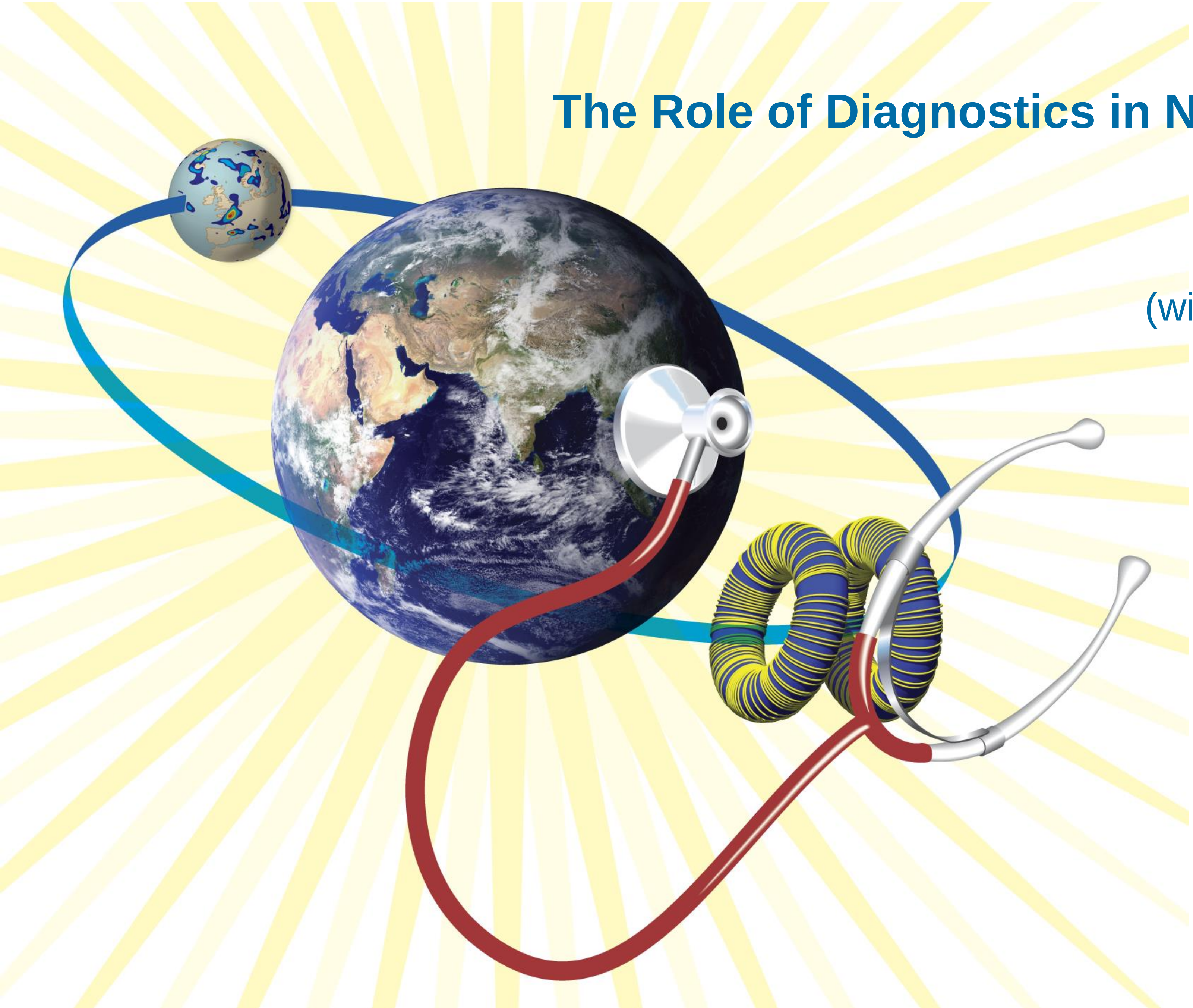


The Role of Diagnostics in Numerical Weather Prediction

Mark Rodwell
(with the support of ECMWF colleagues
and external collaborators)

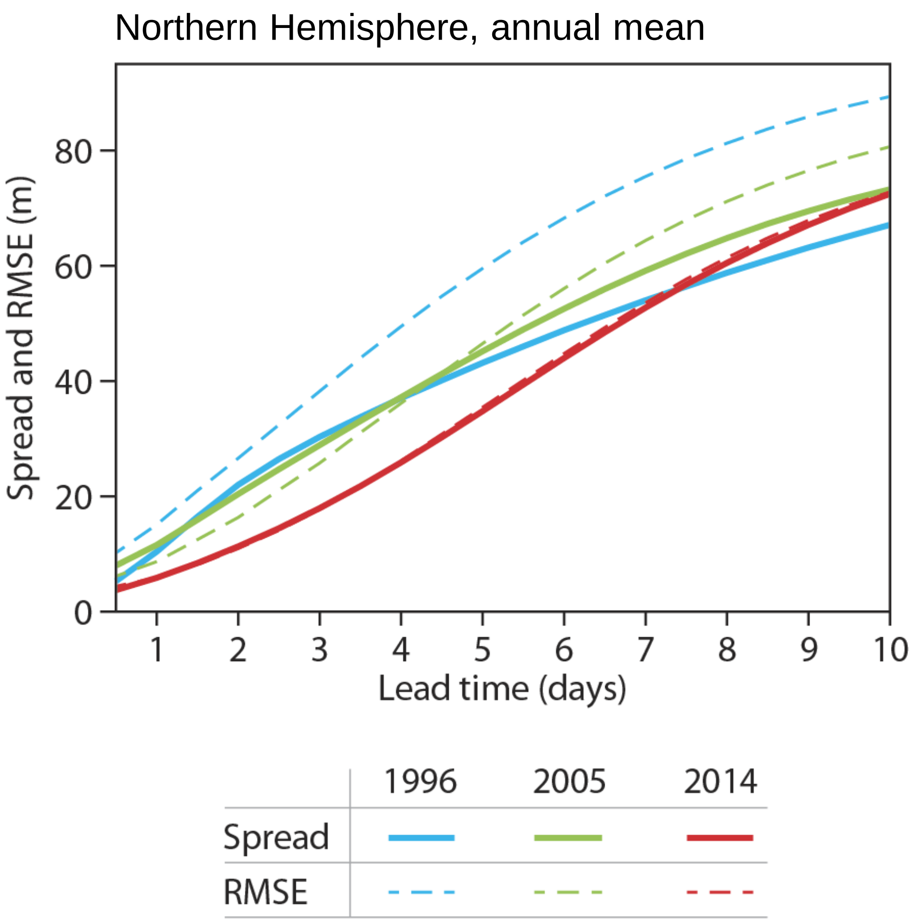
Using ECMWF's Forecasts (UEF2016)

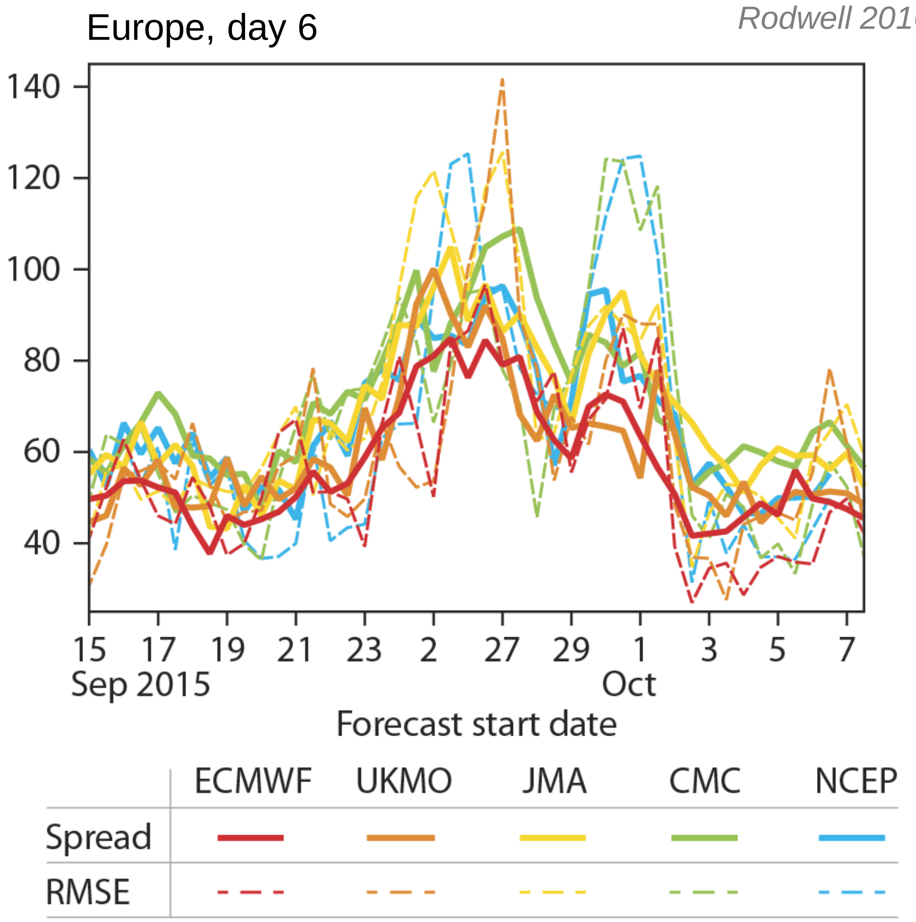
8 June, ECMWF Reading

Ensemble spread and error

Z500

Rodwell 2016, ECMWF Newsletter





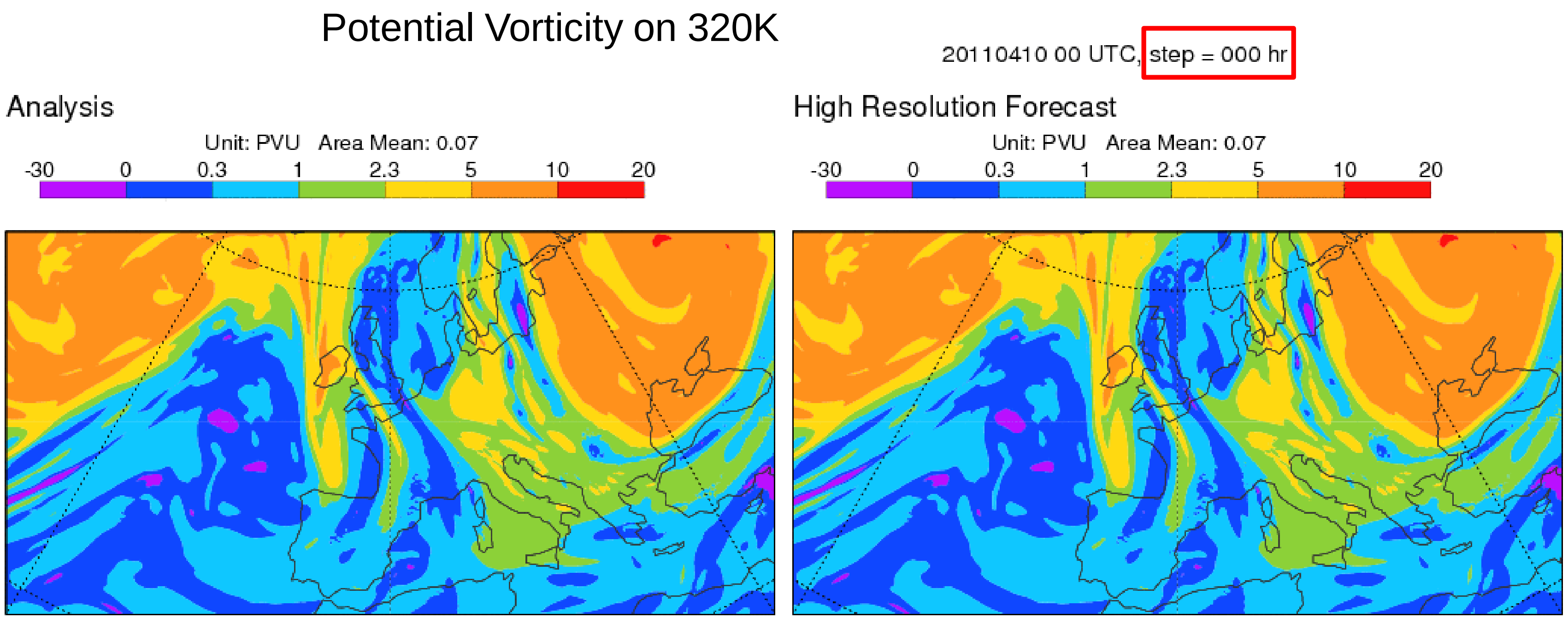
Improvements in sharpness and reliability. Due to:

- Ensemble of data assimilations
- Stochastic physics
- Observations and modelling of observation error

- Spread agreement between centres indicates flow-dependent fluctuations in underlying predictability (reason for ensemble forecasting!)
- Need to assess flow-dependent reliability

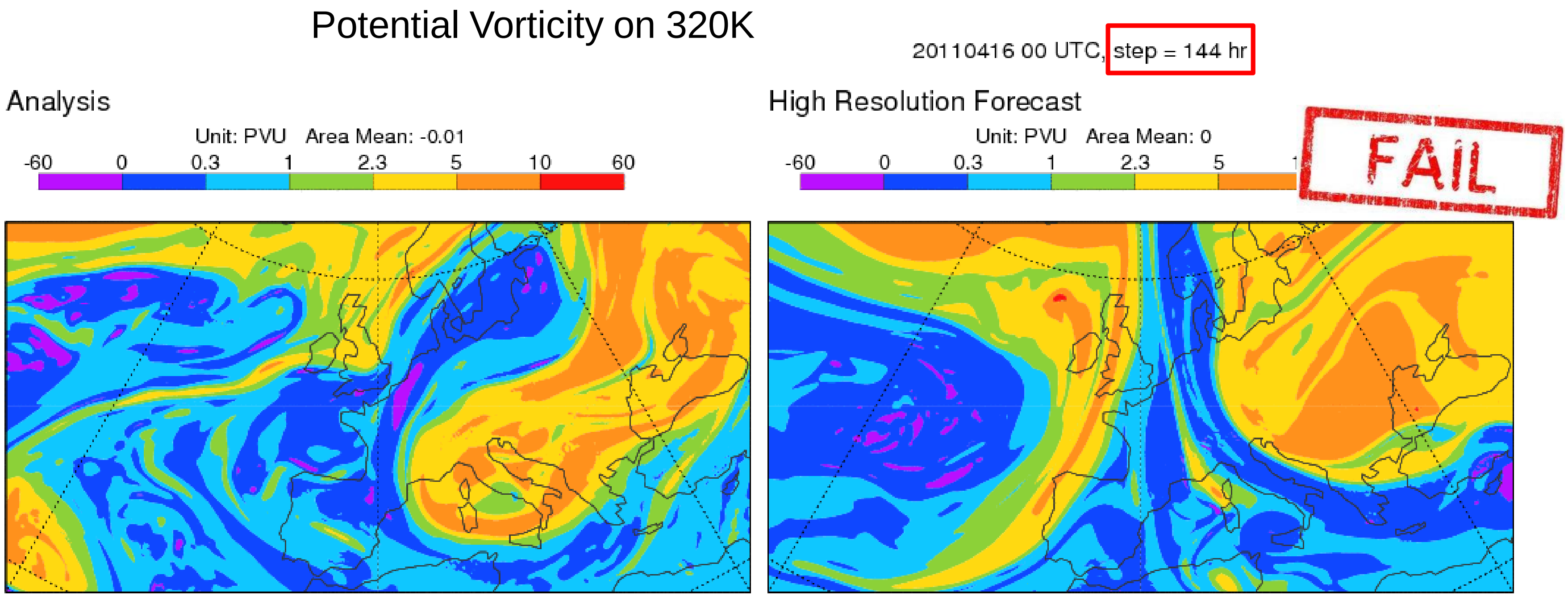
500 hPa geopotential height (Z500). RMSE is of ensemble-mean error. Spread = ensemble standard deviation (scaled to take account of finite ensemble size).

Animation of ‘bust’ forecast: Initial conditions on 10 April 2011



Animation of forecast started at 0 UTC on 10 April 2011

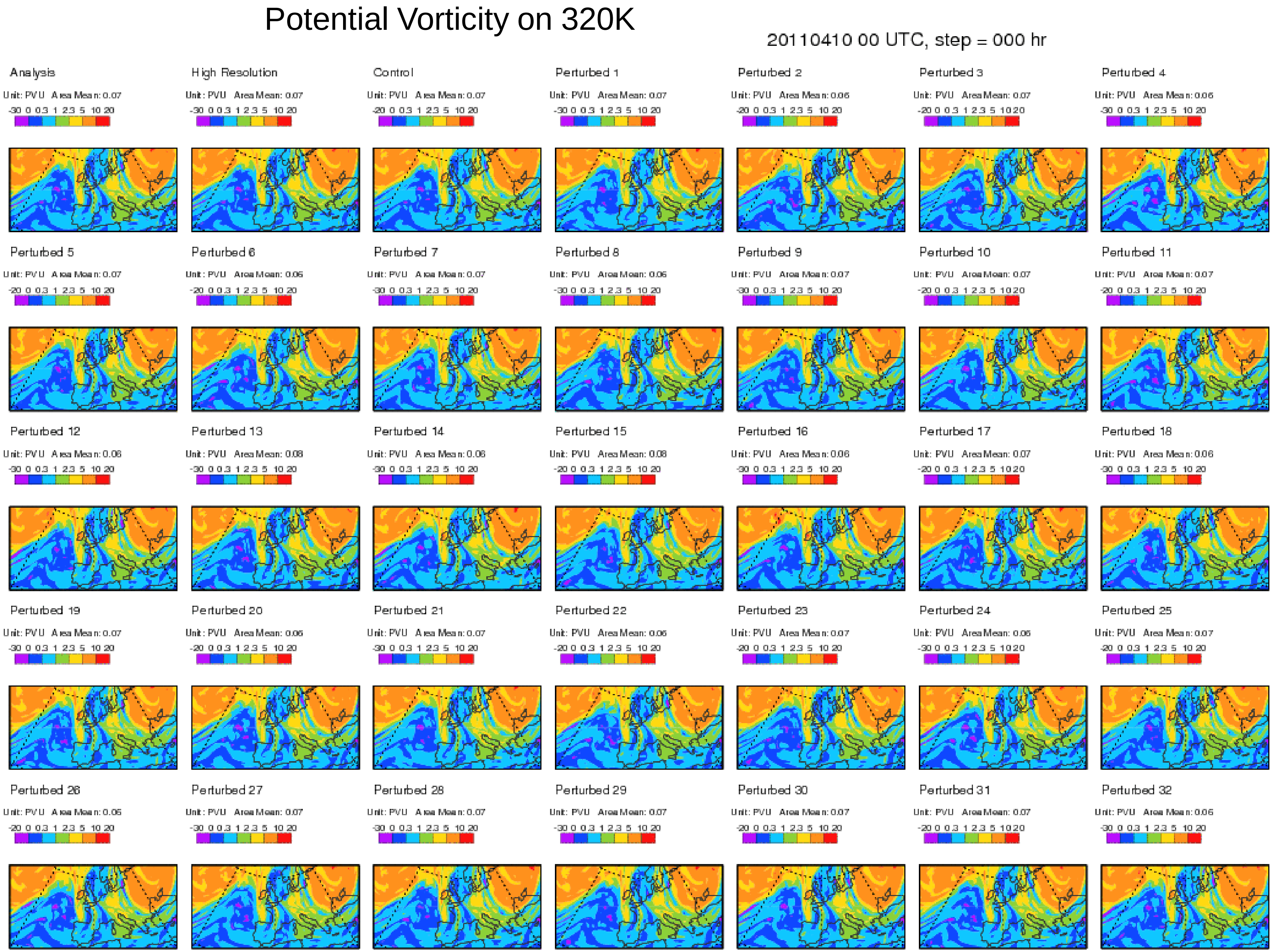
Animation of ‘bust’ forecast: Evolution to day 6



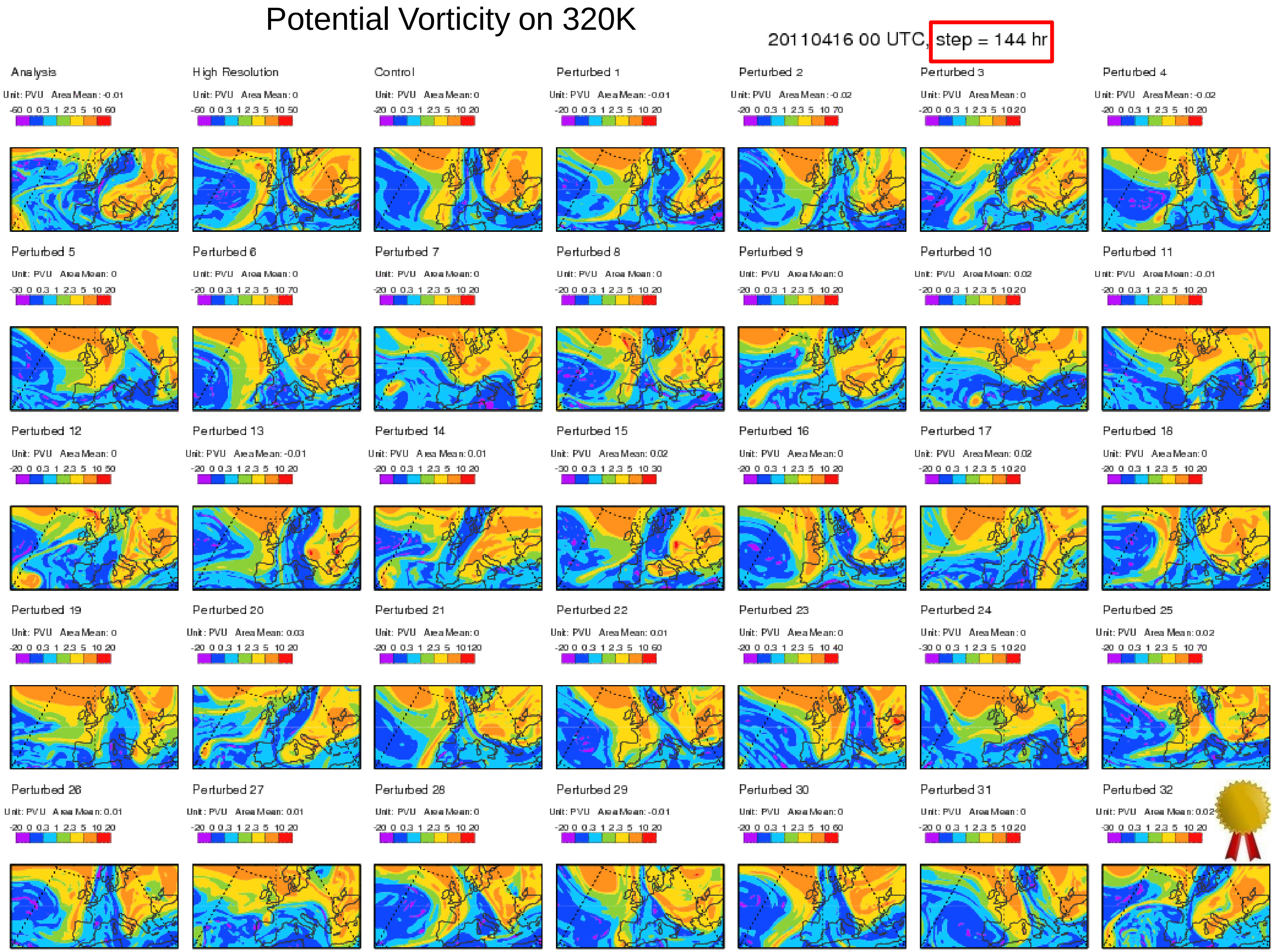
Block forms in observations, but not in forecast

It is difficult, by day 6, to disentangle model error from the natural growth of initial condition uncertainty (chaos)

Animation of ensemble forecast: Initial perturbations on 10 April 2011



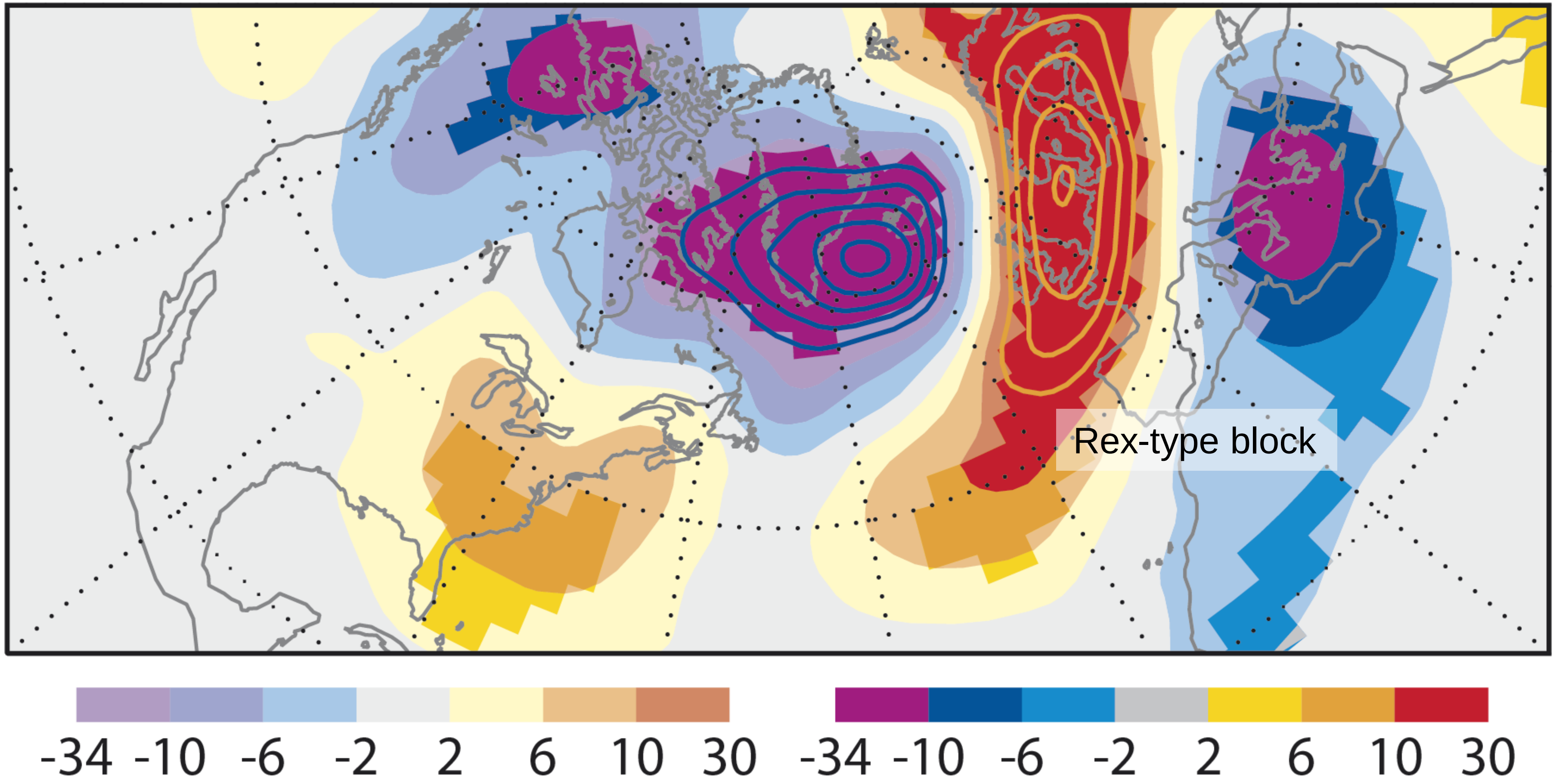
Animation of ensemble forecast: Evolution to day 6



Verifying conditions composited over many bust forecasts

Rodwell et al, 2013, BAMS

500 hPa geopotential height (Z500) anomaly

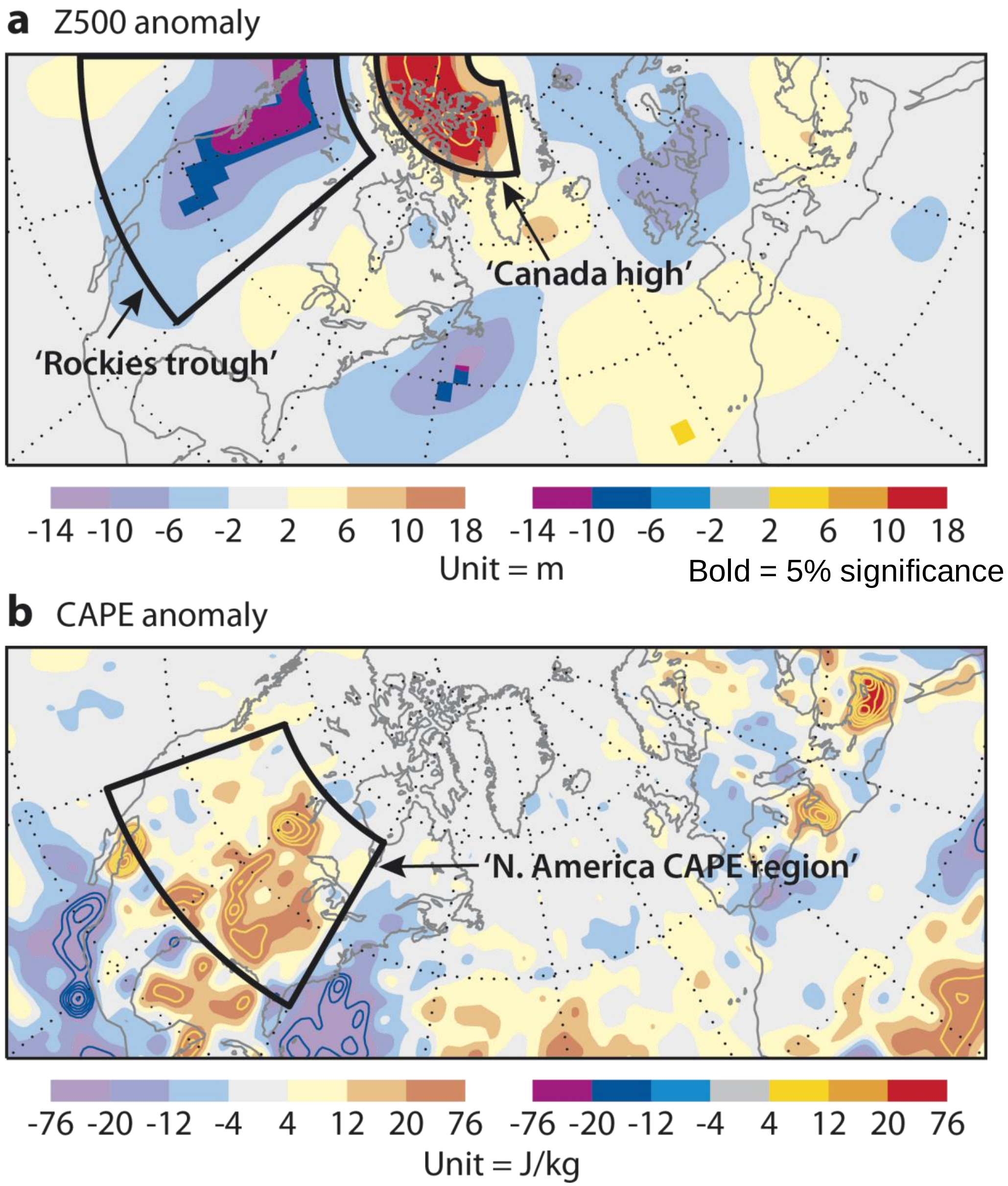


Unit = m   Bold colours = statistical significance at 5% level

Composite of 584 busts in ERA Interim forecast prior to 24 June 2010

Composite initial conditions of bust forecasts

Rodwell et al, 2013, BAMS



There is an initial flow regime: "Rockies trough" with high CAPE ahead

Conducive to the formation of mesoscale convective events (MCS)

Remarkable that we can identify any significant initial conditions 6 days ahead of the busts – this must be due to the large composite (584 events) used

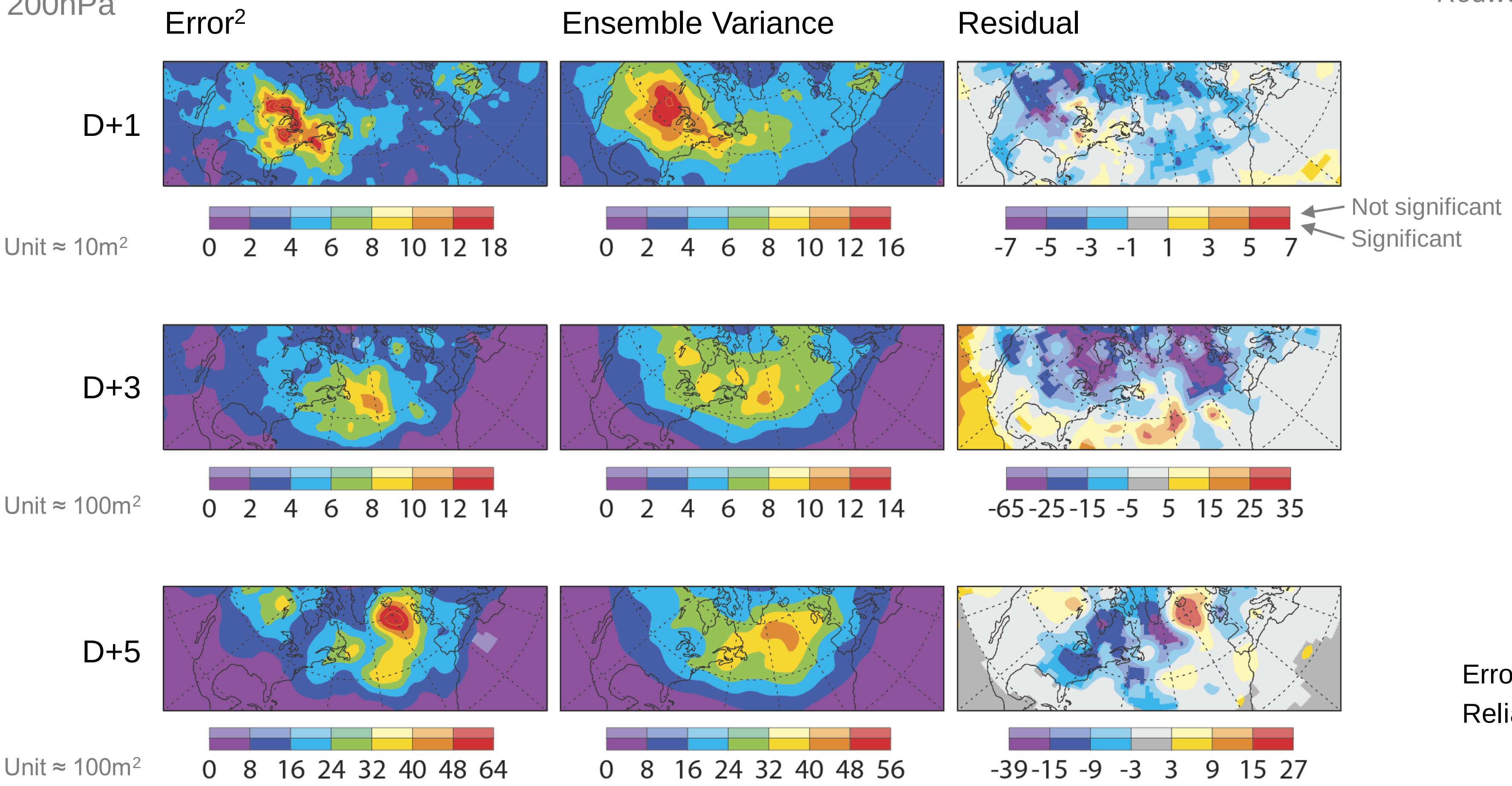
Other bust causes not so geographically fixed and are not highlighted by this composite-mean

'CAPE' = Convective Available Potential Energy

“Spread-Error relationship” for Trough/CAPE composite (NOTE: Independent data)

Rodwell 2016, ECMWF Newsletter

Geopotential at 200hPa
54 cases



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

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

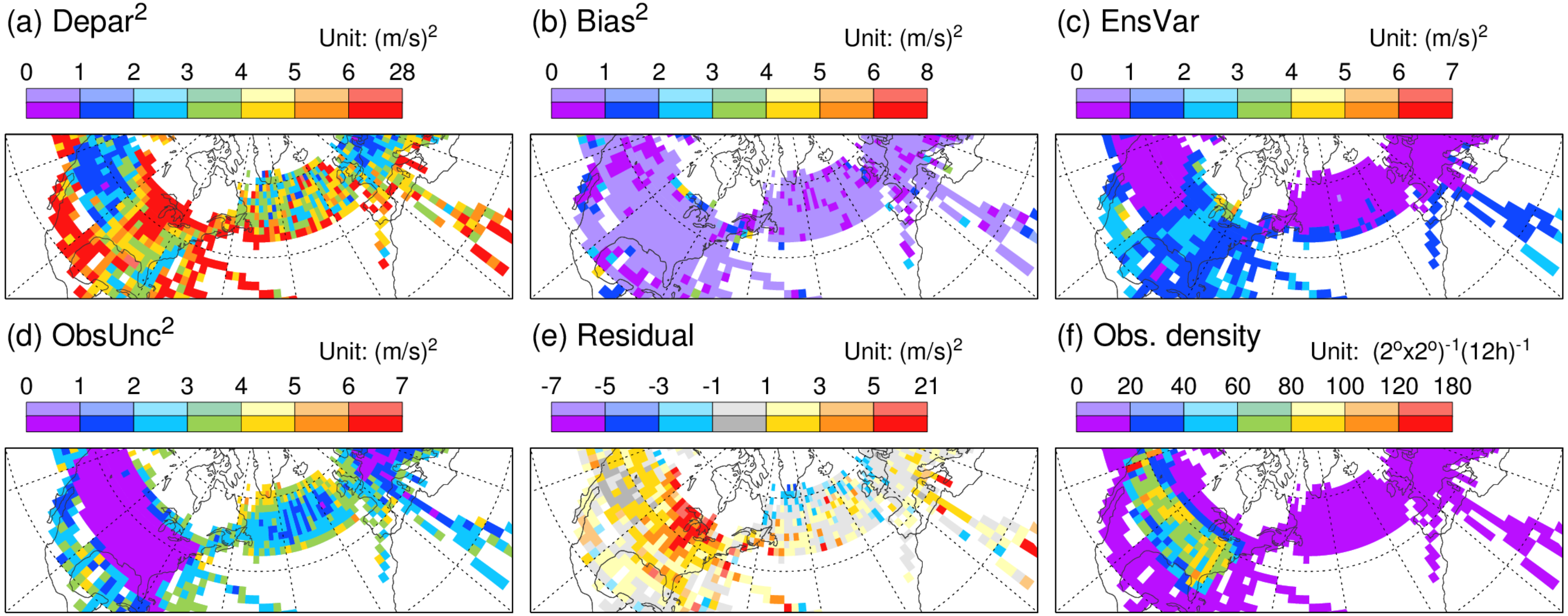
- *Enhanced errors and spread propagate east towards Europe → ‘Busts’. System is reasonably reliable for this initial flow regime* ✓
- *Positive residual at D+5 is not significant. Negative residuals are not specific to trough/CAPE regime (not shown)*
- *Difficult to use the Spread-Error relationship to improve flow-dependent reliability* ✗
- *Need to reduce the effects of Chaos: cannot readily increase sample size, but could reduce leadtime if we took account of analysis uncertainty in estimation of error*

"EDA reliability budget" for Trough/CAPE composite

u200, 54 cases

Rodwell 2016, ECMWF Newsletter

Relative to aircraft observations of zonal wind 200hPa (±15)



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

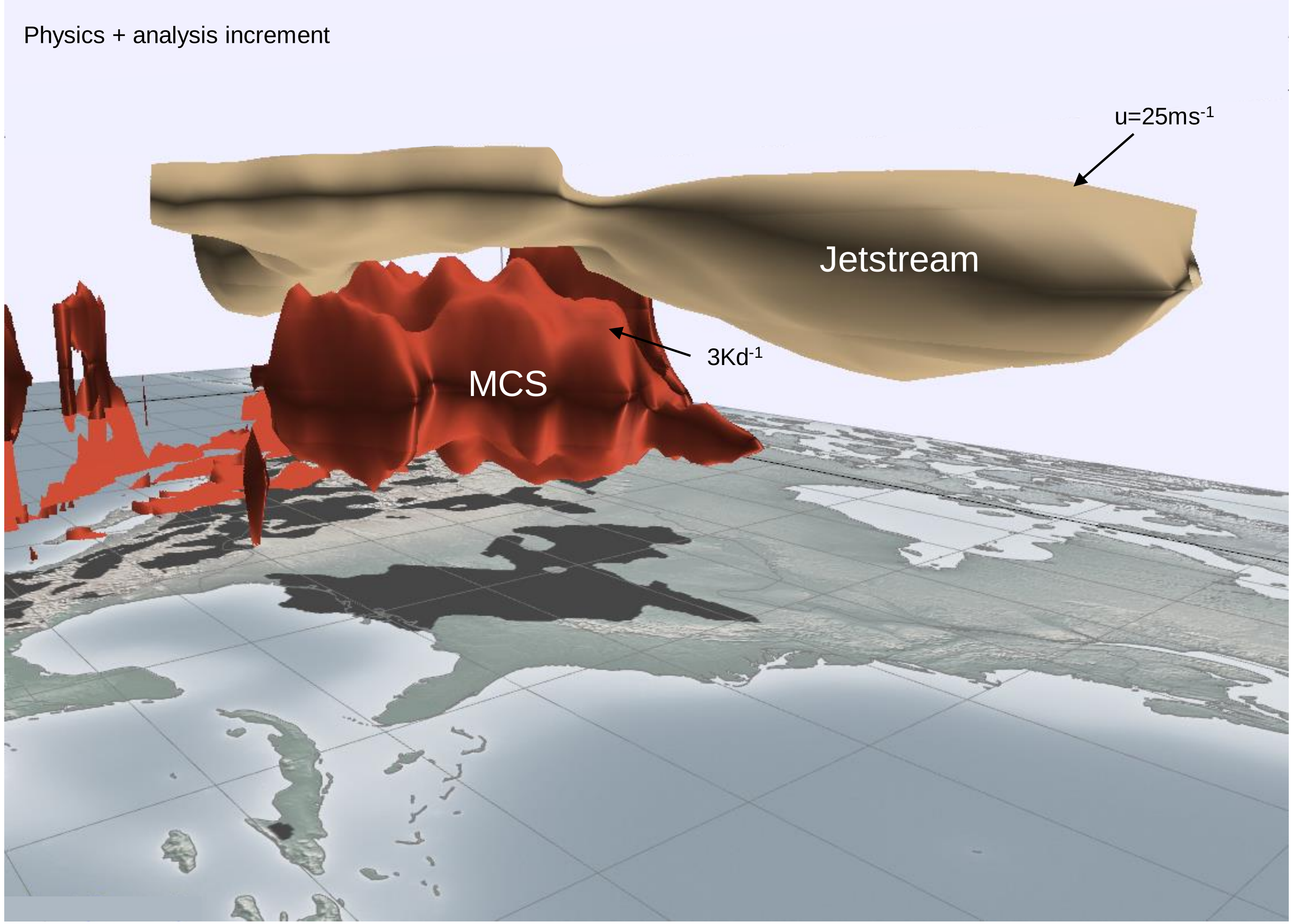
Reliability $\Rightarrow$ E[Residual]=0

- Residual over North America is statistically significant
- EDA reliability budget is able to highlight flow-dependent deficiencies in reliability ✔
- Suggests lack of background variance since observation uncertainty changes should be second-order for this large-scale wind field
- One interpretation: The un-predictability of MCS intensity and location is not adequately reflected in Jetstream uncertainty (with downstream consequences)

A role for systematic model error for the Trough/CAPE composite

54 cases

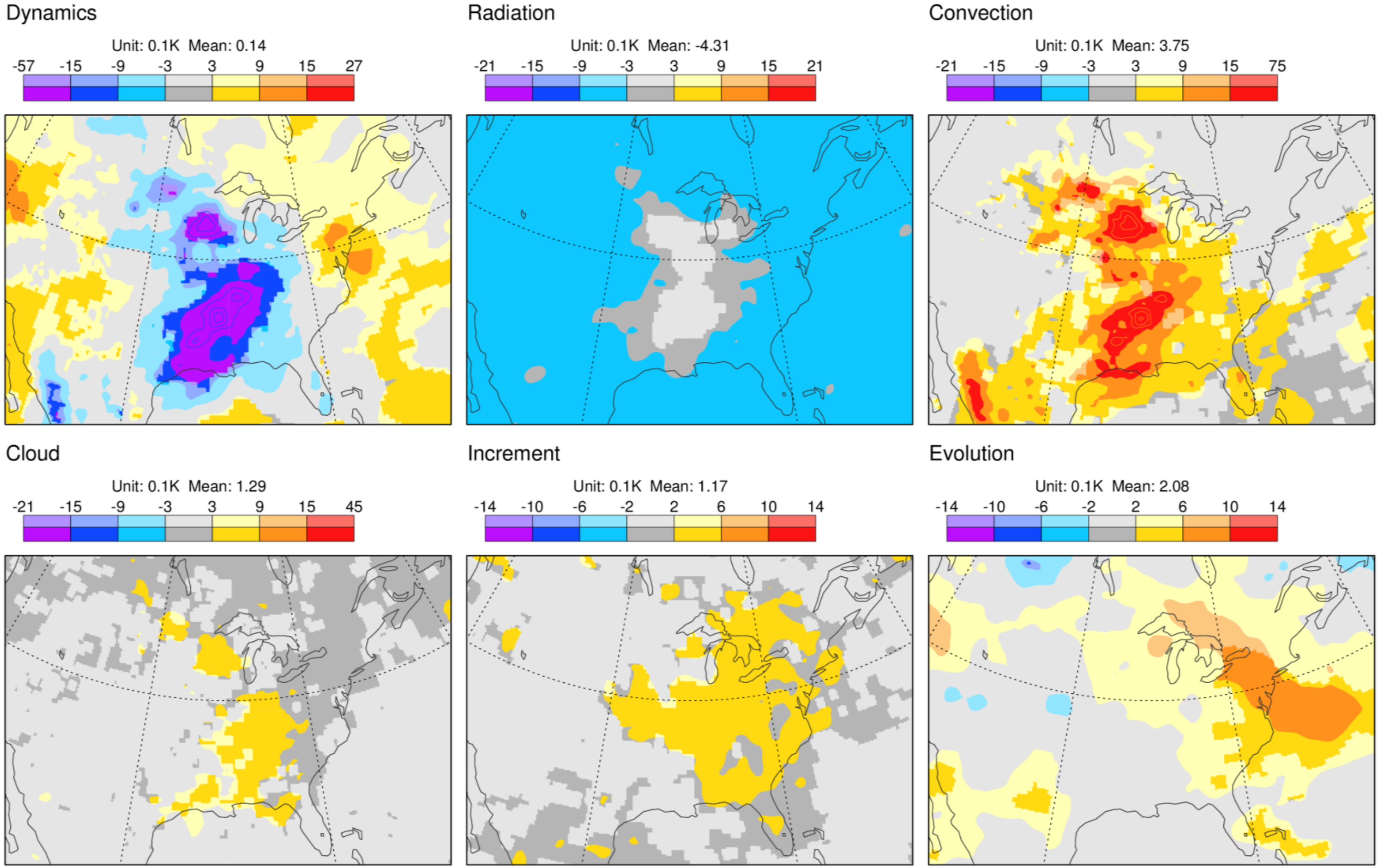
Met3D: Marc Rautenhaus



- Increments highlight a role for model systematic error: MCS does not interact enough with Jetstream
- Also need to strengthen stochastic physics to increase background variance?

“Initial tendency budget” from control background for Trough/CAPE composite

T300, 54 cases

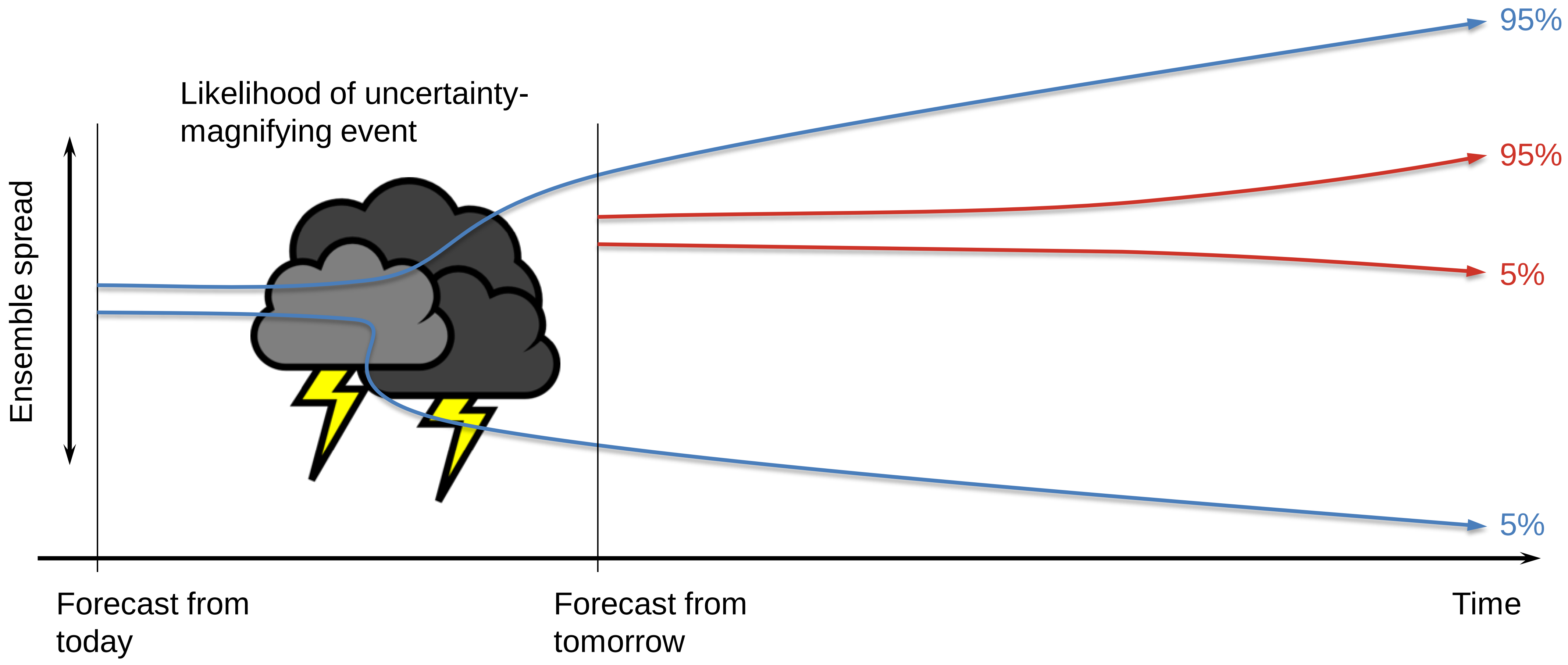


- Decomposing EDA control forecast into process tendencies shows how the model represents dynamics and physics of MCS
- The positive (and statistically significant) increment suggests observations are warmer than the model

Process tendencies accumulated over 12hr background, the analysis increment, and evolution of the flow

New approach to decision-making based on flow-dependent predictability diagnosis

"Forecasts from today are highly uncertainty for Europe next Monday, but we expect uncertainty to reduce markedly in tomorrow's forecast. It may be beneficial to delay decisions by 24 hours"

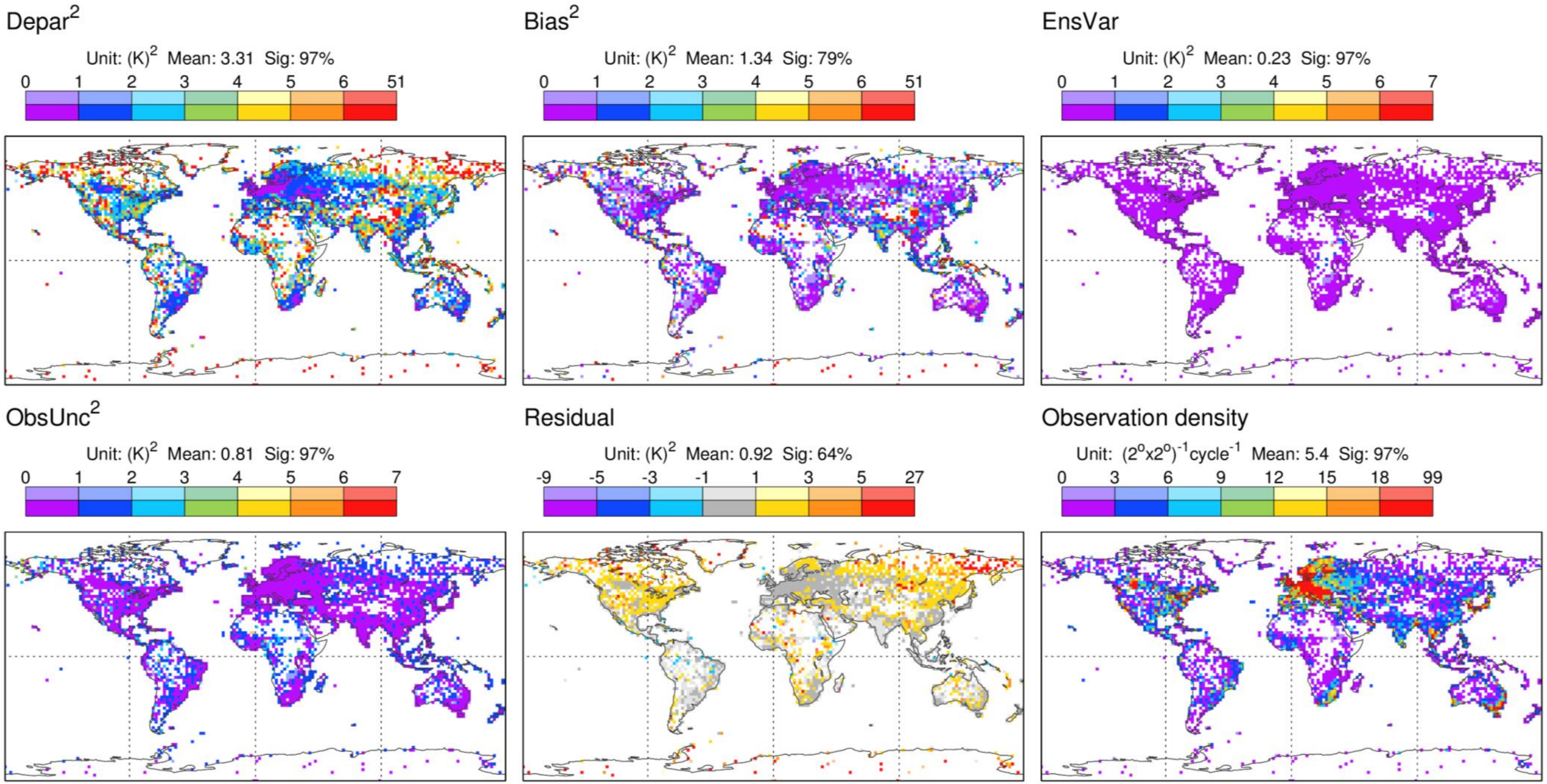


The EDA reliability budget is also sensitive to the modelling of observation error

T2m, March-May 2016

ECMWF “Diagnostics Explorer”

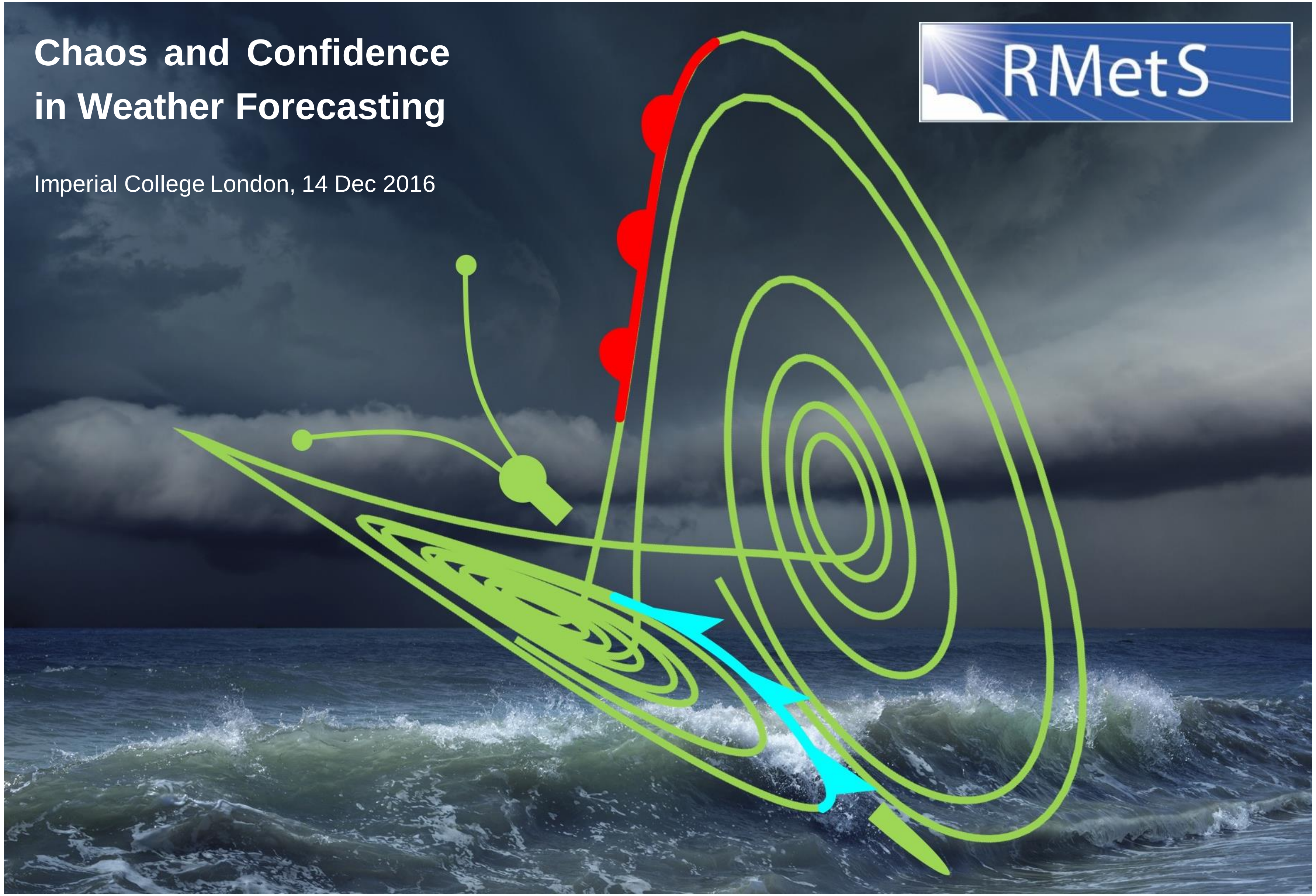
Relative to conventional observations of T2m



- Large departures and positive residuals in regions of low observation density might suggest a lack of representativity
- More general implications for verification against observations

Results based on ECMWF surface data assimilation

RMetS meeting on Ensemble Forecasting - Accessible to a broad audience



<u>Agenda</u>

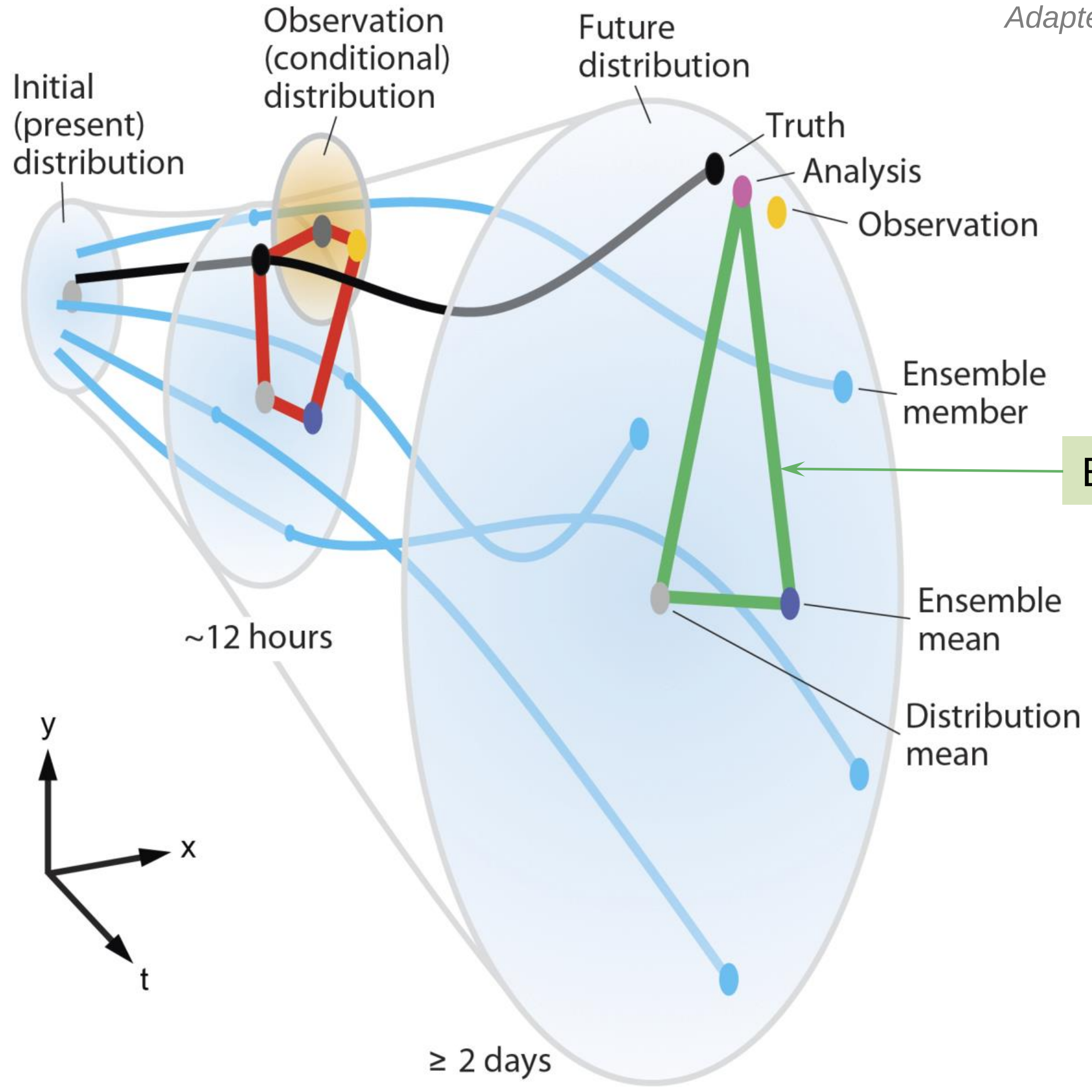
- Chaos in weather forecasting
- The science of chaos & modelling of uncertainty
- Evaluating forecast uncertainty
- Mince pies and movie loops
- Working with uncertainty & confidence
- Confidence in weather forecasts
- Competition – communicating confidence and certainty to the public

Summary and discussion

- Assessment of flow-dependent reliability essential
  - Complementary to reliability tests based on probability/frequency chart (*e.g.* can have the same probability from different initial states, and these will be mixed)
- ENS reasonably reliable for initial state involving trough/CAPE
- "EDA reliability budget" useful (& essential?) to diagnose flow-dependent deficiencies
- "Initial tendencies" and "EDA reliability budget" (& other tools) are in the "Diagnostics Toolbox"
  - Aim: Powerful yet simple identification of key forecast system errors
  - Features: Composite on events, concatenate data sources, model-space and observation-space, statistical significance

Reliability in ensemble forecasting

Adapted from Rodwell et al. (2015) QJRMS

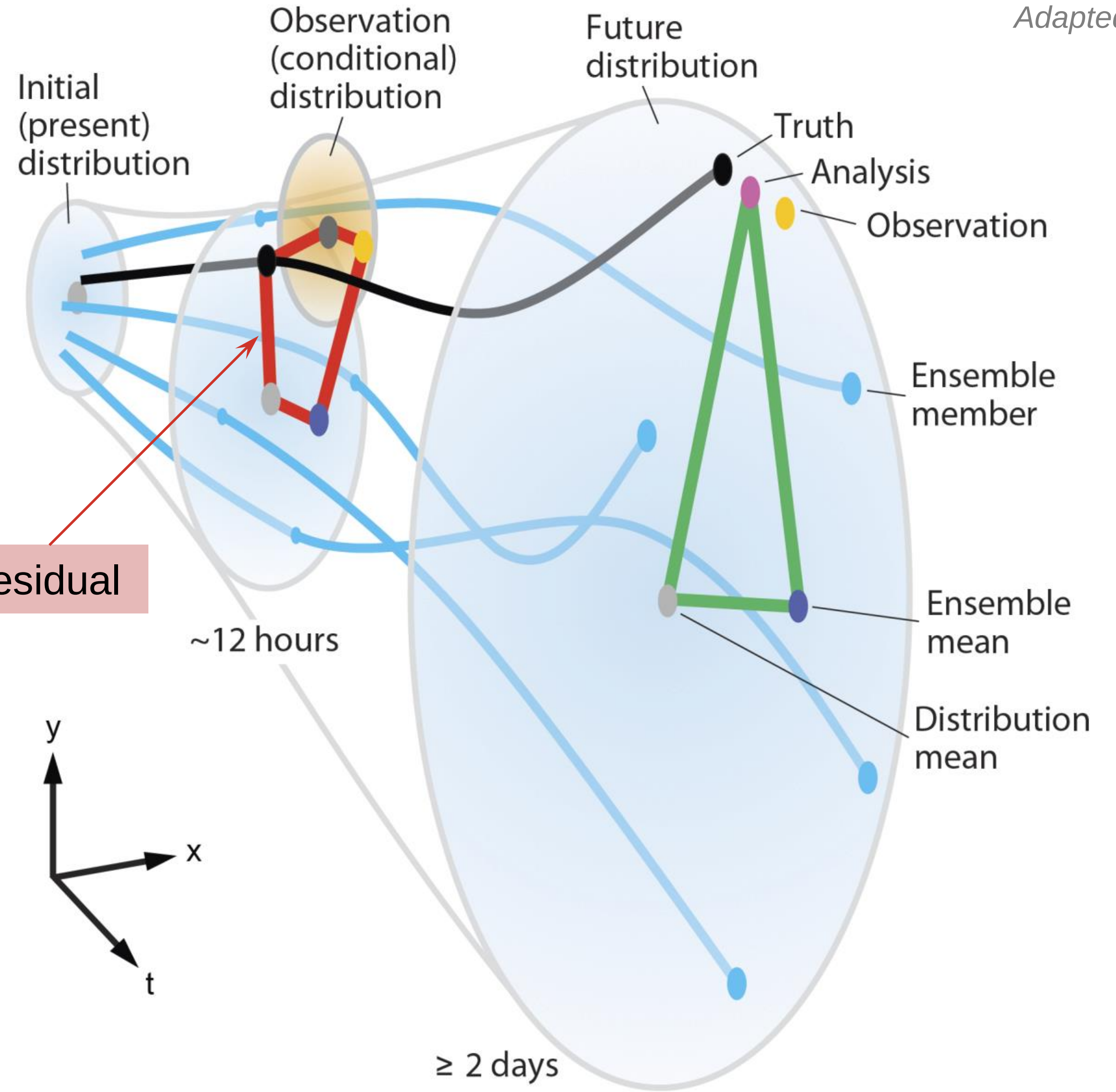


Error^2 = EnsVar + Residual

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

Reliability in ensemble data assimilation

Adapted from Rodwell et al. (2015) QJRMS



Depar^2 = Bias^2 + EnsVar + ObsUnc^2 + Residual

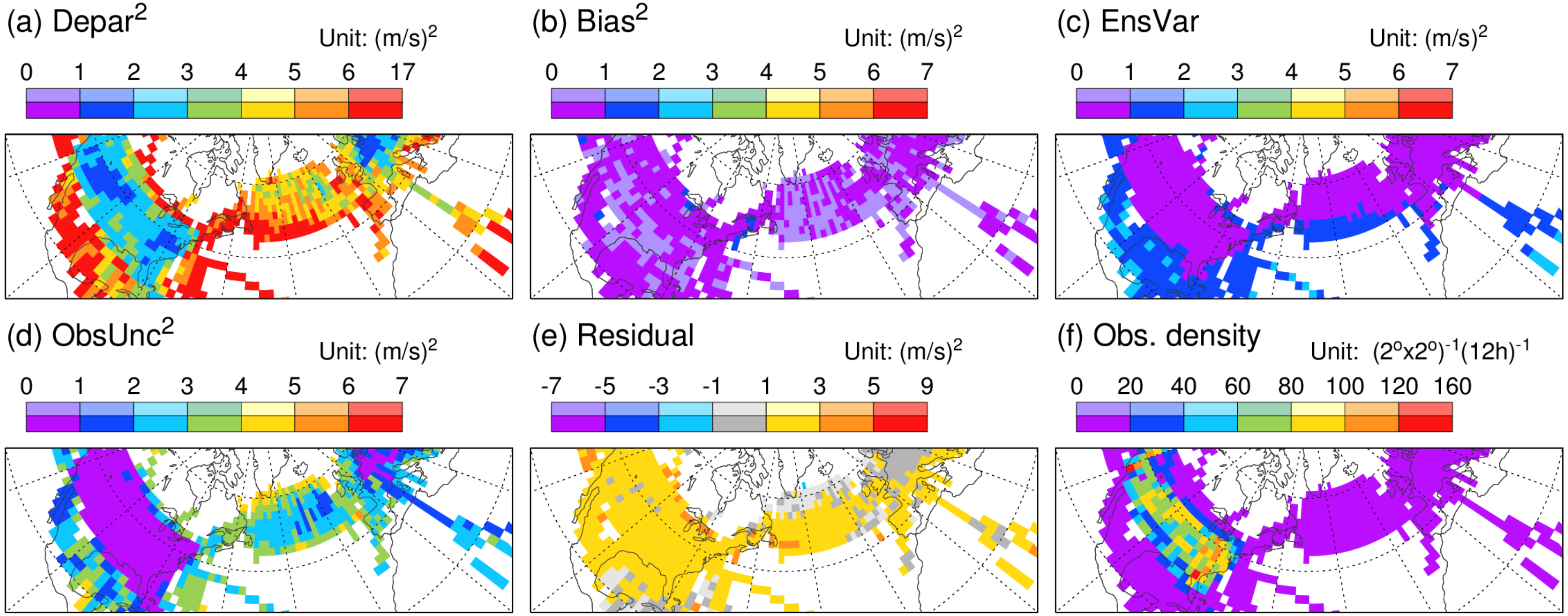
(Cross-terms on squaring have zero expectation. EnsVar is scaled variance to account for finite ensemble-size)

EDA reliability budget: Non-trough/CAPE comp.

u200, ~1000 cases

Rodwell 2016, ECMWF Newsletter

Relative to aircraft observations of zonal wind 200hPa (±15)



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

Reliability $\Rightarrow$ $\mathbb{E}$[Residual]=0

- Residual suggests general underestimation of background variance or observation uncertainty
- Not interested in this here as we are interested in flow-dependent reliability