The Record 2017 Floods in South Asia: State of Prediction and Performance of a Data-based Regional and Local Scale Requisitely Simple Forecast Model

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1 Introduction

Floods cause more than $40 billion in damage annually across the globe, according to Organization for Economic Cooperation and Development (OECD, 2018). As the world experiences unprecedented degradation of ecosystem services and increasing climate variability and change, flooding has become a barrier to sustainable development globally (WMO, 2018). In Monsoon regions of South Asia, the strong seasonal and inter-annual variability of the monsoon rainfall and these large transboundary river basins pose a great challenge to water users and managers alike on how to best manage the resources and achieve water security in a sustainable manner (Webster et al., 2010; Akanda, 2012). Flood forecasting thus remains a major challenge in this region and in the field of hydrology and water resources, requiring considerable research and investment (Biancamaria et al., 2011; Palash et al., 2018).

In August 2017, the major river basins of South Asia—the Ganges and the Brahmaputra (GB) in particular—were affected by devastating floods that caused widespread death, destruction and agricultural loss. Due to heavy rainfall and subsequent rise in streamflow of the rivers, the August 2017 floods inundated a large part of India, Nepal and Bangladesh (Figure 1a); over a thousand people died and 40–45 million people were affected (Gettleman, 2017; Siddique, 2017; SADN, 2017). While the death and destruction that a flood brings are tragic, it presents an opportunity to explore and learn necessary lessons about the hydrometeorology of these river basins and identifies future actions on flood response (SADN, 2017).

Observed rainfall data of the GB basins from gauges in upstream nations are not readily available on a real time basis. This is also true for several other large river basins around the world, where upstream data is prohibited or difficult to collect for downstream nations (Palash et al., 2018). Thus, the hydrology community around the world is increasingly relying on satellite and weather model driven rainfall data for prediction of floods (Biancamaria et al., 2011; Hirpa et al., 2013). Simultaneously, assessing the accuracy of these non-gauge datasets is getting enormous importance and traction in recent times (Bajracharya et al., 2014). Therefore, a detail examination of non-gauge rainfall dataset's ability to capture peak rainfall event prior a large flood like the August 2017 GB flood is warranted.

Although the flood caused widespread damage in parts of Nepal, Eastern India and Northern Bangladesh and generated worldwide attention, the actual flood events were short lived. The hydrometeorology that prevailed before and during the 2017 floods has been partly discussed in several recent publications, Alfieri et al. (2018), Hossain et al. (2019) and Philip et al. (2018); however, key knowledge gaps remain in understanding the evolution of the flood in the context of the GB region hydrometeorology and the basin rainfall-runoff mechanisms at work during 2017 August that have not been fully explored yet.

From August 5, 2017, the eastern part of the Ganges and southwest part of the Brahmaputra basin received continuously high rainfall until mid-August, which led to a sharp rise in Brahmaputra and a steady rise in Ganges water level (WL). The Brahmaputra river in western Assam and northern Bangladesh crossed its danger level (DL) on August 14, reached its recorded highest WL two days later and receded back to below DL on August 20. The Ganges river was still on the rise in Bihar, West Bengal (India) and eastern Bangladesh, reached very close to DL on August 25 and started receding three days later.

On August 12, the Global Flood Awareness System (GloFAS), jointly developed by the European Commission (EC) and the European Centre for Medium-Range Weather Forecasts (ECMWF), issued a forecast that the Ganges and Brahmaputra (GB) basins would face major floods in the next 10 days with a possibility of occurring a 200-year flood in the Brahmaputra basin (http://www.globalfloods.eu/). The GloFAS's prediction were covered widely in local media and led to nervous response among the people of Bangladesh who live in the most downstream regions of these basins. For instance, nearly all national print and electronic media of Bangladesh reported the prediction widely by referring ECMWF where some of the news headlines read like these: "the largest flood is coming, could exceed 1988 floods" (Prothom Alo, August 14); "the largest flood in 200 years is predicted" (Manabzamin, August 14); "most fearful flood in the history of the country is expected" (Banikbarta, August 14, 2017); "people have not seen flood like this before" (Prothom Alo, August 20, 2017). Important to note that, no other international, regional, or local agencies came up with such a prediction during that time.

In reality, the Brahmaputra flood flow measured inside Bangladesh during mid-August corresponds to a 65–75-year return period flood (according to our analysis), which is recorded highest flood event for this river basin also. The Ganges peak flood flow during the same period was an average flood event. So, a record flow in the Brahmaputra and an average flow in the Ganges, despite nearly a peak flow synchronization, did not generate as large a flood as 1988 or 1998, when nearly two-thirds of the country went under water (Mirza et al., 2001). However, the magnitude of the 2017 floods in the Brahmaputra basin caught the basin nations by surprise (Chowdhury, 2017; SANDRP, 2017a).

The challenges and opportunities of forecasting large river basins like the GB basins by using a simpler modeling framework called Requisitely Simple (ReqSim) flood forecast model, which was run on a real-time basis during 2017 flood, are also discussed in this paper. The key questions that we attempt to answer in this paper, therefore, are: a) How severe was the rainfall preceding the flood events of August 2017, and how successfully was that captured in various satellite and numerical weather model generated observed and forecasted data? b) What led to a 200-year flood warning in the Brahmaputra basin and what happened in reality?, c) How did the ReqSim model perform in capturing the 2017 Brahmaputra floods in north Bangladesh?, and d) Can the ReqSim model be adapted for local scale forecasts of streamflow in downstream river points inside Bangladesh?

2 Materials and Methods

Satellite and weather model generated rainfall are known to produce poor agreement at day-to-day or point-to-point data comparisons (*Bajracharya et al. 2014*). Rather these datasets show reasonable accuracy in capturing synoptic rainfall pattern over a large area or temporal aggregation of point rainfall or a combination of both (i.e., space-time aggregated rainfall) (*Bajracharya et al. 2014; Palash et al. 2018*). So, we first compared the spatial coverage of five days (August 9–13) total rainfall that led to the mid-August flood and then daily rainfall of entire 2017 monsoon (June–September) aggregated over four large domains of GB river basins (Figure 1b) with gauge measured rainfall data. Selected non-gauge rainfall datasets include the Tropical Rainfall Measurement Mission (TRMM) 3B42 RT, Global

Precipitation Measurement (GPM) Early Run v.4, ECMWF ERA-Interim, Climate Prediction Center (CPC), and Weather Research and Forecasting (WRF) model.

We investigated the GB hydrometeorology that prevailed before and during the August 2017 floods, examined the river conditions, sequences of monsoon rainfall and attempted to understand the reason that led to a 200-year flood warning in the Brahmaputra basin. We applied extreme value analysis (EVA) of GB basins' rainfall and streamflow to estimate the return period of various hydrometeorological events. We compared the August 2017 flood with two previous large floods in the region, 1998 and 2007, to discuss the mechanisms behind the large floods. Uncertainty in quantitative rainfall observation and forecasts data is widely considered as major limitations of developing short (3–5-day) to mid-range (6–10-day) flood forecasts (*Cloke & Pappenberger 2009; Charba & Samplatsky 2010; Dravitzki & James 2011; Palash et al. 2018*). However, developing lumped to detailed hydrological modeling, employing satellite altimetry, or adopting more complicated hybrid methods (e.g., *Webster et al. 2010; Hopson & Webster, 2010; Hossain et al. 2014; Yucel et al. 2015*) continues with wider acceptability and appreciation towards operational flood forecasts for 5–10-day lead times. Within this context, we examined the utility of a data-based modeling framework with a requisite simplicity approach (*Ward 2005; Stirzaker et al. 2010; Cilliers et al. 2013; Palash et al. 2018*) that identifies key variables and processes of rainfall runoff mechanism of a river basin and developed a Requisitely Simple (ReqSim) 1–10-day flood forecast model for the GBM Rivers. The details of this model, data, approach, and applications have been published earlier in *Palash et al. (2018)*. By using the outputs of the regional scale GBM model, we have developed a follow-up ReqSim model for the local scale—that is, the alluvial river system in the downstream of the GBM river basins inside Bangladesh. Section 6 provides details of the local scale ReqSim model development. Both regional and local scale models were run experimentally during 2017 floods seasons of the region, and this manuscript presents the results of both models.

The ReqSim model relies on easily available precipitation datasets like TRMM and GPM and ground observations at forecast locations (e.g., WL or streamflow). We ran the model at a daily time step for the 2017 flood season and generated real-time forecasts of three most important basin outlet points of the Ganges, Brahmaputra and Meghna (GBM) river basins (Figure 1b) through which about 80% of the flood season water enters Bangladesh (Palash et al. 2014). Generating reliable forecasts of these three river points is usually considered a major challenge to existing flood forecast and disaster management activities in Bangladesh (*Hopson & Webster 2010; Hossain et al. 2014*). We have also expanded the ReqSim model coverage to another 30 downstream river points in the north, east, and central region of Bangladesh during 2017 flood period. The current paper, therefore, presents a holistic performance evaluation of the ReqSim flood forecast model for the 2017 monsoon and the August flood event.

3 Data

We collected observed rainfall, WL and streamflow data of the GB river basin for the August 2017 flood and the historical period from Bangladesh Water Development Board (BWDB) (https://www.bwdb.gov.bd/) and Institute of Water Modeling (IWM) (www.iwmbd.org). For basin historical rainfall data, we relied on the APHRODITE (Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation) dataset for 1957–2007 and TRMM 3B42 for 1998–2017 period. The basin-wide monsoon and 5 and 9-days annual maximum rainfall of these two datasets were compared first for their common period (1998–2007), calculated and applied a bias correction to TRMM for 2008–2017 period and a complete data series for 1957–2017 period was prepared. The satellite and weather model generated rainfall data were collected from: i) TRMM 3B42RT v.7 (special resolution 0.25^0) (Goddard Earth Sciences Data and Information Services Center, 2016), ii) GPM 3IMERGDE v.4 (0.1^0) (Huffman, 2016), iii) ECMWF ERA-Interim (0.5^0) (http://apps.ecmwf.int/datasets/), iv) CPC NOAA (0.5^0) (Chen et al., 2008, https://www.esrl.noaa.gov/psd/data), and v) Weather Research Forecast (WRF) (0.250) from IWM.

4 2017 August Floods

4.1 The peak rainfall events and performance of datasets

Unusually heavy rainfall occurred in the second week of August across southeast Nepal; south Sikkim, north West Bengal, and west Assam provinces of India; southwest Bhutan; and northwest Bangladesh region. According to gauge measured and satellite data, some places in these areas received more than 500 mm rain over a 5 days period from August 9–13 (Figure 1c–1h). An extreme value analysis (EVA) reveals that annual maximum 5 (9) days total rain in the Brahmaputra domain IV, occurred over August 9–13 (August 7–15), were 45 (15)-year return period events. They were 8 (5)-year events in the domain III of the basin. Considering entire basin, the peak rainfalls were 50 (20)-year events, which led to a 65–75-year flood flow in the downstream. So, the peak rainfall event in the lower Brahmaputra region preceding the mid-August 2017 flood was indeed extremely high.

Regarding the non-gauge rainfall dataset's ability to capture extreme rainfall events in the region, TRMM and GPM show a much better coverage of rainfall observations across the region. They also a show close similarity to the distribution of gauge rainfall along the Nepal and India border; south Sikkim, north West Bengal, and east Assam in India; east Bhutan; and northwest Bangladesh region (Figure 1d–1**Error! Reference source not found.**e). The rainfall patterns in the southern coastal and southeast Hilly regions of Bangladesh are also captured well by these two datasets. ECMWF rainfall too successfully captures the overall rainfall patterns in the GB basins (Figure 1f). CPC shows high rainfall in lower parts of the GB (e.g., in Bangladesh), but failed completely along the India-Nepal border, in Assam (India) and Bhutan (Figure 1g). WRF is the only forecasted rainfall considered here that provides 1–6-day rainfall forecasts. Although WRF captures heavy rainfall distribution and magnitudes with reasonable accuracy, it overestimates rain significantly in areas where gauge or other datasets do not show much rain (Figure 1h).

Figure 1 here.

Figure 2 here.

The domain average daily rainfall of all non-gauge dataset shows an impressive agreement with gauge data in all Ganges domains (Figure 2). It is reasonable in domain IV, moderate in domain III, and poor in domains II and I of the Brahmaputra basin. The non-gauge rainfall estimates work better in wet regions (e.g., the eastern Ganges and the southern Brahmaputra) than comparatively arid regions (e.g., the western Ganges and norther Brahmaputra). TRMM and GPM datasets show significantly better correspondence to gauge data. For example, the R^2 of domain I–IV rainfall of TRMM (GPM) vary from 0.43–0.82 (0.32–0.78) in the Ganges and from 0.14–0.78 (0.14–0.73) in the Brahmaputra basin.

The performance of WRF's 1-day forecast is moderate (poor) in the Ganges (Brahmaputra) basin; e.g., R^2 of domain I–IV rain varies from 0.36–0.65 (0.12–0.35). WRF's accuracy drops significantly with forecast lead time increase; gives very poor 6-day forecasts in both river basins. The performance of ECMWF's real-time observation is moderate to reasonable, while the CPC data gives below average to poor results. Comparing rainfall from various sources clearly demonstrates TRMM and GPM's ability to capture large-scale rainfall scenarios in the GB basin, which can be useful in hydrological or data-based flood modeling. The quality of ECMWF and CPC rain is comparatively less than earlier two and allows ample opportunity to improve.

4.2 200-year flood prediction for the Brahmaputra basin

As mentioned earlier, on August 12, 2017, GloFAS predicted large-scale flooding in the GB basins for the next 7–10 days and warned that the Brahmaputra basin might experience a flood "likely to be more than a 200-year return" due to continuous heavy rain in the upstream (http://erccportal.jrc.ec.europa.eu/ECHO-Flash/ECHO-Flash-List/yy/2017/mm/8). The 200-year flood prediction was circulated by Joint Research Center (JRC) of EC at that time, got huge traction by the media in Bangladesh, and disaster managers and experts took initiatives to make people informed about it. However, disseminating an overtly false prediction has a major downside; it is felt not only in millions of people's daily miseries (e.g., increase in food price) but also in a challenge of gaining people's trust back on flood forecasts.

The rainfall event in the lower Brahmaputra basin preceding of August flood was very large and highest flood levels were reported at several monitoring stations along the Brahmaputra and its tributaries in Assam (India), Bhutan and north Bangladesh between August 11 and 17 (SANDRP 2017a). But the flood event did not cross the 70-year return period mark. So, what went wrong in GloFAS's 200-year flood prediction at that time?

From the discussion in the previous section, it can be summarized that a 50-year 5 days rainfall event led to a 65–75-year 2 days peak flood flow (PF) in the Brahmaputra basin during 2017 mid-August. Past analysis of the basin's hydrometeorology though suggests that a 50-year rain could have led to a disproportionately large flood had the basin's monsoon rainfall sequence been steady and streamflow conditions were at or near bankfull stage before that peak rain event.

For instance, in 1998 mid-September, an average rain event for a 5–9 days period generated a 30-year PF in the Brahmaputra basin. It was the 5-year rain and 45-year PF in the Ganges basin at that time. By early September, both basins were already saturated following heavy rainfall in the preceding monsoon months (June–September), and rivers were in a bankfull stage (Figure 3a–3b). As such, even a relatively small peak rain event contributed a very large runoff to already filled rivers and generated a very large PF. Together with the flow synchronization in downstream, the 1998 flood became one of the most severe and longest floods in South Asian history.

Besides the peak events, a 5-year monsoon rain generated a 10-year monsoon flow in the Ganges while it was the 20-year monsoon rain that generated an unusually high monsoon flow with 100-year return period in the Brahmaputra basin in 1998. In contrast, the Brahmaputra received only 10% more rainfall than average during the 2017 monsoon (SANDRP 2017b), yet generated a 20-year monsoon flow. Aside from the two very large rainfall-streamflow events in July and August, the basin received poor rainfall and had low streamflow for the rest of the monsoon (Figure 3h). In the Ganges, both peak and monsoon rain events in 2017 were below normal (Figure 3g); the basin received 15–20% less monsoon rainfall than normal (*Ibid*). Consequently, the downstream peak or monsoon flow of the basin were also below normal.

Thus, it can be concluded that it was the sequence of rainfall events in preceding monsoon months that led to record floods in the GB basins in 1998. In 2017, the Brahmaputra basin was relatively drier, and rivers had much lower streamflow before the 50-year rain event started. Such an extreme event then generated a huge runoff, raised the river WL above DL rapidly, but the floods were short-lived as subsiding rain by mid-August helped to lower the level below DL within a week (Figure 3h–3i). Also, the lower Ganges flow inside

Bangladesh helped to recede the Brahmaputra (Figure 3g–3i). The factors mentioned above worked in tandem in generating a flood not larger than 65–75-year event in August 2017.

Figure 3 here.

In summary, the record rainfall did not lead to record flooding. Generally speaking, it is well established in hydrology literature that extreme rainfall does not always generats a large flood. It depends on multiple factors: a sequence of past rainfall, basin's soil moisture condition, the flow of the river, the length of the peak rainfall event, etc. Normal rain over a lengthy period saturates the basin's soil and causes future rainfall to generate higher runoff and travel faster to the river network. River basins, thus can be thought of having a 'memory' suggesting that the preceding rainfall and streamflow events in the basin control how the river system will respond to future rainfall-runoff events (*Dixon 2018*). Particularly, if the uncertainty in the river basin's initial condition is not resolved accurately enough apart from inaccuracies coming from input (e.g., rainfall) uncertainty. Hydrological models may not accurately account for the river's initial condition, and that poses a limitation of its modeling capabilities. In a combination of all—i.e., uncertainty in input data, initial condition, and model structure—a hydrological flood forecasting model may give an overestimate or underestimate of a flood event by a big margin. And this is what we reckon the GloFAS might have encountered during August 2017 Brahmaputra flood prediction.

5 ReqSim Local and Regional Scale Flood Forecast

5.1 ReqSim model structure

The persistence in the streamflow or WL data—that is, the river flow will remain similar over the next few days (Alfieri et al. 2013)—and the daily rainfall aggregated over large domains in a river basin are a good predictor of downstream river flow, and thus flooding. We first derived isochrones (i.e., flow travel time map), divided upstream contributing basin areas into two to four large domains (depending on basin size, topography, and hydrology), and calculated maximum and minimum flow travel time of each domain to downstream forecast location in no. of days. The domain averaged daily rainfall are then aggregated over travel time range for each forecast lead time (i.e., 1 to 10-day). We integrated this space–time-aggregated rainfalls to streamflow/WL measurement at forecast location in a regression model and thus generated flood forecasts of that location (Figure 3). The model is named as Requisitely Simple (ReqSim) flood forecast model; applied first to GBM river basins for the 2007-2015 period and reported in Palash et al. (2018). The forecast performance was found impressive for up to 10-day lead time at Hardinge Bridge on the Ganges, up to 7-day at Bahadurabad on the Brahmaputra, and up to 3–5-day at Amalshid on the Barak or Upper Meghna River inside Bangladesh. These three river points (Figure 4) are close to the India-Bangladesh international border. Important to note that, predicting the incoming GBM river flow through these river points is generally considered a major challenge for forecasting floods in the alluvial river system in Bangladesh, mainly because of unavailability of gauge measured data from upstream basin countries (*Hopson and Webster 2010; Hossain et al. 2014a; Hossain and Bhuiyan 2016*). We will refer these river points as “base stations” from this point onward.

In our earlier application of the ReqSim model to regional scale (Palash et al. 2018), we presented three levels of model complexity. In this chapter, however, we present the structure of "flow persistence coupled with observed and forecasted rain modeling framework" only. The structure of that modeling framework is:

$$Q_{t+n} = \alpha_n Q_t + \beta_n Q_{t-1} + a_n R_{I,n} + b_n R_{II,n} + c_n R_{III,n} + d_n R_{IV,n} + \gamma_n \quad (1)$$

$$R_{i,n} = average(R_{i,\, t-T_{i,max}+n} \dots \dots\; R_{\mathrm{i},t-T_{i,min}+n}) \quad (2)$$

where, Q_{t+n} is the forecasted streamflow/WL of n-day lead time; Q_t, and Q_{t-1} are observed streamflow/WL on forecast day t and previous day $t-1$, respectively; α_n and β_n are model coefficients related to persistence; and γ_n is a regression interception coefficient. R_I, R_{II}, R_{III} and R_{IV} are lagged space–time-aggregated rainfall of four domains I to IV (Figure 1b); and a_n, b_n , c_n, d_n are corresponding model coefficients. $T_{i,max}$ and $T_{i,min}$ are maximum and minimum flow travel time (in days) for domain i (I to IV) while t is the forecast day (i.e., 0 day), and n is the forecast lead time (i.e., 1 to 10-day). If $t - T_{i,max} + n$ and/or $t - T_{i,min} + n > t$ where t is the forecast day (i.e., 0 day) then forecasted rain of m lead time is considered in the model for domain i providing that $t - T_{i,max} + n$ and $t - T_{i,min} + n \le t + m$.

The satisfactory forecast results from ReqSim regional scale GBM model encouraged us to develop a local scale model for the alluvial river system of Bangladesh by using the outputs of the regional model. We applied a simple forecast transferring mechanism from those three base stations to downstream or upstream river points (Figure 4) by using a regression modeling structure. The structure of the forecast transfer from base stations to immediate upstream/downstream points and then from those points to further upstream/downstream points is as follows:

$$H_{t+n} = \alpha_n H_t + \beta_n H_{t+n}^{us/ds} + \gamma_n \quad (3)$$

where, H_{t+n} is the forecasted water level on n-day lead time at forecast location; H_t is the observed water level on forecast day (i.e., $t = 0$) at the same location*;* $H_{t+n}^{us/ds}$ is already generated forecasted water level at upstream or downstream river points (from where forecasts are about to transfer to target location) on n-day lead time; and α_n, β_n, and γ_n are coefficients of the regression model. The idea of transferring forecast from one river point to another is thus very simple. The linear regression model includes forecast day's water level at target or "to" river point (i.e., H_t) and forecasted water level of "from" river points (i.e., $H_{t+n}^{us/ds}$) to generate forecasts at "to" river point for n-day lead time (i.e., H_{t+n}).

But before transferring forecasts, it was necessary to identify those river points for which the base stations' forecasts can be transferred. Once those river points are identified, the forecast transfer begins from base stations to their immediate downstream or upstream river points and from those points to further downstream or upstream points respectively.

5.2 Identification of local scale forecast locations

We considered cross-correlation function (CCF) between daily water level data of two neighboring river points to identify whether those points share a "similar" riverine hydrologic regime. For instance, we set a CCF value of ≥ 0.8 to identify those similar hydrologic regime points for which a forecast transfer from one river points to another is possible. The CCF is computed by using the following equation:

$$CCF(x, y) = \frac{\sum_{i=1}^{n}[(X_i - \bar{X})(Y_i - \bar{Y})]}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (4)$$

Where, X_i and Y_i are two daily time series data of two river points, $\bar{X}$ and $\bar{Y}$are mean of X_i and Y_i, respectively. Figure 4**Error! Reference source not found.** shows both river points and river stretch for which a similar riverine hydrologic regime has been found. Encircling the highly correlated river points, as shown by dashed black polyline in the figure, thus identifies the river systems and forecast locations for which the ReqSim local scale model has been applied during 2017 flood season.

Figure 4 here.

5.3 Performance of ReqSim operational run during August 2017 flood

The ReqSim regional (i.e., GBM river basins) and local scale (i.e., selected alluvial river systems in the downstream of the GBM inside Bangladesh) models continued its experimental operational run during 2017 South Asia flood season and generated forecasts for three base and other river stations.

Figure 5 here.

The performance of the ReqSim WL forecasts in the Ganges River inside Bangladesh is impressive up to 10-day lead time during 2017 flood season. The R^2, mean absolute error (MAE) and root mean square error (RMSE) of the Ganges forecasts at Hardinge Bridge are 0.92, 0.43 m and 0.57 m for 10-day lead time respectively. The Brahmaputra forecasts at Bahadurabad was reliable up to 7-day lead time; corresponding R^2, MAE, RMSE are 0.59, 0.49 m, 0.63 m respectively. The performance in the Barak (upper Meghna) River at Amalshid was limited up to 5-day lead time; corresponding R^2, MAE, RMSE are 0.49, 0.80 m, 0.98 m respectively. Figure 5a–5d show ReqSim performance at each river points from 3-day to 10-day lead time. Figure 5e–5f show ReqSim's ability to predict August 2017 flood by using a time series comparison, and it had been encouraging. The model successfully captured the Brahmaputra flow rise, peak flood timing and its magnitude with reasonably high accuracy up to 5-7 day lead-times (Figure 5f). For the Ganges, high performance up to a 10-day lead-time had been consistent throughout 2017 monsoon (Figure 5e).

ReqSim's performance at 30 downstream points along the major rivers of Bangladesh was also impressive. For instance, the model performed very well in the Ganges-Mahananda-Gorai system in the west of country up to 10-day lead-time; reasonably well in the Brahmaputra, Old Brahmaputra, Padma, Kumar and other rivers in the central part up to 7-day lead-time; and moderately in the Surma-Kushiyara system in the east up to 5-day lead-time (Table 1 and Figure 5a-5d). These performances are in line with the basin size, terrain and land cover properties; basin hydrometeorology; physical memory of the system (e.g., flow travel and flood response time).

Table 1 here.

6 Conclusion

In this study, we have explored the utility of a data-driven approach and the applicability of various remote sensing and ground-based rainfall datasets to regional and local scale flood forecasting in large river basins influenced by monsoon systems. As part of this approach, we have explored in detail the hydrometeorology of the Ganges and Brahmaputra (GB) river basins that prevailed during and before the record August 2017 floods. We further analyzed the spatial distribution of extreme rainfall events, their effect on streamflow response and resulting widespread flooding unleashed in the eastern Ganges and southwestern Brahmaputra river basin. We found that the basin-wide 5 (9) days cumulative rain from August 9–13 (August 7–15) was a 50 (20)-year event in the Brahmaputra basin.

Rainfall data comparison suggests that the NASA TRMM 3B42 RT and GPM Early Run v.4 datasets give the most promising rainfall coverage with considerable accuracy, particularly in high rainfall regions of the GB basins. The ECMWF rainfall provides moderate accuracy while the CPC data shows poor agreement with gauge data. The performance of WRF's forecast rainfall is moderate at 1-day lead time, and its accuracy falls sharply with forecast lead time increase.

We explored the hydrometeorological conditions behind the 200-year flood prediction for the Brahmaputra river basin made by a European agency GloFAS. Our analysis suggests that a 50 (20)-year rain event over a 5 (9) days period led to a 65–75-year 2 days peak flood flow event in the Brahmaputra basin's downstream region. Failing to account for the past Sequence of rainfall events, basin's initial soil moisture condition, existing streamflow, and length of peak rain event—perhaps played a key role for a rainfall event turning out to be a smaller flood event.

As part of an extended analysis of the August 2017 GB floods and the state of prediction, we presented our data-based Requisitely Simple (ReqSim) flood forecast model's 1–10-day forecast performance in the Ganges, Brahmaputra, and Meghna (GBM) Rivers (regional scale model application) and its major distributaries inside Bangladesh (local scale application). The performance in the Ganges, Brahmaputra and Meghna river system are impressive with an accurate prediction of peak flood rise and fall up to 10-, 7-, and 5-day lead time, respectively. Considering ReqSim's performance throughout 2017 flood season in major rivers of Bangladesh, we believe the model has enormous potential in adding valuable information to existing flood warning and dissemination services in the region.

7 Reference

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