Comparing WRF-based EnKF with 3DVar for an MCV Event during BAMEX

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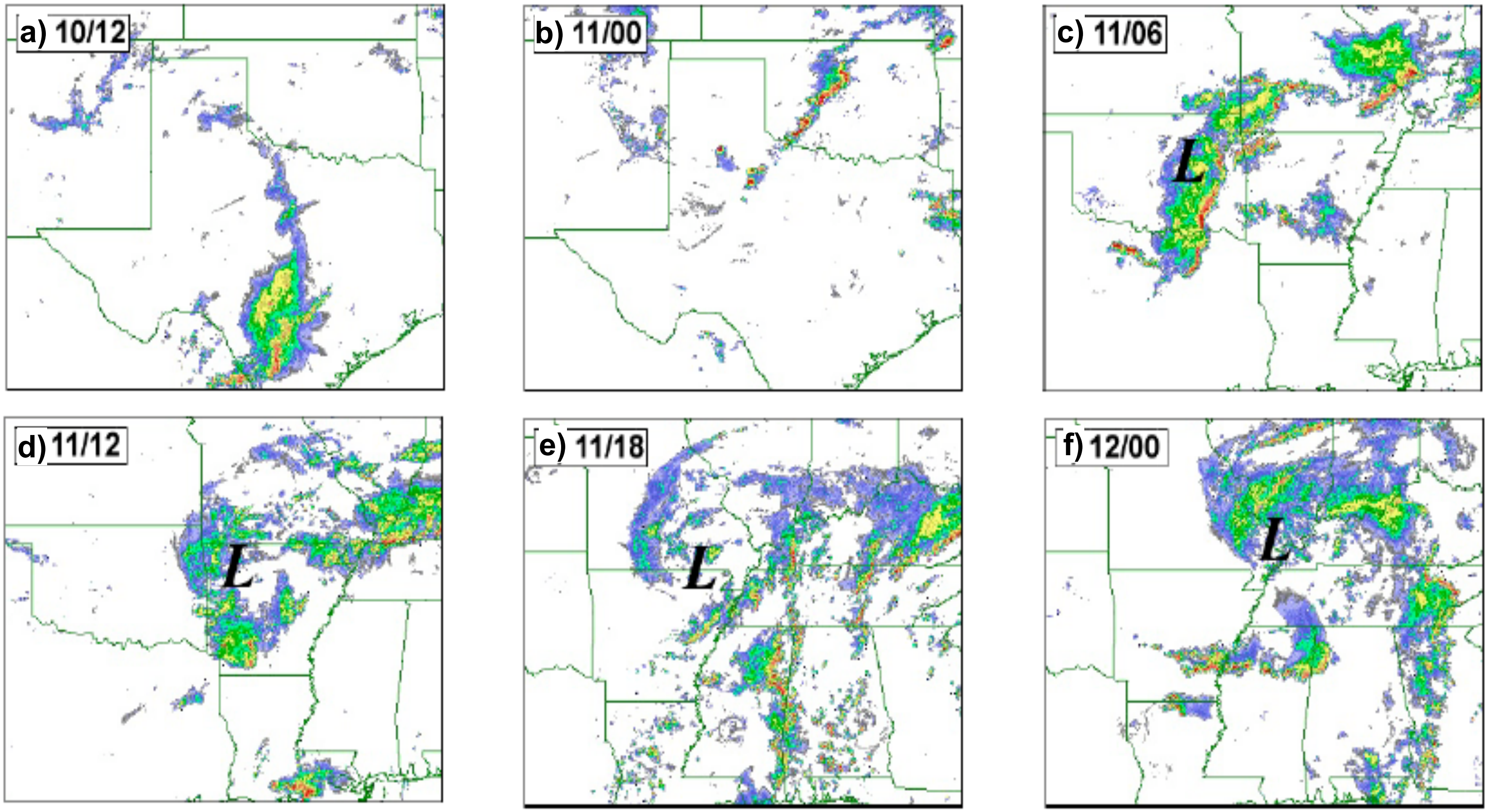
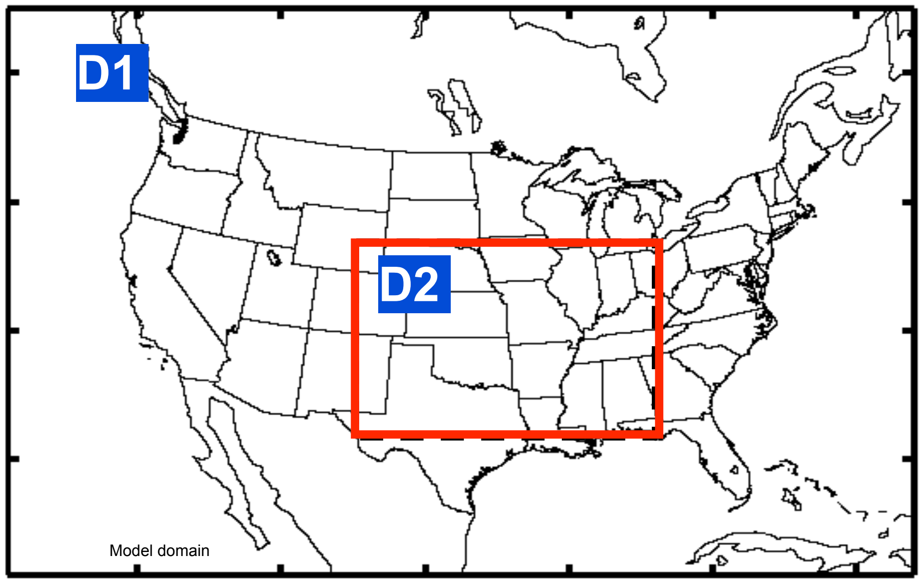
The MCV event of 10-12 June 2003 (IOP 8 of BAMEX)



Forecast Model: WRF2.1



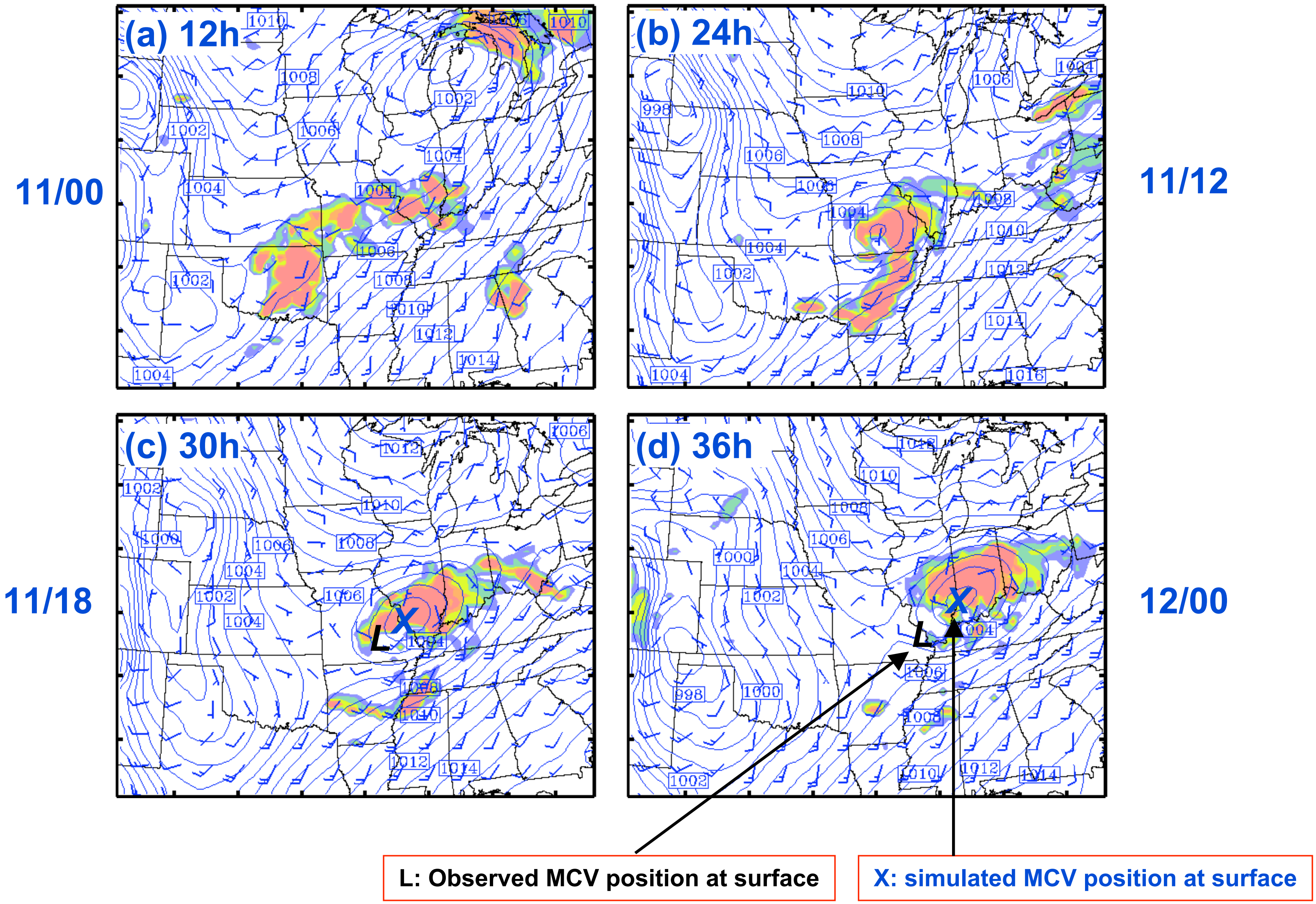
Two domains with grid sizes of 90 & 30 km; one-way nesting

Physical parameterizations: Grell-Devenyi cumulus scheme, WSM 6-class microphysics with graupel, and YSU PBL

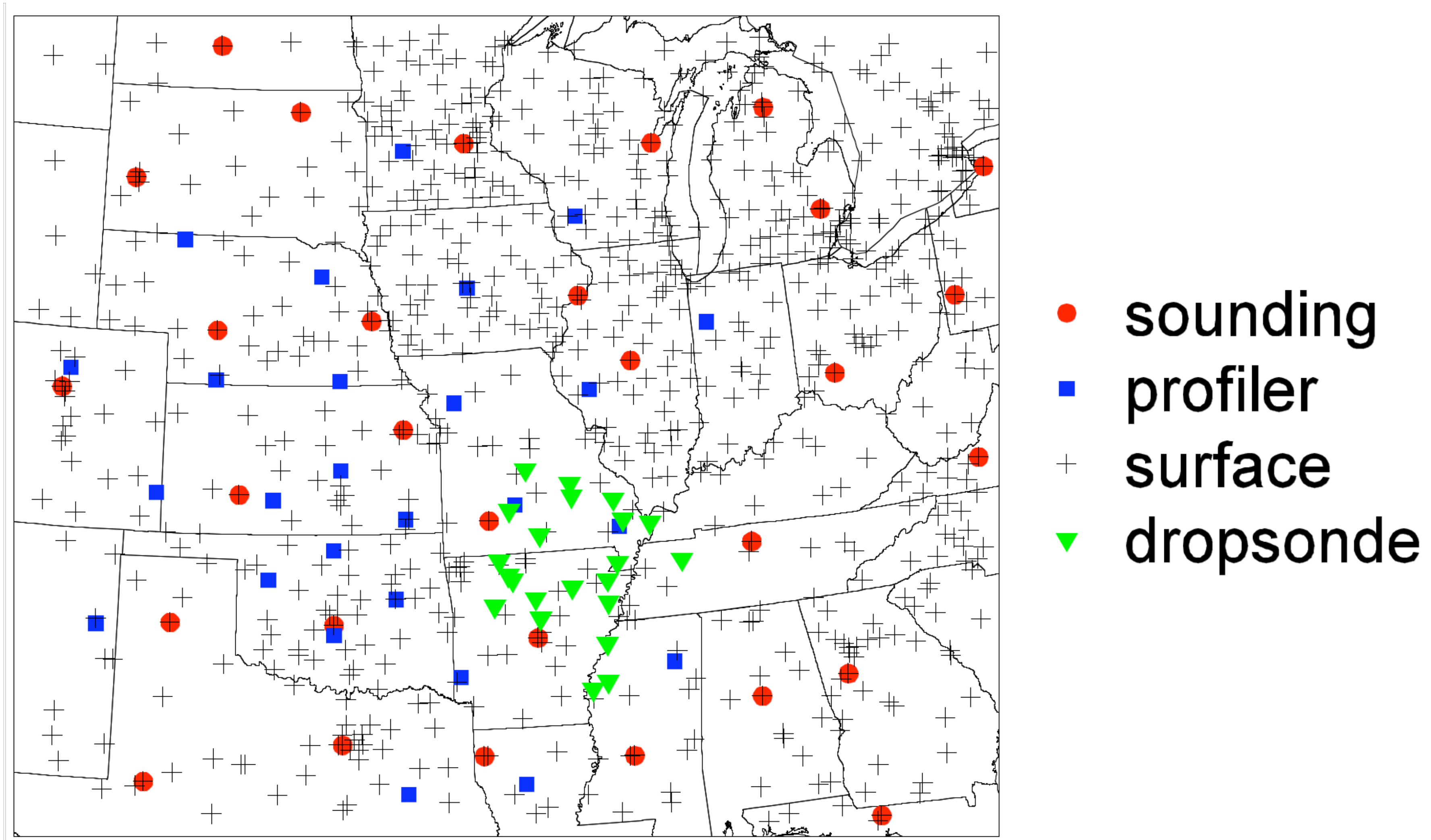
Data assimilation is only performed in D2

Ensemble Forecast in D2

Simulated reflectivity (colored) and MSLP (blue lines, every 2 hPa)



Data to be assimilated



A WRF-based Ensemble Kalman Filter (EnKF)

A sequential filter: Whitaker and Hamill (2002), Snyder and Zhang (2003)

Assimilated variables: u, v ,T, Q and Psfc (assuming observational errors of NCEP)

Ensemble size: 40

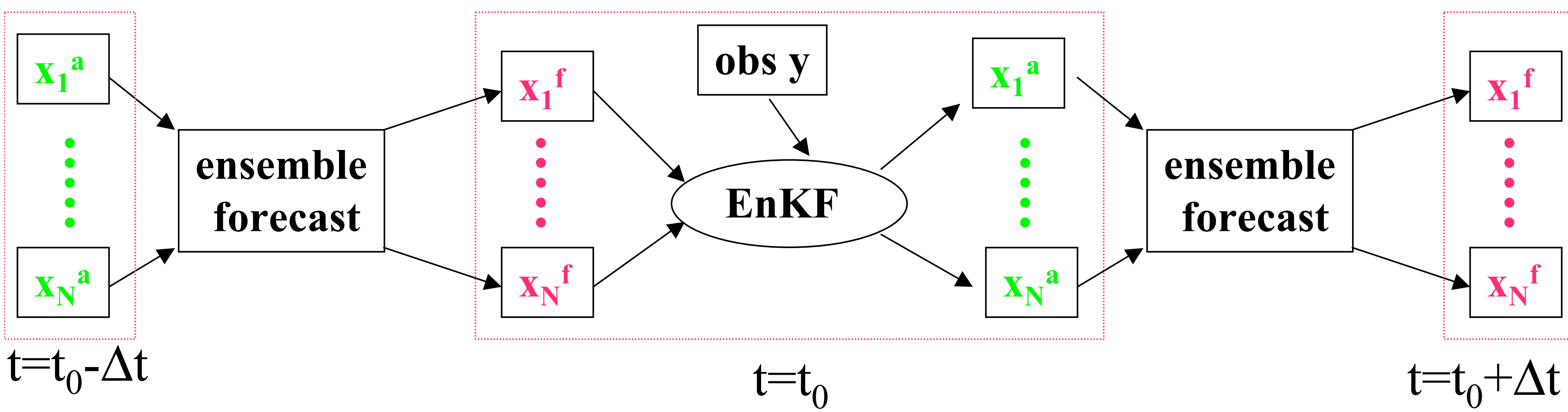
Ensemble generation: randomly sampled from 3Dvar background (Barker et al 2003)

Autoregressive coarse boundary perturbations: Torn and Hakim (2006)

Covariance relaxation to prior: Zhang et al. (2004)

Covariance localization: Gaspari and Cohn (1999)

Nearly identical to our MM5-based EnKF: Zhang et al. (2006)



EnKF: Use ensemble forecast to estimate flow-dependent background error covariance

WRF-3DVAR

(Barker et al. 2005)

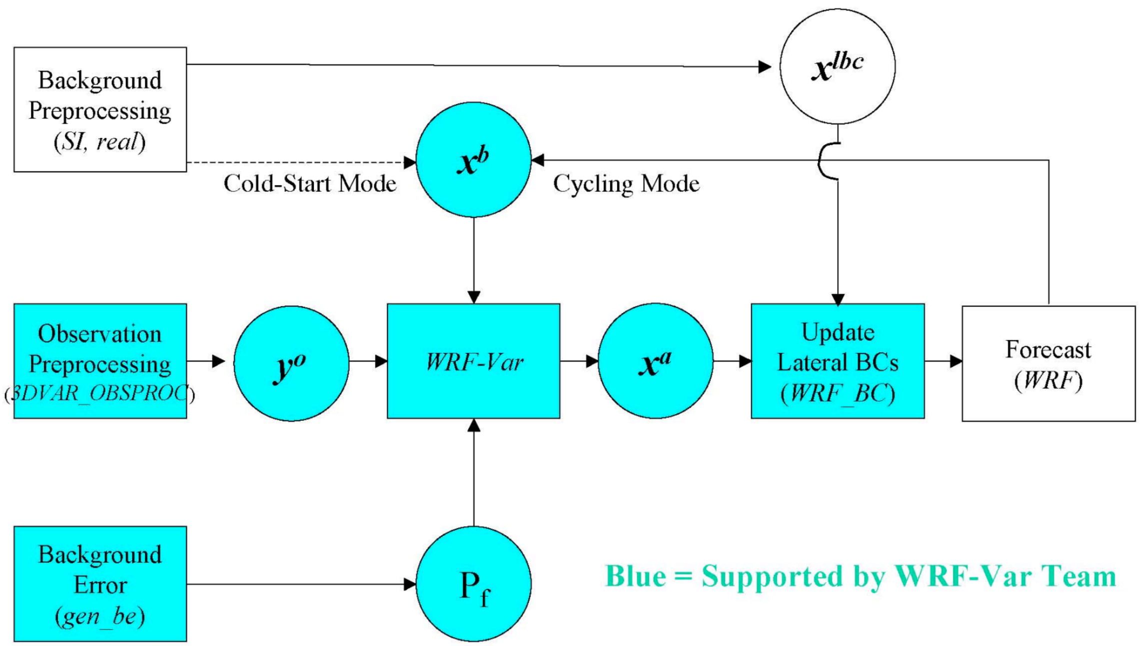
Control variables: stream function, pseudo relative humidity, unbalanced velocity potential, temperature, and surface pressure.

Background error covariance:

cv3 – NCEP/GSI B from NMC method (default in current release)

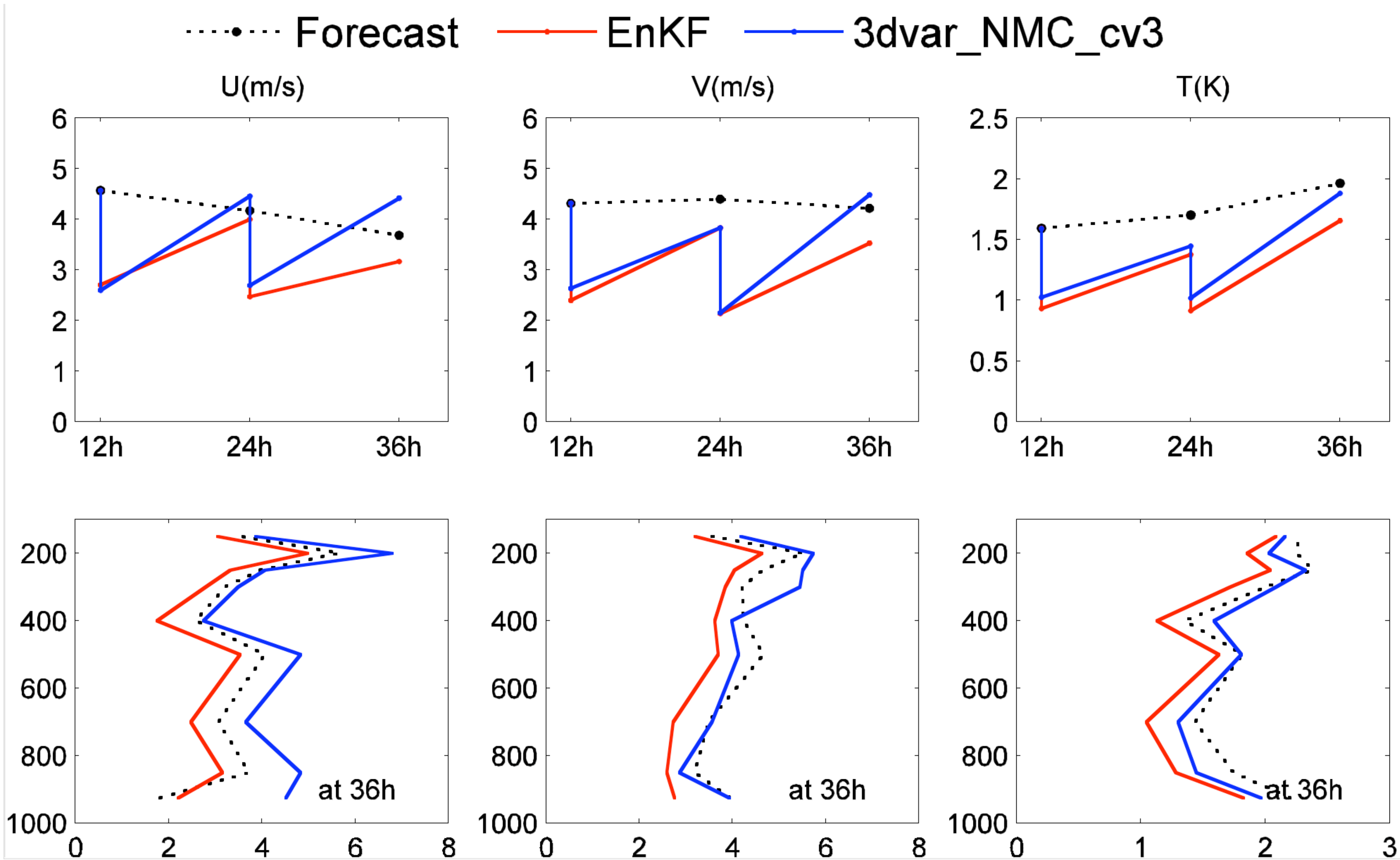
cv5 – NMC method but with WRF simulations through *gen_be*

Minimization: Conjugate gradient method

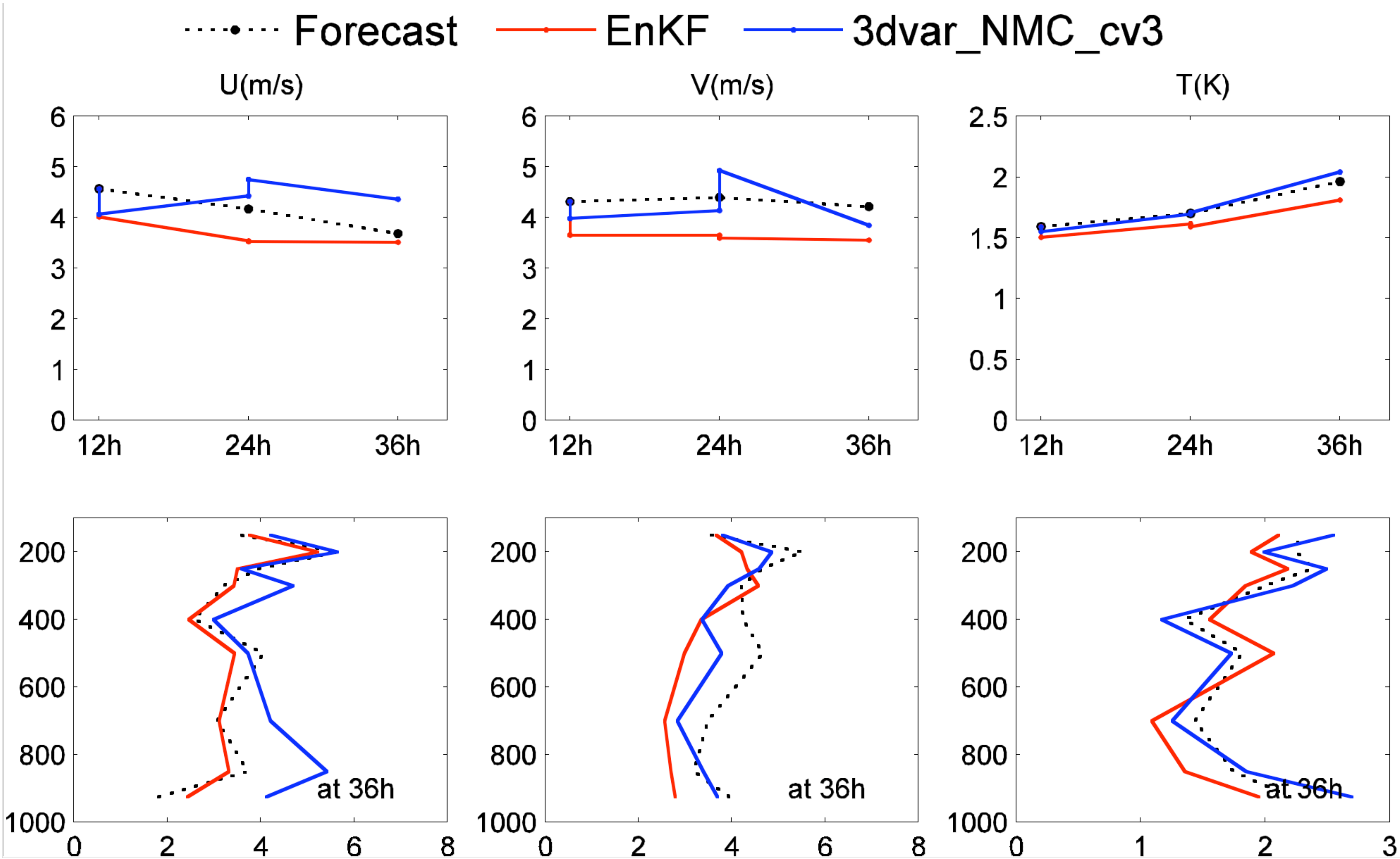


(Diagram copied from Dale Barker's tutorial presentation)

Sounding assimilation - cycling at 12h interval

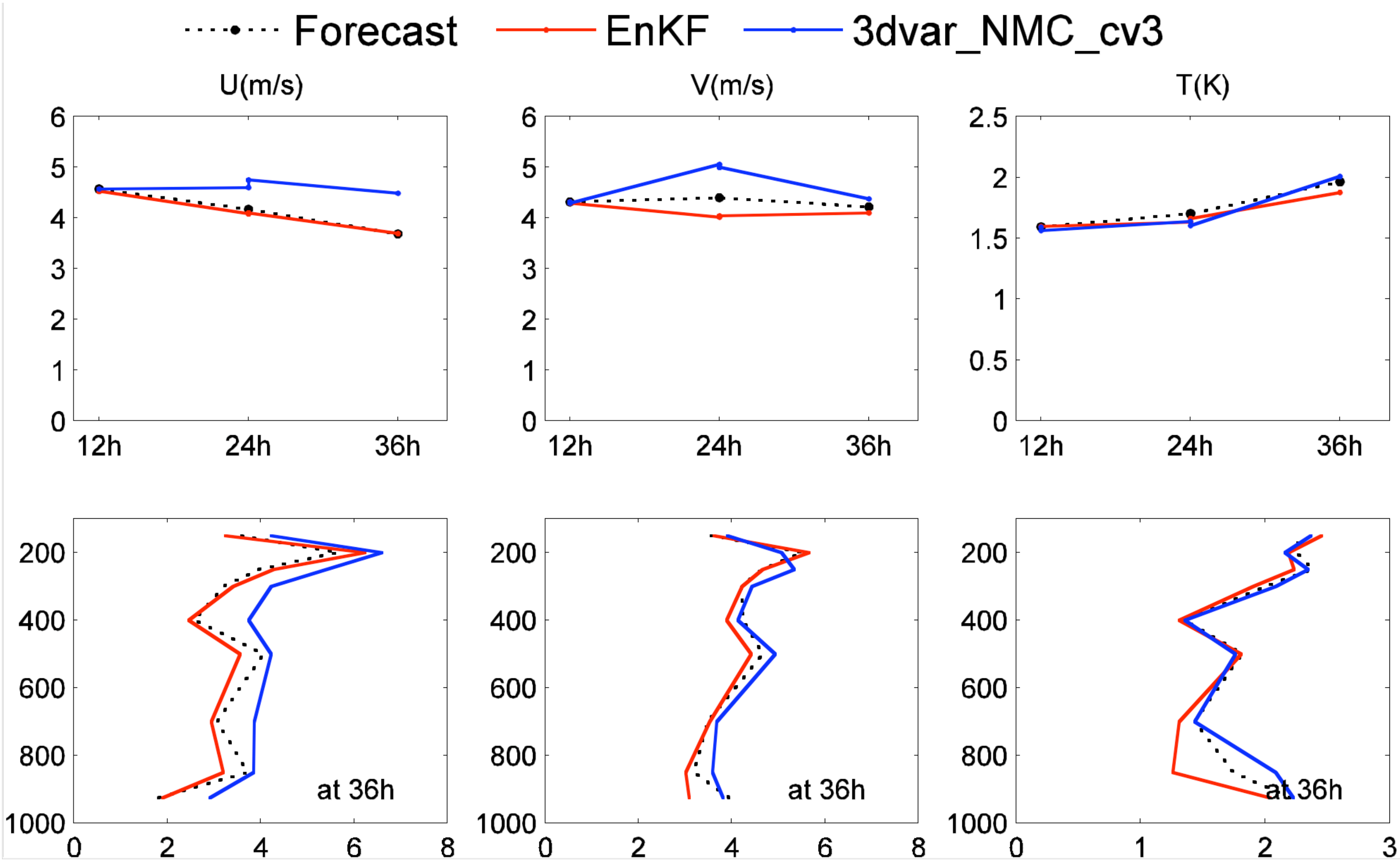


Profiler assimilation - cycling at 3h interval



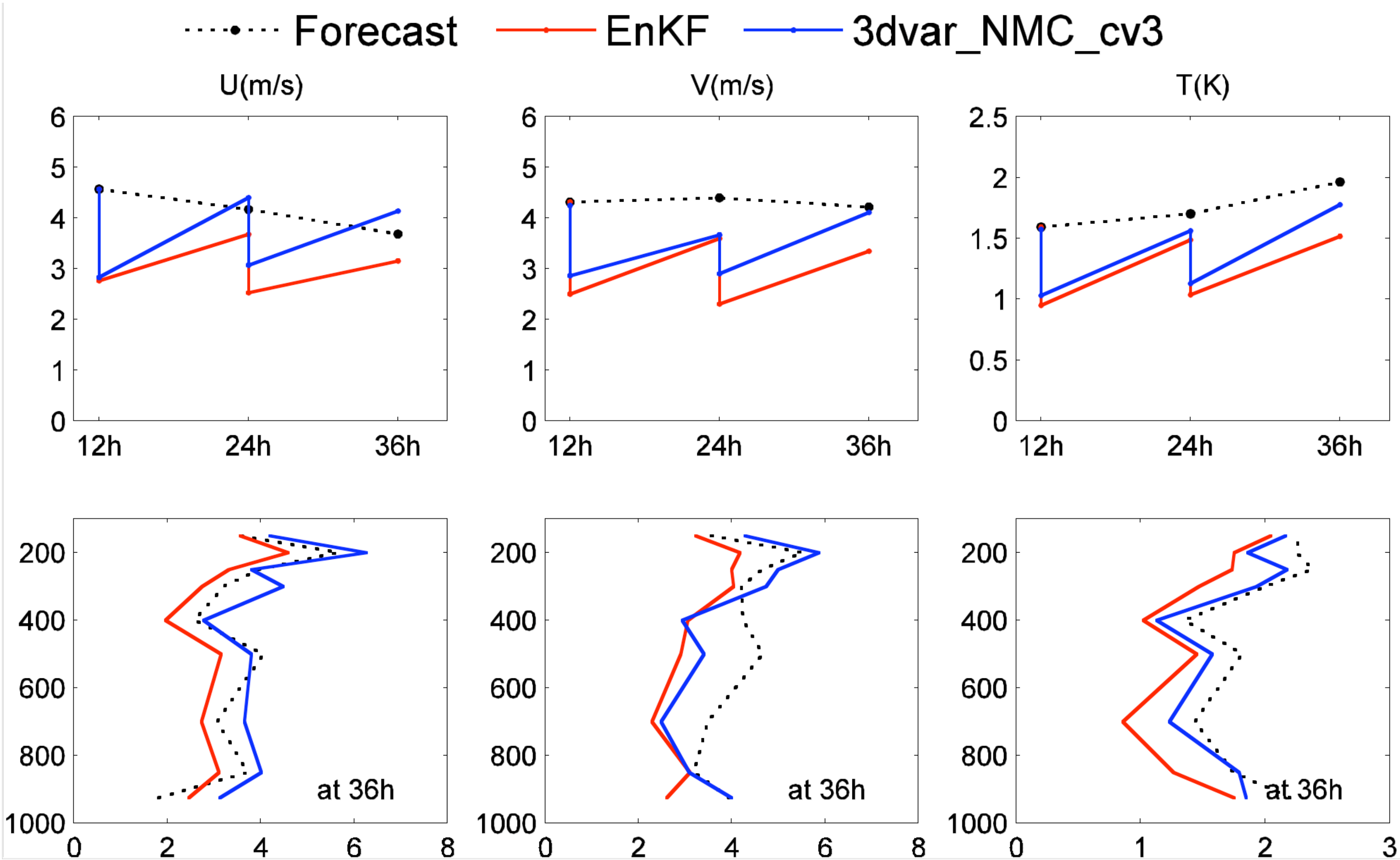
Surface observation assimilation

- Cycling at 3-h interval



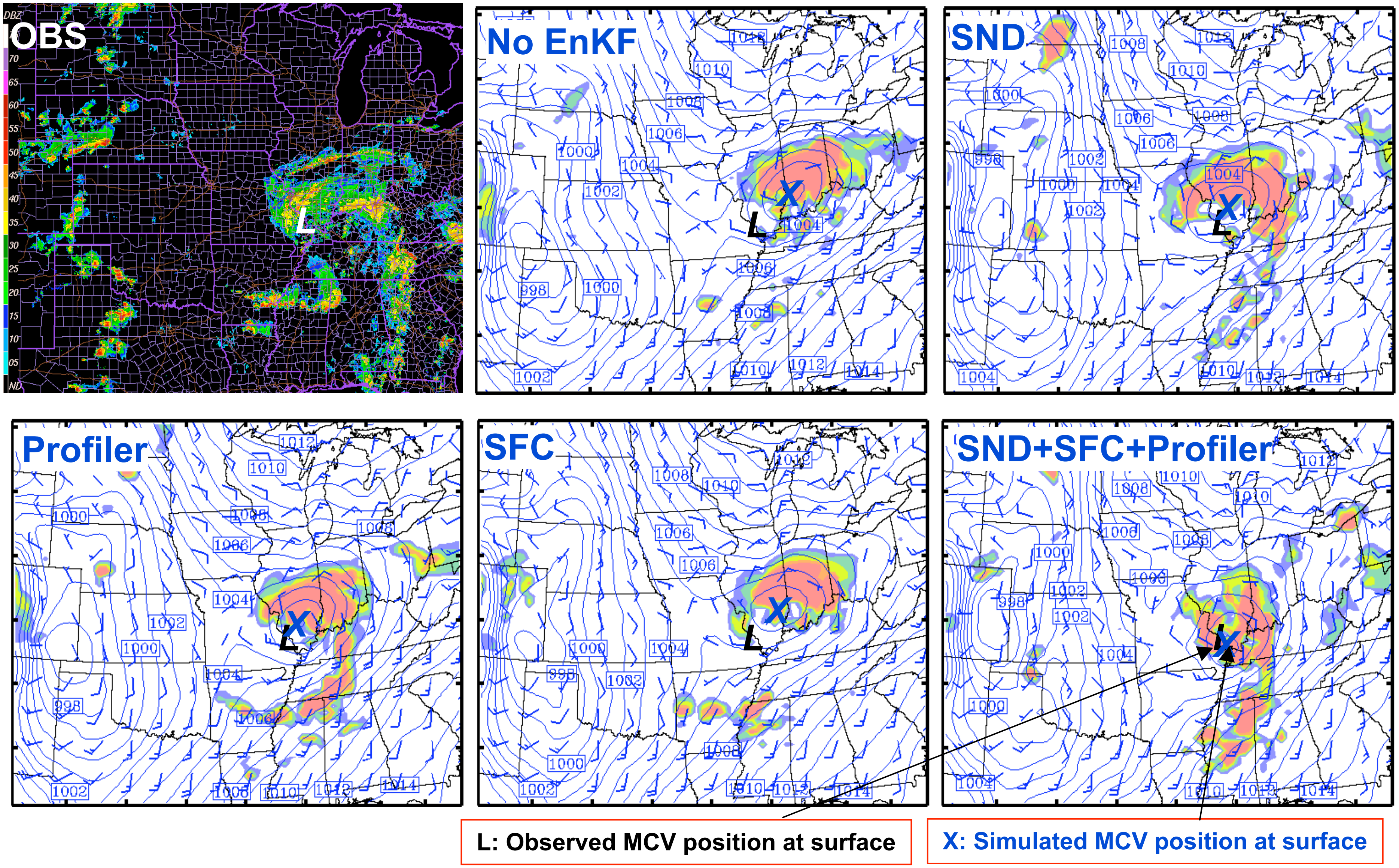
Assimilation of Sounding+Surface+Profiler obs

- Cycling at 3-h interval

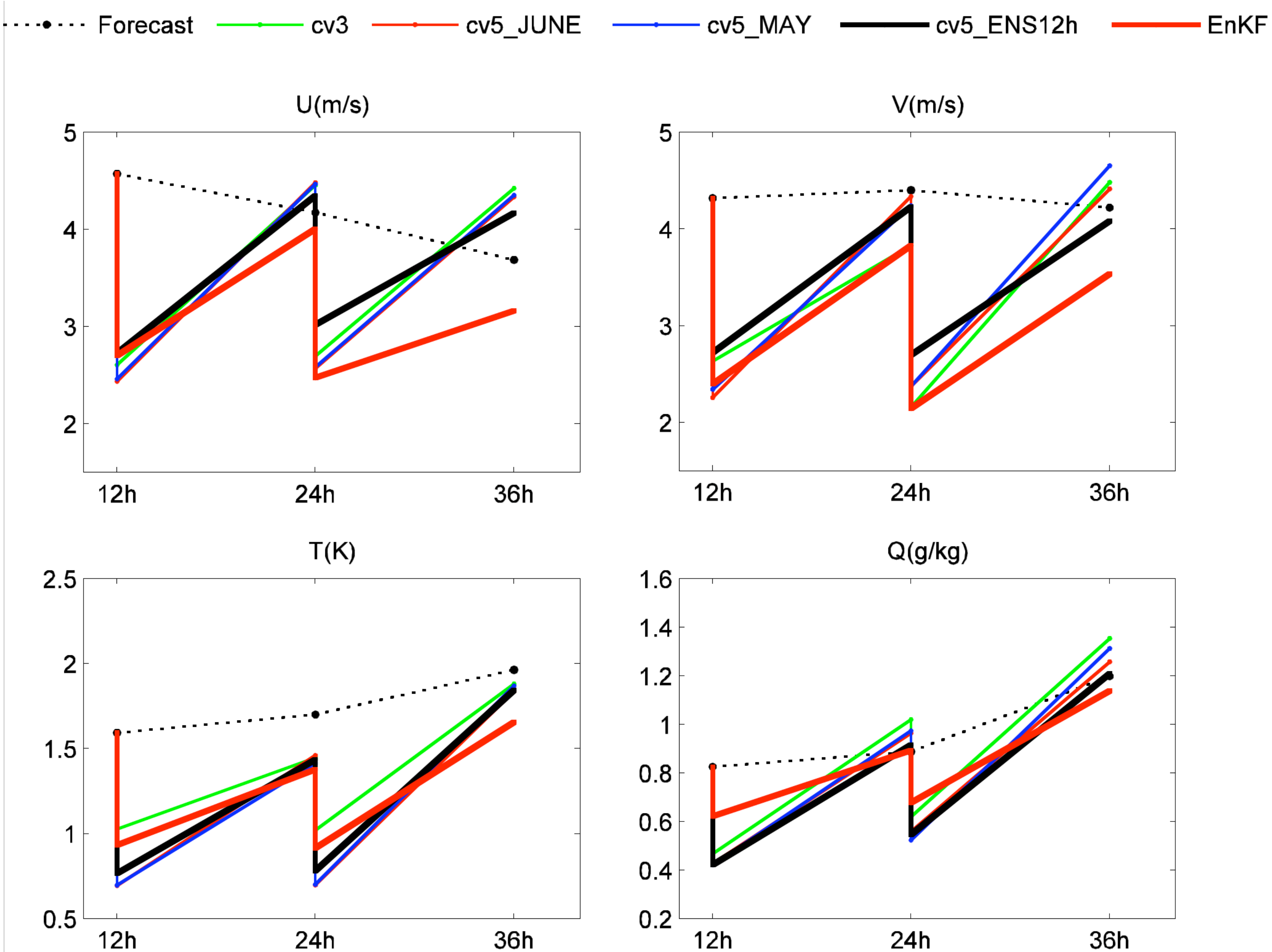


MCV positions at 36h (00UTC Jun.12)

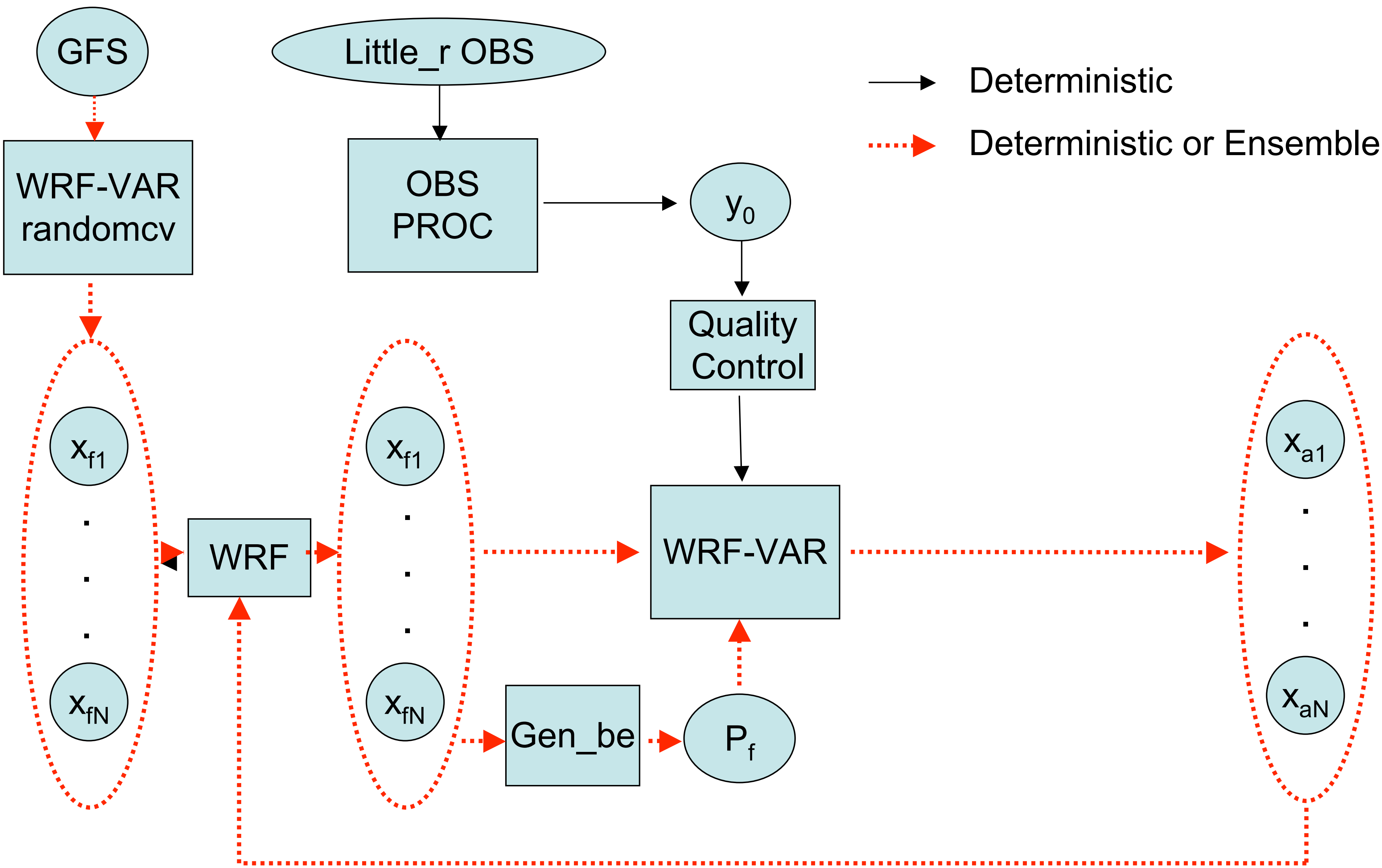
Observed radar echo, simulated reflectivity (colored) and MSLP (blue lines, every 2 hPa)



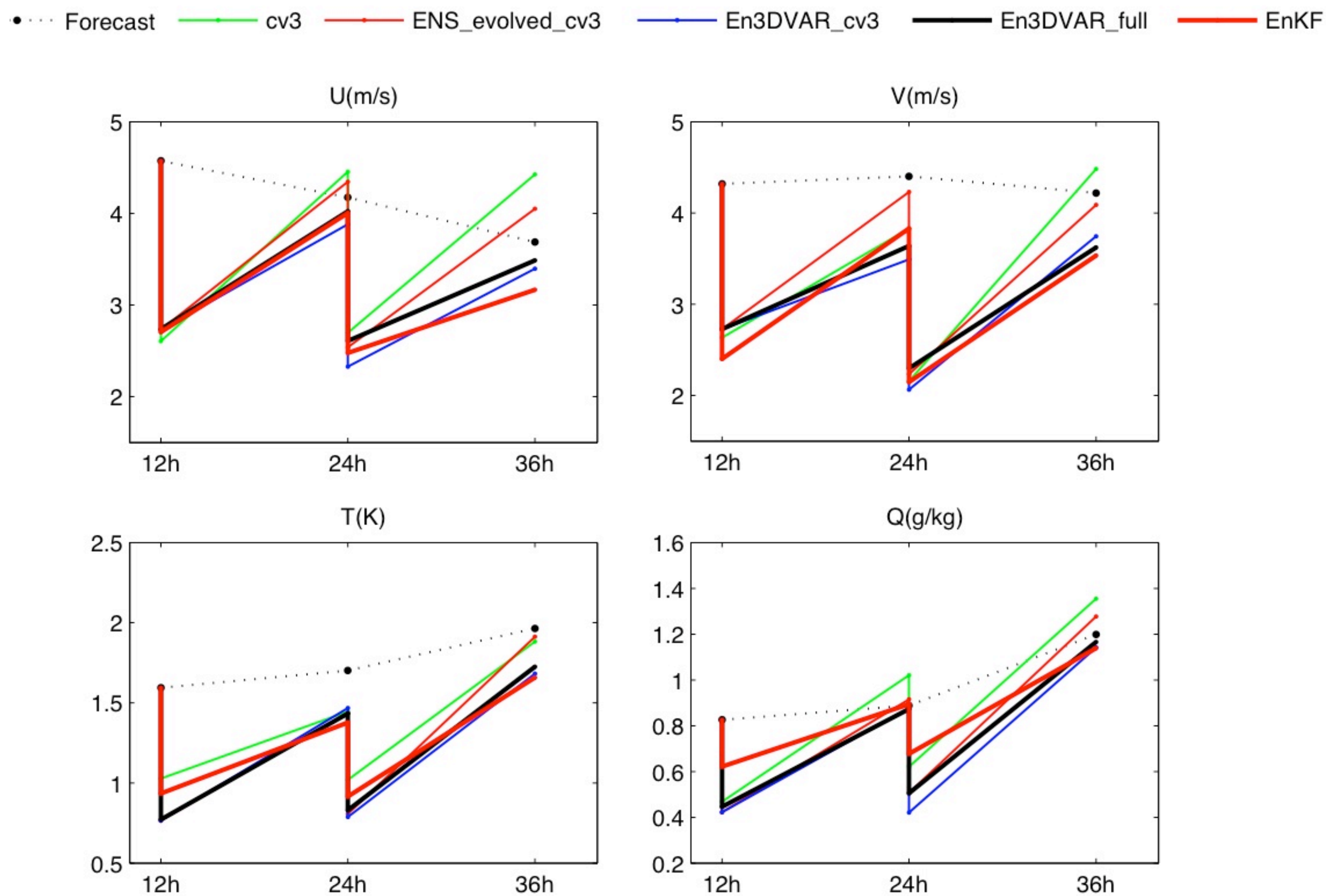
3DVAR: Sensitivity to background error covariance B



Implementing the concept of EnKF in 3DVAR



Implementing the concept of EnKF in 3DVAR



ENS_evolved_cv3: generate B using 12-h forecast ensemble; 3Dvar on prior from single forecast
En3DVAR_cv3: generate B using 12-h forecast ensemble; 3Dvar analysis on ensemble mean
En3DVAR_full: generate B using 12-h forecast ensemble; 3Dvar analysis on each member

Concluding Remarks

- WRF/EnKF behaves well when assimilating real observations
- EnKF performs better than 3DVAR which uses the static NCEP/GFS background error covariance (B) for this event
- The difference between EnKF and 3Dvar becomes smaller when more observations are assimilated
- The difference between EnKF and 3DVAR becomes also becomes smaller when 3DVAR derived more and more event-based ('flow-dependent') B from the WRF simulations
- The 3DVAR performs similar to EnKF if using the ensemble forecast to generate first guess and B
- 3DVAR tends to have smaller analysis error (fits data better) but have comparable or larger 12-h forecast error than EnKF
- The 3DVAR system is much more computationally efficient but to generate case-dependent B can be costly and challenging to many event-based users