Convection, Humidity, and Predictability in a Near-Global Aquaplanet CRM

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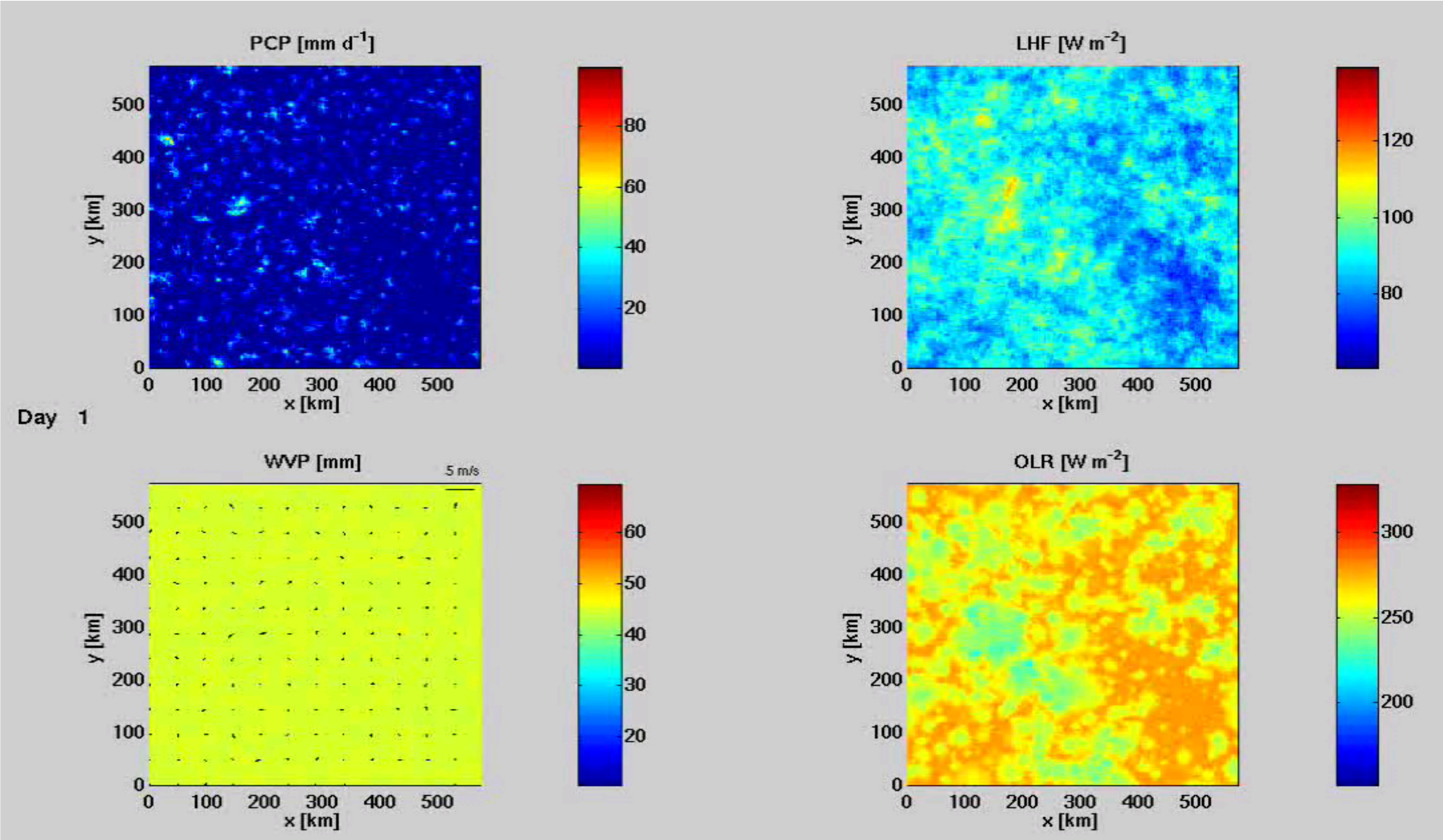
100 day RCE simulation, SST = 301 K, 576x576 km domain

(Bretherton et al. 2005)



Moist static energy budget analysis of self-aggregation

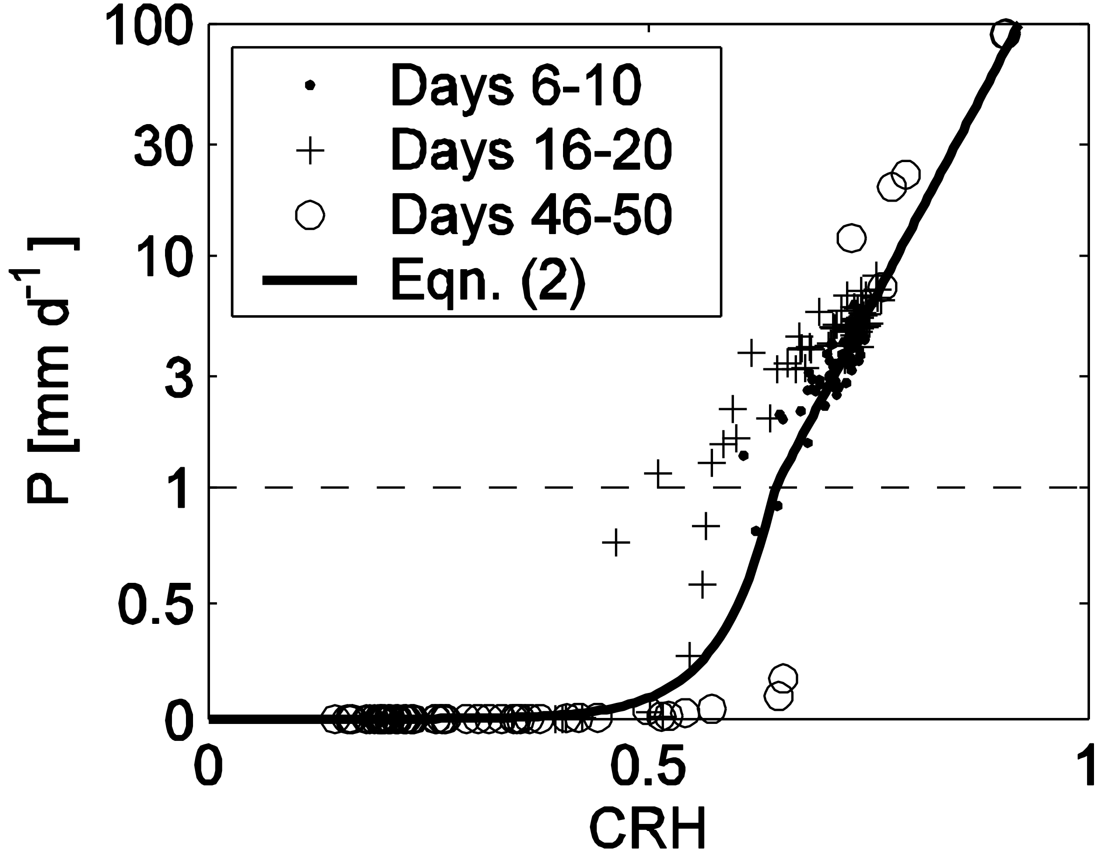
- Use daily horiz. averages over 72x72 km subdomains (space-time averaging on sub-aggregation scale)
- Use subdomain tropospheric column-averaged ‘<>’ budgets of moist static energy $h = c_p T + Lq + gz\ [- L_f q_i]$ to understand self-aggregation feedbacks. Here M = mass of air in column

$$
\begin{aligned}
& M\, d\langle s\rangle/dt = LP + SHF + RAD - \langle div(\mathbf{u}s)\rangle \\
+\ & M\, d\langle Lq\rangle/dt = -LP + LHF \qquad - \langle div(\mathbf{u}q)\rangle \\
\hline
& M\, d\langle h\rangle/dt = THF + RAD - \langle div(\mathbf{u}h)\rangle
\end{aligned}
$$

- Horizontal T variations (′) small, so $\langle h\rangle' \approx \langle Lq\rangle' = PW'/M$, where PW is precipitable water or water vapor path (WVP).
- Self-aggregation if $d\langle h\rangle/dt$ positively correlated to $\langle h\rangle$, so moist regions get moister and dry regions get drier.

Moister blocks precipitate more

Define 'column relative humidity' $r = W/W_{sat}$. Then…



$P \approx P_{RCE} \exp(a_m[r - r_{RCE}])$,

P_{RCE} = 3.5 mm d^{-1},

a_m = 16.6,

r_{RCE} = 0.72.

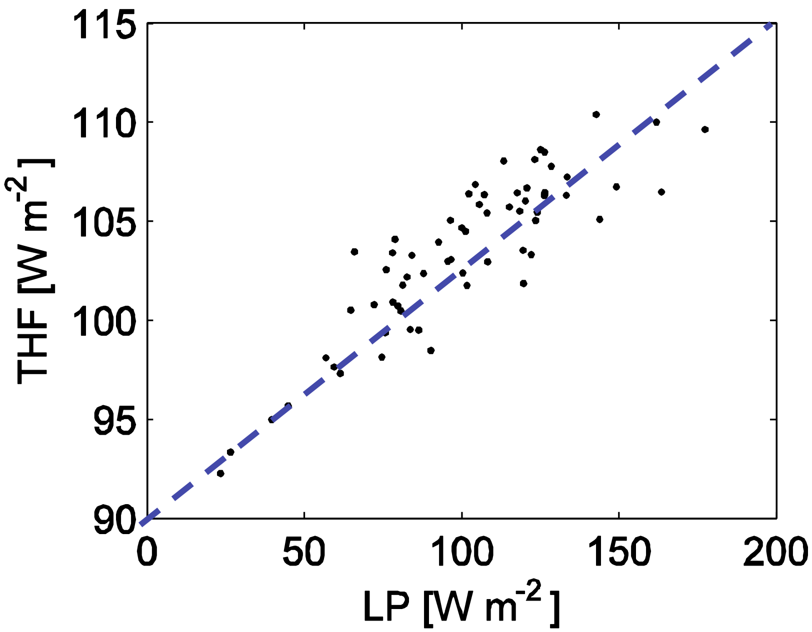
(Bretherton et al. 2005)

(Relationship depends slightly on evolving T profile)

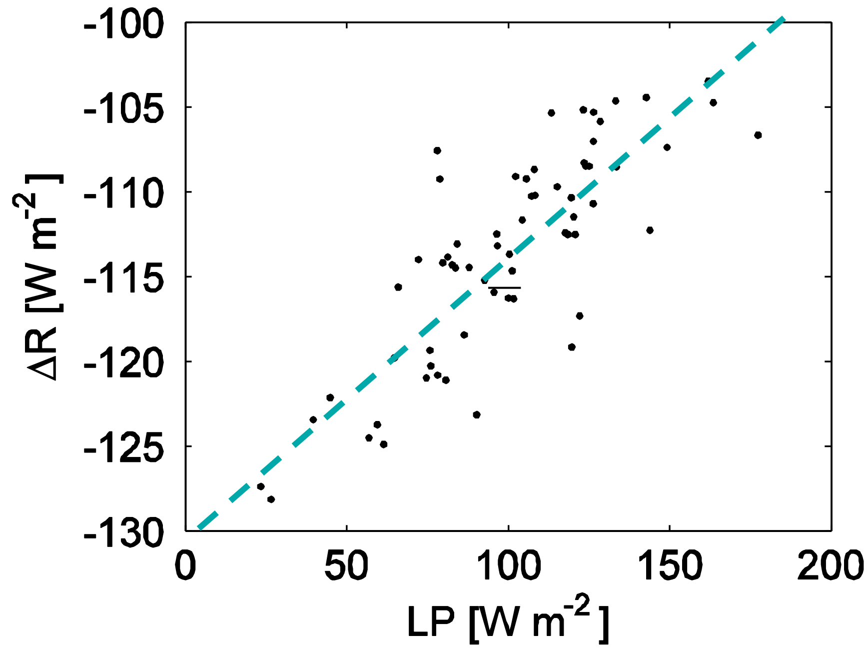
…similar relationship observed over tropical oceans on daily timescales (Bretherton et al. 2004)

Convection influences diabatic forcing

Gustiness (cold pools)



Anvil greenhouse



dTHF/dLP = c_S = 0.12

dRAD/dLP = c_R = 0.17

Bretherton et al. (2005) speculated that these self-aggregation feedbacks might help develop the MJO, and they are important to modern 'moisture mode' theories of the MJO.

Mapes et al 2008: GCRM aquaplanet predictability study

- NICAM GCRM run 30 days from identical initial conditions with 7 km and 14 km horizontal grid ('fraternal twin' experiment)
- Growth of differences is a measure of potential predictability in a model free of dicey cumulus parameterization assumptions.

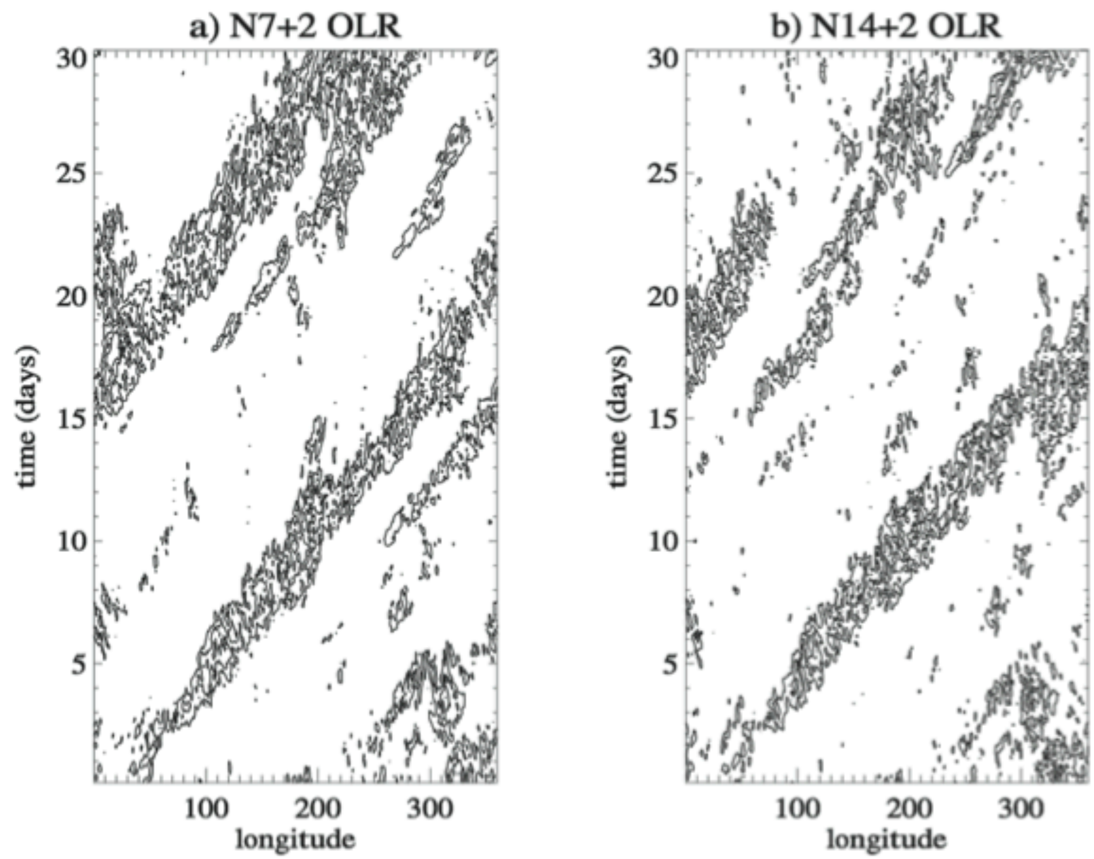
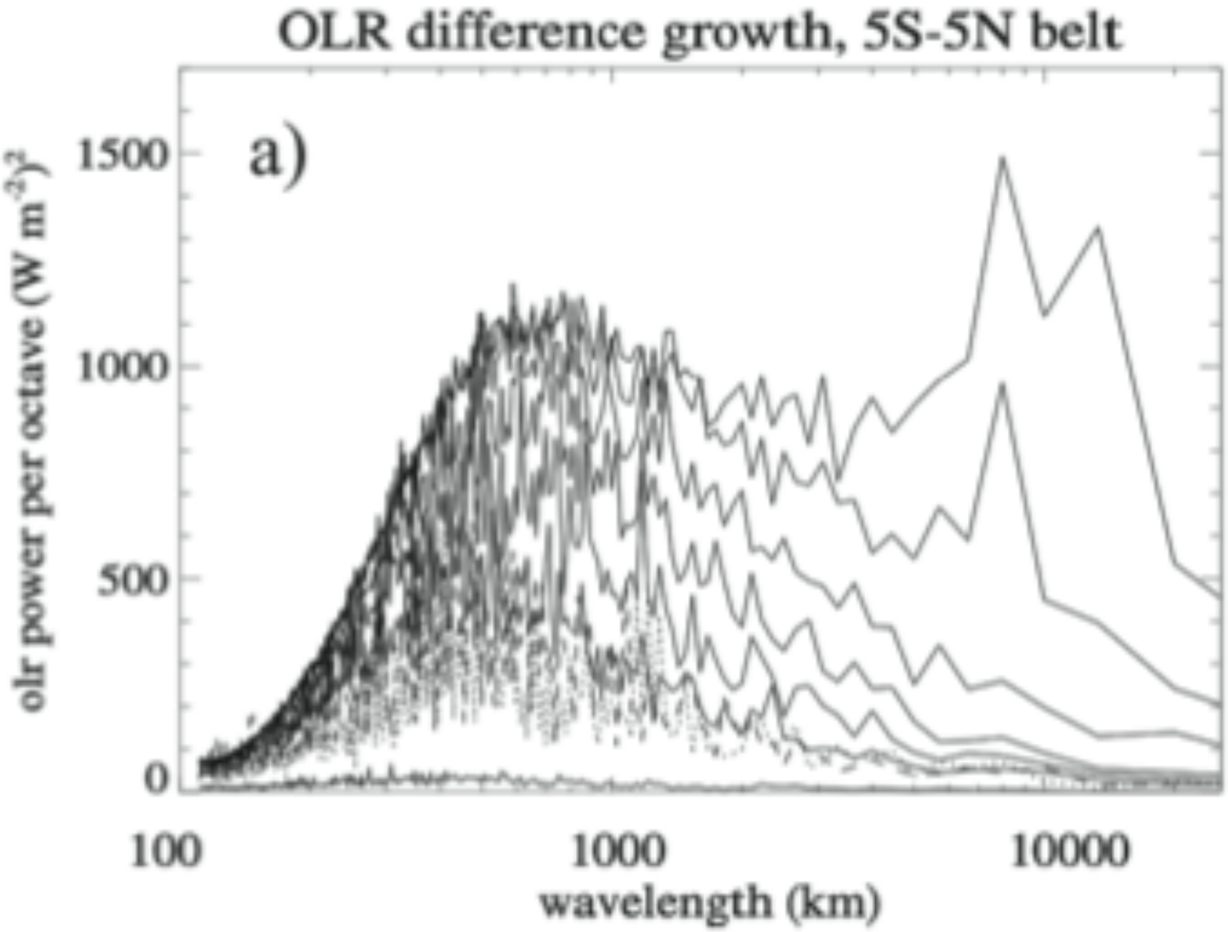


Fig. 1. Time-longitude sections of OLR averaged 10N–10S, for the $N7^{+2K}$ and $N14^{+2K}$ simulation pair. Contours are 180, 210, 240 W m^{-2}.

Scale dependence of perturbation growth



Perturbations grow simultaneously at all scales, saturating at:
λ = 500 km at 8 d,
3000 km at 16 d
longer at global scales.

Fig. 3. Squared differences of OLR between a) N7–N14 and b) $N7^{+2K}$–$N14^{+2K}$ simulations, averaged over the 5N–5S belt, in the log-wavelength domain. The vertical axis is scaled to indicate power per octave, while the horizontal axis covers 8 octaves exactly. The rising sequence of lines represents times of 3h, 6h (dotted). 9h (dashed); then mean differences over 1d, 2d, 4d, 8d, 16d, 30d.

Goals of our study

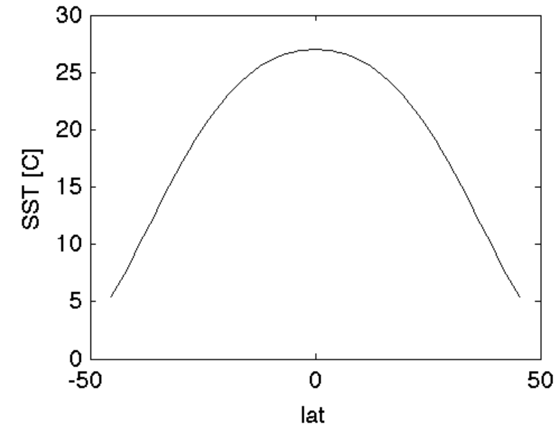
Use a near-global convection-resolving aquaplanet simulation:

1. To diagnose whether surface energy fluxes and atmospheric column radiative cooling have similar positive feedbacks on maintenance and growth of humidity/MSE anomalies as they do in convective self-aggregation simulations, and if so, on what scales.
2. To examine the growth of small humidity perturbations and the time scale on which they limit the predictability of large-scale tropical circulations (Lorenz 1969; Mapes et al. 2008)

A promising but rocky start

- 2013: Marat had good access to IBM BlueGene supercomputer
- He did several 16384 x 8192 km x 32 level CRM simulations (4 km resolution) on a zonally-symmetric aquaplanet (6M core hours)
    - Equatorial beta-plane (36 S- 36 N)
    - Rigid N/S walls, periodic in E-W direction
    - Specified latitudinally-varying SST
    - Interactive radiation with diurnal cycle
    - Each run 100+ days
- I saw obvious potential in results and began collaborating
- In Dec. 2013, all simulations were lost due to BlueGene disk crash and decommissioning shortly thereafter
- Marat, John Helly and I got 1M core hours of XSEDE time to recreate improved versions of the simulations.

New approach



- Use APE standard 'QOBS' SST profile
- Go out to 46 degrees latitude for better simulation of midlats (5120 x2560x32 gridpoints ←→ 20480 x 10240 km)
- Much more efficient spinup using Δ =20 km for 50 days, followed by 10 days of adjustment to Δ = 4 km before sampling (t=0). Now we can do 30 d for 0.1M core hours!
- 2 30 d simulations:

  nopert: continuation of control run

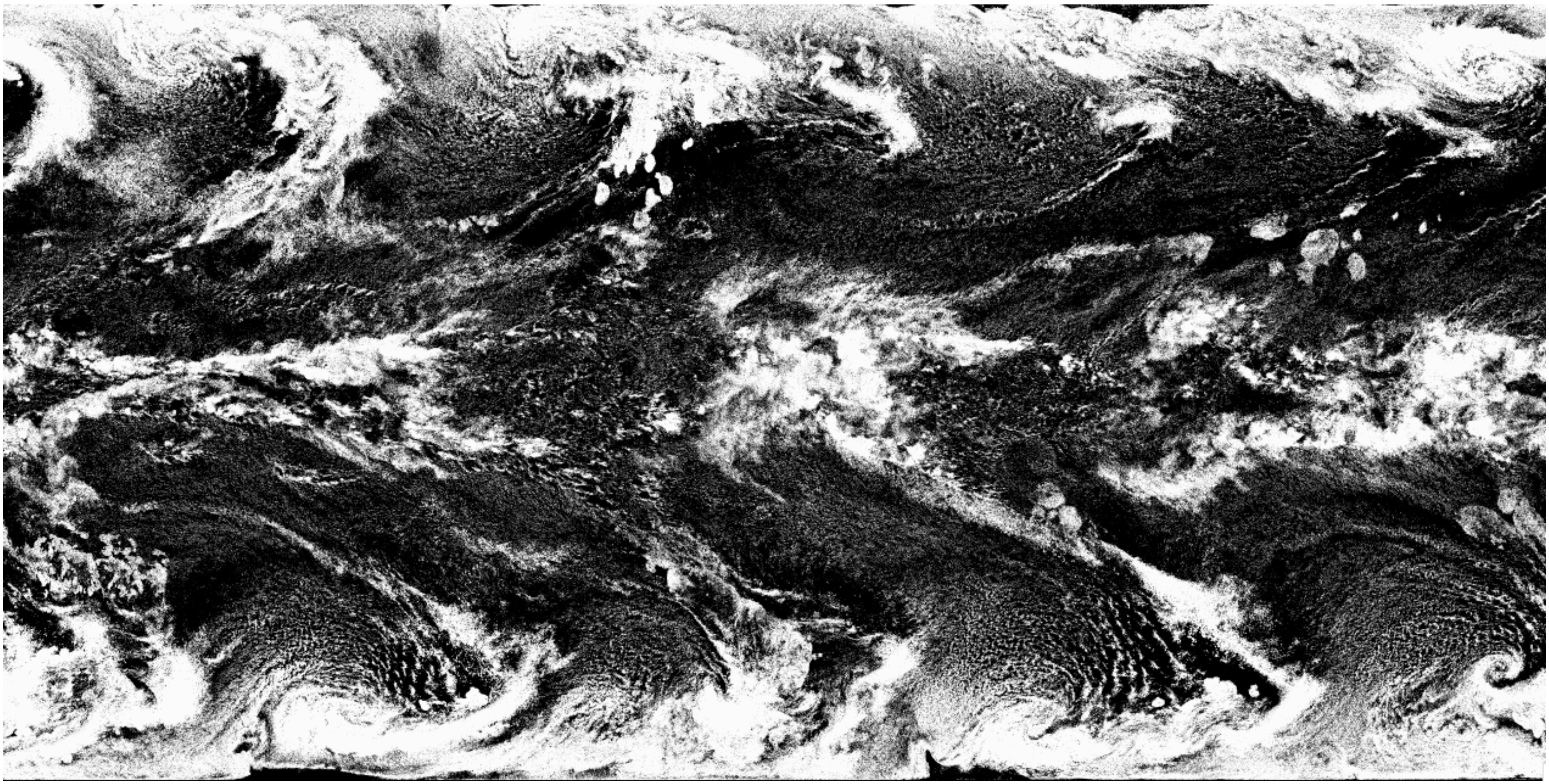
  pert: At t=0, add random, spatially uncorrelated q_v perturbations with std 0.1 g/kg at one model level
- Use nopert to analyze diabatic feedbacks on MSE

  diff = pert – nopert to assess perturbation growth

Analysis of Control Run

Cloud cover at t=0

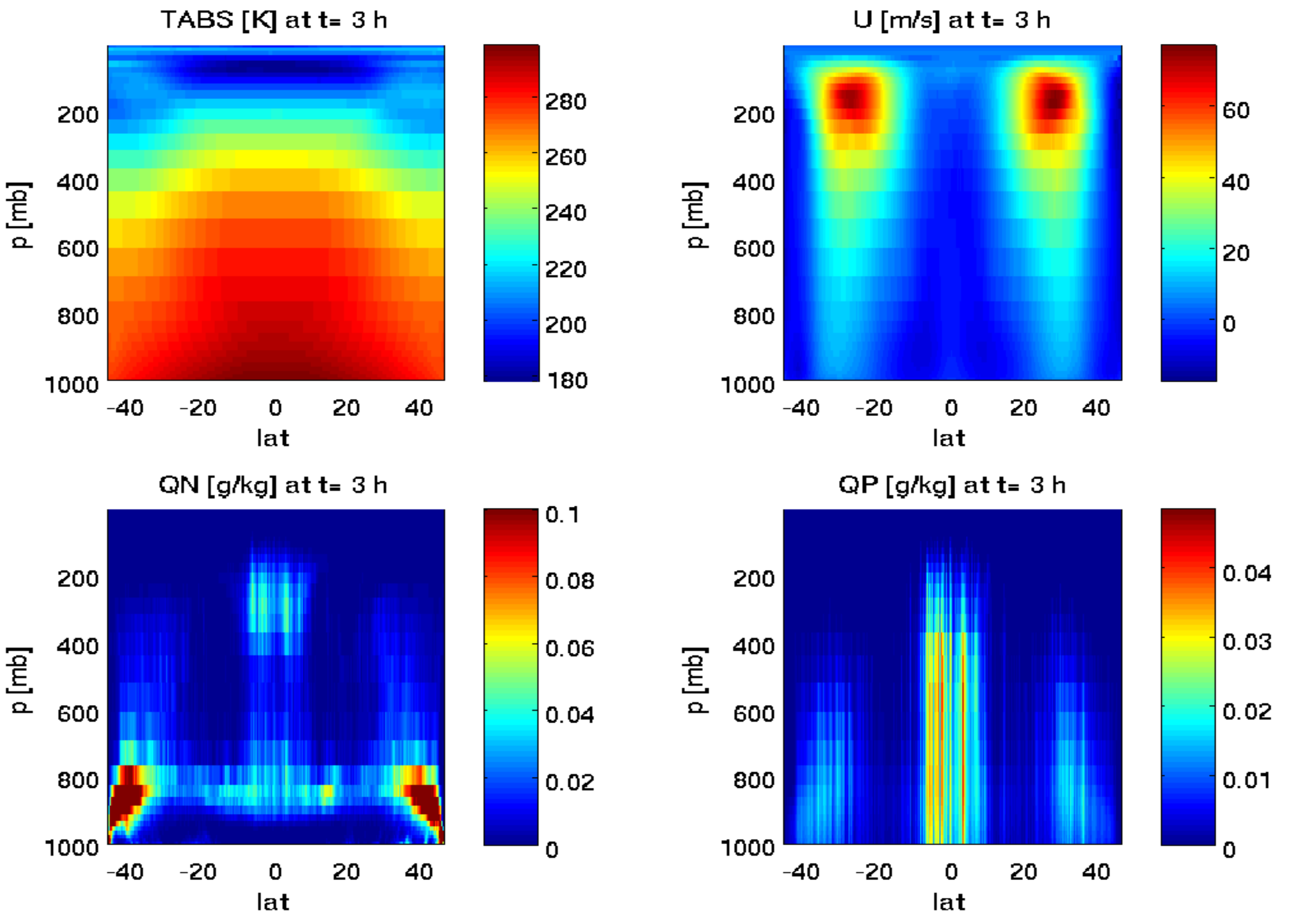
46°N



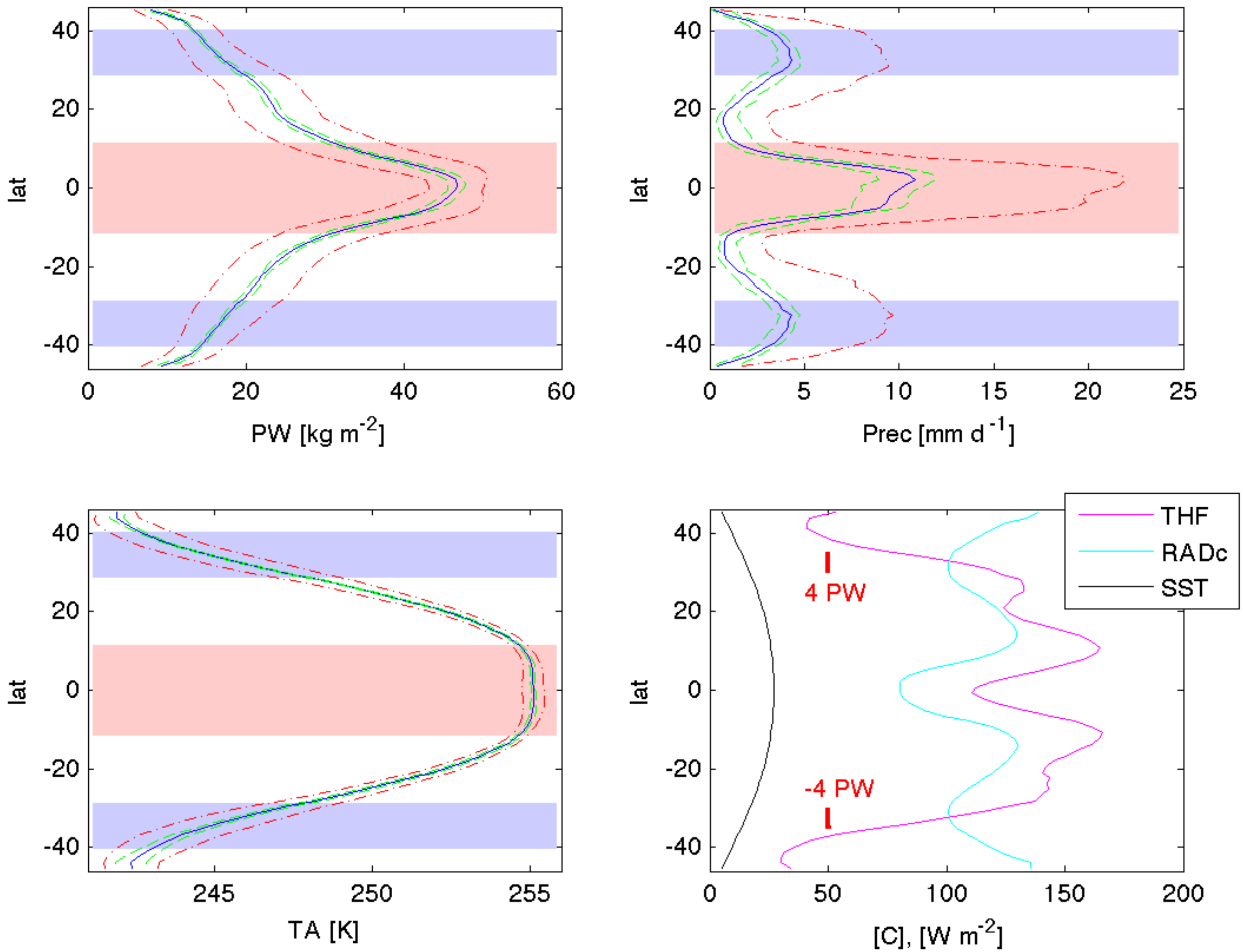
46°S

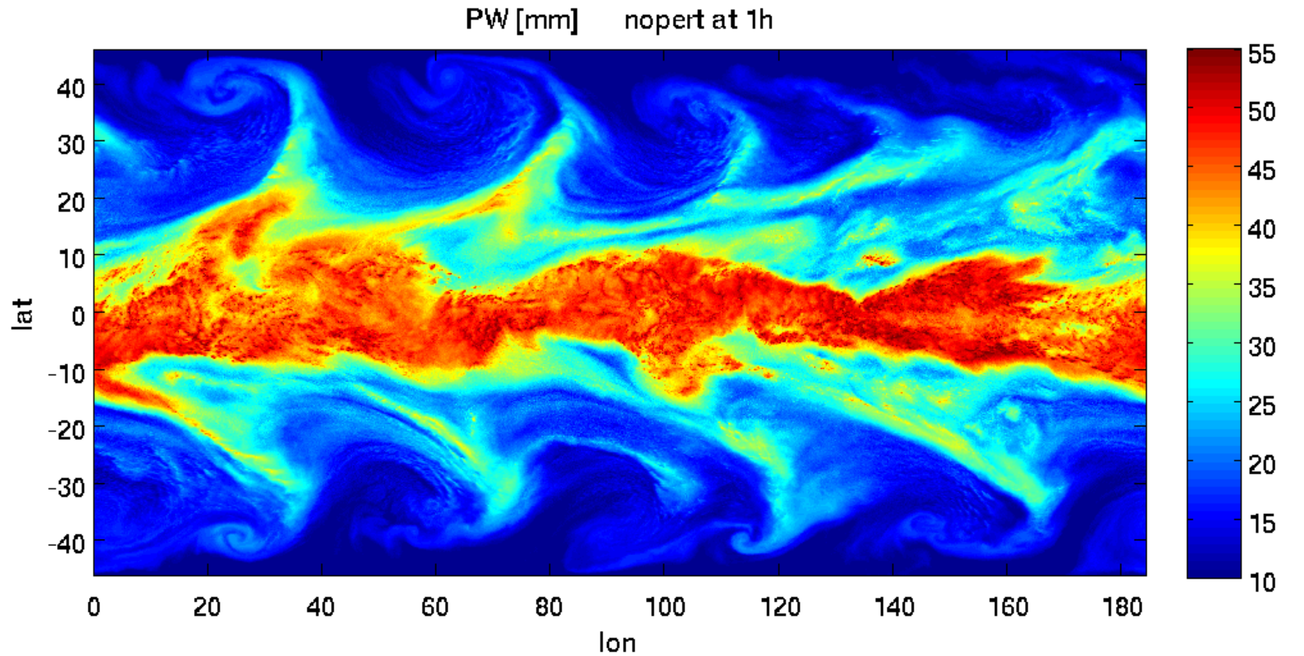
20480 km = 184° longitude

Zonal-mean vertical sections at t = 3 h



30 d zonal means

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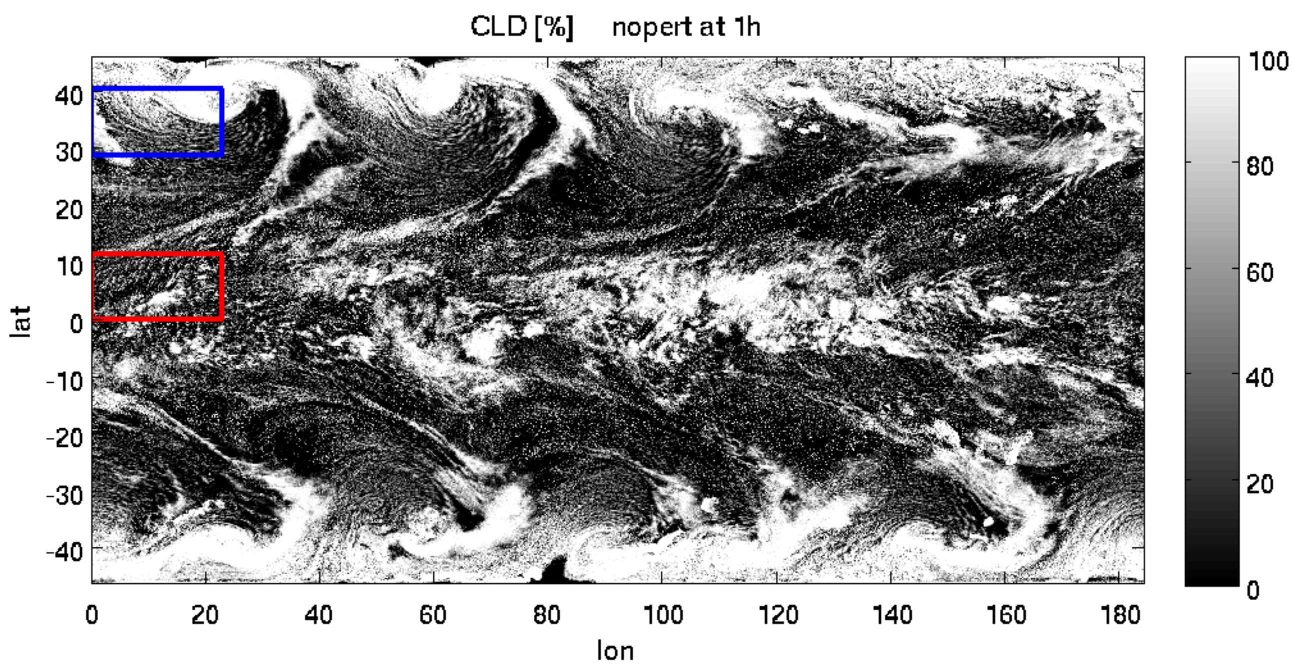
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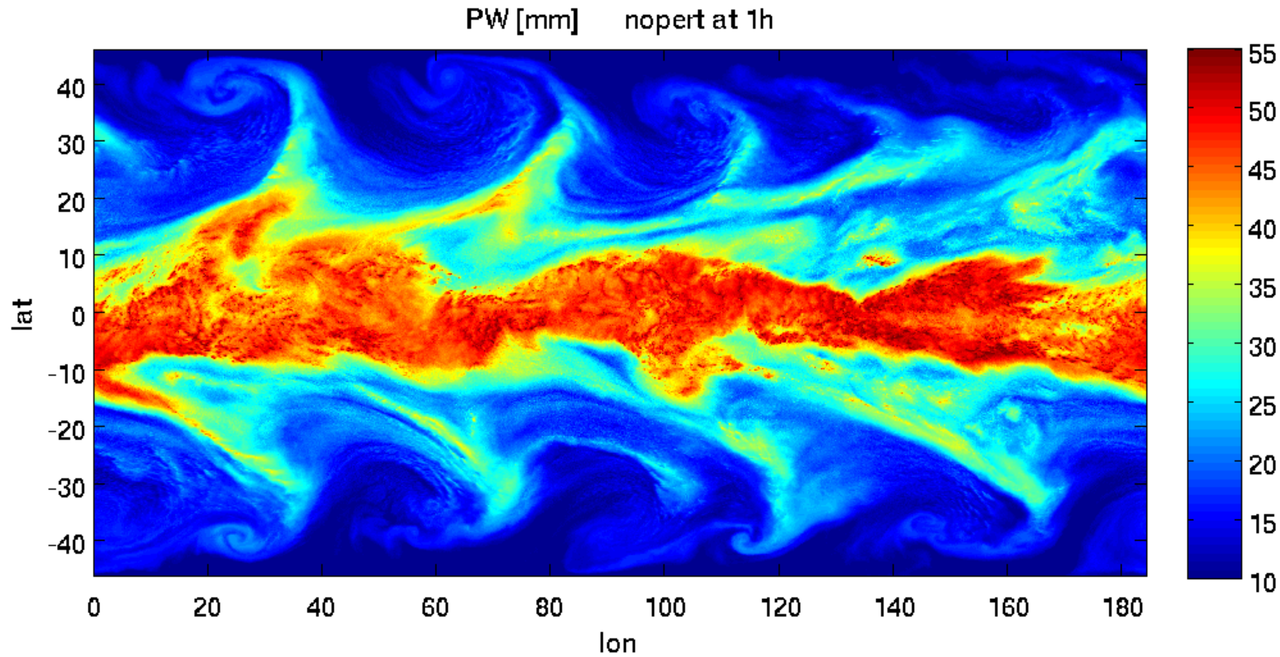
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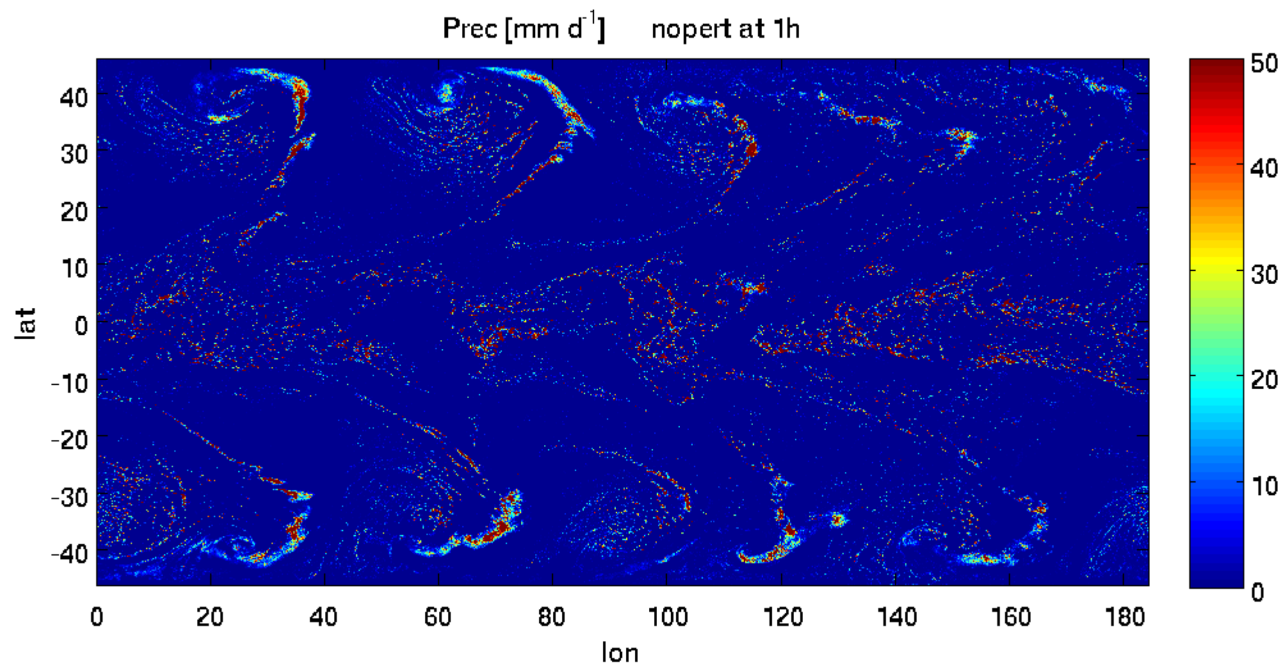
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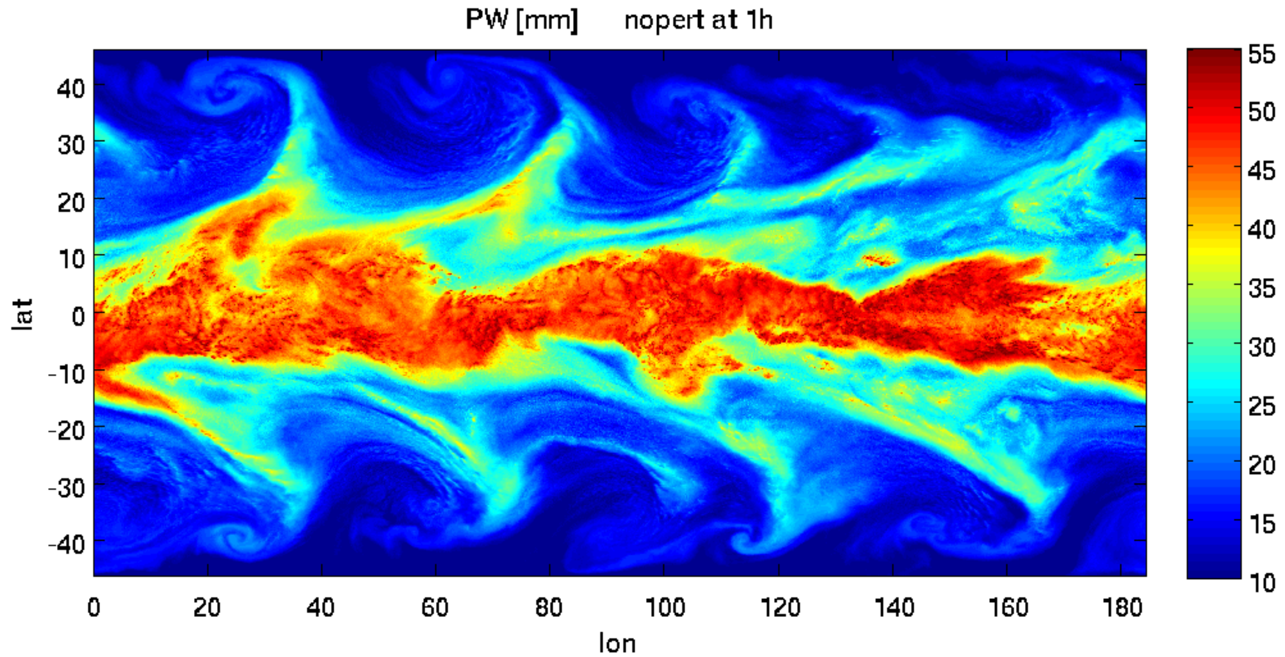
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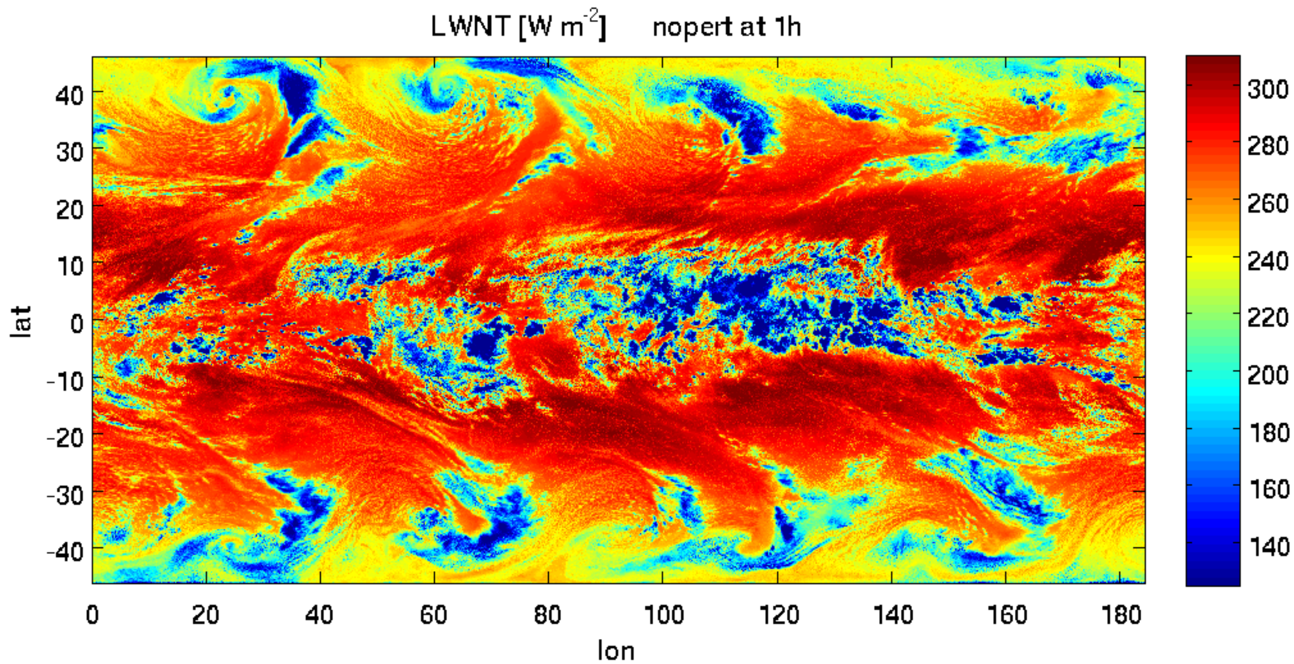
LWNT [W m-2]   nopert at 1h
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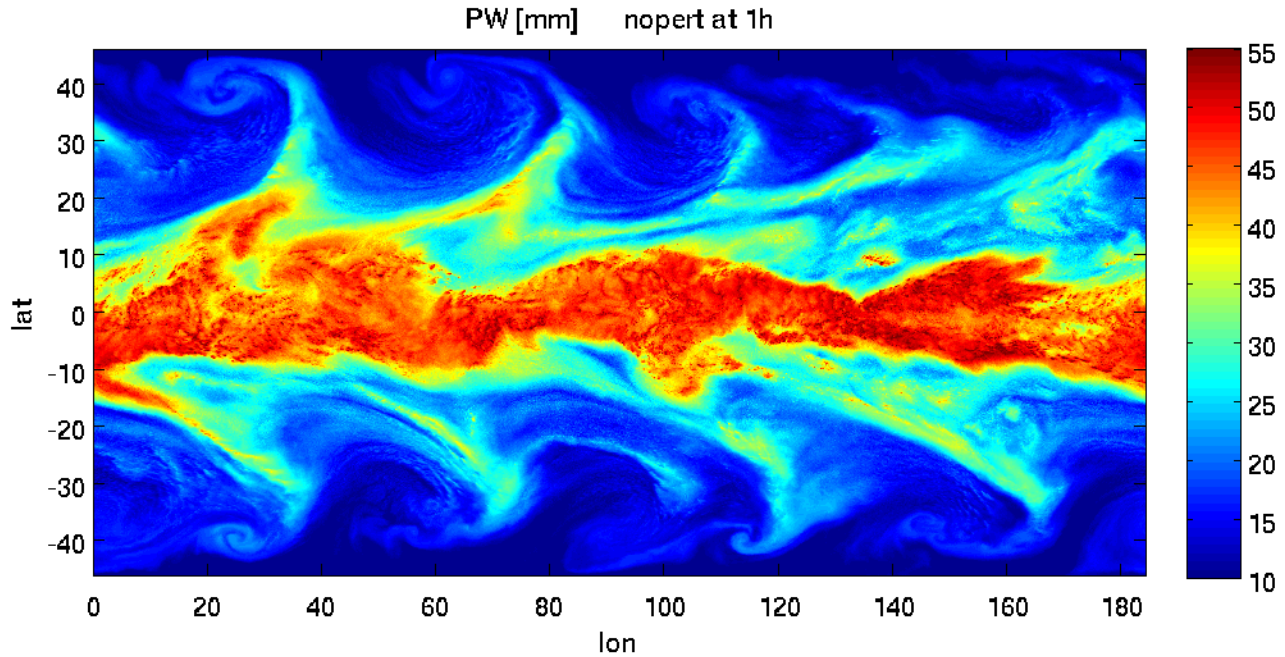
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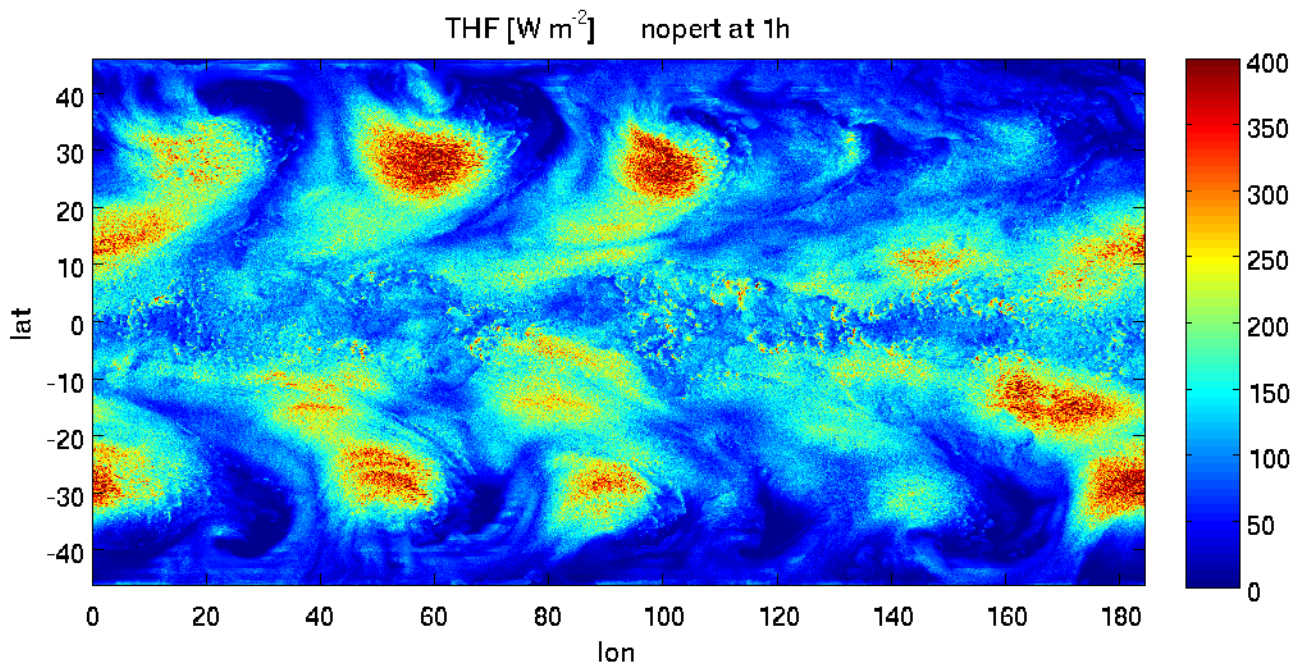
THF [W m^-2] nopert at 1h
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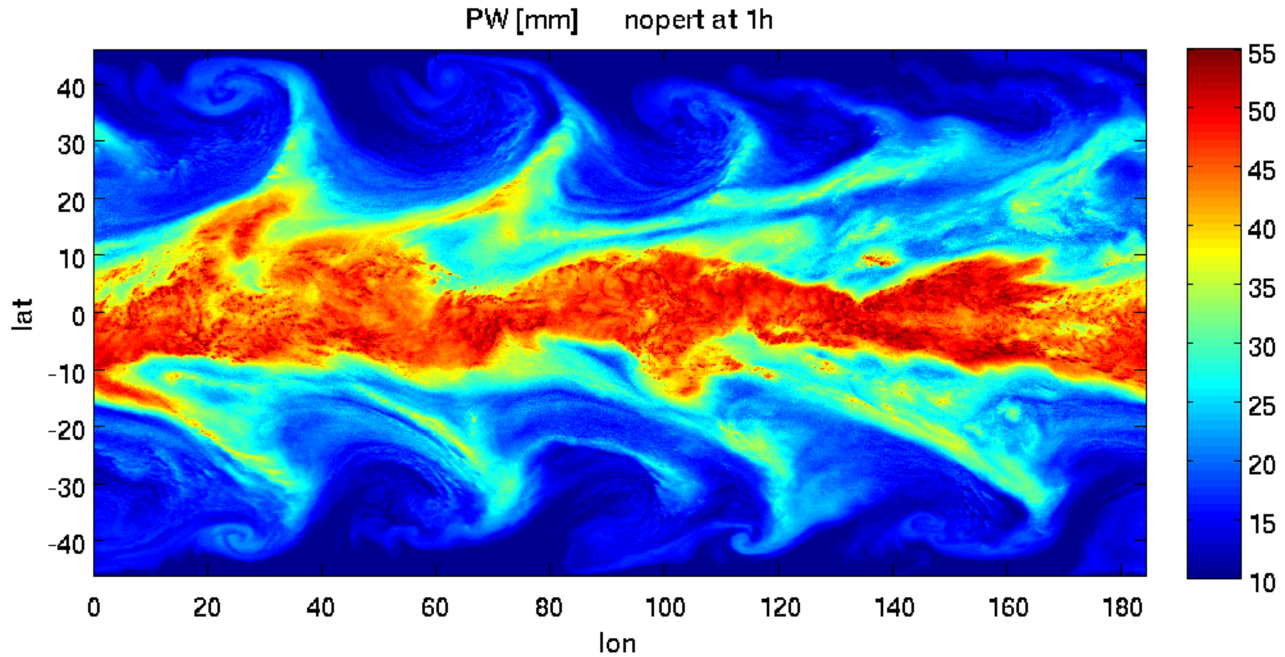
PW [mm] nopert at 1h
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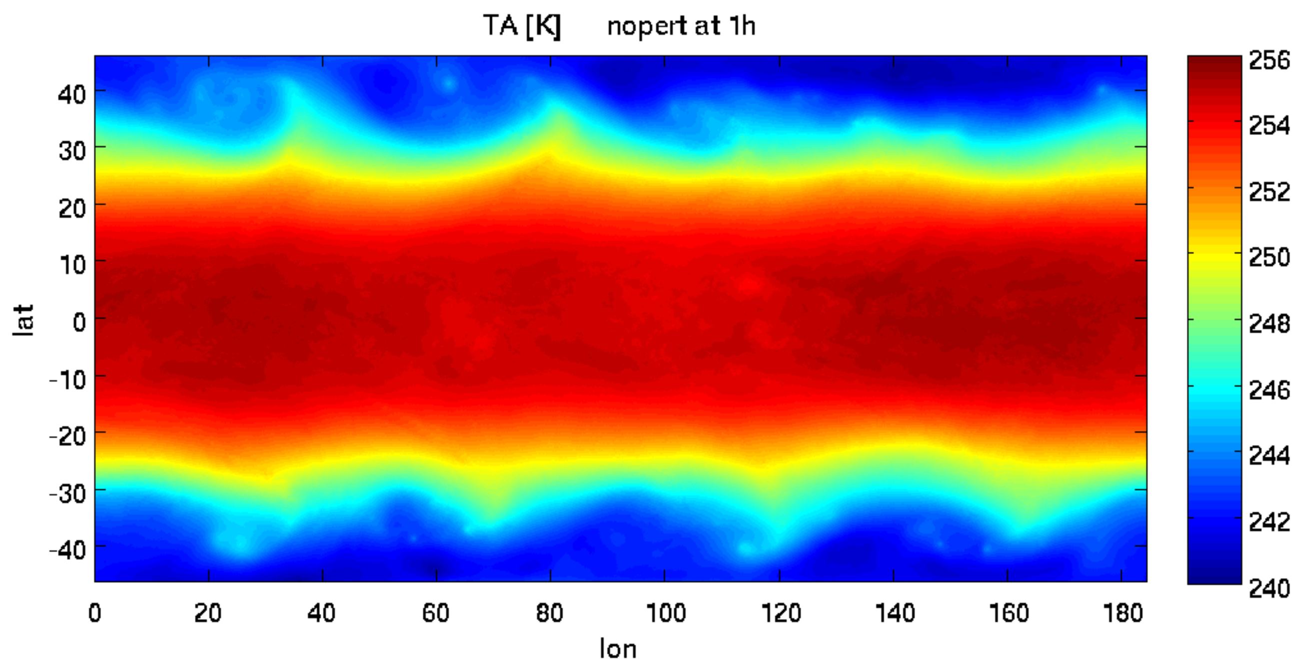
TA [K] nopert at 1h
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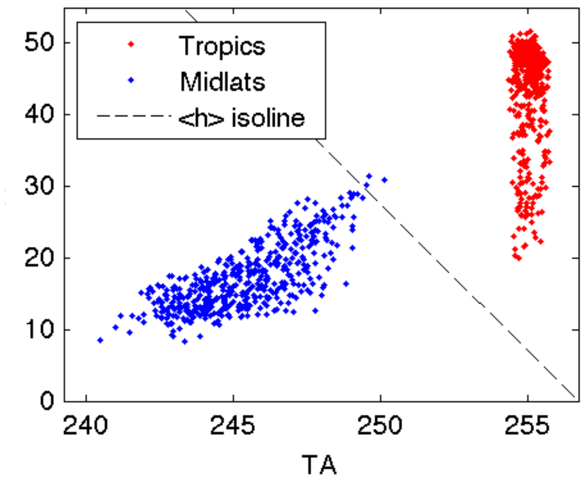
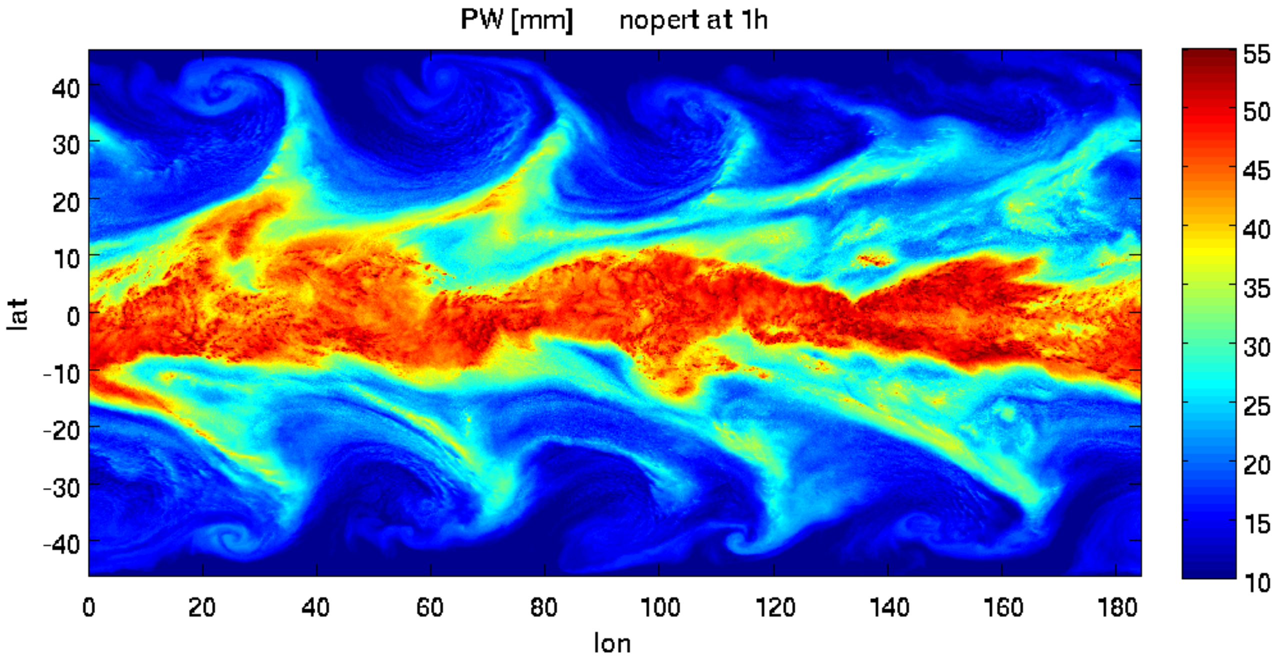

Tropics
Midlats
<h> isoline
TA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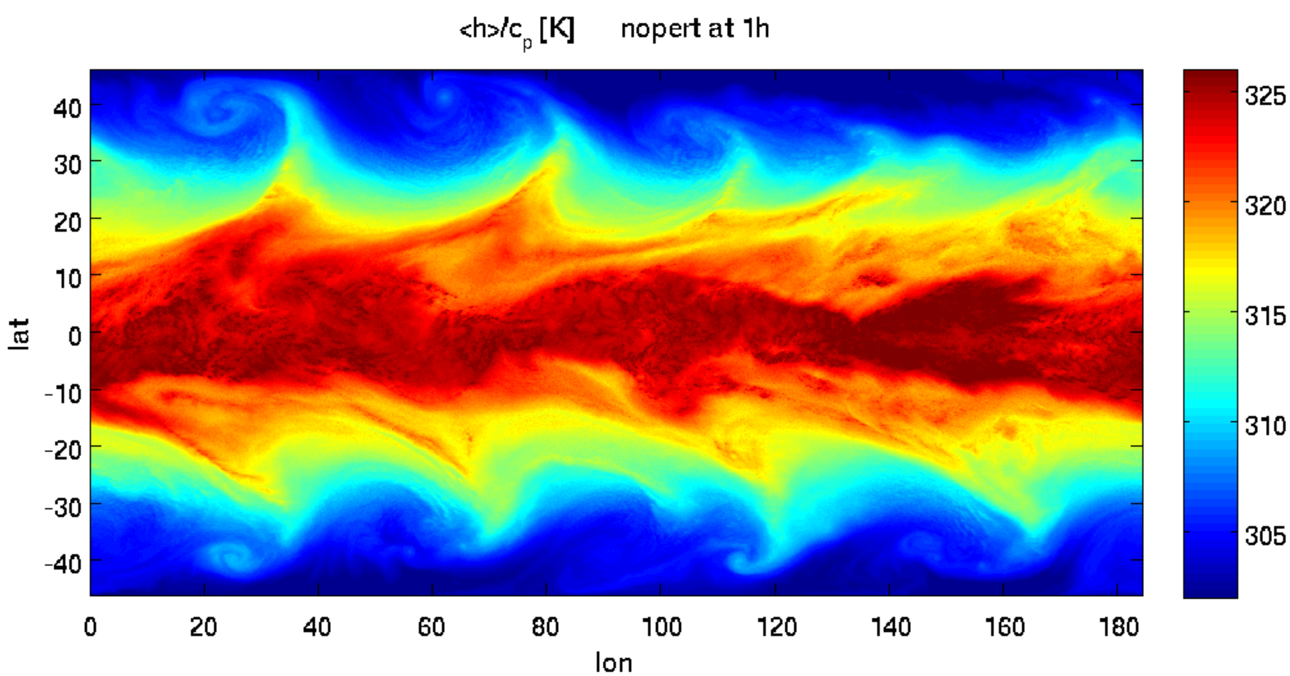
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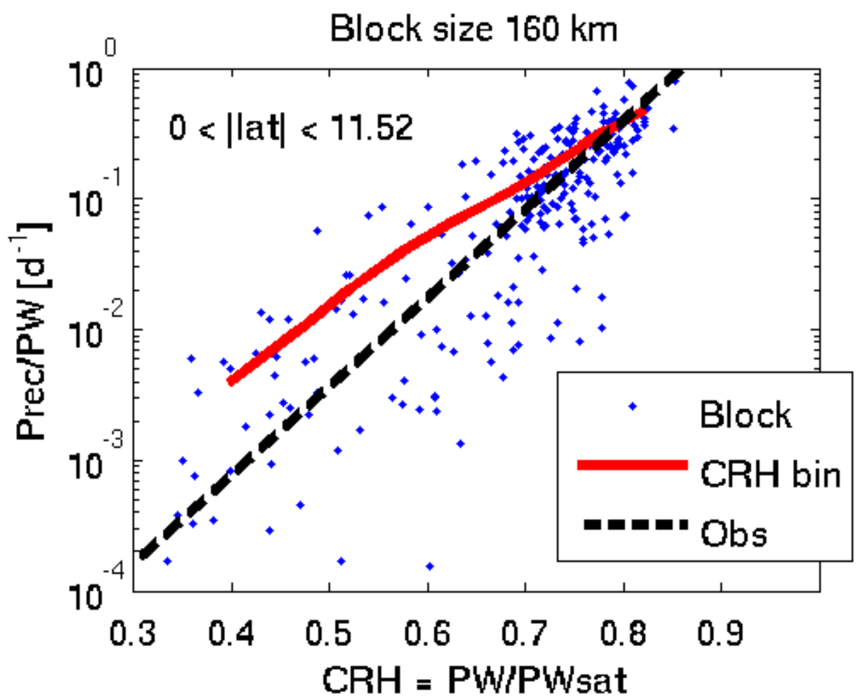
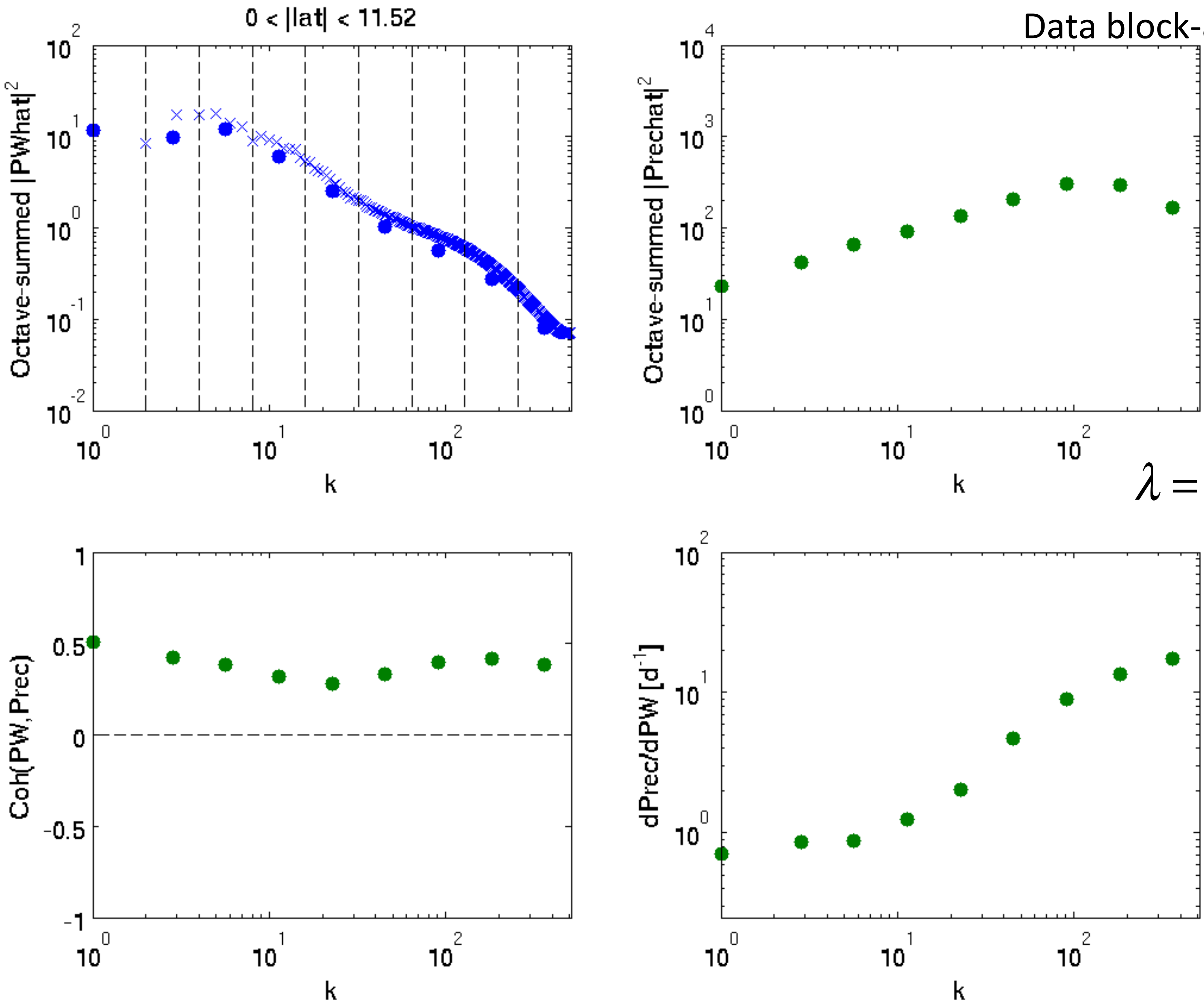
325 320 315 310 305

Comparison with tropical observations



Precipitation vs. PW via zonal Fourier spectral analysis

Data block-avg to 20 km



$$\lambda = \frac{20000\,\mathrm{km}}{k}$$

Diabatic feedbacks in control run

MSE budget:

$$M d\langle h \rangle/dt = THF + RAD + hadv \text{ [+small corrections]}$$

For perturbations from zonal time mean:

$$M d\langle h' \rangle/dt = THF' + RAD' + hadv'$$

In the tropics, $M\langle h' \rangle \approx L \langle PW' \rangle$.

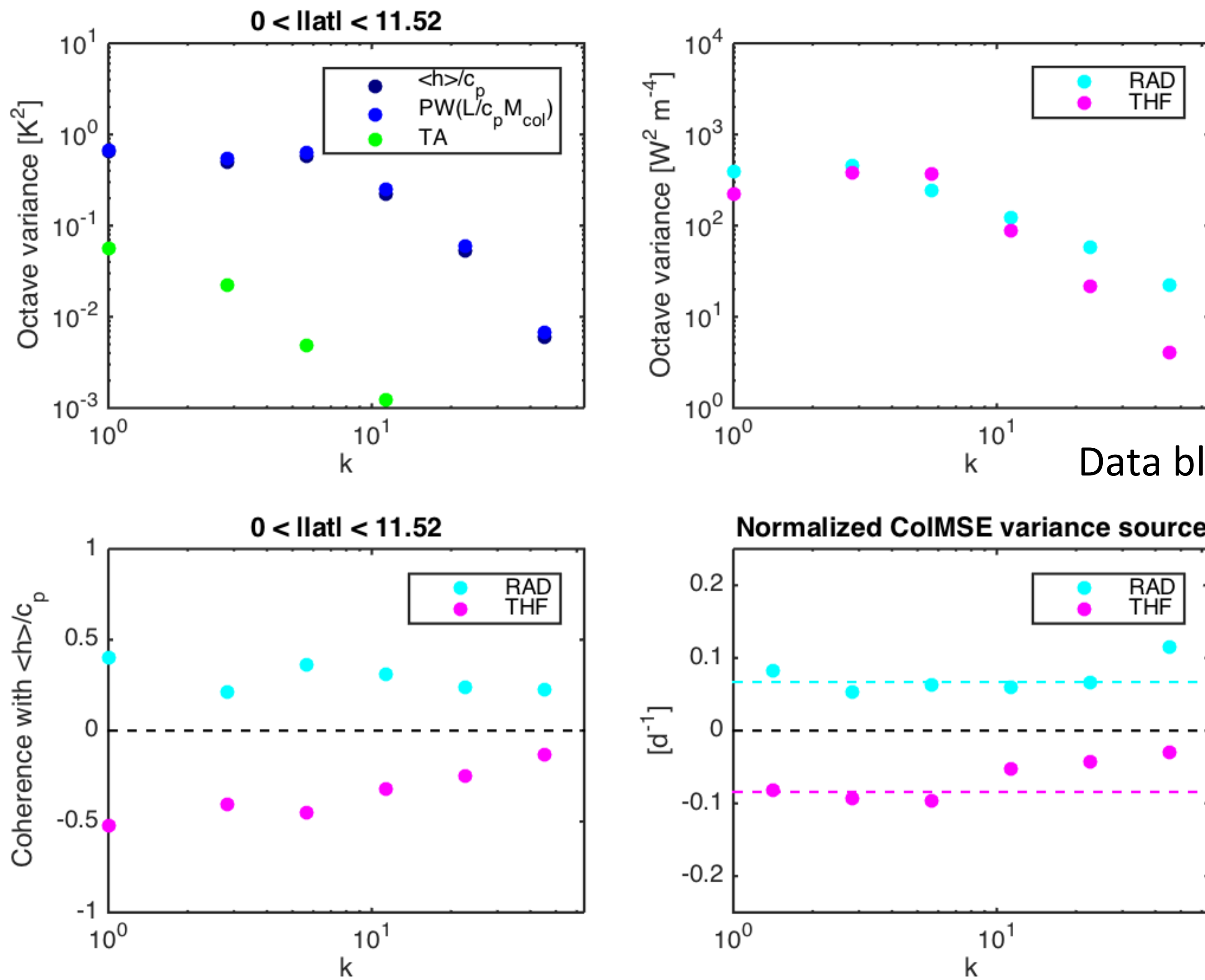
Let [] = zonal average. Variance budget (Wing and Emanuel 2013):

$$L\, d[h'h']/dt \approx [h'THF'] + [h'RAD'] + [h'hadv']$$

… can be partitioned by scale using cross-spectral analysis

Octave-averaged cross-spectra in the control run

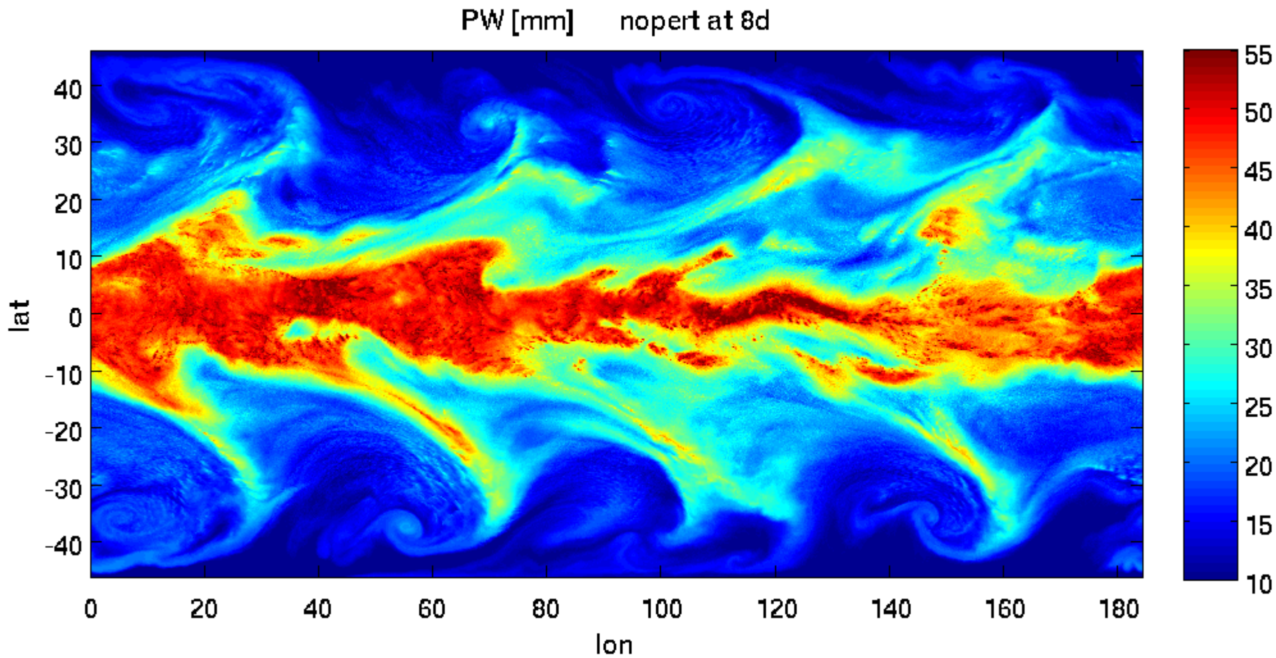
- Positive correlation between RAD’ and h’ at all scales
- *Negative* correlation between THF’ and <h’>, especially at large scales
- Correlations of RAD’ and THF’ with <h’> weaker than in CRM self-aggregation runs



Data block-avg to 160 km

Growth of Humidity Perturbations

- At t=0, seed with white-noise humidity perturbation of std 0.1 g kg^{-1} at a single grid level near z = 3 km.
- Look at perturbation growth by differencing 30 day pert – nopert simulations.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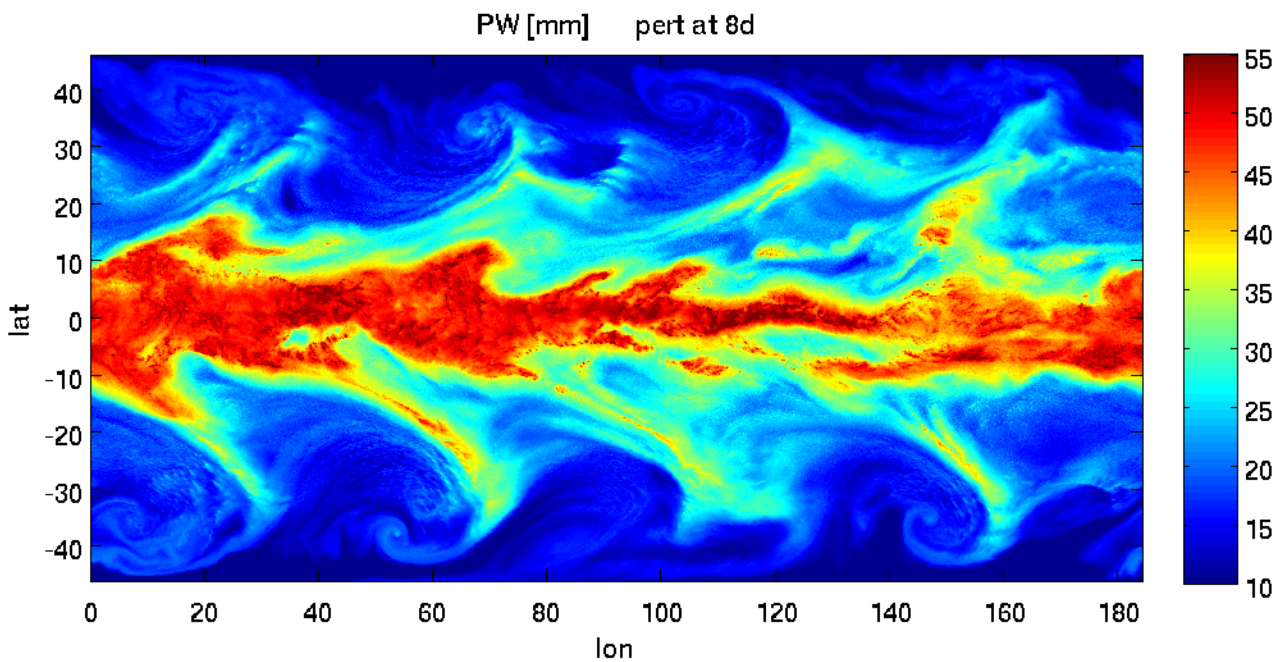
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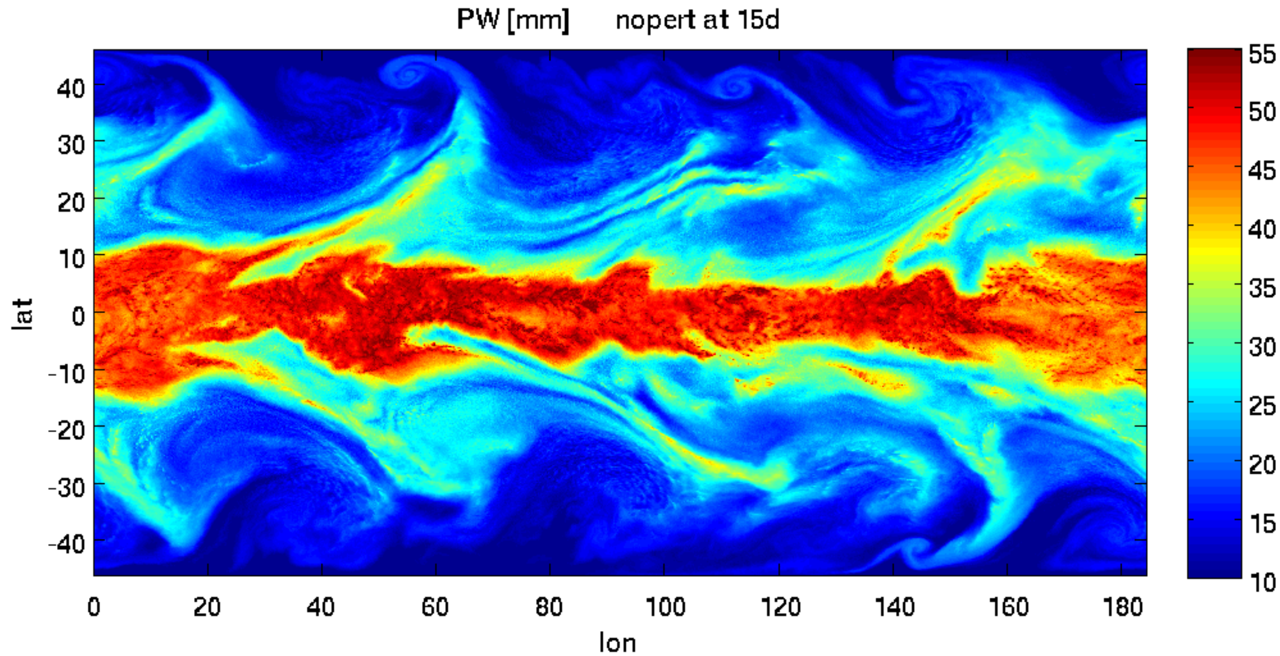
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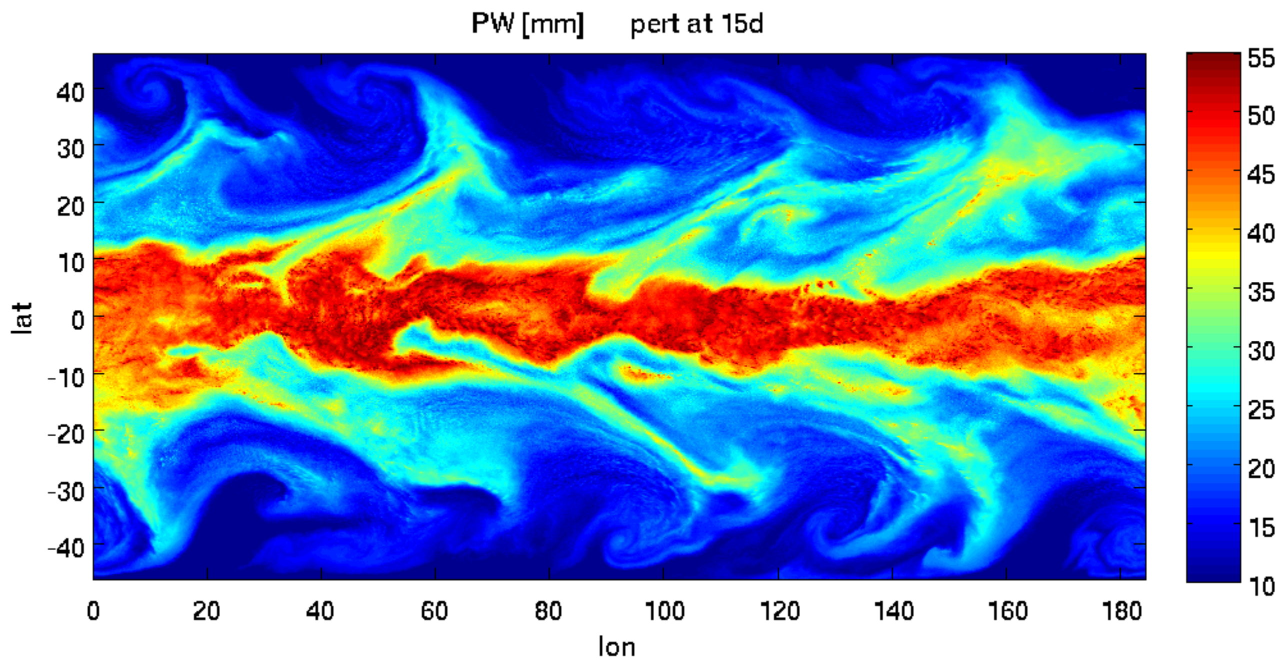
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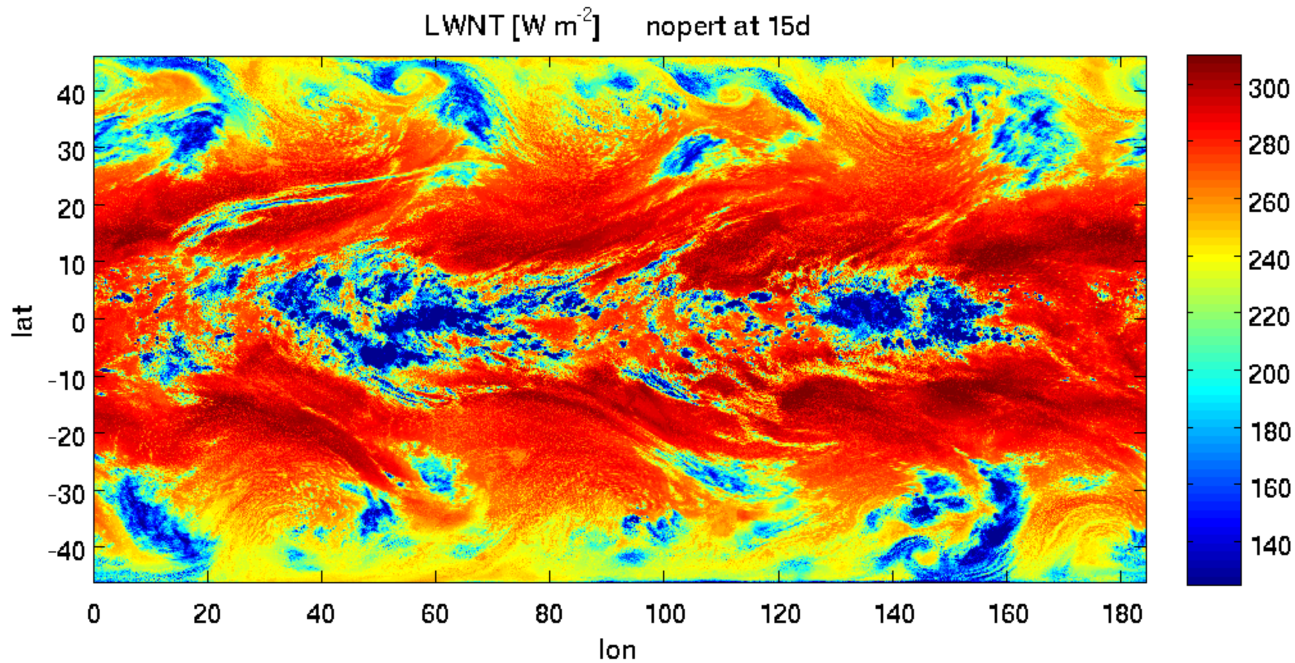
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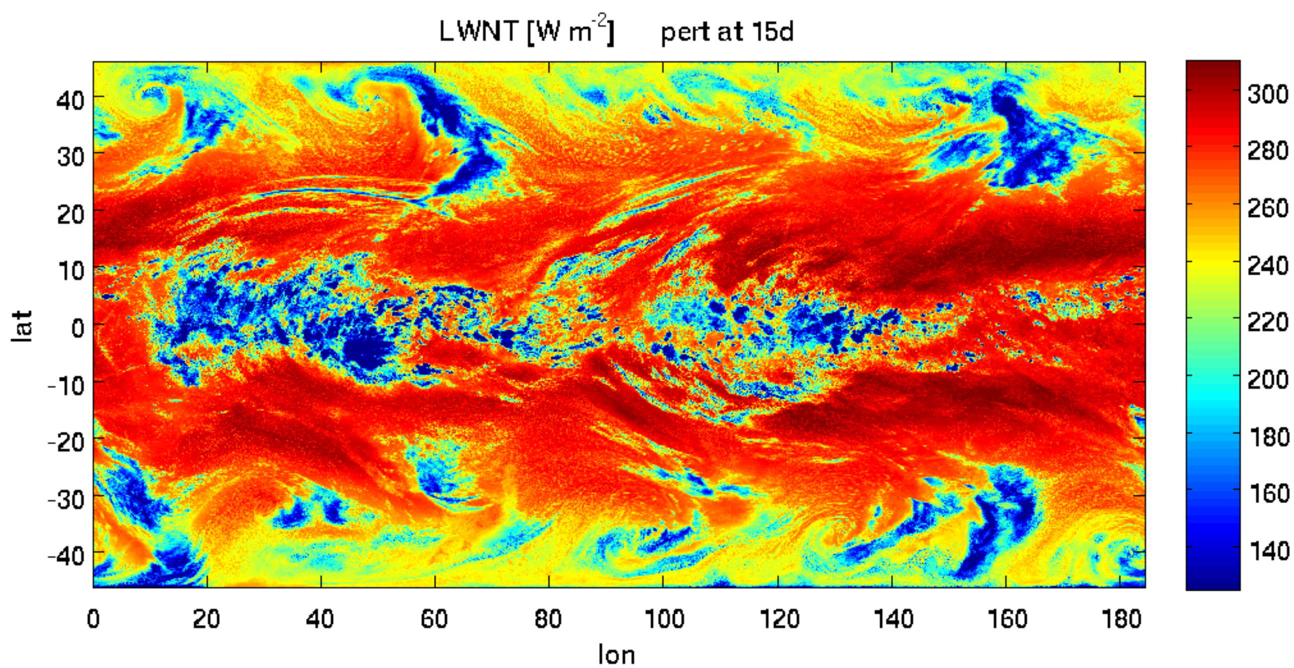
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Diabatic feedbacks in perturbation run

Now let $\delta f(\mathbf{r}, t) = f_{pert}(\mathbf{r}, t) - f_{ctrl}(\mathbf{r}, t)$

The perturbation to the columnwise MSE budget is

$$M d\langle\delta h\rangle/dt = \delta THF + \delta RAD + \delta hadv$$

(in the tropics, $M\langle\delta h\rangle \approx L \langle\delta PW\rangle$).

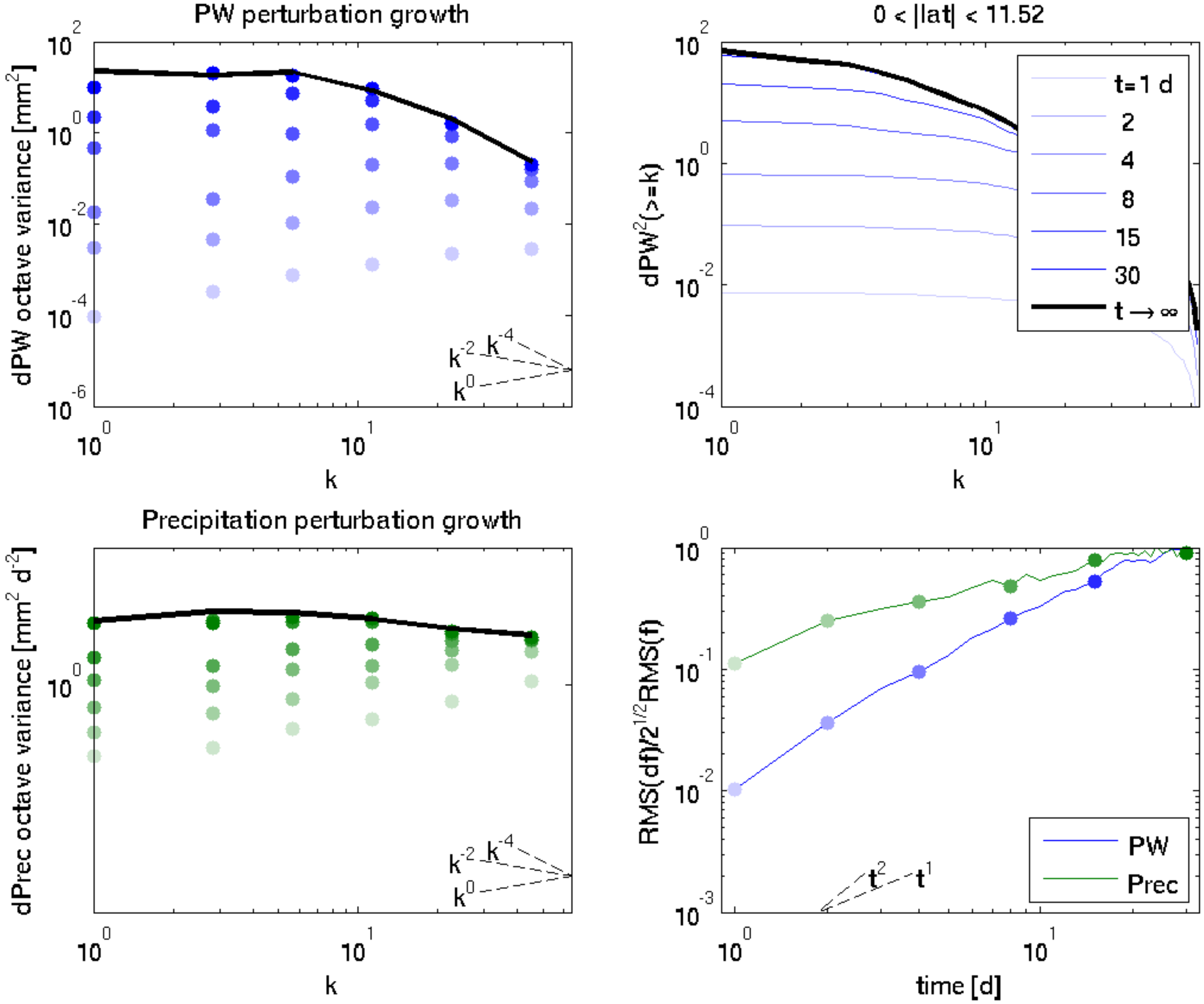
Let [] = zonal average. Perturbation variance budget:

$$M d[\delta h \delta h]/dt \approx [\delta h \delta THF] + [\delta h \delta RAD] + [\delta h \delta hadv]$$

... can again be partitioned by scale using cross-spectral analysis

Tropical PW and precipitation perturbation growth

- δPW (δPrec) perturbation nearly saturated at 30 (15) days at largest scales; much earlier at smaller scales.
- δPW (δPrec) variance grows ~ $t^{1.2}$ ($t^{0.6}$) out to day 15.

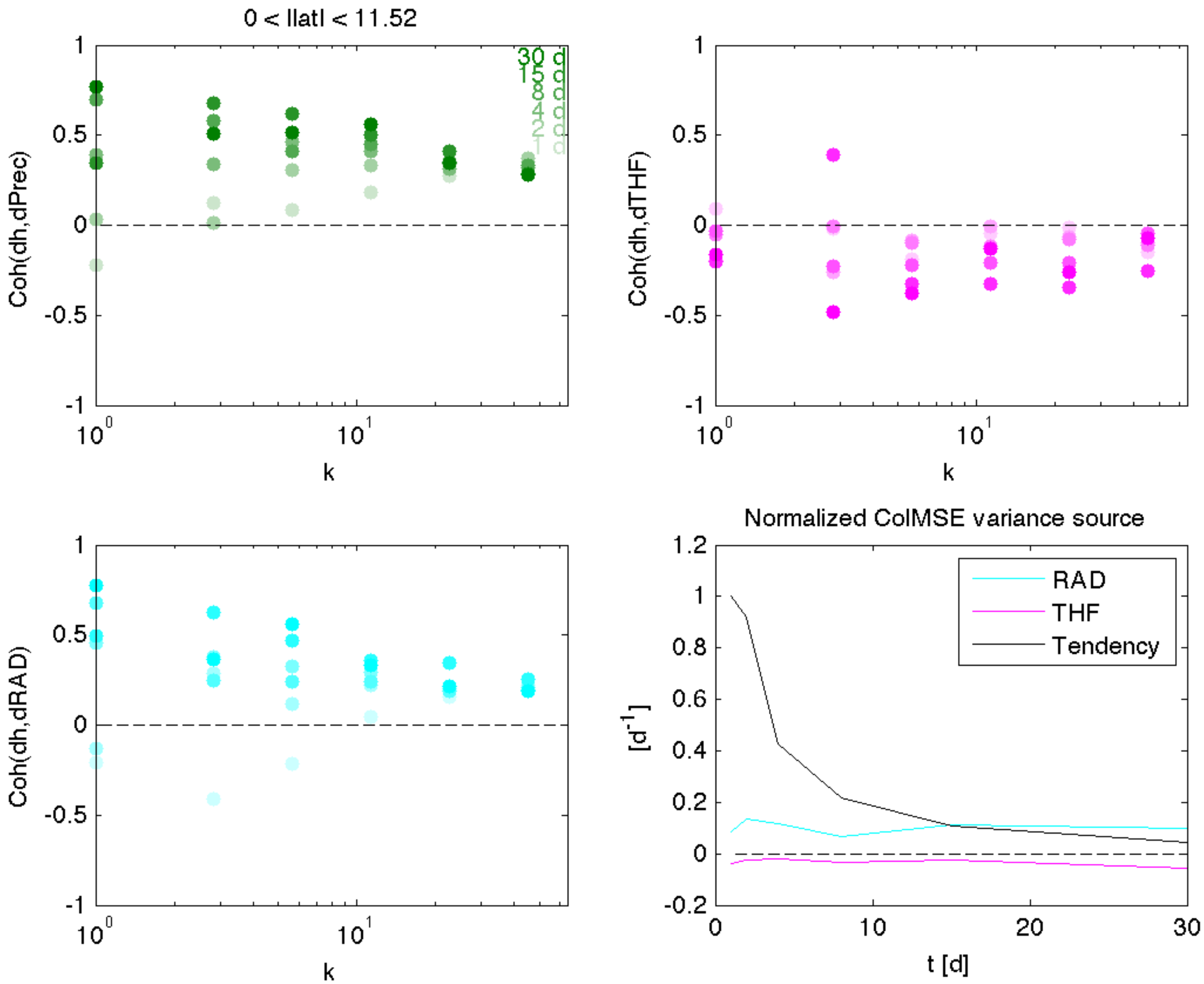


Diabatic feedbacks on tropical MSE perturbation growth

- MSE perturbation growth is dominated by advection out to 15 d.
- Similar to zonal variability in control run:

  Radiative heating feedback amplifies <δh> variance on a slow 10 day timescale

  Surface fluxes weakly damp <δh> variance



Conclusions

- Near-global CRM is an expensive but powerful tool for idealized simulations that are free of a cumulus parameterization.
- In the tropics :

  Atmospheric radiative heating amplifies humidity and MSE anomalies but advectively driven anomaly growth is a stronger driver in our simulations.

  Surface fluxes tend to damp MSE anomalies.

  Potential predictability is largest for broad disturbances.
- With different SST, our aquaplanet CRM will produce tropical cyclones and an MJO, allowing this framework to be applied to their maintenance and predictability.