

July 15, 2015 ICTP, Trieste, Italy

Model Predictability Depends on Model Fidelity:

*Challenges in Improving Model Fidelity
and the Reliability of Seamless Weather and Climate Predictions*

Jagadish Shukla

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

George Mason University (GMU)

Center for Ocean-Land-Atmosphere Studies (COLA)

July 15, 2015



Center of Ocean-Land-
Atmosphere studies



Outline

1. Introduction:

- Predictability of Weather and Climate
- Seamless Prediction

2. Model Fidelity and Predictability

3. Examples:

- Monsoon Predictability and Prediction
- ENSO Prediction

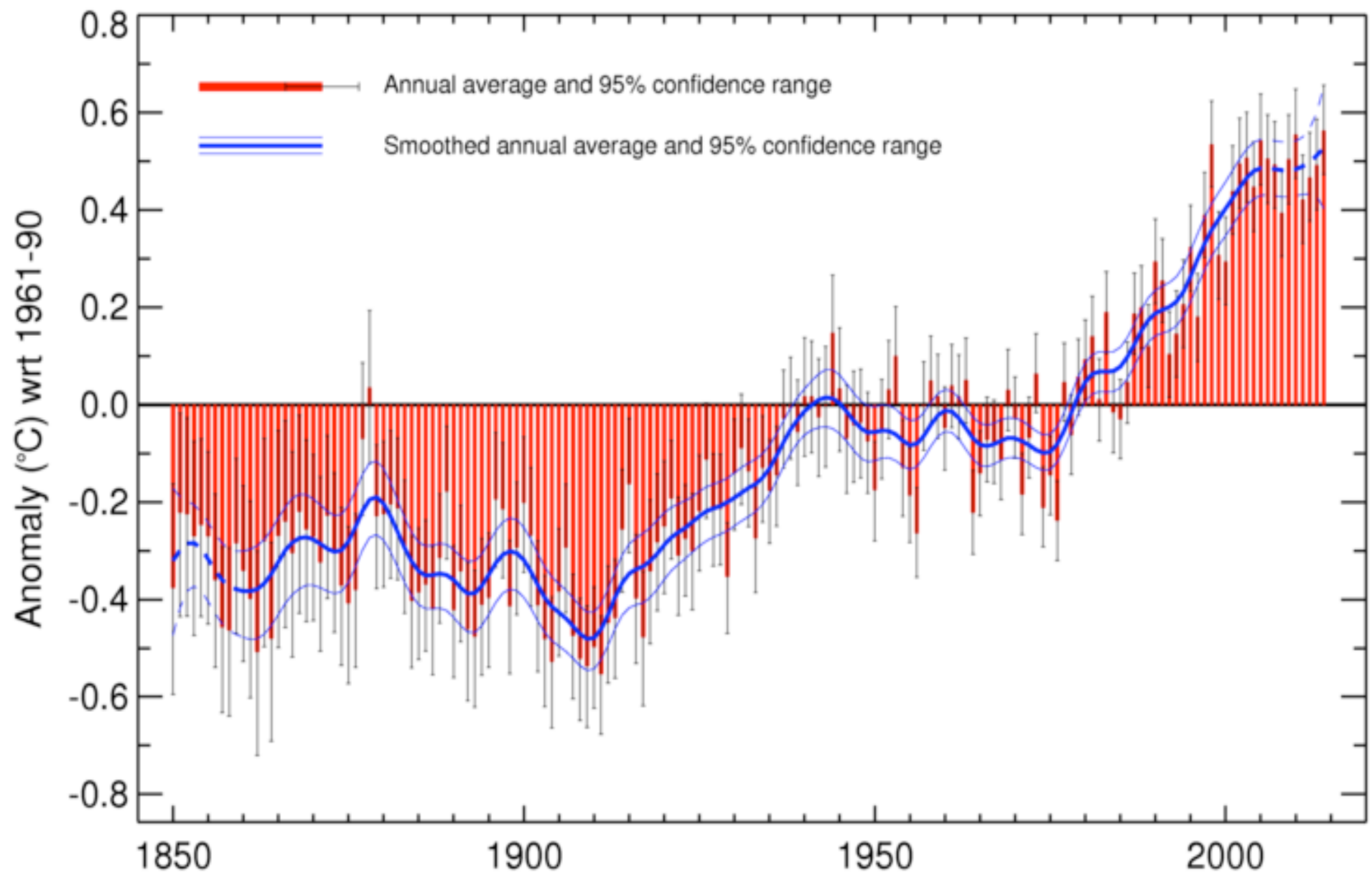
4. Challenges and Strategies for Climate/Earth System Modeling:

- US
- International

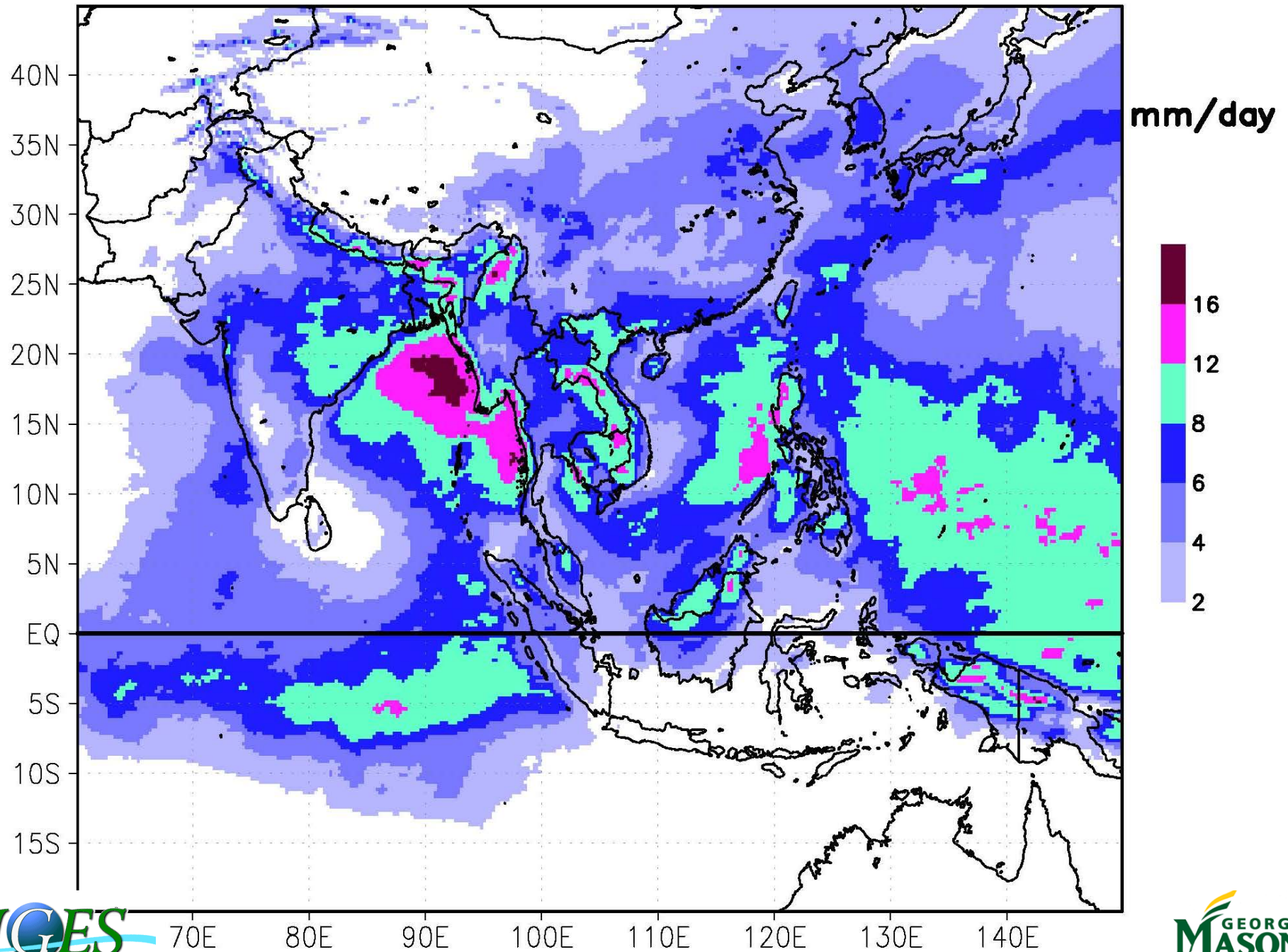
5. Summary

Global average temperature 1850-2014

Updated from Morice et al. 2012



CMORPH OBS Precip Climo JJAS (2003–2006)



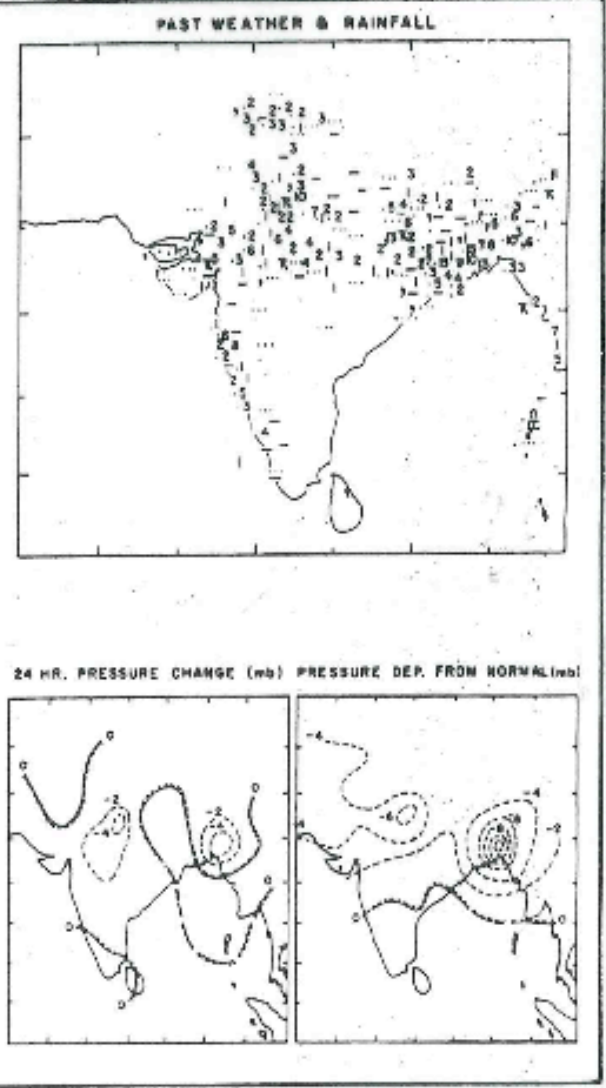
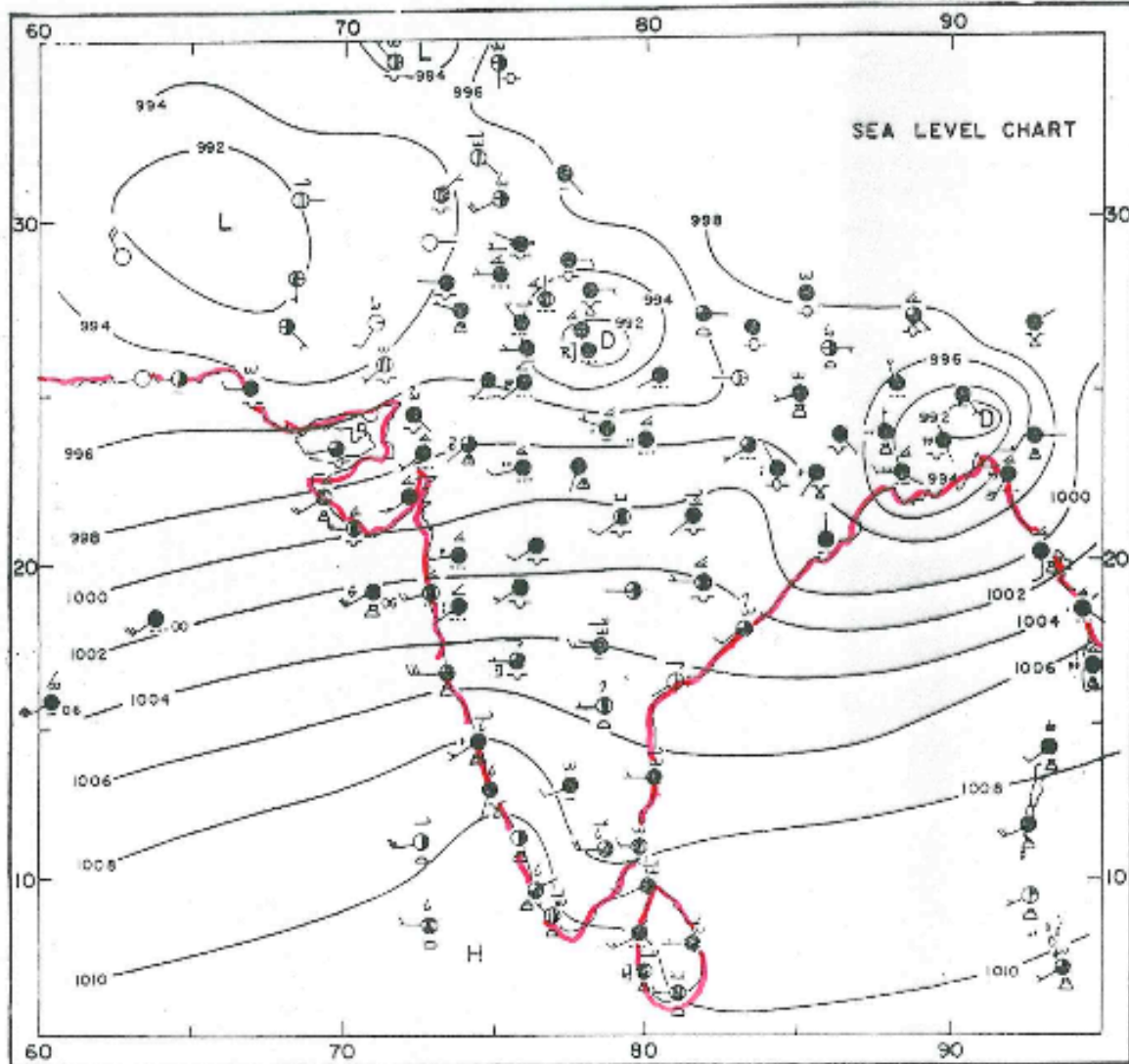
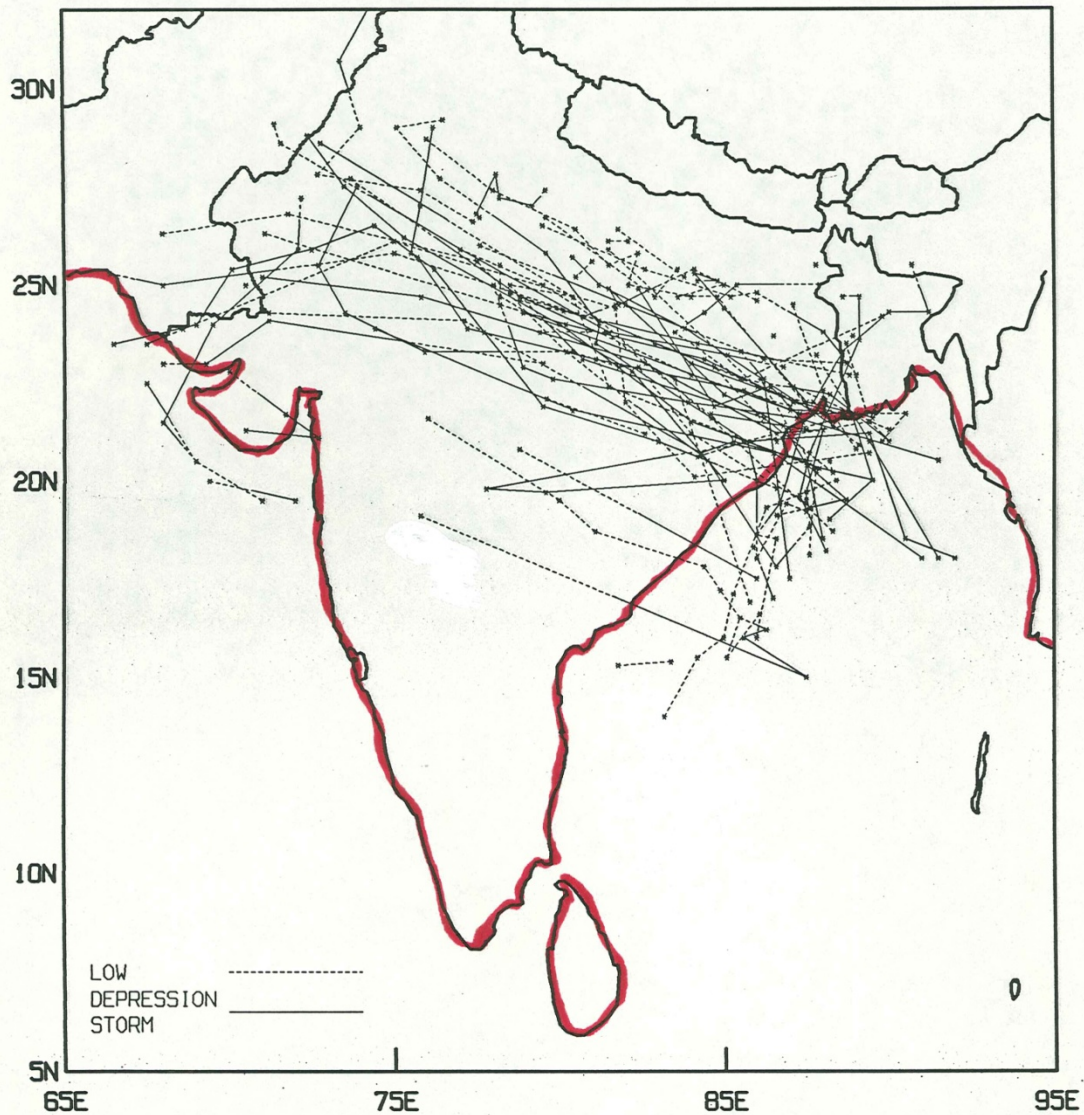


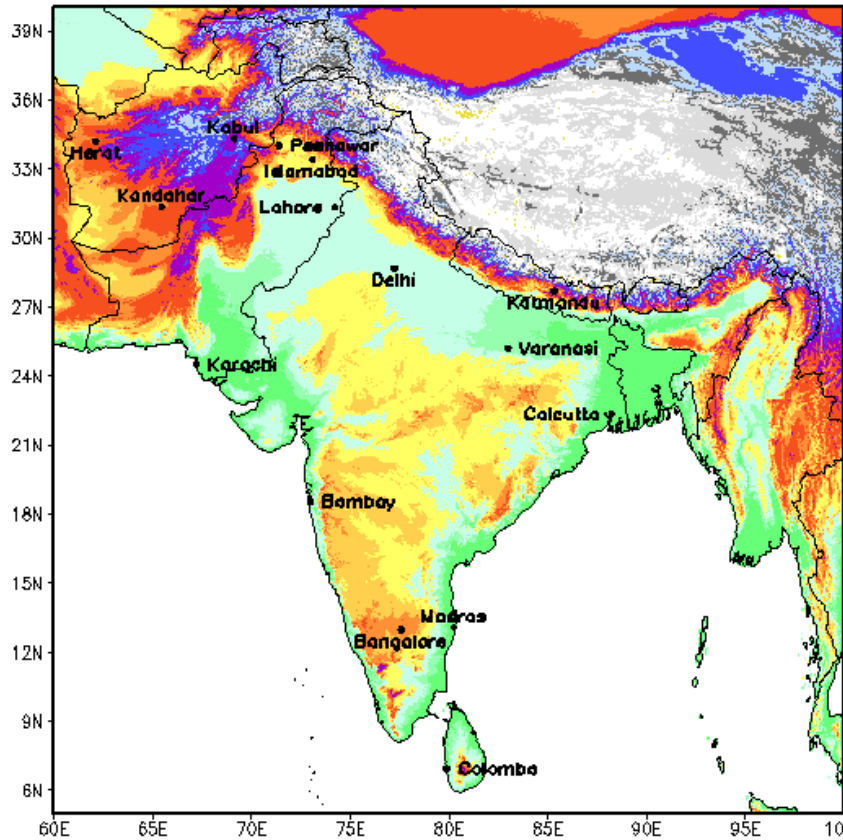
Fig.9.7(h) Synoptic charts 0300 GMT 10 July 1968.

FIVE HIGHEST MONSOON RAINFALL

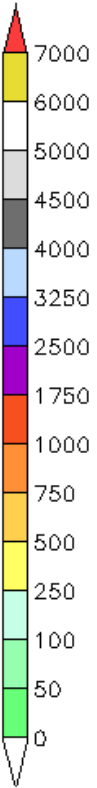
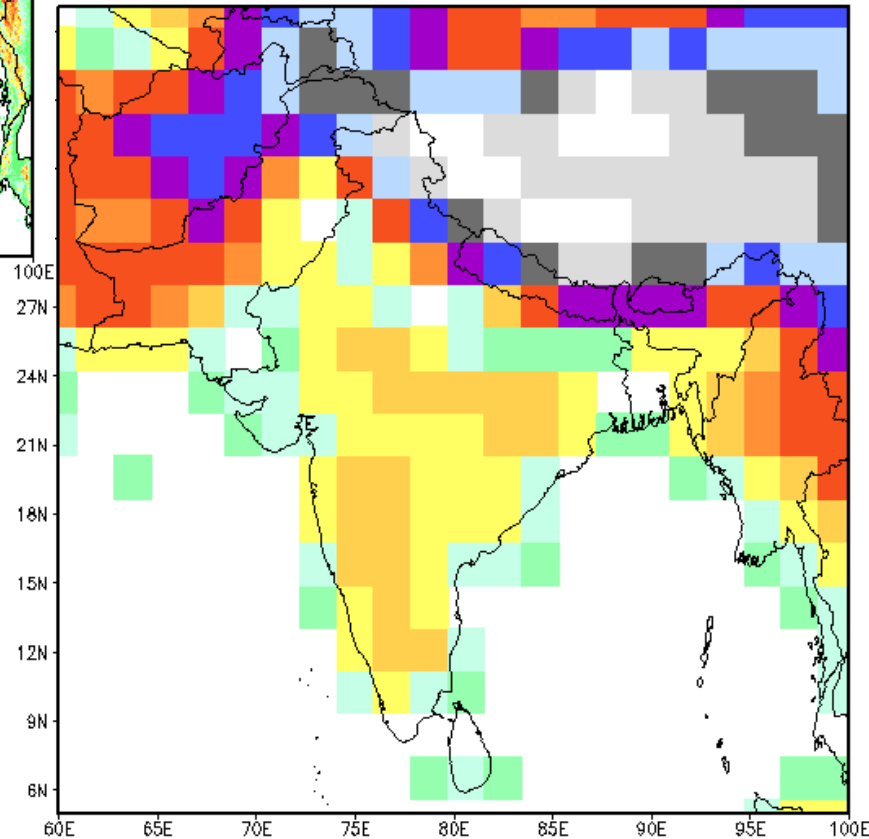
1961, 1917, 1892, 1956, 1933



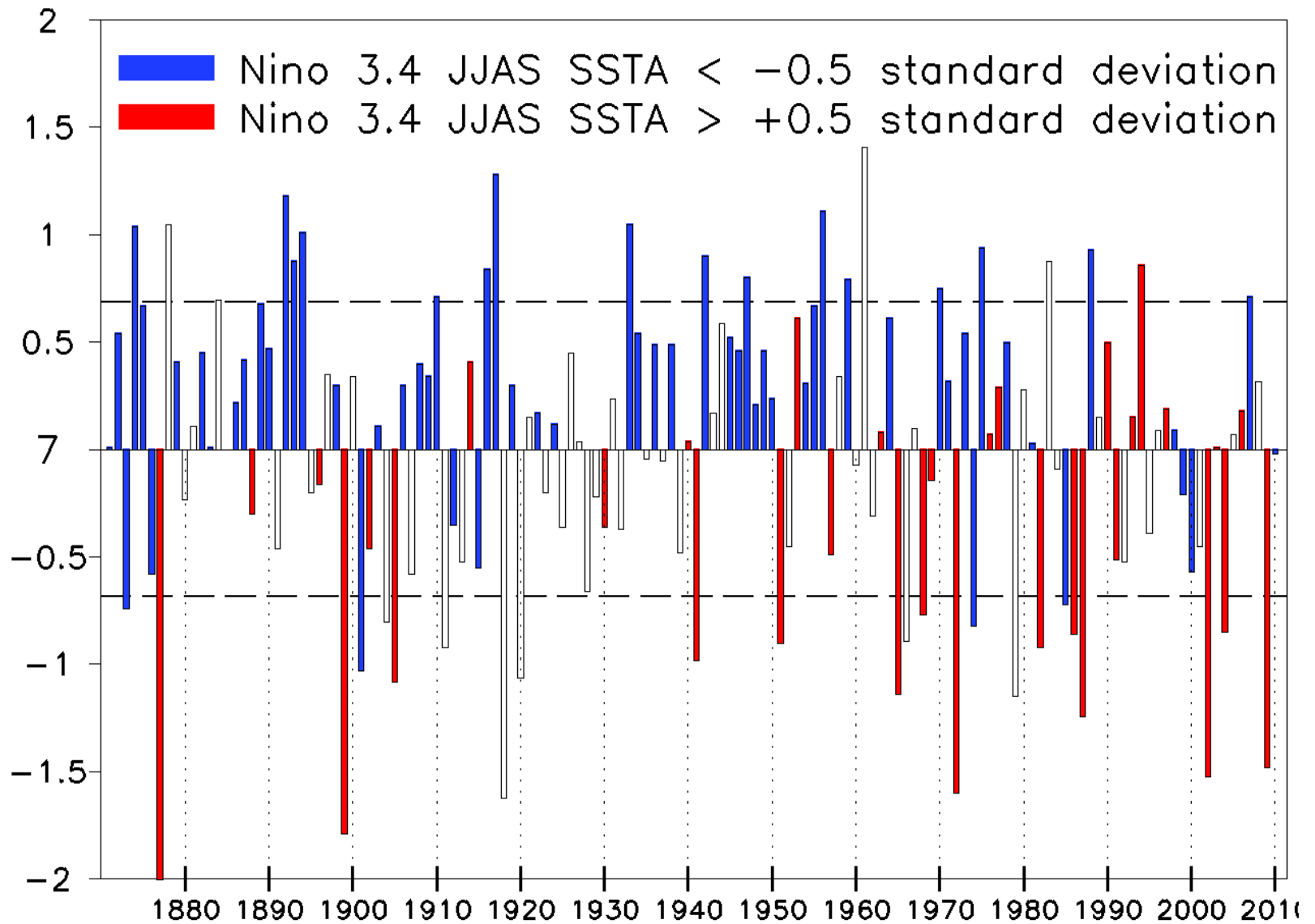
4 km Topography (m)



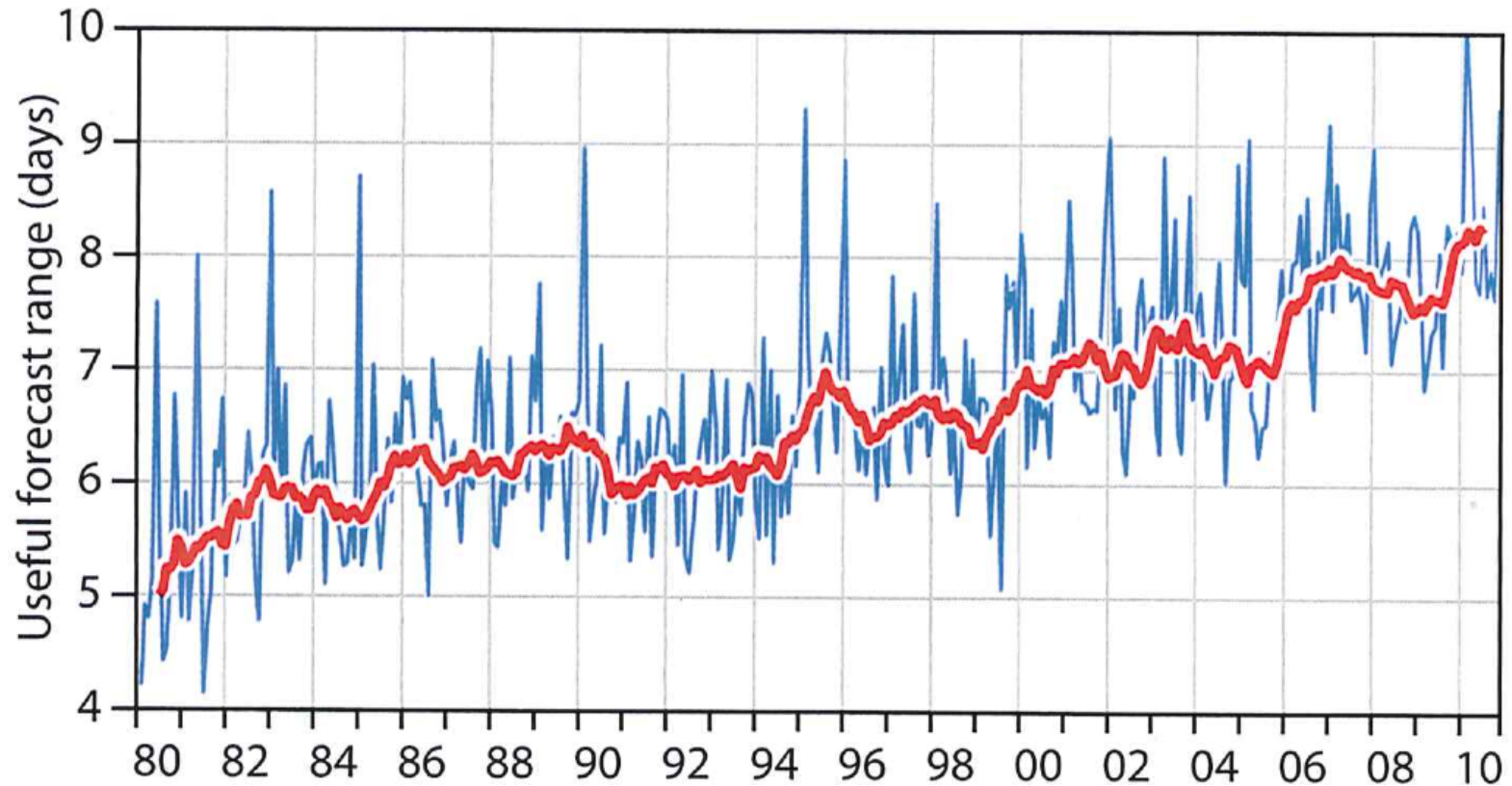
200 km Topography (m)



1871–2010 India Rain JJAS Anom (mm/day)



ECMWF: Useful forecast range (days) for Europe (1980 – 2010)



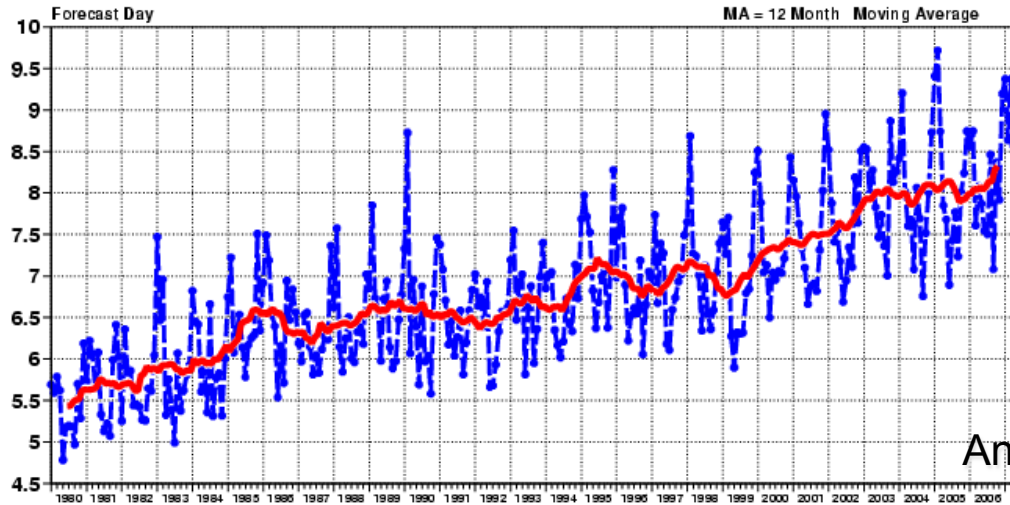
Record performance of the deterministic forecasting system. The useful range of the deterministic forecasts for Europe reached its highest ever monthly value in February 2010. Overall the performance has been consistently good during 2010. The useful forecast range is determined by the time at which the anomaly correlation for 500 hPa height operational forecasts at 12 UTC reached 60%.

ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N

500hPa GEOPOTENTIAL
ANOMALY CORRELATION FORECAST
N.HEM LAT 20.000 TO 90.000 LON -180.000 TO 180.000

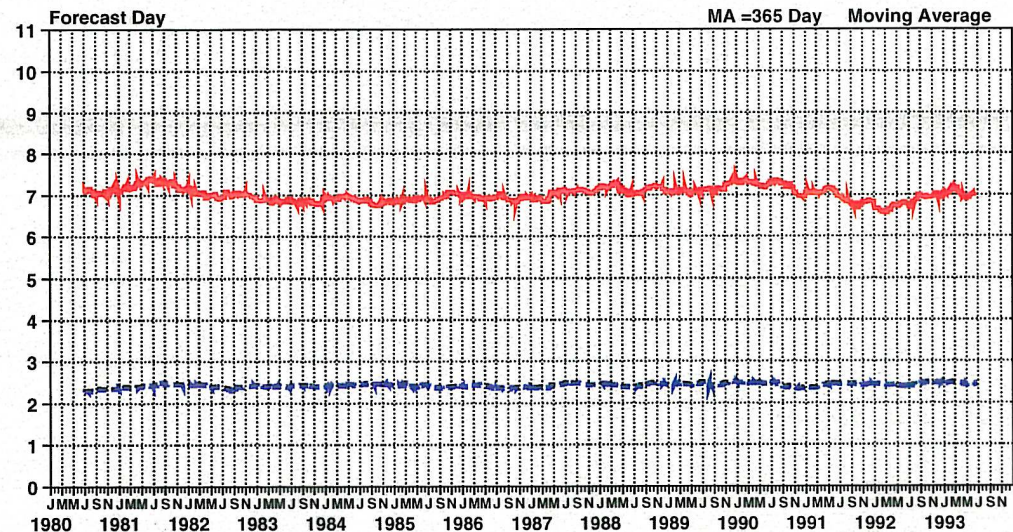
— SCORE REACHES 60.00
— SCORE REACHES 80.00 MA



ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N

— SCORE REACHES 95.00 MA
— SCORE REACHES 60.00 MA



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

(Fallacy of Model Democracy)

(Fallacy of the Assumption that Model Errors and Model Responses of External Forcings (SST, GHG, etc.) are Uncorrelated)

Climate Model Fidelity and Predictability

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

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

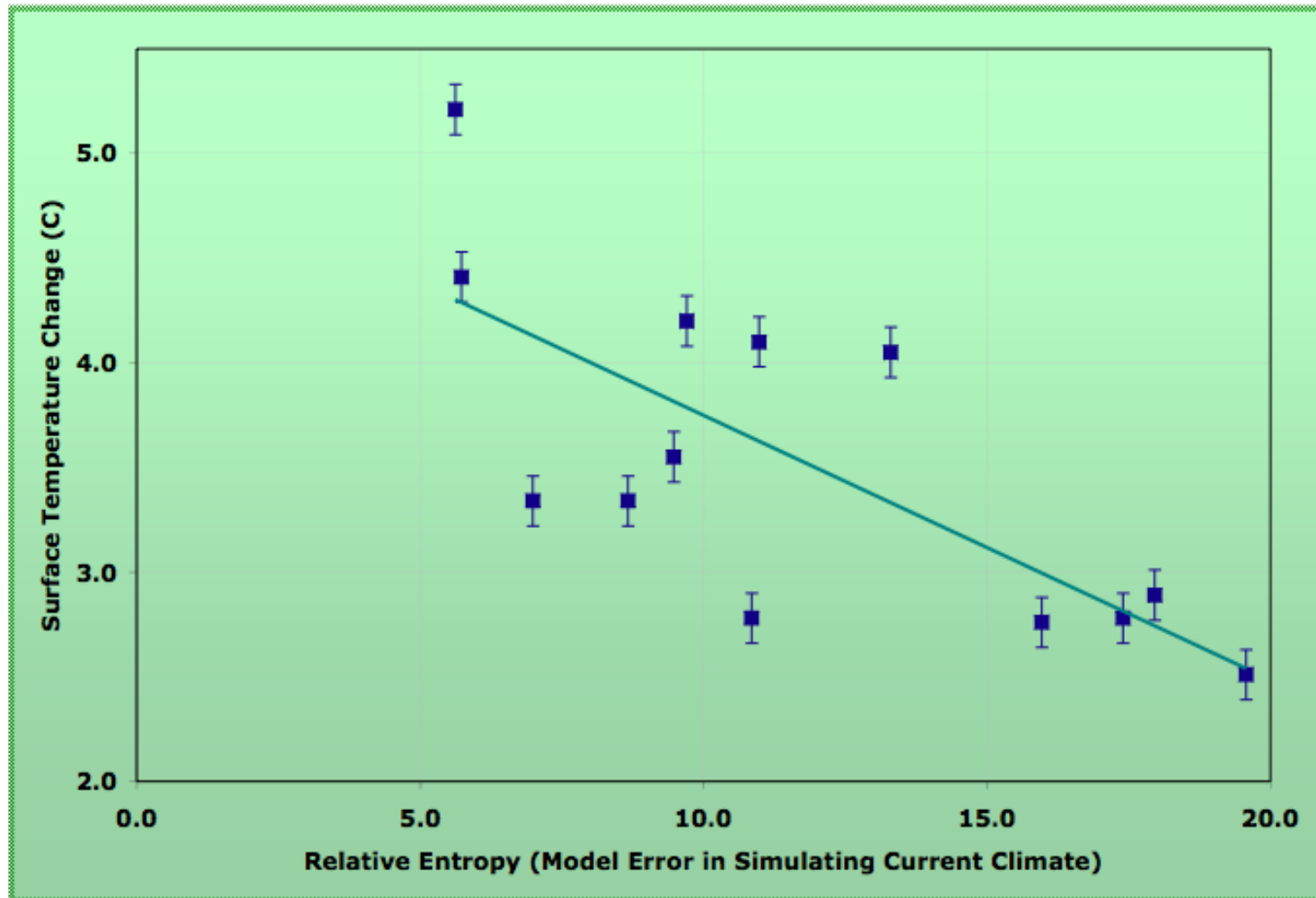
where the integral is a multiple integral over the range of the M -dimensional vector x .

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

where μ_j^k is the mean of $p_j(x)$ in the k th season, representing the annual cycle, Σ_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 .

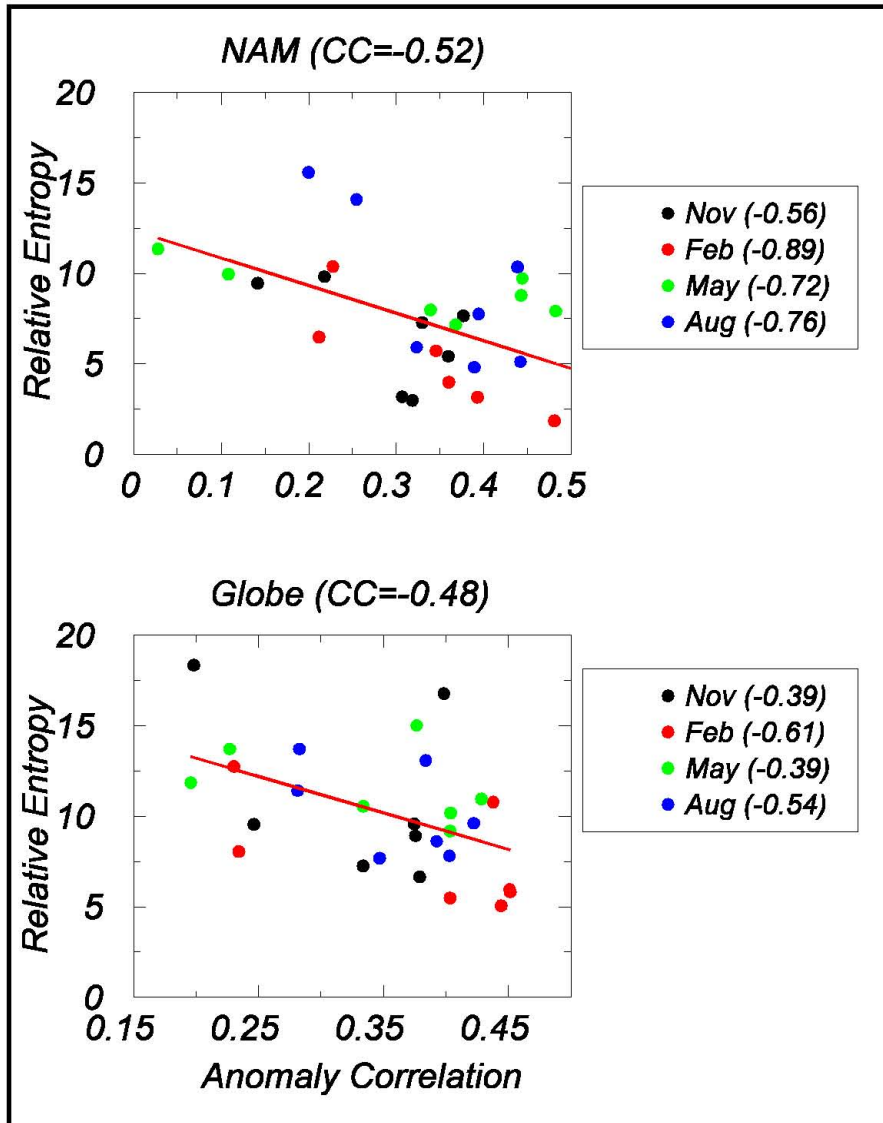
Climate Model Fidelity and Projections of Climate Change

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_2 . 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.

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.

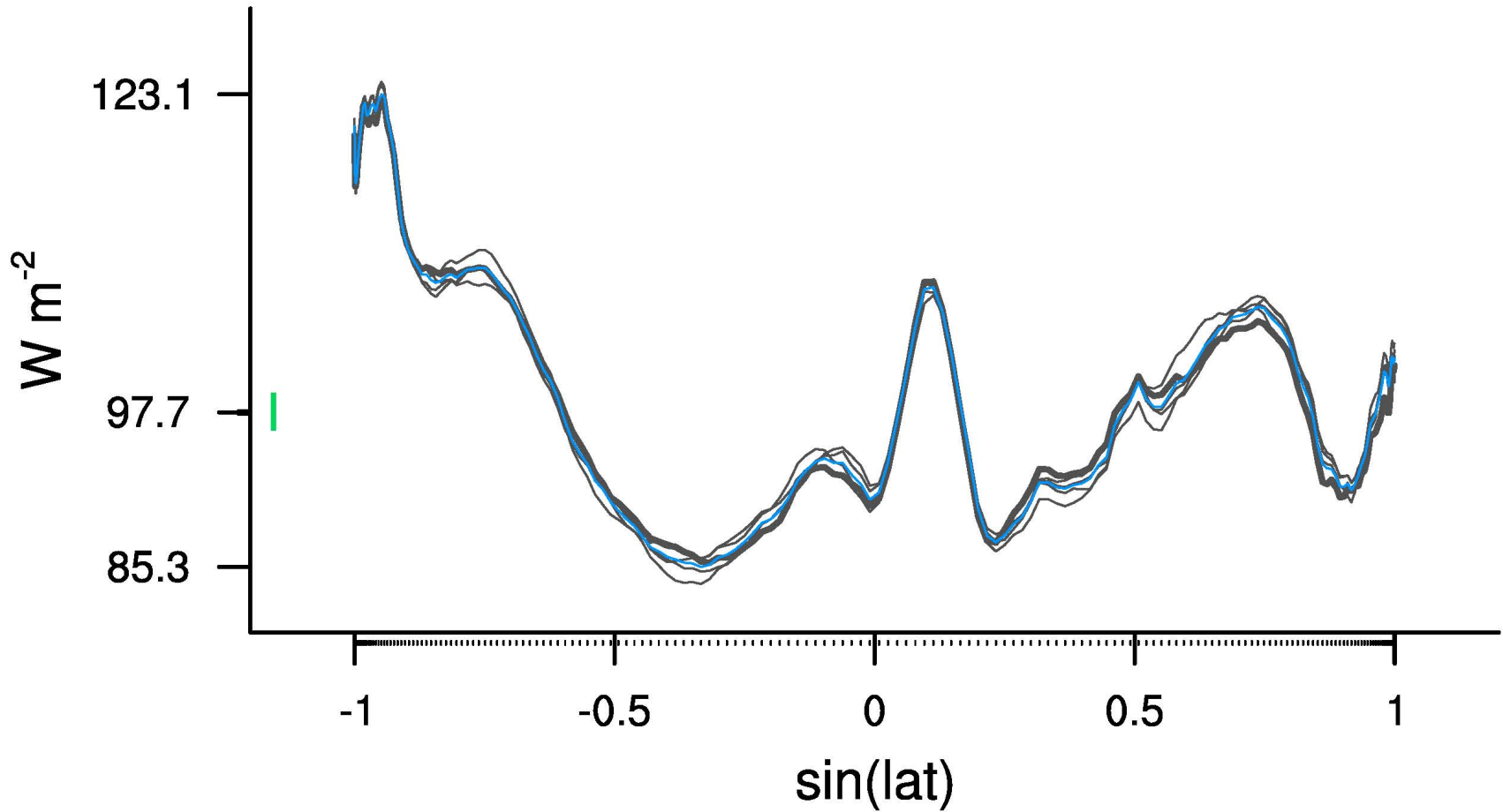
Models with poor climatology tend to have poor skill.

Models with better climatology tend to have better skill.

Courtesy of Tim DelSole

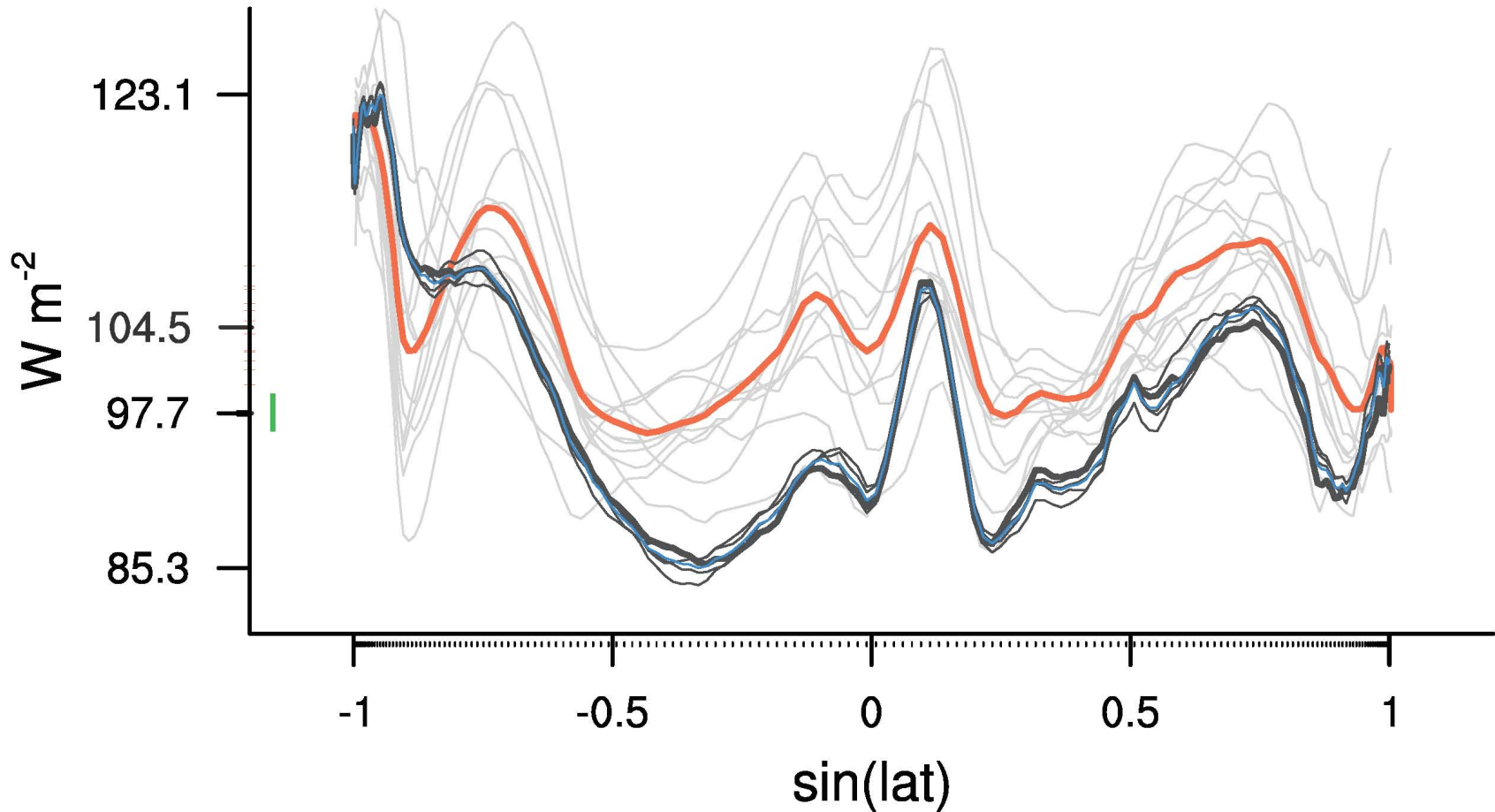
How Good are the Current Climate Models?

Annually & Zonally Averaged Reflected SW Radiation



Bjorn Stevens, UCLA
World Modelling Summit, ECMWF, May 2008

Annually & Zonally Averaged SW Radiation (AR4)

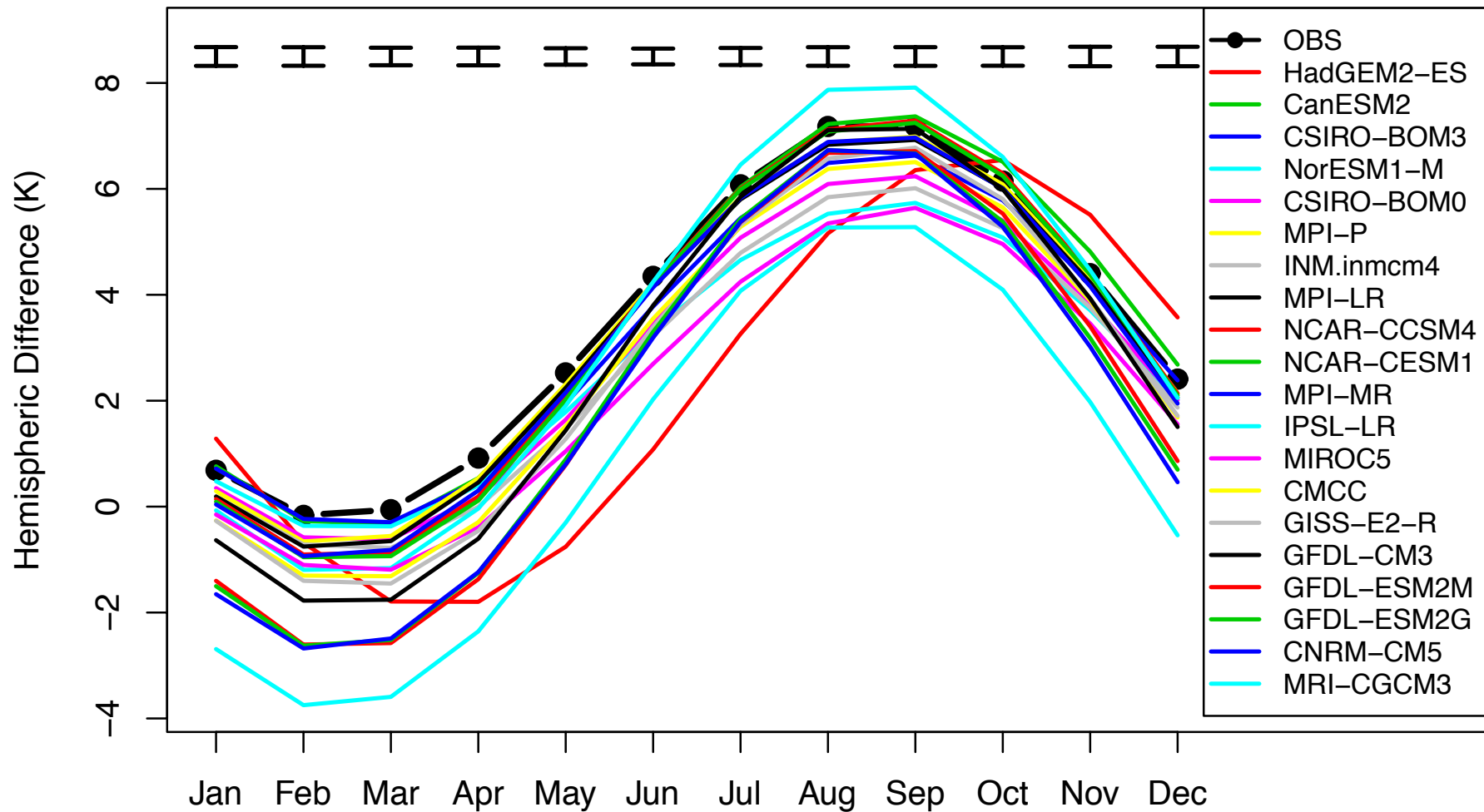


- ▶ 101-106 W/m^2 (Wild et al., survey)
- ▶ 107 W/m^2 (Trenberth and Kiehl (ERBE))
- ▶ 101 W/m^2 (CERES)

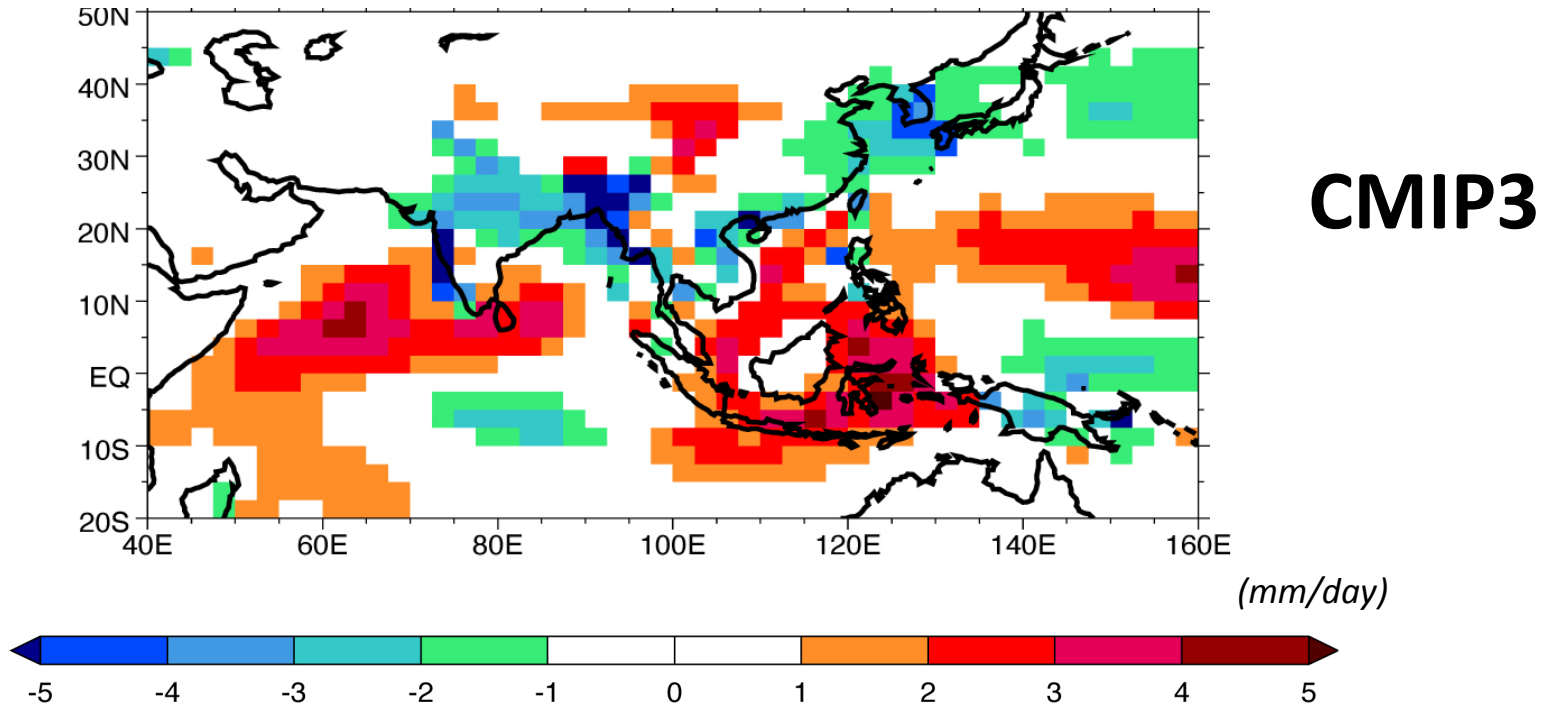
Bjorn Stevens, UCLA
World Modelling Summit, ECMWF, May 2008

Hemispheric Temperature Difference over the Oceans

CMIP5 1950–2000

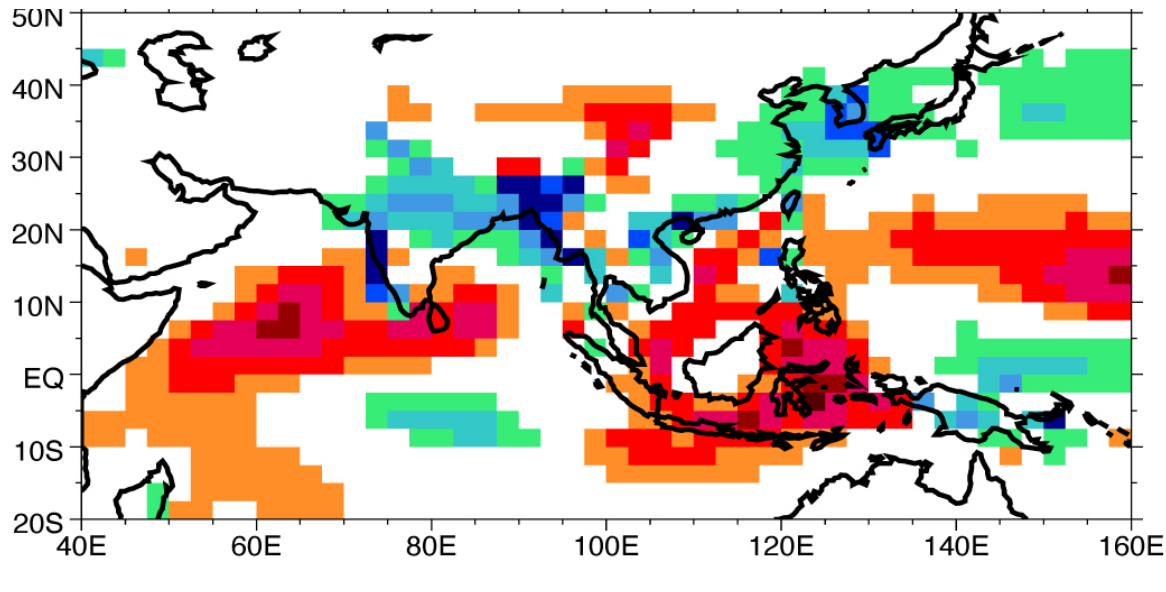


Model Bias in JJAS – Precipitation

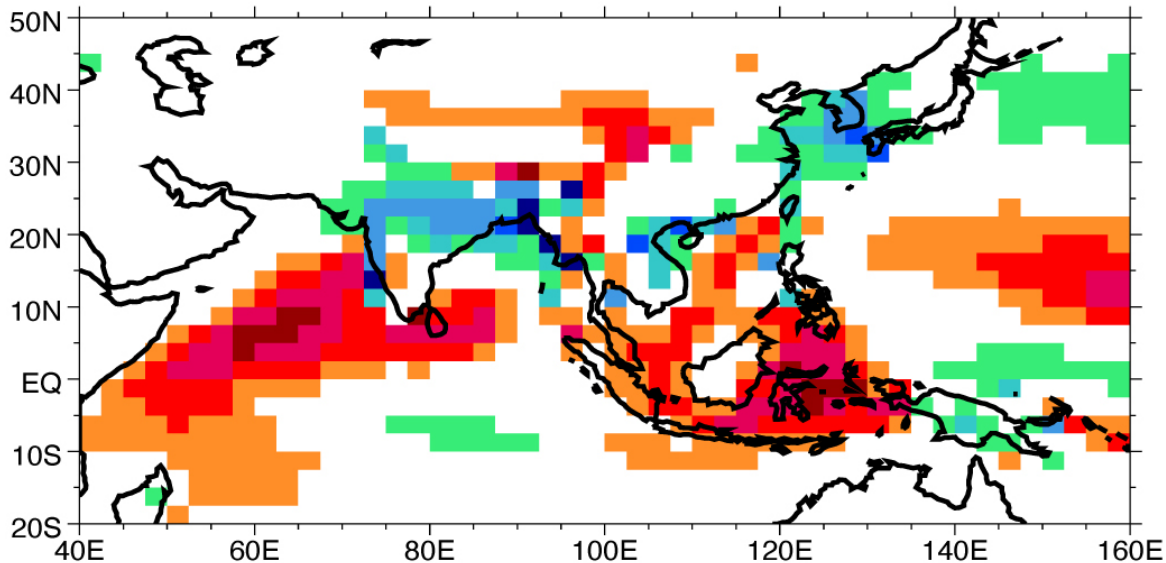
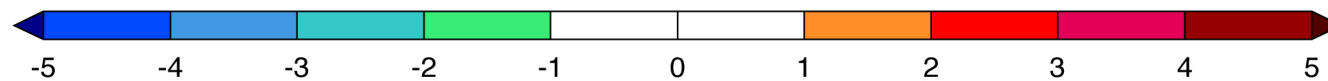


(Sperber, Annamalai et al. 2013)
(Courtesy Annamalai)

Model Bias in JJAS – Precipitation



CMIP3

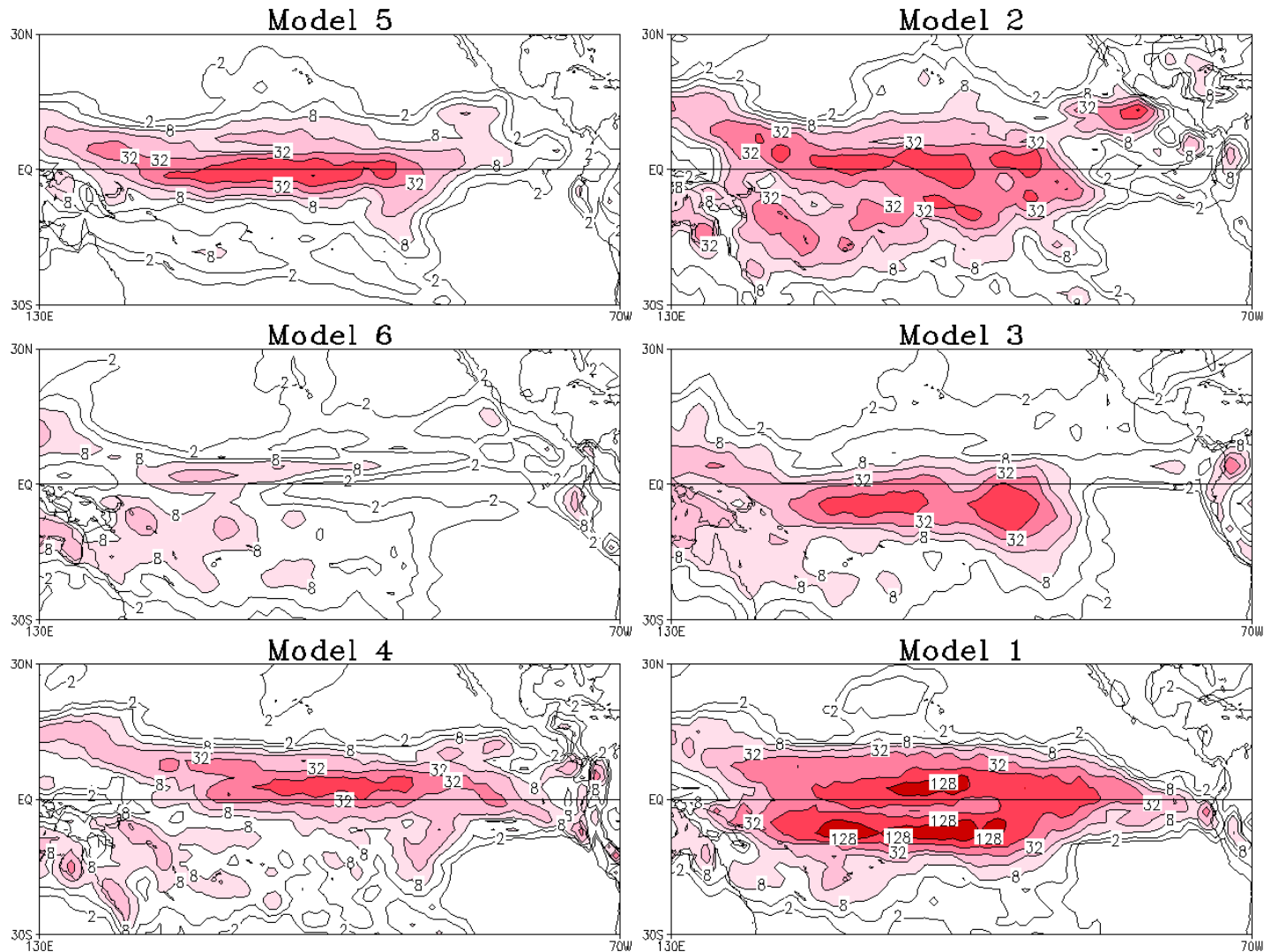


CMIP5

(Sperber, Annamalai et al. 2013)
(Courtesy Annamalai)

Boreal Winter (DJF) Rainfall Variance in AGCMs

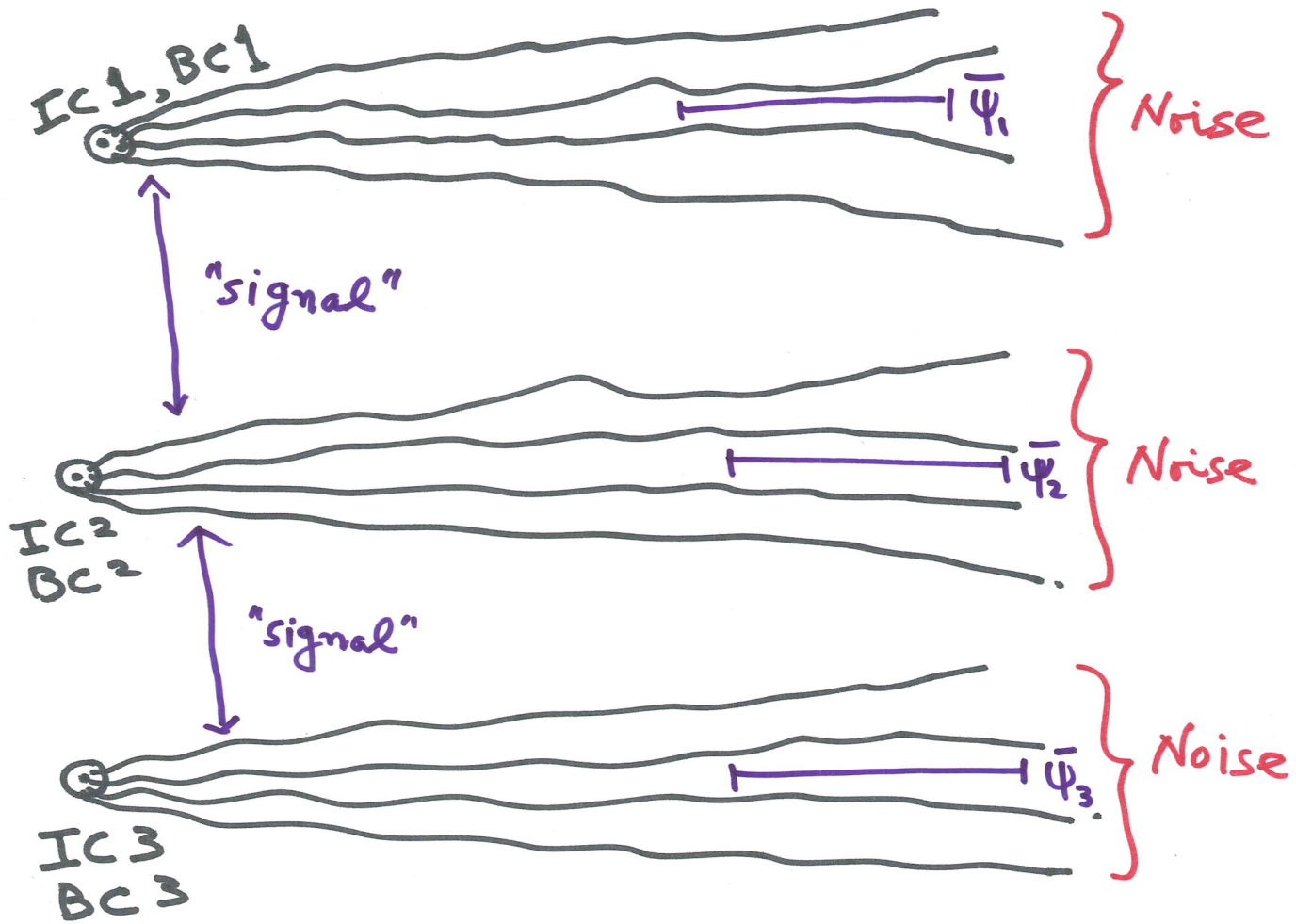
For Identical SST Forcing



(mm²)

Example: Monsoon Predictability and Prediction

Predictability of Time Averages (Seasonal)



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

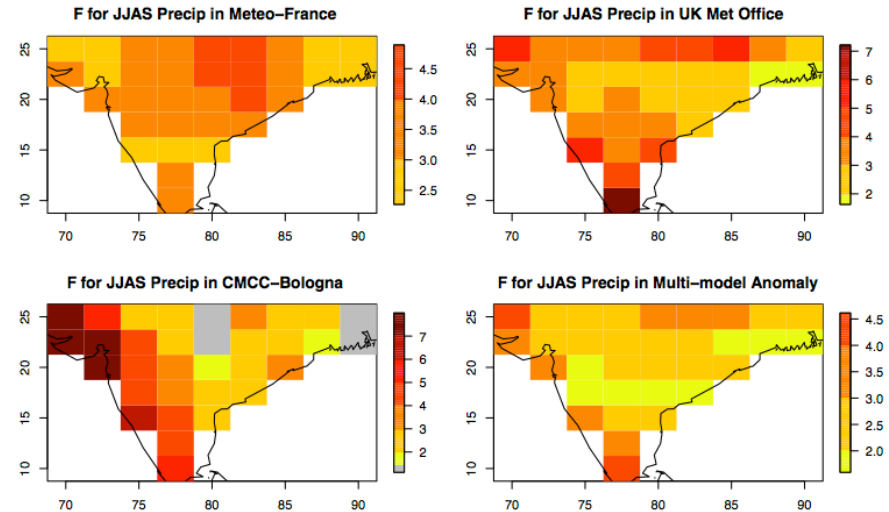
$$\hat{\sigma}_S^2 = \frac{1}{Y-1} \sum_{y=1}^Y (P_{y,e} - \bar{P})^2$$

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

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

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

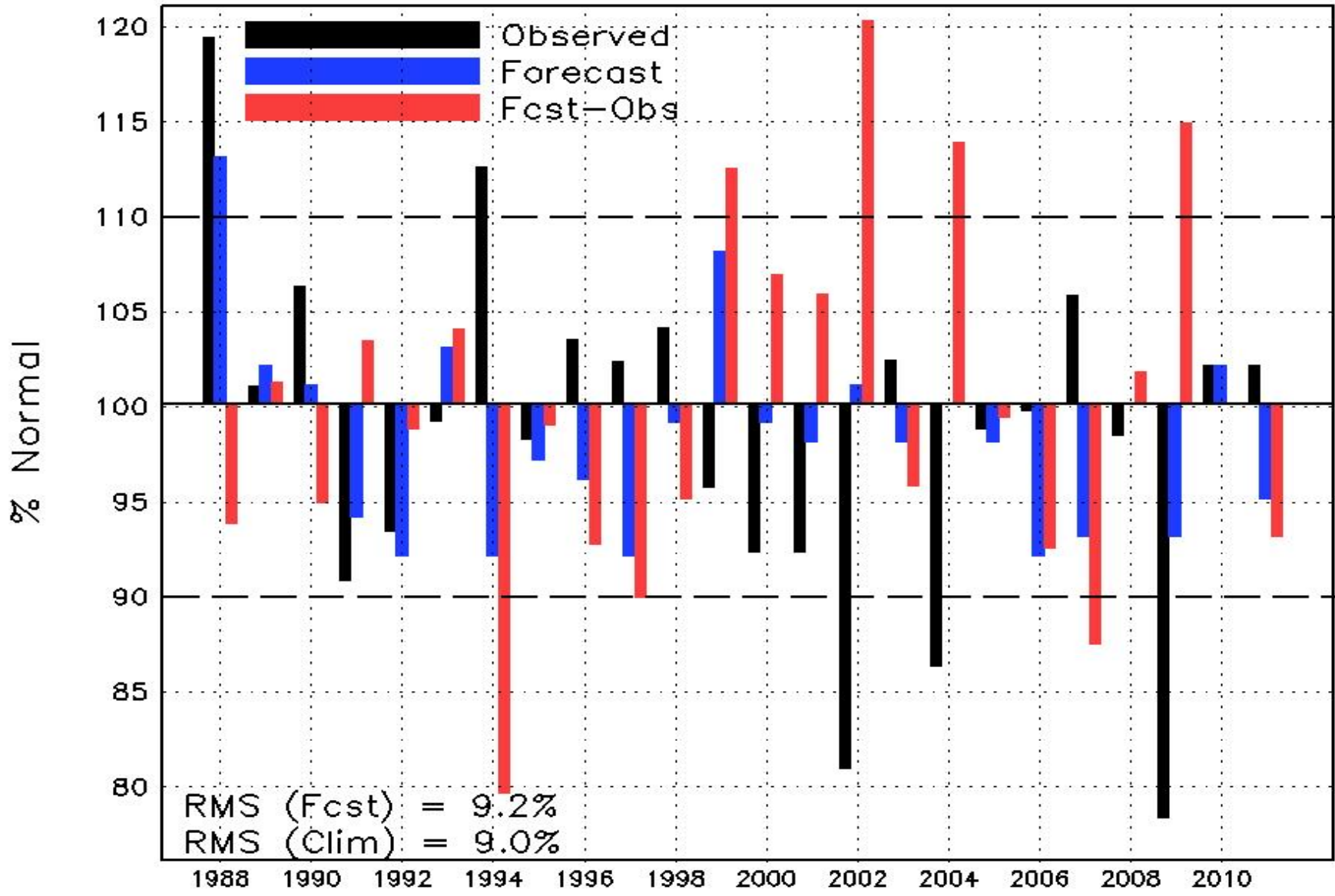
For samples drawn independently from the same normal distribution, and for $Y = 46$ and $E = 9$, the 5% significance threshold of F is 1.40



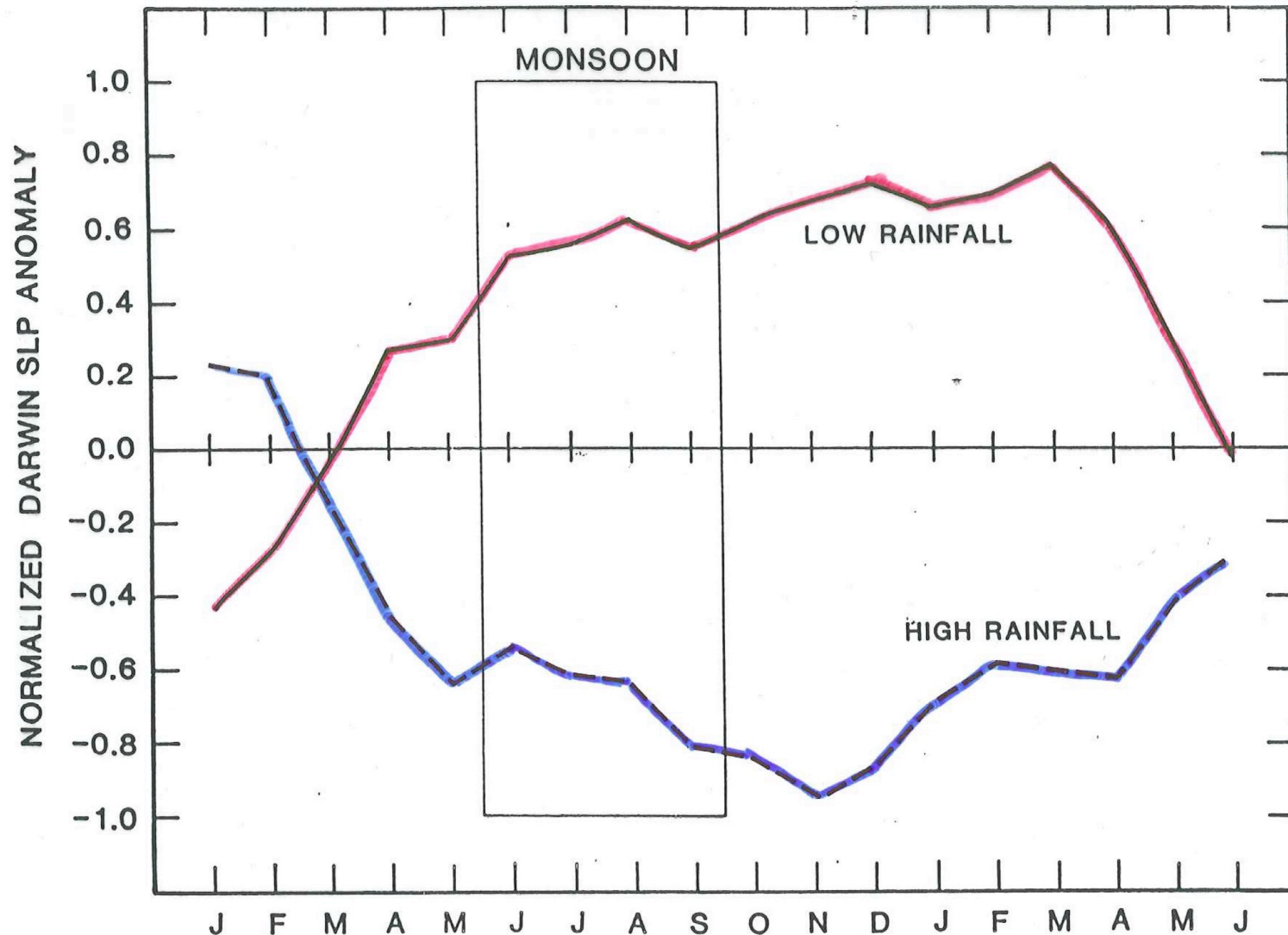
F-values for JJAS precip.
For 46-years and 9 ensemble members the 5% significance is **F=1.4**.
Gray color indicates not statistically significant at 95% confidence interval.

Navigation icons: back, forward, search, etc.

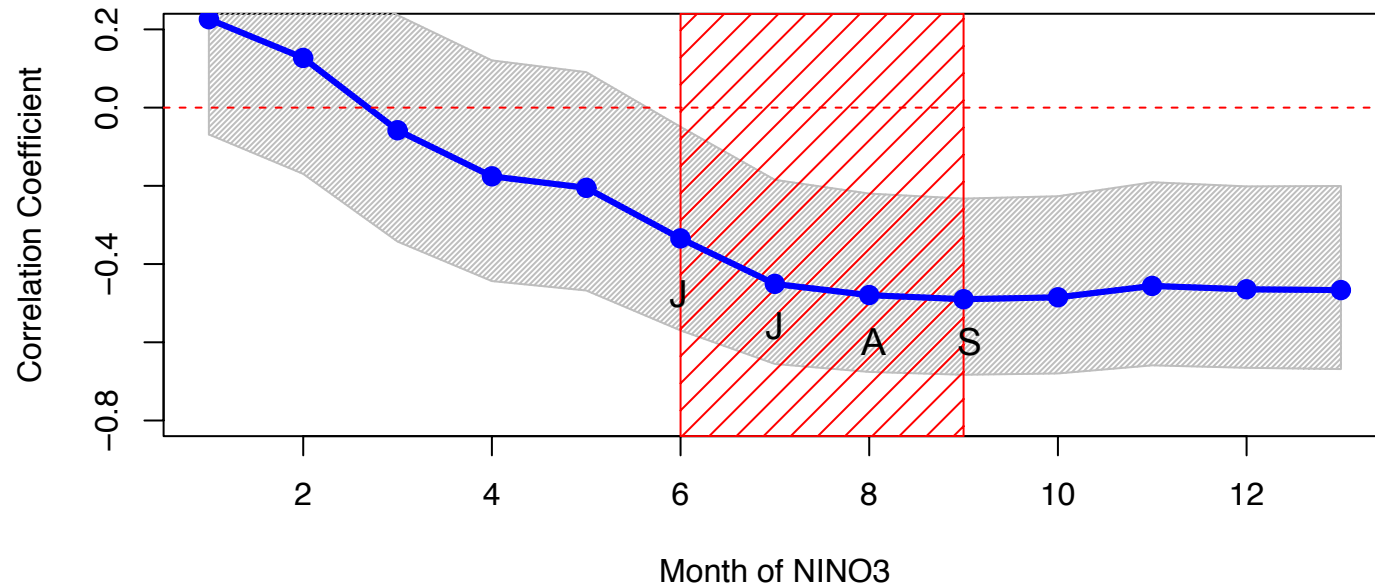
Observed and Forecast(IMD) All-India JJAS rainfall (% Normal)



**ENSO has large amplitude after the monsoon season:
to predict monsoon, we must predict ENSO first**



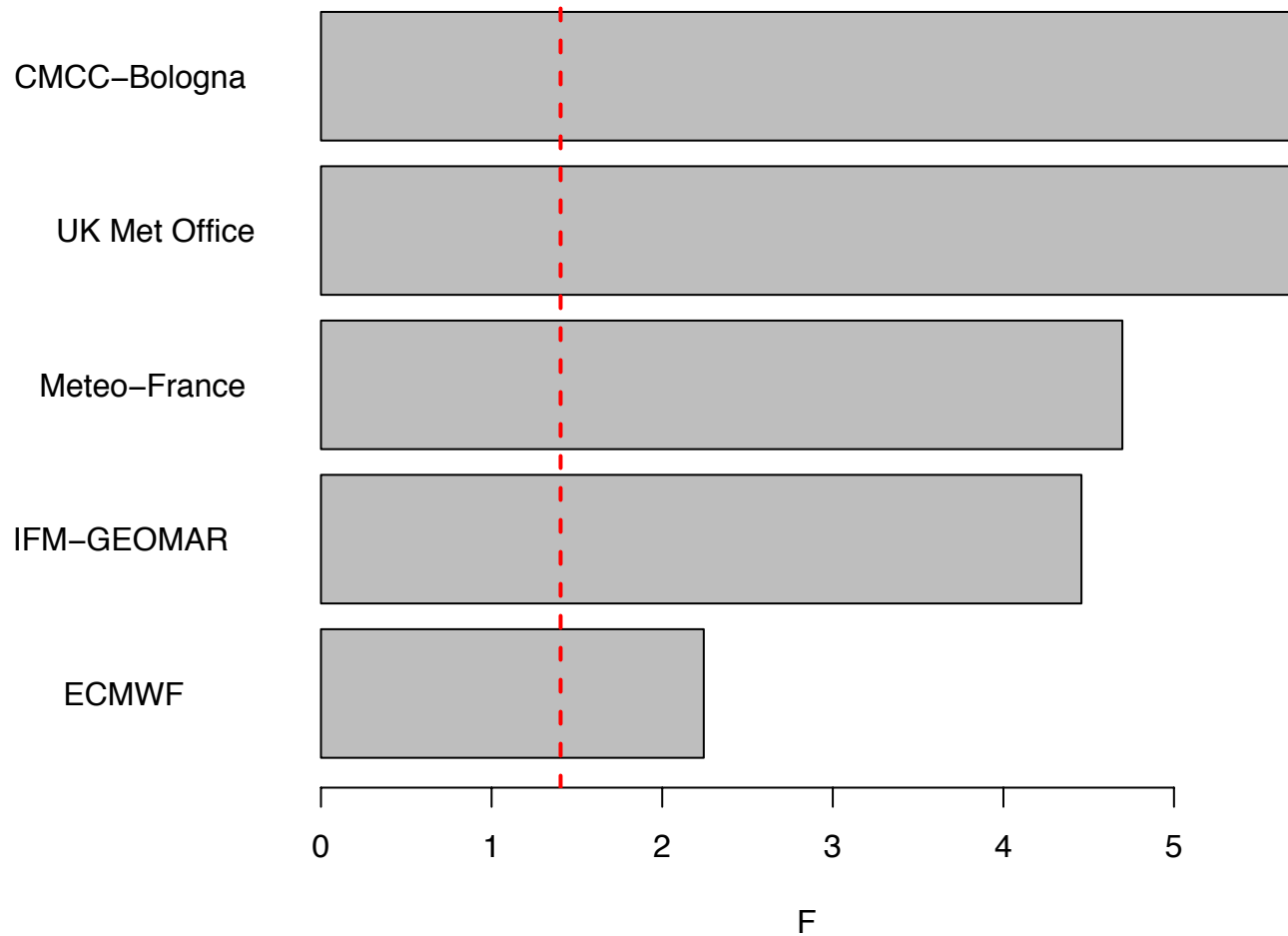
Correlation between NINO3 and All-India JJAS Rainfall 1960-2005



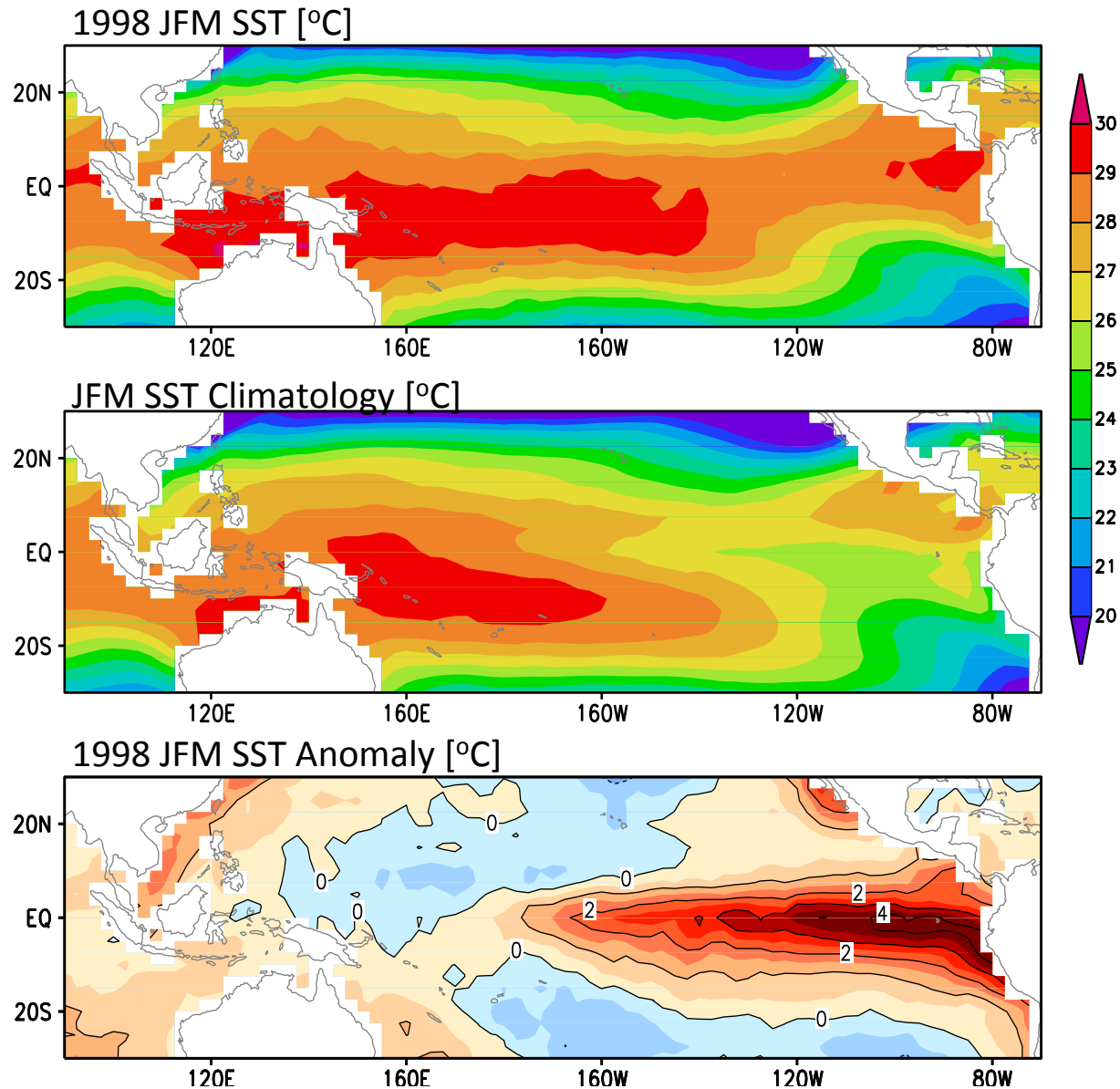
Time lagged correlation between all-India JJAS Monsoon Rainfall and the NINO3 index during the period 1960-2005. The red hatching indicates the JJAS period, the horizontal red dashed line indicates zero, and the grey shading indicates the 95% confidence interval for the time lagged correlation.

F values for JJAS All-India Rainfall from ENSEMBLES

(46 years (1960-2005); Ens.=9)



El Nino/Southern Oscillation

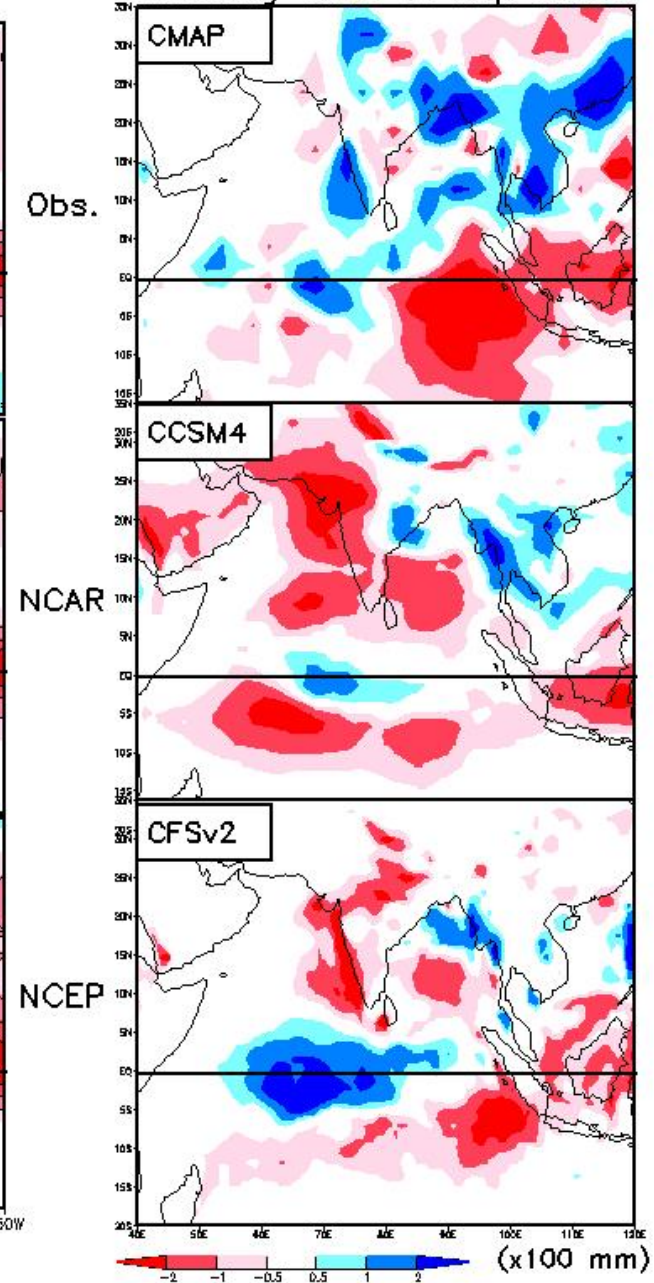
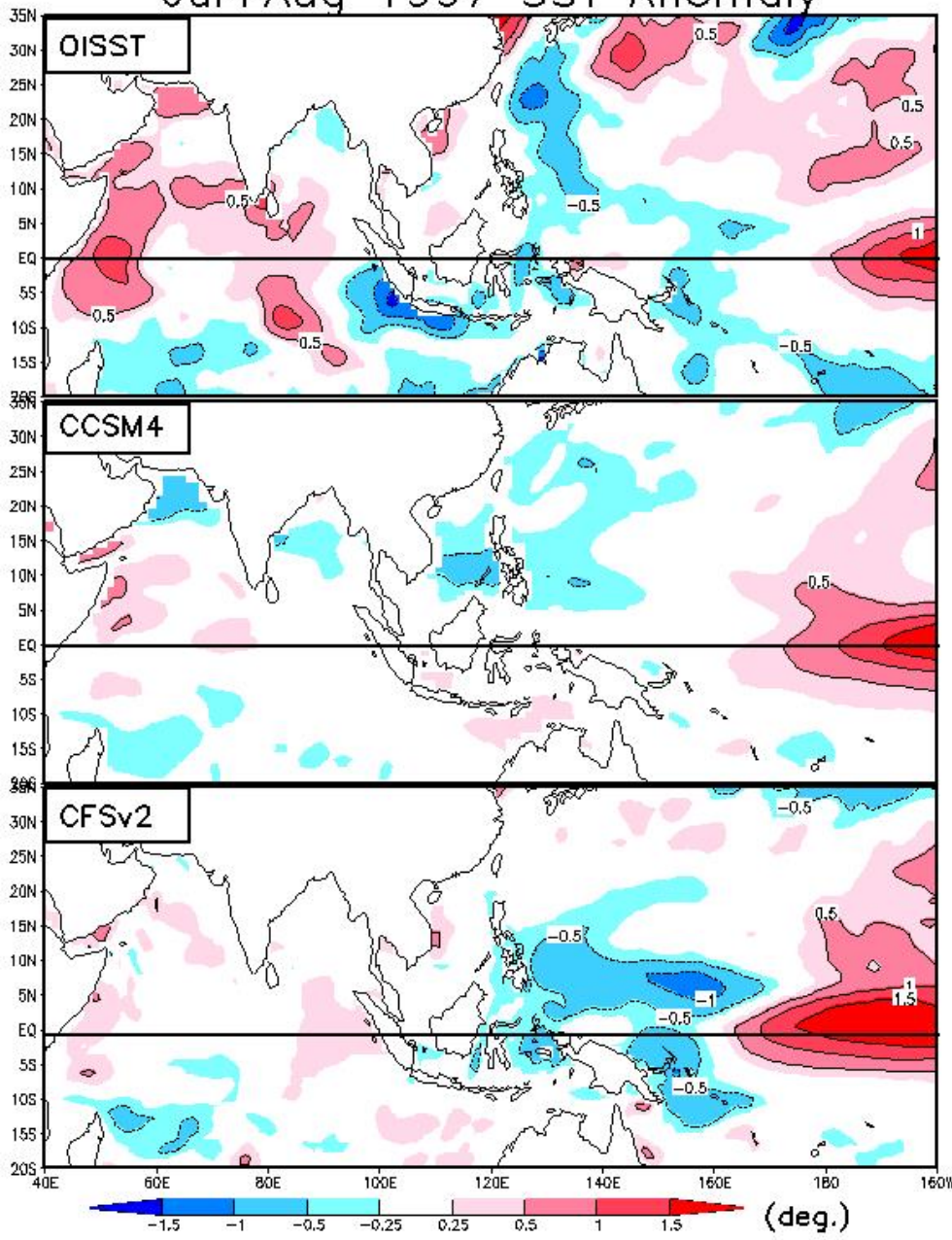


1997

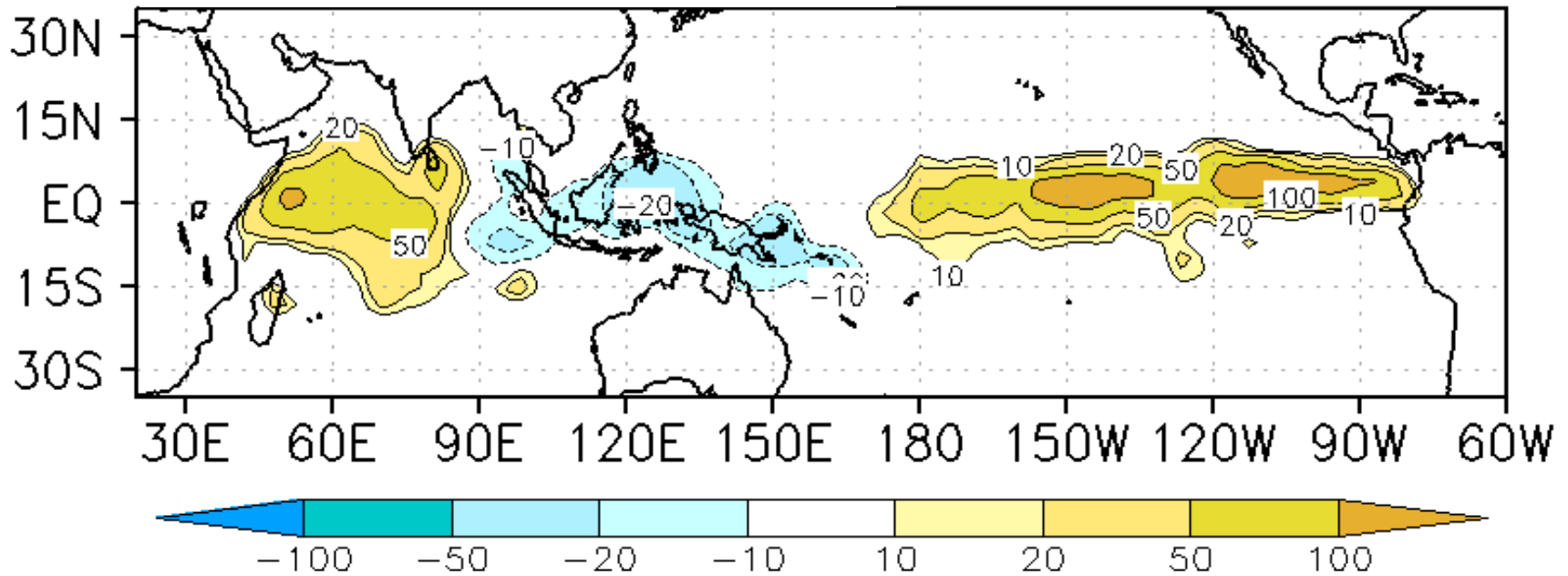
Models on full grid, end-of-April ICs (1982-1995)

Jul+Aug 1997 SST Anomaly

Jul+Aug 1997 Precip Anom

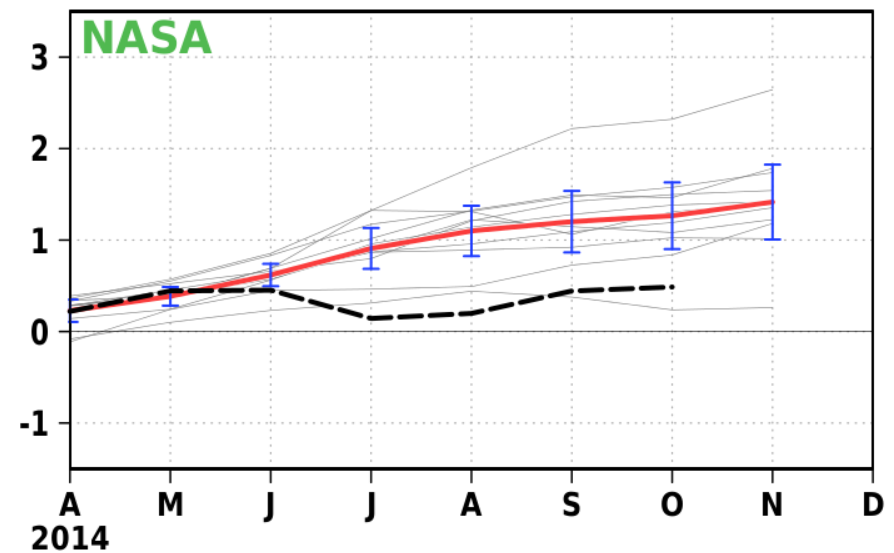
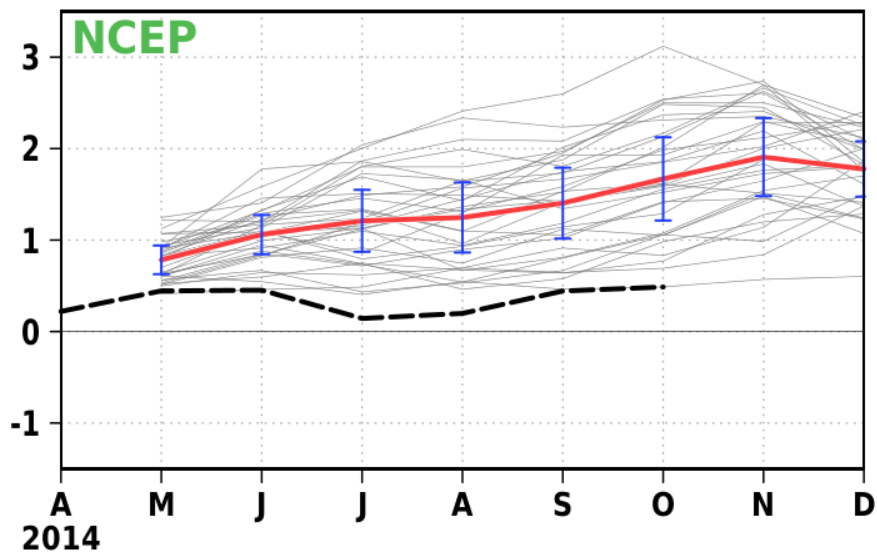
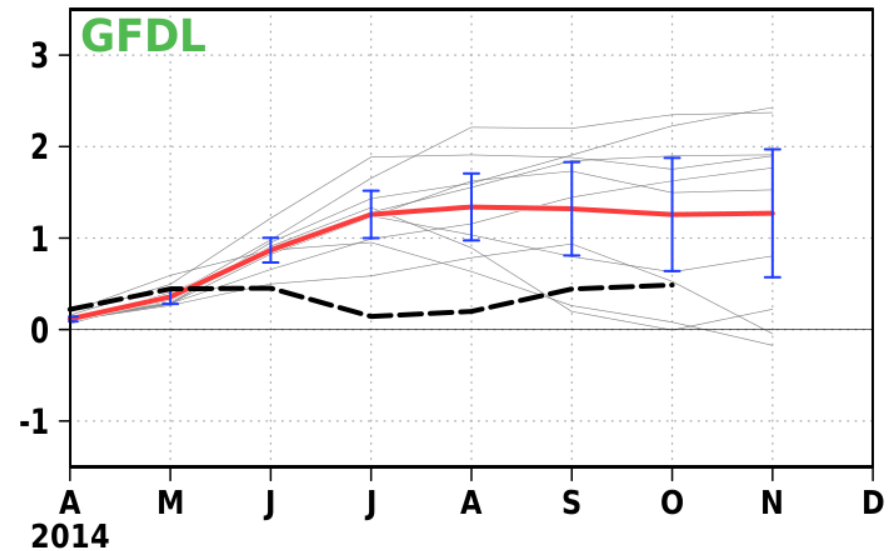
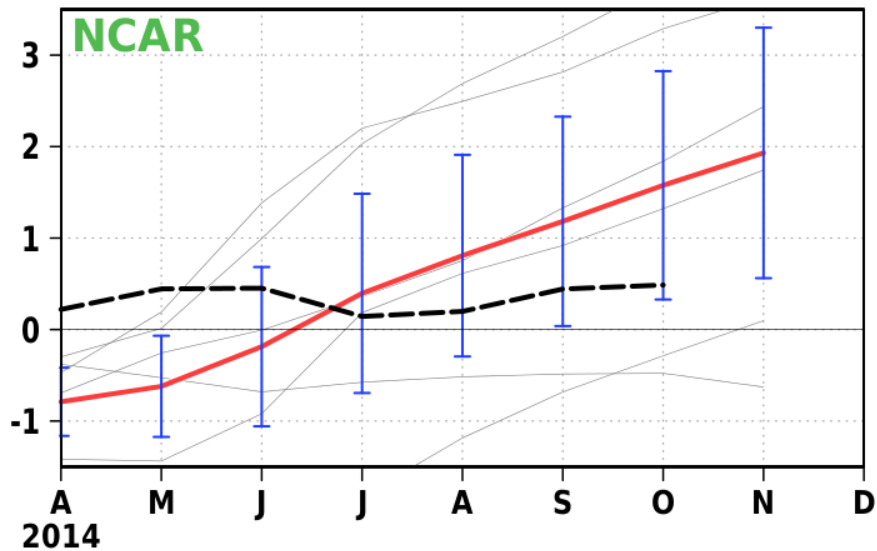


1997 Diabatic Heating Anomaly (W/m^2) (Based on Observations)



Example: ENSO Prediction

Forecasts of Nino3.4 from April 2014 IC (Model Bias Removed)



El Niño and the Southern Oscillation A Scientific Plan

Climate Research Committee
Board on Atmospheric Sciences and Climate
Commission on Physical Sciences, Mathematics,
and Resources
National Research Council

1983

U.S. Participation in the TOGA Program

A Research Strategy

1986

TOGA

*A Review of Progress
and Future Opportunities*

1990

1991

PROSPECTS FOR EXTENDING THE RANGE OF PREDICTION OF THE GLOBAL ATMOSPHERE

1994

GOALS

Global Ocean-Atmosphere-Land System

*for Predicting
Seasonal-to-Interannual
Climate*

1996

*Learning to Predict
Climate Variations Associated with
El Niño and the Southern Oscillation
Accomplishments and Legacies of the TOGA Program*

Dynamical Seasonal Prediction with 4 State-of-the-Art Coupled GCMs (1982-2010)

NOAA/NCEP:	CFSV2 – 24 ENSEMBLE MEMBERS
NOAA/GFDL:	CM2P1 – 10 ENSEMBLE MEMBERS
NASA/GSFC:	GMAO -- 10 ENSEMBLE MEMBERS
NCAR/COLA, RSMAS:	CCSM3 – 6 ENSEMBLE MEMBERS

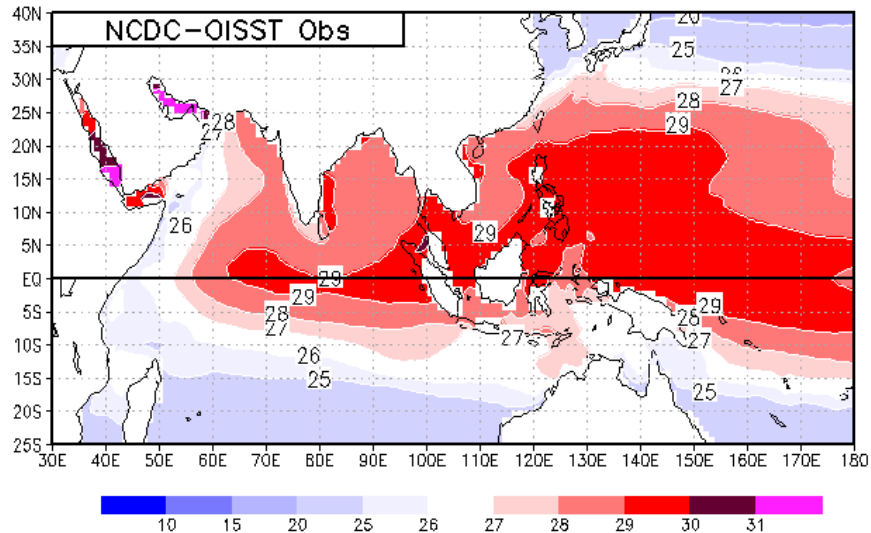
All calculations performed on ensemble mean for JJAS

NMME JJAS 1982–2010 Mean SST

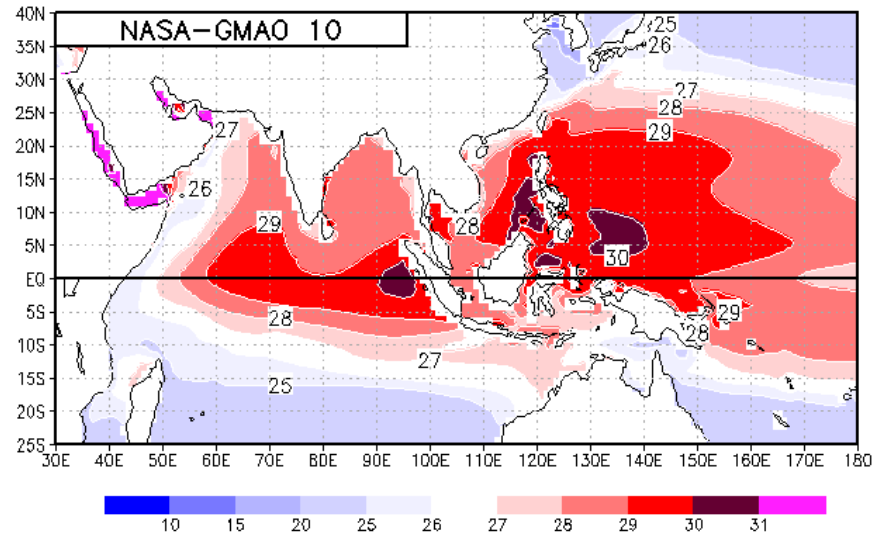
OBS

JJAS SST (1982-2010)

NASA



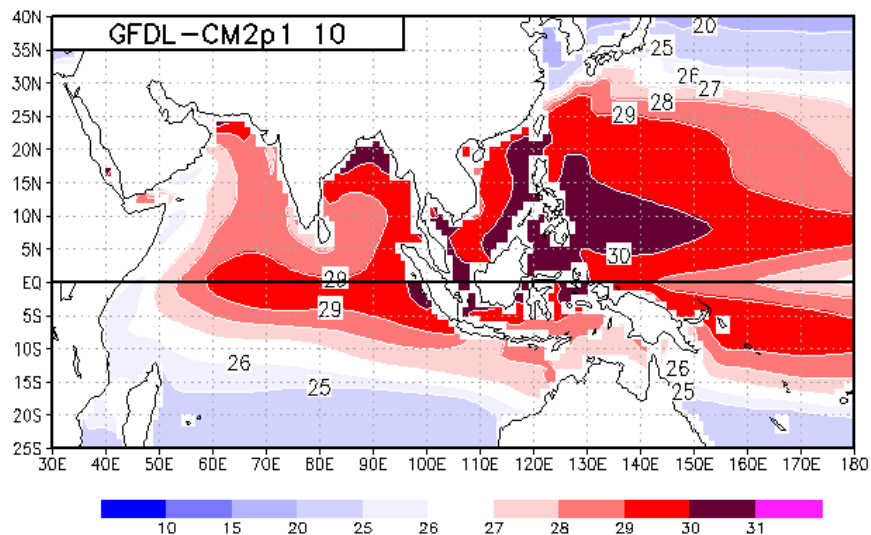
C



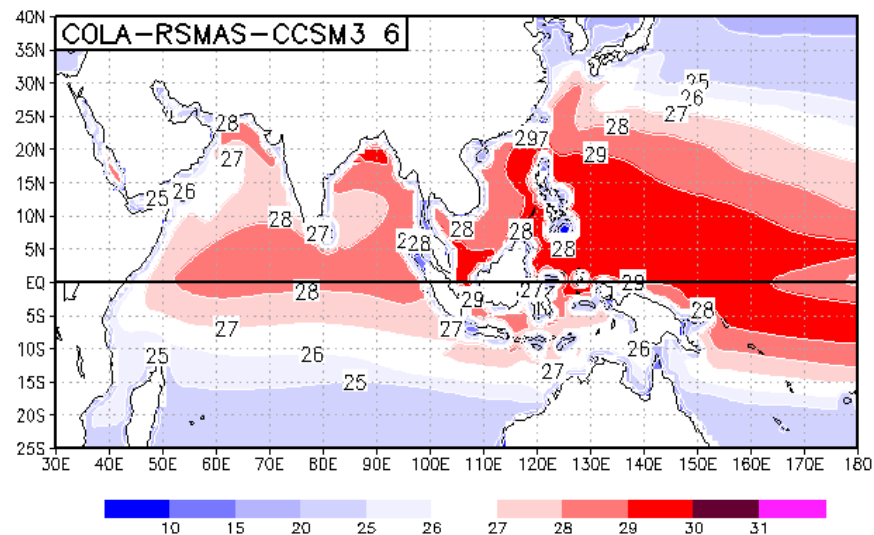
C

GFDL

NCAR



C



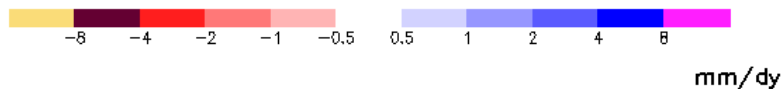
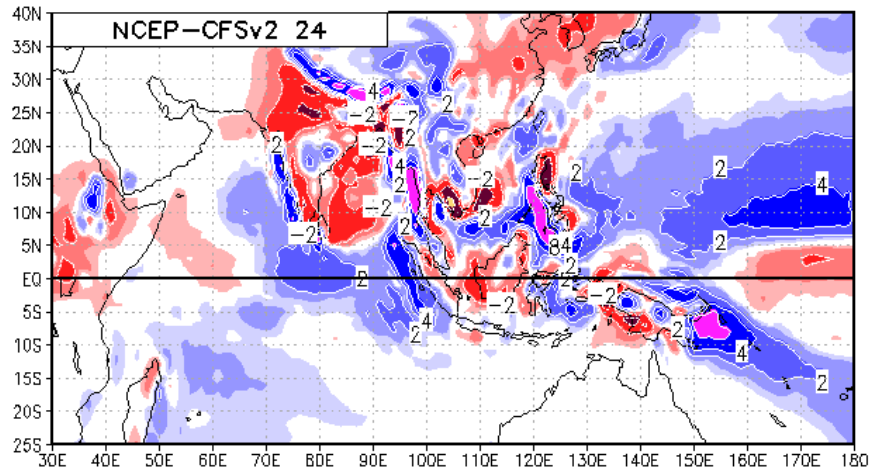
C

NMME 1 May ICS 1982–2010 Precipitation JJAS Mean Bias

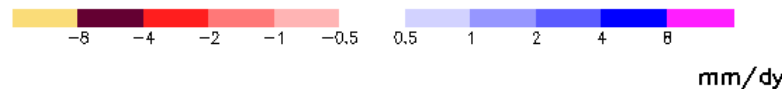
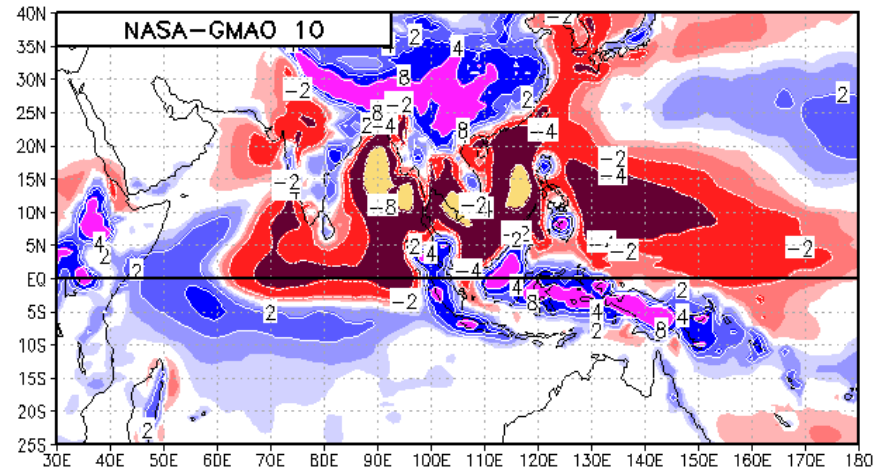
NCEP

JJS PRECIP BIAS

NASA



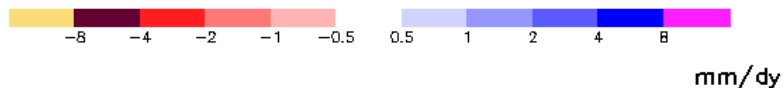
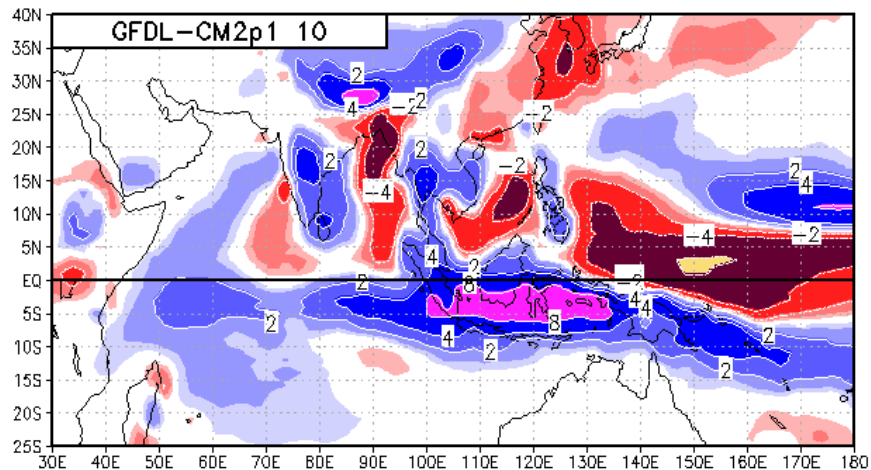
mm/dy



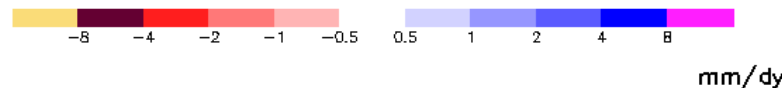
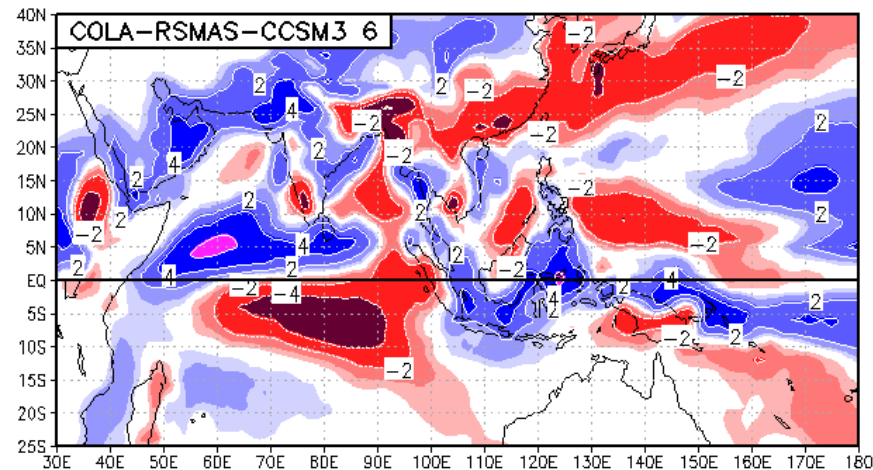
mm/dy

GFDL

NCAR

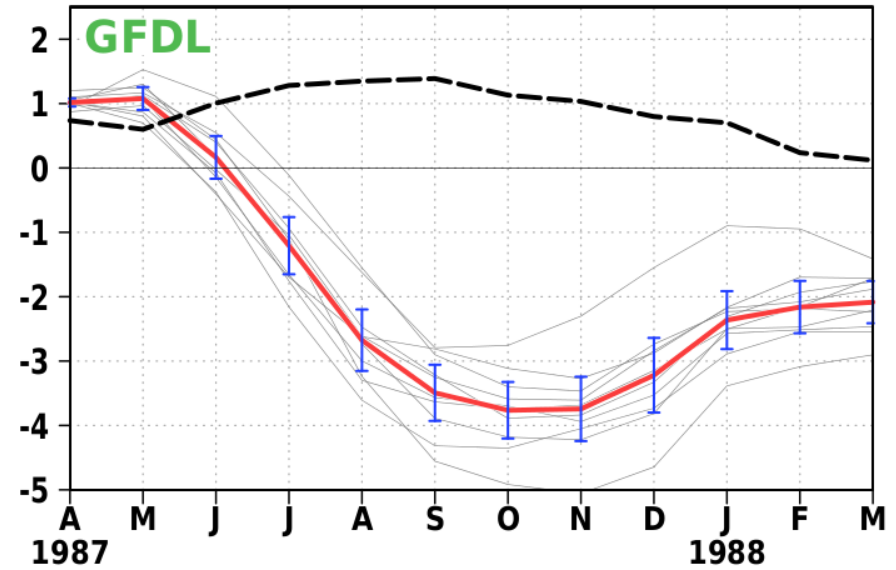
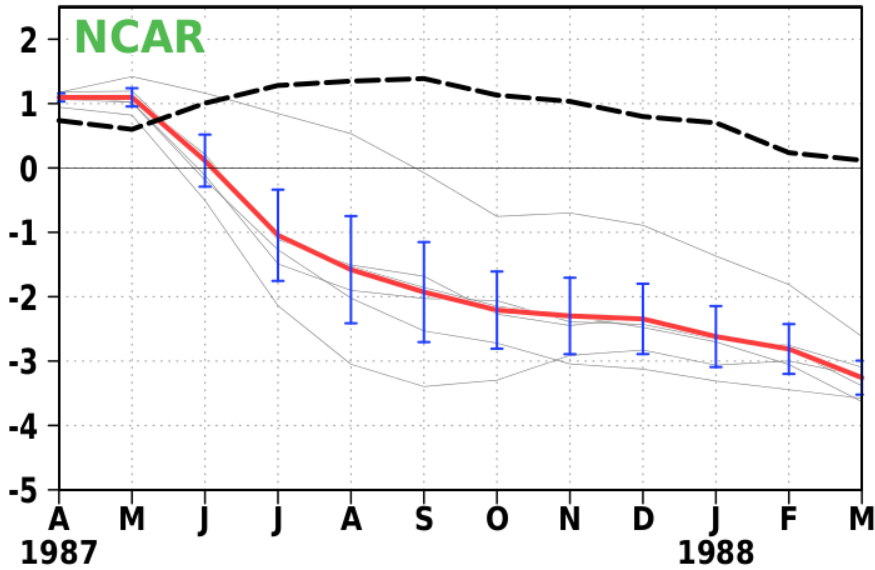


mm/dy



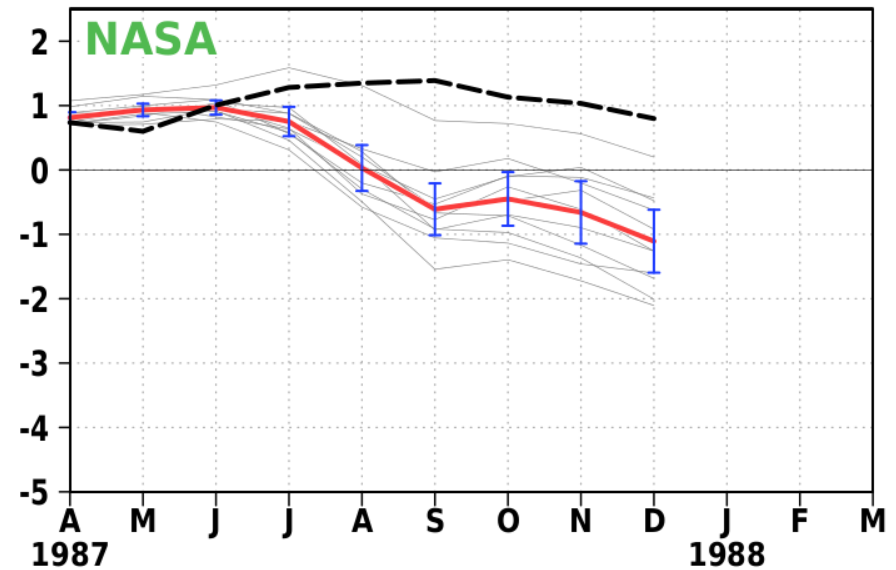
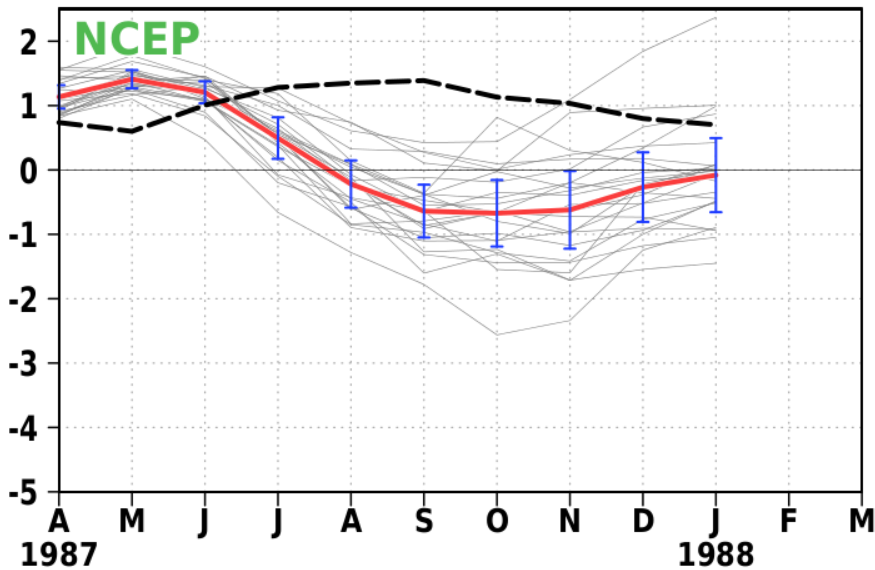
mm/dy

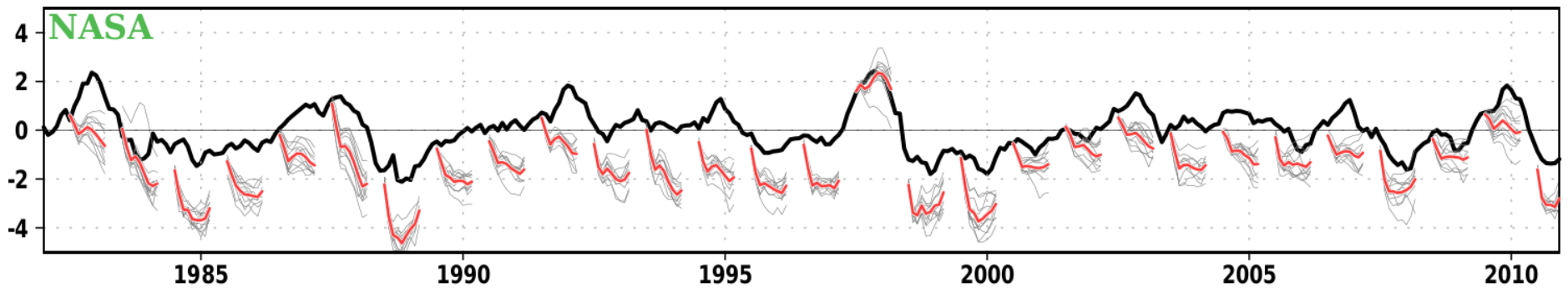
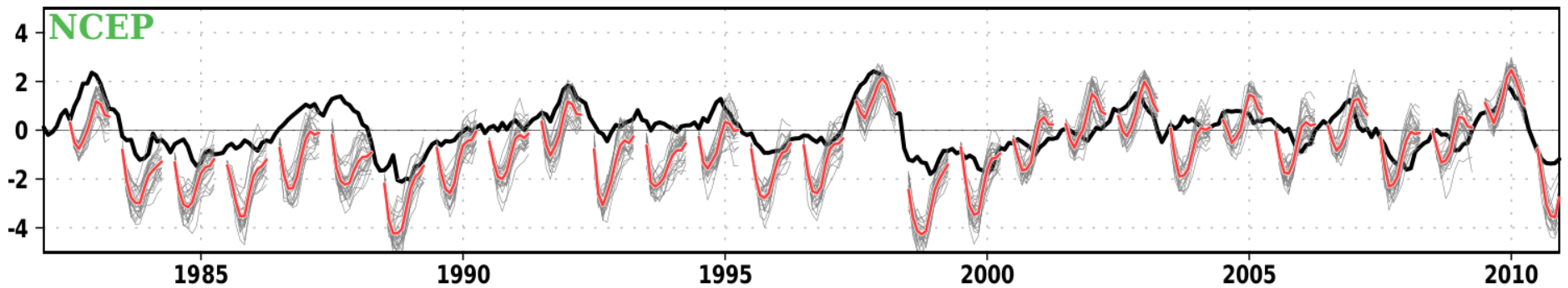
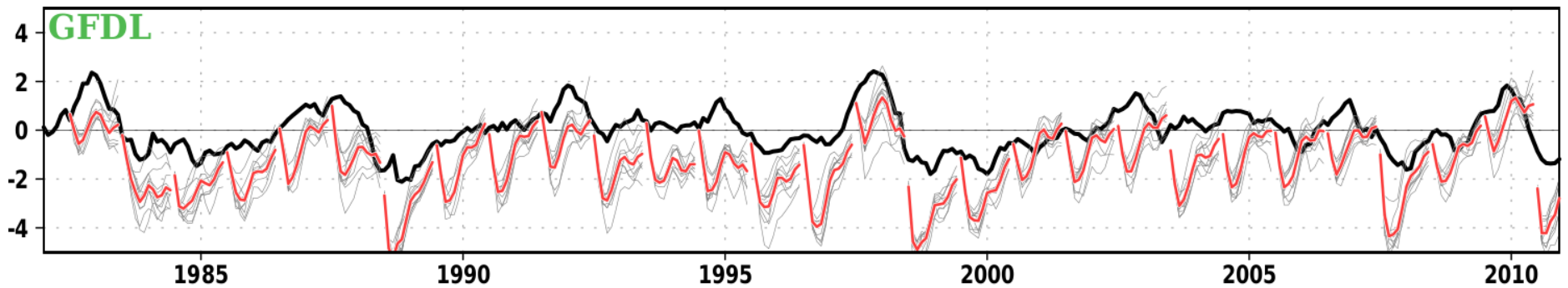
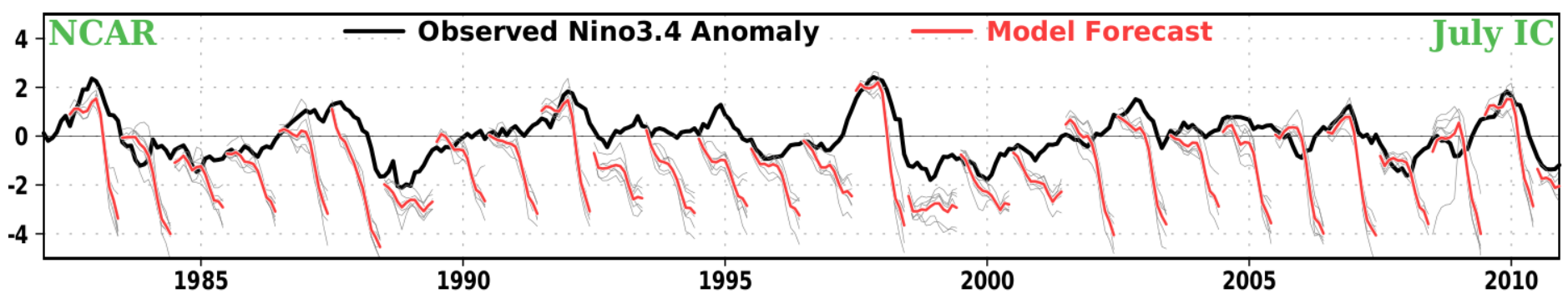
Forecasts of Nino3.4 from April 1987 IC



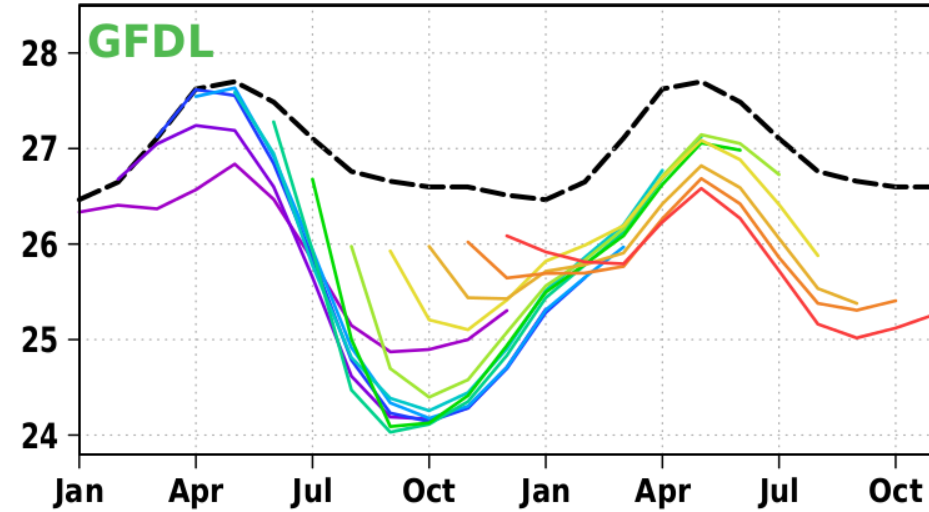
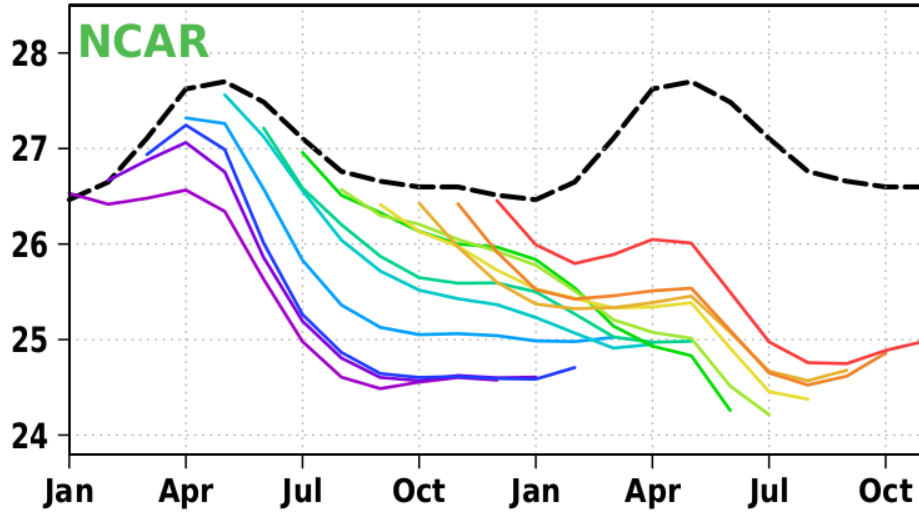
— Model Ensemble Mean

--- Observed Nino3.4 Anomaly

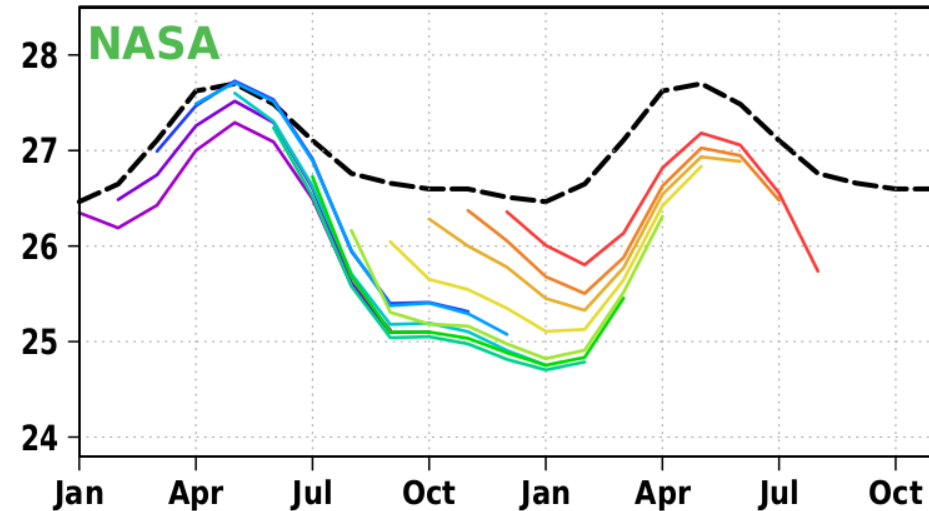
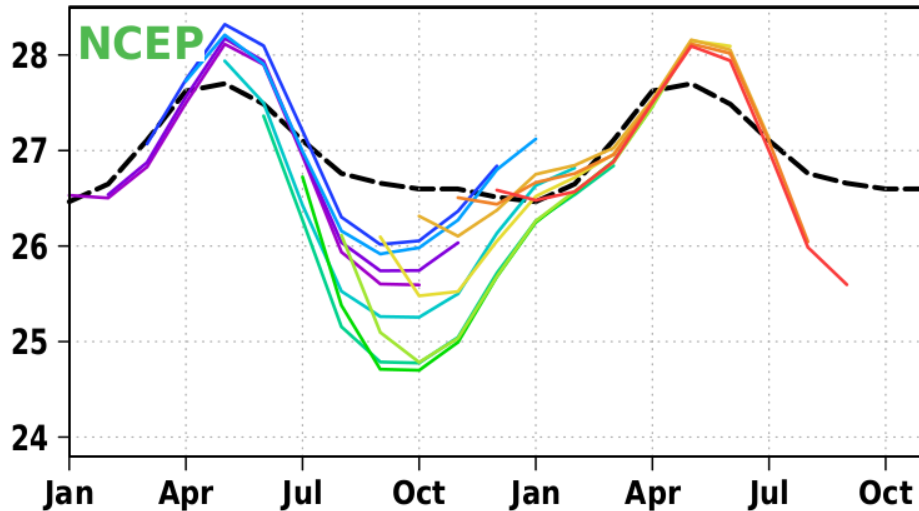




Observed and Model Mean Annual Cycle of Nino3.4 for Different Initial Conditions

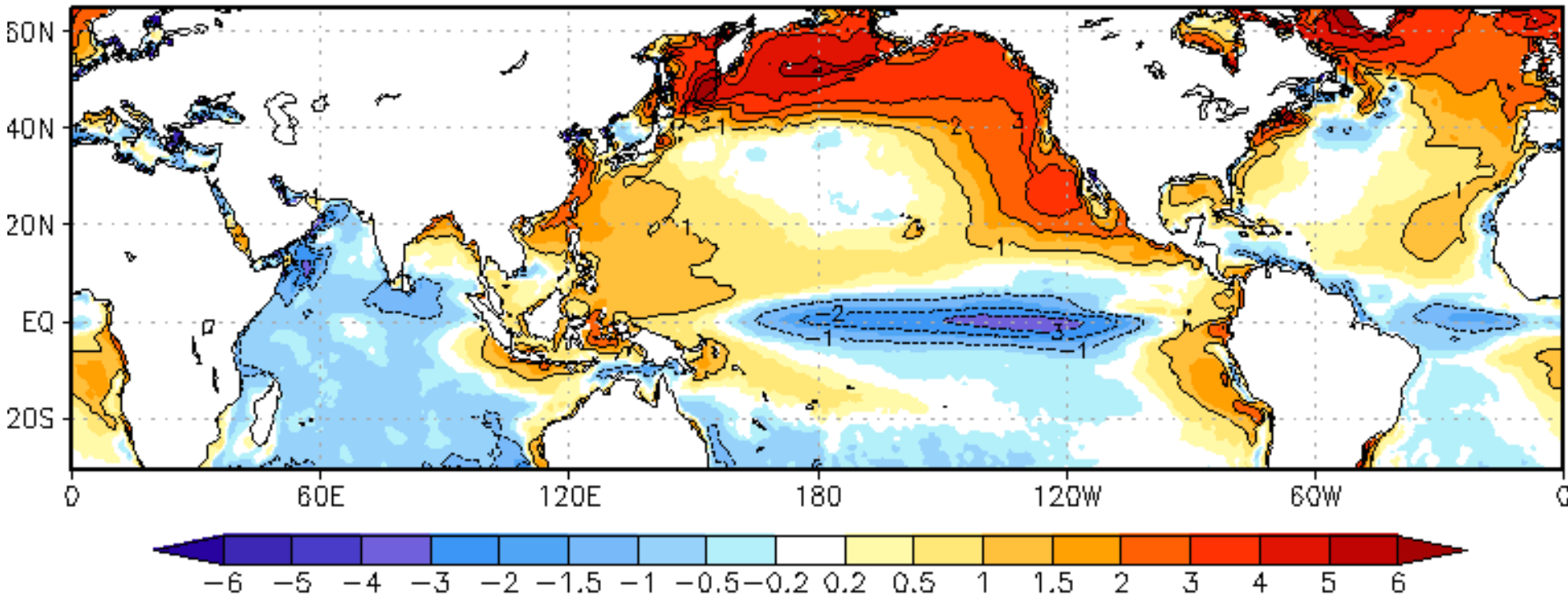


--- Observed Nino3.4 Annual Cycle



SST Bias in 3 Month Forecasts (CFSv2), 1982-2008, I.C. May, 1

Climatological SST Error of the CFSv2 hindcasts in August (lead month 3)



CFSv2 hindcasts (1982-2008)

Atmospheric and Land ICs : first 4 days in May (4 ensemble members), CFSR

Ocean ICs : NEMO reanalysis

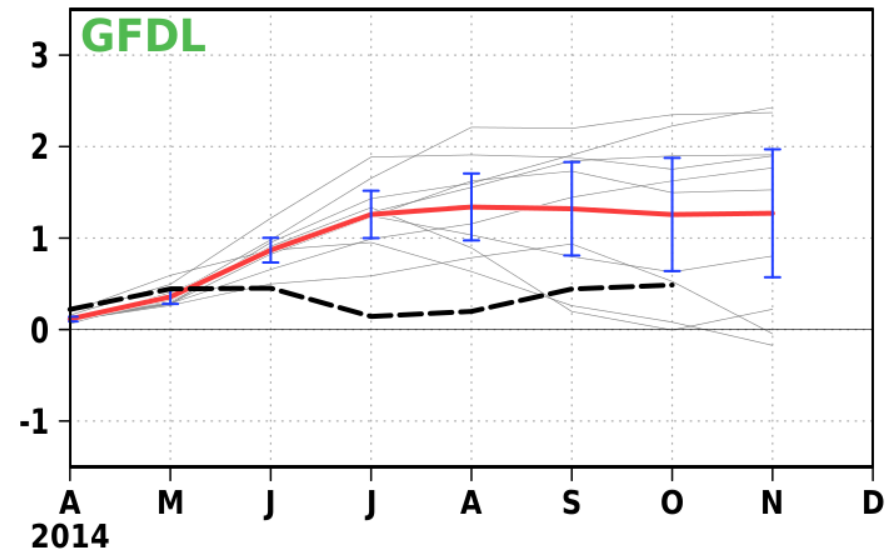
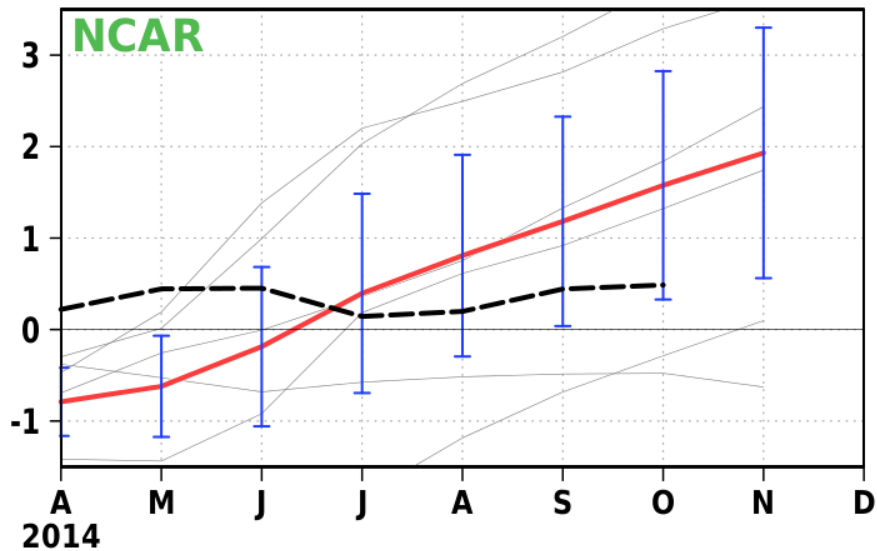
Observation

: daily NOAA OI SST ver2

Statement

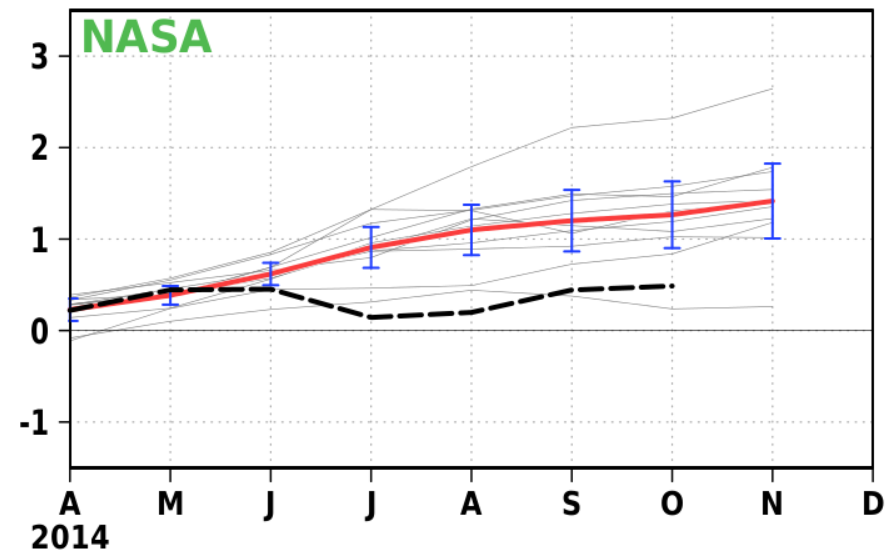
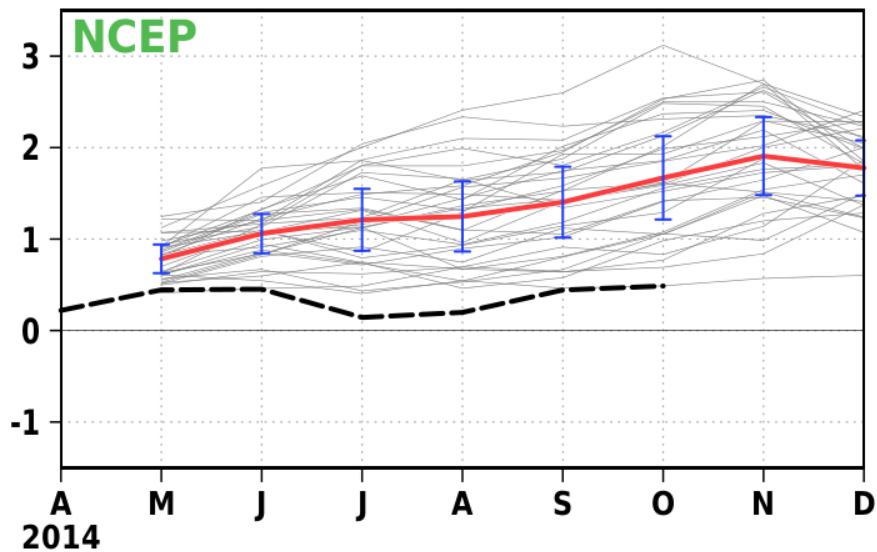
In spite of a million fold increase in the computing power, and enhanced ocean observations since **TOGA**, there has not been any significant improvement in the simulation of mean climate, and prediction of short-term climate variability by climate models.

Forecasts of Nino3.4 from April 2014 IC (Model Bias Removed)

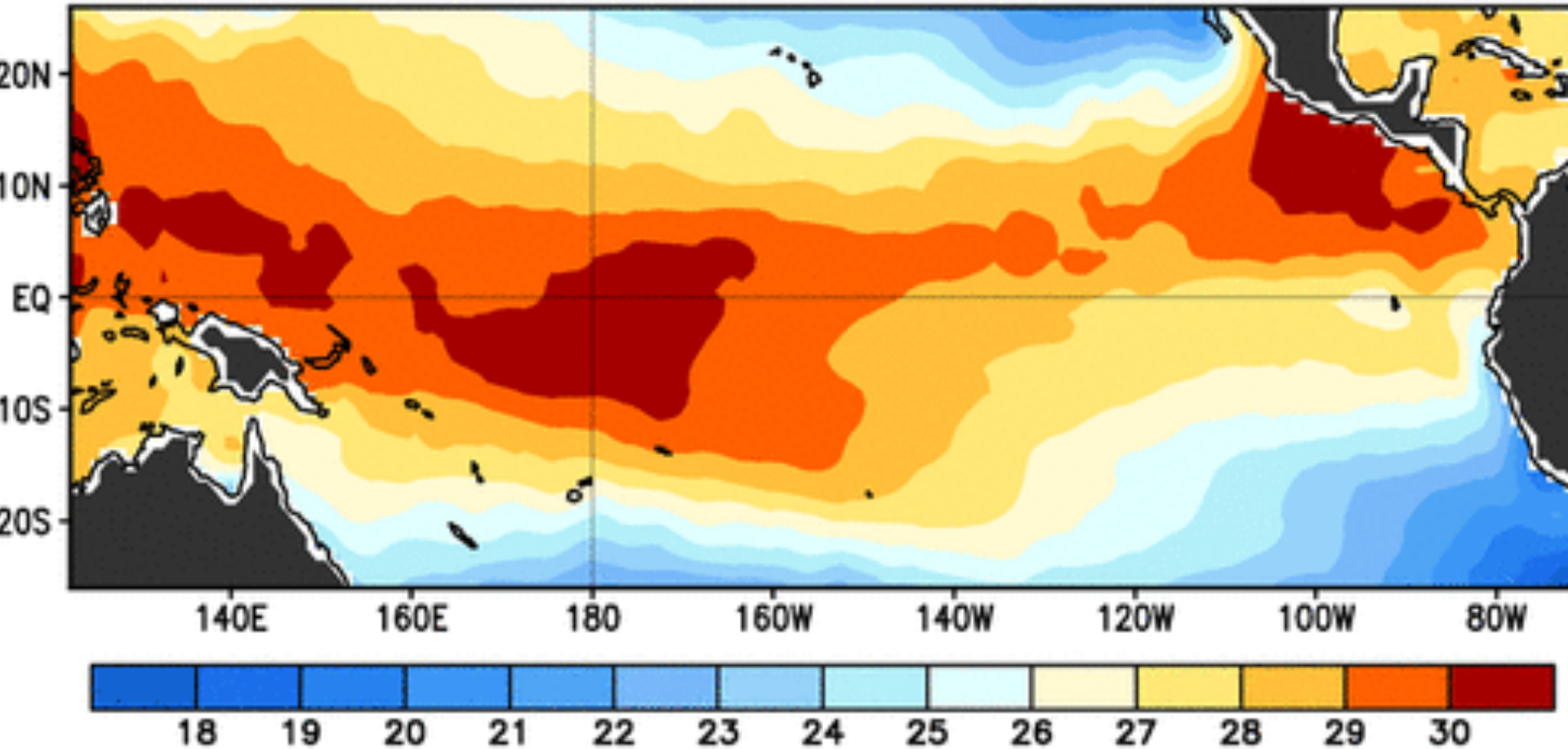


— Model Ensemble Mean

--- Observed Nino3.4 Anomaly

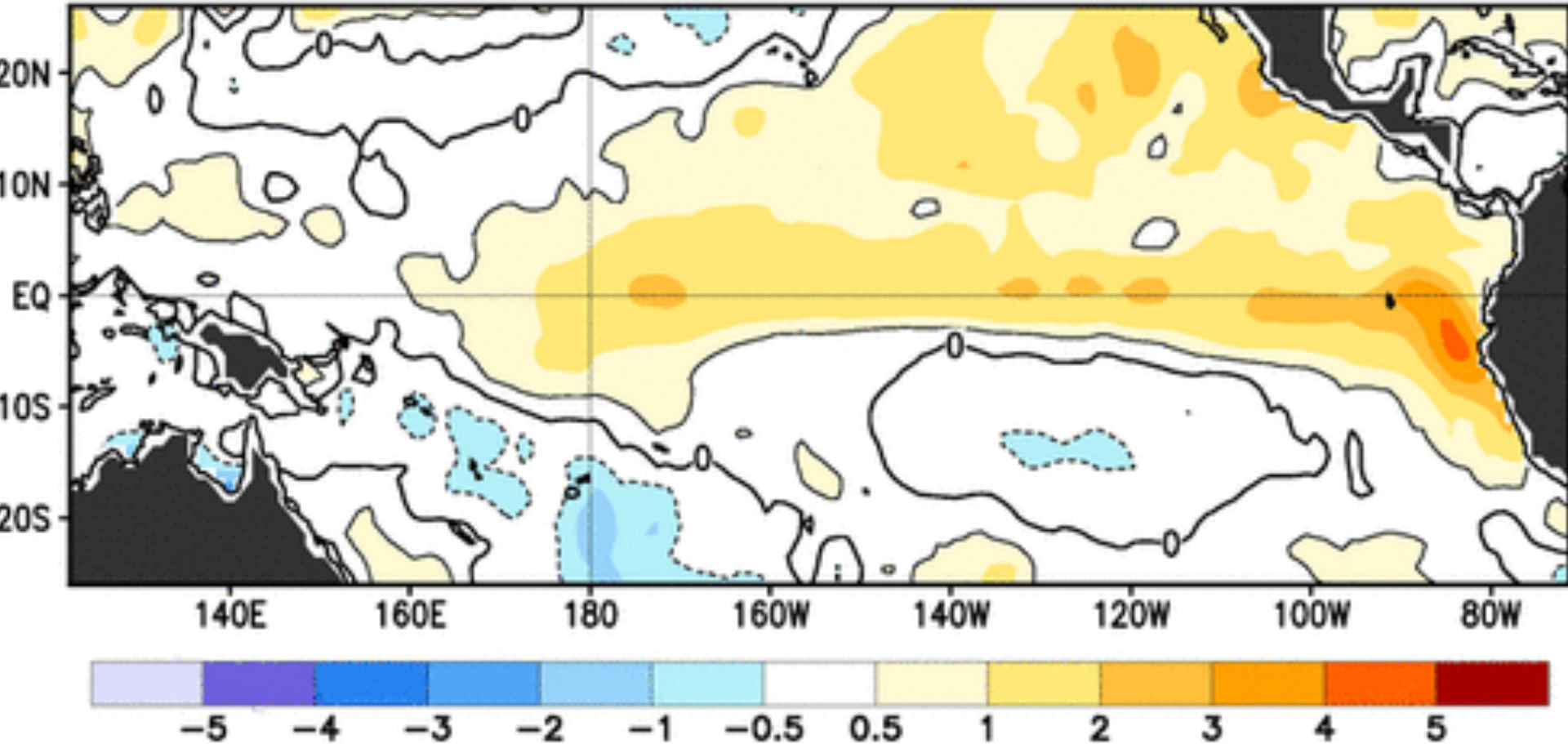


Observed Sea Surface Temperature (°C)



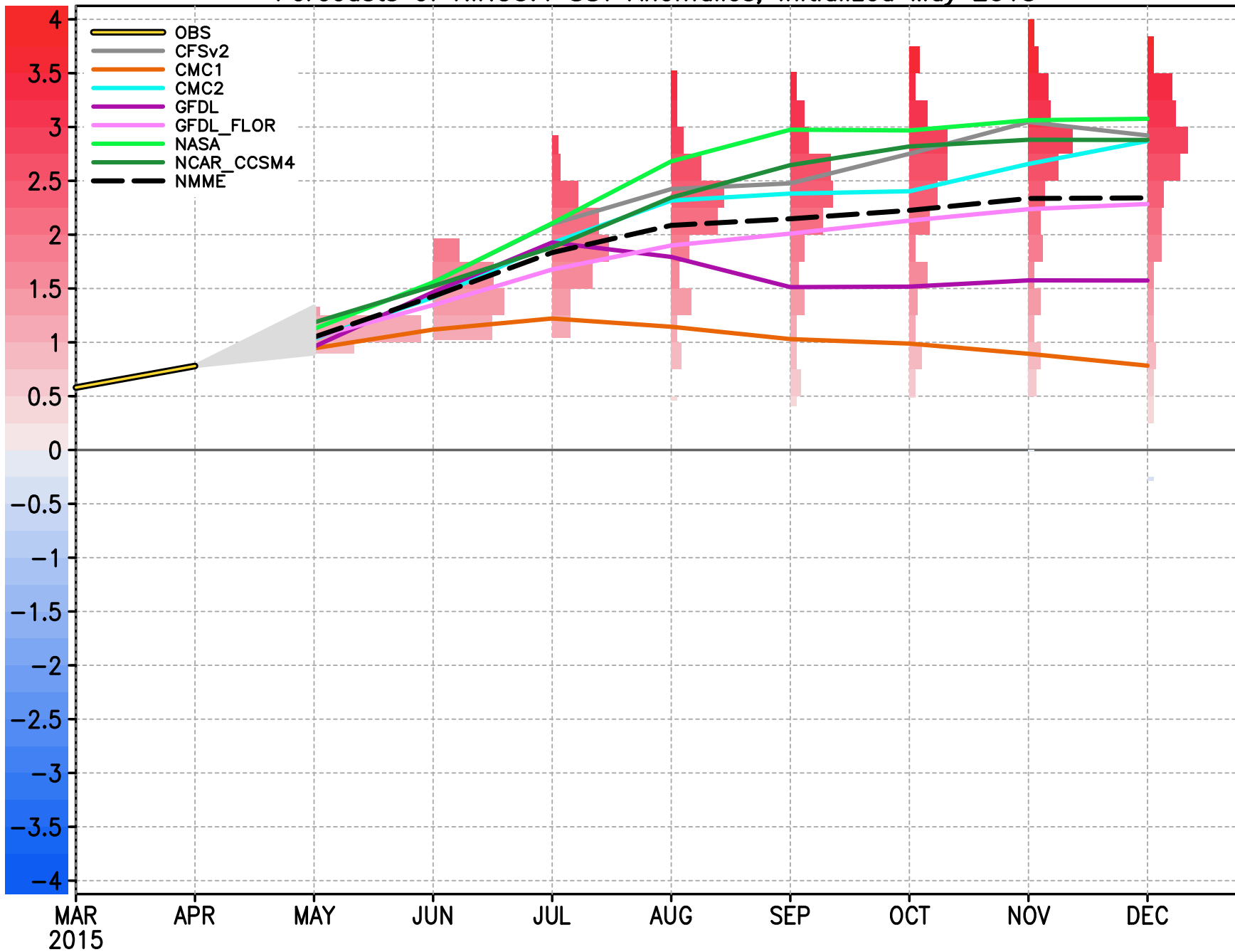
7-Day Average Centered on 27 May 2015

Observed Sea Surface Temperature Anomalies (°C)

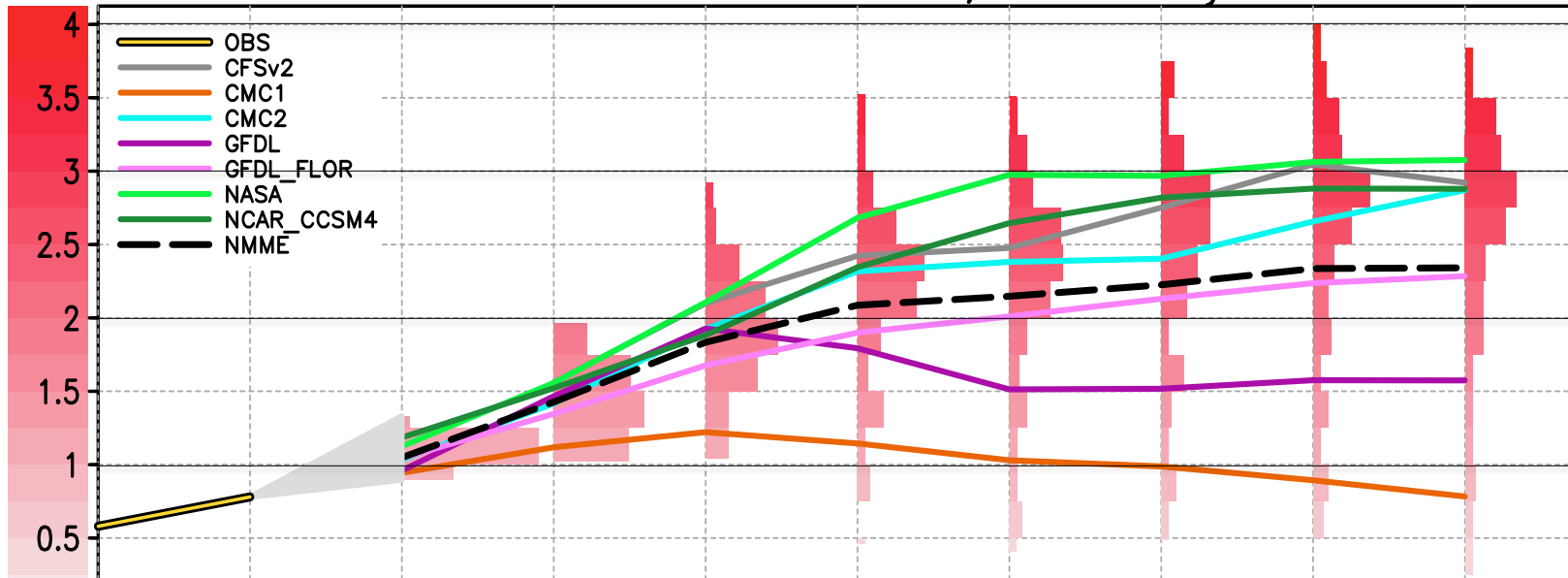


7-Day Average Centered on 27 May 2015

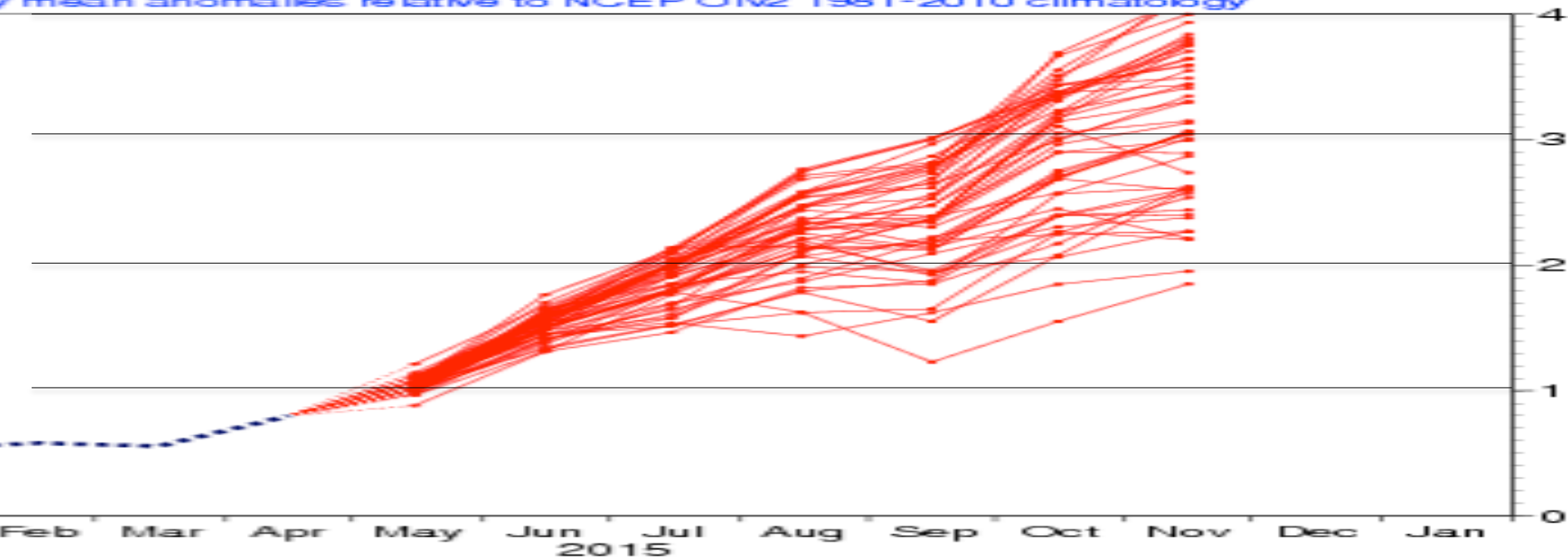
Forecasts of NINO3.4 SST Anomalies, Initialized May 2015



Forecasts of NINO3.4 SST Anomalies, Initialized May 2015



NINO3.4 SST anomaly plume
ECMWF forecast from 1 May 2015
by mean anomalies relative to NCEP OIv2 1981-2010 climatology

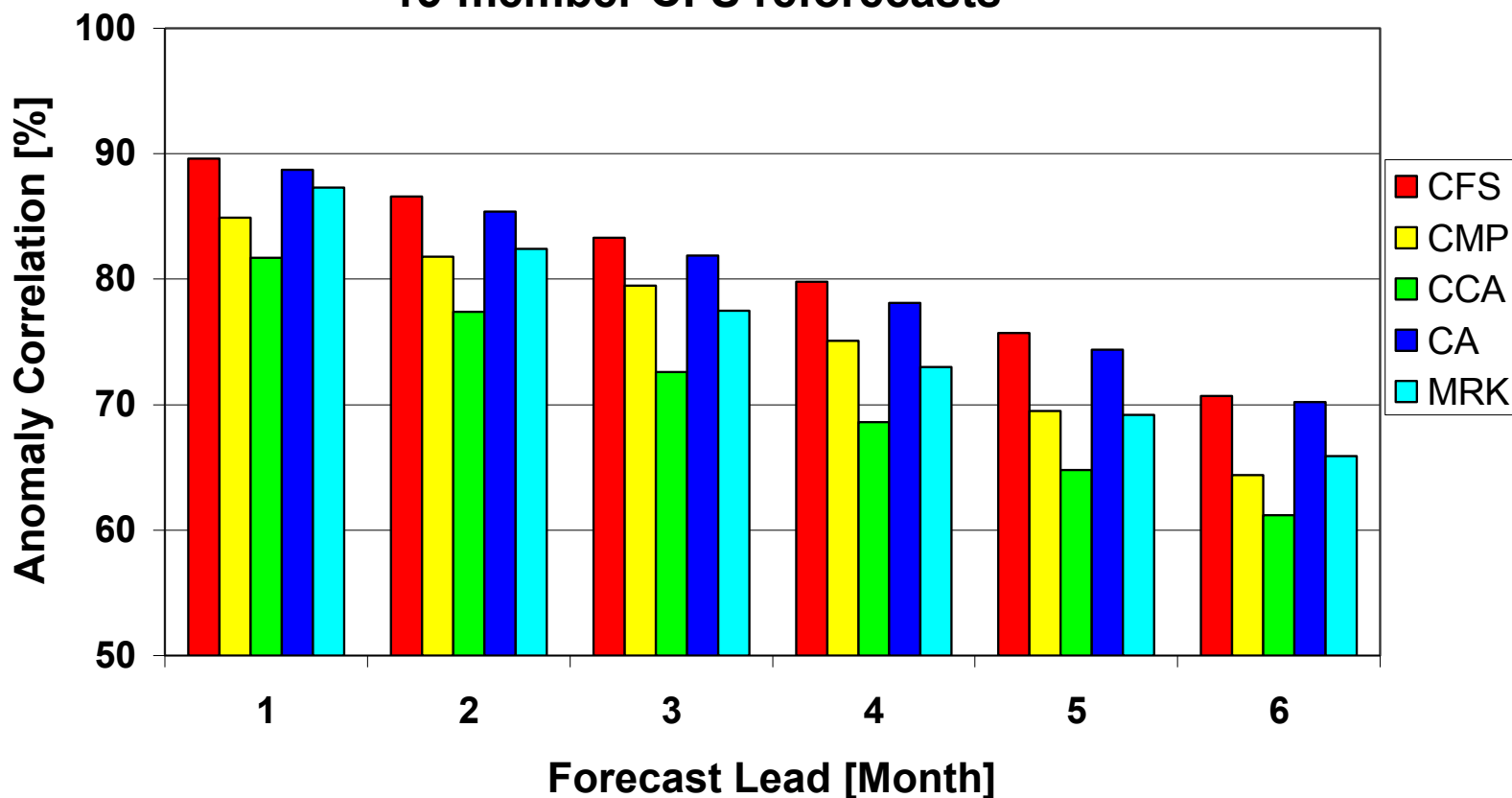


Skill in SST Anomaly Prediction for Nino3.4

A Puzzle: Although model biases are very large, bias corrected anomaly predictions have useful skill.

DJF 1981/82 to AMJ 2004

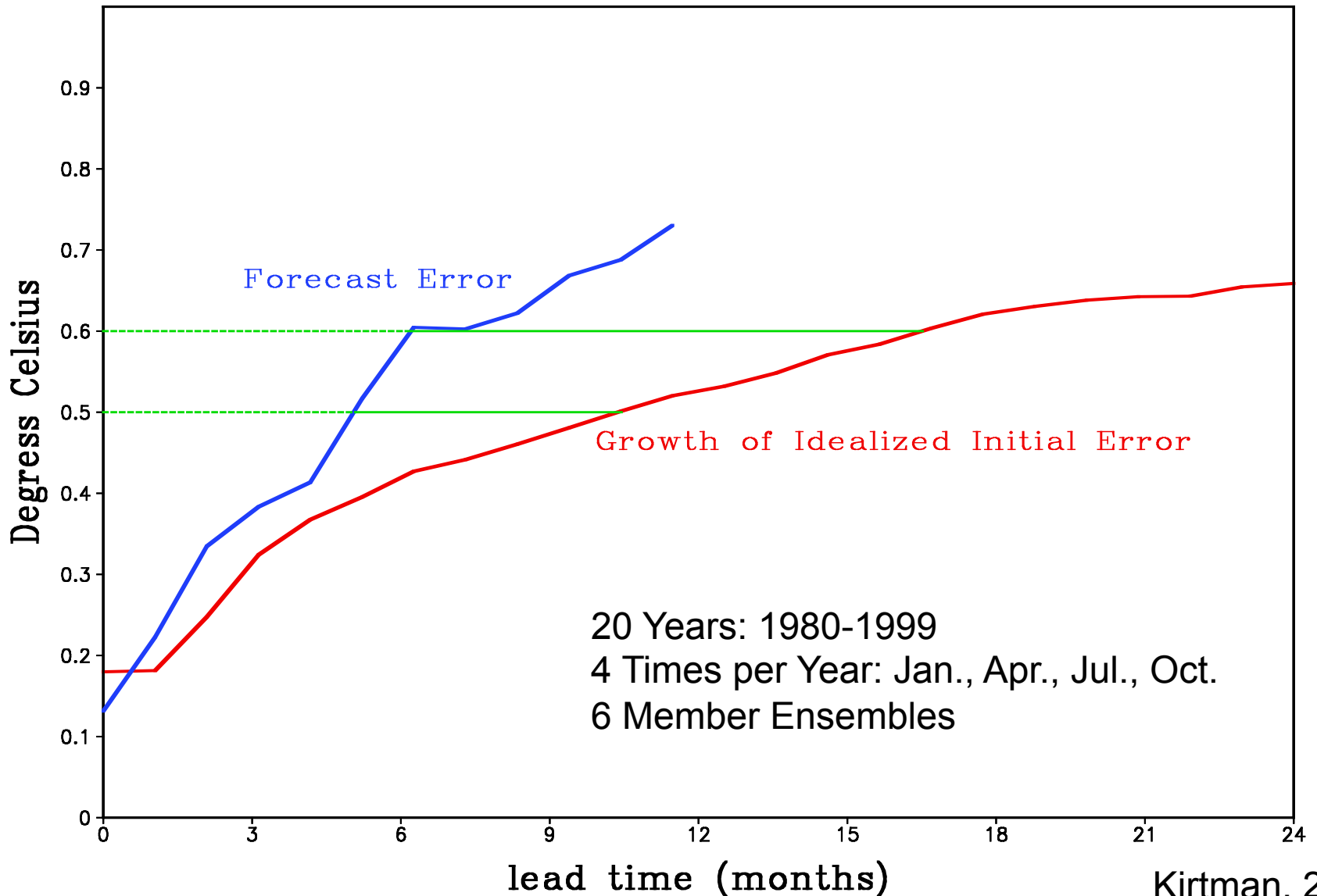
15-member CFS reforecasts



Current Limit of Predictability of ENSO (Nino3.4)

Potential Limit of Predictability of ENSO

Potential Limit of Predictability of ENSO



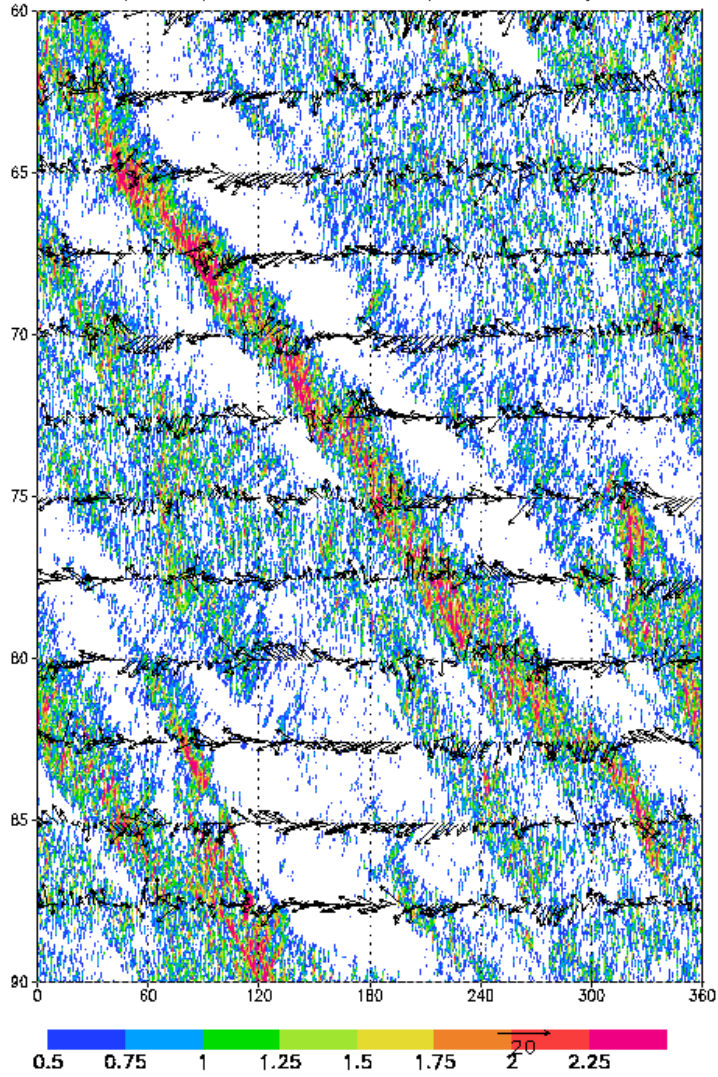
Examples of improved climate simulation by global climate models with higher numerical accuracy (high resolution) and improved physics

Towards a Hypothetical “Perfect” Model

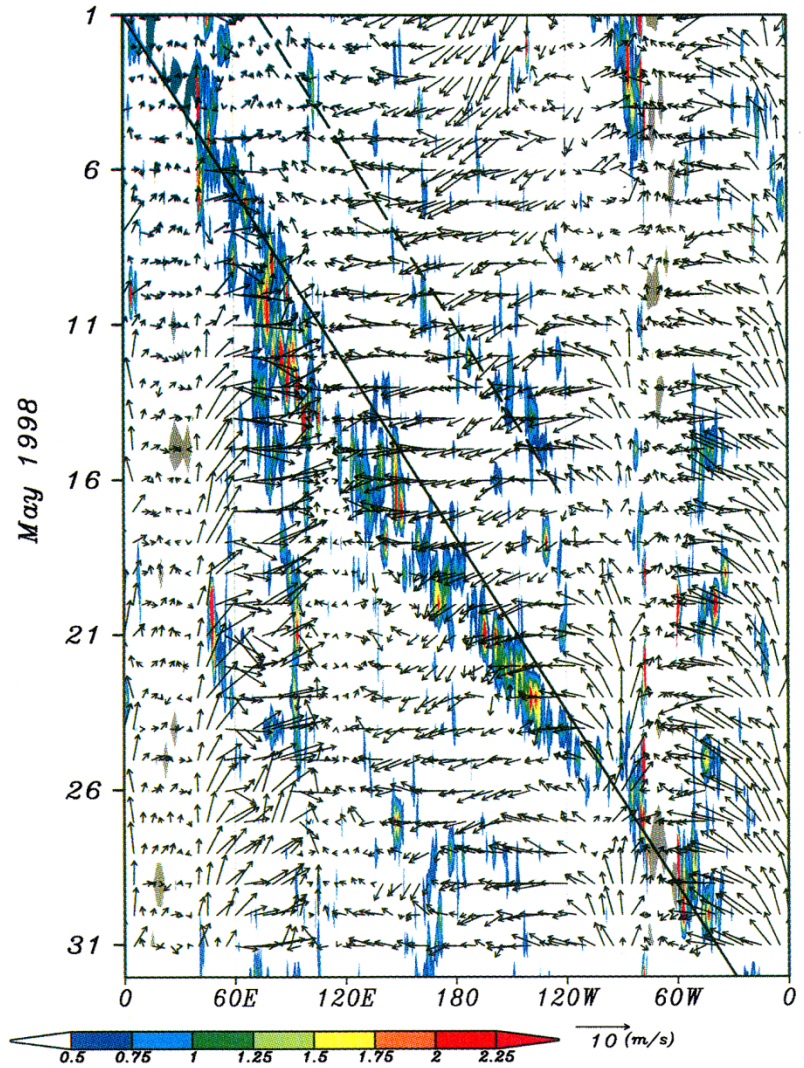
- Replicate the statistical properties of the past and present observed climate
 - Means, variances, covariances, and patterns of covariability
- Utilize this model to estimate the limits of predicting the sequential evolution of climate variability
- Enhance predictive understanding with iterative process of:
Model development and validation \leftrightarrow Predictability \leftrightarrow Prediction

NICAM (7-km)

precipitation rate (10S–10N)



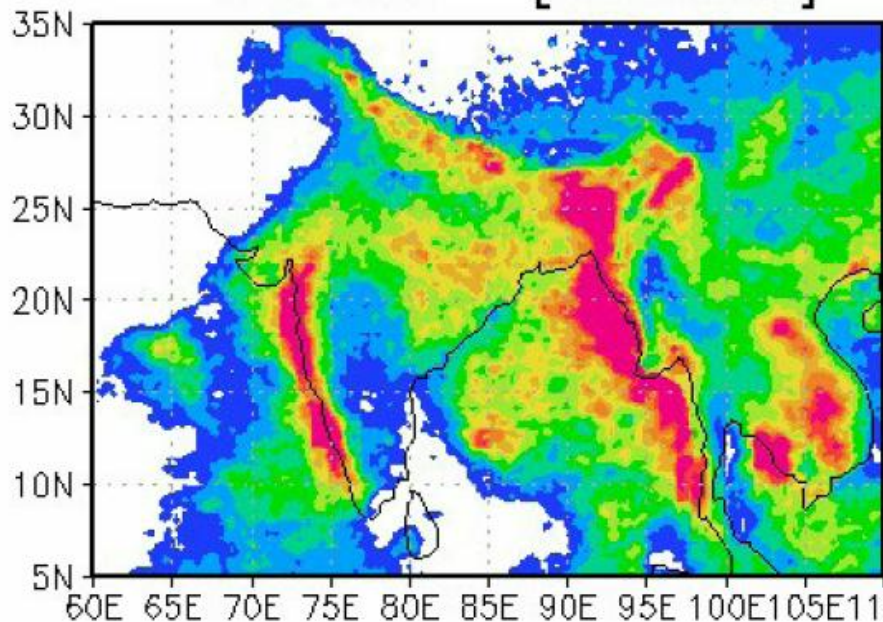
Obs. (Takayabu et al. 1999)



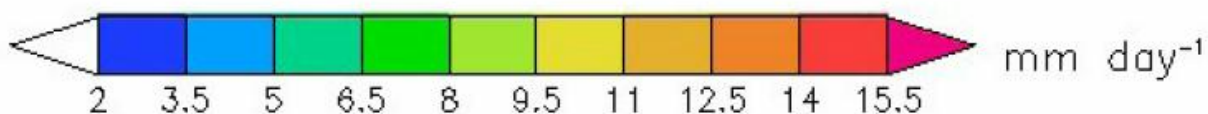
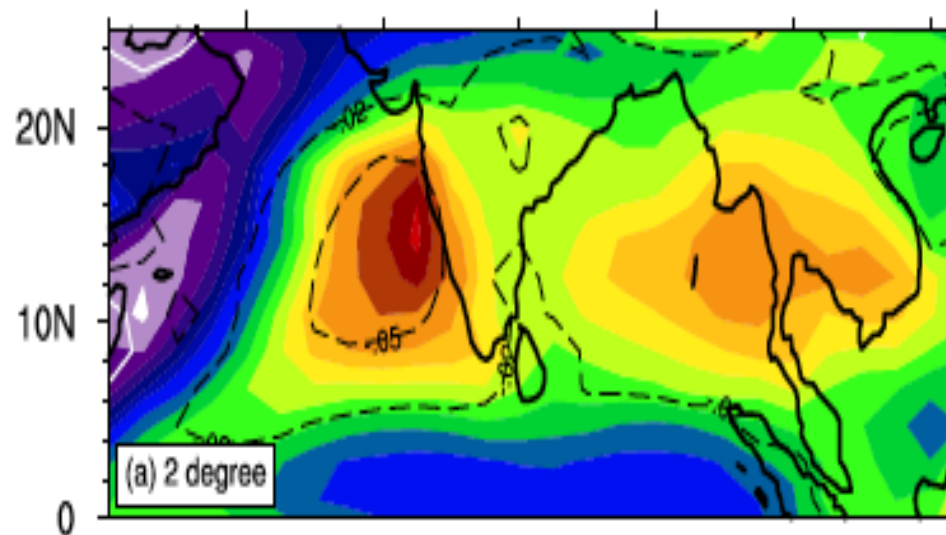
Matsuno (AMS, 2007)

Monsoon Rainfall in Low Resolution Model

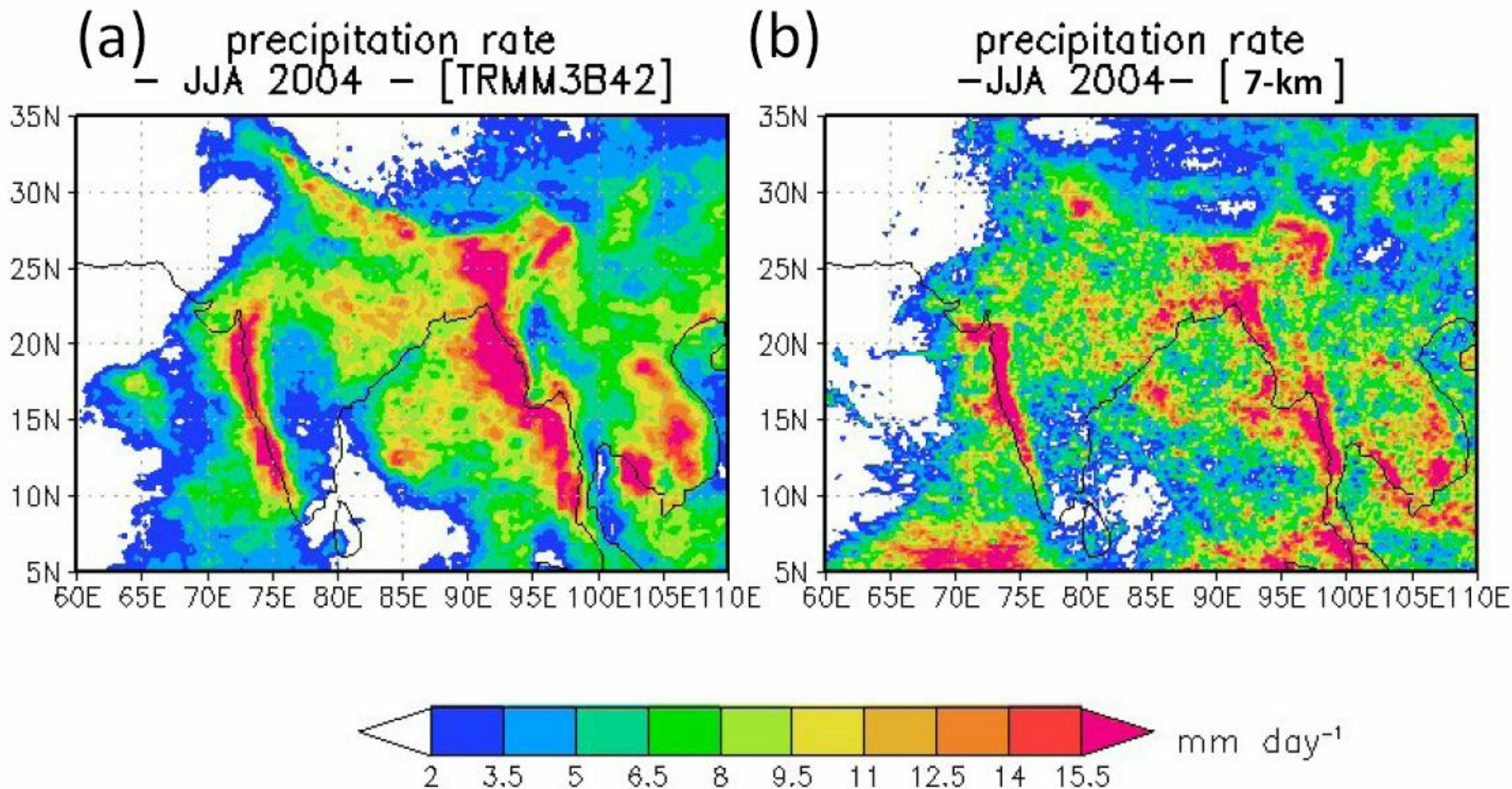
(a) precipitation rate
- JJA 2004 - [TRMM3B42]



(b) Coupled model (2 degree)
- Climatology -

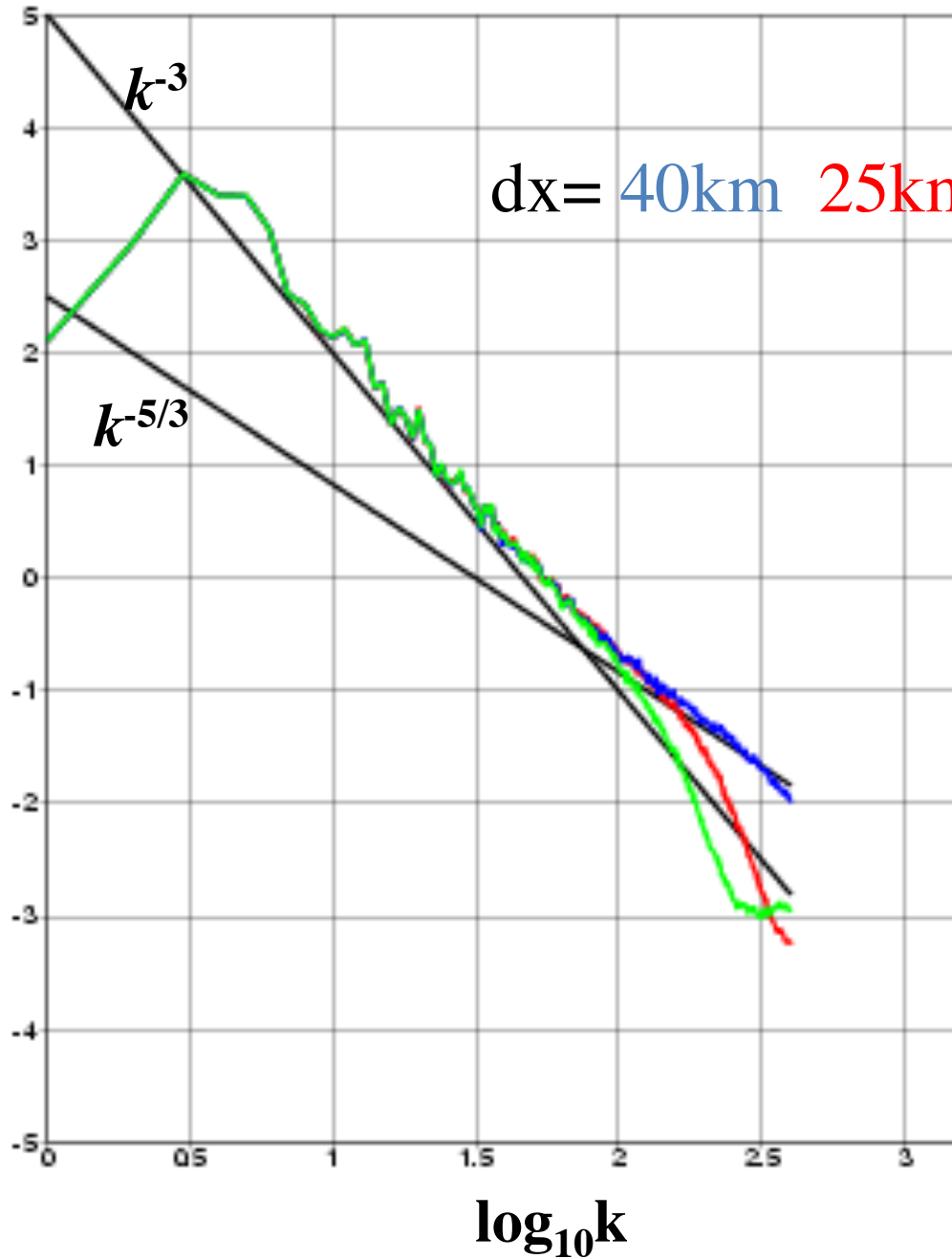


Monsoon Rainfall in High Resolution Model

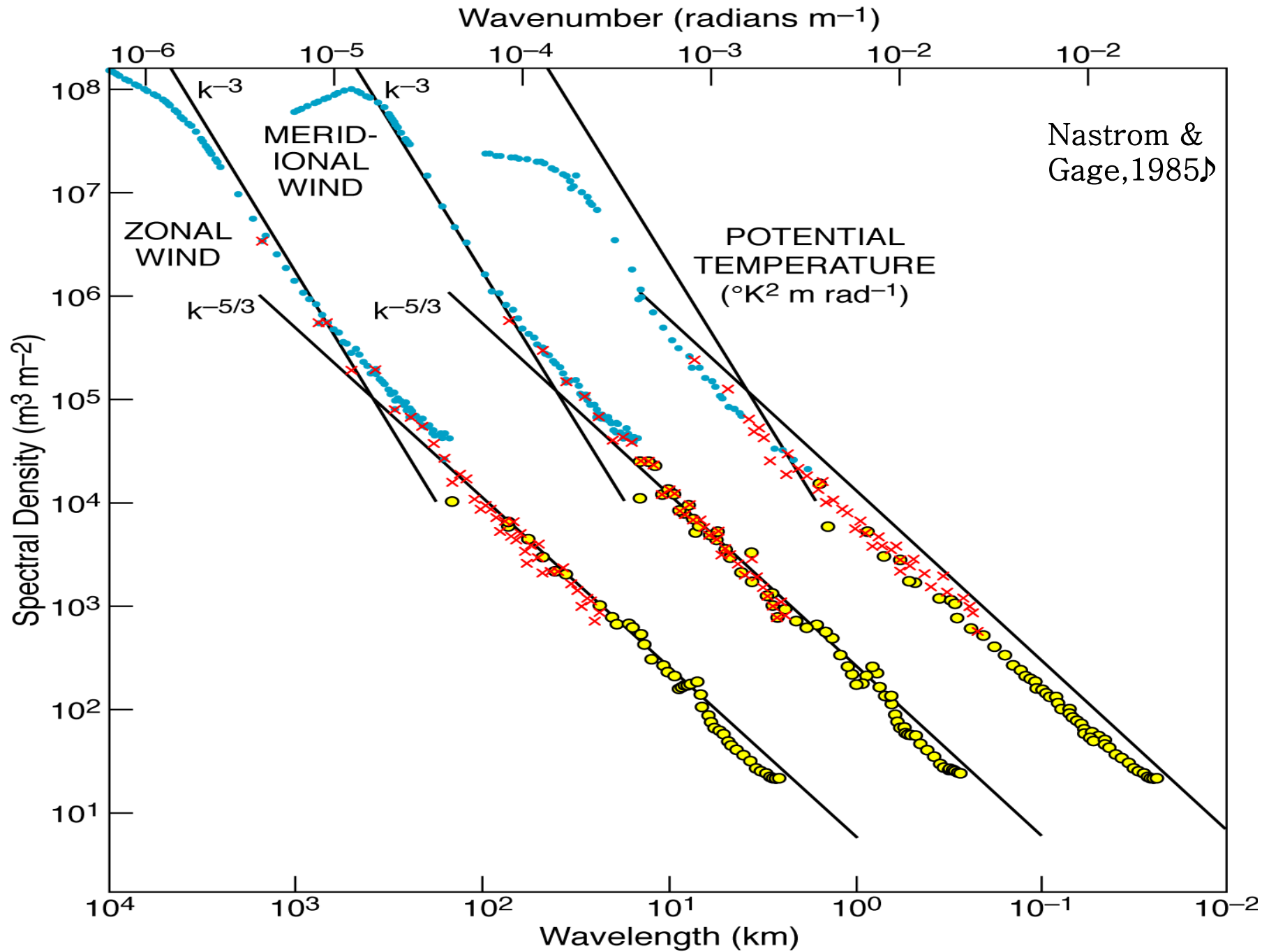


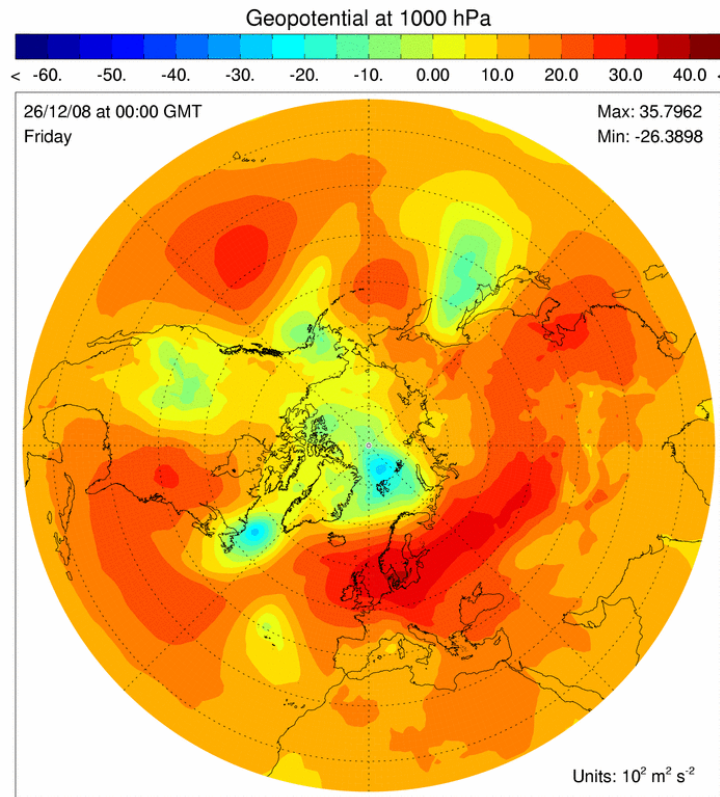
Oouchi et al. 2009: (a) Observed and (b) simulated precipitation rate over the Indo-China monsoon region as June-July-August average (in units of mm day⁻¹). The observed precipitation is from TRMM_3B42, and the simulation is for 7km-mesh run.

Spectra of Total KE

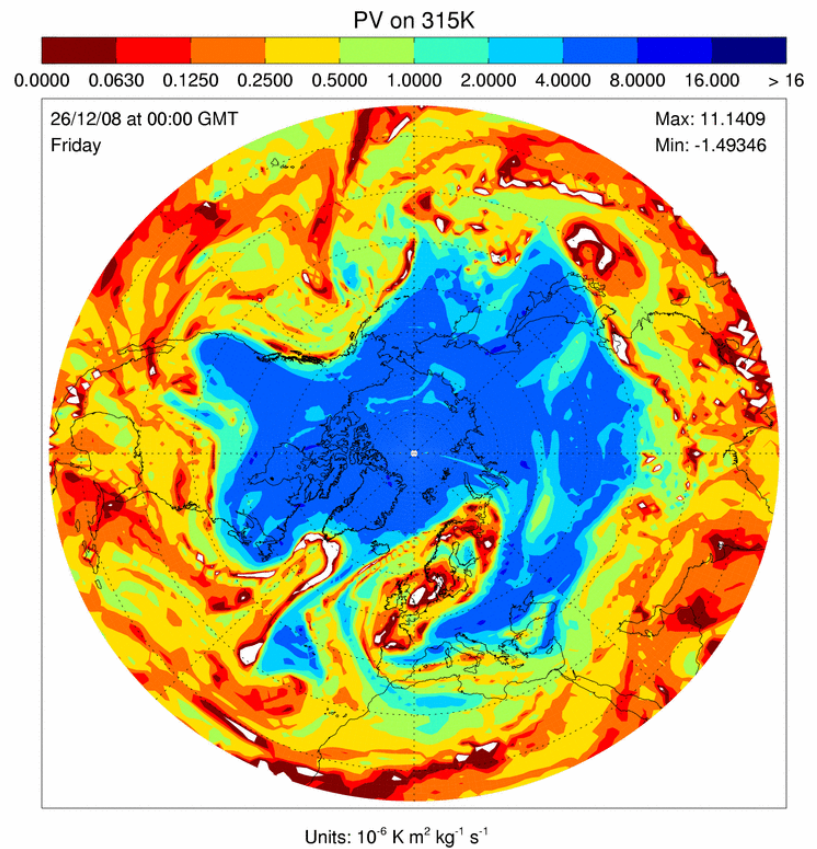


$dx = 40\text{km}$ 25km 10km





**Surface
pressure**

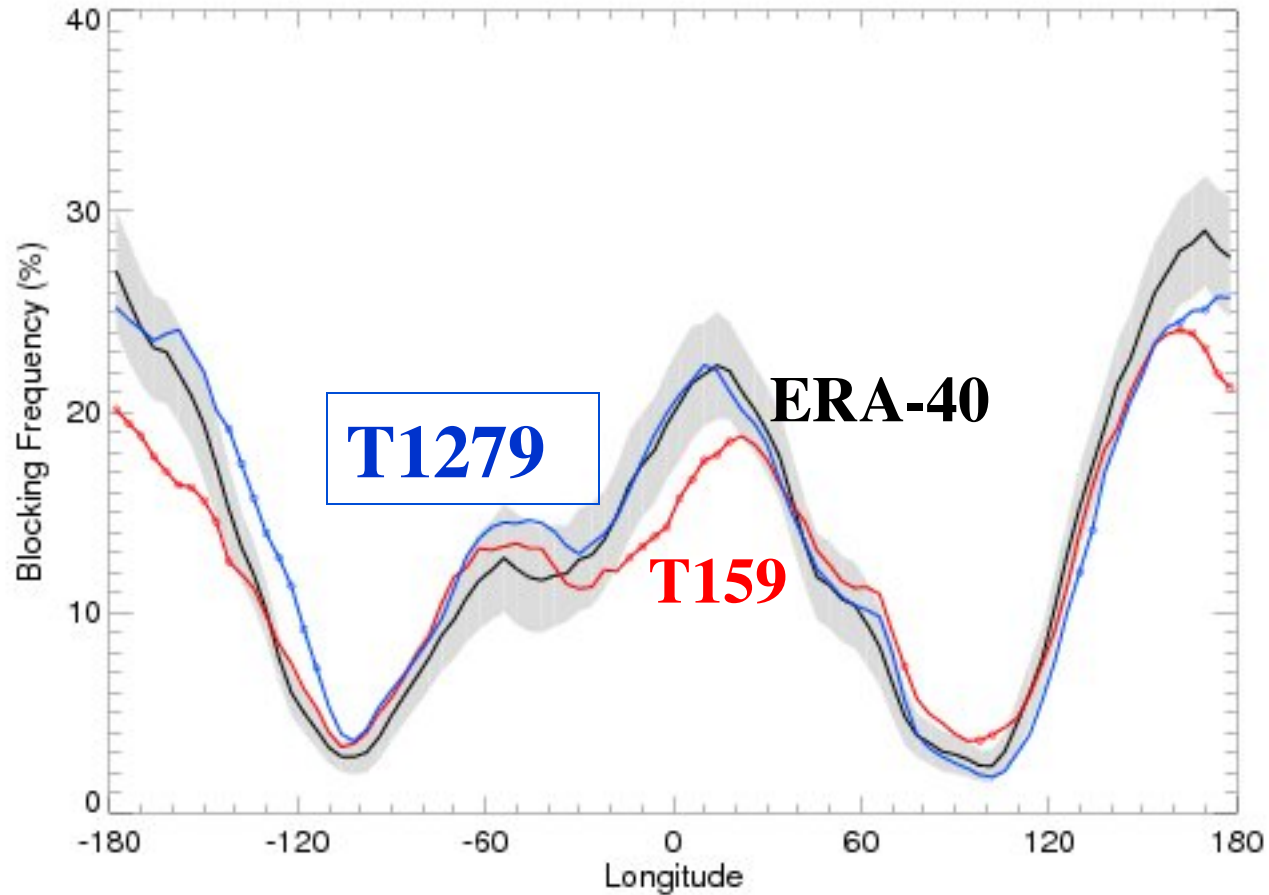


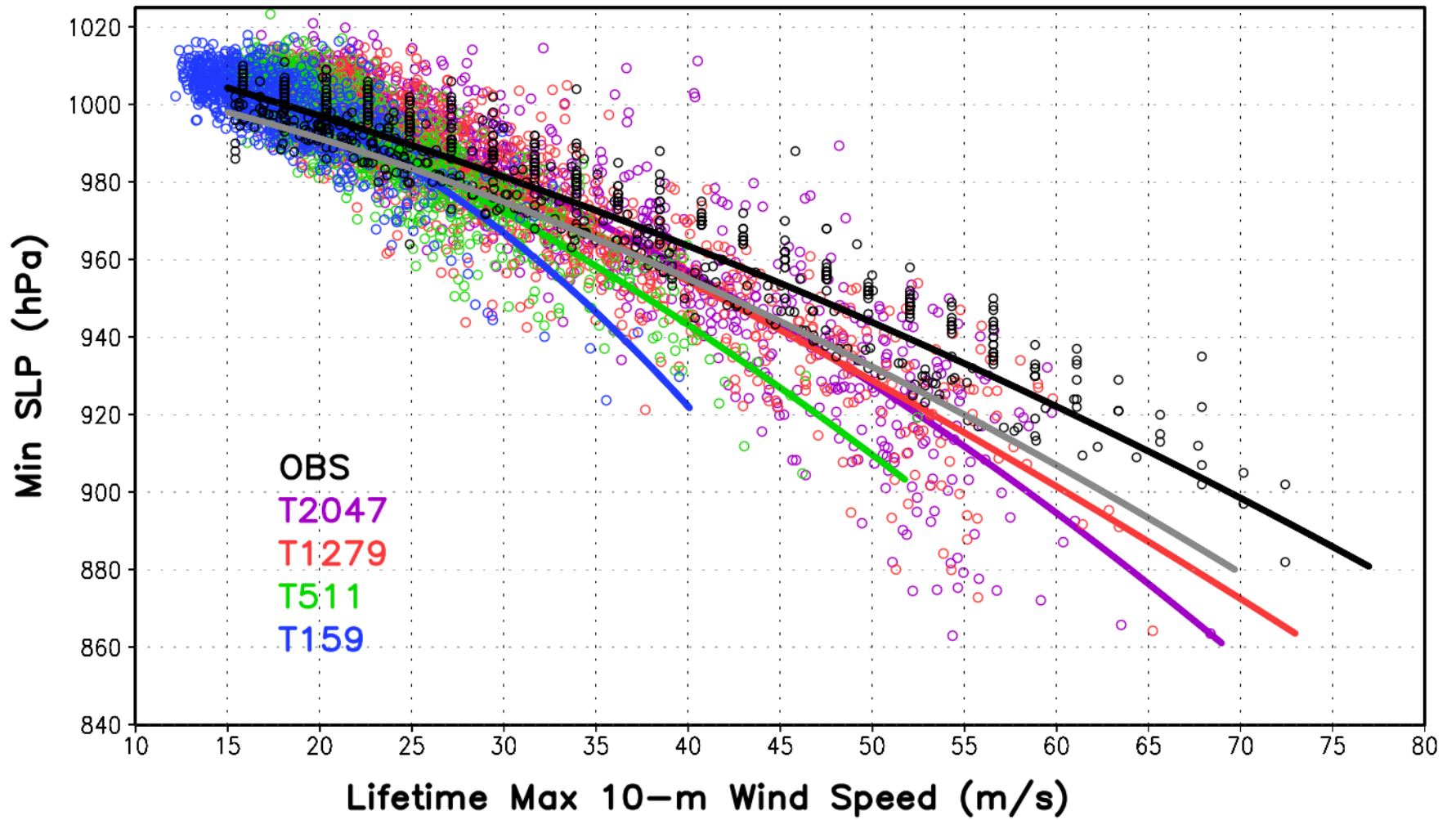
**Potential
Vorticity**

Courtesy of Palmer

Blocking Frequency

Black: Reanalysis (ERA); Red: T 159; Blue: T 1279 (ECMWF)
(Higher Resolution Model Improves Simulation of Blocking Frequency)





Minerva Ensemble Hindcast

SST Mean Bias After 7 Months

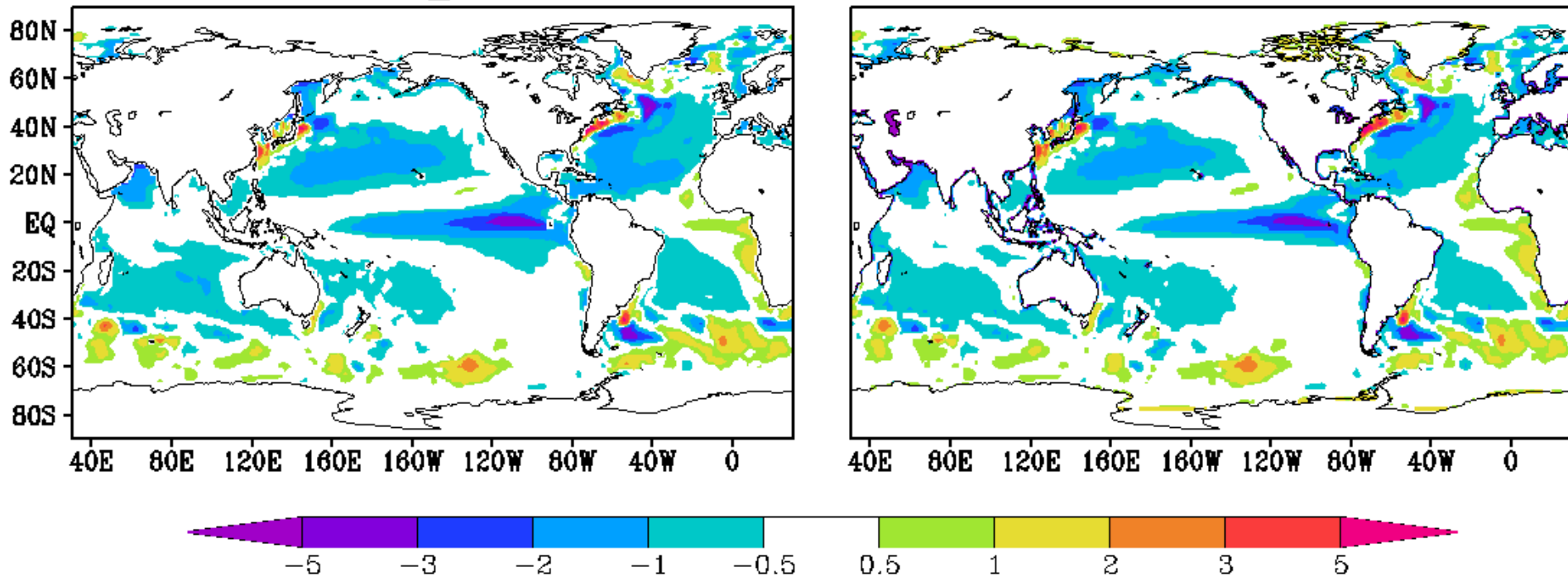
T319

SST Mean Bias: Nov. ICs (1982–2010)
– Leading 7 Months

T639

T319_M15

T639_M15



Increasing Resolution Does Not Necessarily Improve Model Bias

Towards a Hypothetical “Perfect” Model

- Replicate the statistical properties of the past and present observed climate
 - Means, variances, covariances, and patterns of covariability
- Utilize this model to estimate the limits of predicting the sequential evolution of climate variability
- Enhance predictive understanding with iterative process of:
Model development and validation \leftrightarrow Predictability \leftrightarrow Prediction

Predictive Understanding

Prediction Skill and Predictability as a Metric of Understanding

- To enhance predictive understanding, a vigorous, collaborative, and simultaneous effort is needed for **model development, predictability research, and seamless prediction of weather and climate.** Diagnostic evaluation and prediction must be an integral part of model development.
- Advances in NWP did not come by some major theoretical or conceptual breakthrough; it came by comprehensive, persistent, and simultaneous efforts in prediction, model development and predictability research by a team of qualified scientists.

(A similar effort for Dynamical Seasonal Prediction and Climate Change is lacking.)

Challenges

Theoretical:

Enhance predictive understanding of Earth system (seamless weather/climate)

Limits of Predictability (NWP, MJO, ENSO, NAO, PDO, climate change)

Resolving processes explicitly (1 km global models) vs parameterizations

Initialization of coupled climate system

Institutional:

Sustained (10-20 years) computing and staff resources (~ 100 TF; ~ 500 staff)

Exceptional research staff – predictable career path

Effective collaboration – national/international

Education/training of new generation of scientists and software engineers

Management of Resources: (Model Czar vs Adv. Committee)

Fidelity of physical climate simulation vs complexity (biogeo. cycles)

Predictability/prediction of current climate vs future projections

Extremely high-res. short-term simulations vs low resolution long-term

Observational: Inadequate sustained climate observing system

(National efforts focused on IPCC: scenarios; model complexity)

Challenges

Theoretical:

**Enhance predictive understanding of Earth system
(seamless weather/climate)**

Limits of predictability

(NWP, MJO, ENSO, NAO, PDO, droughts, climate change)

Resolving processes explicitly

(1 km global models vs parameterizations)

Initialization of coupled climate system for prediction

Challenges

Institutional:

**Sustained (10-20 years) computing and staff resources
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Observational: Inadequate sustained climate observing system

(National efforts focused on IPCC: scenarios; model complexity)

Challenges (USA)

- To develop multi-agency collaboration **for model development and climate prediction** for the benefit of the US and the global society.
- To enhance the status of climate modeling from “projects” within different labs/centers to a national institution.
- To sustain research on modeling of physical, chemical, and biological processes for **kilometer scale global models**, data assimilation, numerical methods, and adaptive grids etc.

(This will require hardware and software for ~1 million cores and ~1 billion threads, and an appropriate power supply.)

Challenges (USA)

- Are national investments in climate modeling and prediction, including appropriate infrastructure with sufficient computational capacity and critical mass of qualified scientists, commensurate with the impending **threat of global climate change** and the expectations of society?
- Are predictions of regional climate change, including changes in the statistics of extreme events and high-impact weather accurate and reliable enough to develop **adaptation, mitigation, and geoengineering strategies**?

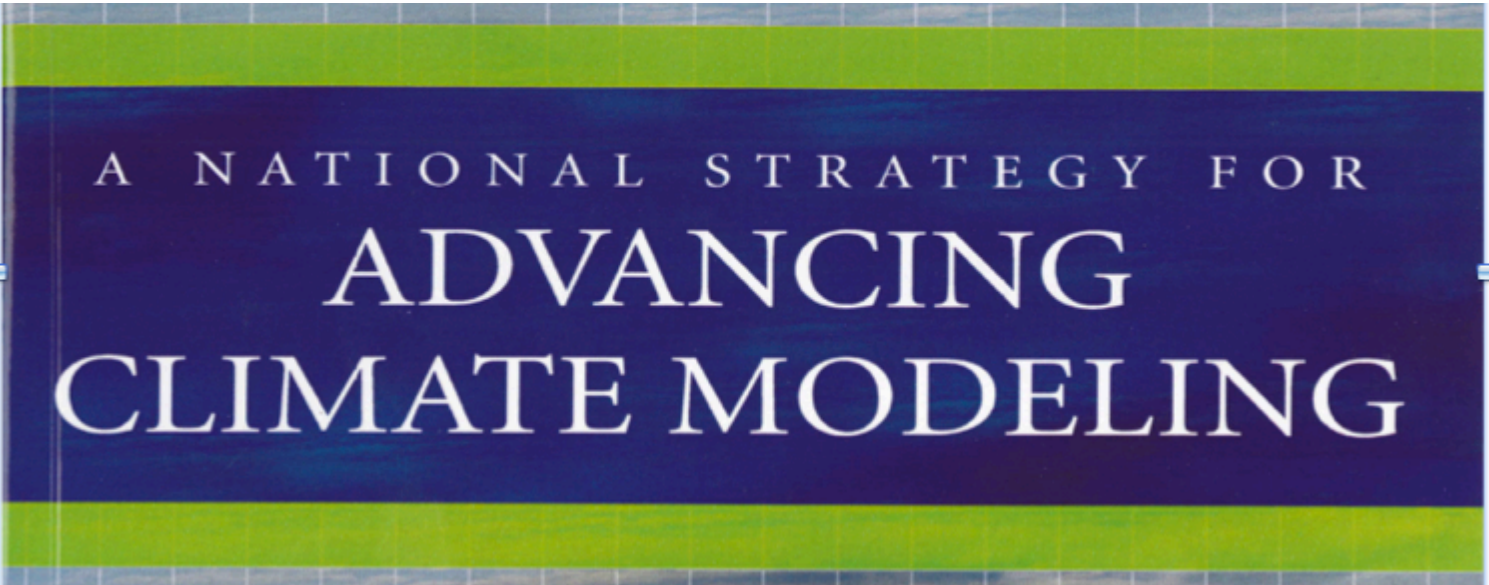
Challenges (USA)

- What should be the relative investments of scientific talent and computing power in building high fidelity models of the physical climate system for **operational weather and climate prediction** versus **running IPCC scenarios** with low resolution and high complexity models?
- How meaningful is the **climate adaptation** research if climate models have large deficiency in simulating regional climate variations (tracks of land falling hurricanes; extreme events)?

A Possible Strategy for the US Climate Modeling

(Inspired by the World Modeling Summit, 2008)

1. In addition to the existing agency based centers, establish a ~100 petaflops national multi-agency computing facility dedicated to climate, accessible to national centers and universities.
2. A distributed multi-institutional model development and data assimilation project for Earth System Prediction.



A NATIONAL STRATEGY FOR
ADVANCING
CLIMATE MODELING

National Research Council 2012

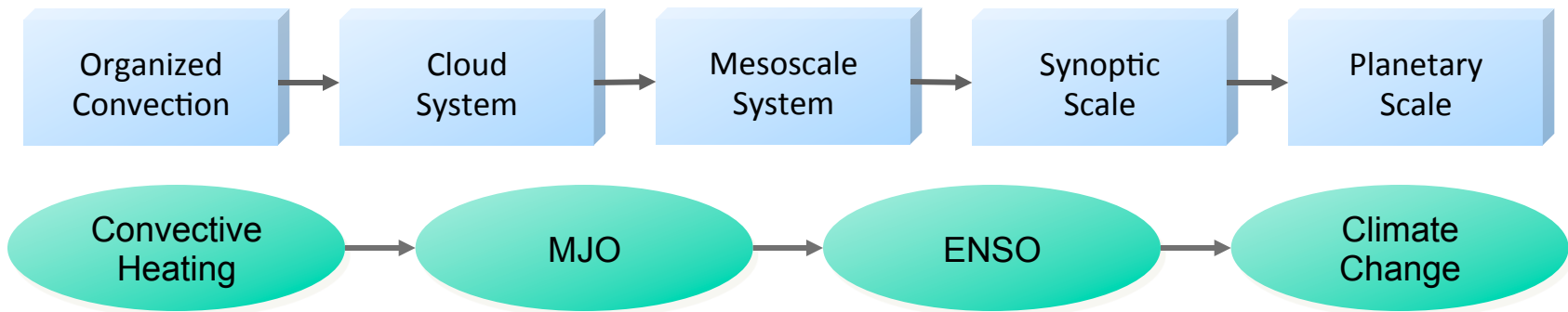
Recommendation 11.1: -----the United States should nurture a unified weather-climate prediction system-----

-----the USGCRP, together with the major national climate and weather modeling institutions, work toward defining a unified modeling strategy-----

Improved operational weather and climate prediction
Optimal utilization of (expensive) space observations
Science based adaptation to climate change

From Cyclone Resolving Global Models to Cloud System Resolving Global Models

1. Planetary Scale Resolving Models (1970~): $\Delta x \sim 500\text{Km}$
2. Cyclone Resolving Models (1980~): $\Delta x \sim 100\text{-}300\text{Km}$
3. Mesoscale Resolving Models (1990~): $\Delta x \sim 10\text{-}30\text{Km}$
4. Cloud System Resolving Models (2000 ~): $\Delta x \sim 3\text{-}5\text{Km}$



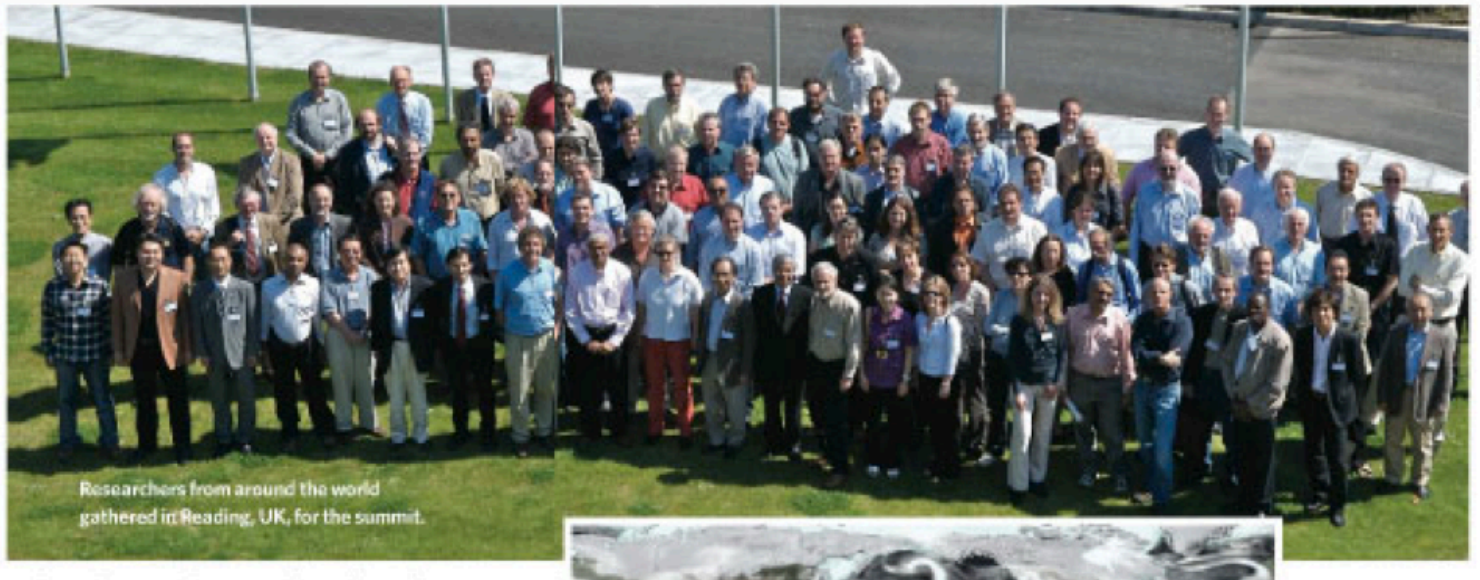
World Modelling Summit, ECMWF (6-9 May 2008).

Participants (~150) from all modelling centers of the world.

They say they want a revolution

Climate scientists call for major new modelling facility.

Article in Nature, May 2008



Examples of Internationally Funded Infrastructures for Advancement of Science

- CERN: European Organization for Nuclear Research ([Geneva, Switzerland](#))
- ITER: International Thermonuclear Experimental Reactor ([Gadarache, France](#))
- ISS: International Space Station ([somewhere in sky..](#))

WHAT ABOUT CLIMATE PREDICTION?

The Hubble Space Telescope was built by the United States space agency NASA, with contributions from the European Space Agency and is operated by the Space Telescope Science Institute.

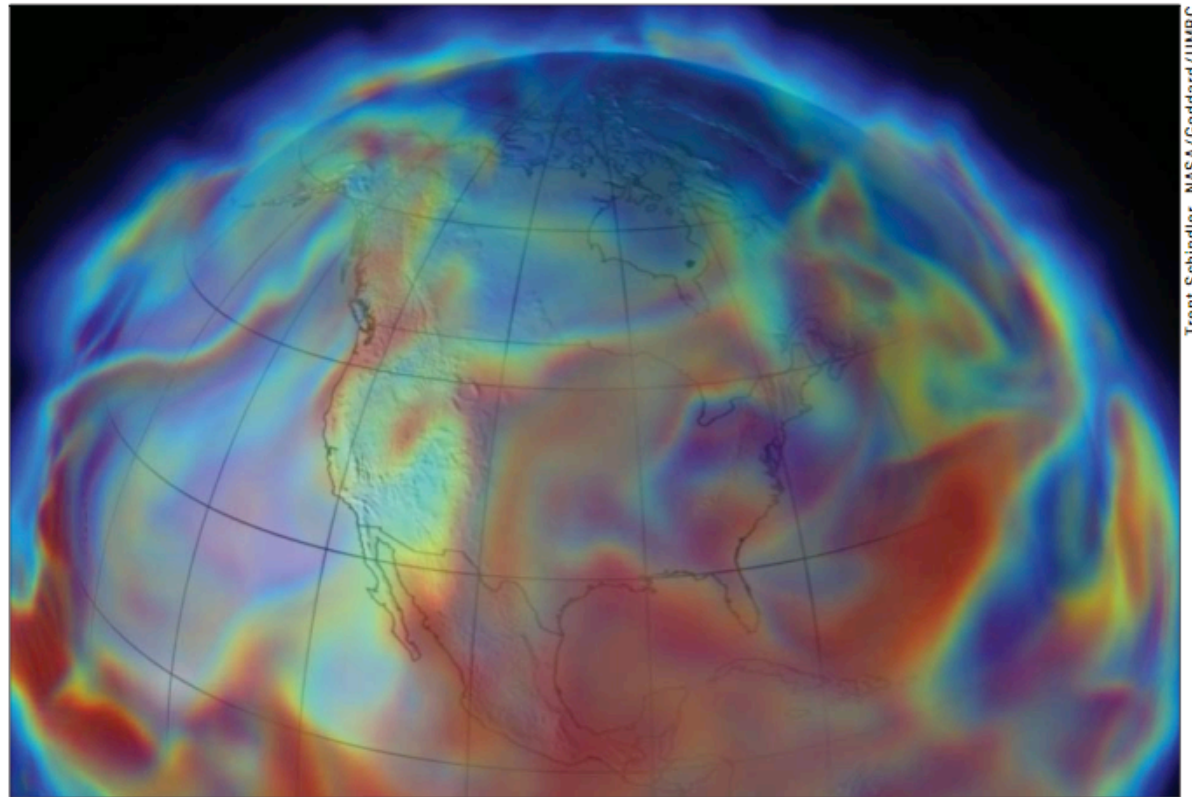


A CERN for climate change?

Providing reliable predictions of the climate requires substantial increases in computing power.

Tim Palmer argues that it is time for a multinational facility fit for studying climate change

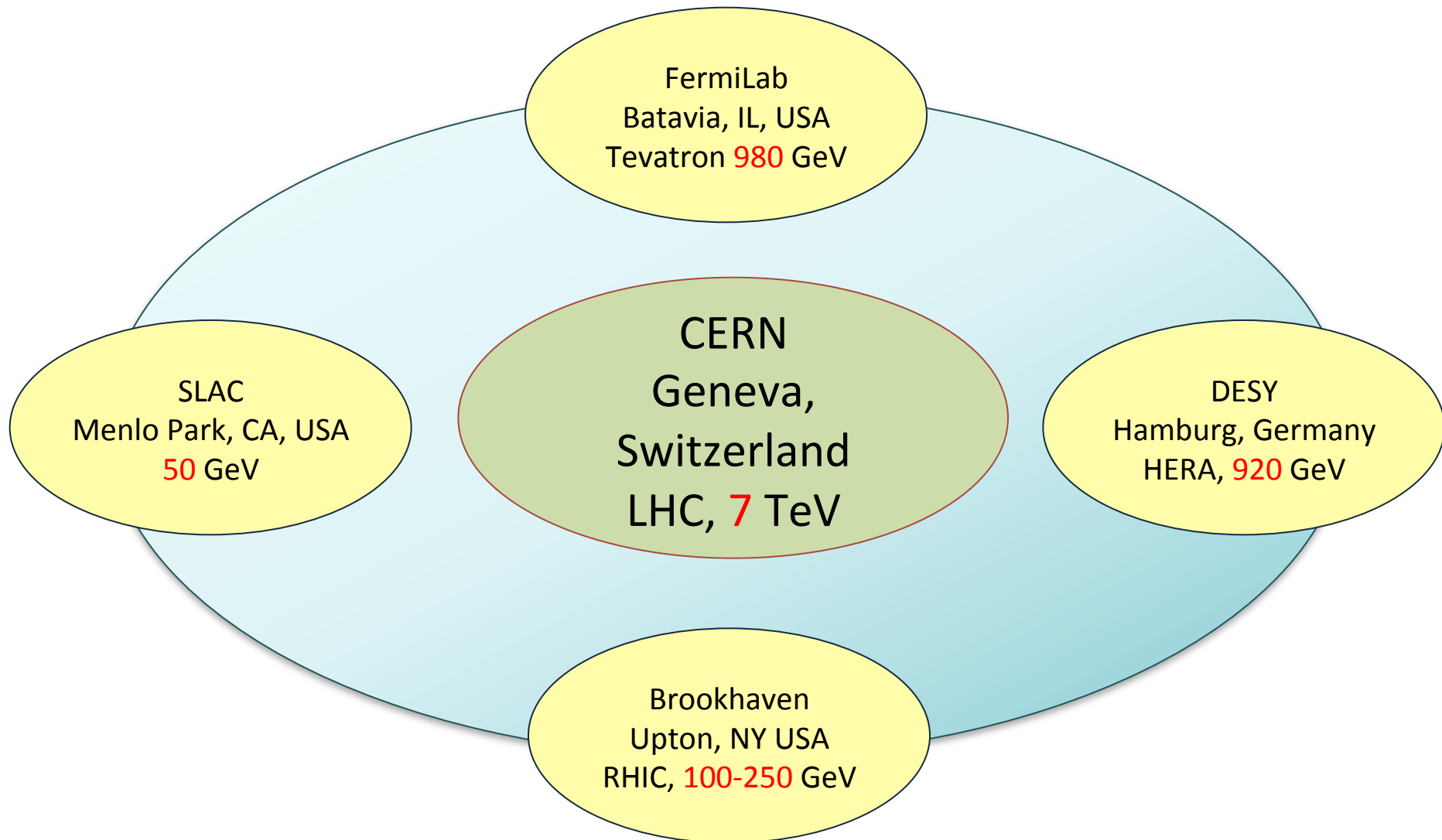
This winter has seen unprecedented levels of travel chaos across Europe and the US. In particular, the UK experienced the coldest December temperatures on record, with snow and ice causing many airports to close. Indeed, George Osborne, the UK's Chancellor of the Exchequer, attributed the country's declining economy in the last quarter of 2010 to this bad weather. A perfectly sensible question to ask is whether this type of weather will become more likely under climate change? Good question, but the trouble is we do not know the answer with any great confidence.



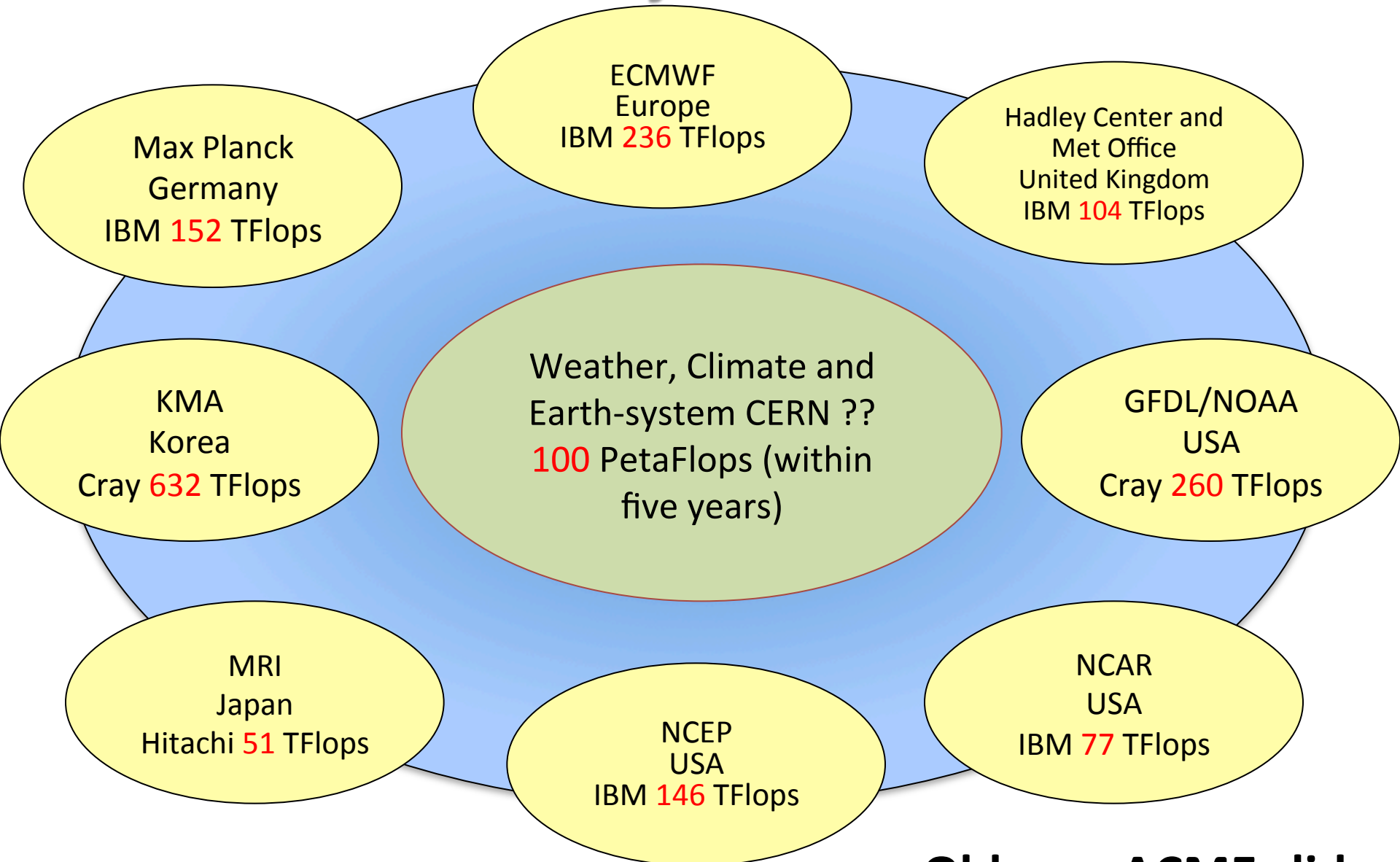
A global approach to a global problem Modelling the climate may require a unified strategy for computing.

In **Physics World** by Tim Palmer

Particle Accelerators for High Energy Physics Research



Supercomputers for Weather, Climate and Earth-System Research



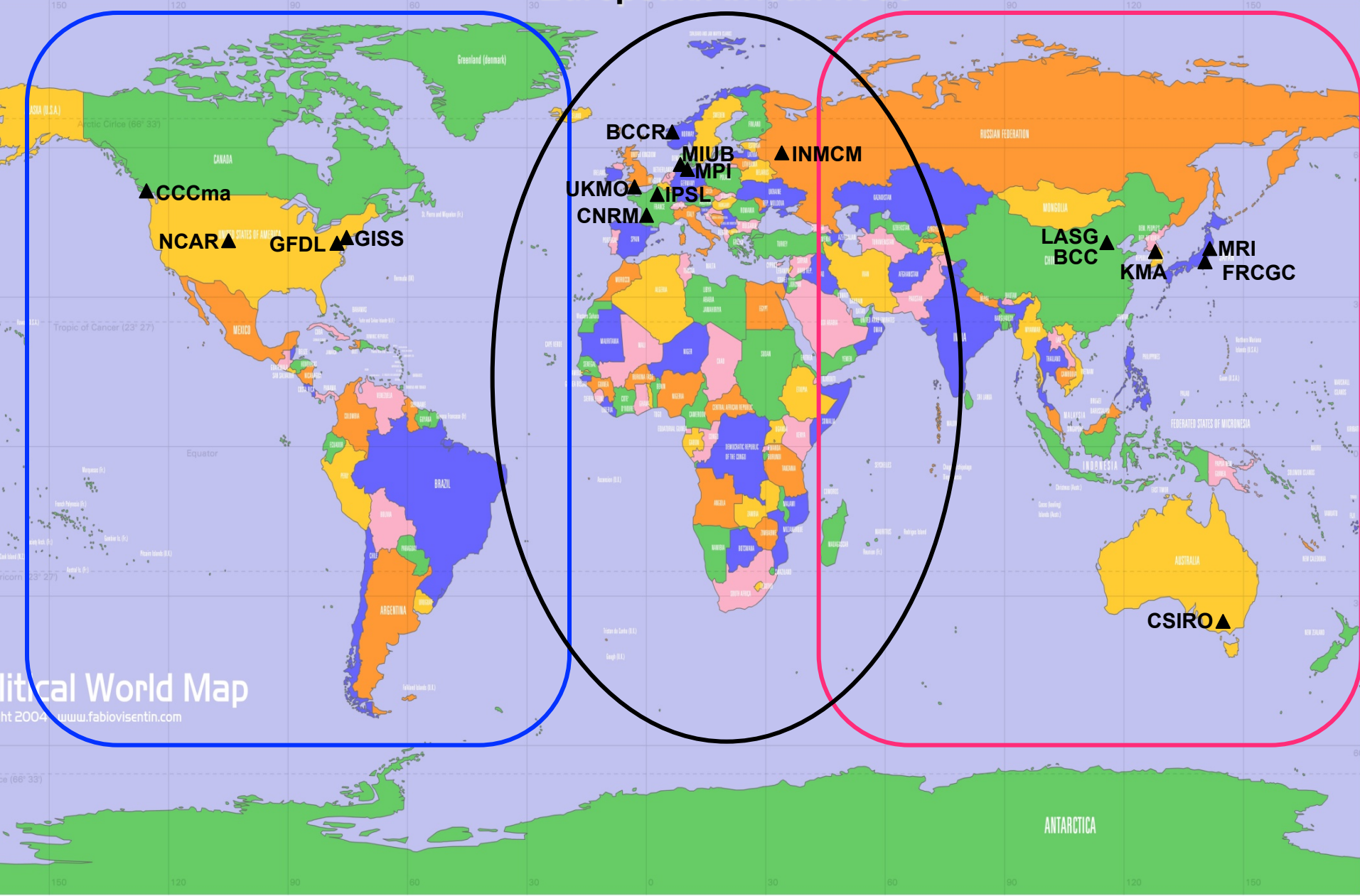
Old, pre-ACME slide

Scientific/Political Domains of Climate Modeling Facilities

American node

European/African node

Asian/Australian node



Summary

- In spite of the $k^{-5/3}$ spectrum, NWP history (~40 years) suggests: Higher resolution models, improved physical parameterizations, and data assimilation techniques reduced initial errors, and increased the range of predictability.
- 35 years ago, Dynamical Seasonal Prediction (DSP) was not conceivable; DSP has achieved a level of skill that is considered useful for some societal applications. However, such successes are limited to periods of large, persistent SST anomalies.
- There is significant unrealized seasonal predictability.

Summary

- The most dominant **obstacle** in realizing the potential predictability of short-term climate variations is **inaccurate models**, and unbalanced initial conditions rather than an intrinsic limit of predictability.

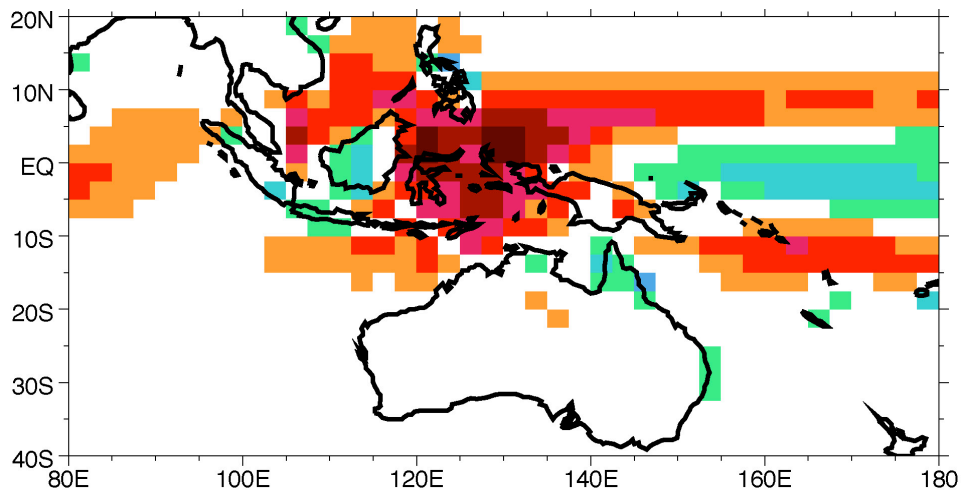
(Models with higher fidelity have higher prediction skill.)

- A multi-institutional (multinational) enhanced research effort and computational infrastructure is needed to develop the next generation of **high fidelity** climate models for **improved climate predictions**, utilization of **space observations**, and to suggest policies and strategies for **adaptation and mitigation**.

THANK YOU!

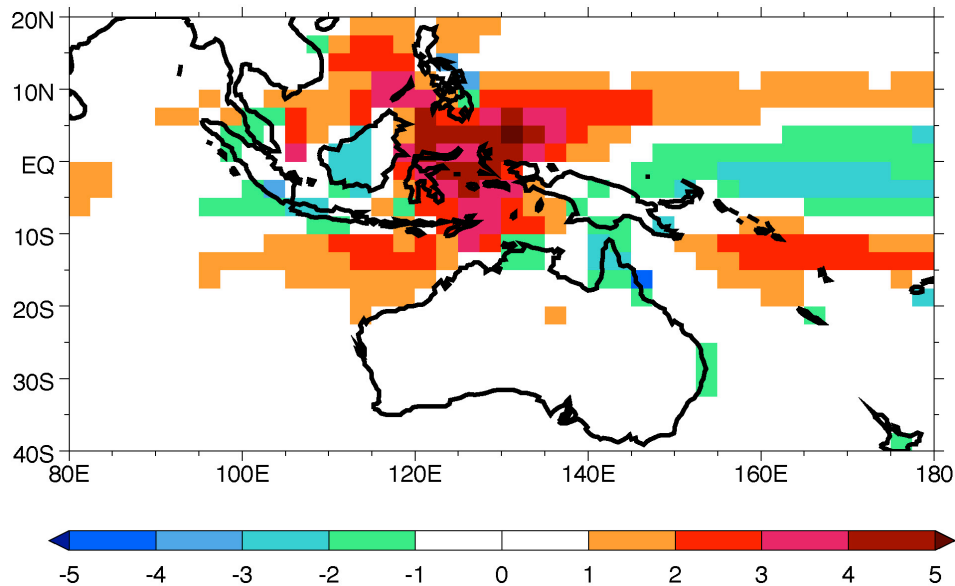
ANY QUESTIONS?

CMIP3 MMM – GPCP



DJF - Precipitation

CMIP5 MMM – GPCP



Positive errors over South China Sea and
Maritime Continent persist throughout the
Annual Cycle

(Sperber, Annamalai et al. 2013)
(Courtesy Annamalai)

“US Climate Modeling”

(Climate Research Committee, 1998 NRC)

“USGCRP [US Global Change Research Program] agencies do not have a coordinated approach (to climate modeling).”

“There are few monetary resources dedicated to high-end climate modeling.”

“A concentrated effort by the relevant agencies is needed to establish a coordinated national strategy for climate modeling.”

“Improving the Effectiveness of US Climate Modeling” (Climate Research Committee, 2001 NRC)

“The panel concluded that the present research infrastructure spread among many research agencies, each operating in its own interests according to its own culture, is not capable of responding to the modeling demands of regular assessment and prediction, nor is the management structure of USGCRP able to instill such a culture ...”

“The climate modeling community faces a severe shortage of qualified technical and scientific staff members.”

“Restructuring Federal Climate Research to Meet the Challenges of Climate Change” (NRC Report, 2009)

“Develop the science base and infrastructure to support a new generation of coupled Earth system models to improve attribution and prediction of high-impact regional weather and climate ...”

Physicists can get away with this!

“Paradoxically, the failures in simulations are evidence for solid scientific success: Modeling has progressed to the state where it can be wrong!”

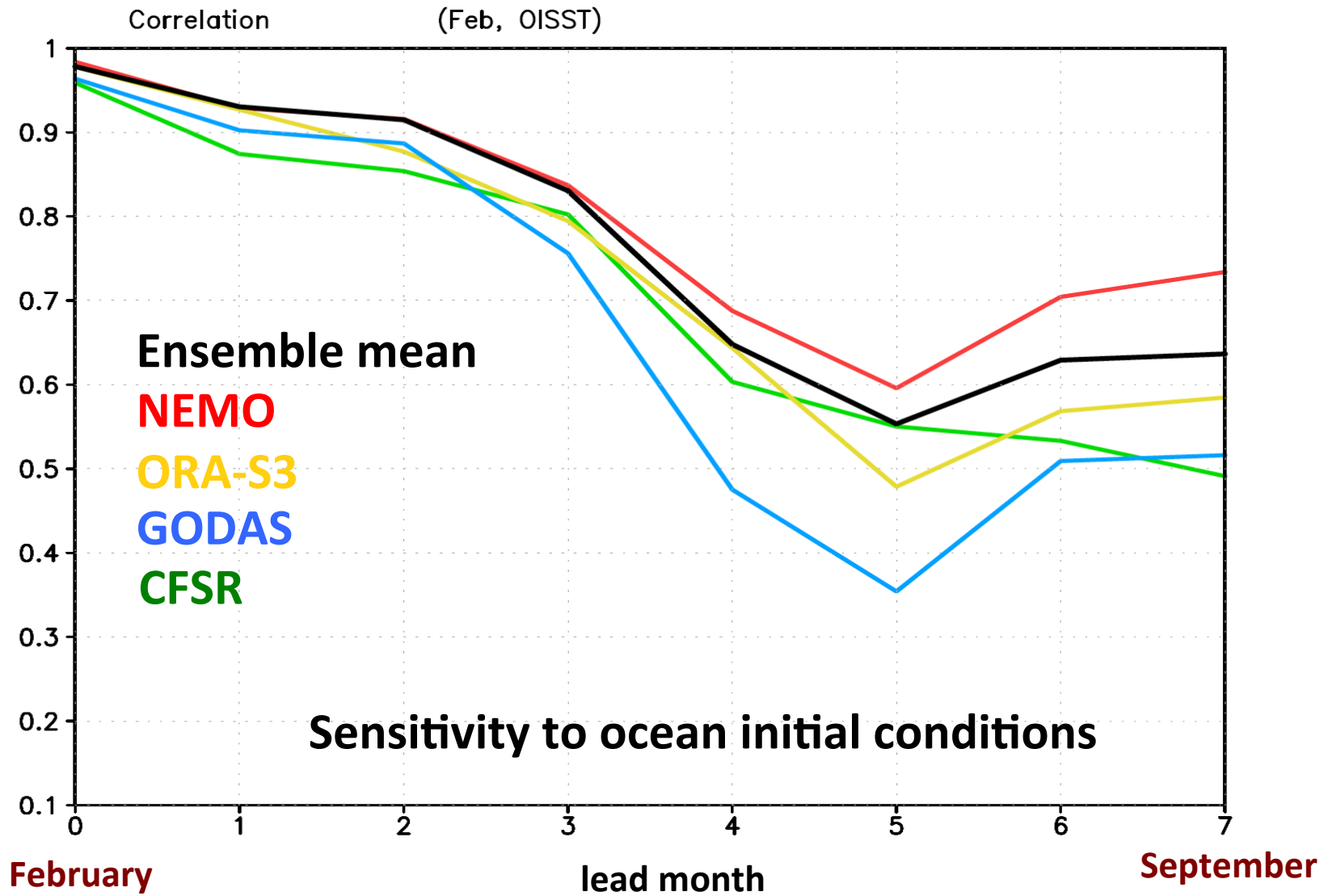
Theoretical Challenges in Understanding Galaxy Evolution: Simulations of Dark Matter Structure;

Jeremiah P. Ostriker and Thorsten Naab, August 2012 (Physics Today, pp. 43 - 49)

Summary (2)

- 1. An unforced, multidecadal SST pattern can explain major multi-decadal fluctuations in global mean temperature in the 20th century.**
- 2. Decadal warming trends of 0.1K/decade are significant and uniform in the 20th century; the decadal cooling trends are not statistically significant.**

CFSv2 Prediction skill of Nino3.4 SSTA (1982-2008)



Multi-ocean analysis ensemble initialization (Zhu et al. 2012; 2013)

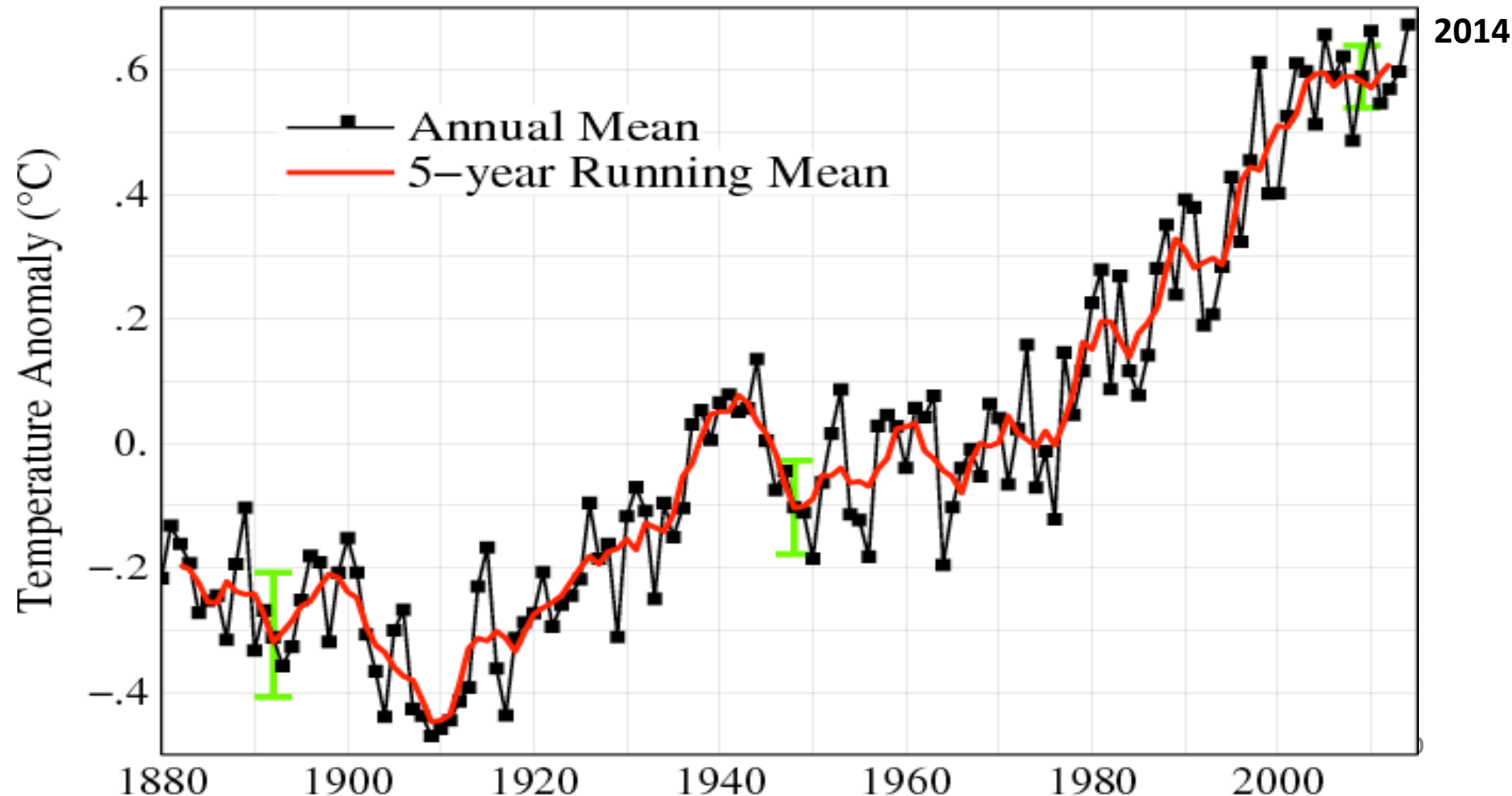
Global Warming Hiatus?

Global Land-Ocean Temperature (1880-2014)

Relative to
1951-1980 mean

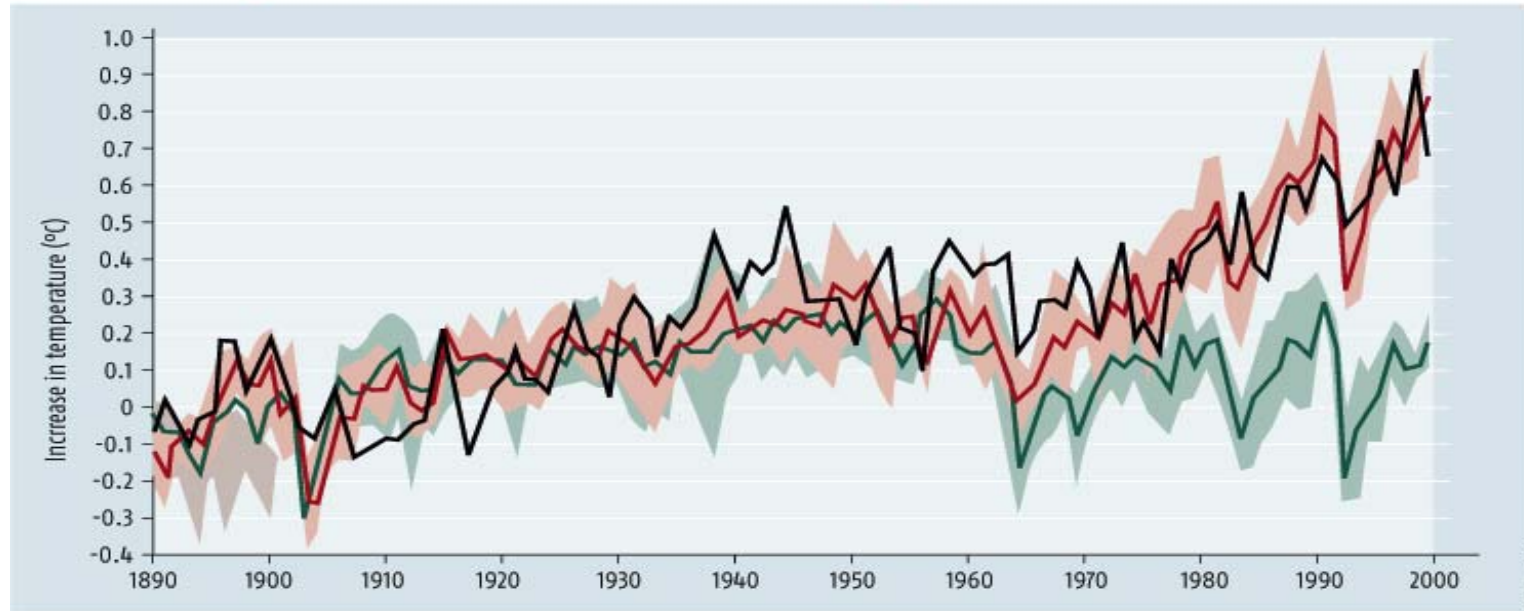
(GISS, New York)

Global Land–Ocean Temperature Index

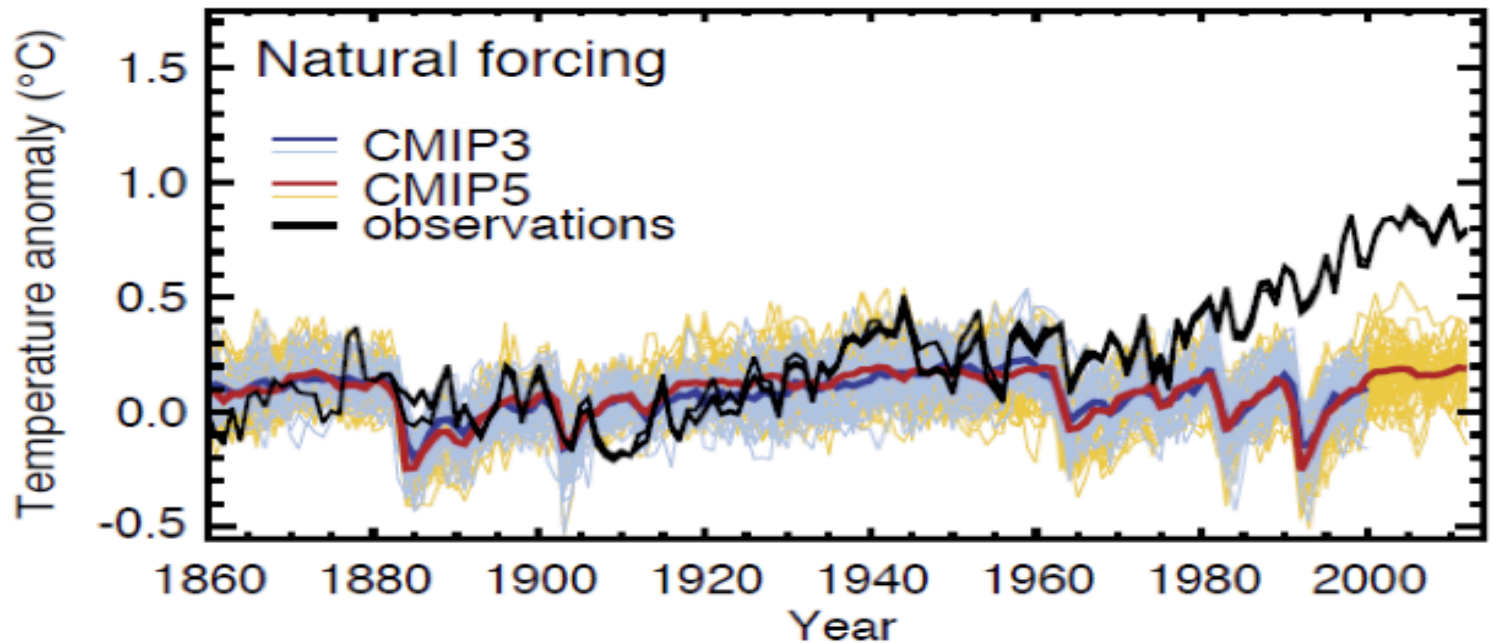


Natural Forcing Cannot Explain Obs. Global Temp. Trend

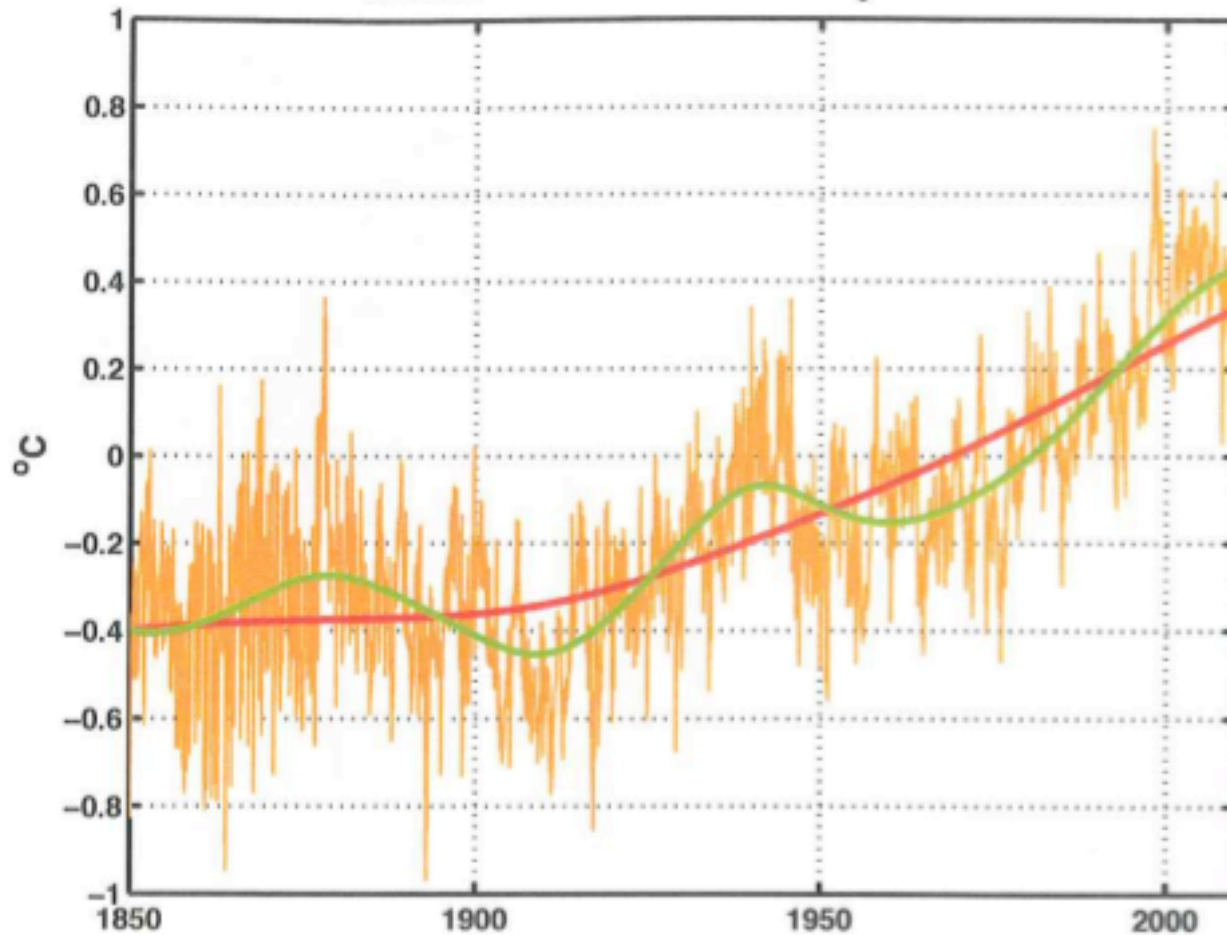
IPCC 2007



IPCC 2013



Global-mean Surface Temperature

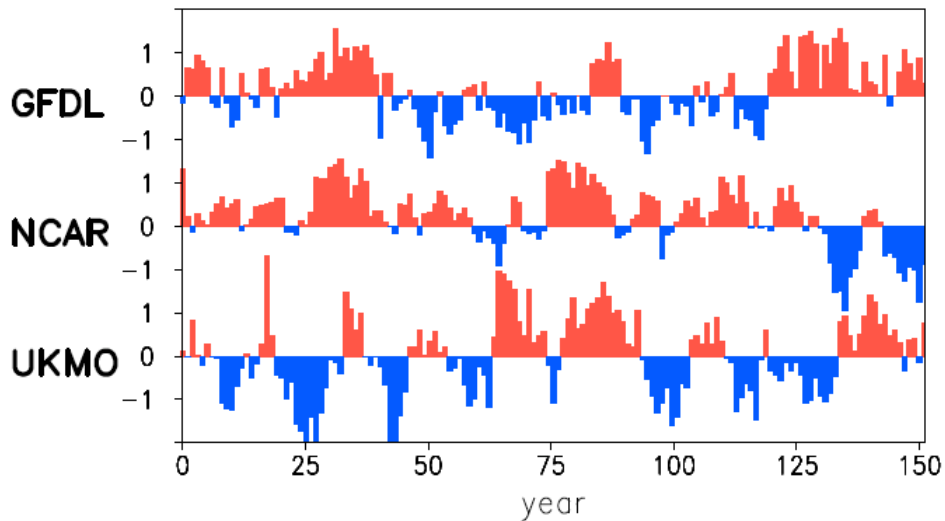
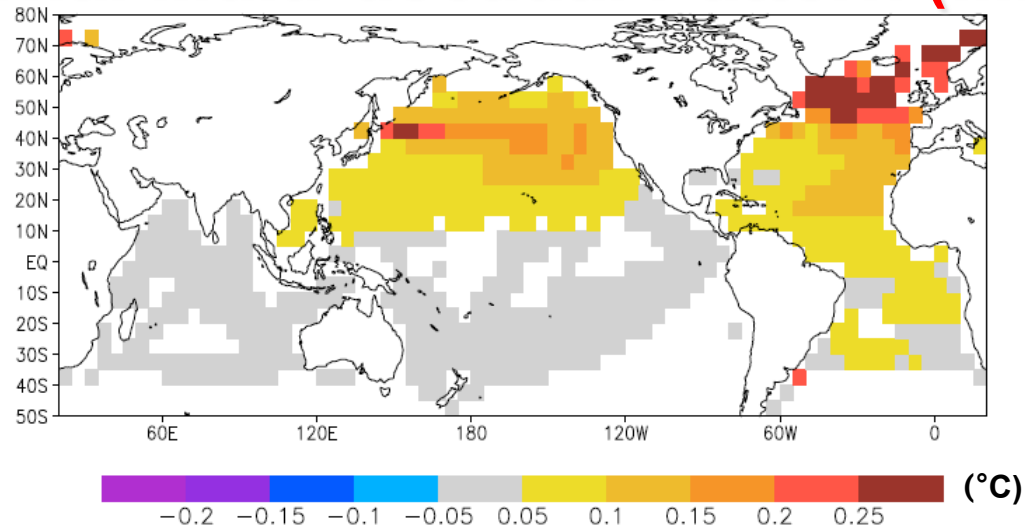


**On the Time-Varying Trend in Global-Mean Surface Temperature
by Huang, Wu, Wallace, Smoliak, Chen, Tucker**

EEMD: Ensemble Empirical Mode Decomposition; MDV: Multi Decadal Variability

Figure 4: Reconstruction of the raw GST time series (brown lines) using ST only (red lines) and ST + MDV (green lines).

Leading Predictable Component (APT): Internal Multi-decadal Pattern (IMP)



A Hypothetical Physical Climate System Model Development Team

Atmosphere

- Dynamical core – 5
- Radiation (clear and cloudy) – 8
- Boundary Layer – 5
- Shallow Convection – 5
- Deep Convection – 10
- Stratosphere – 5
- Cloud Processes – 5

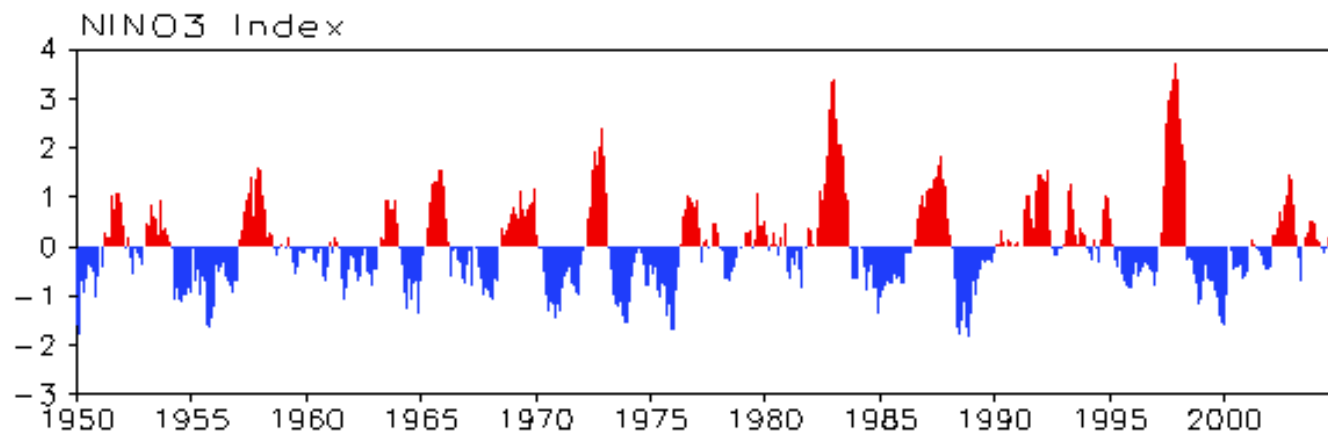
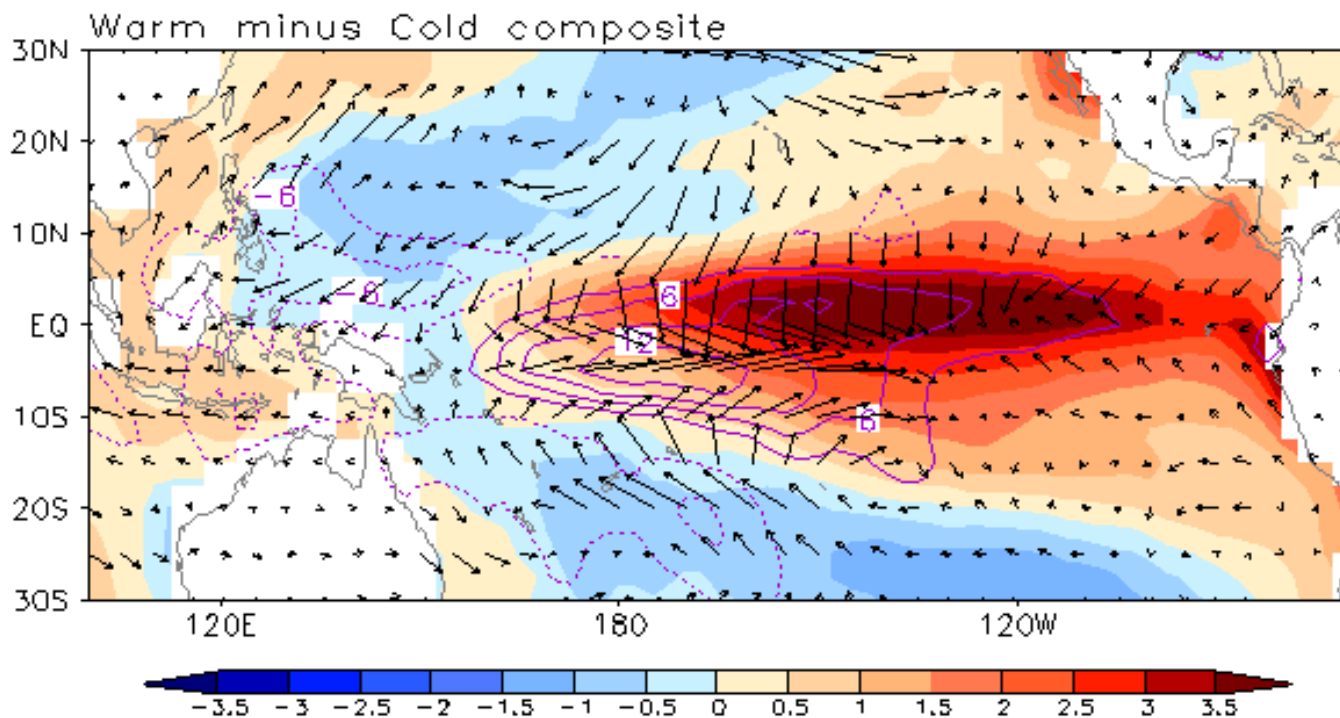
Ocean

- Dynamical Core – 5
- Mixing – 5
- Ocean Eddies – 5
- Boundary Currents – 5
- Ocean-Atmosphere Interaction – 10

Land and Cryosphere

- Soil & Soil Moisture – 5
- Vegetation – 5
- Ground and Subsurface Water – 5

El Nino/Southern Oscillation



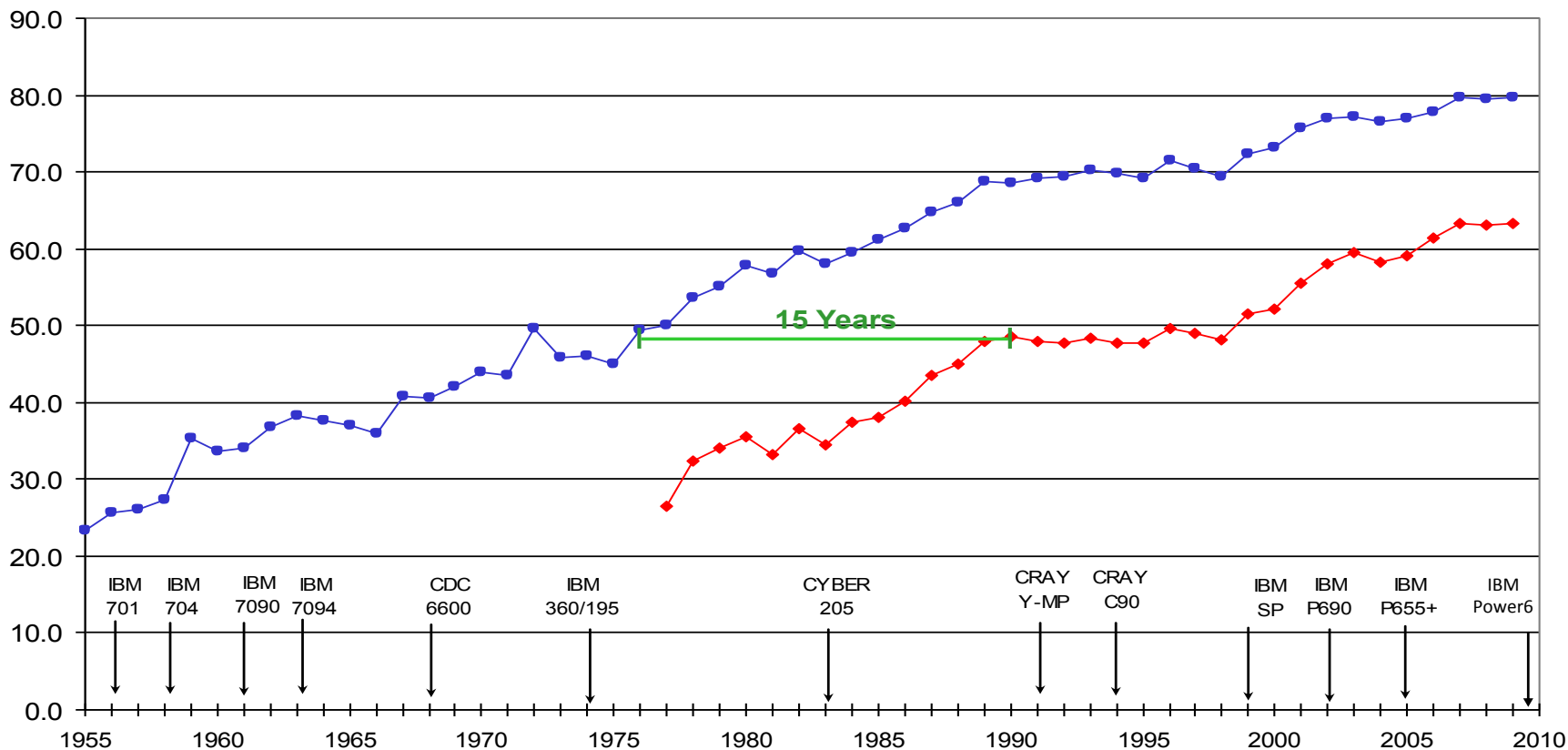


NCEP Operational Forecast Skill

36 and 72 Hour Forecasts @ 500 MB over North America

[100 * (1-S1/70) Method]

—●— 36 Hour Forecast —◆— 72 Hour Forecast



NCEP Central Operations/SIB January 2010



Predictability of ENSO and Monsoon

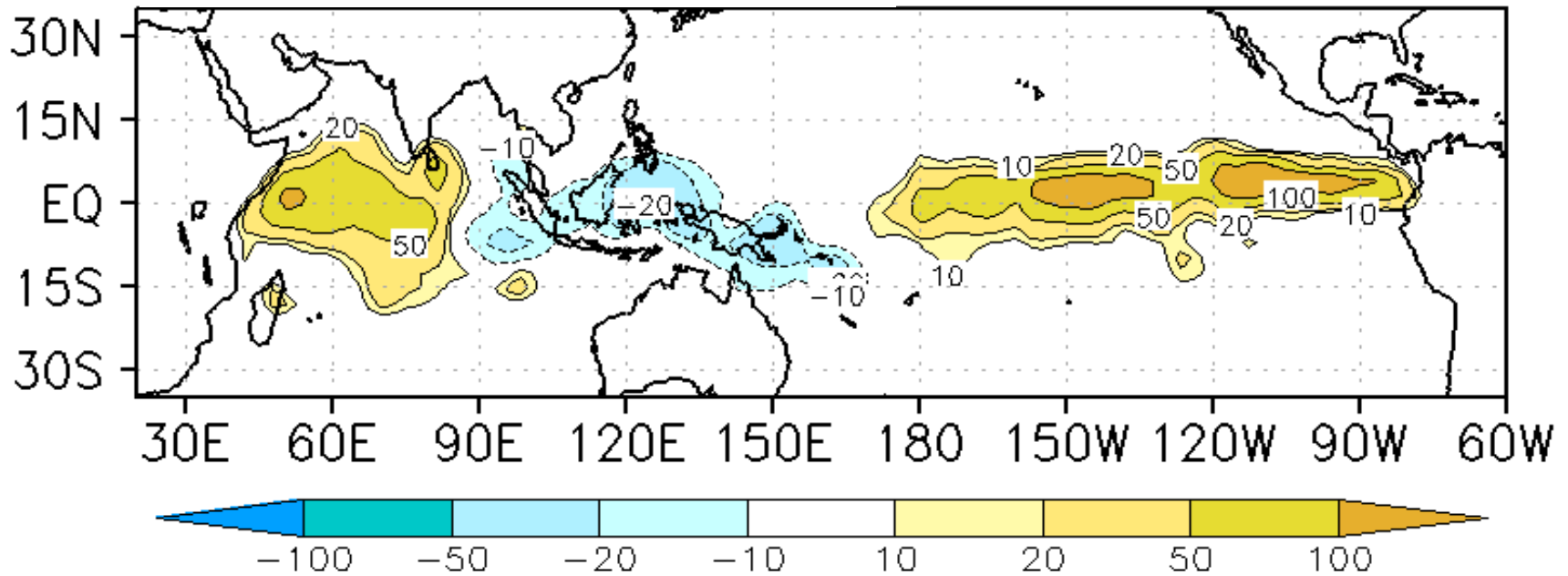
Estimates of predictability using:

- Analysis of Variance
- Classical (a la Lorenz) initial error growth

show high predictability;

Yet, prediction skills are quite low.

1997 Diabatic Heating Anomaly (W/m^2) (Based on Observations)



Challenges

(for Predictive Understanding)

Conceptual/Theoretical: ENSO an unstable oscillator or stochastically forced, damped linear system? (50 years of data support both)

Modeling: Climate models have huge systematic errors; unable to simulate variances and co-variances (**unable to simulate annual cycle**)

Observational: Inadequate sustained ocean observing system

Initialization: Lack of coupled ocean-atmosphere initialization

Computational: Unable to resolve organized convection

(National efforts focused on IPCC: scenarios; model complexity)

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

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

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

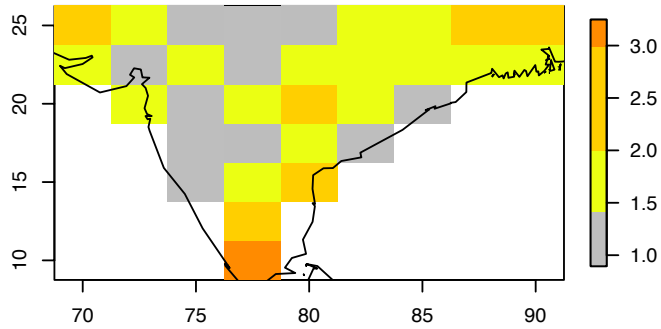
$$\hat{\sigma}_N^2 = \frac{1}{Y(E-1)} \sum_{y=1}^Y \sum_{e=1}^E (P_{y,e} - \bar{P}_y)^2$$

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

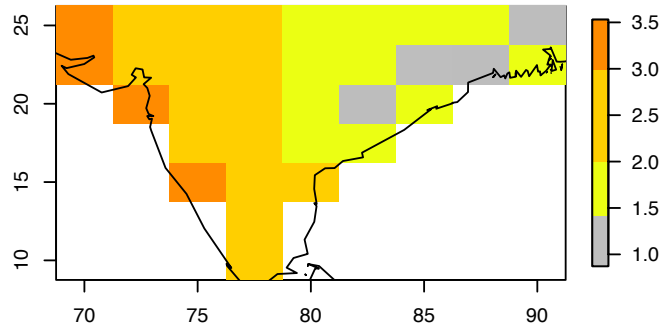
$$\bar{\bar{P}} = \frac{1}{Y} \sum_{y=1}^Y \bar{P}_y$$

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

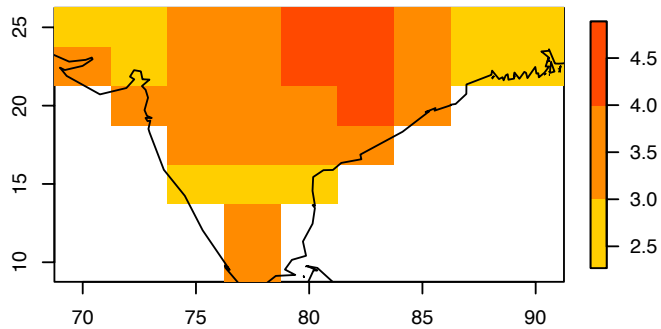
F for JJAS Precip in ECMWF



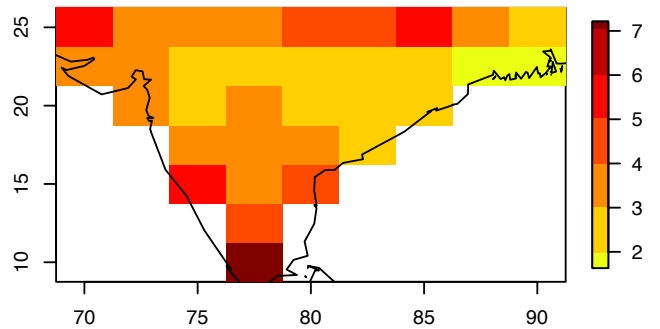
F for JJAS Precip in IFM-GEOMAR



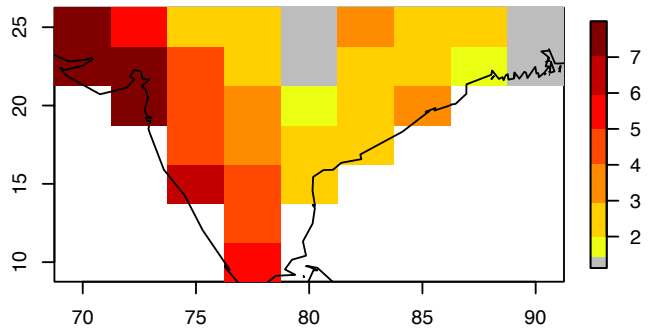
F for JJAS Precip in Meteo-France



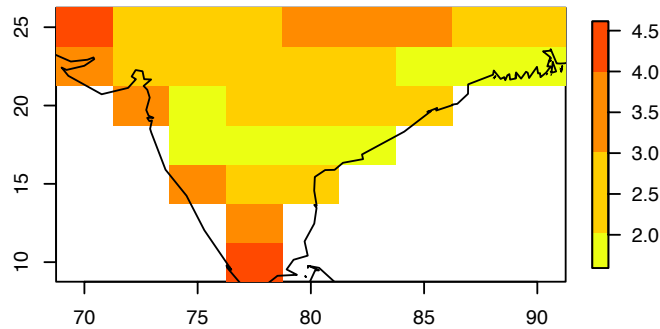
F for JJAS Precip in UK Met Office



F for JJAS Precip in CMCC-Bologna



F for JJAS Precip in Multi-model Anomaly



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.