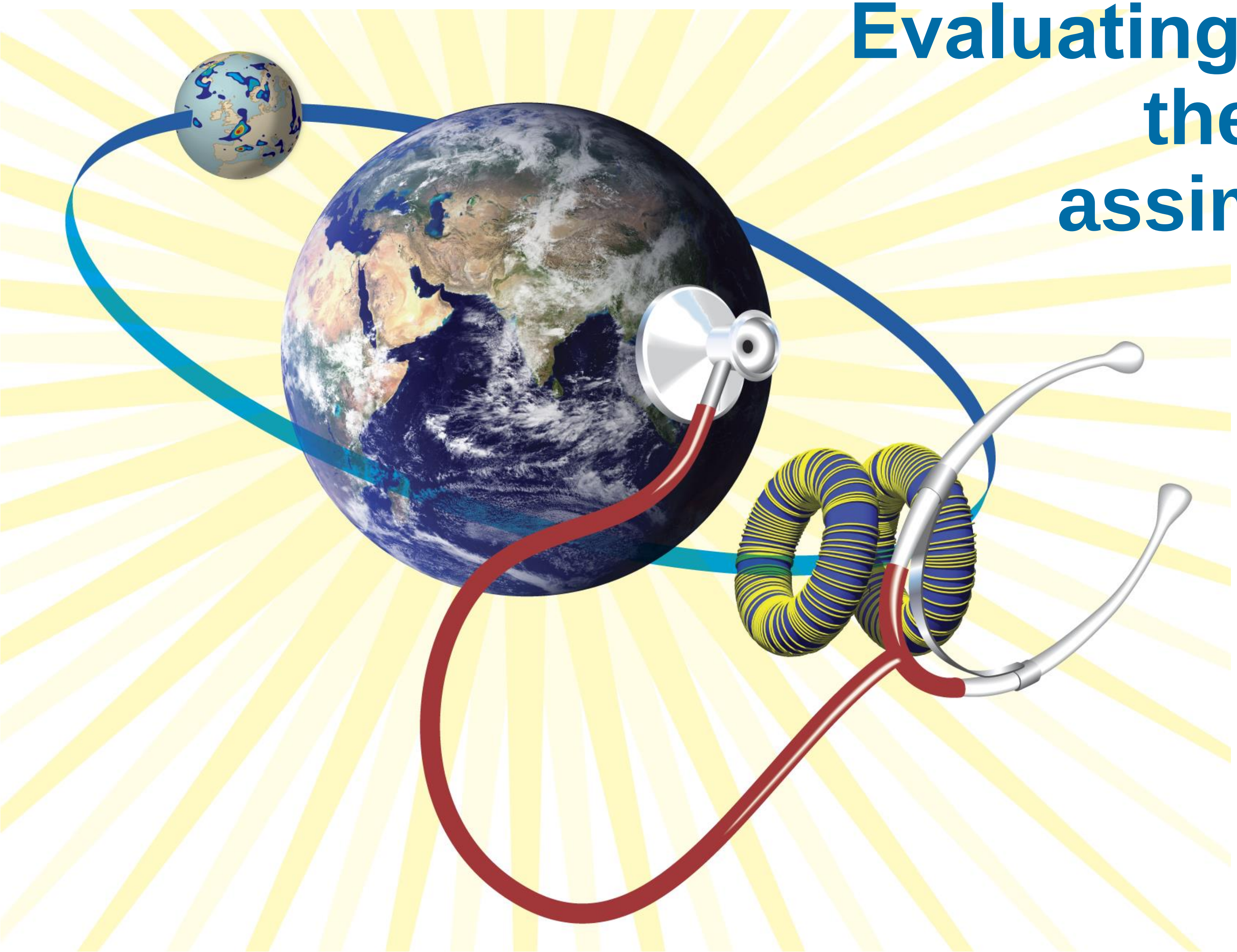

Evaluating ECMWF's model in the tropics using Data assimilation diagnostics

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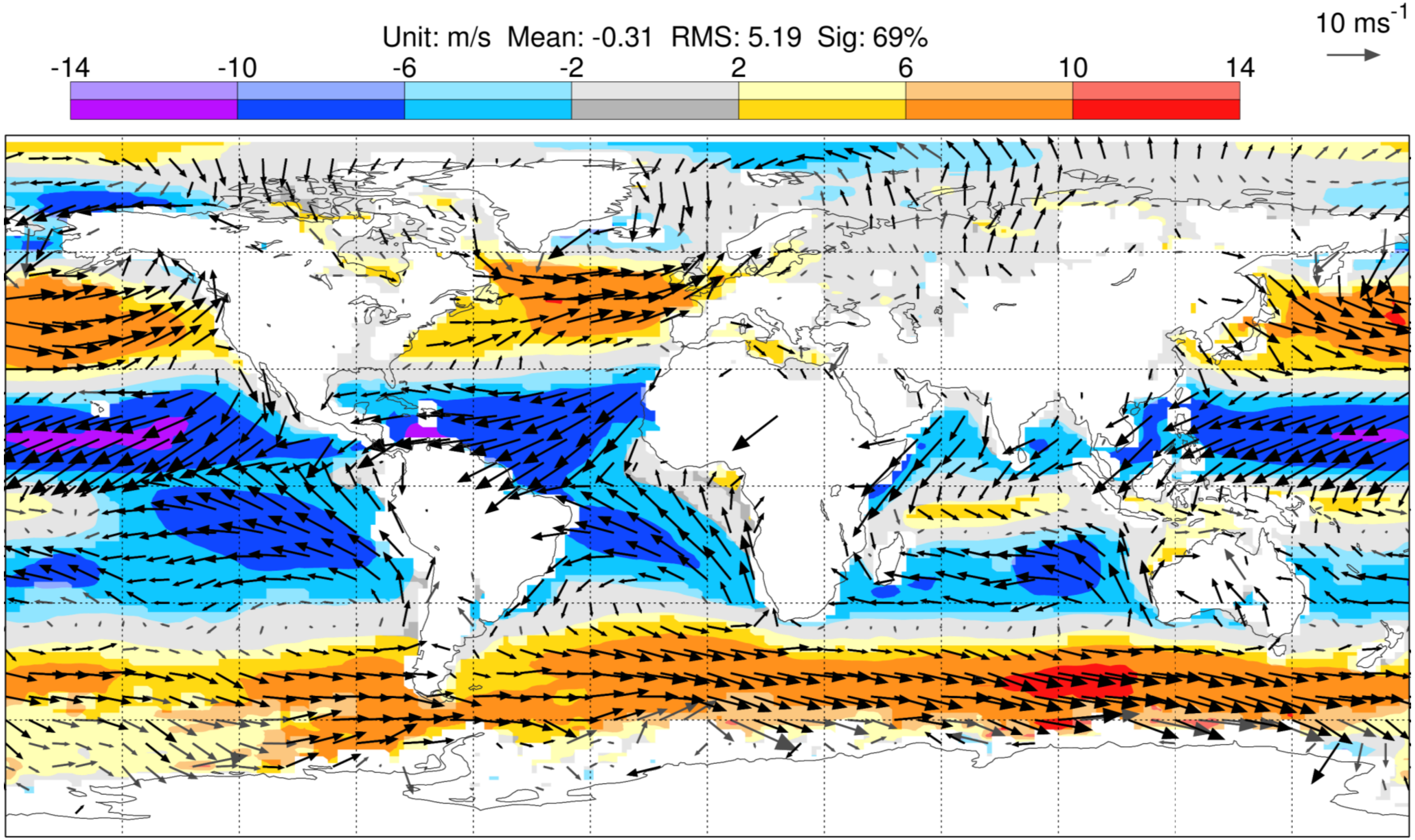
Contents (focus on tropical winds)

- Diagnosis of systematic error | Process tendency / analysis increment budget
- Diagnosis of random error | EDA variance (reliability) budget
- Diagnosis of teleconnection errors | Barotropic vorticity equation and “Rossby Wave Source”

Diagnosing systematic errors

Mean analysed u and wind vectors at 1000hPa (DJF 2016)



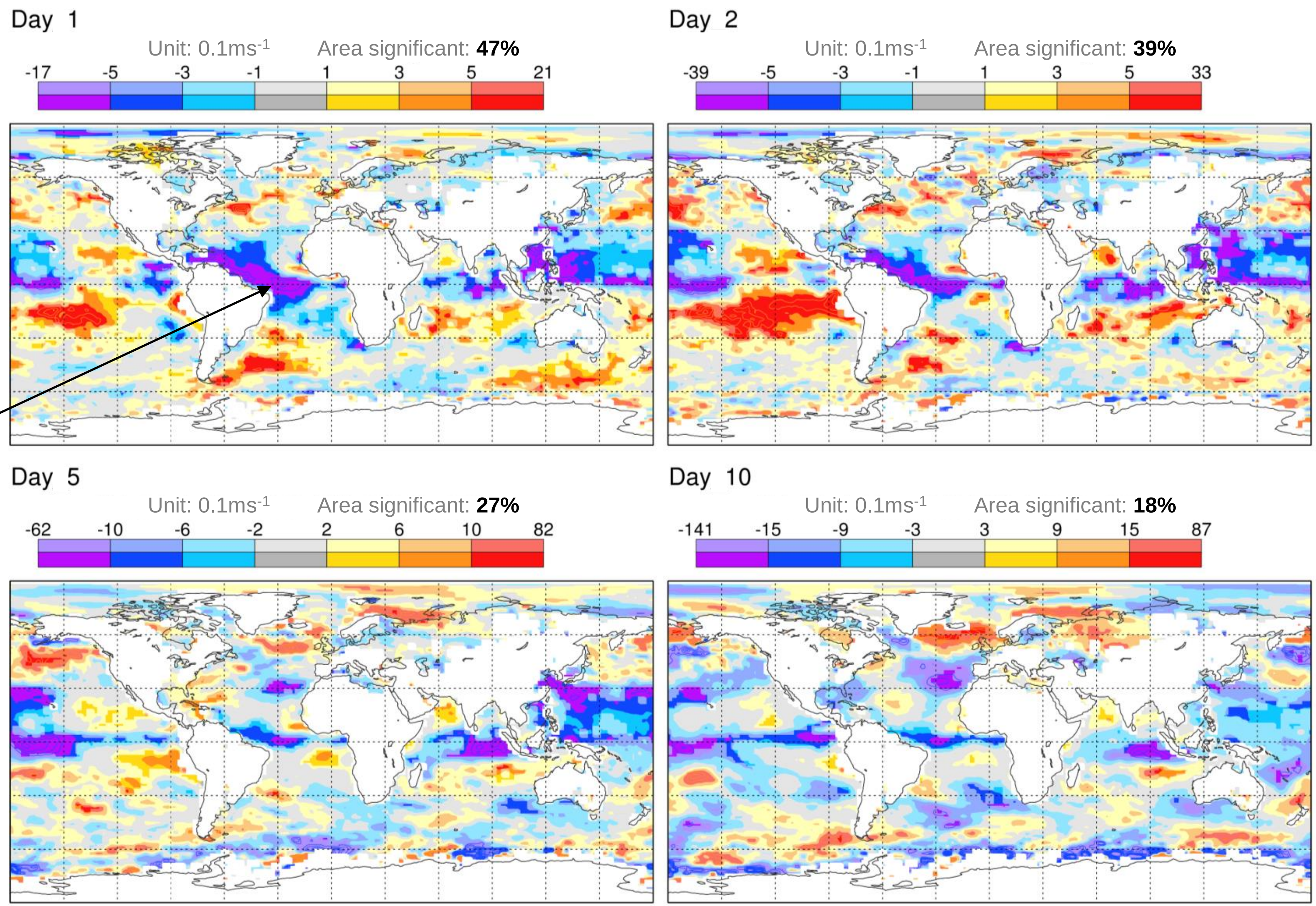
Based on HRES analyses for 0 and 12Z 20151201-20160228

Mean forecast error for u at 1000hPa (DJF 2016)

Errors evolve with leadtime, and a smaller area is statistically significant

…Hence best to look at short lead-times

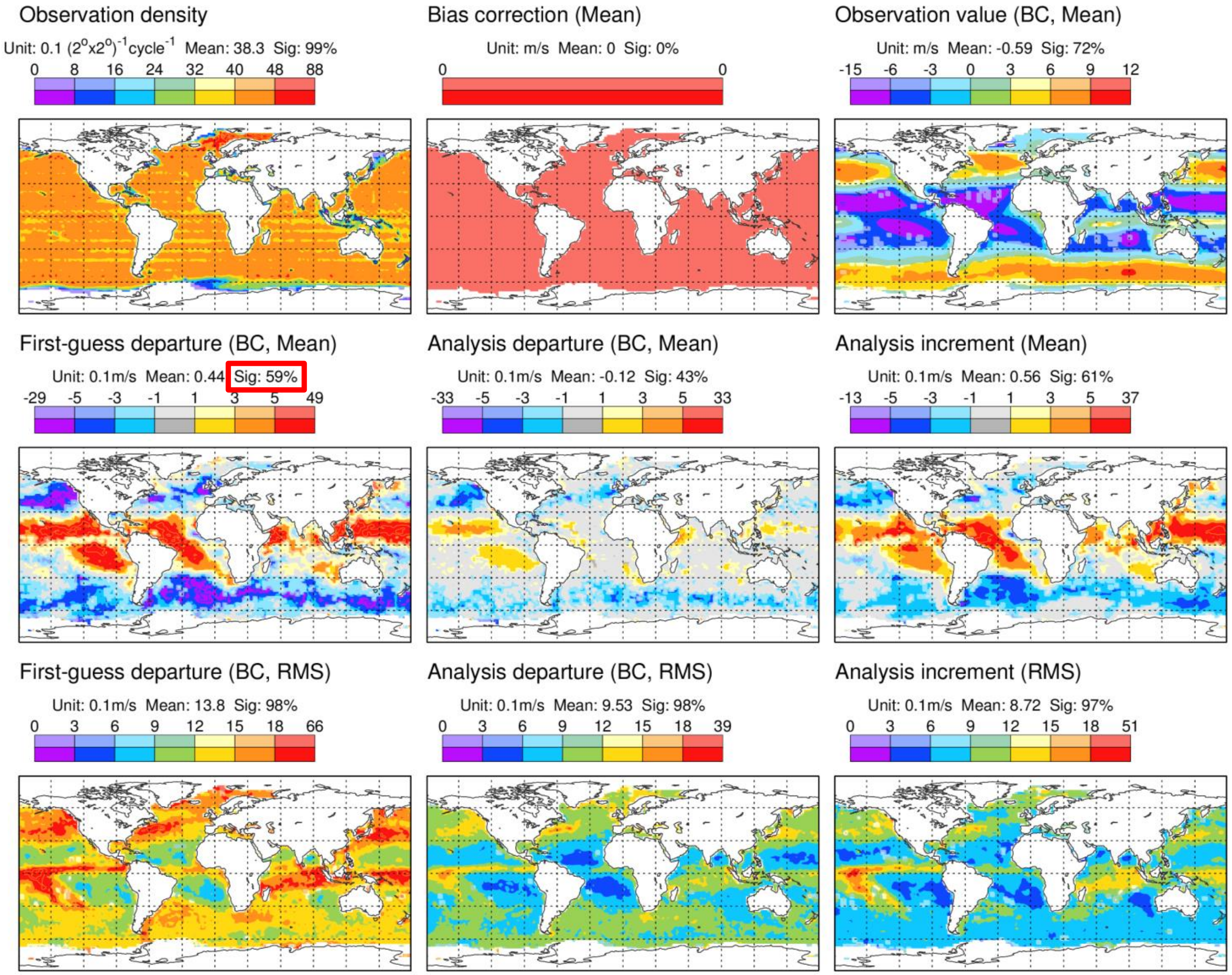
Up to 15% too strong easterlies relative to analysis



Based on HRES forecasts for 0 and 12Z verifying within 20151201-20160228. Statistical significance at the 5% level is indicated with more saturated colours

Data assimilation feedback for ASCAT scatterometer surface u

ASCAT considered to have no bias (by VarBC). Certainly small relative to mean first-guess departures (OBS-FG)



Tropical/subtropical easterlies too strong

Extratropical westerlies too strong (even clearer than in day 1 errors)

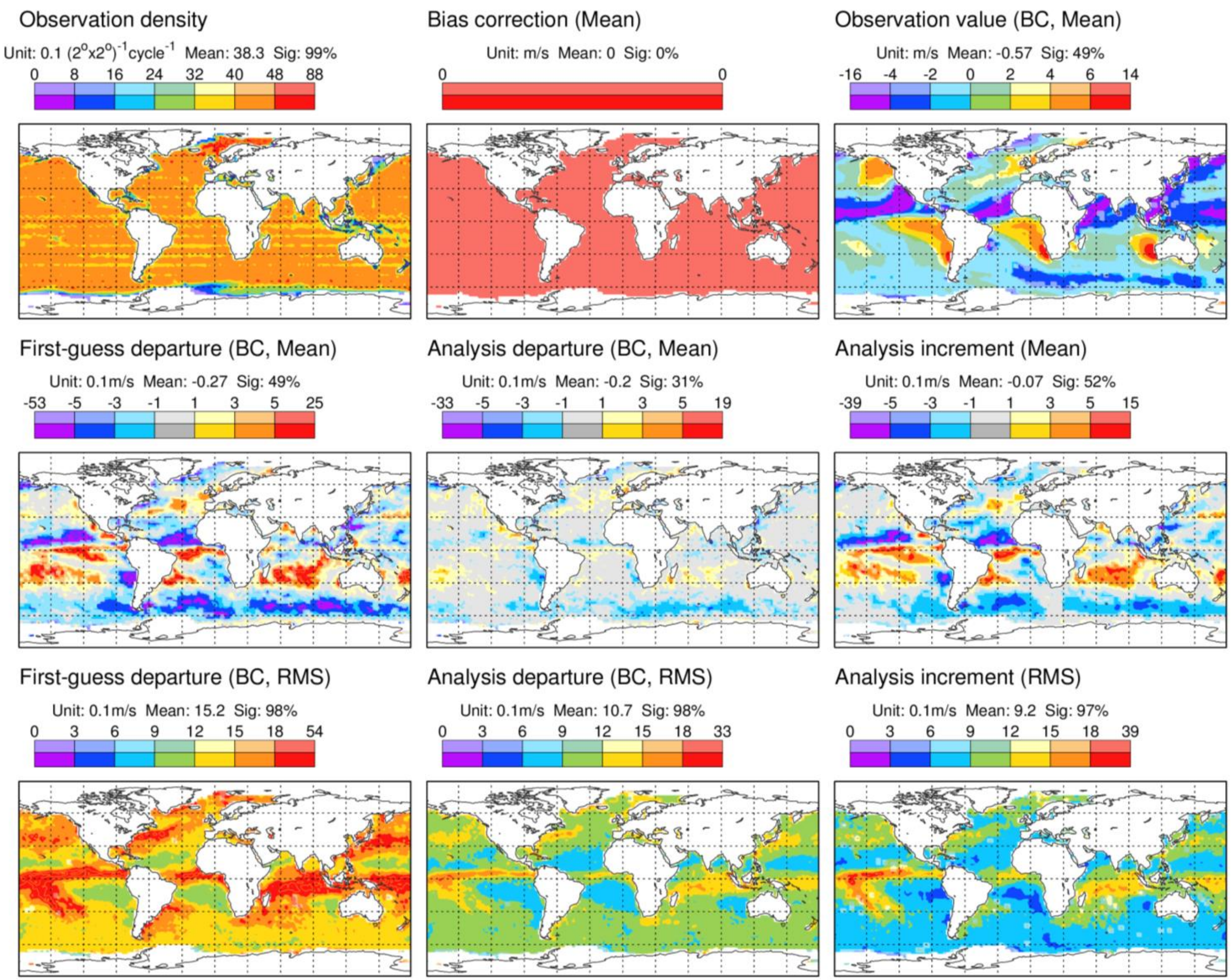
Analysis increments strongly correct the first-guess departures

Based on ASCAT observations from all platforms for DJF 2015/16. Statistical significance at the 5% level is indicated with more saturated colours

Data assimilation feedback for ASCAT scatterometer surface v

Tropical convergence too weak

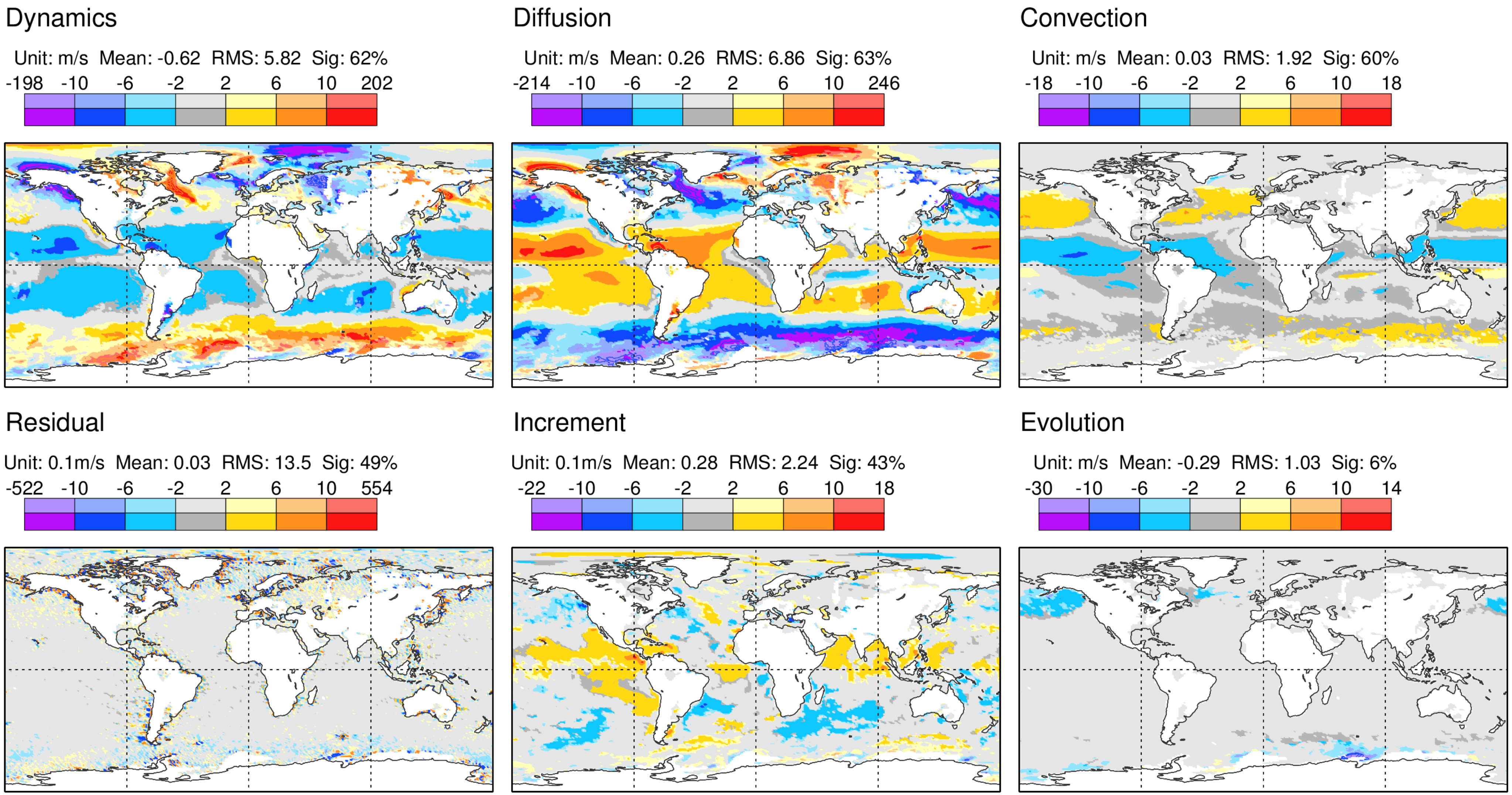
Antarctic convergence too weak



Based on ASCAT observations from all platforms for DJF 2015/16. Statistical significance at the 5% level is indicated with more saturated colours

Budget of mean background process tendencies and analysis increments for u1000

Increments correcting for process error(s)



Tendency/increment budget highlights key processes and possibly the key errors

Diffusion (resulting from drag) and convective momentum transport are key for u1000

Increment is a small residual in the balance between large terms: What process is it correcting?

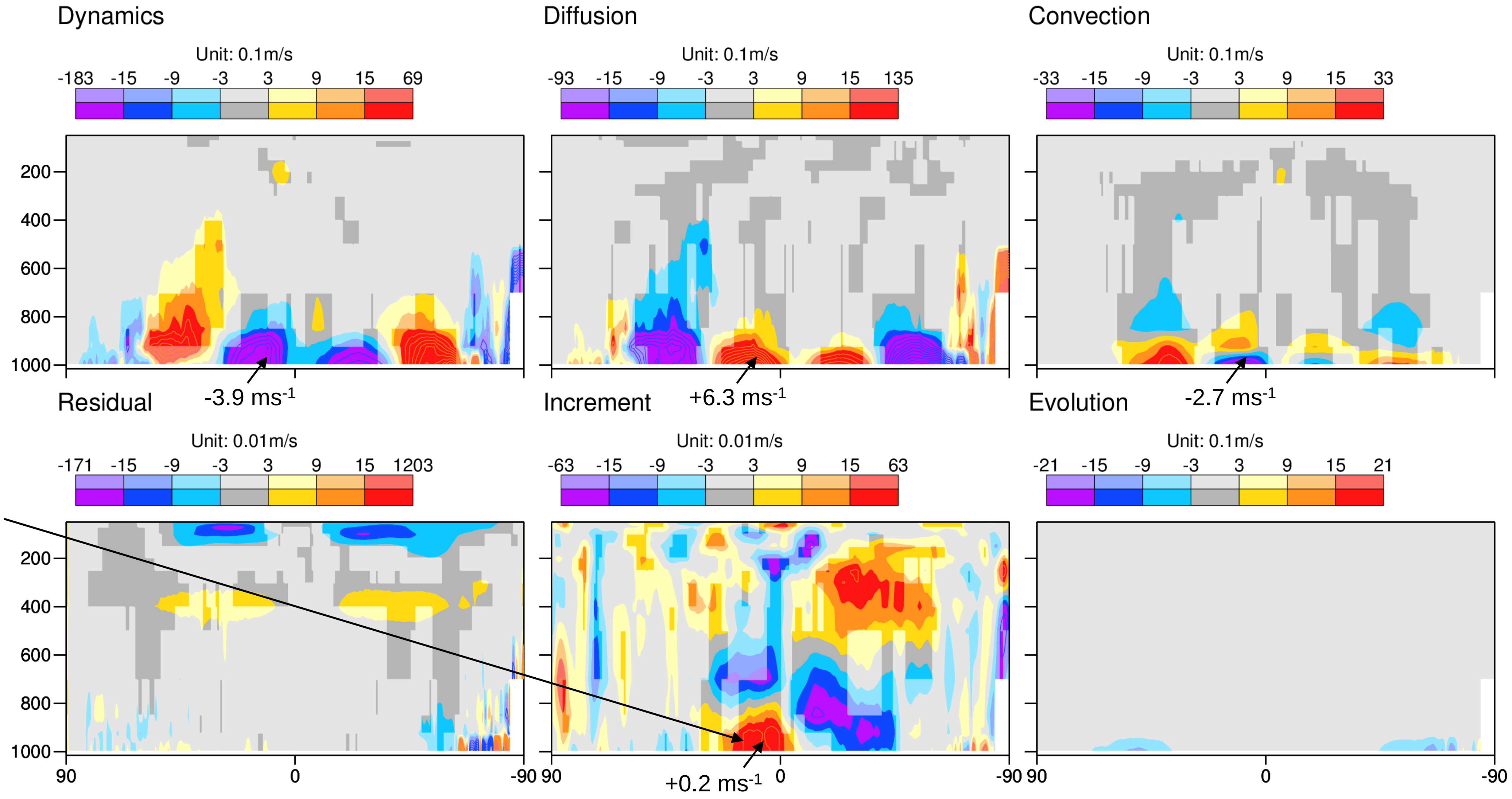
Data based on background forecast of the EDA control for DJF 2015/16. Tendencies are integrated over the data assimilation window (12 hours). Saturated colours: 5% sig.

Budget of mean background process tendencies and analysis increments for [u]

Too weak surface drag is the likely issue

Vertical structure of tropical lower-tropospheric increment projects better onto the Diffusion term than onto the Convective (momentum transport) term

Motivation for drag experiments



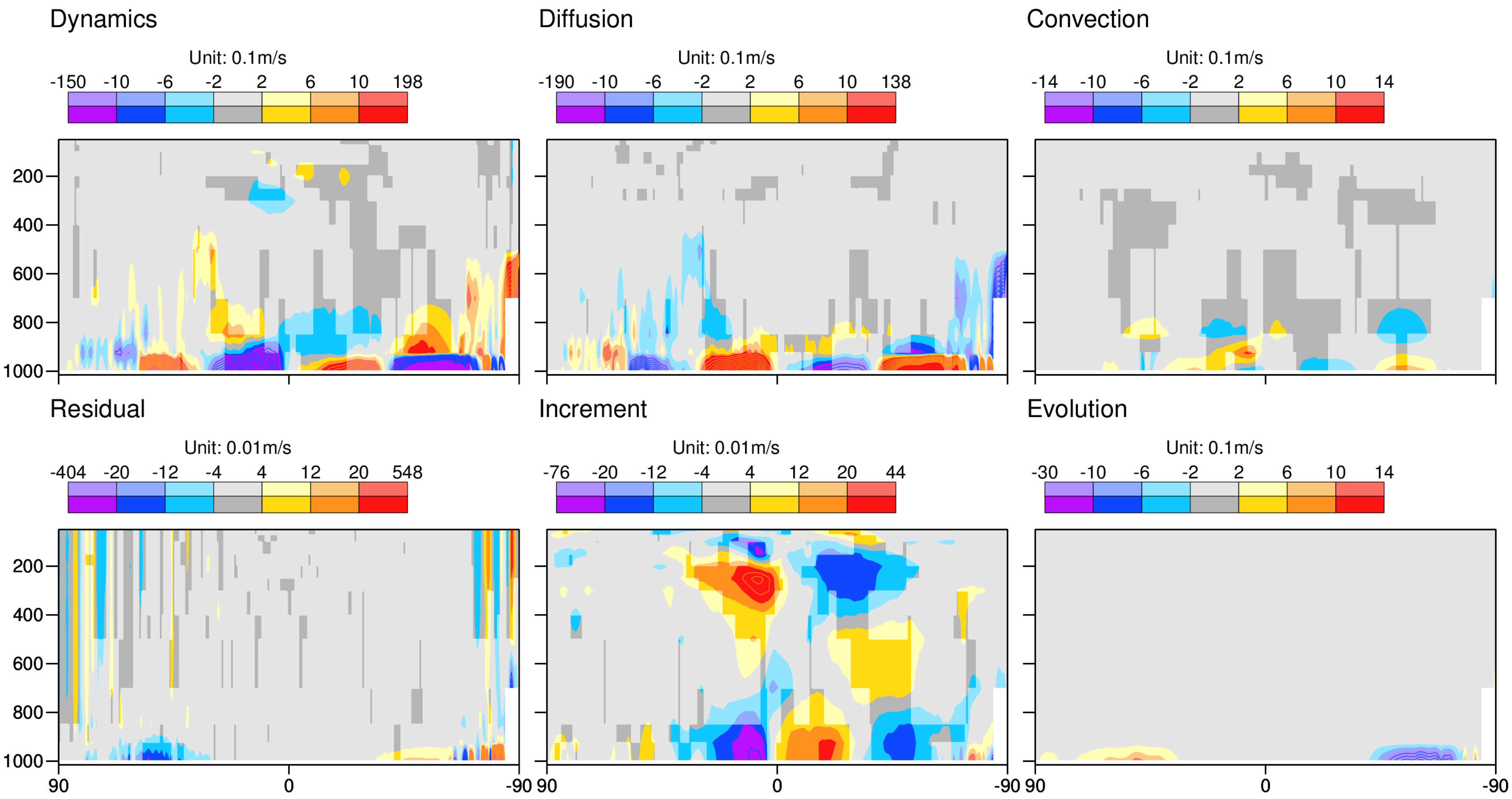
Data based on background forecast of the EDA control for DJF 2015/16. Tendencies are integrated over the data assimilation window (12 hours). Saturated colours: 5% sig.

Budget of mean background process tendencies and analysis increments for [v]

Meridional wind budget gives misleading signal

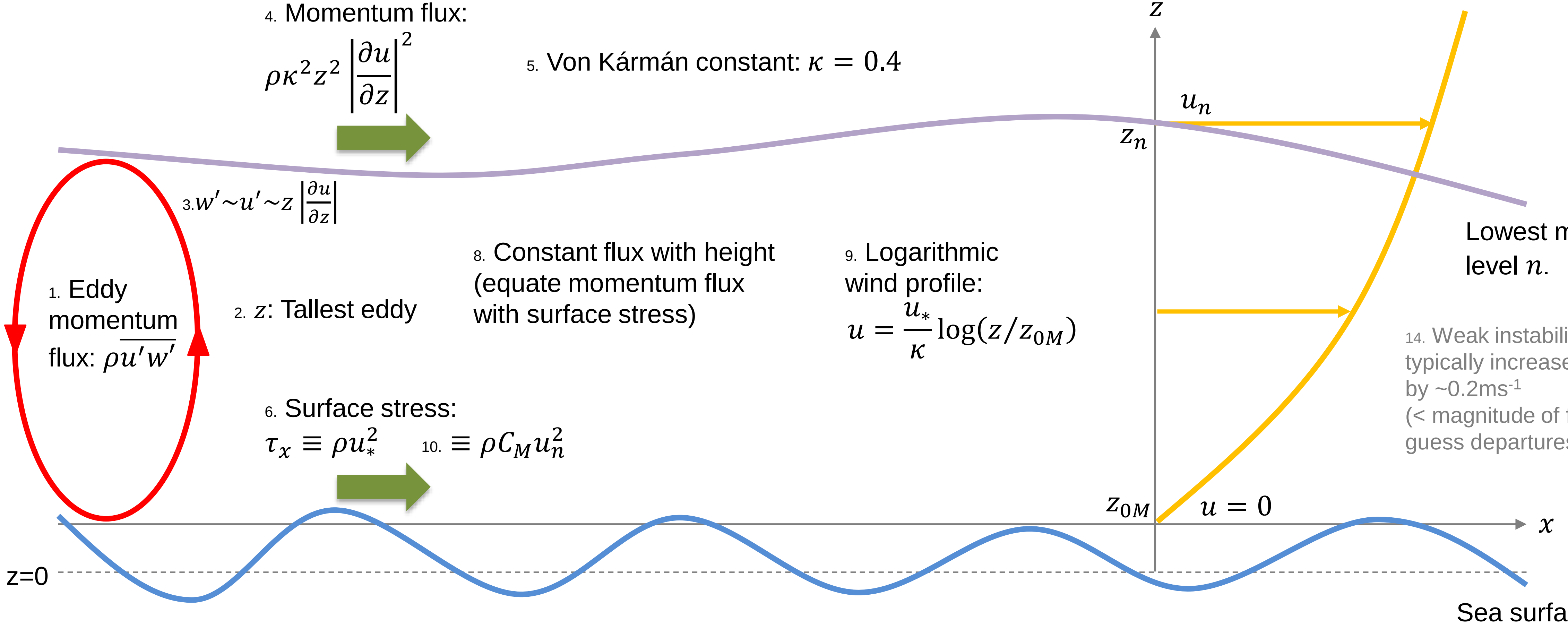
Increments act to strengthen convergence in the ITCZ. In doing so, they are acting against the diffusive tendency associated with surface drag

Will suggest this is an indirect effect (dynamical convergence tendency should be stronger)



Data based on background forecast of the EDA control for DJF 2015/16. Tendencies are integrated over the data assimilation window (12 hours). Saturated colours: 5% sig.

Momentum fluxes in the Surface Boundary Layer (neutrally stable, zonal flow)



1. Eddy momentum flux: $\rho\overline{u'w'}$

2. z: Tallest eddy

3. $w' \sim u' \sim z\left|\frac{\partial u}{\partial z}\right|$

4. Momentum flux: $\rho\kappa^2 z^2\left|\frac{\partial u}{\partial z}\right|^2$

5. Von Kármán constant: $\kappa = 0.4$

6. Surface stress: $\tau_x \equiv \rho u_*^2$ 10. $\equiv \rho C_M u_n^2$

7. Friction velocity: u_*

8. Constant flux with height (equate momentum flux with surface stress)

9. Logarithmic wind profile: $u = \frac{u_*}{\kappa}\log(z/z_{0M})$

11. Transfer coefficient: $C_M = \frac{u_*^2}{u_n^2} = \frac{\kappa^2}{\left(\log(z_n/z_{0M})\right)^2}$

12. Roughness length: $z_{0M} = \alpha_{Ch}\frac{u_*^2}{g}$

13. Charnock Parameter: α_{Ch} (from Wave model)

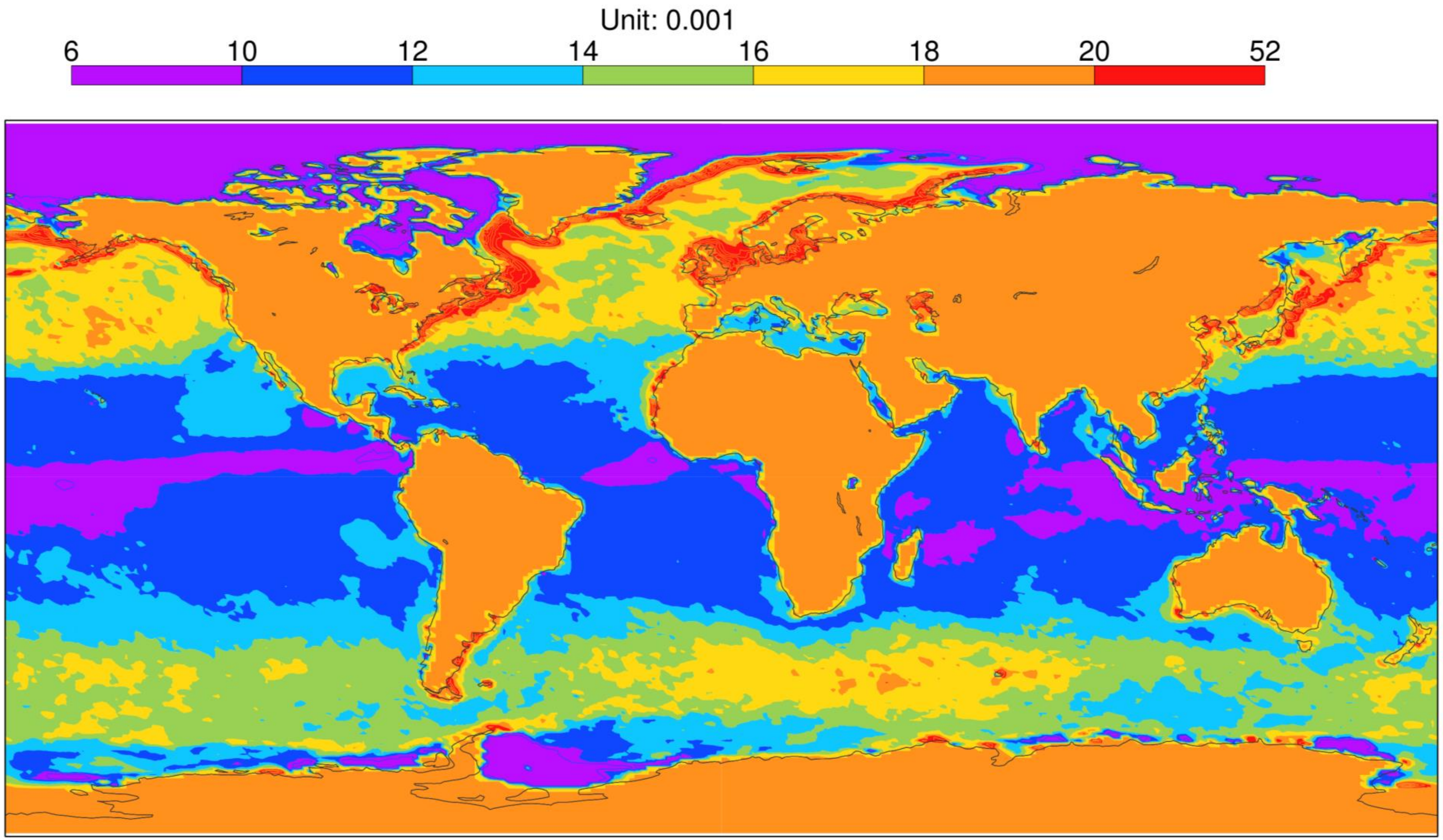
14. Weak instability (M-O) typically increases u_{10m} by ~$0.2ms^{-1}$ (< magnitude of first guess departures)

Turning off wave model fixes $\alpha_{Ch} = 0.018$ and affects coefs for momentum, heat and moisture C_M, C_H, C_Q. In drag expts, C_M alone is scaled.

Charnock parameter from wave model (DJF 2016)

The wave model produces values in the tropics below 0.010.

Turning off the wave model would give a uniform Charnock value of 0.018 (an increase over most of the oceans)



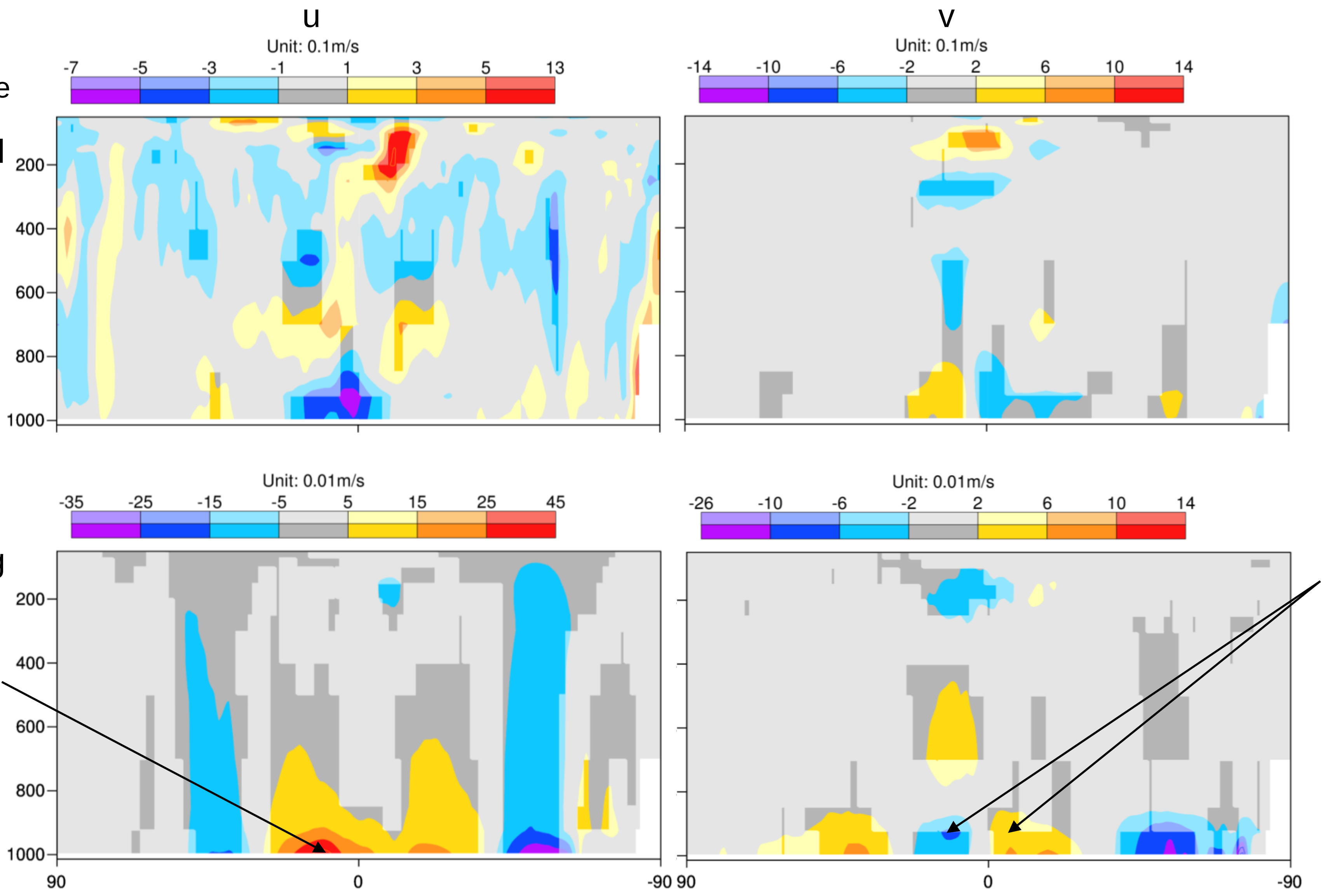
Based on HRES analyses for 0 and 12Z 20151201-20160228

Zonal-mean errors at day 1

Change reduces mean boundary-layer wind errors almost everywhere

Control model

110% drag – 90% drag



Tropical zonal wind error reduced by up to 100%

BL extra-tropical zonal wind errors also greatly reduced

Tropical meridional wind errors also reduced by ~20%

Antarctic convergence error reduced by ~50%

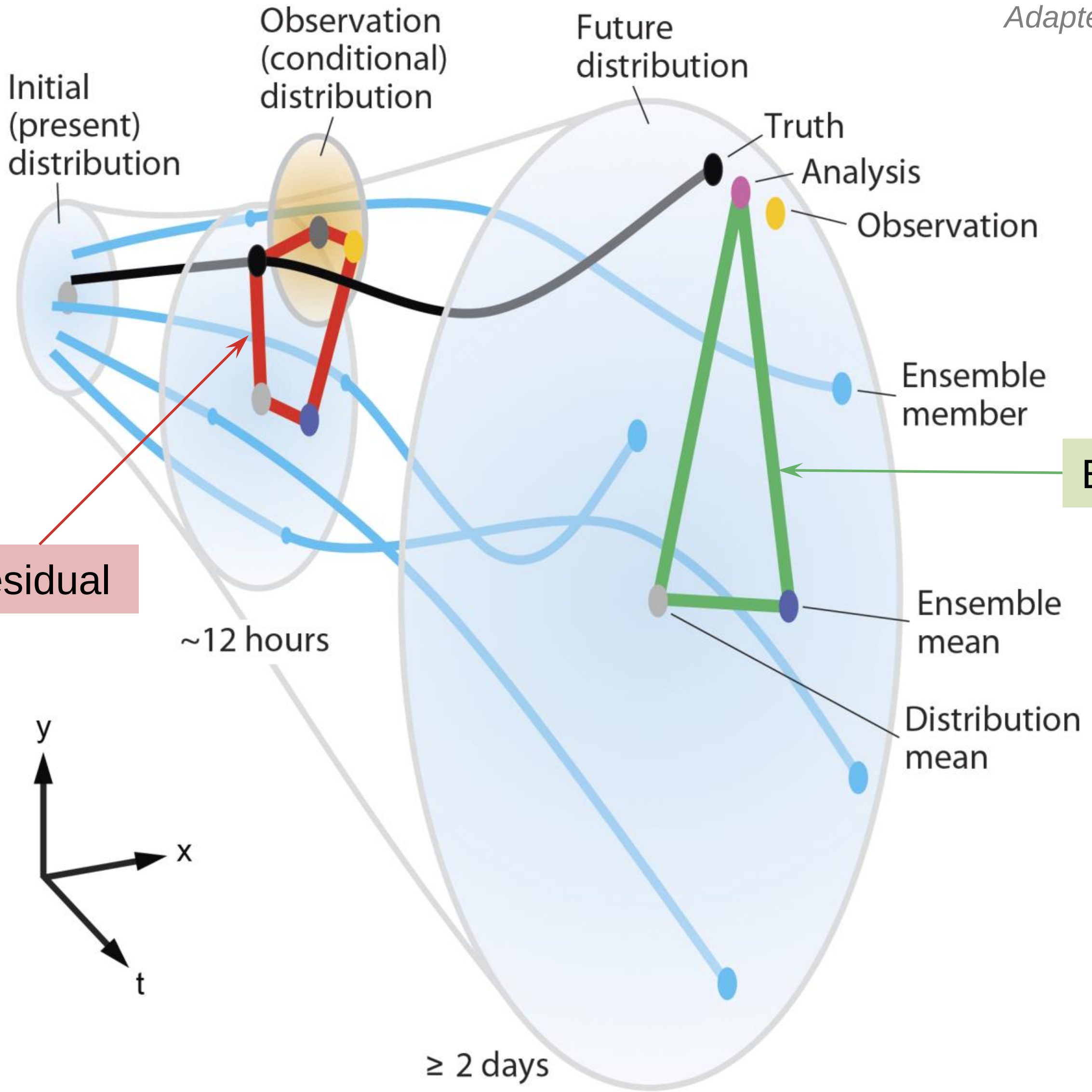
Associated with frictional convergence into low-pressure(?)

Control experiment for 28 forecasts started at 0Z 20140201-20140228. Saturated colours: 5% sig.

Diagnosing error variances

Reliability in ensemble forecasting

Adapted from Rodwell et al. (2015) QJRMS



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

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

Residual can highlight poorly represented sources of uncertainty, and with reasonable sample sizes

Residual does not readily point to poorly represented sources of uncertainty, and requires large samples to obtain robust results

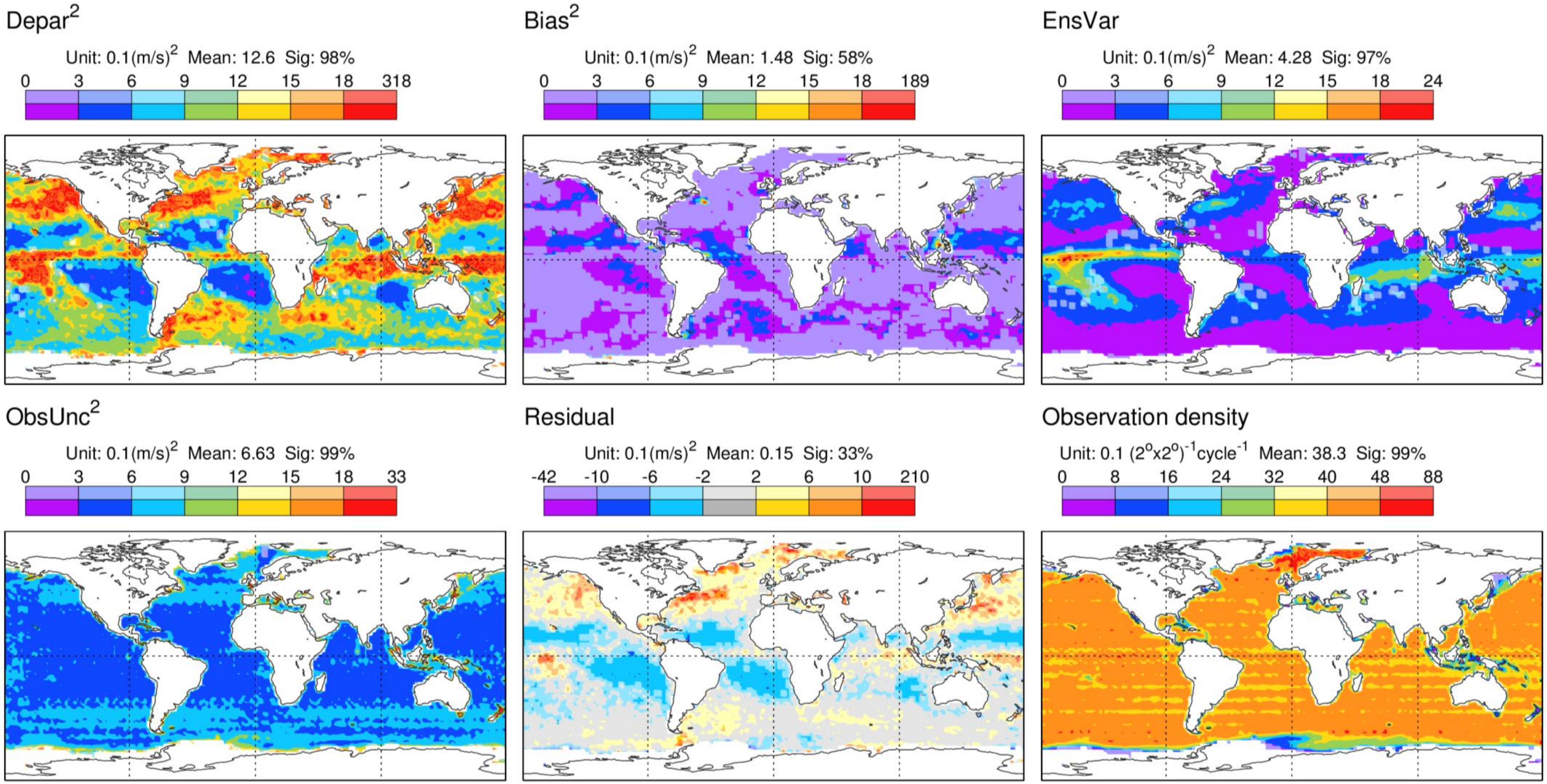
(Cross-terms on squaring have zero expectation. EnsVar is scaled variance to account for finite ensemble-size)

Ensemble data assimilation reliability budget for ASCAT scatterometer surface u

Rodwell et al., QJRMS, 2016

Negative variance residual in subtropical anticyclones (and positive elsewhere) suggests we also need to improve representation of observation and/or model uncertainty

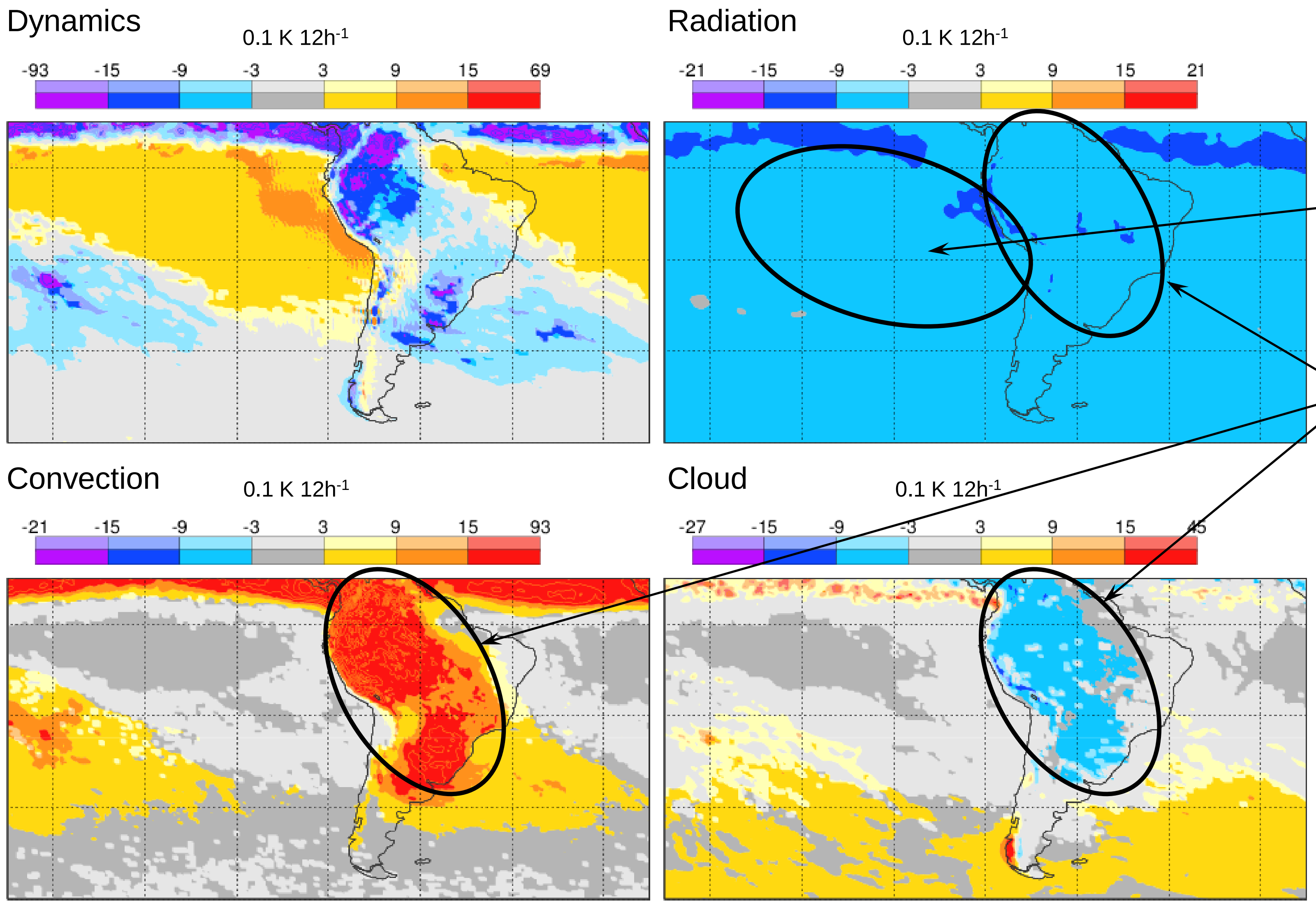
A good representation of observation error will help us develop better stochastic physics schemes



Based on ASCAT observations from all platforms for DJF 2015/16. Saturated colours: 5% sig.

Initial tendencies from control forecast: SON 2014

T500, SON 2014



Stoch.Phys. ≈ αRadiation

Stoch.Phys. ≈ α(Radiation + Convection + Cloud)

At ECMWF stochastic physics is largely a multiplicative scaling of the total physics tendency

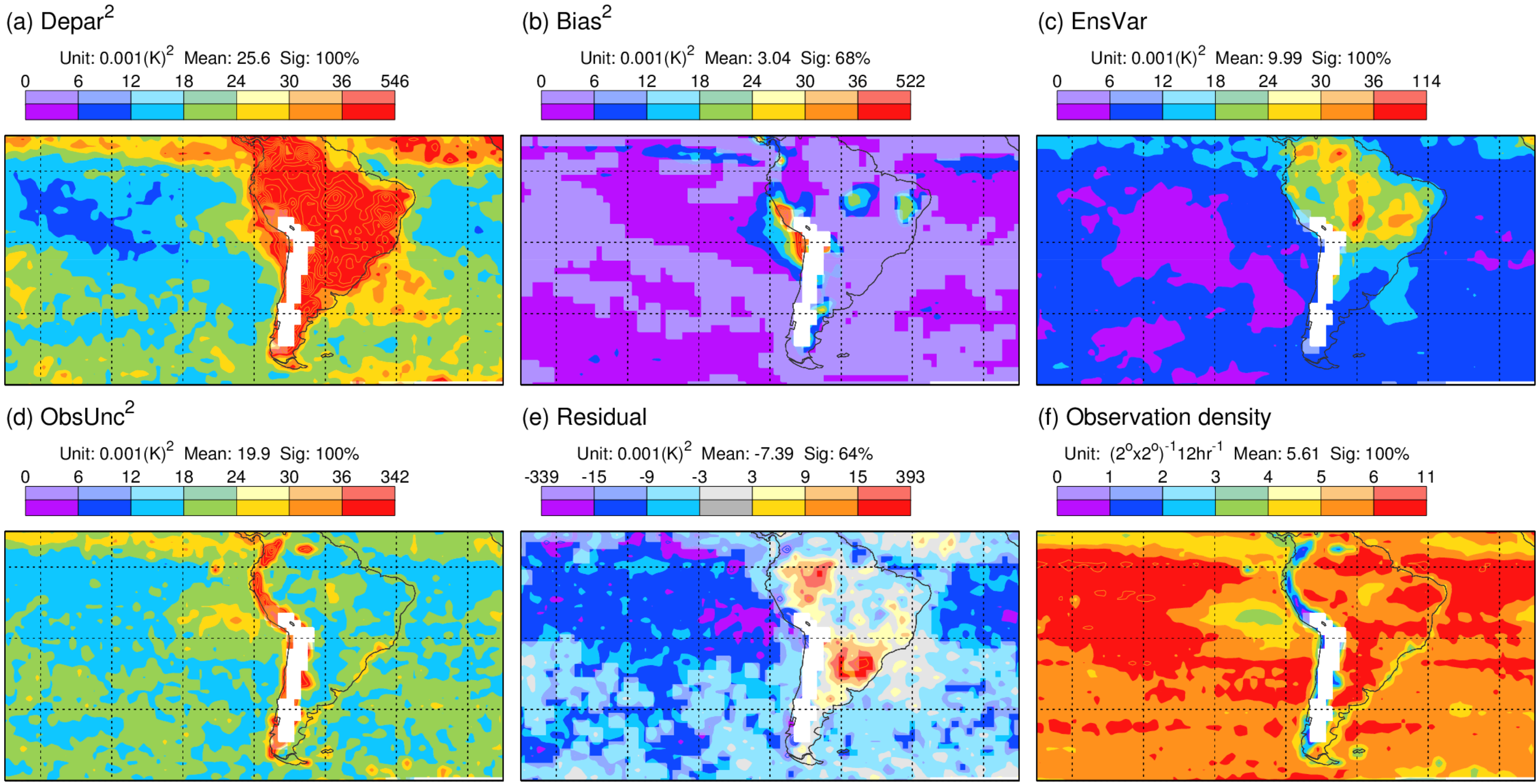
Is physics in subtropical anticyclones as uncertain as Stochastic Physics treats it?

Saturated colours: 5% sig.

EDA reliability budget: Satellite microwave (~T500)

Rodwell et al. (2015) QJRMS

Relative to AMSUA channel 5 microwave brightness observations of mid-tropospheric temperature



Largest departures and ensemble variance in convective regions

Large bias off west coast (associated with errors in cloud detection?)

ObsUnc^2 is sometimes larger than Depar^2 off west coast

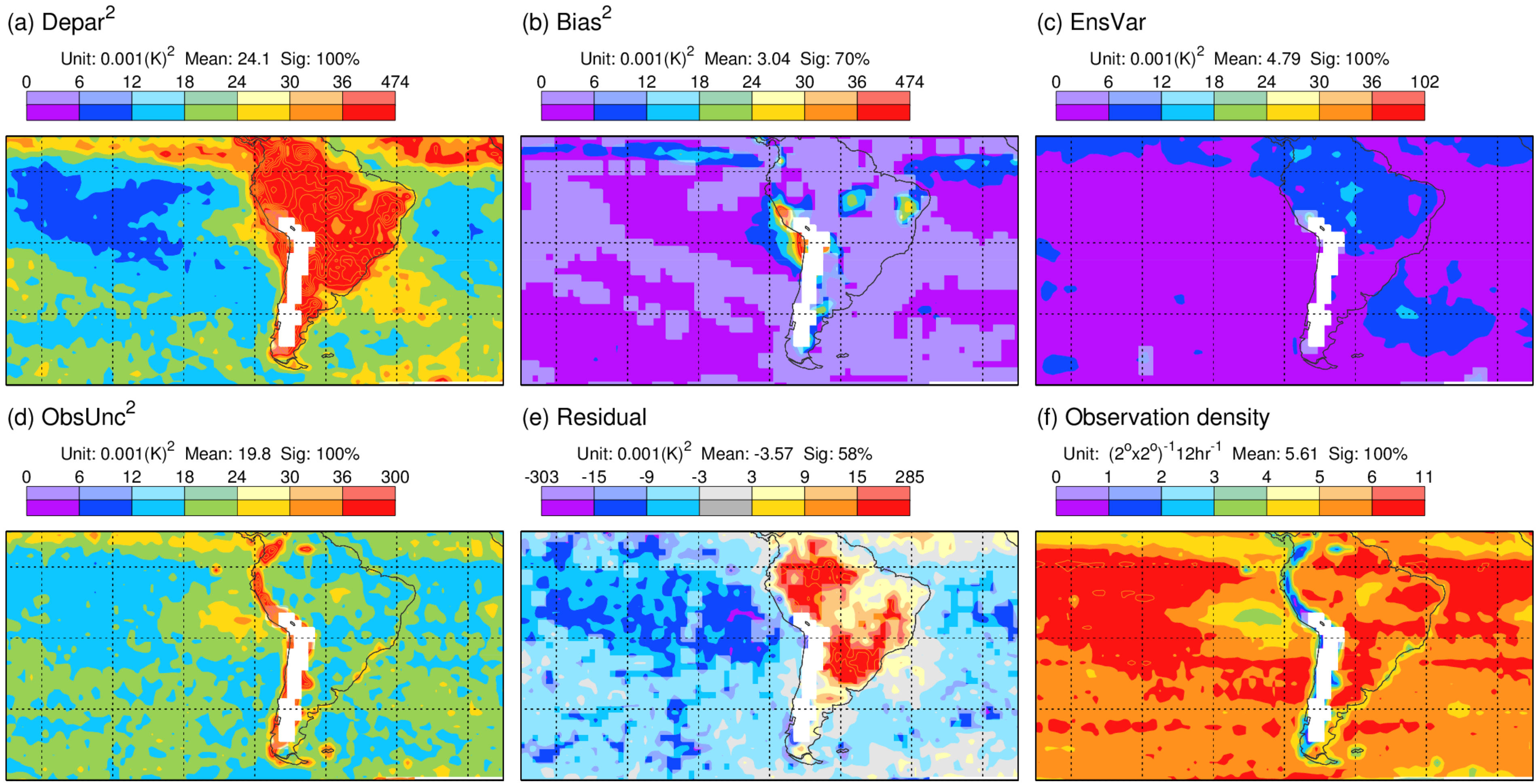
Residual consistent with too much stochastic physics in subtropical anticyclones, too little in convective regions

2 members, 20110812-20111116. Saturated colours: 5% sig.

EDA reliability budget: Satellite microwave (~T500) No Stochastic Physics

Rodwell et al. (2015) QJRMS

Relative to AMSUA channel 5 microwave brightness observations of mid-tropospheric temperature



Reduction in ensemble variance

Improved diagnosed reliability within subtropical anticyclones, but convective regions worse

EDA reliability budget *is* sensitive to *local* changes in Stochastic Physics

Should help development of stochastically-formulated process parametrizations

Note that Obs Error assignment also likely to be an issue in this budget

2 members, 20110812-20111116. Saturated colours: 5% sig.

Diagnosing teleconnection errors

Barotropic vorticity equation, mean analysis DJF 2015/16 (100-300hPa mean)

$-\underline{\nabla}\cdot\zeta\underline{v}_{\chi}$

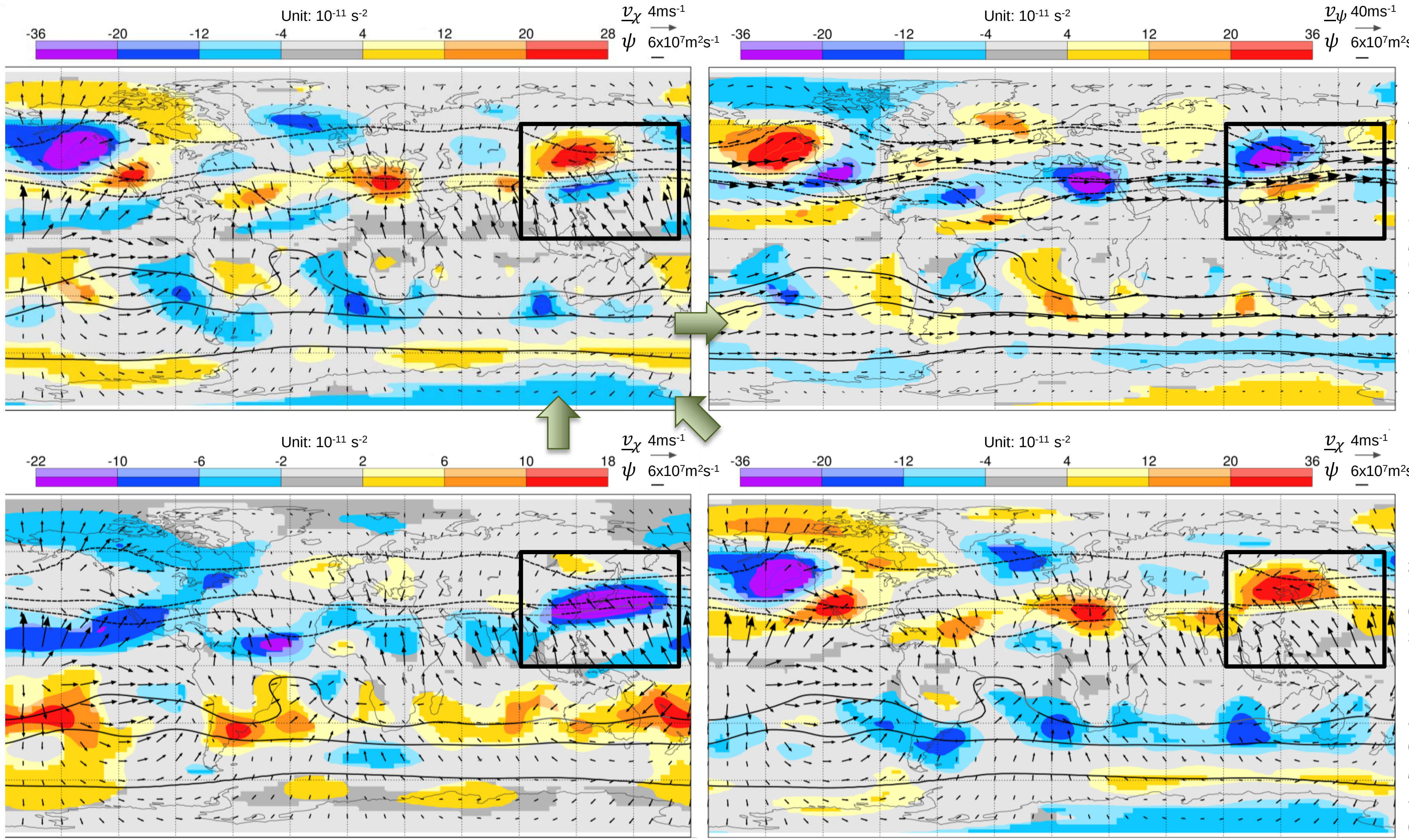
3. Rossby wave source (RWS)

Importance of winds near tropopause level

$-\underline{v}_{\chi}\cdot\underline{\nabla}\zeta$

1. Advection by divergent wind

Warm-pool convection outflow forces Rossby Waves on the extratropical Jet



$-\underline{v}_{\psi}\cdot\underline{\nabla}\zeta$

4. Advection by rotational flow

Seasonal-mean flow "adjusts" so that this largely cancels RWS

$-\zeta\underline{\nabla}\cdot\underline{v}_{\chi}$

2. "Stretching"

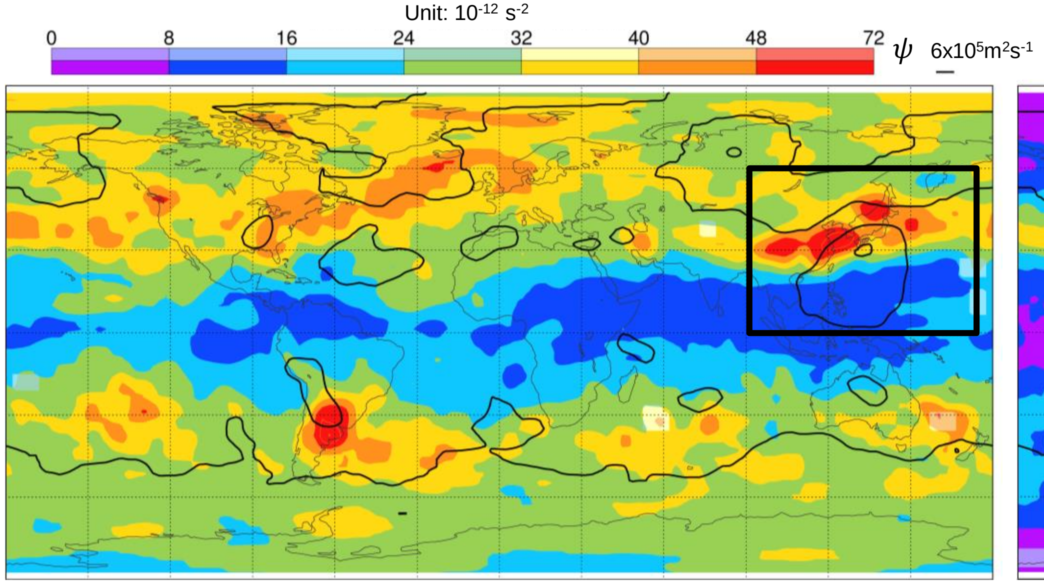
e.g. Down-stream of Tibet

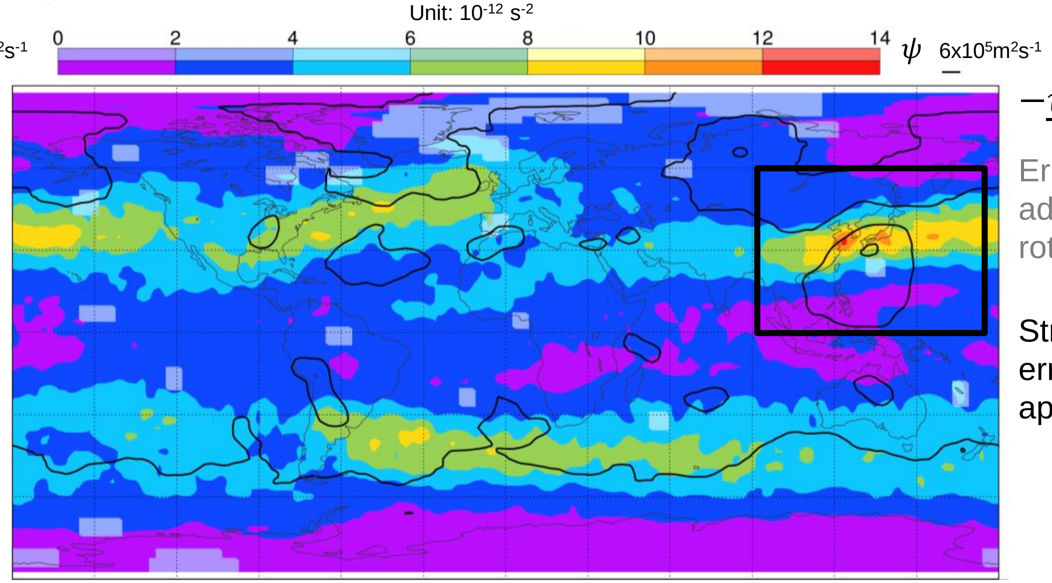
Note: varying contour intervals. Saturated colours: 5% sig.

Barotropic vorticity equation, D+1 RMSE DJF 2015/16 (100-300hPa mean)

$-\underline{\nabla}\cdot\zeta\underline{v}_\chi$

Rossby wave source errors





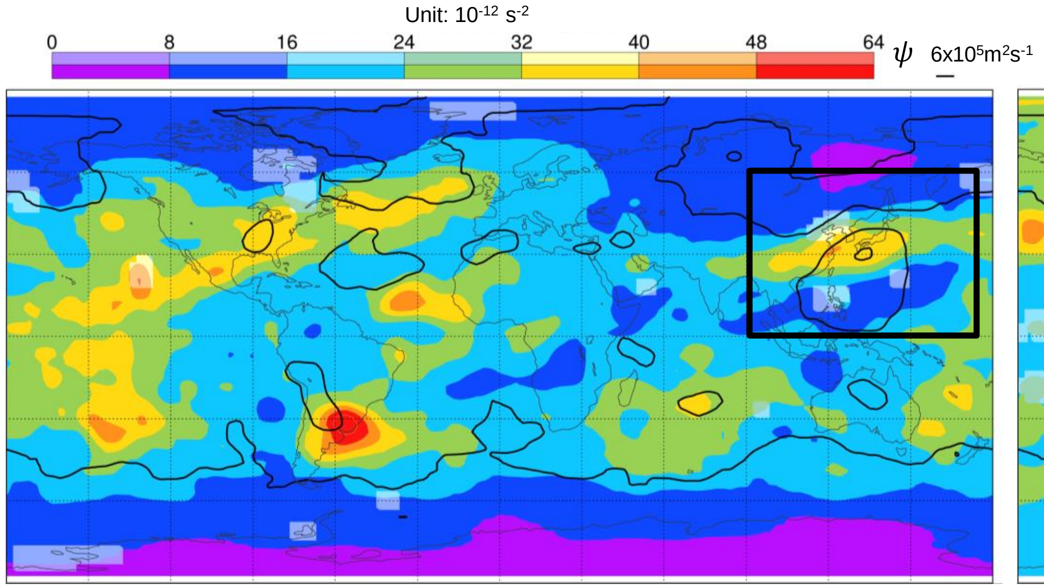
$-\underline{v}_\psi\cdot\underline{\nabla}\zeta$

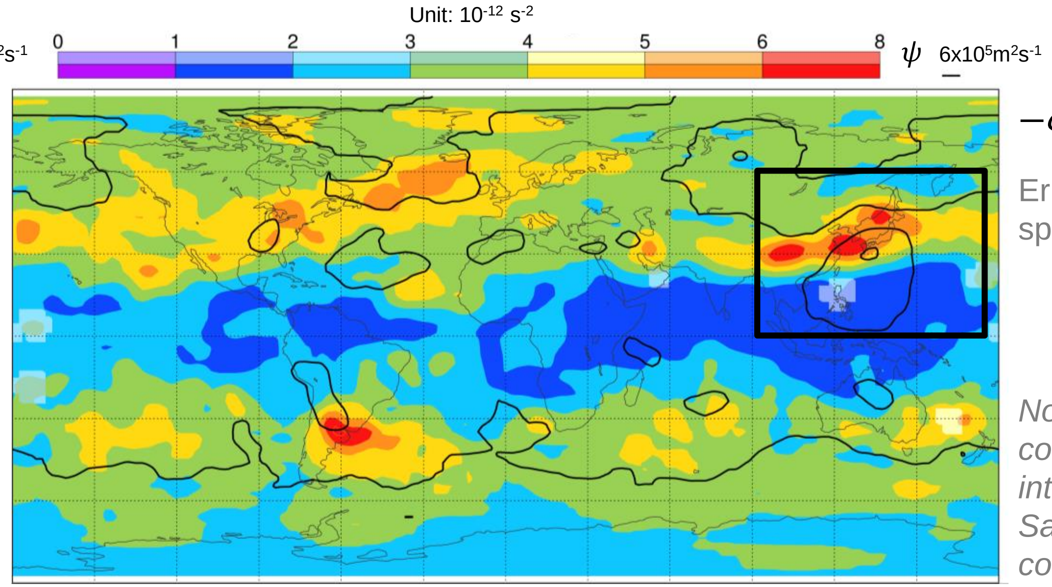
Errors in advection by rotational flow

Streamfunction errors already apparent

$-\underline{v}_\chi\cdot\underline{\nabla}\zeta$

Extratropical errors due to errors in Warm-pool convection





$-\zeta\underline{\nabla}\cdot\underline{v}_\chi$

Errors in local spin-up

Note: varying contour intervals. Saturated colours: 5% sig.

Summary (focus on Tropics and Aeolus wind data)

- Systematic errors | Process tendency budget
  - Key errors in Hadley Circulation and Asian monsoon are sensitive to boundary-layer momentum budget
  - Better wind observations will help improve the model (as well as improve forecast initialisation)
- Flow-dependent reliability | EDA reliability budget
  - Good representation of wind observation errors is important, and will help improve the representation of model uncertainty too
- Tropical forcing of extratropics | Rossby Wave Source
  - Better vertical resolution in observed winds at tropopause (than from radiance measurements) will help diagnose impacts and errors

Abstract

Data assimilation is where models and observations confront each other, and perhaps the best place to diagnose errors in each. (At longer leadtimes, diagnosis will be of evolved errors, which are less easily traceable to their original sources, and require much larger sample sizes to obtain robust results). The key attributes of any probabilistic forecast are its reliability and sharpness, and here I will focus on reliability – the statistical properties of the forecast distribution. With tropical winds in mind, I will demonstrate how a process-tendency/analysis-increment budget can help diagnose the causes of model bias, and how an observation-space variance budget can help evaluate our flow-dependent representations of model and observation uncertainty. Through the use of Rossby-wave source diagnostics (based on the barotropic vorticity equation), I will also demonstrate how we can evaluate the impact of tropical errors on extratropical forecasts.