Seasonal Rainfall Forecasts for the Yangtze River Basin of China in Summer 2019 from an Improved Climate Service

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ABSTRACT

Rainfall forecasts for the summer monsoon season in the Yangtze River basin (YRB) allow decision-makers to plan for possible flooding, which can affect the lives and livelihoods of millions of people. A trial climate service was developed in 2016, producing a prototype seasonal forecast product for use by stakeholders in the region, based on rainfall forecasts directly from a dynamical model. Here, we describe an improved service based on a simple statistical downscaling approach. Through using dynamical forecast of an East Asian summer monsoon (EASM) index, seasonal mean rainfall for the upper and middle/lower reaches of YRB can be forecast separately by use of the statistical downscaling, with significant skills for lead times of up to at least three months. The skill in different sub-basin regions of YRB varies with the target season. The rainfall forecast skill in the middle/lower reaches of YRB is significant in May–June–July (MJJ), and the forecast skill for rainfall in the upper reaches of YRB is significant in June–July–August (JJA). The mean rainfall for the basin as a whole can be skillfully forecast in both MJJ and JJA. The forecasts issued in 2019 gave good guidance for the enhanced rainfall in the MJJ period and the near-average conditions in JJA. Initial feedback from users in the basin suggests that the improved forecasts better meet their needs and will enable more robust decision-making.

Key words: seasonal rainfall forecasts, climate service, Yangtze River basin (YRB), East Asian summer monsoon (EASM)

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1. Introduction

The Yangtze River basin (YRB) has been subject to regular and heavy flooding throughout history (e.g., Plate, 2002; Yu et al., 2009), and in modern times this can affect the lives and livelihoods of millions of people. Advance knowledge of the increased flood risk can allow planning to mitigate the impacts of flooding, for example by reducing the water levels in large hydroelectric dams, such as the Three Gorges Dam, along the Yangtze River and its tributaries. The summer rainfall in the Yangtze region is dominated by the impact of the East Asian summer monsoon (EASM). Being able to forecast the summer Yangtze rainfall and EASM itself at long lead
times has been an important research subject for many decades (Wang et al., 2015; and references therein). Skillful seasonal forecasts of rainfall can be produced directly from a dynamical model (e.g., Li et al., 2016), or by using statistical modeling to exploit relationships between the rainfall and larger-scale climate phenomena (e.g., Zhu et al., 2017). Those statistical predictors could themselves be produced by dynamical seasonal forecasting systems (a hybrid approach), or they could be based on recent observations. For example, El Niño conditions measured in winter sea surface temperatures are linked to greater Yangtze rainfall in the following summer (e.g., Zhang et al., 2016), although this relationship is not straightforward when examined in detail (e.g., Wang et al., 2017; Hardiman et al., 2018). Similarly, Zeng et al. (2019) demonstrated that the sea surface salinity observed in spring can be used as a predictor of summer precipitation in the middle/lower Yangtze River valley. While statistical modeling can often outperform direct dynamical modeling, it has been recognized that combining statistical modeling with dynamical model output is likely to be the optimal approach, and it naturally provides an opportunity for downscaling to the areas of most interest (e.g., Ke et al., 2011; Liu and Fan, 2012; Li and Lin, 2015; Qian et al., 2020).

In 2015, Golding et al. (2017a) identified a clear user requirement for the improved seasonal rainfall forecasts in the YRB region. At the same time, Li et al. (2016) demonstrated significant forecast skill for the YRB rainfall, using the Met Office GloSea5 seasonal forecasting system. A trial climate service was subsequently developed, to deliver prototype seasonal forecasts of YRB average summer rainfall to the China Meteorological Administration (CMA). The first year in which the forecasts were produced followed the large El Niño event in the winter of 2015–2016. Experience of the previous post-El Niño heavy flooding in 1998 (Zong and Chen, 2000; Ye and Glantz, 2005) led to an expectation of the enhanced rainfall for summer 2016. The dynamical seasonal forecasts showed a high probability of above-average rainfall in May–June–July (MJJ), and near-normal rainfall in June–July–August (JJA). These forecasts were borne out by observations (Wang et al., 2017; Yuan et al., 2017; Bett et al., 2018).

The same forecast system was run again in 2017 and 2018, incorporating updates to the GloSea5 system itself to use a larger ensemble and a longer hindcast period. In these cases however, without a strong forecast driver like El Niño, the forecasts had roughly equal probabilities for above and below-average conditions in the summer. The rainfall in the YRB in 2017 was near-normal, although there was severe flooding in southern China (Wang, 2018; Zhang et al., 2018). In 2018, an easterly/northeastern anomalous flow pattern resulted in particularly low rainfall in the region (Zhu et al., 2019), resulting in drought conditions in many areas (Zou et al., 2020).

Golding et al. (2017b) conducted further research on the use of seasonal forecasts for the YRB, including this trial climate service. Two key conclusions (Golding et al., 2019) were a desire for improved spatial resolution and longer lead times. Concurrently, the work of Liu et al. (2018) on the skill of forecasting the EASM suggested a route for simple statistical downscaling that could help satisfy those user requirements. Following development and testing in 2018, forecasts using the enhanced prototype system were produced and issued from early 2019 for the subsequent MJJ and JJA seasons.

Here we report on those changes to our YRB forecasting system, and describe the forecast performance in summer 2019. Section 2 describes the datasets used, and Section 3 describes the methods used in our updated system. Section 4 describes the forecasts issued and compares them with the observed rainfall conditions. Section 5 summarizes our results, and discusses them in the context of seasonal climate service development.

2. Datasets

The GloSea5 seasonal forecasting system (MacLachlan et al., 2015) uses the Hadley Centre Global Environment Model 3 (HadGEM3) climate model in its Global Coupled 2 configuration (GC2; Williams et al., 2015; and references therein). The climate model comprises dynamical models of the atmosphere (the Met Office Unified Model; Walters et al., 2017), land surface (Joint UK Land Environment Simulator (JULES); Best et al., 2011), oceans [Nucleus for European Modelling of the Ocean (NEMO); Madec et al., 2019; Megann et al., 2014], and sea ice [Los Alamos Sea Ice Model (CICE); Hunke and Lipscomb, 2010; Rae et al., 2015]. The atmospheric model grid spacing is 0.83° in longitude and 0.55° in latitude, with 85 vertical levels; and the ocean model uses a 0.25° grid with 75 vertical levels. GloSea5 produces two initialized forecast runs per day, each extending to 210 days. In order to calibrate the forecasts, hindcasts are also produced operationally, covering a 24-yr period (1993–2016), with 7 members initialized on 4 fixed dates each month (1st, 9th, 17th, and 25th).

On any given date, a forecast ensemble can be produced by pooling together the preceding three weeks of forecast runs, making a 42-member forecast ensemble. A corresponding hindcast ensemble can be produced by
pooling the four 7-member hindcast runs closest to each forecast member’s initialization date, and weighting them according to the lead/lag time (see MacLachlan et al., 2015 for details).

The observational precipitation data used in this study are from the monthly 1° × 1° dataset of the Global Precipitation Climatology Centre (GPCC; Schneider et al., 2018a), covering a historical period from 1891 to 2016. For the 2019 precipitation, we use the GPCC monthly monitoring data (Schneider et al., 2018b). For other fields, such as pressure at mean sea level (PMSL) and zonal wind, we use the ECMWF Interim reanalysis data [ERA-Interim (ERAI); Dee et al., 2011] as a proxy for the observational data.

### 3. Forecast methodology

Our forecast method is based on utilizing the relationship between a predictor quantity from GloSea5 and an observed predictand quantity. These need not be the same physical variable, or cover the same geographical region. The forecast system described in Bett et al. (2018) used the GloSea5 model precipitation in a box covering the YRB region (25°–35°N, 91°–122°E), to forecast the rainfall observed in the same box. In this scheme, the historical relationship between the model and observations is characterized by the linear regression between the hindcast ensemble-mean rainfall and the observed rainfall, for a given season each year, and at a given lead time. A future observation is forecast by applying that linear regression relationship to the ensemble-mean forecast from GloSea5; specifically, the regression line gives the central estimate of the forecast, and the uncertainty on the linear regression, in terms of the prediction interval, quantifies the forecast uncertainty around that central estimate. This simple regression technique produces calibrated probabilistic forecasts that are bias- and variance-corrected [see Bett et al., 2019 for more details].

The updated forecasts for 2019 used the same principles, based on the linear regression between the observed precipitation and an ensemble-mean predictor variable from the GloSea5 hindcast. Here, we use an index of the EASM circulation as the predictor variable. The linear regression relationship is then used with ensemble-mean forecasts of the EASM index to yield probabilistic forecasts of the future rainfall in the YRB. Because the rainfall response to the monsoon index is different in different regions and at different periods during the monsoon season, this represents a simple form of statistical downscaling.

We use the EASM index proposed by Wang and Fan (1999). This describes the shear vorticity in the western North Pacific, through the difference between the mean zonal wind at 850 hPa (U850) in two boxes: one centered on the East China Sea, and the other centered on the South China Sea. Wang and Fan (1999) defined the index as the southern box minus the northern box. Although this order is sometimes reversed (e.g., Wang et al., 2008), we follow Liu et al. (2018) by using the original definition. Figure 1 shows the observed circulation and rainfall responses to this EASM index in JJA (similar maps for MJJ are shown in Fig. A1). Low values correspond to anomalously anticyclonic circulation over the western North Pacific, advecting moisture further north within China, enhancing precipitation over the YRB. Conversely, high EASM index values correspond to anomalously cyclonic circulation in the region, leading to reduced rainfall over the YRB, but more rainfall further south in China and Southeast Asia. It is also clear that this EASM index is strongly related to the western Pacific subtropical high (WPSH), with low values corresponding to a stronger (westward-extended) WPSH and vice versa. Wang et al. (2008) showed that this EASM index captures the leading mode of variability in the EASM system: a strong Meiyu front in China, bringing enhanced rainfall to the YRB, associated with a suppressed western North Pacific monsoon trough, easterly vertical shear in the southern South China Sea, and an enhanced southwesternly monsoon over southern China due to the southwestward extension of the WPSH.

Figure 2 maps the observed anticorrelation between the EASM index and YRB precipitation, as well as the corresponding relationship when using the EASM index calculated from the GloSea5 hindcast data. This illustrates the model fidelity in reproducing the relationship between the EASM index and precipitation. Note that, as we forecast area-averages, the spatial patterns do not need to agree in detail for our method to work. GloSea5 also produces skillful forecasts of the EASM index itself. For the hindcast data used at a one-month lead time, the correlation skill for EASM in MJJ is r = 0.87, with a 95% confidence interval from a Fisher’s z-transformation of 0.72–0.94; and for JJA the skill is r = 0.76, with a 95% confidence interval of 0.51–0.89, consistent with Liu et al. (2018). This is also consistent with the high skill of this system in forecasting the WPSH (Camp et al., 2019).

An important feature of these correlation maps is the difference in spatial pattern between the early and late summer periods. The anticorrelation of the EASM index with precipitation is stronger for the western (upper) part
of the basin in JJA, and stronger in the eastern (lower) part of the basin in MJJ. Wang et al. (2009) demonstrated that this westward shift of the rainfall anomalies through the summer, also seen in Wang et al. (2008), is a genuine climatological feature of the EASM—A relatively rapid transition in rainfall patterns occurs between June and July, contrasting with smaller changes from May to June, and from July to August. This is related to the seasonal advance of the WPSH, which moves northwards and eastwards over this period (Wang et al., 2009).

In the earlier part of the summer, rainfall in the eastern (lower) part of the YRB is dominated by the Meiyu front.

Fig. 1. Composite mean responses of the seasonal mean zonal wind $u_{850}$, PMSL (from ERAI), and precipitation rate (from GPCC), for upper and lower terciles of the seasonal mean EASM index in JJA. We use the common period of the datasets here (1979–2016). In all panels, anomalies are shown by colored shading. For the $u_{850}$ and PMSL panels, the patterns of the full-field values are indicated by green contour lines, dashed for negative values. The Yangtze River basin (YRB) and the box used in Bett et al. (2018) are drawn in black, with the Yangtze River itself in blue. The basin is subdivided at 111°E (thin grey dashed line) near the Three Gorges Dam (red point). The boxes used to define the EASM index are drawn with black dashed lines.
From mid-July into August however, other features of the monsoon circulation, such as typhoons and variations in the Intertropical Convergence Zone (ITCZ) come to dominate (Wang and LinHo, 2002; Ding and Chan, 2005). The EASM index we use here characterizes the WPSH circulation that, in the early part of the season, is associated with the Meiyu rainband in particular. Martin et al. (2020) demonstrated that this index (anti-)correlates with rainfall in the middle/lower part of the YRB around June. Conversely, they showed that this EASM index is unrelated to rainfall in this region in July or August.

Although the monsoon processes described above clearly operate on subseasonal timescales, nevertheless there is a benefit to forecasting seasonal (three-month) means: Averaging over a longer time period, just like averaging over a large region, helps to reduce noise and bring out the predictable signal. Furthermore, seasonal periods are commonly used in international and regional climate prediction assessments, and by decision makers. As long as there is robust skill, there is a benefit from using common periods. The study of Martin et al. (2020) complements our work here, by investigating the scope for forecasts of the subseasonal summer periods in different parts of the YRB at long lead times.

We therefore examine the skill of the EASM index to forecast rainfall in different parts of the YRB, in MJJ and JJA separately. The YRB is often divided into upper, middle, and lower reaches, at Yichang and Hukou respectively (e.g., Xia et al., 2016). For our purposes, we divide the basin into two regions based on this definition, by using a straight line of longitude at 111°E, in Yichang, for simplicity. This is close to the Three Gorges Dam, which is marked with a red dot in our figures. We refer to the two resulting sub-basin regions as the upper reaches and middle + lower reaches.

Figure 3 compares the skill, in terms of the correlation magnitude $|r|$, of forecasting MJJ and JJA mean precipitation by using either the hindcast EASM index or precipitation as the predictor in the linear regression. It is important to recall that these correlations are subject to relatively large sampling uncertainty. Under a Fisher’s $z$ test, a correlation of 24 points (years) would have to be $>0.4$ to be statistically different from zero at the 5% level;
that is, a relatively high correlation measurement of 0.6 would have a 95% confidence interval of 0.26–0.81.

Comparing the correlations against each other requires a different test, as they are not independent (they use the same set of years). Using Williams’s test (Steiger, 1980) at the 5% level, the EASM-based correlations and precipitation-based correlations shown in Fig. 3 are mostly not significantly different from each other. The exceptions are for the final three JJA whole-basin forecast dates, and the penultimate forecast date for JJA upper reaches forecasts. Nevertheless, it is reassuring that the results using either predictor show a consistent picture between the different seasons and regions, over the range of lead times available. We now consider each region in turn. Using the EASM index in JJA provides nominally higher skill for the whole basin, at a consistently significant level, although it makes no difference for MJJ. For the upper reaches, the EASM index provides a way of producing significantly skillful forecasts for JJA. The precipitation-based skill in that region for JJA, and for either method in MJJ, are not statistically significant. For the middle + lower reaches, equally-skillful forecasts for MJJ can be produced by using either the EASM or precipitation directly. For JJA in this region, neither method results in a significant skill.

Those skill levels relate to the forecasts of summer 2019, based on the relationship between all 24 years in the hindcast and corresponding observations. A cross-validated assessment of the skill of the method itself can be performed by calculating a series of “forecasts” based on a single hindcast year, and the linear regression using the remaining 23 years. Forecasts produced in this way at 1-month lead time are shown in Fig. 4. The correlation skill values (and 95% confidence intervals) for those cases are $r = 0.54$ (0.16–0.78) for MJJ and $r = 0.16$ (−0.27 to 0.54) for JJA. These are lower than, but consistent with, the results shown in Fig. 3, as the regressions used for each forecast are based on less data than used for the 2019 forecasts. Figure 4 also shows the root mean squared error (RMSE) of the forecast central estimates, and the continuous ranked probability skill score (CRPSS; e.g., Wilks, 2019) for the forecast probability...
distributions with respect to climatology. The CRPSS can also be calculated with respect to the forecasts based on precipitation rather than the EASM index, to compare the two methods. The resulting skill scores are −0.089 for MJJ in the middle + lower reaches, and 0.018 for JJA in the upper reaches, consistent with the differences between the correlation results shown in Fig. 3.

Having established that using the EASM index produces similar or better levels of skill than using precipitation, we implemented this change in our forecast production systems. Forecast documents were produced each week for monitoring purposes, on Sundays from February through June. Forecasts were issued to CMA on the first Wednesday of each month, i.e., those produced on 3rd February, 3rd March, 31st March, and 5th May 2019, as marked in the figures. These dates give forecasts for MJJ and JJA at approximately 3-, 2-, and 1-month lead times, where available. Note that the first release only contained information for MJJ (at a 3-month lead) and the final release only contained information for JJA (at a 1-month lead). A sample forecast document is available as the supplementary material with this paper.

4. Forecasts and verification results

Figures 5 and 6 show the forecasts for the middle + lower reaches in MJJ 2019, and for the upper reaches in JJA 2019, respectively. The forecasts for the whole basin are given in the Appendix (Figs. A2, A3). In all cases, the observed mean precipitation rates are not only well within the forecast prediction intervals, but also very close to the forecast central estimates, across all lead times. The MJJ rainfall was observed to be above average, although still easily within a standard deviation of the climatological average. The rainfall in JJA was very close to the average.

The observed rainfall anomalies are mapped in Fig. 7. This shows the mixed picture across the YRB in May, with heavier rainfall further southward in China. June shows more widespread wet anomalies in the YRB, but the strongest signal is seen in July, particularly south of the river itself and in the middle and lower reaches. The seasonal mean precipitation for MJJ reflects this, with a spatial pattern similar to that of July alone. The signal for JJA is similar again, but weaker. August has a strong drier-than-average anomaly across much of the basin, and it dominates the middle + lower reaches in particular. The area around Shanghai retains a wet anomaly in August, possibly reflecting the impact of Typhoon Lekima.

Communications with users of seasonal forecasts at the Three Gorges Dam suggest that forecasts of above average rainfall received early in the year had prompted management activities designed to release water from the
dam and create space for potential flood waters. The forecasts shared from the system described in this paper gave additional confidence to these decisions, and the consistent signals seen in the forecasts as lead times reduced allowed further management adjustments to be made.

5. Conclusions and discussion

At the meeting of the National People’s Congress in China in March 2019, the Minister for Water Resources highlighted the planned improvements in flood control, and pointed towards the forecasts of CMA, saying “The Yangtze River is likely to suffer heavy flooding this year” (Xinhua News Agency, 2019). Although several severe rainstorm and flooding events in China did occur in summer 2019, overall the impacts were more limited and localized than in previous years, and 2019 exhibited a reduction in deaths/missing persons and direct economic losses compared to the average (Zeng et al., 2020).
The forecasts described in the previous section provided good advice for the seasonal-mean, regional-mean rainfall levels within the YRB region, in MJJ and JJA 2019. The forecast signals were consistent for lead times of up to nearly three months before the start of each season. Many of the improvements made since the original version presented in Bett et al. (2018) were in direct response to clear user requirements, as described in Golding et al. (2019). Whilst a detailed evaluation of the forecast use and value in 2019 has not yet been possible, current indications agree with previous evaluations, suggesting that these updates allow for more robust and more targeted decision-making. In particular, our previous forecasts were unable to distinguish between rainfall in the upper and lower reaches of the YRB, and therefore decision-makers received no information on the relative flooding risk above and below the Three Gorges Dam. This information is particularly important for the management decisions that can be made ahead of time, so this change represents a significant improvement in that regard. In addition, the validation of the 2019 forecasts provides further evidence to users of the capability of the service, and thereby provides increased confidence for decision-making. Ongoing interaction with users throughout the process of forecast development, and the demonstrated effective and willing collaboration between scientists and decision-makers add further value to this climate service (Golding et al., 2017b; Hewitt et al., 2020).

Fig. 7. Observed precipitation anomalies in summer 2019. Each month and season (as labelled) are shown as the standardized anomaly with respect to their 1993–2016 mean and standard deviation. The YRB, our subdivision at 111°E at the Three Gorges Dam, and the Yangtze River itself, are marked as in previous figures.
It is important to note that not all the user requirements identified by Golding et al. (2019) can necessarily be satisfied. Requests such as these must always be considered in the context of advances in the underpinning research and model prediction skill (e.g., Liu et al., 2018; Martin et al., 2020), so that potential improvements can be identified. This process, of trying to find ways of improving forecasts for users, can also lead to the development of other trial climate services. For example, Camp et al. (2019) demonstrated that tropical cyclone landfall can be skillfully forecast based on the WPSH, in a similar way to the use of the EASM described here (indeed, a WPSH index could be another choice of predictor for our YRB forecasts). This has been developed into a trial typhoon landfall forecast for East Asia for JJA 2019 (Camp et al., 2020). Similarly, Martin et al. (2020) demonstrated skill in forecasting rainfall in the middle/ lower reaches of the YRB for June alone (and not for July or August). Preliminary examination of the test forecasts suggests that rainfall in June 2019 was correctly predicted to be slightly greater than normal, consistently at lead times from February to April. Thereby, this prototype has been developed into a trial service in summer 2020.

These improved or novel services stem from discoveries of skill in existing models, together with increased understanding of the phenomena involved through ongoing research around the world. They are also enhanced by improved post-processing techniques that allow that skill to be exploited efficiently without adding more noise (Bett et al., 2019). It is unlikely that large improvements in the immediate future will come directly from improved climate modeling. For example, moderate increases in model resolution (e.g., doubling) are unlikely to provide a step-change in the skill (Scaife et al., 2019).

Therefore, focusing on greater understanding of underlying physical processes, and how they are reproduced in climate models, together with exploitation of the post-processing techniques developed in consideration of user needs, can result in improved climate services, leading to more effective decision-making.

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Appendix

Maps of the observed circulation response to the EASM index in MJJ are given in Fig. 1A. These can be compared with Fig. 1, which shows the response in JJA.

forecasts of rainfall in the Yangtze River basin (YRB) as a whole are presented here in Fig. 2A (for MJJ) and Fig. 3A (for JJA).

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Fig. A1. As in Fig. 1, but here for MJJ.

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**Fig. A2.** As in Fig. 5, but for the whole YRB.

**Fig. A3.** As in Fig. 6, but for the whole YRB.
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