Adaptive Spatially-varying Variance Inflation in an Ensemble Filter

Kevin Raeder, Jeff Anderson, Tim Hoar, Nancy Collins, Hui Liu NCAR Data Assimilation Research Section (DAReS)



Assimilation System Data Assimilation Research Testbed 20-member ensemble filter Sondes, ACARS, Drift Winds 0.2 Gaspari-Cohn Localization <u>Forecast Model</u> Community Atmosphere Model T85L26 Climatological I.C.s January, 2003



Six-hour Forecast RMS Error and Spread: No Inflation

Observation Space for 500 hPa North America ACARS Temperatures.



Sources of insufficient prior spread.



Prior model spread doesn't account for errors (including representativeness).

Result can be treated as lack of spread. Models have too little error growth, too. Expected value of |sample correlation| vs. true correlation is too large for small ensemble sizes.

Observations systematically reduce spread of state variables too much.

One Solution: Prior State Space Inflation



Applied independently to each state variable.

Spatially-varying temporally-adaptive inflation: Hierarchical Bayesian



Adaptive Inflation Applied to DART/CAM January, 2003

Observation Space for 500 hPa North America ACARS Temperatures.



RMS Error Reduced in General: Number of Obs. Rejected Reduced



Spatial and Temporal Structure of Adaptive Inflation Zonal Wind Inflation, 266 hPa





Conclusions (PLUS SEE OUR POSTER: A31B-06)

- 1. Ensemble Assimilations have too little variance.
- 2. Inflation can correct for this.
- 3. Hierarchical Bayesian algorithm automatically gives good inflation.
- 4. Applied to CAM, WRF, other large models without tuning.
- 5. Error is reduced, spread increased.
- 6. Available as part of DART from www.image.ucar.edu/DAReS/.









NCEP

Difference.



CAM gains zonal structure.

After 3 days.

Difference.



NH converged. SH poorly observed.

Raeder et al.: AGU Spring 2007



6-Hour Forecast and Analysis Observation Space Temperature RMS



6-Hour Forecast and Analysis Observation Space Wind RMS

Adding new models, new observations is simple.

- Incorporating existing model requires handful of interfaces.
 A. No need for linear tangents or adjoints.
 B. Finite Volume CAM added in 1-month by postdoc.
- 2. Adding observations also straightforward.
 - A. Only need forward operator (map state to expected observation).
 - B. No linear tangents or adjoints.
 - C. Several different GPS operators added in weeks.

GPS and other novel observations may help detect climate model bias.

GPS provides soundings of temperature and water world-wide.

Assimilating GPS Radio Occultation Observation Assimilated as refractivity along beam path. Complicated function of T, Q, P and ionospheric electric field.



Get a sounding as GPS satellite sets relative to low earth satellite.

DART compliant models (largest set ever with assim system?)

- 1. Many low-order models (Lorenz63, L84, L96, L2004,...).
- 2. Global 2-level PE model (from NOAA/CDC).
- 3. CGD's CAM 2.0, 3.0, 3.1 (global spectral model)
- 3a. CGD's CAM 3.1 FV (global finite volume model) with chemistry.
- 4. GFDL AM GCM (global grid point model).
- 5. MIT GCM (from Jim Hansen; configured for annulus).
- 6. WRF model (regional prediction grid point).
- 6a. WRF column physics model.
- 7. NCEP GFS (operational global spectral; assisted by NOAA/CDC).
- 8. GFDL MOM3/4 (global grid point ocean model).
- 9. ACD's ROSE model (upper atmosphere with chemistry).
- 10. Cane-Zebiak 5 (tropical ocean/atmosphere model).

Also models from outside geophysics.

This allows for a hierarchical approach to filter development.

DART compliant Forward Operators and Datasets

Many linear and non-linear forward operators for low-order models.

U, V, T, Ps, Q, dewpoint for realistic models.

Radar reflectivity, doppler velocity, GPS refractivity for realistic models.

Mopitt CO retrievals.

Can ingest observations from reanalysis or operational BUFR files.

Can create synthetic (perfect model) observations for any of these.

Additional enhancements available for Earth System Analysis

- 1. <u>Smoother</u>: uses observations in past and future to estimate state.
- 2. High performance parallel implementations.
 Filter algorithms are naturally scalable.
 Run many copies of models.
 Impact of observations on model variables can be done in parallel.
 Algorithm has natural reformulations for different platforms.
- 3. Parameter estimation in large models.

Use data to constrain parameters. Implementation is trivial. Interpretation is still VERY tricky. Did this for gravity wave drag efficiency in CAM.

Climate Model Parameter Estimation via Ensemble Data Assimilation



T21 CAM assimilation of gravity wave drag efficiency parameter.

Oceanic values are noise (should be 0).

0< efficiency< ~4 suggested by modelers.

Positive values over NH land expected.

Problem: large negative values over tropical land near convection.

May reduce wind bias in tropical troposphere, but for 'Wrong Reason'.

Assimilation tries to use free parameter to fix ALL model problems

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