Analysis and forecast uncertainties in the tropics: why do we care?

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Open IFS workshop, June 2019, Reading, UK

Outline

Why do we care?

- Global response to tropical heating perturbations

  (*PhD thesis research by Katarina Kosovelj*)

- Vertically propagating equatorial waves to the stratosphere

  (*research by Marten Blaauw*)

- Coupling between the moisture and wind in tropical data assimilation

  (*PhD thesis research by Ziga Zaplotnik*)

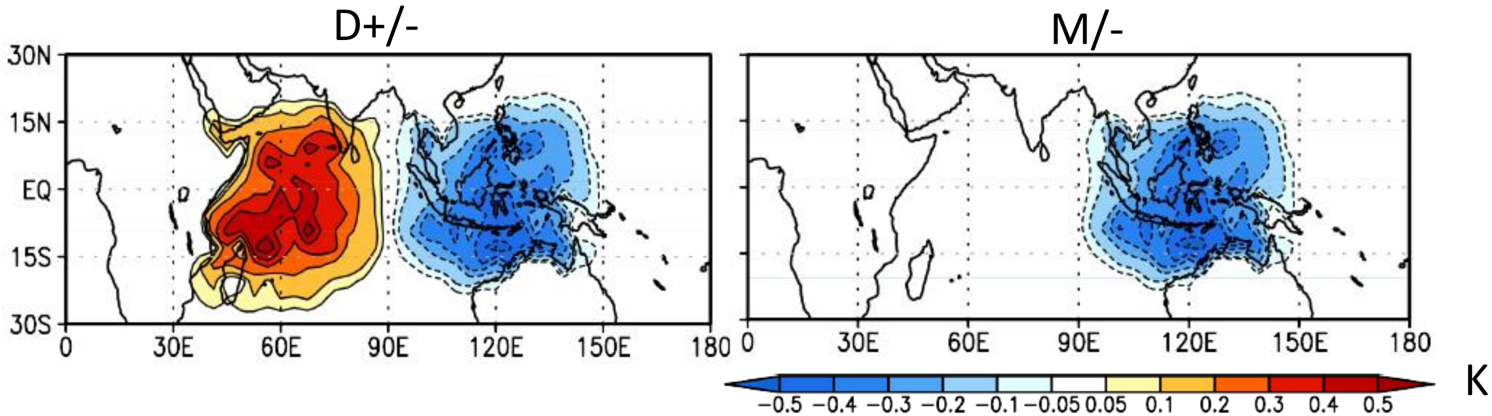
Analysis uncertainties and forecast errors in a perfect model

- Spectra of an/fc uncertainties

Possible implications for global predictablitiy

Summary

Tropical heating perturbations



Perturbations resembling different phases of MJO

Vertical profile of a deep heating with max in the middle troposphere

$$\left(\frac{\partial T}{\partial t}\right)_{\text{pert}}(\lambda,\phi,\sigma) = F_{\text{SST}} H_{\text{pert}}(\lambda,\phi)\left(\frac{\partial T}{\partial t}\right)_{\text{CC}}(\phi,\sigma)$$

horizontal structure*rand(0,1)

T tendencies due to convection and LSC

$$F_{\text{SST}} = k_s(\text{SST} - \text{SST}_{\text{crit}})$$ For SST > SST_{crit} , and zero otherwise

Ensemble of 100 winters (1911-2010), with ERA-20C SST forcing

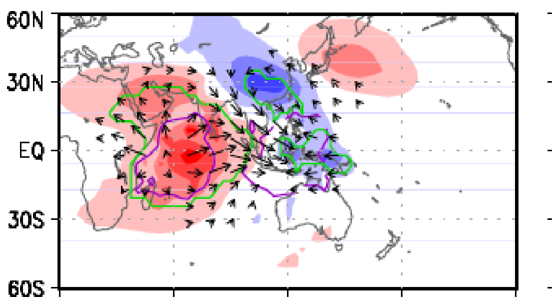
Kosovelj et al., J. Atmos. Sci., May 2019

Response to tropical heating perturbations: day 3, 200 hPa

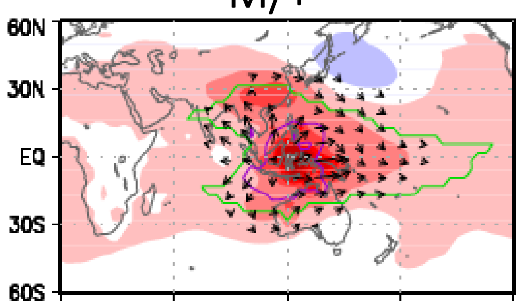
$$\overline{A}(t) = \frac{1}{J}\sum_{j=1}^{J}[A_j(t) - A_0(t)]$$

ensemble-averaged response

D+/-



M/+



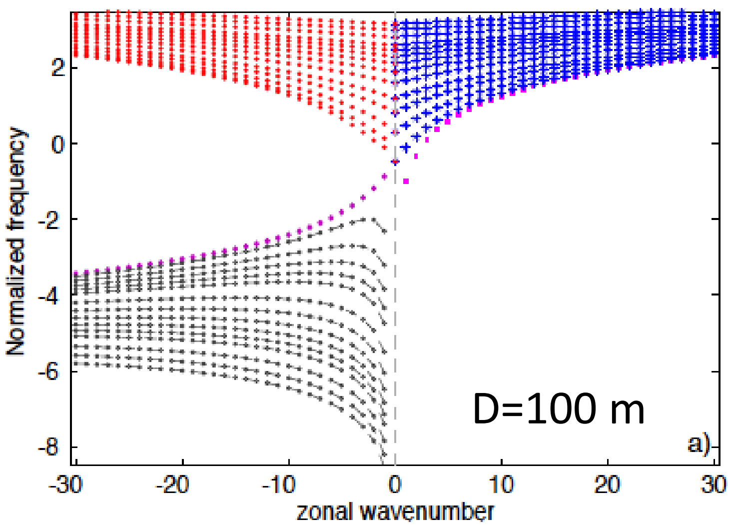
Total response

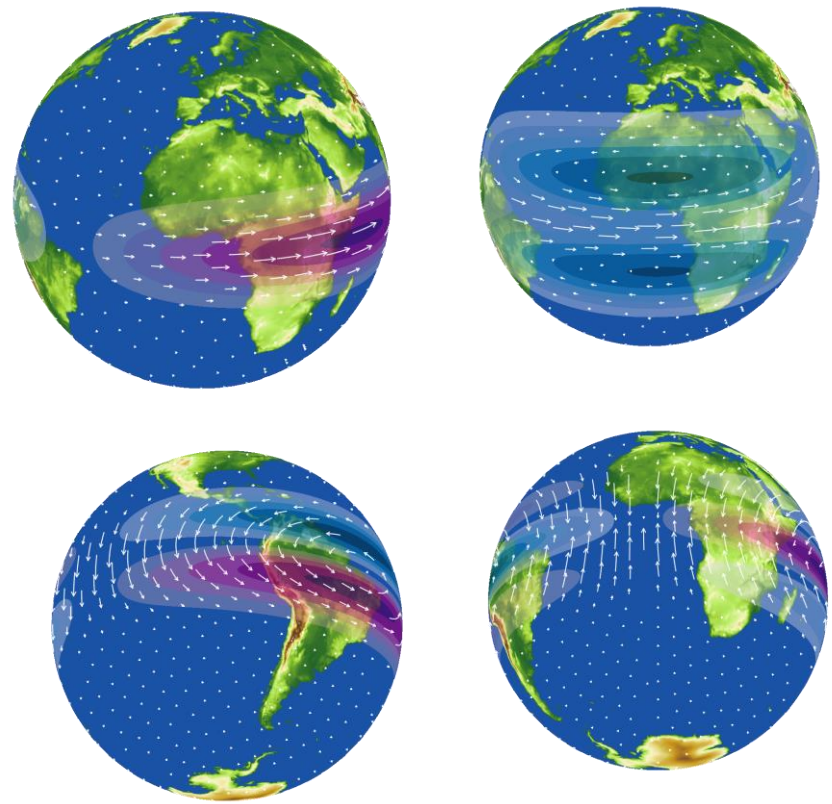
Kosovelj et al.,
J. Atmos. Sci., May 2019

Scale and dynamics decomposition of the response

Diagnostics in terms of the Rossby wave and inertio-gravity waves – normal modes of the linearized primitive equations ⇔ quantification of the response

Dispersion curves





Equatorial trapping $e_{eff} = e + k^2$

$$e = \frac{4W^2 a^2}{gD}$$

J. Boyd

http://modes.fmf.uni-lj.si

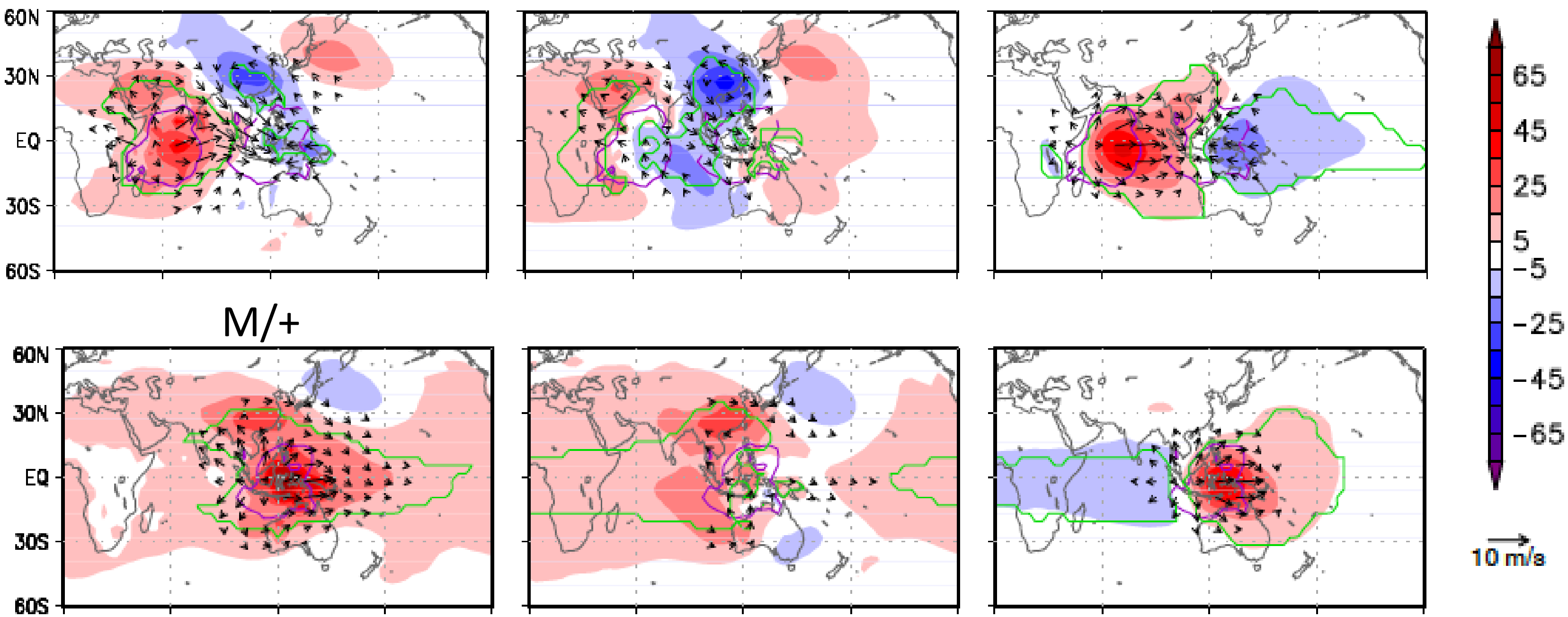
Žagar et al., GMD, 2015

Response to tropical heating perturbations: day 3, 200 hPa

$$\overline{A}(t) = \frac{1}{J}\sum_{j=1}^{J}[A_j(t) - A_0(t)]$$ ensemble-averaged response

D+/-

M/+



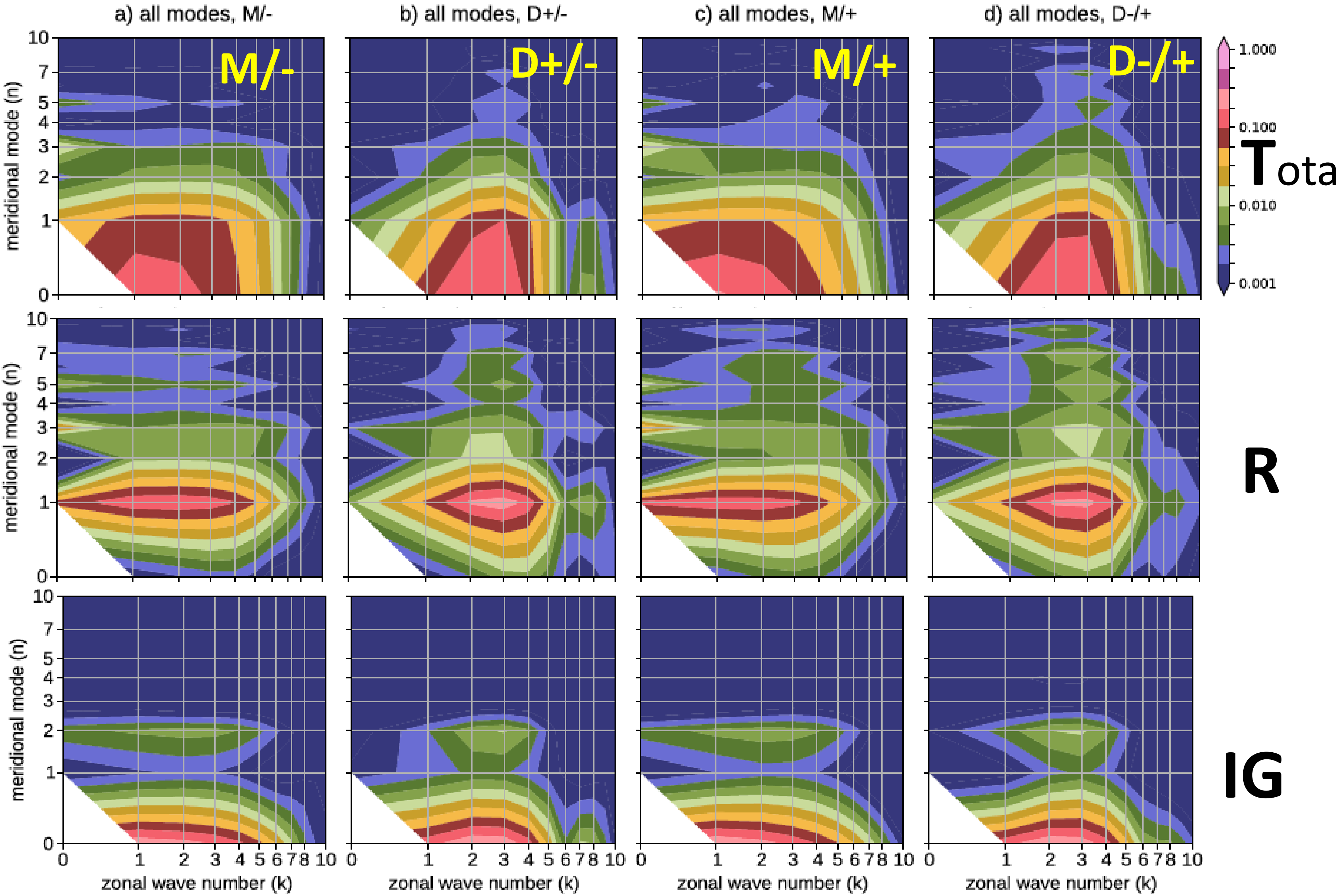
Total response

Balanced part (Rossby waves)

Unbalanced part (inertia-gravity waves)

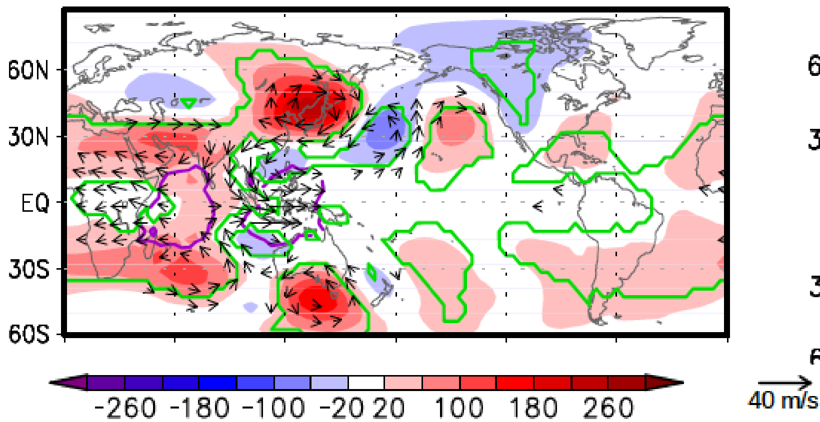
Kosovelj et al., J. Atmos. Sci., May 2019

Spectral distribution of the response: day 3

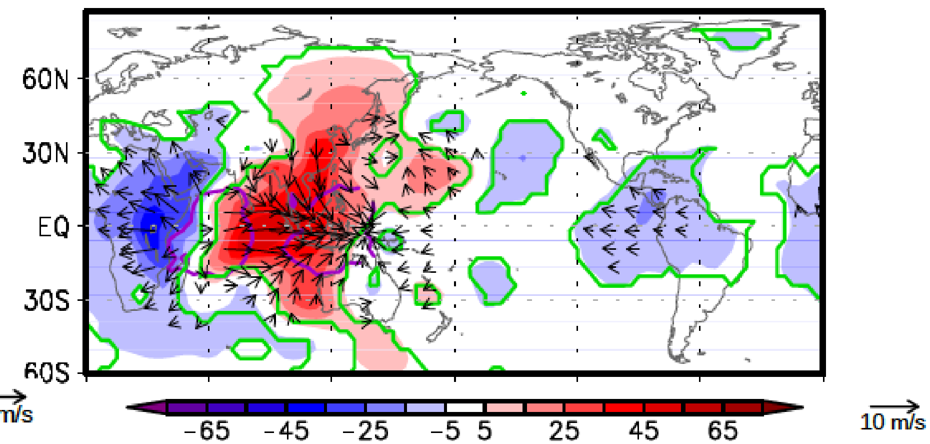


Response to tropical heating perturbations: day 14, 200 hPa, D+/-

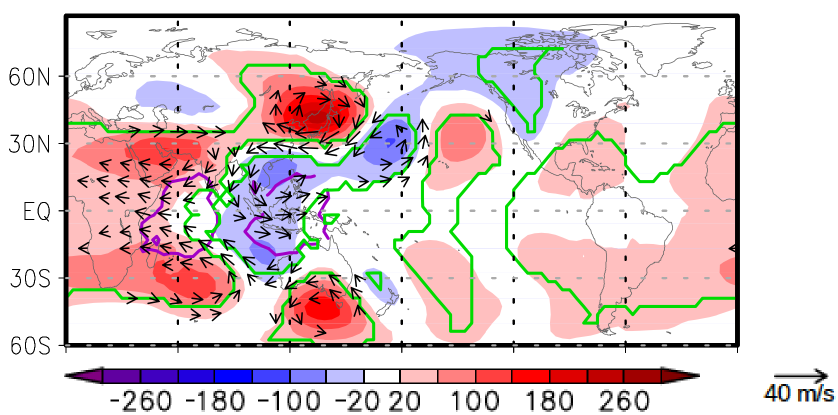
Total



IG modes

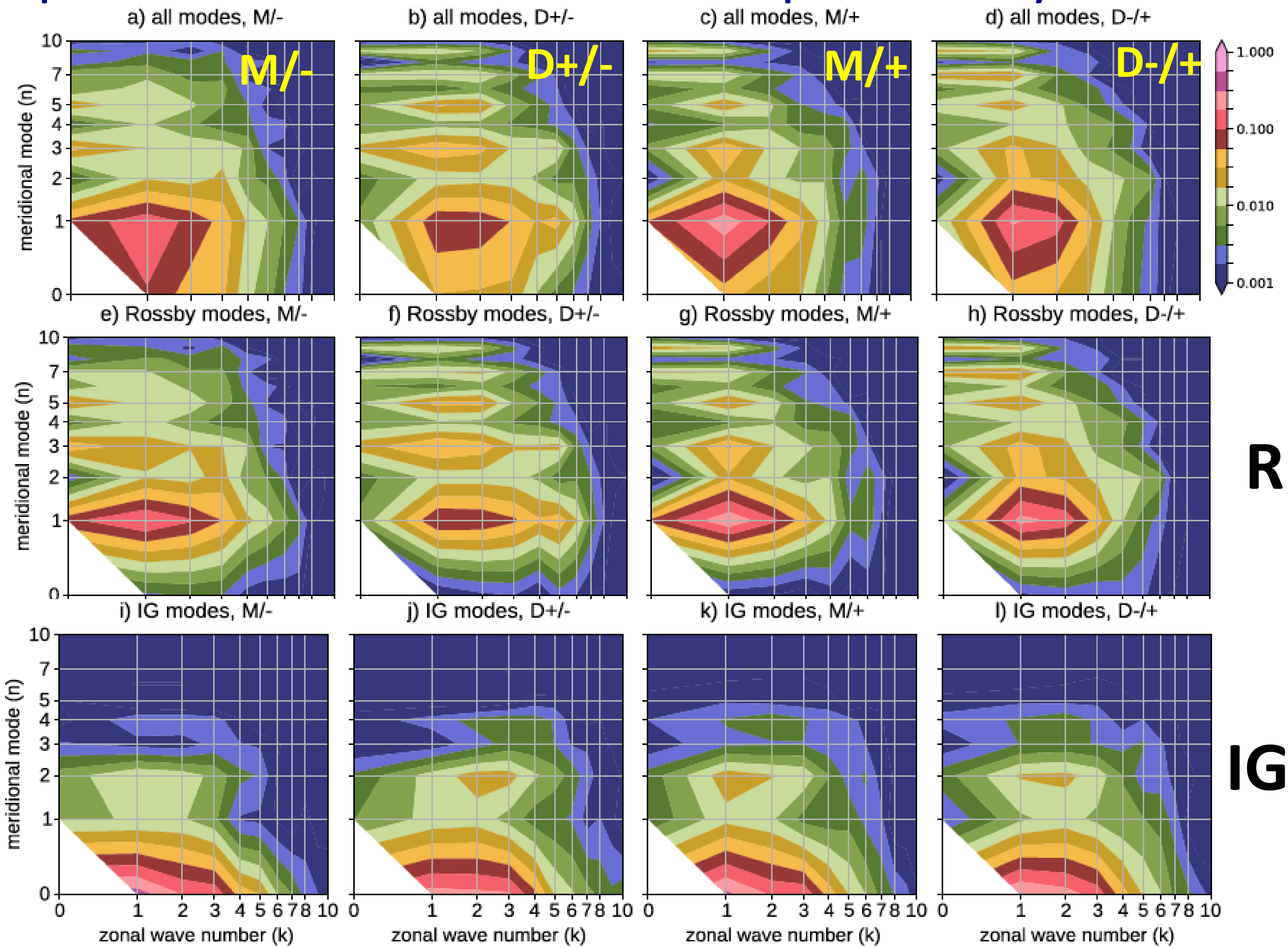


Rossby waves



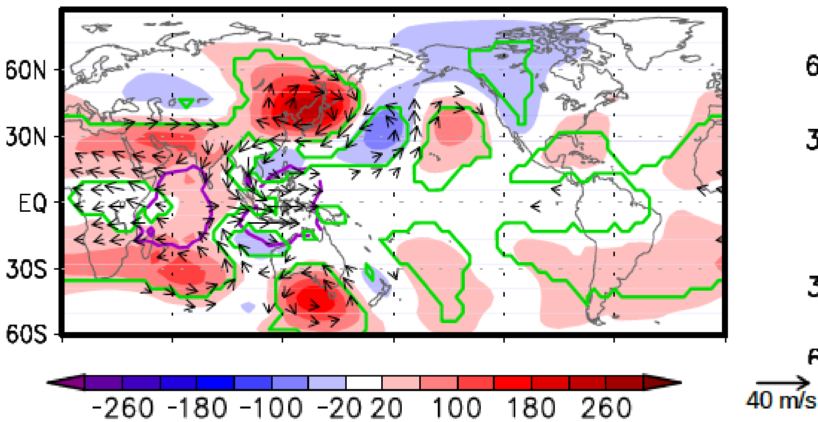
Kosovelj et al.,
J. Atmos. Sci., May 2019

Spectral distribution of the response: day 14

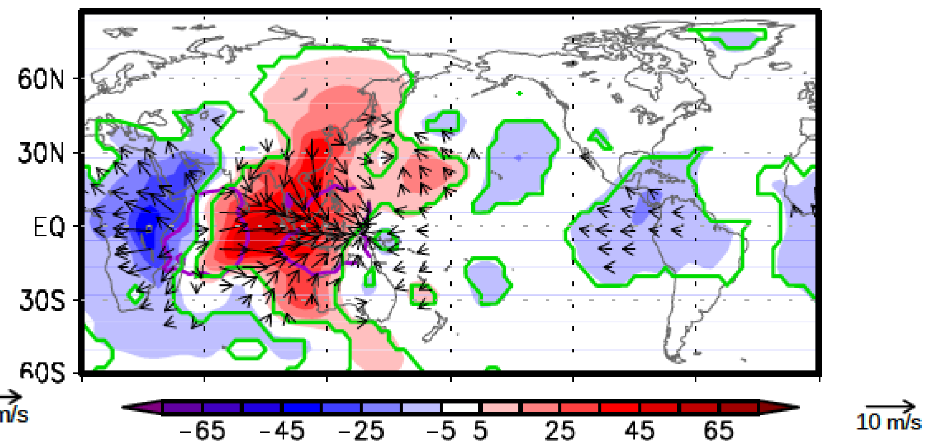


Response to tropical heating perturbations: day 14, 200 hPa, D+/-

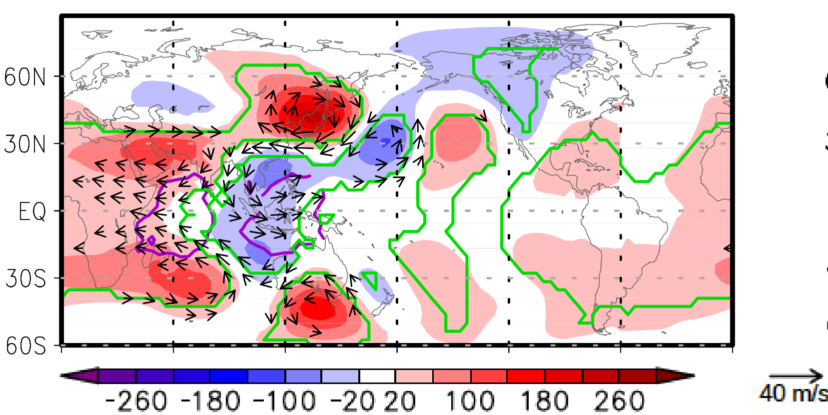
Total



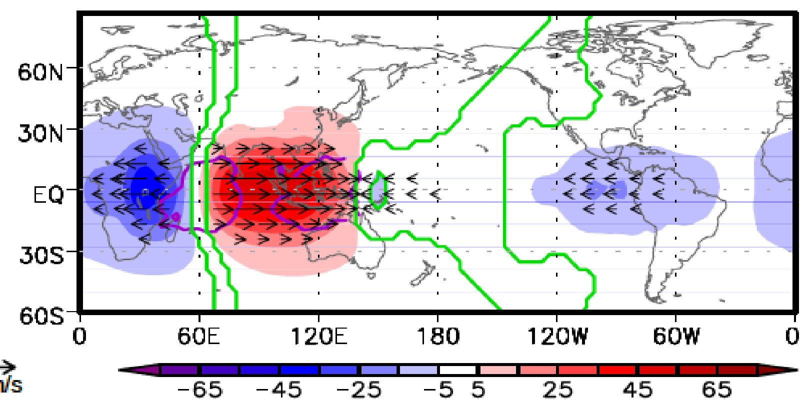
IG modes



Rossby waves

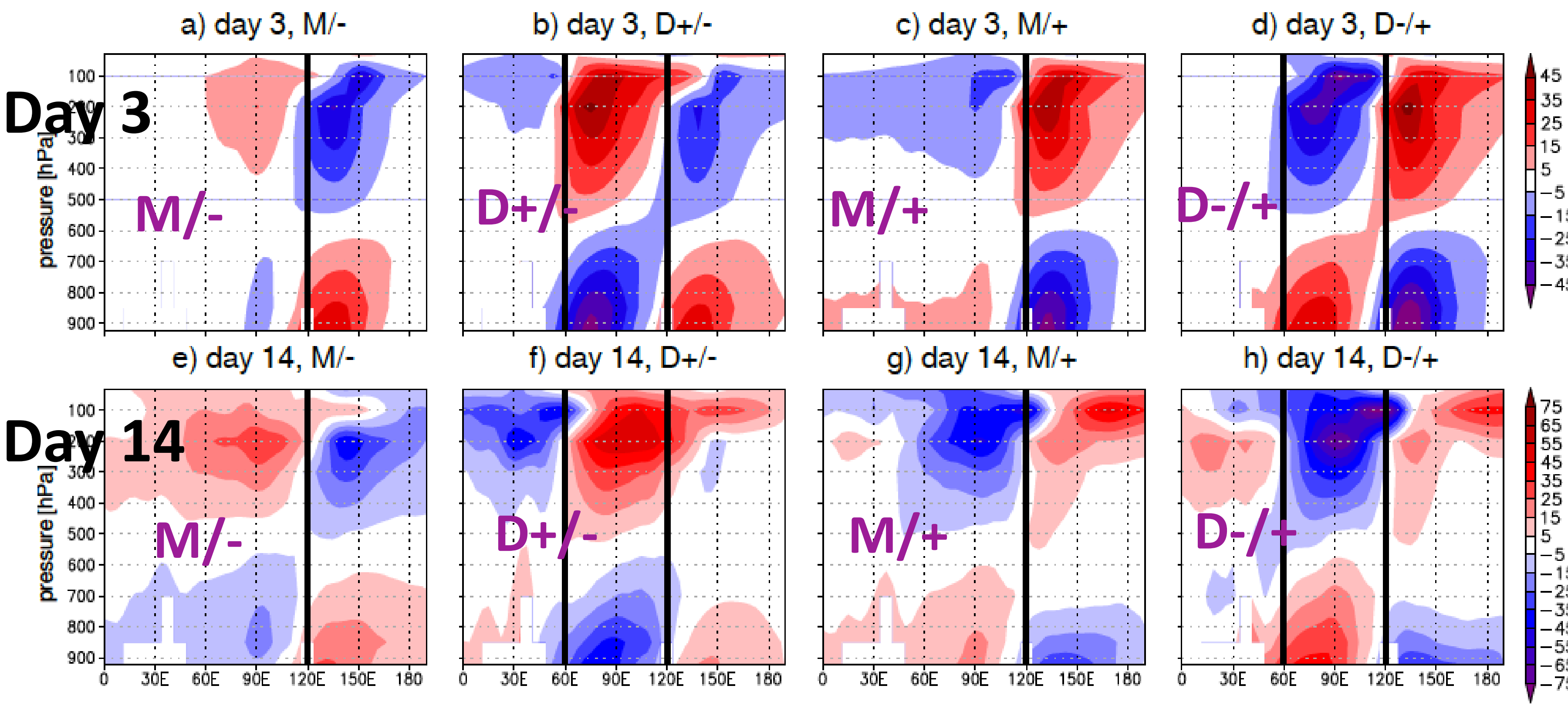


Kelvin wave



Kosovelj et al., J. Atmos. Sci., May 2019

Kelvin wave response to tropical heating perturbations



Vertical cross section of the Kelvin wave response along the EQ
Black line: the central latitude of the heating source

Kosovelj et al.,
J. Atmos. Sci., May 2019

Tropical origin of midlatitude extratropical waves: scale properties

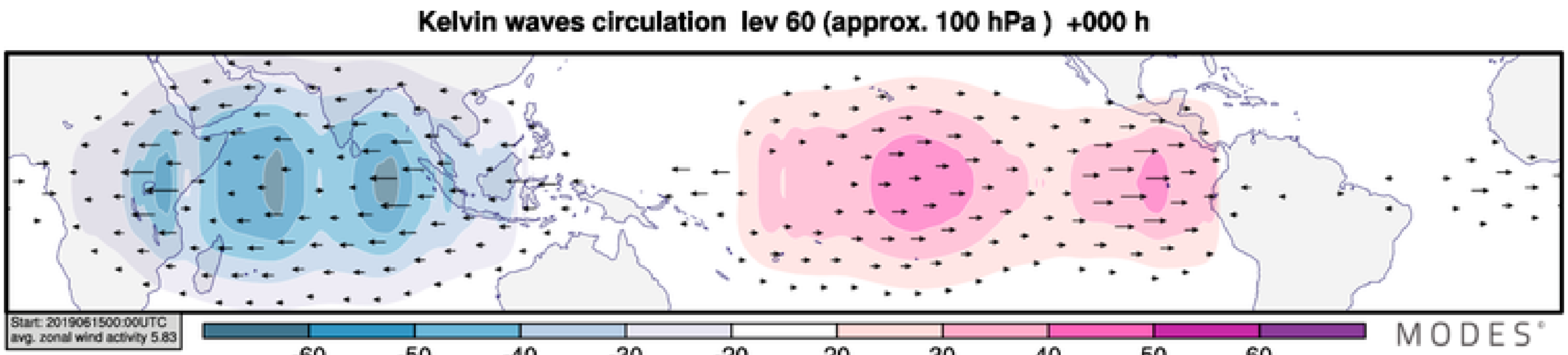
The overall response agrees with findings from previous linear, dry models. Perturbations mimicking phase 6 of MJO have a statistically significant impact over Europe in medium range

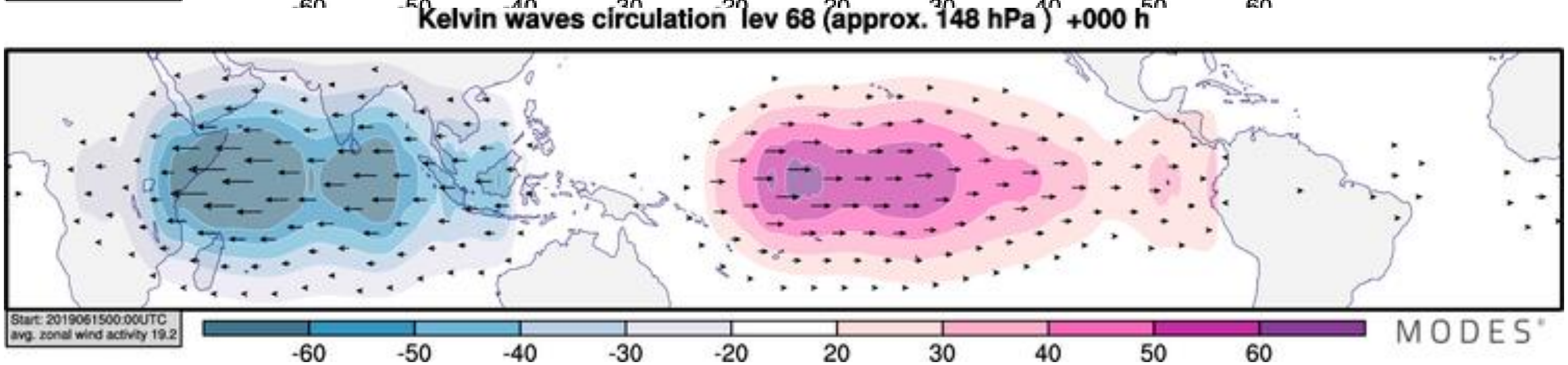
In short range, max response is in k=2-3 for dipole and in k=1 for monopole heating. In medium range, response to all perturbatioms maximizes at k=1, but stronger for dipole ⇔ accuracy of diabatic heating initialization affects the forecast quality on different scales in different MjO phases.

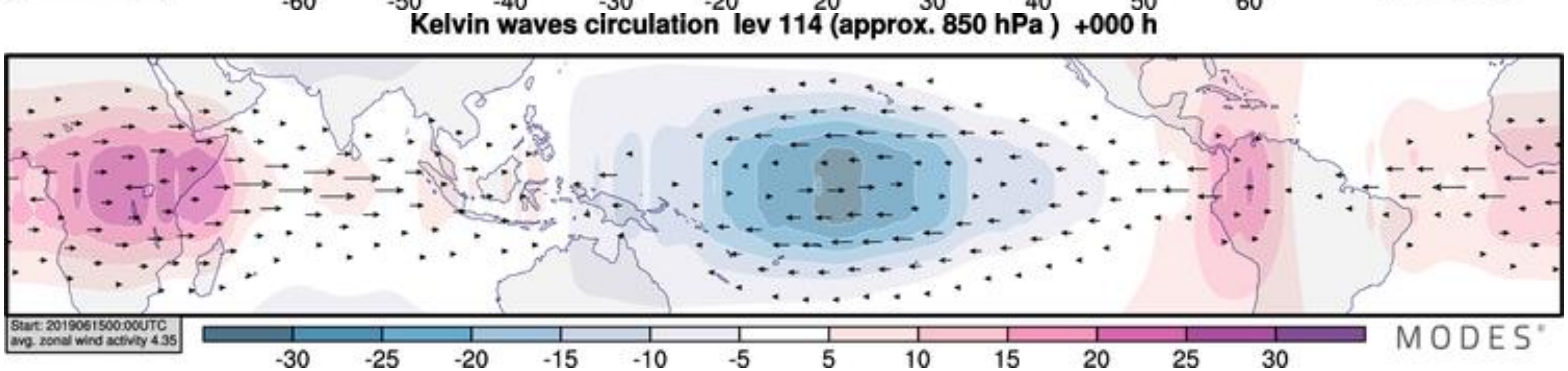
The short-term response is dominated bye the equatorial inertio-gravity waves (60% variance), especially the Kelvin wave (85% of IG variance)

Kosovelj et al.,
J. Atmos. Sci., May 2019

Kelvin wave of the day

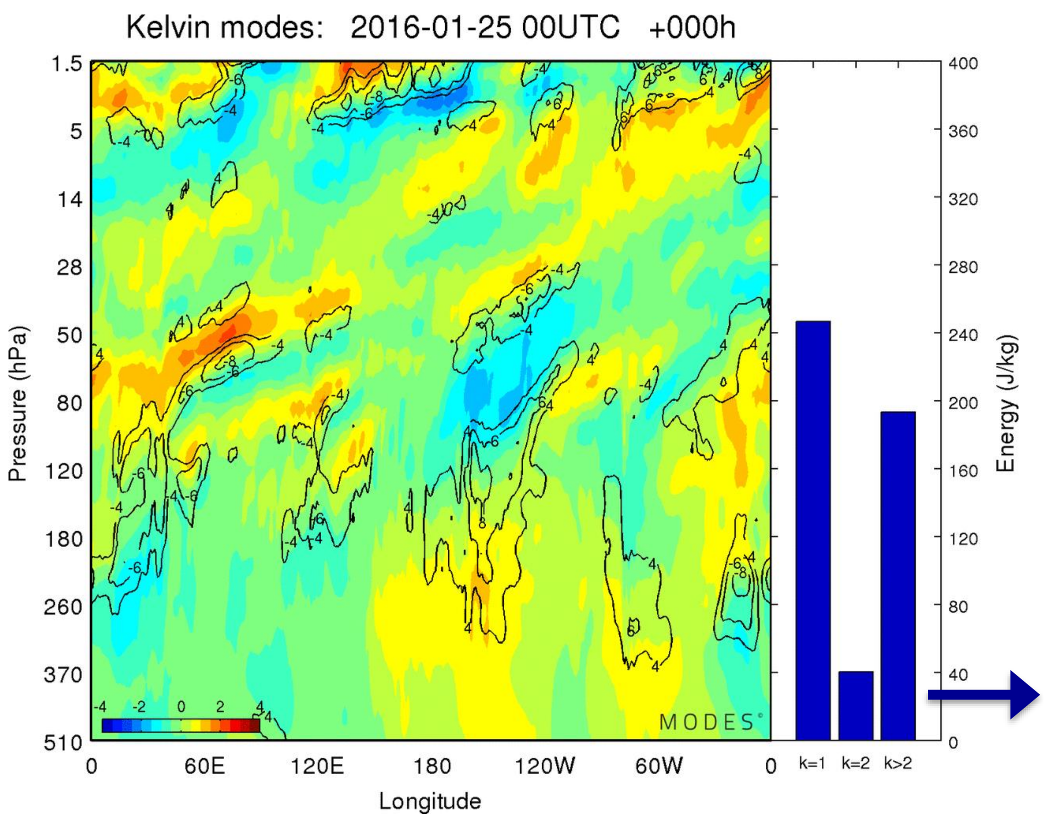






Nearly real Kelvin waves in ECMWF model: *http://modes.fmf.uni-lj.si*

Vertically-propagating Kelvin waves



Kelvin waves

10-day ECMWF forecast

Active MJO

Colors: zonal wind
Isolines: Temperature

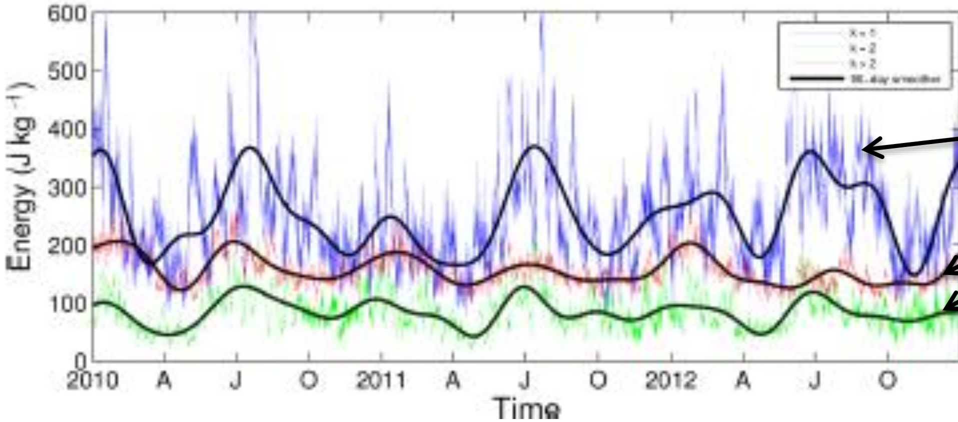
Energy in k=1,2,3

Vertical cross-section of Kelvin waves along the equator. Maximum of wave activity under the tropical tropopause over the Indian ocean

Nearly real Kelvin waves in ECMWF model: *http://modes.fmf.uni-lj.si*

Multi-scale variability of Kelvin waves

L91 6-hourly analyses



Zonal wavenumber k=1

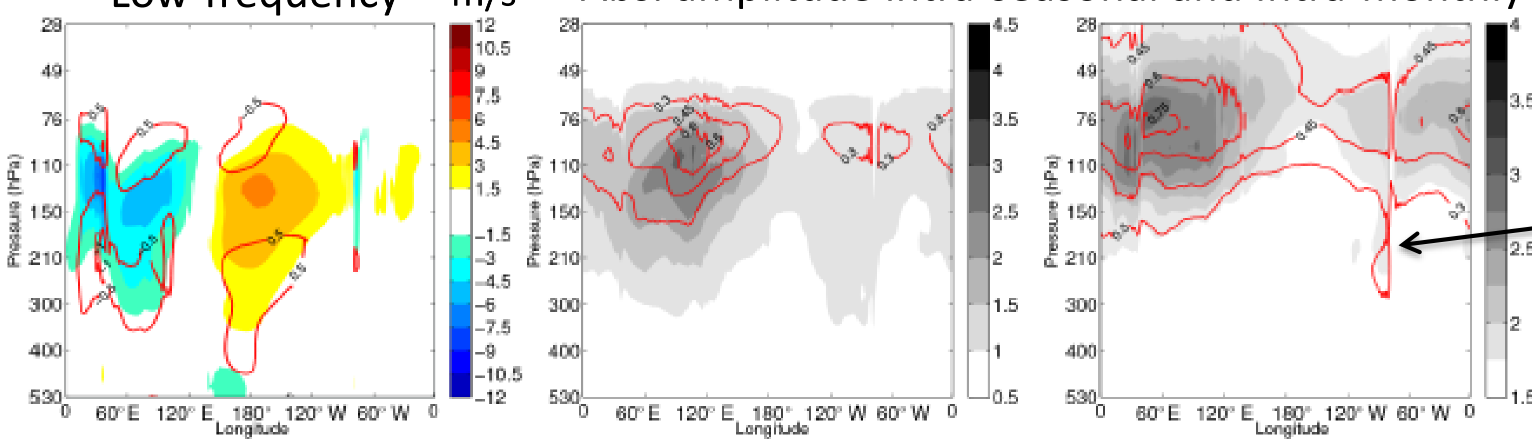
k>2

k=2

black lines: 90-day low-pass filter

Low-frequency m/s

Abs. amplitude intra-seasonal and Intra-monthly



m/s

T

Quadrupole T structure
k=1 structure, Gill-type
20º W of clim. winds

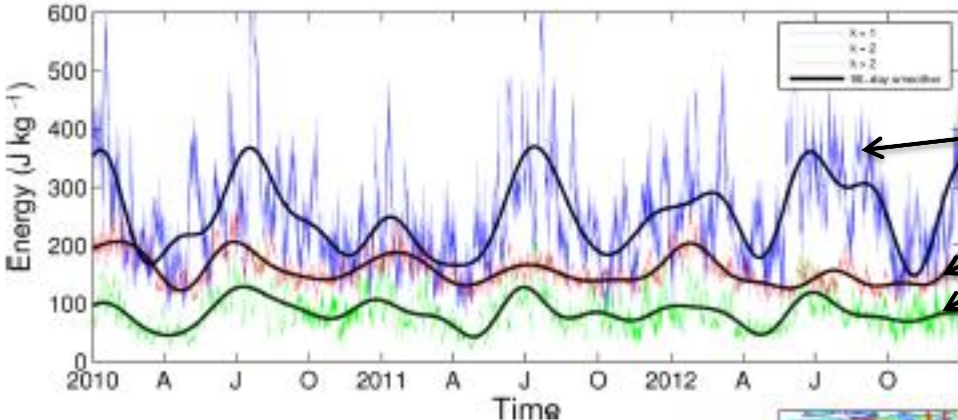
Strongest in DJF
Eastward tilt with height

Max in 70-100 hPa
Modulated by seasonal movement of the TTL

Blauuw and Žagar, 2018, ACP

Multi-scale variability of Kelvin waves

L91 6-hourly analyses



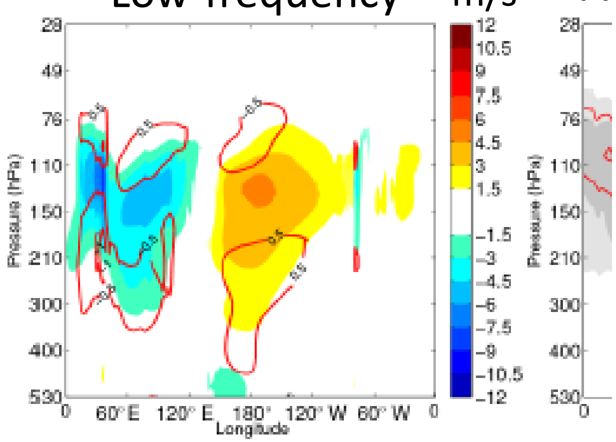
Zonal wavenumber k=1

k>2

k=2

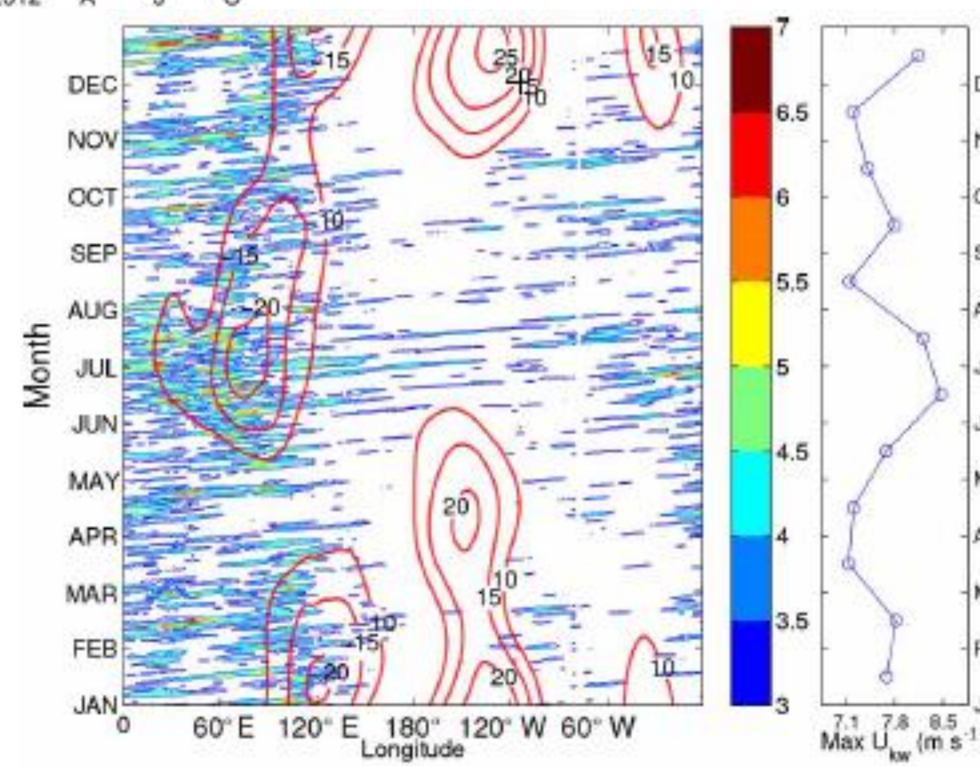
KW zonal wind
~110 hPa

Low-frequency m/s A

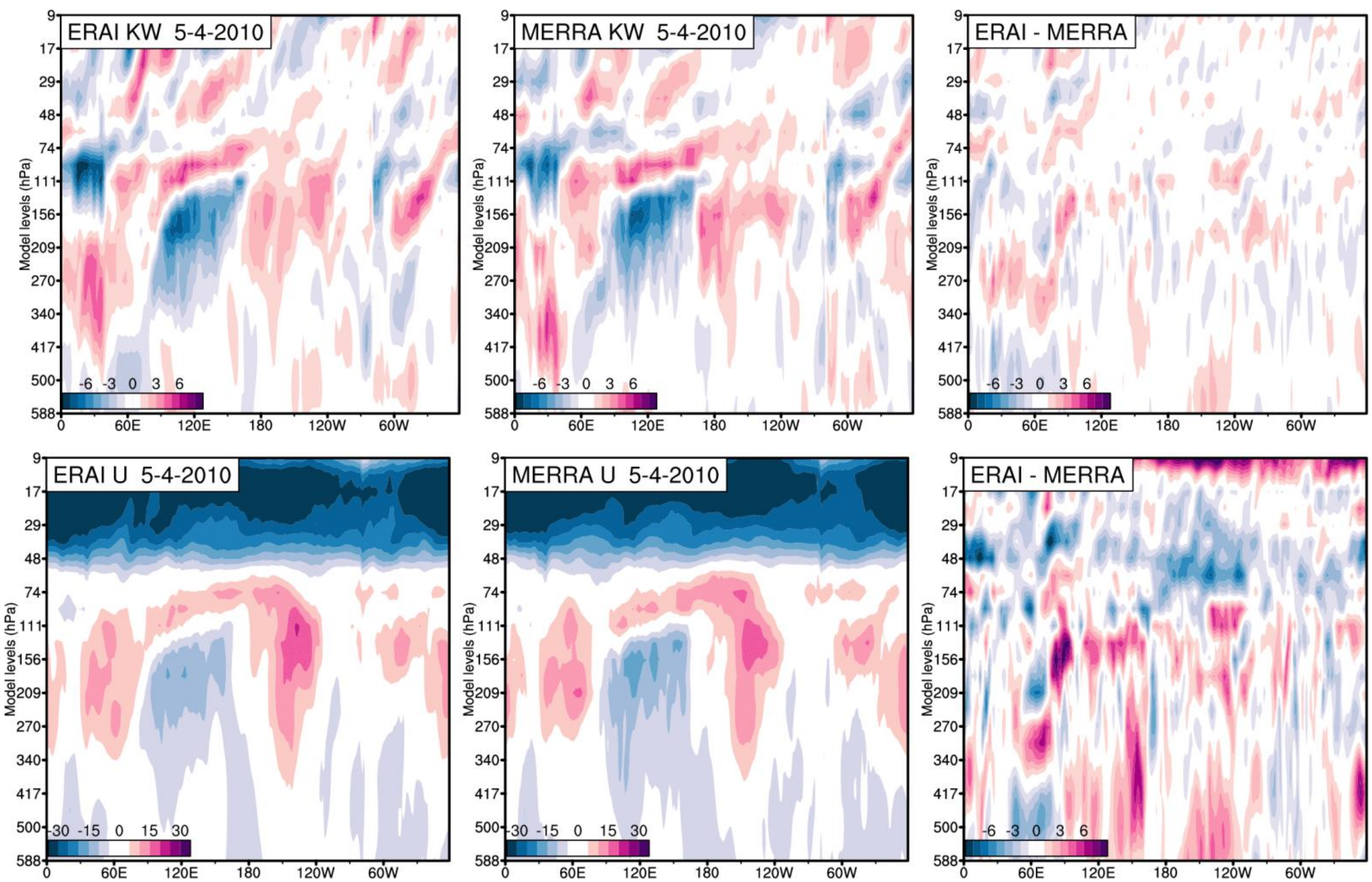


Quadrupole T structure
k=1 structure, Gill-type
20° W of clim. winds

St
Ea



Uncertainties in tropical Kelvin wave analysis: ERA Interim vs. MERRA

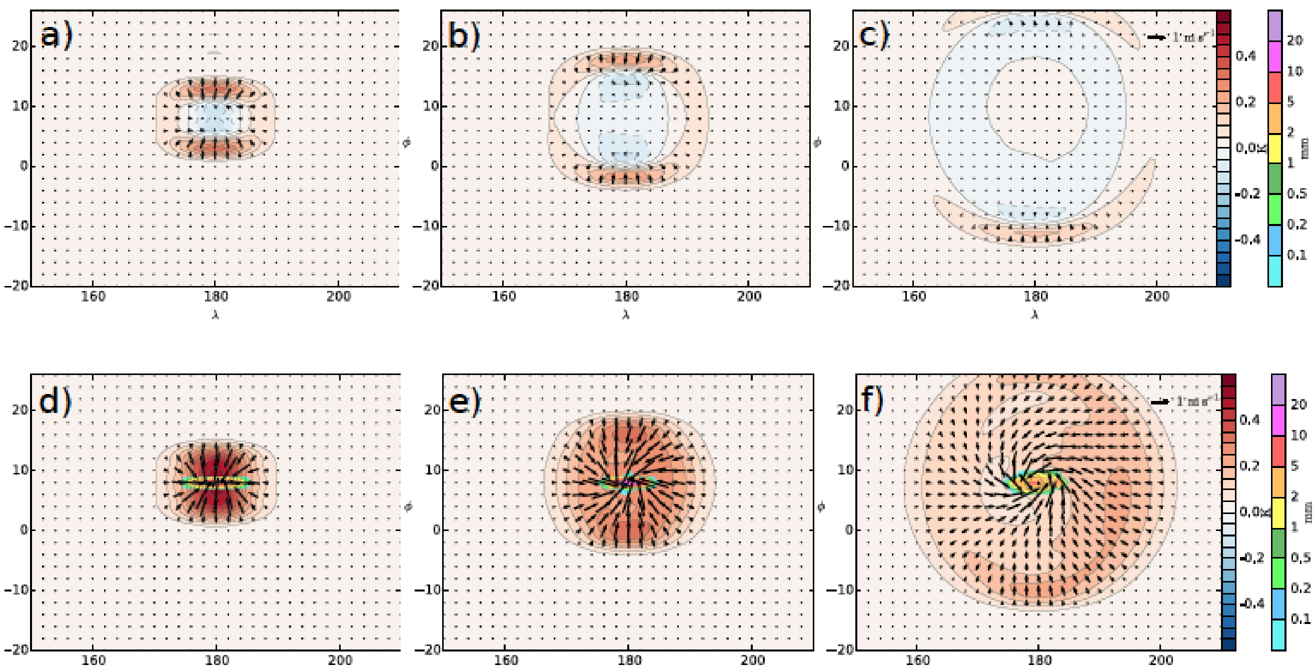


A simplified model of tropical atmosphere

MADDAM: Moist Atmosphere Dynamics Data Assimilation Model

Adjustment to +1 K T perturbation in mid-troposphere over ITCZ

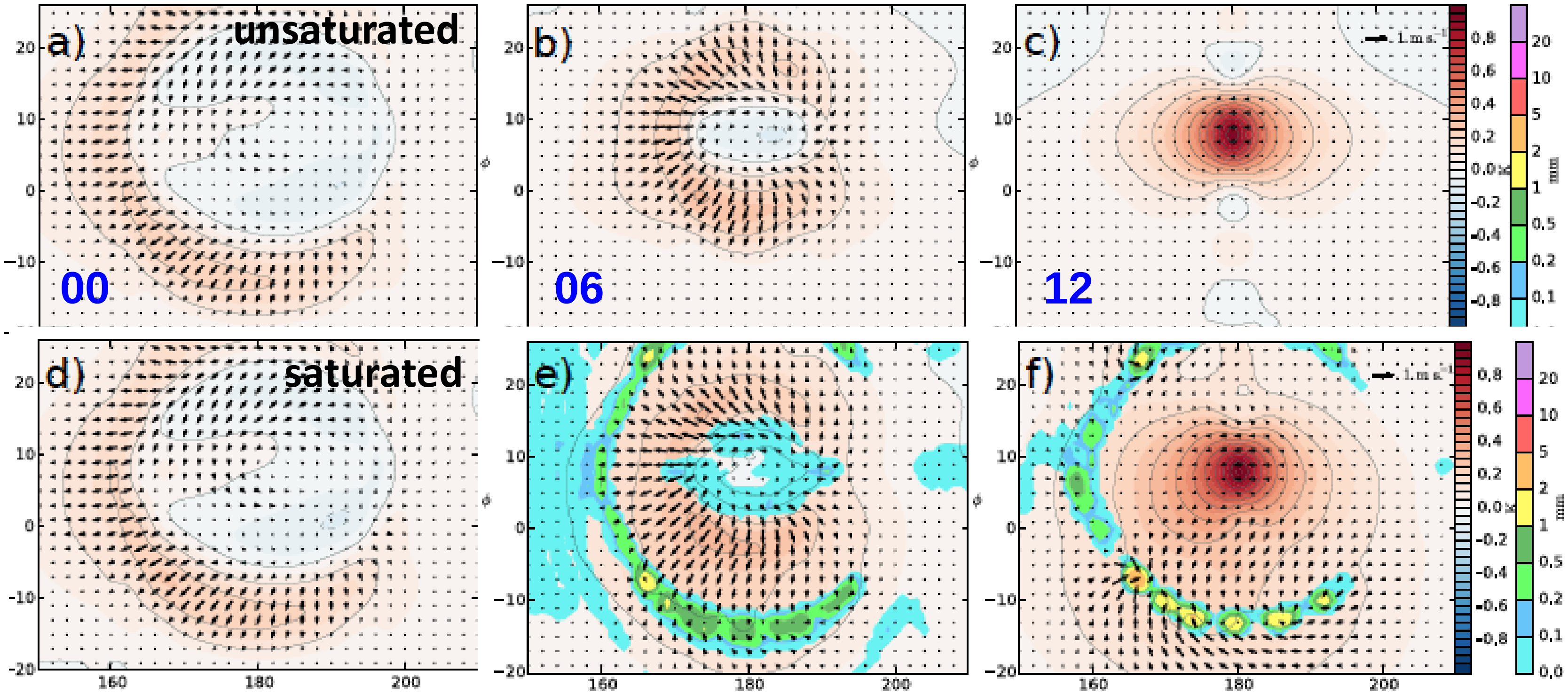
Unsaturated bkg

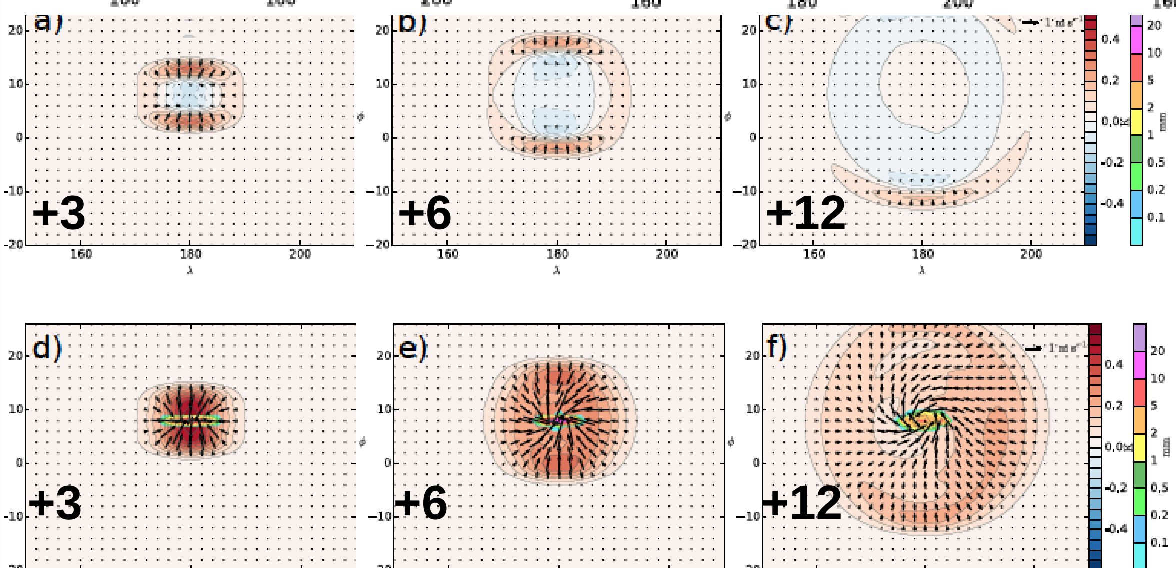


Saturated bkg: more intense IGW dynamics

Zaplotnik et al., 2018, QJRMS

Inertio-gravity waves and 4D-Var in the tropics





A single +2 K T obs at the end of 12-h window

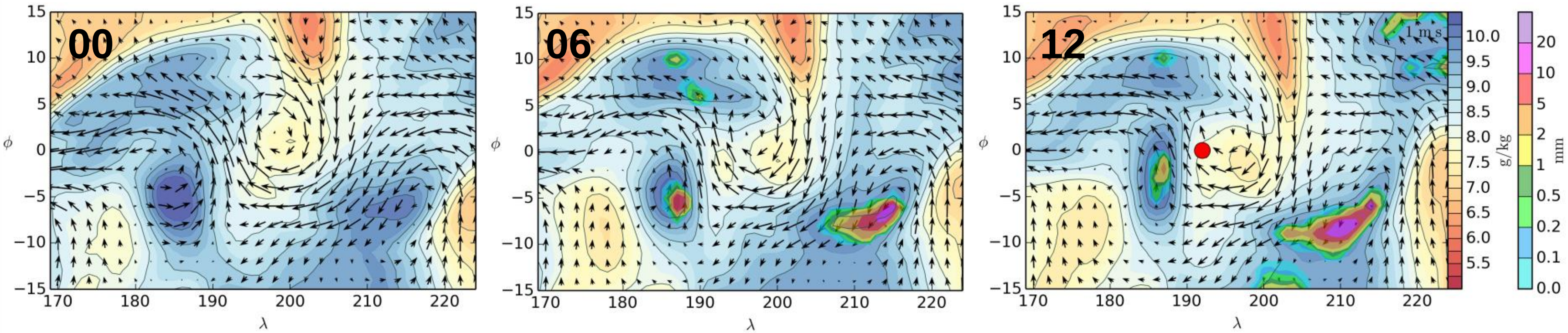
IGW propagates outward backward in time, in AD and inward in TL model

Zaplotnik et al., 2018, QJRMS

Assimilation of moisture observations in the tropics

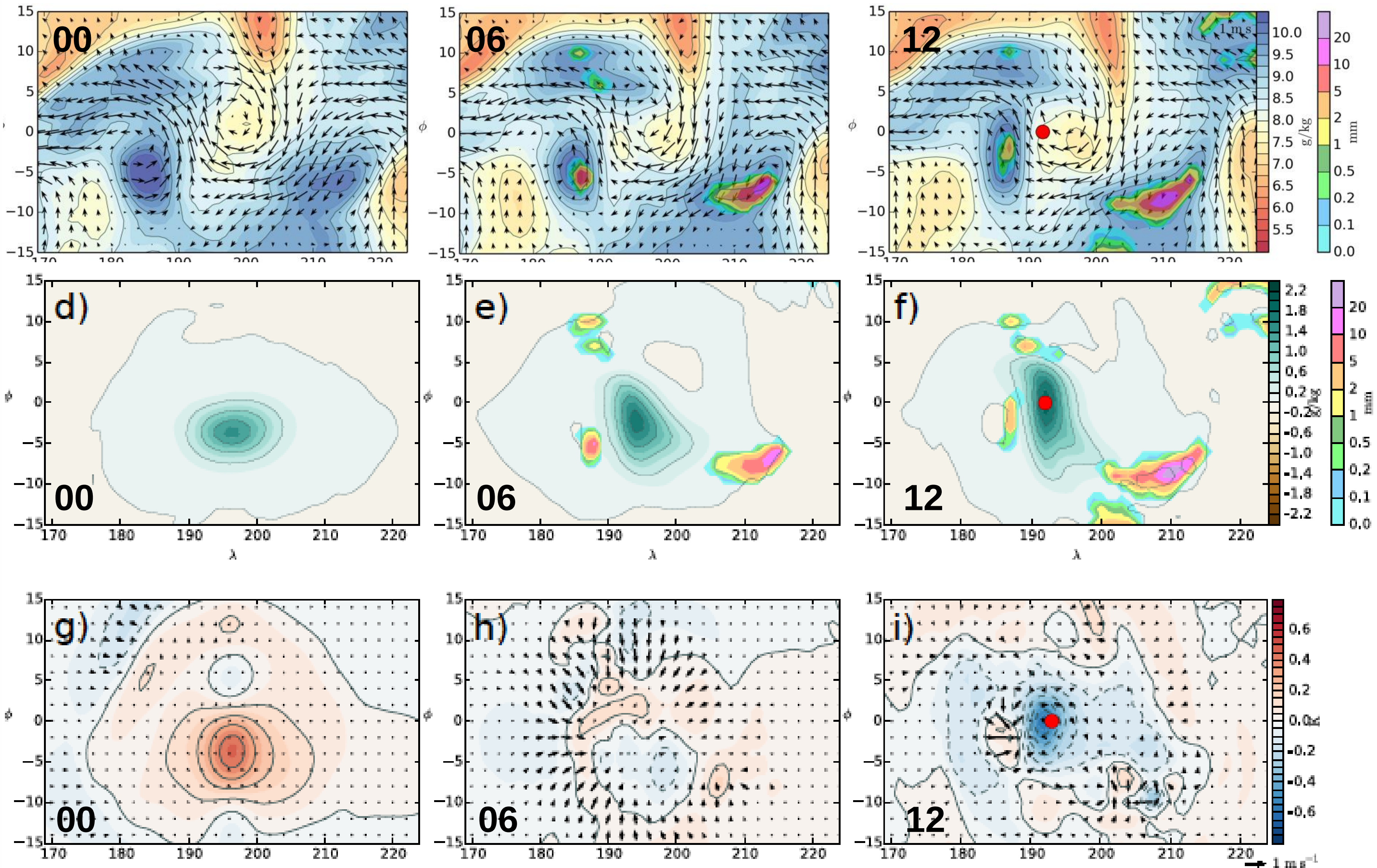
A single moisture observation in MADDAM 12-hour window 4D-Var

Single saturated humidity observation (**RED** dot), 2.4 g/kg, with error 1.1 g/kg
Is located at the end of the window



Zaplotnik et al., 2018, QJRMS

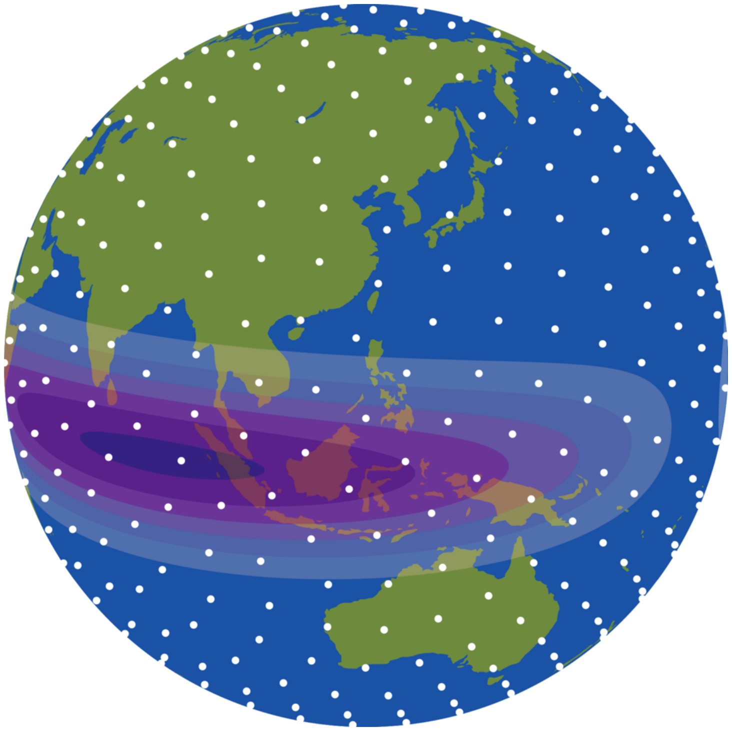
Impact of a single moisture observations in 12-h 4D-Var



Zaplotnik et al., 2018, QJRMS

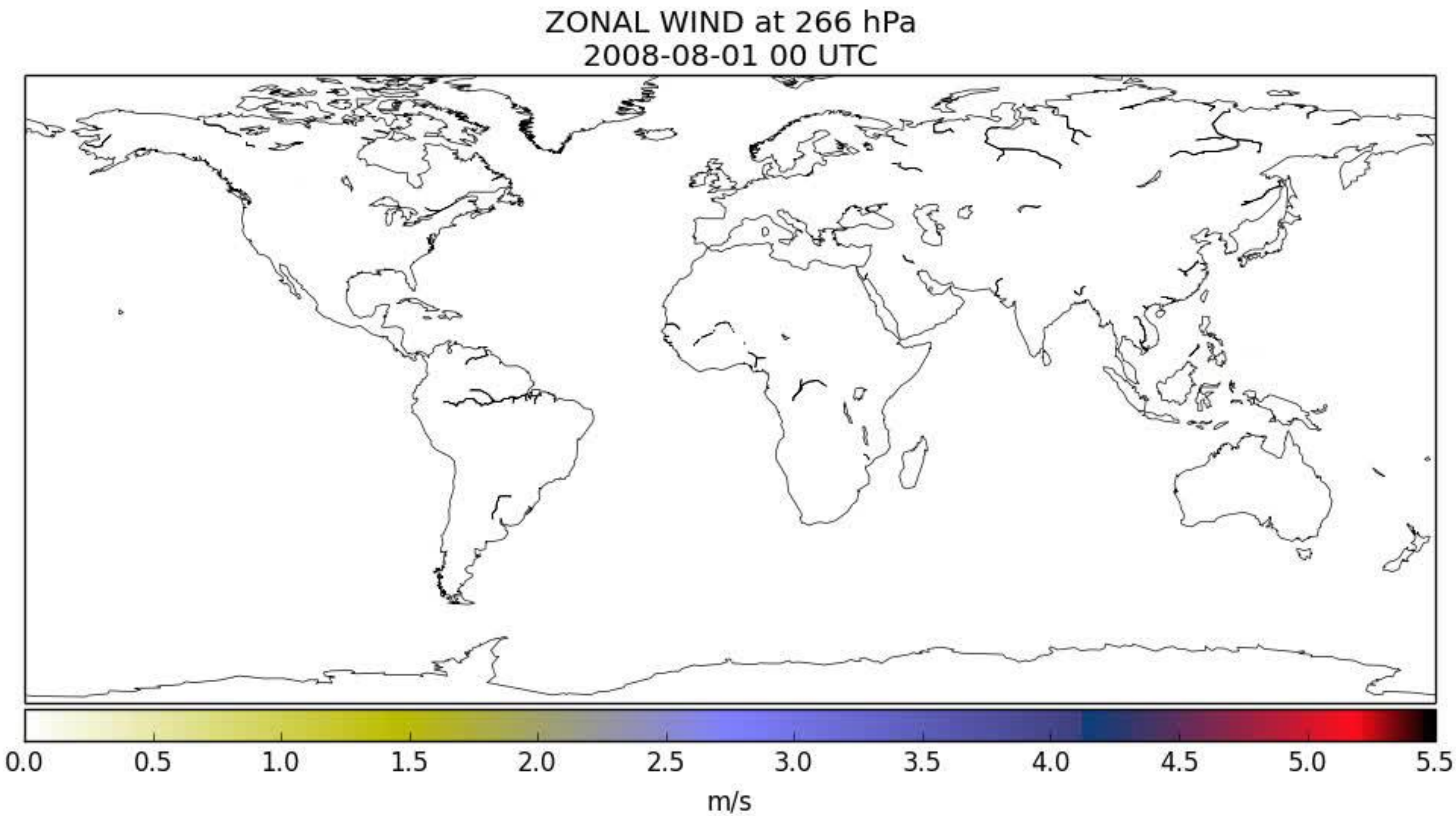
Towards understanding analysis uncertainties

- Perfect-model Observing System Simulation Experiment (OSSE)
- 80-member ensemble and EnKF
- No covariance inflation
- Homogeneous observing network (Δ~920 km)
- Long spin-up (from 1 Jan 2008) with the observed SST to reproduce nature run (‘truth’)
- Observations simulated by the nature run
- Assimilation cycle during three months (Aug-Oct) in 2008
- Data Assimilation Research Testbed (DART), *http://www.image.ucar.edu/DAReS/DART/*
- Model: NCAR T85 Community Atmosphere Model, CAM 4 physics

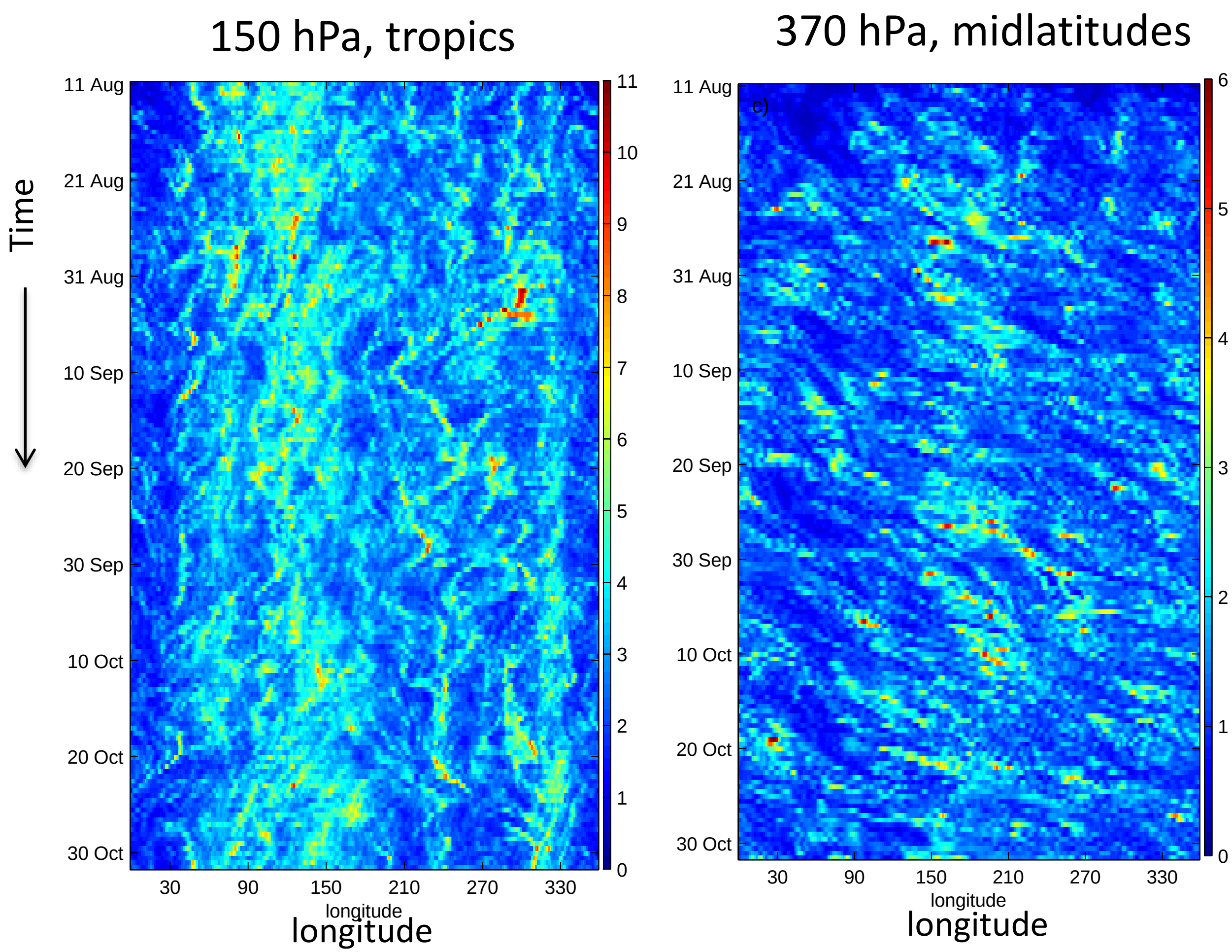


Žagar et al., MWR, 2016

Analysis uncertainties (every 12 hr)



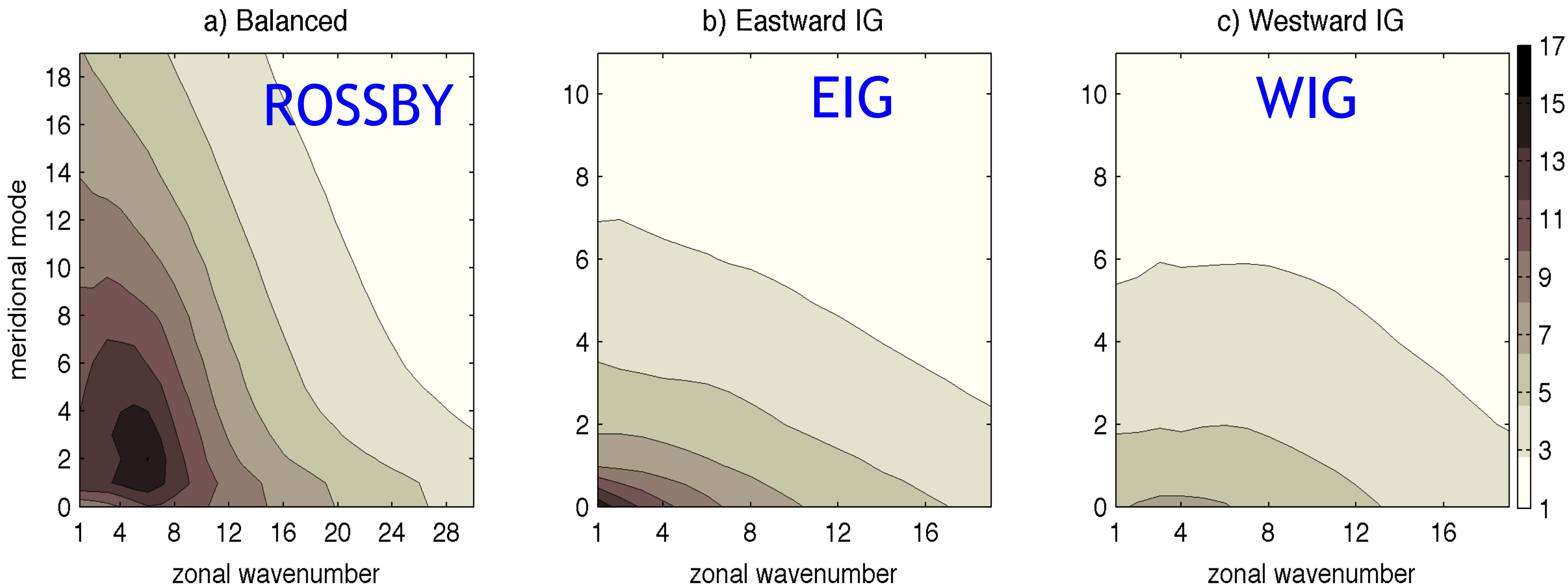
Flow dependency of short-term forecast uncertainties



- Ensemble spread in +12-hr fc zonal wind (m/s) along the latitude circle
- 3-month long experiment with a perfect model
- 12-hour EnKF data assimilation

Žagar et al., MWR, 2016

Short-range global forecast uncertainties in the perfect-model framework

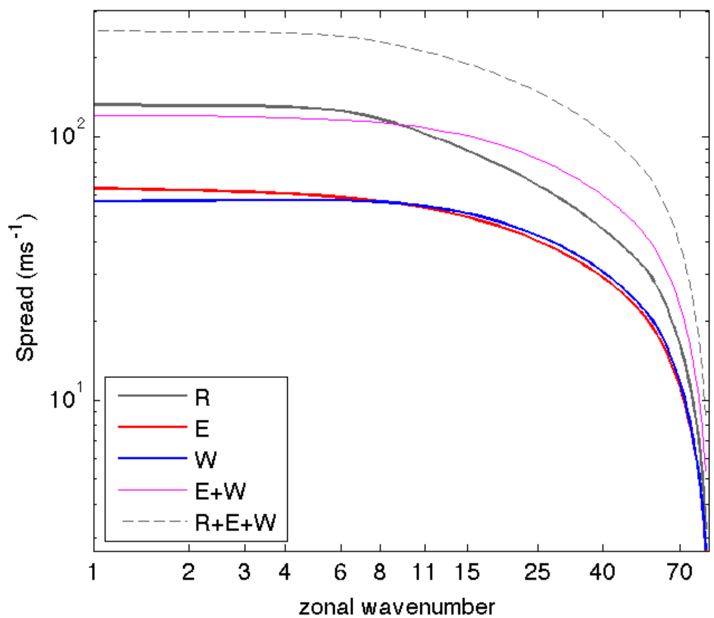


Distribution of the short-term forecast uncertainties derived from the perfect-model ensemble looks similar to that in NWP systems.
The largest variance is in synoptic scales in balanced modes and in the large-scale Kelvin wave

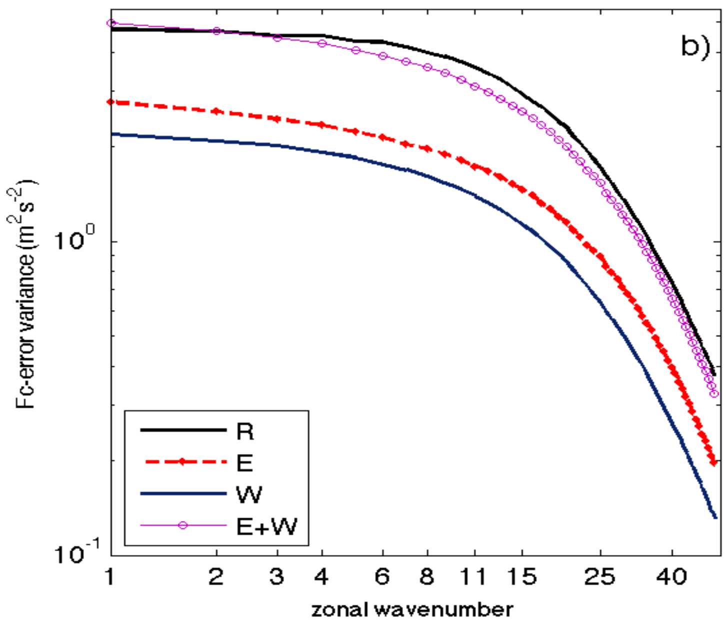
Žagar et al., 2016, MWR

Short-range global forecast uncertainties in the perfect-model framework: 1D spectra

Perfect model exp



ECMWF EDA

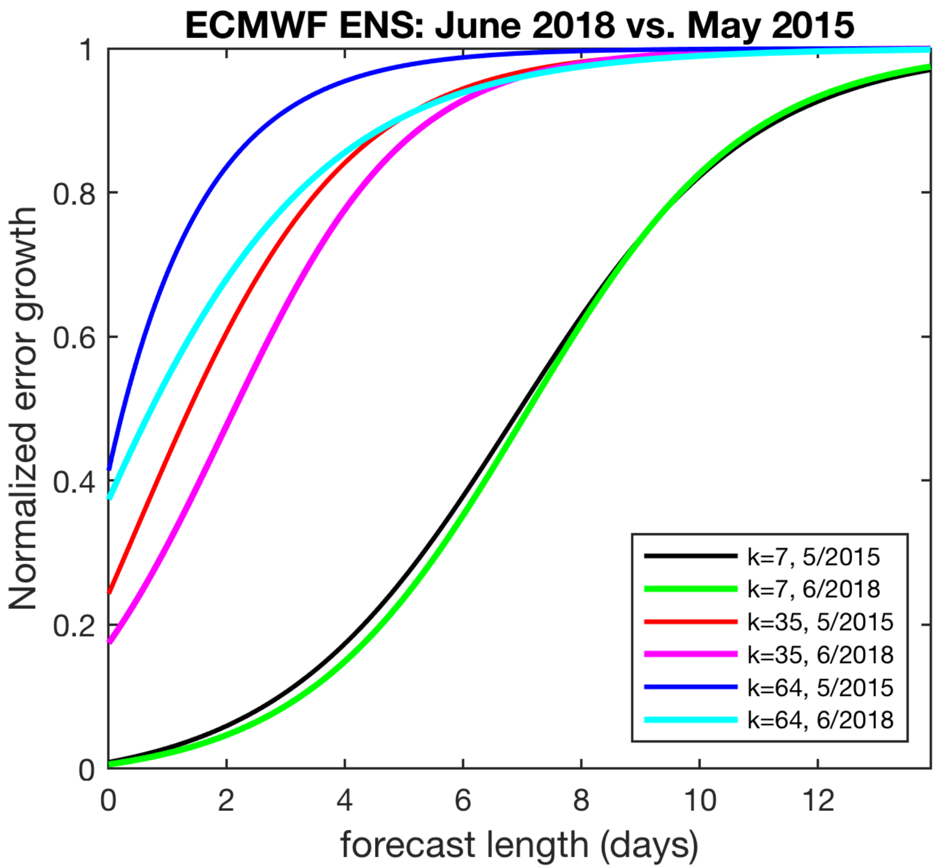


Data assimilation is not efficient in reducing the tropical large scale spread, not even in the perfect model framework

Žagar et al., 2013 QJRMS; 2016, MWR

Possible implications for global predictability

Recent improvements in predictability



ECMWF ENS progress comparison between May 2015 and June 2018

k=7, 2015, 2018
60% predictability limit reached at 7.8 and 7.9 days

k=35, 2015, 2018
60% predictability limit reached at 2.6 and 3.3 days

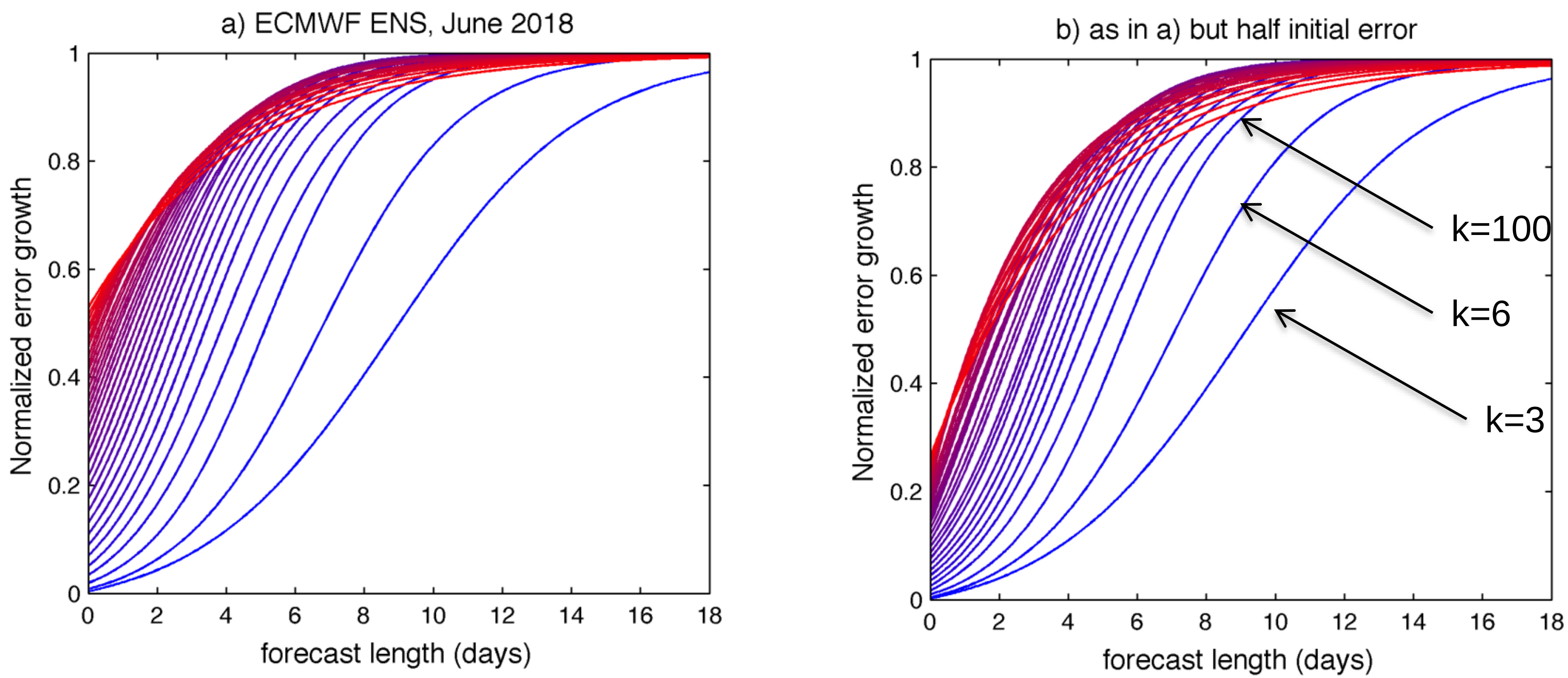
k=64, 2015, 2018
60% predictability limit reached at 0.5 and 1.2 days

Errpr variances normalized by Emax

Fitting method of Žagar et al., 2017, Tellus

On the global predictability limits

same data (June 2018 ENS), 50% smaller analysis-error variances



- Little predictability gain in synoptic waves (+0.3 days for k=7)
- But, k=100 would have the same predictability at day 2 as now k=40, and k=70 would have the same predictability at day 1 as now k=43

Summary

Dynamics:

Perturbations in tropical heating across many spatio-temporal scales influence the global circulation and climate. For heating perturbations resembling MJO, the max response is found in different wavenumbers for different phases => Implications for NWP

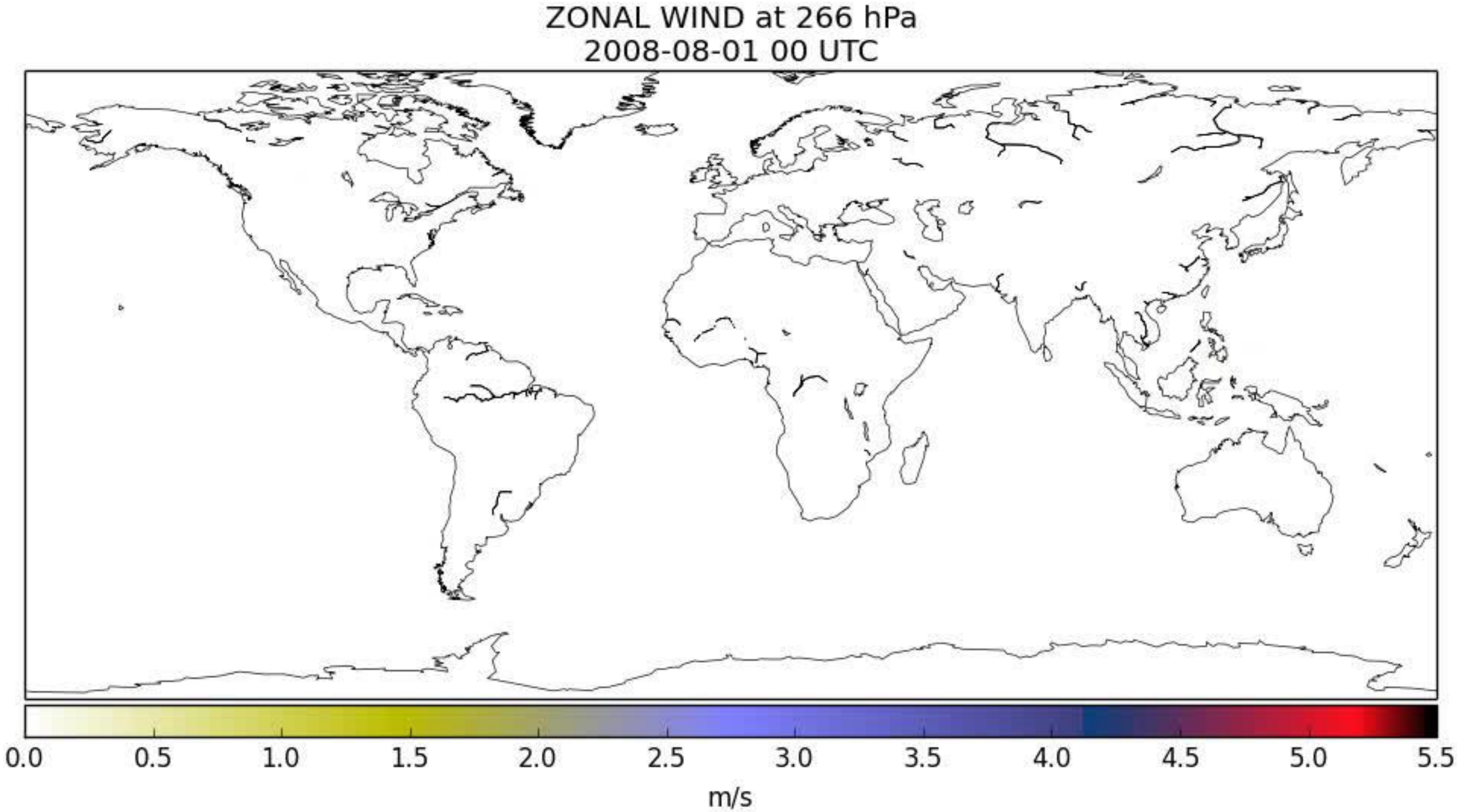
Data assimilation:

Largest analysis uncertainties and largest growth of forecast uncertainties during the first day are in the tropics. They are flow dependent. The uncertainties are on average largest on the largest scales and this applies even to the perfect model.

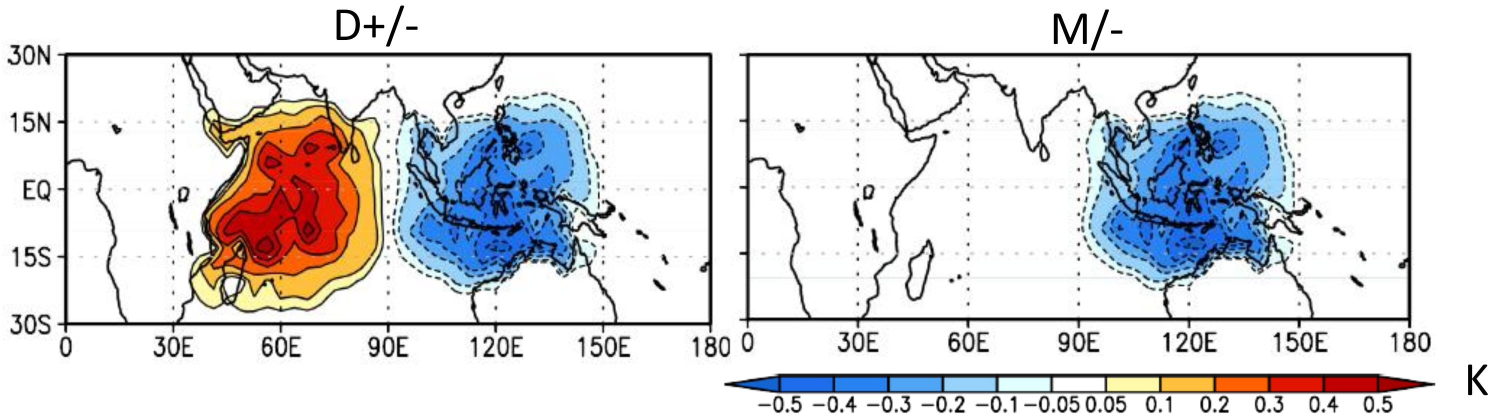
Predictability:

Possible implications for midlatitude day-to-day weather predictability are related to the downscale propagation of large-scale initial condition error and the propagation of tropical uncertainty impact to the extratropics

+12-hr forecast uncertainties (every 12-hr)

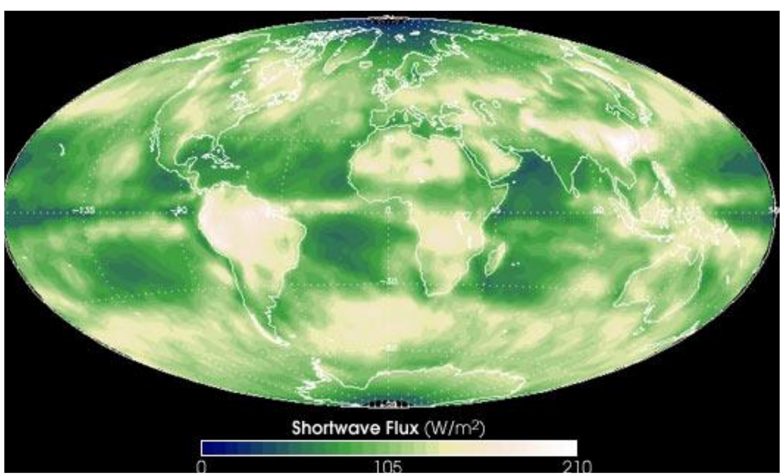


Tropical heating perturbations



Perturbations resembling different phases of MJO

Vertical profile of a deep heating with max in the middle troposphere



Outgoing longwave radiation
March 2000 mean
NASA

Kosovelj et al.,
J. Atmos. Sci., May 2019

NMF expansion: horizontal expansion functions

HSFs are pre-computed for a given number of vertical modes, M

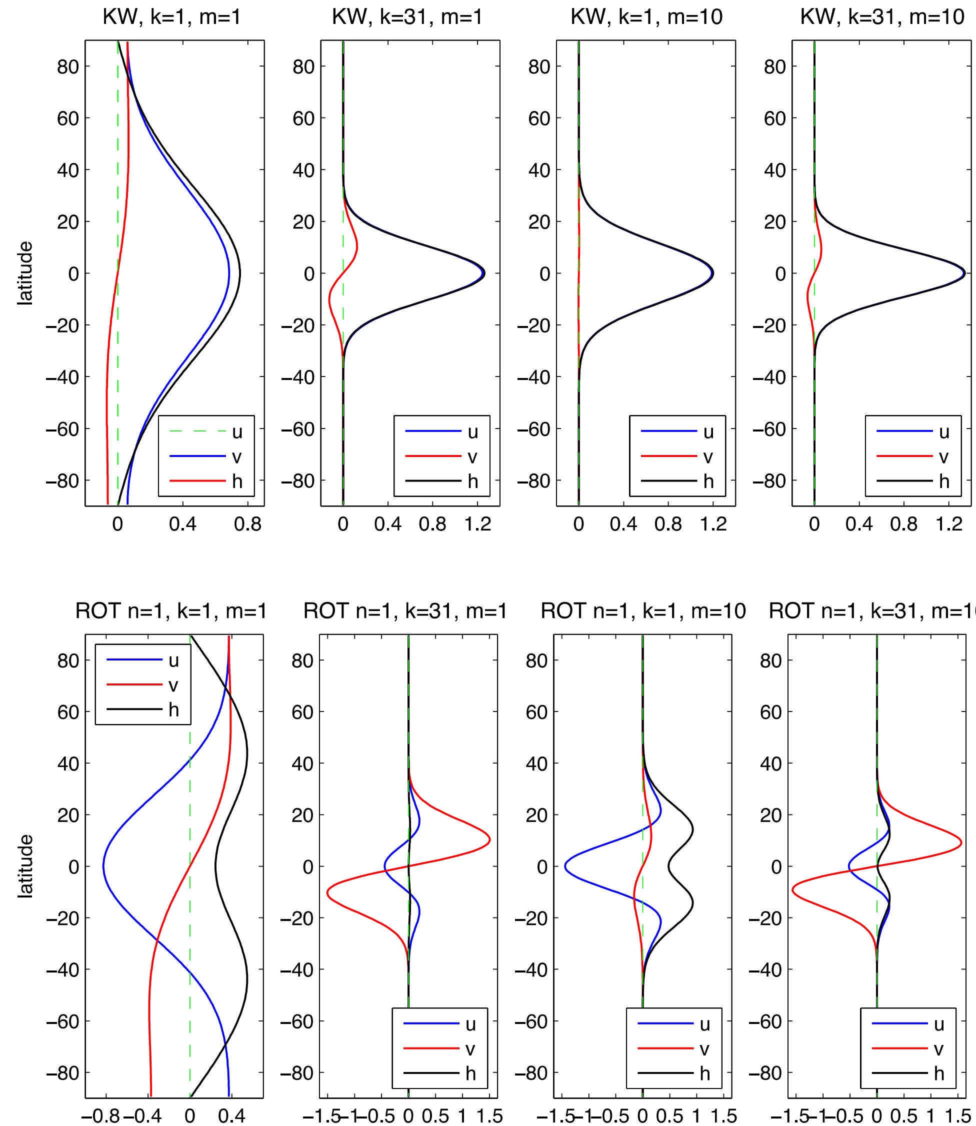
For every m=1,…,M, i.e. for every D_m

Meridional structure for Hough functions is computed for a range of the zonal wavenumbers K,

k=-K,..,0,...,K

and a range of meridional modes for the balanced, N_{ROT}, a range of EIG, N_{EIG}, and a range of WIG, N_{WIG}, modes.

$R=N_{ROT} + N_{EIG} + N_{WIG}$



Scale decomposition of ensemble forecasts

Modal decomposition using the 3D orthogonal normal mode functions
Statistics in modal space (MODES software)

Computation of the ensemble variance (J. Atmos. Sci., 2015):

$$\left[\sigma_n^k(m)\right]^2 = \frac{1}{P-1}\sum_{p=1}^{P} gD_m\left(c_n^k(m;p)\left[c_n^k(m;p)\right]^*\right)$$

Specific modal variance Σ^2

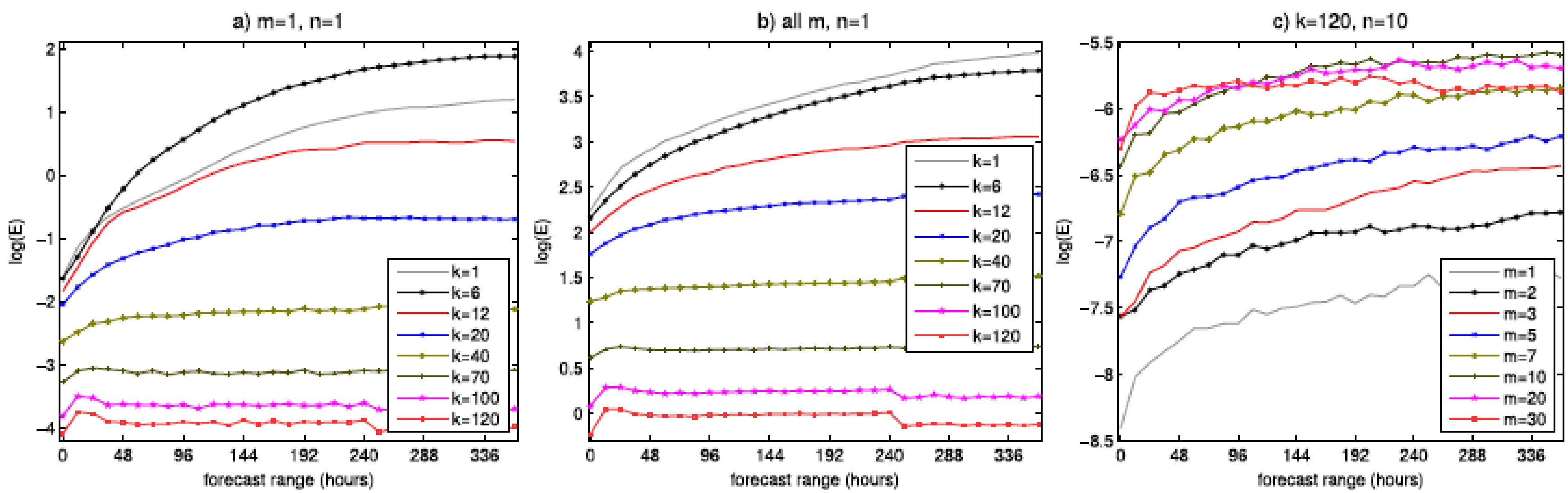
$$\sum_k\sum_n\sum_m\left[\sigma_n^k(m)\right]^2 \quad \text{Is equivalent to} \quad \sum_i\sum_j\sum_m S^2(\lambda_i,\varphi_j,m)$$

$$S^2(\lambda_i,\varphi_j,m) = \frac{1}{P-1}\sum_{p=1}^{P}\left(u_p^2(\lambda_i,\varphi_j,m) + v_p^2(\lambda_i,\varphi_j,m) + \frac{g}{D_m}h_p^2(\lambda_i,\varphi_j,m)\right)$$

specific variance in physical space $\boldsymbol{S}^2$

Different time scales of the error growth

- a rapid growth and an apparent saturation of of errors in smaller spatial scales early in the forecast range,
- a slowly evolving component of error throughout the forecast range,
- uniformly distributed large-scale errors across the spectrum



Growth in different waves (zonal wavenumber), Integrated vertically and meridionally

Growth in different waves in barotropic mode, integrated meridionally

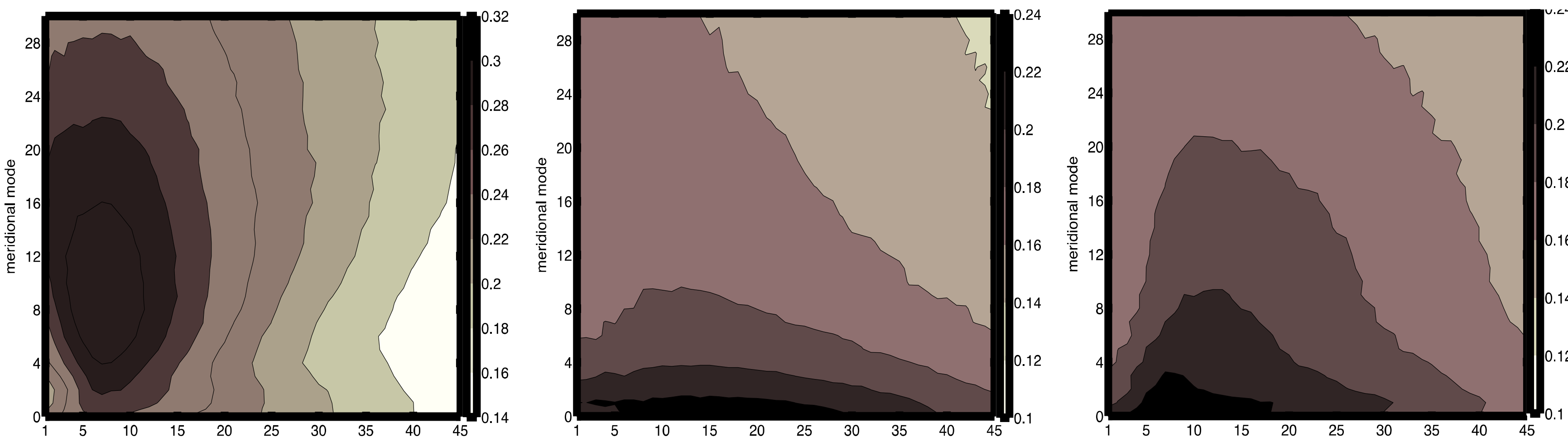
Growth at small scales in midlatitudes for different vertical depths

Tellus A, 2017

Data assimilation efficiency

Efficiency = (po-pr)/pr

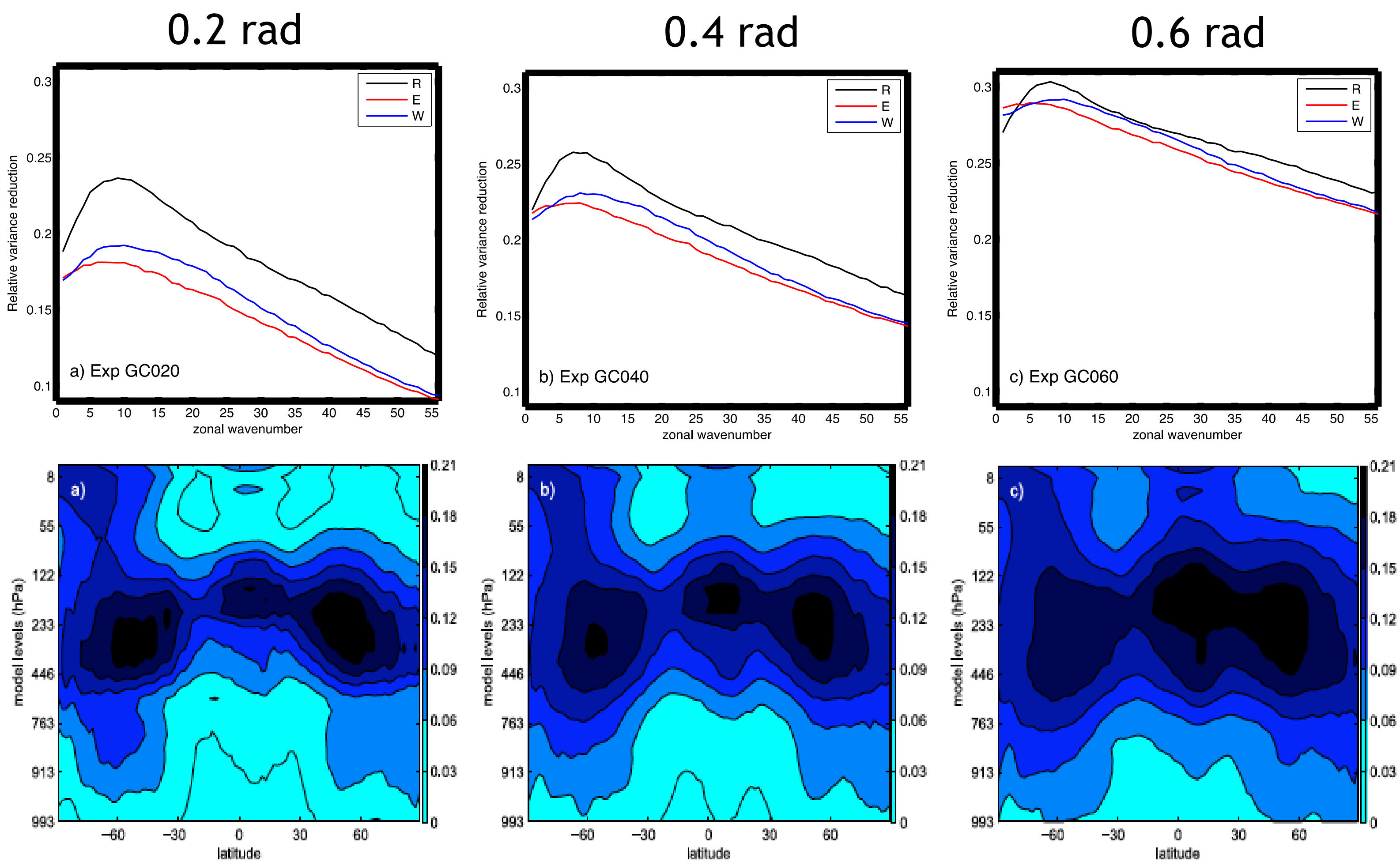
ROSSBY EIG WIG



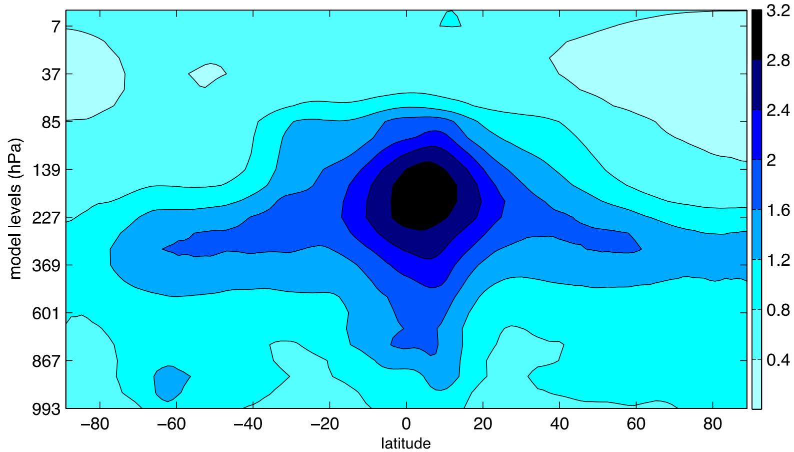
The assimilation is most efficient in synoptic scales, for both balanced and IG motions

Žagar et al., 2016, MWR

Impact of the covariance localization radius



Zonally-averaged 12-hour forecast uncertainties in zonal wind



Spread of 12-hr forecast ensemble
3-month average
Spectral forecast model, T85

Impact of the localization radius for data assimilation