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

Nedjeljka Žagar

Universität Hamburg

DER FORSCHUNG | DER LEHRE | DER BILDUNG

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*)

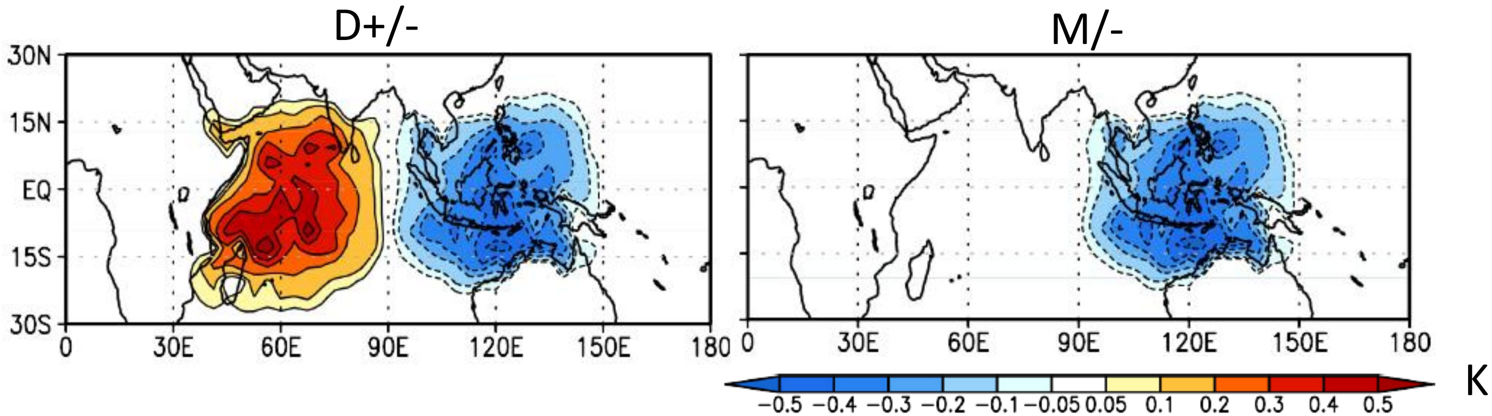
Analysis uncertainties and forecast errors in a perfect model

- Spectra of analysis and forecast uncertainties

Possible implications for global predictablitiy

Summary

Tropical heating perturbations



Perturbations resembling different phases of MJO

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

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

horizontal structure*rand(0,1)

T tendencies due to convection and LSC

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

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

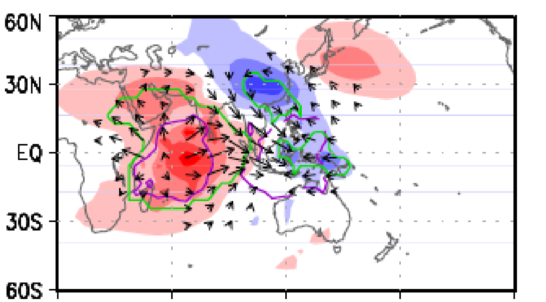
Kosovelj et al., J. Atmos. Sci., May 2019

Response to tropical heating perturbations: day 3, 200 hPa

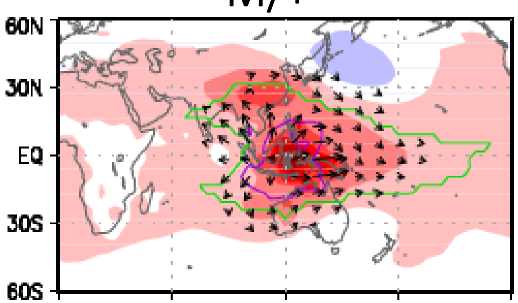
$$\overline{A}(t) = \frac{1}{J}\sum_{j=1}^{J}[A_j(t) - A_0(t)]$$

ensemble-averaged response

D+/-



M/+



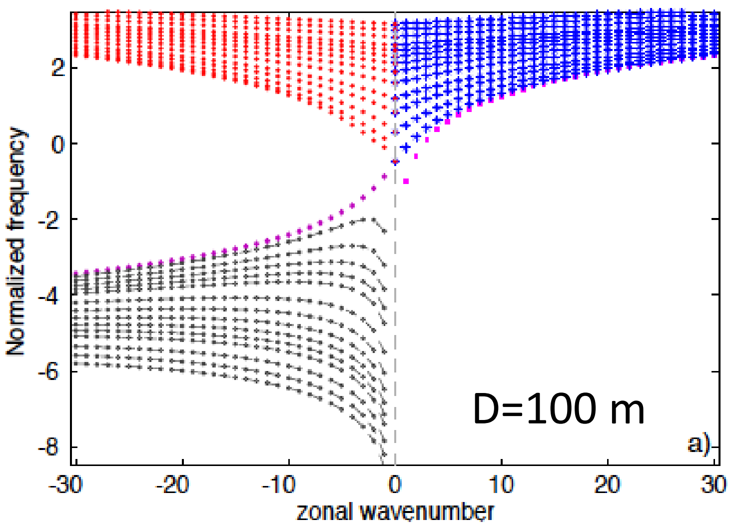
Total response

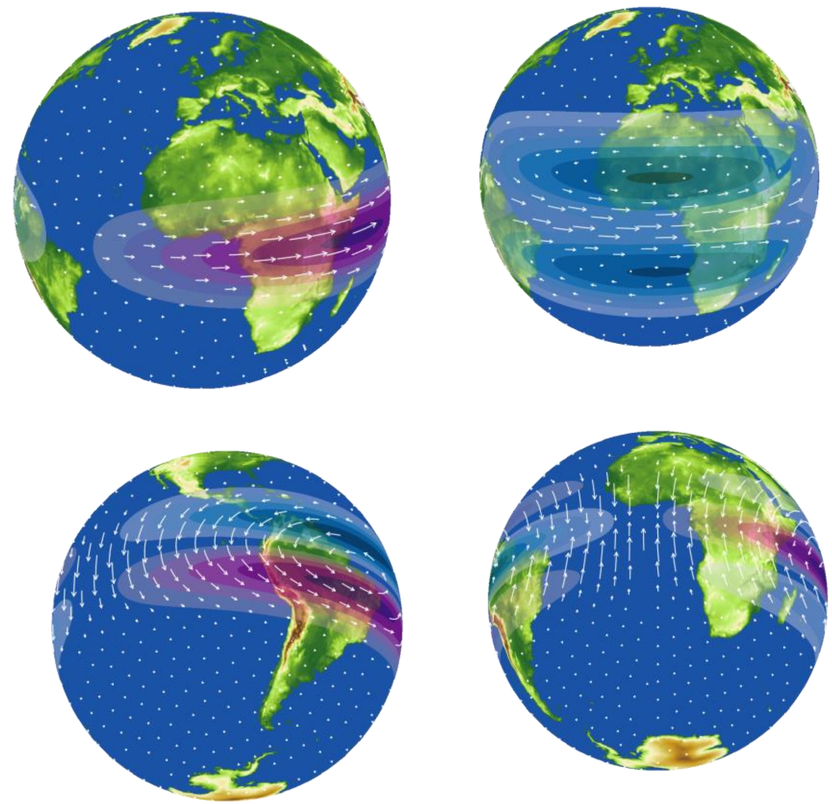
Kosovelj et al.,
J. Atmos. Sci., May 2019

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

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

J. Boyd

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

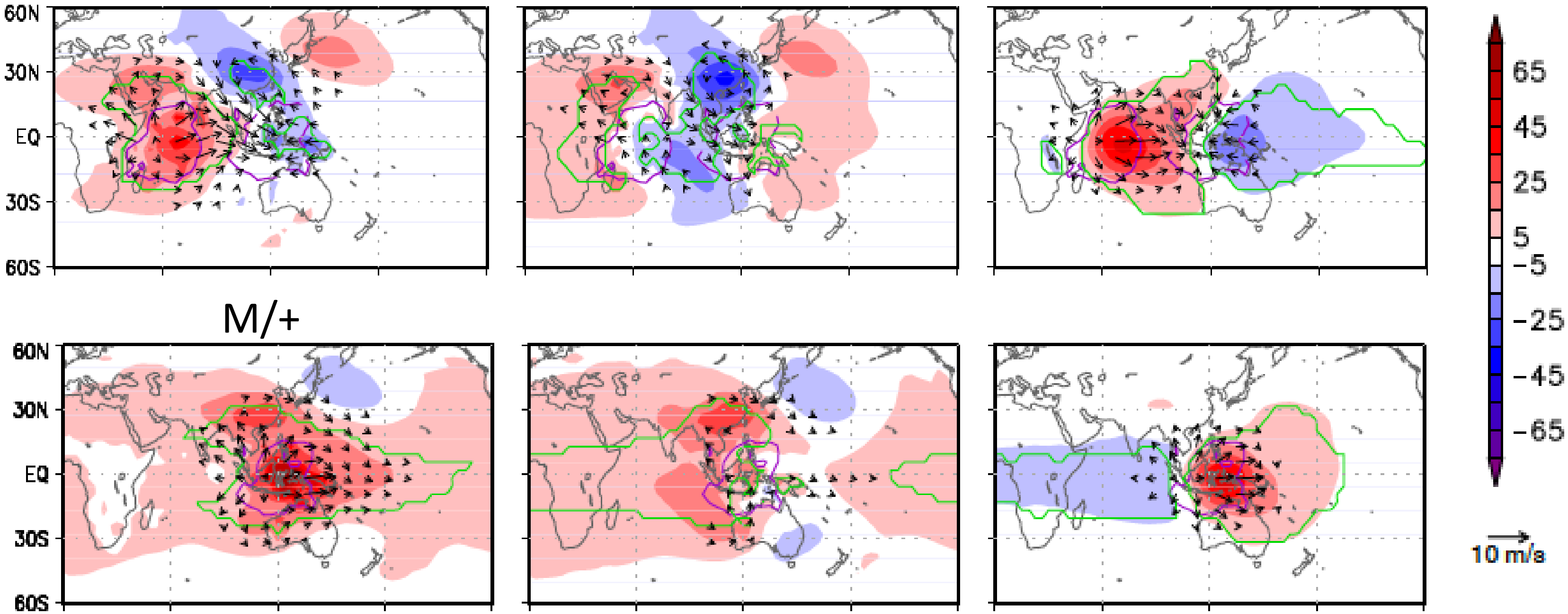
http://modes.fmf.uni-lj.si

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+/-



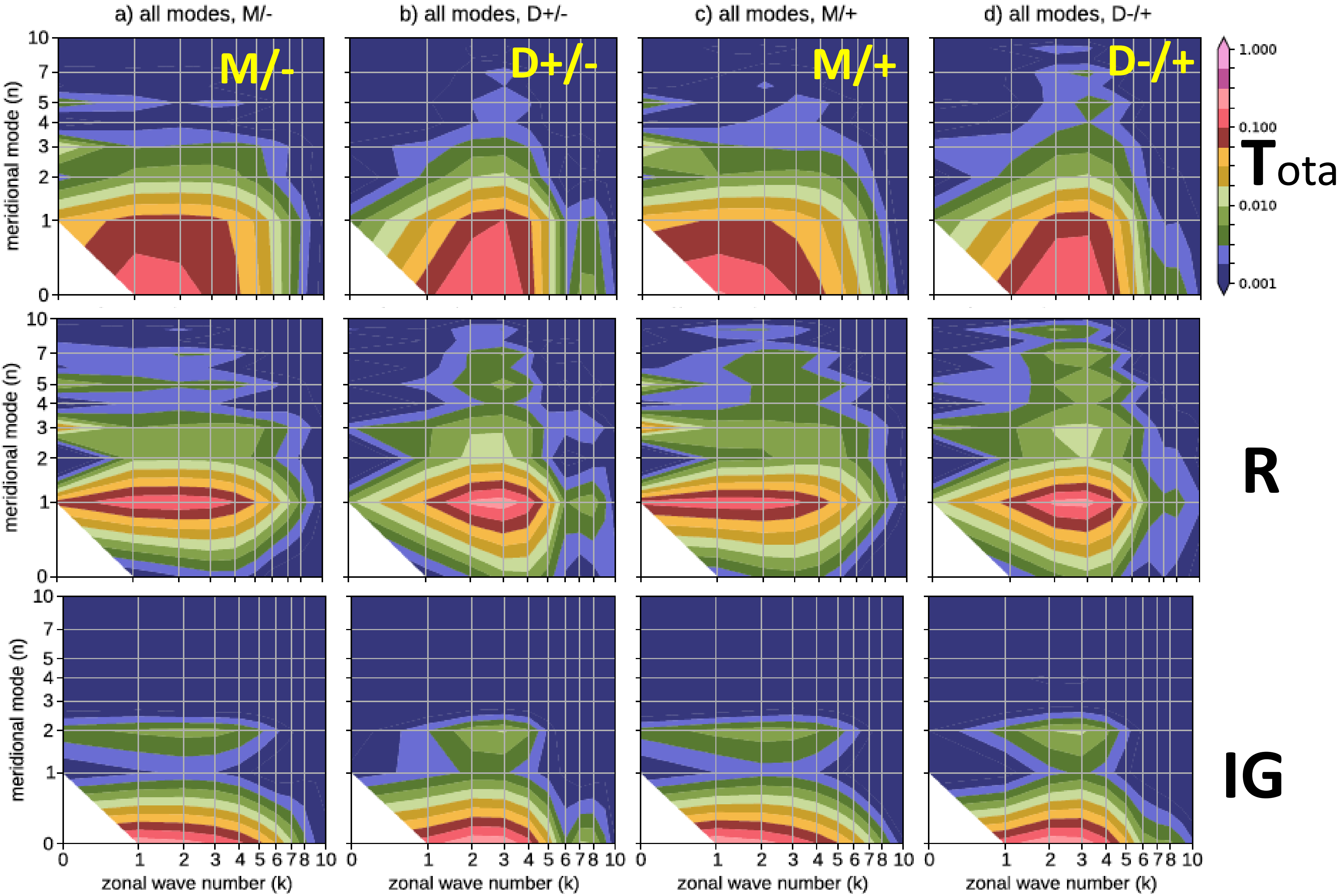
Total response

Balanced part (Rossby waves)

Unbalanced part (inertia-gravity waves)

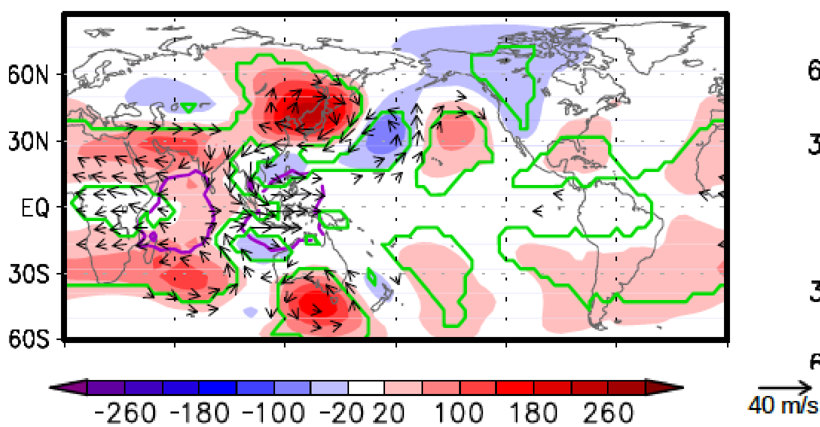
Kosovelj et al.,
J. Atmos. Sci., May 2019

Spectral distribution of the response: day 3

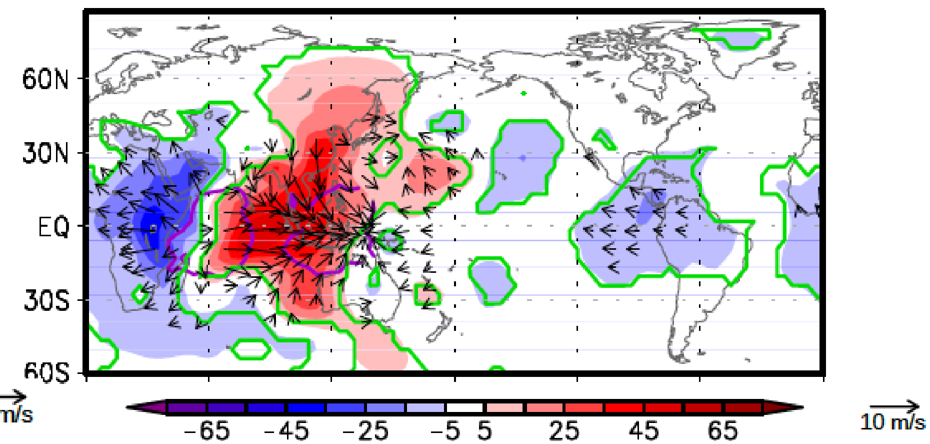


Response to tropical heating perturbations: day 14, 200 hPa, D+/-

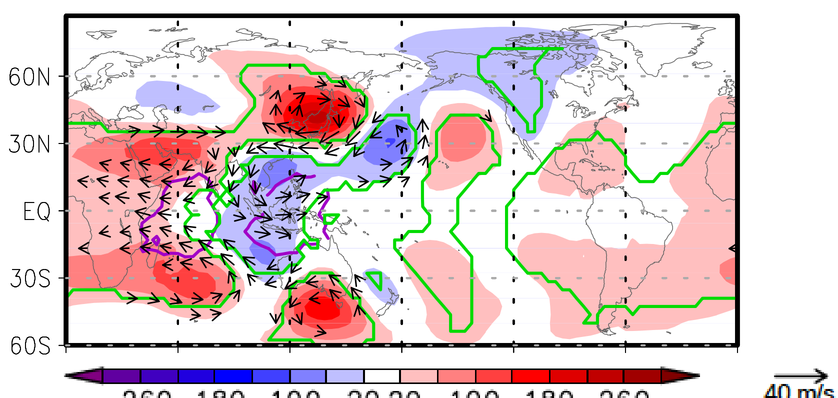
Total



IG modes

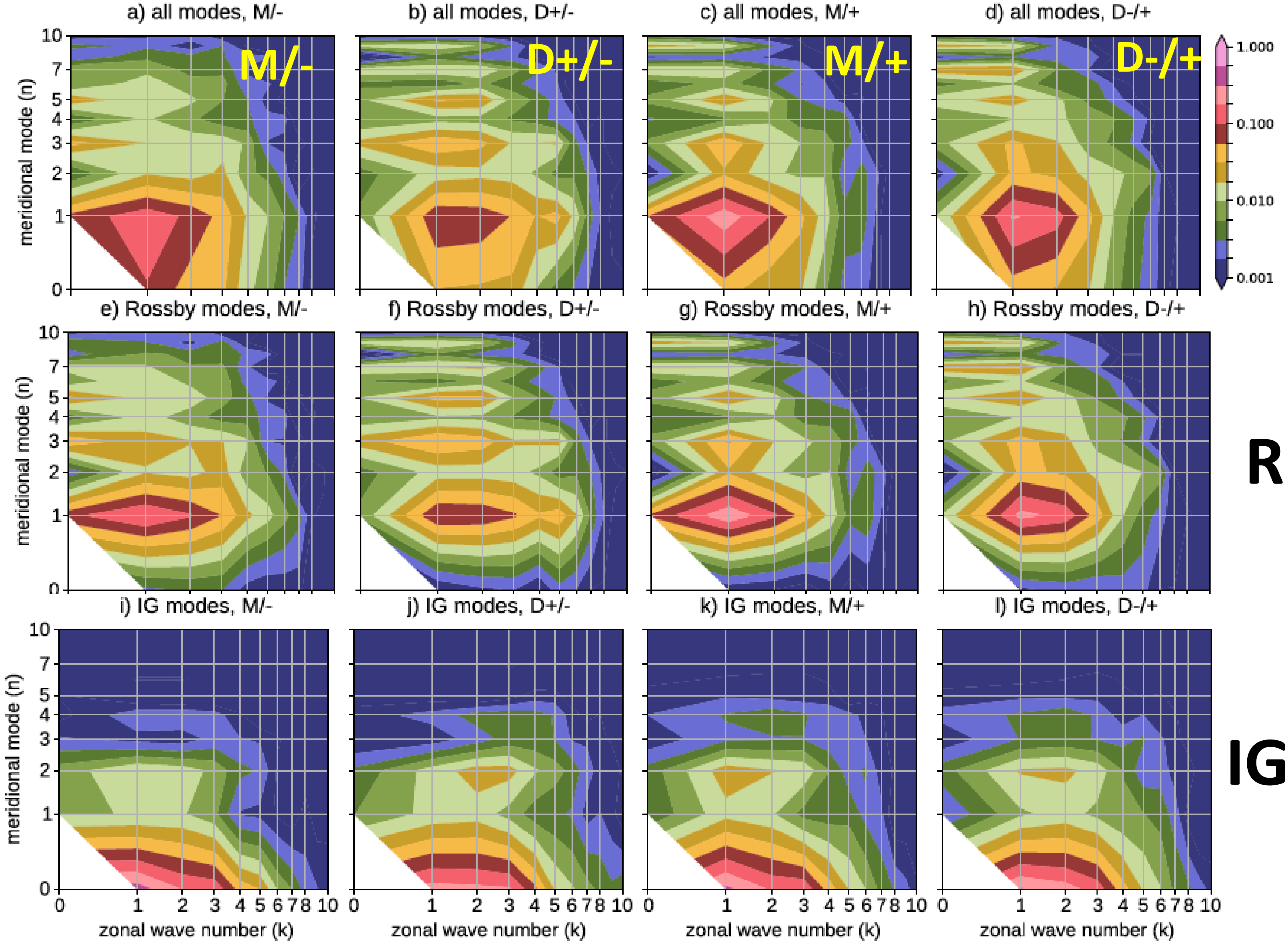


Rossby waves

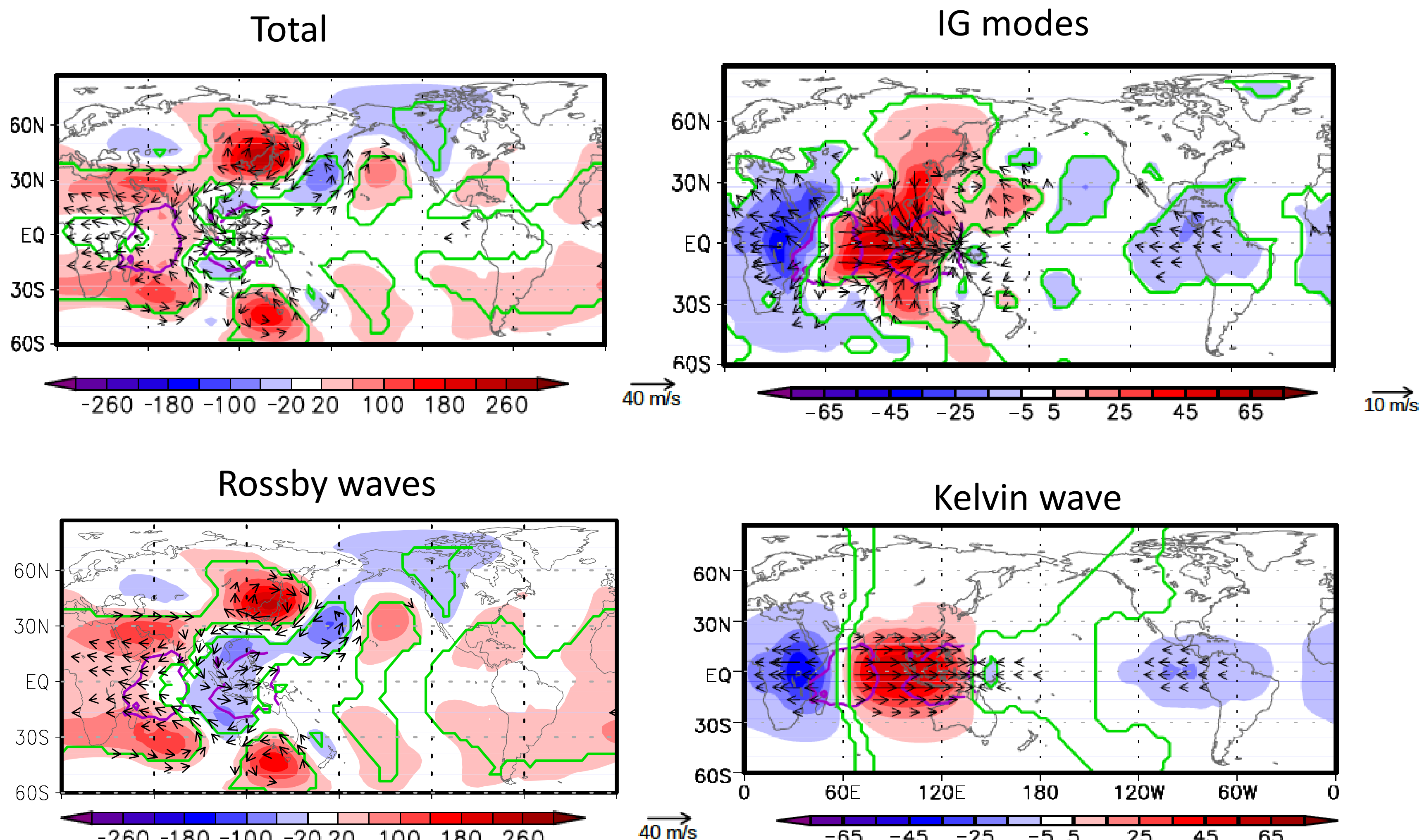


Kosovelj et al.,
J. Atmos. Sci., May 2019

Spectral distribution of the response: day 14

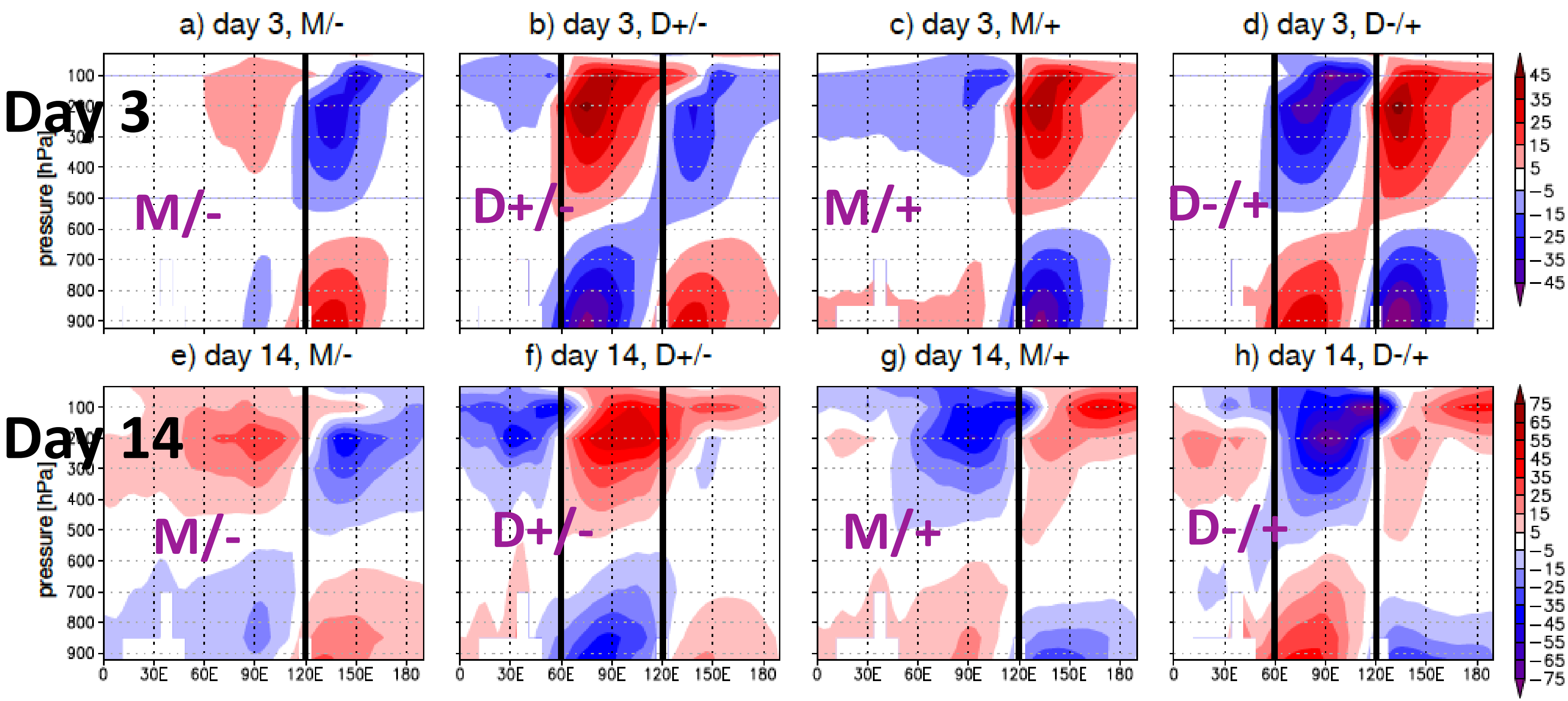


Response to tropical heating perturbations: day 14, 200 hPa, D+/-



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

Scale properties of the response to tropical heating anomalies: summary

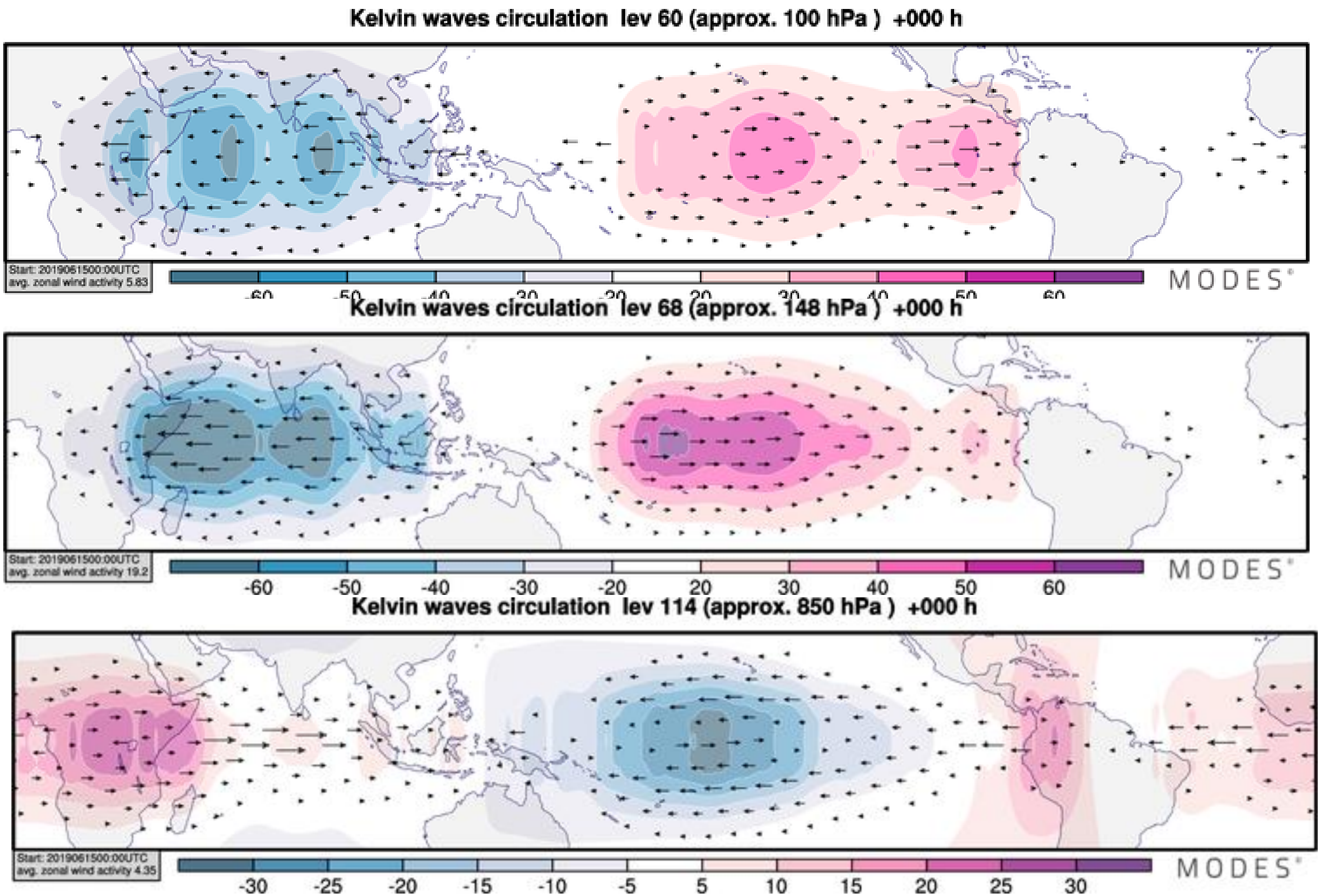
The overall response to perturbations including feedbacks from diabatic moist processes supports previous results from linear, dry models. Perturbations mimicking phase 6 of MJO have a statistically significant impact over Europe in medium range.

In short range, max response is in the zonal wavenumber k=2-3 for dipole and in k=1 for monopole heating. In medium range, response to all perturbations maximizes at k=1, but it is stronger for dipole => Accuracy of diabatic heating initialization affects the forecast quality on different scales in different MJO phases.

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

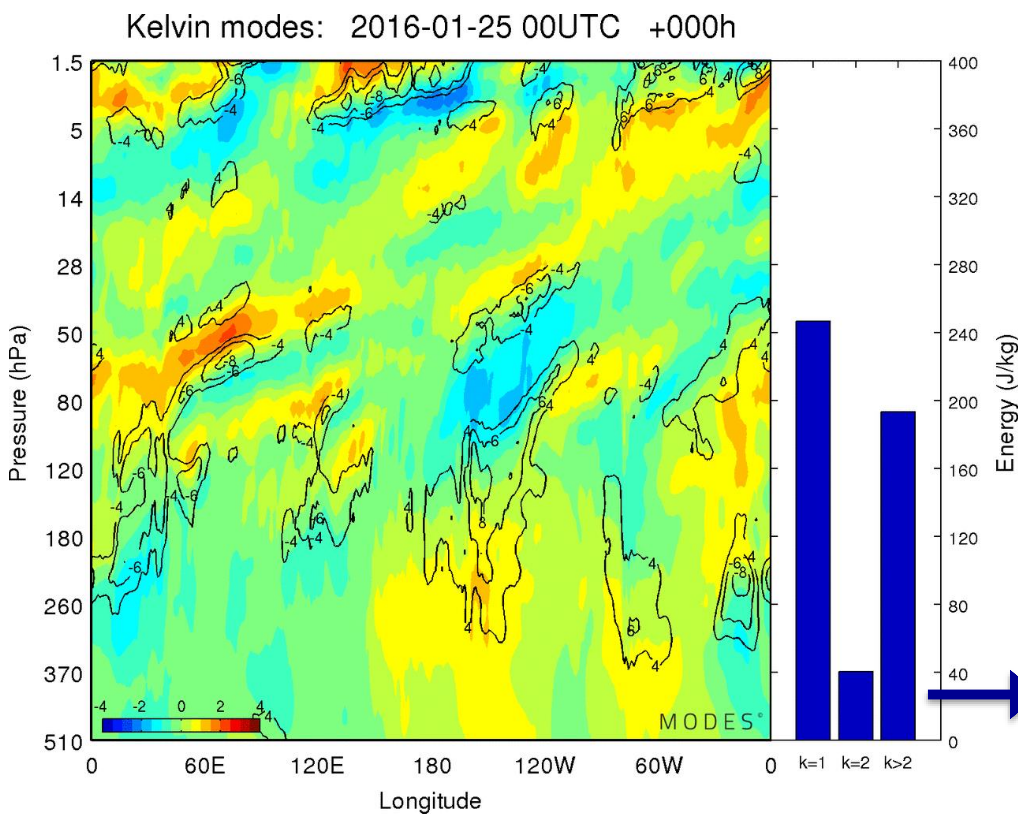
Kosovelj et al.,
J. Atmos. Sci., May 2019

Kelvin wave of the day



Nearly real Kelvin waves in the ECMWF 10-day forecast: *http://modes.fmf.uni-lj.si*

Vertically-propagating Kelvin waves



Kelvin waves

10-day ECMWF forecast

Active MJO

Colors: zonal wind
Isolines: Temperature

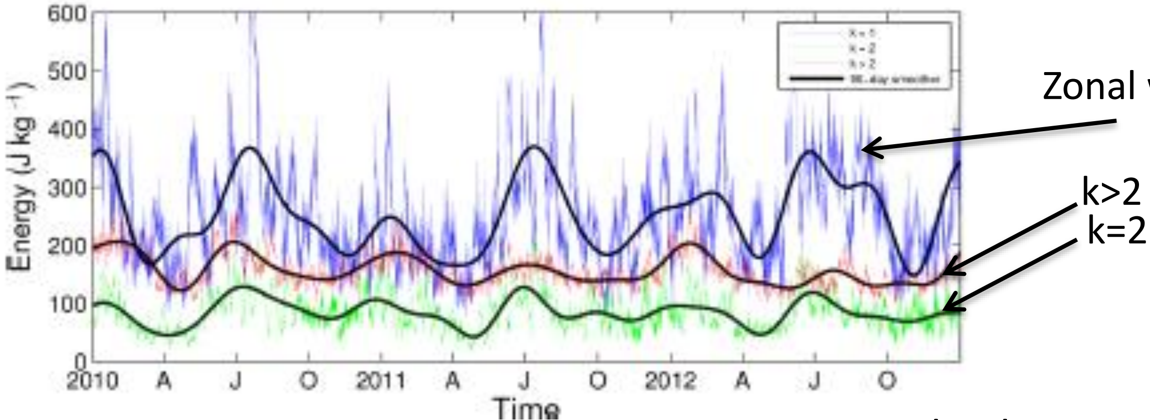
Energy in k=1,2,3

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

Equatorial wave analysis in ECMWF forecasts: *http://modes.fmf.uni-lj.si*

Multi-scale variability of Kelvin waves

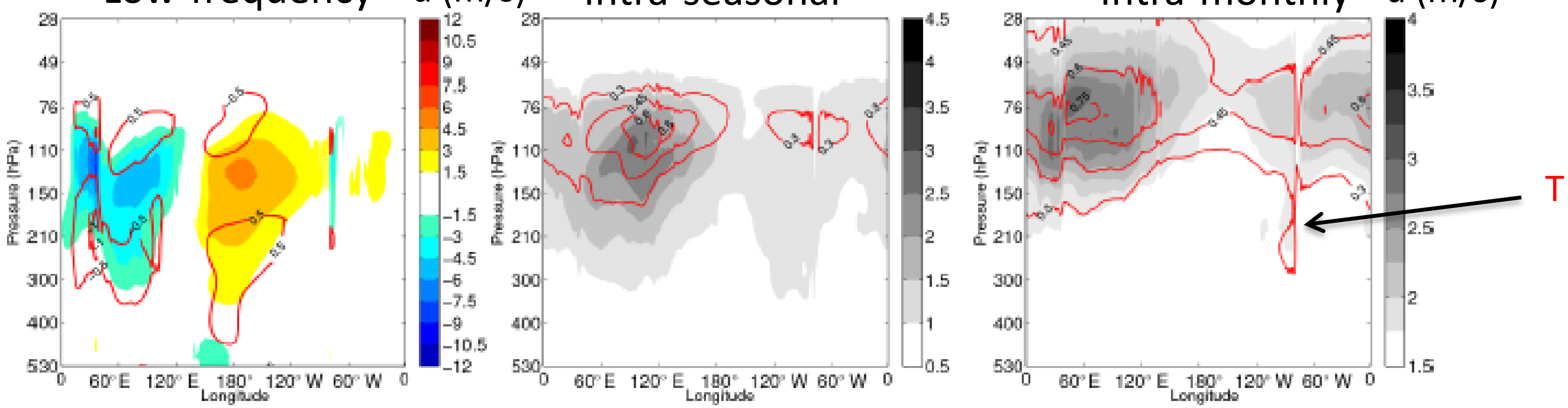
L91 6-hourly analyses



black lines: 90-day low-pass filter

Absolute amplitude

Low-frequency u (m/s) Intra-seasonal Intra-monthly u (m/s)



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

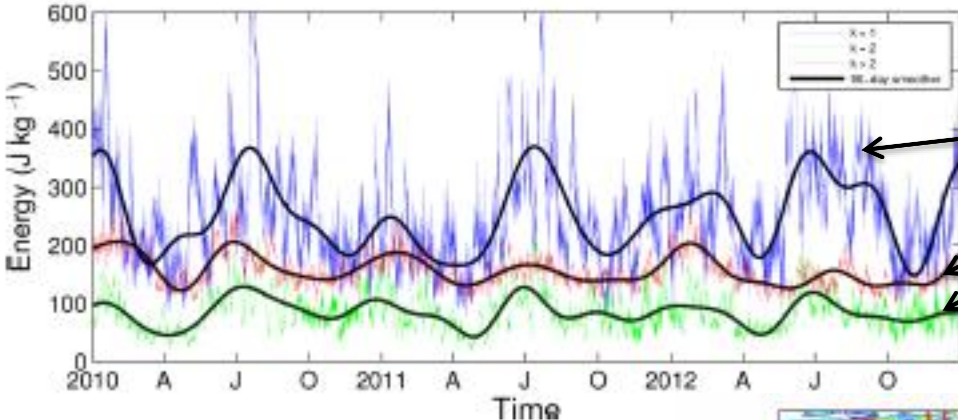
Strongest in DJF
Eastward tilt with height

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



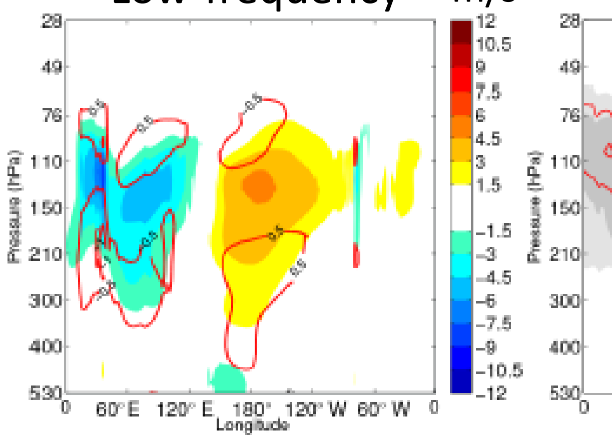
Zonal wavenumber k=1

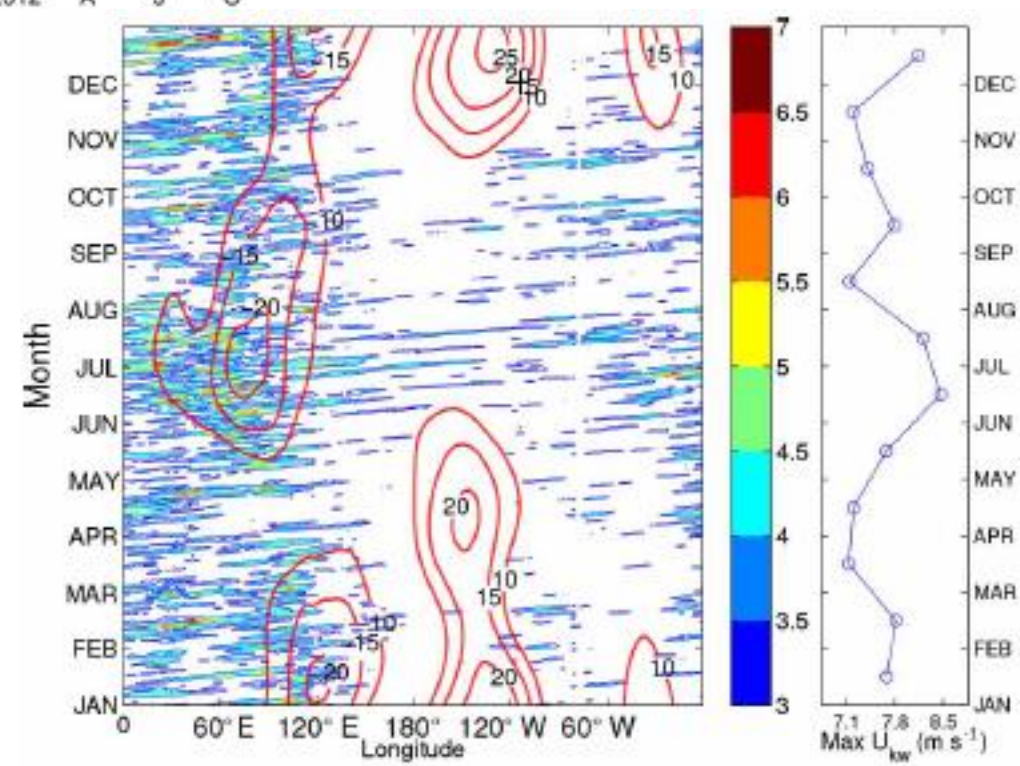
k>2

k=2

KW zonal wind
at ~110 hPa

Low-frequency m/s A

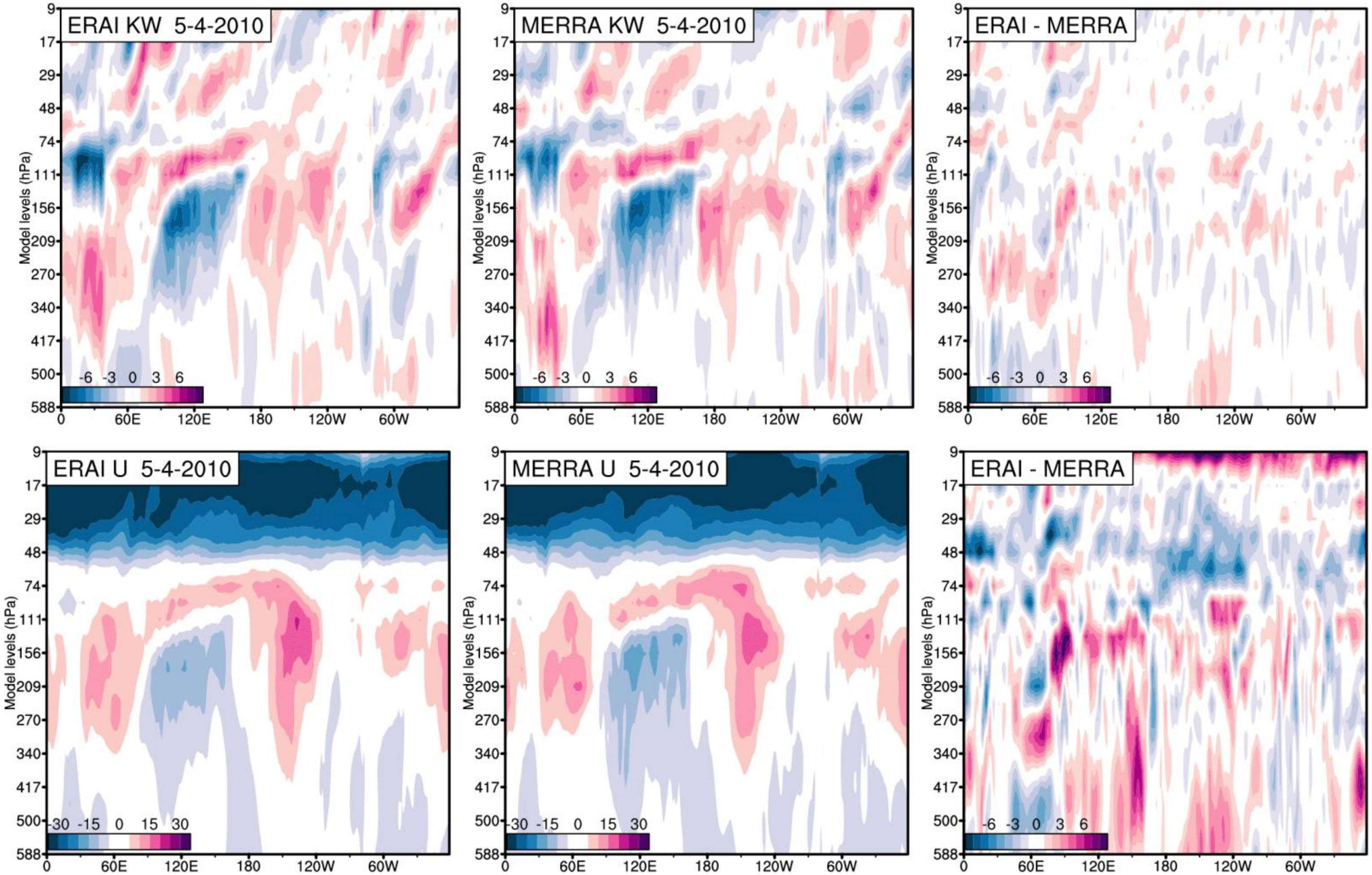




Quadrupole T structure
k=1 structure, Gill-type
20° W of clim. winds

St
Ea

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



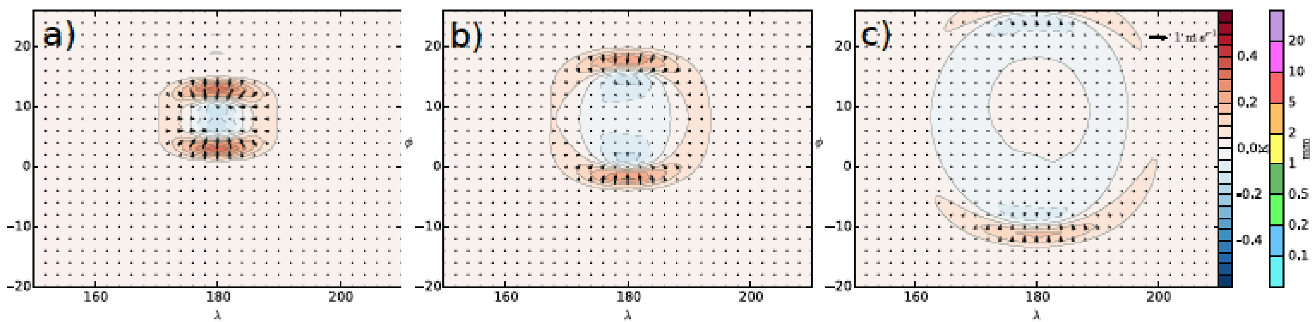
MODES decomposition: *http://modes.fmf.uni-lj.si*

Interaction of moist processes and dynamics in the tropics

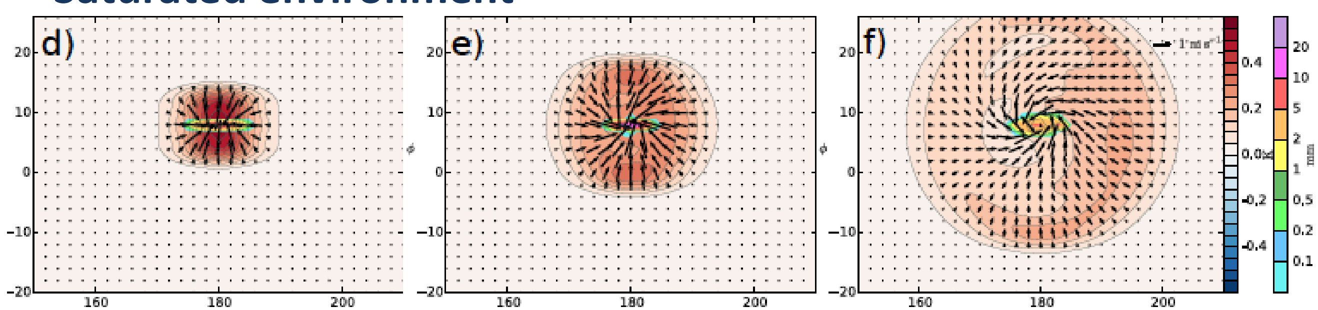
MADDAM: Moist Atmosphere Dynamics Data Assimilation Model

Adjustment to +1 Kelvin temperature perturbation in mid-troposphere over ITCZ

Unsaturated environment

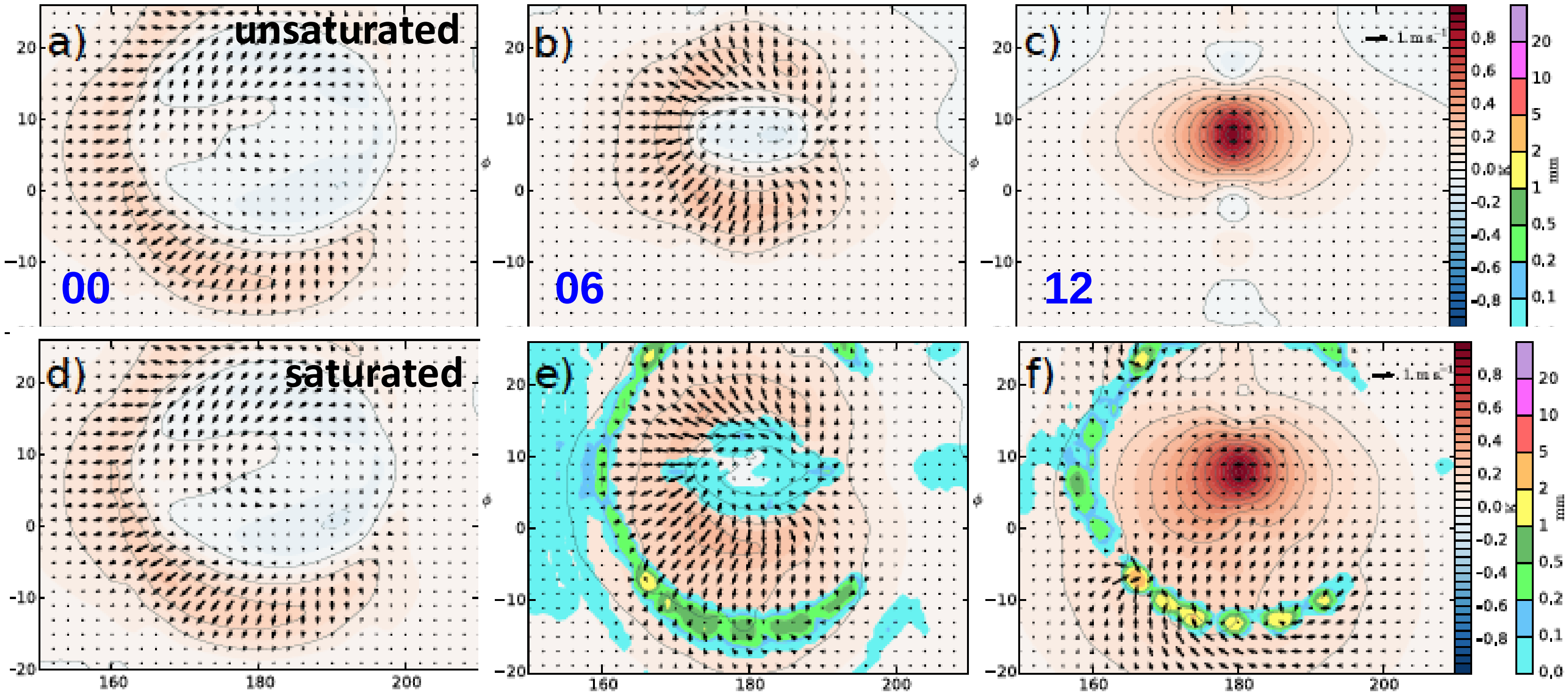


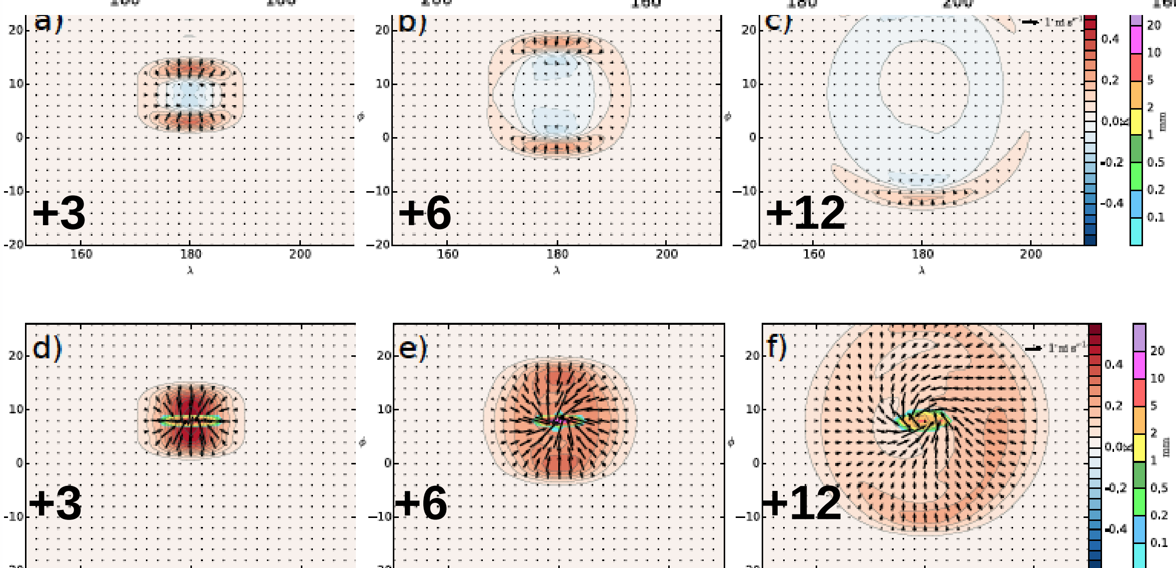
Saturated environment



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

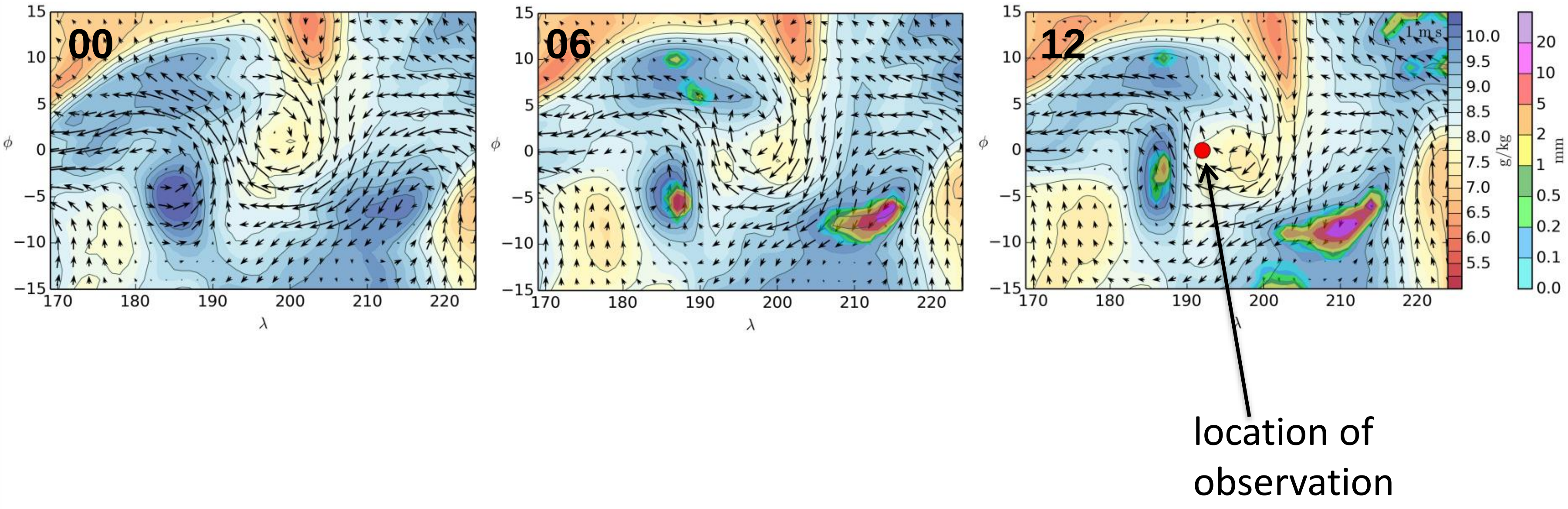
IGW propagates outward backward in time, in AD and inward in TL model

Zaplotnik et al., 2018, QJRMS

Interaction of moist processes and dynamics in 4D-Var in the tropics

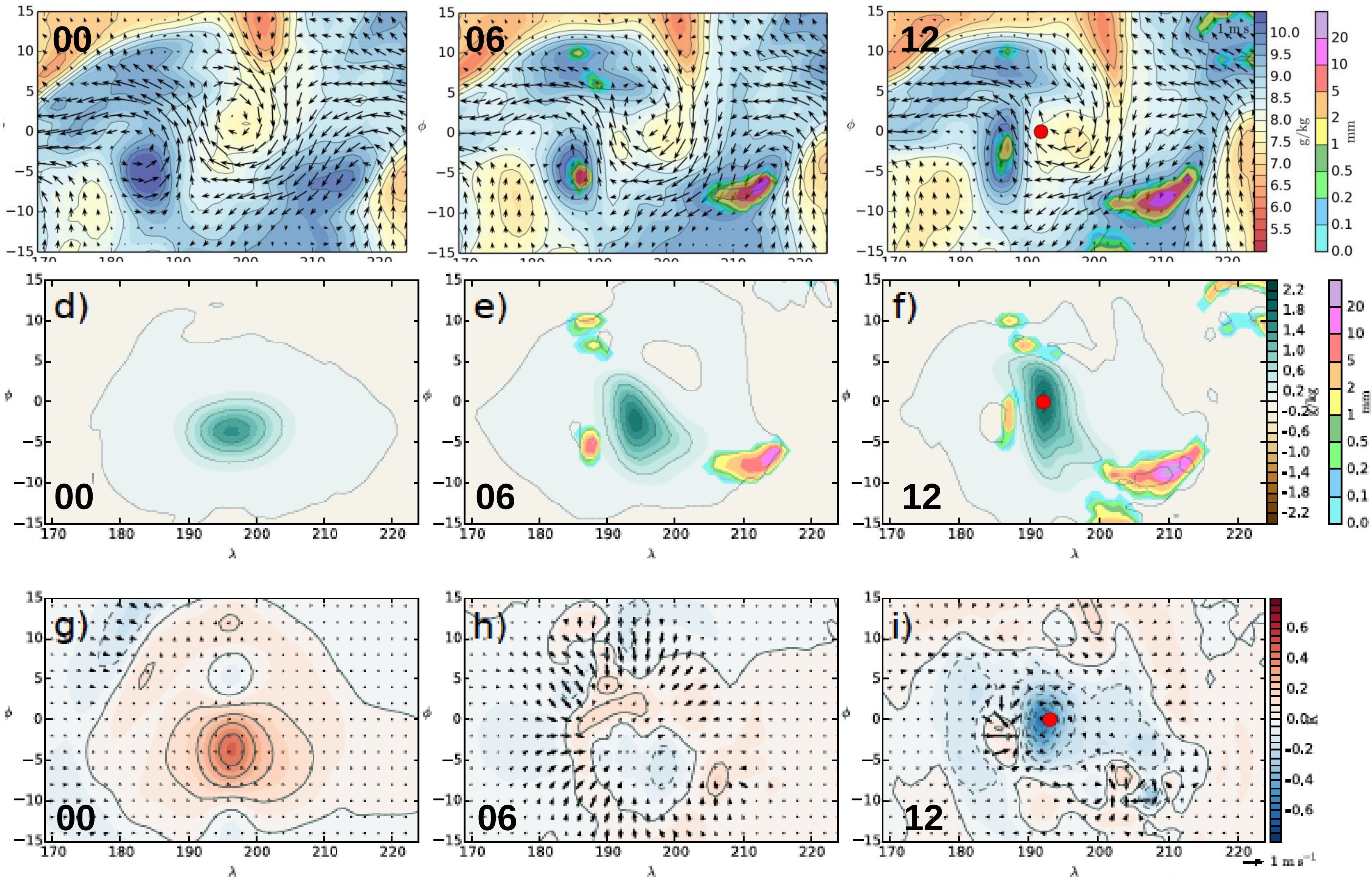
A single moisture observation in MADDAM 12-hour window 4D-Var

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

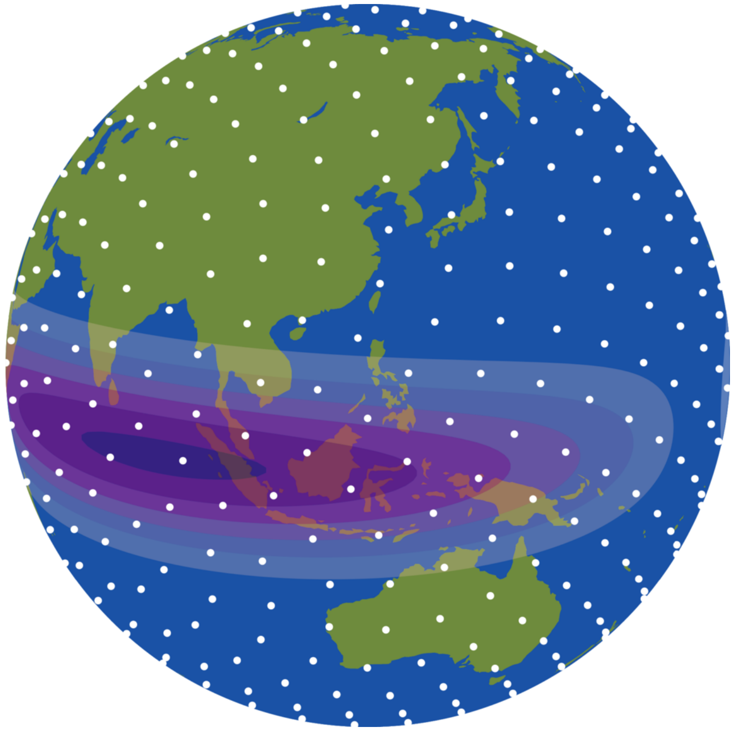
Impact of a single moisture observations in 12-h 4D-Var



Zaplotnik et al., 2018, QJRMS

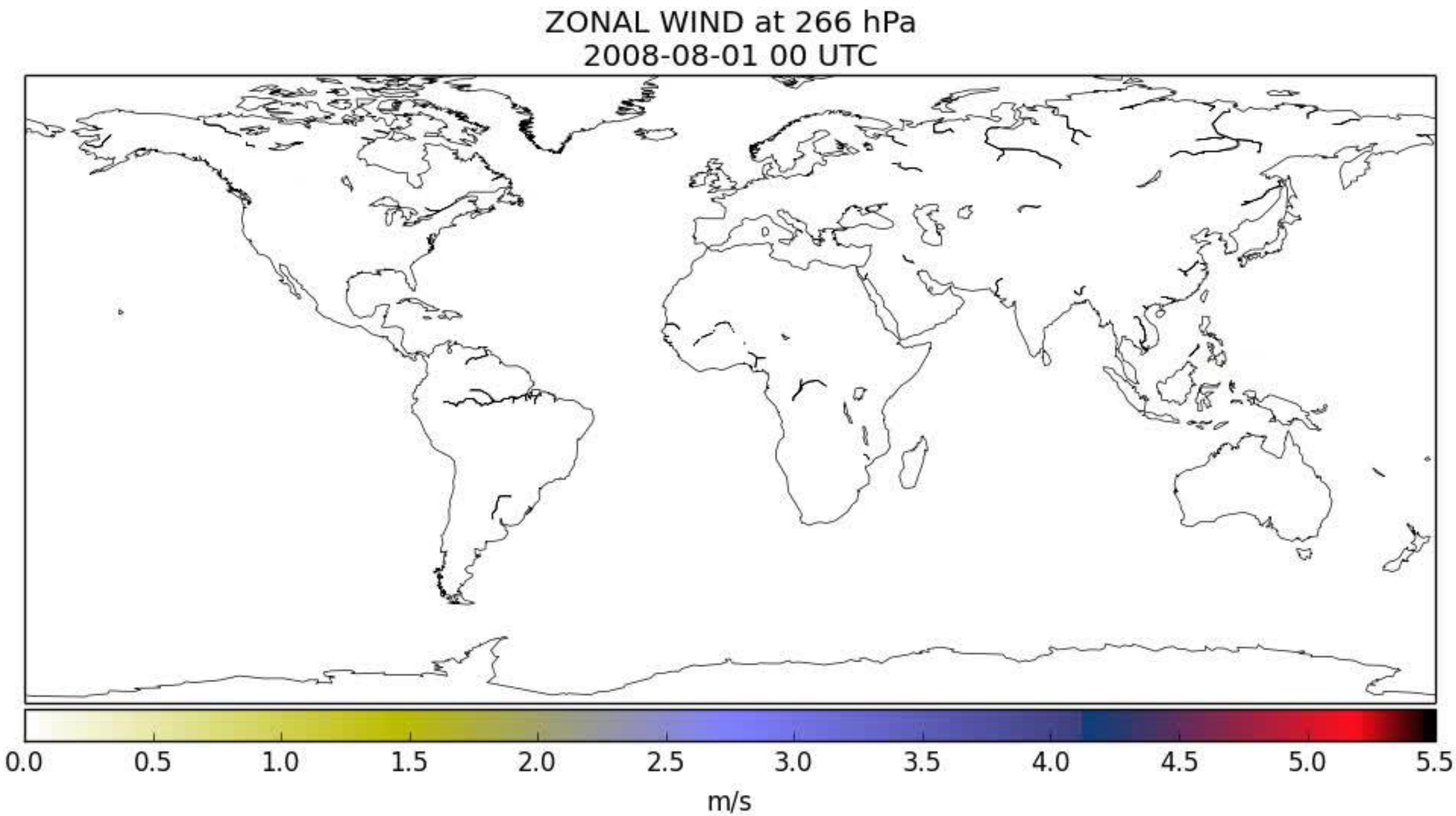
Towards understanding analysis uncertainties

- 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

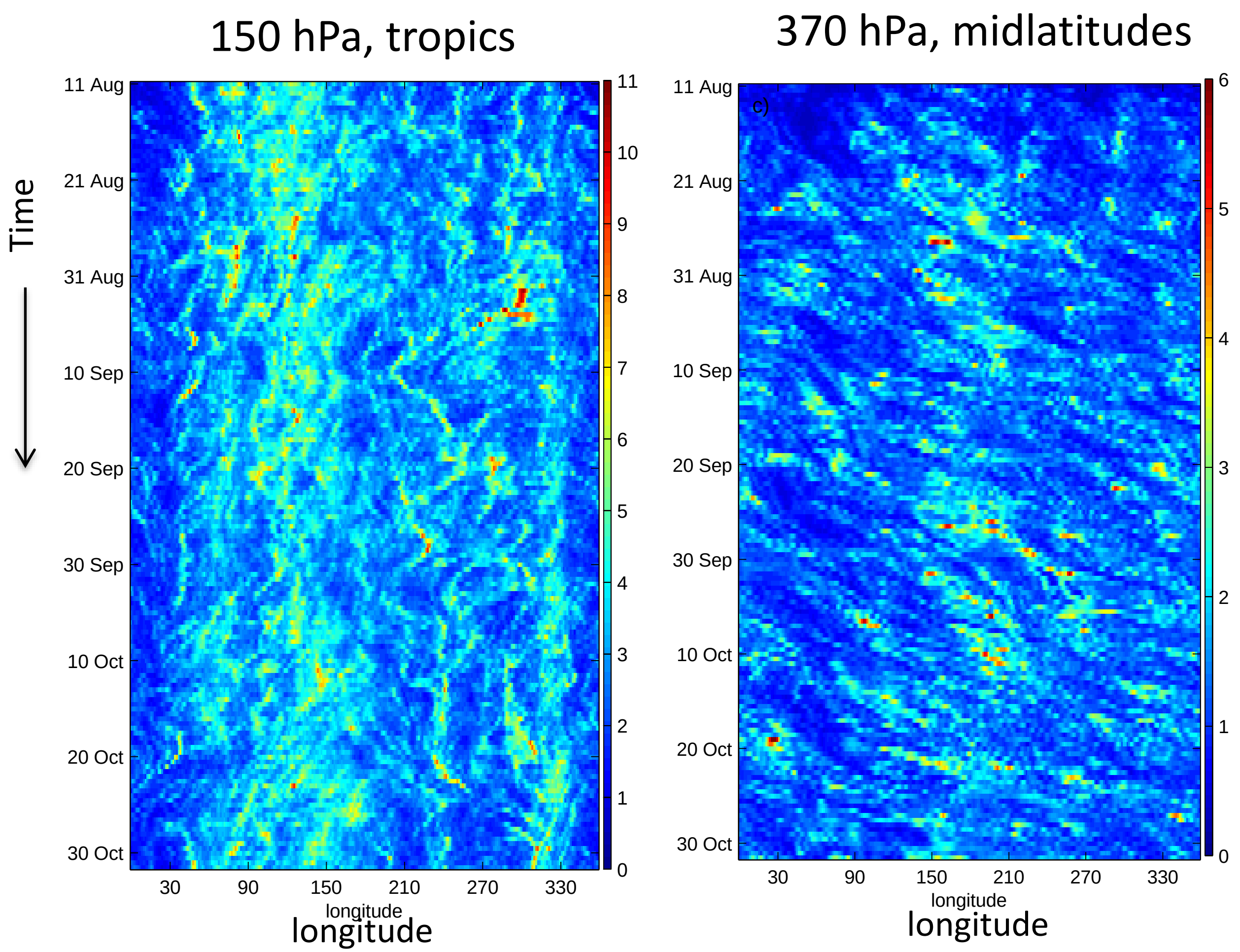


Žagar et al., MWR, 2016

Analysis uncertainties (every 12 hr)



Flow dependency of short-term forecast uncertainties

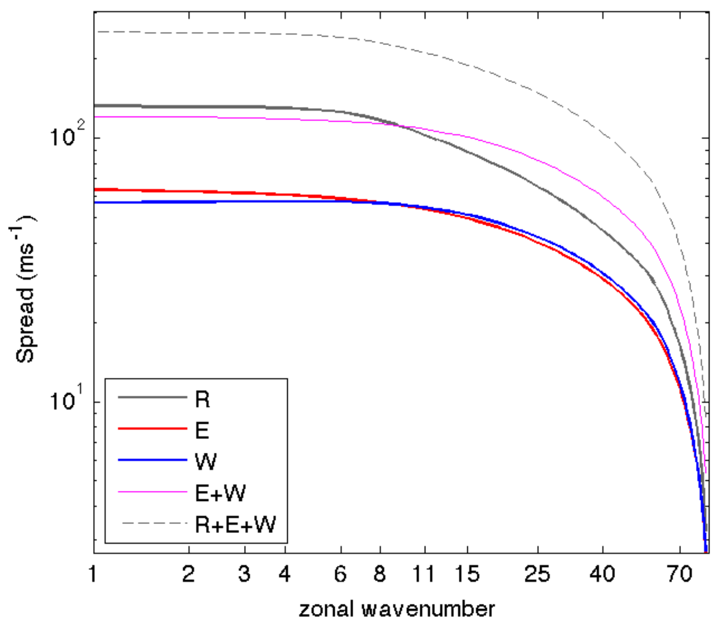


- Ensemble spread in +12-hr fc zonal wind (m/s) along the latitude circle
- 3-month long experiment with a perfect model
- 12-hour EnKF data assimilation

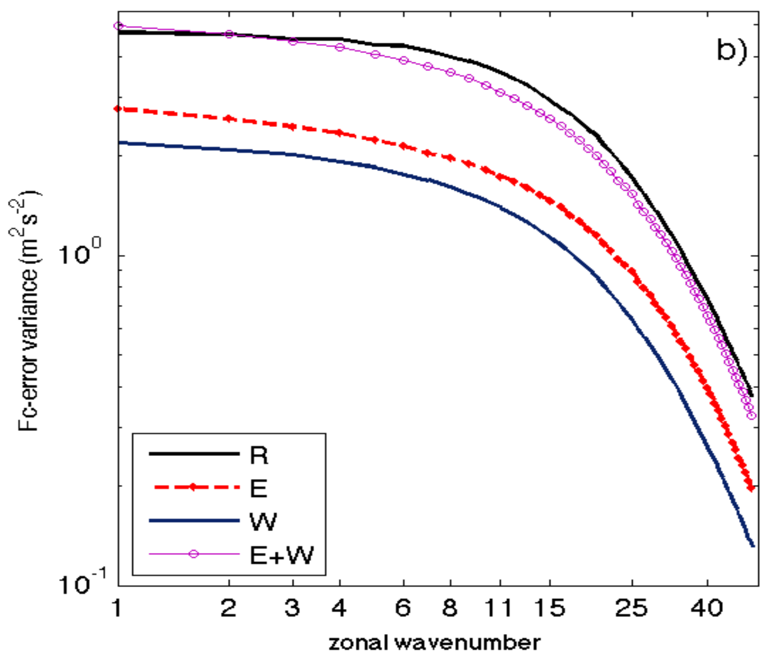
Žagar et al., MWR, 2016

Short-range global forecast uncertainties: 1D spectra

Perfect model experiment



ECMWF EDA

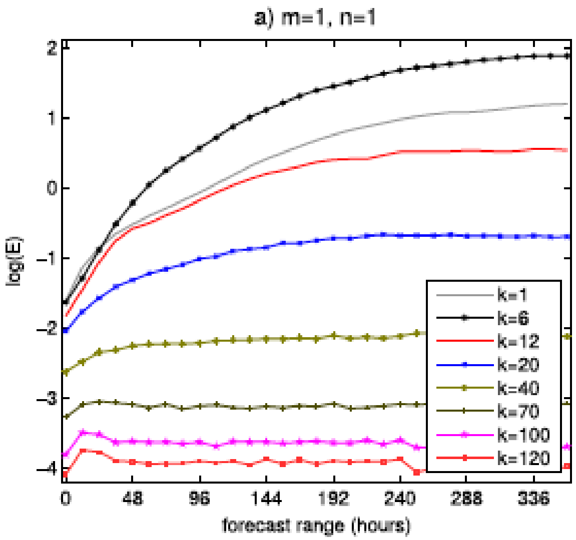


Large-scale uncertainties in the state of the art DA system are not only due to the model error. Data assimilation is not efficient in reducing the tropical large scale spread not even in the perfect model framework (with low-resolution observing network)

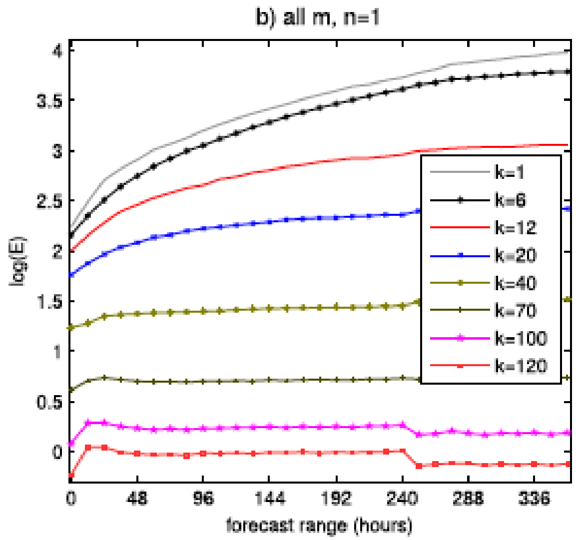
Žagar et al., 2013 QJRMS; 2016, MWR

Different time scales of the error growth

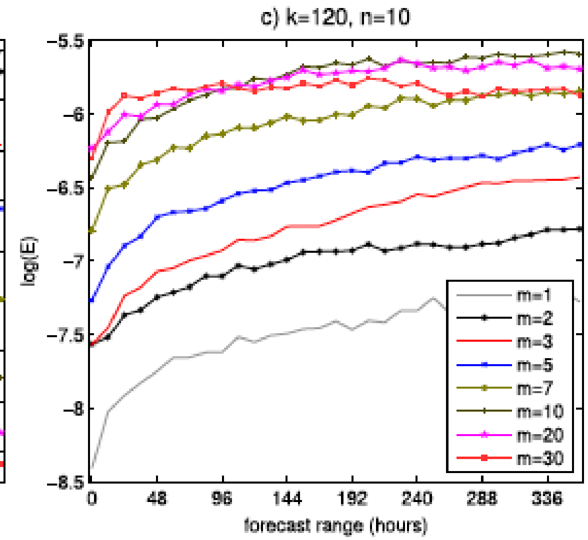
- a rapid growth and an apparent saturation of of errors in smaller spatial scales early in the forecast range
- a slowly evolving component of error throughout the forecast range
- uniformly distributed large-scale errors across the spectrum



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



Growth in different waves in barotropic mode, integrated meridionally

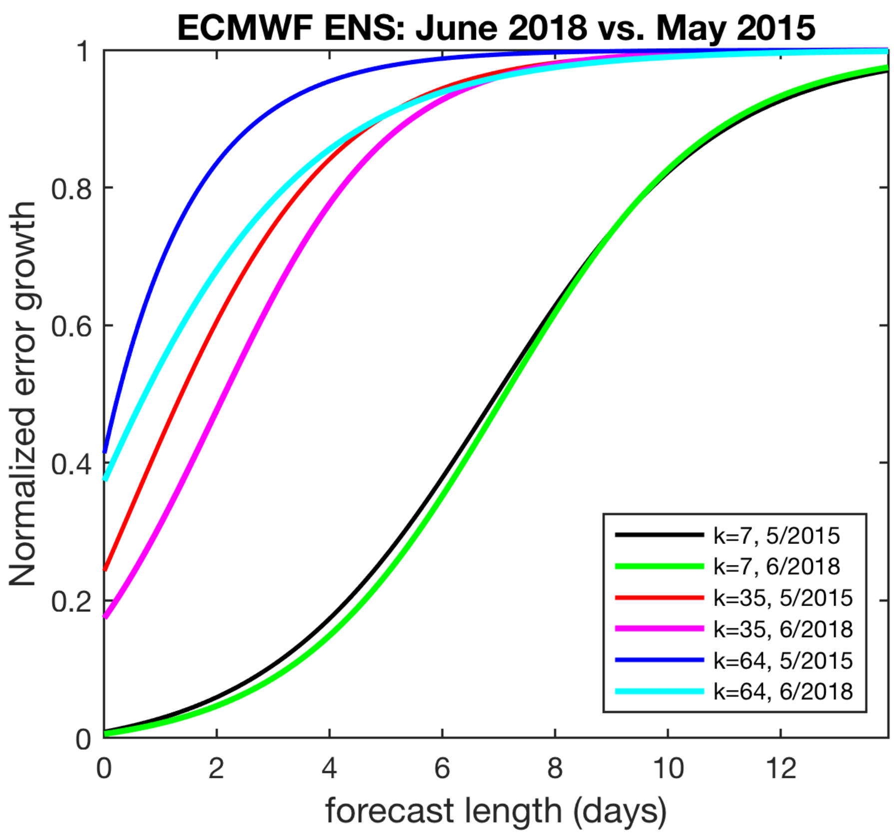


Growth at small scales in midlatitudes for different vertical depths

Žagar, Tellus A, 2017

Possible implications for global predictability

Recent improvements in predictability



Fitting method of Žagar et al., 2017, Tellus

Error variances normalized by Emax

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

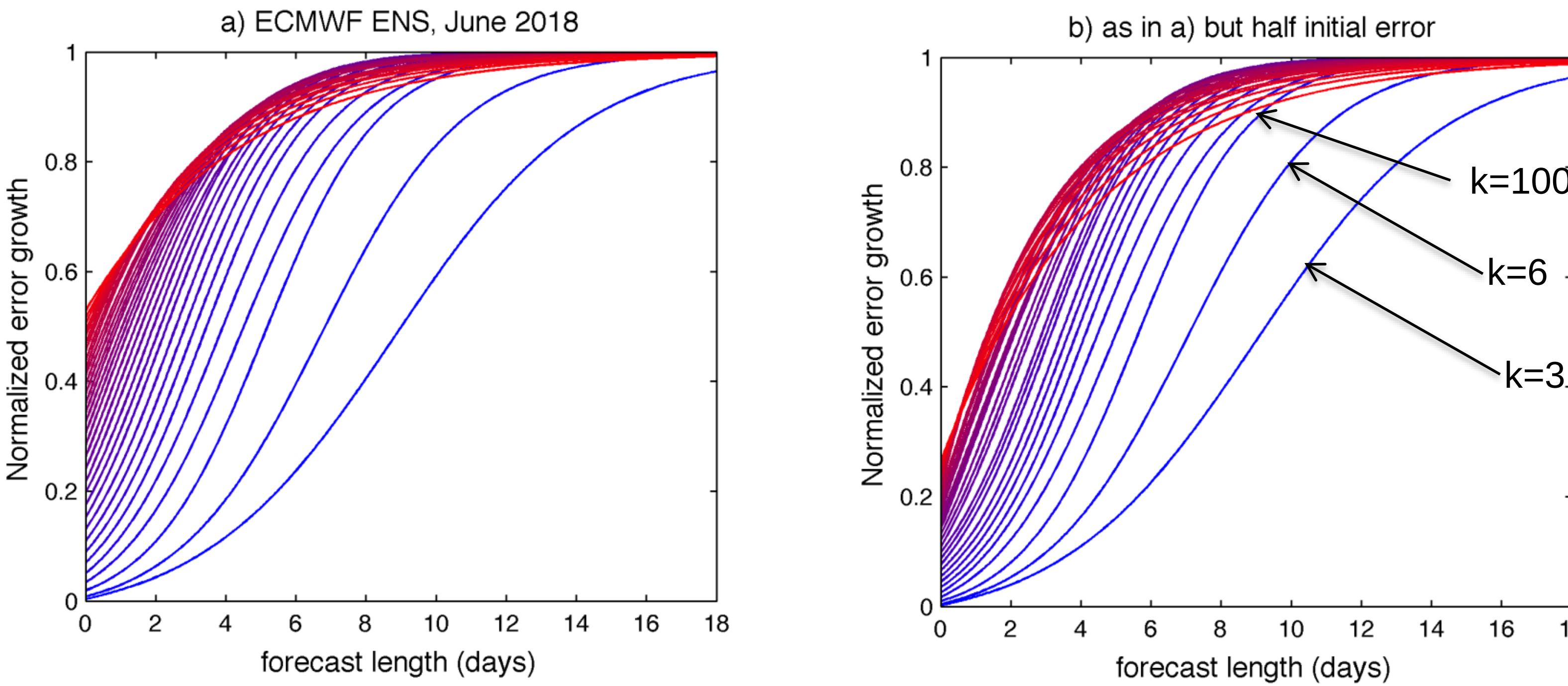
k=35, 2015, 2018
60% predictability limit reached at 2.6 and 3.3 days

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

Žagar and Szunyogh, submitted

On the global predictability limits

same data (June 2018 ENS), but 50% smaller initial condition 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

Žagar and Szunyogh, submitted

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 data assimilation and prediction

Data assimilation:

Largest analysis uncertainties and largest growth of forecast uncertainties during the first day are currently in the tropics. The analysis uncertainties are flow dependent and on average largest on the largest scales.

Predictability:

Implications for midlatitude day-to-day weather predictability are associated with the downscale propagation of large-scale initial condition error and the propagation of tropical initial uncertainties to the extratropics

Contact: nedjeljka.zagar@uni-hamburg.de