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Research papers

Intercomparison of joint bias correction methods for precipitation and flow from a hydrological perspective

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ABSTRACT

The typical framework of the climate change impact assessment on water resources relies on plausible scenarios obtained from global climate models (GCMs) and hydrological models (HMs). Although regional climate models (RCMs) can better simulate local climate at a high-resolution grid, the direct use of model outputs from RCMs is not recommended as inputs for HMs due to systematic error. Existing studies have focused on the bias correction (BC) of climate model outputs without considering uncertainties/biases in hydrological modeling. In this regard, this study proposed an integrated framework that combines the BC of RCM precipitation and the simulated flow from the rainfall-runoff model, considering the underlying uncertainty in the parameters of the distribution function. The regional climate model, HadRM3, and the conceptual rainfall-runoff model, HYMOD, are employed. Observed daily precipitation, evapotranspiration, and discharge time series over the Thorverton catchment are compiled from the UK Meteorological Office. To examine the effectiveness of the combined strategy, four different BC approaches have been explored to reduce systematic biases in the flow simulated through the HMs using the RCM precipitation as input. Here, BCs of RCM and HM outputs have been applied under the condition that the bias-corrected ensembles should be within the range of the observed climate variability. The four BC models are considered: aathe RCM precipitation and flow are corrected by preserving their natural variabilities (Case-4). From a hydrological perspective, the Case-4 model showed the best performance among the four cases in terms of correcting the bias and the spread of the flow ensemble.

1. Introduction

Climate change impacts on water resources are of increasing concern since changes in water resources can be associated with many other aspects of water-related sectors, including agriculture, ecosystem health, water quality, and water quantity management (Arnell and Liv, 2001; Bates et al., 2008). In recent years, an increasing number of studies, particularly in the area of hydro-meteorology, have explored climate model ensembles (Chegwidden et al., 2019; Gosling et al., 2017; Guo et al., 2018; Hattermann et al., 2017; Jackson et al., 2011; Sexton et al., 2019). Although regional climate models (RCMs) provide more detailed climate information, particularly for hydrological applications, spatial scale mismatches can lead to increased uncertainty in the output of the hydrological model (Muerth et al., 2013b). Therefore, bias adjustment of both global and regional climate model-derived hydro-meteorological variables is often required to correct systematic biases (Kim et al., 2015; Piani and Haerter, 2012; Su et al., 2020). Several studies have shown that typical systematic biases in RCMs include over- or under-estimation of hydrometeorological components (e.g., precipitation and temperature), inaccurate seasonal representation of large-scale climate patterns, and overestimation of the wet-day frequency (Ines and Hansen, 2006). Various bias correction (BC) approaches have been explored by Teutschbein and Seibert (2012): 1) parametric local adjustment and power transformation (Fang et al., 2015; Leander et al., 2008; Smitha et al., 2018), and 2) parametric quantile mapping (Cannon, 2018; Cannon et al., 2015; Guo et al., 2019; Kim et al., 2016; Maraun, 2013; Piani et al., 2010; Switanek et al., 2017). BC remains a debatable issue (Ehret et al., 2012b; Muerth et al., 2013a) since (a) applying bias correction may narrow the uncertainty range (ensemble spreads) of climate simulations; (b) bias is assumed to be constant (or stationary), i.e., a set of parameters associated with bias correction under current climate conditions will still be effective under future

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climate. However, the BC approach to climate information, including precipitation and temperature, has been widely applied to assess the impact of climate change on water resources (Chen et al., 2018; Ghimire et al., 2019; Meyer et al., 2019).

Rainfall-runoff modeling systems are indispensable for representing the hydrologic processes that offer guidance for water system design and water resource planning and management (Madsen, 2000; Wagener et al., 2003). Apart from the biases in climate model outputs, hydrological models (HMs) are an imperfect representation of the real world hydrological processes as well, which are affected by input uncertainty (e.g., measurement error, sampling error), model uncertainty, parametric uncertainty, inadequate descriptions of initial and boundary conditions, etc. Several studies have investigated the advantages and disadvantages of using bias-corrected RCM outputs to estimate runoff. For instance, Muerth et al. (2013a) evaluated the effect of BC on runoff projections under climate change and showed that there was a limited influence on the relative changes. In other words, both bias-corrected and bias-uncorrected climate model data demonstrated a similar representation of the changes in runoff through the hydrological modeling process. Meanwhile, Willkofer et al. (2018) emphasized that different BC schemes can lead to differences in future runoff changes, especially for high flows. Although BC of the climate model outputs remains controversial with regard to hydrological impact studies (Hagemann et al., 2011), most recent studies have used bias-corrected climate model outputs as inputs for hydrological impact assessments (Akhtar et al., 2009; Chen et al., 2018; Fiseha et al., 2014; Olsson et al., 2015; Su et al., 2020; Teutschbein and Seibert, 2012).

Various studies have concentrated separately on either the BC process of climate model outputs or the statistical post-processing of outputs obtained from hydrological models. Recent studies, however, have evaluated the impact of bias correction on both the input variables and streamflow, considering the uncertainty in hydrologic modeling (Chen et al., 2021; Li et al., 2019; Tiwari et al., 2021). Chen et al. (2021) compared the performance of the pre-processing and post-processing of HMs. They found that bias correction of climate model outputs was more efficient than post-process hydrological model analysis. Li et al. (2019) concluded that the bias correction procedure could be applied to either precipitation or streamflow simulation for improving hydrological predictions. Tiwari et al. (2021) investigated the effects of bias correction of meteorological and streamflow forecast on hydrological predictions in India. They suggested that the combination of the bias correction of climate model outputs and simulated streamflow could significantly enhance the predictability of streamflow. Several previous studies have not paid attention to the sampling uncertainty. In the case of ensemble forecasts, the bias correction is often applied to adjust the statistical properties of each of the individual ensemble members to those of one observation. This process does not properly take advantage of ensemble spreads, representing model uncertainty, in climate change impact studies. In this study, the natural variability of the observations is first estimated, and then the spread (i.e., variance) of the ensemble is adjusted to the range of natural variability observed over the past three decades by incorporating sampling uncertainty. This study proposes an integrated approach that can combine the BC of RCM precipitation and the flow simulated from the rainfall-runoff model, considering the distributional parametric uncertainty underlying the observations. In other words, in this process, the ensemble spread is preserved to a certain degree after bias correction, which corresponds to the observation sampling uncertainty. Specifically, four different BC models were introduced to reduce systematic biases in the simulated streamflow. The suggested BC schemes were assessed with a conceptual rainfall-runoff model. The underlying assumption in this study is that the flow observations for bias correction are also available. This coupling strategy is expected to better represent the rainfall-runoff relationship. A brief summary of the BC models taken into account in this study is described below.

- Case-1 uses raw RCM precipitation data for simulation of the hydrological model, and it is used as a reference case. The biases of the climate model and hydrological model outputs are not corrected.
- Case-2 uses bias-corrected simulated flow data obtained from the hydrological model and raw RCM precipitation data as inputs.
- Case-3 uses bias-corrected RCM precipitation data as the input for the hydrological model. The bias of the simulated flow from the hydrological model is not corrected.
- Case-4 uses corrected model outputs for both RCM and hydrological models.

We compared the performance of the four BC models with the observed discharge from the calibration period (1961–1990) and the validation period (1991–2014) to address the following questions:

(1) Can the BC models applied in this study minimize systematic errors in RCM and hydrological model outputs for the baseline and future periods?
(2) How does the correction of the bias (i.e., systematic errors) in the RCM precipitation affect the output of the hydrological model? Is it better to use the bias-corrected RCM precipitation as an input for the rainfall-runoff model instead of the uncorrected RCM rainfall?
(3) Should BC apply only to the precipitation in climate models or to the simulated flow in hydrological models? Is the combined BC model more effective in reproducing the observed flow?

Research backgrounds and objectives are introduced in this section. The hydrometeorological data and study area are provided in Section 2. In section 3, the conventional BC method is presented. Next, we demonstrate the importance of preserving the observed natural variability in the BC process. The hydrological model and simulation design used to explore the impact of BC is presented in Section 4. We also discuss the results of this study. Finally, we offer a summary and conclusions.

2. Watershed and climate data

Observed daily hydrologic variables, including catchment-average precipitation data, evapotranspiration, and flow time series, over the Thorverton basin from 1961 to 1990 are compiled from the CAMELS-GB (Catchment Attributes and MEteorology for Large-sample Studies) (Coxon et al., 2020). Its catchment-averaged daily rainfall data have been derived from CEH-GEAR data (Tanguy et al., 2016), a 1 km gridded rainfall estimates interpolated from daily observed rainfall data from the Met Office. The rainfall grids were achieved using the natural neighbor interpolation method, including a normalization step based on average annual rainfall (1961–1990). Its potential evapotranspiration (PET) data were retrieved from the 1 km gridded CHESS-PE dataset (Robinson et al., 2017), which are based on the Penman-Monteith equation (Monteith, 1965) recommended by the FAO guidelines on the reference PET (Allen et al., 1998).

Here, the simulated hydrological variables are obtained from the Met Office Hadley Centre Regional Model Perturbed Physics Ensemble simulations for the 21st Century for the UK domain (HadRM3-PPE-UK). These regional climate change scenarios are dynamically downscaled from the HadCM3 GCM (Murphy et al., 2009). The HadCM3 consists of an 11-member ensemble (one unperturbed member and 10 perturbed members). For the perturbed model, selected parameters are perturbed from the unperturbed model by considering uncertainties in the model parameters for RCM (Collins et al., 2011). The climate simulations at daily time steps for historical and future periods, ranging from 1950 to 2100, are provided with a horizontal resolution of 0.22 degree (approximately 25 km). This study used the daily precipitation data constructed from all ensemble members to explore the integrated BC approach for the reference precipitation during 1961–1990. The

Thorverton basin is highlighted by the red grid box, as represented in Fig. 1 (right panel).

3. Methodology

3.1. Quantile mapping approach for bias correction

The quantile mapping (QM) approach has been widely applied to calibrate the GCM (or RCM) outputs (e.g., temperature, precipitation, and evapotranspiration) at different time scales (e.g., from seasonal to daily scales). A seasonally varying QM model is usually adopted for BC of the climate model outputs to effectively consider seasonal phases with different degrees of bias by considering strong seasonality and variability in precipitation. More importantly, an increase in wet-day frequency with low precipitation intensity (namely drizzle effect) has been a well-known issue in climate models, posing a challenge for effective analysis. In this regard, systematic bias in the rainfall occurrence process obtained from the climate models is adjusted by applying a threshold-based cut-off approach in advance before applying BC. In other words, the wet-day frequency is first forced to match with that of the observed precipitation data by eliminating the drizzle effect. QM is then performed based on probability distribution functions constructed from observed and simulated daily precipitation. The precipitation is assumed to be represented by a Gamma distribution as follows:

$$f(r) = \frac{1}{\theta^k \Gamma(k)} r^{k-1} e^{-r/\theta}; r \geq 0; k, \theta > 0 \tag{1}$$

Here, k and θ represent the shape and scale parameters, respectively, and Γ indicates the gamma function.

In this study, the Gamma-distribution-based QM approach is applied for the BC of the daily RCM precipitation. Gamma distribution is applied to daily data on a monthly basis, and the associated parameters are estimated for each of the 11 RCM ensemble members using the maximum likelihood method. A conceptual representation of the typical QM-based BC scheme is illustrated in Fig. A1. To be more specific, the cumulative distribution functions (CDFs) for both RCM simulations and observations are built for the same period (Fig. A1(a)), and the CDF of RCM simulations is then mapped to the CDF of the observed precipitation. Similarly, QM can also be demonstrated in terms of the parameters of probability density functions (PDFs) (i.e., transfer functions), as presented in Fig. A1(b). Here, a set of distribution parameters of the RCM simulations are transferred to those of the observed data via QM. The bias-corrected RCM precipitation can be obtained from the transfer function (or quantile function), as given in Eq(2):

$$R_c = F^{-1}[F(R_m; \alpha_m \beta_m); \alpha_{obs} \beta_{obs}] \tag{2}$$

Here, R_c denotes the bias-corrected daily precipitation from the modeled precipitation (R_m), while F and F^1 are the cumulative density function and quantile function of the Gamma distribution, respectively, with shape (α) and scale (β) parameters. The subscripts m and obs in these parameters (α and β) represent the model and observed precipitation. Here, BC is done for precipitation and simulated flow data. It should be noted that BC for the simulated flow is done in the same way as it is done for the simulated precipitation.

3.2. Natural variability of precipitation and discharge in BC

The main drawback of existing BC approaches is that the distribution parameters obtained from all the ensemble members are mapped to a point in the parameter space, as illustrated in Fig. 2. More importantly, this may banish model spread from a single model (or multi-model), which represents the uncertainty during the BC process. Moreover, assigning a set of parameters for the BC can be problematic if the sampling error is taken into account, and the obtained parameters from the observed precipitation may only represent one case out of many alternatives. This study adopted the BC approach for the RCM ensemble proposed by Kim et al. [2016], which considers both observational uncertainties (or sampling errors) and natural variability (for details, the reader is referred to Kim et al. [2016]). First, to assess the natural variability of the observed flow, daily flow data were randomly selected 30 times on a yearly basis from 30 years of observed daily flow. Second, sampling was repeatedly performed 1000 times to obtain 1000 sets of 30-year daily flow data. Third, Gamma distribution parameters were estimated for each series of the simulated flow (i.e., 30-year daily flow simulation). The BC for the flow series was done on an annual basis (i.e., 360 days × 30 years = 10,800 data points). Similarly, the natural variation in precipitation was evaluated. It should be noted that seasonally varying transfer functions (TFs) for each month were built from 1961 to 1990. Fig. 2 represents a schematic view of the BC considered in this study, which reflects the natural variability of observed hydrological variables. The main idea of the BC adopted in this study is to maintain the relative distance over the ensemble members seen in RCM simulations after BC; this was done so that variations in the bias-corrected values are able to reproduce those of the population as if all individuals are equally likely drawn from the population that can be regarded as the observed natural variability. It was found that the biases in the 11-member ensemble are effectively removed while maintaining the ensemble spread, as seen in Fig. 2e. For more details about the

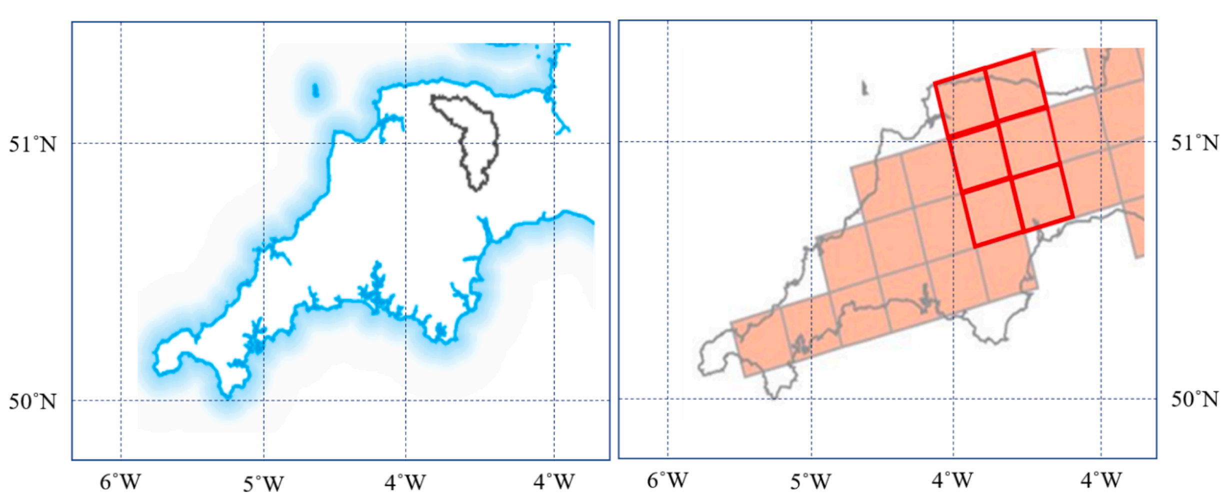


Fig. 1. The map shows the Thorverton basin (left panel) and HadRM3 with a 25 km spatial resolution (right panel). The red grid box highlights the Thorverton basin. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

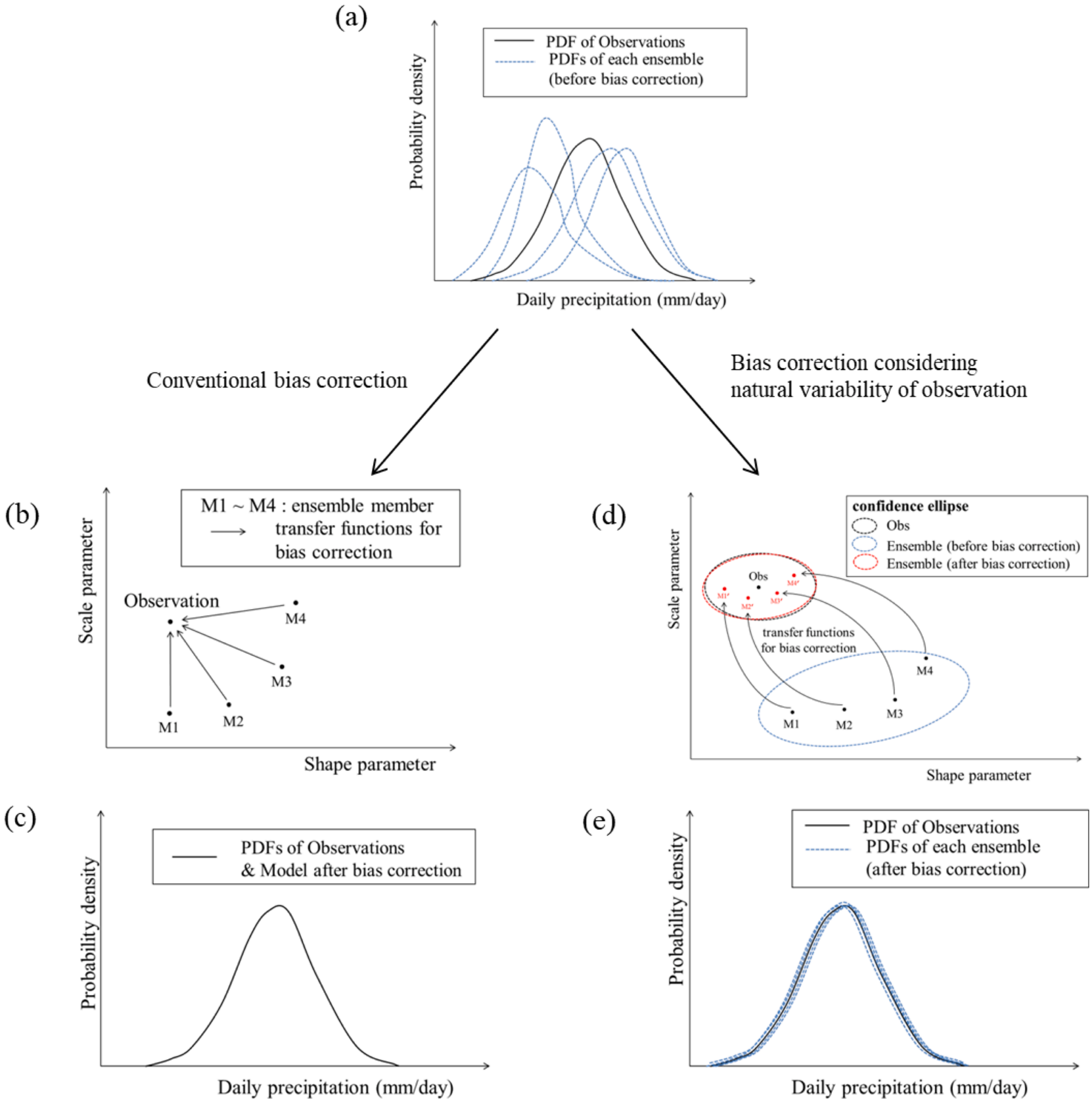


Fig. 2. A conceptual representation of the traditional bias-correction method and the approach used in this study (excerpted from Kim et al. [2016]).

modeling procedure, refer to Kim et al. [2016].

3.3. Hydrological model

This study used the conceptual rainfall-runoff model HYMOD (Moore, 1985), which has five parameters, to explore the impact of BC schemes on modeling flow. A brief description of model parameters is summarized in Table 1, and the schematic representation of the model is given in Fig. 3. The runoff generation process is described by a parsimonious precipitation-runoff model represented through the probability-distributed theory, and it has been widely used in hydrologic researches (Boyle, 2001; De Vos et al., 2010; Gharari et al., 2013; Kollat et al., 2012; Remesan et al., 2014; Vrugt et al., 2003; Wagener et al., 2001). The spatial variability of the water storage capacity (C) can be defined as follows:

Table 1
HYMOD model parameters and their ranges.

Parameter	Unit	Range	Description
C_{max}	mm	1–500	Maximum soil moisture storage capacity
b_{exp}	–	0.01–1.99	Spatial variability of the soil moisture capacity
α	–	0.01–0.99	Quick/slow flow distribution factor
R_s	day	0.01–0.99	Recession parameter for the slow flow tank
R_q	day	0.01–0.99	Recession parameter for the quick flow tank

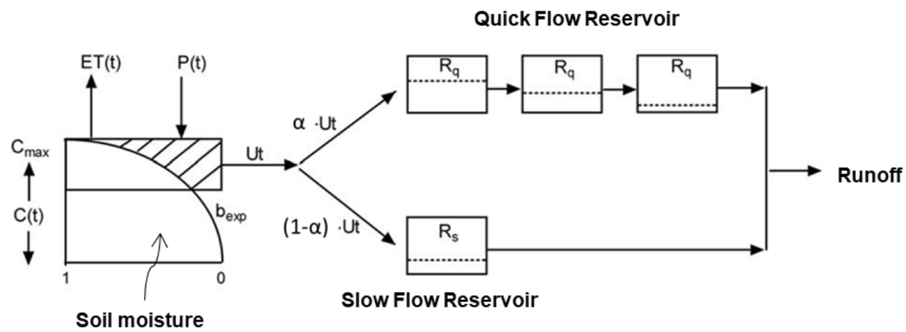


Fig. 3. Schematic representation of the HYMOD model.

$$F(C) = 1 - \left(1 - \frac{C(t)}{C_{max}}\right)^{b_{exp}}, 0 \le C(t) \le C_{max} \tag{3}$$

Here, C_{max} and b_{exp} represent the maximum soil moisture (SM) storage capacity and the degree of spatial variability of the SM capacity in the basin. Based on the weighting factor α, the effective (or excess) rainfall is converted into a quick flow and a slow flow. The discharge is then sequentially routed via parallelly linked three reservoirs representing quick flow simulation in the upper layer and a reservoir for slow flow simulation in the lower layer. The hydrographs are finally synthesized by applying the recession parameters for the fast (R_q) and slow (R_s) flow components at the catchment scale. The HYMOD was calibrated at a daily time step over the first available 30-year period (1961–1990) to obtain the optimized parameters and further validated over the remaining period (1991–2014). The calibration was done to minimize the difference between the observed and simulated flow through an objective function based on the Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q_{obs}})^2} \quad i = 1, \cdots N_{day} \tag{4}$$

where, Q_{sim}, Q_{obs}, $\overline{Q_{obs}}$ are the simulated flow, the observed flow, and the mean of the observed flow, respectively, in the calibration period. We used a dynamically dimensioned search (DDS) (Tolson and Shoemaker, 2007), a heuristic global optimization algorithm. The values of NSE were found to be 0.83 and 0.82 for the calibration and validation periods, respectively, which appear to be effective for rainfall-runoff modeling according to the given criteria (NSE $\ge$ 0.75) (Motovilov et al., 1999).

3.4. Experimental design used to examine the effectiveness of bias correction

The four experimental design cases are presented as follows. The BC is applied to 11 members of RCM precipitation and the simulated flow from the hydrological model. A rigorous inter-comparison between the four cases is provided, as illustrated in Fig. 4.

- (Case-1) The uncorrected 11-member ensemble of RCM precipitation is used as an input for the HM, and the uncorrected flow from HM is obtained (i.e., neither the bias of RCM precipitation nor the bias of the simulated flow are corrected).
- (Case-2) The uncorrected 11-member ensemble of RCM precipitation is used for the HM as an input, and the bias of the simulated flow from HM is then adjusted (i.e., the bias of RCM precipitation is not corrected, while the bias of the simulated flow is corrected).
- (Case-3) The bias of the 11-member ensemble of RCM precipitation is corrected, which is then used for the HM, as an input (i.e., the bias of RCM precipitation is corrected, while the bias of the simulated flow is not corrected).
- (Case-4) The bias of the 11-member ensemble of RCM precipitation is corrected, which is then used for the HM as an input. The bias of the simulated flow from HM is also adjusted (i.e., both the biases of RCM precipitation and the simulated flow are corrected).

Fig. 5 provides a conceptual diagram of the four different proposed BC approaches for the RCM ensemble of RCM precipitation and simulated flow from a distribution parameter estimation point of view. Different transfer functions (TFs) are used to correct each ensemble member, however, the distribution parameters' range for the TFs is restricted to the natural variability in the observed precipitation and flow. Since both the precipitation from the RCM and the simulated flow from a rainfall-runoff model are often affected by systematic errors, the spread of model outputs for Case-1 are significantly biased by the natural variability of the hydrologic variables (e.g., precipitation and flow), as illustrated in Fig. 5(a). For Case-2, the bias-uncorrected RCM precipitation ensemble is used as an input for HM, and the uncertainty range of the simulated flow ensemble is corrected by mapping the TFs based on the natural variability of the observed flow. Therefore, the spread of the simulated flow obtained from the RCM ensemble after BC (blue dotted ellipse) is expected to match well with the spread of the observation data (red ellipse) (Fig. 5(b)). For Case-3, the spread of the RCM precipitation ensemble is corrected (blue dotted ellipse) by mapping the TFs based on the observed natural variability in precipitation (red ellipse). Then, the bias-corrected precipitation ensemble is used as an input for HM, whereas the bias of the outputs from HM is not corrected in this case (Fig. 5(c)). For Case-4, the spread of the RCM precipitation ensemble is corrected (blue dotted ellipse) by mapping the TFs

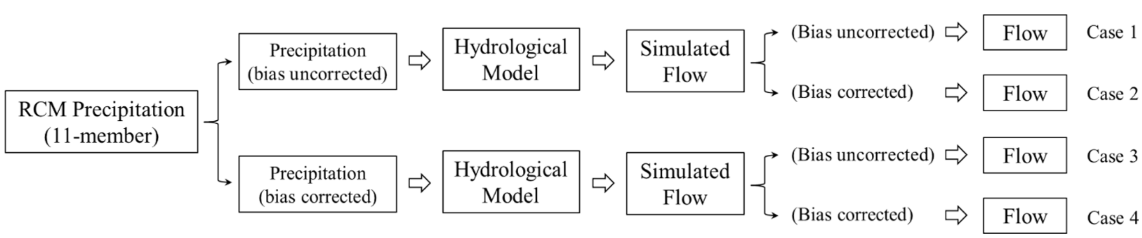


Fig. 4. An experimental design of the bias correction procedure.

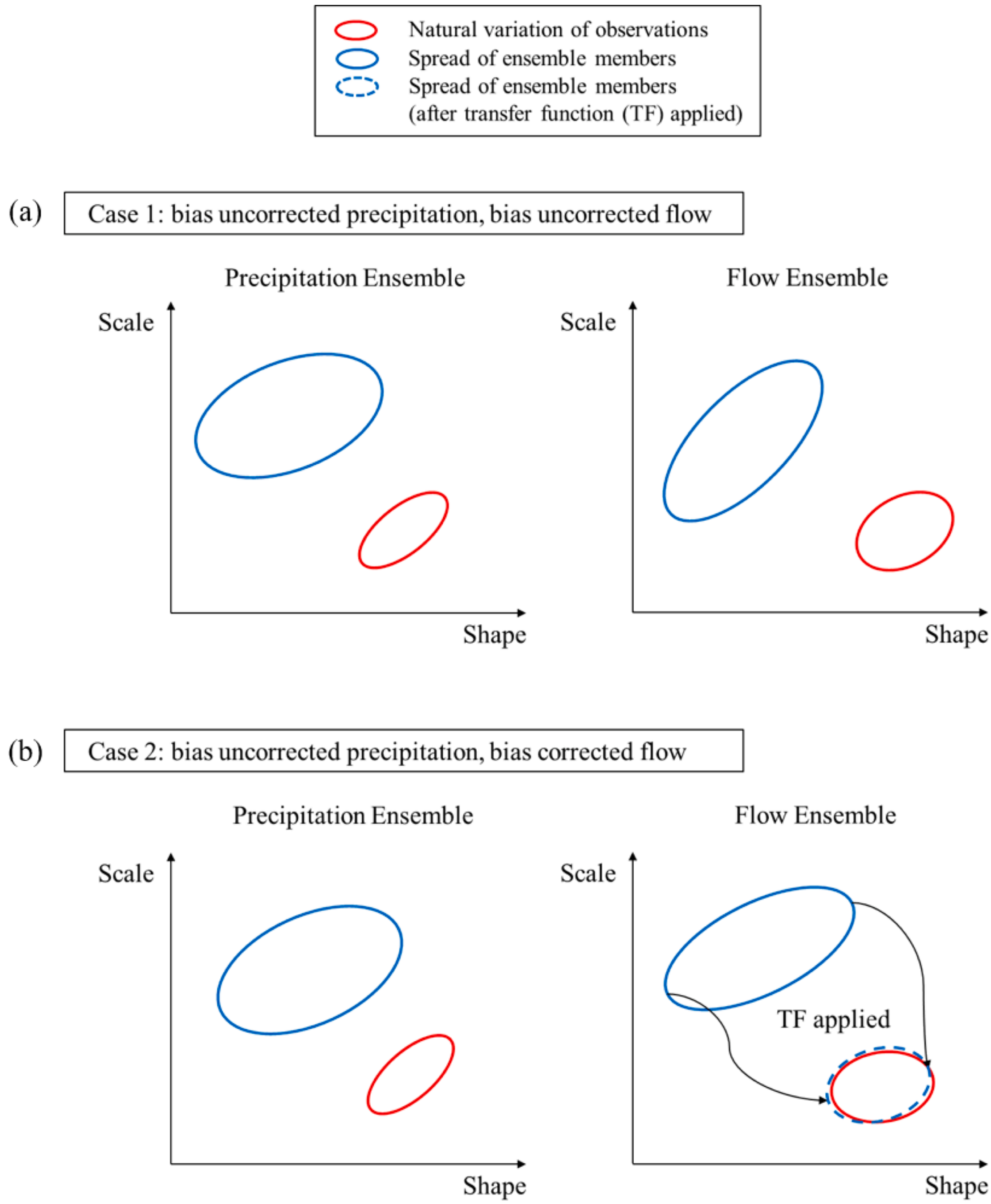


Fig. 5. Conceptual diagrams of the four different proposed BC approaches for RCM ensembles of RCM precipitation and the simulated flow from a distribution parameter estimation point of view. The blue ellipses represent the spread of ensembles from the models (RCM and HM), and the red ellipses depict the observed natural variability (either precipitation or flow). The blue dotted ellipses represent the spread of model outputs after mapping ensemble members to a range of possible observations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

based on the climate variation in the observation (red ellipse), and the bias-corrected precipitation ensemble is used as an input for HM. Furthermore, the bias of the outputs from HM is corrected in this case (Fig. 5(d)).

3.5. Validation of proposed bias correction schemes

To evaluate the TFs for the BC, the hydrological data (i.e., precipitation and flow) are divided into calibration (1961–1990) and validation (1991–2014) periods, representing the unseen data in a cross-validation context. Both the precipitation and the flow, ranging from 1961 to 1990, were used to construct the TFs for BC. The TFs were then applied to the independent data from 1991 to 2008. Note that the climate model outputs have no direct link to the data corresponding to the individual years of observation, i.e., they are not synchronous. For example, RCM precipitations in the year 1961 have no direct relationship with the observed precipitations in the same year. A set of aggregated statistics estimated from both observations and model outputs can be comparable in this regard. Therefore, to explore the effectiveness of BC in both the calibration and validation periods, monthly mean flows were compared for the four cases. A schematic representation of applying the TF to the validation period is presented in Fig. 6. The TF is built under the

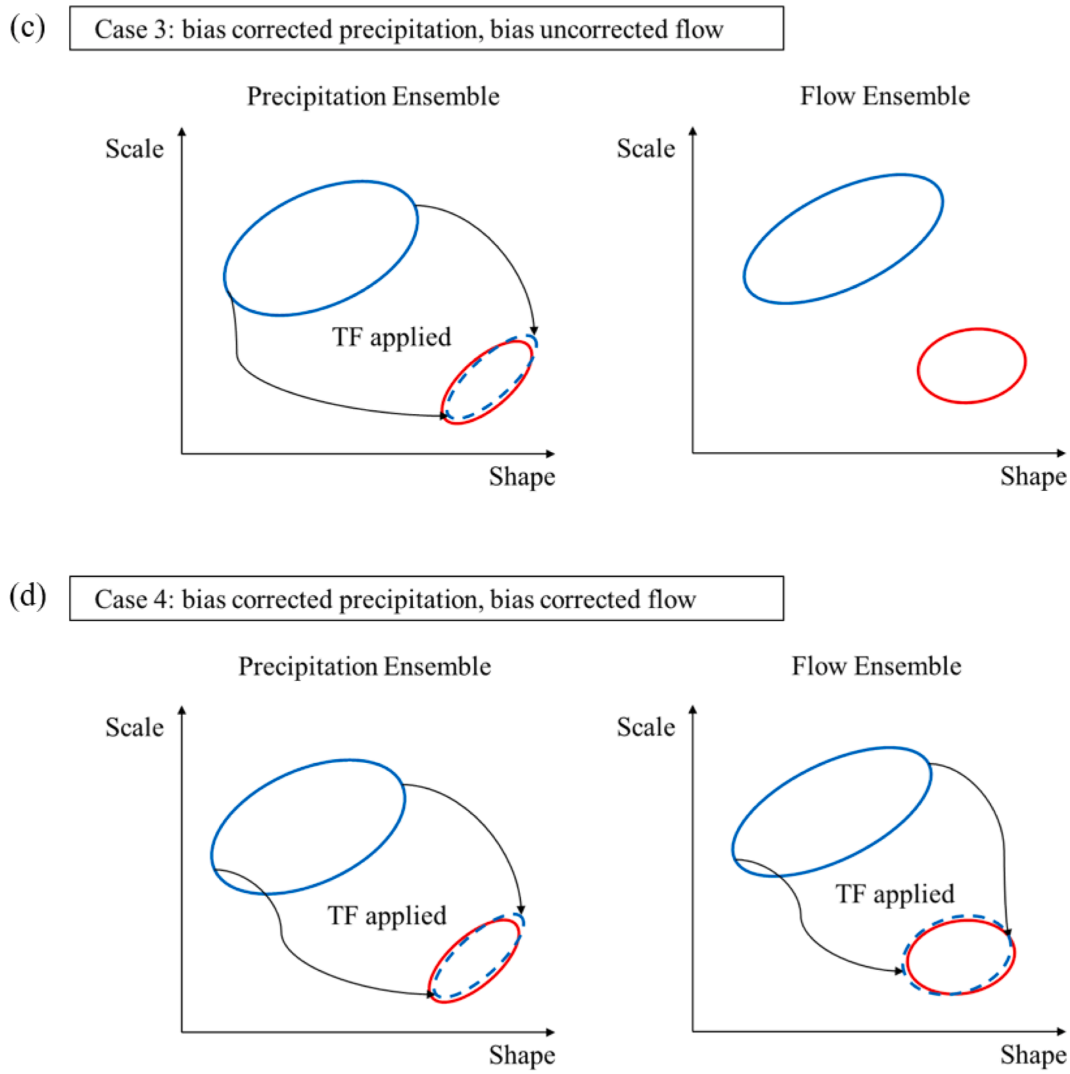


Fig. 5. (*continued*).

assumption that it is still effective for future climate conditions (i.e., the stationarity assumption with the TF, albeit the climate is changed in the future, which is commonly adopted in climate bias corrections) so that the TF is constructed based on the calibration period data (blue and red ellipses). Given the stationarity assumption, the magnitude, direction, and spread of the TF are preserved while being applied to the validation period data (blue dotted ellipse). The BC results (black dotted ellipse) are compared with the natural variability of the observation during the validation period (red dotted ellipse), which is assumed to be the future unseen data.

4. Results

4.1. Calibration period

4.1.1. Bias correction of the RCM precipitation ensemble

Fig. 7 shows the performance of BC for correcting the mean simulated precipitation. Although the seasonality is largely reproduced, the uncorrected monthly average rainfalls of 11 members of HadRM3 for the calibration phase (1961–1990) significantly deviate from those of the observed (left panel of Fig. 7). The ensemble means were generally well simulated in April and June. On the other hand, overestimation is seen in May, and underestimation is largely observed from July to March. After BC, the bias-corrected precipitation of each ensemble member is comparable with that of the observation data on a monthly basis. A comparison of percentage errors of the monthly precipitation between before and after bias correction is presented in Fig. 8. Overall, the systematic bias in the mean was well corrected, and the spread associated with the natural variability was also reasonably well preserved (right panel of Fig. 7 and Fig. 8). In terms of the model spread, the uncorrected model outputs were somewhat overestimated compared with the spread seen in the bias-corrected RCM precipitation, as shown in Figs. 7 and 8.

4.1.2. Comparison of the simulated flows

We compared the monthly mean flows between the observed data and four different model cases. The shaded area representing the model spread is obtained from the precipitation ensemble for the period from 1961 to 1990. The model spread is then compared with the boxplots showing the natural variability of the observed flow (Fig. 9). Overall, the monthly flows simulated from the bias-uncorrected 11-member RCM precipitation (Fig. 9(a)) produces a large bias (mostly underestimated) compared with those of the bias-corrected one (Fig. 9(b), (c), (d)). In addition, the spread of flows simulated from the bias-uncorrected RCM precipitation (Fig. 9(a)) is larger than those of simulated flow from bias-corrected RCM (Fig. 9(c)) and post-processed flows (Fig. 9(b), (d)). Therefore, it is apparent that the simulations without bias correction and post-processing are not able to accurately represent both the climate and the hydrological processes (Fig. 9(a), Case-1). The bias-corrected flow

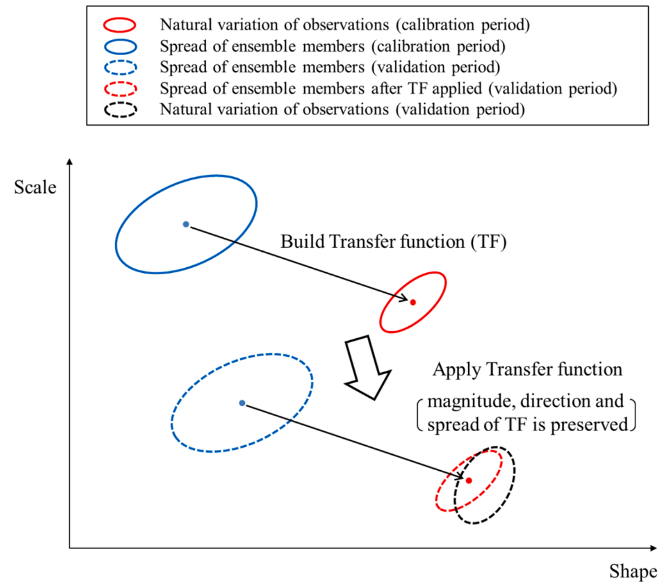


Fig. 6. Schematic representation of building and applying the TF for bias correction. The magnitude, direction, and spread of TF are preserved while being applied to the validation period data.

ensemble (Fig. 9(b), Case-2) is the output of the HYMOD model, which is simulated using bias-uncorrected RCM precipitation followed by correcting the bias of simulated flows. The result showed a narrower range of uncertainty than Case-1. In other words, both the mean and variance of the flow ensemble have been improved because the systematic bias of the flow has been directly corrected. Although the overall model spread and bias of the flow ensemble have been improved after correcting the bias of HM outputs, further improvements are needed to match the natural variability of the observed flow. For example, the spread of HM outputs is larger than those of the observations from December to March and the flow is underestimated from August to November. In Case-3, the flow simulations (ensembles) were obtained by using the bias-corrected precipitation as an input. As shown in Fig. 9(c), the performance of Case-3 is better than that of the approach used in Case-1 in terms of reducing the bias. The ensemble range is well reproduced after BC, which is comparable with the observed natural variation. Although the bias of the flow needs to be further improved, the spread of the simulated flow ensemble is more similar to that of the observation compared with Case-2. This might be due to the use of bias-corrected RCM precipitation as inputs to HM. Thus, one can conclude that BC of the RCM precipitation plays a critical role in achieving objectives that reduce the bias and reproduce the natural variability of the flow. To explore the role of BC in the simulated flow ensemble, the biases of the RCM precipitation and flow were corrected in Case-4 (Fig. 9(d)). As expected, the bias and the spread of the simulated flow ensemble are noticeably smaller than those of Case-2 and Case-3. The spread of bias-corrected flow ensemble mostly fell inside the natural variability of the observed flow. From this result, the Case-4 model, which corrects the biases of both precipitation and flow, shows the best performance among the four cases in terms of correcting the bias and the spread of the flow ensemble.

We further evaluated the model performance with different percentiles to explore the proposed effectiveness of the BC schemes at different flow regimes. Here, 11-member ensembles for the four cases were used to obtain flow distribution information at various percentiles, as shown in Fig. 10. Since 1000 sets of random, long-term precipitation sequences (i.e., 30-year * 365 days * 1000) were sampled to reproduce the natural variability over the past 30-year precipitation, 1000 sets of flow duration curves (FDCs) were constructed. In most percentiles, the flow ensembles (i.e., Case-1 and Case-3) are generally underestimated. Their median values differ from the observed flows, with extended ranges of the simulated flow at most flow regimes. Overall, the findings are in line with the results, as illustrated in Fig. 9. In contrast, the medians and the ranges of the bias-corrected flows (Case-2 and Case-4) were comparable to the observed flow at most flow regimes.

Fig. 11 presents the performance of different cases for the relationship of distribution parameters of the flow data. The red dots represent the estimated parameters associated with the natural variability of the observed flow, which are resampled from the observation data. Details

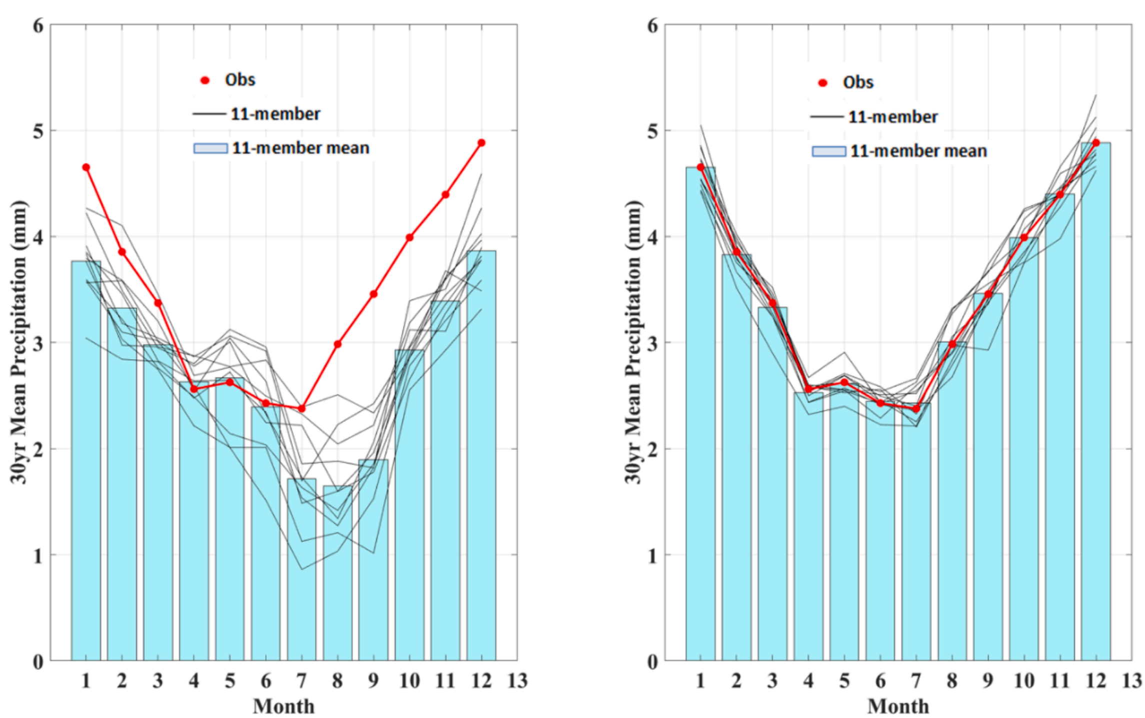


Fig. 7. The monthly distribution of precipitation averaged over an 11-member ensemble for the calibration phase from 1961 to 1990 before bias correction (left panel) and after bias correction (right panel).

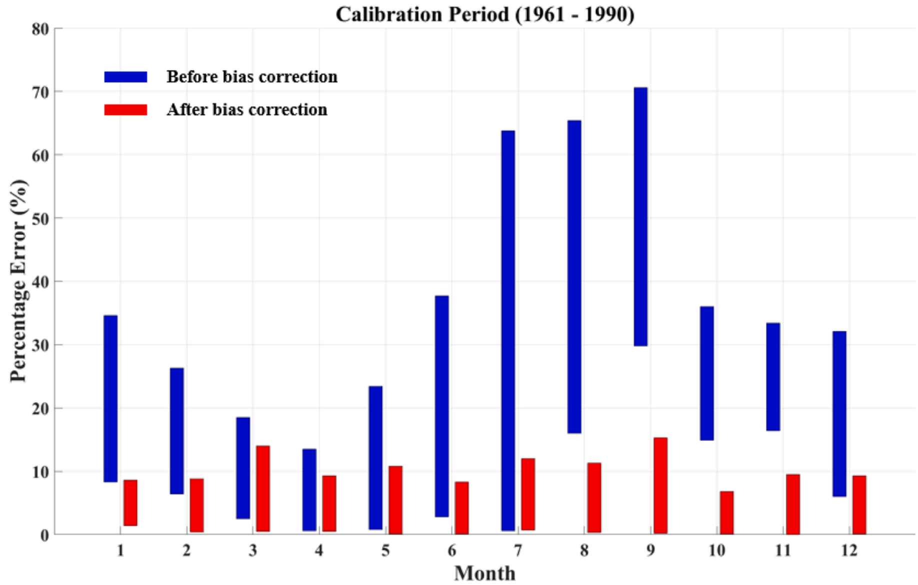


Fig. 8. A comparison of percentage errors of the monthly precipitation between before (blue bars) and after (red bars) bias correction during the calibration period (1961–1990). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

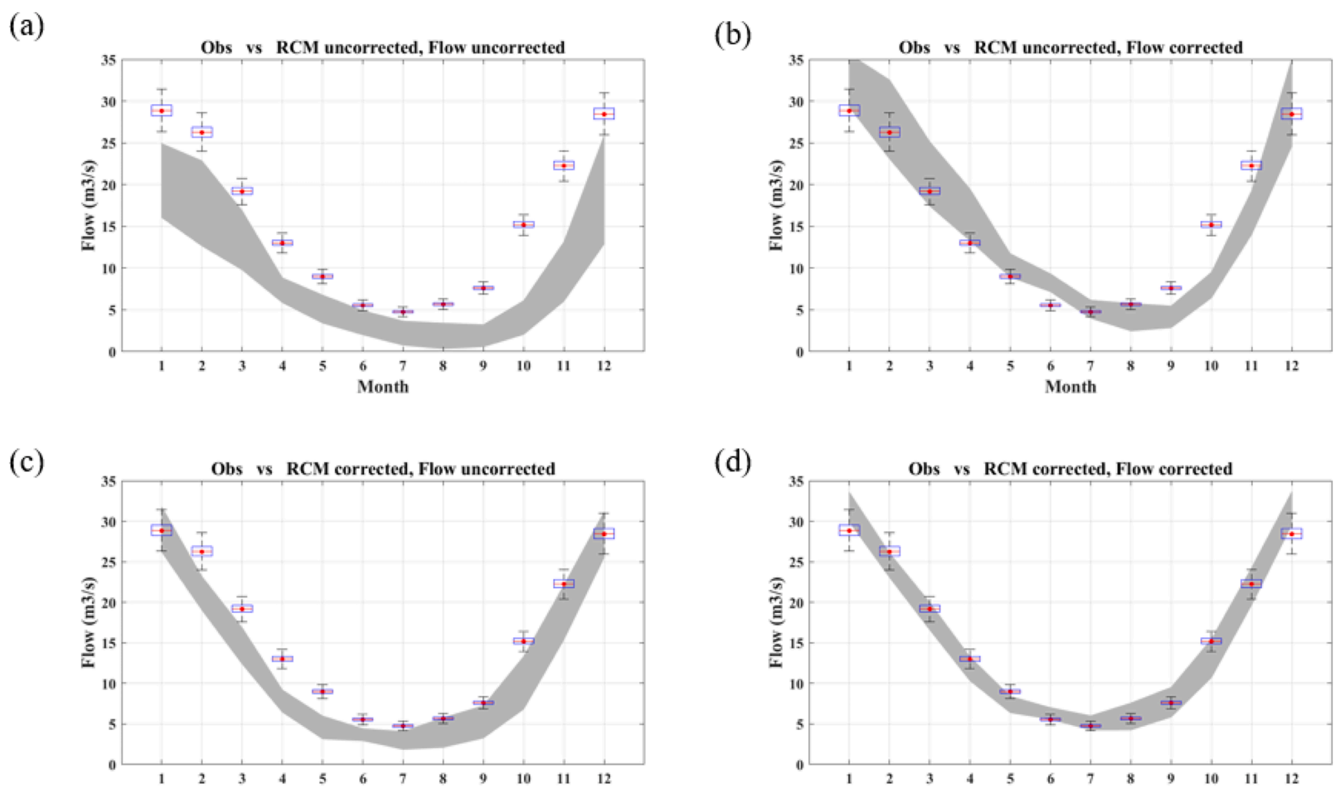


Fig. 9. Monthly distribution of ensemble flow using RCM precipitation ensemble for the four cases compared to the observed natural variability averaged over the calibration period 1961–1990. The shaded area represents the spread of an 11-member simulated flow. (a) Case-1: precipitation uncorrected, flow uncorrected; (b) Case-2: precipitation uncorrected, flow corrected; (c) Case-3: precipitation corrected, flow uncorrected; and (d) Case-4: precipitation corrected, flow corrected.

of estimating the natural variability of the observed flow are presented in Section 3.2. In Fig. 11(a), the unfilled blue dots are the Gamma distribution parameters of the simulated flow from the uncorrected 11-member RCM precipitation (Case-1), and the filled blue triangles are those of the bias-corrected flow with the uncorrected 11-member precipitation sets obtained from the RCM (Case-2). In Fig. 11(b), the unfilled blue dots are the relationship of two parameters of the bias-uncorrected flow simulated from the corrected 11-member RCM precipitation (Case 3), and the filled blue triangles are the relationship between Gamma distribution parameters of the bias-corrected flow simulated from the corrected 11-member RCM precipitation (Case-4). The Gamma distribution parameters of the fixed flow members (Case-2 and Case-4) are all inside the range of the observed natural variability, which indicates that the spread of the 11 members' parameters after BC

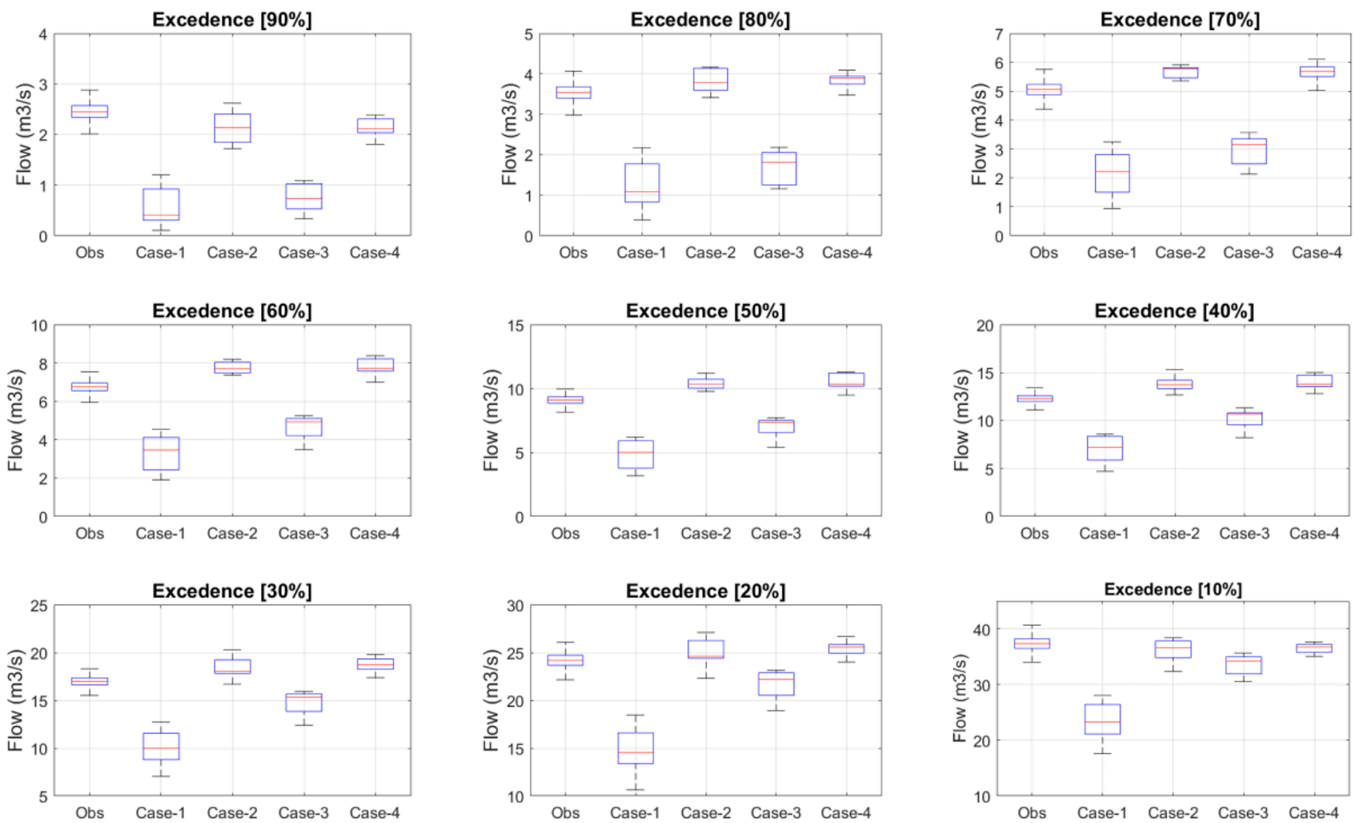


Fig. 10. Comparison of the flow simulated from the four cases with that of the observed, presented in boxplots at different flow regimes. The horizontal line in the box indicates the median flow. The box plot shows the interquartile range from 25th to the 75th percentiles of the flow ensemble.

are reasonably well reproduced. In contrast, the bias-uncorrected flow cases (Case-1 and Case-3) generally deviate from the parameter space shown in the observed flow. Again, these results confirm that using BC for the simulated flow is important in reducing the bias and reproducing the natural variability of the flow.

4.2. Validation period

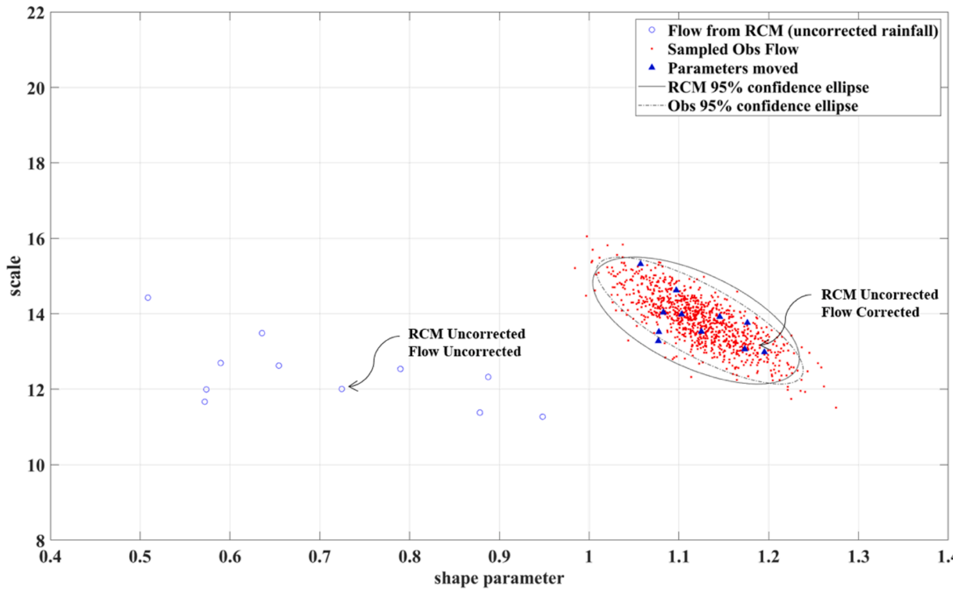
4.2.1. Bias correction of the RCM precipitation ensemble

Fig. 12 represents the bias correction results during the validation period (1991–2014). Here, the observed monthly mean precipitation during the validation period is assumed to be the future precipitation, as done in the climate change study. The difference between the uncorrected precipitation of HadRM3 and the observation data was found for the validation period from 1991 to 2014 (left panel of Fig. 12). More specifically, the precipitation ensemble means were generally overestimated in March and May, whereas an underestimation of the precipitation was observed for the rest of the month. The results are generally consistent with the differences identified in the calibration period. Even considering that the TFs were built during the calibration period, the results demonstrated that the simulated monthly precipitation was reasonably well corrected. A comparison of percentage errors of the monthly precipitation between before and after bias correction during the validation period (1991–2014) is presented in Fig. 13. The overall reduction in the ensemble spread representing the natural variability was also confirmed except for March, April and September (right panel of Figs. 12 and 13). The overestimation of the model spread that exceeded the observed natural variability in precipitation is in line with the calibration results during 1961–1990. Compared to the calibration results during 1961–1990, the proposed approach could be applied for bias correction of unseen data representing the future climate, although there is a slight difference from the observed precipitation. The effectiveness of the proposed BC model can be confirmed overall.

4.2.2. Comparison of the simulated flows

To further explore the proposed BC schemes, the monthly mean flows of the observed data and four different model cases during the validation period (1991–2014) were compared. The shaded area representing the model spread is obtained from the precipitation ensemble for the period from 1991 to 2014. The model spread is then compared with the boxplots showing the natural variability of the observed flow, as illustrated in Fig. 14. Overall, regardless of applying the BC for the RCM precipitation, the flow ensemble simulated from the RCM precipitation (Case-1 and Case-3) was shown to be systematically biased when the simulated flows were not corrected. More specifically, the monthly flows simulated from the bias-uncorrected 11-member RCM precipitation (Fig. 14(a)) produce a large bias (mostly underestimated) compared with those of the bias-corrected flows (Fig. 14(b), (d)). In Case-2, the flow simulations (ensembles) were obtained by using the bias-uncorrected precipitation as an input, followed by correcting the bias of simulated flows. The systematic bias is largely corrected. However, the higher mean value of the flow ensemble than the observed is seen during the first half of the year and vice versa during the rest of the year. The spread of the simulated flows is not clearly reduced compared with Case-1, which implies that the BC process for HM outputs has a limited effect on improving the uncertainty of the simulated flow during the validation period. Although Case-3 during the calibration period (Fig. 9 (c)) showed an improvement in terms of reducing the bias of simulated flows when the bias-corrected RCM precipitations are used as inputs to HM, this is not the case for the validation period (Fig. 14(c)). On the other hand, when both the RCM precipitation and flow biases are corrected (Fig. 14(d), Case-4), it can be seen that the biases of the simulated flow ensemble are noticeably reduced than those observed in Case-3. In summary, Case-4, which corrected the bias of RCM precipitation and simulated flow, showed the best performance among the four cases in terms of correcting the bias of the flow ensemble. The overall model spread of the flow ensemble after correcting the bias of HM outputs was

(a)



(b)

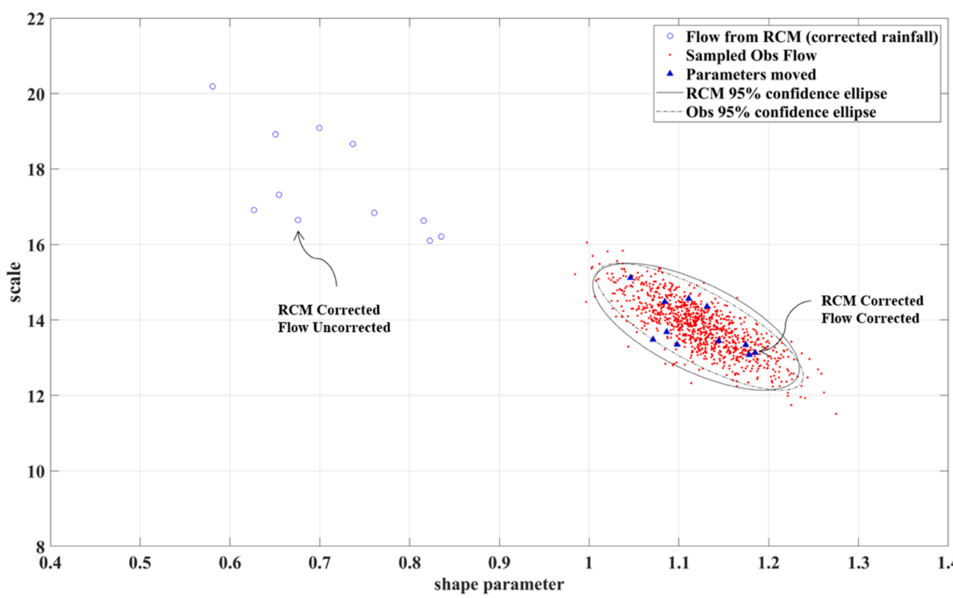


Fig. 11. (a) Results of Case-1 and Case-2 in terms of the distribution parameters of the flow data. (b) Results of Case-3 and Case-4 for the distribution parameters of the flow data.

largely similar to the natural variability of the observation data and mostly fell inside the observed natural variability of the flow. As similarly found in the calibration period, one can conclude that BC of the simulated flow played a crucial role in achieving objectives that reduce the bias of the flow. It should be noted that the overall efficacy of the proposed bias correction approach largely relies on the calibration of the rainfall-runoff model. More specifically, if the rainfall-runoff model is not adequately calibrated, the differences in performance across cases cannot be attributed solely to the bias correction approaches proposed in this study. Here, we did not evaluate the sensitivity of the overall results according to the model performance in the calibration and validation processes. However, we confirmed that the calibration process appears to be effective for rainfall-runoff modeling since the values of NSE were found to be over 0.80 for both the calibration and validation periods

Model performances at different flow regimes are illustrated in Fig. 15, as done in the calibration period in Section 4.1.2. As seen in the calibration period, the bias-uncorrected flows (i.e., Case-1 and Case-3) generally underestimated the observed flow. Their underlying distributions slightly deviated from that of the observed data, with an extended range of the natural variability at most flow regimes. Overall, the findings are in line with the calibration results, whereas the distributions of the bias-corrected flows (Case-2 and Case-4) are largely comparable to the observed flow at most flow regimes.

A comparison of model validation results during 1991–2014, when correcting the parameter space of the flow data over four different schemes, is presented in Fig. 16. As expected, the parameter space of the corrected flow ensemble (Case-2 and Case-4) was comparable to that of the observed data and much closer than the uncorrected flows simulated

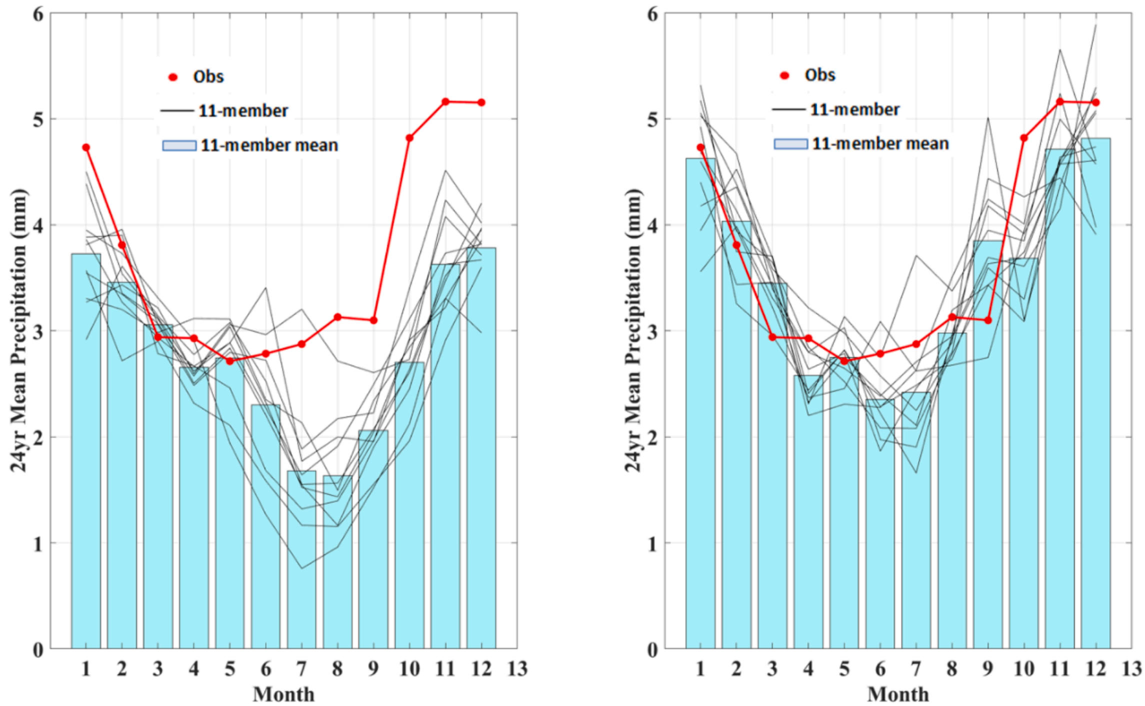


Fig. 12. As in Fig. 7, but for the validation period (1991–2014).

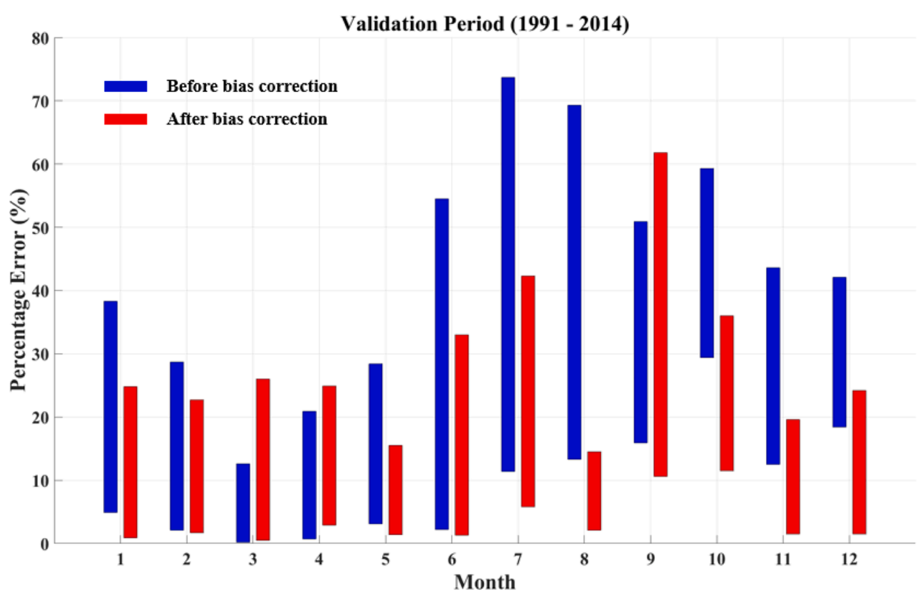


Fig. 13. A comparison of percentage errors of the monthly precipitation between before (blue bars) and after (red bars) bias correction during the validation period (1991–2014). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

from the RCM precipitation, irrespective of correcting the bias of precipitation (i.e., Case-1 and Case-3). However, the estimated parameters from the bias-corrected flow ensemble do not always fall in the range seen in the observed flow. Finally, the results obtained during the validation period reemphasize the relative importance for the BC of the simulated flow.

5. Summary and conclusions

Existing studies have independently focused on either the BC process of climate model outputs (e.g., precipitation and temperature) or the post-processing of hydrological model outputs (e.g., simulated flow). Several recent studies have evaluated the impact of bias correction on both the input variables and streamflow, considering the uncertainty in the hydrologic model simulations. However, these studies neglected the advantage of quantifying uncertainty through the use of ensemble spread in climate change impact studies. In this context, this study is an extended work of these existing studies, combining the bias correction processes of RCM precipitation and the flow simulated from the rainfall-runoff model in an integrated framework, considering the underlying uncertainty in the parameters of the distribution function. To examine the effectiveness of the combined strategy, four different BC approaches have been explored to reduce systematic biases in the streamflow simulated from a conceptual hydrological model. The basic assumption

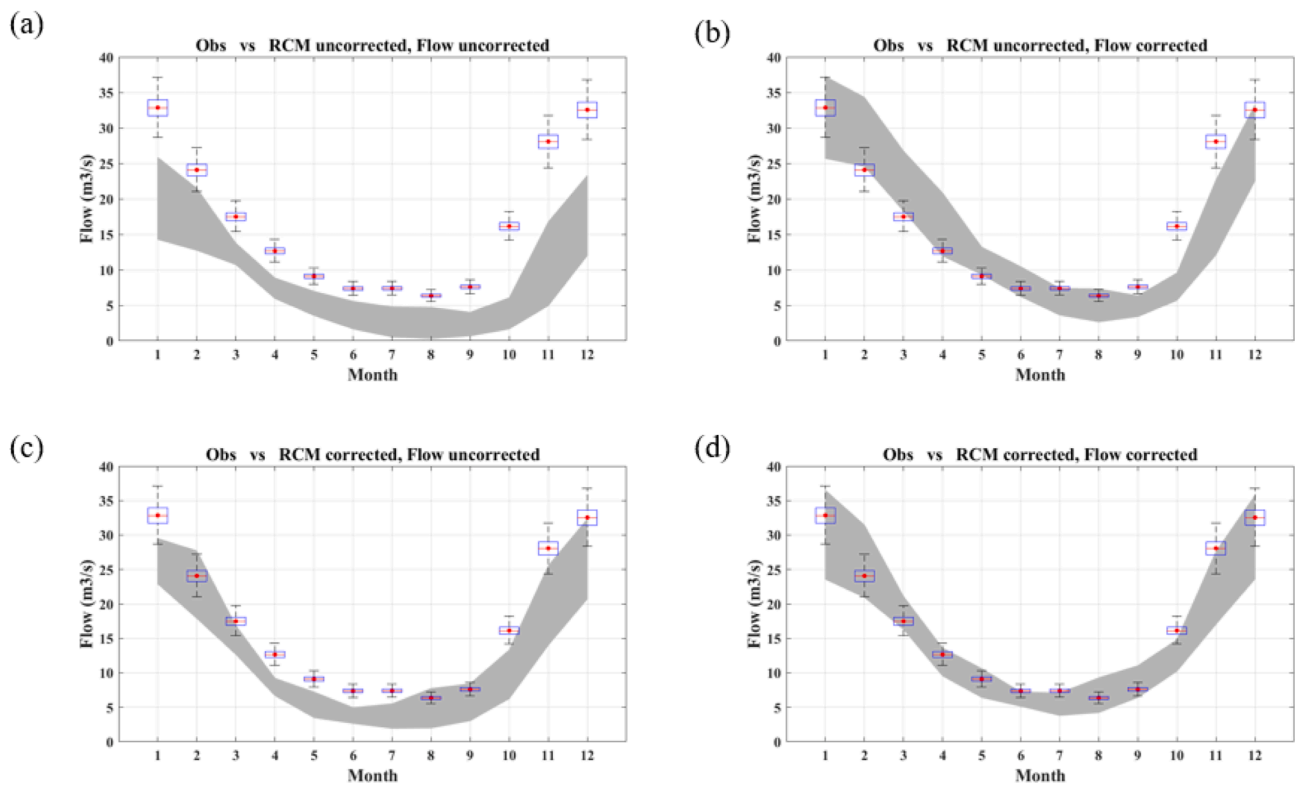


Fig. 14. As in Fig. 9, but for the validation period (1991–2014).

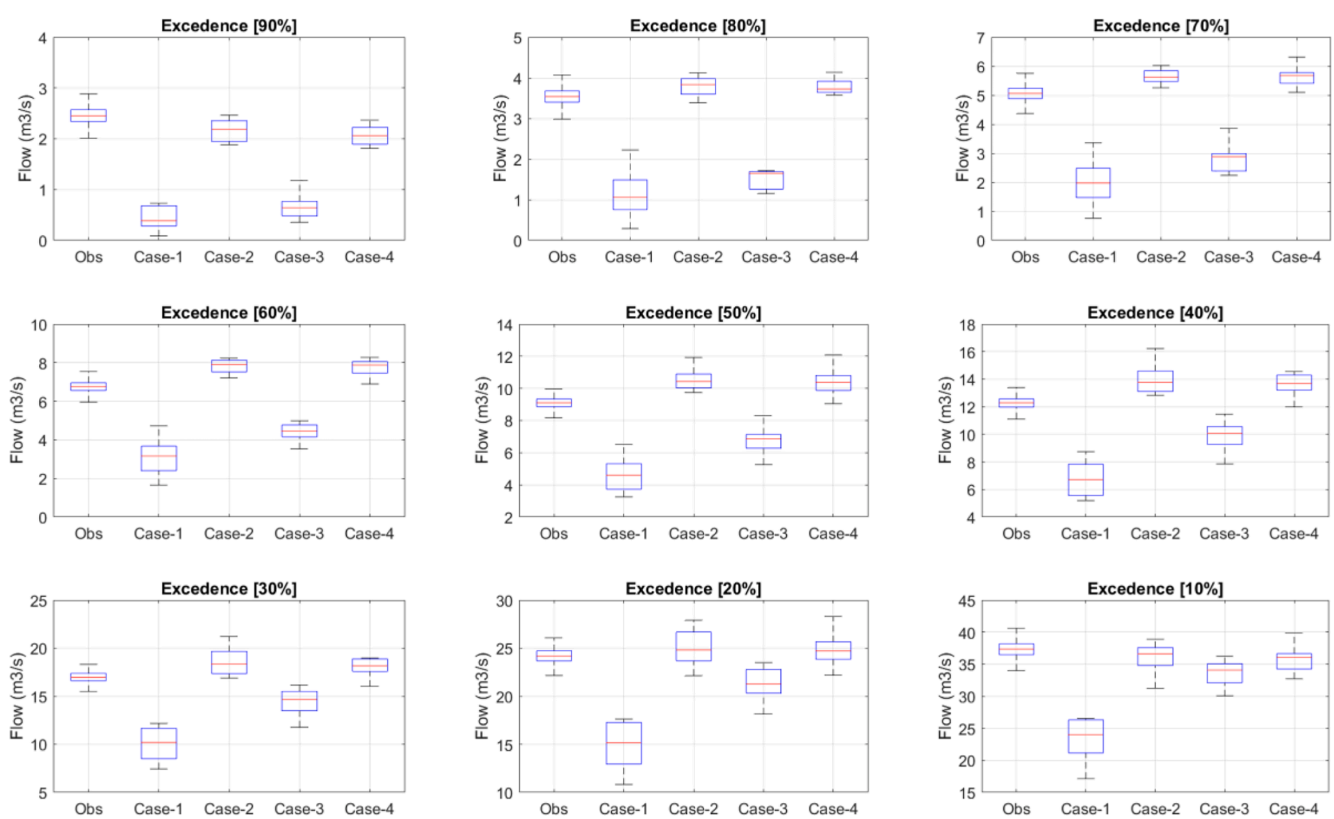


Fig. 15. As in Fig. 10, but for the validation period (1991–2014).

in this study was that both the observed precipitation and the flow data for bias correction were available. Moreover, the proposed BC approaches have been applied under the presumption that the corrected RCM members and the simulated flow with the RCM precipitation should come from within the range of the variation observed in the precipitation and flow data. The four BC models we considered are

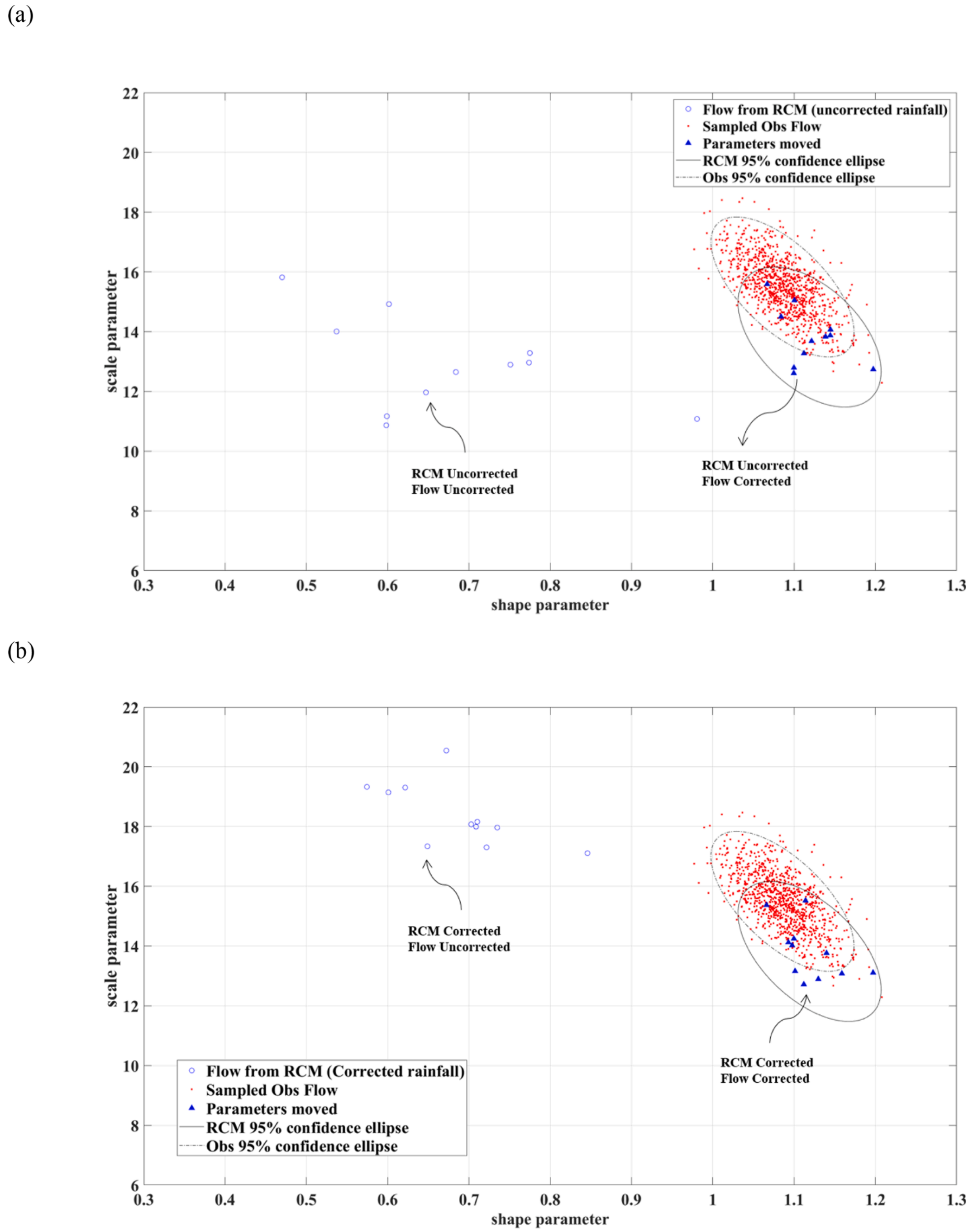


Fig. 16. As in Fig. 11, but for the validation period (1991–2014).

described as follows. In Case-1, the biases of both the climate model and hydrological model outputs are not corrected. In Case-2, the bias of the flow is only corrected with the use of the uncorrected RCM precipitation. In Case-3, the bias of RCM precipitation is solely corrected without BC of the simulated flow. In Case-4, both the RCM precipitation and flow are corrected by preserving their natural variabilities. The performance of these four different cases of combined BC models was compared with the observed flow during both the calibration period (1961–1990) and the validation period (1991–2014). The main summary and key findings from this study are described as follows:

(1) In Case-1, the uncorrected precipitation for the calibration phase differs from the observations. The flow simulated from the uncorrected RCM precipitation was shown to be systematically biased, and the model spread was largely overestimated compared to that in the observations. In Case-2, the bias-corrected flow using the bias-uncorrected precipitation ensemble demonstrated a narrower range of uncertainty than Case-1. The bias-corrected flow ensemble has been improved since the systematic bias of the flow has been directly corrected. Although the overall model spread of the flow ensemble after correcting the bias of the simulated flow was similar to the natural variability of the observed flow, further improvement is needed to match the natural variability of the observed flow
(2) In Case-3, the corrected precipitation was almost identical to that of the observation data. The systematic biases in the precipitation ensemble were well corrected, and the spread associated with the natural variability was also reasonably well preserved. Although

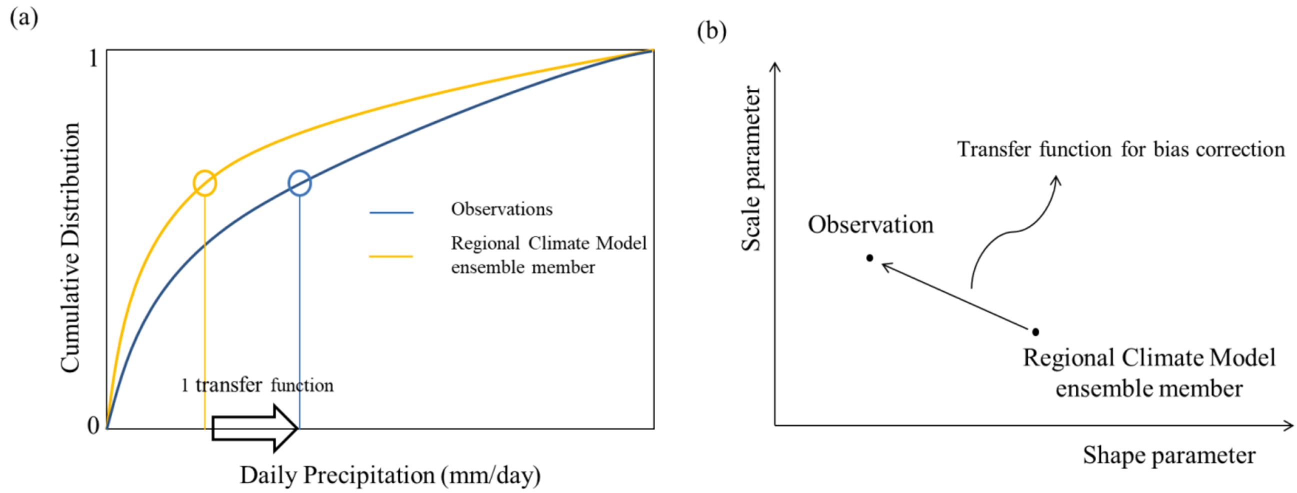


Fig. A1. A conceptual representation of the Quantile Mapping (QM)-based BC approach. (a) Mapping the CDFs of the RCM precipitation to those of the observed. (b) Mapping the Gamma distribution parameters of the RCM outputs to those of the observed.

the bias of the simulated flow needs to be further improved, the spread of the simulated flow ensemble is more similar to that of the observation compared with Case-1. This might be due to the use of bias-corrected RCM precipitation as inputs to HM. In Case-4, both the RCM precipitation and flow biases were corrected. As expected, the bias and the spread of the simulated flow ensemble were noticeably smaller than those in Case-2 and Case-3. The Case-4 model, which corrects the biases of both the precipitation and the flow, showed the best performance among the four cases in terms of correcting the bias and the spread of the flow ensemble. The improved results in terms of bias correction in Case-4 have some interesting implications about the important role of BC for both the RCM precipitation and the simulated flow in reducing the bias and reproducing the natural variability of the flow.

(3) We further explored model performance at different flow regimes. In most percentiles, the flow ensembles obtained from Case-1 and Case-3 were generally underestimated. Their median values differ from the observed flows, with an extended range of the simulated flow at most flow regimes. In contrast, the medians and the ranges of the bias-corrected flows, obtained from Case-2 and Case-4, were comparable to the observed flow at most flow regimes. Finally, the model performance of different cases in terms of the parameter space of the flow ensemble was evaluated. The Gamma distribution parameters of the corrected flow members, obtained from Case-2 and Case-4, were all inside the range of the observed natural variability. It should be noted that the BC of the simulated flow demonstrated the relative importance of reducing the bias and reproducing the natural variability of the flow. During the validation period, the model performances were further evaluated. The Case-4 model was the best in correcting the bias of simulated flows, which are in line with the calibration results. However, from an ensemble uncertainty perspective, the spread of simulated models is not identical to those of the observations, which implies that BC of the model outputs does not play a crucial role in reproducing the spread of the observed flow during the validation period. The difference in the ensemble uncertainty seems to be due to nonstationarity in the flow, leading to a difference in the transfer function for the bias correction.

(4) BC of the RCM precipitation is often criticized due to several aspects (Dosio et al., 2012; Ehret et al., 2012a; Hagemann et al., 2011; Maraun, 2012; Maraun et al., 2010; Teutschbein and Seibert, 2012), such as: 1) a physical justification is missing since the model errors induced by physical causes are not considered; 2) the relationship and spatio-temporal consistency between climate variables are modified after BC; 3) it may not be plausible to correct climate change trends; and 4) the stationarity assumption might not be met under changing climate conditions. However, from a hydrological perspective, we would like to point out that the use of the bias-corrected climate model precipitations as inputs to the hydrological model followed by the BC of the simulated flow from HM is recommended.

6. Data availability

The CAMELS-GB dataset used in this study is available via the UK Centre for Ecology & Hydrology Environmental Information Data Centre.

CRediT authorship contribution statement

Kue Bum Kim: Conceptualization, Data curation, Methodology, Software, Validation, Formal analysis, Writing – original draft. **Hyun-Han Kwon:** Conceptualization, Methodology, Investigation, Supervision, Writing – review & editing, Funding acquisition. **Dawei Han:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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