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RESEARCH PAPER

Improving operational flood forecasting in monsoon climates with bias-corrected quantitative forecasting of precipitation

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ABSTRACT

For flood-prone countries subject to large-scale and seasonal flooding, precipitation forecasting is the single most important factor for improving the skill of flood forecasting for such large river basins dominated by the monsoon. Several flood forecasting agencies in South and Southeast Asia, where monsoon floods dominate (e.g. Bangladesh, Pakistan, India, Thailand and Vietnam), are currently using quantitative precipitation forecast (QPF) from numerical weather prediction (NWP) models. Although there are numerous studies reported in the literature to evaluate QPF precipitation performance, there appears to be lack of studies about the impact on the flood forecasting skill. In this study, we demonstrate tangible improvements in flood forecasting based on NWP precipitation forecast using an approach that is operationally feasible in resource-limited settings of many flood agencies. Our improvement is based on a bias correction methodology for enhancing the skill of QPF using observed and QPF climatology. The proposed approach can be applied to any type of QPF dataset such as those dynamically downscaled from regional NWP. We demonstrate clear and consistent improvement in the enhancement of flood forecasting skill at longer lead times of up to 7 days in three river basins of Ganges, Brahmaputra and Mekong by about 50% (reduction in RMSE) or 25% improvement in correlation when compared to the forecasts obtained from uncorrected QPF. Furthermore, our proposed bias correction methodology yields significantly higher skill improvement in flood forecast for global (non-downscaled) QPF than those dynamically downscaled QPFs for the macroscale hydrologic model used for forecasting stream flows. The simplicity of the QPF bias correction methodology along with the numerical efficiency can be of tremendous appeal to operational flood forecasting agencies of the developing world faced with large-scale monsoonal flooding and limited computational resources and time for disaster response.

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1. Introduction

In large river basins located in the monsoon-dominated climates of Asia and Africa, such as the Ganges, Brahmaputra, Indus, Mekong, Niger and Nile, the most flood-prone country is often located downstream (Katiyar and Hossain 2007). Such countries receive the lion share of flooding as seasonal and transboundary flow (Sood and Mathukumalli 2011). In general, the forecasting of such flooding can be performed in many different ways by operational flood management agencies. Examples of various approaches are: persistence techniques based on auto-regression (Hirpa et al. 2013), statistical-dynamical technique (Cane et al. 2013), use of hydrologic-hydrodynamic models (Maswood and Hossain 2015) or assimilation of weather forecast and satellite data (Biancamaria et al. 2011).

For flood-prone countries, precipitation forecasting is the most critical factor for improving the skill of flood forecasting for such large river basins dominated by the monsoon (Coe 2000). Forecasting of precipitation is needed to increase the lead time of a flood forecast beyond the time of concentration of the river basin. Hereafter, we shall use flood forecast with flow forecast to imply the same physical phenomenon. If we assume that nowcast estimated precipitation (such as satellite multi-sensor precipitation products) provides the most reliable source of precipitation for large river basins, the lead time will remain limited to the hydrologic time of concentration of flow. Thus, one of the most common practices for increasing the flood forecasting lead time beyond the time of concentration is to use Numerical Weather Prediction (NWP) models (Cloke and Pappenberger 2009, Nam et al. 2014, Yucel et al. 2015). NWP models can quantitatively forecast precipitation and their use are becoming widespread among operational flood agencies as data on meteorological forcings and computational resources are more widely available (e.g. Jasper et al. 2002, Liguori et al. 2012, Liu et al. 2015). In this study, NWP forecast precipitation is considered synonymous with Quantitative Precipitation Forecast (QPF).

Many studies have been conducted for real-time flood forecasting using NWP precipitation along with hydrologic and hydrodynamic models (Verbunt et al. 2006, Roberts et al. 2009, Liguori et al. 2012). However, such studies have shown that the precipitation forecasting using the NWP remains challenging (Ebert 2001, Yucel et al. 2015). The high uncertainty of NWP precipitation at longer lead times propagates through the hydrologic transformation of flooding to often results in low skill in forecast of flood level (Bartholmes and Todini 2005, Nam et al. 2014).

Recent studies also show that the use of more regionally constrained NWP models (such as the Weather Research and Forecast-WRF model) can improve the QPF estimates in monsoon climates better than global NWP models (Kumar et al. 2016). Regional NWP models allow one to dynamically predict the mesoscale phenomena comprising convective and cumulus by taking advantage of terrain and

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land use features afforded by a higher resolution model (Rao et al. 2007, Hong and Lee 2009, Ahasan and Khan 2013, Hsiao et al. 2013, Sikder and Hossain 2016).

Several flood forecasting agencies in South and Southeast Asia where monsoon floods dominate (e.g. Bangladesh, Pakistan, India, Thailand and Vietnam) are currently using WRF as the regional NWP model as a source for higher resolution QPF (Shrestha et al. 2015). The Department of Hydrology and Meteorology-Nepal and Department of Hydro-meteorological Services-Bhutan have also begun introducing dynamically downscaled QPF precipitation for flood forecasting (World Bank 2016).

Although there are numerous studies reported in the literature to evaluate global QPF or the dynamically downscaled QPF precipitation performance, there appears to be lack of studies about the impact on the flood or flow forecasting skill. This study is motivated by the current lack of a structured approach to the use of NWP-based QPF forecasting for flow in monsoon dominated flood regimes. In particular, we are motivated by the need to improve the use of global QPFs from NWP in a way that is cognizant of the resource limitations of forecasting agencies of flood-prone countries. Our current study is also a natural progression from a series of two previous works carried out to systematically understand the impact of NWP parameterizations for cloud microphysics, cumulus physics and initial conditions on QPF skill (Sikder and Hossain 2016, 2018). The goal of these two previous studies was to explore a set of core model parameterizations for skilful QPF in monsoonal climates. The goal of this study is to explore the impact of those parameterizations on flow forecasting skill. To help readers understand the background for this study, we list key findings from the previous studies as follows:

(1) An optimal set of core parameterizations and scale exists for South and Southeast Asian regions that can be independently validated (Sikder and Hossain 2016). A regional NWP model can be setup for the monsoon-dominated region using a single set of model parameterizations. This optimized set of model parameterizations is suitable for operational flood forecasting system, where variable parameterization schemes for different events or ensemble forecasting is not a feasible option due to computational limitations.

(2) Betts–Miller–Janjic cumulus parameterization scheme with WRF Single-Moment 5-class, WRF Single-Moment 6-class and Thompson microphysics schemes exhibited the most skill in South Asian region (Sikder and Hossain 2016). These options can be used as the starting point of further studies, such as application of regional NWP for flood forecasting.

(3) Finer spatial resolution (3 km) regional NWP models without cumulus parameterization schemes do not necessarily yield significant improvements, especially if the cloud microphysics scheme is not sufficiently complex (Sikder and Hossain 2016). Use of the relatively coarser resolution (e.g. 10–30 km) model can save computational power and time, since this scale provides similar skill as the finer resolution in the monsoon weather.

(4) The more complex initial condition techniques typically involve more QPF uncertainty and cannot significantly exceed the performance of simple initialization techniques in monsoon weather (Sikder and Hossain 2018). Lack of good quality observed data in this region makes it difficult to improve the initial condition of real-time NWP forecast. Therefore, use of the simple model initialization technique is worthwhile for operational forecast.

The natural extension of above two studies is to now explore how well NWP-based QPF precipitation from global or regionally constrained models (i.e. dynamically downscaled by WRF) performs in flow forecasting during the flood season. An issue worth an investigation for operational flood agencies is whether flood forecasting in large river basins benefits from regionally constrained and higher resolution NWP models that are computationally prohibitive. We test the idea of publicly available global QPFs being sufficient for capturing flooding in large river basins of monsoon climates. The specific research question we ask in this study is 'How can we improve flood forecasting based on NWP precipitation forecast that is skilful and operationally feasible in resource limited settings of flood agencies of monsoon dominated countries?'

2. Study region

For assessment of operational flood forecasting based on NWP QPF, two of the world's largest river basins that experience large scale and seasonal flooding during the monsoonal season were selected. These are: Ganges Brahmaputra Meghna (GBM) basin and the Mekong river basin (MRB).

The Ganges, Brahmaputra and Meghna (GBM) river basins comprise land areas from Bangladesh, India, Nepal, Bhutan and China (Nishat and Rahman 2009, Figure 1). With Meghna river basin being a considerably smaller part of GBM, we shall confine our study to Ganges and Brahmaputra river locations. The total drainage area of GBM is about 1.72 million sq. km, with a population of at least 630 million. The downstream most country (i.e. Bangladesh) is the most flood-prone and occupies only 8% of GBM basin area. All of the basin streamflow flows through that country and discharges into the Bay of Bengal (Nishat and Rahman 2009). For more details about the basin, the reader is referred to Siddique-E-Akbor et al. (2014), while historical evolution of the **AQ3** flood forecasting system of Bangladesh may be found in Webster et al. (2010), Hossain et al. (2014a, 2014b, 2014c).

The MRB (Figure 1) is also a monsoon-dominated river basin currently undergoing rapid development due to increasing water and energy demand (Zarfl et al. 2015). It **AQ4** comprises land areas from China, Myanmar, Thailand, Vietnam, Laos and Cambodia (Kummu and Sarkkula 2008). In **AQ5** addition to development pressures, a changing climate (e.g. a changing Monsoon) and rising sea level are perhaps the biggest threats to livelihood in the MR (Syvitski et al. 2009). For more details on the MRB, the reader is referred to Hossain et al. (2017).

3. Models

3.1. Hydrologic model for QPF-based flood forecasting

The Variable Infiltration Capacity (VIC) model, first developed by Liang et al. (1994) was used as the macroscale distributed hydrological model for forecasting of riverine flooding in GBM and MRB. VIC is a large scale, semi-distributed macroscale hydrological model. It is capable of solving full water

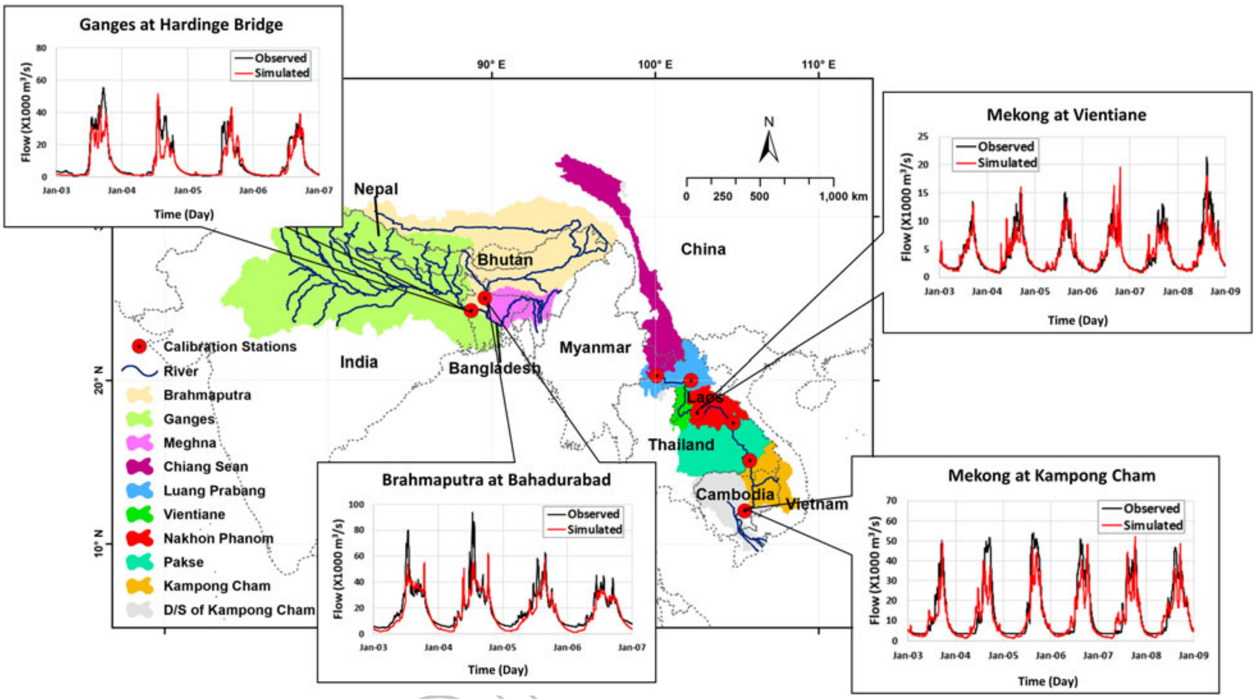

Figure 1. Study region along with VIC Model calibration points.

and energy balances. The basic structure of the VIC model is described in detail by Liang et al. (1994); followed by many papers that provide various updates to the model (e.g. Cherkauer et al. (2003) for cold land process updates, Andreadis et al. (2009) for snow model updates, Bowling and Lettenmaier (2010) for lakes and wetlands, among others). The model has been widely applied for purposes such as seasonal hydrological forecasting, climate change impacts studies, and water and energy budget studies among various other applications. VIC's distinguishing hydrologic features are its representation of the role of sub-grid variability as a control on soil water storage and in turn runoff generation, and its parameterization of base flow, which occurs from a lower soil moisture zone as a nonlinear recession (Dumenil and Todini 1992).

The basic model features of VIC are as follows: (1) The land surface is modelled as a (lumped) grid of large (>1 km), flat, uniform cells; (2) Inputs to the model are time series of daily or sub-daily meteorological drivers (e.g. rainfall, snow, air temperature, wind speed); (3) Land-atmosphere fluxes, and the water and energy balances at the land surface, are simulated at a daily or sub-daily time step; Water can only enter a grid cell via the atmosphere; (4) Grid cells are simulated independently of each other, and entire simulation is run for each grid cell separately, one grid cell at a time, rather than, for each time step, looping over all grid cells; (5) Routeing of streamflow is performed separately from the land surface simulation, using a separate model (i.e. the routeing model of Lohmann et al. 1996, 1998).

The VIC model was set up over Ganges, Brahmaputra and MRB at daily time step with 0.125, 0.25 and 0.1 degree spatial resolution, respectively. The model setups calibrated and subsequently validated based on quality-controlled hydro-meteorological forcing datasets from *in situ* and space platforms. Most of these quality controlled forcings are derived from Global Summary of Day (GSOD) archived by National Climatic Data Center (NCDC). Details of the calibration and validation are available in Siddique-E-Akbor et al. (2014) for GBM and Hossain et al. (2017) for MRB. Currently, this calibrated setup provides routine nowcast of streamflow, soil moisture and runoff operationally for 4 national agencies. These nowcast hydrologic variables are currently rendered for end users on the South Asian Surface Water Modeling System (SASWMS) portal (http://depts.washington.edu/saswe). Figure 1 shows the skill of the VIC model to capture the flow peaks during the Monsoon season for GBM and Mekong. Table 1 provides performance metrics in terms of RMSE and efficiency of the VIC model calibrated using the quality controlled forcing datasets prepared from GSOD. These metrics indicate that the VIC model acceptable for assessing the propagation of NWP-based QPF precipitation forecasts for assessment of skill in flood forecasting.

3.2. NWP model for QPF

The Global Forecasting System (GFS) developed by the National Oceanic and Atmospheric Administration (NOAA) was used as the key source of global NWP model-based QPF. GFS produces global-scale weather forecast every 6 hours up to 16 days lead time at a spatial resolution

Table 1. VIC Hydrologic model calibration and validation metrics for Ganges, Brahmaputra and Mekong river basins. Ganges and Brahmaputra basins were assessed at Hardinge Bridge and Bahadurabad, respectively, while Mekong basin was assessed at Kampong Cham (see Figure 1).

	Basin	Period	RMSE (m^3/s)	Correlation	Efficiency (Nash–Sutcliffe)
Calibration	Ganges	2002–2005	6523	0.89	0.78
	Brahmaputra	2002–2005	7606	0.91	0.86
	Mekong	2003–2008	6390	0.93	0.84
Validation	Ganges	2006–2010	7081	0.89	0.77
	Brahmaputra	2006–2010	10918	0.92	0.82
	Mekong	2009–2013	5615	0.92	0.85

of 1 degree. As a publicly available service for the world, GFS is ideal for short-term weather prediction applications, particularly in South Asia where economic resources are constrained (historical and real-time data are available: https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs). The spatial and temporal resolutions vary with lead time. For first 10 days of lead time, the GFS provides forecasts for every 3 hours, and the outputs are available at 0.25, 0.5, 1.0 and 2.5 degree resolutions. Historical data of this model are available in 0.5 degree resolution since October 2006. Lead time of the historical data varies with time. The 0.5 degree GFS-based NWP model QPFs were used to run this study for propagation through VIC model with or without dynamic downscaling by WRF.

3.3. The WRF model

The WRF model V3.7.1 was used for dynamic downscaling of coarse resolution global NWP weather forecasts, such as from GFS. Such downscaling generated high-resolution precipitation forecast over the GBM and MRB. WRF is a mesoscale cloud resolving NWP model, which is the successor of the MM5 model. It uses non-hydrostatic Euler equations, which are fully compressible in nature. WRF offers various features such as advanced dynamics, physics, and numerical schemes. For computation, the model uses Arakawa-C grid staggering for horizontal discretization, and second or third order Runge–Kutta integration scheme for time separation. WRF uses the terrain-flowing pressure coordinate system. Thus, the upper boundary of the model maintained by a constant pressure level. Further description of WRF physics and dynamics can be found in Skamarock et al. (2008).

The WRF model was recently applied in two previous studies to assess the role of cumulus and cloud microphysics parameterizations with scale (Sikder and Hossain 2016) and initial conditions (Sikder and Hossain 2018) over GBM and Indus river basins. The Sikder and Hossain (2016) study explored the choice of 3 spatial resolutions from 3 to 27 km with 3 cloud microphysics and 5 cumulus parameterizations. A total of 45 combinations of WRF configuration were assessed to identify a set up that was most skilful in predicting precipitation in the monsoon climates of Ganges, Brahmaputra. This optimal set up was later independently verified over Indus (Sikder and Hossain 2016). In the Sikder and Hossain (2018) study, various combinations of initialization of WRF model (known as hot start and cold start) were investigated with the optimal WRF set up identified in the earlier study. In this study, we have applied most optimal WRF set up (comprising the appropriate parameterization and skill) identified in the previous two studies, over GBM and MRB and for investigation of the impact of dynamic downscaling of QPF on flood forecasting. This set up is: 9–27 km spatial resolution; WSM5 or WSM6 or Thompson cloud microphysics scheme and Betts–Miller–Janjic cumulus parameterization with a cold start for model initialization.

4. Assessment methodology

We first investigated the impact of regional NWP (i.e. WRF) based dynamic downscaling of global QPF on flood forecasting by comparing it with flood forecasts generated from global QPFs only. For both basins, a one month time period was selected during the peak of the monsoon. The selected time range for the basins is: 1 August–10 September 2015 (41 days) for GBM; and 1 September–30 September 2011 (30 days) for MRB. These two periods were unusually flood-prone (high flow) episodes and therefore ideal for investigation of QPF-based flood forecasting.

The available 3 hourly GFS forecast data (global QPF and other relevant forcings) have a lead time up to 10 days and 8 days in case of GBM and Mekong basin, respectively. To generate the continuous 10 days WRF forecast within the study period of GBM basin, the WRF model was initialized 9 days before 1 August 2015 (i.e. 23 July 2015, total 50 days of simulation). In this way, continuous 1–10-day WRF simulated forecasts were generated for selected study periods. Similarly, the simulation of the MRB was started 7 days before 1 September to generate a complete 8-day forecast for the study period (total 37 days of simulation). For each day of forecast, the VIC model was spun up with the prior 2 years of data (i.e. GSOD precipitation) to reach equilibrium conditions.

Two different years were selected for these river basins based on the intensity of the monsoon season. The idea was to select years with contrasting intensity of precipitation for testing the forecasting scheme. The years 2009 and 2015 were selected for the GBM basin, where 2009 experienced a relatively less intense monsoon season. Similarly, the monsoon season in the year 2010 was relatively weak in Mekong basin, while 2011 was an extreme flood year. The WRF model was simulated using the selected optimized setup (i.e. WSM5-BMJ with 27 km grid), for these two monsoon seasons starting from June to September of each year. The VIC model then forced by the forecasted precipitation and the first month was excluded from the analysis as model spin-up time. The results of the further study were reported based on the July–September month flow outputs.

5. Results

Figure 2 shows an example of the skill of flood forecast in the MRB at the location of Kampong Cham at a 6-day lead time. The flow forecast pertinent to Julian Day on the *x*-axis that was predicted 6 days ago is presented for various combinations of QPF (global from GFS or regionally downscaled by WRF) and compared against observed streamflow, observed climatology and VIC modelled streamflow. The difference between long-term observed climatology and other flows (i.e. observed and simulated) indicates that 2011 was an extreme flood year in the Mekong basin. The figure indicates that the difference between the optimized WRF setups is not significant. Moreover, the performance of the global NWP (i.e. GFS) is almost similar to the optimized WRF setups. Since the optimized WRF setups performed equally well, we used the computationally less expensive option, the WSM5-BMJ with 27 km grid as the WRF forecast for further study.

Figure 3(a,b) provides a closer look at the performance of flood forecast for various lead times for GBM basin in the context of VIC simulated flow from quality controlled nowcast forcing (shown as 'GSOD' in the figure) as well as observe flow. The various lines represent the forecast as obtained from global QPF (GFS) and downscaled QPF (GFS downscaled by WRF) for a given optimum spatial resolution (i.e. 27 km). A good quality and skilful forecast is one that closely remembers the line obtained with quality controlled nowcast forcings (i.e. from GSOD in Figure 3(a,b)). What is clear from these Figures 2 and 3(a,b) is that the skill of regionally downscaling

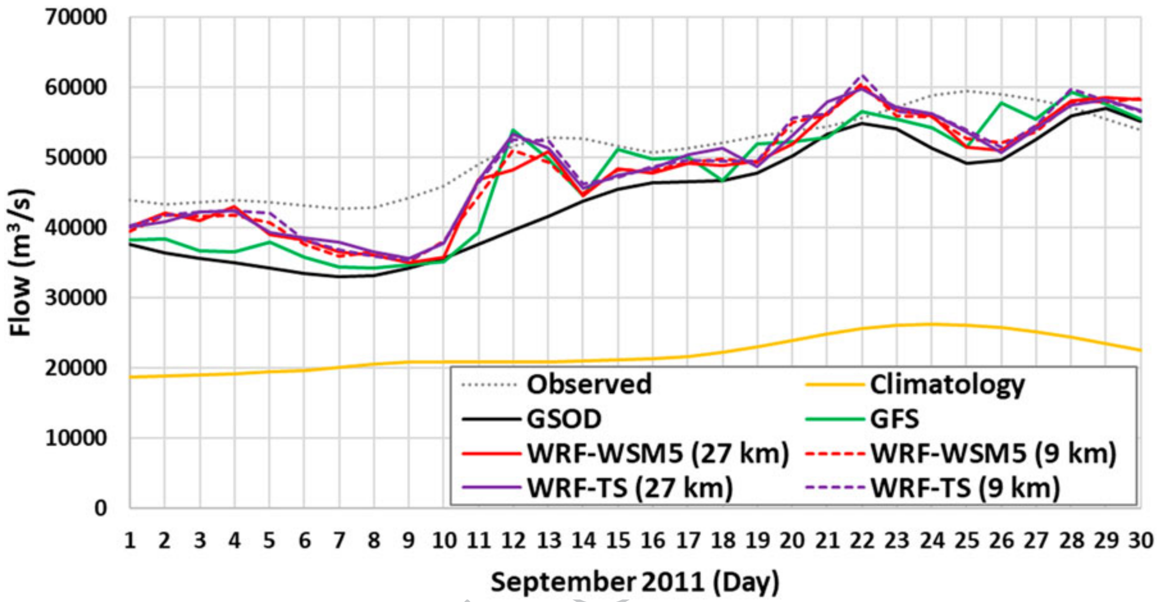

Figure 2. Flow forecast obtained from WRF downscaled GFS forecasts and global QPF (as GFS) and compared with GSOD and observed flow at the 6-day lead time. The comparison was conducted at Kampong Cham in Mekong river (see Figure 1 for location of Kampong Cham). Here: GSOD is Global Summary of Day archive by NCDC and represents the flow simulation by VIC model from quality controlled forcing datasets ; GFS is the flow forecast obtained at 6-day lead using the global QPF in VIC model as is without any dynamic downscaling; All other lines except for 'Observed' represent various combinations of dynamically downscaled QPF via WRF. WSM5 – a cloud microphysics (MP) scheme found optimal for monsoon climates; TS – Thomson cumulus scheme found optimal for monsoon climates. Details on the skill of precipitation forecast for TS and WMS5 parameterizations can be found in Sikder and Hossain (2016, 2018).

global QPF in flood forecasting is comparable to that from using only global QPFs. At times, the global QPF (see GFS-3day in Figure 3(a) for Brahmaputra river basin) seems to outperform modestly the downscaled QPF in flow forecasting. For the Ganges river basin, it appears there is a modest benefit of applying regional NWP for flood forecasting. Overall, due to the very modest gain (or the lack of it) in flood forecasting skill, there is no clear trend that informs an operational flood forecaster that incorporating computationally intensive QPF dynamic downscaling is worthwhile.

It is important to state that the above finding should not be misconstrued as dynamic downscaling being unnecessary in all circumstances. There could be many factors at play for this apparent lack of clarity on the flood forecasting benefits of using downscaled QPF as indicated earlier. There may also be potential dependency on the quality of the hindcast meteorological data used in VIC model due to the hydrological system memory or the lack of appropriate hydrologic process complexity to take advantage of higher resolution and dynamically downscaled QPFs. It is likely that the coarser grid

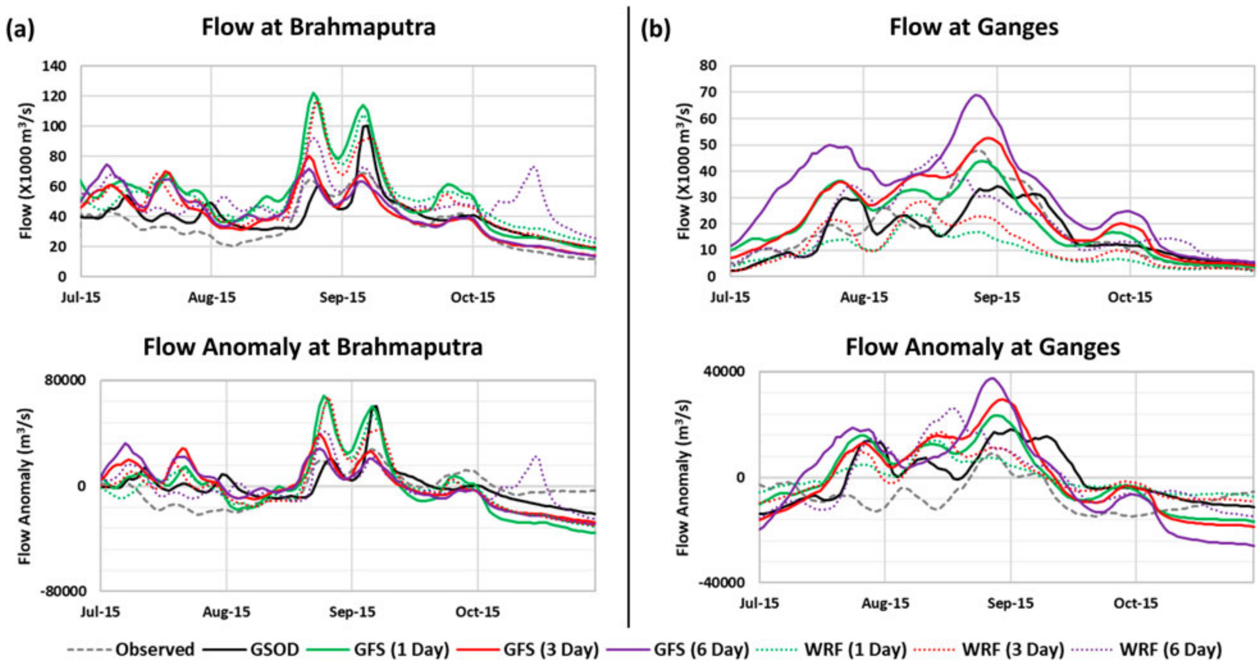

Figure 3. (a) Assessment of flood forecasting from NWP QPF (downscaled or global) for various leads times for Brahmaputra river basin at Bahadurabad location inside Bangladesh (see Figure 1). GFS represents the global QPF forecast as publicly available without any downscaling, while WRF represents the dynamically downscaled QPF via WRF. The WRF configuration pertains to 27 km resolution and WSM5 and BMJ combination. GSOD represents the VIC modelled flow from quality controlled forcing datasets (nowcast). Upper panel shows actual forecasted flows; Lower panel shows flow anomalies relative to the observed flow climatology. (b) Same as Figure 4(a) but for Ganges river basin assessed at Hardinge Bridge location inside Bangladesh (see Figure 1).

increments of global NWP (GFS) are more than compensated by consistent dynamics and parameterizations throughout. However, for very complex terrain where local terrain drives significant mesoscale circulations amplifying precipitation, dynamic downscaling is known to be essential. In large river systems, localized precipitating systems are not the dominant mechanism for riverine flooding. The goal of this study to explore practical and operationally feasible ways where an agency can advance operational flood forecasting using global QPFs that are publicly available (see next section).

Since precipitation data from any NWP model contains systematic bias, it should be corrected before using in hydrologic purpose. Many studies have been conducted to find out an appropriate bias correction approach for global as well as regional NWP precipitation forecast (e.g. Mpelasoka and Chiew 2009, Chen et al. 2013). Few of the studies suggested that the quantile mapping bias correction approach shows relatively better performance in case of heavy precipitation (Themßl et al. 2011). However, it is difficult to identify a bias correction approach that works universally well for all situations (Räty et al. 2014).

Given the apparent lack of overwhelming benefit of dynamically downscaled QPF in flood forecasting for the hydrologic model in question (VIC), our next goal was to develop a practically efficient approach as a correction technique for global QPFs in order to maximize its skill in precipitation. Here, we used the 'delta change' method (Hay et al. 2000), which is reported to be not a significant departure from the distribution mapping approach (Roosmalen et al. 2011). This approach is modular enough that it can be easily applied to downscaled QPFs from WRF as well. The approach is based on climatology of forecasts from NWP and it applies bias correction by taking advantage of anomaly from climatology of observations. We applied the approach on both global QPFs and downscaled QPFs to compare the relative performance.

In delta change (also known as 'constant scaling') bias correction methodology for QPF, the daily gridded precipitation climatology was derived from gridded NCDC–GSOD data that is available in a quality controlled format over a long period. These gridded NCDC–GSOD data were already used for VIC model calibration and validation. This gridded climatology is considered as the true (or observed) climatology of the area or the river basin. Next, the daily gridded climatology was calculated for global NWP QPFs (i.e. GFS) for a given lead time from 1 (L1) to 7 days (L7). The gridded daily anomaly of GFS precipitation for each Julian day of forecasting was then calculated using this global QPF climatology for a given lead time (L1–L7). Finally, this anomaly was added to the true (or observed) gridded climatology from the NCDC–GSOD dataset to derive the bias-corrected NWP QPF for use in operational forecasting. The bias-corrected global QPFs generated for each day was then used to force the VIC model and forecast the consequential flow at river locations. In essence, what the flood forecaster would do every day is extract the global QPF for the forecasting domain or river basin, then derive the anomaly from QPF climatology pertaining to various lead times and finally add that anomaly to the observed climatology for that day.

6. Discussion

In this study, two approaches of 'delta change' bias correction were carried out. Figure 4 demonstrates the concept of the used bias correction methodology (i.e. delta change) to daily QPF using QPF climatology and true climatology using over the GBM basin. At first, the gridded GFS climatology was calculated using only 1-day lead time precipitation forecast. Herein, GFS and QPF imply the same forecast dataset. This 1-day lead time GFS climatology was considered as the constant or universal GFS climatology for different lead times for the sake of computational efficiency. In the second approach, the gridded daily GFS climatology was calculated for different lead times and not just for lead time 1 day or L1. For example, the 3-day lead time (L3) QPF climatology was calculated using the 3-day lead time QPF.

The impact of bias correction analysis was carried out for the monsoon period of 2007–2016. Figure 5 shows the impact of applying this bias correction to QPF for flow forecasting for Brahmaputra, Ganges and Mekong river basins, respectively. These figures are showing the flow climatology (10-year average flow) of three river basins.

Two clear trends are apparent from this figure. First, the bias correction approach based on QPF climatology yields significant improvement in flood forecasting skill with drastic reduction in flow bias between observed and forecast at all lead times for all three river basins. Second, the use of QPF (GFS) climatology pertaining to the corresponding lead time improves flood forecast skill further compared to the use of computationally simpler 1-day QPF climatology (see the middle and lower panels of Figure 5).

In the next step, we implemented the same bias correction approach on downscaled QPF (GFS) derived from WRF to identify the potential net benefit of using regional NWP for flood forecasting. WRF climatology was prepared from the simulated output of 2007–2016 (1-day lead time), like GFS. We used the 1-day QPF climatology as the reference for bias correction to save the computation time required to develop 1–7-day QPF climatology of WRF. To be consistent with the WRF, we used the same approach for the GFS, though 1–7-day climatology was available for GFS. It should be noted that the performance of the bias-corrected QPF can be improved more by using corresponding lead time climatology (lower panel of Figure 5). Table 2 summarizes the forecast performance (skill in terms of correlation and normalized RMSE) for all three river basins after applying the bias correction. As the performance results for all basins follow mostly a similar trend, we show herein results from the MRB as an example (Figure 6). Two contrasting years were picked for the assessment of bias correction of WRF downscaled QPF – 2010 as the relatively weak flood year and 2011 as a very strong flood year. Figure 7 shows the overall performance of the GFS and WRF forced flow forecast in three river basins during strong flood season. The figure indicates that the performance of the QPF-based flow forecast is better than the climatology-based forecast with exception of few cases in higher lead time.

What is also clear from Figures 6 and 7 or Table 2 is that while at lower lead times, there is no apparent difference between the flood forecasting skill of global QPF or downscaled QPF, the bias correction approach yields higher benefits for global QPF at longer lead times. In lower lead times, the performance of the downscaled QPF is mostly dominated by the initial condition of the NWP model, which is essentially the global QPF. At longer lead times, the bias correction methodology for WRF downscaled QPF appears to perform modestly worse than the bias-corrected

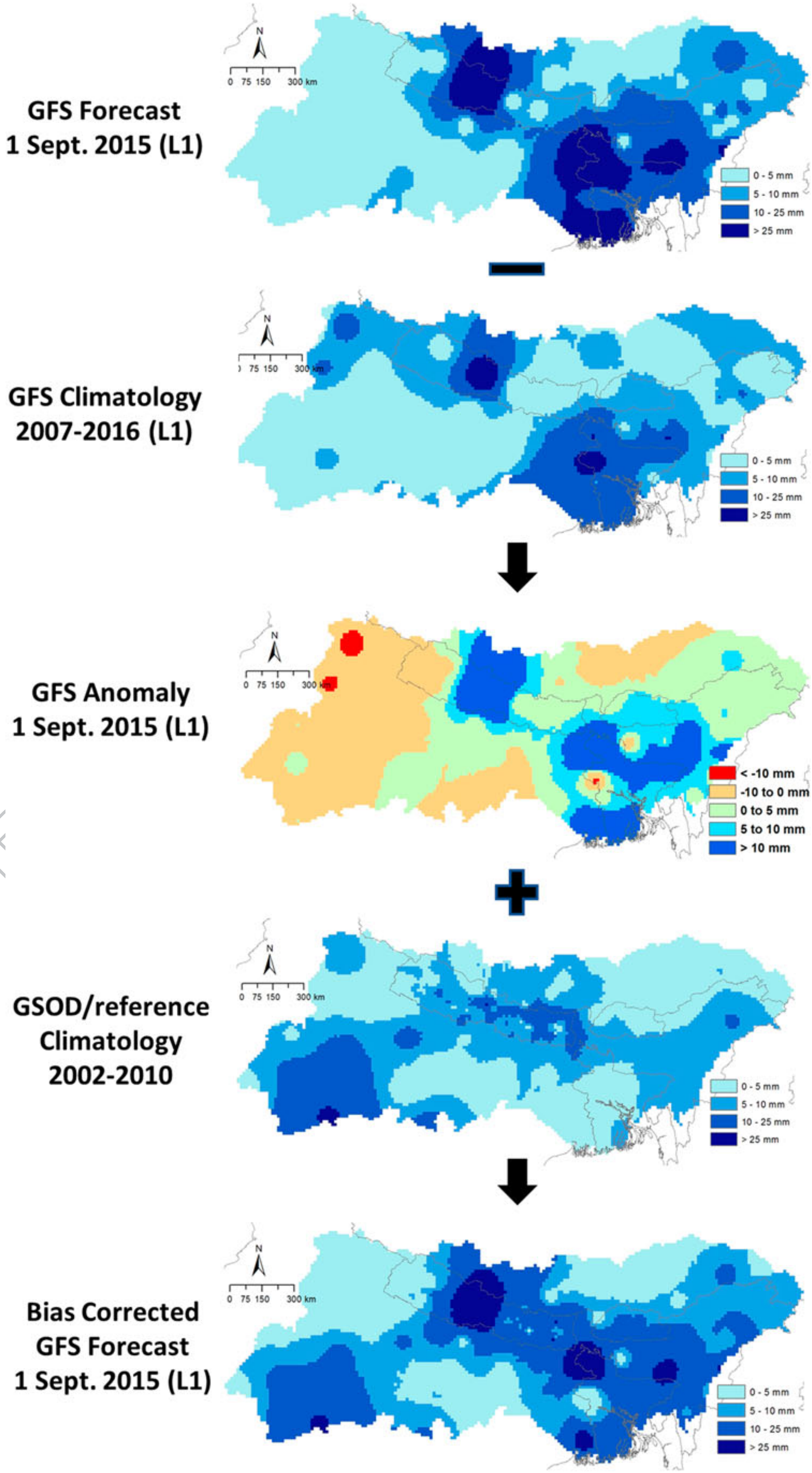

Figure 4. A proposed and simple methodology for bias correction of QPF data based on climatology of observation, QPF or downscaled QPF.

global QPF. There are likely many reasons behind this observation, with the critical ones being hydrologic, and stemming from the choice of hydrologic model, model initialization, hindcast, sensitivity to scale, etc. These physical features of a hydrologic model are known to interact in a nonlinear fashion with higher resolution forcing to often magnify the uncertainty in the simulation of the output (i.e. flow) (Nam et al. 2014). This also brings up the intriguing issue of commensurate hydrologic model complexity in terms of scale and processes that can take advantage of the dynamically

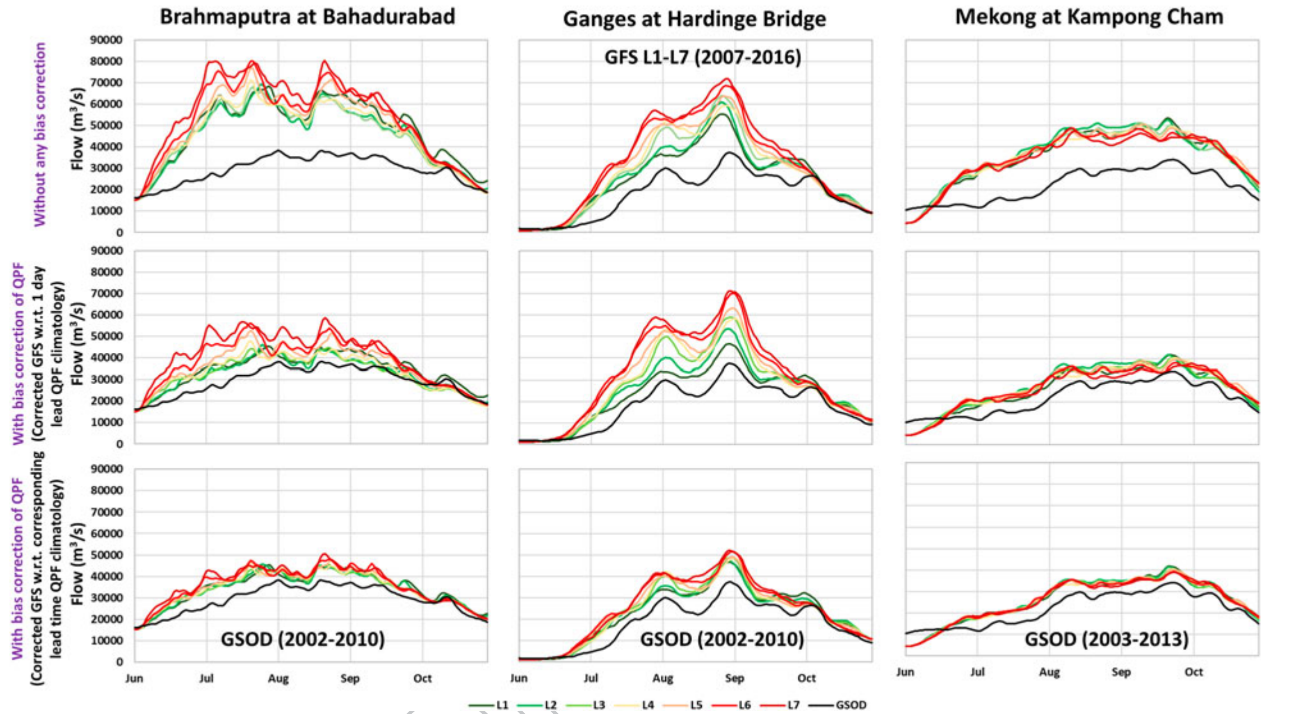

Figure 5. Impact of using bias corrected global QPF (from GFS) on flow climatology, with no dynamic downscaling on flood forecasting for Brahmaputra, Ganges, and Mekong river basin at Bahadurabad, Hardinge Bridge, and Kampong Cham station, respectively. The lower panel is the flood forecast based on bias corrected QPF using QPF climatology of the corresponding lead time; middle panel is bias corrected QPF using QPF climatology corresponding to lead time 1 day as representative climatology for all lead times. The GSOD line is the simulated VIC flow obtained from quality controlled nowcast forcings that can be considered as a benchmark. LX stands for lead time at X day.

downscaled QPFs with higher spatial resolution. Perhaps a higher resolution and more physically distributed and complex hydrologic model (such as MIKE – SHE) would be able to accentuate the benefits of downscaled QPF in flood forecasting. However, the operational agency has to weigh in the benefit of such models in the context of the significant cost to its daily operations.

It is beyond the scope of this study to investigate the underlying hydrologic causes and this study is motivated by the need for an operationally feasible approach in resource-constrained settings of the developing world. We are therefore of the opinion that for an open-source, macroscale (10km × 10 km, daily) hydrologic model like VIC, the use of global QPF with bias correction based on QPF climatology (and without any dynamic downscaling) has great operational appeal to flood forecasters in developing nations. This appeal stems from the fact that the computationally prohibitive WRF need not be applied every day or every time step to update flow forecasts in large and higher order rivers with a lot of hydrologic processes integration. The publicly available global QPFs can be used ‘as is’ after some efficient bias correction to maximize the flood forecasting skill. In our study, the consistent performance of the computationally efficient bias correction approach for global QPFs is the take-home message. We therefore recommend this approach to flood forecasters who routinely use QPF as a practical innovation for improving operational flood forecasting in monsoon dominated flood regimes. We believe such a simple approach has not appeared in flood forecasting literature to the best of our knowledge.

7. Conclusions

Having studied closely in real-world operational forecasting settings (Hossain et al. 2014a, 2014b, 2014c), we have realized that the advancement of existing flood forecasting schemes in monsoon-driven flood regimes requires both computational feasibility as well as enhanced skill at longer lead times (>5 days). The skill requires to be of a nature that allows agencies to issue specific warnings very quickly at specific locations with quantitative clarity well in advance of the hardship the local inhabitants are likely to face. If the forecast generation is time-consuming, then valuable time is lost in disaster response and management. In our study, it is quite clear that flood forecasting systems using macroscale hydrologic models like VIC can benefit modestly from the application of regionally downscaled QPFs by WRF. However, the modest benefit does not appear to justify the significant

Table 2. Performance (correlation and % NRSE in parenthesis) of the bias correction methodology for global QPF (GFS) and WRF downscaled QPF in flow forecast for Ganges, Brahmaputra and Mekong rivers.

	Ganges (July–October 2009, 2015)			Brahmaputra (July–October 2009, 2015)			Mekong (July–October 2010, 2011)		
Lead time (Day)	Refer.	GFS	WRF	Refer.	GFS	WRF	Refer.	GFS	WRF
1	GSOD	0.74 (87.3)	0.62 (81.9)	GSOD	0.86 (27.4)	0.87 (24.7)	GSOD	0.77 (34.4)	0.81 (38)
2	0.82 (39.5)	0.78 (62.2)	0.68 (53.9)	0.7 (29.5)	0.88 (19.7)	0.85 (23.7)	0.86 (24.9)	0.75 (39.8)	0.66 (62.3)
3	Climat.	0.84 (54.4)	0.69 (53.2)	Climat.	0.82 (23.4)	0.81 (27.6)	Climat.	0.73 (38.8)	0.68 (67.8)
4	0.63 (63.5)	0.85 (61.5)	0.76 (54)	0.55 (35)	0.74 (27.8)	0.78 (29.4)	0.63 (62.2)	0.68 (38.7)	0.65 (74.6)
5		0.83 (93.3)	0.83 (61.9)		0.68 (31.7)	0.72 (32)		0.58 (43.3)	0.54 (94.7)
6		0.82 (101.9)	0.76 (78.9)		0.63 (34.5)	0.57 (41.1)		0.54 (42.1)	0.46 (105.2)
7		0.83 (113.1)	0.66 (102.3)		0.44 (53.3)	0.56 (43.6)		0.57 (40.5)	0.32 (96.9)

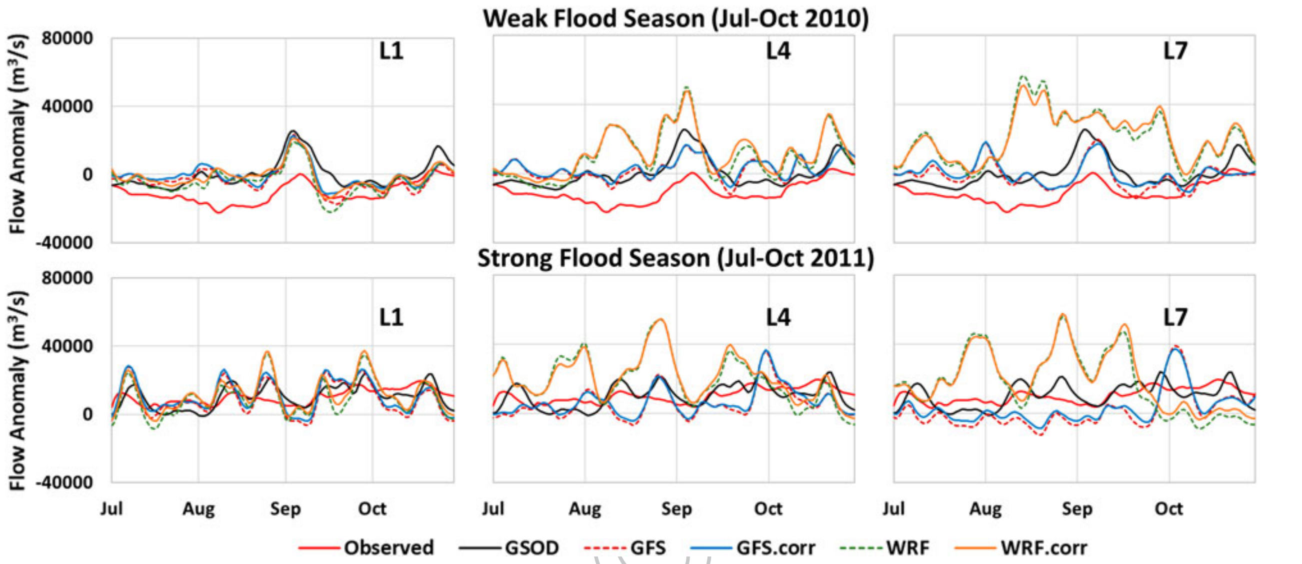

Figure 6. Flow anomaly (relative to climatology of observed flow) for various combinations QPF (bias corrected or downscaled) for Mekong river at Kampong Cham. Suffix '.corr' stands for the bias-corrected QPF.

computational burden of dynamic downscaling when compared with the bias-corrected approach for global QPFs. We have developed our bias correction methodology for global and publicly available QPFs such that flood forecasting agencies can apply it efficiently every day without requiring time-consuming dynamic downscaling. Such a correction approach has been shown to significantly and consistently improve the skill in flood forecast for all three river basins of Ganges, Brahmaputra and Mekong studied here for important flood years. To the best of our knowledge, flood forecasting agencies of the developing world are not yet applying such an efficient approach to take advantage of the global QPFs

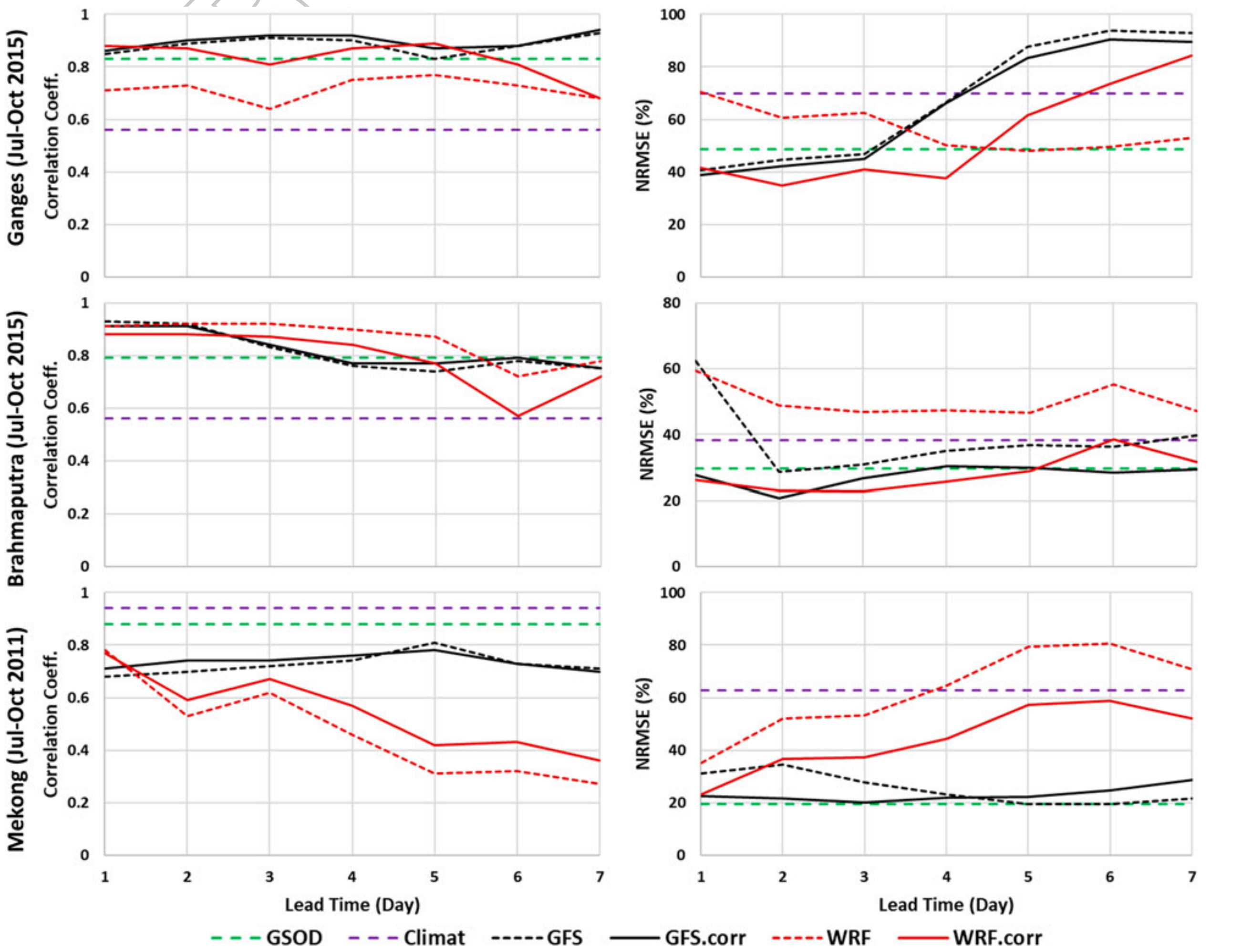

Figure 7. Flood forecasting skill in the three river basins based on bias-corrected and uncorrected QPF data with and without dynamic downscaling on extreme flood year. Upper panel – Ganges at Hardinge Bridge; Middle panel – Brahmaputra at Bahadurabad and lower panel – Mekong at Kampong Cham. NRMSE refers to RMSE of forecasted flow normalized by observed flow and expressed as a %.

that are publicly available. Furthermore, the simplicity of the bias correction methodology implies that it can be applied to any other forecast dataset such as WRF downscaled QPF or those that are not publicly available (e.g. from European Center for Medium Range Forecasting). If agencies are already employing computationally intensive techniques routinely (such as dynamic downscaling at forecasting time step), the bias correction methodology will further improve the skill with the choice of an appropriate hydrologic model. It is our belief therefore that such computationally efficient methodology is the future for most, if not all, flood forecasting agencies that deal with monsoon-driven large-scale flooding in the developing world and require to spend more time on disaster response and management.

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