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Interactive Comment

Interactive comment on "Precipitation ensembles conforming to natural variations derived from Regional Climate Model using a new bias correction scheme" *by* K. B. Kim et al.

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Dear Editor,

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

Anonymous referee #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:

We agree with the reviewer's comments and used a hydrological model to investigate the impact of bias correction methods.

For hydrological application, we used a conceptual hydrological model IHACRES. First, the model parameters have been optimised with the use of observed daily precipitation, temperature and flow data. Second, the optimised parameters and the two different bias corrected precipitation datafrom the conventional and proposed bias correction methods 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.

Figure 1 compares the spreads (5th – 95th percentile) of the flows. As expected, overall, the spread of the monthly mean flow simulated by using conventionally bias corrected precipitation is narrower than that of the flow simulated by using proposed bias correction. This is because the conventional bias correction method uses only one observed precipitation as a reference. In order to validate whether the spread of the simulated flows are appropriate, a long period of flow data is needed. However, since we do not have long observed flow data, we used a resampling method to estimate the natural variability of the observed flow. Eleven time series of flow data is resampled on monthly basis from the daily observation data. The result shows that the spread of the resampled flow is wider than that of both simulated flows. This can be interpreted as the flow spread using conventional bias correction method is too narrow and the proposed method is more reasonable and realistic.

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 σxo/σx 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:

Reply to this comment has been made in the reply to the Specific comments 6 and 7.

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 with 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:

Bias correction is a controversial issue (Ehret et al., 2012) although it is widely used in climate impact studies. In addition, which bias correction method to apply is a controversial subject as well. On the one hand, 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.

References

Brown, J.D., Seo, D.J., 2013. Evaluation of a nonparametric postâĂŘprocessor 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 postâĂŘprocessing 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.

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

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the 11-member ensembles 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 result in the bias corrected ensembles being too narrow or to 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 (external forcing), 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:

As stated in the manuscript, bias correction is a controversial issue. In our view, as each ensemble member has different systematic error, it can be considered as independent from from other ensembles. Therefore, we believe it is reasonable to under-

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take the correction independently.

The main purpose of bias correction is to make simulated climate model output indistinguishable from the real world data series by minimising the systematic error. Since the observation is only one case of many possible realizations, there should be uncertainty associated with natural variability. Therefore, to make the simulated output look like real, the spread of the model ensembles (i.e. model uncertainty) should be adjusted to that of the observation (i.e. natural variability).

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 (i.e. transfer function) is as follows".

We added the explanations 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 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:

We have added the following paragraphs in the discussion section.

Climate model is a simplification of the reality. Therefore the simulated output should look like real. However, there is a systematic error which is a result of the errors in model structure, parameter and initial conditions. The main purpose of bias correction is to make the simulated climate model output indistinguishable from the real world data series by minimising the systematic error. Ideally, after bias correction, 11 members of the RCM output should look like 11 realisations from the real system, i.e. they should have similar spread between the ensembles and the real natural system. If they look obviously different from the realisations, they are not good representation of the real climate condition of the catchment.

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 ensembles will be similar to just one member. Another approach is to

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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 were 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 to wide) and it is a good balance between the two.

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:

We have added the following paragraphs in discussion.

Ideally if we have numerous numbers of observation data, more reliable climate statistics can 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 contrary, initial conditions or parameters in climate models can be perturbed to generate a large number of ensembles. Given the results we achieve, these ensembles need to be examined to ensure that they are plausible.

Figure 2 describes why the bias corrected members should originate from within the bounds of the natural variability of the observation. Suppose that the probability distri-

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butions of the natural variability and climate model uncertainty look like Figure 2. 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 model uncertainty should be similar to that of the climate natural variability.

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 2 (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.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 10261, 2015.

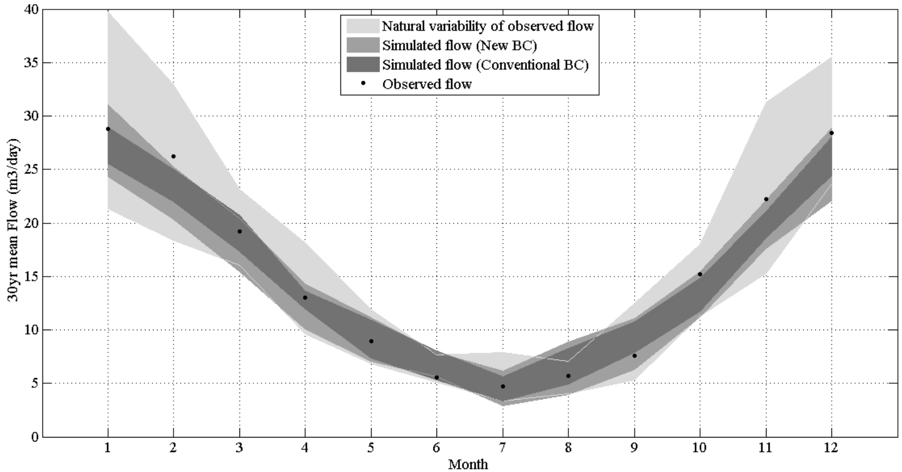

Fig. 1. Comparison of the spread of natural variability of observed flow and simulated flows.

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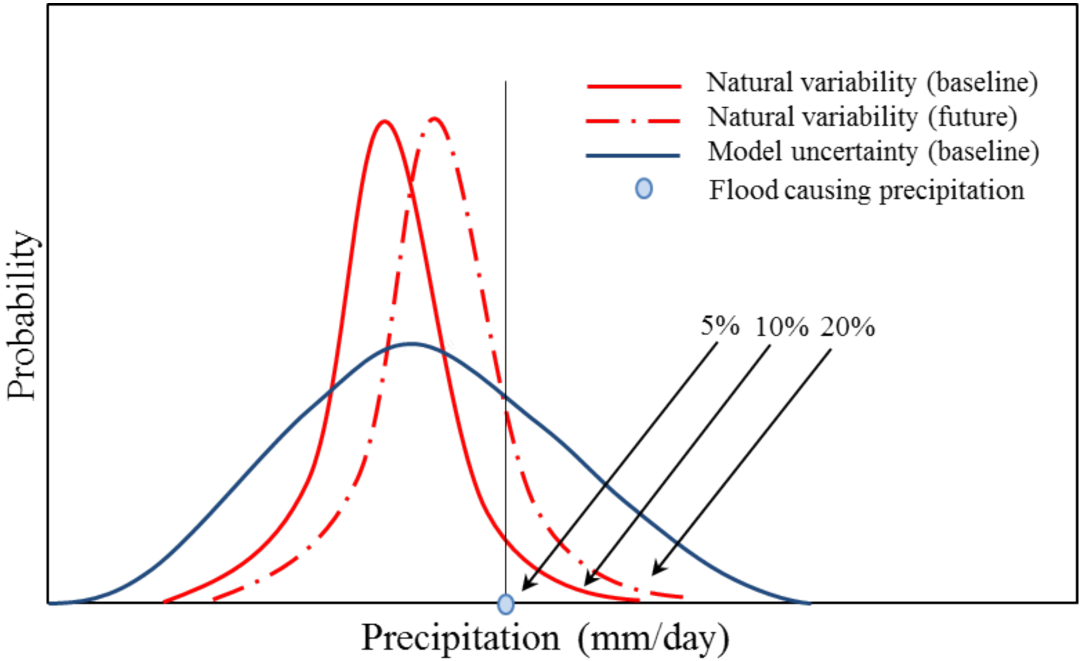

Fig. 2. Probability distributions of natural variability and climate model uncertainty. The thick red curve, dashed red curve and cyan curve are the probability distributions of the baseline natural variabili

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