

# An Efficient Ensemble Data Assimilation Approach To Deal With Range Limited Observation

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# Outline

- Motivation
- Range Limited Observations (RLO):
  - Methodology and Algorithm
- Numerical Experiments
- Conclusion

# Motivation

- Many available measurement in environmental systems are defined within certain interval.
- To use the qualitative information available from the range limited observations.
- Very few studies carried out dealing this issue  
**Borup et. al., (2015)**

# Range limited Observations

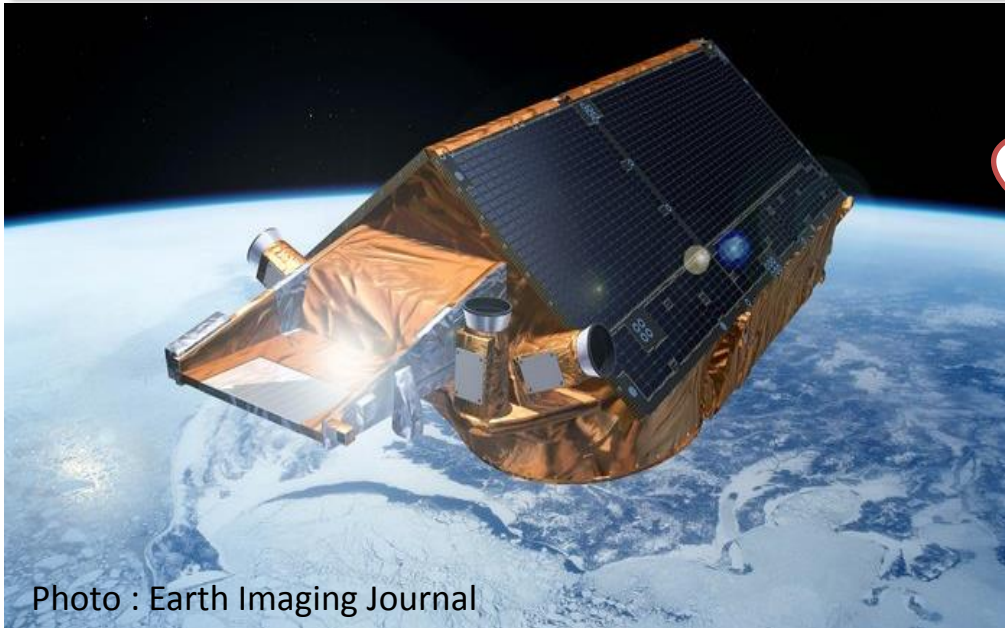


Photo : Earth Imaging Journal

Sea-ice thickness  
only up to 50cm

Soil moisture only  
up to 5cm

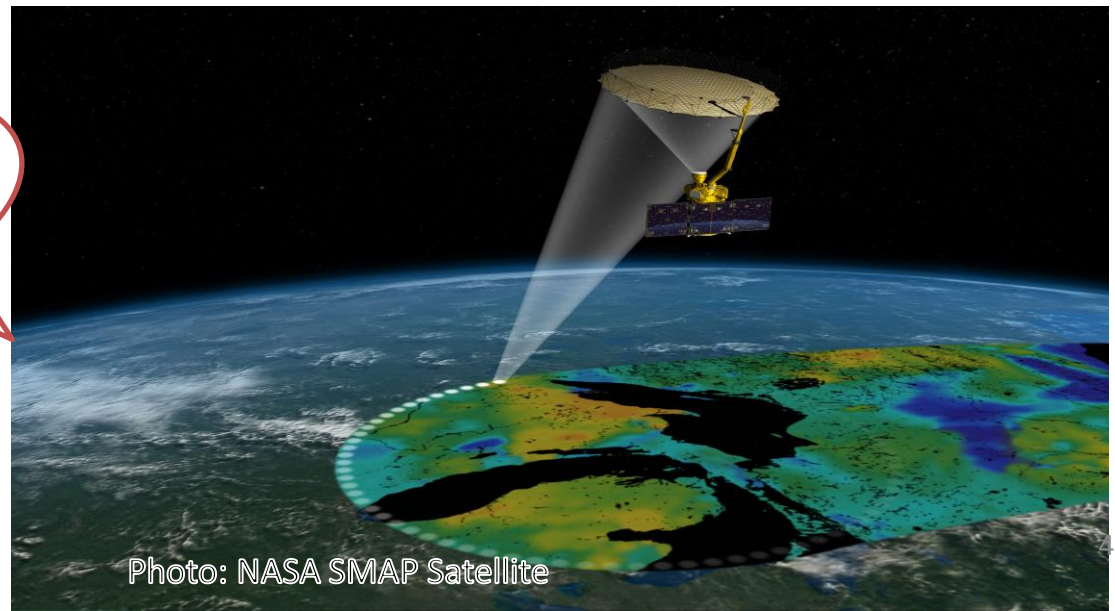


Photo: NASA SMAP Satellite

# Methodology and Algorithm

- Bayesian Rule

$$p(\mathbf{x} | \mathbf{y}) = \frac{p(\mathbf{x}) p(\mathbf{y} | \mathbf{x})}{p(\mathbf{y})}$$

- Borup et. al., (2015):

- Ensemble Partial Updating (EnPU) for RLO
- EnPU will allow us to use qualitative information about data i.e., the posterior will be

$$p(\mathbf{x}_k | \mathbf{y}_{\text{quant}}, \mathbf{y}_{\text{qual}})$$

where  $\mathbf{y}_{\text{quant}}$  and  $\mathbf{y}_{\text{qual}}$  are quantitative and qualitative observation respectively

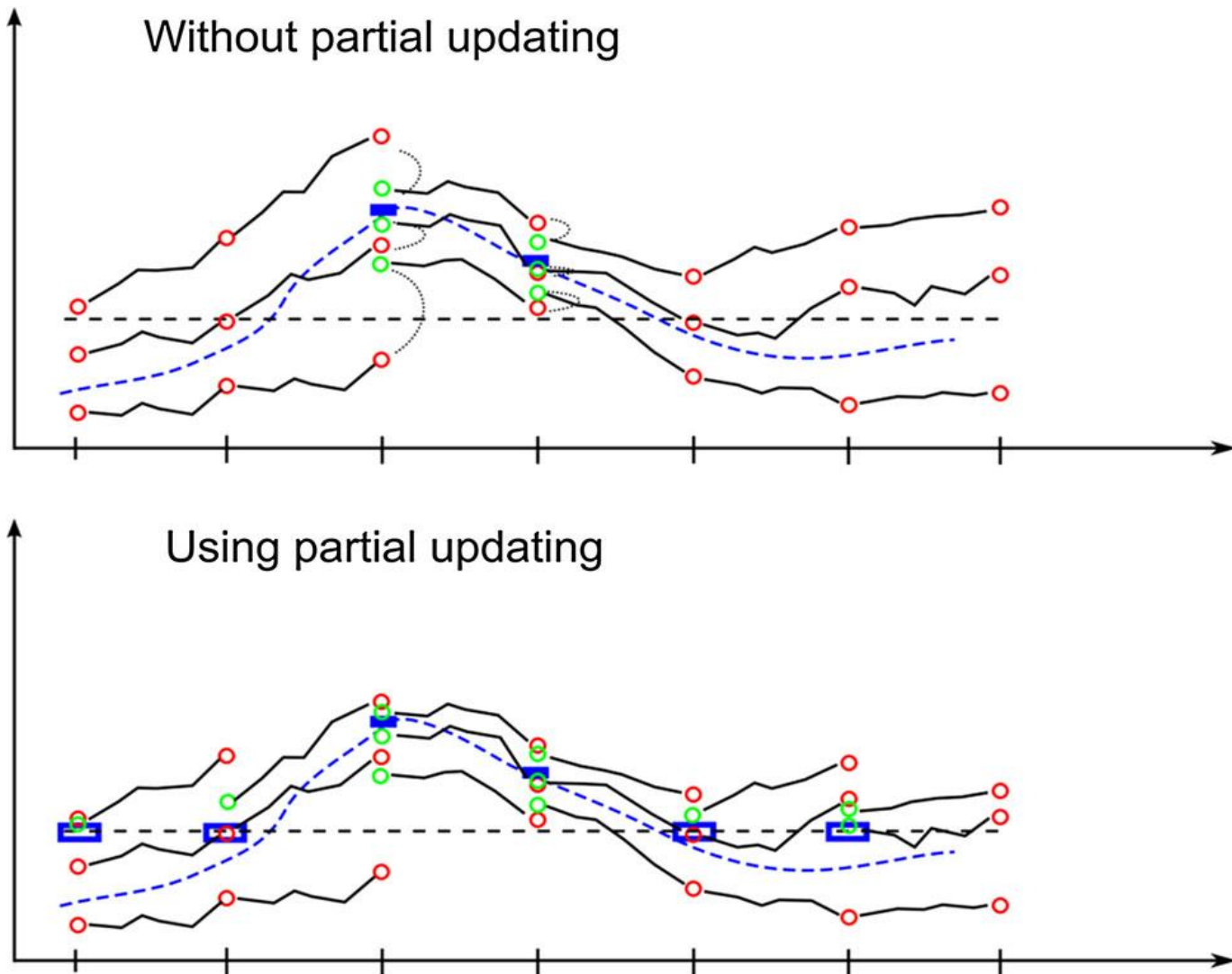


Figure : (Borup et. al., 2015) With and without partial updating when the measurement gauge has lower observation limit

# Partial Ensemble Kalman Filter (PEncKF)

- OR-observation
  - Create virtual observation at threshold limit
  - Data likelihood for perturbing observations
  - Two Piece Gaussian distribution (Fechner's Kollektivmasslehre, 1897)
  - One of the observation variance in 2-piece Gaussian

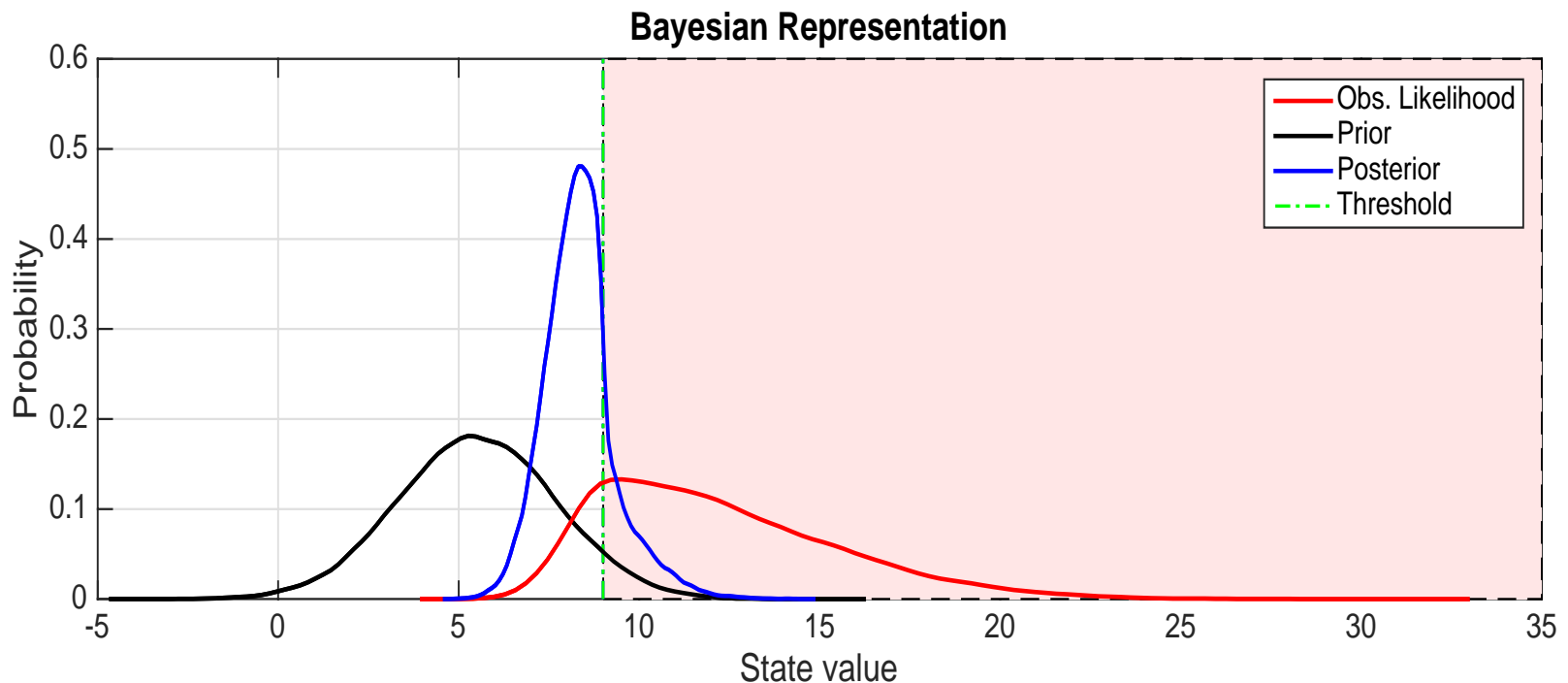
$$S_{or} = p * \left( \mathbf{H} \bar{\mathbf{x}}^f \right)$$

where  $p$  is positive real number

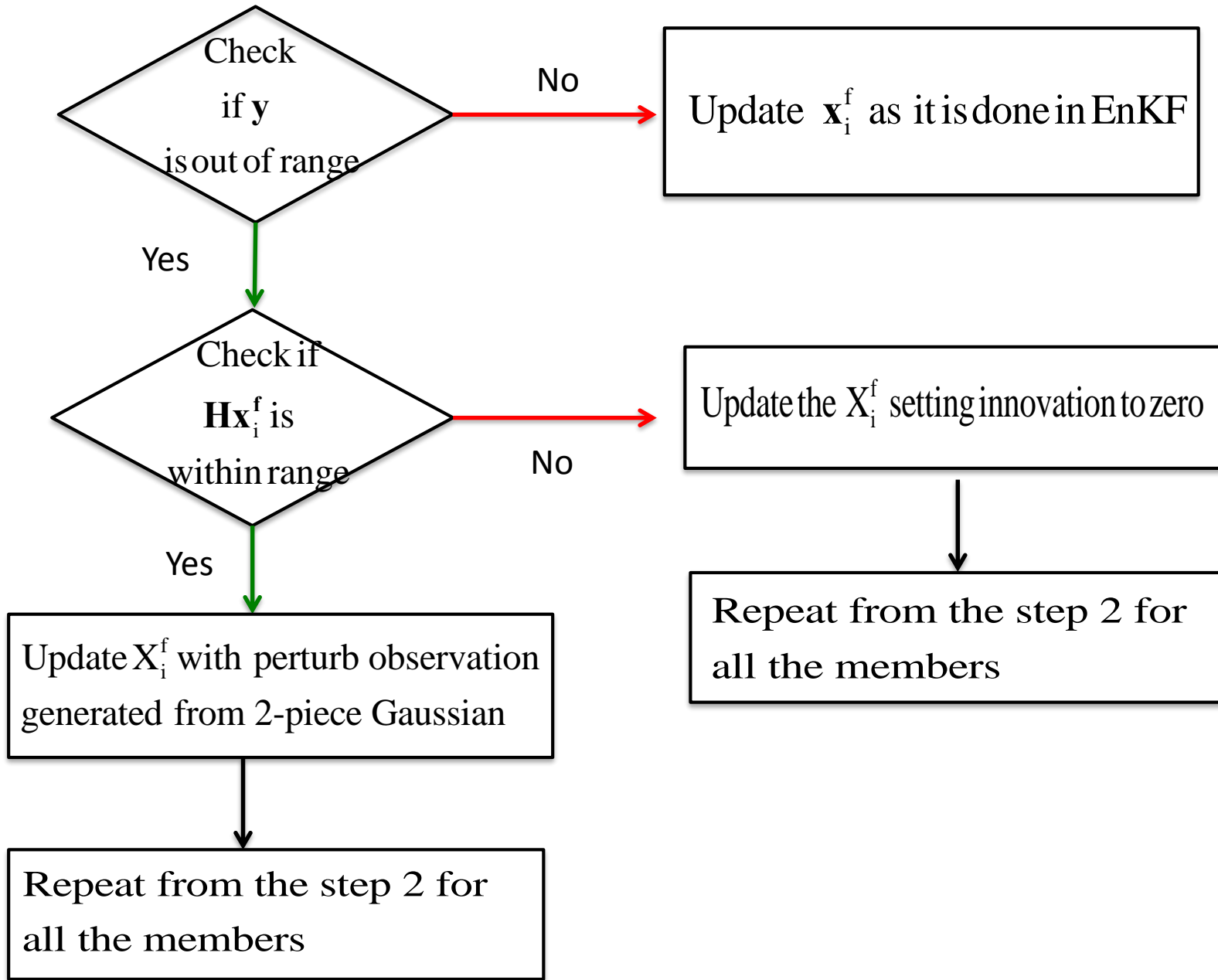
# Cont..

- Posterior when the **prior is in-range**

$$p(\mathbf{x}_k | \mathbf{y}_{\text{quant}}, \mathbf{y}_{\text{qualit}}) \propto \begin{cases} p(\mathbf{x}_k)p(\mathbf{y}_{\text{quant}} | \mathbf{x}_k) \\ p(\mathbf{x}_k)p(\mathbf{y}_{\text{qualit}} | \mathbf{x}_k) \end{cases}$$







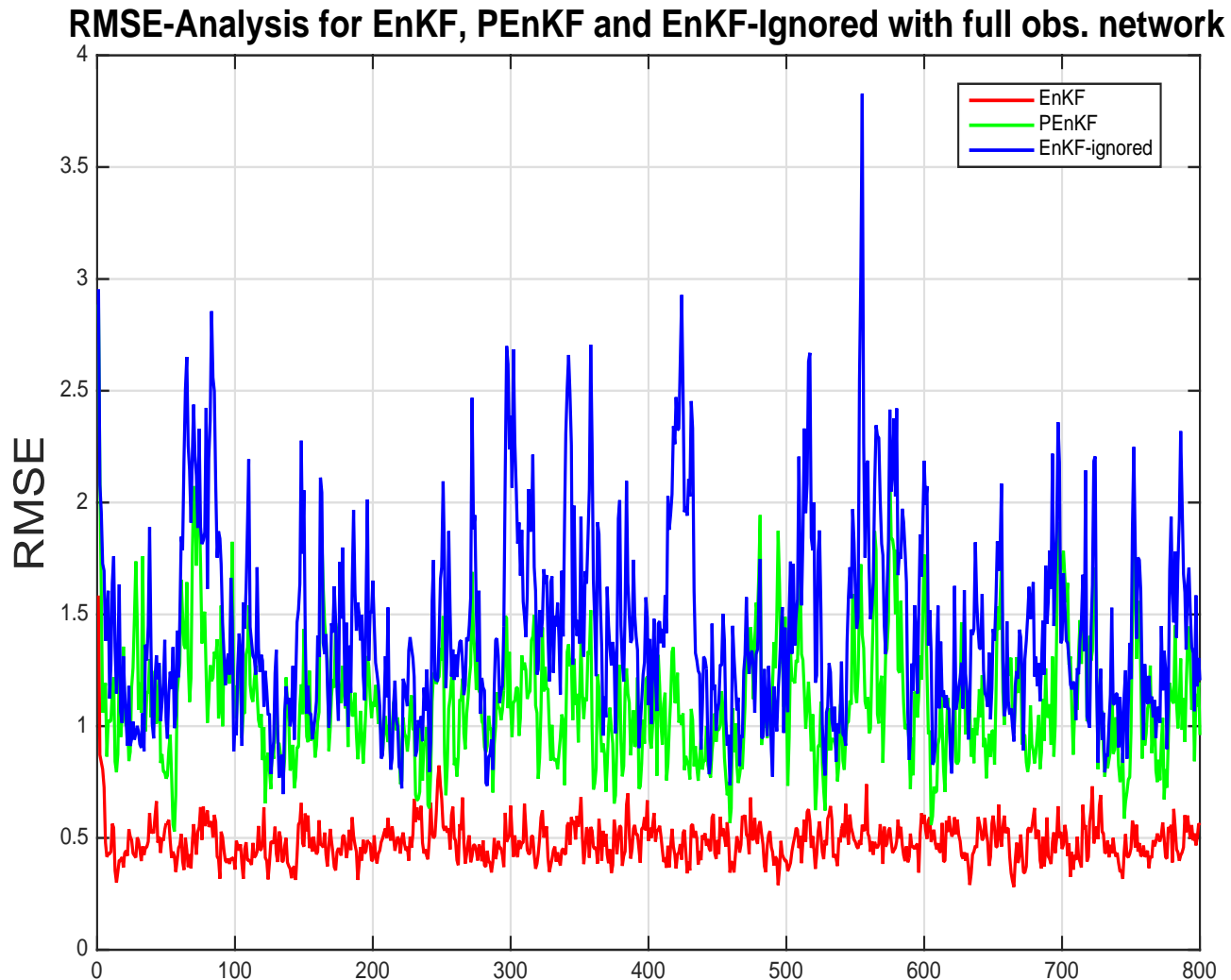
# Numerical Experiments

- EnKF, PEnKF and EnKF-ignored DA methods are tested under the framework of twin experiment.
- Model – Lorenz '96 with configuration as below
  - Number of Ensemble – 100
  - dt - 0.05 (~6 hours)
  - Total time of integration is 5 Years
  - Model error introduced by using wrong forcing - 7.5
  - $S_{\text{obs}} = 1$

# Cont..

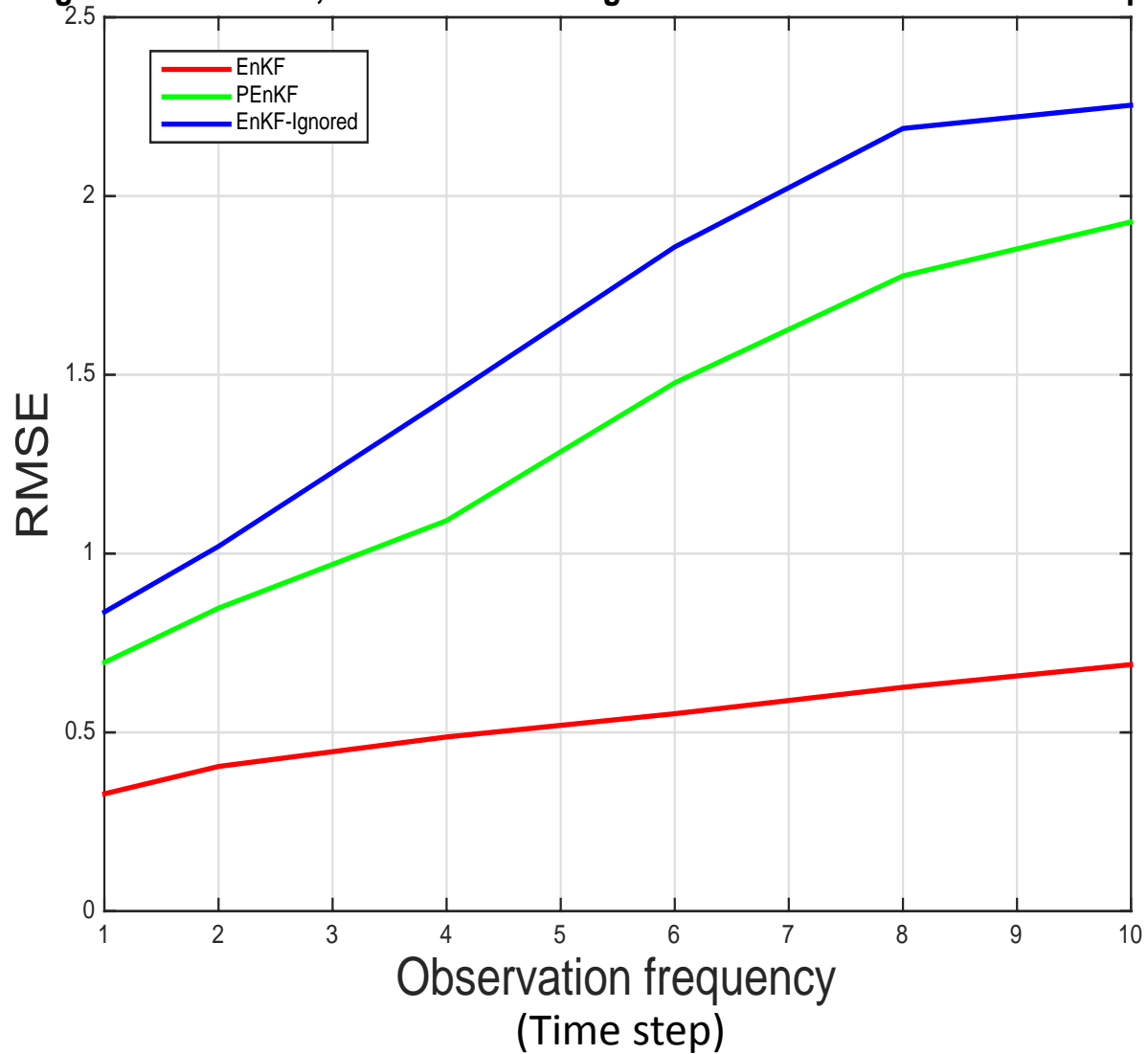
- Experiments for Sensitivity to
  - Number of observation
  - Observation frequency
  - Threshold limit
  - Model error
- Diagnostics tools:
  - Root Mean Square Error
  - Average Ensemble Spread
  - Observation Influence
  - Rank Histograms

# RMSE and Avg. Ensemble Spread

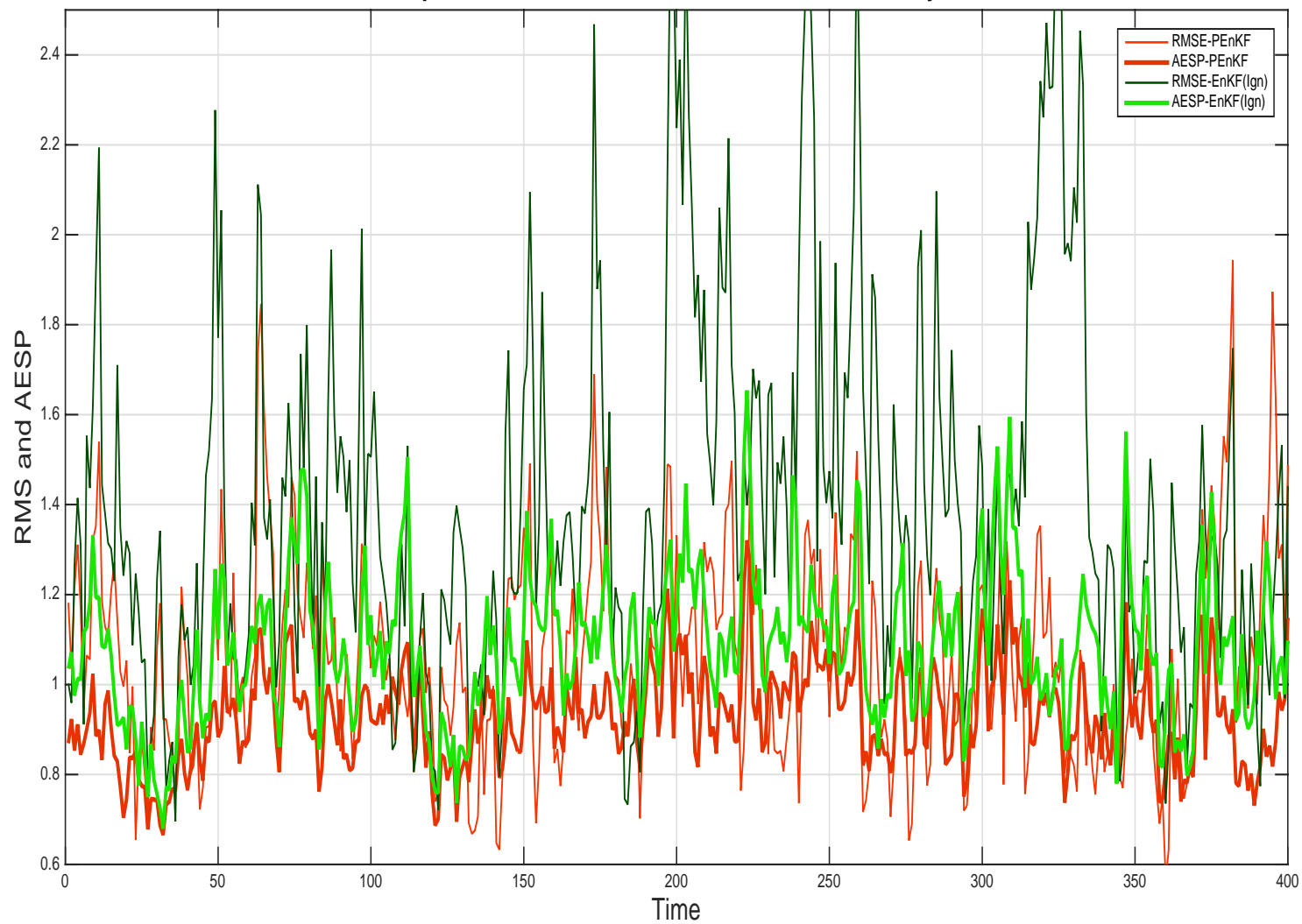


75% of observations are out of range on an average for total time of integration<sub>12</sub>

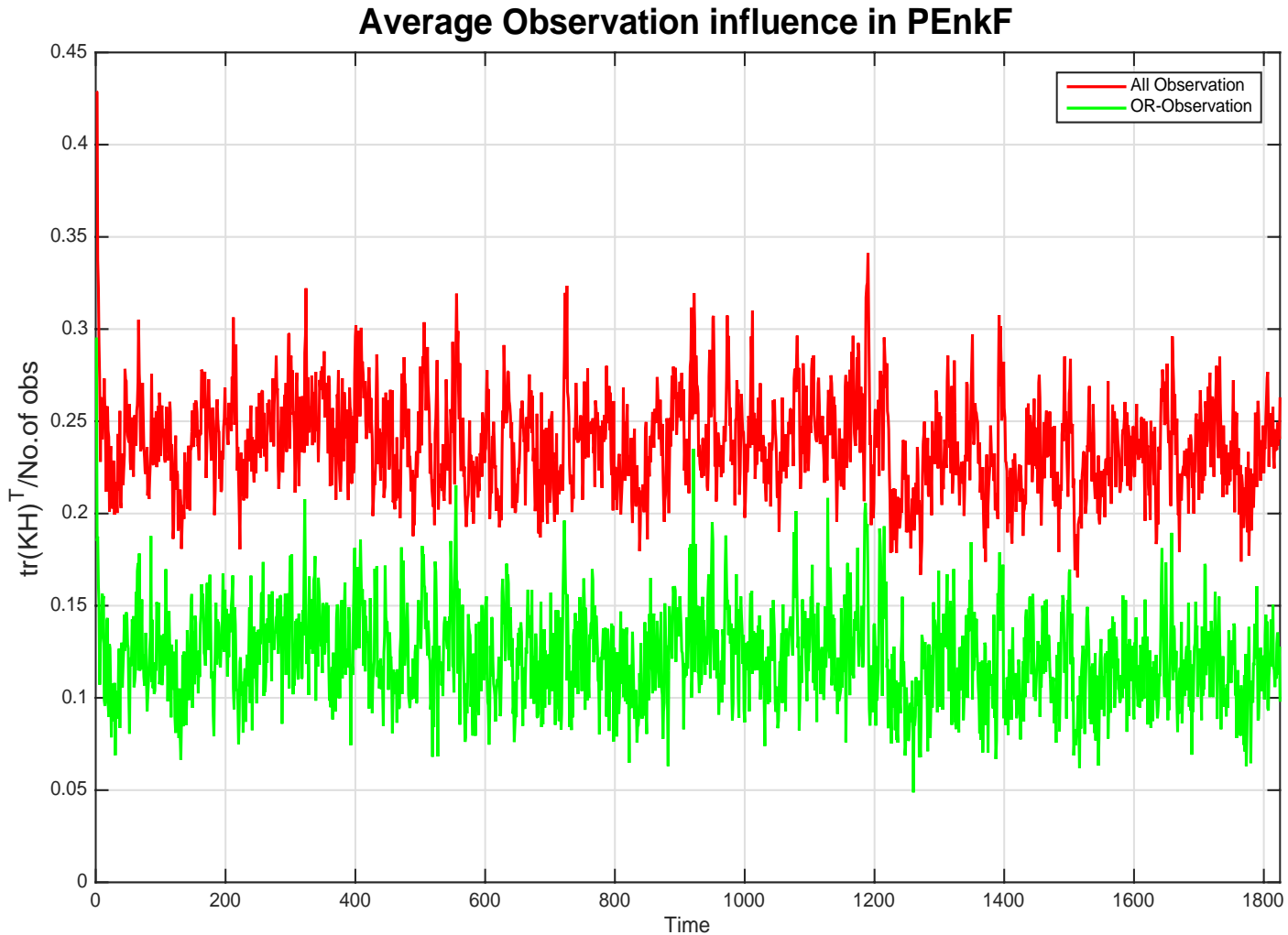
**Avg. RMSE for EnKF, PEnKF and EnKF-Ignored for different observation frequency**



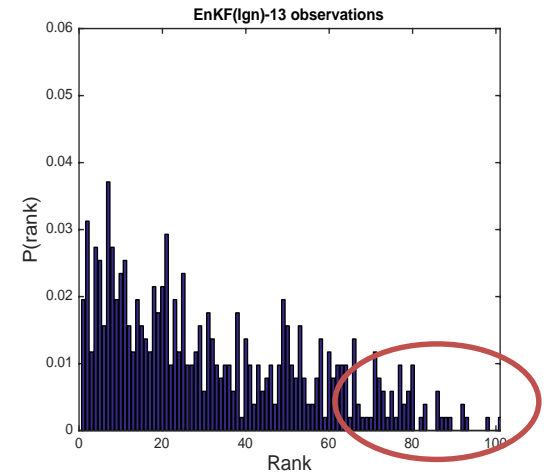
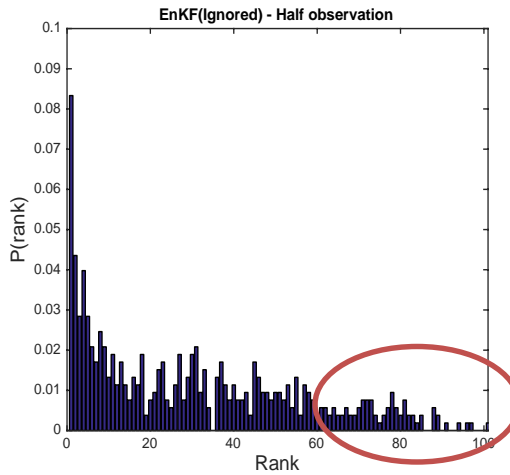
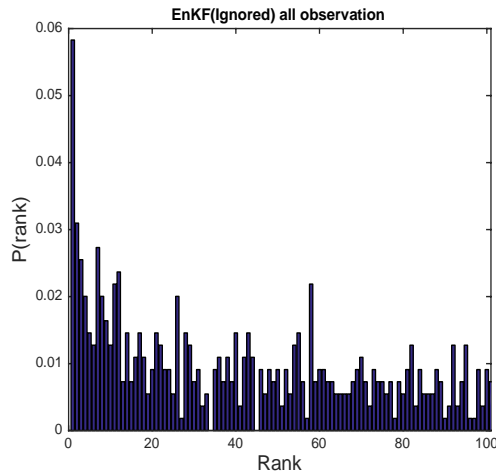
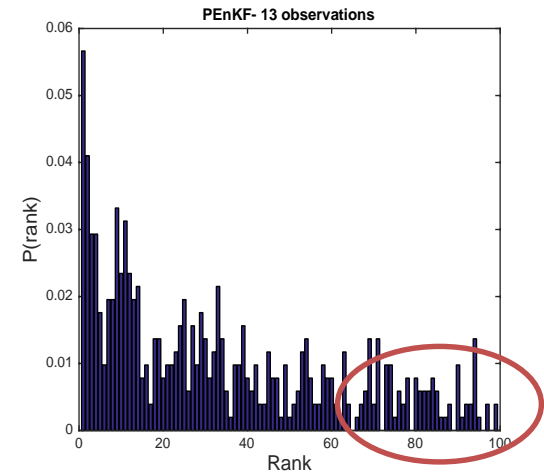
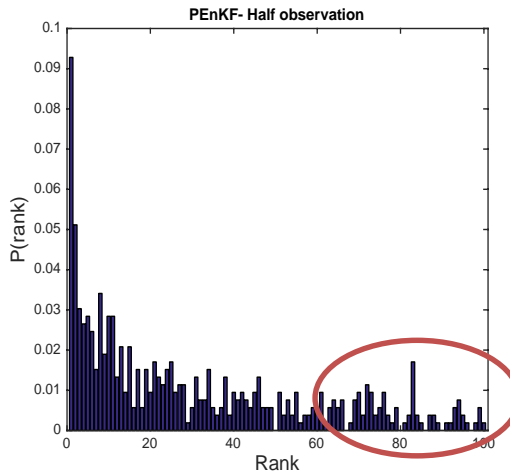
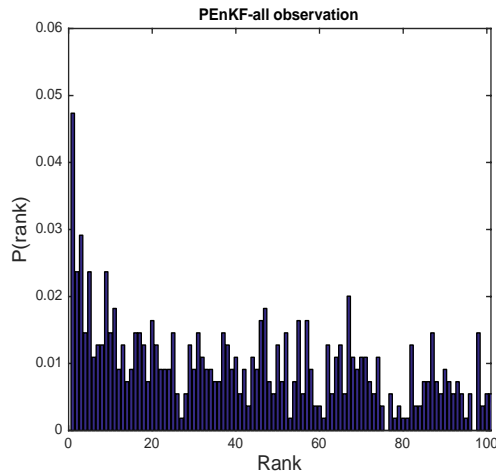
Snap-shot of time series of RMSE and AESP of Analysis



# Observation Influence



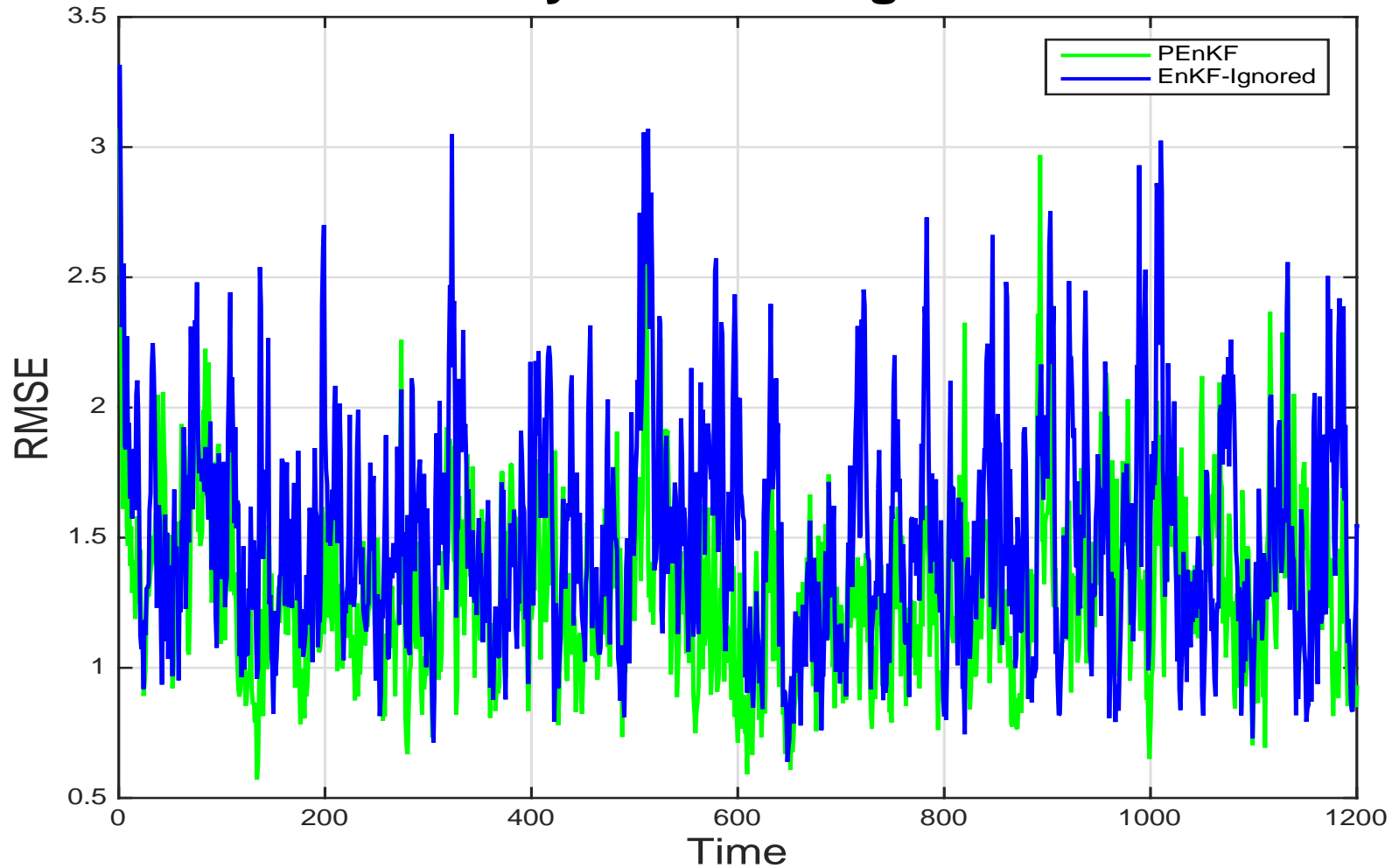
# Rank Histogram(Reliability)





# Sensitivity-Model Error

## RMSE Analysis for strong model error



# Conclusion and future work

- Adding qualitative information with PEnKF
  - Improve quality of forecast
  - Reduce uncertainty
  - Improves reliability of forecast
- Adding strong model error deteriorates the performance of the proposed DA scheme
- Implementation with some real world model and data set
- To investigate further for some possible improvement if possible

