Comparing bias correction methods in downscaling meteorological variables for hydrologic impact study in an arid area in China

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Abstract:

Water resources are essential to the ecosystem and social economy in the desert and oasis of the arid Tarim River Basin, Northwest China, and expected to be vulnerable to climate change. Regional Climate Models (RCM) have been proved to provide more reliable results for regional impact study of climate change (e.g., on water resources) than GCM models. However, it is still necessary to apply bias correction before they are used for water resources research due to often considerable biases. In this paper, after a sensitivity analysis on input meteorological variables based on Sobol' method, we compared five precipitation correction methods and three temperature correction methods to the output of a RCM model with its application to the Kaidu River Basin, one of the headwaters of the Tarim River Basin. Precipitation correction methods include Linear Scaling (LS), LOCal Intensity scaling (LOCI), Power Transformation (PT), Distribution Mapping (DM) and Quantile Mapping (QM); and temperature correction methods include LS, VARIance scaling (VARI) and DM. These corrected precipitation and temperature were compared to the observed meteorological data, and then their impacts on streamflow were also compared by driving a distributed hydrologic model. The results show: 1) Precipitation, temperature, solar radiation are sensitivity to streamflow while relative humidity and wind speed are not; 2) Raw RCM simulations are heavily biased from observed meteorological data,

which results in biases in the simulated streamflows, and all bias correction methods effectively improved theses simulations; 3) For precipitation, PT and QM methods performed equally best in correcting the frequency-based indices (e.g., standard deviation, percentile values) while LOCI method performed best in terms of the time series based indices (e.g., Nash-Sutcliffe coefficient, R^2); 4) For temperature, all bias correction methods performed equally well in correcting raw temperature. 5) For simulated streamflow, precipitation correction methods have more significant influence than temperature correction methods and the performances of streamflow simulations are consistent with these of corrected precipitation, i.e., PT and QM methods performed equally best in correcting flow duration curve and peak flow while LOCI method performed best in terms of the time series based indices. The case study is for an arid area in China based on a specific RCM and hydrologic model, but the methodology and some results can be applied to other area and other models.

1. Introduction

In recent decades, the ecological situation of the Tarim River Basin in China has seriously degraded especially in the lower reaches of the Tarim River due to water scarcity. In the meantime, climate change is significant in this region with a consistent increase in temperature at a rate of 0.33 ~ 0.39 ℃/decade and a slight increase in precipitation (Li et al., 2012) over the past 5 decades. Under the context of regional climate change, water resources in this region are expected to be more unstable and ecosystems are likely to suffer from severe water stress because the hydrologic system is particularly vulnerable to climate change in the arid region (Arnell et al., 1992; Shen and Chen, 2010; Sun et al., 2013; Wang et al., 2013). The impact of climate change on hydrologic system has already been observed and it is expected that the hydrological system will continue to change in the future (Liu et al., 2011; Liu et al., 2010; Chen et al., 2010). Therefore, projecting reliable climate change and its impact on hydrology are important to study the ecology in the Tarim River Basin.

Only recently efforts have been made to evaluate and project the impact of climate change on hydrology in the Tarim River Basin. These studies include research on the relationships of climate variables and streamflow based on the historical measurements (e.g. Chen et al., 2013c; Xu et al., 2013), and use of the output of General Circulation Models (GCMs) to drive a hydrologic model to study the future climate change on water resources (Liu et al., 2010; Liu et al., 2011). Study on historical relationships has limited applications on future water resource management, especially under the global climate change background. And though GCMs have been widely used to study impacts of future climate change on hydrological systems and water resources, they are impeded by their inability to provide reliable information at the hydrological scales (Maraun et al., 2010; Giorgi, 1990). In particular, in mountainous regions, fine scale information such as the altitude-dependent precipitation and temperature information, which is critical for hydrologic modeling, is not represented in GCMs (Seager and Vecchi, 2010). Although there are options to downscale GCM outputs to the regional scale, recent studies tend to use the higher-resolution Regional Climate Models (RCMs) to preserve the physical coherence between atmospheric and land surface variables (Bergstrom et al., 2001; Anderson et al., 2011). As such, when evaluating the impact of climate change on water resources in a watershed scale, the use of RCMs instead of GCMs is preferable since RCMs have been proved to provide more reliable results for impact study of climate change on regional water resources than GCM models (Buytaert et al., 2010; Elguindi et al., 2011). However, the raw RCM simulations may be still biased especially in the mountainous regions (Murphy, 1999; Fowler et al., 2007), which makes the use of RCM outputs as the direct input for hydrological model challenging, thus it is of significance to properly correct the RCM simulated meteorological variables before they are used to drive the hydrological model especially in the arid regions where the hydrology is sensitive to climate change.

Several bias correction methods have been developed to downscale climate variables from the RCMs, ranging from the simple scaling approach to sophisticated distribution mapping (Teutschbein and Seibert, 2012). And their applicability in the arid Tarim River Basin has not been investigated, thereby, evaluating and finding the appropriate bias correction method is necessary to evaluate the impact of climate change to water resources.

This study evaluates performances of five precipitation bias correction methods and three temperature bias correction methods in correcting RCM simulations and applied to the Kaidu River Basin, one of the most important headwaters of the Tarim River. These bias correction methods include most frequently used bias correction methods. We compare their performances in terms of precipitation and temperature and evaluate their impact on streamflow through hydrological modeling.

The remaining is constructed as follows: Section 2 introduces the study area and data; Section 3 describes the bias correction methods for precipitation and temperature along with the hydrological model, sensitivity analysis method and result analysis strategy; and then Section 4 gives results and discussion, followed by conclusions in Section 5.

2 Study area and data

2.1 Study area and observed data

The Kaidu River Basin, with a drainage area of 18,634 km^2 above the Dashankou hydrological station, is located on the south slope of the Tianshan Mountains in Northwest China (Fig. 1). Its altitude ranges from 1,340 m to 4,796 m above sea level (asl) with an average elevation of 2,995 m, and climate is featured by temperate continental climate with alpine climate characteristic. As one of the headwaters of the Tarim River, it provides water resources for agricultural activity and ecological environment of the oasis in the lower reaches. This oasis, with a population of over 1.15 million, is stressed by lack of water and water resources are the main factor constricting the development (Chen et al., 2013b). Therefore, projecting the impact of future climate change on water resources is urgent to the sustainable development of this region.

Daily observed meteorological data, including precipitation, maximum/minimum temperature, wind speed and relative humidity of two meteorological stations (Bayanbulak and Baluntai, stars in Figure 1), are from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). The mean annual maximum and minimum temperature at the Bayanbulak meteorological station are 3.1 ℃ and -10.6 ℃ and mean annual precipitation is 267 mm, and generally precipitation falls as rain from May to September and as snow from October to April of the next year.

The observed streamflow data at the Dashankou hydrologic station (the triangle in Figure 1) are from Xinjiang Tarim River Basin Management Bureau. The average daily flow is around 110 $m^3 s^{-1}$ (equivalent to 185 mm runoff/year), ranging from 15 $m^3 s^{-1}$ to 973 $m^3 s^{-1}$.

2.2 Simulated meteorological variables from the regional climate model

GCM or RCM outputs are generally biased (Ahmed et al., 2013;Teutschbein and Seibert, 2012;Mehrotra and Sharma, 2012), which demonstrates the need for bias correction before their use in regional impact studies. The RCM outputs used in this study are based on the work done by Gao et al (2013). In Gao et al. (2013), the RCM model (RegCM, Giorgi and Mearns, 1999) was driven by a global climate model BCC_CSM1.1 (Beijing Climate Center Climate System Model; Wu et al., 2013; Xin et al., 2013) at a horizontal resolution of 50 km over China.

The RCM outputs were validated with the observational dataset (CN05.1) over China for the period from 1961 to 2005. The RCM outputs show reasonable simulation of temperature and precipitation over China especially when compared with its driving GCM BCC_CSM1.1 (more details refer to Gao et al., 2013). In this paper, meteorological outputs of the RCM model used include maximum/minimum temperature, precipitation, wind speed, solar radiation and humidity.

3 Methodology

3.1 Hydrologic model and sensitivity of input meteorological variables

SWAT (Soil and Water Assessment Tool; Arnold et al., 1998) is a distributed and time continuous watershed hydrologic model. The climatic input (driving force) consists of daily precipitation, maximum/minimum temperature, solar radiation, wind speed and relative humidity, and SWAT uses elevation bands to account for orographic effects on precipitation and temperature. The processes SWAT simulates include snow accumulation, snowmelt, evapotranspiration, surface runoff, lateral flow, and baseflow, sediment erosion, point and non-point pollution, river routing and in-stream water quality processes on a daily basis. More details refer to SWAT manuals (www.brc.tamus.edu/). It has been being widely used for comprehensive modeling of the impact of management practices and climate change on the hydrologic cycle and water resources at a watershed scale (e.g. Arnold et al., 2000; Arnold and Fohrer, 2005; Setegn et al., 2011).

In this study, SWAT model was firstly set up with available DEM, landuse, soil, and observed climate data, and then model parameters were calibrated with the observed streamflow data at the Dashankou station. The simulation results show: 1) model application shows excellent performances for both calibration period (1986 ~ 1989) and validation period (1990 ~ 2001) with "NS"s (Nash-Sutcliffe coefficients, Nash and Sutcliffe, 1970; see the definition in Eq. 16) and "R^2"s over 0.80, which is highly acceptable; 2) model parameters are reasonable and spatial patterns of precipitation and temperature are in agree with other studies in the region (see more details in Fang et al., under submission). Figure 2 shows a comparison of mean hydrographs of the observed ("obs") and simulated flows ("default"). This calibrated model hence provides a basis for evaluation of the impact of different correction methods on streamflow.

To study the relative importance of the five meteorological variables, the Sobol' sensitivity analysis method (Sobol', 2001) was applied. The Sobol' method is based on the decomposition of the variance V of objective function:

$$\mathrm{V} = \sum_i V_i + \sum_i \sum_{j>i} V_{ij} + \cdots + V_{1,2,\cdots,n} \tag{1}$$

where

$$\mathrm{V_i} = V(\mu(Y|X_i))$$

$$\mathrm{V}_{\mathrm{ij}} = V\left(\mu\left(Y\middle|X_i, X_j\right)\right) - \mathrm{V}_{\mathrm{i}} - \mathrm{V}_{\mathrm{j}}$$

and so on. Herein, $V(.)$ denotes the variance operator, V is the total variance, and V_{i} and V_{ij} are main variance of X_{i} (the i$^{\mathrm{th}}$ factor of X) and partial variance of X_{i} and X_{j}. Here factors X are the changes applied to these five meteorological variables, respectively (see Table 1 for a list of these factors). In practice, normalized indices are often used as sensitivity measures:

$$S_i = \frac{\mathrm{V}_{\mathrm{i}}}{\mathrm{V}}, 1 \le i \le n \tag{2}$$

$$S_{ij} = \frac{\mathrm{V}_{\mathrm{ij}}}{\mathrm{V}}, 1 \le i < j \le n \tag{3}$$

$$S_{Ti} = S_i + \sum_j S_{ij} + \sum_j \sum_k S_{ijk} + \cdots + S_{1,2,\ldots,n}, \;\; 1 \le i \le n \tag{4}$$

Where S_{i}, S_{ij} and S_{Ti} are the main effect of X_{i}, first order interaction between X_{i} and X_{j}, and total effect of X_{i}. S_{Ti} ranges from 0 to 1 and denotes the importance of the factor to model output. The larger S_{Ti}, the more important this factor is. The difference between S_{Ti} and S_{i} denotes the significance of the interaction of this factor with other factors. As a result, the larger this difference, the more significant the interaction is.

3.2 Bias correction methods

In this study, five bias correction methods were used for precipitation, and three for temperature. These methods are listed in Table 2. All these bias correction methods were conducted on a daily basis from 1975 to 2005.

3.2.1 Linear Scaling (LS) of precipitation and temperature

LS method aims to perfectly match the monthly mean of corrected values with that of observed ones (Lenderink et al., 2007). It operates with monthly correction values based on the differences between observed and raw data (raw RCM simulated data in this case). Precipitation is typically corrected with a multiplier and temperature with an additive term on a monthly basis:

$$P_{cor,m,d} = P_{raw,m,d} \times \frac{\mu(P_{obs,m})}{\mu(P_{raw,m})} \tag{5}$$

$$T_{cor,m,d} = T_{raw,m,d} + \mu(T_{obs,m}) - \mu(T_{raw,m}) \tag{6}$$

where $P_{cor,m,d}$ and $T_{cor,m,d}$ are corrected precipitation and temperature on the d^{th} day of m^{th} month and $P_{raw,m,d}$ and $T_{raw,m,d}$ are the raw precipitation and temperature on the d^{th} day of m^{th} month. $\mu(.)$ represents the expectation operator (e.g., $\mu(T_{obs,m})$ represents the mean value of observed precipitation at given month m).

3.2.2 LOCal Intensity scaling (LOCI) of precipitation

LOCI method (Schmidli et al., 2006) corrects the wet-day frequencies and intensities and can effectively improve the raw data which have too many drizzle days (defined as days with little precipitation). It normally involves two steps: firstly, a wet-day threshold for the m^{th} month $P_{thres,m}$ is determined from the raw precipitation series to ensure that the threshold exceedance matches the wet-day frequency of the observation; secondly, a scaling factor $s_m = \frac{\mu(P_{obs,m,d}|P_{obs,m,d}>0)}{\mu(P_{raw,m,d}|P_{raw,m,d}>P_{thres,m})}$ is calculated and used to ensure that the mean of the corrected precipitation is equal to that of the observed precipitation:

$$P_{cor,m,d} = \begin{cases} 0, & if\ P_{raw,m,d} < P_{thres,m} \\ P_{raw,m,d} \times S_m, & otherwise \end{cases} \tag{7}$$

3.2.3 Power Transformation (PT) of precipitation

While the LS and LOCI account for the bias in the mean precipitation, it does not correct biases in the variance. PT method uses an exponential form to further adjust the standard deviation of precipitation series. Since PT has the limitation in correcting the wet day probability (Teutschbein and Seibert, 2012), which was also confirmed in our study (not shown), LOCI method is applied to correct precipitation prior to the correction by PT method.

Therefore, to implement this PT method, firstly, we estimate b_m that minimizes:

$$f(b_m) = \frac{\sigma(P_{obs,m})}{\mu(P_{obs,m})} - \frac{\sigma(P_{LOCI,m}^{b_m})}{\mu(P_{LOCI,m}^{b_m})} \quad (8)$$

where b_m is the exponent for the m^{th} month, $\sigma(.)$ represents the standard deviation operator, and $P_{LOCI,m}$ is the LOCI-corrected precipitation in the m^{th} month. If b_m is larger than one, it indicates that the LOCI-corrected precipitation underestimates its coefficient of variance in month m.

After finding the optimal b_m, the parameter $s_m = \frac{\mu(P_{obs,m})}{\mu\left(P_{LOCI,m}^{b_m}\right)}$ is then determined such that the mean of the corrected values corresponds to the observed mean. The corrected precipitation series are obtained based on the LOCI corrected precipitation $P_{\text{cor,m,d}}$:

$$P_{cor,m,d} = s_m \times P_{LOCI,m,d}^{b_m} \quad (9)$$

3.2.4 Variance scaling (VARI) of temperature

The PT method is an effective method to correct both the mean and the variance of precipitation, but it cannot be used to correct temperature time series, as temperature is known to be approximately normally distributed (Terink et al., 2010). VARI method was developed to correct both the mean and variance of normally distributed variable such as temperature (Teutschbein and Seibert, 2012; Terink et al., 2010). Temperature is normally corrected using VARI method with Eq. (10).

$$T_{cor,m,d} = \left[T_{raw,m,d} - \mu\left(T_{raw,m}\right)\right] \times \frac{\sigma\left(T_{obs,m}\right)}{\sigma\left(T_{raw,m}\right)} + \mu\left(T_{obs,m}\right) \tag{10}$$

3.2.5 Distribution mapping (DM) of precipitation and temperature

DM method is to match the distribution function of raw data to that of observation. It is used to adjust mean, standard deviation and quantiles. Furthermore, it preserves the extremes (Themeßl et al., 2012). However, it also has its limitation due to the assumption that both the observed and raw climate variables follow the same proposed distribution, which may introduce potential new biases.

For precipitation, the Gamma distribution (Thom, 1958) with shape parameter α and scale parameter β is often used for precipitation distribution and has been proven to be effective (e.g., Block et al., 2009; Piani et al., 2010):

$$f_r(x|\alpha,\beta) = x^{\alpha-1} \times \frac{1}{\beta^{\alpha} \times \Gamma(\alpha)} \times e^{\frac{-x}{\beta}}; x \geq 0, \alpha, \beta > 0 \tag{11}$$

where $\Gamma(.)$ is the Gamma function. Since the raw RCM-simulated precipitation contains a large number of drizzle days, which may substantially distort the raw precipitation distribution, the correction is done on LOCI corrected precipitation $P_{LOCI,m,d}$:

$$P_{cor,m,d} = F_r^{-1}\left(F_r\left(P_{LOCI,m,d}\middle|\alpha_{LOCI,m}, \beta_{LOCI,m}\right)\middle|\alpha_{obs,m}, \beta_{obs,m}\right) \tag{12}$$

Where F_r (.) and F_r^{-1}(.) are Gamma CDF (cumulative distribution function) and its inverse. $\alpha_{LOCI,m}$ and $\beta_{LOCI,m}$ are the fitted Gamma parameter for the LOCI corrected precipitation in a given month m, and $\alpha_{obs,m}$ and $\beta_{obs,m}$ are these for observation.

For temperature, the Gaussian distribution (or normal distribution) with mean μ and standard deviation σ is usually assumed to fit temperature best (Teutschbein and Seibert, 2012):

$$f_N(x|\mu,\sigma) = \frac{1}{\sigma\times\sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\sigma^2}}; x \in \mathbf{R} \tag{13}$$

And then similarly the corrected temperature can be expressed as:

$$T_{cor,m,d} = F_N^{-1}\left(F_N\left(T_{raw,m,d}\middle|\mu_{raw,m},\sigma_{raw,m}\right)\middle|\mu_{obs,m},\sigma_{obs,m}\right) \tag{14}$$

where $F_N(.)$ and $F_N^{-1}(.)$ are Gaussian CDF and its inverse, $\mu_{raw,m}$ and $\mu_{obs,m}$are the fitted and observed means for the raw and observed precipitation series at a given month m, and $\sigma_{raw,m}$ and $\sigma_{obs,m}$ are the corresponding standard deviations, respectively.

3.2.6 Quantile Mapping (QM) of precipitation

QM method is a non-parametric bias correction method and is generally applicable for all possible distributions of precipitation without any assumption on precipitation distribution. This approach originates from the empirical transformation (Themeßl et al., 2012) and was successfully implemented in the bias correction of RCM simulated precipitation (Sun et al., 2011; Themeßl et al., 2012; Chen et al., 2013a; Wilcke et al., 2013). It can effectively correct bias in the mean, standard deviation and wet day frequency as well as quantiles.

For precipitation, the adjustment of precipitation using QM can be expressed in terms of the empirical CDF (*ecdf*) and its inverse ($ecdf^{-1}$):

$$P_{cor,m,d} = ecdf_{obs,m}^{-1}(ecdf_{raw,m}(P_{raw,m,d}) \quad (15)$$

3.3 Performance evaluation

The performance evaluation of these correction methods is based on their abilities to reproduce precipitation, temperature, and streamflow simulated with a hydrological model (SWAT) driven by bias corrected RCM simulations, specifically. When evaluating ability to reproduce streamflow, streamflow is firstly simulated by running the hydrological model driven by 15 different combinations of corrected precipitation, max/min temperature with different correction methods (these hydrologic simulations are then referred to as simulations 1 to 15, which are listed in Table 3) together with hydrologic simulations driven by observed meteorological data (“default”) and raw RCM simulation (“raw”). These 15 simulations were then compared with observed streamflows and “default” and “raw”.

The performance evaluation of precipitation, temperature and streamflow with different correction methods are:

1) For corrected precipitation, frequency-based indices and time series performances are compared with observed precipitation data. The frequency-based indices include mean, median, standard deviation, 90th percentile, probability of wet days, and intensity of wet day while time series based metrics include NS, Percent bias

(P_{BIAS}), R^2 and Mean Absolute Error (MAE):

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)^2} \tag{16}$$

$$P_{BIAS} = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)} \tag{17}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|Y_i^{obs} - Y_i^{sim}\right|}{n} \tag{18}$$

Where Y_i^{obs} and Y_i^{sim} are the i^{th} observed and simulated variables, Y^{mean} is the mean of observed variables, and n is the total number of observations.

NS indicates how well the simulation matches the observation and it ranges between -∞ and 1.0, with NS =1 meaning a perfect fit. The higher this value, the more reliable the model is. P_{BIAS} measures the average tendency of the simulated data to their observed counterparts. Positive values indicate an overestimation of observation, while negative values indicate an underestimation. The optimal value of P_{BIAS} is 0.0, with low-magnitude values indicating accurate model simulations.

2) For corrected temperature, frequency-based indices and time series performances are compared with observed temperature data. The frequency-based indices include mean, median, standard deviation, and 10^{th}, 90^{th} percentiles while time series based metrics include NS, P_{BIAS}, R^2 and MAE.

3) For simulated streamflow driven by corrected RCM simulations, the frequency-based indices are visualized using boxplot, exceedance probability curve, and exceedance probabilities of 7-day peak flow and low flow. Time series based metrics include NS, P_{BIAS}, R^2 and MAE.

4 Results

4.1. Initial streamflow simulation driven with raw RCM simulations and sensitivity analysis

To illustrate the necessity of bias correction in climate change impact on hydrology, we re-calibrated SWAT using the raw RCM simulations while keeping all SWAT parameters in their reasonable ranges. The assumption is that if the re-calibrated hydrological model driven by the raw RCM simulations performs well and model parameters are reasonable, then there is no need for bias correction. The streamflow simulated by the re-calibrated model was plotted in Fig. 2, and it systematically overestimates the observation a lot with NS equals to -6.65. Therefore, it is necessary to correct the climate variables before they can be used for hydrological impact study.

And then the Sobol' method was applied to study which meteorological variables should be corrected for hydrological modeling. Table 1 lists the sensitivity results for these five meteorological variables. As it can be seen, precipitation is the most sensitive (the main effect S_i is 44.0% and total effect S_{Ti} is 74.0%), followed by temperature (S_i = 15.0% and S_{Ti} = 36.9%) and solar radiation (S_i = 7.7% and S_{Ti} = 22.6%), and the interactions between these factors are large. The relative humidity and wind speed are insensitive in this case. This means precipitation, temperature and solar radiation need to be bias corrected before applied to hydrologic models.

4.2 Evaluation of corrected precipitation and temperature

The bias correction was done on RCM simulated precipitation, minimum temperature, maximum temperature, and solar radiation (for solar radiation, LS and VARI methods were used) for two meteorological stations Bayanbulak and Baluntai. Results show: 1) for solar radiation, there is no significant difference for different correction methods. There the results are not shown. 2) Similar results were obtained for minimum temperature and maximum temperature, and for Bayanbulak and Baluntai. Therefore we only list and discuss results for Bayanbulak, and maximum temperature.

Table 4 lists the frequency-based statistics of observed, raw RCM-simulated and corrected precipitation data at the Bayanbulak Station. This station has a low precipitation (daily mean 0.73mm or annual mean 266mm) and precipitation falls in 32% days in a year with a mean intensity 2.3mm. Compared to the observation, the raw RCM simulations deviate significantly from observation, with overestimation of all the statistics. All the bias-correction methods improves the raw RCM simulated precipitation, however, there are differences between their corrected statistics. LS method has a good estimation of the mean while it shows a large bias in other measures, e.g., it largely overestimated the probability of wet days (e.g., up to 41% overestimation) and underestimated the standard deviation (up to 0.91 mm underestimation). LOCI method provides a good estimation in the mean, median, wet-day probability and wet-day intensity; however, there is a slight underestimation in the standard deviation and therefore 90th percentile. Compared to LS and LOCI, PT method performs well in all these metrics. In spite of slight better estimation of standard deviation, probability of wet days and intensity of wet day, DM method has an overestimation of the mean and an underestimation of standard deviation. This means that precipitation does not follow the assumed Gamma distribution. On the contrary, QM method doesn't have this assumption and it provides an excellent estimation of these statistics. These results are consistent with previous studies (Themeßl et al., 2011; Themeßl et al., 2012; Wilcke et al., 2013; Graham et al., 2007), but are different from the research by Piani et al (2010) who found that performance of DM method is unexpectedly well for the humid Europe region. This non-uniformity can be partly attributed to the precipitation regime for different regions: better fit of the assumed distribution lead to better performance of DM.

Table 5 lists the frequency-based statistics of observed, raw RCM simulated and bias-corrected maximum temperature data at the Bayanbulak Station. The mean and standard deviation are 3.08 and 14.5 ℃, with the 90^{th} percentile being 19.2 ℃. Analysis of the raw RCM simulations indicates deviation from observation, with an overestimation of the mean, and underestimations of the median, standard deviation, and 90^{th} percentile. All three bias-correction methods corrected biases in RCM simulated temperature and improved estimations of the statistics. LS has a correct estimation of mean but a slight underestimation of median and standard deviation, while VARI and DM have a good match with observations for all the frequency-based statistics. These results are in accordance with Teutschbein and Seibert (2012), i.e., LS method doesn't adjust the standard deviation and the 10^{th}/90^{th} percentiles while VARI and DM methods do.

Figure 3 shows the exceedance probability curves of the observed and corrected precipitation and temperature. For precipitation, the raw RCM simulations are heavily biased (as also shown by statistics in Table 4). All correction methods effectively, but in different extent, correct biases in raw precipitation. The LS method underestimates the high precipitation with probability below 0.06 and overestimates the low precipitation with probability between 0.06 ~ 0.32. The overestimation of precipitation with probability between 0.32 ~ 0.73 indicates LS method has a very limited ability in reproducing dry day precipitation (below 1 mm). Similar to LS method, the LOCI method also overestimates the low precipitation with probability between 0.08 ~ 0.32 and underestimates the high precipitation with probability below 0.08. However, unlike LS method, LOCI method performs well on the estimation of the dry days with precipitation below 1 mm. The PT, DM and QM methods well adjust precipitation exceedance except that DM method slightly overestimates the precipitation with probability between 0.12 ~ 0.28. For temperature, the raw temperature overestimates low temperature with probability above 0.65 and underestimates high temperature with probability below 0.65. All temperature correction methods adjust the biases in raw temperature and the corrected temperature has the similar quantiles with the observation. They performed equally well and differences among each correction method are negligible.

Time series based performances were evaluated and results are listed in Fig. 4 and Table 6. For precipitation, all bias correction methods significantly improve the raw RCM simulations. However, as shown in the right plot of Fig. 4, there is a systematic mismatch between observation and corrections which follow the pattern of RCM simulated precipitation. In addition, this mismatch differs between different methods, among which the difference is smaller for LS and LOCI methods than for PT, DM, and QM methods. This resulted in a slightly better squared difference based measures (e.g., NS, R^2) for LS and LOCI than PT, DM and QM methods, as indicated in Table 6. Similar to precipitation, all correction methods significantly improved the raw RCM simulated temperature. Differences between observation and raw temperature (e.g., 1.1 ℃ in spring, 1.0 ℃ in summer, 3.3 ℃ in autumn, and up to 7.6 ℃ in winter) were significantly corrected. These three correction methods performed equally well and no significant differences exist between the average annual daily temperature graphs.

Table 6 lists performances of correction methods for monthly time series of precipitation and temperature at the Bayanbulak Station. For precipitation, the performance of the RCM simulated precipitation is very poor with NS=-6.78, P_{BIAS}=293.28% and MAE=64.40 for monthly data, and the improvements of correction are obvious. The"P_{BIAS}"s of the corrected precipitation are within ±5 % and "NS"s approach 0.64. It is worth noting that LS and LOCI methods perform better than PT and QM methods in terms of time series performances. For temperature, although the raw RCM simulation obtains an acceptable NS value (0.84), it severely overestimates the observation (P_{BIAS} = 15.78 % and MAE = 4.31 ℃). The "P_{BIAS}"s of the corrected temperatures are within ±5% and "NS"s are over 94% (better than that of the "raw") for all three correction methods and there is no significant difference between these results, which indicates the corrected monthly temperature series are in good agreement with the observation.

4.3 Evaluation of streamflow simulations

Figure 5 compares the mean, median, first and third quantiles of daily observed streamflows ("obs") with simulated streamflows driven by observed meteorological inputs ("default"), raw RCM simulations ("raw"), and 15 combinations of corrected precipitation and corrected temperature (i.e., simulations 1 to 15). The overestimation of simulated streamflow using raw RCM simulations (i.e., "raw") is obvious. For simulations 1 to 3, streamflow overestimations are also observed and they substantially overestimate the mean streamflow by over 100%, while simulations 4 to 15 reproduce similar streamflows as the observation or simulation "default". As the major difference between simulations 1 to 3 and other simulations is that simulations 1 to 3 use the LS-corrected precipitation, this means precipitation corrected with LS method is not suitable for flow simulation in this study.

To investigate the performances of bias correction methods for different hydrological regimes, we divided the streamflow into two different periods according to the hydrograph (Fig. 2): wet period is from April to September and dry period is from October to March of next year. It is indicated that the performances of bias correction methods are, except for magnitudes, similar for both wet and dry period (not shown), which demonstrates that the evaluation is robust and can proved useful information for both dry and wet season.

Figure 6 shows the exceedance probability curves (flow duration curves) of the observed flow, and flows with simulation “default” and simulations 4 to 15. Generally all simulations are in good agreement with the observation for frequencies between 0.12 and 0.72, and precipitation correction methods have more significant influence than temperature correction methods. This confirms the previous sensitivity result that precipitation is the most sensitive driving force to streamflow simulation. Similar to performances of bias corrected precipitation, simulations with DM-corrected precipitation (i.e. simulations 10 to 12) deviates the observation the most, followed these with LOCI corrected precipitation (i.e., simulations 4 to 6), and then with PT method and QM method. All simulations encounter the problem to correctly mimic the low flow part (i.e. exceedance larger than 0.7). This might be a systematic problem of the calibrated hydrologic model (as indicated by simulation “default”), e.g., the objective function of the hydrological modeling is not focused on baseflow. Differences among streamflows driven by different temperature but same precipitation are insignificant. This result differs from the study of Teutschbien and Seibert (2012). This may be related to the chosen RCM model or watershed characteristic.

The time series performances of simulation “default”, simulation “raw” and simulations 1 to 15 at daily and monthly time steps are summarized in Table 3. The "default" performs well with NS reaching 0.80 for daily and 0.90 for monthly streamflow and daily MAE within 25 m^3/s. The "raw" is heavily biased with NS close to -53.4 and P_{BIAS} as large as 421 % for monthly data. All the 15 simulations improve the statistics of the "raw" scenario significantly. For simulations 1 to 3, whose precipitation series are corrected by LS method, NS ranges from -3.10 to -2.87 for monthly streamflow and they substantially overestimate the streamflow with P_{BIAS} over 110%. For simulations 4 to 15, monthly "NS"s are over 0.60, which indicates they can reproduce satisfactory monthly streamflow in this watershed, and simulations with precipitation corrected by LOCI (simulations 4 to 6) have best "NS"s and "P_{BIAS}"s. However, these indices of daily streamflow are lower (the highest NS is 0.50 for simulations 5 and 6), and this is related to the mismatch between corrected and observed precipitation time series (see top plot in Figure 4), which is intrinsic from the RCM model and cannot be improved through these correction methods.

It is worth noting that simulations 1 to 3 and simulations 4 to 6, whose precipitation is corrected by LS and LOCI, respectively, vary significantly. The difference between LS and LOCI is that LOCI introduces a threshold for the wet day precipitation to correct the wet day probability while LS doesn't. That is a simple but quite pragmatic approach since the raw RCM simulated precipitation usually has too many drizzle days (Teutschbein and Seibert, 2012). Obviously, wet day probability is crucial to streamflow simulation in this study.

Figure 7 shows the simulated monthly mean flow and exceedance probability curves of 7-day peak and 7-day low flow. For the monthly mean streamflow, obviously the “raw” is heavily biased with deviations ranging from 282% to 426%. Simulations 1, 2 and 3 also overestimate the observation, while simulations 4 to 15 reproduced good monthly mean streamflow especially for simulations 4, 5 and 6. The annual peak flow and low flow is presented in Fig. 7 to investigate the impact of bias correction methods on extreme flows. For the peak flow, the exceedance probabilities of the simulations 4 to 15 are close to the observation while “raw” and simulations 1 to 3 deviate significantly (not shown). It is worth noting that simulations 4, 5 and 6, which perform the best in terms of the “NS”s, slightly underestimate the peak flow by 1% ~ 28%. The reason may be that the LOCI method adjusts all precipitation events in a certain month with a same scaling factor, which leads to the underestimation of the standard deviation (Table 4) and high precipitation intensity, and finally results in an underestimation of the peak streamflow. Results show slightly better performance of PT, DM and QM methods than LOCI in predicting extreme flood, which is consistent with previous study, e.g., Chen et al. (2013a) and Teutschbein and Seibert (2012), who validated the effectiveness of bias correction methods for un-stationary conditions.

For the low flow, all simulations overestimate the observation, but are in good agreement with the “default”, which can be attributed to the systematic deficit of the hydrological model.

For the peak flow and low flow, both DM and QM methods perform well and QM method is slightly better than DM method as the latter overestimates both peak flow and low flow. However, there is an essential problem of QM method when comes to correcting future climate since it fails to resolve the “new extreme” (modeled values beyond the observed range) problem (Themeßl et al., 2012) as the corrected precipitation always falls between the maximum and minimum values.

5 Conclusions

This work compared the abilities of five precipitation bias correction methods and three temperature bias correction methods in correcting RCM simulations for an arid region. The evaluation includes their abilities to reproduce precipitation, temperature and streamflow simulated using a hydrological model driven by corrected variables.

Sensitivity analysis shows precipitation is the most sensitive driving force to streamflow simulation, followed by temperature and solar radiation, while relative humidity and wind speed are not sensitive.

The raw RCM simulations are heavily biased from observed data, and this results in biases in the simulated streamflows which cannot be corrected by model calibration; and all bias correction methods effectively improve these simulations.

For precipitation, the PT and QM methods performed equally best in terms of the frequency-based indices, (e.g., mean, standard deviation, percentiles); while LOCI method performed best in terms of the time series based indices (e.g., NS, P_{BIAS} and R^2).

For temperature, the raw RCM simulated temperature is highly relevant to the observation but generally biased (R^2 = 0.88 and P_{BIAS} = 15.78% for monthly data). All correction methods effectively corrected biases in the raw RCM simulated temperature and they performed almost equally well for both frequency-based indices and time series based indices.

For simulated streamflow, precipitation correction methods have more significant influence than temperature correction methods and their performances of streamflow simulations are consistent with these of corrected precipitation, i.e., PT and QM methods performed equally best in correcting flow duration curve and peak flow while LOCI method performed best in terms of the time series based indices (e.g., NS = 0.69, $|P_{BIAS}| < 5\%$). Besides, the wet day probability is vital in simulating streamflow in this study and it is recommended the LOCI method be applied to correct precipitation prior to the correction by PT method.

This study also stresses the need for bias correction when assessing the impact of climate change on hydrology using the RCM simulations. The most appropriate bias correction method for RCM simulations may differ regarding to climate conditions or evaluation indices. As such, it is necessary to find an appropriate bias correction method based on the study purpose.

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Table 1. Sensitivity indices of the five meteorological variables based on the Sobol' method.

Factor	Meaning	Factor range	Main effect S_i (%)	Total effect S_{Ti} (%)
a__tmp	Additive change to temperature	[-5,5]	15.0	36.9
r__pcp	Relative change to precipitation	[-0.5,0.5]	44.0	74.0
r__hmd	Relative change to humidity	[-0.5,0.5]	0.0	0.0
r__slr	Relative change to solar radiation	[-0.5,0.5]	7.7	22.6
r__wnd	Relative change to wind speed	[-0.5,0.5]	0.3	0.9

Table 2. Bias correction methods for RCM-simulated precipitation and temperature.

Bias correction for precipitation	Bias correction for temperature
Linear Scaling (LS)	Linear Scaling (LS)
LOCal Intensity scaling (LOCI)	VARIance scaling (VARI)
Power Transformation (PT)	Distribution Mapping for temperature using Gaussian distribution (DM)
Distribution Mapping for precipitation using Gamma distribution (DM)	
Quantile Mapping (QM)	

Table 3. Performances of simulated streamflows driven by observed (default), raw RCM-simulated (raw), and 15 combinations of bias-corrected precipitation and temperature during the period 1986 ~ 2001. For all combinations, solar radiation is corrected with Linear Scaling (LS) method. (Values are given with one decimal except for NS).

Bias correction method			Daily				Monthly			
	Precipitation	Temperature	NS	P_{BIAS}	R^2	MAE (m^3/s)	NS	P_{BIAS}	R^2	MAE (m^3/s)
default	obs	obs	0.80	4.3	0.8	24.2	0.90	4.3	0.9	16.6
raw	raw	raw	-44.91	420.5	0.4	487.9	-53.35	421.1	0.6	487.0
1	LS	LS	-2.65	115.6	0.5	136.4	-3.10	115.8	0.7	134.0
2	LS	VARI	-2.43	112.7	0.5	133.3	-2.87	113.0	0.7	130.6
3	LS	DM	-2.43	112.7	0.5	133.3	-2.87	113.0	0.7	130.6
4	LOCI	LS	0.49	-3.7	0.5	35.9	0.69	-3.7	0.7	25.3
5	LOCI	VARI	0.50	-4.5	0.5	35.6	0.69	-4.4	0.7	25.4
6	LOCI	DM	0.50	-4.5	0.5	35.6	0.69	-4.4	0.7	25.4
7	PT	LS	0.37	1.1	0.4	40.1	0.62	1.1	0.6	28.7
8	PT	VARI	0.38	0.3	0.4	39.8	0.63	0.3	0.6	28.6
9	PT	DM	0.38	8.3	0.5	41.2	0.62	8.3	0.7	30.6
10	DM	LS	0.40	7.5	0.5	40.7	0.63	6.7	0.6	30.3
11	DM	VARI	0.40	7.5	0.5	40.7	0.63	5.9	0.6	30.3
12	DM	DM	0.38	0.3	0.4	39.8	0.63	5.9	0.6	28.6
13	QM	LS	0.37	1.8	0.4	39.9	0.63	1.9	0.6	28.6
14	QM	VARI	0.38	1.0	0.4	39.5	0.63	1.0	0.6	28.4
15	QM	DM	0.38	1.0	0.4	39.5	0.63	1.0	0.6	28.4

Table 4. Frequency-based statistics of daily observed ("obs"), raw RCM-simulated ("raw") and bias-corrected precipitations at the Bayanbulak Station (values are given with two decimal digits).

	Mean (mm)	Median (mm)	Standard deviation (mm)	90th percentile (mm)	Probability of wet days (%)	Intensity of wet day (mm)
obs	0.73	0.00	2.44	1.90	32	2.30
raw	2.87	1.44	4.09	7.44	86	3.34
LS	0.73	0.20	1.53	2.10	73	1.00
LOCI	0.73	0.00	1.70	2.40	32	2.29
PT	0.73	0.00	2.44	1.80	32	2.30
DM	0.78	0.00	2.30	2.11	32	2.46
QM	0.73	0.00	2.44	1.90	32	2.31

Table 5. Frequency based statistics (unit: ℃) of daily observed ("obs"), raw RCM simulated ("raw") and bias corrected maximum temperatures at the Bayanbulak Station (values are given with two decimals).

	Mean	Median	Standard deviation	10th percentile	90th percentile
obs	3.08	7.20	14.50	-18.70	19.20
raw	3.45	3.21	10.88	-10.34	17.90
LS	3.08	6.65	14.14	-17.33	19.40
VARI	3.08	6.85	14.50	-17.76	19.36
DM	3.08	6.85	14.50	-17.76	19.36

Table 6. Time series based metrics of bias-corrected precipitation and temperature calculated on a monthly scale at the Bayanbulak Station (values are given with two decimals).

		NS	P_{BIAS} (%)	R^2	MAE (mm or ℃)
Precipitation	raw	-6.78	293.28	0.42	65.40
	LS	0.64	0.06	0.65	9.66
	LOCI	0.61	-0.71	0.64	10.14
	PT	0.42	-0.09	0.53	11.98
	DM	0.46	6.64	0.56	11.78
	QM	0.44	0.03	0.54	11.99
Temperature	raw	0.84	15.78	0.88	4.31
	LS	0.95	3.04	0.95	2.35
	VARI	0.94	4.78	0.94	2.52
	DM	0.94	4.74	0.94	2.52

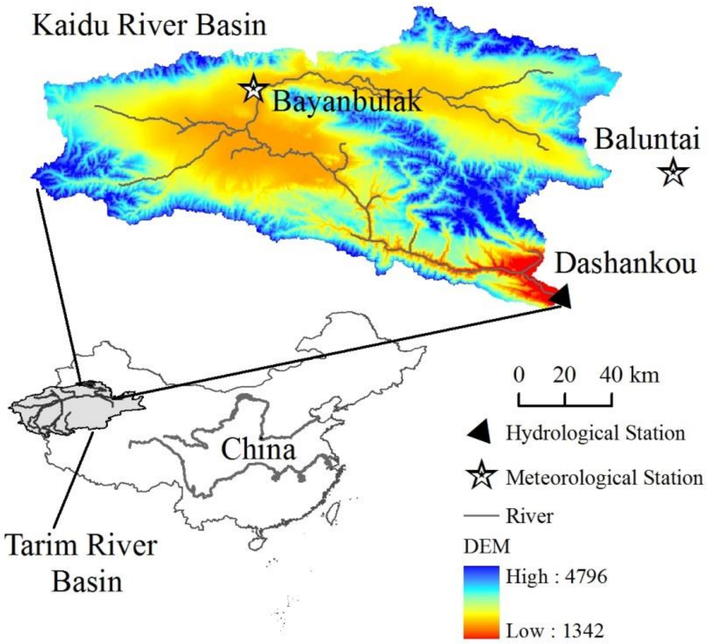

Fig. 1. Location of the study area, two meteorological stations and one hydrological station.

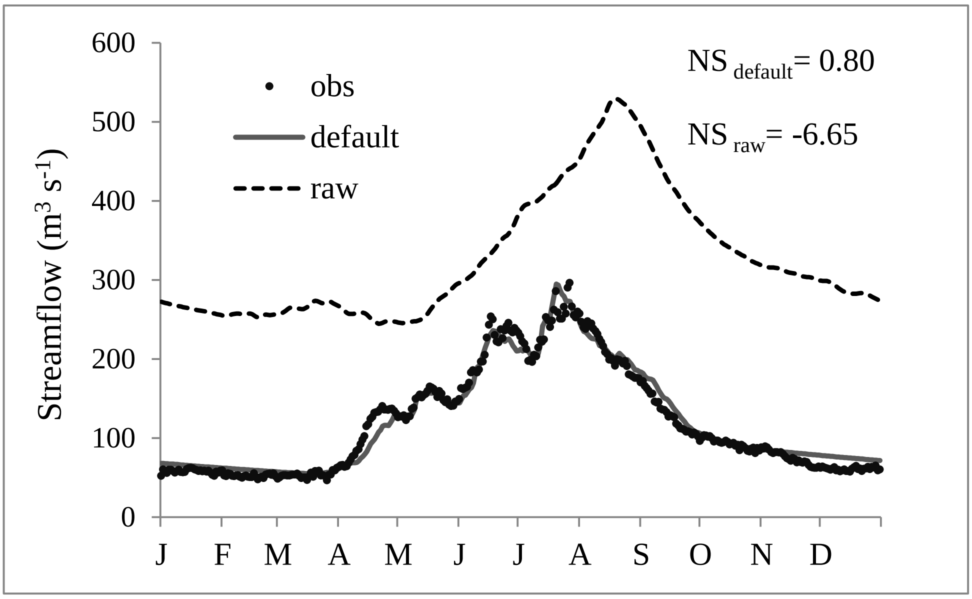

Fig. 2. Mean annual hydrographs of observed streamflow ("obs") and simulated streamflow using observed meteorological data ("default") during the period of 1986 ~ 2001 at the Dashankou Station. The simulated streamflow using raw RCM-simulated meteorological data after re-calibration ("raw") is also plotted. The NS values are for the daily continuous data and not for the mean hydrograph.

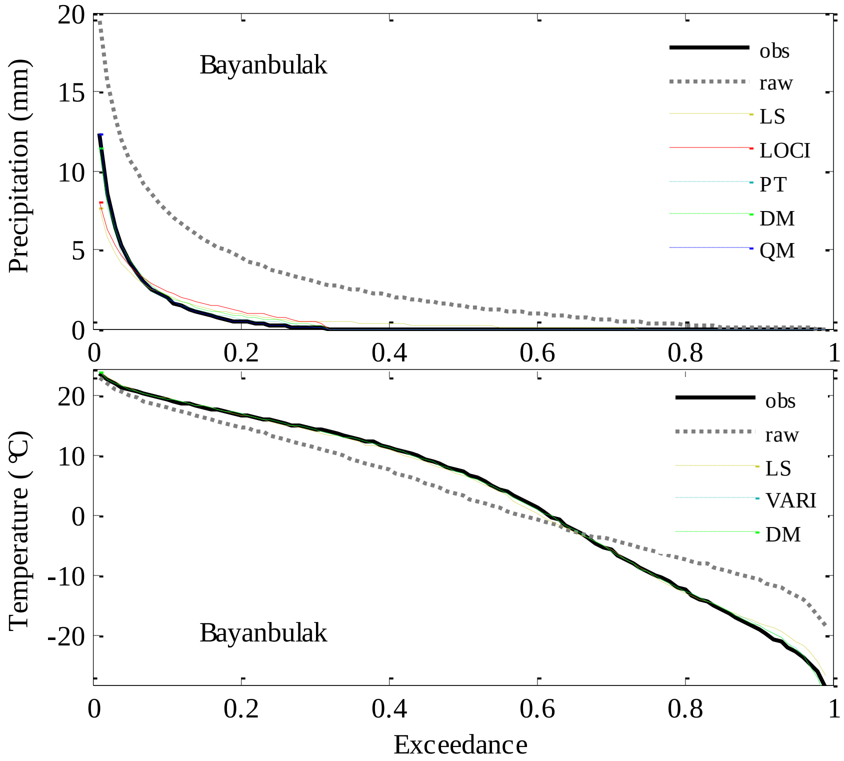

Fig. 3. Exceedance probabilities of the observed ("obs"), raw, and bias-corrected precipitation (top) and temperature (bottom) at the Bayanbulak Station.

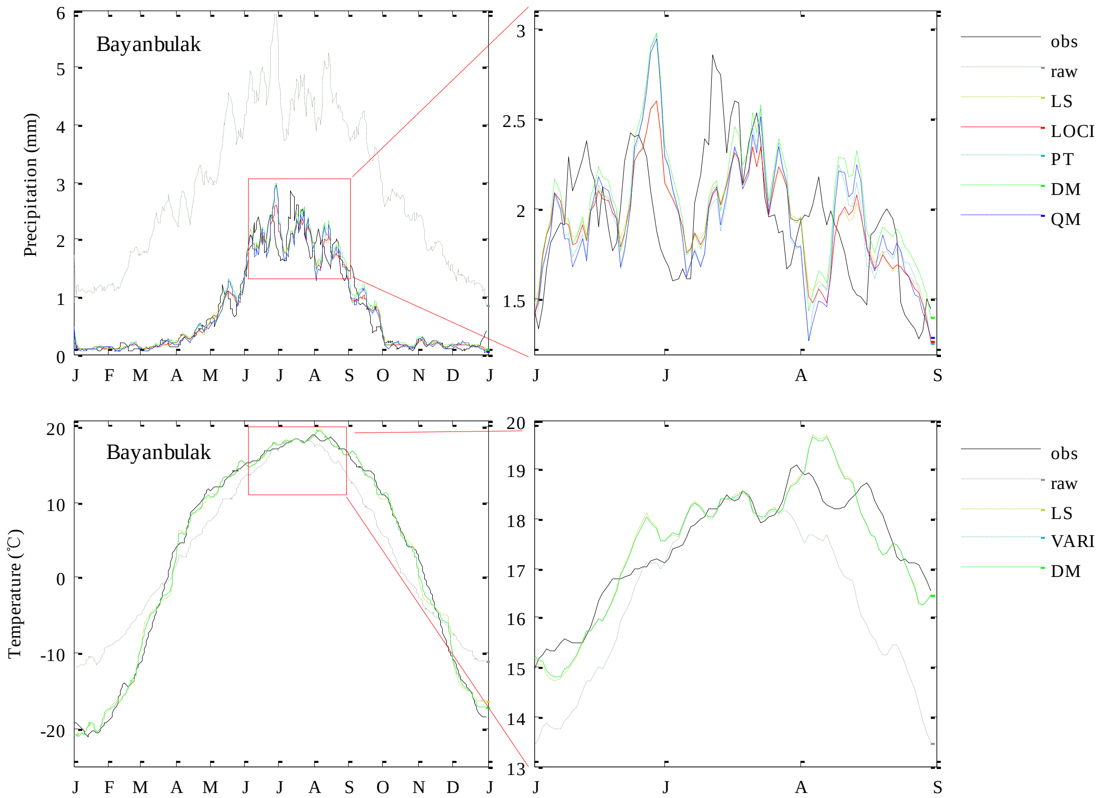

Fig. 4. Average precipitation and temperature hydrographs of observed ("obs"), raw RCM simulated ("raw"), and bias corrected values at Bayanbulak Station, which were smoothed with 7-day moving average method. The precipitation and temperature during May to August is amplified to inspect the performance of each correction method.

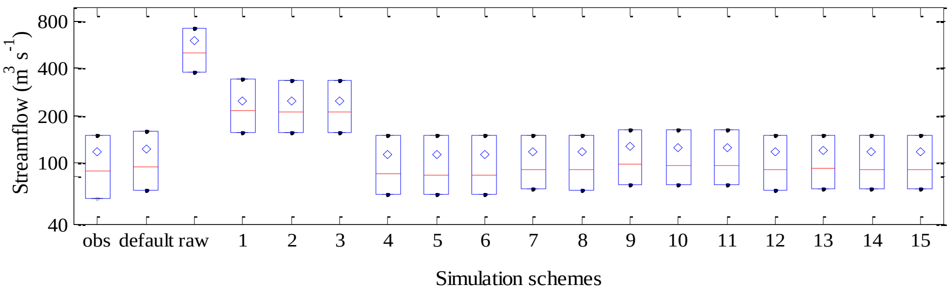

Fig. 5. Box plots of observed ("obs") and simulated daily streamflows using observed ("default"), raw RCM simulated ("raw") and corrected meteorological data (numbers from 1 to 15; see Table 3 for setup of these 15 simulations). Solid boxes signify values from 1st to 3rd quantile while the median value is shown in the interior of the box, and the mean values are shown with diamonds.

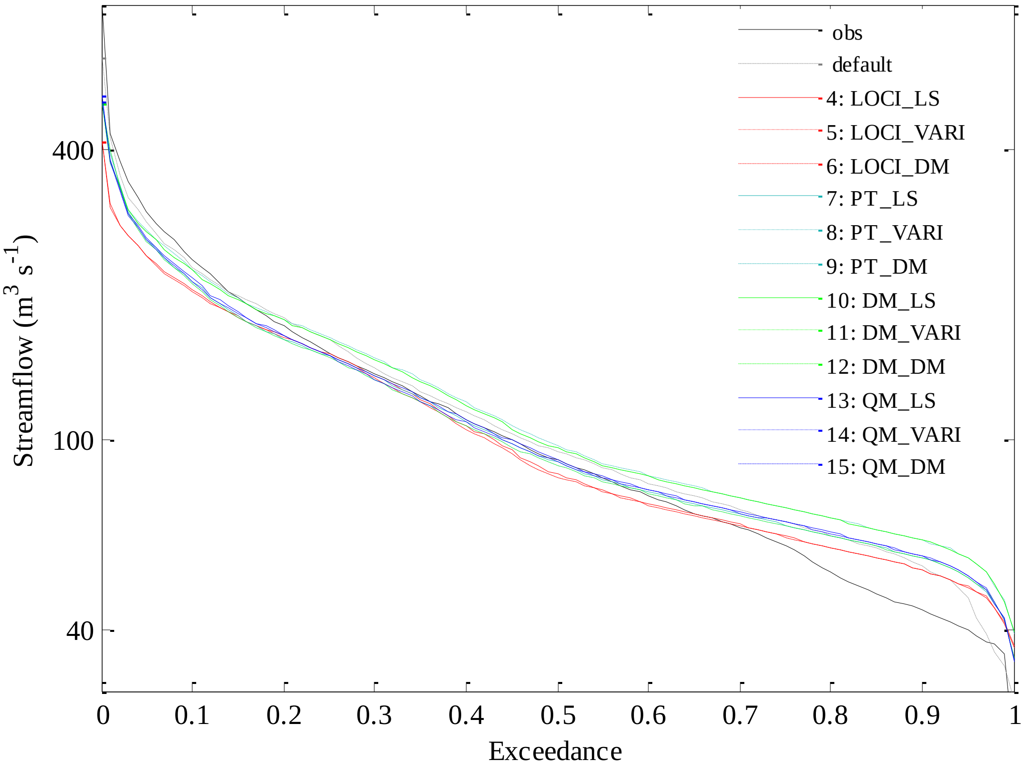

Fig. 6. Exceedance probability curves of observed ("obs") and simulated streamflow driven by observed ("default"), and bias-corrected meteorological data (numbers from 4 to 15; also see Table 3 for detail setup of these 12 simulations) For plotting purpose, simulations "raw" and 1 to 3 are not shown.

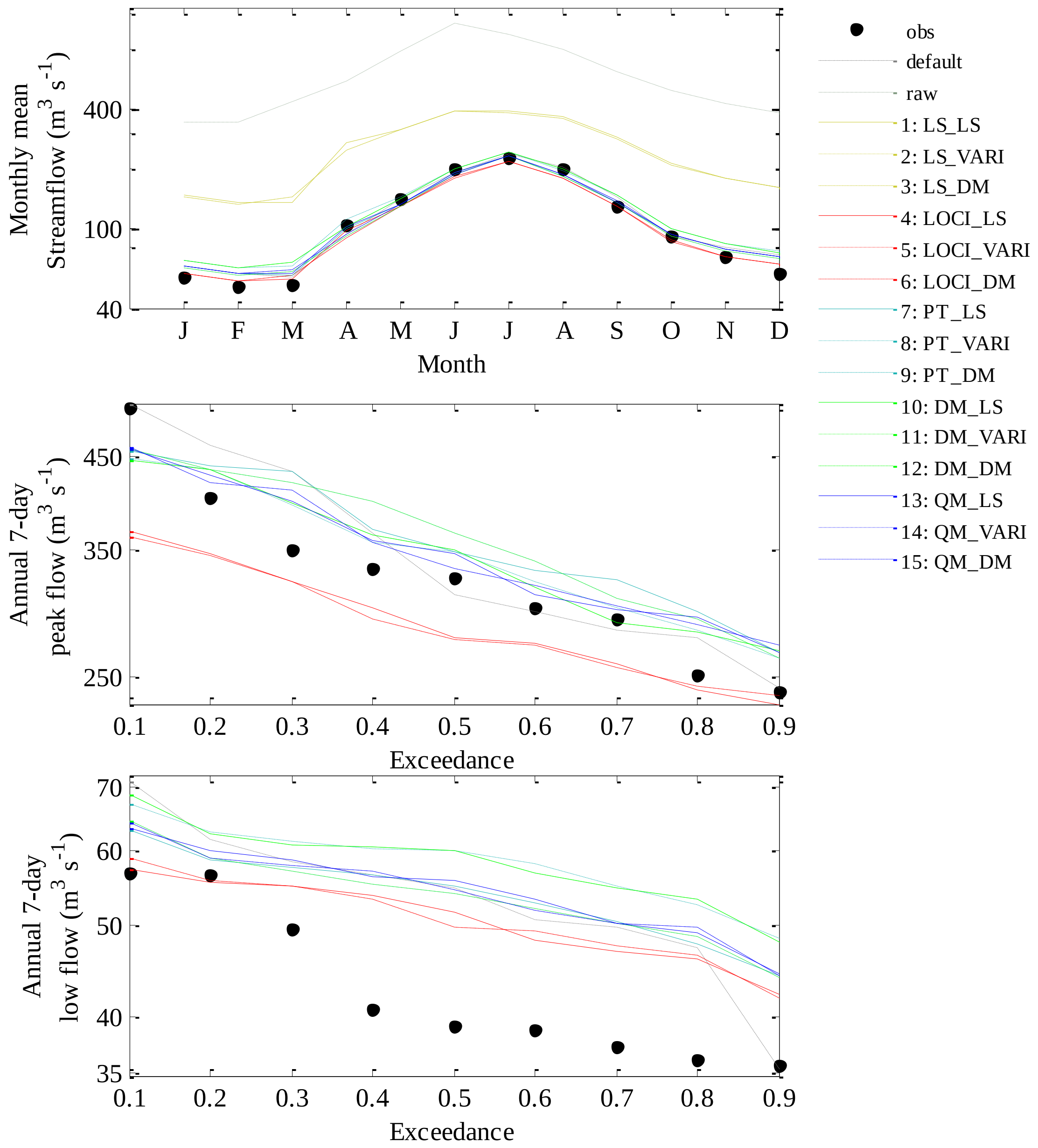

Fig. 7. Monthly mean streamflow (top) and exceedance probability curves of annual 7-day peak flow (middle) and annual 7-day low flow (bottom) during 1986 ~ 2001 in the Kaidu River Basin. The observation ("obs"), and simulated streamflows using observed ("default"), raw RCM-simulated ("raw") and bias-corrected (numbers from 1 to 15; also see Table 3 for detail setup of these 15 simulations) meteorological data are also shown in the monthly mean plot. For peak flow and low flow, the raw and simulations 1 to 3 are not shown as they are heavily biased.