Response to the Editor's comments

Dear Editor,

We would like to thank you for the detailed and useful comments on our paper. The constructive comments have helped to improve this article considerably.

Editor (Dr. B. van den Hurk):

1. On the observational uncertainty I agree that a bootstrap method to produce distributions of the parameters of the underlying gamma-distributions is a good way to estimate this for daily data. However, although you nicely state that the observations are just a single possible realisation from a large ensemble of (likely plausible) observational records, there is no way in which you can describe observational uncertainty that is not included in the observations that you use. For instance, variability of observations on a slow time scale (decadal or centennial), or realisations of precipitation amounts with very long return times (exceeding the record length of this observation data set) cannot be estimated, but may be highly relevant. So although you rightly point at the fact that observations are uncertain dus to natural variability, you do not adequately address the time scale at which natural variability that can be quantified by your bootstrap method.

Reply:

Thanks for the useful comments. The editor's comment is very true and there is no way to describe the observational uncertainty that is not captured by the 30 years of observations. We have added the following discussion in the manuscript.

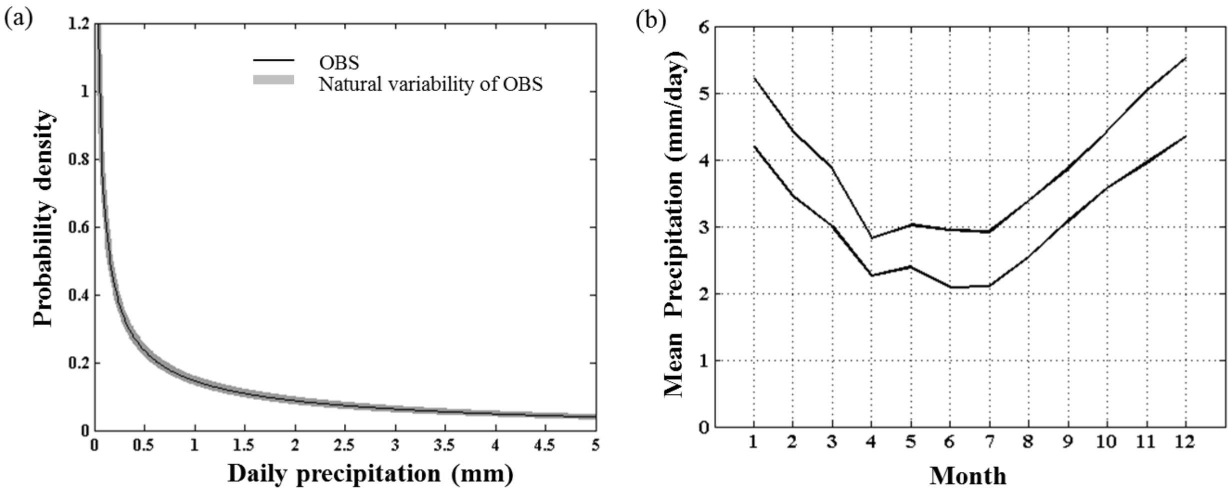
> We would like to point out some limitations of this study. (….) Second, depending on how to estimate the observational uncertainty the interpretation of Figures 13 and 14 can be different. In this study, we have used a bootstrap method to describe the observational uncertainty from 30 year of observation data. However, there is no way to describe the uncertainty that is not captured by the 30 years of observations. For instance, variability of observations on a slow time scale (decadal or centennial), or realisations of precipitation amounts with very long return periods (exceeding the record length of this observation data set) cannot be estimated, but may be highly relevant. It may well be that the ensemble is more able to capture modes of variability (both decadal oscillations and unprecedented extremes) that may not be captured by the observations. In that sense, it may be possible that the estimated spread of observational uncertainty in Figure 13 could be narrower than the true spread and the result of using one transfer function may be more realistic than that from our proposed method. Likewise, in Figure 14, it is possible that it is

not an overestimation of flood probability by the ensemble, but an underestimation by the observations. In summary, if the natural variability is fully obtainable from the observation, our proposed methodology, in theory, should work better than the conventional method. However, it should be pointed out that the natural variability may not be fully captured by the decades of observation. Therefore, further studies are needed to explore how to capture the natural variability beyond the local observation. In this regard, a simulation technique based on multiscale approaches (e.g. wavelet transform analysis and empirical mode decomposition technique) could be a way to better represent the natural variability.

2. An editorial remark related to this is that it would be very illustrative if the natural variability that your bootstrap quantifies is not only quantified in the plots showing the scale and shape parameters, but also the distribution of daily observations themselves (e.g.fig 3A, 4A and 10).

Reply:

Thanks for the useful comments. We have added the PDFs of the observed and resampled precipitation and the natural variability of monthly mean precipitation.



3. The point raised by the anonymous reviewer (and by me) that the application of a separate transfer function to every ensemble member may delete some of the variability that you want to generate with an ensemble is not satisfactorily commented. It may well be that the ensemble is much better able to capture modes of variability (both decadal oscillations and unprecedented extremes) that is not captured by the observations. In that sense your figure 13 can evenly be considered to be misleading: it is possible that it is not an overestimation of flood probability by

the ensemble, but an underestimation by the observations. Therefore I find it a bit surprising that you did not include any extreme value analysis to evaluate the effect of your bias correction.

Reply:

Thanks for the useful comments. The editor's comment is very true and we have added this issue in the manuscript. A few decades of short period observations may misrepresent the reality. The solution is either to have long term observation data which is not usually available at the study site or if there is a proxy data that could be used such as tree rings or other indirect observations. The novelty of this study is to open a view point for the hydrological community to understand that the natural variability should be considered in the bias correction of climate ensembles which is largely ignored by the community. If the natural variability is fully obtainable from the observation, the proposed methodology, in theory, should work better than the conventional method. However, it should be pointed out that the natural variability may not be fully captured by the decades of observation. Therefore, further studies are needed to explore how to capture the natural variability beyond the local observation.

Please refer to the reply to the 1st comment.

4. L28: "proposed methodology": it is very unclear at this point what this "proposed methodology" is about

Reply:

Thanks for the comment. To clarify, the "proposed methodology" has been replaced by "a new bias correction scheme conforming to RCM precipitation ensembles" in the revised manuscript.

5. Introduction: you did not follow reviewer's 2 suggestions for structuring your introduction section of the paper by starting with a discussion on possible problems of biases in practice.

Reply:

In the beginning of the introduction section, we have added the following sentence regarding the problem of bias. In addition, we have mentioned the problems of mismatching scales and systematic model errors of RCMs, which led to many developed correction approaches.

> The statistical properties of simulated precipitation are affected by bias in the mean, variance (variability) and the skewness (dry days, drizzle, inability to reproduce extreme events etc) (Baigorria et al., 2007; Leander and Buishand, 2007).

6. L65-66: “distribution mapping is the best” but also suffers from severe overfitting!

Reply: The manuscript has been revised as follows.

(Manuscript) The results have shown that the distribution mapping method is the best, although all the four bias correction methods could improve the raw RCM precipitation.

(Revised) The results have shown that all the four bias correction methods could improve the raw RCM precipitation. Among them, the distribution mapping method is the best, however it has a drawback of overfitting.

7. L88: replace “all the” by “each of the individual”

Reply: Corrected as per the suggestions.

8. Fig 2 is not very helpful: it shows the bias but not the bias correction you propose

Reply:

Thanks for the comment. Figure 2 has been inserted not to represent our proposed method but to illustrate the basic concept of the conventional quantile mapping method. To clarify we have revised the manuscript.

(Manuscript) A schematic representation of the <u>quantile mapping method adopted in this study</u> is shown in Figure 2 and a general process is described as follows.

(Revised) A schematic representation of the <u>concept of conventional quantile mapping method</u> is shown in Figure 2 and a general process is described as follows.

9. L168: unclear. I think you mean “daily bias correction is applied for each month separately”

Reply:

Yes you are right. We have corrected as per the suggestions.

10. L186: these characteristics of natural variability are NOT analysed in your sensitivity study, that only monitors the size of the bootstrap. You need to think on how these characteristics affect your methodology.

Reply:

To clarify, we have moved the paragraph of the reviewed literature (Addor and Fischer, 2015) from the Methodology section to the Introduction section since the main point of the literature is not directly related to the optimised number of resamplings in our study.

11. Fig 11 needs a better caption text.

Reply:

We have revised the caption of Figure 12 (in the revised manuscript) as follows:

Figure 12. (a) The spread of monthly mean flow simulated from the precipitation ensembles for the period 1961-1990 (5-95 percentile spread); (b) The range of monthly spread; (c) Annual average value of the spread range.

12. I think Fig 12 and its discussion needs to be moved to the results section, and should be complemented by argumentation that actually supports that the spread that you generate this way is possibly realistic

Reply: We have corrected it as per the suggestions.

13. L488: please acknowledge the reviewers.

Reply:

We have acknowledged the reviewers as follows:

We are grateful to the Editor B. van den Hurk, reviewer C. S. Photiadou and one anonymous reviewer for their valuable comments and suggestions on the manuscript.

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 realisations due to the climate natural variability, a successful bias correction scheme should preserve the ensemble spread within the bounds of its natural variability (i.e. sampling uncertainty). To demonstrate a new bias correction scheme conforming to RCM precipitation ensembles~~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 is nearly identical to the observation, i.e. the ensemble spread is removed. In contrast, the proposed method corrects the bias while maintain the ensemble spread within the natural variability of the observations.

Keywords: bias correction, RCM ensemble, spread, natural variability

1. Introduction

The growing evidence of global climate change is clear in the past century (Stocker, 2013). Therefore, future projections of climate that incorporate the effects of an underlying changing climate are of great importance, particularly because of reliance of mitigation and adaptation on realistic 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; Compagnucci et al., 2001). Global Climate Models (GCMs) are usually used for the projection of future climate and the accuracy of GCMs has been enhanced in simulating large scale global climate. Nevertheless, GCMs have difficulties in providing reliable climate data at local scales due to their coarse resolutions (100-250km) (Maraun et al., 2010). Therefore, for regional impact studies Regional Climate Models (RCMs) have been widely used which are compatible to the catchment scales (25-50km). Although RCMs provide detailed information, for hydrological application, there is still a mismatch of scales especially for meso- and small-scale catchments. In addition, ~~Although RCMs produce more reliable information than GCMs at a regional scale,~~ 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). The statistical properties of simulated precipitation are affected by bias in the mean, variance (variability) and skewness (dry days, drizzle, inability to reproduce extreme events etc) (Baigorria et al., 2007; Leander and Buishand, 2007). Therefore, for hydrological impact studies, post processing of the model outputs is normally needed to reduce biases (Chen et al., 2013). ~~(Baigorria et al., 2007; Leander and Buishand, 2007)~~Research has shown that systematic model errors of RCMs are due to imperfect parameterisation, 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 there are relatively too many low intensity wet days compared with the observations (Ehret et al., 2012; Ines and Hansen, 2006).

The errors along with the mismatching scales have caused numerous studies on developing and evaluating the ~~Numerous studies have been done to develop and evaluate the b~~bias correction methods (Chen et al., 2011a; Chen et al., 2011b; 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 the long-term observation and model data. However, the 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 observation. The results have shown that all the four bias correction methods could improve the raw RCM precipitation. Among them, the distribution mapping method is the best, however it has a drawback of overfitting.~~The results have shown that the distribution mapping method is the best, although all the four bias correction methods could improve 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 narrower, i.e. “hides rather than reduces uncertainty” (Ehret et al., 2012). In this study we address the issue which most conventional bias correction methods implicitly neglect: the uncertainty associated with the 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 (structures and parameters) 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 parameterisation 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; Solomon, 2007; Taylor et al., 2012). However, when bias correction is applied to the ensemble of the GCM/RCM scenario simulation, the advantage of the ensemble in representing the uncertainty is often negated. The statistical properties of each of the individual~~all~~ ~~the~~ ensemble members are usually matched to that of the observations so that the advantage of the ensemble with respect to a single model simulation is lost. Therefore, the natural variability of the observation should be estimated first, and then the spread (i.e. variance) of the ensemble 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. There has been relevant work recently around the influence of natural variability on bias characterisation in RCM simulations (Addor and Fischer, 2015). They show that different methods of estimating natural variability give different measures, depending on the method, season, and temporal scale of the observation record which in return influence the bias correction. Overall, they argue that observational uncertainties and natural variability need to be considered for bias correction of RCM simulations.

Another issue presented in this study is associated with how to correct the PPEs' bias to preserve the spread. Should the bias correction be applied individually for each ensemble member or applied as an ensemble? The former method is to apply different transfer functions for different ensemble members, while the latter method is to apply only one transfer function for the whole ensemble members. In stochastic hydrology, the synthetic rainfall and streamflow should have statistical properties (e.g. mean, variance, skewness, etc) similar to the real system so that they are not distinguishable between the observed data and the modelled data. In this study we have followed the same philosophy. The bias corrected rainfall ensembles should have statistical properties (in this study, the mean value and the spread of ensembles) similar to the observations. The same principle has been applied to the UKCP09 Weather Generator (Jones et al., 2009) (WG) used in the UK. The synthetic weather variables from WG have statistical properties similar to the observations since the WG is calibrated on the observations.

There are many aspects (e.g. mean, variance, skewness, autocorrelation etc) of the rainfall series which cannot be all corrected simultaneously. The way of correcting the RCM data should therefore depend on what properties are relevant to the data usage. In this study we have focused on the mean value and the spread of bias-corrected RCM precipitation.

The paper is structured as follows: Section 2 describes the study catchment and data; in Section 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 ensemble is evaluated. Finally the concepts of conventional and proposed bias correction methods are compared. In Section 4 we show the results followed by discussion and conclusions in Section 5 and Section 6.

2. Catchment and data

The Thorverton catchment is used as the case study site. It has an area of 606 km^2, and is a sub-catchment of the Exe catchment. The Exe catchment is located in the southwest of England with an area of 1,530 km^2 and an average annual rainfall of 1,088 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.

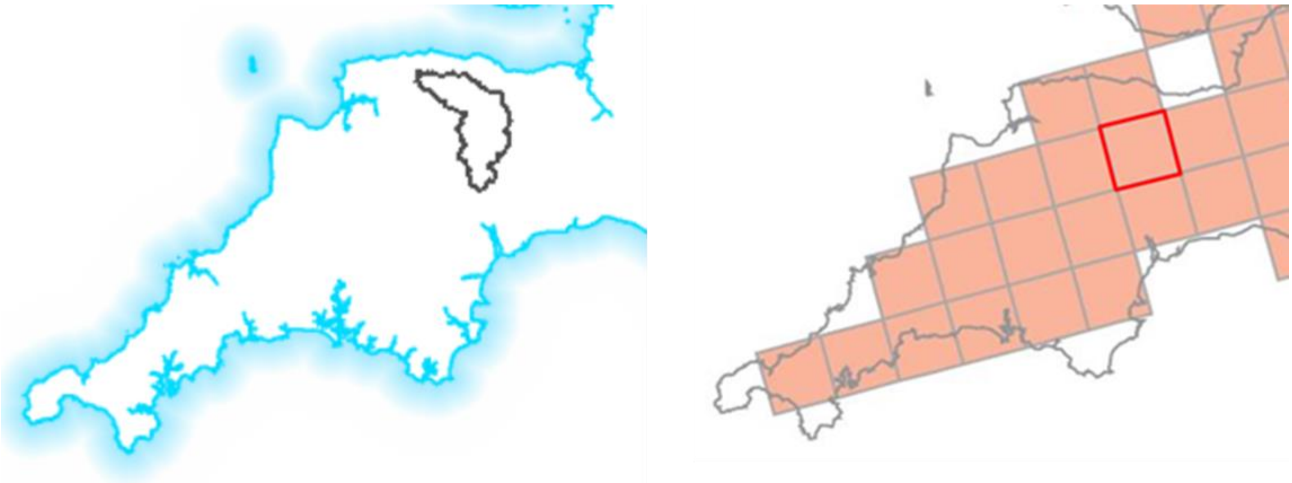


Figure 1. Location of the Thorverton catchment (the left panel) and HadRM3 25km grid boxes (the right panel). The highlighted grid box in red is selected to cover the Thorverton catchment.

The climate data used in this study is the Hadley Centre Regional Climate Model (HadRM3-PPE) Data which was generated by the 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 representing radiation, land surface, boundary layer, sea-ice, cloud, atmospheric dynamics and convection (Collins et al., 2011). The dataset provides the time series of climate data in the period 1950-2100 for the historical and future medium emission scenario A1B. The temporal and spatial resolutions of the HadRM3 climate data are daily and 25km respectively. As presented in Figure 1, the RCM grid boxes are rotated by 0.22^{o}. 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 to 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 the seasonal GCM variables (e.g. precipitation and temperature) and later extended to the daily time scale. Individual months are usually processed independently from each other, 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:

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

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 concept of conventional quantile mapping method ~~adopted in this study~~ is shown in Figure 2 and a general process is described as follows. First, before doing the bias correction, the wet-day frequencies of the observed 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 precipitation value corresponding to the cumulative probability is found in the fitted Gamma distribution of the observation. This value is the bias corrected RCM precipitation as described by Eq(2):

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

where, X_{cor} is the bias corrected RCM precipitation, F is Gamma cumulative distribution function (CDF), F^{-1} is the 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.

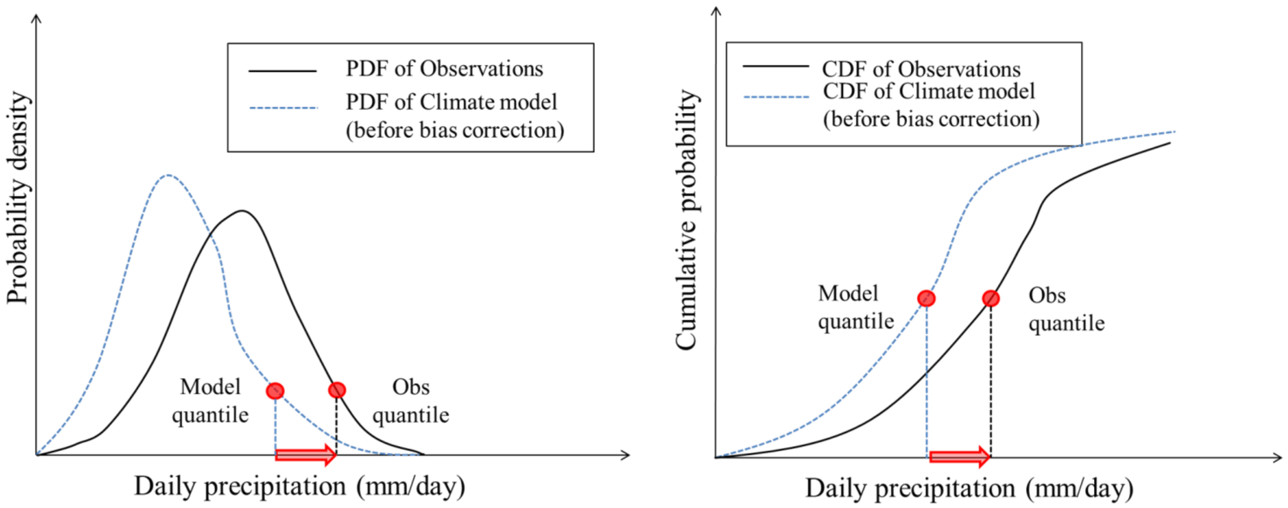


Figure 2. A schematic representation of the concept of conventional quantile mapping method for bias correction.

In this study, daily bias correction is applied for each month separately~~monthly bias correction for precipitation is carried out 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 the 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 realisations. 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 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 the simulations due to the observation sampling uncertainty. In this study, the distribution of 100,000 sets of parameters is assumed to represent the natural variability of 30-year daily precipitation.

~~There has been relevant work recently around the influence of natural variability on bias characterisation in RCM simulations (Addor and Fischer, 2015). They show that different methods of estimating natural variability give different measures, depending on the method, season, and temporal scale of the observation record which in return influence the bias correction. Overall, they argue that observational uncertainties and natural variability need to be considered for bias correction of RCM simulations.~~ In order to find the optimised number of resampling, the sensitivity analysis between the numbers of resampling and the mean value of the observed precipitation has been done. The result has shown that beyond 20,000 resamples, the mean value becomes stable. Since the running time does not take long in this study we have resampled 100,000 times which are sufficient.

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 Figure 3. The observed daily precipitation is assumed to follow the Gamma distribution defined by the shape and scale parameters. The distribution of the parameters can be derived from the resampling procedure as mentioned in Section 3.2 (Figure 3(a)). Then we compare the distributions of the observation and ensemble members' parameters (Figure 3(b) ~ (c)). If the parameter distribution of an ensemble member looks like Figure 3(b), 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 resembles something closer to Figure 3(c). Both of these "cases" indicate the need for bias correction. On the other hand, if the parameter distribution of an ensemble member resembles Figure 3(d) (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.

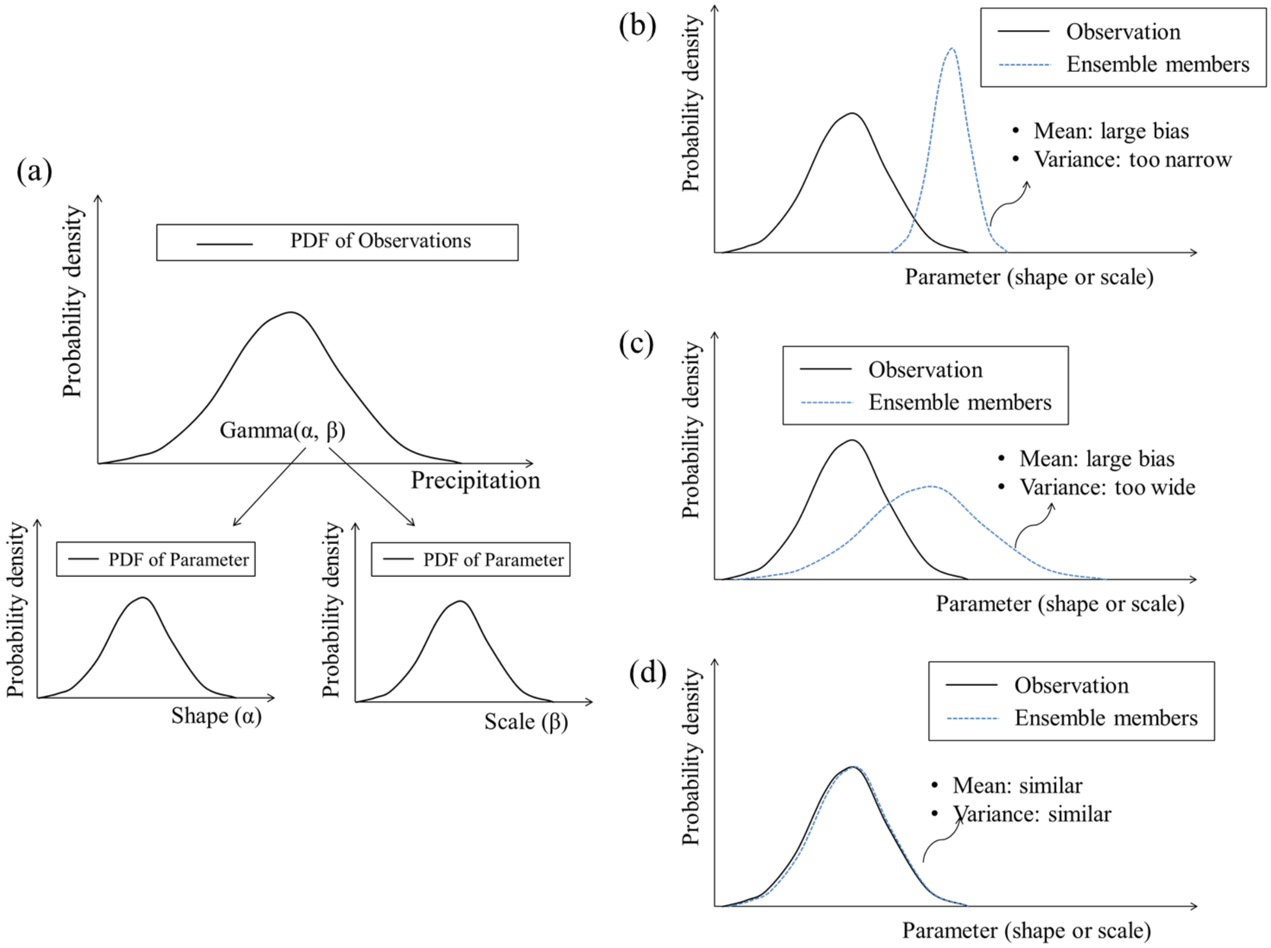


Figure 3. A schematic representation of the evaluation of ensemble members.

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 Figure 4. As mentioned in Section 3.1, the objective of the quantile mapping method is to match the statistical properties between the observed and climate model precipitation. Figure 4(a) 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 (Figure 4(b)). Therefore, the PDFs (or CDFs) of the observation and each ensemble member become identical after bias correction (Figure 4(c)). 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 for 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 4(d) 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 the ensemble (Figure 4(e)).

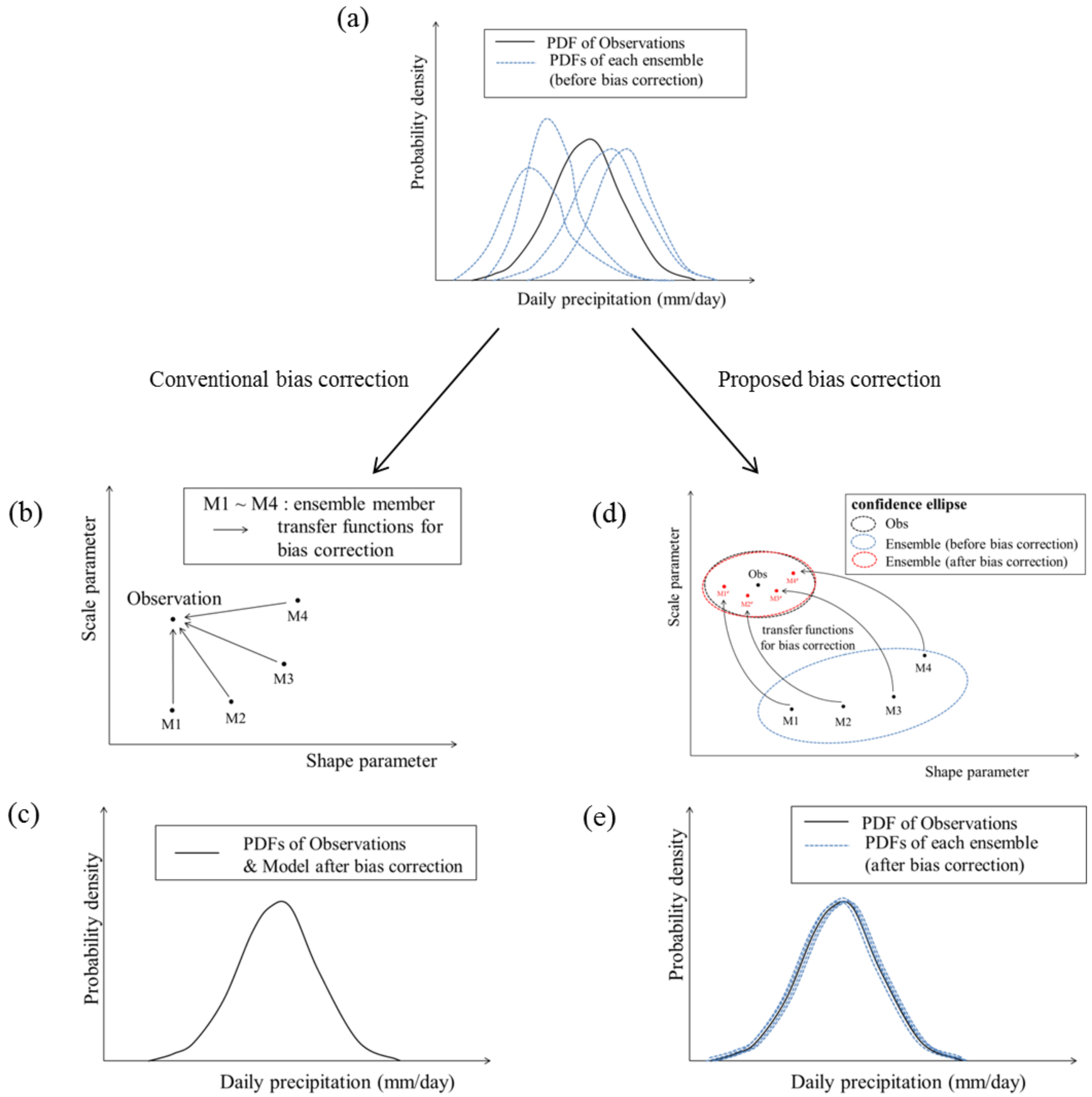


Figure 4. A schematic representation of the conventional bias correction method and the proposed bias correction method

A step by step summary of the proposed procedure is presented as follows and in Figure 5.

- (Step 1) Natural variability of the observation is estimated by first randomly resampling precipitation from a Gamma distribution with parameters obtained by fitting the observed precipitation. Next, the parameters of each resampled precipitation time series are estimated, and the bivariate distribution of these parameters over all the samples is established. The shaded area in Figure 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.
- (Step 2) Normalise the parameters of the ensemble members using Eq(3).

$$x_N = \frac{x-\mu_x}{\sigma_x}\ , \quad y_N = \frac{y-\mu_y}{\sigma_y} \tag{3}$$

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 the parameters of all ensemble members, x_N, y_N are the normalised shape and scale parameters.

- (Step 3) De-normalise the parameters of the ensemble members by matching the mean and standard deviation to those of the observation as shown in Eq(4).

$$x' = x_N \cdot \sigma_{xo} + \mu_{xo}\ , \quad y' = y_N \cdot \sigma_{yo} + \mu_{yo} \tag{4}$$

where, μ_{xo}, μ_{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) In Step 3, the coordinate of the centre of the denormalised ensemble parameter sets is (0, 0). This coordinate is shifted to that of the observation (i.e. black dot in Figure 5 Step 4), which results in the ensemble members' parameter sets to fall into the boundary of the natural variation of the observations. From this, transfer functions for the bias correction can be built.

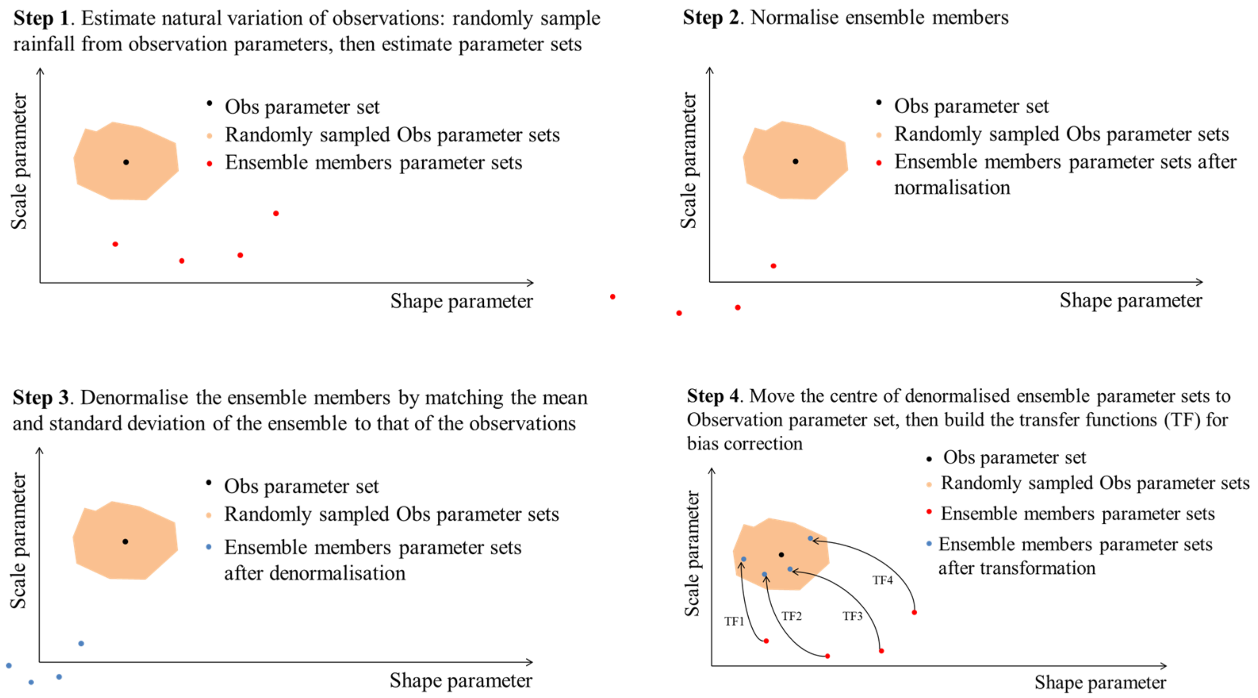


Figure 5. The four step procedure of the proposed bias correction method.

3.5 Hydrological application

To investigate the impact of different bias correction schemes on flow, we have used a conceptual rainfall-runoff model called IHACRES (Jakeman and Hornberger, 1993). This model has been widely applied to a variety of catchments for hydrological analysis and climate impact studies (Jakeman et al., 1993; Kim and Lee, 2014; Letcher et al., 2001; Littlewood, 1999). The model is composed of a non-linear module and a linear module as shown in Figure 6 and the model parameters are listed in Table 1. A non-linear module converts total rainfall to effective rainfall which is calculated from Eq(5).

$$U_k = [C(\emptyset_k - l)]^p r_k \tag{5}$$

where, r_k is the observed rainfall, C is the mass balance, l is the soil moisture index threshold and p is the power on soil moisture respectively. The soil moisture ($\emptyset_k$) is calculated from:

$$\emptyset_k = r_k + (1 - \frac{1}{\tau_k})\emptyset_{k-1} \tag{6}$$

where, τ_k is the drying rate given by:

$$\tau_k = \tau_w \exp[0.062 f(t_r - t_k)] \tag{7}$$

where, τ_w is the drying rate at the reference temperature, f is the temperature modulation, t_r is the reference temperature, and t_k is the observed temperature. A linear module assumes that there is a linear relationship between the effective rainfall and flow. Two components in this module, quick flow and slow flow, can be connected in parallel or in series. In this study two parallel storages in the linear module are used because such a combination reflects the catchment conditions and the streamflow (x_k) at time step k is defined by the following equations:

$$x_k = x_k^{(q)} + x_k^{(s)} \tag{8}$$

$$x_k^{(q)} = \beta_q U_k - \alpha_q x_{k-1}^{(q)} \tag{9}$$

$$x_k^{(s)} = \beta_s U_k - \alpha_s x_{k-1}^{(s)} \tag{10}$$

where, $x_k^{(q)}$ and $x_k^{(s)}$ are quick flow and slow flow respectively, and α and β are recession rate and peak response respectively. The relative volumes of quick flow and slow flow can be calculated from:

$$V_q = 1 - V_s = \frac{\beta_q}{1+\alpha_q} = 1 - \frac{\beta_s}{1+\alpha_s} \tag{11}$$

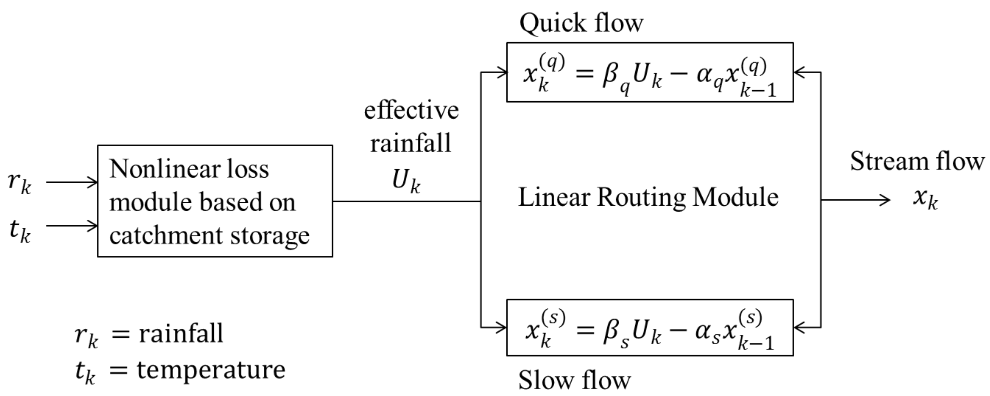


Figure 6. Structure of the IHACRES model.

Table 1. Parameters in the IHACRES model

Module	Parameter	Description
Non-linear	c	Mass balance
	τ_w	Reference drying rate
	f	Temperature modulation of drying rate
Linear	α_q, α_s,	Quick and slow flow recession rate
	β_q, β_s	Fractions of effective rainfall for peak response
	τ_s	Slow flow recession time constant, $\tau_s = -\Delta/\ln(-\alpha_s)$

τ_q	Quick flow recession time constant, $\tau_q = -\Delta/\ln(-\alpha_q)$

The hydrological application has been done as follows. First, the model parameters have been optimised with the use of the observed daily precipitation, temperature and flow data.

Second, the observed precipitation and the two different bias corrected precipitation data from the conventional and proposed bias correction methods are randomly resampled to estimate the spread of the simulated flow ensembles. Third, the optimised parameters and the precipitation time series are then used to simulate daily flow ensembles. Finally, from this daily simulated flow data, thirty-year mean monthly flow has been estimated since the bias correction has been done on monthly basis, and then compared under different bias correction schemes.

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 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 7(a) shows the PDFs of the observed and simulated precipitation. The parameter space (i.e. shape vs scale parameter) of these distributions is plotted in Figure 7(b). Note again the parameter space is defined by resampling from the observation, and the distribution of 100,000 sets of parameters is assumed as the natural variability of daily precipitation as illustrated in section 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 7(c) 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 bias correction is needed.

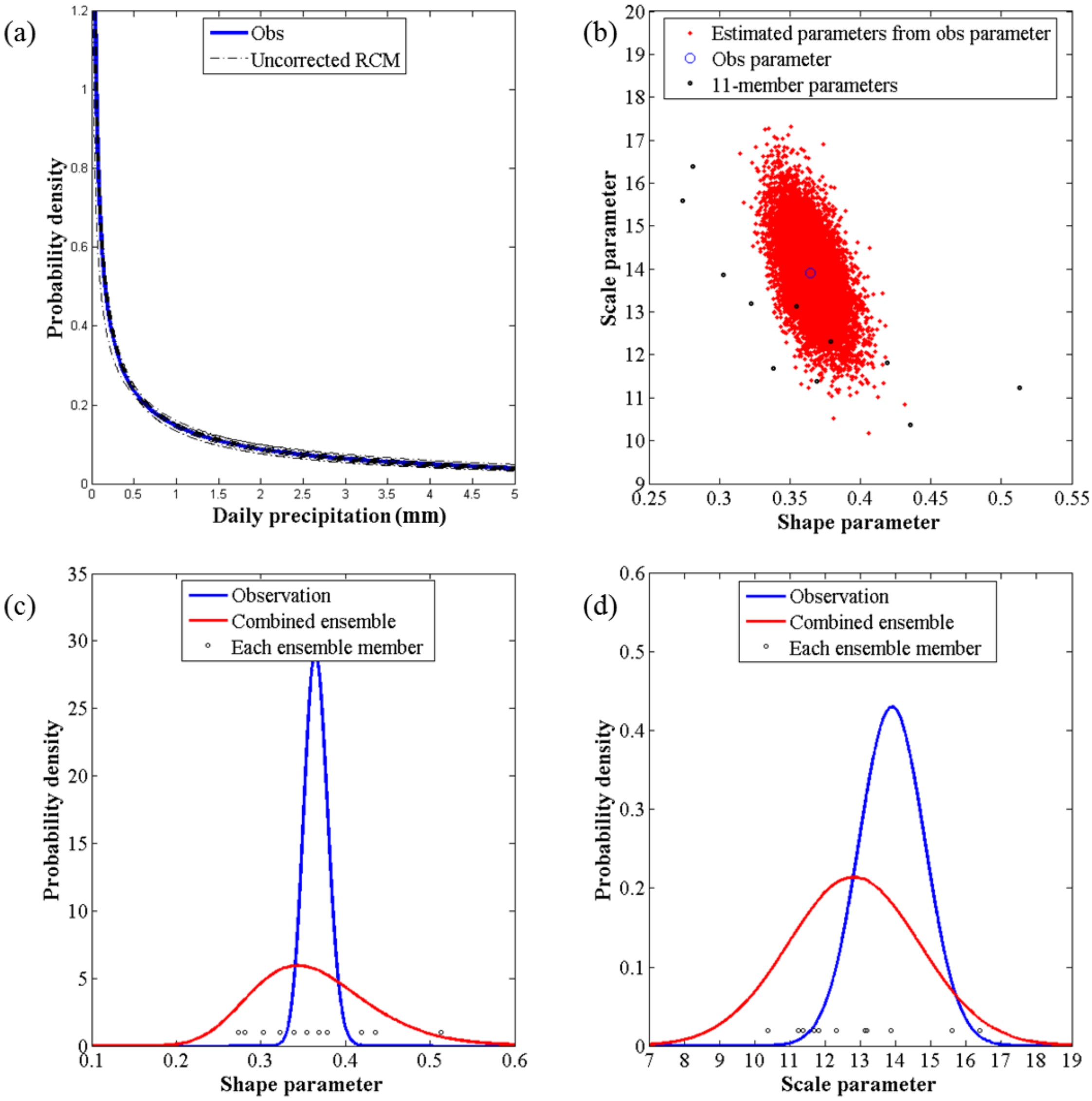


Figure 7. Parameter distributions of the observation and 11-members: (a) Probability density function of the observed and 11-member precipitation time series before bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias uncorrected precipitation; (c) - (d) Probability density functions of shape and scale parameters for the observed and bias uncorrected precipitation.

Figure 8(a) presents the PDFs of the observed precipitation and the resampled precipitation which represents the natural variability of the observation. Figure 8(b) shows the natural variability of monthly mean precipitation which has been estimated from the resampled precipitation.

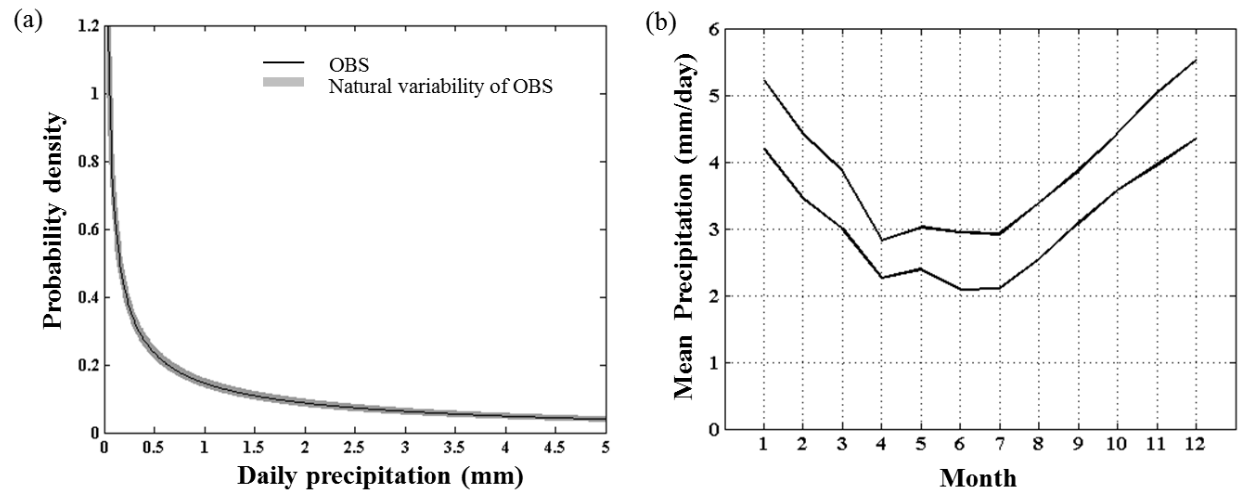


Figure 8. (a) PDFs of the observed precipitation and the resampled precipitation; (b) Natural variability of monthly mean precipitation.

4.2 Conventional bias correction

Figure 9~~8~~ 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 (Figure 9~~8~~(a)) and the parameters of the corrected precipitation are all in the centre of the parameter space of the observation (Figure ~~8~~9(b), (c) and (d)). 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 different model runs.

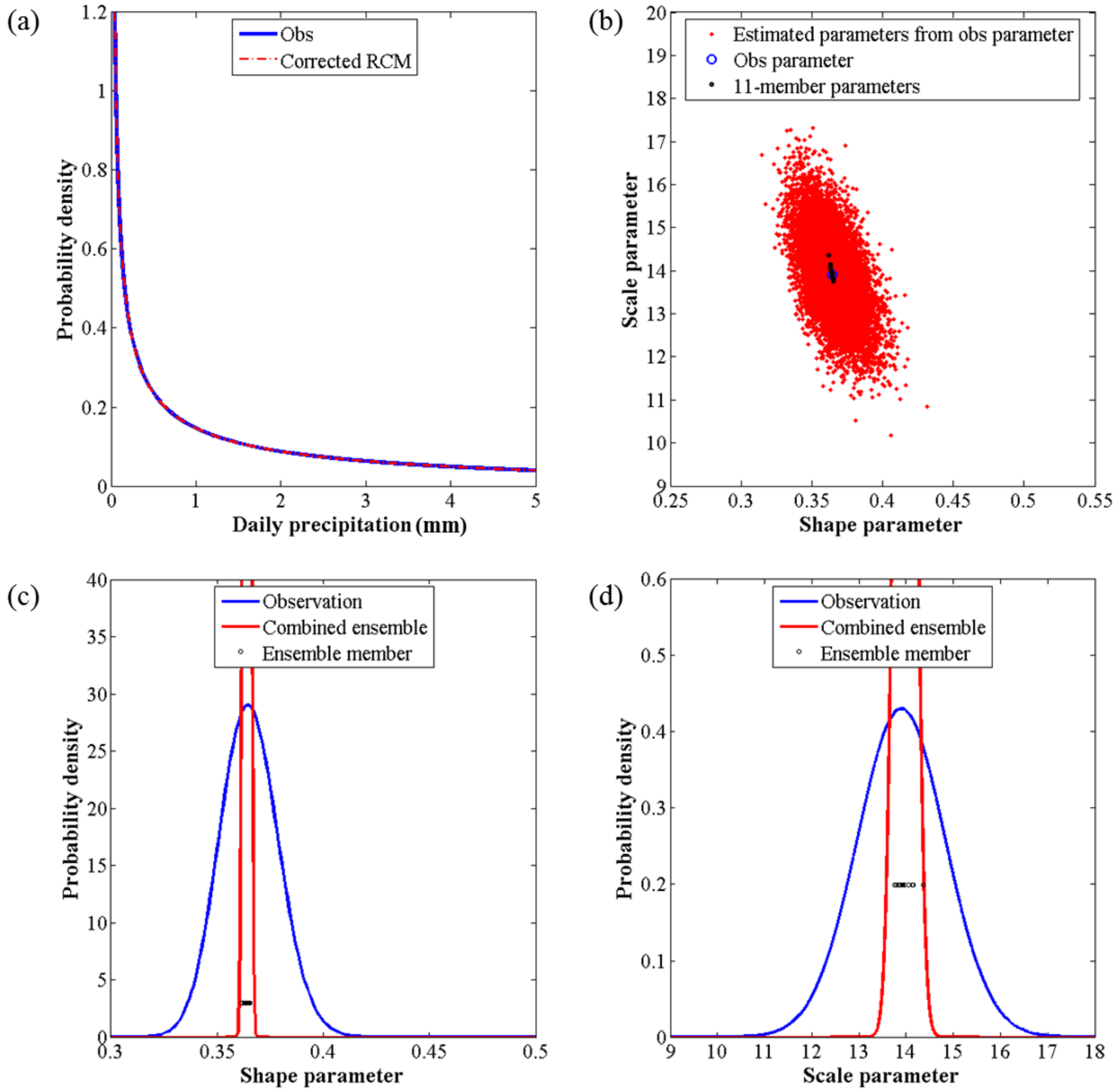


Figure 9~~8~~. Results of the conventional bias correction method: (a) Probability density functions of the observed and simulated (i.e. 11-member) precipitation after bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias corrected precipitation; (c)-(d) Probability density functions of the shape and scale parameters of the observed and bias corrected precipitation.

4.3 Proposed bias correction

To preserve the spread of the ensemble members, a systematic modelling scheme is proposed. Figure 10~~9~~(a) 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 (Figure 10~~9~~(b)). The parameters of the corrected members are all within the boundary of the 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 (Figure 10~~9~~(c) and (d)). Therefore, one can assume that all ensemble members represent realistic precipitation scenarios when the natural variability is considered.

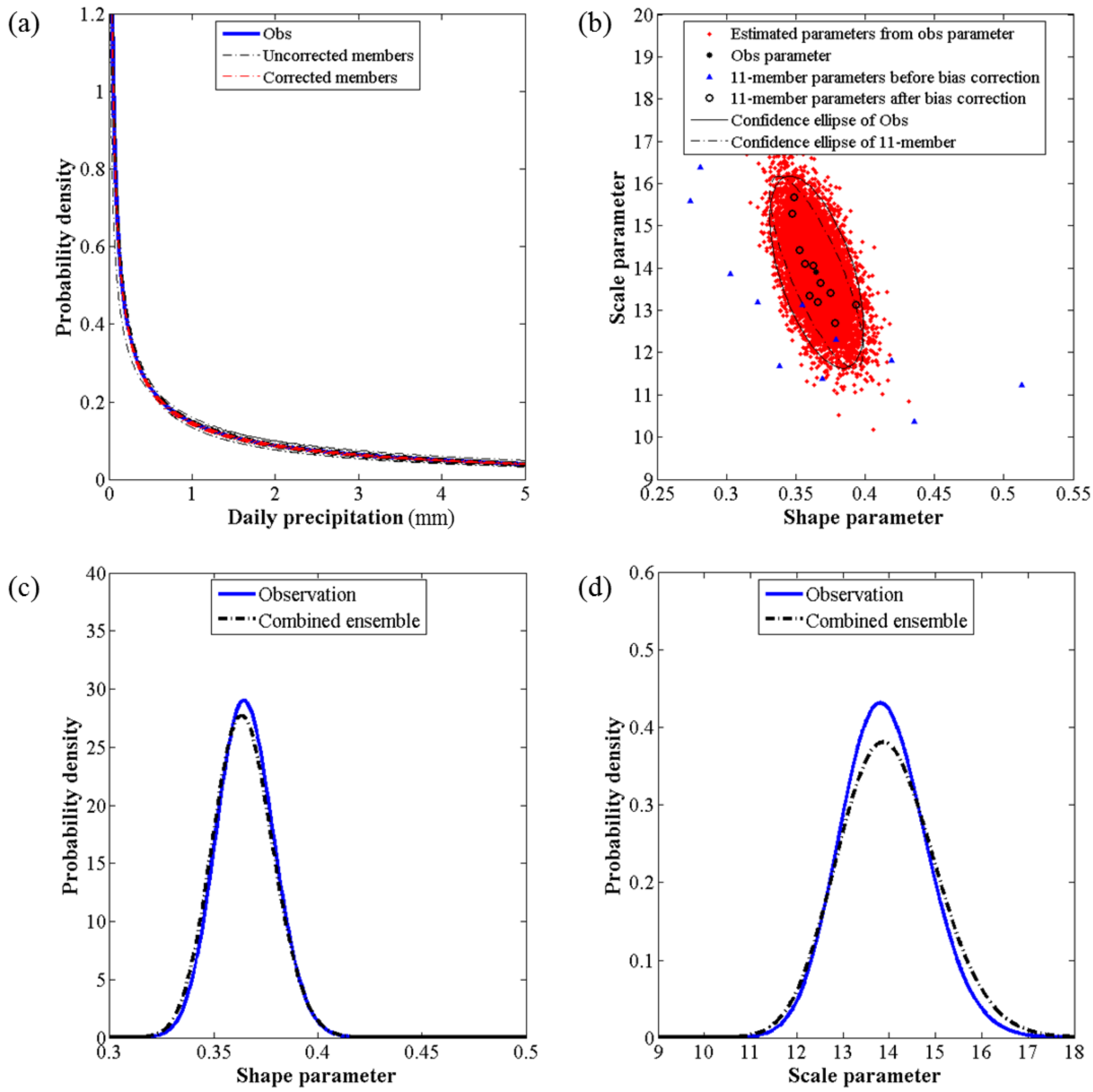


Figure 10~~9~~. Results of the proposed bias correction method: (a) Probability density functions of the observed, bias uncorrected and bias corrected precipitation; (b) Scatter plot between the shape and scale parameters of the observed, bias uncorrected and bias corrected precipitation; (c)-(d) Probability density functions of the shape and scale parameters of the observed and bias corrected precipitation.

4.4 Comparison of bias corrected monthly mean precipitation

Figure 11~~0~~ compares the result of the conventional and proposed bias correction schemes in terms of reproducing the mean precipitation. Figure 11~~0~~ (a) 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 (Figure 11~~0~~ (b)). 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 the natural variability (Figure 11~~0~~ (c)).

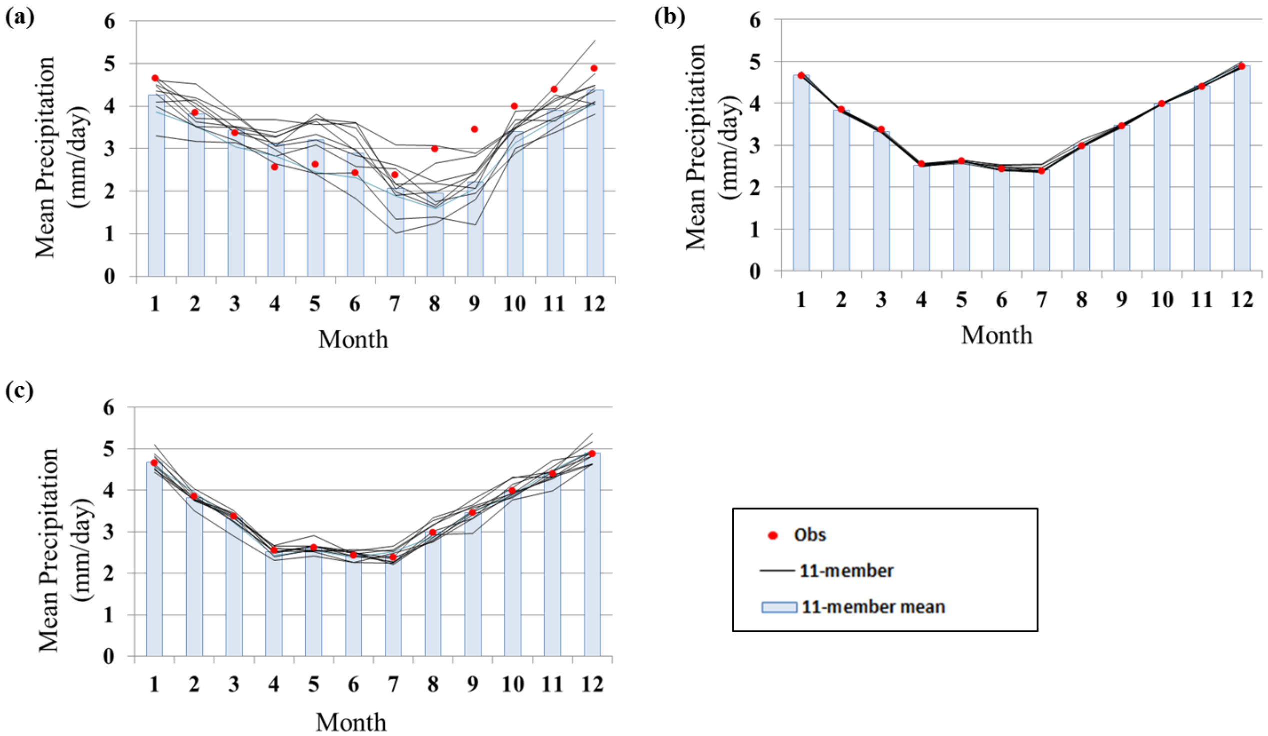


Figure 11~~0~~. Monthly mean precipitation for the period 1961-1990 derived from the simulated precipitation. The mean values for the observation and 11-members are displayed as well. (a) Uncorrected 11-members; (b) Corrected 11-members by the conventional bias correction; and (c) Corrected 11-member by the proposed bias correction.

4.5 Hydrological application

As presented in Figure 11~~0~~, the bias and spread of monthly mean precipitation using the proposed bias correction method is more realistic than the conventional method. Next, to investigate the impact of these two different bias correction schemes on flow simulations, we used the aforementioned hydrological model

IHACRES. Since the focus of the proposed bias correction scheme is on correcting the mean value and the spread of RCM precipitation ensembles, the same characteristics have been examined in the simulated flow. Figure 12~~1~~(a) shows the spread of monthly mean flow simulated from the precipitation ensembles for the period 1961-1990. The 5-95 percentile spread has been plotted. Figure 12~~1~~(b) shows the range of monthly spread and Figure 12~~1~~(c) shows the annual average value of the spread range. The flow ensemble simulated from the uncorrected 11-member (blue dashed line) obviously has bias and the range of the spread is inconsistent compared with that of the observed flow (black straight line). The flow ensemble simulated using bias corrected RCM precipitation (both conventional and proposed methods) is similar to that of the observed flow since the bias of the precipitation has been removed. However, when we focus on the range of the spread, the overall trend of using the proposed method (blue straight line) is closer to the observation than using the conventional method (red straight line). Specifically, in wet seasons, it is apparent that the proposed method is better while in dry seasons, there are no differences between different bias correction schemes. From this result, our new bias correction scheme is indeed an improvement to the current practice in agreeing with the spread of the simulated flow ensemble.

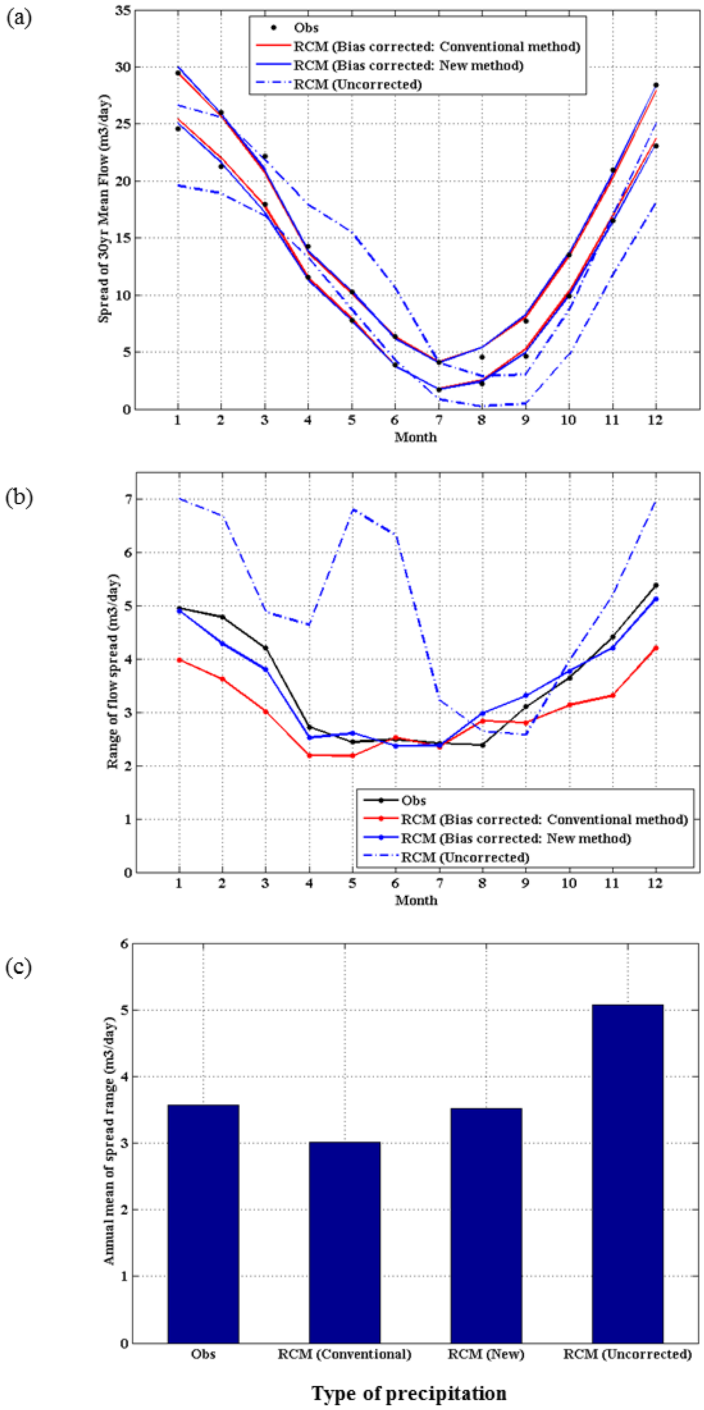


Figure 12~~1~~. (a) The spread of monthly mean flow simulated from the precipitation ensembles for the period 1961-1990 (5-95 percentile spread); (b) The range of monthly spread; (c) Annual average value of the spread range.~~The spread of monthly mean flow for the period 1961-1990 derived from the precipitation ensembles.~~

4.6 One transfer function for eleven members

An experiment is carried out to identify whether to correct each member individually or to treat them as a group. 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, those 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 13~~2~~ 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 ensemble spread. However, on the other hand, the result of applying one transfer function can also be a possible realisation depending on how to estimate the natural variability of the observation which is discussed in the next section.

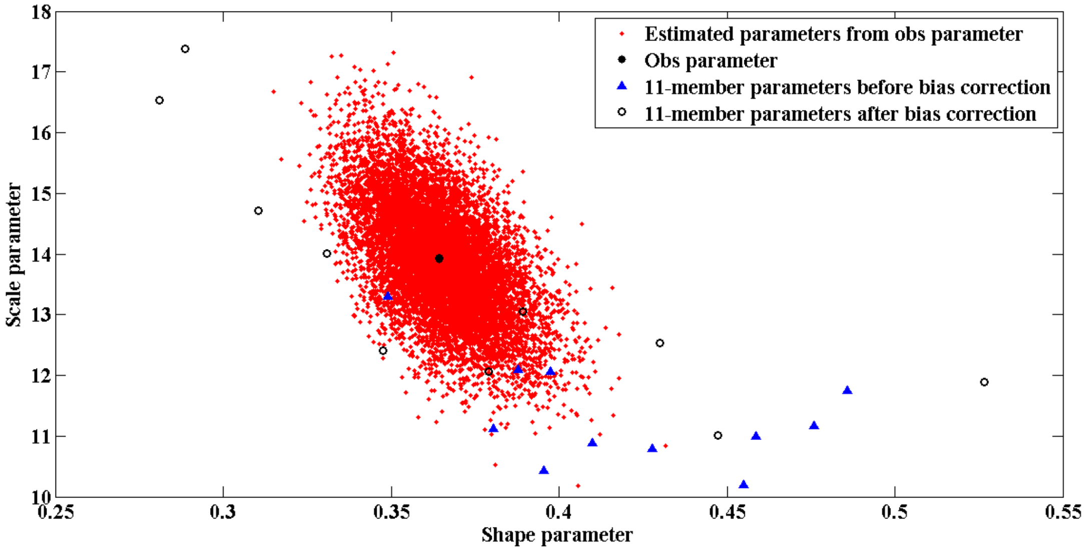
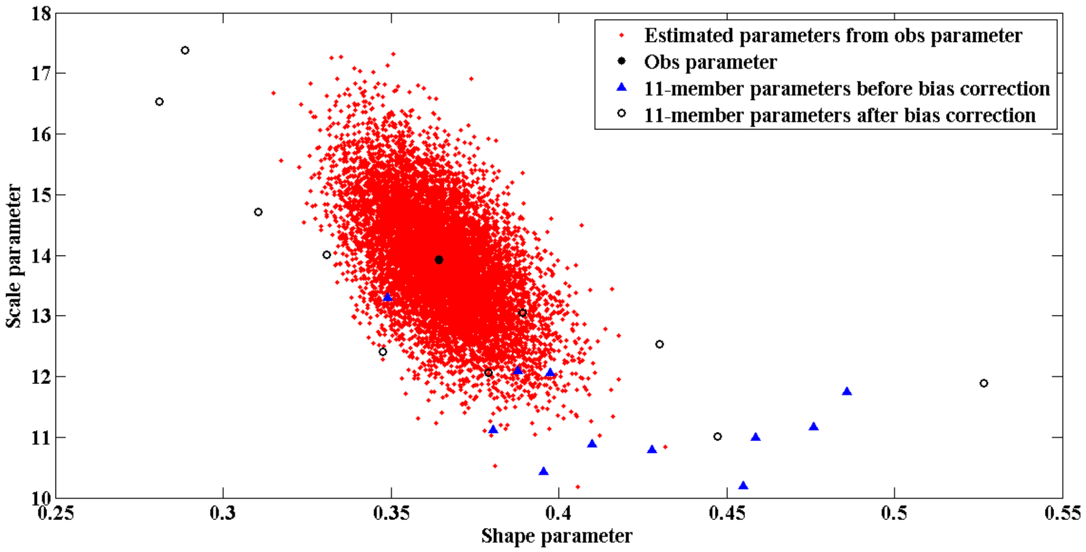


Figure 13~~2~~. Result of using one transfer function for bias correction.

5. Discussion

Climate change scenarios are generated using climate models (e.g. GCMs and RCMs) and emission scenarios, and are the key information for understanding future changes in hydrologic systems. While RCMs are designed to better simulate local climate at a finer spatial and temporal scales, 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 ensemble members are matched to that of the observations in terms of statistical characteristics so that the advantage of the ensemble 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.

Bias in climate models can be introduced by imperfect parameterisation of some climate processes (Ehret et al., 2012; Teutschbein and Seibert, 2012), incorrect boundary conditions and initialization (Bromwich et al., 2013), inadequate reference data sets such as reanalysis data (Dee et al., 2011; Thorne and Vose, 2010), and limitations in input data resolution (Wood et al., 2011). Eleven ensemble members of HadRM3 consist of one unperturbed member and 10 members with different perturbations to the atmospheric parametrisations. Since different members are the outputs from different parameterisations, they would have different biases and be considered as independent (although not totally independent) from other ensembles. Therefore, we believe it is more reasonable to undertake the bias correction independently for each member rather than correcting them with the same bias. ~~An experiment is carried out to identify whether to correct each member individually or to treat them as a group. 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 12 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 ensemble spread.~~



~~Figure 12. Result of using one transfer function for bias correction.~~

Ideally if we have numerous numbers of observation data, more reliable climate statistics could be derived. However, in reality, 30 years of observation data have been used as the reference climate which is just one realisation of many possibilities, and the uncertainty associated with distributional parametric uncertainty needs to be considered in designing and conducting impact studies of climate change. Distributional parametric uncertainty exists when limited amounts of hydrologic data are used to estimate the parameters of PDF. On the other hand, initial conditions or parameters in climate models can be perturbed to generate a large number of ensemble members. Given the results we achieve, these ensemble members need to be examined to ensure that they are plausible.

Figure 14~~3~~ describes why the bias corrected members should originate from within the bounds of the natural variability of the observation. It is supposed that the probability distributions of the natural variability and climate model uncertainty look like Figure 14~~3~~. The range of both the baseline and hypothetical future natural variability are similar while the model uncertainty is larger. In this case, the chances of floods (i.e. area of the PDF which are above the flood causing precipitation) for the baseline period and future are 5% and 10% respectively which we assume are the true values. However, according to the model uncertainty, the odds of the floods in the future are overestimated by 20% which means more actions are needed to mitigate the flood risk than in reality. This misinterpretation may, in turn, lead to inefficient efforts to improve the water system since it is related to the mitigation and adaptation plan. Therefore, the spread of the model uncertainty should be similar to that of the climate natural variability.

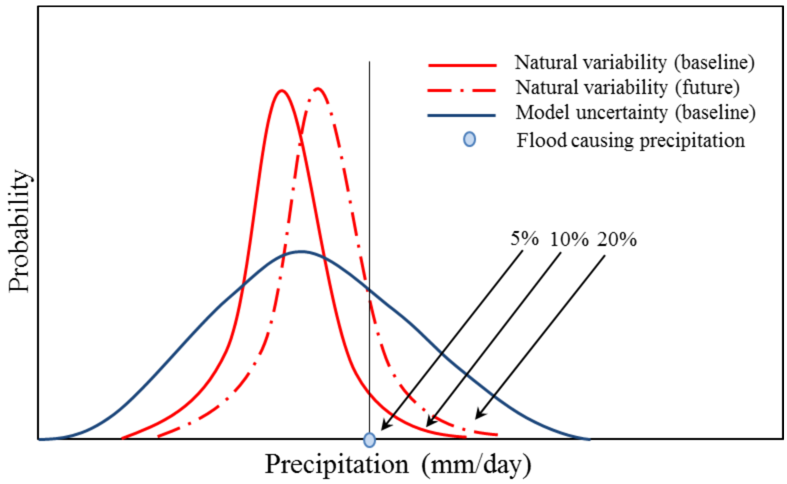


Figure 14~~3~~. Probability distributions of natural variability and climate model uncertainty. The thick red curve, dashed red curve and cyan curve are the probability distributions of the baseline natural variability, future natural variability and baseline model uncertainty respectively. The thick black line is a threshold for flood causing precipitation. The real probabilities of floods for the baseline and the future are 5% and 10% respectively, while the model overestimates the flood risk by 20%.

This study attempts to evaluate the reliability of the RCM ensemble in terms of natural variability and to propose a new bias correction scheme conforming to the RCM ensembles. However, the proposed scheme is just one of the necessity conditions to assess the RCM ensembles and a comprehensive scheme including more conditions needs to be further developed. It does not mean that the RCM which meets this condition is a good model, but if it does not meet this condition, the RCM ensemble fails to represent the natural climate variation as described in Figure 14~~3~~ (hence such a condition is a necessity condition, not a sufficiency condition). We believe that there should be a set of necessity conditions to better assess and improve future climate projections in various aspects of uncertainty analysis.

We would like to point out some~~a~~ limitations of this study. First, a~~A~~s previously mentioned, bias correction is a controversial issue. In addition, there is no generic one-suit-fits-all bias correction methods for rainfall data since rainfall time series has many aspects and cannot be all corrected simultaneously. The way of correcting the bias should depend on the data purpose, since the bias depends on the specific rainfall characteristic (Kew et al., 2011). In this study, we have focused on matching underlying statistical properties between the observed and simulated rainfall, which are the cumulative probability distribution and the spread of rainfall series. In the future, other statistical properties for parameter distributions may also be included. Second, depending on how to estimate the observational uncertainty the interpretation of Figures 13 and 14 can be different. In this study, we have used a bootstrap method to describe the observational uncertainty from 30 year of observation data. However, in reality, there is no way to describe the uncertainty that is not captured by the 30 years of observations. For instance, variability of observations on a slow time scale (decadal or centennial), or realisations of precipitation amounts with very long return periods (exceeding the record length of this observation data set) cannot be estimated, but may be highly relevant. It may well be that the ensemble is more able to capture modes of variability (both decadal oscillations and unprecedented extremes) that may not be captured by the observations. In that sense, it may be possible that the estimated spread of observational uncertainty in Figure 13 could be narrower than the true spread and the result of using one transfer function may be more realistic than that from our proposed method. Likewise, in Figure 14, it is possible that it is not an overestimation of flood probability by the ensemble, but an underestimation by the observations. In summary, if the natural variability is fully obtainable from the observation, our proposed methodology, in theory, should work better than the conventional method. However, it should be pointed out that the natural variability may not be fully captured by the decades of observation. Therefore, further studies are needed to explore how to capture the natural variability beyond the local observation. In this regard, a simulation technique based on multiscale approaches (e.g. wavelet transform analysis and empirical mode decomposition technique) could be a way to better represent the natural variability.

6. Conclusions

Conventionally, all climate model simulations are corrected to the observation. With this scheme, the uncertainty of the model from the ensembles will be lost and as a result the 11-member ensemble will be similar to just one member. Another approach is to apply one transfer function based on the unperturbed member to the rest 10 members. This will keep the spread properties of the ensemble but this spread may not conform to the spread from the real natural system. Therefore they do not look like as if they are drawn from the natural system. In this study, we have proposed a new scheme which overcomes the shortcomings of the aforementioned two schemes (i.e. 11 transfer functions all conformed to one observed realisation or one transfer function for 11 members which result in the bias corrected ensembles too narrow or too wide), and the proposed method is a good balance between the two. Therefore, the 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 the 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.

~~We would like to point out a limitation of this study. As previously mentioned, bias correction is a controversial issue. In addition, there is no generic one-suit-fits-all bias correction methods for rainfall data since rainfall time series has many aspects and cannot be all corrected simultaneously. The way of correcting the bias should depend on the data purpose, since the bias depends on the specific rainfall characteristic (Kew et al., 2011). In this study, we have focused on matching underlying statistical properties between the observed and simulated rainfall, which are the cumulative probability distribution and the spread of rainfall series. In the future, other statistical properties for parameter distributions may also be included.~~

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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 realisations due to the climate natural variability, a successful bias correction scheme should preserve the ensemble spread within the bounds of its natural variability (i.e. sampling uncertainty). To demonstrate a new bias correction scheme conforming to RCM precipitation ensembles, 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 is nearly identical to the observation, i.e. the ensemble spread is removed. In contrast, the proposed method corrects the bias while maintain the ensemble spread within the natural variability of the observations.

Keywords: bias correction, RCM ensemble, spread, natural variability

1. Introduction

The growing evidence of global climate change is clear in the past century (Stocker, 2013). Therefore, future projections of climate that incorporate the effects of an underlying changing climate are of great importance, particularly because of reliance of mitigation and adaptation on realistic 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; Compagnucci et al., 2001). Global Climate Models (GCMs) are usually used for the projection of future climate and the accuracy of GCMs has been enhanced in simulating large scale global climate. Nevertheless, GCMs have difficulties in providing reliable climate data at local scales due to their coarse resolutions (100-250km) (Maraun et al., 2010). Therefore, for regional impact studies Regional Climate Models (RCMs) have been widely used which are compatible to the catchment scales (25-50km).

Although RCMs provide detailed information, for hydrological application, there is still a mismatch of scales especially for meso- and small-scale catchments. In addition, 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). The statistical properties of simulated precipitation are affected by bias in the mean, variance (variability) and skewness (dry days, drizzle, inability to reproduce extreme events etc) (Baigorria et al., 2007; Leander and Buishand, 2007). 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 parameterisation, 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 there are relatively too many low intensity wet days compared with the observations (Ehret et al., 2012; Ines and Hansen, 2006).

The errors along with the mismatching scales have caused numerous studies on developing and evaluating the bias correction methods (Chen et al., 2011a; Chen et al., 2011b; 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 the long-term observation and model data. However, the 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 observation. The results have shown that all the four bias correction methods could improve the raw RCM precipitation. Among them, the distribution mapping method is the best, however it has a drawback of overfitting. 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 narrower, i.e. “hides rather than reduces uncertainty” (Ehret et al., 2012). In this study we address the issue which most conventional bias correction methods implicitly neglect: the uncertainty associated with the 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 (structures and parameters) 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 parameterisation 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; Solomon, 2007; Taylor et al., 2012). However, when bias correction is applied to the ensemble of the GCM/RCM scenario simulation, the advantage of the ensemble in representing the uncertainty is often negated. The statistical properties of each of the individual ensemble members are usually matched to that of the observations so that the advantage of the ensemble with respect to a single model simulation is lost. Therefore, the natural variability of the observation should be estimated first, and then the spread (i.e. variance) of the ensemble 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. There has been relevant work recently around the influence of natural variability on bias characterisation in RCM simulations (Addor and Fischer, 2015). They show that different methods of estimating natural variability give different measures, depending on the method, season, and temporal scale of the observation record which in return influence the bias correction. Overall, they argue that observational uncertainties and natural variability need to be considered for bias correction of RCM simulations.

Another issue presented in this study is associated with how to correct the PPEs' bias to preserve the spread. Should the bias correction be applied individually for each ensemble member or applied as an ensemble? The former method is to apply different transfer functions for different ensemble members, while the latter method is to apply only one transfer function for the whole ensemble members. In stochastic hydrology, the synthetic rainfall and streamflow should have statistical properties (e.g. mean, variance, skewness, etc) similar to the real system so that they are not distinguishable between the observed data and the modelled data. In this study we have followed the same philosophy. The bias corrected rainfall ensembles should have statistical properties (in this study, the mean value and the spread of ensembles) similar to the observations. The same principle has been applied to the UKCP09 Weather Generator (Jones et al., 2009) (WG) used in the UK. The synthetic weather variables from WG have statistical properties similar to the observations since the WG is calibrated on the observations.

There are many aspects (e.g. mean, variance, skewness, autocorrelation etc) of the rainfall series which cannot be all corrected simultaneously. The way of correcting the RCM data should therefore depend on what properties are relevant to the data usage. In this study we have focused on the mean value and the spread of bias-corrected RCM precipitation.

The paper is structured as follows: Section 2 describes the study catchment and data; in Section 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 ensemble is evaluated. Finally the concepts of conventional and proposed bias correction methods are compared. In Section 4 we show the results followed by discussion and conclusions in Section 5 and Section 6.

2. Catchment and data

The Thorverton catchment is used as the case study site. It has an area of 606 km^2, and is a sub-catchment of the Exe catchment. The Exe catchment is located in the southwest of England with an area of 1,530 km^2 and an average annual rainfall of 1,088 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.

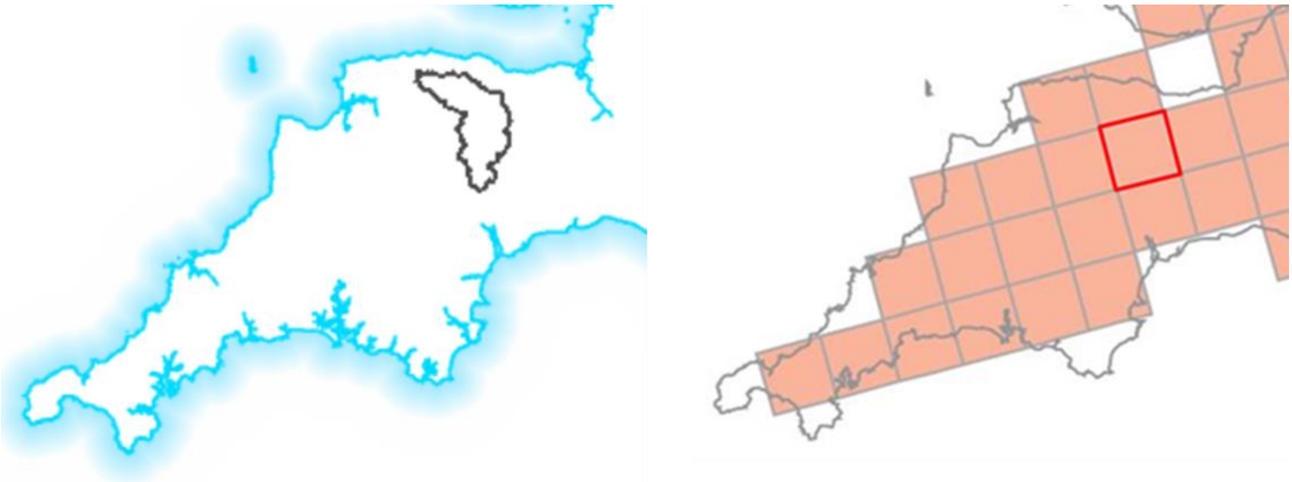

Figure 1. Location of the Thorverton catchment (the left panel) and HadRM3 25km grid boxes (the right panel). The highlighted grid box in red is selected to cover the Thorverton catchment.

The climate data used in this study is the Hadley Centre Regional Climate Model (HadRM3-PPE) Data which was generated by the 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 representing radiation, land surface, boundary layer, sea-ice, cloud, atmospheric dynamics and convection (Collins et al., 2011). The dataset provides the time series of climate data in the period 1950-2100 for the historical and future medium emission scenario A1B. The temporal and spatial resolutions of the HadRM3 climate data are daily and 25km respectively. As presented in Figure 1, the RCM grid boxes are rotated by 0.22^{o}. 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 to 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 the seasonal GCM variables (e.g. precipitation and temperature) and later extended to the daily time scale. Individual months are usually processed independently from each other, 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:

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

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 concept of conventional quantile mapping method is shown in Figure 2 and a general process is described as follows. First, before doing the bias correction, the wet-day frequencies of the observed 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 precipitation value corresponding to the cumulative probability is found in the fitted Gamma distribution of the observation. This value is the bias corrected RCM precipitation as described by Eq(2):

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

where, X_{cor} is the bias corrected RCM precipitation, F is Gamma cumulative distribution function (CDF), F^{-1} is the 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.

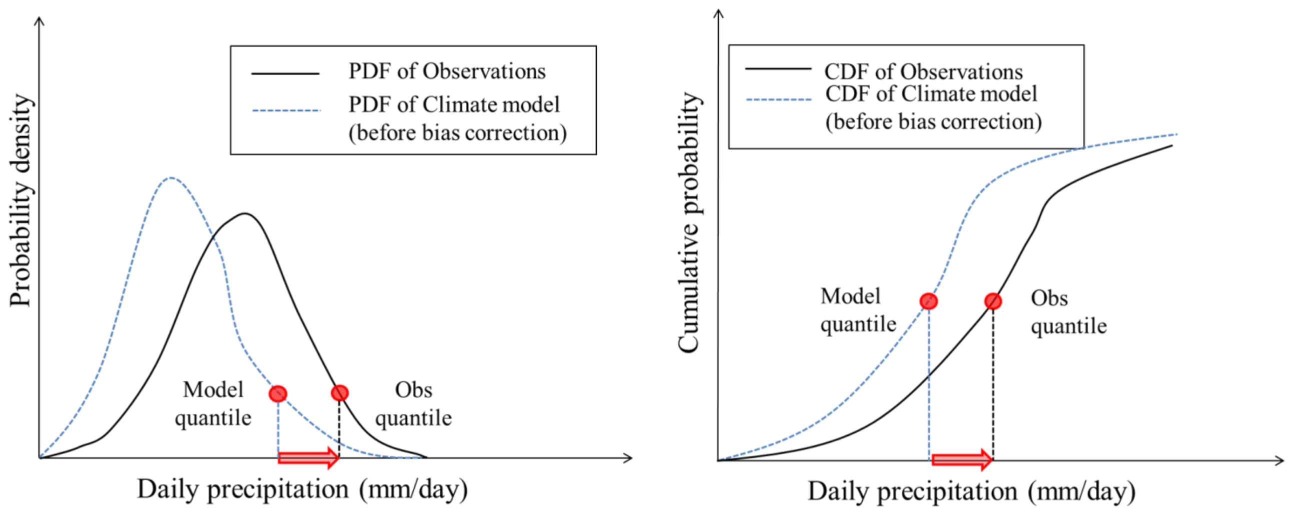

Figure 2. A schematic representation of the concept of conventional quantile mapping method for bias correction.

In this study, daily bias correction is applied for each month separately. 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 the 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 realisations. 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 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 the simulations due to the observation sampling uncertainty. In this study, the distribution of 100,000 sets of parameters is assumed to represent the natural variability of 30-year daily precipitation. In order to find the optimised number of resampling, the sensitivity analysis between the numbers of resampling and the mean value of the observed precipitation has been done. The result has shown that beyond 20,000 resamples, the mean value becomes stable. Since the running time does not take long in this study we have resampled 100,000 times which are sufficient.

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 Figure 3. The observed daily precipitation is assumed to follow the Gamma distribution defined by the shape and scale parameters. The distribution of the parameters can be derived from the resampling procedure as mentioned in Section 3.2 (Figure 3(a)). Then we compare the distributions of the observation and ensemble members' parameters (Figure 3(b) ~ (c)). If the parameter distribution of an ensemble member looks like Figure 3(b), 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 resembles something closer to Figure 3(c). Both of these "cases" indicate the need for bias correction. On the other hand, if the parameter distribution of an ensemble member resembles Figure 3(d) (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.

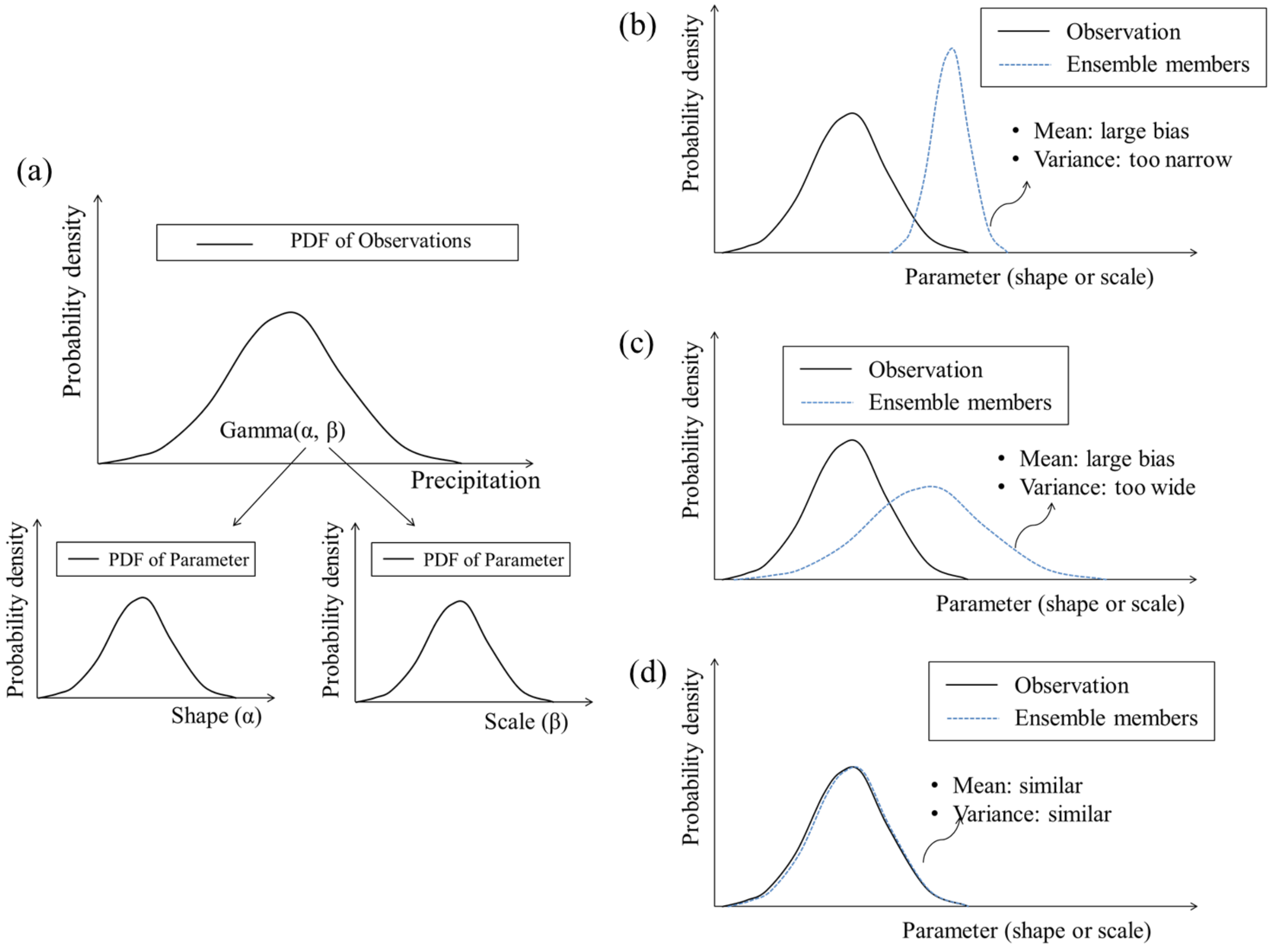

Figure 3. A schematic representation of the evaluation of ensemble members.

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 Figure 4. As mentioned in Section 3.1, the objective of the quantile mapping method is to match the statistical properties between the observed and climate model precipitation. Figure 4(a) 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 (Figure 4(b)). Therefore, the PDFs (or CDFs) of the observation and each ensemble member become identical after bias correction (Figure 4(c)). 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 for 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 4(d) 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 the ensemble (Figure 4(e)).

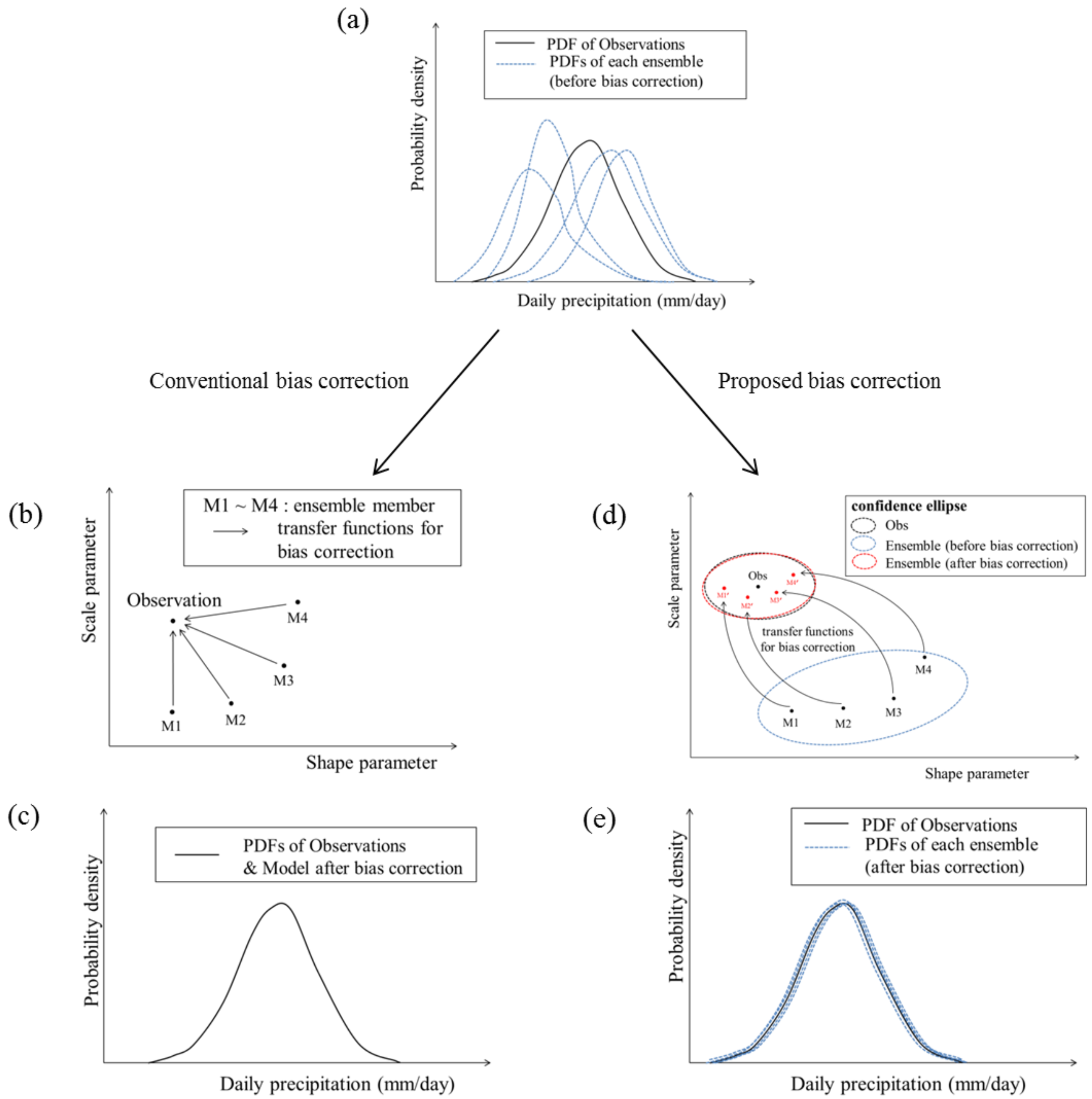

Figure 4. A schematic representation of the conventional bias correction method and the proposed bias correction method

A step by step summary of the proposed procedure is presented as follows and in Figure 5.

- (Step 1) Natural variability of the observation is estimated by first randomly resampling precipitation from a Gamma distribution with parameters obtained by fitting the observed precipitation. Next, the parameters of each resampled precipitation time series are estimated, and the bivariate distribution of these parameters over all the samples is established. The shaded area in Figure 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.
- (Step 2) Normalise the parameters of the ensemble members using Eq(3).

$$x_N = \frac{x-\mu_x}{\sigma_x}\ , \quad y_N = \frac{y-\mu_y}{\sigma_y} \tag{3}$$

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 the parameters of all ensemble members, x_N, y_N are the normalised shape and scale parameters.

- (Step 3) De-normalise the parameters of the ensemble members by matching the mean and standard deviation to those of the observation as shown in Eq(4).

$$x' = x_N \cdot \sigma_{xo} + \mu_{xo}\ , \quad y' = y_N \cdot \sigma_{yo} + \mu_{yo} \tag{4}$$

where, μ_{xo}, μ_{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) In Step 3, the coordinate of the centre of the denormalised ensemble parameter sets is (0, 0). This coordinate is shifted to that of the observation (i.e. black dot in Figure 5 Step 4), which results in the ensemble members' parameter sets to fall into the boundary of the natural variation of the observations. From this, transfer functions for the bias correction can be built.

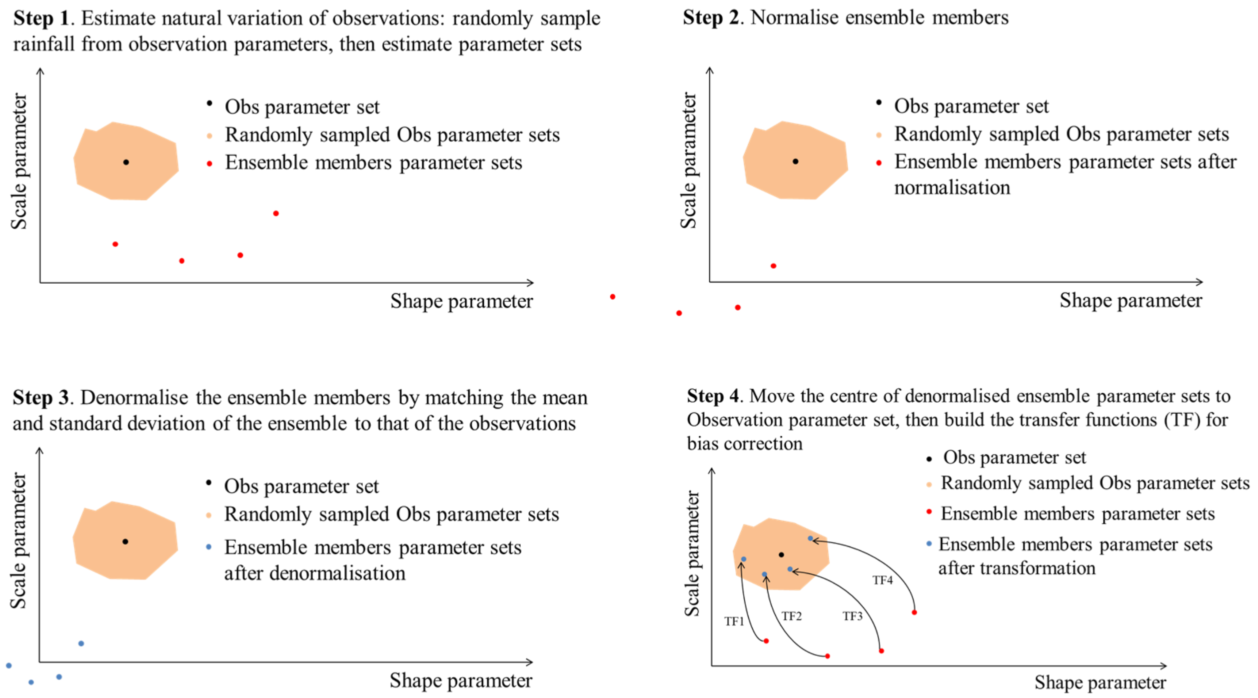

Figure 5. The four step procedure of the proposed bias correction method.

3.5 Hydrological application

To investigate the impact of different bias correction schemes on flow, we have used a conceptual rainfall-runoff model called IHACRES (Jakeman and Hornberger, 1993). This model has been widely applied to a variety of catchments for hydrological analysis and climate impact studies (Jakeman et al., 1993; Kim and Lee, 2014; Letcher et al., 2001; Littlewood, 1999). The model is composed of a non-linear module and a linear module as shown in Figure 6 and the model parameters are listed in Table 1. A non-linear module converts total rainfall to effective rainfall which is calculated from Eq(5).

$$U_k = [C(\emptyset_k - l)]^p r_k \tag{5}$$

where, r_k is the observed rainfall, C is the mass balance, l is the soil moisture index threshold and p is the power on soil moisture respectively. The soil moisture ($\emptyset_k$) is calculated from:

$$\emptyset_k = r_k + (1 - \frac{1}{\tau_k})\emptyset_{k-1} \tag{6}$$

where, τ_k is the drying rate given by:

$$\tau_k = \tau_w \exp[0.062 f(t_r - t_k)] \tag{7}$$

where, τ_w is the drying rate at the reference temperature, f is the temperature modulation, t_r is the reference temperature, and t_k is the observed temperature. A linear module assumes that there is a linear relationship between the effective rainfall and flow. Two components in this module, quick flow and slow flow, can be connected in parallel or in series. In this study two parallel storages in the linear module are used because such a combination reflects the catchment conditions and the streamflow (x_k) at time step k is defined by the following equations:

$$x_k = x_k^{(q)} + x_k^{(s)} \tag{8}$$

$$x_k^{(q)} = \beta_q U_k - \alpha_q x_{k-1}^{(q)} \tag{9}$$

$$x_k^{(s)} = \beta_s U_k - \alpha_s x_{k-1}^{(s)} \tag{10}$$

where, $x_k^{(q)}$ and $x_k^{(s)}$ are quick flow and slow flow respectively, and α and β are recession rate and peak response respectively. The relative volumes of quick flow and slow flow can be calculated from:

$$V_q = 1 - V_s = \frac{\beta_q}{1+\alpha_q} = 1 - \frac{\beta_s}{1+\alpha_s} \tag{11}$$

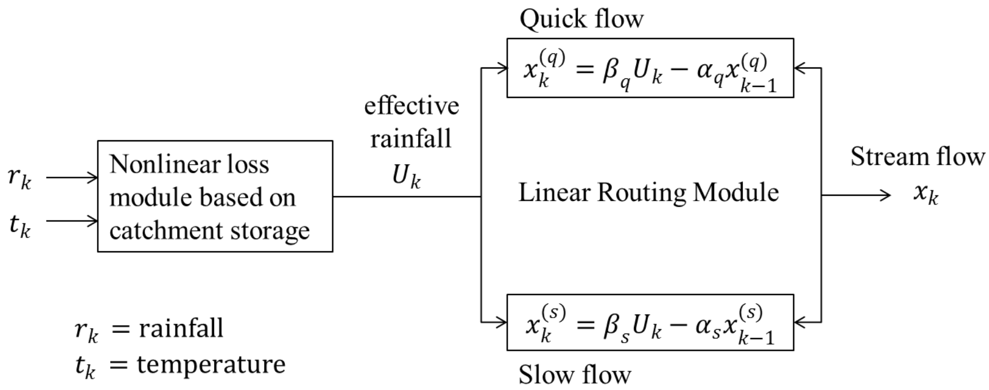

Figure 6. Structure of the IHACRES model.

Table 1. Parameters in the IHACRES model

Module	Parameter	Description
Non-linear	c	Mass balance
	τ_w	Reference drying rate
	f	Temperature modulation of drying rate
Linear	α_q, α_s,	Quick and slow flow recession rate
	β_q, β_s	Fractions of effective rainfall for peak response
	τ_s	Slow flow recession time constant, $\tau_s = -\Delta/\ln(-\alpha_s)$
	τ_q	Quick flow recession time constant, $\tau_q = -\Delta/\ln(-\alpha_q)$

The hydrological application has been done as follows. First, the model parameters have been optimised with the use of the observed daily precipitation, temperature and flow data.

Second, the observed precipitation and the two different bias corrected precipitation data from the conventional and proposed bias correction methods are randomly resampled to estimate the spread of the simulated flow ensembles. Third, the optimised parameters and the precipitation time series are then used to simulate daily flow ensembles. Finally, from this daily simulated flow data, thirty-year mean monthly flow has been estimated since the bias correction has been done on monthly basis, and then compared under different bias correction schemes.

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 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 7(a) shows the PDFs of the observed and simulated precipitation. The parameter space (i.e. shape vs scale parameter) of these distributions is plotted in Figure 7(b). Note again the parameter space is defined by resampling from the observation, and the distribution of 100,000 sets of parameters is assumed as the natural variability of daily precipitation as illustrated in section 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 7(c) 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 bias correction is needed.

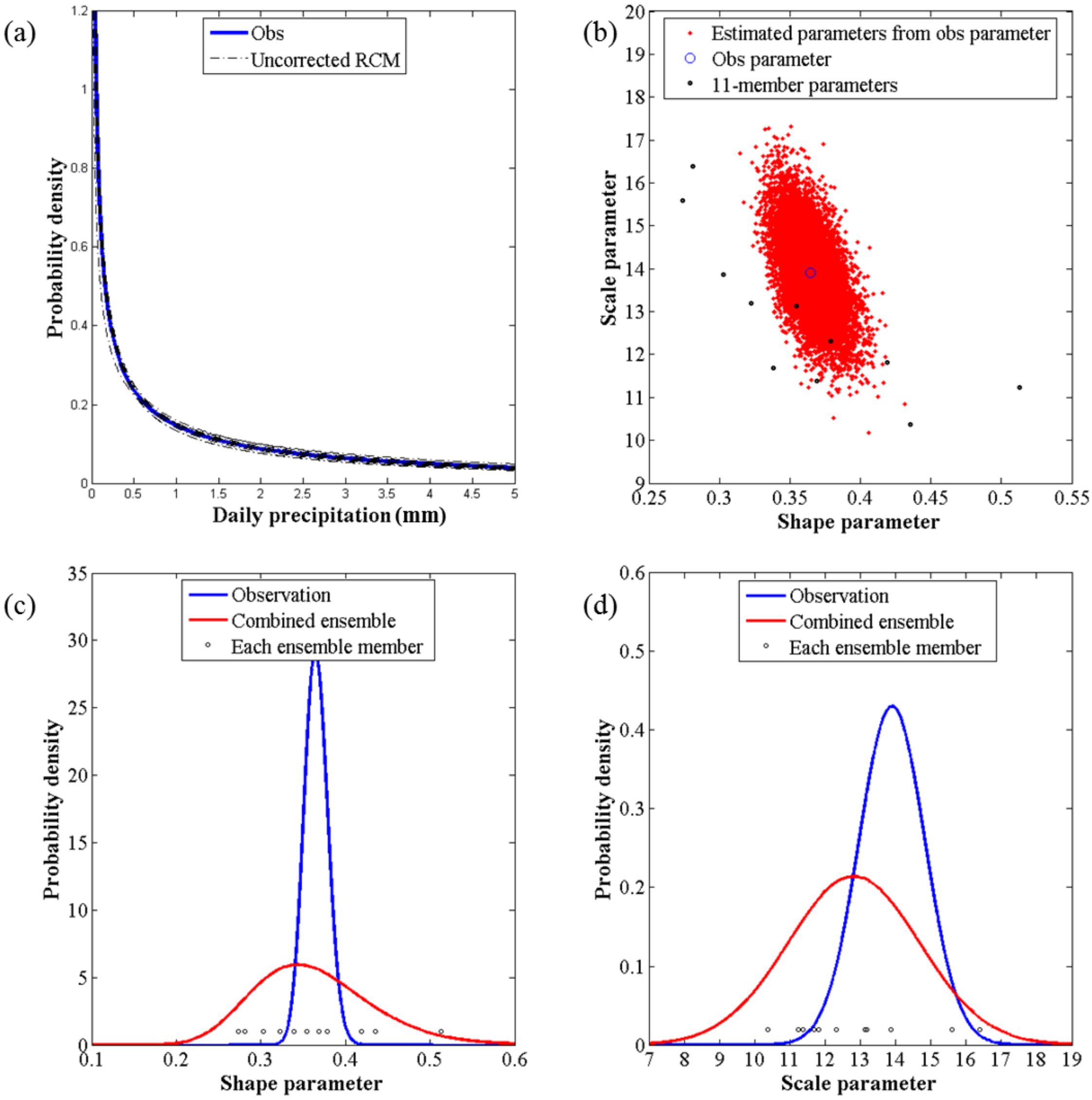

Figure 7. Parameter distributions of the observation and 11-members: (a) Probability density function of the observed and 11-member precipitation time series before bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias uncorrected precipitation; (c) - (d) Probability density functions of shape and scale parameters for the observed and bias uncorrected precipitation.

Figure 8(a) presents the PDFs of the observed precipitation and the resampled precipitation which represents the natural variability of the observation. Figure 8(b) shows the natural variability of monthly mean precipitation which has been estimated from the resampled precipitation.

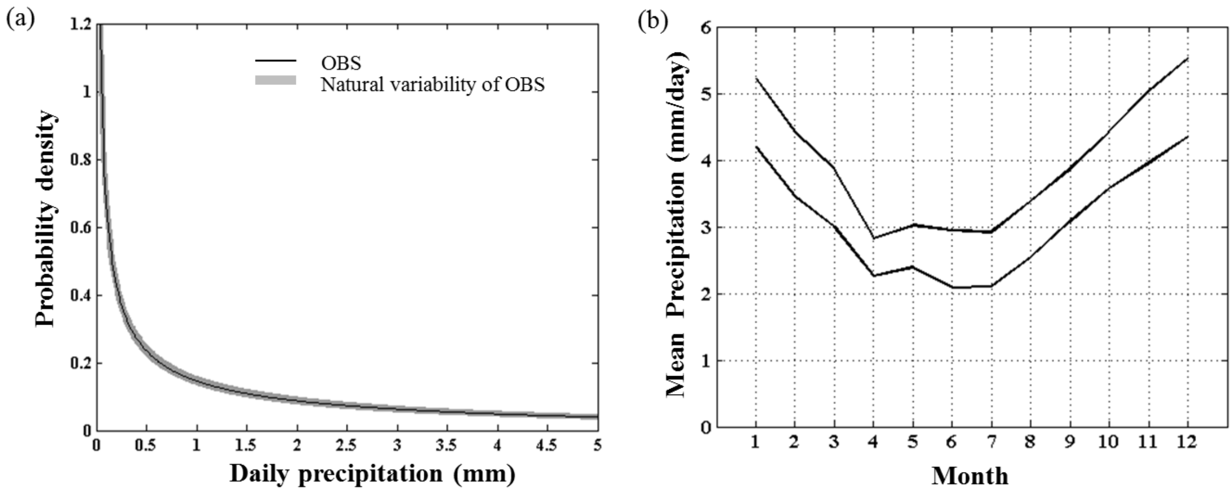

Figure 8. (a) PDFs of the observed precipitation and the resampled precipitation; (b) Natural variability of monthly mean precipitation.

4.2 Conventional bias correction

Figure 9 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 (Figure 9(a)) and the parameters of the corrected precipitation are all in the centre of the parameter space of the observation (Figure 9(b), (c) and (d)). 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 different model runs.

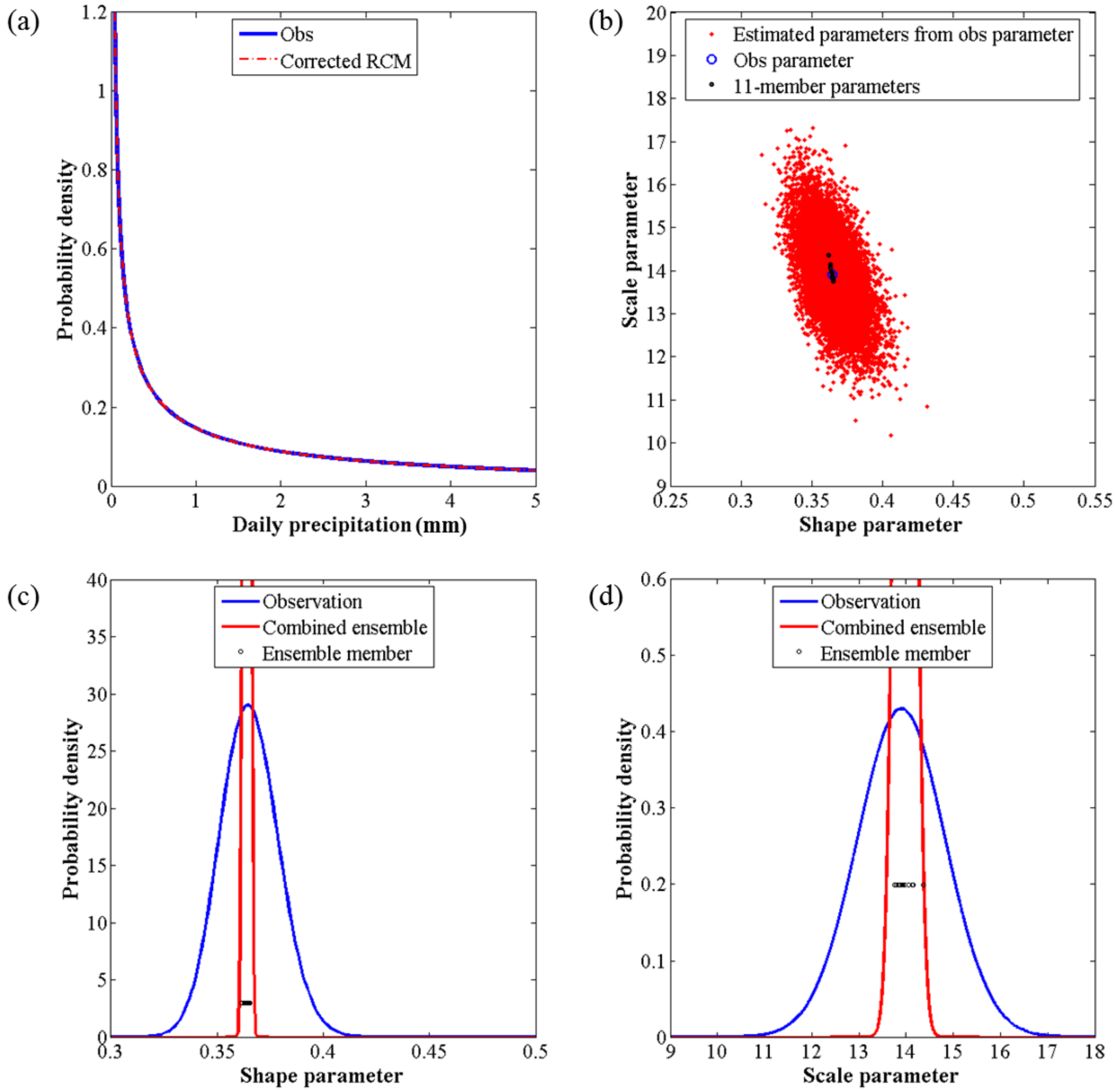

Figure 9. Results of the conventional bias correction method: (a) Probability density functions of the observed and simulated (i.e. 11-member) precipitation after bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias corrected precipitation; (c)-(d) Probability density functions of the shape and scale parameters of the observed and bias corrected precipitation.

4.3 Proposed bias correction

To preserve the spread of the ensemble members, a systematic modelling scheme is proposed. Figure 10(a) 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 (Figure 10(b)). The parameters of the corrected members are all within the boundary of the 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 (Figure 10(c) and (d)). Therefore, one can assume that all ensemble members represent realistic precipitation scenarios when the natural variability is considered.

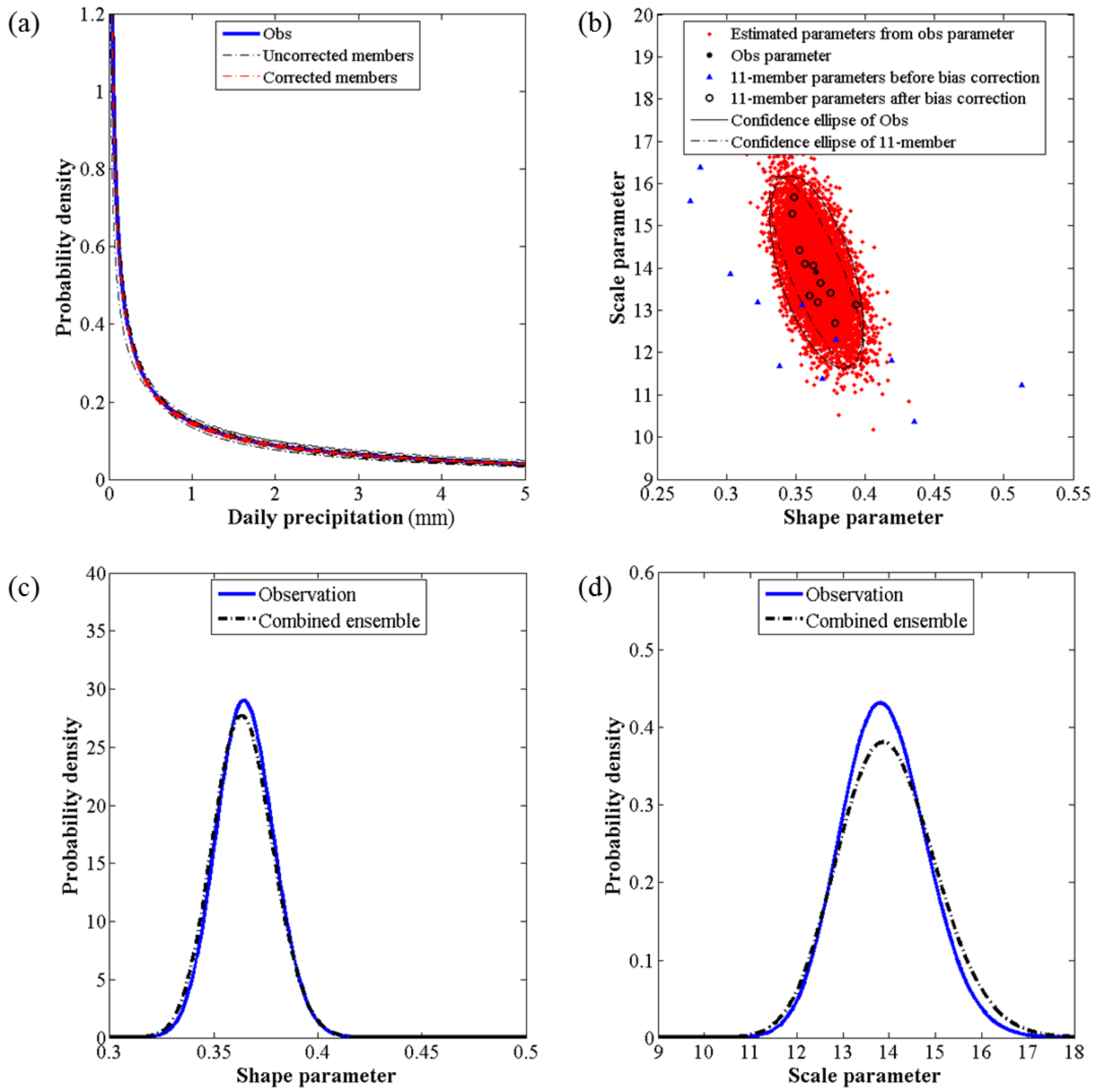

Figure 10. Results of the proposed bias correction method: (a) Probability density functions of the observed, bias uncorrected and bias corrected precipitation; (b) Scatter plot between the shape and scale parameters of the observed, bias uncorrected and bias corrected precipitation; (c)-(d) Probability density functions of the shape and scale parameters of the observed and bias corrected precipitation.

4.4 Comparison of bias corrected monthly mean precipitation

Figure 11 compares the result of the conventional and proposed bias correction schemes in terms of reproducing the mean precipitation. Figure 11 (a) 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 (Figure 11 (b)). 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 the natural variability (Figure 11 (c)).

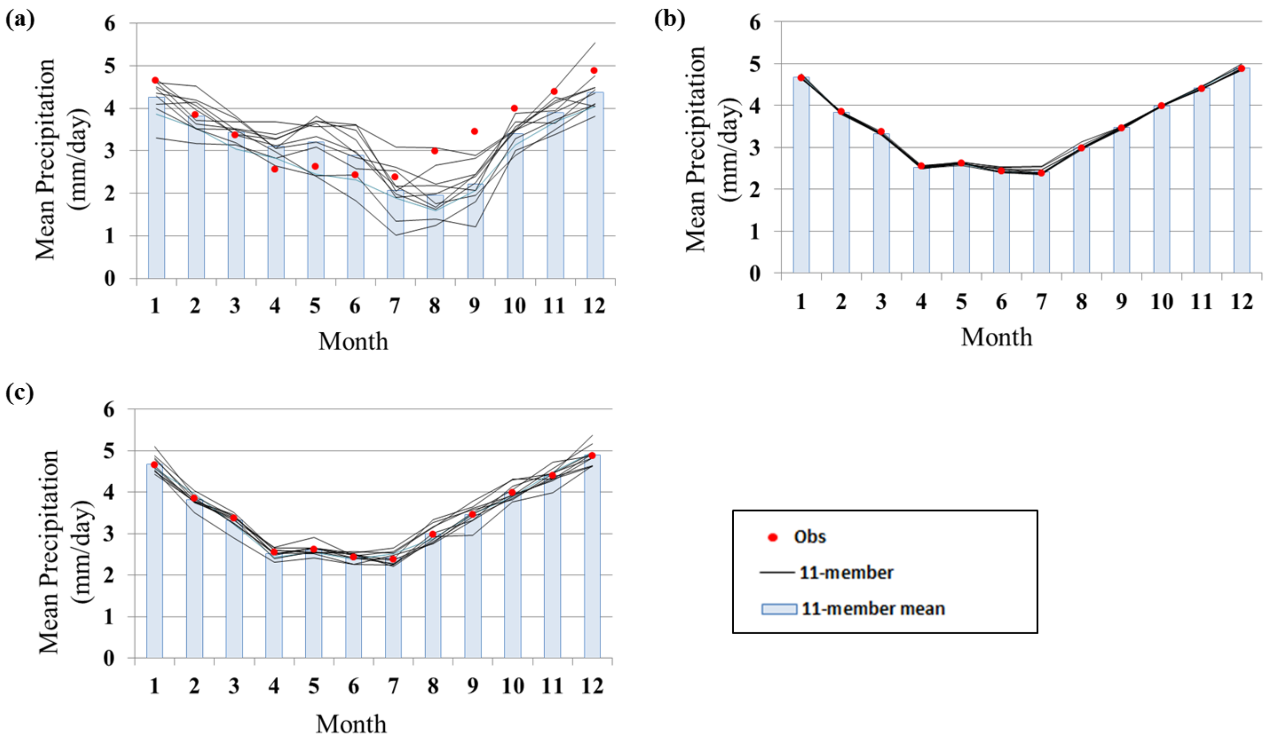

Figure 11. Monthly mean precipitation for the period 1961-1990 derived from the simulated precipitation. The mean values for the observation and 11-members are displayed as well. (a) Uncorrected 11-members; (b) Corrected 11-members by the conventional bias correction; and (c) Corrected 11-member by the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

4.5 Hydrological application

As presented in Figure 11, the bias and spread of monthly mean precipitation using the proposed bias correction method is more realistic than the conventional method. Next, to investigate the impact of these two different bias correction schemes on flow simulations, we used the aforementioned hydrological model

IHACRES. Since the focus of the proposed bias correction scheme is on correcting the mean value and the spread of RCM precipitation ensembles, the same characteristics have been examined in the simulated flow. Figure 12(a) shows the spread of monthly mean flow simulated from the precipitation ensembles for the period 1961-1990. The 5-95 percentile spread has been plotted. Figure 12(b) shows the range of monthly spread and Figure 12(c) shows the annual average value of the spread range. The flow ensemble simulated from the uncorrected 11-member (blue dashed line) obviously has bias and the range of the spread is inconsistent compared with that of the observed flow (black straight line). The flow ensemble simulated using bias corrected RCM precipitation (both conventional and proposed methods) is similar to that of the observed flow since the bias of the precipitation has been removed. However, when we focus on the range of the spread, the overall trend of using the proposed method (blue straight line) is closer to the observation than using the conventional method (red straight line). Specifically, in wet seasons, it is apparent that the proposed method is better while in dry seasons, there are no differences between different bias correction schemes. From this result, our new bias correction scheme is indeed an improvement to the current practice in agreeing with the spread of the simulated flow ensemble.

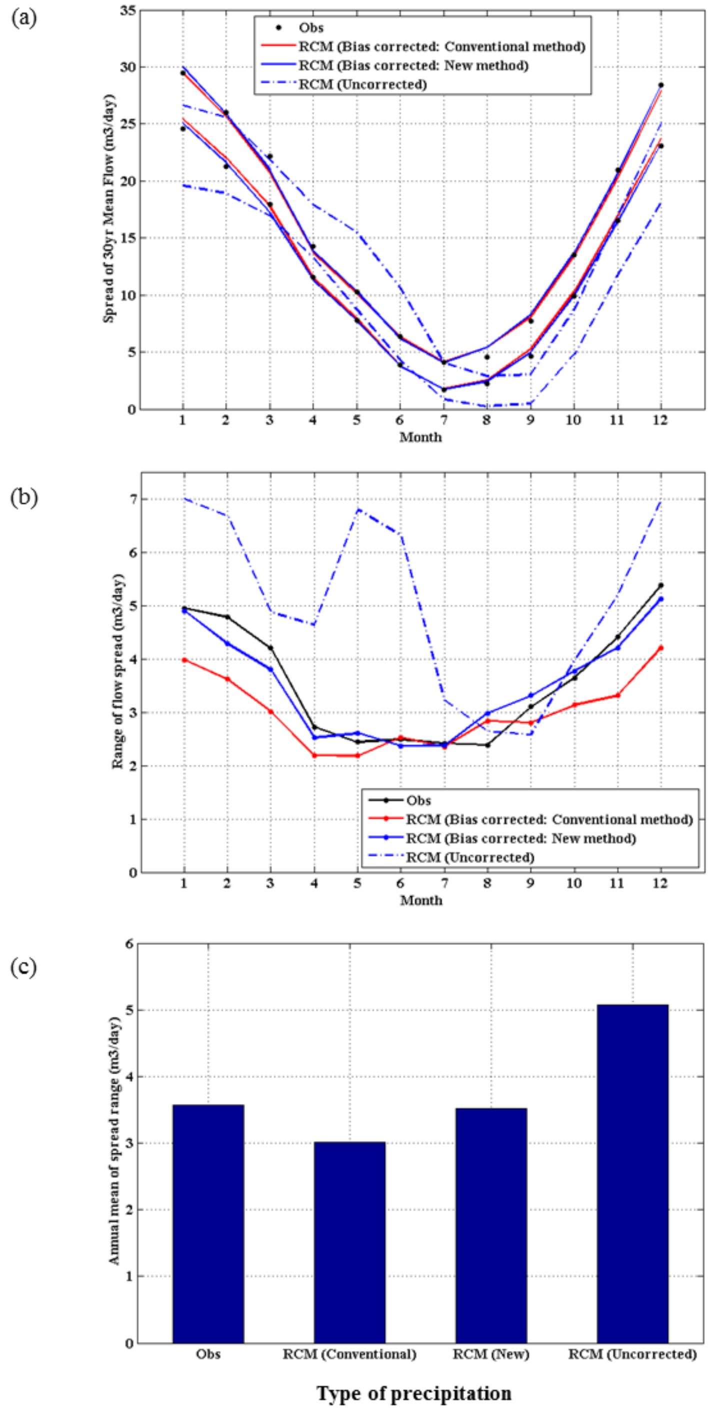

Figure 12. (a) The spread of monthly mean flow simulated from the precipitation ensembles for the period 1961-1990 (5-95 percentile spread); (b) The range of monthly spread; (c) Annual average value of the spread range.

4.6 One transfer function for eleven members

An experiment is carried out to identify whether to correct each member individually or to treat them as a group. 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, those 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 13 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, , 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 ensemble spread. However, on the other hand, the result of applying one transfer function can also be a possible realisation depending on how to estimate the natural variability of the observation which is discussed in the next section.

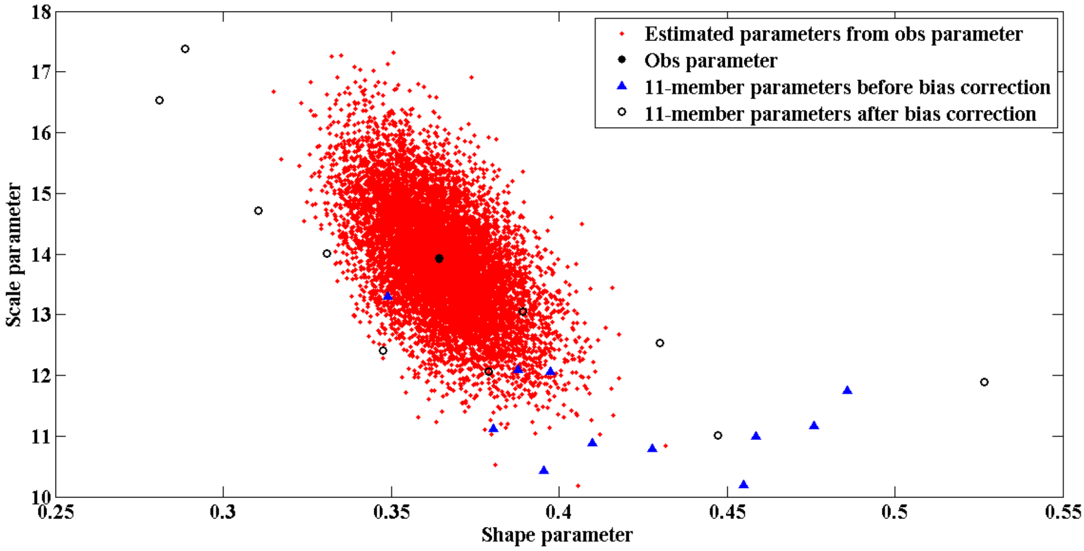

Figure 13. Result of using one transfer function for bias correction.

5. Discussion

Climate change scenarios are generated using climate models (e.g. GCMs and RCMs) and emission scenarios, and are the key information for understanding future changes in hydrologic systems. While RCMs are designed to better simulate local climate at a finer spatial and temporal scales, 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 ensemble members are matched to that of the observations in terms of statistical characteristics so that the advantage of the ensemble 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.

Bias in climate models can be introduced by imperfect parameterisation of some climate processes (Ehret et al., 2012; Teutschbein and Seibert, 2012), incorrect boundary conditions and initialization (Bromwich et al., 2013), inadequate reference data sets such as reanalysis data (Dee et al., 2011; Thorne and Vose, 2010), and limitations in input data resolution (Wood et al., 2011). Eleven ensemble members of HadRM3 consist of one unperturbed member and 10 members with different perturbations to the atmospheric parametrisations. Since different members are the outputs from different parameterisations, they would have different biases and be considered as independent (although not totally independent) from other ensembles. Therefore, we believe it is more reasonable to undertake the bias correction independently for each member rather than correcting them with the same bias.

Ideally if we have numerous numbers of observation data, more reliable climate statistics could be derived. However, in reality, 30 years of observation data have been used as the reference climate which is just one realisation of many possibilities, and the uncertainty associated with distributional parametric uncertainty needs to be considered in designing and conducting impact studies of climate change. Distributional parametric uncertainty exists when limited amounts of hydrologic data are used to estimate the parameters of PDF. On the other hand, initial conditions or parameters in climate models can be perturbed to generate a large number of ensemble members. Given the results we achieve, these ensemble members need to be examined to ensure that they are plausible.

Figure 14 describes why the bias corrected members should originate from within the bounds of the natural variability of the observation. It is supposed that the probability distributions of the natural variability and climate model uncertainty look like Figure 14. The range of both the baseline and hypothetical future natural variability are similar while the model uncertainty is larger. In this case, the chances of floods (i.e. area of the

PDF which are above the flood causing precipitation) for the baseline period and future are 5% and 10% respectively which we assume are the true values. However, according to the model uncertainty, the odds of the floods in the future are overestimated by 20% which means more actions are needed to mitigate the flood risk than in reality. This misinterpretation may, in turn, lead to inefficient efforts to improve the water system since it is related to the mitigation and adaptation plan. Therefore, the spread of the model uncertainty should be similar to that of the climate natural variability.

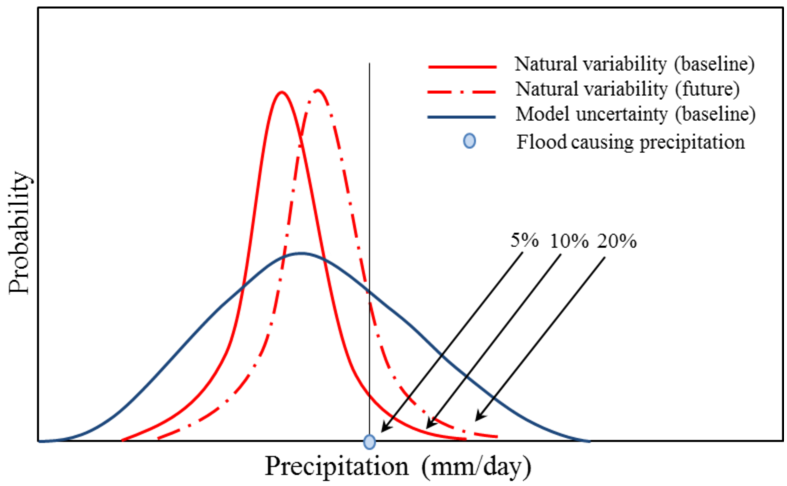

Figure 14. Probability distributions of natural variability and climate model uncertainty. The thick red curve, dashed red curve and cyan curve are the probability distributions of the baseline natural variability, future natural variability and baseline model uncertainty respectively. The thick black line is a threshold for flood causing precipitation. The real probabilities of floods for the baseline and the future are 5% and 10% respectively, while the model overestimates the flood risk by 20%.

This study attempts to evaluate the reliability of the RCM ensemble in terms of natural variability and to propose a new bias correction scheme conforming to the RCM ensembles. However, the proposed scheme is just one of the necessity conditions to assess the RCM ensembles and a comprehensive scheme including more conditions needs to be further developed. It does not mean that the RCM which meets this condition is a good model, but if it does not meet this condition, the RCM ensemble fails to represent the natural climate variation as described in Figure 14 (hence such a condition is a necessity condition, not a sufficiency condition). We believe that there should be a set of necessity conditions to better assess and improve future climate projections in various aspects of uncertainty analysis.

We would like to point out some limitations of this study. First, as previously mentioned, bias correction is a controversial issue. In addition, there is no generic one-suit-fits-all bias correction methods for rainfall data since rainfall time series has many aspects and cannot be all corrected simultaneously. The way of correcting the bias should depend on the data purpose, since the bias depends on the specific rainfall characteristic (Kew et al., 2011). In this study, we have focused on matching underlying statistical properties between the observed and simulated rainfall, which are the cumulative probability distribution and the spread of rainfall series. In the future, other statistical properties for parameter distributions may also be included. Second, depending on how to estimate the observational uncertainty the interpretation of Figures 13 and 14 can be different. In this study, we have used a bootstrap method to describe the observational uncertainty from 30 year of observation data. However, in reality, there is no way to describe the uncertainty that is not captured by the 30 years of observations. For instance, variability of observations on a slow time scale (decadal or centennial), or realisations of precipitation amounts with very long return periods (exceeding the record length of this observation data set) cannot be estimated, but may be highly relevant. It may well be that the ensemble is more able to capture modes of variability (both decadal oscillations and unprecedented extremes) that may not be captured by the observations. In that sense, it may be possible that the estimated spread of observational uncertainty in Figure 13 could be narrower than the true spread and the result of using one transfer function may be more realistic than that from our proposed method. Likewise, in Figure 14, it is possible that it is not an overestimation of flood probability by the ensemble, but an underestimation by the observations. In summary, if the natural variability is fully obtainable from the observation, our proposed methodology, in theory, should work better than the conventional method. However, it should be pointed out that the natural variability may not be fully captured by the decades of observation. Therefore, further studies are needed to explore how to capture the natural variability beyond the local observation. In this regard, a simulation technique based on multiscale approaches (e.g. wavelet transform analysis and empirical mode decomposition technique) could be a way to better represent the natural variability.

6. Conclusions

Conventionally, all climate model simulations are corrected to the observation. With this scheme, the uncertainty of the model from the ensembles will be lost and as a result the 11-member ensemble will be similar to just one member. Another approach is to apply one transfer function based on the unperturbed member to the rest 10 members. This will keep the spread properties of the ensemble but this spread may not conform to the spread from the real natural system. Therefore they do not look like as if they are drawn from the natural system. In this study, we have proposed a new scheme which overcomes the shortcomings of the aforementioned two schemes (i.e. 11 transfer functions all conformed to one observed realisation or one transfer function for 11 members which result in the bias corrected ensembles too narrow or too wide), and the proposed method is a good balance between the two. Therefore, the 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 the 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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