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Evaluation of model error using data assimilation

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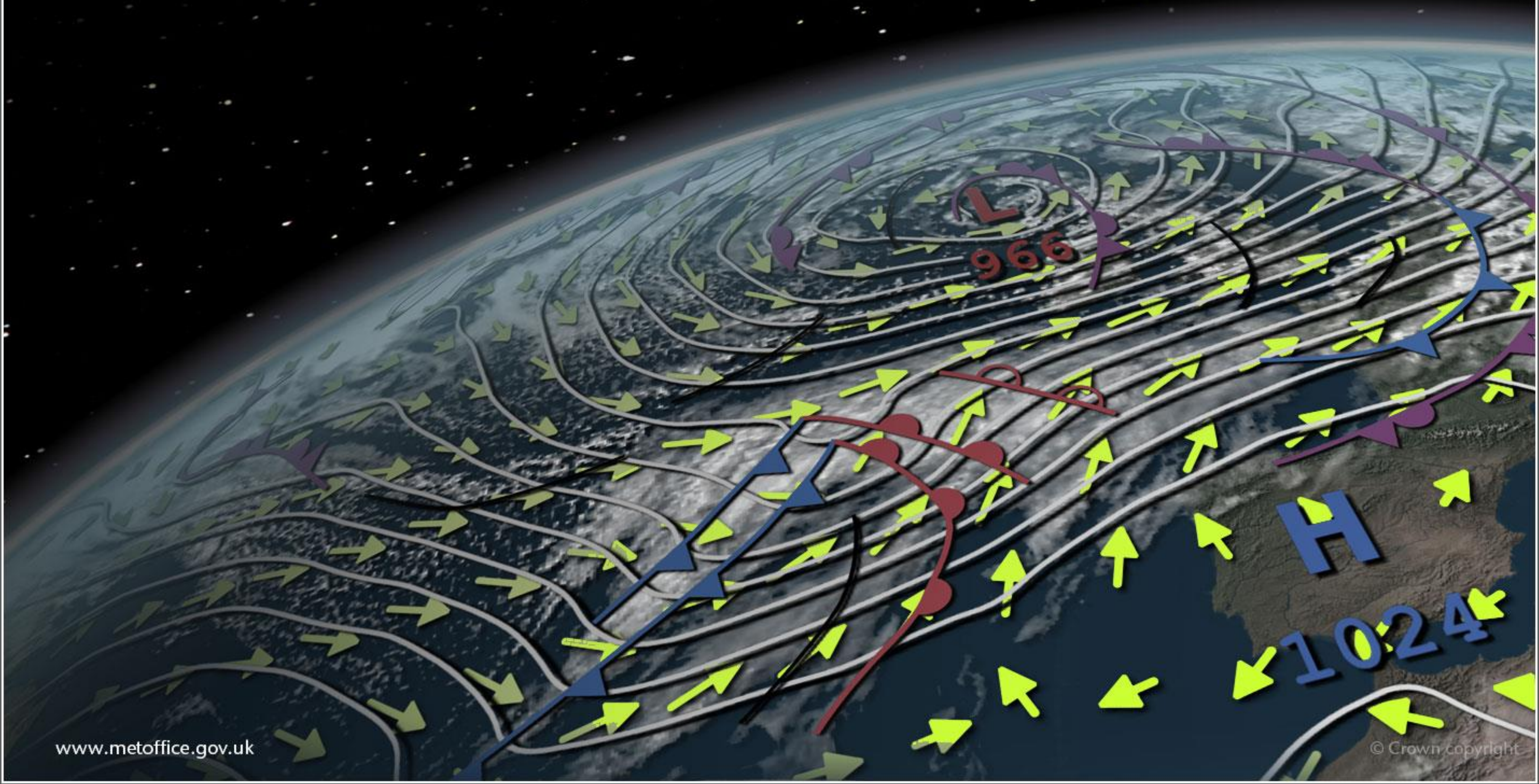

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Motivation and model error calibration

Ensemble forecasting

- Requirements:

  The truth should be statistically indistinguishable from a random ensemble member at all lead times.

  The error of the ensemble mean should be as small as possible.

- Method:

  Use an ensemble data assimilation system to represent initial uncertainty.

  Use observations to estimate model errors.

Ensemble data assimilation

- Requirement:

  The truth should be statistically indistinguishable from a random analysis member.

- Method:

  The prior and observation ensembles 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: no update is performed if the truth is chosen from both ensembles.

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Achieving ensemble resolution

- Regard the truth as the real state projected onto the model grid.
- Then the true evolution is stochastic (it depends on information not represented on the grid).
- The errors in a deterministic model prediction will also be stochastic.

Strategy:

- Minimise error of ensemble mean by using the best available deterministic model, estimating the statistics of its error and adding a random forcing with those statistics to generate a stochastic model.

Model error estimation

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- Use observations. Data assimilation allows us to use all available observations with allowance for observation error.
- Data assimilation requires a prior pdf which needs to include the effect of model error.
- Therefore we can not do data assimilation if the statistics of the model error are unknown.
- First, use cycled deterministic data assimilation to estimate the model error.
- Second, use the model error statistics to generate a stochastic forcing term in an EnDA system.

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Implementation in an EnDA system:

- EnDA set-up
- random assumption of analysis increments

EnDA set-up

- Estimate the model error using weak constraint 4dVar with assumed error covariance **D** chosen to be the same as the **B** used in operational (strong constraint) 4dVar.

- Use an ensemble of strong constraint 4dVars with the operational **B**:
  - 10 independent 4dVars with perturbed obs, SSTs;
  - Choose new random model error forcing term every 6 hours;

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

Random assumption of analysis increments

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

- If the prior and observation ‘ensembles’ are reliable, then the truth will be statistically indistinguishable from a random member of the analysis ensemble.

- If so, verification against a randomly chosen analysis ensemble member is equivalent to verifying against the truth (Bowler *et al.* (2015)).

- We compare the T+6h ensemble spread with the RMSE of the ensemble mean measured against a random analysis member.

Random assumption of analysis increments (u@850hPa)

	RMSE T+6 h	Spread T+6 h	Rel. Diff (%)
NH	1.9822	1.9347	2.40+/-1.87
Tropics	2.0950	2.1458	-2.42+/-1.67
SH	2.6728	2.7443	-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' integrations

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Performance in longer forecasts

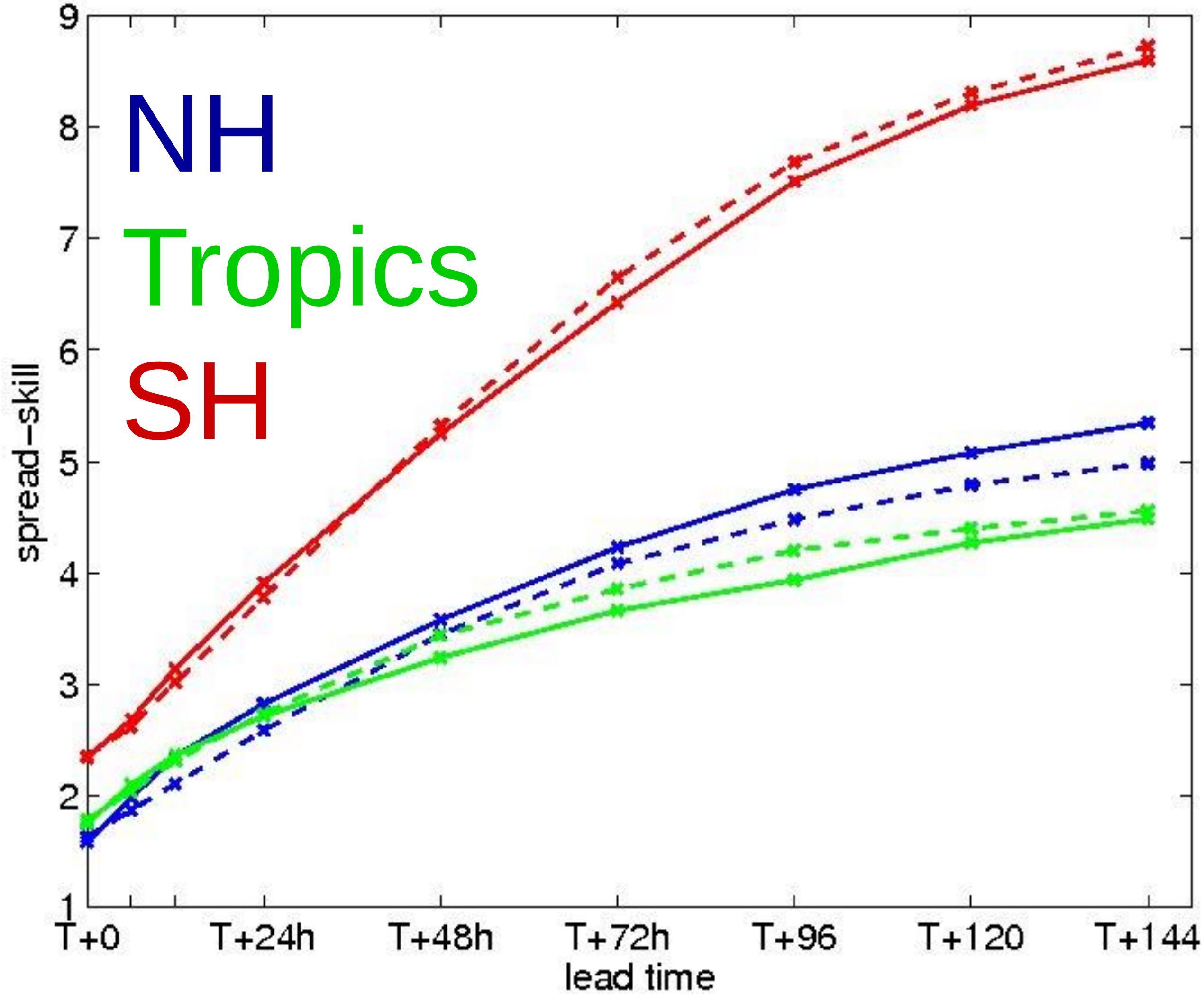
Illustrate performance in longer-range forecasts using the spread-skill verification.

Also illustrate performance in ‘climate’ integrations verified against ERA-interim.

Expect results to match Met Office reanalyses. Differences in observation use mean that there may be differences from ERA data.

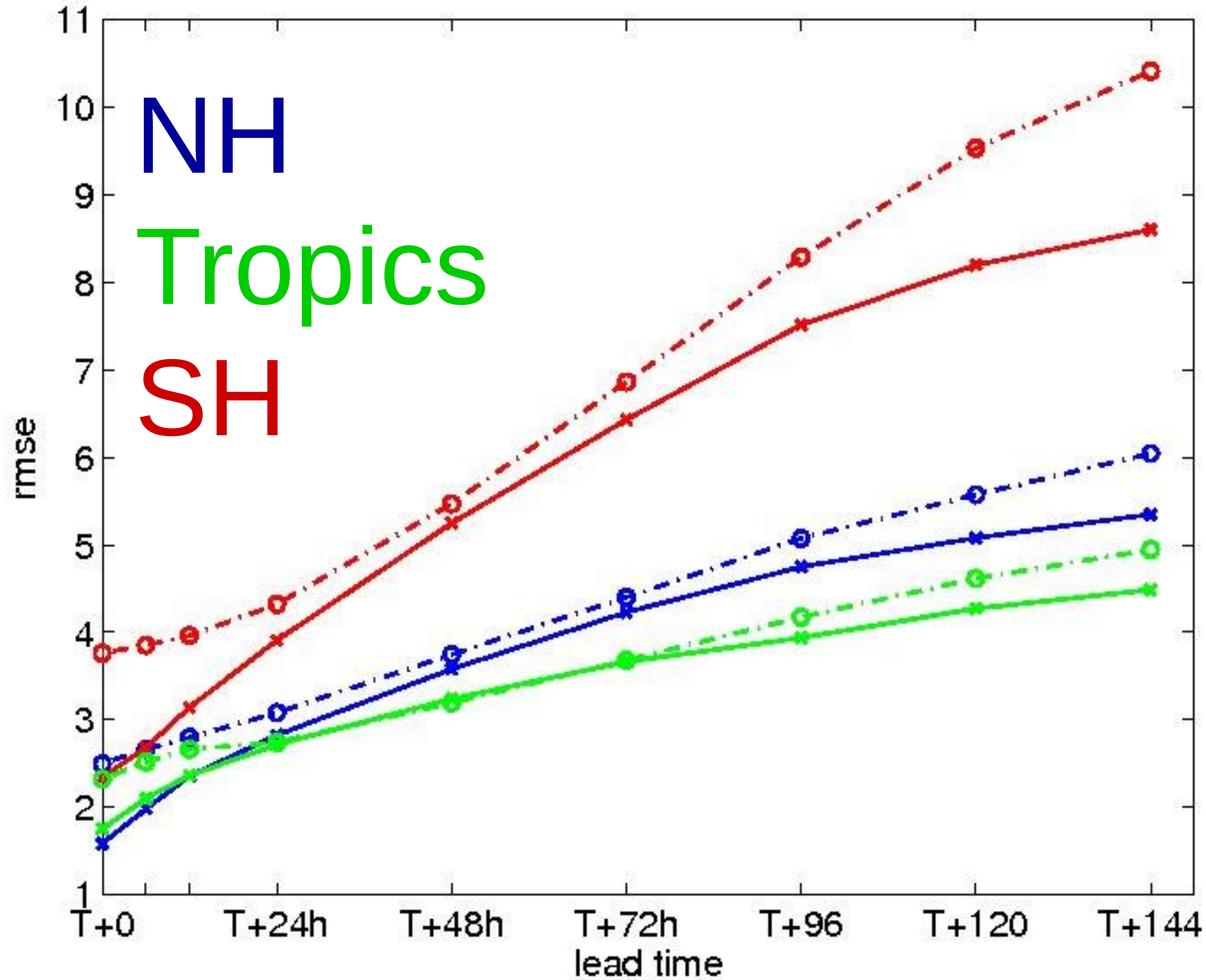
RMSE versus Spread at longer lead times

Solid: RMSE
Dashed: spread
u@850 hPa



Ensemble mean vs deterministic RMSE

Solid:
ens mean
Dash-dot:
control
u@850 hPa



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

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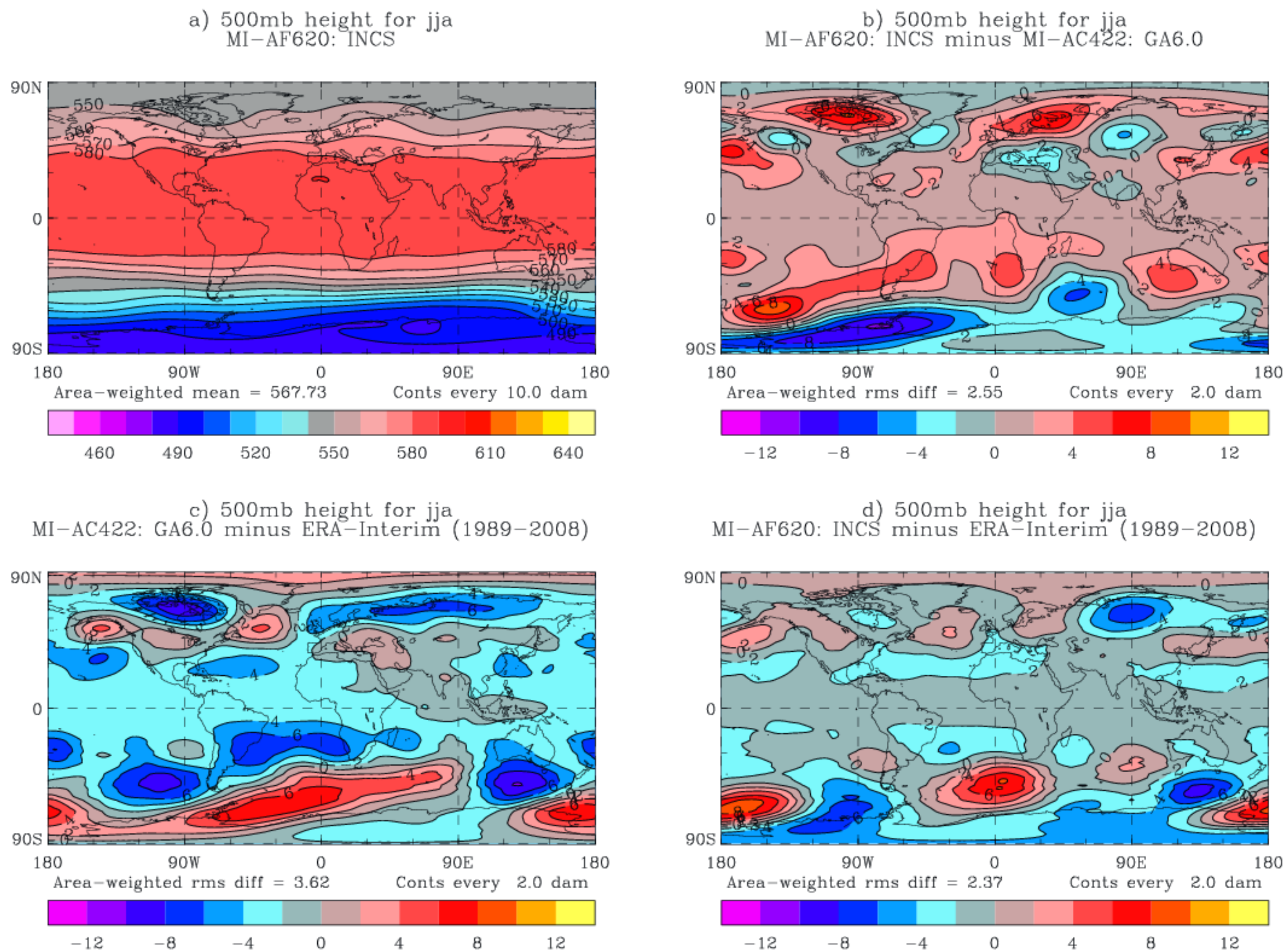
Model resolution 125 km

34% better



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

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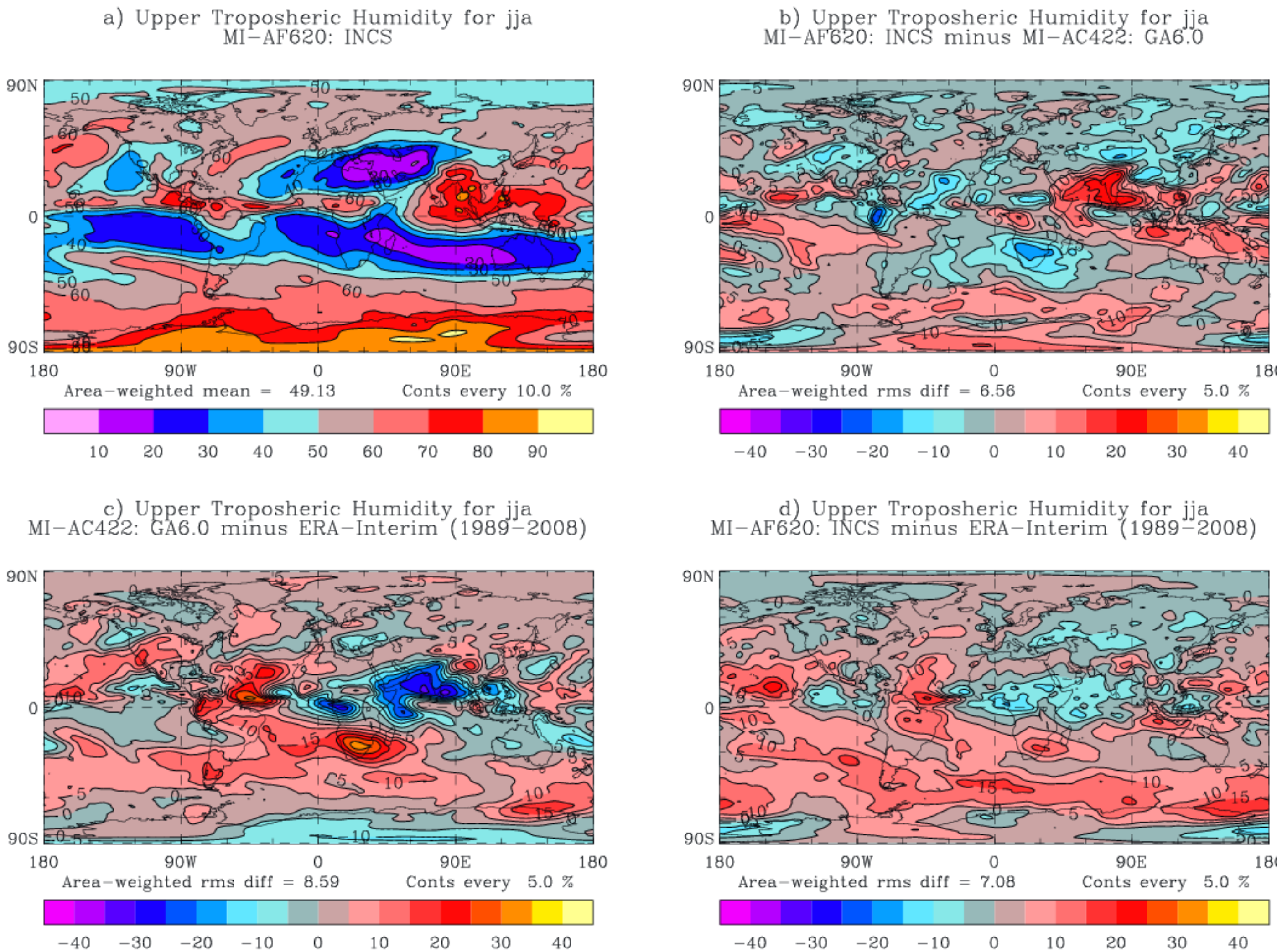
Model resolution 125 km

Tropical tropopause bias:
17% better



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Comparison with physically based stochastic forcing

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 model error forcing derived from data assimilation?

- ➢ MOGREPS-15 (same initial conditions)
- ➢ Verification against observations

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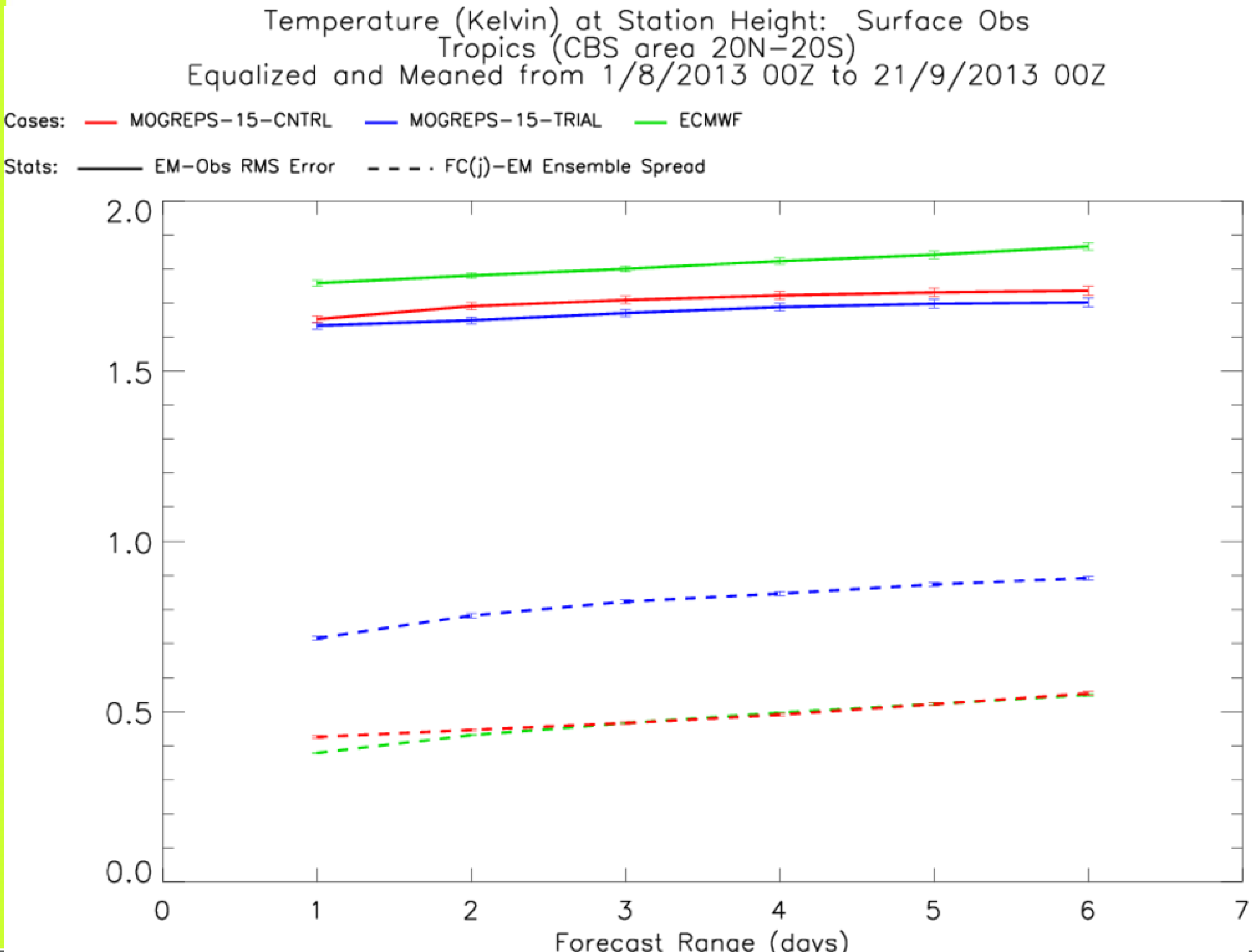
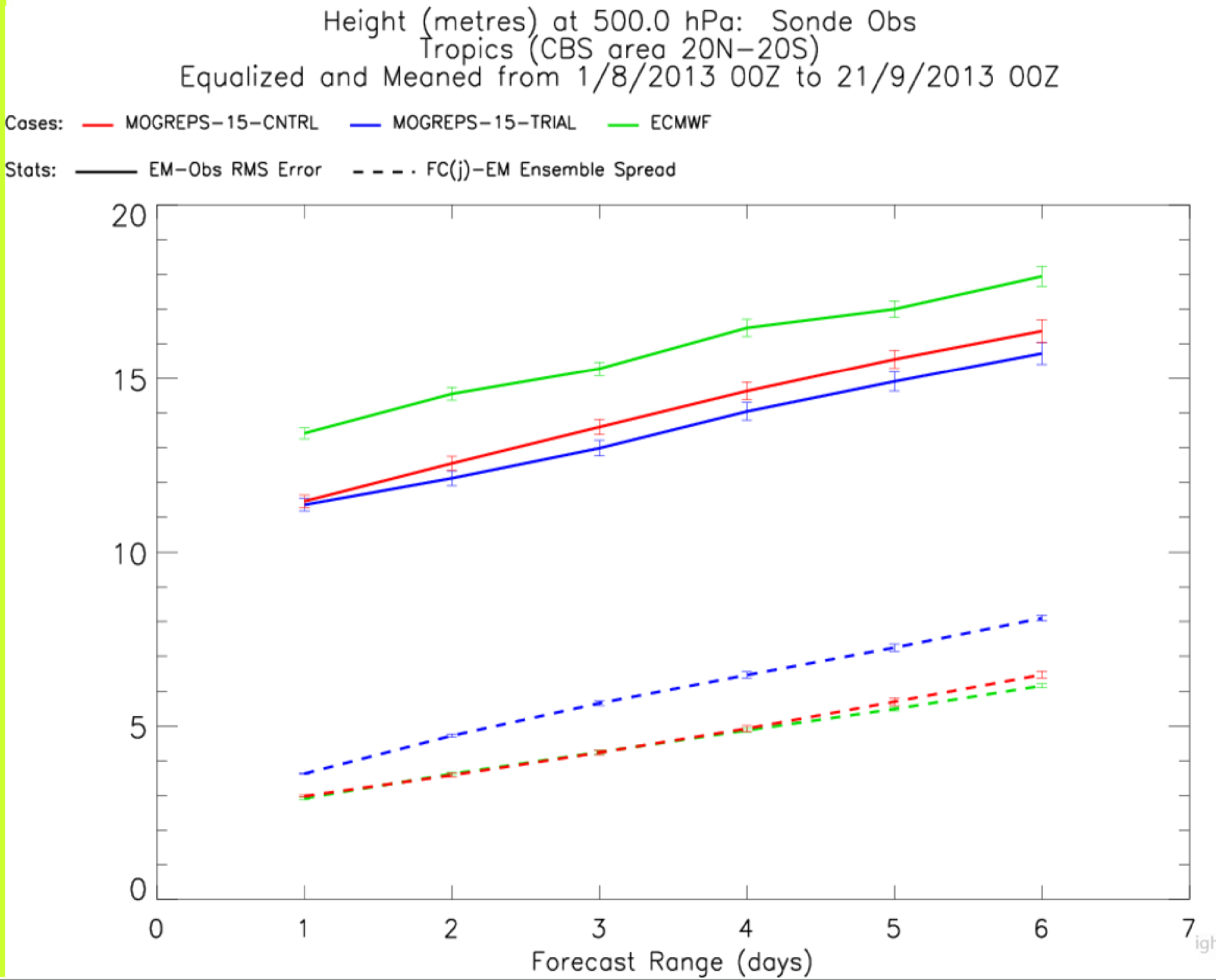
MOGREPS-15 (ND N216L85)
Surface temperature - tropics



Resolution:
EC 31 km
MO 60 km

MOGREPS-15 (ND N216L85)
height at 500 hPa - tropics



EC 31 km
MO 60 km

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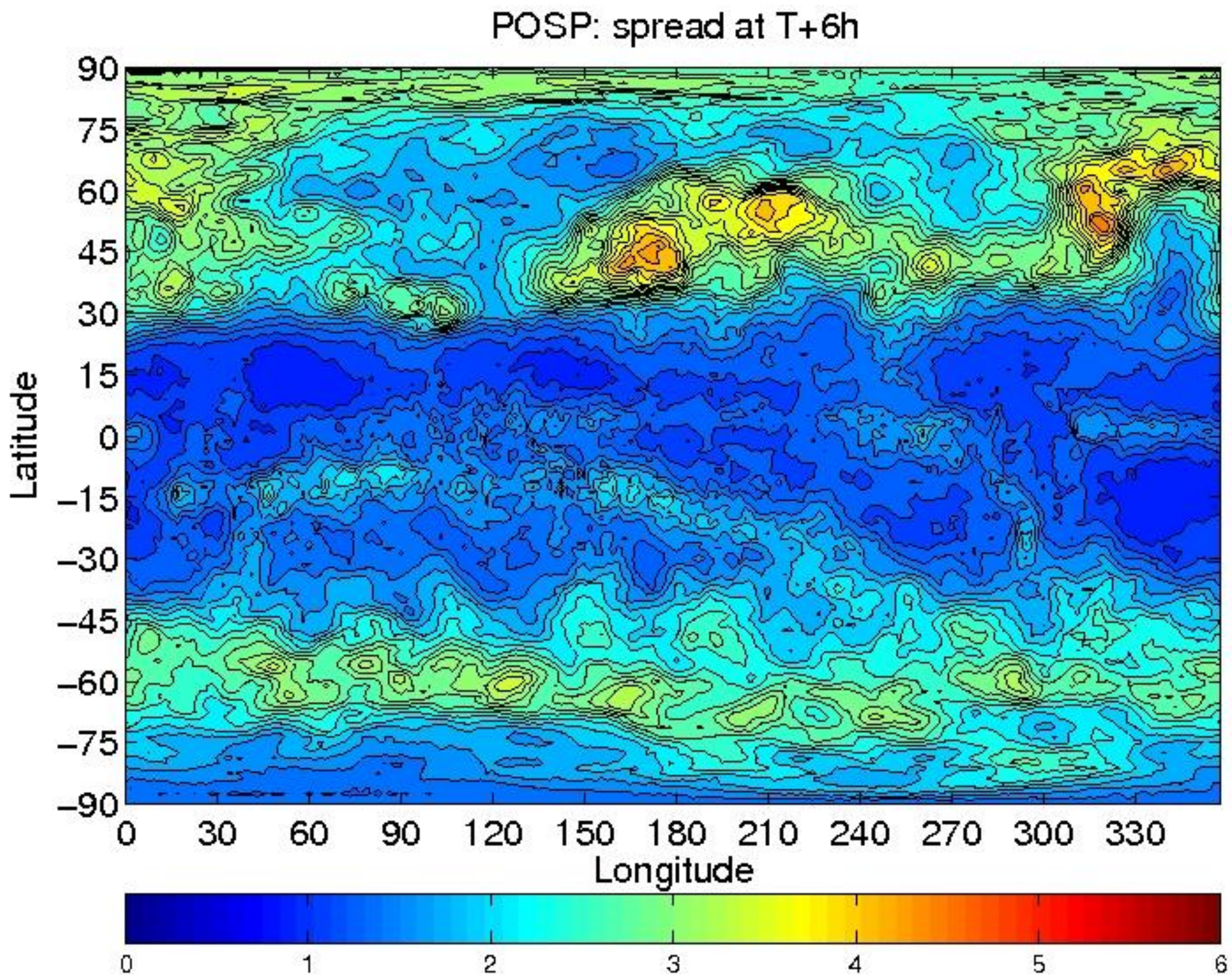
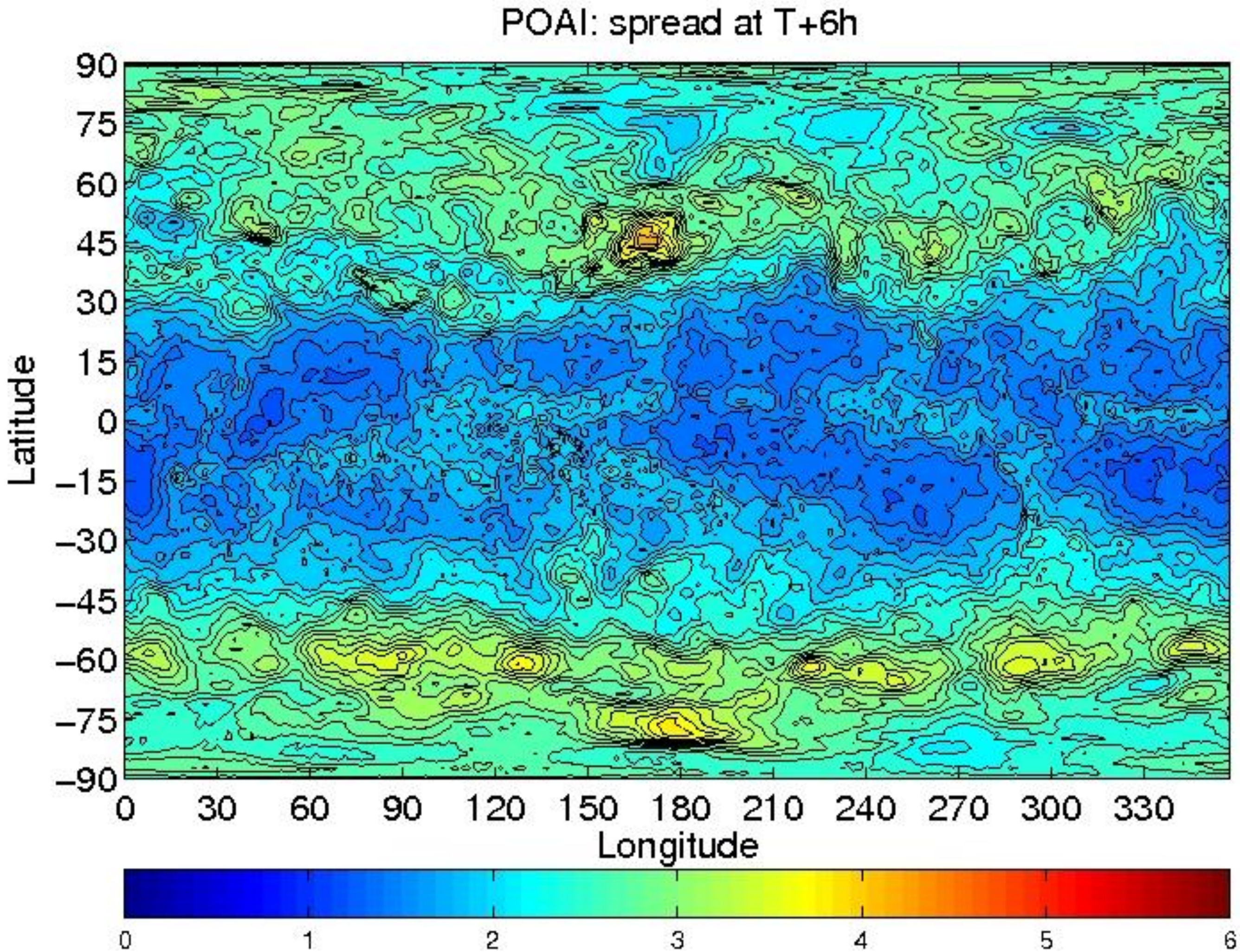
Geographical variation of spread at T+6 h (stochastic physics)

Example taken from lower resolution tests (N96, 125km)

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



Geographical variation of spread at T+6 h (analysis increments)



The data assimilation derived model error forcing picks up the NH storm track it also better represents the error in the SH.

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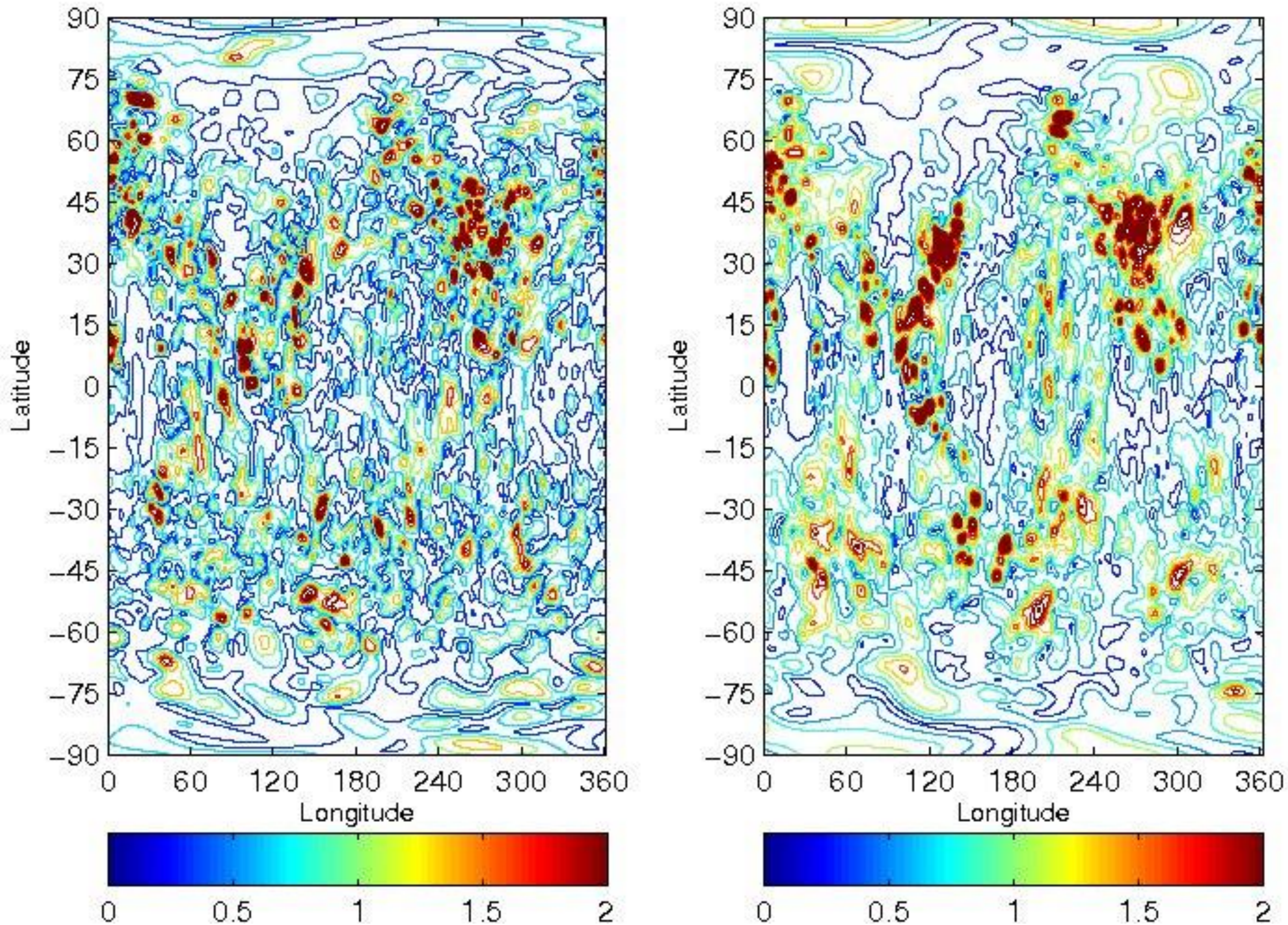
Further issues

Further issues

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

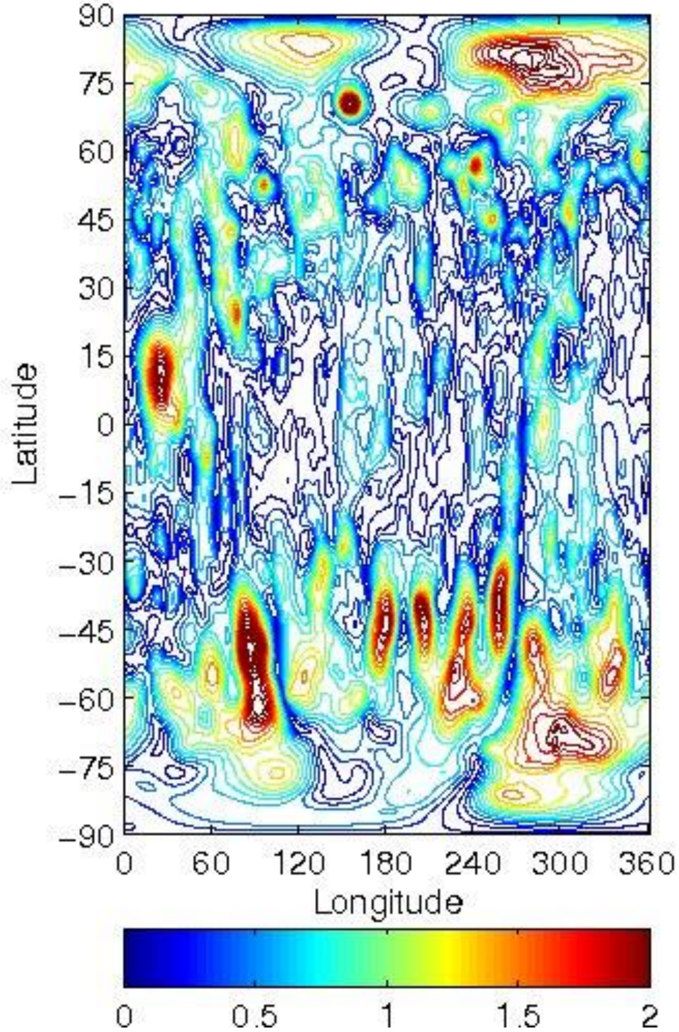
The results shown use a new random forcing term every 6 hours. Probably the time correlation of the analysis increments should be allowed for.

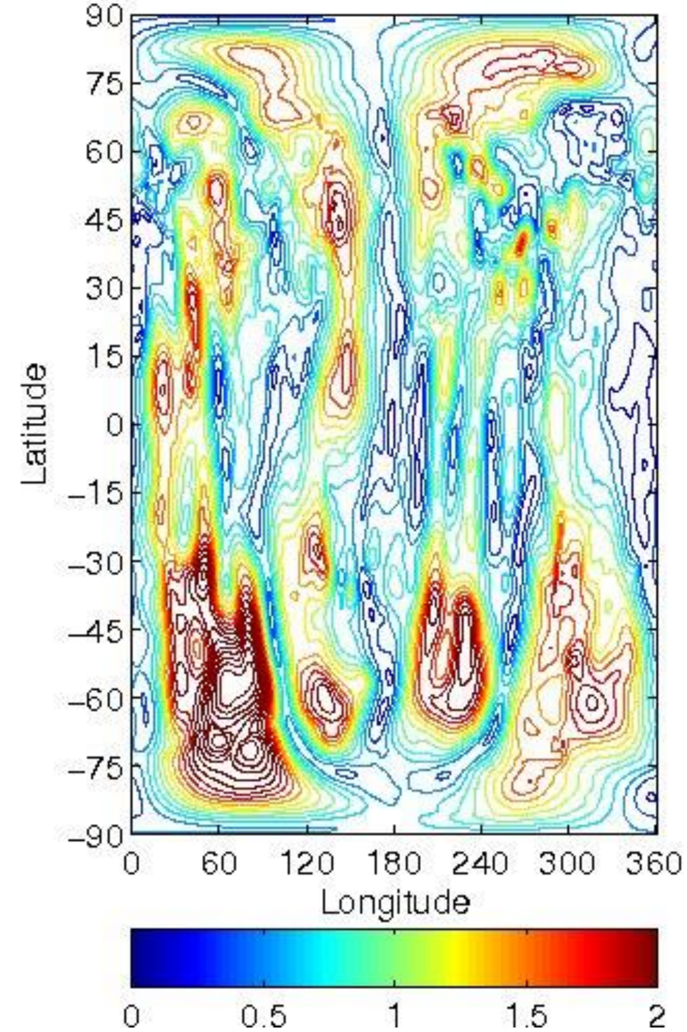
Compare strong and weak constraint analysis increments (u at 850 hPa)



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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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.

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

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Any questions?
Thank you for your attention