Improved Streamflow Prediction using WRF-Hydro and DART: Recent Advances and Developments

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Motivation and Objectives

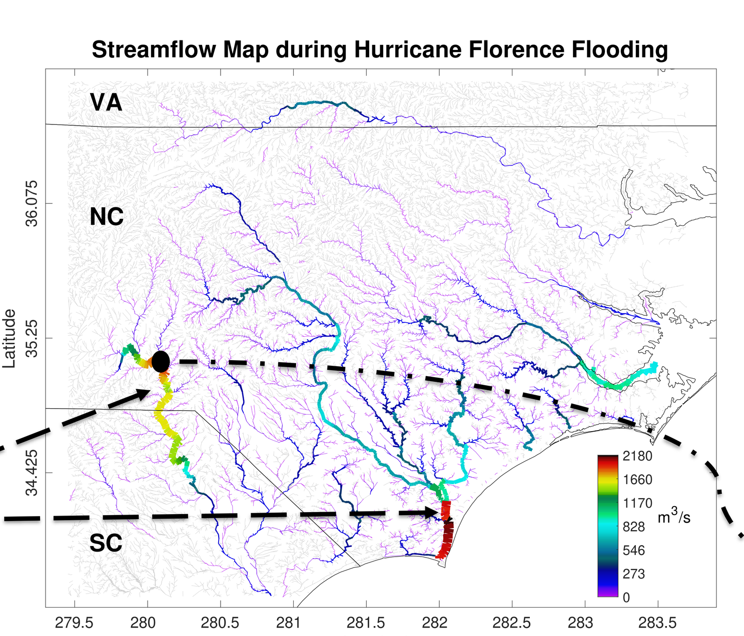
- Hurricane Florence evolved from a tropical wave, off the west coast of Africa, into a tropical storm and then a Category 4 hurricane over the Carolinas in Sep. 2018
- It made landfall on Sep. 14th with winds up to 150 mph
- It caused catastrophic damages to coastal communities, with estimated losses of ~ $25 billion
- It was reported that flooding magnitude greatly exceeded the levels observed due to Hurricane Matthew in 2016

- *Top right:* Satellite image of Hurricane Florence on Sep. 11 (source: NWS)
- *Bottom right:* Total Precipitation along the Hurricane's track (> 35 inches)
- *Top left:* Flooding in Lumberton, NC

The goal of this study: Interface the Data Assimilation Research Testbed (DART; Anderson et al., 2009) with WRF-Hydro (NOAA's NWM; Gochis et al., 2020) to enhance flood prediction

The Coupled Framework

- Regional subdomain of the NWM CONUS with ~67,000 reaches
- Streamflow+Bucket Configuration



- DART latest Manhattan Release (https://github.com/NCAR/DART)
- We employ an Ensemble Adjustment Kalman Filter (80 members)
- We perform hourly assimilation of streamflow data using 107 USGS gauges distributed in the study area
- Multiphysics Approach: Perturb 6 model (channel geometry) parameters to create realistic internal variability in the ensemble

Key Data Assimilation Enhancements

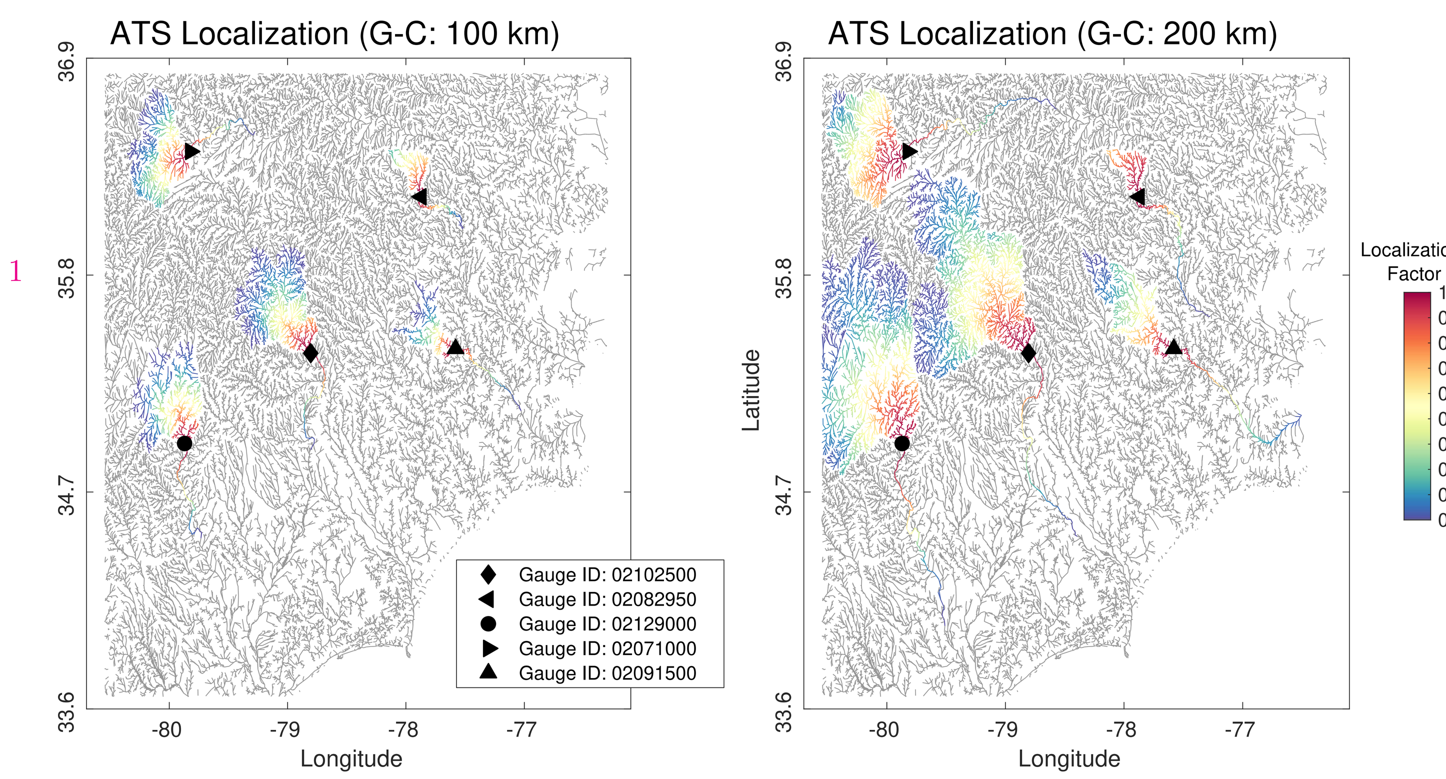
I. Along-The-Stream (ATS) Localization

ATS Localization (El Gharamti et al., 2020): aims to mitigate not only spurious correlations, due to limited ensemble size, but also physically incorrect correlations between unconnected state variables in the river network

$$x^{a(i)}_{j,k} = x^{f(i)}_{j,k} + \alpha \Delta x^{(i)}_{j}, \quad j,k,i: \{\text{space, time, ensemble}\} \quad 0 < \alpha < 1$$

During the update, state increments are multiplied with a localization factor (α) before regression. A correlation function, e.g., Gaspari-Cohn (G-C), is used to compute α

- Sensitivity experiments showed that 100 km radius yielded the best performance
- ATS localization produces significantly better (in terms of RMSE) streamflow estimates than regular Euclidean distance-based localization



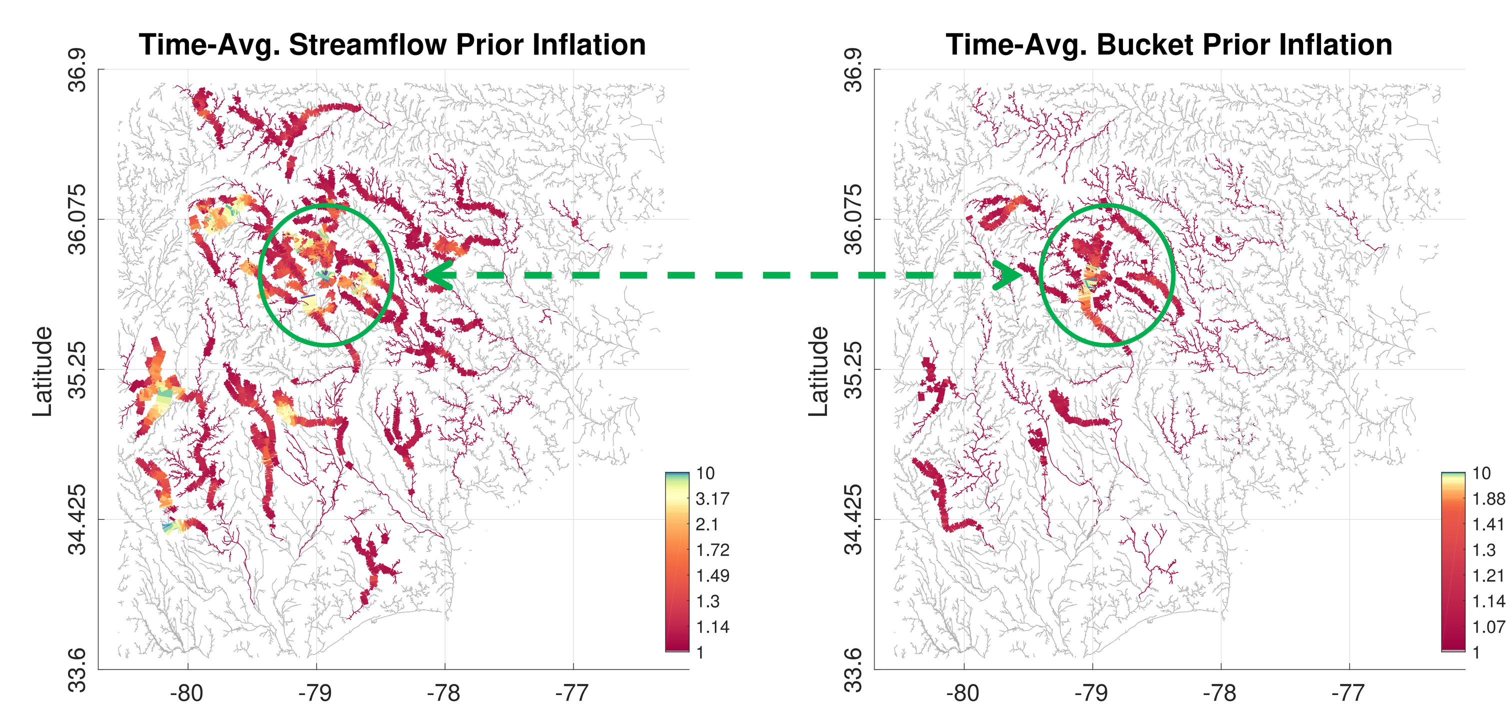
II. Spatially and Temporally Varying Adaptive Inflation

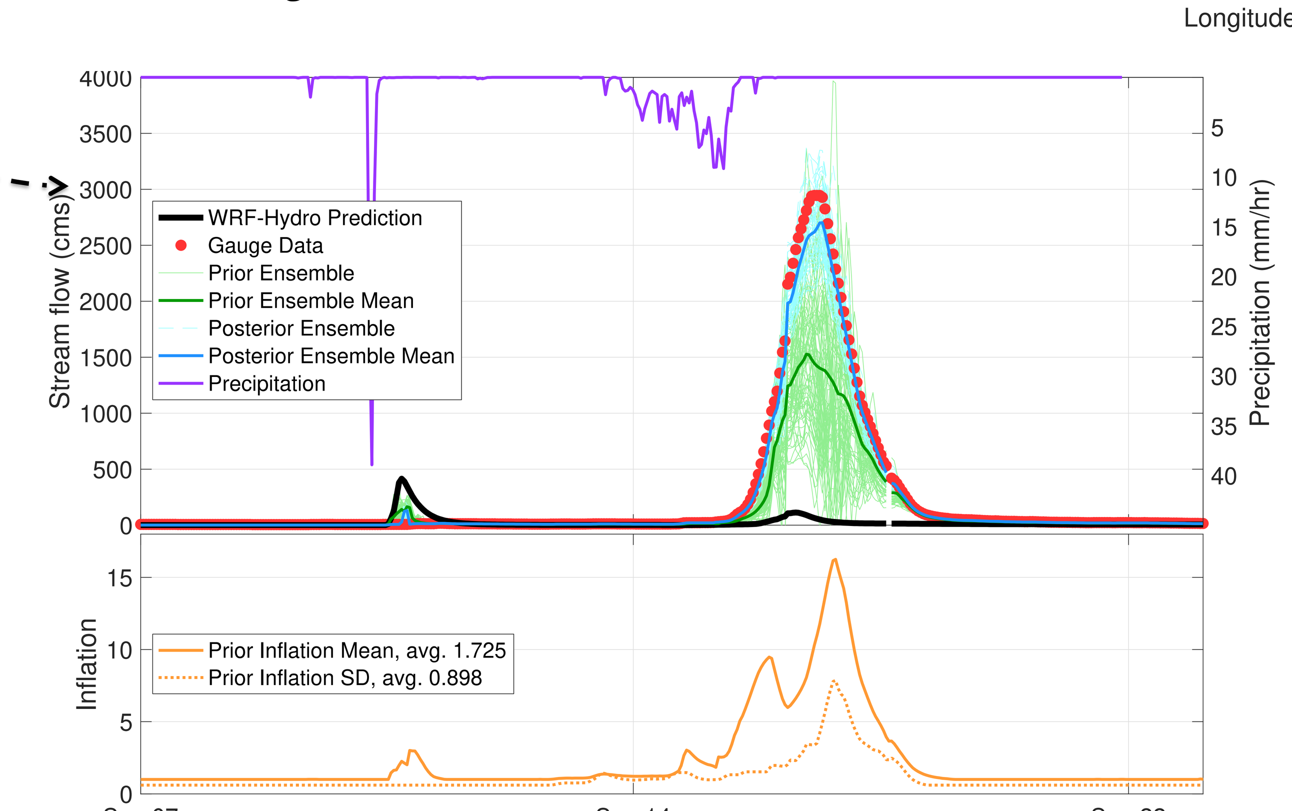
$$\underbrace{p\left(\lambda | d^{f|a}\right)}_{\text{Posterior}} \approx \underbrace{p\left(d^{f|a} | \lambda\right)}_{\text{Likelihood}} \cdot \underbrace{p(\lambda)}_{\text{Prior}}$$

- The algorithm (El Gharamti, 2018) is adaptive in time, based on Bayes' theorem, and results in spatially varying inflation fields
- Prior inflation is aimed at mitigating model biases while posterior inflation is able to tackle sampling errors

Inflation factor is denoted by λ (typically larger than 1). The forecast or the analysis innovations are given by $d^{f|a}$. The algorithm is sequential such that the posterior pdf after the update is used as the prior in the next cycle.

The Figure to the right shows the prior inflation maps (averaged over a few DA cycles) for the streamflow (left) and the bucket (right) states. Densely observed regions have large inflation values. Since it's directly observed, streamflow inflation is larger than the bucket.





The hydrograph to the left shows a severe streamflow underestimation by the model along the Pee Dee River. The is mainly due to biases in the boundary conditions such as precipitation (shown in purple). After landfall, the prior ensemble (in green) shows massive improvements over the model's prediction. The posteriors (in blue) fit the observations almost perfectly.

Adaptive prior inflation plays a significant role in eliminating model biases. As can be seen in the bottom panel, the inflation mean grows to ~15 on Sep. 17. By increasing the ensemble spread, the filter is able to bring the streamflow forecast closer to the data.

References

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Summary

- The National Water Model (NWM) configuration of the WRF-Hydro framework is coupled to the Data Assimilation Research Testbed (DART) to improve ensemble streamflow forecasts under extreme rainfall conditions during Hurricane Florence in Sep. 2018.
- A topologically based "along-the-stream" (ATS) localization is proposed. The scheme is shown to improve information propagation during the Kalman update. ATS localization specifically eliminates error-covariances between unconnected streams (i.e., streams in different basins or watersheds).
- We demonstrate the utility of spatially and temporally varying adaptive inflation in hydrologic applications, particularly to help control model bias. Results show that inflation is able to play an indispensable bias correction role, without which, the quality of the streamflow prediction would be poor.
- Future research will focus on: [1] medium and long-range forecasts (up to 18 hours) and [2] studying the impacts of Gaussian anamorphosis on the bounded streamflow state during the update.