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Bias Correction Methods for Regional Climate Model Simulations Considering the Distributional Parametric Uncertainty Underlying the Observations

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Abstract

In this paper, we present a comparative study of bias correction methods for regional climate model simulations considering the distributional parametric uncertainty underlying the observations/models. In traditional bias correction schemes, the statistics of the simulated model outputs are adjusted to those of the observation data. However, the model output and the observation data are only one case (i.e., realization) out of many possibilities, rather than being sampled from the entire population of a certain distribution due to internal climate variability. This issue has not been considered in the bias correction schemes of the existing climate change studies. Here, three approaches are employed to explore this issue, with the intention of providing a practical tool for bias correction of daily rainfall for use in hydrologic models ((1) conventional method, (2) non-informative Bayesian method, and (3) informative Bayesian method using a weather generator (WG) data). The results show some plausible uncertainty ranges of precipitation after correcting for the bias of RCM precipitation. The informative Bayesian approach shows a narrower uncertainty range by approximately 25% to 45% than the non-informative Bayesian method after bias correction for the baseline period. This indicates that the prior distribution derived from WG may assist in reducing the uncertainty associated with parameters. The implications of our results are of great importance in hydrological impact assessments of climate change because they are related to actions for mitigation and adaptation to climate change. Since this is a proof of concept study that mainly illustrates the logic of the analysis for uncertainty-based bias correction, future research exploring the impacts of uncertainty on climate impact assessments and how to utilize uncertainty while planning mitigation and adaptation strategies is still needed.

Keywords: climate change, internal climate variability, uncertainty, Bayesian, likelihood

1. Introduction

Quantifying uncertainty in estimates of future climate change for use in climate impact simulations is a necessary step for detection, attribution, and mitigation and adaptation strategies (Deser et al., 2012b). Hence, demand for more quantitative analyses of future climate change is increasing (Collins et al., 2012). These uncertainties are due to scenario uncertainty, model uncertainty, and internal climate variability (Hawkins and Sutton, 2009; Tebaldi and Knutti, 2007). Internal climate variability results from natural fluctuations. Some recent studies have drawn attention to the contributions of natural variability to climate change (Deser et al., 2012a; Hawkins and Sutton, 2009; Kendon et al., 2008; Knutti and Sedláček, 2013; Tebaldi et al., 2011; Zunz et al., 2013). The uncertainties of climate projections due to natural variability are considered to be irreducible (Fischer et al., 2013; Smith et al., 2007).

Although bias correction is controversial (Ehret et al., 2012; Muerth et al., 2013), bias correction methods have been successfully and widely applied in climate change studies (Dosio and Paruolo, 2011; Piani and Haerter, 2012; Rojas et al., 2011). In climate change studies, 30 years of observation data are generally used as a reference, as defined by the World Meteorological Organization (WMO). However, each observation is only one case out of many possibilities, rather than being sampled from the entire population of a certain distribution, due to distributional parametric uncertainties that have not been considered in the existing bias correction schemes used in the past climate change studies. This has particularly important implications for uncertainties associated with the parameters of the probability density function (PDF) used for correcting bias in climate model outputs, since in traditional bias correction schemes the statistics of the simulated model outputs are adjusted to those of the observation data, which is only one realization of many possibilities. The uncertainty in parameter estimates is directly related to the sample size and the quality of available information. In other words, distributional parametric uncertainty exists when limited amounts of hydrologic data are used to estimate the parameters of PDF. Both the natural randomness of hydrologic data and the distributional parametric uncertainty in bias correction may contribute to the uncertainty in future climate change projections. However, most studies of uncertainties in hydrologic studies have focused on measurement uncertainties mainly resulting from the spatial integration of measurements across different sites. Here we do not consider measurement error, but concentrate on distributional parametric uncertainty. In other

words, measurement error and its impact on bias correction for future projections are not included in this study, but could be added in future analyses if needed.

In this paper, we explore the following questions:

(1) Can uncertainties in observation and regional climate model output with respect to distributional parametric uncertainty be modelled simultaneously and consistently?

(2) Climate change studies use weather generators (WG) informed by global climate model (GCM) or regional climate model (RCM) integration (forecast or climate change) for downscaling.

   A. Is it better to use precipitation sequences simulated from the WG as a prior distribution instead of a non-informative prior? Does the WG really add value?

   B. Does a combination of the WG and Bayesian model better inform uncertainty?

(3) Can a Bayesian-based bias correction model offer useful scenarios of daily precipitation for climate change studies?

In this study, three approaches are employed to explore these questions, with the intention of providing a practical tool for bias correction of daily rainfall for use in hydrologic models. The approaches are based on the quantile mapping method: 1) the conventional method and two new approaches, 2) the non-informative Bayesian (NIB) method and 3) the informative Bayesian (IB) method. In this study, we aim to quantify distributional parametric uncertainty and show some plausible range of precipitation after correcting for the bias of RCM precipitation. The proposed methodology is applied to three catchments located in the southwest of England. One emission scenario (A1B) and one-member (Q0) among 11 members of the HadRM3 model output driven by the GCM HadCM3 (Murphy et al., 2009) are used for the analysis because the purpose of this study is not to prove the two proposed bias correction methods (NIB and IB methods) or to determine which method is the best among the three approaches. The aim is mainly to introduce a new concept, the logic underlying uncertainty based bias correction and how this concept can be extended to conventional approaches. Hence, we believe three cases are sufficient.

2. Data and Weather Generator

Three catchments in the southwest of England are used in this study. The catchments have varying rainfall regimes (i.e., low, medium, and high rainfall) and are representative of the range of rainfall distributions in

this region. The Avon River at Melksham (665.6 km^2) has low rainfall (797 mm/year), the Exe River at Thorverton (606km^2) has medium rainfall (1260 mm/year), and the Tamar River at Gunnislake (916.9 km^2) has high rainfall (1751 mm/year). Daily time series of the observed precipitation data are obtained from the UK Met Office. For the model output, we have obtained the HadRM3 Perturbed Physics Experiment Dataset (HadRM3-PPE-UK, resolution 25×25km), which provides time series data from 1950 to 2100. Among the data, only one ensemble member is used in the analysis. The UKCP09 Weather Generator (Jones et al., 2009) (WG) data is used for the prior distribution (Gamma distribution). The WG generates statistically plausible time series of nine climate variables (i.e., precipitation, temperature, vapor pressure, wind, sunshine, potential evapotranspiration, diffuse radiation and direct radiation) at a 5km resolution. According to the official UK government guidelines on climate change, the UKCP09 WG is trained using the 5 km daily-observed baseline for 1961–1995. This means that the WG model baseline is fitted to the 1961–1995 historical observations. The WG data are the officially approved data for climate change studies in the UK. Precipitation is generated using the Neyman-Scott Rectangular Processes (NSRP) model (Cowpertwait et al., 1996; Jones et al., 2009), and other variables are then simulated given the simulated precipitation. The NSRP model is a clustered point process model comprised of clusters and rectangular impulse models for rainfall occurrence and amount (Onof et al., 2000). The NSRP model describes storm origins, durations and the intensity of each rain cell as a set of random variables. The more detailed structure of the NSRP model is described as follows: First, storm origins are represented by a Poisson distribution with parameter **α** relating to the arrival times of the storms; Second, the storm origin randomly generates numbers **ν** of rain cells departing from the storm origin at time intervals that are simulated by an exponential distribution with parameter **β**; Third, the durations of the rain cells are generated by an exponential distribution with parameter **γ**; Fourth, the intensities of the rain cells are again simulated by exponential distributions with parameter **δ**; Finally, rainfall intensity is calculated by summing the intensity of each rain cell. A schematic representation of the NSRP model is shown in Figure 1.

[Insert Figure 1]

The parameters of the NSRP model are estimated separately for each month to better characterize intra-annual rainfall variability. Expected values of rainfall statistics, such as the mean rainfall amount, the proportion of dry days, the variance and skewness of daily rainfall amounts, and the lag-1 autocorrelation (Cowpertwait et

al., 2002), are analytically derived with respect to the five parameters of the NSRP model. These parameters are as follows: (1) the average waiting time between subsequent storm origins; (2) the average waiting time of the rain cells after the storm origin; (3) the average cell duration; (4) the average number of cells per storm; and (5) the average cell intensity. These expected parameter values are then used to optimize a set of parameters by minimizing an objective function using an optimization algorithm. The required rainfall statistics for UKCP09 are estimated based on a gridded rainfall dataset at 5×5 km resolution compiled by Perry and Hollis (2005a, b) that covers the UK for the period 1961–1990.

3. Methodology

3.1 Bias correction methods

Numerous studies have assessed the impacts of climate change on water resources using climate variables from global climate models (GCMs) and water resources models (Fung et al., 2011). However, because of the relatively low spatial resolution (100-250km) of GCMs, regional climate models (RCMs) are widely used for regional impact studies at catchment scales (25-50km) climate variables (Fowler et al., 2007; Qin et al., 2007). Although RCMs are able to simulate local climate at finer resolutions, outputs from RCMs cannot be used as direct input data for hydrological models due to systematic errors and require post processing of the model outputs to remove biases (Christensen et al., 2008; Hansen et al., 2006; Sharma et al., 2007). Typical systematic model errors of RCMs include errors in estimation (over or under) of climate variables, incorrect estimates of seasonal variations of precipitation (Christensen et al., 2008; Terink et al., 2009; Teutschbein and Seibert, 2010), and simulations of more wet days of low intensity rainfall (drizzle effect) than the actually observed (Ines and Hansen, 2006).

Two types of statistical approaches, bias correction and stochastic downscaling methods, have been widely used to alleviate the limitations of the current climate models (i.e., GCM and RCM). A main objective of the bias correction method (e.g., quantile mapping) is to provide a set of rescaled variables by removing the effects of systematic errors in climate model outputs. The stochastic downscaling method is used to provide series of synthetic weather variables for future periods based on parametric (or nonparametric) relations identified between the observed target variables and daily climatic variables (e.g., precipitation, temperature,

sea level pressure, and geopotential height). The model is parameterized using the observed data, and produces plausible scenarios using future-factored climate variables informed by global climate models.

Several recent studies of bias correction methods have used the methods from simple linear scaling to sophisticated quantile mapping (Chen et al., 2011a; Chen et al., 2011b; Johnson and Sharma, 2011; Piani et al., 2010; Teutschbein and Seibert, 2012). Teutschbein and Seibert (2012) conducted a statistical evaluation of four bias correction procedures for precipitation: 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) a 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 approach corrects the mean values based on differences between the observed and model data. It considers bias in the mean, using a correction factor based on the ratio of the long-term mean observed and modelled data. Local intensity scaling is an advanced method that accounts not only for the bias in the mean but also wet day frequencies and wet day intensities. Power transformation adjusts the mean as well as the variance of precipitation time series. Distribution mapping is conducted to adjust the distributions of model outputs to those of the observed data using a transfer function. The results of the bias correction methods show improvements over the raw RCM precipitation data and distribution mapping was found to be the best correction procedure.

3.2 Quantile mapping method

Bias correction was initially proposed for calibrating seasonal GCM variables (e.g., precipitation and temperature) and extended to the daily time scale. Each month is usually processed independently from the others, in order to correct seasonal phase errors, after modifying wet-day frequencies of the RCM simulated precipitation according to the wet-day observed frequencies by applying a cut-off threshold. Usually the simulated precipitation values from climate models overestimate the number of days with low precipitation compared with the observed precipitation. The general process of quantile mapping is as follows. First, a cut-off threshold is used to remove low precipitation values from the model output in order to adjust the wet-day frequency of the simulated precipitation according to the observed values before applying the quantile mapping method; Second, Gamma distribution functions are built monthly for both the observed and RCM precipitations from 1961 to 1990. The Gamma distribution is the same for each month for all years, but differs

between months. The RCM precipitation is found in the Gamma CDF and the corresponding cumulative probability drawn from the observed Gamma CDF; Third, the value of precipitation with the same cumulative probability is derived from the observed Gamma CDF. This value is the bias corrected value of the RCM precipitation. The equation can be expressed as follows:

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

where, F is Gamma CDF, F^{-1} is its inverse function, X_{cor} is the bias corrected model output in the baseline period, α and β are the shape and scale parameters of the Gamma distribution, respectively. The subscripts *model* and *obs* indicate the parameters from the RCM and observed precipitation.

Figure 2 represents a schematic concept of the conventional bias correction method based on quantile mapping (QM). The transfer function for bias correction is built for the distribution of the RCM simulations to match the CDF of the observations for the same period (Figure 2(a)). This can also be represented in terms of parameters of the PDF. As illustrated in Figure 2(b), a set of parameters for climate simulations are shifted to those of the data observed through the QM.

[Insert Figure 2]

3.3 Proposed bias correction method

3.3.1 Basic concept

A problem with the conventional bias correction method is that the statistical properties of the RCM precipitation are matched to those of the sample data from the underlying distribution of the observed data. In fact, these observations can be regarded as only one case of many possible realizations due to internal climate variability. Internal climate variability represents natural fluctuations that occur without any external forcing to the climate system. Such variability occurs naturally in populations across time and space and has no deterministic patterns (Hayes, 2011). We propose a method that considers epistemic uncertainty and internal climate variability due to distributional parametric uncertainty in the bias correction process. The epistemic uncertainty is due to incomplete knowledge about the structure of a system, and the distributional parametric uncertainty by the limited amounts of hydrologic data used to estimate each set of parameters.

Figure 3 illustrates the concept of uncertainty analysis of the observations. Suppose we know the population, i.e., the underlying distribution of parameters estimated from the observed precipitation (black line). Then, the

parameter representing 30 years of the observed precipitation for the baseline period (1961-1990), α_{obs}, which is only one case of many possible realizations, may be located at any suitable place in this population distribution. The uncertainty of the parameter, α_{obs}, can be quantified by estimating the likelihood (black dashed line). Likewise there may be another possible realization, α_1, which is equally likely to happen based on the population distribution. Therefore, using only one set of 30 years of the observation data would result in uncertainty while, if another data source (α_1) is available, we hypothesize that the distributional parametric uncertainty underlying the observations can be reduced by combining the two data sources. The WG data can be regarded as true realizations since they are calibrated based on the historical data, hence, it is possible to consider that the distribution of the WG parameter (α_{WG}) is derived from α_1. If the mean and variance of α_{WG} are similar to those of α_{obs}, it is most likely that the WG data are calibrated based on the same historical observations. In this case, the WG data could provide the duplicate information for estimating the true distribution. On the other hand, if the distributions of α_{WG} and α_{obs} are different, then the WG data could have been derived from independent (or partially independent) observation data, which may assist in estimating the population. The Bayesian approach is used to combine different data sources, the distributions of α_{obs} and α_{WG}. The likelihood is calculated from the observations and the WG is used as prior information to estimate the posterior distribution, which is assumed to represent the uncertainty of the true distribution.

[Insert Figure 3]

This concept of data uncertainty is applied to the bias correction procedure in this study. The idea is that both RCM and observation precipitation have distributional parametric uncertainties, and such uncertainties can be quantified as illustrated in Figure 4(a). In contrast with the conventional method, this results in a certain distribution of the bias corrected model outputs, instead of only one value. The group of parameters, which represents uncertainty in the parameters of statistical distributions underlying the observations/models, are used to build transfer functions (Figure 4(b)). In other words, the distributions of RCM parameters are moved forward to those observed after the bias correction (Figure 4(c)).

[Insert Figure 4]

3.3.2 Quantifying the distributional parametric uncertainty underlying observations/models

We have used two different methods to quantify the distributional parametric uncertainty underlying the data. First, the NIB method quantifies the uncertainty in terms of the likelihood of the data. The reason that we refer to this as a NIB method is because a Bayesian approach using a non-informative prior (i.e., uniform prior) produces the same posterior as the likelihood. Second, an IB approach is applied using the likelihood of the data and prior information. To quantify the uncertainty, the NIB method is only used for the model output (Figure 5(b)) and both NIB (Figure 5(c)) and IB (Figure 5(d)) methods are applied for the observations. A graphical representation of this quantification is illustrated in Figure 5.

[Insert Figure 5]

3.3.3 Two proposed bias correction methods

Since the uncertainty can be quantified in two ways for the observations, there are two different approaches of applying the quantile mapping method. The first proposed method is a NIB method that intends to rectify the CDFs of the simulated data using those of the observed data, consisting of 1,000 sets of parameters of the Gamma distribution randomly sampled from the distribution of the likelihood for both the RCM (Figure 5(b)) and observed precipitation (Figure 5(c)), i.e., 1,000 transfer functions are evaluated for bias correction. In other words, the distributions of the RCM parameters (Figure 5(b)) are matched to those of the observations (Figure 5(c)). The second proposed method is an IB approach that aims to match the CDFs of the RCM precipitation, which derives parameters from the distribution of the likelihood using those of the observations, whose parameters are derived from posterior distributions based on the integration of the likelihood of the observations and the prior (i.e., estimated from WG). Likewise, 1,000 sets of the parameters of the Gamma distribution are randomly sampled from each distribution. In other words, the distributions of RCM parameters (Figure 5(b)) are matched to those of the observations (Figure 5(d)). We apply these 1,000 transfer functions to correct future precipitation projections. The role of time dependent bias should be considered, but here we assume the bias to be stationary, i.e., that the functional relationship in terms of the probability distribution under current conditions will still be valid under future climate conditions. The NIB and the IB approaches can be written as Equations (2) and (3), respectively.

$$X_{cor,i}^N = F^{-1}\left[F\left(X_{model};\alpha_{model,i}^N \beta_{model,i}^N\right); \alpha_{obs,i}^N \beta_{obs,i}^N\right] \quad (i = 1, \dots , 1{,}000) \qquad (2)$$

$$X_{cor,i}^B = F^{-1}\left[F\left(X_{model};\alpha_{model,i}^N \beta_{model,i}^N\right); \alpha_{obs,i}^B \beta_{obs,i}^B\right] \quad (i = 1, \dots , 1{,}000) \qquad (3)$$

where, F is Gamma CDF, F^{-1} is its inverse Gamma function, X_{cor} is the bias corrected model output in the baseline period, α and β are shape and scale parameters of the Gamma distribution, respectively, and i indicates the number of samples. The subscripts *model* and *obs* indicate the parameters from the RCM and observed precipitation, and the superscripts *N* and *B* indicate the parameters from the NIB method and the IB approach, respectively.

A Bayesian-based bias correction method is proposed to accommodate the uncertainty in the parameters of statistical distributions underlying the observations. An objective of the Bayesian methods is to compute the posterior distributions of the desired variables, in this case the parameters of the daily precipitation distribution. The posterior distribution of the parameter vector $\boldsymbol{\theta}$, is $p(\boldsymbol{\theta}|\mathrm{x})$, given by the Bayes Theorem as follows:

$$p(\theta|x) = \frac{p(\theta) \times p(x|\theta)}{p(x)} = \frac{p(\theta) \times p(x|\theta)}{\int_{\Theta} p(\theta) \times p(x|\theta)d\theta} \propto p(\theta) \times p(x|\theta) \qquad (4)$$

where θ is the parameter vector of the distribution to be fitted, Θ is the space parameter, $p(x|\theta)$ is the likelihood function, x is the observation vector, and $p(\theta)$ is the prior distribution. Here, we present a method for incorporating the information from the WG into the updated estimates of parameters for the probability distribution used to represent daily precipitation. Using the Gamma distribution, the distribution of the daily precipitation $R(t)$ can be modelled as follows:

$$R(t) \sim Gamma(\alpha, \beta) \qquad (5)$$
$$\alpha \sim Gamma(\alpha_\alpha, \alpha_\beta) \qquad (6)$$
$$\beta \sim Gamma(\beta_\alpha, \beta_\beta) \qquad (7)$$

The Bayesian approach allows us to estimate the parameters, and parameterization of each parameter (i.e., α and β) is more common in Bayesian statistics than in other methods. A prior distribution must be assigned to reflect our prior beliefs regarding the parameters, and the parameters are then estimated by sampling from these distributions to maximize the likelihood under the model (Kwon et al., 2008), in this case the Gamma distribution. Here, we assign the Gamma distributions for α and β that reflect our prior beliefs regarding their

values. If the posterior distribution is in the same family as the prior distribution, the prior is regarded as a conjugate prior. Hence, the use of the conjugate prior ensures that the posterior distribution is the same as the assumed likelihood function. The Gamma distribution is the conjugate prior distribution for many distributions such as the Poisson, exponential, Pareto, and Gamma, with known shape parameters. However, a conjugate prior for the Gamma distribution with unknown shape and scale parameters is not directly available, and therefore in this study we used the Gamma distributions for parameters of interest. The Gamma distribution is most appropriate for use as the prior distribution of the parameters based on a goodness-of-fit test using the parameters sampled from Monte Carlo simulations. The Gamma distribution is also a good choice to ensure that both parameters are positive real numbers.

3.4 Step by step procedure of the proposed bias correction method

The thirty-year daily rainfall distribution is assumed to follow a two-parameter Gamma distribution, since it is fitted better to such a distribution than to any other distributions. A two-dimensional grid likelihood profile of a two parameter Gamma distribution (i.e., shape and scale parameters) is applied to estimate the likelihood. The likelihood function is evaluated at every point on the grid, and then uncertainties are derived given the assumed parameters. For the IB approach, the WG is used as a prior distribution since the WG is created from a different set of rain gauges, which can be assumed to be an alternative to the observations used in this study. For prior distributions, 1,000 sets of precipitations from 1961 to 1990 are generated. Combining these priors from the WG and likelihoods from the observations should result in better estimates of the parameters of interest.

Figure 6 illustrates the step-by-step procedure of the proposed bias correction method. First, the wet-day frequencies of RCM precipitation and the observations are matched (Step 1). Next, the parameter uncertainties of the transfer functions are quantified for the two different data sets. The distributions of the shape (α) and scale (β) parameters of the Gamma distribution represent distributional parametric uncertainty underlying observations/models (Step 2). Note that the posterior parameter distributions of the RCM and observations in the NIB method (Step 2 (1) and (2) in Figure 6) are the same as the likelihoods, because uniform priors are used. In other words, the parameters are randomly sampled from the data without considering the prior, which is considered to be additional information. Then, the parameters are randomly sampled from these posterior

distributions, and these parameters are further used to build transfer functions for quantile mapping (Step 3). Finally, the quantile mapping method is applied (Step 4). The NIB method matches the distributions of the RCM parameters (Step 2(1)) to those of the observations (Step 2(2)), and the IB approach matches the distributions of RCM parameters (Step 2(1)) to those of the observations (Step 2(3)).

[Insert Figure 6]

4. Results

4.1 Estimation of posterior distribution for the parameter

Again, note that we regard the observations as a single case among many possible realizations, rather than as a sample drawn from the entire population of a certain distribution, due to uncertainties in the parameters of statistical distributions underlying the observations. We performed an experimental study to further investigate the roles of the WG, which can be partially independent from the observations, as a source of prior information in order to update it to the posterior about unknown parameters. Our main assumption is that the WG is capable of generating statistically plausible rainfall sequences. Figure 7 represents the distributional parametric uncertainty underlying the observations/models of precipitation. Here, only January precipitation is illustrated to explain the concept. The distributional parametric uncertainty of the RCM (blue dots) is quantified by estimating the likelihood of the data for the Gamma distribution with the given parameters. The uncertainty estimates associated with the parameters are quantified in two different ways: the NIB method (black dots in Figure 7(a)) using the likelihood of the data and the IB approach (red dots in Figure 7(b)) using both the likelihood of the observations and the prior information from the WG. It is apparent that the parameter spaces of the RCM precipitation are quite different from both posteriors (NIB method and IB approach), which indicates that bias correction is needed. Therefore, the transfer functions for the NIB method are built by matching the ranges of blue dots to black dots and the transfer functions for the IB approach are built by matching the ranges of blue dots to red dots.

[Insert Figure 7]

The uncertainty is illustrated in terms of the posterior distribution of the parameters in Figure 8. As noted in Figure 7, the posterior distributions of the observed data are estimated by the NIB method (black lines in

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Figure 8) and the IB approach (red lines in Figure 8). The distributions of the parameters are assumed to follow a Gamma distribution.

[Insert Figure 8]

In Figure 9 the quantified uncertainty is represented by boxplots. Monthly mean precipitation for the time period from 1961 to 1990 is compared for the NIB and IB methods. As expected, for all the months, the IB approach has a narrower range of uncertainty (i.e., the interquartile range of the boxplot) than the NIB method, by 28% to 43%. The other two catchments show similar results. This indicates that the prior distribution derived from the WG helps reducing uncertainty associated with the parameters.

[Insert Figure 9]

4.2 Comparisons of bias corrected precipitation

Next, we performed monthly quantile mapping bias correction while considering the uncertainties of the data. Figure 10 shows that after the bias correction, the parameters for January RCM (blue dots) precipitation have moved to those of the observations (black dots and red dots). Figure 11 represents the same results in terms of the posterior distribution associated with the parameters.

[Insert Figure 10]

[Insert Figure 11]

In Figure 12, monthly mean precipitation is illustrated for the time period from 1961 to 1990. The observations, uncorrected RCM, and corrected RCM precipitation (both NIB and IB approaches) are compared for the baseline period. Both NIB- and IB-based bias correction methods show plausible uncertainty ranges, and the differences between uncertainty ranges according to NIB and IB methods are illustrated in Figure 13.

[Insert Figure 12]

Figure 13 represents the 5th to 95th percentile differences between the NIB and IB methods (i.e., NIB-IB) after the bias correction for the three catchments, so that a positive value indicates that the NIB has greater

uncertainty than the IB. All catchments indicate that the uncertainty band of the bias corrected model output is narrower in the IB approach than the NIB method, by approximately 25% to 45%.

[Insert Figure 13]

Figure 14 shows a time series of the bias corrected precipitation in December when the IB approach is applied to considering the uncertainty for the baseline period and the future. The range of precipitation estimates over time is even wider when we consider the uncertainty in bias correction compared with the conventional methods.

[Insert Figure 14]

4.3 Cross validation

To evaluate the IB method, we performed two fold cross-validation for the IB approach. Since there are no direct relationships between the individual years of the observations and model outputs (e.g., RCM data in 1961 have no direct link with the observations in 1961), only the 30-year monthly mean precipitations in both observations and bias-corrected outputs were estimated and compared. The first half (1961-1975) of the data was used for training, i.e., to build the transfer functions for bias correction, and we then applied these functions to the second half (1976-1990) of the data. Next, the second half of the data was used for training and then we applied the derived functions to the rest of the data. Finally, two 15-year validated data were grouped into a whole set of 30 years to be evaluated with 30 years of the observation data. As presented in Figure 15, all the observed data points fall entirely inside the credible uncertainty bounds, which indicates that the performance of the IB scheme is better than that of the existing approaches.

[Insert Figure 15]

5. Discussion and Conclusions

The distributional parametric uncertainty involved in the observations and climate model data has yet to be considered for bias correction of the RCM precipitation, which will accumulate the total uncertainty in terms of climate impacts. In addition, from the perspective of policy makers, not only the magnitude of future

uncertainties but also economic, political, and cultural aspects should be considered to design an optimum strategy of mitigation and adaptation (Dessai et al., 2009).

In this study, we investigated three bias correction methods. First, the conventional bias correction method is proved to be simple to apply but to lack the ability to perform uncertainty estimation; Second, the NIB method provides uncertainty bounds that are more realistic than the conventional method, but the uncertainty bounds are much larger than those of the IB approach; Third, the IB approach is able to integrate additional information (e.g., the prior information from the WG), hence, its probabilistic estimates of uncertainty should be more realistic than those of the other two approaches. The results of this study might be different under different climatic conditions and for different application purposes. This study is a proof of concept and is a preliminary attempt to address distributional parametric uncertainty underlying observations in climate change impact studies.

It is important to note that 30 years of the observation data represent just one realization of many possibilities, and that distributional parametric uncertainties underlying the observations/models need to be considered when designing and conducting studies of climate change impact assessments. To overcome this shortcoming, the WG is applied in a case study that covers a wider range of realizations. Therefore, there are three options for engineers to choose from: 1) WG data, which are the officially approved data and the default data in the UK; 2) data locally collected by individuals; and 3) integrated data using the WG as a prior and locally collected data as the likelihood. The question is which method is the most reliable. And if one is tasked with designing a new reservoir, which data should be used? If the client is someone else, we choose Option 1 because it is official, eliminating worries regarding being sued in the future if things go wrong. However, if we design the reservoir for ourselves (i.e., our own money is to be used in building the reservoir), we use Option 2 because we trust our collected data more than the data from the WG. Since both Option 1 and Option 2 are likely to be used by some people, the integration of both data sets may be more trustworthy. One of the purposes of this paper is to raise this important question and attract the attention of the community to discuss ways to deal with the paradox in which the choice of data depends on the clients, and why a Bayesian approach is unlikely to be accepted under Option 1 or Option 2.

We hope that whether the uncertainty band is reduced or increased, the IB approach is able to provide a method for quantifying uncertainty in bias correction schemes. However, there are some important issues that

remain unsolved by this study. First, the issue of independence of the prior information from the WG is important and needs to be solved. We attempted to determine the differences between the stations used to train the WG and the stations used for the observations, but could not due to the lack of detailed information. In addition, even though the WG is trained using different observations, these station data are likely correlated with the observations used for the non-informative method, since all observations are based on the same sample realization of actual internal climate variability in 1961-1990, and since precipitation is correlated in space. Thus, the assumption of complete prior independence is not satisfied and further research is needed to potentially alleviate this issue. Nevertheless, unless those two sources of the data are completely correlated, they still provide complementary information from each other; Second, further research about the impacts of uncertainty on climate impact assessments is needed, since uncertainties may increase due to their propagation through every stage of the assessment; Third, only one member is used in this study to introduce the new concept, the logic of analysis for uncertainty based bias correction methods and how this concept can be applied. However, HadRM3 has 11 members and there are questions regarding how to consider the spread of this ensemble for the proposed bias correction method which represents another potential research area. Without retaining the variance of these members after the bias correction, there are no benefits associated with the ensemble data.

We hope this paper will stimulate more research activities regarding how to validate and evaluate the three methods we have outlined, and how to reflect uncertainties in planning mitigation and adaptation strategies.

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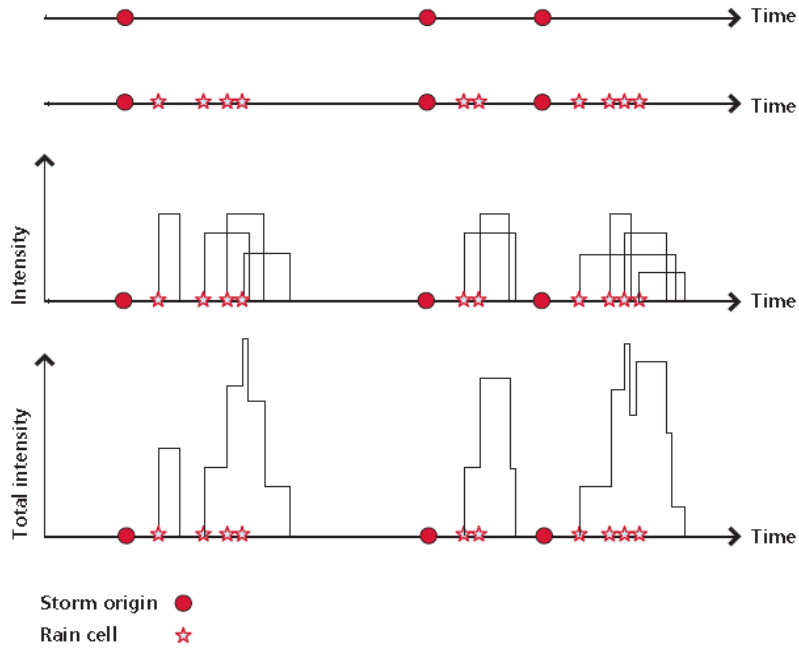
Figure 1. A schematic representation of the NSRP model. The red circle indicates the location of the storm origin and the star represents a rain cell from a report by Jones et al (2010).
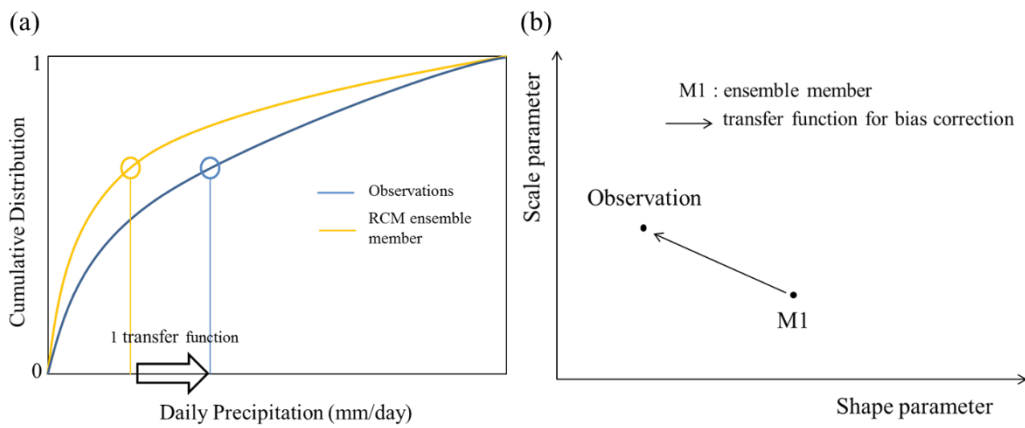
Figure 2. A schematic representation of the conventional bias correction method using quantile mapping. (a) Matching the quantile of the RCM to that of the observations; (b) Matching the shape and scale parameters of RCM to those of the observations.
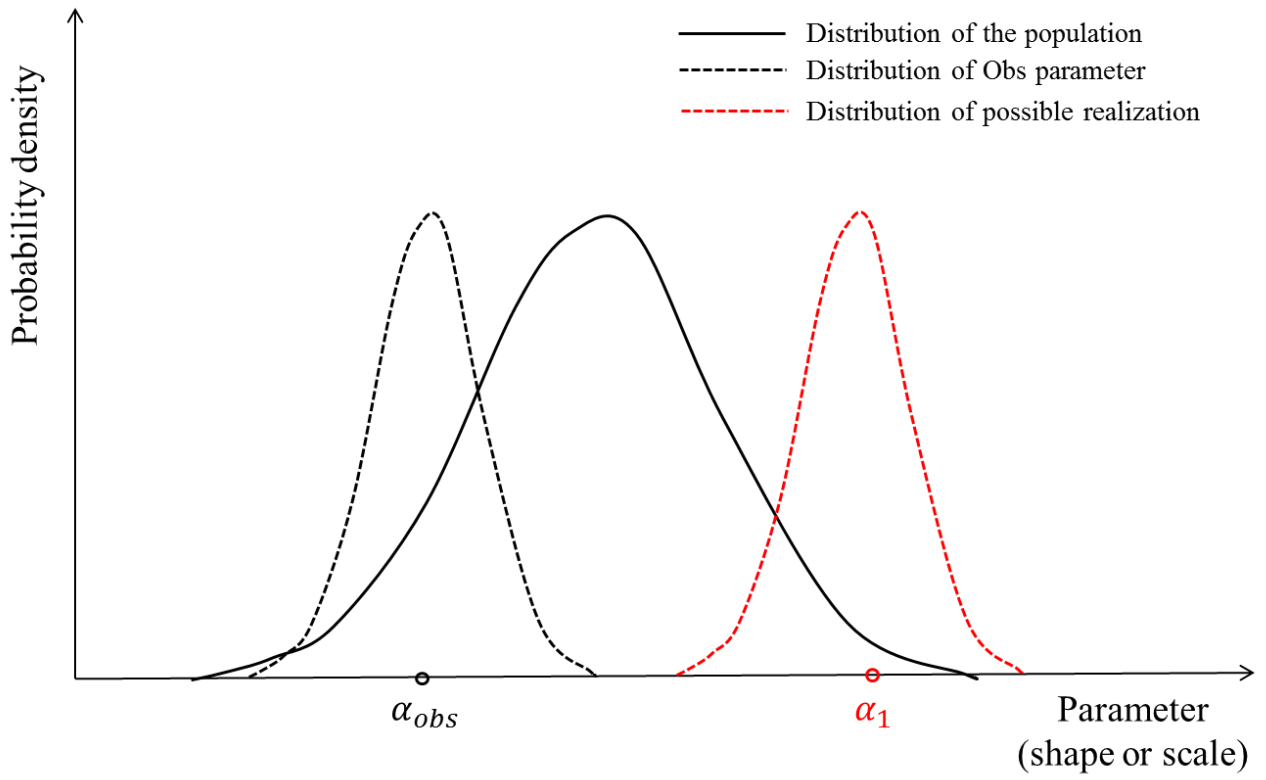
Figure 3. A schematic representation of uncertainty analysis of the observation data.
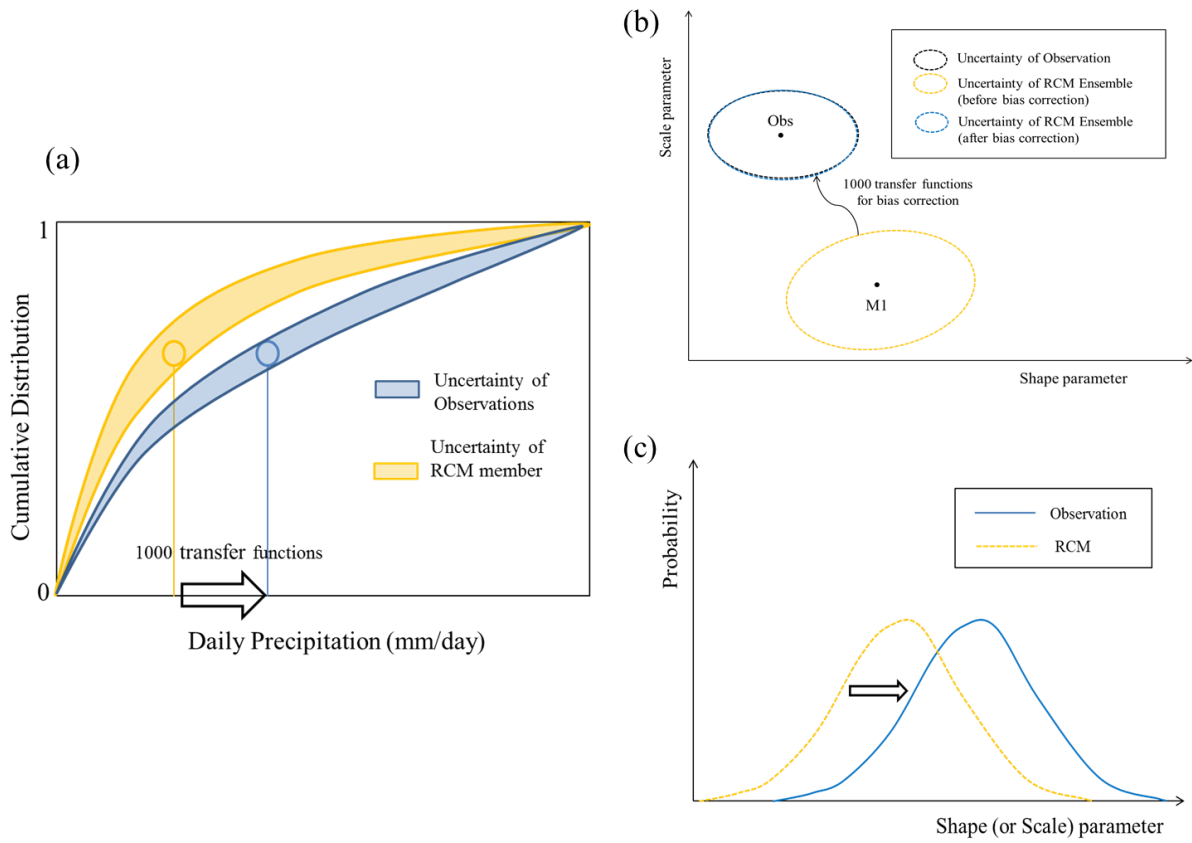
Figure 4. A schematic representation of the proposed bias correction method. (a) Matching the quantile of RCM to that of observations; (b) Matching the parameter spaces of shape and scale parameters of RCM to those of the observed data; (c) Matching the PDF of RCM parameters to those of the observations.
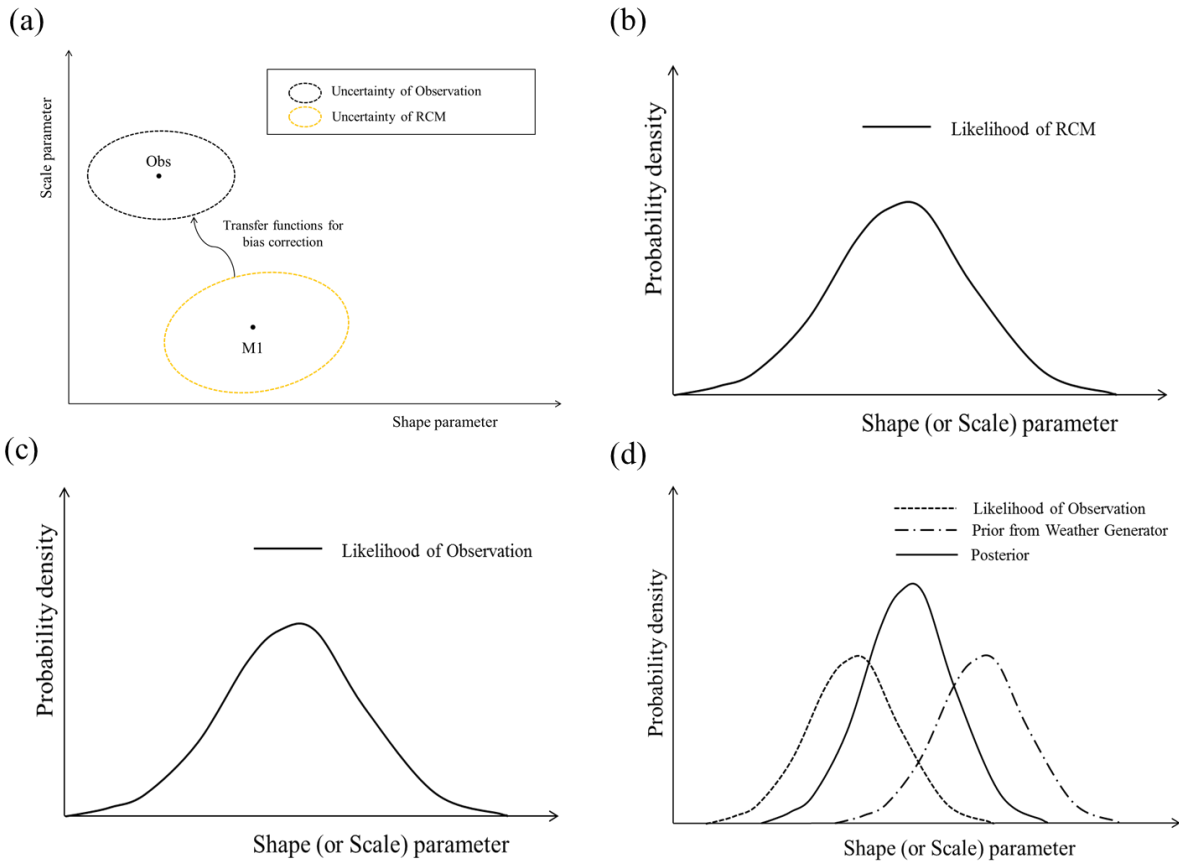
Figure 5. A schematic representation quantifying the uncertainty of both observations and RCM. (a) Matching the spaces of shape and scale parameters of RCM to those of the observations; (b) Distributions of shape (or scale) parameters from the likelihood of the RCM data; (c) Distributions of shape (or scale) parameters from the likelihood of the observation data; (d) Posterior distributions of shape (or scale) parameters derived by multiplying the prior and likelihood.

Step 1. Adjust wet-day frequency of the RCM to the observed

Step 2. Quantify the uncertainty of RCM and observed data (the two proposed method)

- Uncertainty of RCM
- Uncertainty of Observed data

(1) Non-informative   (2) Non-informative   (3) Informative
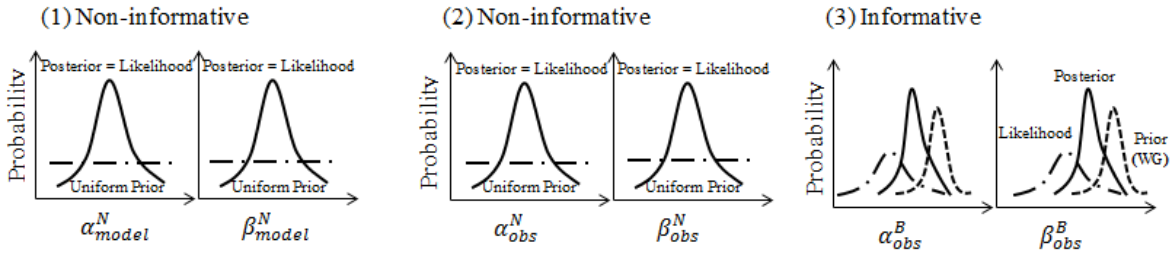
Step 3. Build Gamma distribution functions each month for RCM and observed precipitation

- Conventional method: 1 set of parameters for both RCM and observed precipitation
- Non-informative and Bayesian method: Randomly generate 1,000 set of parameters from distributions in Step2 for each of the three cases

Step 4. Apply quantile mapping method for bias correction

- Conventional method: Equation (1) and Figure 2 (a)
- Non-informative method: Equation (2) and Figure 3 (a)
- Bayesian approach: Equation (3) and Figure 3 (a)

Figure 6. Illustration of the bias correction method for considering uncertainties due to the sampling error.
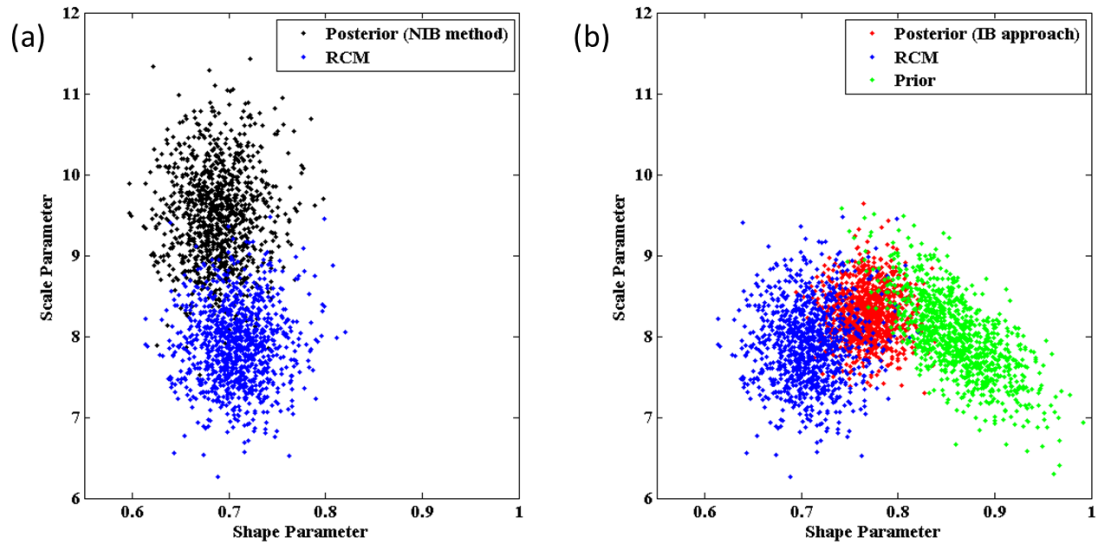
Figure 7. Posterior distribution of Gamma parameters for the observed and RCM January precipitation. (a) Uncertainty of the observations (black dots) is quantified by the Non-IB method (i.e., using the likelihood of observation); (b) Uncertainty of the observations (red dots) is quantified by the IB method (i.e., using both the likelihood of observations and prior information from the WG).
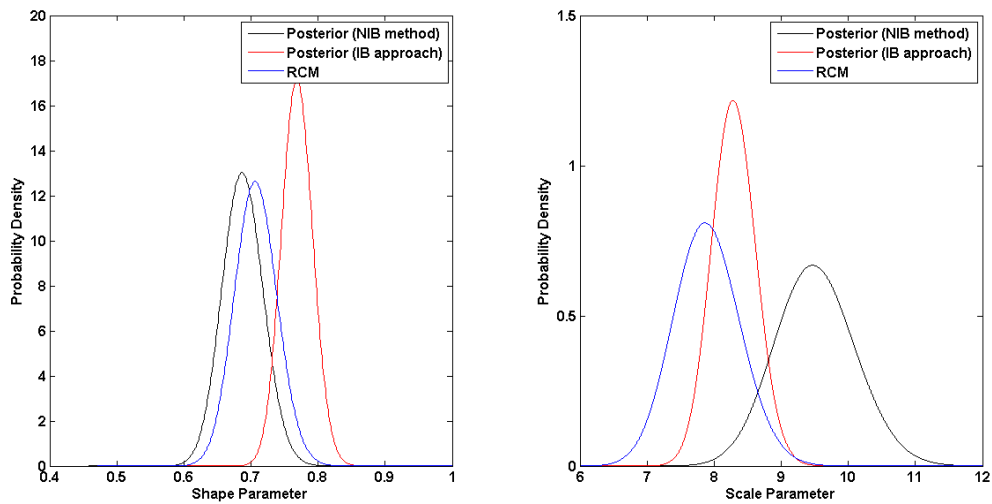

Figure 8. Uncertainties of the observed and the RCM January precipitation represented in terms of posterior distributions of the parameters. Uncertainty of the observation is quantified by estimating the likelihood of observation (black line, NIB method) or by estimating the likelihood of the observation and prior information from the WG (red line, IB method).
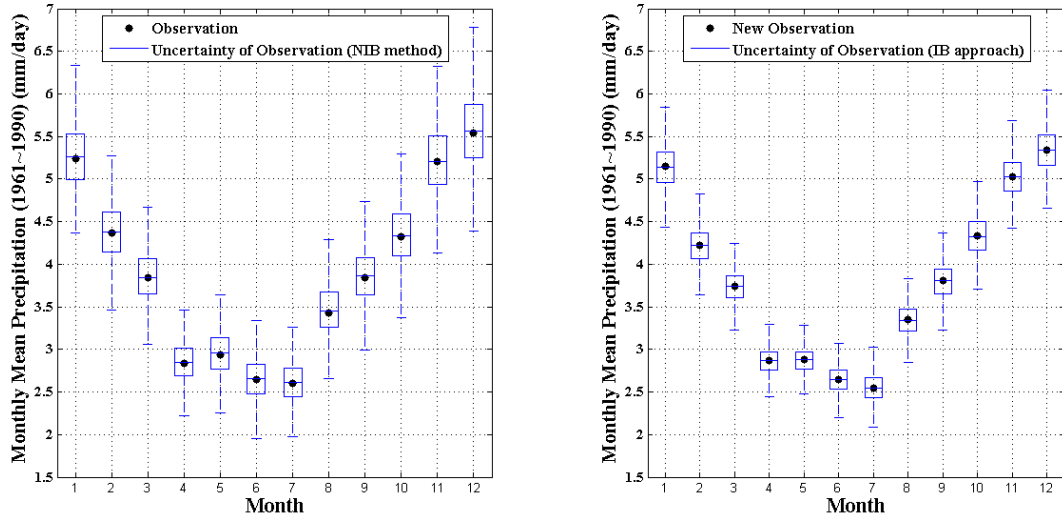
Figure 9. Comparisons of the uncertainty ranges of the observations between the NIB method (left panel) and IB method (right panel) for the Thorverton catchment. The 'New Observation' on the right panel is the monthly mean value of the posterior distribution. The box plots show the median (horizontal line), interquartile range (box), and range with maximum 1.5 interquartile range (whiskers).
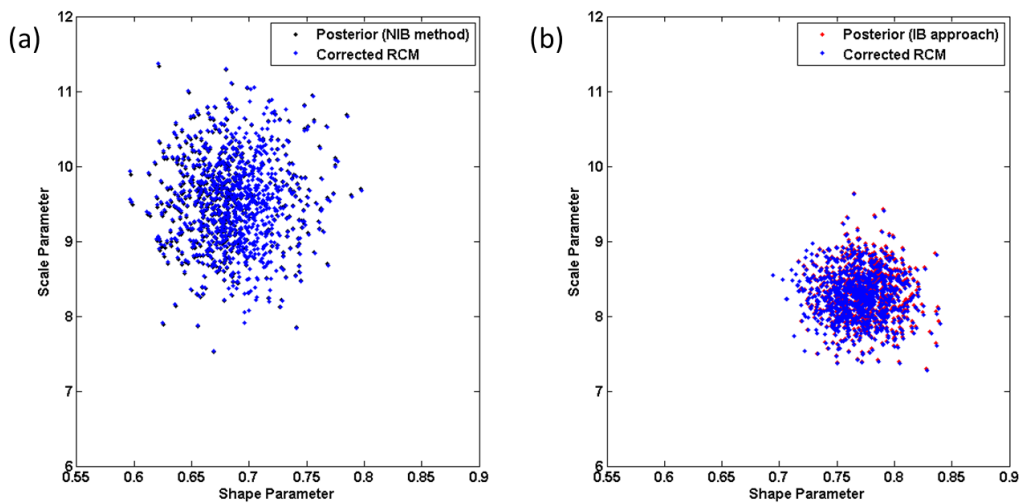

Figure 10. Uncertainties of the observed and RCM January precipitation after bias correction represented in terms of parameters. (a) Uncertainty of the observation (black dots) is quantified by estimating the likelihood of the observation (NIB method); (b) Uncertainty of the observation (red dots) is quantified by estimating the posterior (IB method).
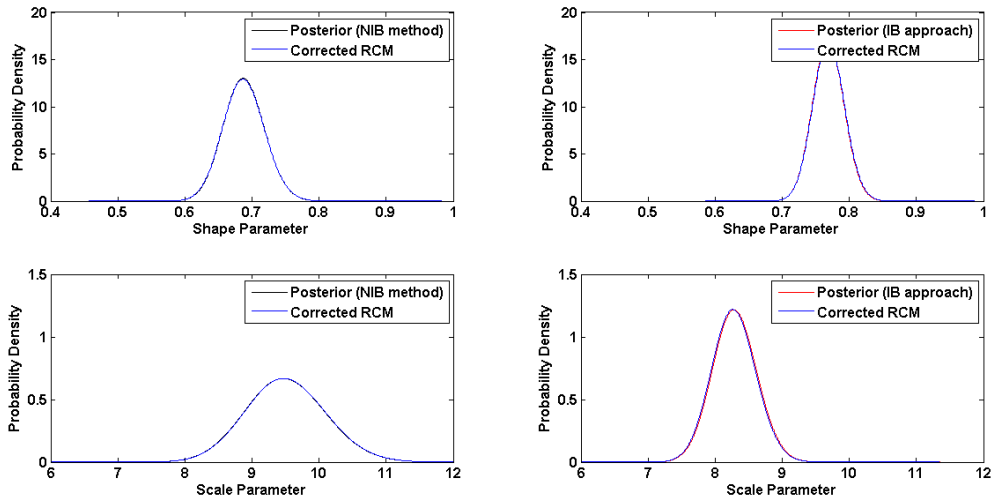
Figure 11. Posterior distributions of the observed and RCM January precipitation after bias correction represented in terms of distributions of parameters.
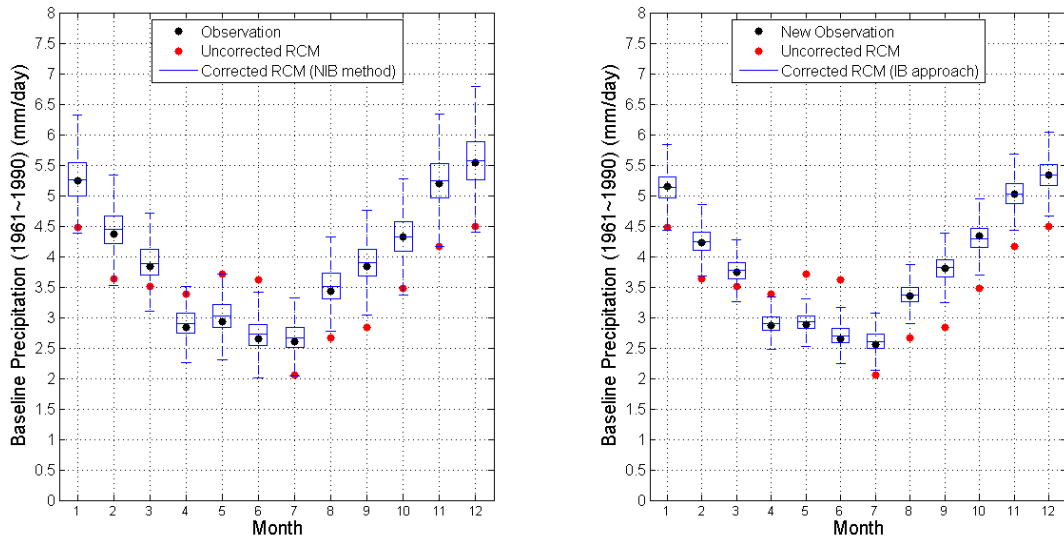

Figure 12. Comparisons of the uncertainty of the bias corrected data between the NIB method (left panel) and the IB approach (right panel). The box plots show the median (horizontal line), interquartile range (box), and range with maximum 1.5 interquartile range (whiskers).
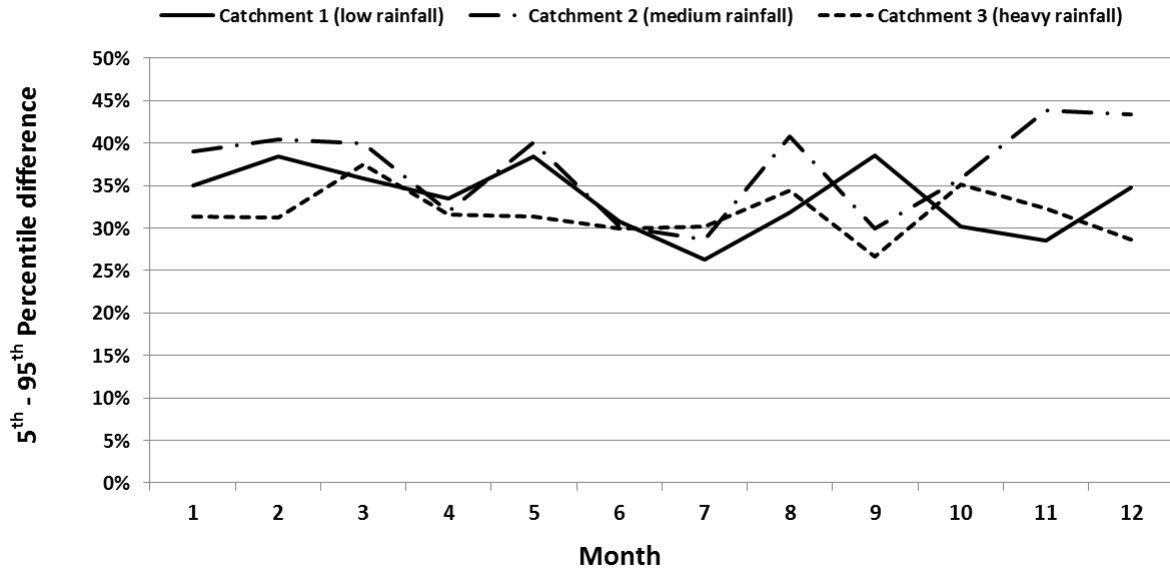
Baseline period (1961-1990)

Figure 13. The 5th to 95th percentile difference between the NIB and IB approaches after the bias correction for the three catchments.
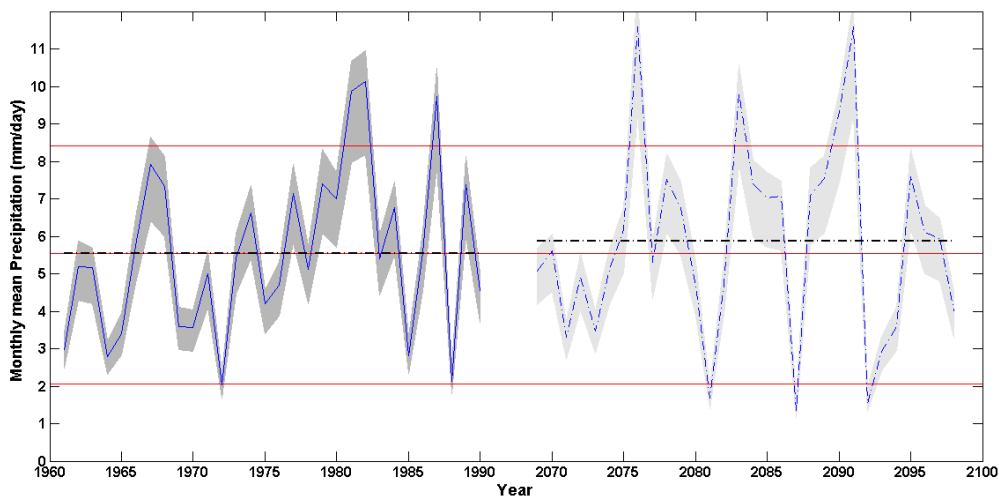

Figure 14. A time series of the bias corrected precipitation in December for the baseline and future periods. Solid red lines indicate 5%, median, and 95% of observed precipitation, respectively. Solid and dotted blue lines indicate the median values from the posterior distribution of the bias corrected precipitation, and horizontal dotted black lines show the mean precipitation in the baseline and the future, respectively.
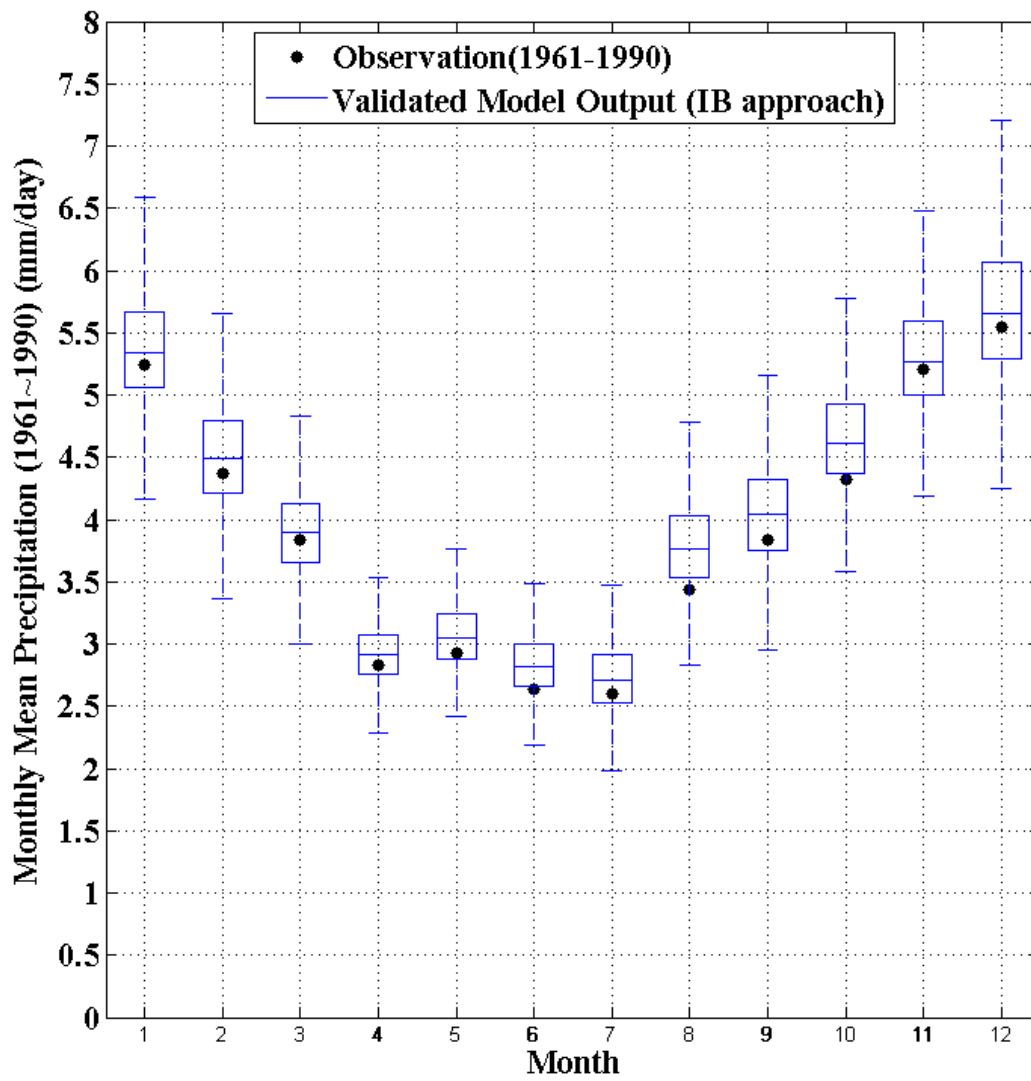
Figure 15. Two-fold cross validation of the IB approach.