Background Error Statistics with a Mesoscale Model over Antarctica

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[1] Météo-France, CNRM/GMAP

[2] work accomplished while at the National Center for Atmospheric Research (NCAR/MMM)

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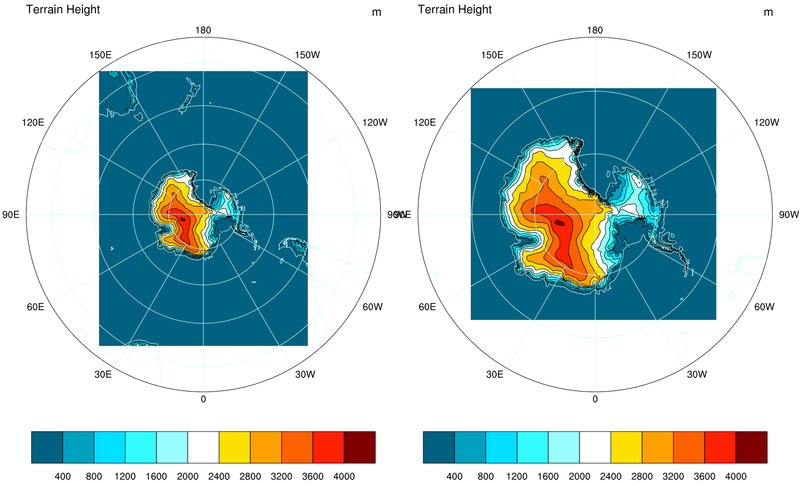
AMPS is a version of WRF regional model adapted to the polar physics of Antarctica. Data assimilation is performed for the two nested 45 km and 15 km resolution domains.



Variational assimilation minimizes a cost function:

$$J(\mathbf{v}) = \frac{1}{2}\mathbf{v}^{\mathrm{T}}\mathbf{B}^{-1}\mathbf{v} + (\mathbf{d} - \mathbf{Hv})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{d} - \mathbf{Hv})$$

where the background error covariance matrix $\mathbf{B}$ is usually too large ($\sim 10^{14}$) to be either stored or estimated.
$\mathbf{B}$ is modeled through a sequence of operators (Control Variable Transform) describing the *average* covariances of background errors.
In WRFVAR, the formulation is the sequence of four transforms:

$$\mathbf{v} = \mathbf{B}^{1/2}\chi = \mathbf{U}_p\mathbf{U}_v\mathbf{U}_{\mathrm{ih}}\mathbf{S}\chi$$

- $\mathbf{U}_p$ describes locally-averaged physical balances of errors between variables $\longrightarrow$ use of grid-point statistical regressions,
- $\mathbf{U}_v$ describes domain-averaged vertical autocorrelations $\longrightarrow$ use of Empirical Orthogonal Functions
- $\mathbf{U}_{\mathrm{ih}}$ describes locally-averaged horizontal autocorrelations $\longrightarrow$ use of inhomogeneous recursive filters,
- $\mathbf{S}$ describes locally-averaged variances.

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2. The Physical Transform
3. Vertical Correlations
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The balance $\mathbf{U}_p$ aims to represent the cross-correlations between errors that are linked with atmospheric dynamics

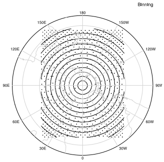
$$\begin{pmatrix} \psi \\ \chi \\ t \\ Ps \\ rh \end{pmatrix} = \begin{pmatrix} \mathbf{I} & 0 & 0 & 0 & 0 \\ \mathbf{M} & \mathbf{I} & 0 & 0 & 0 \\ \mathbf{N} & \mathbf{P} & \mathbf{I} & 0 & 0 \\ \mathbf{Q} & \mathbf{R} & \mathbf{S} & \mathbf{I} & 0 \\ 0 & 0 & 0 & 0 & \mathbf{I} \end{pmatrix} \begin{pmatrix} \psi \\ \chi_u \\ t_u \\ Ps_u \\ rh \end{pmatrix}$$

The balance represents geostrophic coupling between wind and mass fields, surface friction effects, and tracer-like relationships.

This matrices are computed from local or domain-averaged regressions.

Latitude-binning

A new latitude-binning accounts for the special AMPS stereographic polar projection, and allows to represent large scale inhomogeneities in the balance.



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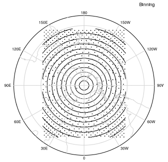

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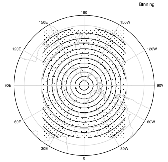

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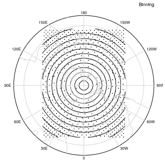

Inhomogeneous Background Error Modeling: Balance

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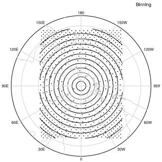


The $\chi - \psi$ balance

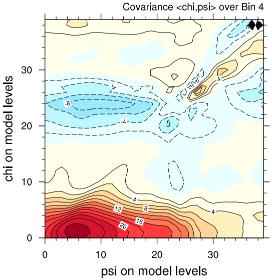
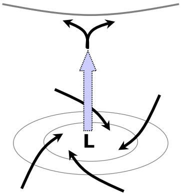


Figure: Cross-covariances $\chi - \psi$ at 60 S



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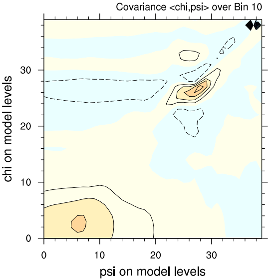
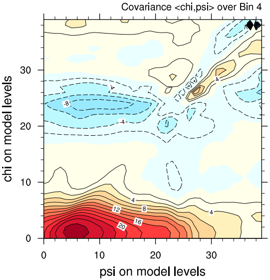


Figure: Cross-covariances $\chi - \psi$ at 30 S



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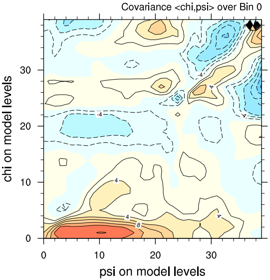
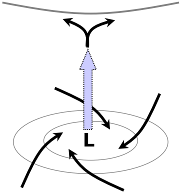


Figure: Cross-covariances $\chi - \psi$ at 90 S

Decrease of $\chi - \psi$ balance at the equator is well known and linked with decrease of geostrophy.



Decrease of $\chi - \psi$ balance may be explained by topography effects over the Antarctic plateau.

The $t - \psi$ balance

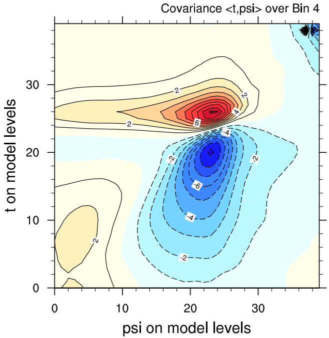


Figure: Cross-covariances $t - \psi$ at 60 S

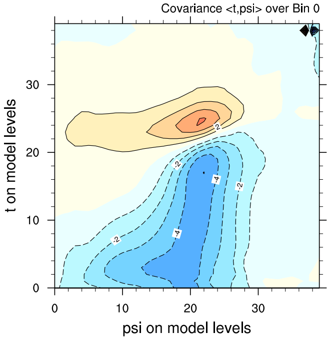
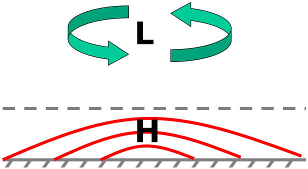


Figure: Cross-covariances $t - \psi$ at 90 S



Temperature inversion through radiative cooling in clear sky conditions ?

How do the cross-covariances compare with classical results (Derber and Bouttier 1999, Berre 2000, Ingleby 2001...)?

Some similarities with mid-latitude band balance

- Strong geostrophic coupling $\psi - t$ and $\psi - P_s$
- Surface friction (Ekman) $\psi - \chi$

Some new features

- Geostrophic coupling weaker over steep slopes,
- Change of sign of $< \psi, t >$ over the plateau (*temperatures inversions?*)
- Coupling between temperature and divergence exhibits some latudinal variation (*link with large scale convergence associated with katabatic winds?*)

An inhomogeneous formulation is required to take into account this features.

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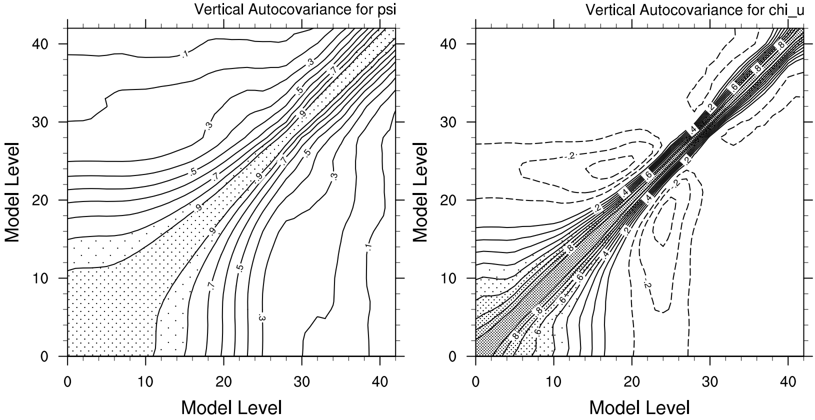

Figure: Vertical correlations for ψ and χ_u (Domain 1)

$\psi-$correlations are generally positive with a local widening at the tropopause.
χ_u-correlations are much sharper and have a negative lobe that is consistent with the fact that total divergence is $\sim$ zero.

Vertical Correlations

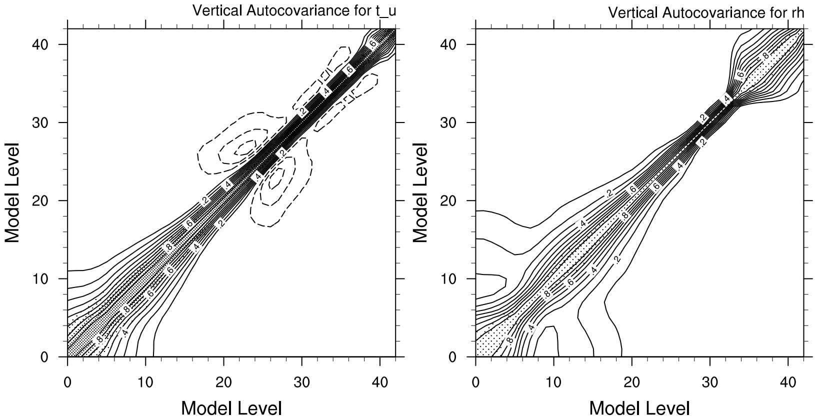

Figure: Vertical correlations for t_u and rh (Domain 1)

$rh-$correlations are found to be sharp, with partial decorrelation between upper-air and boundary layer errors.

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Sample background errors are decomposed on the EOF modes of the average vertical covariances. Their horizontal correlations are prescribed through the use of recursive filters (Purser *et. al.*, 2003a,b).

Recursive filters are a fast $\mathcal{O}(N)$ grid smoothing technique that can be applied to correlation modeling. Their inhomogeneous version has two advantages:

- Representation of the spatial variations of background error lengthscales
- Use of large grids featuring high map projection factors.

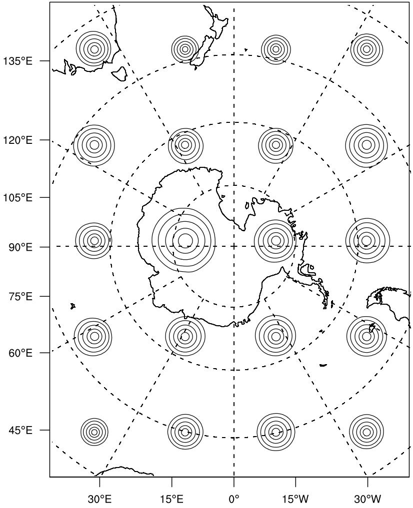

Figure: Inhomogeneous recursive filters over AMPS domain with a map factor and P_s lengthscales.

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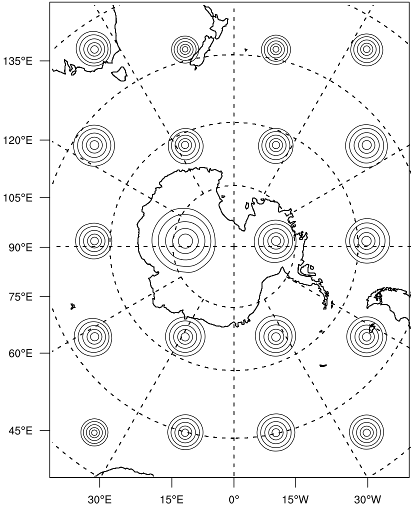

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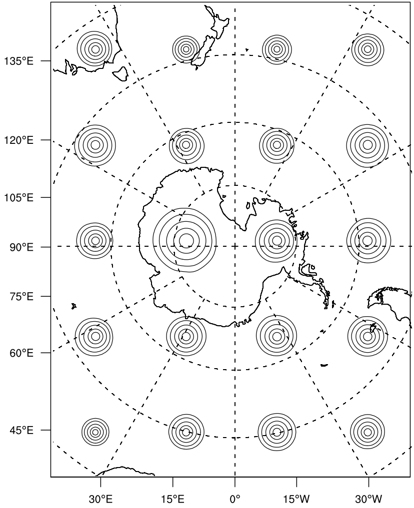

Figure: Inhomogeneous recursive filters over AMPS domain with a map factor and P_s lengthscales.

Lengthscales estimates

A new economical estimate of lengthscales is performed through the computation of the ratio of variance a field over the variance of the Laplacian:

$$L = \left(8 \frac{V(\psi)}{V(\xi)} \right)^{1/4}$$

Inhomogeneous recursive filters require the lengthscales maps to be smooth (*e.g.* filtered) to work properly.

Lengthscales geographical variations

For balanced variables, geostrophic scaling may be written

$$\Delta L = \frac{N}{f_0} \Delta Z$$

$\Delta Z, 1/f_0 \searrow$ going poleward such that one expects $\Delta L \searrow$ going poleward. Data density and topography effects may be important as well.

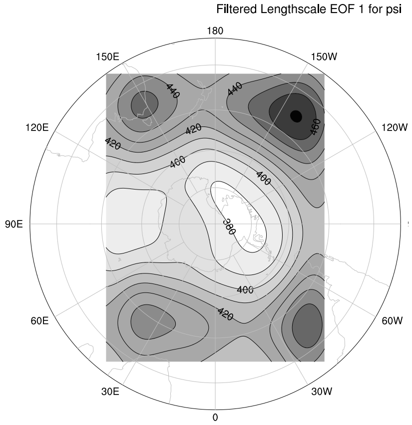

Figure: ψ local lengthscale (km)

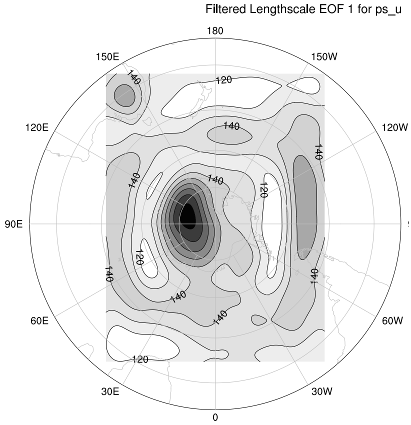

Figure: Ps_u local lengthscale (km)

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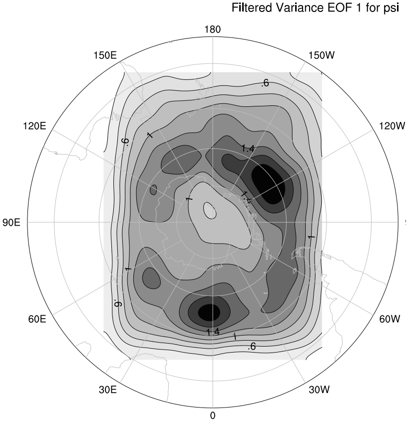

Figure: ψ local variance rescaling factor

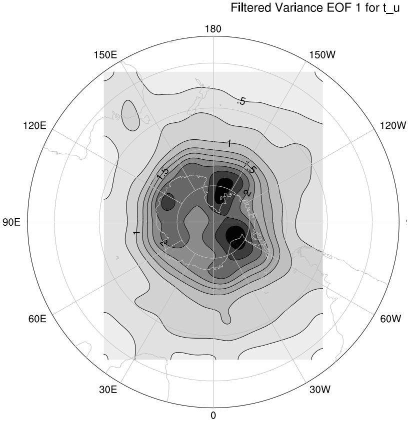

Figure: t_u local variance rescaling factor

Background error modeling

A newly developed formulation of **B** in WRFVAR allows main climatological *inhomogeneities* to be represented for the balance, lengthscales and variances parts.

Antarctic Background error

- Application to the Antarctic region with WRFVAR/AMPS shows strong similarities with mid-latitude estimates. However *interesting differences* can be pointed out, and related to special properties of this region (strong topography, boundary layer, sea/ice).
- Local lengthscale estimates show 'geostrophic' inhomogeneity for ψ and rh, as well as *local* inhomogeneity for χ_u, t_u, Ps_u (featuring a local maximum over the plateau).
- Local variances are higher in storm tracks (ψ, rh, Ps_u) or in contrary over the plateau (t_u), or more complicated (χ_u)

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More details (including more on inhomogeneous **B**-modeling and more on the differences obtained when comparing **B** over domain 1 and 2) in

Michel Y. and Auligné T. (2010) Inhomogeneous Background Error Modeling and Estimation over Antarctica. *Mon. Wea. Rev.*, In Press.

Thank you for your attention.

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