

**Estimates of analysis error,
forecast error, and predictability
using the adjoint of 4D-Var**

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Outline

- **Analysis error covariance**
- **TL and AD of 4D-Var**
- **Functions of the state vector**
- **Examples for the California Current**
- **Forecast errors (and predictability)**

Expected Analysis Error

Analysis: $\mathbf{x}_a = \mathbf{x}_b + \mathbf{Kd}$

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

Gain: $\mathbf{K} = \mathbf{B}\mathbf{H}^T (\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$

Analysis error covariance:

$$\mathbf{A} = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{B}(\mathbf{I} - \mathbf{K}\mathbf{H})^T + \mathbf{K}\mathbf{R}\mathbf{K}^T$$

In general: $\mathbf{K} \rightarrow \tilde{\mathbf{K}}$ (the “practical gain” matrix)

$$\tilde{\mathbf{A}} = (\mathbf{I} - \tilde{\mathbf{K}}\mathbf{H})\mathbf{B}(\mathbf{I} - \tilde{\mathbf{K}}\mathbf{H})^T + \tilde{\mathbf{K}}\mathbf{R}\tilde{\mathbf{K}}^T$$

Practical Estimates of A

- **Reduced rank approx of A**
(e.g. Fisher & Courtier, 1995)
 - over estimates expected errors
- **Ensemble Kalman Filters**
 - localization and inflation issues
- **Ensemble 4D-Var**
(e.g. Belo Pereira & Berre, 2006)
 - ensemble covariance mimics A
 - computationally demanding

TL and AD of 4D-Var

Analysis: $\mathbf{x}_a = \mathbf{x}_b + \mathcal{K}(\mathbf{d}, p_a, p_m)$

Inspired by ensemble 4D-Var:

$$\delta \mathbf{x}_a \simeq (\partial \mathcal{K} / \partial \mathbf{d}) \delta \mathbf{d}$$

$\delta \mathbf{y}$ with covariance \mathbf{R}
 $\delta \mathbf{x}_b$ with covariance \mathbf{B}

Expected analysis error covariance:

$$\hat{\mathbf{A}} = \langle \delta \mathbf{x}_a \delta \mathbf{x}_a^T \rangle$$

$$\hat{\mathbf{A}} = (\mathbf{I} - (\partial \mathcal{K} / \partial \mathbf{d}) \mathbf{H}) \mathbf{B} (\mathbf{I} - (\partial \mathcal{K} / \partial \mathbf{d}) \mathbf{H})^T + (\partial \mathcal{K} / \partial \mathbf{d}) \mathbf{R} (\partial \mathcal{K} / \partial \mathbf{d})^T$$

At limit of convergence: $(\partial \mathcal{K} / \partial \mathbf{d}) = \mathbf{K}$

Expected Analysis Errors of Functions

Linear scalar functions: $\mathcal{J}(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$
(e.g. transport, heat content)

Quadratic scalar functions: $\mathcal{J}(\mathbf{x}) = \mathbf{x}^T \mathbf{L} \mathbf{x}$
(e.g. eddy kinetic energy)

For linear functions:

Prior error variance $\left(\sigma_{\mathcal{J}}^b\right)^2 = \mathbf{w}^T \mathbf{B} \mathbf{w}$

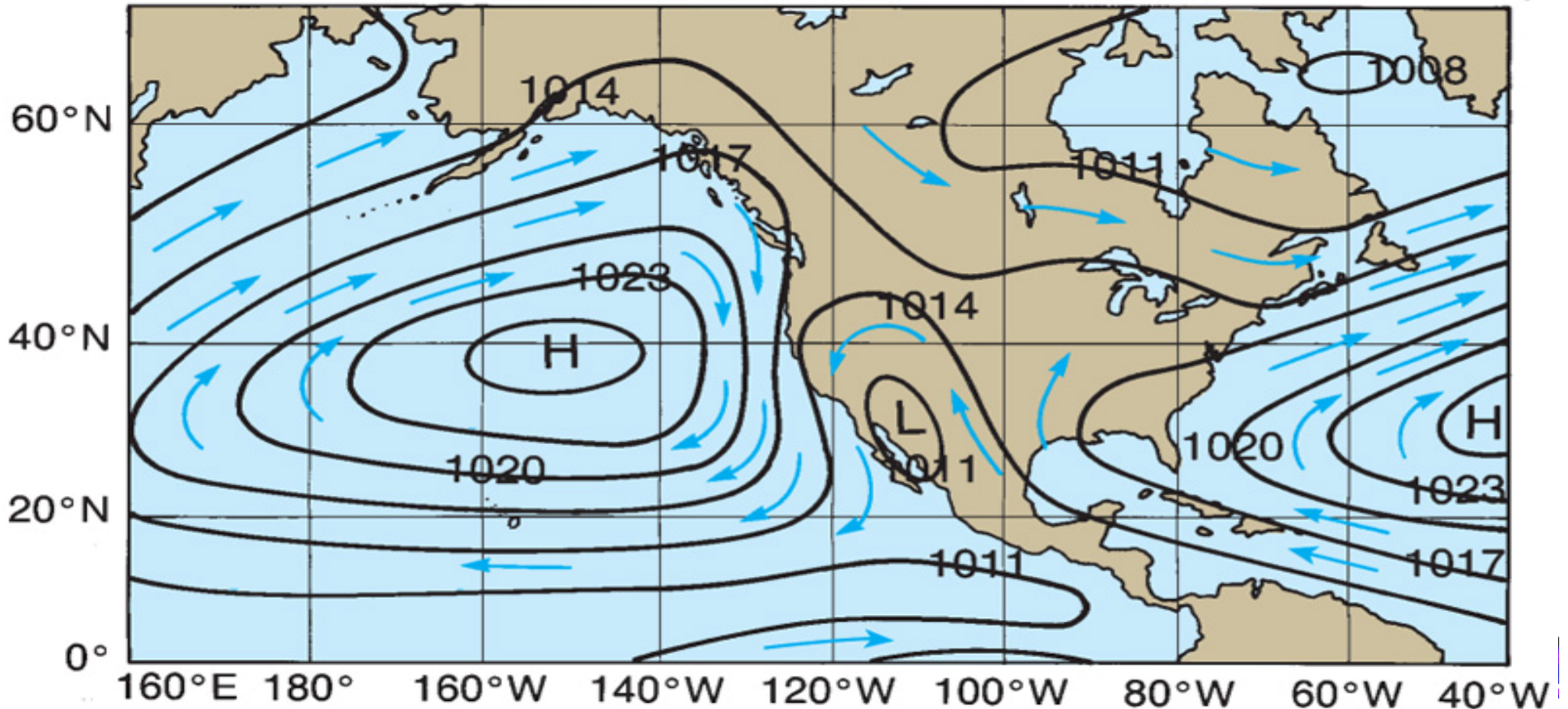
Posterior error variance $\left(\sigma_{\mathcal{J}}^a\right)^2 = \mathbf{w}^T \mathbf{A} \mathbf{w}$

\mathbf{A} is given by $\hat{\mathbf{A}}$ or $\tilde{\mathbf{A}}$



**Results pertain to an infinite
theoretical ensemble**

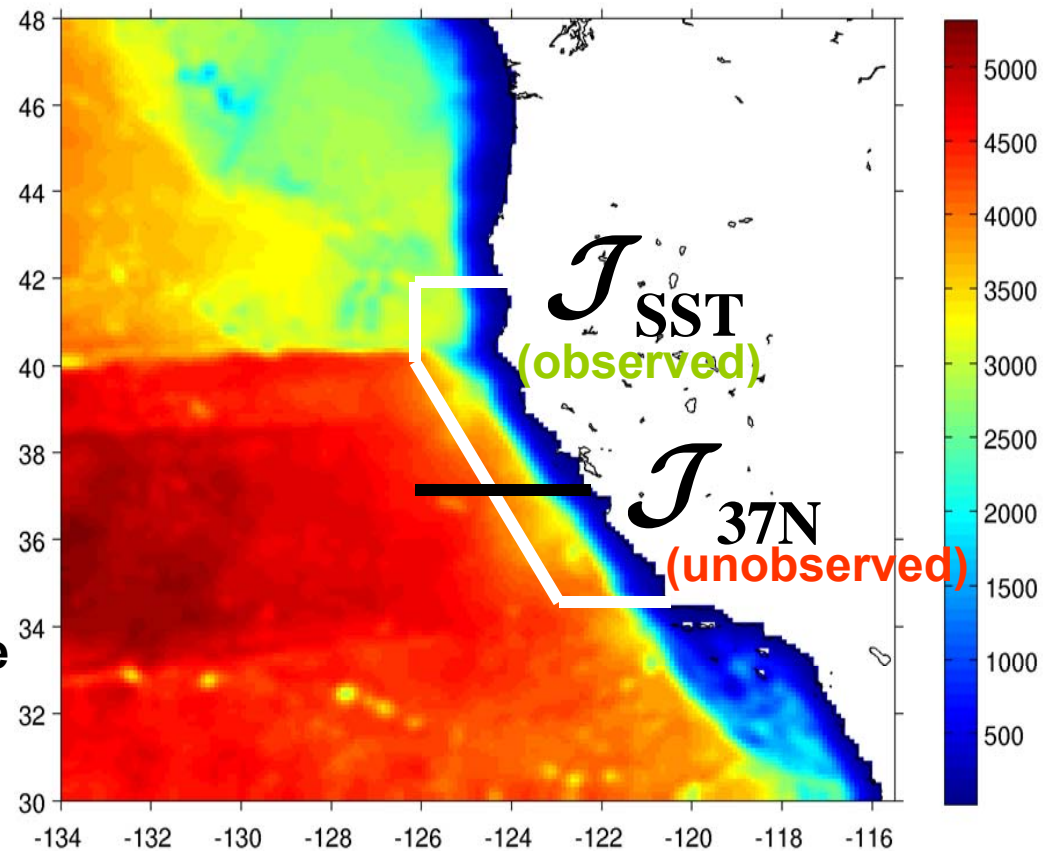
The California Current



ROMS: California Current System (CCS)

(Regional Ocean Modeling System)

- ROMS: PE, hydrostatic, sigma
- 30 km, 30 levels
- 4D-Var: Dual, 1 outer, 60 inner
- Minimum residual descent
- Control vector: $\mathbf{x}(0)$, $\mathbf{f}(t)$, $\mathbf{b}(t)$
- COAMPS forcing, $\mathbf{f}_b(t)$
- ECCO open b.c.s, $\mathbf{b}_b(t)$
- *Prior* $\mathbf{x}_b(0)$ from previous cycle
- 7 day assimilation cycles
- July 2002 – Dec. 2004

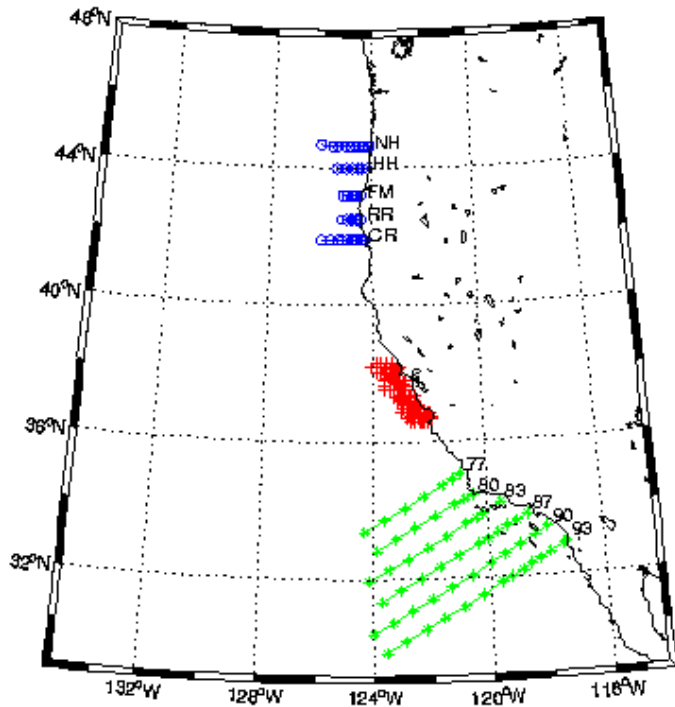


Veneziani et al (2009)

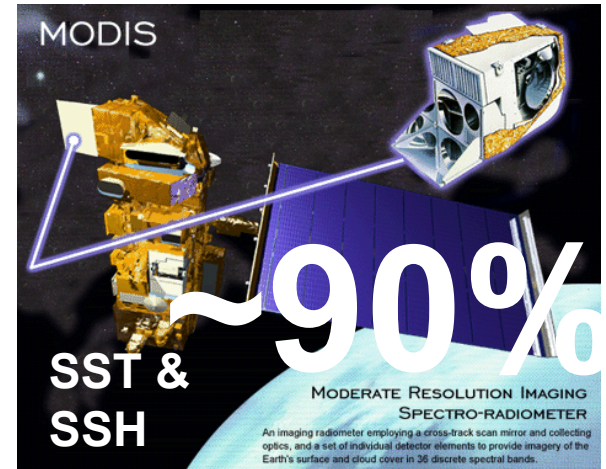
Broquet et al (2009a,b, 2011)

Moore et al (2011a,b,c)

Observations (y)

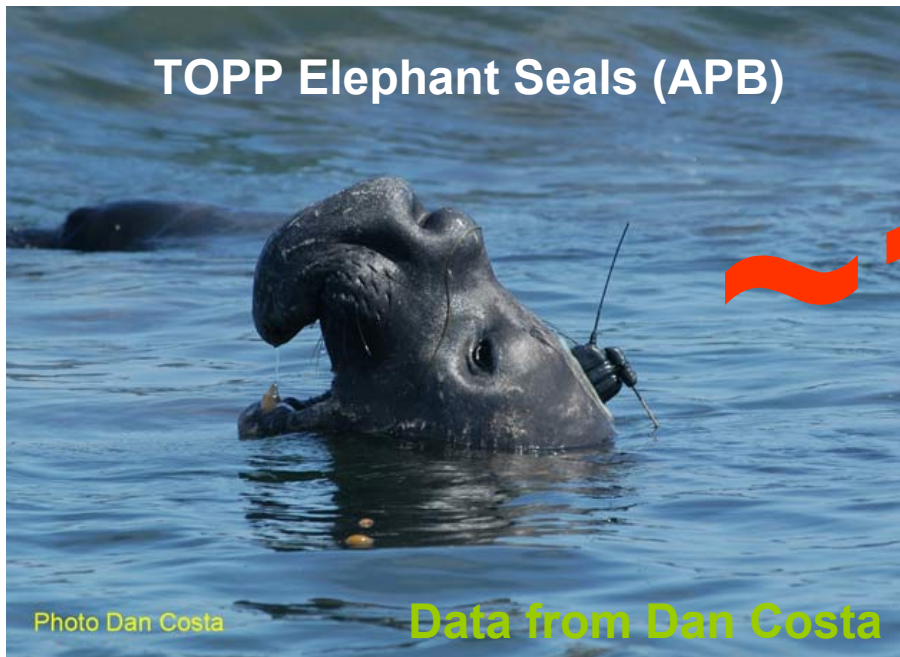


CalCOFI &
GLOBEC



EN3

Ingleby and
Huddleston (2007)



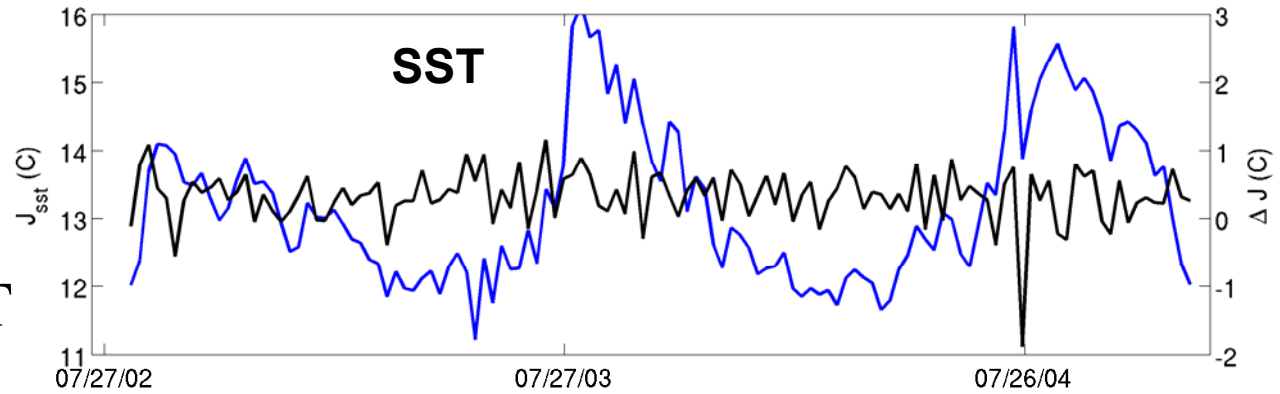
~10%



Time Series of \mathcal{J}_{SST} and $\mathcal{J}_{37\text{N}}$

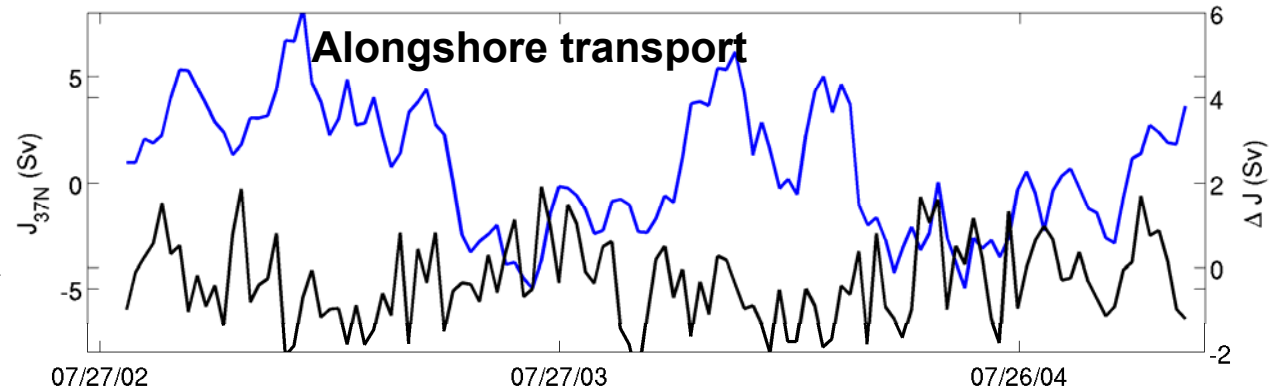
relaxation relaxation

— $\mathcal{J}_{\text{SST}}^b$
— $\Delta \mathcal{J}_{\text{SST}}$



upwelling upwelling

— $\mathcal{J}_{37\text{N}}^b$
— $\Delta \mathcal{J}_{37\text{N}}$

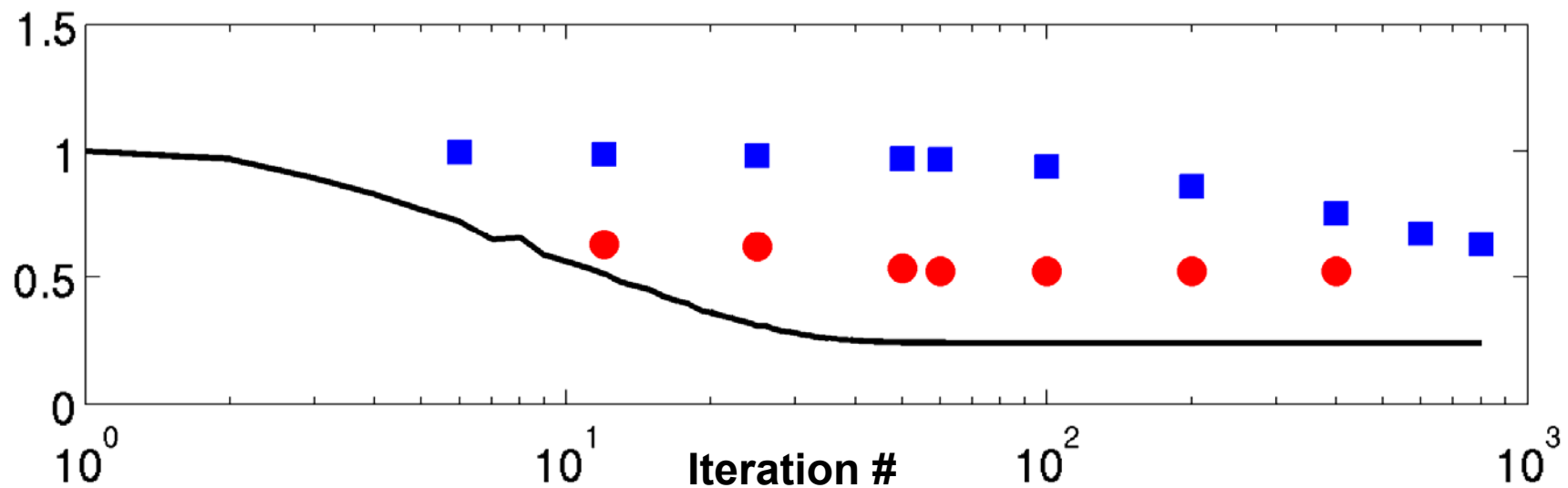


Convergence Properties of $\tilde{\mathbf{A}}$ and $\hat{\mathbf{A}}$

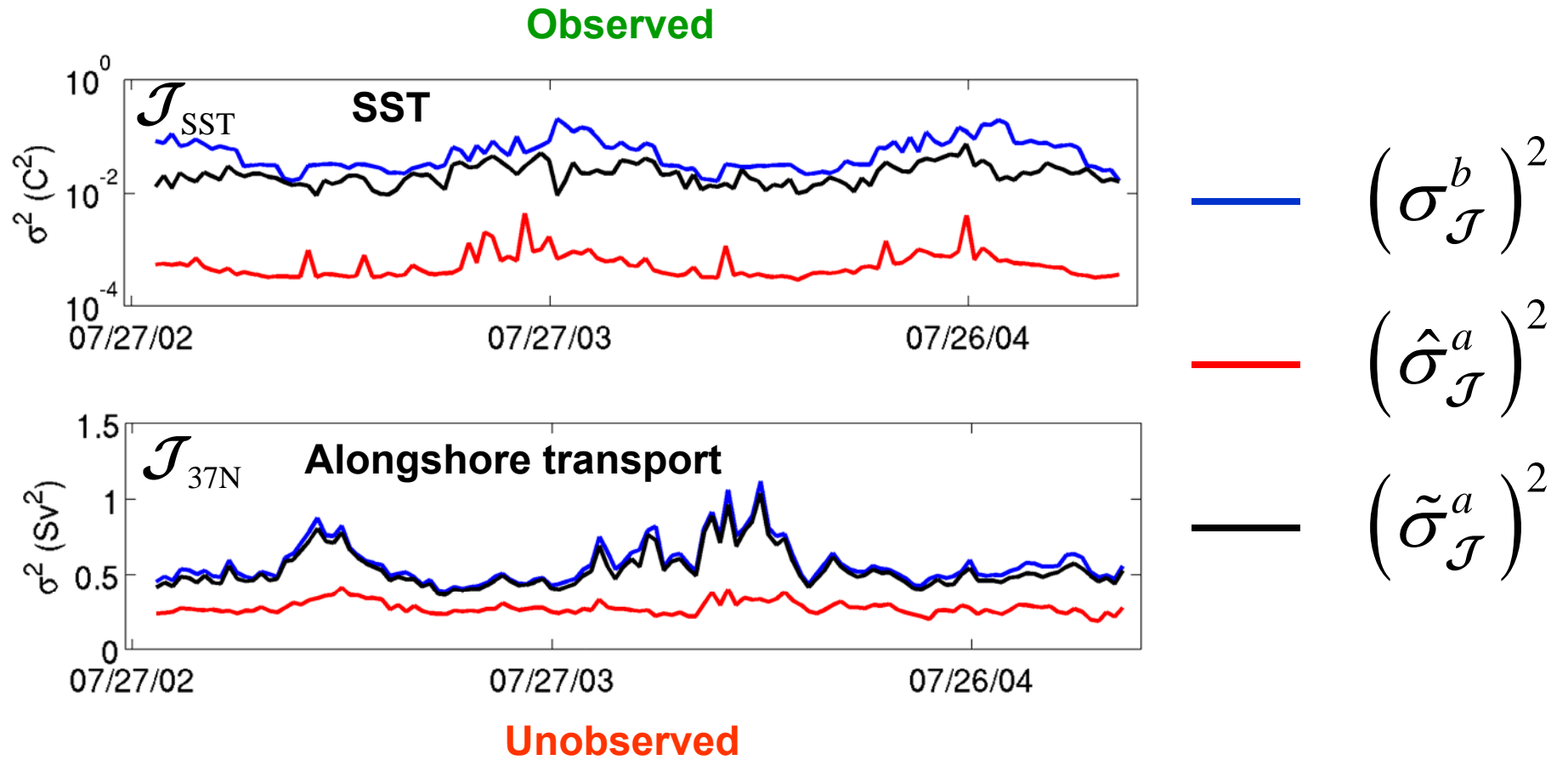
$$\tilde{\mathbf{A}} = (\mathbf{I} - \tilde{\mathbf{K}}\mathbf{H})\mathbf{B}(\mathbf{I} - \tilde{\mathbf{K}}\mathbf{H})^T + \tilde{\mathbf{K}}\mathbf{R}\tilde{\mathbf{K}}^T$$

$$\hat{\mathbf{A}} = \left(\mathbf{I} - \left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right) \mathbf{H} \right) \mathbf{B} \left(\mathbf{I} - \left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right) \mathbf{H} \right)^T + \left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right) \mathbf{R} \left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right)^T$$

■ $\tilde{\sigma}_a^2 / \sigma_b^2$ ● $\hat{\sigma}_a^2 / \sigma_b^2$ — J



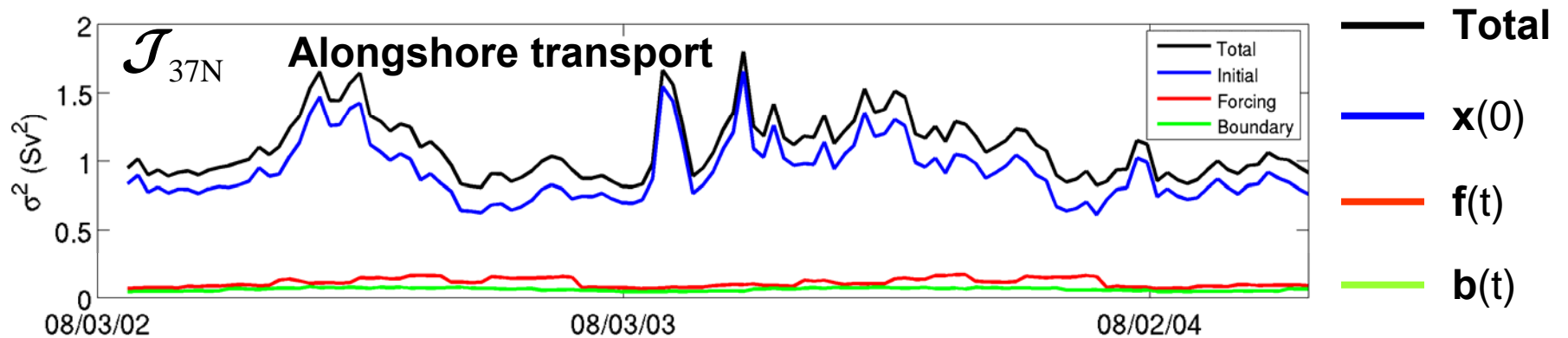
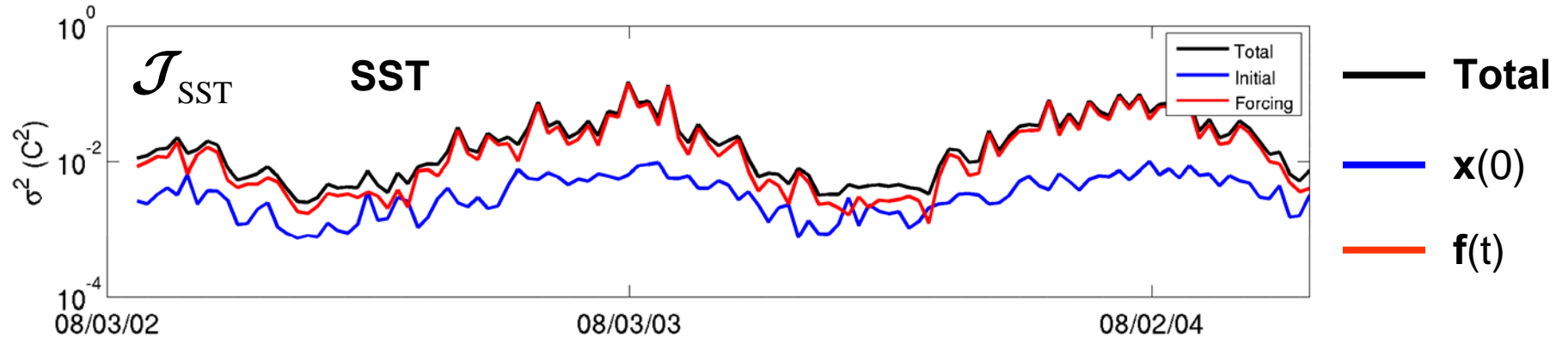
Prior and Posterior Errors



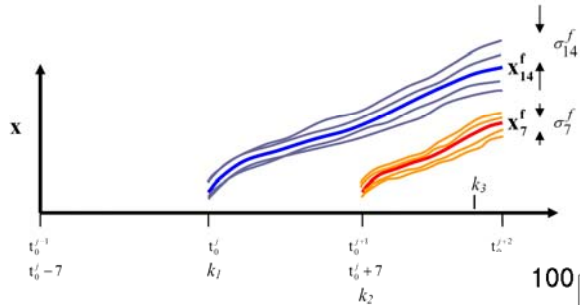
Expected Forecast Errors

$$\mathbf{P}^f \approx \mathbf{M}_f \mathbf{D} \mathbf{M}_f^T \quad \mathbf{D} = \text{diag} \left(\mathbf{M}_a \hat{\mathbf{A}} \mathbf{M}_a^T, \mathbf{B}_f, \mathbf{B}_b \right)$$

$$\left(\sigma_{\mathcal{J}}^f \right)^2 = \mathbf{w}^T \mathbf{P}^f \mathbf{w}$$



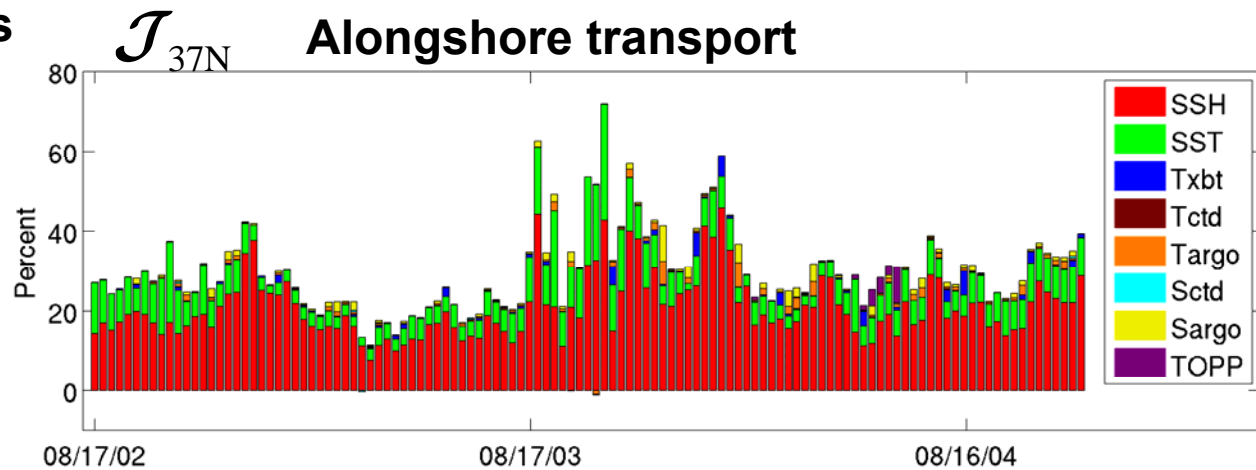
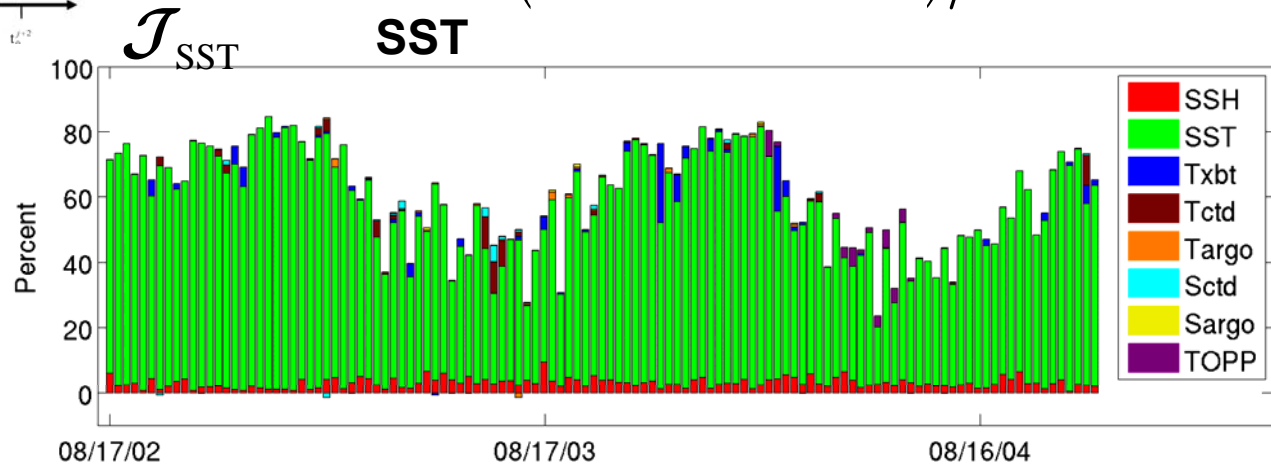
Predictability



$$r = 100 \left(\frac{(\sigma_{14}^f)^2 - (\sigma_7^f)^2}{(\sigma_{14}^f)^2} \right)$$

$r > 0$

positive impact of obs
on predictability



Analogous to obs impact (Langland & Baker; Errico; Gelaro et al)

Final Remarks

- **One integration of $(\partial\mathcal{K}/\partial\mathbf{d})^T$ per function**

- **Consistency checks:**

$$\boxed{\mathcal{J}^a - \mathcal{J}^b \sim N\left(0, (\sigma_b^2 - \sigma_a^2)^{1/2}\right)} \quad \pm 2(\sigma_b^2 - \sigma_a^2)^{1/2} \quad \text{(69-82\%)}$$

$$\boxed{\mathcal{J}^f - \mathcal{J}^a \sim N(0, \sigma^f)} \quad \pm 2\sigma^f \quad \text{46\% } (\mathcal{J}_{\text{SST}}) \quad \text{91\% } (\mathcal{J}_{37\text{N}})$$

→ reliability

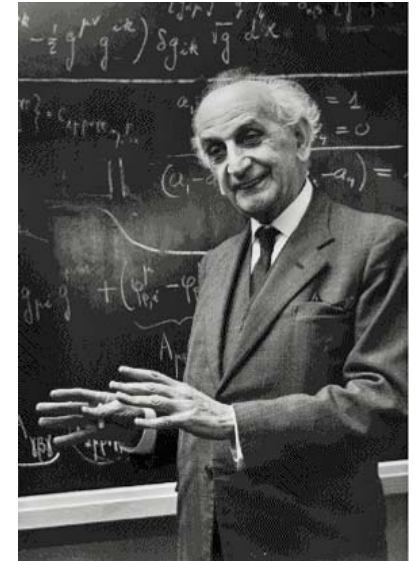
- **Extension to quadratic functions**

- **$(\partial\mathcal{K}/\partial\mathbf{d})^T$ can predict change in error covariance due to withhold obs → optimal array design**

Lanczos Factorization

$$\tilde{\mathbf{K}} \approx \mathbf{B}\mathbf{H}^T \mathbf{V}_m \mathbf{W}_m \mathbf{V}_m^T \quad \text{Dual form} \\ m \ll N_{\text{obs}}$$

\mathbf{V}_m is the matrix of orthonormal Lanczos vectors
 m is the number of inner-loops



Cornelius
 Lanczos
 (1893-1974)

$$\delta \mathbf{x}_a \simeq \left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right) \Delta \mathbf{d} \simeq \mathbf{B}\mathbf{H}^T \mathbf{V}_m \mathbf{W}_m \mathbf{V}_m^T \Delta \mathbf{d} +$$

$$\mathbf{B}\mathbf{H}^T \left[\mathbf{V}_m \mathbf{W}_m \Delta \mathbf{V}_m^T \dots \right]$$

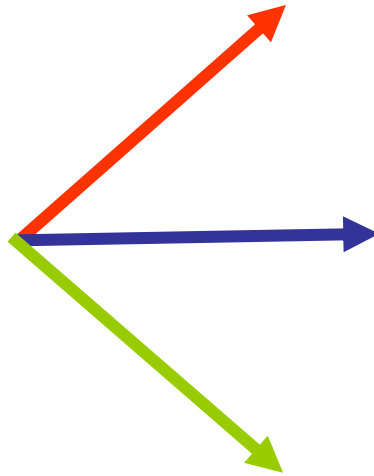
$$+ \mathbf{V}_m \Delta \mathbf{W}_m \mathbf{V}_m^T \dots$$

$$+ \left[\Delta \mathbf{V}_m \mathbf{W}_m \mathbf{V}_m^T \right] \mathbf{d}$$

The perturbed Lanczos vectors $\Delta \mathbf{V}_m$ span obs space via $\langle \bullet \rangle$

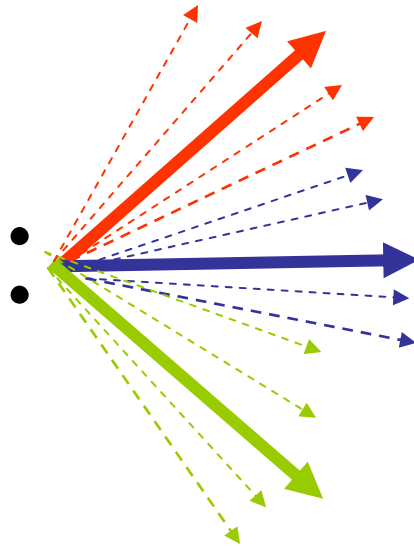
Perturbation Lanczos Vectors

$\tilde{\mathbf{K}} :$



m orthonormal Lanczos vectors
in obs space where
 $m \ll N_{obs}$

$\left(\frac{\partial \mathcal{K}}{\partial \mathbf{d}} \right)^T$



Perturbed Lanczos vectors
(via $\langle \rangle$) more effectively span
obs space