Data assimilation for the inner ring Los Alamos current using RAM-SCB



Data Assimilation effort for SHIELDS project

- Ring Current-Atmosphere Interactions Model with Self-Consistent Magnetic field (RAM-SCB)
- physics-based model used to simulate ring current dynamics
- The RAM-SCB computes particle phase space distributions for ions and electrons on the equator inside the geosynchronous orbit for different pitch angles and energies in prescribed electric and magnetic fields





Van Allen Probes Observations (July 18, 2013)





FDPU - Unidirectional Differential Electron Flux



Spin-averaged differential proton flux from RBSP-A Probe (top plot) and RBSP-B probe (bottom plot), valid for July 18, 2013. A substorm took place around 14:00 UTC, as seen as a decrease in electron flux in the plot. https://www.rbsp-ect.lanl.gov/ UNCLASSIFIED



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Local Ensemble Transform Kalman Filter

- Update only parts of the state that are "close" to observed data.
- Localization operates an a small part of the state space for which a full rank covariance can be computed.
- Successfully developed and used for atmospheric models



Brian R. Hunt, Eric J. Kostelich, Istvan Szunyogh, *Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter*, Physica D, 230, 112-126, 2007







LETKF Results







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LETKF results (cont.)









Decompose the state into a combination of a small number of basis vectors. The state is replaced by the basis weights for which a full rank covariance can be computed. **Project onto basis and perform EnKF.**

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Reduced Basis EnKF Results





RMS error



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Summary

- Applied a Localized Ensemble Kalman Filter for RAM SC BABORATORY fluxes.
- LETKF reduces error, but does not provide injection (not noticeable)
- Developed/Implemented assimilation algorithm using Singular Value Decomposition (SVD) to define new basis; captures main model signals; Update weights of basis using EnKF
- Results look very promising, reduces error and provides an injection behavior
- Outer boundary is important for injection, investigating empirical injection models on boundary
- Thanks to the RBSP-ECT tead for the data (https://www.rbspect.lanl.gov/)

SHIELDS

Work done as part of SHIELDS project



Data Assimilation



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Ensemble Kalman Filter



x contains the state, fluxes (size $\sim 10^7$)

M is the forward model, RAM-SCB

y contains the observations, Van Allen probes (size ~ 100s)

H interpolates the model to the observation

K calibrates the adjustment based on the covariance of the ensembles (**P**) and the observation error (**R**).

P is the empirical covariance of the ensemble of states.

N is size of ensembles (~30)

LDS

$$\mathbf{x}^{f}(t_{i}) = \mathbf{M} \Big[\mathbf{x}^{f}(t_{i-1}) \Big]$$
$$\mathbf{x}^{a} = \mathbf{x}^{f} + \mathbf{K} \Big(\mathbf{y}^{o} - \mathbf{H} \mathbf{x}^{f} \Big)$$
$$\mathbf{K} = \mathbf{P} \mathbf{H}^{T} \Big(\mathbf{H} \mathbf{P} \mathbf{H}^{T} + \mathbf{R} \Big)^{-1}$$
$$\mathbf{P} = \frac{1}{N-1} \sum_{i=1}^{N} \Big(\mathbf{x}_{i}^{f} - \overline{\mathbf{x}} \Big) \Big(\mathbf{x}_{i}^{f} - \overline{\mathbf{x}} \Big)^{T}$$

The size of ensembles is much less than the size of the state, so the naïve estimate of P is not full rank. Modeling P is the challenge.





Reduced Basis EnKF Method

Define ensemble matrix $X = [x_1 \ x_2 \ \dots \ x_N]$ and compute the singular value decomposition (PCA)

 $\mathbf{X} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T$

define a basis

DS

$$\mathbf{B} = \frac{1}{\sqrt{N-1}} \mathbf{U}_k \boldsymbol{\Sigma}_k$$

project (weights)

$\mathbf{w}_i = \left(\mathbf{B}^T \mathbf{B}\right)^{-1} \mathbf{B}^T \mathbf{x}_i$ Perform EnKF on the weights.

