–85. https://doi.org/10.1016/j.atmosres.2014.05.001

Yang, X. L., Wood, E. F., Sheffield, J., Ren, L., Zhang, M., & Wang, Y. (2018). Bias correction of historical and future simulations of precipitation and temperature for China from CMIP5 models. *Journal of Hydrometeorology, 19*(3), 609–623. https://doi.org/10.1175/JHM-D-17-0180.1

Zhang, W. X., Zhou, T. J., Zou, L. W., Zhang, L. X., & Chen, X. L. (2018). Reduced exposure to extreme precipitation from 0.5 °C less warming in global land monsoon regions. *Nature Communications, 9*(1). https://doi.org/10.1038/s41467-018-05633-3

Zhou, B. T. (2016). The Asian–Pacific Oscillation pattern in CMIP5 simulations of historical and future climate. *International Journal of Climatology, 36*(15), 4778–4789. https://doi.org/10.1002/joc.4668