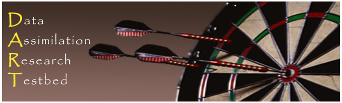

Adaptive (Prior|Posterior?) Inflation for Ensemble Kalman Filters

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Data Assimilation [APPM 5510]

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NCAR
NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

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The EnKF

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

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

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- Successive Forecast and Update (Analysis) stages:

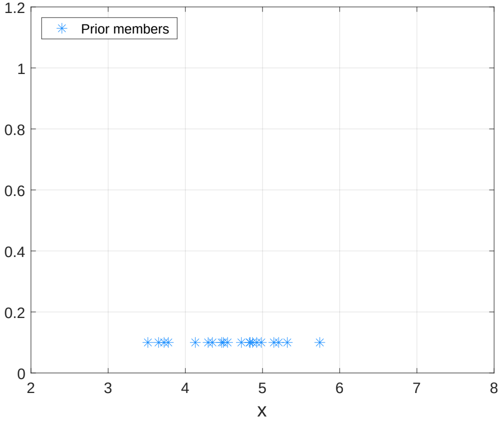
$$x_f^i = \mathcal{M}\left(x_a^i\right)$$

$$\overline{x}_f = \frac{1}{N}\sum_{i=1}^{N} x_f^i, \qquad \widehat{\sigma}_f^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_f^i - \overline{x}_f\right)\left(x_f^i - \overline{x}_f\right)^T$$

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

N is the ensemble size

The EnKF cont.



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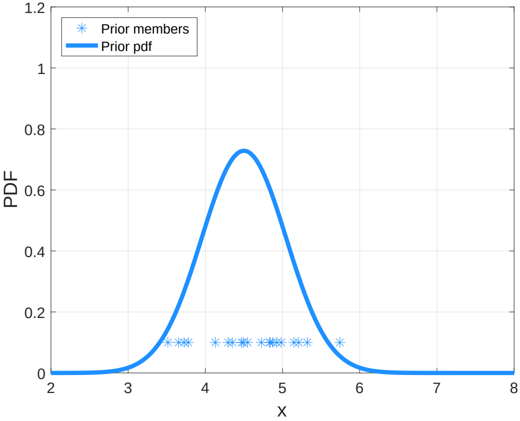

$\overline{x}_f = 4.5, \widehat{\sigma}_f^2 = 0.30$

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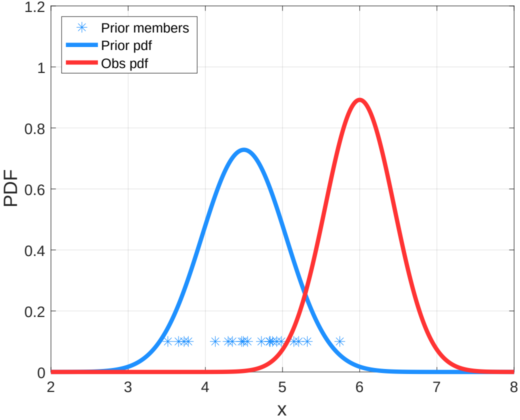

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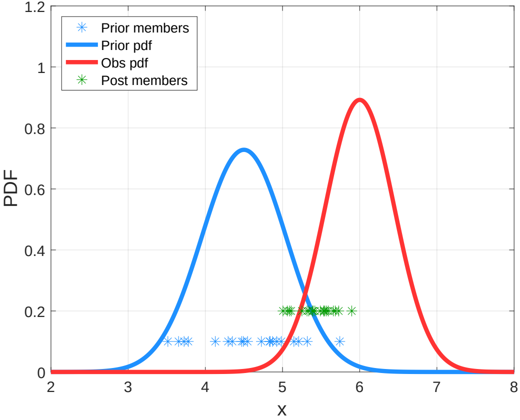

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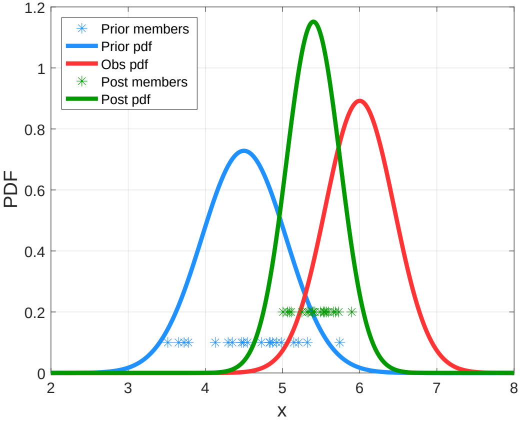

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$\overline{x}_a = 5.43, \widehat{\sigma}_a^2 = 0.06$

The EnKF cont.

Some Drawbacks

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

$$\lim_{N \to \infty} \widehat{\sigma}_f^2(N) = \sigma_f^2$$

   - When N is small, $\widehat{\sigma}_f^2$ 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:

$$x^i \leftarrow \sqrt{\lambda}\left(x^i - \overline{x}\right) + \overline{x} \tag{2}$$

while preserving the ensemble mean.

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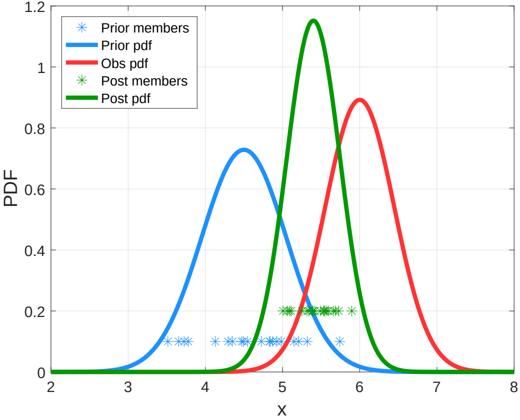
  while preserving the ensemble mean.
- Which variance to inflate: Prior (after the forecast) or posterior (after the update)?
- What to choose for λ? 1.02 (2%), 1.04, 1.2, 10, ... ?
- Why this is useful?

Inflation



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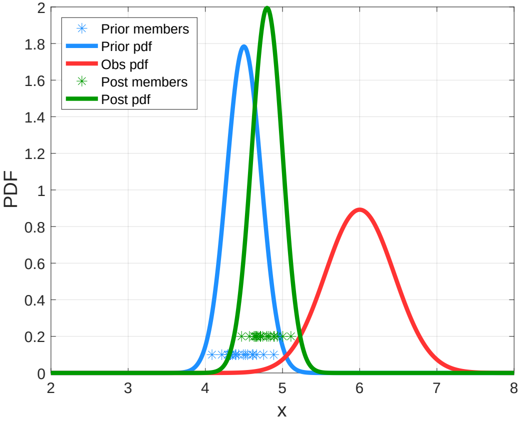

$\overline{x}_f = 4.5, \sigma_f^2 = \mathbf{0.05}$

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

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

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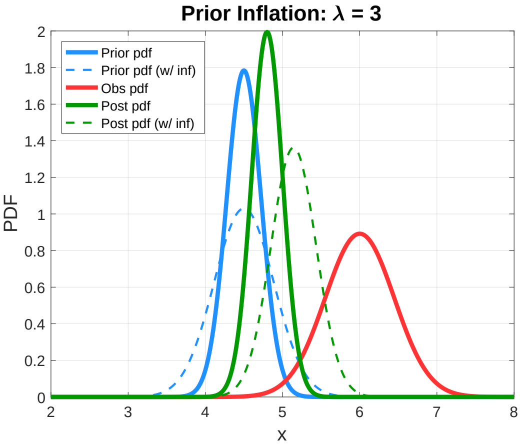

σ_f^2 : **0.05** $\rightarrow$ **0.15**

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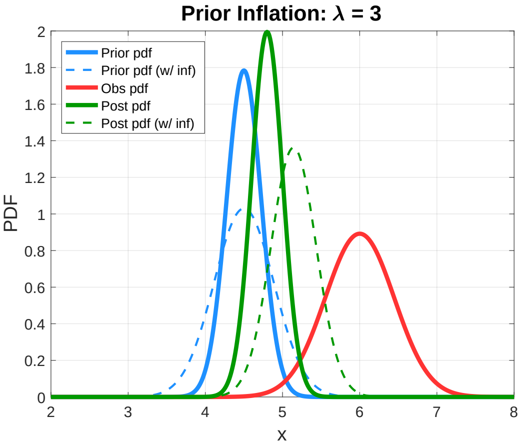

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Higher spread: Larger uncertainty (less confidence in the estimates)!

Adaptive Prior Inflation I

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For a single variable case, denote the following:

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The forecast innovation (discrepancy):

$$d_f = y - \overline{x}_f = y - x_t + x_t - \overline{x}_f = \varepsilon_o - \varepsilon_f, \tag{6}$$

where x_t is the true value of the variable.

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

$$p\left(\lambda|d_f\right) \propto p\left(\lambda\right) \cdot p\left(d_f|\lambda\right) \tag{7}$$

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$$= \mathbb{E}\left[\varepsilon_o^2 - \varepsilon_o\varepsilon_f - \varepsilon_f\varepsilon_o + \varepsilon_f^2\right] \tag{10}$$

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

Adaptive Prior Inflation III

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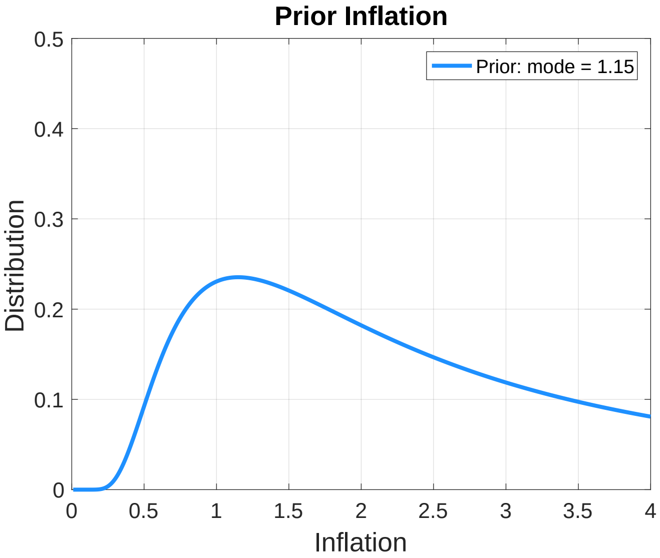
  - To find the posterior mode, need to maximize $p(\lambda|d_f)$. Not easy!
  - Linearizing the Likelihood will simplify the problem:

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

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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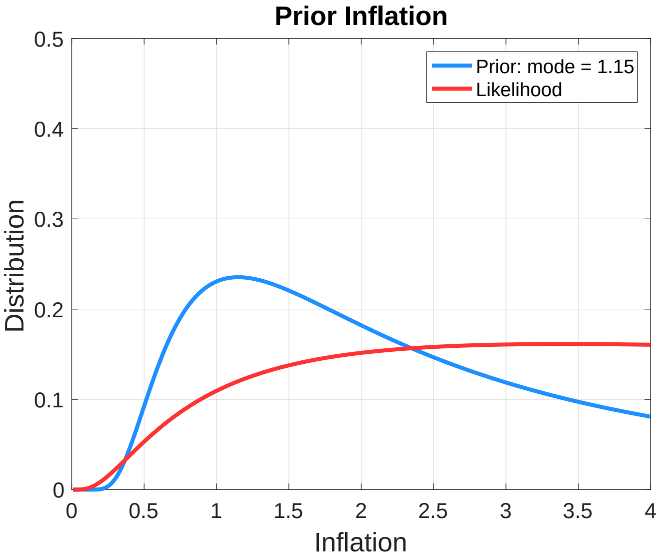

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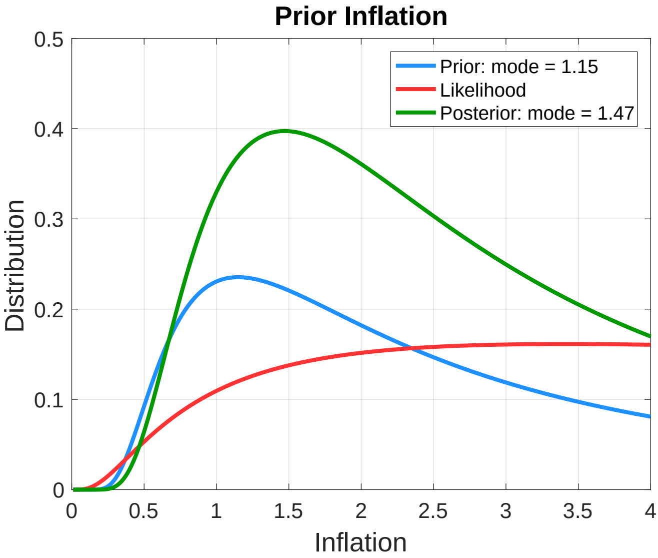

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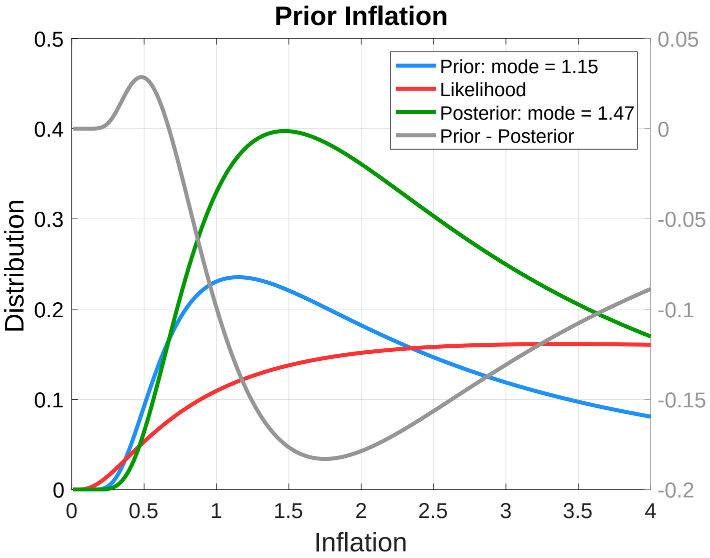

Can the inflation variance increase after the update?

Adaptive Posterior Inflation

Follow similar Bayes' formulation:

$$p\left(\lambda | d_a\right) \propto p(\lambda) \cdot p\left(d_a | \lambda\right) \tag{17}$$

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

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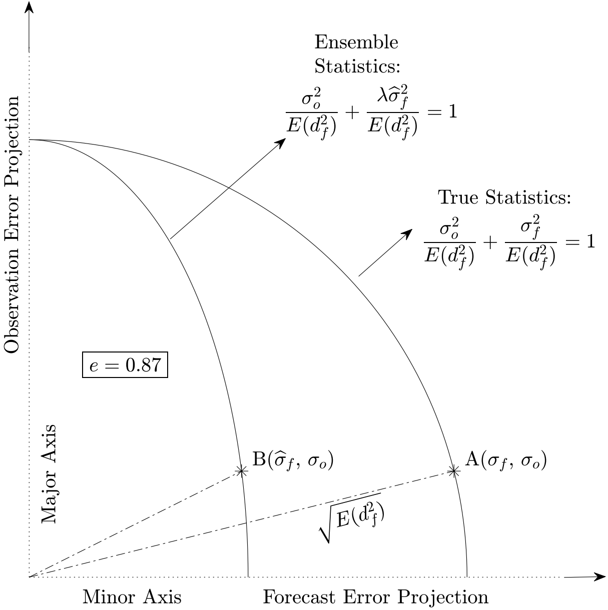
where $K = \sigma_f^2\left(\sigma_o^2 + \sigma_f^2\right)^{-1}$. Thus,

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

Geometrical Interpretation (Prior vs Posterior)



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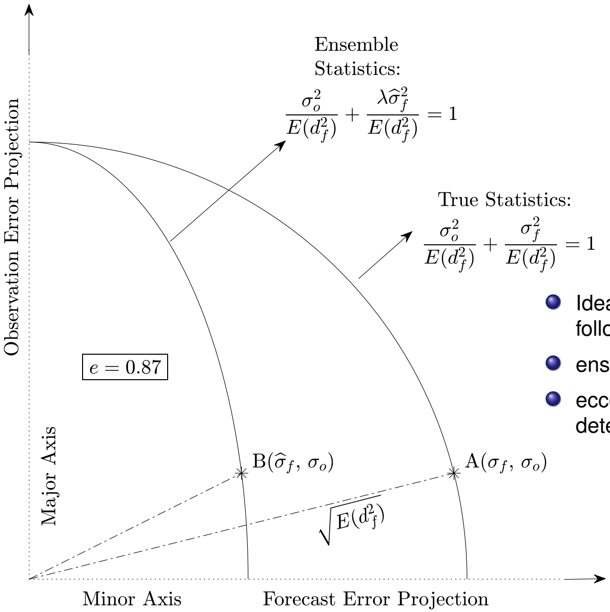

- Ideal state and observation statistics follow a circle
- ensemble ones satisfy an ellipse
- eccentricity, $0 < e < 1$, a measure to determine the deviation from circle

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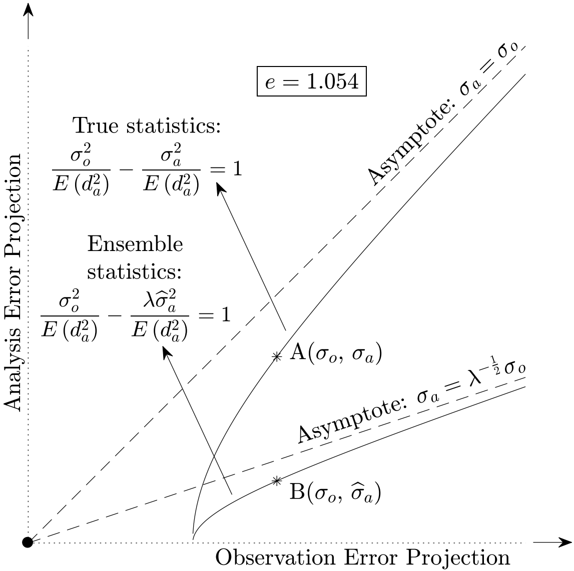
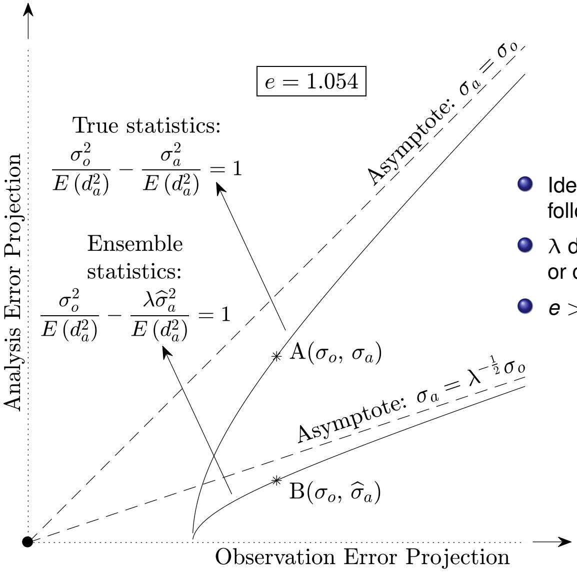


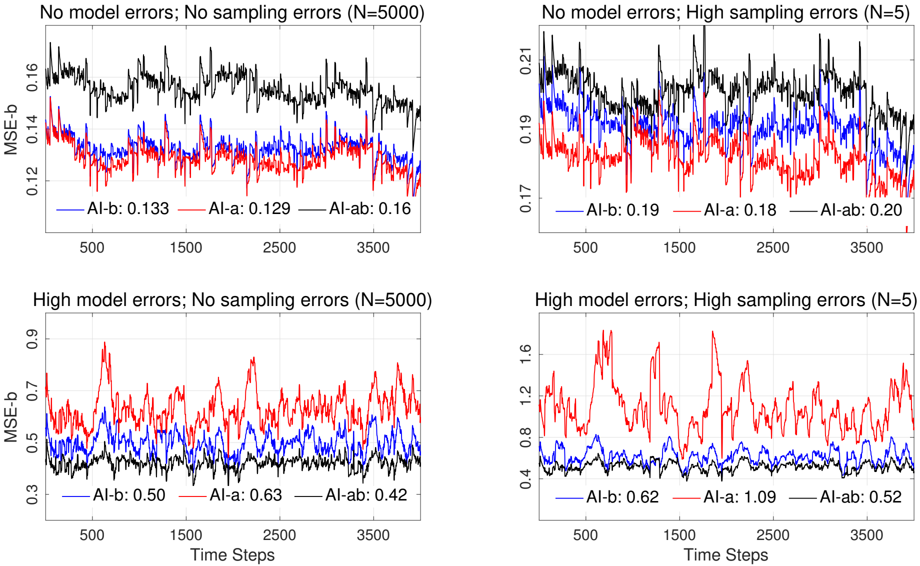
Geometrical Interpretation (Prior vs Posterior)



- 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

Low-Order Models: Lorenz-63



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).

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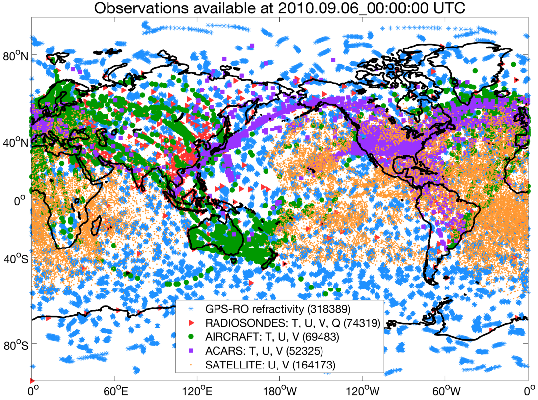
- 80 members
- data available every 6 hours



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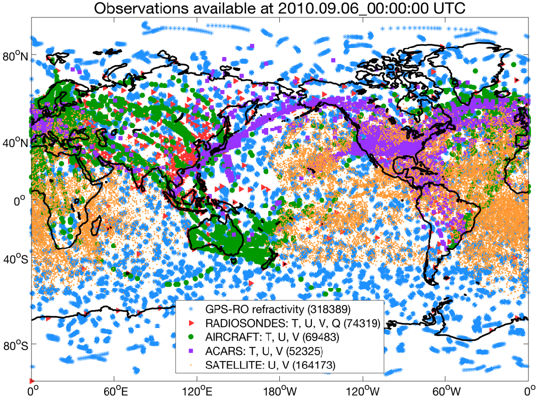
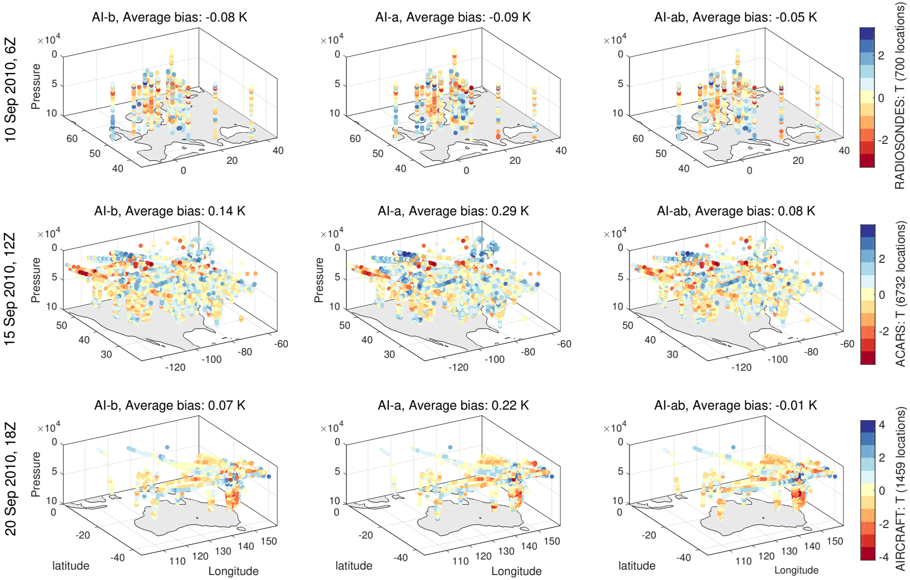
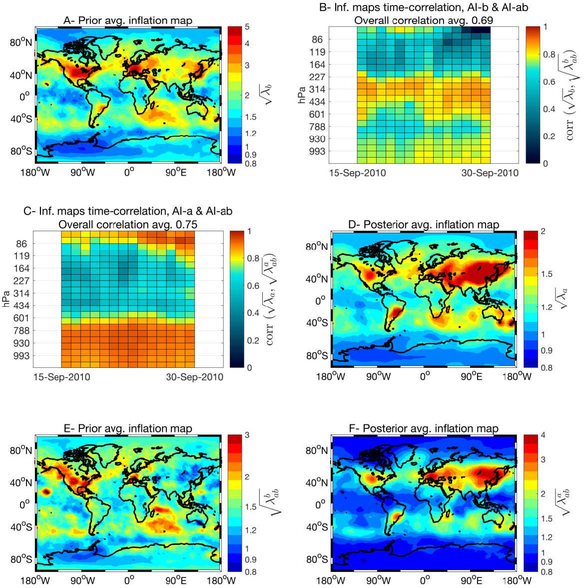
- Horizontal localization: ≈ 960 km
- DART: latest 'Manhattan' release



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/