

# **Lecture 4: 4D-Var Diagnostics**

# Outline

- Posterior/analysis error estimates
- Consistency checks, hypothesis tests, degrees of freedom & information content
- Array modes
- Clipped analyses

# Posterior Error Estimates

# Posterior/Analysis Error Estimates

Posterior error covariance:

$$\begin{aligned}\mathbf{E}^a &= \left\langle (\mathbf{z}_a - \mathbf{z}_t)(\mathbf{z}_a - \mathbf{z}_t)^T \right\rangle \\ &= \left\langle (\mathbf{z}_b + \delta\mathbf{z}_a - \mathbf{z}_t)(\mathbf{z}_b + \delta\mathbf{z}_a - \mathbf{z}_t)^T \right\rangle \\ &= (\mathbf{I} - \mathbf{K}\mathbf{G})\mathbf{D}(\mathbf{I} - \mathbf{K}\mathbf{G})^T + \mathbf{K}\mathbf{R}\mathbf{K}^T\end{aligned}$$

(Caveat:  $\mathbf{E}^a$  correct only if  $\mathbf{D}$  and  $\mathbf{R}$  are correct)

But for dual Lanczos vector formulation:

$$\mathbf{K} \approx \tilde{\mathbf{K}}_k = \mathbf{D}\mathbf{G}^T\mathbf{R}^{-1/2}\mathbf{V}_k\mathbf{T}_k^{-1}\mathbf{V}_k^T\mathbf{R}^{-1/2}$$

Lanczos vectors are orthonormal, and normal to subspace neglected by  $\tilde{\mathbf{K}}_k$  :

$$\mathbf{E}^a \approx \tilde{\mathbf{E}}^a = (\mathbf{I} - \tilde{\mathbf{K}}\mathbf{G})\mathbf{D}$$

# Posterior/Analysis Error Estimates

Approx. posterior error covariance:

$$\mathbf{E}^a \approx \tilde{\mathbf{E}}^a = (\mathbf{I} - \tilde{\mathbf{K}}\mathbf{G})\mathbf{D}$$
$$\tilde{\mathbf{E}}^a = \underbrace{\left( \mathbf{I} - \mathbf{D}\mathbf{G}^T \mathbf{R}^{-1/2} \mathbf{V}_k \mathbf{T}_k^T \mathbf{V}_k^T \mathbf{R}^{-1/2} \mathbf{G} \right)} \mathbf{D}$$

Everything is available during inner-loops  
of 4D-PSAS and R4D-Var, at no extra cost

$$\tilde{\mathbf{E}}^a \sim N_{\text{model}} \times N_{\text{model}} \quad \text{HUGE!}$$

Diagonal elements – *posterior* variances

define POSTERIOR\_ERROR\_I

Cross-covariance information from EOFs of  $\tilde{\mathbf{E}}^a$

define POSTERIOR\_EOFS

# Posterior/Analysis Error Estimates

For the primal formulation:

$$\mathbf{E}^a = \left( \mathbf{D}^{-1} + \mathbf{G}^T \mathbf{R}^{-1} \mathbf{G} \right)^{-1}$$

$$\mathbf{E}^a \approx \tilde{\mathbf{E}}^a = \mathbf{D}^{1/2} \mathbf{V}_k \mathbf{T}_k^{-1} \mathbf{V}_k^T \mathbf{D}^{1/2}$$

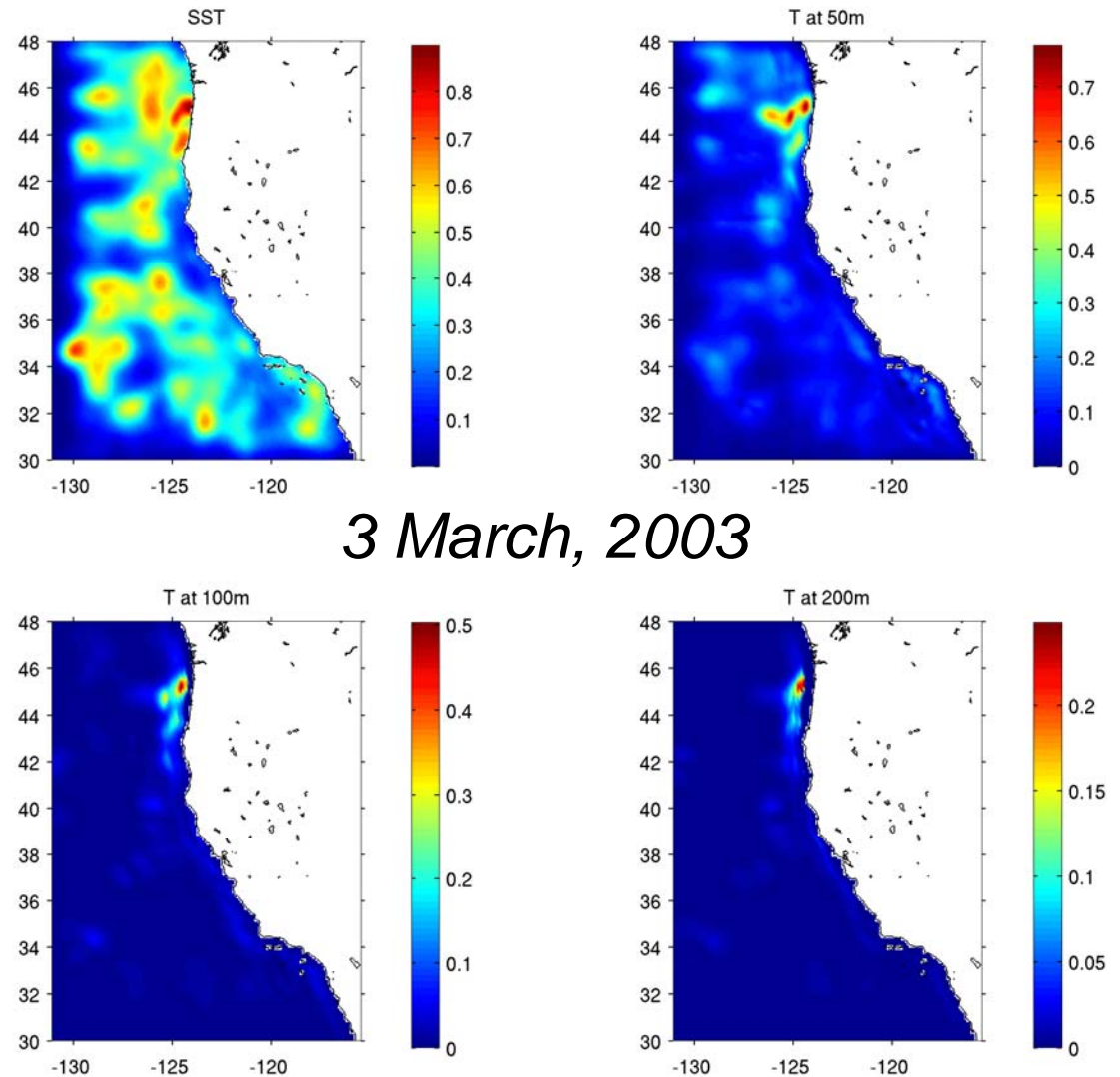
**Straightforward but not yet implemented in  
ROMS I4D-Var (due to large I/O requirements)**

# Expected Posterior Error

R4D-Var  
1 outer-loop  
100 inner-loops

3-10 March, 2003  
(10km, 42 levels)

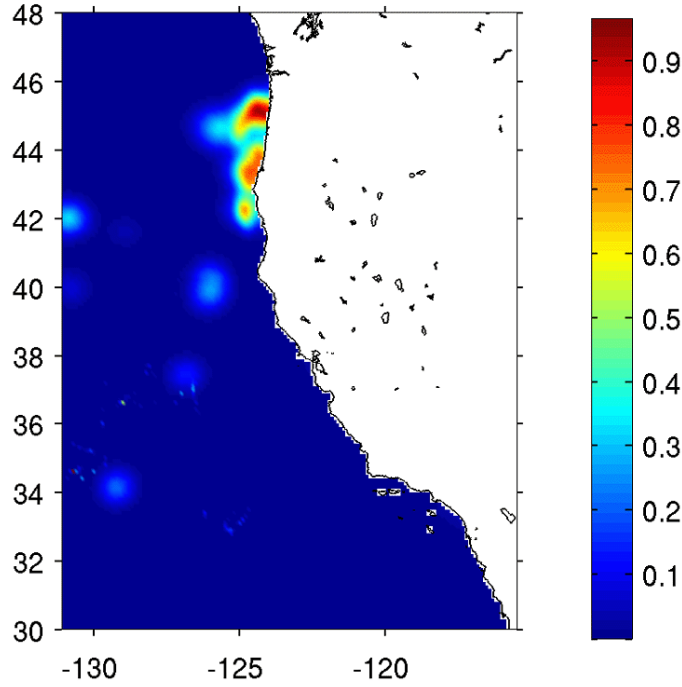
$\sigma_b = \text{prior error std}$   
 $\sigma_a = \text{posterior error std}$



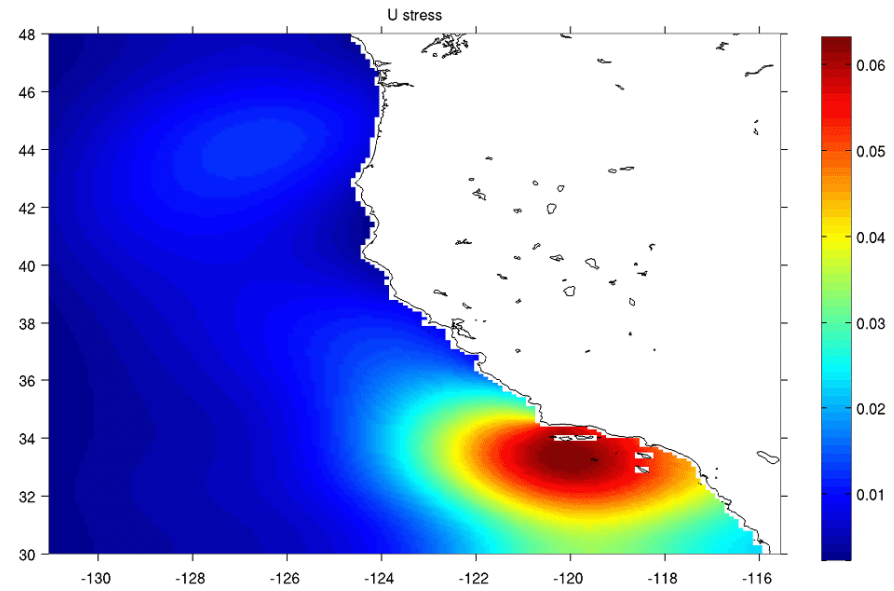
3 March, 2003

$$(\sigma_b - \sigma_a) / \sigma_b$$

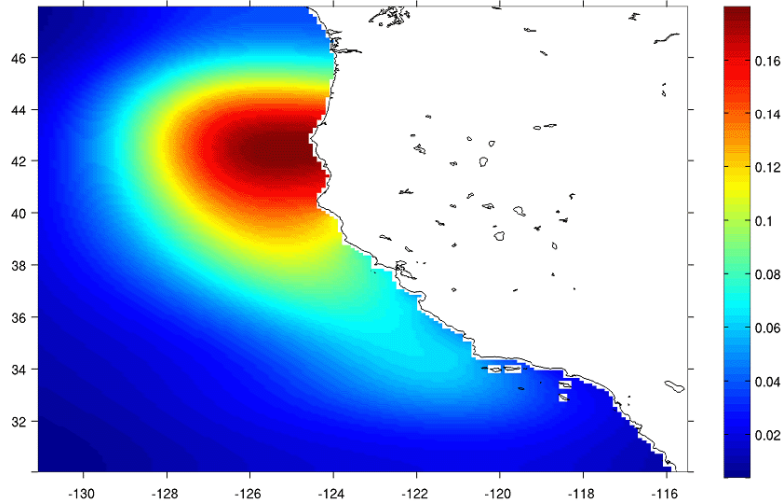
### SSS



### Zonal wind stress

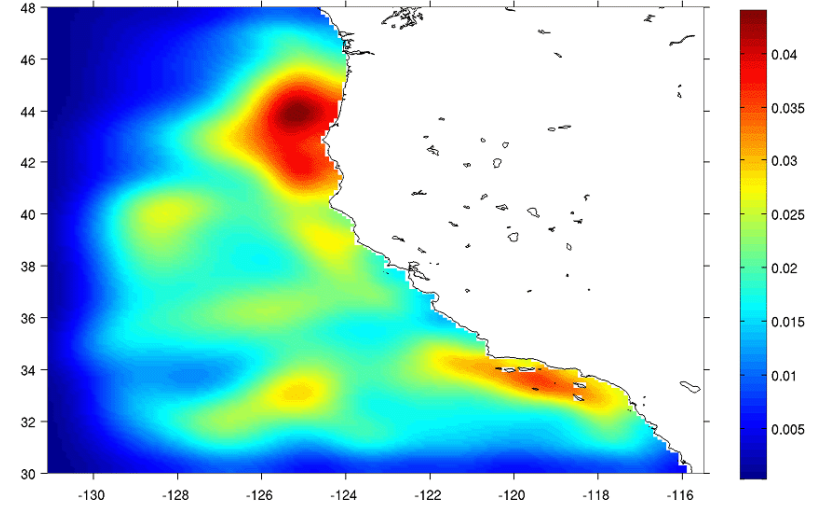


### V stress



### Meridional wind stress

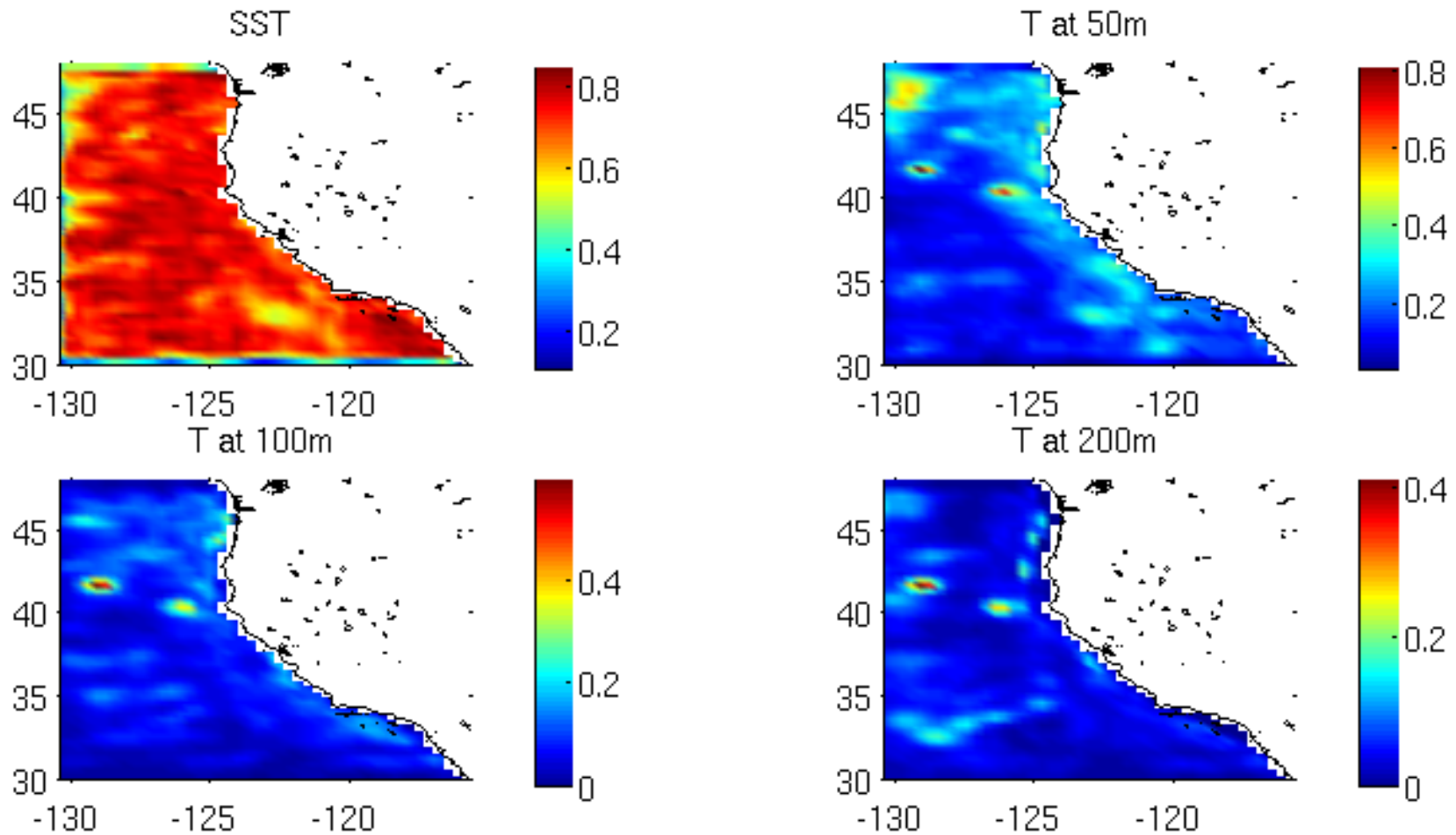
### Heat Flux



### Heat Flux



# Cautionary Note about $E^a$ Estimates



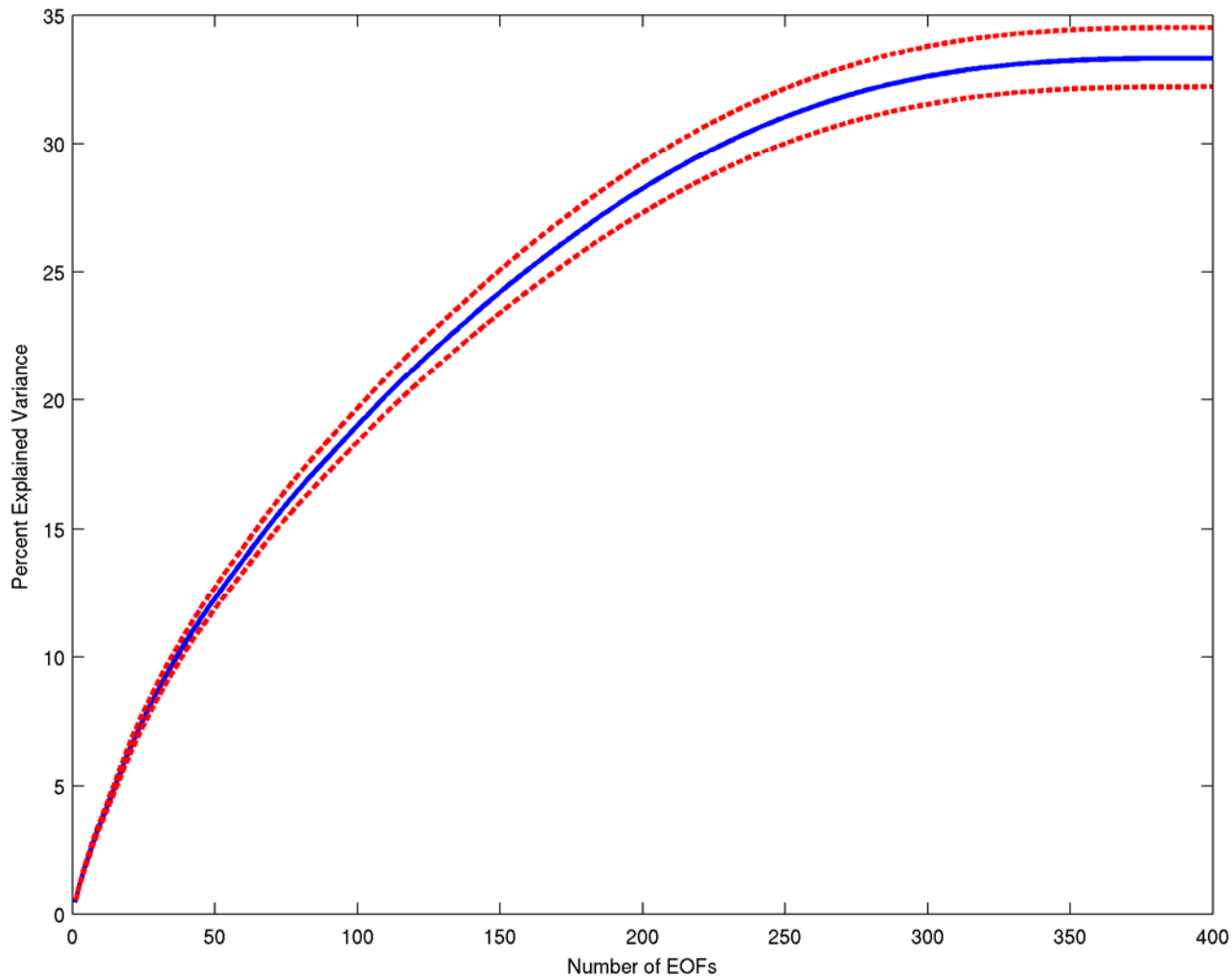
**800 Lanczos vectors vs 100 Lanczos vectors (30 km)**

$$(\sigma_{800}^2 - \sigma_{100}^2) / \sigma_{100}^2$$

**EOF spectrum is quite “flat”**

# Expected Posterior Error EOFs

Flat spectrum - perhaps due to preconditioning  
which clusters eigenvalues of  $(R^{1/2}GDG^TR^{1/2}+I)$  around 1.



**Consistency checks,  
hypothesis tests, degrees of  
freedom & information content**

# Consistency Checks in Obs Space

Statistics of the innovation vectors following  
Desroziers et al (2005):

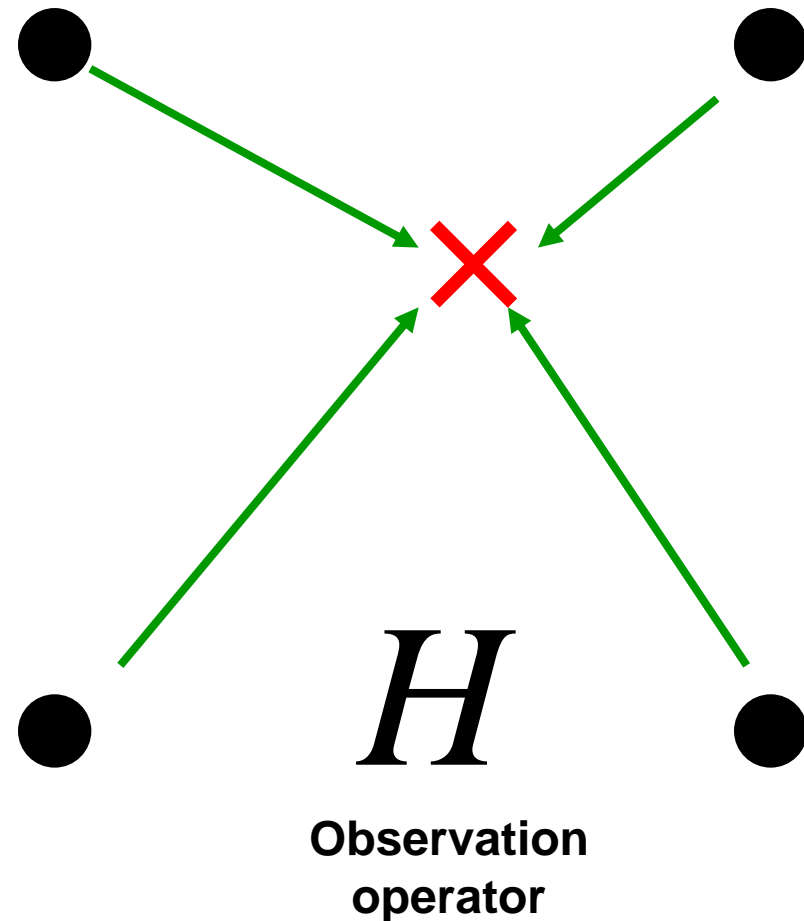
$$\mathbf{d} = (\mathbf{y} - H(\mathbf{x}_b))$$

$$\mathbf{d}_a^o = (\mathbf{y} - H(\mathbf{x}_a))$$

$$\mathbf{d}_b^a = (H(\mathbf{x}_a) - H(\mathbf{x}_b))$$

$$\tilde{\sigma}_b^2 = (\mathbf{d}_b^a)^T \mathbf{d} / p$$

$$\tilde{\sigma}_o^2 = (\mathbf{d}_a^o)^T \mathbf{d} / p$$



Compare  $\tilde{\sigma}_o$  with  $\sigma_o$  &  $\tilde{\sigma}_b$  with  $\sigma_b$

# Consistency Checks in Obs Space

Statistics of the innovation vectors following

Desroziers et al (2005):

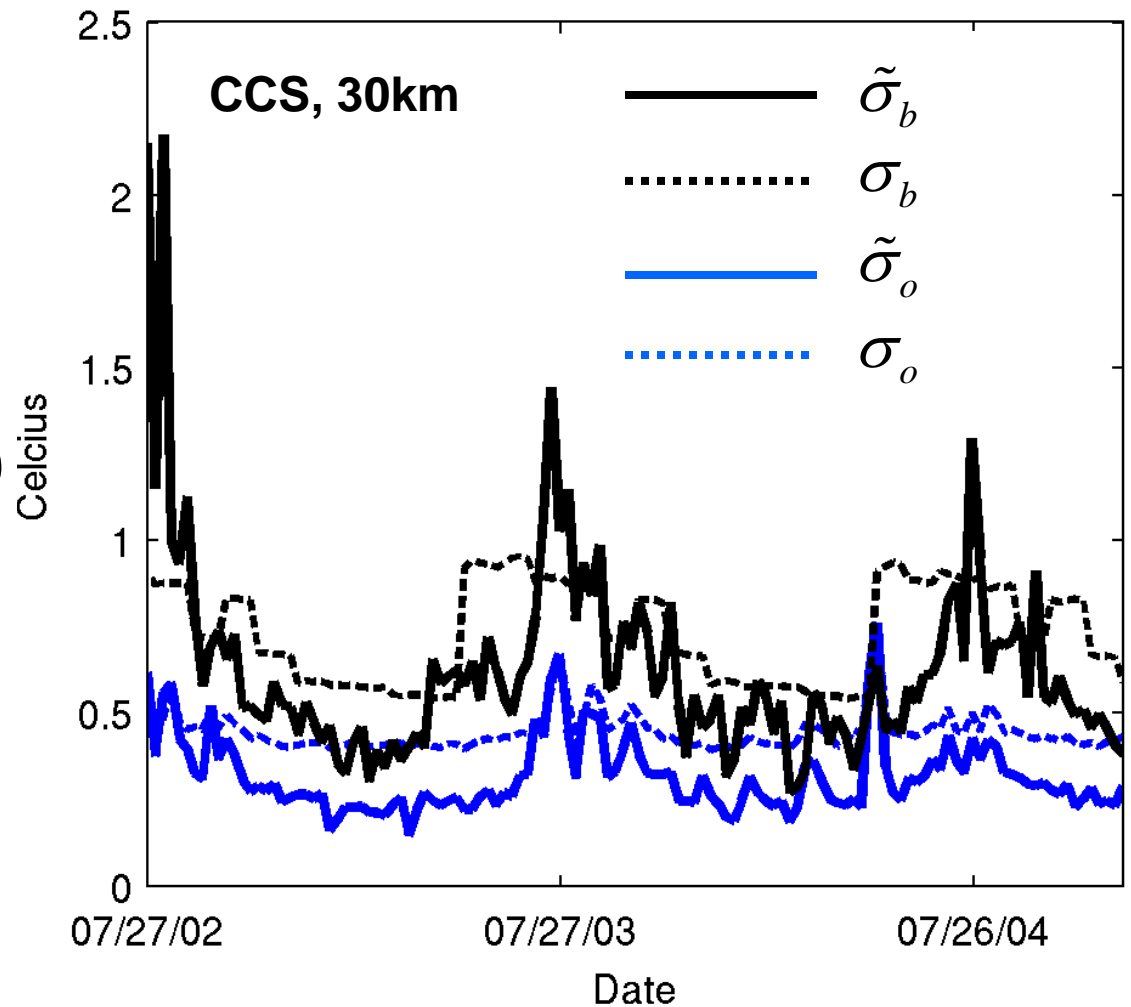
$$\mathbf{d} = (\mathbf{y} - H(\mathbf{x}_b))$$

$$\mathbf{d}_a^o = (\mathbf{y} - H(\mathbf{x}_a))$$

$$\mathbf{d}_b^a = (H(\mathbf{x}_a) - H(\mathbf{x}_b))$$

$$\tilde{\sigma}_b^2 = (\mathbf{d}_b^a)^T \mathbf{d} / p$$

$$\tilde{\sigma}_o^2 = (\mathbf{d}_a^o)^T \mathbf{d} / p$$



Compare  $\tilde{\sigma}_o$  with  $\sigma_o$  &  $\tilde{\sigma}_b$  with  $\sigma_b$

# Hypothesis Tests & Degrees of Freedom

Recall that the optimal increments minimize:

$$J = \underbrace{\frac{1}{2} \delta \mathbf{z}^T \mathbf{D}^{-1} \delta \mathbf{z}}_{J_b} + \underbrace{\frac{1}{2} (\mathbf{G} \delta \mathbf{z} - \mathbf{d})^T \mathbf{R}^{-1} (\mathbf{G} \delta \mathbf{z} - \mathbf{d})}_{J_o}$$

Theoretical min:  $J_{\min} = N_{\text{obs}} / 2$

No. of dof in obs  $\longrightarrow (J_b)_{\min} = \text{Tr}(\mathbf{KG}) / 2$

No. of dof in *prior*  $\longrightarrow (J_o)_{\min} = (N_{\text{obs}} - \text{Tr}(\mathbf{KG})) / 2$

“dof” – degrees of freedom

(Bennett et al, 1993;  
Cardinali et al, 2004;  
Desroziers et al., 2009)

# Degrees of Freedom & Information Content

Degrees of freedom in the obs:

$$(J_b)_{\min} = \text{Tr}(\mathbf{K}\mathbf{G}) / 2$$

But for  $m = N_{obs}$ :

$$\mathbf{K} = \mathbf{D}\mathbf{G}^T \mathbf{R}^{-1/2} \mathbf{V}_m \mathbf{T}_m^{-1} \mathbf{V}_m^T \mathbf{R}^{-1/2}$$

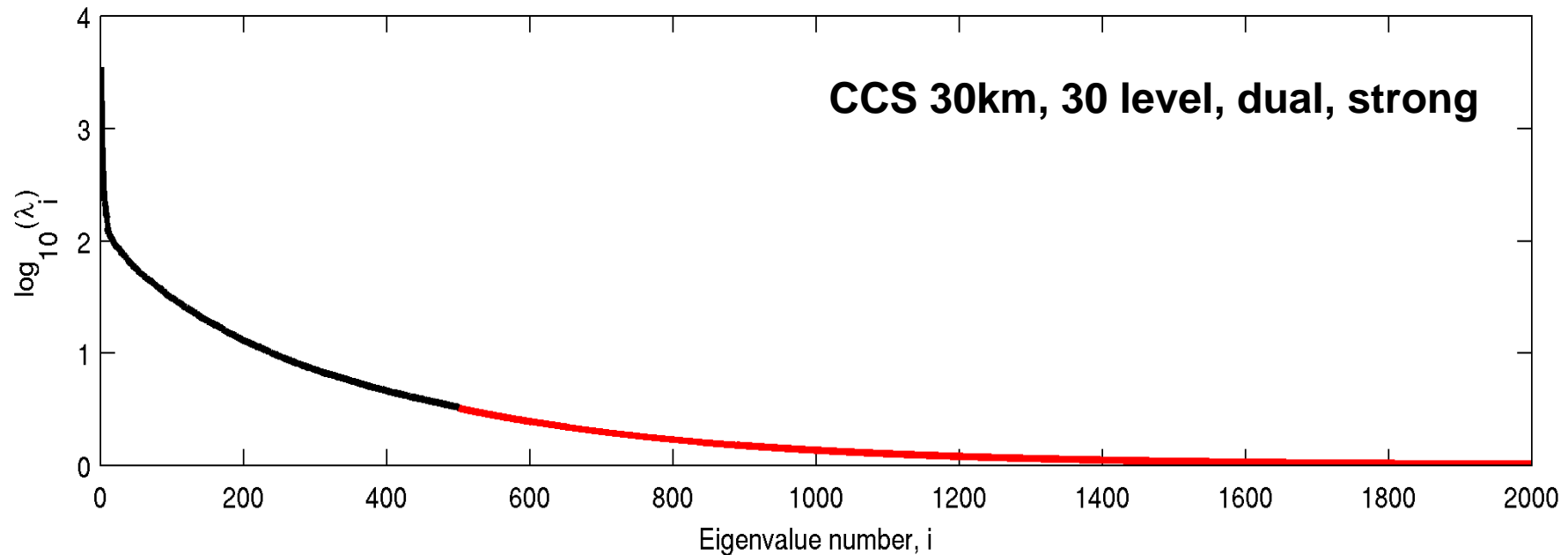
So:

$$\begin{aligned} (J_b)_{\min} &= \frac{1}{2} (N_{obs} - \text{Tr}(\mathbf{T}_m^{-1})) \\ &= \frac{1}{2} \left( N_{obs} - \sum_{i=1}^{N_{obs}} \lambda_i^{-1} \right) \end{aligned}$$

Eigenvalues  
of  $\mathbf{T}_m^{-1}$

# Degrees of Freedom & Information Content

(LhessianEV=T, s4dvar.in)



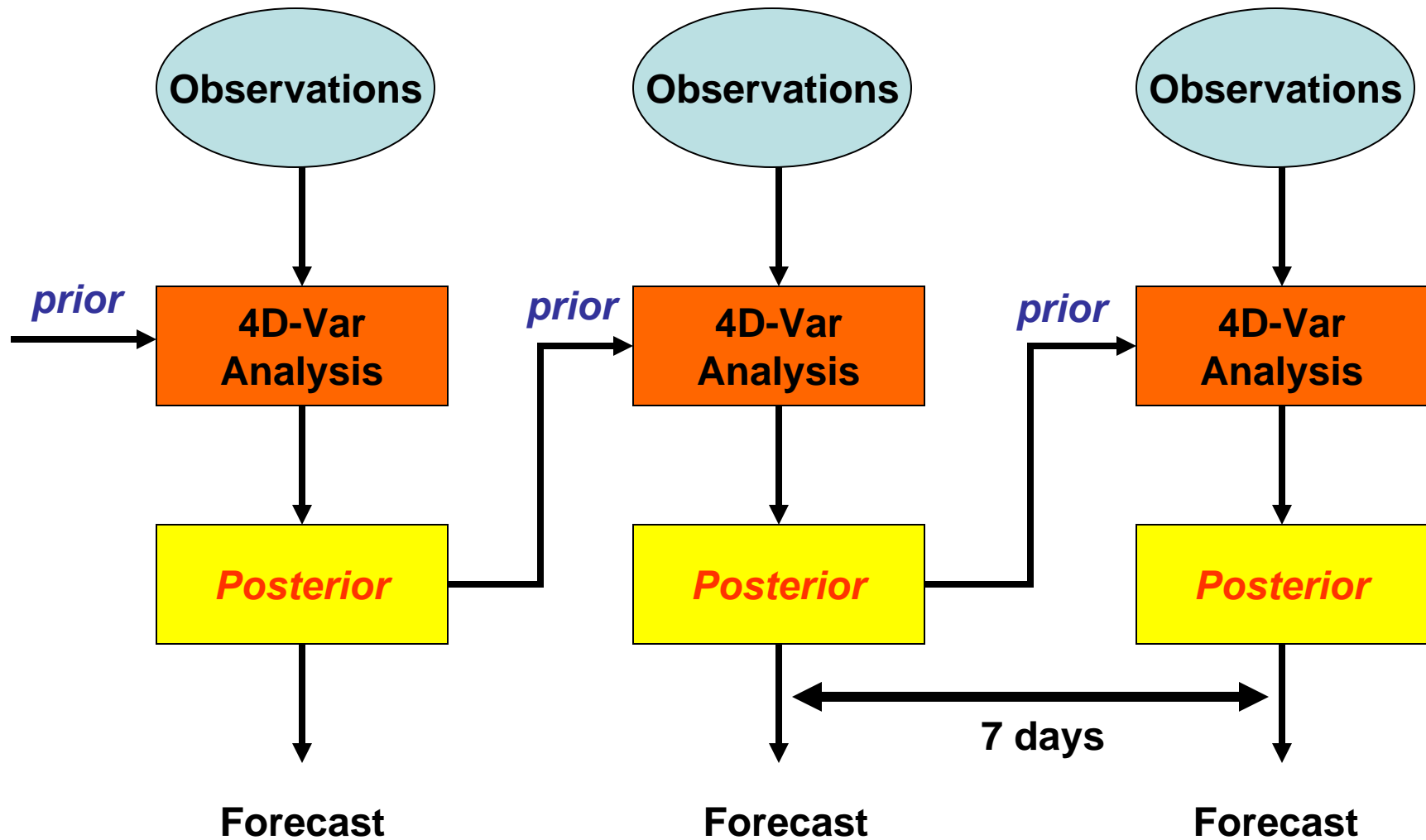
— Computed directly during R4D-Var

— Computed from a curve fit

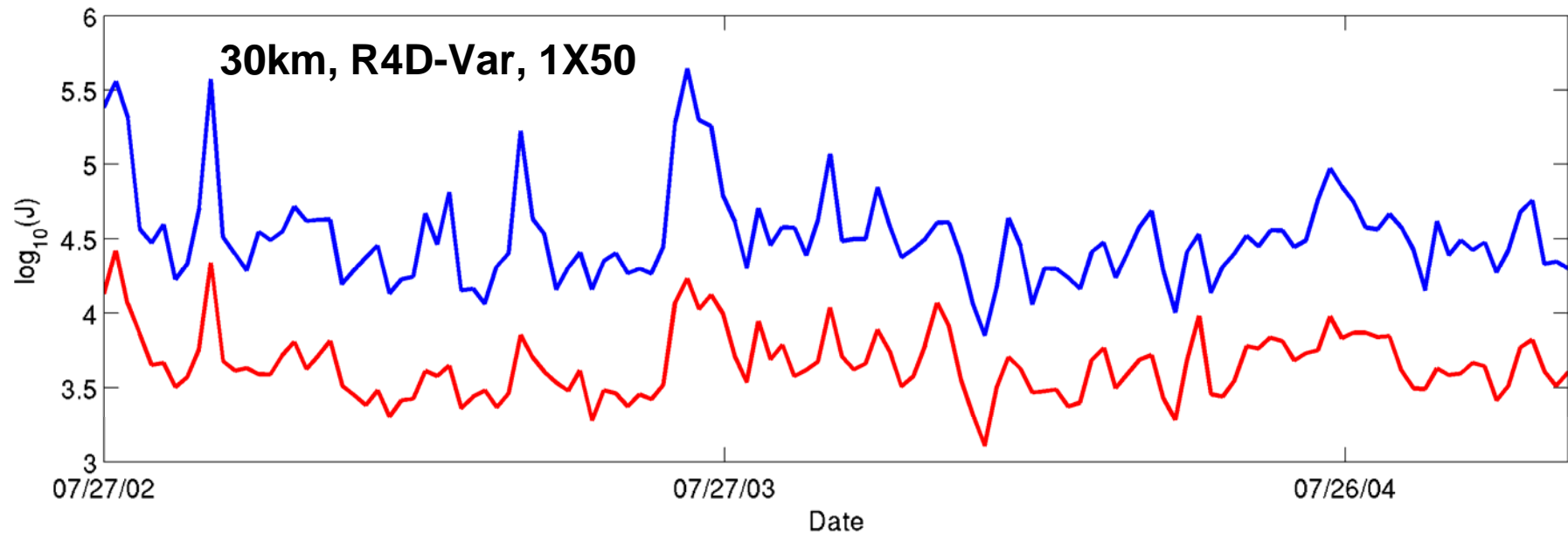
$$\log_{10}(\lambda_i) = ae^{-bi}, \quad a = 1.684, \quad b = 2.7 \times 10^{-3}$$



# Sequential 4D-Var with 30km CCS ROMS



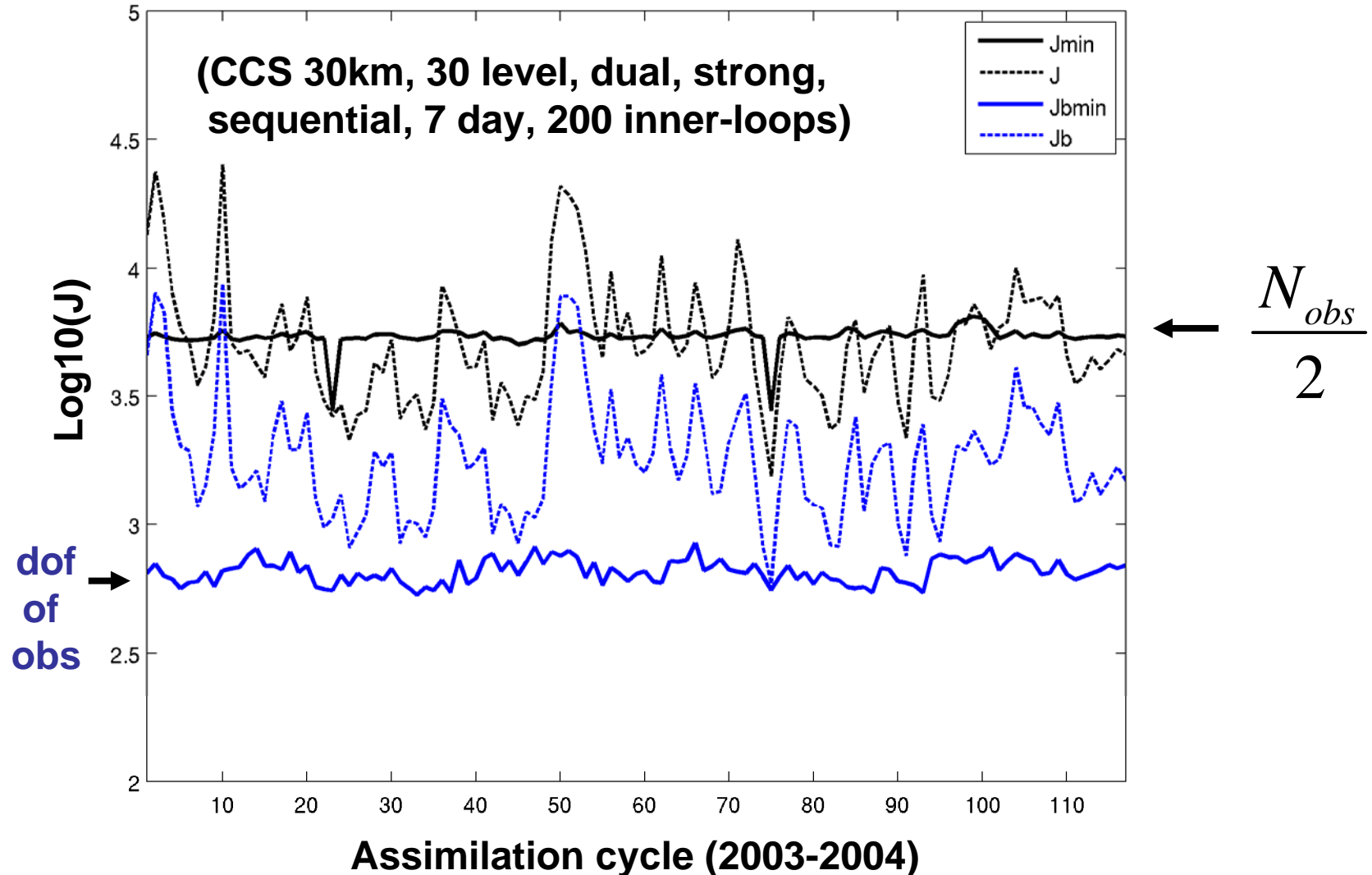
# Sequential 4D-Var CCS ROMS



— J initial

— J final

# Degrees of Freedom & Information Content



- Less than 10% of all observations provide independent info
- LOTS OF REDUNDANCY!
- $J_b > (J_b)_{min}$  and indicates over fitting to the obs
- $J \neq J_{min}$  and indicates that *prior* hypotheses are incorrect

# Array Modes

The eigenvalues  $\lambda_j$  of  $\mathbf{T}_m$  are also the eigenvalues of  $(\mathbf{R}^{1/2}\mathbf{G}\mathbf{D}\mathbf{G}^T\mathbf{R}^{1/2}+\mathbf{I})$ , the preconditioned “stabilized representer matrix.”

Consider the eigenpairs:  $(\lambda_i, \hat{\mathbf{w}}_i)$

Following Bennett (1985):

$$\begin{aligned}\delta\mathbf{x}_a(t) &= \mathcal{R}(t)\mathbf{R}^{-1/2}\mathbf{W}\mathbf{\Lambda}^{-1}\mathbf{W}^T\mathbf{R}^{-1/2}\mathbf{d} \\ &= \sum_{i=1}^{N_{obs}} \lambda_i^{-1} \left( \hat{\mathbf{w}}_i^T \mathbf{R}^{-1/2} \mathbf{d} \right) \Psi_i(t)\end{aligned}$$

Analysis state-  
vector increment

$$\Psi_i(t) = \sum_{j=1}^{N_{obs}} w'_{ji} \mathbf{r}_j(t) \quad \text{“array modes”}$$

$$\mathbf{w}'_i = (w'_{ji}) = \mathbf{R}^{-1/2} \hat{\mathbf{w}}_i$$

# Array Modes

**State-vector analysis increment:**

$$\delta \mathbf{x}_a(t) = \sum_{i=1}^{N_{obs}} \lambda_i^{-1} \left( \hat{\mathbf{w}}_i^T \mathbf{R}^{-1/2} \mathbf{d} \right) \Psi_i(t)$$

**Largest eigenvalue  $\lambda_1$  associated with  $\Psi_1(t)$ , nominally contributes least to analysis increment.**

**Thus  $\Psi_1(t)$  represents the most stable component of  $\delta \mathbf{x}_a$  with respect to changes in  $\mathbf{d}$ .**

**Array modes can be readily computed after dual 4D-Var:**

$$\Psi_j(t) = \mathcal{M}_b(t, t_0) \mathbf{D} \mathbf{G}^T \mathbf{R}^{-1/2} \hat{\mathbf{w}}_j$$

**(define ARRAY\_MODES)**

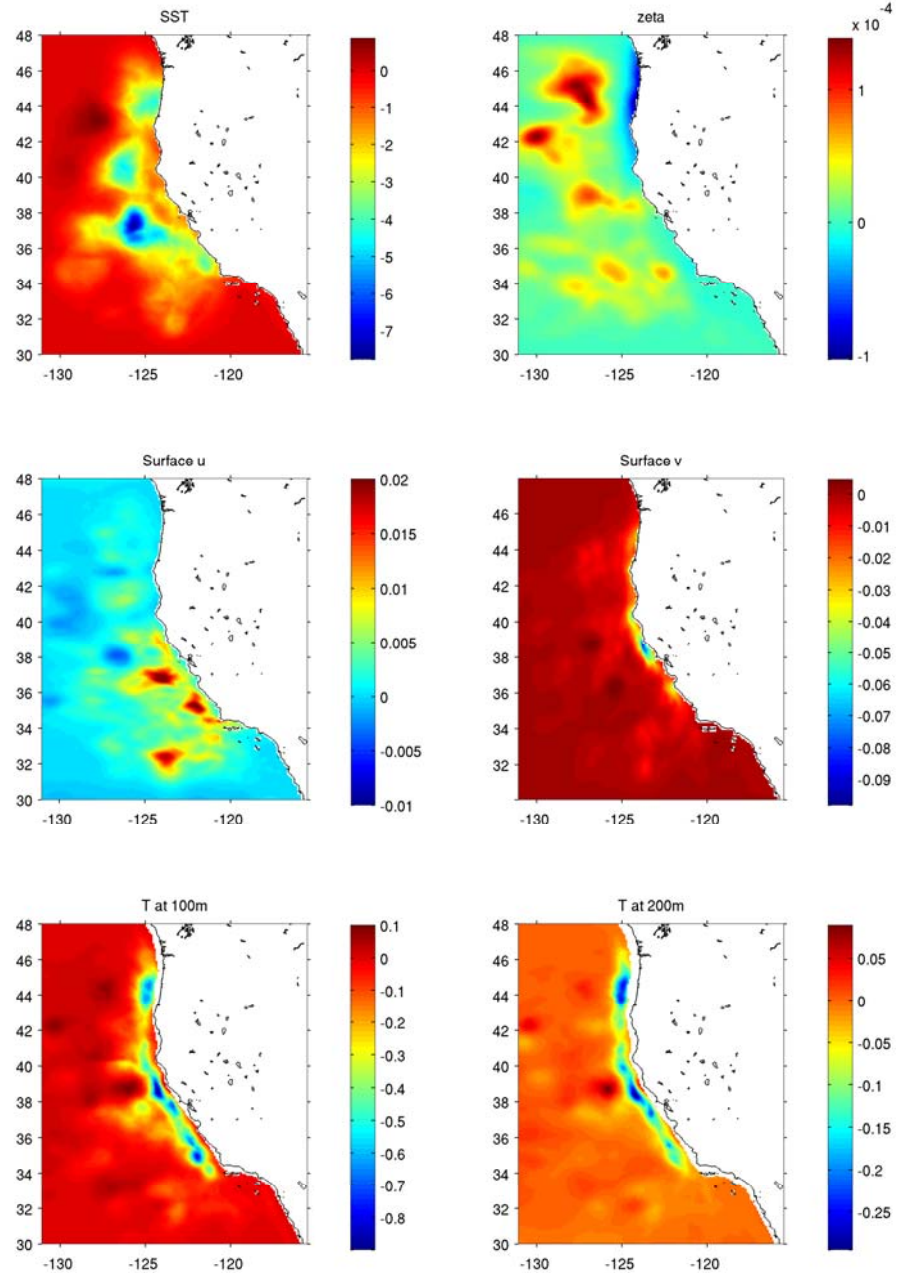
# Example:

CCS, 10km

R4D-Var

3-7 March, 2003

# $\Psi_1$ 3 March



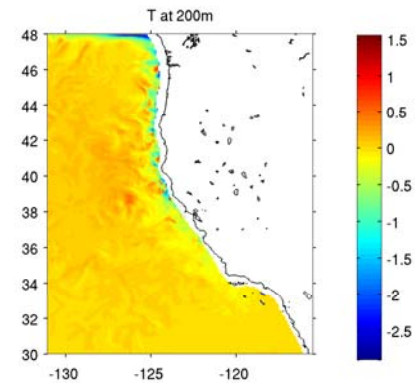
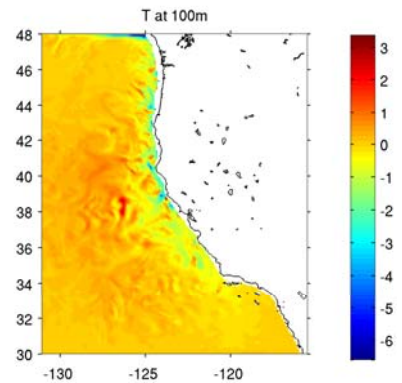
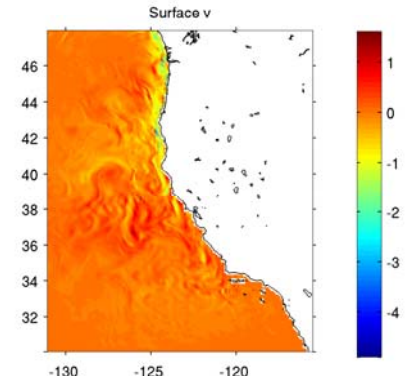
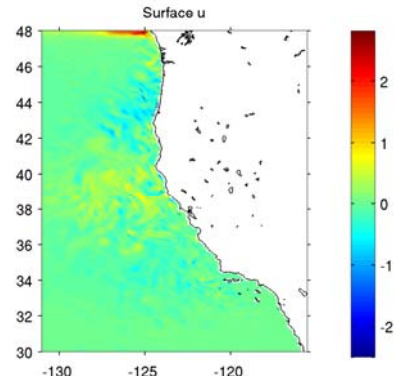
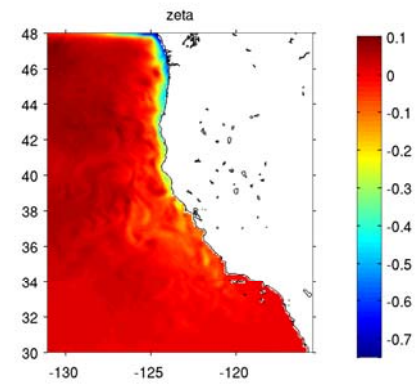
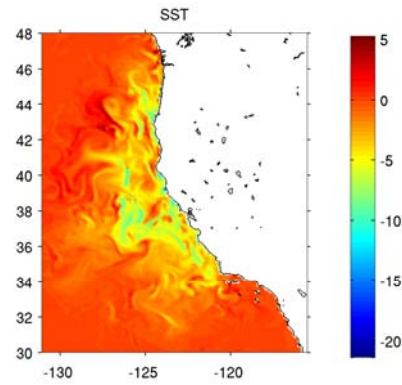
# Example:

CCS, 10km

R4D-Var

3-7 March, 2003

$\Psi_1$  7 March



# Example:

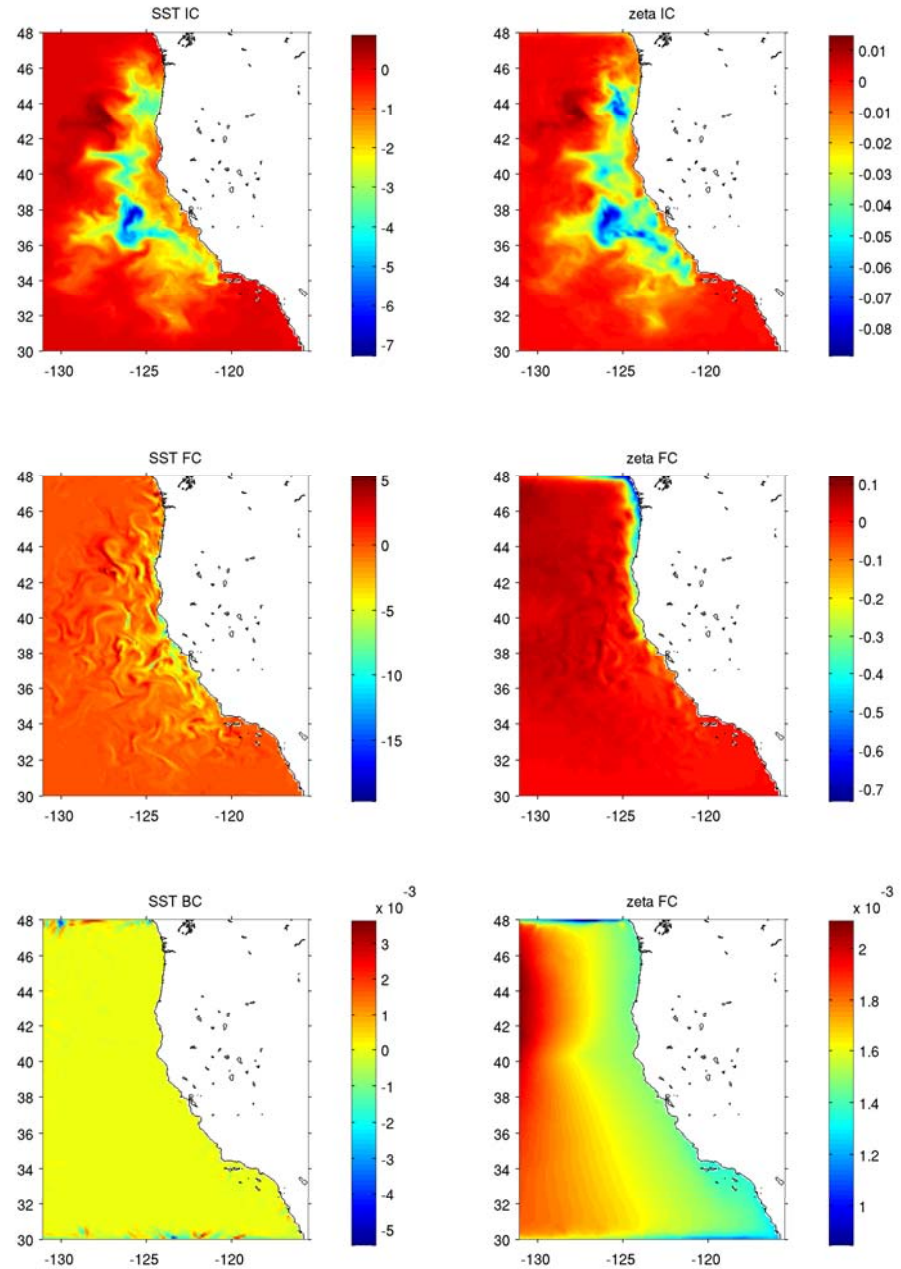
CCS, 10km

R4D-Var

3-7 March, 2003

# $\Psi_1$ 3 March

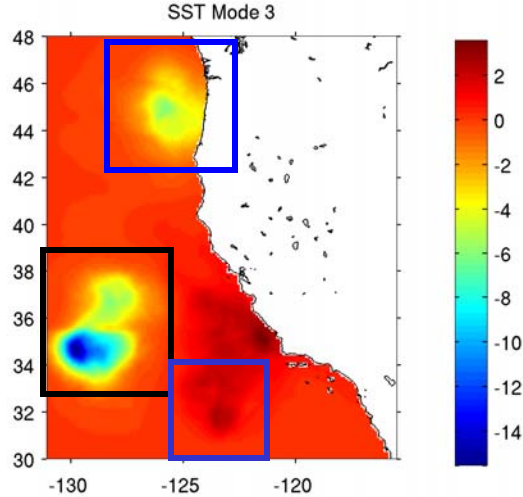
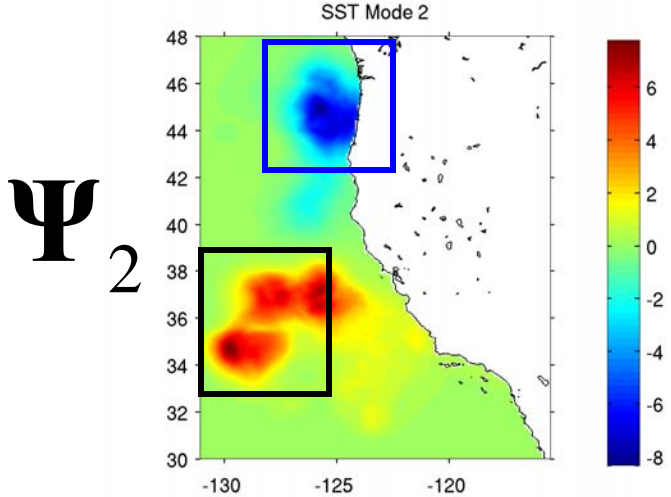
## Control vector contributions



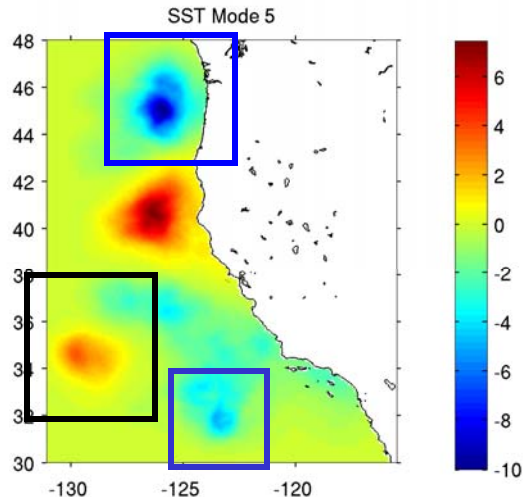
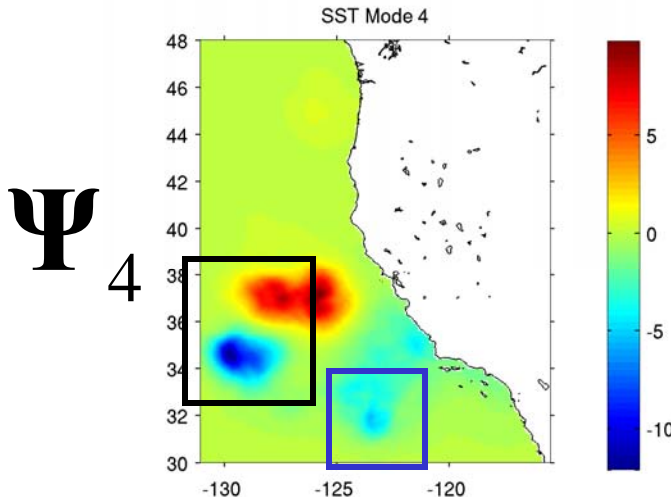


# Array Mode SST: 3 March

Obs redundancy?



Obs redundancy?



Obs redundancy?

# Clipped Analyses

Following Bennett (1985)

$$\delta \mathbf{x}_a(t) = \sum_{i=1}^{\boxed{M}} \lambda_i^{-1} \left( \hat{\mathbf{w}}_i^T \mathbf{R}^{-1/2} \mathbf{d} \right) \Psi_i(t)$$

Truncate (“clip”) the summation, discarding array modes  $\Psi_i$  for  $i > M$

$M$  is based on a criteria that reflects information content (i.e.  $\lambda_i < \alpha \lambda_1$  for  $i > M$ ).

$\alpha$  chosen so  $\Psi_i$  have scales  $<$  model resolution for  $i > M$

# Clipping using Indirect Representer Algorithm

Clipped analyses can be computed **AFTER** running R4D-Var or 4D-PSAS by exploiting the indirect representer algorithm according to:

$$\delta \mathbf{X}_a(t) = \mathcal{M}_b(t, t_0) \mathbf{D} \mathbf{G}^T \sum_{i=1}^M \lambda_i^{-1} \left( \hat{\mathbf{w}}_i^T \mathbf{R}^{-1/2} \mathbf{d} \right) \hat{\mathbf{w}}_i$$

where  $\mathcal{M}_b(t, t_0)$  is TLROMS linearized about the *prior/background*.

(Moore et al, 2010b)

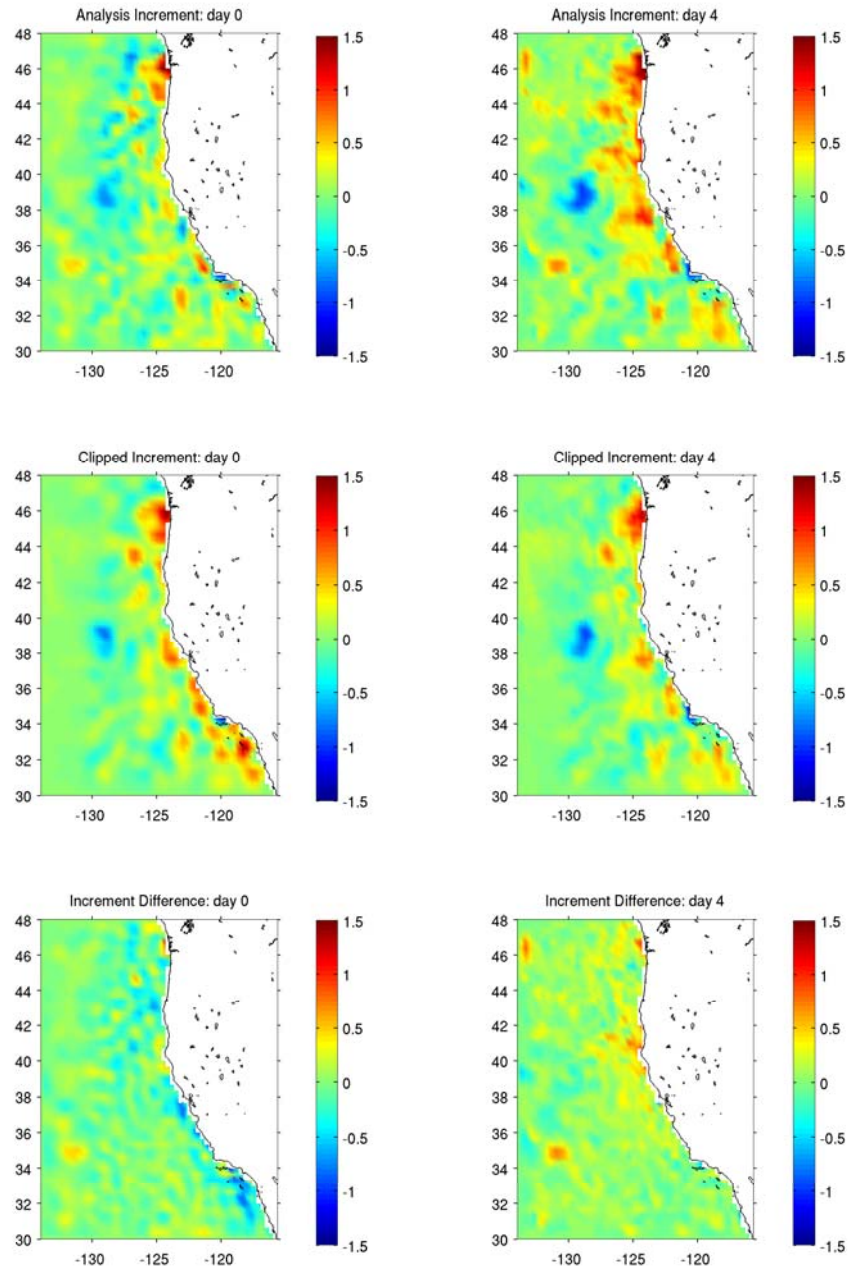
**Example:**  
**CCS, 30km**  
**R4D-Var**  
**3-7 March, 2003**  
**1 outer-loop**  
**800 inner-loops**

**Clipped using**  
**“1% rule” of**  
**Bennett & McIntosh**  
**(1985)**

**Discard  $\Psi_i$  for which**

$$\lambda_i < 0.01\lambda_1$$

$$M = 255$$



# Issues, Things to do, & Coming Soon

- *Posterior* error estimates available for 4D-PSAS & R4D-Var  
- available soon for I4D-Var
- *Posterior* error estimates are likely over estimates due to span of observation or model space by Lanczos vectors
- (4D-Var)<sup>T</sup> provides more reliable estimates (Lecture 5)

# Summary

- Posterior error estimates available via the utility afforded by the Lanczos algorithm.
- Posterior errors tend to be overestimates since  $m \ll N_{obs}$
- Consistency checks and hypothesis tests are useful indicators of validity of *prior* hypotheses and info content.
- Array modes provide info about possible data redundancy.
- Clipping can remove unphysical features from analyses.

# References

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- Desroziers, G., L. Berre, B. Chapnik and P. Poli, 2005: Diagnosis of observation, background and analysis-error statistics in observation space. *Q. J. R. Meteorol. Soc.*, **131**, 3385-3396.
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# References

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- Moore, A.M., H.G. Arango, G. Broquet, C.. Edwards, M. Veneziani, B.S. Powell, D. Foley, J. Doyle, D. Costa and P. Robinson, 2010b: The Regional Ocean Modeling System (ROMS) 4-dimensional data assimilation systems: Part II – Performance and application to the California Current System. *Ocean Modelling*, Submitted.