Response to the Editor and Reviewer comments

Dear Editor,

We would like to thank both editor and reviewers for their detailed and useful comments on our paper. The constructive comments have helped to improve this article considerably.

Editor (Dr. B. van den Hurk):

1. Both reviewers suggested to complement your study with a hydrological application, and so I welcome your initiative to include the IHACRES model. However, I do advise you to redesign the structure of the paper in line with the suggestions put forward by reviewer 2, to convince the reader that your new bias correction is indeed an improvement to current practice.

Reply:

Thanks for the useful comments. We have revised the manuscript according to Reviewer 2's suggestions.

2. In response to the 5th specific comment of reviewer 2 you state "In our view, as each ensemble member has different systematic error, it can be considered as independent from other ensembles". This in itself is a bit controversial, as systematic bias is (implicitly) assumed to originate from a structural error in the model, and thus should be the same across the ensemble members. You have to make clear why you disagree with this notion and what other sources of systematic error could contribute to ensemble spread that needs to be corrected. Please put this discussion in the introduction section of your revised manuscript.

Reply:

Thanks for the helpful comments. We have revised the reply and included the following discussion in the manuscript.

- 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., 2011a; 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 each member is the output from different parameterisations, they would have different biases and be considered as independent (although not totally independent) from other ensembles. Therefore, it is reasonable to undertake the bias correction independently for each member rather than correcting them with the same bias.

3. I also tend to disagree with your statement that "the purpose of a model simulation is to be indistinguishable from the real world". Natural variability is one reason why this will never be the case. But a more philosophical objection against this statement is that any model, no matter how complex, will always be different from the real world since it is essentially a schematization. You might argue that a model simulation should allow you to extract relevant information on how the real world works (see first comment reviewer 2), but that is something different than a model that has to be indistinguishable from the real world.

Reply:

Thanks for the helpful comments. Yes, any climate model would be different from the real world due to the natural variability. Our argument is not that the model simulation should be identical to the real world but that the underlying statistical properties of the model output should be similar to the real system. To clarify, the following discussion has been included in the manuscript.

- 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.

4. Your new figure 1 could have a display of the spread of the uncorrected RCM data as well, to see where the bias correction changed the representation of natural variability.
The shading in figure 1 leaves some room for various interpretations: does the darkest area fall entirely within the range of the lighter shaded area, or does the dark area just point at a (partial) overlap between the two bc methods?

Reply:

In the previous reply, there was a mistake in the hydrological application. We have performed the analysis again and included the following results in the manuscript.

- To investigate the impact of these two different bias correction schemes on flow, we used a hydrological model IHACRES. As previously mentioned that our 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 11(a) shows the spread of the monthly mean flow simulated from the precipitation ensembles for the period 1961-1990. The 5-95 percentile spread has been plotted. Figure 11(b) shows the range of monthly spread and Figure 11(c) shows the annual average value of the spread range. The flow ensembles simulated from the uncorrected 11-member (blue dashed line) obviously have biases and the range of the spread is inconsistent compared with that of the observed flow (black straight line). The flow ensembles simulated using bias corrected RCM precipitation (both conventional and proposed methods) are 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 ensembles.

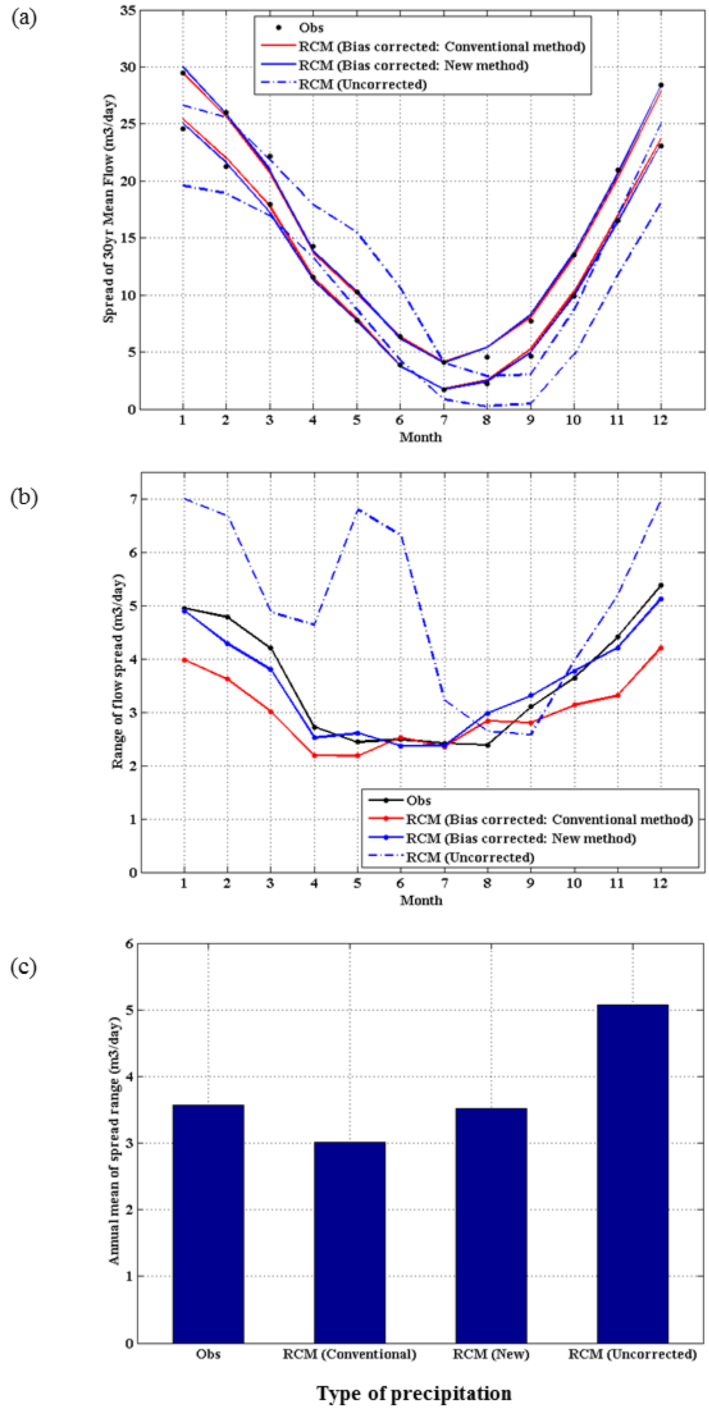

Figure 11. The spread of monthly mean flow for the period 1961-1990 derived from the precipitation ensembles.

5. I don't understand very well your reply to the third comment of reviewer Photiadou. She doubts whether a bias correction is necessary, and you reply with a demonstration of variability between ensemble members that could well represent natural variability, a feature that you want to preserve in your bias correction method. Please motivate the need for a bias correction a bit stronger.

Reply: The reply to the reviewer has been revised. We have added the following paragraph.

- Meanwhile, although the CDFs show the spread which is a feature to be preserved during bias correction, the distributions of the parameters (Figure 6(c) and (d) in the manuscript) for the combined ensemble often show relatively large biases in both the mean and the variance compared with those of the observation. Therefore, bias correction is needed to match not only the mean value but the variance (i.e. spread) of the parameters.

6. The second point of reviewer 2, about the dependence of bias on the specific rainfall characteristic, is nicely demonstrated in Kew et al (http://www.hydrol-earthsyst-sci.net/15/1157/2011 /hess-15-1157-2011.pdf.)

Reply:

Thanks for the helpful comments. We have included the following discussion and the suggested reference in the manuscript.

- 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 so 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 parameters' distribution. Other statistical properties for the parameter distributions may also be included in the future.

7. Textual corrections are required. I suggest invoking the help of a native English speaker or using the editorial service of HESSD.

Reply: The manuscript has been carefully checked and revised to improve its readability.

References

Ehret, U., E. Zehe, V. Wulfmeyer, K. Warrach-Sagi, and J. Liebert (2012), HESS opinions ‘‘Should we apply bias correction to global and regional climate model data?,’’ Hydrol. Earth Syst. Sci. Discuss., 9, 5355–5387.

Teutschbein, C., and J. Seibert (2012), Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods, J. Hydrol., 456–457, 12–29, doi:10.1016/j.jhydrol.2012.05.052.

Bromwich, D. H., Otieno, F. O., Hines, K. M., Manning, K., and Shilo, E.: Comprehensive evaluation of polar weather research and forecasting model performance in the Arctic, J. Geophys. Res.-Atmos., 118, 274–292, 2013.

Dee, D. P., Kaellen, E., Simmons, A. J., and Haimberger, L.: Comments on "Reanalyses Suitable for Characterizing Long-Term Trends," Bull. Am. Meteorol. Soc., 92, 65–70, 2011a.

Thorne, P. W. and Vose, R. S.: Reanalyses Suitable for Characterizing Long-Term Trends, Bull. Amer. Meteor. Soc., 91, 353–361, 2010.

Wood, E. F., Roundy, J. K., Troy, T. J., van Beek, L. P. H., Bierkens, M. F. P., Blyth, E., de Roo, A., Doell, P., Ek, M., Famiglietti, J., Gochis, D., van de Giesen, N., Houser, P., Jaffe, P. R., Kollet, S., Lehner, B., Lettenmaier, D. P., Peters-Lidard, C., Sivapalan, M., Sheffield, J., Wade, A., and Whitehead, P.: Hyper resolution global land surface modeling: Meeting a grand challenge for monitoring Earth's terrestrial water, Water Resour. Res., 47, W05301, doi:10.1029/2010WR010090, 2011.

Jones P, Kilsby C, Harpham C, Glenis V, Burton A. 2009. UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator. University of Newcastle, UK.

Kew S, Selten F, Lenderink G, Hazeleger W. 2011. Robust assessment of future changes in extreme precipitation over the Rhine basin using a GCM. Hydrology and Earth System Sciences, 15: 1157-1166.

Reviewer #1 (Dr. C. S. Photiadou):

1. The study is applied in a single catchment since the argument is that the regional models are used in impact studies. However, it is not demonstrated how this bias correction will influence an impact study. I am suggesting that a hydrological application is presented to make the bias correction stronger.

Reply:

Please refer to the reply to the 4th comment of Editor.

2. A recent published study by Addor N. and Fischer E. M. shows the influence of natural variability on bias characterization in RCM simulations. They show that different methods of estimating natural variability give different measures, depending on the method, season, and time scale of your observation record. This in return will influence the bias correction. I think it will add value to the study if the authors will comment on this and then justify the procedure to generate the natural variability. For example the authors used a resampling of the 30 years by 100000 times using the parameters of the observations but did you use any maximum stopping point? The aforementioned study suggests that also the number of times one that the resampling occurs should be maximized for each case. How was the resampling procedure optimized then?

Reply:

Thanks for the suggestion. We have added the recommended reference and commented on the influence of natural variability on bias characterization in the RCM simulations as follows.

- There has been relevant work recently around the influence of natural variability on bias characterization in the 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 the RCM simulations.

Regarding the optimised number of resampling, we have added the following paragraph.

- 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 in this study does not take long, we have resampled 100,000 times which are sufficient.

3. Fig 6a shows the probability density function of daily observed and the 11-member precipitation before any bias correction. From this figure I would say that a bias correction is not necessary.

Reply:

- It seems that the bias correction is not necessarily required given Fig 7a (in the revised manuscript) since the PDFs of the observation and ensembles look similar. However, the quantiles (precipitation) for the same cumulative probability could be quite different in the quantile mapping process. For example, as presented in the figure below, when the cumulative probability is 0.8, the observed precipitation is 8.1 mm/day, while the uncorrected RCM ensemble precipitation ranges from 6.2 mm/day to 9.5 mm/day which are 23.5% less and 17.3% more than the observation respectively. In addition, when the cumulative probability is 0.9, the difference range becomes wider than before as described in the table below.

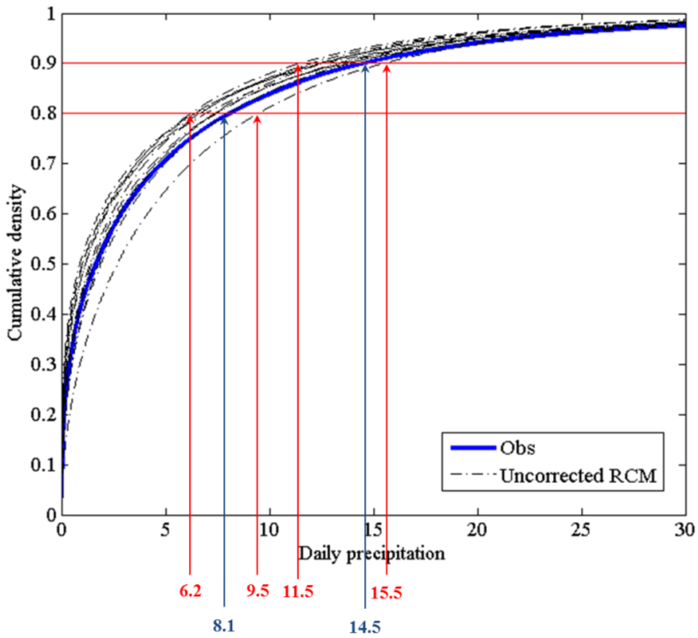

Figure R3. CDFs of the observed and 11-member precipitation time series before bias correction.

Table R3. Precipitation values at CDFs are 0.8 and 0.9.

	CDF = 0.8		CDF = 0.9	
	Precipitation (mm/day)	**Difference (%)**	**Precipitation (mm/day)**	**Difference (%)**
Obs	8.1		14.5	
RCM (minimum)	6.2	-23.5	11.5	-20.7
RCM (maximum)	9.5	17.3	15.5	6.9
Total		40.7		27.6

- Meanwhile, although the CDFs show the spread which is a feature to be preserved during bias correction, the distributions of the parameters (Figure 7(c) and (d) in the revised manuscript) for the combined ensemble often show relatively large biases in both the mean and the variance compared with those of the observation. Therefore, bias correction is needed to match not only the mean value but the variance (i.e. spread) of the parameters.

4. On the other hand, Fig. 9a shows the bias on a monthly scale; how about the bias in a daily scale? Also at page 10267, line 13, it is stated that the goal is to obtain monthly bias corrected precipitation and not daily. Explain why the preference on monthly data, why the correction is done on a daily scale instead of a monthly scale, and it is interesting to see that daily natural variability improves monthly means.

Reply:

In this study, we used daily precipitation, while bias correction has been done on monthly basis with the daily data. In other words, monthly statistical properties from 1961 to 1990 are adjusted between the observed daily precipitation and simulated daily precipitation.

The reason that we have used the time series of daily precipitation for bias correction is because the hydrological model IHACRES used in this study requires daily precipitation for its input data.

Then the issue can be the time steps for bias correction. Monthly bias correction is to match the statistical properties between the observation and RCM data (daily precipitation in this study) based on the monthly time period, while seasonal bias correction is to match the statistics based on the seasonal time period (see the figure below). The time steps can be monthly (12 groups), seasonal (4 groups), annual (1 group) or something else. The more groups we divide the time for bias correction, the less biased the corrected data will be. This is because if a bias correction period is shorter, temporal distribution of the time series can be considered with more details than a longer bias correction period. As a result rainfall characteristics can be matched more sophisticatedly between the observation and the simulated data. However, on the other hand, the higher the number of groups, the higher the variance will be. This is a well-known trade-off between bias and variance in mathematical modelling. What is an optimal time steps for bias correction can be another research topic. In this study, we have used monthly bias correction because it is the most popular duration used in practise.

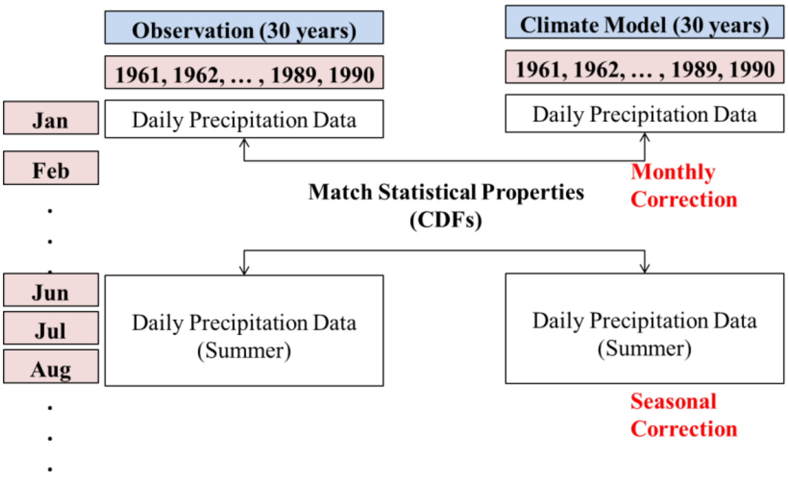

Figure R4. Schematic of monthly bias correction and seasonal bias correction.

5. Also explain if the by the 11-member precipitation series you mean a mean of the 11 member.

Reply:

The "Probability Density Function of the 11-member precipitation time series before bias correction" in Fig. 6a's caption means not the mean of 11-member but 11 individual members. The black dashed lines in this figure represent the PDFs of individual 11-member precipitation time series.

6. Page 10270 line 15: Step 4 is unclear on the "move to the centre" procedure. Please explain briefly how this is done.

Reply:

Thank you for pointing out this somewhat unclear explanation. To clarify, we have revised the explanation for Step 4 as follows:

- (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.

7. Improve caption for Fig. 1. The grid box in red represents the entire catchment?

Reply:

The grid box is selected, which covers most part of the Thorverton catchment. To clarify, we have revised the caption as follows:

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

8. Fig.10 is misleading. It is stated that this plot is an example of the use of a one transfer function thus an example of the conventional bias correction. However, Fig. 7b is also a result from the conventional bias correction but has totally different behaviour. Please explain if I misunderstood.

Reply:

The bias correction schemes applied in Fig. 8b (in the revised manuscript) and Fig. 12 (in the revised manuscript) are different. In Fig. 8b, each 11-ensemble member is treated individually. Therefore, different 11 transfer functions are applied to different members. However, in Fig. 12, only one transfer function (from the unperturbed member) is used to correct the entire 11 members.

9. Also maybe add at in the discussion section a paragraph on the actual results you presented and discussing the physical meaning of the proposed bias correction.

Reply:

Thanks for the suggestion. We have added the following paragraphs.

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.

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-ensemble members 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 ensembles 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 results in the bias corrected ensembles too narrow or too wide), and the proposed one is a good balance between the two.

Reference

Addor, N. and Fischer, E. M.: The influence of natural variability and interpolation errors on bias characterization in RCM simulations, Journal of Geophysical Research: Atmospheres, 120, 2015.

Anonymous reviewer #2:

General comments

1. The paper by itself is well-written and the concepts conveyed in a clear manner and can be easily understood. However, I am missing the practical framework of the proposed method. I would structure the paper (any paper on bias-correction methods) as follows:
   - Find an application of the bias corrected data, e.g. rainfall-runoff simulation.
   - Discuss the characteristics relevant to this application (e.g. variability of catchment precipitation at a certain timescale) and their bias.
   - Explain why the proposed bias-correction method should properly correct these characteristics properly.
   - Discuss what variability of the ensemble should be preserved.
   - Demonstrate the skills of the method for just the abovementioned features using the catchment example.
   - Discuss the shortcomings of the method, if any.
   - Speculate on the effects of these shortcomings on the practical application.

Reply:

Please refer to the reply to the 4th comment of Editor and the revised manuscript.

2. The reason is that I am sceptical about generic one-suit-fits-all bias-correction methods for rainfall data. There are so many aspects of rainfall series; they cannot be all corrected simultaneously. The way of correcting should therefore depend on what properties are relevant the application. For instance, one has a multi-model ensemble, the members of which are known to be systematically biased in certain characteristics (i.e. mean rainfall) in the same way in their scenario runs as in their current-climate run and one wants to obtain an `unbiased' ensemble of scenario runs to drive hydrological simulations, which are sensitive to the variability of n-day rainfall. The method raises some questions. Why is the spread of the parameter set also corrected? (I mean σ_{xo}/σ_x in eqns 4 and 5)? In doing so, the variability in the observation parameter sets is imposed onto the simulated parameter sets. The variability of the latter is lost in this action, thereby the added value of an ensemble of simulations. I would only apply the shifting to remove systematic bias in the parameters and accept the spread from the simulation.

Reply:

Thanks for the good comments. We have included the following discussion in the manuscript. In addition, reply to the comment “why is the spread of the parameter set also corrected” has been made in the reply to the Specific comments 7 and 8.

- 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.

Specific comments

1. pg 10264: line 1: "..distribution mapping was the best..." Why and in what way? (references) What is the criterion?

Reply:

According to Teutschbein and Seibert (2012), the distribution mapping method performed best in terms of the performance that conformed to the CDF fit (i.e. the calculated mean absolute error).

2. In the next line: "... correcting the model output towards the corresponding observation is still a controversial issue... Of all mentioned methods this is most true for distribution mapping. It is not even preserving the models distribution shape. With this method the corrected rainfall becomes the most similar to observed rainfall.

Reply:

Thanks for the helpful comments. We agree that bias correction is a controversial issue (Ehret et al., 2012) and the community is divided on this while it is still widely used in climate impact studies. In addition, which bias correction method to apply is a controversial subject as well. Some studies argue that there is a flaw with the distribution mapping (Madadgar et al., 2014) and claim that the conditional bias correction methodologies produce better results than the distribution mapping which is an unconditional approach (Brown and Seo, 2013; Madadgar et al., 2014; Verkade et al., 2013). On the other hand, the distribution mapping has been used in many practical datasets widely adopted by practitioners such as the well-known ‘Future Flows Climate’ (Prudhomme et al., 2012) dataset which is an 11-member ensemble climate projection for Great Britain at a 1-km resolution. In this study we are not arguing that the distribution mapping is the only and the best method. Instead, it is used as one of the conventional bias correction methods to illustrate the problem in adjusting all the ensemble members to one observation as a reference value. Any other conventional bias correction methods have the same problem.

3. pg 10264, line 8: .. uncertainty associated with the observation sampling uncertainty ....". But what about the model uncertainty? How do you preserve that?

Reply:

This study attempts to jointly investigate the uncertainties associated with climate natural variability and model uncertainty. The model uncertainty is preserved by matching the spread of the ensemble members to that of the natural variability of the observation.

Conventionally, all climate model simulations are corrected to the observation. With this scheme, the uncertainty of the model from the ensembles is lost and as a result the 11-ensembles members 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 being too narrow or too wide) and it is a good balance between the two.

4. pg 10264, line 13: "boundary condition" = "external forcing"

Reply:

We have added the term "external forcing" in the parenthesis as below.

- … boundary condition (<u>external forcing</u>), model structure and natural variability …

5. pg 10264, line 24: In PPE's, would you rather correct ensemble members individually or as an ensemble (since it is the same model)? In the latter case, the argument of disregarding the ensemble spread does not hold.
   pg 10269, line 14: .. each member is corrected by a different transfer function.... Why is that? I think this is not common practice, the parameter uncertainty gives you the spread you are looking for. The bias-correction is only a remedy for a systematic deviation, a tendency of the model.

Reply:

- 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., 2011a; 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 each member is the output from different parameterisations, they would have different biases and be considered as independent (although not totally independent) from other ensembles. Therefore, it is reasonable to undertake the bias correction independently for each member rather than correcting them with the same bias.

- 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.

6. pg 10270, line 16: The transfer function is expressed in equation (2), but not all reader will realize that. Please refer to that equation. You could be a little more elaborate on Step 4.

Reply:

Thanks for the suggestion. To clarify, we have added the "transfer function" in the parenthesis as below.

- This value is the bias corrected RCM precipitation and the equation (<u>i.e. transfer function</u>) is as follows.

Thank you for pointing us on this somewhat unclear explanation. To clarify, we have revised the explanation for Step 4 as follows:

- (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 bias correction can be built.

7. pg 10273-10274: The discussion conclusion is maybe the most interesting part: (Just note, RCM runs for downscaling give more accurate results on a local scale, but their circulation derives from the GCMs. Often, circulation bias is the origin of rainfall bias. So downscaling doesn't help there, no matter how detailed the RCM, if it is driven by a biased GCM.). You say that the spread

of the ensemble should be preserved, but your method scales the ensemble's variability of the distributional parameters to those of the resampled observations (generated ensemble supposed to resemble natural variability, which can also be debated, because this variability also contains 'non-stationarity'). In that case, the original variability of the ensemble is lost. Then it is mentioned (or suggested?) that only a single transfer function is used for the ensemble, which I understand is common practice. After that I am lost: the spread is not matched by that of the observations … therefore .. fails to reproduce to preserve the spread of the ensemble. I think these are two entirely different spreads, the former refers to the natural variability, the latter to the sensitivity of the model to uncertainty in the perturbed parameters. If a single transfer function for the complete ensemble, only correcting for a systematic shift in the parameters, then the ensemble of transformed parameters still has the same spread as before. Then why is the benefit of the ensemble negated by this transformation?

Reply:

Please refer to the reply to the 9^{th} comment of Reviewer #1.

8. Finally, I fail to understand why the transfer functions should be built under the assumption that the corrected members must originate from within the bounds of the natural variability of the observation. A slightly different aspect potentially interesting to the reader is that not only the ensemble has its spread, but also the observation used to correct to.

Reply:

Thanks for the comments. To clarify, we have added the following paragraphs in discussion.

- 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 13 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 13. 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.

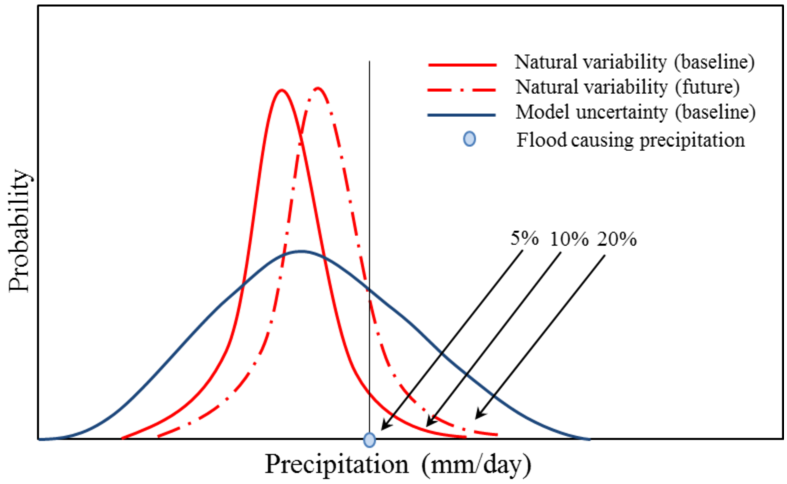

Figure 13. Probability distributions of natural variability and climate model uncertainty. The thick red curve, dashed red curve and cyan curve are the probability distributions of the baseline natural variability, future natural variability and baseline model uncertainty respectively. The thick black 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 13 (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.

References

Kew S, Selten F, Lenderink G, Hazeleger W. 2011. Robust assessment of future changes in extreme precipitation over the Rhine basin using a GCM. Hydrology and Earth System Sciences, 15: 1157-1166.

Brown, J.D., Seo, D.J., 2013. Evaluation of a nonparametric post-processor for bias correction and uncertainty estimation of hydrologic predictions. Hydrol Process, 27(1): 83-105.

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., Liebert, J., 2012. HESS Opinions" Should we apply bias correction to global and regional climate model data?". Hydrology and Earth System Sciences Discussions, 9(4): 5355-5387.

Madadgar, S., Moradkhani, H., Garen, D., 2014. Towards improved post-processing of hydrologic forecast ensembles. Hydrol Process, 28(1): 104-122.

Prudhomme, C. et al., 2012. Future Flows Climate: an ensemble of 1-km climate change projections for hydrological application in Great Britain. Earth System Science Data Discussions, 5(1): 475-490.

Teutschbein, C., Seibert, J., 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. Journal of Hydrology, 456: 12-29.

Verkade, J., Brown, J., Reggiani, P., Weerts, A., 2013. Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting at various spatial scales. Journal of Hydrology, 501: 73-91.

Jones P, Kilsby C, Harpham C, Glenis V, Burton A. 2009. UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator. University of Newcastle, UK.

Precipitation Ensembles conforming to Natural Variations derived from Regional Climate Model using a New Bias Correction Scheme

Kue Bum Kim[1], Hyun-Han Kwon[2*] and Dawei Han[1]

[1] Water and Environmental Management Research Centre, Department of Civil Engineering, University of Bristol, Bristol, UK
[2] Department of Civil Engineering, Chonbuk National University, Jeonju-si, Jeollabuk-do, South Korea
* Corresponding author: hkwon@jbnu.ac.kr

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 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 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). 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).

Numerous studies have been done to develop and evaluate 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 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 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.

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 606km^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.

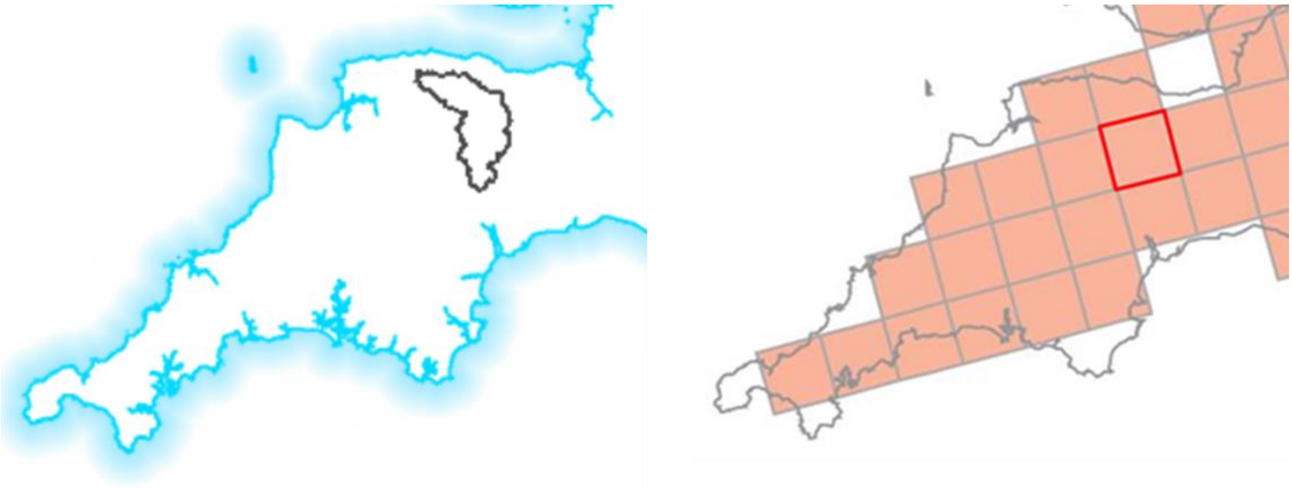

Figure 1. Location of the Thorverton catchment (the left panel) and HadRM3 25km grid boxes (the right panel). The highlighted grid box in red is selected to cover the Thorverton catchment.

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 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):

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

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.

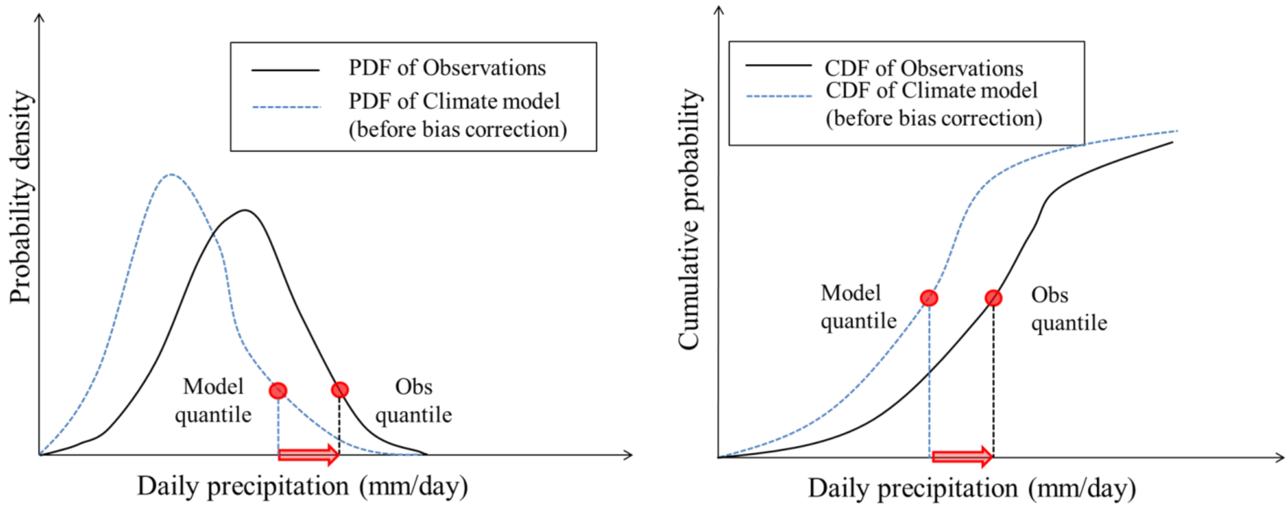

Figure 2. A schematic representation of the quantile mapping method for bias correction.

In this study, 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.

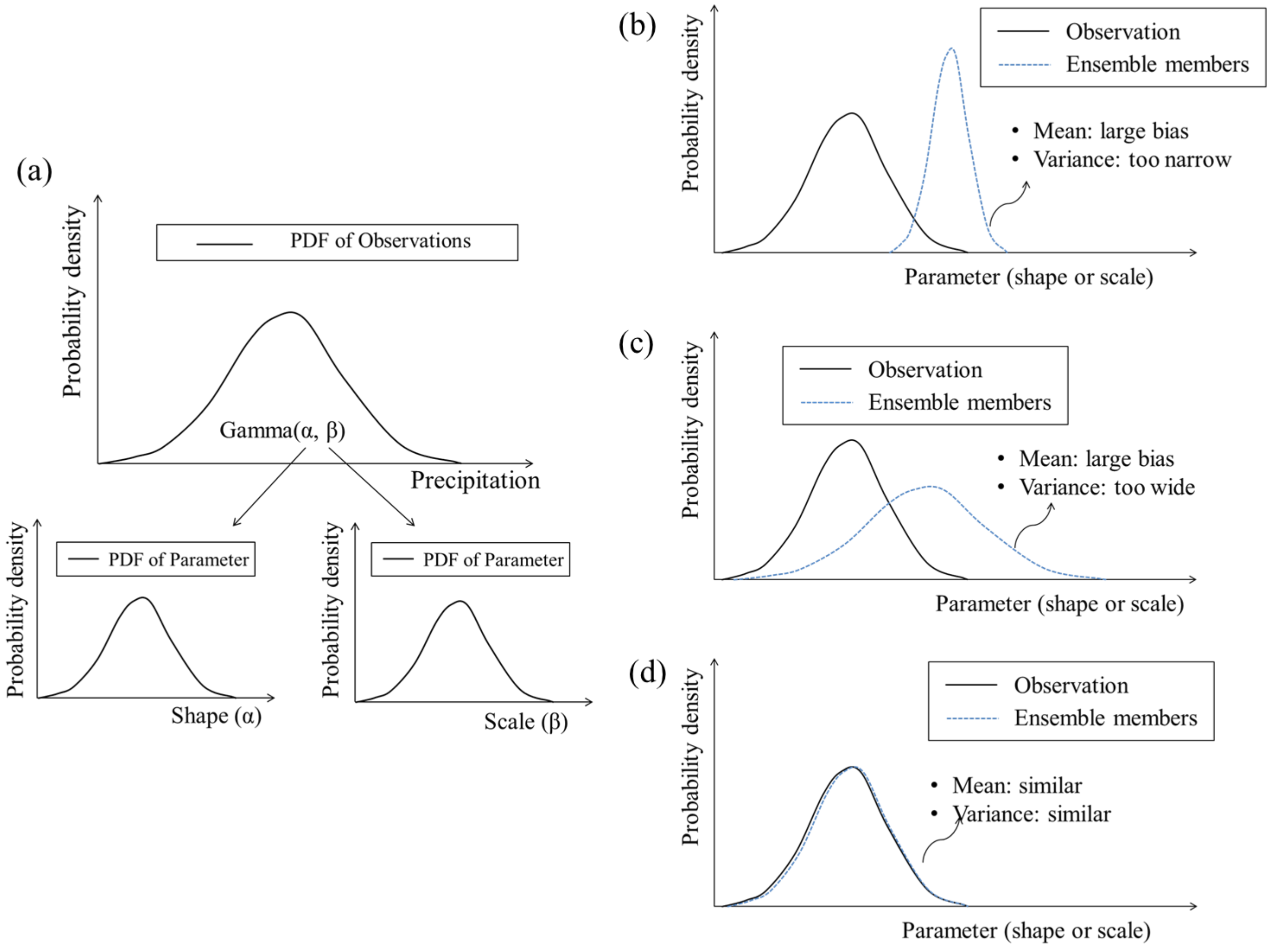

Figure 3. A schematic representation of the evaluation of ensemble members.

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)).

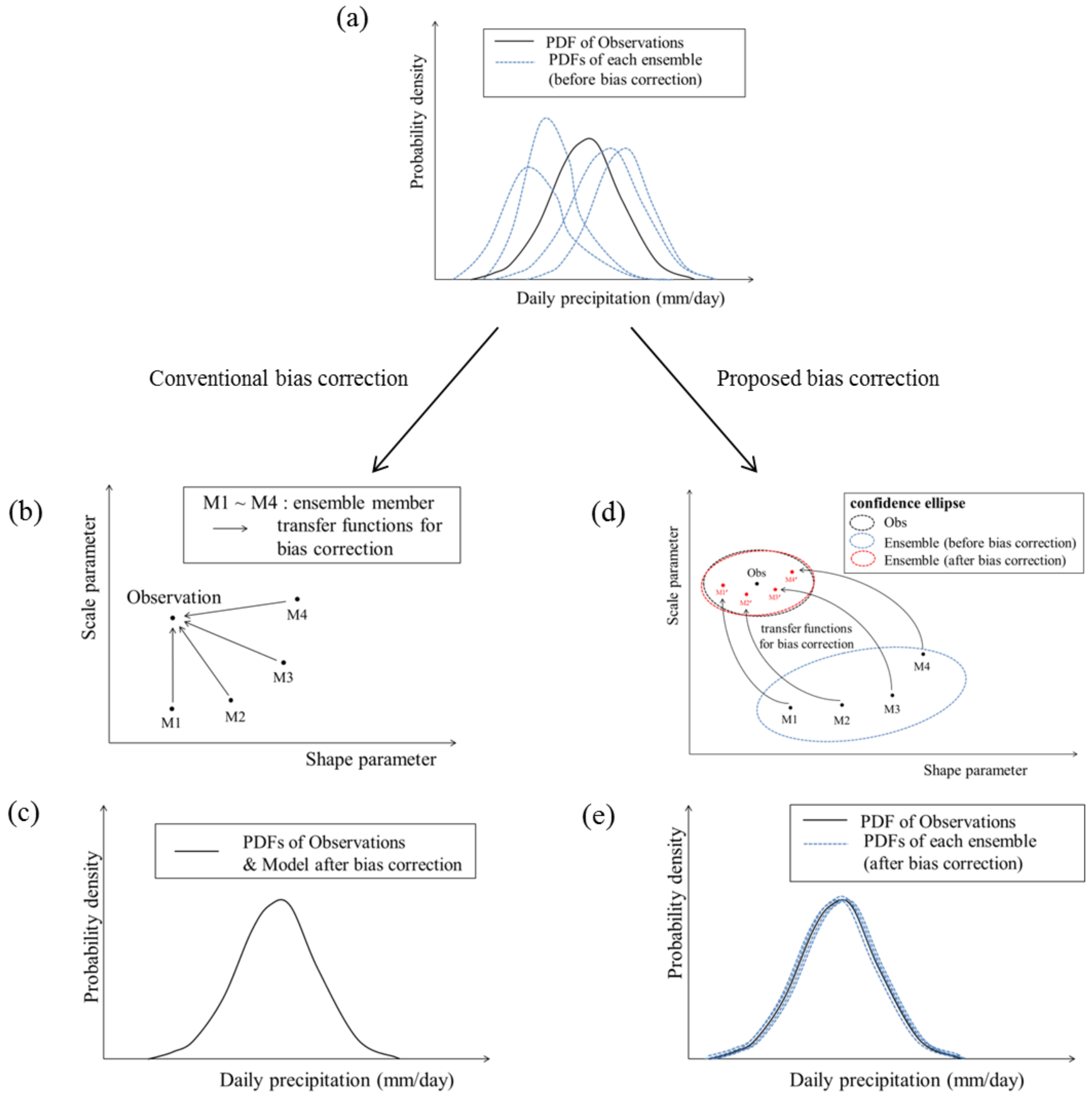

Figure 4. A schematic representation of the conventional bias correction method and the proposed bias correction method

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.

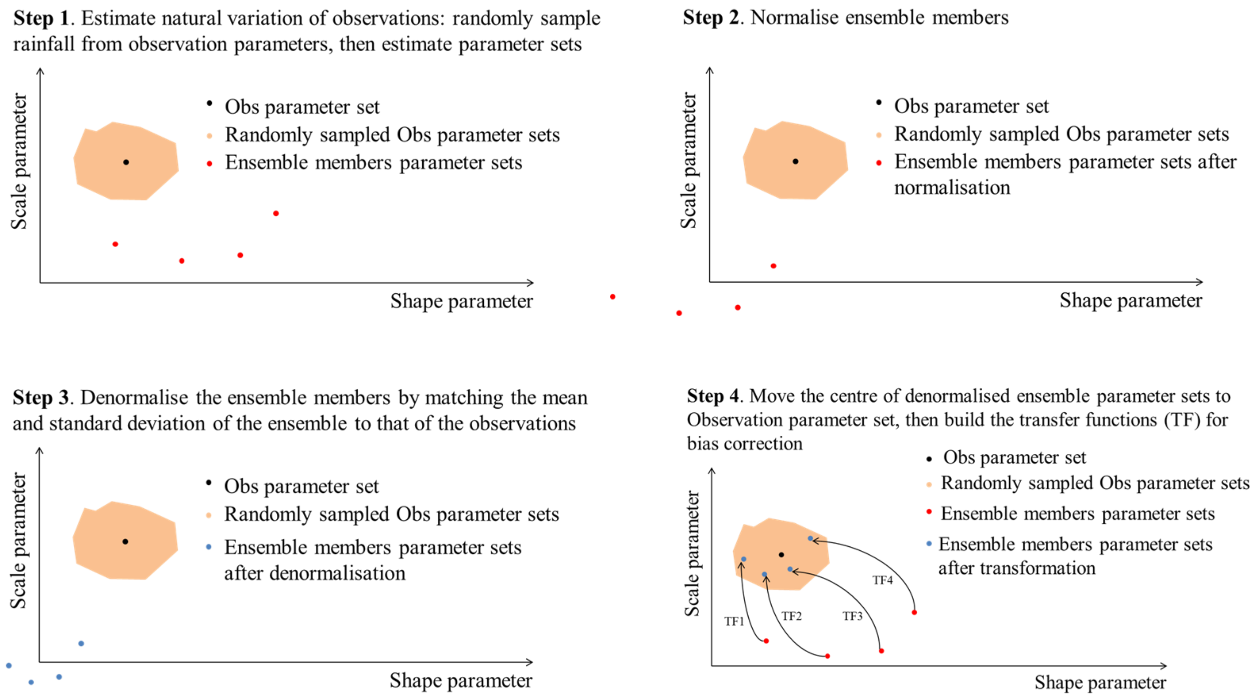

Figure 5. The four step procedure of the proposed bias correction method.

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).

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

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:

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

where, τ_k is the drying rate given by:

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

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:

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

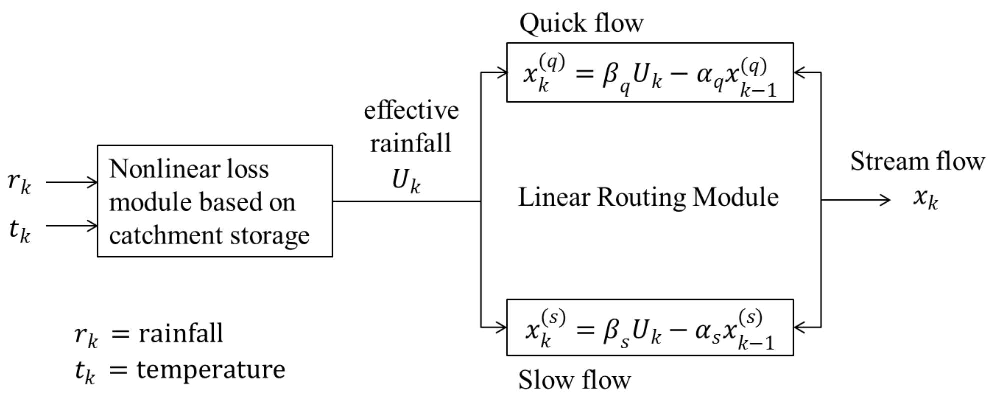

Figure 6. Structure of the IHACRES model.

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.

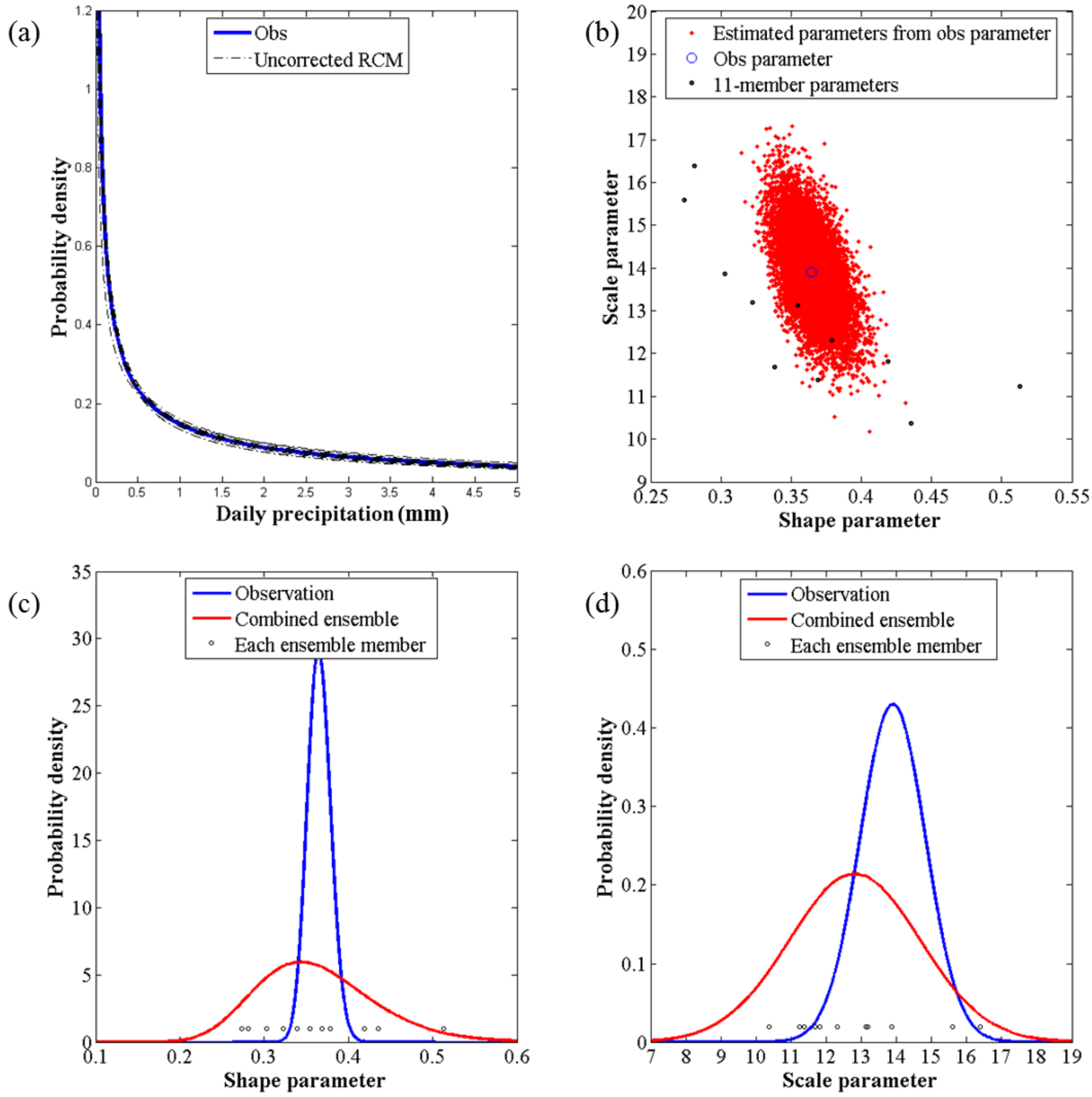

Figure 7. Parameter distributions of the observation and 11-members: (a) Probability density function of the observed and 11-member precipitation time series before bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias uncorrected precipitation; (c) - (d) Probability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

4.2 Conventional bias correction

Figure 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 8(a)) and the parameters of the corrected precipitation are all in the centre of the parameter space of the observation (Figure 8(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.

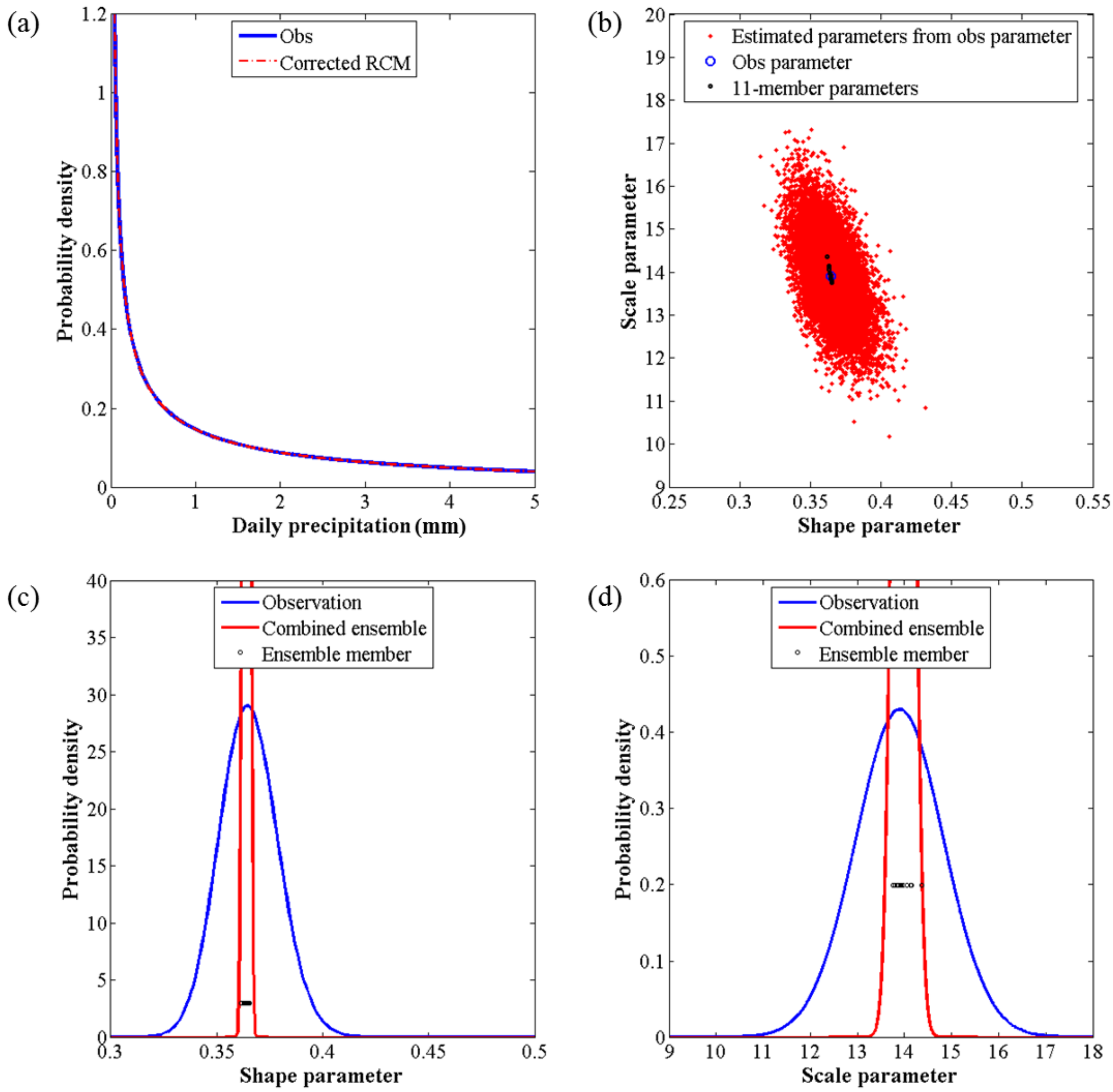

Figure 8. Results of the conventional bias correction method: (a) Probability density functions of the observed and simulated (i.e. 11-member) precipitation after bias correction; (b) Scatter plot between shape and scale parameters of the observed and bias corrected precipitation; (c)-(d) Probability 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 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 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 9(c) and (d)). Therefore, one can assume that all ensemble members represent realistic precipitation scenarios when the natural variability is considered.

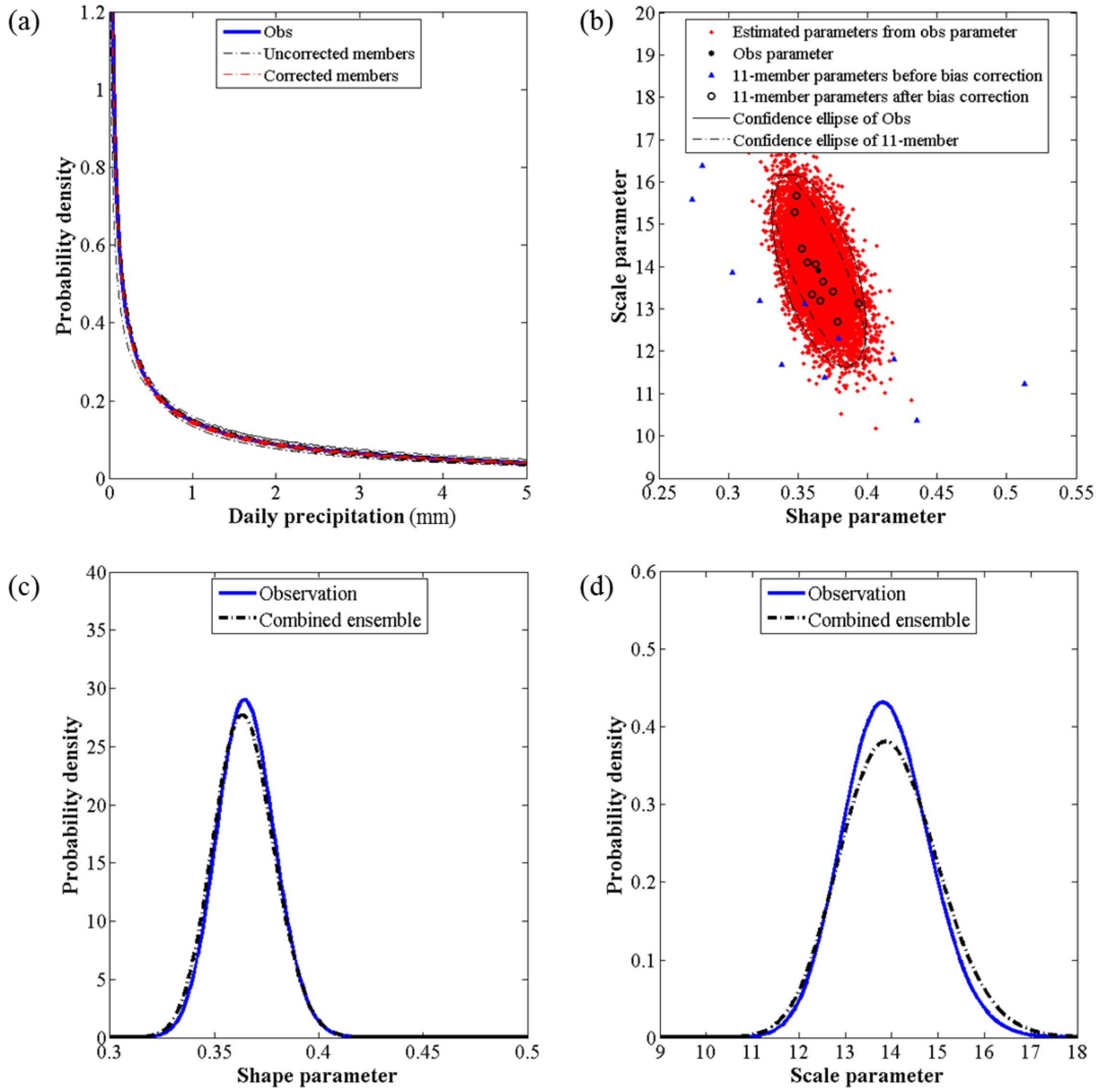

Figure 9. Results of the proposed bias correction method: (a) Probability density functions of the observed, bias uncorrected and bias corrected precipitation; (b) Scatter plot between the shape and scale parameters of the observed, bias uncorrected and bias corrected precipitation; (c)-(d) Probability 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 10 compares the result of the conventional and proposed bias correction schemes in terms of reproducing the mean precipitation. Figure 10 (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 10 (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 10 (c)).

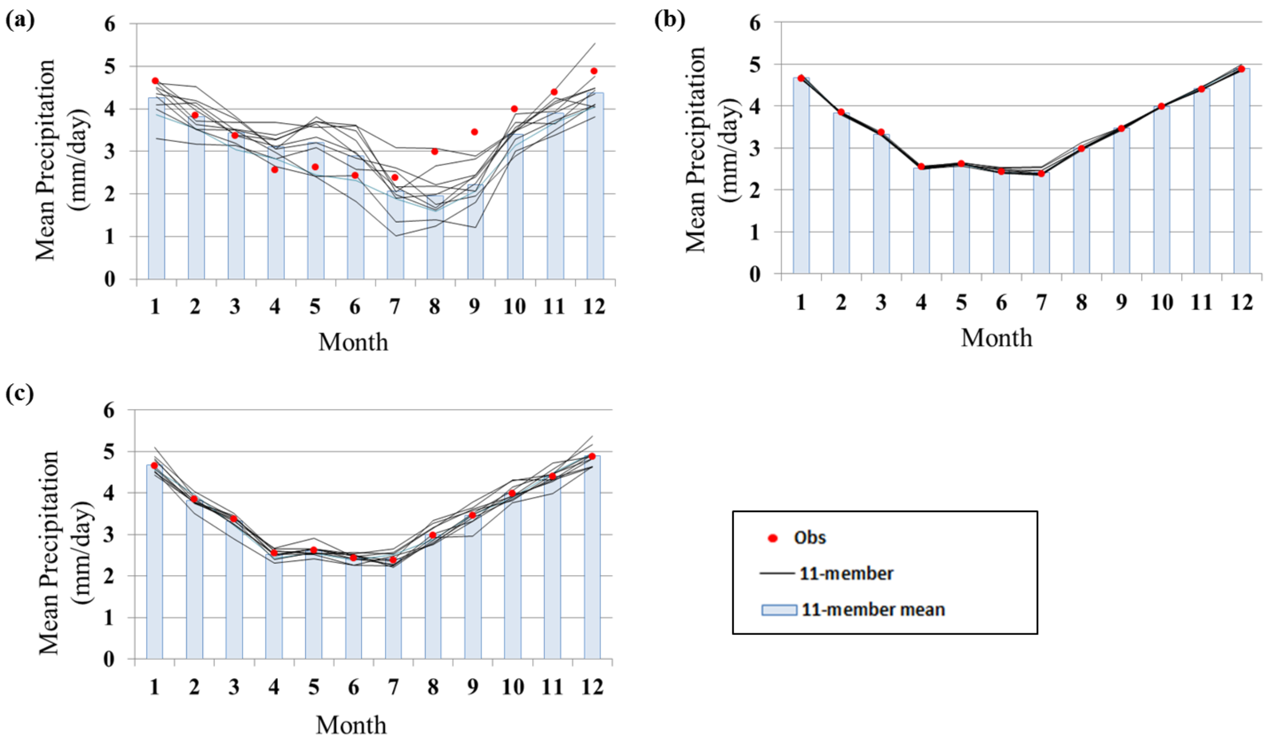

Figure 10. Monthly mean precipitation for the period 1961-1990 derived from the simulated precipitation. The mean values for the observation and 11-members are displayed as well. (a) Uncorrected 11-members; (b) Corrected 11-members by the conventional bias correction; and (c) Corrected 11-member by the proposed bias correction.

4.5 Hydrological application

As presented in Figure 10, 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 11(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 11(b) shows the range of monthly spread and Figure 11(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.

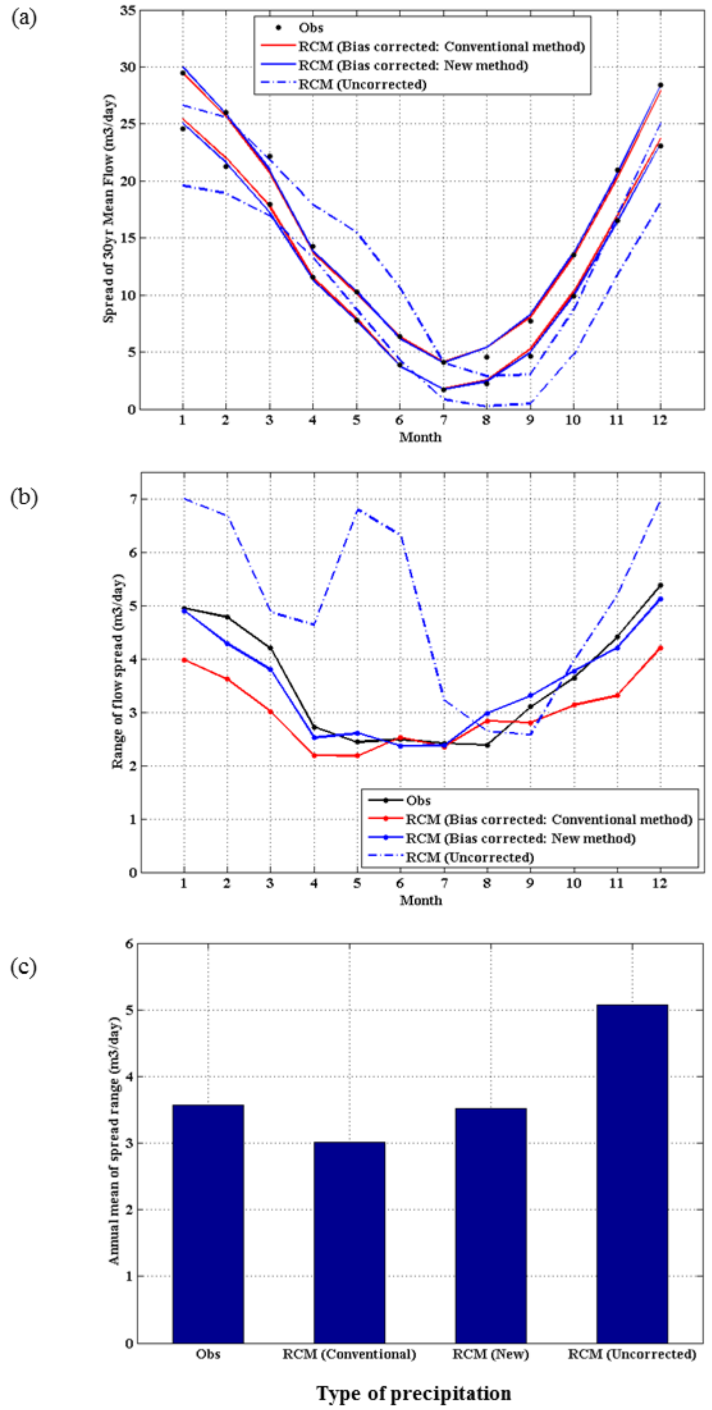

Figure 11. The spread of monthly mean flow for the period 1961-1990 derived from the precipitation ensembles.

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.

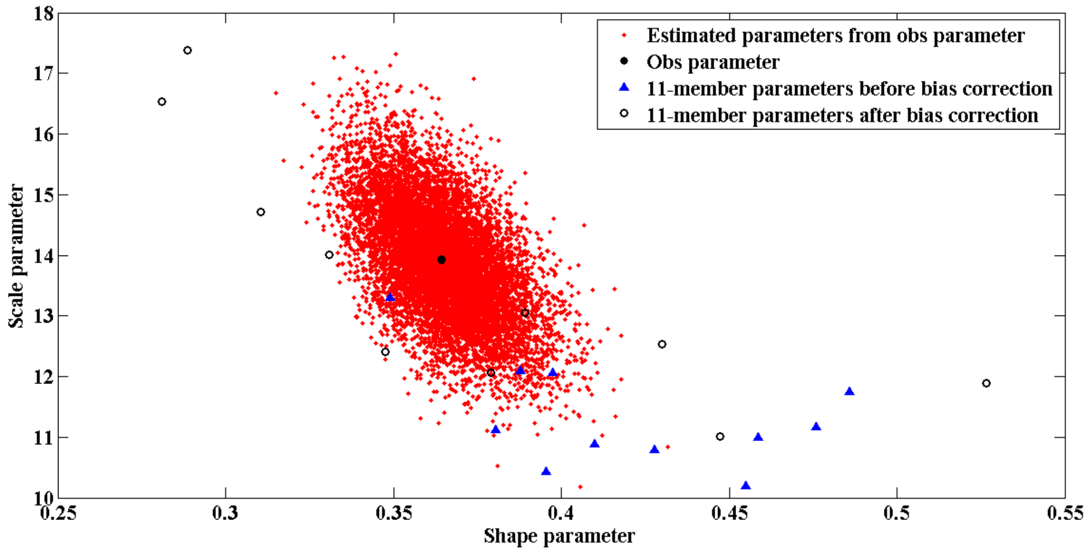

Figure 12. Result of using one transfer function for bias correction.

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 13 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 13. 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.

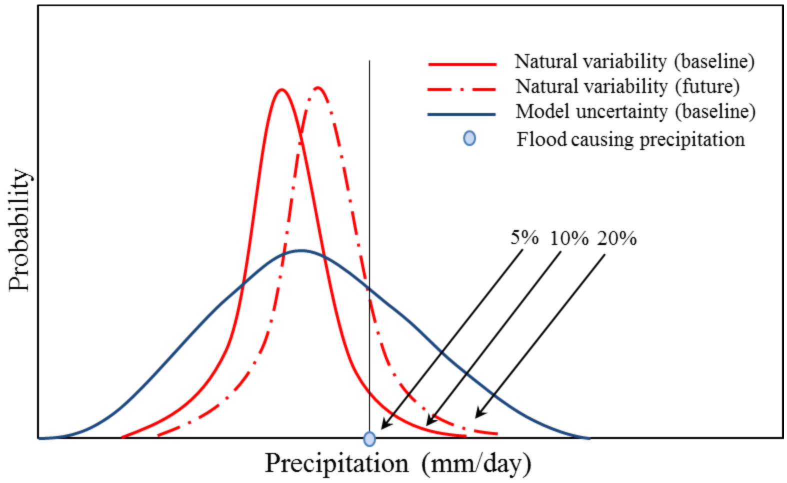

Figure 13. Probability distributions of natural variability and climate model uncertainty. The thick red curve, dashed red curve and cyan curve are the probability distributions of the baseline natural variability, future natural variability and baseline model uncertainty respectively. The thick black 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 13 (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.

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.

Acknowledgement

The first author is grateful for the financial support from the Government of Republic of Korea for carrying out his PhD study in the University of Bristol. The second author was supported by a Grant (13SCIPA01) from Smart Civil Infrastructure Research Program funded by the Ministry of Land, Infrastructure and Transport (MOLIT) of Korea government and the Korea Agency for Infrastructure Technology Advancement (KAIA). The data used in this study are available upon request from the corresponding author via email (hkwon@jbnu.ac.kr).

References

Addor, N. and Fischer, E. M.: The influence of natural variability and interpolation errors on bias characterization in RCM simulations, Journal of Geophysical Research: Atmospheres, 120, 2015.

Bates, B., Kundzewicz, Z. W., Wu, S., and Palutikof, J.: Climate change and water, Intergovernmental Panel on Climate Change (IPCC), 2008.

Block, P. J., Souza Filho, F. A., Sun, L., and Kwon, H. H.: A Streamflow Forecasting Framework using Multiple Climate and Hydrological Models1, JAWRA Journal of the American Water Resources Association, 45, 828-843, 2009.

Bromwich, D. H., Otieno, F. O., Hines, K. M., Manning, K. W., and Shilo, E.: Comprehensive evaluation of polar weather research and forecasting model performance in the Antarctic, Journal of Geophysical Research: Atmospheres, 118, 274-292, 2013.

Chen, J., Brissette, F. P., Chaumont, D., and Braun, M.: Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America, Water Resour Res, 49, 4187-4205, 2013.

Chen, J., Brissette, F. P., and Leconte, R.: Uncertainty of downscaling method in quantifying the impact of climate change on hydrology, Journal of Hydrology, 401, 190-202, 2011a.

Chen, J., Brissette, F. P., Poulin, A., and Leconte, R.: Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed, Water Resour Res, 47, 2011b.

Collins, M., Booth, B. B., Bhaskaran, B., Harris, G. R., Murphy, J. M., Sexton, D. M., and Webb, M. J.: Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles, Climate Dynamics, 36, 1737-1766, 2011.

Collins, M., Booth, B. B., Harris, G. R., Murphy, J. M., Sexton, D. M., and Webb, M. J.: Towards quantifying uncertainty in transient climate change, Climate Dynamics, 27, 127-147, 2006.

Compagnucci, R., Da Cunha, L., Hanaki, K., Howe, C., Mailu, G., Shiklomanov, I., and Stakhiv, E.: Hydrology and water resources, Climate change, 2001. 191-233, 2001.

Déqué, M., Rowell, D., Lüthi, D., Giorgi, F., Christensen, J., Rockel, B., Jacob, D., Kjellström, E., De Castro, M., and van den Hurk, B.: An intercomparison of regional climate simulations for Europe: assessing uncertainties in model projections, Climatic Change, 81, 53-70, 2007.

Dee, D., Källén, E., Simmons, A., and Haimberger, L.: Comments on “Reanalyses suitable for characterizing long-term trends”, Bulletin of the American Meteorological Society, 92, 65-70, 2011.

Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., and Liebert, J.: HESS Opinions" Should we apply bias correction to global and regional climate model data?", Hydrology and Earth System Sciences, 16, 3391-3404, 2012.

Feddersen, H. and Andersen, U.: A method for statistical downscaling of seasonal ensemble predictions, Tellus A, 57, 398-408, 2005.

Good, P. and Lowe, J.: Emergent behavior and uncertainty in multimodel climate projections of precipitation trends at small spatial scales, J Climate, 19, 5554-5569, 2006.

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in regional climate predictions, Bulletin of the American Meteorological Society, 90, 1095-1107, 2009.

Ines, A. V. and Hansen, J. W.: Bias correction of daily GCM rainfall for crop simulation studies, Agricultural and forest meteorology, 138, 44-53, 2006.

Jakeman, A. and Hornberger, G.: How much complexity is warranted in a rainfall-runoff model?, Water Resour Res, 29, 2637-2649, 1993.

Jakeman, A., Littlewood, I., and Whitehead, P.: An assessment of the dynamic response characteristics of streamflow in the Balquhidder catchments, Journal of Hydrology, 145, 337-355, 1993.

Johnson, F. and Sharma, A.: Accounting for interannual variability: A comparison of options for water resources climate change impact assessments, Water Resour Res, 47, 2011.

Jones, P., Kilsby, C., Harpham, C., Glenis, V., and Burton, A.: UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator, University of Newcastle, UK, 2009. 2009.

Kew, S., Selten, F., Lenderink, G., and Hazeleger, W.: Robust assessment of future changes in extreme precipitation over the Rhine basin using a GCM, Hydrology and Earth System Sciences, 15, 1157-1166, 2011.

Kim, H. and Lee, S.: Assessment of a seasonal calibration technique using multiple objectives in rainfall–runoff analysis, Hydrol Process, 28, 2159-2173, 2014.
Kotlarski, S., Block, A., Böhm, U., Jacob, D., Keuler, K., Knoche, R., Rechid, D., and Walter, A.: Regional climate model simulations as input for hydrological applications: evaluation of uncertainties, Advances in Geosciences, 5, 119-125, 2005.
Leander, R. and Buishand, T. A.: Resampling of regional climate model output for the simulation of extreme river flows, Journal of Hydrology, 332, 487-496, 2007.
Leander, R., Buishand, T. A., van den Hurk, B. J., and de Wit, M. J.: Estimated changes in flood quantiles of the river Meuse from resampling of regional climate model output, Journal of Hydrology, 351, 331-343, 2008.
Lenderink, G., Buishand, A., and Deursen, W. v.: Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach, Hydrology and Earth System Sciences, 11, 1145-1159, 2007.
Letcher, R., Schreider, S. Y., Jakeman, A., Neal, B., and Nathan, R.: Methods for the analysis of trends in streamflow response due to changes in catchment condition, Environmetrics, 12, 613-630, 2001.
Littlewood, I.: Improved unit hydrograph characterisation of the daily flow regime (including low flows) for the River Teifi, Wales: towards better rainfall-streamflow models for regionalisation, Hydrology and Earth System Sciences, 6, 899-911, 1999.
Maraun, D., Wetterhall, F., Ireson, A., Chandler, R., Kendon, E., Widmann, M., Brienen, S., Rust, H., Sauter, T., and Themeßl, M.: Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user, Reviews of Geophysics, 48, 2010.
Meehl, G. A., Arblaster, J. M., and Tebaldi, C.: Understanding future patterns of increased precipitation intensity in climate model simulations, Geophys Res Lett, 32, 2005.
Meehl, G. A., Covey, C., Taylor, K. E., Delworth, T., Stouffer, R. J., Latif, M., McAvaney, B., and Mitchell, J. F.: The WCRP CMIP3 multimodel dataset: A new era in climate change research, Bulletin of the American Meteorological Society, 88, 1383-1394, 2007.
Murphy, J., Sexton, D., Jenkins, G., Boorman, P., Booth, B., Brown, K., Clark, R., Collins, M., Harris, G., and Kendon, E.: UKCP09 Climate change projections, Met Office Hadley Centre, Exeter, 2009. 2009.
Murphy, J. M., Sexton, D. M., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., and Stainforth, D. A.: Quantification of modelling uncertainties in a large ensemble of climate change simulations, Nature, 430, 768-772, 2004.
Palmer, T. and Räisänen, J.: Quantifying the risk of extreme seasonal precipitation events in a changing climate, Nature, 415, 512-514, 2002.
Piani, C., Haerter, J., and Coppola, E.: Statistical bias correction for daily precipitation in regional climate models over Europe, Theoretical and Applied Climatology, 99, 187-192, 2010.
Schmidli, J., Frei, C., and Vidale, P. L.: Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods, Int J Climatol, 26, 679-689, 2006.
Solomon, S.: Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC, Cambridge University Press, 2007.
Stainforth, D. A., Aina, T., Christensen, C., Collins, M., Faull, N., Frame, D., Kettleborough, J., Knight, S., Martin, A., and Murphy, J.: Uncertainty in predictions of the climate response to rising levels of greenhouse gases, Nature, 433, 403-406, 2005.
Stocker, D. Q.: Climate change 2013: The physical science basis, Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Summary for Policymakers, IPCC, 2013. 2013.
Sun, F., Roderick, M. L., Lim, W. H., and Farquhar, G. D.: Hydroclimatic projections for the Murray-Darling Basin based on an ensemble derived from Intergovernmental Panel on Climate Change AR4 climate models, Water Resour Res, 47, 2011.
Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, Bulletin of the American Meteorological Society, 93, 485-498, 2012.
Tebaldi, C., Hayhoe, K., Arblaster, J. M., and Meehl, G. A.: Going to the extremes, Climatic change, 79, 185-211, 2006.

Teutschbein, C. and Seibert, J.: Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods, Journal of Hydrology, 456, 12-29, 2012.
Thorne, P. and Vose, R.: Reanalyses suitable for characterizing long-term trends: Are they really achievable?, Bulletin of the American Meteorological Society, 91, 353-361, 2010.
Webb, M., Senior, C., Sexton, D., Ingram, W., Williams, K., Ringer, M., McAvaney, B., Colman, R., Soden, B., and Gudgel, R.: On the contribution of local feedback mechanisms to the range of climate sensitivity in two GCM ensembles, Climate Dynamics, 27, 17-38, 2006.
Weisheimer, A. and Palmer, T.: Changing frequency of occurrence of extreme seasonal temperatures under global warming, Geophys Res Lett, 32, 2005.
Wood, E. F., Roundy, J. K., Troy, T. J., Van Beek, L., Bierkens, M. F., Blyth, E., de Roo, A., Döll, P., Ek, M., and Famiglietti, J.: Hyperresolution global land surface modeling: Meeting a grand challenge for monitoring Earth's terrestrial water, Water Resour Res, 47, 2011.