Mesoscale Ensemble Data Assimilation with WRF and the Data Assimilation Research Testbed

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Mesoscale Ensemble Data Assimilation with WRF and the Data Assimilation Research Testbed

DART development: Jeff Anderson, Nancy Collins, Tim Hoar

Assimilation of surface obs: David Dowell, Soyoung Ha

Tropical cyclone results: Ryan Torn (SUNY Albany)

Assimilation of radar obs: Altug Aksoy (U Miami), David Dowell

Plus: Alain Caya (Environment Canada), Yongsheng Chen (York U), Josh Hacker, Hui Liu, Bill Skamarock
Challenges of Meso- and Convective-Scale DA

Dynamics are complex
- Mass-wind balances are limited or absent
- Strong role of parameterized, diabatic processes

Observations are incomplete
- E.g., single component or single level of \( \mathbf{v} \)

Forecasts are less skillful than at large scales
- 30 minutes is “medium range” at convective scale
- Models may have large deficiencies
The Ensemble Kalman Filter (EnKF)

Basics of the EnKF
- Estimate covariances at each analysis time from ensemble of short-range forecasts

Attractions for mesoscale applications
- Minimal assumptions about covariances; does not rely on large-scale balances
- Flexible to details of model, such as complex microphysical schemes
- Ease of implementation and parallelization
How the EnKF works

Suppose we wish to assimilate an observation of $v_r$
Consider how assimilation affects a model variable, say $w$.

Begin with:
- ensemble of short-range forecasts (of model variables)
- Observed value of $v_r$
How the EnKF works (cont.)

1. Compute $v_r$ for each ensemble member
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How the EnKF works (cont.)

2. Compute best-fit line that relates $v_r$ and $w$
3. Analysis moves toward observed value of $v_r$ and along best-fit line.
3. Analysis moves toward observed value of $v_r$, and along best-fit line
... have gained information about unobserved variable, $w$
How the EnKF works (cont.)

4. Update deviation of each ensemble member about the mean as well.

Yields initial conditions for ensemble forecast to time of next observation.
Data Assimilation Research Testbed (DART)

Provides general, model-independent algorithms for ensemble filtering

Numerous DART-compliant models
  – ARW, CAM, COAMPS, ...

Parallel analysis scheme that scales well to 100’s of processors

See http://www.image.ucar.edu/DARes/DART/
WRF/DART

Interfaces for WRF in DART
– WRF variables on model grid ↔ DART state vector
– Distance between any two elements of state vector

Suite of observation operators
– Includes Doppler radar and various GPS; no radiances

Scripts for advancing WRF under DART control
EnKF Details

“Deterministic, square-root, serial”

Between 50 and 100 ensemble members

Covariance localization
  – Single observation influences analysis only within specified radius

Ensemble of lateral BCs, to account for their uncertainty

Explicitly account for model uncertainty only in surface-obs experiments
Assimilation of Surface Observations

60-km resolution, CONUS domain

Ensemble covariances localized within radius of ~500 km.

6-hourly analyses
  - Assimilate radiosondes, ACARS, satellite winds
  - Test with and without 2-m T, T_d and 10-m u,v

“Multi-physics” ensemble
  - Each member uses distinct configuration of WRF
  - Choose from 3 PBL, 3 cumulus, 2 shortwave radiation
  - Hope to capture, at least partially, uncertainty of forecast model
Assimilation of Surface Observations (cont.)

Comparison against radiosonde temperature
Control physics, multi-physics, multi-physics with surface obs

![Graph showing comparison against radiosonde temperature with RMS and total spread values.](chart)
Assimilation of Surface Observations (cont.)

Comparison against radiosonde temperature at 925 hPa

Control physics, multi-physics, multi-physics with surface obs

Representing model error in EnKF significantly improves results for T

… but effect is neutral for wind and above PBL.
Assimilation for Tropical Cyclones

Courtesy R. Torn (SUNY Albany)
Assimilation for Tropical Cyclones (cont.)

36-km resolution, CONUS + W Atlantic + Caribbean domain

Ensemble covariances localized within 2000-km radius

10 HFIP cases

6-hourly analyses, beginning 4 days prior to depression
  – Radiosondes, ACARS, satellite winds, surface pressure
  – Also TC position and “synoptic” dropsondes
Assimilation for Tropical Cyclones (cont.)

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No TC bogussing or bogus observations
Assimilation for Tropical Cyclones (cont.)

RMS track and intensity errors, averaged over 10 cases

TC Forecast Track Errors

TC Forecast Intensity Errors

WRF EnKF  Ens. Std. Dev.  GFS  WRF-GFS  NHC
Radar Assimilation for Convective Storms

See earlier talk by D. Dowell

2-km resolution, local domains of ~300 km x 300 km, open lateral BCs

Ensemble covariances localized within 5-km radius

Analyses every 2 min
  - Radial velocity and reflectivity from single radar
  - Each elevation scan assimilated separately
  - Automated velocity unfolding within EnKF

Nearby radiosonde provides “environment”
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Status and Future Directions

WRF/DART is a research-ready system applicable across a range of scales and phenomena

Ongoing activities

- Combining mesoscale analyses with high-resolution assimilation of Doppler radar
- Techniques to account for model error: multi-physics, multi-parameter, stochastic backscatter, adaptive inflation
- Application to WRF-Chem and PlanetWRF
- Assimilation of radiance observations
HFIP domain + snap-shot of observations

Observation distribution valid 2005071200
Comparison of EnKF and 4DVar

- **Simulated** observations of radial velocity and reflectivity for supercell storm (perfect model), available every 5 min
- 4DVar: full fields (not incremental), mesoscale background, simple covariance model, 10-min window
- EnKF: 100 members, initialized with noise in T where first scan shows reflectivity

Comparison with 4DVar

- rms errors over entire domain; obs of both $v_r$ and reflectivity
- EnKF (thin) and 4DVar (thick w/ boxes)
Comparison of EnKF and 4DVar

Kalman filter/smooother and 4DVar are mathematically equivalent for linear, Gaussian systems
- Result also assumes both use same P, R, etc.

Overall, EnKF and 4DVar perform comparably in this case

After multiple cycles (30-40 min), EnKF beats 4DVar
- EnKF propagates information from previous obs through cycling of $P'$
- In principle, updating of P could be included in 4DVar too

Given only obs over limited period (10-20 min), 4DVar beats EnKF
- Estimation errors large with limited obs, so nonlinear effect more important and 4DVar has advantage?