Nonlinear Data Assimilation Employing Maximum Likelihood Ensemble Filter (MLEF) and WRF model
Dusanka Zupanski and Milija Zupanski
Colorado State University/CIRA, Fort Collins, CO
Corresponding author E-mail: zupanski@cira.colostate.edu

EGU General Assembly "NP5.2 Data assimilation in the presence of nonlinearities", Vienna, Austria, 19-24 April 2009

Objectives
• Develop an ensemble data assimilation approach suitable for non-linear and discontinuous problems (e.g., involving atmospheric models with cloud-microphysical variables)
• Evaluate this approach in applications to simplified and complex forecast models and observation operators
• Assimilate non-linear radiance data (real and synthetic) from the current and future satellite missions (e.g., AMSR-E, GOES-R radiances)

Data Assimilation Method
Maximum Likelihood Ensemble Filter (MLEF)
(Zupanski et al. 2008, QJRMS)

MLEF includes a non-differentiable minimization and has an advantage over gradient-based minimization methods for nonlinear optimization (Zupanski et al. 2008, QJRMS).

References:

MLEF applications to Weather Research and Forecasting (WRF) model

Optimization performance with nonlinear observation operator \( y = x^3 \)

1-dimensional Burgers model simulating a shock-wave

Iterative minimization of the cost-function

\[ J = \frac{1}{2}(x-x_o)^T P_r^{-1} (x-x_0) + \frac{1}{2} (H(x) - y_{obs})^T R_1^{-1} (H(x) - y_{obs}) = \text{min} \]

Control variable transformation (preconditioning)

\[ C = Z \cdot Z^T \quad C \text{ is information matrix in ensemble subspace (of dim } N_{ens} \times N_{ens}) \]

\[ \zeta = R^{-1} H (x + \xi) - R^{-1} H (x) \quad \zeta \text{'s are columns of } Z \]

\[ P_r = M (x + \xi) - M (x) - \mu_r \text{ and } \mu_r \text{'s are columns of } P_r \text{ (forecast error cov)} \]

\[ P_{an} \text{ - Observations vector of dim } N_{obs} \]

\[ Z = M_{ens} \cdot (x_{ens}) \quad \text{Dynamical forecast model} \]

\[ x_{ens} = H^{-1} (x_{ens}) \quad \text{Observation operator} \]

Assimilate non-linear radiance data (real and synthetic) from the current and future satellite missions (e.g., AMSR-E, GOES-R radiances)

Assimilation of conventional observations (surface, upper air, aircraft) and AMSR-E data

Data assimilation improves the analysis and the background. Analysis uncertainty and DFS are flow-dependent, indicating larger uncertainties and more DFS in the cloudy areas (circled).

Exp. 1: GOES-R radiance assimilation (DA Cycle 7)

Data assimilation increases/decreases rain mixing ratio to improve background fit to the rain-sensitive AMSR-E brightness temperature. The analysis increments are localized in the area of the storm.

Exp. 2: Conventional + AMSR-E radiance data (DA Cycle 17, GRID 2)

MLEF increases/decreases rain mixing ratio to improve background fit to the rain-sensitive AMSR-E brightness temperature. The analysis increments are localized in the area of the storm.

Conclusions

Future Work

Acknowledgments:
Financial support was provided by NOAA grant No. NA17RJ1228, NASA contract No. NNH07AD79G and NSF grants ATM-0627851 and ATM-0228158.