An ensemble Kalman filter for WRF and a comparison with 3D-Var

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3D-Var / EnKF Comparison

- Compare using same model (WRF), same obs
- Benefit of flow-dependent covariances in a LAM?
  - Suppressed by ad hoc treatment of BC uncertainty
  - Enhanced by local effects (e.g. orography)
- Imbalance introduced by the assimilation
- Dependence of above on model resolution and observation density
Data Assimilation Research Testbed

http://www.cgd.ucar.edu/DAI/

• Ensemble-based data assimilation schemes
• Compliant models:
  1. Many low-order models (Lorenz63, L84, L96, ...)
  2. Global 2-level PE model (from NOAA/CDC)
  3. CGD’s CAM 2.0 & 3.0 (global spectral model)
  4. GFDL FMS B-grid GCM (global grid point model)
  5. MIT GCM (from Jim Hansen)
  6. Weather Research and Forecast model
  7. NCEP GFS (assisted by NOAA/CDC)
  8. GFDL MOM3/4 ocean model
  9. ACD’s ROSE model (upper atmosphere with chemistry)
WRF 3D-VAR

- Background covariance model given by recursive filters
  - Variances and correlation lengths from “NMC method” using global forecasts; not specifically tuned for this application

- Control variables: balanced $\psi$, unbalanced $\chi$, $T$, $p_s$, and pseudo RH.
Experimental Setup

• Simulated observations and perfect model:
  – “True” state is a WRF simulation
  – Simulated observations available every 12 h
  – CONUS domain, 45x45, 200 km horizontal resolution

• 3D-Var begins from AVN analysis (1 Jan 03), and uses AVN analyses as LBCs

• EnKF uses same for initial ensemble mean and ensemble mean LBCs
Initializing “True” State and Ensemble BCs

• Construct N+1 initial states
  – AVN analysis (1 Jan 03) + perturbations
  – Perturbations are deviations from Jan climatology, scaled by 0.2

• Construct N+1 lateral BCs
  – AVN analyses (1-10 Jan 03) + perturbations
  – Perturbations are deviations from Jan climatology, scaled by 0.2

• EnKF uses first N LBCs; true state uses the N+1 initial state and LBCs
  – Ensemble and true state LBCs drawn from same pdf
Observation Network

Simulated radiosondes:
• U, V wind components
• Temperature
Wind Observational Errors

No observational-error covariances

Standard Deviation (m/s) vs Pressure (hPa)
EnKF Setup

- Deterministic ensemble (square-root) filter
- 40 ensemble members
- No inflation
- Horizontal localization half-width: ~ 1280 km
- No vertical localization
Temperature Correlations

(T-obs at 850 hPa)

3D-Var
Initial
EnKF

T (K) 850 (hPa) 2003-01-01 00:00:00

T (K) 850 (hPa) 146927 days 0 sec
Zonal-wind Increments

(T-obs at 850 hPa)

3D-Var  Initial  EnKF
Temperature Correlations
(T-obs at 850 hPa)

3D-Var

Final

EnKF

T (K) 850 (hPa) 2003-01-11 00:00:00

T (K) 850 (hPa) 146837 days 0 sec
EnKF Error Statistics and Spread
5-day Assimilation
Temperature Errors

![Graph showing temperature errors over days for different assimilation methods: No assim, 3D-Var, EnKF.](Image)
RMS of Surface Pressure Tendency
10-day average of rms surface pressure tendency

![Graph showing the 10-day average of rms surface pressure tendency with different localization half-widths for EnKF, 3D-Var, no assimilation, peak EnKF, and peak 3D-Var.](image-url)
Conclusion 1

- The rms errors are smaller in the EnKF than in the 3D-Var analyses:
  - 3D-Var may improve with tuning of its forecast-error statistics.
  - The difference between the 2 schemes should be smaller with a larger variety of observations.
  - Non-stationary forecast-error statistics in the EnKF are beneficial.
Conclusion 2

- The EnKF introduces somewhat more imbalance than 3D-Var:
  - Need larger ensemble?
  - More sophisticated localization? (group filter)
  - Initialization? (digital filter, build balance constraints in the EnKF scheme?)