Ensemble data assimilation using an unified representation of model error

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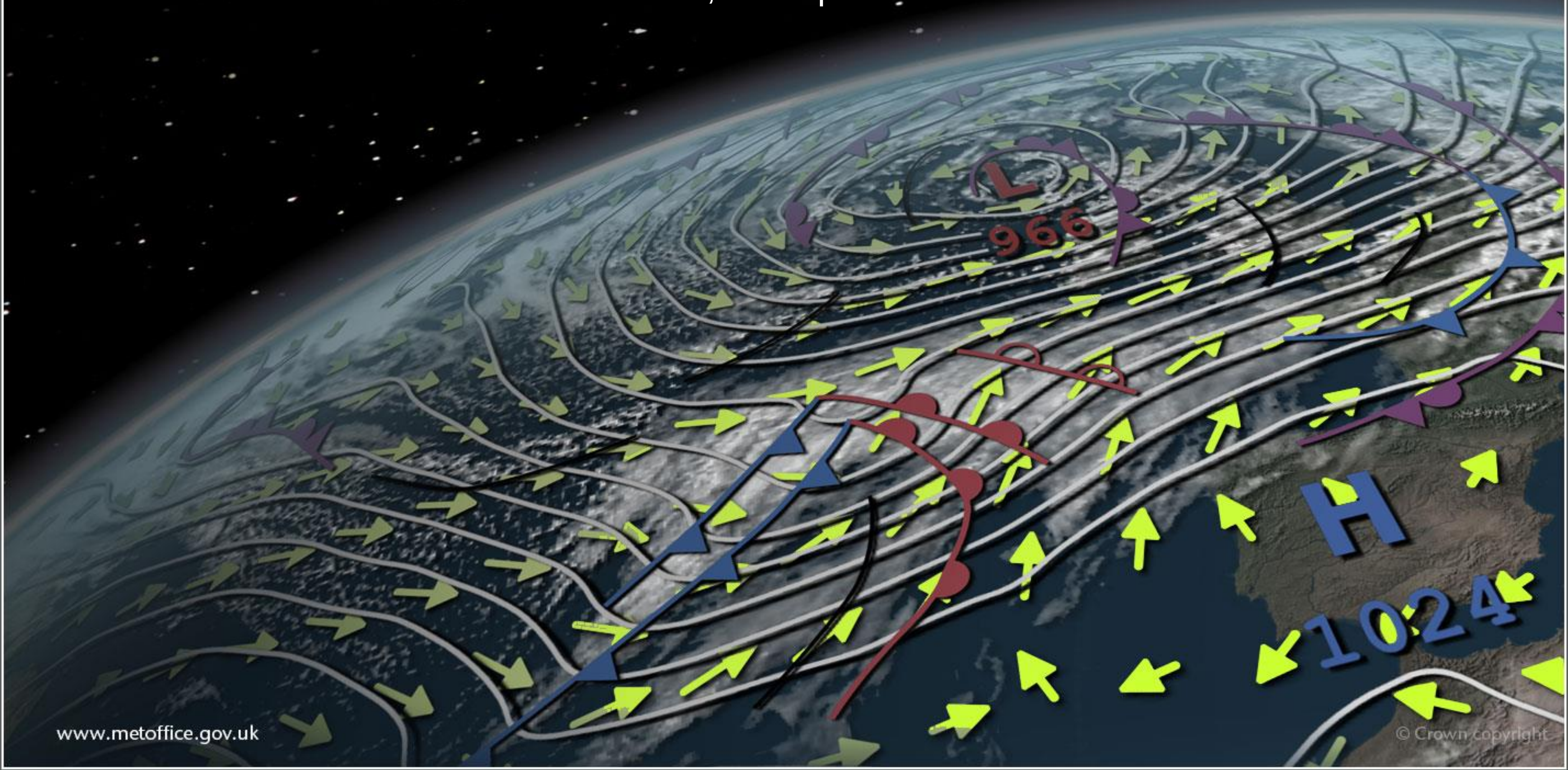

Summary

- To generate a reliable ensemble it is important to have consistency between initial conditions and model error
- This can be obtained by using an Ensemble Data Assimilation (EDA) system
- We rely on the fact that a reliable prior ensemble and a set of reliable perturbed observations can be combined to give a reliable *analysis ensemble*.
- This requires the **same** model error representation in EDA and EPS (Ensemble Prediction System)

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  - Random assumption of the analysis increments
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- Summary

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Motivation

Ensembles

Define the truth state $\mathbf{x}_T$ as the real state of the atmosphere averaged to the model grid.

The true evolution is now stochastic, as it depends on information missing from $\mathbf{x}_T$

The truth $\mathbf{x}_T$ should be statistically indistinguishable from a randomly chosen ensemble member at any time – reliability

Observations measure (imperfectly) a single realisation of this stochastic model.

EDA

The prior ensemble and observation ensemble should be reliable.

The *analysis ensemble* is constructed by combining random prior members with random choices of perturbed observations.

Then the *analysis ensemble* will be reliable.

EPS

Use an ensemble data assimilation system to represent initial uncertainty.

Use observations to estimate model errors.

The model error needs to be treated in the same way throughout the data assimilation stage (EDA) and the subsequent forecast step (EPS).

Ensembles quality

There are two important ensemble properties:

Reliability: the truth is statistically indistinguishable from a randomly chosen ensemble member at any time (measured by comparing the ensemble spread and the RMSE of the ensemble mean at all lead times)

Accuracy: the error in the ensemble mean should be as small as possible (measured by improving the RMSE of the ensemble mean at all lead times)

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Model error calibration

Choice of model error

We can evolve the prior pdf using the stochastic model:

$$d\mathbf{x} = F(\mathbf{x})dt + dW$$

where F is the deterministic model and dW is the stochastic term with covariance **Q** (which includes the model error).

The statistics of dW can be characterised by using observations (and making stationary assumption) or alternatively using stochastic schemes that simulate model error within the model itself.

The latter methods are widely used but they only represent specific sources of errors.

Using DA methods allow to exploit all available observations (taking into account their observation errors) to estimate model errors which represent all sources of errors.

Model error estimation using DA methods

Data assimilation methods require a prior pdf.

First step: use cycled deterministic data assimilation to estimate the model error (calibration step):

- Since observations measure only a single realisation of the truth at each time, the statistics of model error can only be inferred by accumulation over a large number of cases.
- Calculate statistics from archive - assuming stationary statistics
- This works if there are sufficient observations available (good enough in the atmosphere; not clear in the ocean)

Calibration step:

1. Generate an archive of analysis increments (with stationary statistics);
2. Use same model that will be used in the EDA.

Calibration step

Assuming that the truth state evolution is given by:

$$\mathbf{x}_i = M_i(\mathbf{x}_{i-1}) + \eta_i$$

We use a reduced version of the cost function from Trémolet (2007) :

$$J(\eta) = \frac{1}{2}\sum_{i=1}^{n} \eta_i^T \mathbf{Q}^{-1} \eta_i + \frac{1}{2}\sum_{i=1}^{n} (H_i(\mathbf{x}_i) - \mathbf{y}_i)^T \mathbf{R}^{-1} (H_i(\mathbf{x}_i) - \mathbf{y}_i)$$

where:

$$\eta = \mathbf{Q}\mathbf{H}^T (\mathbf{R} + \mathbf{H}\mathbf{Q}\mathbf{H}^T)^{-1} (H(\mathbf{x}_0) - \mathbf{y})$$

where **H** includes the evolution of the deterministic model from the times the model error are added up to the observation times.

Alternative DA based approaches

Q can also be inferred from a standard weak-constraint data assimilation cycle which calculates both a background and a model error increment.

Alternative DA method to derive **Q**: diagnose model error statistics using weak-constraint data assimilation (extension of Desroziers method - Bowler 2017, QJ).

Assumption of uncorrelated errors:

- background and observation errors - uncorrelated
- background and model errors - correlated
- model errors are correlated in time

We therefore can not reliably estimate **Q** in a realistic case. So we propose to use the analysis increments from the weak-constraint data assimilation calculated in the calibration step.

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Implementation in an EDA system:

- EDA set-up
- random assumption of analysis increments

Ensemble DA set-up

Second step: use the model error statistics to generate a stochastic forcing term in an EDA system:

- Random analysis increments drawn from an archive are used to force each member of the ensemble forecast.
- Minimise error of ensemble mean by using the best available deterministic model in the calibration step.

Ensemble DA system:

1. Use an ensemble of 10 independent 4dVars with perturbed observations and SSTs;
2. Draw every 6 hours random analysis increments from the archive;
3. Add at each time step over a window of 6 hours (time-window of DA system) perturbations consistent with the statistics of the analysis increments, over the overall period of forecast integration.

Model – Met Office N320L70 UM, i.e. 40km horizontal resolution and 70 levels (80 km model top).

Ensemble of 4D-Vars using analysis increments as forcing term

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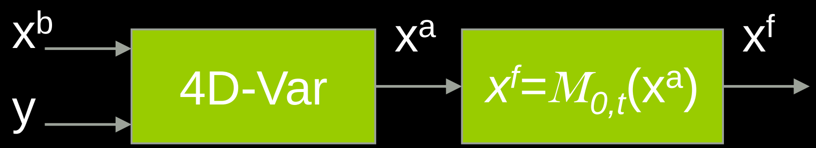
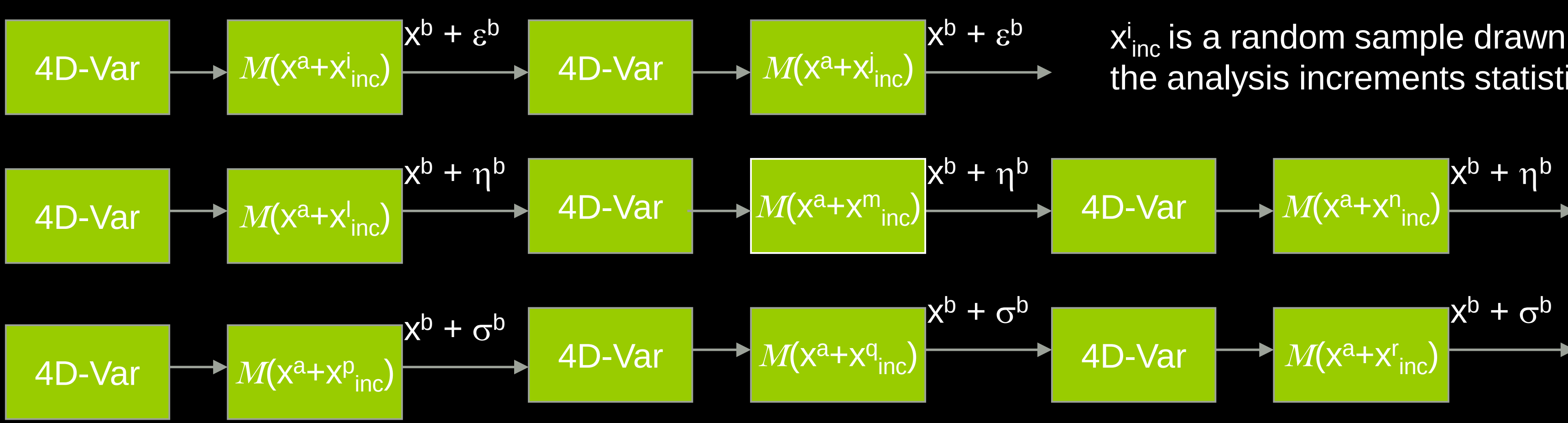
Calibration Step



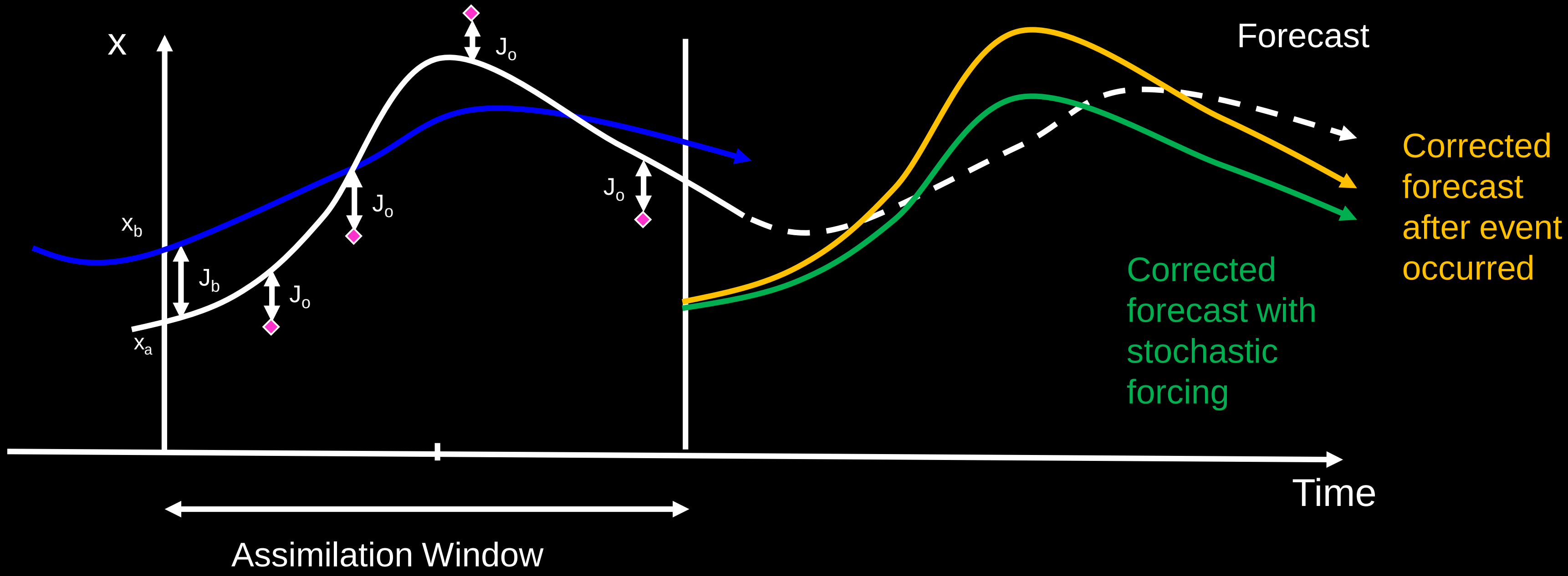
Take a large sample of the analysis increments: $x_{inc} = x^a - x^b$

Ensemble of 4D-Vars using analysis increment statistics as model error



x^i_{inc} is a random sample drawn from the analysis increments statistics

As reanalysis ...



If the analysis increments can be considered as a random draw from an archive with stationary statistics, a reanalysis trajectory will be statistically indistinguishable from a random realisation of the model with the stochastic forcing.

Random assumption of analysis increments (u@850hPa)

To test this assumption, we compare the T+6 hours ensemble spread with the RMSE of the ensemble mean measured against a random analysis member as the truth (Bowler et al. 2015).

	RMSE T+6 h	Spread T+6 h	Rel. Diff (%)
NH	1.98	1.93	2.40+/-1.87
Tropics	2.09	2.15	-2.42+/-1.67
SH	2.67	2.74	-2.68+/-2.02

+/- indicates 95% confidence interval.

So difference between spread and RMSE are not statistically different from zero.

Thus if the analysis ensemble is reliable, the prior ensemble will be reliable at the next cycle.

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Performance at longer lead times:

- ensemble spread skill
- deterministic verification of ‘climate’ integration

Performance in longer forecasts

We look at the performance of the ensemble prediction system (EPS) at longer-range forecasts using the spread-skill verification: ensemble spread versus RMSE of ensemble mean.

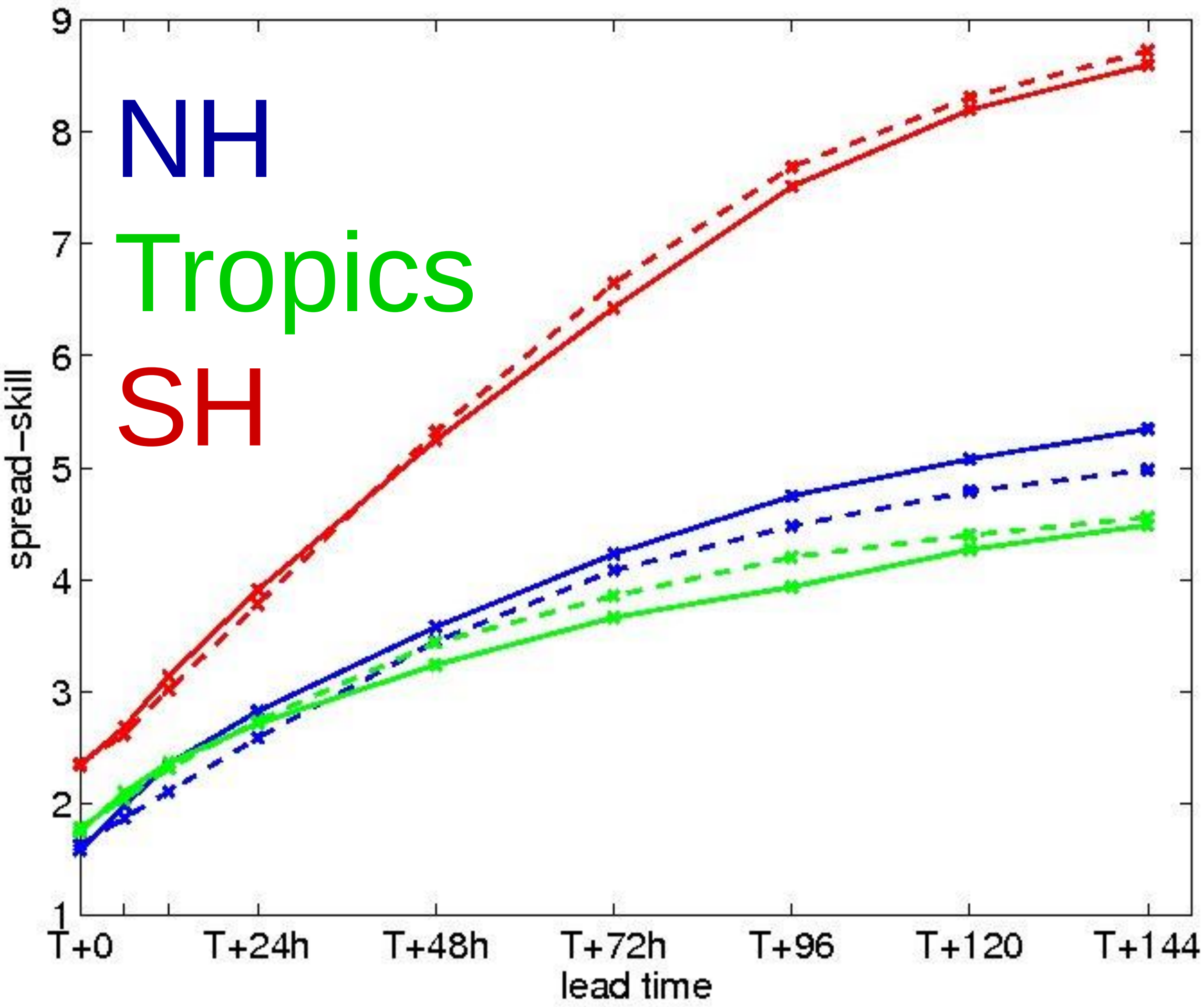
We also look at the performance in 'climate' integrations verified against ERA-interim.

In the latter, we expect results to match Met Office reanalyses and not ERA-interim reanalysis (differences in observation use, difference in background error covariance modelling, etc).

RMSE versus spread at longer lead times

Solid: RMSE
Dash: spread

u@850 hPa



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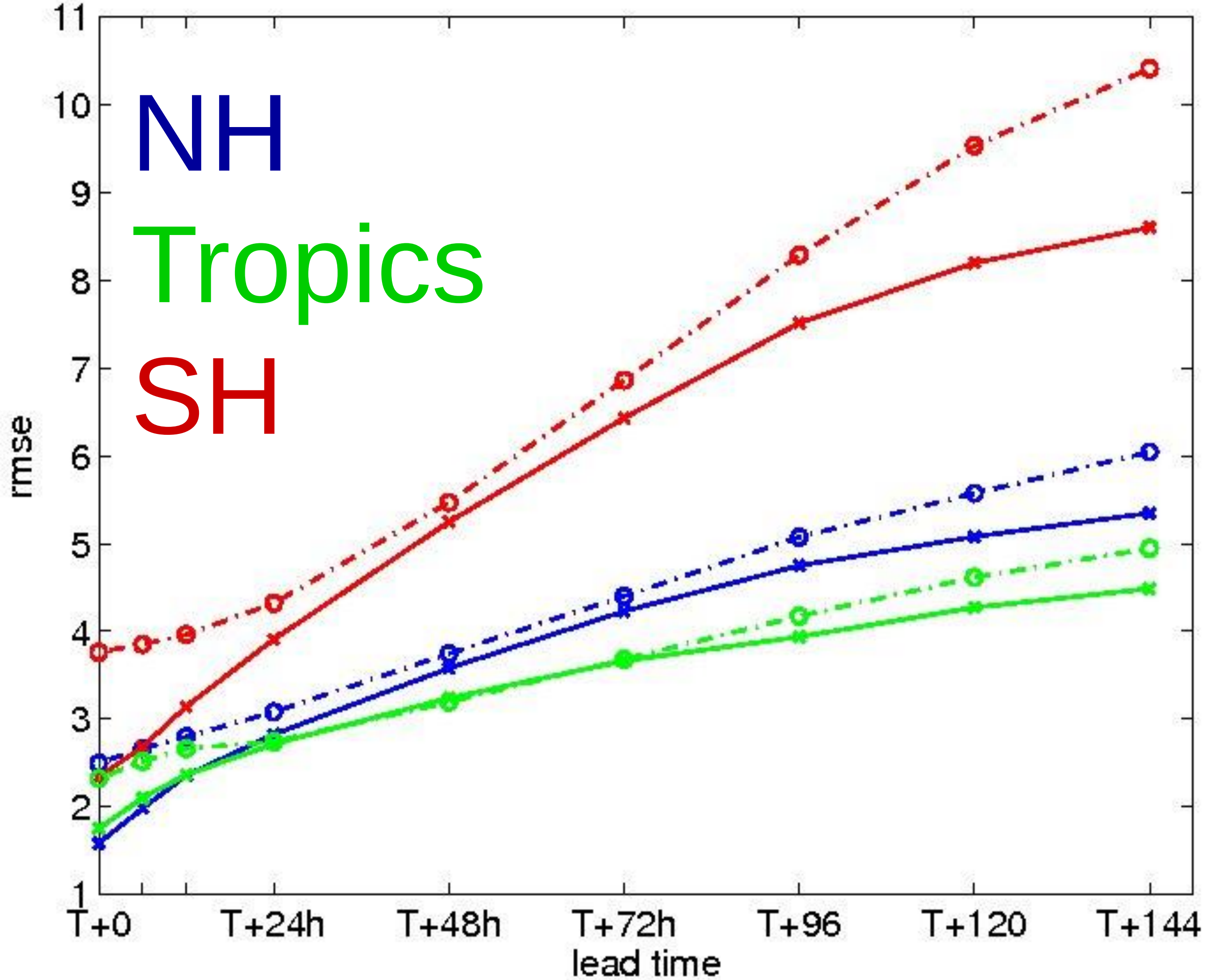
Ensemble mean versus deterministic RMSE

Solid:
ens mean

Dash-dot:
control

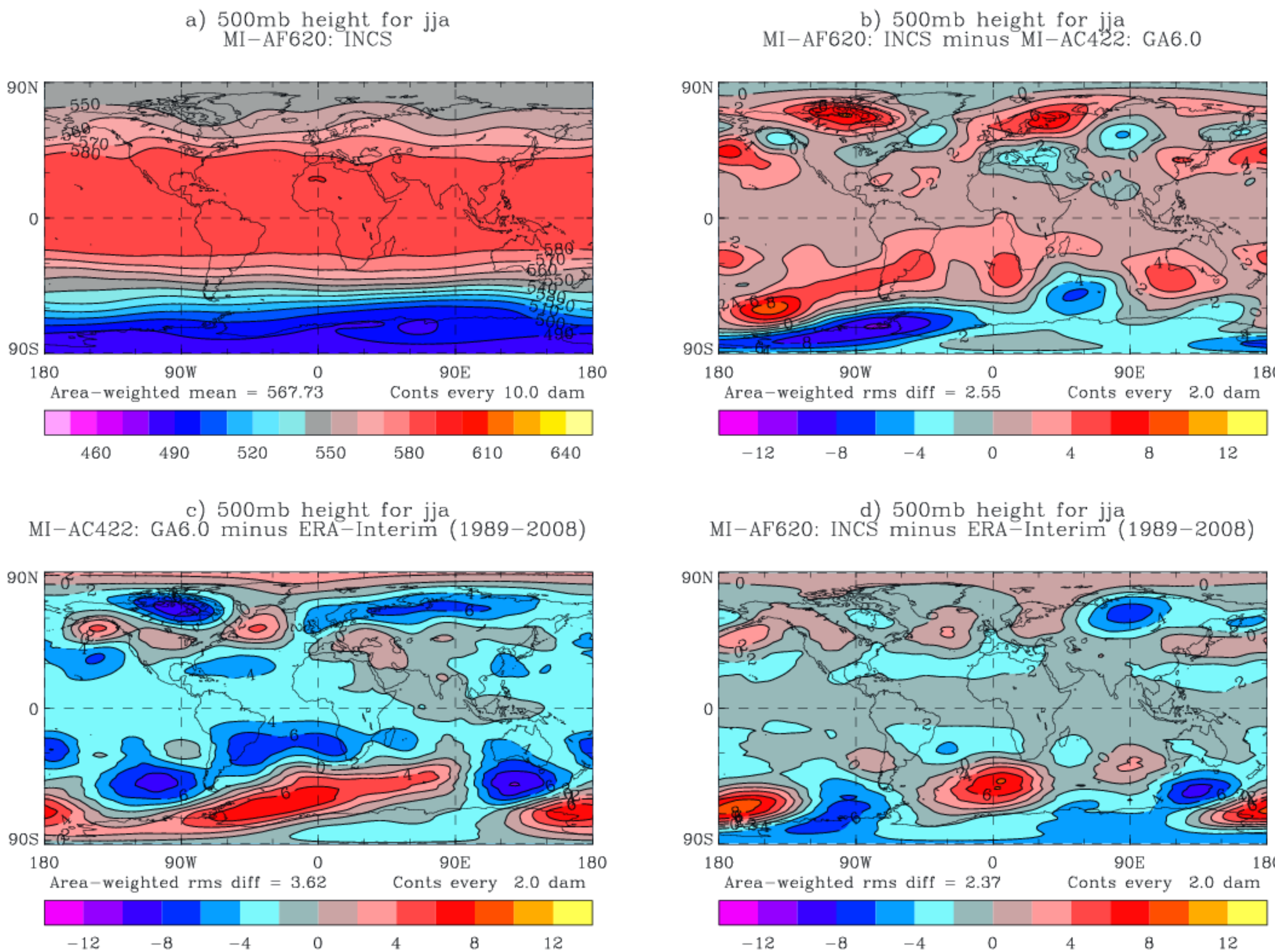
u@850 hPa



10 years average vs ERA-Interim
height at 500 hPa - jja

Model resolution 125 km

34% better



10 years average vs ERA-Interim upper tropospheric humidity - jja

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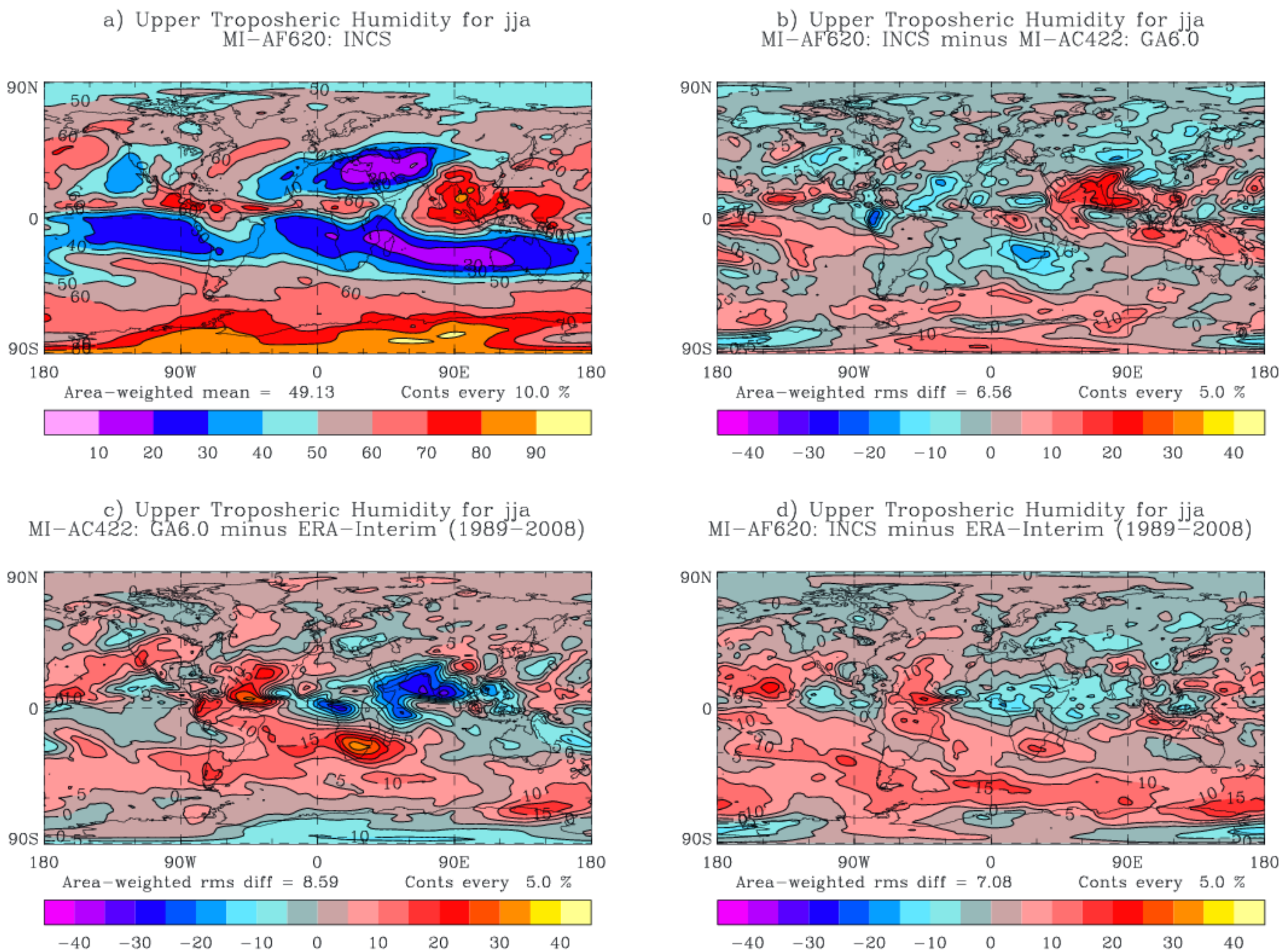
Model resolution 125 km

Tropical tropopause bias: 17% better



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Comparison with stochastic schemes

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CNT

SPT

AI

Stochastic schemes

There are various stochastic scheme to simulate the model error within the model itself.

Operational MOGREPS uses:

- Random perturbations to physical parameters (RP)
- Stochastic Kinetic Energy Backscatter (SKEB)

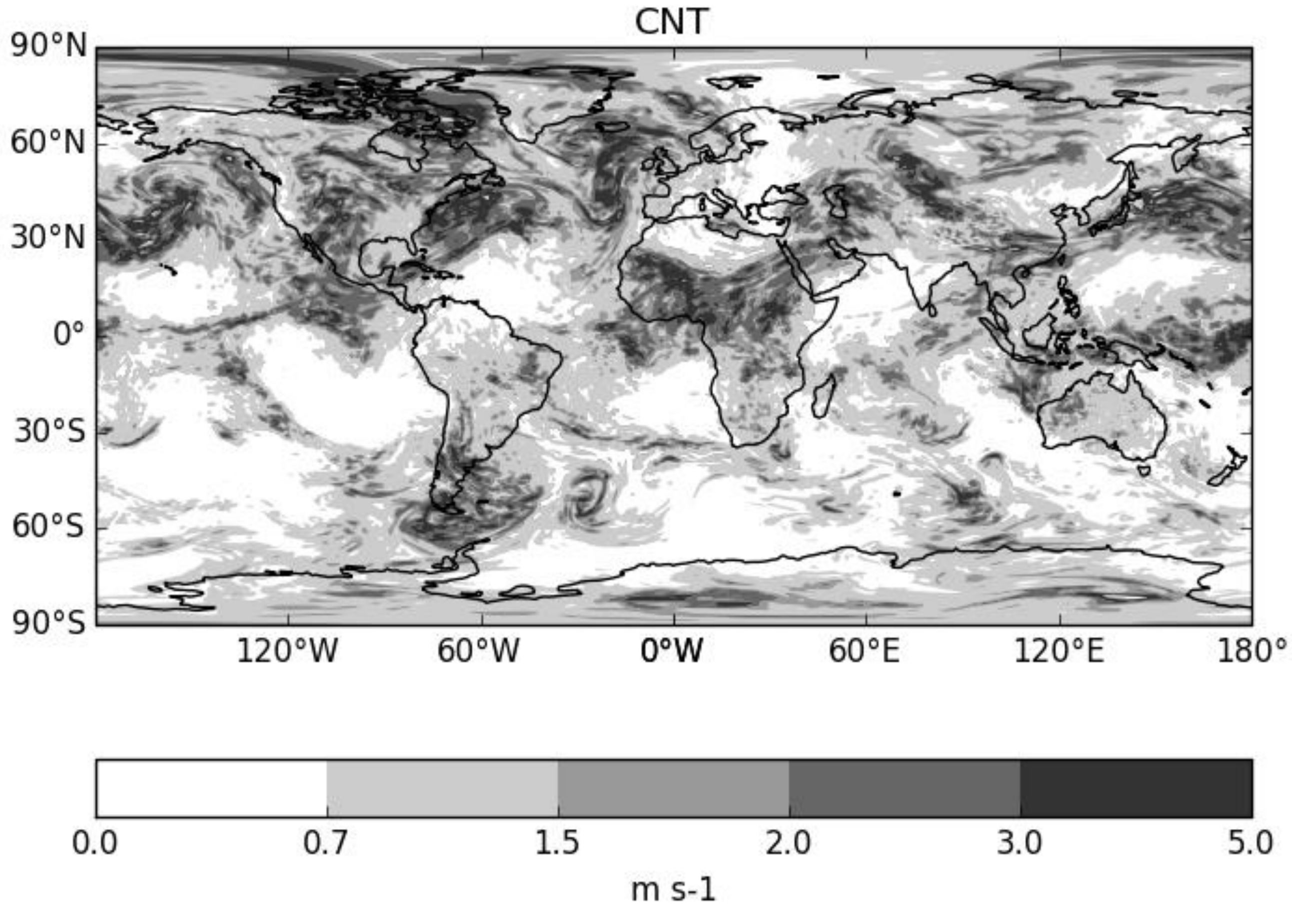
Alternative methods (e.g. used at ECMWF) use:

- Stochastic Perturbation of Tendencies (SPT)
- Stochastic Kinetic Energy Backscatter (SKEB)

How does these schemes compare with analysis increments forcing derived from data assimilation?

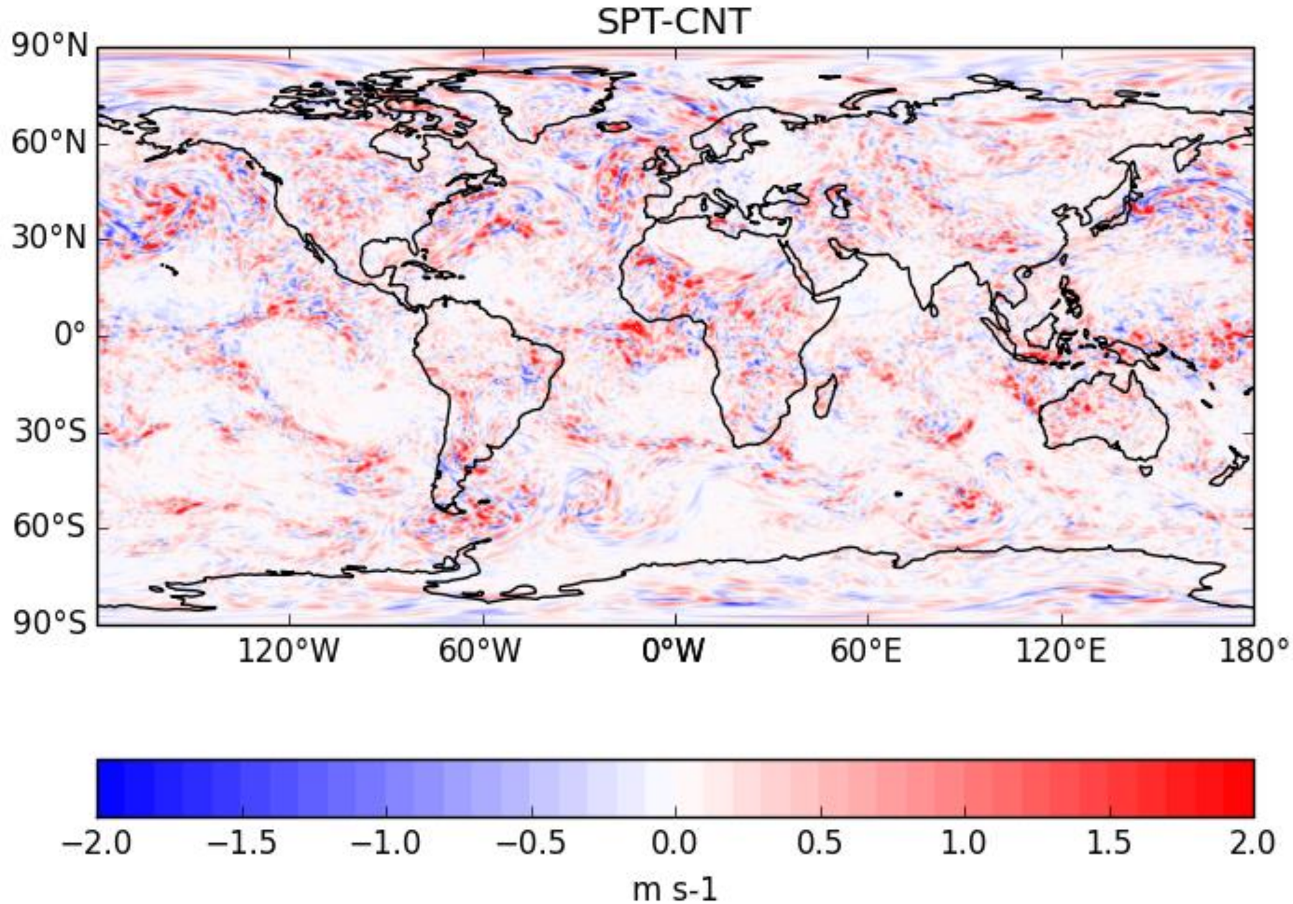
The <u>initial conditions</u> are generated by an ETKF (EnsembleTransform Kalman Filter) and they are centered around the deterministic 4d-Var analysis.

Geographical variation of spread at T+6 h (CNT: RP+SKEB)



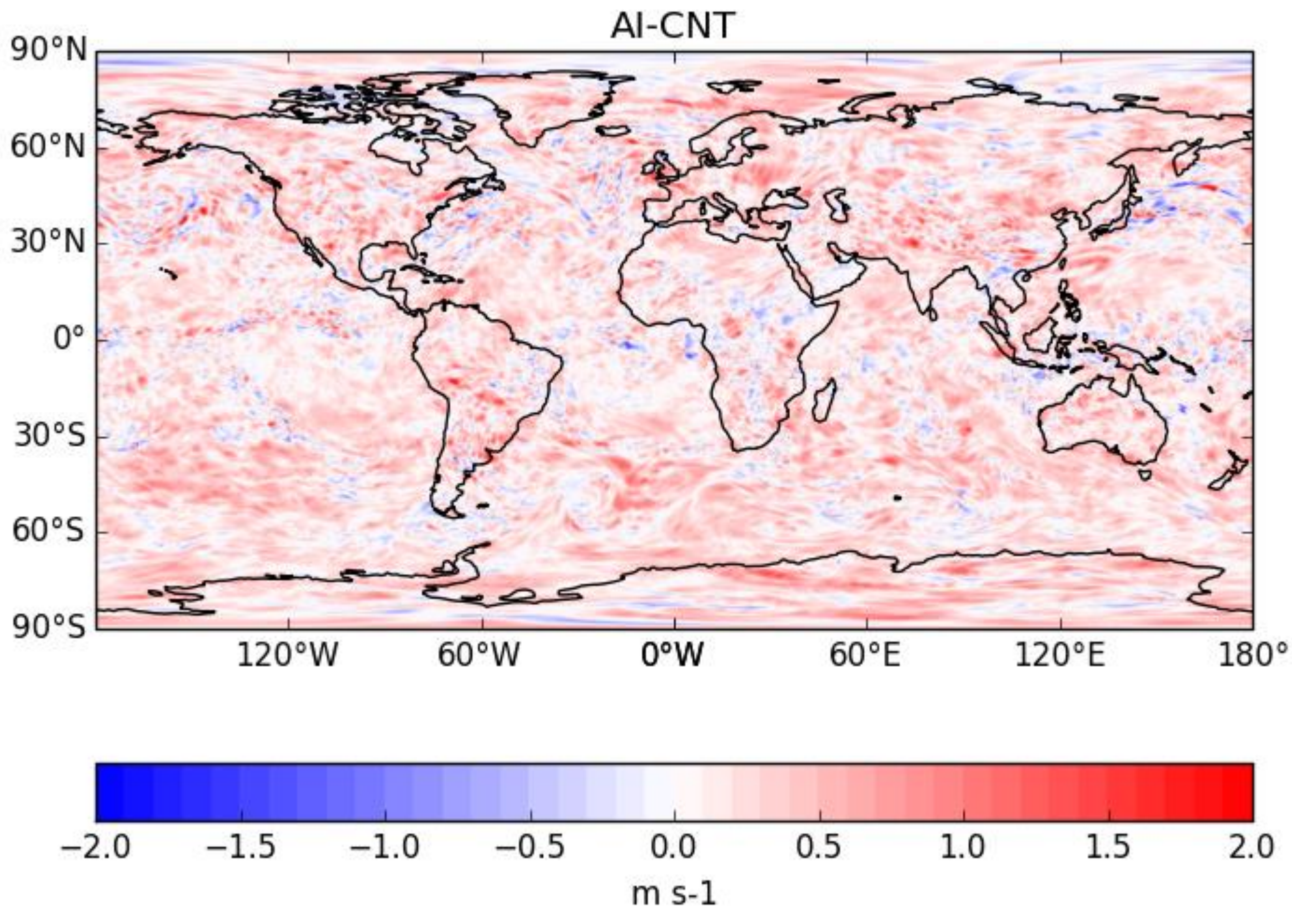
CNT picks up sources of model error mainly in the NH storm track.

Geographical variation of spread at T+6 h (SPT- CNT)



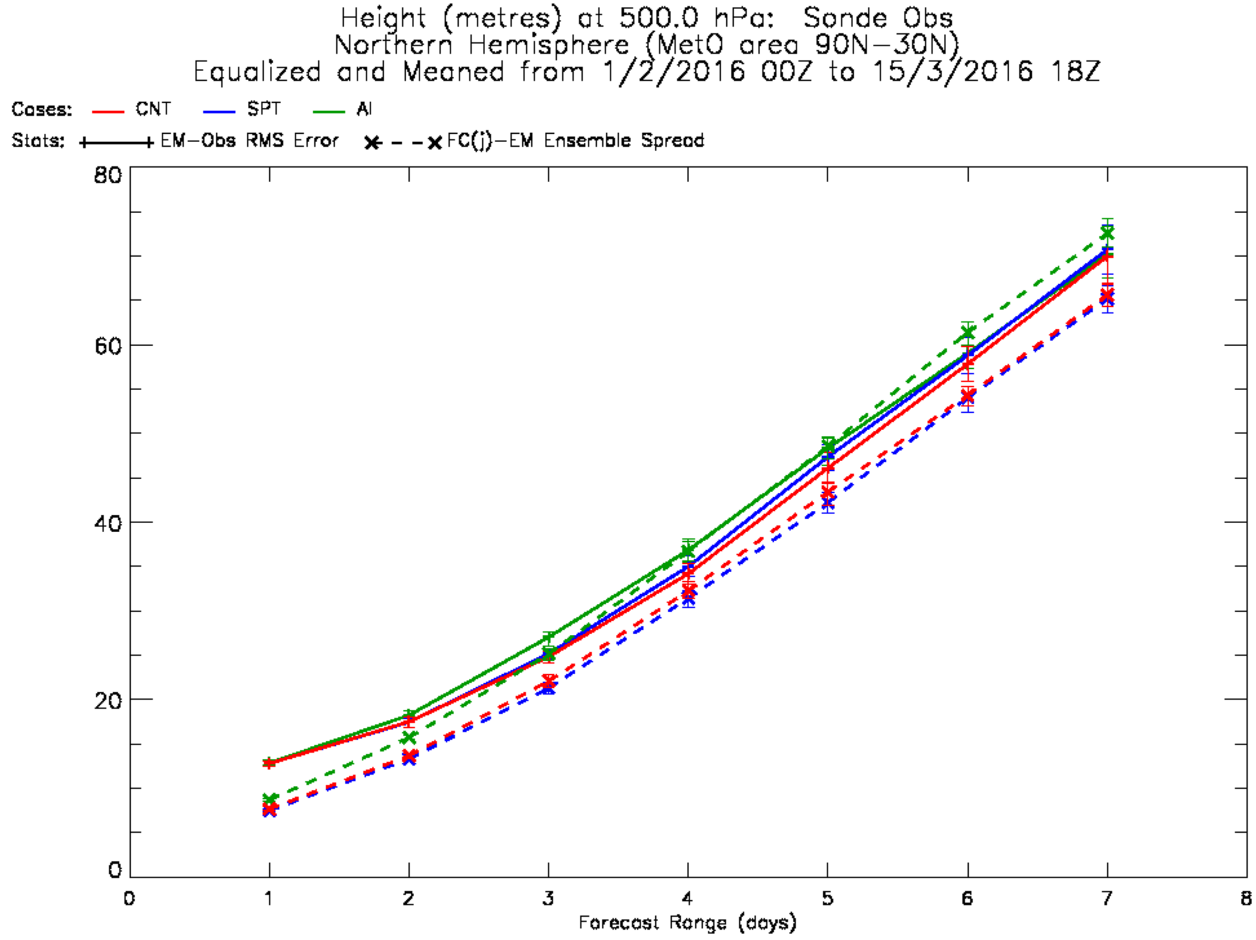
SPT shows localised increase of spread in the NH storm track and tropics.

Geographical variation of spread at T+6 h (AI - CNT)



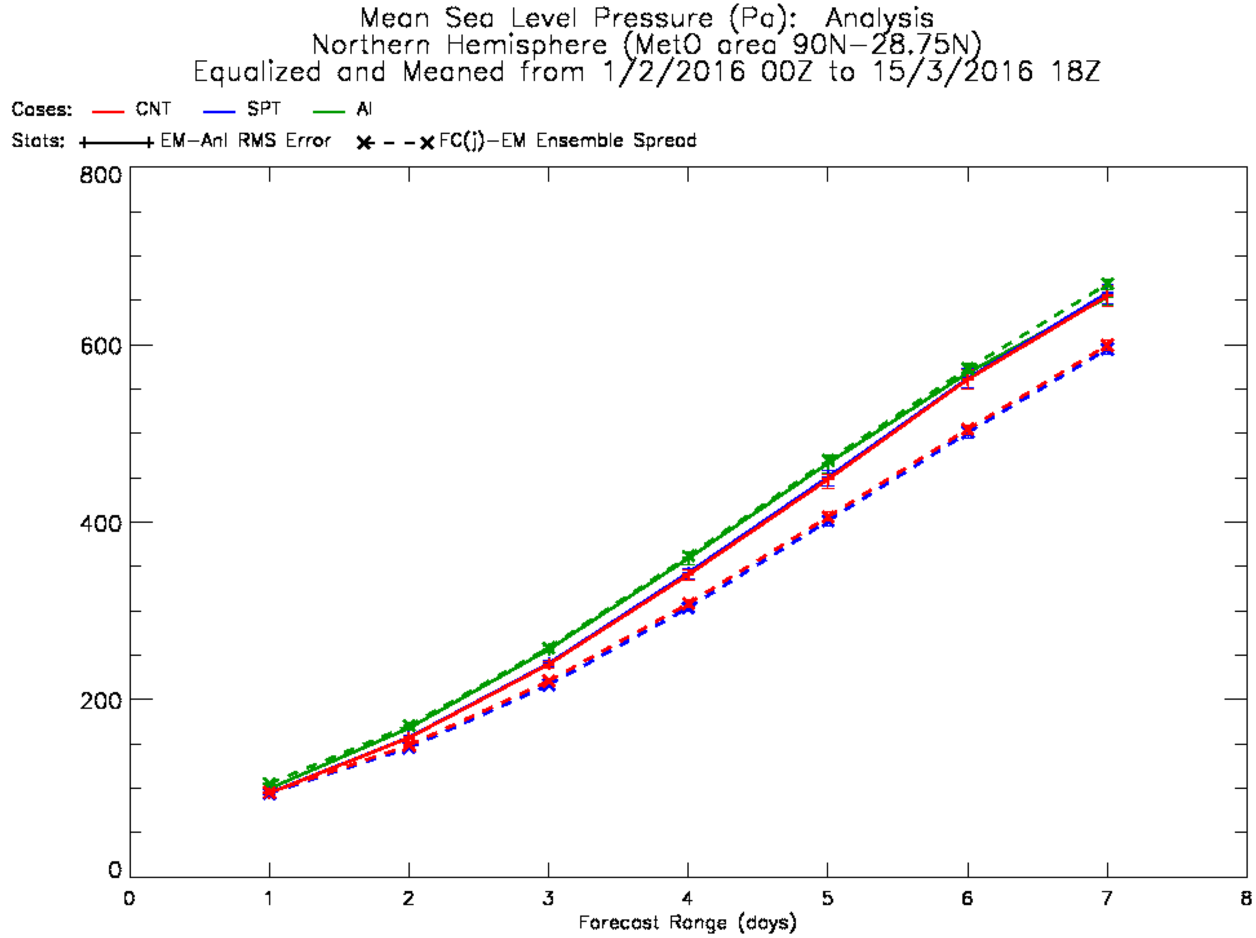
AI introduces more large scale spread across all regions but lacks flow-dependency. It also better represents the error in the SH and tropics.

MOGREPS
Verification against sondes
500 hPa height (m) - NH



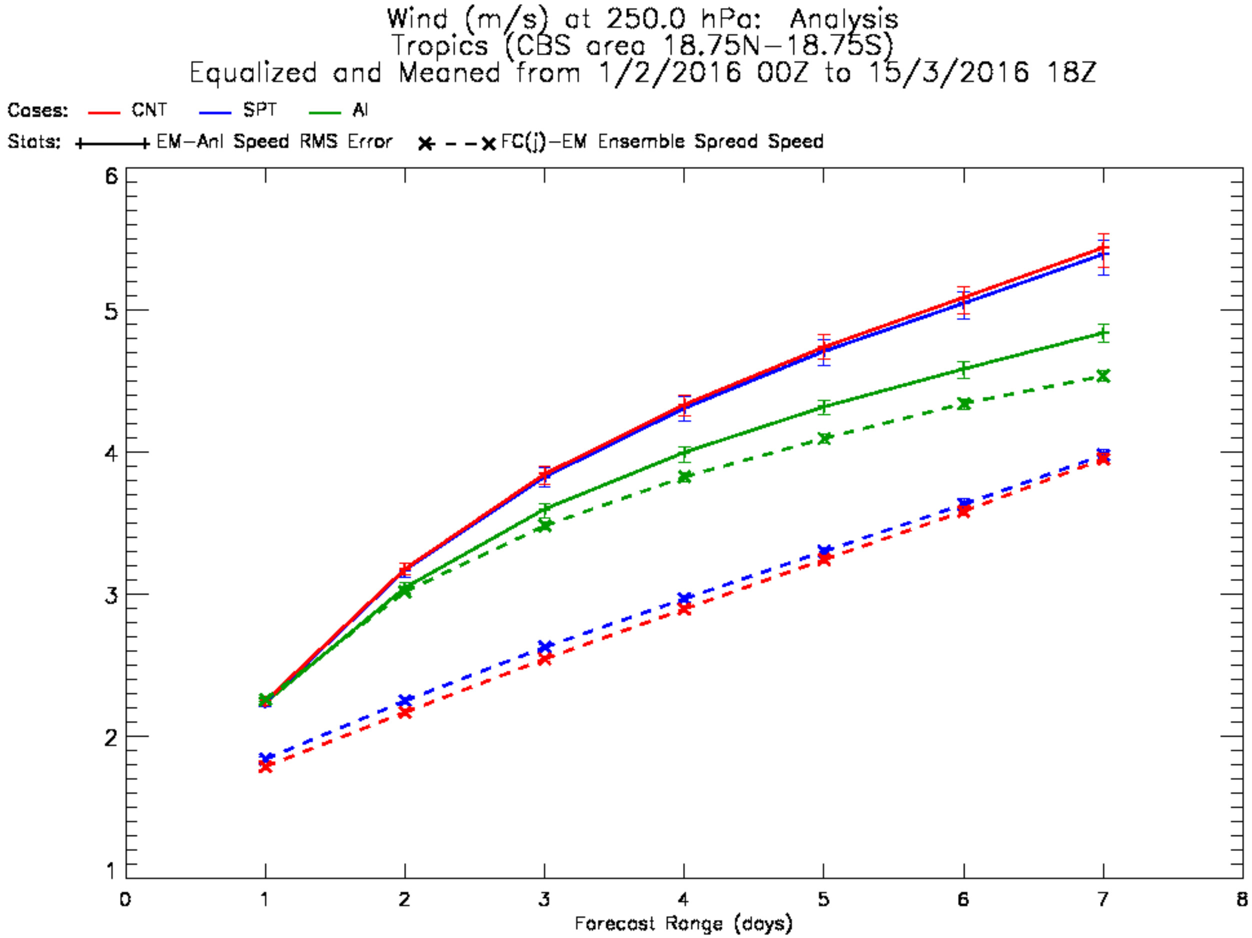
Solid: RMSE
Dash: spread

MOGREPS
Verification against analysis
Mean Sea Level Pressure (Pa) - NH



Solid: RMSE
Dash: spread

MOGREPS
Verification against analysis
250 hPa winds (m/s) - Tropics



Solid: RMSE
Dash: spread

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Top left:
T+72h error

Top right:
T+72 h CNT
spread

Bottom left:
T+72h SPT
spread

Bottom right:
T+72h AI
spread

Solid: ens. mean
Dash: analysis

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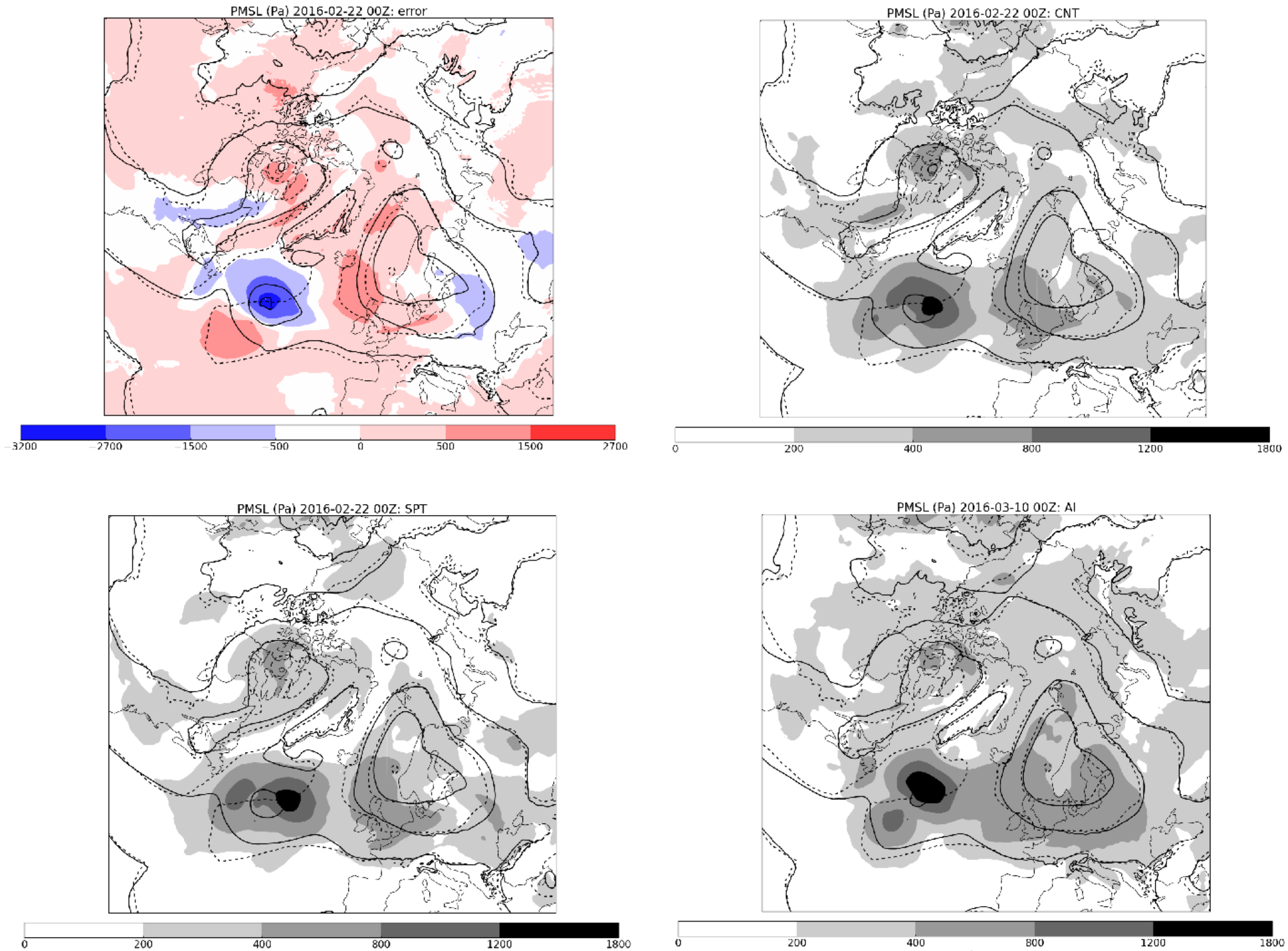
MOGREPS
Mean Sea Level Pressure (Pa) - NH



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Impact within En-4DEnVar

En-4DEnVar

Ensemble of four-dimensional ensemble-variational DA:

- hybrid 4D-Var
- perturbed observations
- 44 members
- recentred around deterministic 4D-Var analysis

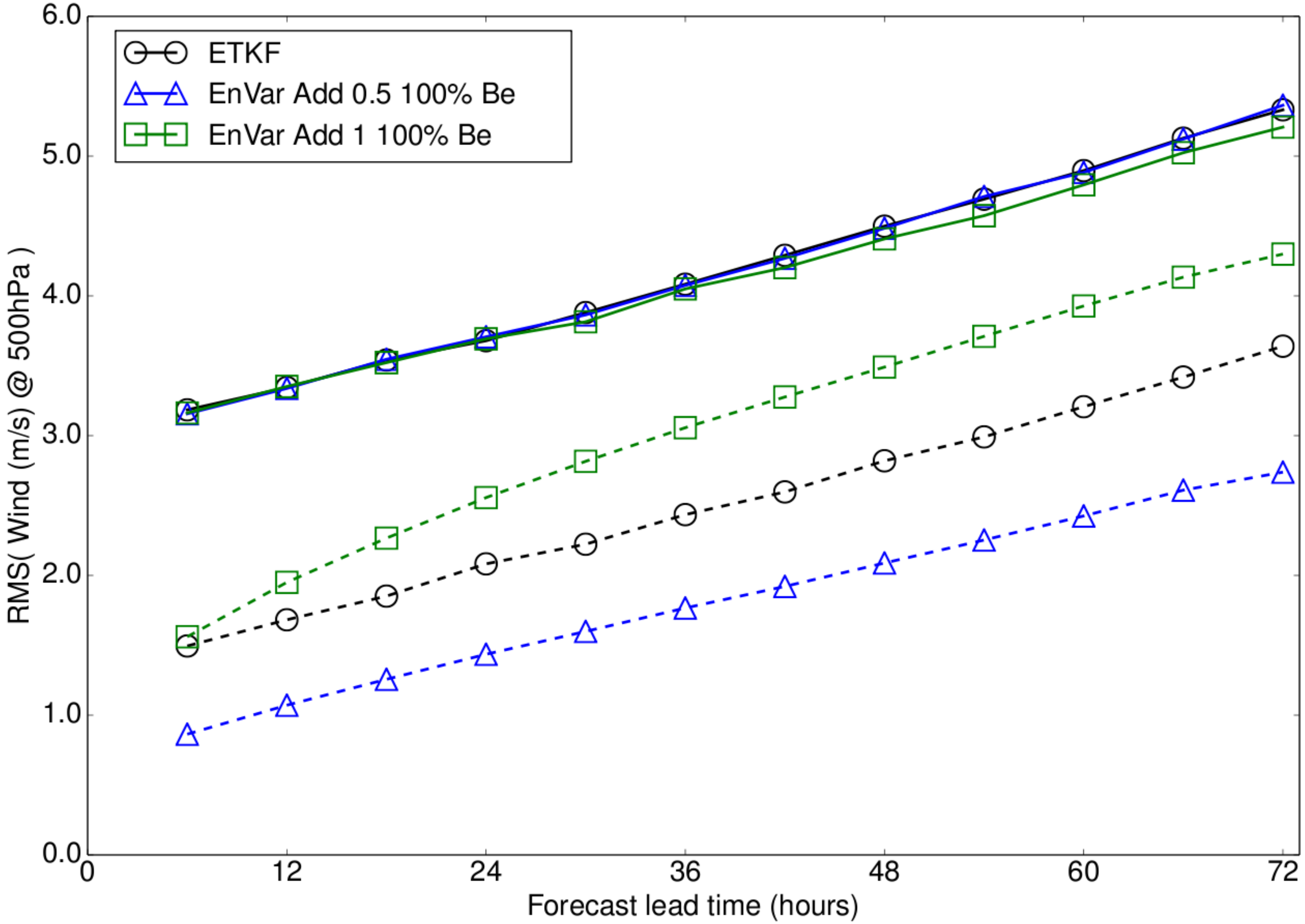
Model – Met Office N216L70 UM, i.e. 60 km horizontal resolution and 70 levels (80 km model top).

En-4DEnVar system substantially better than ETKF:

- Large benefit from using additive inflation
- Large portion of the benefit comes from bias correction
- Need to use right season and correct model for the generation of the analysis increments in the calibration step

Bowler et al., QJ, 2017.

En-4DEnVar versus ETKF
Verification against sondes
500 hPa winds (m) - NH



AI x 0.5

AI

Solid: RMSE
Dash: spread

Bowler et al., QJ, 2017.

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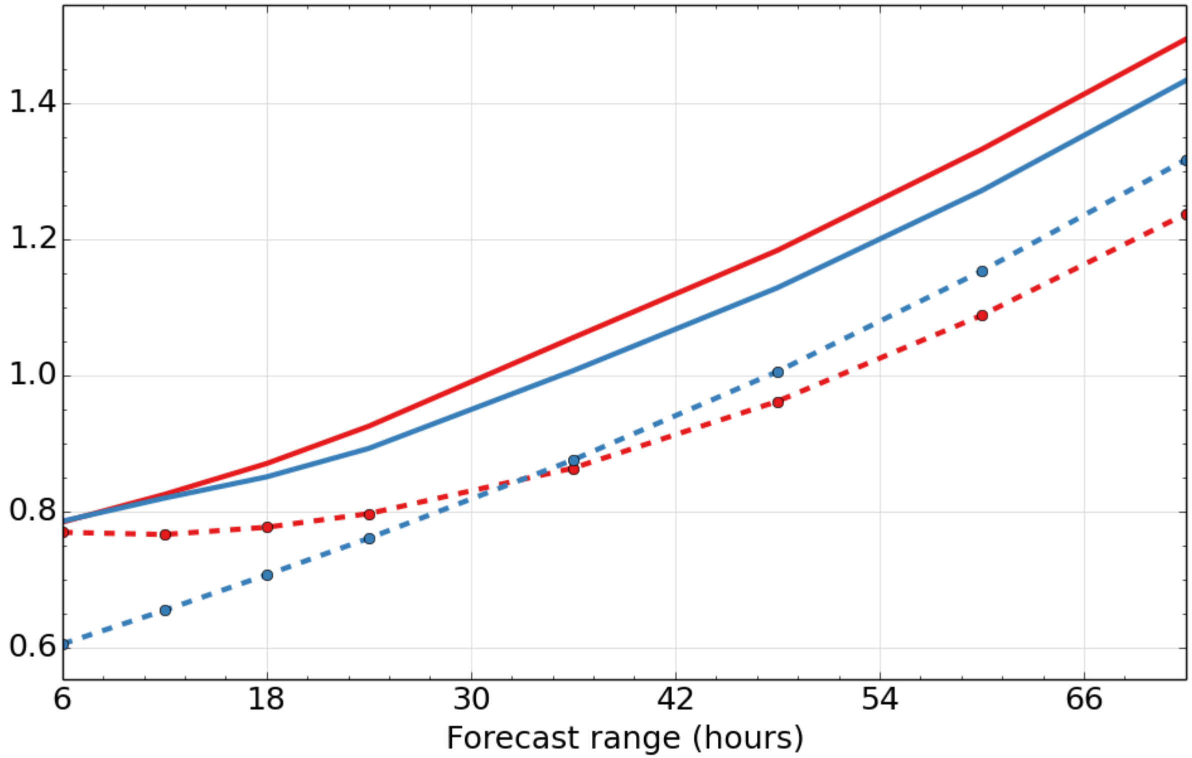
En-4DEnVar versus ETKF
Verification against analysis
850 hPa Temperature (K) - NH



ETKF

En-4DEnVar

Solid: RMSE
Dash: spread

Operational implementation: the perturbations are scaled by a factor 0.5 (as a “top-up” of the stochastic physics schemes, rather than replace them)

T850 is a variable where we have large biases, so the bias correction due to the additive inflation is playing a substantial role here.

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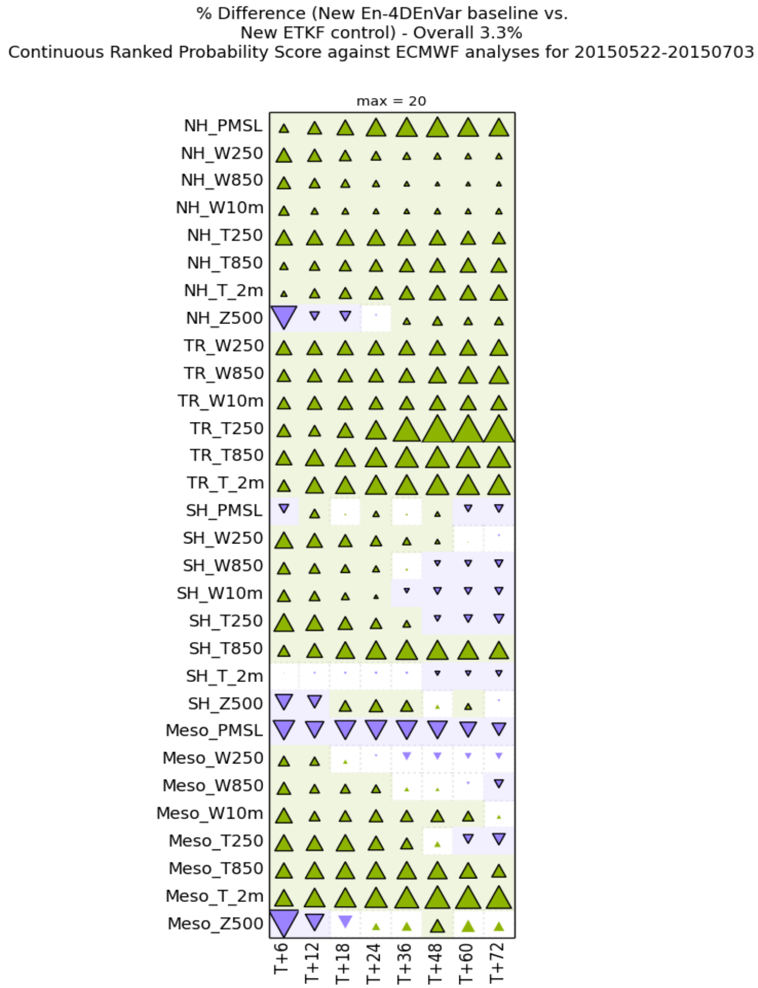
Better CRPS

Worse CRPS

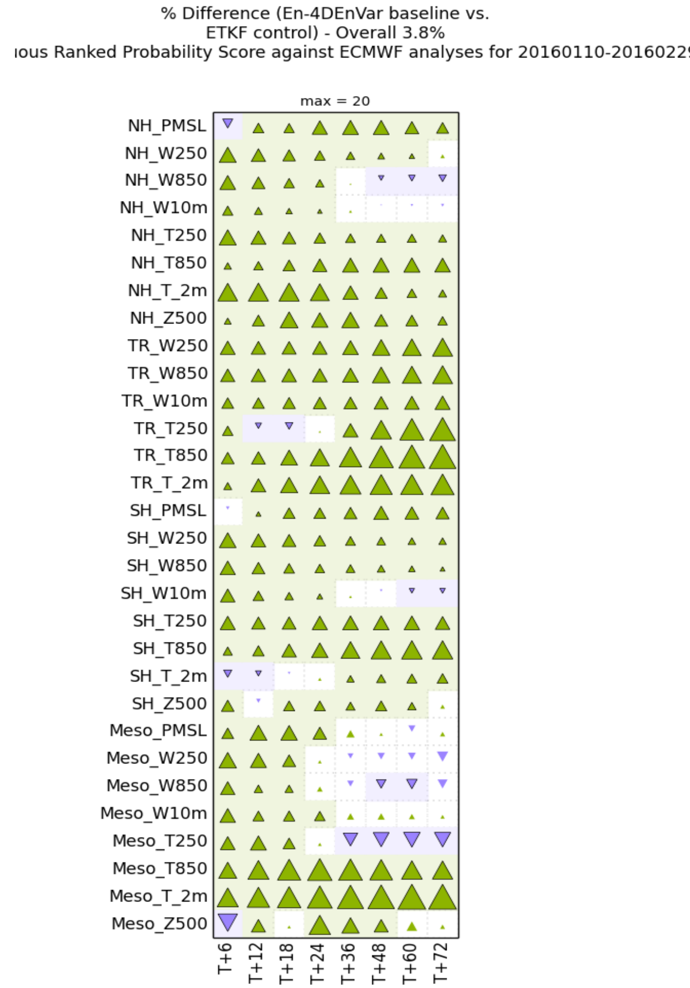
Continuous Ranked Probability Score

En-4DEnVar versus ETKF

Verification against ECMWF analysis



May/June 2015



Jan/Feb 2016

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Summary

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Summary

We rely on the fact that a reliable prior ensemble and a set of reliable perturbed observations can be combined to give a reliable analysis ensemble.

We rely on the randomness of analysis increments, which means that a reanalysis trajectory is statistically indistinguishable from a realisation of the model forced with analysis increments.

We demonstrate the benefits of exploiting these properties in an EDA and EPS.

C. Piccolo and M. Cullen, 2016, MWR, 144, 213-224

Any questions?
Thank you for your attention

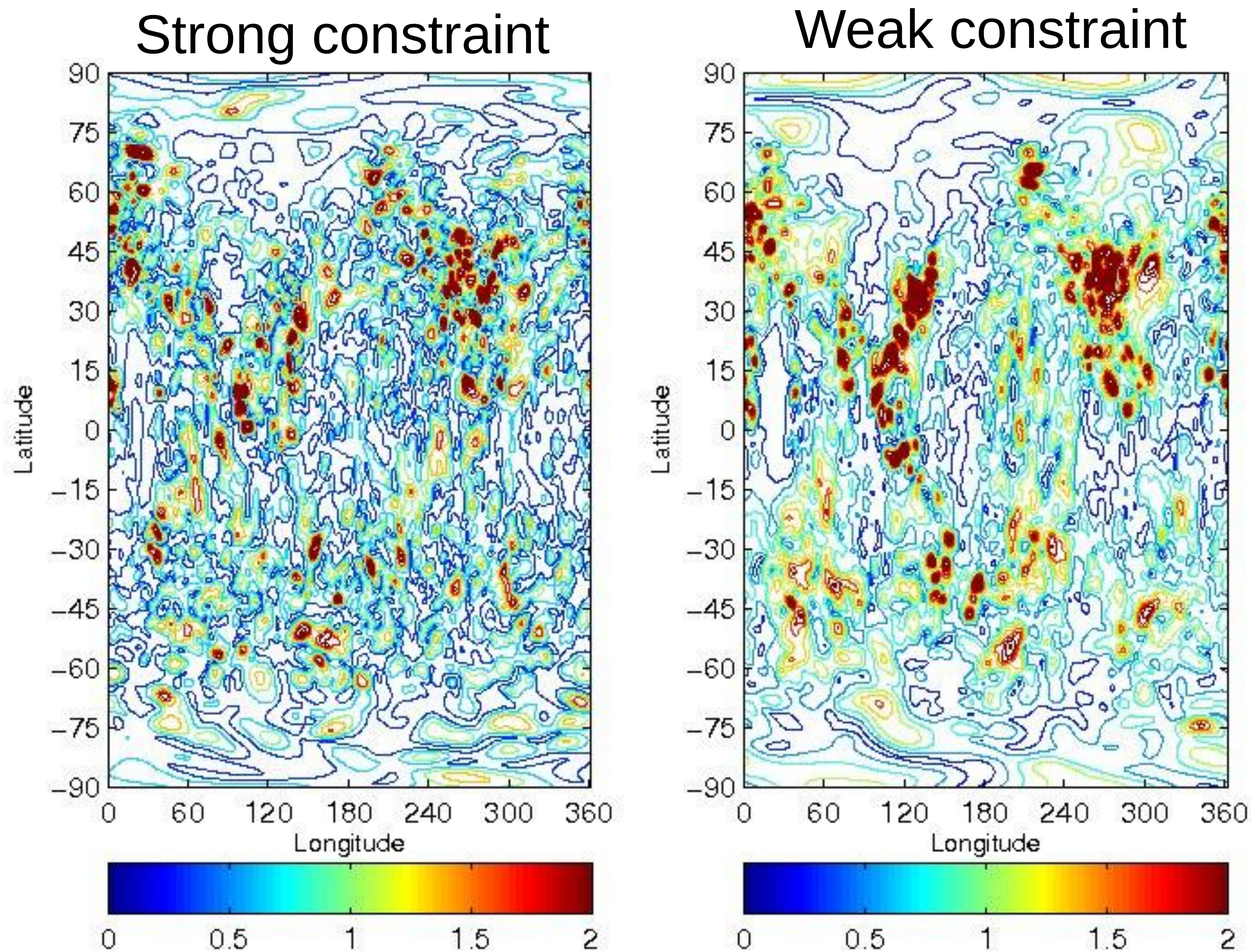
Further issues

Further issues

Demonstrate importance of using weak-constraint 4dVar to derive forcing increments.

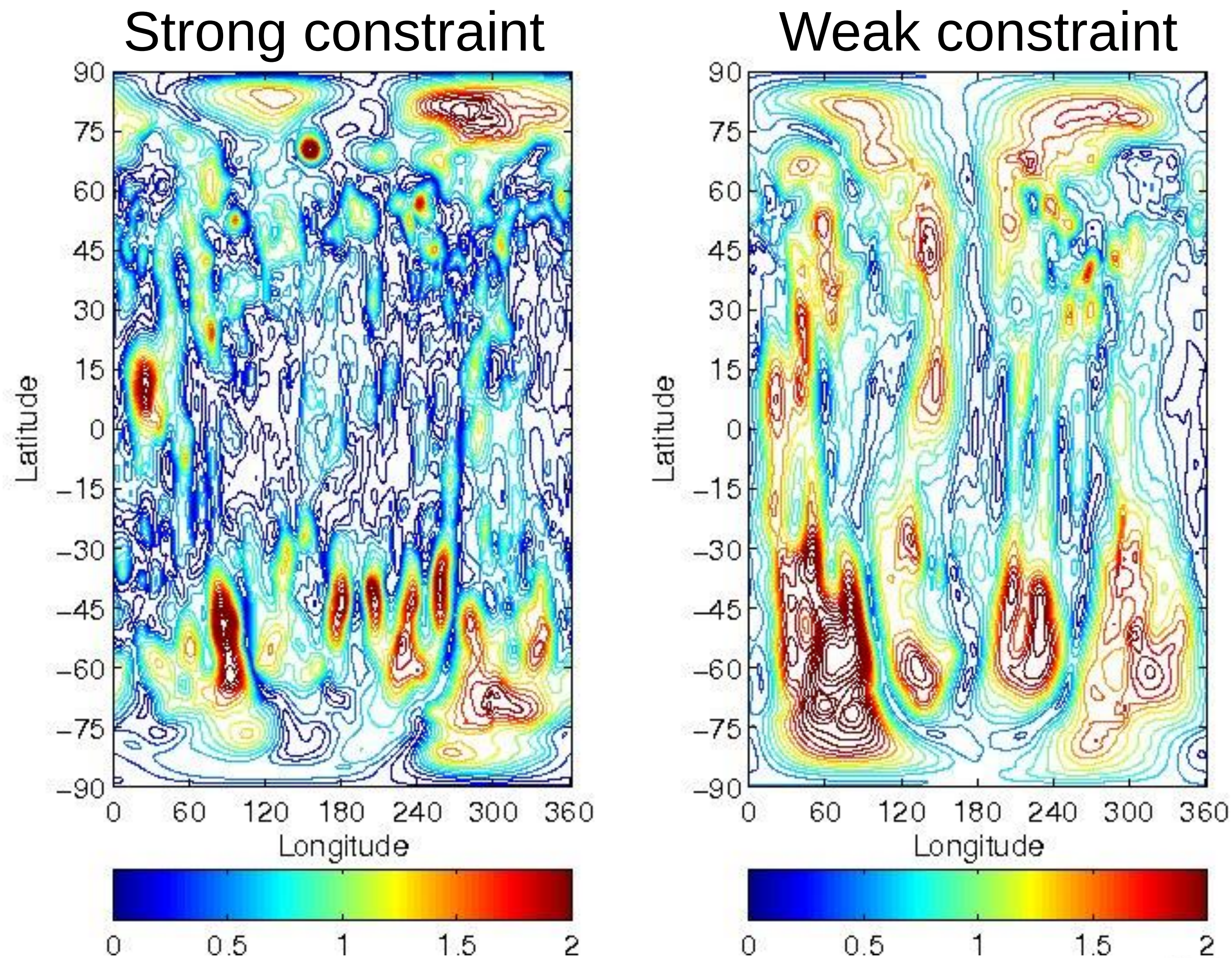
The results shown use a new random forcing term every 6 hours. Probably the time correlation of the analysis increments should be allowed for.

Compare strong and weak constraint analysis increments (u at 850 hPa)



More variance and larger scale if consistent.

Compare strong and weak constraint analysis increments(Θ at 850 hPa)



More variance and larger scale if consistent: bigger effect!

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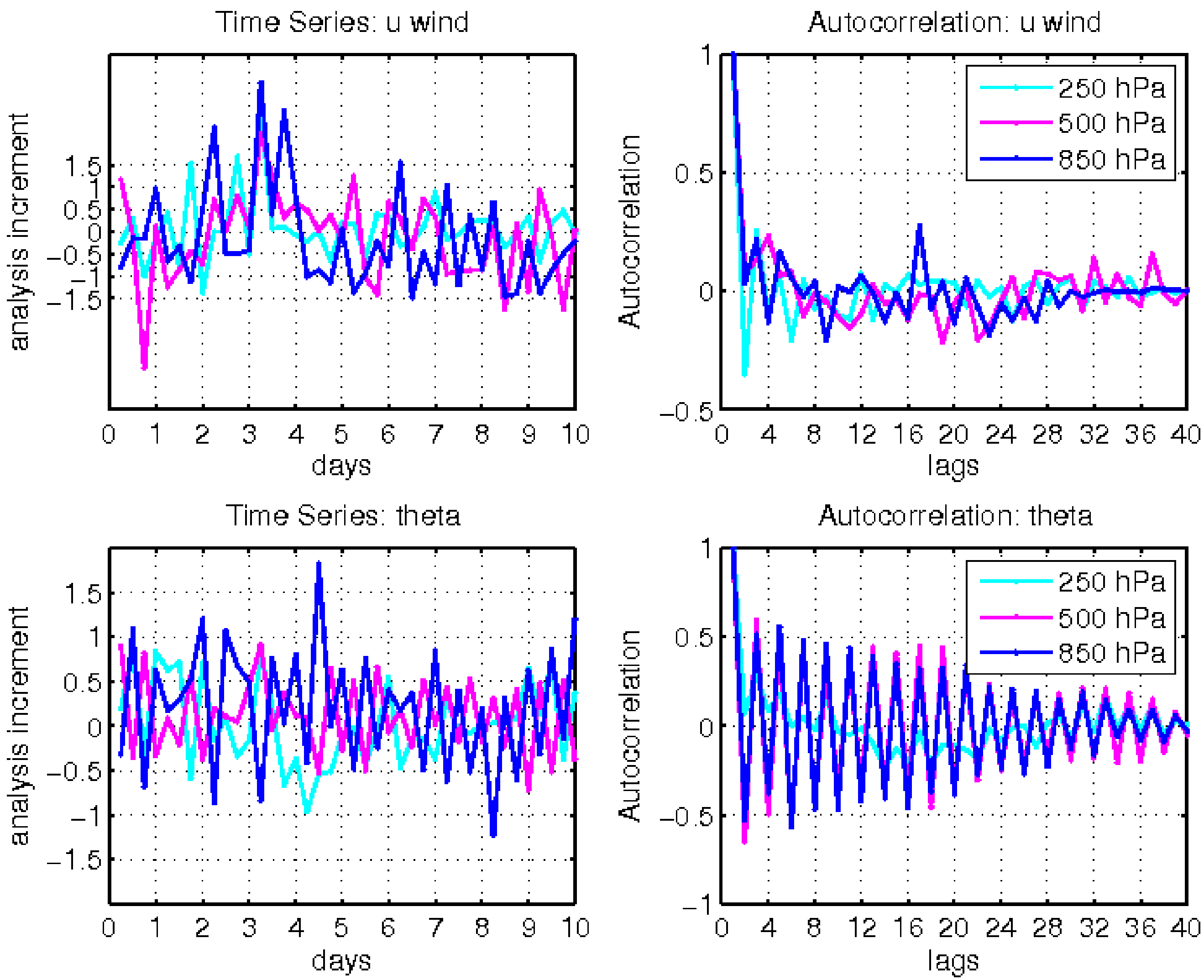
Time correlation of analysis increments (NH)

Diurnal correlation for u wind?

Strong semi-diurnal correlation for Θ.



Time correlation of analysis increments (EQU)

Significant longer time correlation for u wind.

Diurnal correlation for Θ.