Applications of EnKF (vs. VAR) in Limited-area Mesoscale Models

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First Test of EnKF for LAMs: Assimilation of Radar Observations of Supercells

(Snyder and Zhang 2003; Zhang, Snyder and Sun 2004; Dowell et al. 2004; all in MWR)

Observations: radial velocity V_r only, available every 5 minutes where reflectivity dBZ>12

Vertical velocity at 5km (colored) and surface cold pool (black lines, every 2K)



Also refer to comparison with 4DVAR in Supercell OSSEs: Caya, Sun and Snyder (2005, MWR)

Regional-scale EnKF: OSSE Results

(Zhang, Meng and Aksoy 2006 MWR; Meng and Zhang 2007 MWR)

- Case in study: the "surprise" snowstorm of 24-26 January 2000 (ZSR2002, 2003)
- Forecast model: MM5, 30-km grid spacing over CONUS domain (190x120xL27)
- A 40-member ensemble: initiated at 00Z 24 Jan with random but balanced perturbations using MM5 3Dvar background error statistics (Barker et al. 2004)
- Perfect-model OSSE: truth as one of the ensemble members; no model error
- OBS type: sounding obs of u, v, T from truth run at (300 km)² spacing, every 12h surface obs of u, v, T from truth run at (60 km)² spacing, every 3h
- **OBS error:** 1 K for T and 2 m/s for u&v; uncorrelated
- Square-root sequential EnKF: Whitaker and Hamill (2002)
- Radius of influence: 1800 km with Gaspari and Cohn (1999) cutoff
- **Covariance inflation:** relaxation to prior (Zhang, Snyder and Sun 2004, MWR)

 $(\mathbf{x}_{new}^{a})' = (1 - \alpha) (\mathbf{x}^{a})' + \alpha (\mathbf{x}^{f})'$

Performance: Forecast Error (above) vs. Analysis Error (below)

RMS error of difference total energy (every 2m/s); RM_DTE = $\sqrt{\frac{1}{N}\sum_{n=1}^{N}(u'^2 + v'^2 + kT'^2)}$



EnKF Performance: Time Evolution of EnKF Analysis Error (solid) vs. Forecast Error (dotted) and ensemble spread (gray)



EnKF Performance: Spectral Analysis of Forecast Error (dotted) vs. Analysis Error (solid) at 0h (green), 12h (red), 24h (blue) and 36h (black)



Imperfect model OSSEs: benefit of multi-scheme ensemble

Cumulus Scheme in truth: GR; single wrong scheme: KF; Scheme used for multi-physics ensemble: KF2, KF, BM, KUO



Multi-scheme has smaller analysis error than that of imperfect single schemes

(Meng and Zhang 2007 MWR)

Imperfect model OSSEs: why multi-scheme ensemble?



Multi-scheme has a better prior forecast

Multi-scheme is less vulnerable to filter divergence due to larger ensemble spread



Exchange covariance between ...

Multi-scheme has a better background error covariance structure

Regional-scale Real-data EnKF vs. 3Dvar for Jun'03

WRF/EnKF: 40 multi-physics-scheme ensemble (27 combinations)

Boundary conditions: D1 updated by 12 hourly GFS/FNL analyses

3DVar (Barker et al. 2005): Updated B with May 2003 forecasts via NMC method (Parrish and Derber 1992; Xiao and Sun 2007)

Observations: Soundings every 12 h QC'd by 3Dvar in D2, assuming observational errors of NCEP.

Verification: against soundings at 12-h forecast time and at standard pressure levels

Inflation: covariance relaxation

(Zhang et al. 2004 MWR)

$$(\mathbf{x}_{new}^{a})' = (1 - \alpha) (\mathbf{x}^{a})' + \alpha (\mathbf{x}^{f})'$$



(Meng and Zhang 2008a, bMWR)





FNL_GFS has a generally smaller 12-h forecast error than wrf-3DVar.

Vertical Distribution of 12-h Forecast RMSE for June 2003

--- EnKF --- 3DVar_WRF



EnKF performs clearly better than WRF-3DVar in almost every vertical level

prior forecast 4.8 4.7 4.7 4.61 4.6 RM-DTE (m/s) 4.5 4.43 4.4 4.3 4.26 4.2 4.1 4 EnKF_m EnKF_s 3DVar_WRF FNL_GFS

Monthly Averaged 12-h-Forecast RM-DTE for June 2003

EnKF has significantly smaller overall 12-h forecast error than both WRF-3DVar and FNL_GFS.
 FNL_GFS has smaller overall forecast error than WRF-3DVar.

Monthly Averaged Forecast Error at Different Lead times initialized from respective analyses (every 12h, 60 samples)



EnKF/3DVar forecast (1730UTC) vs. BAMEX dropsondes Dropsonde time :1604UTC - 1905UTC June 11, black



Forecast starting from EnKF analysis shows improved MCV structure than that from 3DVar analysis



Vertical error distribution verified against dropsondes

EnKF_m performs better than WRF 3DVar. EnKF_m also performs better than EnKF_s especially for T and q.

MCV case: Impact of background error covariance (3DVar)

NMC – use a month-long 24h and 12h forecast differences ENS – use the statistics of one-time short-term ensemble forecast EVO – ENS change with time and thus have some flow-dependence



• 3DVar can be improved significantly by using ensemble-mean for state estimation.

• Including some flow-dependence in the background error covariance can result in noticeable improvement.

Convective-scale Vr Assimilation for Hurricanes

(Zhang et al. 2008 MWR, in review)

- WRF domains: D1-D2-D3-D4 grid sizes---40.5, 13.5, 4.5, 1.5km (movable) – Physics: WSM 6-class microphysics; YSU PBL; Grell-Devenyi CPS
- EnKF (Meng & Zhang 2008b): except for 30-member w/o multi-scheme ensemble

- Initialized at 00Z 12 using 3DVar background uncertainty with FNL analysis; GFS forecast used for boundary condition in forecasts

• Data assimilated: WSR88D Vr at KCRP, KHGX & from KLCH 09Z12 to 12Z 13 Sept 2007; Successive covariance localization; obs err 3m/s

⁽GFS ops run and WRF run from GFS)

Super-Obs: QC and thinning of WSR-88D Vr Obs

Define SO position depended on the radial distance
Average10 nearest data points in the raw polar scan to create a SO
Averaging bin is 5km max radial range and 5° max azimuthally resolution
There are at least 4 valid velocity data within an averaging bin.
The standard deviation checking of the velocities.

Assimilate WSR88D Vr Obs: Number of SOs

-WRF/EnKF starts assimilating hourly Vr obs of CRP, HGX and LCH WSR88D radars from 09Z/12 to 21Z/12 after a 9-h ensemble forecast from GFS/FNL analysis -Successive covariance localization with different ROIs for different subset of SOs

Successive Covariance Localization (SCL)

SCL is designed to assimilate dense observations that contain information about the state of the atmosphere at different scales, as is the case for hurricanes

The method is also designed to reduce computation cost and sampling errors

Rationale: Assuming larger-scale errors will have larger correlation length scales and smaller-scale errors have much smaller correlation length scales, fewer observations with larger radii of influence (ROIs) are needed to constrain large-scale errors, and a larger number of observations are needed to constrain small-scale errors

SCL is similar to the successive correction method (SCM) used in some earlier empirical objective analysis schemes (e.g., Barnes 1964), though in the EnKF experiment here the same observation will not be used twice

Successive Covariance Localization (SCL) Details for this case

CNTL experiments: SCL with different radii of influence (ROIs):

1200km (1/10 of SOs) characteristic scale for large-scale flow

400km (3/10 of SOs) for subsynoptic or TC storm scale,

135km (5/10 of SOs) for mesoscale to convective-scale details

Another 1/10 of SOs is reserved for verification purpose

Sensitivity experiments:

Fix ROI for all SOs at 1200km and 400km respectively ROI=30dx at different grids for different group of SOs

KHGX base Vr EnKF Analysis Mean Pure EF Mean w/o EnKF *09Z/12* 18Z/12 03Z/13

CNTL EnKF Analysis vs. KHGX Obs vs. NoDA

Forecast initialized with EnKF Assimilating WSR88D Vr

WRF single forecasts initialized with EnKF analysis at 18Z or 21Z September 12 captures well the rapid TC formation and deepening (red and brown)

Comparison with WRF/3DVAR Assimilating the Same OBS

Without flow-dependent background error covariance, WRF/3DVAR forecast failed to develop the storm despite fit to the best-track obs better at 18Z

Impact of Using SCL vs. fixed ROIs for all SOs

Forecasts from CNTL analysis with SCL appears to perform better than using fixed ROIs at 1200km or 400km

Experiment using 30DX at different domains also performs well

Airborne Doppler Radar Scanning Geometry

Fig. 2.5 Tail radar scanning geometry for both the NOAA P-3s and the NRL P-3. The left plot shows a schematic of the antenna scanning methodology. A horizontal projection of the beams is shown on the right.

Impacts of Airborne Vr EnKF for Katrina (2005)

4.5-km (top, 126h) vs. 1.5-km (bottom, 102h) ensemble fcsts

Towards Real-time Assimilation of Airborne Radar Observations with EnKF

WRF/ARW triply-nested domains for both EnKF analyses and free forecasts: D1: 121x160x40.5km x 35 levels (similar to GFDL coarse domain) D2: 121x160x13.5km x 35 levels D3: 253x253x 4.5km x 35 levels (moving nest in forecast mode) D4: 253x253x 1.5km x 35 levels (moving nest in forecast mode) Time performance of standard real-time WRF/ARW forecast initialized with GFS Waiting time for GFS completion: 4.5 h Transfer GFS analysis and forecasts from NCEP to TACC: 0.3 h Initialization of WRF/ARW with GFS using WPS: 0.4 h 126-h WRF free forecast with 512 processors: 2.7 h Total time lapse: 7.9 h (3.4 h after GFS completion, 1.5 km is 7 h after) Estimated real-time WRF/ARW forecast initialized assimilating airborne Vr data EnKF ensemble initialized with most recent available GFS: no waiting time Quality control and super-observation (SO) of Airborne data per hour: 0.3h Transfer airborne ~3000 SOs from P3 to TACC: 0.2 h EnKF assimilation of 1-h SOs: 0.5 h 126-h WRF free forecast with 512 processors: 2.7 h Total time lapse: 3.7 h (1.5-km is 7 h) after Doppler observations taken

Running on TACC computer Ranger with Number of Cores: 62,976; Total Memory: 123TB

Realtime Tests of Hurricane Ike (2008) SOs Generated/assimilated during P3 mission

ARW from GFS at 12Z/9; Vr SOs during 21-24Z/09

Realtime ARW Performance with Vr EnKF IKE2008 126h 4.5km Ensemble Forecast started at 2008091000

80 ¥

SO time: 2125-2227 & 2301-2341; Track

Summary on Regional-scale EnKF

- The EnDA systematically outperforms WRF-3DVar for the BAMEX month-long experiment and promising for cloud-resolving hurricane prediction.
- The better performance of EnDA over 3DVar is possibly due to using an ensemble mean for state estimation and its flow-dependent covariance.
- EnDA can benefit from using a mutli-scheme ensemble that partially accounts for model errors in physical parameterizations. This benefit is more pronounced in the thermodynamic variables than the wind fields.
- Covariance inflation by relaxing to prior appears to be effective for mesoscales using 30-40 ensemble members.
- Successive covariance localization appears to be helpful in assimilating dense radar obs in multiscale phenomena like tropical cyclones.

Issues Specific to LAM NWP EnKF vs. VAR

Multi-scale in nature

- **Balance versus imbalance**
- Moist error growth dynamics at meso/convective scales
- Significance of model error, esp. in moist physics and boundary layer
- Strong inhomogeneity in data coverage, lack of good thermodynamic obs
- Localization challenge: moving beyond empirical tuning?
- Ensemble initiation, startup vs. lead time, DFI windows
- Needs for lateral boundary conditions and nesting
 - Perturbation availability and consistency from global models
 - Multiple domain updating, one-way versus two-way nesting
 - Related: Unified model, dual resolution
- Satellite data assimilation for mesoscales
 - **Bias correction**
 - Model top
- Validation and inter-comparison with variational methods
 - Lack of common domains and metrics
 - Lack of compatible 4Dvar
 - **Grid-point RMSE versus feature-based verifications**