



GSI Tutorial 2011

Background and Observation Errors: Estimation and Tuning

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Background Errors

1. Background error covariance
2. Multivariate relationships
3. Estimating/tuning background errors
4. Balance
5. Flow dependence



3DVAR Cost Function

$$J_{\text{Var}}(\mathbf{x}') = \frac{1}{2}(\mathbf{x}')^T \mathbf{B}_{\text{Var}}^{-1}(\mathbf{x}') + \frac{1}{2}(\mathbf{H}\mathbf{x}' - \mathbf{y}'_o)^T \mathbf{R}^{-1}(\mathbf{H}\mathbf{x}' - \mathbf{y}'_o) + J_c$$


- J : Penalty (Fit to background + Fit to observations + Constraints)
- \mathbf{x}' : Analysis increment ($\mathbf{x}_a - \mathbf{x}_b$) ; where \mathbf{x}_b is a background
- \mathbf{B}_{Var} : Background error covariance
- \mathbf{H} : Observations (forward) operator
- \mathbf{R} : Observation error covariance (Instrument + Representativeness)
- \mathbf{y}'_o : Observation innovations/residuals ($\mathbf{y}_o - \mathbf{H}\mathbf{x}_b$)
- J_c : Constraints (physical quantities, balance/noise, etc.)



Background Error Covariance



- Vital for controlling amplitude and structure for correction to model first guess (background)
- Covariance matrix
 - Controls influence distance
 - Contains multivariate information
 - Controls amplitude of correction to background
- For NWP (WRF, GFS, etc.), matrix is prohibitively large
 - Many components are modeled or ignored
- Typically estimated a-priori, offline



Analysis (control) variables

- Analysis is often performed using non-model variables
 - Background errors defined for analysis/control (not model) variables
- Control variables for GSI (NCEP GFS application):
 - **Streamfunction (Ψ)**
 - Unbalanced Velocity Potential ($\chi_{\text{unbalanced}}$)
 - Unbalanced Virtual Temperature ($T_{\text{unbalanced}}$)
 - Unbalanced Surface Pressure ($P_{s_{\text{unbalanced}}}$)
 - Relative Humidity
 - Two options
 - Ozone mixing ratio
 - Cloud water mixing ratio
 - Skin temperature
 - Analyzed, but not passed onto GFS model



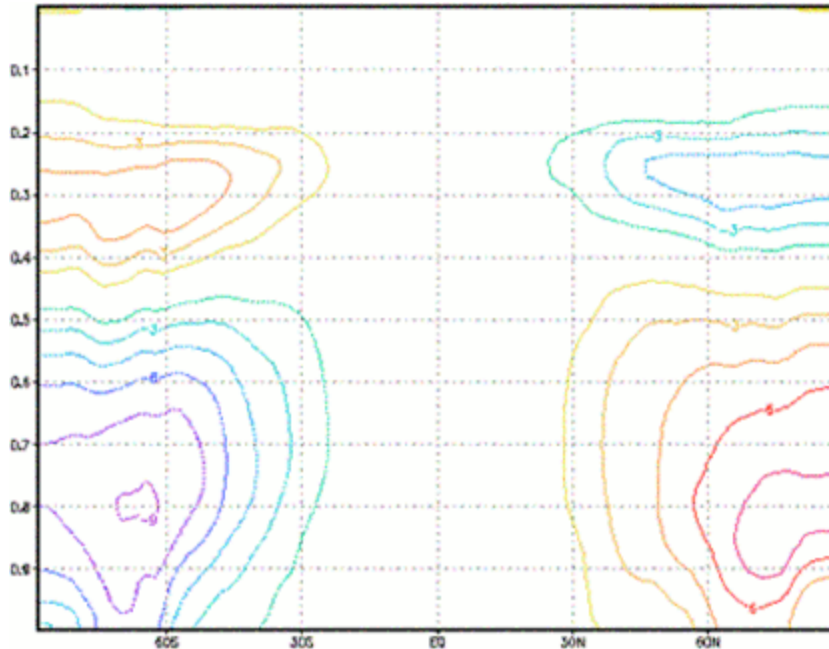
Multivariate Definition

- $\chi = \chi_{\text{unbalanced}} + \mathbf{c} \Psi$
- $T = T_{\text{unbalanced}} + \mathbf{G} \Psi$
- $P_S = P_{S_{\text{unbalanced}}} + \mathbf{W} \Psi$

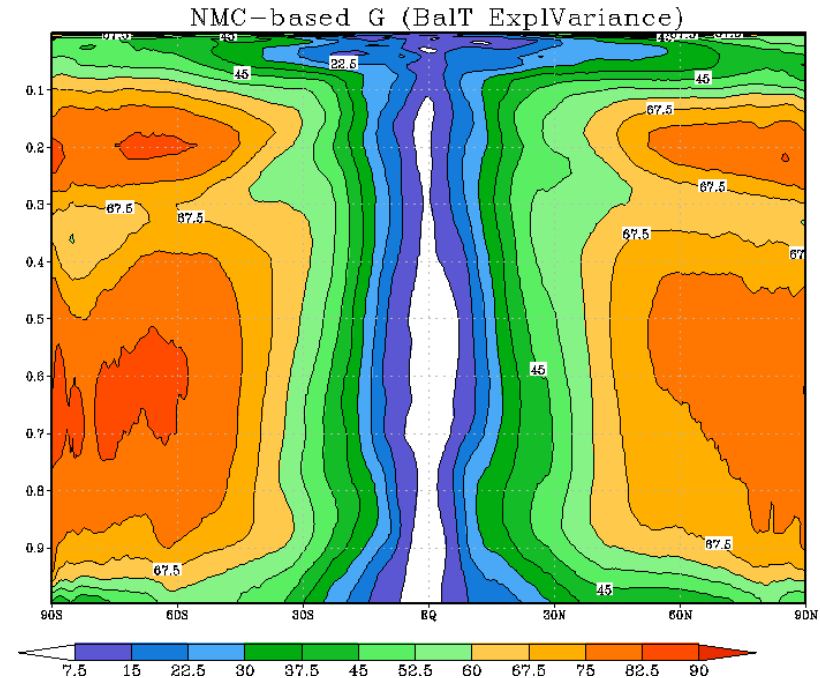
- Streamfunction is a key variable
 - defines a large percentage of temperature, velocity potential and surface pressure increment
- \mathbf{G} , \mathbf{W} , \mathbf{c} are empirical matrices (estimated with linear regression) to project stream function increment onto balanced component of other variables

Multivariate Variable Definition

$$T_b = G\psi$$



Projection of ψ at vertical level 25 onto vertical profile of balanced temperature (G_{25})



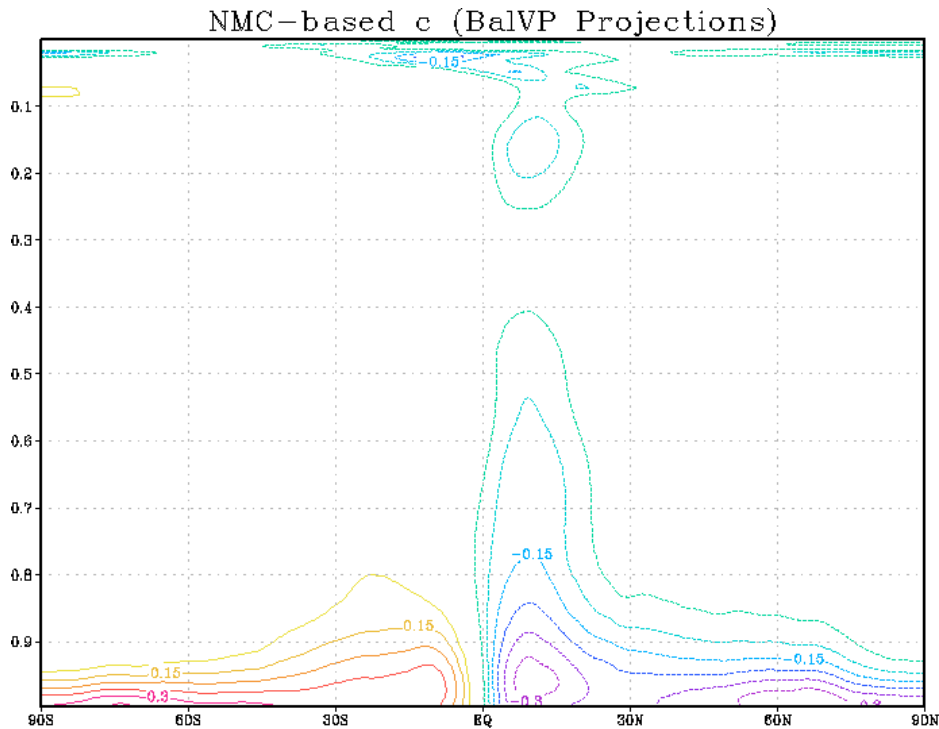
Percentage of full temperature variance explained by the balance projection



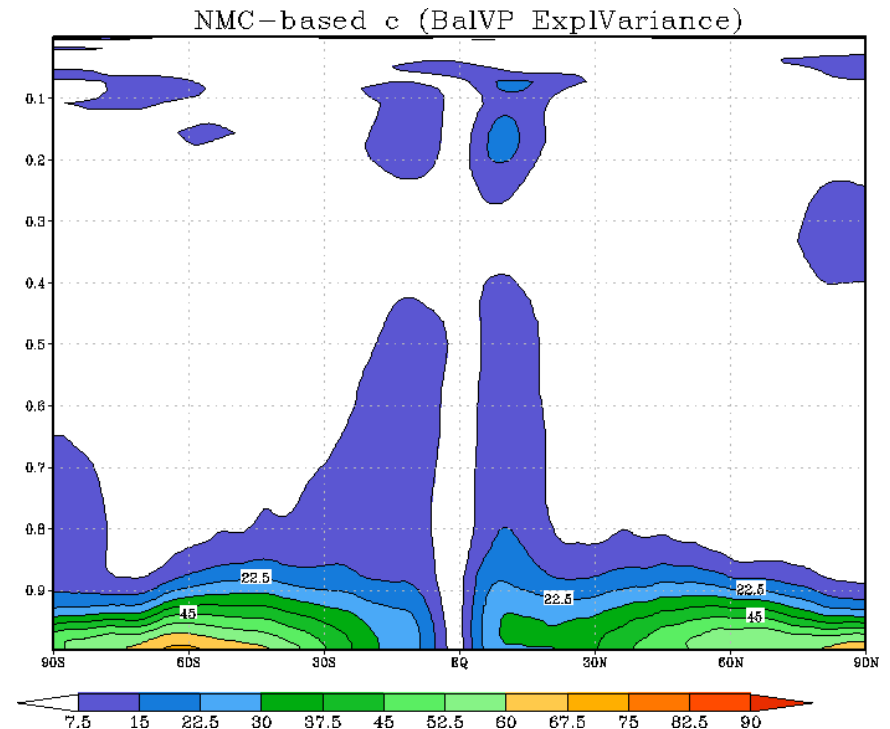
Multivariate Variable Definition



$$\chi_b = c\psi$$



Projection of ψ onto balanced velocity potential (c)



Percentage of full velocity potential variance explained by the balance projection

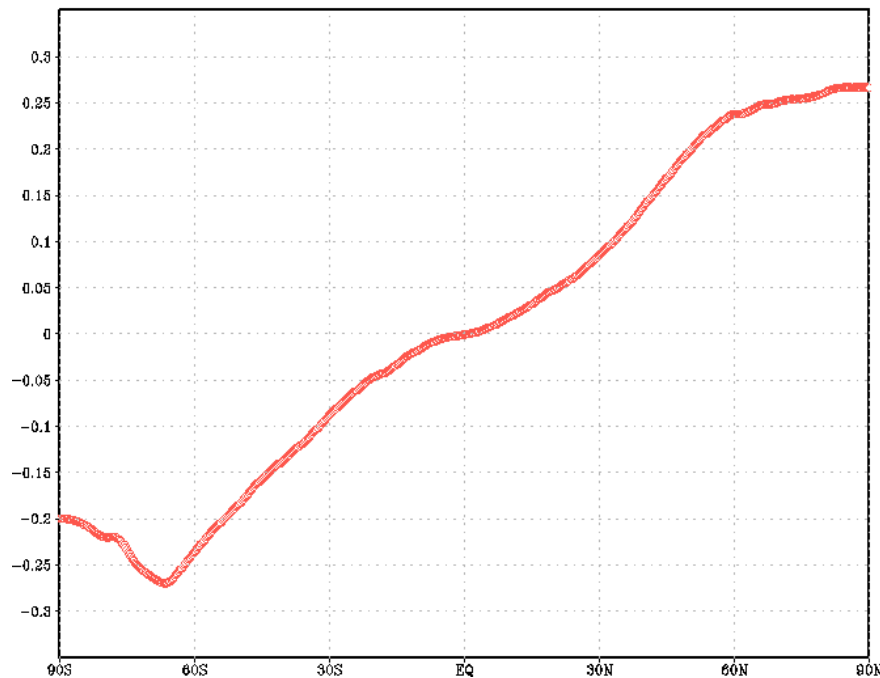


Multivariate Variable Definition



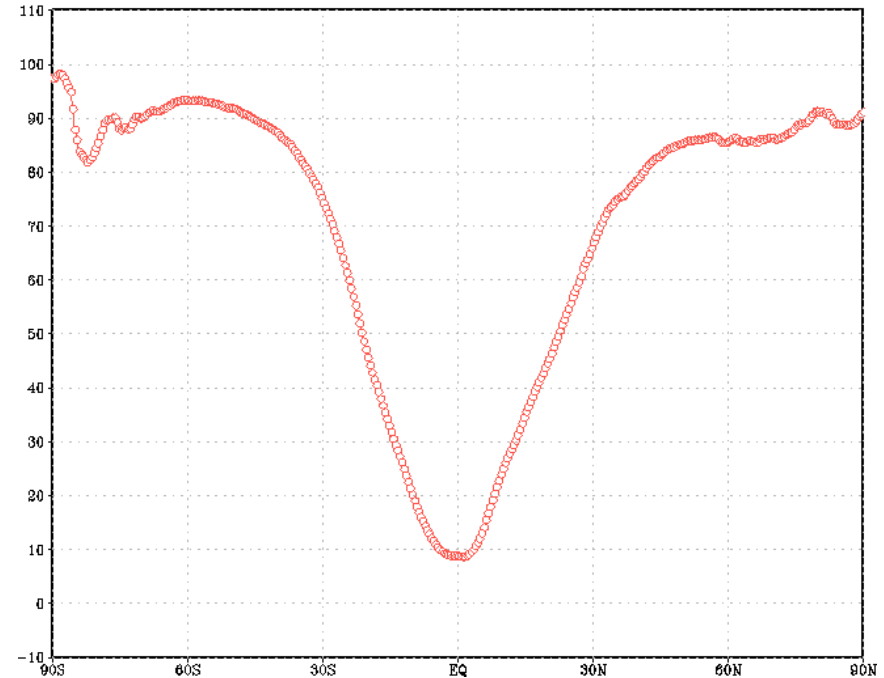
$$Ps_b = \mathbf{w}\psi$$

NMC-based W (BalPs Projections; $1e-6$)



Projection of ψ onto balanced surface pressure (\mathbf{w})

NMC-based W (BalPs Explained Variance)



Percentage of full surface pressure variance explained by the balance projection



Testing Background Error

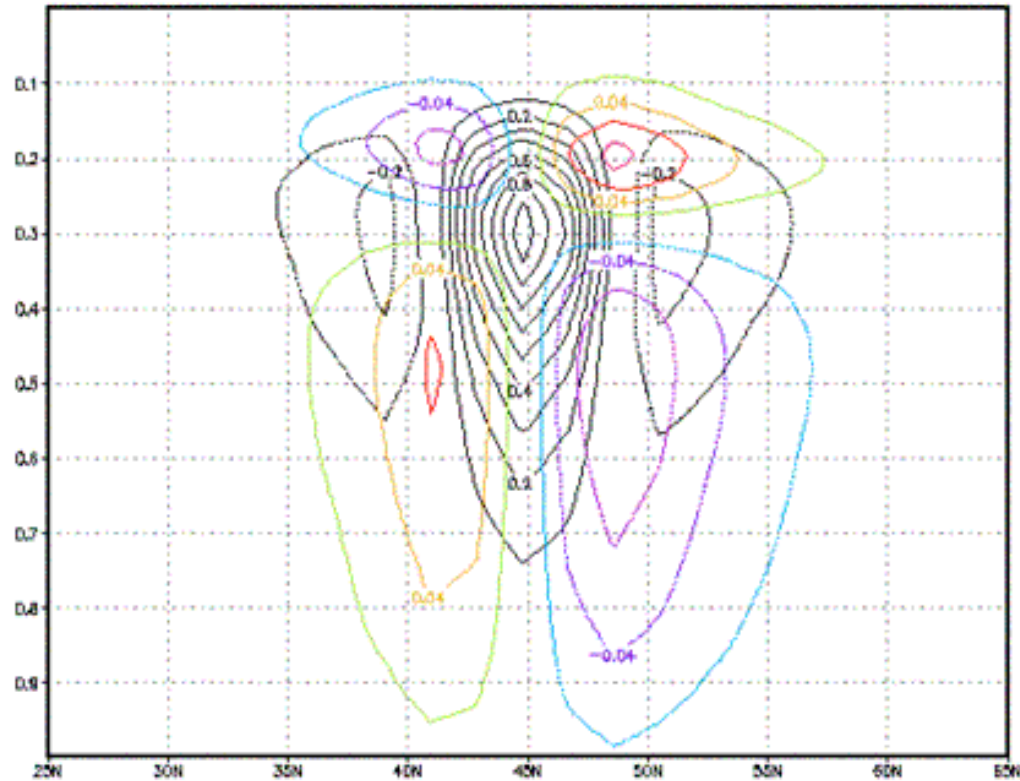


- Best way to test background error covariance is through single observation experiments (as shown in some previous plots)
- Easy to run within GSI, namelist options:
 &SETUP
 oneobtest=.true.
 &SINGLEOB_TEST
 maginnov=1.,magoberr=1.,oneob_type='u',oblat=45.,oblon=180,
 obpres=300.,obdattime= 2010101312,obhourset=0.,



Multivariate Example

Single zonal wind observation (1.0 ms^{-1} O-F and error)



u increment (black, interval 0.1 ms^{-1}) and T increment (color, interval 0.02K) from GSI



Moisture Variable

- Option 1
 - Pseudo-RH (univariate within inner loop)
- Option 2*
 - Normalized relative humidity
 - **Multivariate with temperature and pressure**
 - Standard Deviation a function of background relative humidity

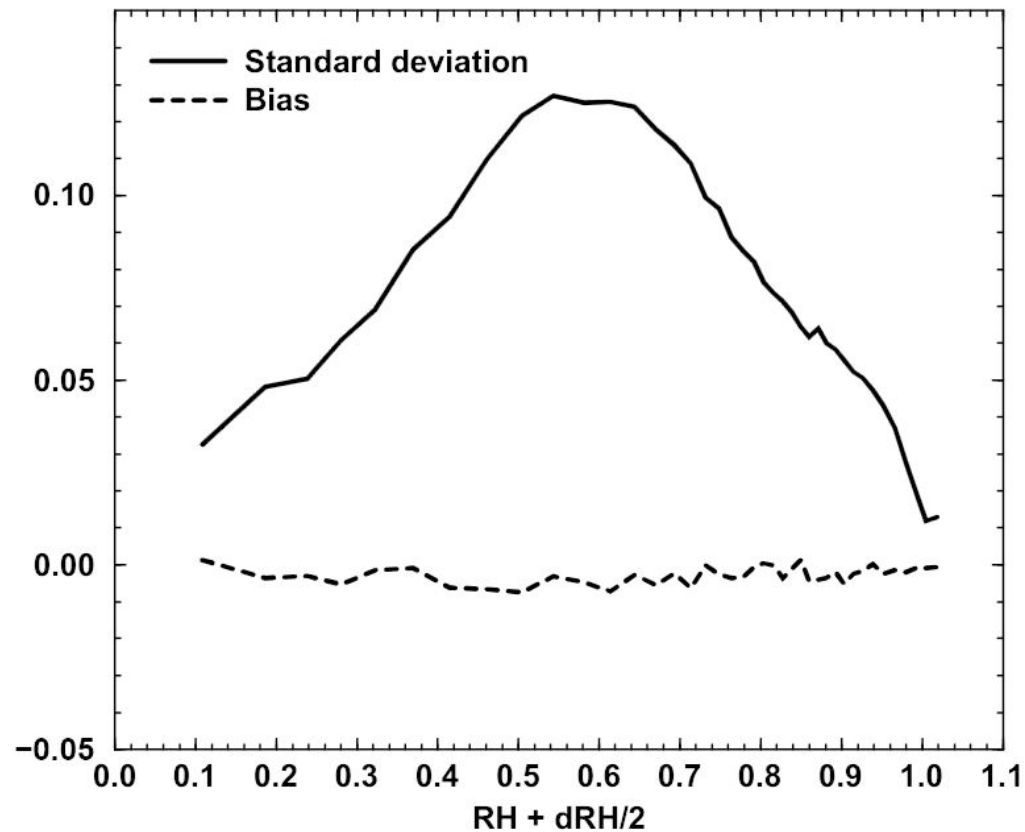
$$\frac{\delta RH}{\sigma(RH^b)} = RH^b \left(\frac{\delta p}{p^b} + \frac{\delta q}{q^b} - \frac{\delta T}{\alpha^b} \right)$$

$$\alpha^b = \frac{-1}{\left(\frac{\partial RH}{\partial T} \right)}$$

- Holm (2002) ECMWF Tech. Memo



Background Error Variance for RH Option 2



- Figure 23 in Holm et al. (2002); ECMWF Tech Memo



Elements needed for GSI

- For each analysis variable
 - Amplitude (variance)
 - Recursive filter parameters
 - Horizontal length scale (km, for Gaussian)
 - Vertical length scale (grid units, for Gaussian)
 - 3D variables only
- Additionally, balance coefficients
 - **G**, **W**, and **c** from previous slides



Estimating (static) Background Error



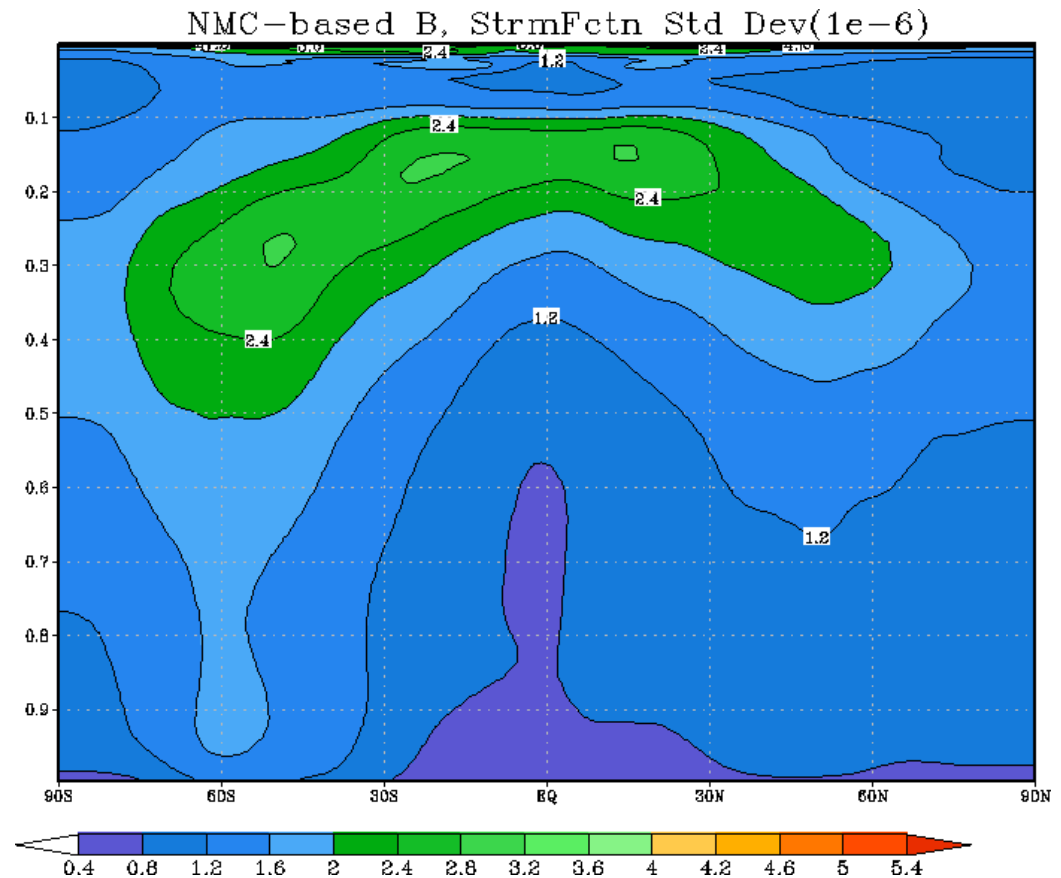
- ***NMC Method****
 - Lagged forecast pairs (i.e. 24/48 hr forecasts valid at same time, 12/24 hr lagged pairs, etc.)
 - Assume: Linear error growth
 - Easy to generate statistics from previously generated (operational) forecast pairs
- **Ensemble Method**
 - Ensemble differences of forecasts
 - Assume: Ensemble represents actual error
- **Observation Method**
 - Difference between forecast and observations
 - Difficulties: observation coverage and multivariate components



Amplitude (standard deviation)



- Function of latitude and height
- Larger in midlatitudes than in the tropics
- Larger in Southern Hemisphere than Northern Hemisphere



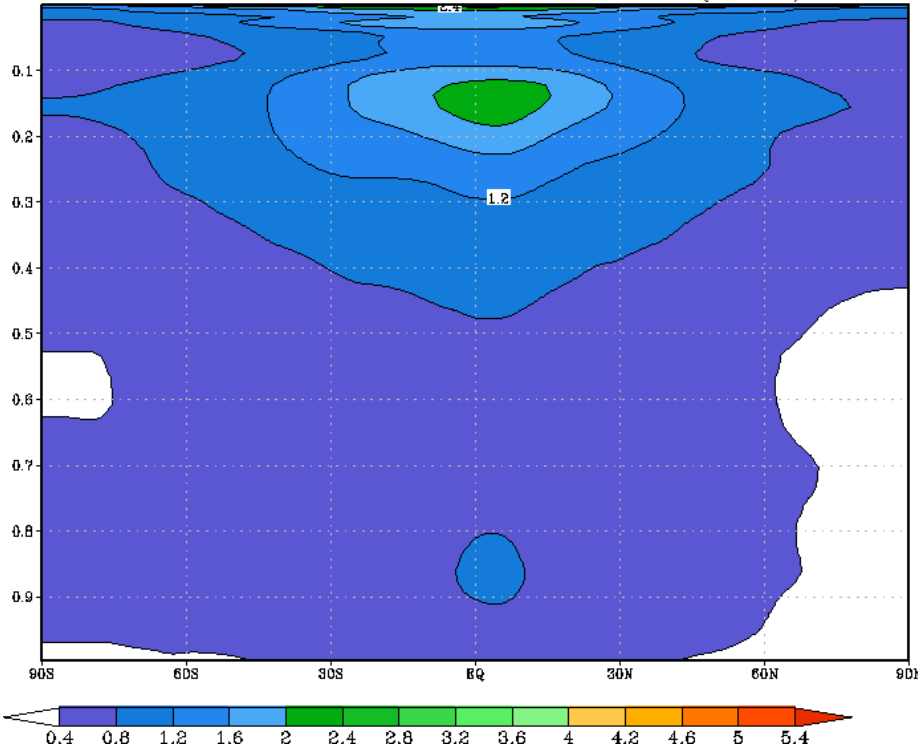
NMC-estimated standard deviation for **streamfunction**, from lagged 24/48hr GFS forecasts



Amplitude (standard deviation)

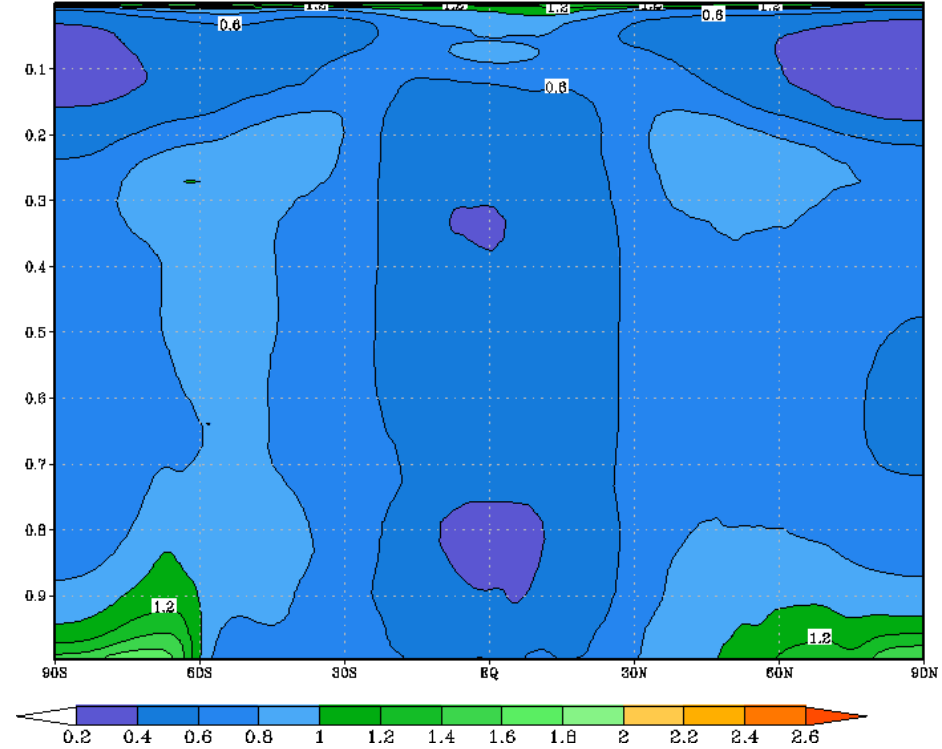


NMC-based B, UnbalVP Std Dev($1e-6$)



NMC-estimated standard deviation for **unbalanced velocity potential**, from lagged 24/48hr GFS forecasts

NMC-based B, UnbalT Std Dev



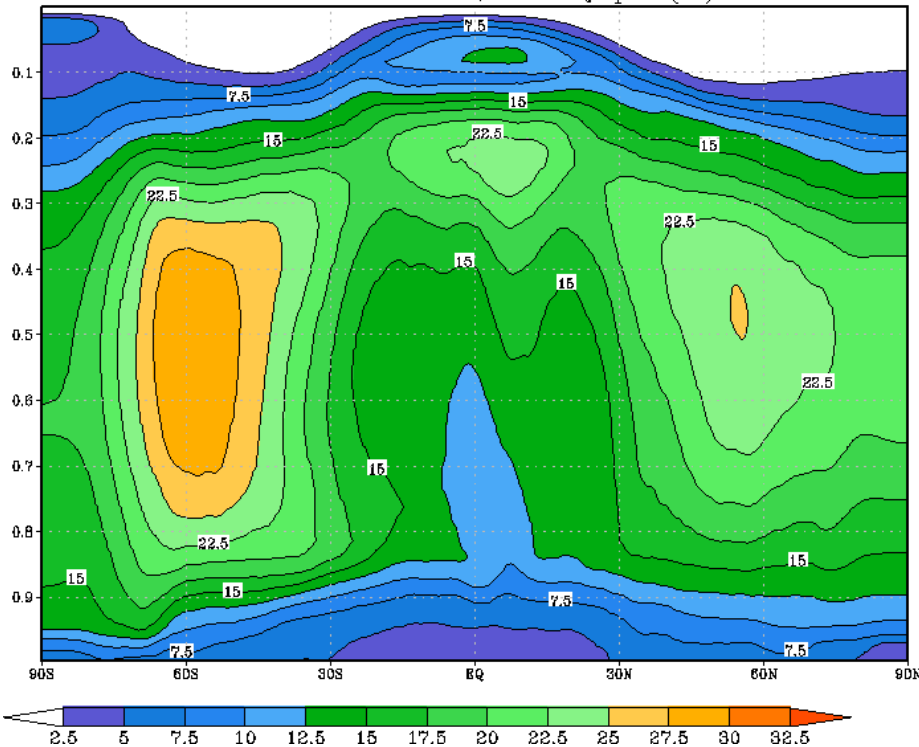
NMC-estimated standard deviation for **unbalanced virtual temperature**, from lagged 24/48hr GFS forecasts



Amplitude (standard deviation)

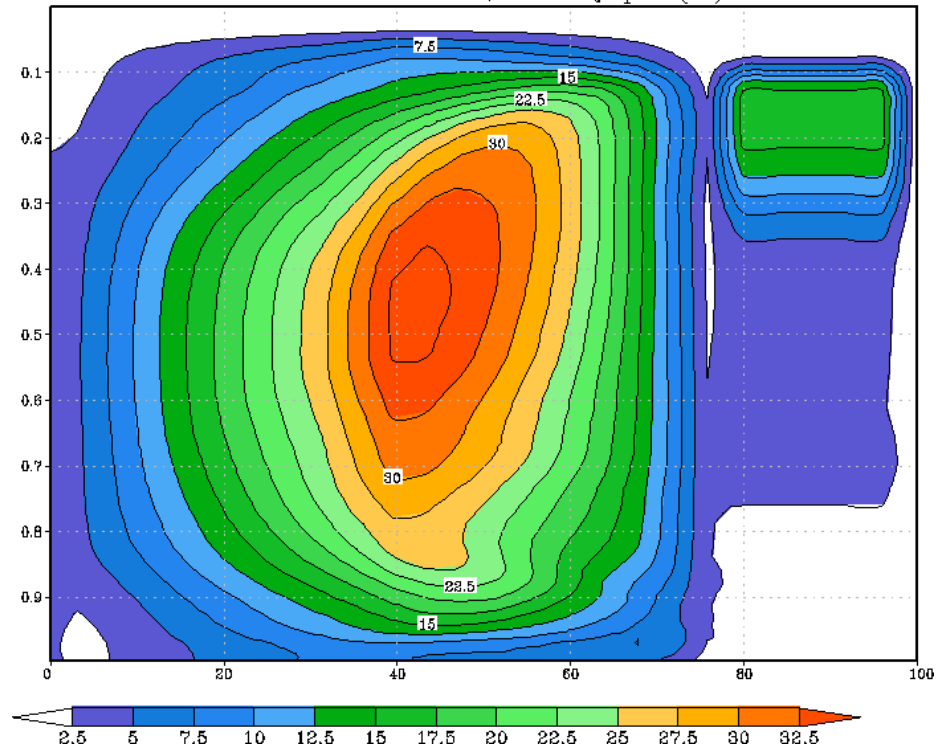


NMC-based B, RH-Qopt1(%)



NMC-estimated standard deviation for **pseudo RH (q-option 1)**, from lagged 24/48hr GFS forecasts

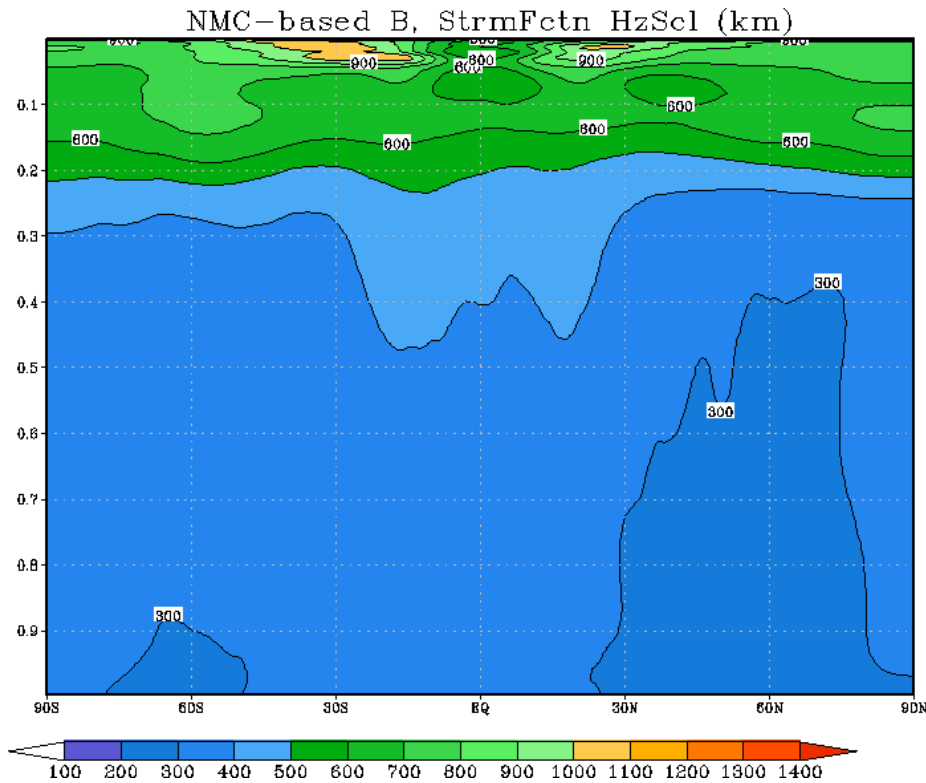
NMC-based B, RH-Qopt2(%)



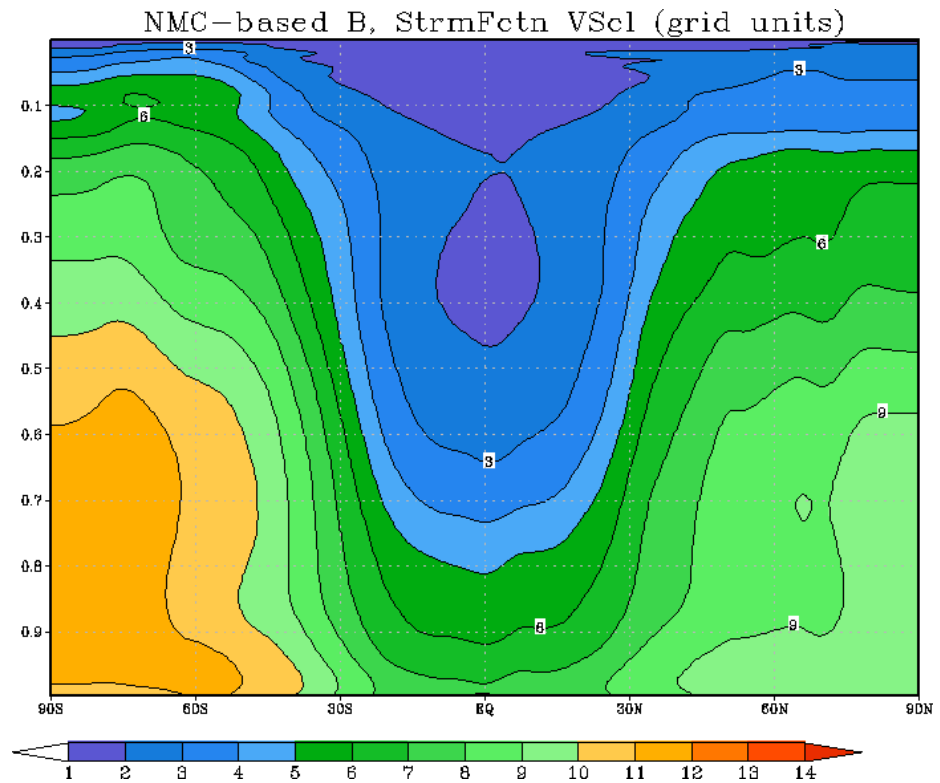
NMC-estimated standard deviation for **normalized pseudo RH (q-option 2)**, from lagged 24/48hr GFS forecasts



Length Scales



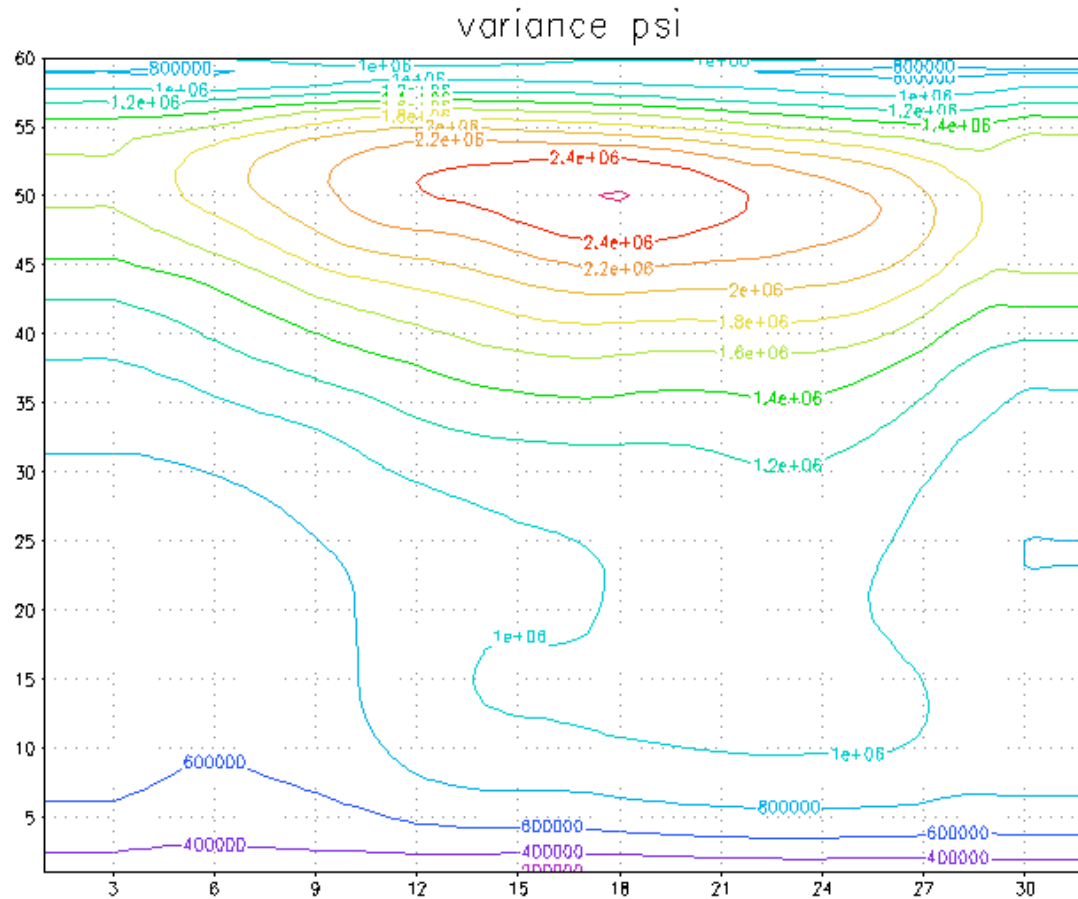
NMC-estimated horizontal length scales (km) for **streamfunction**, from lagged 24/48hr GFS forecasts



NMC-estimated vertical length scales (grid units) for **streamfunction**, from lagged 24/48hr GFS forecasts



Regional (8km NMM) Estimated NMC Method

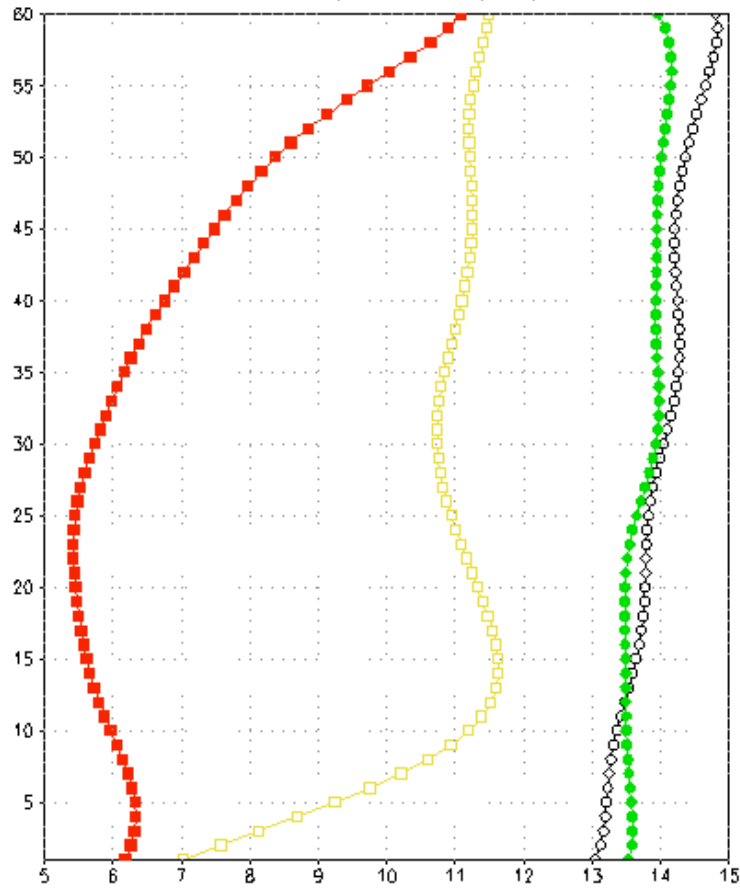




Regional Scales

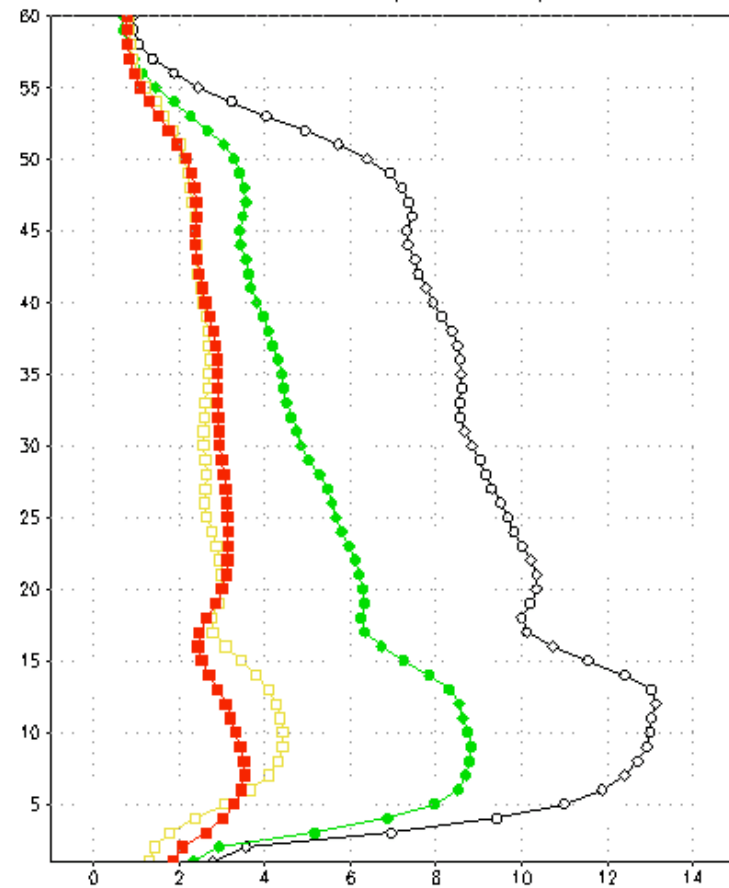


h scales q t chi psi/8km



Horizontal Length Scales

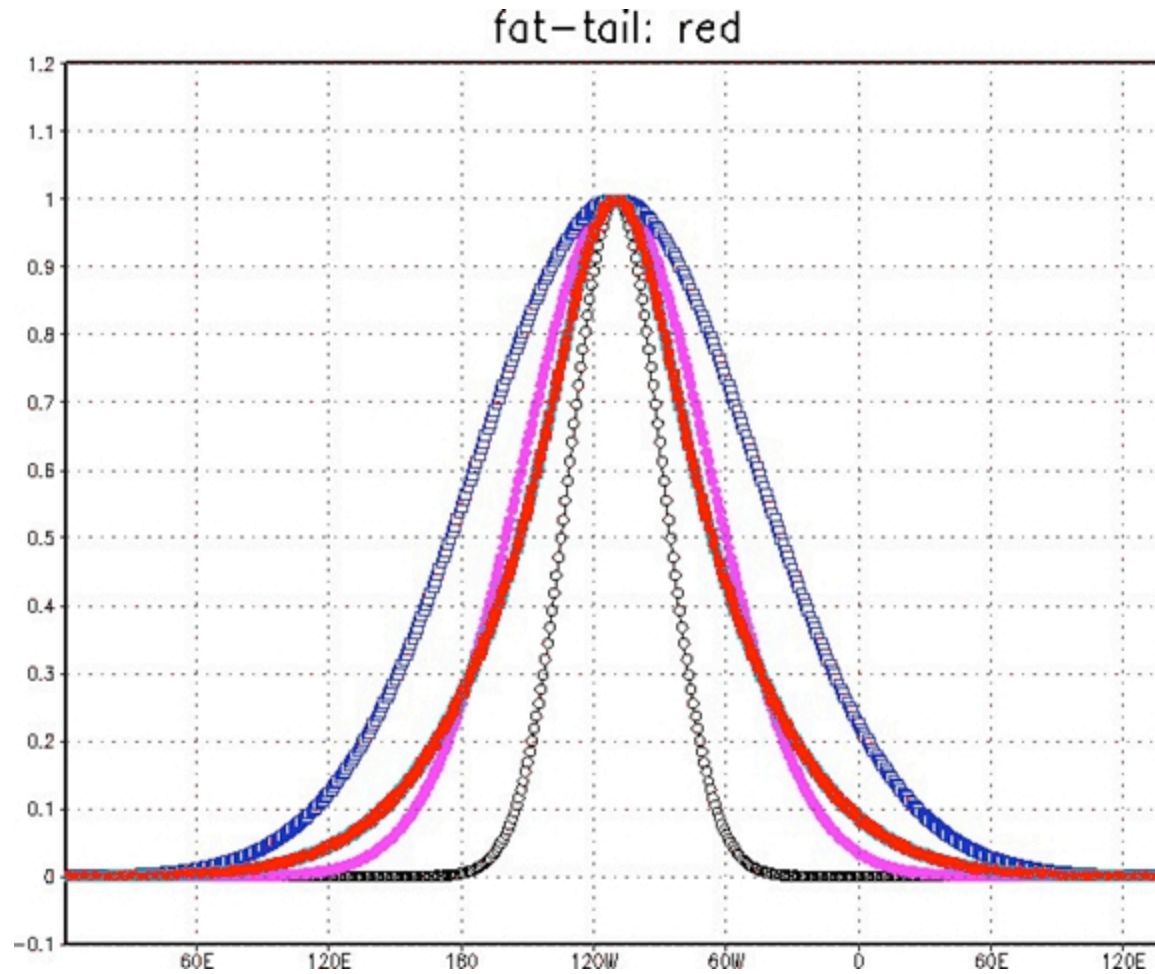
v scales q t chi psi



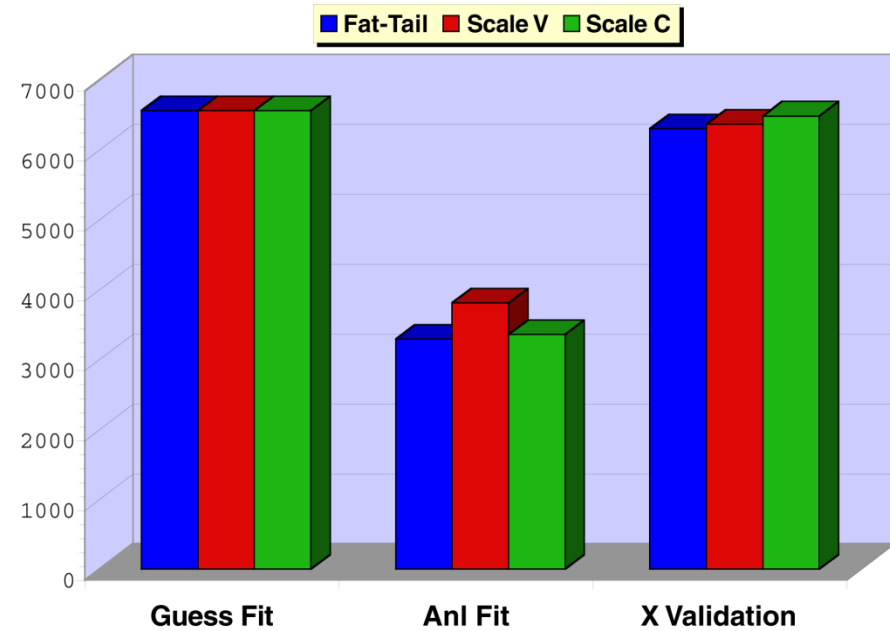
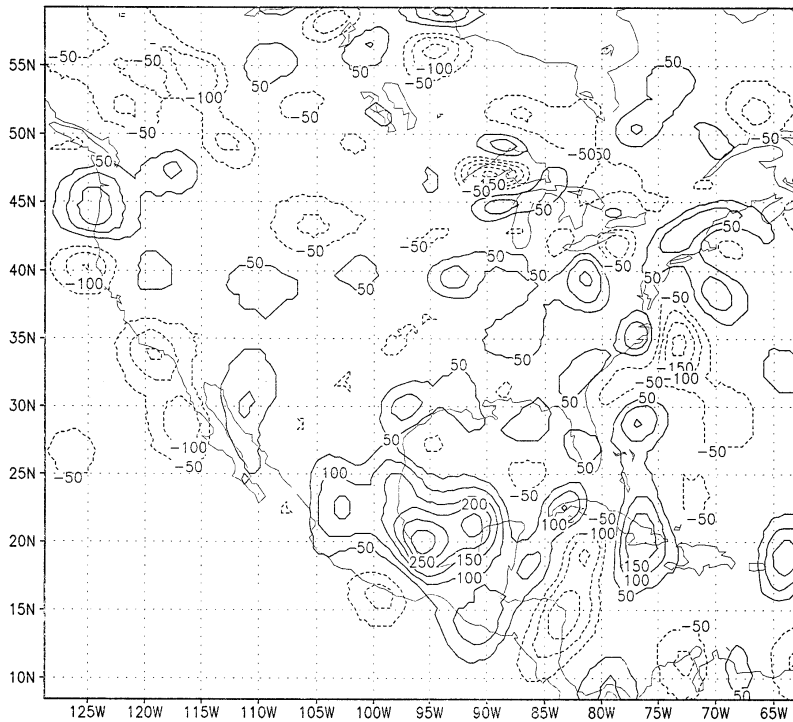
Vertical Length Scales



Fat-tailed power spectrum



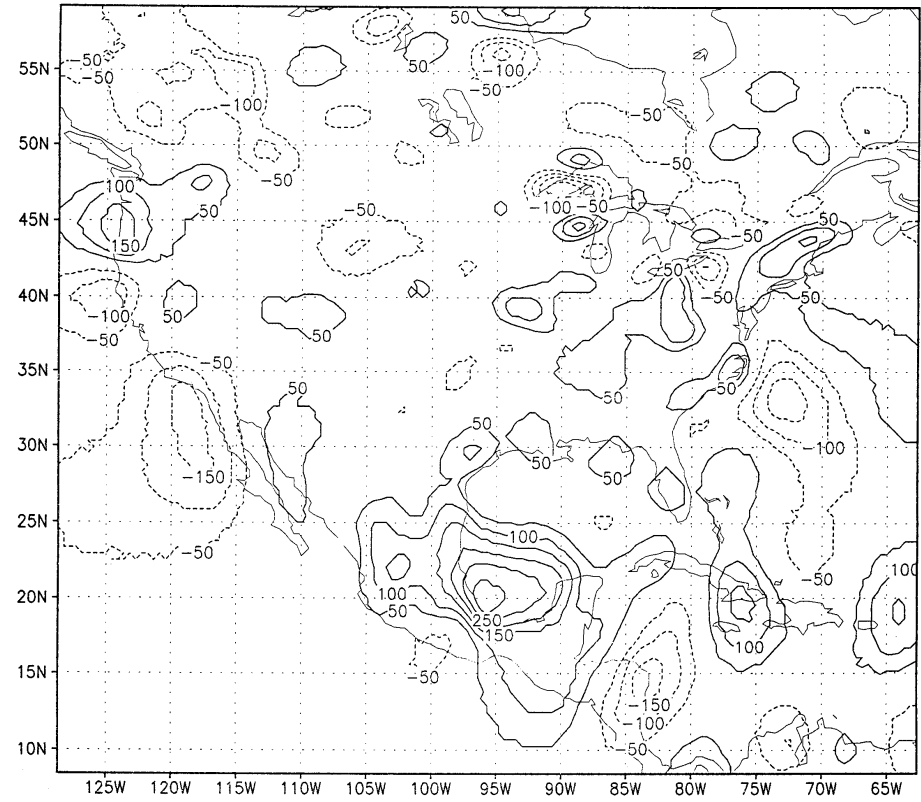
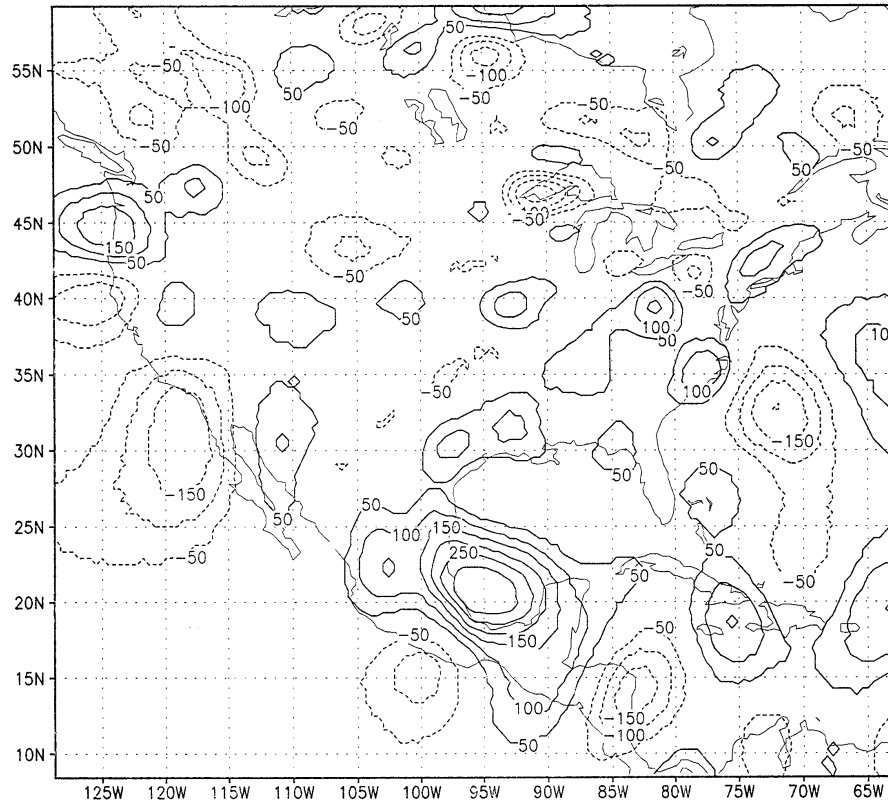
Fat-tailed Spectrum



Surface pressure increment with homogeneous scales using single recursive filter



Fat-tailed Spectrum



Surface pressure increment with inhomogeneous scales using single recursive filter, single scale (left) and multiple recursive filter: fat-tail (right)



Tuning Parameters

- GSI assumes binary fixed file with aforementioned variables
 - Example: `berror=$fixdir/global_berror.164y578.f77`
- Anavinfo file contains information about control variables and their background error amplitude tuning weights

control_vector::

!var	level	itracer	as/tsfc_sdv	an_amp0	source	funcof
sf	64	0	0.60	-1.0	state	u,v
vp	64	0	0.60	-1.0	state	u,v
ps	1	0	0.75	-1.0	state	p3d
t	64	0	0.75	-1.0	state	tv
q	64	1	0.75	-1.0	state	q
oz	64	1	0.75	-1.0	state	oz
sst	1	0	1.00	-1.0	state	sst
cw	64	1	1.00	-1.0	state	cw
stl	1	0	3.00	-1.0	motley	sst
sti	1	0	3.00	-1.0	motley	sst



Tuning Parameters

- Length scale tuning controlled via GSI namelist &BKGERR

$$\text{hzscl} = 1.7, 0.8, 0.5$$
$$\text{hswgt} = 0.45, 0.3, 0.25$$

$\text{vs}=0.7$ [separable from horizontal scales]

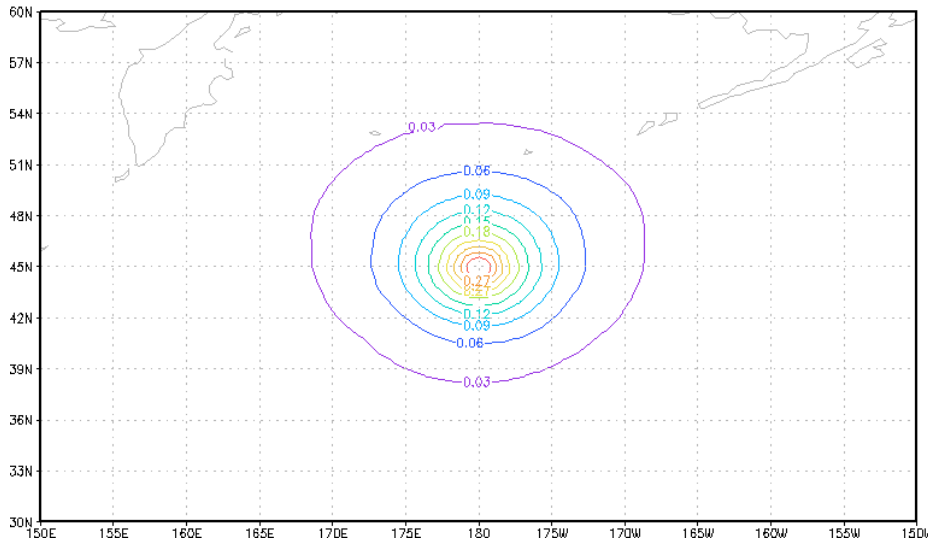
- Hzscl/vs/as are all multiplying factors (relative to contents of “berror” fixed file)
- Three scales specified for horizontal (along with corresponding relative weights, hswgt)



Tuning Example (Scales)



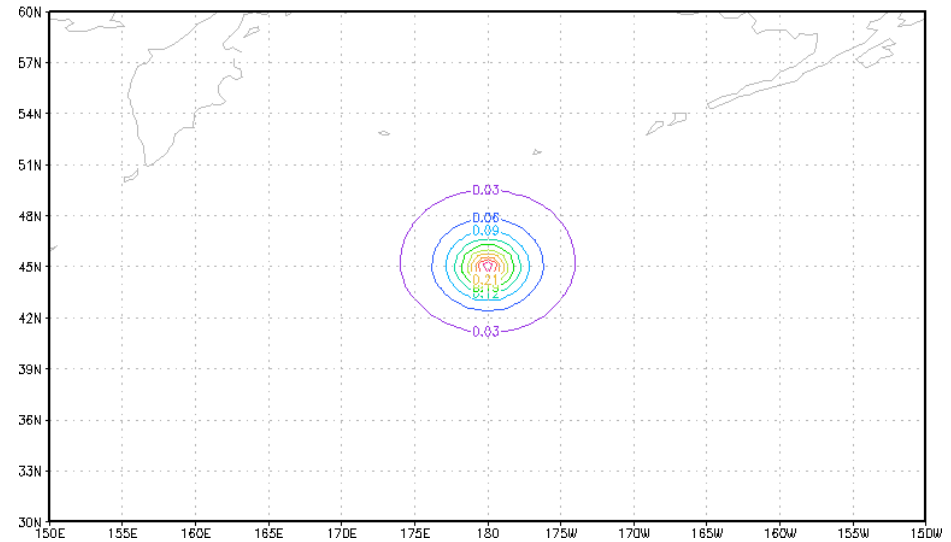
Temp Increment (z=25, Default HsHw)



Hzscl = 1.7, 0.8, 0.5

Hswgt = 0.45, 0.3, 0.25

Temp Increment (z=25, Smaller Hs)



Hzscl = 0.9, 0.4, 0.25

Hswgt = 0.45, 0.3, 0.25

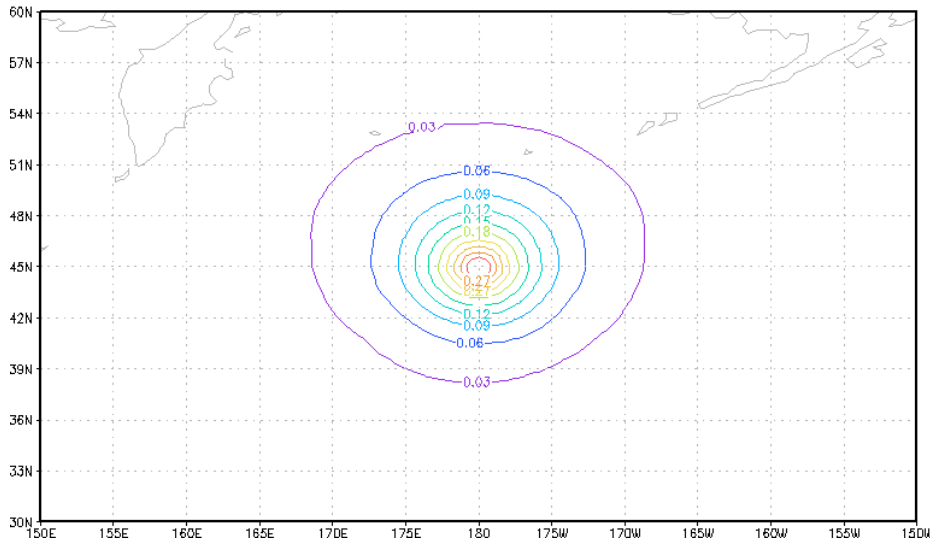
500 hPa temperature increment (K) from a single temperature observation utilizing GFS default (left) and tuned (smaller scales) error statistics.



Tuning Example (Weights)



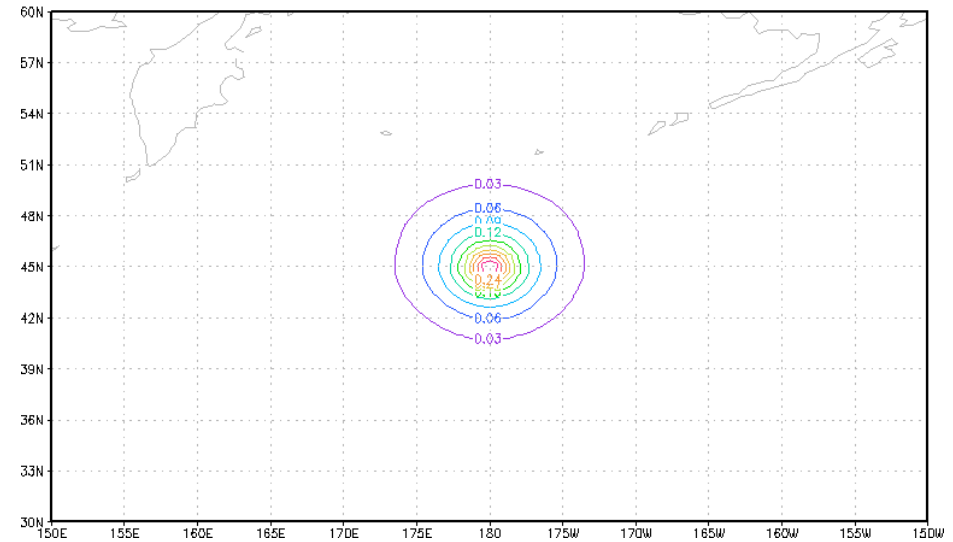
Temp Increment (z=25, Default HsHw)



$H_{zscl} = 1.7, 0.8, 0.5$

$H_{swgt} = 0.45, 0.3, 0.25$

Temp Increment (z=25, Tuned Hwt)



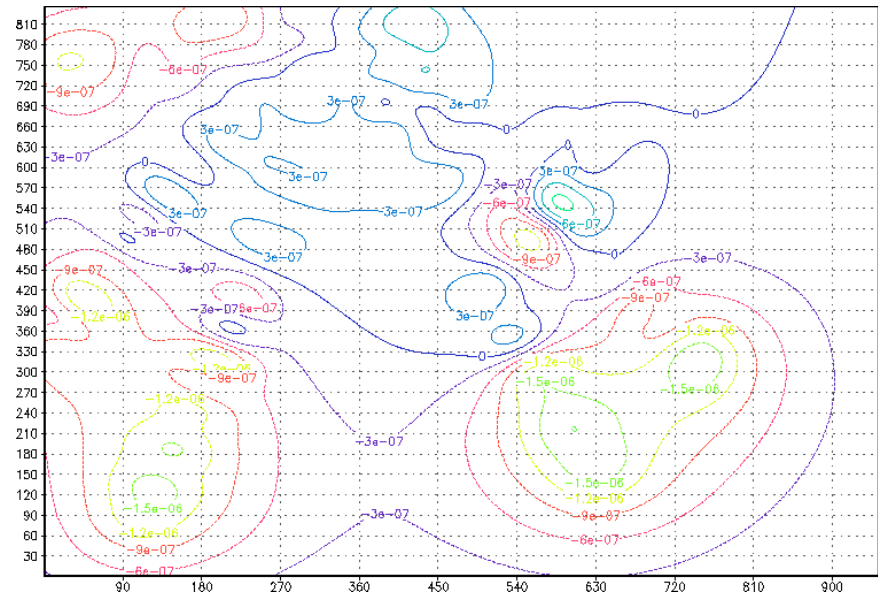
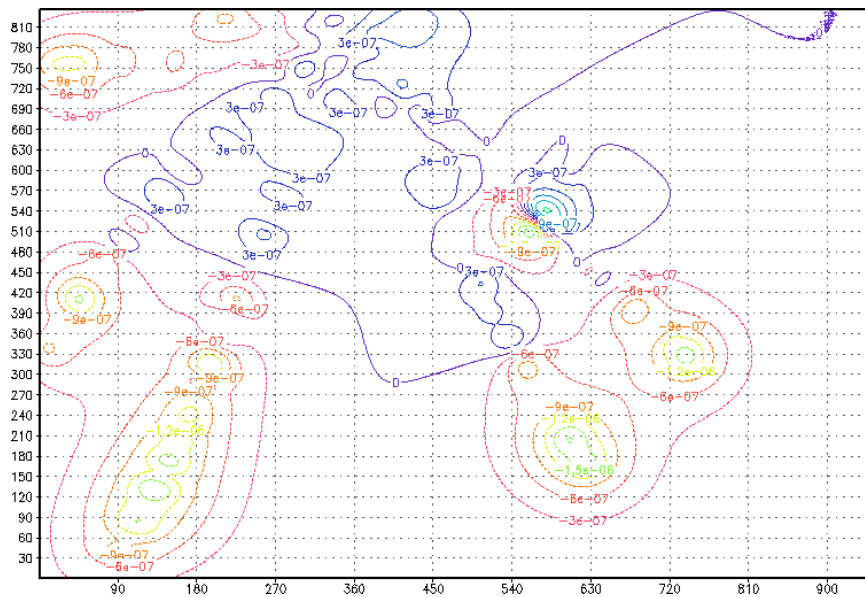
$H_{zscl} = 1.7, 0.8, 0.5$

$H_{swgt} = 0.1, 0.3, 0.6$

500 hPa temperature increment (K) from a single temperature observation utilizing GFS default (left) and tuned (weights for scales) error statistics.



Tuning Example (ozone)



Ozone analysis increment (mixing ratio) utilizing default (left) and tuned (larger scales) error statistics.



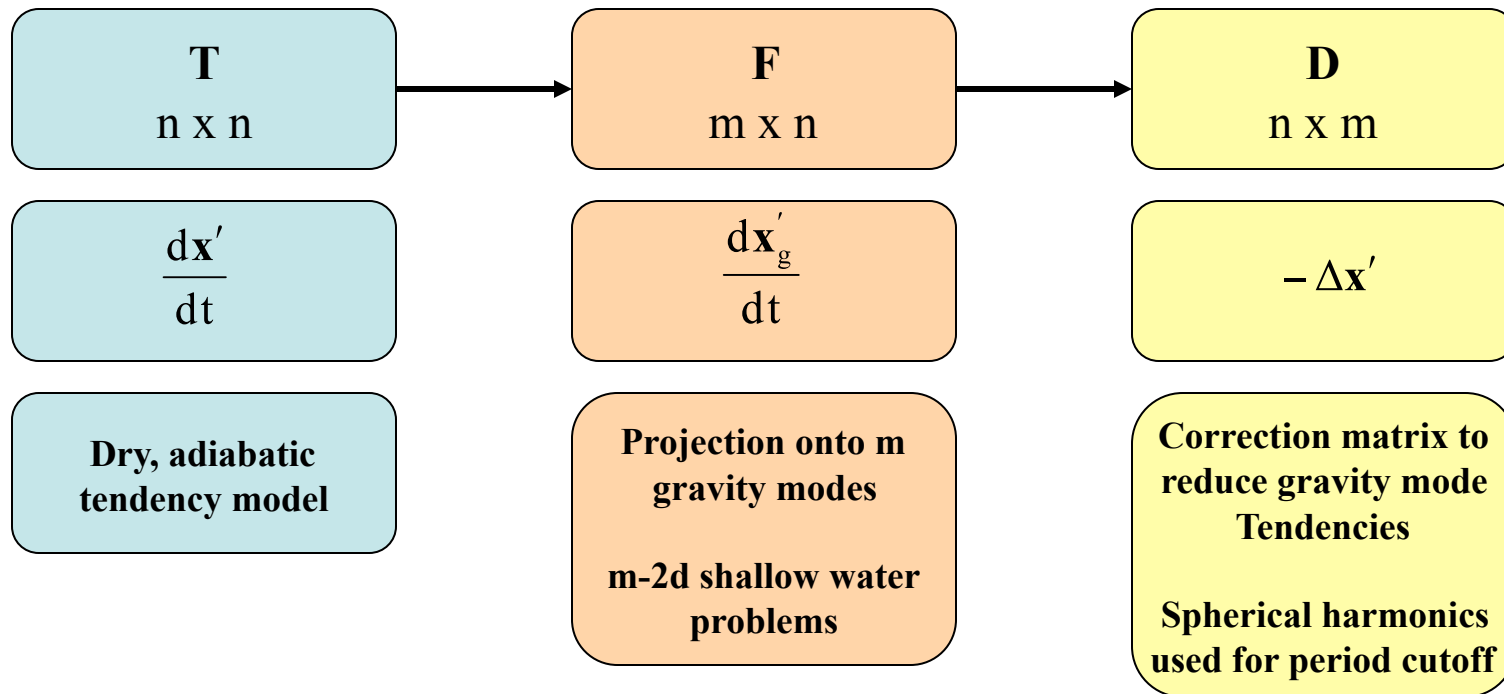
Balance/Noise

- In addition to statistically derived matrices, an optional (incremental) normal mode operator exists
 - **Not (yet) working well for regional applications**
 - Operational in global application (GFS/GDAS)

$$J(\mathbf{x}'_c) = \frac{1}{2}(\mathbf{x}'_c)^T \mathbf{C}^{-T} \mathbf{B}^{-1} \mathbf{C}^{-1} (\mathbf{x}'_c) + \frac{1}{2}(\mathbf{y}'_o - \mathbf{H}\mathbf{x}'_c)^T \mathbf{R}^{-1} (\mathbf{y}'_o - \mathbf{H}\mathbf{x}'_c) + J_c$$
$$\mathbf{x}'_c = \mathbf{C}\mathbf{x}'$$

- \mathbf{C} = Correction from incremental normal mode initialization (NMI)
 - represents correction to analysis increment that filters out the unwanted projection onto fast modes
- No change necessary for \mathbf{B} in this formulation

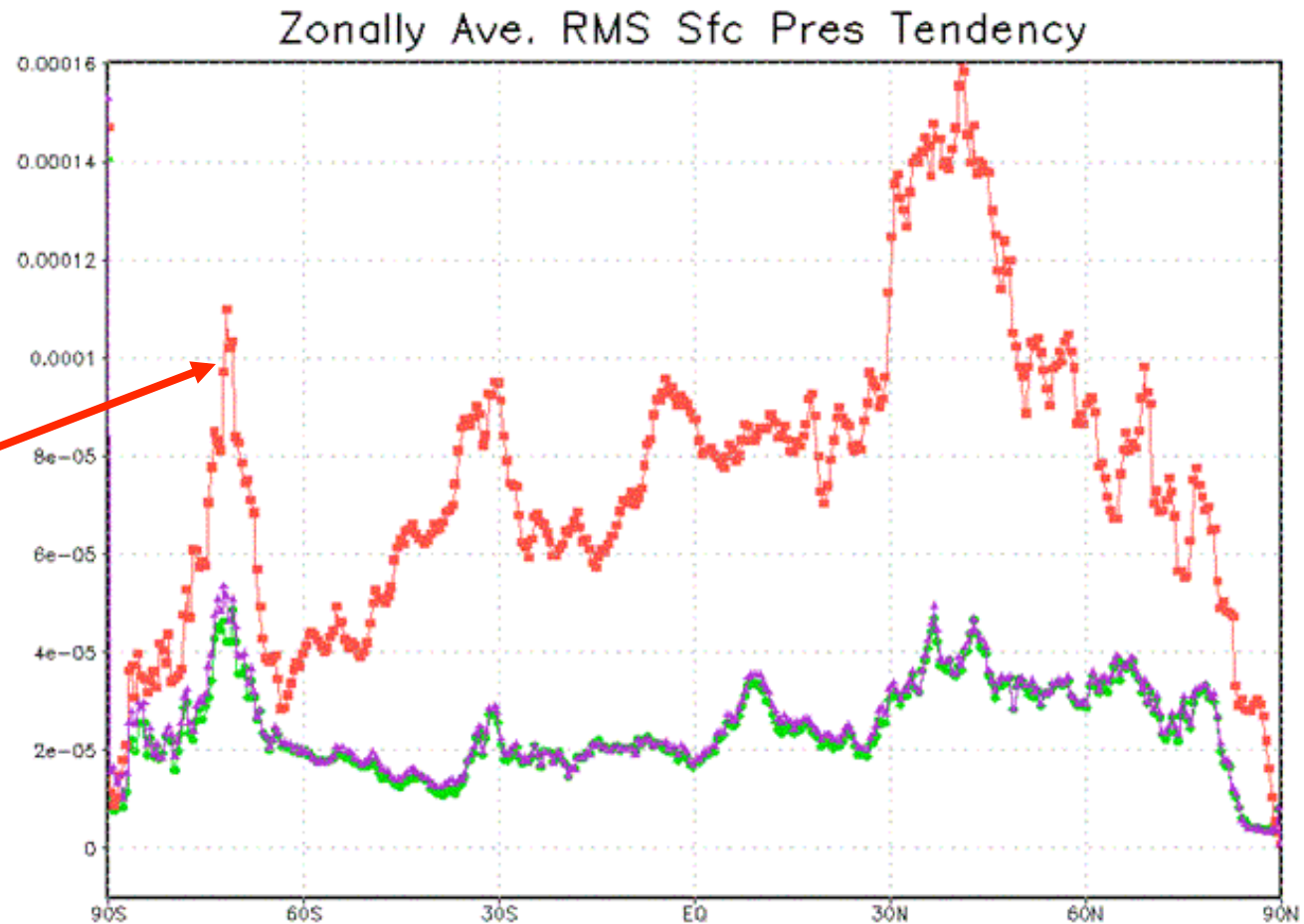
$$C = [I - DFT]x'$$



- **Practical Considerations:**

- **C** is operating on x' only, and is the tangent linear of NNMI operator
- Only need one iteration in practice for good results
- Adjoint of each procedure needed as part of variational procedure

Noise/Balance Control



Substantial increase
without constraint

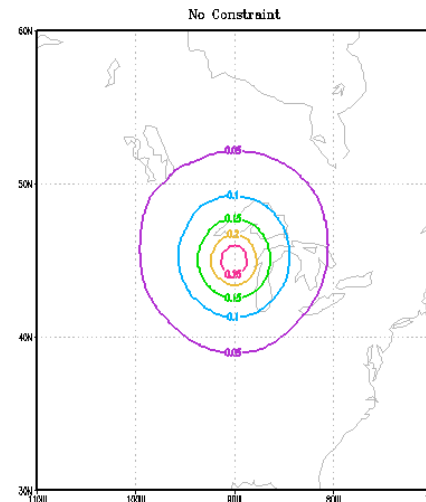
Zonal-average surface pressure tendency for background (green), unconstrained GSI analysis (red), and GSI analysis with TLNMC (purple).



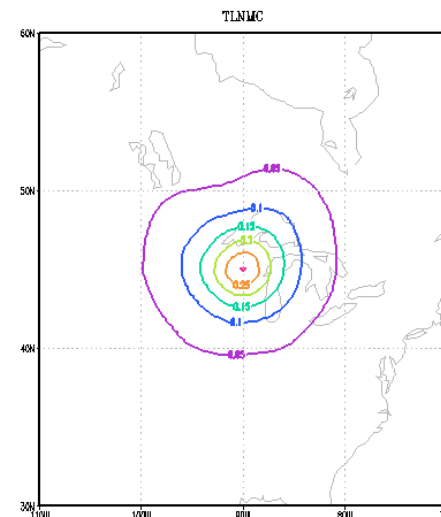
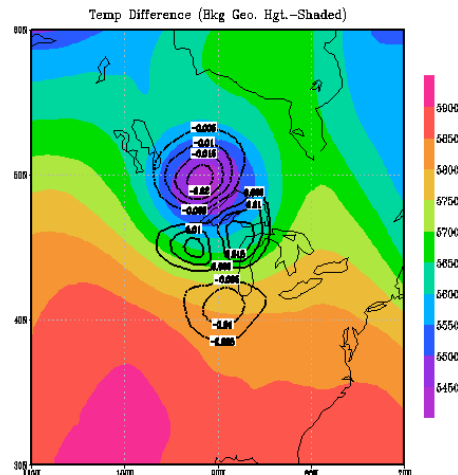
Example: Impact of Constraint



- Magnitude of TLNMC correction is small
- TLNMC adds flow dependence even when using same isotropic **B**



Isotropic response



Flow dependence added

500 hPa temperature increment (right) and analysis difference (left, along with background geopotential height) valid at 12Z 09 October 2007 for a single 500 hPa temperature observation (1K O-F and observation error)

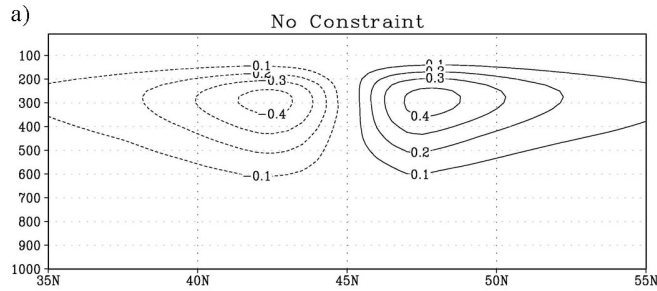


Single observation test (T observation)

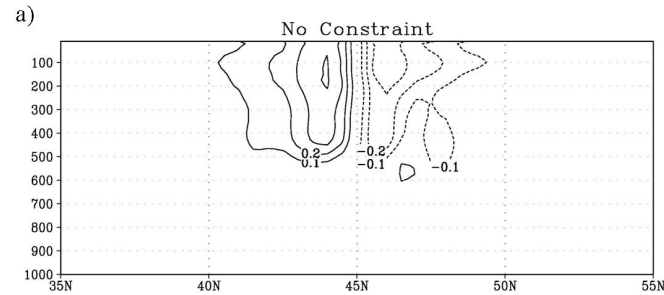


From
multivariate B

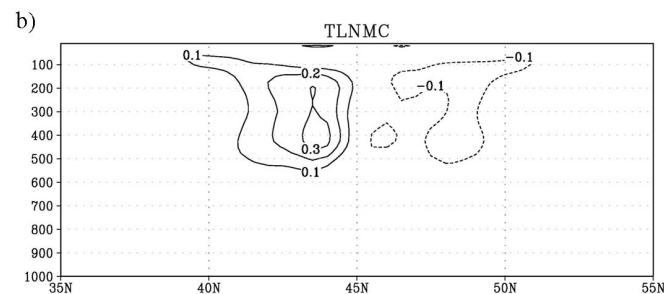
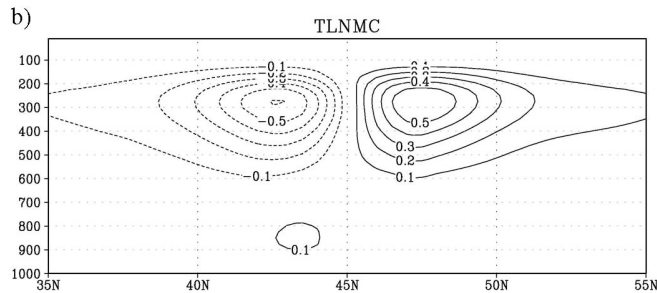
U wind



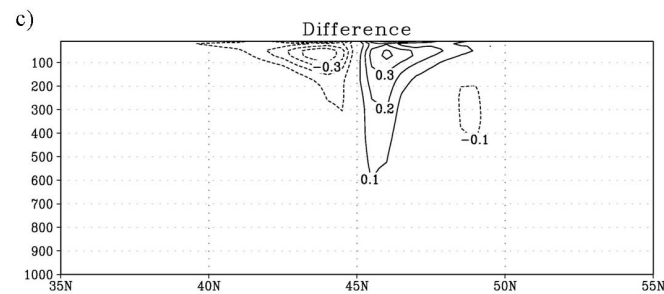
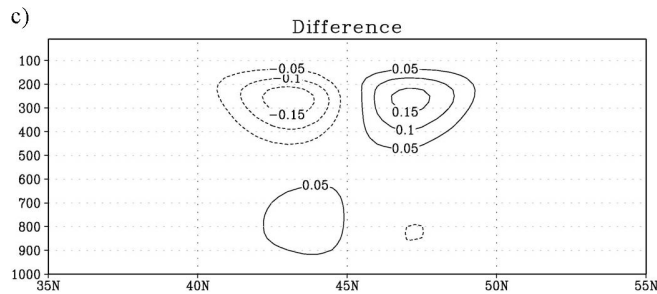
Ageostrophic U wind



TLNMC
corrects



Smaller
ageostrophic
component



Cross section of zonal wind increment (and analysis difference) valid at 12Z 09 October 2007 for a single 500 hPa *temperature* observation (1K O-F and observation error)



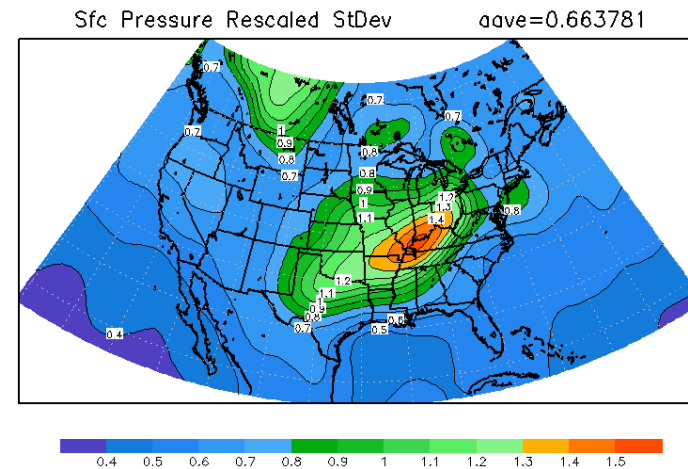
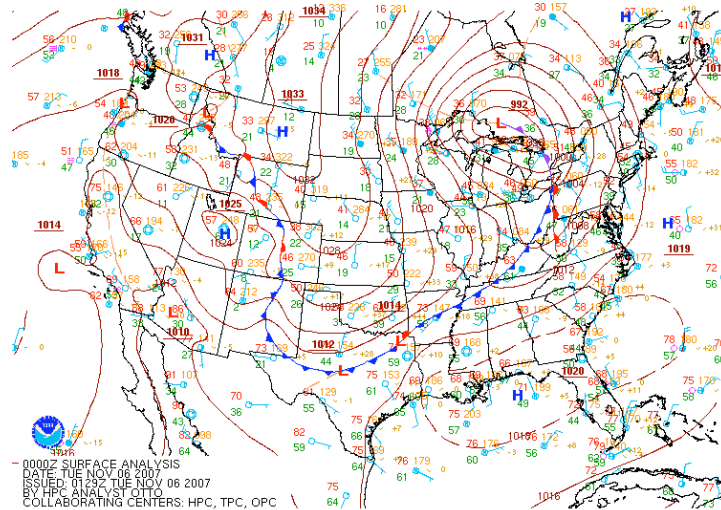
Adding Flow Dependence



- One motivation for GSI was to permit flow dependent variability in background error
- Take advantage of FGAT (guess at multiple times) to modify variances based on 9h-3h differences
 - Variance increased in regions of large tendency
 - Variance decreased in regions of small tendency
 - Global mean variance \sim preserved
- Perform reweighting on streamfunction, velocity potential, virtual temperature, and surface pressure only

Currently global only, but simple algorithm that could easily be adapted for any application

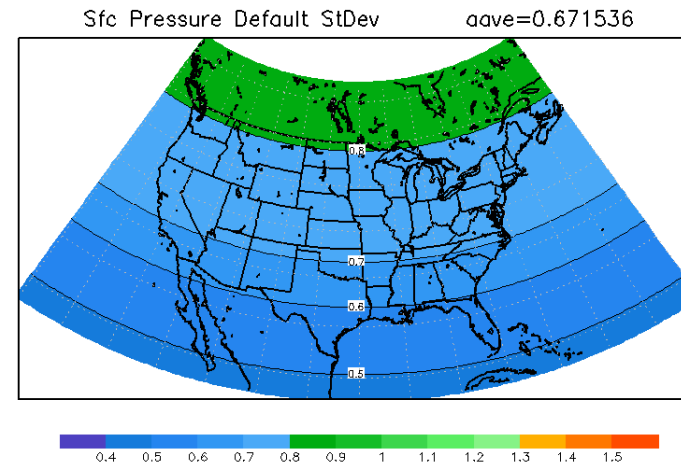
Variance Reweighting



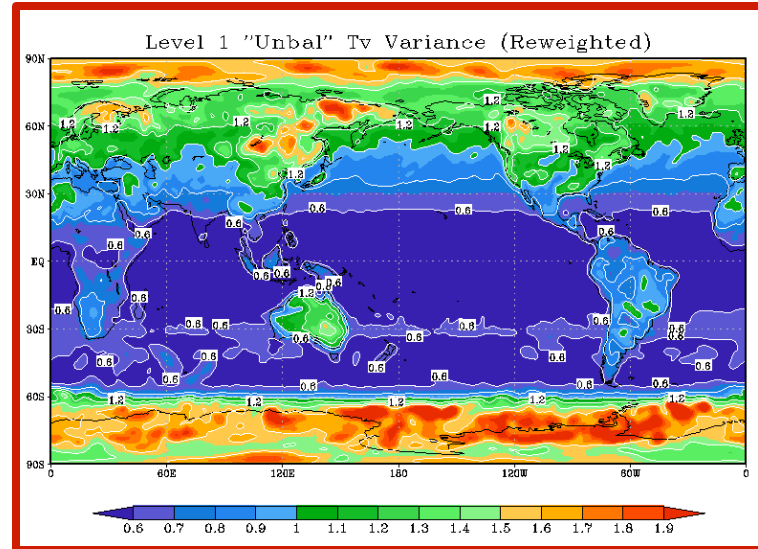
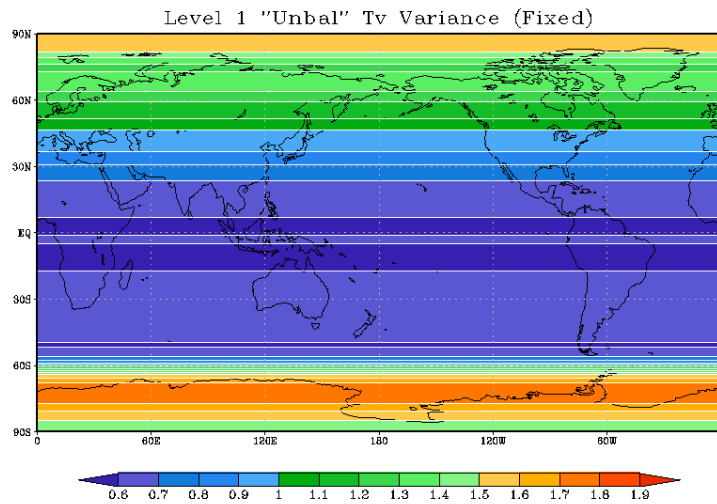
Surface pressure background error standard deviation fields

- a) with flow dependent re-scaling
- b) without re-scaling

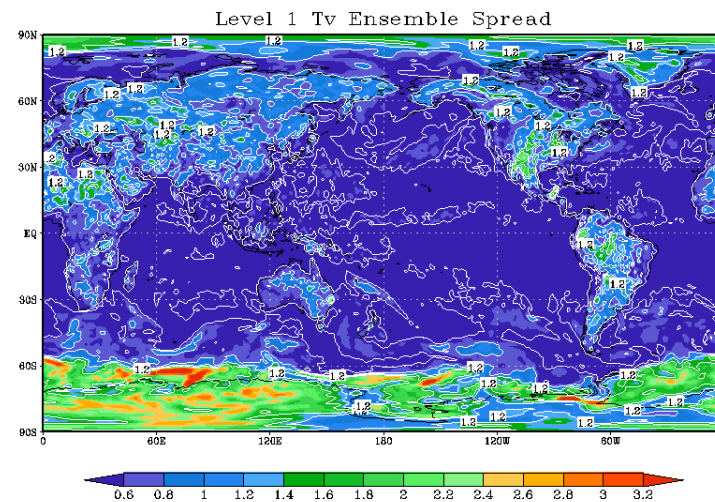
Valid: 00 UTC November 2007



Variance Reweighting



- Although flow-dependent *variances* are used, confined to be a rescaling of fixed estimate based on time tendencies
 - No cross-variable or length scale information used
 - Does not necessarily capture ‘errors of the day’
- Plots valid 00 UTC 12 September 2008





Hybrid Variational-Ensemble



- Incorporate ensemble perturbations directly into variational cost function through extended control variable
 - Lorenc (2003), Buehner (2005), Wang et. al. (2007), etc.

$$J(\mathbf{x}'_f, \alpha) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} (\alpha)^T \mathbf{L}^{-1} (\alpha) + \frac{1}{2} (\mathbf{y}'_o - \mathbf{H}\mathbf{x}'_t)^T \mathbf{R}^{-1} (\mathbf{y}'_o - \mathbf{H}\mathbf{x}'_t)$$

$$\mathbf{x}'_t = \mathbf{x}'_f + \sum_{n=1}^N (\alpha^n \circ \mathbf{x}_e^n) \quad \frac{1}{\beta_f} + \frac{1}{\beta_e} = 1$$

β_f & β_e : weighting coefficients for fixed and ensemble covariance respectively

\mathbf{x}'_t : (total increment) sum of increment from fixed/static $\mathbf{B}(\mathbf{x}_f)$ and ensemble \mathbf{B}

α^n : extended control variable; \mathbf{x}_e^n : ensemble perturbations

\mathbf{L} : correlation matrix [localization on ensemble perturbations]

2:30 GSI/ETKF Regional Hybrid Data Assimilation - Arthur Mizzi (MMM/NCAR)




Observation Errors

1. Overview
2. Adaptive Tuning



3DVAR Cost Function

$$J_{\text{Var}}(\mathbf{x}') = \frac{1}{2}(\mathbf{x}')^T \mathbf{B}_{\text{Var}}^{-1}(\mathbf{x}') + \frac{1}{2}(\mathbf{H}\mathbf{x}' - \mathbf{y}'_o)^T (\mathbf{R})^{-1}(\mathbf{H}\mathbf{x}' - \mathbf{y}'_o) + J_c$$


- J : Penalty (Fit to background + Fit to observations + Constraints)
- \mathbf{x}' : Analysis increment ($\mathbf{x}_a - \mathbf{x}_b$) ; where \mathbf{x}_b is a background
- \mathbf{B}_{Var} : Background error covariance
- \mathbf{H} : Observations (forward) operator
- **\mathbf{R} : Observation error covariance (Instrument + Representativeness)**
 - Almost always assumed to be diagonal
- \mathbf{y}'_o : Observation innovations/residuals ($\mathbf{y}_o - \mathbf{H}\mathbf{x}_b$)
- J_c : Constraints (physical quantities, balance/noise, etc.)



Tuning



- Observation errors contain two parts
 - Instrument error
 - Representativeness error
- In general, tune the observation errors so that they are about the same as the background fit to the data
- In practice, observation errors and background errors can not be tuned independently



Adaptive tuning

- Talagrand (1997) on $E[J(\mathbf{x}_a)]$
- Desroziers & Ivanov (2001)
 - $E[J_o] = \frac{1}{2} \text{Tr}(\mathbf{I} - \mathbf{H}\mathbf{K})$
 - $E[J_b] = \frac{1}{2} \text{Tr}(\mathbf{K}\mathbf{H})$
 - \mathbf{K} is Kalman gain matrix
 - \mathbf{H} is linearized observation forward operator
- Chapnik et al. (2004)
 - robust even when \mathbf{B} is incorrectly specified



Adaptive tuning

Tuning Procedure:
$$J(\delta \mathbf{x}) = \frac{1}{\varepsilon_b^2} J_b(\delta \mathbf{x}) + \frac{1}{\varepsilon_o^2} J_o(\delta \mathbf{x})$$

Where ε_b and ε_o are background and observation error weighting parameters

$$\varepsilon_o = \sqrt{\frac{2 J_o}{\text{Tr}(\mathbf{I} - \mathbf{H}\mathbf{K})}}$$

$$\text{Tr}(\mathbf{I} - \mathbf{H}\mathbf{K}) = N_{\text{obs}} - \left(\sum \xi \mathbf{R}^{-\frac{1}{2}} \mathbf{H} \delta \mathbf{x}_a \left(\mathbf{y} + \xi \mathbf{R}^{\frac{1}{2}} \right) + \sum \xi \mathbf{R}^{-\frac{1}{2}} \mathbf{H} \delta \mathbf{x}_a (\mathbf{y}) \right)$$

Where ξ is a random number with standard normal distribution (mean:0, variance:1)



Adaptive tuning

1) &SETUP

oberror_tune=.true.

2) If Global mode:

&OBSQC

oberrflg=.true.

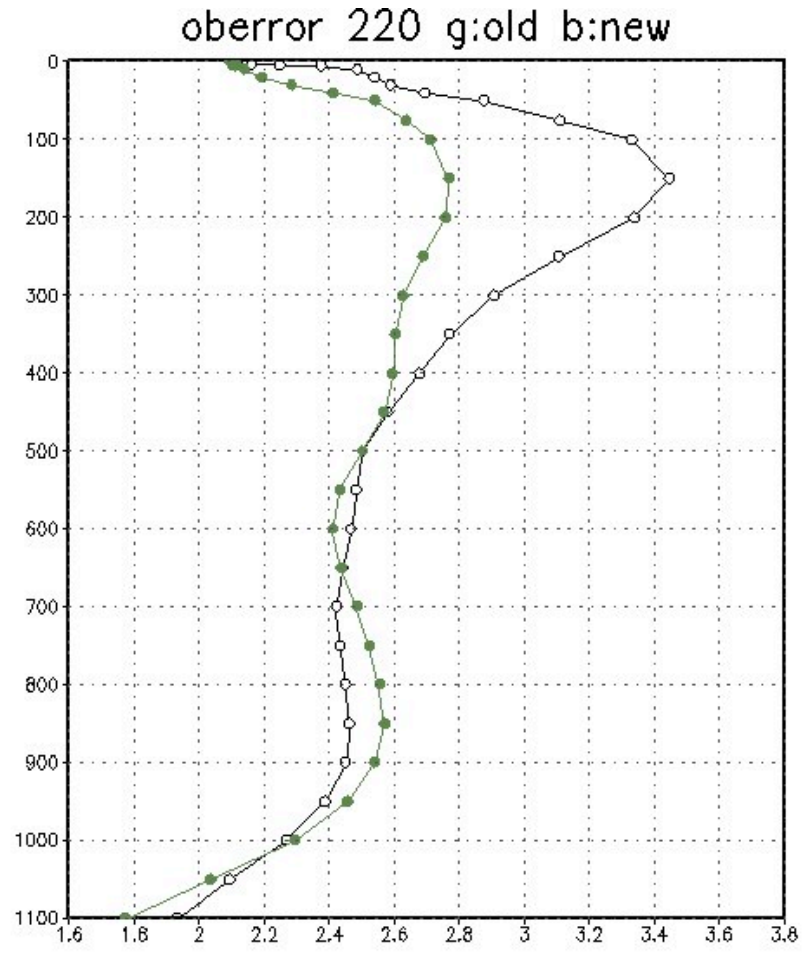
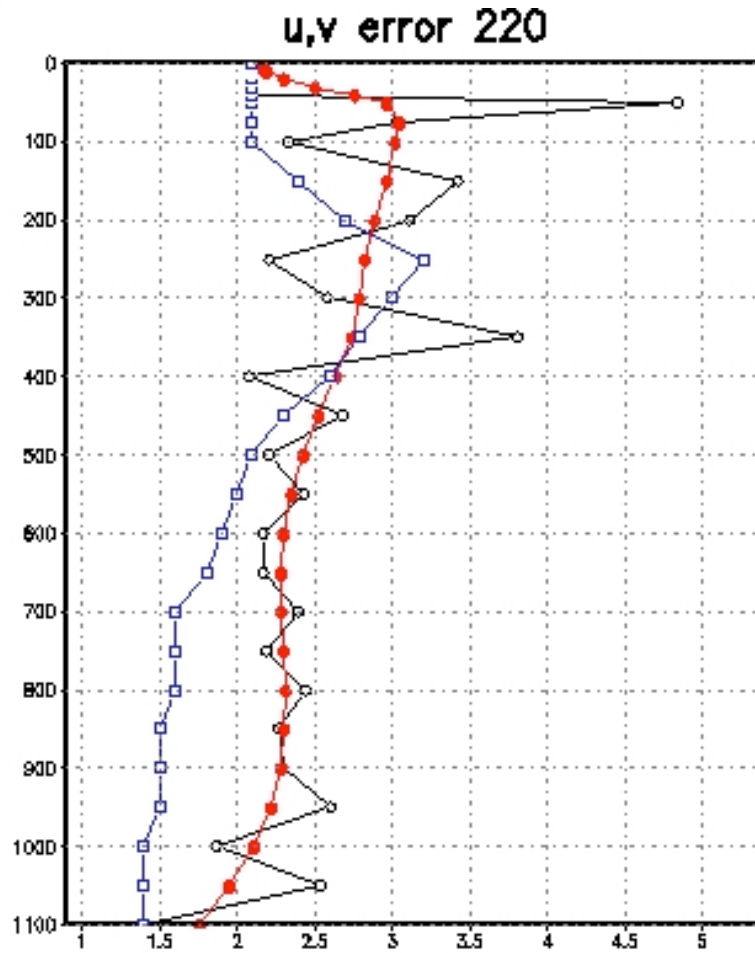
(Regional mode: oberrflg=.true. is default)

Note: GSI does not produce a 'valid analysis' under the setup

Aside: Perturbed observations option can also be used to estimate background error tuning (ensemble generation)!



Adaptive Tuning





Alternative: Monitoring Observations from Cycled Experiment



1. Calculate the covariance of observation minus background (O-B) and observation minus analysis (O-A) in observation space
 $(O-B)*(O-B)$, $(O-A)*(O-A)$, $(O-A)*(O-B)$, $(A-B)*(O-B)$
2. Compare the adjusted observation errors in the analysis with original errors
3. Calculate the observation penalty $((o-b)/r)**2$
4. Examine the observation regions



Summary



- Background error covariance
 - Vital to any data assimilation system
 - Computational considerations
 - Recent move toward fully flow-dependent, ensemble based (hybrid) methods
- Observation error covariance
 - Typically assumed to be diagonal
 - Methods for estimating variance are well established in the literature
- Experience has shown that despite all of the nice theory, error estimation and tuning involves a lot of trial and error