The Met Office hybrid data assimilation scheme

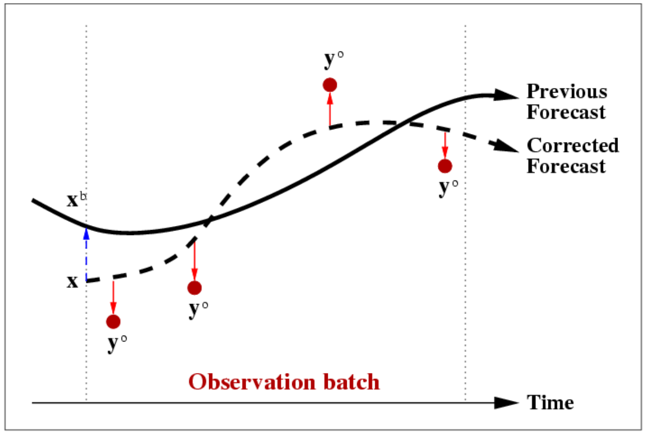
Using ensemble information to improve deterministic forecasts

Adam Clayton, Dale Barker, Neill Bowler, Peter Jermey, **Andrew Lorenc**, Rick Rawlins, Mike Thurlow

9th Adjoint Workshop, October 2011

Introduction

- Since late 2004, Met Office global data assimilation has been done using 4D-Var:



- **Key question**: How do we specify the “background” error characteristics at the beginning of the window?
- **Traditional approach**: Explicitly model (parameterise) the covariances.
- **Main problem**: Difficult to incorporate to “Errors of the Day”
- **Solution**: Blend in covariance data from an ensemble system, creating a “hybrid” covariance model
- Hybrid system implemented 20th July 2011, coupling to MOGREPS-G ensemble system

➢ Increasing synergy between ensemble forecasting and data assimilation

Most slides prepared by Adam Clayton, who has led the implementation project.

Outline of talk

- Climatological vs. ensemble covariances
- Hybrid VAR formulation
- Pre-operational trials, and verification
- Plans

(History)

(References)

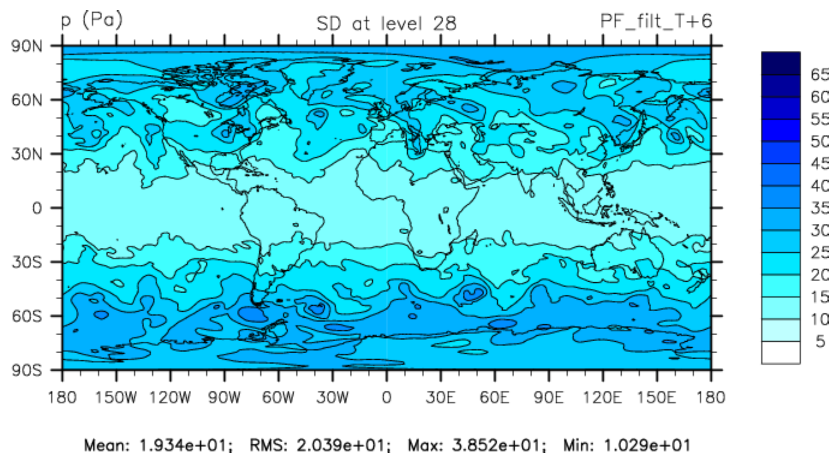
Climatological covariances ($\mathbf{B}_c$)

- Until July 2011, 4D-Var was based wholly on climatological covariances:
  - Choose control variable fields that are approximately uncorrelated:

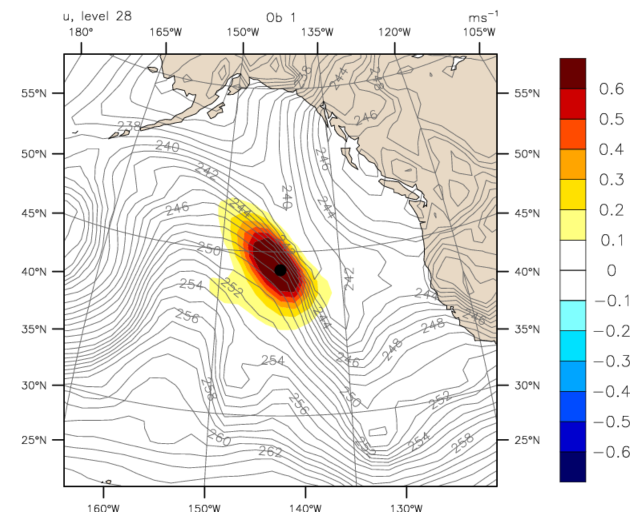
ψ: streamfunction	χ: velocity potential
Ap: Unbalanced pressure	μ: humidity

  - Assume their covariances are horizontally isotropic and zonally uniform.
  - Get parameters from training data. (Currently, the ECMWF 4D-Var ensemble)

SD (pressure)



Pseudo ob test (u)



<u>End</u> of window

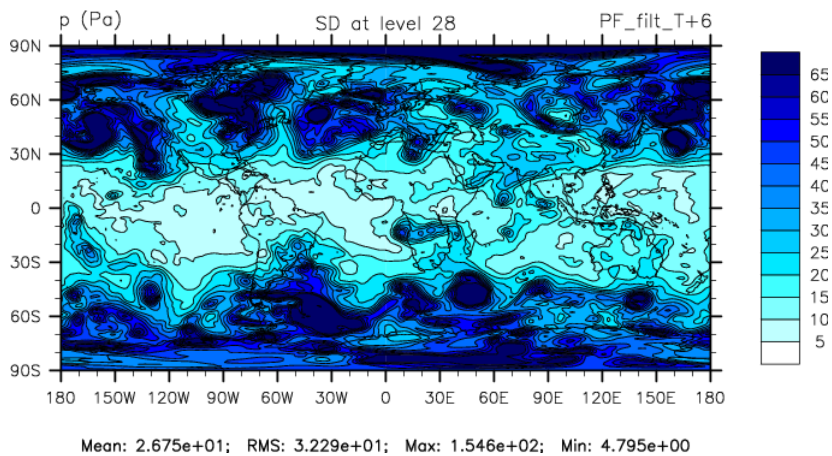
Ensemble covariances ($\mathbf{P}_e$)

- MOGREPS-G:
  - 23 perturbed members (N216L70), aimed at the short-range
  - Ensemble covariance is a simple outer product of the forecast perturbations:

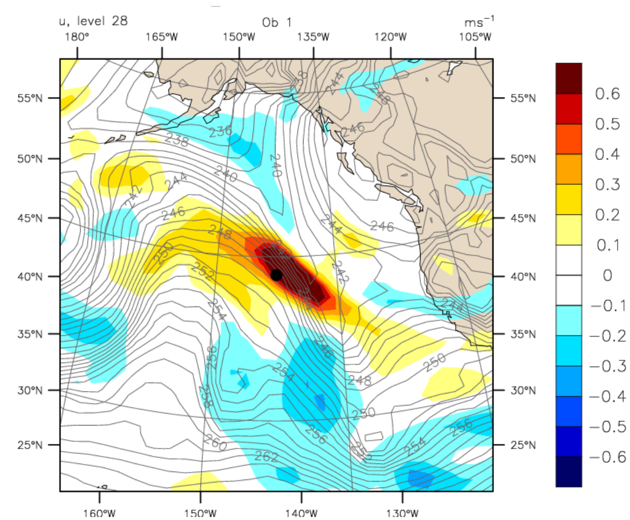
$$\boldsymbol{P}_e = \boldsymbol{X}\boldsymbol{X}^T; \qquad \boldsymbol{X} = \frac{1}{\sqrt{K-1}}\left(\boldsymbol{x}_1 - \overline{\boldsymbol{x}}, \boldsymbol{x}_2 - \overline{\boldsymbol{x}}, \ldots, \boldsymbol{x}_K - \overline{\boldsymbol{x}}\right)$$

  - Provides covariances that should reflect the observation distribution, and the effects of recent instabilities; i.e., the "Errors of the Day"

SD (pressure)



Pseudo ob test (u)



<u>End</u> of window

The need to localise $\mathbf{P}_e$

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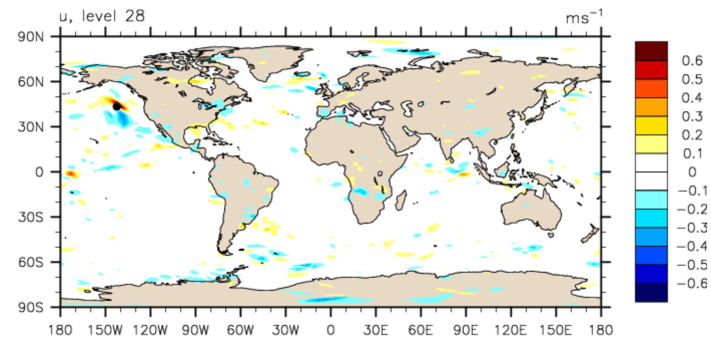
- Ensemble covariances are noisy. In particular, there are spurious long-range correlations:

$\mathbf{P}_e \longrightarrow$

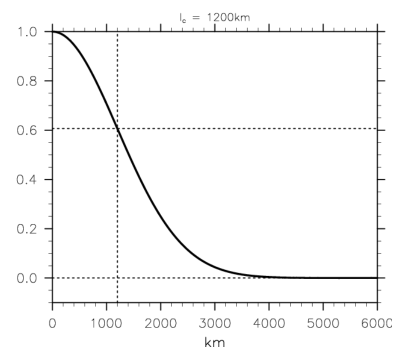


- Solution is to "**localise**" the covariances, by multiplying pointwise with a localising covariance $\mathbf{C}_{loc}$:

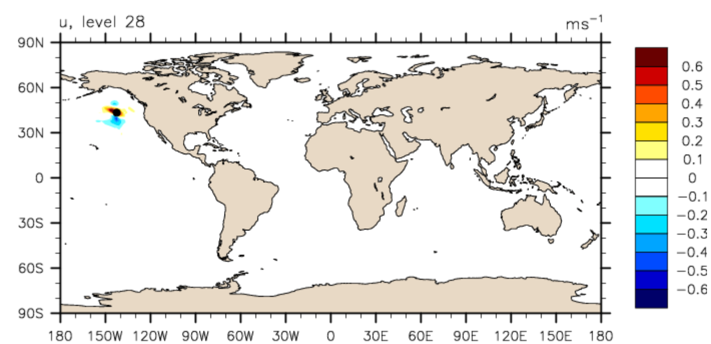
$$\mathbf{P}_e \rightarrow \mathbf{P}_e \circ \mathbf{C}_{loc}:$$

(Lorenc 2003)

$\mathbf{P}_e \circ$



$\longrightarrow$



- Crucially, localisation also increases the "**rank**" of the ensemble covariances: the number of independent structures available to fit the observations.
- (No localisation implies just 23 global structures!)

Hybrid covariances

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- In summary, we have two approaches to modelling **B** (there is a 3rd):
  - $\mathbf{B}_c$: Traditional climatological covariance
    - **Full-rank, but heavily modelled/parametrised, and insensitive to "Errors of the Day"**
  - $\mathbf{P}_e \circ \mathbf{C}_{loc}$: Localised ensemble covariance
    - **Reflect errors of the day, but relatively low-rank, and may be damaged by the need to localise**
- Which is better?
  - Depends on the ensemble size/quality, and how well $\mathbf{B}_c/\mathbf{C}_{loc}$ are modelled
  - Buehner et al. 2010 showed they're competitive. (96-member EnKF provided the modes)
  - **But** e.g. Wang et al 2008 show that a hybrid is better:

$$\mathbf{B} = \underline{\beta_c^2}\mathbf{B}_c + \underline{\beta_e^2}\mathbf{P}_e \circ \mathbf{C}_{loc}$$

  - (Hybrid also provides a smooth path to fuller use of $\mathbf{P}_e \circ \mathbf{C}_{loc}$ as ensemble size increases)

Hybrid VAR formulation

- Basic code written in late 90's! (Barker and Lorenc)
- VAR with climatological covariance $\mathbf{B}_c$:

$$\mathbf{B_c} = \mathbf{U}\mathbf{U}^{\mathrm{T}} \qquad\qquad \delta\boldsymbol{w}_c = \mathbf{U}\boldsymbol{v} = \mathbf{U}_{\mathrm{p}}\mathbf{U}_{\mathrm{v}}\mathbf{U}_{\mathrm{h}}\boldsymbol{v}$$

- VAR with localised ensemble covariance $\mathbf{P}_e \circ \mathbf{C}_{loc}$:

$$\mathbf{C}_{loc} = \mathbf{U}^{\alpha}\mathbf{U}^{\alpha\mathrm{T}} \qquad \boldsymbol{\alpha}_i = \mathbf{U}^{\alpha}\boldsymbol{v}_i^{\alpha} \qquad \delta\boldsymbol{w}_e = \frac{1}{\sqrt{K-1}}\sum_{i=1}^{K}(\boldsymbol{x}_i\text{-}\overline{\boldsymbol{x}}) \circ \boldsymbol{\alpha}_i$$

- **Note**: We are now modelling $\mathbf{C}_{loc}$ rather than the full covariance $\mathbf{B}_c$.
- Hybrid VAR:

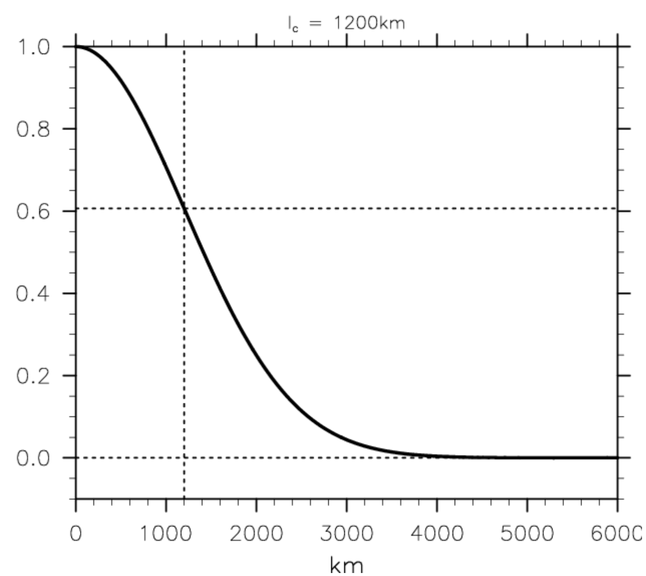
$$\delta\boldsymbol{w} = \underline{\beta_c}\,\delta\boldsymbol{w}_c + \underline{\beta_e\delta\boldsymbol{w}_e} \qquad J = \frac{1}{2}\boldsymbol{v}^T\boldsymbol{v} + \underline{\frac{1}{2}\boldsymbol{v}^{\alpha T}\boldsymbol{v}^{\alpha}} + J_o + J_c$$

Design of localisation

- Localisation performed in control variable space (ψ, χ, A***p,*** μ) to help preserve balances.
- Localisation then separated into horizontal and vertical parts:

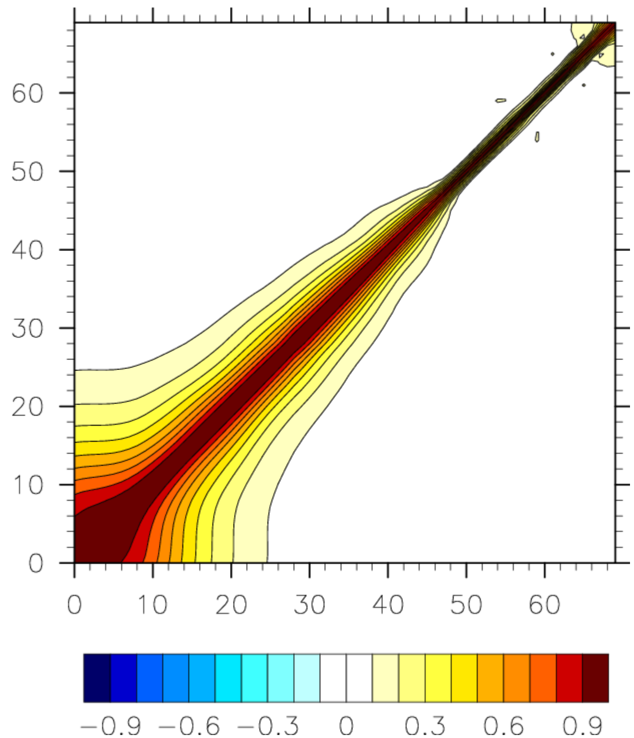
$$\mathbf{U}^{\alpha} = \mathbf{U}_{v}^{\alpha}\mathbf{U}_{h}^{\alpha}$$

- Horizontal part a simple (Gaussian) function of separation:

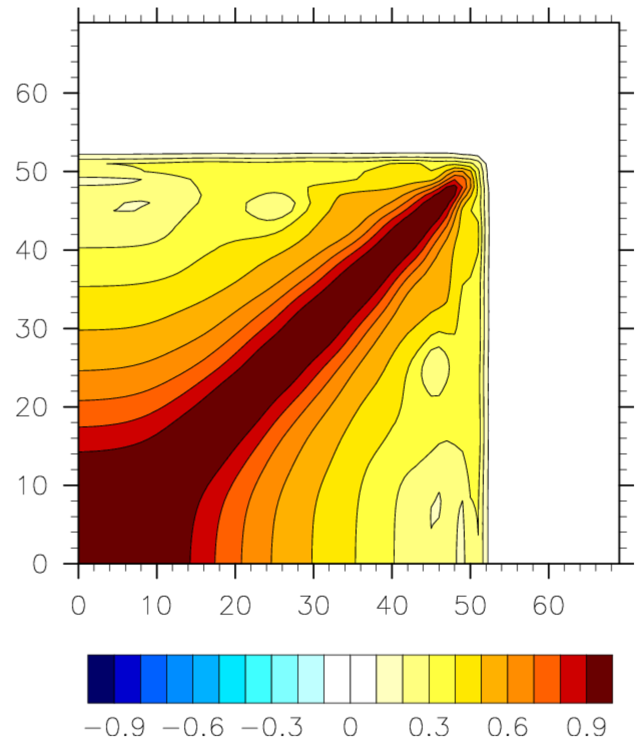


Design of localisation

- Vertical localisation obtained by modifying the streamfunction correlations from $\mathbf{B}_c$:



Absolute climatological ψ correlations



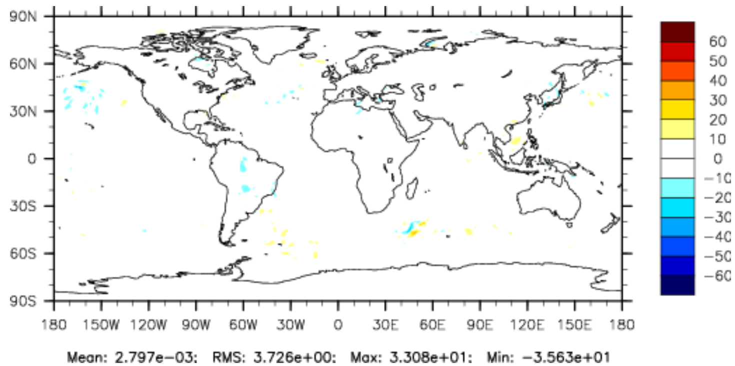
Localising covariance

- Ensemble covariance removed above 21 km (~ level 54), for safety!

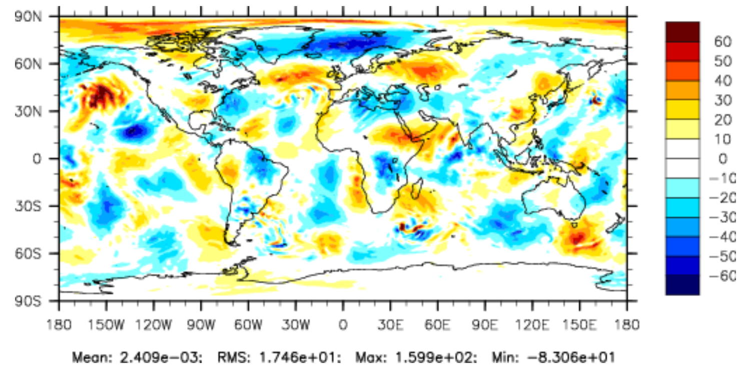
High-pass “anti-aliasing” filter

- MOGREPS modes are well-balanced on entry to VAR, but horizontal localisation causes problems:

p1 time-filter increment (Pa): without localisation

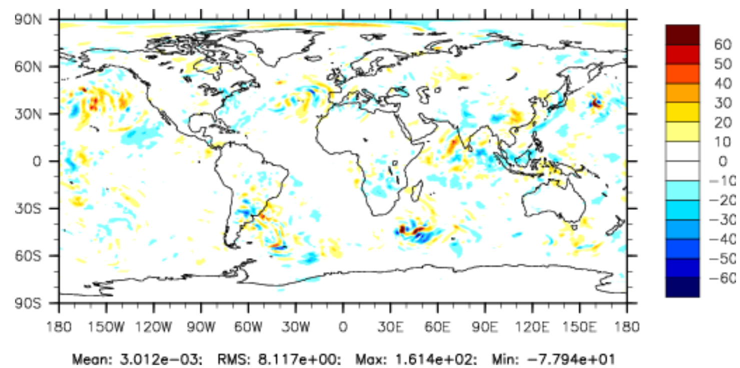


with localisation



- **Why?** Larger scales in the error modes alias onto the localisation scales.
- **Solution**: Apply a high-pass “anti-aliasing” filter to the error modes to downweight larger scales.
- This has the desired effect:

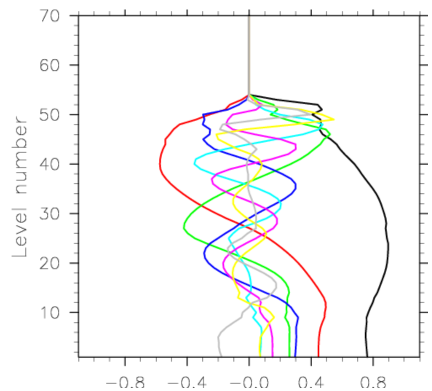
with localisation and high-pass filtering

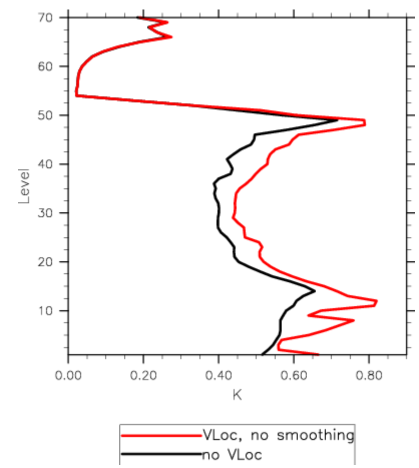


Smoothing of vertical modes

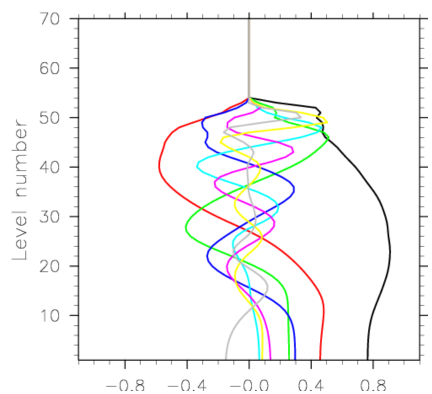
Vertical modes **Implied temperature SD**

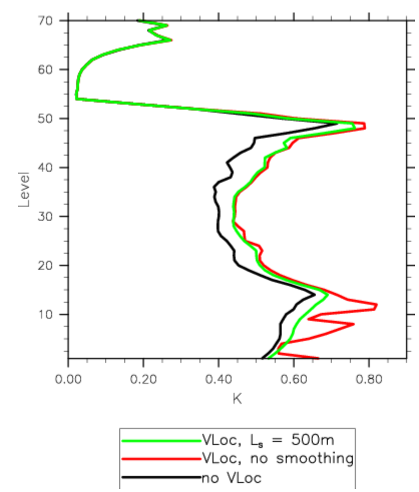
- Original set of vertical modes gave spurious temperature increments near the surface:





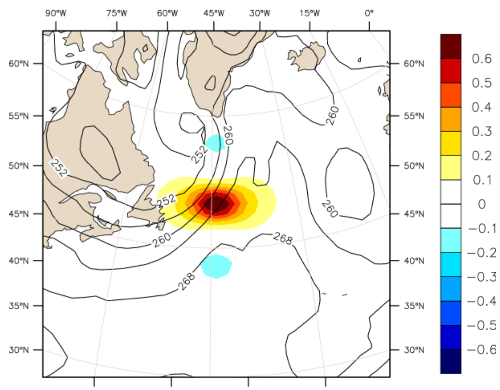
- Smoothing the modes largely removes the problem:



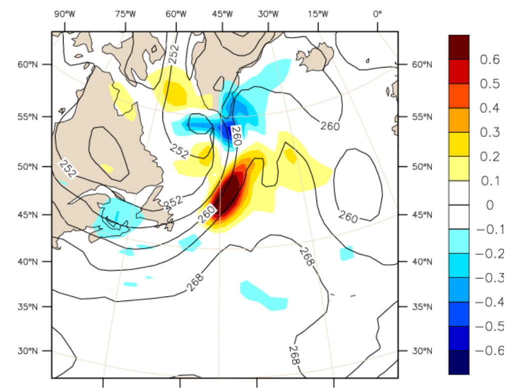


Single observation tests

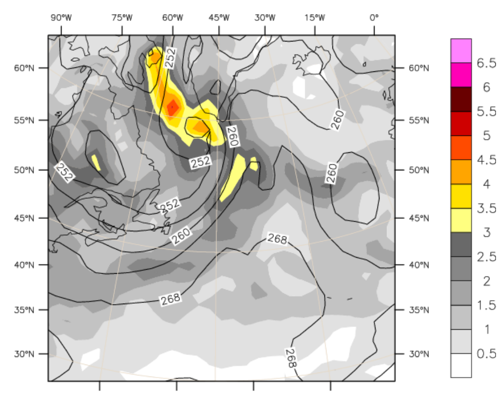
u response to a single u observation at centre of window



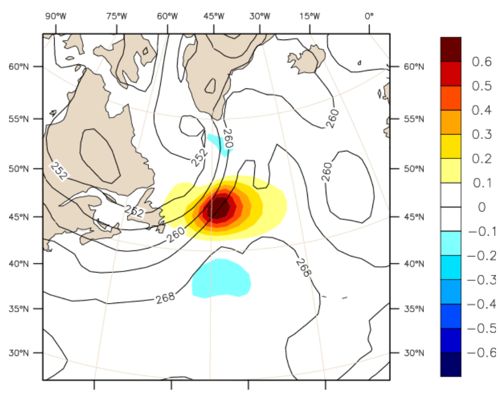
Standard 3D-Var



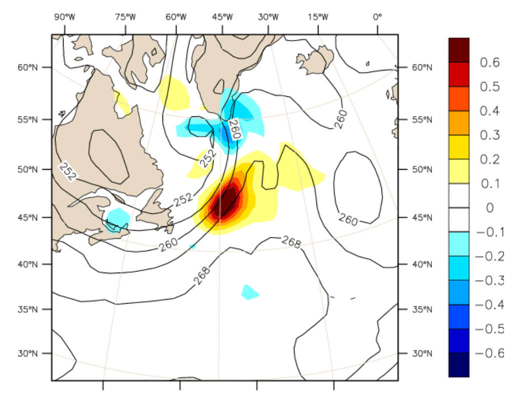
Pure ensemble 3D-Var



Ensemble RMS



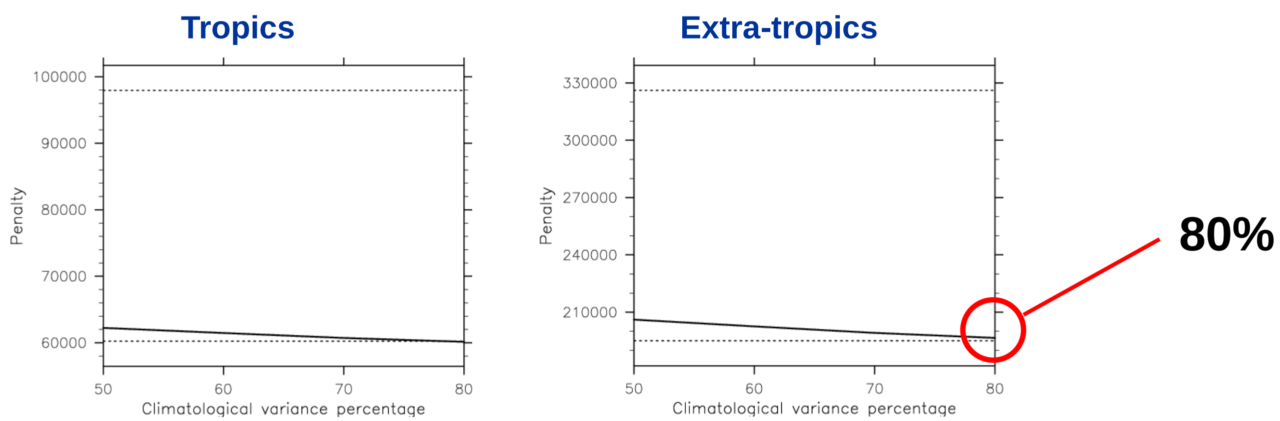
Standard 4D-Var



50/50 hybrid 3D-Var

Tuning of climatological / ensemble COV percentages

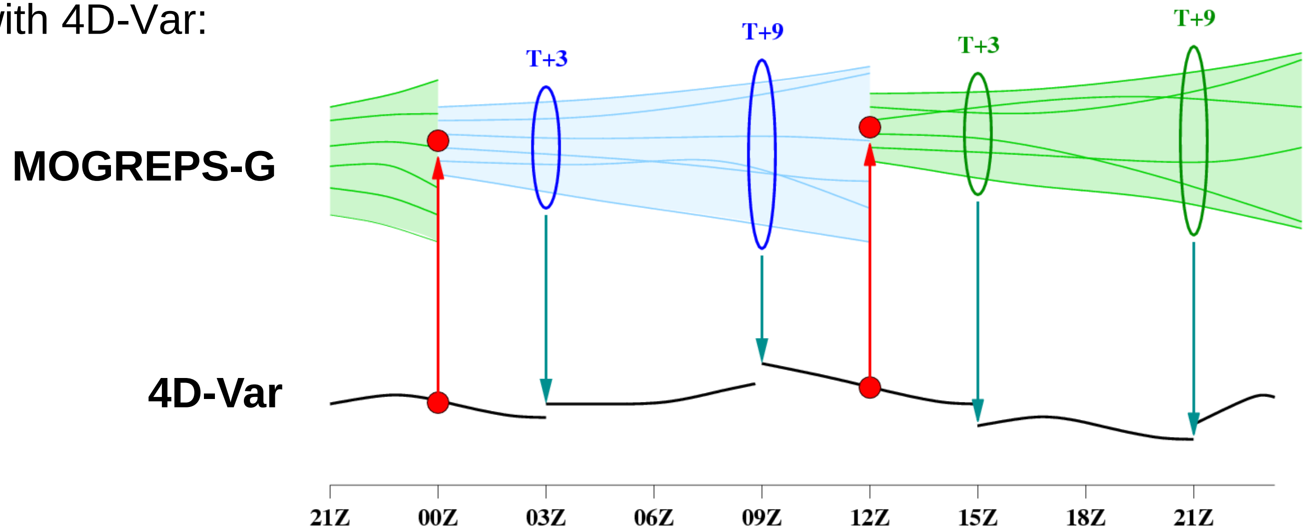
- Low-rank of ensemble covariances means that the available variance is not fully utilised in the analysis.
- 50%-50% climatological/ensemble usage gives final observation penalties ~8-9% higher in both 3D-Var and 4D-Var.
- **Tuning strategy**: Use 50% ensemble covariance, and inflate climatological covariance to preserve analysis fit to obs
- Final observation penalty as a function of climatological percentage, with ensemble covariance usage fixed at 50%:



(………… : Initial and final penalties from control analysis)

Coupling to MOGREPS

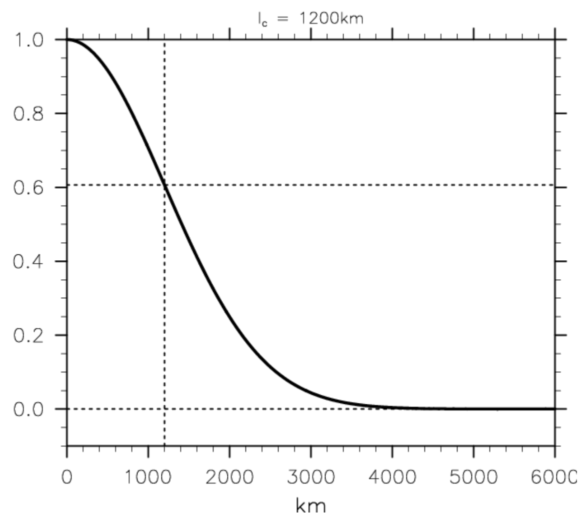
- MOGREPS-G:
  - 23 perturbed members + one control member
  - 12-hour cycle, recentring around deterministic 4D-Var analysis (●)
- Coupling with 4D-Var:

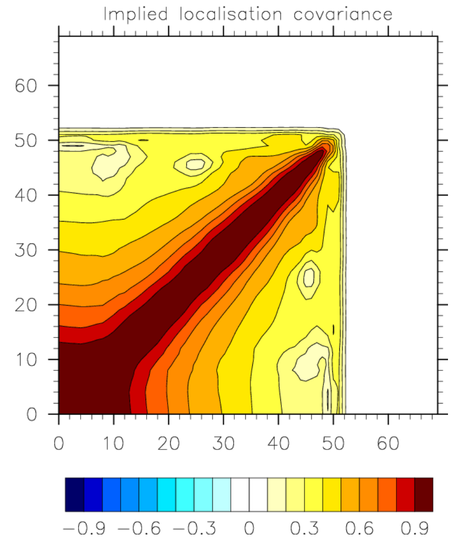


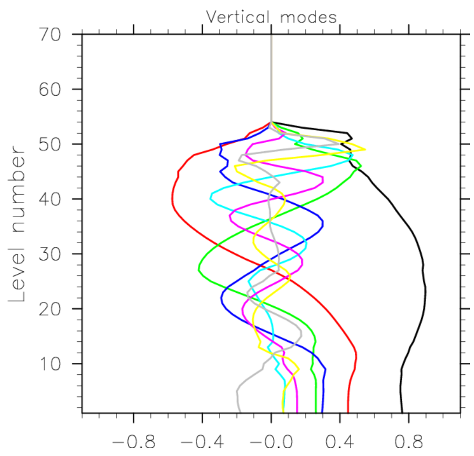
- Pre-hybrid: **4D-Var** → **MOGREPS**
- Post-hybrid: **4D-Var** ←→ **MOGREPS**
- **Note**: 00Z and 12Z analyses use T+9 error modes, with the “wrong” analysis time.

Pre-operational hybrid trials

- Two periods: Dec09/Jan10 (29 days, uncoupled); Jun10 (28 days, coupled + uncoupled)
- **Forecast model**: N320L70: ~40km, 70 levels
- **MOGREPS-G**: N216L70: ~60km. 23 perturbed members
- **VAR**: N108L70/N216L70: ~120km→~60km.
- Horizontal localisation scale L_c = 1200km. (The distance at which the correlation reaches $e^{-1/2}$)
- Relaxation to standard climatological covariances between 16 and 21km
- **Note**: Trials run without smoothing of vertical modes (to remove spurious T variances)







Pre-operational hybrid trials

Verification vs. obs

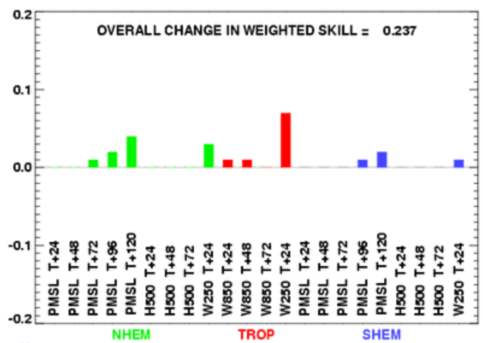
Better/neutral/worse

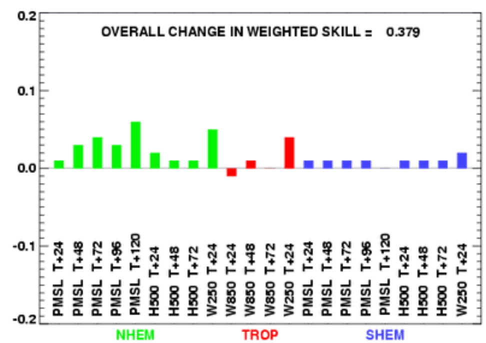
	NH	TR	SH
Dec uncoupled (29 days)	29/94/0	6/117/0	12/109/2
Jun coupled (28 days)	34/89/0	9/114/0	46/74/3

Dec uncoupled: 1.211 (0.874%)

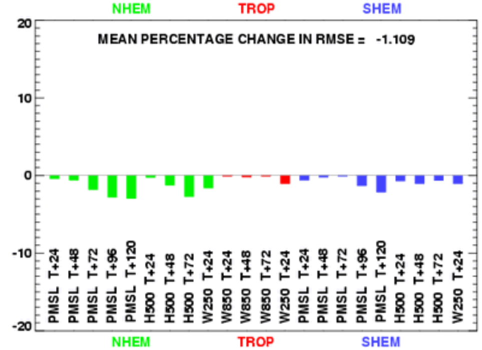
Jun coupled: 1.587 (1.226%)

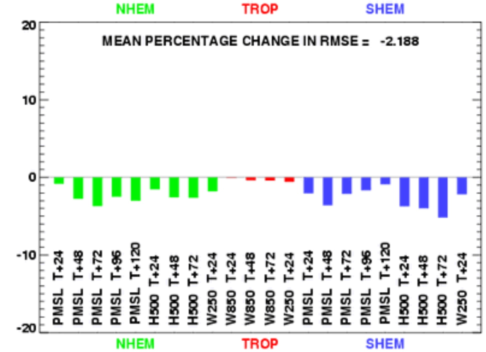
Skill:





RMSE:



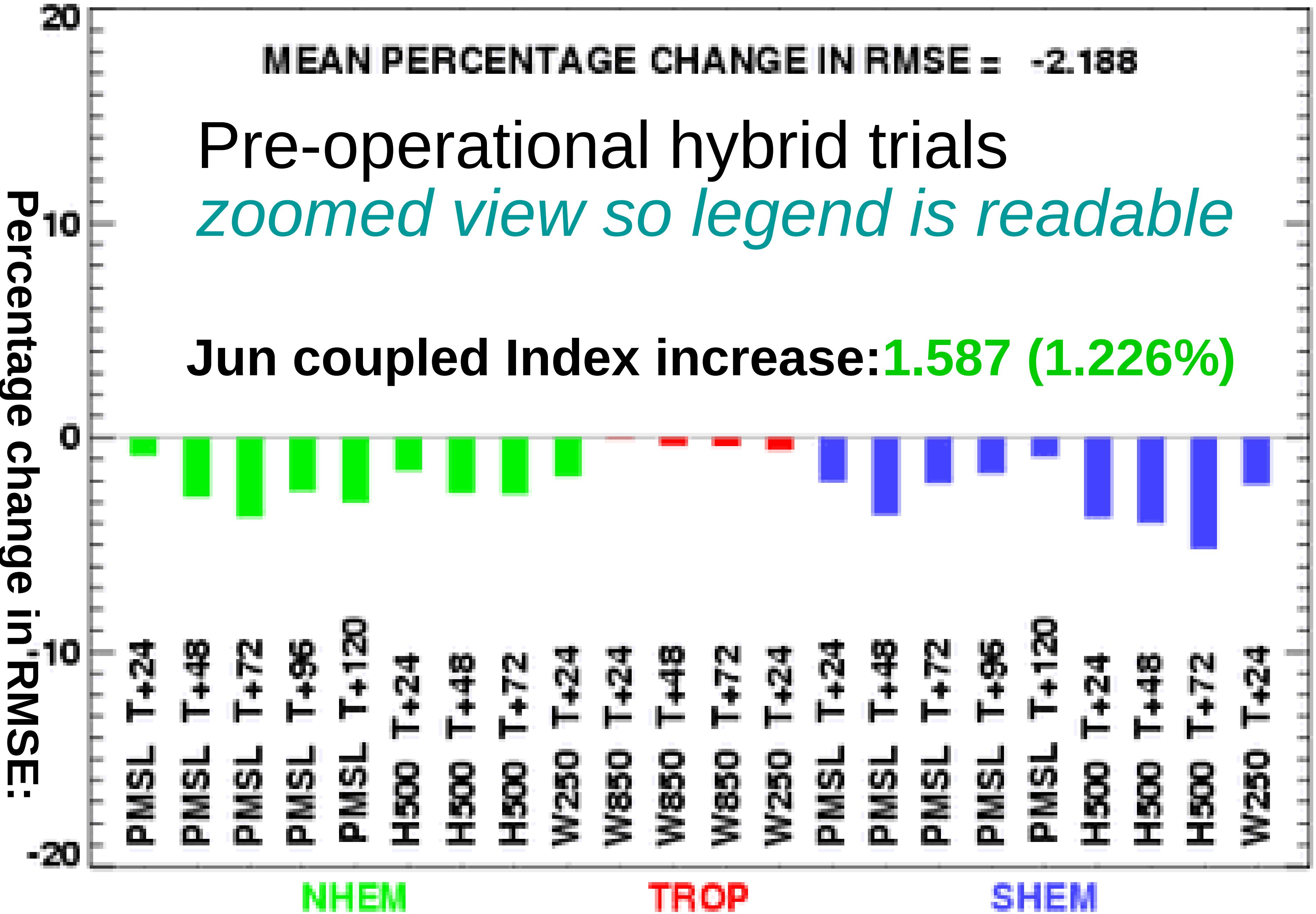


 Andrew Lorenc

Pre-operational hybrid trials

zoomed view so legend is readable

Jun coupled Index increase:1.587 (1.226%)



Pre-operational hybrid trials

Verification vs. own analyses

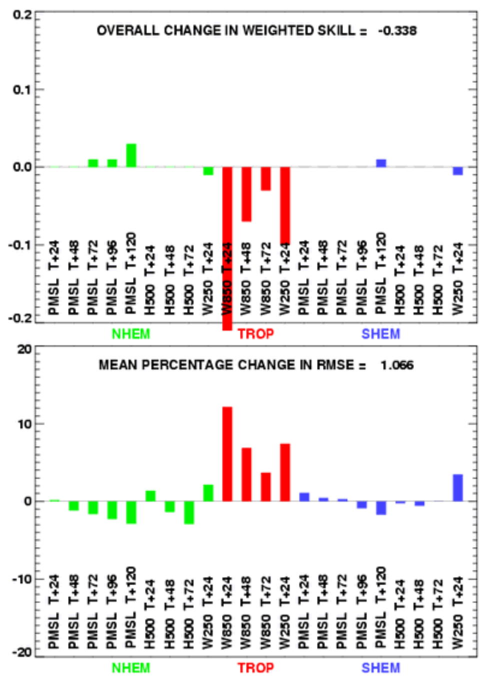
Better/neutral/worse

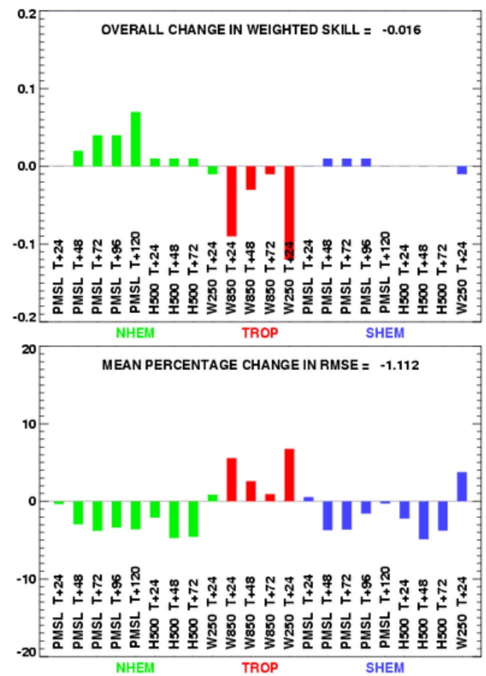
	NH	TR	SH
Dec uncoupled (29 days)	16/91/16	7/69/47	3/106/14
Jun coupled (28 days)	49/63/11	9/86/28	18/82/23

Dec uncoupled: -3.972 (-2.415%) **Jun coupled: -0.151 (-0.100%)**

Skill:

RMSE:





Pre-operational hybrid trials

Verification vs. ECMWF analyses

Better/neutral/worse

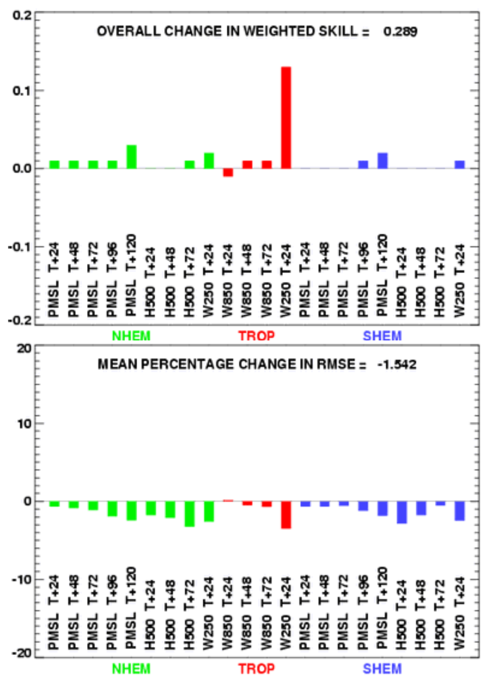
	NH	TR	SH
Dec uncoupled (29 days)	**35/79/0**	**39/75/0**	**14/100/0**
Jun coupled (28 days)	**63/51/0**	**29/85/0**	**47/65/2**

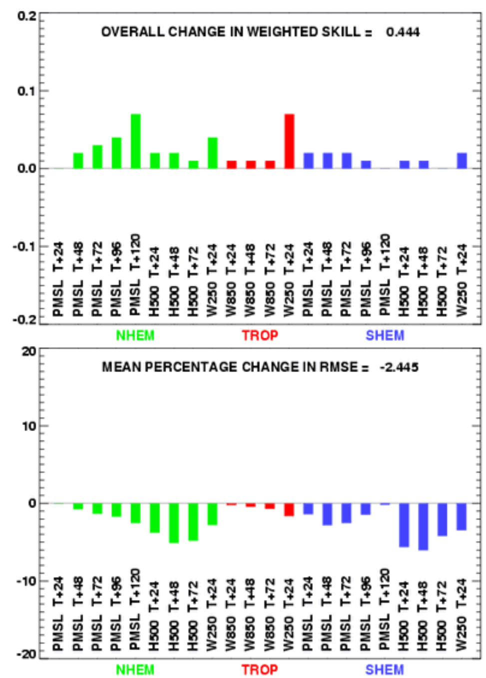
Dec uncoupled: 1.721 (1.338%)

Jun coupled: 1.311 (1.287%)

Skill:

RMSE:



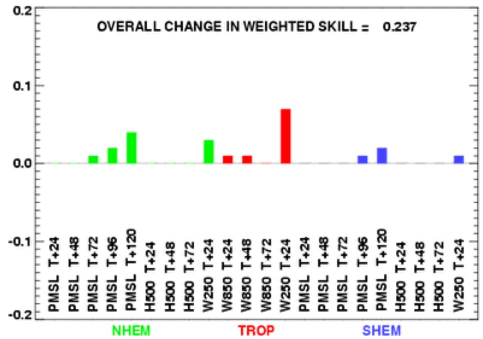


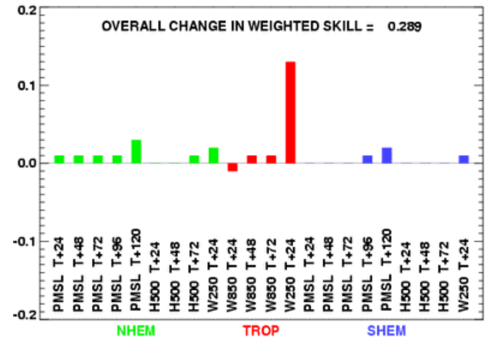
Pre-operational hybrid trials

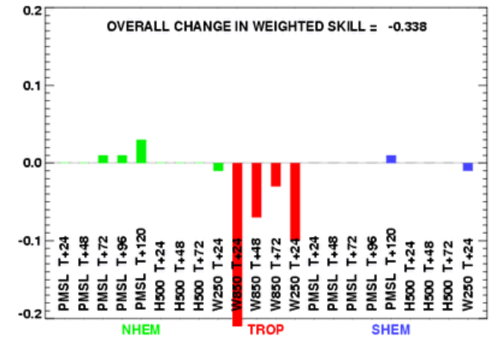
Summary of skill scores

vs. obs | **vs. ECMWF analyses** | **vs. own analyses**

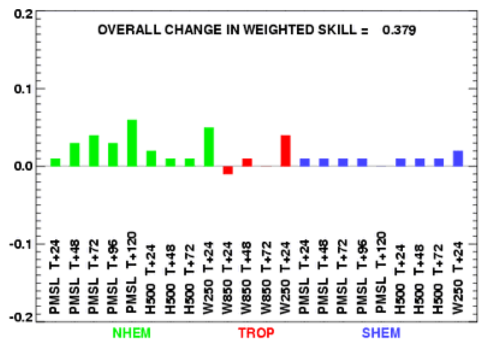
Dec uncoupled:

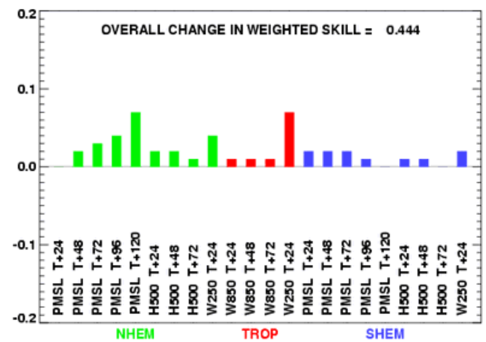


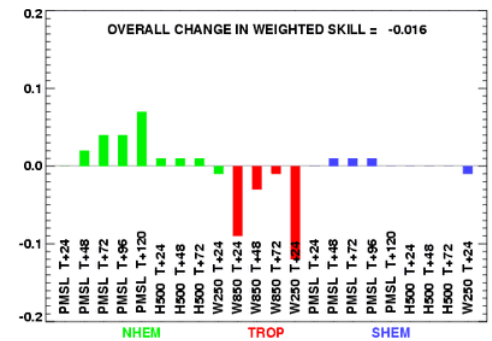




Jun coupled:



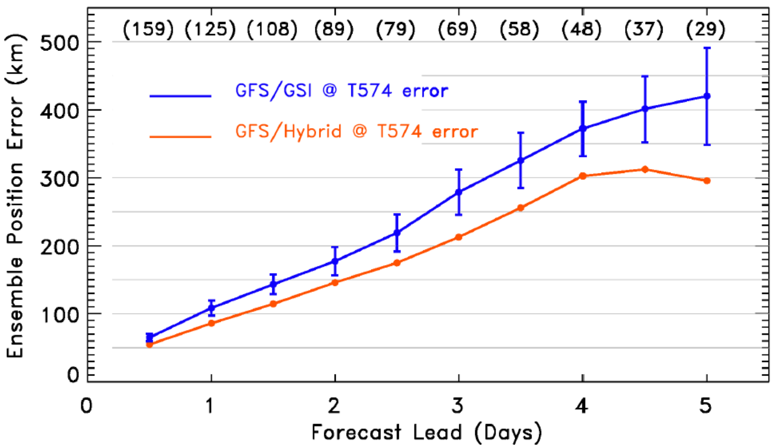




- Scores vs. ECMWF analyses more consistent with scores vs. obs
- When changing the character of the analysis, verification against own analyses is incestuous and misleading, so we are looking to change the NWP index
- (WMO CBS scores will remain flawed!)

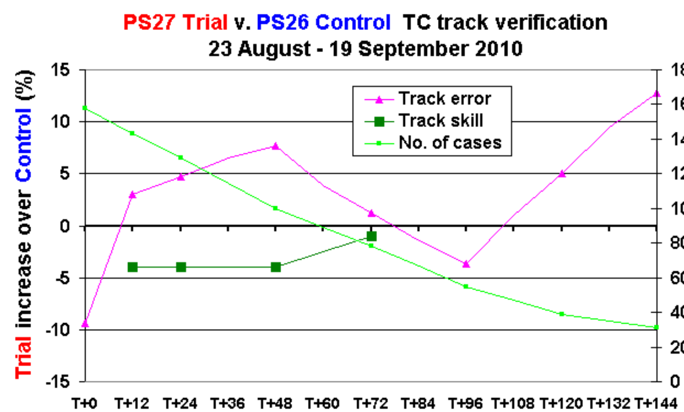
Effect on tropical cyclones (Julian Heming)

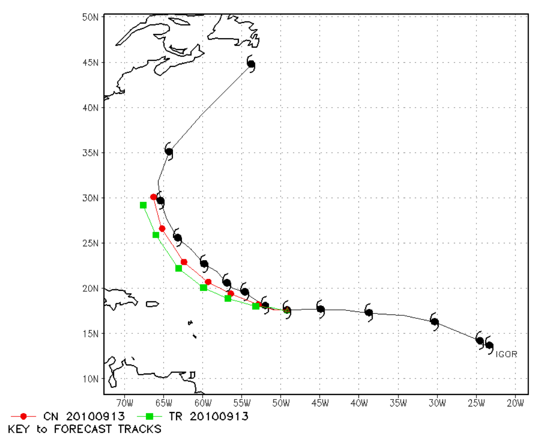
- TC track error much improved in GSI 3D-Var hybrid (80 ensemble members):

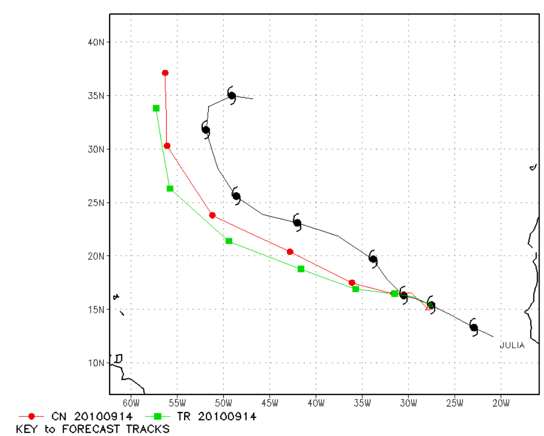


(Jeff Whitaker)

- If anything, our hybrid makes track errors worse:



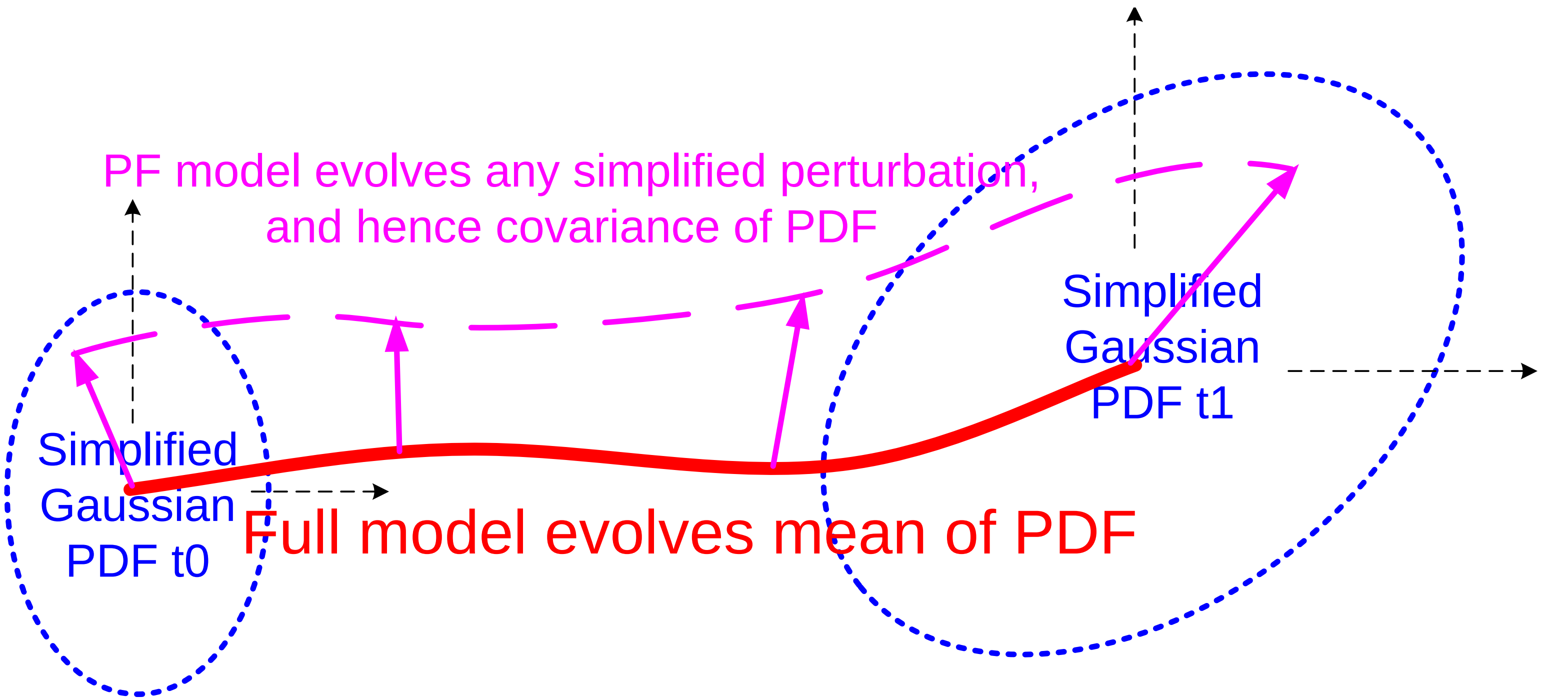




Plans

- Publish paper.
- Ensemble (MOGREPS-G) changes:
  - Move to 6-hour cycling.
  - Increase horizontal resolution
  - Increase ensemble size.
- Hybrid development:
  - Waveband localisation (Buehner 2011)
  - Investigate reasons for disappointing TC performance
  - Improve vertical localisation’s effect on balance
  - Better understanding of optimal localisation scales
- Possible Limited-Area version
- 4D-Ensemble-Var.

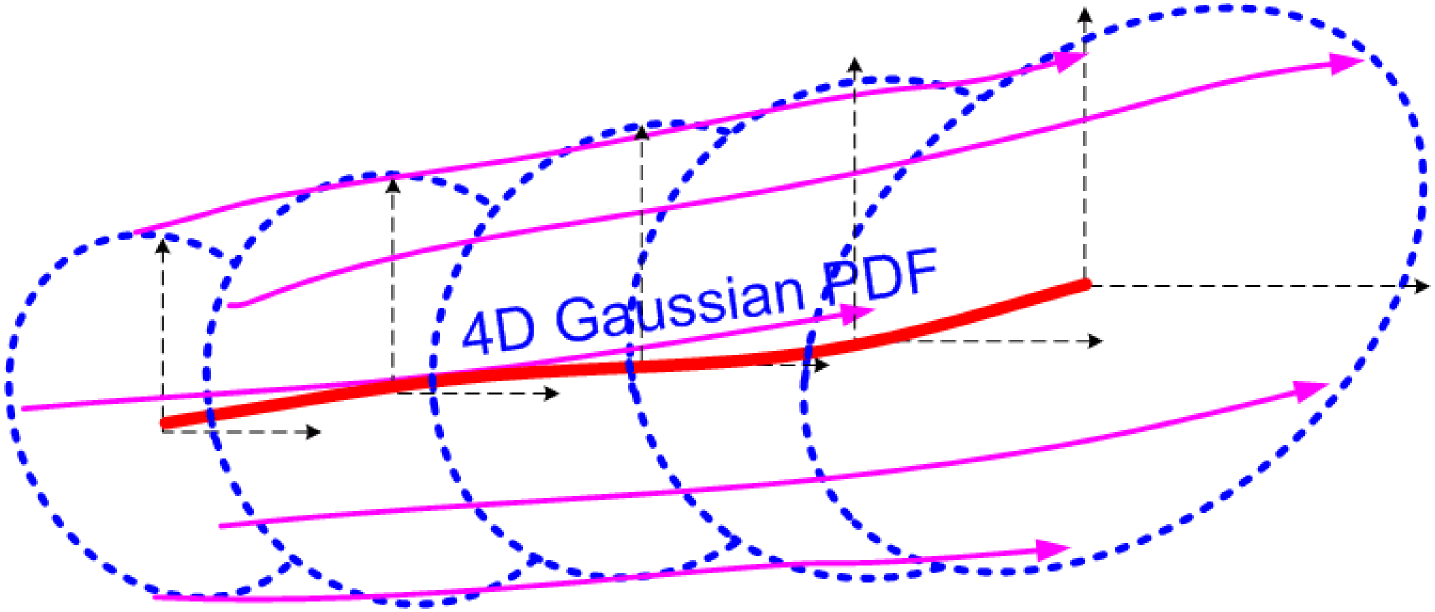
Statistical, incremental 4D-Var



Statistical 4D-Var approximates entire PDF by a Gaussian.

4D analysis increment is a trajectory of the PF model,
optionally augmented by a model error correction term.

Incremental 4D-Ensemble-Var



Trajectories of perturbations from ensemble mean

Full model evolves mean of PDF

Localised trajectories define 4D PDF of possible increments

4D analysis is a (localised) linear combination of nonlinear trajectories. It is not itself a trajectory.

4D-En-Var - equations

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Analysis variables are the localisation fields $\underline{\boldsymbol{\alpha}}_i$ multiplying each perturbation trajectory $\underline{\mathbf{x}}'_i$ to make the increment trajectory:

Lorenc (2003b), Liu *et al.* (2008), Buehner *et al.* (2010)

$$\delta\underline{\mathbf{x}} = \sum \underline{\boldsymbol{\alpha}}_i \circ \underline{\mathbf{x}}'_i$$

The increment trajectory plus the guess are interpolated to the obs:

$$\underline{\mathbf{y}} = \underline{\mathbf{H}}\delta\underline{\mathbf{x}} + \underline{H}\left(\underline{M}\left(\mathbf{x}^g, \underline{\boldsymbol{\eta}}^g\right)\right)$$

The penalty function is more akin to 3D-Var than 4D-Var:

$$J\left(\underline{\boldsymbol{\alpha}}\right) = \sum \tfrac{1}{2}\underline{\boldsymbol{\alpha}}_i{}^T\underline{\mathbf{C}}^{-1}\underline{\boldsymbol{\alpha}}_i + \tfrac{1}{2}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)^T\mathbf{R}^{-1}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)$$

We use standard transforms to model the spatial correlations in $\mathbf{C}$

Benefit of outer-loop

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- The outer-loop is normally justified as a re-linearisation of a non-quadratic minimisation.
- It can also be thought of as a way of correcting for an imperfect Perturbation model, by reducing the amplitude of the perturbations whose trajectory is approximated:

$$\underline{\mathbf{y}} = \underline{\tilde{\mathbf{H}}}\underline{\tilde{\mathbf{M}}}\left(\delta\mathbf{x}, \underline{\boldsymbol{\eta}}\right) + \underline{\bar{H}}\left(\underline{\bar{M}}\left(\mathbf{x}^g, \underline{\boldsymbol{\eta}}^g\right)\right)$$

- Of course, with an imperfect perturbation model, there is no guarantee that an outer-loop will converge.

Thanks for listening

History of hybrid at Met Office
(based on Lorenc 2007)

- 1990s: Dale Barker works on EOTD as part of Andrew Lorenc's VAR team. α control variable method developed. The idea was a development of Kalnay and Toth (1994).
- Tests using "Bred Modes" (Adrian Semple 2001, 2003) encouraging, but ensemble (1 perturbation) too small! EOTD project suspended pending an operational Met Office ensemble. (Dale continues research at NCAR.)
- While reviewing EnKF methods, Andrew Lorenc realised that the α control variable method was precisely equivalent to covariance localisation (Lorenc 2003).
- 2008: Project restarted by Andrew Lorenc, Dale Barker & Adam Clayton.
- 2009: 1st version (no vertical localisation) improves 3D-Var but neutral with 4D-Var.
- 2011: Improved version (as described here) implemented.

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