### **ECO-RAP**

A new adaptive error covariance localization tool for 4-dimensional ensemble data assimilation

Craig H. Bishop, Daniel Hodyss, William. F. Campbell, and Justin G. Mclay

Naval Research Laboratory, Monterey, California

# Outline

- Motivation
- How ECO-RAP works
- Idealized tests
- Review
- Computational considerations/speed-up
- Preliminary experiment with NWP model
- Conclusions

#### **Small Ensembles and Spurious Correlations**



Ensembles give flow dependent, but noisy correlations

### **Small Ensembles and Spurious Correlations**



#### Today's fixed localization functions limit adaptivity

### **CALECO**



- Ensemble correlations contain propagation and length scale information.
- Ensemble correlations corresponding to large true correlations are bigger than those corresponding to true zero correlations. (Variance of spurious is 1/K).
- Raising ensemble correlations to a power attenuates small values more than large values.
- Sandwiching *non-adaptive* localization matrix between ensemble correlation matrices raised to a power yields *adaptive* localization matrix.

### **Length Scale Variability Experiment**



Tune for short error length scales then test on broad

## Length Scale Variability Experiment



• Tune ECO-RAP and Non-Adaptive localization methods for lowest analysis error at scale d = 16 with 156 obs

• Compare the performance of the two schemes when the true error correlation length scale is broader than that for d=16

256

### **Single ob. 4D Data Assimilation Test (16 members)**

- 32 variables in periodic domain
- •Truth moves to the right one grid point per time step
- One ob. per time step at variable 16 (very small ob error variance)
- •After 32 time steps use all 32 collocated observations to estimate the initial state

### **Single ob. 4D Data Assimilation Test (16 members)**





- No localization produces an inaccurate estimate everywhere
- Non-adaptive localization can only use observations close to the analysis time
- ECO-RAP recovers the true state

### **Localization or Moderation?**

- 1) Are the variables whose forecast errors correlate with another variable confined to the geographic neighbourhood of that variable?
- 2) What is "local" about forecast errors due to a misspecification of the albedo of stratus clouds?
- 3) What is "local" about errors associated with a sudden stratospheric warming event?
- 4) ECO-RAP can moderate spurious correlations even when the answer to (1) is "No".

#### **Localization or Moderation?**



## Review

- ECO-RAP is a new flow-adaptive localization method for ensemble DA.
- It raises ensemble correlations to powers (Hadamard products) to selectively reduce spurious correlations.
- Broad localization functions are obtained by sandwiching non-adaptive localization matrices between correlation matrices raised to a power.
- ECO-RAP adapts to changes in the propagation and scale characteristics of errors.
- ECO-RAP is as good as non-adaptive localization when error distribution is invariant.

- *N*=number of model variables
- $\mathbf{C}_{\text{ECO-RAP}} = \overline{\mathbf{C}_{K}^{\circ n} \tilde{\mathbf{E}} \tilde{\boldsymbol{\Lambda}} \tilde{\mathbf{E}}^{T} \mathbf{C}_{K}^{\circ n}}$  has  $N^{2}$  elements
- So does the Covariances Adaptively Localized with ECO-rap (CALECO) matrix

$$\mathbf{P}_{CALECO}^{f} = \mathbf{P}_{K}^{f} \circ \left[ \overline{\mathbf{C}_{K}^{\circ n} \tilde{\mathbf{E}} \tilde{\boldsymbol{\Lambda}} \tilde{\mathbf{E}}^{T} \mathbf{C}_{K}^{\circ n}} \right]$$



If covariance of turbulence ensemble was CALECO then computer memory would only need to store "energy containing eddies". Is there a turbulence ensemble whose covariance is CALECO?

### **Turbulence ensemble for CALECO**

It may be shown that if

$$\mathbf{A} = \mathbf{U}\mathbf{U}^T$$
 and  $\mathbf{B} = \mathbf{V}\mathbf{V}^T$  then  $\mathbf{A} \circ \mathbf{B} = [\mathbf{U} \otimes \mathbf{V}][\mathbf{U} \otimes \mathbf{V}]^T$ ,

where  $U \otimes V$  indicates the matrix whose columns list all possible non-linear products of the columns of U and V.

Consequently, covariance of turbulence ensemble one obtains by taking all possible non-linear products of "energy containing eddies" U and V is the element-wise product of the covariances of U and V. Hence, since

$$\mathbf{P}_{K}^{f} = \mathbf{Z}_{K} \mathbf{Z}_{K}^{T} \text{ and } \mathbf{C}_{\text{ECO-RAP}} = \overline{\mathbf{C}_{K}^{\circ n} \tilde{\mathbf{E}} \tilde{\boldsymbol{\Lambda}} \tilde{\mathbf{E}}^{T} \mathbf{C}_{K}^{\circ n}} = \left[ \overline{\mathbf{C}_{K}^{\circ n} \tilde{\mathbf{E}} \tilde{\boldsymbol{\Lambda}}^{1/2}} \right] \left[ \overline{\mathbf{C}_{K}^{\circ n} \tilde{\mathbf{E}} \tilde{\boldsymbol{\Lambda}}^{1/2}} \right]^{T}$$

It follows that the energy containing eddies for the turbulence ensemble whose covariance is CALECO are

$$\mathbf{Z}_{K}$$
 and  $\left[\overline{\mathbf{C}_{K}^{\circ n}\tilde{\mathbf{E}}\tilde{\Lambda}^{1/2}}\right]$   
Since columns of  $\left[\overline{\mathbf{C}_{K}^{\circ n}\tilde{\mathbf{E}}\tilde{\Lambda}^{1/2}}\right]$  are in spectral space, for broad localization functions can truncate leaving  $\left[\overline{\mathbf{C}_{K}^{\circ n}\tilde{\mathbf{E}}\tilde{\Lambda}^{1/2}}\right]$  only has *L* columns (*L* < *N*).

### **Separability assumption for ECO-RAP**

The cost of computing  $\mathbf{C}_{K}^{\circ n}$  may be reduced from  $N^{2}$  to  $(nx + ny + nz)^{*}nv^{*}nt$ by approximating the rows of  $\mathbf{C}_{K}^{\circ n}$  by separable functions of (x,t), (y,t) and (z,t).

This separability assumption also reduces markedly reduces the computation and memory requirements for  $\left[\overline{\mathbf{C}_{K}^{\circ n}\tilde{\mathbf{E}}\tilde{\Lambda}^{1/2}}\right]$ , the square root of ECO-RAP.

#### v Increment From a Single T Ob.



#### **Example ECO-RAP Localization Functions**

3 Z



6 Z







3 Z



6 Z



9 Z



### **LETKF using CALECO: Preliminary Experiment**

- K = 27 member ensemble, T119L30 NWP model (NOGAPS).
- 7x7x30 grid box size .
- 3° grid resolution.
- We observe *u*,*v*,*T* at every point within the box at 3Z and 9Z, and attempt to estimate the state at 6Z.
- 'Truth' is assumed to be a 21-27 hour forecast.
- First guess/ensemble come from last 6 hrs of 9 hr forecast valid at the same time.
- Observations are the 'truth' plus random number
- Observation error variance is  $1 \text{ m}^2/\text{s}^2$  and  $1 \text{ K}^2$
- Number of obs = 8820, Number of variables=13230
- K\_Turbulence=1640
- Smoothed ensemble perturbations before applying ECO-RAP
- Correlations were raised to the 12<sup>th</sup> power

#### **Globally Averaged Results**



### Summary

- Ensemble localization is equivalent to running ensemble through a 1-step turbulent cascade where energy containing eddies are the raw ensemble and the columns of the square root of the localization covariance matrix.
- Turbulence analogy, separability, and spectral truncation enable computationally efficient DA algorithm cost governed by error dimension.
- ECO-RAP allows larger observation volumes in LETKF outperforms raw ensemble.

## Review

- ECO-RAP is a new flow-adaptive localization method for ensemble DA.
- It raises ensemble correlations to powers (Hadamard products) to selectively reduce spurious correlations.
- Broad localization functions are obtained by sandwiching non-adaptive localization matrices between correlation matrices raised to a power.
- ECO-RAP adapts to changes in the propagation and scale characteristics of errors.
- ECO-RAP is as good as non-adaptive localization when error distribution is invariant.

## **Intermediate Summary**

- ECO-RAP is a new flow-adaptive localization function for ensemble DA, which uses:
  - The largest ensemble correlations to predict the location and scale of evolving error correlation structures
  - Raises ensemble correlations to powers (Hadamard products) to selectively reduce spurious correlations
  - Uses matrix products and spectral smoothing to obtain broad, smooth localization functions
- ECO-RAP pays no penalty when the true errors are not varying
- ECO-RAP adapts to error correlation structures undergoing both propagation and scale changes

### **Local Ensemble Transform Kalman Filter**

- Local Ensemble Transform Kalman Filter (LETKF) [Hunt et al (2007; Physica D)]
  - Each grid point is updated only with the observations lying within grid point's observation volume.
  - Each grid point can be updated independently so algorithm is scalable.
  - Finite observation volume is needed to limit the effect of spurious long-distance correlations.
  - Problematic for observations of vertical integrals of model variables such as satellite obs.
  - Problematic for 4D assimilation when errors propagate further than the localization width over the time window of interest.
  - Redundancy in observation processing since there is a high degree of overlap between volumes.

### **LETKF using CALECO turbulence**

- When CALECO is used in LETKF size of observation volumes is unconstrained because localization is implicit in CALECO.
- Larger observation volumes are appropriate for satellite DA and 4D-DA
- Larger observation volumes enable entire grid columns (or indeed the entire globe) to be updated simultaneously and hence avoids redundancy in observation processing.
- Note that ensemble size is now given by the size of the turbulence ensemble.
- The size of the turbulence ensemble is an upper bound on the dimension of the error and is usually < number of obs.

### **Multi-variate or Uni-variate ECO-RAP**

- ECO-RAP can provide multi-variate "localization".
- However, in this experiment, to further increase the computational efficiency of ECO-RAP, we chose a single variable  $\theta_e$  to localize *u*,*v*,*T*
- Future work will consider fully multivariate ECO-RAP together with alternative univariate formulations (e.g. using φ)

### ECO-RAP, Part 2: Inexpensive Huge Ensembles

Craig H. Bishop, Daniel Hodyss, William. F. Campbell, and Justin G. Mclay

Naval Research Laboratory, Monterey, California

#### **ECORAP** versus No Localization

#### No Localization



**ECORAP** 



#### **ECORAP** in the LETKF



### **Length Scale Variability Experiments**



### **Small Ensembles and Spurious Correlations**

• Current ensemble localization functions poorly represent propagating error correlations.



#### Today's fixed localization functions limit ensemble-based 4D DA

### **Small Ensembles and Spurious Correlations**

• Current ensemble localization functions poorly represent propagating error correlations.



#### Today's fixed localization functions limit ensemble-based 4D DA