



# Inhomogeneous Background Error Modeling and Estimation over Antarctica with WRF-Var/AMPS

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10<sup>th</sup> Annual WRF Users' Workshop

 $23^{\rm th}$ June 2009

# Numerical Weather Prediction over Antarctica with WRF/AMPS

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.



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Variational assimilation minimizes a cost function:

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

where the background error covariance matrix **B** is usually too large (~  $10^{12}$ ) to be either stored or estimated.

**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:

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

- $\mathbf{U}_p$  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
- $U_{\rm ih}$  describes locally-averaged horizontal autocorrelations  $\longrightarrow$  use of inhomogeneous recursive filters,
- **S** describes locally-averaged variances.

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# Introduction

# **2** The Physical Transform

**3** Horizontal Correlations

4 Variances



A B K A B K

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

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



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#### Latitude-binning





 $\chi - \psi$  at 60 S





# 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 ?

## Introduction

# <sup>(2)</sup> The Physical Transform

# **3** Horizontal Correlations



# 5 Summary

Recursive filters are a fast  $\mathcal{O}(N)$  grid smoothing technique that can be applied to correlation modeling.

Inhomogeneous recursive filters have two main 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 Recursive filters are a fast  $\mathcal{O}(N)$  grid smoothing technique that can be applied to correlation modeling.

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Figure: Inhomogeneous recursive filters over AMPS domain with a map factor

### 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:

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

#### 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.

## Grid-Point Lengthscales



Figure:  $\psi$  local lengthscale (km)



Figure:  $Ps_u$  local lengthscale (km)

## Introduction

- <sup>(2)</sup> The Physical Transform
- **3** Horizontal Correlations





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Figure:  $\psi$  local variance rescaling factor Figure:  $t_u$  local variance rescaling factor

## Background error modeling

A newly developed formulation of  $\mathbf{B}$  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).

**4** Local variances are higher in storm tracks ( $\psi$ , rh,  $Ps_u$ ) or in contrary over the plateau ( $t_u$ ), or more complicated ( $\chi_u$ )

**♣** Local lengthscale estimates show 'geostrophic' inhomogeneity for  $\psi$  and rh, as well as *local* inhomogeneity for  $\chi_u$ ,  $t_u$ ,  $Ps_u$  (featuring a local maximum over the plateau).

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