Evaluation of an Ensemble Kalman Filter for WRF against a 3D-Var Assimilation System

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Outline

• Motivations
• Brief introduction to data assimilation
• Description of the EnKF and 3D-Var methods
• Model, observations, experimental design
• Observation space diagnostics
• Imbalance introduced by the assimilation
• Conclusions
Motivations

• Develop an Ensemble Kalman Filter for the research community;
• Potential for a wide range of applications and scales;
• Ensemble gives an error estimate;
• Base for ensemble forecasting.
Data Assimilation Research Testbed

http://www.image.ucar.edu/DAI/DART

- 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)
Data Assimilation

\[
p(x_t | Y_t) = \frac{p(y_t | x_t)p(x_t | Y_{t-1})}{\int p(y_t | x)p(x | Y_{t-1}) dx}
\]
Assuming normal statistics…

\[ y = Hx + \hat{a}_r, \quad \hat{a}_r \sim N(0, R) \]

\[
p(x_t | Y_t) \propto e^{-(x-x_b)^T P^{b^{-1}} (x-x_b)} e^{-(Hx-y)^T R^{-1} (Hx-y)}
\]

\[ \Downarrow \]

\[
J(x) = (x - x_b)^T P^{b^{-1}} (x - x_b) + (Hx - y)^T R^{-1} (Hx - y)
\]
True forecast-error statistics

• Are
  – Inhomogeneous, anisotropic, non-stationary

• Depend on
  – **Model**: error statistics, resolution, forecast range, …
  – **Observations**: error statistics, distribution, frequency, …
(Ensemble) Kalman filter

$$\bar{x}^a = \bar{x}^b + \frac{P^b H^T}{H P^b H^T + R} (y - H \bar{x}^b)$$

$$P^b H^T \equiv \frac{1}{n-1} \sum_{i=1}^{n} x_i'^b (H x_i'^b)$$

$$H P^b H^T \equiv \frac{1}{n-1} \sum_{i=1}^{n} (H x_i'^b) (H x_i'^b)$$
Ensemble Kalman filter

- $x'^a$ are obtained using the square-root filter approach.
- 56 ensemble members.
- No inflation.
- Observations assimilated serially, one at a time.
- Horizontal localization half-width: $\sim 2500$ km.
Temperature Increments
(T-obs at 850 hPa, initial time)

EnKF

With Localization

3D-Var

T (K) 850 (hPa) 146827 days 0 sec
T (K) 850 (hPa) 146827 days 0 sec
T (K) 850 (hPa) 2003-01-01 00:00:00
Zonal-wind Increments

(T-obs at 850 hPa, initial time)

EnKF

3D-Var
WRF 3D-VAR
http://box.mmm.ucar.edu/wrf/WG4/

- Background covariance model given by recursive filters (Wu et al., 2002, MWR)
- isotropic - inhomogeneous
- Control variables:
  - streamfunction ($\psi$),
  - unbalanced velocity potential ($\chi$),
  - unbalanced temperature ($T$),
  - unbalanced surface pressure ($p_s$),
  - pseudo-relative humidity.
- Linear balance equation
WRF 3D-VAR Background Error Covariance

- “NMC” method.
- 48 – 24-hour GFS forecasts with T170 resolution valid at the same time for 357 cases distributed over one year.
- Amplitudes and scales have been tuned for WRF.
http://wrf-model.org

- Regional, atmospheric model
- Non-hydrostatic, fully compressible
- Multiple nested domains
- Movable grids
Observation Network

Real observations:
• NCEP radiosonde data set
• U, V wind components
• Temperature
• No background check
Observational Errors

No observational-error covariances

- Pressure (hPa)
- Temperature (K)
- Wind (m/s)
Experimental Setup

- North America, 45x45 grid, 200 km resolution,
- Real observations available every 12 h,
- 3D-Var uses NCEP/FNL global analyses as ICs (1 Jan 03) and LBCs,
- EnKF uses same for initial ensemble mean and ensemble mean LBCs,
- EnKF ICs and LBCs perturbations are drawn from 3D-Var background-error statistics.
EnKF

Temperature Fit to RAOBS

500 hPa

- no assimilation, mean
- no assimilation, spread
- 12-h forecast mean
- analysis mean
- 12-h forecast spread
- analysis spread

RMS (K)

days
EnKF
Wind Fit to RAOBS
500 hPa

RMS (m/s)

days

no assimilation, mean
no assimilation, spread
12-h forecast mean
analysis mean
12-h forecast spread
analysis spread
EnKF vs 3D-Var

Temperature Fit to RA0BS

500 hPa
EnKF vs 3D-Var

Wind Fit to RAOBS

500 hPa

| No Assimilation | 3D-Var 12-h Forecast | 3D-Var Analysis | EnKF 12-h Forecast | EnKF Analysis |
|-----------------|----------------------|-----------------|--------------------|--------------|--------------|

RMS (m/s) vs Days

0 5 10 15 20 25 30
EnKF vs 3D-Var

(F – O)

Temperature Fit to RAOBS

- no assimilation
- 3D-Var 12-h forecast
- 3D-Var analysis
- EnKF 12-h forecast
- EnKF analysis
EnKF vs 3D-Var

(F - O) Wind Fit to RAOBS

Pressure (hPa)

Bias

RMS (m/s)

-2 0 2 4 6 8 10 12 14 16

no assimilation
3D-Var 12-h forecast
3D-Var analysis
EnKF 12-h forecast
EnKF analysis
Imbalance

3D-Var: ~0.057
EnKF: ~0.048
Free: ~0.026
Conclusion 1

• Results indicate good performance of the EnKF at synoptic scale with WRF.
• The 12-hour forecasts from EnKF are closer to the observations than 3D-Var 12-hour forecasts:
  – Consistent with earlier OSSE experiments.
  – Non-stationary forecast-error statistics in the EnKF are beneficial.
  – Both schemes may improve with further tuning.
Conclusion 2

• The EnKF introduces somewhat less imbalance than 3D-Var:
  – OSSE experiments reported earlier indicated that more imbalance is introduced by the EnKF
  – Initialization? (digital filter, build balance constraints in the EnKF scheme?)
  – Need larger ensemble?
  – More sophisticated localization? (group filter)
Ongoing work with WRF EnKF

- Humidity observations assimilation
- Satellite data assimilation (retrievals)
- Surface observations
- Radar data assimilation:
  - Radial velocities
  - Reflectivities