

On the influence of random wind stress errors on the four dimensional, mid-latitude, ocean inverse problem

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- Introduction
- Background of 4DVAR analysis
- Experiments
- Discussions

4DVAR Ocean Circulation Estimation

Cost Function

$$J[\mathbf{x}_{4D}] = \Delta \mathbf{x}_0^T \mathbf{B}^{-1} \Delta \mathbf{x}_0 + \Delta \boldsymbol{\tau}^T \mathbf{Q}_\tau^{-1} \Delta \boldsymbol{\tau} + \Delta \mathbf{q}^T \mathbf{Q}_q^{-1} \Delta \mathbf{q} \\ + (\mathbf{y} - \mathbf{H} \mathbf{x}_{4D})^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H} \mathbf{x}_{4D})$$

Constrain

$$\mathbf{M} \mathbf{x}_{4D} = \mathbf{f}$$

- Error covariance matrix \mathbf{Q} for wind stress error is often modeled by a diagonal matrix.
- If we model \mathbf{Q} by a non-diagonal matrix, what is its impact to the 4DVAR ocean circulation analysis?
- If the impact is significant, what is the dynamical reason behind?

4DVAR analysis : Dynamical Constraint

Linear Ocean General Circulation Model (OGCM)

$$\begin{aligned}\mathbf{x}_0 &= \mathbf{x}_{\text{init}} \\ \mathbf{x}_1 &= \mathbf{M}_{1,0} \mathbf{x}_0 + \mathbf{f}_1 \\ &\vdots \\ \mathbf{x}_K &= \mathbf{M}_{K,K-1} \mathbf{x}_{K-1} + \mathbf{f}_K\end{aligned}$$

Linear OGCM as a Dynamical Constraint

$$\underbrace{\begin{bmatrix} \mathbf{x}_0 \\ \mathbf{x}_1 - \mathbf{M}_{1,0} \mathbf{x}_0 \\ \vdots \\ \mathbf{x}_K - \mathbf{M}_{K,K-1} \mathbf{x}_0 \end{bmatrix}}_{\mathbf{M} \mathbf{x}_{4D}} = \underbrace{\begin{bmatrix} \mathbf{x}_{\text{init}} \\ \mathbf{f}_1 \\ \vdots \\ \mathbf{f}_K \end{bmatrix}}_{\mathbf{f}_{4D}} + \underbrace{\begin{bmatrix} \Delta \mathbf{x}_{\text{init}} \\ \Delta \mathbf{f}_1 \\ \vdots \\ \Delta \mathbf{f}_K \end{bmatrix}}_{\Delta \mathbf{f}_{4D}}$$

: initial error

: external forcing
(boundary value) error

$$\mathbf{M} \mathbf{x}_{4D} = \mathbf{f}_{4D} + \Delta \mathbf{f}_{4D}$$

4DVAR analysis : Cost Function

Dynamical Constraints

$$\mathbf{M} \mathbf{x} = \mathbf{f} + \Delta \mathbf{f}$$

Observational Constraints

$$\mathbf{H} \mathbf{x} = \mathbf{y} + \Delta \mathbf{y}$$

Cost Function (Estimator)

$$J[\mathbf{x}] = \frac{1}{2} \Delta \mathbf{f}^T \mathbf{Q}^{-1} \Delta \mathbf{f} + \frac{1}{2} \Delta \mathbf{y}^T \mathbf{R}^{-1} \Delta \mathbf{y}$$

Assumptions

$$\begin{aligned} \langle \Delta \mathbf{f} \Delta \mathbf{f}^T \rangle &= \mathbf{Q}, & \langle \Delta \mathbf{f} \rangle &= 0 & & : \text{model error} \\ \langle \Delta \mathbf{y} \Delta \mathbf{y}^T \rangle &= \mathbf{R}, & \langle \Delta \mathbf{y} \rangle &= 0 & & : \text{measurement error} \end{aligned}$$

4DVAR analysis : Incremental Formulation of Cost Function

Background Estimation

$$\mathbf{M} \mathbf{x}^b = \mathbf{f}$$

Analysis Increment and Innovation vector

$$\Delta \mathbf{x} = \mathbf{x} - \mathbf{x}^b, \quad \mathbf{d} = \mathbf{y} - \mathbf{H} \mathbf{x}^b$$

Dynamical Constraints in Incremental Formulation

$$\mathbf{M} \Delta \mathbf{x} = \Delta \mathbf{f}$$

Observational Constraints in Incremental Formulation

$$\mathbf{H} \Delta \mathbf{x} - \mathbf{d} = \Delta \mathbf{y}$$

Cost Function

$$2J[\mathbf{x}] = \Delta \mathbf{f}^T \mathbf{Q}^{-1} \Delta \mathbf{f} + \Delta \mathbf{y}^T \mathbf{R}^{-1} \Delta \mathbf{y}$$

4DVAR analysis : Incremental Formulation of Cost Function

Background Estimation

$$\mathbf{M} \mathbf{x}^b = \mathbf{f}$$

Analysis Increment and Innovation vector

$$\Delta \mathbf{x} = \mathbf{x} - \mathbf{x}^b, \quad \mathbf{d} = \mathbf{y} - \mathbf{H} \mathbf{x}^b$$

Dynamical Constraints in Incremental Formulation

$$\mathbf{M} \Delta \mathbf{x} = \Delta \mathbf{f}$$

Observational Constraints in Incremental Formulation

$$\mathbf{H} \Delta \mathbf{x} - \mathbf{d} = \Delta \mathbf{y}$$

Cost Function in Incremental Formulation

$$2J[\Delta \mathbf{x}] = \Delta \mathbf{x}^T \mathbf{M}^T \mathbf{Q}^{-1} \mathbf{M} \Delta \mathbf{x} \\ + (\mathbf{H} \Delta \mathbf{x} - \mathbf{d})^T \mathbf{R}^{-1} (\mathbf{H} \Delta \mathbf{x} - \mathbf{d})$$

4DVAR analysis : Optimal Solution

4DVAR Cost Function

$$2J[\Delta \mathbf{x}_{4D}] = \Delta \mathbf{x}_{4D}^T \mathbf{P}^{-1} \Delta \mathbf{x}_{4D} + \left(\mathbf{H}_{4D} \Delta \mathbf{x}_{4D} - \mathbf{d}_{4D} \right)^T \mathbf{R}_{4D}^{-1} \left(\mathbf{H}_{4D} \Delta \mathbf{x}_{4D} - \mathbf{d}_{4D} \right)$$

$$\mathbf{P}^{-1} = \mathbf{M}^T \mathbf{Q}^{-1} \mathbf{M}$$

3DVAR (OI:Optimal Interpolation) Cost Function

$$2J[\Delta \mathbf{x}_{3D}] = \Delta \mathbf{x}_{3D}^T \mathbf{B}^{-1} \Delta \mathbf{x}_{3D} + \left(\mathbf{H}_{3D} \Delta \mathbf{x}_{3D} - \mathbf{d}_{3D} \right)^T \mathbf{R}_{3D}^{-1} \left(\mathbf{H}_{3D} \Delta \mathbf{x}_{3D} - \mathbf{d}_{3D} \right)$$

Optimal Solution

$$\Delta \mathbf{x}_{4D} = \mathbf{P} \mathbf{H}_{4D}^T \left(\mathbf{H}_{4D} \mathbf{P} \mathbf{H}_{4D}^T + \mathbf{R}_{4D} \right)^{-1} \mathbf{d}_{4D}$$

4DVAR analysis : Role of P-matrix and Q-matrix

Optimal Solution

$$\Delta \mathbf{x}_{4D} = \underbrace{\mathbf{P}}_{\text{model space}} \mathbf{H}_{4D}^T \underbrace{\left(\mathbf{H}_{4D} \mathbf{P} \mathbf{H}_{4D}^T + \mathbf{R}_{4D} \right)^{-1}}_{\text{data space}} \mathbf{d}_{4D}$$

- P-matrix has all information about how the data are extrapolated to its surrounding area/time.

P-matrix

$$\mathbf{P}^{-1} = \mathbf{M}^T \mathbf{Q}^{-1} \mathbf{M}$$

$$\mathbf{M} \mathbf{P} \mathbf{M}^T = \mathbf{Q}$$

- P-matrix is a function of Q-matrix.
 - ▶ in 4DVAR, (4D) background error covariance matrix (P-matrix) is parameterized by Q-matrix

4DVAR analysis : Two approaches to evaluate P-matrix

P-matrix defined by ensemble average

$$\begin{aligned}\mathbf{P} &= \left\langle (\mathbf{x} - \mathbf{x}^b)(\mathbf{x} - \mathbf{x}^b)^T \right\rangle \\ &= \lim_{M \rightarrow \infty} M^{-1} \sum_{m=1}^M (\mathbf{x}^{(m)} - \mathbf{x}^b)(\mathbf{x}^{(m)} - \mathbf{x}^b)^T\end{aligned}$$

$\mathbf{M} \mathbf{x}^b = \mathbf{f}$: background estimation (deterministic)

$\mathbf{M} \mathbf{x}^{(m)} = \mathbf{f} + \Delta \mathbf{f}^{(m)}$: perturbed solution (stochastic)

$$\left\langle \Delta \mathbf{f} \Delta \mathbf{f}^T \right\rangle = \mathbf{Q}, \quad \left\langle \Delta \mathbf{f} \right\rangle = 0$$

Inverse of P-matrix

$$\mathbf{P}^{-1} = \mathbf{M}^T \mathbf{Q}^{-1} \mathbf{M}$$

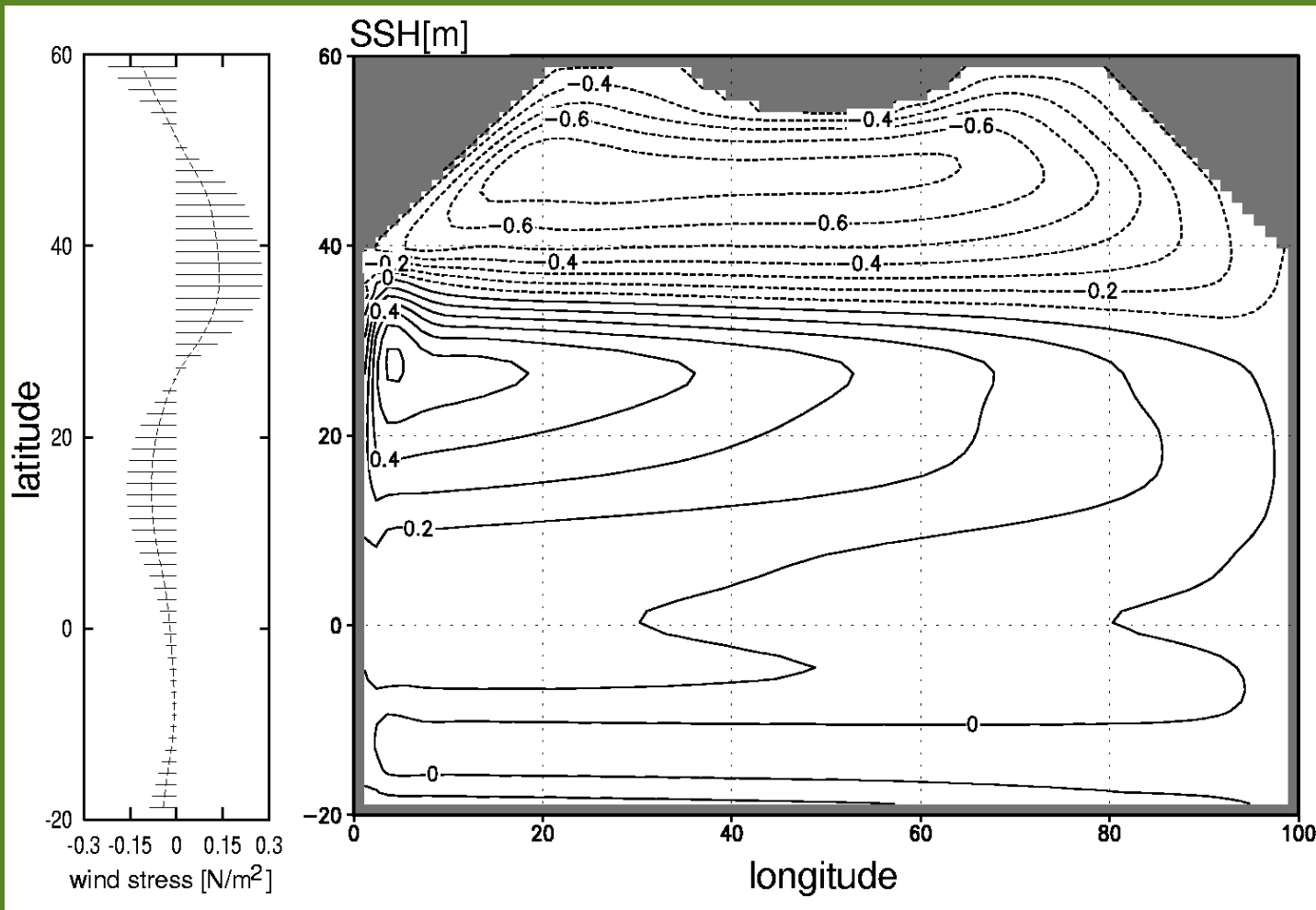
Experiments : Settings

Cost Function

$$J[\mathbf{x}_{4D}] = \Delta \boldsymbol{\tau}^T \mathbf{Q}_\tau^{-1} \Delta \boldsymbol{\tau} + (\boldsymbol{\eta} - \mathbf{H} \mathbf{x}_{4D})^T \mathbf{R}^{-1} (\boldsymbol{\eta} - \mathbf{H} \mathbf{x}_{4D})$$

Constrain

$$\mathbf{M} \mathbf{x}_{4D} = \mathbf{f} + \Delta \mathbf{f} : \text{tangent linear ocean model}$$



period: 1 year
resolution: 1.2 degree

$$\rightarrow \mathbf{P} = \mathbf{F} [\mathbf{Q}_\tau]$$

Experiments : Wind stress error covariance model

Wind Stress Error

$$\Delta \boldsymbol{\tau}(\mathbf{r}, t) = (\Delta \tau_x(\mathbf{r}, t), 0)$$

$$\begin{aligned} \langle \Delta \tau_x(\mathbf{r}_1, t_1) \Delta \tau_x(\mathbf{r}_2, t_2) \rangle &= Q_\tau(\mathbf{r}_1, t_1; \mathbf{r}_2, t_2) \\ \langle \Delta \tau_x(\mathbf{r}, t) \rangle &= 0 \end{aligned}$$

Wind Stress Error Covariance Model

$$\begin{aligned} Q_\tau(\mathbf{r}_1, t_1; \mathbf{r}_2, t_2) &= \sigma(\mathbf{r}_1) \rho(\tilde{\mathbf{r}}, \tilde{t}) \sigma(\mathbf{r}_2) \\ \tilde{\mathbf{r}} &= \mathbf{r}_1 - \mathbf{r}_2, \tilde{t} = t_1 - t_2 \end{aligned}$$

Wind Stress Error Correlation Model

$$\rho(\tilde{\mathbf{r}}, \tilde{t}) = \exp\left(-\frac{\tilde{x}^2}{L_x^2}\right) \exp\left(-\frac{\tilde{y}^2}{L_y^2}\right) \exp\left(-\frac{\tilde{t}}{L_t}\right)$$

Experiments : Wind stress error covariance model

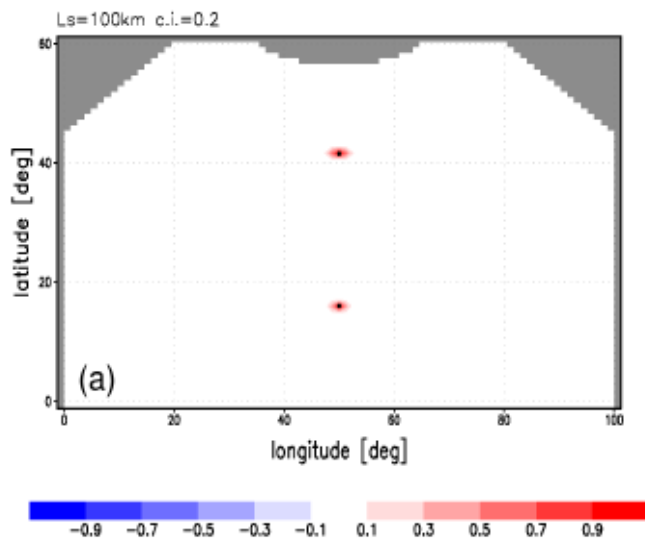
Wind Stress Error Covariance Model

$$Q_{\tau}(\mathbf{r}_1, t_1; \mathbf{r}_2, t_2) = \sigma(y_1) \rho(\tilde{\mathbf{r}}, \tilde{t}) \sigma(y_2)$$

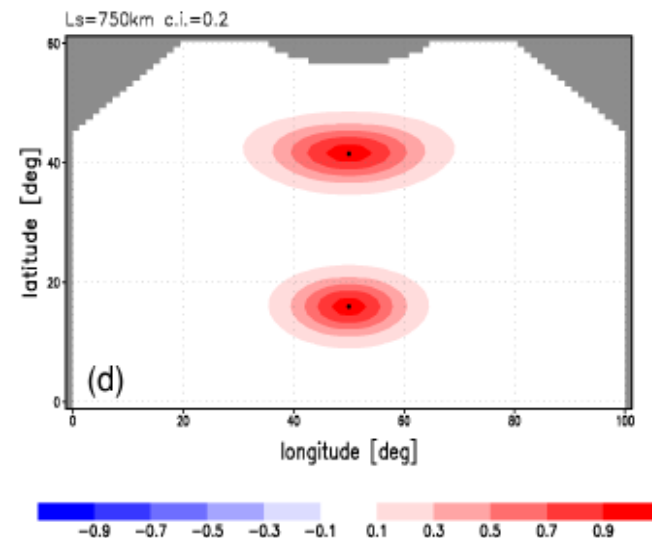
Wind Stress Error Correlation Model

$$\rho(\tilde{\mathbf{r}}, \tilde{t}) = \exp\left(-\frac{\tilde{x}^2}{L_x^2}\right) \exp\left(-\frac{\tilde{y}^2}{L_y^2}\right) \exp\left(-\frac{\tilde{t}}{L_t}\right)$$

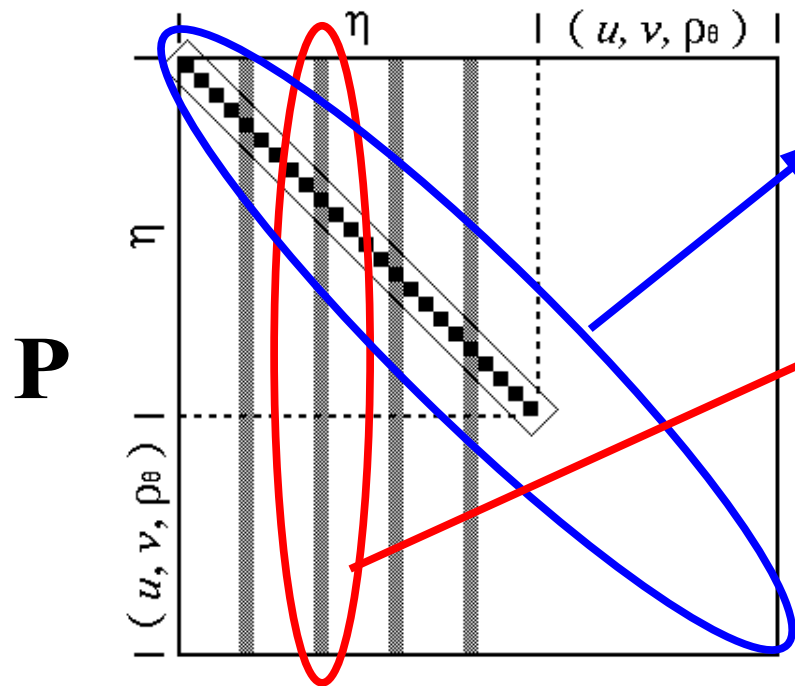
$L_s = \Delta r$ (near – diagonal)



$L_s = 750\text{km}$ (non – diagonal)



Experiments : Subspace of P-matrix

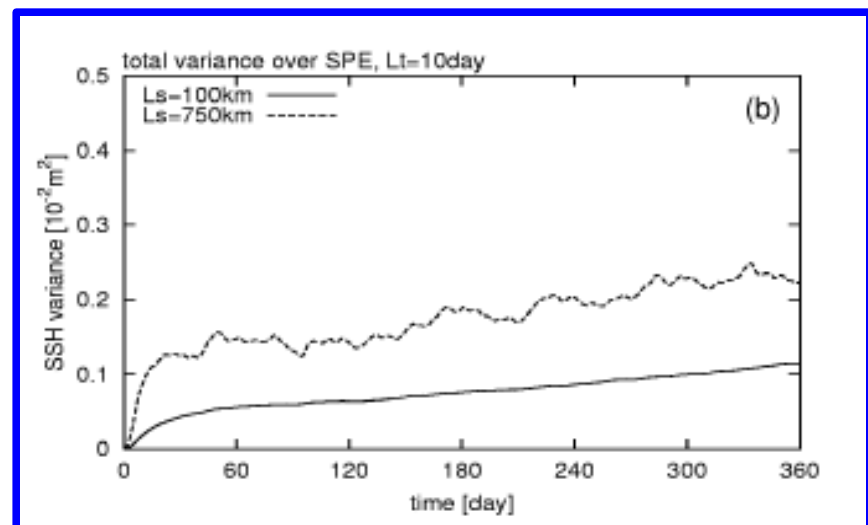
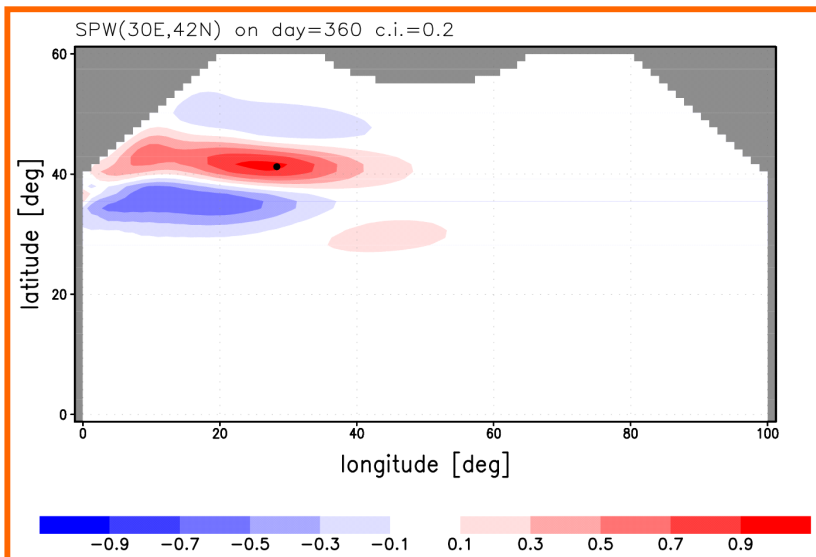


diagonal component=error variance

$$\sigma^2 = \langle (\mathbf{x} - \mathbf{x}^b)^2 \rangle$$

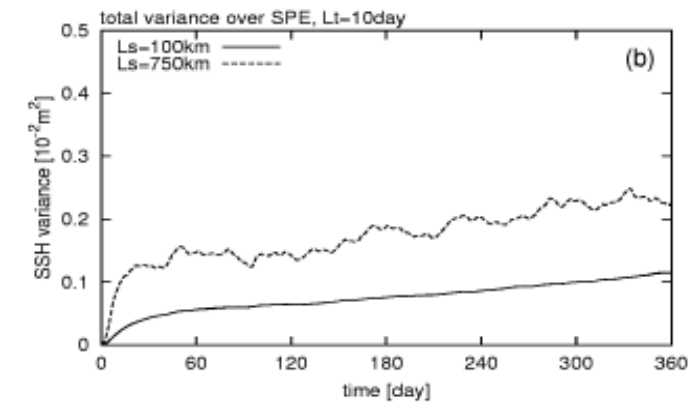
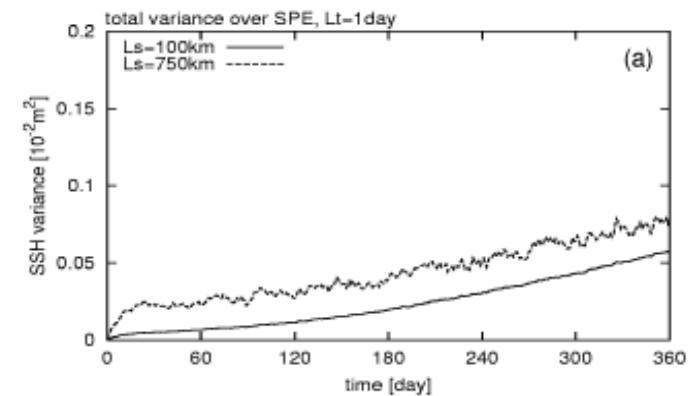
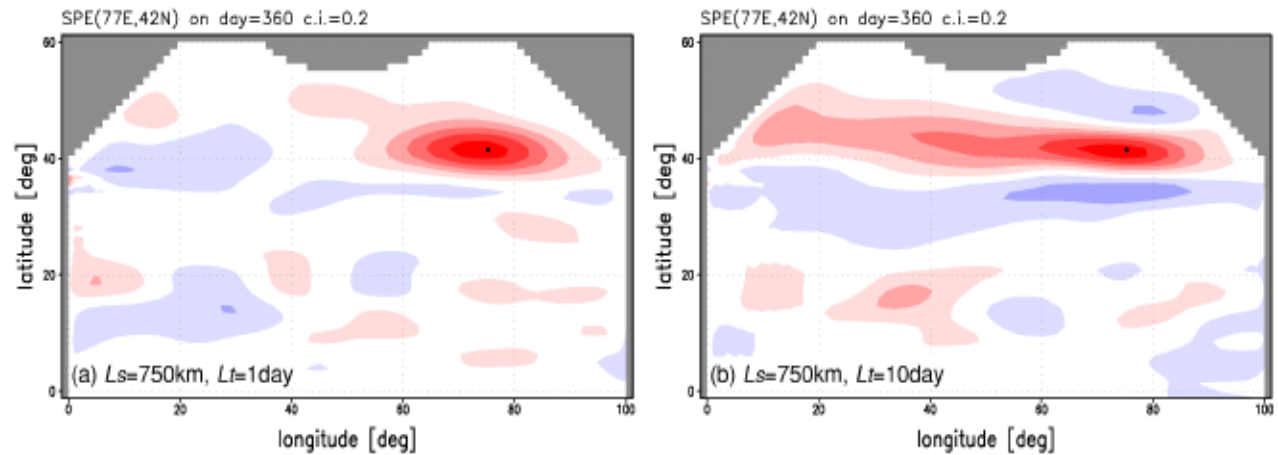
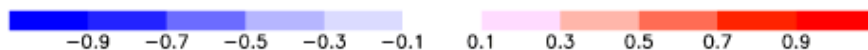
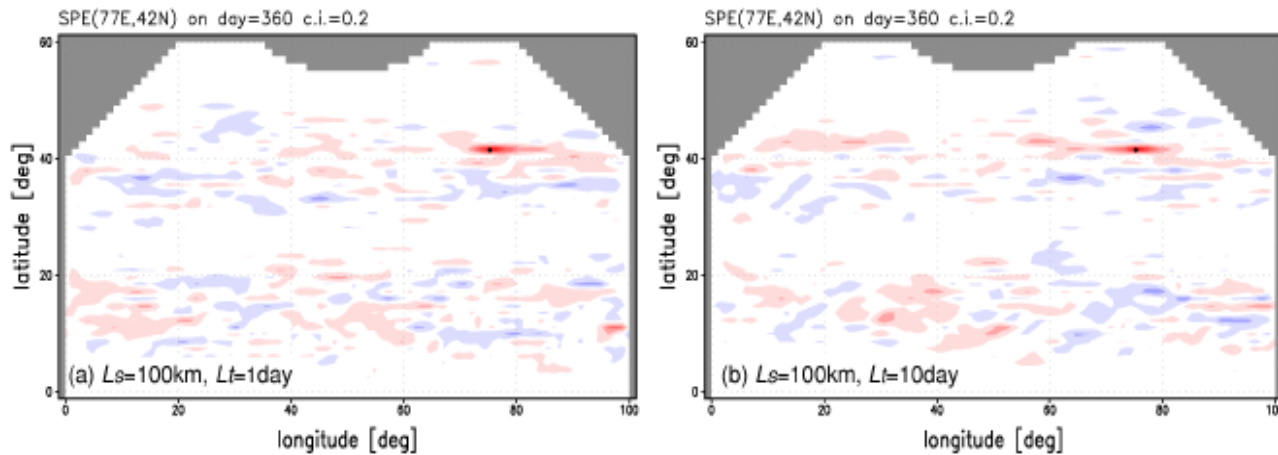
column of P-matrix=representer

$$\mathbf{p}_m = \mathbf{P} \mathbf{h}_m$$



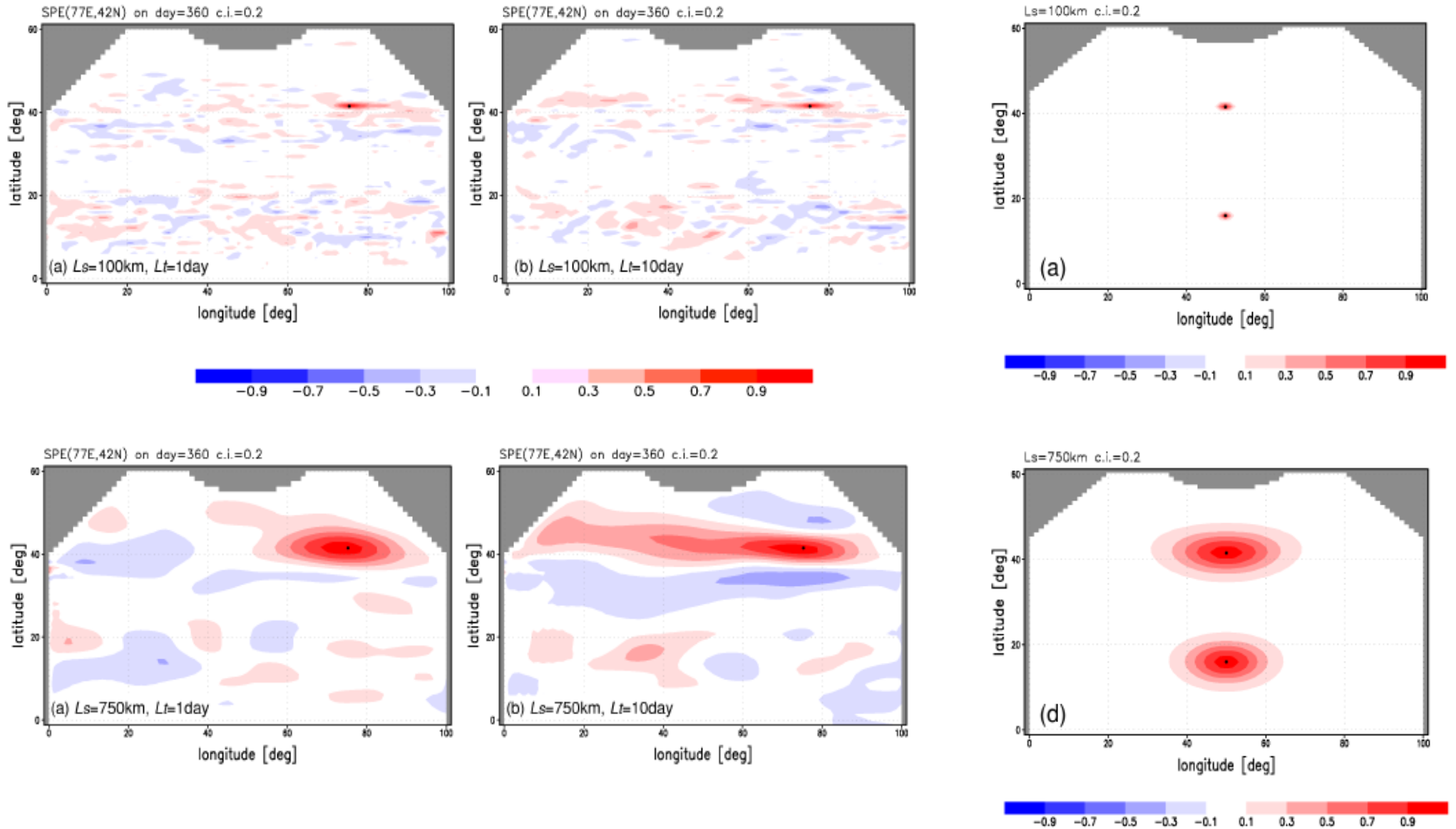
Experiments : Sensitivity of P-matrix to Q-matrix

Sensitivity to a decorrelation length scale L_s and time scale L_t



Experiments : Sensitivity of P-matrix to Q-matrix

Sensitivity to a decorrelation length scale L_s and time scale L_t



Interpretations : Wind stress curl error covariance

Wind Stress Error Covariance Model

$$Q_{\tau}(\mathbf{r}_1, t_1; \mathbf{r}_2, t_2) = \sigma(y_1)_x \rho(\tilde{\mathbf{r}}, \tilde{t}) \sigma(y_2)_x$$

wind stress error :

$$\Delta \tau_x(\mathbf{r}) = \sigma_x(y) \widehat{\Delta \tau}_x(\mathbf{r})$$

wind stress curl error :

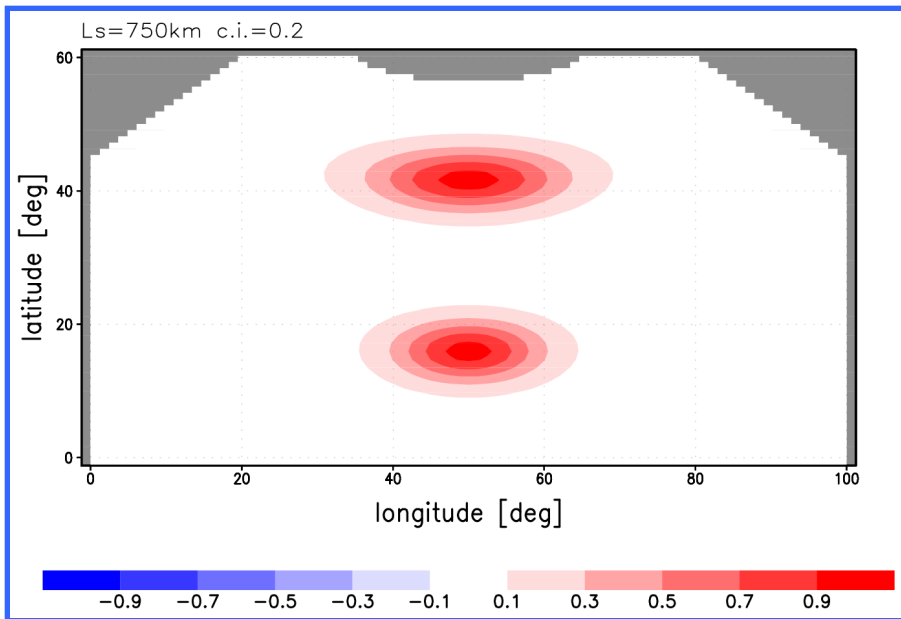
$$\Delta \zeta(\mathbf{r}) = - \frac{\partial \sigma_x(y)}{\partial y} \widehat{\Delta \tau}_x(\mathbf{r}) - \sigma_x(y) \frac{\partial \widehat{\Delta \tau}_x(\mathbf{r})}{\partial y}$$

wind stress curl error covariance :

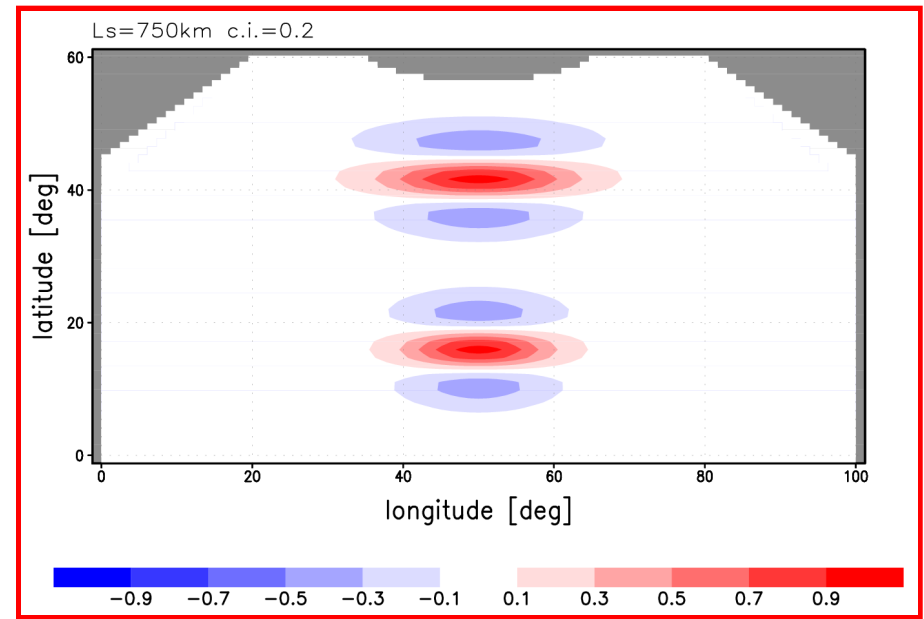
$$\begin{aligned} Q_{\Delta \zeta}(\mathbf{r}, \mathbf{r}') &= \frac{\partial \sigma_x(y)}{\partial y} \left\langle \widehat{\Delta \tau}_x(\mathbf{r}) \widehat{\Delta \tau}_x(\mathbf{r}') \right\rangle \frac{\partial \sigma_x(y')}{\partial y} \\ &+ \sigma_x(y) \left\langle \frac{\partial \widehat{\Delta \tau}_x(\mathbf{r})}{\partial y} \frac{\partial \widehat{\Delta \tau}_x(\mathbf{r}')}{\partial y} \right\rangle \sigma_x(y') \\ &+ \frac{\partial \sigma_x(y)}{\partial y} \left\langle \widehat{\Delta \tau}_x(\mathbf{r}) \frac{\partial \widehat{\Delta \tau}_x(\mathbf{r}')}{\partial y} \right\rangle \sigma_x(y') \end{aligned}$$

Interpretations : Wind stress curl error covariance

$$Q_{\Delta\zeta}(\mathbf{r};\mathbf{r}') = \left(\frac{\partial \sigma_x(y)}{\partial y} \right) \rho_{\Delta\tau_x}(\mathbf{r};\mathbf{r}') \left(\frac{\partial \sigma_x(y')}{\partial y} \right) + \frac{\sqrt{2}\sigma_x(y)}{L_y} \rho_{\partial\Delta\tau_x/\partial y}(\mathbf{r};\mathbf{r}') \frac{\sqrt{2}\sigma_x(y')}{L_y} + (\text{cross covariance})$$



$$\rho_{\Delta\tau_x}(\mathbf{r};\mathbf{r}')$$

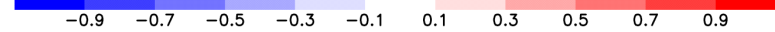
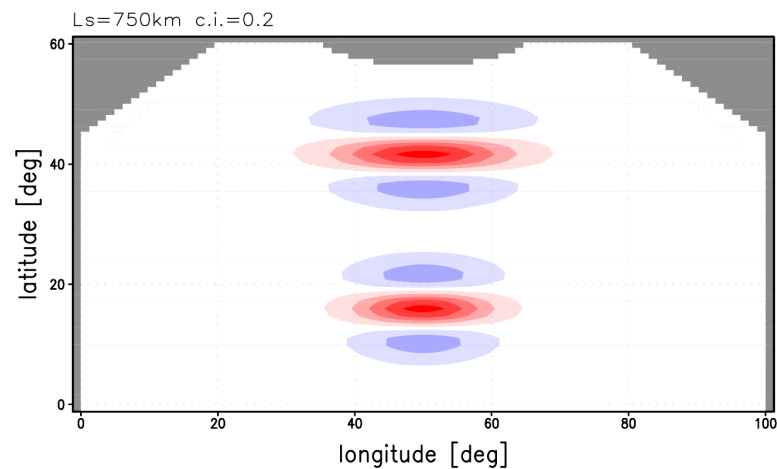
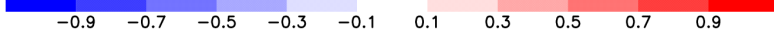
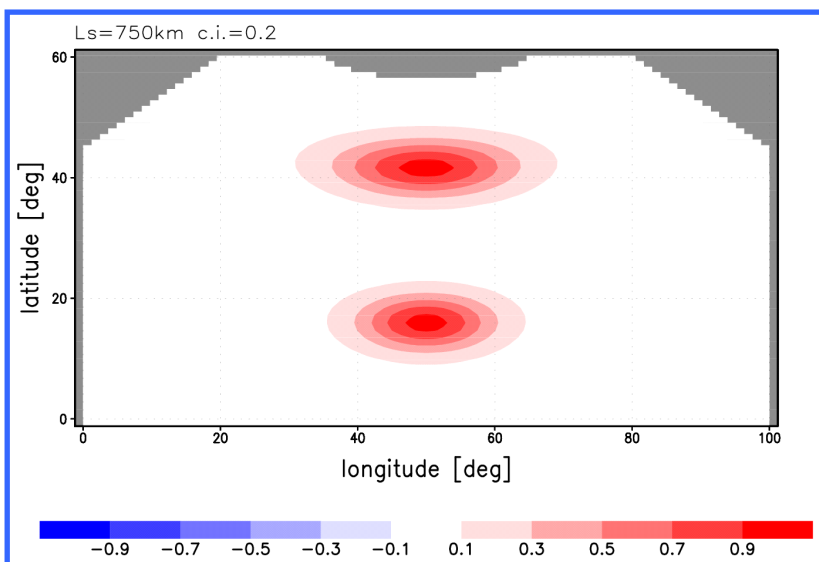
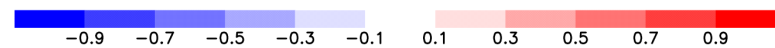
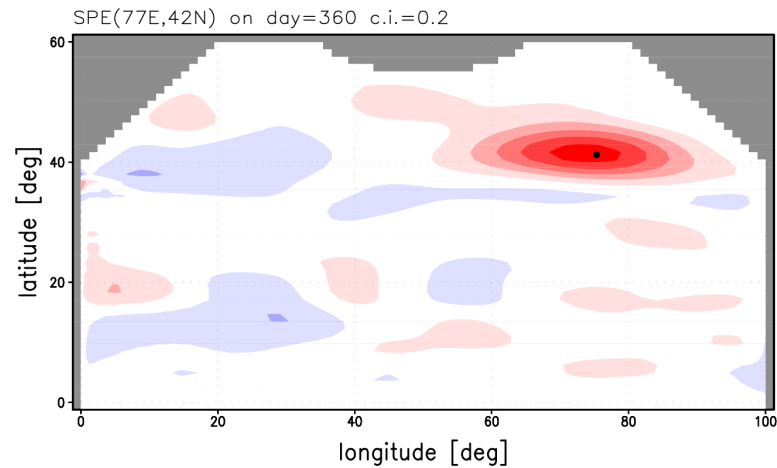
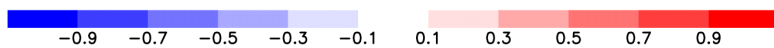
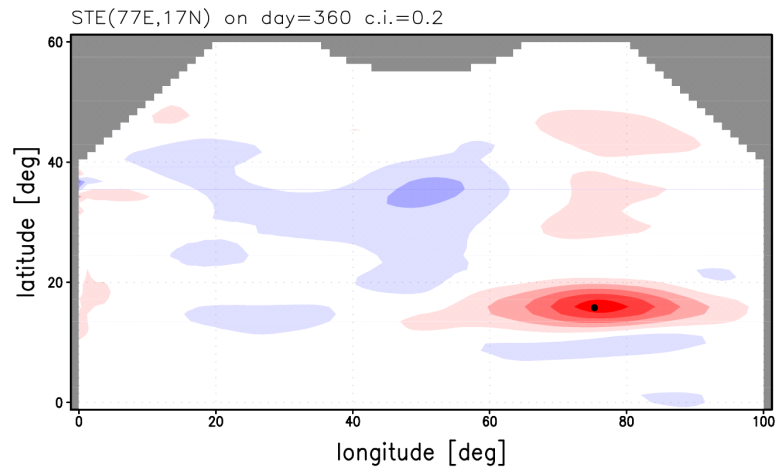


$$\rho_{\partial\Delta\tau_x/\partial y}(\mathbf{r};\mathbf{r}')$$

spatial structure of the correlation functions for $L_{x(y)}=750\text{km}$

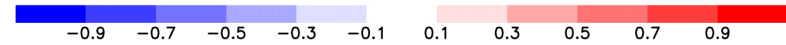
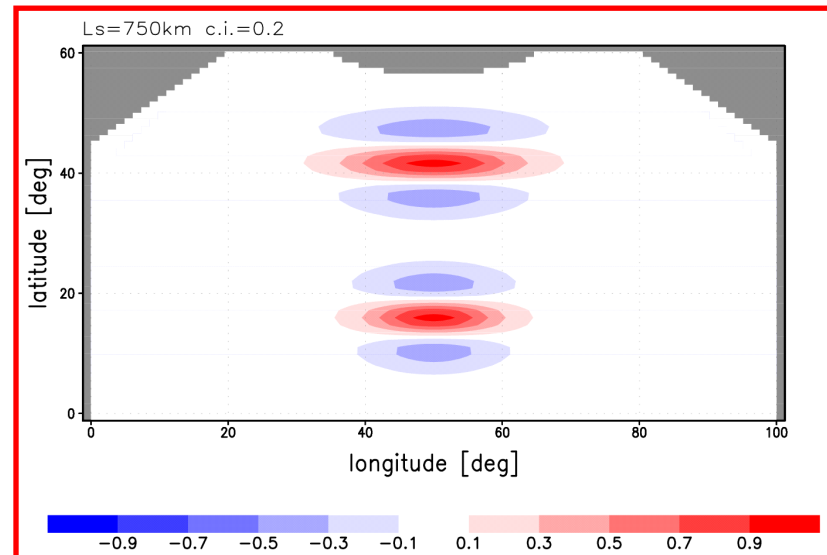
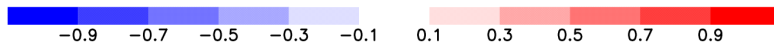
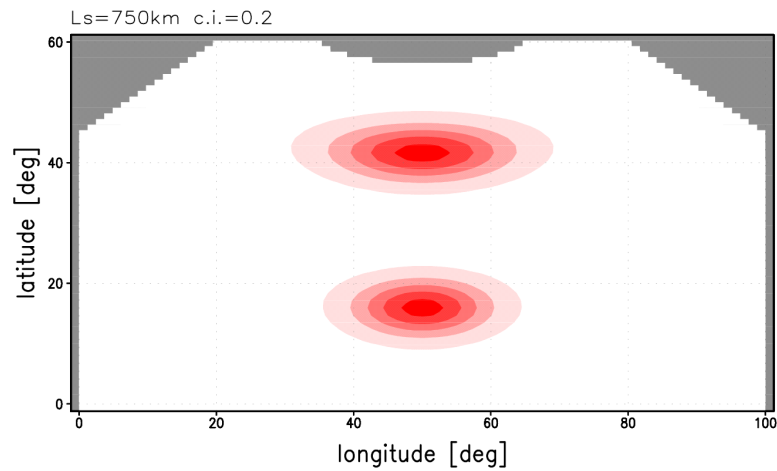
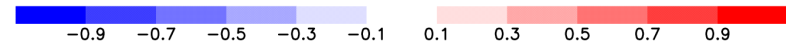
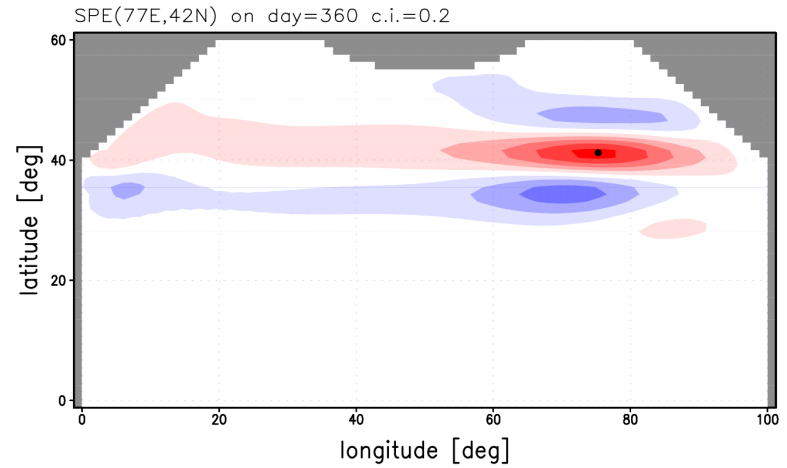
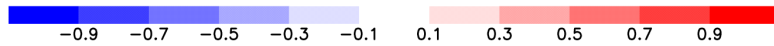
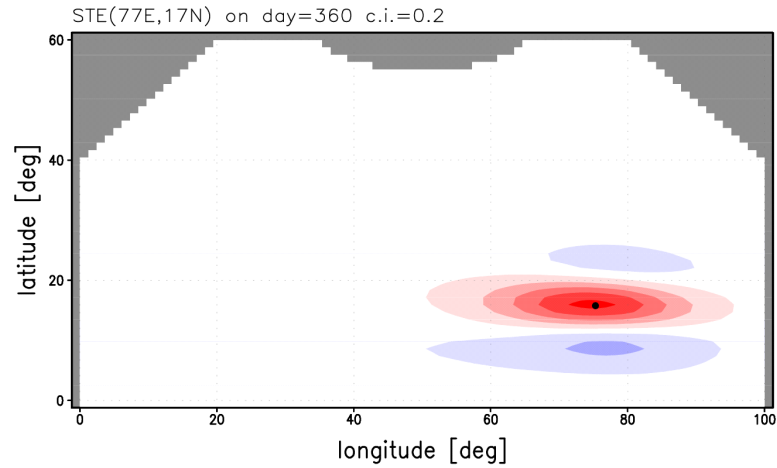
Interpretations : Wind stress curl error covariance

representer at day 360: $L_s = 750\text{km}$, $L_t = 1\text{day}$



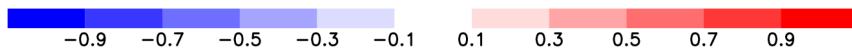
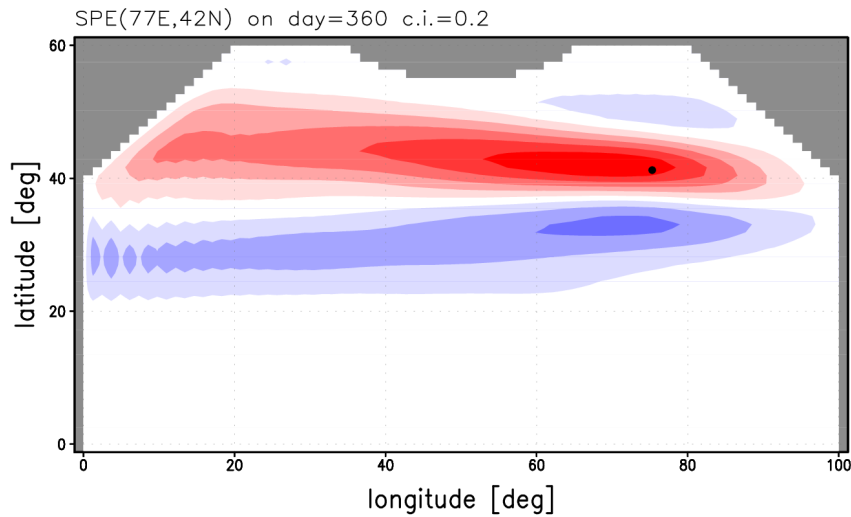
Interpretations : Wind stress curl error covariance

representer at day 360: $L_s = 750\text{km}$, $L_t = 10\text{day}$

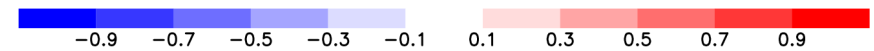
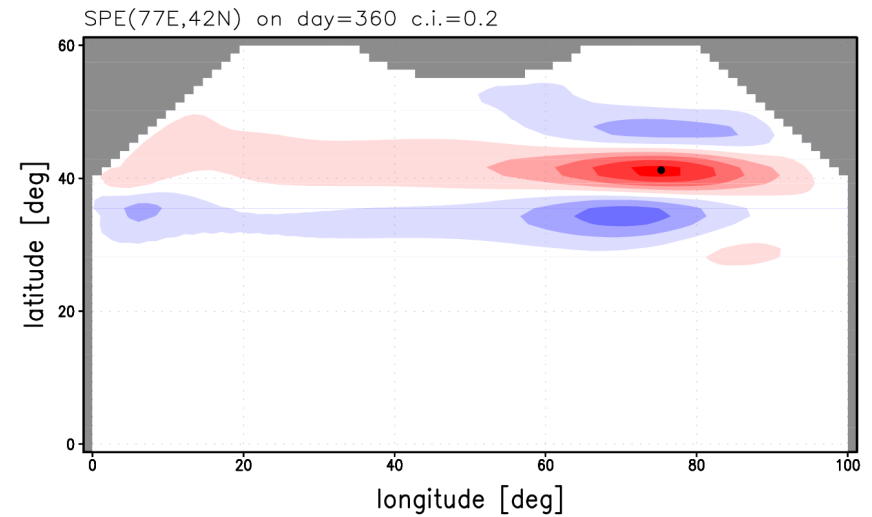


Interpretations : Role of barotropic dynamics

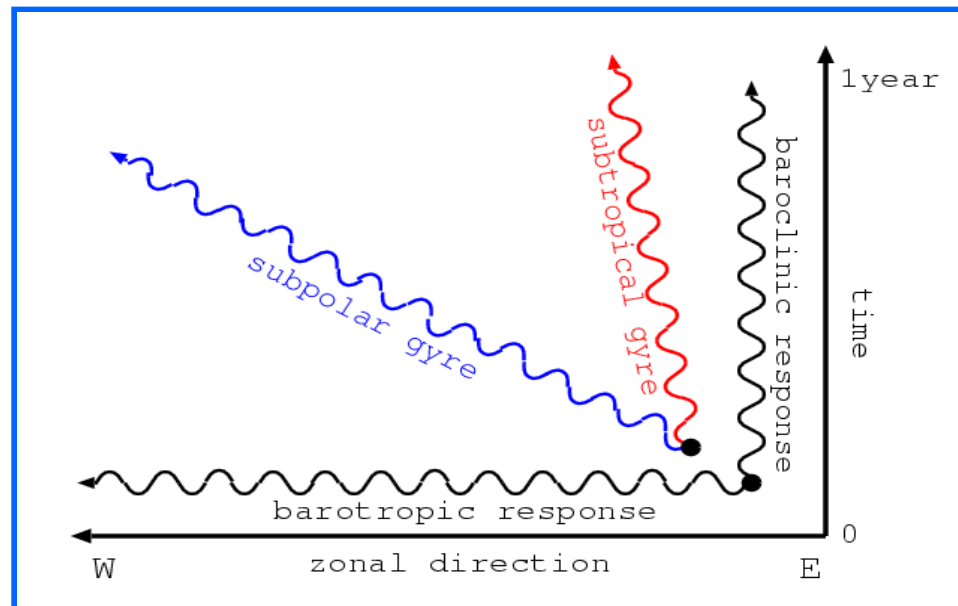
representer at day 360: $L_s = 750\text{km}$, $L_t = 10\text{day}$



Barotropic Run



Baroclinic Run



Summary

Impact of wind stress error covariance in the 4DVAR analysis with one year integration period was studied.

- Diagonal wind stress covariance model leads to highly localized structure in P-matrix
- Explicit specification of wind stress error covariance in 4DVAR system leads to implicit specification of wind stress curl error covariance.
- The *a priori* model state error in the *subtropical* gyre due to a wind stress error is dominated by baroclinic response. The *a priori* error in the *subpolar* gyre is determined by both barotropic and baroclinic responses. The barotropic and baroclinic responses are near-independent