# Inflation in Ensemble Filters: Why, How and When?

## Real High-Dimensional Atmospheric and Hydrologic Applications

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National Center for Atmospheric Research

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CISL Computational & Information Systems Lab

siam Society for Industrial and Applied Mathematics

NCAR NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

# The questions: Why, How, & When?

# 1. Ensemble Covariance Inflation: Why?

- Simply, because we're not in optimal EnKF settings:
    1. Highly nonlinear models
    2. Massive model dimensions forces us to use small ensemble sizes; can never really satisfy this:

$$\boxed{\lim_{N\to\infty} \widehat{\mathbf{P}} = \mathbf{B}}$$

    3. Deal with many non-Gaussian phenomena (e.g., precipitation)
    4. Unavoidable model errors

# 2. Ensemble Covariance Inflation: How?

**Spatially and Temporally Varying Adaptive Covariance Inflation:**

$$p(\lambda|d) \propto p(\lambda) \cdot p(d|\lambda) \tag{1}$$

- **Prior** $p(\lambda)$; assumed Inverse Gamma
- **Likelihood** $p(d|\lambda)$; a Gaussian density where
  - $d = |y^o - \overline{x}_b|$ is the innovation
  - formulated using innovation statistics [Derosiers et al. 2005]
    $\mathbb{E}(d) = 0; \quad \mathbb{E}(d^2) = \sigma_o^2 + \lambda \widehat{\sigma_b}^2$
- **Posterior** $p(\lambda|d)$

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## Characteristics

- Adaptive in time; posterior becomes prior the next DA cycle
- Varies in space (affects the rank of the covariance)
- Variance increase is proportional to the size of the innovation

# 3. Ensemble Covariance Inflation: When?

The algorithm can be used to inflate the prior covariance [Anderson 2009; El Gharamti 2018], the posterior covariance [e.g., El Gharamti et al. 2019], or both actually. So, what to do?

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Answer: It depends!

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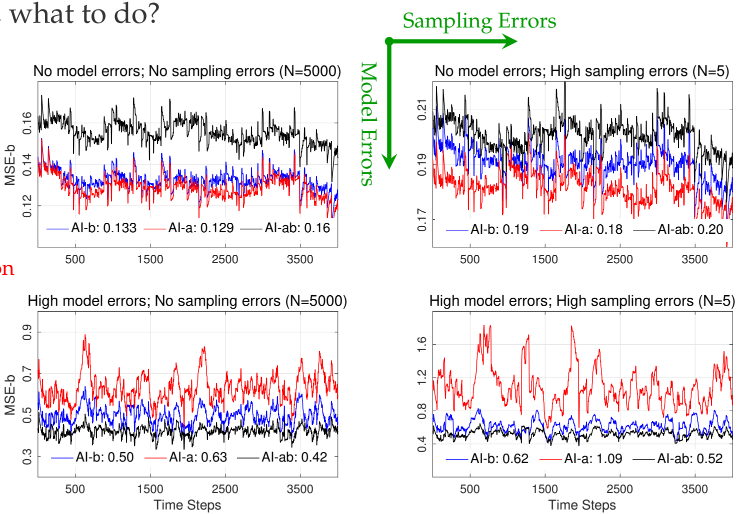
Lorenz-63 System

◇ prior inflation
◇ posterior inflation
◇ both



# Application I: Atmospheric DA

# 4.1 Atmospheric DA: Configuration

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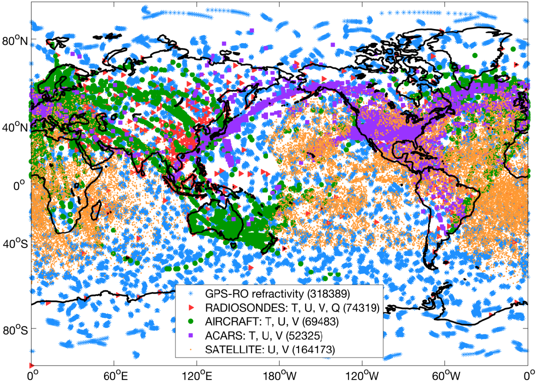
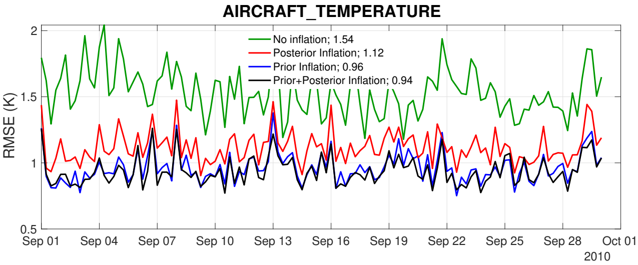
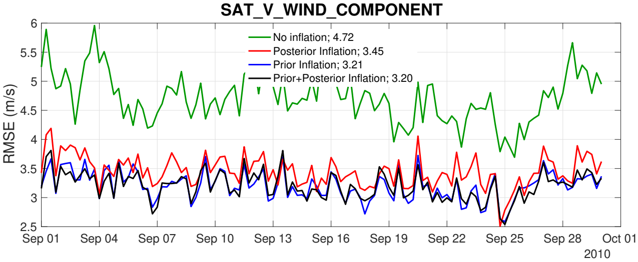
- $2°$ model + 26 levels
- 80 members; 6 weeks
- Localization: GC ~ 960 km
- Variables: `PS`, `T`, `U`, `V`, `Q`, ..




Typical observations assimilated every 6 hours over CONUS

# 4.2 Atmospheric DA: Obs-space diagnostics

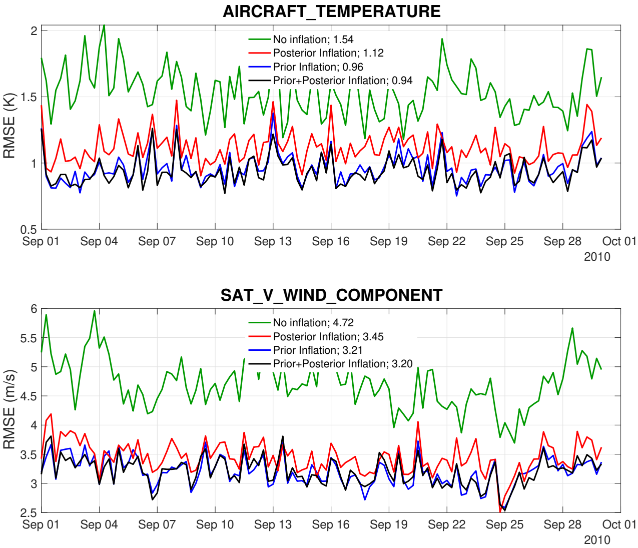



Time-series of T and V over the tropics (i.e., −20:20° N) and averaged over all layers

# 4.2 Atmospheric DA: Obs-space diagnostics

- Failing to use inflation yields low-quality estimates
- Posterior inflation performs fairly well
- Prior inflation outperforms posterior inflation
- Best accuracy is obtained after combining both inflation schemes

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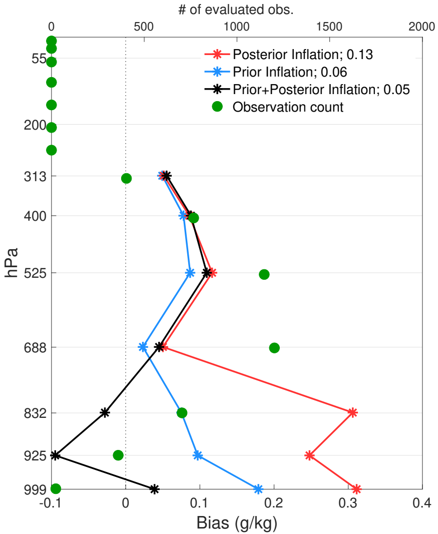
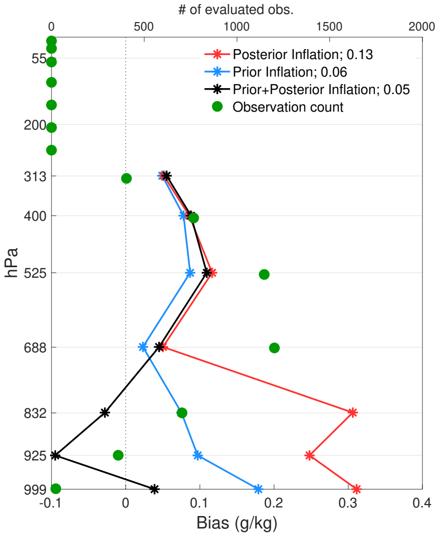



Bias profile of Q over the Northern Hemisphere (i.e., 20:90° N)

# 4.2 Atmospheric DA: Obs-space diagnostics

- Radiosonde specific humidity (Q) was not assimilated. It was kept aside for verification purposes only
- Largest biases are observed near the surface
- Prior inflation is more effective than posterior inflation at mitigating the bias

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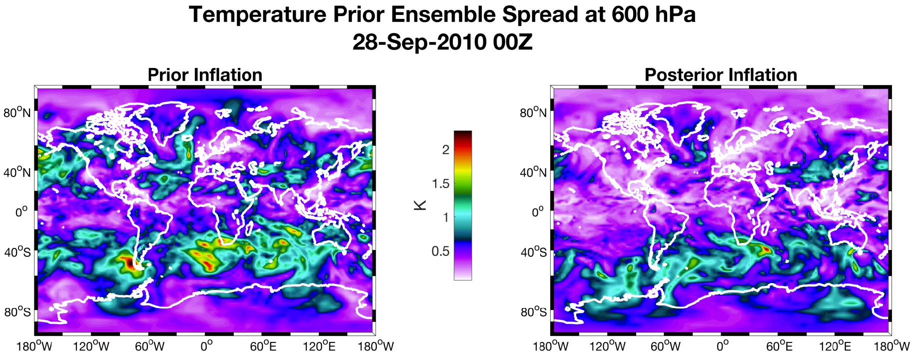
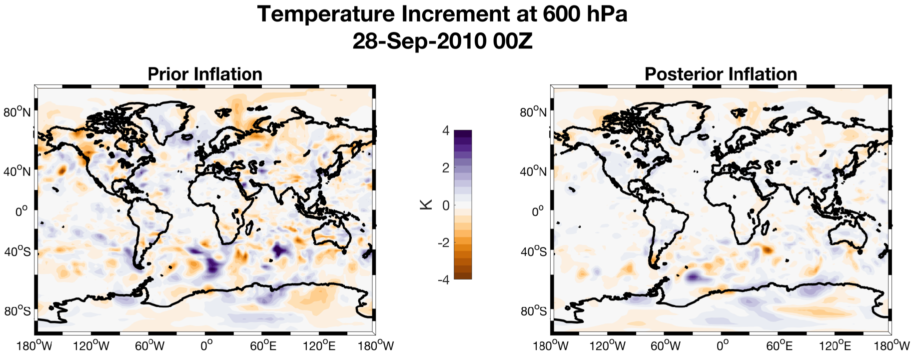
# 4.3 Atmospheric DA: State-space diagnostics

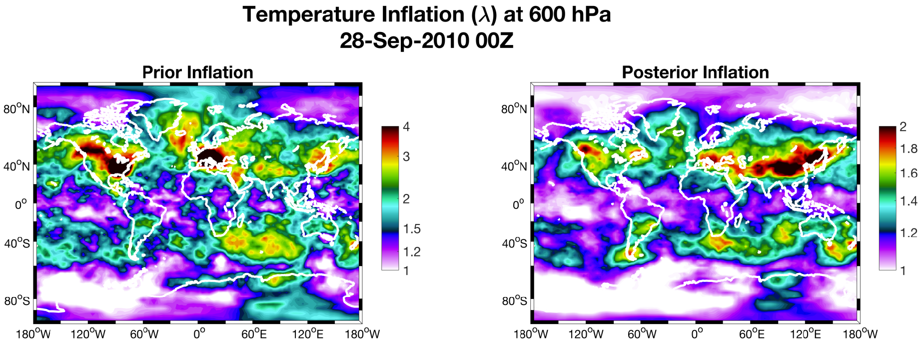



- Largest uncertainties are present in the Southern Ocean (sparsely observed)
- Prior inflation yields larger ensemble spread than posterior inflation at this elevation

# 4.3 Atmospheric DA: State-space diagnostics




- Largest increments where the ensemble spread is high
- Larger DA increments suggested by prior inflation

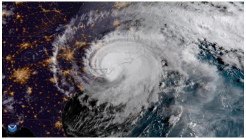



- Prior inflation is the largest in the vicinity of the observations (e.g., CONUS, Europe)
- Posterior inflation could point to locations where sampling error is the largest?

# Application II: Flood Prediction

# 5.1 Hurricane Florence Flooding

- **Category 4 hurricane:** Carolinas on Sep. 14, 2018
- Precipitation exceeded 35″ in certain areas
- Caused major flooding and catastrophic damages



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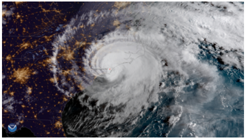

∼ 50 casualties and $25B losses in coastal communities

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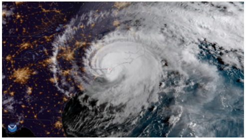
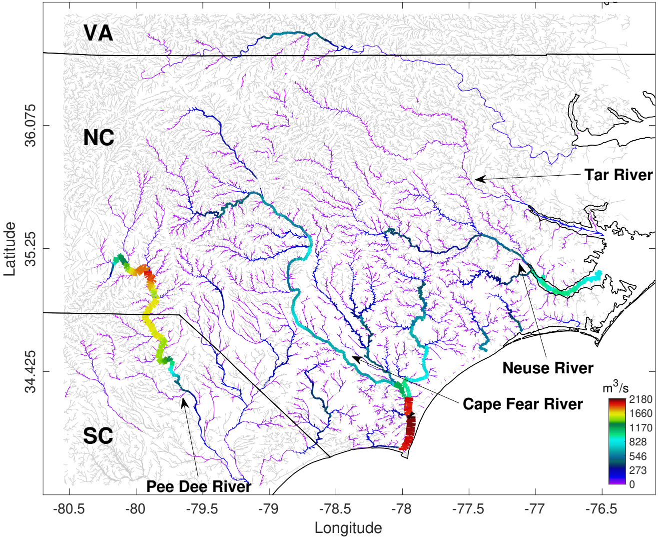


Can we enhance flood prediction using DA and available streamflow models?

$\sim$ 50 casualties and \$25B losses in coastal communities

# 5.2 WRF-Hydro and DA Configuration

- Interface DART to WRF-Hydro (NOAA's NWM; Gochis, 2020)




- Total of ~ 70K reaches (streams)

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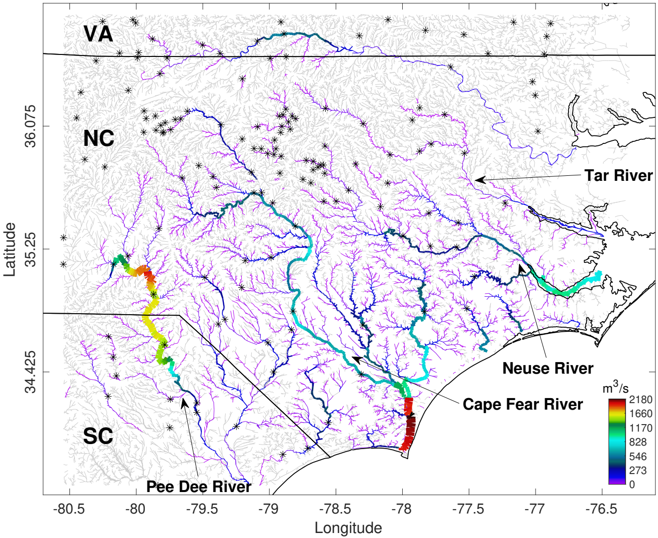
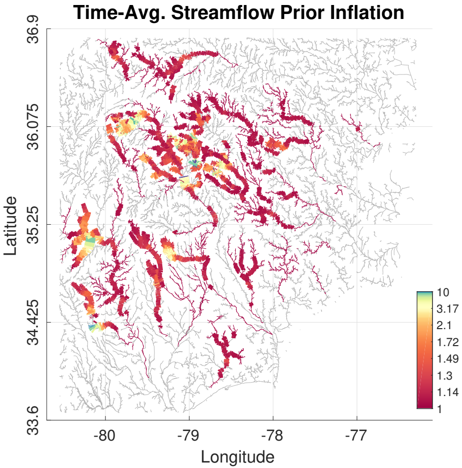



- Total of ~ 70K reaches (streams)
- Hourly streamflow assimilation
- 107 USGS gauges

# 5.3 Streamflow Inflation in Space



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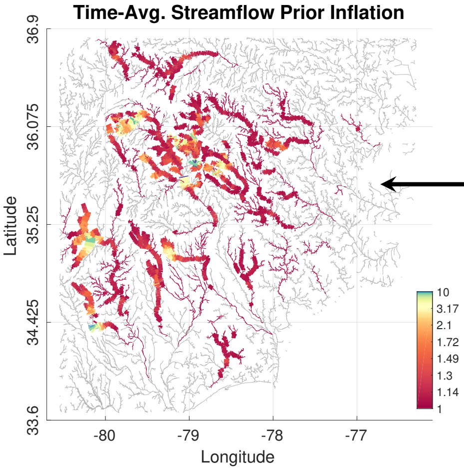


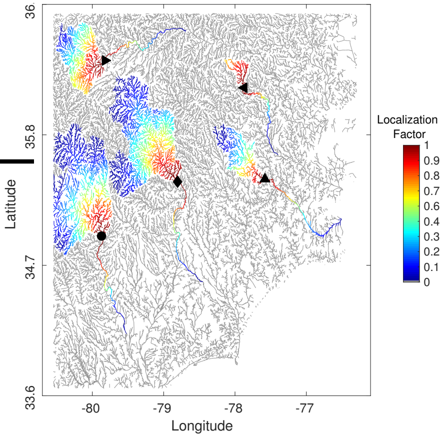


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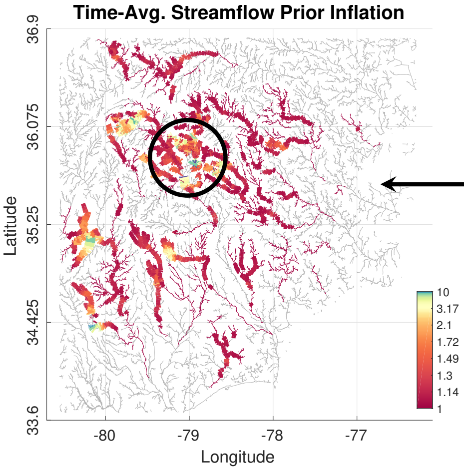
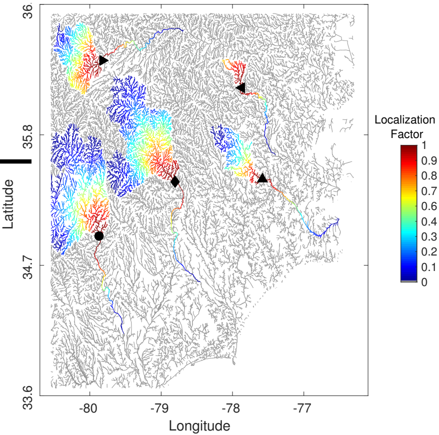
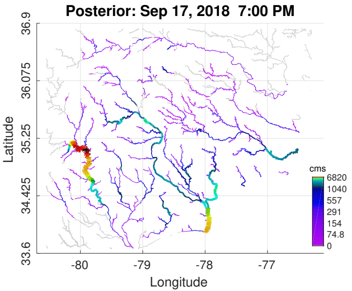


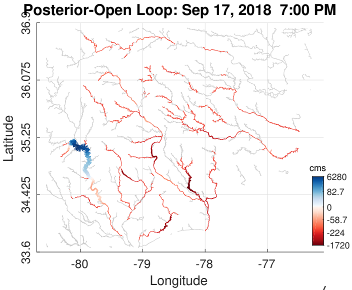




- Inflation confined in space to the stream network thanks to Along-The-Stream Localization (El Gharamti et al. 2021)
- Larger inflation in densely observed watersheds

# 5.4 Streamflow Bias Mitigation

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



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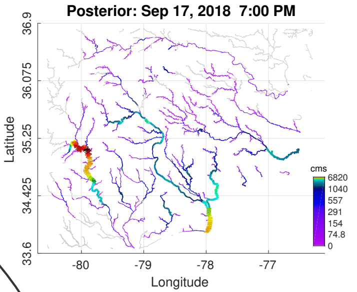


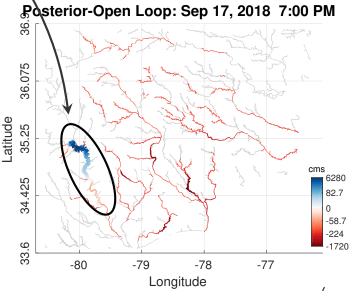

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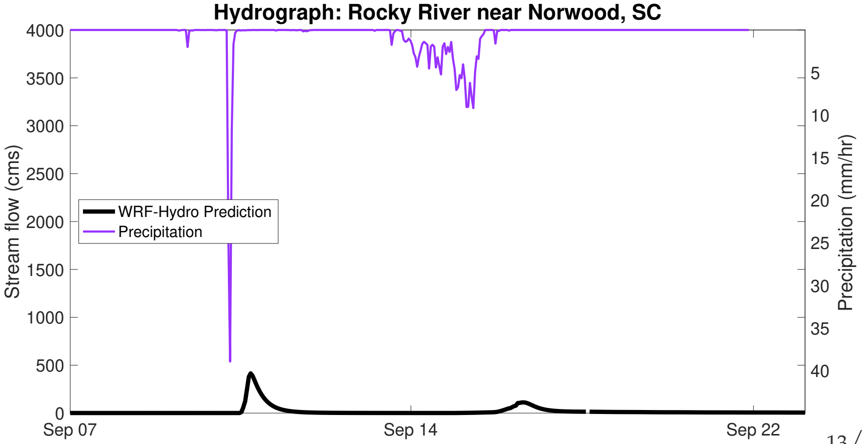

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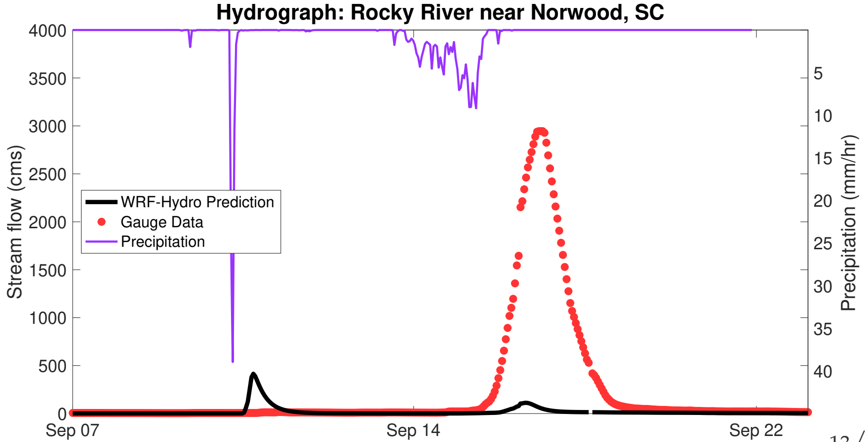

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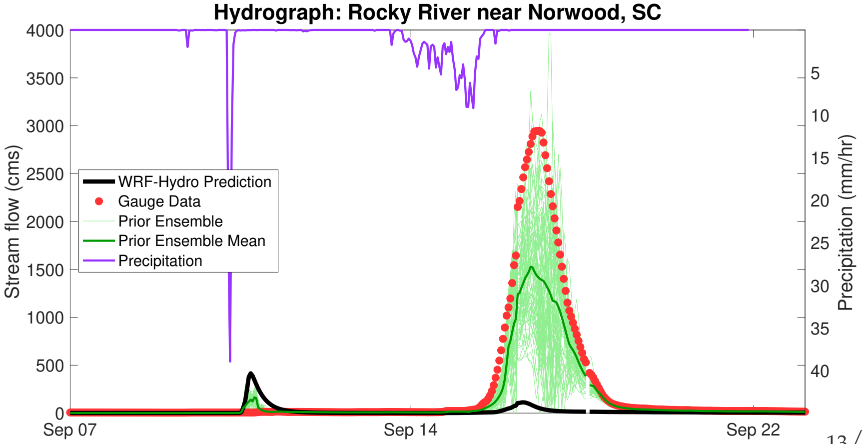

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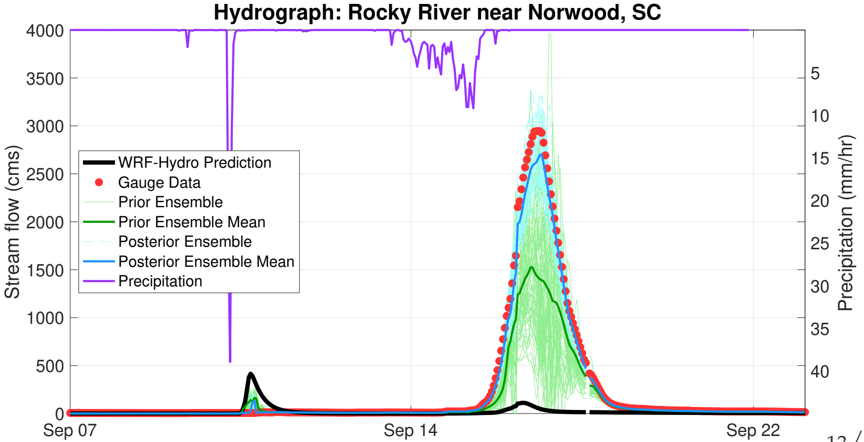

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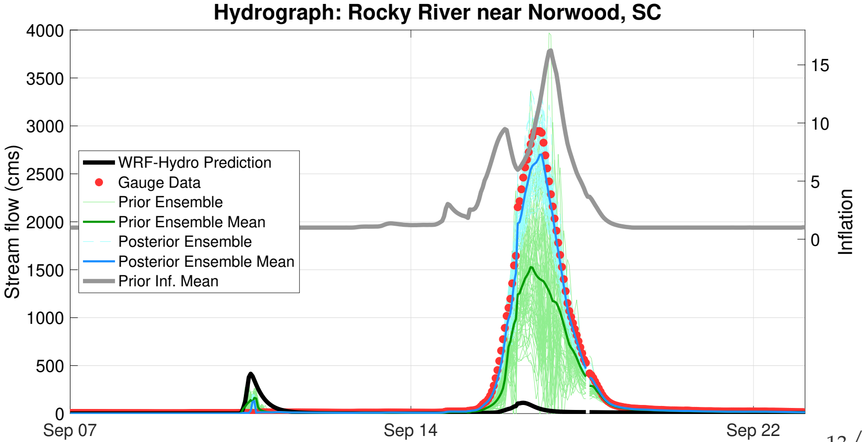

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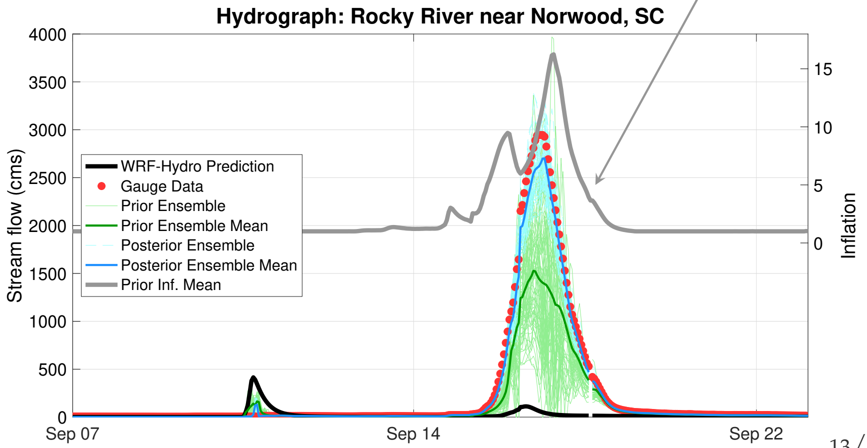
A sizable increase in prior inflation to counter the bias in the modeled streamflow!



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Thank You!