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# **Seasonal Prediction of Asian Summer Monsoon Rainfall with Coupled Models: Problems and Prospects**

Jagadish Shukla

Department of Atmospheric, Oceanic and Earth Sciences (AOES),

*George Mason University (GMU)*

Center for Ocean-Land-Atmosphere Studies (COLA)

*Institute of Global Environment and Society (IGES)*



# Outline

1. *Introduction: DSP with 4 Models  
(GFDL, NASA, NCAR, NCEP)*
2. *Influence of Ocean IC*
3. *Influence of Land IC*
4. *Quantifying Predictability*
5. *Model Fidelity and Predictability*
6. *Summary*

# Dynamical Seasonal Prediction (DSP)

*Source of predictability: Dynamical memory of atmos. IC  
+ Boundary forcing (SST, SW, snow, sea ice)*

*DSP = NWP + IC of Ocean, Land, Atmosphere*

- *dynamically coupled and consistent IC*
- *Global ocean (especially upper ocean); sea ice (volume)*
- *Global Atmos. including stratosphere (IC)*
- *Global GHG (especially CO<sub>2</sub>, O<sub>3</sub>)*
- *Global land (soil moisture, vegetation, snow depth) IC*

Tier 1: Fully coupled models (CGCM) to predict Boundary Forcing

Tier 2: Predict Boundary Forcing separately; use AGCM

•(NWP=Atmos. IC + SST IC)

# **DYNAMIC SEASONAL PREDICTION WITH 4 STATE-OF-THE-ART COUPLED GCMS (NCEP/CFSV2, GFDL, NCAR, NASA)**

**ANALYZE 4 NMME (PHASE I) COUPLED MODELS:**

**NCEP CFSV2 – 24 ENSEMBLE MEMBERS**

**GFDL CM2P1 – 10 ENSEMBLE MEMBERS**

**NASA GMAO – 10 ENSEMBLE MEMBERS**

**COLA RSMAS CCSM3 – 6 ENSEMBLE MEMBERS**

**1982-2010 FORECASTS INITIALIZED FROM 01 MAY OBSERVED  
STATE OF EACH YEAR**

**ALL OUTPUT ANALYZED ON 1 DEGREE GRID VERSUS OBSERVATIONS:**

**NCEP CPC CMAP PRECIPITATION**

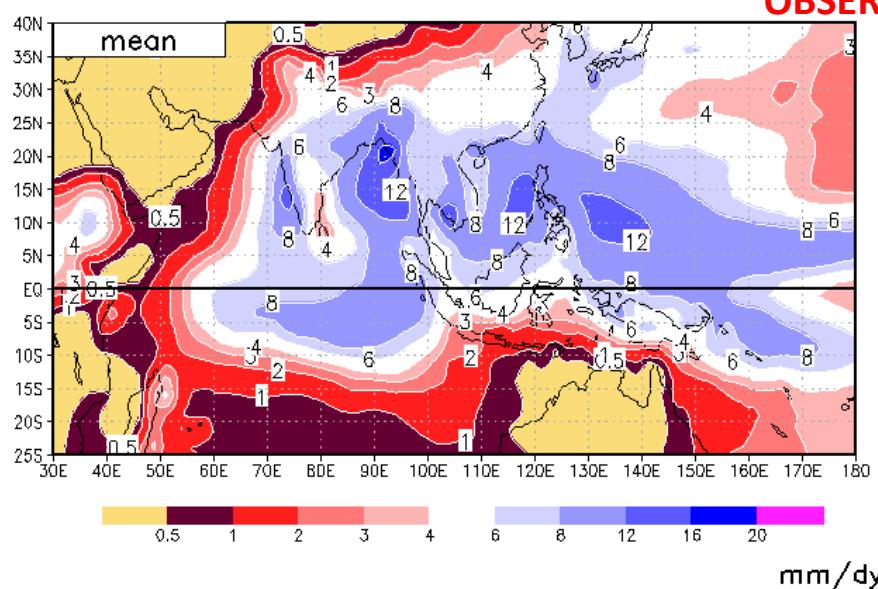
**NCDC OISST SEA SURFACE TEMPERATURE**

**All calculations performed on ensemble mean for JJAS**

**All India Rainfall: Average of Land Points**

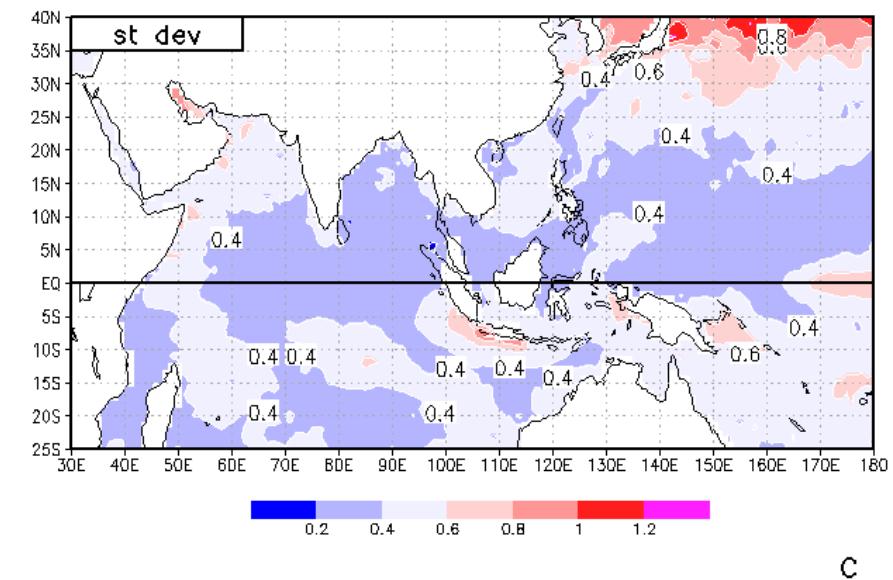
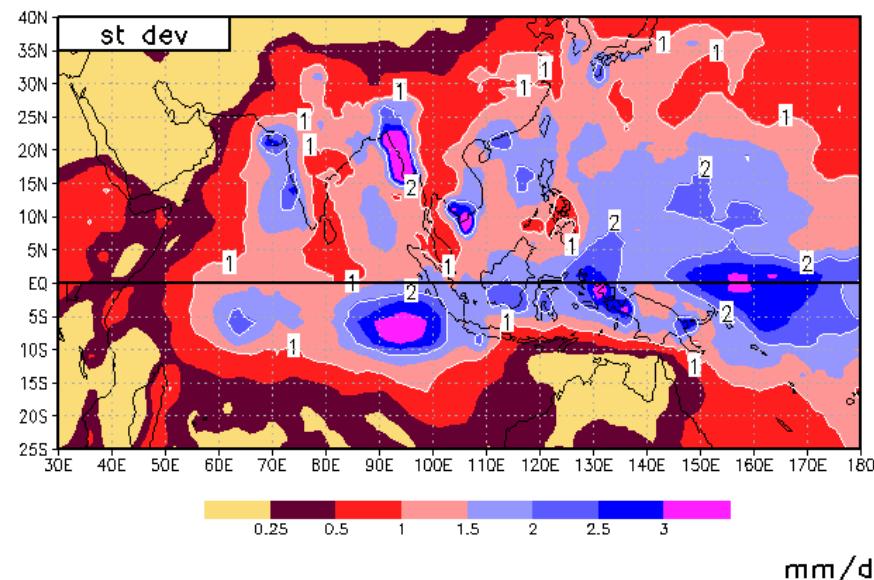
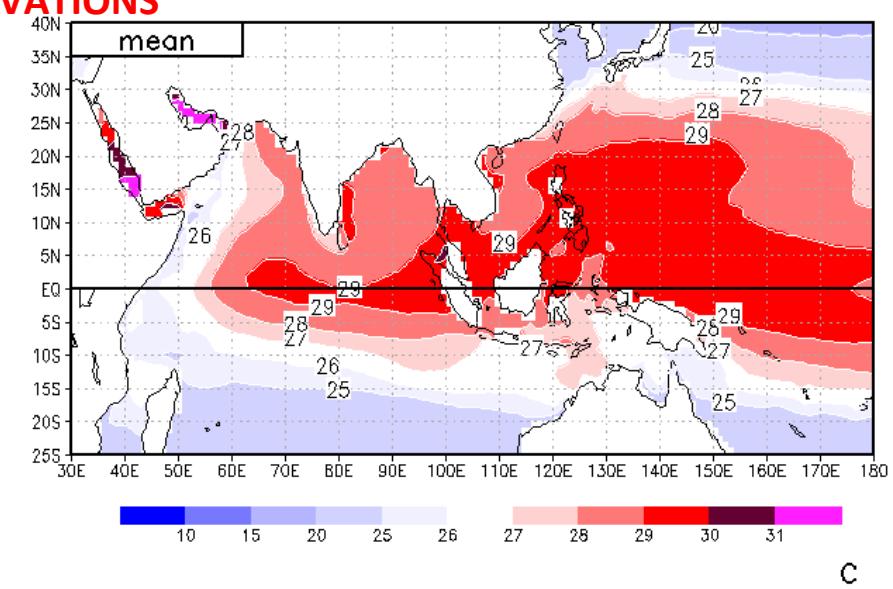
# JJAS 1982–2010 Observations

CPC–CMAP Precipitation



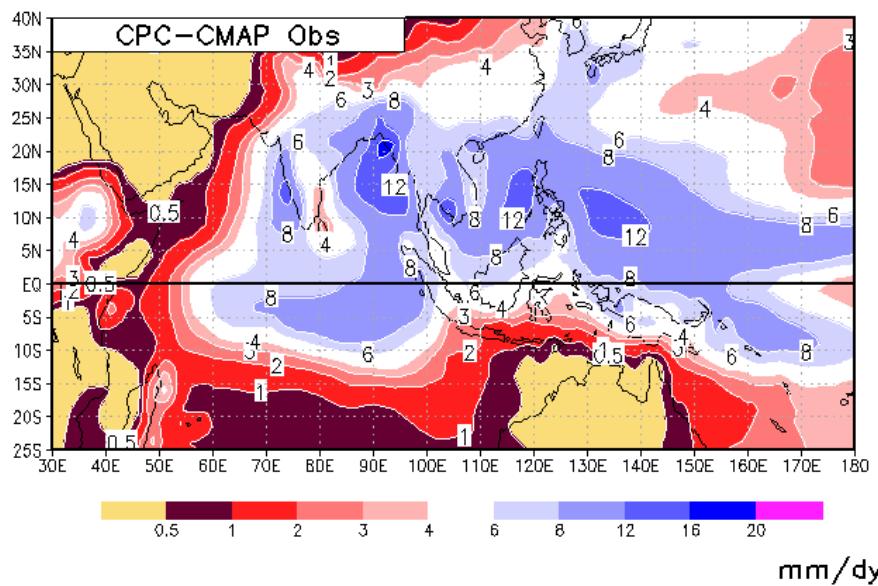
NCDC–OISST Sea\_Surface\_Temperature

## OBSERVATIONS

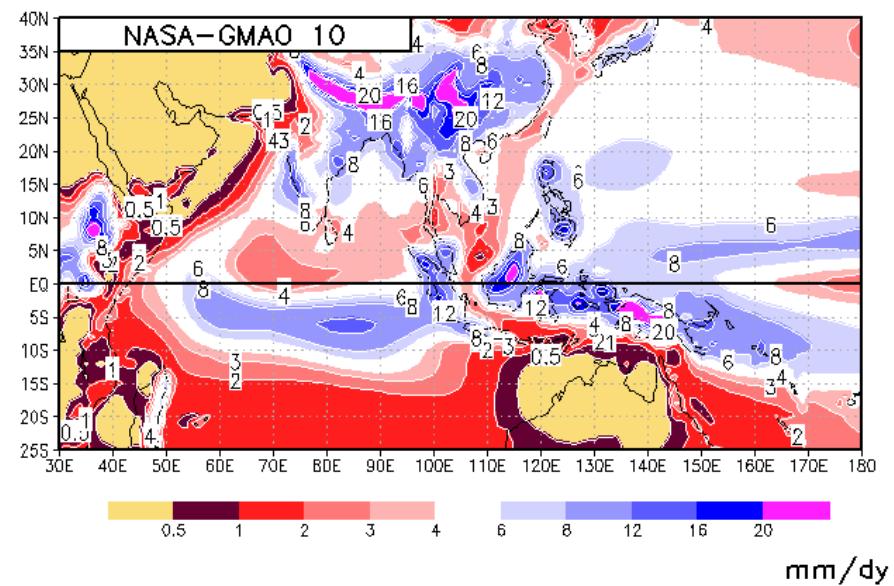


# NMME JJAS 1982–2010 Mean Precip

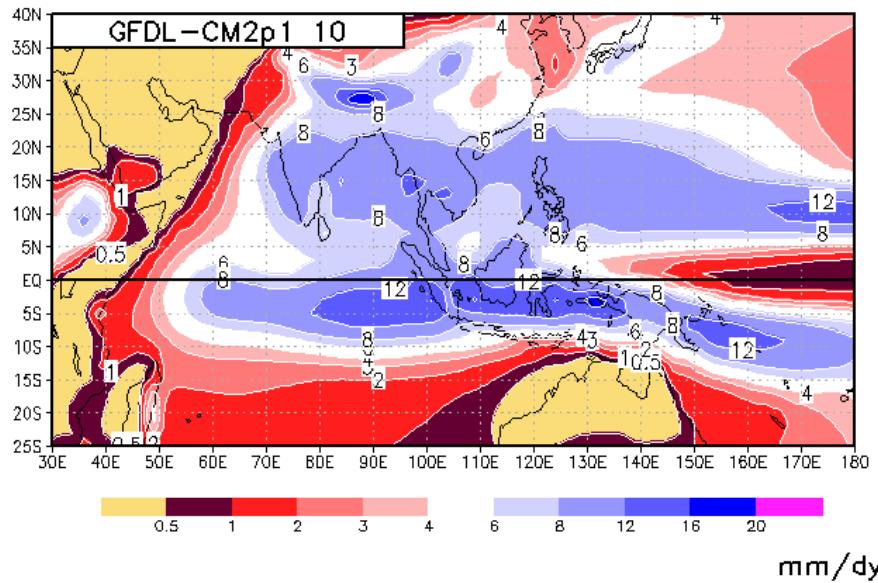
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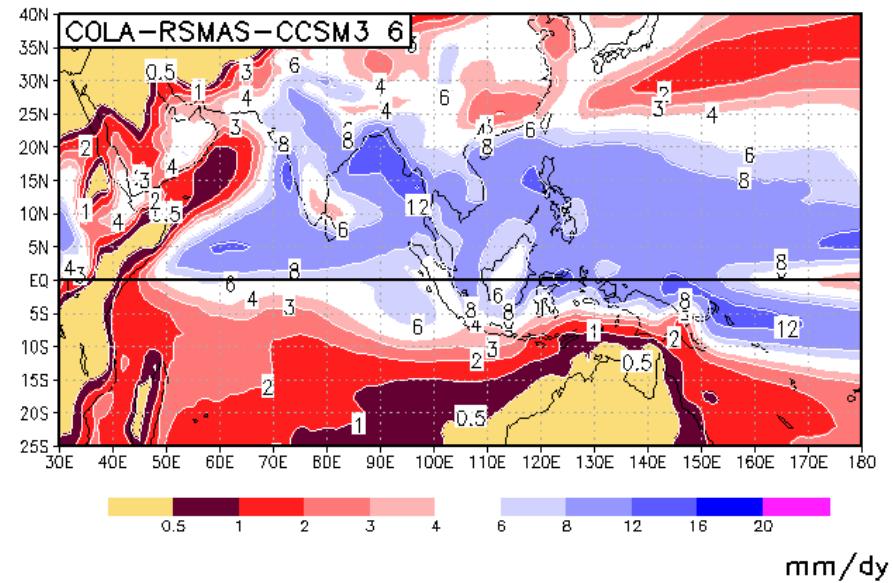
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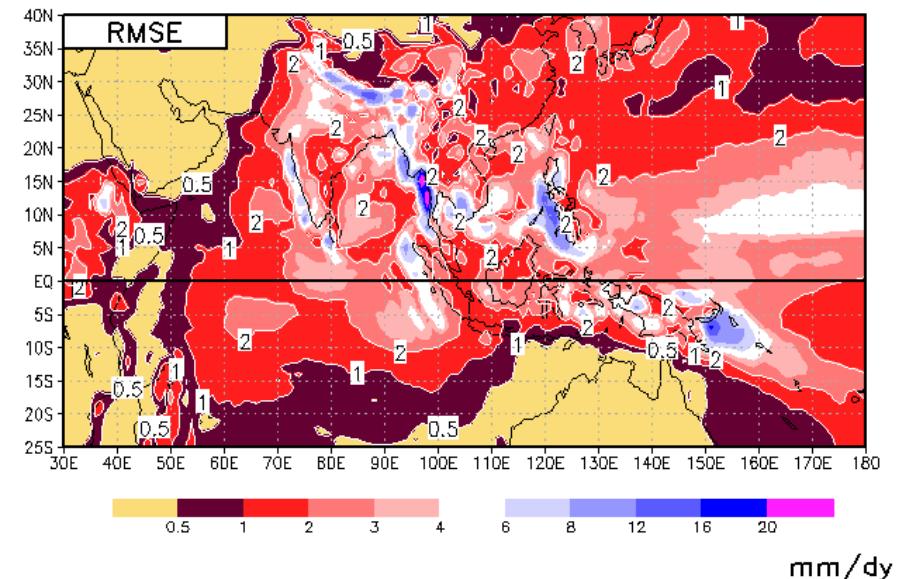
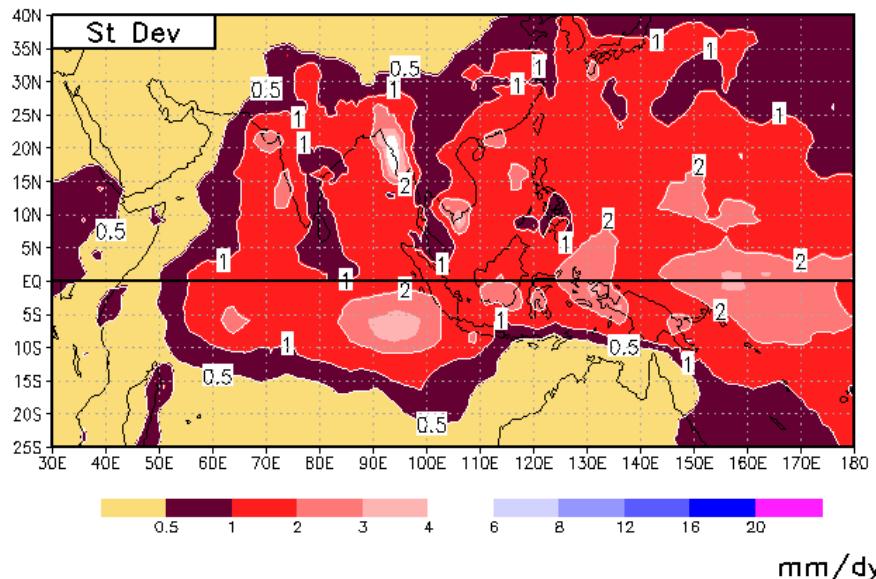
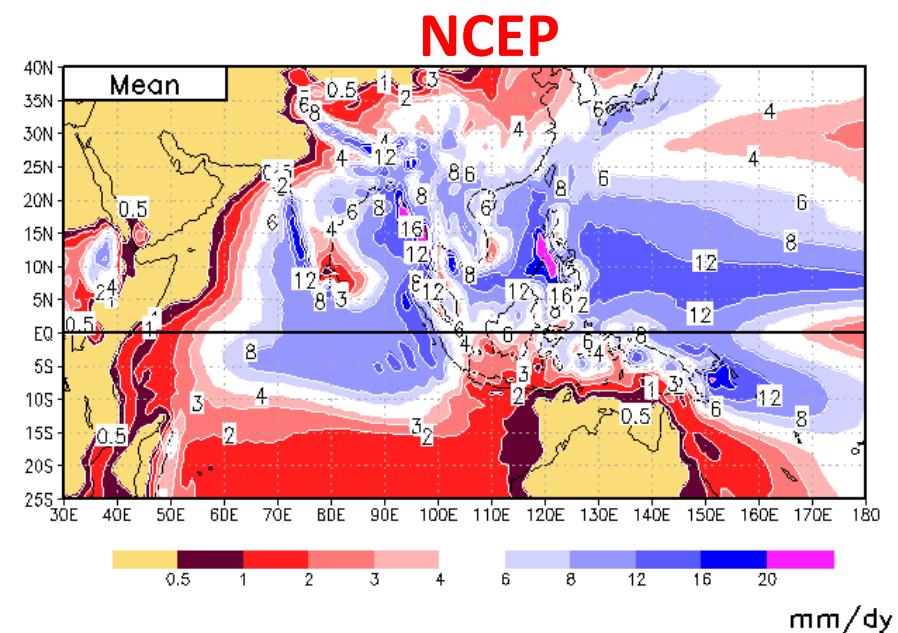
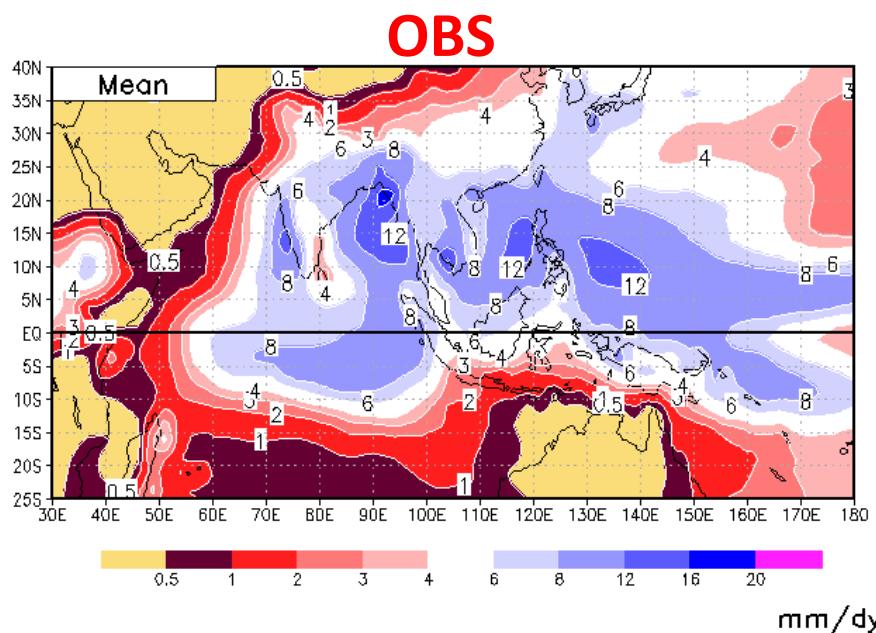
GFDL



NCAR

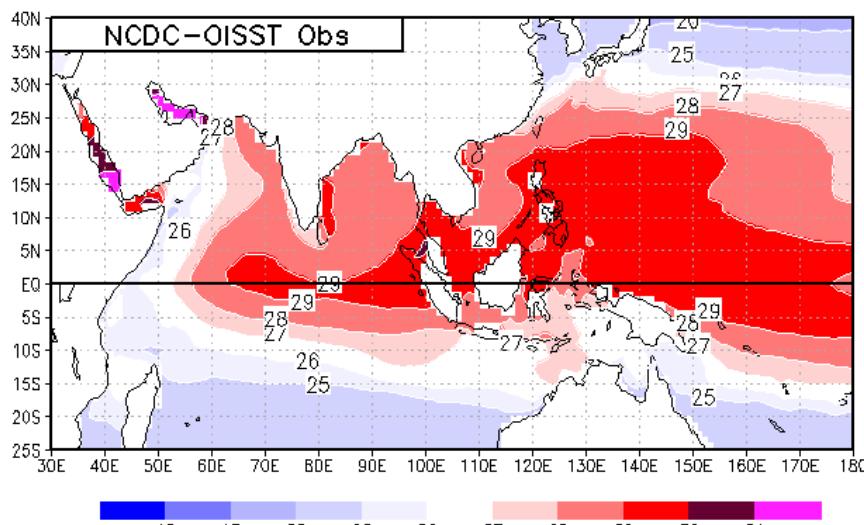


NMME JJAS 1982–2010 Precip  
CPC–CMAP Obs      NCEP–CFSv2 24

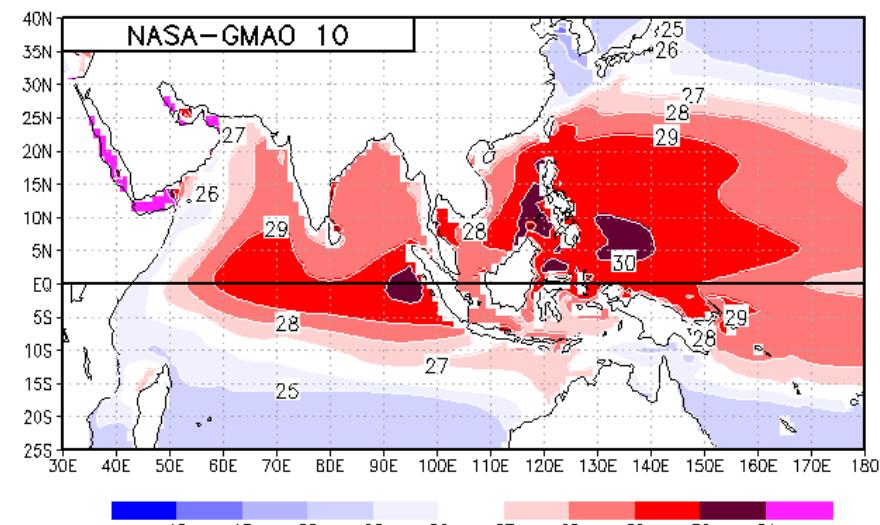


# NMME JJAS 1982–2010 Mean SST

**OBS**



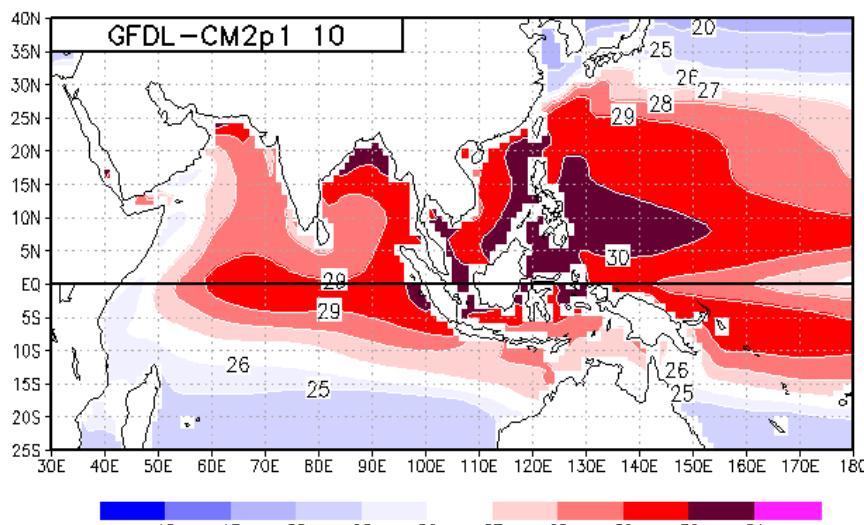
**NASA**



C

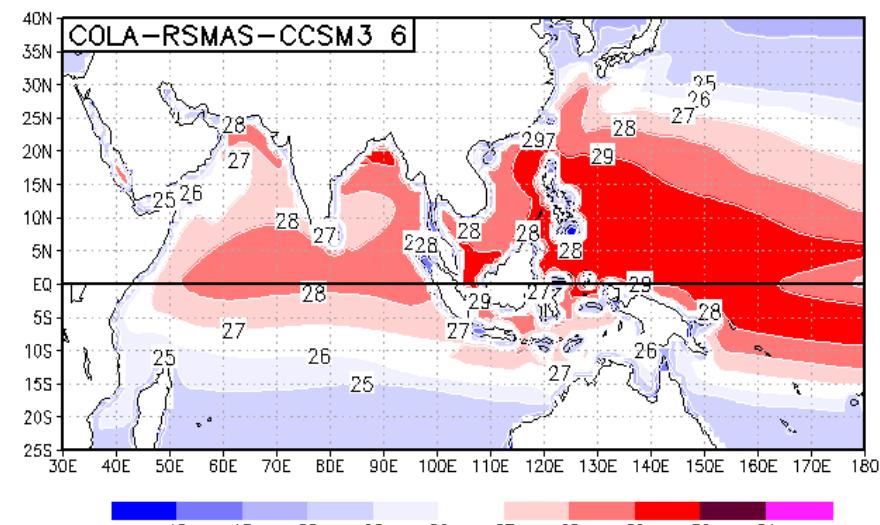
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**GFDL**



C

**NCAR**



C

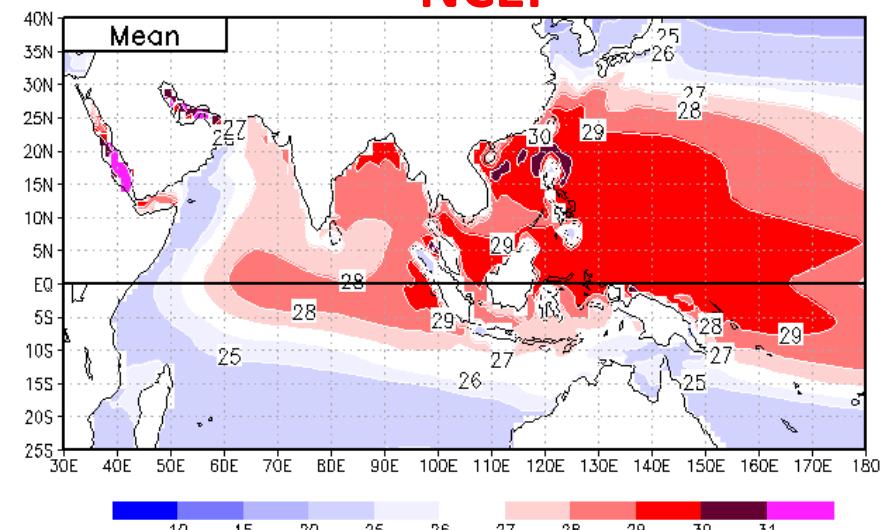
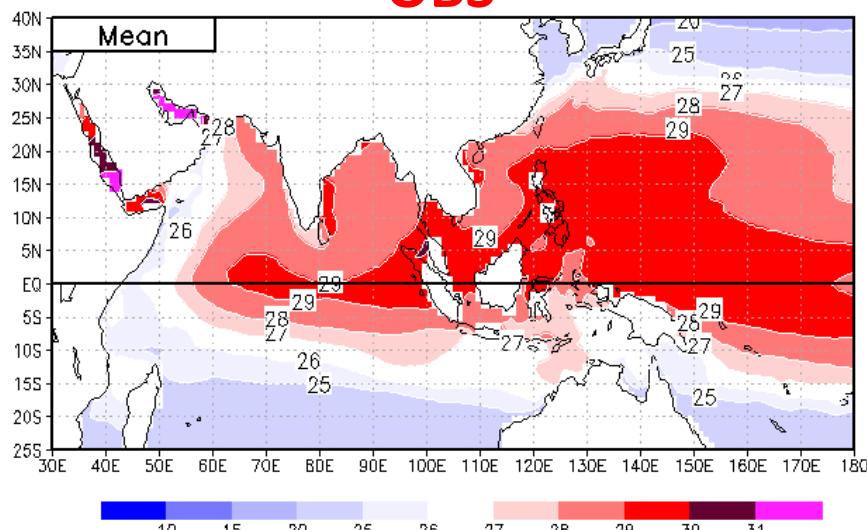
# NMME JJAS 1982–2010 SST

NCDC-OISST Obs

NCEP-CFSv2 24

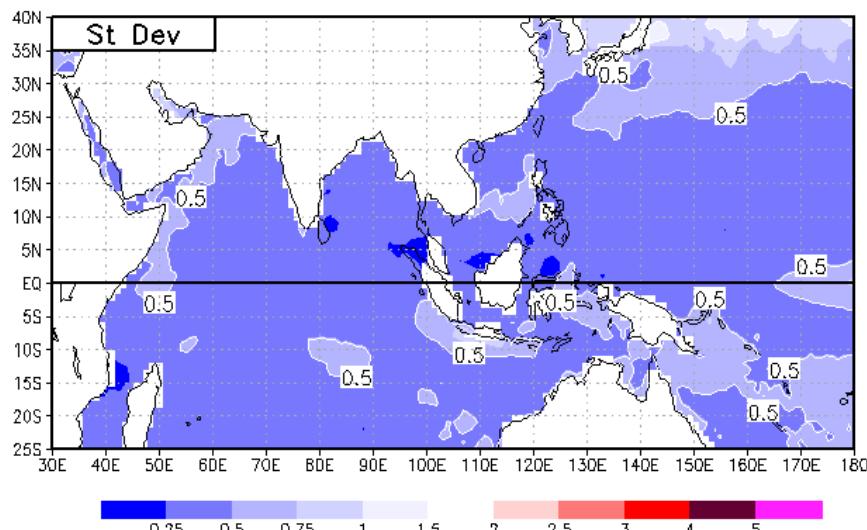
**OBS**

**NCEP**

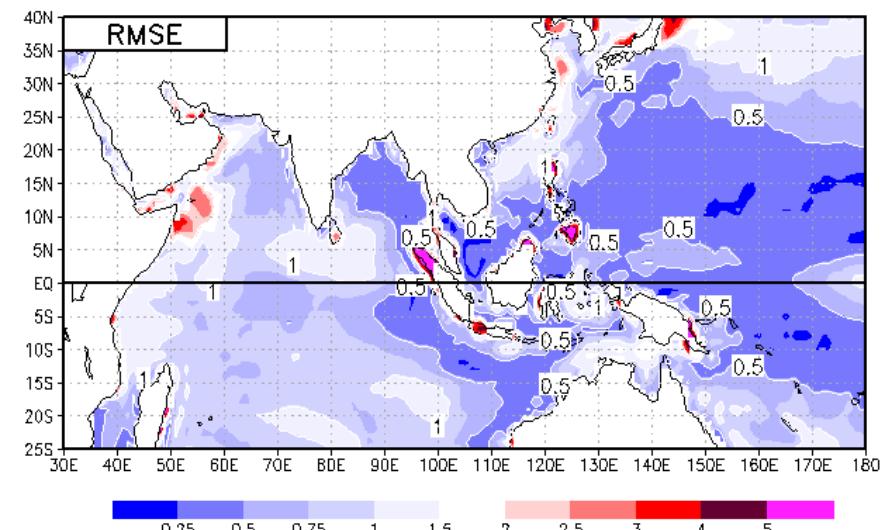


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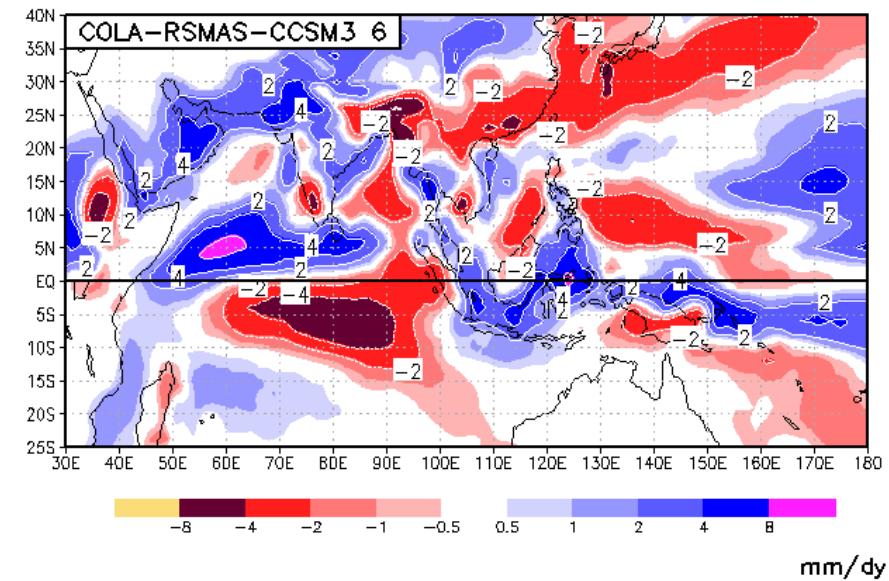
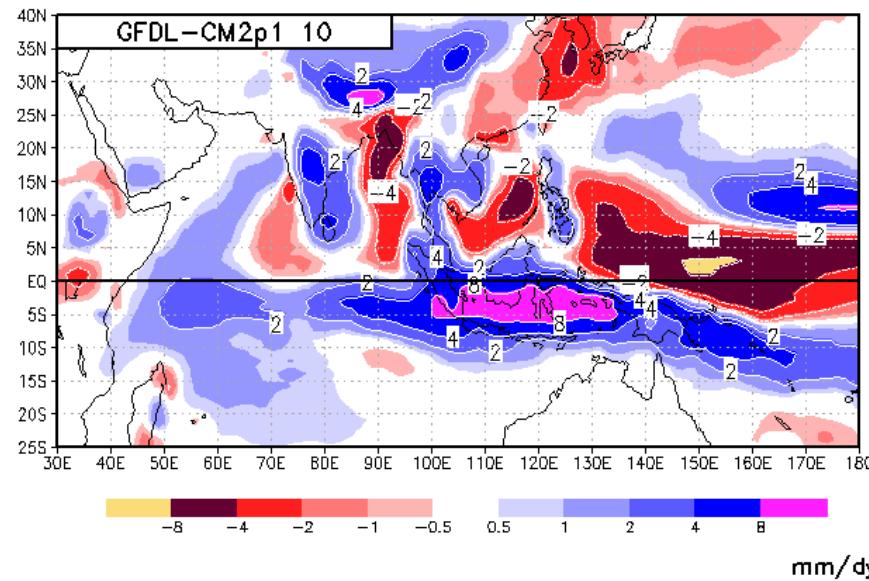
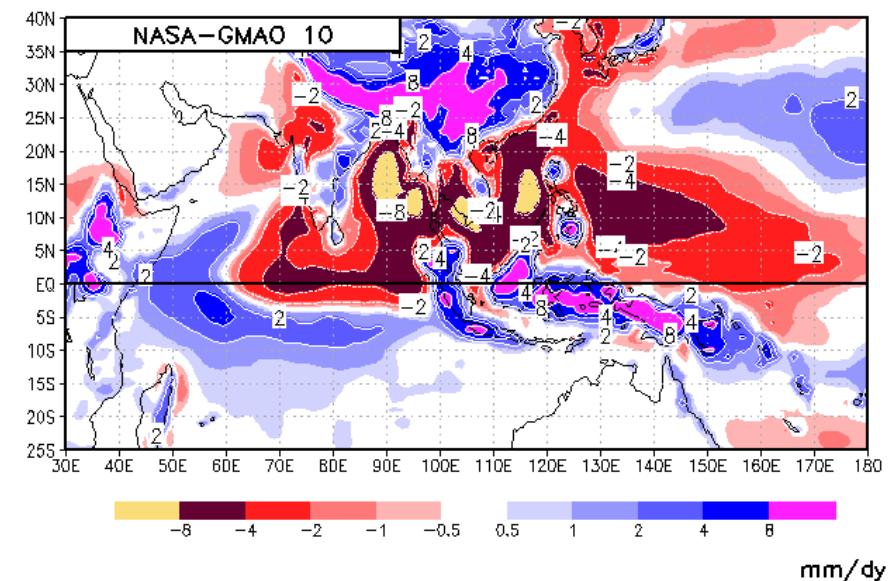
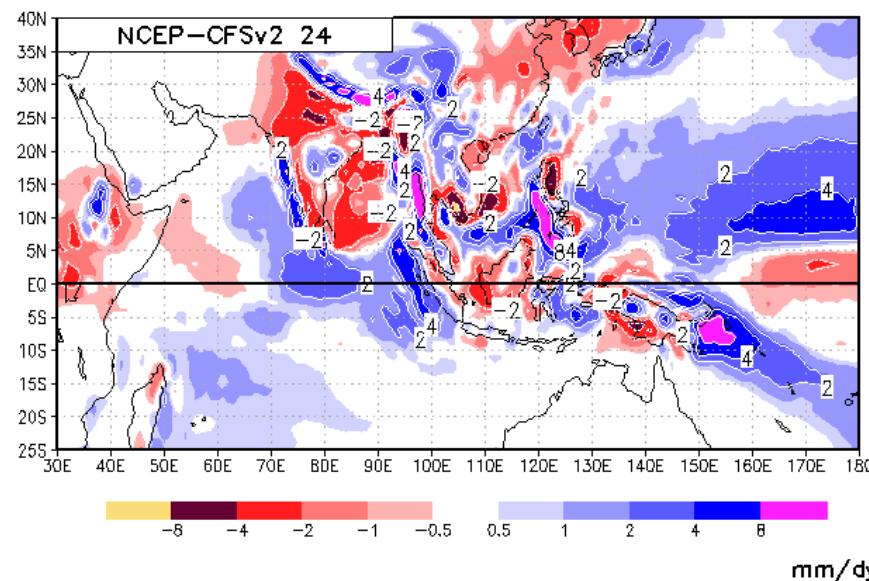
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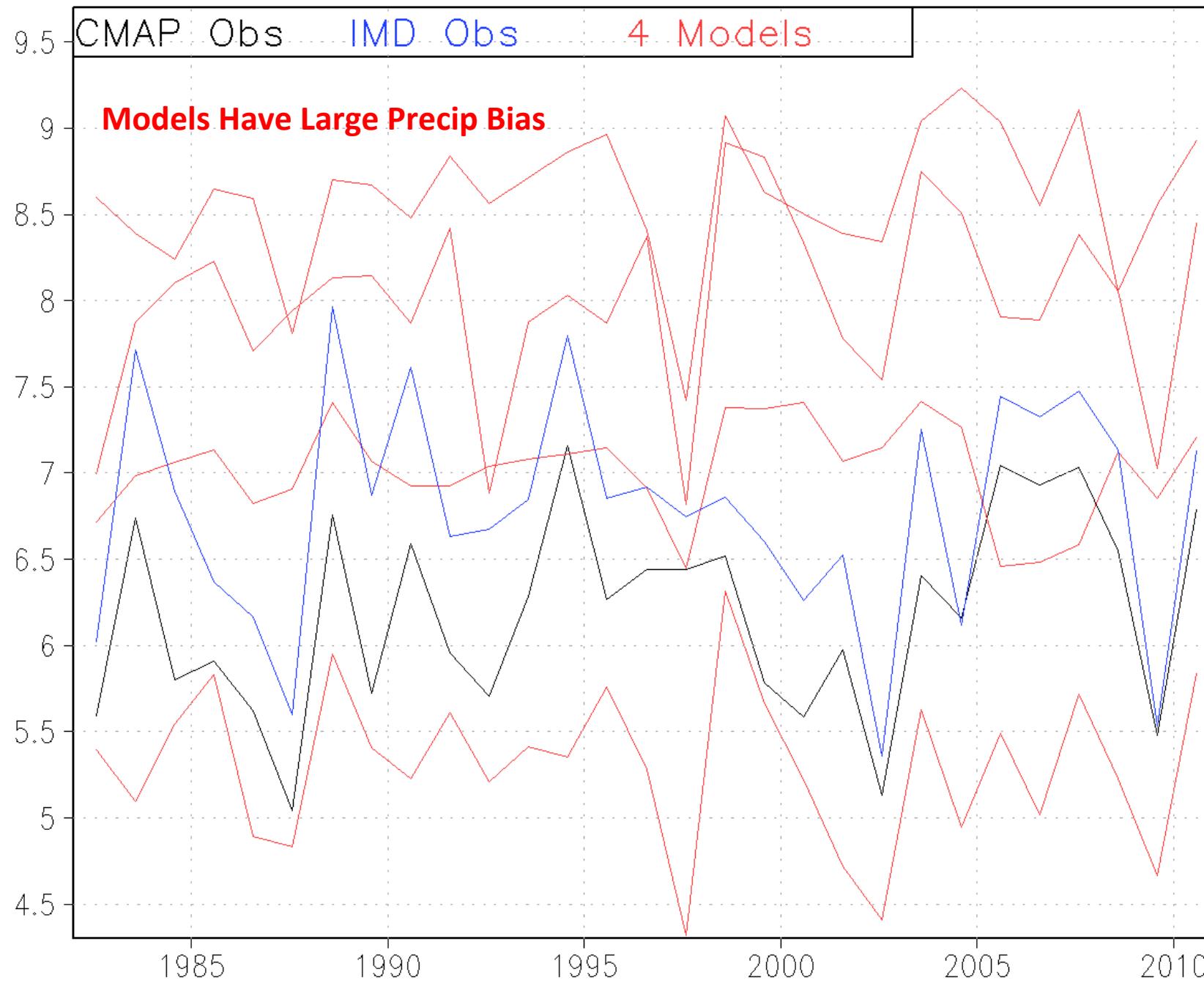
C

NMME 1 May ICS 1982–2010 Precipitation JJAS Mean Bias

## PRECIP BIAS

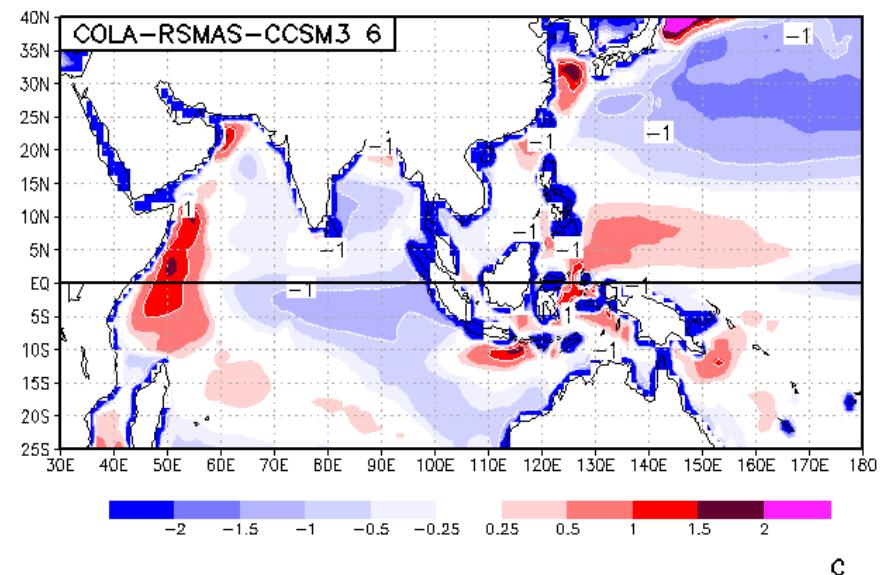
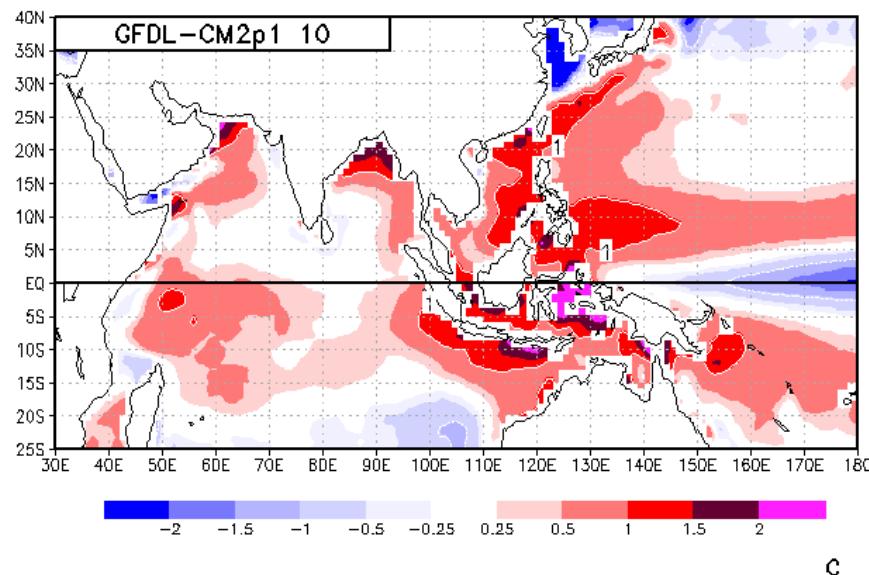
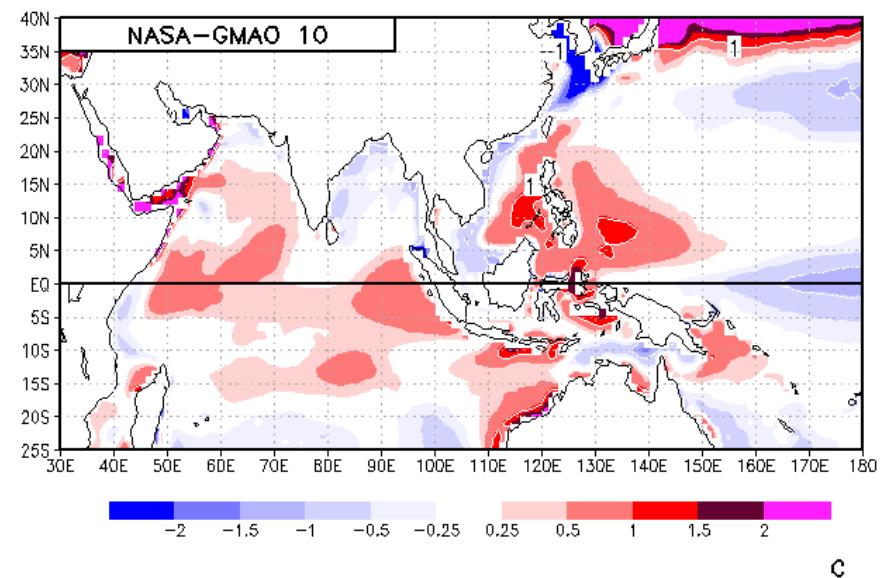
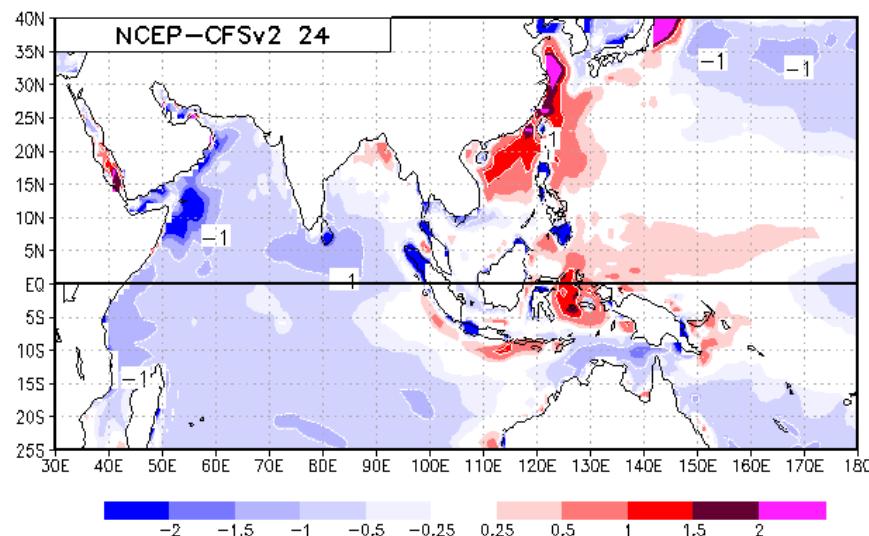


JJAS 1982–2010 All India Precipitation (mm/dy) 01May Model ICs



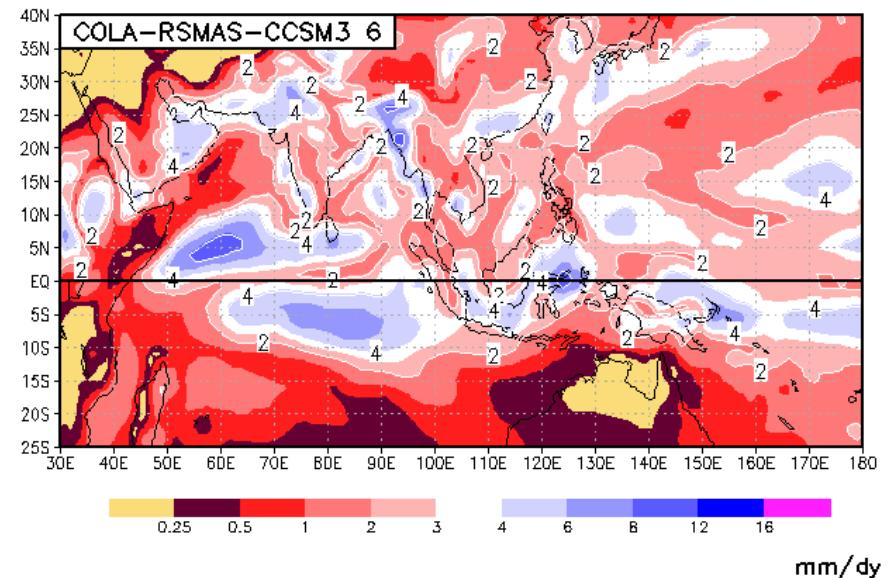
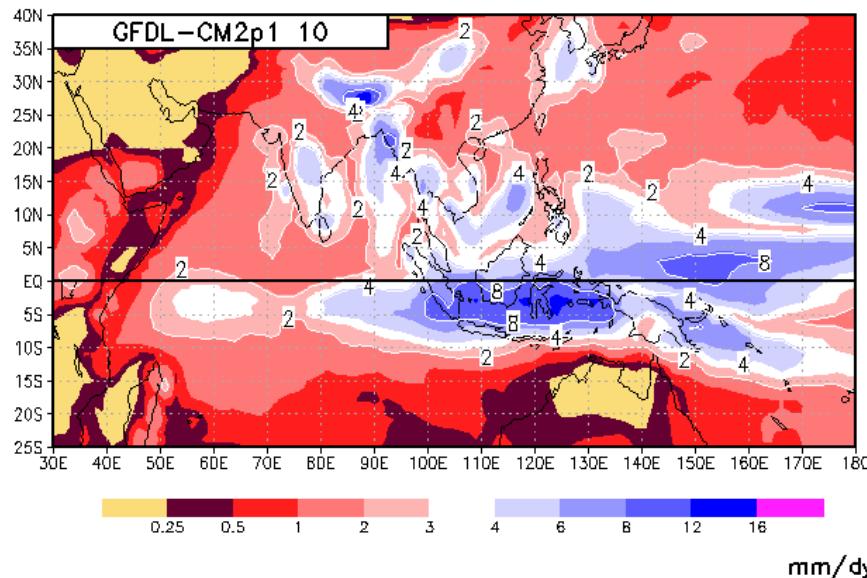
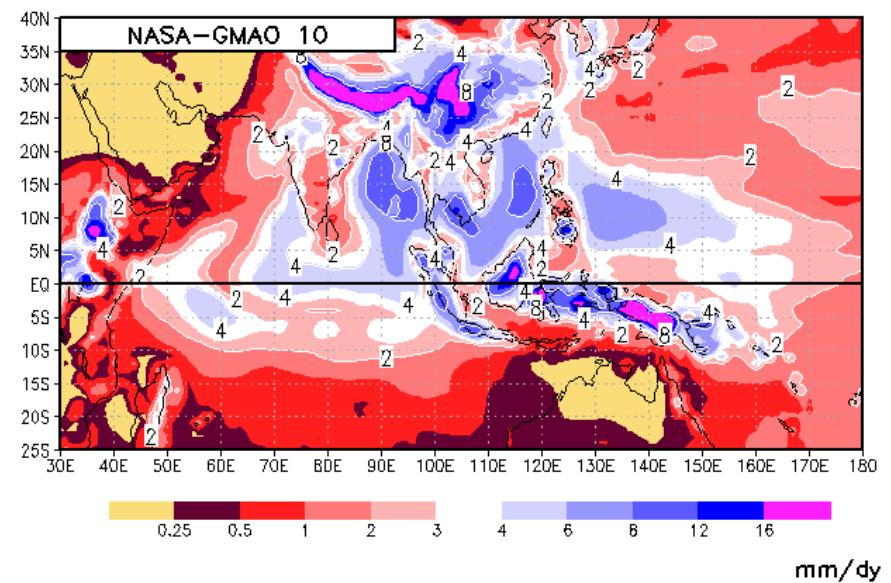
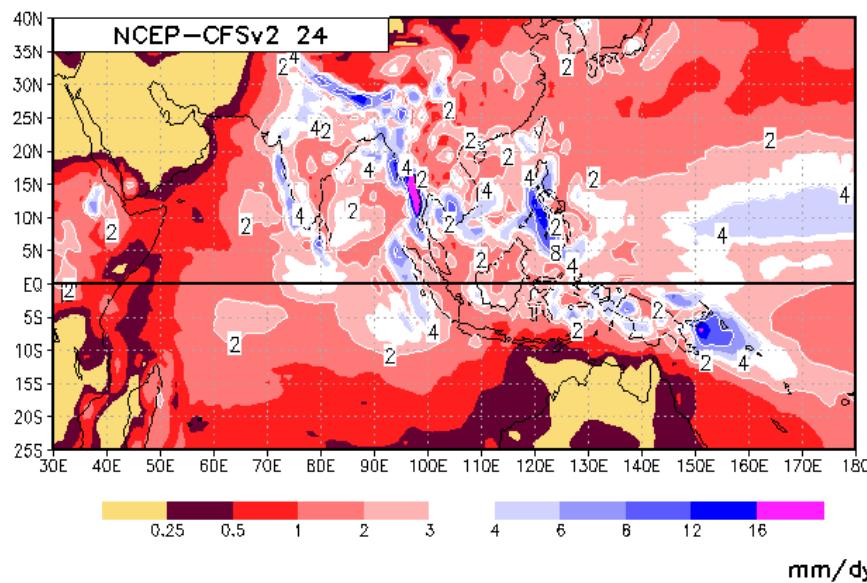
NMME 1 May ICS 1982–2010 Sea\_Surface\_Temperature JJAS Mean Bias

## SST BIAS



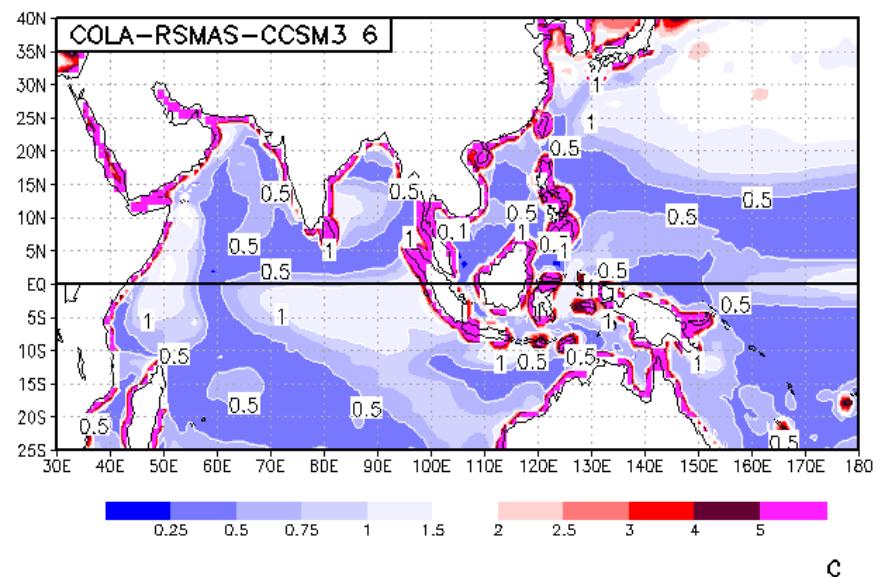
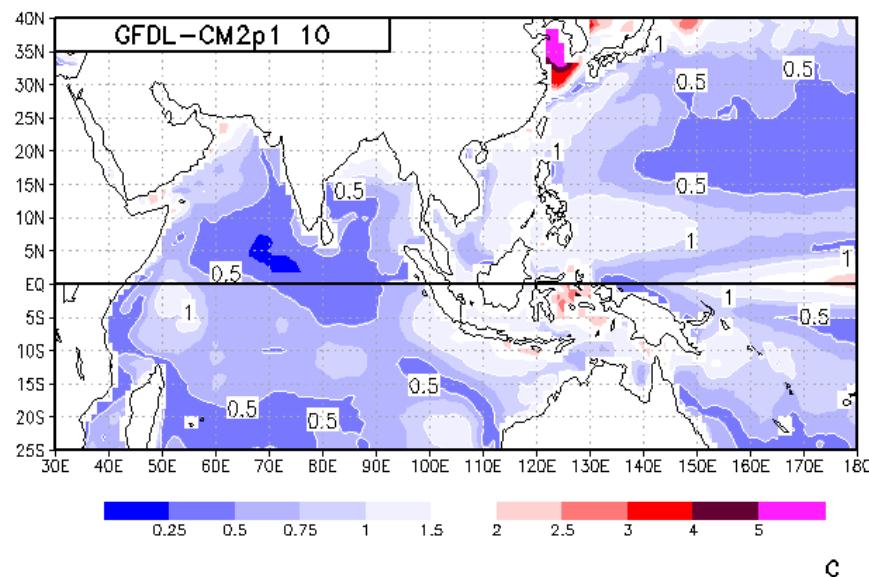
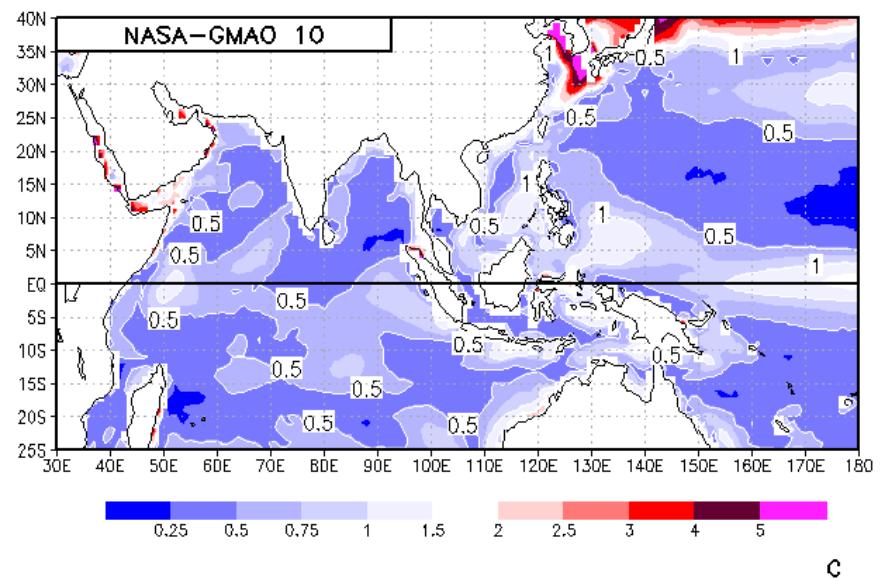
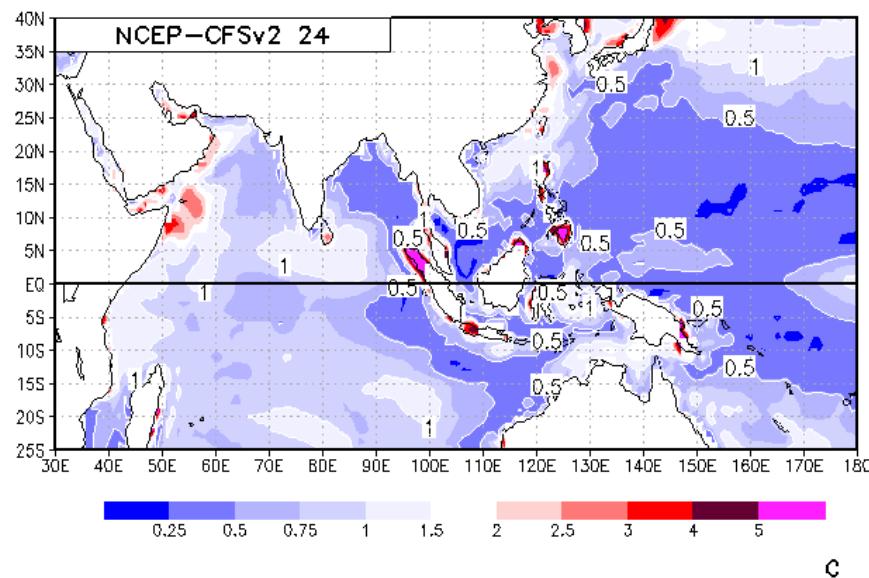
NMME 1 May ICS 1982–2010 Precipitation JJAS Forecast Error (RMSE)

## FORECAST PRECIP RMSE



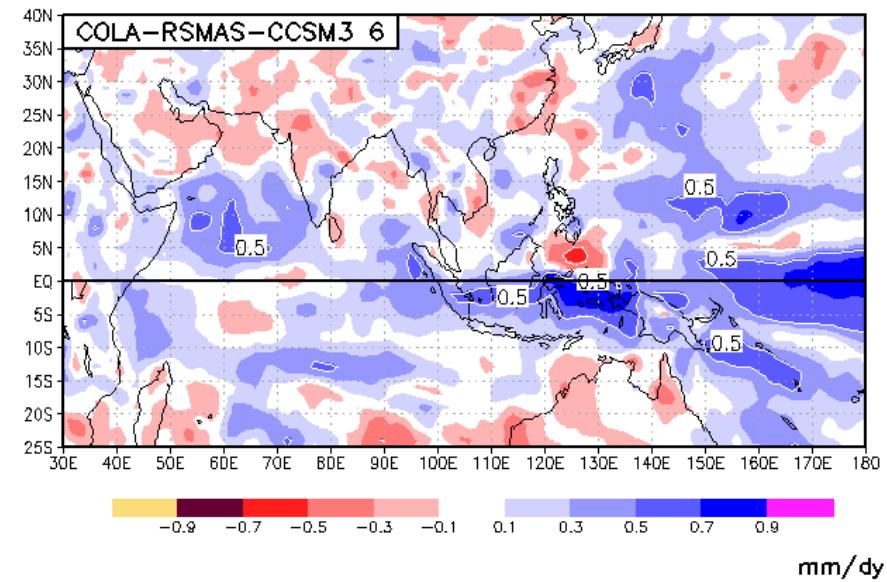
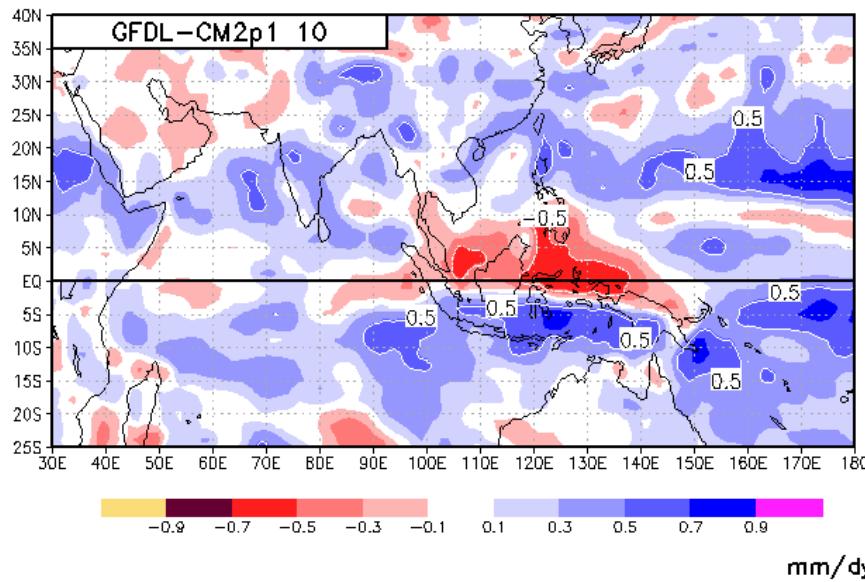
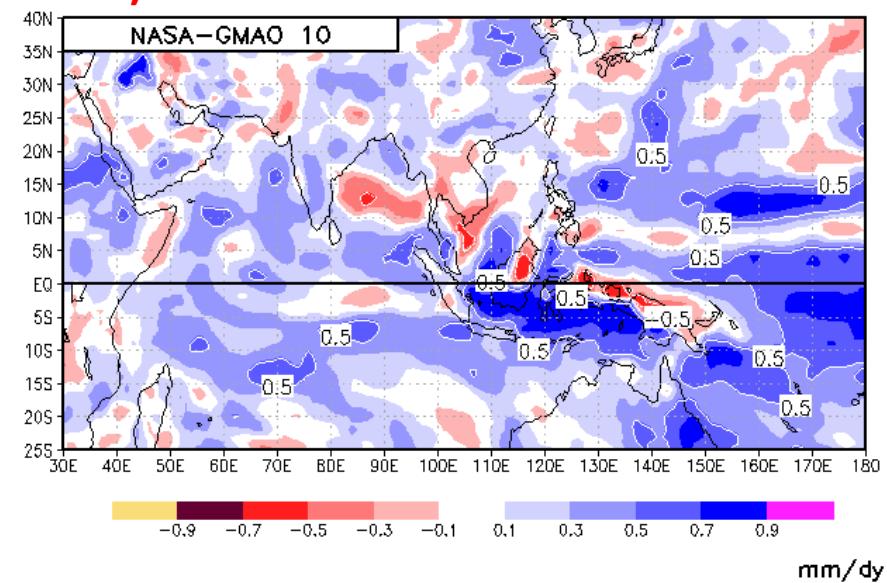
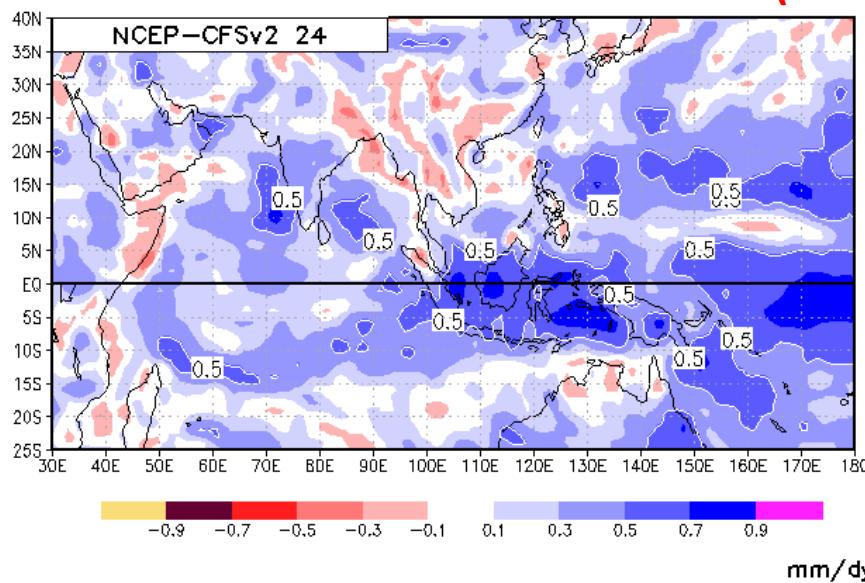
NMME 1 May ICS 1982–2010 Sea\_Surface\_Temperature JJAS Forecast Error (RMSE)

## FORECAST SST RMSE



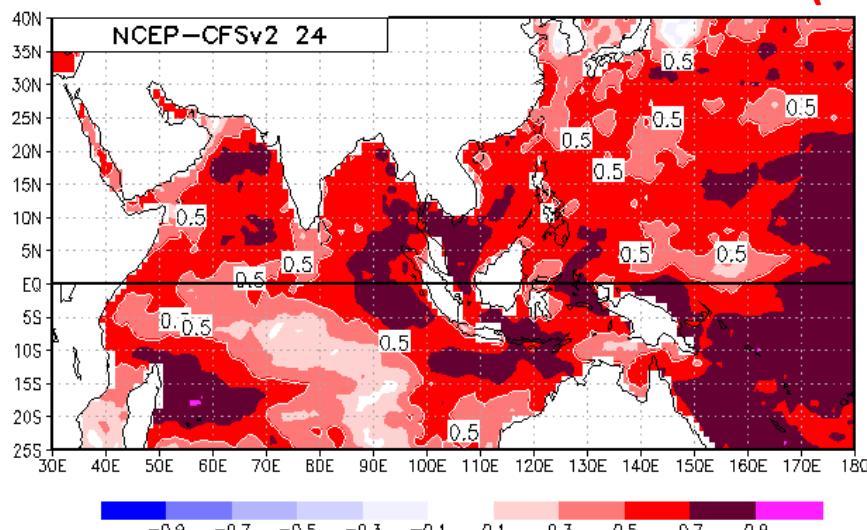
NMME 1 May ICS 1982–2010 Precipitation JJAS  
Anomaly Correlation Coefficient

(PRECIP ACC)

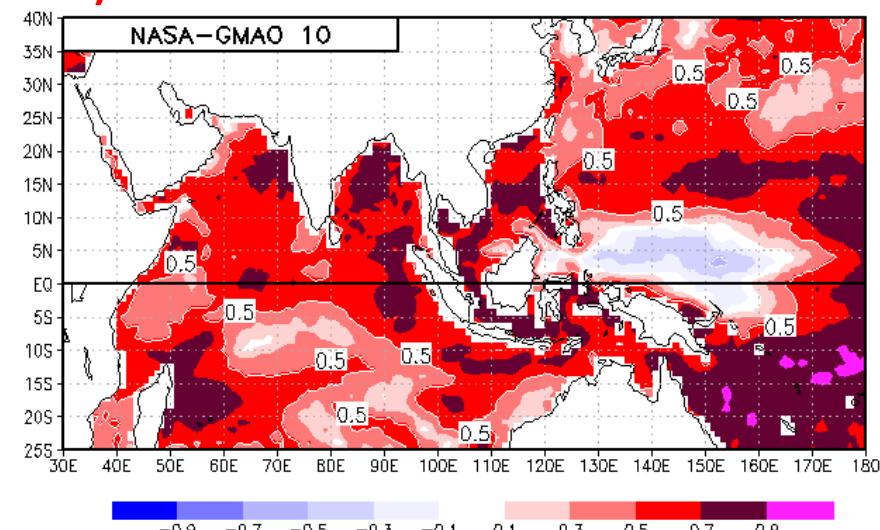


NMME 1 May ICS 1982–2010 Sea\_Surface\_Temperature JJAS  
Anomaly Correlation Coefficient

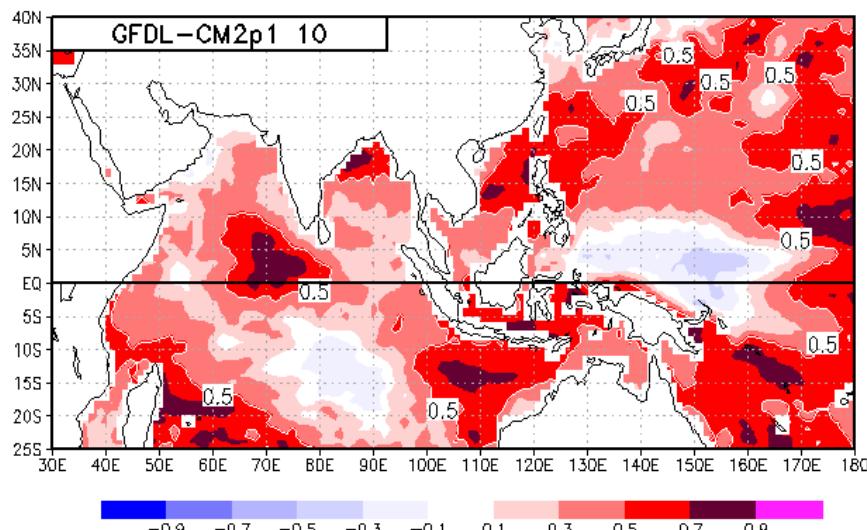
(SST ACC)



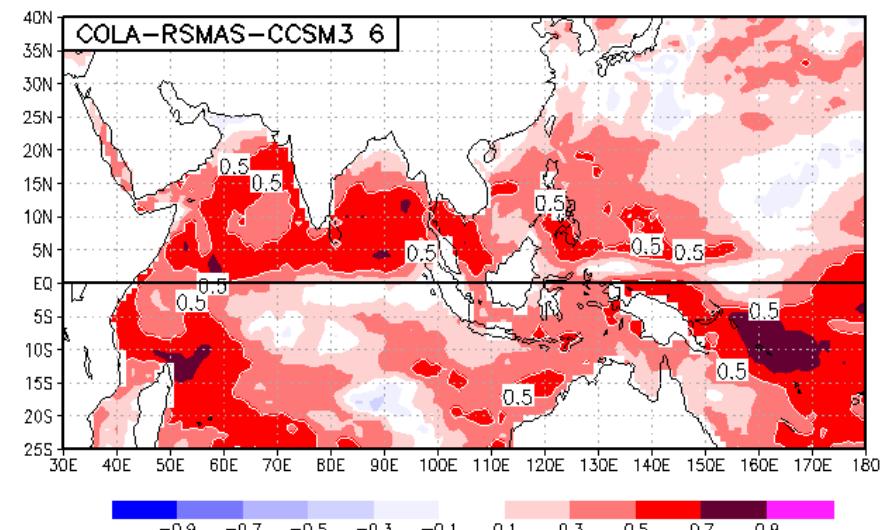
c



c



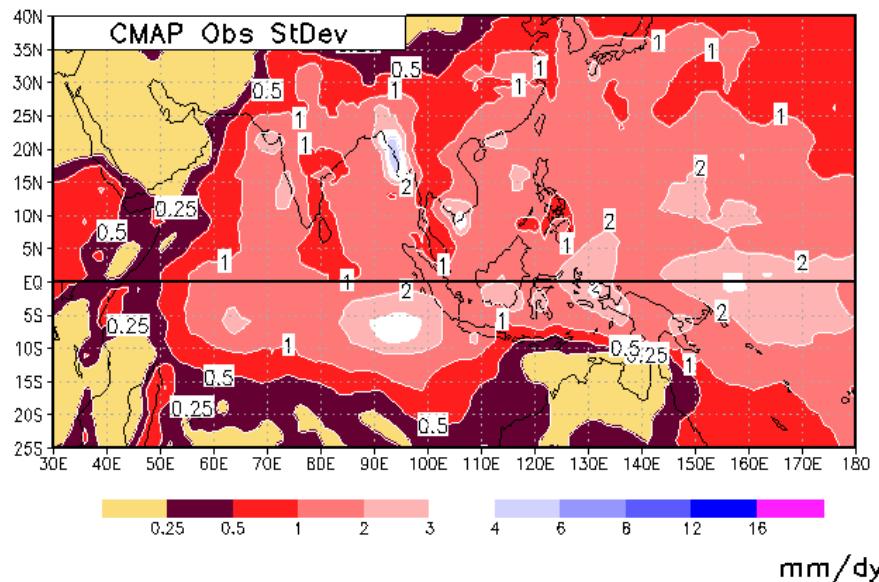
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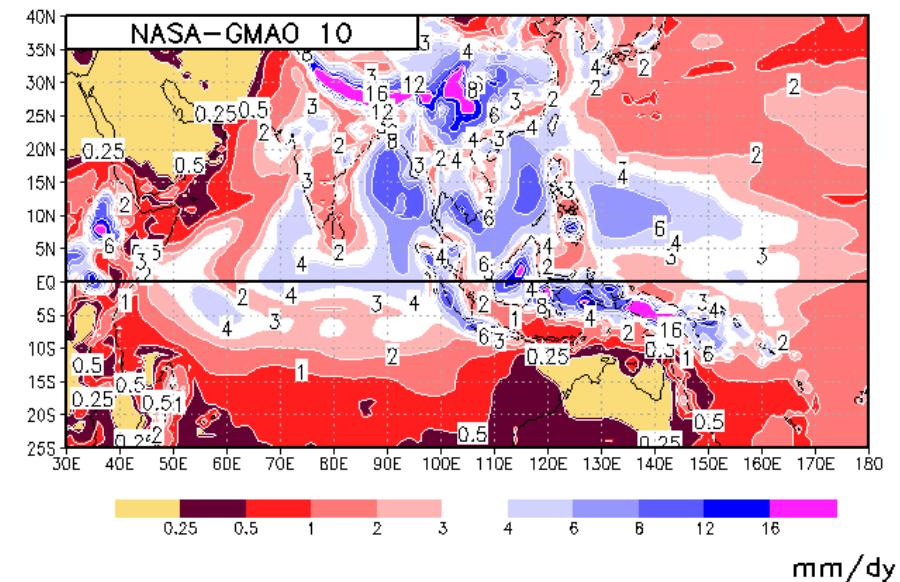
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NMME JJAS 1982–2010 RMSE Precip **PRECIP RMSE**

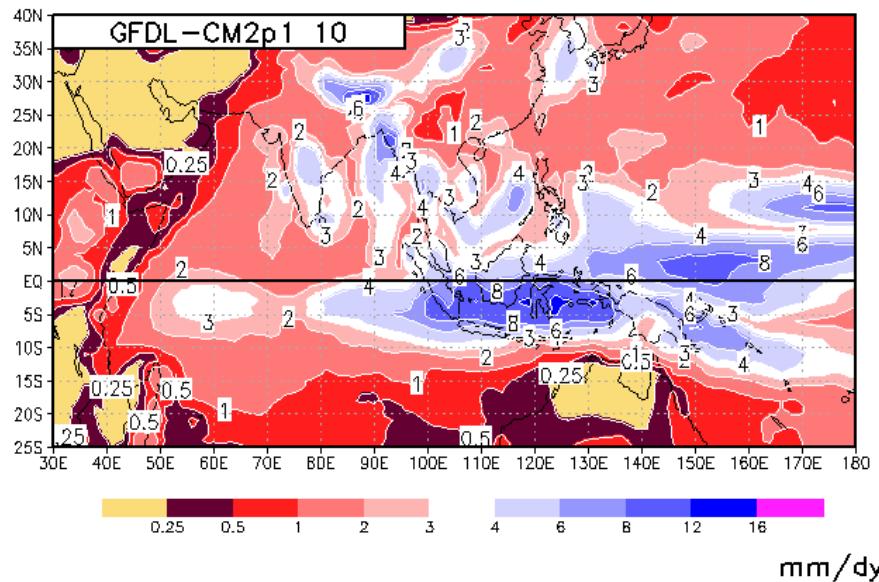
## OBS St. Dev



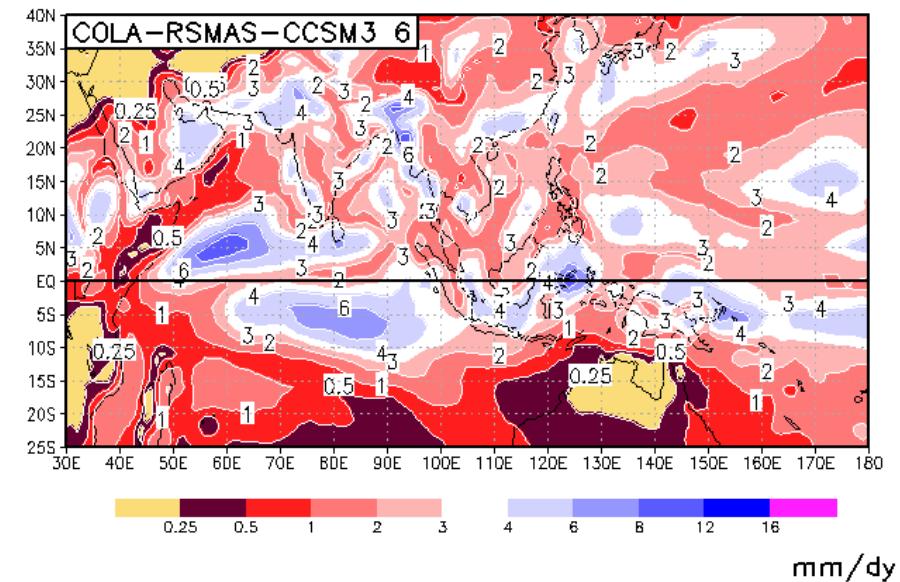
## NASA



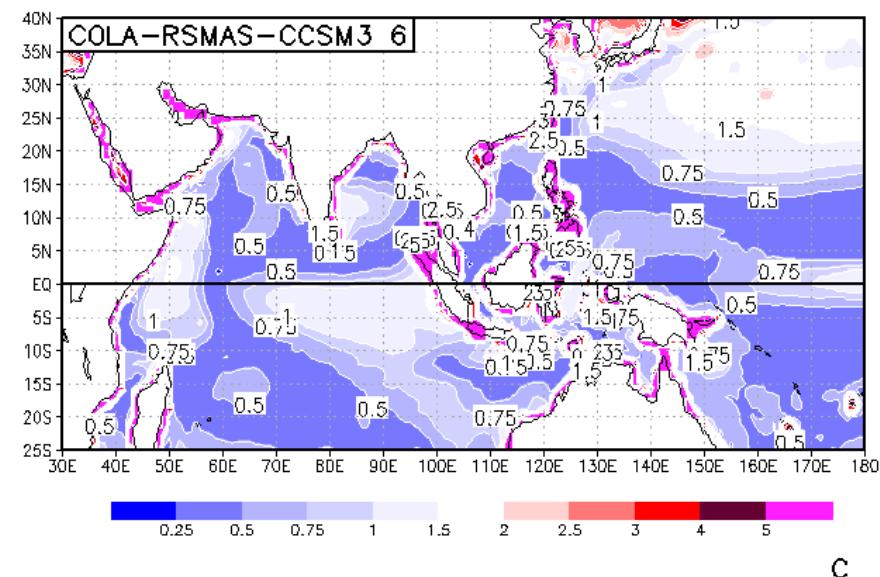
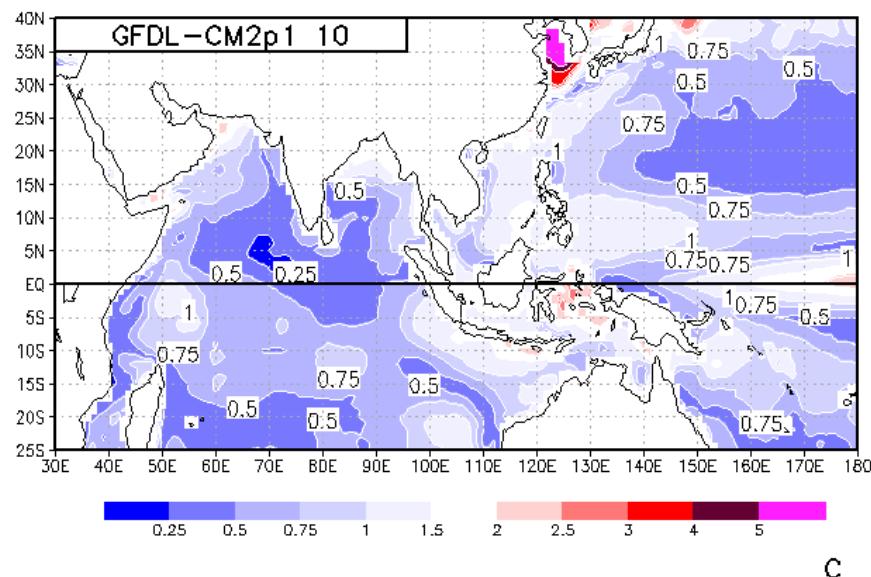
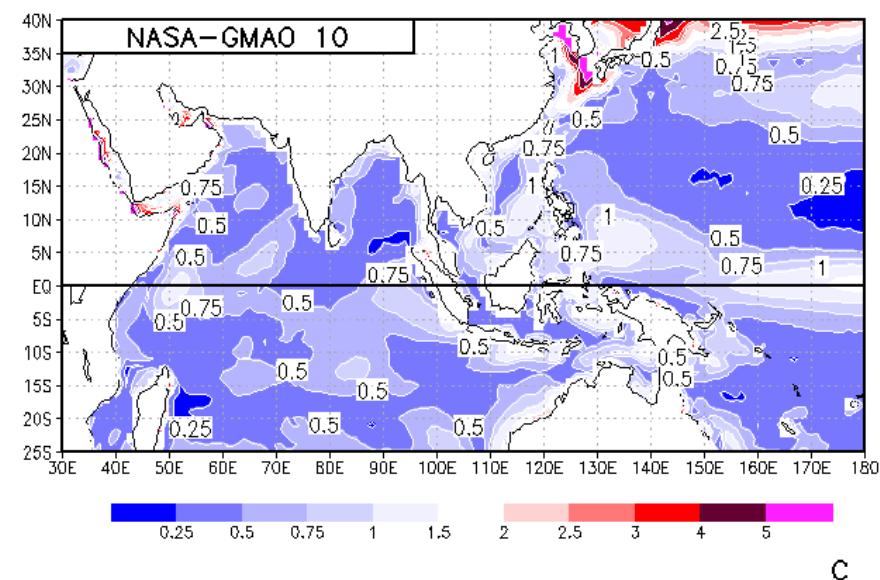
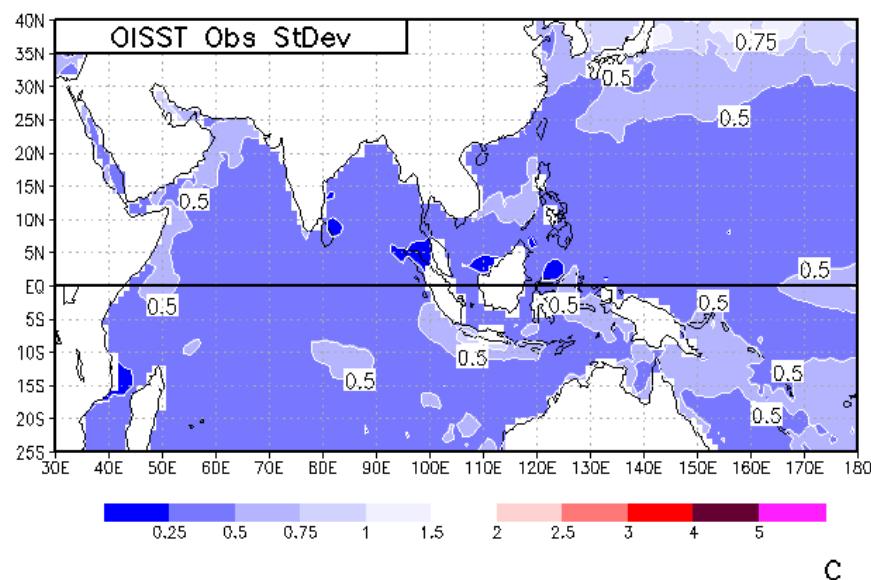
## GFDL



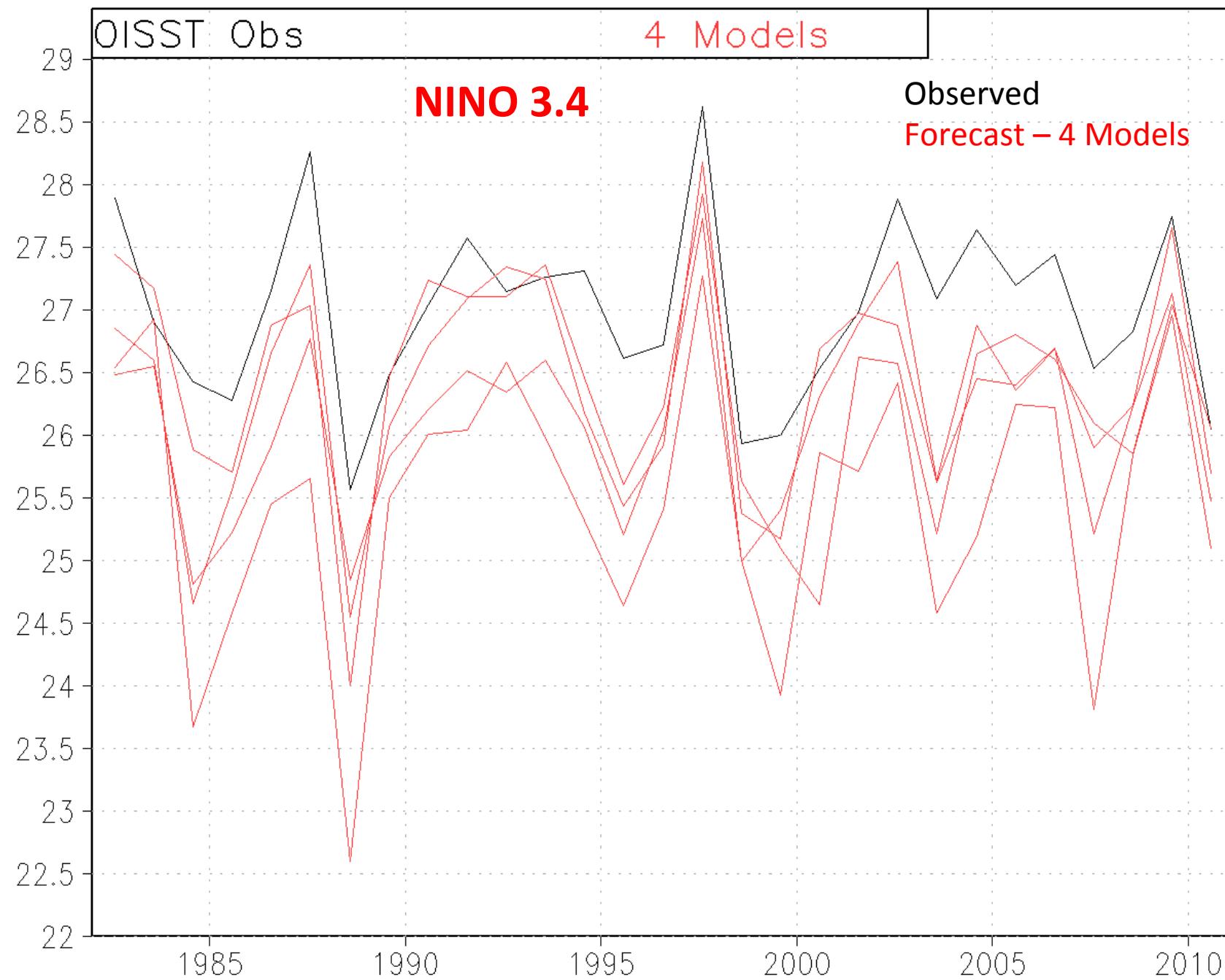
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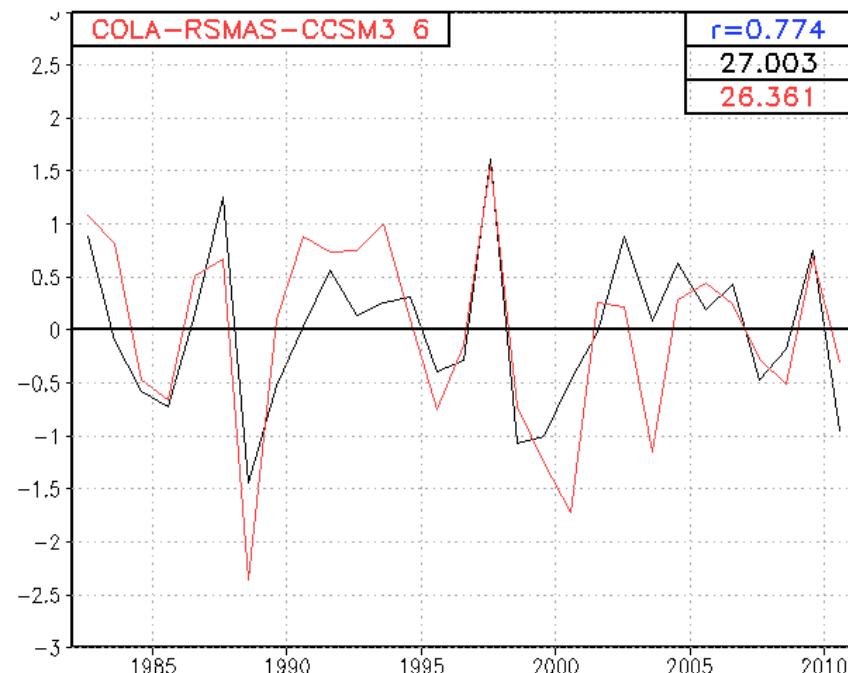
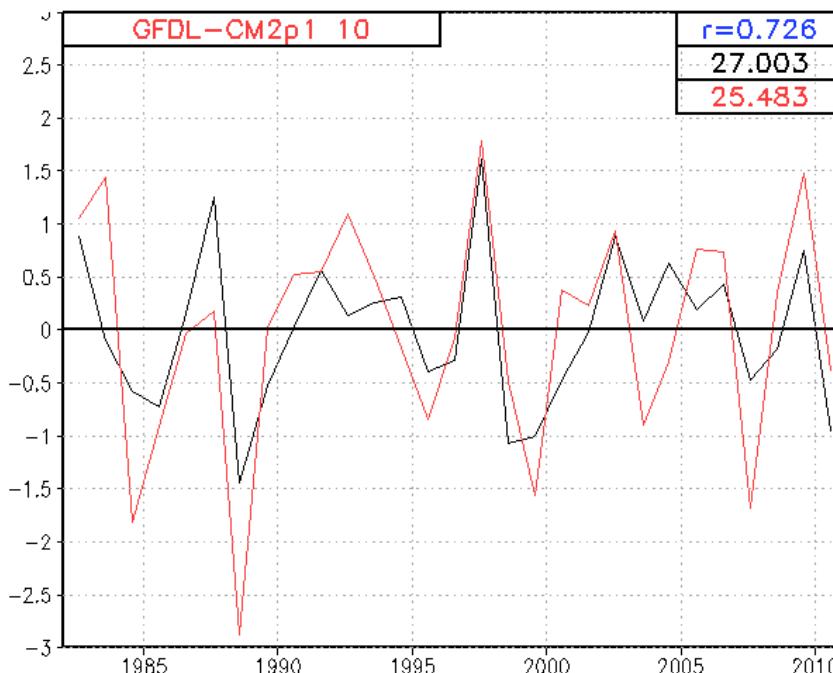
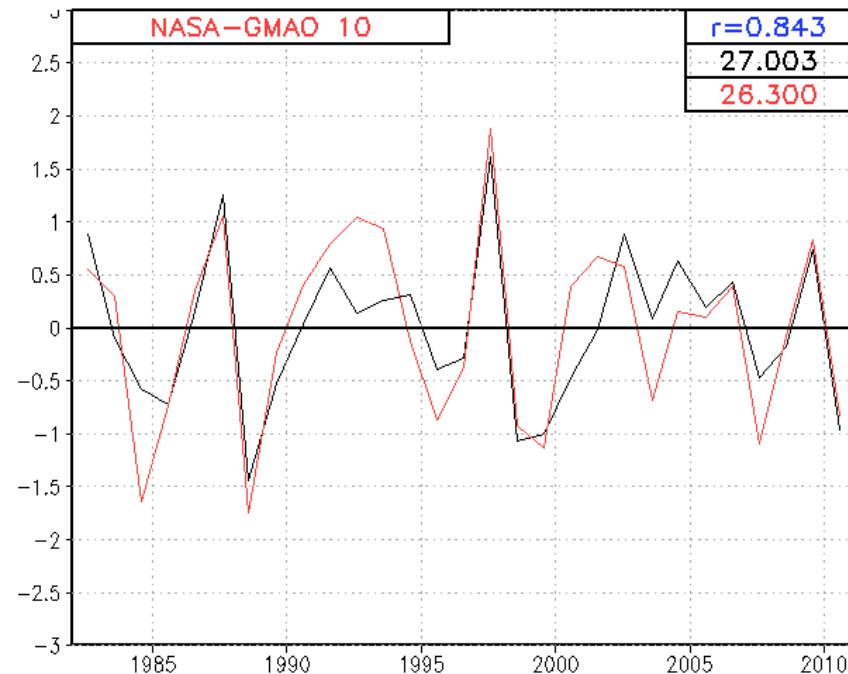
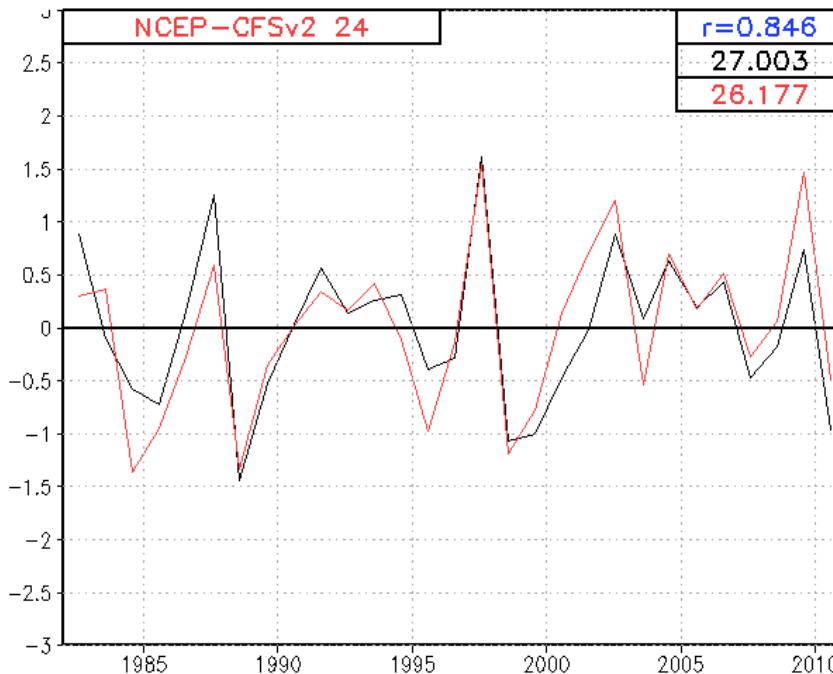
# NMME JJAS 1982–2010 RMSE SST



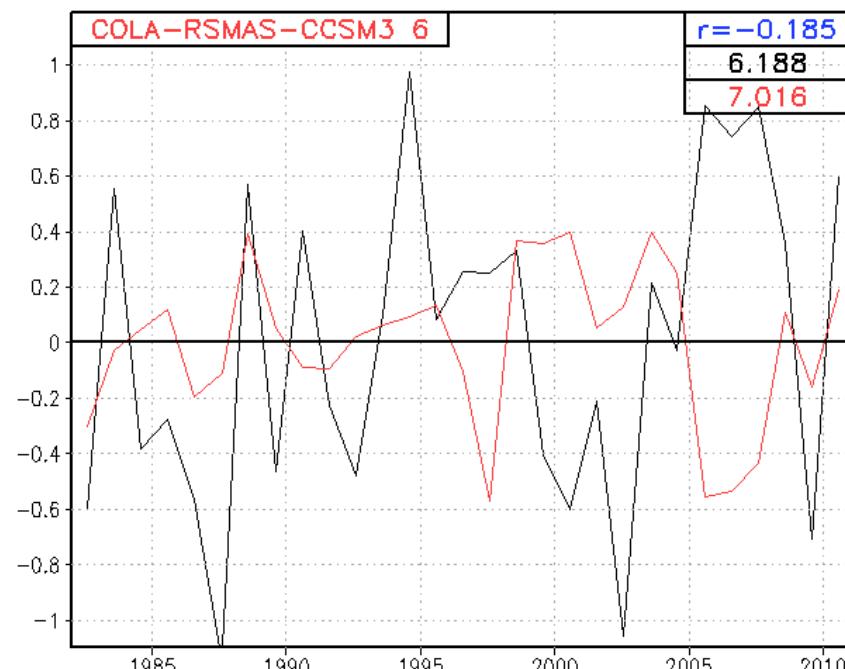
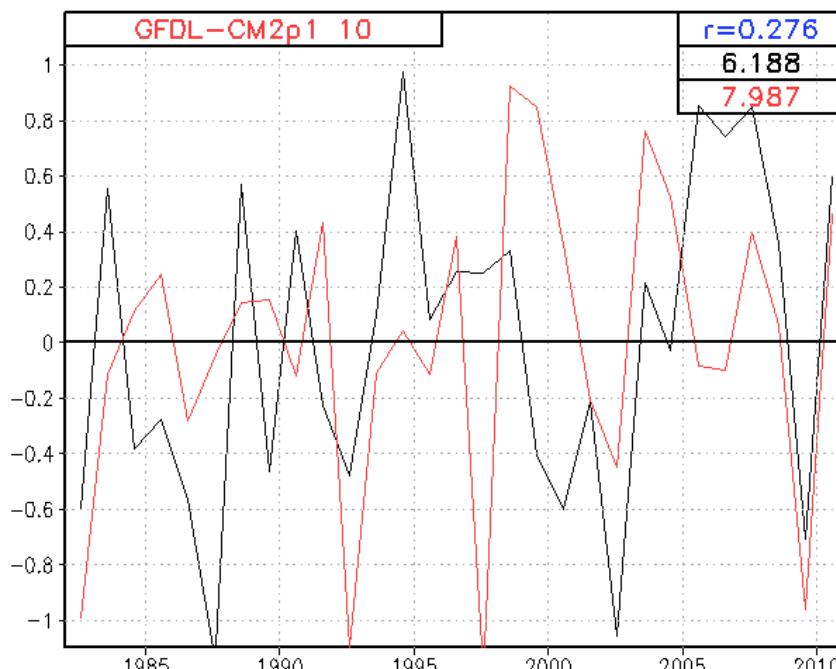
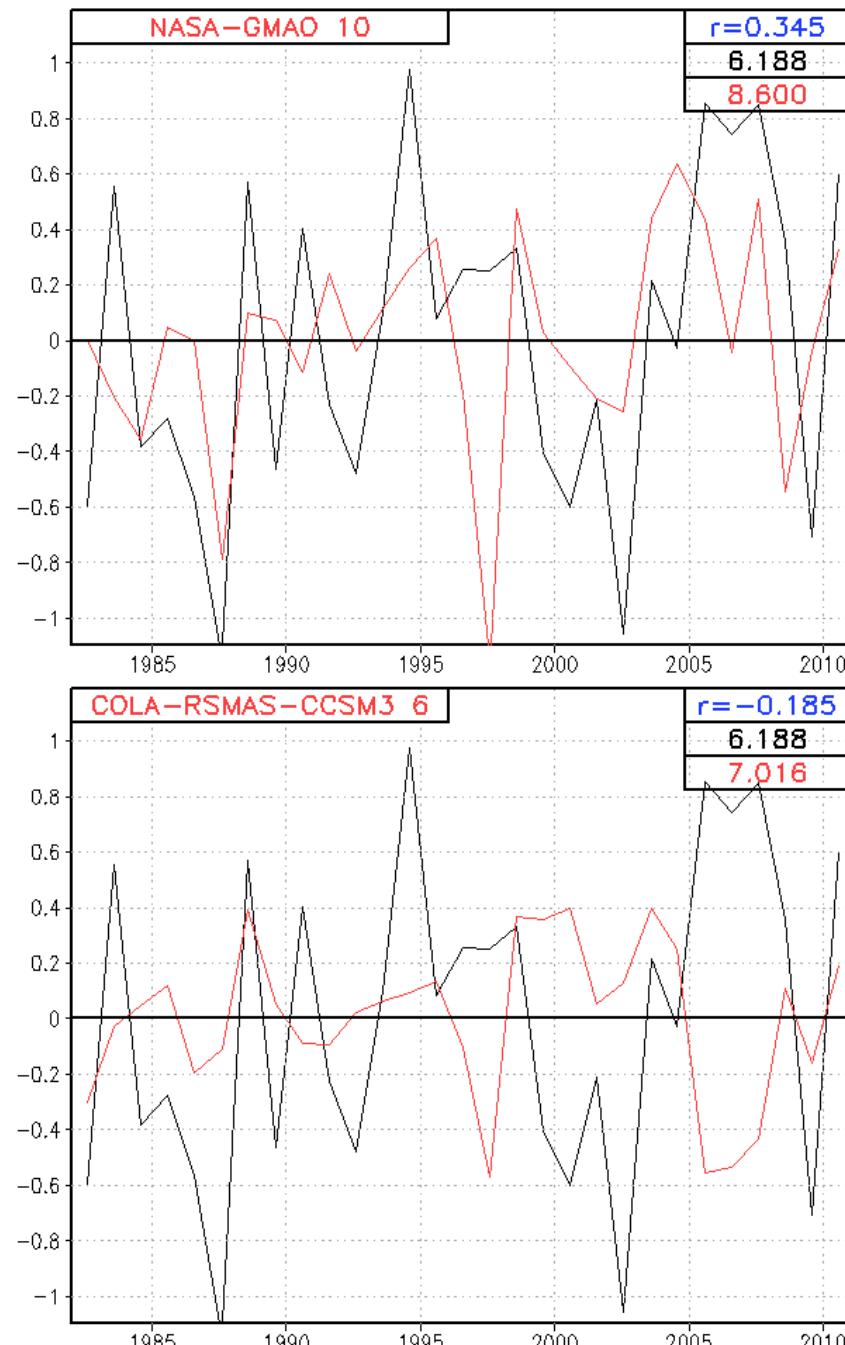
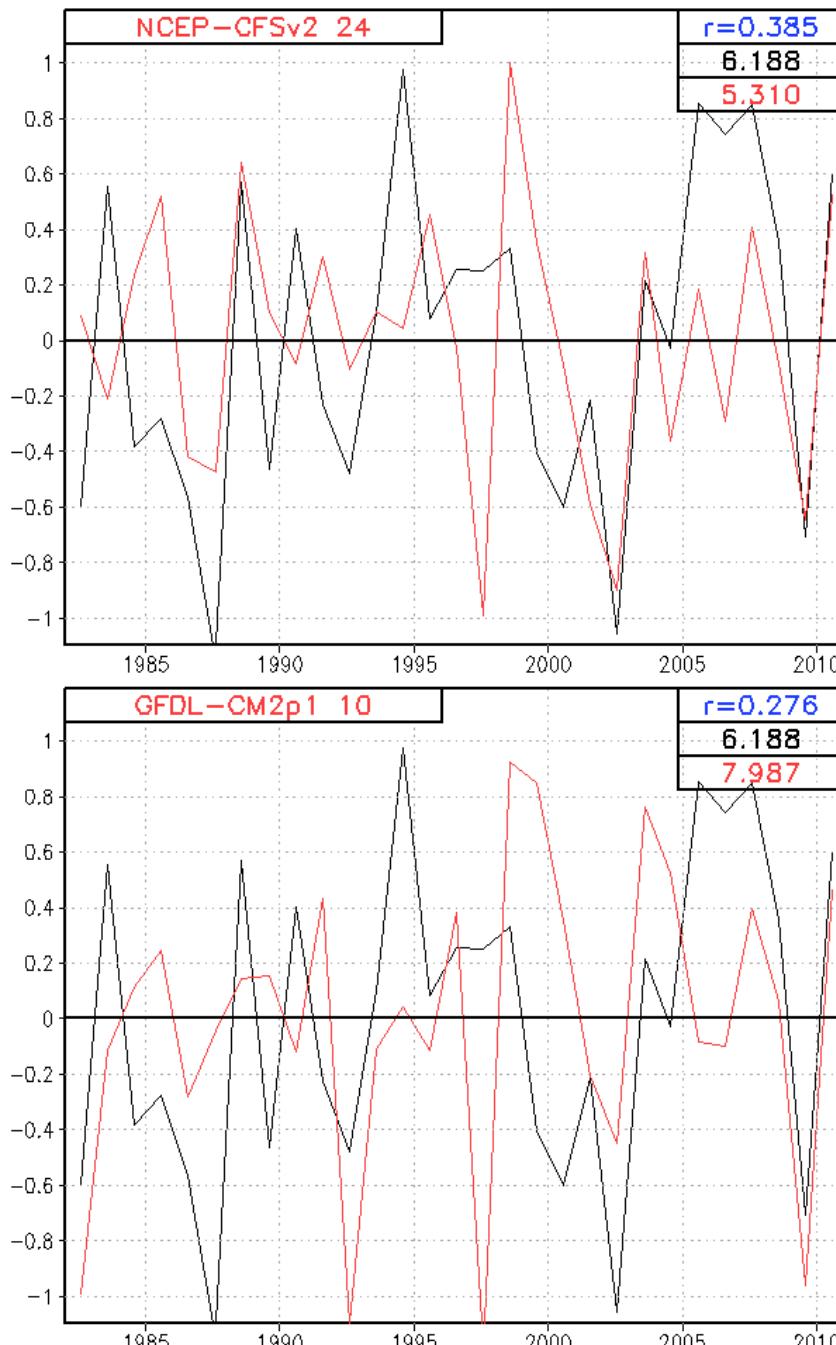
JJAS 1982–2010 NCDC–OISST NINO3.4 Sea\_Surface\_Temperature (C) 01MayIC



JJAS 1982–2010 NCDC–OISST NINO3.4 Sea\_Surface\_Temperature Anomaly (C) 01MayIC



JJAS 1982–2010 CPC–CMAP All India Precipitation Anomaly (mm/dy) 01MayIC



## CFSv2 Rforecasts

### Model

CFSv2 Rforecasts from NCEP  
1982-2009

February initial conditions: 20 ensemble members  
00Z, 06Z, 12Z and 18Z  
Feb 5, 10, 15, 20, 25

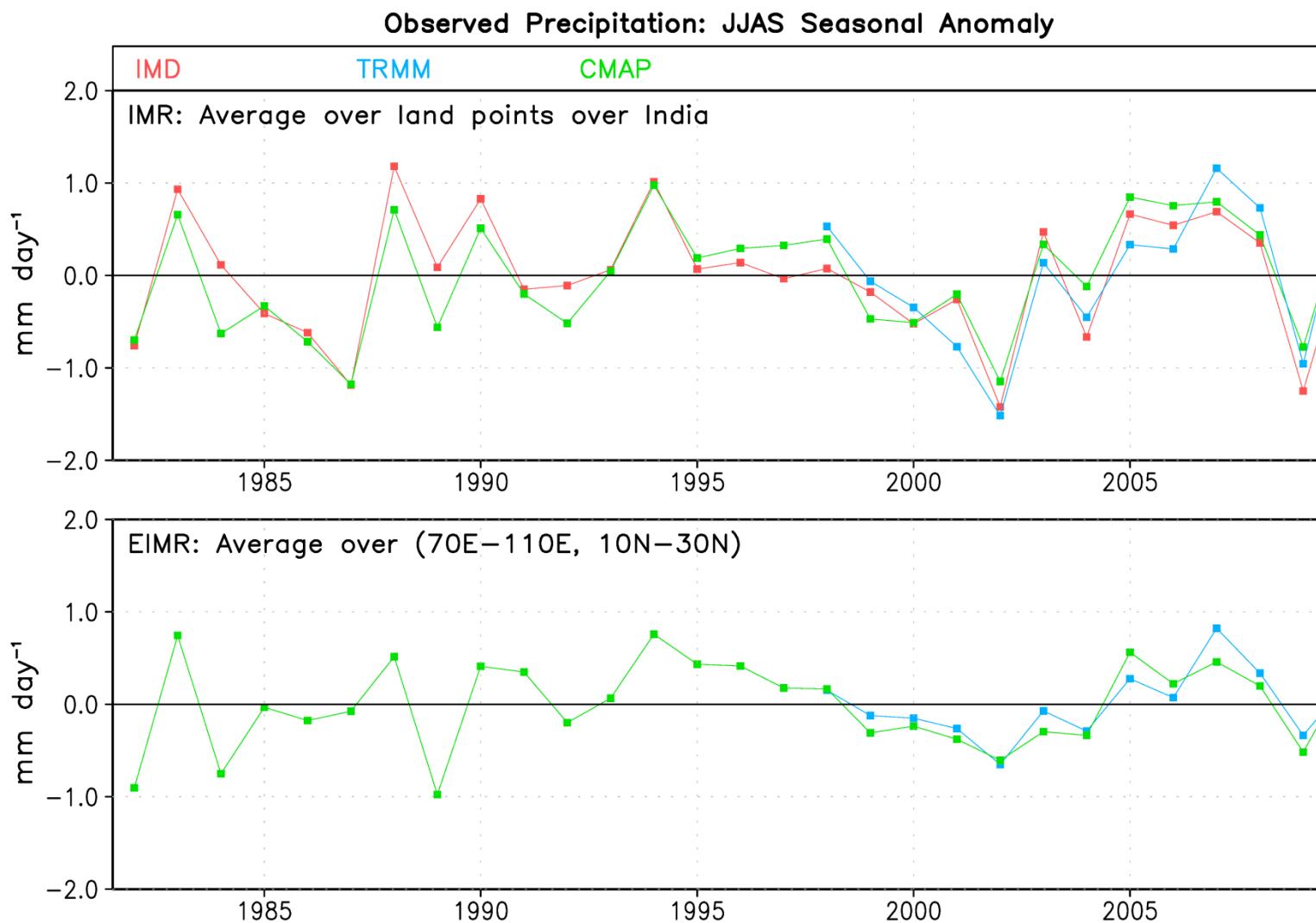
May initial conditions: 28 ensemble members  
00Z, 06Z, 12Z and 18Z  
May 1, 6, 11, 16, 21, 26, 31

### Observation

IMD rainfall data 1982-2009  
TRMM (version 7) rainfall data 1998-2009

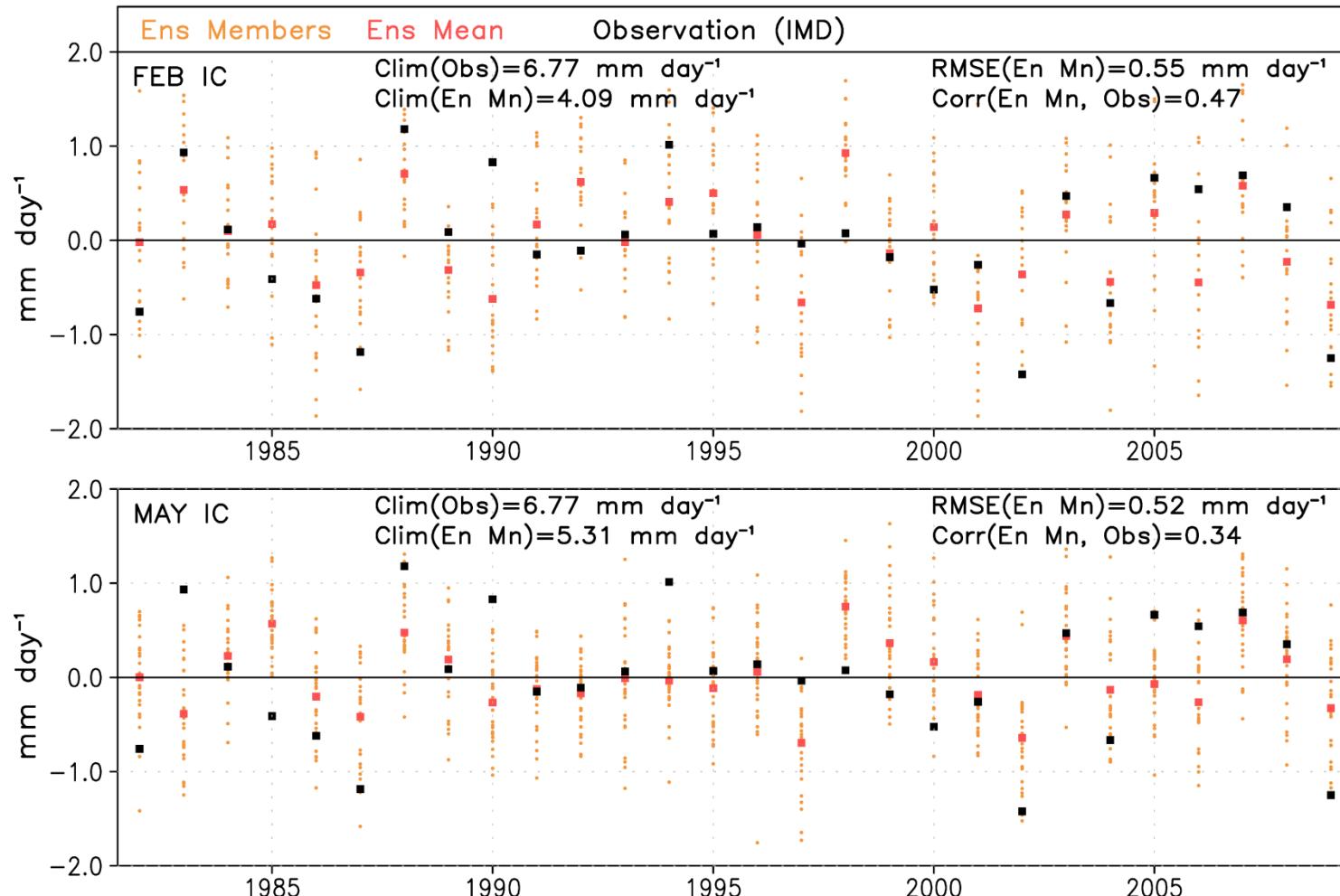
Krishnamurthy, V., 2014: Predictability of the Indian monsoon in CFSv2 on interannual and intraseasonal time scales (in preparation)

## Observations



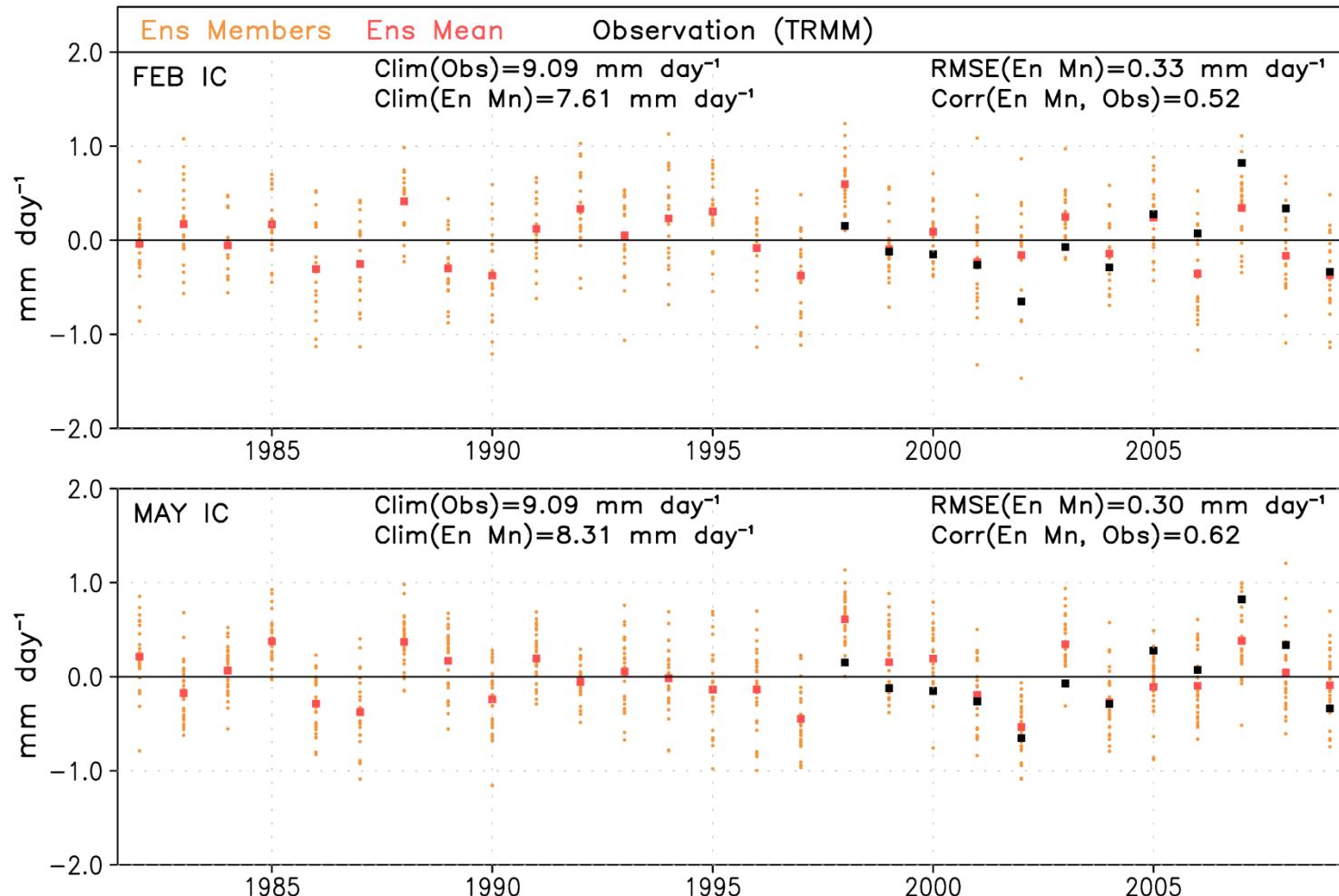
## CFSv2 Reforecasts

CFSv2 Reforecasts and Observed IMD Precipitation: JJAS Seasonal Anomaly  
IMR index: Area average over land points over India



# CFSv2 Reforecasts

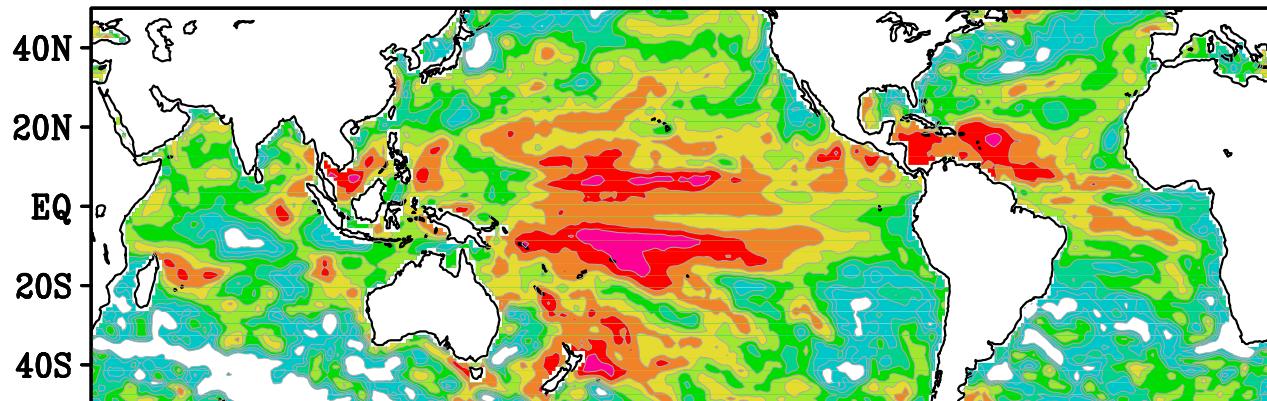
CFSv2 Reforecasts and Observed TRMM Precipitation: JJAS Seasonal Anomaly  
EIMR index: Area average over (70E–110E, 10N–30N)



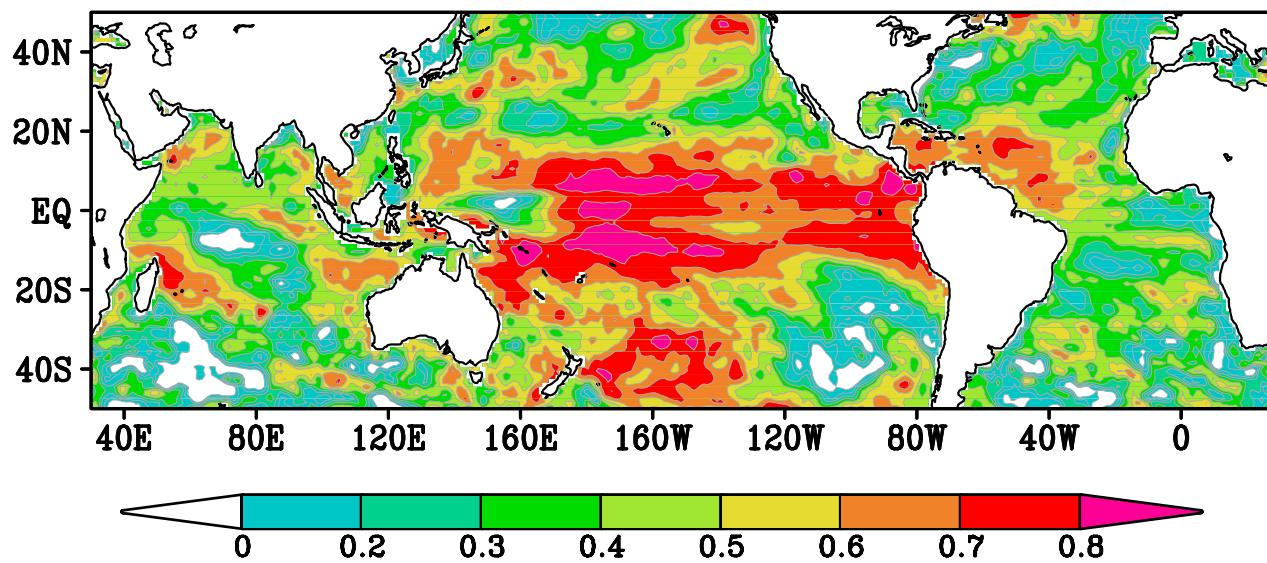
# Impact of Ocean IC on Prediction of JJAS SST

Prediction Skill of JJAS Mean SSTA from CFSv2  
(Prediction vs. OISST); 1–4 April ICs; 1982–2009

(a) Ocean Initial Condition from NCEP(CFSR)



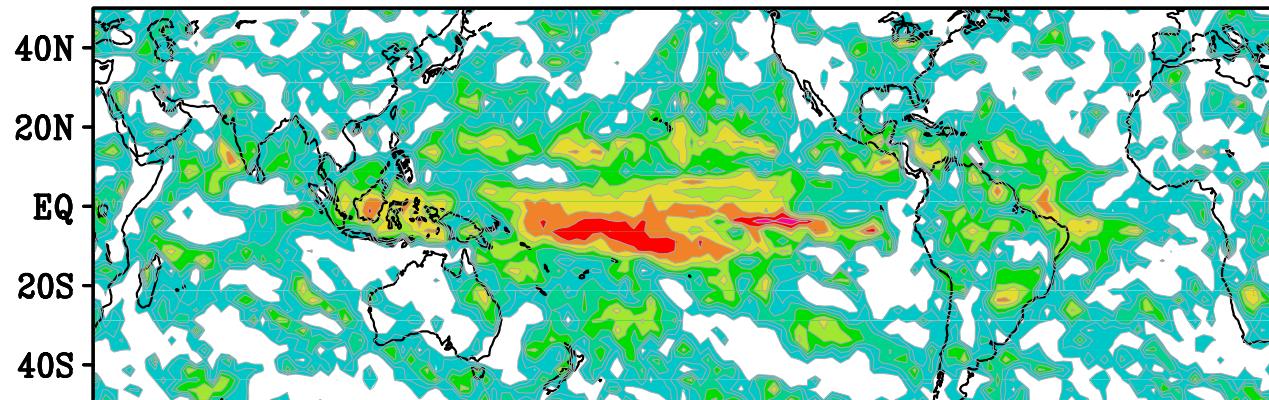
(b) Ocean Initial Condition from ECMWF(ORA-S4)



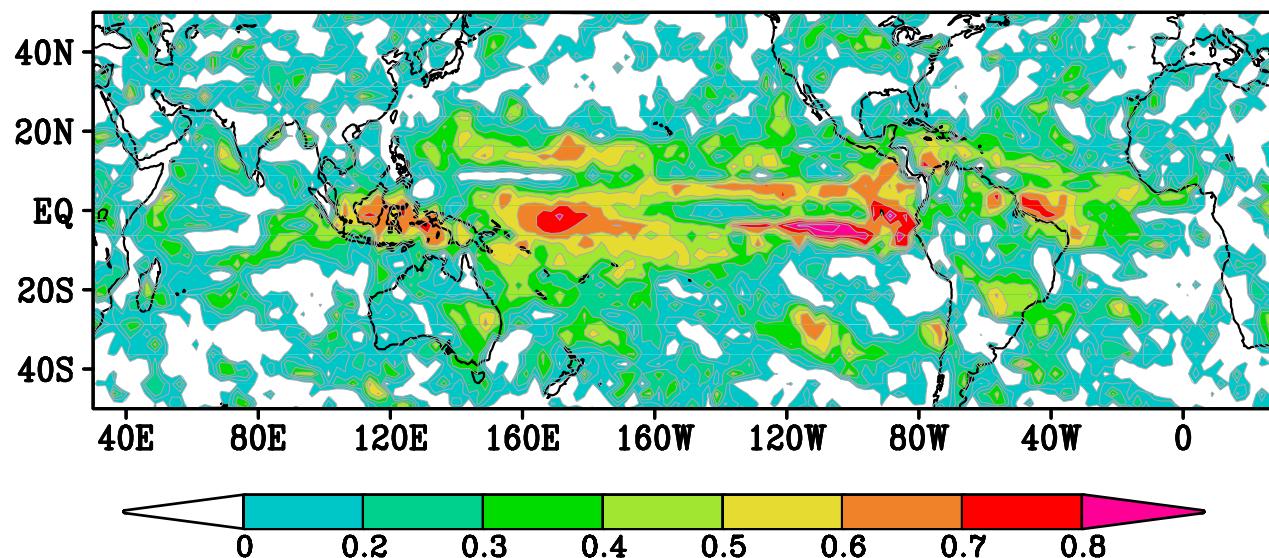
# Impact of Ocean IC on Prediction of JJAS Precip.

Prediction Skill of JJAS Mean Precip. from CFSv2  
(Prediction vs. CMAP); 1–4 April ICs; 1982–2009

(a) Ocean Initial Condition from NCEP(CFSR)



(b) Ocean Initial Condition from ECMWF(ORA-S4)

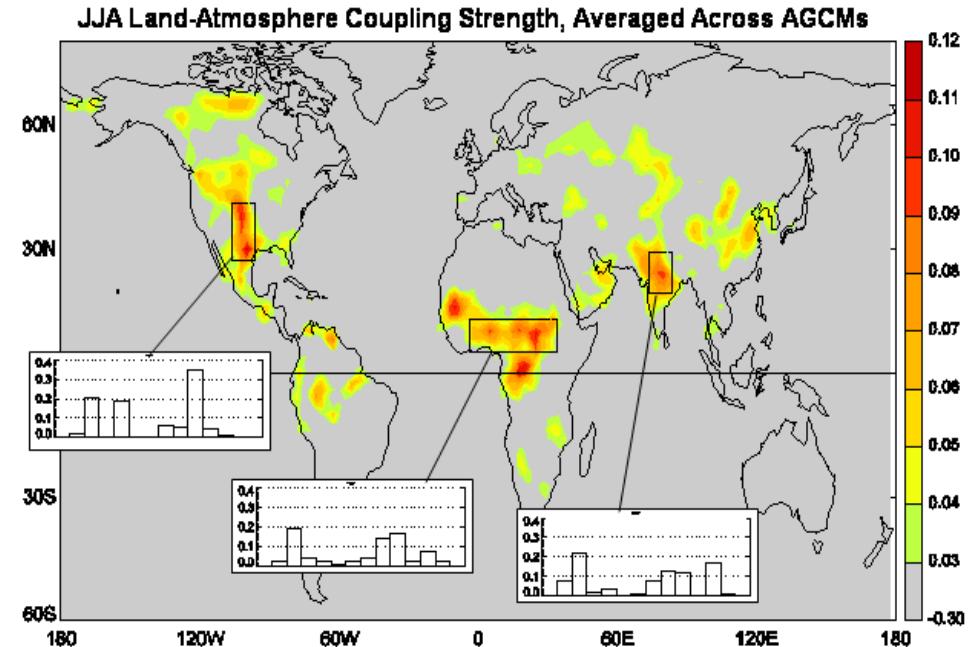


# **Impact of Land Initial Conditions on Subseasonal to Seasonal Prediction**

Thanks: Dirmeyer and Guo

# Hot Spots

The Global Land-  
Atmosphere Coupling  
Experiment (GLACE) :  
A joint GEWEX/CLIVAR  
modeling study



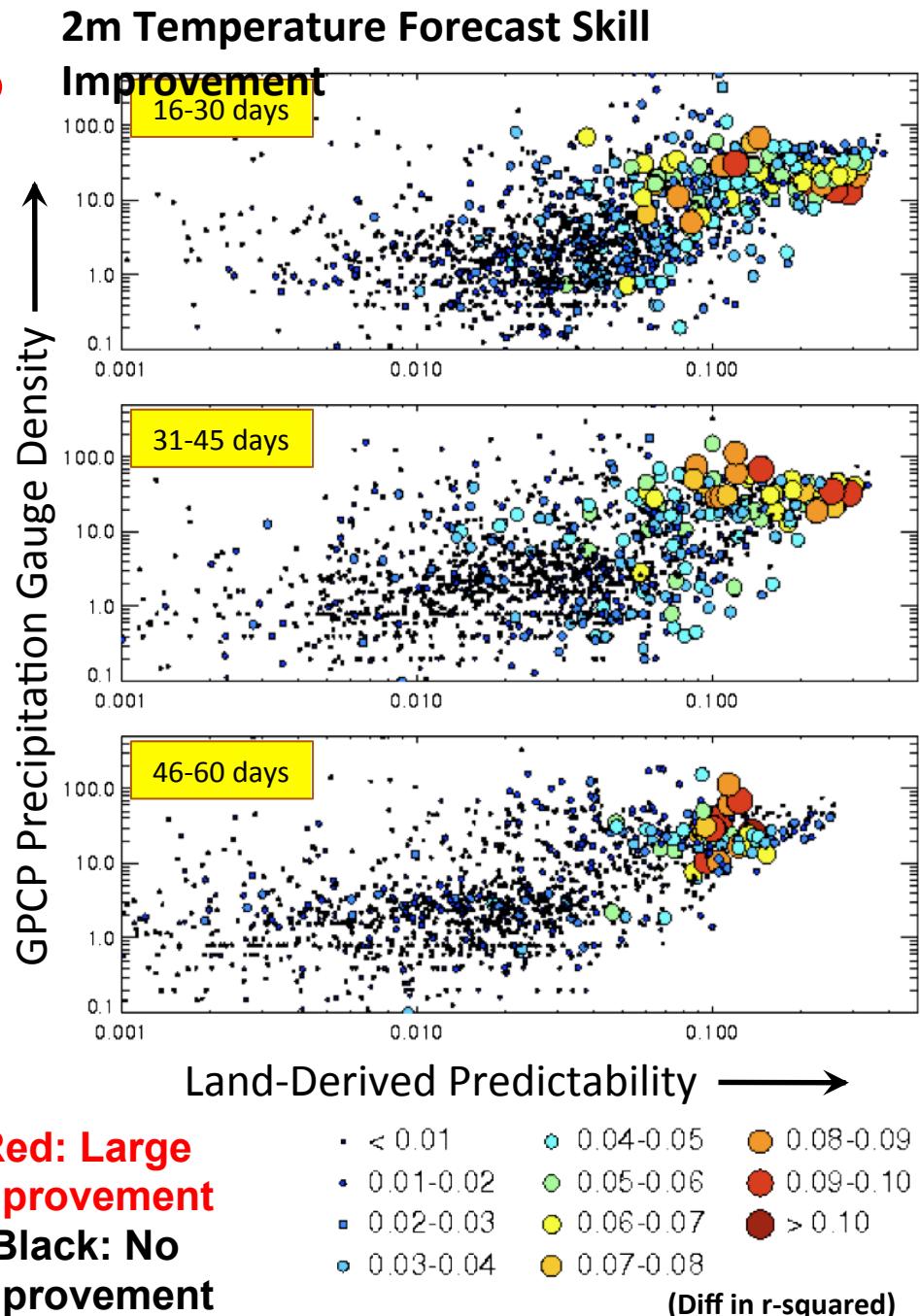
- Multi-model results indicate that there are geographic “hot spots” where the atmosphere is responsive to the state of the land surface (soil moisture) = potential predictability.
- There have been many subsequent studies using models, analyses and observations that corroborate and help explain this result.

Koster, et al., 2004: *Science*, 1138-.  
Dirmeyer, et al., 2006: *JHM*, 1177-.  
Guo, et al., 2006: *JHM*, 611-.  
Koster, et al., 2006: *JHM*, 590-.

# Skill Contributors

- GLACE-2 prediction study (11 GCMs, 1986-1995, forecasts validating during JJA).
- Places that see the greatest skill impact from realistic land surface initialization have **high gauge density** (good rainfall data to generate initial soil moisture states) and **high land-derived predictability** (hot spots).

Koster et al., 2011: *JHM*, 805-.



# National Monsoon Mission of India and COLA Joint Research to Enhance Monsoon Prediction

COLA Project: “Ocean-Land-Atmosphere Coupling and Initialization Strategies to Improve CFSv2 and Monsoon Prediction”

- Improve the coupled ocean-land-atmosphere model (CFSv2) performance.
- Better initialization of ocean and land states in the pre-monsoon season to improve forecasts of onset, monsoon season precipitation.
- Better land surface analyses require better timely precipitation data.

## **The Challenge**

Predictability of Asian Summer Monsoon Rainfall is High

**but**

**Prediction Skill is Low**

# Mechanisms of Seasonal-Interannual Variability

- INTERNAL DYNAMICS
- BOUNDARY FORCING

Atmosphere-Ocean Interaction

Atmosphere-Land Interaction

Atmosphere-Ocean-Land Interaction

(CLIM 710)

# Mechanisms of Variability

## Internal

**Weather:** 1. Internal Dynamics of Atmosphere

**Climate:** (seasonal-decadal) 2. Internal Dynamics of Coupled Ocean-Land-Atmosphere

**Climate Change:** 3. Internal Dynamics of Sun-Earth System

## External

- Boundary Condition of SST, Soil wetness, Snow, Sea ice, etc.

- Solar, Volcanoes

- Human effects: (Greenhouse gases, Aerosols, land use changes)

*Decadal and multi-decadal variability has contributions from internal dynamics of the coupled climate system and external forcing.*

# **What Determines The Limits Of Weather And Climate Prediction?**

- **Weather Prediction:**

- Accuracy of observations to describe current weather
- Realism of physical-dynamical models
- Chaos: sensitive dependence on initial conditions

- **Seasonal Prediction:**

- Weather prediction +
- Global sea surface temperature, snow, soil wetness, etc.
- Coupling of ocean-atmosphere-land
- Power of computers

- **Climate change:**

- Weather and seasonal prediction +
- Human-induced changes in greenhouse gases
- Deforestation
- Uncertainty of future population, policy, technology

# Sources of Predictability

- Weather: IC (A,L) + SBF
- Intraseasonal: IC (A,O,L) + SBF + AOL Coupling
- Seasonal: IC (A,O,L) + AOL Coupling + SBF
- Decadal: AOLC coupling + EF + IC (AOLC)
- Climate Change: EF + AOLC coupling

IC: Initial Condition, SBF: Surface Boundary Forcing

A: Atmosphere; O: Ocean; L: Land; C: Cryosphere

EF: External Forcing (GHG, solar, volcanoes, Land use etc.)

# Dynamical Seasonal Prediction (DSP)

*Source of predictability: Dynamical memory of atmos. IC  
+ Boundary forcing (SST, SW, snow, sea ice)*

*DSP = NWP + IC of Ocean, Land, Atmosphere*

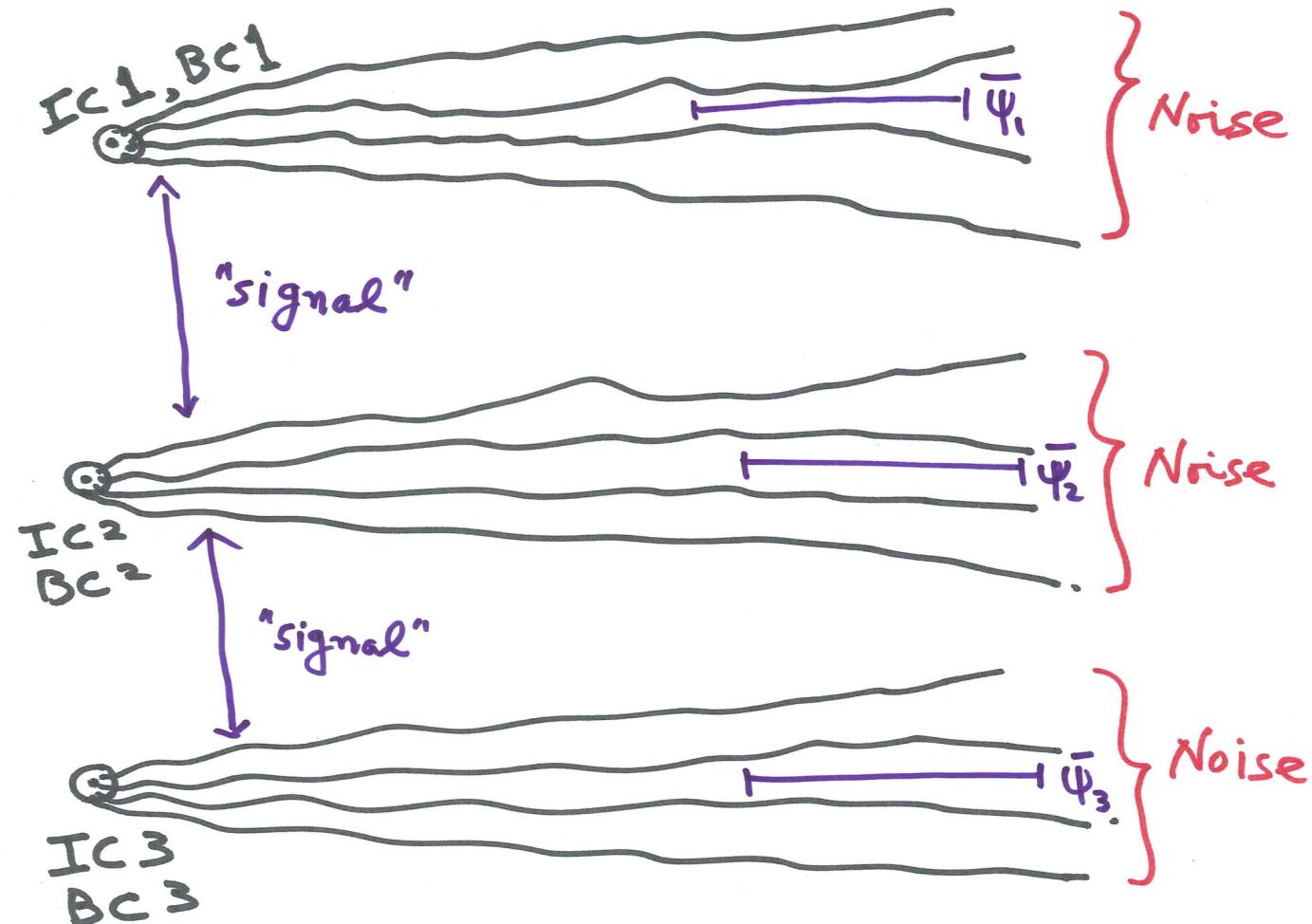
- *dynamically coupled and consistent IC*
- *Global ocean (especially upper ocean); sea ice (volume)*
- *Global Atmos. including stratosphere (IC)*
- *Global GHG (especially CO<sub>2</sub>, O<sub>3</sub>)*
- *Global land (soil moisture, vegetation, snow depth) IC*

Tier 1: Fully coupled models (CGCM) to predict Boundary Forcing

Tier 2: Predict Boundary Forcing separately; use AGCM

•(NWP=Atmos. IC + SST IC)

## Predictability of Time (Seasonal) Mean



Predictability  
of "mean":  
 $= \frac{\text{Signal Var.}}{\text{Noise Var.}}$

## Analysis of Variance: F as a measure of predictability

### 5 CGCMs, 46 years, 9 ensembles

Measure of predictability is

$$F = E \frac{\hat{\sigma}_S^2}{\hat{\sigma}_N^2}$$

where

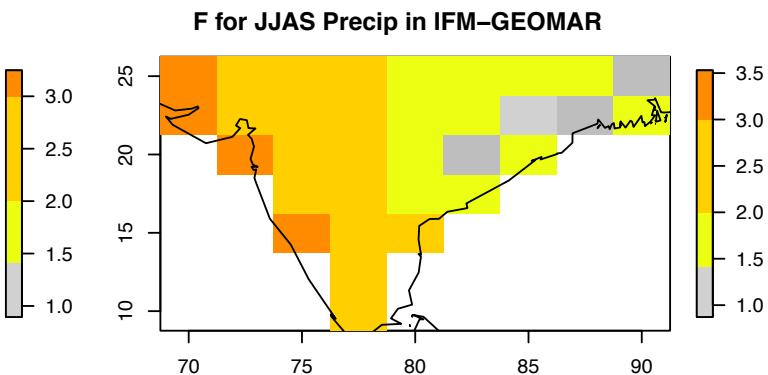
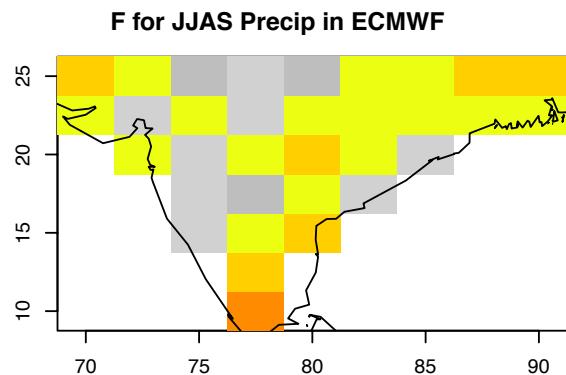
$$\hat{\sigma}_S^2 = \frac{1}{Y-1} \sum_{y=1}^Y \left( P_{y,e} - \bar{\bar{P}} \right)^2$$

$$\hat{\sigma}_N^2 = \frac{1}{Y(E-1)} \sum_{y=1}^Y \sum_{e=1}^E \left( P_{y,e} - \bar{P}_y \right)^2$$

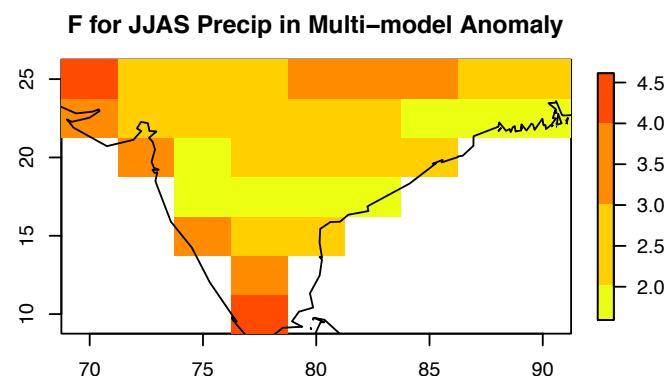
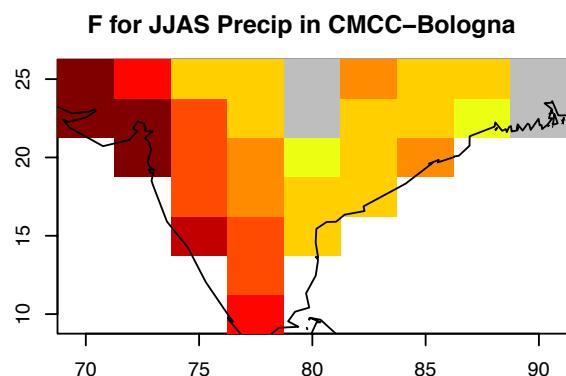
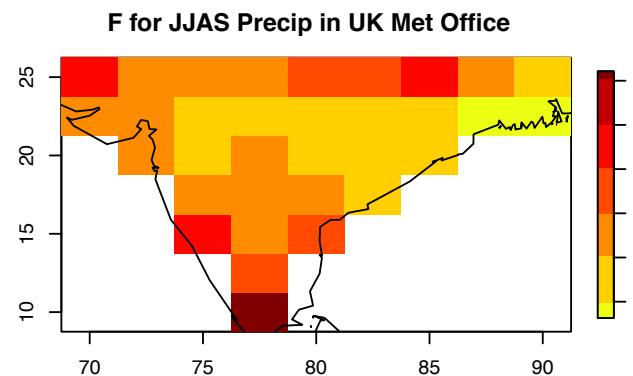
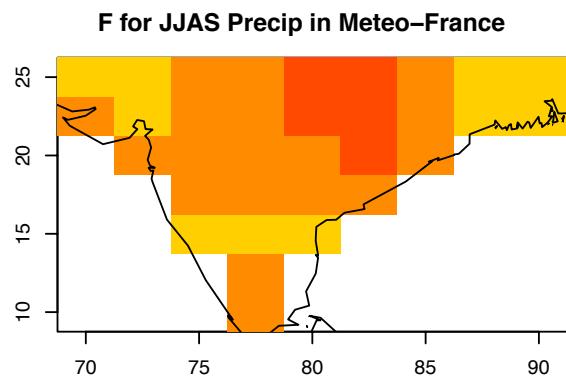
$$\bar{P}_y = \frac{1}{E} \sum_{e=1}^E P_{y,e}$$

$$\bar{\bar{P}} = \frac{1}{Y} \sum_{y=1}^Y \bar{P}_y$$

For samples drawn independently from the same normal distribution, and for  $Y = 46$  and  $E = 9$ , the 5% significance threshold of  $F$  is 1.40



F-values for JJAS precip.  
For 46-years and 9 ensemble members the 5% significance is **F=1.4**.  
Gray color indicates not statistically significant at 95% confidence interval.



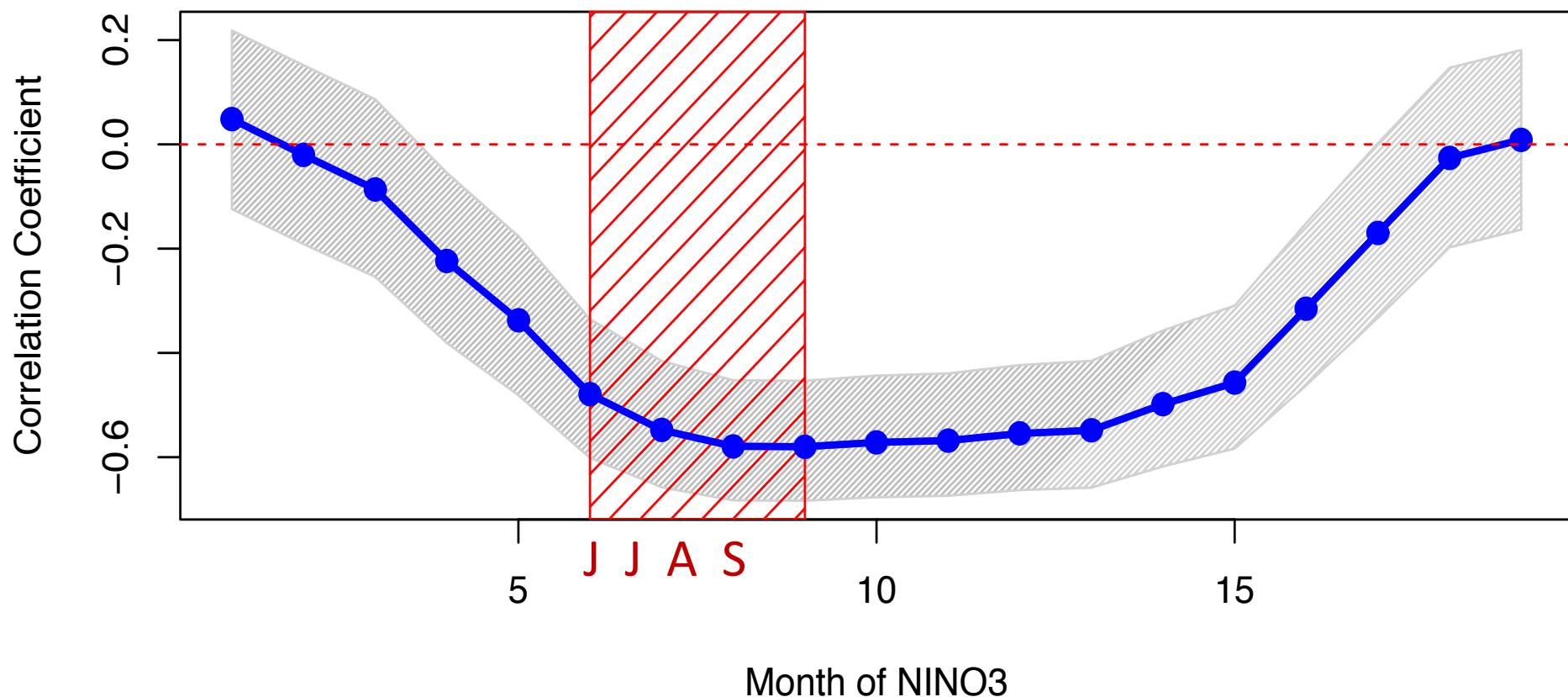
## **The Challenge**

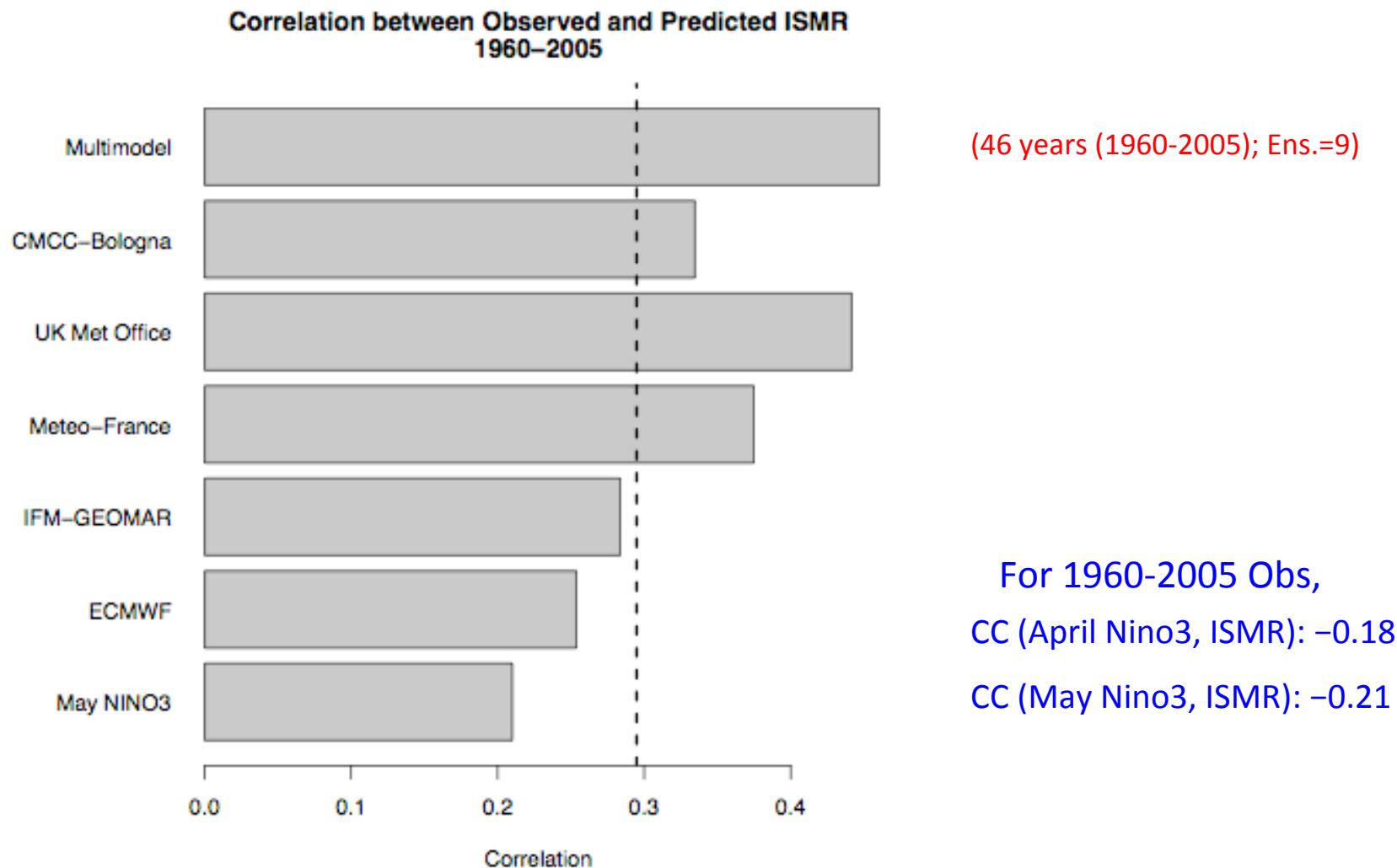
Predictability of Asian Summer Monsoon Rainfall is High

**but**

**Prediction Skill is Low**

## Correlation between NINO3 and All-India JJAS Rainfall 1880–2010





Correlation between observed and predicted JJAS all-India rainfall for hindcasts in the ENSEMBLES data set for the period 1960-2005. All-India rainfall in dynamical models is defined as the total land precipitation within 70E – 90E and 10N – 25N .

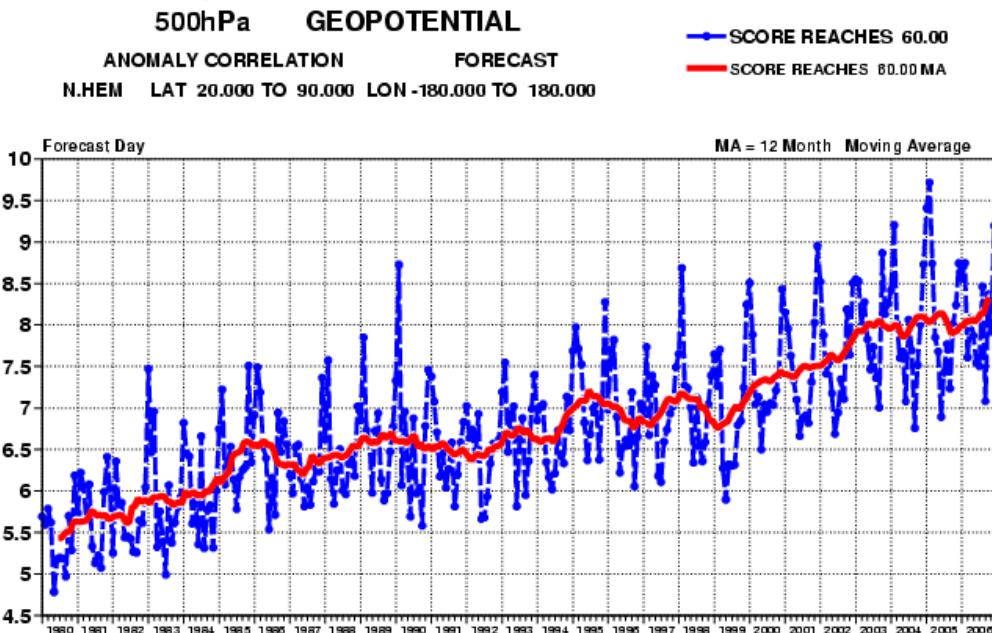
Last row shows empirical prediction using observed May NINO3.

# Dynamical Prediction Experience

Model predictability depends on model  
fidelity

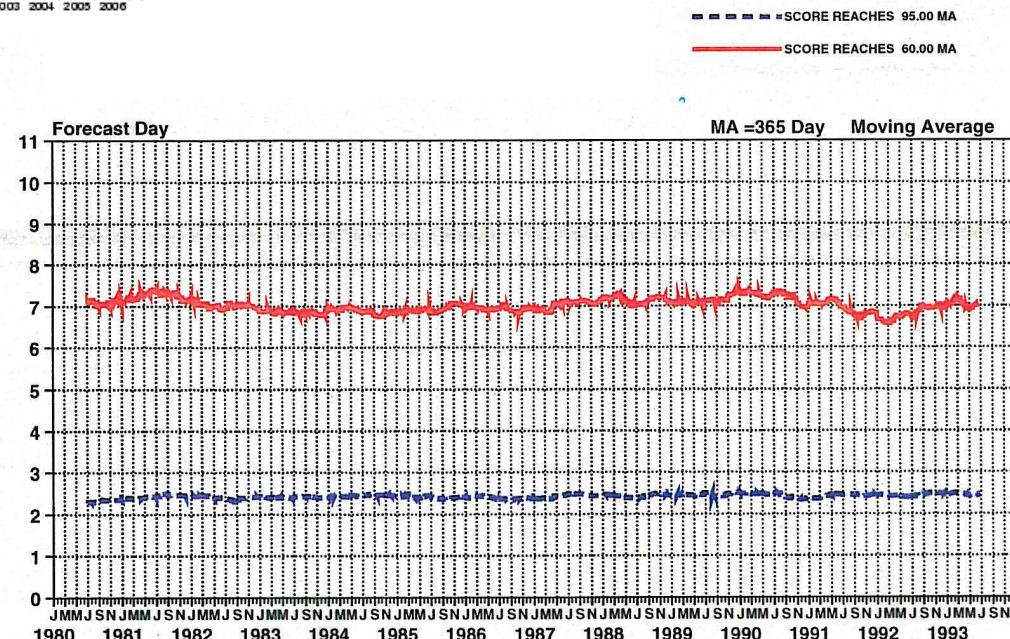
## ERA Forecast Verification

## Anomaly Correlation of 500 hPa GPH, 20-90N



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# Hypothesis

Models that simulate climatology “better”  
make better predictions.

**Definition:** Fidelity refers to the degree to which the climatology of the forecasts (including the mean and variance) matches the observed climatology

# Testing the Hypothesis: Data

## DEMETER Data

- 7 global coupled atmosphere-ocean models
- 9 ensemble members
- 1980-2001 (22 years)
- Initial conditions: 1 February, 1 May, 1 August, 1 November
- Integration length: 6 months

# Climate Model Fidelity and Predictability

Relative Entropy: The relative entropy between two distributions,  $p_1(x)$  and  $p_2(x)$ , is defined as

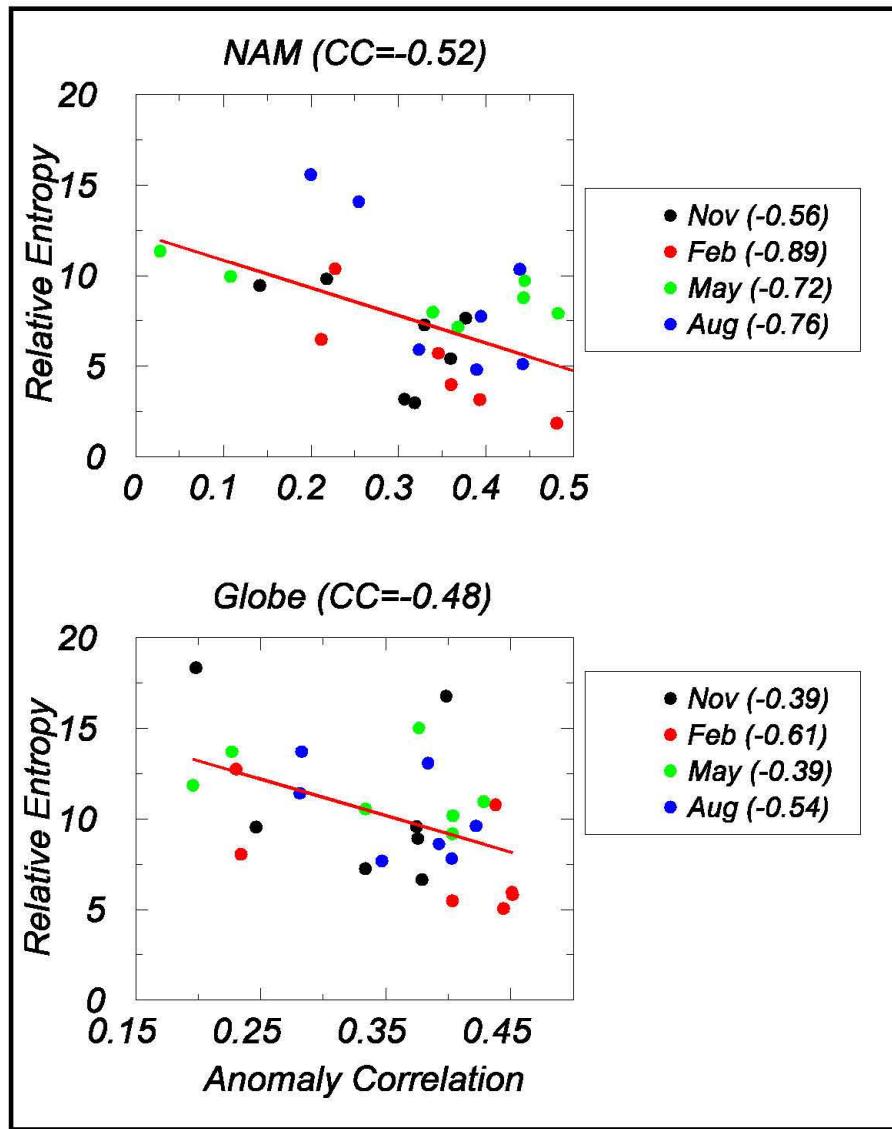
$$R(p_1, p_2) = \int_{\mathbb{R}^M} p_1 \log \left( \frac{p_1}{p_2} \right) dx \quad (1)$$

where the integral is a multiple integral over the range of the  $M$ -dimensional vector  $x$ .

$$R(p_1, p_2) = \frac{1}{2} \log \left( \frac{|\Sigma_2|}{|\Sigma_1|} \right) + \frac{1}{2} \text{Tr} \left\{ \Sigma_1 \left( \Sigma_2^{-1} - \Sigma_1^{-1} \right) \right\} + \sum_{k=1}^4 \frac{1}{2} (\mu_1^k - \mu_2^k)^T \Sigma_1^{-1} (\mu_1^k - \mu_2^k) \quad (2)$$

where  $\mu_j^k$  is the mean of  $p_j(x)$  in the  $k$ th season, representing the annual cycle,  $\Sigma_j$  is the covariance matrix of  $p_j(x)$ , assumed independent of season and based on seasonal anomalies. The distribution of observed temperature is appropriately identified with  $p_1$ , and the distribution of model simulated temperature with  $p_2$ .

# Fidelity vs. Skill



## Fidelity vs. Skill DEMETER 1980-2001 Seasonal Forecasts

7 models, 4 initial conditions

Lead Time = 0 months

Fidelity and Skill are related.

**Models with poor climatology tend to have poor skill.**

**Models with better climatology tend to have better skill.**

Courtesy of Tim DelSole

# Dynamical Prediction Experience

(~30 years)

- Weather  $\approx 500,000$  (30 years X 365 days X 50 centers)
- Seasonal  $\approx 5,000$  (30 years X 12 months X 15 centers)
- Decadal  $\approx 5$



# Summary

- There is significant unrealized seasonal predictability. **Progress in dynamical seasonal prediction in the future depends critically on improvement of coupled ocean-atmosphere-land models**, improved observations, and the ability to assimilate those observations in coupled ocean-atmosphere models to produce dynamically consistent initial conditions.

# THANK YOU!

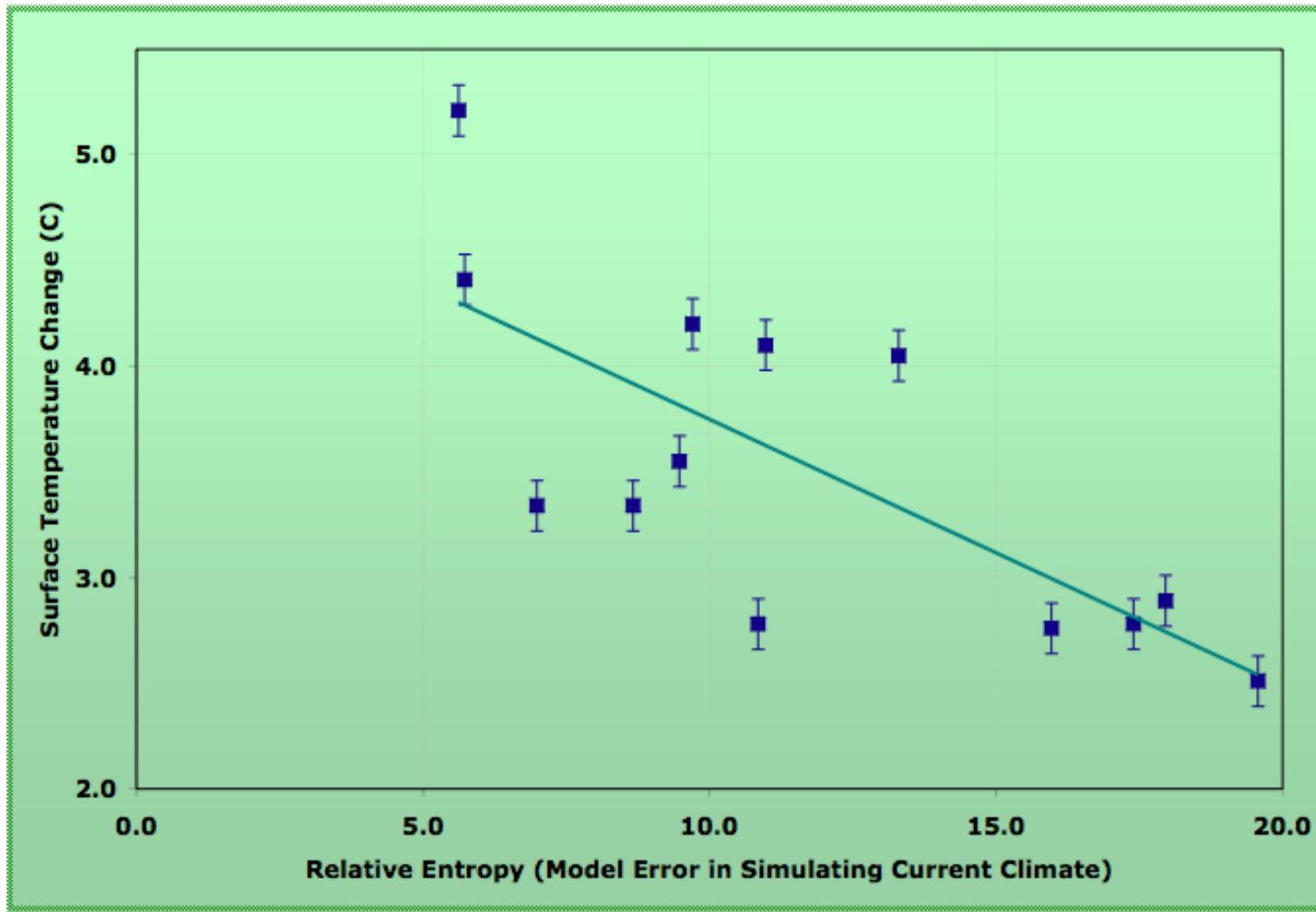
## ANY QUESTIONS?



# Climate Model Fidelity and Projections of Climate Change

J. Shukla, T. DelSole, M. Fennessy, J. Kinter and D. Paolino

Geophys. Research Letters, 33, doi10.1029/2005GL025579, 2006



Model sensitivity versus model relative entropy for 13 IPCC AR4 models. Sensitivity is defined as the surface air temperature change over land at the time of doubling of CO<sub>2</sub>. Relative entropy is proportional to the model error in simulating current climate. Estimates of the uncertainty in the sensitivity (based on the average standard deviation among ensemble members for those models for which multiple realizations are available) are shown as vertical error bars. The line is a least-squares fit to the values.