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Precipitation ensembles conforming to natural variations derived from Regional Climate Model using a new bias correction scheme

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Abstract

This study presents a novel bias correction scheme for Regional Climate Model (RCM) precipitation ensembles. A primary advantage of using model ensembles for climate change impact studies is that the uncertainties associated with the systematic error can be quantified through the ensemble spread. Currently, however, most of the conventional bias correction methods adjust all the ensemble members to one reference observation. As a result, the ensemble spread is degraded during bias correction. Since the observation is only one case of many possible realizations due to the climate natural variability, bias correction scheme should preserve ensemble spread within the bounds of natural variability (i.e. sampling uncertainty). To demonstrate the proposed methodology, an application to the Thorverton catchment in the southwest of England is presented. For the ensemble, 11-members from the Hadley Centre Regional Climate Model (HadRM3-PPE) Data are used and monthly bias correction has been done for the baseline time period from 1961 to 1990. In the typical conventional method, monthly mean precipitation of each of the ensemble members are nearly identical to the observation, i.e. the ensemble spread is removed. In contrast, the proposed method corrects the biases while maintain ensemble spread within the natural variability of observations.

1 Introduction

The growing evidence of global warming is clear in the past century (Stocker et al., 2013). Therefore, future projections of climate that incorporate the effects of an underlying changing climate are of great importance, particularly because of mitigation and adaptation planning's reliance on accurate projections. Interest in the impacts of climate change is increasing from water resources managers in the context of the hydrological cycle and water resources (Bates et al., 2008; Arnell et al., 2001). Global Climate Models (GCMs) are usually used for the projection of future climate

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and the accuracy of GCMs has been enhanced in simulating large scales recently. Nevertheless, GCMs have difficulties in providing reliable climate data at local scale due to the coarse resolution (100–250 km) (Maraun et al., 2010). Therefore, for the regional impact studies Regional Climate Models (RCMs) have been widely used which are compatible to the catchment scales (25–50 km).

Although RCMs produce more reliable information than GCMs at a regional scale, the hydrological variables from RCMs still cannot be used directly in hydrological models because of the systematic errors (i.e., biases) (Chen et al., 2011b; Feddersen and Andersen, 2005). Therefore, for hydrological impact studies, post processing of the model outputs is normally needed to reduce biases (Chen et al., 2013). Research has shown that systematic model errors of RCMs are due to imperfect parameterization, spatial discretisation and spatial averaging within grids (Ehret et al., 2012; Teutschbein and Seibert, 2012). Typical errors are over- or underestimation of climate variables and seasonal dependency (Kotlarski et al., 2005; Maraun et al., 2010), and relatively too many low intensity wet days compared with the observations (Ehret et al., 2012; Ines and Hansen, 2006).

Numerous studies have been done to develop and evaluate the bias correction methods (Chen et al., 2011a, b; Johnson and Sharma, 2011; Piani et al., 2010; Teutschbein and Seibert, 2012). Evaluation of different bias correction methods has been done by Teutschbein and Seibert (2012): (1) linear scaling (Lenderink et al., 2007), (2) local intensity scaling (Schmidli et al., 2006), (3) power transformation (Leander and Buishand, 2007; Leander et al., 2008) and (4) distribution mapping method (Block et al., 2009; Déqué et al., 2007; Johnson and Sharma, 2011; Piani et al., 2010; Sun et al., 2011). The linear scaling method adjusts the mean value of the model to that of the observation by applying a correction factor which is the ratio between long-term observation and model data. However, local intensity scaling method considers wet-day frequency and wet-day intensity as well as the bias in the mean. The power transformation method corrects the mean and variance of the data. The distribution mapping method fits the distribution function of the climate model data to that of the

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observation. The results showed that the distribution mapping method was the best, although all the four bias correction methods improved the raw RCM precipitation. Although the bias correction is commonly applied in climate change studies, correcting the model output towards the corresponding observation is still a controversial issue and applying bias correction could make the uncertainty range of the simulations narrow, i.e. "hides rather than reduces uncertainty" (Ehret et al., 2012).

In this study we address the issue that most conventional bias correction methods implicitly neglect the uncertainty associated with observation sampling uncertainty. We note that adjusting the statistical properties of each of the ensemble members to one observation does not preserve the spread across the ensemble members, thus negating the advantage of quantifying uncertainty through the use of ensemble spread in climate change impact studies. In general, uncertainties in climate change projections can be grouped by three main sources: boundary condition, model structure and natural variability (Hawkins and Sutton, 2009). To account for these sources of uncertainties, ensemble modelling is a generally accepted way by producing a number of simulations using multiple scenarios, different models and initial conditions (Collins et al., 2006; Good and Lowe, 2006; Meehl et al., 2005; Murphy et al., 2004; Palmer and Räisänen, 2002; Stainforth et al., 2005; Tebaldi et al., 2006; Webb et al., 2006; Weisheimer and Palmer, 2005) which are possible due to increase in data availability through high-performance computing systems. There are two approaches for ensemble schemes in the context of model uncertainty. The first is multi-model ensembles (MMEs) method to address the structural uncertainty associated with the understanding and parameterization of the GCMs. The second is the perturbed-physics ensembles (PPEs) method which is complementary to the MME approach, and is applied in the Intergovernmental Panel on Climate Change (IPCC) assessments (Meehl et al., 2007; Lemke et al., 2007; Taylor et al., 2012). However, when bias correction is applied to the ensemble of the GCM/RCM scenario simulation, the advantage of ensemble in representing the uncertainty is often negated. The statistical properties of all the ensembles are usually matched to that of the observations so

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that the advantage of ensembles with respect to single models is lost. Therefore, the natural variability of the observation should be estimated first, and then the spread (i.e. variance) of the ensembles should be adjusted to not only one observation but to range of the possible observations, through incorporating sampling uncertainty. In this study we propose a new bias correction scheme which conforms to the ensemble spread. In other words, in this scheme the ensemble spread is preserved to a certain degree, after bias correction, which corresponds to the observation sampling uncertainty.

The paper is structured as follows: Sect. 2 describes the study catchment and data; in Sect. 3 the conventional bias correction method is presented. Next we show how the observation sampling uncertainty (i.e. natural variability) is estimated and how the ensembles can be evaluated. Finally the concepts of conventional and proposed bias correction methods are compared. In Sect. 4 we show the results followed by discussion and conclusions in Sect. 5.

2 Catchment and data

The Thorverton catchment is used in this study. The Thorverton has an area of 606 km^2, and is a sub-catchment of the Exe catchments. The Exe catchment is located in the southwest of England, has an area of 1530 km^2 and an average annual rainfall of 1088 mm. Figure 1 shows the overview of the Exe catchment area. Daily time series of the observed precipitation data (1961–1990) over the Thorverton catchment is obtained from the UK Met Office.

The climate data used in this study is the Hadley Centre Regional Climate Model (HadRM3-PPE) Data which was generated by a Met Office Hadley Centre. This dataset is used to dynamically downscale regional projections of the future climate from the GCM, HadCM3 (Murphy et al., 2009). It is comprised of 11 members, one unperturbed and 10 perturbed members. For the perturbation, 31 parameters are chosen from the unperturbed member which represent radiation, land surface, boundary layer, sea-ice, cloud, atmospheric dynamics and convection (Collins et al., 2011). The dataset

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provides the time series of climate data in the period 1950–2100 for historical and future medium emission scenario A1B. The temporal and spatial resolutions of HadRM3 climate data are daily and 25 km respectively. As presented in Fig. 1, the RCM grid boxes are rotated 0.22°. Here, the daily precipitation series from all 11 members are used to evaluate the ensemble and to test the proposed new bias correction scheme for the baseline period of 1961–1990. The grid is chosen to cover the study catchment.

3 Methodology

3.1 Conventional bias correction method

Bias correction has been initially proposed for calibrating seasonal GCM variables (e.g. precipitation and temperature) and later extended to the daily time scale. Each month is usually processed independently from the others, in order to correct seasonal phase errors, after modifying the wet-day frequency of the climate model precipitation on the wet-day observed frequency by applying a cut-off threshold. Compared with the observations, the climate model precipitations usually have more wet days at low precipitation. In this study the two-parameter Gamma distribution is used to fit the observed precipitation:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}; \quad x \geq 0; \quad \alpha\beta > 0 \tag{1}$$

where, Γ is the gamma function, α and β are the shape and scale parameters respectively.

For the bias correction of the daily RCM precipitation, the quantile mapping method based on the Gamma distribution which is also referred to as “probability mapping” and “distribution mapping” in the literature is applied. A schematic representation of the quantile mapping method is shown in Fig. 2 and a general process is as follows. First, before doing the bias correction, the wet-day frequencies of the observed

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precipitation and the RCM precipitation are matched by removing the RCM low precipitation. Second, Gamma distribution functions are fitted to individual months for both the observed and RCM daily precipitations for the baseline period. The cumulative probability of the RCM is calculated from the fitted Gamma distribution of the RCM-simulated precipitation. Third, the value of precipitation corresponding to the cumulative probability is found in the fitted Gamma distribution of the observation. This value is the bias corrected RCM precipitation and the equation is as follows:

$$X_{\text{cor}} = F^{-1}\left[F(X_{\text{model}}; \alpha_{\text{model}}\beta_{\text{model}}); \alpha_{\text{obs}}\beta_{\text{obs}}\right] \tag{2}$$

where, X_{cor} is the bias corrected RCM precipitation, F is Gamma cumulative distribution function (CDF), F^{-1} is inverse function of F, α is the shape parameter and β is the scale parameter. The subscripts model and obs indicate the parameters from the RCM and observed precipitation.

In this study, monthly bias correction for precipitation is completed for all months. December, which is a wet period in the study catchment, is used to illustrate the new bias correction method in more detail.

3.2 Natural variability of observation

The problem with the conventional bias correction methods is that all the ensemble members are adjusted to one observation as a reference value. As a result, the spread of ensemble which represents the uncertainty is removed after bias correction. However, due to the observational sampling uncertainty in terms of climate variability, the observation is only one case of many possible realizations. Climate natural variability is a natural fluctuation that occurs without external forcing to the climate system. To estimate the natural variability of the observed precipitation, the parameters of the Gamma distribution for December daily precipitation from 1961 to 1990 are assumed to be the true parameters. We use 100 000 sets of 30-year daily precipitation random samples from the true parameters. For each sample (i.e. 30-year daily rainfall

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simulation), we estimate a set of new Gamma parameters (i.e. shape and scale parameter). The re-estimated parameters are different to those used in simulations due to the observation sampling uncertainty. In this study, the distribution of the 100 000 sets of parameters is assumed to represent the natural variability of 30-year daily precipitation.

3.3 Evaluation of ensemble members

The ensemble members must first be evaluated to assess whether bias correction is necessary. The idea of evaluating the ensemble members is illustrated in Fig. 3. The observed daily precipitation is assumed to follow the Gamma distribution with shape and scale parameters. The distribution of the parameters can be derived from the resampling procedure as mentioned in Sect. 3.2 (Fig. 3a). Then we compare the distributions of the observation and ensemble members' parameters (Fig. 3b and c). If the parameter distribution of an ensemble member looks like Fig. 3b, the member has bias in mean and variance (in the form of a shifted and narrow parameter distribution). If the parameter distribution were biased in the mean and had a wide variance, it resemble something closer to Fig. 3c. Both of these "cases" indicate the need for bias correction. On the other hand, if the parameter distribution of an ensemble member resembled Fig. 3d (i.e. similar mean and variance of the ensemble member and empirical estimate) then bias correction is not necessary. The basic idea of the proposed bias correction is to match the shapes of parameter distribution between the observation and ensemble members so that they are similar after bias correction rather than matching point estimates of the parameters.

3.4 Comparison between the conventional and proposed bias correction schemes

A schematic representation of the conventional bias correction and the proposed bias correction methods are presented in Fig. 4. As mentioned in Sect. 3.1, the objective of

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the quantile mapping method is to match the statistical properties between observed and climate model precipitation. Figure 4a shows the PDFs of the observation and each ensemble member. In the conventional method, transfer functions are built by matching the shape and scale parameters of each ensemble member to those of the observation (Fig. 4b). Therefore, the PDFs (or CDFs) of the observation and each ensemble member becomes identical after bias correction (Fig. 4c). However, the problem of this approach is that if every ensemble member is matched to the observation through bias correction, there is no point of using the ensemble scenarios since the spread of the ensemble is removed. Hence, we propose a new scheme of bias correction. The idea is to maintain the variation of the ensemble after bias correction so that they match the variation of the population as if each member is randomly (i.e., equally likely) taken from the population. The population here is assumed to be the natural variability of the observation. Figure 4d illustrates the concept of the new bias correction method. Each member is corrected by different transfer functions but the parameters' space for the transfer functions is limited to the natural variability of the observation. As a result, the biases of 11 members are reasonably well corrected without eliminating the spread of ensemble (Fig. 4e).

A step by step summary of the procedure is presented below and in Fig. 5.

- (Step 1) Natural variability of the observation is estimated by first randomly resampling precipitation from a Gamma distribution with parameters obtained by fitting on the observed precipitation. Next, the parameters of each resampled precipitation time series are estimated, and the bivariate distribution of these parameters over all samples is established. The shaded area in Fig. 5 represents the natural variability of the observation. If the parameters of the ensemble members are in the shaded area, there is no need to do bias correction.

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- (Step 2) Normalise the parameters of the ensemble members by using the following equation.

$$x_\mathrm{N} = \frac{x - \mu_x}{\sigma_x}, \qquad y_\mathrm{N} = \frac{y - \mu_y}{\sigma_y} \tag{3}$$

  where, x and y are the shape and scale parameters of the distribution of each ensemble member, μ_x, μ_y are the mean values and σ_x, σ_y are the standard deviations of parameters of all ensemble members, x_N, y_N are the normalised shape and scale parameters.

- (Step 3) De-normalize the parameters of the ensemble members by matching the mean and standard deviation to those of the observation. The equation can be expressed as follows:

$$x' = x_\mathrm{N} \cdot \sigma_\mathrm{xo} + \mu_\mathrm{xo}, \qquad y' = y_\mathrm{N} \cdot \sigma_\mathrm{yo} + \mu_\mathrm{yo} \tag{4}$$

  where, $\mu_\mathrm{xo}, \mu_\mathrm{yo}$ are the mean values and σ_xo, σ_yo are the standard deviations of the parameters of the observation, x', y' are the de-normalized shape and scale parameters.

- (Step 4) Move the centre of the de-normalized ensemble parameter sets to that of the observation parameter set, then build transfer functions for bias correction.

4 Results

The first part of this section compares the parameter distribution of the observed precipitation and bias-uncorrected precipitation. The next part shows the result of the conventional bias correction followed by the proposed bias correction method. In each part, PDFs of precipitation, shape and scale parameter space and PDFs of shape

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and scale parameters have been evaluated and compared. Finally, the monthly mean precipitation for the time period from 1961 to 1990 is compared among the observation, uncorrected ensemble members and corrected ensemble members by applying both the conventional and new methods.

4.1 Parameter distribution of the observed and RCM precipitation

Before correcting the bias of each member, we compare the statistical properties with the observed precipitation. Figure 6a shows the PDFs of the observed and simulated precipitation. The parameter space (i.e. shape vs. scale parameter) of these distributions is plotted in Fig. 6b. Note again the parameter space was defined by resampling from the observation, and the distribution of 100 000 sets of parameters was assumed as the natural variability of daily precipitation as illustrated in Sect. 3.2. The red dots represent the natural variability of the observation which is estimated from the observed parameters. Most of the members' parameters are outside the boundary of the natural variability. Figure 6c and d compare the distribution of each parameter. The distribution of the parameter for the combined ensemble shows large biases of the mean and variance. Since both the mean and variance of 11-members are quite different to those of the observation, it is apparent that the bias correction is needed.

4.2 Conventional bias correction

Figure 7 illustrates the result of the conventional bias correction method. As expected the PDFs of the observation and 11-member ensemble are nearly identical to one another (Fig. 7a) and the parameters of the corrected precipitation are all in the centre of the parameter space of the observation (Fig. 7b and c). As previously noted, the spread of the ensemble under this conventional approach is greatly reduced, and in turn, the overall characteristics of hydro-climate variables are nearly identical across model runs.

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4.3 Proposed bias correction

To preserve the spread of ensemble members, a systematic modelling scheme is proposed. Figure 8a presents the PDFs of the observation, bias uncorrected members and bias corrected members. One can see that the corrected members, although they are not exactly the same as the observation, are closer to the observation than the uncorrected members. It is clearer if we see the result in terms of the parameter space (Fig. 8b). The parameters of the corrected members are all within the boundary of natural variability of the observed precipitation. In addition, the distributions of the 11-members' parameters after bias correction are quite similar to those of the observation (Fig. 8c and d). Therefore, one can assume that all ensemble members represent realistic precipitation scenarios when considering natural variability.

4.4 Comparison of bias corrected monthly mean precipitation

Figure 9 compares the result of the conventional and proposed bias correction schemes in terms of reproducing the mean precipitation. Figure 9a shows that the monthly mean precipitations of 11-members for the period 1961–1990 are quite different to that of the observation. The ensemble means are similar to the observation only in February and March. The ensemble means generally overestimate the observations from April to June and underestimate the observations from July to January. When we apply the conventional method, the corrected monthly mean precipitation of all 11-members is very similar to the observation and the spread of ensemble is almost entirely removed (Fig. 9b). Correction through the proposed method results in simulated rainfall that has reasonable means, does not have systematic bias in the mean (i.e. no consistent over- or under-estimation is not present), and represents the spread due to natural variability (Fig. 9c).

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5 Discussion and conclusions

Climate change scenarios are generated using climate models (e.g. GCMs and RCMs) and emission scenarios, and are the key information to understand future changes in hydrologic patterns. While RCMs are designed to better simulate local climate at a finer spatial and temporal scale, it has been acknowledged that bias correction for the outputs from RCMs is generally required to reduce biases due to systematic errors. An ensemble approach has previously been introduced to deal with the systematic errors (i.e. uncertainties) and to provide more relevant scenarios informed by a probability density function. However, the spread of the ensemble, with useful information to understand uncertainties, has not been properly considered in the existing bias correction scheme. In other words, all the ensembles are matched to that of the observations in terms of statistical characteristics so that the advantage of ensembles with respect to a single model output is excluded. The major contribution of this study is the proposal of a new bias correction scheme, which reasonably preserves the spread of the RCM ensemble members.

The experiment for correcting the bias of the ensemble is carried out. The idea is that in order to maintain the spread of 11-members, instead of using each transfer function for an individual member, only one transfer function from the unperturbed member is built based on the conventional method and then this transfer function is applied to the rest of the members. If only one transfer function is used for correcting the biases of 11-members, 11-members may maintain the spread after bias correction. However, if the spread is not properly preserved, the corrected ensemble will not represent the true variation of 11-members. Figure 10 shows an example of using one transfer function. The transfer function is built by matching the CDF of an unperturbed member to that of the observation and this transfer function is applied to the other 10 members. As shown in the figure, however, the spread of the 11-member parameters after bias correction is not matched by the spread of the observation. Therefore, the existing approach based on the conventional bias correction scheme generally fails to preserve the spread of ensemble.

In conclusion, each ensemble member should naturally be different to the other members due to perturbation effect but if 11 members are all matched to the observation as the conventional method, then the benefit from the spread of the ensemble is negated. Therefore, the proposed new bias correction scheme for RCM ensembles is novel and makes better use of the ensemble information. In this scheme the spread of the ensemble is maintained to a certain degree after bias correction which is compatible with natural variability (i.e. sampling uncertainty) of the observation. This is because the transfer functions are built under the assumption that the corrected members must originate from within the bounds of the natural variability of the observation.

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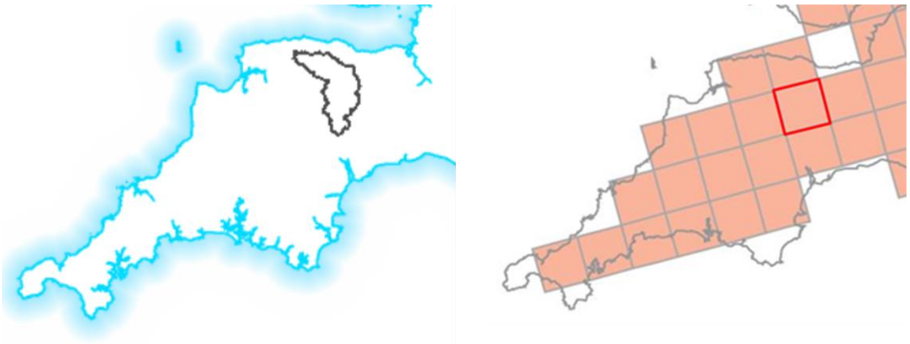

Figure 1. Location of the Thorverton catchment (left panel) and HadRM3 25 km grid boxes (right panel).

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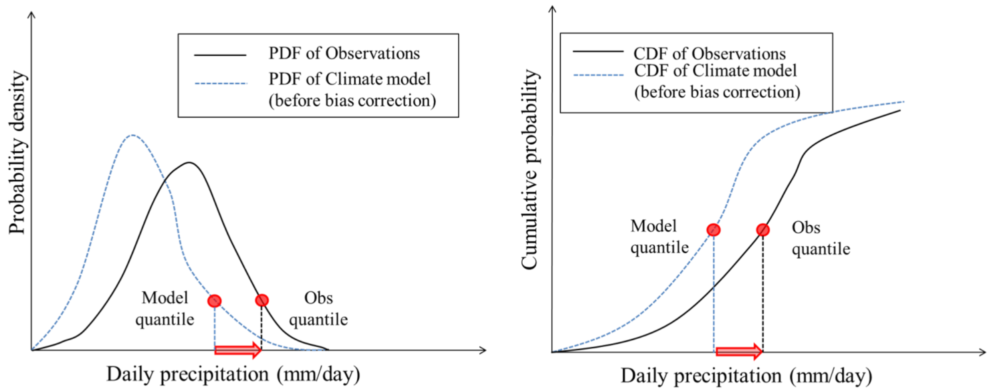

Figure 2. A schematic representation of the quantile mapping method for bias correction.

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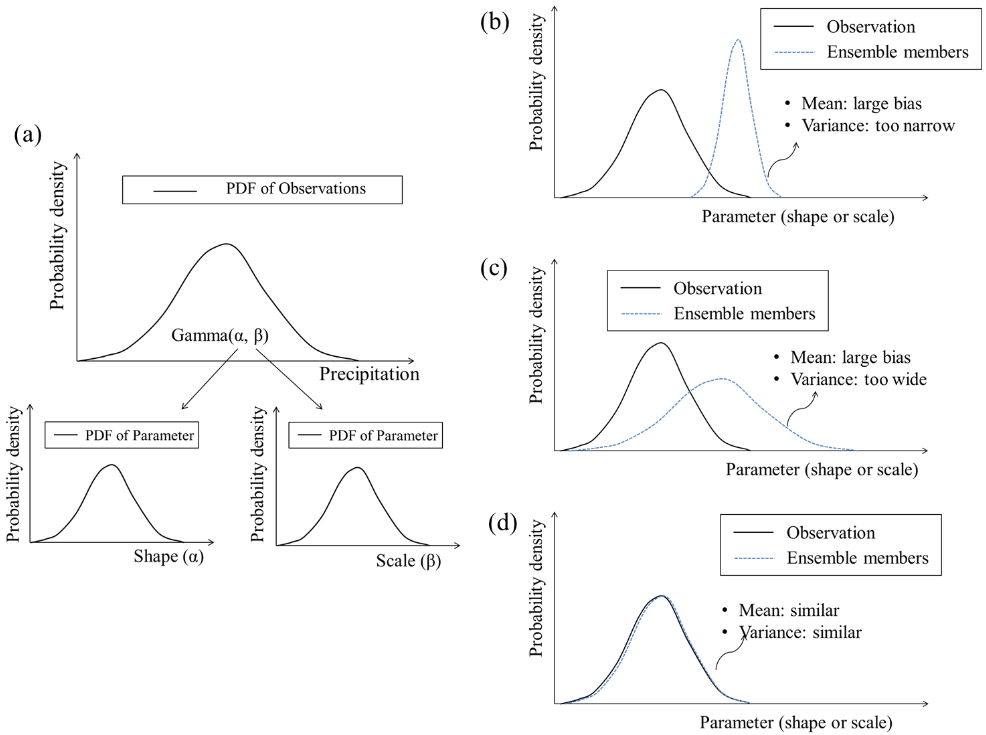

Figure 3. A schematic representation of the evaluation of ensemble members.

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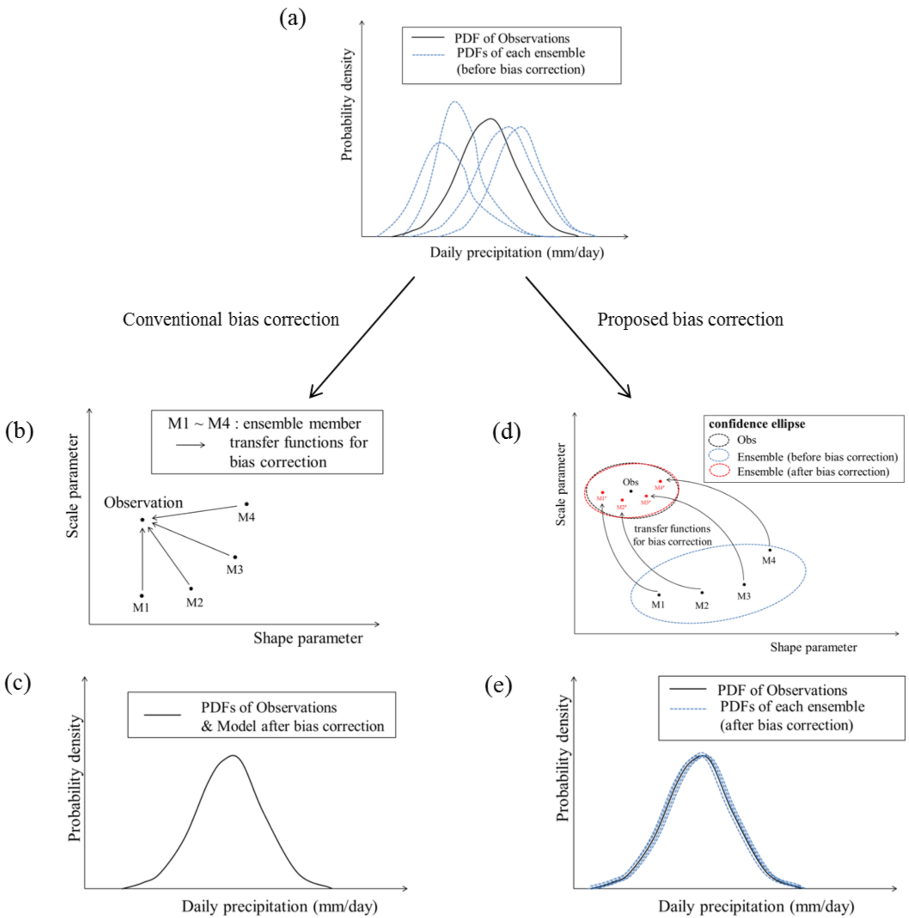

Figure 4. A schematic representation of the conventional bias correction method and the proposed bias correction method.

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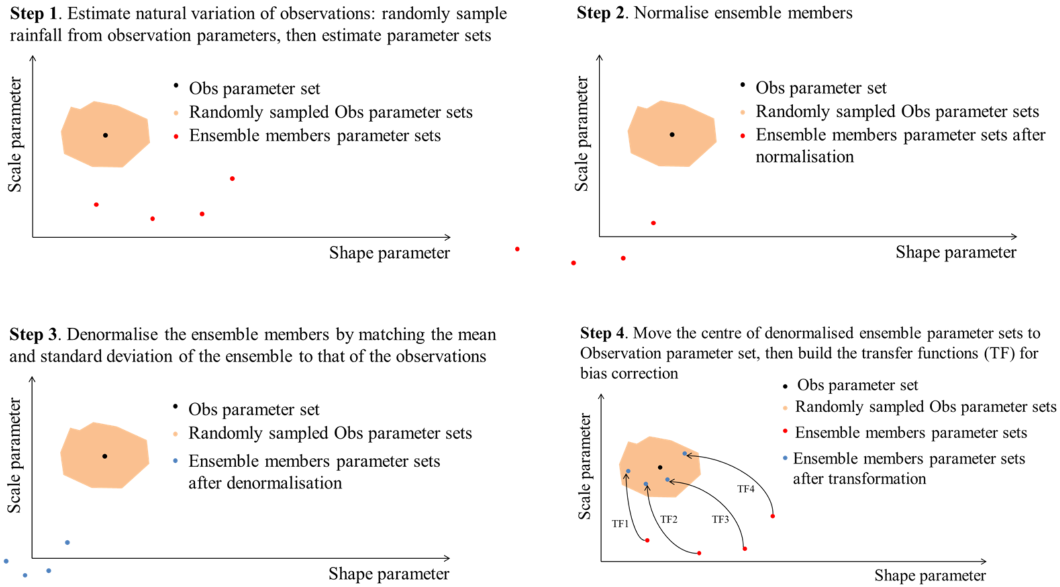

Figure 5. The four step procedure of the proposed bias correction method.

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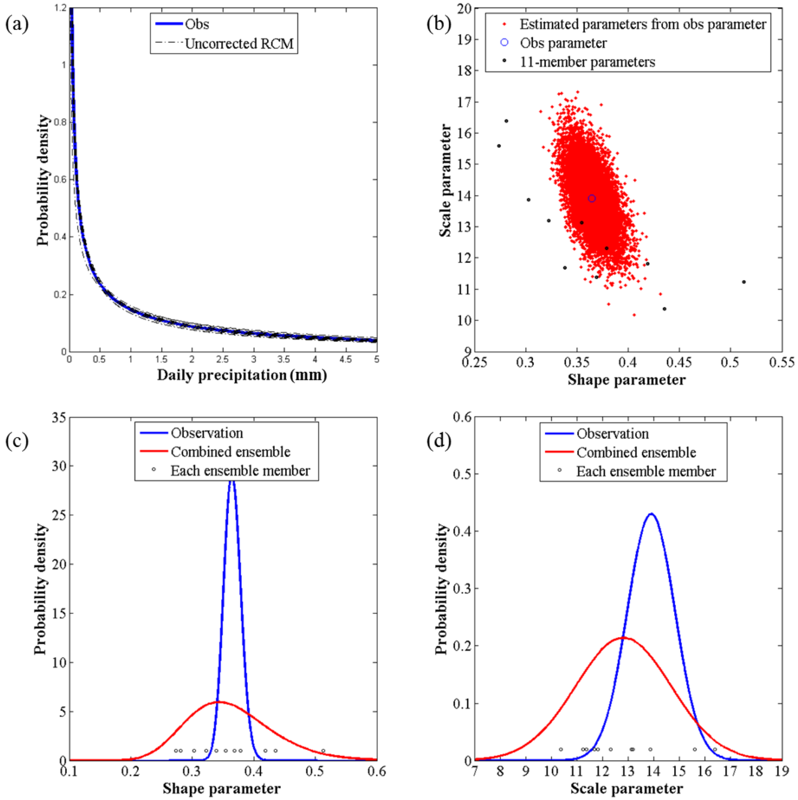

Figure 6. Parameter distributions of the observation and 11-members. **(a)** Probability density function of the observed and 11-member precipitation time series before bias correction. **(b)** Scatter plot between shape and scale parameters of the observed and bias uncorrected precipitation. **(c, d)** Probability density functions of shape and scale parameters for the observed and bias uncorrected precipitation.

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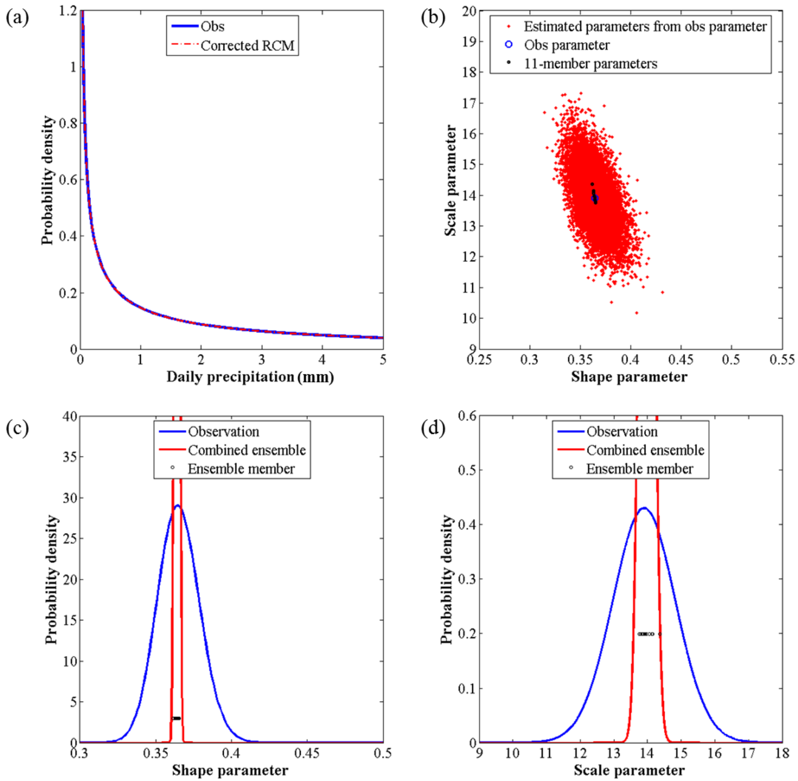

Figure 7. Results of the conventional bias correction method. **(a)** Probability density functions of the observed and simulated (i.e. 11-member) precipitation after bias correction. **(b)** Scatter plot between shape and scale parameters of the observed and bias corrected precipitation. **(c, d)** Probability density functions of shape and scale parameters of the observed and bias corrected precipitation.

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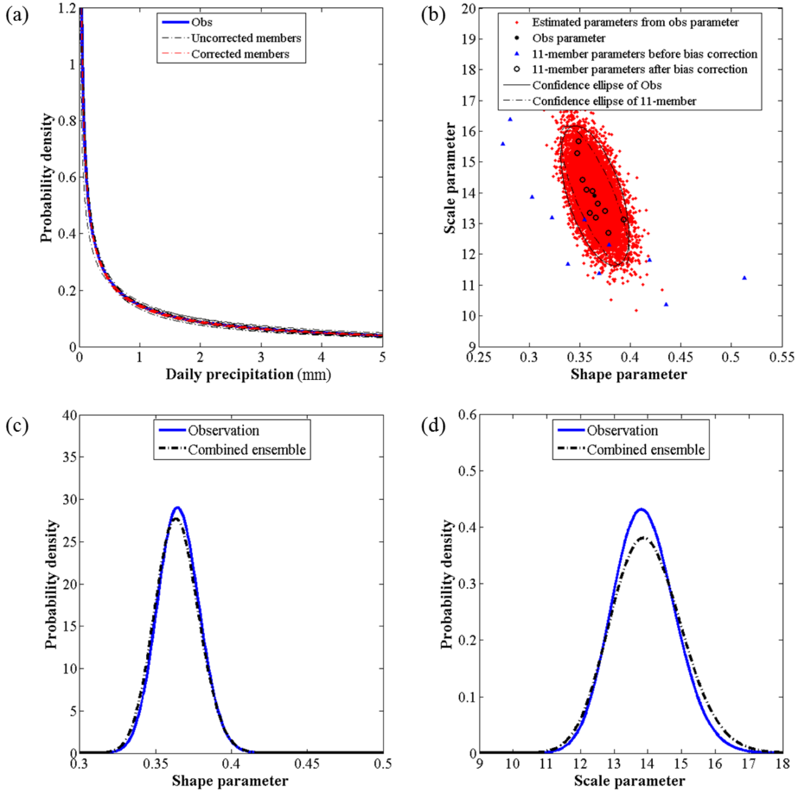

Figure 8. Results of the proposed bias correction method. **(a)** Probability density functions of the observed, bias uncorrected and bias corrected precipitation. **(b)** Scatter plot between shape and scale parameters of the observed, bias uncorrected and bias corrected precipitation. **(c, d)** Probability density functions of shape and scale parameters of the observed and bias corrected precipitation.

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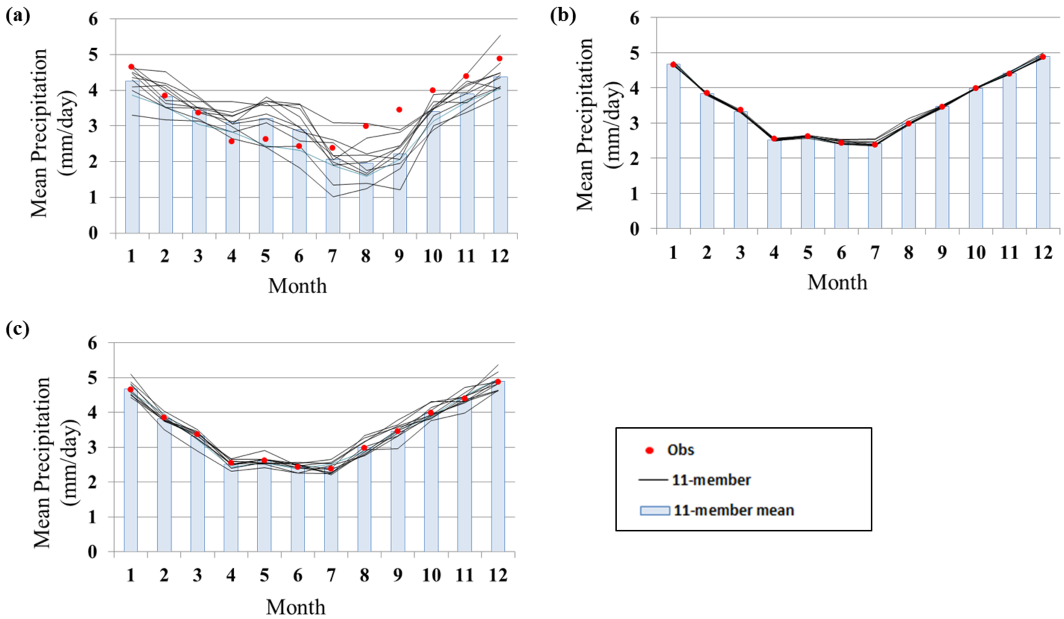

Figure 9. Monthly mean precipitation for the period 1961–1990 derived from the simulated precipitation. The mean values for the observation and 11-members are displayed as well. **(a)** Uncorrected 11-members. **(b)** Corrected 11-members by the conventional bias correction. **(c)** Corrected 11-member by the proposed bias correction.

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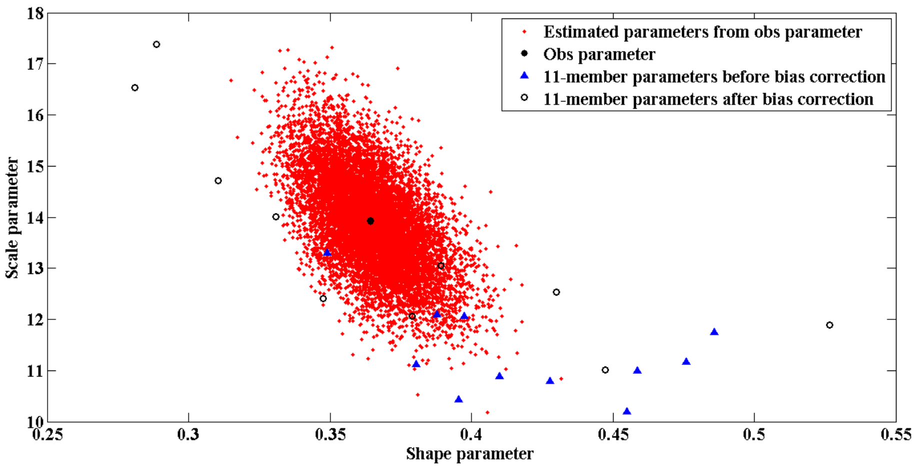

Figure 10. Result of using one transfer function for bias correction.

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