

#### **Strategies For The Use Of Ensemble Information in Data Assimilation**

Dale Barker Adjoint Workshop, 13 October 2011

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#### Outline

- Motivation.
- The Issues.
- Where Next?

# Met Office

#### Motivation

- Current atmospheric DA conceived in 80's-90's. Time for a review!
- Comparison of EnDA vs VarDA indicates competitive performance.
- Computational efficiency of 4D-Var on next-gen HPC under question.
- Forecast model likely to change radically in next 5-10yrs. Should DA?
- Increasing range of applications for DA. Should effort be more 'seamless'?
- What is best method for Met Office for next 5-10 years?



# EnKF - Current state of the art

ECMWF EnKF vs 12-h 4DVar (T159), conv obs only

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Mean curves
500hPa Geopotential
Root mean square error forecast
N.hem Lat 20.0 to 90.0 Lon -180.0 to 180.0
Date: 20050101 00UTC to 20050131 00UTC
Mean calculation method: standard
Population: 31,31,31,31,31,31,31,31,31,31,31,31,31 (averaged)

operations t799l91 all obs



enkf t159l60 conv. obs



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# Relative Contribution of Changes In NWP+DA vs. Observing Network

(JMA Reanalysis/NWP Performance)



- Most of forecast benefit over 25yr period due to better models and DA systems, rather than observations (especially in NH).
- Caveat: Not true for all metrics (e.g. precipitation shows bigger impact of obs).



#### July 2011 Global DA/SA Upgrade

%Reduction in RMSE For Critical Met Office Forecast Parameters:

**Vs. Observations** 

**Vs. Met Office analyses** 



• Biggest reduction in overall global forecast error for many years.

• First time in memory that all parameters have reduced error vs obs. (usually a mix).



#### Computational Efficiency: 4D-Var Scalability on IBM P6



- Code optimization + increased resolution improve scalability.
- Significant algorithmic changes unavoidable for next-generation DA, e.g. weak-constraint 4D-Var, reduced cost linear model, etc.



Increased complexity + total cost.

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#### 4D-Var

• The cost function J is typically

$$J\left[\mathbf{x}(t_{0})\right] = \frac{1}{2}\left[\mathbf{x}(t_{0}) - \mathbf{x}^{b}(t_{0})\right]^{T} \mathbf{B}_{o}^{-1}\left[\mathbf{x}(t_{0}) - \mathbf{x}^{b}(t_{0})\right] + \frac{1}{2}\sum_{k=0}^{K}\left[\mathbf{y}_{k} - \mathbf{y}_{k}^{o}\right]^{T} \mathbf{R}_{k}^{-1}\left[\mathbf{y}_{k} - \mathbf{y}_{k}^{o}\right] \\ \left(\mathbf{y}_{k} = HM_{k}\left[\mathbf{x}^{b}(t_{0}) + \delta\mathbf{x}(t_{0})\right] = HM_{k}\left[\mathbf{x}^{b}(t_{0})\right] + \mathbf{HM}_{k}\mathbf{x}^{b}(t_{0})\right] + \mathbf{HM}_{k}\mathbf{x}^{b}(t_{0})\right]$$

- *M* is nonlinear model. **M** is linear model (not usually tangent linear).  $\mathbf{B}_0$  is the background error covariance (includes variable transformation e.g. streamfunction, potential vorticity, etc).
- Efficient minimization of cost function requires gradient

$$\begin{bmatrix} \frac{\partial J}{\partial \mathbf{x}(t_0)} \end{bmatrix}^T = \mathbf{B}_o^{-1} \begin{bmatrix} \mathbf{x}(t_0) - \mathbf{x}^b(t_0) \end{bmatrix} + \sum_{k=0}^K \begin{bmatrix} \mathbf{M}(t_{k+1}, t_0) \mathbf{H}_k^T \mathbf{R}_k^{-1} (\mathbf{y}_k - \mathbf{y}_k^o) \end{bmatrix}$$
  

$$\mathbf{M}^T \text{ is the transpose (adjoint) of } \mathbf{M}. \qquad \mathbf{M}(t_k, t_o)^T = \prod_{j=0}^{k-1} \mathbf{M}(t_{j+1}, t_j)^T$$
  
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# The Ensemble Kalman Filter (Example: Stochastic EnKF)

• Forecast step (for ensemble member *n*, observation time *i*):

$$\mathbf{X}_{n}^{f}(t_{i}) \neq M_{i-1} \left[ \mathbf{X}_{n}^{a}(t_{i-1}) \right]$$
$$\mathbf{P}_{ens}^{f} = \frac{1}{N_{e} - 1} \mathbf{X}^{\prime f} \mathbf{X}^{\prime f^{T}}$$

• Update step:

$$\mathbf{x}_{n}^{a}(t_{i}) = \mathbf{x}_{n}^{f}(t_{i}) + \mathbf{K}_{ens}(\mathbf{y}_{i}^{op}) + H_{i}(\mathbf{x}_{n}^{f}(t_{i}))),$$
$$\mathbf{K}_{ensi} = \mathbf{P}_{ens}^{f}(t_{i})\mathbf{H}_{i}^{T}(\mathbf{H}_{i}\mathbf{P}_{ens}^{f}(t_{i})\mathbf{H}_{i}^{T} + \mathbf{R}_{i})^{-1}$$

- $\mathbf{y}_i^{op}$  are observations perturbed with random noise (called stochastic EnKF).
- No linear model so EnKF less tied than 4D-Var to particular model.
- Adjoints not required.
- Covariance modelling still required (localization, inflation, etc).



#### Plans For NWP Model: Spring 2013 (Tentative)

#### <u>Global</u>

- 16-20km 85L (85km top)
  Hybrid 4DVAR (40km inner-loop)
- ≻60 hour forecast twice/day
- ►144 hour forecast twice/day
- ≻48/12member 40km MOGREPS-G 4\*

#### **MOGREPS-EU**

Common NWP/reanalysis domain.
12Km 70L (40km top)
3D-Var (or NoDA)
48 hour forecast
12 members ; 4 times per day

#### <u>UKV</u>

1.5km 70L (40km top)
3DVAR (hourly)
36 hour forecast, 4 times per day
12 member 2.2km MOGREPS-UK

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- 2012 ENDGAME (ND with v at poles, higher order accuracy)
- 2015 Ying-Yang option (stitch two ND regional domains together).
- 2020 Next-Generation MetOffice Dynamical Core (GUNGHO)
- Radical change to dynamical core need to rewrite 4D-Var?
- Or, move to less model-dependent DA?



#### DA For the Earth System Model

- MetO DA activities:
  - Atmosphere: VAR (Hybrid three/four-dimensional variational DA)
  - Ocean: NEMOVAR
  - Land: Nudging (now) -> EKF (2012) -> EnKF (later).
  - Coupled DA: (WG formed, begin with coupled initialization).
  - Not yet: Space weather, Chemical, Sea-ice.
- Increasingly diverse applications of DA.
- Do we need to rationalize range of techniques/systems or rely on increased application-specific collaboration (e.g. NEMOVAR)?
- Do we need strongly-coupled ESM DA (atmosphere-ocean-land-etc). If so, how does that influence the design of next-generation DA algorithms?



• Need for strongly-coupling (unified DA) not yet clear.





#### Where we are now: Hybrid Variational/Ensemble DA

Scientific Motivation:

- 4D-Var provides flow-dependent covariances via the linear (perturbation forecast) model. However, still limited by climatological background error covariance.
- Current MetO Ensemble has only 24 members likely to suffer from significant sampling error for DA.
- Mix (hybrid) covariances can ameliorate weaknesses of both VarDA and EnDA.
- Lorenc 2003 indicates hybrid equivalent to deterministic EnSRF so no realt incentive to consider reaplcing with EnSRF.
- Hybrid permits leveraging of additional attractive features of variational algorithm: outer-loop for nonlinear DA, simultaneous treatment of all observations, balance constraints, etc, etc.
- Evolutionary (not revolutionary) path from VarDA to EnDA for operational NWP as future computers allow larger ensembles.





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Ensemble Increment, A=A<sub>h</sub>

# Estimation of Ensemble Sampling Error

**Met Office** Method: Simulate ensemble by sampling climatological **B**. Study effect of ensemble size, localization, hybrid on minimization.

Pure Ensemble Covariance

Hybrid Covariance



- Pure ensemble covariance still significantly underfitting observations, even with O(400) ensemble members, and reduced localization scales.
- Hybrid approach likely to be valid for the significant future.

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Good, Bad (only sample of issues shown)

- Hybrid 3/4D-Var + EnsFilter (MetO + NCEP, NRL, HIRLAM, etc)
  - Reaps benefits of variational framework (e.g. outer-loop, Huber norms, etc).
  - Hybrid forecast error covariances ameliorate ensemble sampling error.
  - Model-error treatment possible through weak-constraint formulism.
  - Inconsistent Kalman Gain between DA and EPS two DA algorithms.
  - Computational efficiency compromised by 4D-Var scalability and scheduling.
  - Inflexible to alternative model/application.
  - ETKF Localization issues (could replace with e.g. EnSRF).

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#### EnDA: The contenders Good, Mixed, Bad (only sample of issues shown)

- EnKF Serial EnSRF, Serial EnKF, ETKF, EAKF, LETKF, MLEF, EnKF-GLS
  - Bypasses need to develop adjoint/linear model (but still need covariance modelling).
  - Scalable (at least forecast step), flexible.
  - Consistent Kalman Gain between DA and EPS.
  - Increased reliance on input data (ensembles) rather than explicit DA modelling.
  - Does not reap benefits of variational framework (e.g. simultaneous treatment of obs).
  - Model-error and sampling error confused during inflation process.
  - Can reproduce/improve EnKF with hybrid, so why bother?



#### MF/ECMWF: EnDA = Ensembles of 4D-Var (Courtesy Lars Isaksen)

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EDA Cycle: 10 x Low-Res T95/159 4D-Var. Perturbed obs/SSTs:



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Good, Bad (only sample of issues shown)

- Ensemble of Weak-Constraint 4D-Vars (e.g. MF, ECMWF)
- Reaps benefits of variational framework.
- Model-error treatment possible through weak-constraint formulism.
- DA scalable (small ensemble+WK4DV).
- Consistent Kalman Gain between DA and EPS
- Analysis step costly compared to forecast step.
- Inflexible to alternative model/application (OOPS will help).
- Limited ensemble size (e.g. 10) enables only conservative use of ensemble covariances (e.g. variances, lengthscales, etc).
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Good, Bad (only sample of issues shown)

- Particle filter
- True nonlinear/non-Gaussian DA.
- DA scalable, flexible.
- Pure PF unaffordable (the 'curse of dimensionality' will never be able to afford pure PF for NWP).
- Does not reap benefits of variational framework. Radical, risky change at present!
- Perception that PFs are still a black art? 'You can do what you like' Peter Jan.
- Promising results combining PF ideas with e.g. nudging, WEnKF, 4D-Var (but practical solutions may not be that different to other current options e.g. ensembles of 4D-Var, hybrid nudging-EnKF systems, etc).

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• Ensemble of 4D-Ensemble-Var (Var mimicking the EnKF):





4D-Ensemble-Var (dashed), Hybrid 4D-Var (dotted), Hybrid 3D-Var (solid).



Good, Bad (only sample of issues shown)

- 4D-Ensemble-Var (Var mimicking the EnKF).
  - Reaps benefits of variational framework (including e.g. outer-loop).
  - Bypasses need to develop adjoint/linear model.
  - Model-error possible through weak-constraint formulism (e.g. MECV).
  - DA scalable, flexible.
  - Hybrid forecast error covariances (natural extension to current hybrid).
  - Minimization cost similar to 3D-Var, EnKF significantly less that 4D-Var.
  - Increased reliance on data (ensembles) rather than physical knowledge (linear model, balance) to provide covariance info.
  - Large I/O and memory requirement.
  - Output is not a model solution. Where to start forecast?
  - Inconsistent Kalman Gain between DA and EPS (solution: 'Ensemble of 4D-Ensemble-Vars').



# Strategy Going Forward

 Improve 4D-Var efficiency: SE + algorithmic changes + leave door open for potential ensemble of WK4DV as 'plan B'.

Plan A:

- Continue to develop hybrid for short/medium-term (1997-2015):
  - Increase ensemble size, more sophisticated localization, etc.
  - Consider replacing ETKF as ensemble perturbation generator.
  - Develop convective-scale hybrid 3/4D-Var (2012-2015).
- Develop 4D-Ensemble-Var for medium/long-term:
  - Code and test within current VAR framework (2011-2012).
  - Extend to an 'Ensemble of 4D-Ensemble-Vars' (2012-2015).
  - Retire PF model if/when 4D-Ensemble-Var beats 4D-Var.



#### Summary

- DA continues to provide major NWP performance improvements.
- 4D-Var/EnKF competitive. Combination even better.
- Practical issues (cost, maintenance, flexibility, scheduling) have major impact on strategy for operational NWP.
- Many centres opting for 'Ensemble Variational Data Assimilation' as way forward.
- For MetO, plan A is hybrid, then 4D-Ensemble-Var if beats hybrid 4D-Var.