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ORIGINAL ARTICLE

Reducing bias-corrected precipitation projection uncertainties: a Bayesian-based indicator-weighting approach

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Abstract In this paper, a Bayesian-based indicator-weighting approach is developed to reduce the uncertainty resulting from bias-correcting projection outputs from multiple general circulations models (GCMs). The approach decides whether or not a projection from a given GCM output should be used depending on how close output from the GCM's retrospective run was to past observation (bias criterion) *and* agrees with the consensus (convergence criterion) estimate of all future GCM projections in a "truth-centered" statistical framework. Indicator weights are derived by equating present day versus future changes in mean precipitation of individual GCM output to the one obtained from the posterior distribution of all GCMs using a Markov Chain Monte Carlo algorithm. Use of GCMs outputs in hydrological impact studies requires downscaling and/or bias correction steps in order to account for discrepancies between small and large scale land-atmospheric processes. One of the most popular techniques for bias-correcting retrospective GCM outputs is the cumulative distribution functions matching approach based on observed precipitation. Future GCM projections are then adjusted depending on the bias correction results of retrospective outputs. In this sense, the bias correction process introduces variability/uncertainty into GCM outputs resulting in a wide range of projected values. If more than one GCM is used, the range of variability/uncertainty further increases. The approach that is used to reduce this uncertainty is demonstrated using 23 GCM outputs of CMIP5 model runs for west central Florida.

Keywords Bayesian model weighting · GCM projections · Uncertainty

Introduction

It is well established that coarse-resolution general circulation models (GCMs) outputs impede their use directly in hydrological impact studies at local or regional watershed scale (Wood et al. 2002; Li et al. 2010). Downscaling addresses the spatial scale mismatch between large scale processes represented in GCMs (scale of hundreds of kilometers) and regional scale processes (order of a tens of kilometers). Bias correction methods attempt to inject local scale variability into otherwise much smoother outputs of the parent GCMs. The use of regional climate models (RCM) is one approach used to downscale GCM output to finer resolution scales. But recent studies have shown that even RCM outputs need bias corrections for use in regional hydrological modeling (Sharma et al. 2011; Hwang et al. 2012). These bias correction steps introduce uncertainty/variability into the raw GCM or RCM outputs. Reducing uncertainties in bias-corrected GCM or RCM has not gotten attention yet. This paper looks at uncertainties introduced while bias-correcting GCM outputs and propose a methodology in reducing them.

For hydrological impact studies, bias correction methods of future precipitation projections may be categorized into two groups depending on how those future projections are derived: (1) "delta method"—using precipitation changes from one or more GCM projections versus retrospective GCM runs and applying this difference to historical records

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to obtain future precipitation values. In this case, GCM-projected precipitation values are not used directly; rather the changes are applied to the historical records. There are different flavor in this: One can use mean precipitation, precipitation at a given percentage or range, and it may be further applied at a seasonal or aggregated time scales (see Anandhi et al. 2011 for more detail). (2) Match the entire cumulative distribution functions (CDFs) of a GCM projection to observed values. There are two ways in this approach. The first method derives the future precipitation values by first projecting them on retrospective GCM CDFs to obtain the exceedance probabilities and then selecting the corresponding precipitation values from historical data (Wood et al. 2004; Maurer and Hidalgo 2008). In this case, future GCM precipitation distributions are not directly used. The second method modifies future GCM projections depending on the mismatch between observed and retrospective GCM CDFs (Li et al. 2010).

Data

Outputs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) model runs for 23 GCMs were obtained using Koninklijk Nederlands Meteorologisch Instituut (KNMI) Climate Explorer tool (http://climexp.knmi.nl/) for RCP2.6 emission and concentration pathways (van Vuuren et al. 2011). The data represent a mitigation scenario aiming to limit the increase in global mean temperature to 2 °C. These scenarios are from the lower end of the scenario literature in terms of emissions and radiative forcing often showing negative emissions from energy use in the second half of the twenty-first century. The South East US bounded by 25 N:35 N and 90 W:75 W, 24 pixels in total, was used to extract the data for the case study. Average monthly data of the two long-term NOAA rainfall stations (St Leo and Plant City) with over 110 years of historical data at GCM cell centered at 81.25 W and 28.75 N and corresponding GCM outputs for the cell were used to demonstrate the technique reported here (Fig. 1).

Methods

Bias correction for Retrospective Runs

The well-established CDF matching approach for bias correction of retrospective GCM outputs (past and present period, usually this is termed as training or calibration period) was used in this study (Panofsky and Brier 1968; Wood et al. 2002; Maurer and Hidalgo 2008). For a precipitation variable x, the adjustment may be summarized as (Li et al. 2010)

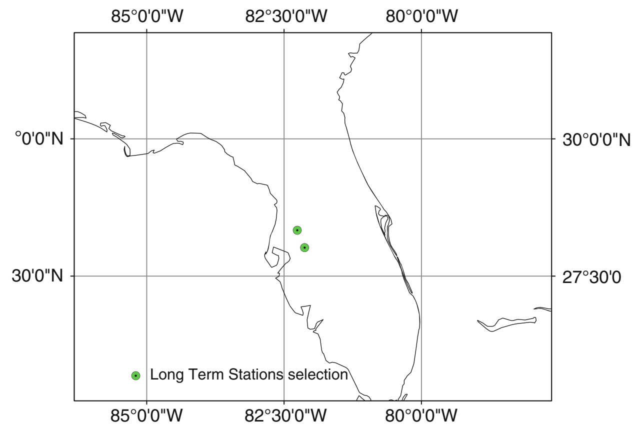

Fig. 1 GCM grids and long-term rainfall station that are used for bias corrections

$$x_{\mathrm{m-r.adjst}} = F^{-1}_{\mathrm{o-c}}(F_{\mathrm{m-c}}(x_{\mathrm{m-r}})) \tag{1}$$

where F is the CDF of either the observations (o) or model (m) for historical training or current period (c), retrospective runs (r), or for future projection period (p). In this method, for a given rainfall amount $x_{\mathrm{m-r}}$, one first finds the percentile value of $F_{\mathrm{m-c}}(x_{\mathrm{m-r}})$ using model CDF and then calculate the adjusted rainfall amount using the observed CDF, $F^{-1}_{\mathrm{o-c}}$. Once this step is finished the bias-corrected GCM CDF will match exactly that of the observed. Figures 2 and 3 show the error distribution found while matching the CDFs using this approach for each season of the year. The light gray color represents the range of projected precipitation (in this case representing the 1 and 99 % values) from the 23 GCMs, while the dark gray represents the 25–75 % range. It is clear from both of these plots that wet season rainfall (June through September) are under predicted, while dry season rainfall (October through May) are over predicted for the twentieth century simulations. In addition, uncertainty in dry season rainfall (represented by error band) is higher in dry/winter season than wet/summer season. Some of this can be explained by the high coefficient of variation in dry season rainfall. These results are based on 110 years of observed data. In addition, three 30-year periods (1901–1930, 1931–1960, and 1961–1990) (figures not shown) are analyzed with similar results; except uncertainty in winter rainfall, specifically October through December is much wider. Supplemental Figure 2 and Figure 3 show plots of rainfall versus error rather than exceedance probabilities.

Bias-correcting future projections

Equation (1) can also be used for correcting future GCM outputs (Wood et al. 2002; Maurer and Hidalgo 2008) by simply substituting $x_{\mathrm{m-r}}$, the retrospective output, with that

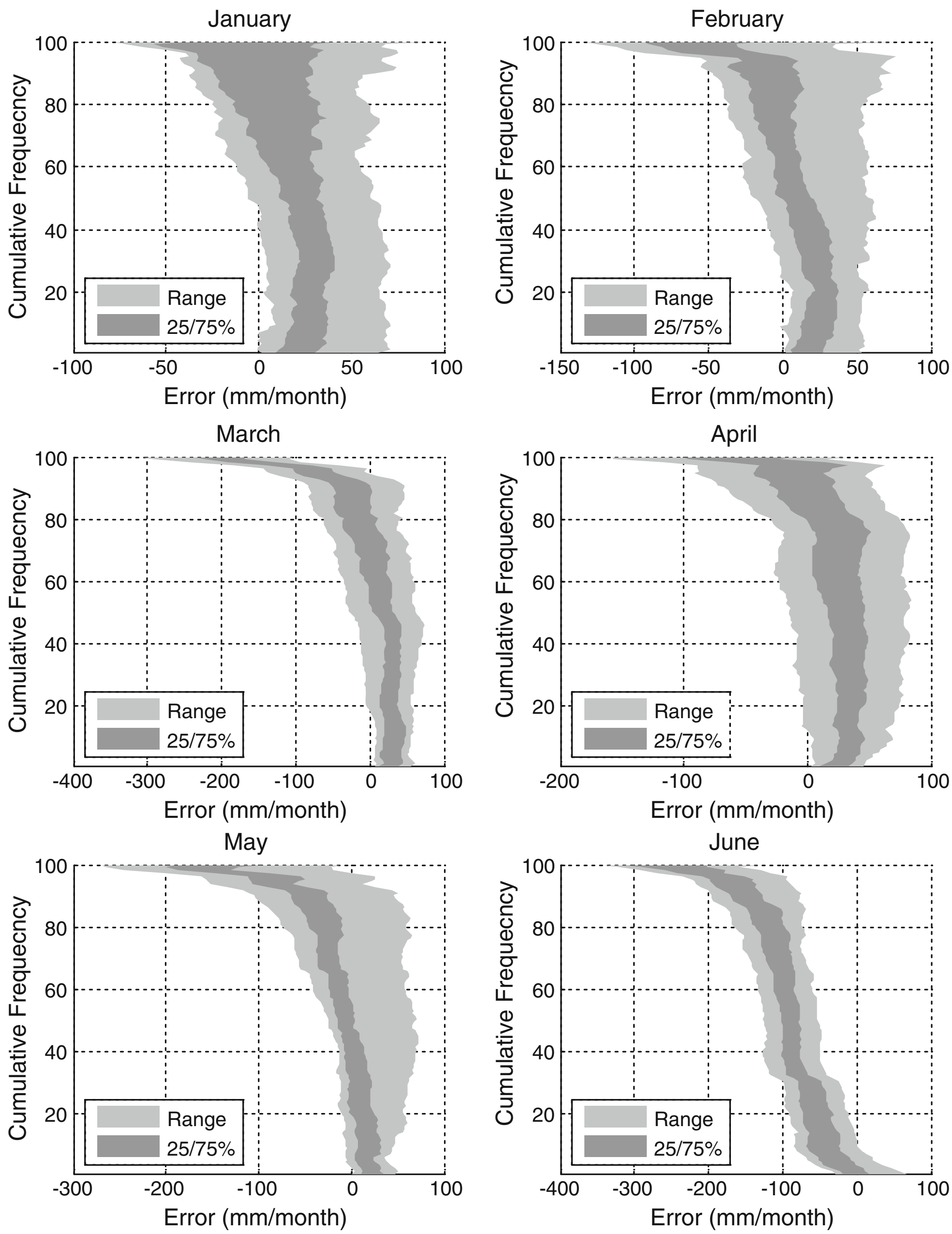

Fig. 2 CDF matching error of 23 RCP2.6 GCM model outputs (simulation minus observation)

of the projection period, $x_{\mathrm{m-p}}$, and repeating the CDF matching process. But such an approach explicitly assumes that the precipitation variability does not change in the future and that assumption may not hold (Milly et al. 2008). A modification to this technique is the one proposed by Li et al. (2010) that is used in this paper. This method accounts for the difference between future and present CDFs. Mathematically, it can be written as:

$$x_{\mathrm{m-p.adjst}} = x_{\mathrm{m-p}} + F^{-1}_{\mathrm{o-c}}(F_{\mathrm{m-p}}(x_{\mathrm{m-p}})) - F^{-1}_{\mathrm{m-c}}(F_{\mathrm{m-p}}(x_{\mathrm{m-p}})) \tag{2}$$

In short, for a p % future precipitation projection, $x_{\mathrm{m-p}}$, the adjustment (error) obtained from CDF matching between observation and GCM retrospective model run for that percentile (shown in Figs. 2, 3) is determined and used to modify future projection. Figures 4 and 5 show CDF of rainfall projection for the year 2011–2040. Consistent with Figs. 2 and 3, again uncertainties in dry season (October through May) rainfall are higher than those in wet season rainfall (June through September). Focusing on the dry season, small dry season rainfall, especially those with cumulative probability of 20 % or less, have huge

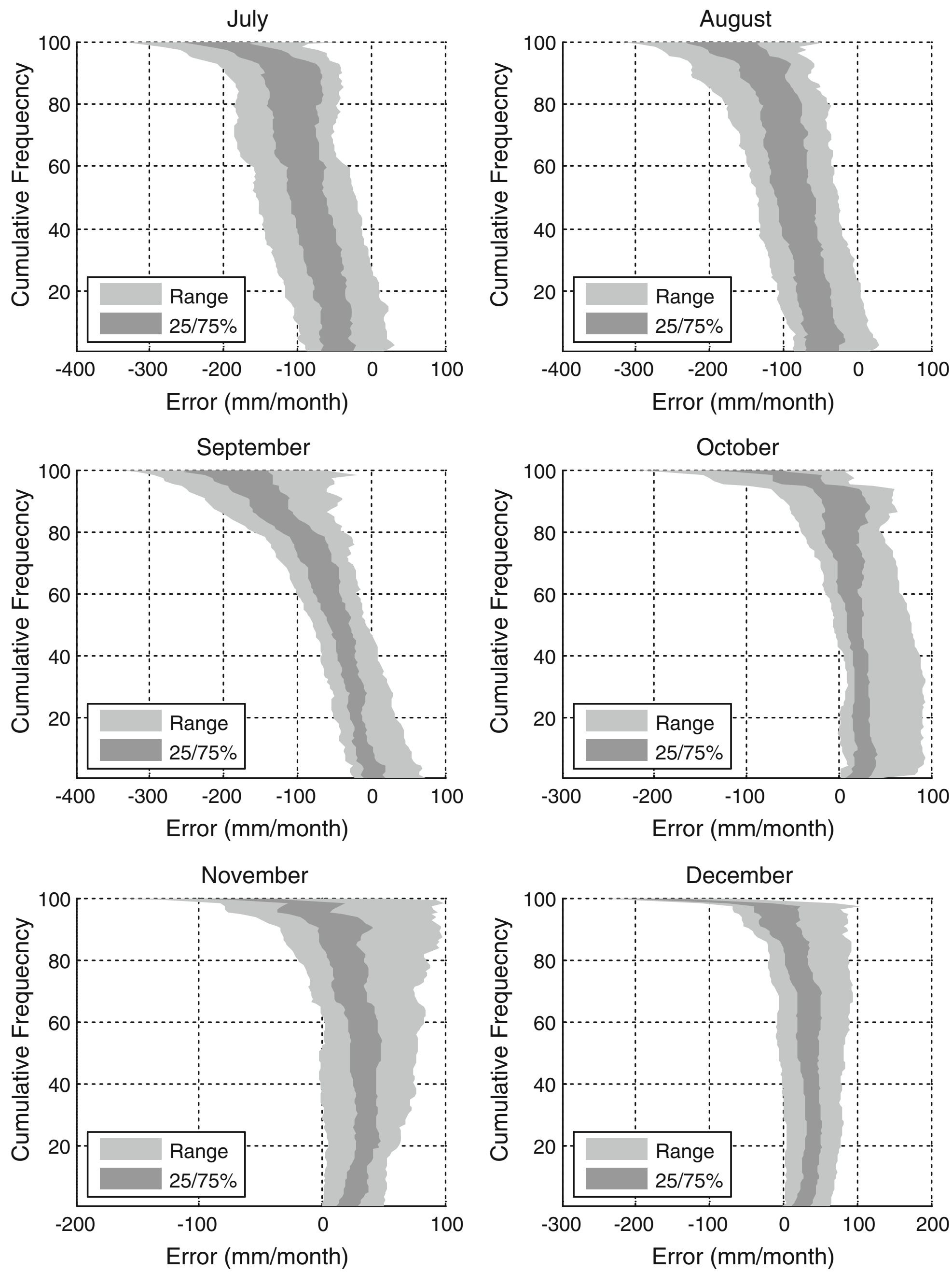

Fig. 3 Same as Fig. 2 but for July–December

uncertainties. Winter rainfall in central Florida is highly influenced by the prevailing ENSO phase. Current GCMs are not accurately modeling ENSO phases, and this may account in part for high uncertainties (Lin 2007).

Uncertainties in GCMs projections

The range of rainfall outputs from different GCM models for the same geographical area is different, reflecting uncertainties in those models. Some of the uncertainties stem from (Knutti et al. 2010): (1) uncertainty in the process being modeled, that is, the inability to understand the process in the first place; (2) uncertainty in model parameters, and (3) structural uncertainty as a result of the inability to describe a known process accurately. Because of these, each GCM will have a different level of uncertainty reproducing relevant parameters (e.g., precipitation, temperature) for a given region. It is widely recognized that using an ensemble of models is more robust than output from a single GCM (Knutti et al. 2010). While it is straight forward to assess the accuracy of GCMs on retrospective runs (using past and present observations), it is not possible to do so on future projections, unless certain statistical assumptions are made. There are two schools of thought for using GCM ensembles

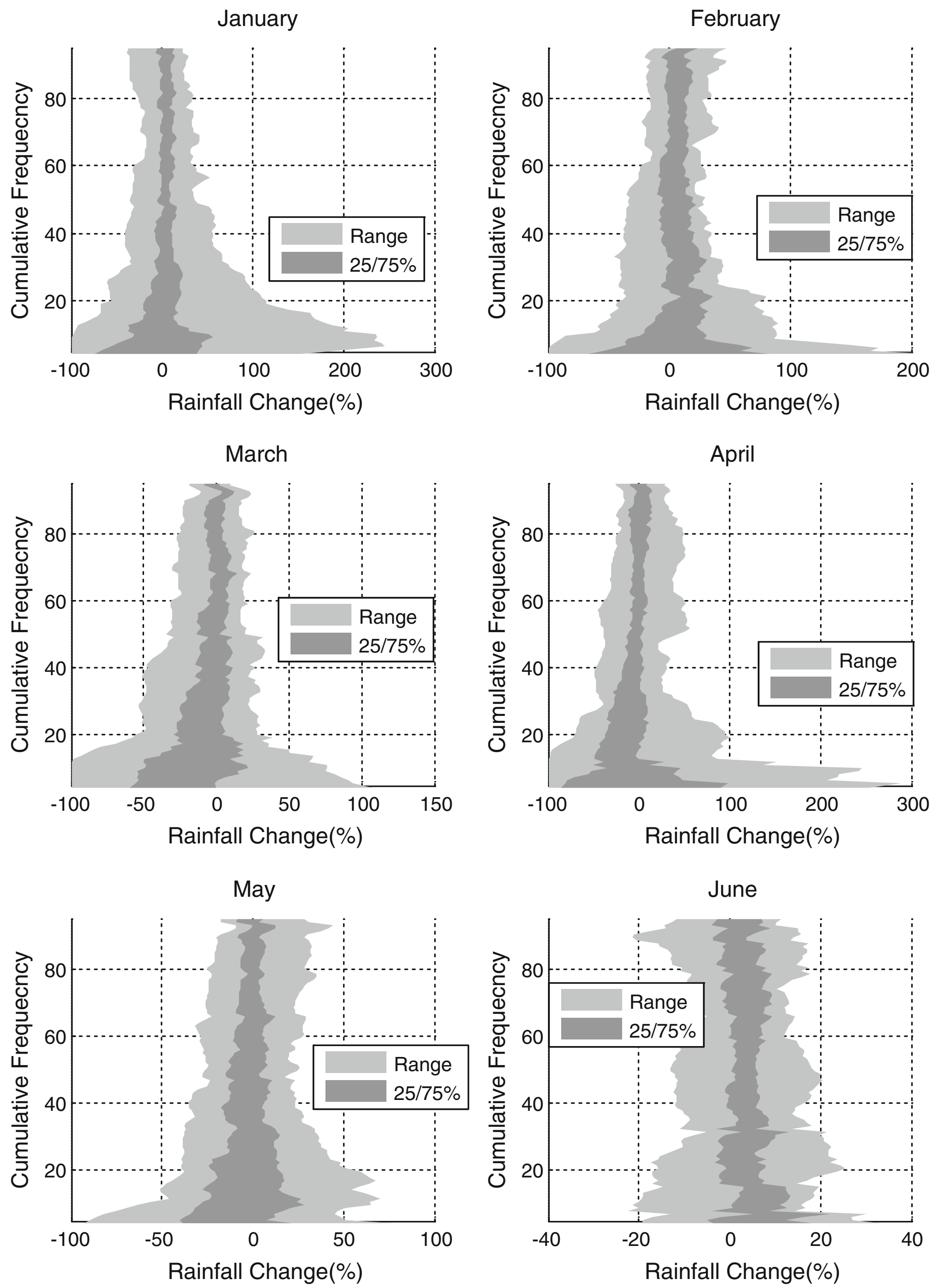

Fig. 4 Rainfall projections (2011–2040) of 23 GCM

(IPCC 2010): (1) Those that assume that an ensemble member is sampled from a distribution centered on the truth. In this approach, retrospective GCM runs are assumed to be sampled from a distribution that is centered on observation plus error, while future projections are centered on the mean of GCM ensemble. (2) Those that assume each member of the ensemble is exchangeable with other members and with the natural system (current observations) such that the observation themselves are one random sample from a distribution that encompasses all possible outcomes. Under the first assumption, using more GCMs will result in uncertainty converging toward zero, while in the latter case, the uncertainty converges toward the distribution of all outcomes. The challenges of combining GCM outputs from multiple models are reviewed in Knutti et al. (2010).

Bayesian-based truth-centered indicator-weighting approach

The method presented here was first proposed by Giorgi and Mearns (2002) as a reliability ensemble average (REA)

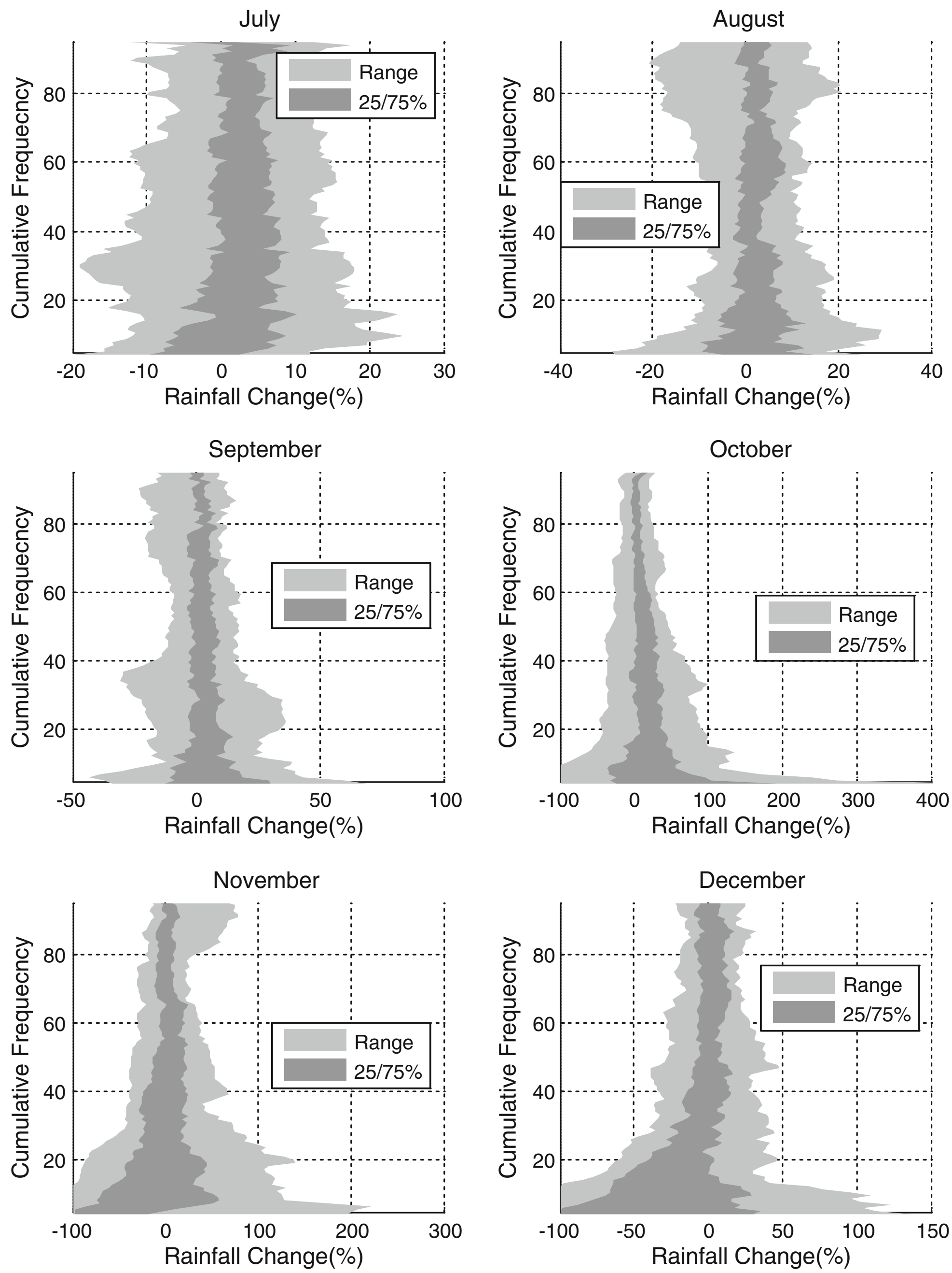

Fig. 5 Same as Fig. 4 but for July–December (2011–2040) of 23 GCM

technique that defines two criteria of bias and convergence in evaluating multiple outputs of GCMs to produce an ensemble estimate that is a weighted average of individual GCMs. The method was formalized in a Bayesian framework by Tebaldi et al. (2005) and extended by Smith et al. (2009). In summary, for n GCMs, each model i simulates present and past (X_i) and future (Y_i) precipitations. Under the truth-centered approach, the statistical model is assumed to be:

$$X_i = \mu + \eta_i, \quad i = 1, \ldots n \tag{3}$$

$$Y_i = \upsilon + \beta(X_i - \mu) + \xi_i/\sqrt{\theta}, \quad i = 1, \ldots n \tag{4}$$

where μ and υ are true but uncertain climate means for present and future precipitation; β is the correlation between current and future precipitation simulation and assumed to be constant across GCMs (it is possible to relax this constraint but that would increase the number of parameters to be estimated); θ is the variance scaling parameter between current and future simulations; and $\eta_i \sim N(0, \lambda^{-1})$ and $\xi_i \sim N(0, \lambda^{-1})$ are Gaussian error terms. All parameters are considered random variables with a prior distribution that is usually defined as an informative as possible. Using standard Bayesian updating technique, the posterior mean υ is expressed as weighted by the

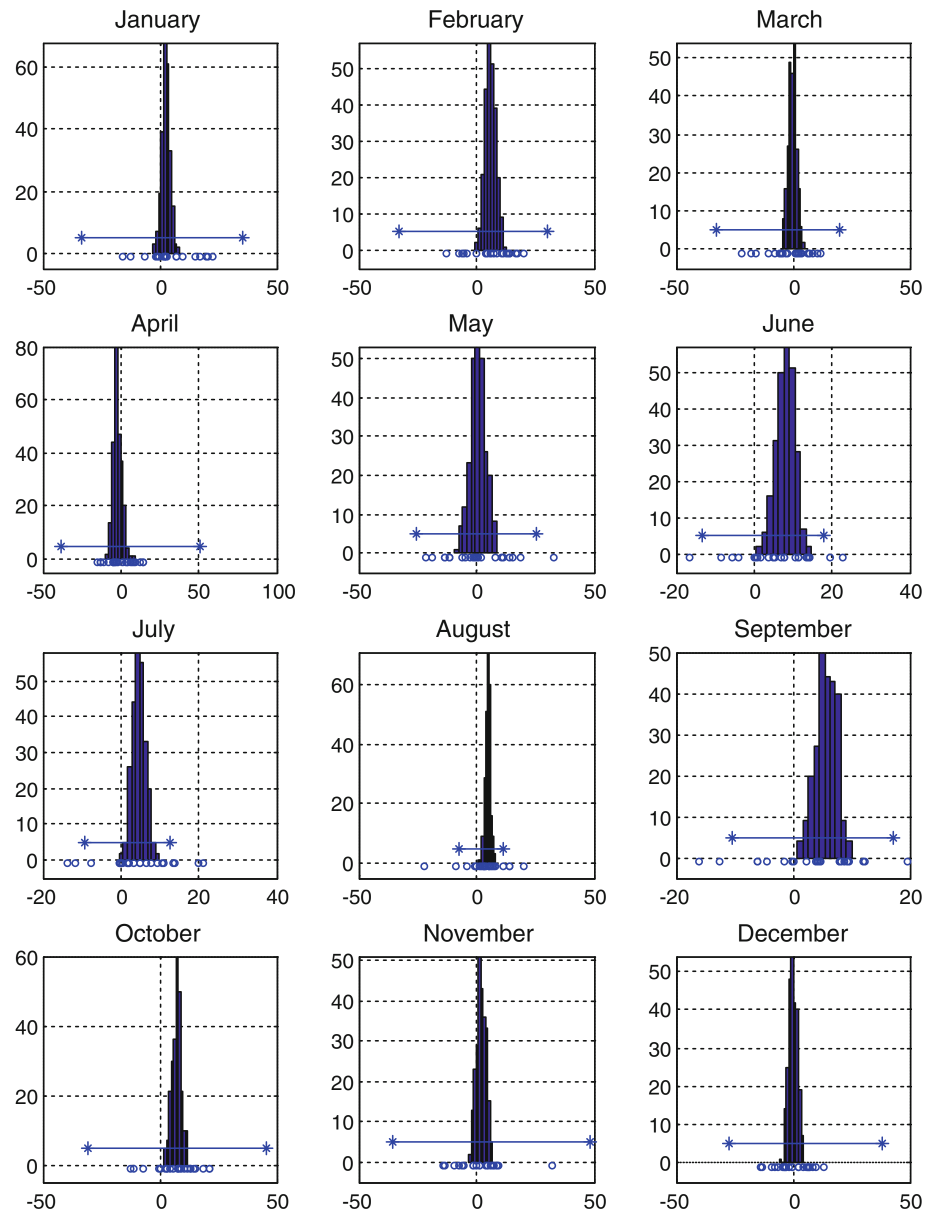

Fig. 6 Histogram for the posterior mean rainfall change (%) for 2011–2040 using Bayesian framework. The *open circles* indicate changes in mean precipitation of individual GCM's raw output data. The *line with asterisk* represents the median rainfall change (bias correction method Eq. (2))

inverse of the model-specific error variance of λ_i as $\upsilon = \sum \lambda_i [Y_i - \beta(X_i - \mu)] / \sum \lambda_i$. An approximation to the posterior probability distribution of λ_i is then given by

$$E(\lambda_i | \{X_{0,} \ldots X_n, Y_1, \ldots Y_n\}) \approx \frac{a+1}{b + \frac{1}{2}[(X_i - \tilde{\mu})^2 + \theta(Y_i - \tilde{\upsilon})^2]} \quad (5)$$

where a and b are parameters of the Gamma prior distribution of λ_i, $\tilde{\mu}$ and $\tilde{\upsilon}$ are the posterior means of μ and υ (Tebaldi et al. 2005). From Eq. 5, it can be seen that the weighting factor λ_i is large if $|X_i - \tilde{\mu}|$ and $|Y_i - \tilde{\upsilon}|$ are small. These two quantities represent, respectively, the bias and convergence criteria of Giorgi and Mearns (2002). To reduce uncertainties in GCM predictions, an indicator variable, IV_j, is introduced to discriminate individual GCM outputs that are outside of the consensus (estimated by all GCMs) precipitation changes obtained as a posterior of the Bayesian model. Specifically, it has the following forms:

$$IV_j = \begin{cases} 1, & \text{if} \quad \bigcup_{i=1}^{n} |\tilde{Y}_i - \tilde{X}_i| \bigcap Y_i - X_i \\ 0, & \quad \text{otherwise} \end{cases} \quad (6)$$

where $\tilde{Y}_i$ and $\tilde{X}_i$ are a posterior estimates of Y_i and X_i. In other words, if a prior prediction of precipitation changes by a GCM is outside of the posterior precipitation changes of all GCMs, zero weight is assigned to that prediction; otherwise, it has a value of one. Note that this approach assigns equal weight to all GCM outputs that behave similar to the majority of the output and disregards

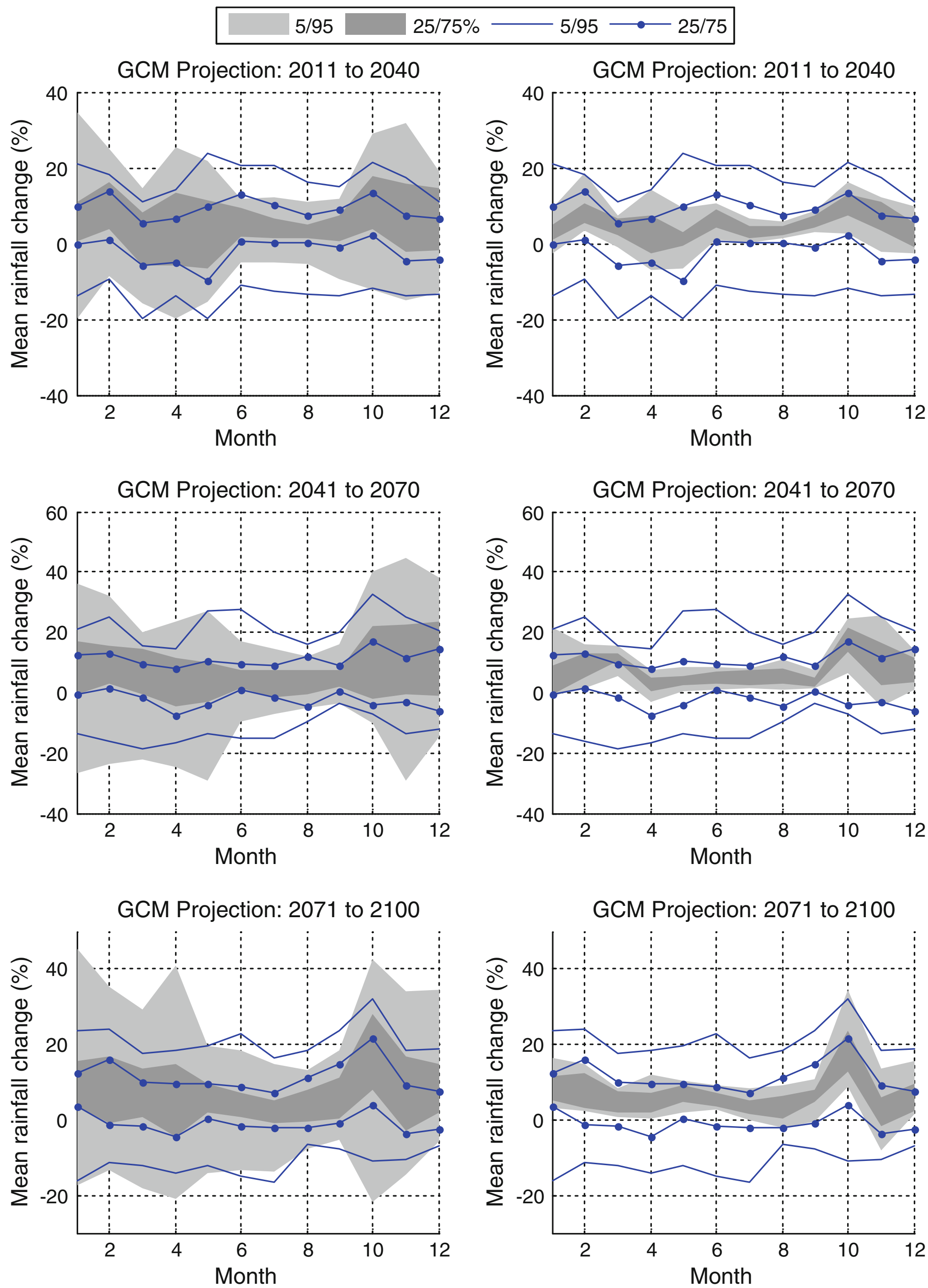

Fig. 7 Bias-corrected rainfall projections change. The *left panels* are raw GCM and future bias-corrected mean rainfall change. The *right panels* are bias-corrected projections using the indicator-weighting factor approach. *Lines* are raw GCM outputs

projections that may be regarded as "outliers" (those outside of the consensus projections). The approach is implemented using a Markov Chain Monte Carlo (MCMC) algorithm of Smith et al. (2009) that relaxes some constraints and extends Tebaldi et al. (2005) by having hyper parameter distribution of their own for parameters a and b in Eq. (5). Figure 6 shows histograms for the posterior mean rainfall change (%) for each season from 2011 to 2040. The open circles represent individual GCM mean rainfall changes. Note that the Bayesian approach described above used raw GCM output (i.e., not bias corrected). The line connecting two asterisks represents the median-projected rainfall change using the bias correction technique described in Sect. 3.2. In all cases, the posterior mean rainfall change shows a narrower uncertainty range than both the raw GCM and bias-corrected GCM outputs.

Therefore, by design the Bayesian approach, through its truth-centered statistical framework, ignores outputs from GCMs that are non-conforming to the historical data as well as the future consensus estimates. Comparing raw GCMs changes in mean rainfall projections (i.e., delta method) to the bias-corrected mean rainfall projections show seasonal dependent results. During the dry season (October through April), the bias correction seems to introduce more uncertainty/variability compared to the raw GCM outputs, whereas during the rainy season (June through September), the variation in bias-corrected precipitation projections is smaller than the raw GCM outputs. The month of May seems to be a transition period between the two. Figure 7 shows GCM projections of mean rainfall changes for the twenty-first century. The left panels depict bias-corrected results using Eq. (2) for all GCMs and raw GCM outputs (lines). The right panels have the bias-corrected results with an indicator-weighting factor applied to them. From the left panels, it is clear that bias-corrected results have more uncertainty during the dry season than the raw GCMs. Also the range of uncertainty is higher in dry seasons than summer seasons. The indicator-weighting approach significantly reduces these uncertainties as shown in the right panels.

Discussions and conclusions

CMIP5 retrospective GCM ensemble outputs have shown over estimation of dry season rainfall but under estimation of summer rainfall for the twentieth century for the study area considered here. Uncertainties in GCM outputs and the challenges of reducing it through model weighting schemes have been at the center of recent studies (IPCC 2010; Knutti et al. 2010). Assessing the performance of a GCM on retrospective data is straight forward—it either reproduces what has happened adequately or not. Assessment of GCMs future simulation is not straight forward and needs certain statistical assumptions. Here, the assumption is if there is sufficiently large number of GCMs, their results will converge to “reality.” The truth-centered statistical framework of the Bayesian approach presented here has been applied previously to raw GCM outputs (e.g., Tebaldi et al. 2005) and dynamically downscaled RCM outputs (Manning et al. 2009), but not to bias-corrected outputs. Here, we show its applications to bias-corrected GCM outputs. For precipitation changes, bias correction introduces additional variability to future GCM projections depending on the variability of historical records used for bias correction. In our case, dry season rainfall (October through May) with higher coefficient of variations in recorded data have shown more variability than summer rainfall and hence have a wider uncertainty bound in future projections once bias is corrected. Dry season rainfall is also highly influenced by ENSO, and the effects of ENSO are not yet fully captured in the current generation of GCMs. The bias correction techniques used in this study accounts for future precipitation CDF changes; however, the results may not be as useful because of wider bands of uncertainty inherent in the approach. The uncertainty is now a combination of both historical data variability and GCM output uncertainties. Higher uncertainty levels result in smaller value of information that can be used for planning and adaptation purposes. Consequently, there is a need to reduce these uncertainties in some formalized manner than simply throwing out GCM output that may appear to be “outliers.” In order to reduce this uncertainty, we introduced a Bayesian-based indicator-weighting approach to keep model outputs based on their past performance (bias criterion) as well as agreement with the consensus for future projections. It is possible that the majority of models could go wrong but the assumption here is that they will get it right. The weights for selecting a given GCM’s output were derived by comparing individual GCM projection changes with the consensus estimate posterior change (results of all GCMs and over the distribution of the change). This is the key difference between the current approach and previously reported ones (Tebaldi et al. 2005; Smith et al. 2009, and Manning et al. 2009). It is important to note that the current approach is limited to reducing the uncertainty of bias-corrected GCMs projections of mean precipitation changes. Application of the method for time series simulation, a requirement of hydrological models, is the next step.

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