

TRANSFORMS AND PRECONDITIONING IN THE MET OFFICE 3D VAR SCHEME

Ross Bannister
D.A.R.C.

Cost Function in w -space (reduced resolution, real space):

$$J(\vec{w}') = J_b(\vec{w}') + J_o(\vec{w}')$$

$$J_b(\vec{w}') = \frac{1}{2} (\vec{w}'^b - \vec{w}')^T \mathbf{B}^{-1} (\vec{w}'^b - \vec{w}')$$

$$J_o(\vec{w}') = \frac{1}{2} (\vec{y}^o - H(\vec{w}', \vec{w}^g))^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\vec{w}', \vec{w}^g))$$

Gradients w.r.t. w' :

$$\frac{dJ_b}{d\vec{w}'} = -\mathbf{B}^{-1} (\vec{w}'^b - \vec{w}')$$

$$\frac{dJ_o}{d\vec{w}'} = -\mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\vec{w}', \vec{w}^g))$$

Hessian,

$$\frac{d^2 J_b}{d\vec{w}'^2} = \mathbf{B}^{-1}$$

$$\frac{d^2 J_o}{d\vec{w}'^2} = \mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} \mathbf{H}$$

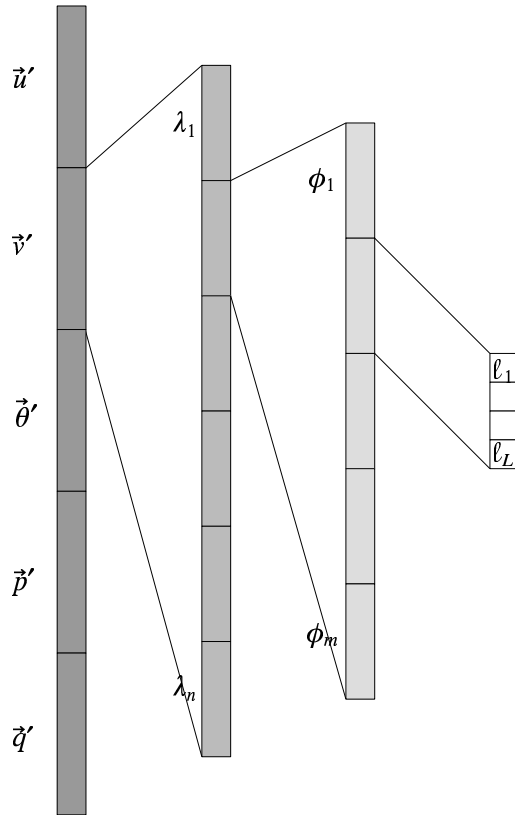
Construct a control variable, \vec{v} :

Transform	$\vec{w}' = U(\vec{v})$	$\frac{d^2 J_b}{d\vec{v}^2} = \mathbf{I}$
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Inverse	$\vec{v} = T(\vec{w}')$
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Such that

What is the basis of a \vec{w}' vector?



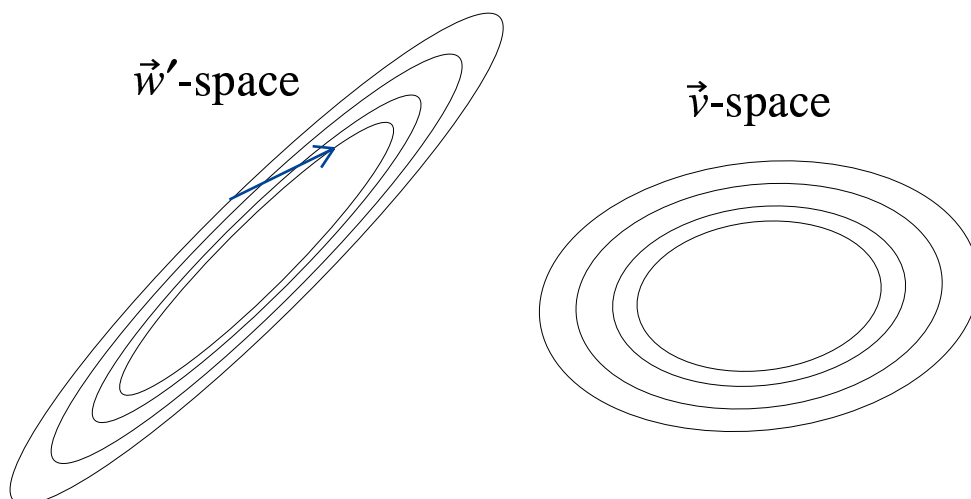
Perturbations are from a guess state:

$$\vec{w}' = \vec{w} - \vec{w}_g$$

$$\vec{w}'^b = \vec{w}^b - \vec{w}_g$$

Why do we want to make a transformation to \vec{v} -space?

- Makes the problem manageable.
- Preconditioning - makes the minimization process more efficient and accurate.
- No preconditioning: (Largest e.v.)/(smallest e.v.) $\sim 10^{10}$!
- Makes the scheme more complicated to understand.
- Balance problems?



What is the principle of the preconditioning transform?

To make the 'weight' of each control variable equal.

$$\vec{w}' = \mathbf{U}\vec{v} \quad \vec{v} = \mathbf{T}\vec{w}'$$

$$\mathbf{U} = \mathbf{T}^{-1}$$

$$\begin{aligned} J_b &= \frac{1}{2} (\mathbf{U}\vec{v}^b - \mathbf{U}\vec{v})^T \mathbf{B}^{-1} (\mathbf{U}\vec{v}^b - \mathbf{U}\vec{v}) \\ &= \frac{1}{2} (\vec{v}^b - \vec{v})^T \mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} (\vec{v}^b - \vec{v}) \end{aligned}$$

Choose \mathbf{U} such that $\mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} = \mathbf{I}$

$$\mathbf{U}^{-1} \mathbf{B} (\mathbf{U}^T)^{-1} = \mathbf{I} \quad \Rightarrow \quad \mathbf{B} = \mathbf{U} \mathbf{U}^T$$

$$\mathbf{T} \mathbf{B} \mathbf{T}^T = \mathbf{I}$$

\mathbf{U} is not a unitary or orthogonal transform, instead it is like the square-root of \mathbf{B} .

The information regarding the covariances is transferred into the transformation itself (and inverts \mathbf{B} !).

This is done in two steps:

$$\text{Let } \mathbf{U} = \mathbf{U}_2 \mathbf{U}_1$$

$$\mathbf{U}_1^{-1} \mathbf{U}_2^{-1} \mathbf{B} (\mathbf{U}_2^T)^{-1} (\mathbf{U}_1^T)^{-1} = \mathbf{I} \quad *$$

Consider \mathbf{B} afresh. Diagonalize with a transform \mathbf{Y}^T :

$$\mathbf{Y}^T \mathbf{B} \mathbf{Y} = \Lambda$$

eigenfunctions, rows of \mathbf{Y}^T

eigenvalues, diagonal matrix Λ

There are, by definition, no co-variances between the eigenmodes. Can now 'remove' the variance by:

$$\Lambda^{-1/2} \mathbf{Y}^T \mathbf{B} \mathbf{Y} \Lambda^{-1/2} = \mathbf{I}$$

c.f. (*) to show that:

$$\mathbf{U}_1 = \Lambda^{1/2} \quad \Rightarrow \quad \mathbf{T}_1 = \Lambda^{-1/2}$$

$$\mathbf{U}_2 = \mathbf{Y} \quad \Rightarrow \quad \mathbf{T}_2 = \mathbf{Y}^T$$

Problem: \mathbf{B} is too large to work with (even at half resolution).

# fields	# long. points	# lat. points	# levels	# elements \mathbf{B}
5	216	163	30	$> 10^{13}$
5	48	37	42	$> 10^{11}$

The solution in three easy stages ...

Assume that:

- We can choose an alternative set of physical parameters which are only weakly correlated,
- The covariances within each parameter can be 'removed' separately (e.g. vertical and horizontal parts normalized independently).
- We can use the last section as a guide.

- (i) The **first stage** of the **T-transform** (**parameter transform**).
- (ii) The **second stage** is a **vertical** transformation.
- (iii) The **third stage** is a **horizontal** transformation.

$$\mathbf{T} = \mathbf{T}_h \mathbf{T}_v \mathbf{T}_p$$

(i) The parameter transform

Parameter	Eqs.
ψ	$\nabla^2 \psi = \vec{k} \cdot \nabla \times \vec{u}$
χ	$\nabla^2 \chi = \nabla \cdot \vec{u}$
${}^A p$	$p = {}^G p + {}^A p$
μ	q / q_{sat}

	ψ	χ	${}^A p$	μ
ψ	\mathbf{B}_ψ	0	0	0
χ	0	\mathbf{B}_χ	0	0
${}^A p$	0	0	$\mathbf{B}_{{}^A p}$	0
μ	0	0	0	\mathbf{B}_μ

\mathbf{B}^{-1}
has a similar structure

Background term is written (in terms of parameter perturbations),

$$\begin{aligned}
 J_B(v_p) &= \frac{1}{2} (\vec{v}_p^b - \vec{v}_p)^T \mathbf{B}^{-1} (\vec{v}_p^b - \vec{v}_p) \\
 &= \frac{1}{2} (\vec{\psi}^b - \vec{\psi})^T \mathbf{B}_{\psi}^{-1} (\vec{\psi}^b - \vec{\psi}) \\
 &\quad + \frac{1}{2} (\vec{\chi}^b - \vec{\chi})^T \mathbf{B}_{\chi}^{-1} (\vec{\chi}^b - \vec{\chi}) + \dots
 \end{aligned}$$

$$\vec{v}_p = \mathbf{T}_p \vec{w}' = \begin{pmatrix} \vec{\psi} \\ \vec{\chi} \\ {}^A\vec{p} \\ \vec{\mu} \end{pmatrix}$$

Cov. matrices for each parameter (e.g. ψ) - *outer* or *tensor* product:

$$\text{Cov} = \overline{(\vec{\psi} - \vec{\psi}_t)(\vec{\psi} - \vec{\psi}_t)^T}$$

The size of these covariance matrices is still too large.

Do remaining transformations for each parameter separately.

(ii) Vertical transform

Aim (each parameter):

Reformulate (i) the state variable and (ii) the cov. matrix in terms of modes which are **uncorrelated** in the vertical, each of which having **unit variance**.

We can calculate the vertical covariances for each column:

$$\text{Cov}(\lambda, \phi; \ell, \ell') = \frac{(\psi(\lambda, \phi, t; \ell) - \psi_t(\lambda, \phi, t; \ell)) \times (\psi(\lambda, \phi, t; \ell') - \psi_t(\lambda, \phi, t; \ell'))}{}$$

Average over all (λ, ϕ) to form global covariance matrix:

$$\text{Let } \mathbf{B}_{\psi}^{\text{vert}}(\ell, \ell') = \langle \text{Cov}(\lambda, \phi; \ell, \ell') \rangle$$

Decompose this such that $\mathbf{B}_{\psi}^{\text{vert}} = \mathbf{I}$, as before (with weighting).

$$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P} \mathbf{B}_{\psi}^{\text{vert}} \mathbf{P} \mathbf{F}_v \Lambda_v^{-1/2} = \mathbf{I}$$

$$\mathbf{T}_v^{\text{vert}}(\text{global av.}) = \Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$$

How can we make this into a transform acting on $\vec{\psi}$?

$$\vec{\psi}_{EOF} = \mathbf{T}_v \vec{\psi}$$

(λ_1, ϕ_1)	EOF1	$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$	0	0	0	0	(λ_1, ϕ_1)	ℓ_1
(λ_2, ϕ_2)	EOF2	0	$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$	0	0	0	(λ_2, ϕ_2)	ℓ_2
(λ_3, ϕ_3)	EOF1	0	0	$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$	0	0	(λ_3, ϕ_3)	ℓ_L
	EOF2	0	0	0	$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$	0		ℓ_1
	EOF1	0	0	0	0	$\Lambda_v^{-1/2} \mathbf{F}_v^T \mathbf{P}$		ℓ_2
	EOF2	0	0	0	0	0		ℓ_L

$$\mathbf{T}_v \mathbf{B}_\psi \mathbf{T}_v^T$$

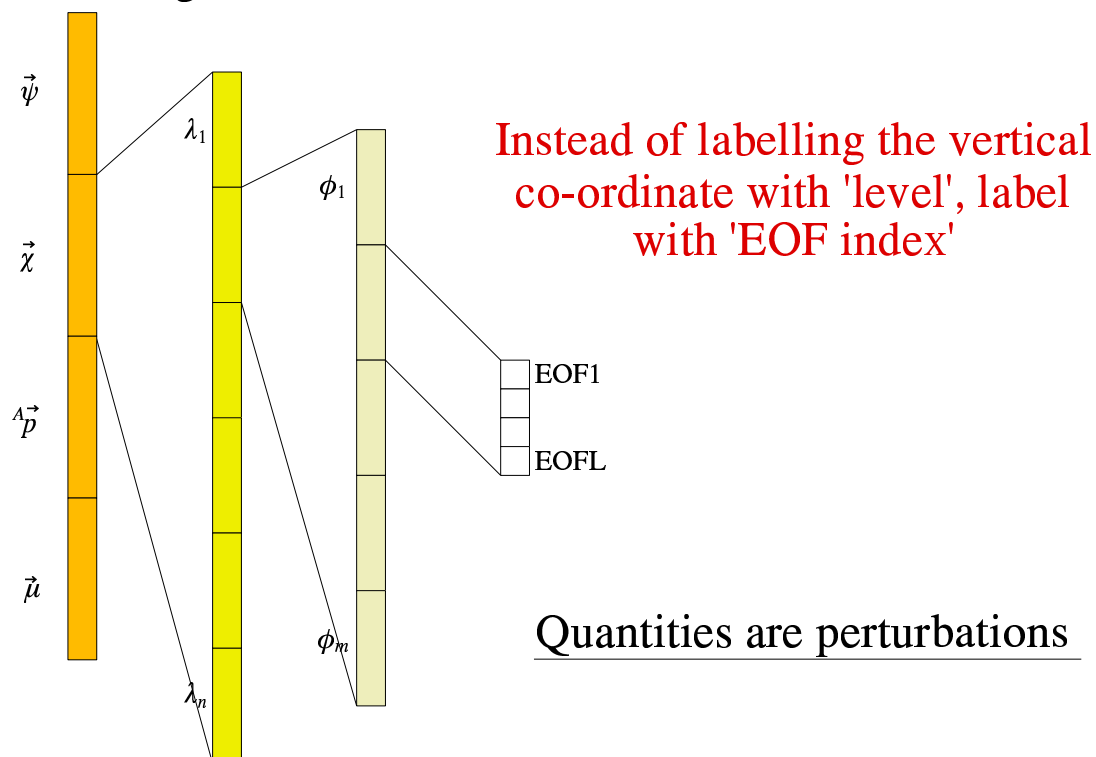
	(λ_1, ϕ_1)		(λ_2, ϕ_2)		(λ_3, ϕ_3)		
	EE	EO	EE	EO	EE	EO	EO
	FF	FL	FF	FL	FF	FL	FL
	1	2	1	2	1	2	1
(λ_1, ϕ_1)	EOF1	EOF2	EOF1	EOF2	EOF1	EOF2	EOF1
(λ_2, ϕ_2)	EOF1	EOF2	EOF1	EOF2	EOF1	EOF2	EOF1
(λ_3, ϕ_3)	EOF1	EOF2	EOF1	EOF2	EOF1	EOF2	EOF1

Include lat. variation

$$\Lambda_y \rightarrow \Lambda_y(\phi)$$


$$\Lambda_v(\phi) = \mathbf{F}_v^T \mathbf{P} \mathbf{B}_{\psi}^{vert}(\phi) \mathbf{P} \mathbf{F}_v$$

Transforming the state vector: $\vec{v}_v = \mathbf{T}_v \vec{v}_v$



Think of surfaces of constant vertical EOF index.

This is the result of the vertical transform.

Horizontal transform 

(iii) Horizontal Transform

Aim (each parameter):

Reformulate (i) the state variable and (ii) the cov. matrix in terms of modes which are **uncorrelated** in the horizontal, each of which having **unit variance**.

Decompose into modes which we assume are uncorrelated.
Effectively (for one ψ -EOF surface):

$$\Lambda_h^{-1/2} \mathbf{F}_h^T \mathbf{P} \mathbf{B}_\psi^{hor} \mathbf{P} \mathbf{F}_h \Lambda_h^{-1/2} = \mathbf{I}$$

$$\mathbf{T}_h^{hor} = \Lambda_h^{-1/2} \mathbf{F}_h^T \mathbf{P}$$

\mathbf{B}_ψ^{hor} is not explicitly calculated. Choose:

\mathbf{P} as a weight matrix, different from before,

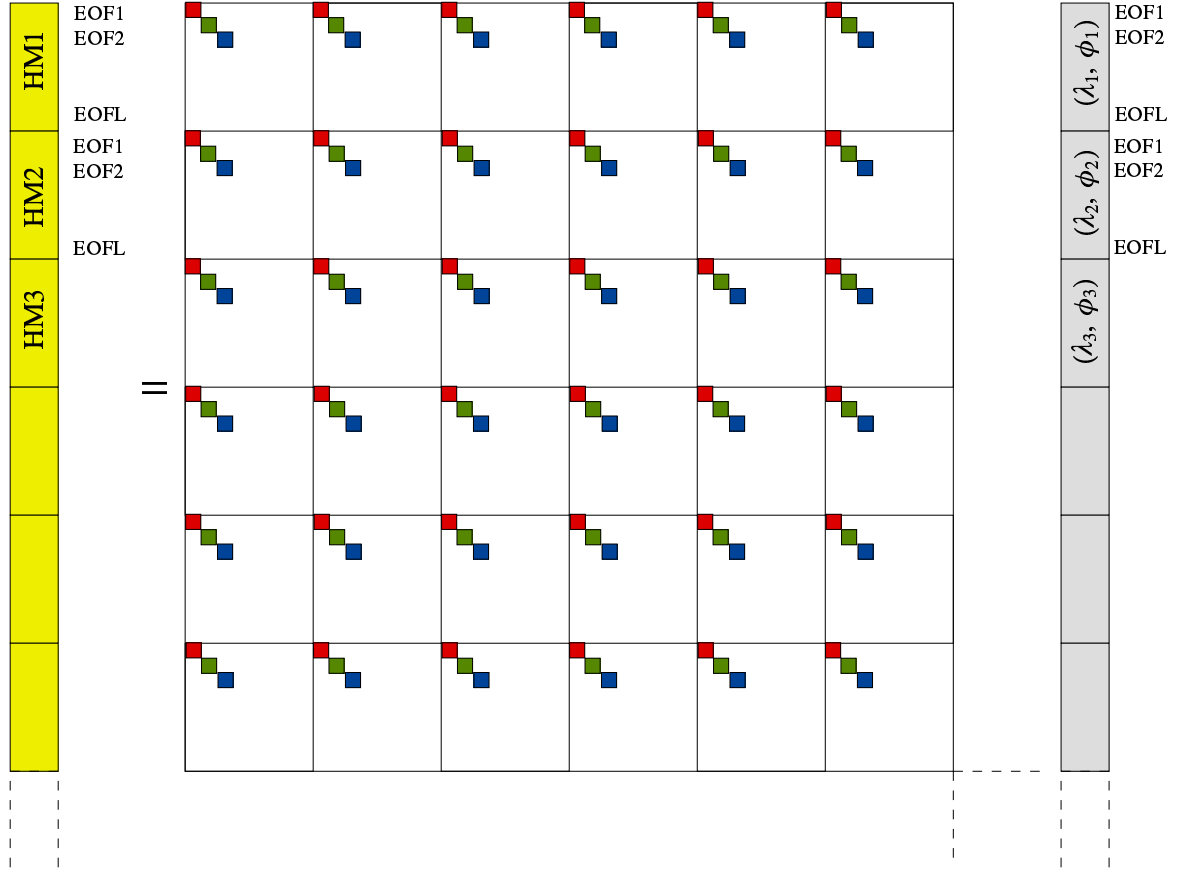
\mathbf{F}_v^T as a horizontal spectral transform, and

$\Lambda_h^{1/2}$ as the correlation spectrum of the modes.

What does the horizontal transform look like (acts on $\vec{\psi}_{EOF}$)?

Transforming the state vector ($\vec{\psi}$):

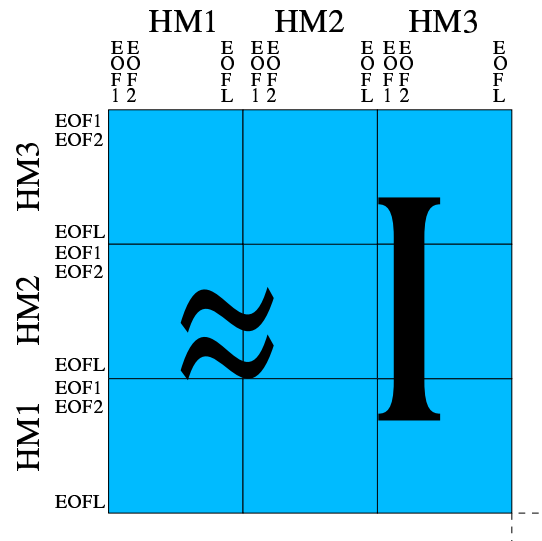
$$\vec{\psi}_{v-space} = \mathbf{T}_h \vec{\psi}_{EOF}$$



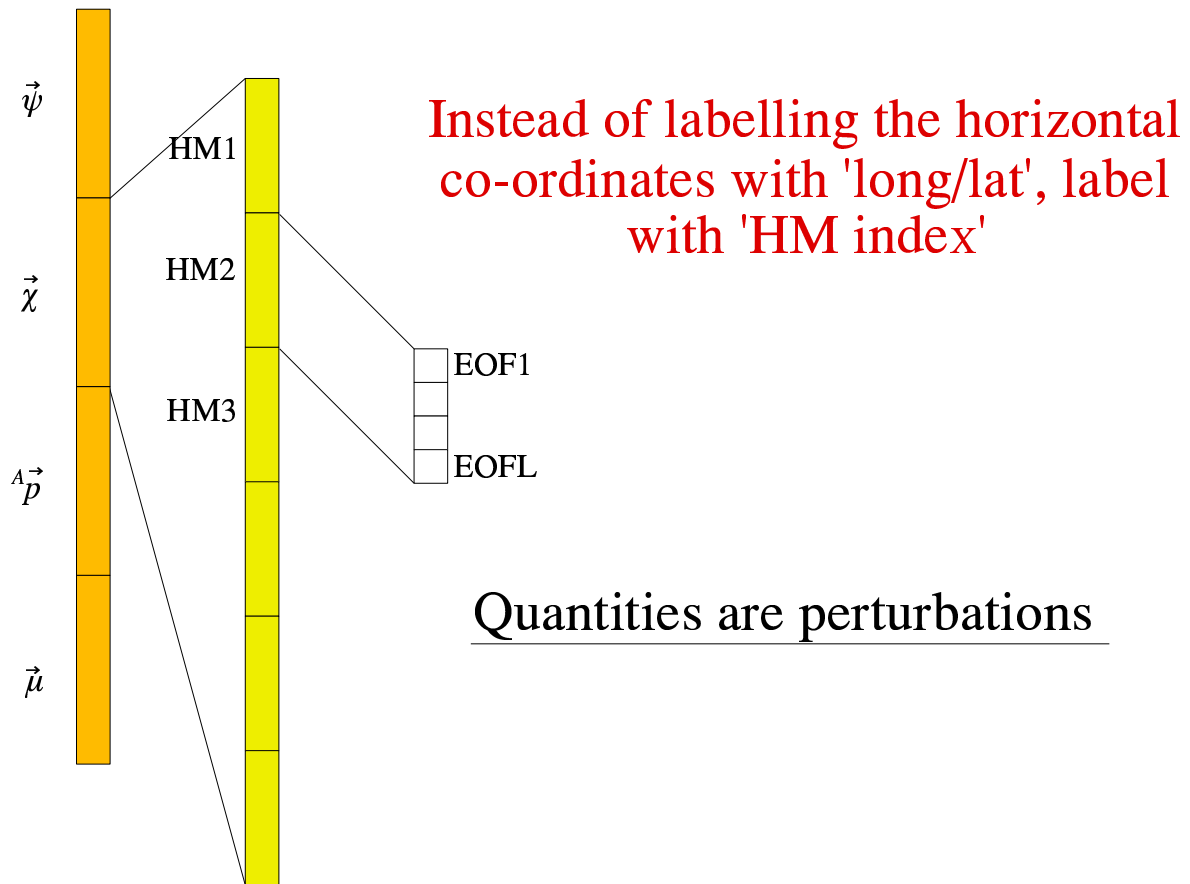
- \mathbf{T}_h^{hor} Transform associated with surface EOF1
- \mathbf{T}_h^{hor} Transform associated with surface EOF2
- \mathbf{T}_h^{hor} Transform associated with surface EOF3, etc

Transforming the error covariance matrix:

$$\mathbf{T}_h \mathbf{T}_v \mathbf{B}_\psi \mathbf{T}_v^T \mathbf{T}_h^T \approx \mathbf{I}$$



The transformed state vector: $\vec{v} = \mathbf{T}_h \vec{v}_v$



This is the result of all three transforms

Perform descent algorithm in this space

Summary of Equations

1. \vec{w} -space formulation

$$J(\vec{w}') = \frac{1}{2} (\vec{w}'^b - \vec{w}')^T \mathbf{B}^{-1} (\vec{w}'^b - \vec{w}') +$$

$$\frac{1}{2} (\vec{y}^o - H(\vec{w}', \vec{w}^g))^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\vec{w}', \vec{w}^g))$$

$$\frac{dJ}{d\vec{w}'} = -\mathbf{B}^{-1} (\vec{w}'^b - \vec{w}') - \mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\vec{w}', \vec{w}^g))$$

$$\frac{d^2 J_b}{d\vec{w}'^2} = \mathbf{B}^{-1} + \mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} \mathbf{H}$$

\vec{w} = model state (' pertbtn, b backgrnd, g guess)

$$H(\vec{w}', \vec{w}^g) \approx H(\vec{w}^g) + \mathbf{H}\vec{w}'$$

2. \vec{v} -space formulation

$$\vec{v} = \mathbf{T}\vec{w}' \quad \vec{w}' = \mathbf{U}\vec{v} \quad \mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} = \mathbf{I}$$

$$J(\vec{v}) = \frac{1}{2} (\vec{v}^b - \vec{v})^T \mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} (\vec{v}^b - \vec{v}) +$$

$$\frac{1}{2} (\vec{y}^o - H(\mathbf{U}\vec{v}, \vec{w}^g))^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\mathbf{U}\vec{v}, \vec{w}^g))$$

$$\frac{dJ}{d\vec{v}} = -\mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} (\vec{v}^b - \vec{v}) - \mathbf{U}^T \mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} (\vec{y}^o - H(\mathbf{U}\vec{v}, \vec{w}^g))$$

$$\frac{d^2 J_b}{d\vec{v}^2} = \mathbf{U}^T \mathbf{B}^{-1} \mathbf{U} + \mathbf{U}^T \mathbf{H}^T (\mathbf{E} + \mathbf{F})^{-1} \mathbf{H} \mathbf{U}$$