Annual TRAMPAS Meeting. 24 October 2023
(Palma, Spain)

"Ensemble Squeeze" enabled Multiscale Localisation for the Local EAKF/EnSRF/EnKF - (MLEnKF)

Diego S. Carrió[1], Craig H. Bishop[2] and Xuguang Wang[3]

University of the Balearic Islands, km 7.5 Cra. Valldemossa km 7.5, Palma, Spain
Centre of Excellence for Climate Extremes and the School of Geography, Earth and Atmospheric Sciences, The University of Melbourne, Parkville, Victoria, Australia
Mesoscale Data Assimilation and Predictability (MAP) Laboratory, University of Oklahoma, Norman, USA

Main Motivation

Main Motivation of the "Ensemble Squeeze" Localization

- **MAIN MOTIVATION:**

- Implementation of the Local version of the *Gamma Inverse-Gamma* (**GIG**; *Bishop, 2016*) in a **LETKF framework, widely used in Operational Centers**.
- LETKF uses the "**Ob-Error-Inflation localization"** technique.

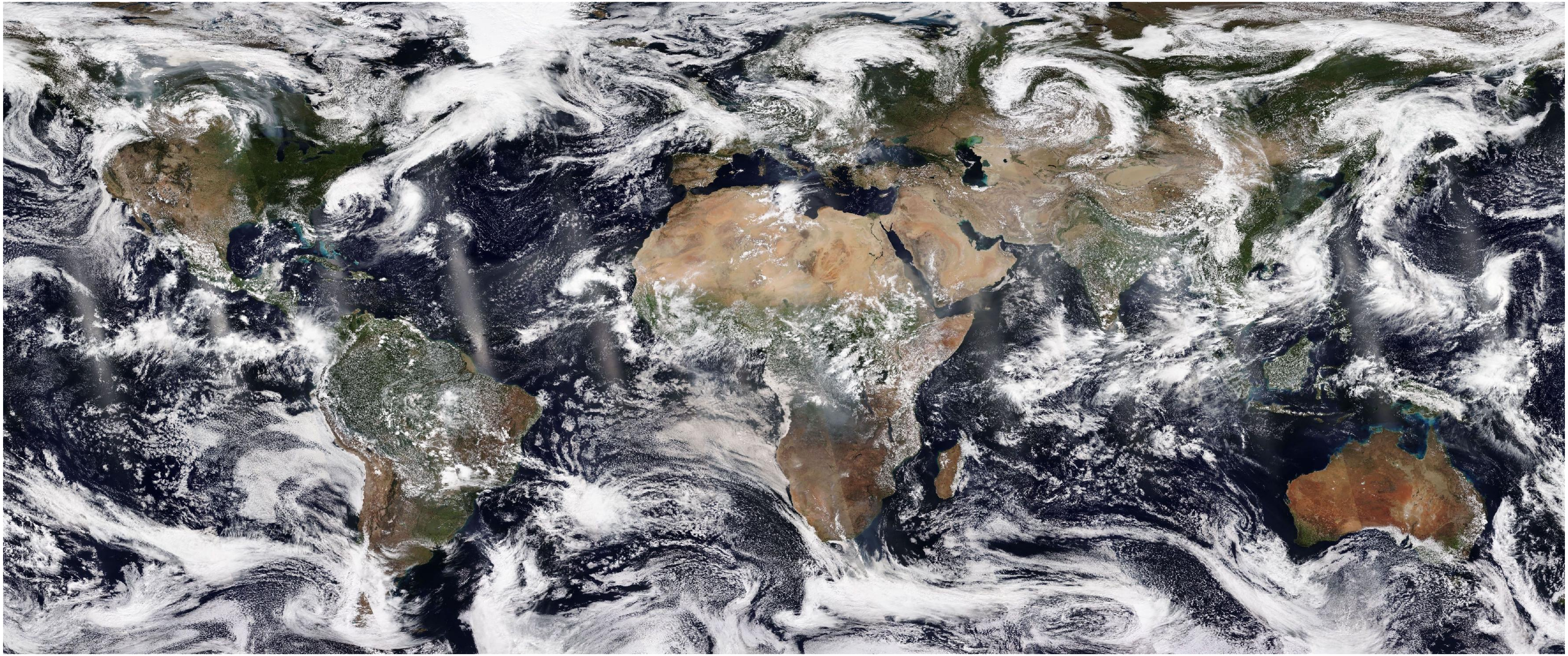
- **MAIN PROBLEM**:

- "**Ob-Error-Inflation**" localization method does not work for **GIG.**

- **SOLUTIONS:**

- Development of a **new localization technique "Ensemble Squeeze"** suitable for **GIG** which is **equivalent** to the "**Ob-Error-Inflation**" localization.
- The **"Ensemble Squeeze"** localization technique **can be applied to any other ensemble-based DA system.**

Main Motivation of this presentation



Brute Force Optimal Localization Length Scale

Main Results

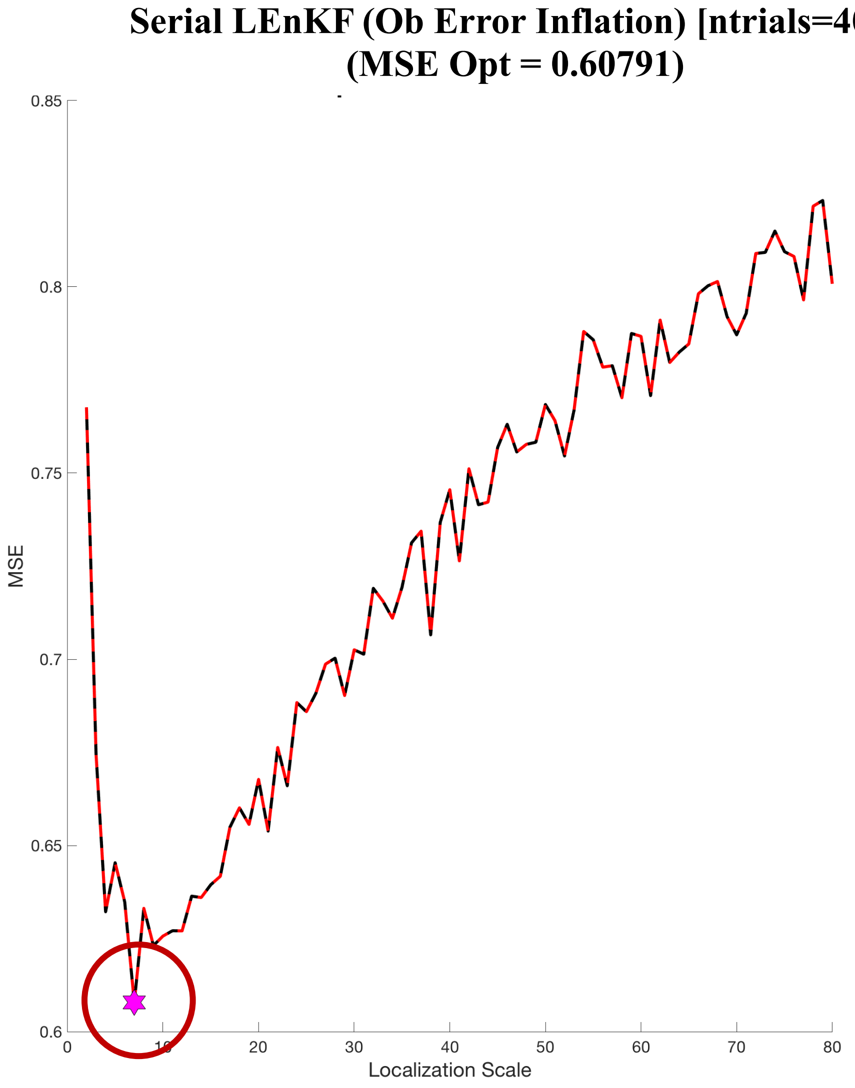
n=120

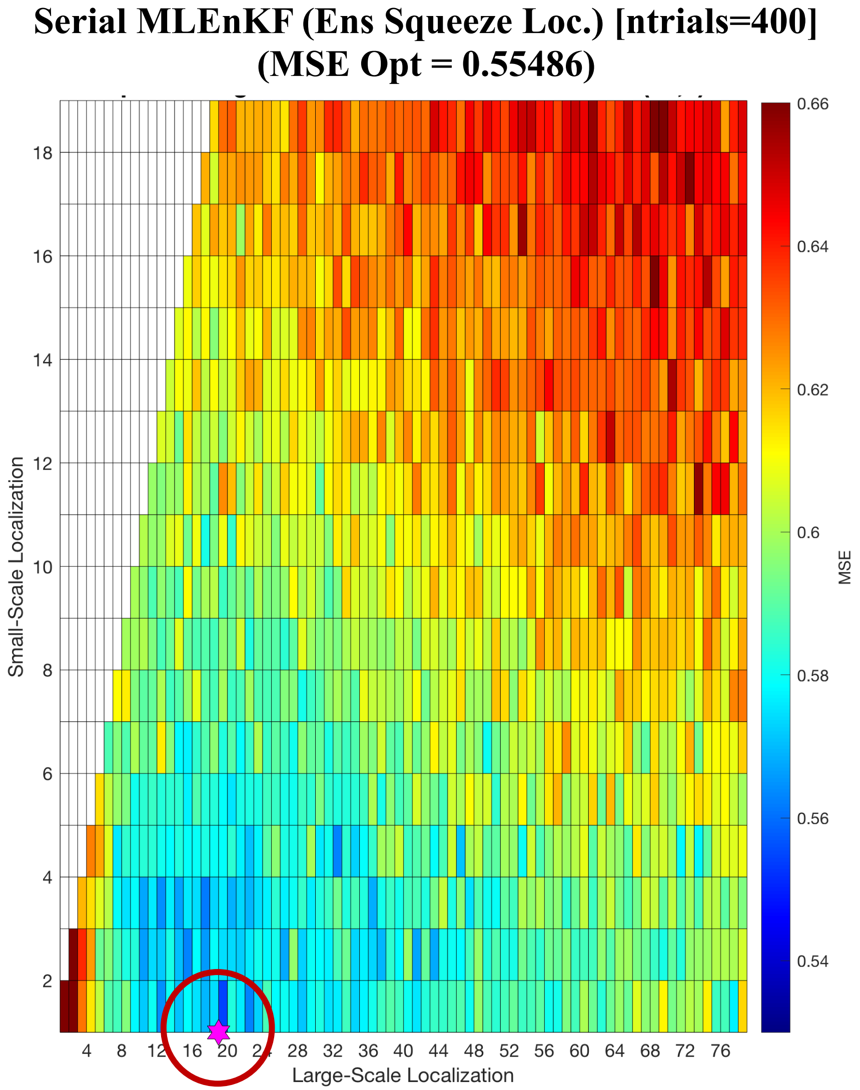
K=10

p=30

ntrials=400

Ob Error var = 1.0

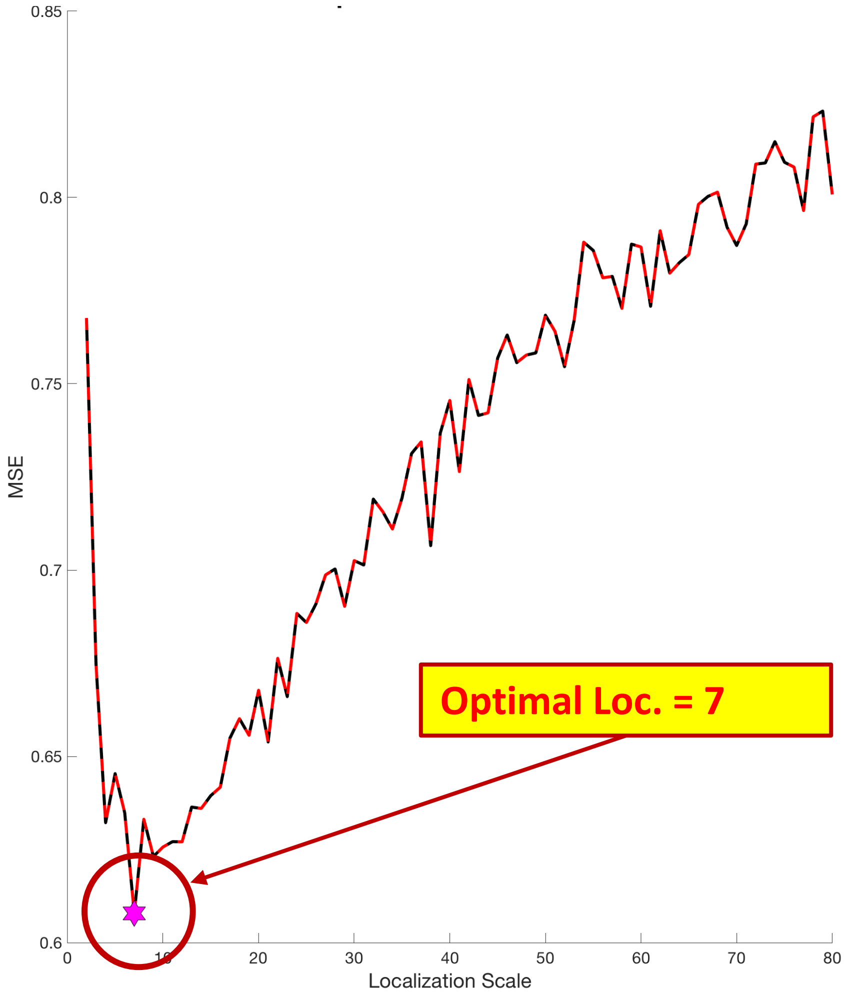




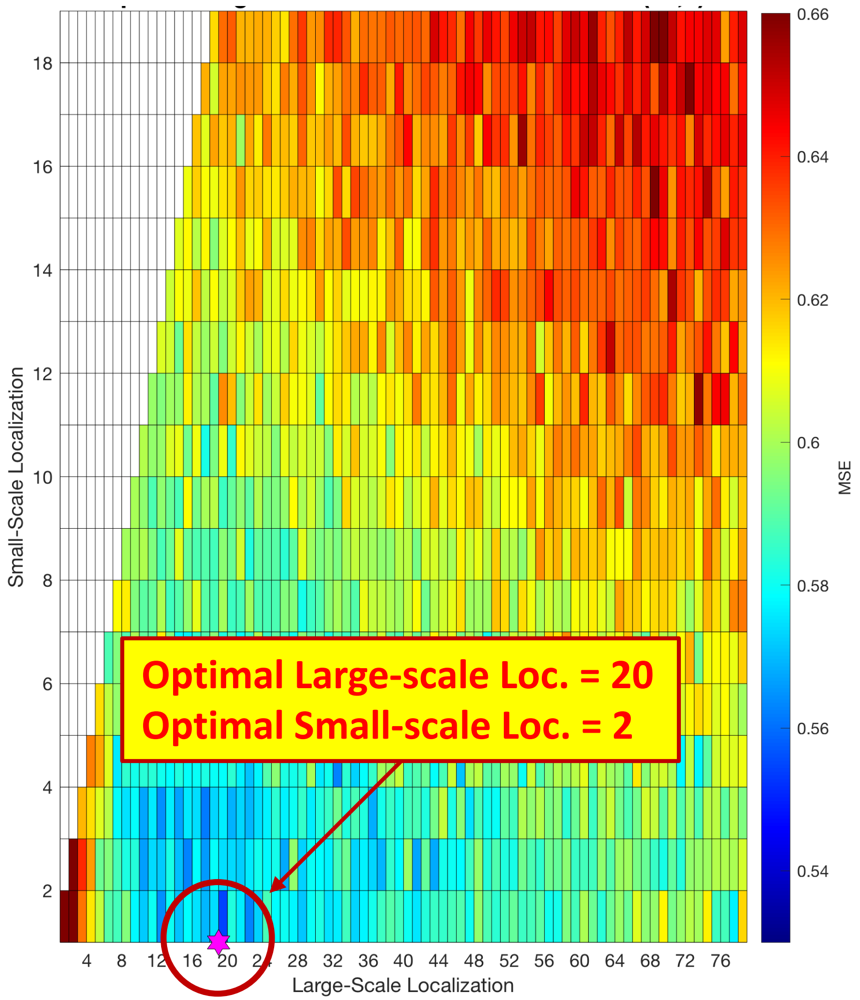
Main Results

n=120
K=10
p=30
ntrials=400
Ob Error var = 1.0

Serial LEnKF (Ob Error Inflation) [ntrials=400]
(MSE Opt = 0.60791)



Serial MLEnKF (Ens Squeeze Loc.) [ntrials=400]
(MSE Opt = 0.55486)



Main Results

n=120

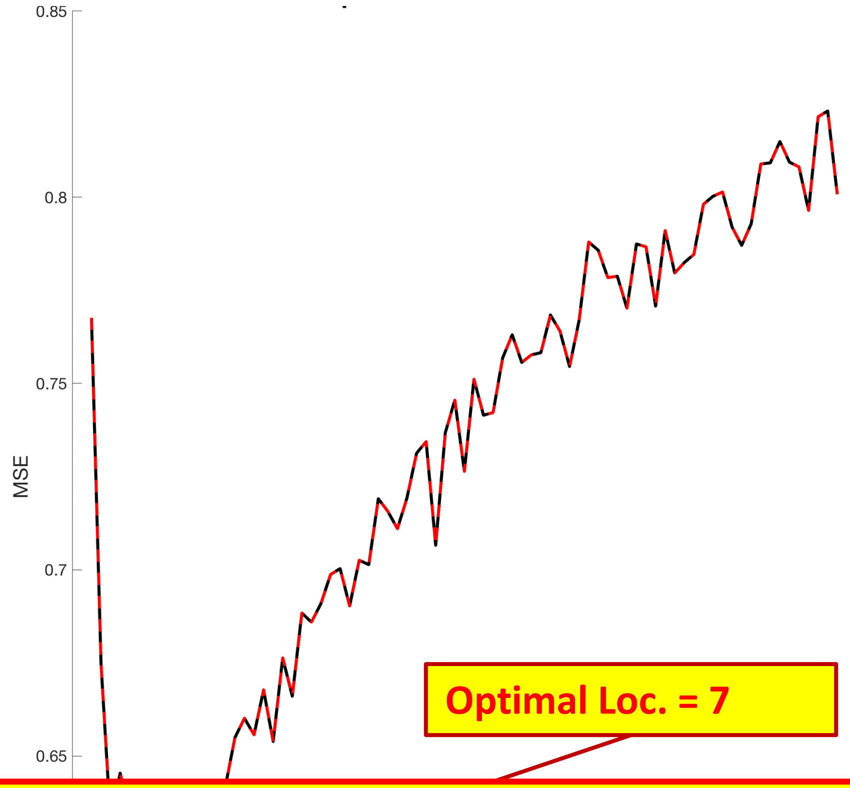
K=10

p=30

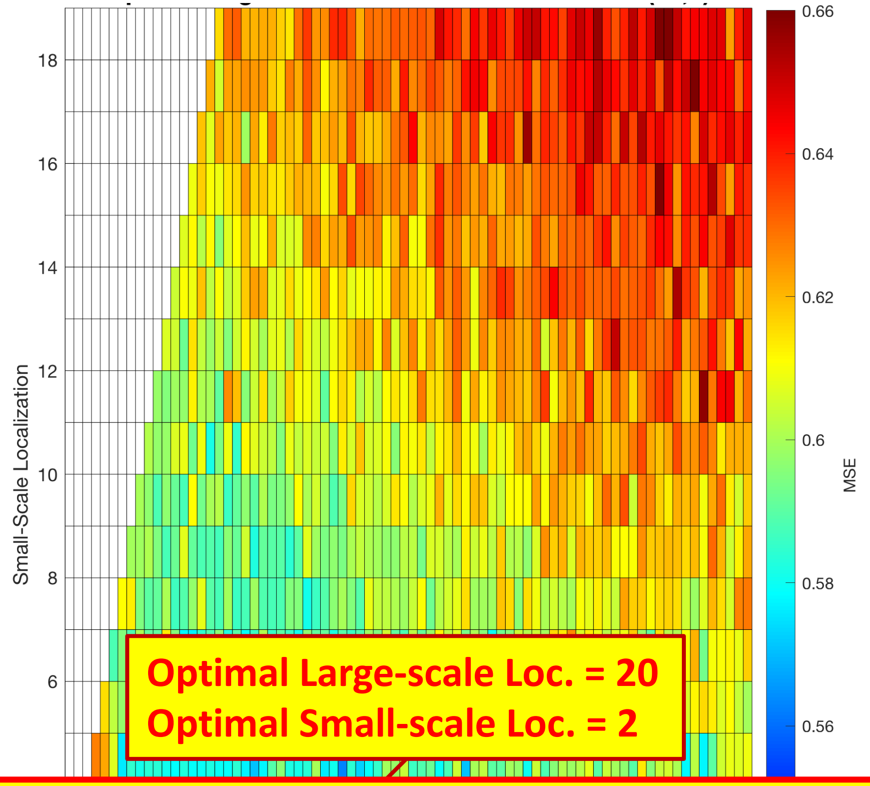
ntrials=400

Ob Error var = 1.0

Serial LEnKF (Ob Error Inflation) [ntrials=400]
(MSE Opt = 0.60791)



Serial MLEnKF (Ens Squeeze Loc.) [ntrials=400]
(MSE Opt = 0.55486)



Multi-Scale MLEnKF (MSE=0.55486) outperforms Single-Scale LEnKF (MSE=0.60791)

Approach to the "Optimal" Multi-Scale Localization Length Scale

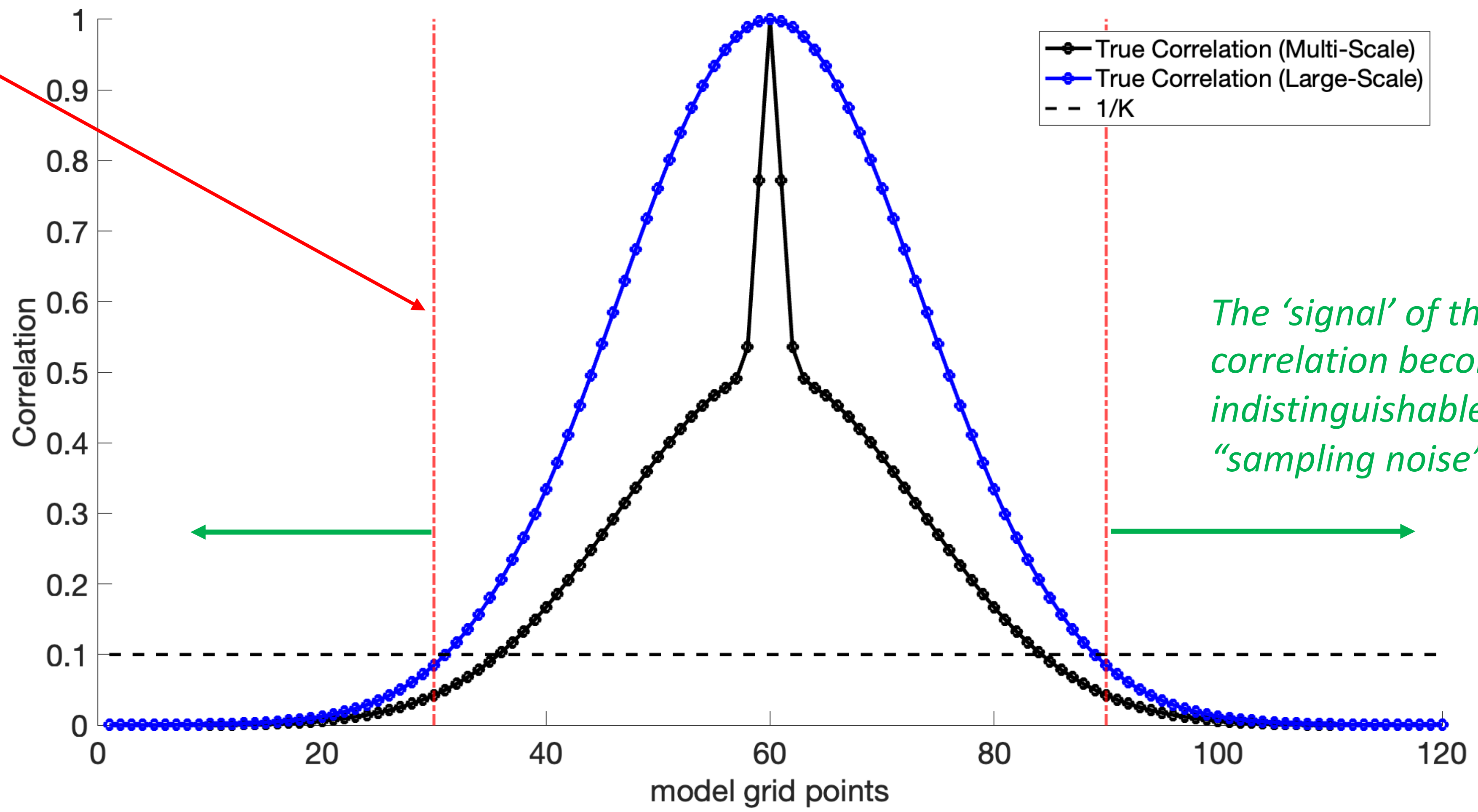
1/K Rule: Getting "Optimal" Localization Length Scale from the Multi-Scale True Correlation Function.

Intersection 1/K with large-scale correlation function at a 30 grid model point distance.

"optimal" localization is 30.

Brute force localization was 20

K=10, n=120, p=30



The 'signal' of the true correlation becomes indistinguishable from the "sampling noise"

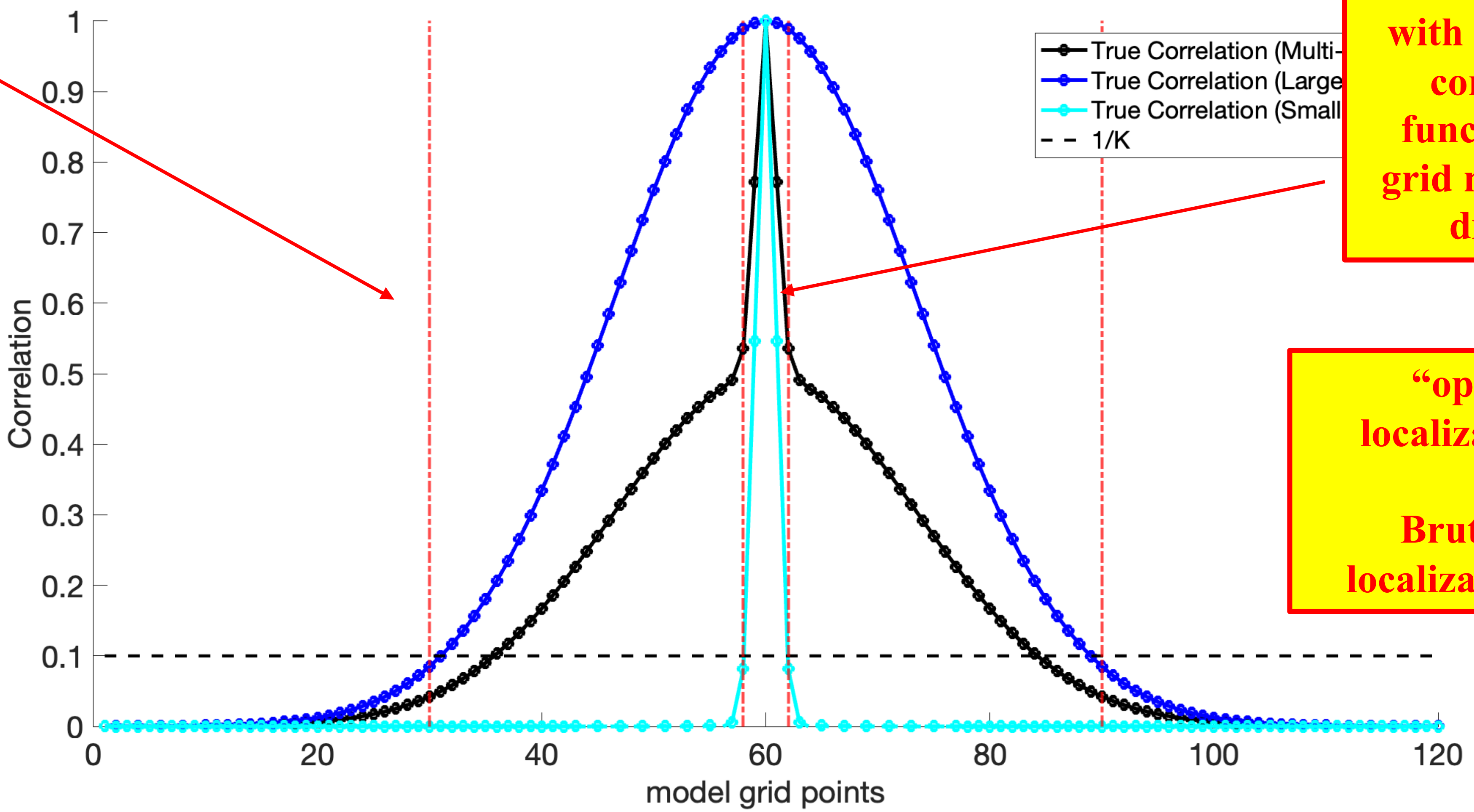
1/K Rule: Getting "Optimal" Localization Length Scale from the Multi-Scale True Correlation Function.

Intersection 1/K with large-scale correlation function at a 30 grid model point distance.

"optimal" localization is 30.

Brute force localization was 20

K=10, n=120, p=30



Intersection 1/K with small-scale correlation function at a 2 grid model point distance.

"optimal" localization is 2.

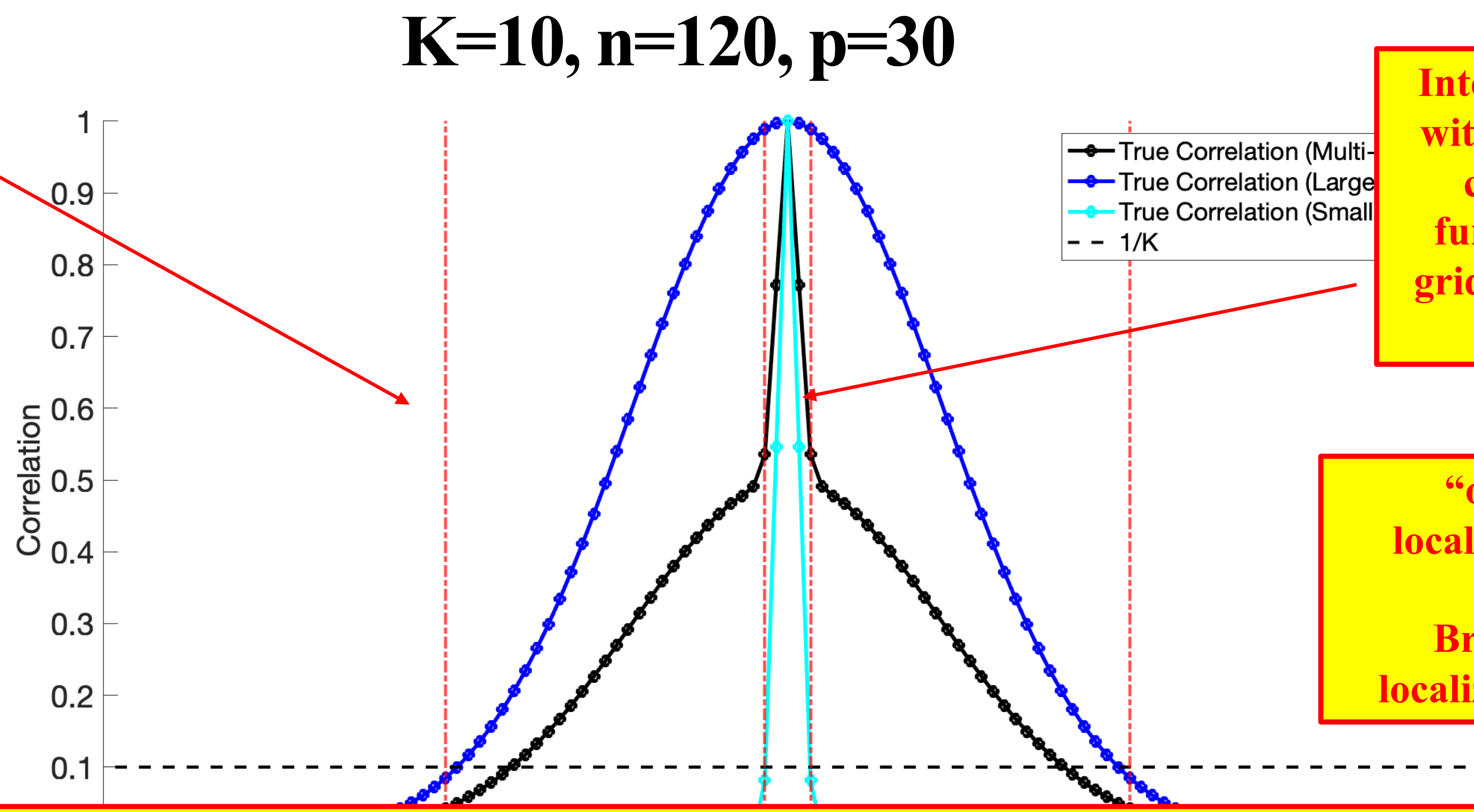
Brute force localization was 2

1/K Rule: Getting "Optimal" Localization Length Scale from the Multi-Scale True Correlation Function.

Intersection 1/K with large-scale correlation function at a 30 grid model point distance.

"optimal" localization is 30.

Brute force localization was 20



Intersection 1/K with small-scale correlation function at a 2 grid model point distance.

"optimal" localization is 2.

Brute force localization was 2

Results so far suggest that the intersection of 1/K with the climatological covariance function might help speed the tuning of the localization.

Theoretical aspects behind the "*Ensemble Squeeze*" Localization Method

The idea of "*Ob-Error-Inflation*" (Local Volume LETKF Perspective)

Serial EAKF (NCAR-DART)

for $j = 1 : p$;   % where p is the number of observations

Step 1 : Obtain the observed value y_j^o, and the associated observation error variance, R_{jj}

Step 2 : Update the ensemble estimate of the observed variable using

$$\langle y_j^a \rangle = \langle y_j^f \rangle + \frac{H_j \mathbf{Z} (H_j \mathbf{Z})^T}{H_j \mathbf{Z} (H_j \mathbf{Z})^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right) = \langle y_j^f \rangle + \frac{H_j \mathbf{P}^f H_j^T}{H_j \mathbf{P}^f H_j^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right), \text{ and}$$

$$y_{ji}^a = \langle y_j^a \rangle + \sqrt{\left[1 - P^f \left(P^f + R_{jj} \right)^{-1} \right]} \left(y_{ji}^f - \langle y_j^f \rangle \right), \qquad \text{for } i = 1,2,\ldots,K \quad \left(P^f = H_j \mathbf{P}^f H_j^T \right)$$

Step 3 : Find corresponding analysis ensemble for observations and model variables using

$$y_{ki}^a = y_{ki}^f + \frac{H_k \mathbf{Z} (H_j \mathbf{Z})^T}{(H_j \mathbf{Z})(H_j \mathbf{Z})^T} \left(y_{ji}^a - y_{ji}^f \right) \text{ for } k = 1,2,\ldots,p \text{ and } i = 1,2,\ldots,K, \text{ and}$$

$$x_{\mu i}^a = x_{\mu i}^f + \frac{\mathbf{Z}(\mu,:)(H_j \mathbf{Z})^T}{(H_j \mathbf{Z})(H_j \mathbf{Z})^T} \left(y_{ji}^a - y_{ji}^f \right) \text{ for } \mu = 1,2,\ldots,n, \text{ and } i = 1,2,\ldots,K$$

Step 4 : Let the analysis ensemble be the prior ensemble for the next observation

$y_{ki}^f = y_{ki}^a$, for $k = 1,2,\ldots,p$; $i = 1,2,\ldots,K$

$x_{\mu i}^f = x_{\mu i}^a$, for $\mu = 1,2,\ldots,n$; $i = 1,2,\ldots,K$

end

The idea of "*Ob-Error-Inflation*" (Local Volume LETKF Perspective)

Local Serial EAKF "*Ob-Error-Inflation Localization*"

for $j = 1 : p$; % where p is the number of observations

Step 1 : Obtain the observed value y_j^o, and the associated observation error variance, R_{jj}

Step 2 : Update the ensemble estimate of the observed variable using ob error inflation factor $a_{\mu j}$

$$\langle y_j^a \rangle = \langle y_j^f \rangle + \frac{H_j \mathbf{Z}\left(H_j \mathbf{Z}\right)^T}{H_j \mathbf{Z}\left(H_j \mathbf{Z}\right)^T + a_{\mu j} R_{jj}} \left(y_j^o - \langle y_j^f \rangle\right) = \langle y_j^f \rangle + \frac{H_j \mathbf{P}^f H_j^T}{H_j \mathbf{P}^f H_j^T + a_{\mu j} R_{jj}} \left(y_j^o - \langle y_j^f \rangle\right), \text{ and}$$

$$y_{ji}^a = \langle y_j^a \rangle + \sqrt{\left[1 - P^f \left(P^f + a_{\mu j} R_{jj}\right)^{-1}\right]} \left(y_{ji}^f - \langle y_j^f \rangle\right) \text{ for } i = 1,2,\ldots,K \quad \left(P^f = H_j \mathbf{P}^f H_j^T\right)$$

Step 3 : Find corresponding analysis ensemble for observations and model variables using

$$y_{ki}^a = y_{ki}^f + \frac{H_k \mathbf{Z}\left(H_j \mathbf{Z}\right)^T}{\left(H_j \mathbf{Z}\right)\left(H_j \mathbf{Z}\right)^T} \left(y_{ji}^a - y_{ji}^f\right) \text{ for } k = 1,2,\ldots,p \text{ and } i = 1,2,\ldots,K, \text{ and}$$

$$x_{\mu i}^a = x_{\mu i}^f + \frac{\mathbf{Z}(\mu,:)\left(H_j \mathbf{Z}\right)^T}{\left(H_j \mathbf{Z}\right)\left(H_j \mathbf{Z}\right)^T} \left(y_{ji}^a - y_{ji}^f\right) \text{ for } \mu = 1,2,\ldots,n, \text{ and } i = 1,2,\ldots,K$$

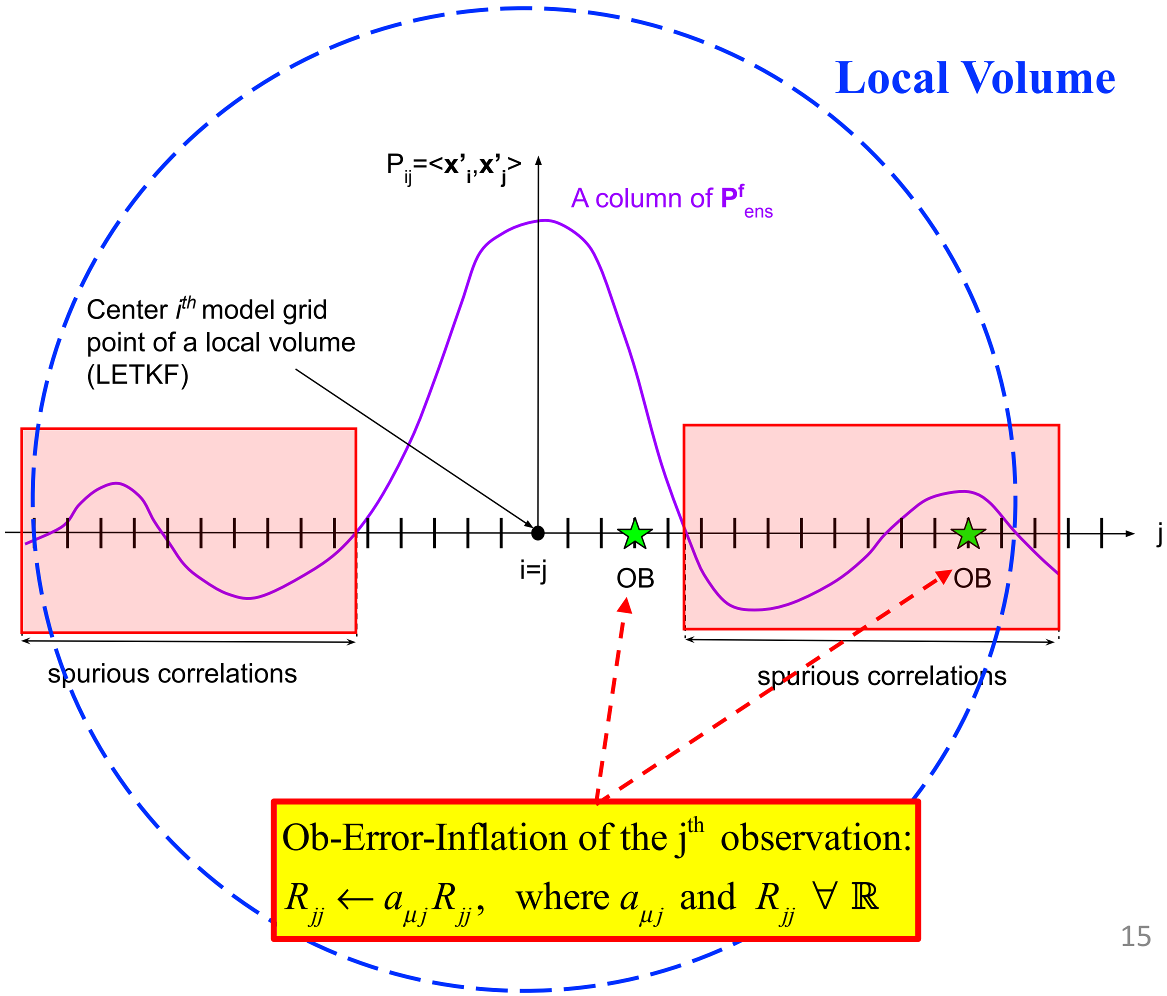
Step 4 : Let the analysis ensemble be the prior ensemble for the next observation

$y_{ki}^f = y_{ki}^a$, for $k = 1,2,\ldots,p$; $i = 1,2,\ldots,K$

$x_{\mu i}^f = x_{\mu i}^a$, for $\mu = 1,2,\ldots,n$; $i = 1,2,\ldots,K$

end

1-dimensional "Ob-Error-Inflation" localization example



The Local Serial Observation EAKF (“*Ensemble Squeeze*” localization)

Local Serial EAKF *“Ensemble Squeeze Localization”*

for $j=1:p$;   % where p is the number of observations

Step 1 : Obtain the observed value y_j^o, and the associated observation error variance, R_{jj}

Step 2 : Update the ensemble estimate of the observed variable using the ensemble squeeze factor $b_{\mu j} = a_{\mu j}^{-1/2}$

$$\langle y_j^a \rangle = \langle y_j^f \rangle + \frac{b_{\mu j} H_j \mathbf{Z} (H_j \mathbf{Z})^T}{b_{\mu j} H_j \mathbf{Z} (b_{\mu j} H_j \mathbf{Z})^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right) = \langle y_j^f \rangle + \frac{b_{\mu j}^2 H_j \mathbf{P}^f H_j^T}{b_{\mu j}^2 H_j \mathbf{P}^f H_j^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right), \text{ and}$$

$$y_{ji}^a = \langle y_j^a \rangle + \sqrt{\left[1 - b_{\mu j}^2 P^f \left(b_{\mu j}^2 P^f + R_{jj} \right)^{-1} \right]} \left(y_{ji}^f - \langle y_j^f \rangle \right) \text{ for } i = 1,2,\ldots,K$$

where $P^f = H_j \mathbf{P}^f H_j^T$.

Step 3 : Find corresponding analysis ensemble for observations and model variables using

$$y_{ki}^a = y_{ki}^f + \frac{H_k \mathbf{Z} (H_j \mathbf{Z})^T}{(H_j \mathbf{Z})(H_j \mathbf{Z})^T} \left(y_{ji}^a - y_{ji}^f \right) \text{ for } k = 1,2,\ldots,p \text{ and } i = 1,2,\ldots,K, \text{ and}$$

$$x_{\mu i}^a = x_{\mu i}^f + \frac{\mathbf{Z}(\mu,:)(H_j \mathbf{Z})^T}{(H_j \mathbf{Z})(H_j \mathbf{Z})^T} \left(y_{ji}^a - y_{ji}^f \right) \text{ for } \mu = 1,2,\ldots,n, \text{ and } i = 1,2,\ldots,K$$

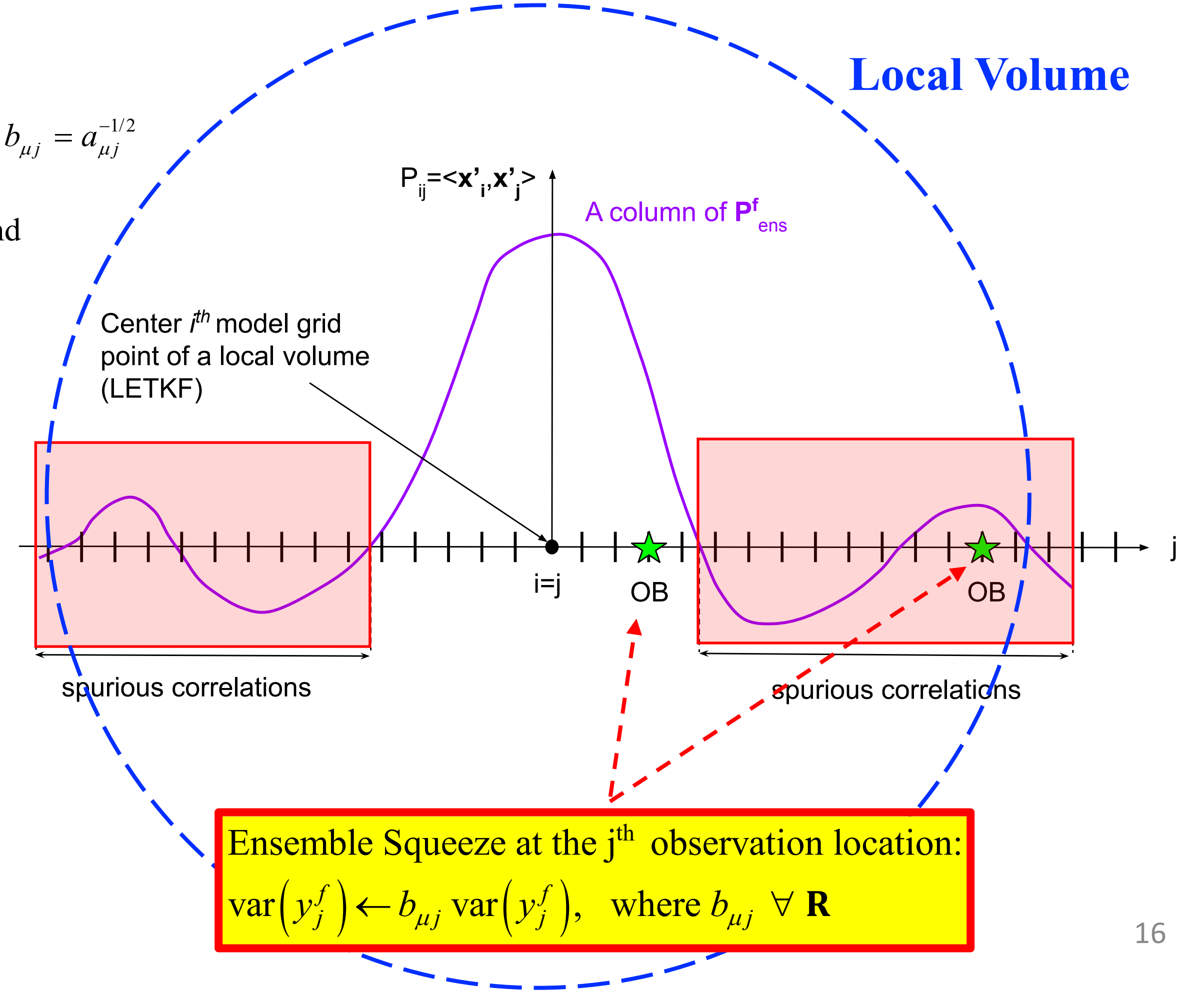
Step 4 : Let the analysis ensemble be the prior ensemble for the next observation

$y_{ki}^f = y_{ki}^a$, for $k = 1,2,\ldots,p$; $i = 1,2,\ldots,K$

$x_{\mu i}^f = x_{\mu i}^a$, for $\mu = 1,2,\ldots,n$; $i = 1,2,\ldots,K$

end

1-dimensional “*Ensemble Squeeze*” localization example

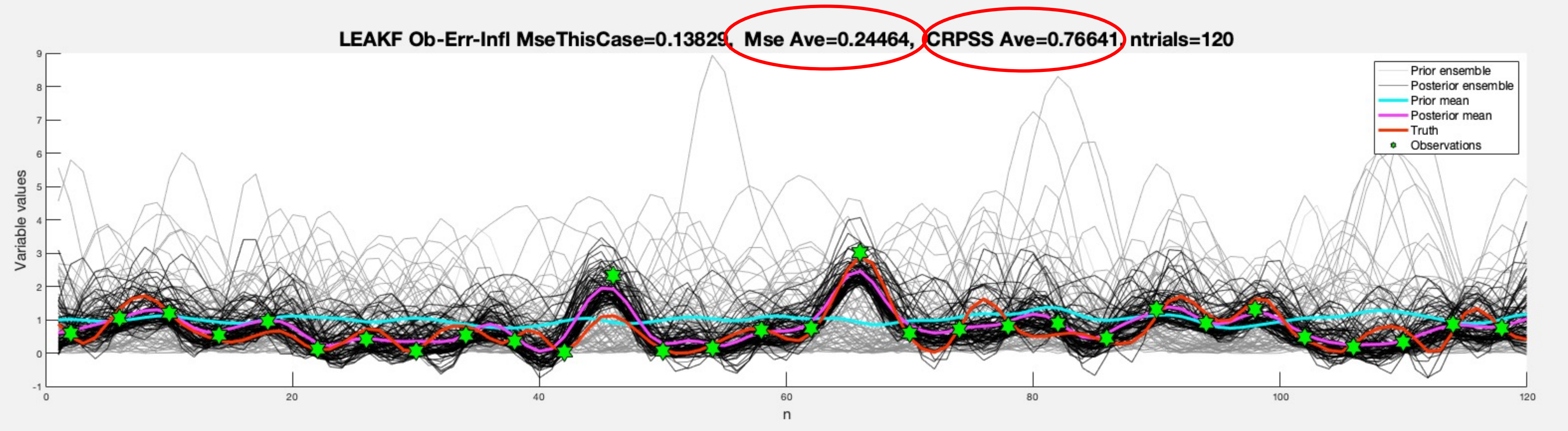


Ensemble Squeeze at the j[th] observation location:

$\mathrm{var}(y_j^f) \leftarrow b_{\mu j}\, \mathrm{var}(y_j^f)$, where $b_{\mu j}\ \forall\ \mathbf{R}$

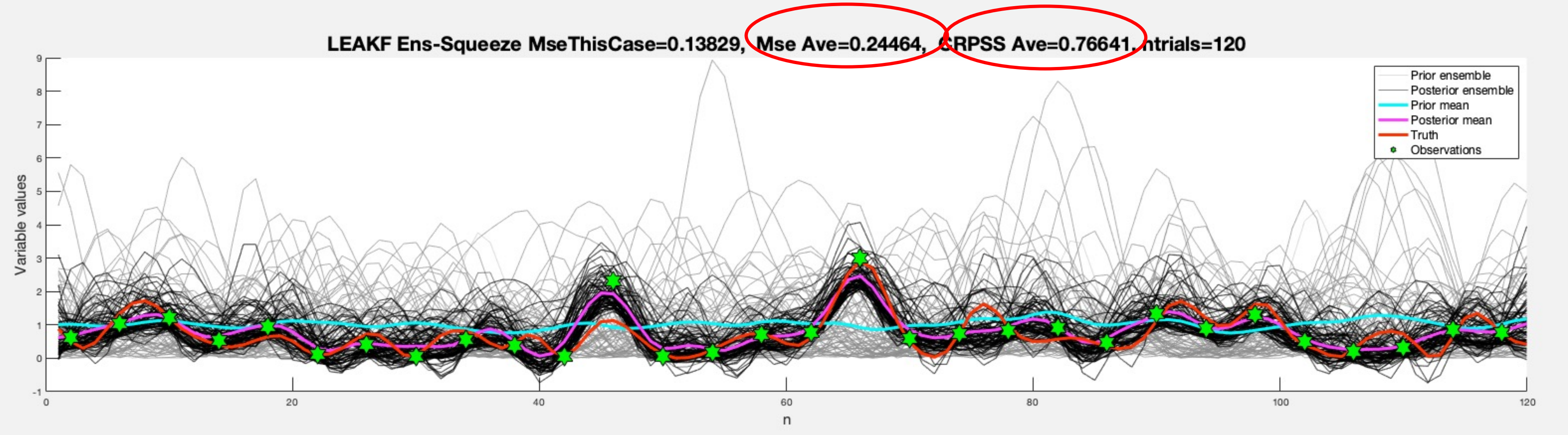
Equivalence Local Serial EAKF (*Ob-Error-Inflation*) vs Local Serial EAKF (*Ens Squeeze*)

LEAKF (*Ob-Err-Infl*)



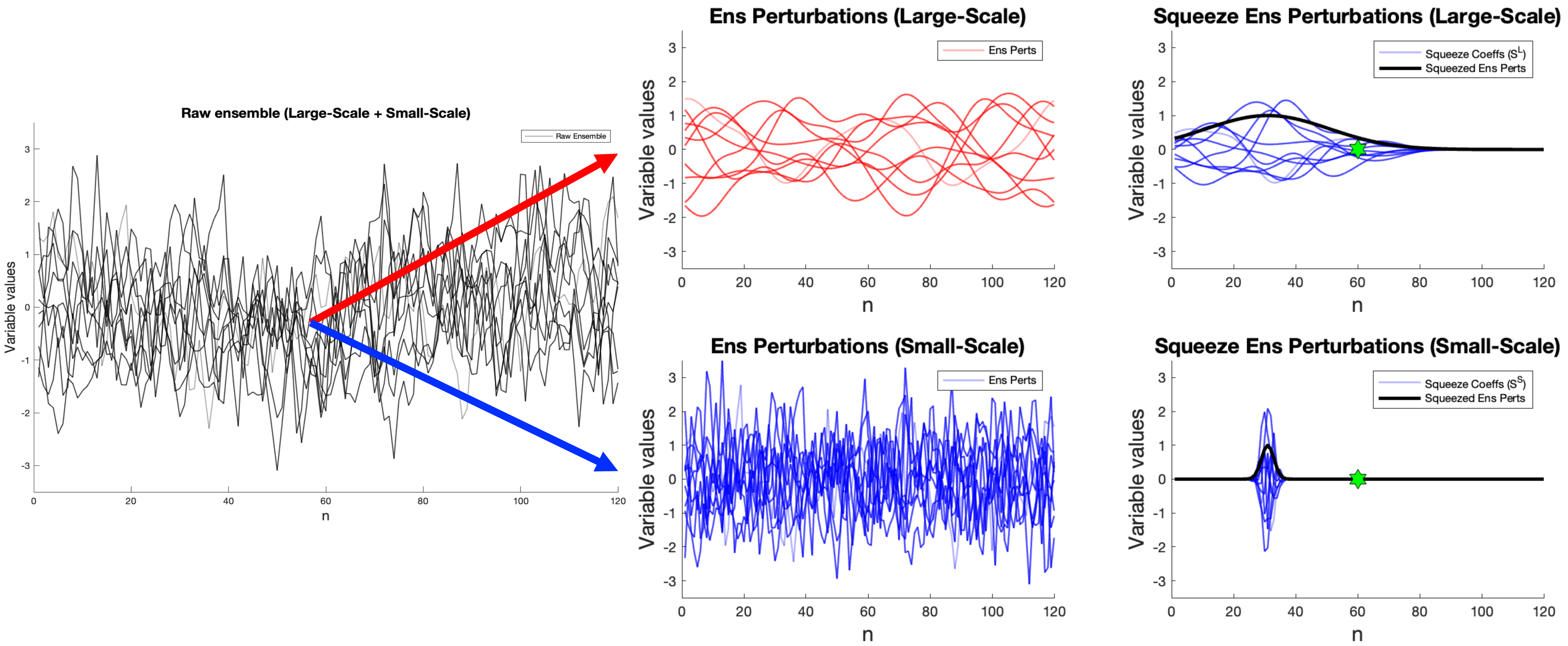
Both localization methods produce precisely the same results!!

LEAKF (*Ens-Squeeze*)



The “*Ensemble Squeeze*” Localization applied to the Multi-Scale DA problem

The Multi-Scale Localization (Main Idea)



Multi-Scale Local MLEnKF using "Ensemble Squeeze Localization" (Pseudo-Code)

for $j = 1 : p$; % where p is the number of observations in the local volume

Step 0a**:** Find omk=$\mathbf{o}_{ji} = \left[\mathbf{o}^L_{ji}, \mathbf{o}^S_{ji}\right]$, for $i = 1, 2, \dots, K$ such that $y^f_{ji} = h_j\left(\mathbf{o}_{ji}\right) \cong h_j\left(\overline{\mathbf{o}_{ji}}\right) + \mathbf{h}^T_j\left(\mathbf{o}_{ji} - \overline{\mathbf{o}_{ji}}\right)$

Step 0b**:** omk_squeeze=$\mathbf{o}^{squeeze}_{ji} = \left(\overline{\mathbf{o}_{ji}}\right) + \mathbf{s} \odot \left(\mathbf{o}_{ji} - \overline{\mathbf{o}_{ji}}\right) = \left[\left(\overline{\mathbf{o}^L_{ji}}\right) + \mathbf{s}^L \odot \left(\mathbf{o}^L_{ji} - \overline{\mathbf{o}^L_{ji}}\right), \left(\overline{\mathbf{o}^S_{ji}}\right) + \mathbf{s}^S \odot \left(\mathbf{o}^S_{ji} - \overline{\mathbf{o}^S_{ji}}\right)\right]$,

where elements of $\mathbf{s}$ squeeze the perturbations based on how far they are from the grid point being updated.

We define $H_j \mathbf{Z}^{squeeze}_{omk}$ as:

$$H_j \mathbf{Z}^{squeeze}_{omk} = \left[\mathbf{h}^T_j\left[\mathbf{s}^L \odot \left(\mathbf{o}^L_{ji} - \overline{\mathbf{o}^L_{ji}}\right)\right], \mathbf{h}^T_j\left[\mathbf{s}^S \odot \left(\mathbf{o}^S_{ji} - \overline{\mathbf{o}^S_{ji}}\right)\right]\right] = \left[s^L \mathbf{Z}^L[omk,:], s^S \mathbf{Z}^S[omk,:]\right]\left(\sqrt{K-1}\right)$$

Also note that:

$$H_k \mathbf{Z}^{squeeze}_{omk} = \left[\mathbf{h}^T_k\left[\mathbf{s}^L \odot \left(\mathbf{o}^L_{ki} - \overline{\mathbf{o}^L_{ki}}\right)\right], \mathbf{h}^T_k\left[\mathbf{s}^S \odot \left(\mathbf{o}^S_{ki} - \overline{\mathbf{o}^S_{ki}}\right)\right]\right] = \left[s^L \mathbf{H}_k \mathbf{Z}^L[:,:], s^S \mathbf{H}_k \mathbf{Z}^S[:,:]\right]\left(\sqrt{K-1}\right)$$

Step0c: squeeze_average $= \left[s_L, s_S\right] = mean(\left[\mathbf{s}^L, \mathbf{s}^S\right], 1)$, then compute

$$w_L = \frac{s_L}{\sqrt{s_L^2 + s_S^2}} \text{ and } w_S = \frac{s_S}{\sqrt{s_L^2 + s_S^2}}, \text{ so that } w_L^2 + w_S^2 = 1$$

Step 1: Do univariate Gaussian assimilation of y_j using squeezing factor to obtain y^a_{ji}, $i = 1, 2, \dots, K$

$$\left\langle y^a_j \right\rangle = \left\langle y^f_j \right\rangle + \frac{\left[s^L \mathbf{Z}^L[omk,:], s^S \mathbf{Z}^S[omk,:]\right]\left[s^L \mathbf{Z}^L[omk,:], s^S \mathbf{Z}^S[omk,:]\right]^T}{\left[s^L \mathbf{Z}^L[omk,:], s^S \mathbf{Z}^S[omk,:]\right]\left[s^L \mathbf{Z}^L[omk,:], s^S \mathbf{Z}^S[omk,:]\right]^T + R_{jj}}\left(y^o_j - \left\langle y^f_j \right\rangle\right)$$

$$= \left\langle y^f_j \right\rangle + \frac{H_j \mathbf{Z}^{squeeze}_{omk}\left(H_j \mathbf{Z}^{squeeze}_{omk}\right)^T}{H_j \mathbf{Z}^{squeeze}_{omk}\left(H_j \mathbf{Z}^{squeeze}_{omk}\right)^T + R_{jj}}\left(y^o_j - \left\langle y^f_j \right\rangle\right)$$

$$y^a_{ji} = \left\langle y^a_j \right\rangle\left(1 - \frac{H_j \mathbf{Z}^{squeeze}_{omk}\left(H_j \mathbf{Z}^{squeeze}_{omk}\right)^T}{H_j \mathbf{Z}^{squeeze}_{omk}\left(H_j \mathbf{Z}^{squeeze}_{omk}\right)^T + R_{jj}}\right)^{1/2}\left[y^f_{ji} - \left\langle y^f_j \right\rangle\right], \qquad \text{for } i = 1, 2, \dots, 2K$$

OMK (Observation Model Kernel) variables $\mathbf{o}_j$ refers to the minimum list of model variables required to predict the y^f_j observation.

Multi-Scale LEAKF (Ens Squeeze Localization)

Multi-Scale Local MLEnKF using “Ensemble Squeeze Localization” (Pseudo-Code)

Step 2 : Find corresponding analysis ensemble for observations and model variables using

$$y_{ki}^{a} = y_{ki}^{f} + \frac{\left\langle \mathbf{h}_k^T\left[w_L\left(\mathbf{o}_{ki}^L - \overline{\mathbf{o}}_{ki}^L\right), w_S\left(\mathbf{o}_{ki}^S - \overline{\mathbf{o}}_{ki}^S\right)\right]\right]\left[\mathbf{h}_j^T\left[w_L\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_S\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]\right]^T\right\rangle}{\left\langle\left[\mathbf{h}_j^T\left[w_L\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_S\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]\right]\mathbf{h}_j^T\left[w_L\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_L\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]^T\right\rangle}\left(y_{ji}^a - y_{ji}^f\right) \text{ for } k = 1,2,\ldots,p \text{ and } i = 1,2,\ldots,2K,$$

$$x_{\mu i}^{a} = x_{\mu i}^{f} + \frac{\left\langle\left[w_L\left(x_{\mu i}^{Lf} - \overline{x}_{\mu}^{Lf}\right), w_S\left(x_{\mu i}^{Sf} - \overline{x}_{\mu}^{Sf}\right)\right]\right], \left[w_L\mathbf{h}_j^T\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_S\mathbf{h}_j^T\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]^T\right\rangle}{\left\langle\left[\mathbf{h}_j^T\left[w_L\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_S\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]\right]\mathbf{h}_j^T\left[w_L\left(\mathbf{o}_{ji}^L - \overline{\mathbf{o}}_{ji}^L\right), w_S\left(\mathbf{o}_{ji}^S - \overline{\mathbf{o}}_{ji}^S\right)\right]^T\right\rangle}\left(y_{ji}^a - y_{ji}^f\right) \text{ for } \mu = 1,2,\ldots,n, \text{ and } i = 1,2,\ldots,K$$

Step 3 : Let the analysis ensemble perturbation be the prior ensemble perturbations for the next observation

$$\mathbf{Z} = \frac{1}{\sqrt{2K-1}}\left(\mathbf{X}^a - \mathbf{x}^a\right)$$

Step 4 : Let the analysis ensemble be the prior ensemble for the next observation

$y_{ki}^f = y_{ki}^a$, for $k = 1,2,\ldots,p;\ i = 1,2,\ldots,2K$

$x_{\mu i}^f = x_{\mu i}^a$, for $\mu = 1,2,\ldots,n;\ i = 1,2,\ldots,2K$

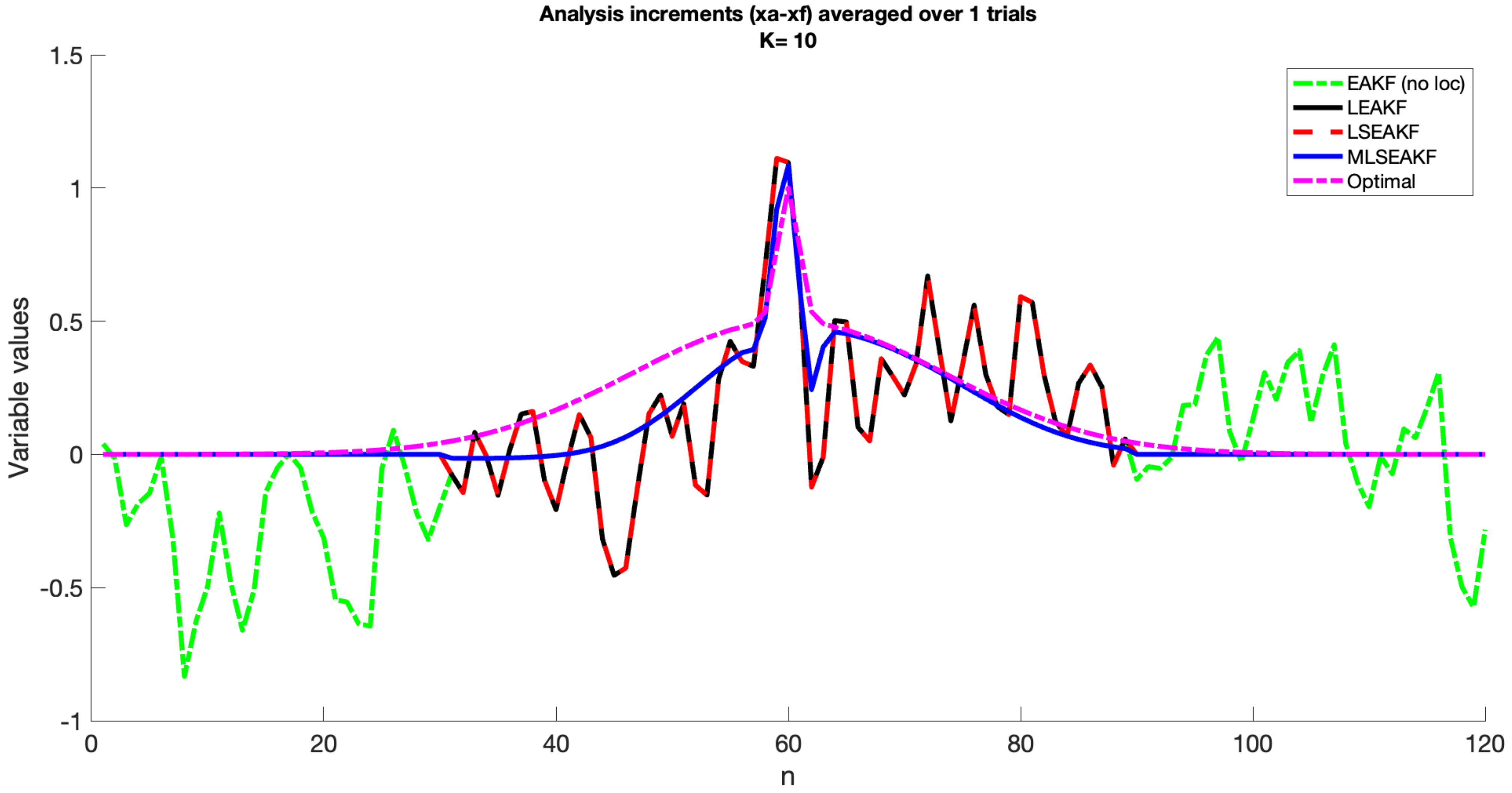
end

$$\mathbf{X}^a = \mathbf{x}^a + \sqrt{K-1}\left((\mathbf{E}\Lambda_L\mathbf{E}^T)\mathbf{Z}^L + (\mathbf{E}\Lambda_S\mathbf{E}^T)\mathbf{Z}^S\right)$$

Multi-Scale LEAKF (Ens Squeeze Localization)

Results

Single Ob DA Correction (Optimal)



Comparison Single-Scale LEnKF and Multi-Scale MLEnKF with very accurate observations

1-dim **Multi-Scale** statistical model:

K = 10

n = 120

p = 30

ntrials = 200

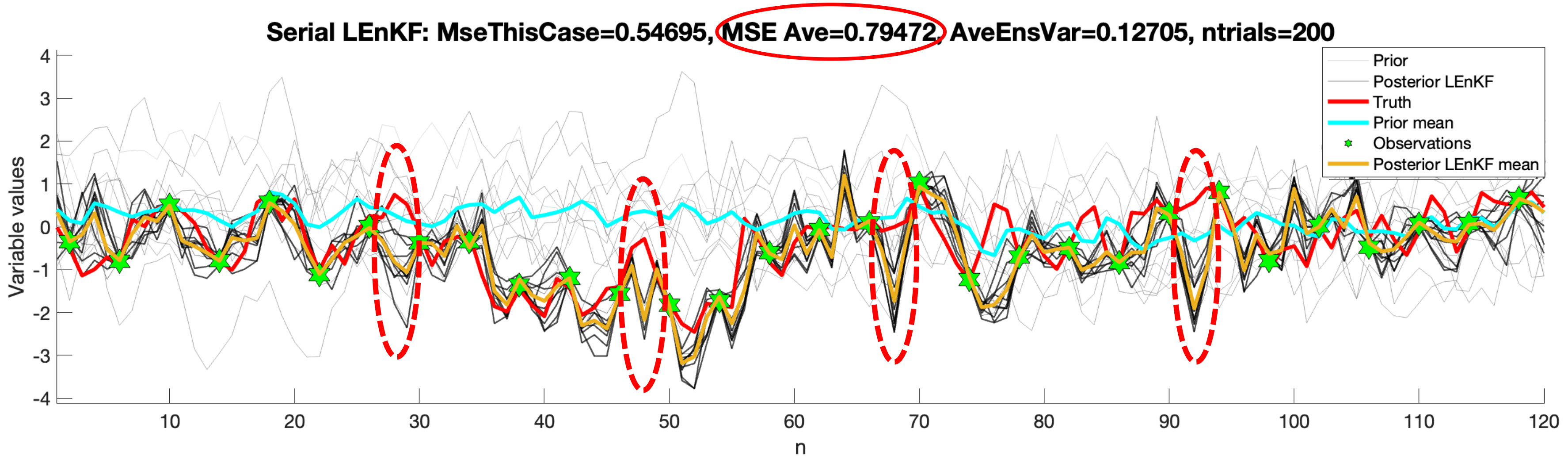
Ob error var = 0.01

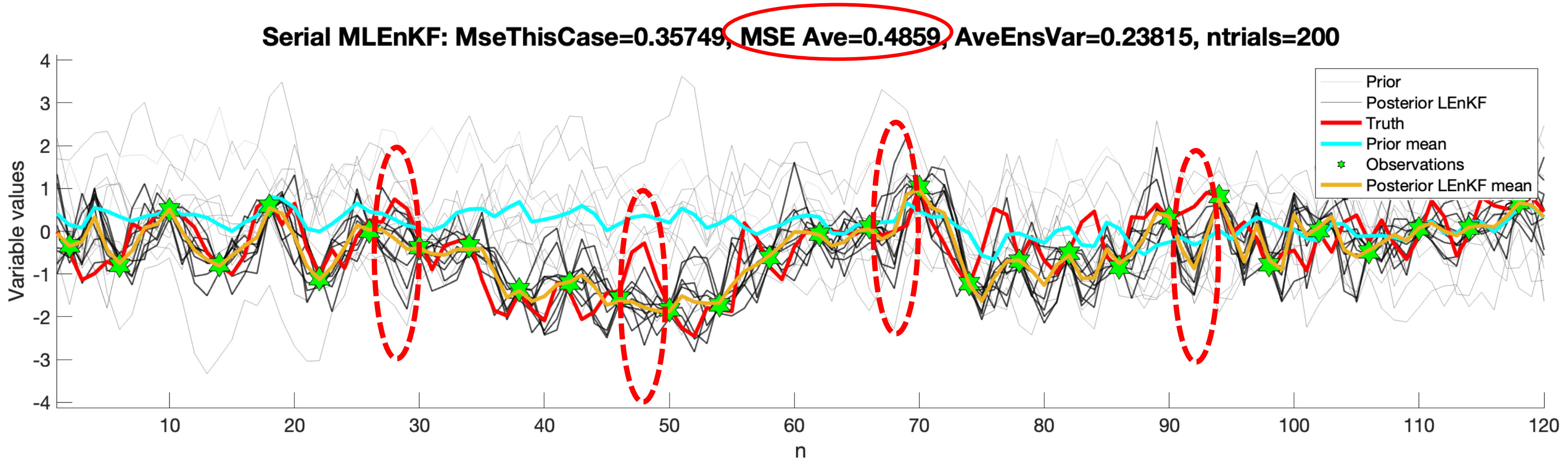
Loc. single-scale = 7

Loc. Large multi-scale = 20

Loc. Small multi-scale = 2

Multi-Scale LEAKF (MSE=0.4859) beats the single-scale LEAKF (MSE=0.79472)





Comparison Single-Scale LEnKF and Multi-Scale MLEnKF with very accurate observations

1-dim **Multi-Scale** statistical model:

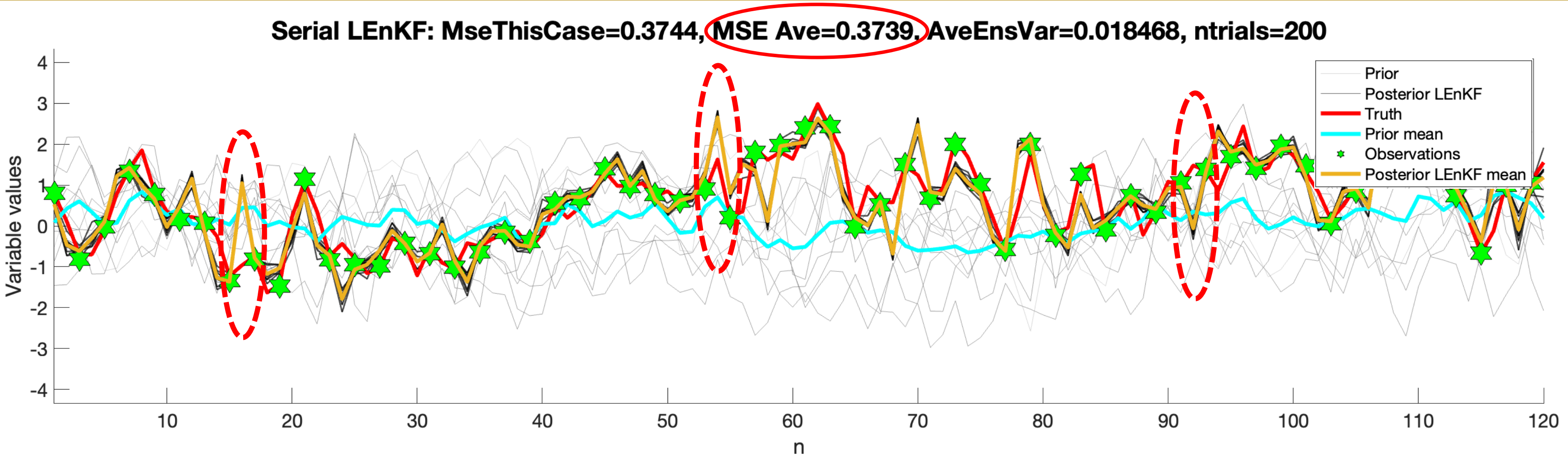
K = 10

n = 120

p = 60

ntrials = 200

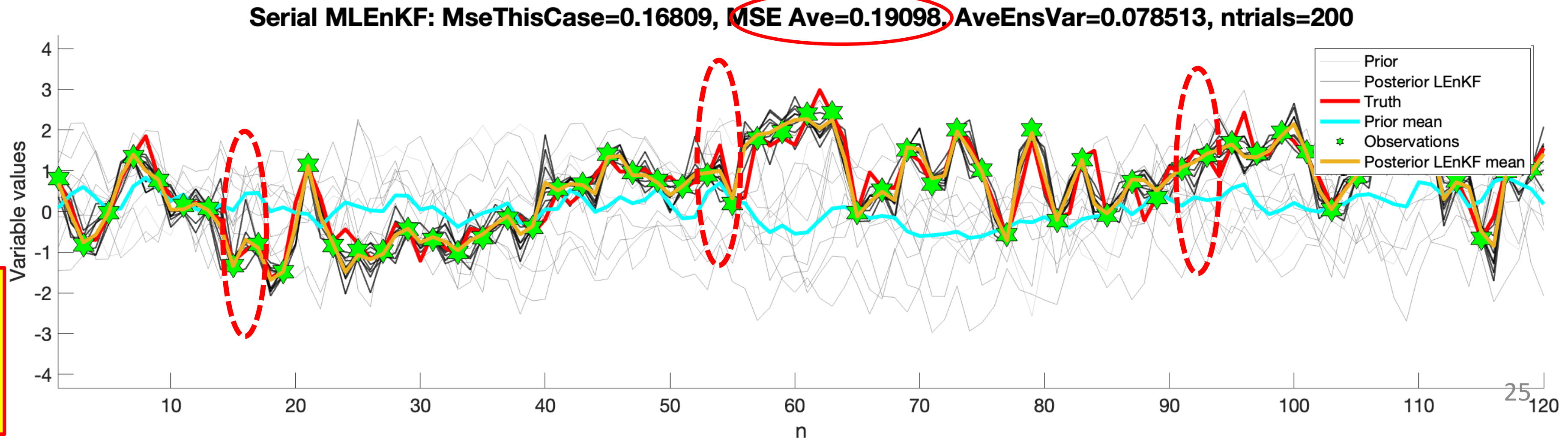
Ob error var = 0.01



Loc. single-scale = 7

Loc. Large multi-scale = 20

Loc. Small multi-scale = 2



Multi-Scale LEAKF (MSE=0.19098) beats the single-scale LEAKF (MSE=0.3739)

Comparison Single-Scale LEnKF and Multi-Scale MLEnKF with less accurate observations

1-dim **Multi-Scale** statistical model:

K = 10

n = 120

p = 30

ntrials = 200

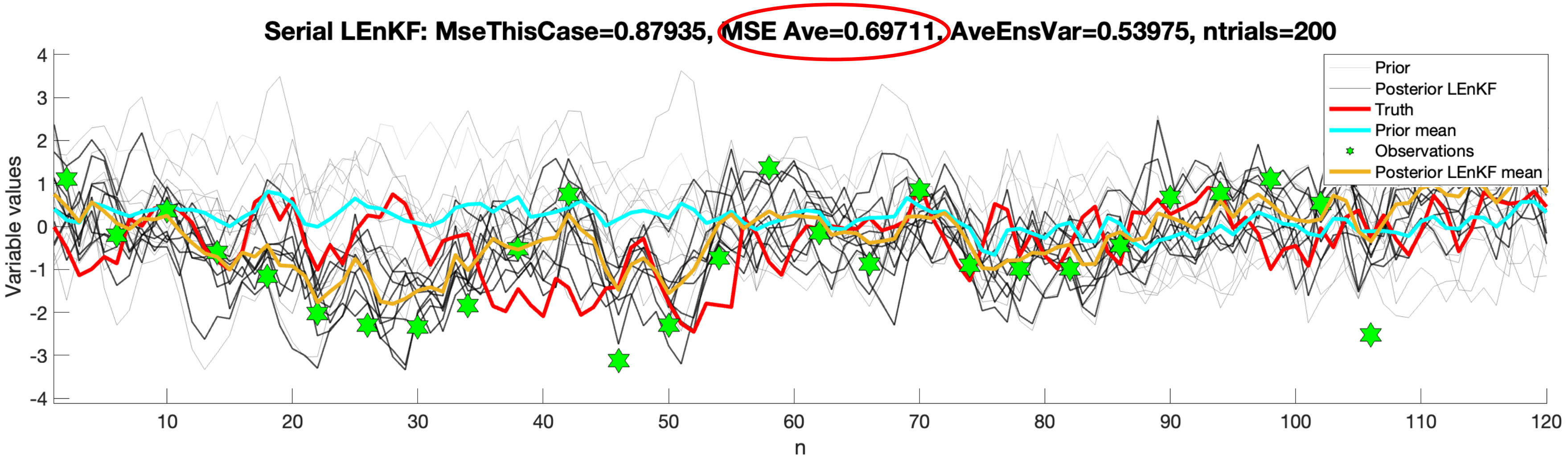
Ob error var = 1.0

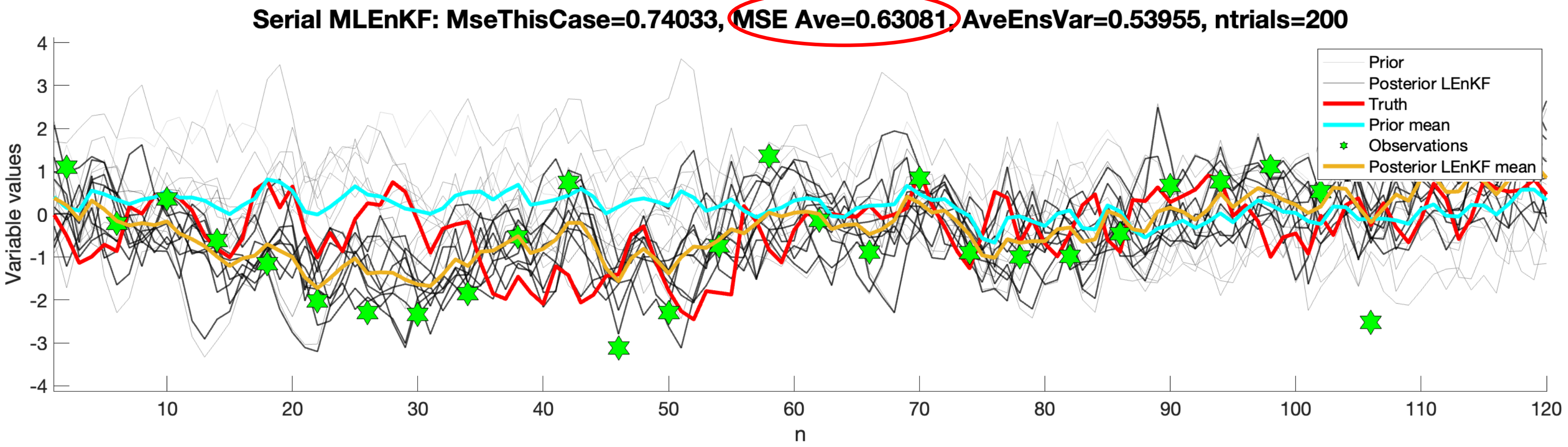
Loc. single-scale = 7

Loc. Large multi-scale = 20

Loc. Small multi-scale = 2

Multi-Scale LEAKF (MSE=0.63081) beats the single-scale LEAKF (MSE=0.69711)





Comparison Single-Scale LEnKF and Multi-Scale MLEnKF with less accurate observations

1-dim **Multi-Scale** statistical model:

$K = 10$

$n = 120$

$p = 60$

ntrials = 200

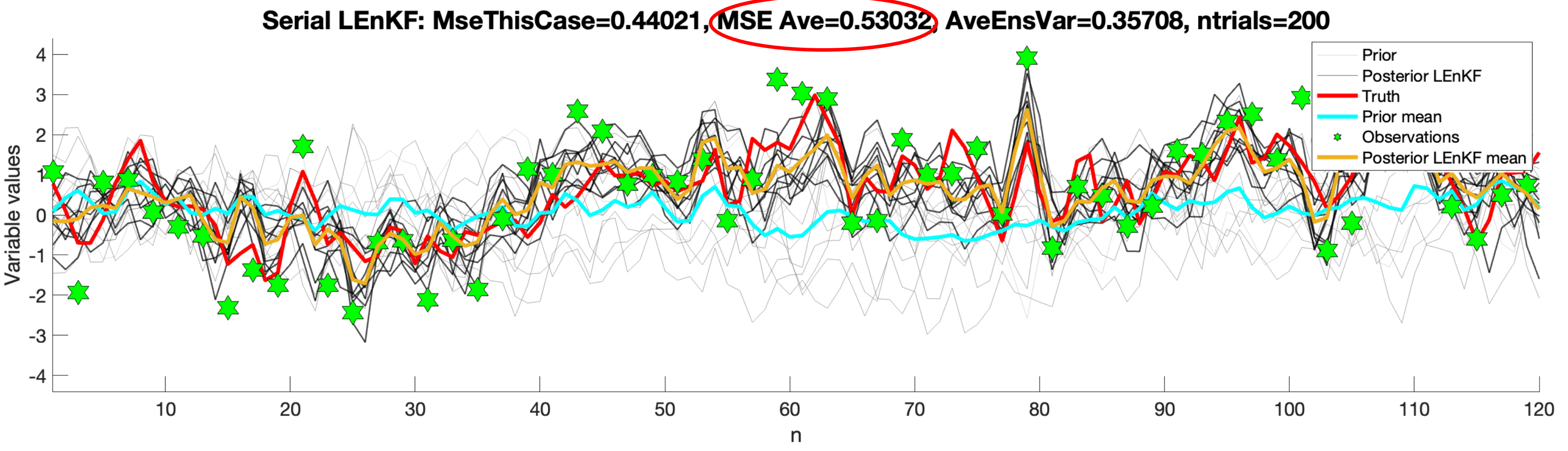
Ob error var = 1.0

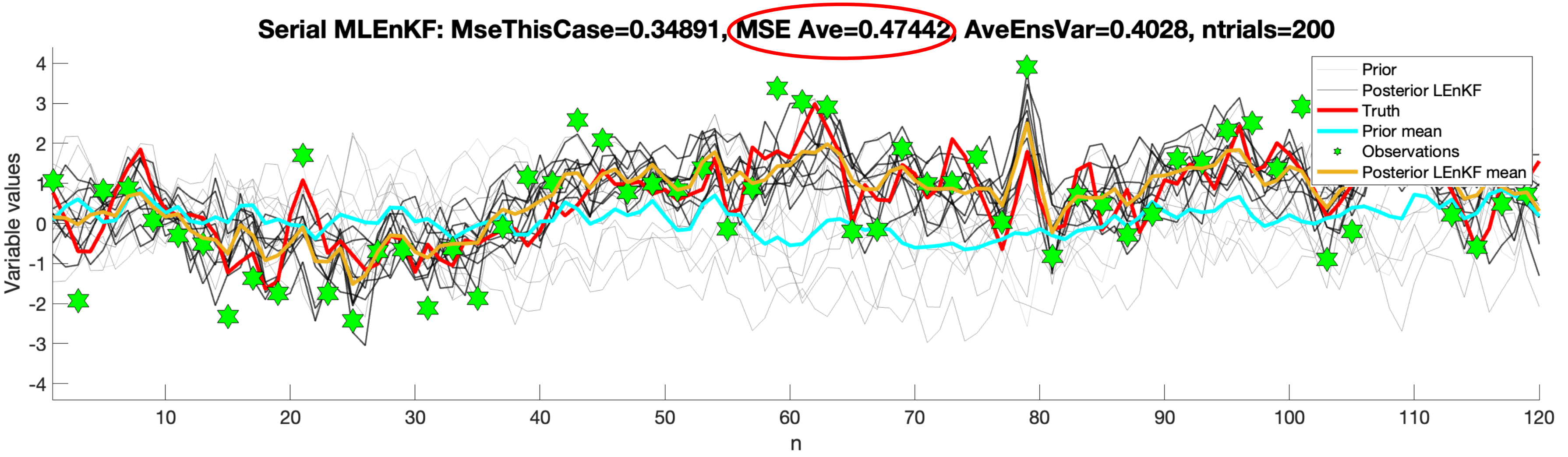
Loc. single-scale = 7

Loc. Large multi-scale = 20

Loc. Small multi-scale = 2

Multi-Scale LEAKF (MSE=0.47442) beats the single-scale LEAKF (MSE=0.53032)





Concluding Remarks

- ***“Ensemble Squeeze”* is equivalent to the *“Ob-Error-Inflation”* localization** for same computational cost.

- ***“Ensemble Squeeze” localization*** works in a **serial framework** where we assimilate one observation after the other and it is **SIMPLER** to implement than other model space localization methods (e.g., Shunji et al, 2021).

- Preliminary results suggests that the **multi-scale DA** using the “***Ensemble Squeeze***” seems to produce **similar percentage error reduction** to the ones observed in Xuguang et al., 2020.

Potential use of the **“*Ensemble Squeeze*”** localization:

- **“*Ensemble Squeeze*”** localization could be useful for observations that are integral of the model state **(e.g., Satellite DA)**

FOR MORE DETAILS, PLEASE TALK WITH US LATER!!

Acknowledgements

The first author acknowledges the *Ministerio de Universidades* (**Plan de Recuperación, Transformación y Resiliencia**) funded by the European Union (**NextGenerationEU**), with the participation of the *University of the Balearic Islands*, which supports his current postdoctoral position as a ***Maria Zambrano* Fellowship.**

Financiado por la Unión Europea
NextGenerationEU

Plan de Recuperación, Transformación y Resiliencia

GOBIERNO DE ESPAÑA
ESPAÑA PUEDE

GOBIERNO DE ESPAÑA
MINISTERIO DE UNIVERSIDADES