Hydro-DART: Ensemble Streamflow Data Assimilation using WRF-Hydro and DART

Application to Hurricane Florence

Moha Gharamti
https://dart.ucar.edu/
gharamti@ucar.edu

Date: Nov. 20, 2020

National Center for Atmospheric Research
Data Assimilation Research Section (DAReS) - TDD - CISL

CISL Computational & Information Systems Lab

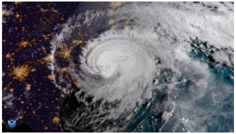
AGU

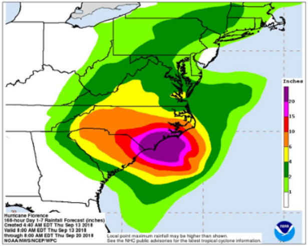
NCAR NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

Motivation

Hurricane Florence

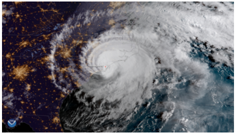
- Tropical wave ⇝ tropical storm ⇝ **Category 4 Hurricane**
- Landfall on Sep. 14 (Carolinas) with winds up to 150 mph
- Catastrophic damages to coastal communities [$25 billion]
- Flooding magnitude greatly exceeded the levels observed due to Hurricane Matthew in 2016

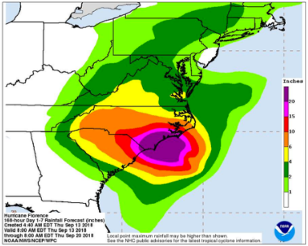




Hurricane Florence

- Tropical wave $\rightsquigarrow$ tropical storm $\rightsquigarrow$ **Category 4 Hurricane**
- Landfall on Sep. 14 (Carolinas) with winds up to 150 mph
- Catastrophic damages to coastal communities [$25 billion]
- Flooding magnitude greatly exceeded the levels observed due to Hurricane Matthew in 2016



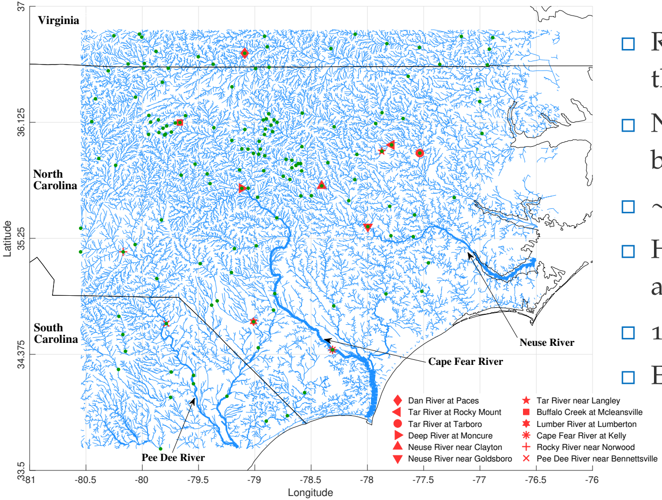


Hurricane Florence cont.

- The **goal** is to interface the Data Assimilation Research Testbed (DART; Anderson, 2003) with WRF-Hydro (NOAA's NWM; Gochis, 2020) to enhance flood prediction during Hurricane Florence

Hurricane Florence cont.

- The **goal** is to interface the Data Assimilation Research Testbed (DART; Anderson, 2003) with WRF-Hydro (NOAA's NWM; Gochis, 2020) to enhance flood prediction during Hurricane Florence



- Regional subdomain of the NWM CONUS
- NWM channel network based on NHDPlus v.2
- ~ 67K reaches
- Hourly streamflow assimilation
- 107 USGS gauges
- EAKF: 80 members

The Coupled Hydrologic-Assimilation Framework

The Hydrologic Model

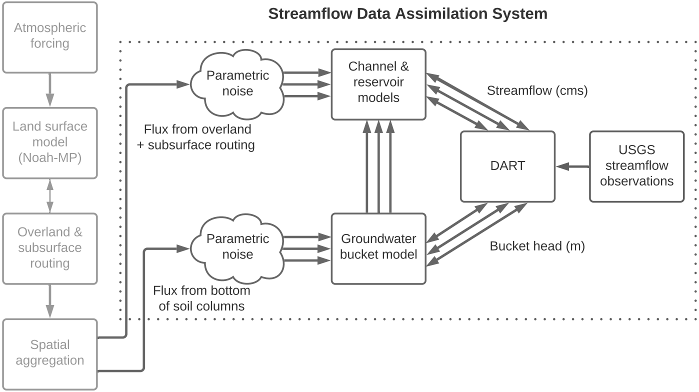
Channel + Bucket Configuration:

- **Streamflow Model:** Muskingum-Cunge hydrograph routing
- **Groundwater Bucket Model:** Mitigate baseflow deficiencies

The Hydrologic Model

Channel + Bucket Configuration:

- **Streamflow Model:** Muskingum-Cunge hydrograph routing
- **Groundwater Bucket Model:** Mitigate baseflow deficiencies



The Hydrologic Model

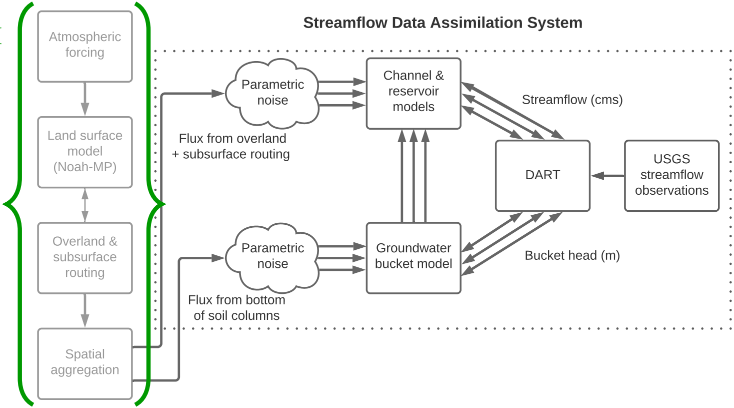
Channel + Bucket Configuration:

- Streamflow Model: Muskingum-Cunge hydrograph routing
- Groundwater Bucket Model: Mitigate baseflow deficiencies

Full model run from 2010-10-01 to 2018-07-01

beyond 2010-07-01: NWM operational analysis

Deterministic NWM model chain from forcing through aggregation



The Hydrologic Model

Channel + Bucket Configuration:

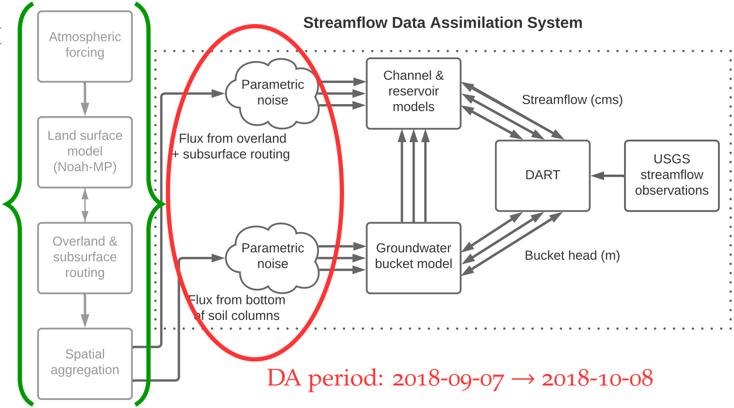
- **Streamflow Model:** Muskingum-Cunge hydrograph routing
- **Groundwater Bucket Model:** Mitigate baseflow deficiencies

Full model run from 2010-10-01 to 2018-07-01

beyond 2010-07-01: NWM operational analysis

Deterministic NWM model chain from forcing through aggregation

One-way runoff fluxes used as input forcing to the channel+bucket sub-model



DA period: 2018-09-07 → 2018-10-08

Forcing and Ensemble Uncertainty

- Apply Gaussian perturbations to the boundary fluxes to the streamflow and bucket models every hourly forecast step
- To create realistic model variability, we follow a "multi-physics" approach (Berner et al., 2011) and perturb the channel parameters:
  1. top width, T
  2. bottom width, B
  3. side slope, m
  4. Manning's N, n
  5. width of compound channel, T_{cc}
  6. Manning's N of compound channel, n_{cc}

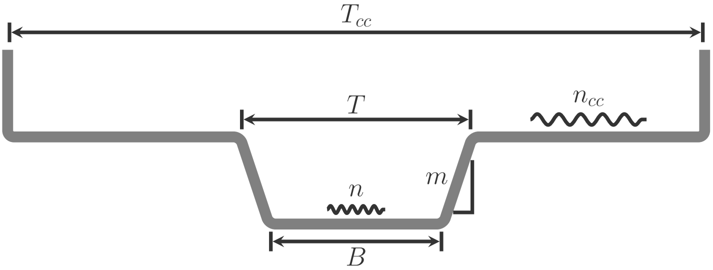
  Sampling uniformly under some physical constraints!

Forcing and Ensemble Uncertainty

- Apply Gaussian perturbations to the boundary fluxes to the streamflow and bucket models every hourly forecast step
- To create realistic model variability, we follow a "multi-physics" approach (Berner et al., 2011) and perturb the channel parameters:

1. top width, T
2. bottom width, B
3. side slope, m
4. Manning's N, n
5. width of compound channel, T_{cc}
6. Manning's N of compound channel, n_{cc}

Sampling uniformly under some physical constraints!



DART: The Data Assimilation Research Testbed

- Serial DA scheme: process observations one after the other
- State: [1] Streamflow & [2] groundwater bucket at every reach

How to mitigate typical filtering issues?

i. **Sampling Errors:** due to limited ensemble size

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

$\longrightarrow$ Along-The-Stream (ATS) Localization $[0 < \alpha < 1]$

ii. **Model Biases:** e.g., physical parameters, boundary conditions, ...

$$\mathbf{x}_{j}^{f|a(i)} = \sqrt{\lambda}\left(\mathbf{x}_{j}^{f|a(i)} - \overline{\mathbf{x}}_{j}^{f|a}\right) + \overline{\mathbf{x}}_{j}^{f|a}; \quad f|a : \{\text{forecast or analysis}\}$$

$\longrightarrow$ Spatially and Temporally Varying Adaptive Inflation $[\sqrt{\lambda} \geq 1]$

DART: The Data Assimilation Research Testbed

- Serial DA scheme: process observations one after the other
- State: [1] Streamflow & [2] groundwater bucket at every reach

How to mitigate typical filtering issues?

i. **Sampling Errors:** due to limited ensemble size

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

$\rightarrow$ Along-The-Stream (ATS) Localization $[0 < \alpha < 1]$

ii. **Model Biases:** e.g., physical parameters, boundary conditions, ...

$$\mathbf{x}_j^{f|a(i)} = \sqrt{\lambda} \left(\mathbf{x}_j^{f|a(i)} - \overline{\mathbf{x}}_j^{f|a} \right) + \overline{\mathbf{x}}_j^{f|a}; \quad f|a : \{\text{forecast or analysis}\}$$

$\rightarrow$ Spatially and Temporally Varying Adaptive Inflation $[\sqrt{\lambda} \geq 1]$

DART: The Data Assimilation Research Testbed

- Serial DA scheme: process observations one after the other
- State: [1] Streamflow & [2] groundwater bucket at every reach

How to mitigate typical filtering issues?

i. **Sampling Errors:** due to limited ensemble size

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

$\rightarrow$ Along-The-Stream (ATS) Localization $[0 < \alpha < 1]$

ii. **Model Biases:** e.g., physical parameters, boundary conditions, ...

$$\mathbf{x}_j^{f|a(i)} = \sqrt{\lambda} \left(\mathbf{x}_j^{f|a(i)} - \overline{\mathbf{x}}_j^{f|a} \right) + \overline{\mathbf{x}}_j^{f|a}; \quad f|a : \{\text{forecast or analysis}\}$$

$\rightarrow$ Spatially and Temporally Varying Adaptive Inflation $[\sqrt{\lambda} \geq 1]$

DART: The Data Assimilation Research Testbed

- Serial DA scheme: process observations one after the other
- State: [1] Streamflow & [2] groundwater bucket at every reach

How to mitigate typical filtering issues?

i. **Sampling Errors:** due to limited ensemble size

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

$\rightarrow$ Along-The-Stream (ATS) Localization $[0 < \alpha < 1]$

ii. **Model Biases:** e.g., physical parameters, boundary conditions, ...

$$\mathbf{x}_j^{f|a(i)} = \sqrt{\lambda}\left(\mathbf{x}_j^{f|a(i)} - \overline{\mathbf{x}}_j^{f|a}\right) + \overline{\mathbf{x}}_j^{f|a}; \quad f|a : \{\text{forecast or analysis}\}$$

$\rightarrow$ Spatially and Temporally Varying Adaptive Inflation $[\sqrt{\lambda} \geq 1]$

DART: The Data Assimilation Research Testbed

- Serial DA scheme: process observations one after the other
- State: [1] Streamflow & [2] groundwater bucket at every reach

How to mitigate typical filtering issues?

i. **Sampling Errors:** due to limited ensemble size

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

→ Along-The-Stream (ATS) Localization $[0 < \alpha < 1]$

ii. **Model Biases:** e.g., physical parameters, boundary conditions, ...

$$\mathbf{x}_j^{f|a(i)} = \sqrt{\lambda}\left(\mathbf{x}_j^{f|a(i)} - \overline{\mathbf{x}}_j^{f|a}\right) + \overline{\mathbf{x}}_j^{f|a}; \quad f|a : \{\text{forecast or analysis}\}$$

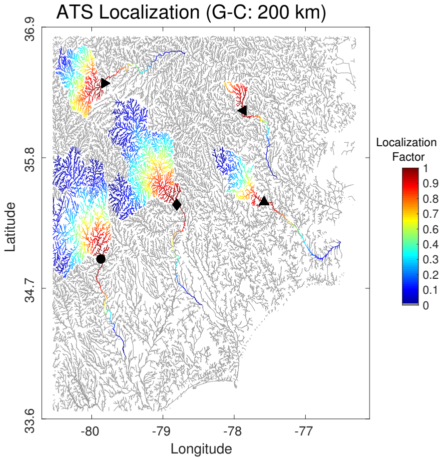
→ Spatially and Temporally Varying Adaptive Inflation $[\sqrt{\lambda} \geq 1]$

Along-The-Stream (ATS) Localization

ATS localization 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

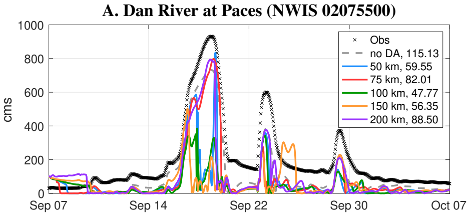
Along-The-Stream (ATS) Localization

ATS localization 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

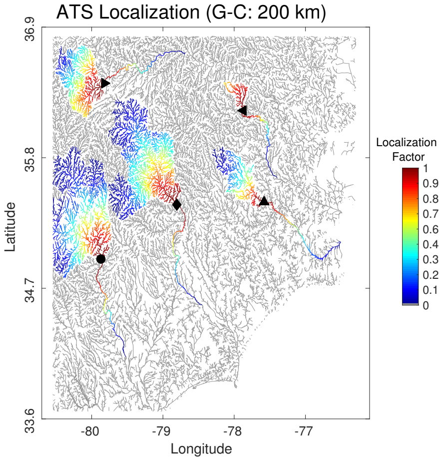


Along-The-Stream (ATS) Localization

ATS localization 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



- best performance using 100 km
- larger radii give rise to spurious correlations and smaller ones limit the amount of useful information
- G-C outperforms other correlation functions



ATS vs Regular Localization

		ATS	Reg 20	Reg 10	Reg 5	Reg 2	Reg 1
Tar River at Tarboro (NWIS 02083500)	Prior RMSE	5.58	18.54	8.86	33.46	41.61	34.32
	Posterior RMSE	4.93	17.82	6.75	25.11	33.66	26.41
	Prior Bias	-1.13	-11.65	-1.71	-20.24	-18.09	-11.07
	Posterior Bias	-0.85	-11.41	-0.74	-20.37	-17.16	-10.01
	Prior Spread	1.20	3.29	2.80	10.90	10.84	9.54
	Posterior Spread	1.55	3.00	2.27	6.28	6.43	5.17

- Performance using ATS localization is significantly better ($\sim$ 40%)
- Using ATS, one can increase the effective localization radius
- Regular localization with large radii fails (correlating physically unrelated variables)

Adaptive Covariance Inflation

The algorithm is adaptive in time, based on Bayes' theorem, and results in spatially varying fields (El Gharamti, 2018):

$$p\left(\lambda|d^{f|a}\right) \approx p\left(d^{f|a}|\lambda\right) \cdot p(\lambda)$$

The algorithm is adaptive in time, based on Bayes' theorem, and results in spatially varying fields (El Gharamti, 2018):

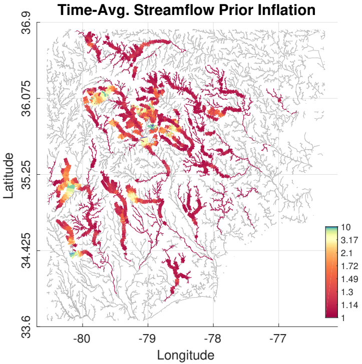
$$\underbrace{p\left(\lambda|d^{f|a}\right)}_{\text{Posterior pdf}} \approx \underbrace{p\left(d^{f|a}|\lambda\right)}_{\text{Likelihood}} \cdot \underbrace{p(\lambda)}_{\text{Prior pdf Inverse Gamma}}$$

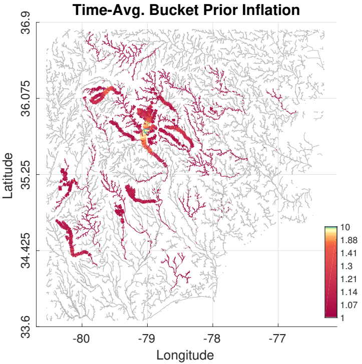
Adaptive Covariance Inflation

The algorithm is adaptive in time, based on Bayes' theorem, and results in spatially varying fields (El Gharamti, 2018):

Posterior pdf $p\left(\lambda|d^{f|a}\right) \approx p\left(d^{f|a}|\lambda\right) \cdot p(\lambda)$ Prior pdf Inverse Gamma

Likelihood

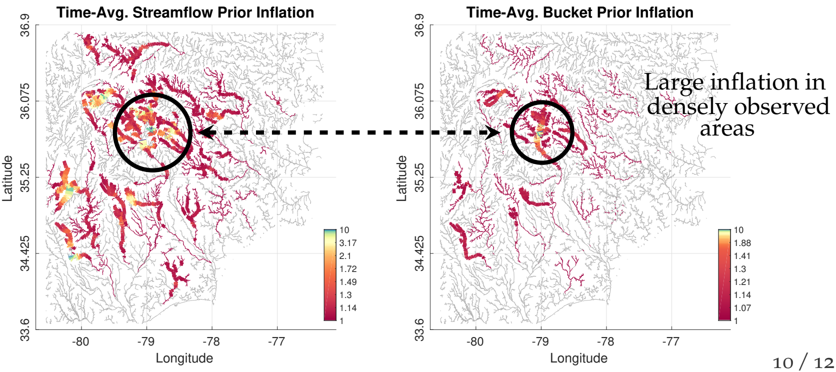




Adaptive Covariance Inflation

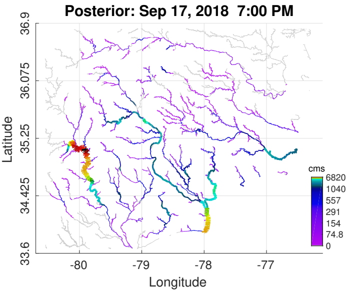
The algorithm is adaptive in time, based on Bayes' theorem, and results in spatially varying fields (El Gharamti, 2018):

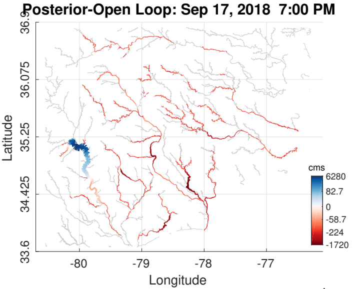
$$\underbrace{p\left(\lambda|d^{f|a}\right)}_{\text{Posterior pdf}} \approx \underbrace{p\left(d^{f|a}|\lambda\right)}_{\text{Likelihood}} \cdot \underbrace{p(\lambda)}_{\text{Prior pdf, Inverse Gamma}}$$



Bias Mitigation

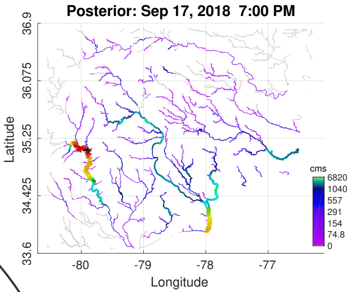
After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina

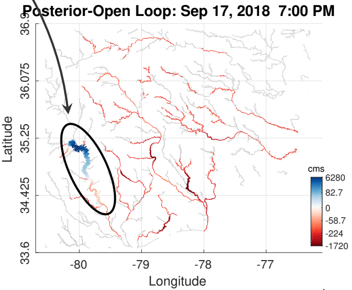




Bias Mitigation

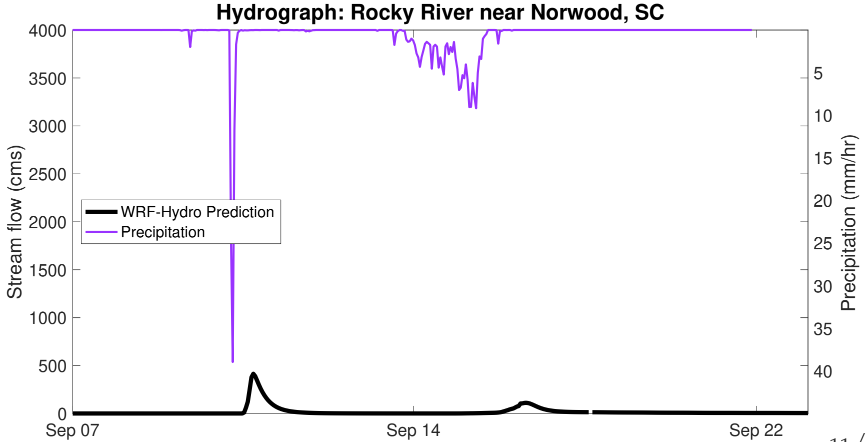
After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina





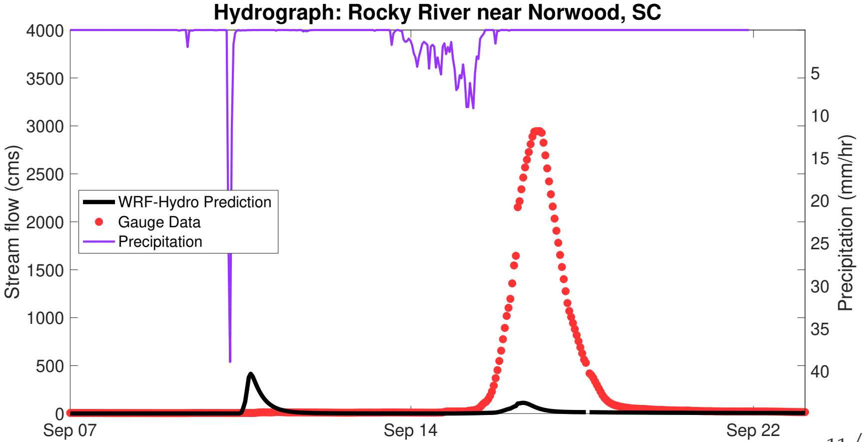
Bias Mitigation

After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina



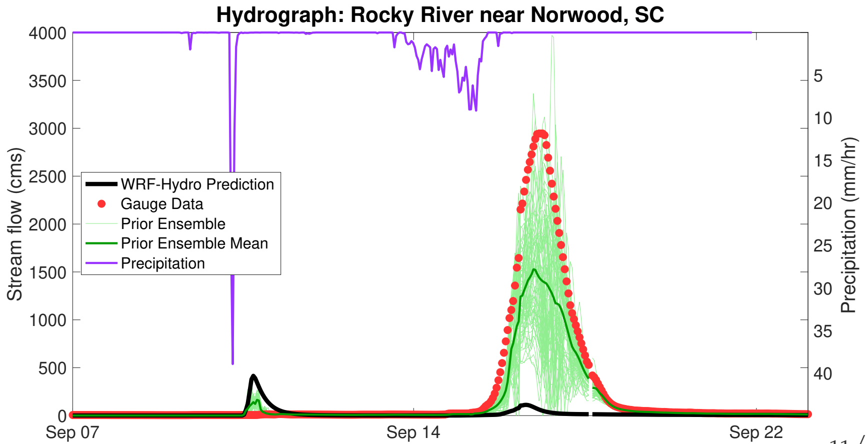
Bias Mitigation

After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina



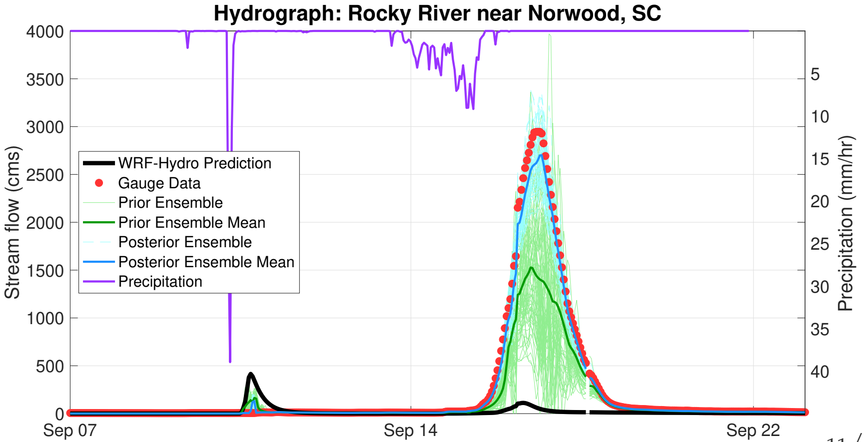
Bias Mitigation

After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina



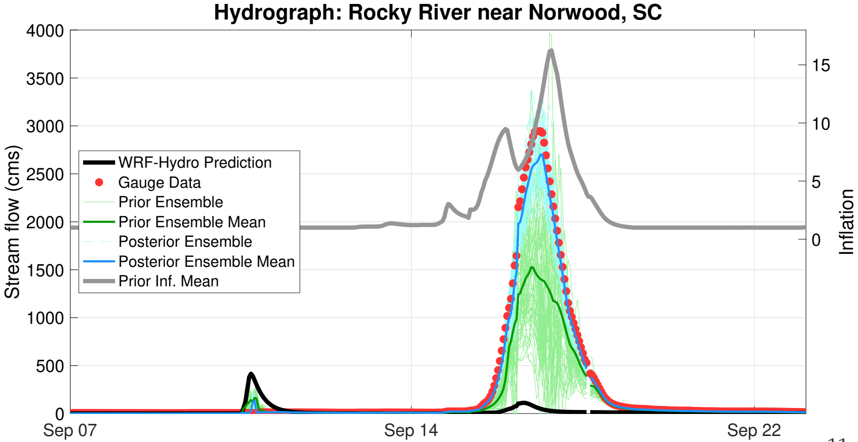
Bias Mitigation

After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina



Bias Mitigation

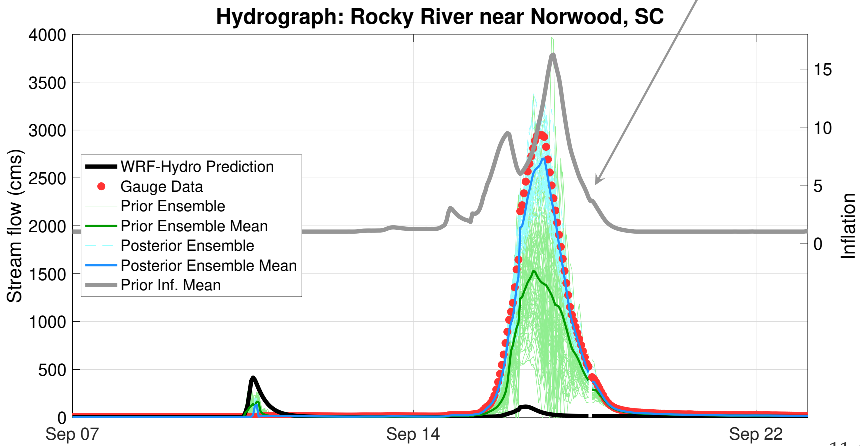
After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina



Bias Mitigation

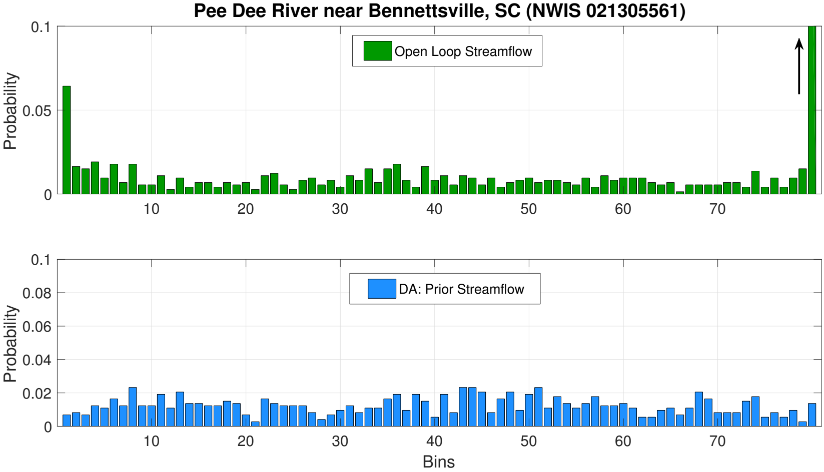
After landfall, the model's streamflow prediction (Open Loop) is significantly smaller than the posterior along Pee-Dee River in South Carolina

A sizable increase in prior inflation to counter the bias in the modeled streamflow!



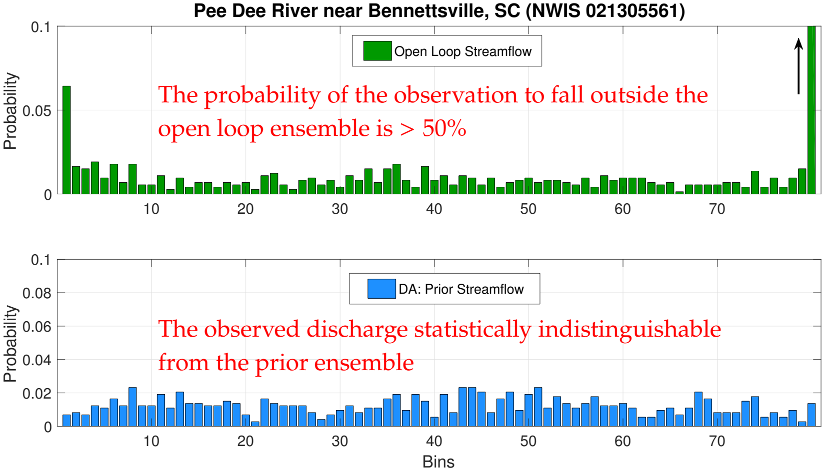
Bias Mitigation

The rank histogram for the open loop is heavily skewed to the right indicating that the gauge data is larger than the ensemble



Bias Mitigation

The rank histogram for the open loop is heavily skewed to the right indicating that the gauge data is larger than the ensemble



Summary

- NOAA's National Water Model 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
- To address sampling errors, **Along-The-Stream (ATS) Localization** is proposed. The algorithm provides improved information propagation in the stream network
- **Adaptive Inflation** is extremely useful and is able to serve as a vigorous bias correction scheme which varies both spatially and temporally

Summary

- NOAA's National Water Model 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
- To address sampling errors, **Along-The-Stream (ATS) Localization** is proposed. The algorithm provides improved information propagation in the stream network
- **Adaptive Inflation** is extremely useful and is able to serve as a vigorous bias correction scheme which varies both spatially and temporally

Summary

- NOAA's National Water Model 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
- To address sampling errors, **Along-The-Stream (ATS) Localization** is proposed. The algorithm provides improved information propagation in the stream network
- **Adaptive Inflation** is extremely useful and is able to serve as a vigorous bias correction scheme which varies both spatially and temporally

Summary

- NOAA's National Water Model 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
- To address sampling errors, **Along-The-Stream (ATS) Localization** is proposed. The algorithm provides improved information propagation in the stream network
- **Adaptive Inflation** is extremely useful and is able to serve as a vigorous bias correction scheme which varies both spatially and temporally

https://dart.ucar.edu/

Thank You!