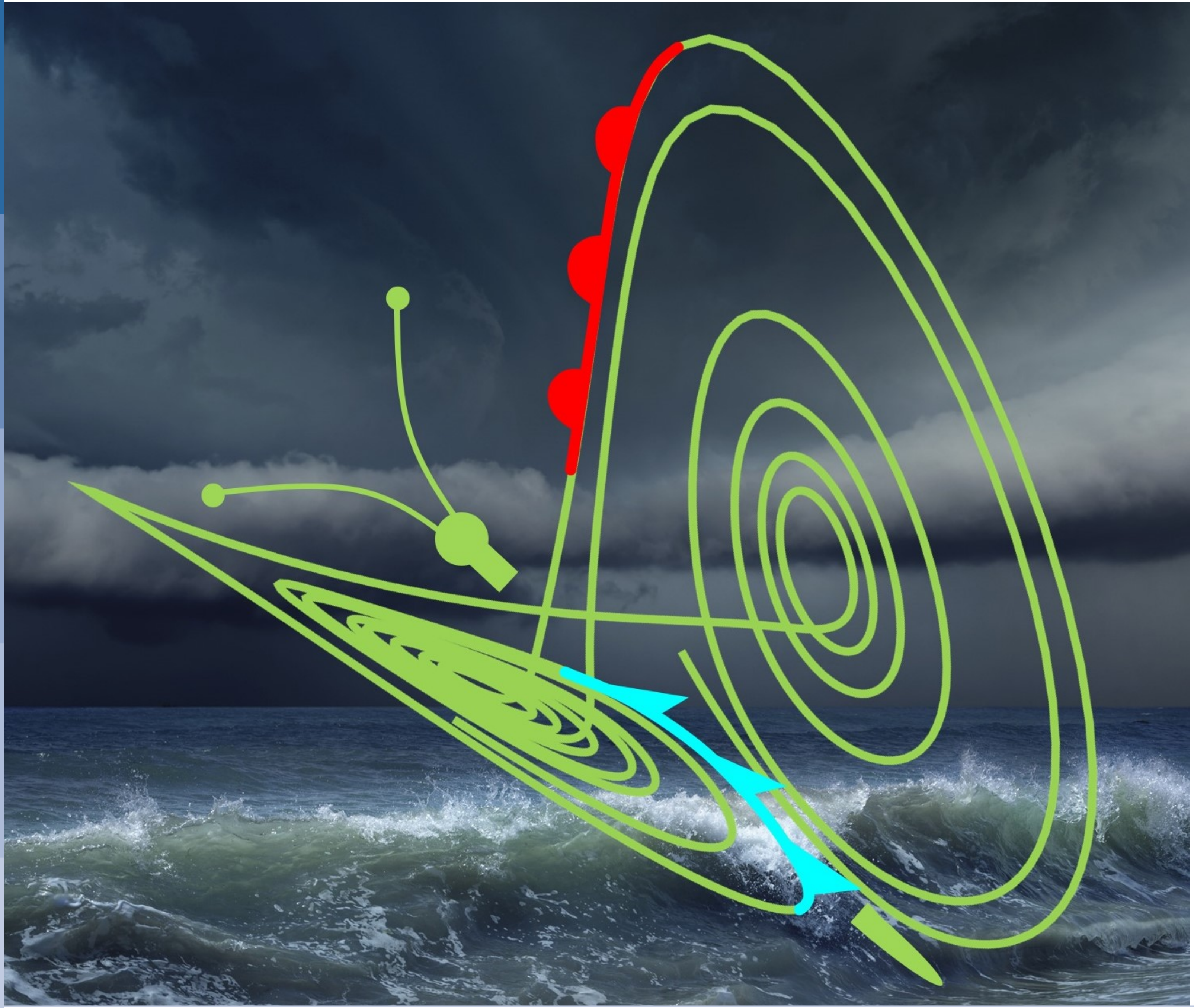


Flow-dependent reliability: A practical route to more skilful ensemble forecasts

Mark Rodwell

With

David Richardson
Heini Wernli
Dave Parsons
Simon Lang … and many others

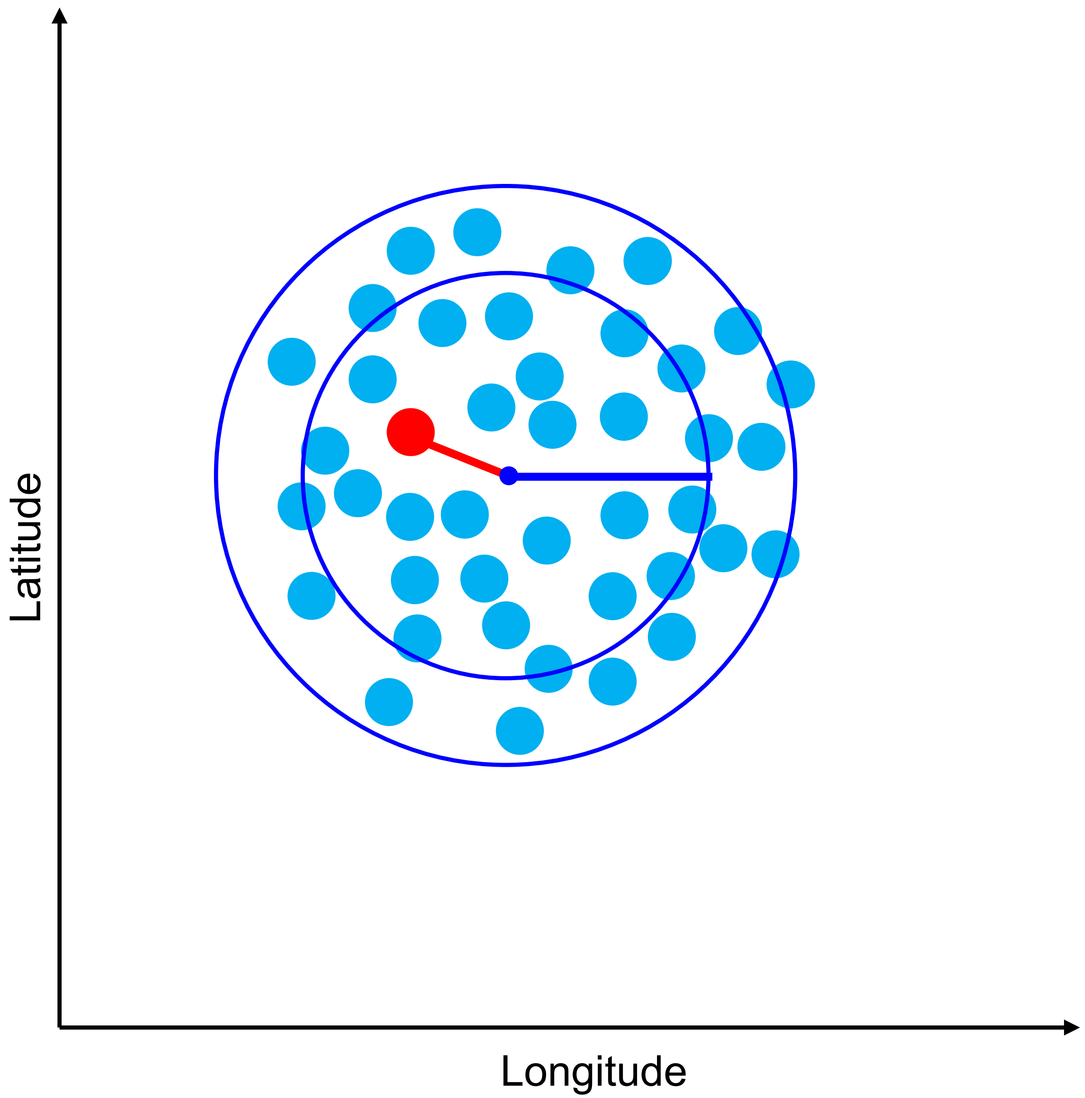
5th WGNE workshop on systematic errors in weather and climate models

21 June 2017
Montréal, Canada

mark.rodwell@ecmwf.int

Forecast reliability

Ensemble forecast of storm location



In a "**reliable**" forecast system, the truth can be considered as another ensemble member

Reliability is very useful: if we predict an event with probability 70%, it will happen with frequency 70%

A testable consequence of reliability is that:

average Error = average Spread

(averaged over many forecast start dates)

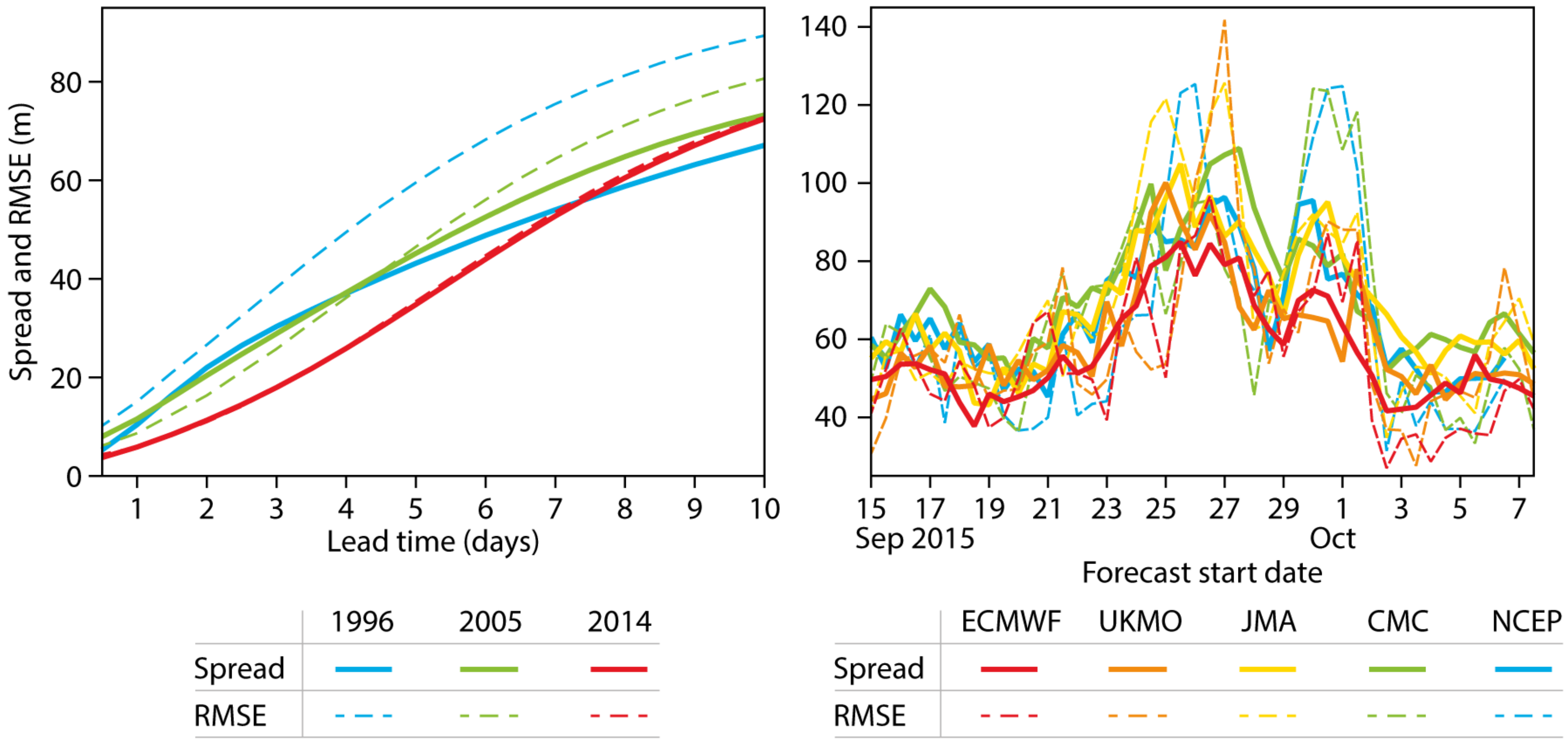
Given we had a reliable system, progress would be …

Predicting "**sharper**" (tighter) distributions **while retaining reliability**

Ensemble spread and error

Z500

Rodwell 2016, ECMWF Newsletter



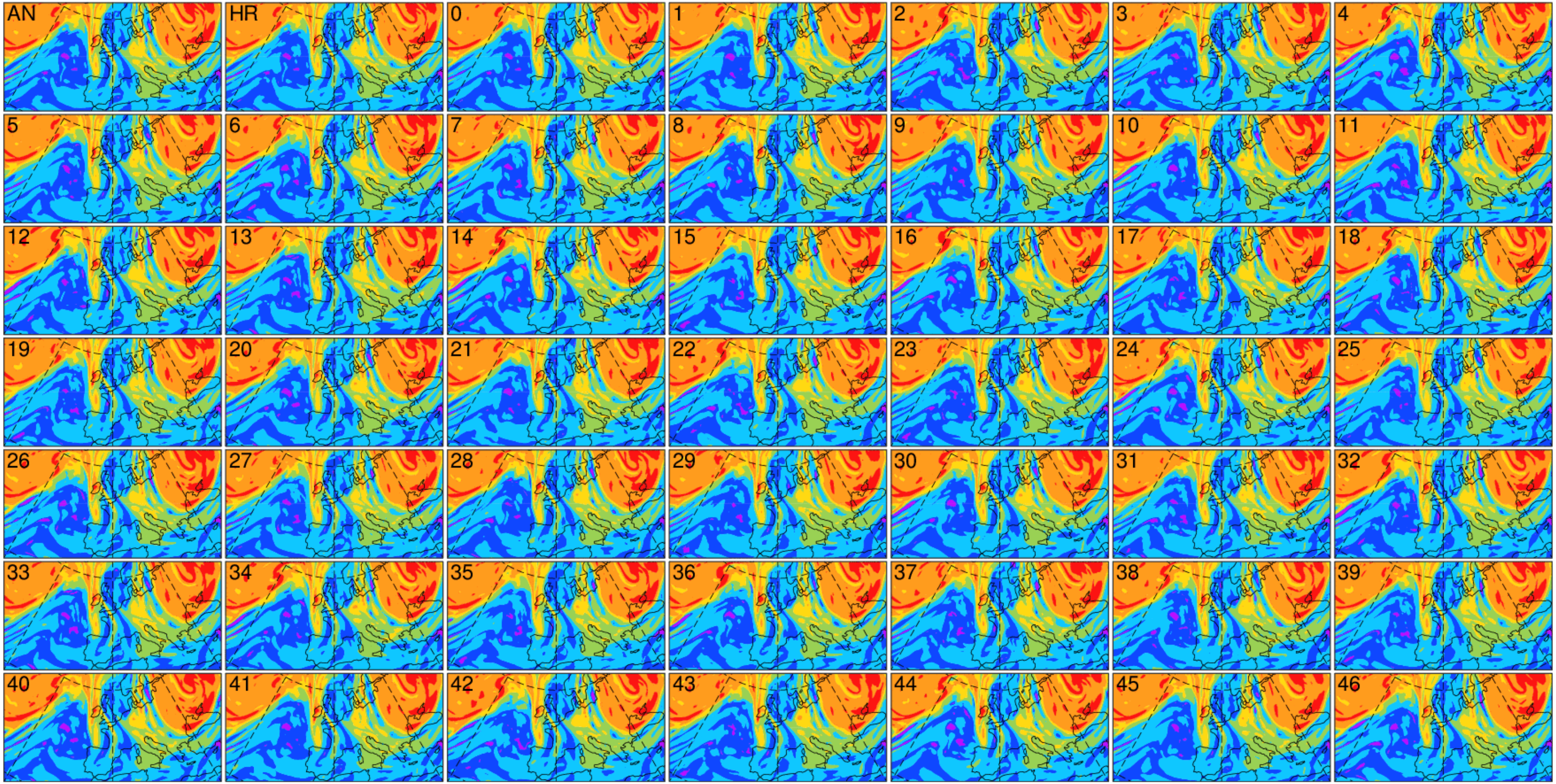
In 1996, Spread ≈ RMSE to D+2 due to Singular Vector (SV) initial perturbations. Since then, Error and Spread have converged and reduced throughout forecast range due to improved observations, model, representation of observation and model uncertainty, and introduction of Ensemble of Data Assimilations (EDA); allowing weaker SV perturbations

… but uncertainty varies from day-to-day. The real reason we make ensemble forecasts. What causes this, and how can we evaluate it in our forecasts?

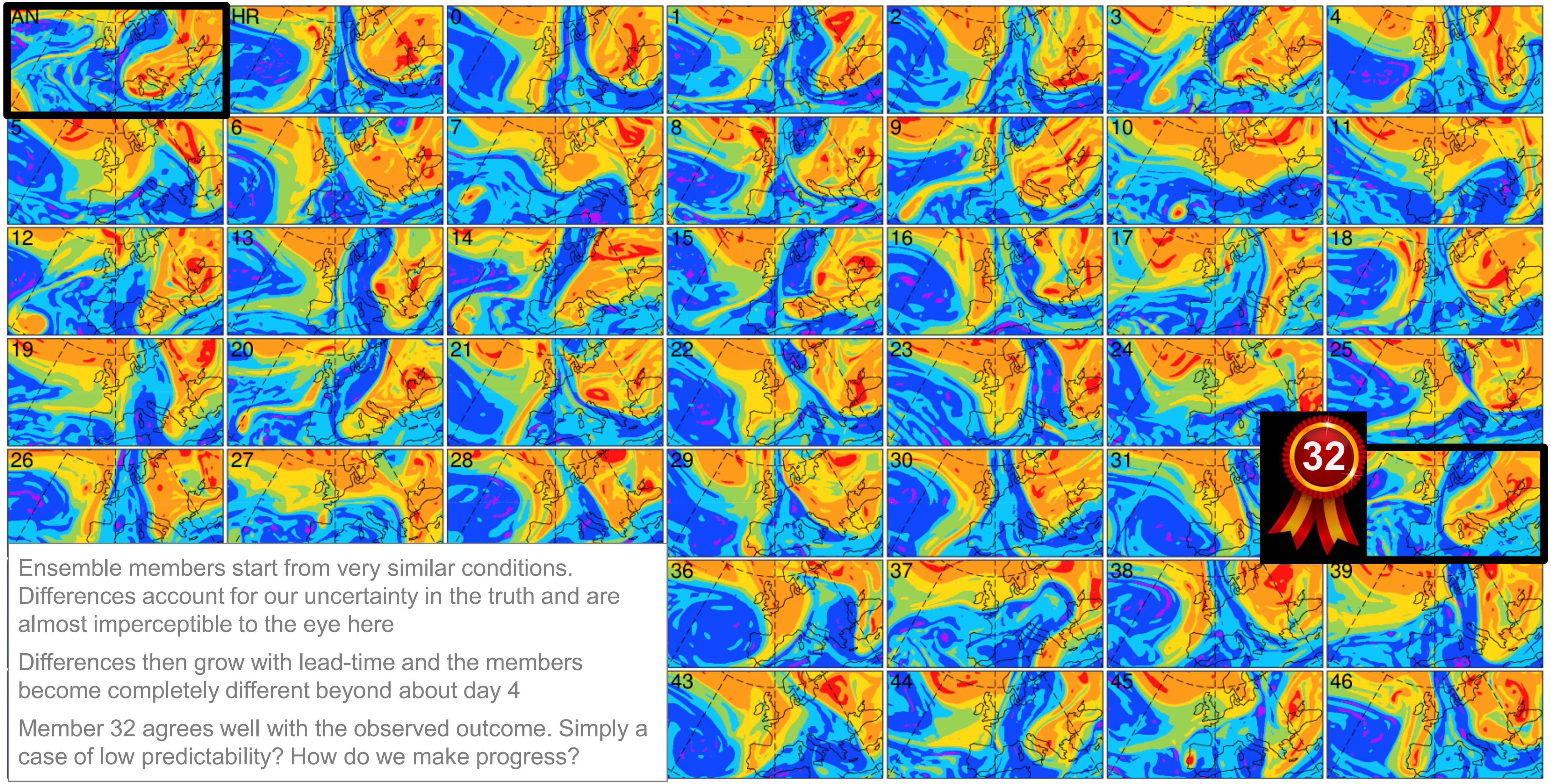
500 hPa geopotential height (Z500). "Error" is RMS of ensemble-mean error

Spread = ensemble standard deviation (scaled to account for finite ensemble size)

Potential Vorticity on the Potential Temperature = 320K surface. 20110410 0 UTC. Step (days, hours) = 0 00.0



Potential Vorticity on the Potential Temperature = 320K surface. 20110410 0 UTC. Step (days, hours) = 6 00.0

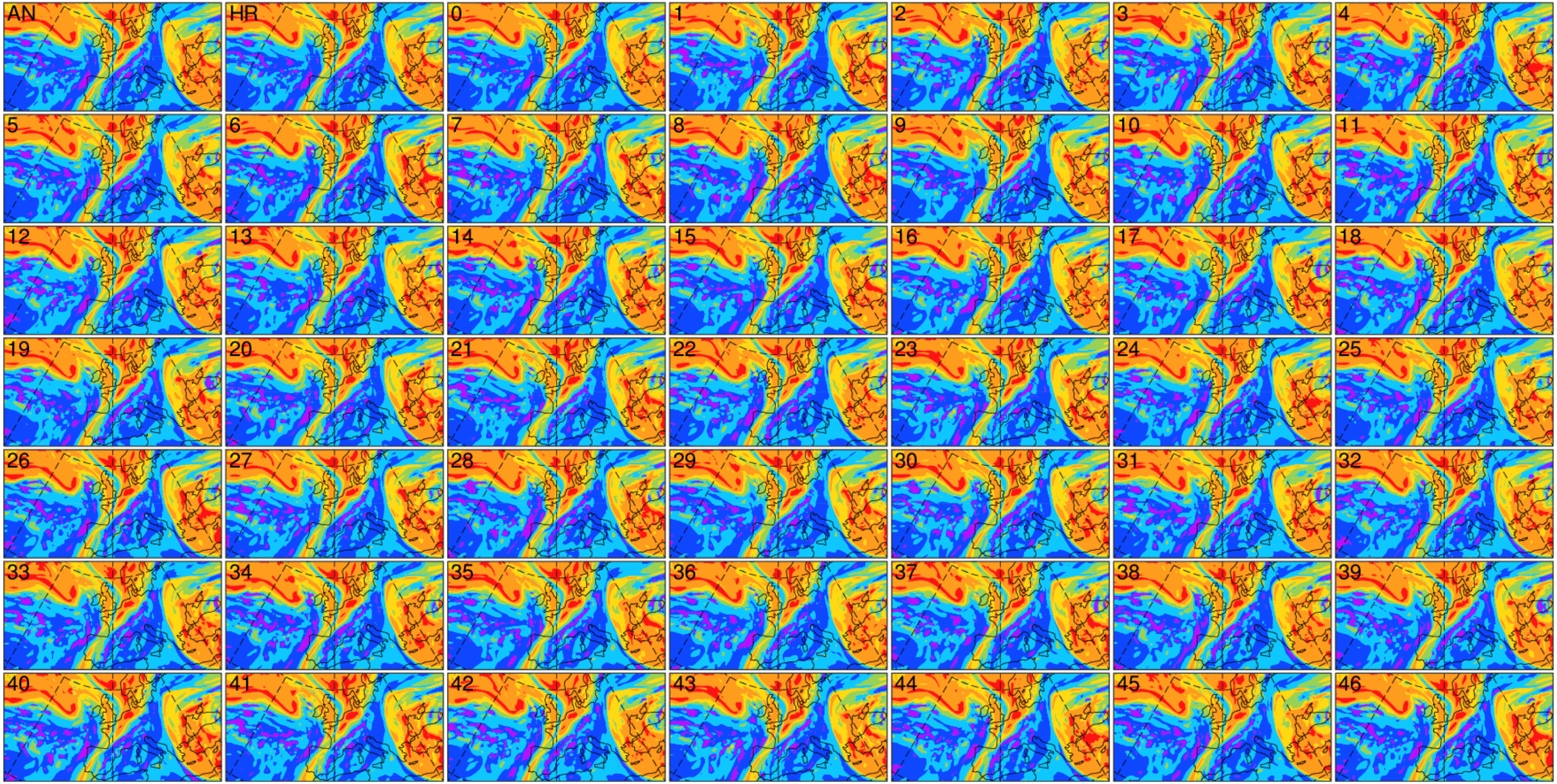


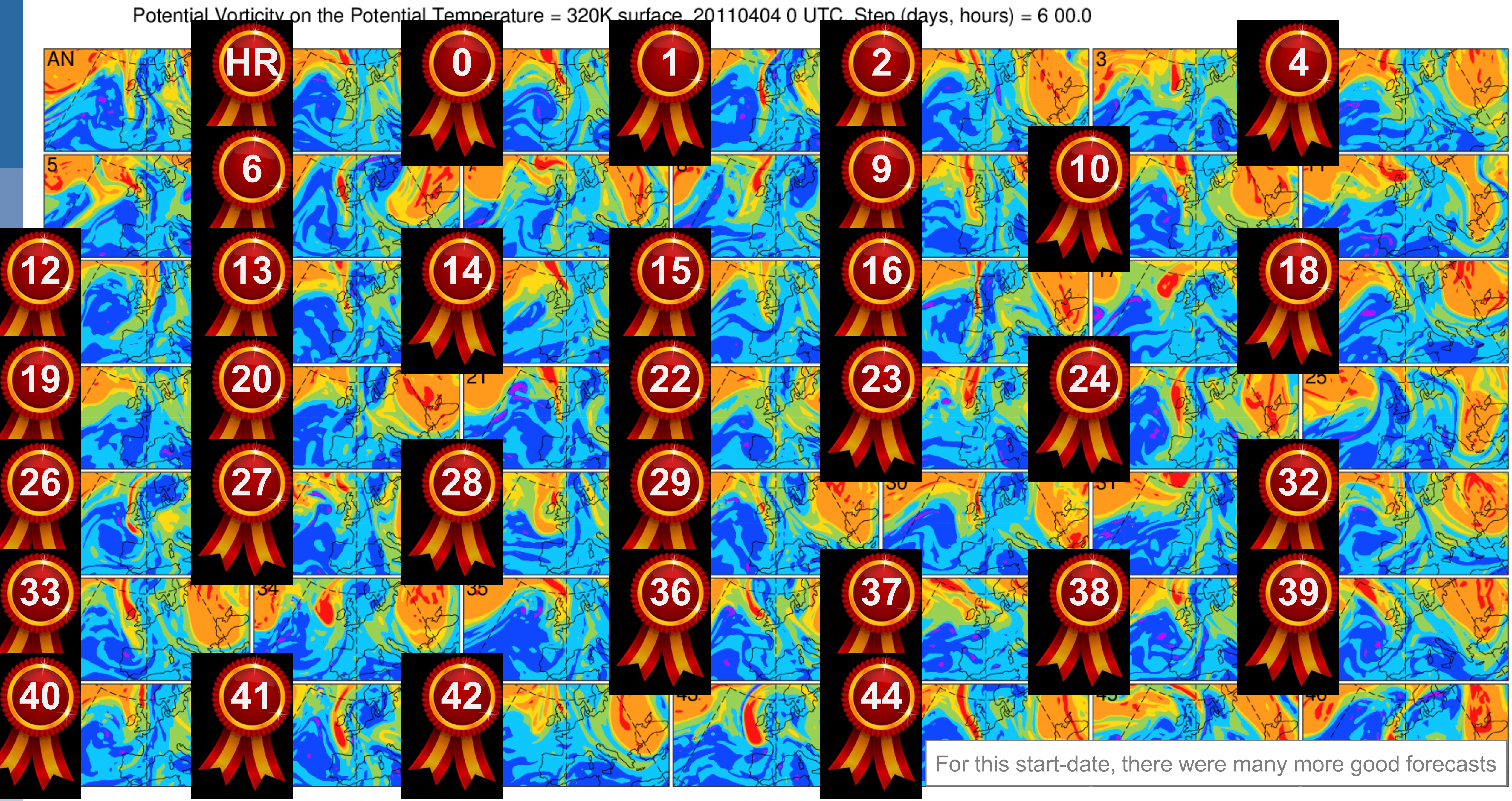
Ensemble members start from very similar conditions. Differences account for our uncertainty in the truth and are almost imperceptible to the eye here

Differences then grow with lead-time and the members become completely different beyond about day 4

Member 32 agrees well with the observed outcome. Simply a case of low predictability? How do we make progress?

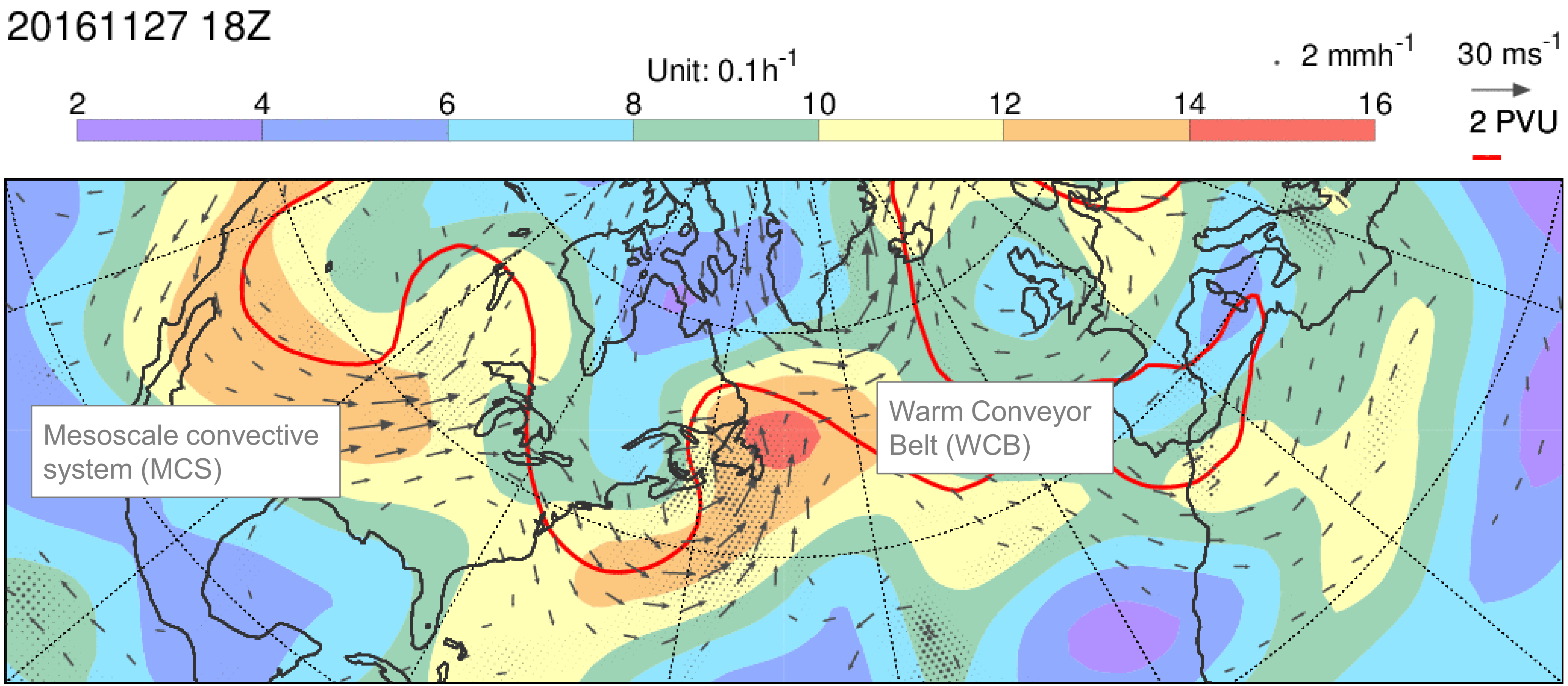
Potential Vorticity on the Potential Temperature = 320K surface. 20110404 0 UTC. Step (days, hours) = 0 00.0





For this start-date, there were many more good forecasts

Animation of v_{850}, Total precip., PV_{315}=2 (tropopause), $\hat{\sigma}_{PV_t}/\hat{\sigma}_{PV}$ (tendency uncertainty)



Ensembles represent the integral of instantaneous uncertainty growth-rate; would like to diagnose deficiencies in the instantaneous growth-rate

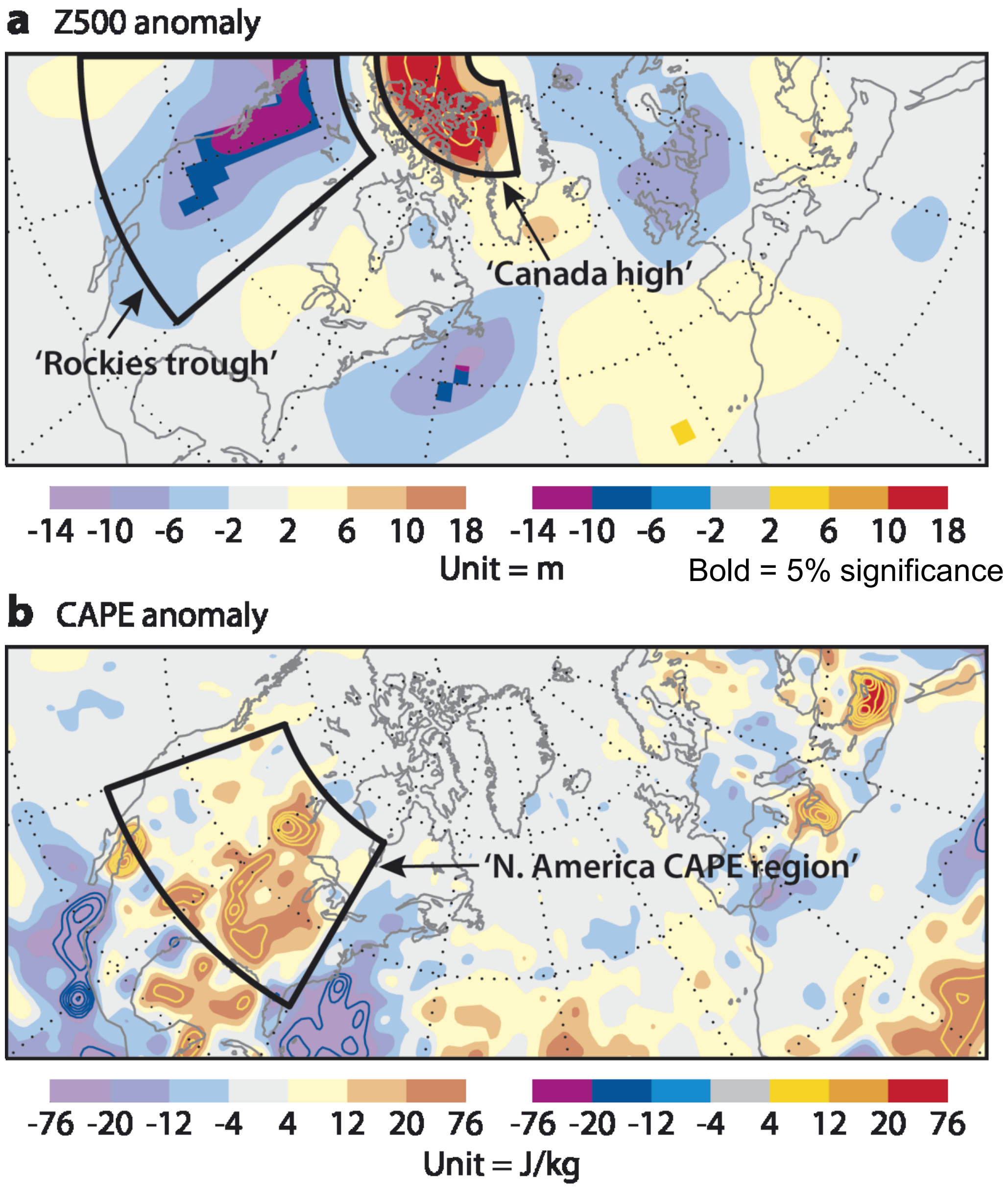
Here consider 1h tendencies in EDA background forecasts. Filter to T21, 1d to emphasise growth-rate within synoptic-scale systems

$\hat{\sigma}_{PV_t}$ used to highlight dynamical (*e.g.* baroclinic) and physical (*e.g.* stochastic) sources of uncertainty. 315K $\Rightarrow$ strong propagation in Jetstream

Results emphasise role of moist processes (MCS, WCB); intrinsic to real system or artefact of *e.g.* deficiencies in model uncertainty? Key question

Average initial conditions of 584 single forecast “busts” over Europe at day 6

Rodwell et al, 2013, BAMS



Trough over the Rocky mountains, with high convective potential ahead

Conducive to the formation of mesoscale convection

Interesting flow regime to evaluate ‘instantaneous’ uncertainty growth-rate

(Using different set of dates to avoid misleading results)

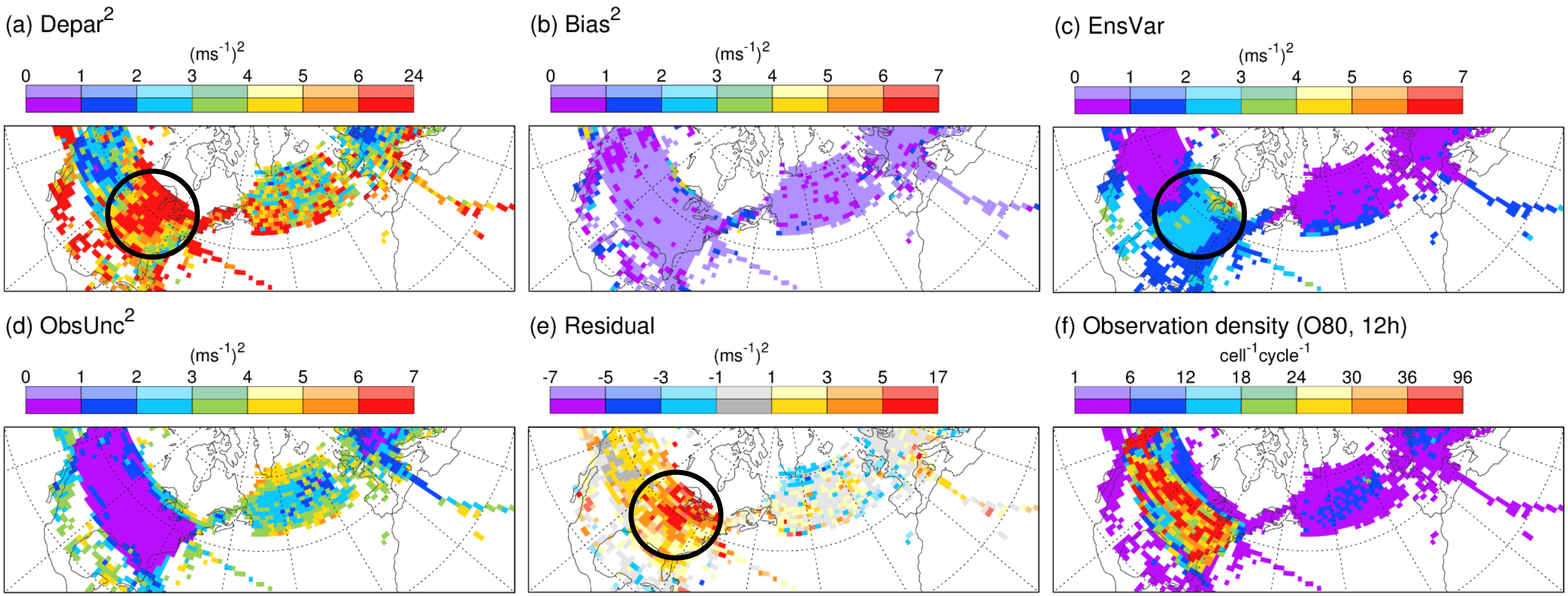
‘CAPE’ = Convective Available Potential Energy

Short-range variance assessment for u200 in "trough/CAPE" situations using EDA

54 cases

Relative to aircraft west-east wind observations at 200hPa (±15)

Rodwell 2016, ECMWF Newsletter



Enhanced uncertainty (EnsVar) around the Great Lakes / Mississippi Region, large 'errors' ($Depar^2$)

Observation uncertainty ($ObsUnc^2$) quite small so a statistically significant positive Residual ⇒

ENS does not inject enough uncertainty into global circulation. Forecasts will be too confident

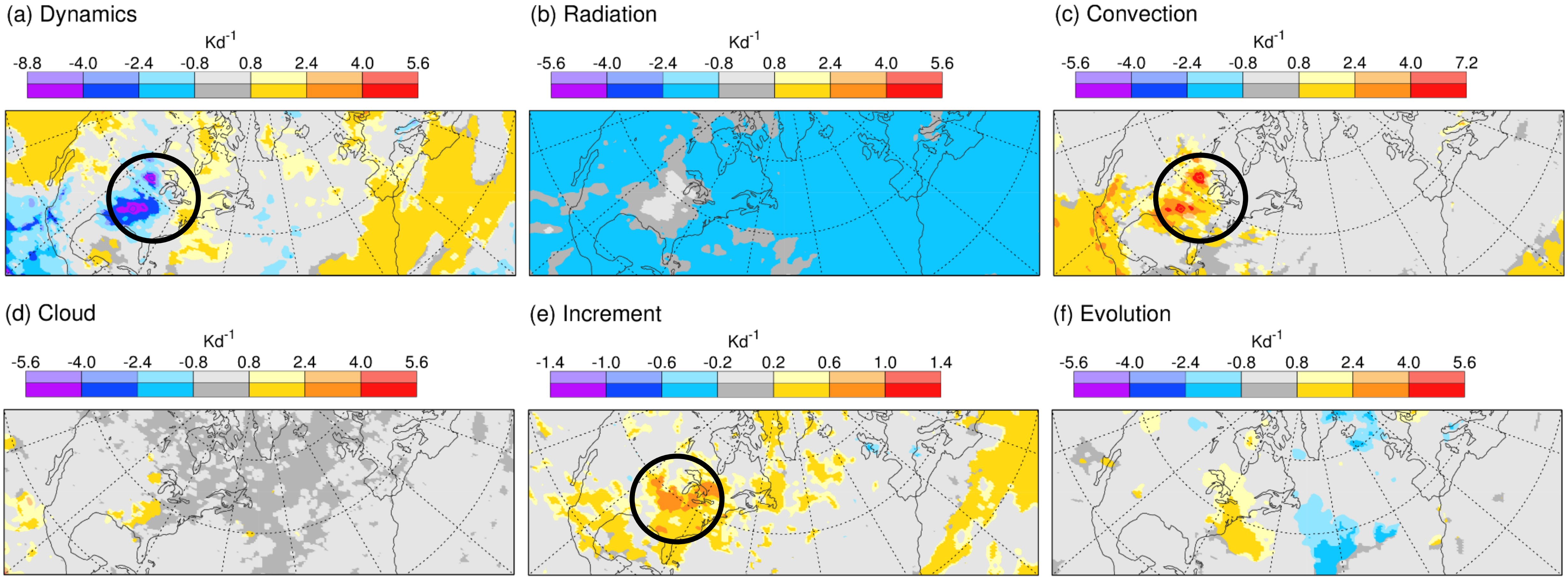
$Depar^2 = Bias^2 + Spread^2 + ObsUnc^2 + Residual$

Reliability ⇒ $\mathrm{E}[Residual]=0$

Short-range mean error assessment for T300 in “trough/CAPE” situations using DA

54 cases

Model-space process tendency and analysis increment budget



Likelihood of (mesoscale) convective heating, dynamical cooling

Cloud microphysics, ‘hole’ in radiative cooling

Statistically significant Increment implies flow-dependent model (or observation) bias

Dynamics + Radiation + Convection + Cloud + Increment ≈ Evolution

Reliability ⇒ E[Increment]=0

The Jetstream and mesoscale convection: “The piano string and hammer”

54 cases

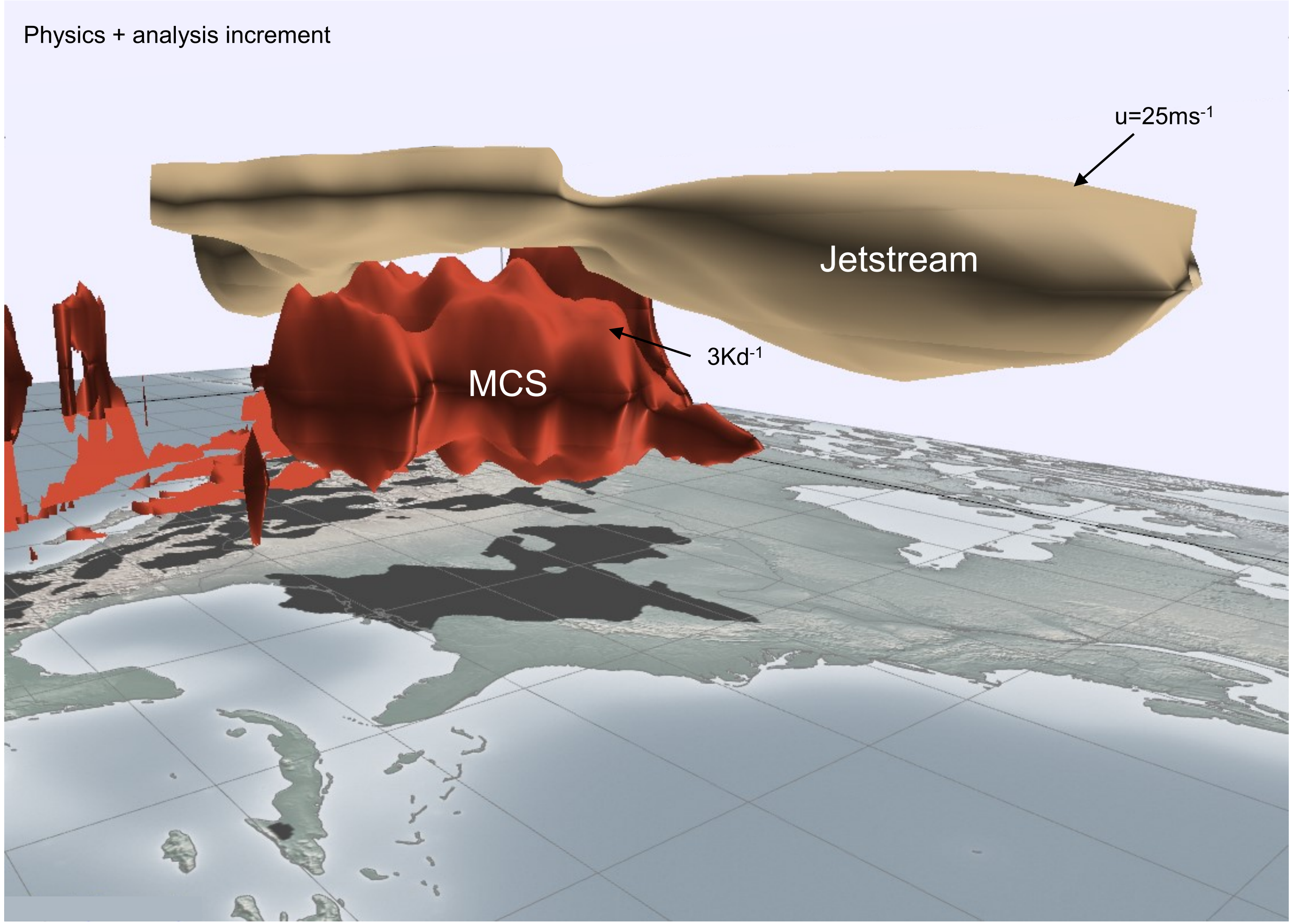
Met3D: Marc Rautenhaus

If we don’t hit the string hard enough, the wave in the string will be too weak

If we hit the string at the wrong time, the wave will arrive over Europe at the wrong time

We do not know when to press the key (mesoscale convection itself involves chaotic uncertainty)

What we want is that the ensemble members generate such convection with the “right” uncertainty

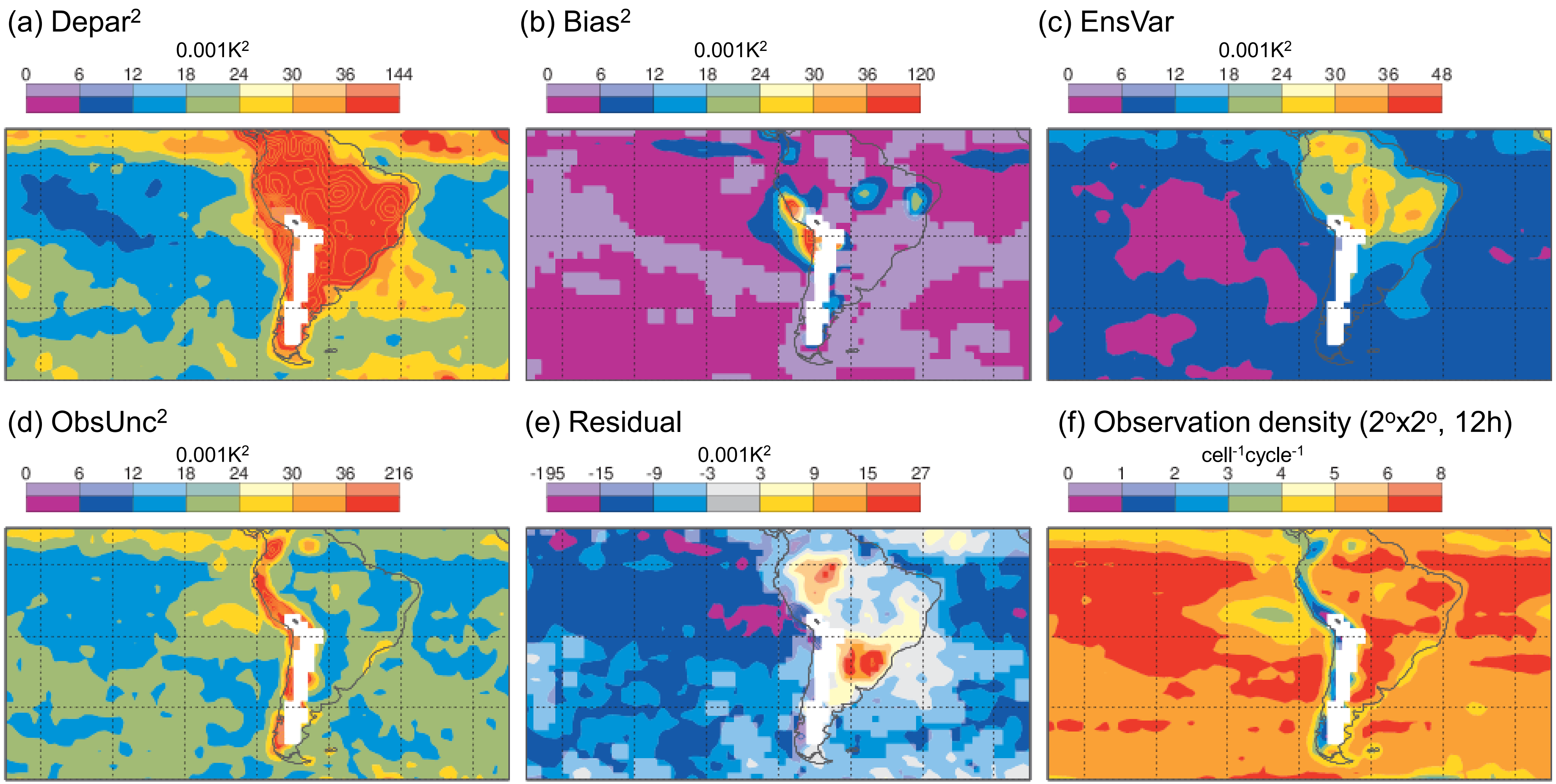


Short-range variance assessment for mid-tropospheric temperatures: Control

20110812-20111116, 2 members

Relative to AMSUA channel 5 microwave brightness temperatures

Rodwell et al, 2015, QJRMS



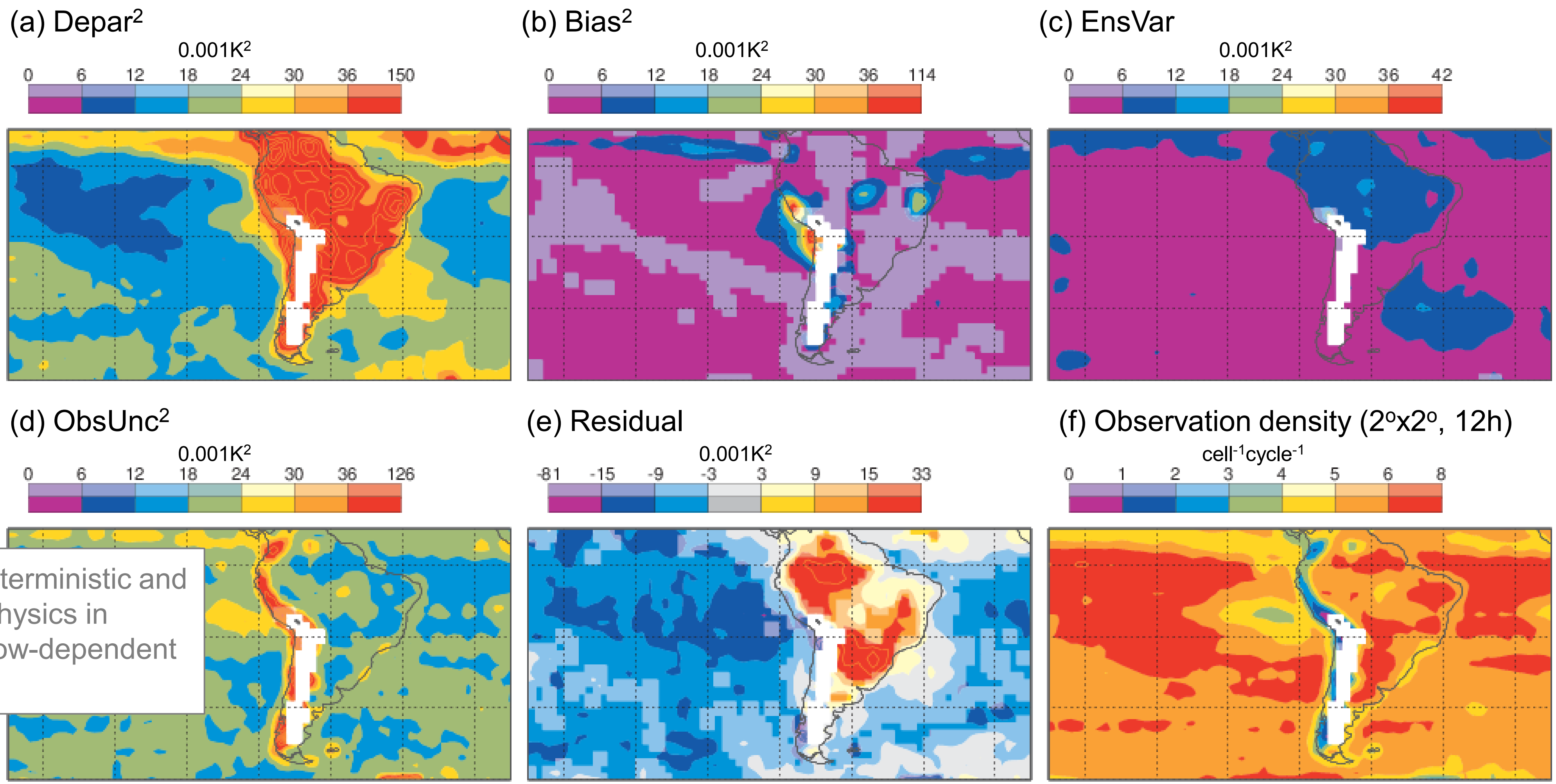
Residual suggests EnsVar underestimates (overestimates) uncertainty in convective (clear-sky) regions (and/or deficiencies in ObsUnc^2)

Short-range variance assessment for mid-tropospheric temperatures: No stoch. phys.

20110812-20111116, 2 members

Relative to AMSUA channel 5 microwave brightness temperatures

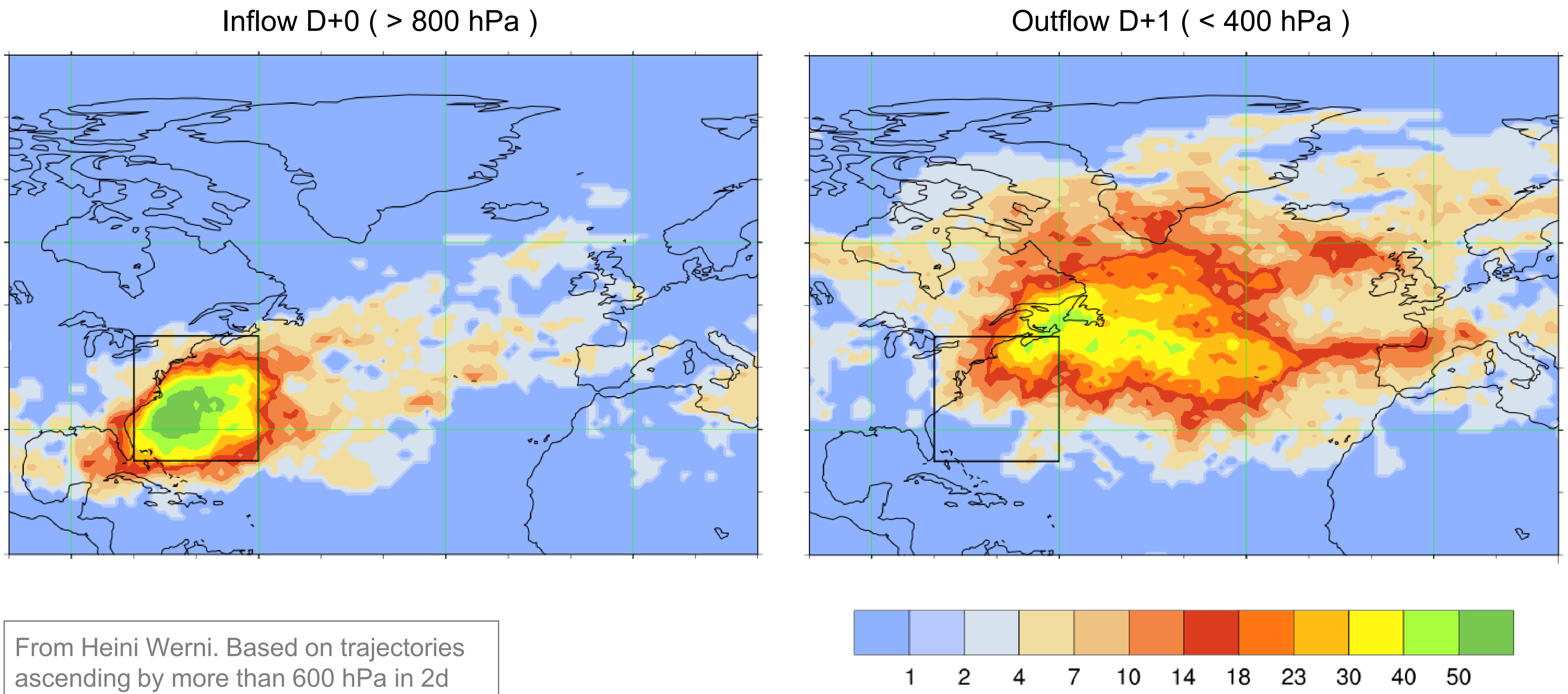
Experiments by Simon Lang



A role for deterministic and stochastic physics in improving flow-dependent reliability

EnsVar is highly sensitive to representation of model uncertainty. Turning it off deteriorates (improves) Residual in convective (clear-sky) regions

Top 50 Warm Conveyor Belt inflow events in box indicated from Nov 15 – Oct 16



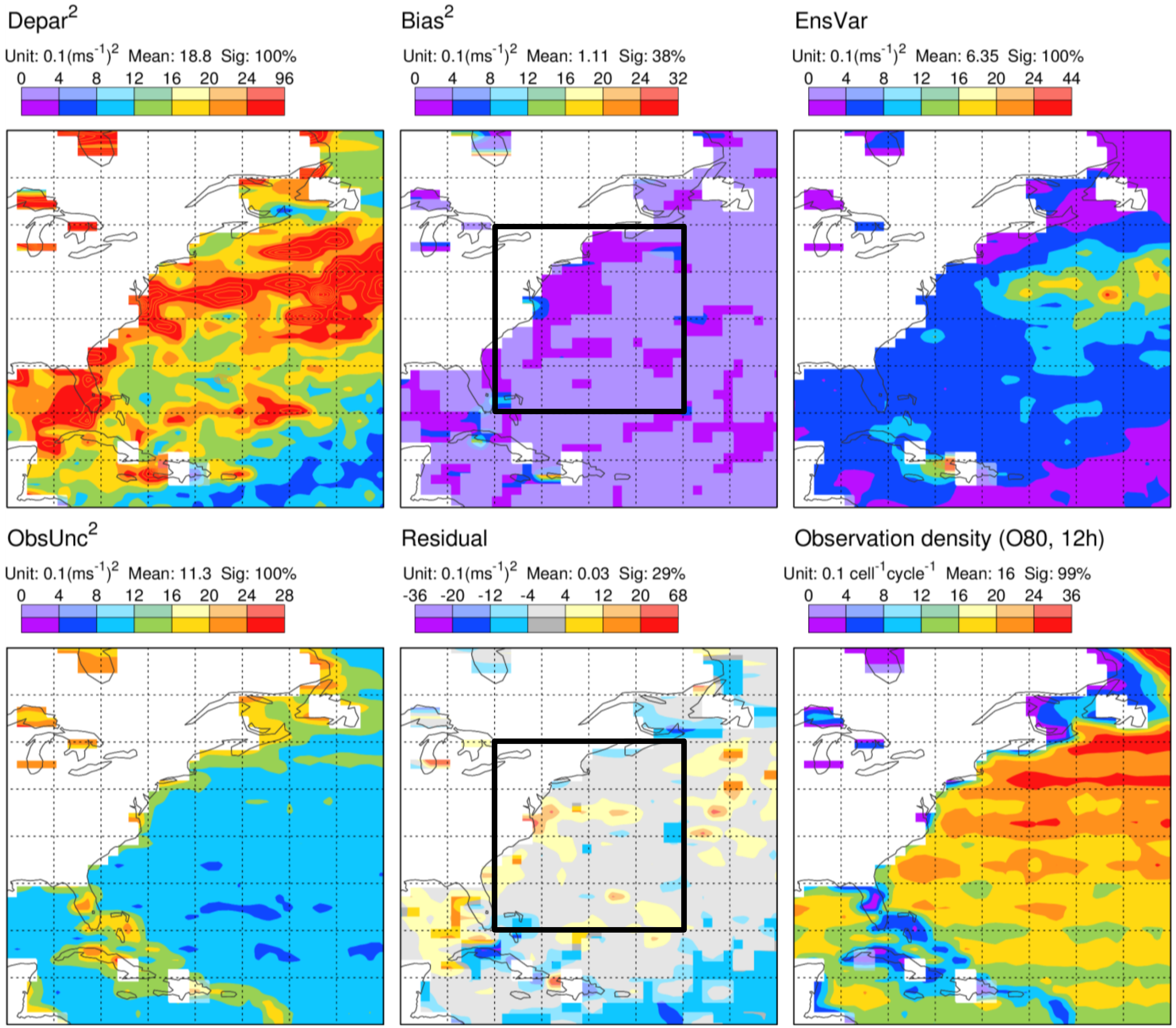
From Heini Werni. Based on trajectories ascending by more than 600 hPa in 2d

EDA variance assessment with ASCAT surface v wind: Non-WCB composite

87 cases

Bias² and Residual are not significant in absence of WCBs.

ObsUnc² a large component



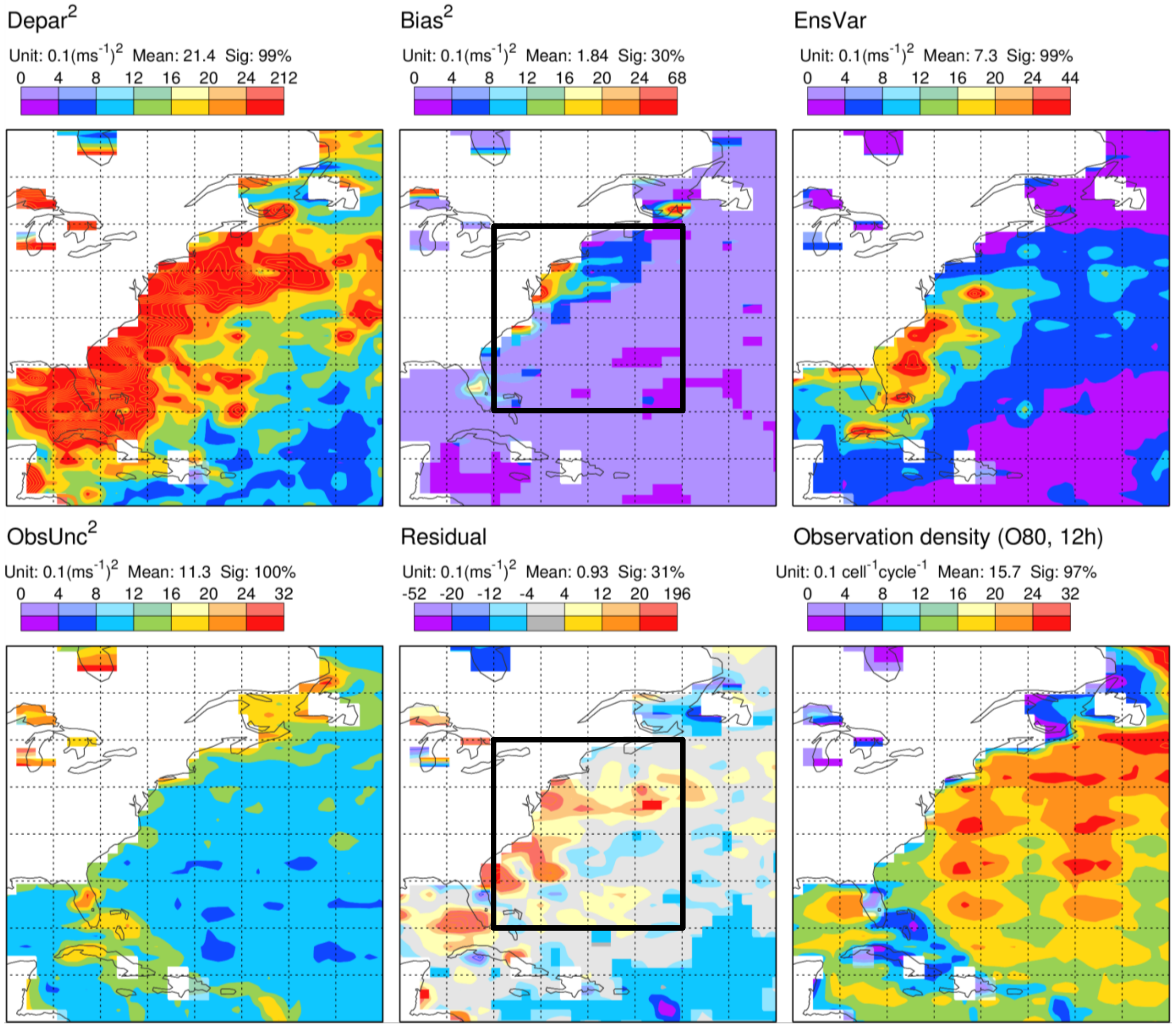
EDA variance assessment with ASCAT surface v wind: WCB (inflow) composite

50 cases

Larger EnsVar and Depar^2 so a more uncertainty situation

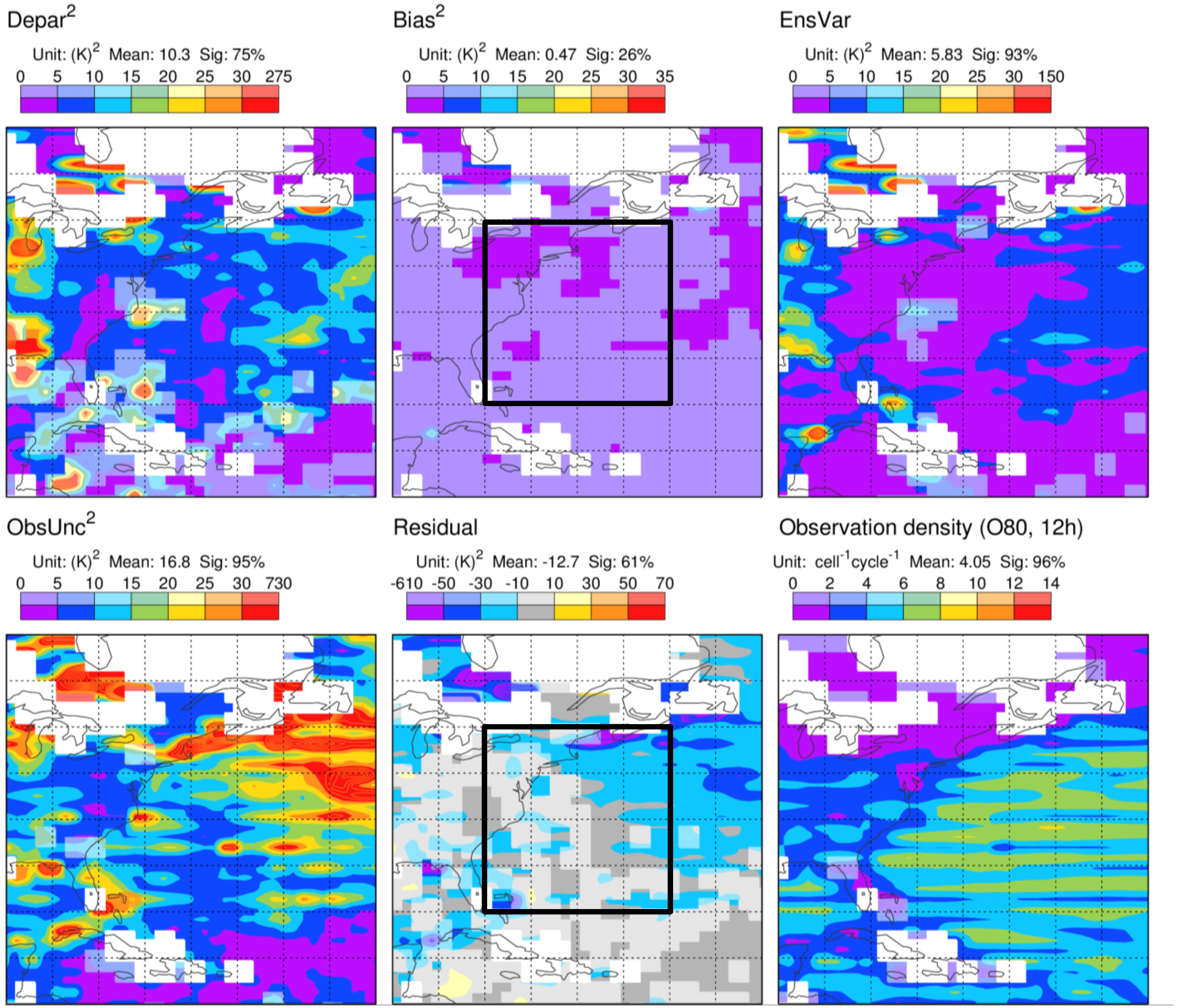
Increased Bias^2 (first moment error)

Positive Residual but not significant: possibly insufficient spread associated with cyclogenesis, or underestimation of observation uncertainty within the WCB region?



EDA variance assessment with MHS “all sky” mid-tropospheric humidity: Non-WCB

87 cases

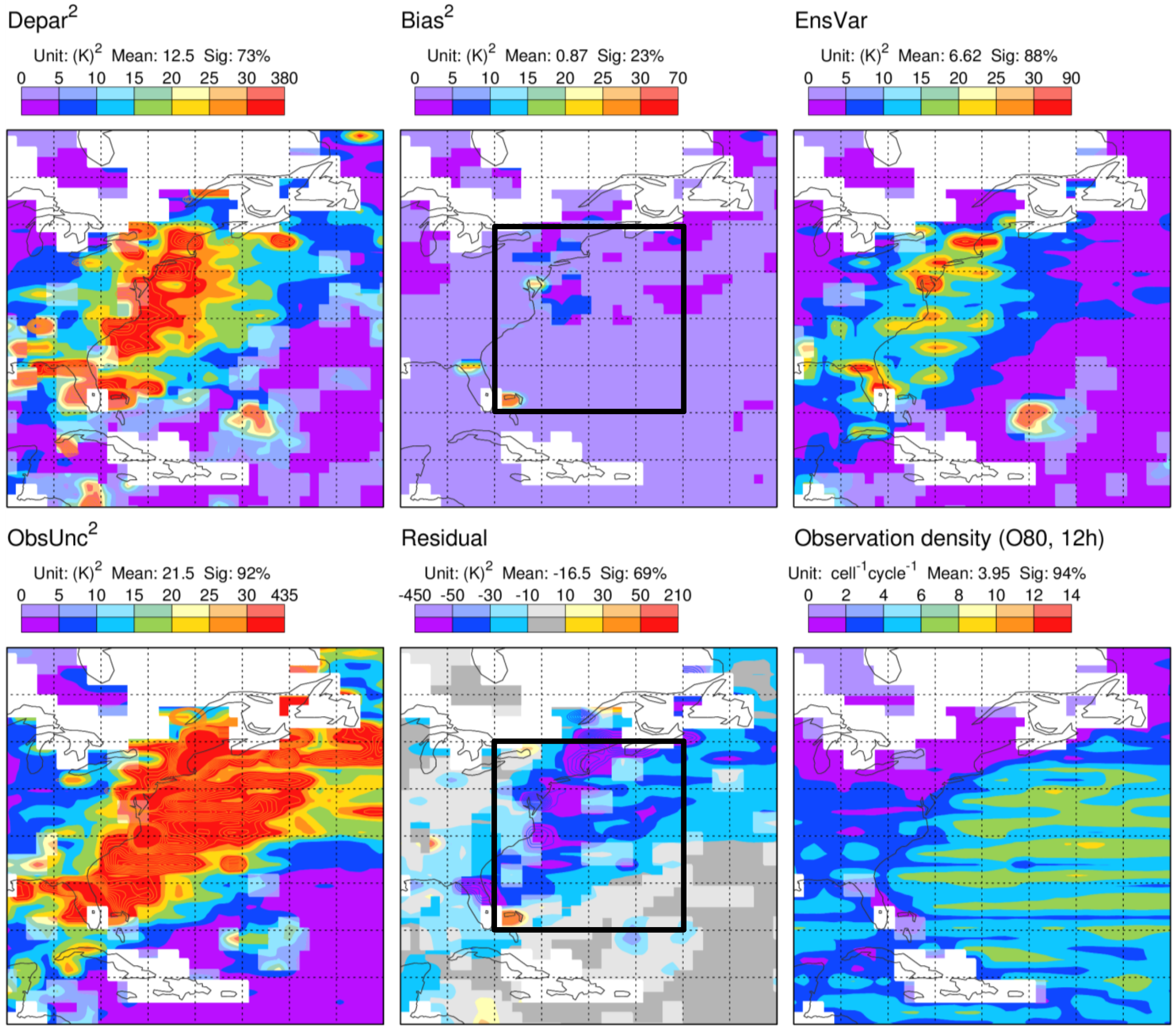


Bias and residual are not significant in absence of WCBs

Microwave channel 5

EDA variance assessment with MHS “all sky” mid-tropospheric humidity: WCB events

50 cases



Increased $Depar^2$ and EnsVar for inflow composite

Difficult to say if EnsVar is reasonable since negative residual is dominated by the overestimation of $ObsUnc^2$ in WCB region (it is larger than the departures!)

The aim of the diagnostic is to indicate deficiencies and chart our progress towards the ultimate target, but it is not practical to get there immediately

Microwave channel 5

Short-range flow-dependent reliability† – a practical route to forecast improvement‡

Summary, implications and future directions

- Forecast system improvement ≡ Minimisation of a proper score
- Proper Score = Reliability – Resolution + Uncertainty
- Red curve (constant forecast) = Black curve (climatological distribution)

  Perfectly reliable (Reliability = 0), but no resolution (Resolution = 0)
- Green and blue forecasts based on (local) partition of phase-space

  If we work to make these reliable (Residual = 0 in EDA budget) then:

  Model uncertainty is likely to be well-represented and …

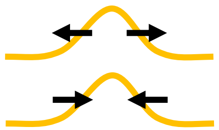
  Shaded regions ⇒ Resolution > 0 ⇒ **More skill** (into medium-range?)

‡ Practical but not trivial. Need to improve model and representation of model and observation uncertainty

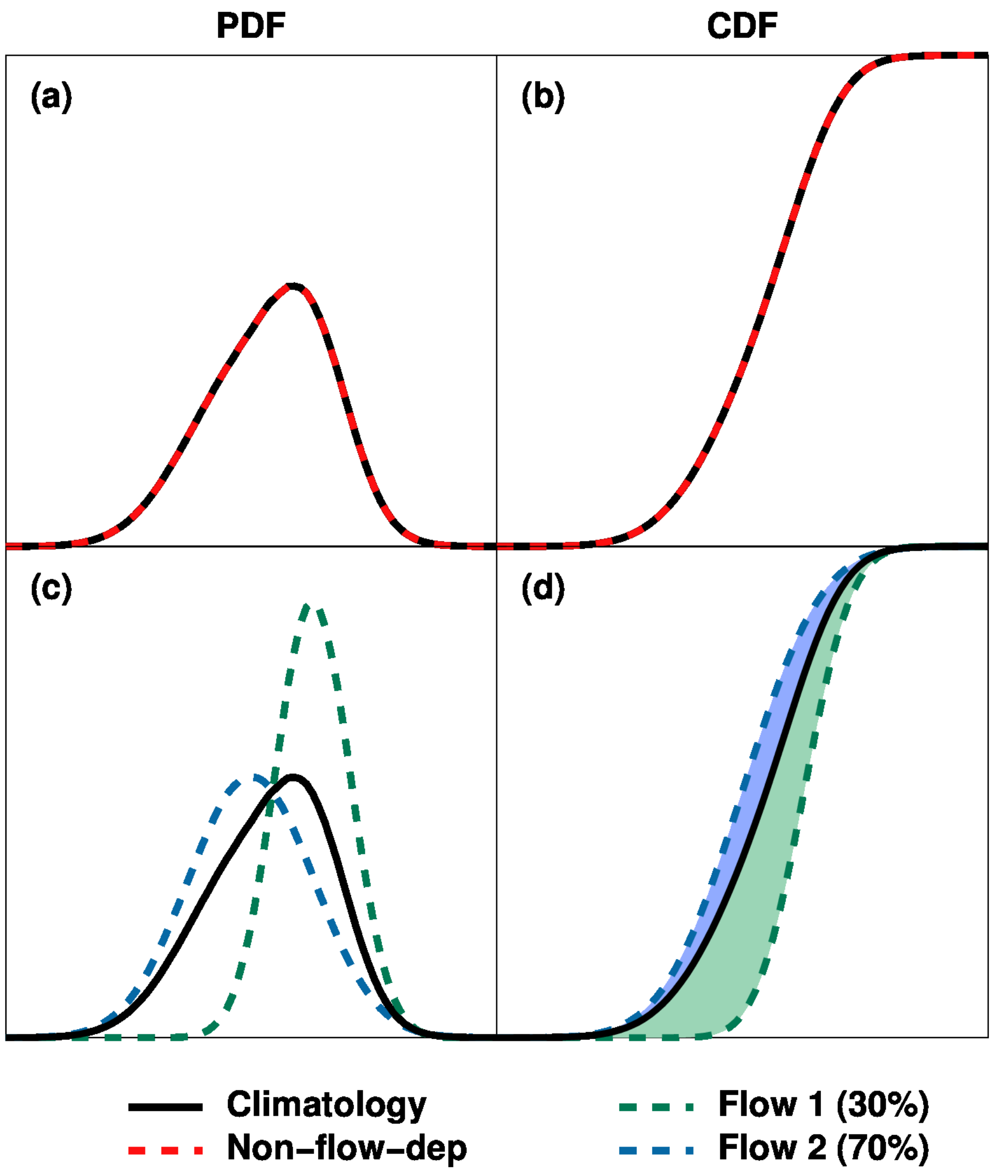
† Better (and more numerous) observations will help increase sharpness; Can view as a separate important task

The instantaneous uncertainty growth-rate can be written as:

$$\frac{1}{\sigma_X}\frac{\partial \sigma_X}{\partial t} = \rho_{XX_t}\frac{\sigma_{X_t}}{\sigma_X}$$



My animation showed the $\hat{\sigma}_{X_t}/\hat{\sigma}_X$ part. Do the random numbers used in some model uncertainty formulations deteriorate the correlation aspect?

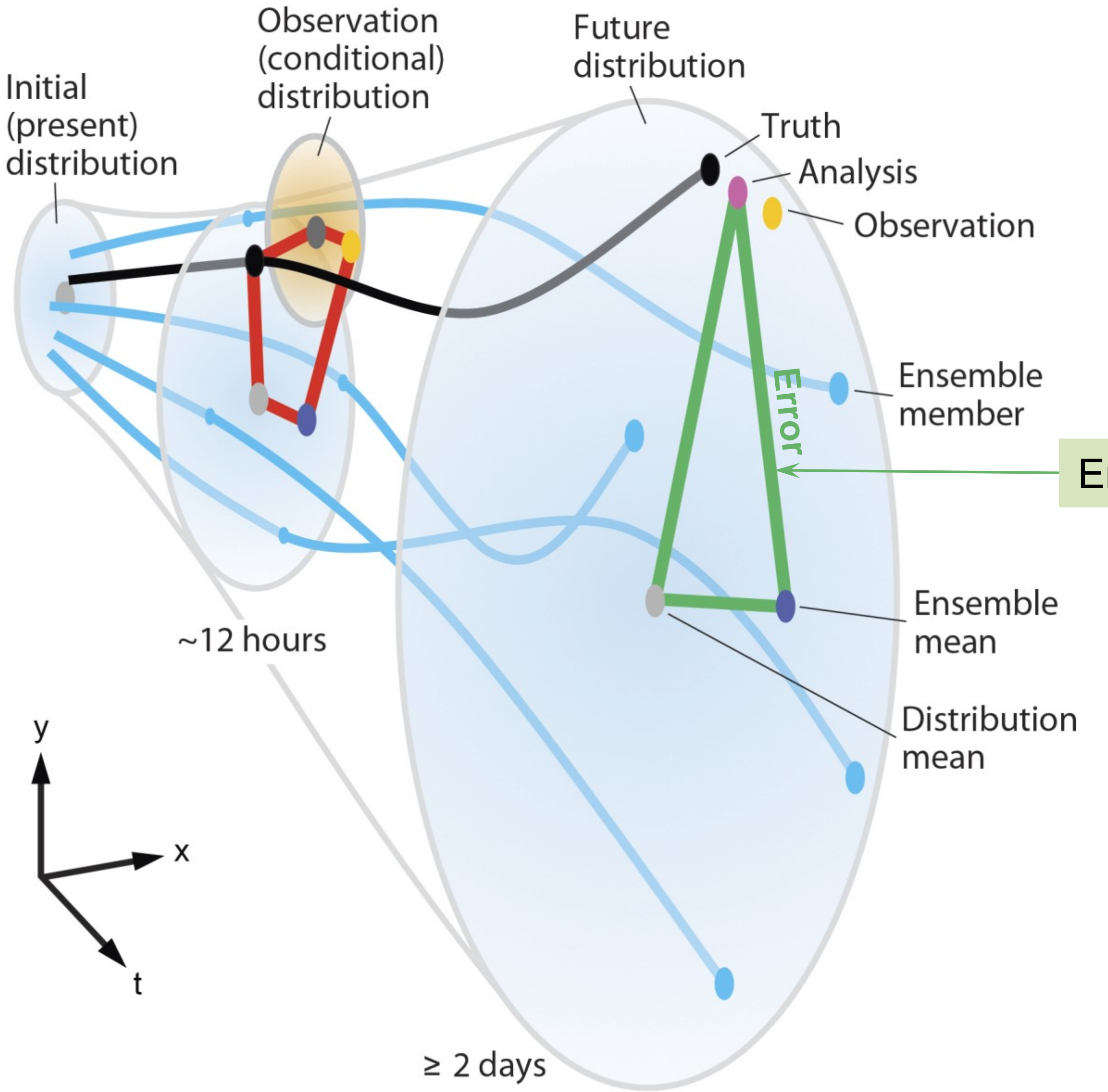


Thank you

Extra slides

Reliability in ensemble forecasting

Adapted from Rodwell et al. (2015) QJRMS



$\text{Error}^2 = \text{EnsVar} + \text{Residual}$

Error ≈ Spread

(when averaged over enough start dates - a consequence of statistical "reliability")

Progress: While maintaining this relationship, we wish to reduce both error and spread (i.e. "shrink diagram in x,y")

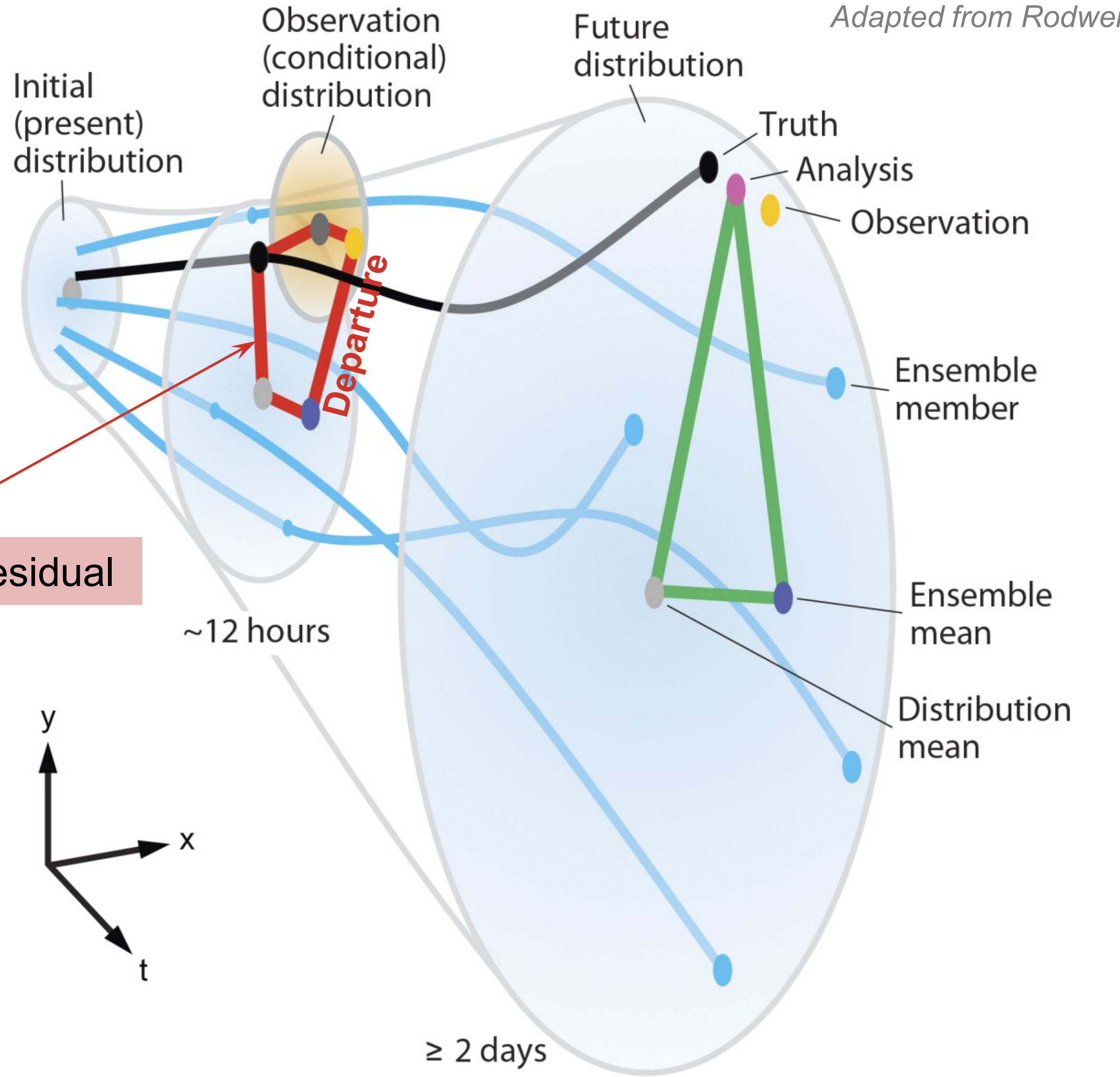
Proper scores (Brier, CRPS, Ignorance etc.) help ensure that development decisions lead us in this direction

(Cross-terms on squaring have zero expectation. EnsVar is scaled variance to account for finite ensemble-size)

Reliability in ensemble data assimilation

- Chaos makes it difficult to identify problems in the medium-range using the spread-error relationship
- Go to much shorter lead-times – within ensemble data assimilation process
- Need to take account for observation error
- Obtain diagnostic equation to evaluate "instantaneous" growth of uncertainty

Adapted from Rodwell et al. (2015) QJRMS

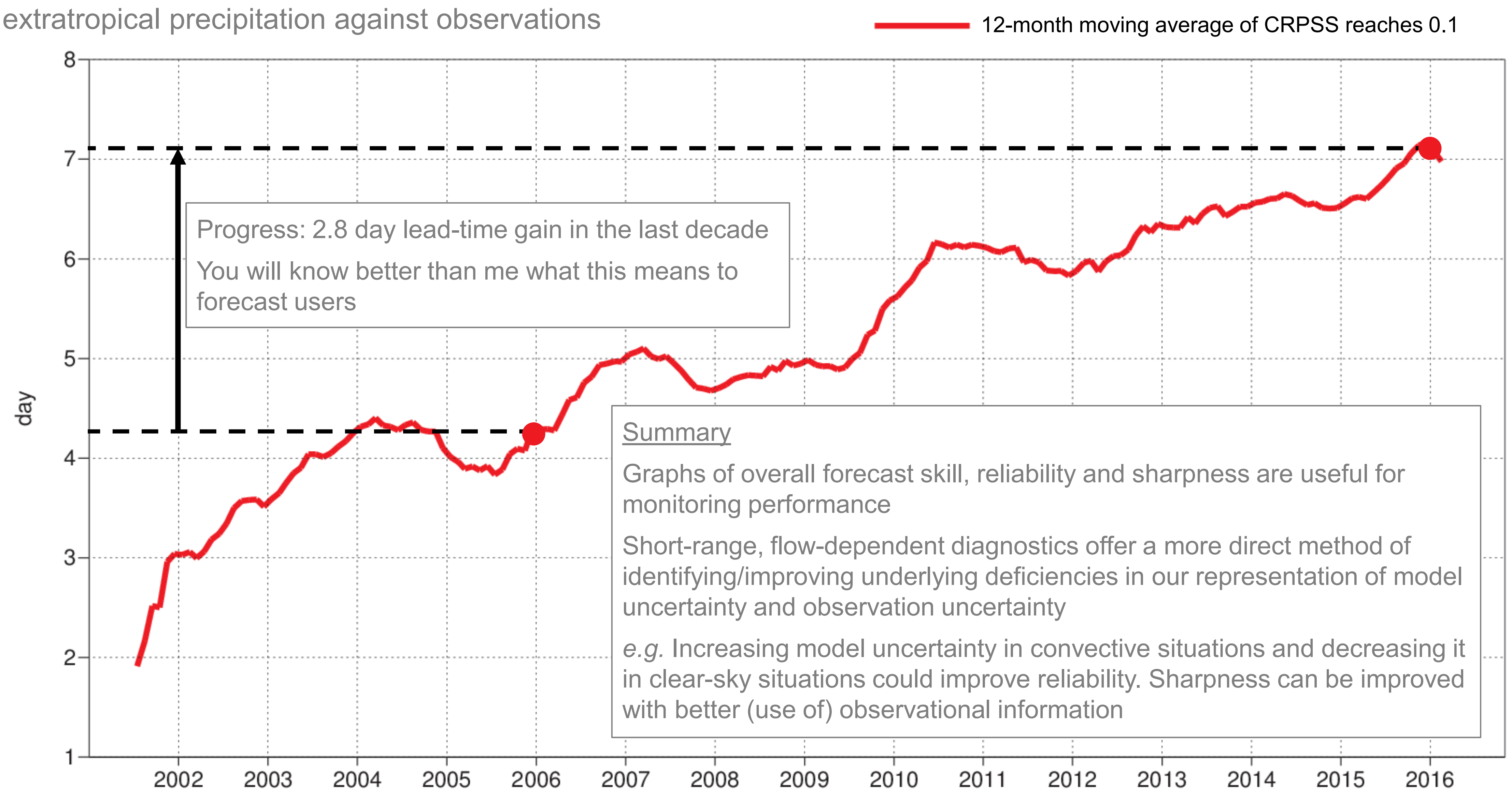


$$\text{Depar}^2 = \text{Bias}^2 + \text{EnsVar} + \text{ObsUnc}^2 + \text{Residual}$$

(Cross-terms on squaring have zero expectation. EnsVar is scaled variance to account for finite ensemble-size)

Trend in probabilistic forecast performance & Summary

CRPSS, extratropical precipitation against observations



Summary

Graphs of overall forecast skill, reliability and sharpness are useful for monitoring performance

Short-range, flow-dependent diagnostics offer a more direct method of identifying/improving underlying deficiencies in our representation of model uncertainty and observation uncertainty

e.g. Increasing model uncertainty in convective situations and decreasing it in clear-sky situations could improve reliability. Sharpness can be improved with better (use of) observational information