

Adaptive (Prior|Posterior?) Inflation for Ensemble Kalman Filters

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Data Assimilation [APPM 5510]

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NATIONAL CENTER FOR ATMOSPHERIC RESEARCH



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The EnKF

- State estimation tool
- Given an observation y of state x , use Bayes:

$$p(x_k|y_k, Y_{k-1}) \approx p(x_k|Y_{k-1}) \cdot p(y_k|x_k, Y_{k-1}) \quad (1)$$

$Y_k: \{y_1, y_2, \dots, y_{k-1}, y_k\}$, k is time index

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- Successive Forecast and Update (Analysis) stages:

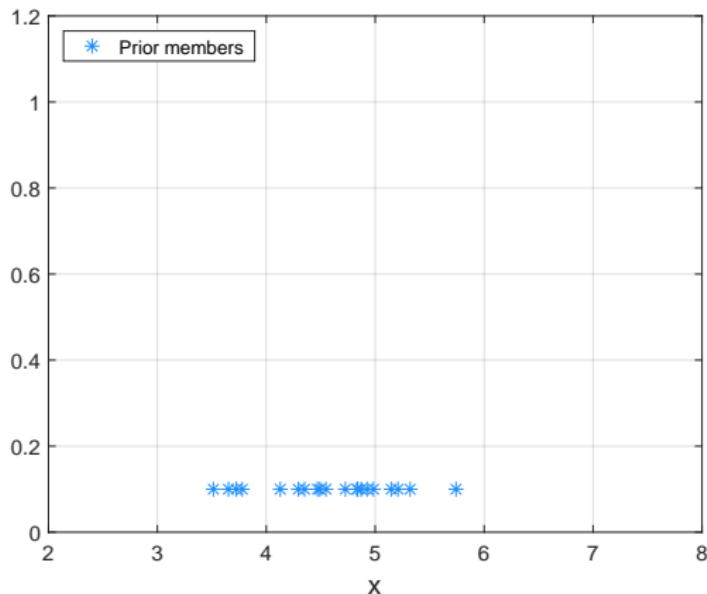
$$x_f^i = \mathcal{M}(x_a^i)$$

$$\bar{x}_f = \frac{1}{N} \sum_{i=1}^N x_f^i, \quad \hat{\sigma}_f^2 = \frac{1}{N-1} \sum_{i=1}^N (x_f^i - \bar{x}_f) (x_f^i - \bar{x}_f)^T$$

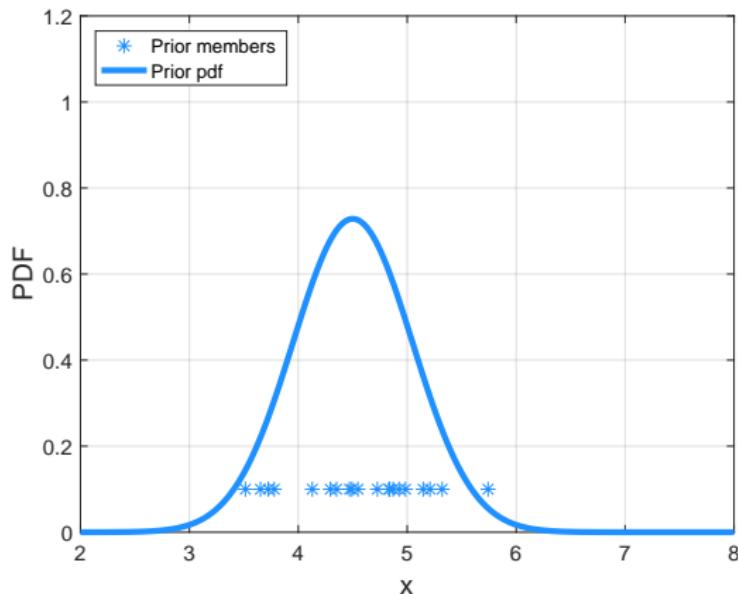
$$x_a^i = x_f^i + \frac{\hat{\sigma}_f^2}{\sigma_o^2 + \hat{\sigma}_f^2} (y^i - x_f^i)$$

N is the ensemble size

The EnKF cont.

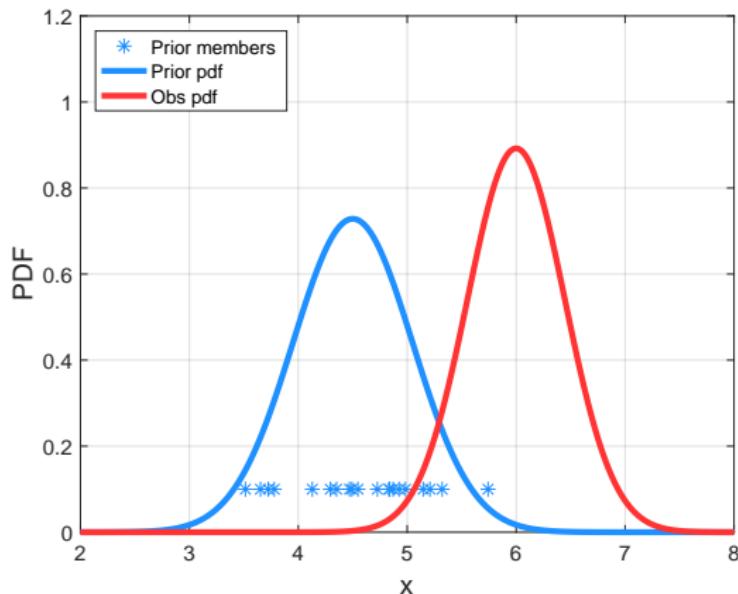


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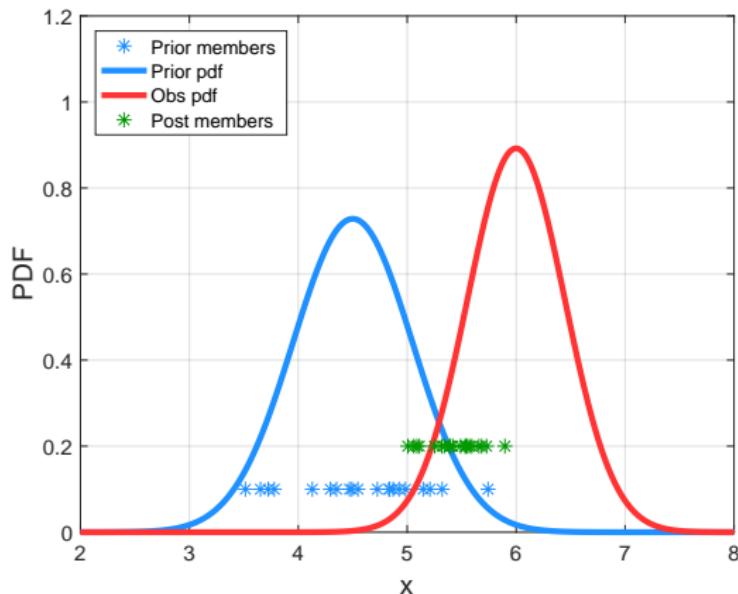
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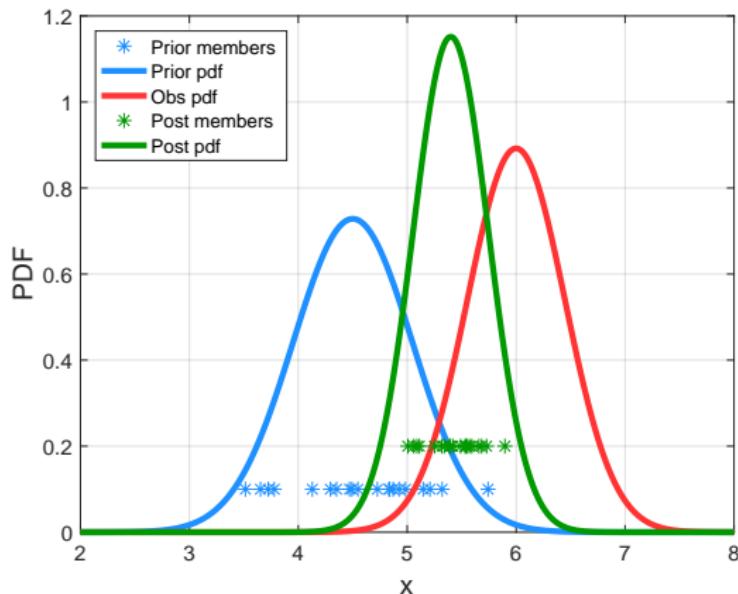
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$$y = 6.0, \sigma_o^2 = 0.20$$

$$\bar{x}_a = 5.43, \hat{\sigma}_a^2 = 0.06$$

Some Drawbacks

1. Sampling Errors:

- Ideal scenario: $N = \infty$; σ_f^2 is out-of-reach!
- $\hat{\sigma}_f^2$ depends on the ensemble size

$$\lim_{N \rightarrow \infty} \hat{\sigma}_f^2(N) = \sigma_f^2$$

- When N is small, $\hat{\sigma}_f^2$ may underestimate σ_f^2

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The goal is to maintain *enough* spread in the ensemble

Inflation

- One way to increase of the variance of the ensemble is to inflate:

$$x^i \leftarrow \sqrt{\lambda} (x^i - \bar{x}) + \bar{x} \quad (2)$$

while preserving the ensemble mean.

Inflation

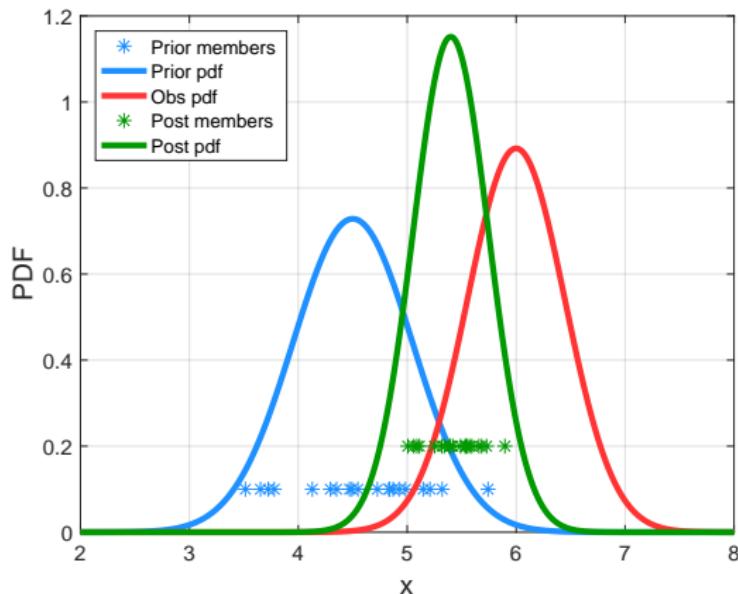
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- Which variance to inflate: Prior (after the forecast) or posterior (after the update)?
- What to choose for λ ? 1.02 (2%), 1.04, 1.2, 10, ... ?
- Why this is useful?

Inflation

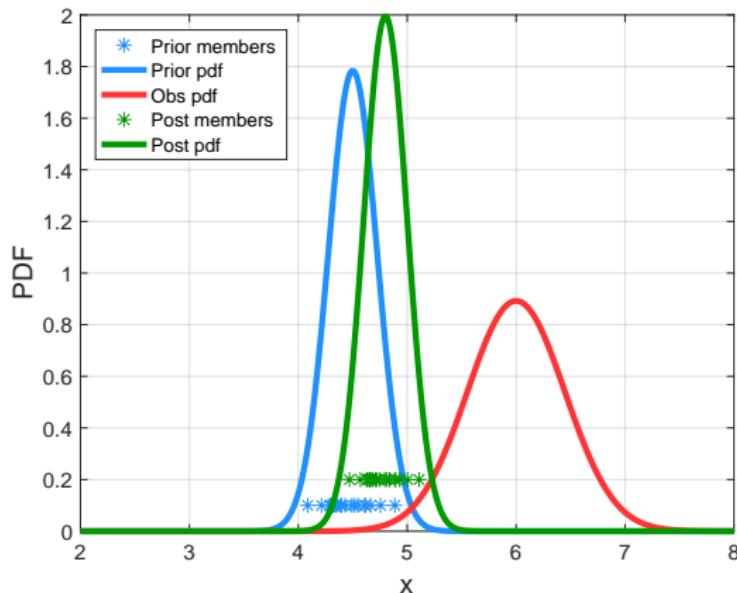


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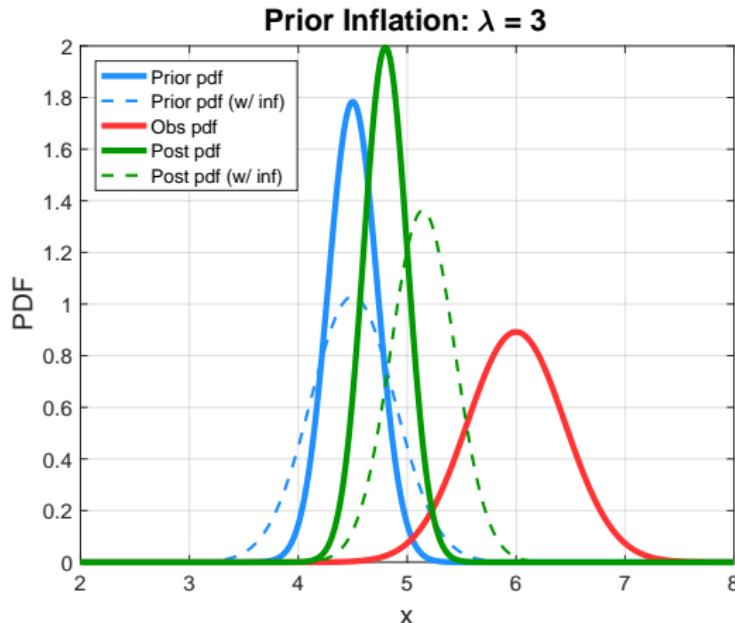


$$\bar{x}_f = 4.5, \sigma_f^2 = 0.05$$

$$y = 6.0, \sigma_o^2 = 0.20$$

$$\bar{x}_a = 4.75, \sigma_a^2 = 0.02$$

Inflation

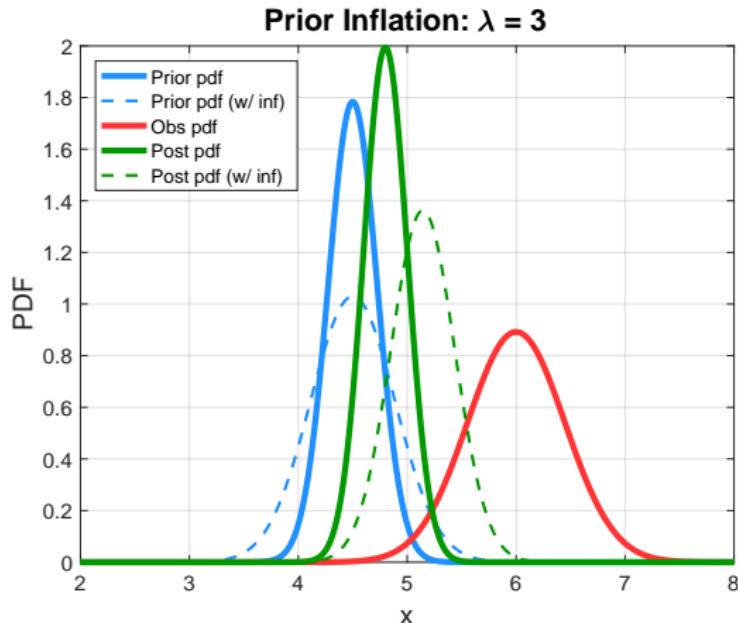


$$\sigma_f^2 : 0.05 \rightarrow 0.15$$

$$\bar{x}_a = 4.75 \rightarrow 5.18$$

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Higher spread: Larger uncertainty (less confidence in the estimates)!

Adaptive Prior Inflation I

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For a single variable case, denote the following:

$$\text{Forecast (Background) error: } \varepsilon_f \sim \mathcal{N}(0, \sigma_f^2), \quad (3)$$

$$\text{Observation error: } \varepsilon_o \sim \mathcal{N}(0, \sigma_o^2), \quad (4)$$

$$\text{Analysis error: } \varepsilon_a \sim \mathcal{N}(0, \sigma_a^2); \sigma_a^2 \stackrel{\text{Kalman}}{=} \sigma_o^2 \sigma_f^2 / (\sigma_o^2 + \sigma_f^2). \quad (5)$$

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The forecast innovation (discrepancy):

$$d_f = y - \bar{x}_f = y - x_t + x_t - \bar{x}_f = \varepsilon_o - \varepsilon_f, \quad (6)$$

where x_t is the true value of the variable.

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Bayesian Approach [Anderson 2007, Anderson 2009, El Gharamti 2018]

$$p(\lambda|d_f) \propto p(\lambda) \cdot p(d_f|\lambda) \quad (7)$$

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$$= \mathbb{E}[\varepsilon_o^2 - \varepsilon_o \varepsilon_f - \varepsilon_f \varepsilon_o + \varepsilon_f^2] \quad (10)$$

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3. Inflating the ensemble variance by λ will match the theoretical (hidden) forecast variance

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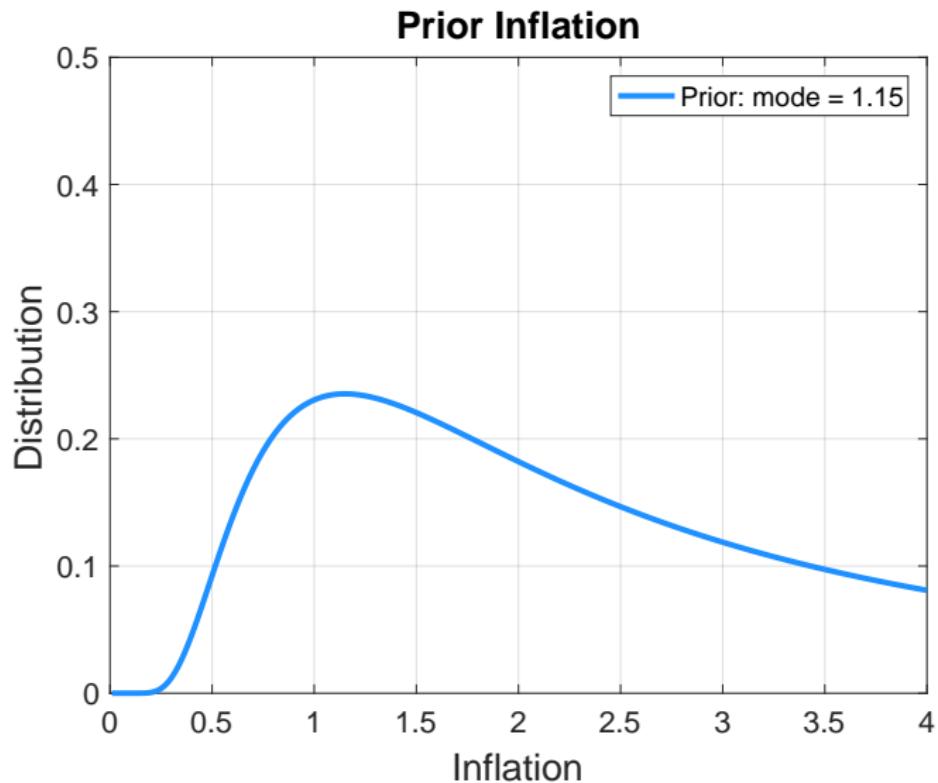
- Form very close to being inverse-gamma
- To find the posterior mode, need to maximize $p(\lambda|d_f)$. Not easy!
- Linearizing the Likelihood will simplify the problem:

$$p(d_f|\lambda) \approx \underbrace{p(d_f|\lambda_f)}_{\bar{\ell}} + \underbrace{\frac{\partial p(d_f|\lambda)}{\partial \lambda}}_{\ell'} \Big|_{\lambda_f} (\lambda - \lambda_f), \quad (15)$$

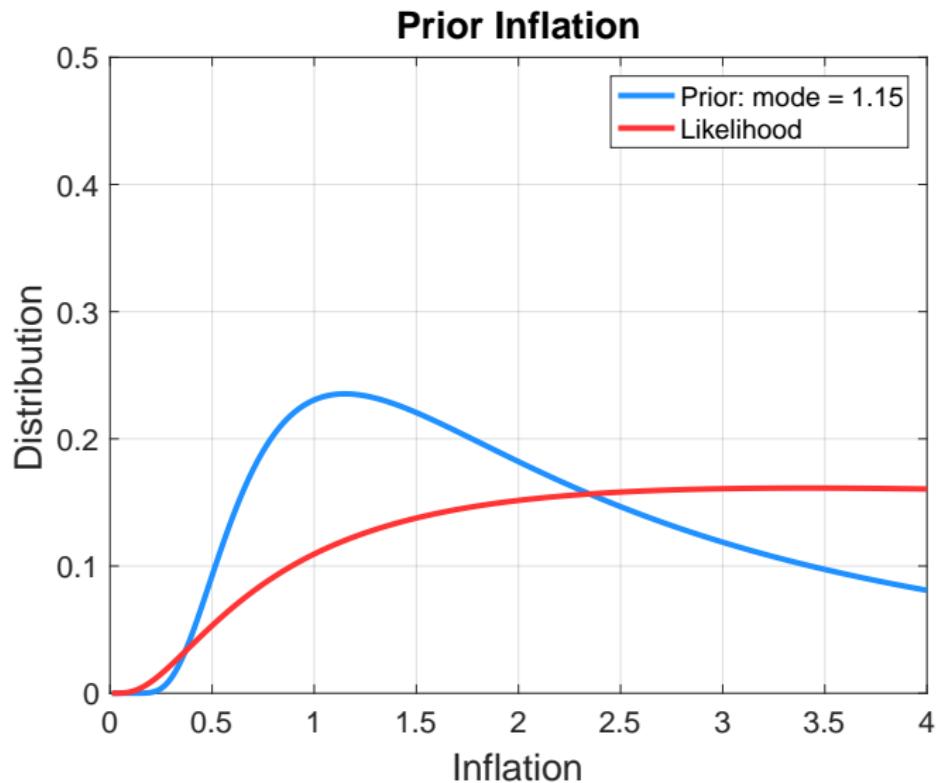
λ_f is the mode of the prior distribution. Set $\ell = \bar{\ell}/\ell'$:

$$(1 - \lambda_f/\beta) \lambda^2 + (\ell - 2\lambda_f) \lambda + (\lambda_f^2 - \lambda_f \ell) = 0 \quad (16)$$

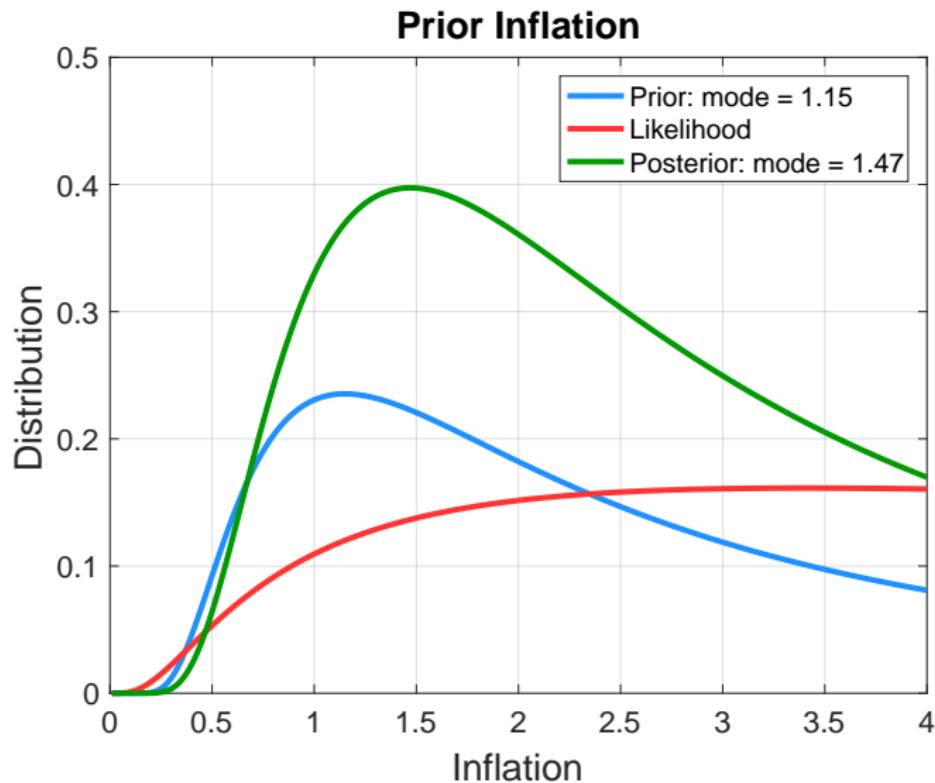
Adaptive Prior Inflation IV



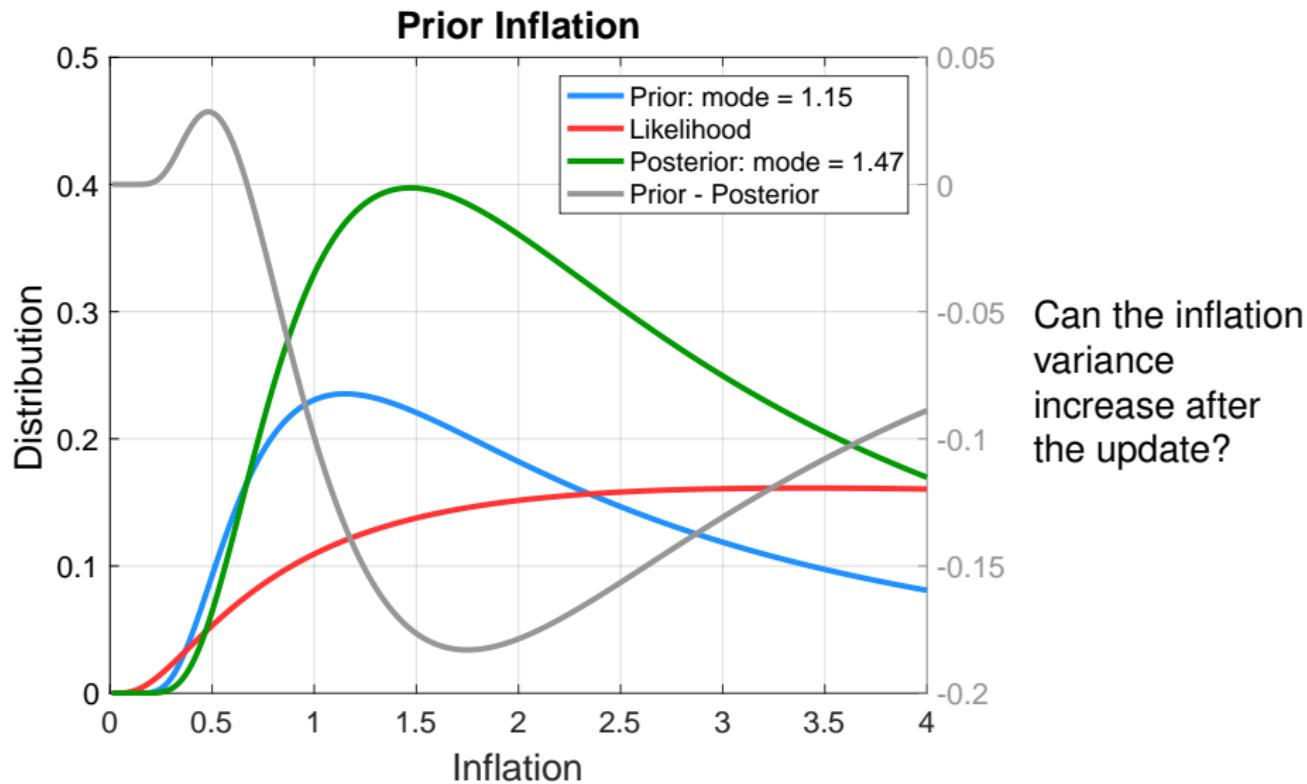
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where $K = \sigma_f^2 (\sigma_o^2 + \sigma_f^2)^{-1}$. Thus,

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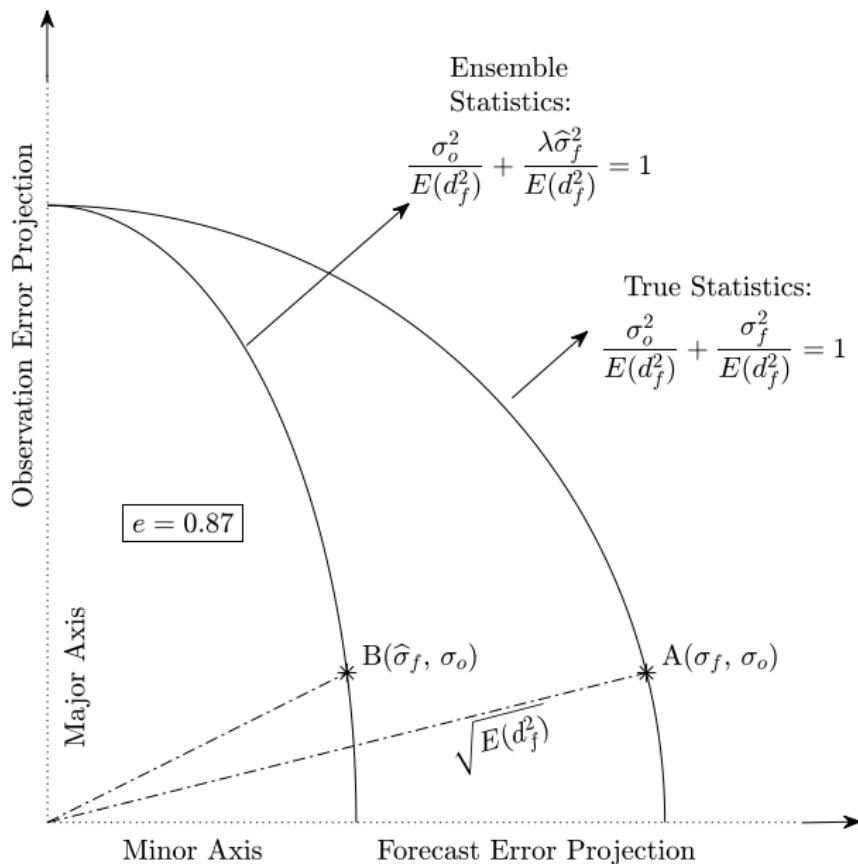
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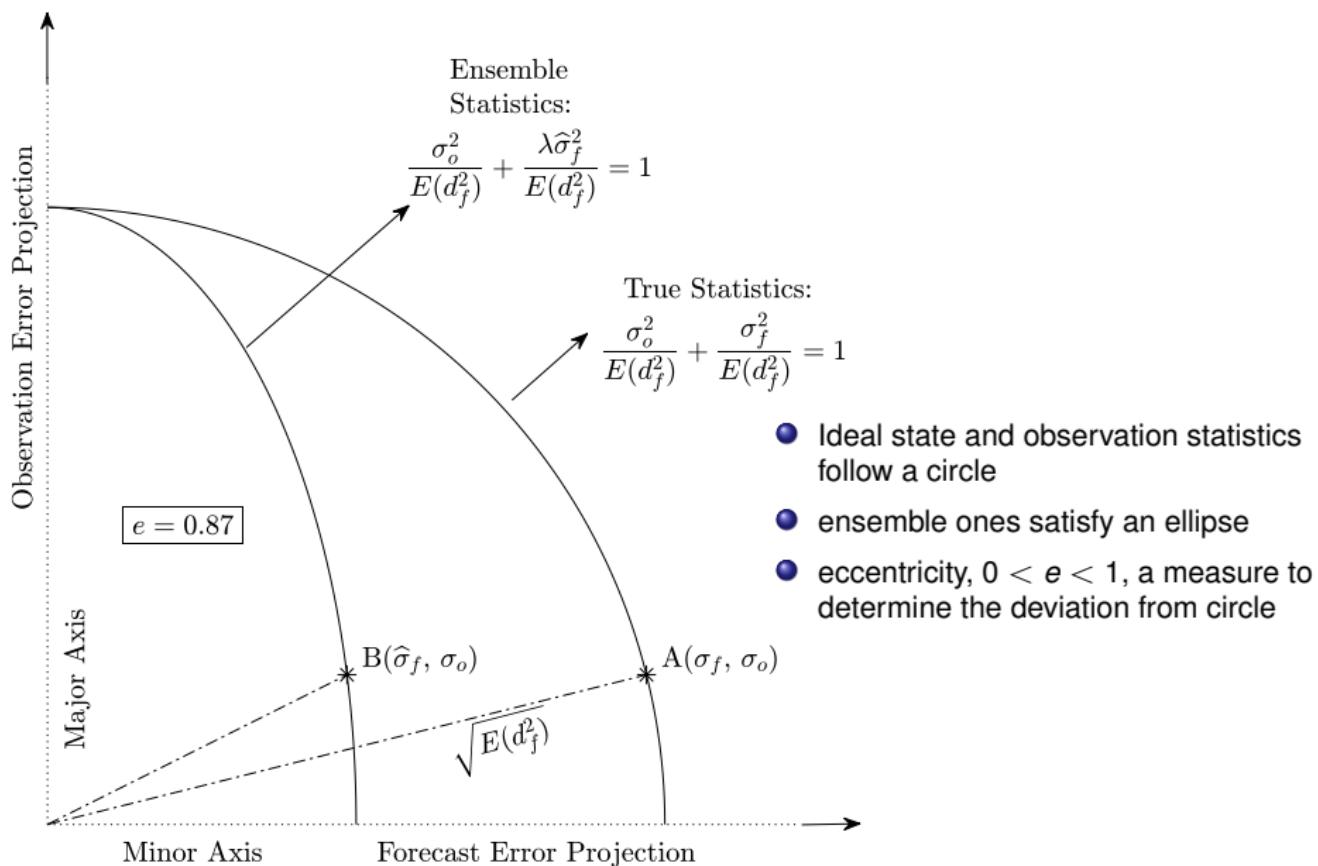
where $K = \sigma_f^2 (\sigma_o^2 + \sigma_f^2)^{-1}$. Thus,

$$p(d_a|\lambda) = (2\pi)^{-\frac{1}{2}} \exp\left[-\frac{d_a^2}{2}(\sigma_o^2 - \lambda \hat{\sigma}_a^2)^{-1}\right] \left(\sigma_o^2 + \lambda \hat{\sigma}_a^2\right)^{-\frac{1}{2}}. \quad (20)$$

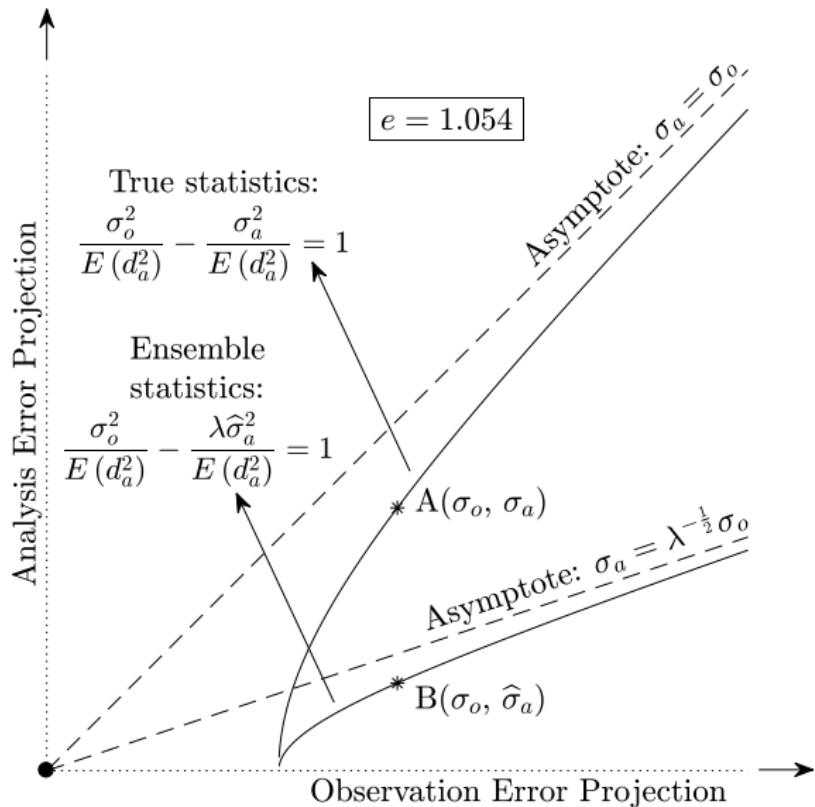
Geometrical Interpretation (Prior vs Posterior)



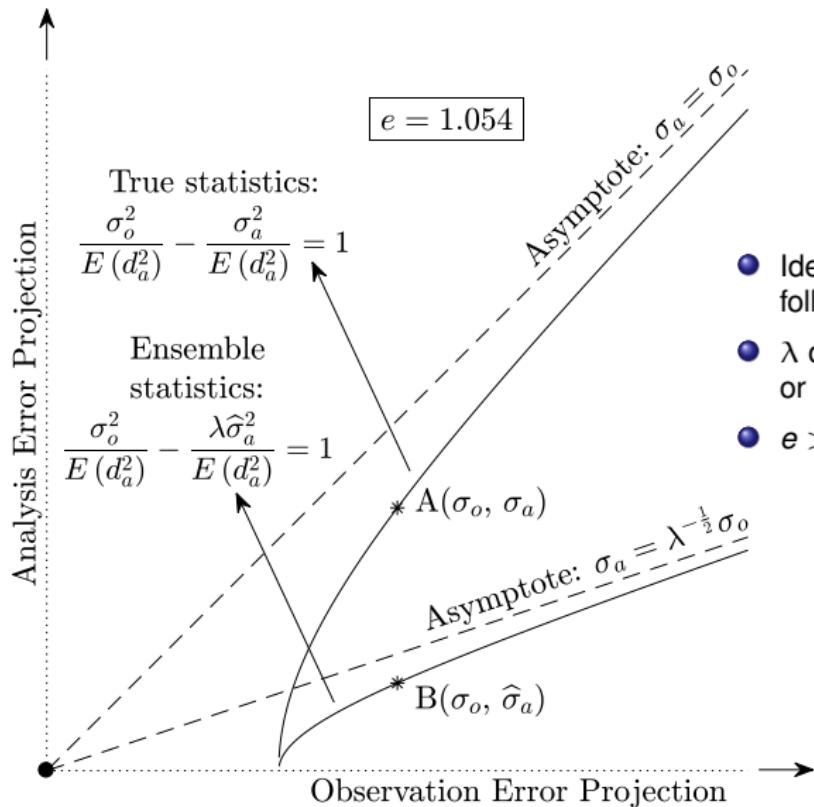
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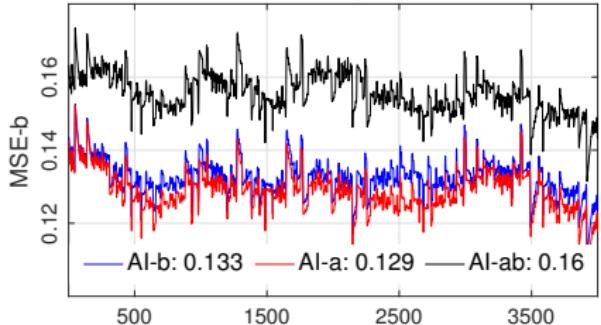


- Ideal and ensemble-based statistics follow hyperbolas
- λ determines the degree of expansion or contraction of the hyperbola
- $e > 1$ also a measure of deviation

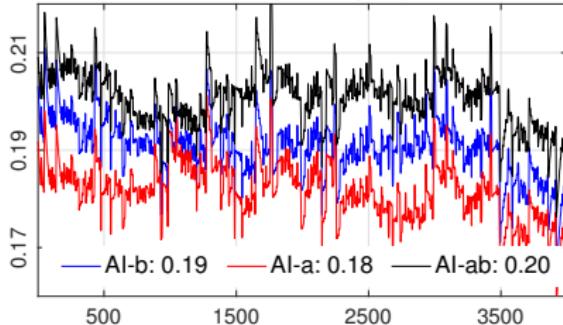
Low-Order Models: Lorenz-96

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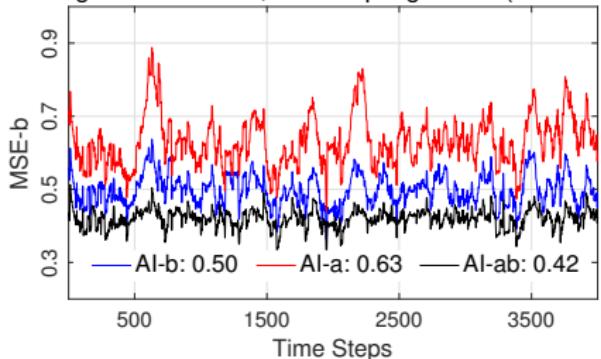
No model errors; No sampling errors (N=5000)



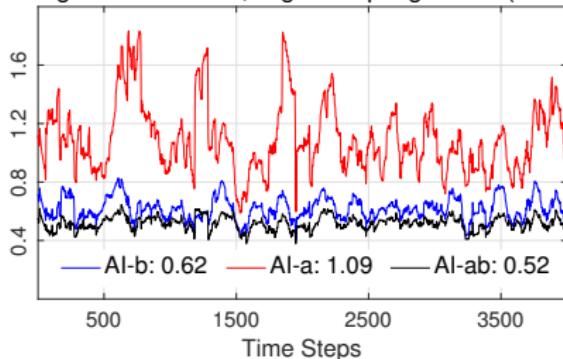
No model errors; High sampling errors (N=5)



High model errors; No sampling errors (N=5000)



High model errors; High sampling errors (N=5)

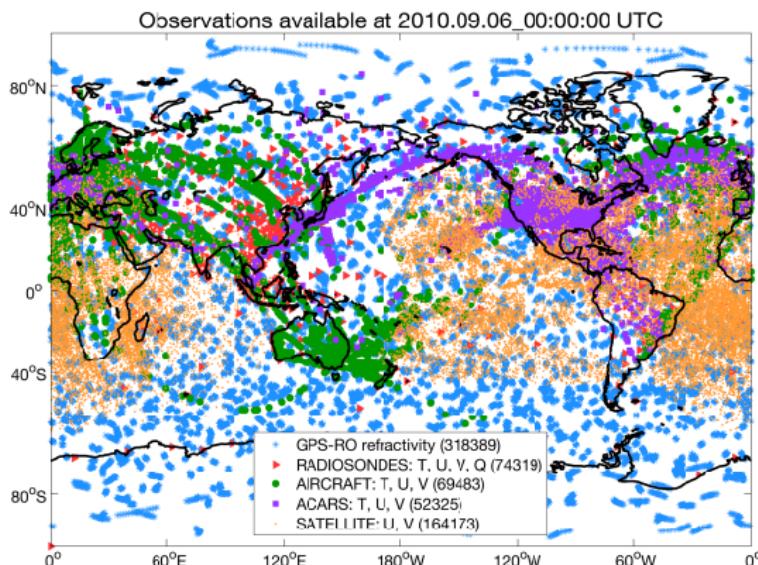


CAM (The Community Atmosphere Model)

- version: CESM2_0_beta05
- resolution: $1.9^\circ \times 1.9^\circ$ FV core;
LAT: 96, LON: 144, LEV: 26
- State variables: surface pressure
(PS), sensible temperature (T),
wind components (U and V),
specific humidity (Q), cloud liquid
water (CLDLIQ) and cloud ice
(CLDICE).

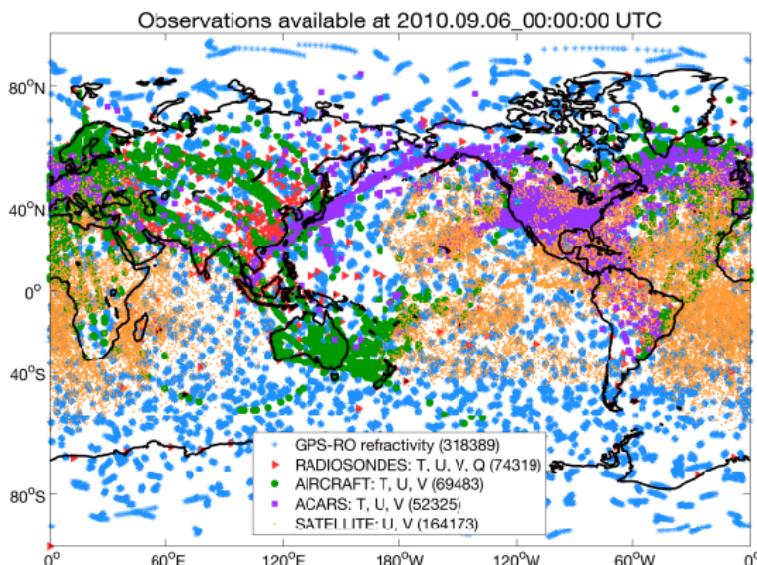
CAM (The Community Atmosphere Model)

- version: CESM2_0_beta05
- resolution: $1.9^\circ \times 1.9^\circ$ FV core;
LAT: 96, LON: 144, LEV: 26
- State variables: surface pressure (PS), sensible temperature (T), wind components (U and V), specific humidity (Q), cloud liquid water (CLDLIQ) and cloud ice (CLDICE).
- DA: 08.16.2010 to 09.30.2010
- 80 members
- data available every 6 hours

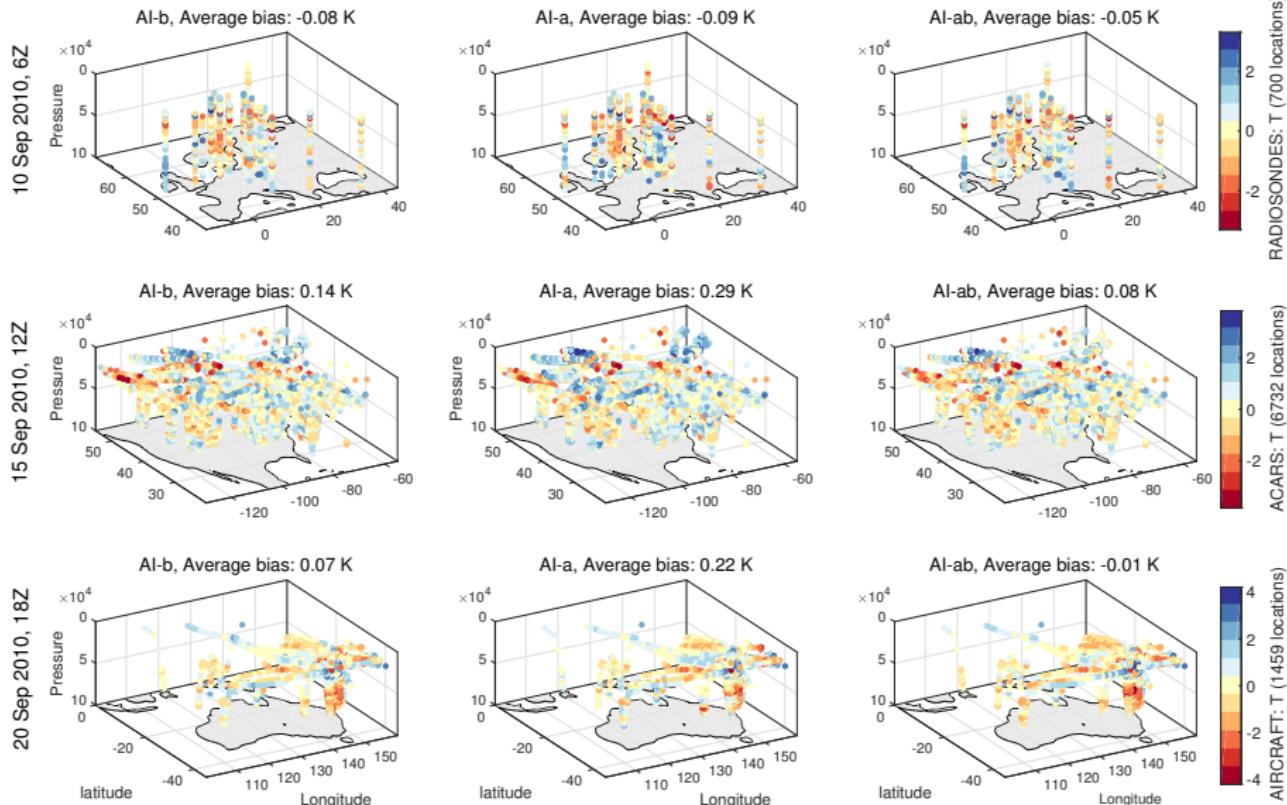


CAM (The Community Atmosphere Model)

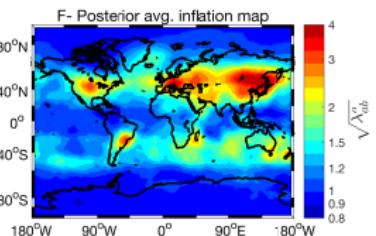
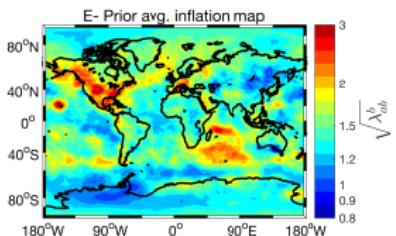
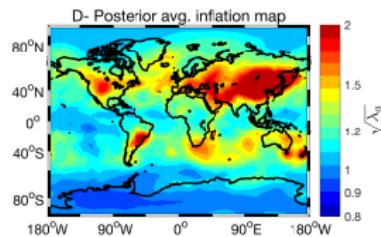
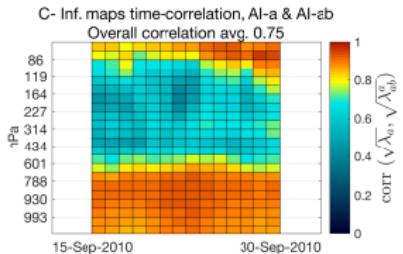
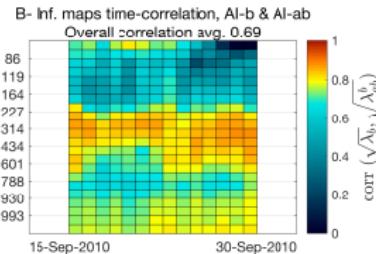
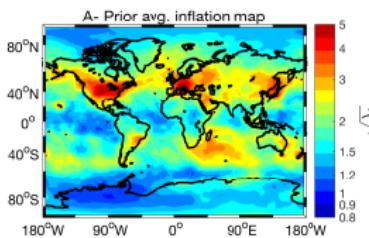
- version: CESM2_0_beta05
- resolution: $1.9^\circ \times 1.9^\circ$ FV core;
LAT: 96, LON: 144, LEV: 26
- State variables: surface pressure (PS), sensible temperature (T), wind components (U and V), specific humidity (Q), cloud liquid water (CLDLIQ) and cloud ice (CLDICE).
- DA: 08.16.2010 to 09.30.2010
- 80 members
- data available every 6 hours
- Horizontal localization: ≈ 960 km
- DART: latest 'Manhattan' release



CAM Assimilation Results: Bias Treatment



CAM Assimilation Results: Inflation Fields



Conclusion

- Inflation is an important tool for ensemble Kalman filters
- The adaptive algorithm is based on Bayes' and uses forecast/analysis innovations to update the inflation
- With no model errors, posterior inflation produces higher quality estimates than prior inflation (better treatment of sampling errors)
- When model errors are dominant, as in CAM4, posterior inflation is found less useful
- Compelling results obtained by combining both prior and posterior inflation

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Papers

- **Gharamti, M. E.** (2018) "Enhanced Adaptive Inflation Algorithm for Ensemble Filters." *Monthly Weather Review*, 2, 623-640
- **Gharamti, M. E.**, Raeder, K., Anderson, J. and Wang, X. (2019) "Comparing Adaptive Prior and Posterior Inflation for Ensemble Filters Using an Atmospheric General Circulation Model." *Monthly Weather Review*, 147, 2535-2553

THANK YOU

DART webpage: <https://dart.ucar.edu/>

The screenshot shows the homepage of the NCAR DART website. At the top, there is a large orange "THANK YOU" message. Below it, the text "DART webpage: <https://dart.ucar.edu/>" is displayed in blue. The main header features the text "NCAR | DART" in white on a dark background. To the right of the header, the text "National Center for Atmospheric Research" is visible. A navigation bar below the header includes links for "DOCUMENTATION", "RESEARCH", "ABOUT US", "SUPPORT", and "RELEASES". The central content area has a teal background and contains the heading "WELCOME TO DART" in yellow. Below this, a paragraph of text describes DART's capabilities and support for various models. A "DOWNLOAD" button with a right-pointing arrow is located at the bottom of this section. The footer area has a light gray background and contains the heading "THE DATA ASSIMILATION RESEARCH TESTBED (DART)" in large black text. A smaller paragraph of text follows, describing DART's purpose and benefits. On the right side of the footer, there is a decorative graphic consisting of several thin, curved white lines of varying lengths.

NCAR | DART

National Center for
Atmospheric Research

DOCUMENTATION RESEARCH ABOUT US SUPPORT RELEASES

WELCOME TO DART

DART has been reformulated to better support the ensemble data assimilation needs of researchers who are interested in native netCDF support, less filesystem I/O, better computational performance, good scaling for large processor counts, and support for the memory requirements of very large models. Manhattan has support for many of our larger models (*WRF, POP, CAM, CICE, CLM, ROMS, MPAS_ATM, ...*) with many more being added as time permits.

DOWNLOAD

THE DATA ASSIMILATION RESEARCH TESTBED (DART)

DART is a community facility for ensemble DA developed and maintained by the Data Assimilation Research Section (DAREs) at the National Center for Atmospheric Research (NCAR). DART provides modelers, observational scientists, and geophysicists with powerful, flexible DA tools that are easy to implement and use and can be customized to support efficient operational DA applications. DART is a software environment that makes it easy to explore a variety of data assimilation methods and