En4D-Var: An Innovative Data Assimilation Technique Combining Ensemble Forecast with 4D-Var

Qingnong Xiao[1], Chengsi Liu[1,2], and Bin Wang[2]

1. National Center for Atmospheric Research/MMM, Boulder, Colorado
2. Institute of Atmospheric Physics/LASG, Beijing, China

Advanced data assimilation

- 4D-Var
  - ✓ It is a non-sequential data assimilation technique, fitting observations in the whole assimilation window (optimal trajectory).
  - ✓ It is applied in many operational centers.
  - ✓ However, there are disadvantages compared with EnKF technique (TL and AD are difficult to code; background error covariance is evolved only within assimilation window and it is usually static at analysis time).
- Ensemble Kalman filter
  - ✓ It is a hot topic in recent years, and research shows promising results.
  - ✓ It is easy to design and code, and can include any physical process as needed.
  - ✓ One of the prominent advantages is its flow-dependent background error covariance.

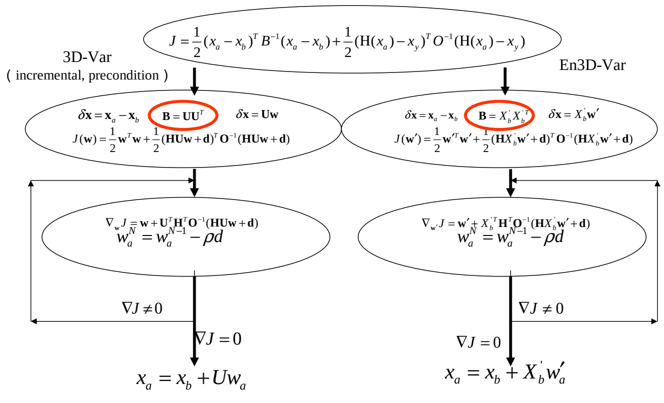
Will EnKF replace 4D-Var in operational application?

- Although EnKF is promising in research, no evidence shows it can definitely outperform 4D-Var in operational. It has its own disadvantage, such as sampling errors.
- Variational data assimilation is well established in operational, it is difficult to be replaced, politically and technically.

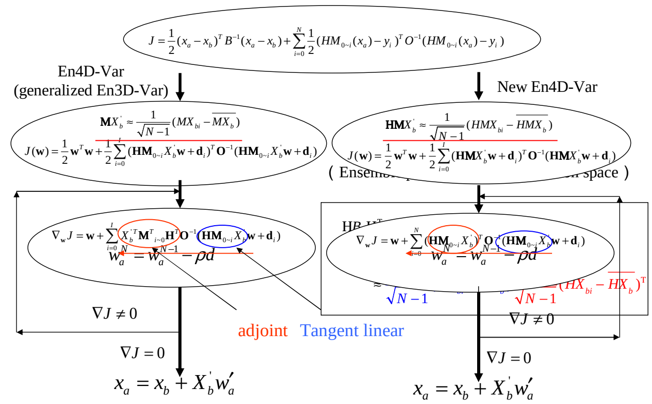
How should we do?

- My perspective is
  - ✓ to include the flow-dependent background error covariance from ensemble forecast into 4D-Var, without significant change of the existing setup of operational 4D-Var system,
  - ✓ to use the ensemble perturbation matrix in the 4D-Var formulation and avoid tangent linear and adjoint model development in the 4D-Var setup.

En3D-Var (Lorenc 2003)



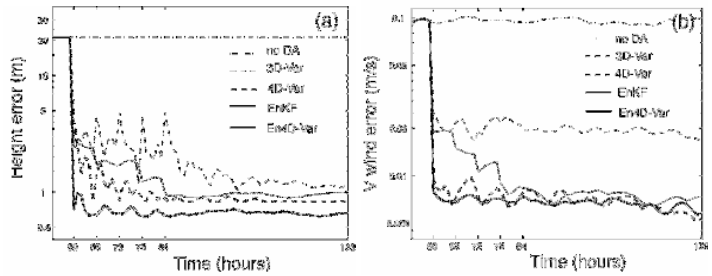
En4D-Var



Some characteristics of En4D-Var

- En4D-Var uses the flow-dependent B matrix from ensemble forecast.
- It avoids tangent linear and adjoint models in its formulation.
- It couples incremental approach with preconditioning using ensemble perturbation matrix.
- But sampling errors are introduced to En4D-Var.

Proof-of-concept test with shallow water model



Evolution of domain-average RMSE

WRF En4D-Var

- The success of En4D-Var with simple models gives us great motivations to implement the technique using WRF model.
- The biggest challenge for En4D-Var in real atmospheric model (e.g. WRF) is how to deal with sampling errors.

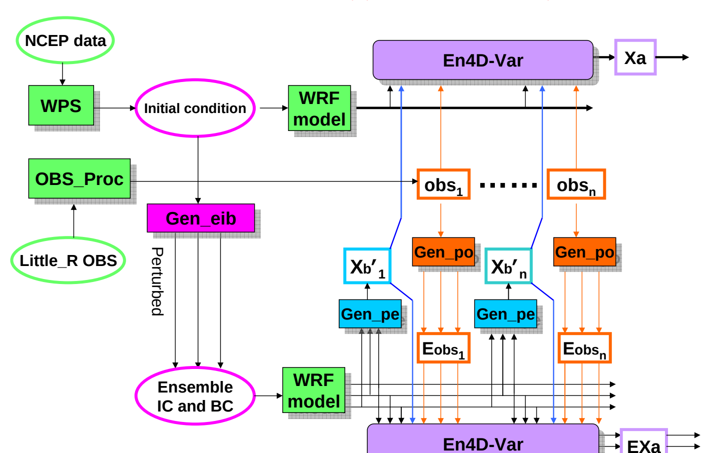
Localization in ensemble-based data assimilation

- Why
  - Imperfect ensemble => sampling errors => analysis increment noise
  - Ensemble dimension is far less than model dimension => B matrix rank is restricted to the low-dimension sub-space => deficient rank and underdetermined problem
- How
  - local truncation (Houtekamer and Mitchell 1998)
  - hybrid scheme (Hamill and Snyder 2001, Lorenc 2003)
  - Schur product (Houtekamer and Mitchell 2001, Lorenc 2003, Buehner 2005)

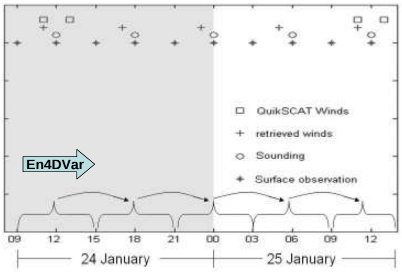
WRF En4D-Var

- We conduct horizontal and vertical localizations using Schur operator to deal with spatial sampling errors, similar to the method in EnKF localizations.
- We empirically put the analysis time at the mid of assimilation window to alleviate the temporal sampling errors.

Flow Chart for WRF-En4DVar



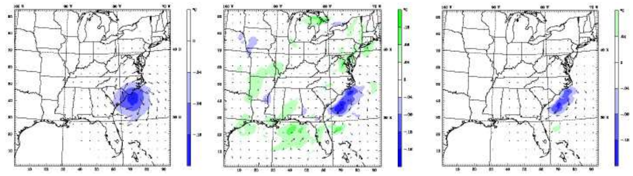
En4D-Var OSSE design



- Test with the “blizzard of 2000” case: 24-25 January 2000
- Assimilation window: 6 hours
- Cycling: From 0900 UCT 24 to 1500 UTC 25 Januare 2000
- Observations are simulated with real positions

Single observation test

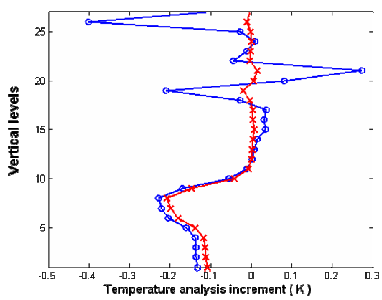
(single T observation at 850hpa at 24-12Z Jan.)



WRF-Var En4D-Var without localization En4D-Var with localization

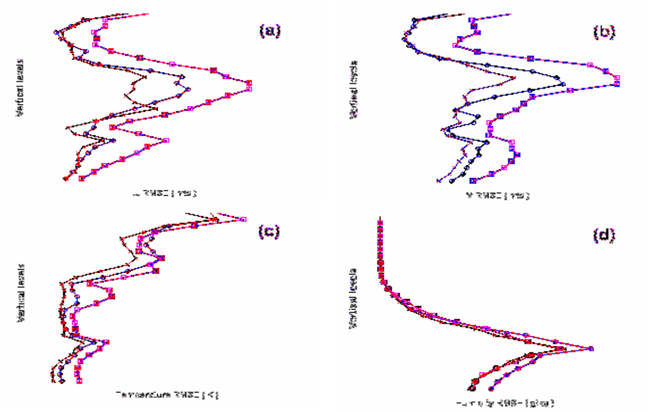
Increments of wind vector and temperature at 1000hpa

Cross-section of temperature increment



Blue Circle-line : analysis increment without localization
Red Cross-line : analysis increment with localization

RMSE at different analysis time

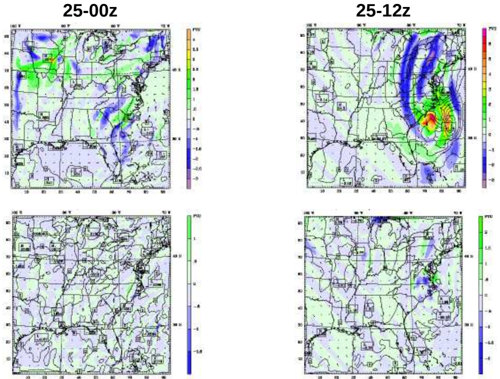


Analysis at the beginning (pink), mid (red), and end (blue) of assimilation window

Analysis error at 300hpa

25-00z 25-12z

CTL
PV
Wind
Height

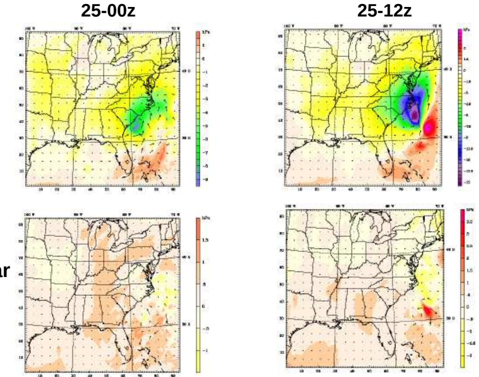


En4Dvar
PV
Wind
Height

Analysis error at 1000hpa

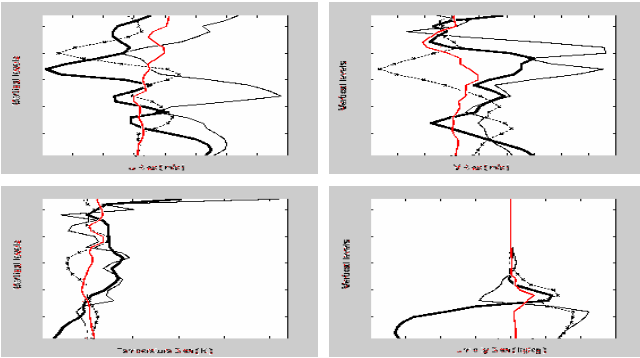
25-00z 25-12z

CTL
SLP
Wind



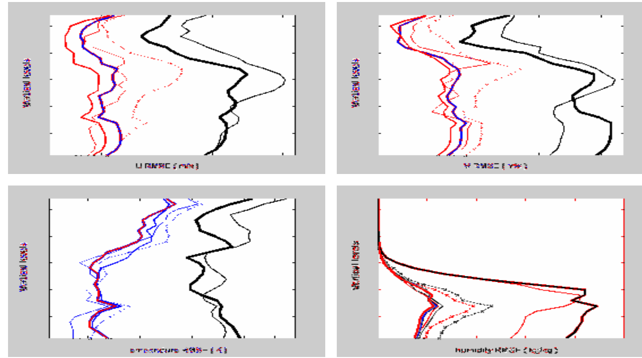
En4DVar
SLP
Wind

Vertical bias at 24-12Z/25-00Z/25-12Z



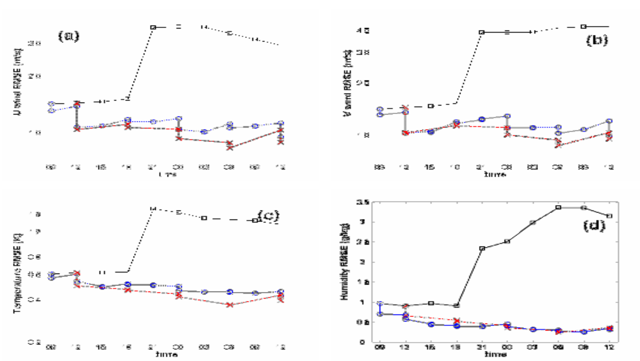
Red: analysis **Black: CTL**
Dot-cross: 24-12Z thin line: 25-00Z thick line: 25-12Z

Vertical RMSE at 24-12Z/25-00Z/25-12Z



Red: En4D-Var analysis **Blue: forecast** **Black: CTL**
Dot-cross: 24-12Z thin line: 25-00z thick line: 25-12Z

Domain average RMSE in cycling



Black: CTL Blue: En3DVar Red: En4DVar

Summary

- WRF En4D-Var shows flow-dependant structure in its analysis increments.
- The localization with Schur operator can greatly reduce the analysis noise.
- The WRF En4D-Var optimal analysis time is at the middle (instead of the beginning) of assimilation window.
- OSSEs indicate that the analysis error using WRF En4D-Var is much less than that of control experiment.
- WRF En4D-Var gets a better analysis comparing with En3D-Var cycling.
- Comparison of WRF En4D-Var with WRF 4D-Var is under way.

Related publications:

Liu, C., Q. Xiao, and B. Wang, 2008: An ensemble-based four-dimensional variational data assimilation scheme: Part I: Technical formulation and preliminary test. *Mon. Wea. Rev.*, **136**, 3363-3373.

Liu, C., Q. Xiao, and B. Wang, 2008: An ensemble-based four-dimensional variational data assimilation scheme: Part II: Observing system simulation experiments with Advanced Research WRF (ARW). *Mon. Wea. Rev.*, early online release at
http://ams.allenpress.com/perlserv/?request=get-abstract&doi=10.1175%2F2008MWR2699.1

Thank you!