ASPECTS OF STRATOSPHERIC ENSEMBLE DATA ASSIMILATION

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Context and Objectives

Context

Fast Chemistry-Climate Model (CCM) tuned for the stratosphere.

First implementation of ensemble data assimilation with a CCM.

perfect twin $\rightarrow$ imperfect twin $\rightarrow$ real observations

Possible applications: stratospheric reanalysis, guidelines for operational systems.

Objectives

Test the applicability and possible benefits of ensemble data assimilation to a sparsely-observed, multivariate, nonlinear system like the stratosphere.

Improve the unobserved stratospheric winds (Daley, 1995; Riishojgaard, 1996), through multivariate ensemble data assimilation.

Outline

- EnKF-CCM system
- Chemical-dynamical interaction
- Ensemble Kalman smoother

ENSEMBLE KALMAN FILTERING

with a

CHEMISTRY CLIMATE MODEL

Experimental setup : EnKF

EnKF with perturbed obs (Evensen, 1994; Burgers, 1998)

$$\boxed{\delta \mathrm{x} = \mathbf{K}_e \; \mathrm{d}}$$

$\delta \mathrm{x} = \mathrm{x}^{\mathrm{a}} - \mathrm{x}^{\mathrm{f}} =$ analysis increments

$\mathrm{d} = \mathrm{y} - \mathcal{H}(\mathrm{x}^{\mathrm{f}}) =$ observation innovations

$\mathbf{K}_e = \mathbf{P}_e^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} (\mathbf{H} \mathbf{P}_e^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} + \mathbf{R})^{-1} =$ Kalman Gain

$$\mathbf{P}_e^{\mathrm{f}} = \frac{1}{\mathrm{M}} \sum_{m=1}^{\mathrm{M}} (\mathrm{x}_m^f - \overline{\mathrm{x}^f})(\mathrm{x}_m^f - \overline{\mathrm{x}^f})^{\mathrm{T}}$$

$=$ sample background error-covariance matrix

$\mathbf{R} =$ observations error-covariance matrix (prescribed)

$\mathcal{H} =$ measurement operator

Experimental Setup : CCM

CHEMISTRY-CLIMATE MODEL (CCM)

IGCM (Forster et al, 2000):

- Multilayer spectral GCM run at T21L26, lid at 0.1 hPa
- Intermediate-complexity physics parametrization
- Prescribed surface temperatures

FASTOC (Taylor and Bourqui, 2005):

- Fast surrogate chemistry scheme
- Based upon comprehensive box model by Fish and Burton (1997), with JPL02 rates.
- Timestep: 24 hrs (diurnal-averaged chemistry)
- Represented catalytic cycles: $\mathrm{O_x}$, $\mathrm{HO_x}$, $\mathrm{NO_x}$.
- Advected species: $\mathrm{O_x}$, $\mathrm{N_2O_5}$, $\mathrm{NO_x}$, $\mathrm{HNO_3}$

Experimental Setup : Filter Configurations

model state vector

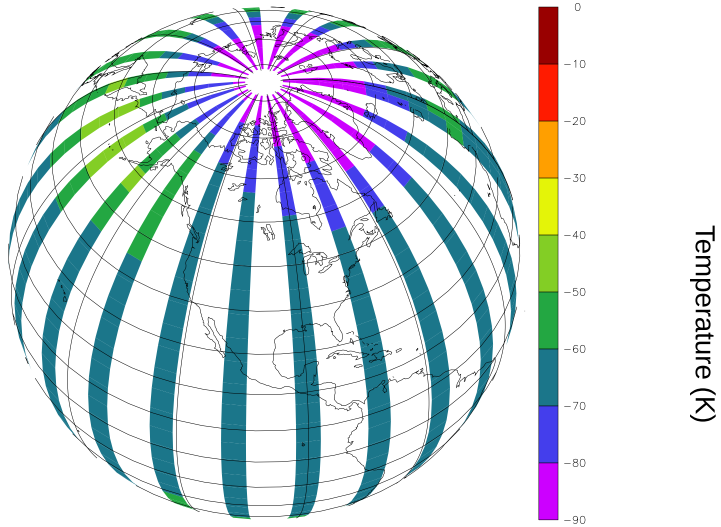
$$\begin{pmatrix} \mathbf{u} \\ \mathbf{v} \\ \mathbf{T} \\ \mathbf{P_s} \\ \mathbf{Q} \\ \mathbf{O_x} \\ \mathbf{N_2O_5} \\ \mathbf{NO_x} \\ \mathbf{HNO_3} \end{pmatrix}$$

- Perfect-twin experiment
- Initial ensemble is climatological with 128 members (Jan 1^{st} of each year)
- Sequential Double-EnKF assimilation of observations by batches (Houtekamer & Mitchell, 2001)
- Separate horizontal and vertical covariance localization parameters for ozone and temperature covariances
- No covariance inflation
- Analysis performed every 24 hours

Experimental Setup : Observations

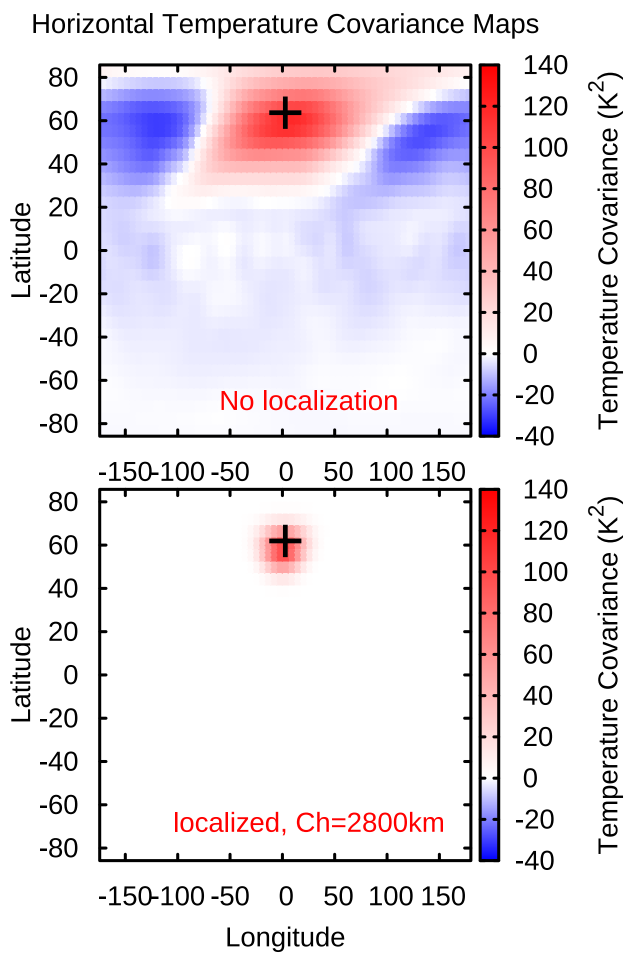
- Synthetic MIPAS-like temperature retrievals with 2K error
- Synthetic MIPAS-like ozone retrievals with 10% error
- Diagonal $\mathbf{R}$ matrix
- Obs instantaneous at 00UTC
- Vertical coverage between 4hPa and 200hPa on pressure levels

- Horizontal coverage on model grid points :



Localization

Localization: $\rho_v \circ \rho_h \circ \mathbf{P^f}$



+ Increase rank of background error-covariance matrix.

+ Remove (far-away) sampling noise.

- Lose the natural anisotropy : risk of introducing imbalance.

$\rightarrow$ Ideally, find optimal decorrelation length

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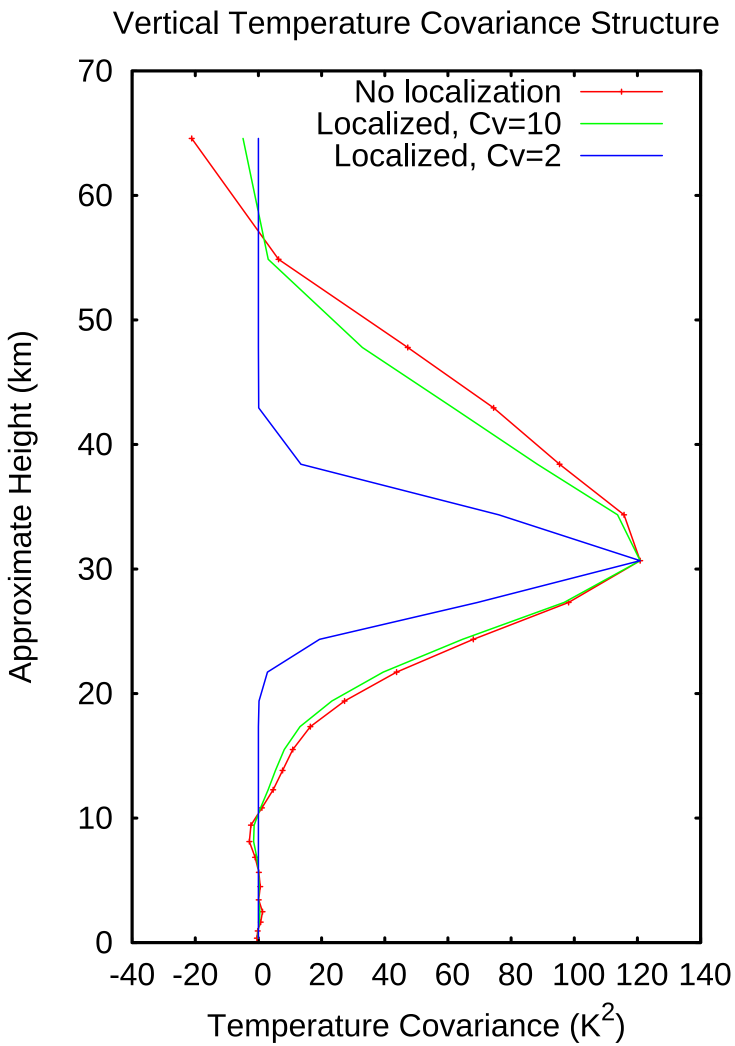

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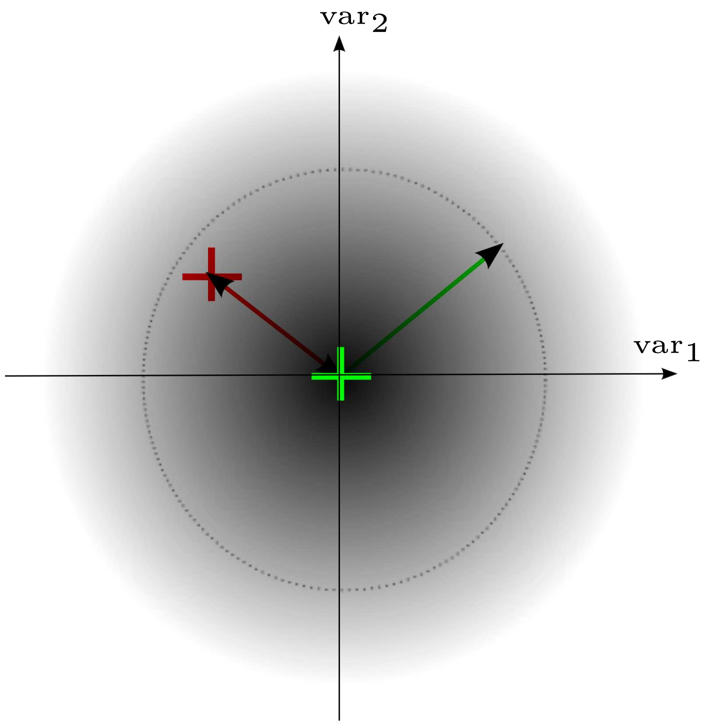
$\rightarrow$ Ideally, find optimal decorrelation length

Diagnostics: RMSE and SPREAD

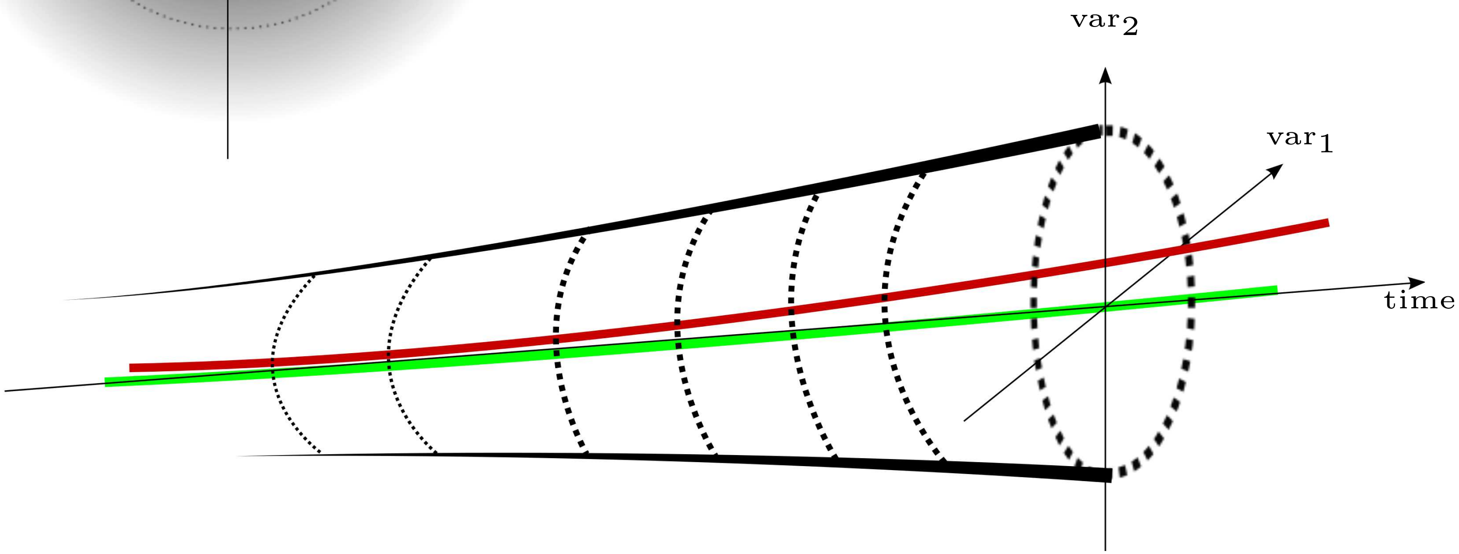


True state

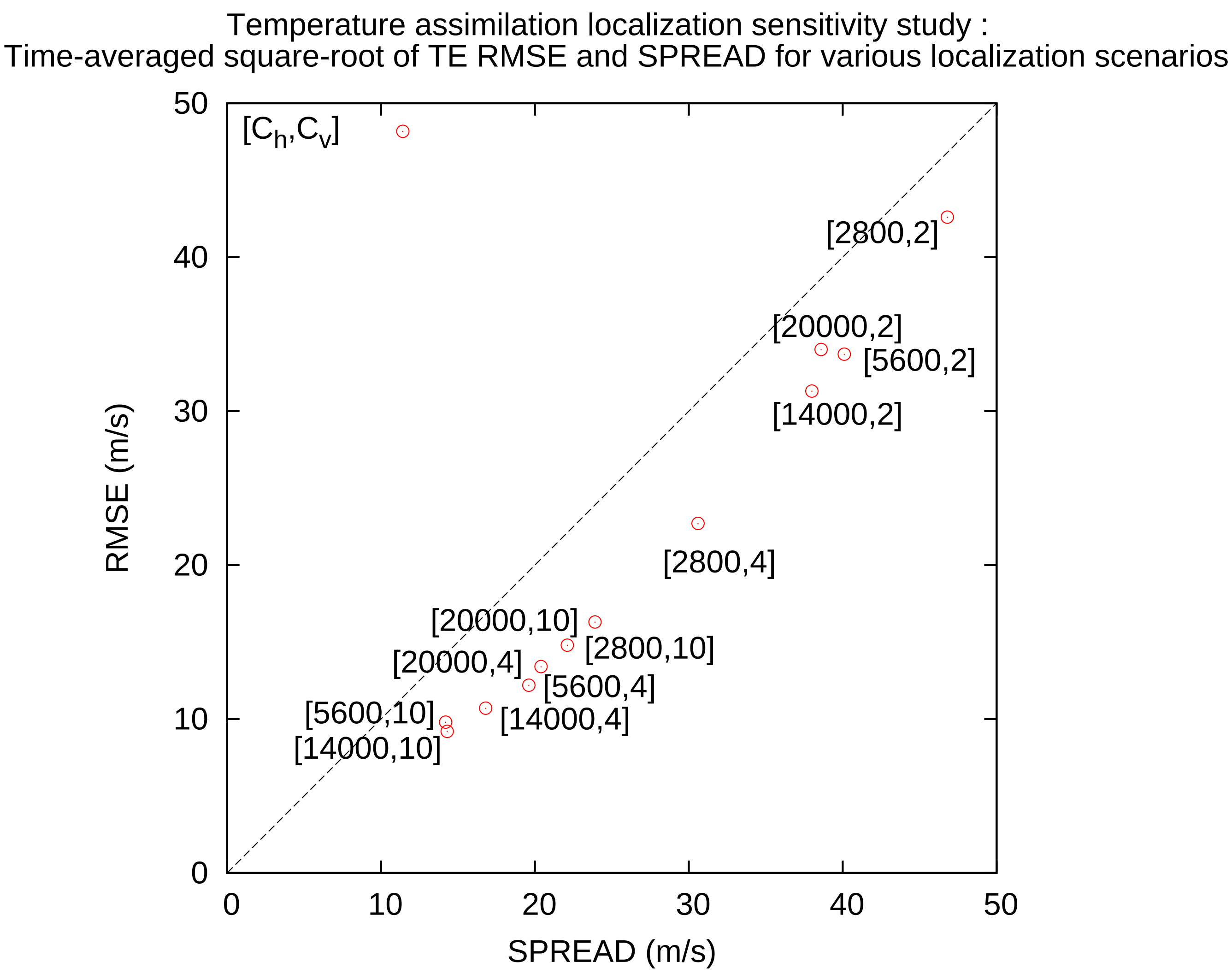
$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N} \frac{(\overline{x_i} - x_i^t)^2}{N}}$$

Ensemble mean

$$\mathrm{SPREAD} = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M-1} \frac{(x_{i,j} - \overline{x_i})^2}{N(M-1)}}$$



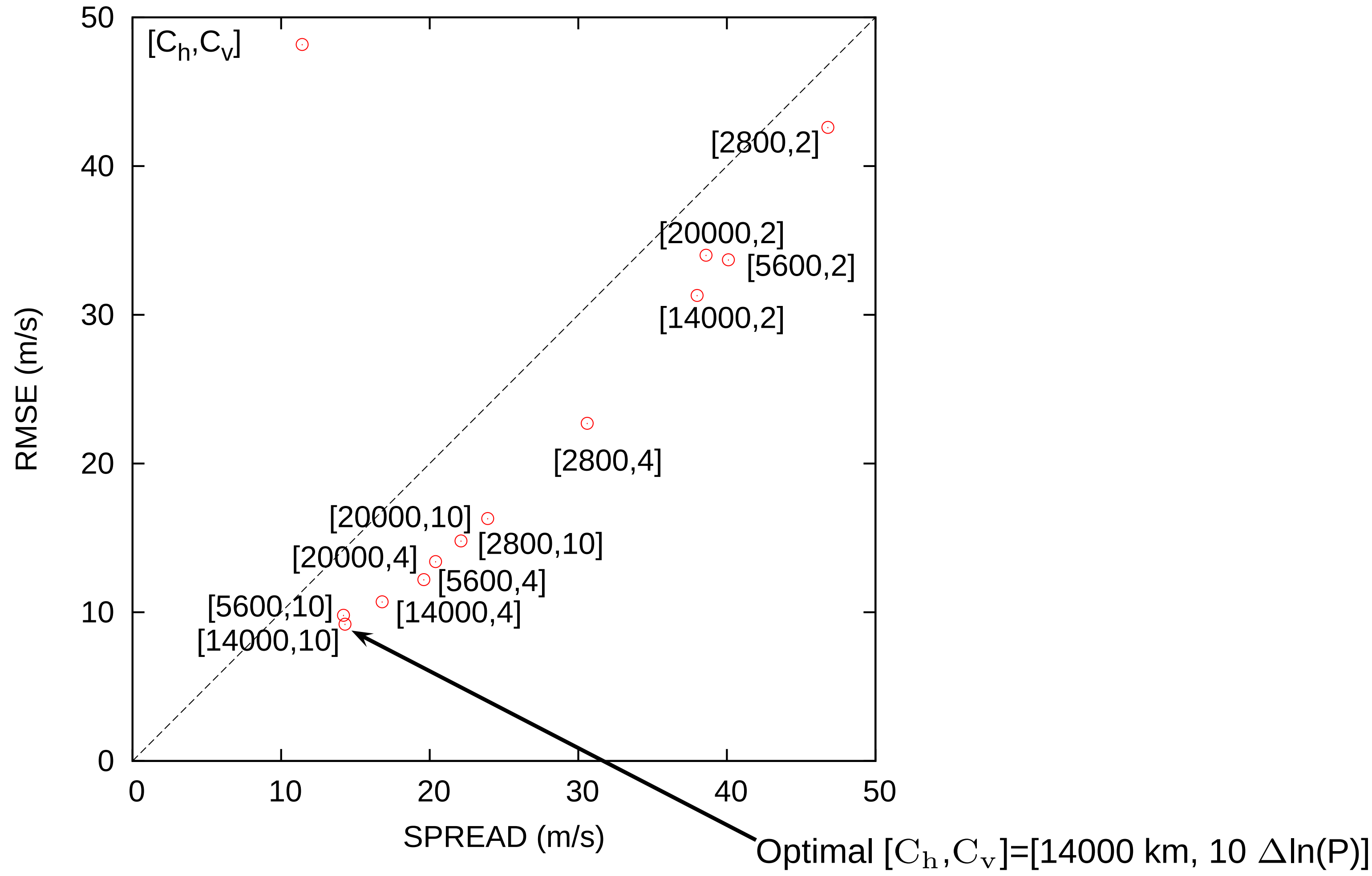
Optimal Localization: T Assimilation



$$\mathrm{TE} = \frac{u'^2}{2} + \frac{v'^2}{2} + \frac{C_p}{T_{ref}} T'^2 + R_\alpha T_{ref} \left(\frac{P'_s}{P_{ref}}\right)^2$$

Optimal Localization: T Assimilation

Temperature assimilation localization sensitivity study :
Time-averaged square-root of TE RMSE and SPREAD for various localization scenarios



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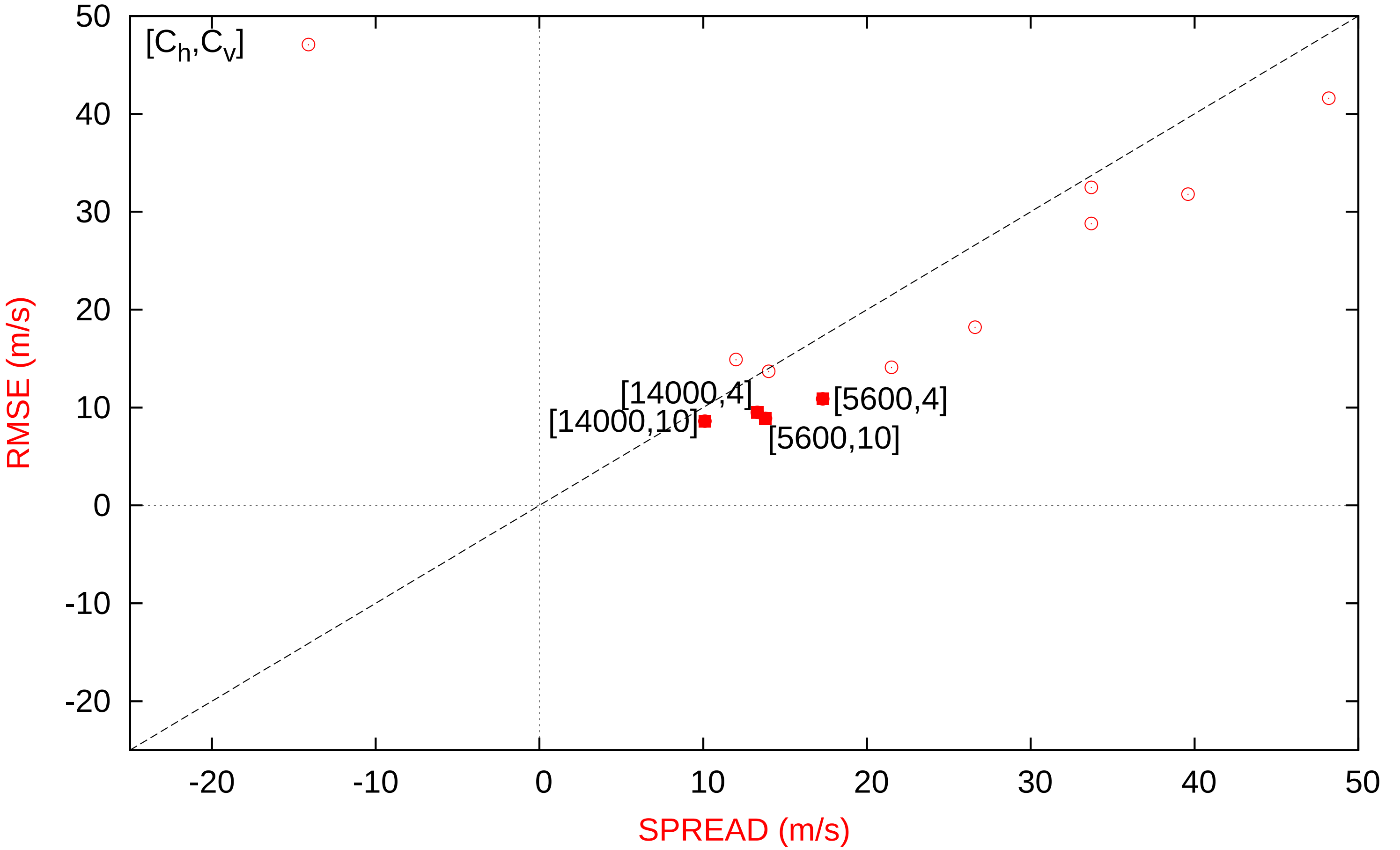
Optimal Localization: $\mathrm{O_x}$ Assimilation

Ozone assimilation localization sensitivity study :
Time-averaged square-root of TE RMSE and SPREAD, alpha and beta for various localization scenarios



Optimal Localization: $\mathrm{O}_{\mathbf{x}}$ Assimilation

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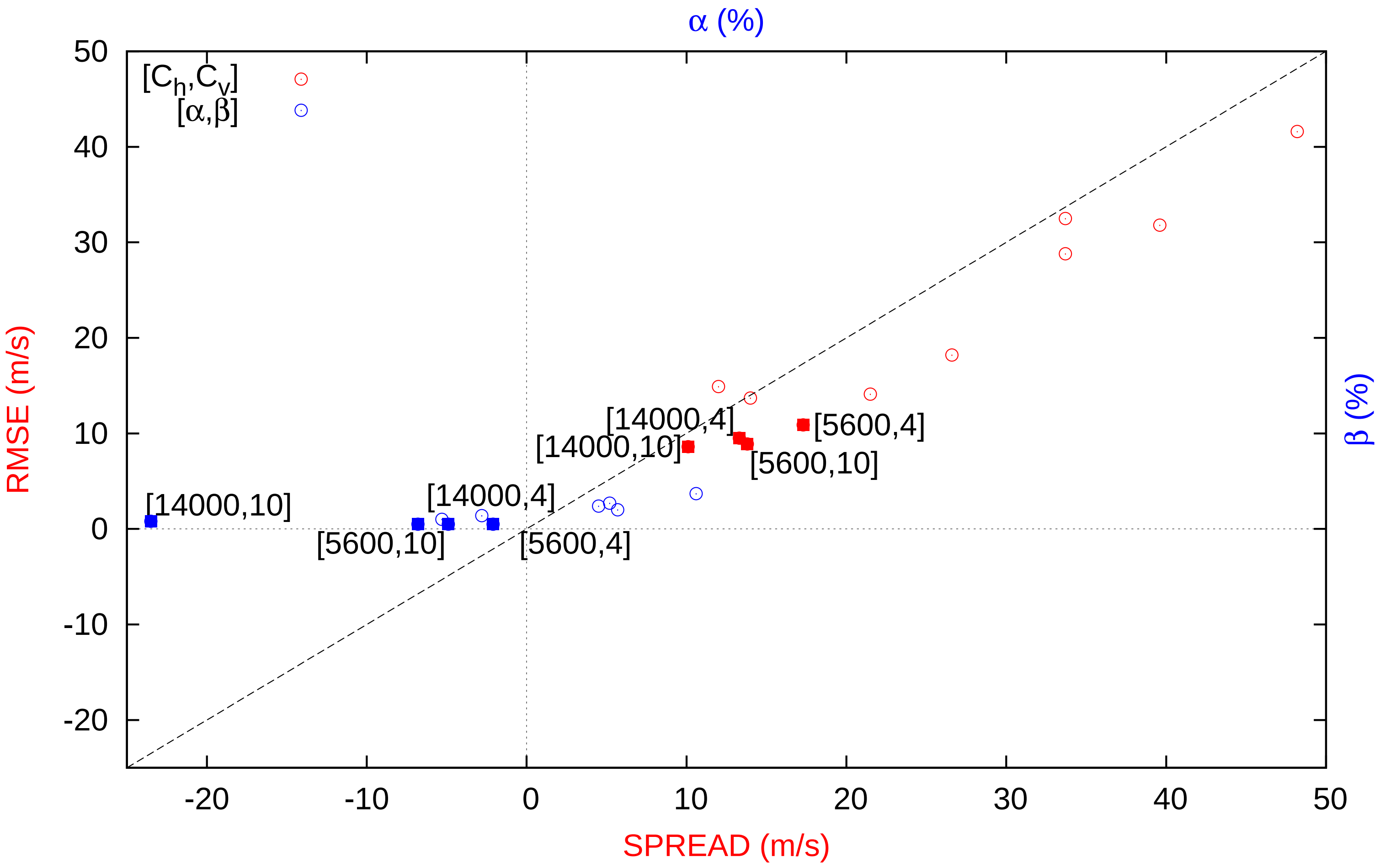

$$\alpha = \left(\frac{\mathrm{Tr}(<(\mathcal{H}(\mathbf{x}^{\mathrm{a}})-\mathcal{H}(\mathbf{x}^{\mathrm{f}}))(\mathbf{y}-\mathcal{H}(\mathbf{x}^{\mathrm{f}}))^{\mathrm{T}}>)}{\mathrm{Tr}(\mathbf{H}\mathbf{P}_e^{\mathrm{f}}\mathbf{H}^{\mathrm{T}})} - 1\right)\cdot 100\%, \quad \beta = \left(\frac{\mathrm{Tr}(<(\mathbf{y}-\mathcal{H}(\mathbf{x}^{\mathrm{a}}))(\mathbf{y}-\mathcal{H}(\mathbf{x}^{\mathrm{f}}))^{\mathrm{T}}>)}{\mathrm{Tr}(\tilde{\mathbf{R}})} - 1\right)\cdot 100\%$$

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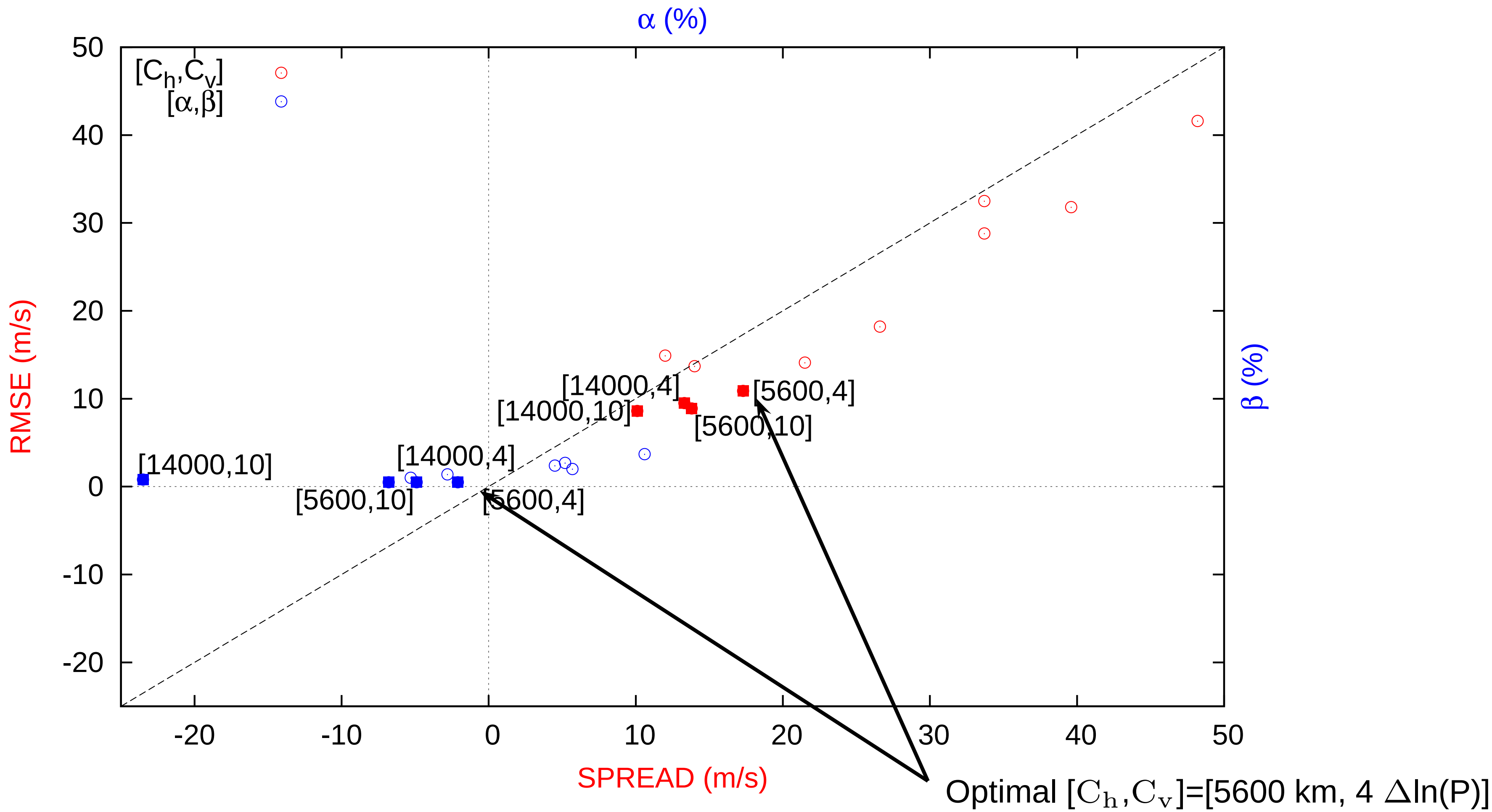

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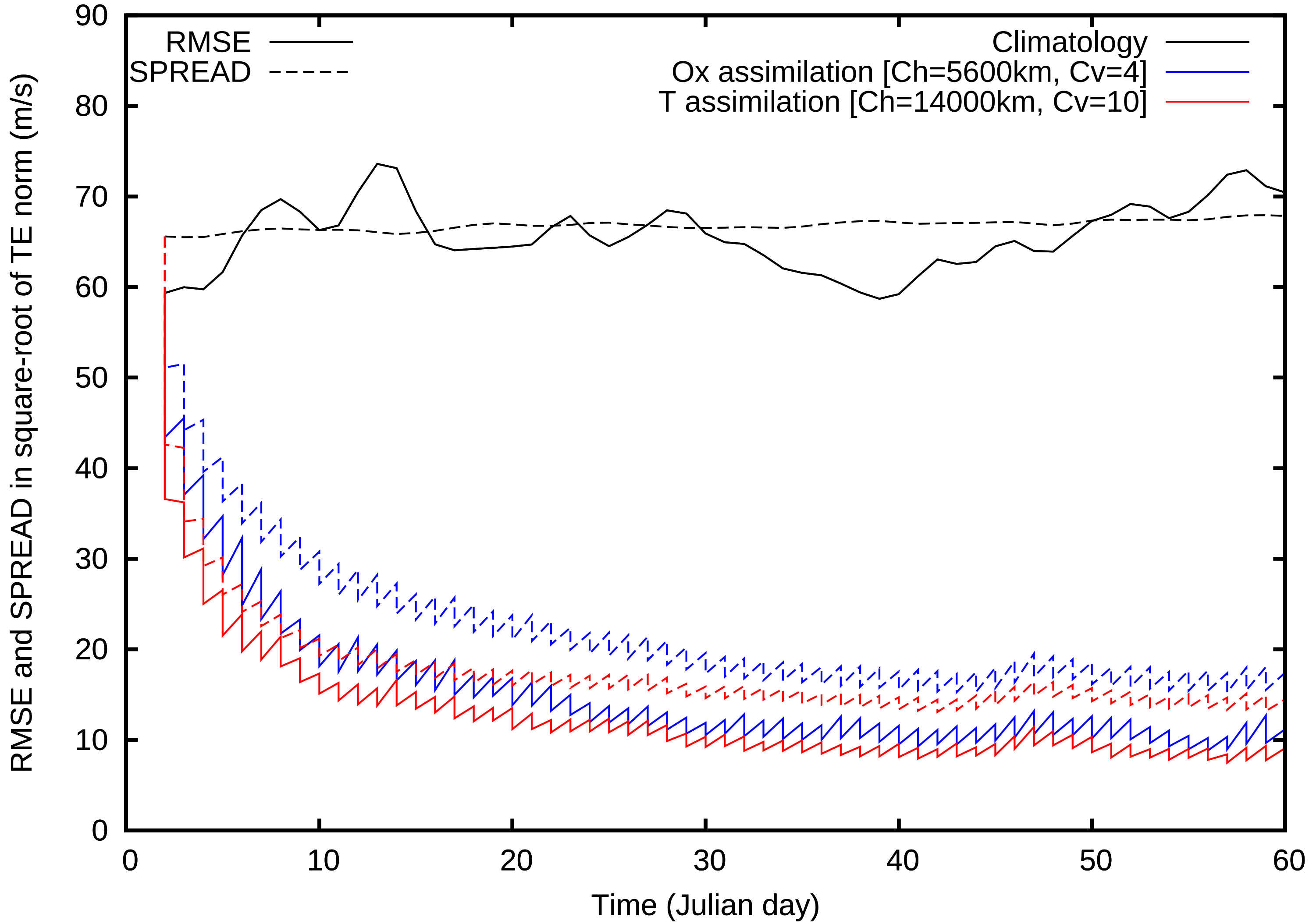
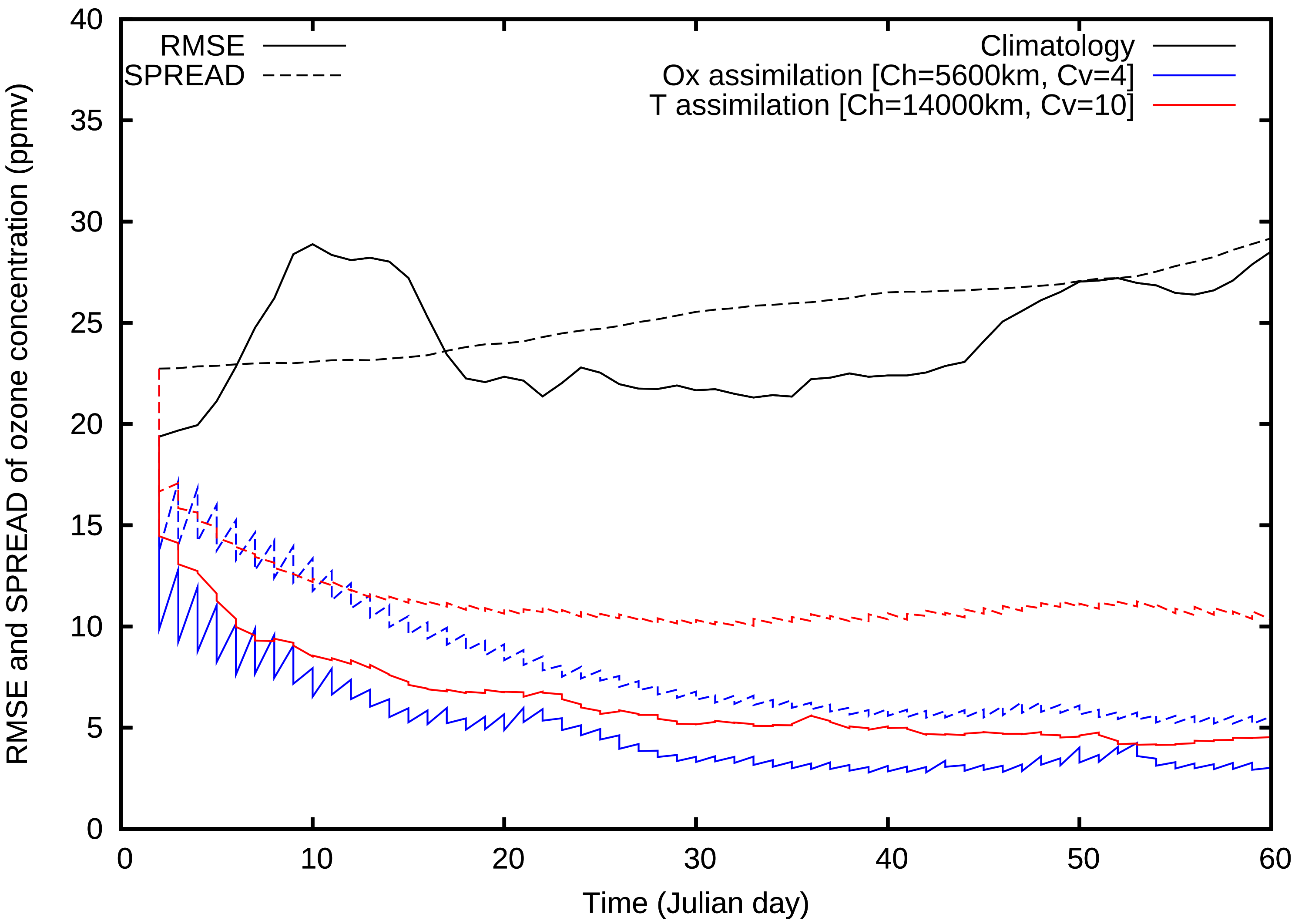
Evolution of Optimal Simulation: Total Energy

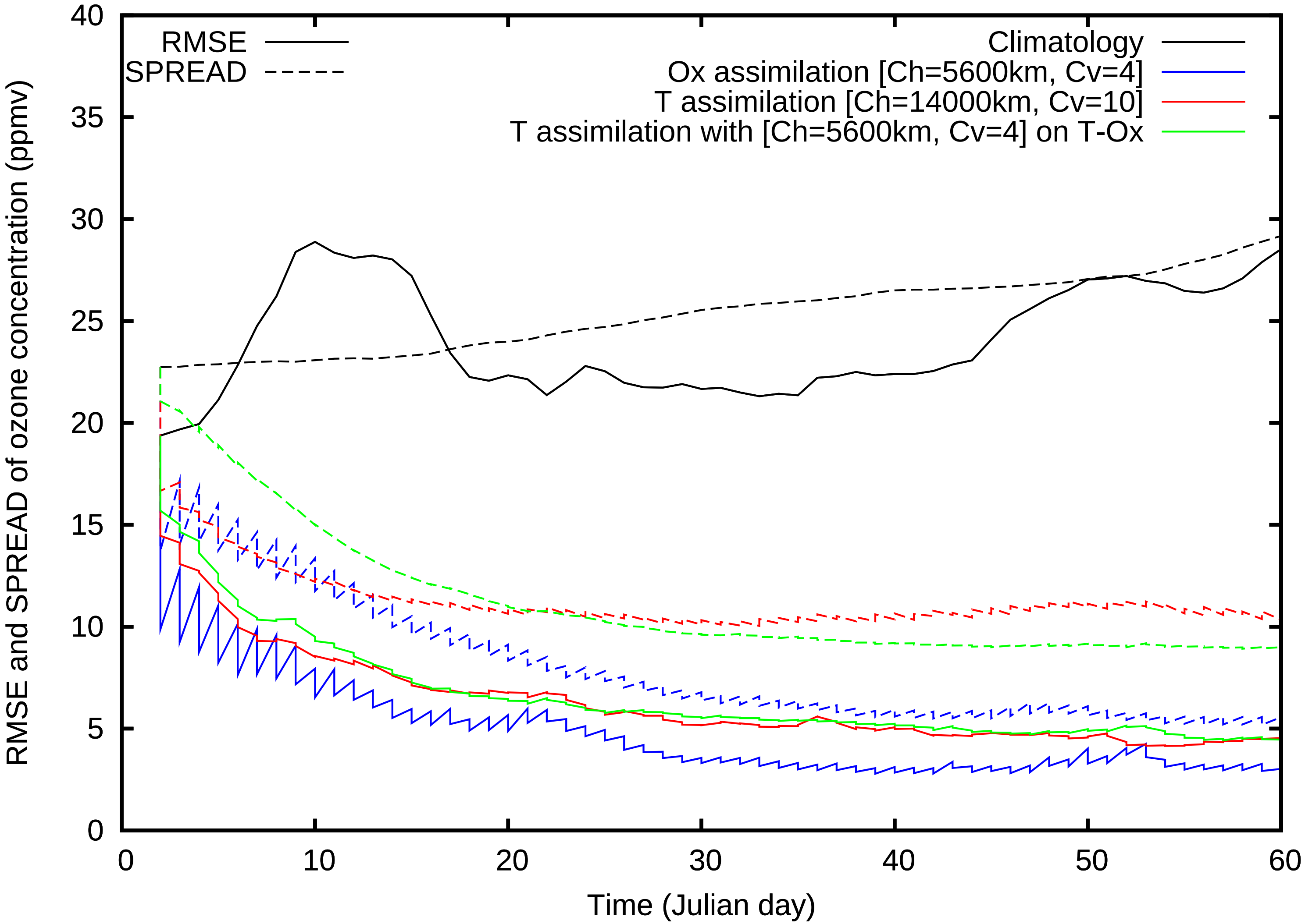


$$\mathrm{TE} = \frac{u'^2}{2} + \frac{v'^2}{2} + \frac{C_p}{T_{ref}} T'^2 + R_\alpha T_{ref} \left(\frac{P'_s}{P_{ref}} \right)^2$$

Evolution of Optimal Simulation: Ozone



Evolution of Optimal Simulation: Ozone

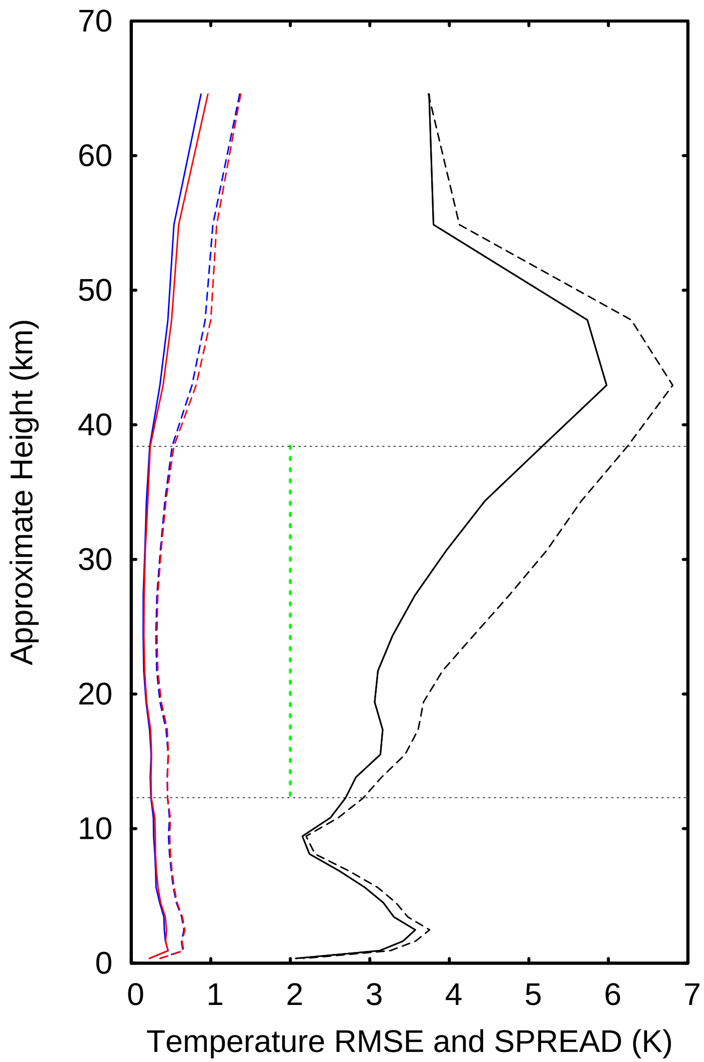


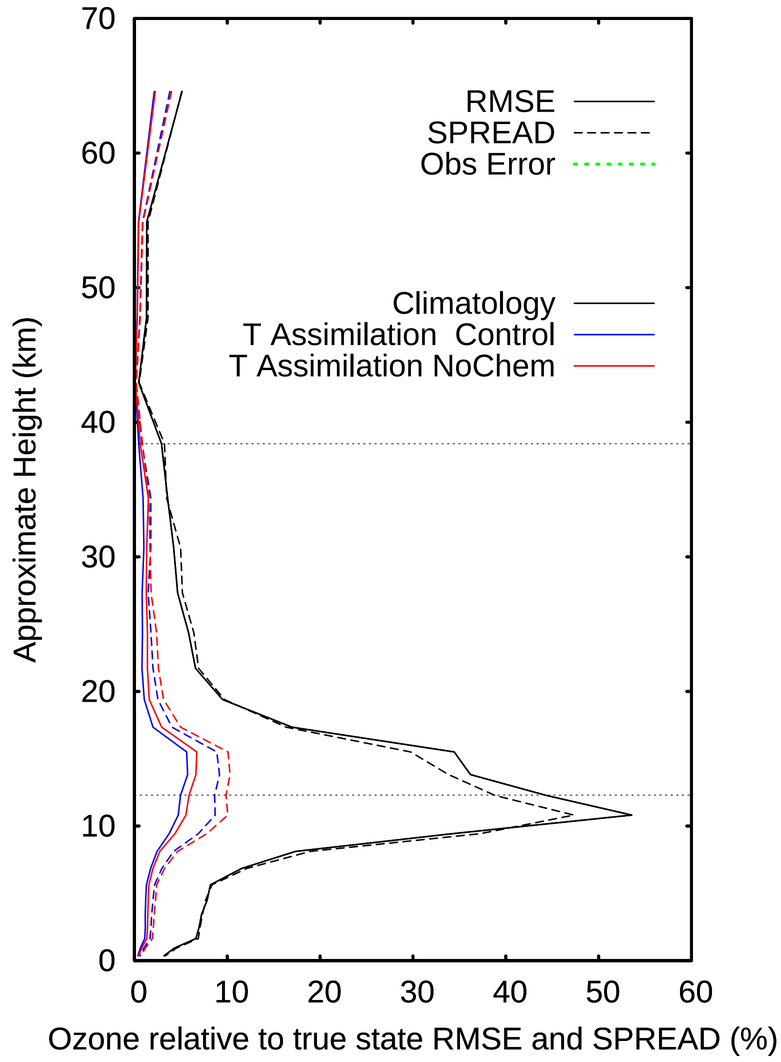
CHEMISTRY-DYNAMICS INTERACTION

Experiments

$\mathbf{T}$ **assimilation**	$\mathbf{O_x}$ **assimilation**
Control $\mathbf{T}$ obs transmit their information to all variables	**Control** $\mathbf{O_x}$ obs transmit their information to all variables
NoChem $\mathbf{T}$ obs transmit their information only to $\mathbf{u}$, $\mathbf{v}$, $\mathbf{T}$, $\mathbf{q}$ and $\mathbf{P_s}$	**NoDyn** $\mathbf{O_x}$ obs transmit their information only to $\mathbf{O_x}$, $\mathbf{N_2O_5}$, $\mathbf{NO_x}$, $\mathbf{HNO_3}$ and $\mathbf{P_s}$
	NoTemp $\mathbf{O_x}$ obs transmit their information to all variables except $\mathbf{T}$
	NoWinds $\mathbf{O_x}$ obs transmit their information to all variables except $\mathbf{u}$ and $\mathbf{v}$

T Assimilation: Time-Averaged Global Analyses

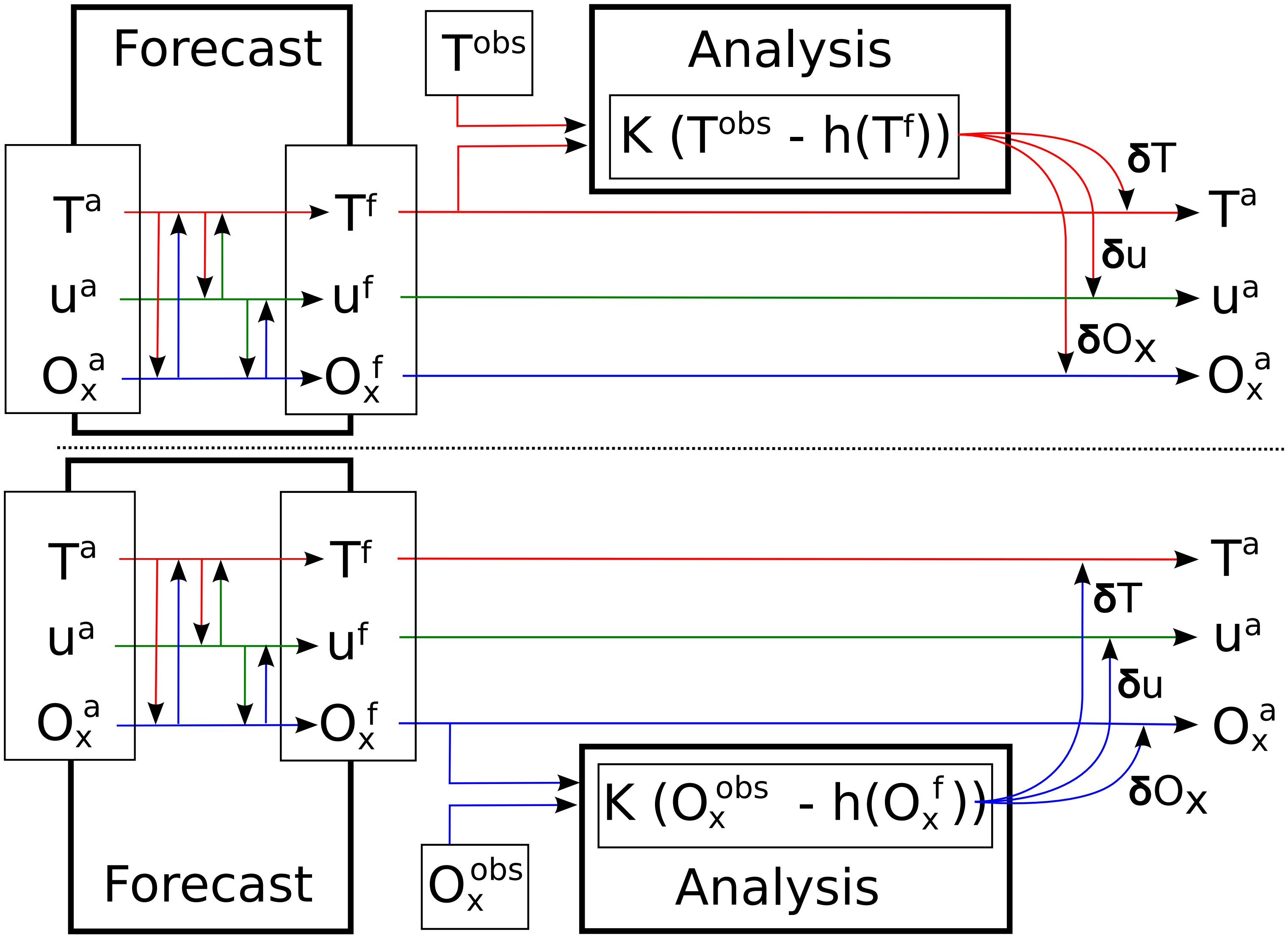




$\longrightarrow$ useless T-Chem error covariances or ineffective radiation ?

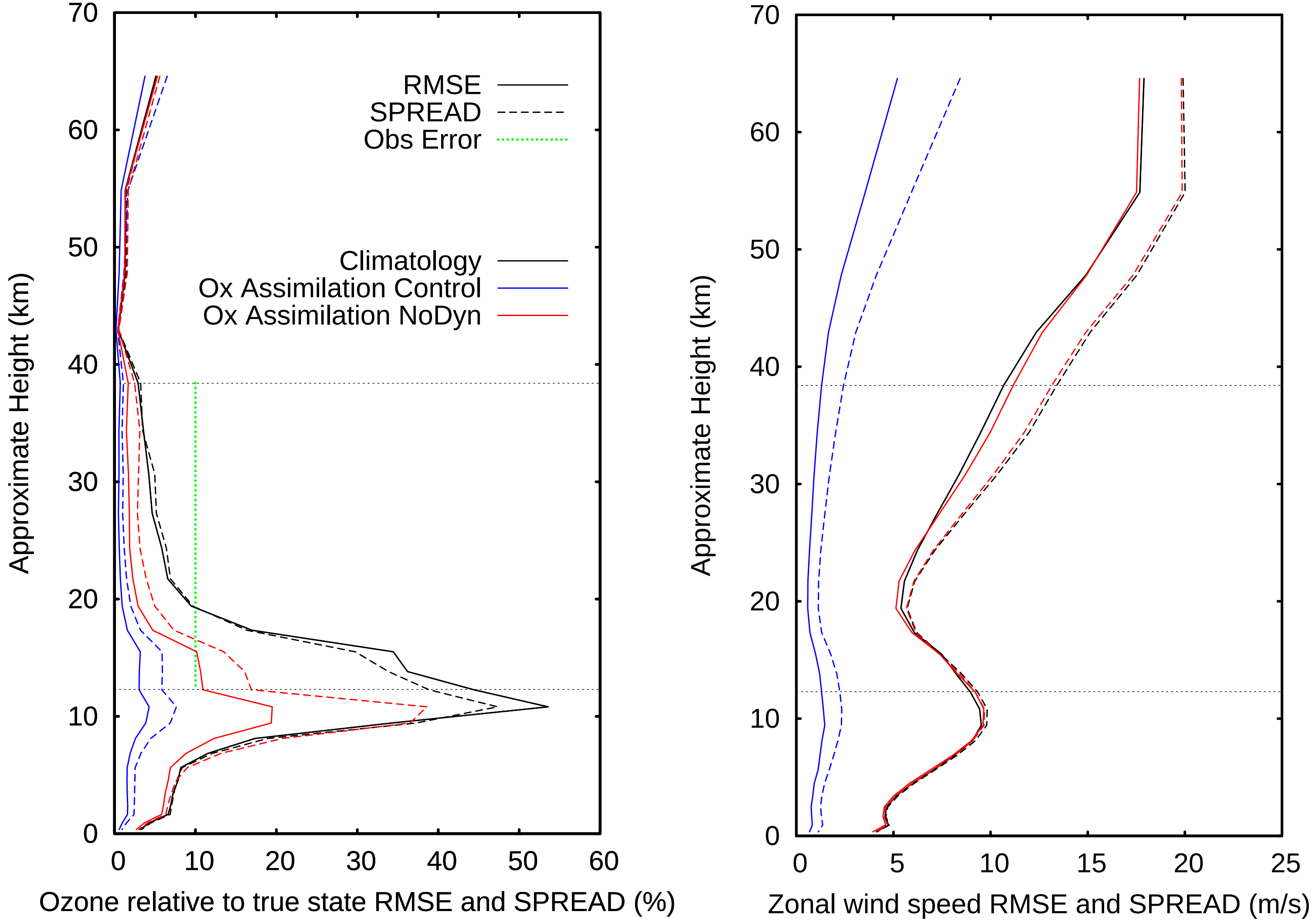
$\longrightarrow$ T-Chem error covariances further reduce $\mathrm{O_x}$ error.

Schematics



Forecast
T^{obs}
Analysis
$K\,(T^{obs} - h(T^f))$
T^a
u^a
O_x^a
T^f
u^f
O_x^f
δT
δu
δO_x
T^a
u^a
O_x^a
T^a
u^a
O_x^a
T^f
u^f
O_x^f
δT
δu
δO_x
T^a
u^a
O_x^a
$K\,(O_x^{obs} - h(O_x^f))$
Forecast
O_x^{obs}
Analysis

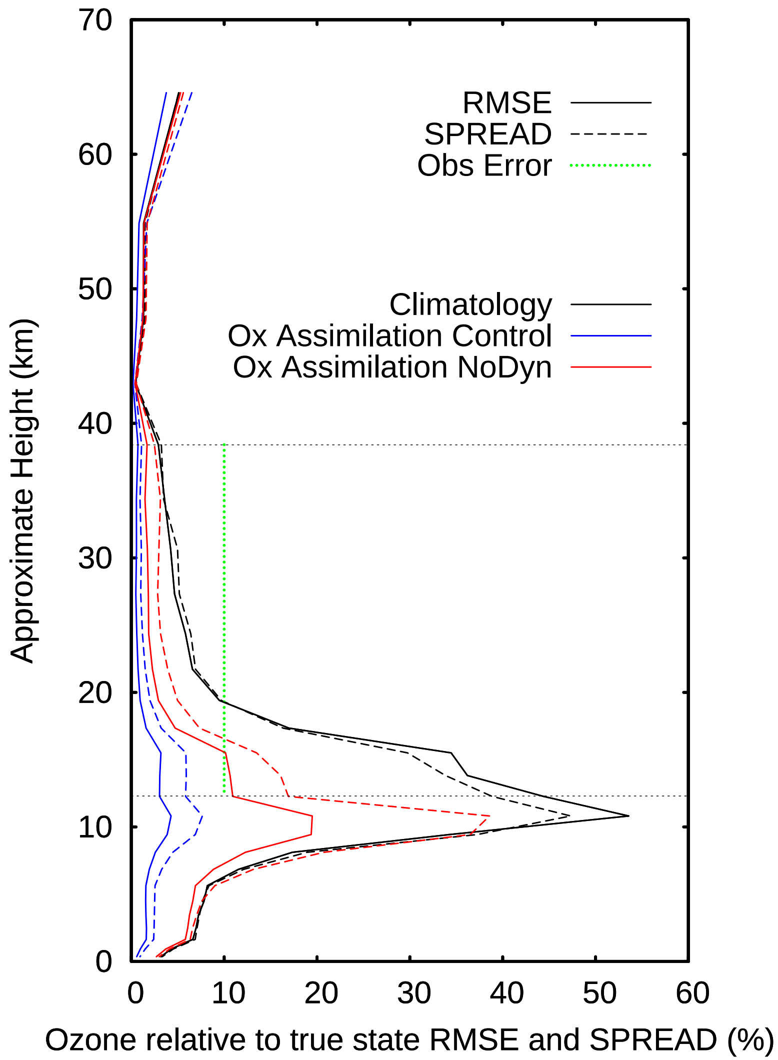
O_x Assimilation: Time-Averaged Global Analyses

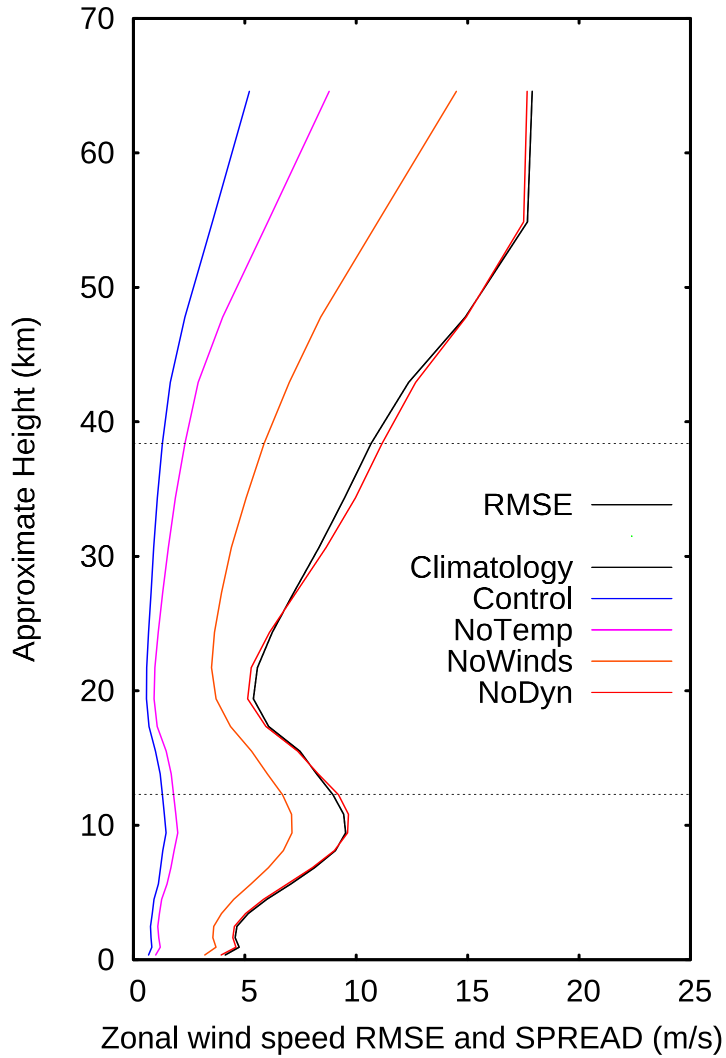


→ O_x-Dyn error covariances account for about half the O_x error reduction.

→ O_x-Dyn covariances are necessary to constrain well the u error.

O_x Assimilation: Time-Averaged Global Analyses



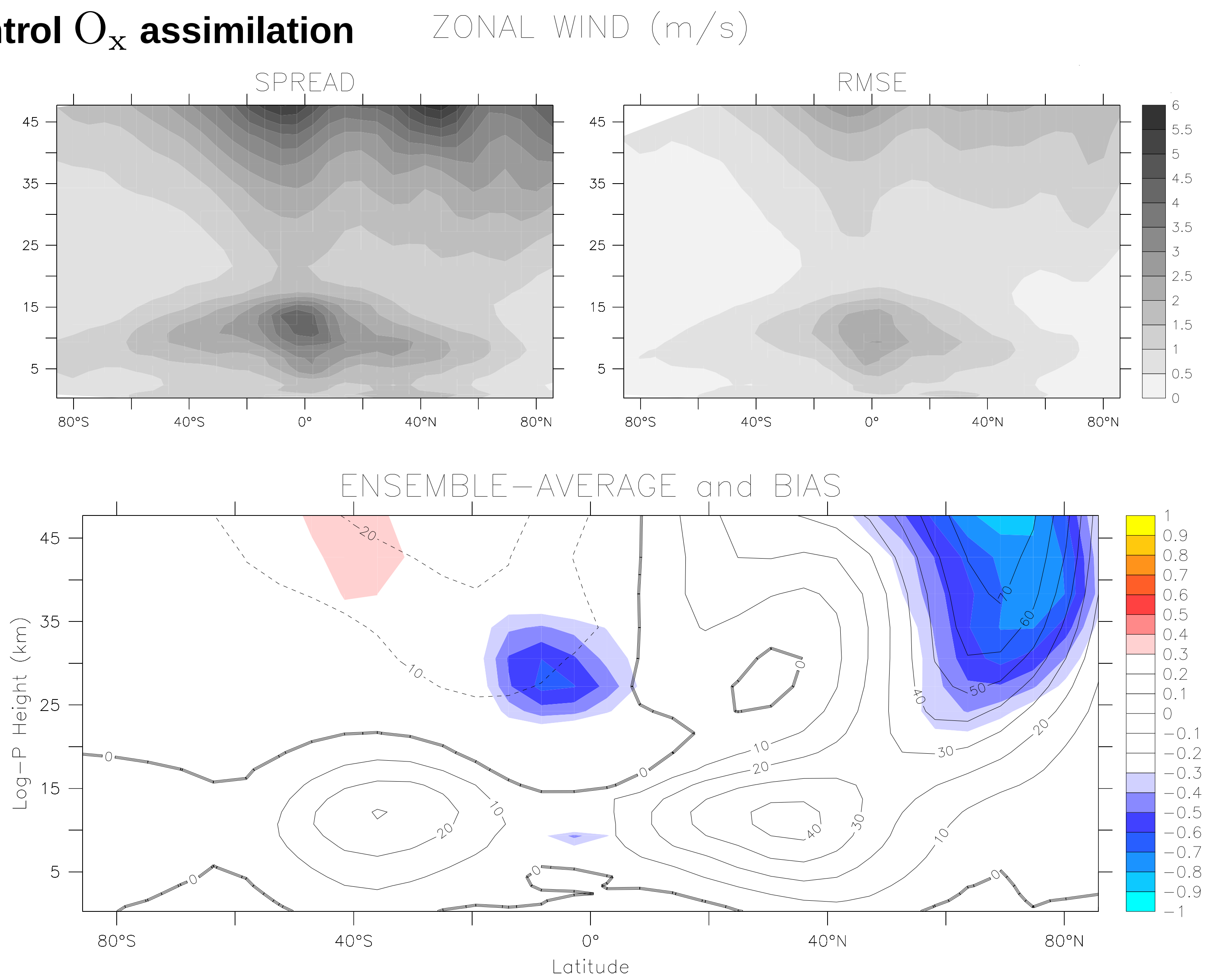


→ O_x-Dyn error covariances account for about half the O_x error reduction.

→ O_x-Wind error covariances are the most critical to constrain the dynamics.

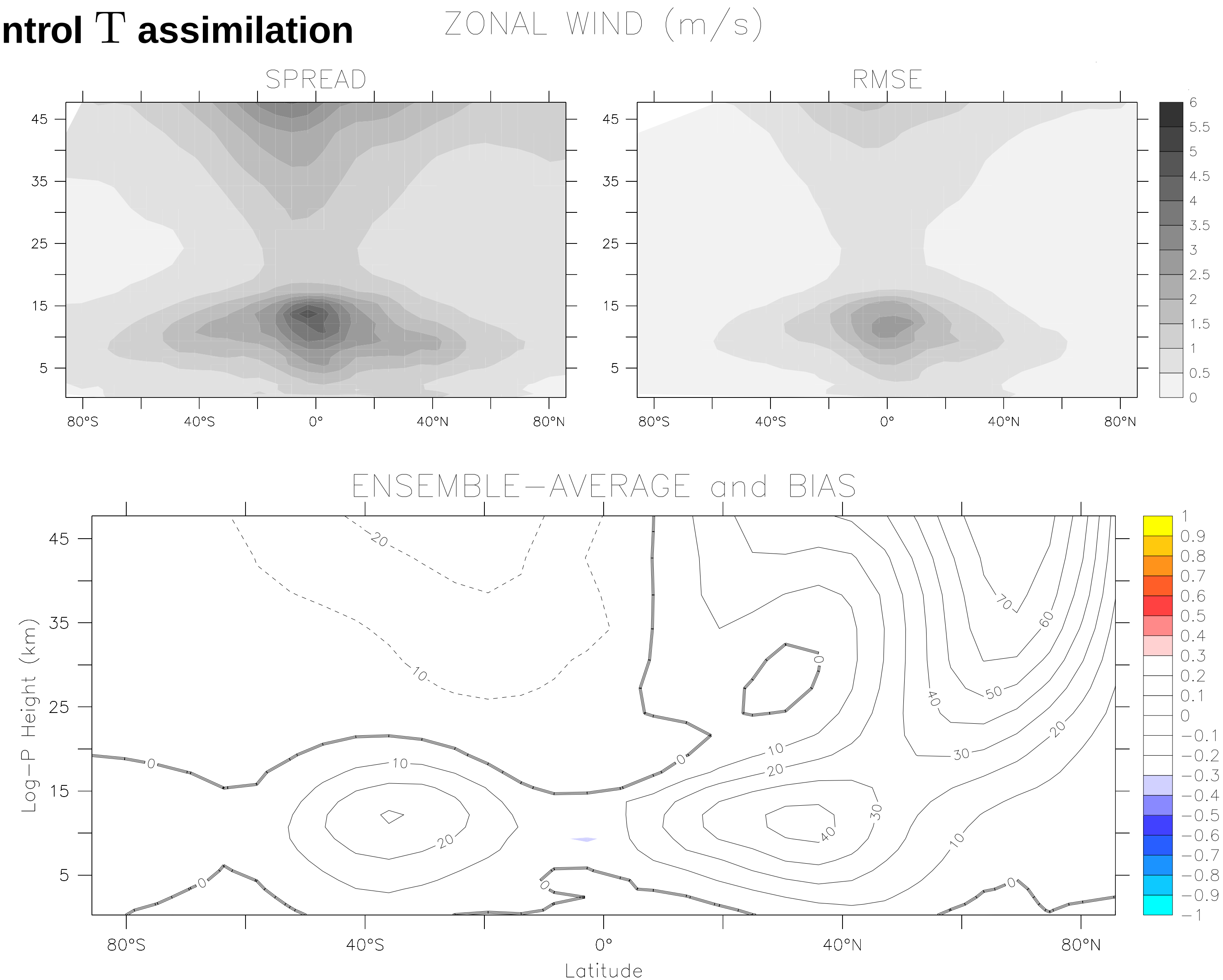
Zonally-Averaged Zonal Wind Analyses

Control $\mathrm{O_x}$ assimilation



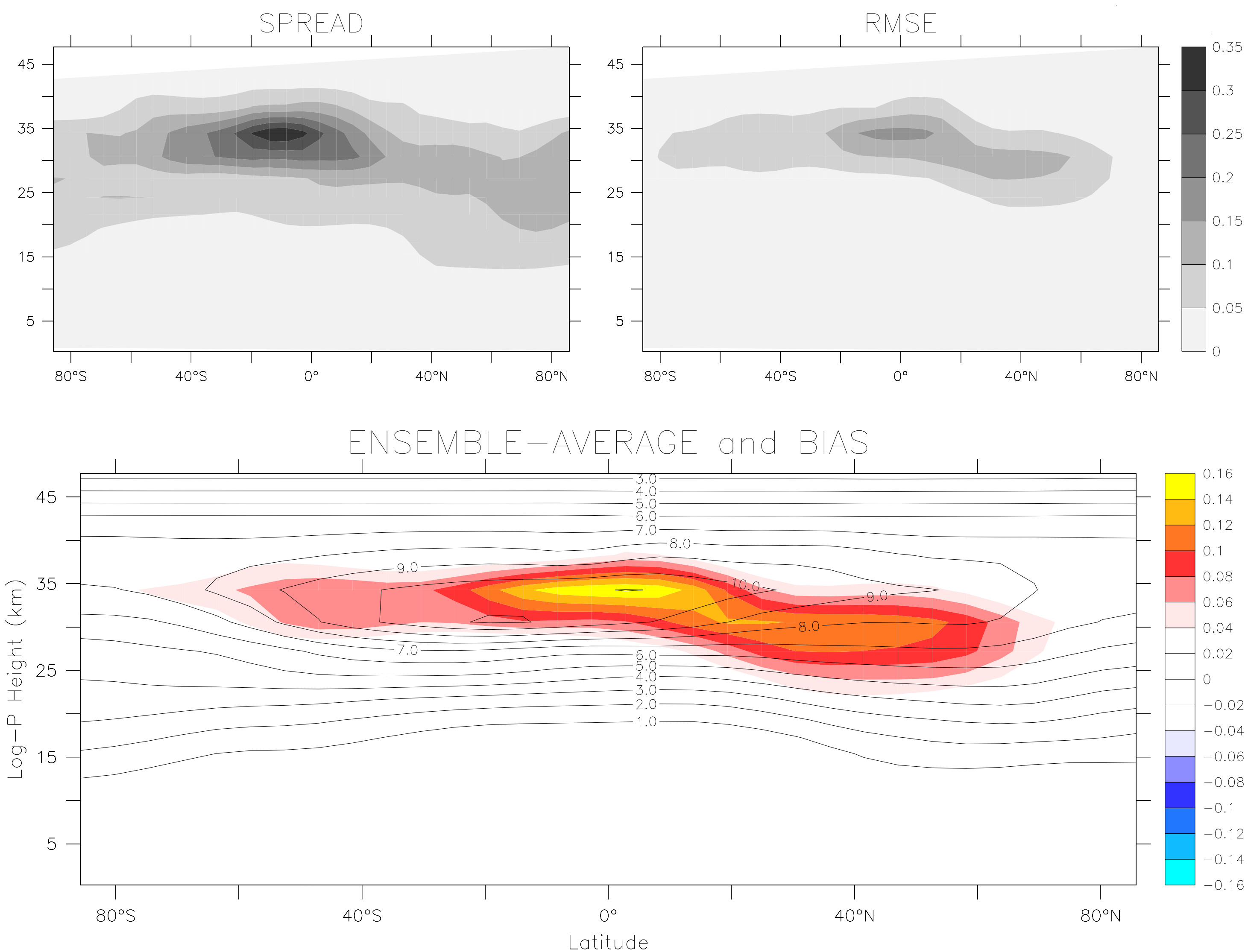
Zonally-Averaged Zonal Wind Analyses

Control T assimilation



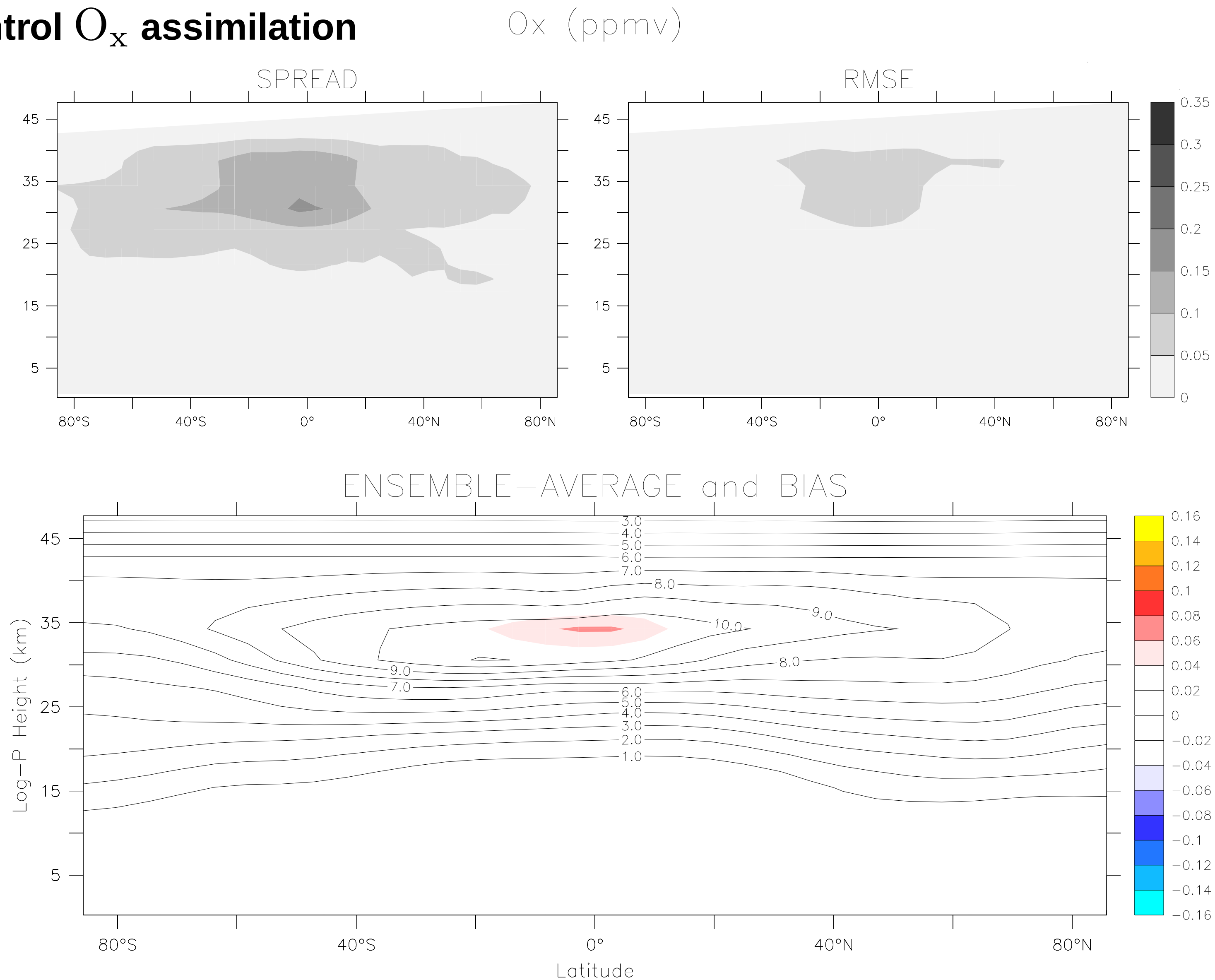
Zonally-Averaged Ozone Analyses

Control T assimilation



Zonally-Averaged Ozone Analyses

Control $\mathrm{O_x}$ assimilation



ENSEMBLE KALMAN SMOOTHER

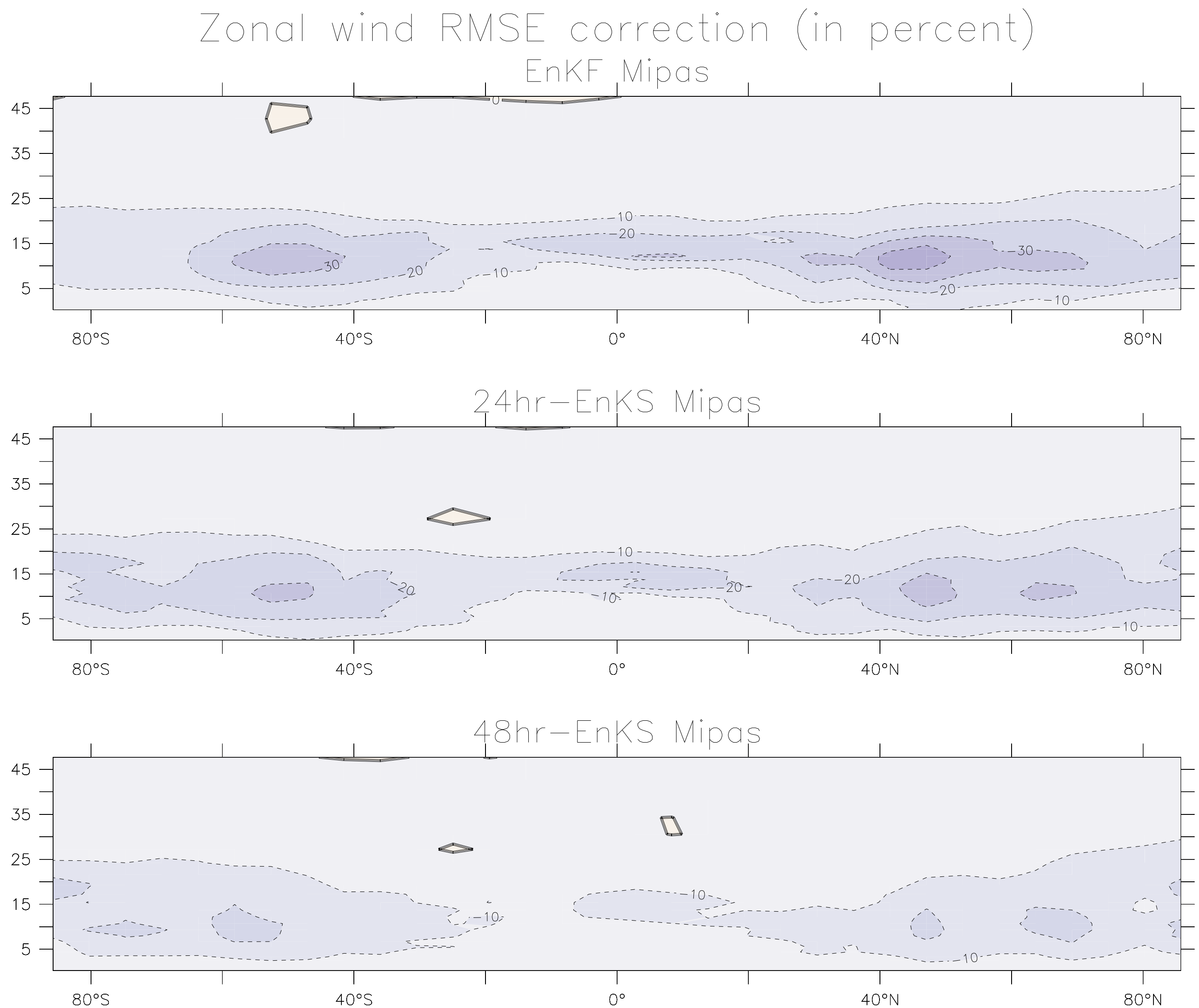
EnKS Configurations

model state vector

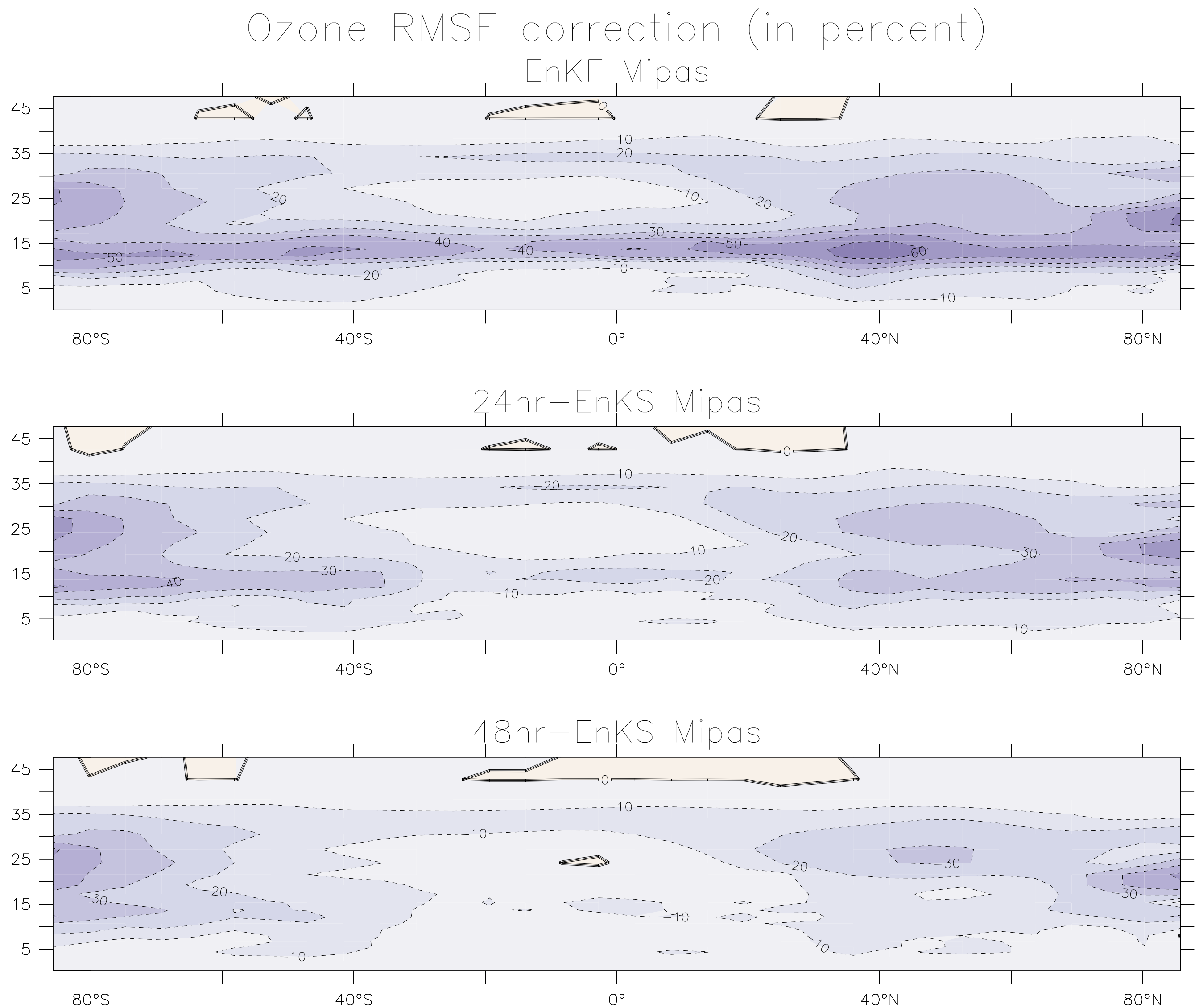
$$\begin{pmatrix} \mathbf{u} \\ \mathbf{v} \\ \mathbf{T} \\ \mathbf{P_s} \\ \mathbf{Q} \\ \mathbf{O_x} \\ \mathbf{N_2O_5} \\ \mathbf{NO_x} \\ \mathbf{HNO_3} \end{pmatrix}$$

- Perfect-model twin experiment
- Initial ensemble is **ensemble of analyses from Control Mipas** $\mathrm{O_x}$ **and Mipas** T **assimilation experiments, every three days in February**
- Double-**EnKS** assimilation of a **single-batch** of daily observations
- **Compressed Row Storage (CRS) for sparse background error-covariance matrix**
- No covariance inflation

O_x Assimilation: Time-Lagged EnKS Analyses



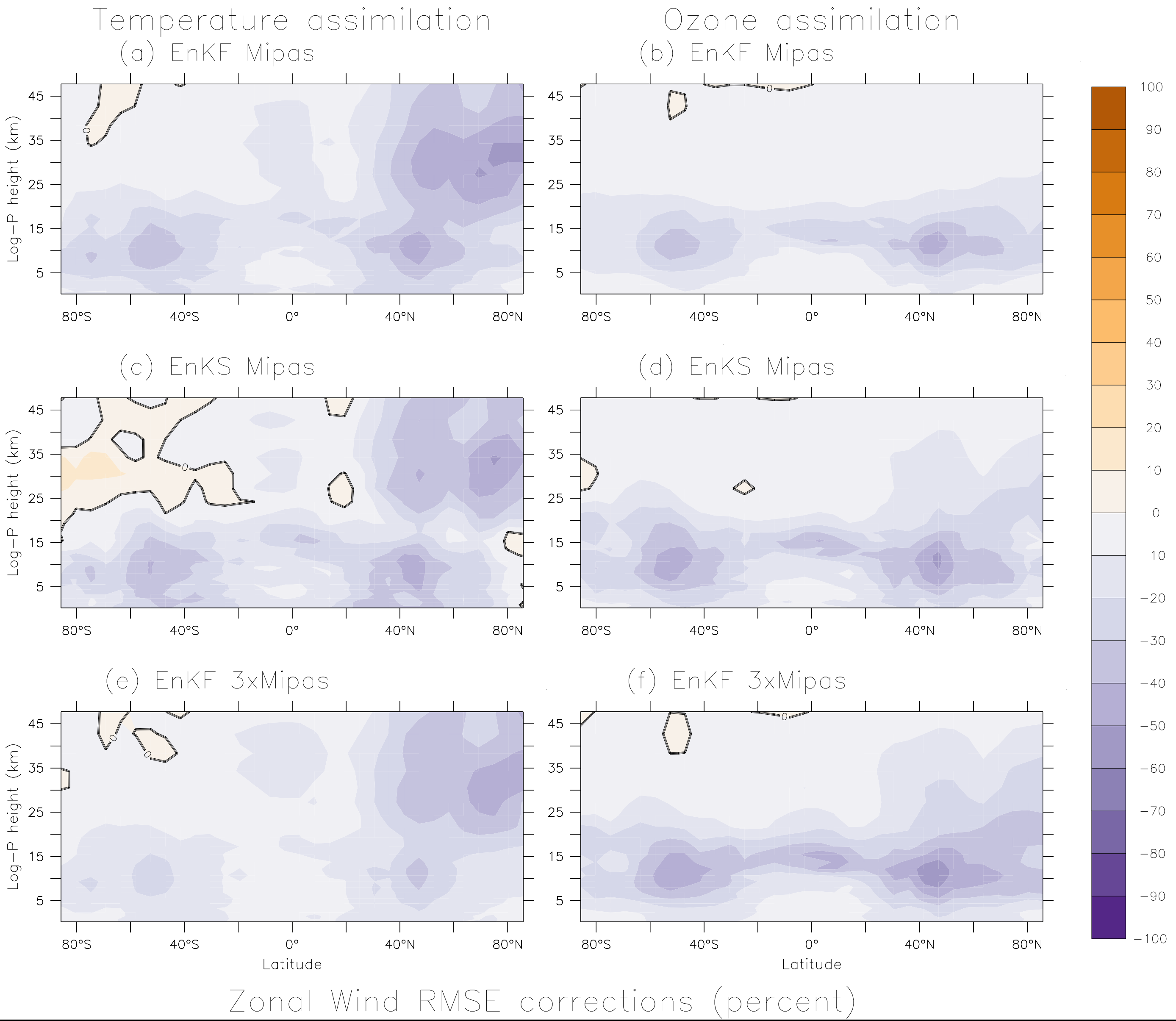
O_x Assimilation: Time-Lagged EnKS Analyses



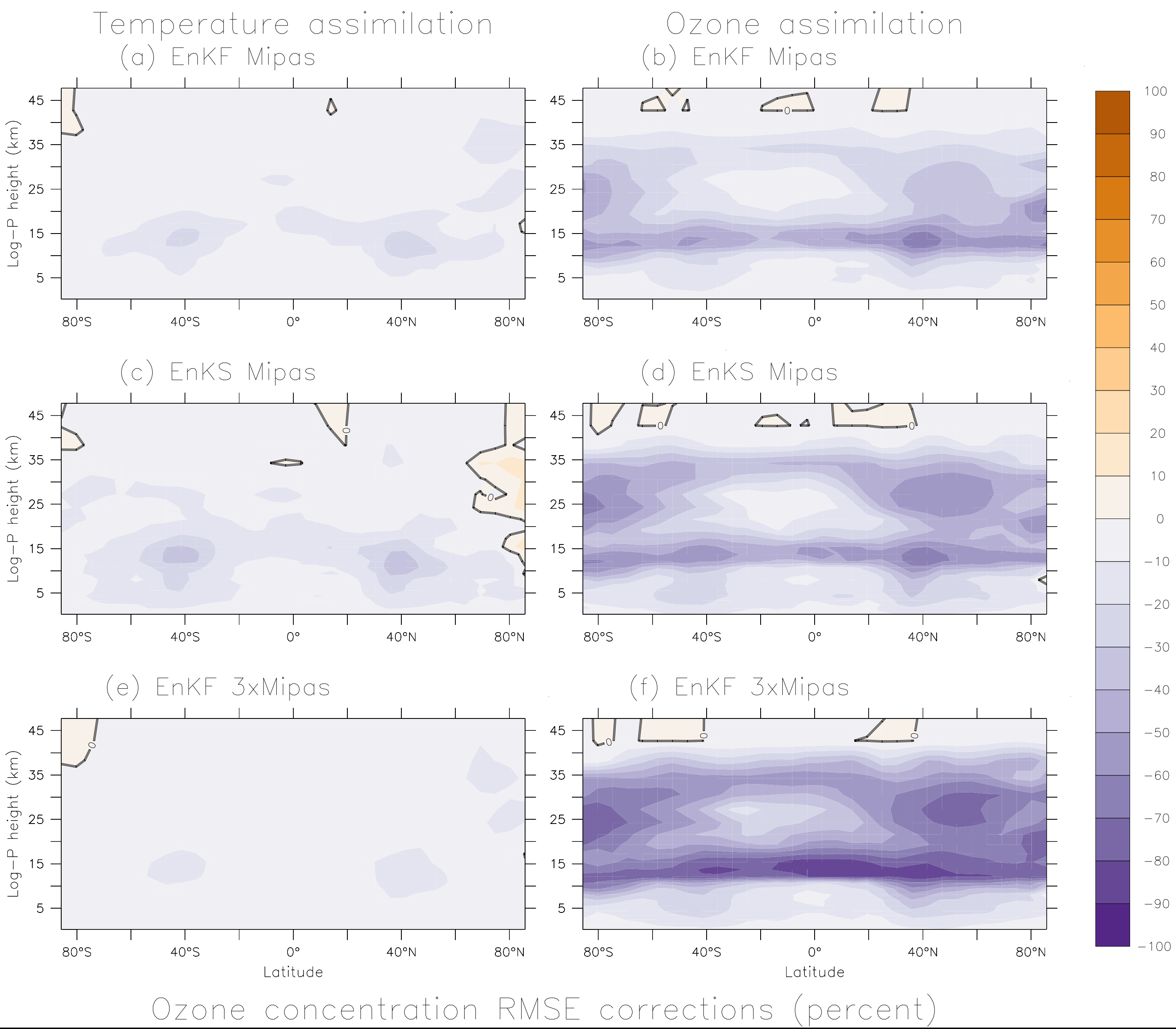
Experiments

EnKF Mipas	daily Mipas data assimilation
EnKS Mipas	daily **EnKF Mipas** data assimilation + two days of posterior Mipas data assimilation
EnKF $3\times$**Mipas**	daily assimilation of three times the amount of Mipas data, same amount of observations as **EnKS Mipas**

EnKF vs. EnKS: U RMSE Corrections



EnKF vs. EnKS: Ox RMSE Corrections



CONCLUSIONS AND FUTURE WORK

Summary

EnKF-CCM :

- EnKF assimilation of MIPAS-like stratospheric observations in the IGCM-FASTOC can efficiently constrain the whole model state.
- Two-month ozone (10% error) or temperature (2K error) assimilation experiments yield approximately the same constraint on the dynamical state of the system.
- Temperature assimilation has however more problems constraining the chemical state.

CHEMISTRY-DYNAMICS INTERACTION:

- $\mathbf{T}\rightarrow\mathbf{O_x}$ covariances permit to slightly improve the ozone analysis, compared to using only $\mathbf{T}\rightarrow$dynamics covariances.
- $\mathbf{O_x}\rightarrow\mathbf{u}$ and $\mathbf{O_x}\rightarrow\mathbf{T}$ covariances permit to constrain wind motion during ozone assimilation, but particularly $\mathbf{O_x}\rightarrow\mathbf{u}$ covariances.

Milewski, T. and M.S. Bourqui, 2011a: Assimilation of stratospheric temperature and ozone with an Ensemble Kalman Filter in a Chemistry-Climate Model. Monthly Weather Review 139, pp.3389-3404

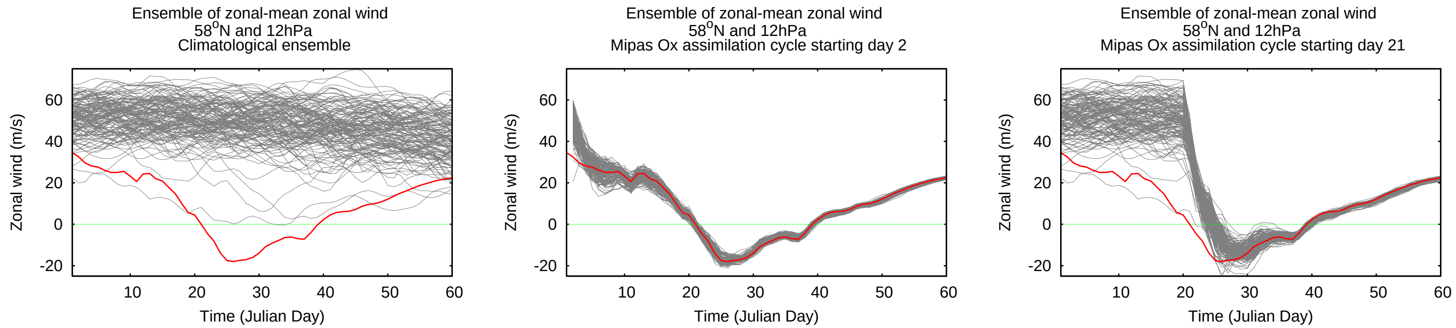
ENSEMBLE KALMAN SMOOTHING :

- Steady decrease of analysis corrections with time-lag, but still beneficial corrections for 48 hours.
- For $\mathbf{O_x}$ assimilation, analysis improvements from adding posterior data almost as good as from adding horizontal data.

Milewski, T. and M.S. Bourqui, 2011b: Impact of synchronous and asynchronous ensemble assimilation of stratospheric observations. In preparation.

Future Work

- Extreme events : stratospheric sudden warmings



- Imperfect-twin experiment : model errors
  → Additive or multiplicative inflation do not work in sparsely-observed systems.
  → Bias correction.

THANK YOU !

ANY FEEDBACK IS HIGHLY APPRECIATED

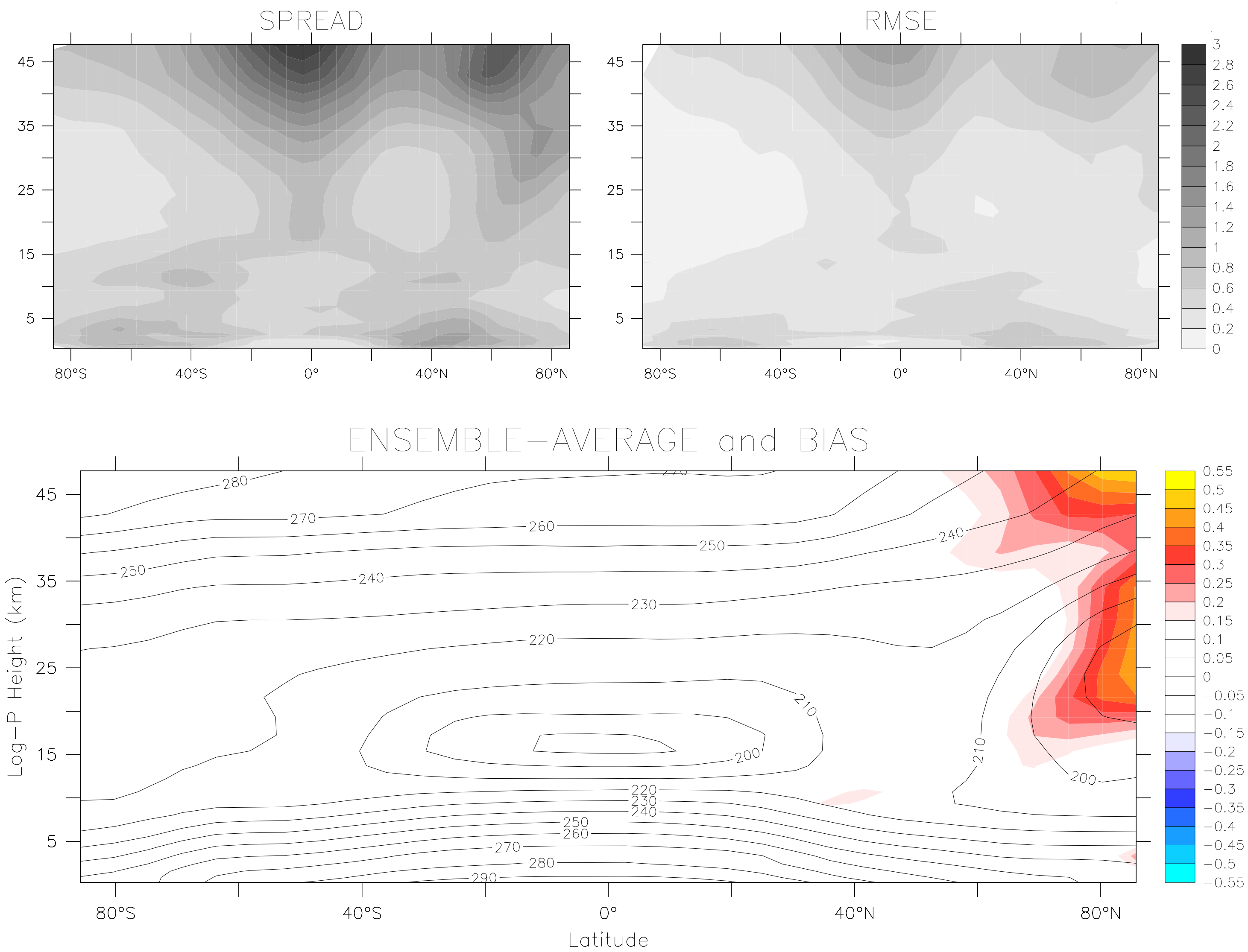
EXTRA FIGURES

Zonally-Averaged Temperature Analyses

INTRODUCTION
EnKF-CCM
CHEMISTRY-DYNAMICS INTERACTION
ENSEMBLE KALMAN SMOOTHER
CONCLUSIONS AND FUTURE WORK
EXTRA FIGURES

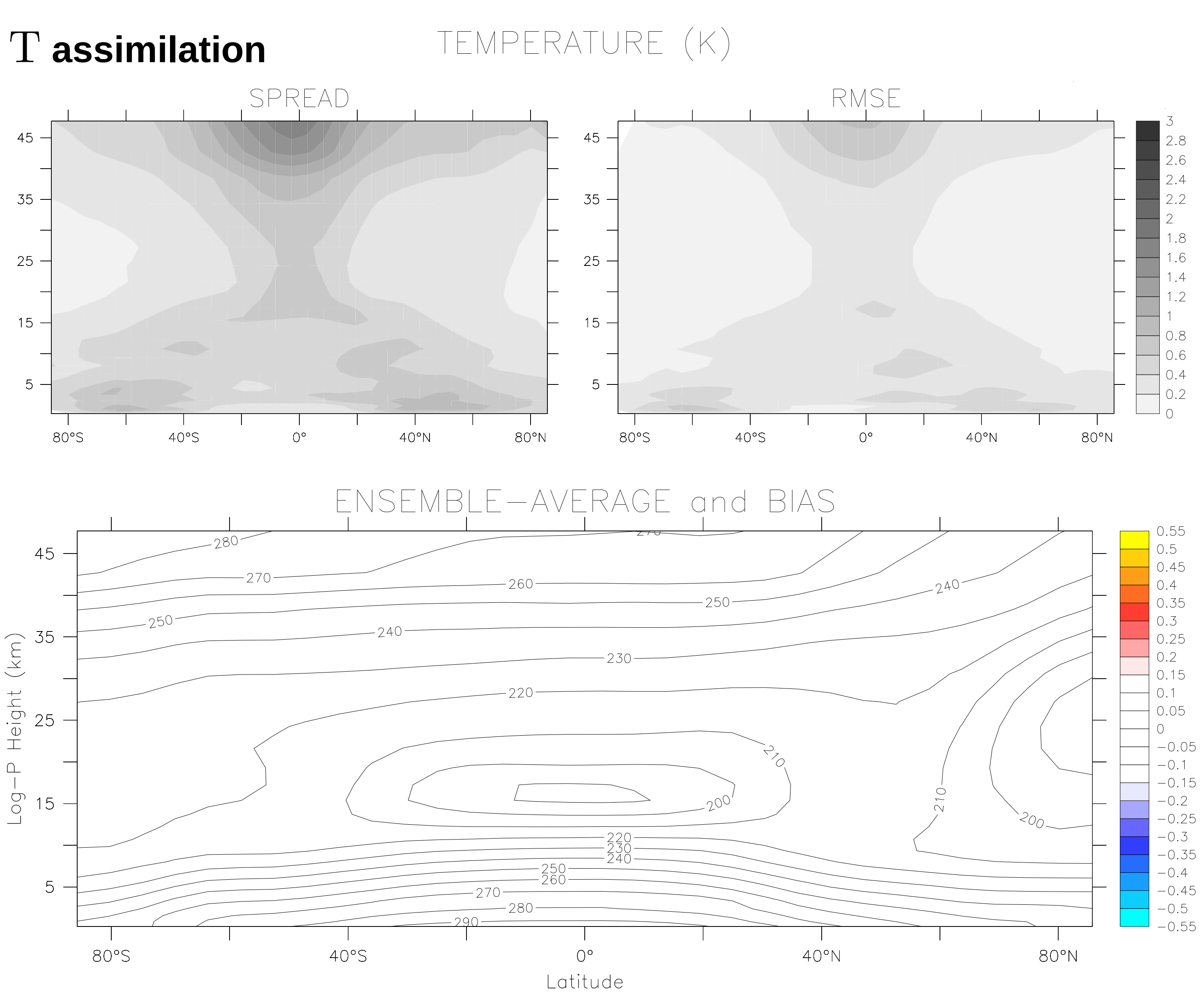
O_x assimilation

TEMPERATURE (K)



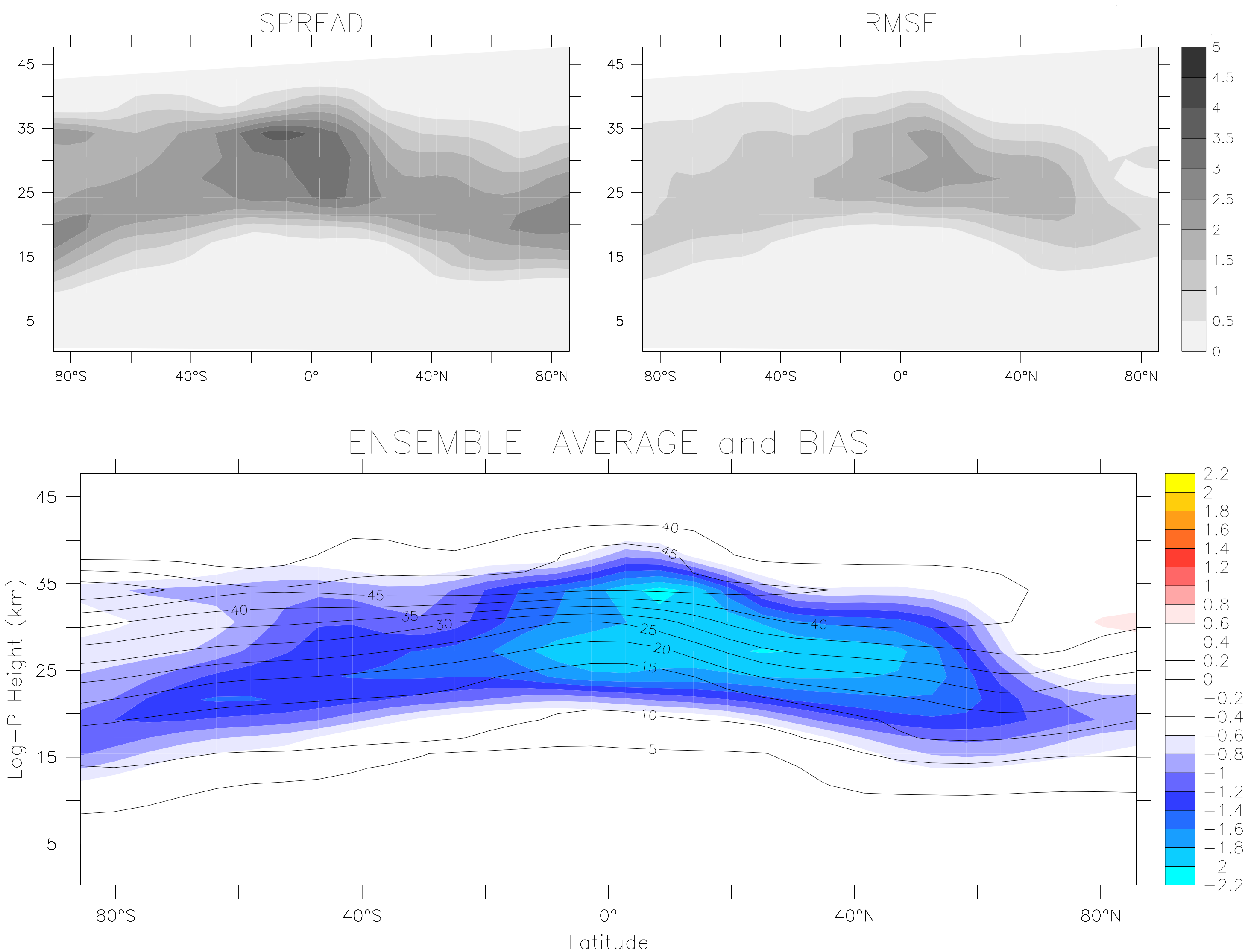
Zonally-Averaged Temperature Analyses

T assimilation



Zonally-Averaged Odd Nitrogen Analyses

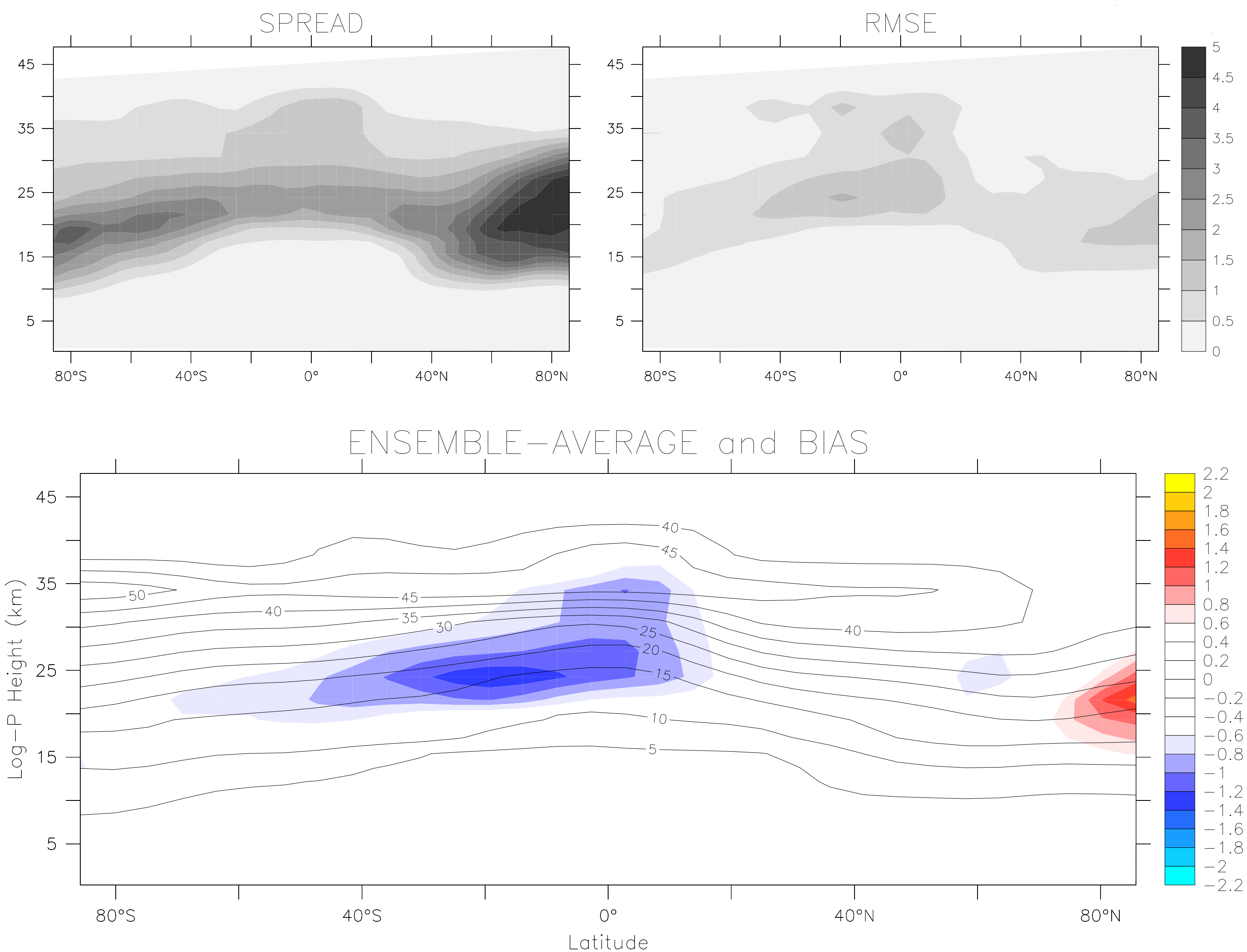
T assimilation

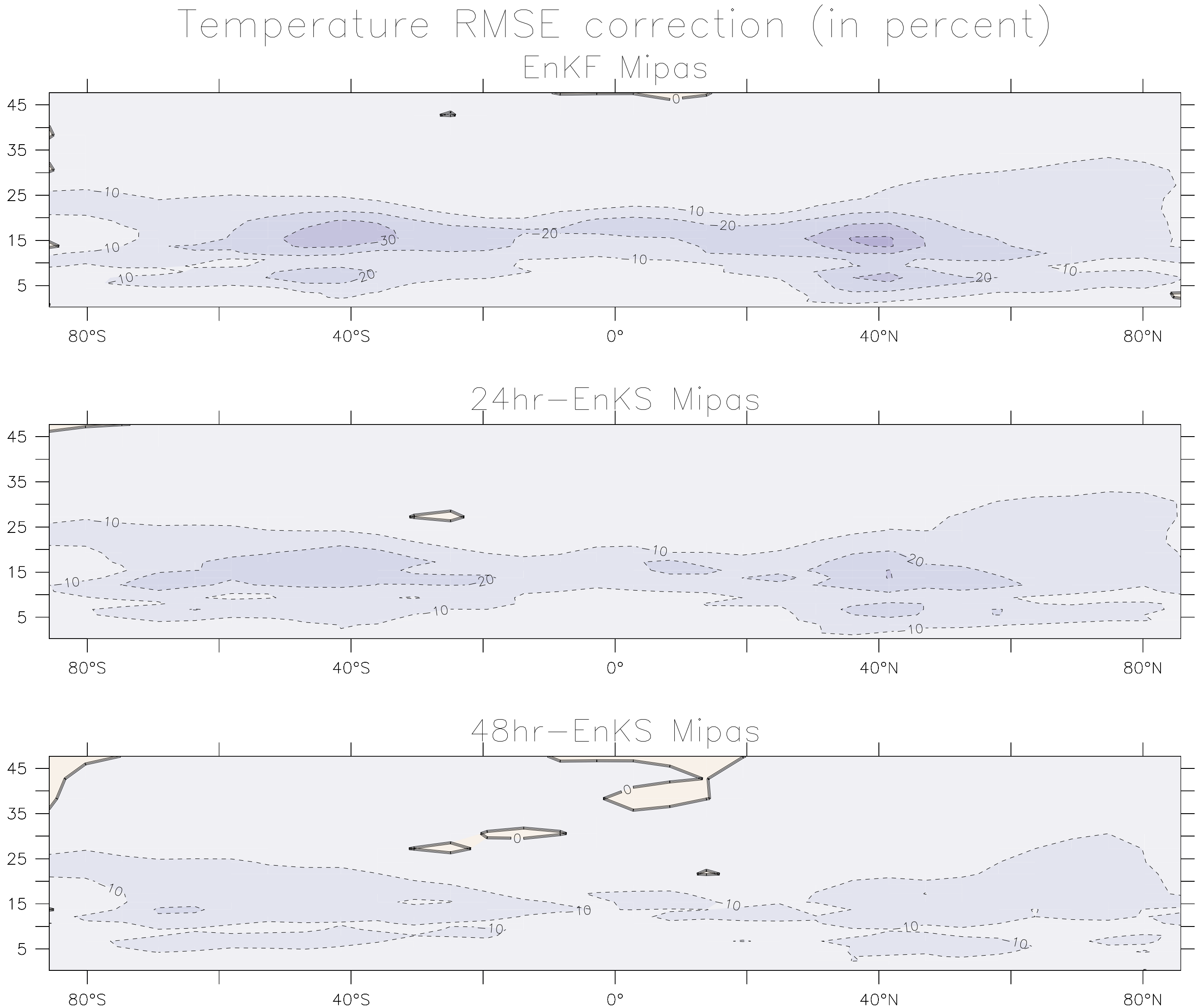


Zonally-Averaged Odd Nitrogen Analyses

O_x assimilation

ODD NITROGEN




Temperature RMSE correction (in percent)
EnKF Mipas
24hr–EnKS Mipas
48hr–EnKS Mipas
45
35
25
15
5
80°S
40°S
0°
40°N
80°N
10
20
30
0