Evaluation of model error using data assimilation

Chiara Piccolo and Mike Cullen

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Motivation and the method

Motivation

- We wish to use an ensemble of data assimilations to quantify the effect of model errors.
- We use observations to determine the effect of model error since model error is unknowable a priori.
- We use an ensemble of data assimilation in which the state is evolved by a stochastic model where the stochastic term contains the model uncertainty.

Method

- We use the fix-lag smoother property of 4d-Var to deduce information about the effect of model error from observations.

- We use random samples of analysis increments instead of stochastic physically based methods as additive inflation in the forecast ensemble.

- We show some consistency tests and results from a 10 member ensemble of 4d-Vars using operational data at 125km resolution and 85 levels.

Met Office

Results: random assumption of the analysis increments

Random assumption of analysis increments

- We use the stochastic model: $d\mathbf{x} = M(\mathbf{x})dt + dW$ with dW defined using the analysis increments.
- This ensemble may not contain the truth, if the analysis increments are not random.
- We test this hypothesis by verifying the ensemble mean forecast against a random member of the ensemble of analyses.
- We compare the T+6h ensemble spread with the RMSE of the ensemble mean.

Random analysis increments assumption (Z@500hPa)

The randomness assumption fails with less than 20% error:

- there is some degree of time correlation
- *dW* should include time correlation.

	RMSE T+6 FC	Spread T+6 FC	Rel.diff (%)
NH	4.2499	3.8984	8.3
SH	4.0049	3.2328	19.3
Tropics	2.1312	1.9636	7.9
Global	3.3127	2.9094	12.2

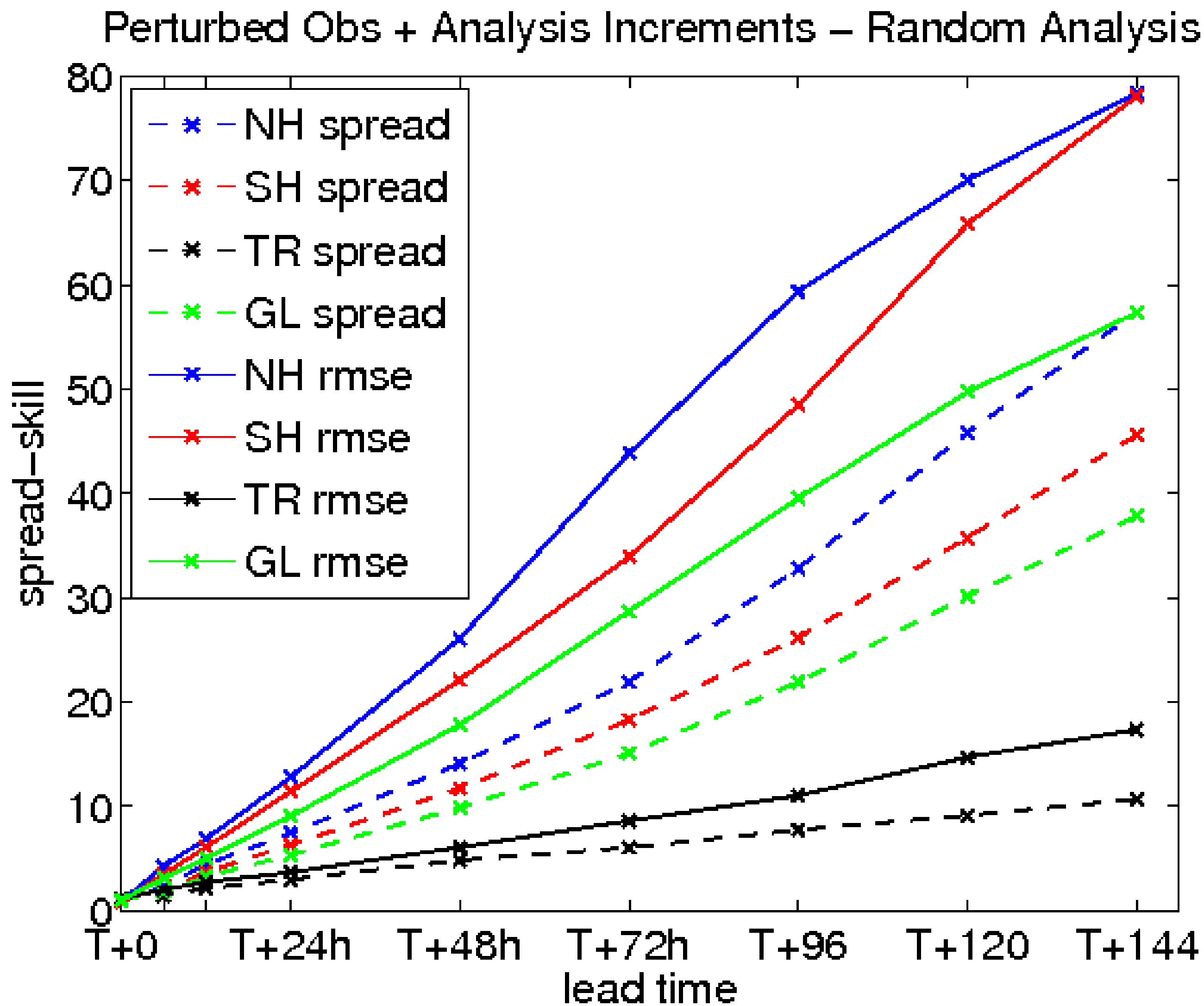
SH score is more plausible:

- the model error forcing is more homogeneous because there is no semi-diurnal variability due to sondes.

Results: spread skill at longer lead times and MST rank histograms

Met Office

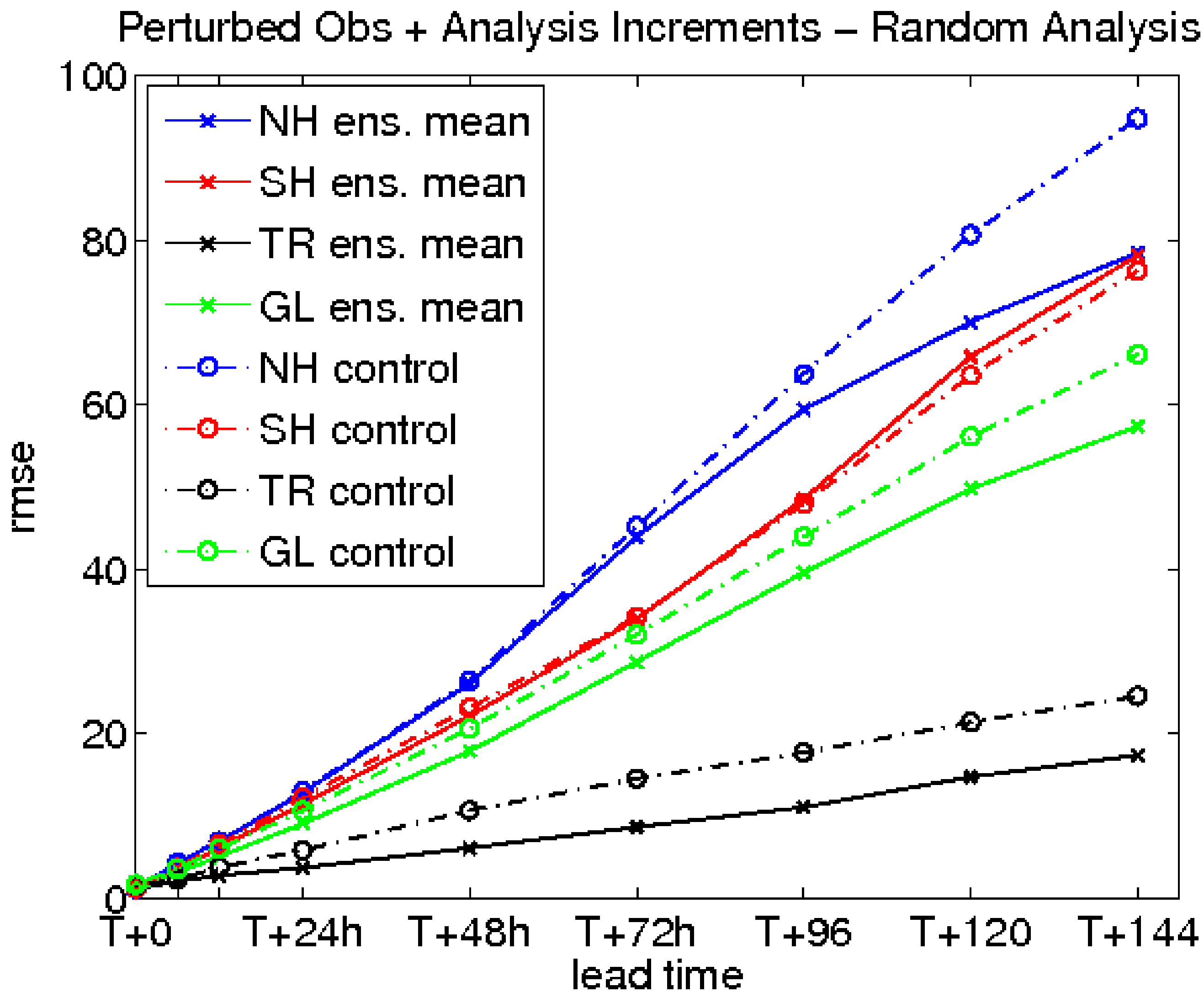
RMSE versus Spread at longer lead times



Z@500 hPa

Errors in the randomness assumption are a bit bigger than at T+6h.

Ensemble mean vs deterministic RMSE



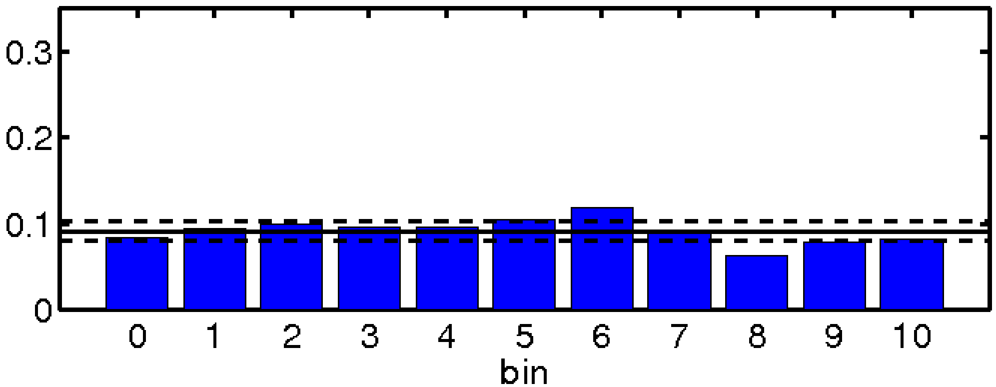
Z@500 hPa
Reduction of the RMSE in the tropics and NH.

Verifying covariance structure

- ❖The Minimum Spanning Tree (MST) rank histogram: structure of the ensemble covariance
- ❖Correct the ensemble data for bias and spread.
- ❖Assess correlation scale by using verification points with different choices of separation distance.
- ❖MST rank histogram should be essentially uniform over a large number of forecast occasions.

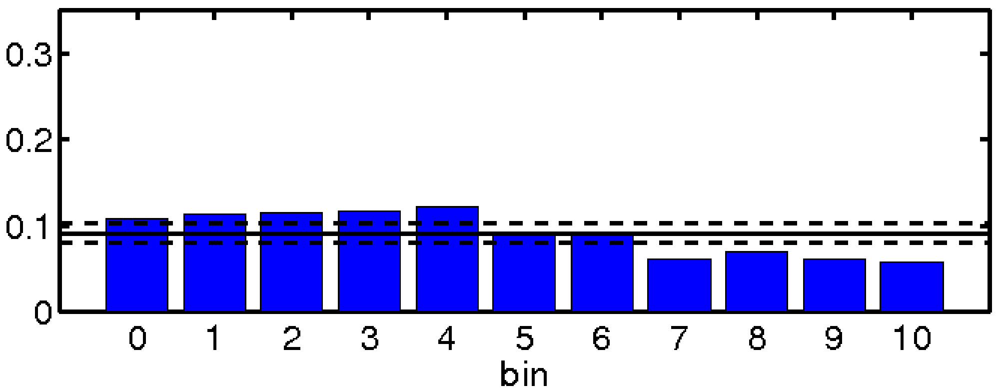
Z@500hPa MST rank histogram

T+6h ensemble forecast



Points close together

The ensemble and the verification are sampled from the same pdf.



Points far apart

The ensemble perturbations are more correlated than the ensemble mean errors.

Implication for convective scale

Deterministic convective scale data assimilation

- We want to do a convective scale deterministic analysis conditioned to a large scale background;

- the ensemble represents the error in the deterministic analysis;

- all ensemble members need to be conditioned to the same large scale background.

Implementation

1. Run deterministic DA (after removing large scale error) to collect an archive of analysis increments

2. For given large scale conditions, run a convective scale EnDA system forced by analysis increments collected at point 1.

The analysis increments forcing is not state dependent, while the effect is strongly state dependent.

Summary

Summary

We use observations to determine the effect of model error since model error is unknowable a priori.

We use an EnDA system in which the state is evolved by a stochastic model where the stochastic term contains the model uncertainty.

We use random samples of analysis increments as additive inflation in the forecast ensemble.

This method can be applied on convective scale for a given large scale background.

Thank you for your attention

Failure of the random assumption

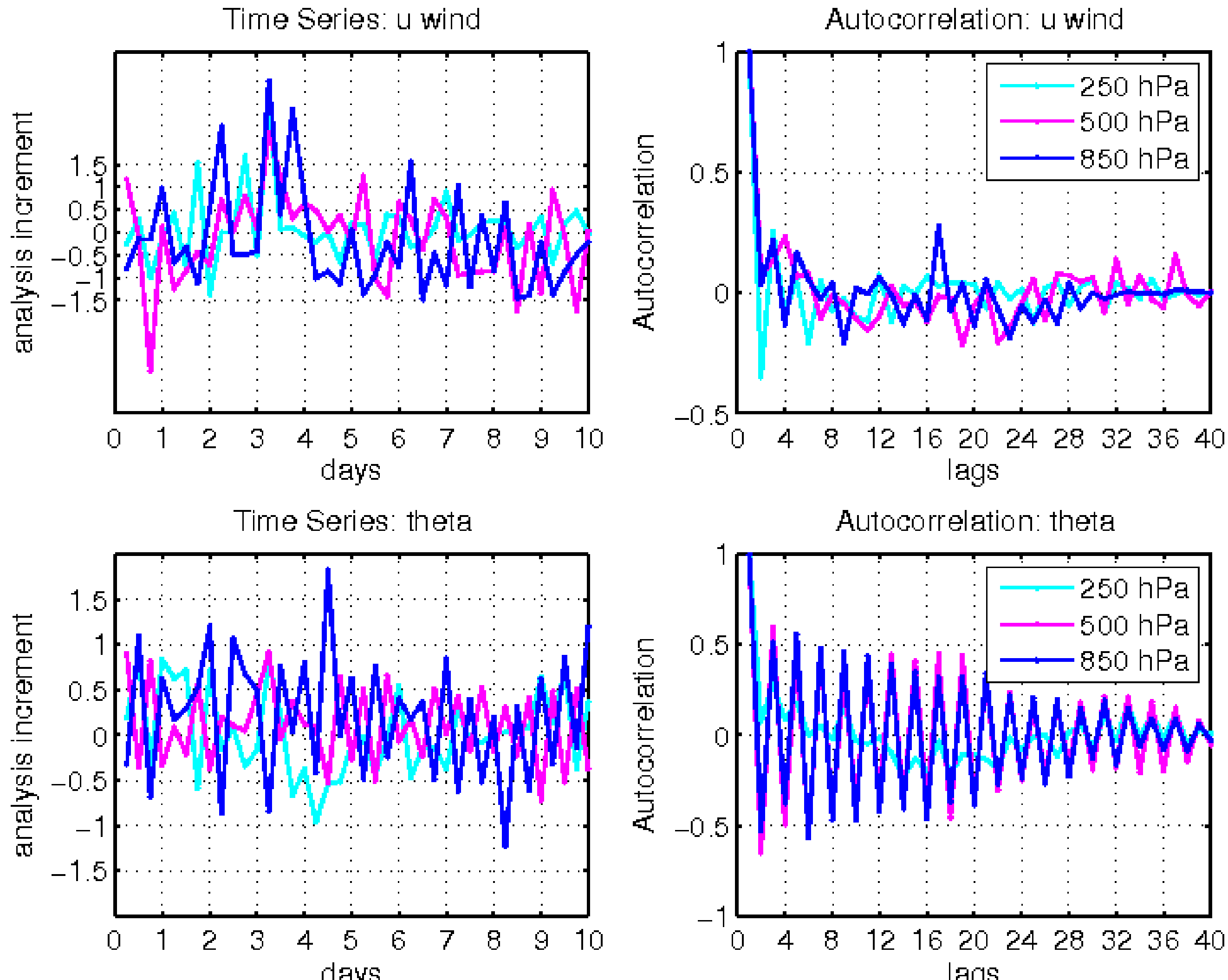
What could explain the 20% mismatch?

- ❖The analyses are non-optimal;
- ❖The assimilation procedure is not consistent with the choice of the prior error covariance;
- ➢The analysis increments are correlated in time;
- ➢There is inconsistency between the analysis increments and the forcing term.

Time correlation of analysis increments (NH)

Diurnal correlation for u wind?

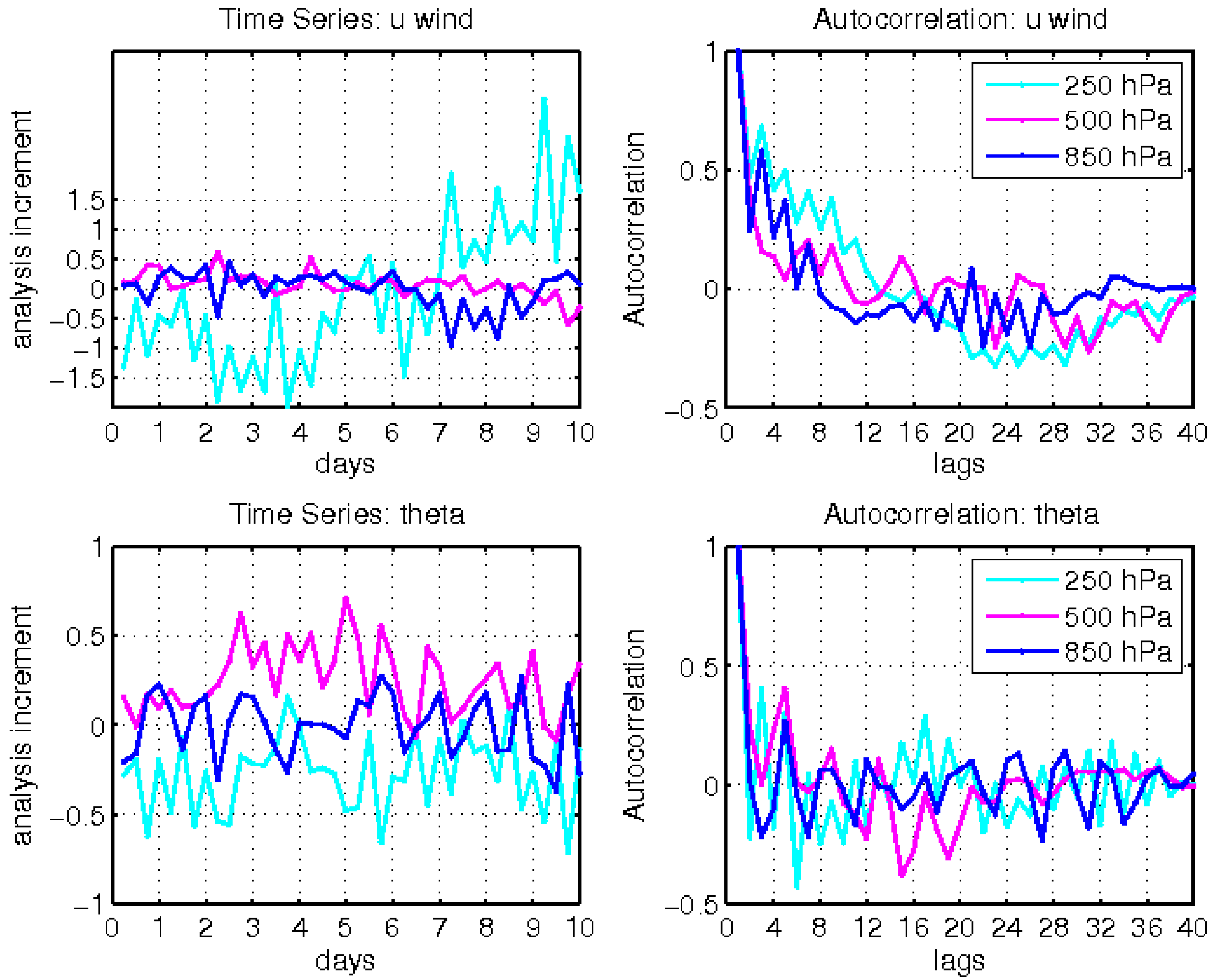
Strong semi-diurnal correlation for Θ.



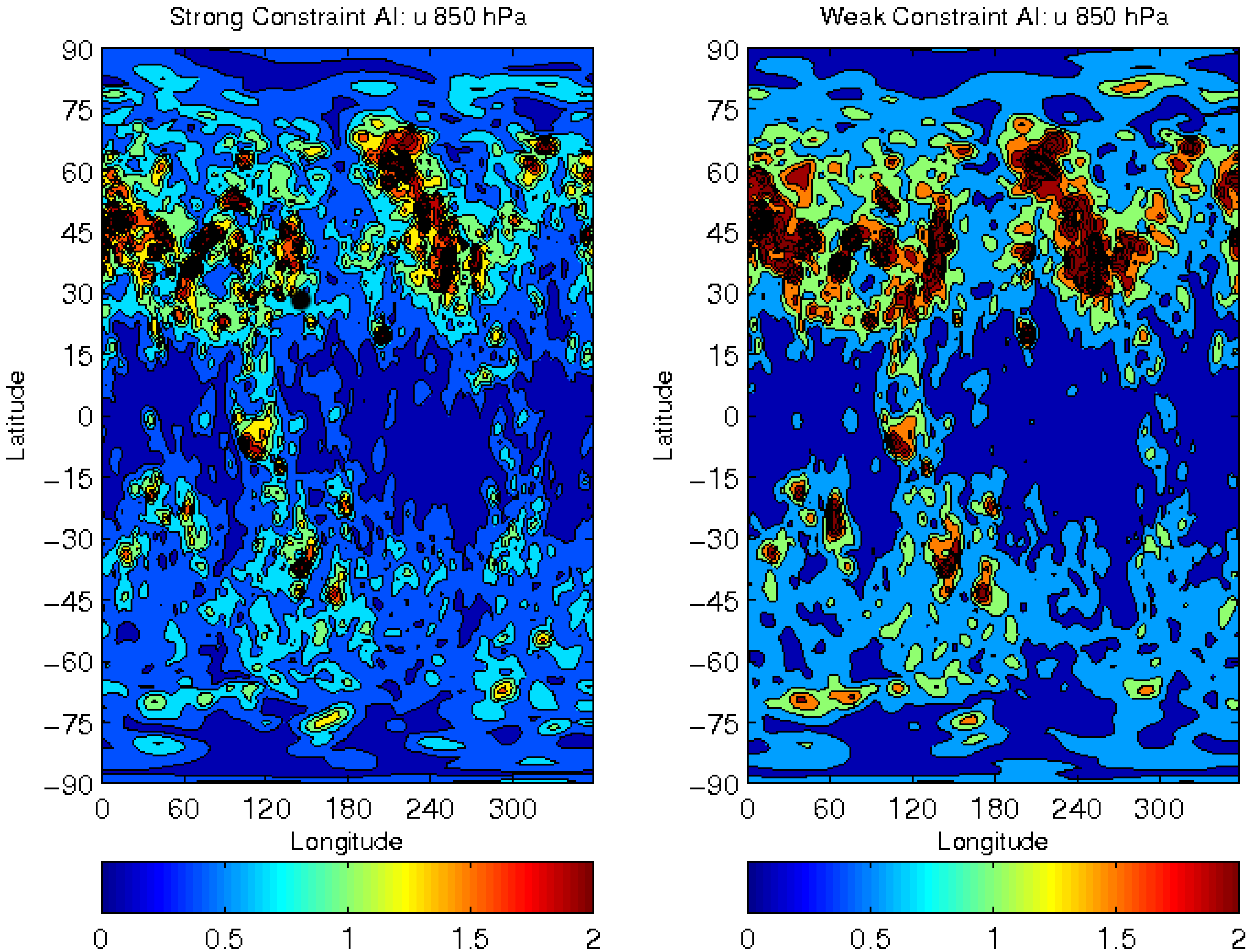
Time correlation of analysis increments (EQU)

Significant longer time correlation for u wind.

Diurnal correlation for Θ.

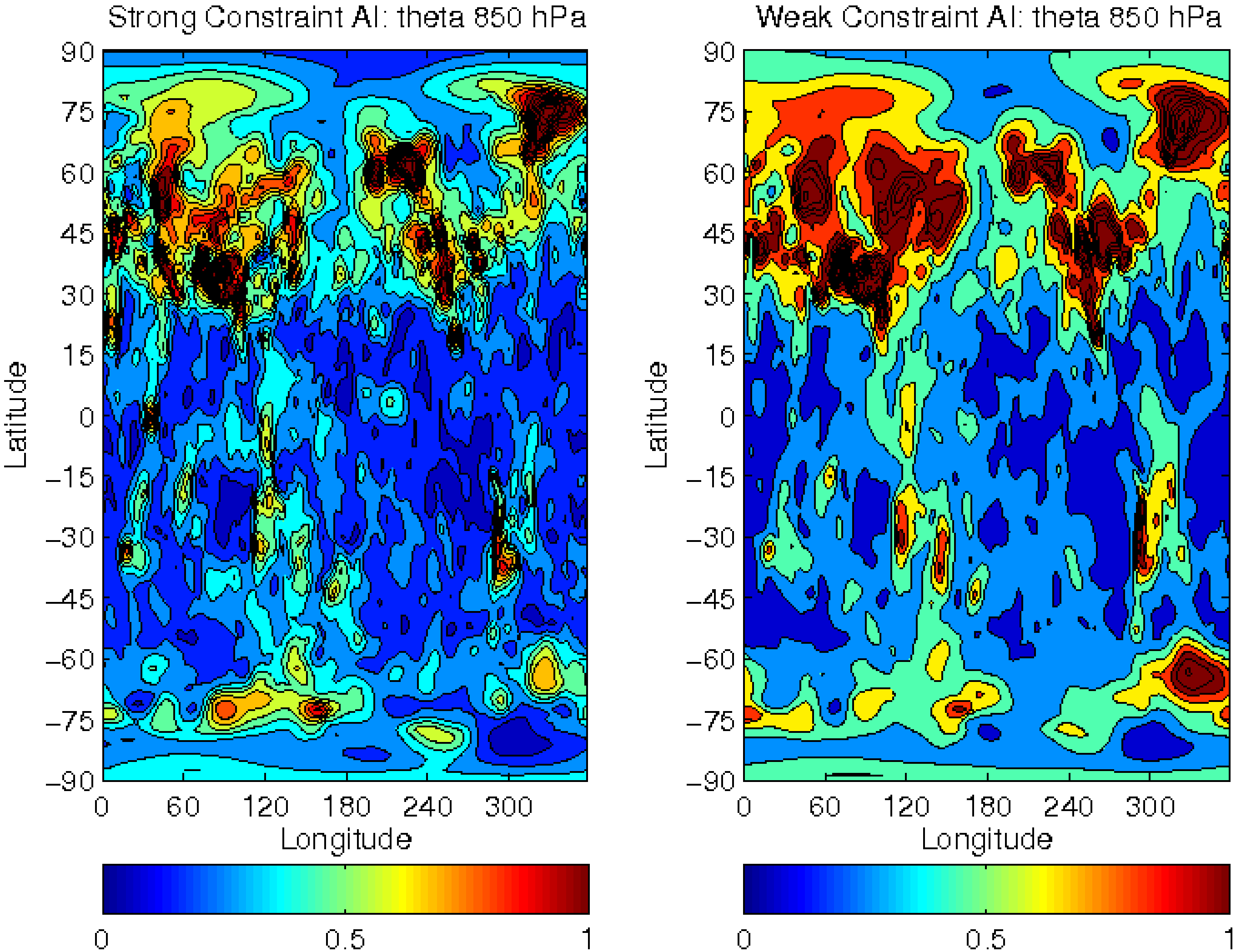


Simplified vs consistent assimilation in presence of model error (u at 850 hPa)



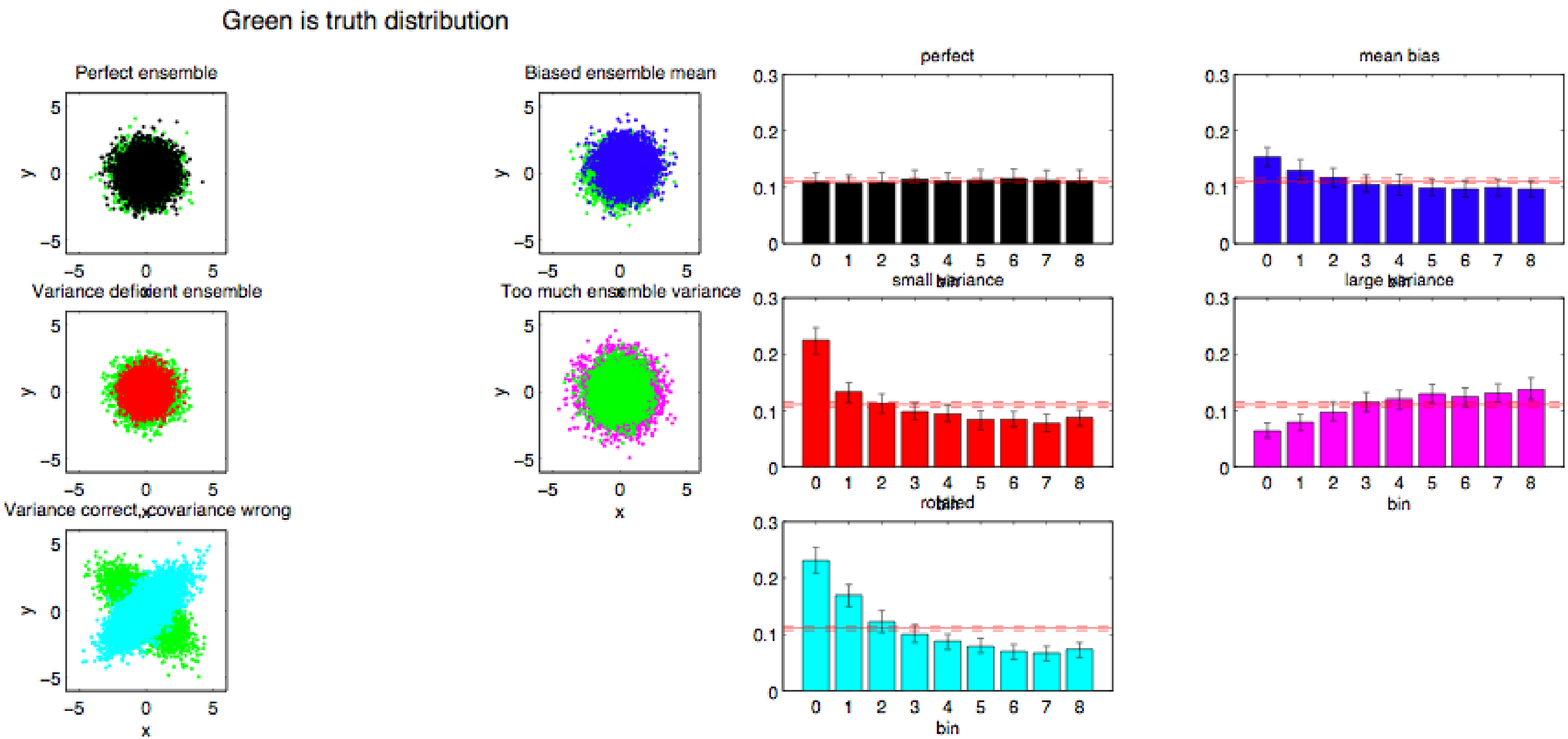
More variance and larger scale if consistent.

Simplified vs consistent assimilation in presence of model error (Θ at 850 hPa)



More variance and larger scale if consistent: bigger effect!

Minimum Spanning Tree (MST) Rank Histogram



Courtesy of Jim Hansen, NRL

Comparison with the stochastic physics

Physically based stochastic forcing

There are various physically-based stochastic models.

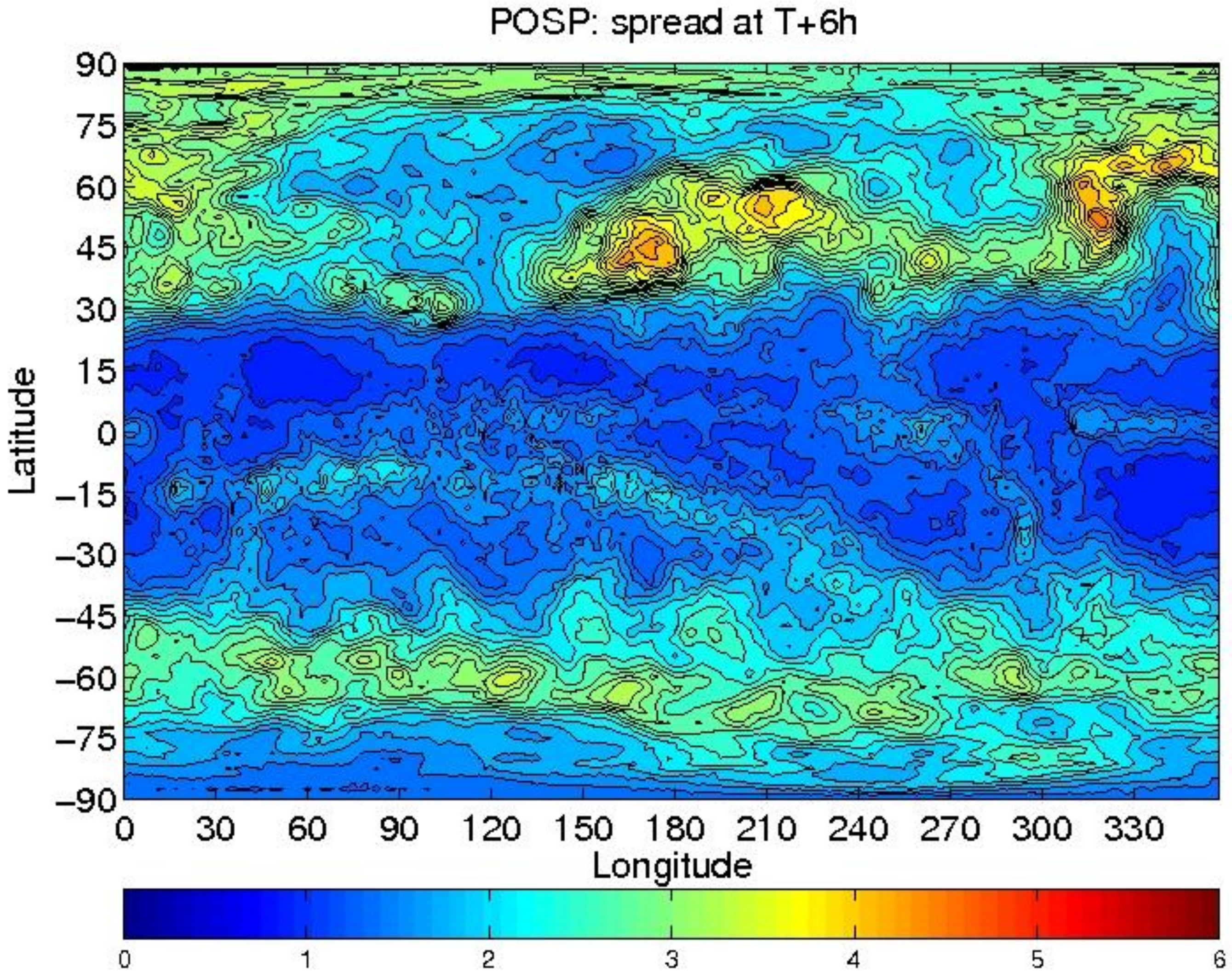
MOGREPS, the Met Office operational EPS, uses:

- ❖Random perturbations to physical parameteres
- ❖Stochastic kinetic energy backscatter (SKEB)

How does this scheme compare with the data-driven model error forcing?

- ➢ ensemble of 4d-Vars with stochastic physics
- ➢ still low resolution with no optimal tuning

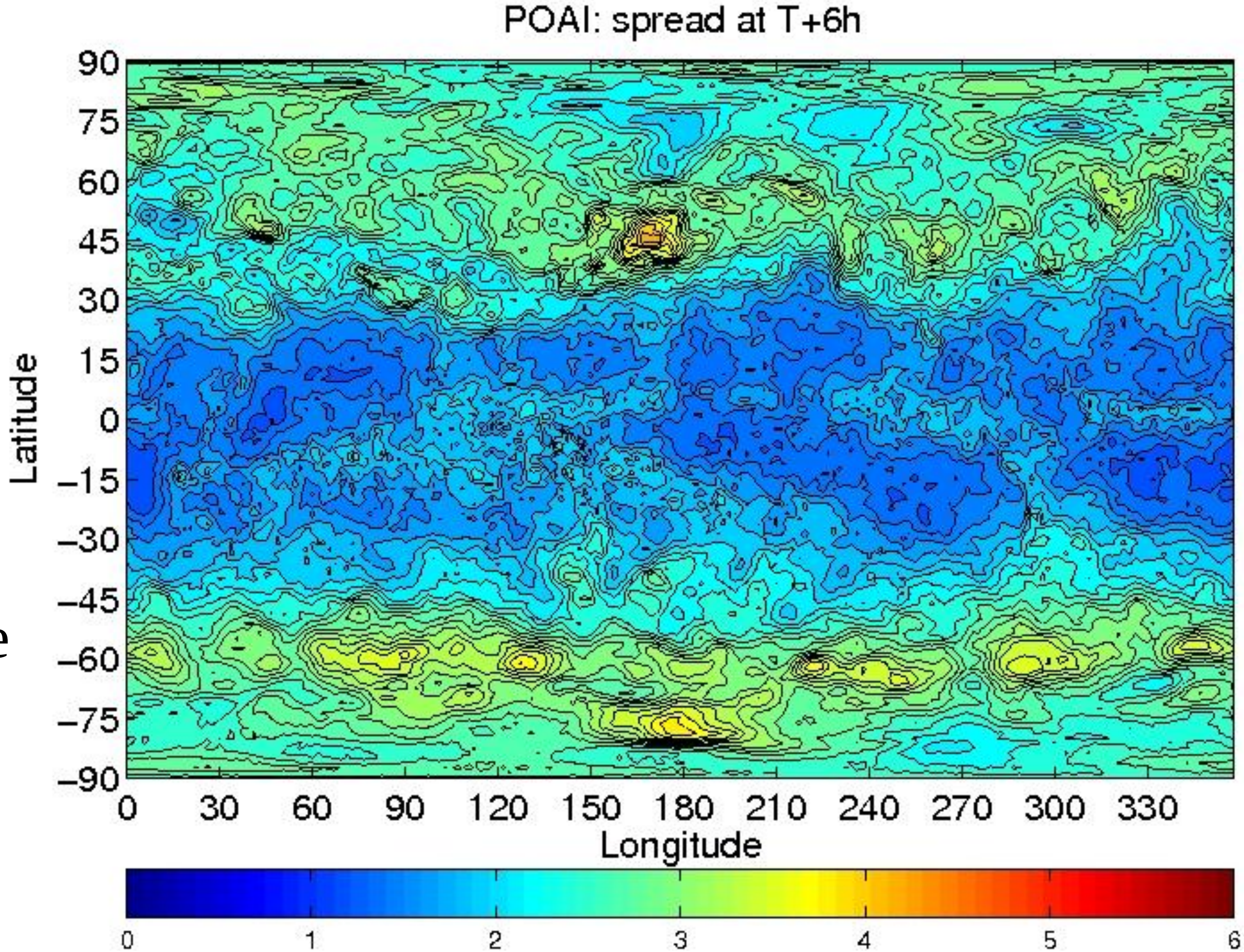
Geographical variation of spread at T+6h (stochastic physics)



The stochastic physics model error forcing picks up sources of model error mainly in the NH storm track.

Geographical variation of spread at T+6h (data-driven)

The data-driven model error forcing as well as picking up the NH storm track it also better represents the error in the SH.



EnDA implementation and set-up

- We use an ensemble of 4d-Vars with prior error covariance **Q**:
  - 10 independent 4d-Vars with perturbed obs, SST;
  - apply random model error forcing every 6 hours;
  - **Q** = operational **B**, then recalculated using analysis increments.

- We use the Met Office N96L85 UM at 125km resolution and 85 levels (85 km model top).

- We use high resolution operational settings, therefore the system is not optimally tuned for this low resolution.