

Status of monsoon prediction

Dr Andy Turner

Part I

- ❖ Basis for seasonal prediction & statistical implementation
- ❖ Climate model performance for the Asian monsoon
- ❖ The monsoon-ENSO teleconnection
 - ❖ Role of coupling
 - ❖ Impact of mean-state biases
 - ❖ Awareness of long-term variations
 - ❖ Flavours of El Niño
 - ❖ Climate change and monsoon-ENSO
- ❖ Seasonal prediction status
- ❖ Benefits of other factors in seasonal prediction

Monsoon prediction

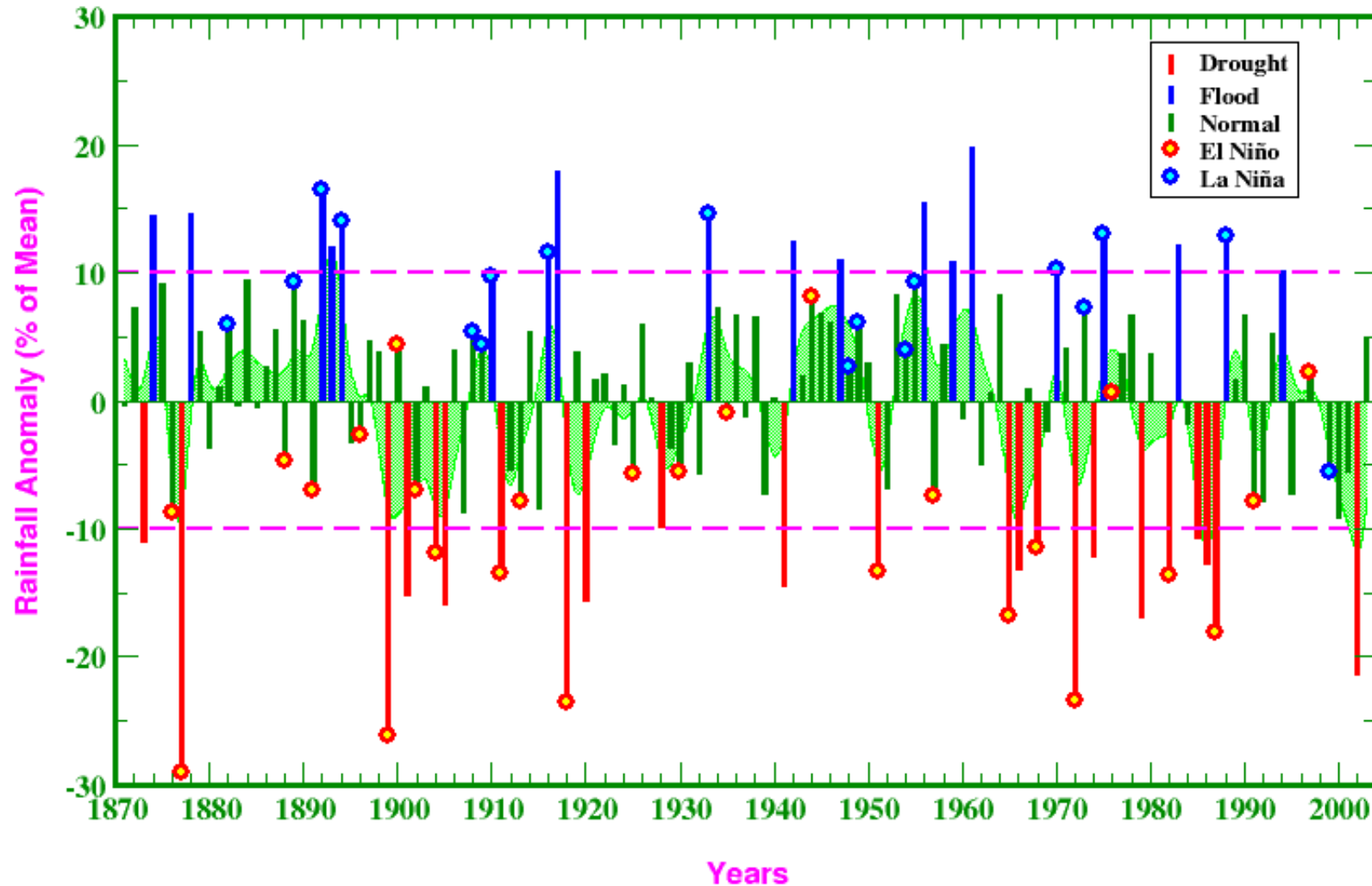
BASIS FOR MONSOON SEASONAL PREDICTION

- ❖ Some of the earliest attempts at statistical seasonal forecasts were by the [India Meteorological Department](#) (H.F. Blanford, 1886)
- ❖ Since then IMD have refined their statistical models
- ❖ These forecasts reflect the potential predictability of tropical rainfall anomalies implied by slow variations in lower boundary conditions (Charney & Shukla, 1981)
- ❖ The IMD summer monsoon forecast is one of the best known and eagerly anticipated operational statistical forecasts — the forecast can significantly affect the Indian stock market

Monsoon-ENSO co-variation

All-India Summer Monsoon Rainfall, 1871-2003

(Based on IITM Homogeneous Indian Monthly Rainfall Data Set)



© Rupa Kumar Kolli, IITM, Pune, India (April 23, 2004)

The IMD model uses power regression:

$$R = C_0 + \sum_{i=1}^{i=n} C_i X_i^{P_i}$$

R is rainfall, X_i are the predictors and C_i and P_i are constants

An initial forecast is issued in April, using a variety of parameters (some of which are SST, some are atmospheric and one is land surface)

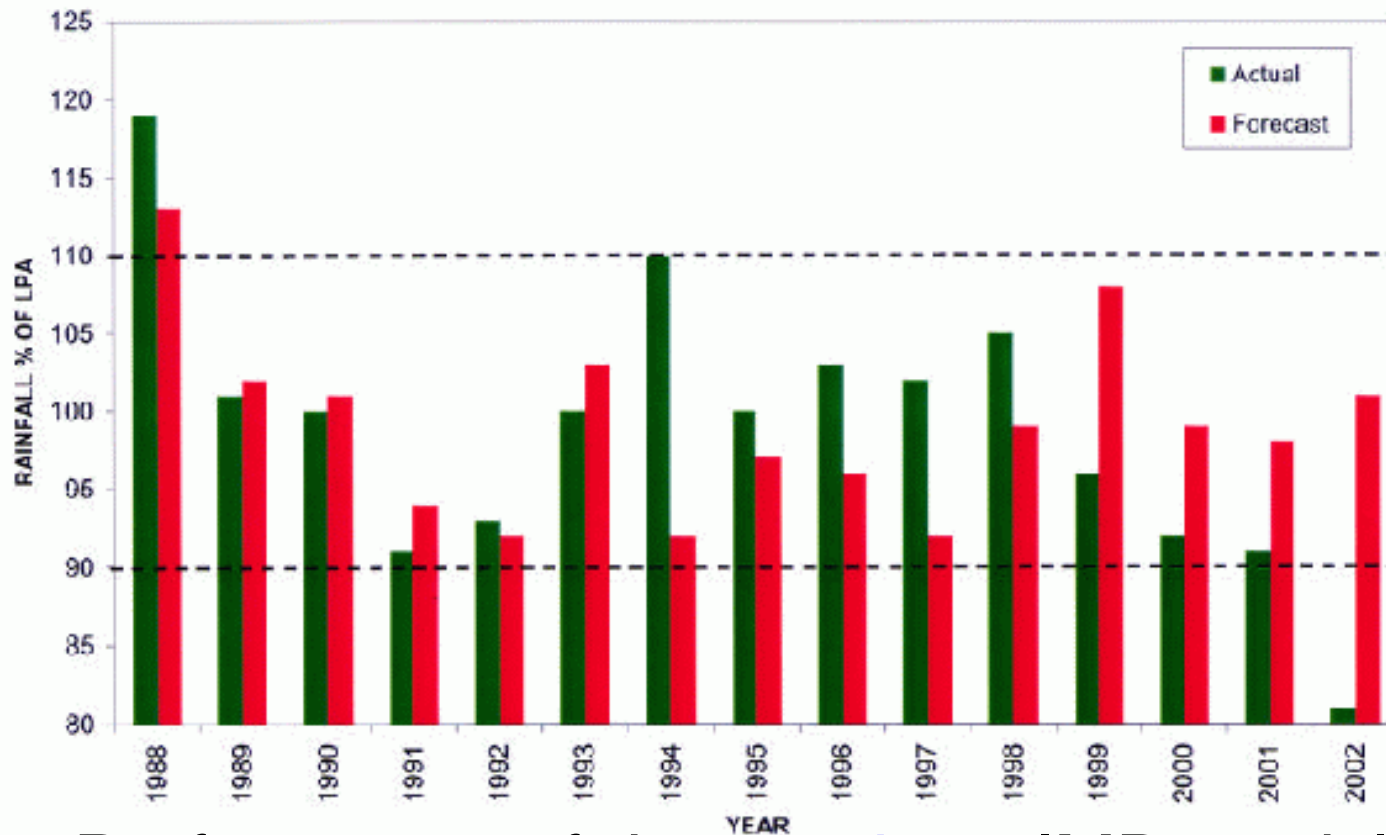
A revised forecast is made at the beginning of July (one month into the monsoon) changing some parameters

(V. Old) Indian monsoon statistical forecasting

The 10 parameters (and their correlation coefficients with AIR*) are:

1. Arabian Sea SST (Jan and Feb) 0.55
2. Eurasian snow cover (Dec) -0.46
3. NW Europe Temperature (Jan) 0.46
4. NINO3 SST anomaly (Jul-Sep previous year) 0.42
5. South Indian Ocean SST (Mar) 0.47
6. East Asia Pressure (Feb and Mar) 0.61
7. Northern Hemisphere 50 hPa wind pattern (Jan) -0.51
8. Europe Pressure Gradient (Jan) 0.42
9. South Indian Ocean 850 hPa zonal wind (Jun) -0.45
10. NINO3.4 SST tendency (between Jan and Jun) -0.46

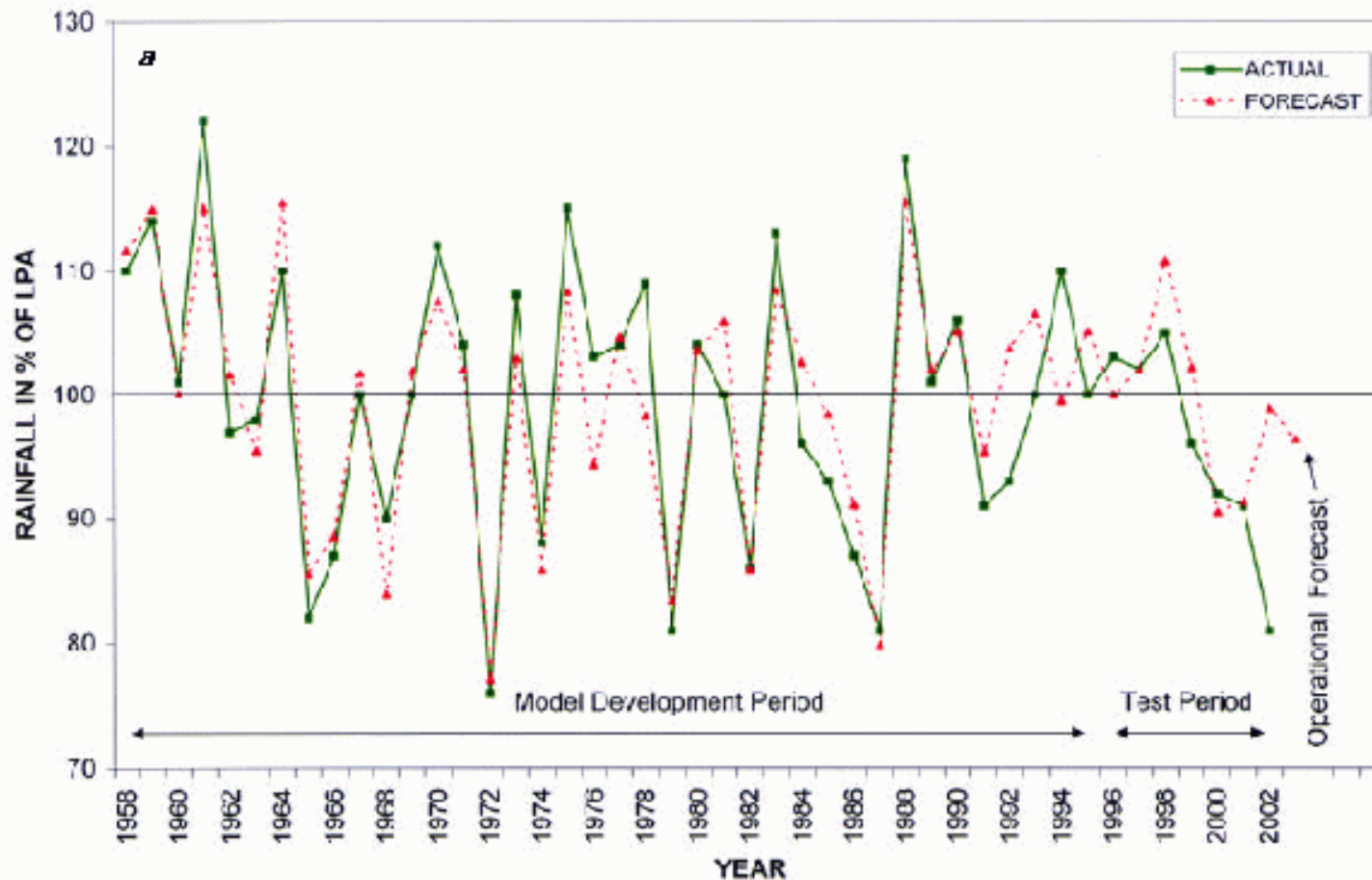
*AIR = All India Rainfall



From Rajeevan et al.
(2004) *Current
Science*

- ❖ Performance of the **previous** IMD model (16 parameter power regression)
- ❖ Note the gradual deterioration in skill and the failure to predict the 2002 drought

Statistical forecast construction & model testing



Performance of the **new** IMD model (8 parameter power regression) through the development period (1958-95) and test period (1996-2002).

This new model still failed to “predict” the 2002 drought!

Table 1 Details of predictors used for the first stage forecast (SET-I)

No.	Parameter	Period	Spatial domain	CC with ISMR (1958–2000)
A1	North Atlantic SST anomaly	December + January	20N–30N, 100W–80W	–0.45**
A2	Equatorial SE Indian Ocean SST anomaly	February + March	20S–10S, 100E–120E	0.52**
A3	East Asia surface pressure anomaly	February + March	35N–45N, 120E–130E	0.36*
A4	Europe land surface air temperature anomaly	January	Five stations	0.42**
A5	Northwest Europe surface pressure anomaly tendency	DJF(0) – SON (–1)	65N–75N, 20E–40E	–0.40**
A6	WWV anomaly	February + March	5S–5N, 120E–80W	–0.32*

*Significant at and above 5% level

**Significant at and above 1% level

Yet another change to the forecast methodology in 2005! This new model uses ensemble multiple regression (Rajeevan *et al.*, 2006, *Clim. Dyn.*)

Table 2 Details of predictors used for the second stage forecast (SET-II)

No.	Parameter	Period	Spatial domain	CC with ISMR (1958–2000)
J1	North Atlantic SST anomaly	December ++ January	20N–30N, 100W–80W	–0.45**
J2	Equatorial SE Indian Ocean SST anomaly	February ++ March	20S–10S, 100E–120E	0.52**
J3	East Asia surface pressure anomaly	February ++ March	35N–45N, 120E–130E	0.36*
J4	Nino-3.4 SST anomaly tendency	MAM(0) – DJF(0)	5S–5N, 170W–120W	–0.46**
J5	North Atlantic surface pressure anomaly	May	35N–45N, 30W–10W	–0.42**
J6	North Central Pacific zonal wind anomaly at 850 hPa	May	5N–15N, 180E–150W	–0.55**

*Significant at and above 5% level

**Significant at and above 1% level

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A3	Fig. 1 Geographical locations of the nine predictors listed in Tables 1 and 2			
A4				
A5				
A6				
—				
*Si				
**S				
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Tal

No.

J1

J2

J3 East Asia surface pressure anomaly

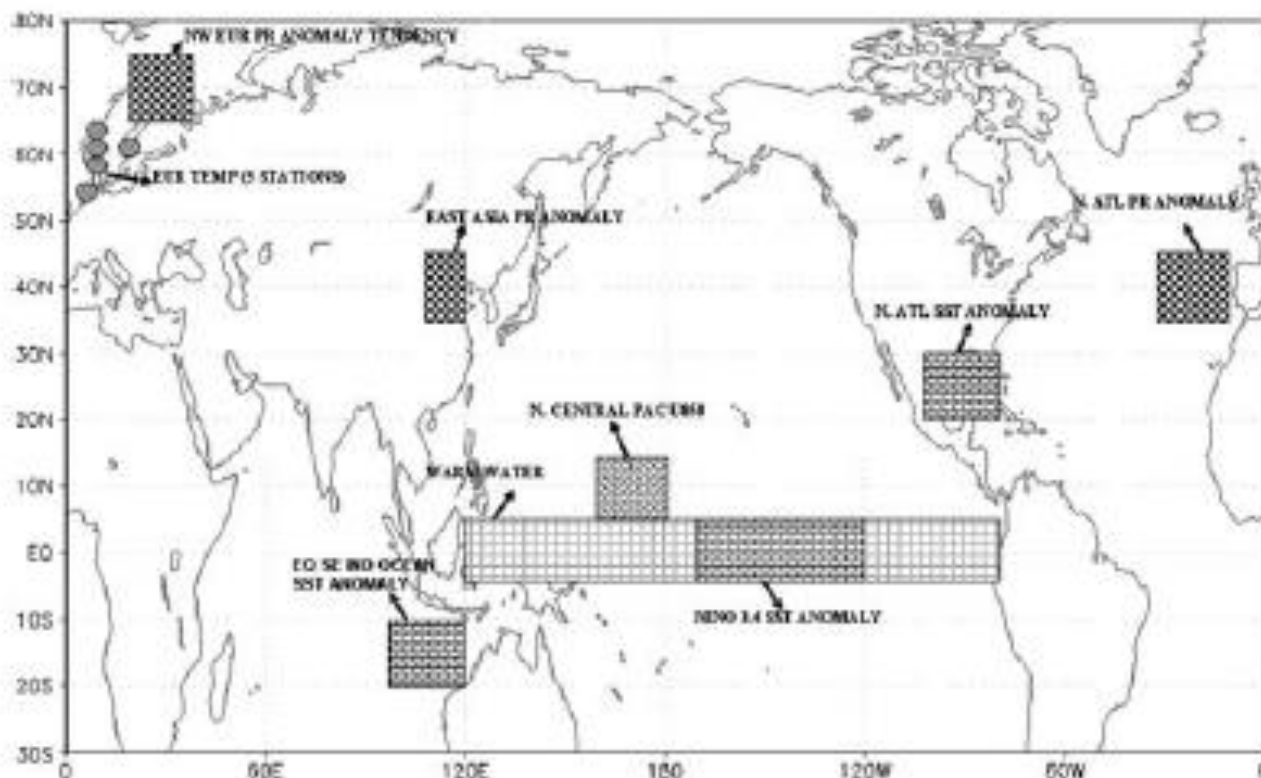
J4 Nino-3.4 SST anomaly tendency

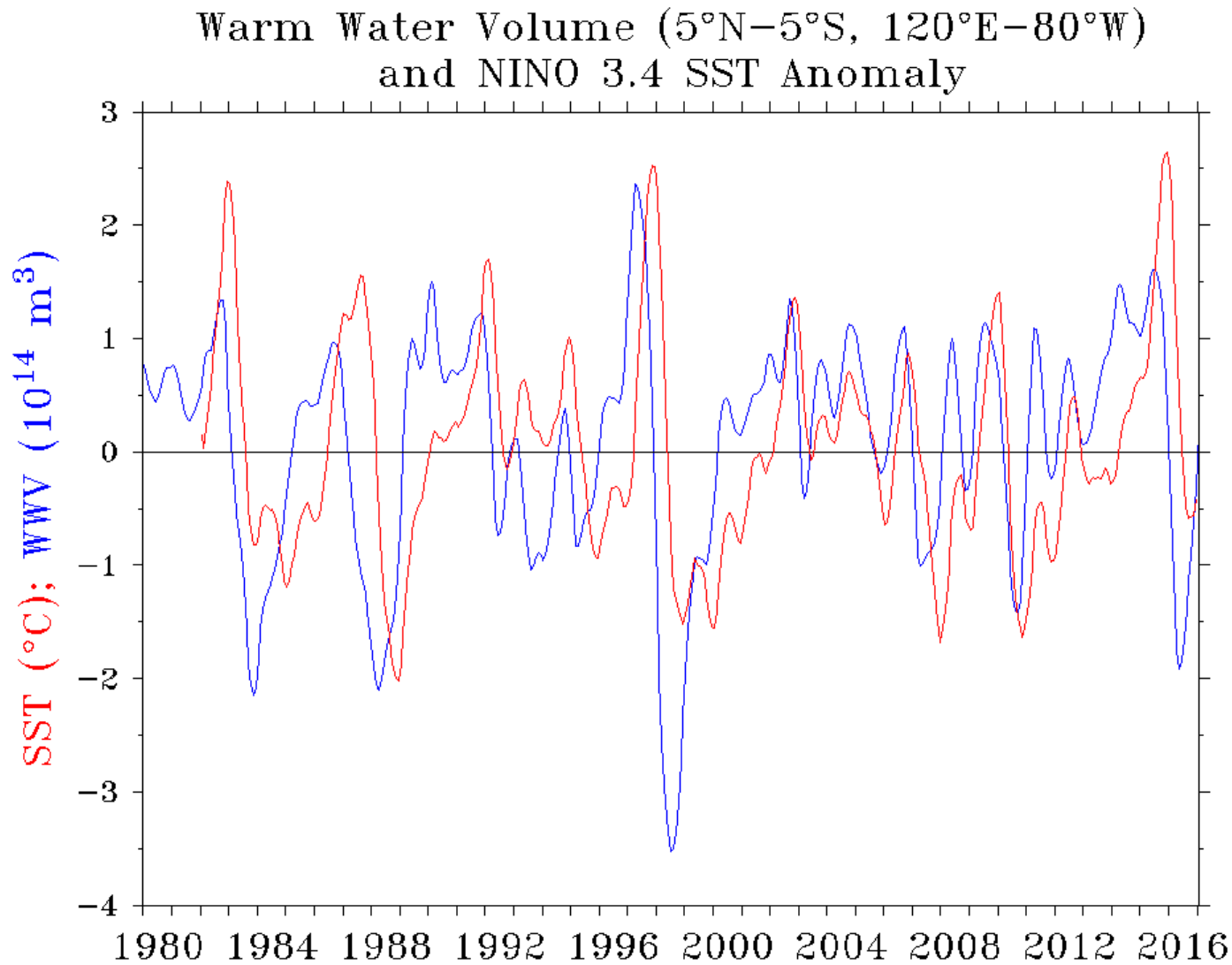
J5 North Atlantic surface pressure anomaly

J6 North Central Pacific zonal wind anomaly at 850 hPa

*Significant at and above 5% level

**Significant at and above 1% level





www.pmel.noaaa.gov/elhino/upper-ocean-het-content-and-enso

The gradual deterioration in skill of the old IMD model highlights several problems with statistical techniques:

- ❖ The correlations between *predictors* and *predictands* are not necessarily stationary in time
- ❖ When the forecast fails (e.g. 2002) you don't necessarily know why
- ❖ The method requires high frequency variability (“noise”) to have a small impact compared to the low-frequency predictable “signal”

- ❖ Dynamical models (coupled ocean-atmosphere GCMs) are beginning to be used for seasonal forecasting of the monsoon
- ❖ But they still retain large biases compared to observations – even in the most recent models...

Monsoon prediction

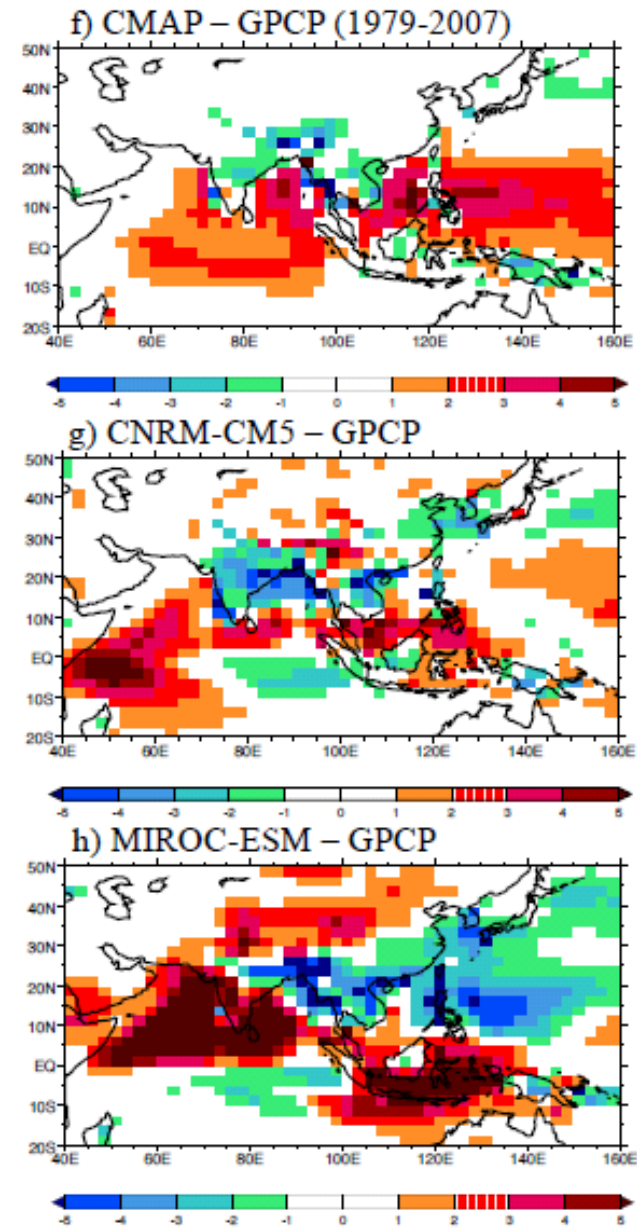
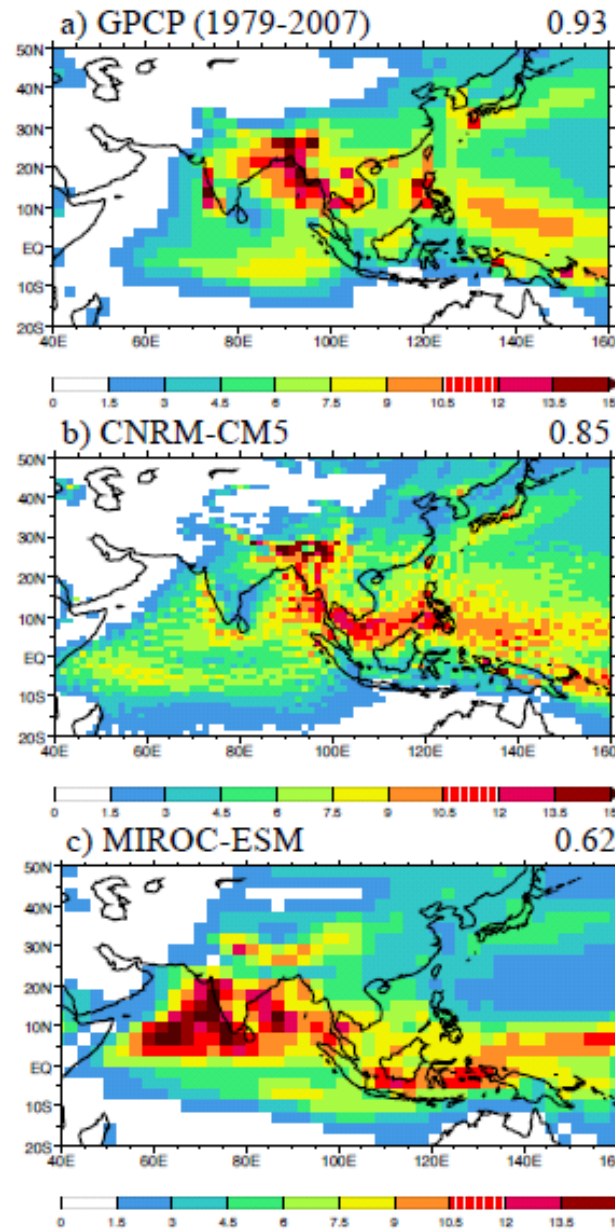
CMIP MODEL PERFORMANCE FOR THE ASIAN MONSOON

Monsoon precipitation biases

Large range of
skill at simulating
the mean
monsoon
precipitation in
CMIP3 and CMIP5
models

**Mean JJAS precipitation
(left) and bias versus GPCP
obs (right)**

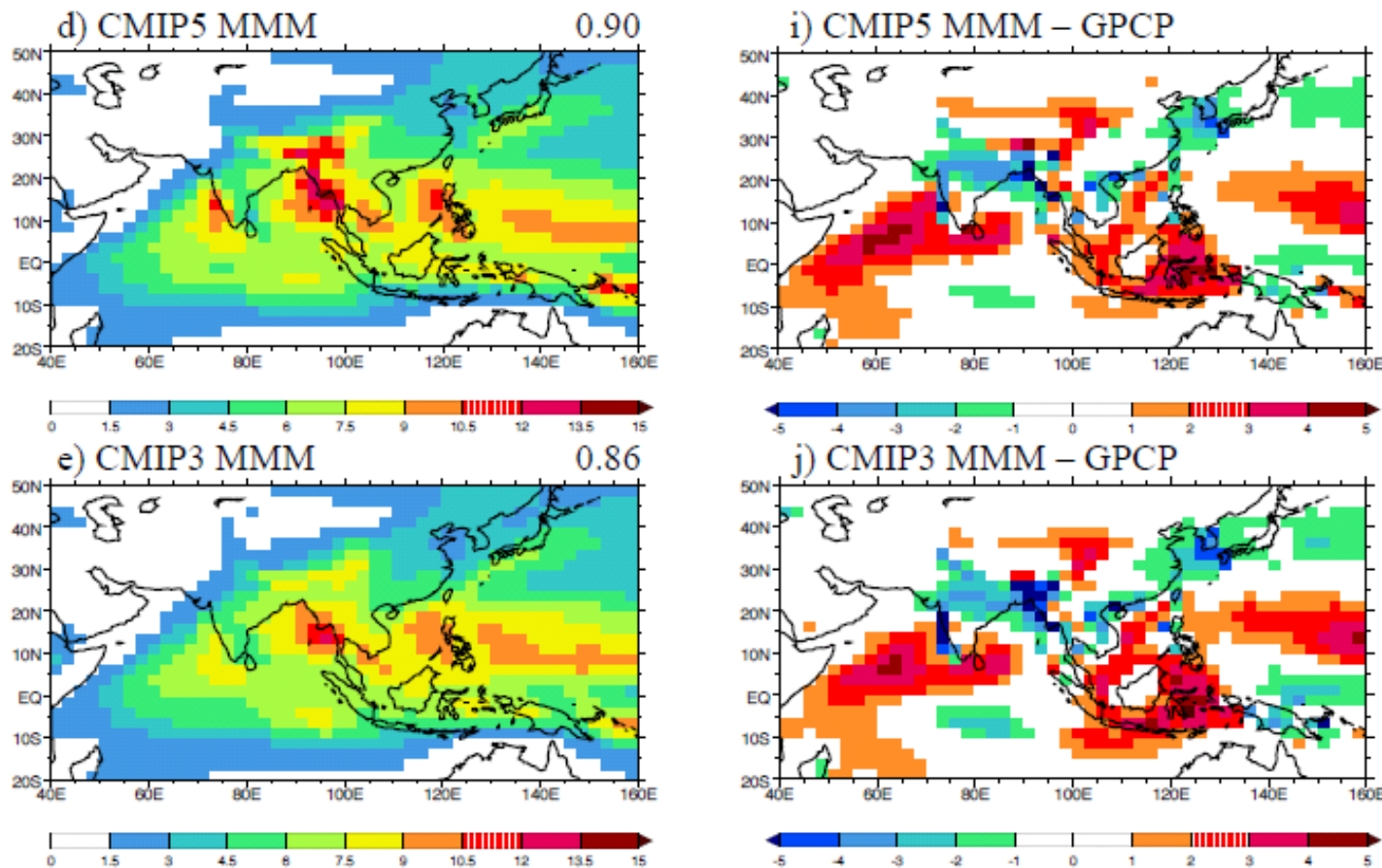
See Sperber *et al.* (2013) *Climate
Dynamics*



Multi-model mean monsoon precipitation biases in CMIP/5

- ❖ Large biases in CMIP3 and CMIP5 models

Mean JJAS precipitation (left) and bias versus GPCP obs (right)

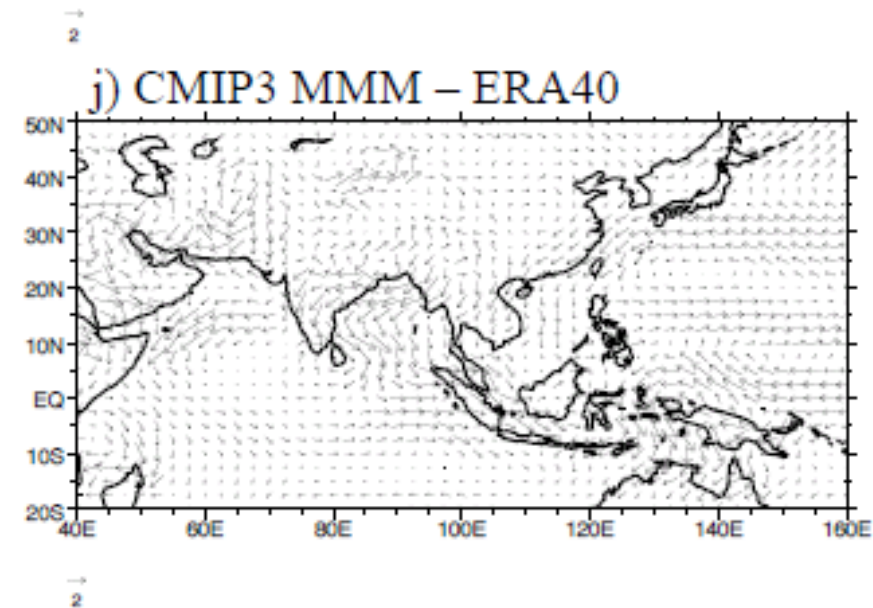
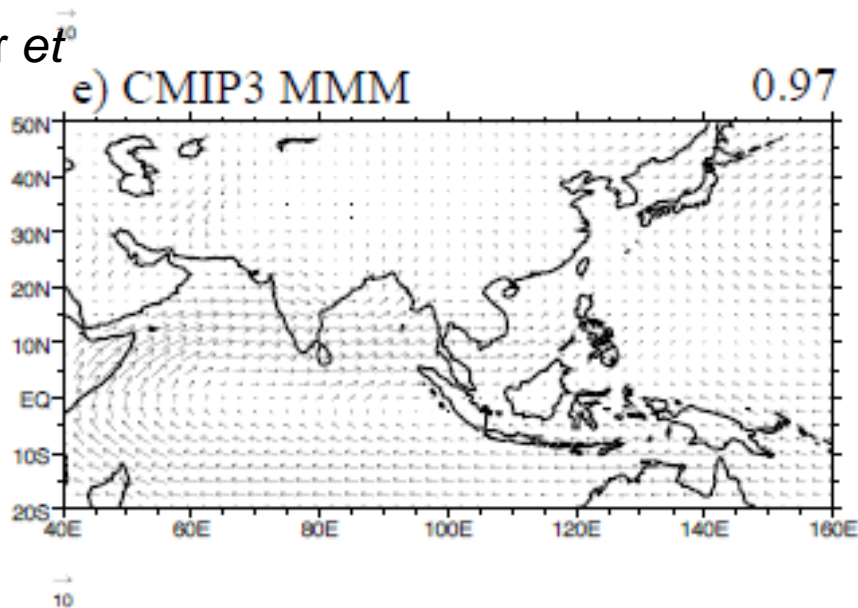
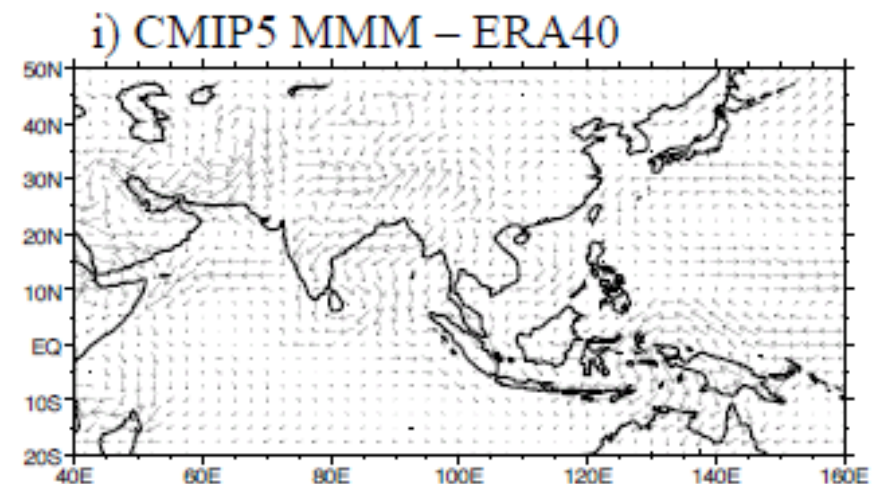
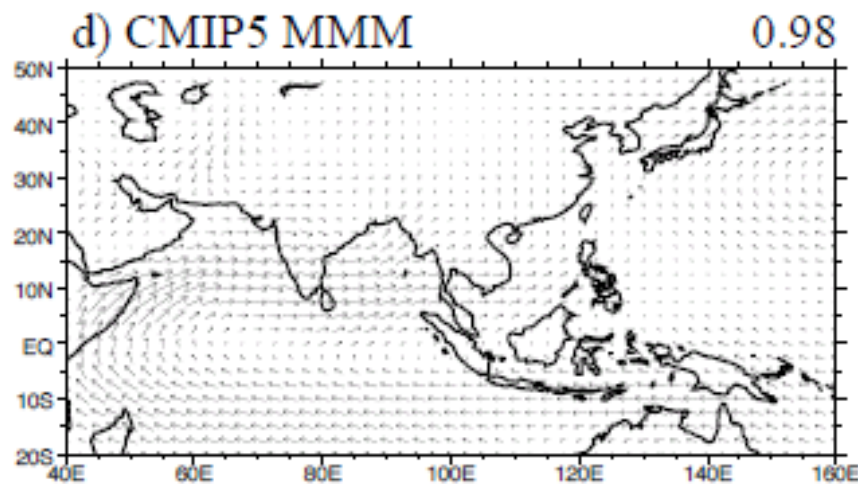


See Sperber *et al.* (2013)
Climate Dynamics

Multi-model mean circulation biases in CMIP3/5

❖ Weak Somali Jet in CMIP3 and CMIP5

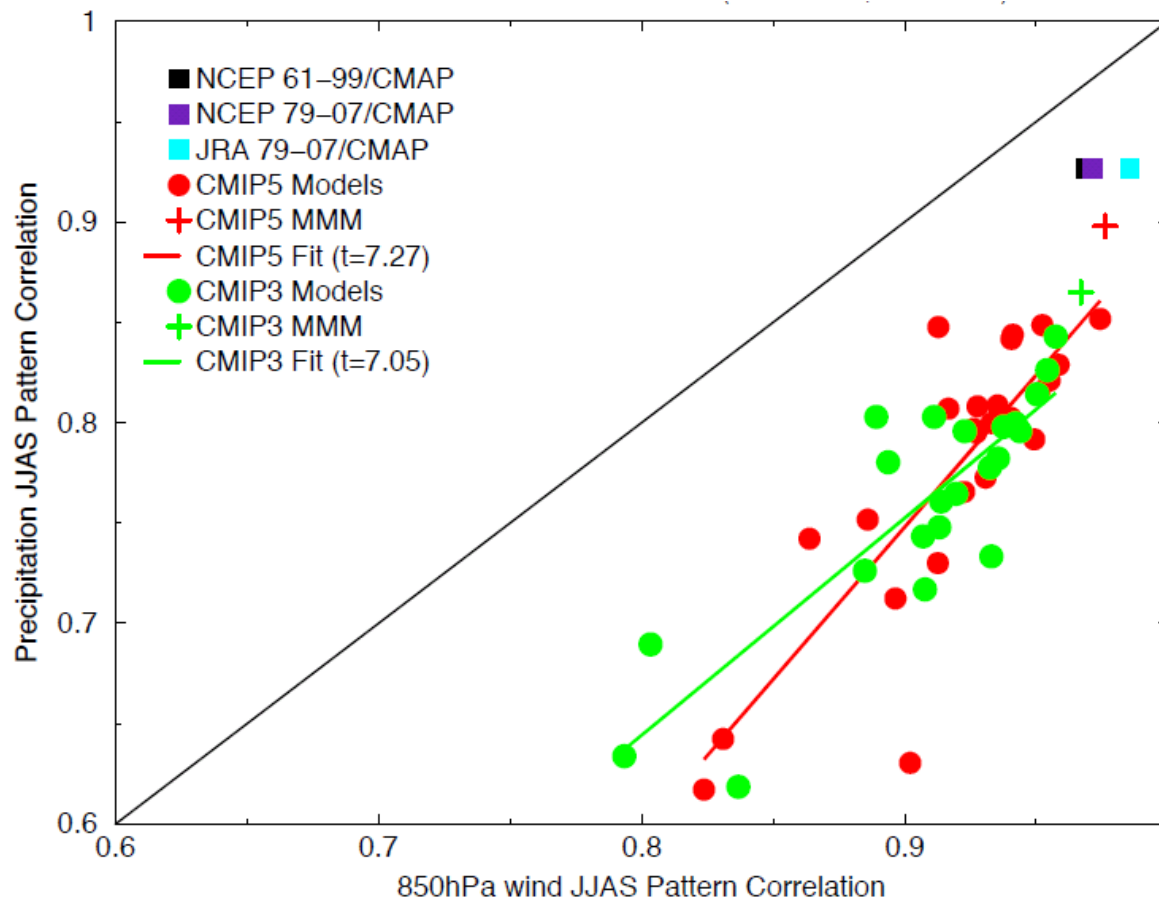
Mean JJAS 850hPa winds (left) and bias versus ERA-40 (right)



See Sperber *et al.* (2013)
Climate Dynamics

Relationship between circulation and precipitation biases in CMIP3/5

Scatter diagram of
pattern correlations of
simulation of JJAS
precipitation & 850hPa
winds



See Sperber *et al.* (2013)
Climate Dynamics

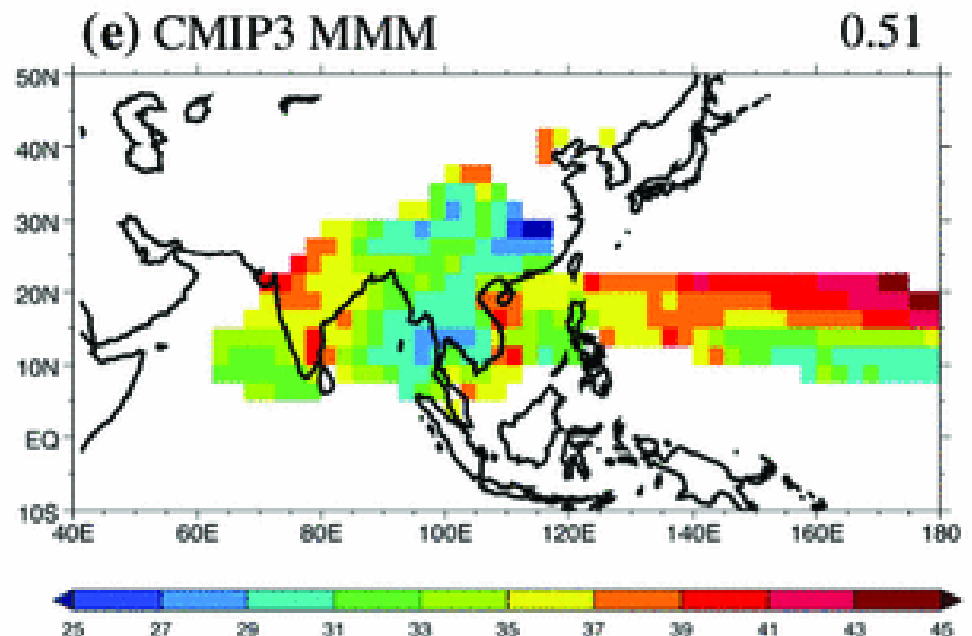
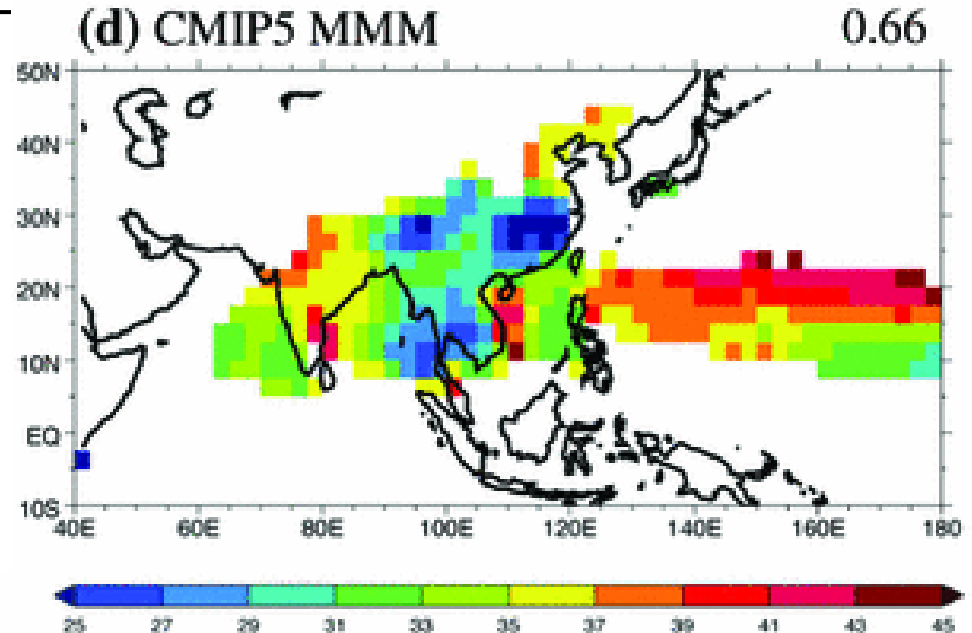
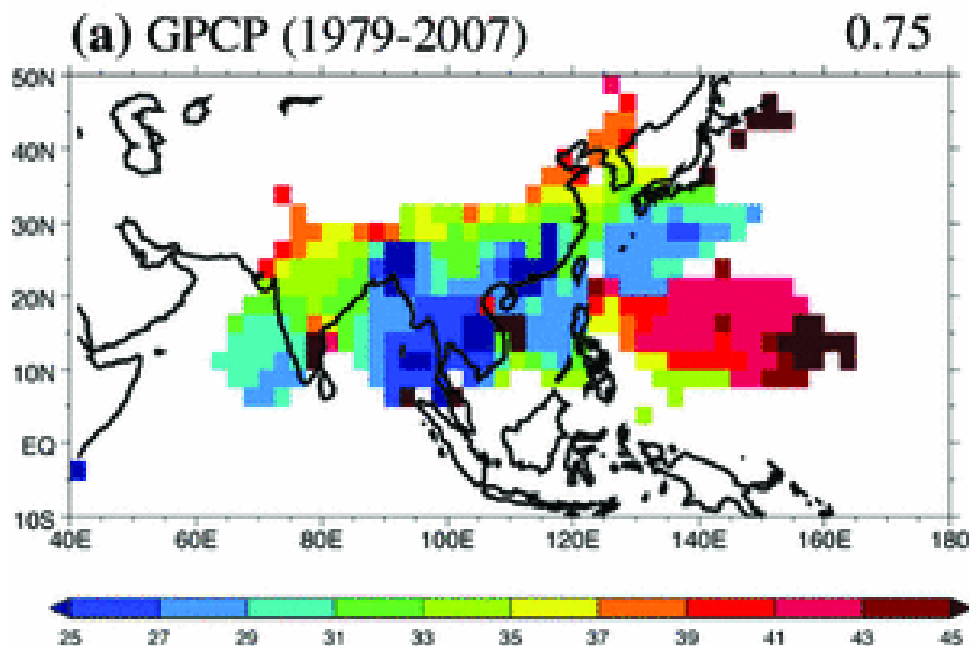
❖ Strong evidence for connection between biases in monsoon circulation and precipitation

Biases in the monsoon onset

- ❖ Onset pentad using method of Wang & Linho
- ❖ Delayed onset in CMIP3 and CMIP5 models

From Sperber *et al.* (2013) *Clim. Dyn.* (also see Sperber & Annamalai (2014) *Clim. Dyn.*)

Onset



- ❖ In practice we would want to use initialised models for forecasting, not free running climate models
- ❖ But it is still useful to understand their biases...
- ❖ Now let's take a step back to monsoon predictability

Monsoon prediction

IMPACT OF OCEAN- ATMOSPHERE COUPLING

- ❖ Examination of importance of ocean-atmosphere coupling by Krishna Kumar et al. (2005)
- ❖ Other works by Bin Wang etc. and many others

GEOPHYSICAL RESEARCH LETTERS, VOL. 32, L08704, doi:10.1029/2004GL021979, 2005

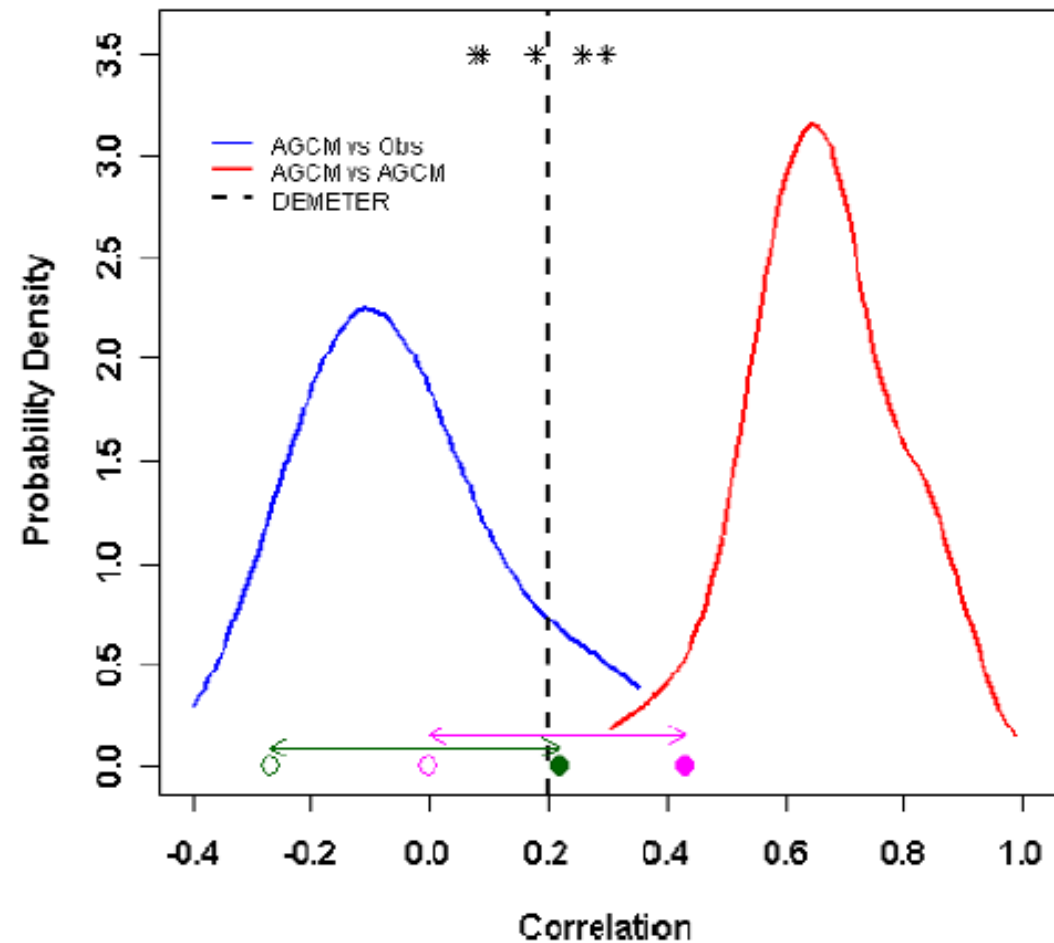
Advancing dynamical prediction of Indian monsoon rainfall

K. Krishna Kumar,^{1,2} Martin Hoerling,¹ and Balaji Rajagopalan^{1,3}

Received 11 November 2004; revised 6 January 2005; accepted 2 March 2005; published 21 April 2005.

Monsoon predictability

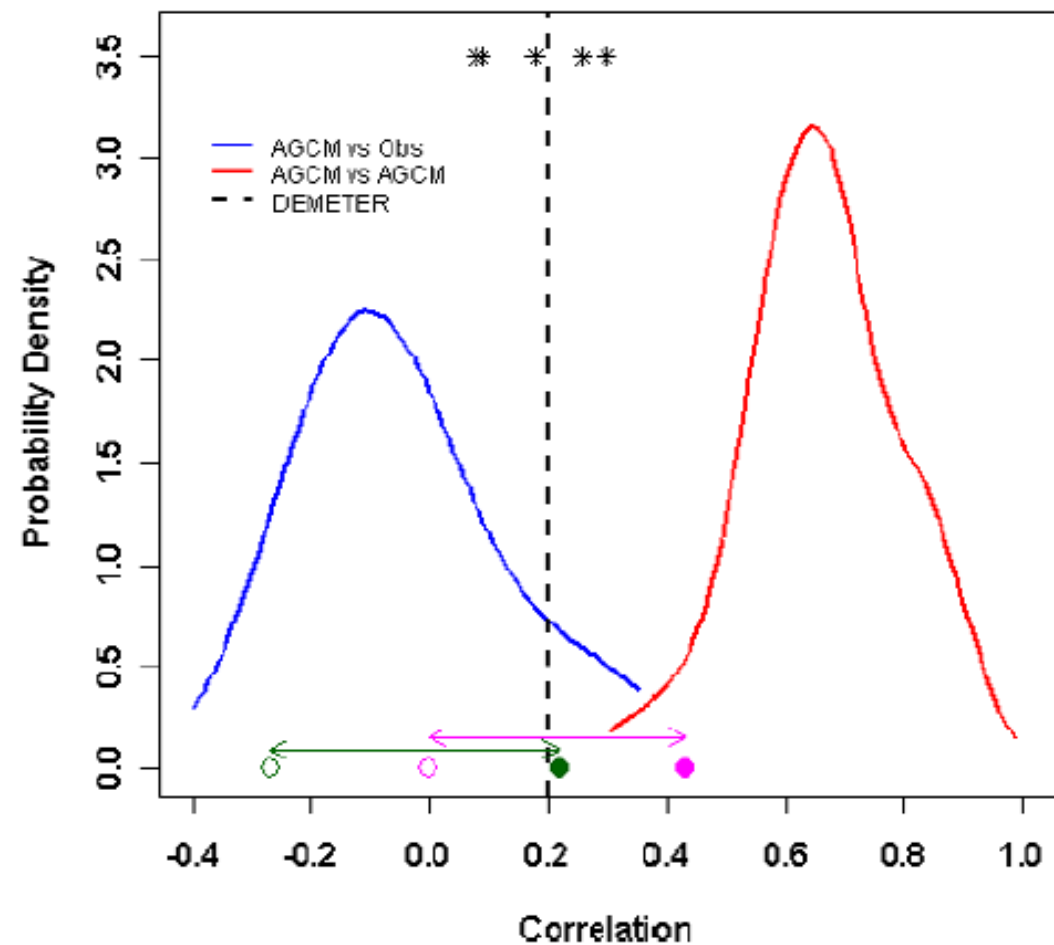
- ❖ Krishna Kumar's approach used AGCM ensembles to simulate the monsoon in response to observed SST
- ❖ 10 different AGCMs each with several ensemble members



- ❖ Red shows the *perfect model* approach: PDF based on correlating each member with mean of all other members
- ❖ The common factor is the SSTs used, suggests around 40% variability potentially could be explained by SST

Monsoon predictability

- ❖ Krishna Kumar's approach used AGCM ensembles to simulate the monsoon in response to observed SST
- ❖ 10 different AGCMs each with several ensemble members
- ❖ Blue shows PDF of the correlations between rainfall in each member and observations
- ❖ Implies essentially no real skill



Lack of coupling problem

- ❖ Warm minus cold ENSO composites based on 1950-1999
- ❖ AGCM ensemble gets entirely the wrong sign of correlation

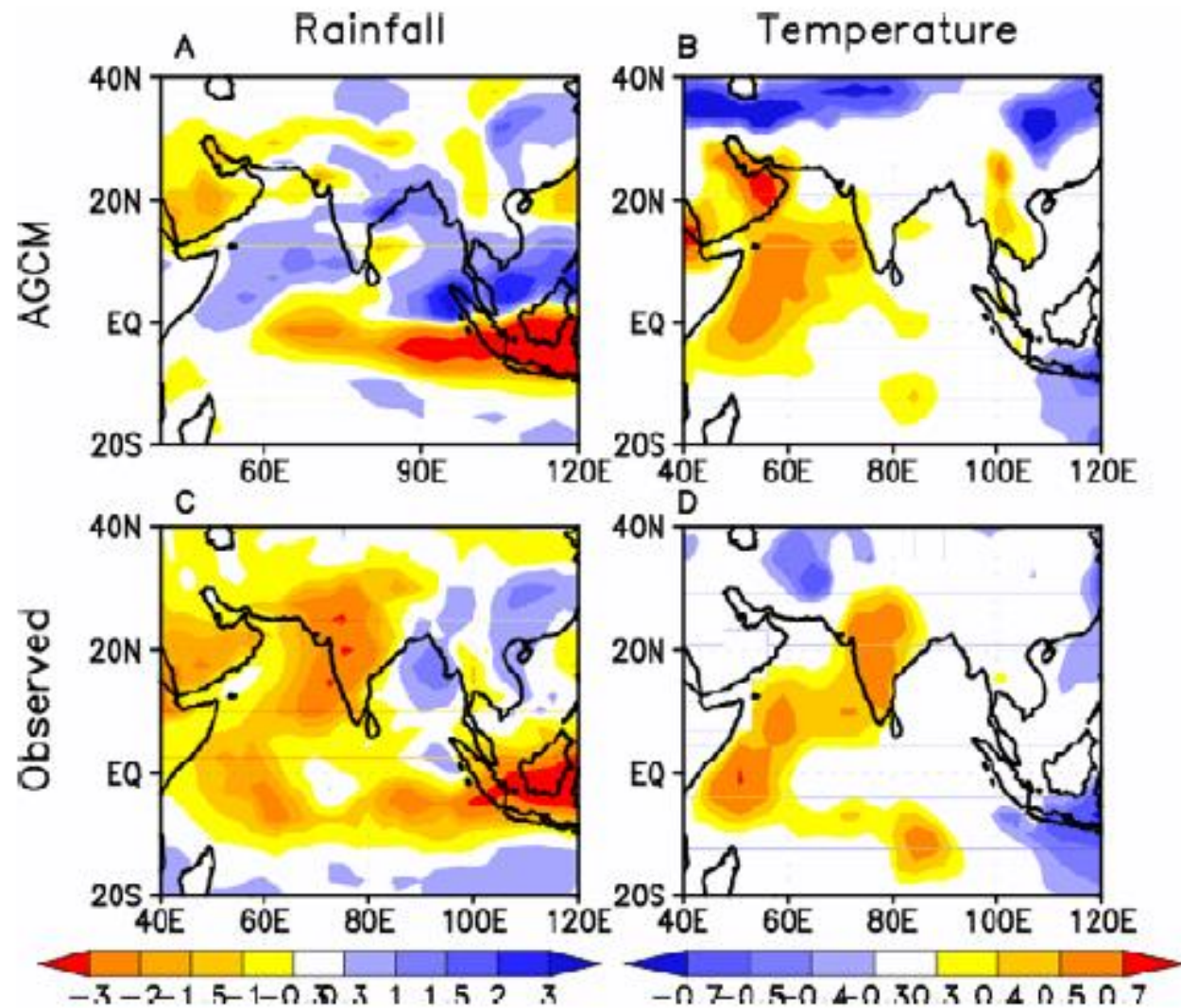
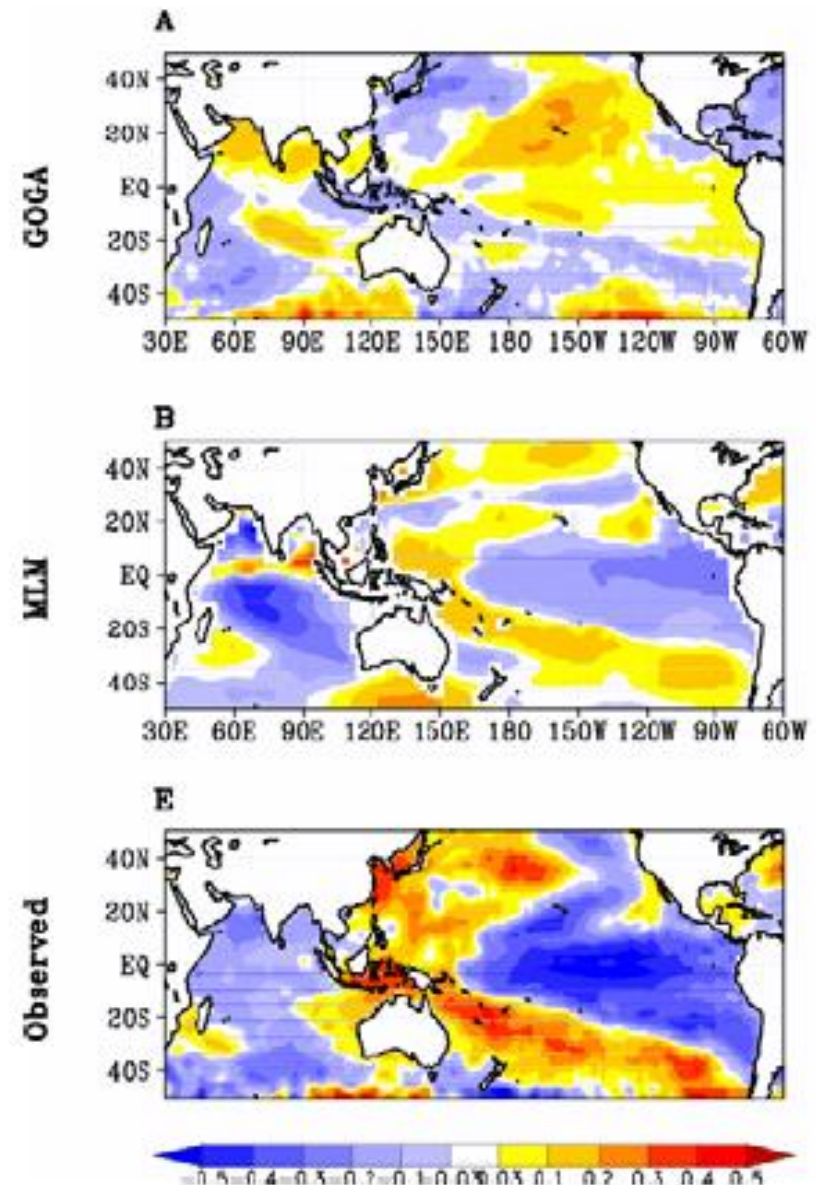


Figure 2. Monsoon season warm minus cold ENSO climate signals of, (a) ensemble mean rainfall (mm/day) from NCAR/CCM3 AGCM, (b) same as A but for surface temperatures (°C), (c) same as A but for satellite estimated rainfall derived from outgoing long-wave radiation (OLR) (d) same as B but for observed temperature. Note that SSTs have been prescribed in the AGCM. Period of analysis is 1950–1999, except 1975–2002 for OLR.

Benefits of a coupled ocean

Showing instantaneous summer correlation between Indian rainfall and SST

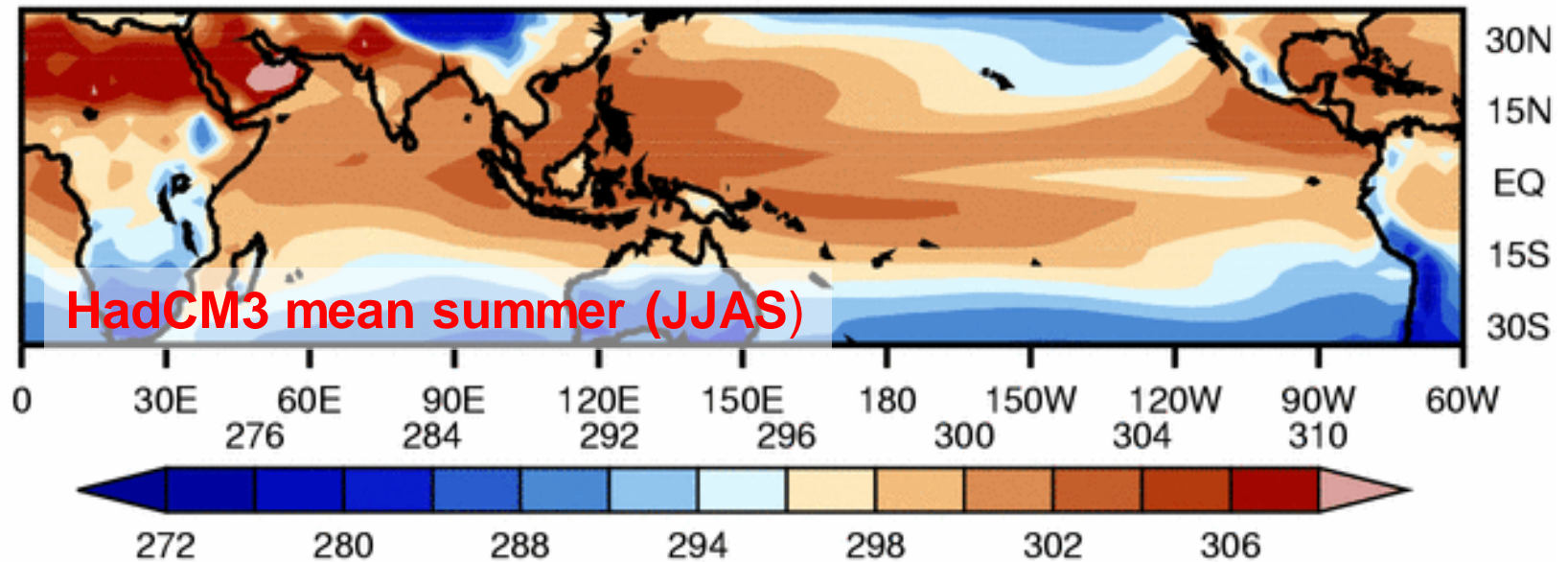
- ❖ In Krishna Kumar's framework, replacing most of the prescribed SST with a mixed layer model (and prescribing SST only in the central/east Pacific) gives a much more faithful reproduction of the ENSO teleconnections to the monsoon



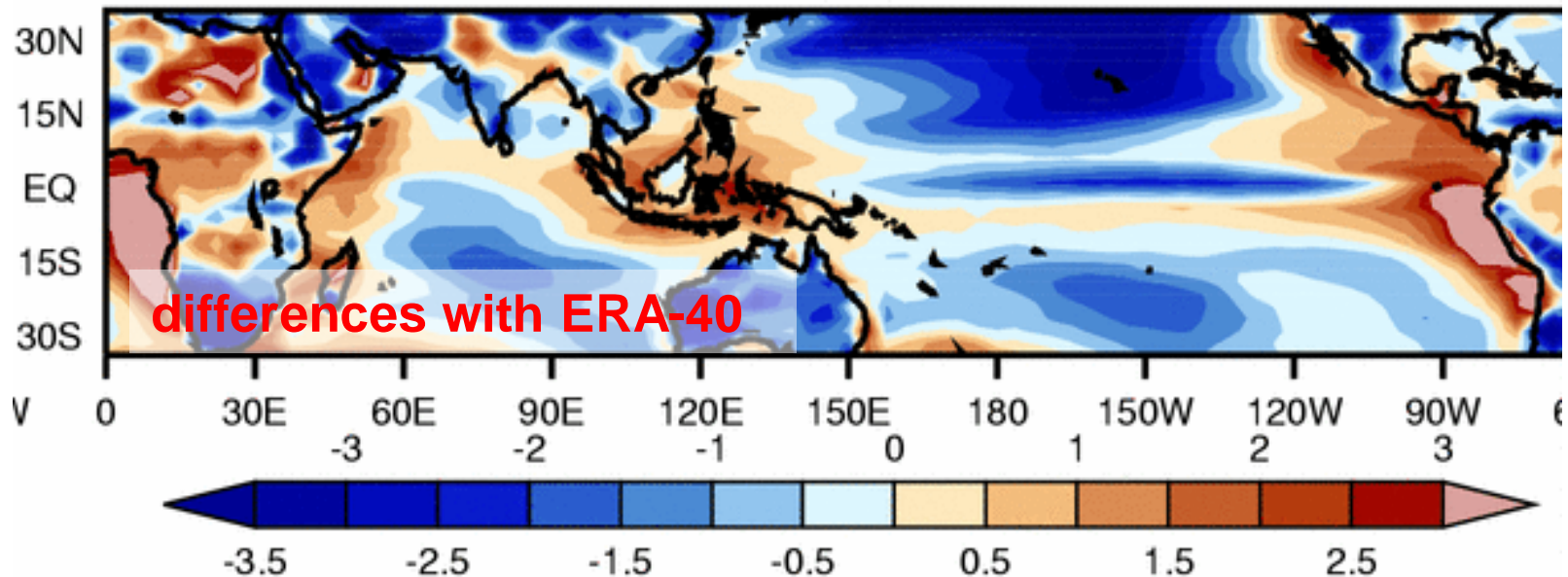
Monsoon prediction

IMPACT OF COUPLED SST BIASES

Example coupled SST bias

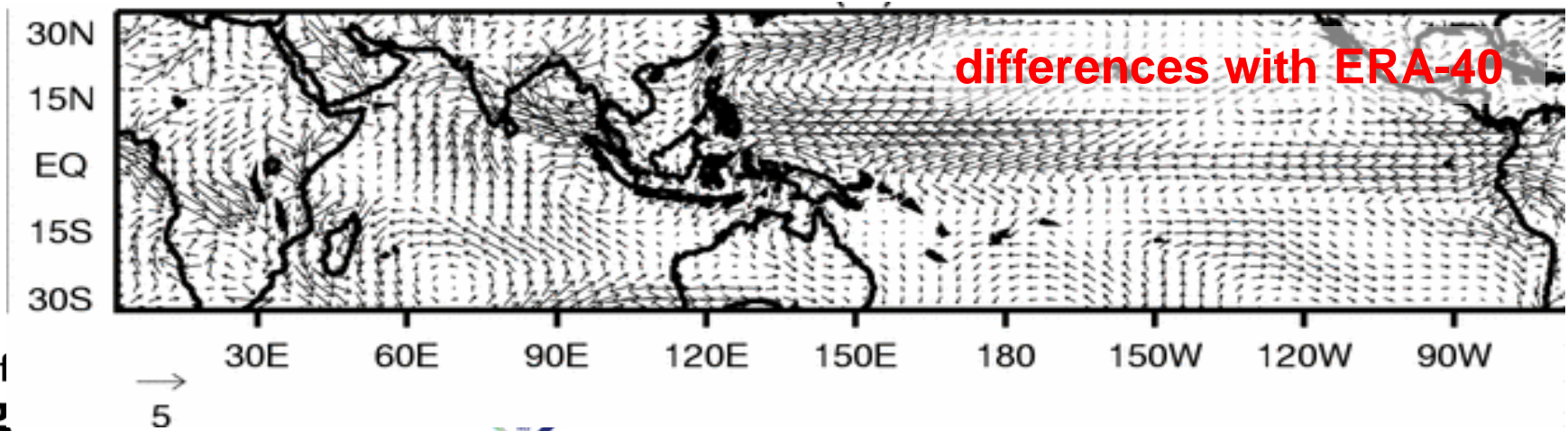
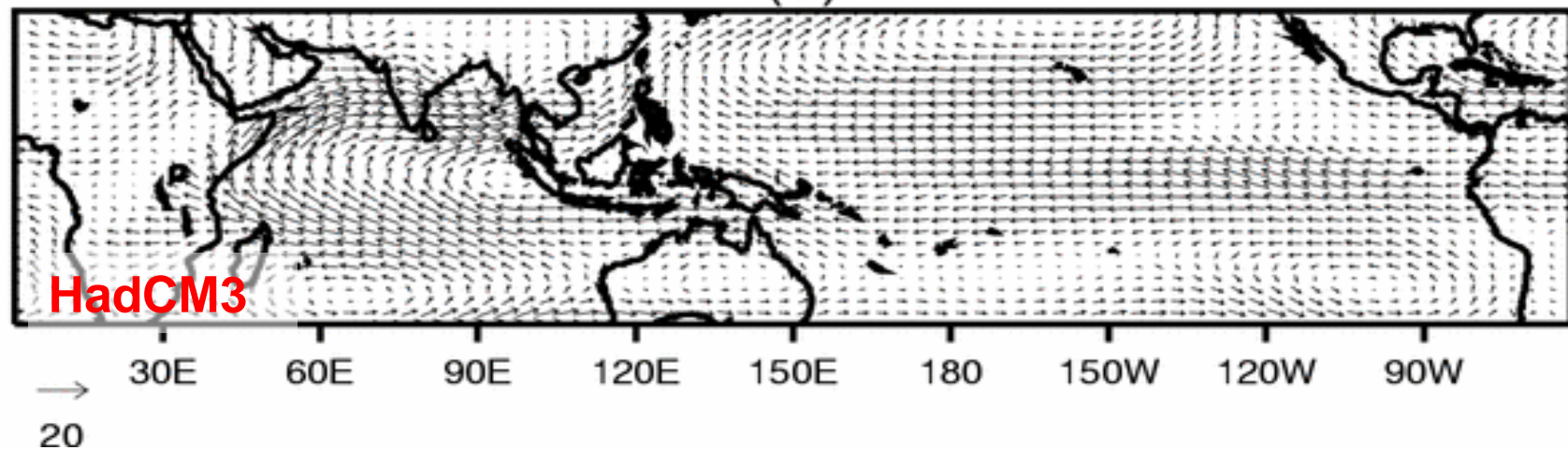


From Turner *et al.*
(2005) *QJRMS*



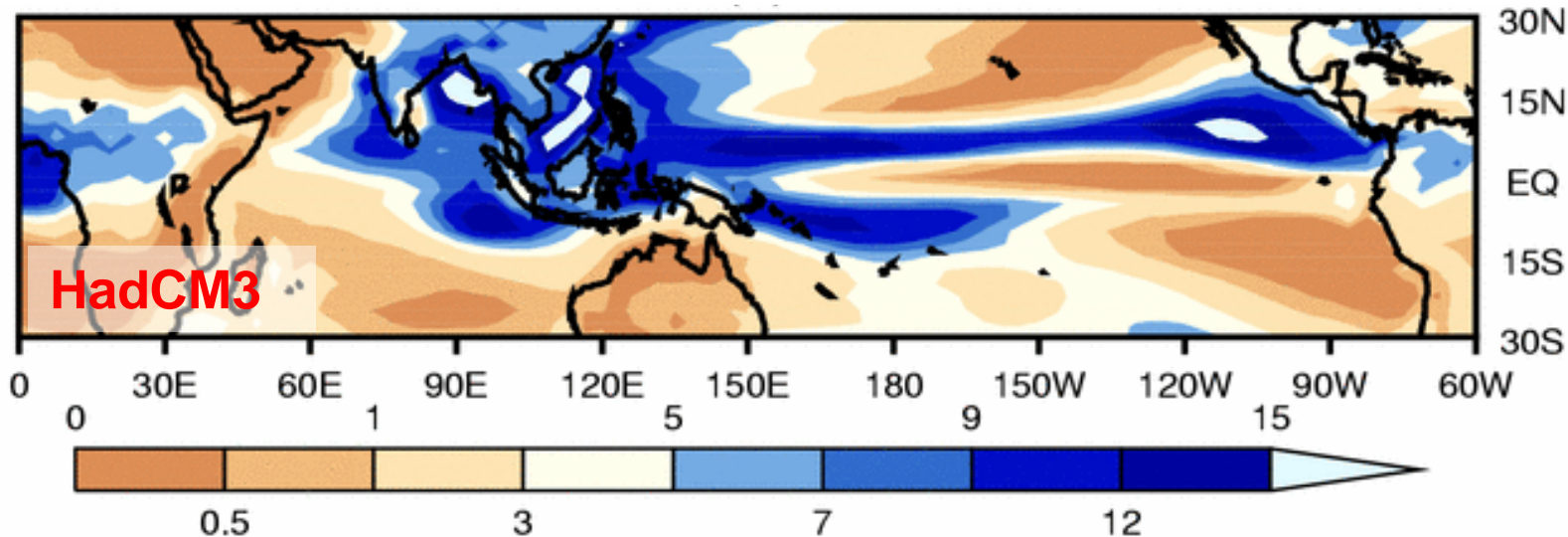
Mean summer (JJAS) 850hPa winds

- ❖ SST biases are also couple to biases in the circulation, especially on the equator...

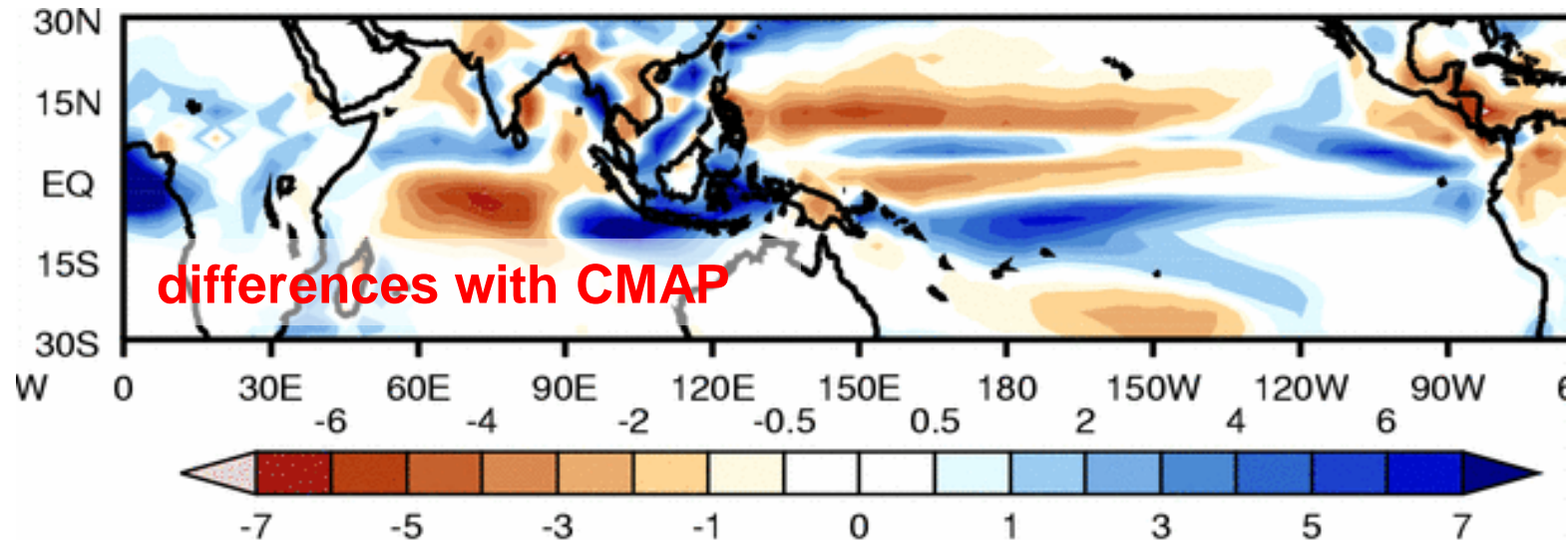


Mean summer (JJAS) precipitation

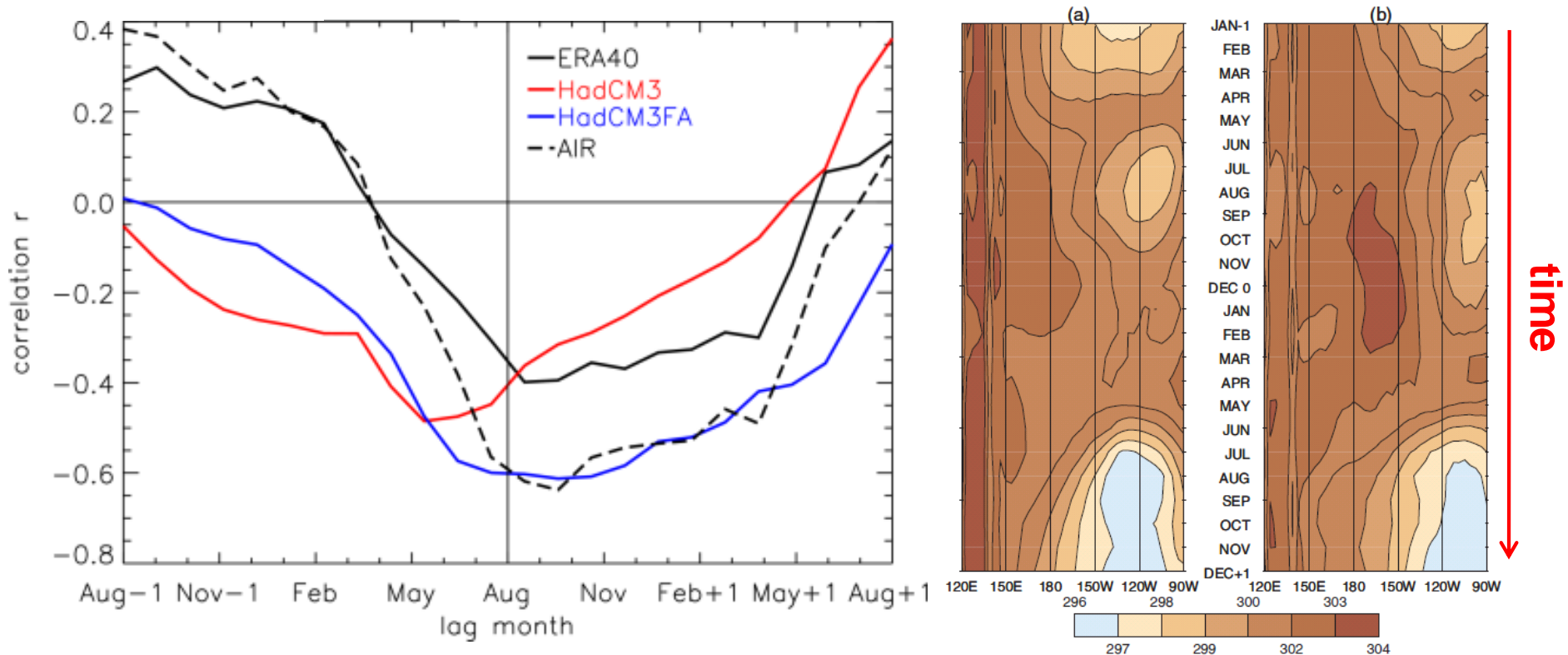
- ❖ SST biases are also coupled to biases in the circulation, especially on the equator...and in rainfall



From Turner *et al.*
(2005) *QJRMS*



Impact of tropical Pacific mean state SST on monsoon-ENSO teleconnection



- ❖ By using heat flux adjustments to correct equatorial SST biases, Turner *et al.* (2005) showed that the monsoon-ENSO teleconnection could be improved in HadCM3
- ❖ Composite El Niño events show the warmest waters to move further east in the flux corrected model

Impact of tropical diabatic heating on teleconnection in the CMIP3 models

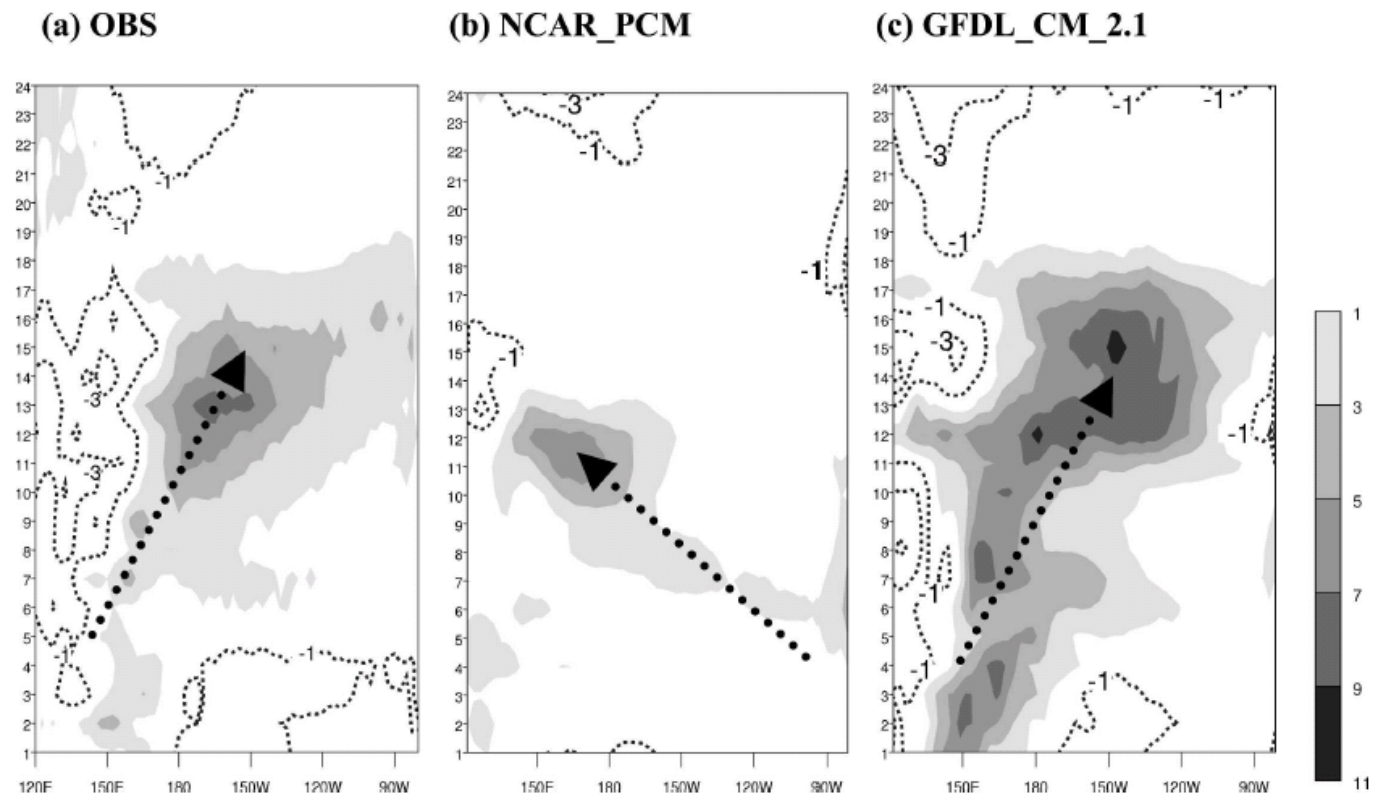


FIG. 4. As in Fig. 3 but for precipitation anomalies: (a) observations, (b) NCAR_PCM, and (c) GFDL_CM_2.1. Positive values are shaded progressively while negative values are shown in contours with an interval of 2.0 mm day^{-1} .

- ❖ Annamalai *et al.* (2007) showed importance of the correct location of diabatic heating anomalies in the equatorial Pacific to simulation of the monsoon-ENSO teleconnection

The importance of the mean state: summary

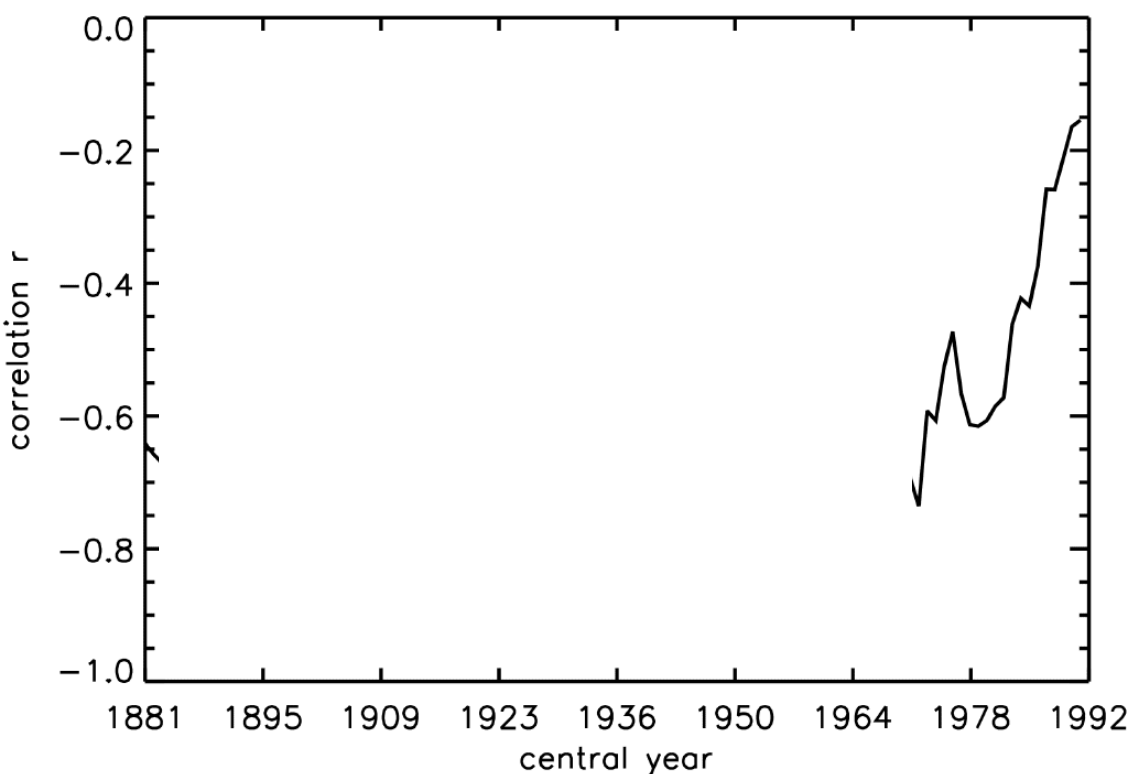
- ❖ Coupled models can resolve the approximate sign and timing of monsoon-ENSO teleconnection
- ❖ Systematic biases in the tropics contribute to poorly resolved monsoon-ENSO teleconnection
- ❖ Cold bias leads to incorrect placement of diabatic heating anomalies during El Niño
- ❖ Further evidence that models must capture the full spectrum of monsoon variability

Monsoon prediction

AWARENESS OF LONG-TERM VARIATIONS IN TELECONNECTIONS

Modulation of the ENSO-monsoon teleconnection: apparent weakening?

Moving correlation between AIR and Niño-3 SST during JJAS

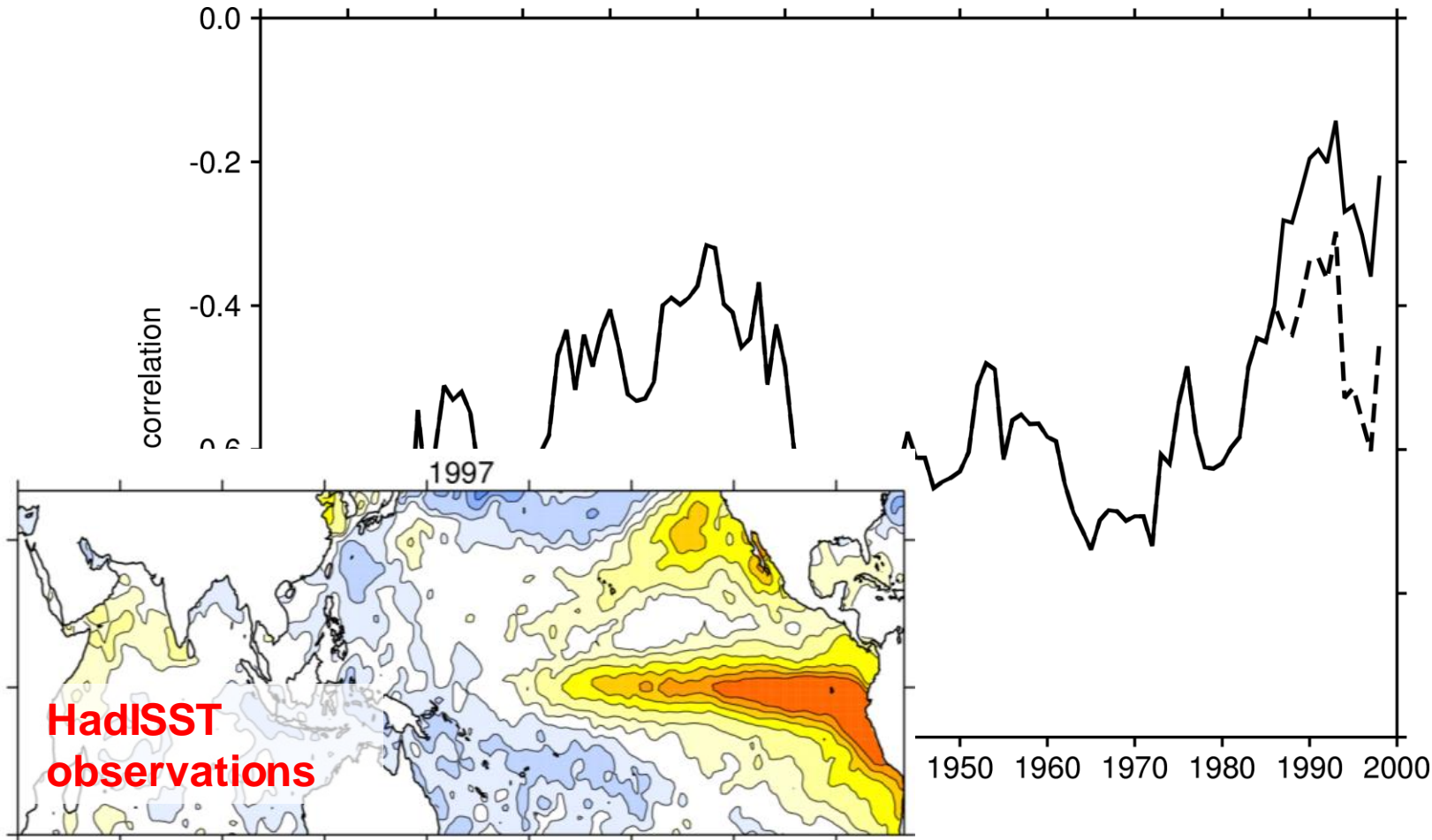


- ❖ The monsoon-ENSO teleconnection has been characterized by apparent recent weakening, but...
- ❖ Considerable interdecadal variability in the past
- ❖ Recent El Niño events (2002, 2004, 2009) have again been related to monsoon droughts of (81%, 87%, 78% LPA AIR)

Is recent “weakening” related to warming (e.g. Krishna Kumar *et al.*, 1999)?

Decadal variability in the monsoon-ENSO teleconnection

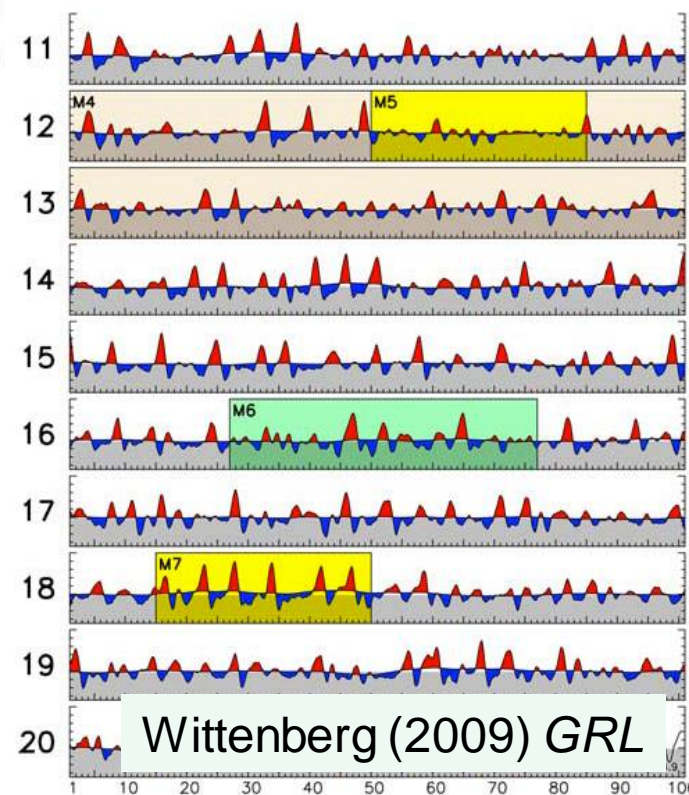
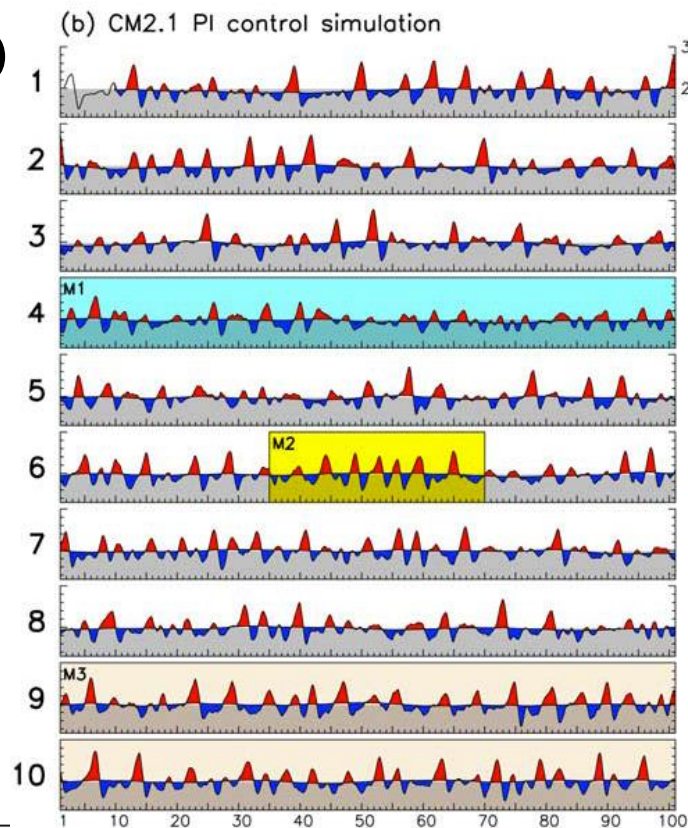
21-year moving correlation between Indian rainfall (JJAS) and Niño-3 SST anomalies



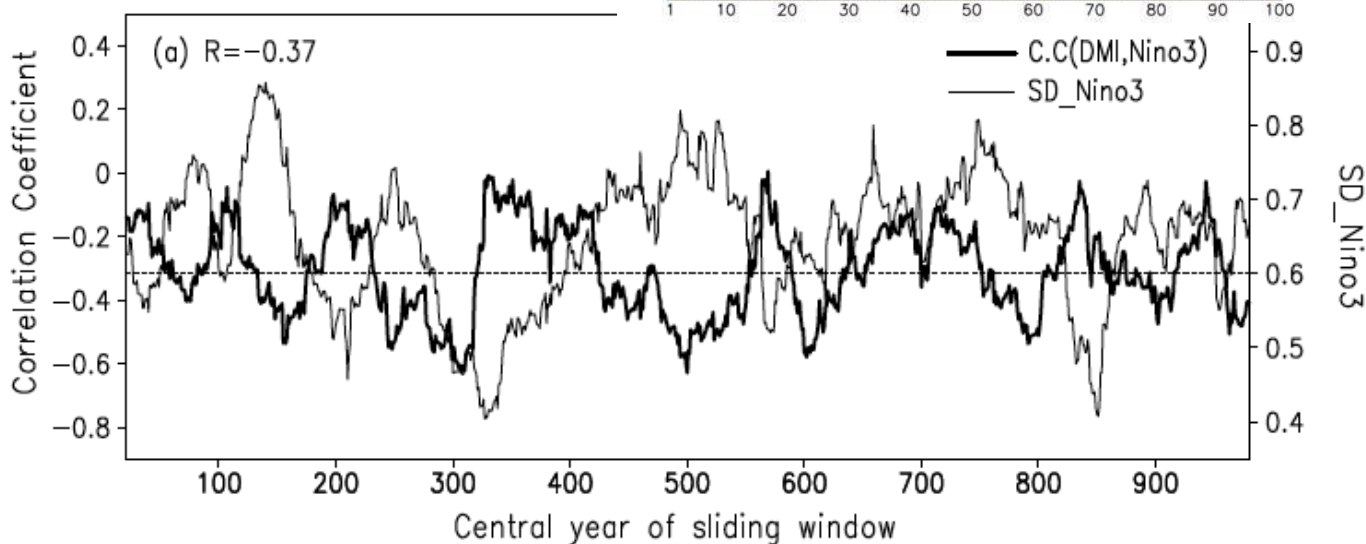
Dashed line shows the correlation recalculated without 1997 (largest El Niño on record).

ENSO variance and variations in the monsoon-ENSO teleconnection

- ❖ Ability of ENSO to vary internally
- ❖ Modulation of ENSO variance can alter teleconnection



Wittenberg (2009) *GRL*



Chen et al. (2010) *GRL*

← remember: negative correlation=strong mE teleconnection

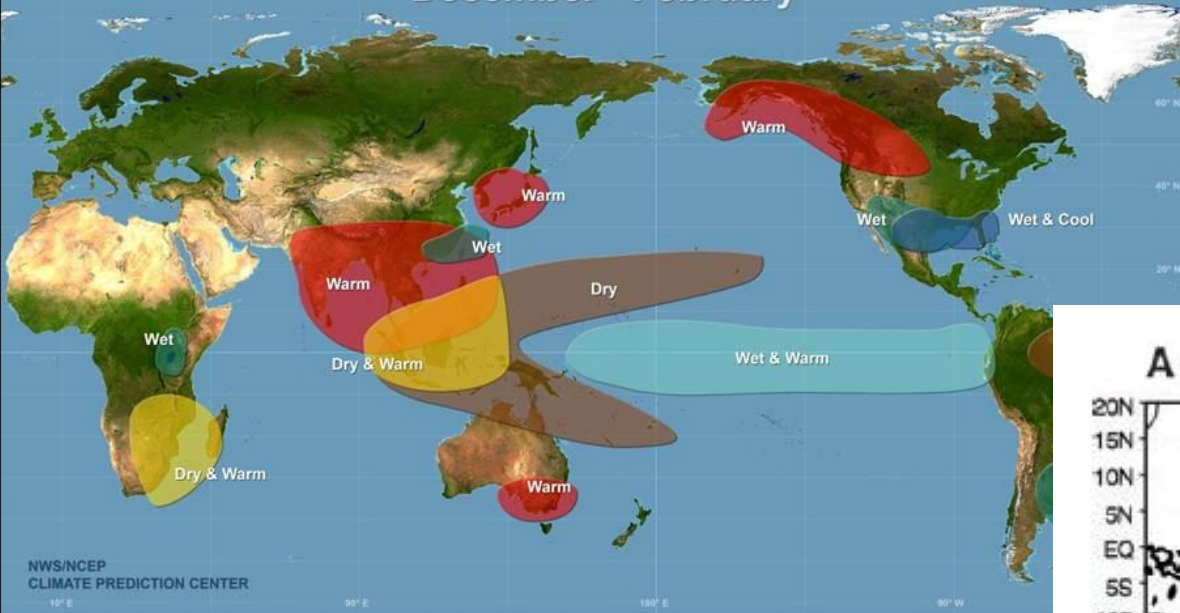
Monsoon prediction

FLAVOURS OF EL NIÑO



Warm Episode Relationships

December - February



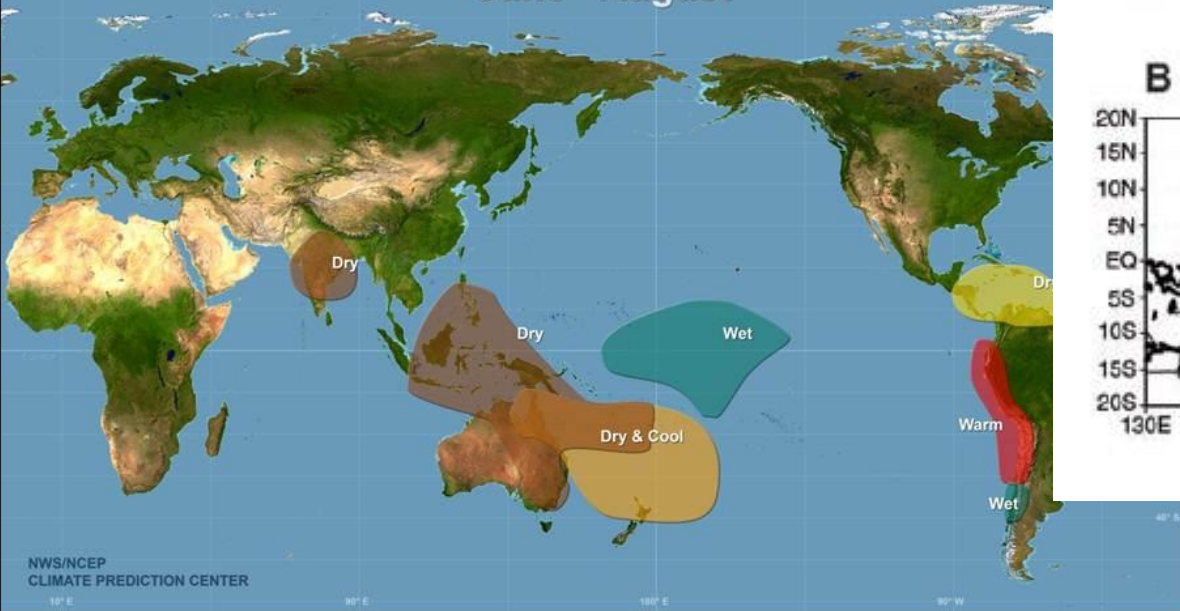
National Centre for
Atmospheric Science
NATURAL ENVIRONMENT RESEARCH COUNCIL

From Krishna
Kumar *et al.* (2006)
Science

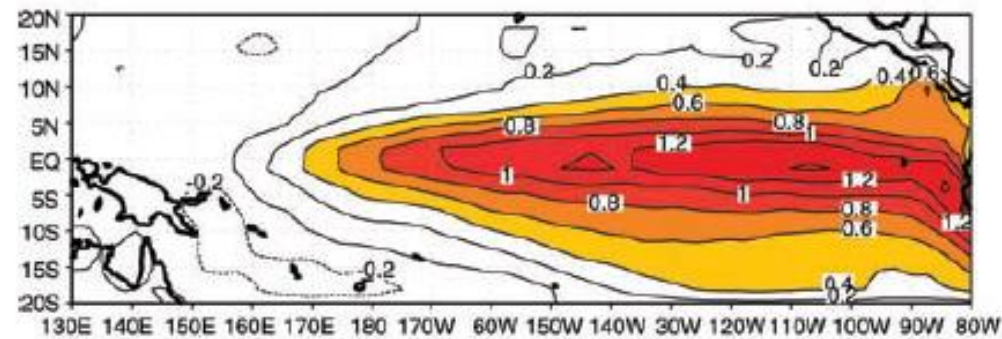


Warm Episode Relationships

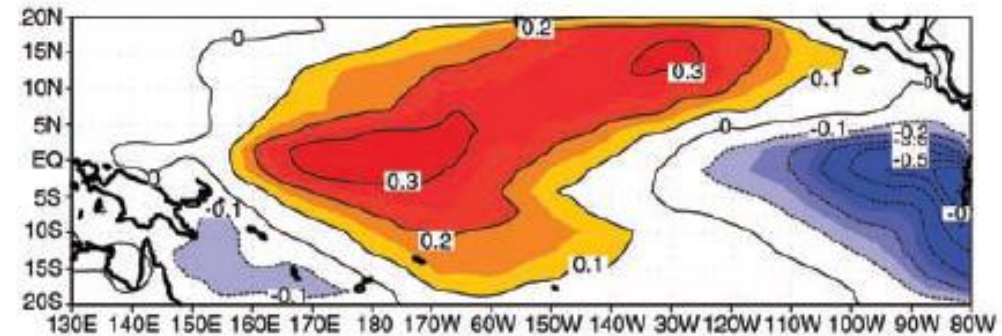
June - August



A



B



High Resolution Images can be found at:
<http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ENSO/ENSO-Global-Impacts/>

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Effect of different types of El Nino event on occurrence of monsoon drought

2nd mode of tropical Pacific SST variability is related to E/W

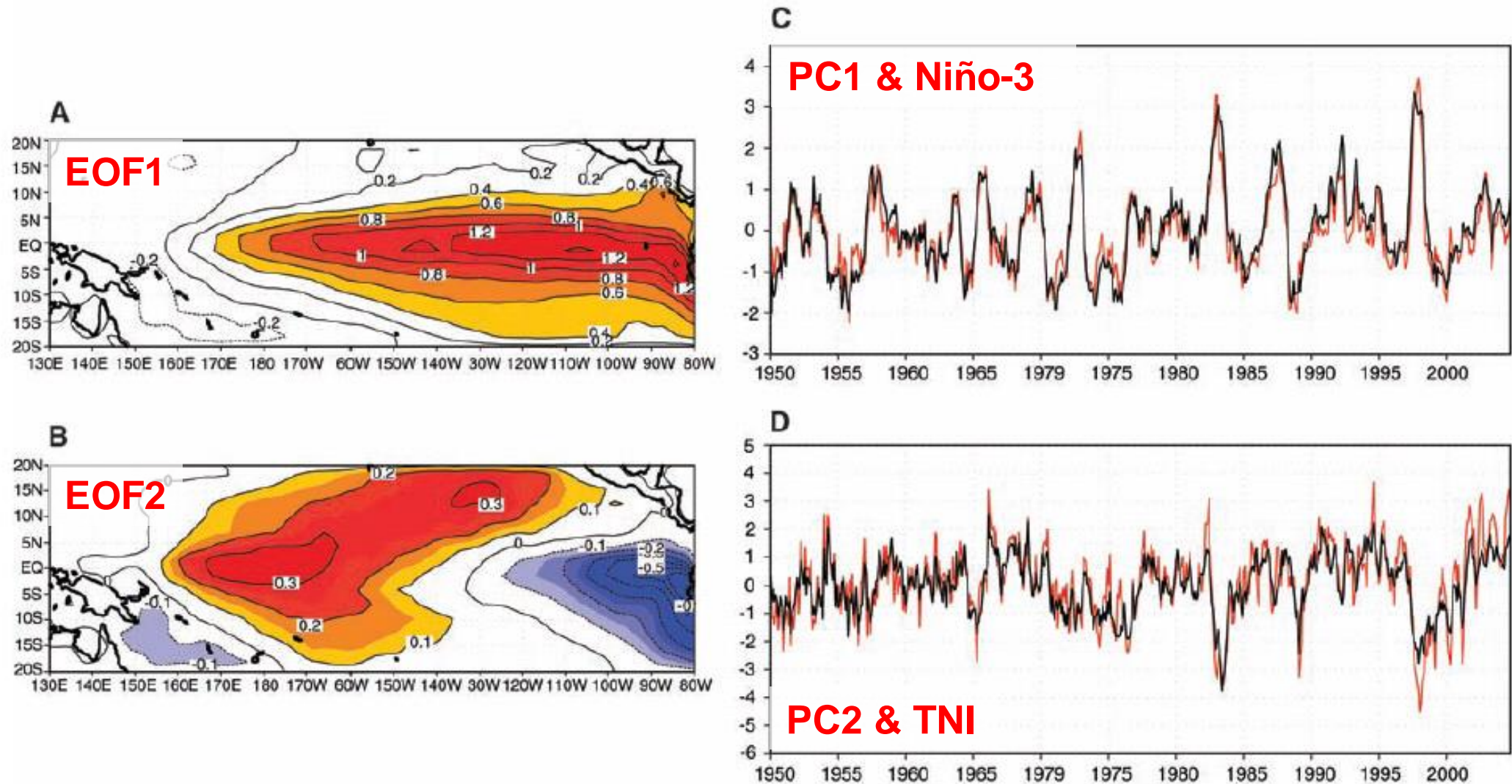


Fig. 3. (A) The first leading pattern of the tropical Pacific SST variability. (B) Same as (A) but for the second leading pattern. (C) The first leading temporal pattern (black line) overlaid with the monthly NINO3 index (red line). (D) The second leading temporal pattern (black line) overlaid with the trans-Niño index (TNI) (red line).

Effect of different types of El Niño event on occurrence of monsoon drought

- ❖ Krishna Kumar *et al.* (2006) looked at the difference between drought and non-drought monsoons during El Niño
- ❖ Severe droughts occurred during central Pacific events

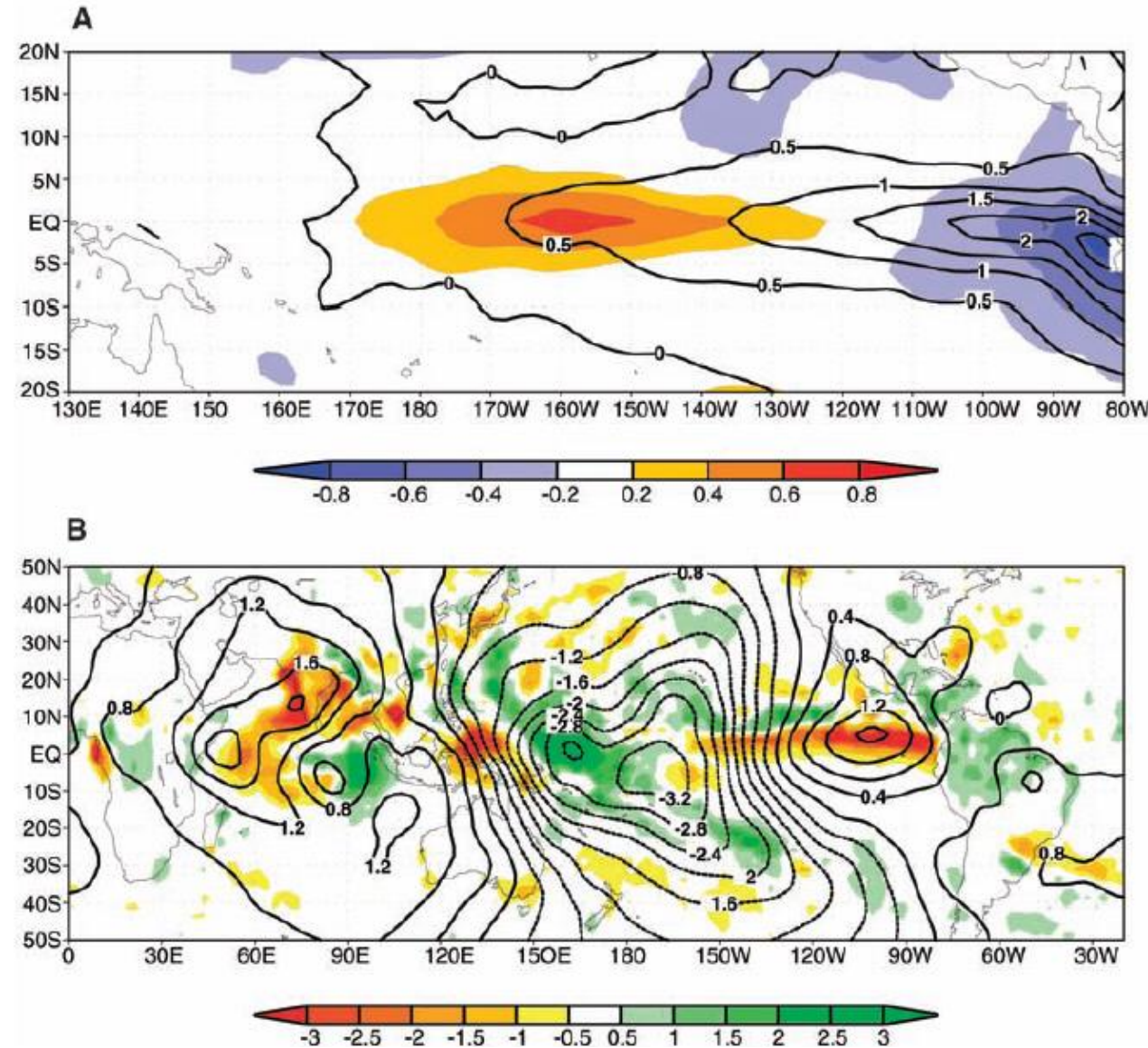


Fig. 2. (A) Composite SST difference pattern between severe drought (shaded) and drought-free El Niño years. Composite SST anomaly patterns of drought-free years are shown as contours. (B) Composite difference pattern between severe drought and drought-free years of velocity potential (contours) and rainfall (shaded). (C) PDF of all-India summer monsoon

Monsoon prediction

CLIMATE CHANGE AND MONSOON-ENSO

Decadal variability in the monsoon-ENSO teleconnection

- ❖ Long control integrations show much variability in monsoon-ENSO relationship despite absence of external forcing
- ❖ Phase of correlation change in CMIP3 20c3m integrations does not match that in observations

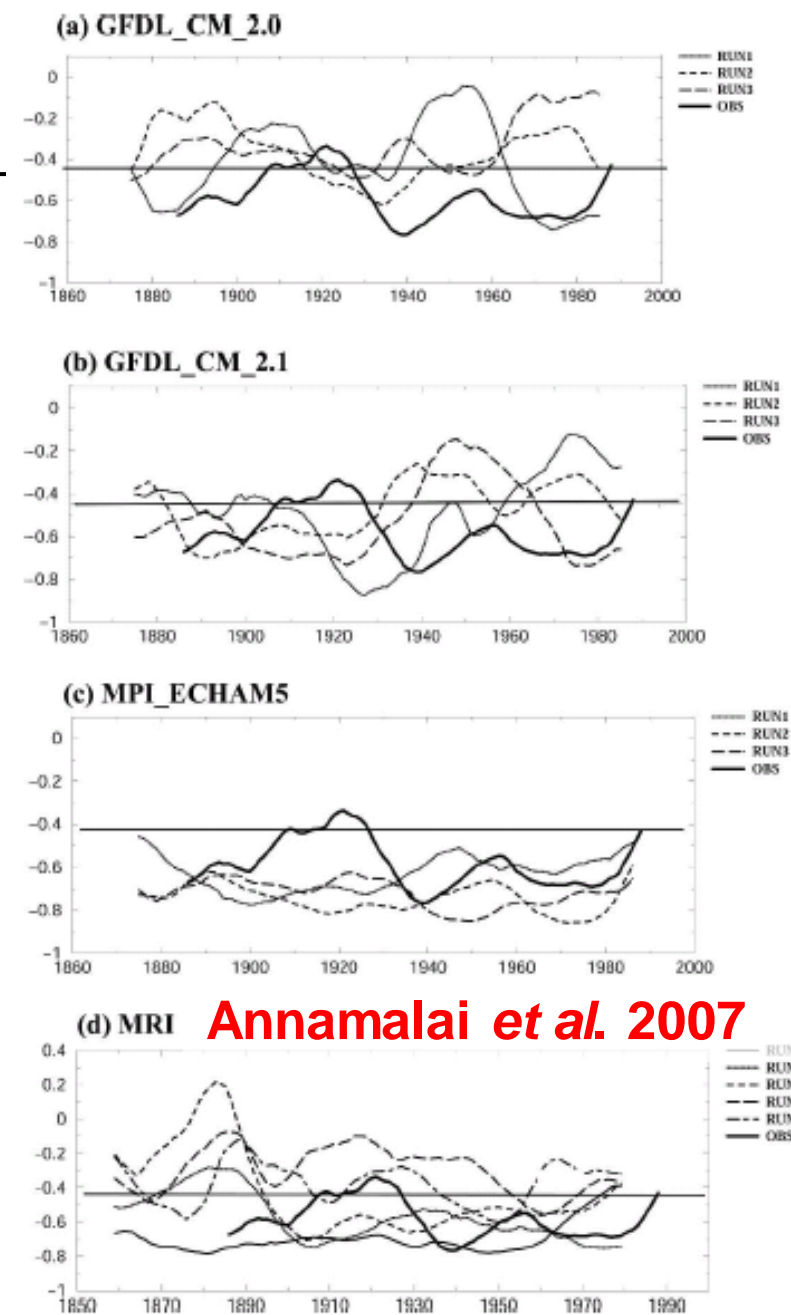
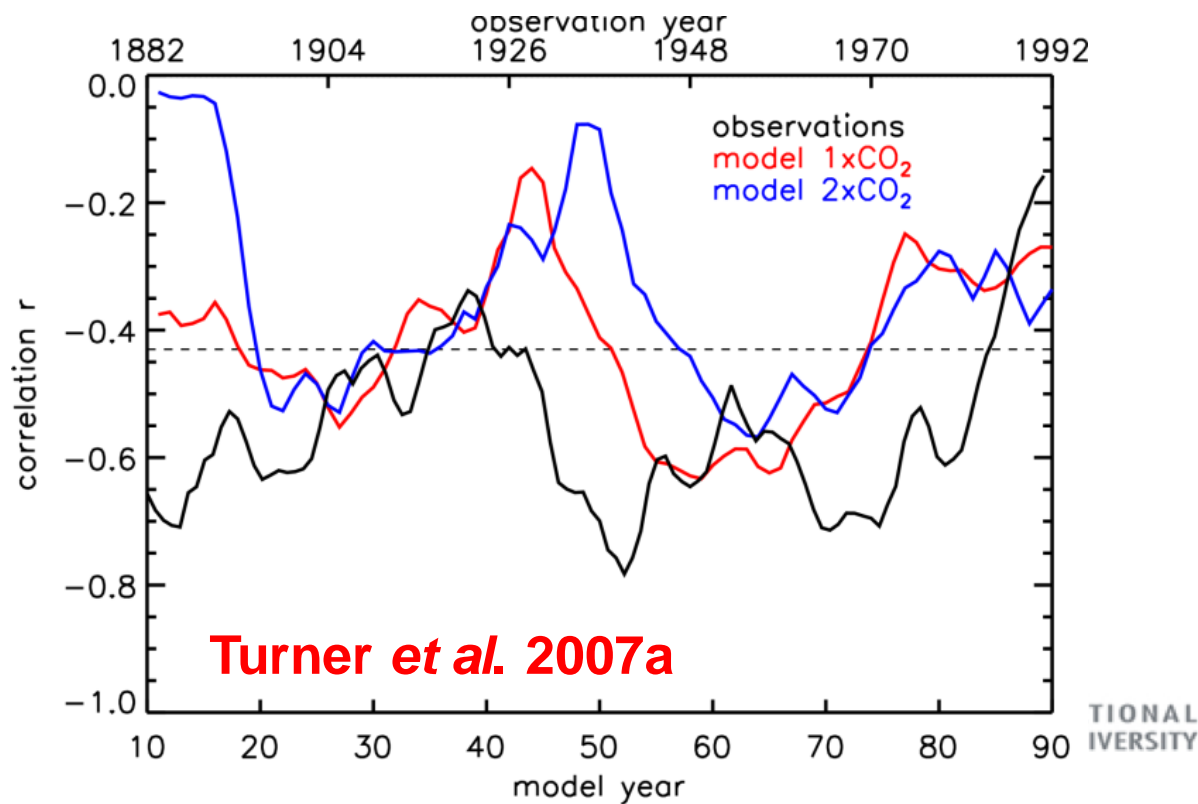
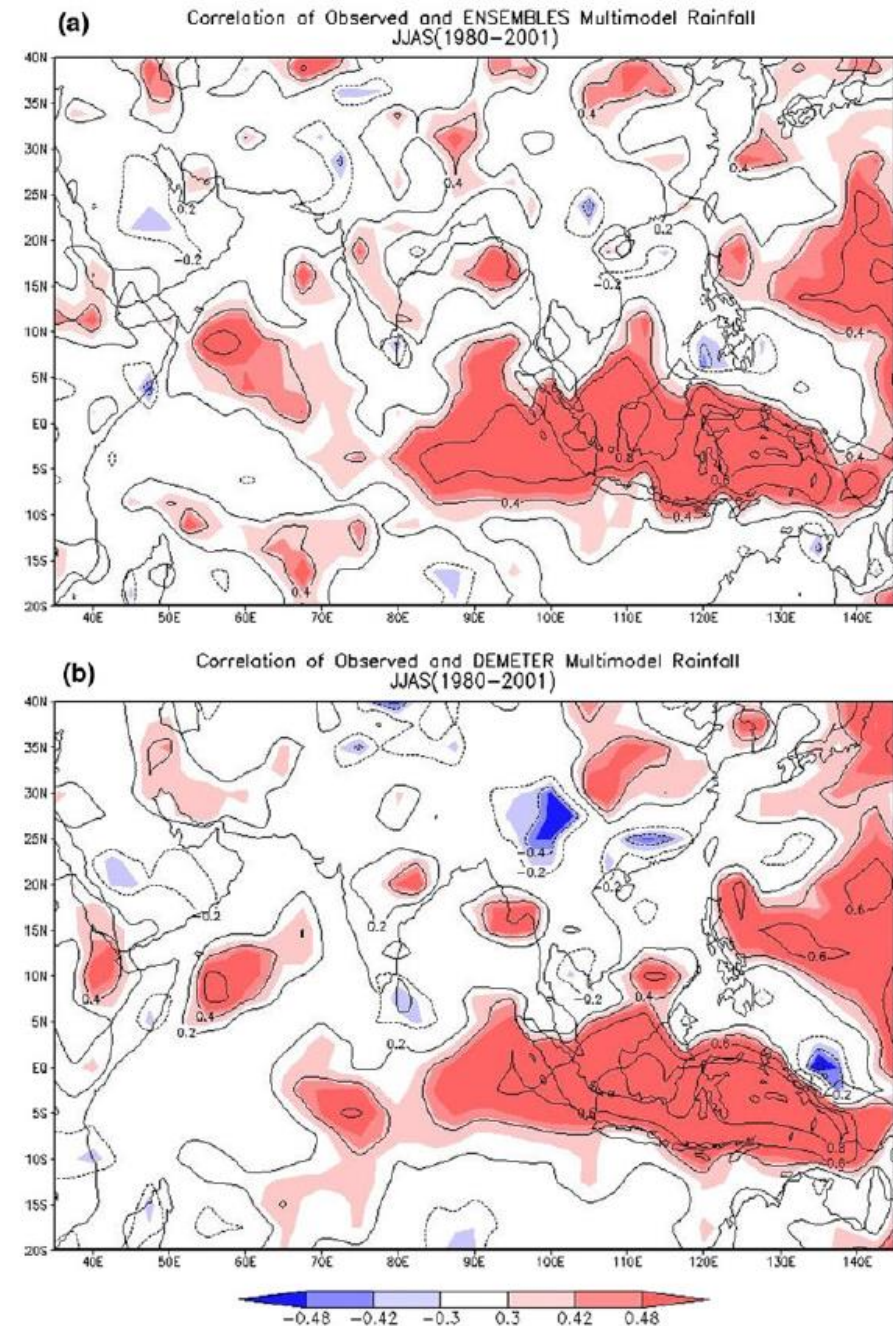


FIG. 13. Shown are 21-yr sliding correlations between AIR and Niño-3.4 SST anomalies (JJAS) for the individual realizations: (a) GFDL_CM_2.0, (b) GFDL_CM_2.1, (c) MPI_ECHAM5, and (d) MRI. In (a)–(d), results from the observation are also shown. The horizontal line shows the 5% significance level.

Monsoon prediction

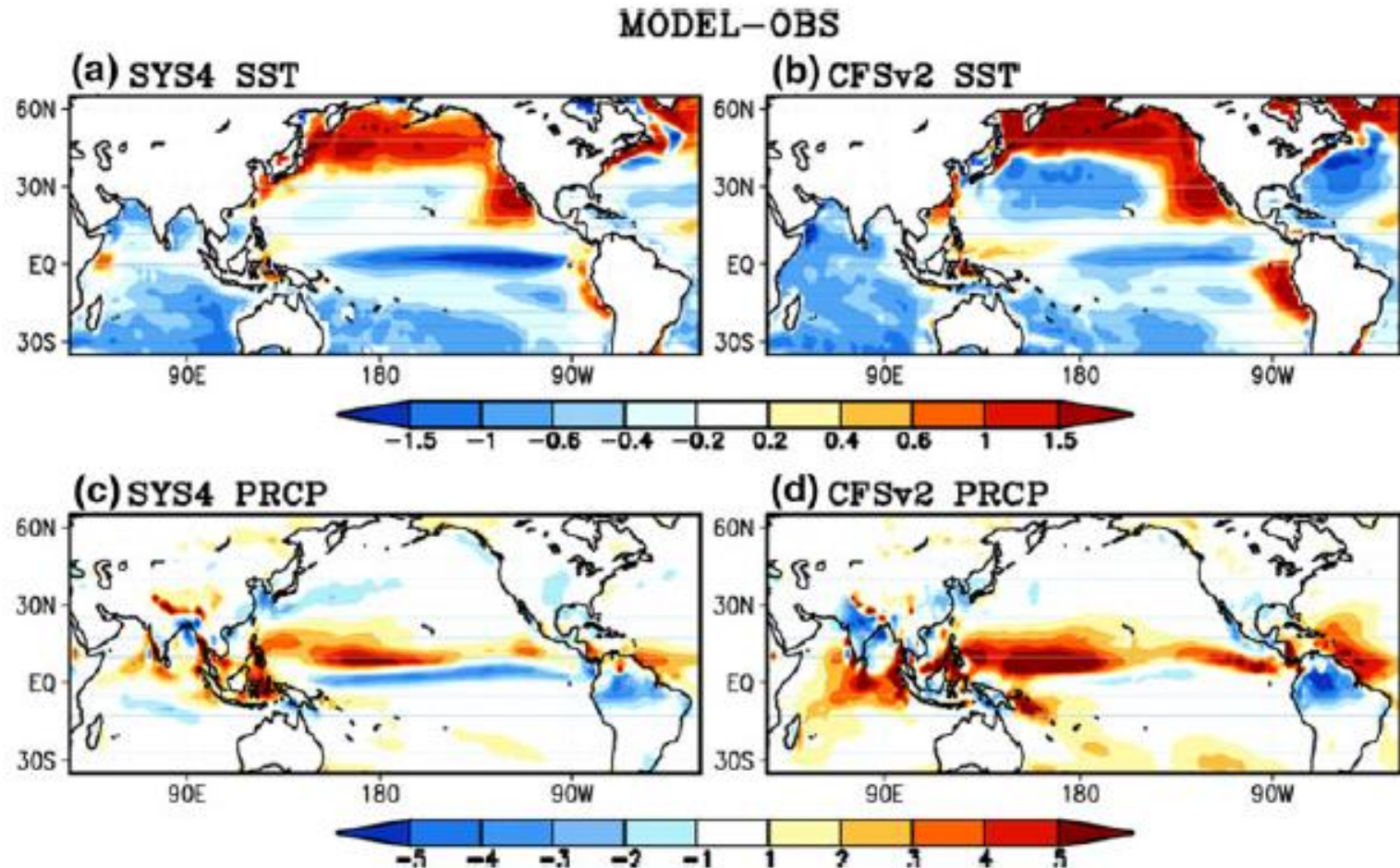
SEASONAL PREDICTION STATUS

- ❖ Rajeevan et al. (2012) show some agreement with observed anomalies in monsoon region (interannual correlation 1980-2001)
- ❖ Example: exceeding 0.4 over parts of India
- ❖ Much stronger and more spatially consistent over the Maritime Continent



- ❖ Reminder that coupled models suffer SST biases, even a month or so after initialization

Fig. 1 Climatological summer mean (JJA) bias (model-observation) of (top) SST (K) and (bottom) precipitation (mm/day) for (a, c) SYS4 and (b, d) CFSv2

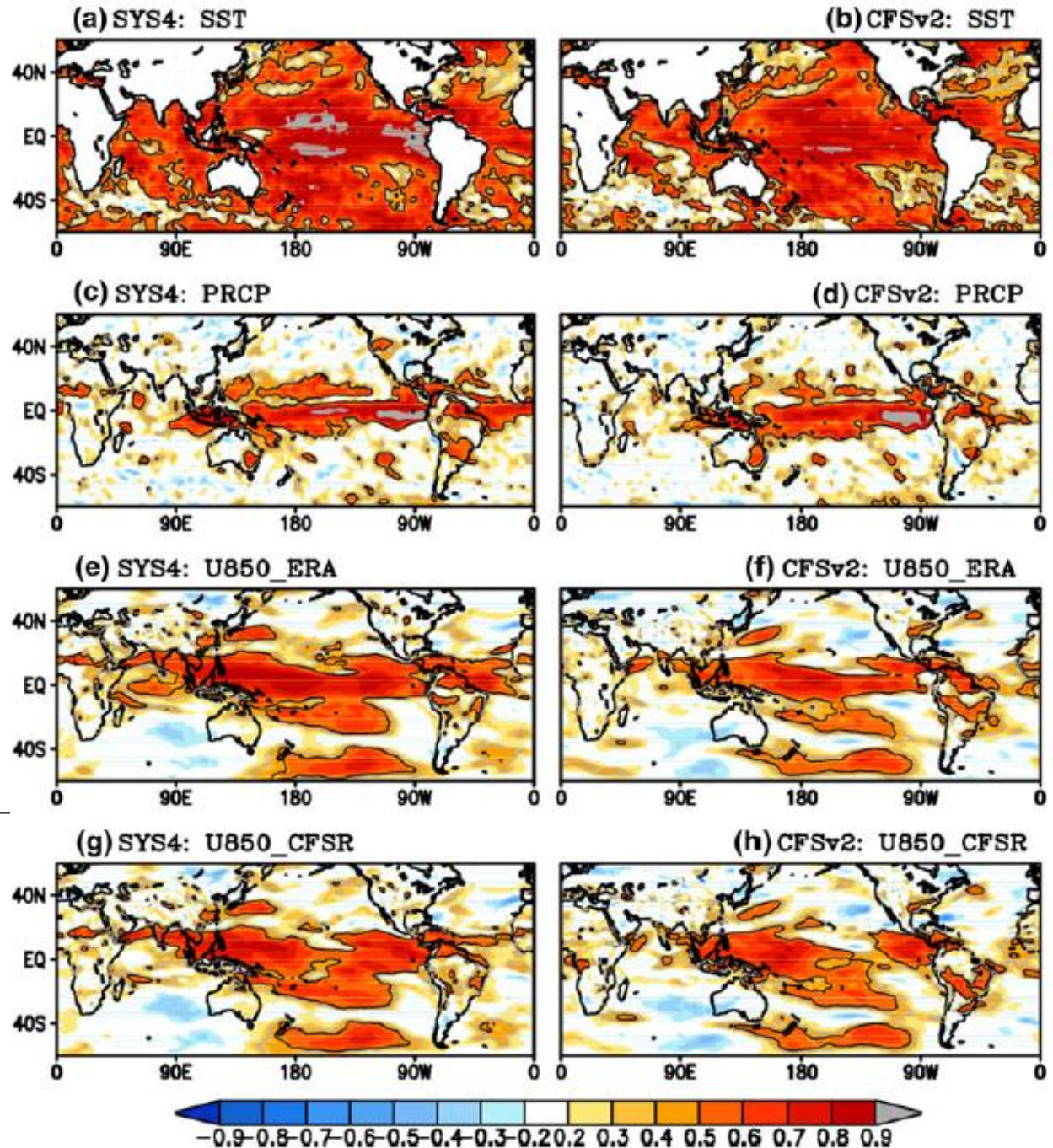


From Kim *et al.*
(2012) *Clim. Dyn.*

More recent seasonal forecasts

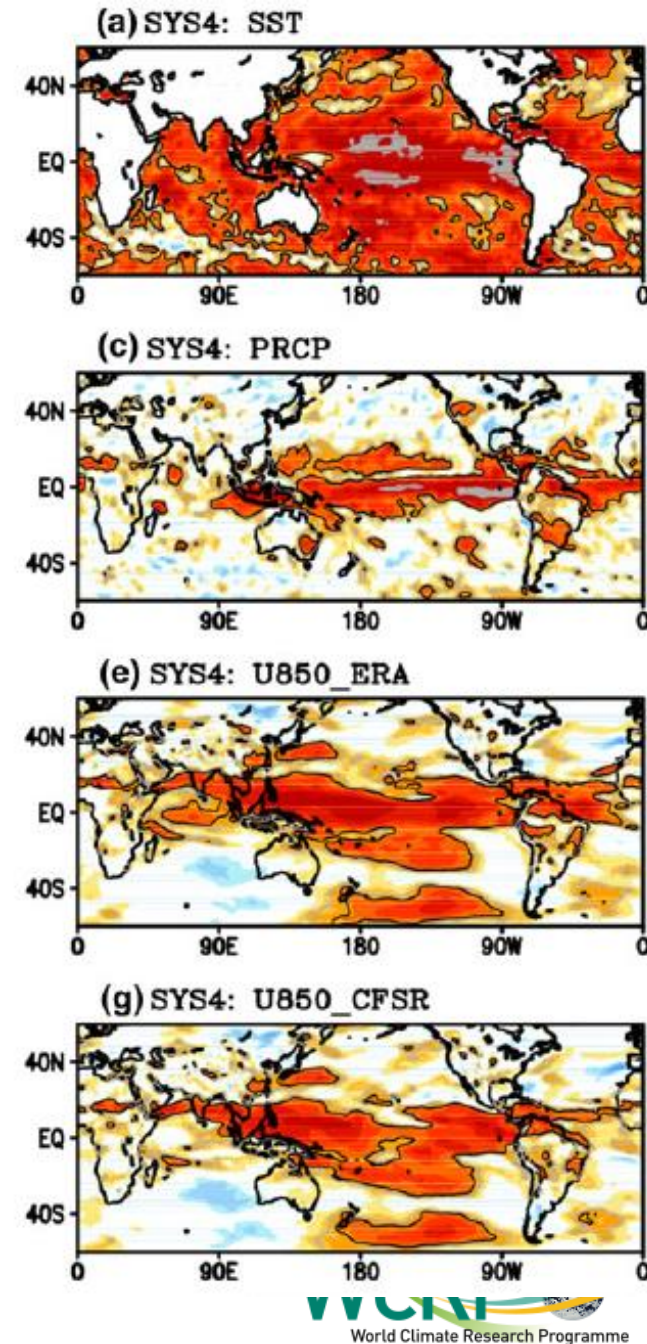
Fig. 4 Correlation coefficients for (first line) SST (second line) precipitation and zonal wind at 850 hPa with (third line) ERA interim and (fourth line) CFS reanalysis for (left) SYS4 and (right) CFSv2. Solid black (gray) line represents statistical significance of the correlation coefficients at 99 % (95 %) confidence level

These are interannual correlations of predicted JJA-mean quantities with obs



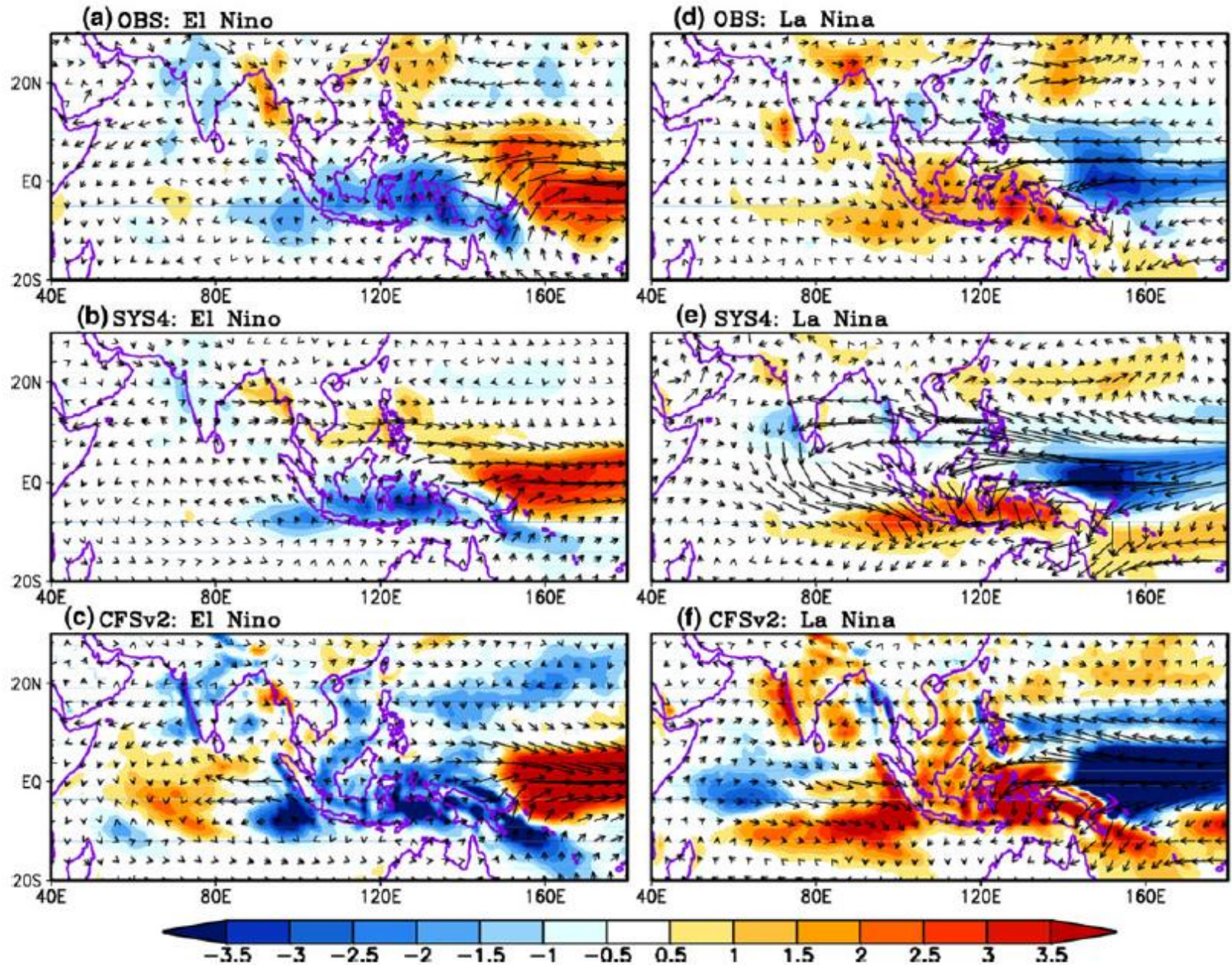
More recent seasonal forecasts

- ❖ Interannual variations in tropical SST generally well predicted (inherent longer time scales of variation than in the atmosphere)
- ❖ Especially for the monsoon regions, models perform better at interannual correlations of circulation (U850) than precipitation
 - An inherently large-scale field (less noisy)
 - Still huge problems and model diversity in parametrizing tropical convection



ENSO composite comparisons

Composite: PRCP and 850hPa wind anom.

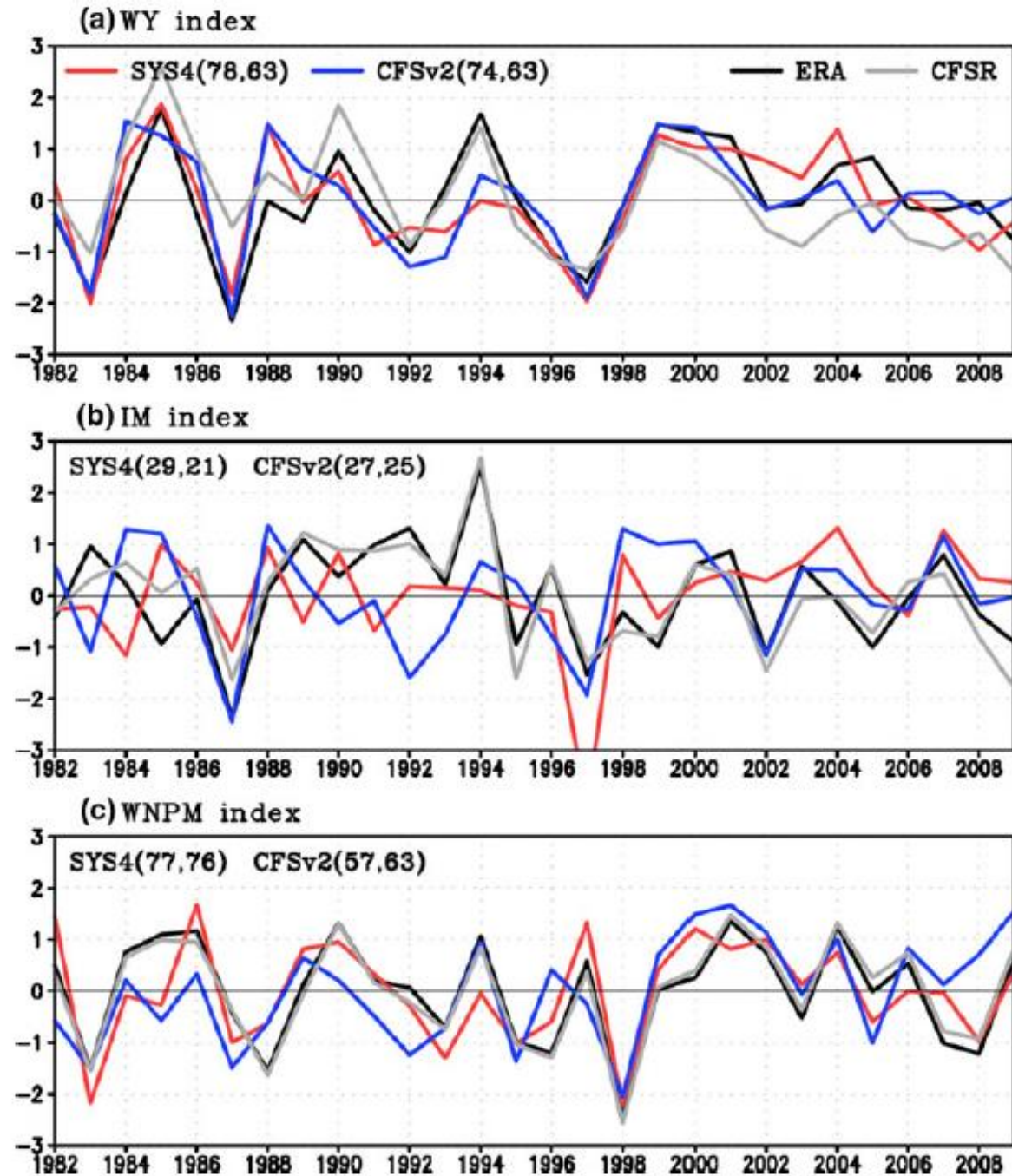


From Kim *et al.*
(2012) *Clim. Dyn.*

Skill of circulation vs. precipitation IAV

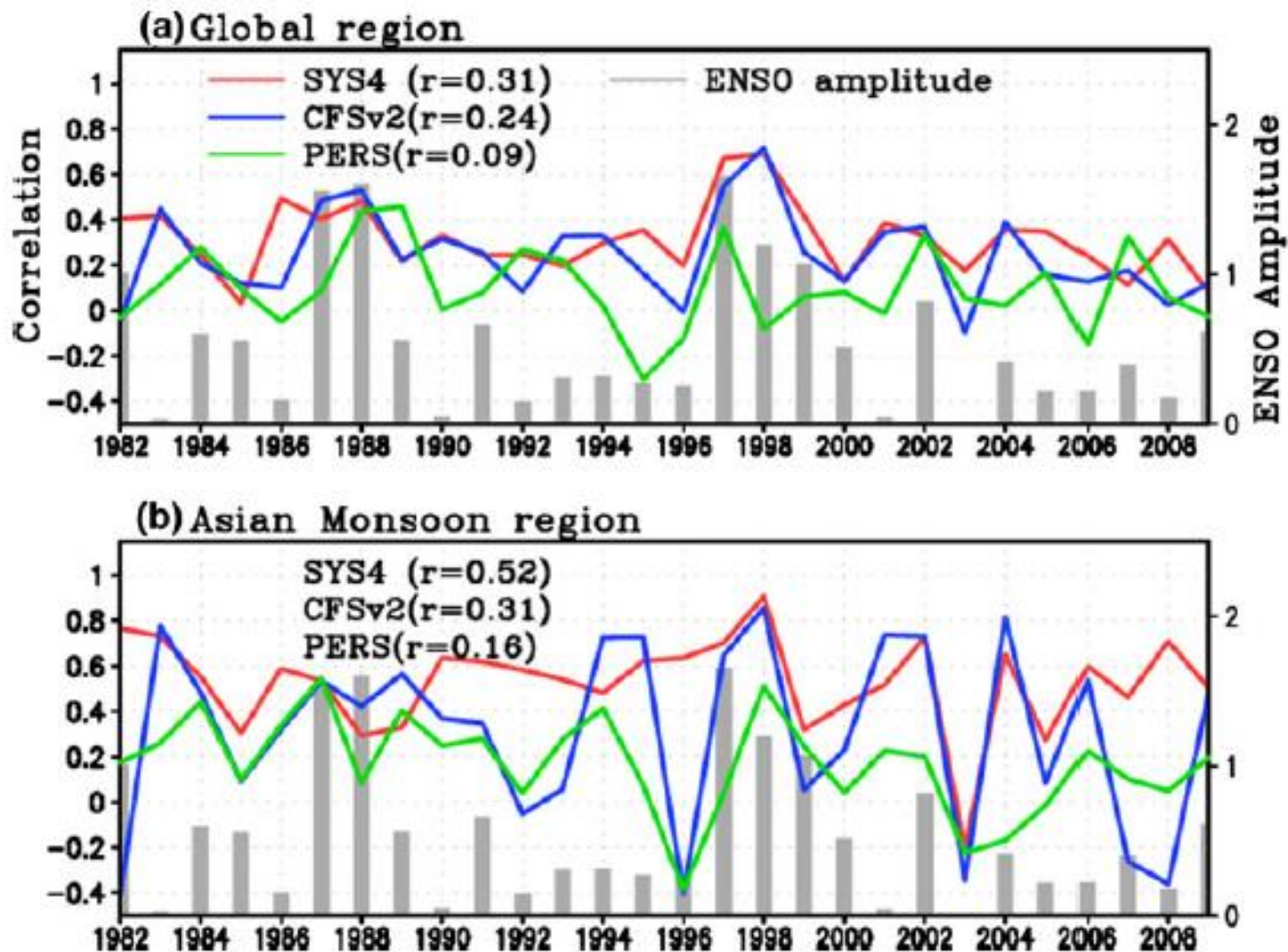
Fig. 5 Monsoon indices:
(a) WY index (b) IM index and
(c) WNPM index from 1982 to
2009 for ERA interim (black),
CFS reanalysis (gray), SYS4
(red) and CFSv2 (blue).
Numbers indicate the temporal
correlation coefficient
(multiplied by 100) compared
with (left) ERA interim and
(right) CFS reanalysis

Interannual variations of
circulation (top, bottom)
show much better skill
than regional rainfall
(India, shown middle)



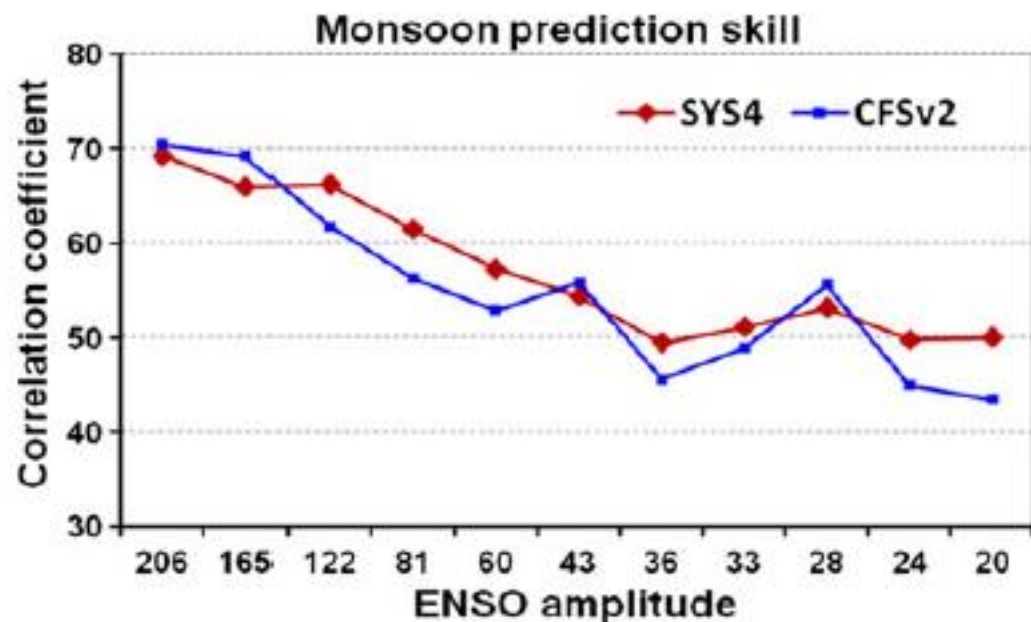
Impact of ENSO amplitude on prediction skill

Fig. 10 Anomaly pattern correlation for (a) global region and (b) Asian Monsoon region of the zonal wind at 850 hPa for SYS4 (red), CFSv2 (blue) and persistence prediction (green). The gray bar represents the ENSO amplitude for boreal summer. Numbers indicate the mean correlation coefficient over 28 years



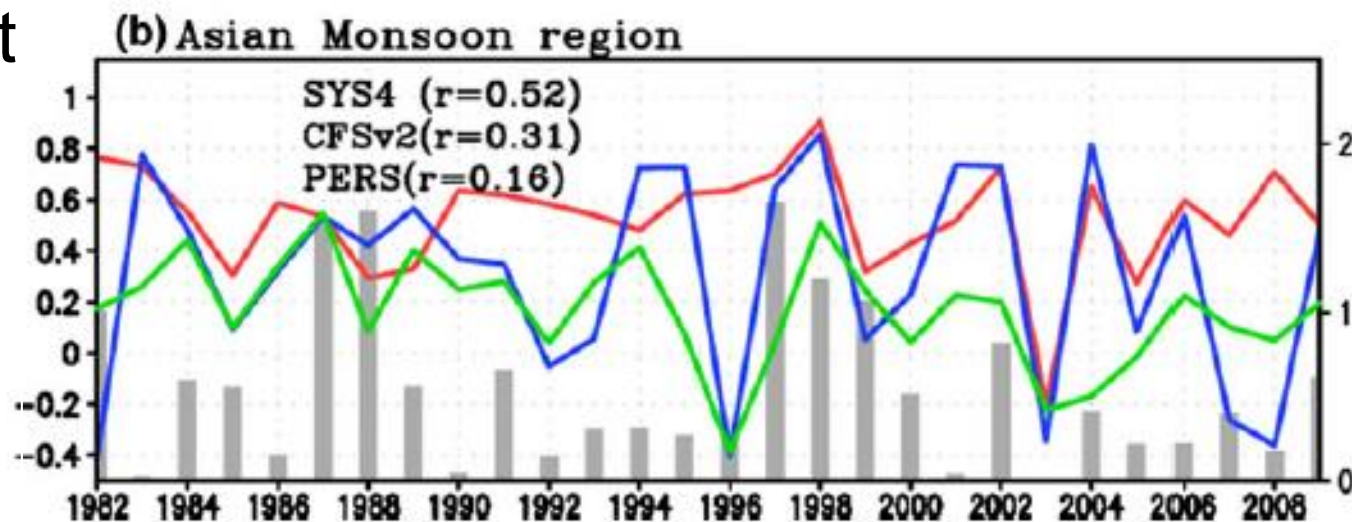
Here “skill” is measured by the spatial pattern correlation of u -wind for each year

Impact of ENSO amplitude on prediction skill

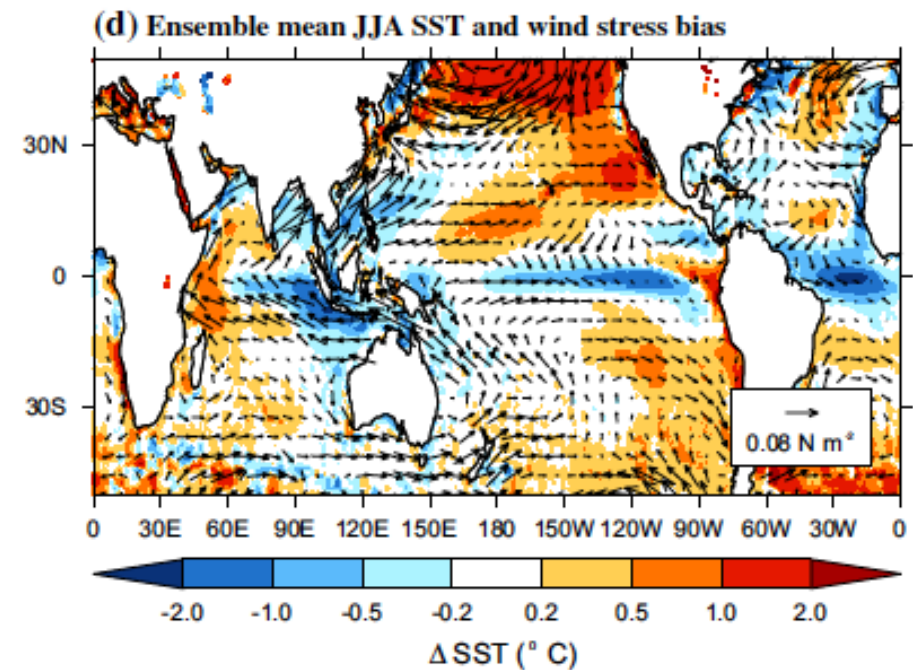
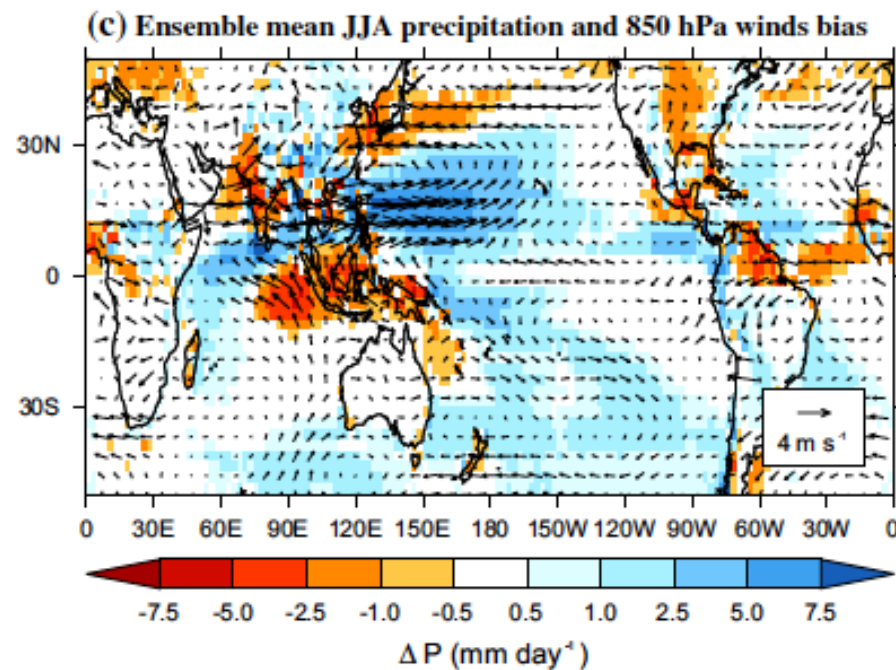
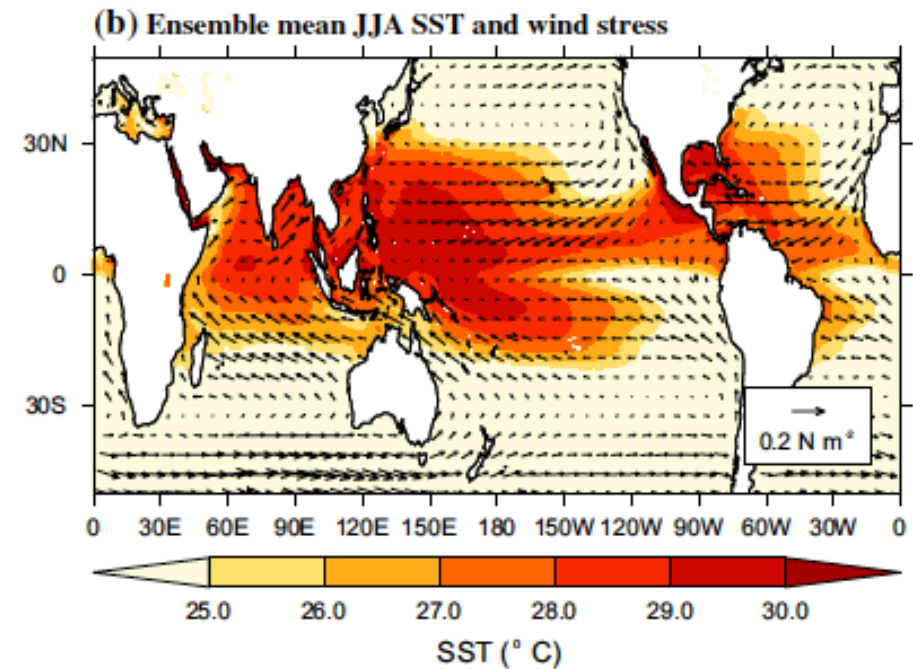
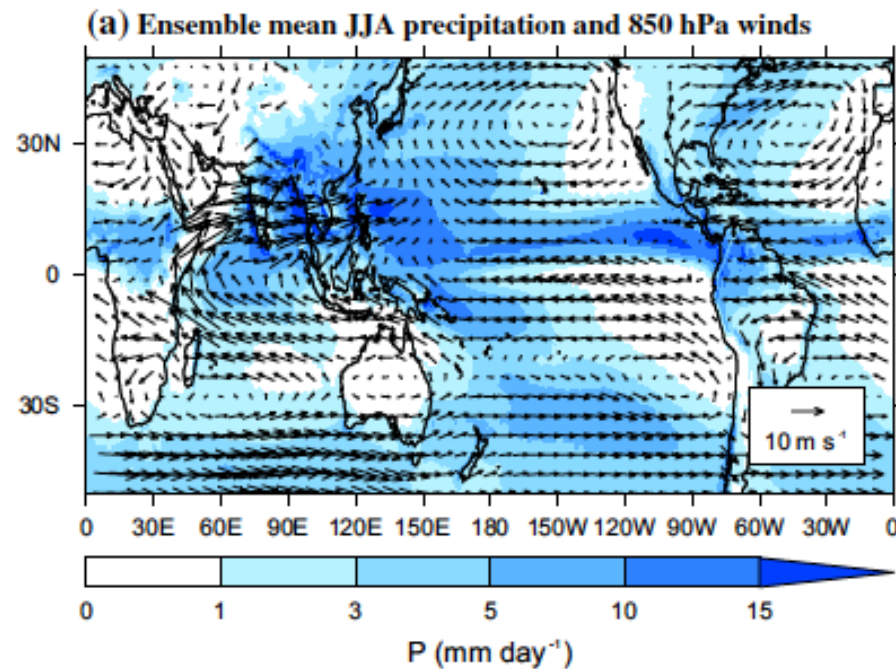


Now showing the pattern correlations taken from the below plot, as a function of ENSO amplitude (the grey bars)

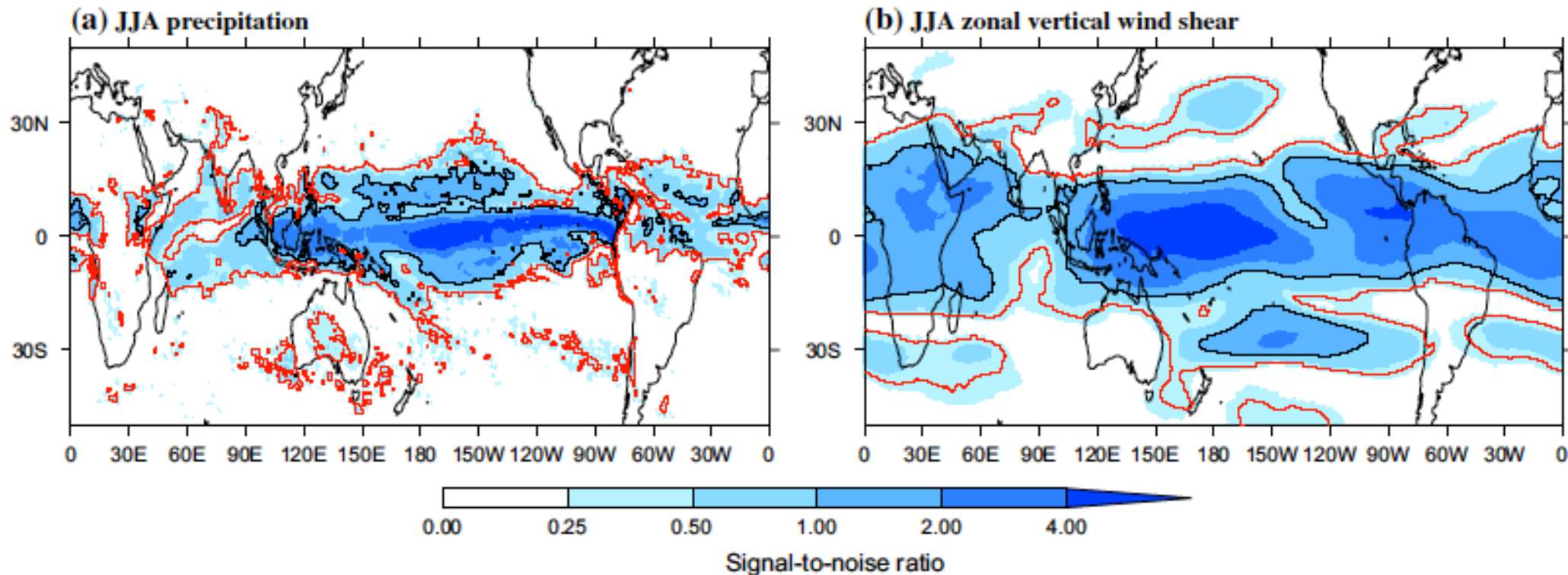
Nicely illustrates that in the absence of a strong driving forcing (ENSO) then there is far more noise



JJA seasonal forecast biases in MetUM



- ❖ As in the CFS/EC models of Kim et al., MetUM shows more signal in Asian monsoon region for circulation



S/N defined as ratio of variance of interannual timeseries of ensemble mean to time-mean of variances of ensemble for each year

- ❖ As in the CFS/EC models of Kim et al., MetUM shows more signal in Asian monsoon region for circulation

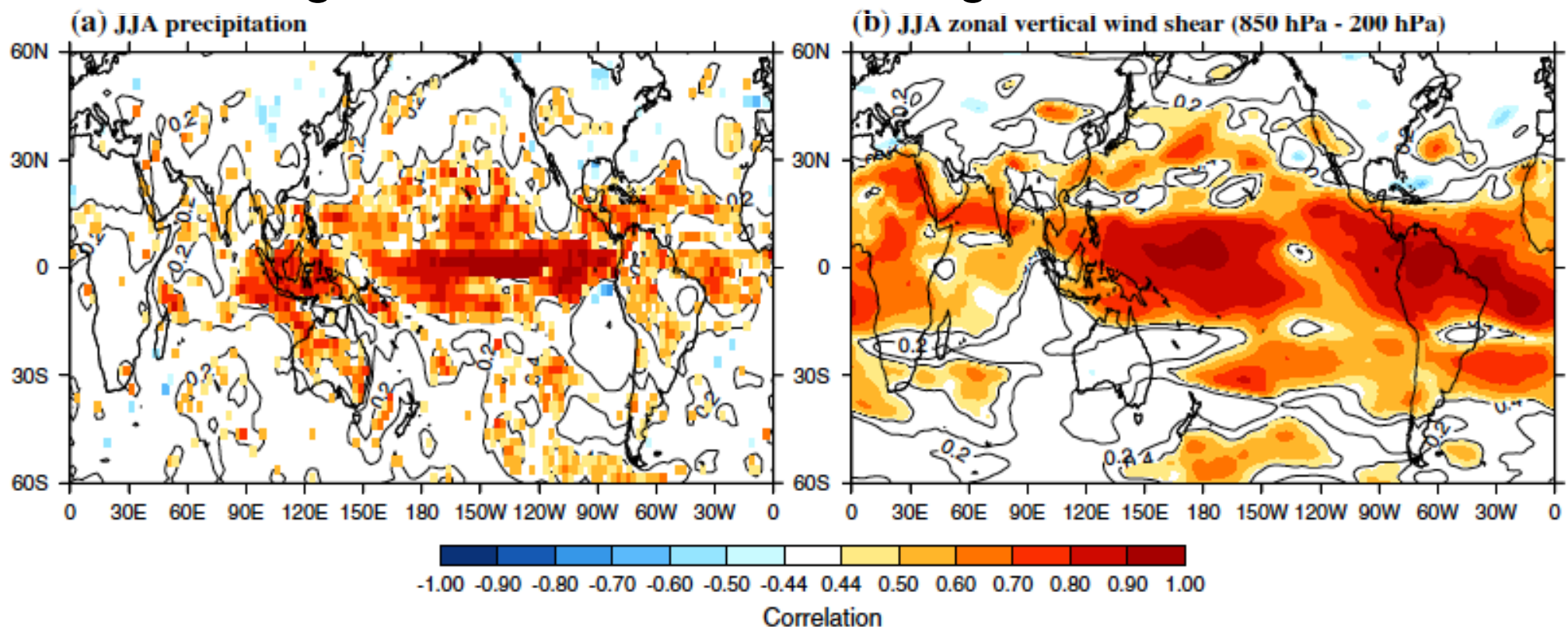
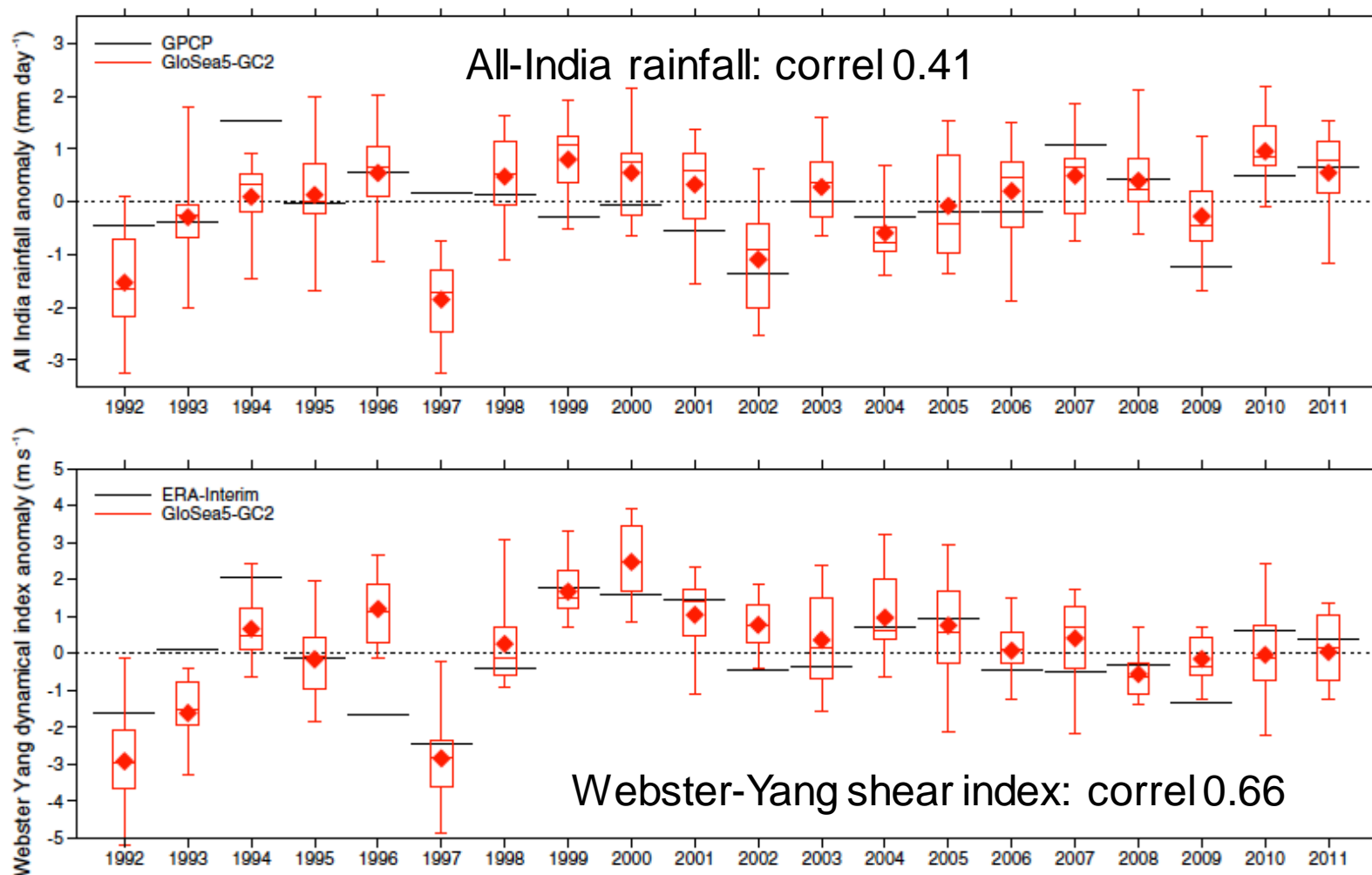


Fig. 3 Grid-point anomaly correlations of GPCP JJA precipitation and ERA-Interim JJA vertical wind shear with their GloSea5-GC2 ensemble mean equivalents. Significant skill (0.44, $p < 0.05$) is shaded, while lower skill is contoured at 0.2 and 0.4

Large-scale
circulation
measures
outperform
localized
rainfall



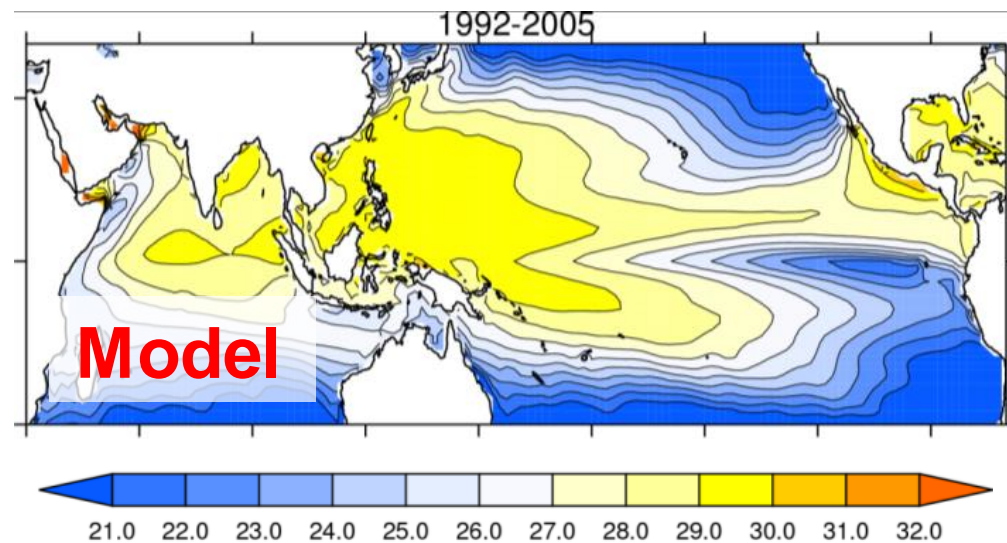
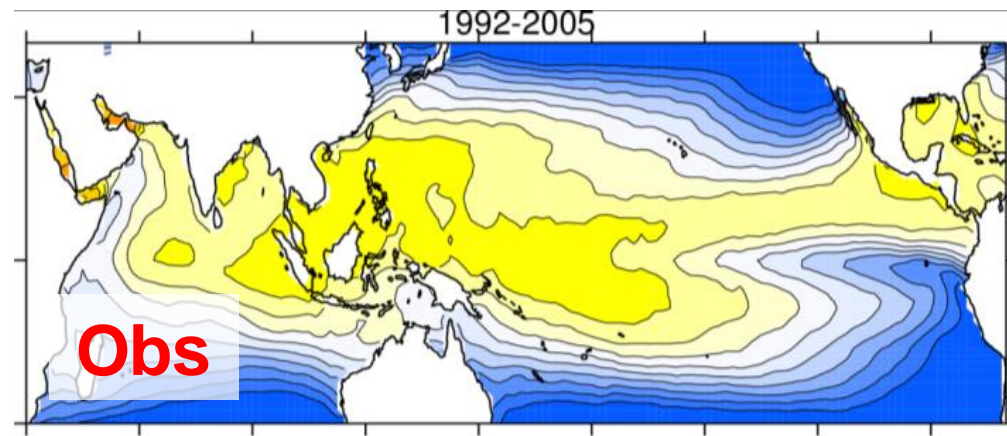
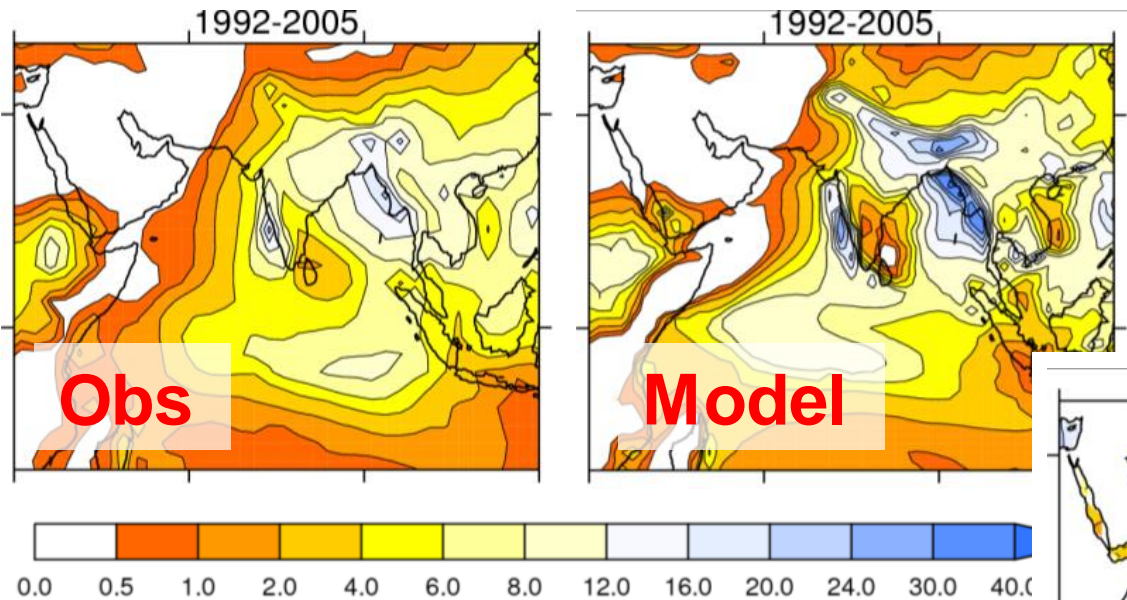
From Johnson *et al.*
(2016) *Clim. Dyn.*

	Correlation of ensemble mean
AIR	0.41
Wang-Fan index	0.36
Webster-Yang index	0.66

Monsoon prediction

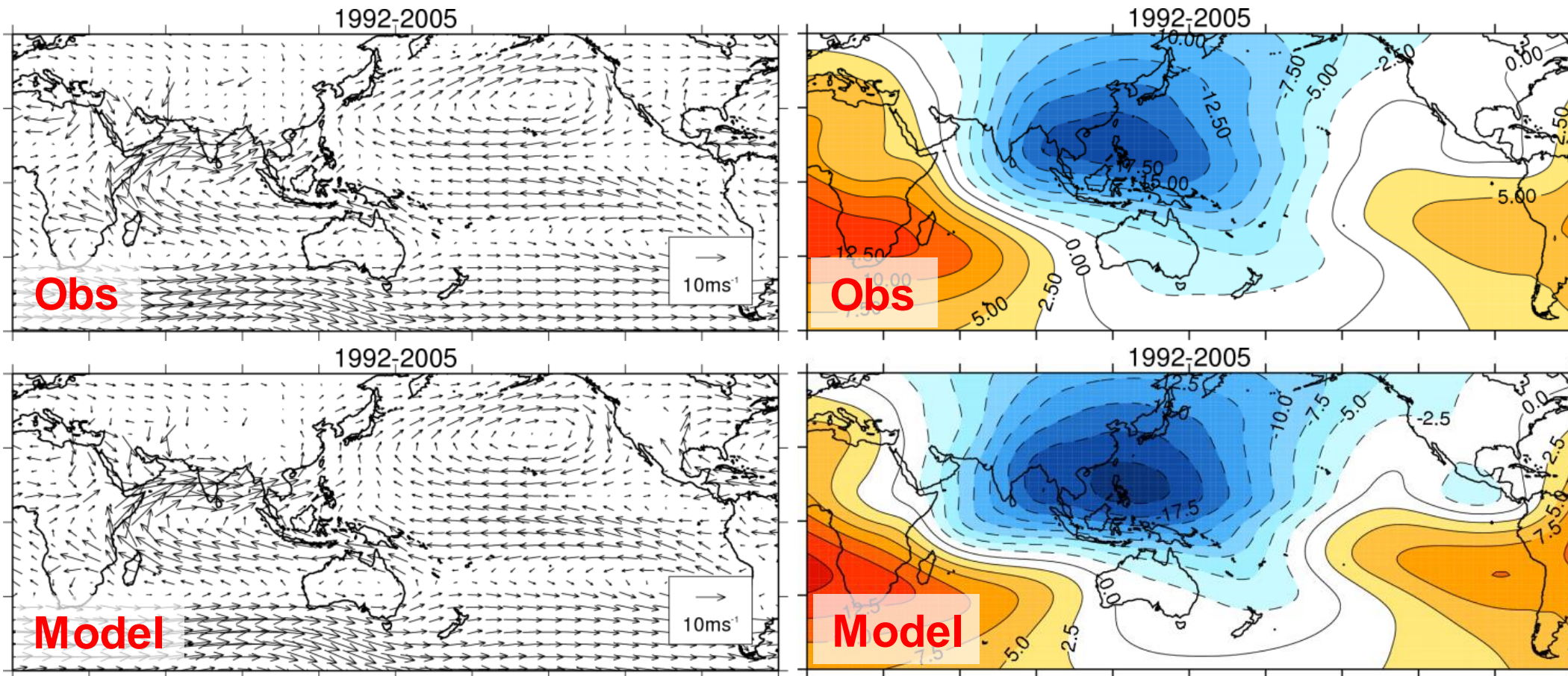
ENSO FLAVORS IN SEASONAL FORECASTING

Mean state representation #1 (precip, SST)

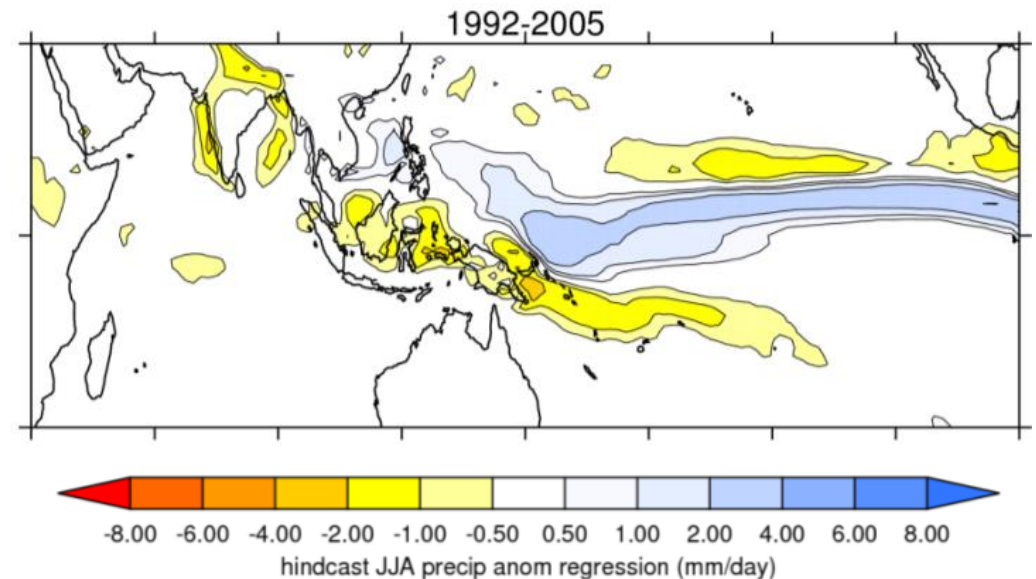


- ❖ Indian precipitation pattern 'reasonable'
- ❖ Clear westward bias in mean state SST (JJA): confined warm pool and extended cold tongue

Mean state representation #2 (circulation)

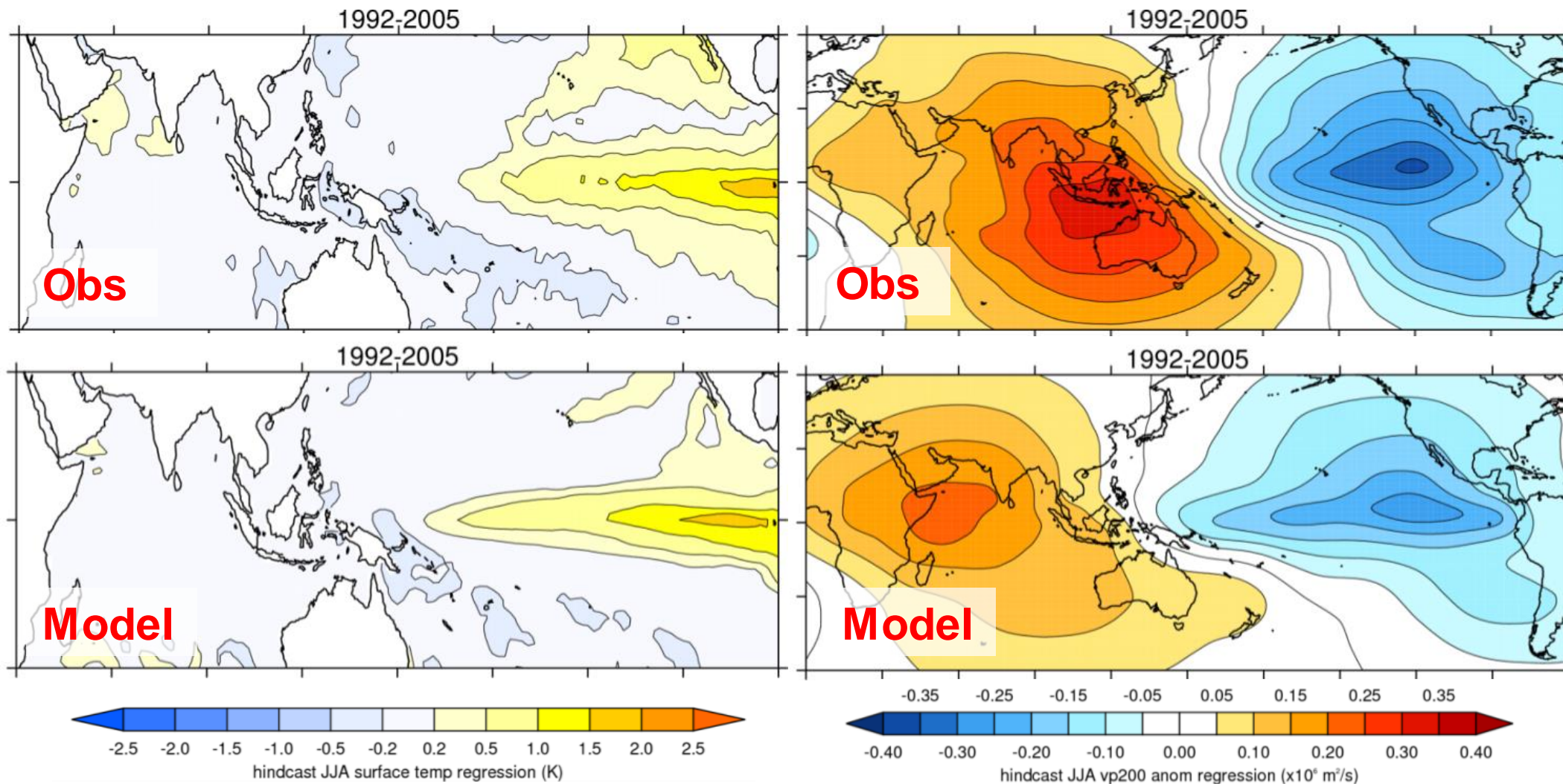


- ❖ Trade winds too strong in the western Pacific in GloSea4
- ❖ Mean Walker circulation contains slight westward bias



- ❖ Initially, hindcast precipitation response over India does not look unreasonable
- ❖ However, largest signals are west of the coast and over the Himalaya and may not be reflected in observed AIR
- ❖ As we shall see, response in some individual cases is not ideal

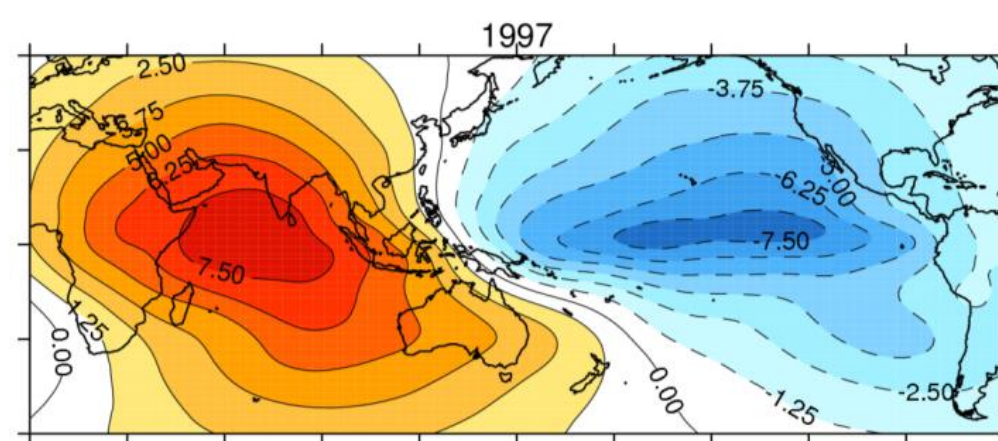
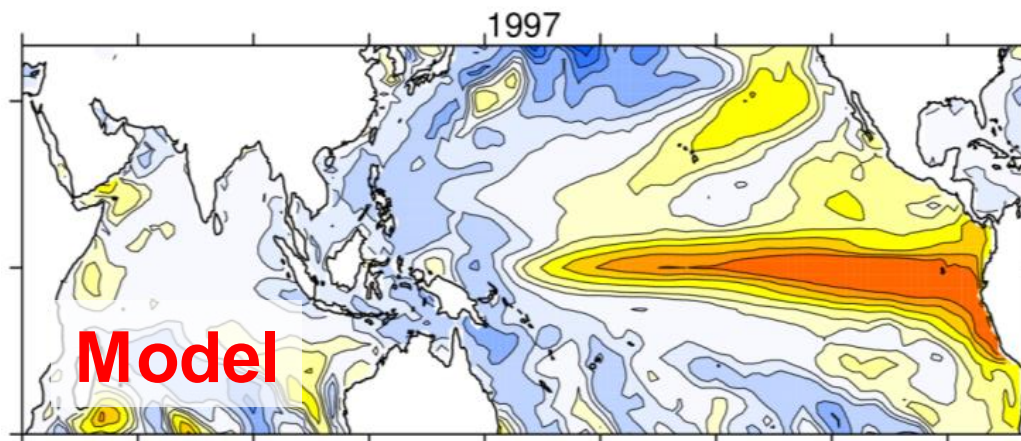
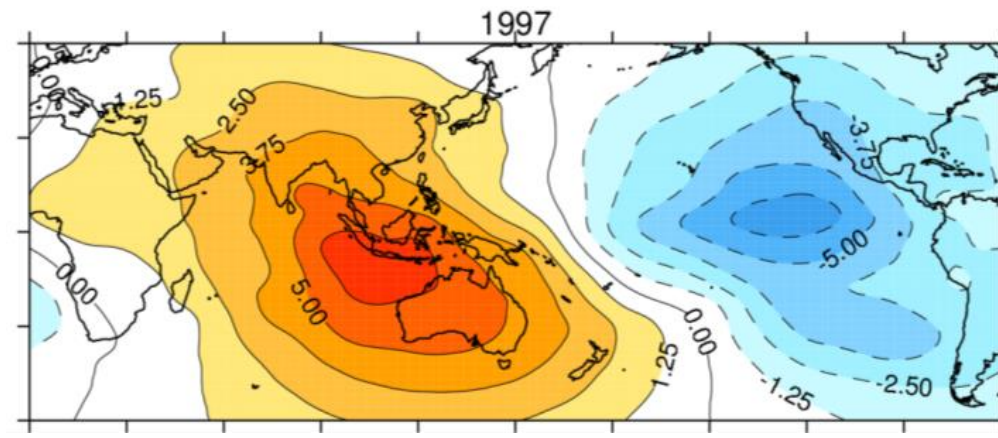
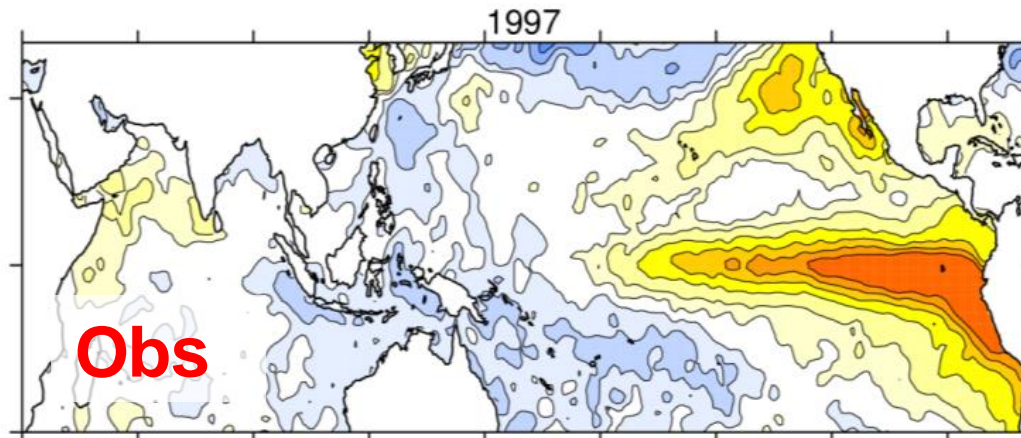
Regressions onto Niño-3 #2



- ❖ Evidence of westward bias of SST and perturbations to the large scale circulation

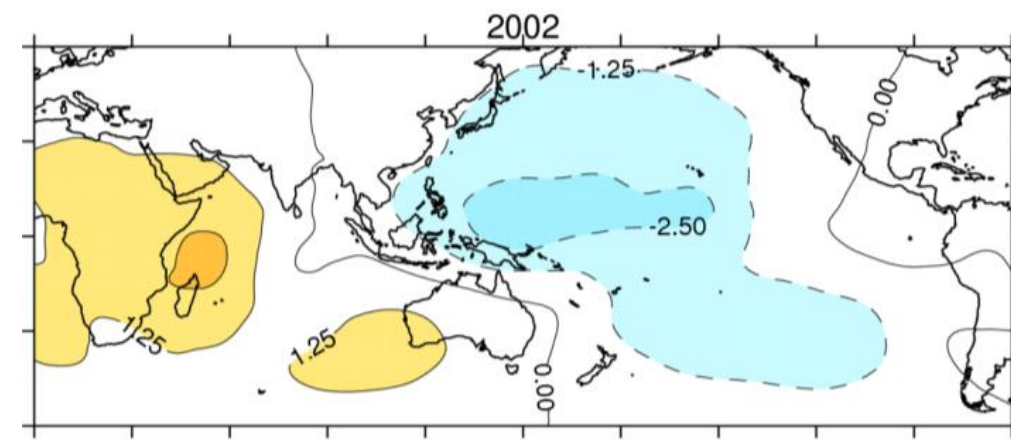
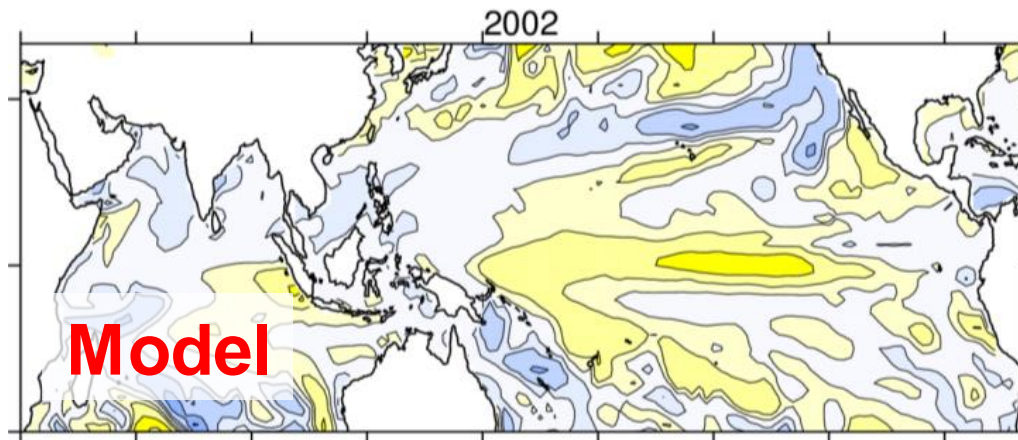
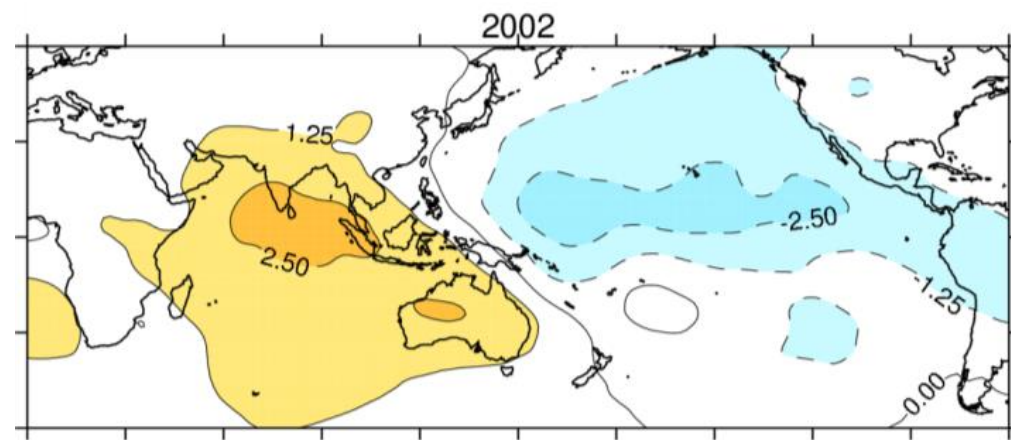
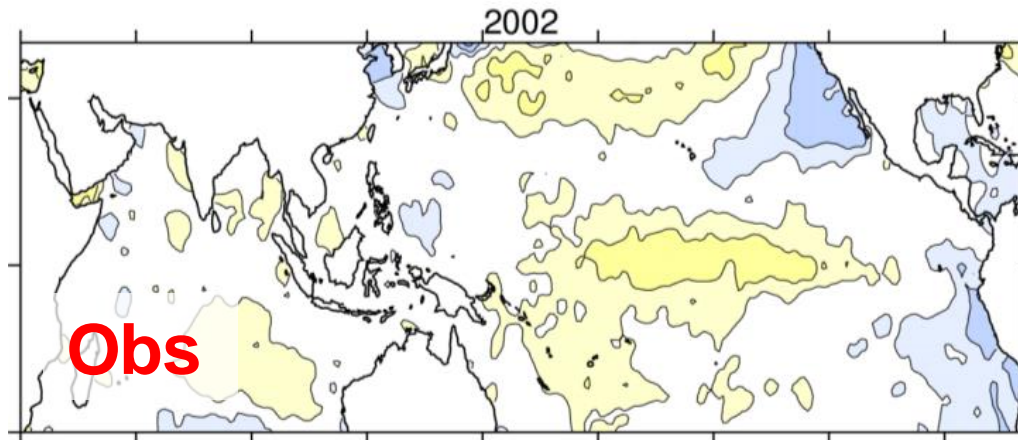
- ❖ 1997 and 2002 chosen owing to their diversity and unusual effects on the monsoon (hence a tough test of the seasonal forecast model)
- ❖ 1997: large, east Pacific El Niño, normal monsoon (102% AIR)
- ❖ 2002: more moderate, central Pacific El Niño, monsoon drought (81% AIR)

Case studies: 1997 (SST & vp200 anomalies)



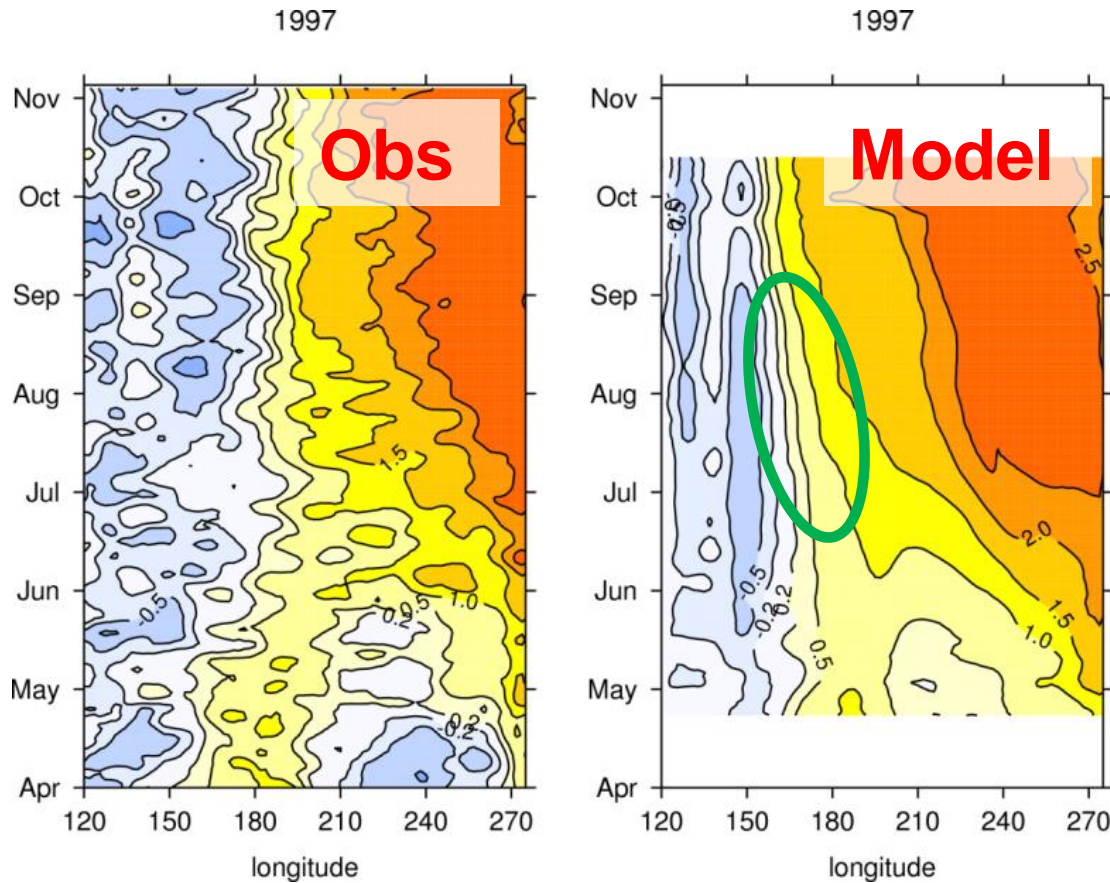
- ❖ Warm El Niño anomalies extend $\sim 30^\circ$ too far west
- ❖ Anomalous ascent over warm SST pushes into the Maritime Continent, shifting anomalous subsidence west over India

Case studies: 2002 (SST & vp200 anomalies)



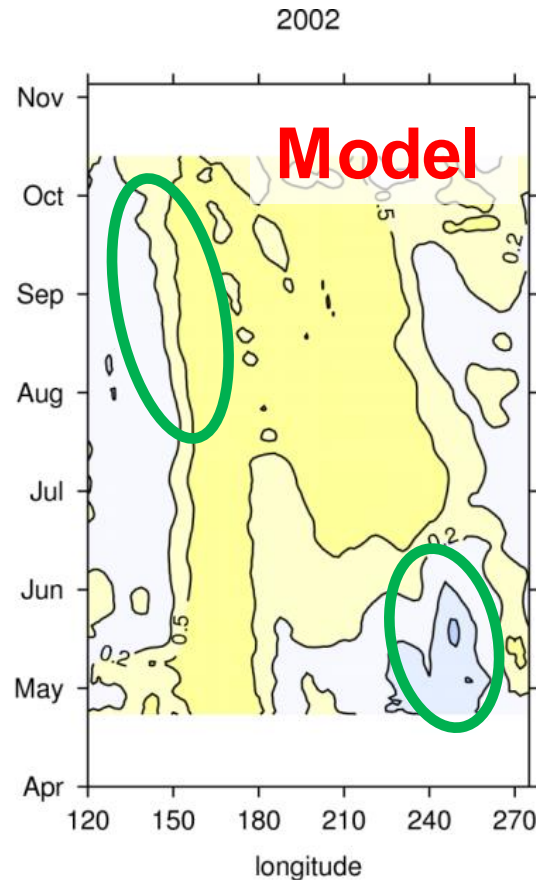
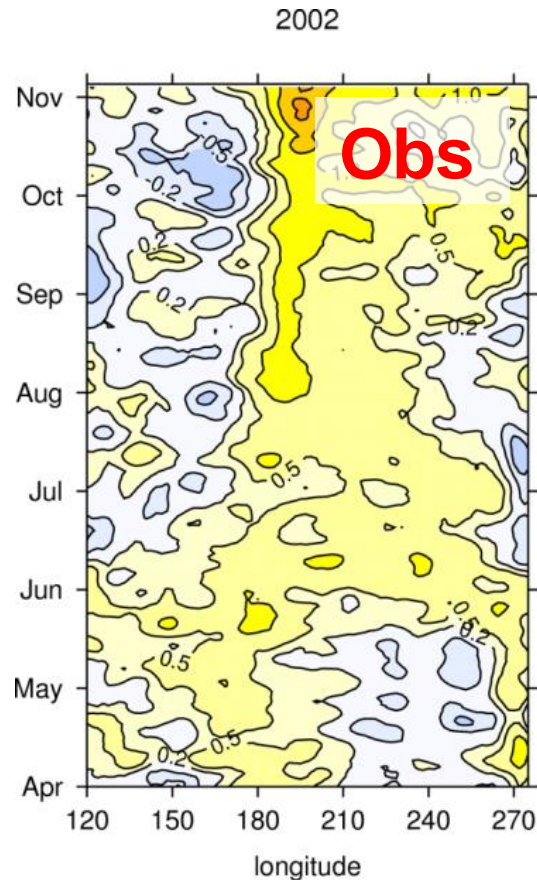
- ❖ Warm El Niño anomalies again extend too far west
- ❖ Anomalous subsidence over Indian is shifted too far west, as far as East Africa

Case studies: 1997 (daily equatorial SST evolution)



Following
initialisation model
shows rapid
development of warm
SST error west of the
date line.

Case studies: 2002 (daily equatorial SST evolution)



Following
initialisation model
shows rapid
development of warm
SST error west of the
date line.

Cold bias is evident
further east.

Coupled model seasonal forecasting: summary

- ❖ Initialized coupled seasonal forecasting systems show reasonable skill at predicting monsoon IAV
- ❖ Perhaps not yet reaching predictability limit

Monsoon prediction

ADDED BENEFIT FROM OTHER FACTORS

- ❖ Early ideas of Blanford (1884) on role of Himalayan snow in weakening the meridional temperature gradient
- ❖ Various modelling studies (Bamzai; Barnett; Fasullo etc.)
- ❖ A fairly simple and unsurprising mechanism
- ❖ The following shows an idealised AGCM set up with climatological SST (i.e., there are no ENSO, IOD etc.)

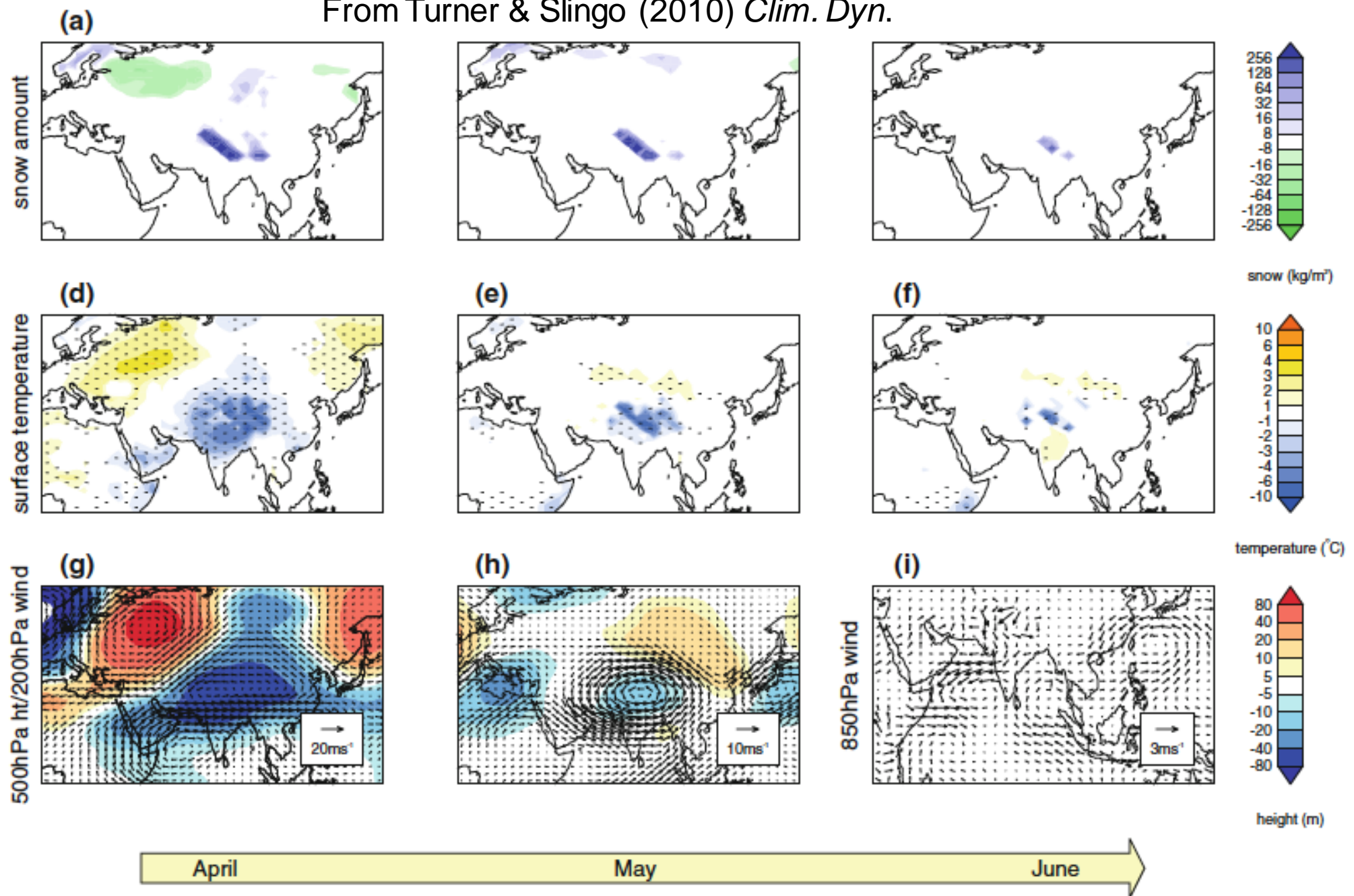
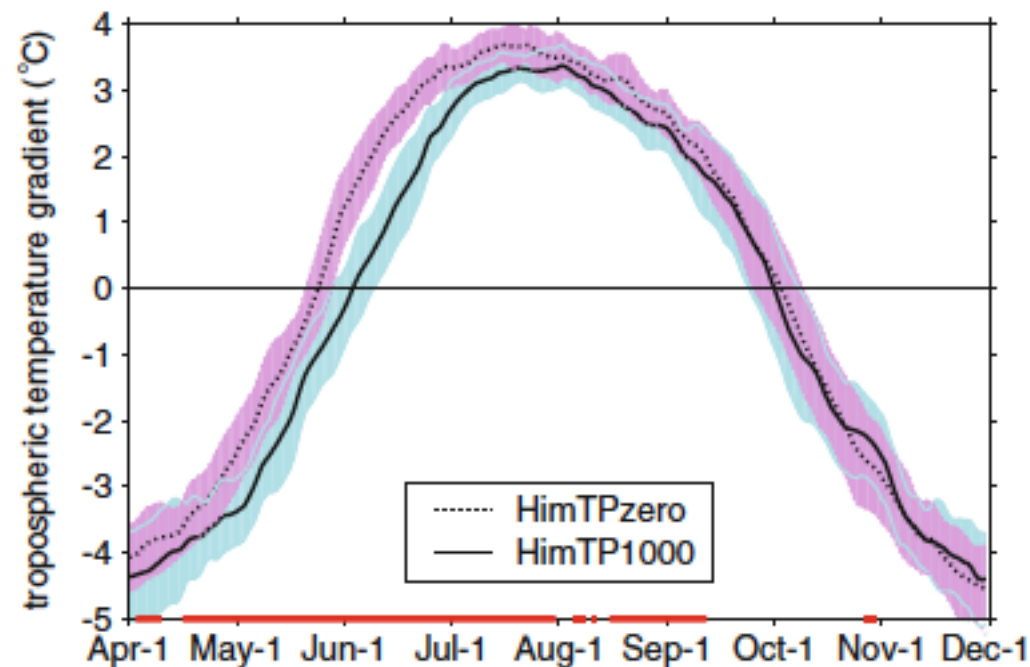
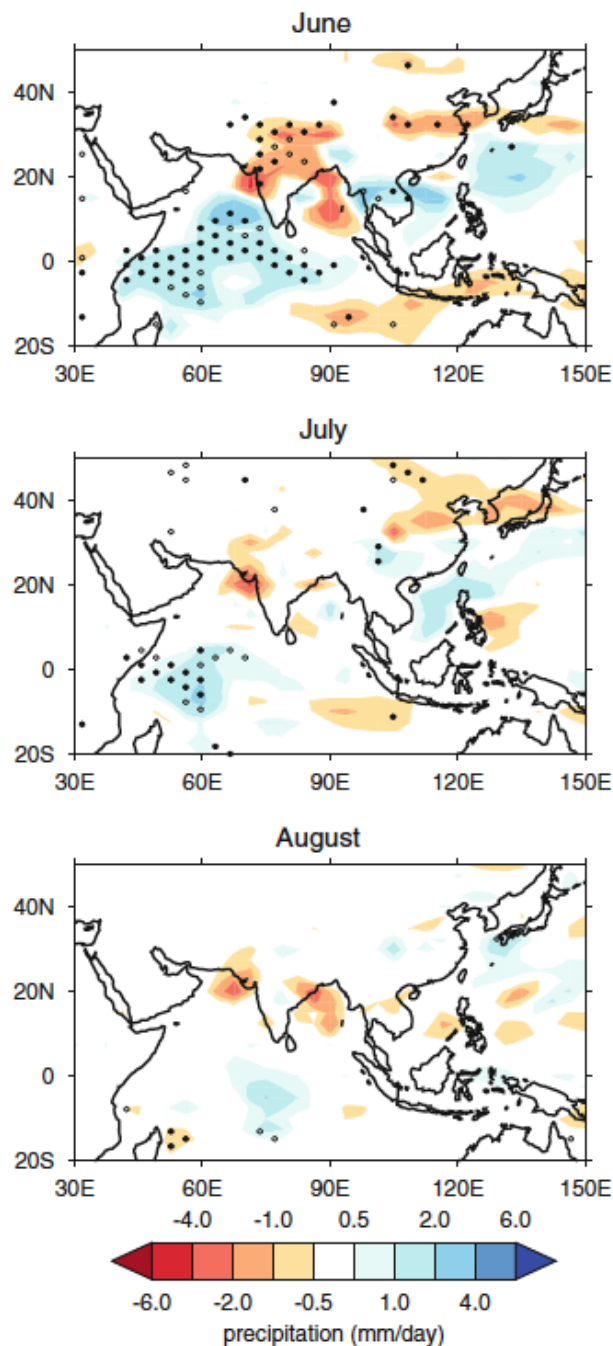


Fig. 8 Ensemble mean differences in various atmospheric and surface fields between HimTPpos and HimTPneg HadAM3 ensemble experiments in April (left), May (centre), June (right). Top snow amount (kg m^{-2}), middle surface temperature ($^{\circ}\text{C}$), bottom April and

May 500 hPa geopotential height (m) and 200 hPa winds (m s^{-1}), June 850 hPa winds (m s^{-1}). Stipples on surface temperature indicate significance at the 95% level

Himalayan snow reduces rainfall during onset period



- ❖ Himalayan snow weakens the meridional temperature contrast
- ❖ But what about a non-idealised framework?

From Turner & Slingo
(2010) *Clim. Dyn.*


Impact of initialized surface observations in Himalaya region

ECMWF group showed that initializing snow-related fields in April results in some (but marginal) improvement in monsoon onset forecast

Clim Dyn (2016) 47:2709–2725
DOI 10.1007/s00382-016-2993-y

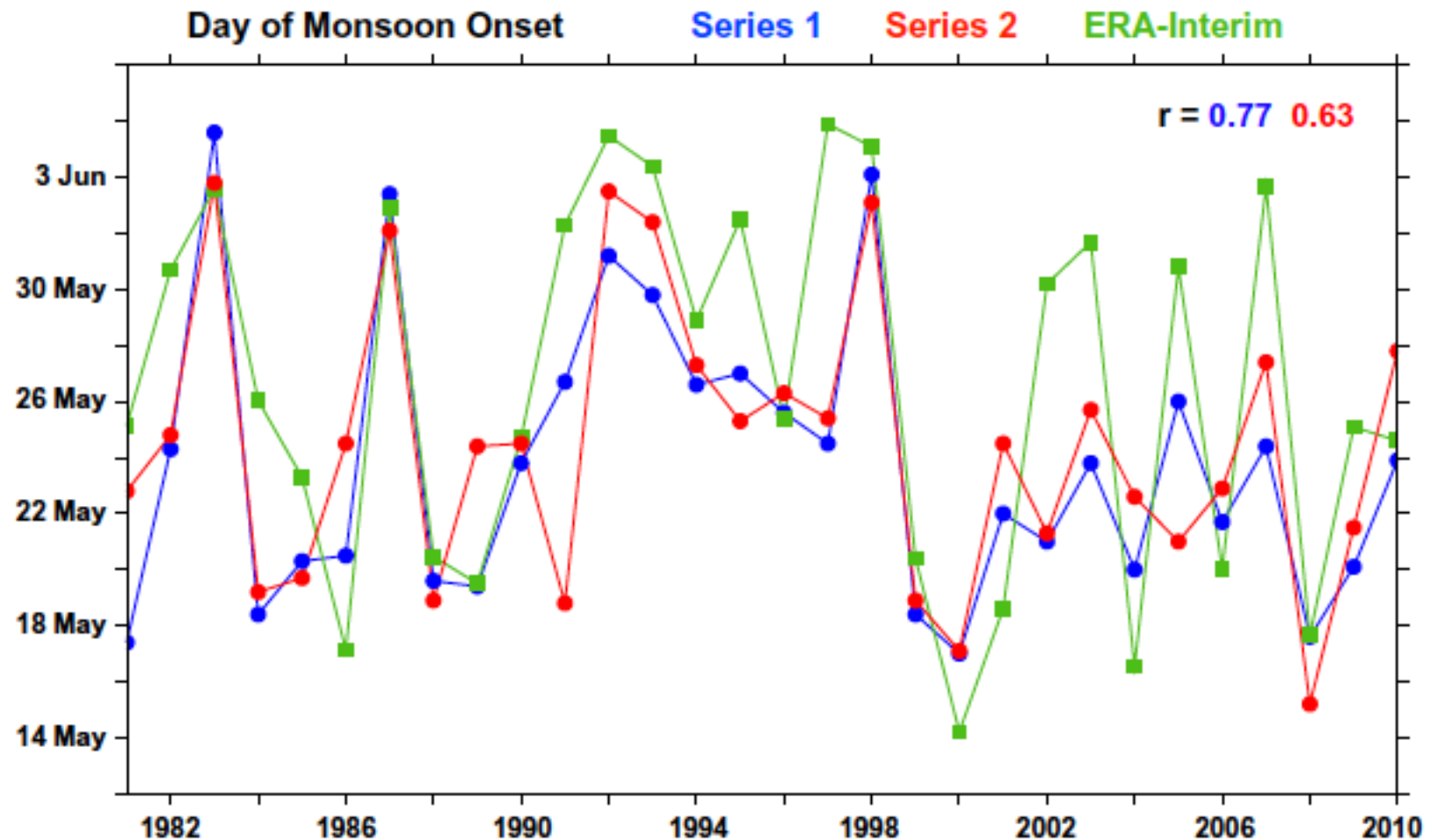


Impact of springtime Himalayan–Tibetan Plateau snowpack on the onset of the Indian summer monsoon in coupled seasonal forecasts

Retish Senan^{1,2}  · Yvan J. Orsolini^{3,4} · Antje Weisheimer^{5,6} · Frédéric Vitart⁵ ·
Gianpaolo Balsamo⁵ · Timothy N. Stockdale⁵ · Emanuel Dutra⁵ ·
Francisco J. Doblas-Reyes^{7,8,9} · Droma Basang^{10,11}

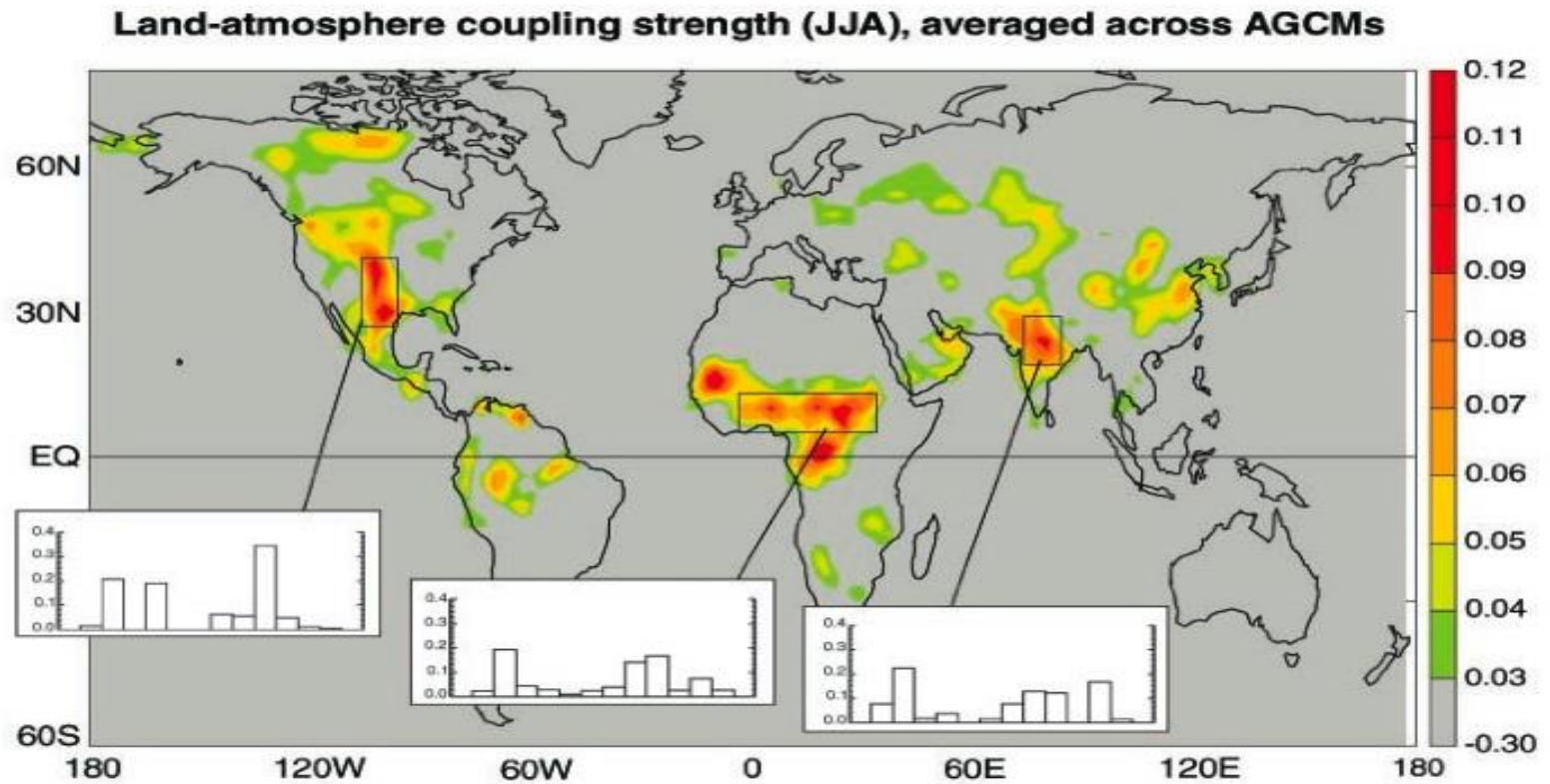
Impact of initialized surface observations in Himalaya region

Comparison of series 1 (initialized) with series 2 (snow-related fields in Himalaya-TP region randomized) suggests minor improvement in skill relating to snow



From Senan *et al.*
(2016) *Clim. Dyn.*

Strong coupling between land and atmosphere on seasonal and subseasonal time scales implies potential to enhance prediction skill using soil moisture initialization

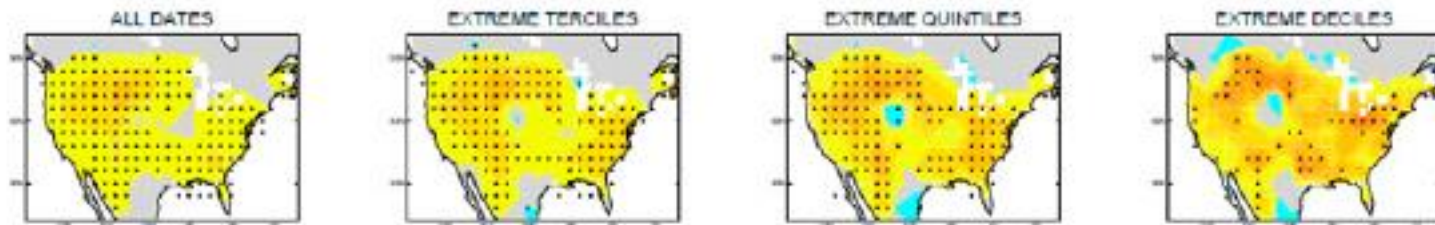


Benefit of land surface initialization

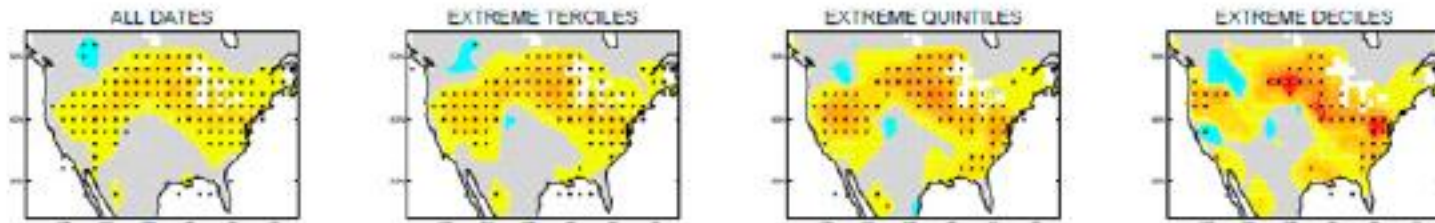
Koster et al. demonstration of improvement in surface temperature and precipitation forecasts on subseasonal-to-seasonal time scales when land surface is initialized

1b. AIR TEMPERATURE FORECAST SKILL (r^2 with land ICs minus r^2 w/o land ICs)

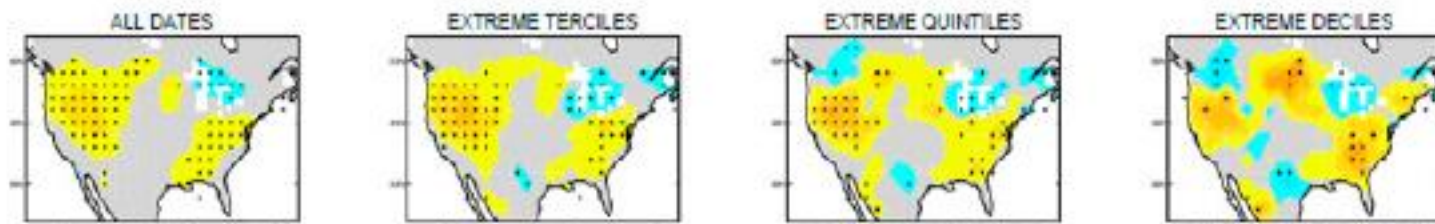
16-30 days



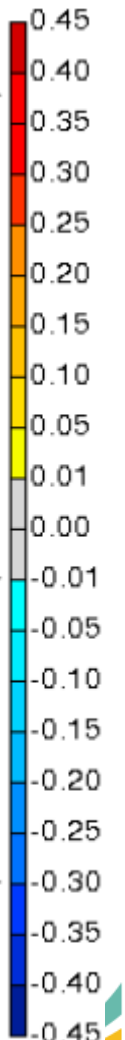
31-45 days



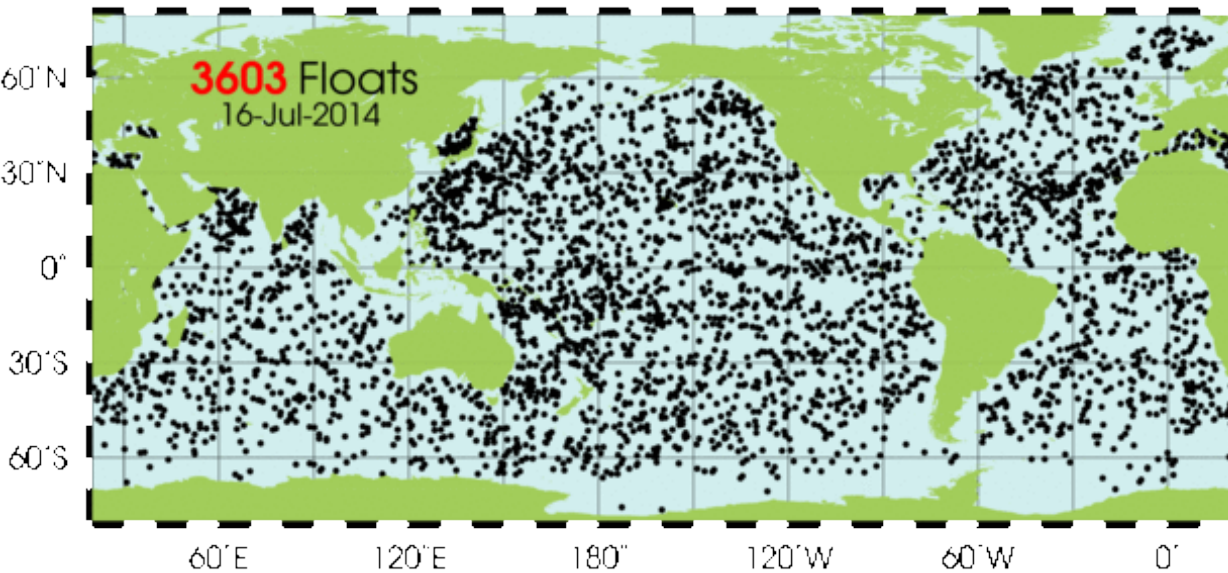
46-60 days



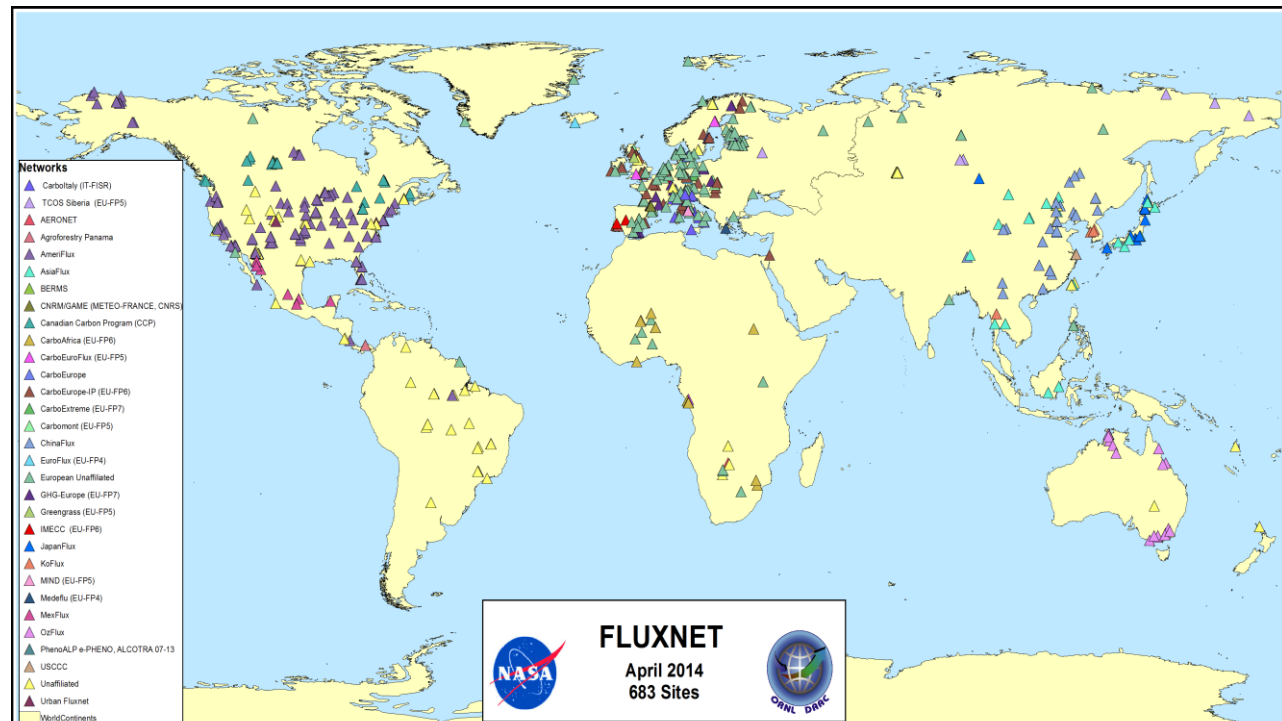
Dates for conditioning vary w/location



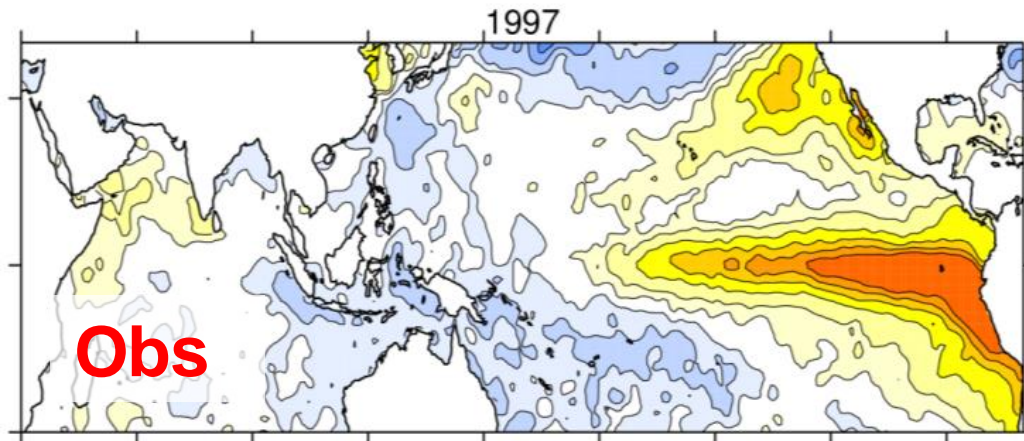
Surface flux observations



- ❖ Few regions of the tropics have adequate sampling of surface fluxes, soil moisture etc.



- ❖ I haven't mentioned the Indian Ocean (dipole) at all...



- ❖ Summer SST anomalies in 1997 suggest that IOD+ may play a role in counteracting impact of El Nino on the Indian monsoon

Thank you!

a.g.turner@reading.ac.uk