A Requisitely Simple Flood Forecasting Model for the GBM Basins

Study findings of PhD research
08 August 2017

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Structure of today's presentation

1) Background
2) Motivation
3) Complexity Science and Requisite Simplicity
   - Theory and application
4) GBM River Basins Forecasts
   - Methods and results
5) Bangladesh Flood Forecasts
   - Methods and results

Structure of today's presentation

6) Forecast Performance

- Historical (1998-2015) and real-time (2017)

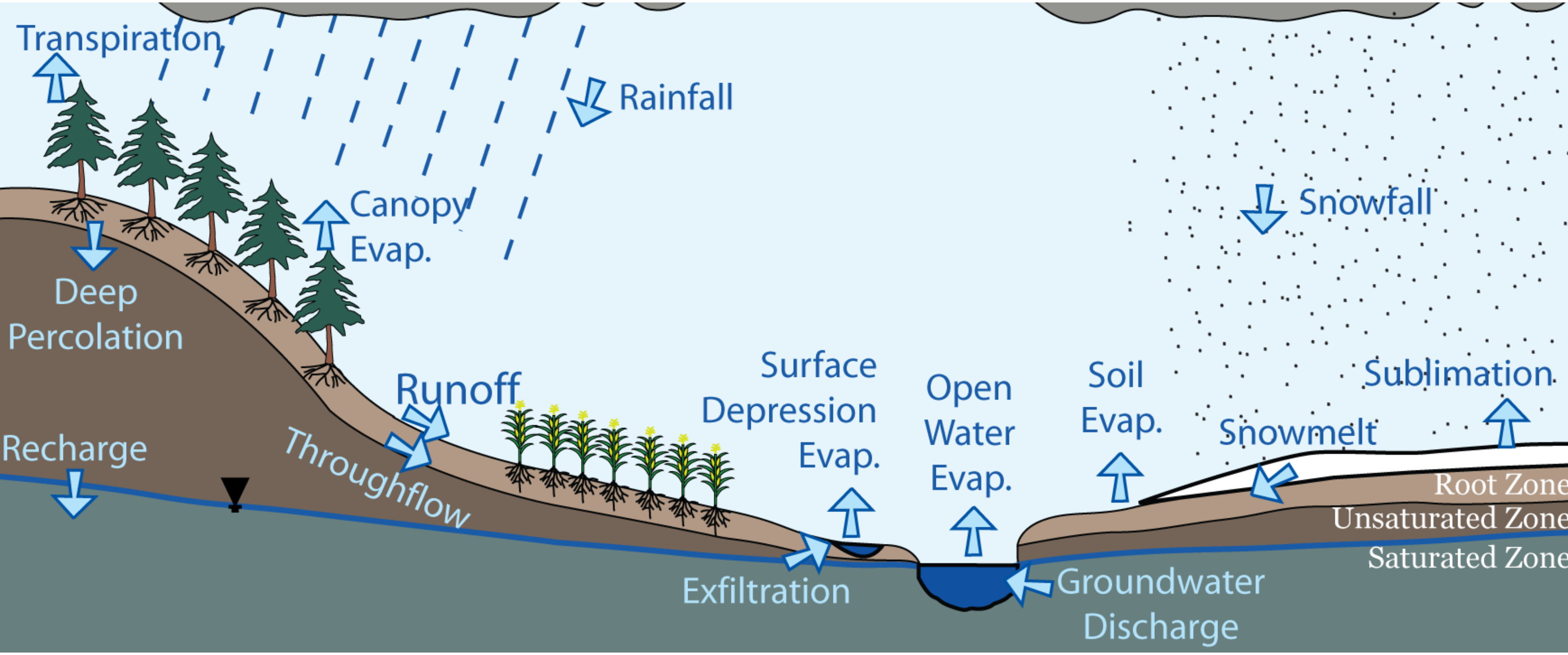
7) Application of Requisitely Simple forecasting in other river basins

- Future works

8) Conclusion

Background

- Flood in a river basin is a complex natural process dealing with large number of variables and processes with non-linear interactions and feedback.



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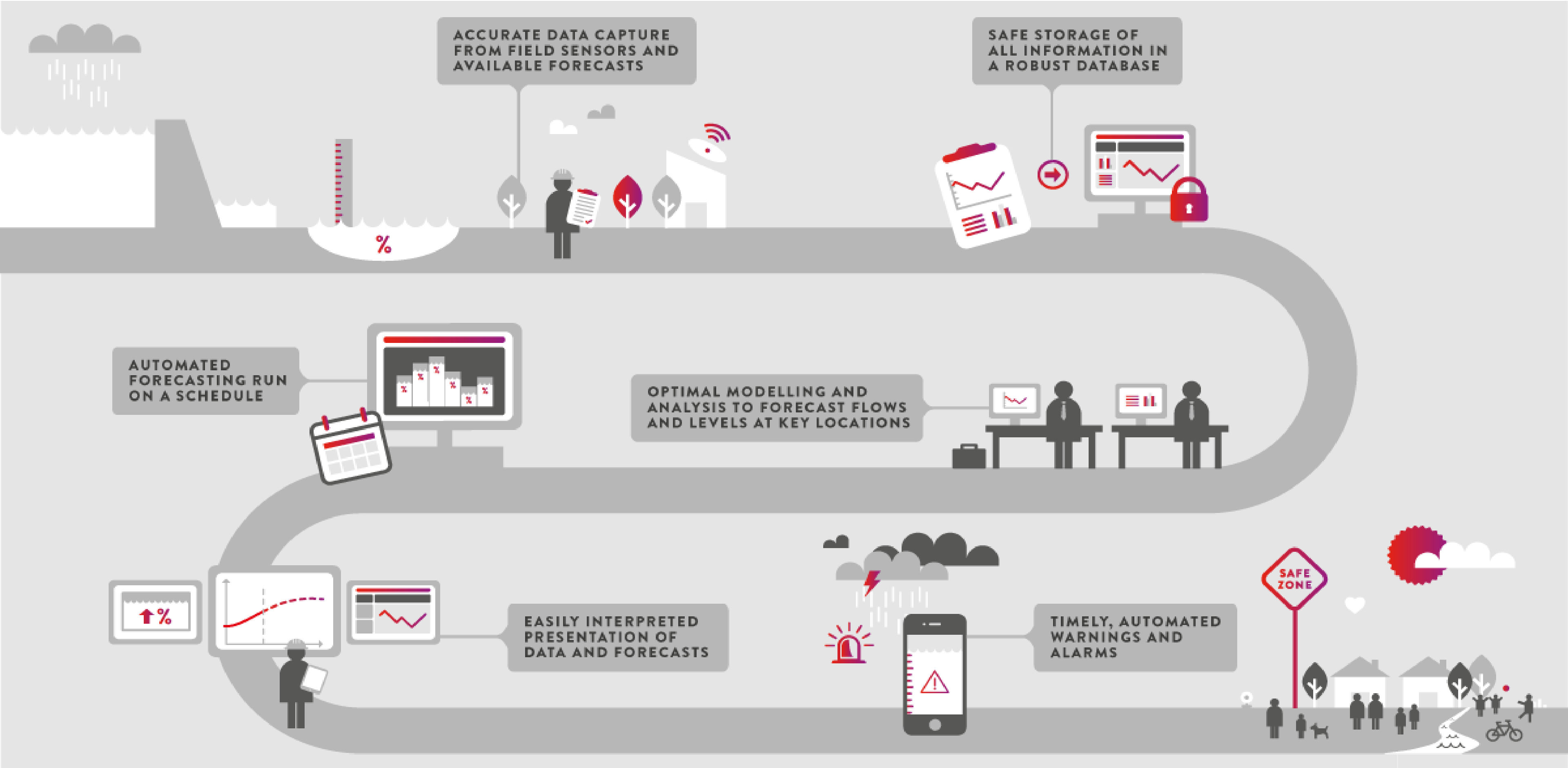
- Flood in a river basin is a complex natural process dealing with large number of variables and processes with non-linear interactions and feedback.
- When flood reaches communities involving many actors and institutions, flooding becomes more complex because of interactions with infrastructures and involvement of human and social agents.
- We may understand each of the individual components of a complex system like flood and flooding effects, but the non-linear interactions and feedback between components make such a system hard to understand, model, and predict.

Background

- For example, a flood forecasting system – from basin to floodplain – usually includes large number of nonlinear relationships with feedback.



Background

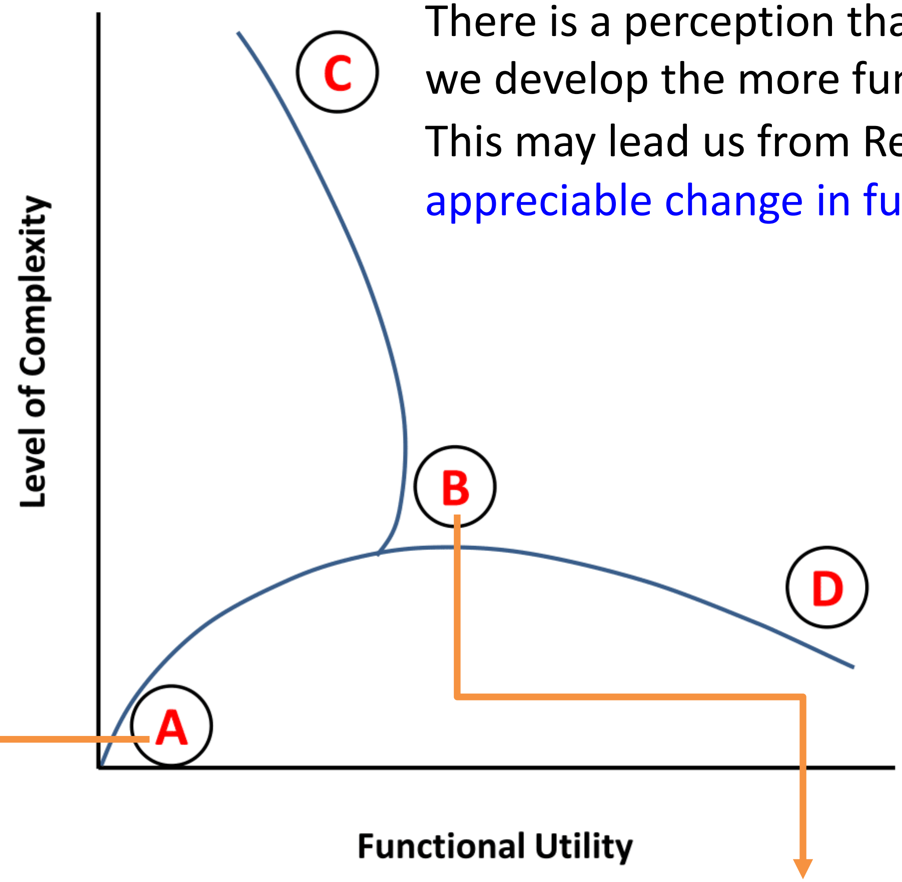
How do we, then, manage such a complex system?

Identifying requisite simplicity for a complex system like flooding may help us in this regard.

A requisite simplicity provides a framework by discarding some details while maintaining conceptual clarity and scientific precision.

Complexity Science and Requisite Simplicity

Requisite Simplicity adapted from Ward (2005)



There is a perception that the more complex model we develop the more functional utility we achieve. This may lead us from Region B to C without appreciable change in functional utility

Simplification may be achieved as we move from Region B to D by taking a closer look at the dominant processes of complex system and reducing the model to its essential components

The system is simple cause-effect relationships known, modeling guided by fundamental principles, and mathematically tractable solutions are possible

Adding more realism (variables, processes, and dynamics) or increased model complexity leads to better functional utility

Applying Requisite Simplicity in flood forecast model development

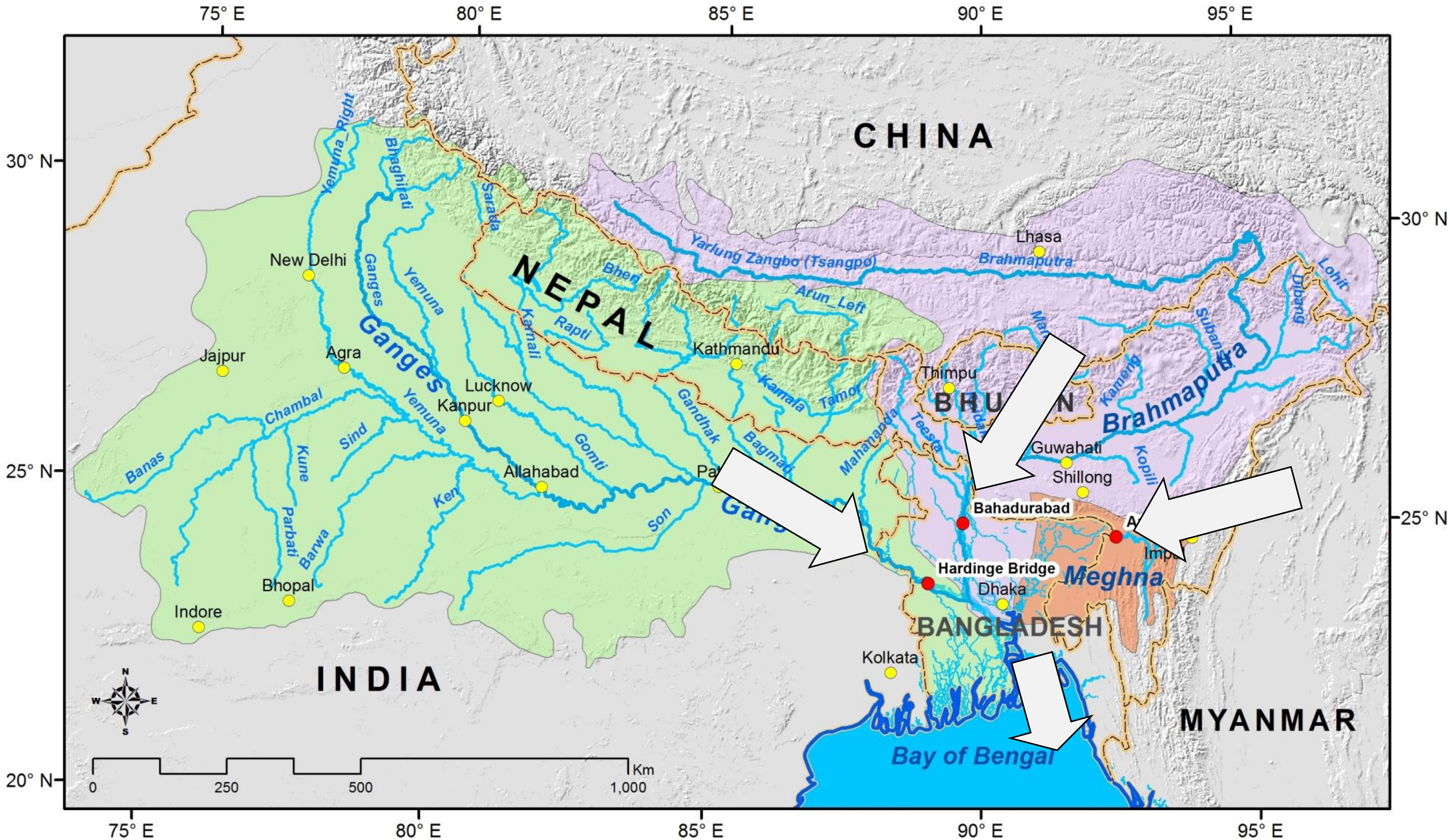
We argue that the requisite simplicity – to paraphrase Einstein *simple but not simpler* – may be achieved by taking

- a closer look at the dominant processes of flood and flood forecasting system and adding new perspective to create actionable knowledge;
- reducing the system to its essential components;
- identifying emergent properties of flooding system; and
- following simple ways to track their evolution and performance.

River basin forecast

- Develop regression-based linear model by using river flow or water level persistence and upstream aggregated rainfall over broadly divided basin domains with runoff travel time lag adjustment.
    - Generate isochrones (runoff travel time map) and divide basin into four large domains.
    - Calculate spatial and temporal average domain rainfall to be used as input data of linear model.
    - Streamflow or water level data of origin of forecast day and previous day provides flow or water level component of the regression.

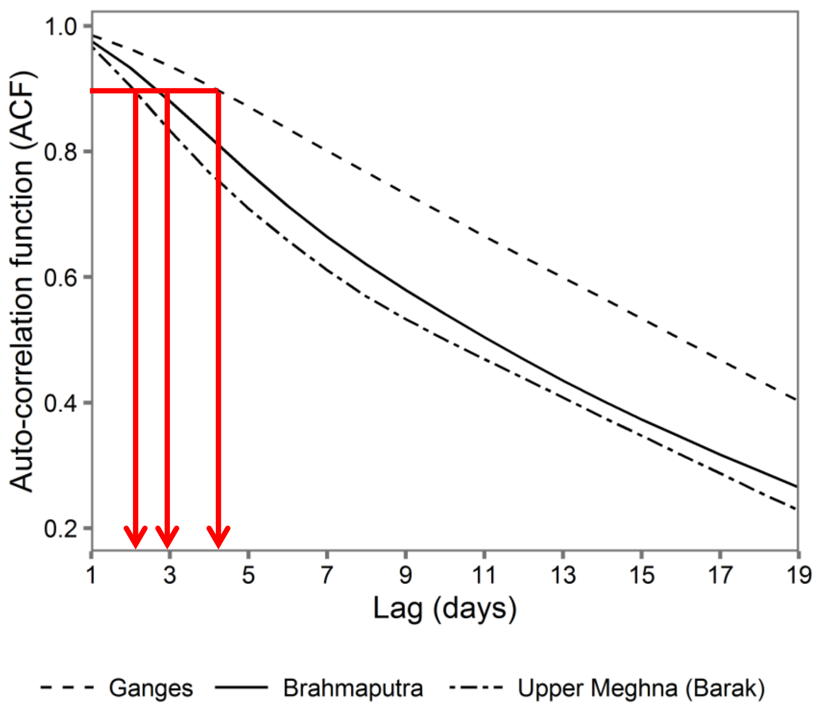
GBM River Basins Forecasts



Flow persistence

Persistence in daily streamflow

$$ACF(k) = \frac{\sum_{k=1}^{N-K}[(X_t - \mu)(X_{t+k} - \mu)]}{\sigma^2}$$



Persistence (up to 0.9)

Ganges: 4 days

Brahmaputra: 3 days

Upper Meghna (Barak): < 2 days

Origin of forecast day flow or water level

$$Q_{t+n} = \alpha_n Q_t + \beta_n Q_{t-1} + \gamma_n$$

Forecast at n lead time

Flow or WL of previous day's of origin of forecast day

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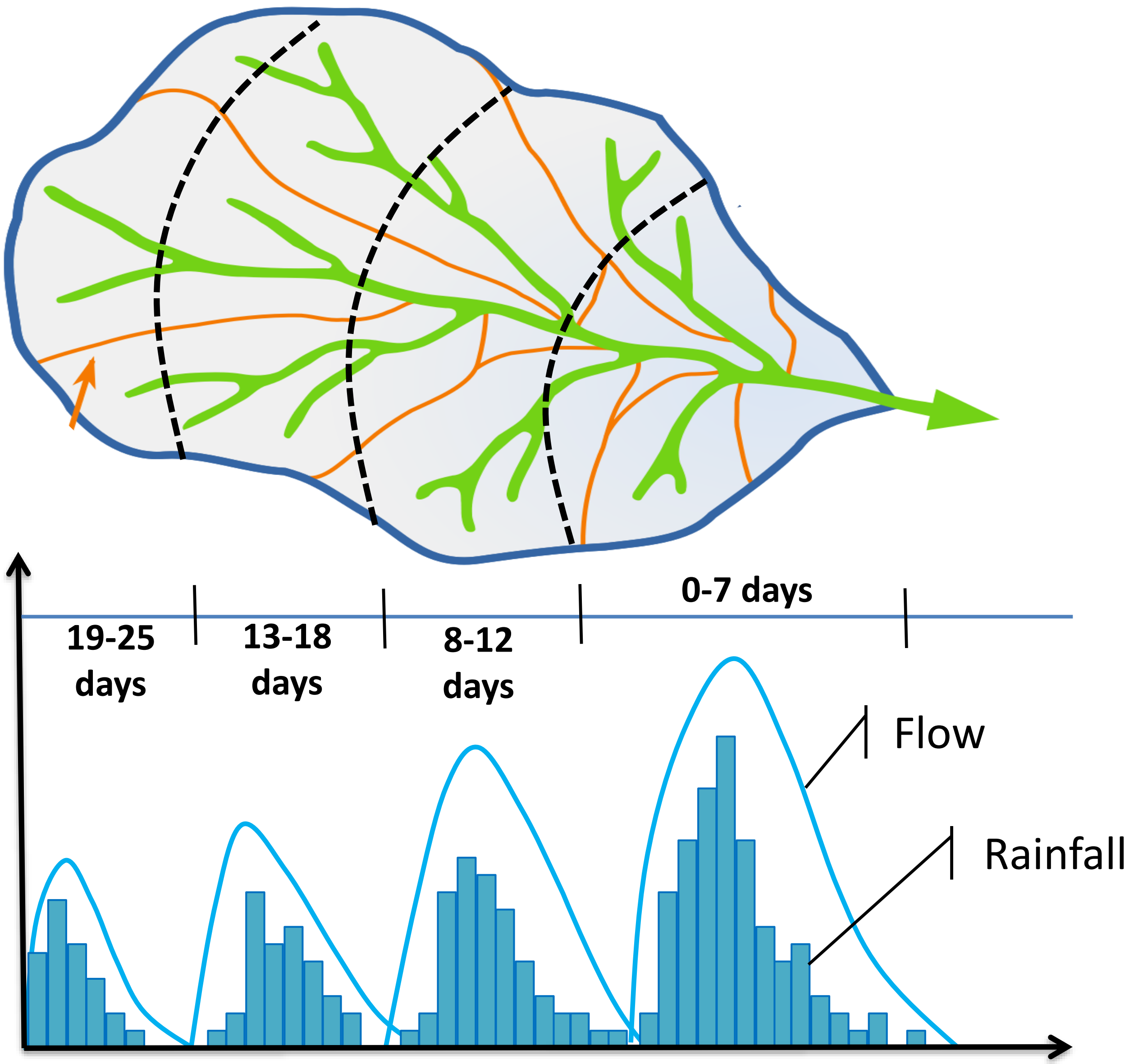
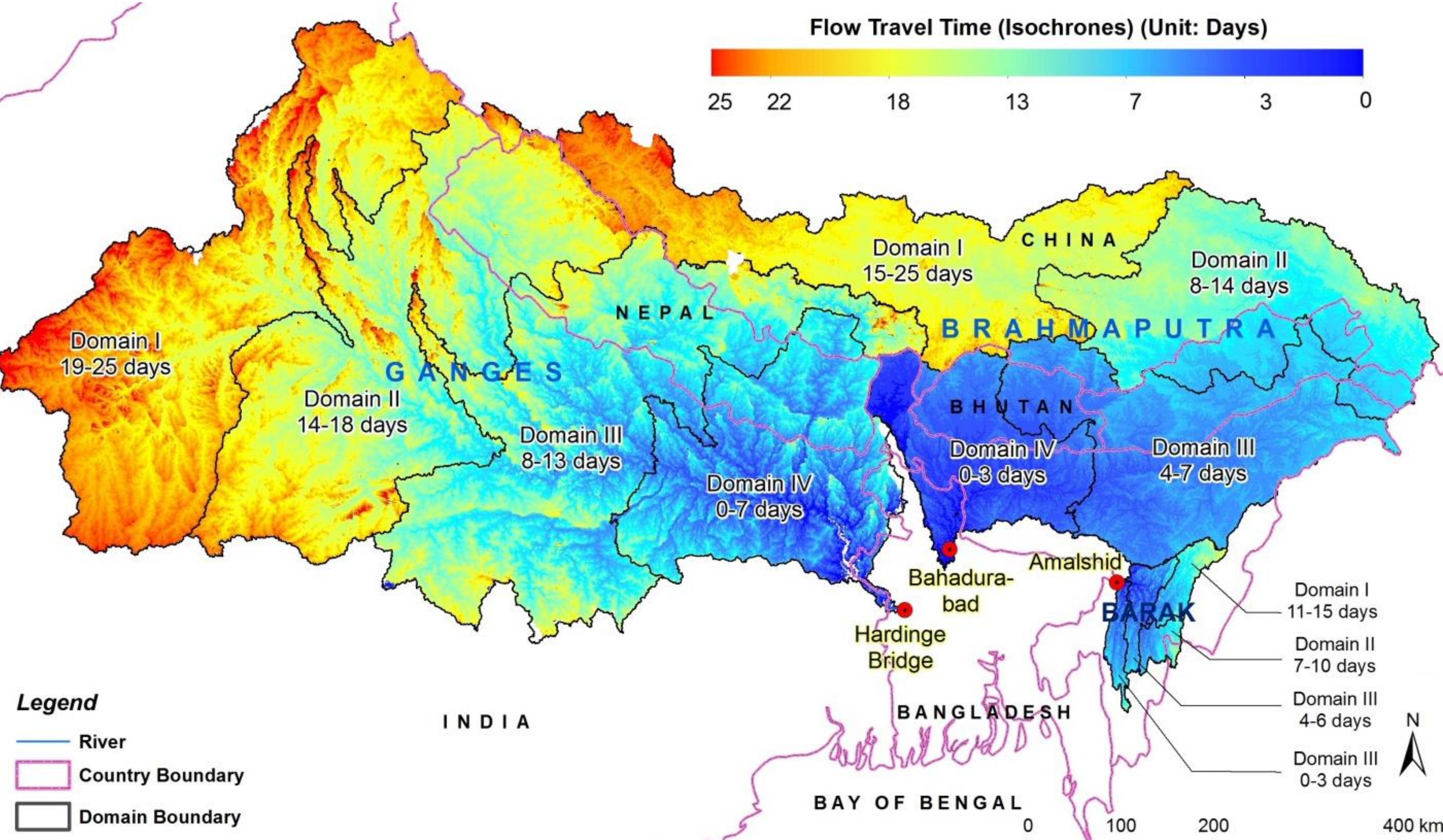
Space-time averaged rainfall and flow travel time

Adding domain's space-time aggregated rainfall to persistence

Flow travel time



Space-time averaged rainfall and flow travel time



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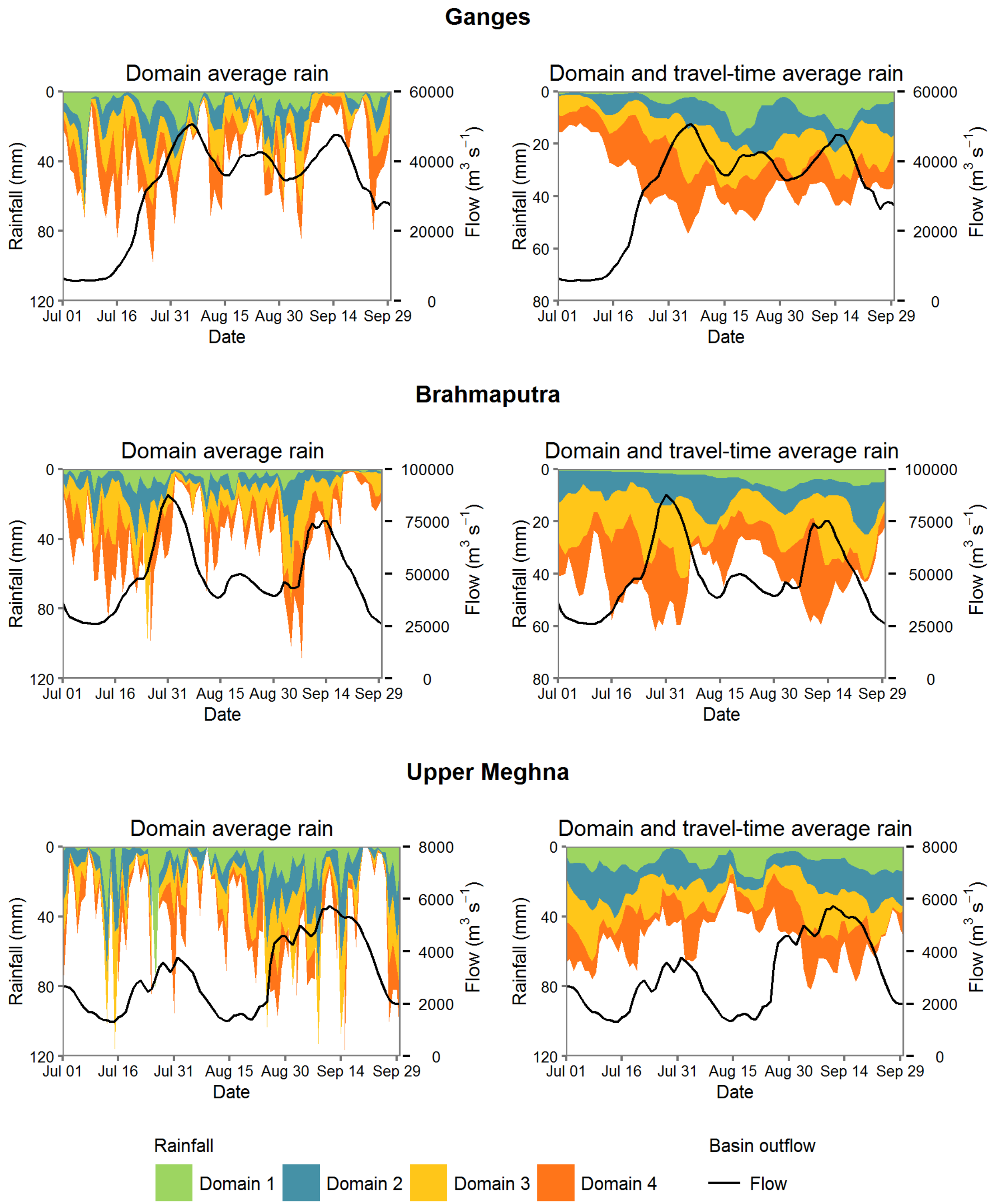

Spatial and temporal average domain rainfall: becomes nicely correlated to d/s flow

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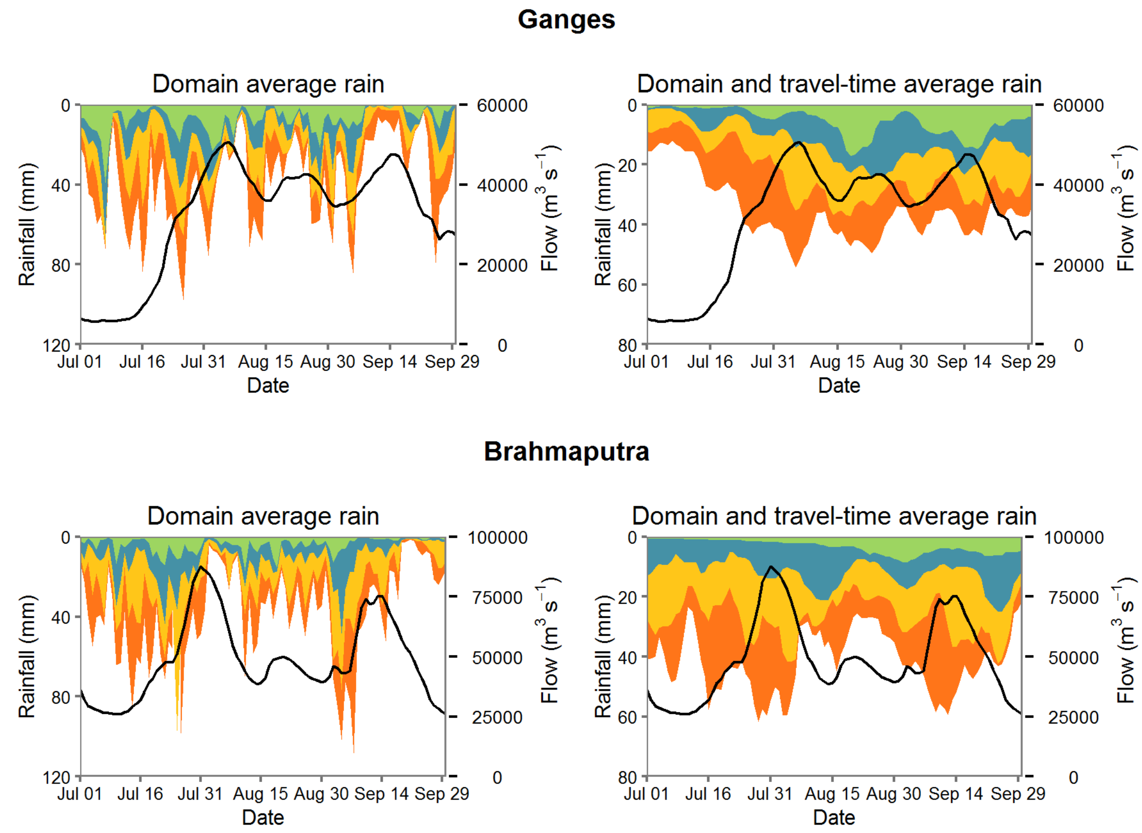
Requisitely Simple (ReqSim) model structure



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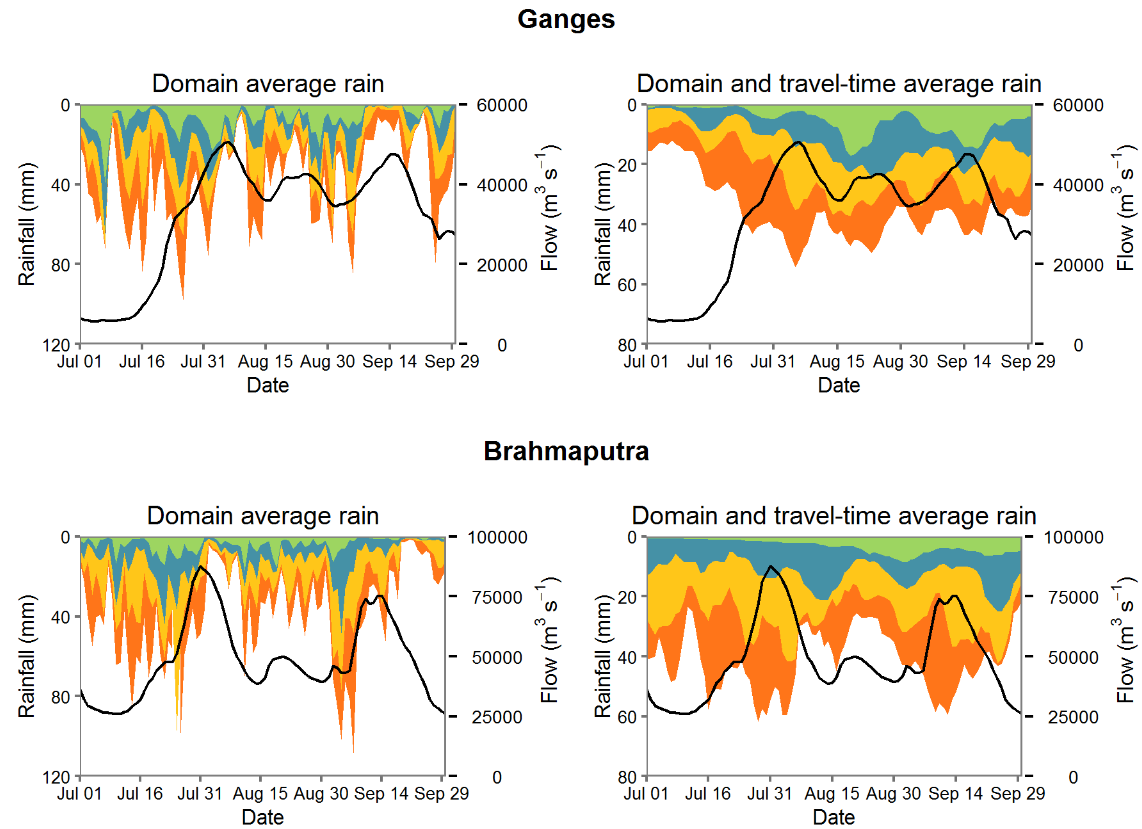


Rainfall: Domain 1, Domain 2, Domain 3, Domain 4

Basin outflow: — Flow

Origin of forecast day flow or water level

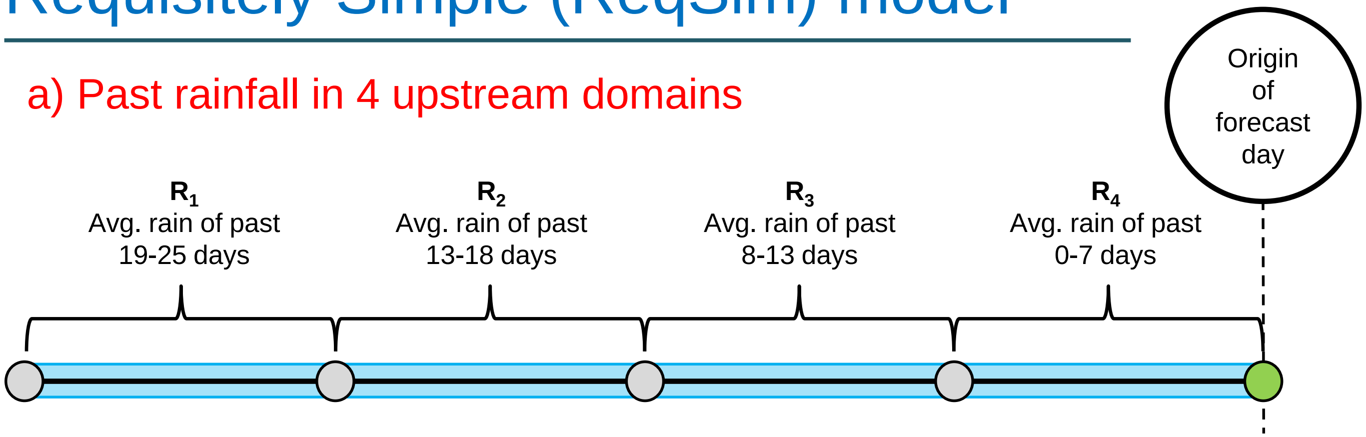
$$Q_{t+n} = \alpha_n Q_t + \beta_n Q_{t-1} + a_n R_1 + b_n R_2 + c_n R_3 + d_n R_4 + \gamma_n$$

Forecast at n lead time

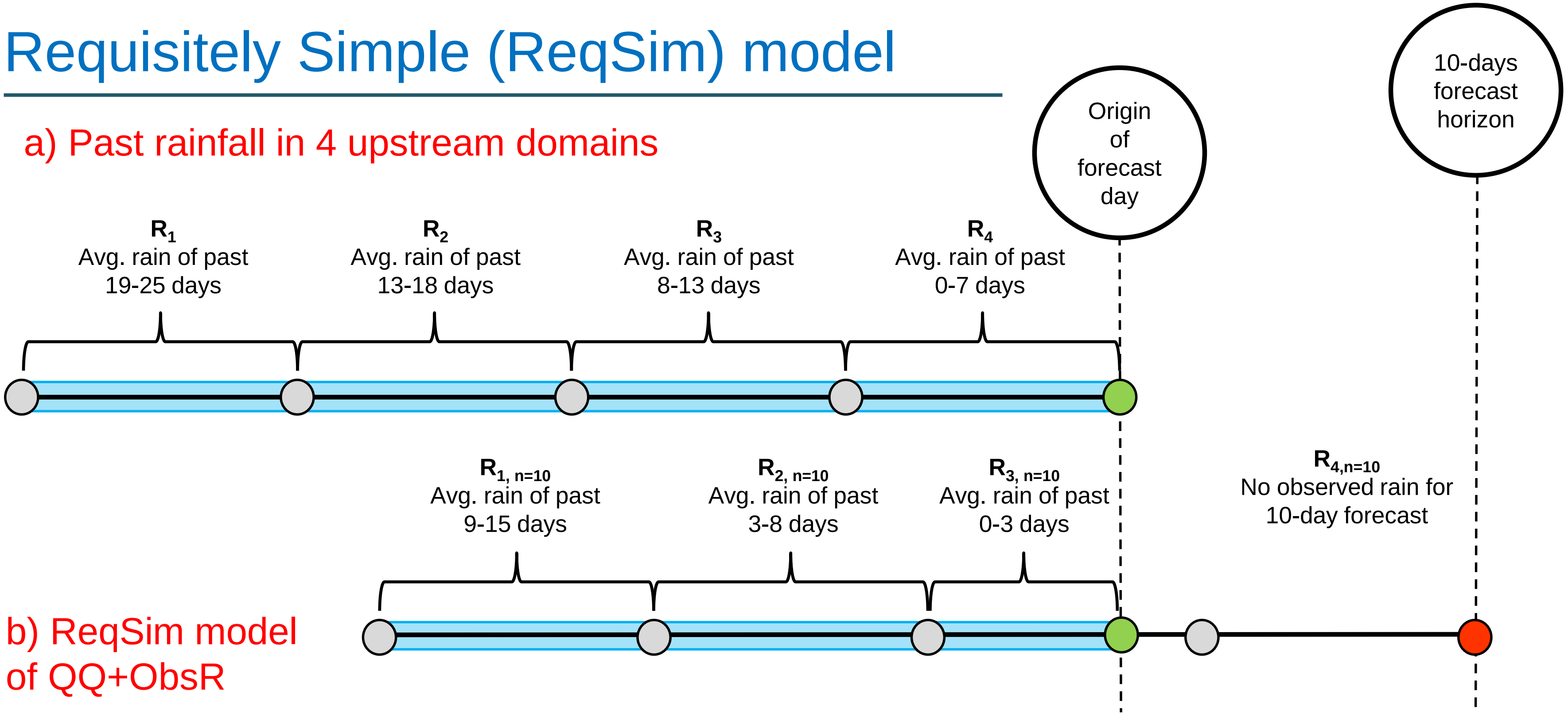
Flow or WL of previous day's of origin of forecast day

Requisitely Simple (ReqSim) model

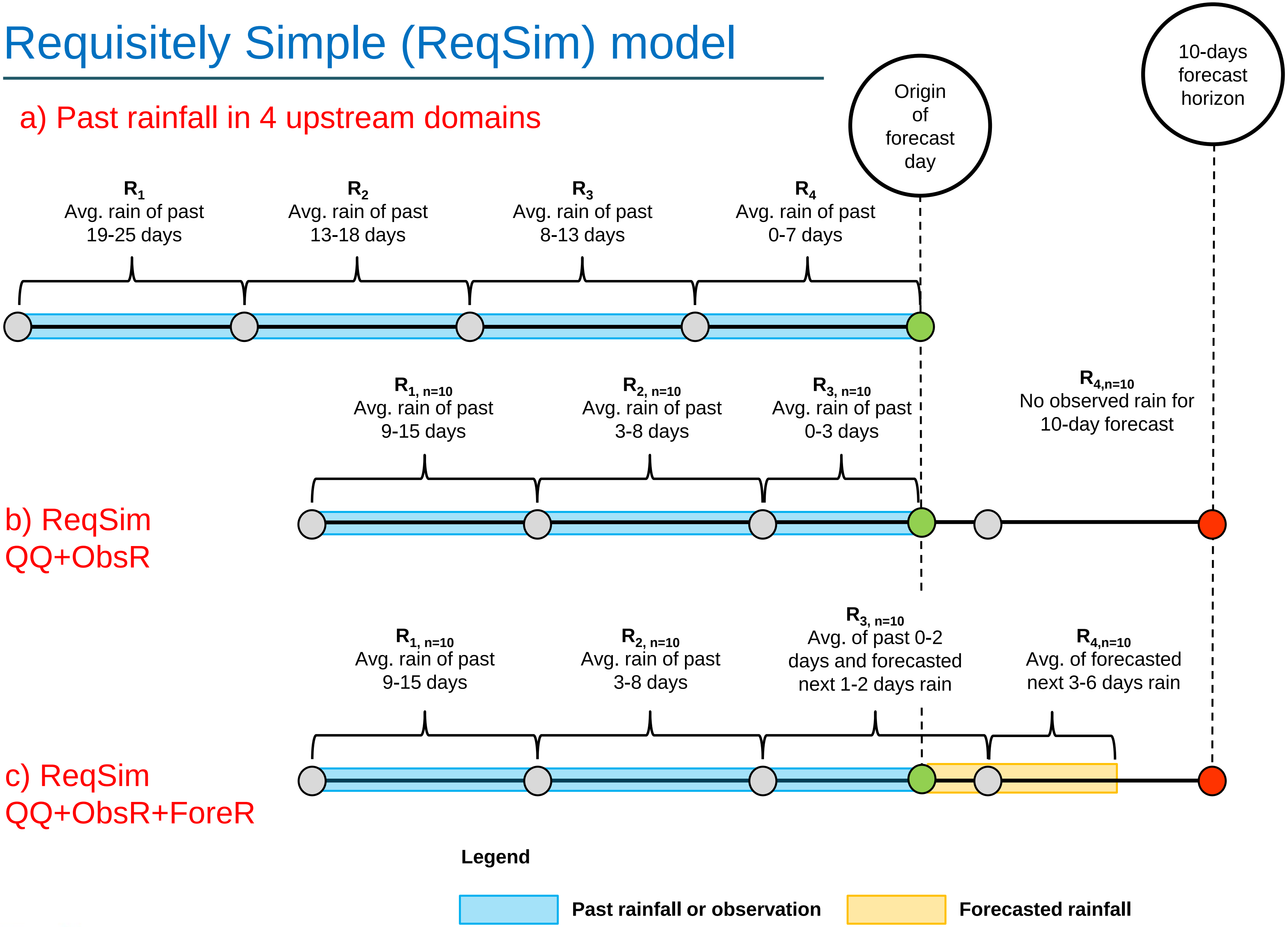
a) Past rainfall in 4 upstream domains



Requisitely Simple (ReqSim) model



Requisitely Simple (ReqSim) model



A Streamflow and Water Level Forecasting Model for the Ganges, Brahmaputra and Meghna Rivers with Requisite Simplicity

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3 Water Diplomacy, The Fletcher School of Law and Diplomacy, Tufts University, MA, USA

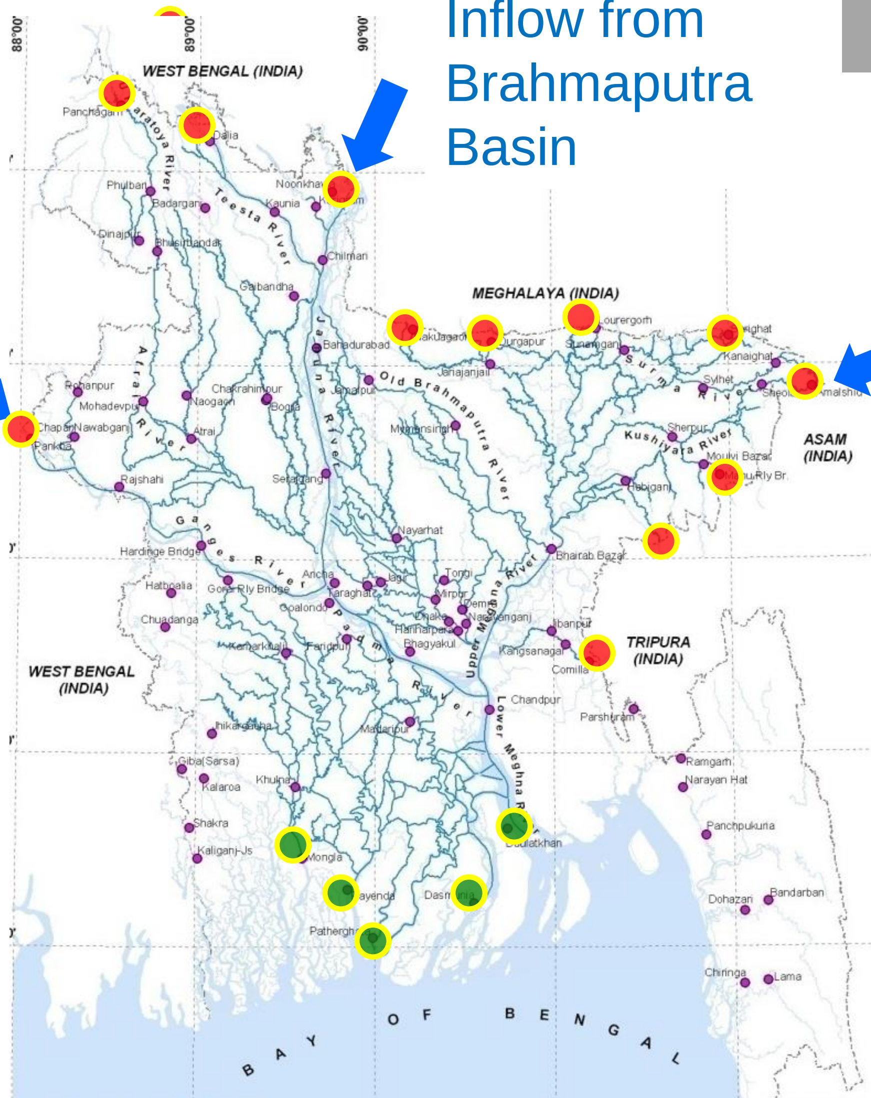
Bangladesh flood forecasting

The main challenge of increasing the lead-time is to predict the future river condition

Inflow from Brahmaputra Basin

Inflow from Ganges Basin

Inflow from Meghna Basin

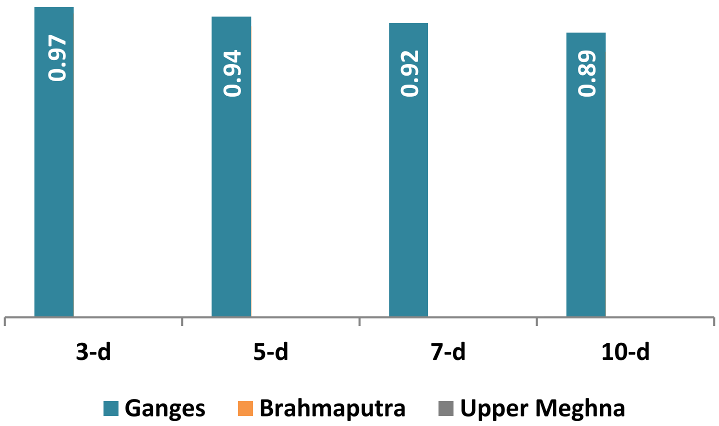


Boundary Type

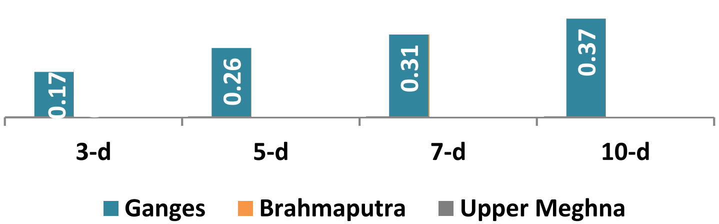
- Flow /Discharge
- Water Level

GBM results (2007-2015)

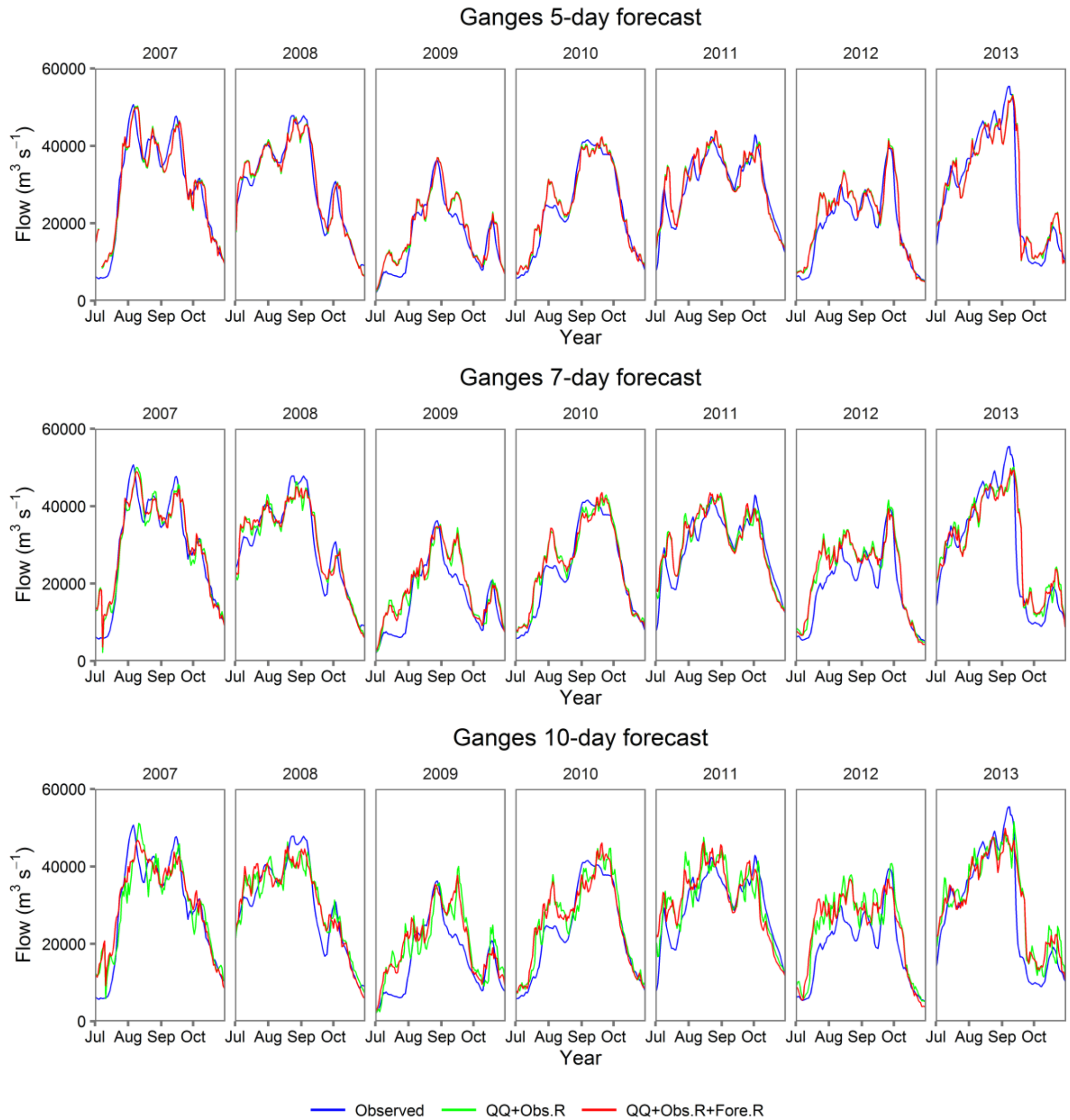
Nash-Sutcliffe Coefficient (NSF)



Mean absolute error (MAE), m



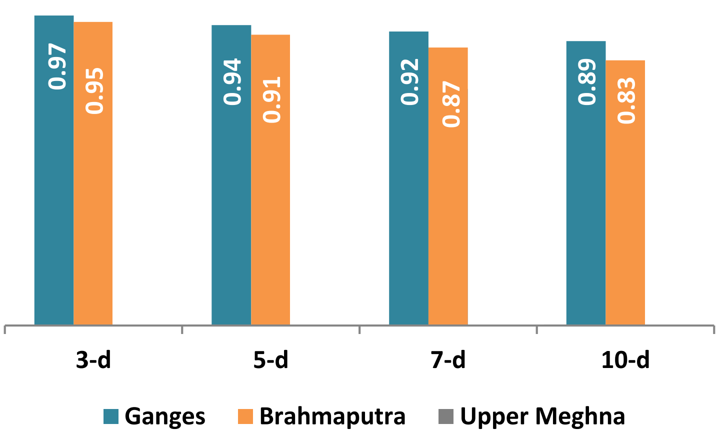
Ganges



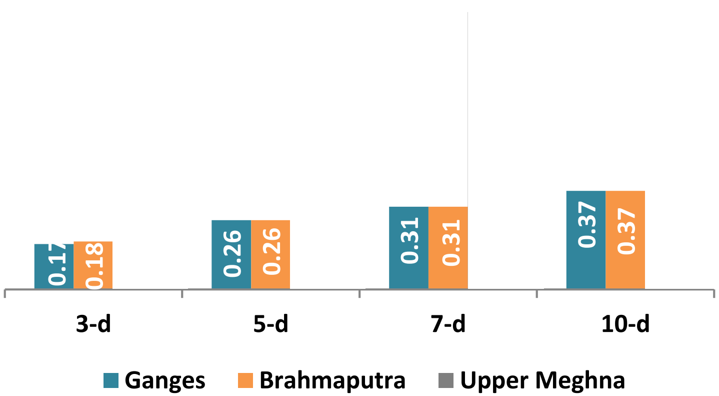
GBM results (2007-2015)

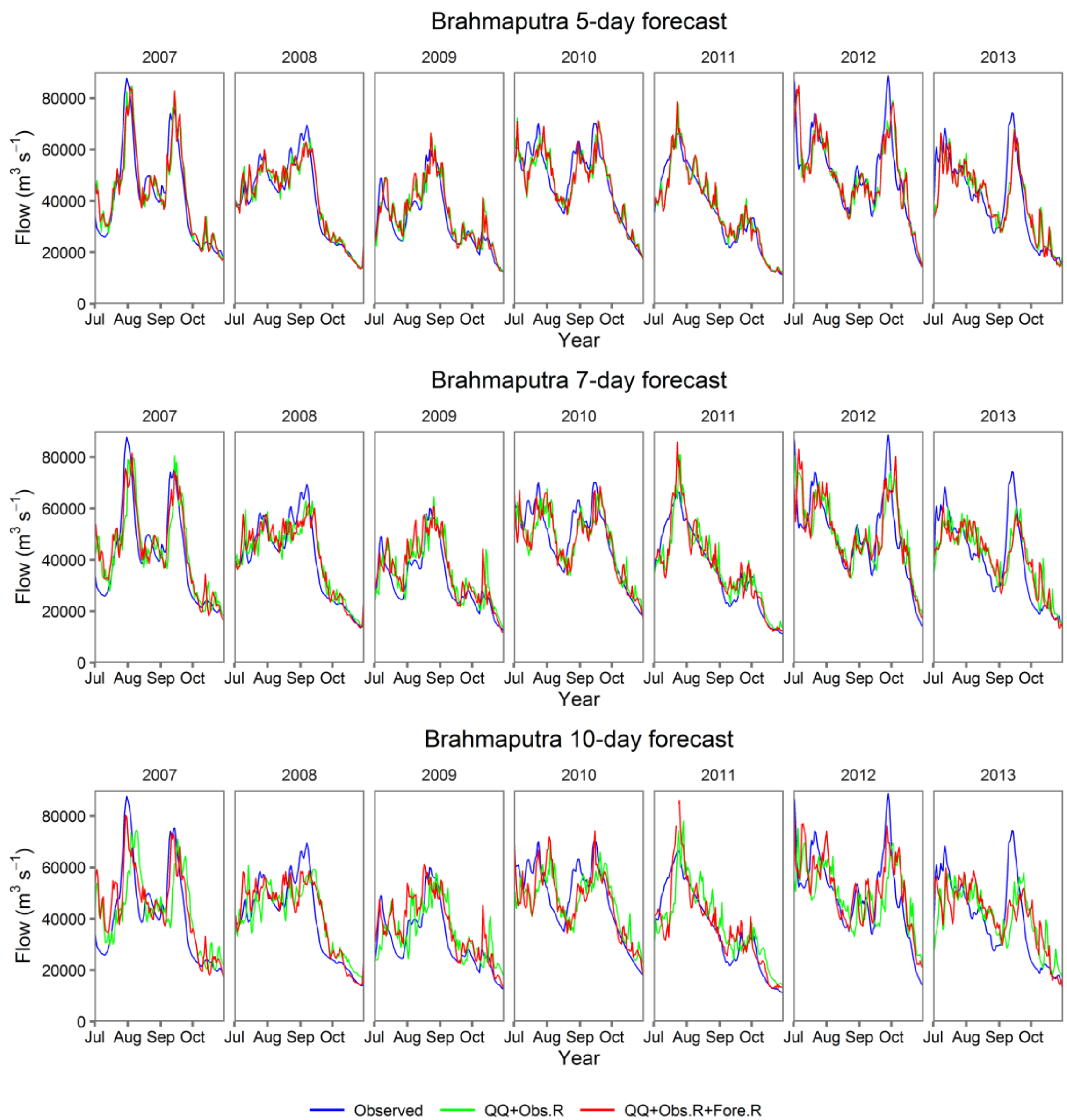
Brahmaputra

Nash-Sutcliffe Coefficient (NSF)



Mean absolute error (MAE), m

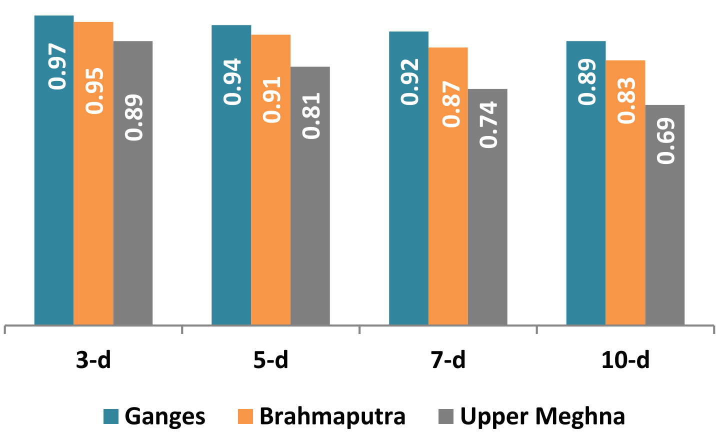




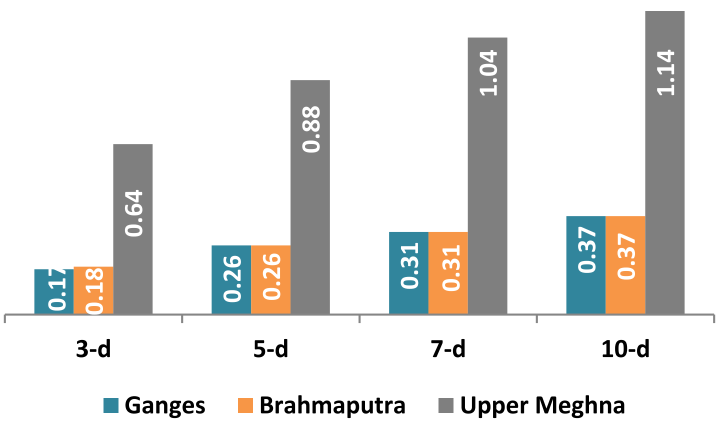
GBM results (2007-2015)

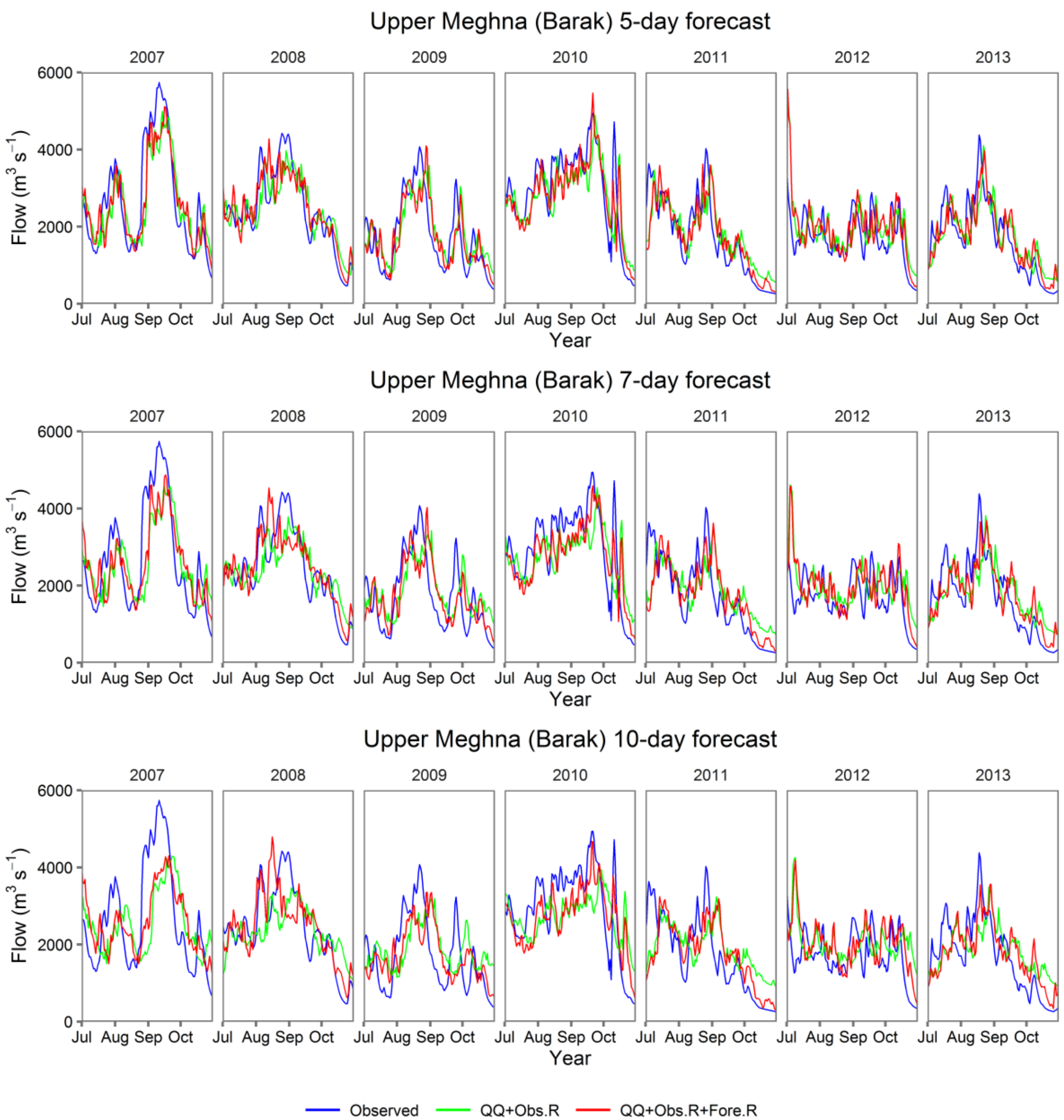
Upper Meghna

Nash-Sutcliffe Coefficient (NSF)



Mean absolute error (MAE), m



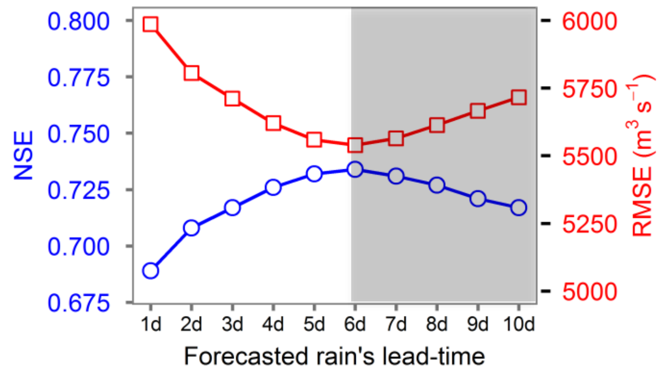


GBM results

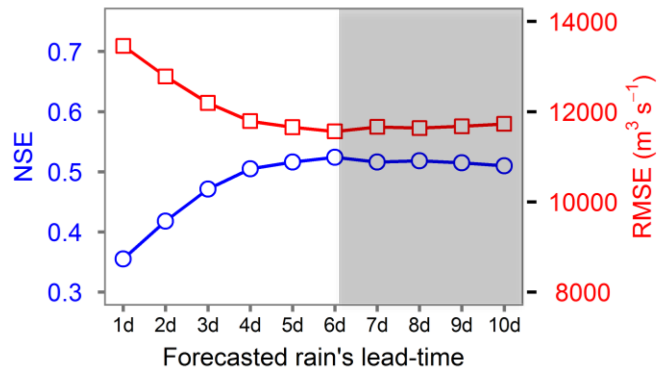
Utility of forecasted rain

NSE RMSE

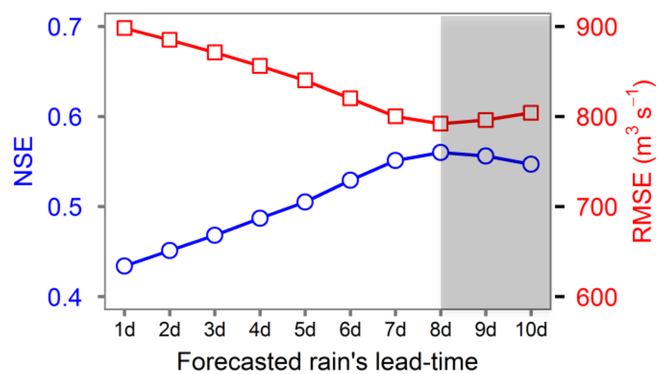
Ganges



Brahma



Upper Meghna or Barak



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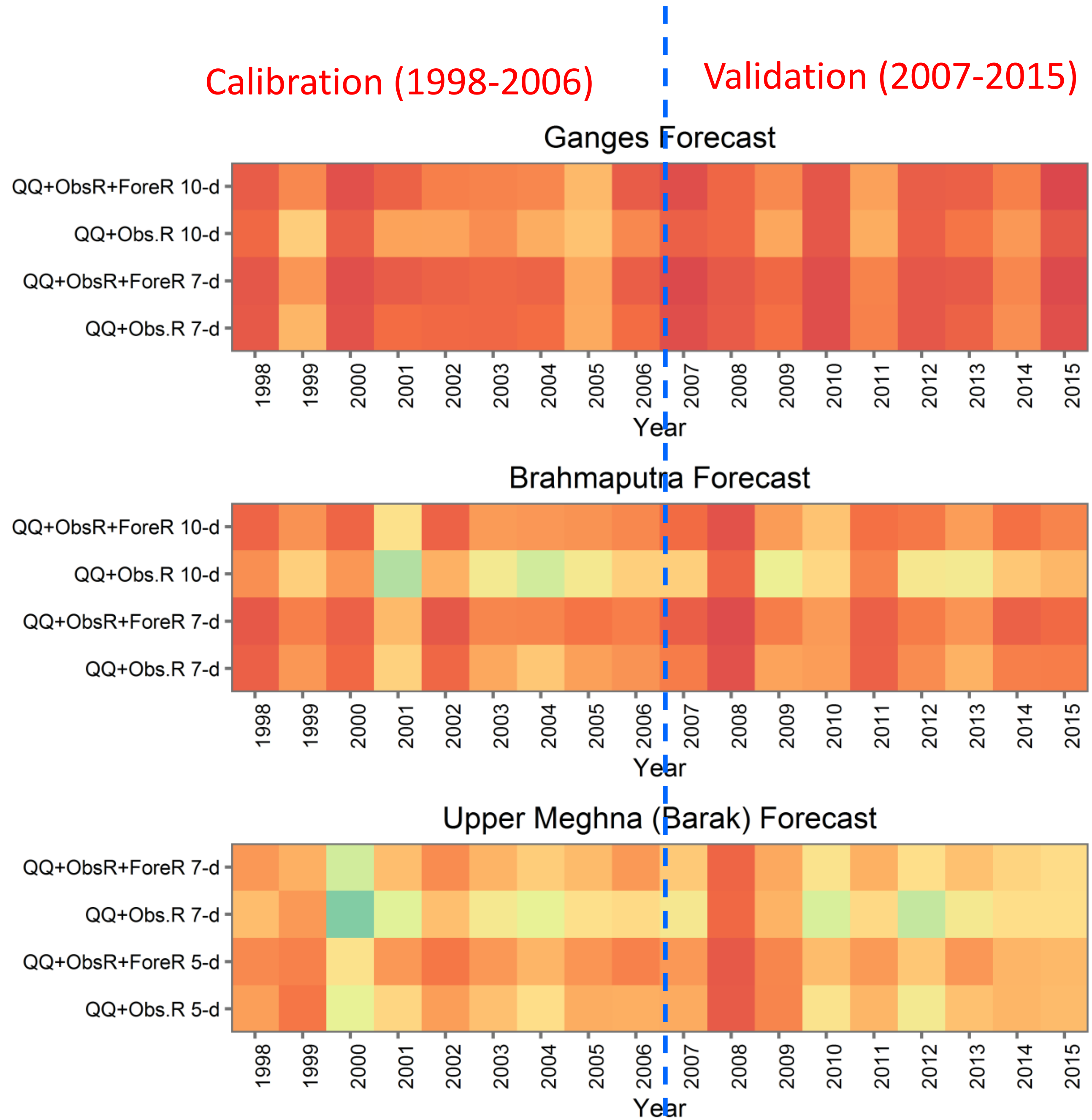
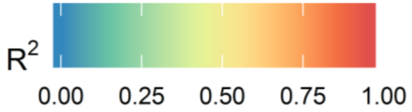
GBM results

Coefficient of determination (R^2)





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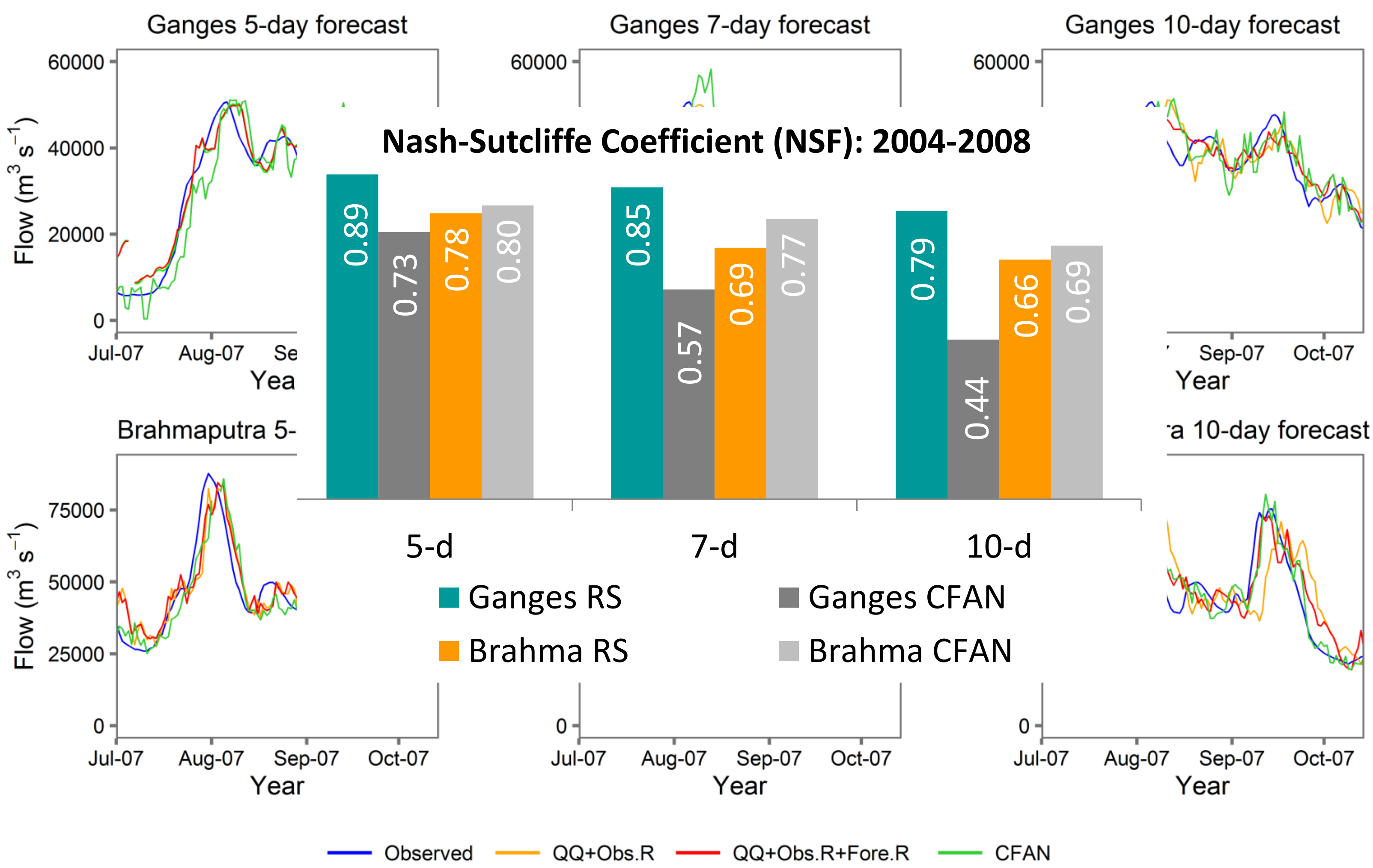
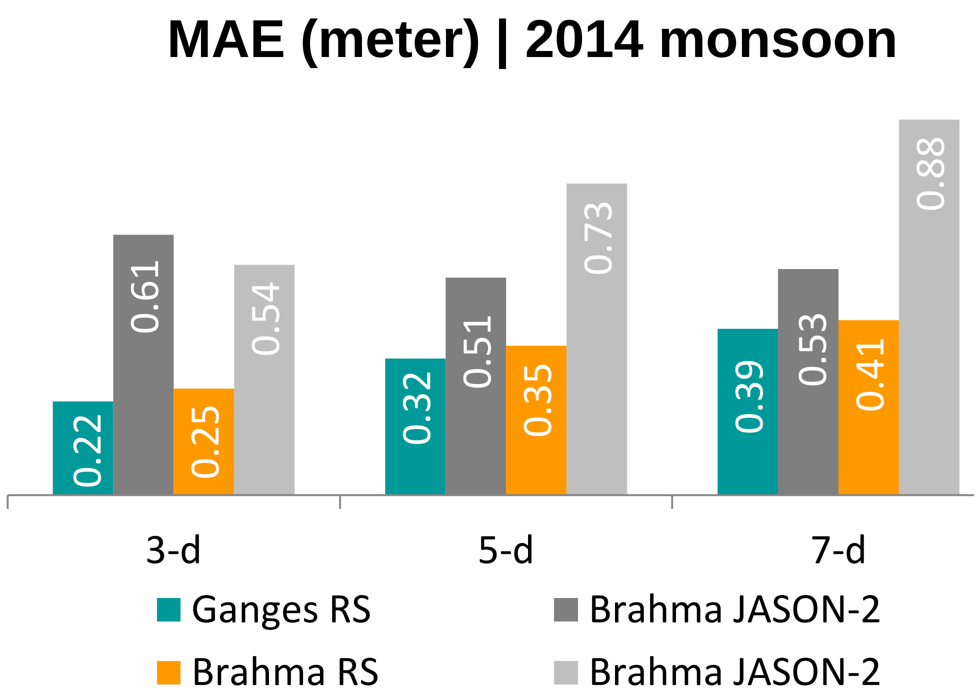
GBM results (comparison with CFAN)



CFAN: Climate Forecast Application Network (Webster et al., 2010).

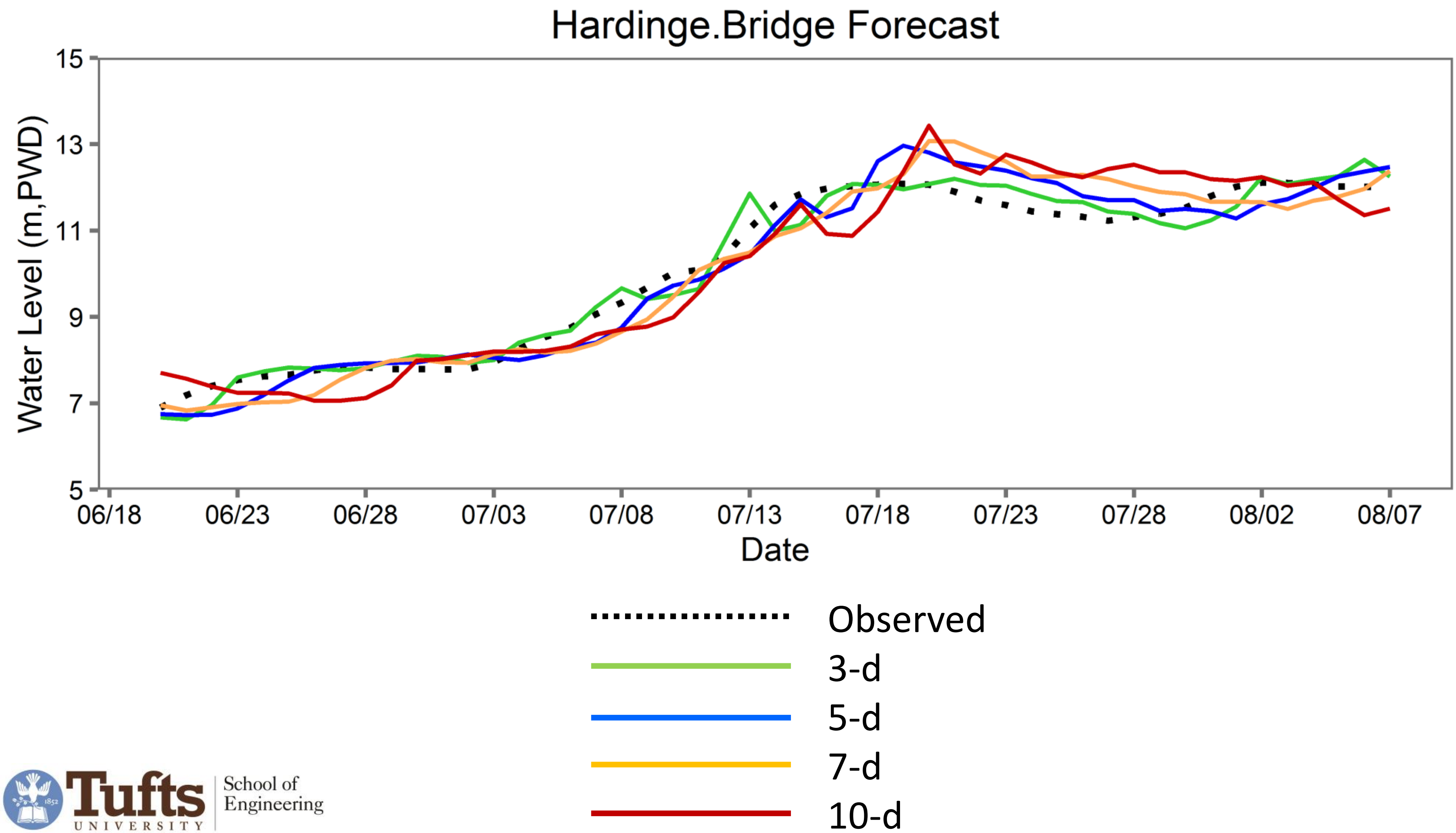
GBM results (comparison with JASON-2)



JASON-2 Altimetry-derived water level forecast (Hossain et al., 2014).

GBM Real-time forecasts (2017 monsoon)

Ganges



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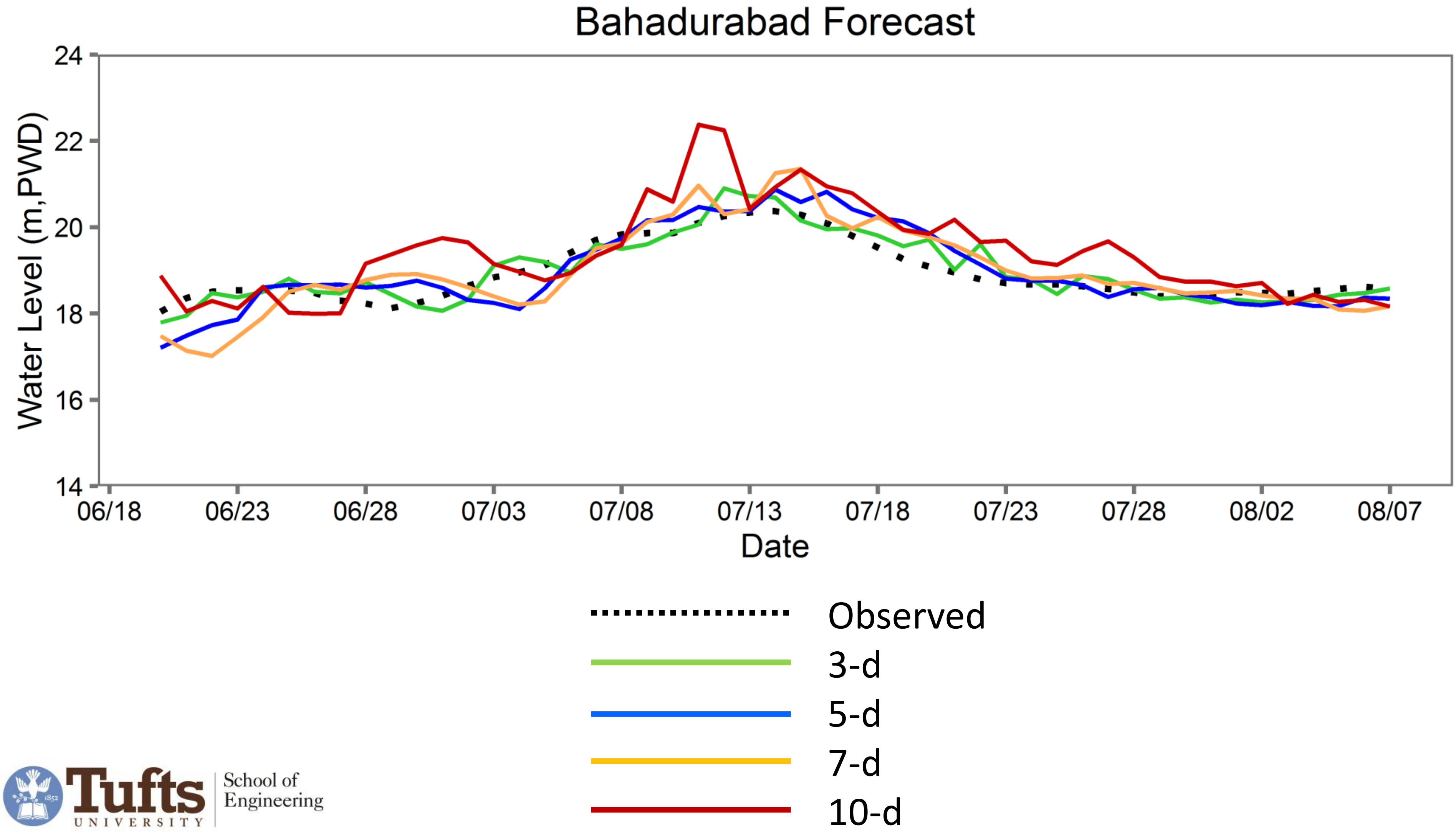
GBM Real-time forecasts (2017 monsoon)

Brahmaputra



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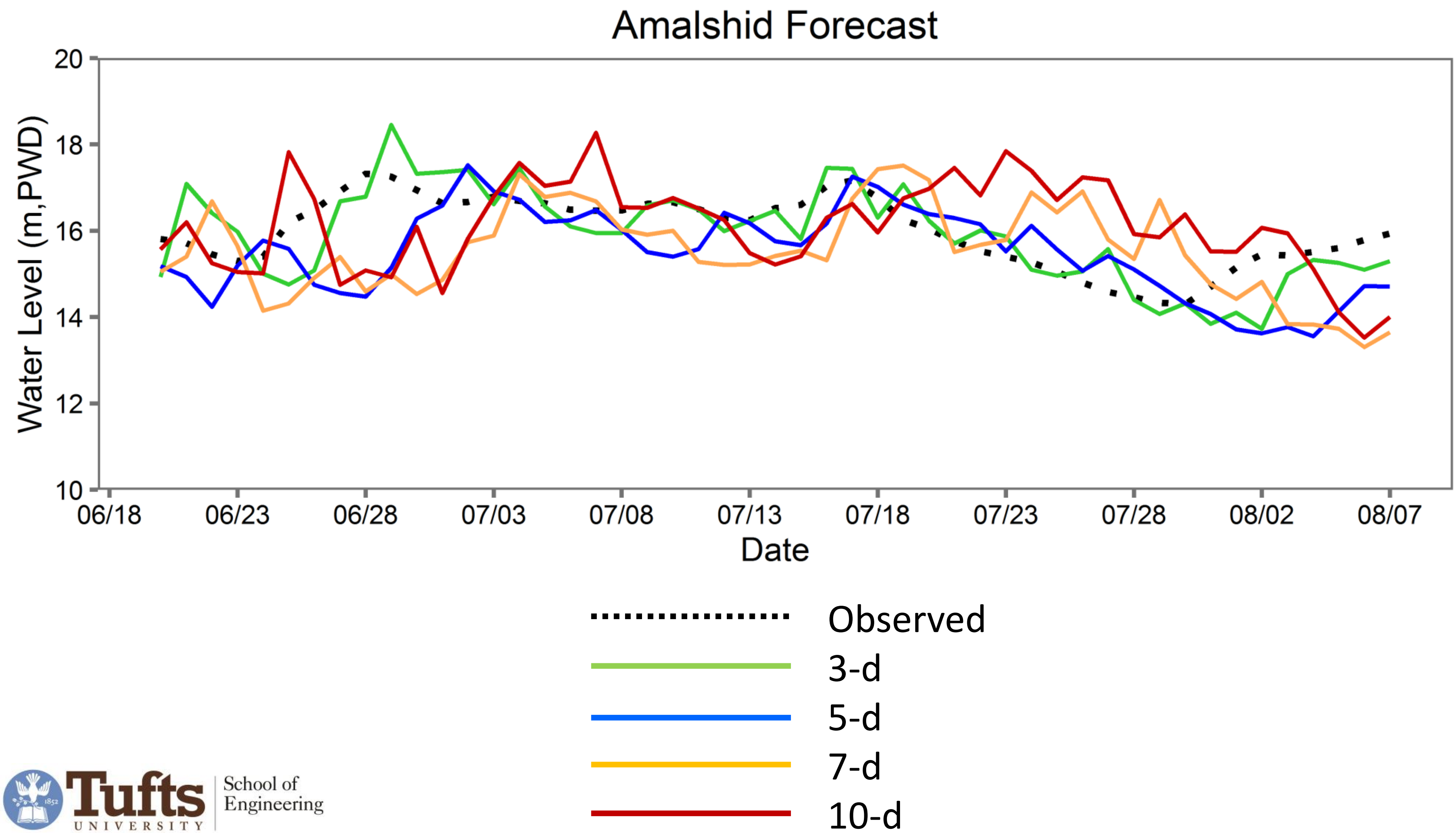
GBM Real-time forecasts (2017 monsoon)

Barak



Mean Absolute Error (MAE)
0.26
0.3
0.56
0.43
0.45
0.83
0.53
0.55
1.11
0.6
0.68
1
3d
5d
7d
10d
Hardinge Bridge
Bahadurabad
Amalshid
Root Mean Square Error (RMSE)
0.32
0.41
0.73
0.5
0.59
1.08
0.63
0.69
1.31
0.7
0.82
1.26
3d
5d
7d
10d
Hardinge Bridge
Bahadurabad
Amalshid
Coefficient of Determination (R2)
0.98
0.86
0.54
0.95
0.74
.17
0.92
0.63
0.9
0.7
3d
5d
7d
10d
Hardinge Bridge
Bahadurabad
Amalshid
Kling Gupta Efficiency (KGE)
0.99
0.85
0.64
0.95
0.68
0.39
0.93
0.65
0.13
0.92
0.56
0.13
3d
5d
7d
10d
Hardinge Bridge
Bahadurabad
Amalshid

GBM forecast: Summary

- RS model provides high forecast accuracy up to 10-days for the Ganges and Brahmaputra and 5-days for Meghna River.
- The contribution of adding upstream observed rainfall to a persistence model appears to significantly enhance forecasting lead-time.
- Forecasted rain's lead-time needs not to be equal to the flood forecast's target lead-time to produce skilled forecasting accuracy for a large river system like the GBM basins.
- The RS model can be used for those gauging locations where flow data is not available continuously.

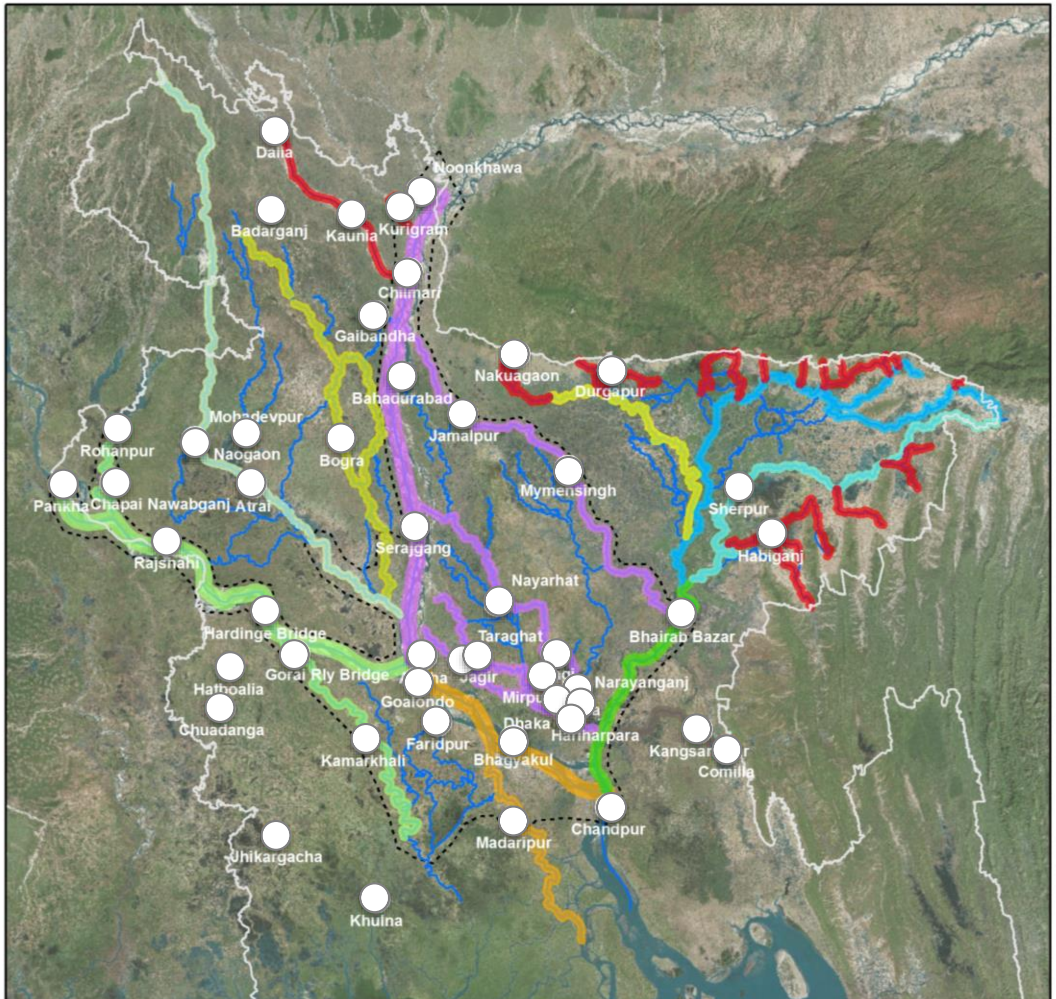
GBM forecast: Summary

- Large-scale weather captured in satellite estimates (TRMM) and weather model (WRF) are useful in a data-driven model to obtain skilled GBM forecasts (fourth major requisite simplicity).
- This model will have greater application in those basins where availability and access to upstream ground data are limited and detail hydrological modeling are expensive, resource intensive and operationally prohibitive.
- Easy to develop, implement and institutionalize for early flood warning operation.

Bangladesh Flood Forecasts

Transferring basin outlet forecasts at different lead-times (i.e., made on in the second component) to multi-location forecasts in the GBM alluvial river system inside Bangladesh by identifying requisite simplicity in the river hydraulics of regional flooding process.

Bangladesh Flood Forecasts



Bangladesh Flood Forecasts

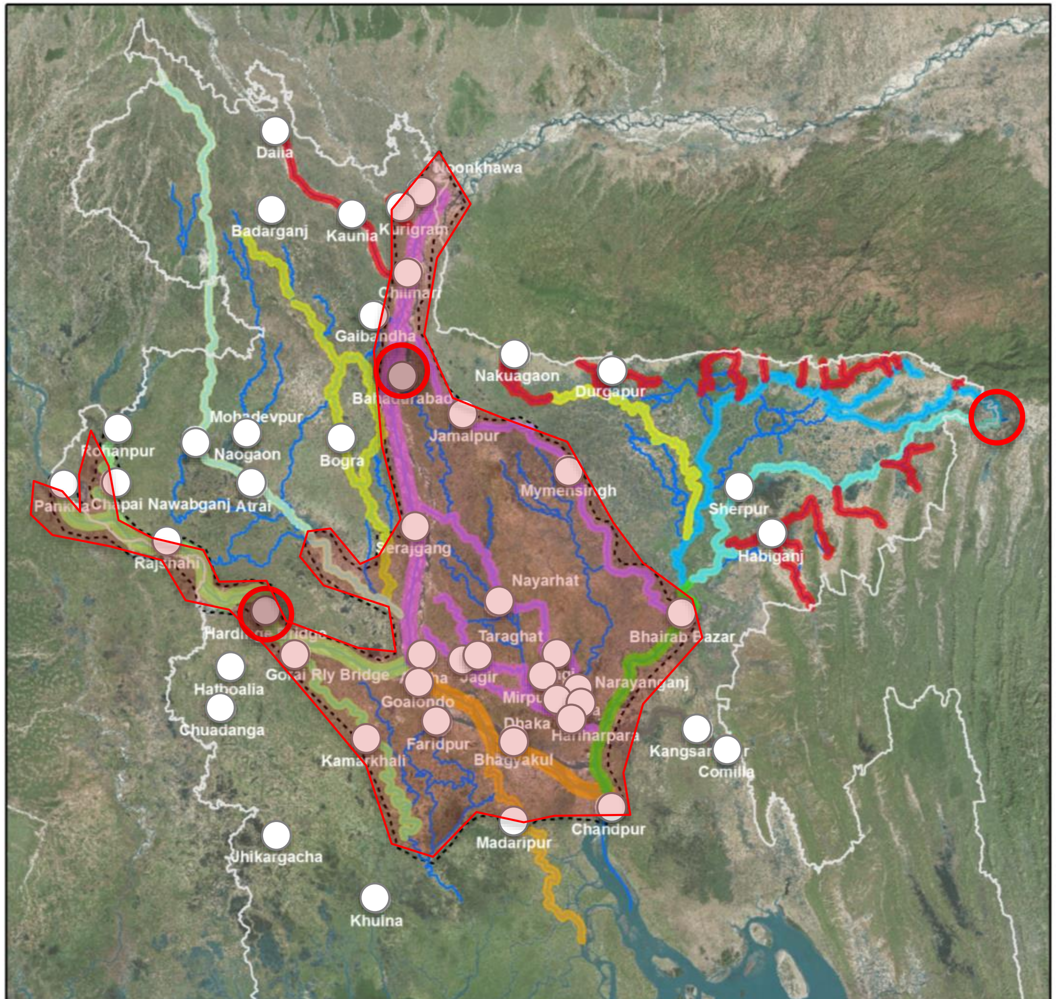
- Translating or transferring GBM basin outlet forecasts to downstream (in some case upstream) gauging locations along the rivers by using a linear model.
- Identify gauging location with similar riverine hydrology for which the said forecasts transferring could be possible. CCF helps to identify those river points.

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

Bangladesh Flood Forecasts

CCF

- <= 0.6
- 0.61-0.7
- 0.71-0.8
- 0.81-0.9
- 0.9-1.0

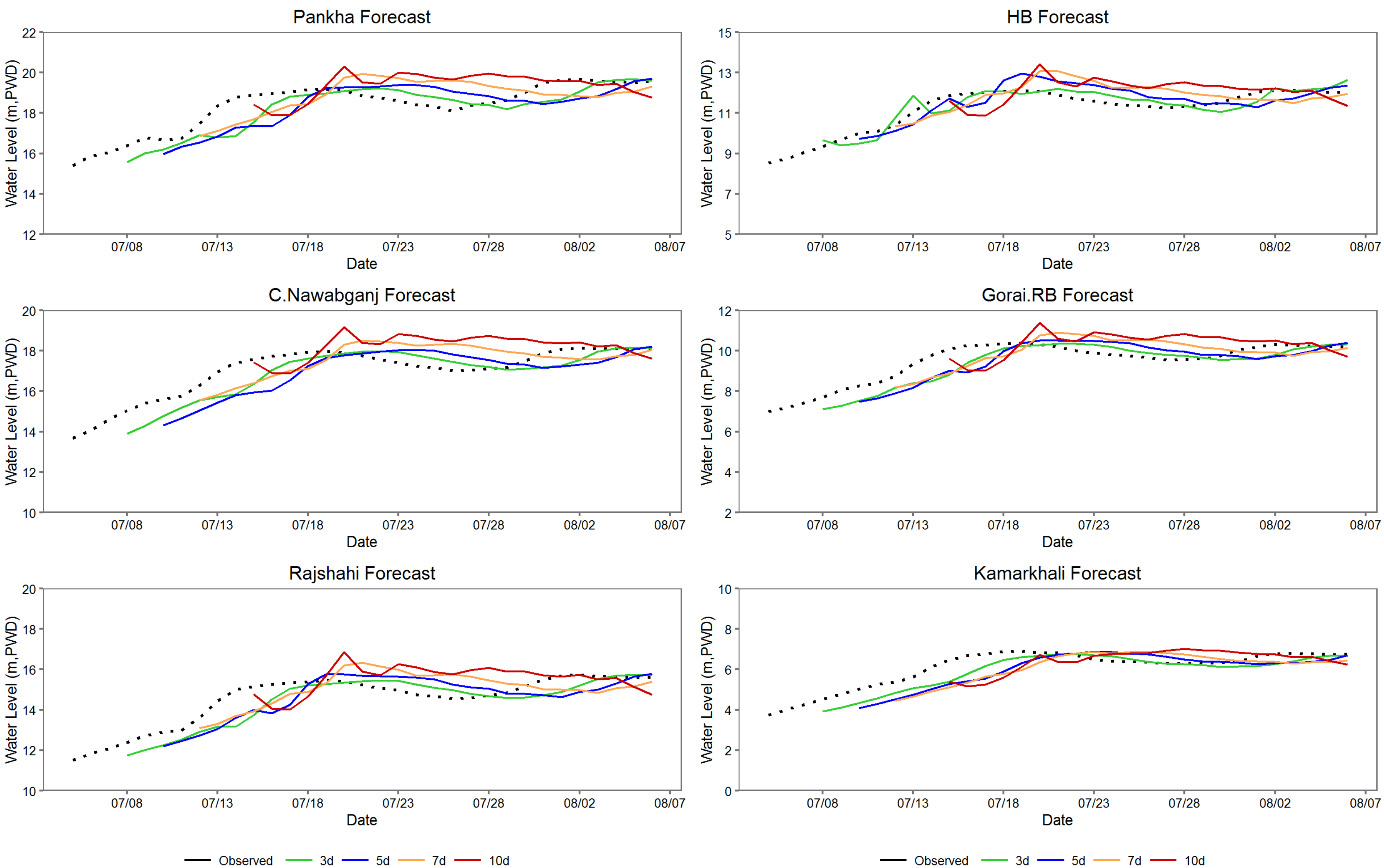


Bangladesh Flood Forecasts

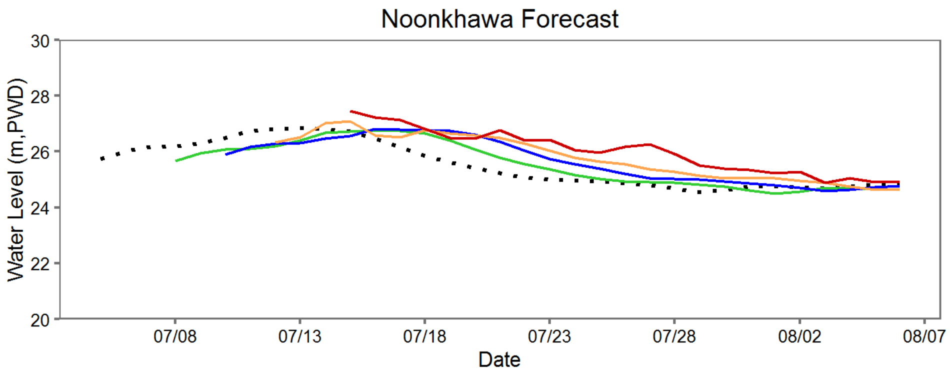
- The linear model uses already generated forecasts of ‘from’ river point and origin of forecast day’s observation at ‘to’ or ‘target’ river point to make forecasts at this point.

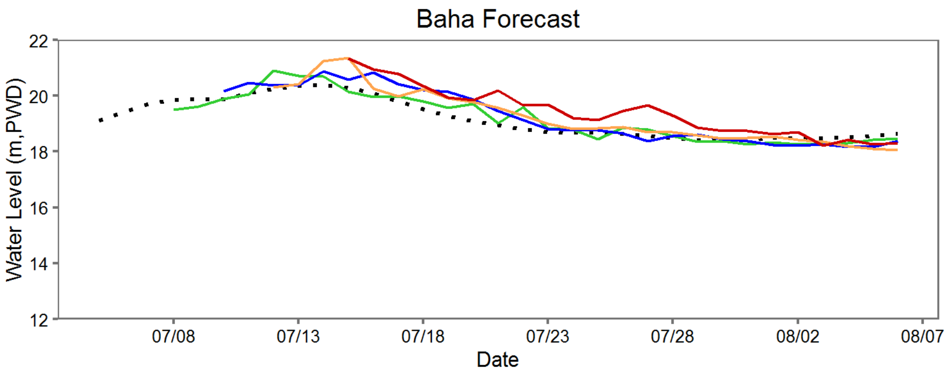
$$H_{t+n} = \alpha_n H_t + \beta_n {H_{us/ds}}_{t+n} + \gamma_n$$

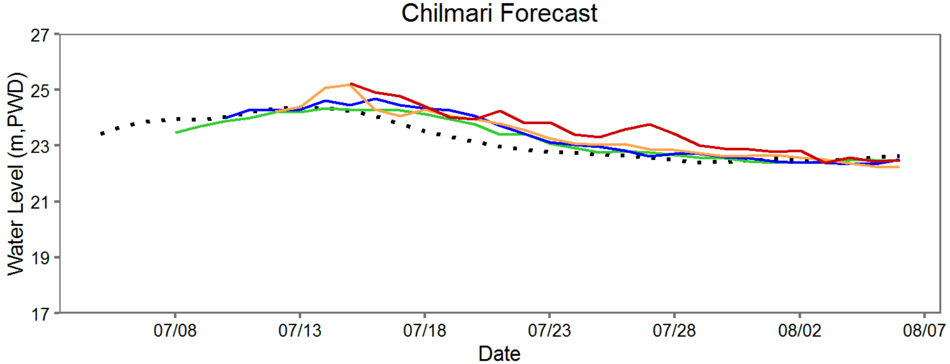
Bangladesh Flood Forecasts: 2017 Monsoon

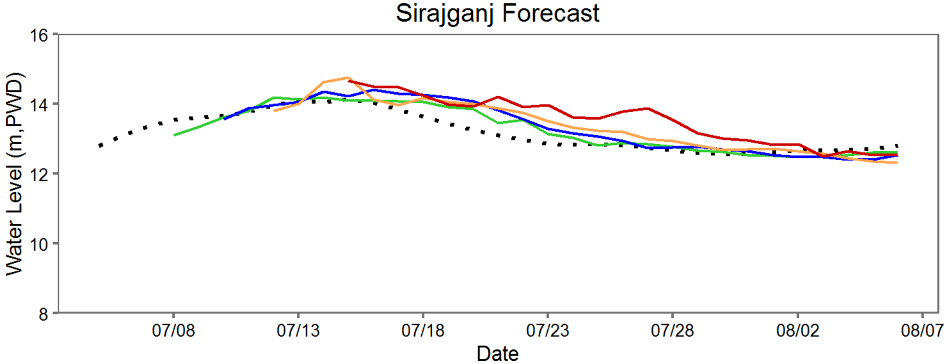


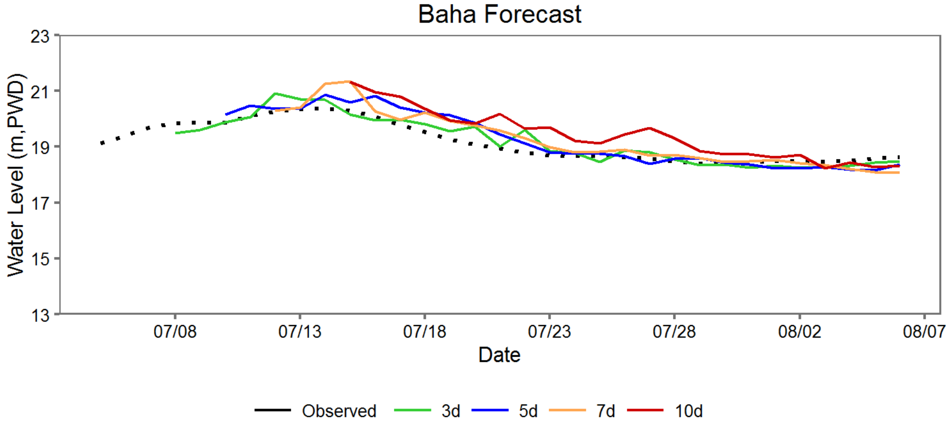
Bangladesh Flood Forecasts: 2017 Monsoon

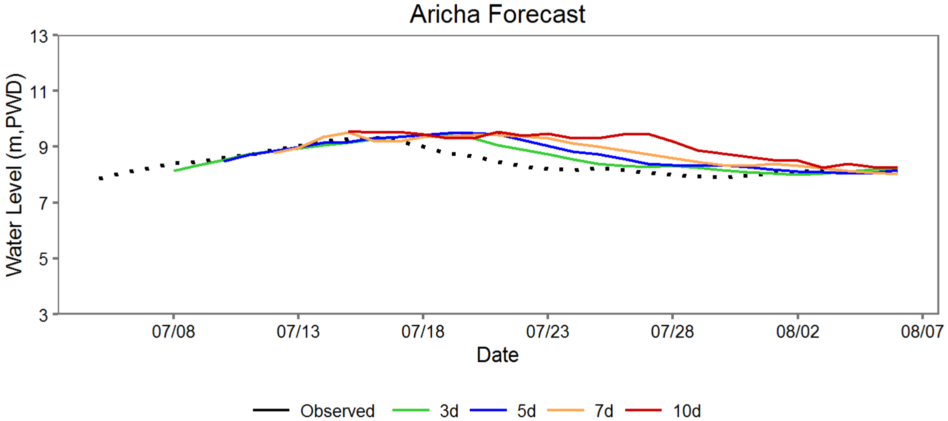




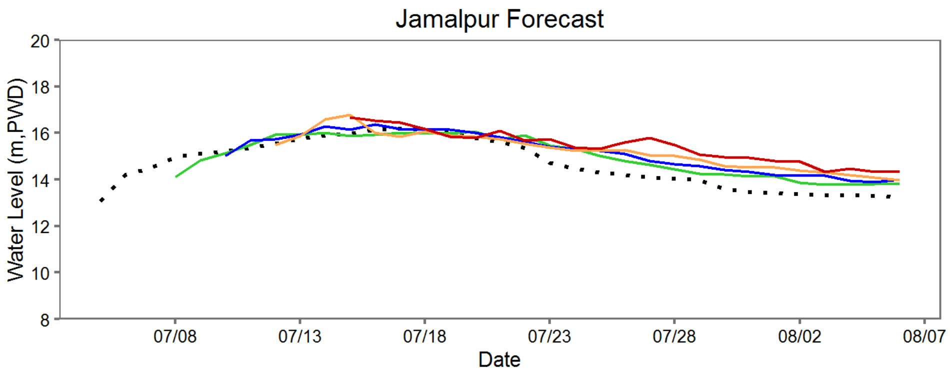


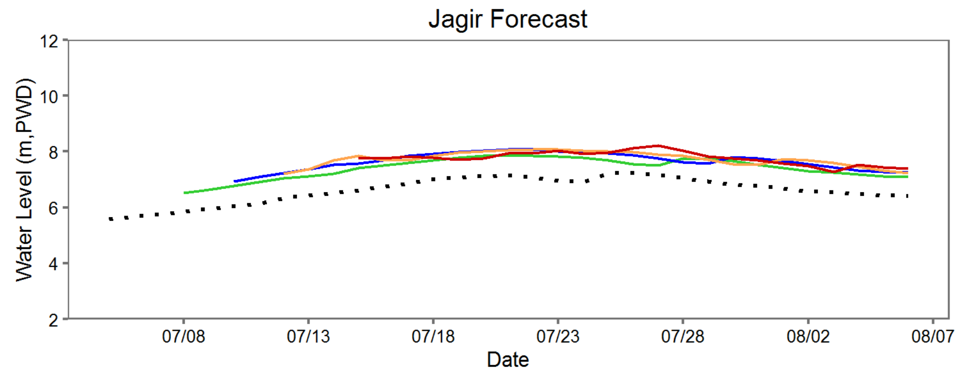


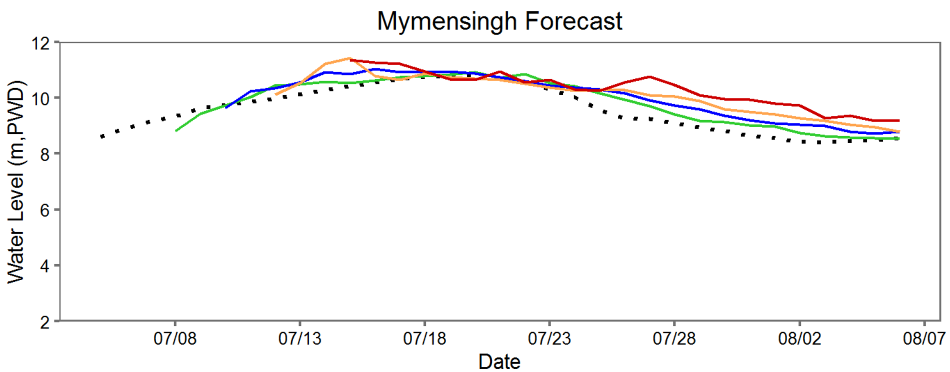


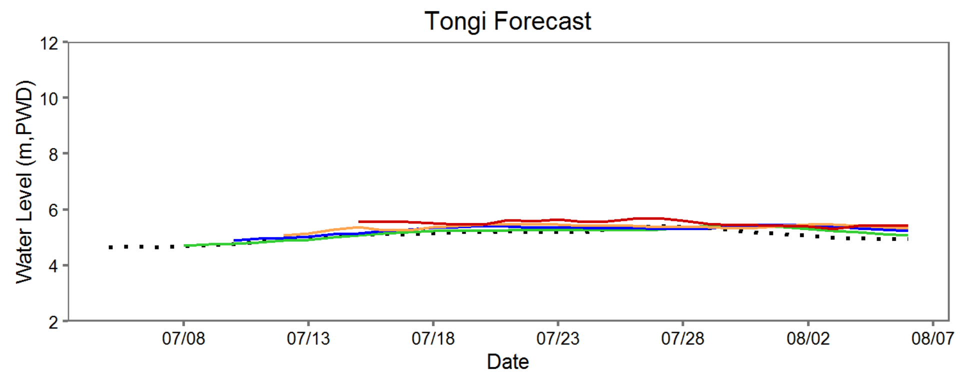


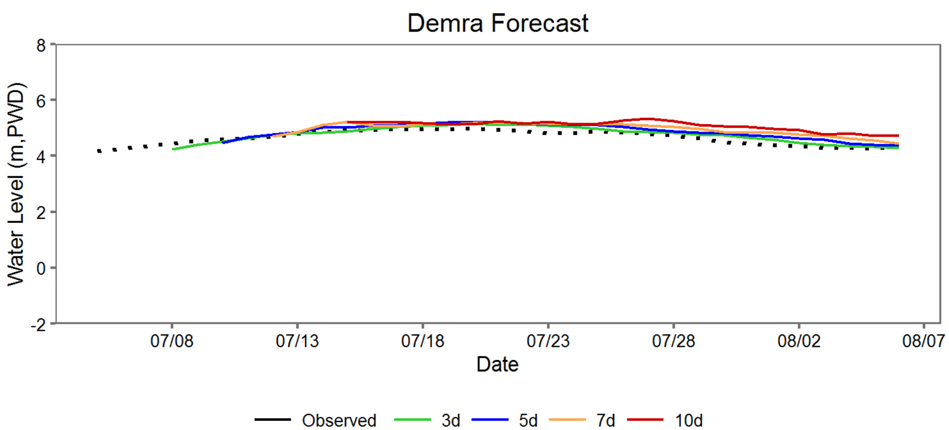
Bangladesh Flood Forecasts: 2017 Monsoon

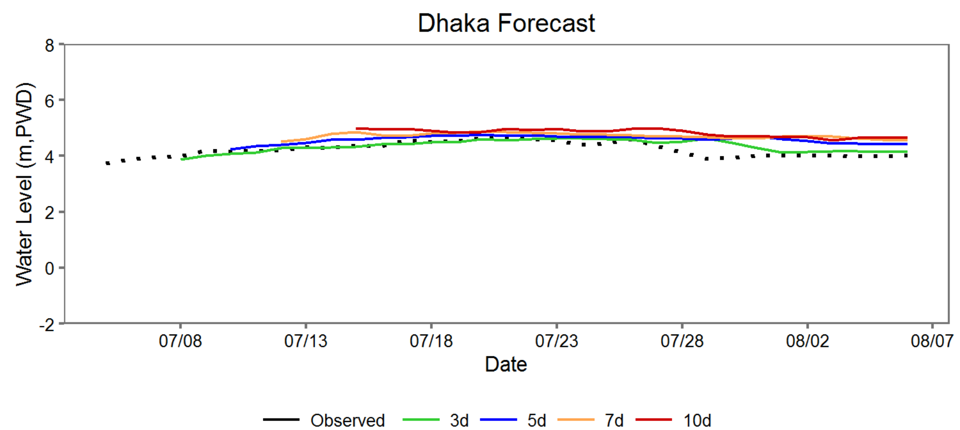




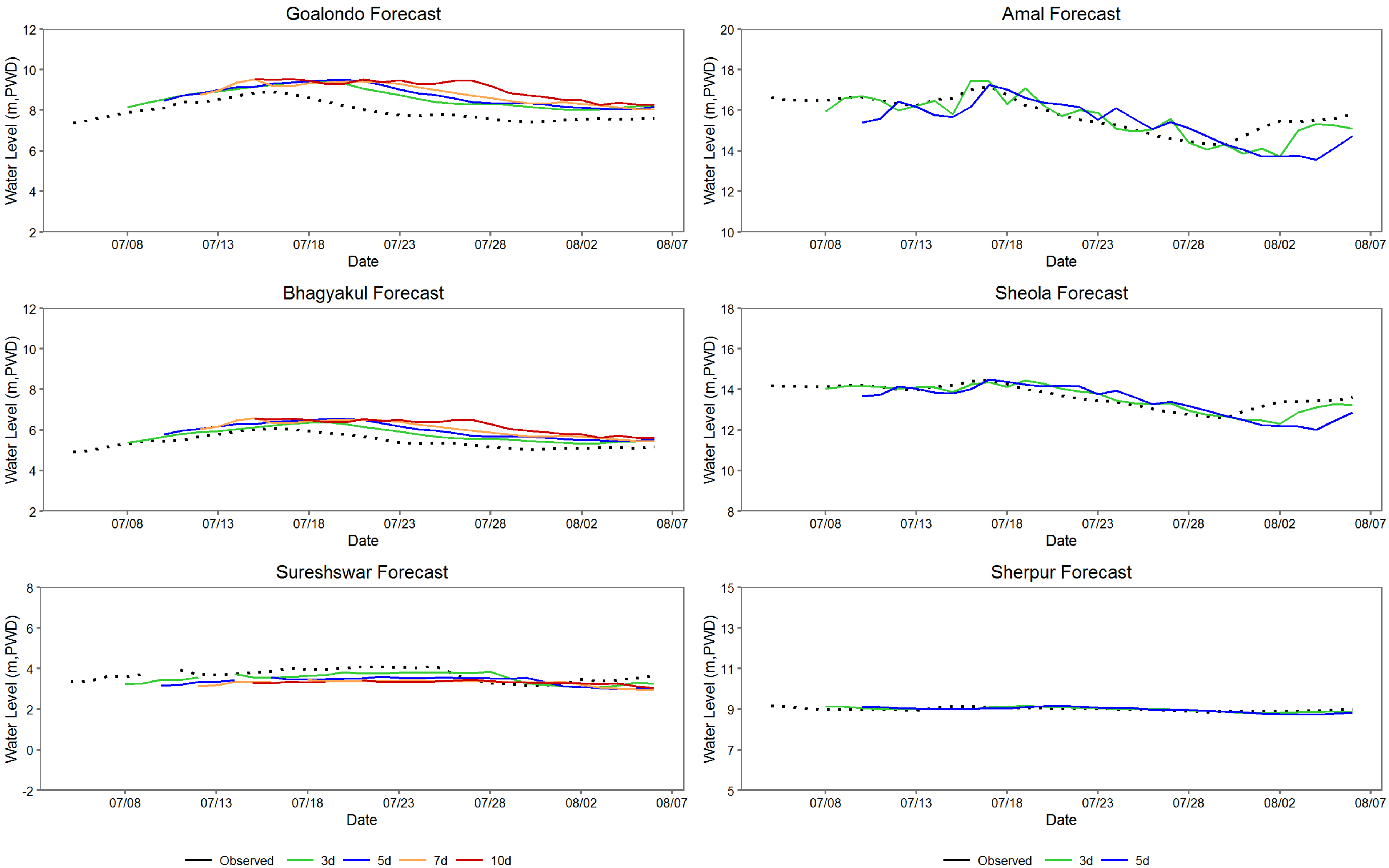




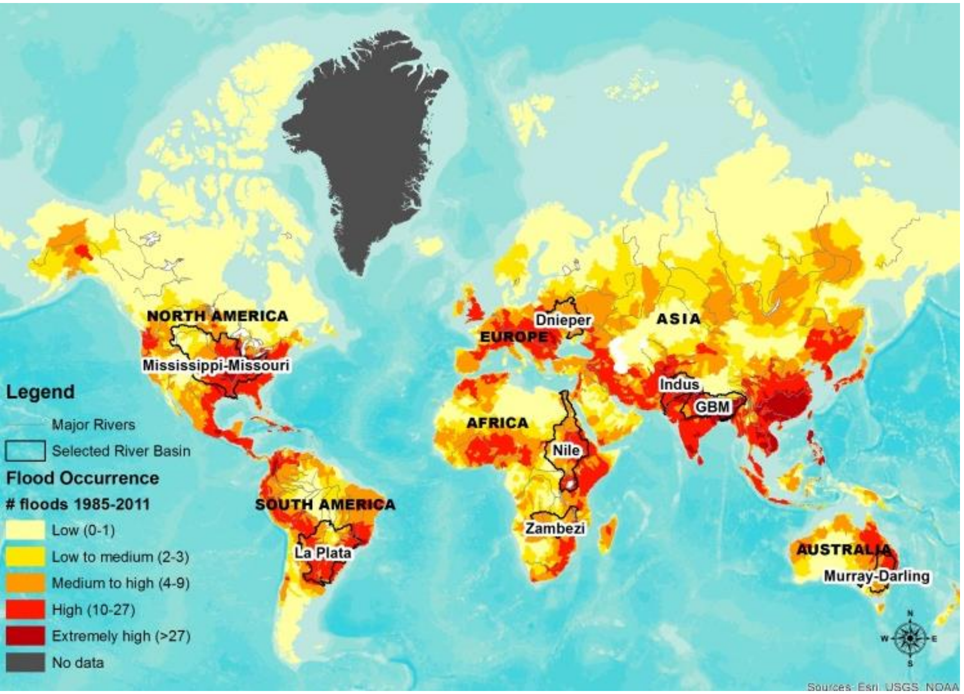


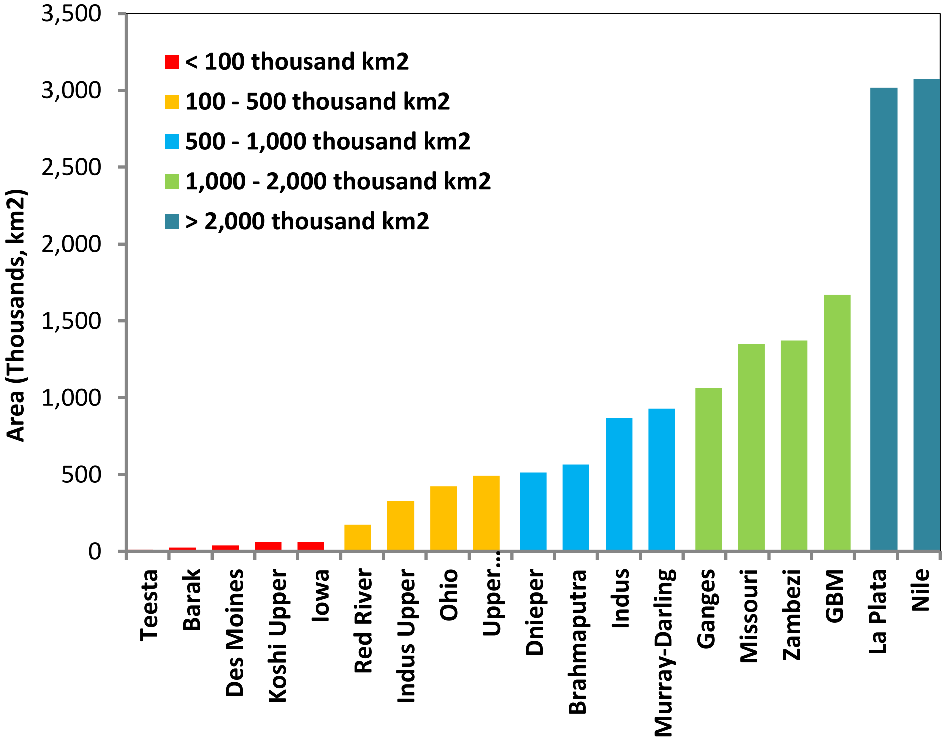


Bangladesh Flood Forecasts: 2017 Monsoon



Application of Requisitely Simple forecasting in other river basins





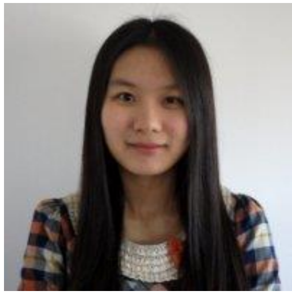
Conclusion

- The ReqSim model will have greater application in those basins where availability and access to upstream ground data are limited and detail hydrological modeling are expensive, resource intensive and operationally prohibitive.
- To apply our method, one needs observed WL or streamflow data at forecast location and upstream basin rainfall (from precipitation measuring satellites/models).
- Easy to develop, implement and institutionalize for early flood warning operation.
- The approach may not be work well for a river basin that is heavily controlled by upstream regulators. Flow travel time is easy to calculate.

Conclusion

- We hope the notion of requisite simplicity – examining the tradeoff between modeling complexity and functional utility – will be used as a guiding principle to enhance flood forecasting accuracy of large rivers.
- We are not against detail modelling. At the same time, choice of model depends on objectives.
- We are ready to provide/share our forecasts for Bangladesh flood from 2018 monsoon.

Research Team



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Thank you

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