Evaluation and Bias Correction of S2S Precipitation for Hydrological Extremes[✉]

WEI LI,^a JIE CHEN,^{a,b} LU LI,^c HUA CHEN,^a BINGYI LIU,^a CHONG-YU XU,^{a,d} AND XIANGQUAN LI^a

^a State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan, China

^b Hubei Provincial Key Laboratory of Water System Science for Sponge City Construction, Wuhan University, Wuhan, China

^c NORCE Norwegian Research Centre, Bjerknes Centre for Climate Research, Bergen, Norway

^d Department of Geosciences, University of Oslo, Oslo, Norway

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ABSTRACT

Subseasonal to seasonal (S2S) weather forecasting has made significant advances and several products have been made available. However, to date few studies utilize these products to extend the hydrological forecast time range. This study evaluates S2S precipitation from eight model ensembles in the hydrological simulation of extreme events at the catchment scale. A superior bias correction method is used to correct the bias of S2S precipitation for hydrological forecasts, and the results are compared with direct bias correction of hydrological forecasts using raw precipitation forecasts as input. The study shows that the S2S models can skillfully forecast daily precipitation within a lead time of 11 days. The S2S precipitation data from the European Centre for Medium-Range Weather Forecasts (ECMWF), Korea Meteorological Administration (KMA), and United Kingdom's Met Office (UKMO) models present lower mean error than that of other models and have higher correlation coefficients with observations. Precipitation data from the ECMWF, KMA, and UKMO models also perform better than that of other models in simulating multiple-day precipitation processes. The bias correction method effectively reduces the mean error of daily S2S precipitation for all models while also improving the correlation with observations. Moreover, this study found that the bias correction procedure can apply to either precipitation or streamflow simulations for improving the hydrological forecasts, even though the degree of improvement is dependent on the hydrological variables. Overall, S2S precipitation has a potential to be applied for hydrological forecasts, and a superior bias correction method can increase the forecasts' reliability, although further studies are still needed to confirm its effect.

1. Introduction

Forecasting on the subseasonal to seasonal (S2S) time scale bridges the gap between medium-range weather forecasts and seasonal climate predictions. Given the many difficulties involved, studies about the source of predictability above this time scale are relatively few, and so it is often considered as a “desert of predictability” (Vitart et al. 2017). However, with the increasing demands for forecasts above this time scale in the operational prediction and application communities, more and more attention is being paid to this time range.

A growing number of studies indicate that some predictability sources can provide helpful information for S2S time scale forecasts, such as the Madden–Julian oscillation (MJO; Zhang 2005; Yamasaki 2011; Liu et al. 2017; Krishnamurthy 2018), one of the most important predictability sources, stratospheric initial conditions (Baldwin and Dunkerton 2001; Cohen et al. 2010; Stockdale et al. 2015), land surface soil moisture (Koster et al. 2010, 2011; Guo et al. 2011; Asoka and Mishra 2015), snow initial conditions (Jeong et al. 2013; Thomas et al. 2016), and sea surface temperature (Chelton and Wentz 2005; Ward and Folland 1991). Based on the advances in these predictability sources, forecasting on an S2S time scale has gradually become possible.

Many studies have shown that meteorological variables can be reasonably predicted at the S2S time scale. For instance, Vitart (2009) showed that the risk of tropical storm landfall could be predicted by the ECMWF's

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Corresponding authors: Jie Chen, jiechen@whu.edu.cn; Lu Li, luli@norceresearch.no

atmospheric model (IFS), which is skillful in predicting the evolution of MJO up to 20 days. Marshall and Hendon (2015) presented that version 2 of the Predictive Ocean Atmosphere Model for Australia (POAMAv2) could predict monsoon rainfall anomalies at a lead time of 2 weeks. Li et al. (2017) used daily data from the reforecasts of 45-day integrations by the National Centers for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFSv2) to predict East Asian cold surges. They found that the frequency, intensity, and location of cold surges at a lead time of about 2 weeks can be well captured. In addition to exploring the predictability of meteorological variables at S2S time scales, some studies also succeeded in extending the lead time of hydrologic forecasts to the subseasonal time scale. For example, Alfieri et al. (2013) showed that the use of the Global Flood Awareness System (GloFAS) could detect hazardous events in large river basins with a forecast horizon of up to 1 month. Alfieri et al. (2014) then found that skillful predictions could be made in medium-to-large river basins for 10-day lead time in Europe by the European Flood Awareness System (EFAS).

To improve forecasting skill, an extensive database project focused on S2S forecasts and reforecasts was launched by the World Weather Research Program (WWRP) and World Climate Research Program (WCRP) in 2013 (<https://public.wmo.int/en/projects/subseasonal-seasonal-prediction-project>). Eleven data centers have begun to produce S2S forecasts, and a number of studies have been done to evaluate the forecast skill of S2S data. For example, Bombardi et al. (2017) used S2S reforecasts from NCEP, the China Meteorological Administration (CMA), and the Japan Meteorological Agency (JMA) to predict the rainy season over South America, East Asia, and northern Australia at up to 30 lead days and found that data from these three centers help to identify the onset and demise dates of the rainy season. Liang and Lin (2018) determined that a significant forecast skill can be achieved for precipitation over ~5–11 lead days when using S2S data from Environment and Climate Change Canada (ECCC). Zeng and Yuan (2018) found that S2S models that best reproduce the land–atmosphere coupling and its changes with monsoonal rain belt shifts also have the best precipitation forecast skill.

However, directly applying S2S data to hydrological models may result in biased hydrological forecasts, since climate model outputs sometimes lack precision and reliability (Zalachori et al. 2012). To minimize systematic errors, bias correction is usually applied to weather forecasts before applying them to hydrological forecasts (Weerts et al. 2011; Verkade et al. 2013; Madadgar et al. 2014). The evaluation of multiple bias

correction methods has shown that bias-corrected weather forecasts can significantly increase the reliability of hydrological forecasts (Hashino et al. 2007; Crochemore et al. 2016). In addition, some studies have applied the bias correction method for hydrological forecasts at the S2S time scale. For instance, Yuan et al. (2014) combined quantile mapping and conditional distribution methods to bias correct NCEP precipitation for streamflow forecasts over the Ohio basin in eastern United States. Ye et al. (2017) found that streamflow forecasts using ensemble preprocessing method corrected precipitation have longer lead times and higher accuracy than those using raw GEFS and CFSv2 precipitation forecasts. Moreover, Yuan and Wood (2012) pointed out that the direct bias correction of the simulated streamflow can also improve the skill of hydrological forecasts.

Although the number and scale of studies on operationalizing S2S forecasts and on developing and demonstrating the potential value of applications-relevant information are increasing (Robertson et al. 2015), S2S forecasting is still a new frontier for predictability research (White et al. 2015), especially in China. In particular, how to best apply the S2S database to existing hydrological models is an essential aspect of promoting its uptake by operational centers and the applications community.

The Yangtze River basin (in particular the densely populated Xiangjiang River basin) in China has suffered from flood hazards for many years. The rapid development of the society and economy has created an urgent need for reliable hydrological forecasts to reduce the damages from floods. The traditional forecasting system is limited by its short lead time. Extending the lead time of forecasting systems to the S2S time range will allow for better response to disasters and provide more time for decision-makers to minimize their impact.

This study first evaluates the forecast skills of S2S precipitation data from eight modeling centers using climatology forecasts based on resampling of the observed historical precipitation as a benchmark. A superior bias correction method is then used to reduce the bias of S2S precipitation and compare it with non-corrected data. The performance of bias-corrected precipitation for streamflow forecasts is also compared with that of directly bias-corrected streamflow forecasts. Through this study, we aim to verify the performance of precipitation forecasts by S2S data and the effects of different bias correction strategies on streamflow forecasts over the Xiangjiang River basin, providing the reference information and knowledge for further applications of S2S data in hydrological predictions.

FIG. 1. The location and topography of Xiangjiang River basin and the location of four subbasins with stream gauge stations.

2. Study area and data

a. Study area

The study was conducted over the Xiangjiang River basin (Fig. 1), one of the largest subbasins of the Yangtze River basin. The Xiangjiang River basin is located between 24° and 29° N and between 110° and 114° E with a total area of approximately $94\,660\text{ km}^2$. Its climate is heavily influenced by the subtropical monsoon, which results in heavy rainfall coming from the south in summer. The annual precipitation over the basin is about 1580 mm (Xu et al. 2013), and around 61% of this precipitation occurs from April to August. For this study, the Xiangjiang River basin is divided into four subbasins according to four streamflow stations, that is, Daxitan, Xiangxiang, Ganxi, and Hengyang. The drainage areas of the four subbasins are 3312 , 6053 , 9972 , and $52\,150\text{ km}^2$ respectively, with 87 , 118 , 263 , and $1361\text{ m}^3\text{ s}^{-1}$ of daily mean discharge, respectively.

b. Observed data

The observed hydrometeorological data used in this study include daily maximum ($T_{\max}$) and minimum ($T_{\min}$) temperatures, precipitation, and streamflow over all subbasins for the 1980–2009 period. Among these, temperature data over eight temperature stations were

provided by the China Meteorological Data Sharing Service System, and precipitation data over 97 precipitation stations were provided by the Hunan Water Resources Bureau. Streamflow data were observed at four streamflow stations. All of the data were quality controlled and have been used in previous studies (Xu et al. 2015; Zeng et al. 2015; Wang et al. 2018).

c. Forecast products

There are 11 model ensembles of the S2S database (Table 1). We wanted to ensure that there were at least four forecast events available within each month so that enough data could be used to evaluate S2S forecast products more reliably. Eight models were chosen from the S2S database in this study: the Australian Bureau of Meteorology (BoM), the CMA, the ECCC, the ECMWF, the Hydrometeorological Centre of Russia (HMCR), the Institute of Atmospheric Sciences and Climate of the National Research Council (CNR-ISAC), the KMA, and the U.K. Met Office (UKMO). These models share a common reforecast period 1996–2009 with the observed data, which was used for evaluation and bias correction.

Among the eight chosen models, reforecasts from the ECCC, ECMWF, HMCR, KMA, and UKMO models were produced for the same calendar day of the real-time forecast. Others were produced all at once, before

TABLE 1. Eleven models of the S2S database and their reforecast frequency (Rfc freq).

Model	Rfc freq
Australian Bureau of Meteorology (BoM)	Six per month
China Meteorological Administration (CMA)	Daily
Environment and Climate Change Canada (ECCC)	Weekly
European Centre for Medium-Range Weather Forecasts (ECMWF)	Two per week
Hydrometeorological Centre of Russia (HMCR)	Weekly
Institute of Atmospheric Sciences and Climate of the National Research Council (CNR-ISAC)	Every 5 days
Japan Meteorological Agency (JMA)	Three per month
Korea Meteorological Administration (KMA)	Four per month
Météo-France/Centre National de Recherche Météorologiques (CNRM)	Two per month
National Centers for Environmental Prediction (NCEP)	Daily
United Kingdom's Met Office (UKMO)	Four per month

operational implementation. This study only used reforecasts produced by the control forecast. More details of the S2S database can be found in Vitart et al. (2017).

3. Methodology

a. Bias correction method

A quantile mapping (QM) bias correction method was proposed to reduce the systematic biases of S2S precipitation. This bias correction method can be considered as a modified version of Themeßl et al. (2011, 2012) and Chen et al. (2013). The observed data (OBS) were first divided into six classes based on their magnitude percentile ($<10\%$, $10\%–30\%$, $30\%–50\%$, $50\%–70\%$, $70\%–90\%$, and $>90\%$). The S2S data corresponding to each class were then corrected using the bias corrections method. For the data in each class, bias correction was operated on a seasonal scale. When 1 year of data in one season (e.g., spring) was selected for bias correction, the remaining 13 seasons over 13 years were used as a reference. Specifically, empirical cumulative distribution functions (ecdfs) were fitted for OBS and S2S data at the reference period, and the differences between these two distribution functions were calculated and defined as correction factors (CFs). The estimated CFs were then used to correct the distribution function of S2S data at the validation period. The above method was used to correct either S2S precipitation or its simulated streamflow to investigate effect of these two strategies.

b. Hydrological modeling

The Xinanjiang (XAJ) hydrological model, developed by Zhao (1992), was applied to simulate streamflow. XAJ is a deterministic lumped hydrological model composed of water source partitioning, evapotranspiration calculation, saturation excess streamflow, and flow concentration. The main characteristic of the XAJ model is the

concept of saturation excess streamflow, which means that it will not generate streamflow until the soil moisture content reaches the filled capacity. This attribute allows the model to perform reasonably well in continuous hydrological simulations of humid and semihumid regions (Zeng et al. 2015). The XAJ model has been successfully used for streamflow simulation all around the world (Zhao and Liu 1995; Perrin et al. 2001; L. Li et al. 2013; Z. Li et al. 2013; Pachepsky et al. 2016).

The data required to run the XAJ model are daily precipitation and potential evapotranspiration. In this study, potential evapotranspiration was calculated using observed daily $T_{\max}$ and $T_{\min}$ with the Oudin formula (Oudin et al. 2005). All of the data from stations or grids were averaged over the basins by the arithmetic mean method, as there are a large number of stations and grids within the river basin. The observed datasets were divided into the 1980–95 period for model calibration and the 1996–2009 period for validation. The Nash–Sutcliffe efficiency coefficient was chosen as the evaluation criterion for getting an optimal parameter set. In all four subbasins, the Nash–Sutcliffe efficiency coefficients were above 0.90 for calibration and above 0.85 for validation. For illustration purpose, Fig. 2 presents the observed and simulated streamflow time series for both calibration and validation periods.

c. Climatology forecasts

A climatology forecast based on a historical resampling method (Chen and Brissette 2015) was used as a benchmark to determine the added value of using S2S precipitation forecasts. The resampling method was based on the hypothesis that historical events would occur in the future. Thus, this method only used climate information from historical observations. Resampling was conducted based on the data of the basin-averaged historical precipitation for the 1996–2009 period. The resampled window length was set to 32 days to compare

FIG. 2. Observed and simulated monthly hydrographs for four subbasins.

with the S2S forecast products, which have 32 lead days. The reason to resample the time series is to maintain the autocorrelation of daily precipitation. Specifically, given 14 years of available observations, when making a resampled forecast for a specific year, the remaining 13 years of data will be used for resampling. For example, when forecasting precipitation for 1 January–1 February 2009, the observed precipitation data from 1 January to 1 February of the remaining 13 years from 1996 to 2008 was used for resampling. Precipitation data of 32-day time series were randomly extracted from 1996 to 2008 for the same period. To better represent the expectation of precipitation series, the historical precipitation was first resampled 1000 times to construct a 1000-member ensemble. The ensemble mean of these 1000 members was then calculated to compare the deterministic S2S precipitation forecasts.

For hydrological forecasts, 1000 precipitation members were individually used as inputs of the hydrological model to generate 1000 streamflow time series. The ensemble mean of these 1000 hydrological simulations

was then calculated to compare the S2S-based deterministic streamflow forecasts.

d. Forecast evaluation

To evaluate the overall forecast skill of S2S precipitation, three metrics were used as criteria, the correlation coefficient (r), the mean absolute error (MAE), and the mean relative error (MRE), detailed in Eqs. (1)–(3), respectively. The r and MAE were used to evaluate the S2S precipitation, while the MRE was used instead of the MAE for hydrological evaluations. The term r represents the linear correlation between model and OBS data, and it varies from -1 to 1 . The closer the r is to 1 , the better the correlation. MAE and MRE show the mean error of S2S precipitation; a lower value represents a better result. In Eqs. (1)–(3) below,

$$r = \frac{\sum_{i=1}^N [(x_{\text{obs},i} - \bar{x}_{\text{obs}})(x_{\text{sim},i} - \bar{x}_{\text{sim}})]}{\sqrt{\sum_{i=1}^N (x_{\text{obs},i} - \bar{x}_{\text{obs}})^2} \sqrt{\sum_{i=1}^N (x_{\text{sim},i} - \bar{x}_{\text{sim}})^2}}, \quad (1)$$

FIG. 3. Correlation (r) and mean absolute error (MAE) of S2S precipitation and resampling precipitation compared to observed precipitation. Each row represents a different subbasin.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |x_{\text{obs},i} - x_{\text{sim},i}|, \quad \text{and} \quad (2)$$

$$\text{MRE} = \frac{1}{N} \sum_{i=1}^N \left| \frac{x_{\text{obs},i} - x_{\text{sim},i}}{x_{\text{obs},i}} \right|, \quad (3)$$

where the subscript obs represents the observed data and the subscript sim represents the S2S precipitation or streamflow simulated by S2S precipitation.

In addition to the above overall evaluation, the reliability of S2S data in capturing multiple-day precipitation and streamflow processes was also evaluated. Annual maximum 1-, 3-, 5-, and 7-day precipitation, and annual maximum (minimum) 1-, 3-, 5-, and 7-day flow were chosen as the evaluation statistics for precipitation and streamflow, respectively. The MRE of the accumulated precipitation (streamflow) and its associated extreme values (i.e., peak precipitation, peak flow, and

FIG. 4. The mean relative error (MRE) of annual maximum 1-, 3-, 5-, and 7-day precipitation of S2S precipitation and resampling precipitation compared to observed precipitation in the four subbasins.

lowest flow), and the MAE of the occurrence time of extreme events were calculated.

After bias correction, the changes in all of the above metrics (Δr , ΔMAR , and ΔMRE) were calculated to evaluate the effects of the bias correction methods. Specifically, an improvement was achieved by bias correction when Δr is positive and ΔMAR or ΔMRE are negative.

For all figures in section 4, when evaluating the overall skill of precipitation and streamflow forecasts, the ensemble mean represented the average of a specific metric across eight S2S models for a subbasin. But when evaluating the reliability of S2S data in capturing multiple-day precipitation and streamflow processes, the ensemble mean was calculated as the average of eight models. In addition, since the climatology forecasts were generated based on observed precipitation, they do not have lead time. Thus, when evaluating the overall skill of precipitation and streamflow forecasts, the values of a metric are the same from lead days 1 to 32, which was reflected as a horizontal line in the figure.

4. Results

a. Evaluation of S2S precipitation

Figure 3 presents the correlation coefficient r between the S2S and OBS precipitation, and the MAE of the S2S precipitation relative to the OBS data. Each row represents a single subbasin. The value of r decreases with the increase in the lead time. The S2S precipitation from

the ECMWF, KMA, and UKMO models shows a slightly higher correlation, while the correlations of S2S precipitation from the BoM and CMA models are relatively lower than those of the other models within 14 lead days. Beyond a lead time of 5 days, r decreases to be less than 0.5 for all models over every watershed. When the lead time increases to be more than 14 days, r tends to be stable and close to 0. The r values of resampling precipitation forecasts range between 0.1 and 0.2. Within 1 week of lead time, the r value of the resampling precipitation forecasts is lower than that of the S2S model forecasts, and the r value of the ensemble mean across all eight models decreases to the resampling line at around 11 days. In addition, the MAE increases with increasing lead time. Within 7 lead days, the MAEs of S2S precipitation from the CMA, ECMWF, KMA, and UKMO models are smaller than the others, while the MAE from the HMCN model is obviously higher, and the MAE from the HMCN model changes little over the whole lead time. The MAE of every model becomes stable when the lead time is longer than 11 days, and varies between 5 and 7 mm. After they become stable, the MAE from the CMA and CNR-ISAC models are the upper and bottom limit values, respectively. The MAEs of the resampling precipitation forecasts range between 5 and 6 mm. The MAE of the ensemble mean across eight models is always lower than that of the resampling precipitation forecasts within 1-week lead time. The four subbasins present similar results.

FIG. 5. (a)–(c) The MRE of the peak value in annual maximum 3-, 5-, and 7-day precipitation of S2S precipitation and resampling precipitation compared to observed precipitation; (d)–(f) MAE of the occurrence time of the peak value in annual maximum 3-, 5-, and 7-day precipitation of S2S precipitation and resampling precipitation compared to observed precipitation.

Figures 4 and 5 present the reliability of S2S products in capturing daily to multiple-day precipitation processes. Figure 4a shows the MRE of the annual maximum 1-day precipitation of S2S forecasts. The MREs from the BoM, CMA, and HMCRC models are larger than those from the others, that is, the ECMWF, CNR-ISAC, KMA, and UKMO models. The MRE of the resampling precipitation is larger than that of all S2S models and the ensemble mean. Similar results can also be found in annual maximum 3-, 5-, and 7-day precipitation (Figs. 4b–d), and are more pronounced for the peak values (Figs. 5a–c). As for the MAE of the peak precipitation occurrence time (Figs. 5d–f), the results do not clearly indicate which S2S model performs the best. While the data from the UKMO model and the ensemble mean perform slightly better than that of other models. In addition, the MAE of the resampling precipitation is the largest one for annual maximum 3-day precipitation in Hengyang subbasin (Fig. 5d) and annual maximum 5-day precipitation in Xiangxiang subbasin

(Fig. 5e). For the other two subbasins, the MAEs of the resampling precipitation are just slightly larger than that of the ensemble mean except for annual maximum 3-day precipitation in Daxitan subbasin (Fig. 5d). With the increase of the time period of the selected precipitation process, the MREs of accumulated precipitation and the peak values increase only very slightly. However, the MAE of occurrence time becomes large from the 3- to 7-day time periods, which is foreseeable as the MAE of occurrence time is limited by the time length of the precipitation process.

b. Performance of the bias-corrected precipitation

Figure 6 presents the Δr and ΔMAE between bias-corrected and noncorrected S2S precipitation. After bias correction, considering the fact that the correlations of all S2S models are obviously higher than that of the resampling precipitation, and the MAEs of all S2S models are obviously smaller than that of the resampling precipitation, only the changes between the raw and bias-corrected S2S precipitation are presented in Fig. 6, while the

FIG. 6. The change of r (Δr) and the change of MAE (ΔMAE) between the bias-corrected and noncorrected S2S precipitation compared to observed precipitation.

differences between the resample precipitation and bias-corrected ensemble mean are not shown. The Δr increases as lead time increases from 1 to 8 lead days and is positive for all 32 lead days. After the eighth lead day, Δr tends to be stable. For all models except the HMCR, Δr reaches up to 0.2–0.4. The Δr from the HMCR model is the largest among the models, reaching up to 0.6–0.8. The Δr values from the ECMWF, KMA, and UKMO models are relatively smaller than that of the others for 1–8 lead days. On average, the Δr values of the ensemble

mean at lead days 1 and 32 are 0.12 and 0.39, respectively. The ΔMAE is negative and decreases with the lead time, which means the MAE of precipitation becomes smaller after bias correction. At the first lead day, ΔMAE is between -0.8 and -4.0 , and at lead day 32, ΔMAE is between -1.7 and -4.1 . The ΔMAEs of data from the CMA and HMCR models are the upper and bottom limit values, respectively. The ΔMAE of data from the HMCR model shows little change with the increase of the lead time. On average, the ΔMAE values of

FIG. 7. The change of MRE (Δ MRE) of the annual maximum 1-, 3-, 5-, and 7-day precipitation between the bias-corrected and noncorrected S2S precipitation compared to observed precipitation.

the ensemble mean lead days 1 and 32 are -1.49 and -3.02 , respectively. In addition, there are no significant differences among the four subbasins in terms of Δr and Δ MAE.

An evaluation of the effects of precipitation bias correction on multiple-day precipitation processes is shown in Figs. 7 and 8. Similar to Fig. 6, only the changes between the raw and bias-corrected S2S precipitation are presented. After bias correction, the Δ MREs of annual maximum 1-day precipitation are all below 0, which means that the biases of precipitation amounts have been effectively reduced (Fig. 7a). The bias correction performance is dependent on the S2S models. For annual maximum 3-, 5-, and 7-day precipitation (Figs. 7b–d), the accumulated precipitation amounts from most models are more accurate after bias correction, as the Δ MREs are negative. However, there are some cases where the MRE changes in an opposite direction. For example, the MRE of the CNR-ISAC model becomes larger for annual maximum 3-, 5-, and 7-day precipitation for three subbasins, and the MRE of the KMA model increases for annual maximum 7-day precipitation over all four subbasins.

The Δ MREs of the peak value in annual maximum 3-, 5-, and 7-day precipitation are presented in Figs. 8a–c. In general, the bias correction method is able to reduce the biases in peak precipitation, except for the CNR-ISAC and KMA models. This result is very similar to the Δ MREs of annual maximum 3-, 5-, and 7-day precipitation. As indicated by the Δ MAE of the peak precipitation occurrence time in Figs. 8d–f, the occurrence time is closer to the OBS value in most cases after bias

correction, although there are some cases where the Δ MAE is greater than 0.

c. Performance of streamflow forecasts: Bias-correcting precipitation versus bias-correcting streamflow

As bias correction is usually a routine procedure when using precipitation forecast from weather or climate models for hydrological forecasts, the performance of using raw S2S models for streamflow forecasts is not presented. The focus of this study is on comparing the performance of streamflow forecasts with bias correcting precipitation against bias correcting streamflow. Figure 9 presents the Δr and Δ MRE of simulated streamflow using bias-corrected S2S precipitation. The Δr increases with the increase in the lead time. Except for a few cases, Δr is generally between 0 and 0.4. The Δ MRE is negative except for values at the first and second lead days, which are slightly greater than 0. From 1 to 32 lead days, the absolute values of Δ MRE increase with the lead time, which means the effects of bias correction gradually become more significant. The Δ MRE from the CMA model is always at the upper limit, indicating that the bias correction effect of the CMA model is relatively less remarkable than that of the other models. At lead day 32, Δ MRE from HMCRC model has the smallest value, which means that the bias correction effect of HMCRC model is the most remarkable one at then. Δ MRE at the lead day 32 is between -14.5% and -138.4% for all four subbasins. Figure 10 presents the Δr and Δ MRE of bias-corrected streamflow

FIG. 8. (a)–(c) The ΔMRE of the peak value in annual maximum 3-, 5-, and 7-day precipitation between the bias-corrected and noncorrected S2S precipitation compared to observed precipitation; (d)–(f) ΔMAE of the occurrence time of the peak value in annual maximum 3-, 5-, and 7-day precipitation between the bias-corrected and noncorrected S2S precipitation compared to observed precipitation.

simulated using raw S2S precipitation for hydrological simulation. Generally, the results are very similar to those of streamflow simulated using bias-corrected precipitation.

The ΔMRE s of annual maximum and minimum 1-day flow are shown in Fig. 11. Figures 11a and 11b present the results of bias correcting precipitation while Figs. 11c and 11d present those of bias correcting streamflow. For the annual maximum 1-day flow using bias-corrected precipitation (Fig. 11a), the ΔMRE of streamflow simulated using the CMA model's precipitation is slightly larger than 0 in the Daxitan, Xiangxiang, and Hengyang subbasins, while the maximum positive value comes from the KMA model in the Xiangxiang subbasin. For the annual maximum 1-day flow calculated from bias-corrected streamflow (Fig. 11c), the ΔMRE of streamflow simulated using the CMA model's precipitation is also slightly larger than 0 in the Daxitan, Xiangxiang, and Hengyang subbasins. However, although cases where positive values exist, they are very small compared with the ΔMRE of

the KMA model in the Xiangxiang subbasin (Fig. 11a). For the annual minimum 1-day flow simulated using bias-corrected precipitation (Fig. 11b), the ΔMRE from the BoM and CMA models is positive in the Xiangxiang, Ganxi, and Hengyang subbasins, indicating that the bias correction effects of the BoM and CMA models are not obvious. For the annual minimum 1-day flow calculated from bias-corrected streamflow (Fig. 11d), the ΔMRE s of streamflow in the Ganxi subbasin are all positive except for the HMC model with large ΔMRE values. For ΔMRE s with negative values, the absolute values of them are smaller than those of same models in same subbasins in Fig. 11b, which means the effect of bias correcting streamflow is less remarkable.

The bias-corrected results of annual maximum 3-, 5-, and 7-day flows are shown in Fig. 12. For the annual maximum flows, the MRE s of most models are reduced when using the bias-corrected precipitation. The ΔMRE s from the ECMWF and UKMO models for annual maximum 5-day flow (Fig. 12b) and the ΔMRE from the BoM

FIG. 9. The Δr and ΔMRE of streamflow simulated by the bias-corrected S2S precipitation compared to the streamflow simulated by the noncorrected S2S precipitation.

model for annual maximum 7-day flow (Fig. 12c) are slightly greater than 0 over three of the four subbasins. However, for some other models, that is, the CNR-ISAC and KMA, the bias correction method shows minor effects. The ΔMRE s from the CNR-ISAC and KMA models are larger than 0 for annual maximum 5- and 7-day flows (Figs. 12b,c) over more than half of the subbasins, and are extremely high in the Daxitan and Xiangxiang subbasins. When bias correcting streamflow, the ΔMRE s of the CNR-ISAC model (Fig. 12f)

are greater than 0 for the annual maximum 3- and 5-day flow (Figs. 12d,e) and the ΔMRE of the KMA model is greater than 0 for the annual maximum 7-day flow over three of the four subbasins. Compared with the annual maximum flows simulated using bias-corrected precipitation (Figs. 12a-c), the number of cases where ΔMRE s are positive is less than that of the bias-corrected streamflow.

The bias correction effects of annual minimum 3-, 5-, and 7-day flows are presented in Fig. S1 in the online supplemental material. For the results of using bias-corrected

FIG. 10. The Δr and ΔMRE of the bias-corrected streamflow compared to the noncorrected streamflow.

precipitation, the annual minimum flow is better represented after bias correction. Although ΔMRE can be larger than 0 for a few cases, the values are quite small. As for the results of bias correcting streamflow, there are some positive ΔMRE s in the Ganxi subbasin. Overall, the bias correction effect of bias correcting streamflow is less remarkable compared with that of bias correcting precipitation.

Figure 13 presents the ΔMRE of the peak value in annual maximum 3-, 5-, and 7-day flows. From Fig. 13 we can see that either bias correcting precipitation for

streamflow simulation or directly bias correcting streamflow can improve the reliability of streamflow forecasts, as the ΔMRE s are all negative. For bias correcting precipitation, the bias correction effects of the CNR-ISAC and KMA models are not obvious in some cases, that is, for annual 3-, 5-, and 7-day peak flows, ΔMRE s from the CNR-ISAC and KMA models are extremely high in the Daxitan and Xiangxiang subbasins, respectively. In addition, the ΔMRE s from the ECMWF model for annual 7-day peak flow and from the UKMO model

FIG. 11. (a),(b) The Δ MRE of the annual maximum 1-day and minimum 1-day flow simulated by the bias-corrected S2S precipitation compared to the streamflow simulated by the noncorrected S2S precipitation; (c),(d) Δ MRE of the annual maximum 1-day and minimum 1-day flow from the bias-corrected streamflow compared to the noncorrected streamflow.

for annual 5- and 7-day peak flows are slightly larger than 0 over three of the four subbasins. For bias correcting streamflow, Δ MREs of the ECMWF, CNR-ISAC, and KMA models are greater than 0 for annual 5- and 7-day peak flow over three of four subbasins, which means that the effects of bias correcting streamflow are negative for peak values for these three models. The positive values from bias correcting streamflow are less remarkable compared with those from bias correcting precipitation, but bias correcting streamflow has negative effects for almost all models in the Hengyang subbasin.

The bias correction effects of the lowest flow are presented in Fig. S2. Both bias correcting precipitation and bias correcting streamflow present few positive values for Δ MRE; however, they are all very close to 0. Moreover, the lowest flow simulated using the bias-corrected S2S precipitation from HMCR model is dramatically improved in some cases, that is, the annual 5-day lowest flow for the Daxitan (Figs. S2b,e) and the annual 7-day lowest flow for the Daxitan and Ganxi subbasins (Figs. S2c,f). But when bias correcting streamflow, the effect is negative in the Ganxi subbasin as the MREs of most models become worse after bias correction.

The improvements of streamflow simulation using bias-corrected S2S precipitation are more obvious in the occurrence time of the peak flow compared with previous statistics (Fig. 14). With the bias correction method, almost

all occurrence time of peak flow are better captured. Only the Δ MAE of the CNR-ISAC model in the Hengyang subbasin is slightly larger than 0. The results of bias correcting streamflow are quite different. For most models, bias correcting streamflow has little or even negative effects on the occurrence time of 3- and 5-day peak flow. It is worth noting that in some subfigures, the ensemble mean has positive values while all models have negative values, for instance, in Fig. 14a in Xiangxiang subbasin and in Fig. 14f in Ganxi subbasin. This is possible as the occurrence time of the peak values is calculated from the position of the peak values in multiple-day streamflow process. That is, after getting the ensemble mean through calculating the arithmetic mean of all eight models, it is still needed to find the position of the maximum values to obtain the occurrence time of the peak values, which makes the relationship between the occurrence time of the peak values from the ensemble mean and the eight models nonlinear.

For the lowest flow occurrence time (Fig. S3), when bias correcting precipitation, the variation range of Δ MAE is larger than that of the time to peak flow. The results from the HMCR model and the ensemble mean are improved the most by bias correction, which is not obvious in the results for the peak flow occurrence time. But when bias correcting streamflow, the results are the same as that of the peak flow occurrence time as there are no obvious effects for most models.

FIG. 12. (a)–(c) The Δ MRE of the annual maximum 3-, 5-, and 7-day flows simulated by the bias-corrected S2S precipitation compared to the streamflow simulated by the noncorrected S2S precipitation; (d)–(f) Δ MRE of the annual maximum 3-, 5-, and 7-day flows from the bias-corrected streamflow compared to the noncorrected streamflow.

5. Discussion

The reliability of S2S data from eight different models was assessed in terms of precipitation and hydrological forecasts over the Xiangjiang River basin. The results show that the raw S2S precipitation data from the ECMWF, KMA, and UKMO models have higher correlation to observations and lower mean error than other models. In terms of simulating the multiday precipitation process, the data from these same three models also show a better performance than data from the others. Although the CMA model's precipitation also has a low mean error, its correlation to observations is relatively lower than the other six models, except for the BoM. S2S models perform much better than climatology forecasts, that is, the historical resampling. Although S2S forecasts consistently perform better than the climatology forecasts in representing precipitation amounts, they may lack of the reliability in simulating the occurrence time of extreme values. In general, precipitation

can be skillfully forecasted by S2S models up to a lead time of 11 days. A similar result can also be found in previous studies by [Liang and Lin \(2018\)](#) and [Marshall and Hendon \(2015\)](#) for other regions.

In general, the bias correction method is capable of reducing the biases of S2S precipitation in terms of correlation and mean error. Correlation and mean error have been effectively improved for lead times from 1 to 32 days. The effect of bias correction for the HMCR model is the most remarkable. As for simulating the precipitation process, the bias correction method performs well for all but two models, CNR-ISAC and KMA.

For streamflow forecasts, two bias correction strategies were used. One is bias correcting precipitation for hydrological simulation and the other is directly bias correcting streamflow. Overall, two bias correction strategies can improve S2S model-simulated streamflow significantly in terms of the correlation and mean error. Similar conclusion has also been drawn in [Yuan and Wood \(2012\)](#). However, for streamflow process

FIG. 13. (a)–(c) The Δ MRE of the peak value in annual maximum 3-, 5-, and 7-day flows simulated by the bias-corrected S2S precipitation compared to the streamflow simulated by the noncorrected S2S precipitation; (d)–(f) Δ MRE of the peak value in annual maximum 3-, 5-, and 7-day flows from the bias-corrected streamflow compared to the noncorrected streamflow.

simulations, the effects of these two bias correction strategies are various. Specifically, bias correcting precipitation performs better than bias correcting streamflow in simulating the amount of minimum continuous flow and the lowest flow, as well as the occurrence time of extreme flow, that is, peak flow and the lowest flow, while bias correcting streamflow performs better at simulating the amount of maximum continuous flow and the peak flow. Although differences exist between these two bias correction strategies, there are some things in common. For instance, just as for the precipitation process, the effects of the bias correction for the CNR-ISAC and KMA models are not obvious. The effect of bias correcting the HMCRC model is the most remarkable, especially for low flow. Except for the abovementioned S2S models, the streamflow simulation results from the other S2S models were effectively corrected and the effects of bias correction vary with each model. Since data from different centers have different features, it is almost impossible to find a bias correction method that can correct the error of all models.

Although a comprehensive assessment of both raw and bias-corrected S2S precipitation was conducted in this study, some questions remain. The study area in this paper is limited to a subtropical region. However, S2S data have climate adaptability, as the forecast skills of some S2S models vary with climate zone. For instance, the ECMWF model performs better when used to forecast rainfall in tropical regions than in the extratropics (Vitart 2014). Comparing the performance of S2S data in different regions is an important aspect with which to promote the application of S2S products. In this study, we focus on the forecast skill of S2S precipitation and its performance in streamflow simulation. The reliability of S2S temperature was not evaluated. In addition, the joint effect of S2S precipitation and temperature on streamflow was not investigated. These would be worthwhile avenues to explore in further studies.

In addition, one of the main objectives of this study is to verify the effects of bias correction on S2S precipitation rather than comparing the performance of different bias

FIG. 14. (a)–(c) The Δ MAE of the occurrence time of the peak value in annual maximum 3-, 5-, and 7-day flows simulated by the bias-corrected S2S precipitation compared to the streamflow simulated by the noncorrected S2S precipitation; (d)–(f) Δ MAE of the occurrence time of the peak value in annual maximum 3-, 5-, and 7-day flows from the bias-corrected streamflow compared to the noncorrected streamflow.

correction methods, while only one superior bias correction method based on quantile mapping was applied. This method has been successfully used in many studies (Wood et al. 2002; Shah et al. 2017; Zhuan et al. 2018). However, some studies have shown that the choice of a bias correction method is one of the major sources of uncertainty for climate and hydrological forecasts (e.g., Chen et al. 2011, 2013; Teutschbein and Seibert 2012). The uncertainty related to the bias correction method may need to be investigated by using multiple methods. Furthermore, this study only applied one lumped hydrological model for streamflow simulation. Since the lumped hydrological model may ignore the spatial distribution and inhomogeneity of model inputs, adding distributed hydrological models for comparison may yield more comprehensive results.

6. Conclusions

The S2S precipitation data from eight modeling centers were evaluated and compared in hydrological

forecasts at four subbasins of the Xiangjiang River basin in south China. In addition, a quantile mapping bias correction method was used to improve the performance of S2S precipitation. The skills of the S2S precipitation forecasts were evaluated before and after bias correction. Furthermore, the performances of streamflow forecasts with two bias correction strategies (i.e., bias correcting precipitation and bias correcting streamflow) were also compared. The main conclusions are outlined below:

- 1) Precipitation can be skillfully forecasted by S2S models up to a lead time of 11 days, and the skills of S2S precipitation forecasts decrease with the increase of the lead time. The S2S precipitation data from the ECMWF, KMA, and UKMO models had higher correlations with observations and lower mean error than data from the other models. As for simulating the multiday process of precipitation, data from the ECMWF, KMA, and UKMO models also perform better than data from the other models.

- 2) The bias correction method reduced the biases for precipitation forecasts and showed better performance at representing watershed streamflow compared to noncorrected data in terms of correlation and mean error. Furthermore, regarding multiday precipitation or the streamflow process, the results improved effectively by bias correction method, although the effects vary with each model. For instance, the effect of the bias correcting the HMCR model is the most remarkable, especially for low flow, while the effects of the bias correcting the CNR-ISAC and KMA models are not obvious.
- 3) Even though both bias correcting precipitation and bias correcting streamflow can improve the reliability of streamflow forecasts, they have different performances in terms of streamflow variables. Bias correcting precipitation performs better at simulating the amount of minimum continuous flow and the lowest flow, and the occurrence time of extreme flow, that is, peak flow and lowest flow, while bias correcting streamflow performs better at simulating the amount of maximum continuous flow and the peak flow.

Overall, S2S products present reliable forecasting skill in precipitation and have the potential to be applied for hydrological research and operation. However, bias correction is still needed for S2S applications (i.e., hydrological forecasting) at local scale, although various bias correction strategies may result in slightly different results. For a complete evaluation, other bias correction methods and distributed hydrological models should be used in further studies.

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