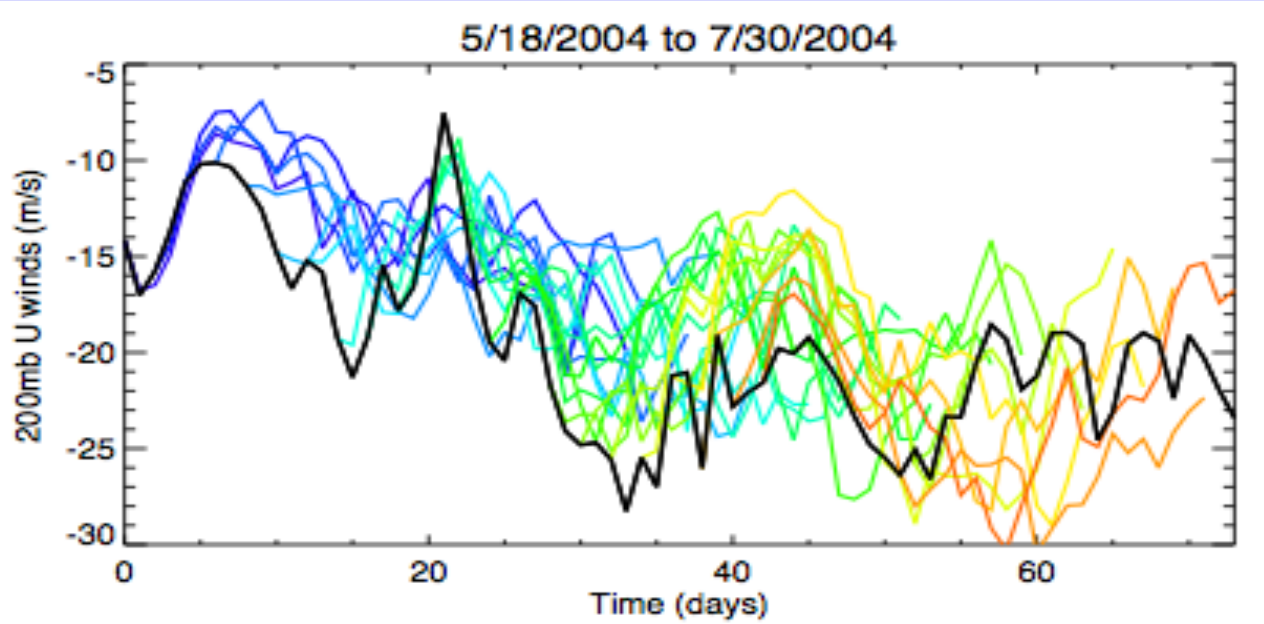
Predictability of Intraseasonal Variability



Serial forecasts of ISO

Peter J. Webster & Hye-mi Kim

School of Earth & Atmospheric Sciences

Georgia Institute of Technology

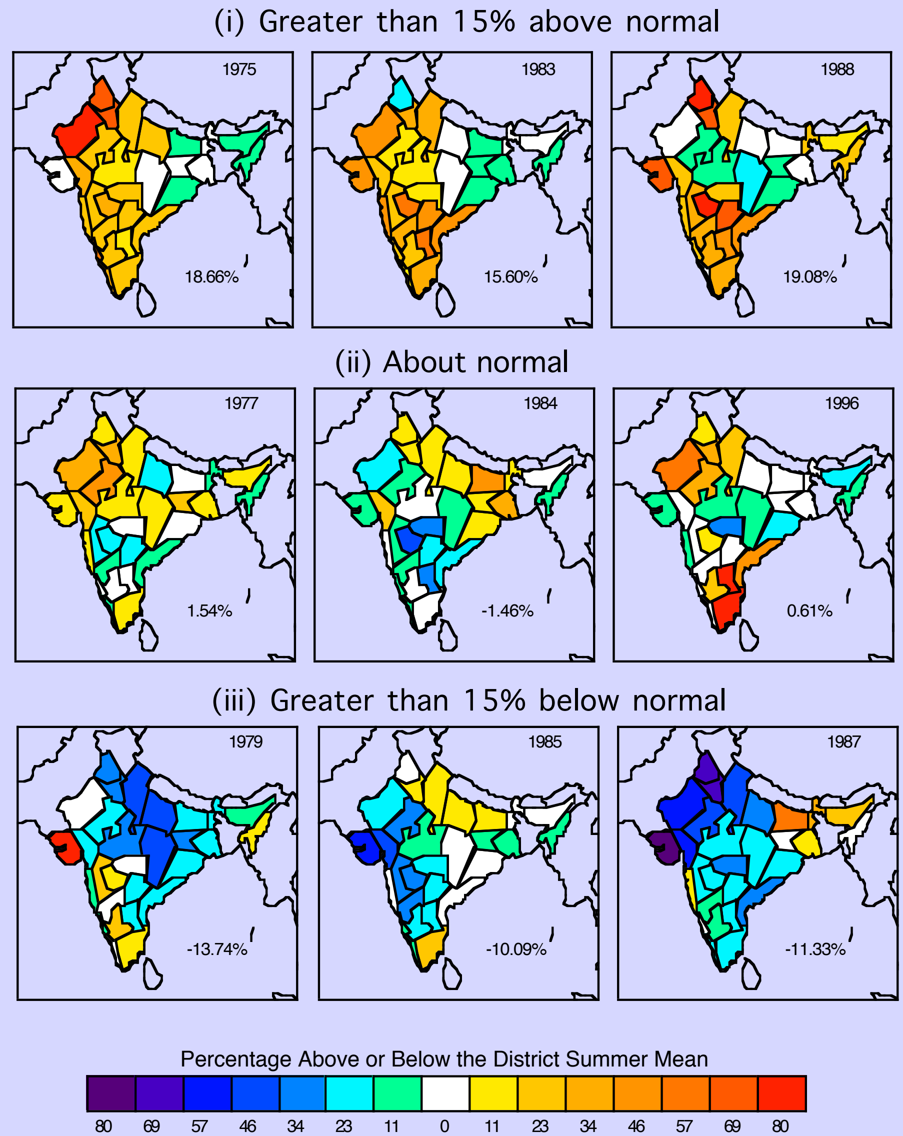
Discussion points:

- Coupled nature of ISO in IO region: Role of ISO in heat balance of the IO region
- Empirical prediction: a clue to the extend=t of predictability
- Numerical prediction: interesting but …….
- Serial integration: Determination of error growth
- "Tricks", "cheats" or creative methods of error reduction

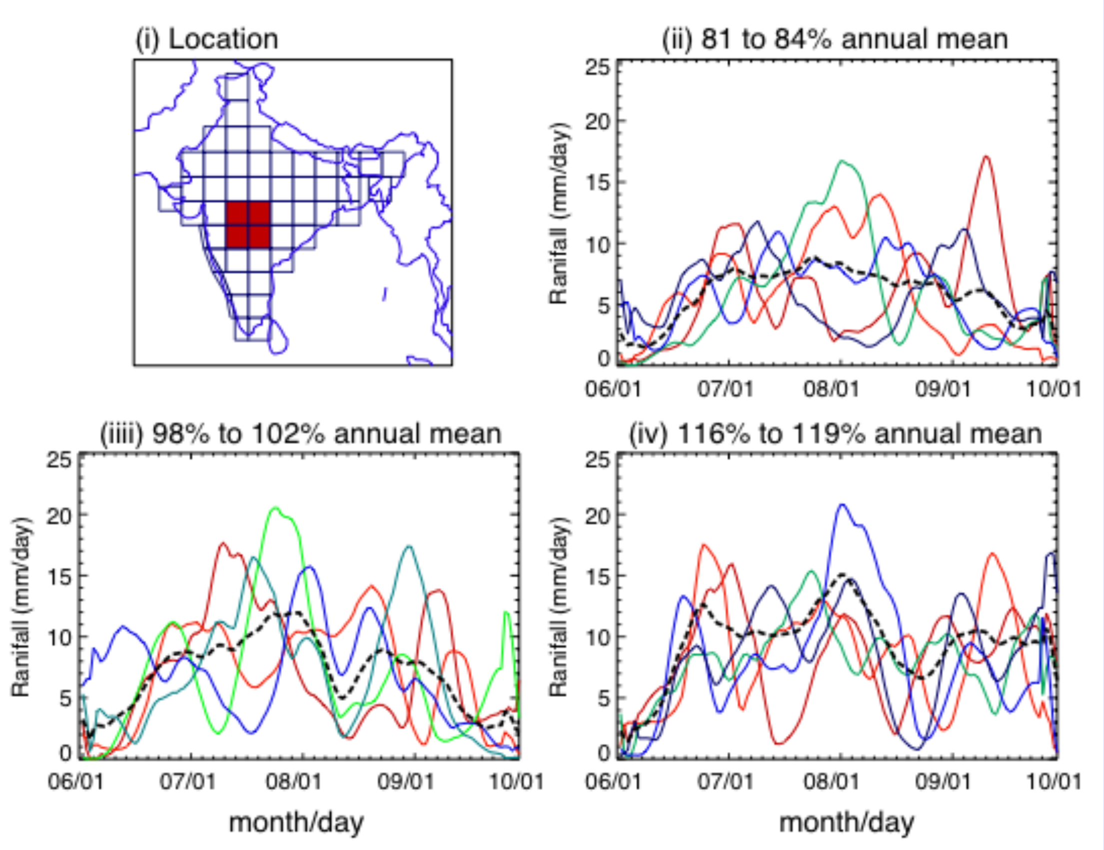
Depends on motivation and is a test of your purity or pragmatism!

Seasonal forecasts (not an Alchemist's stone)

- For the last 100 years, emphasis has been on the forecasting of monsoon interannual variability of the Indian monsoon
- How useful are such forecasts?
  - SD +/- 10%
  - Mean AIRI not related to regional rainfall except in extremes
  - Not useful for consumer even if perfect!

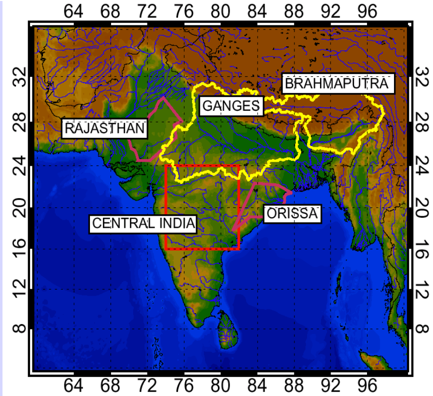


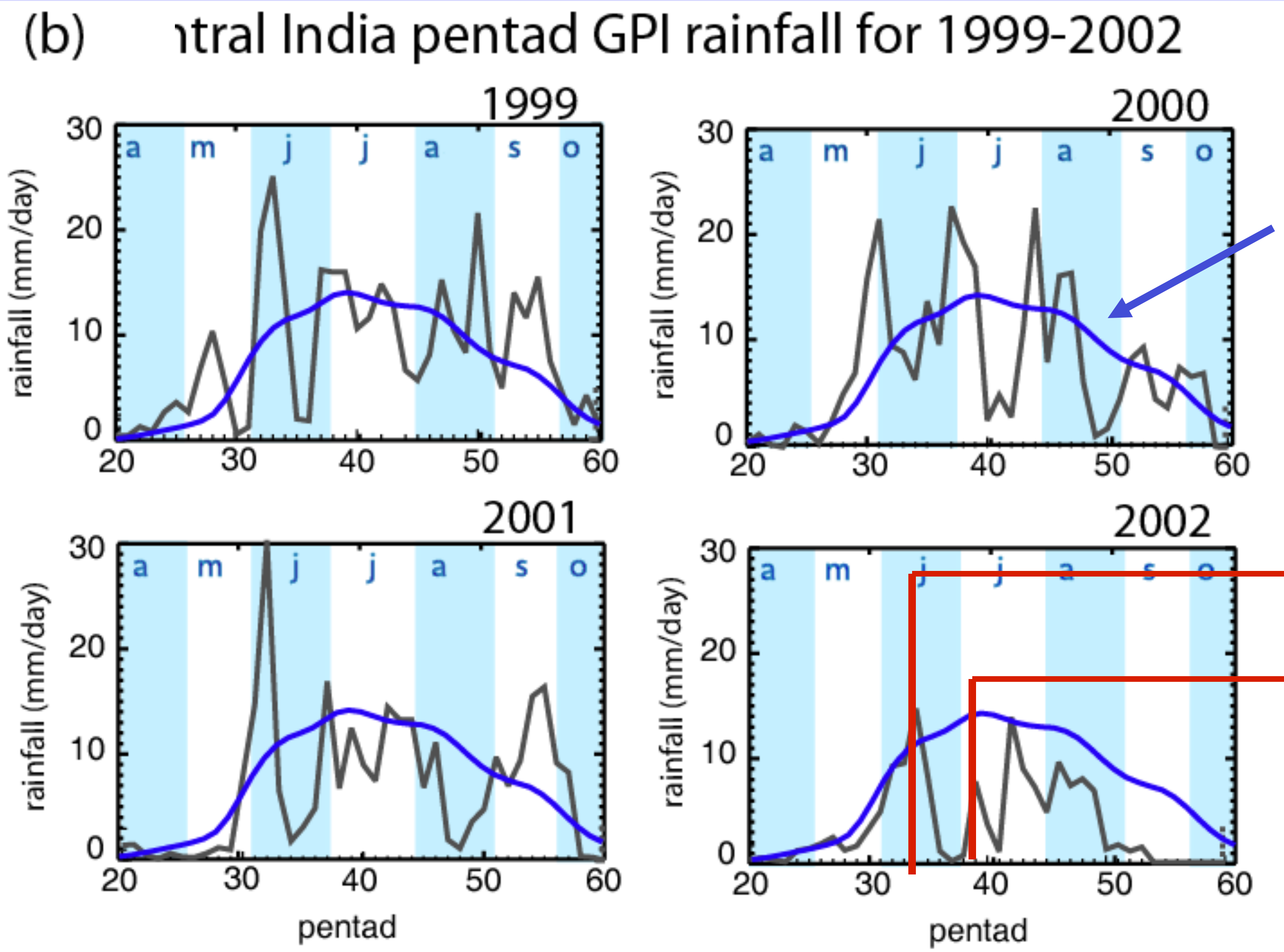
In any one location, a perfect seasonal forecast does not indicate where/when rainfall will occur?



Majority of interannual variability comes from ISO interannual variability (Hoyos & Webster, 2007: “Role of intraseasonal variability in South Asian rainfall”)

ISO rainfall accounts for the largest oscillations on all time scales



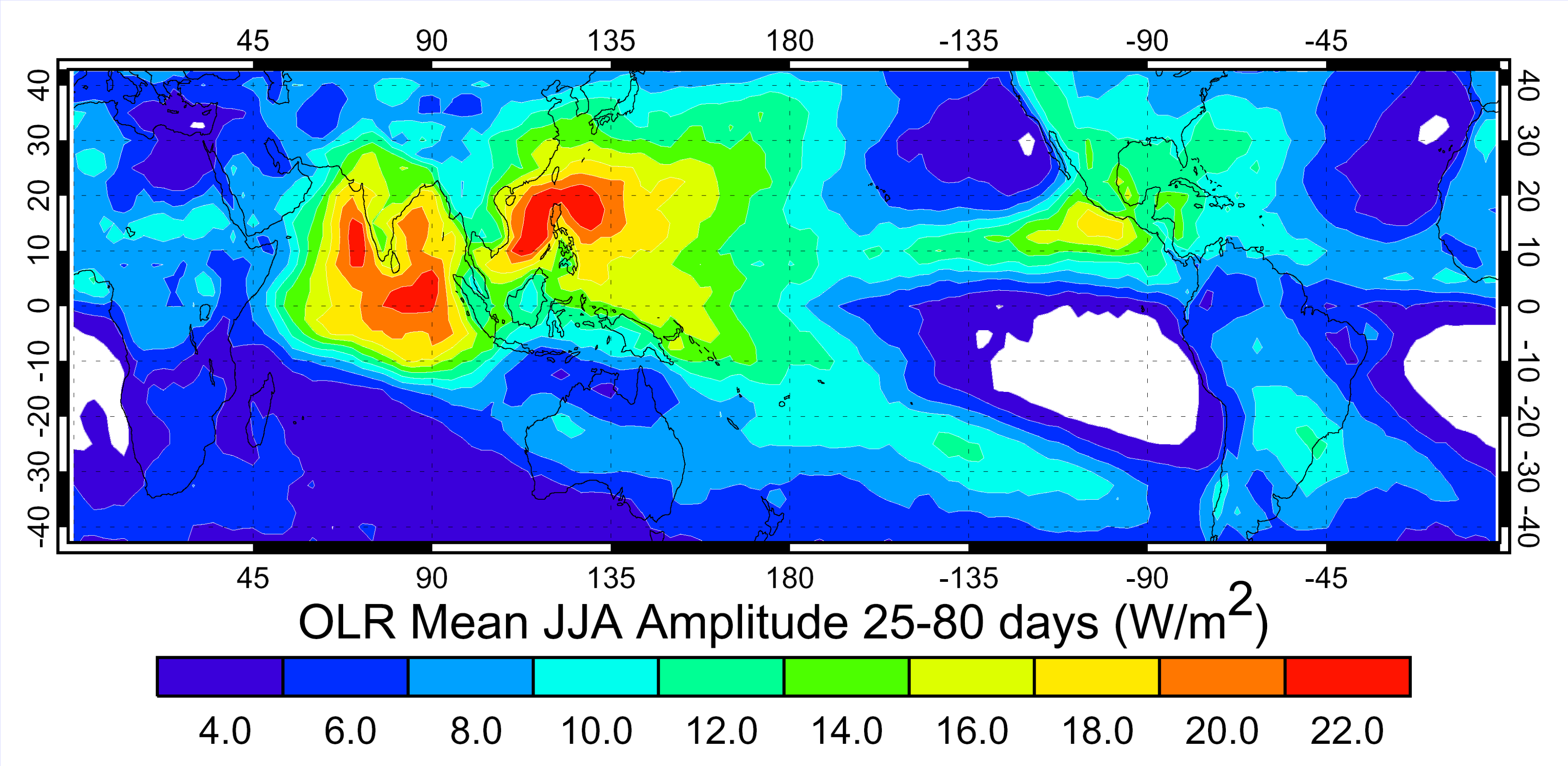


Long-term climatology

20-day forecast

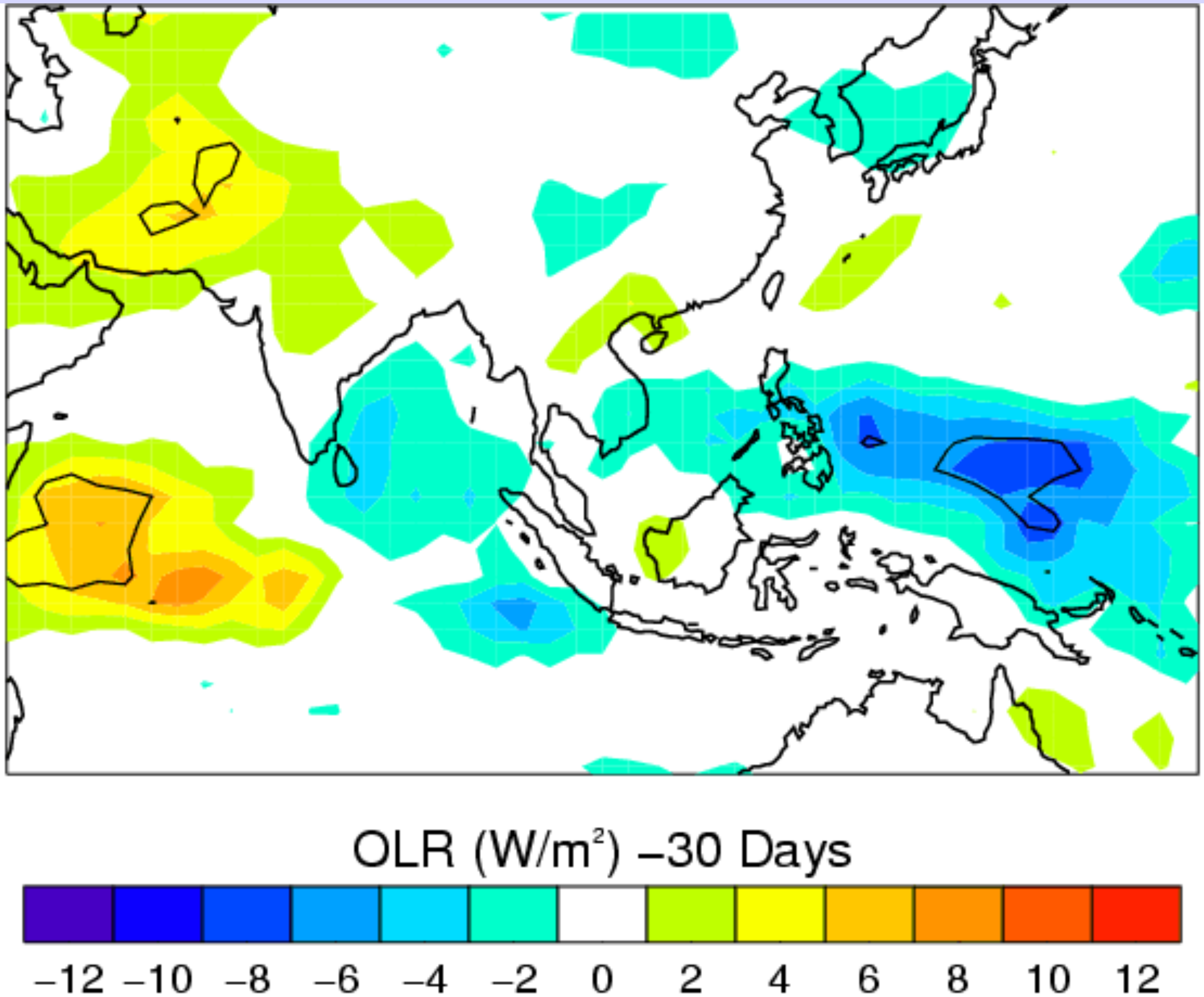
Could have saved the season

Summer Intraseasonal variability



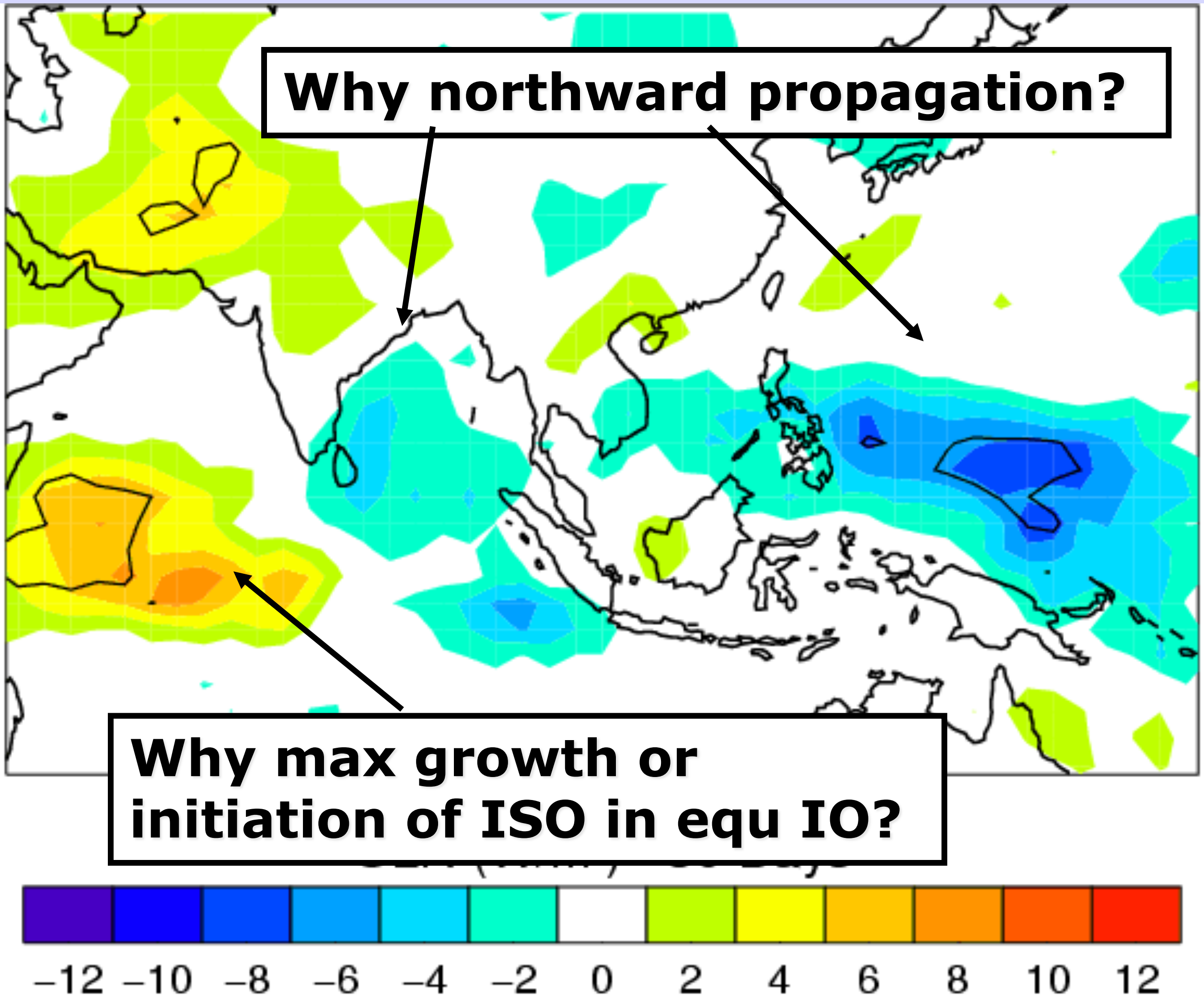
(1) Part of planetary scale phenomena

OLR Composites: 25-80 days variability

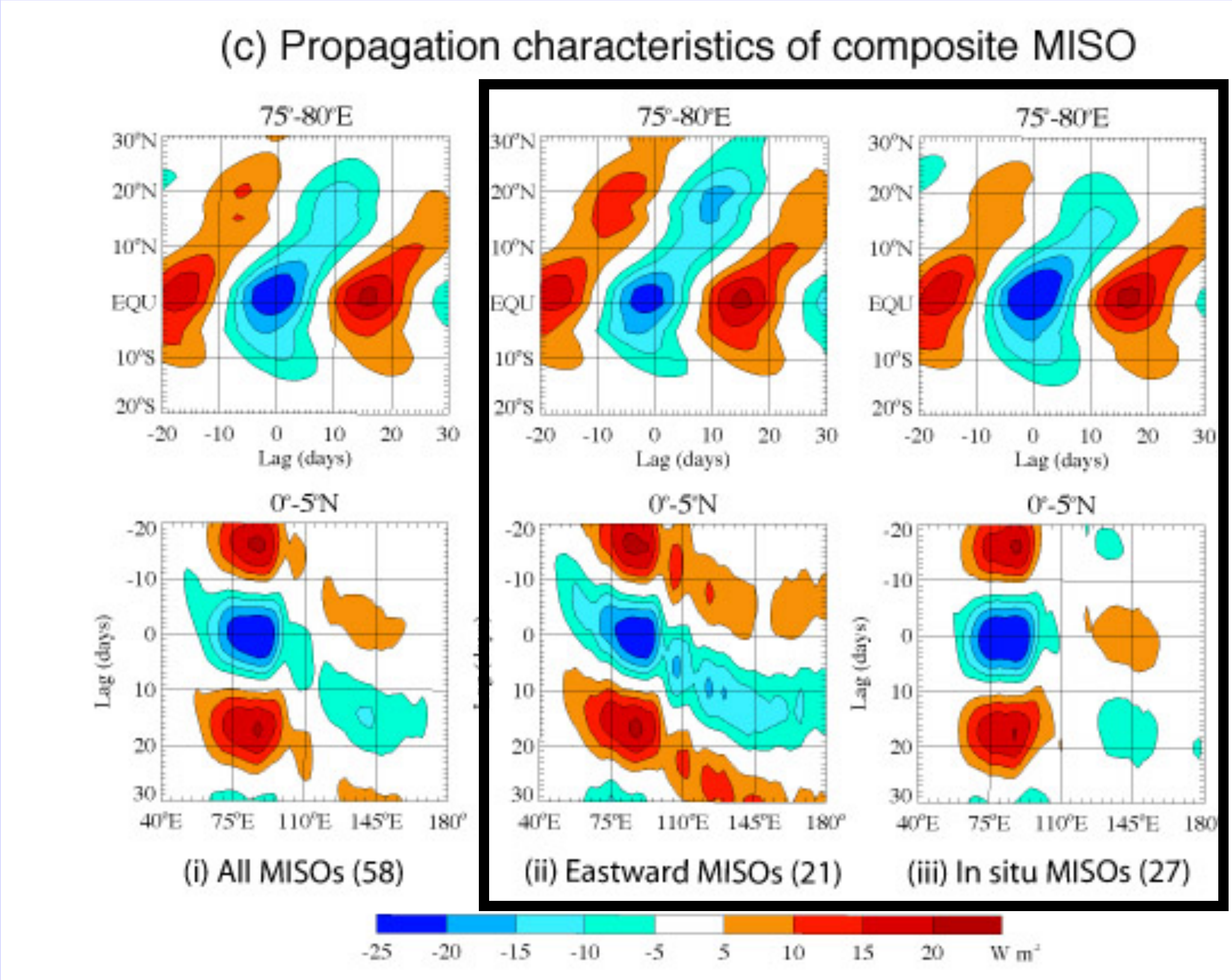


(2) Part of low-frequency propagating high amplitude phenomena

Defines a SLOW MANIFOLD of convection

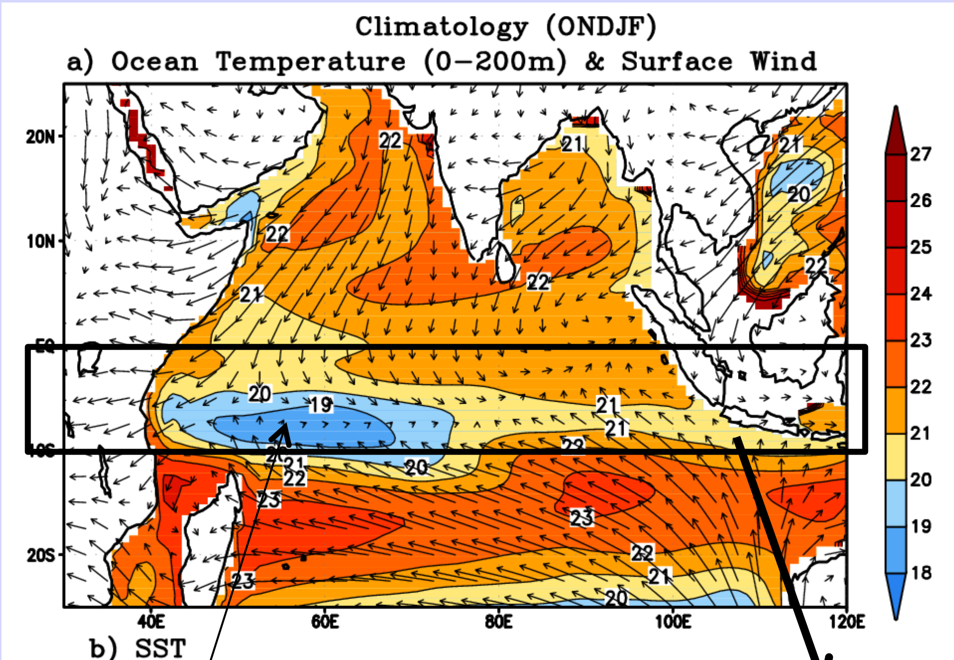


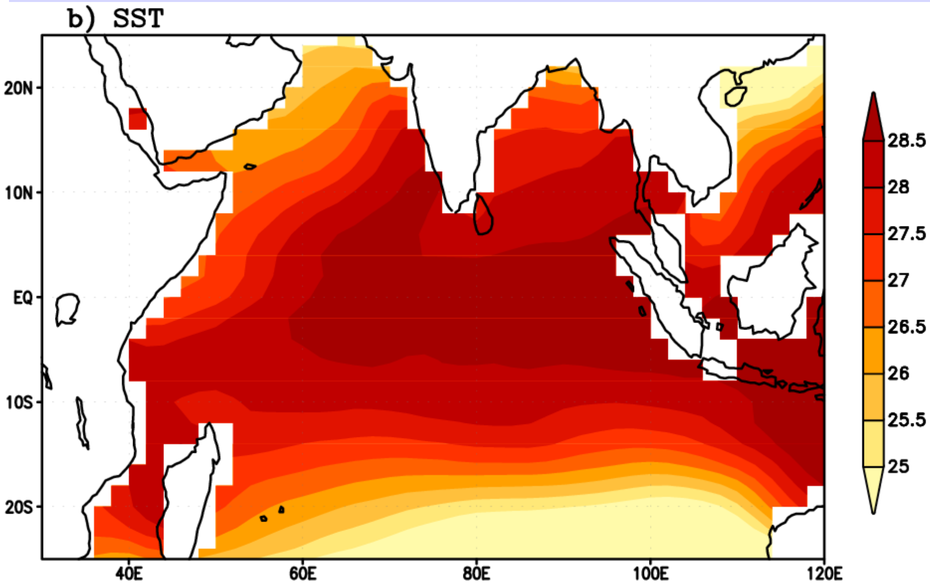
Lawrence and Webster (2002)



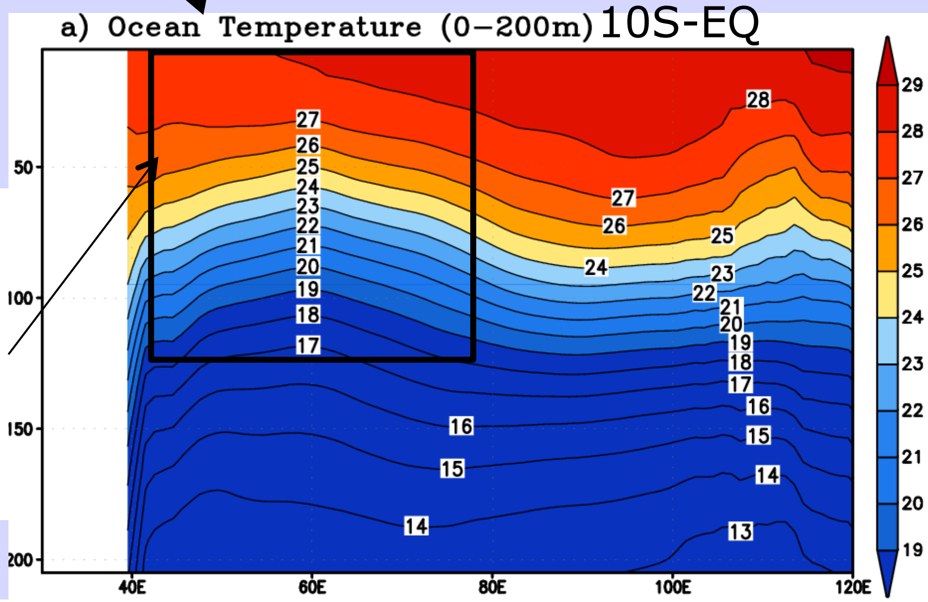
50:50

Mean state: Boreal Winter (ONDJF)





Seychelles Chagos Thermocline ridge (SCTR)



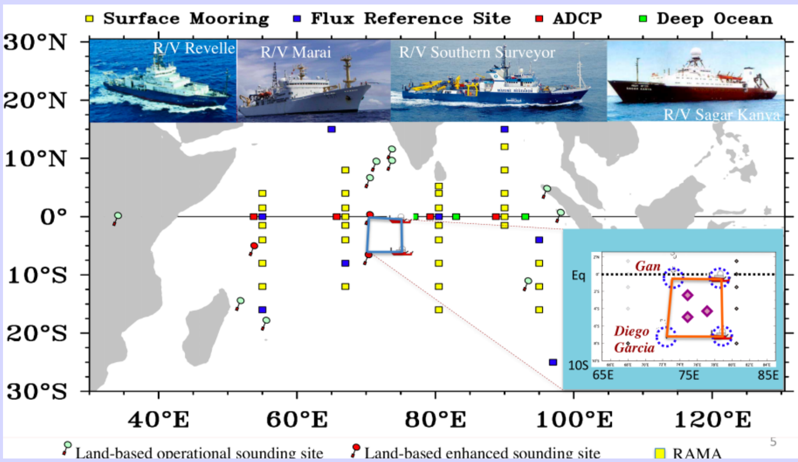
Strong coupling in SCTR

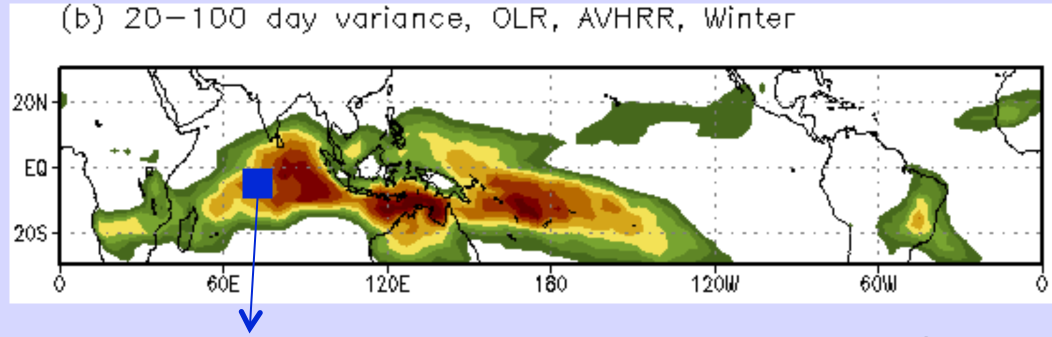
1. Shallow thermocline:
→Mixed layer is sensitive to atmospheric heat flux

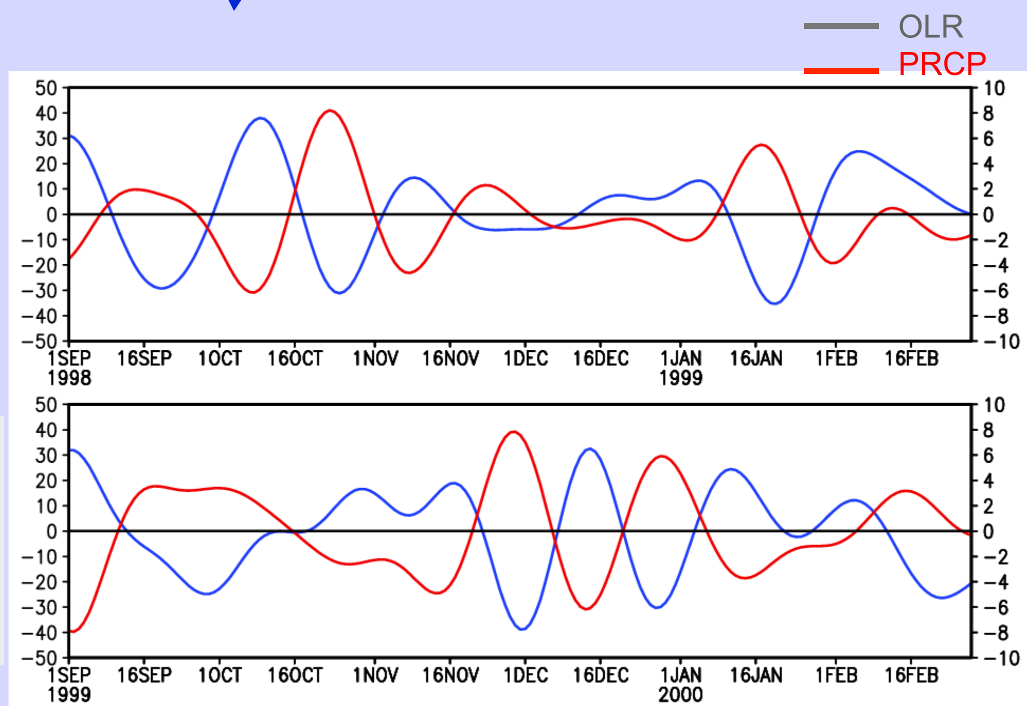
2. SST above 27C: Atmosphere is sensitive to SST variation

20-100 day filtered daily OLR (10S-0, 70-80E, ONDJF)

a) General location and configuration of the DYNAMO/CINDY2011 field experiment

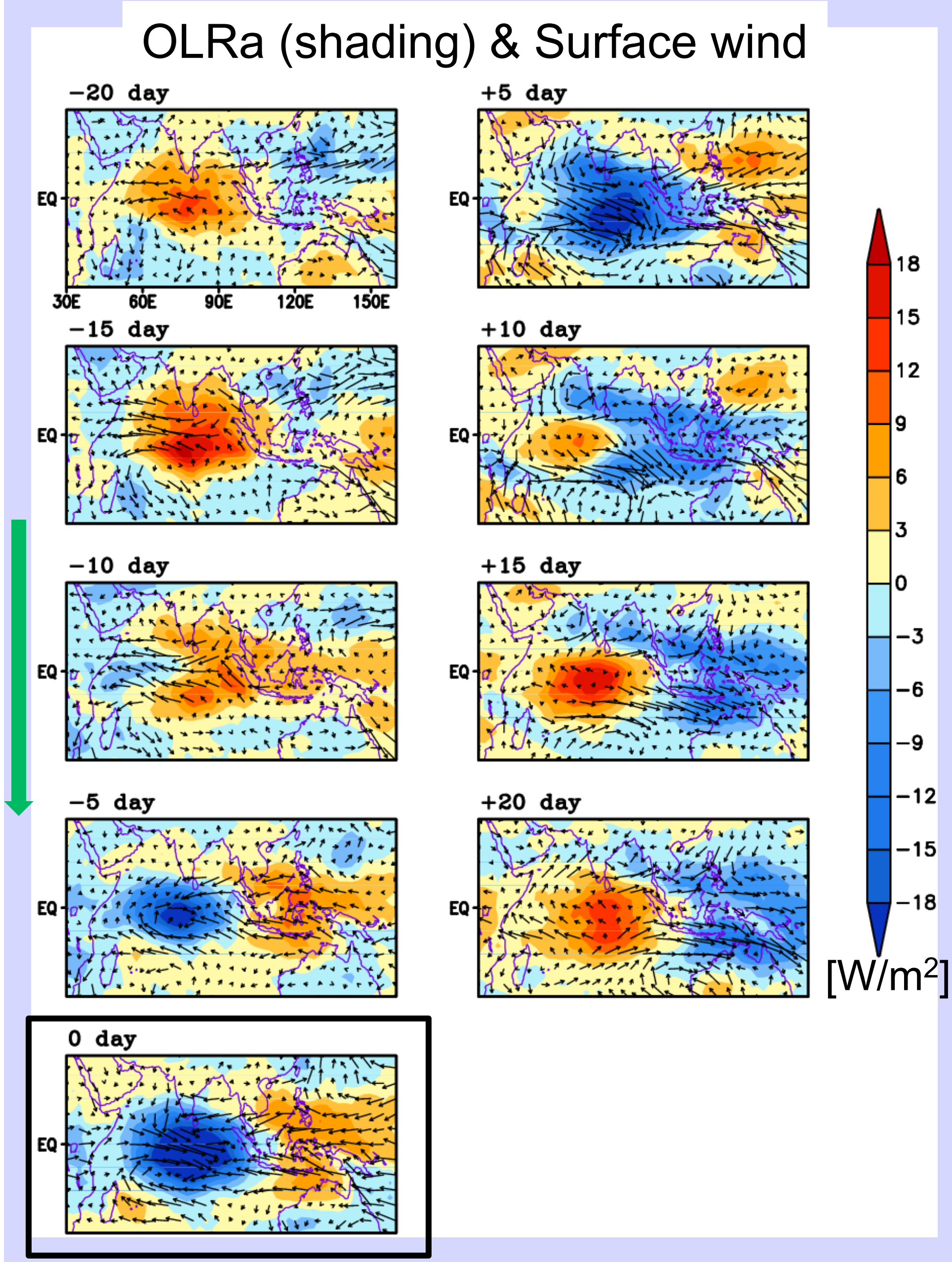


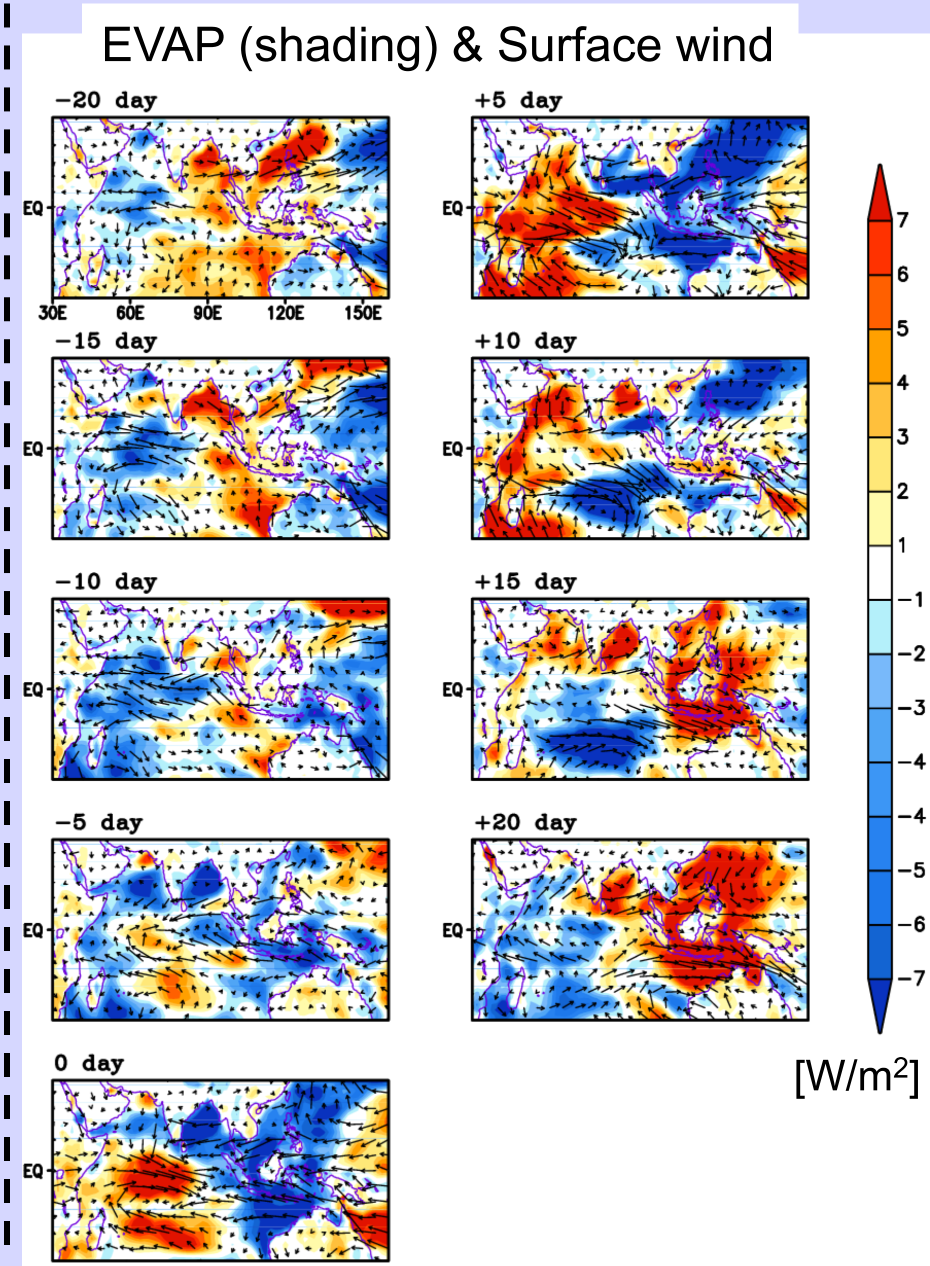




•Lag composite analysis is based on the filtered OLR anomaly timeseries; OLRa (10S-EQ, 70-80E average) < -1std

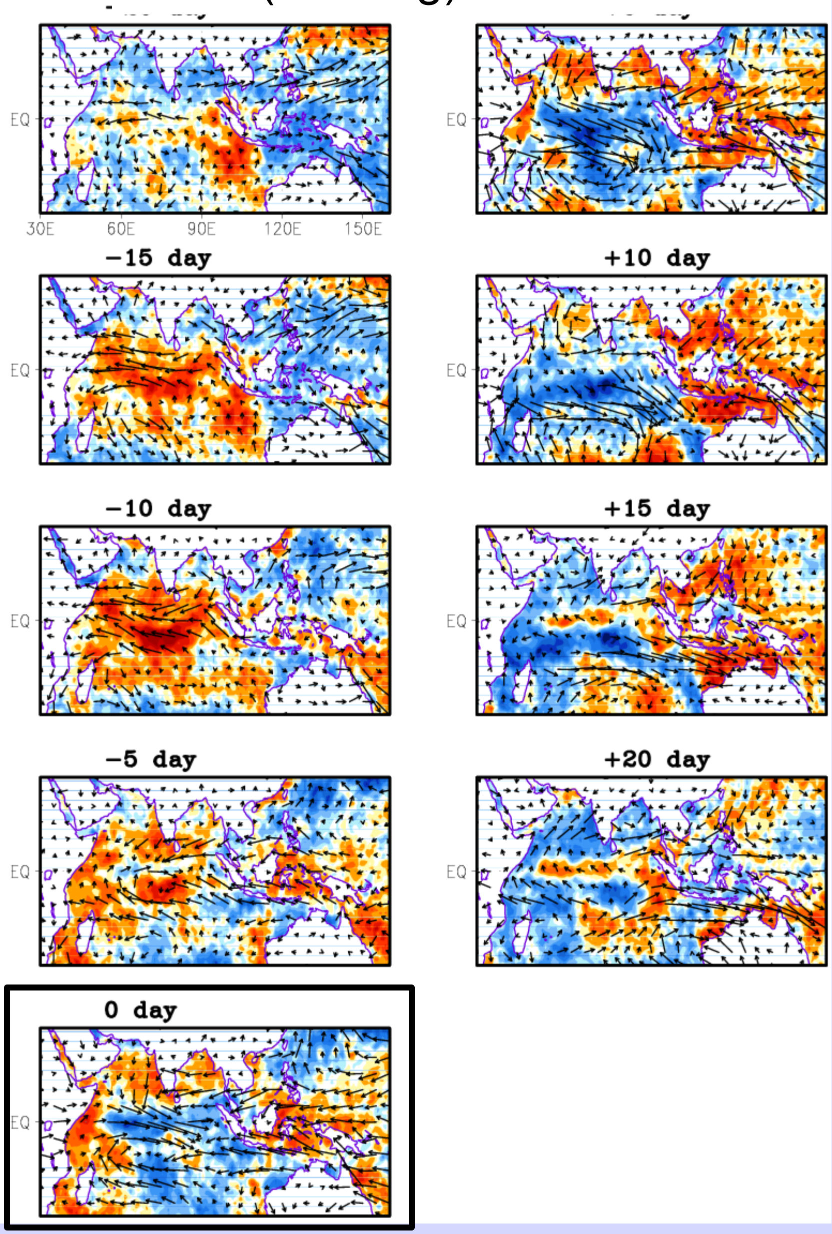
Lag Composite analysis



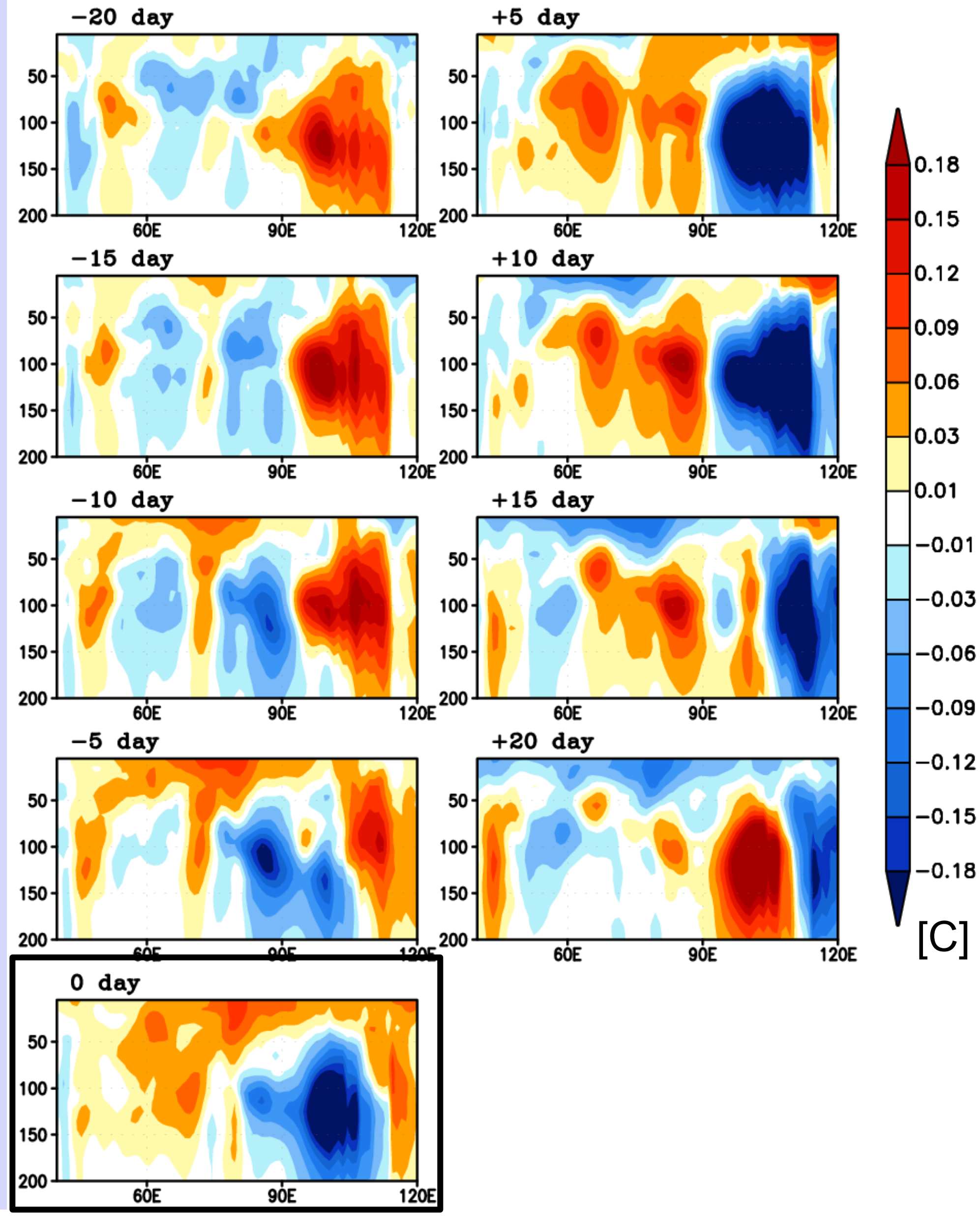


Lag Composite analysis

SSTa (shading) & Surface wind

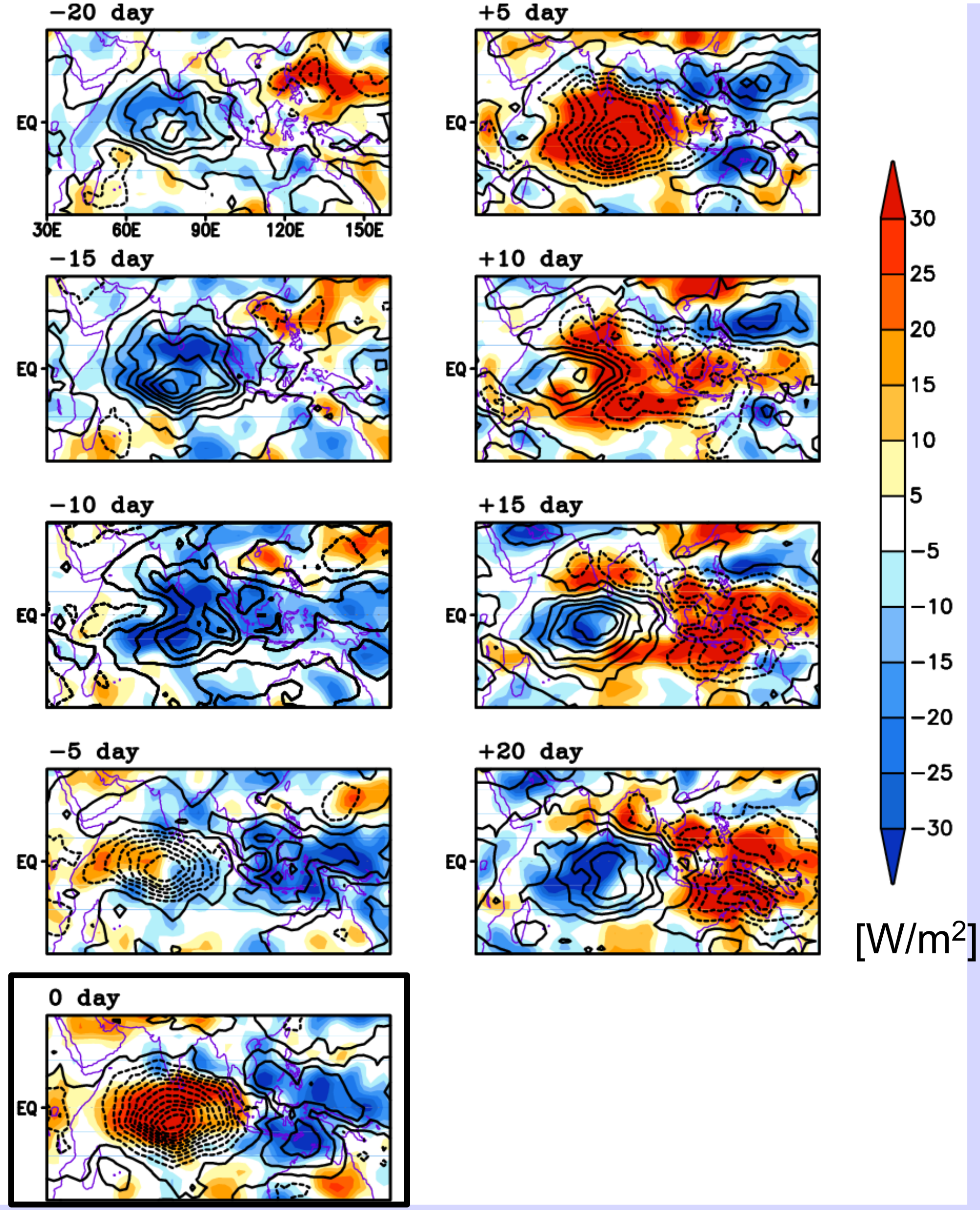


Subsurface Temperature (10S-EQ mean)

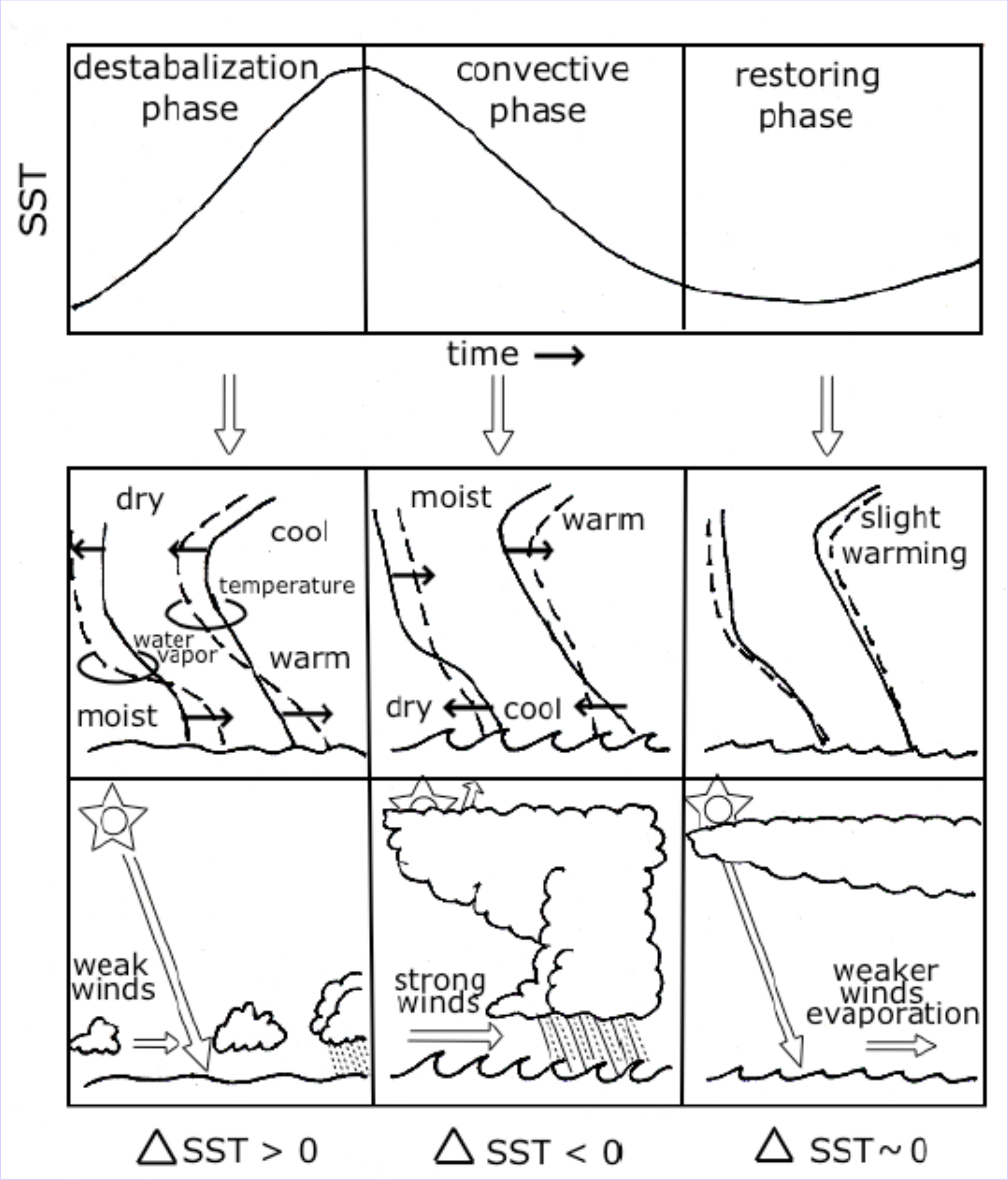


Lag Composite analysis

Vertically Integrated Heating (Shading) & OLR (contour)

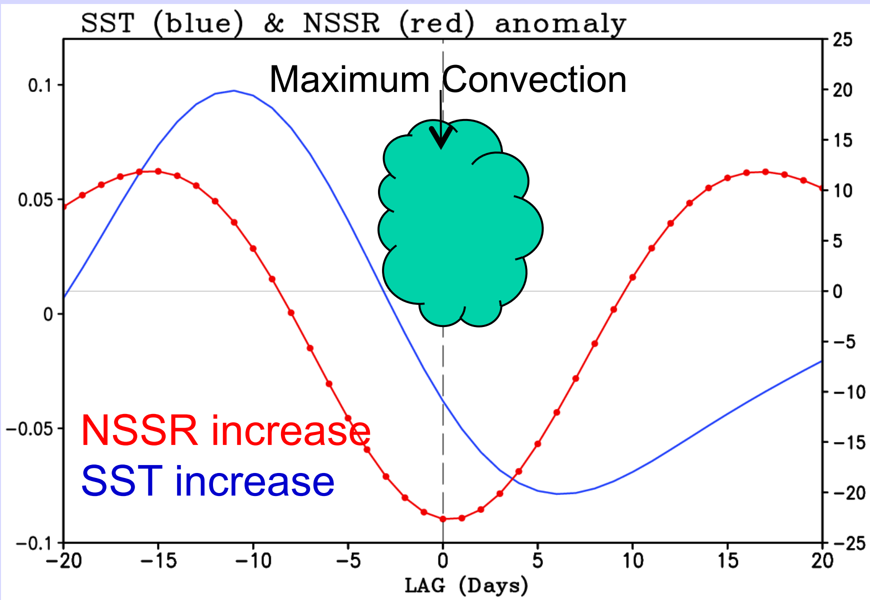


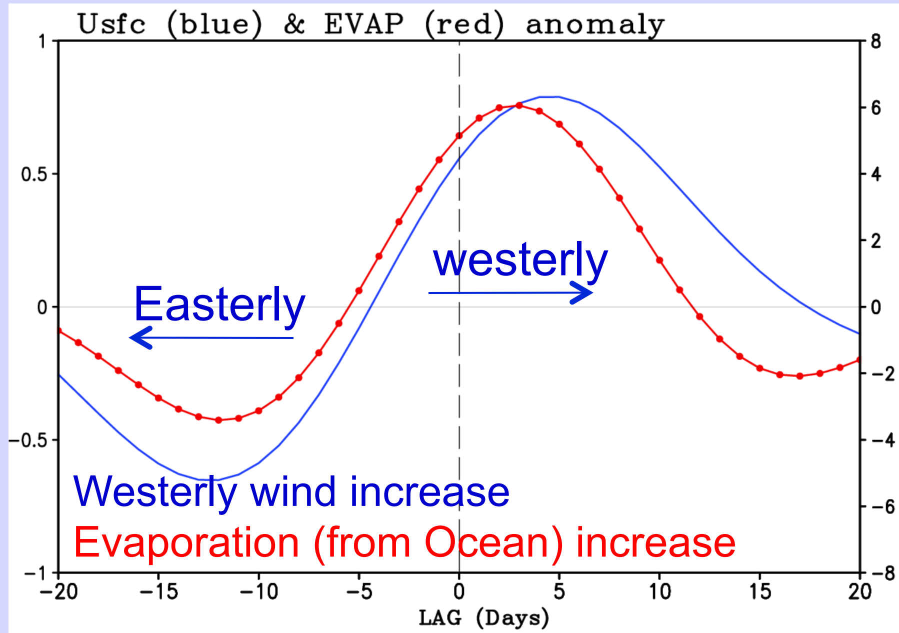
Humidistat Feedback (Stephens, Webster, et al. 2004)

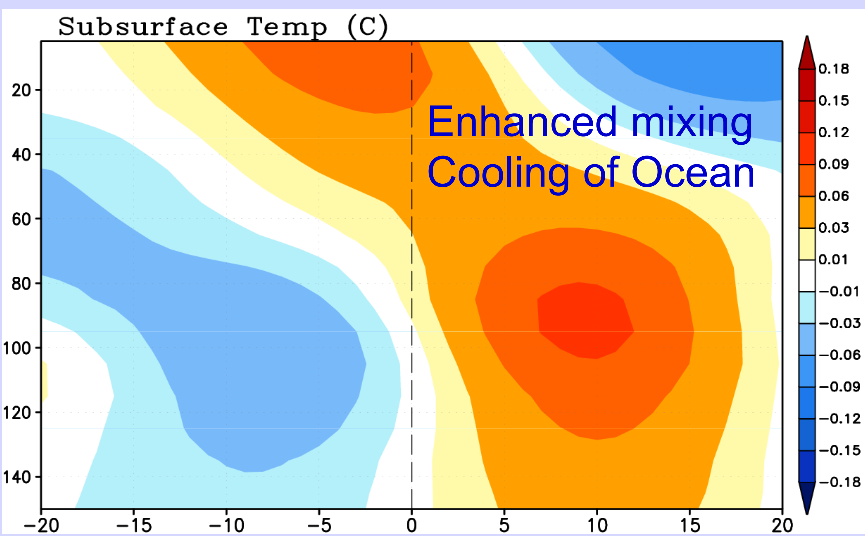


Feedback from Observation

From Destabilization phase to Convective phase





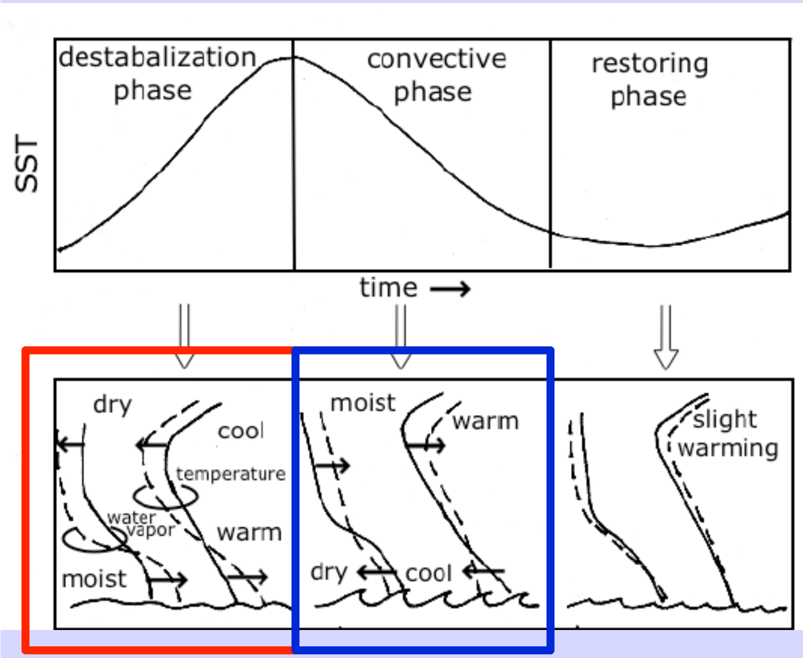


Data: OISST, ISCCP, NCEP REAN, GODAS
Period: 1980-2005 (except, ISCCP, EVAP)
Area mean: -10S-5N, 60-90E

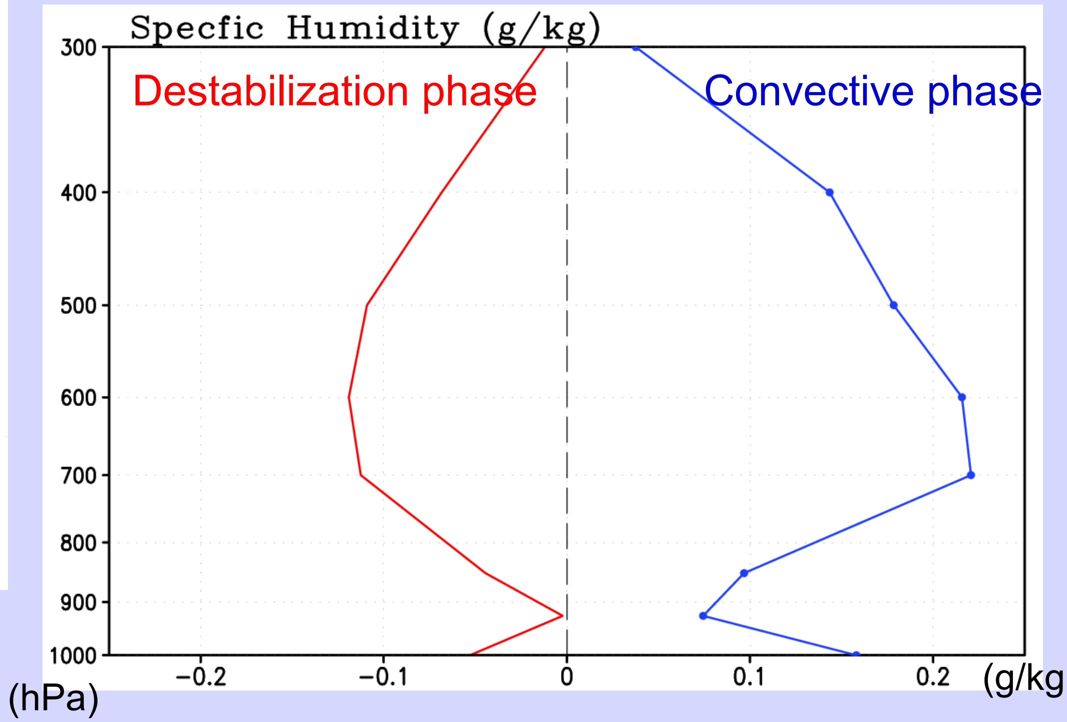
* NSSR : Net Surface Shortwave Rad (ISCCP)

Feedback in Observation

From Destabilization phase to Convective phase



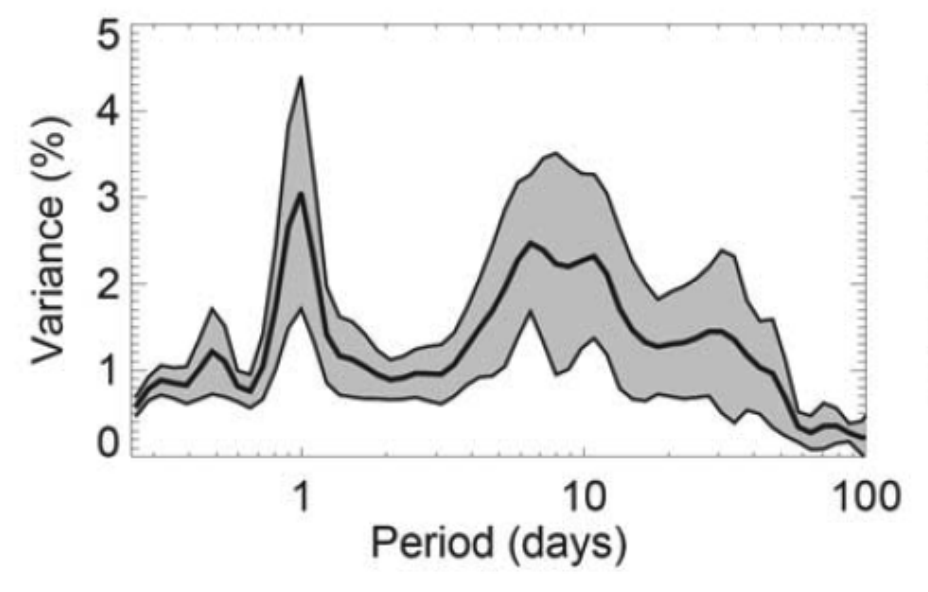
(Stephens, Webster, et al. 2004)



Shallow convection
→Moisten the Low levels

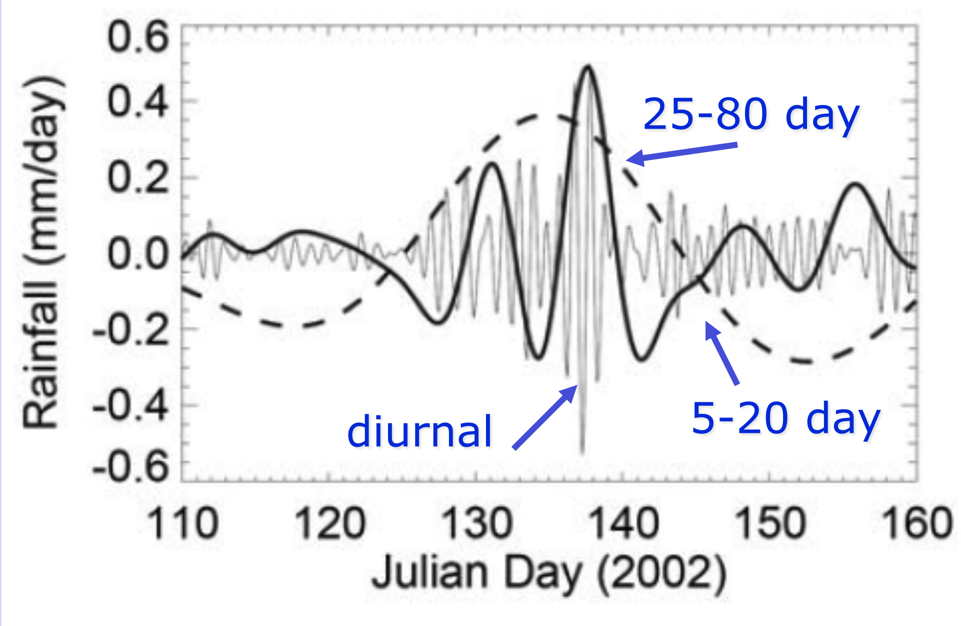
Strong convection, cold SST
→ Moistening the upper level/Drying the low levels

(3) Modulates higher frequency monsoon variance (monsoon weather)

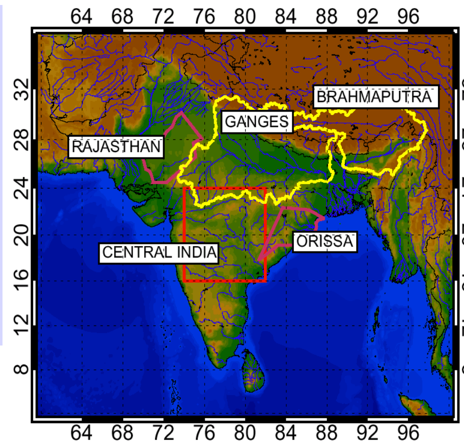


TRMM spectra of 3-hourly rainfall over Bay of Bengal

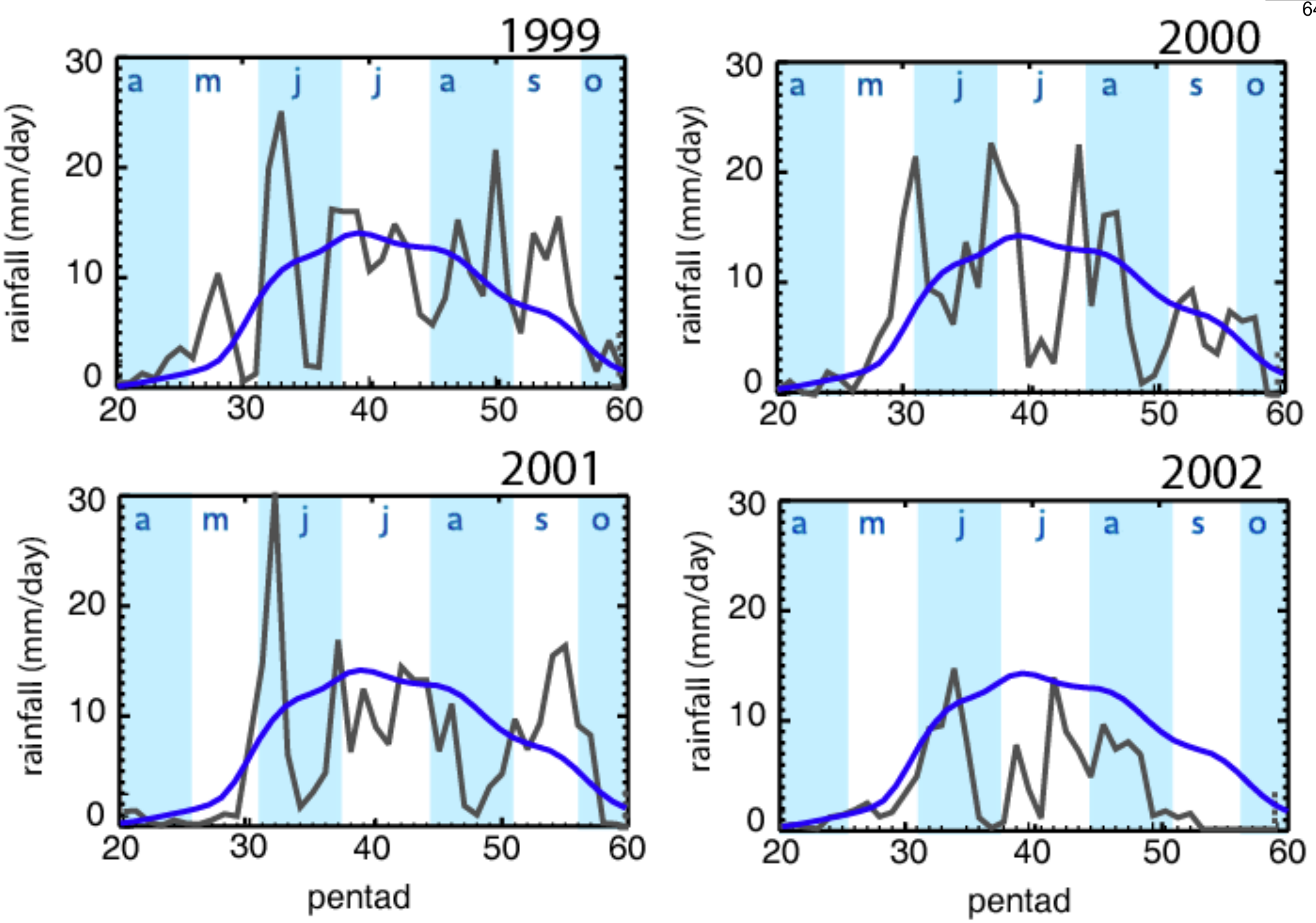
TRMM data organized into three spectral bands (diurnal, 5-20 days and 25-80 day). Summer 2002



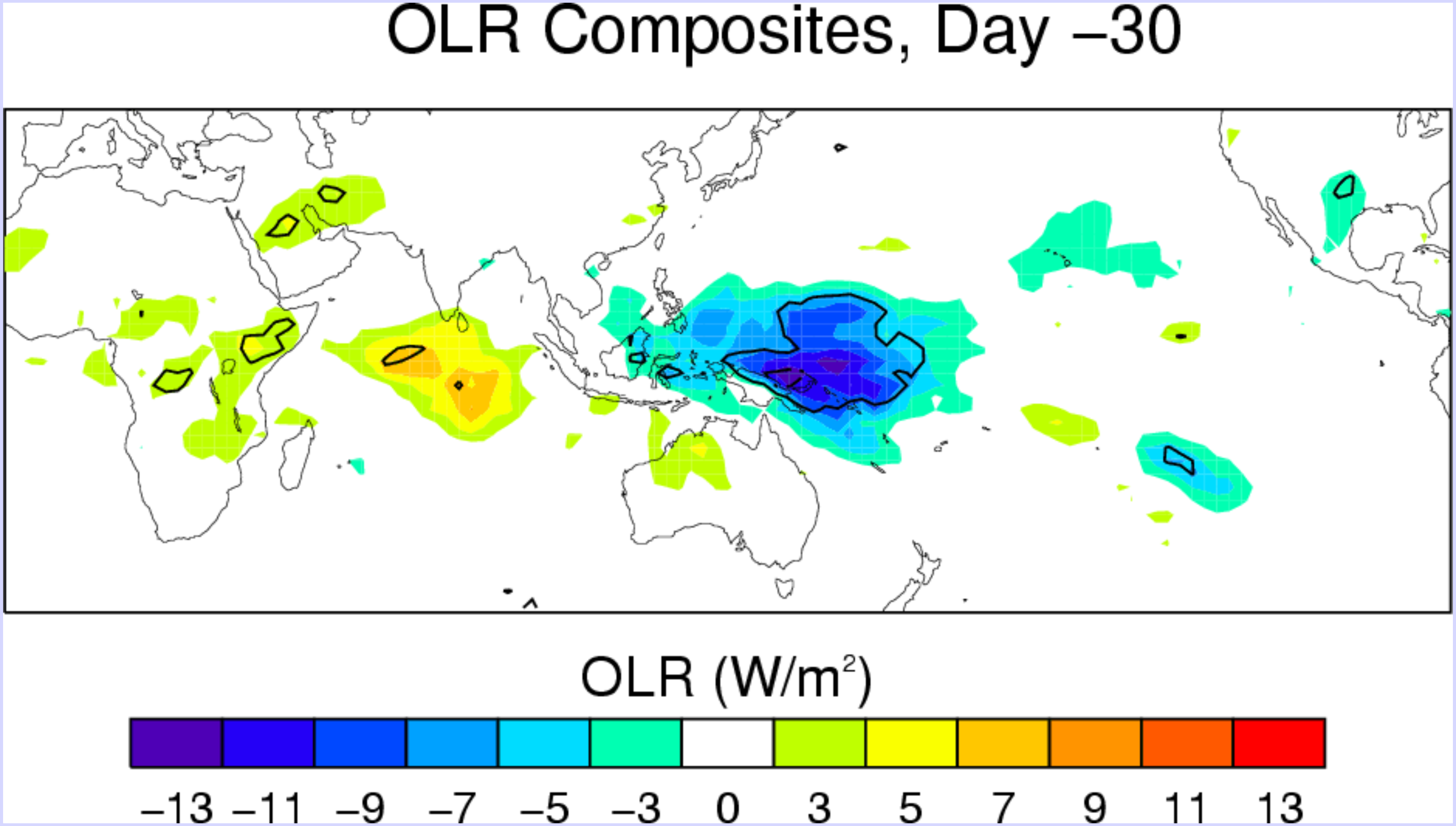
Forecasting Intraseasonal Variability



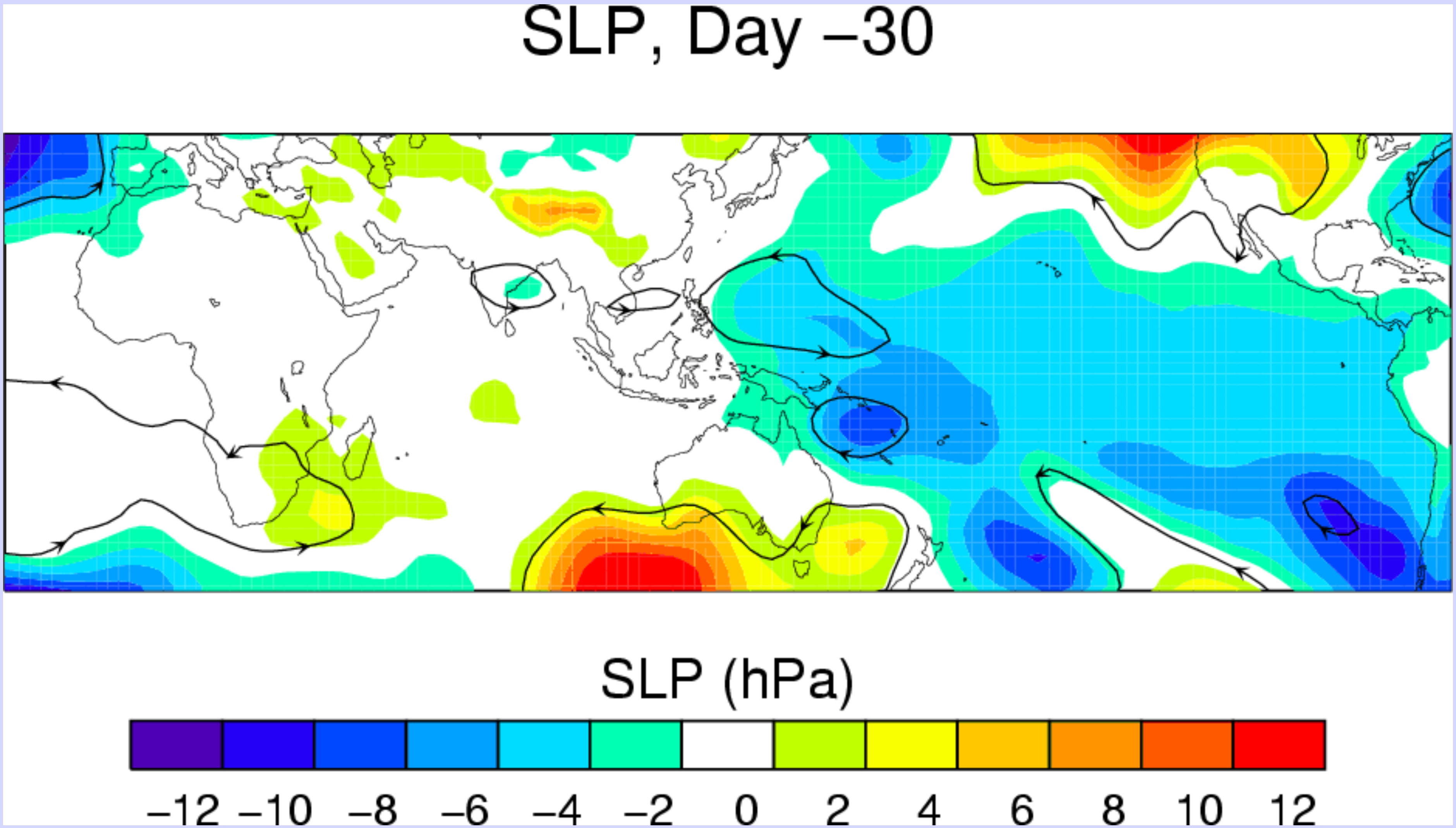
(b) Central India pentad GPI rainfall for 1999-2002



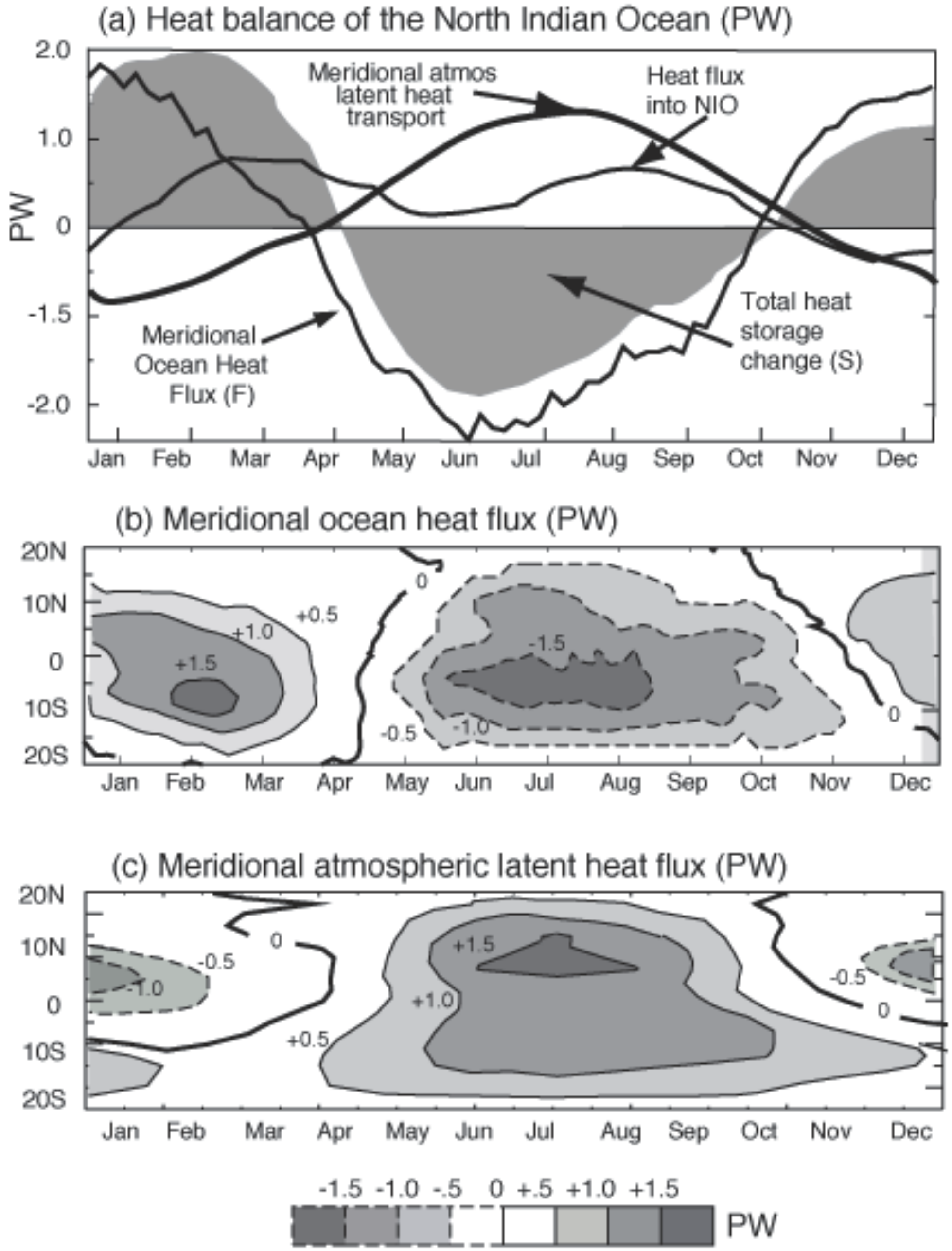
OLR Composites: Winter

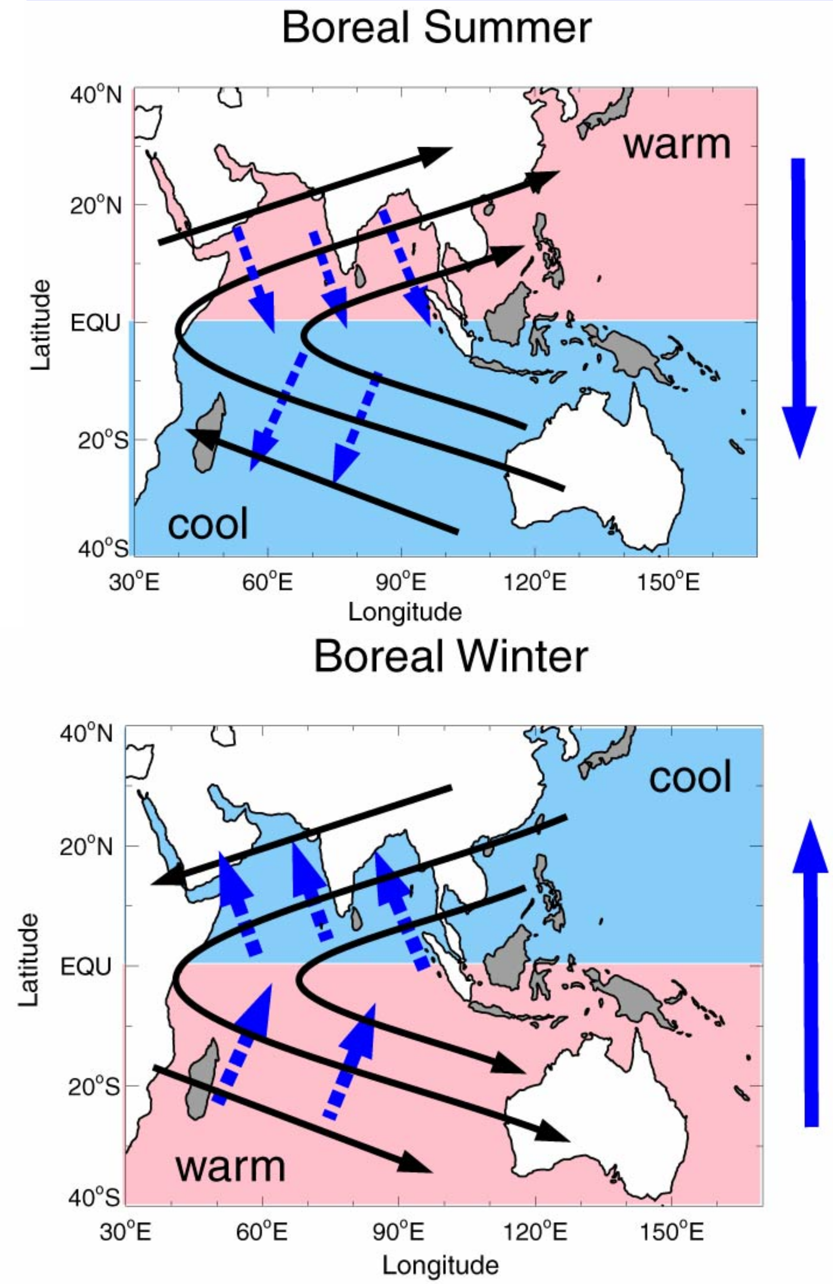


Sea Level Pressure: Winter



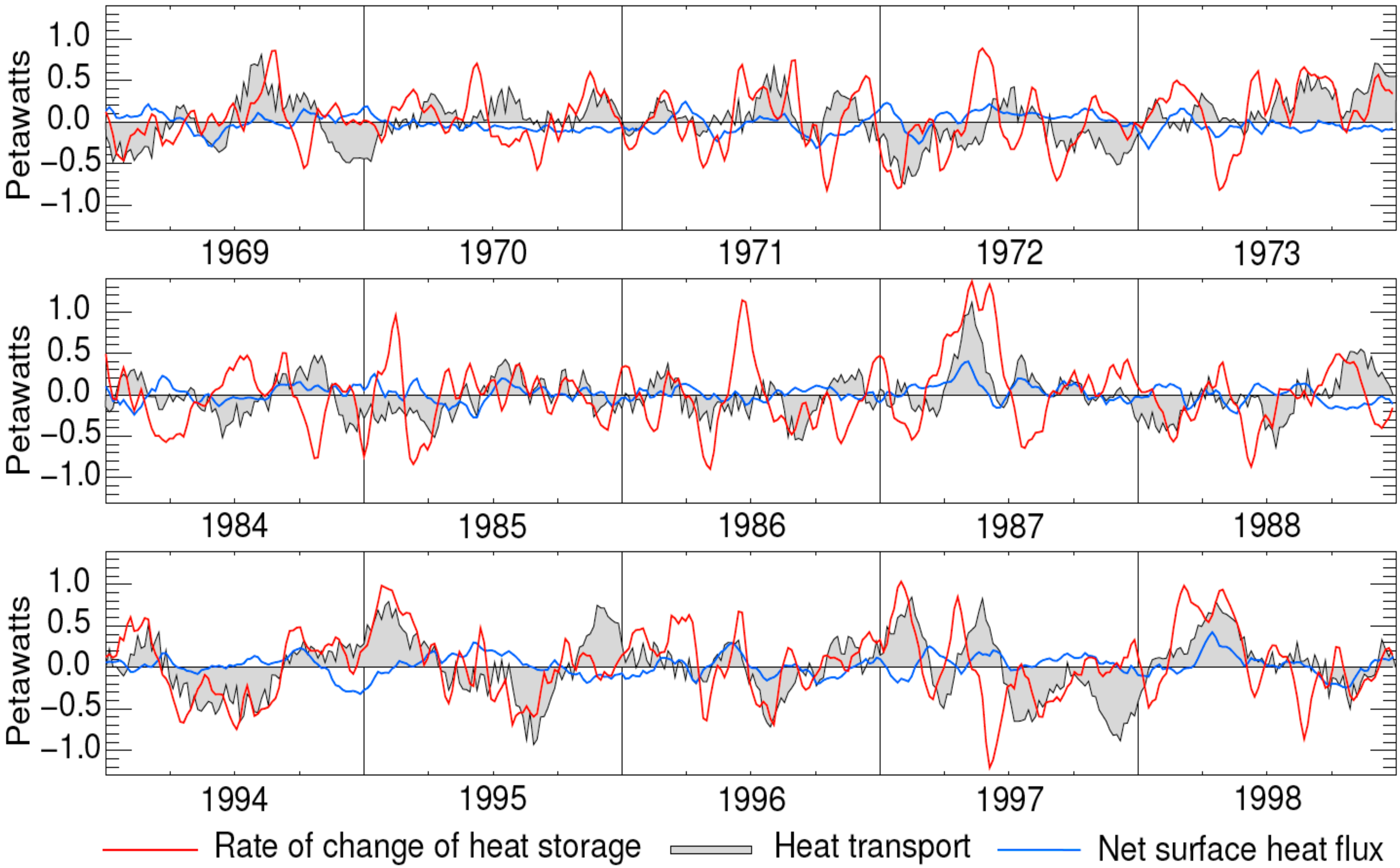
THE ISO AND THE HEAT BALANCE OF THE INDIAN OCEAN



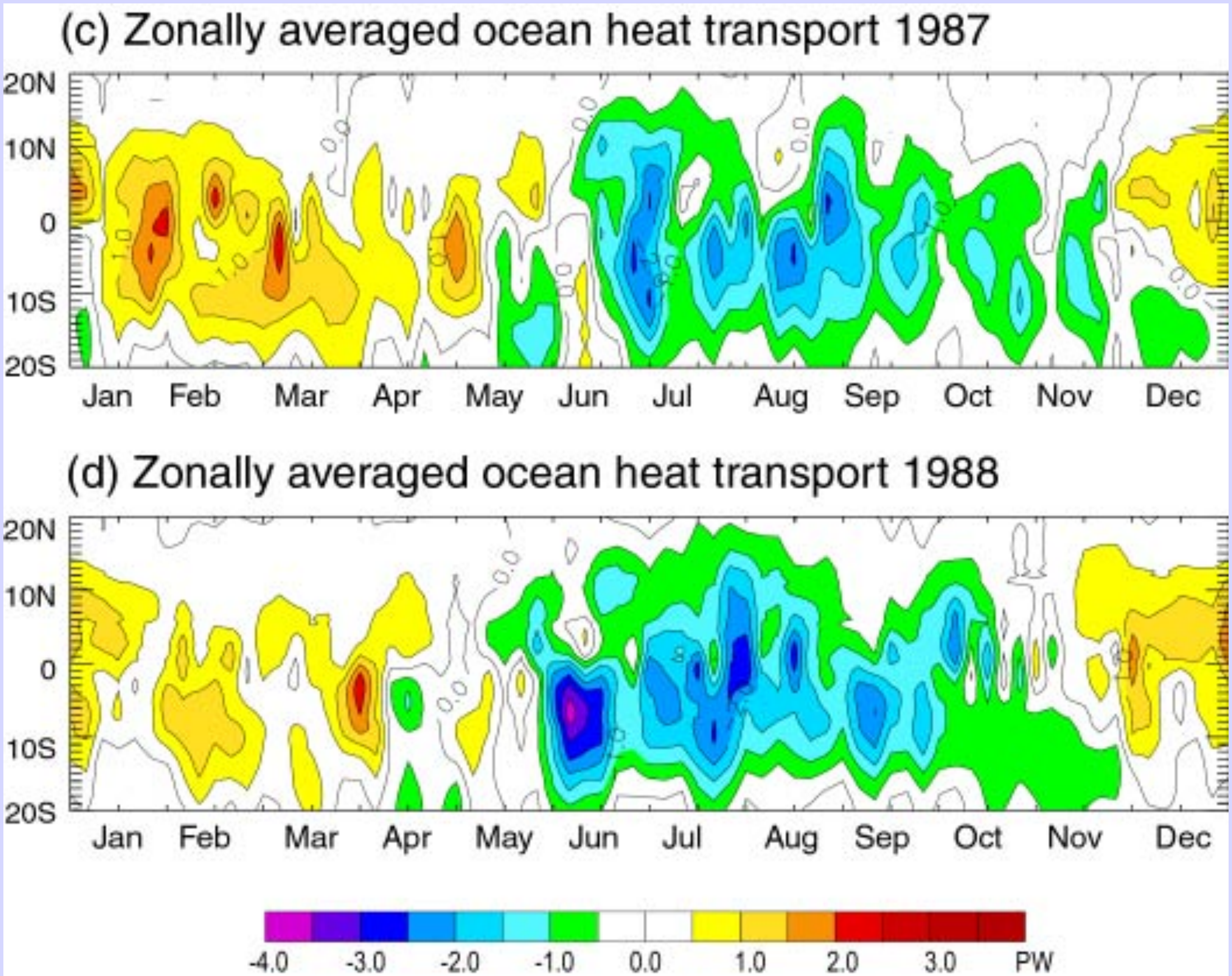


NIO Heat Balance Anomalies: 1969-73, 1984-88, and 1994-98

2



ISO ACCOMPLISHES ALMOST ALL CROSS-EQU OCEAN HEAT TRANSPORT



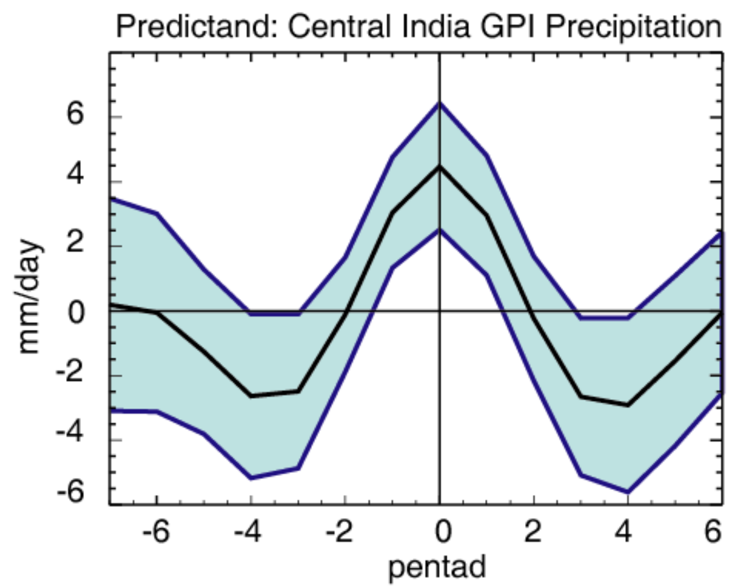
In both summer and winter, the ISO is:

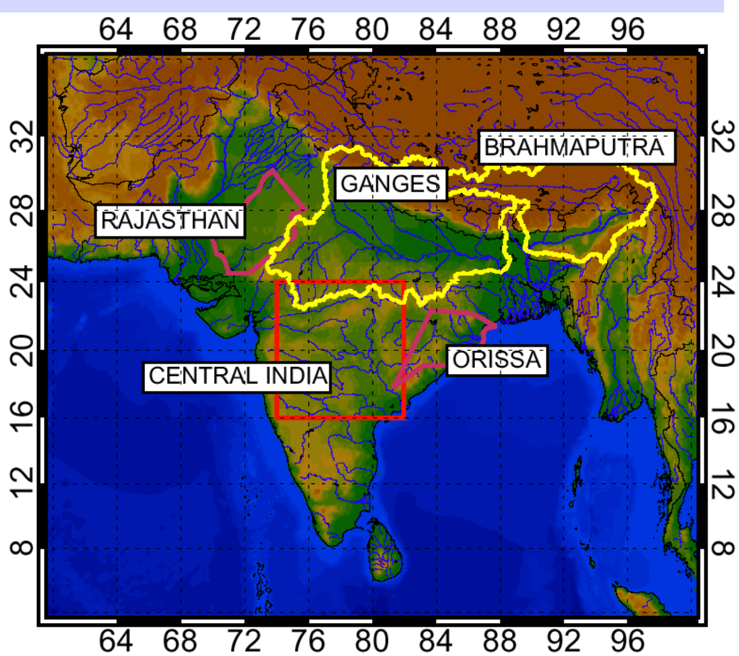
- Large scale
- Low frequency slowly propagating
- High amplitude
- Relatively robust with repeatable behavior
- Coupled ocean-atmosphere (dyn and thermo)

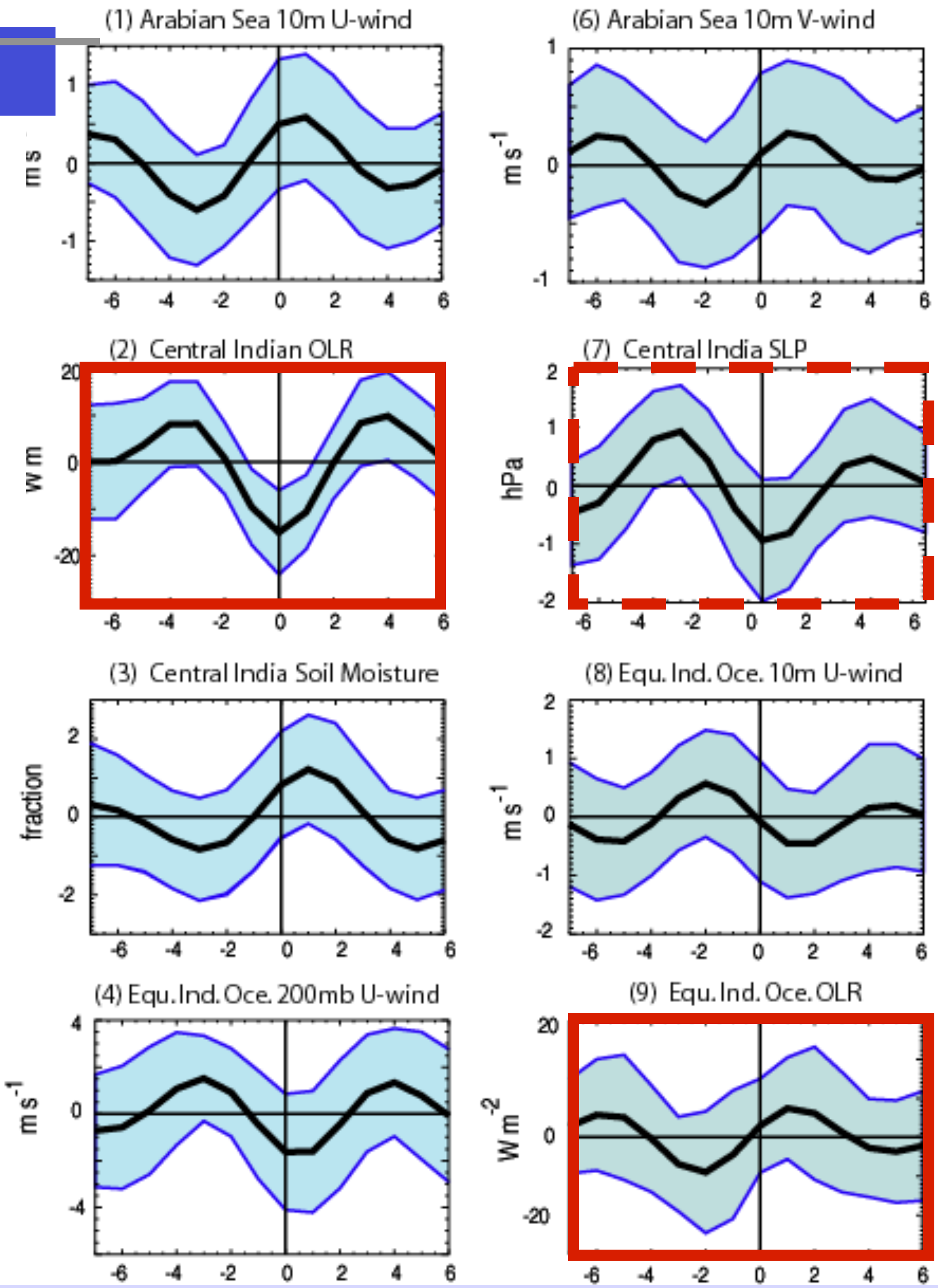
In fact, empirical models show the existence of predictability

Why do numerical models have troubles emulating this skill?

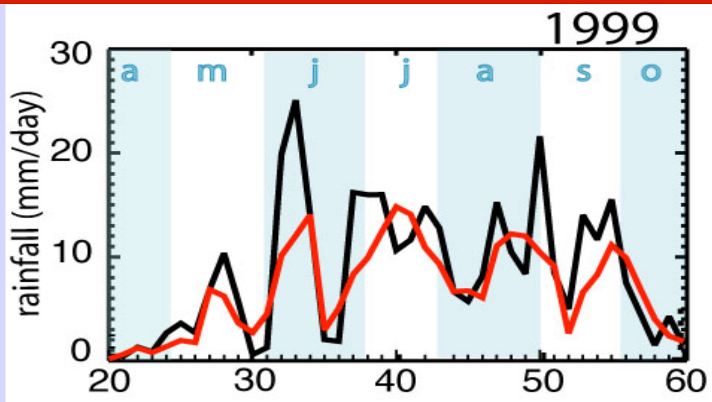
Composites of Predictors

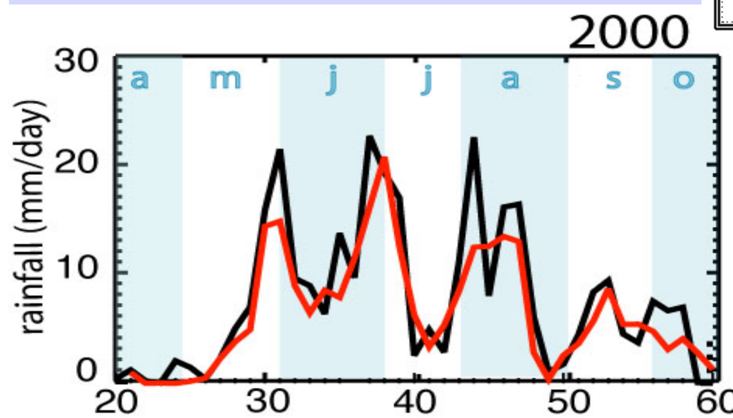


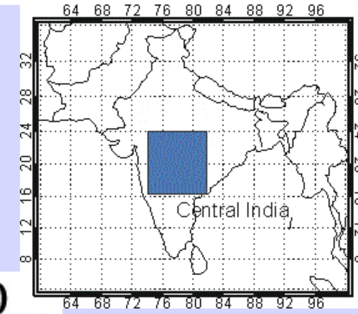


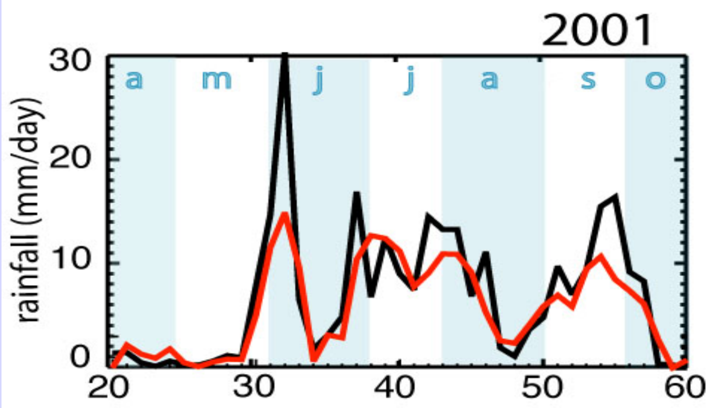


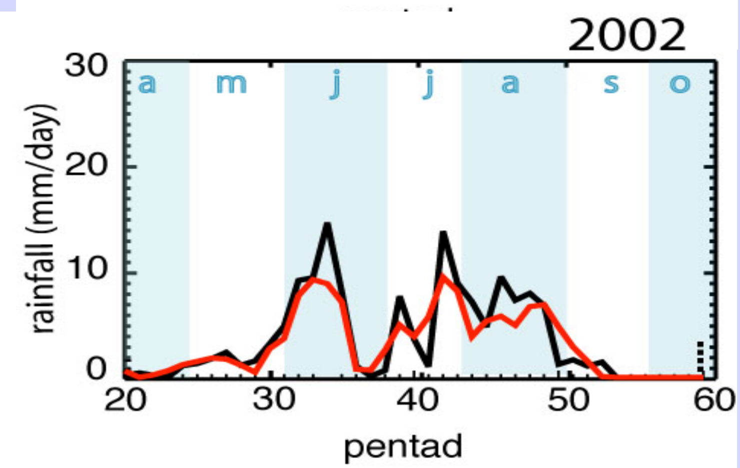
20-day forecasts for Central India

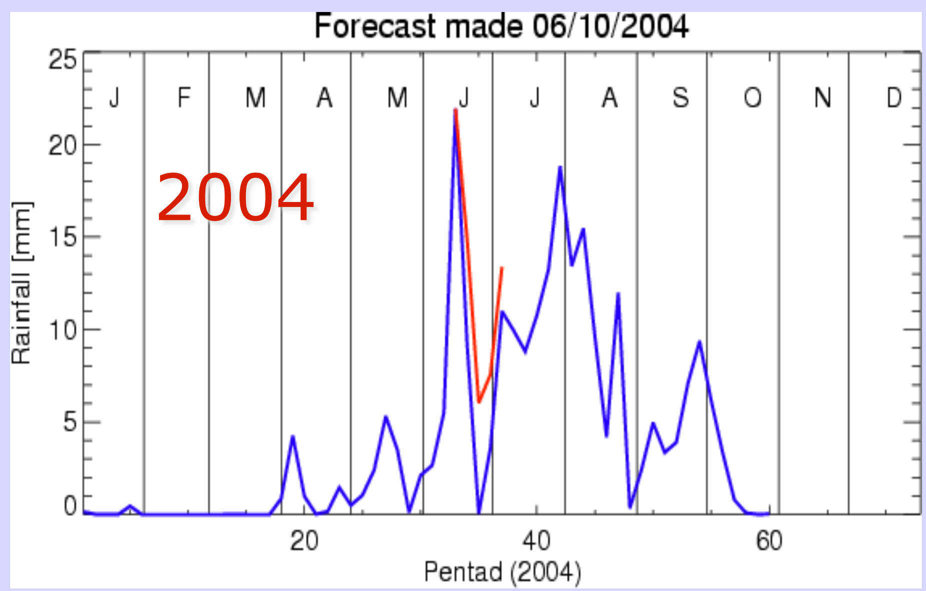












Wavelet banding scheme

Forecasting of Intraseasonal variability

Coupled Ocean-Atmosphere modeling:
Traditional approach. Series of experiments will show that errors grow rapidly and predictability is rapidly eroded by error growth (convection?)

Bayesian Empirical Prediction:
Conditional probability scheme provides 20-day forecasts using a Banded wavelet technique. Banding "protects" longer term variability In time series from high frequency noise

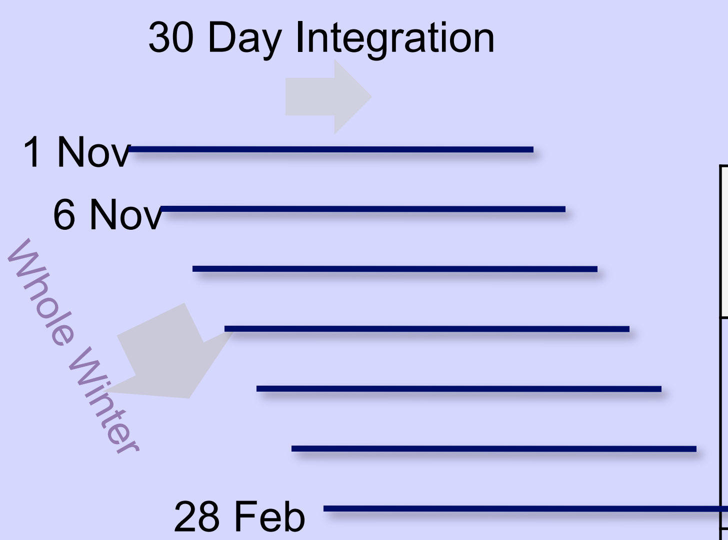
Slow manifold Modeling:
Takes coupled ocean-atmosphere model and applies "banding" technique Allowing operational (real-time) 30-day forecasts. Early results suggest Considerable skill using this method.

SERIAL MODELING:ECMWF & SNU COUPLED MODEL

- Series of experiments runs using the ECMWF and Korean climate model (Kim and Kang) coupled operational climate models
- Summer and winter cases
- 30 days of integration initialized each successive day
- 5 ensemble members
- Events chosen so that model initialized before, during and after ISO event to identify when error growth occurs

Experimental design

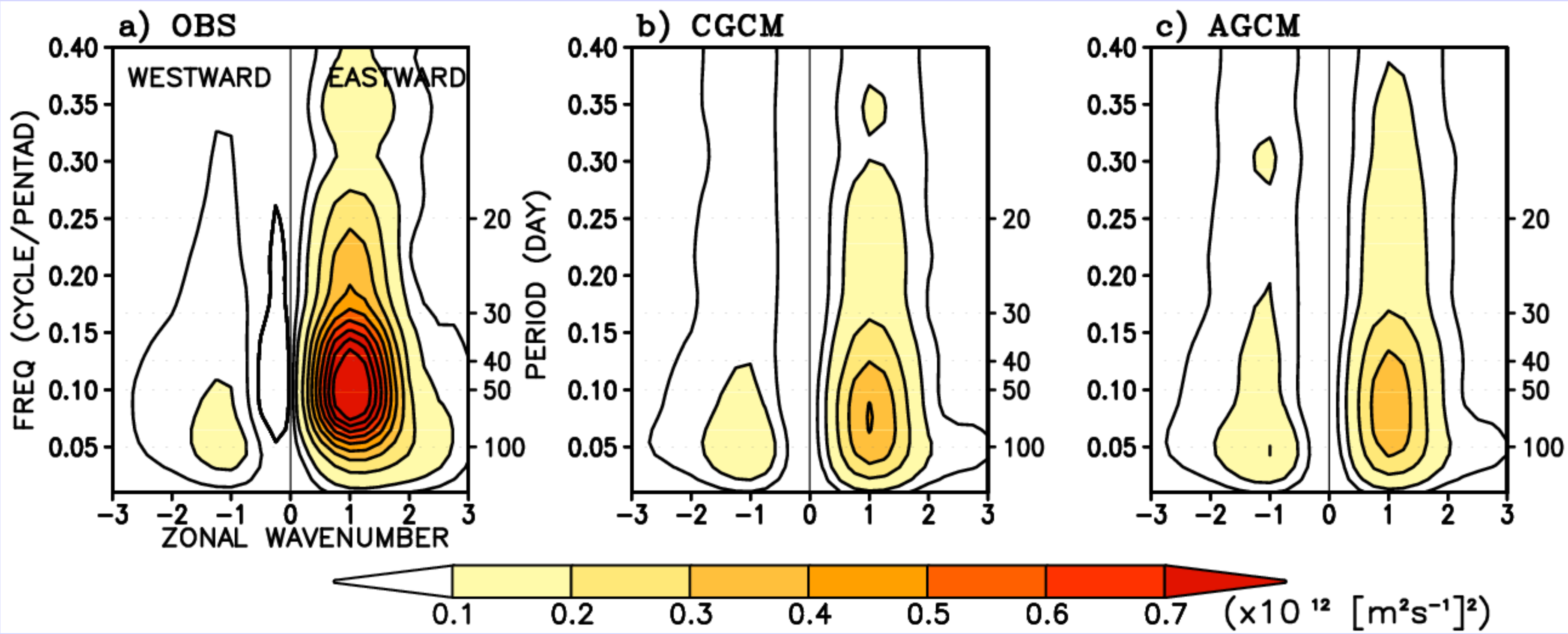
Serial integration through all phases of MJO life cycle



Serial run with SNU GCM

EXP	Period	Total 30-day forecasts
AGCM (Persistent SST)	26-year (80-05)	598
CGCM	26-year (80-05)	

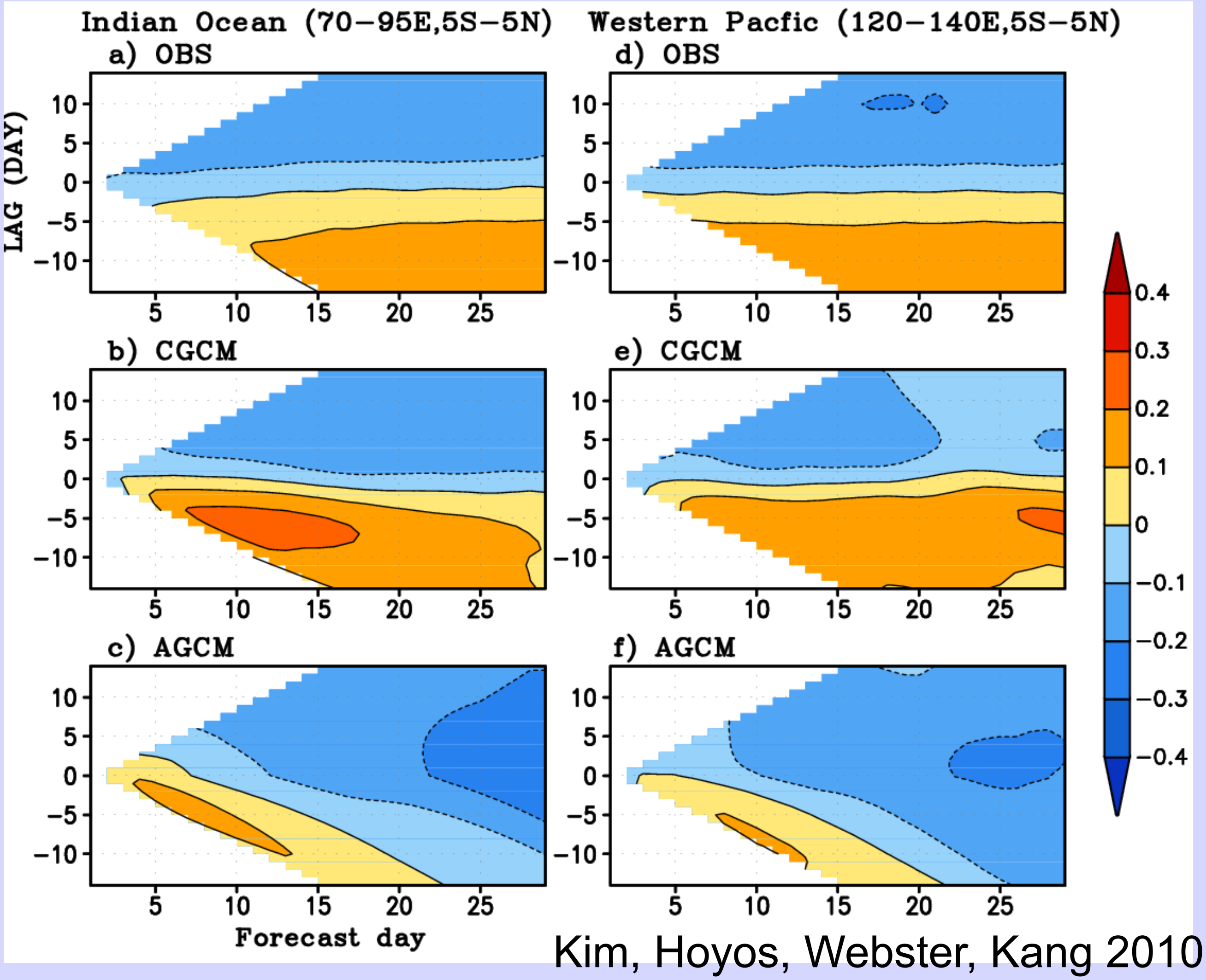
Lag Correlation: OLR & SST



Kim, Hoyos, Webster, Kang 2010 (Climate Dyn)

Wavenumber-frequency power spectra computed for the equatorial band (10˚S-10˚N) for VP200 averaged from 1-day to 30-day forecasts

Lag Correlation: OLR & SST

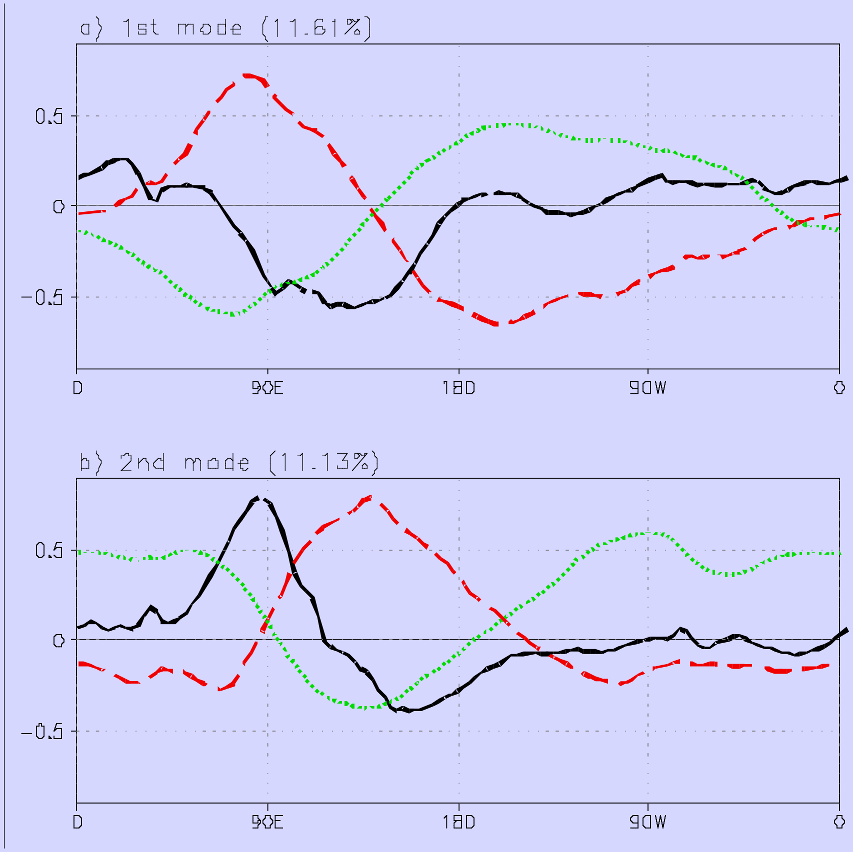


Kim, Hoyos, Webster, Kang 2010 (Climate Dyn)

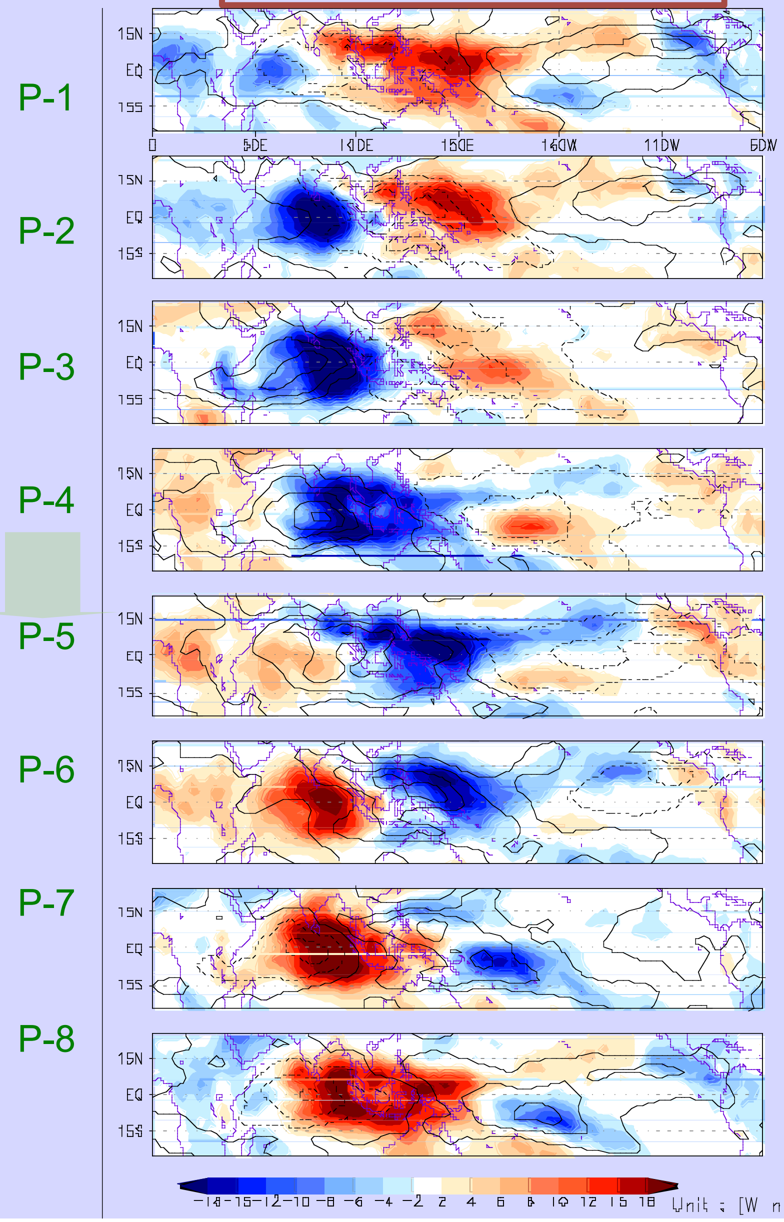
Lag-correlation coefficients between filtered OLR and SST anomalies as a function of forecast lead time. From the observed fields, positive SST leads enhanced convection.

Predictand: RMM index (Wheeler and Hendon 04)

- Eigen Vector of Combined EOF



8-Phases : OLR & U850



Observation Data Information

Variables	Period
OLR (AVHRR/NOAA)	**1979-2006 (28-years)**
Zonal wind (NCEP/NCAR R-2)	

Empirical model: Multi-linear regression

Kang and Kim (2010)

Predictability:
Predicted Reconstructed OLR and observed unfiltered OLR

Multi-linear regression

Prediction of RMMs
(multi-linear regression)

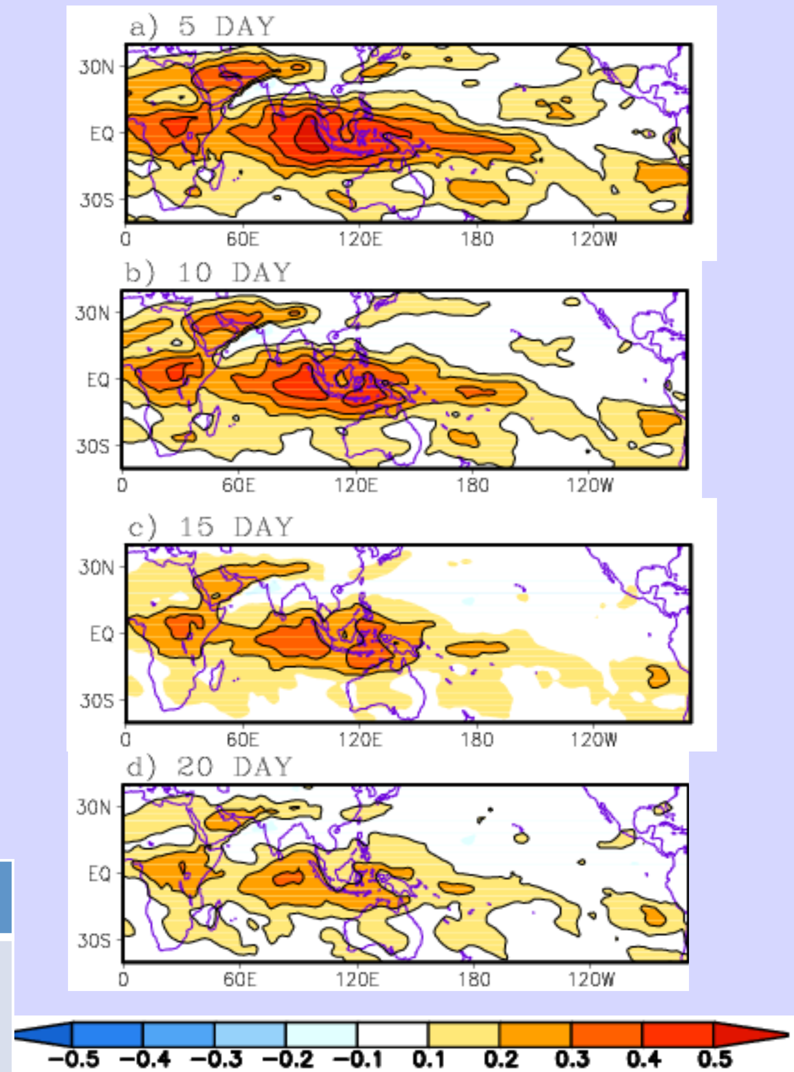
$$RMM_1(t_0+\tau)=\sum_{p=1}^{m} B_{1p}(\tau)RMM_p(t_0)$$

$$RMM_2(t_0+\tau)=\sum_{p=1}^{m} B_{2p}(\tau)RMM_p(t_0)$$

$m : PC(=2)$

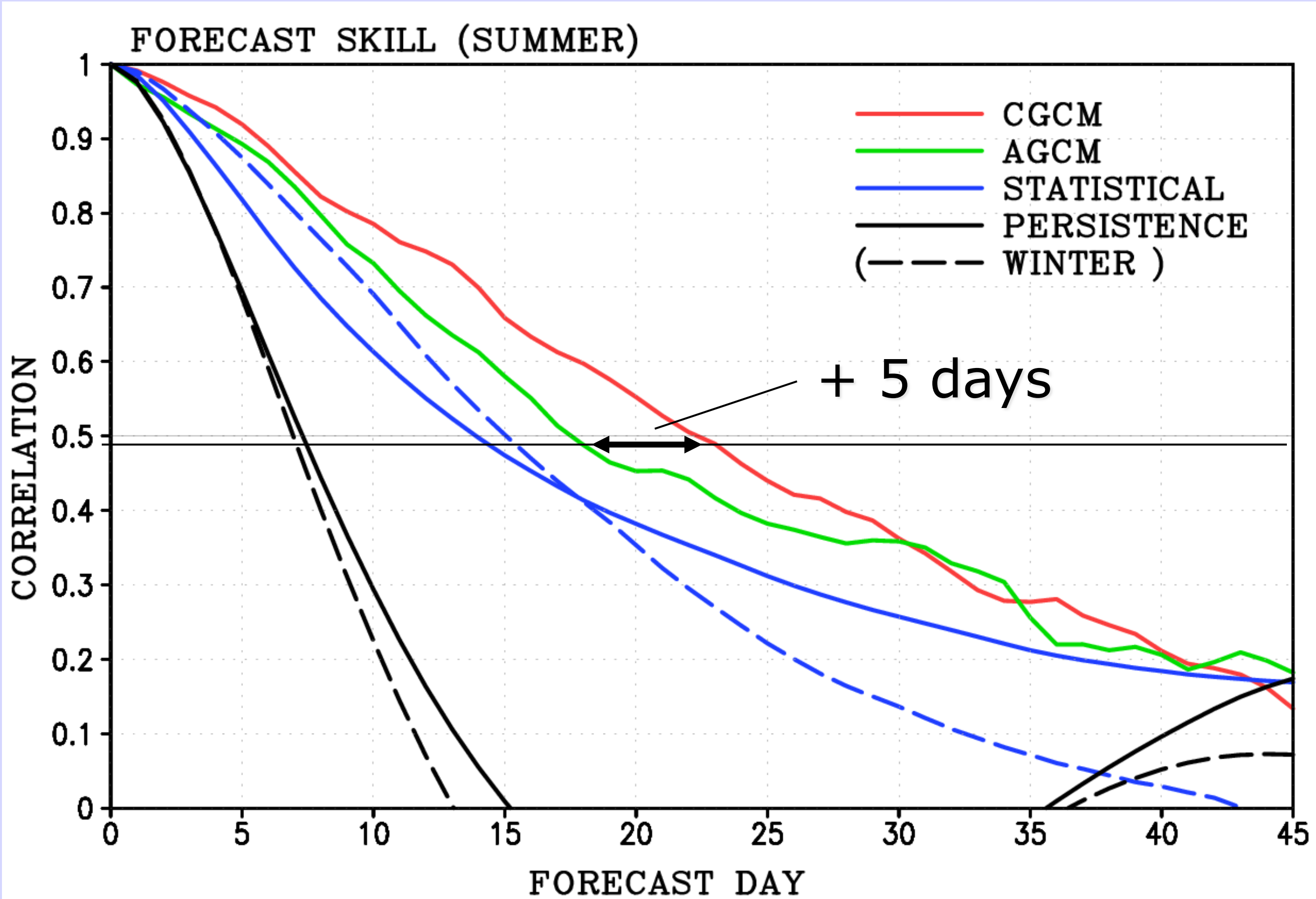
$B_{1,2p} : regression\ coeff$

$\tau : lead\ time$



Variables	Period
OLR (AVHRR/NOAA)	**1979-2006 (28-years)**
Zonal wind (NCEP/NCAR R-2)	

Forecast skill of RMM index



❖ The skills of dynamical models are better than those of the statistical predictions, especially when the ocean-atmosphere coupling is included.

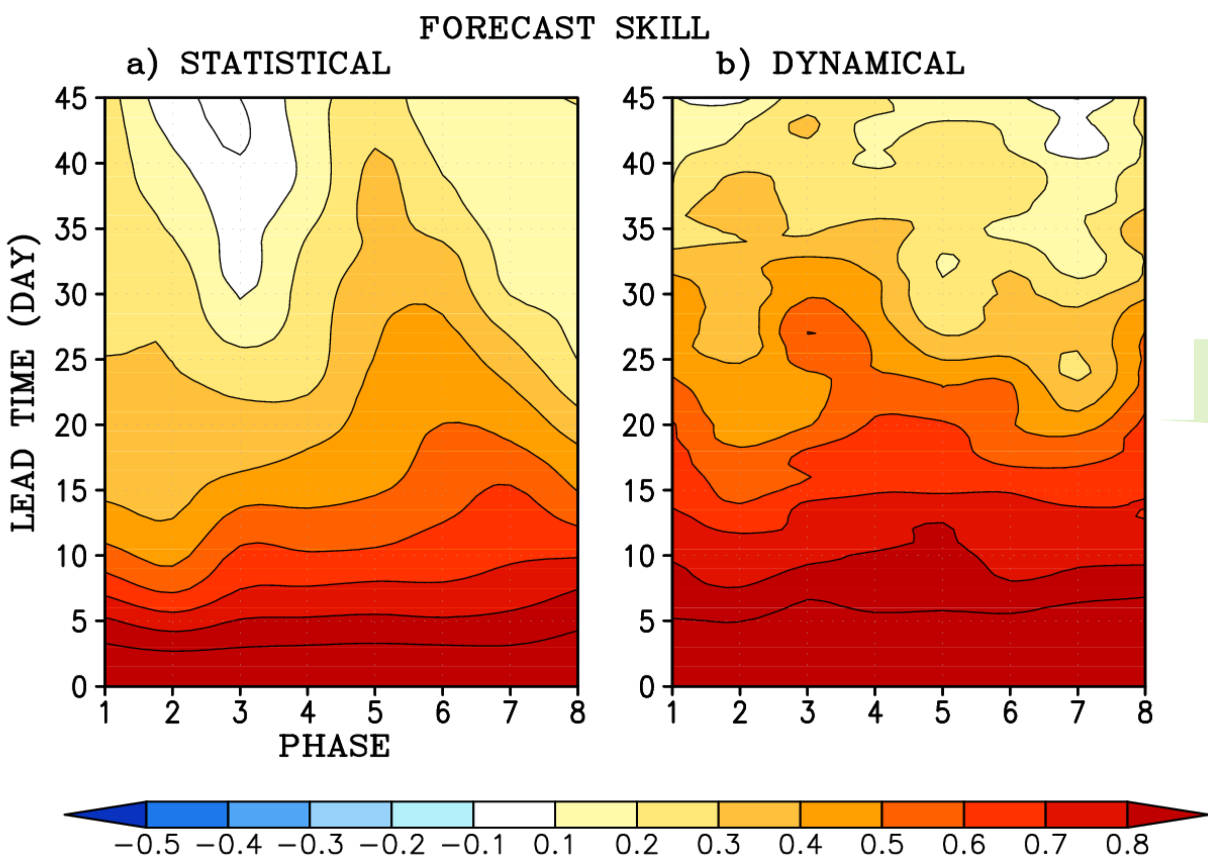
Correlation of RMM index =

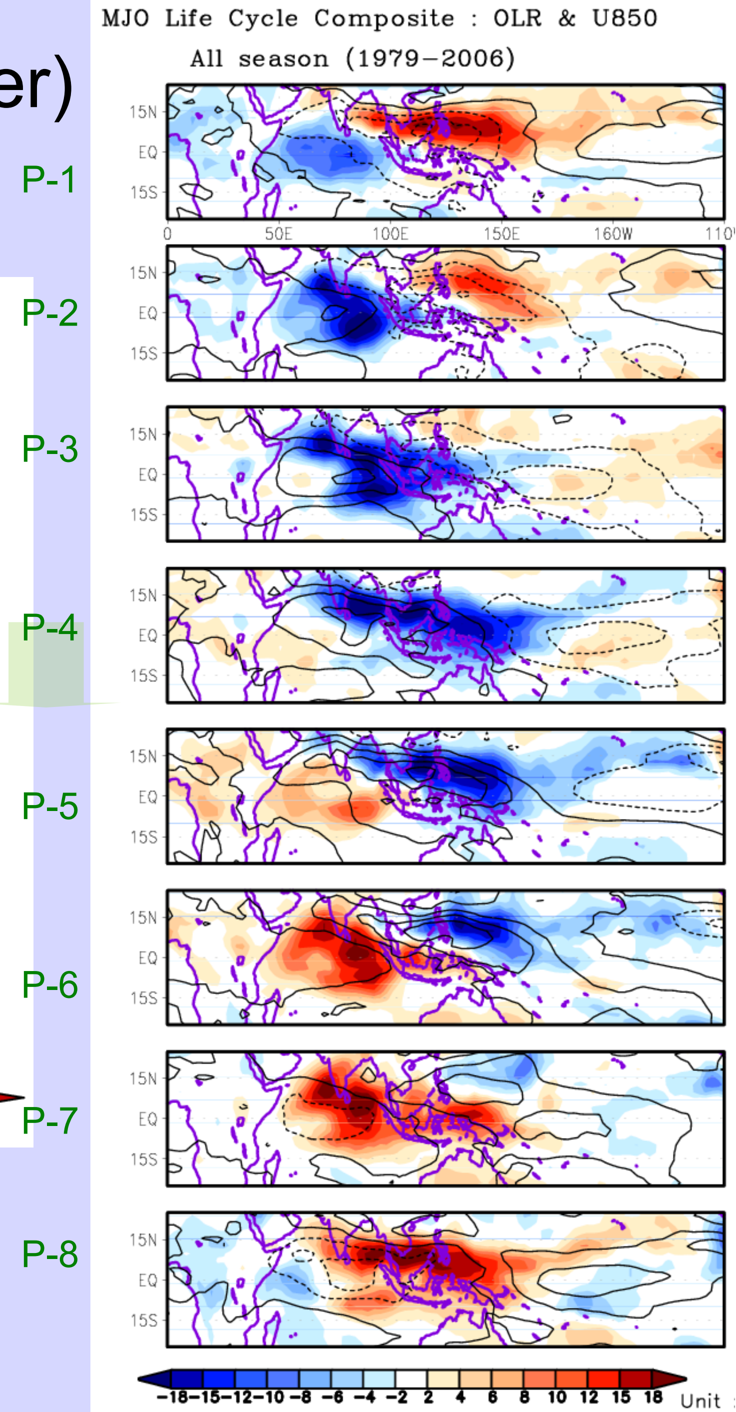
$$\frac{\left[\sum_{i=1}^{N} a_1(t)\cdot b_1(t) + a_2(t)\cdot b_2(t)\right]}{\sqrt{\sum_{i=1}^{N}[a^2{}_1(t)+a^2{}_2(t)]}\cdot\sqrt{\sum_{i=1}^{N}[b^2{}_1(t)+b^2{}_2(t)]}}$$

$a_1(t), a_2(t)$: observed RMM1,2 at day t

$b_1(t), b_2(t)$: simulated RMM1,2 at day t

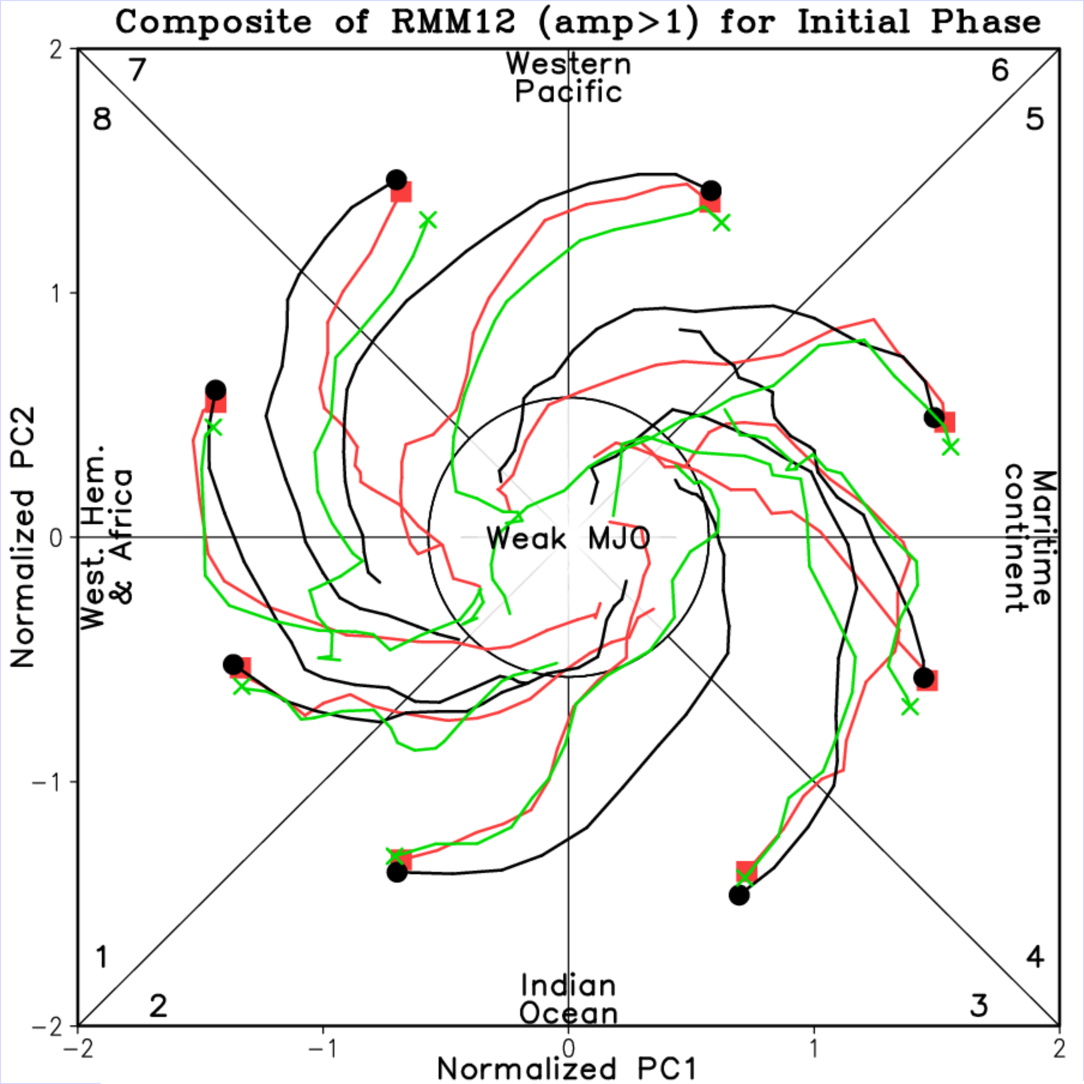
Forecast skill of RMM index (Summer)





The skill of the dynamical model shows little sensitivity to the initial MJO phase out to 15 days, while statistical model shows lower skill in phase 1-2 when MJO convection is developing in the Indian Ocean.

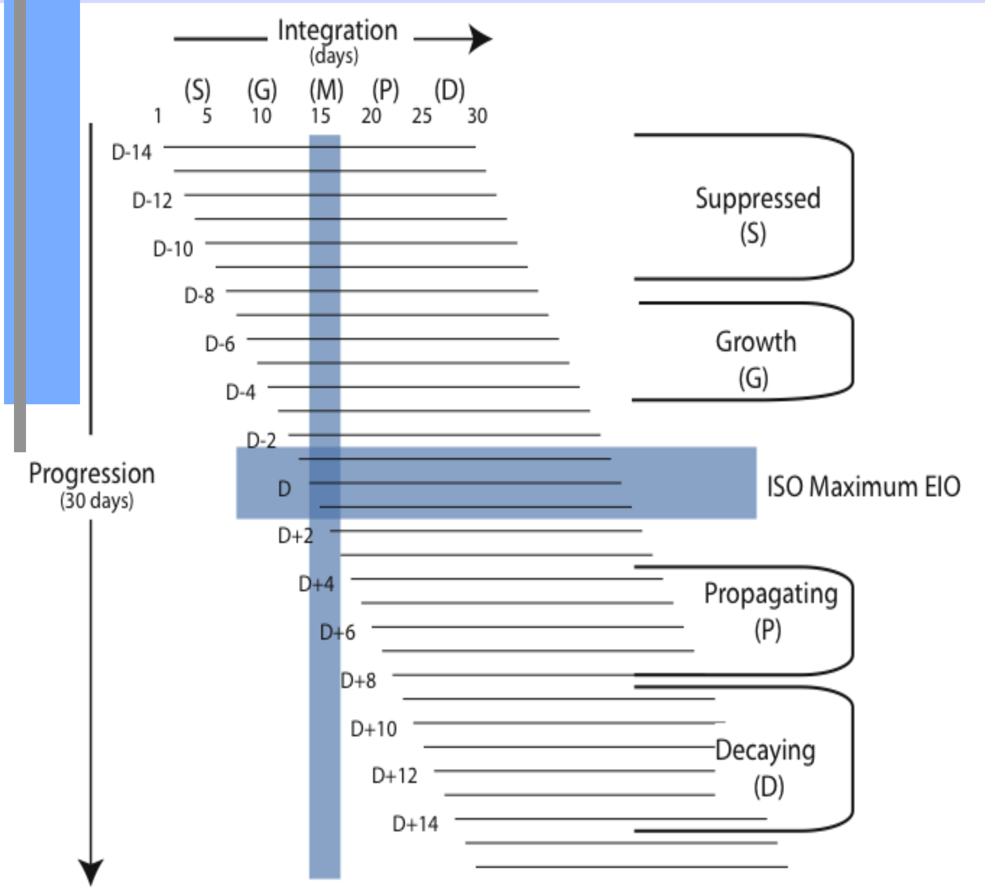
Forecast skill of RMM index (Summer)



-------- OBS -------- CGCM -------- AGCM

Error analysis from serial runs

Successive daily integration through all phases of ISO life cycle

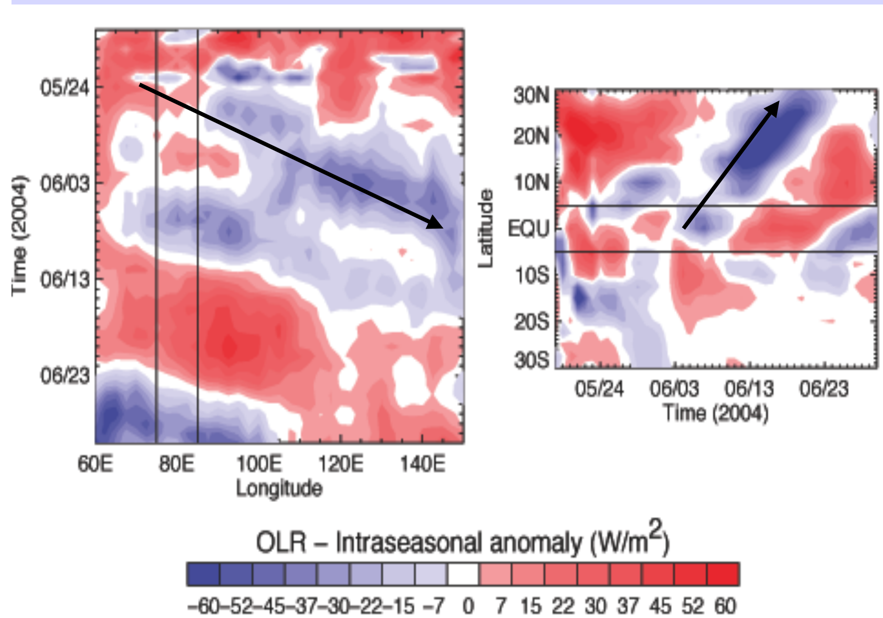


Use ECMWF climate model run for 30 day forecasts on 45 successive days in ensemble mode (5/day)

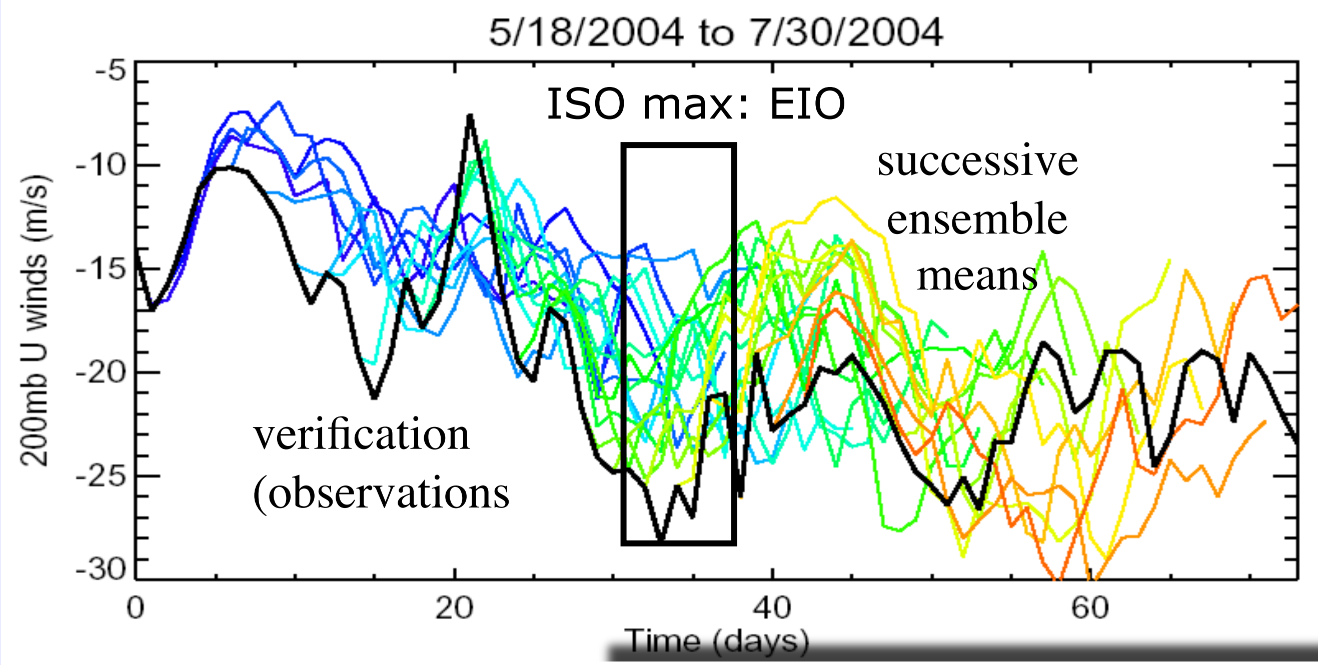
Three cases:

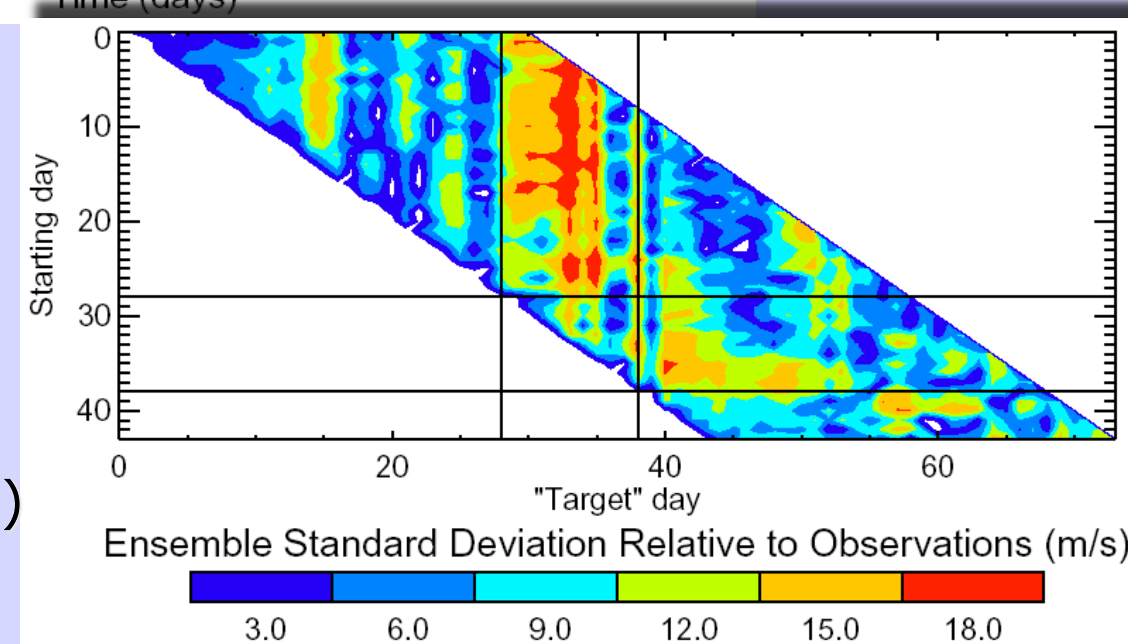
- o Winter: TOGA COARE, 1992/93
- o Summer: May/June 2004
- o Summer 2002

OLR variability through summer case



Results of the Coupled Ocean-Atmosphere Simulations





Where do the errors come from that destroy the strong intraseasonal signal?

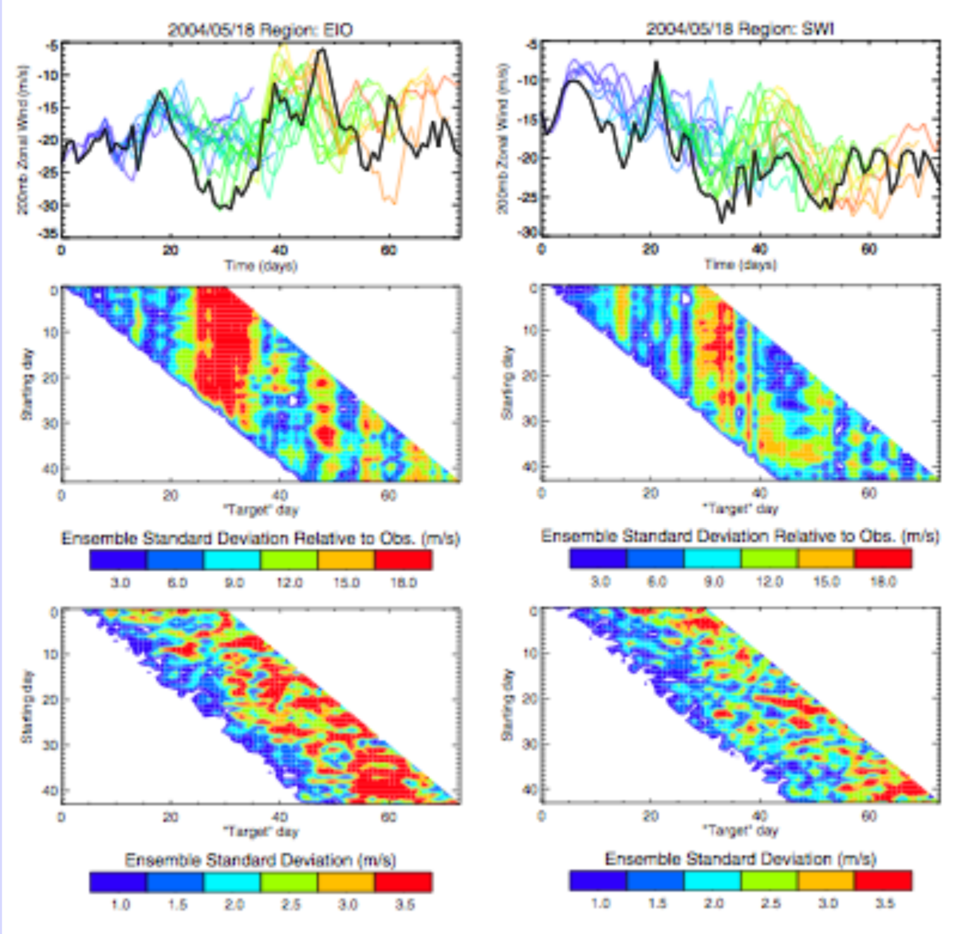
Hoyos and Webster (2007)
Kim et al. (2007)

Regional errors growth (200 mb wind field) Summer 2004

Errors grow with time and at times of intense convection

Equ IO

SW India



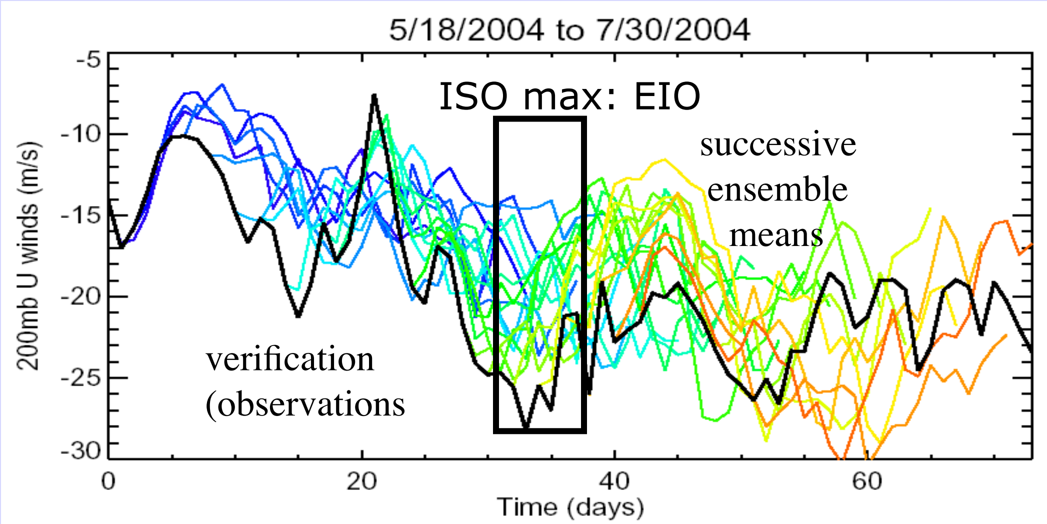
Ensemble mean evolution

Error growth relative to Observations

Error growth in ensemble spread

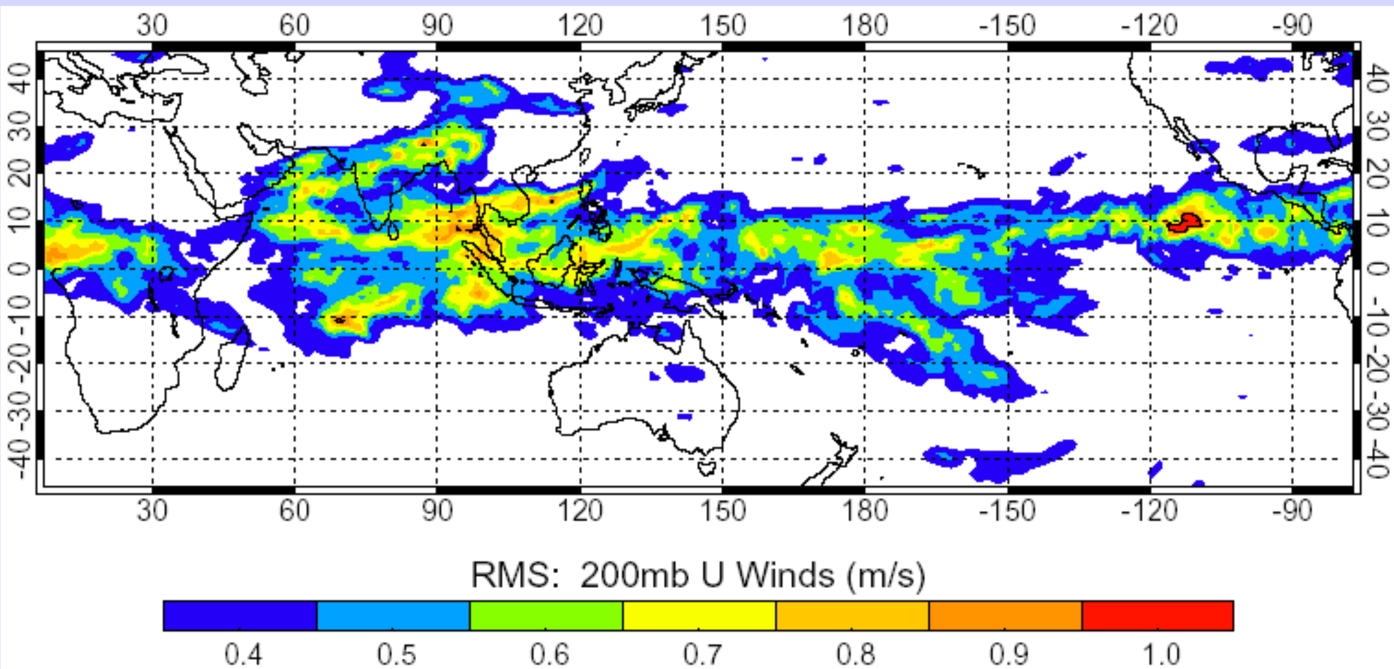
Hoyos and Webster (2007)
Kim et al. (2008)

Where do the errors come from?



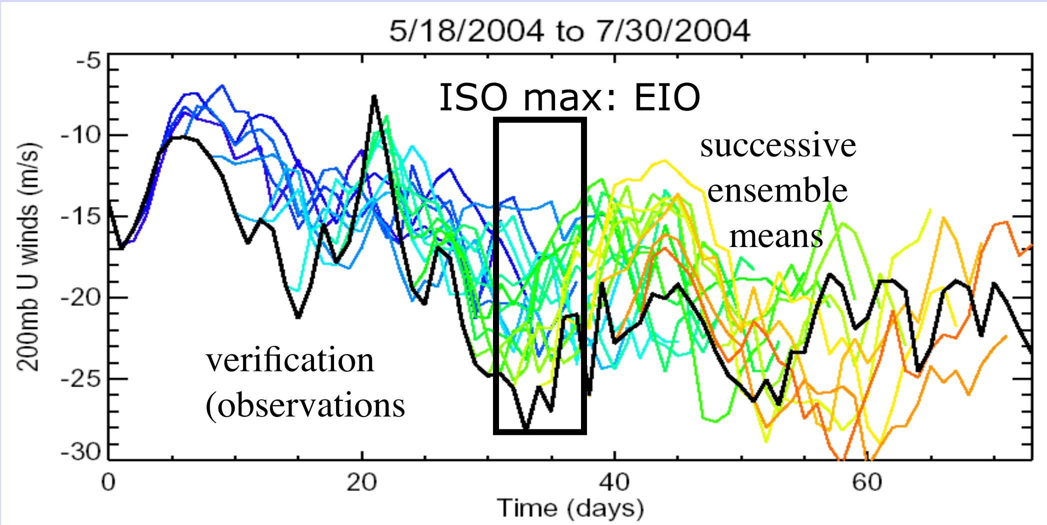
30-day integrations:

Show relatively good predictability out to 10-days except in regions of, or at times of high convective activity of the ISO



Day 1 Errors

Where do the errors come from?



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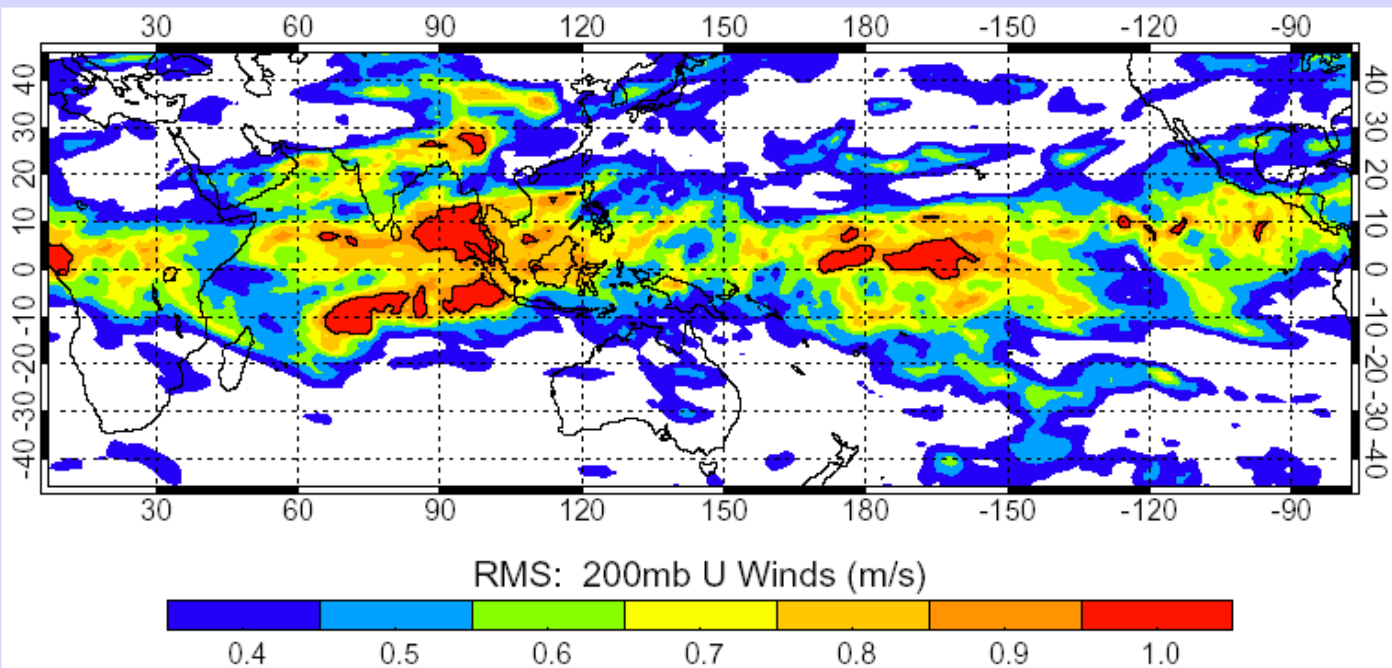
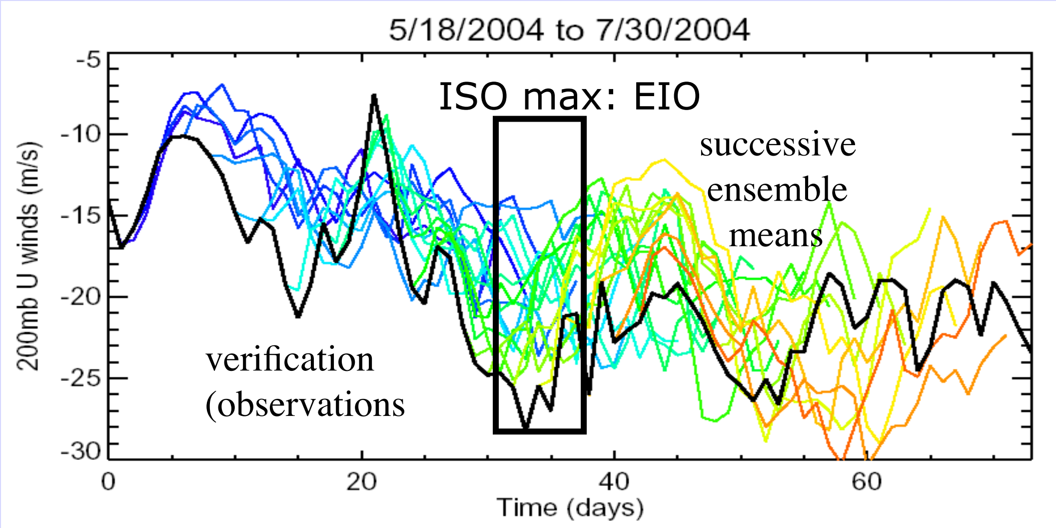


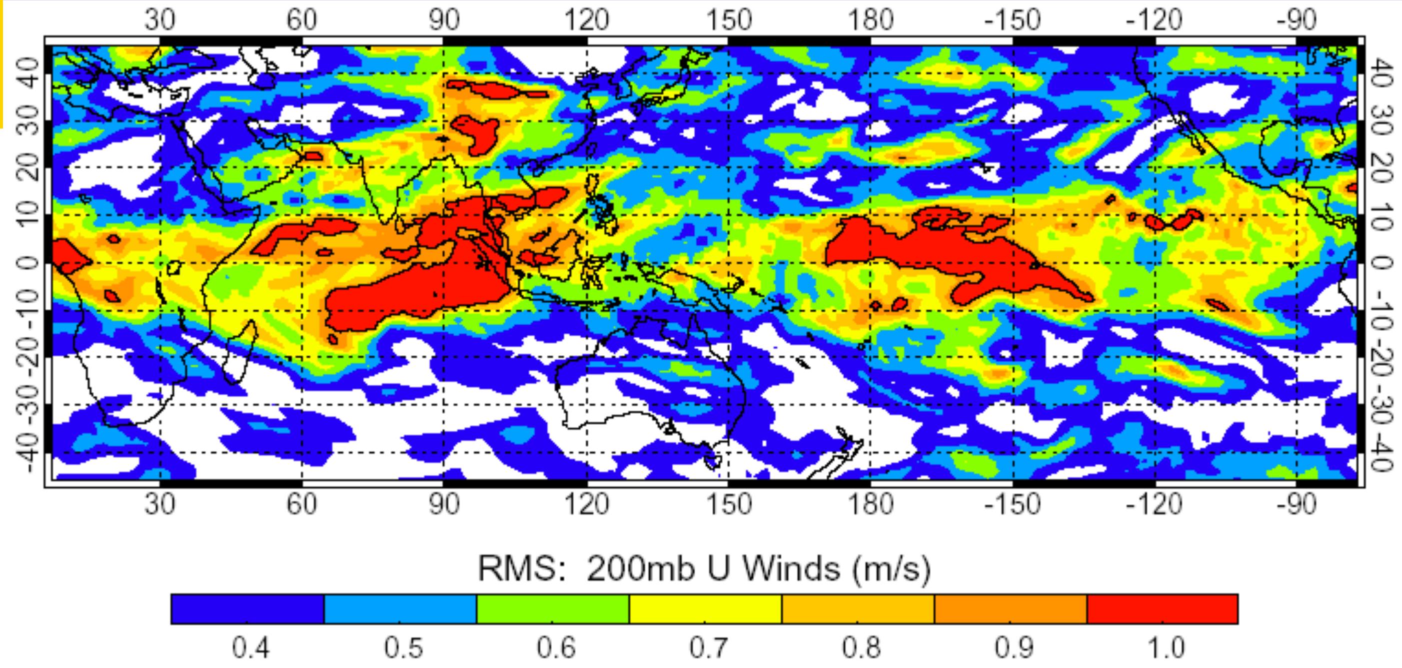
Day 2 Errors

Where do the errors come from?



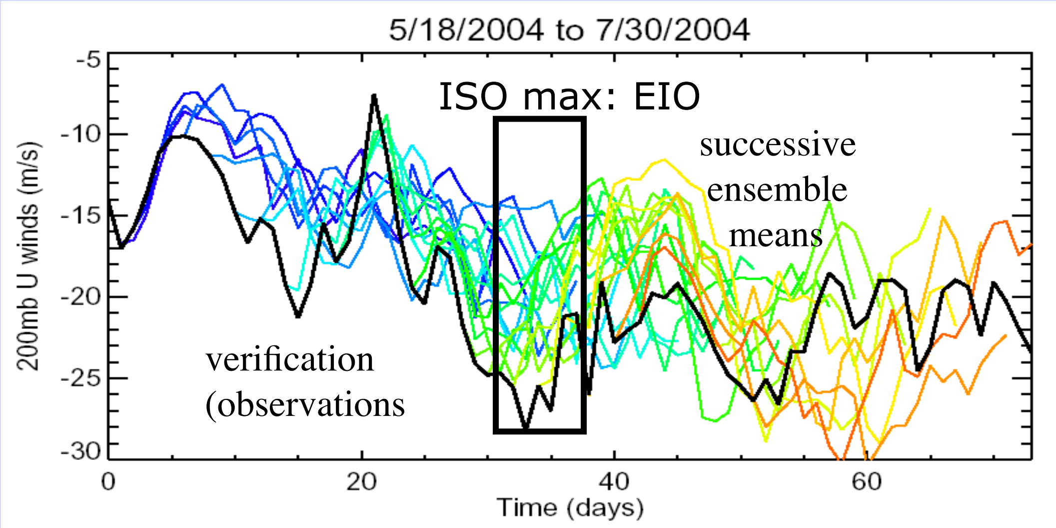
30-day integrations:

Show relatively good predictability out to 10-days except in regions of, or at times of high convective activity of the ISO



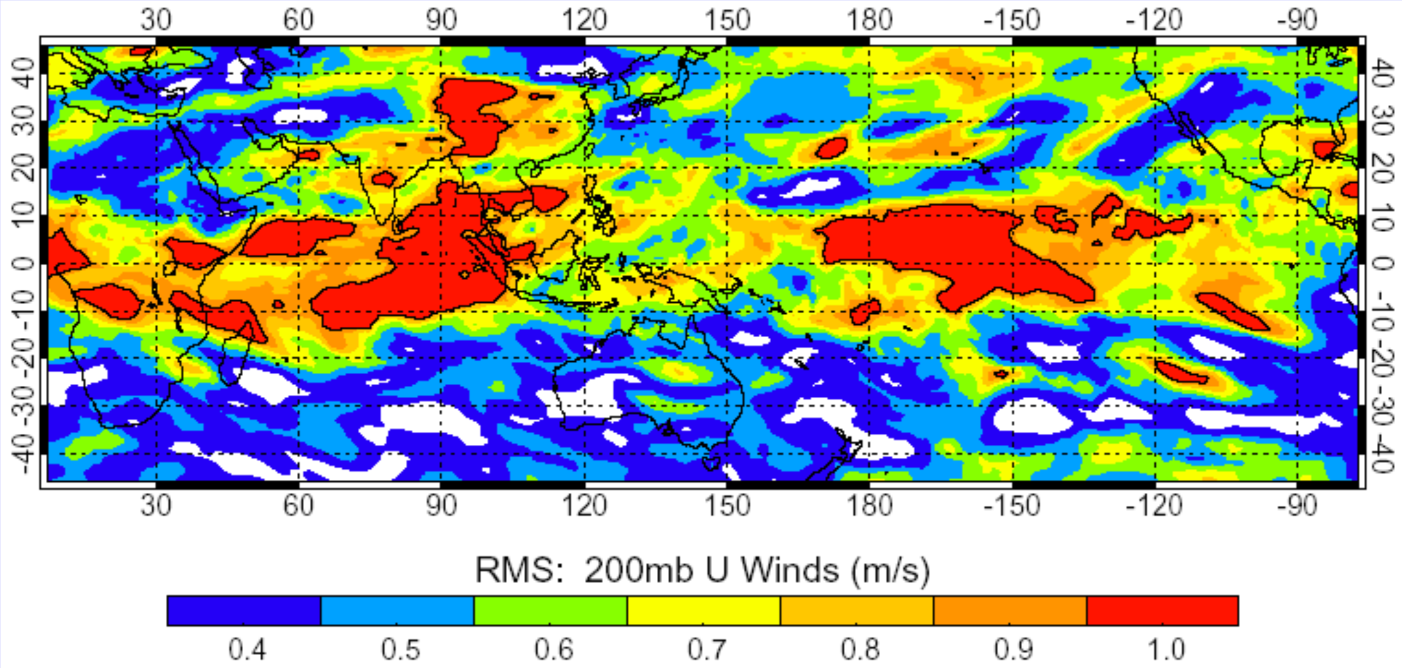
Day 3 Errors

Where do the errors come from?



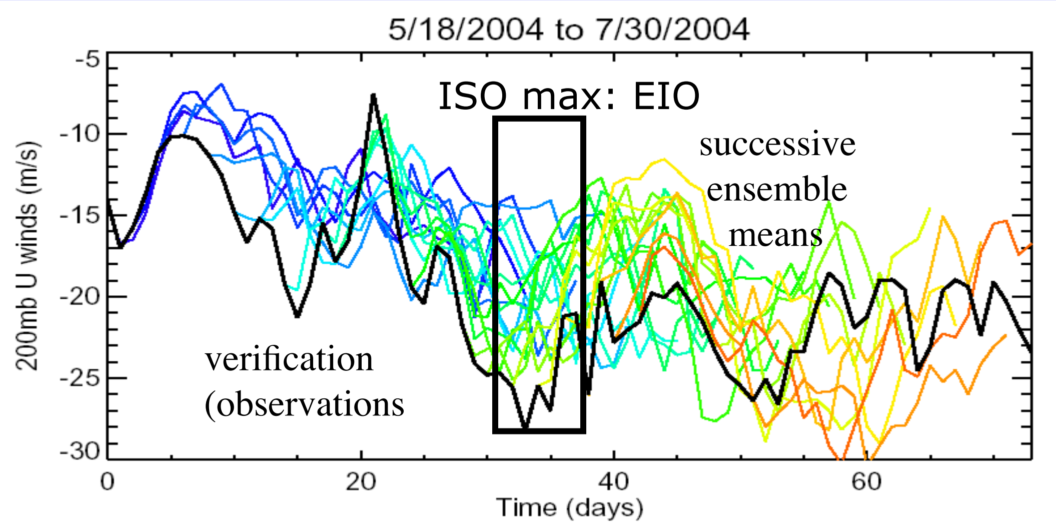
30-day integrations:

Show relatively good predictability out to 10-days except in regions of, or at times of high convective activity of the ISO



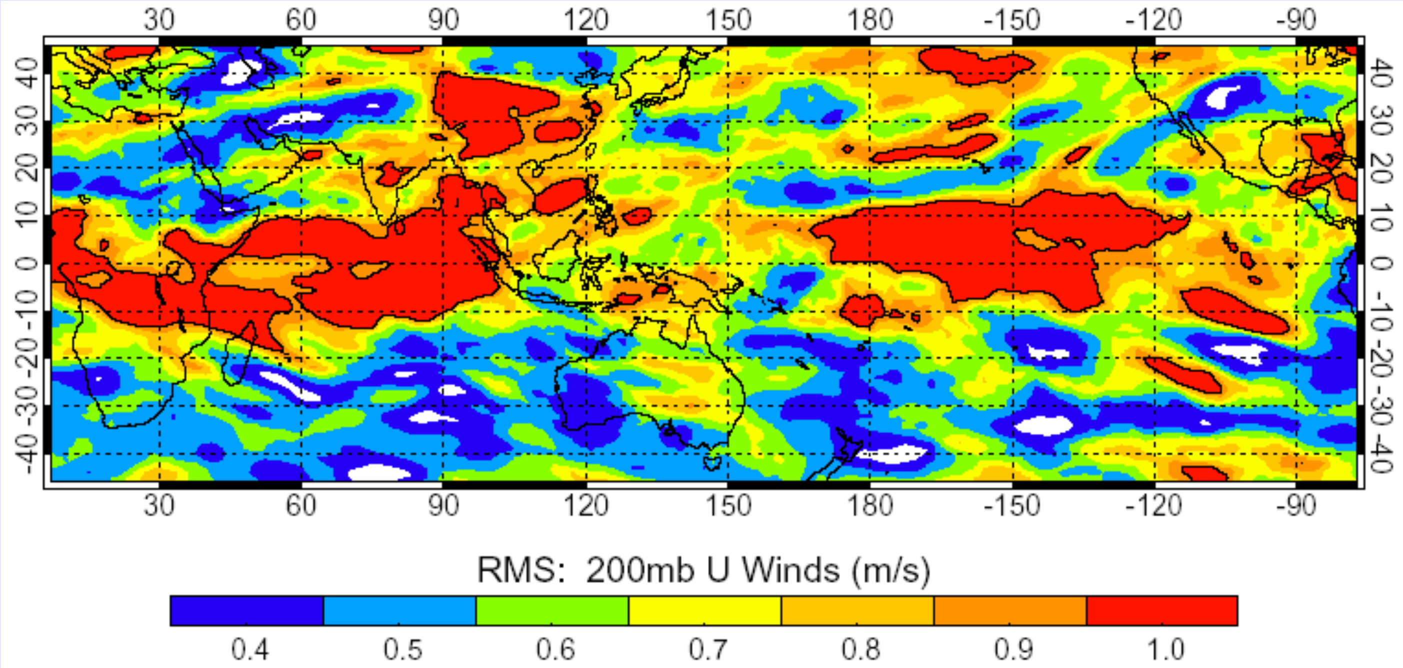
Day 4 Errors

Where do the errors come from?



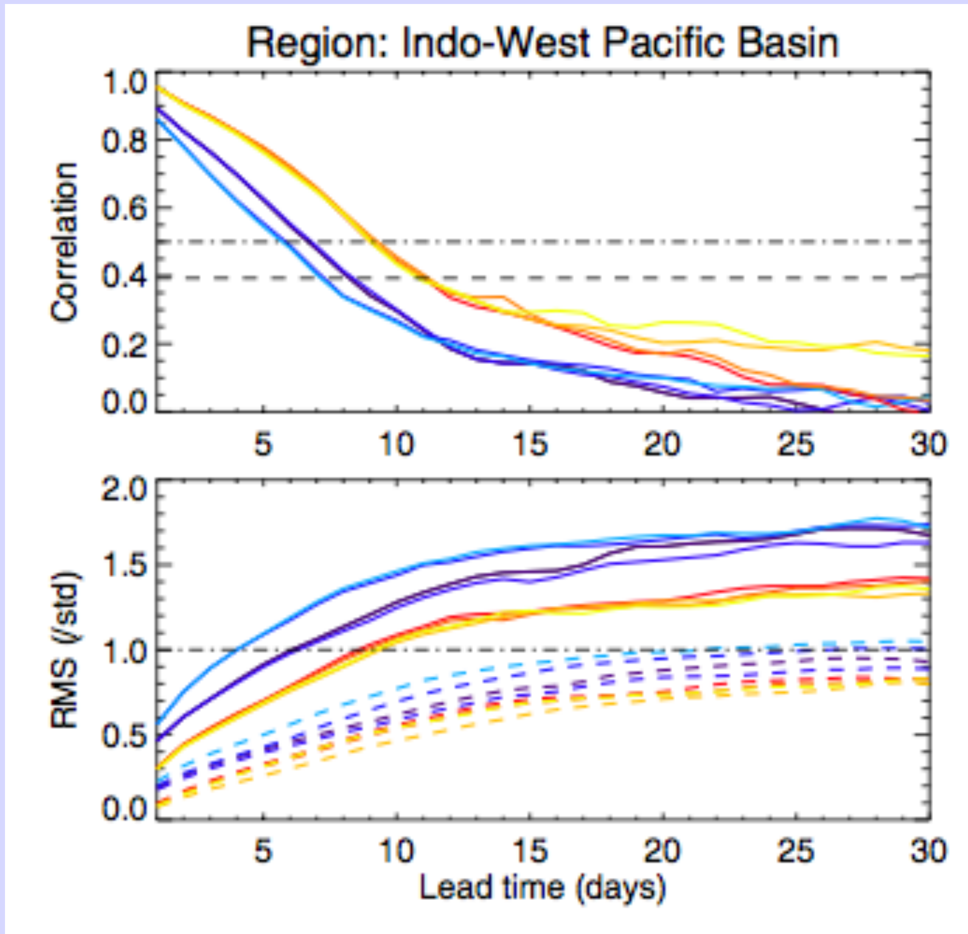
30-day integrations:

Show relatively good predictability out to 10-days except in regions of, or at times of high convective activity of the ISO



Day 5 Errors

Indian/West Pacific average correlation and RMS error evolution for OLR ( ) and 200 mb winds ( )

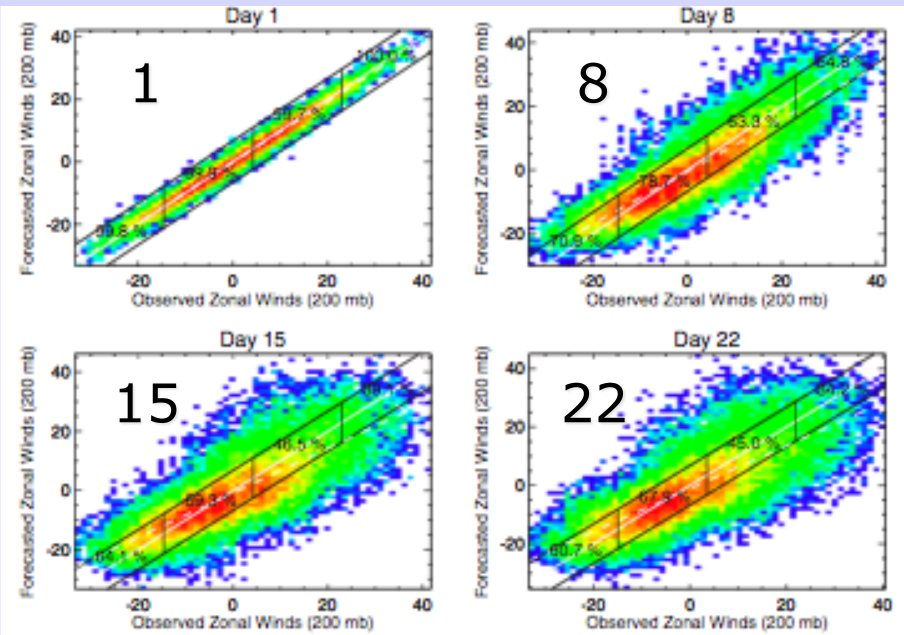


OLR tends to degrade more quickly than dynamic fields

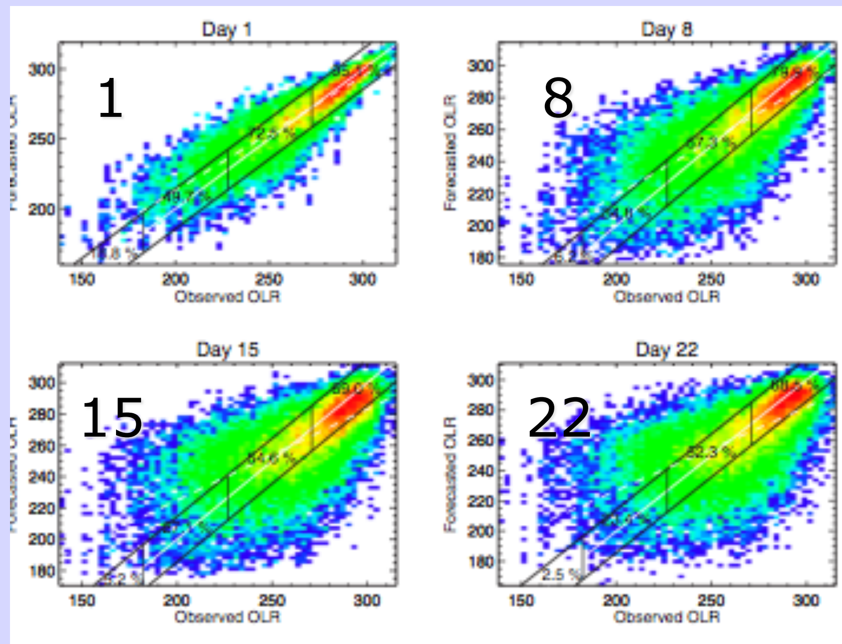
(Agudelo et al 2008)

Joint probability density function of 200mb wind field and OLR over the entire tropical belt (20S-20N, 0-360E)

200 mb wind field



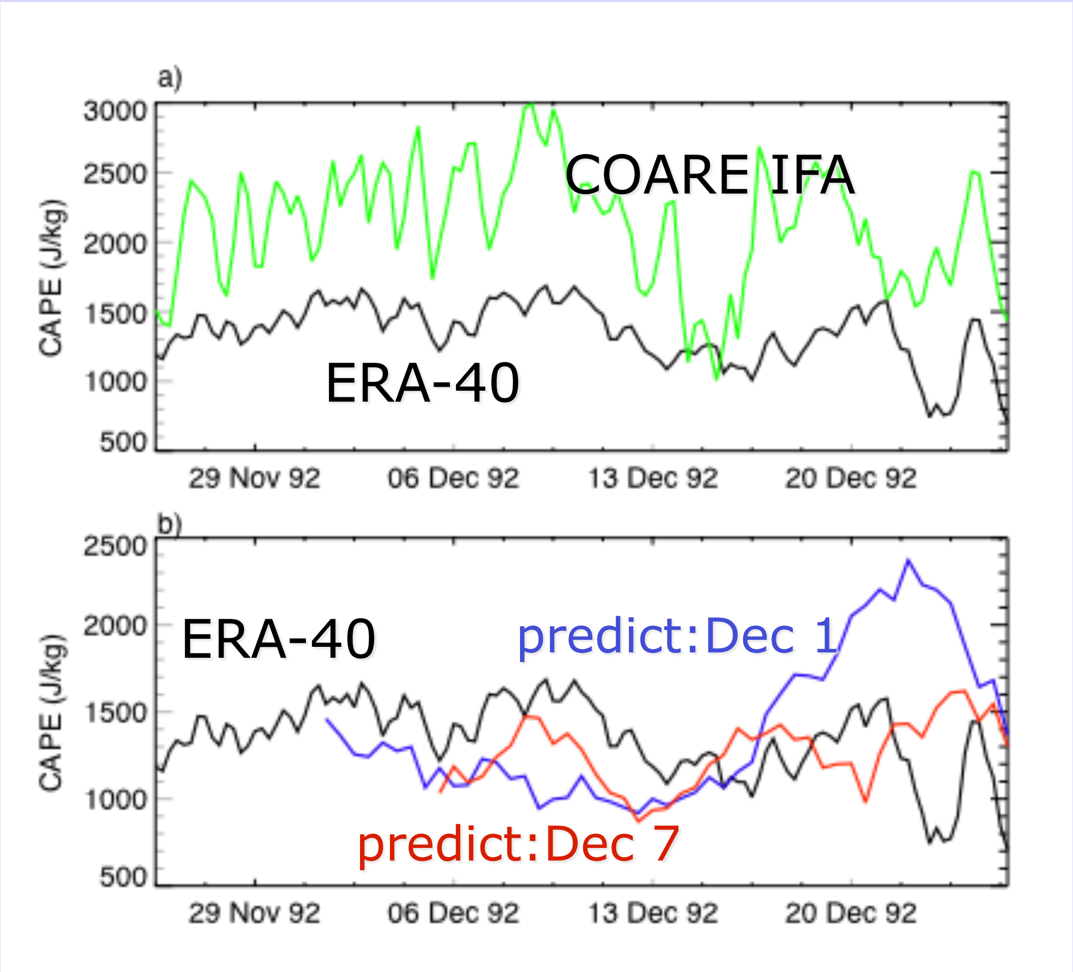
OLR



- ❑ OLR shows overall greater error spread with time
- ❑ Dynamic field errors uniform across range. OLR possesses largest errors at low values (or when there is deep convection)

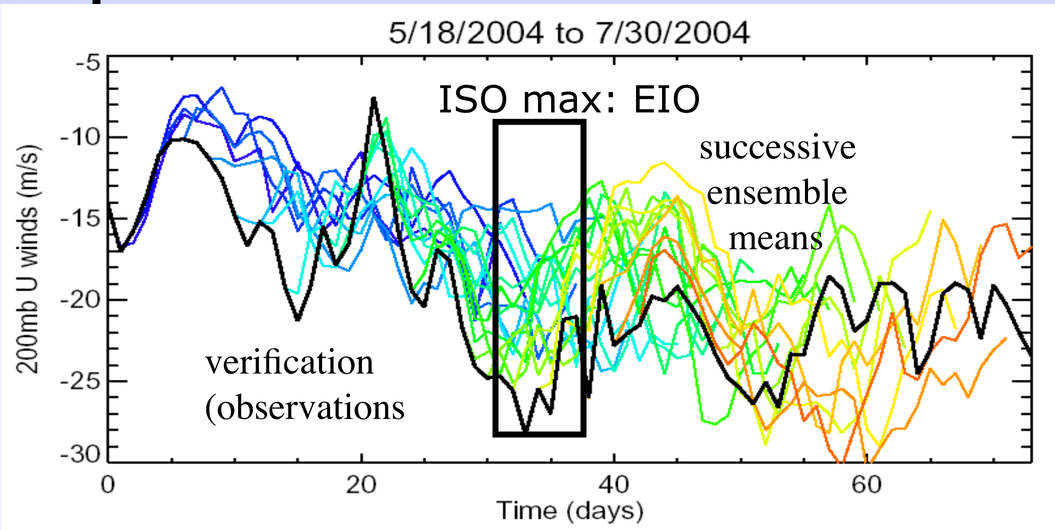
(Agudelo et al 2008)

CAPE Comparisons and moisture sensitivity: Winter case: Agudelo et al. (2008)



- Model does not simulate well CAPE evolution
- Sensitivity to initial conditions esp. in dry phase
- Need for model to simulate properly the suppressed and transitional phases of the ISO

SUMMARY of SERIAL INTEGRATIONS



30-day integrations:

Moderate predictability out to 10 days except in regions and times of deep convection

- Errors rapidly grow in the regions of maximum convection
- Error growth so rapid from small scale convection that variability at longer scales is eroded and loses identity
- As intraseasonal prediction is important and the need is immediate we have to face reality and develop a new modeling paradigm:

Modifying numerical modeling

- Convective parameterization continues to be a problem and is a likely culprit for ISO degradation.
- How to maintain the “real” convective heating signal while minimizing randon heating errors.
- We employ a **TRICK** to statistically achieve this in numerical prediction

Modifying numerical modeling

- Convective parameterization continues to be a problem and is a likely culprit for ISO degradation.
- How to maintain the “real” convective heating signal while minimizing randon heating errors.
- We ~~employ a **TRICK**~~ **CHEAT** to statistically achieve this in numerical prediction

Modifying numerical modeling

- Convective parameterization continues to be a problem and is a likely culprit for ISO degradation.
- How to maintain the "real" convective heating signal while minimizing randon heating errors.
- We ~~employ a **TRICK CHEAT**~~ **USE A REMARKABLY CLEVER TECHNIQUE** to statistically achieve this in numerical prediction
- The technique is based on wavelet banding used in the empirical forecasts

CAUTION: The Director of WCRP has issued a warning that modeling purists may be offended by the following material. It is recommended that graduate students and those without tenure refrain from viewing the following slides!

“Slow Manifold Modeling” of Intraseasonal Variability: Concept

(1) Hypothesis:

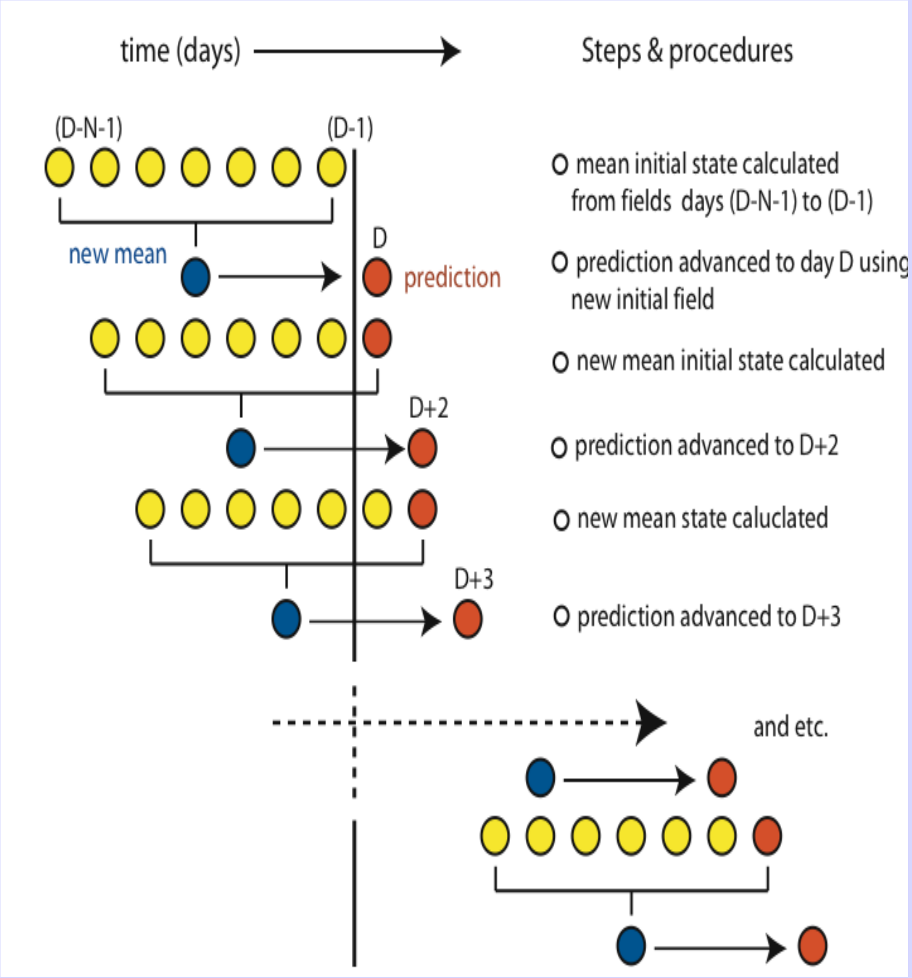
- Separation of convective noise and slow manifold intraseasonal variability will increase 20-40 day predictability

(2) Strategy:

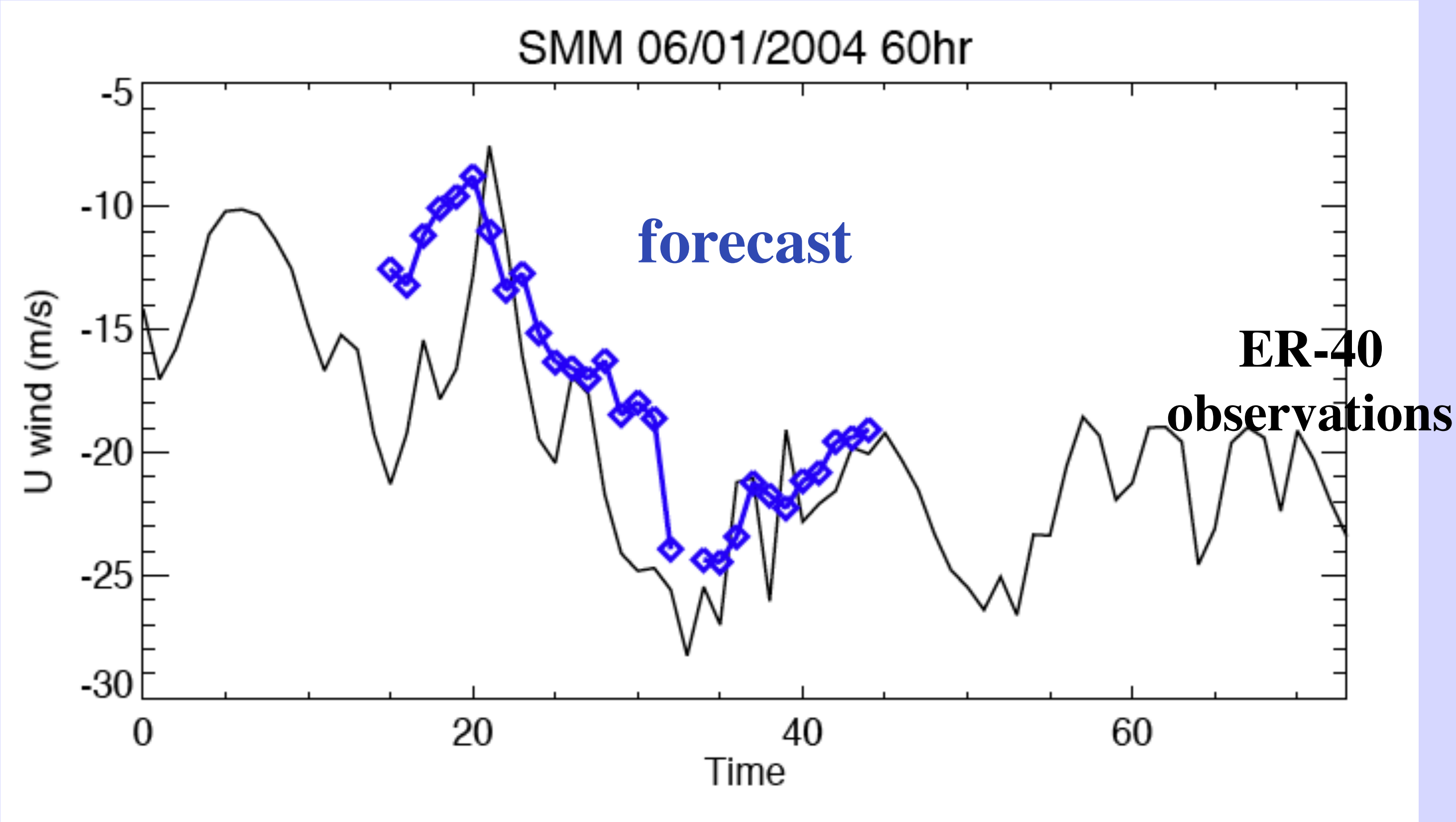
- Quell upscale destructive influence of convective parameterization error by “creeping” integration
- Scale separation similar to the “banded wavelet” scheme of Webster and Hoyos (2004)

(3) Status:

- Currently running experimentally at ECMWF



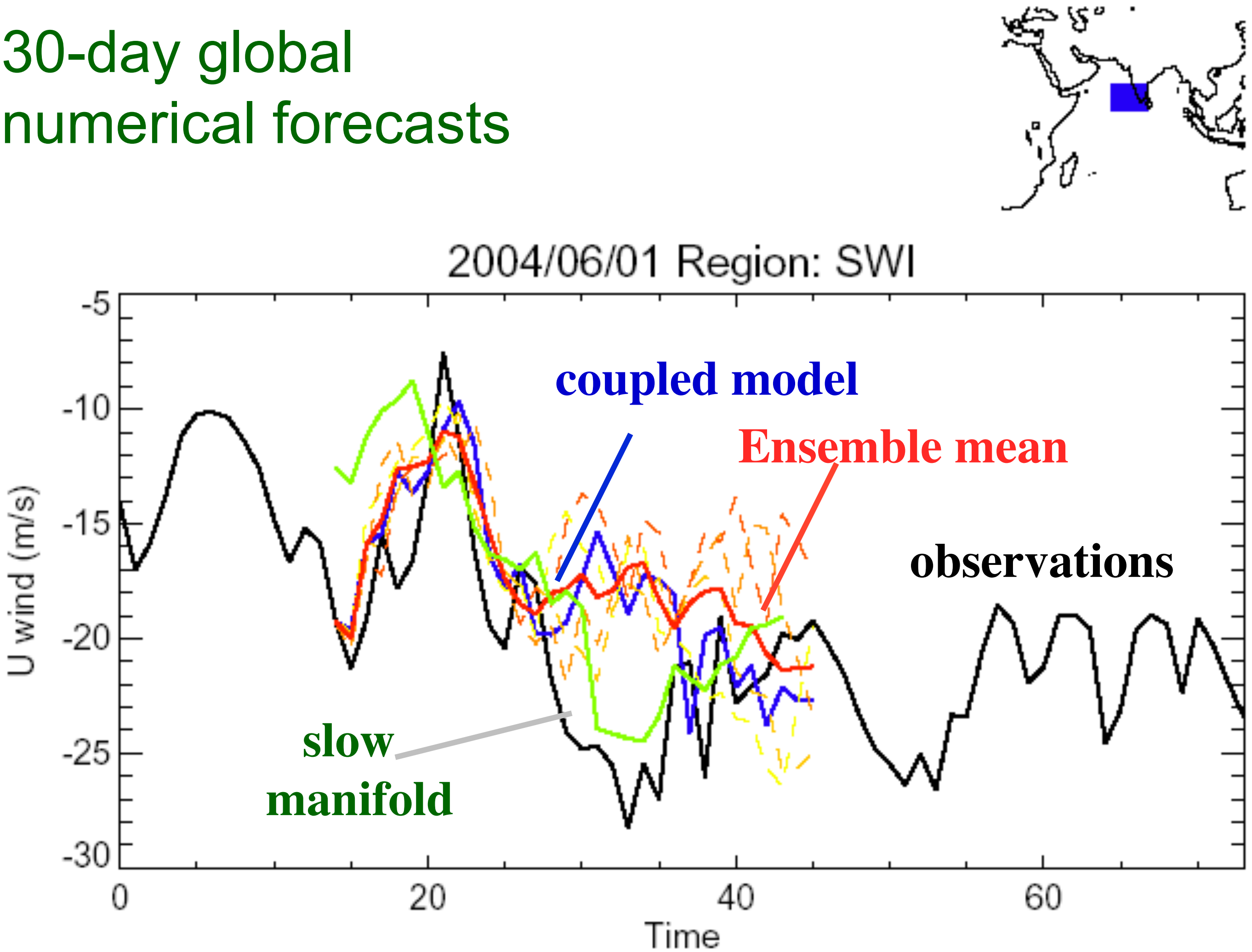
30-day forecast using SMM



SMM models this aspect of the the intraseasonal variability of the monsoon quite well. Field is 200mb wind field over southern India. This result uses N=7

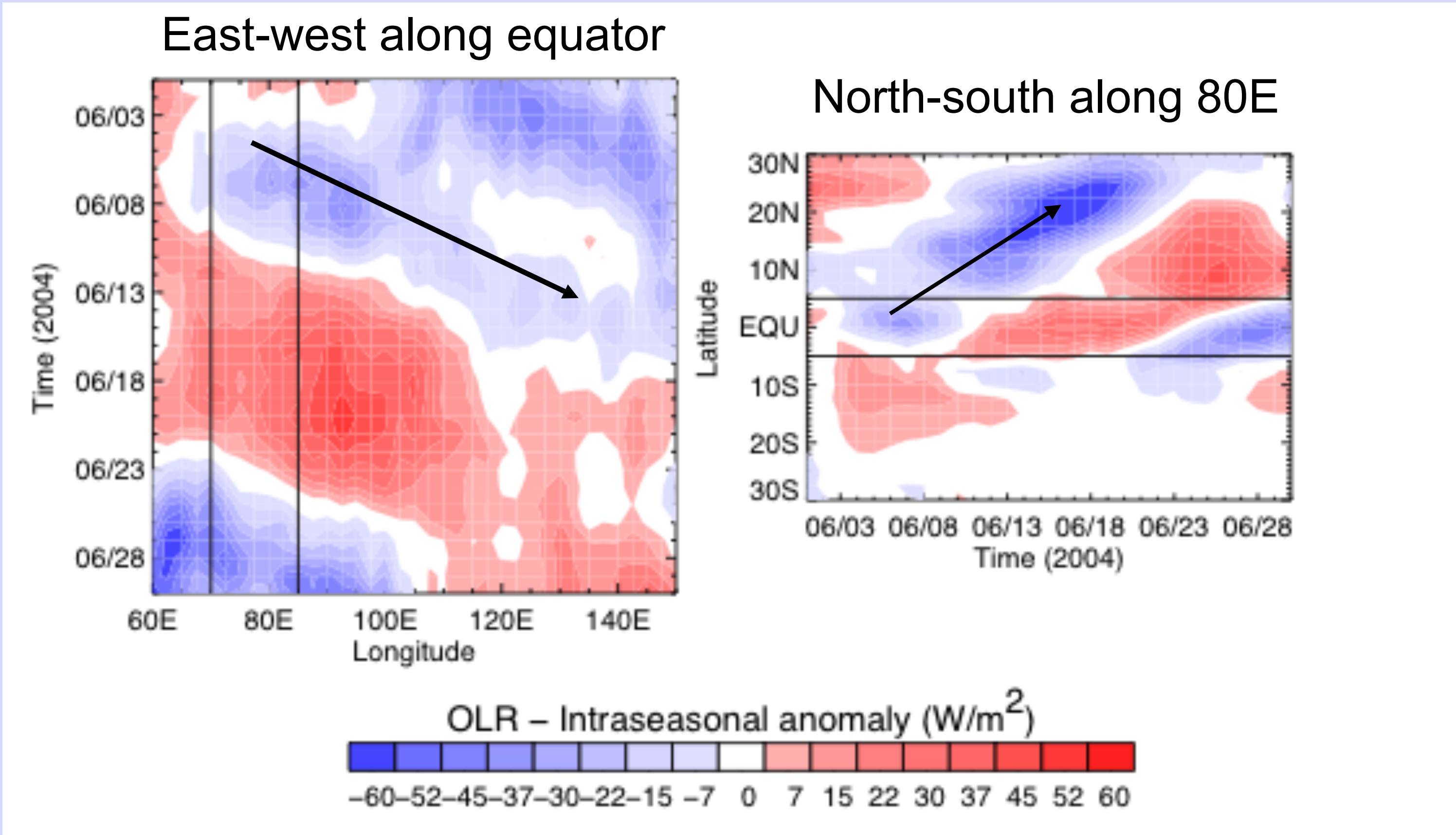
Comparison of Slow Manifold Model with coupled climate model

30-day global
numerical forecasts

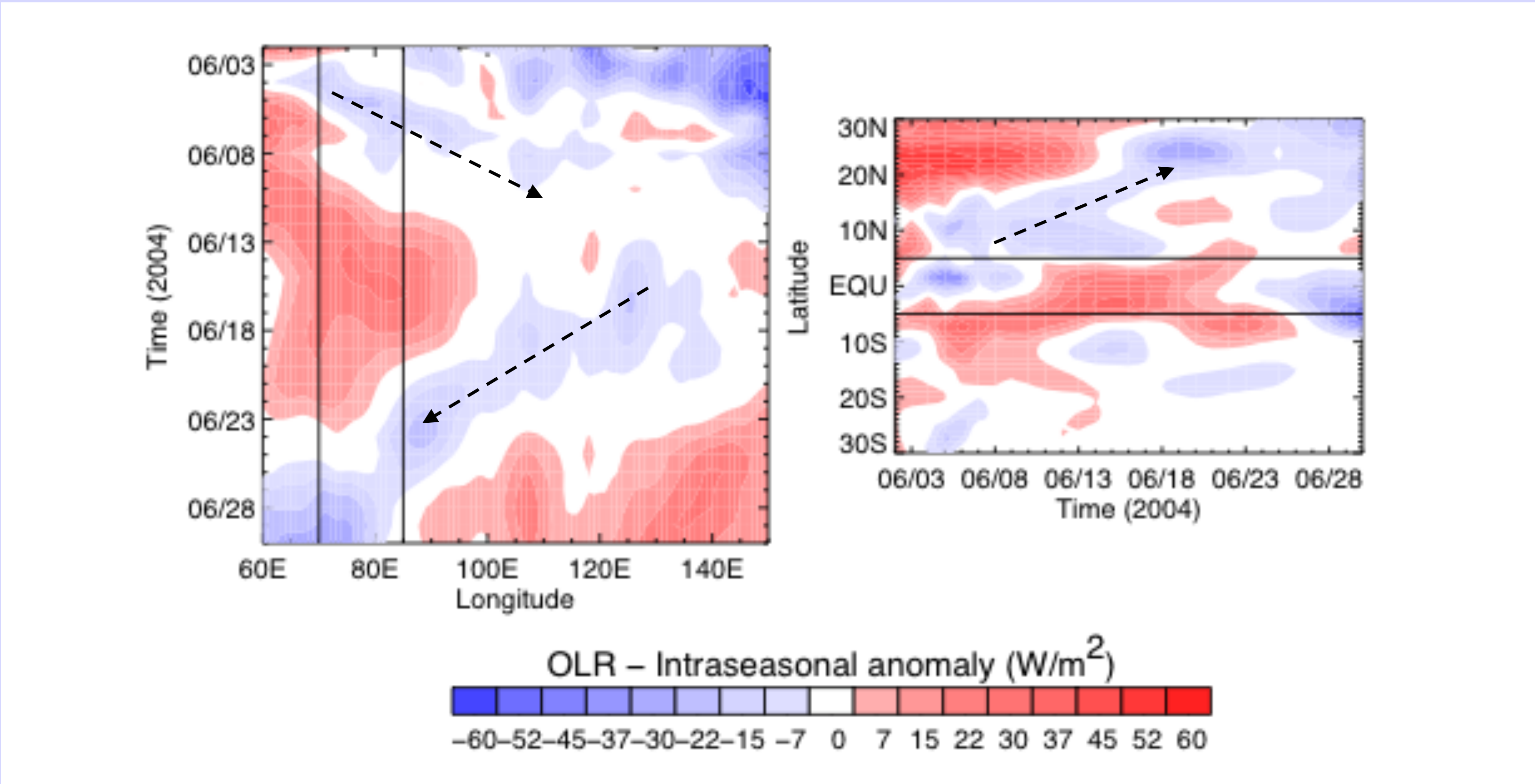


Slow Manifold technique provides more accurate longer term prediction

The CDC OLR evolution during May 2004 in Indian Ocean

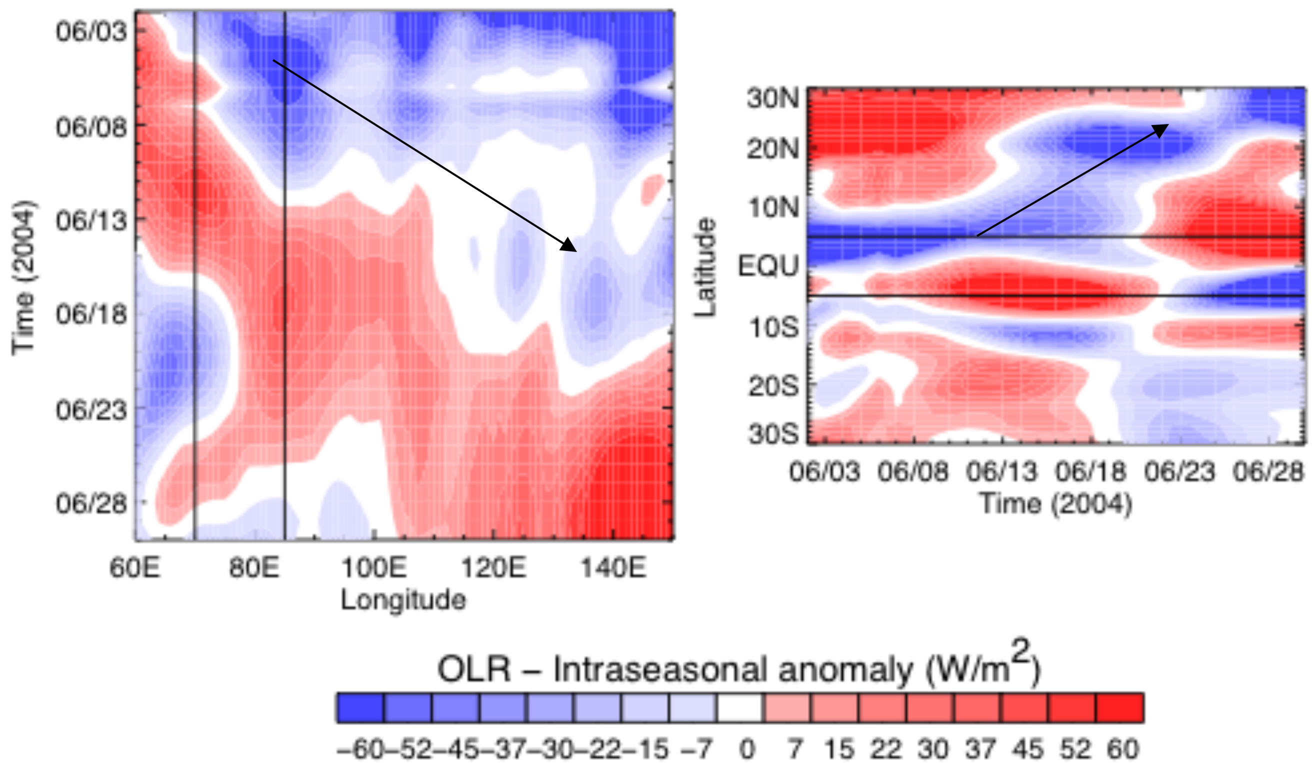


OLR of Ensemble mean of EC-CM



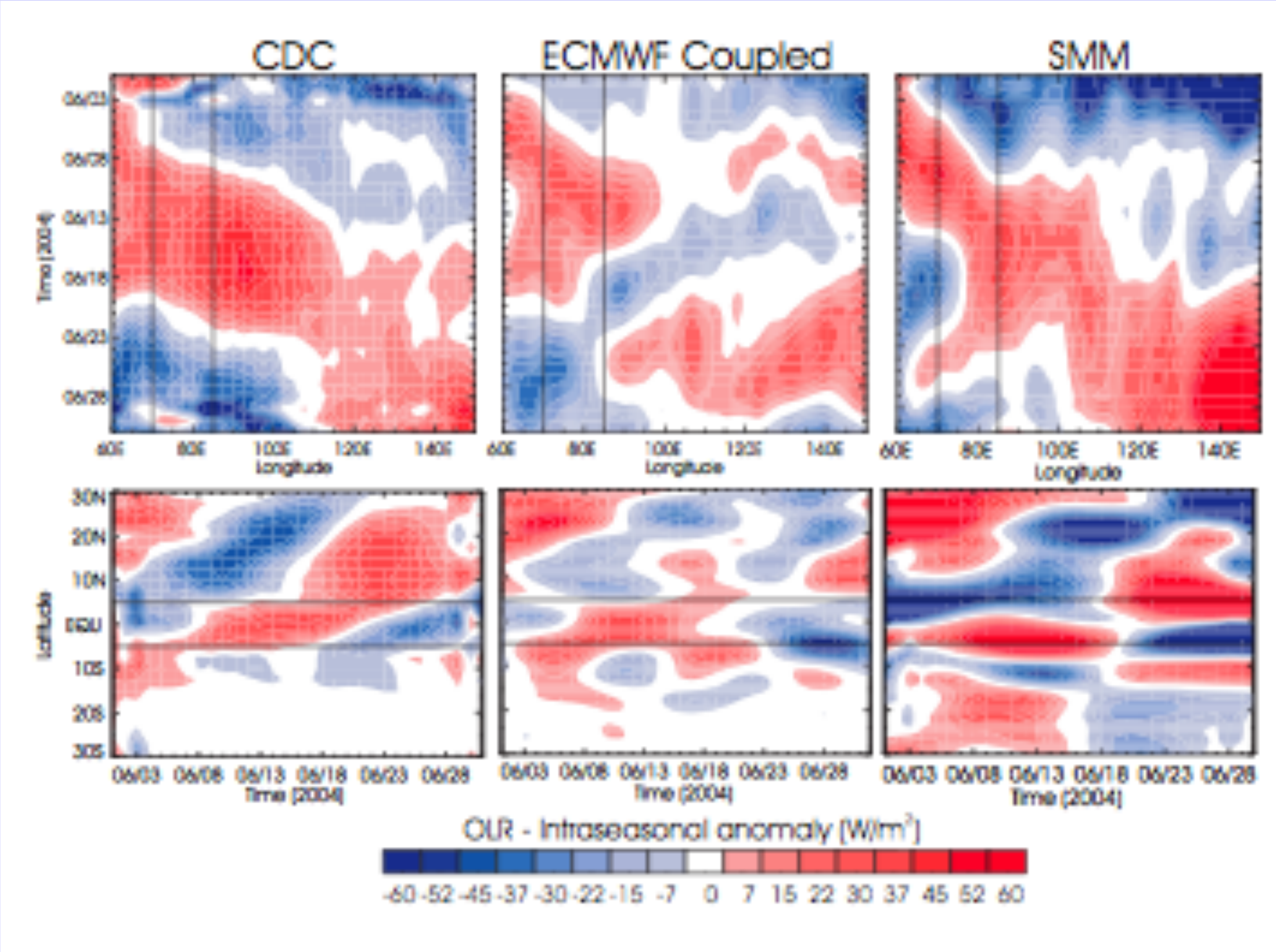
Note that the precipitation events rapidly loses identity as it propagates eastward and is replaced by a mode moving towards the west.

OLR of SMM (I.e., the EC-CM with the SMM modifications N=5)



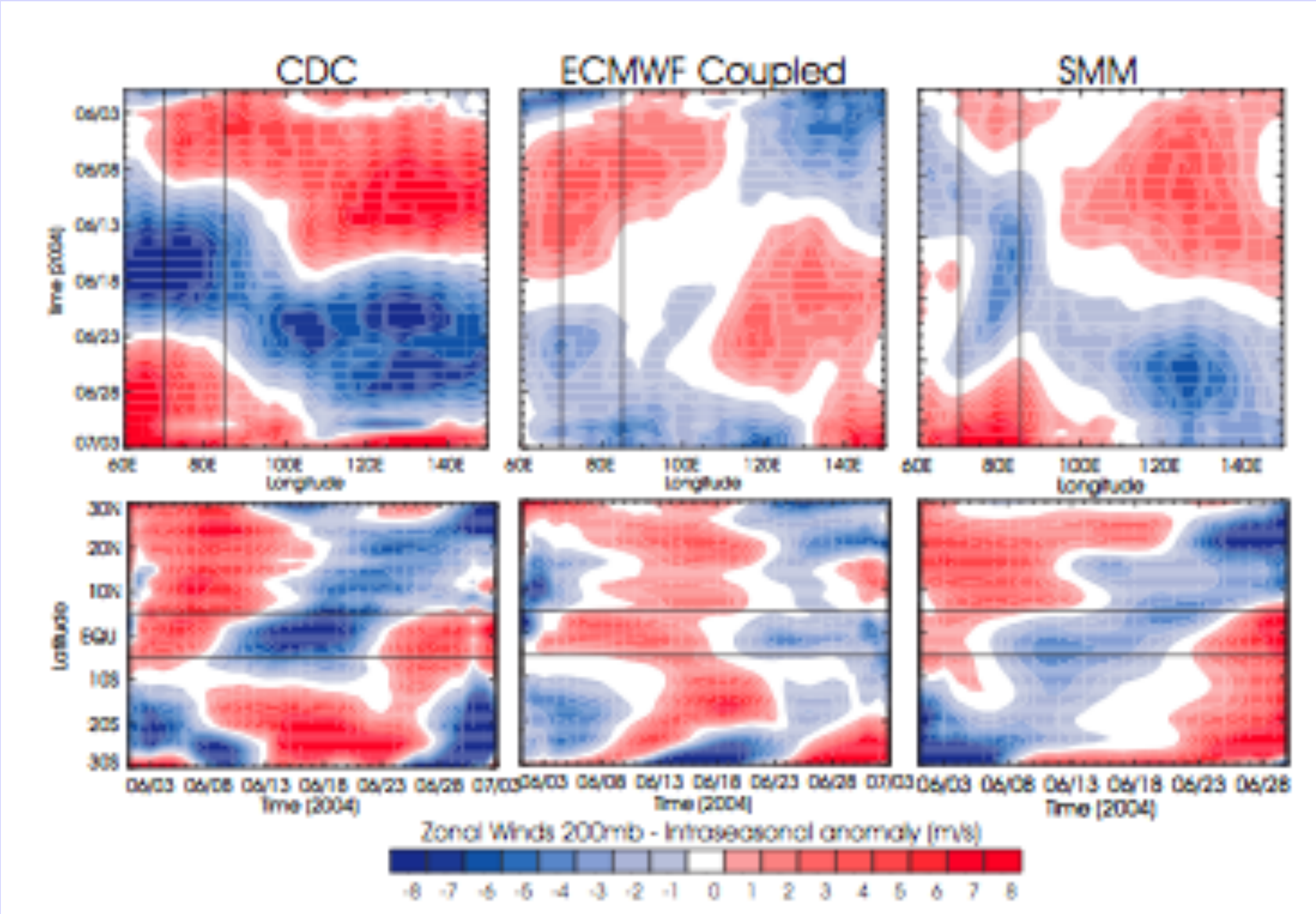
The SMM appears to hold the intensity and mode propagation direction of the monsoon ISO. The results are quite heartening but still much to do.

Comparison of observed, ECMWF model and SMM OLR: N=5, monsoon 2004



Hoyos and Webster (2007)

Comparison of observed, ECMWF model and SMM 200 mb U: N=5, monsoon 2004

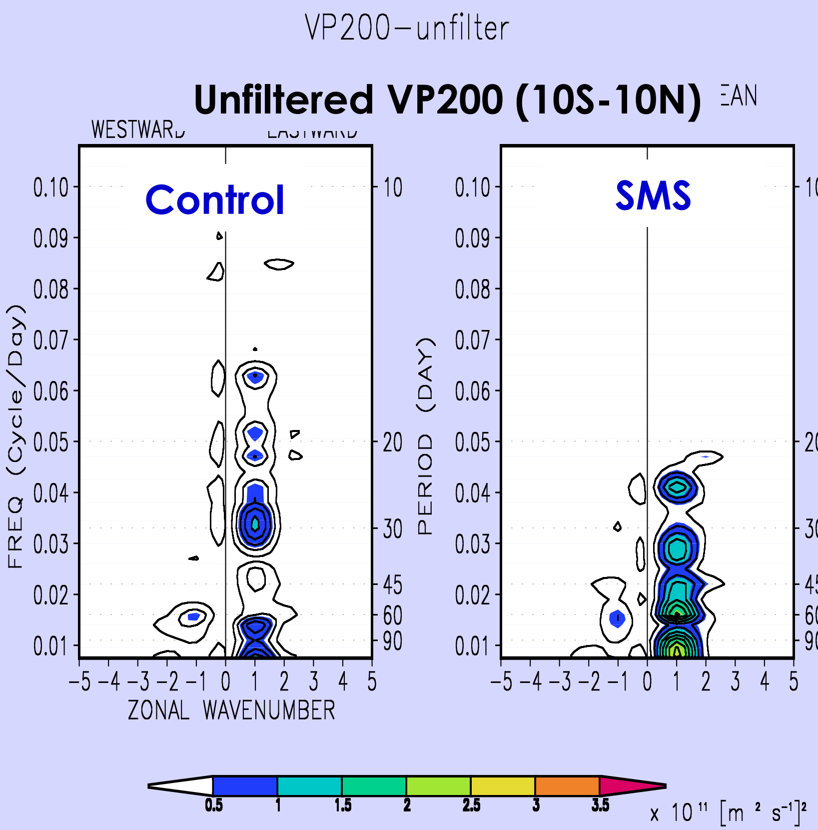


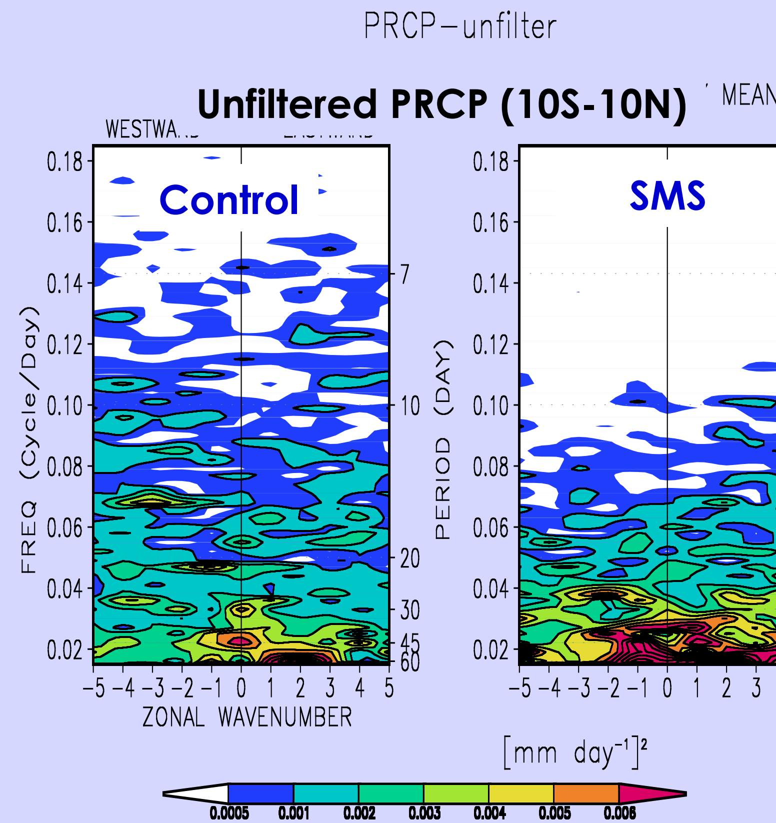
Hoyos and Webster (2007)

Corroborating Work for SMM

- Prof. In-Sik Kang and Dr. Hye-Mi Kim (now GT) of Climate Research Group of Seoul National University have used the SMM scheme in collaboration with Georgia Tech for AGCM and CGCM simulations
- Using an N=3 format, they find:
    - Increase in magnitude of intraseasonal mode after extended integration
    - Reduction of high frequency error
    - Overall increase in predictive skill

SMM-control space-time spectra

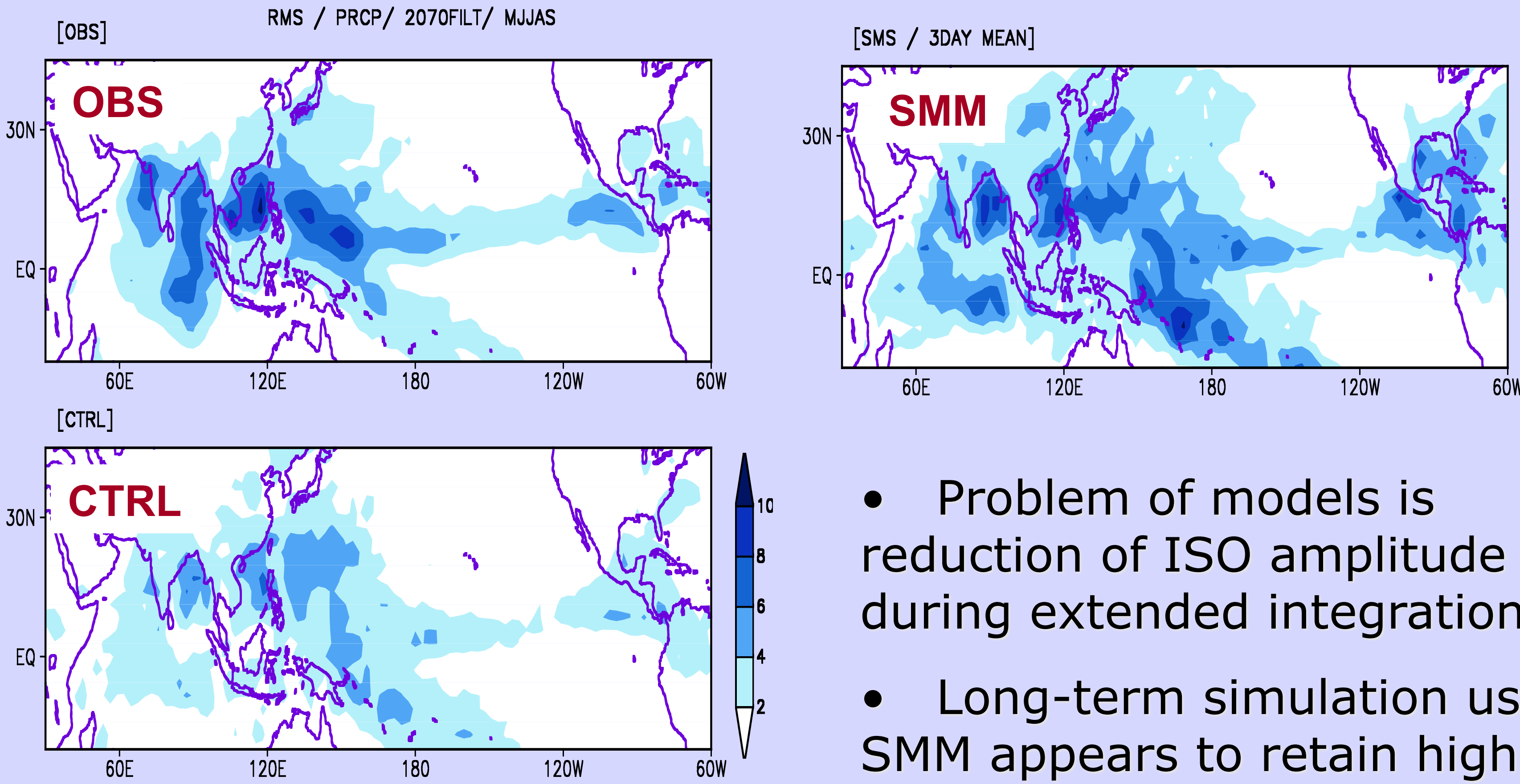




- In SMM, high frequency perturbations (<20days), strong in the control, decreases while low freq (40-70day) k=1 increases.

- Note strong low-frequency eastward modes retained at higher amplitude

Comparative ISO amplitudes of observed, control and SMM



- Problem of models is reduction of ISO amplitude during extended integration
- Long-term simulation using SMM appears to retain higher amplitude ISO signal.

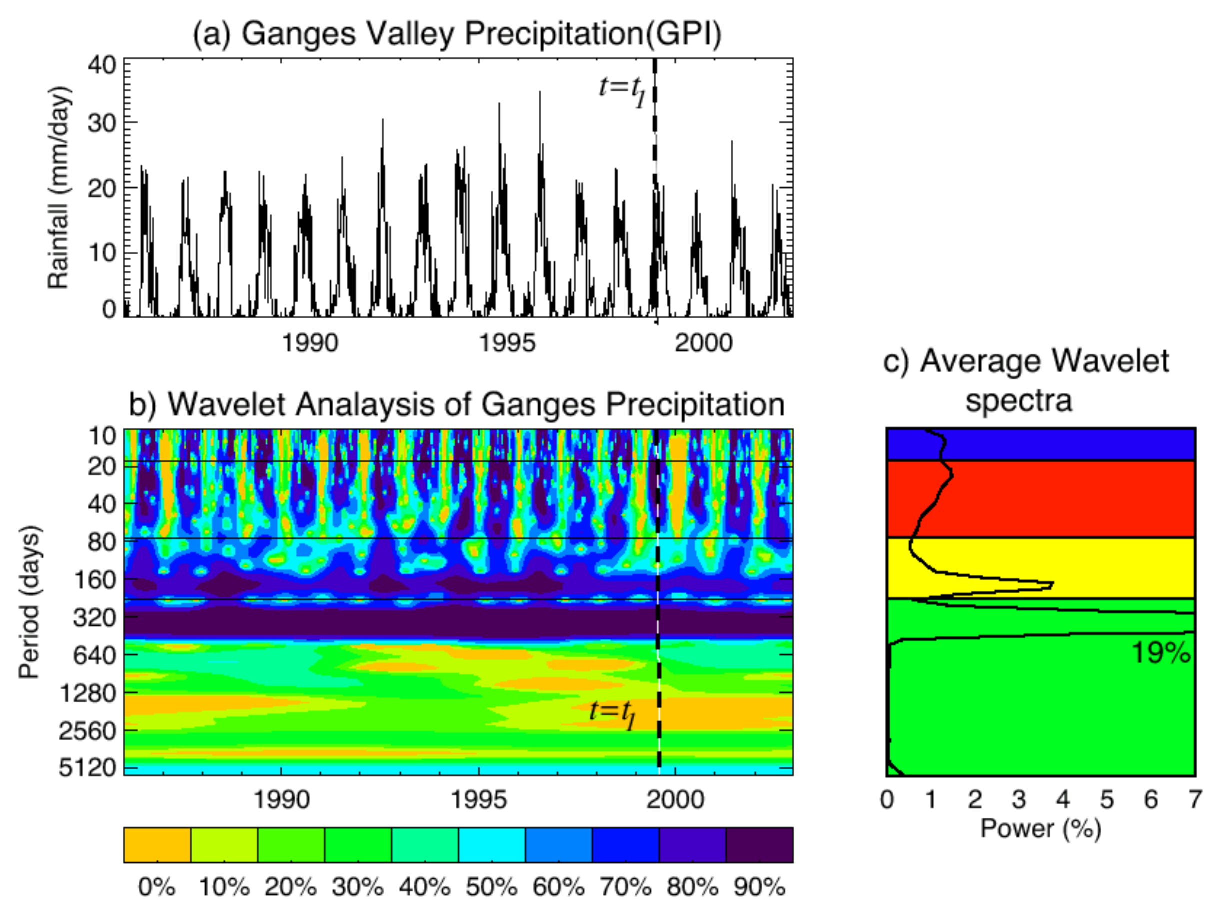
Courtesy H-M Kim, SNU

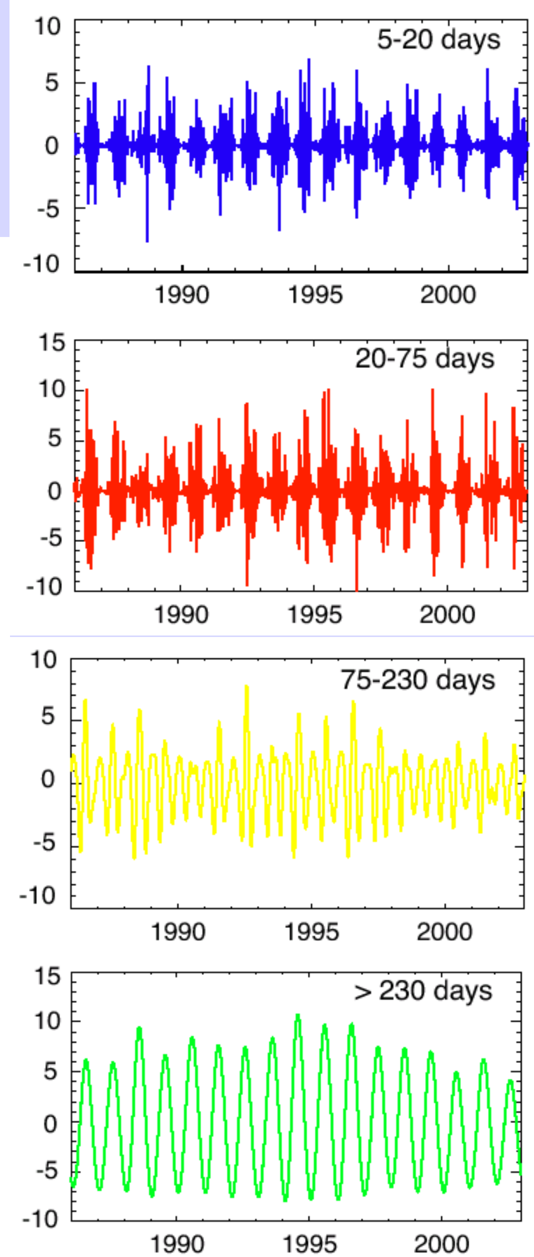
Summary….. Empirical prediction

- Bayesian empirical modeling points towards predictability
- Numerical models do not do well because of cumulus parameterization error growth
- Possible (without revolutionary break through in convective parameterization) that present day methodologies do not work?
- Given the pragmatic need for forecasts on the 20+ time scale either we go completely empirical or be creative in "rendering" numerical results systematically?

Statistical Scheme: Wavelet Banding

Statistical scheme uses wavelets to determine spectral structure of predictand.





Based on the definition of the bands in the predictand, the predictors are also banded identically

Statistical Scheme: Regression Scheme

Linear regression sets are formed between predictand and predictor and advanced in time.