17 Mar 2011, Dept. of Atmospheric and Oceanic Science
Univ. of Maryland, Seminar

It is Necessary to Revolutionize Climate Prediction: Is it Possible?

Jagadish Shukla

Department of Atmospheric, Oceanic and Earth Sciences (AOES),
George Mason University (GMU)
COLA/Institute of Global Environment and Society (IGES)

IGES

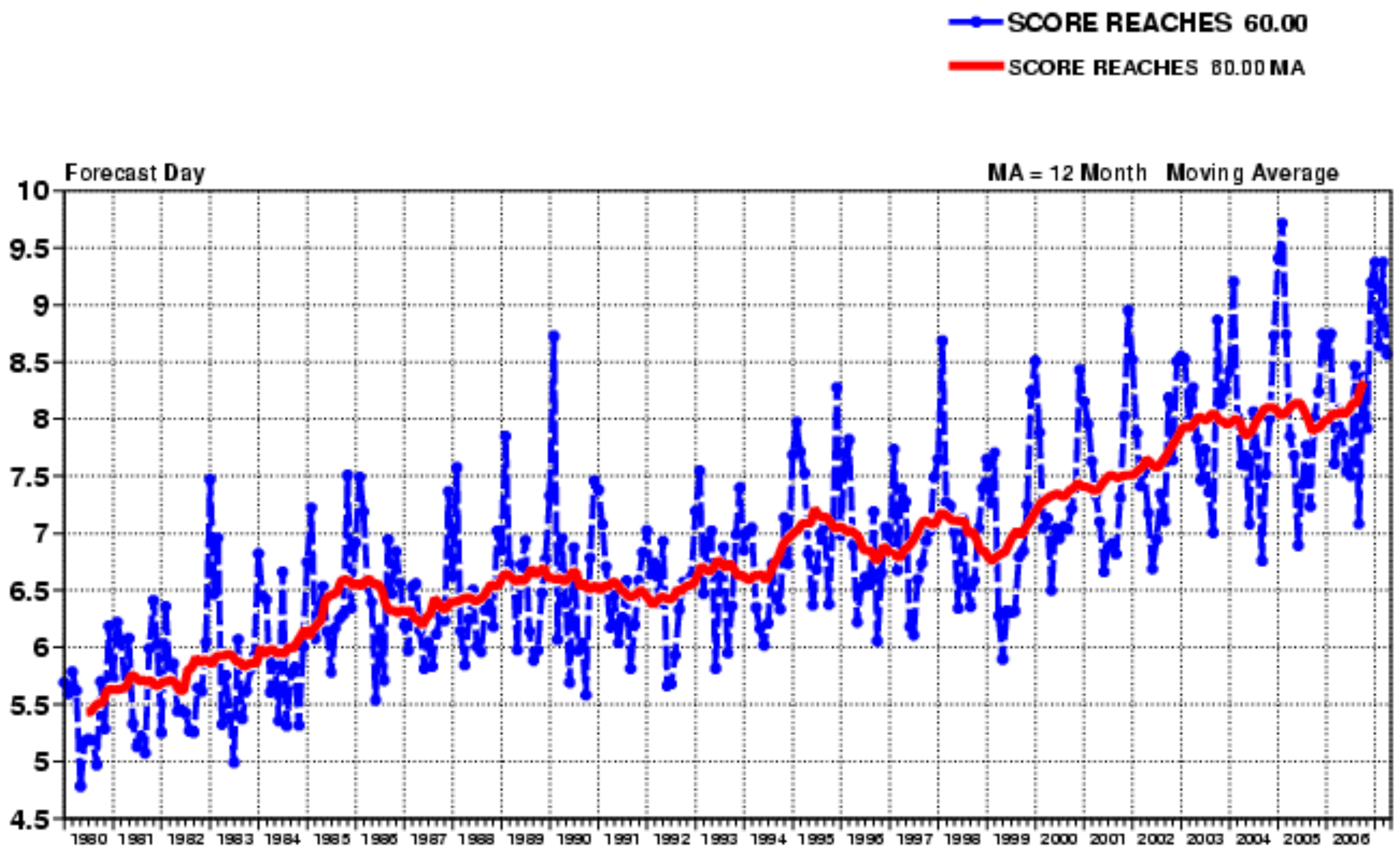
Center of Ocean-Land-Atmosphere studies COLA

CREW Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N



IGES

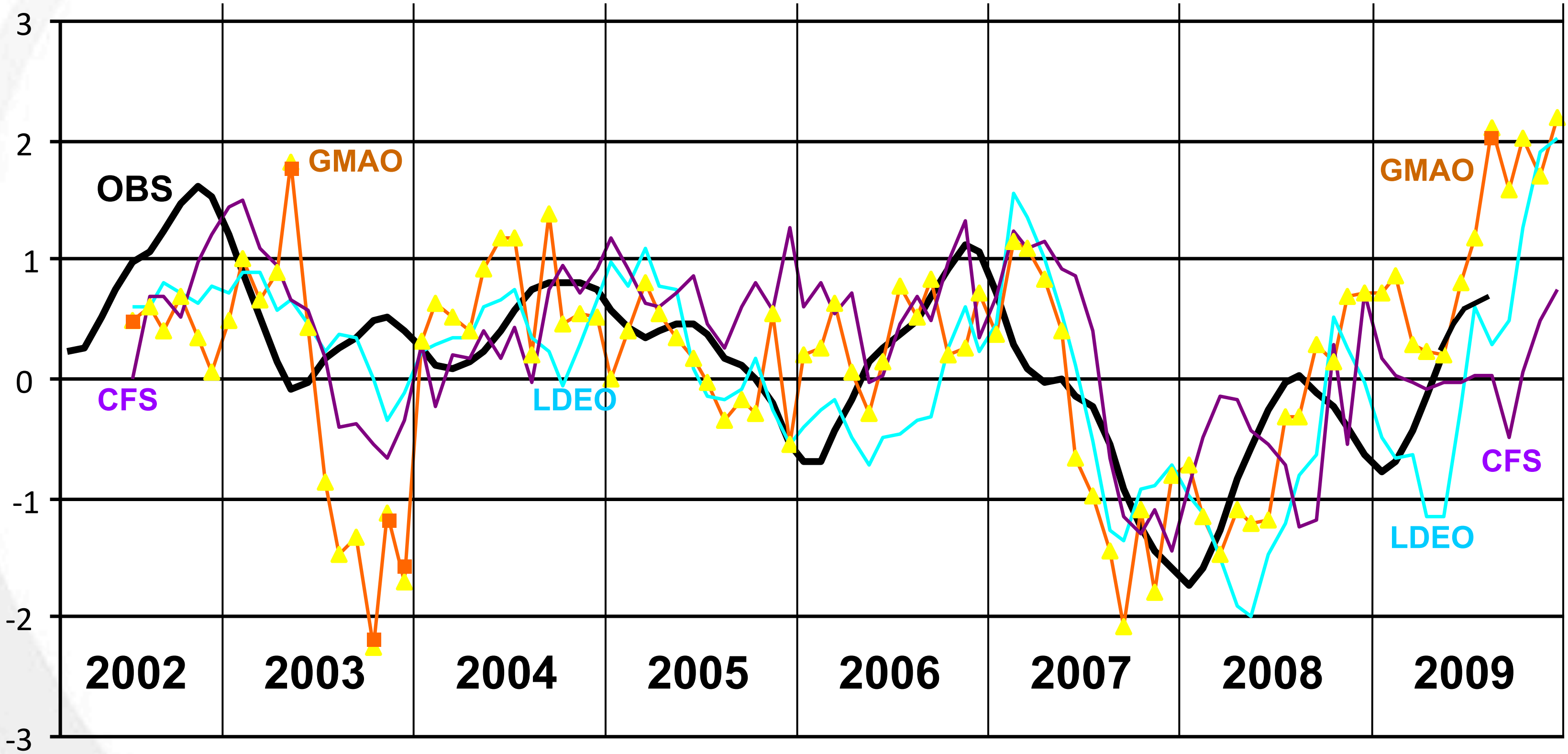
Center of Ocean-Land-Atmosphere studies

COLA

CREW
Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

Selected Dynamical Models, 5-month lead

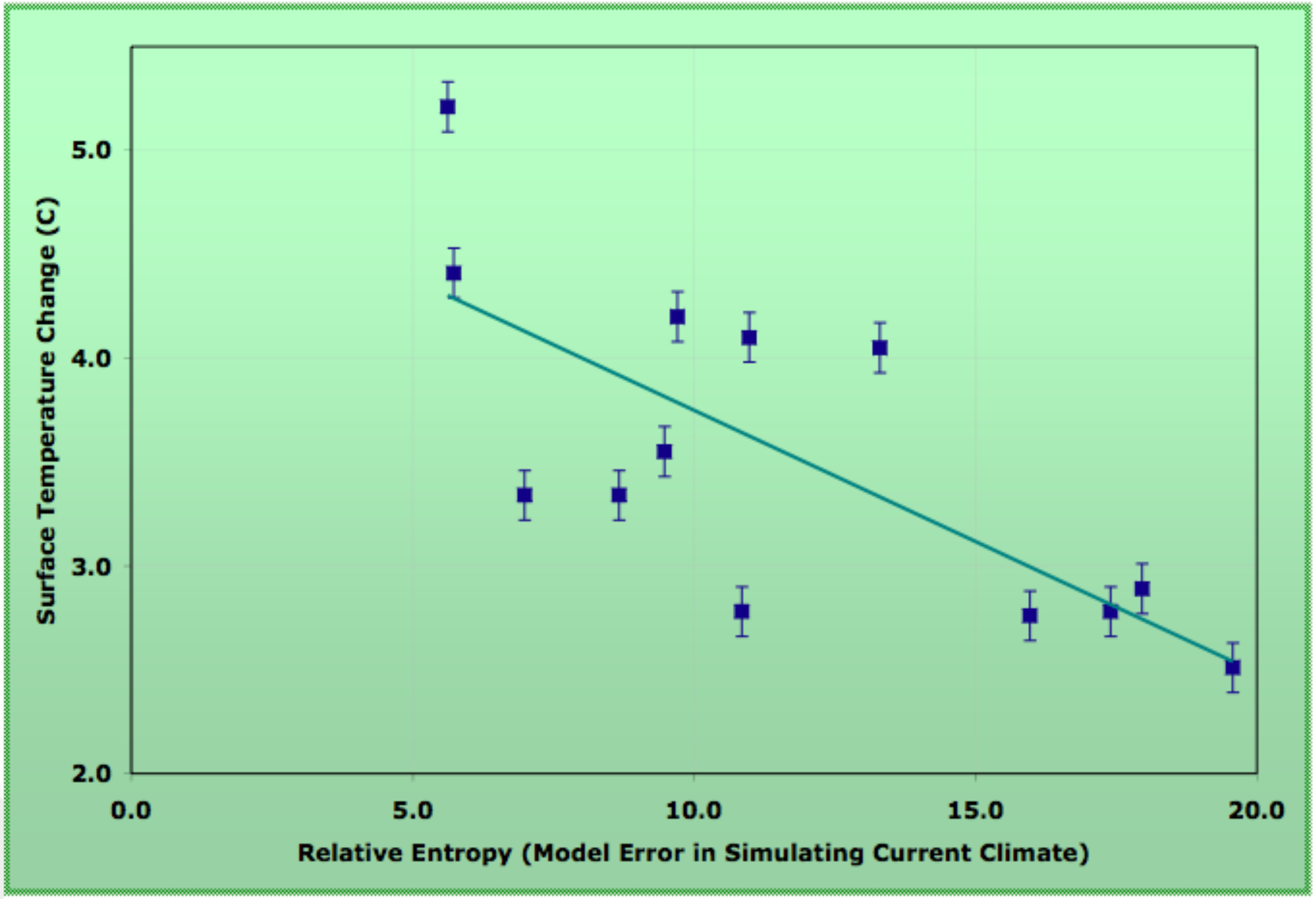


Tony Barnston and Mike Tippett

Climate Model Fidelity and Projections of Climate Change

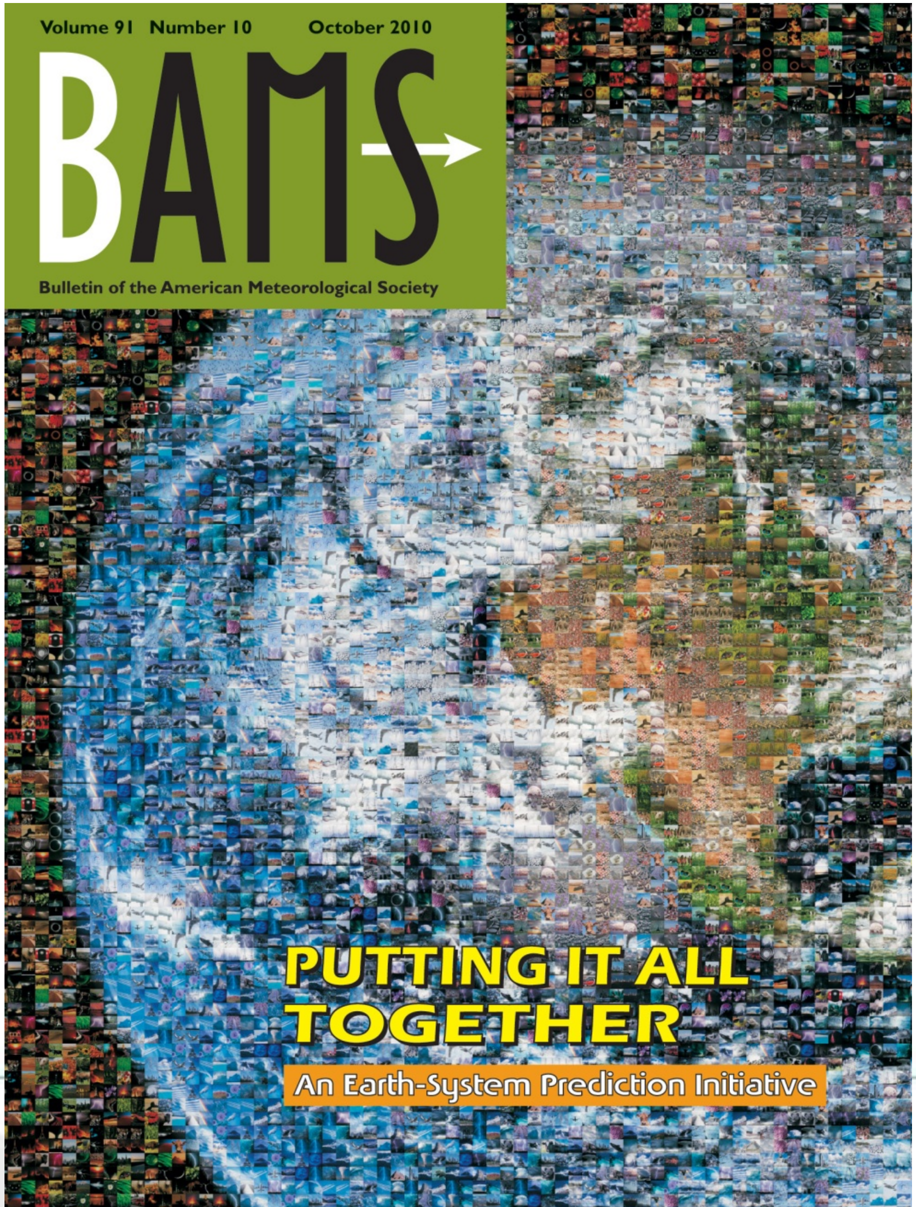
J. Shukla, T. DelSole, M. Fennessy, J. Kinter and D. Paolino

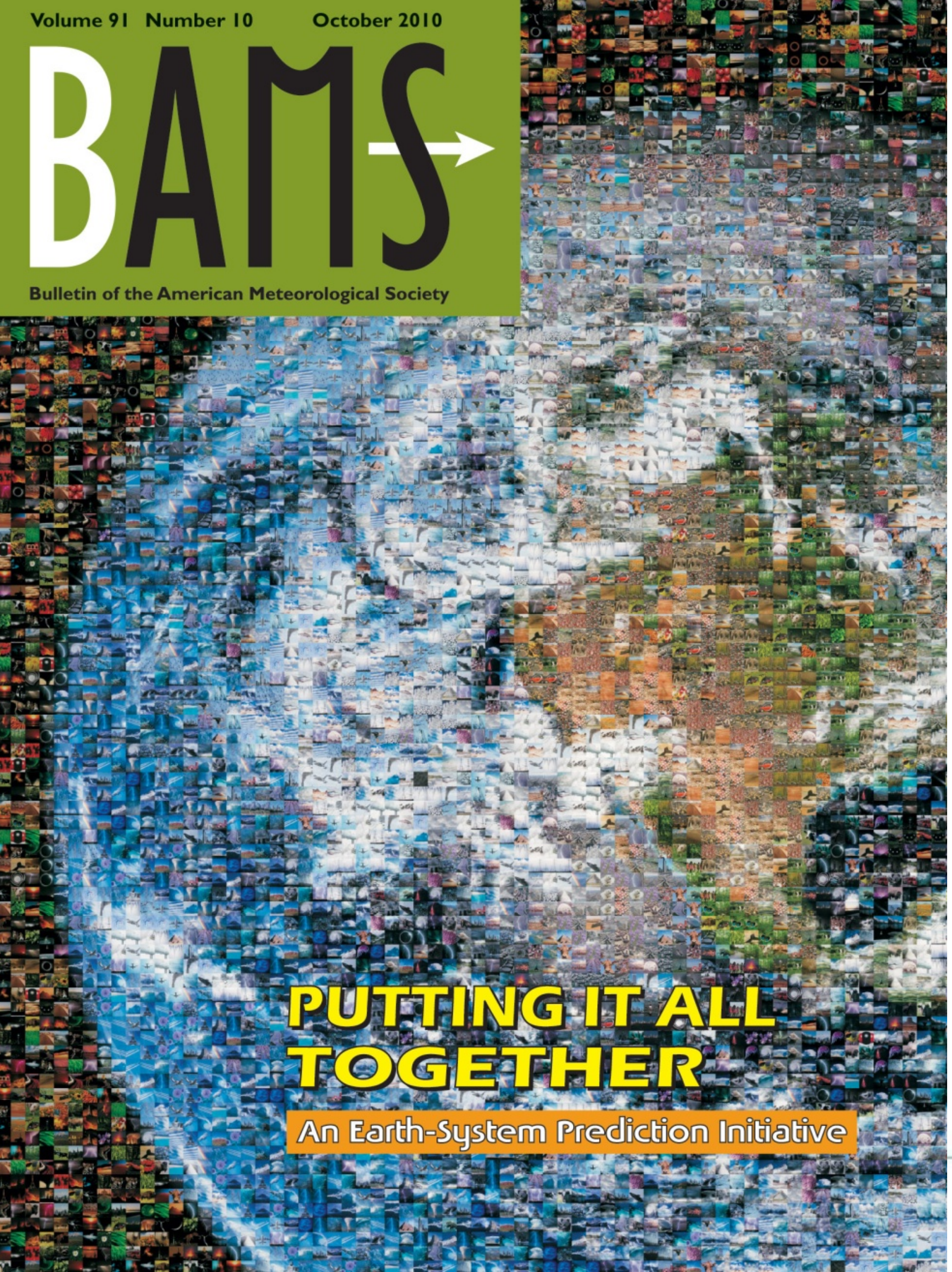
Geophys. Research Letters, 33, doi10.1029/2005GL025579, 2006



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.

An Earth system Prediction Initiative: Putting it All Together





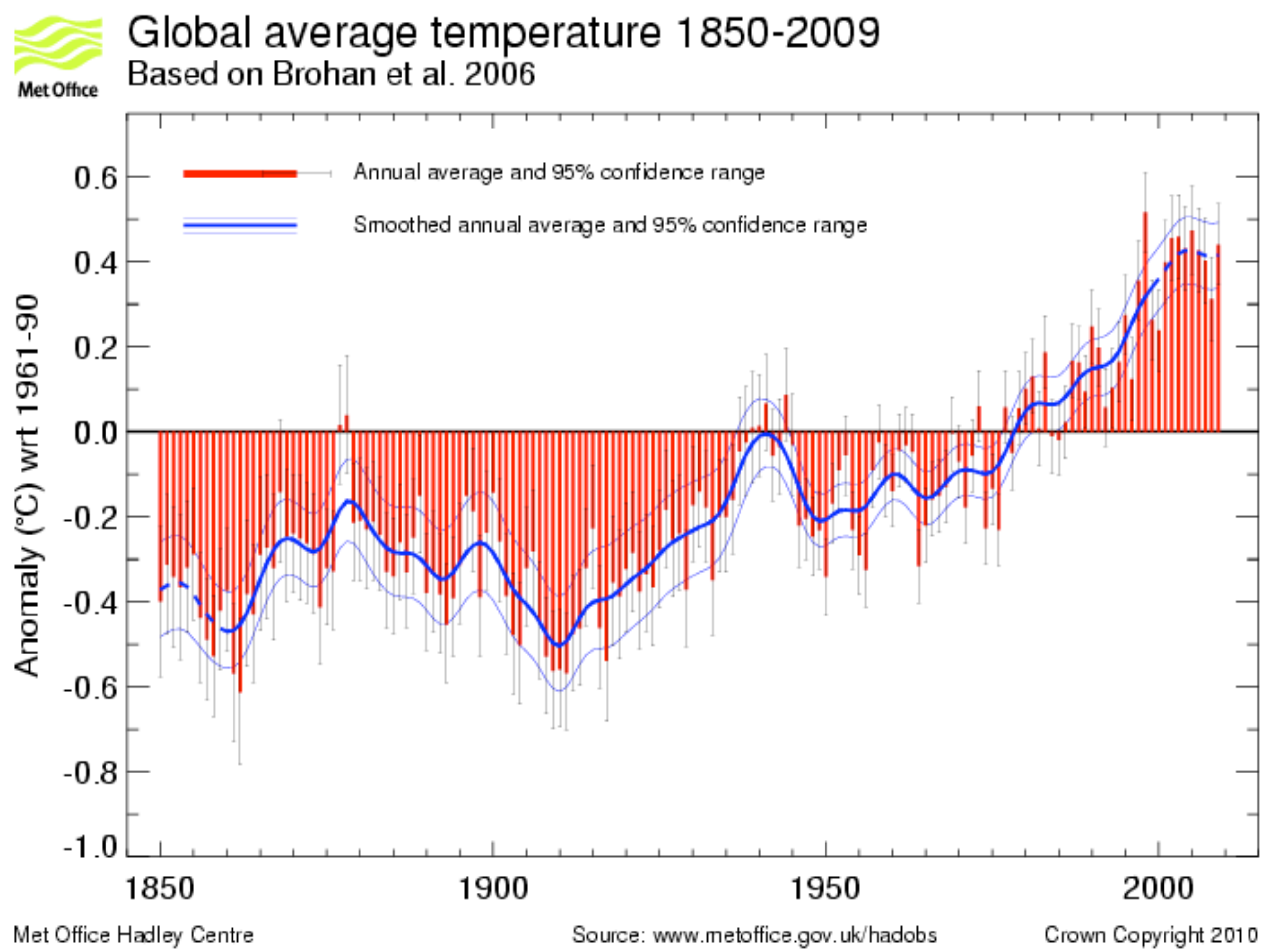
Brunet, G., et al, 2010: Collaboration of the Weather and Climate Communities to Advance Sub-Seasonal to Seasonal Prediction. *BAMS, Vol. 91, 1397-1406*

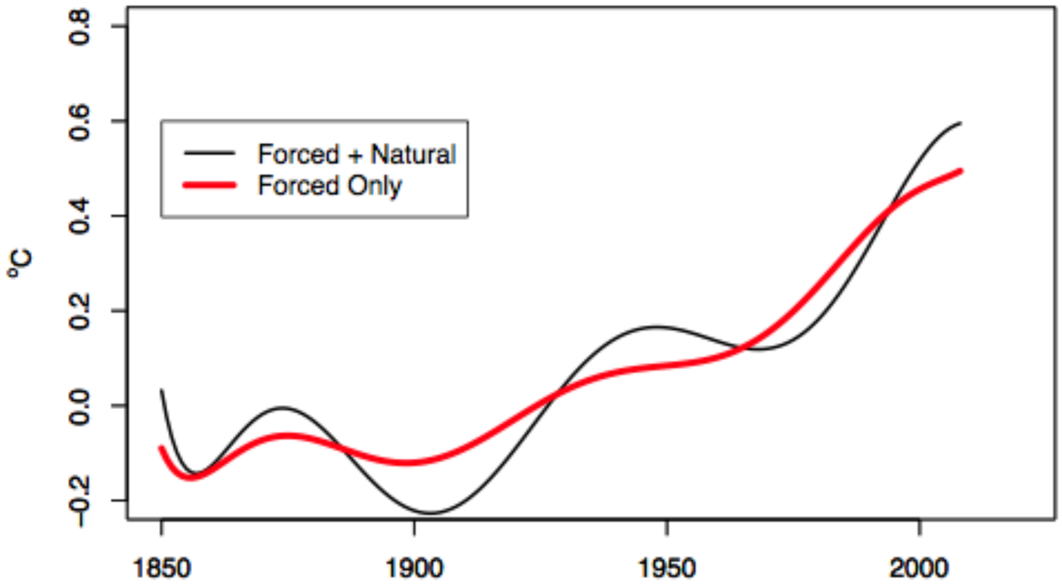
Shapiro, M., J. Shukla, et al, 2010: An Earth-System Prediction Initiative for the 21st Century. *BAMS, Vol.91, 1377-1388*

Shukla, J., T.N. Palmer, R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, and J. Slingo, 2010: Towards a New Generation of World Climate Research and Computing Facilities. *BAMS, Vol.91, 1407-1412*

Shukla, J., R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, T.N. Palmer, and J. Slingo, 2009: Revolution in climate Prediction is Both Necessary and Possible: A Declaration at the World Modelling Summit for Climate Prediction. *BAMS*, *Vol.90*, 16-19

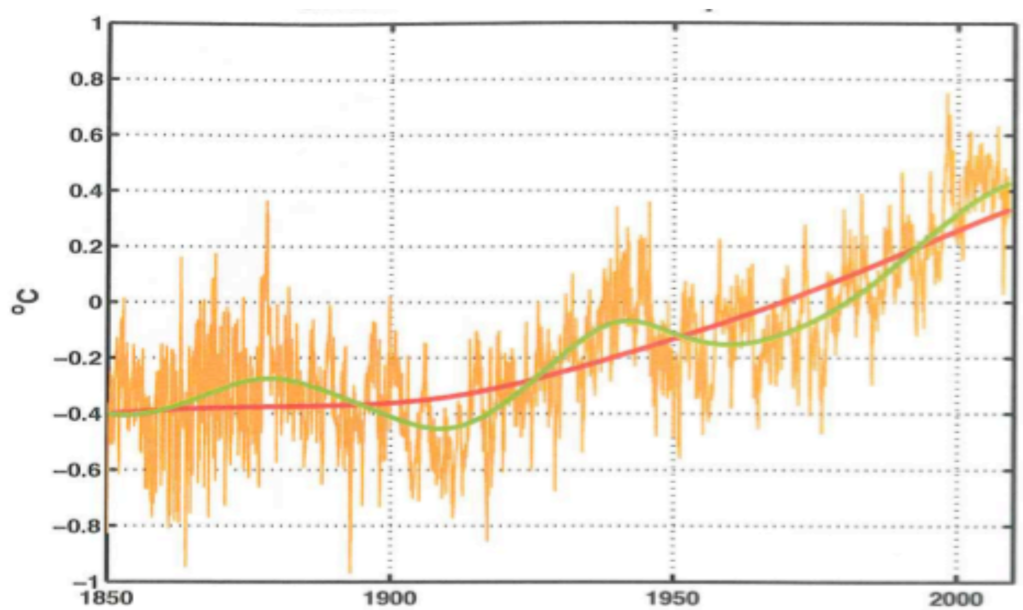
An Earth system Prediction Initiative


Met Office
Global average temperature 1850-2009
Based on Brohan et al. 2006
Annual average and 95% confidence range
Smoothed annual average and 95% confidence range
Anomaly (°C) wrt 1961-90
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1850
1900
1950
2000
Met Office Hadley Centre
Source: www.metoffice.gov.uk/hadobs
Crown Copyright 2010



(DelSole et. al.)

(Huang et. al.)



Reconstruction of the raw GST time series using ST only (Red lines) and ST+MDV (Green lines)

Outline

1. Overview: Predictability
    - Weather, Seasons, decade, climate change

2. Factors Limiting Climate Predictability
    - Understanding: Processes & Mechanisms
    - Observations; Assimilation; IC
    - Model Fidelity & Predictability
    - Institutional

3. What About a Climate CERN?
    - Justification and challenges
    - Requirements

4. Summary

Outline

1. Overview: Predictability
   - Weather, Seasons, decade, climate change

"Atmospheric Modeling, Data Assimilation and Predictability" by Eugenia Kalnay

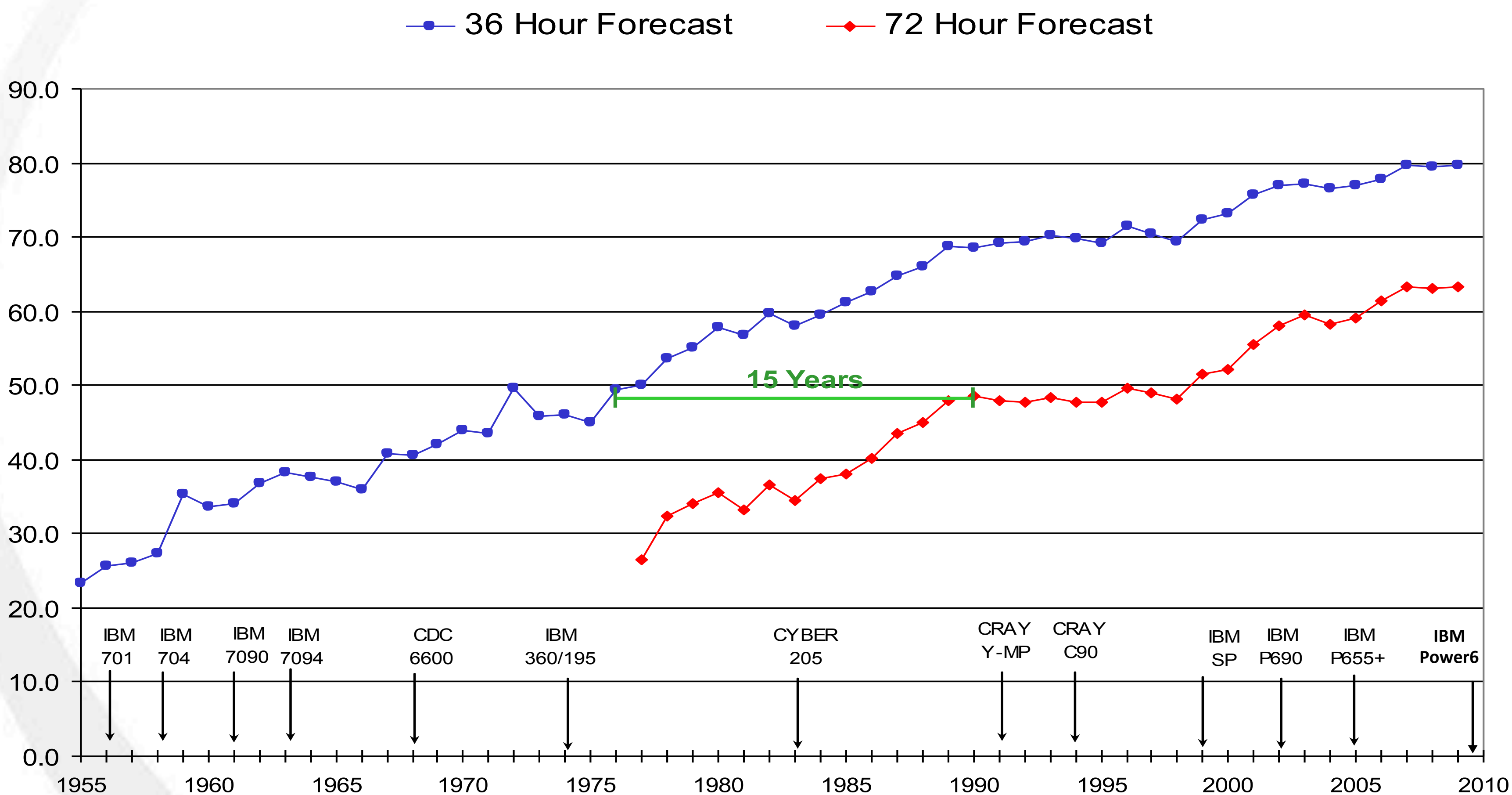
1. Factors Limiting Climate Predictability
   - Understanding: Processes & Mechanisms
   - Observations; Assimilation; IC
   - Model Fidelity & Predictability
   - Institutional

2. What About a Climate CERN?
   - Justification and challenges
   - Requirements

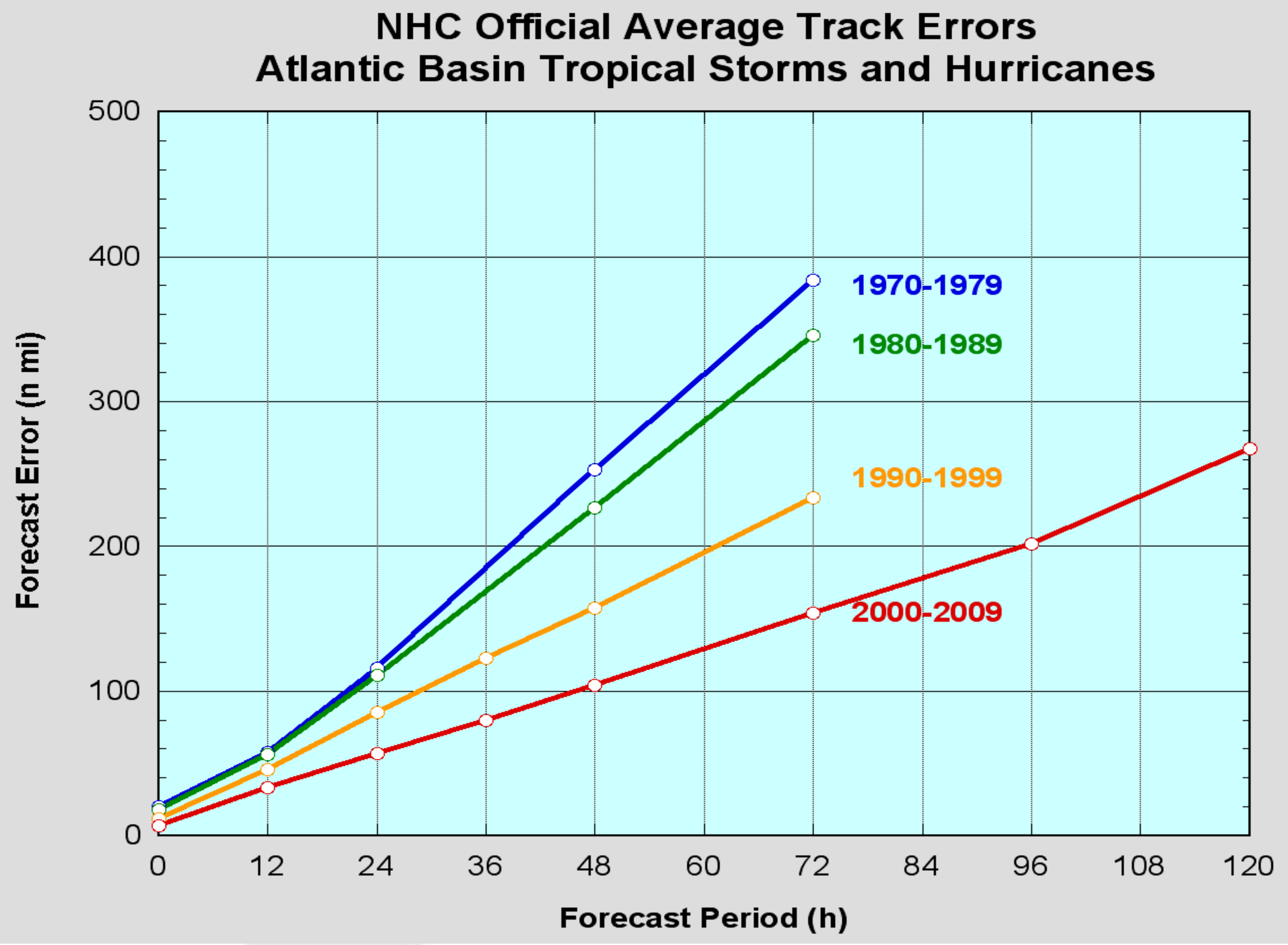
3. Summary

NCEP Operational Forecast Skill

36 and 72 Hour Forecasts @ 500 MB over North America
[100 * (1-S1/70) Method]



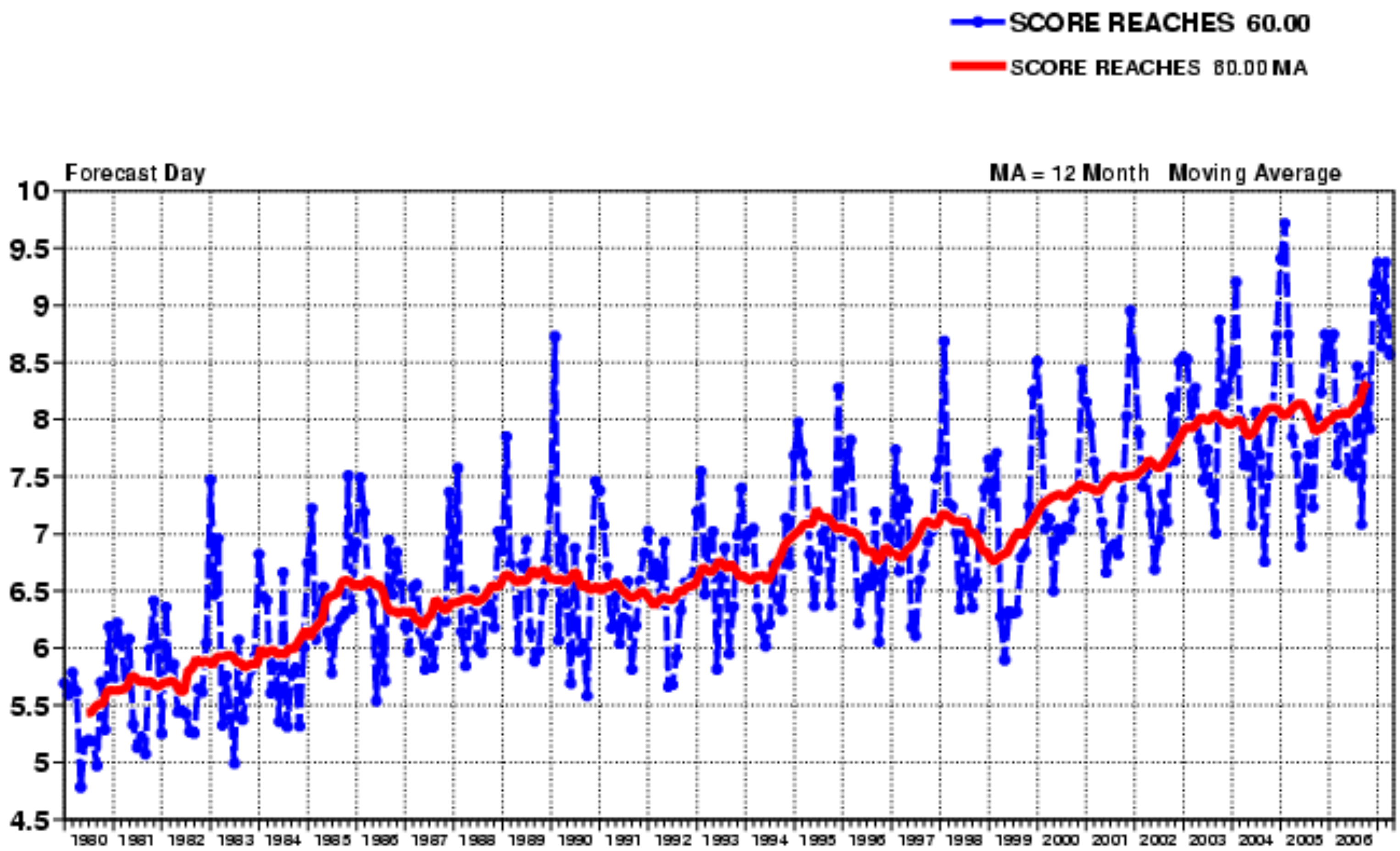
NCEP Central Operations/SIB January 2010



NHC Official Average Track Errors
Atlantic Basin Tropical Storms and Hurricanes
Forecast Error (n mi)
0
100
200
300
400
500
0
12
24
36
48
60
72
84
96
108
120
Forecast Period (h)
1970-1979
1980-1989
1990-1999
2000-2009

ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N



Lorenz Model

Lorenz model is a low-order convection model described by just three ordinary differential equations. It is one of the simplest forced dissipative nonlinear systems.

$$\frac{dX}{dt} = -\sigma X + \sigma Y$$

$$\frac{dY}{dt} = -XZ + rX - Y$$

$$\frac{dZ}{dt} = XY - bZ$$

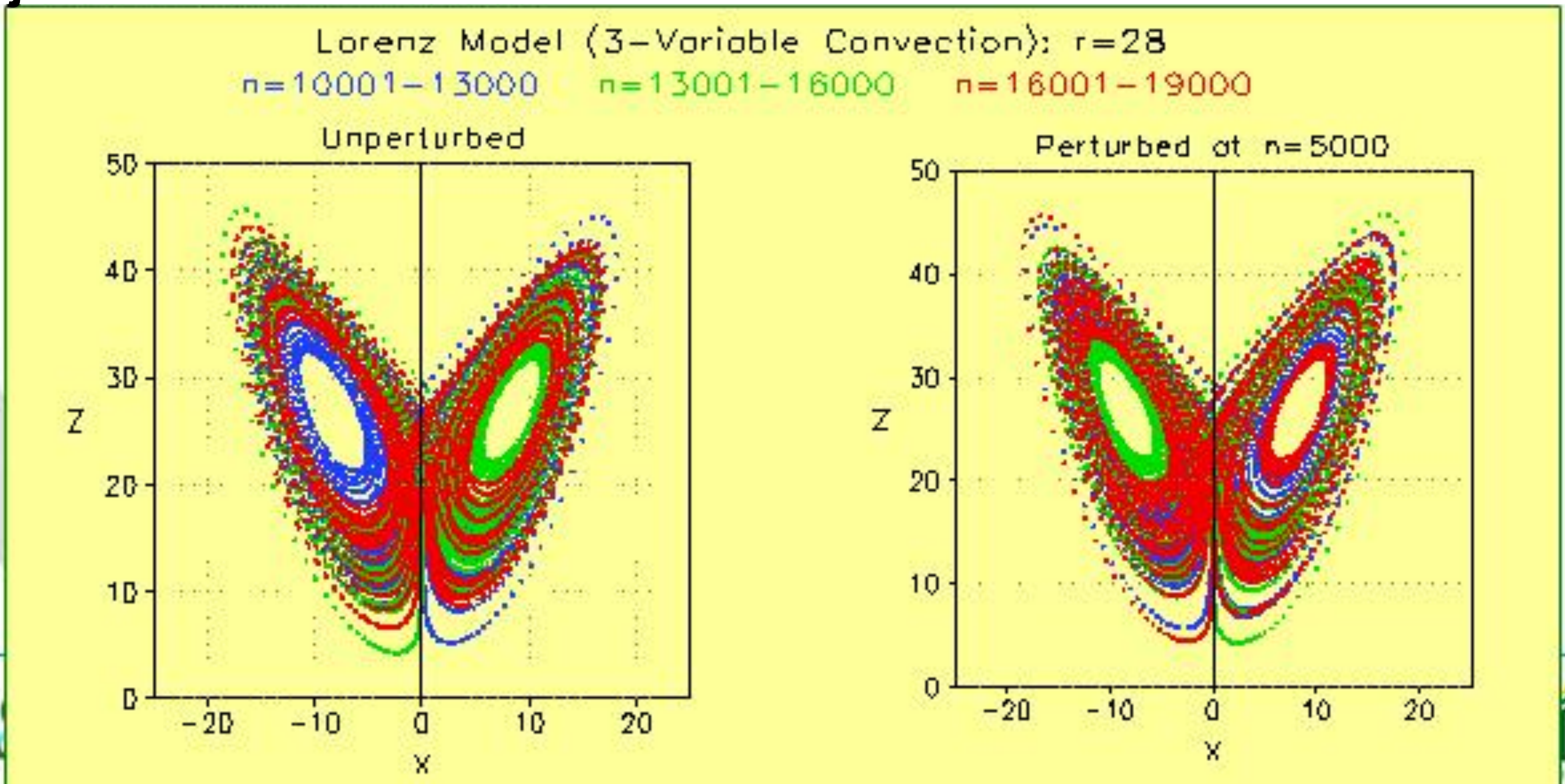
X, Y, Z: Dynamical variables
r: Forcing
σ, b: Dissipation
Parameter values: $\sigma = 10,\quad b = 8/3,\quad r = 28$
Initial condition: $X = 0.0,\ Y = 1.0, Z = 0.0$
Time increment for integration: $\Delta t = 0.01$

Predictability Experiment 1 in Lorenz Model

The Lorenz model is first integrated up to the time step *n* = 10000.

At *n* = 10001, this unpertubed integration is continued, and a new integration is carried out with a small perturbation added to the state from the unpertubed integration.

The same projections of unperturbed and perturbed trajectories are shown in different colors for different segments of time, the divergence of trajectories become clear.



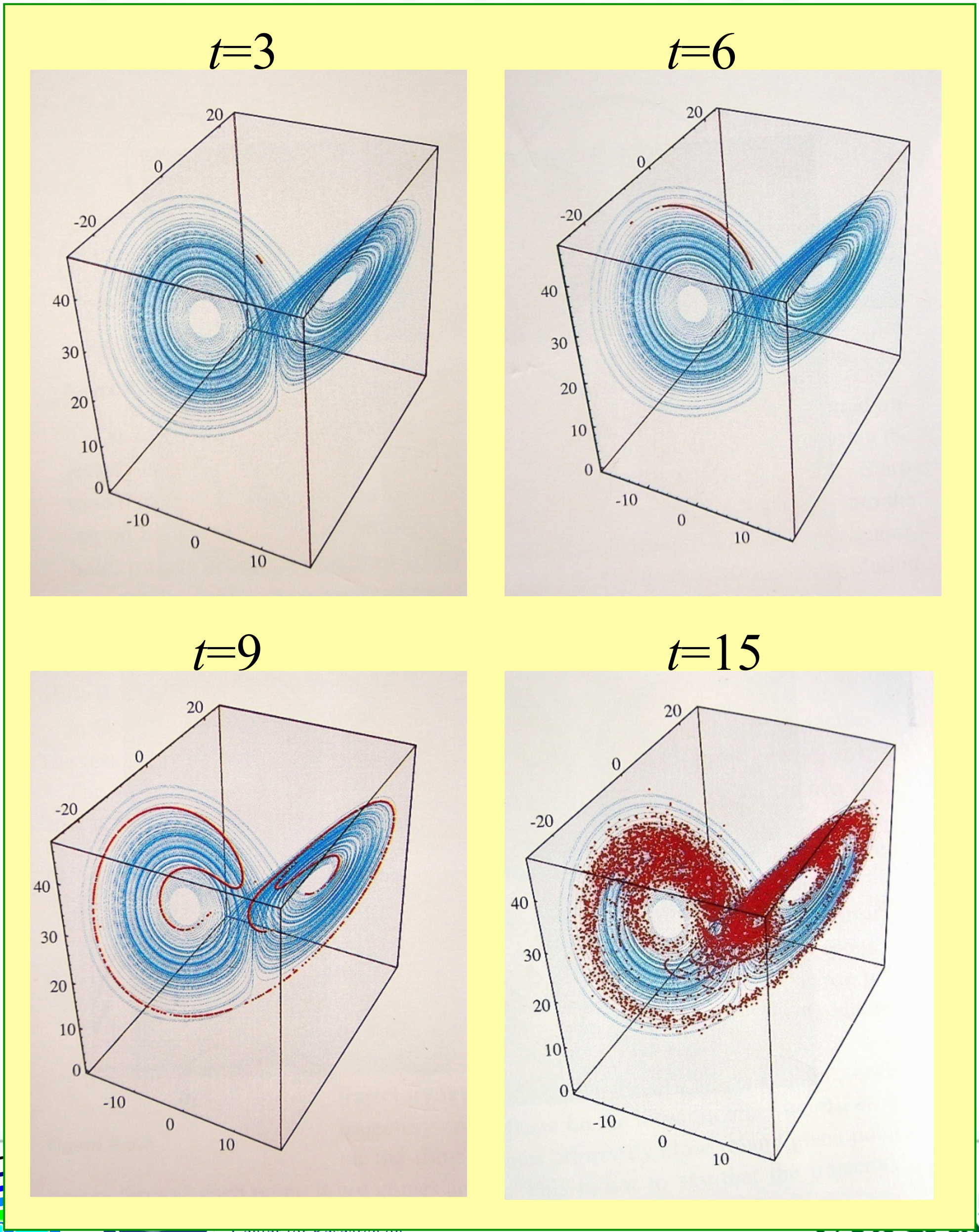
Predictability Experiment 2 in Lorenz Model

From Strogatz, S. H., 1994: *Nonlinear dynamics and chaos*, Westview Press

An ensemble of 10000 nearby points at an initial $t = 0$ around a basic state is allowed to evolve in Lorenz model.

Blue points are from unperturbed integration.
Red points show the evolution of the perturbed initial states.

"As each point moves according to Lorenz equations, the blob is stretched into a thin filament… Ultimately, the points spread over … showing that the final state could be almost anywhere, even though the initial conditions were almost identical."



The Growth of Very Small Errors

Lorenz, E. N., 1969: The Predictability of a Flow Which Contains Many Scales of Motion. *Tellus*, 21, 289-307

- ***Basic Idea*** **– Reduce the Size of the Initial Error by putting it on smaller and smaller scales**
- ***Ultimate Predictability*** **controlled by the predictability time T = time necessary for the error to propagate "upscale" from very, very small initial scale to a finite, pre-chosen scale**
- ***How does T behave as the initial error gets infinitely small?*** **0 –This tells us if we have TYPE 2 or TYPE 3 behavior!**
- **For a Spectrum E(k) ~ k^{-3} *or steeper* :**

  T becomes infinite (thus TYPE 2)
- **For a Spectrum E(k) *less steep than* k^{-3} :**

  T is finite (thus TYPE 3)

The Knife's Edge

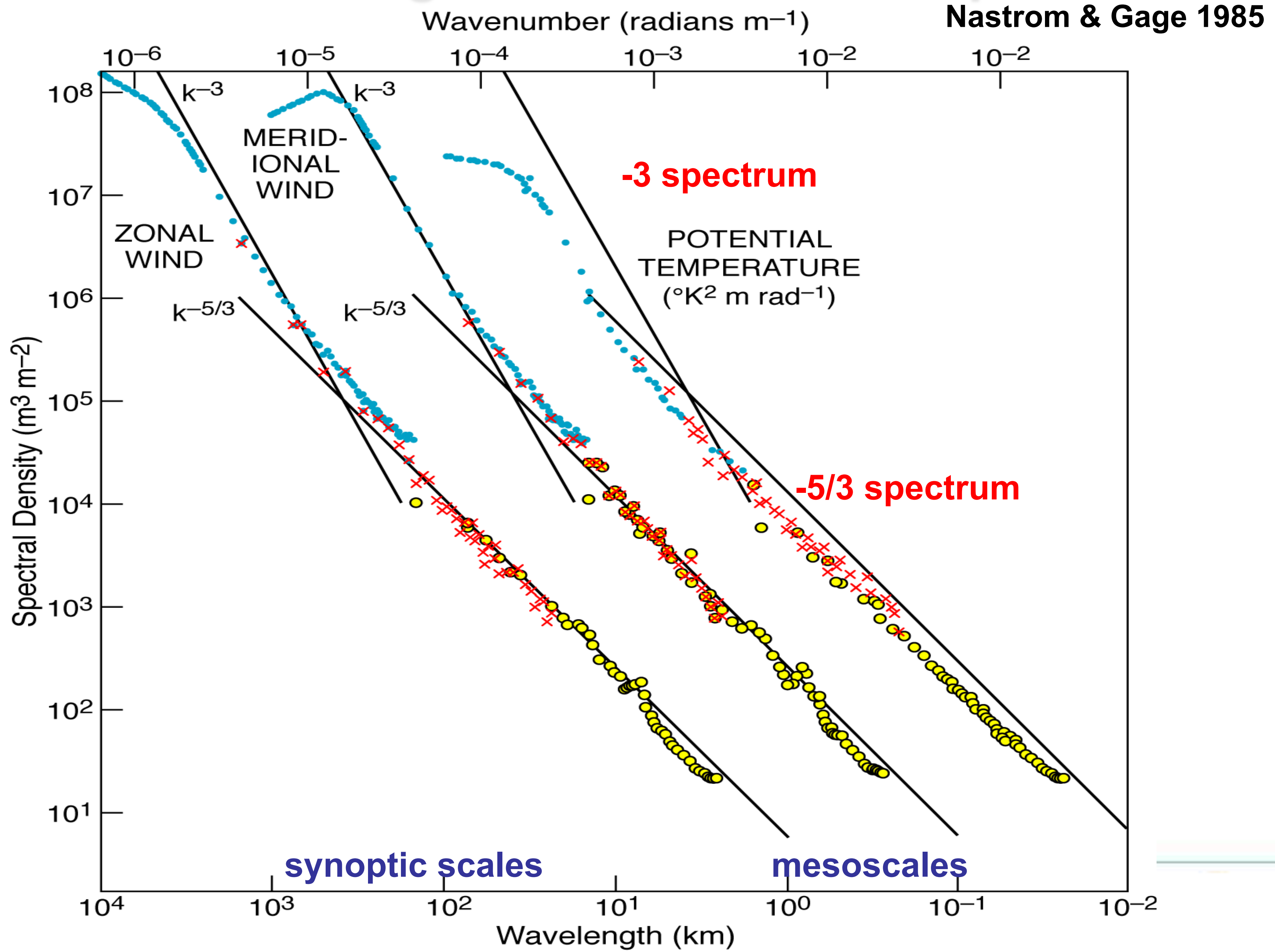
"…if the energy per unit wave number obeys a minus-three or higher negative power law, … the series for [the range of predictability] would fail to converge."

Translation: Range of Predictability can be increased indefinitely by reducing initial observation error.

-Lorenz, 1969: The predictability of a flow which possesses many scales of motion. Tellus, pg. 304.

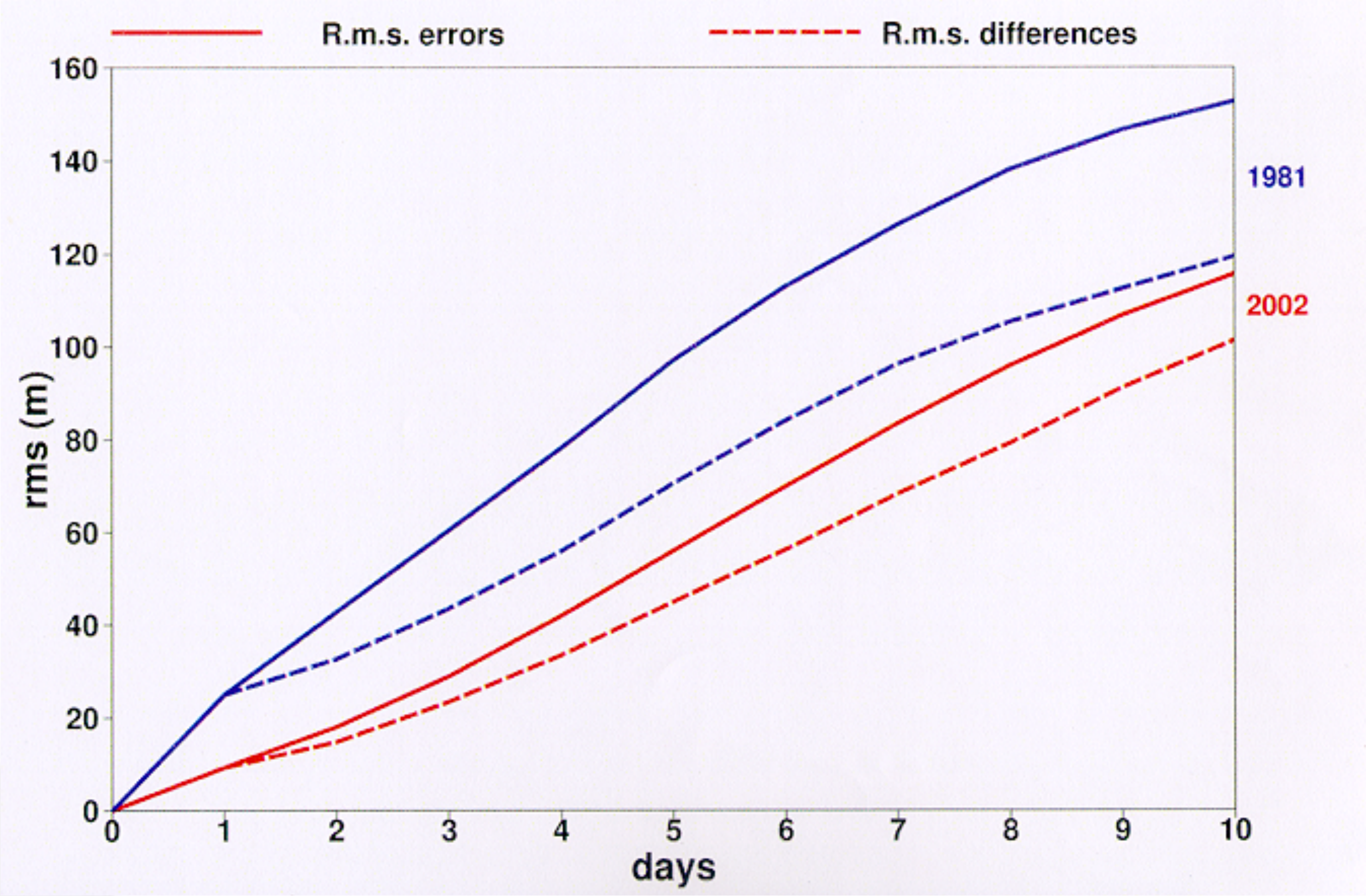
The "Knife's Edge" – The Observed Spectrum

Nastrom & Gage 1985



RMS Error and Differences between Successive Forecasts

Northern Hemisphere 500 hPa Height in Winter



Current Limits of Predictability, A. Hollingsworth, Savannah, Feb 2003

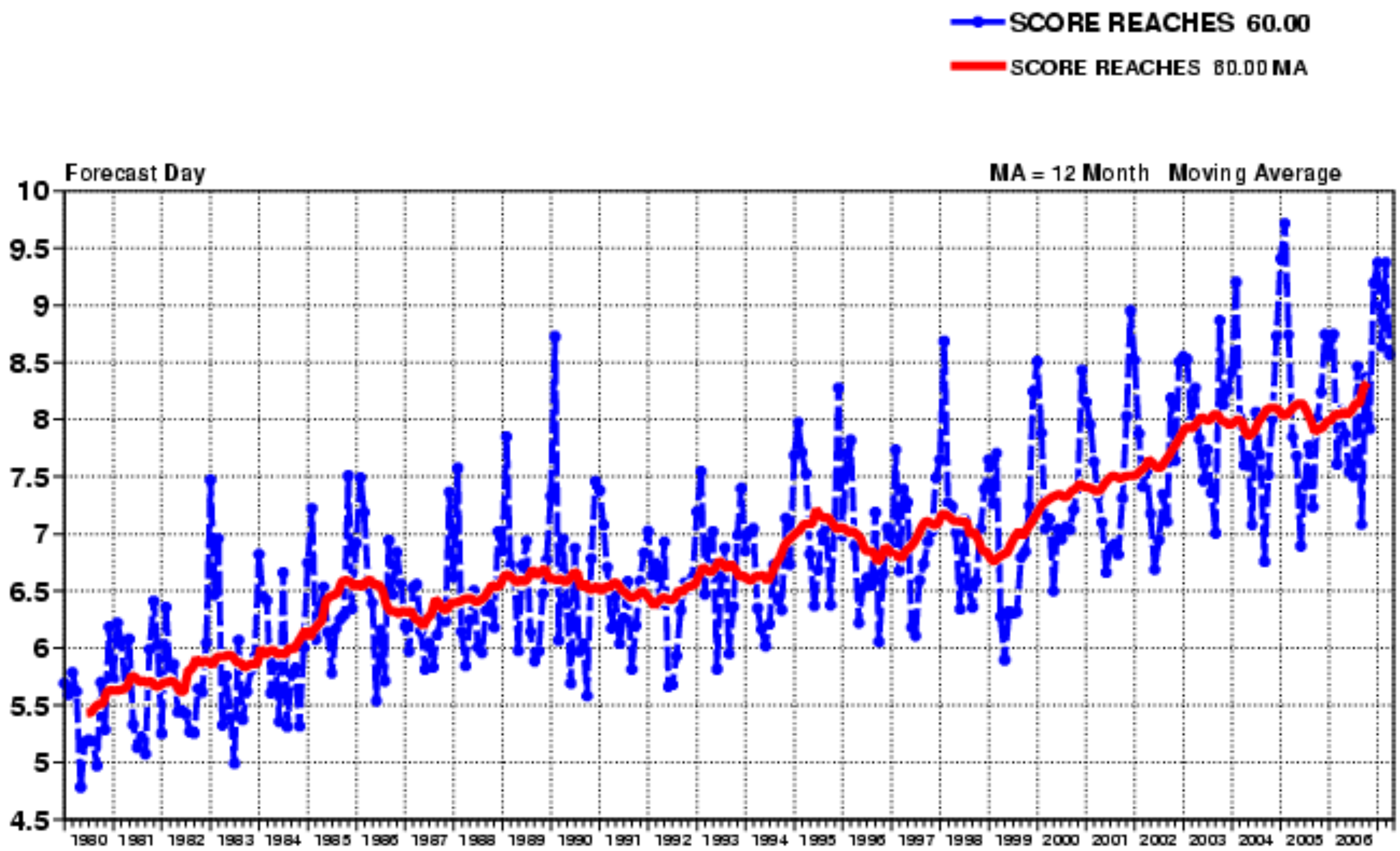
Evolution of 1-Day Forecast Error, Lorenz Error Growth, and Forecast Skill for ECMWF Model

(500 hPa NH Winter)

	1982	1987	1992	1997	2002
"Initial error" (1-day forecast error) [m]	20	15	14	14	8
Doubling time [days]	1.9	1.6	1.5	1.5	1.2
Forecast skill [day 5 ACC]	0.65	0.72	0.75	0.78	0.84

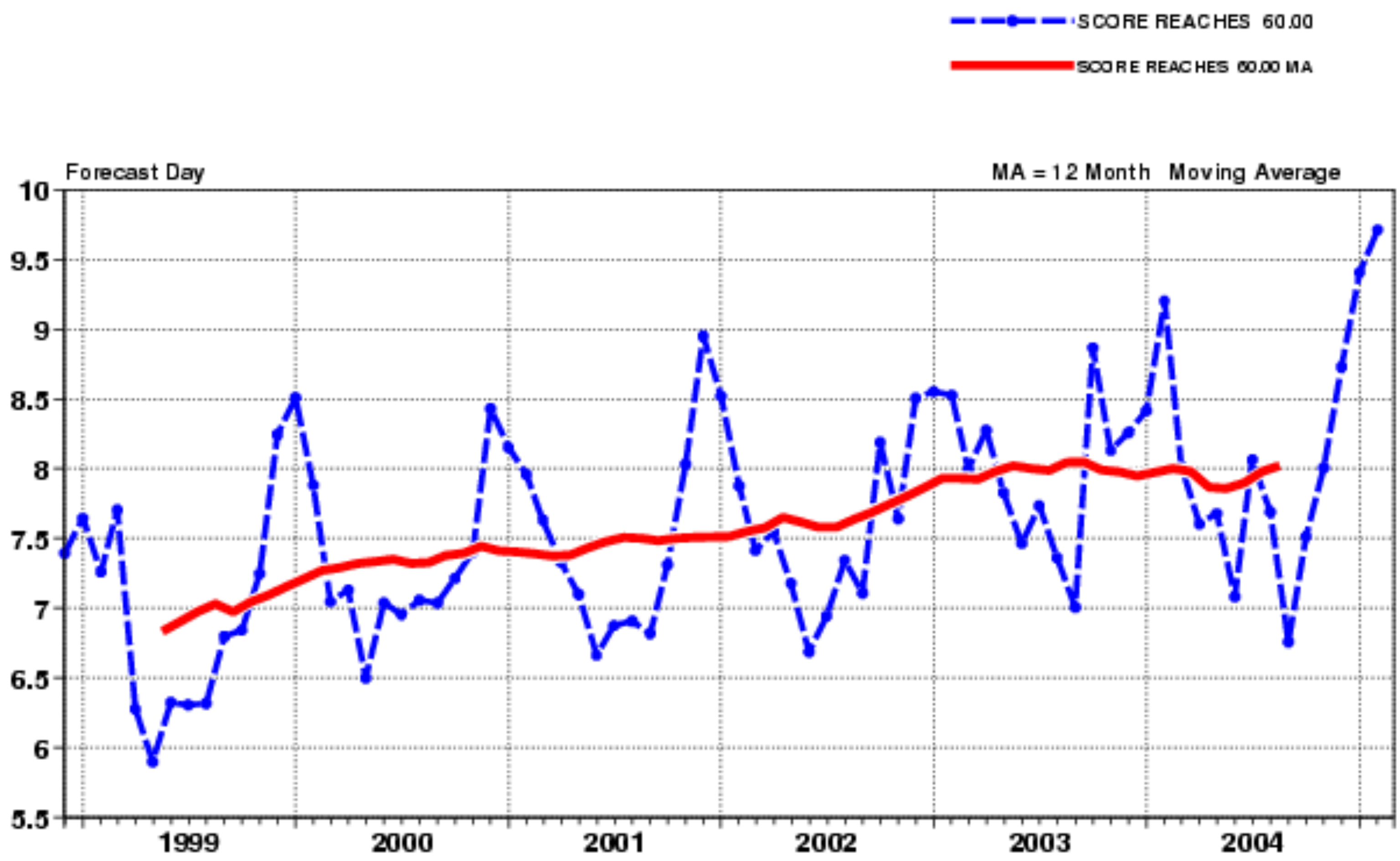
ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N



ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N



Interim Summary (NWP)

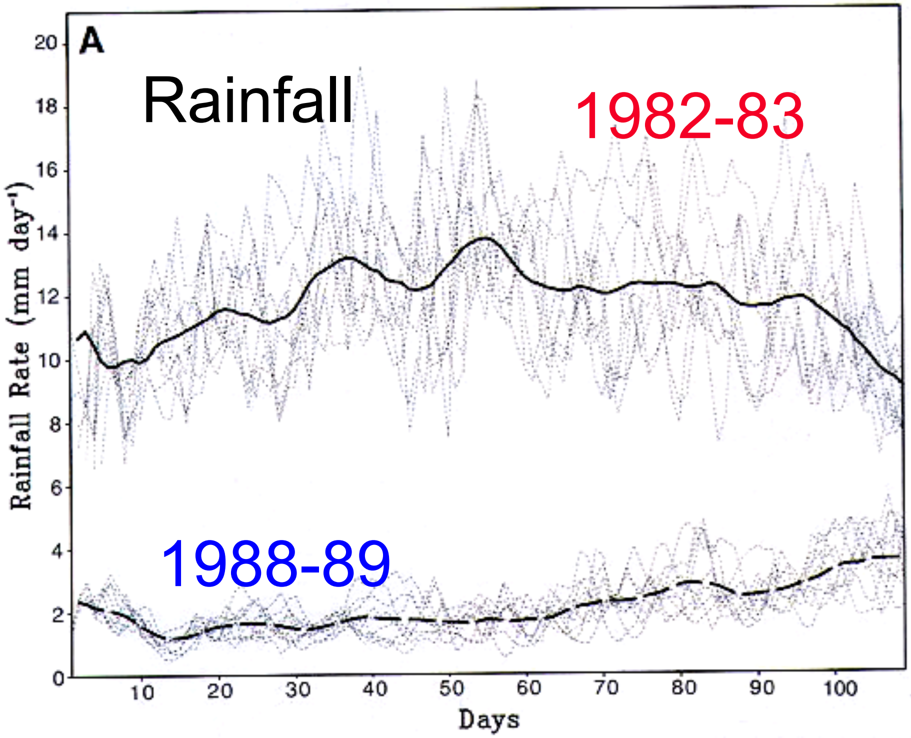
- In spite of the $k^{-5/3}$ spectrum,

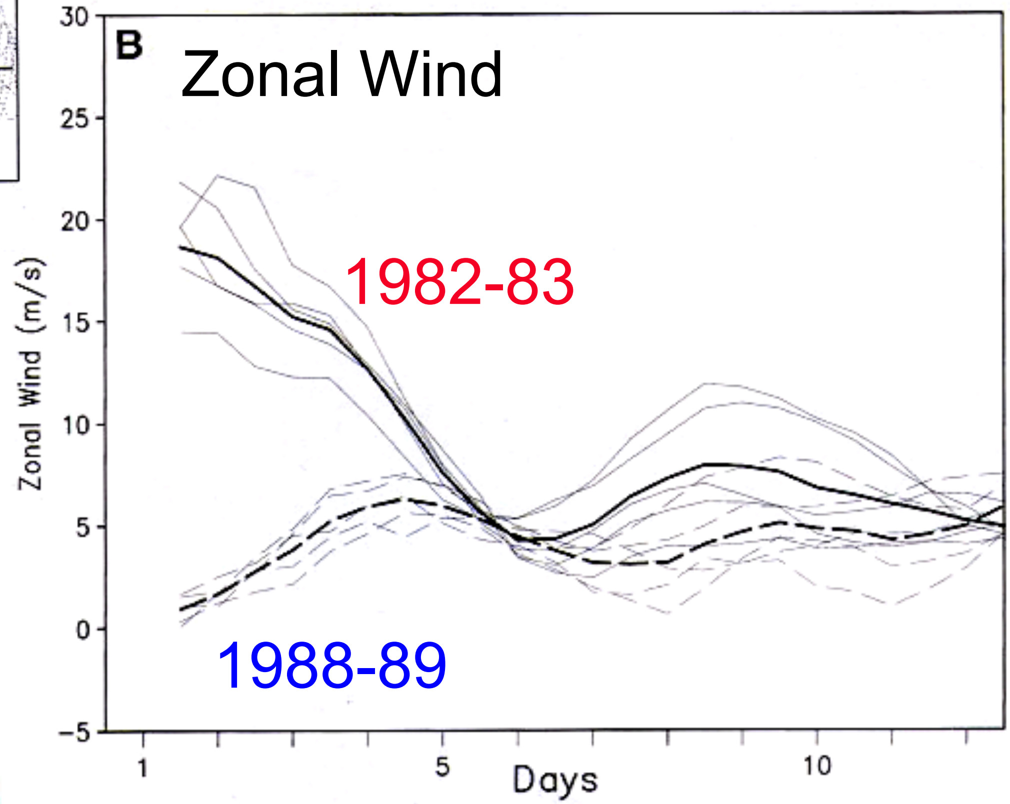
- NWP history (~40 years) suggests: Higher resolution models, improved physical parameterizations, and data assimilation techniques reduced initial errors; Increased the range of predictability (even though initial error growth increased).

- Despite 40 years of research, we still cannot definitively state whether the range of predictability cannot be increased indefinitely

From Numerical Weather Prediction (NWP) To Dynamical Seasonal Prediction (DSP) (1975-2004)

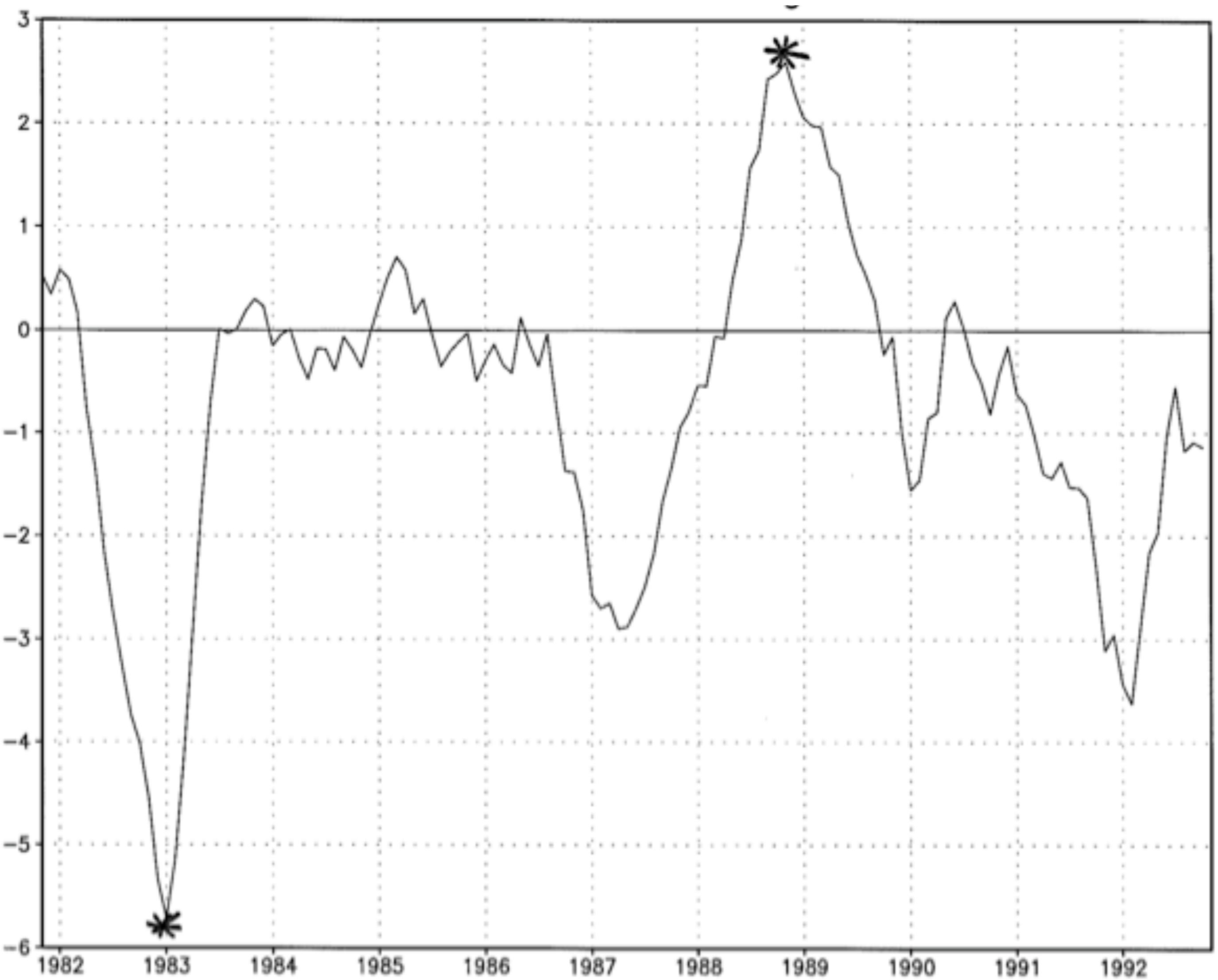
- **Operational Short-Range NWP: was already in place**
- **Predictability and Prediction of Monthly Means: DERF: Shukla; Miyakoda**
- **Boundary Forcing: predictability of monthly & seasonal means (Charney & Shukla)**
- **AGCM Experiments: prescribed SST, soil wetness, & snow to explain observed atmospheric circulation anomalies (COLA)**
- **OGCM Experiments: prescribed observed surface wind to simulate tropical Pacific sea level & SST (Busalacchi & O' Brien; Philander & Seigel)**
- **Prediction of ENSO: simple coupled ocean-atmosphere model (Cane, Zebiak)**
- **Coupled Ocean-Land-Atmosphere Models: predict short-term climate fluctuations**



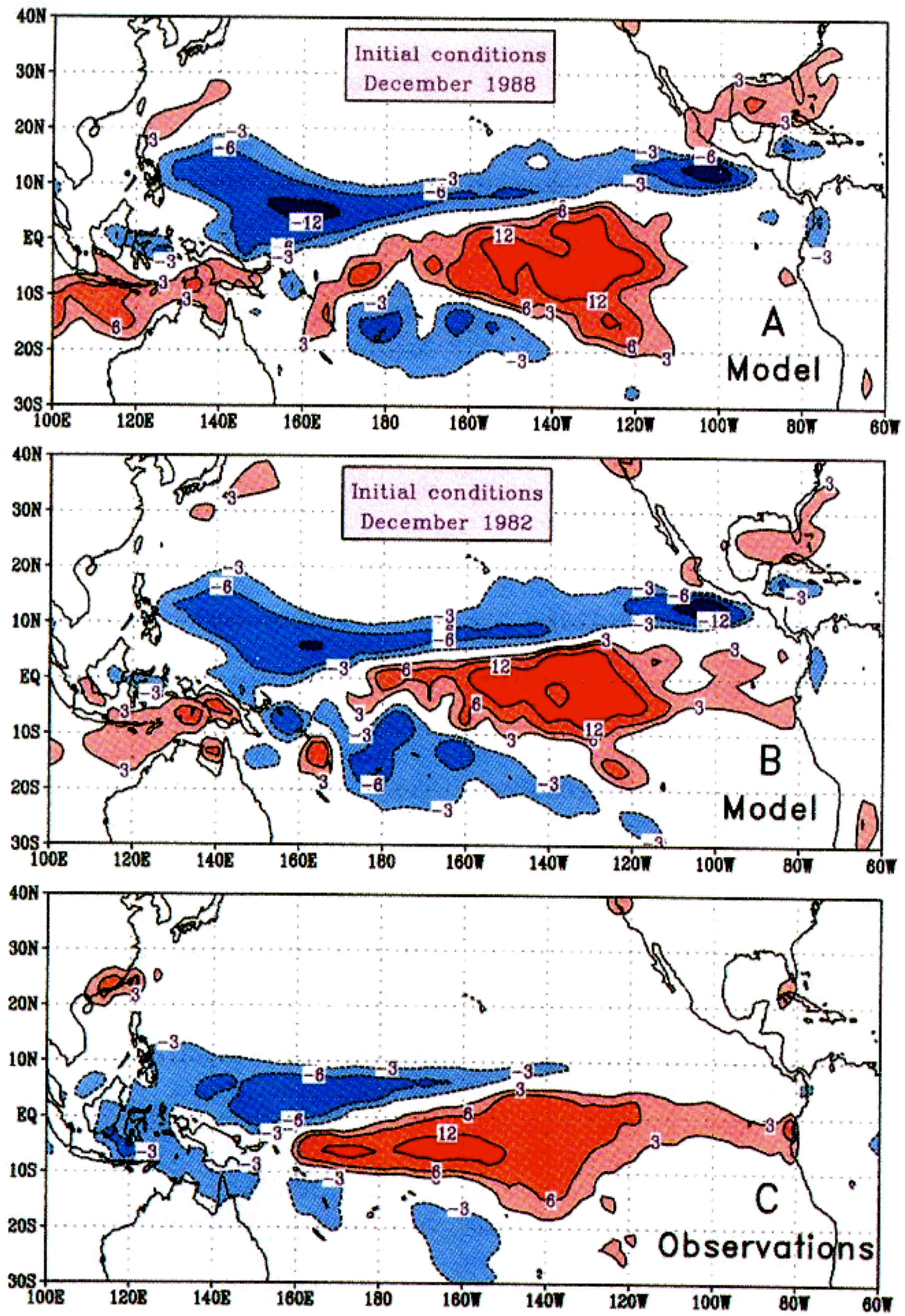


The atmosphere is so strongly forced by the underlying ocean that integrations with fairly large differences in the atmospheric initial conditions converge, when forced by the same SST (Shukla, 1982).

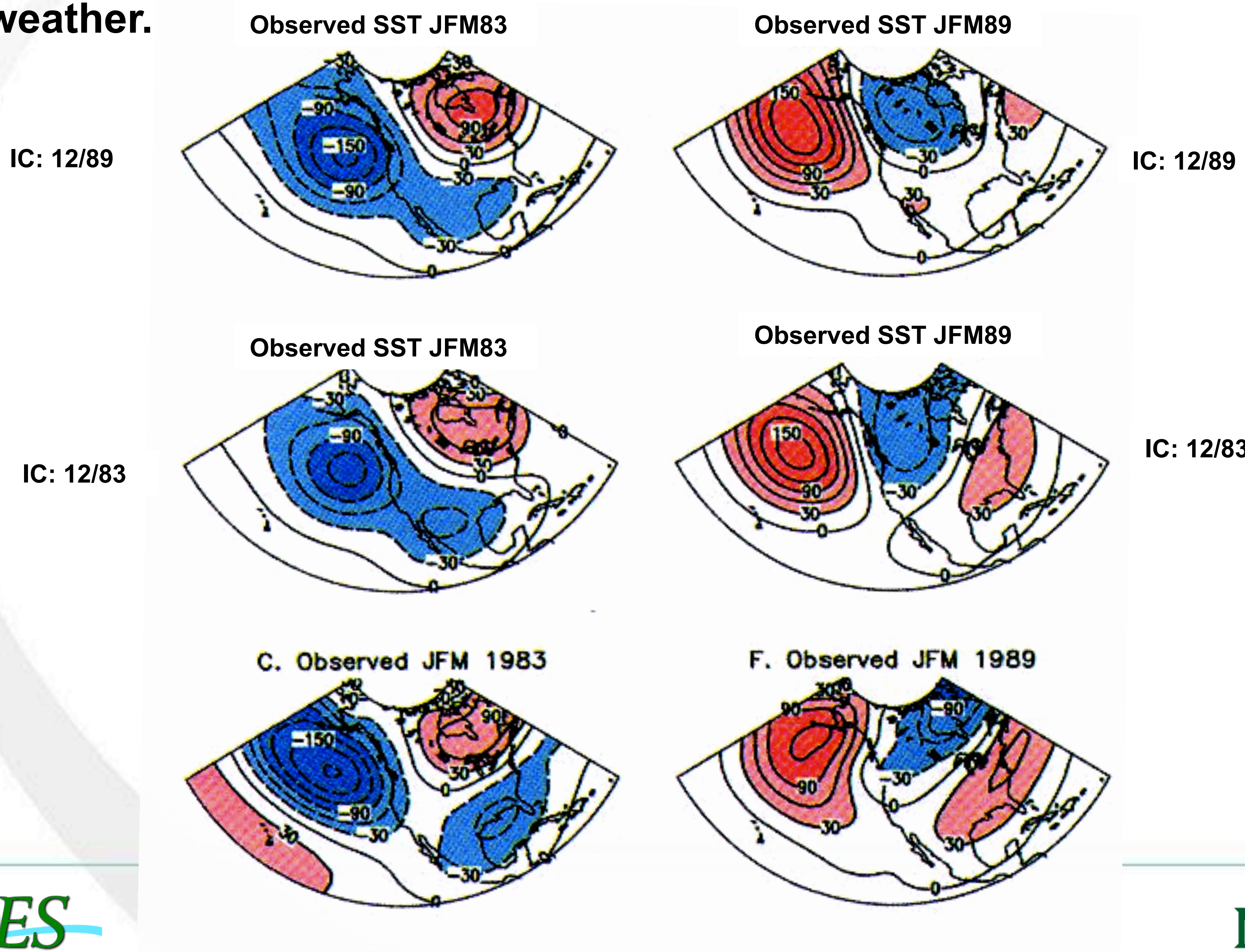
Observed 5-month running mean SOI



Rainfall Anomalies

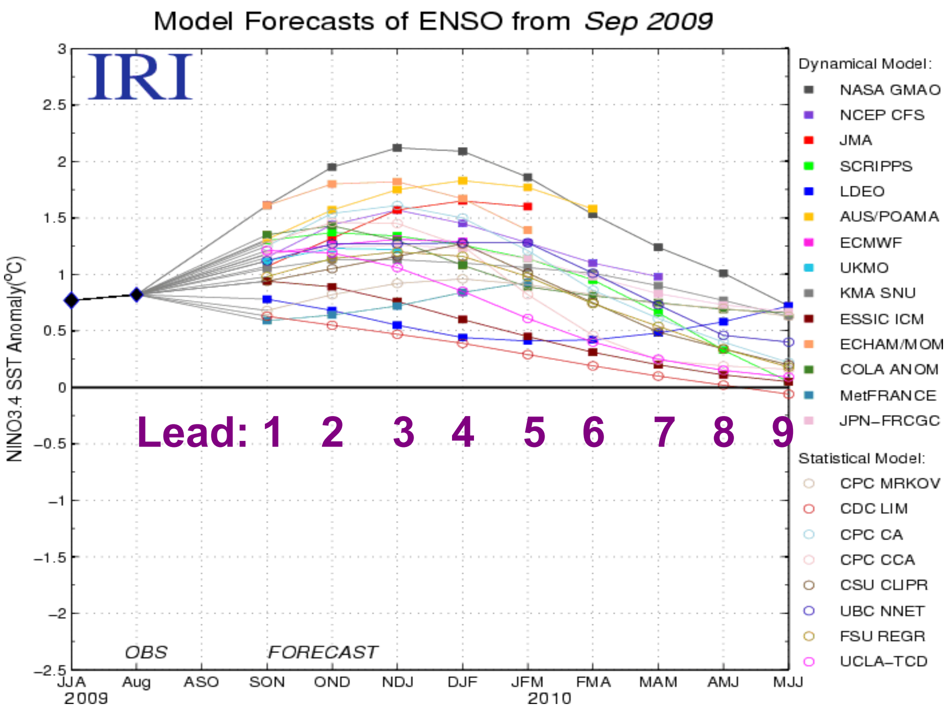


When tropical forcing is very strong, it can enhance even the predictability of extratropical seasonal mean circulation, which, in the absence of anomalous SST, has no predictability beyond weather.

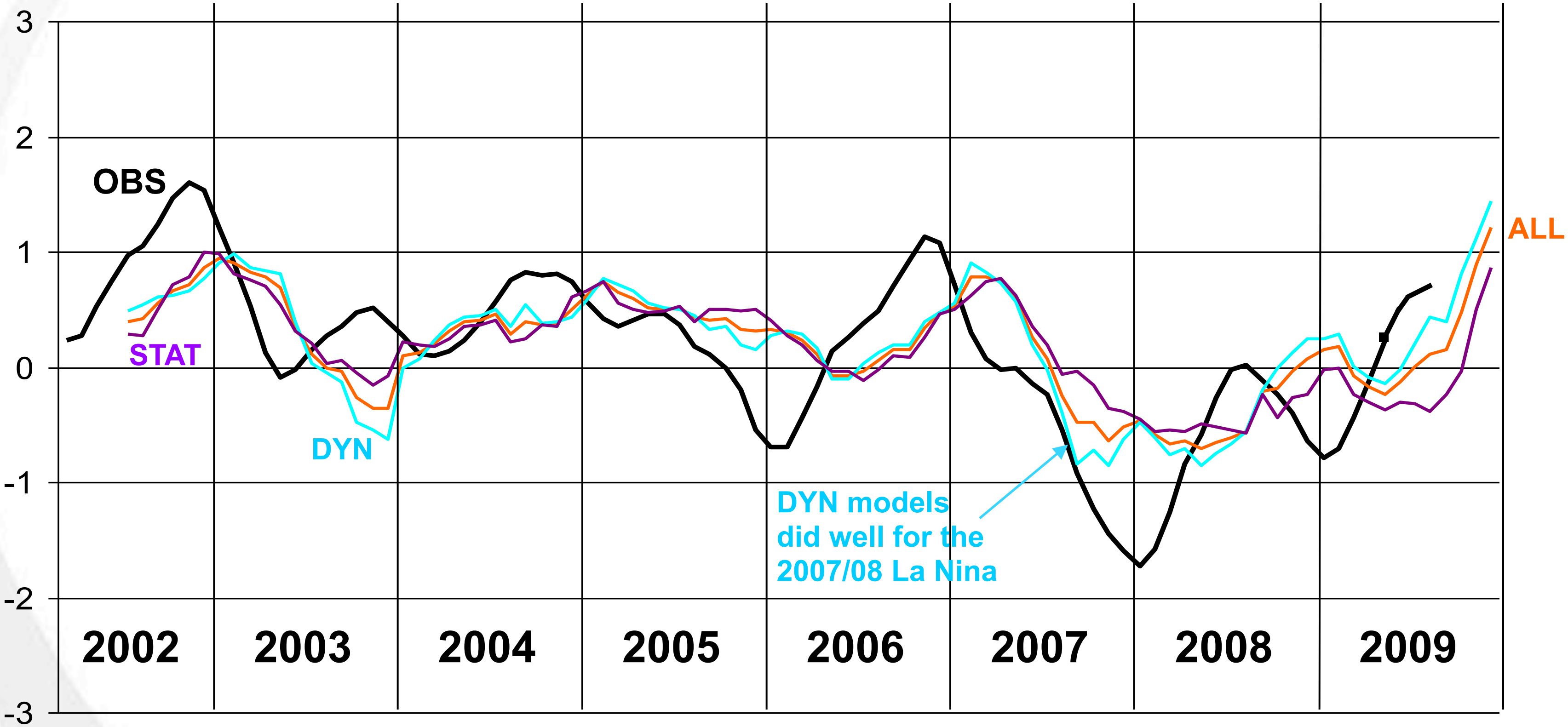


An evaluation of the skill of ENSO forecasts during 2002-2009

Tony Barnston and Mike Tippett
IRI

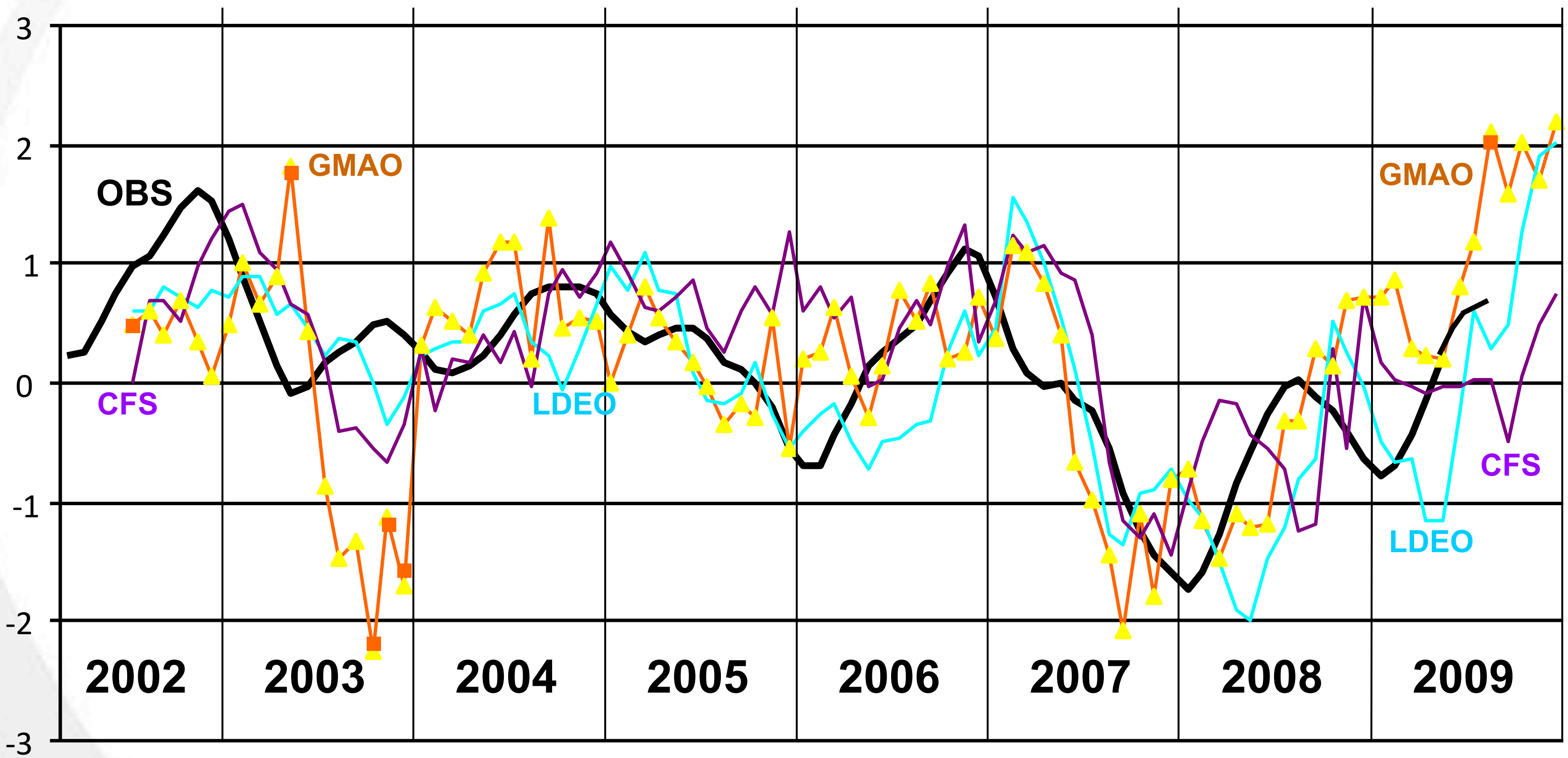


MME Mean by Model Type, 5-month lead



Tony Barnston and Mike Tippett

Selected Dynamical Models, 5-month lead



Tony Barnston and Mike Tippett

Conclusions

Tony Barnston and Mike Tippett

Our ENSO prediction skill is not much different this decade from how it was in the previous two decades.

Decadal variations in ENSO prediction skill appears to be a stronger function of decadal variability of ENSO amplitude than of improvements in our models and/or prediction methodologies.

Hypothesis

Models that simulate climatology "better" make better predictions.

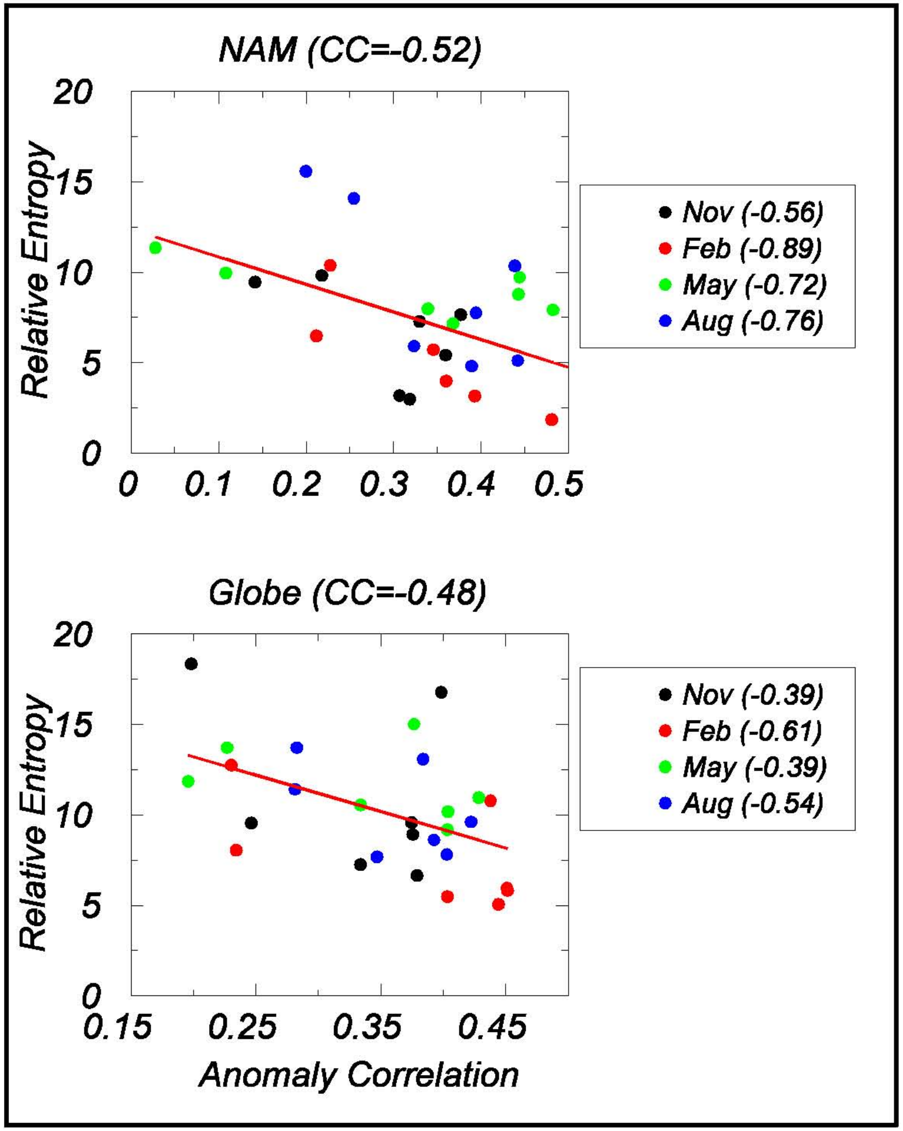
Definition: Fidelity refers to the degree to which the climatology of the forecasts (including the mean and variance) matches the observed climatology

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

Fidelity vs. Skill



Fidelity vs. Skill
DEMETER 1980-2001
Seasonal Forecasts

7 models, 4 initial conditions

Lead Time = 0 months

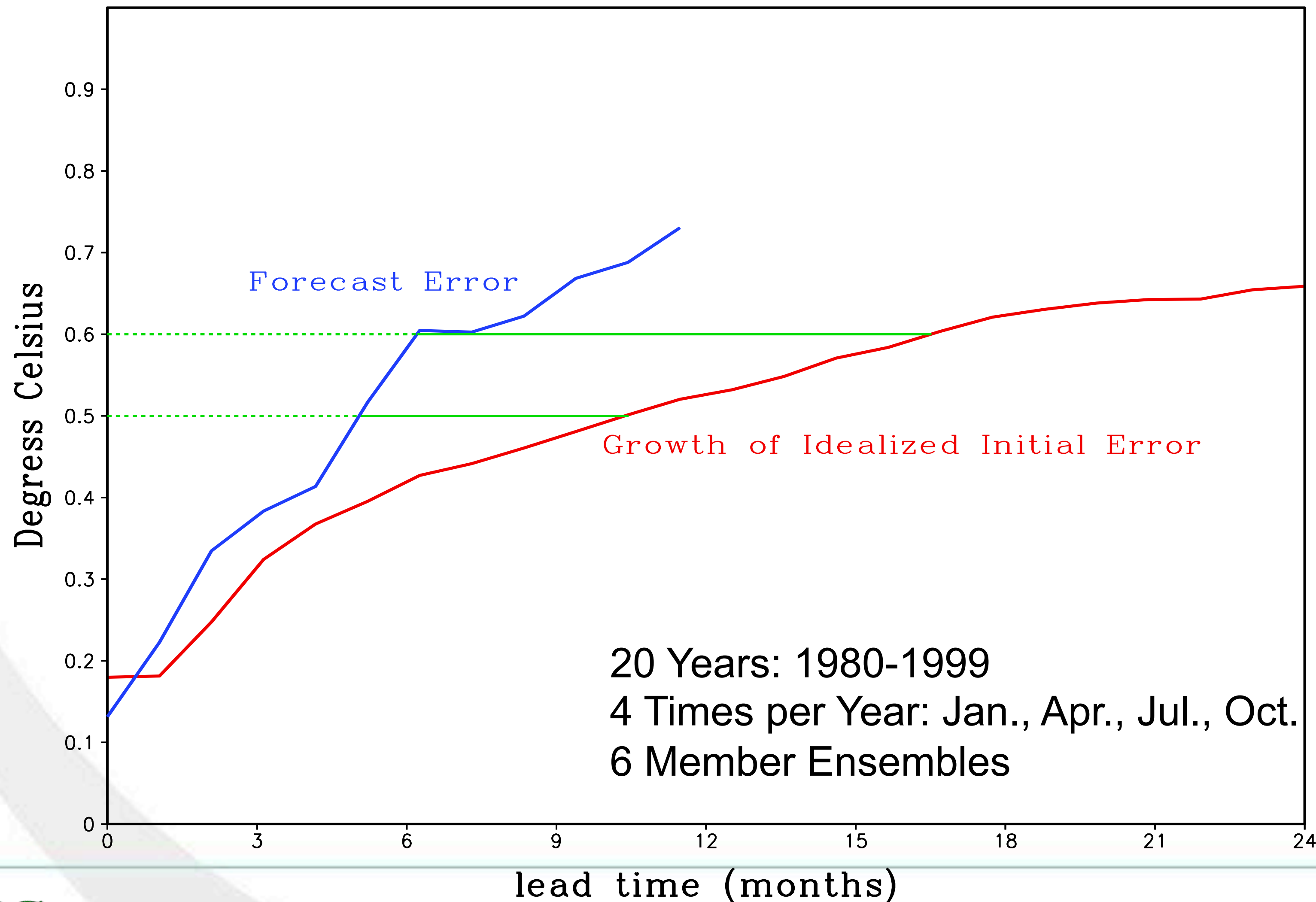
Fidelity and Skill are related.

Models with poor climatology tend to have poor skill.

Models with better climatology tend to have better skill.

Courtesy of Tim DelSole

Current Limit of Predictability of ENSO (Nino3.4)
Potential Limit of Predictability of ENSO



Kirtman, 2003

Interim Summary (Seasonal Prediction)

- 35 years ago, dynamical seasonal climate prediction was not conceivable.
- Dynamical seasonal climate prediction 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.
- The most dominant obstacle in realizing the potential predictability of intraseasonal and seasonal variations is inaccurate models, and unbalanced initial conditions rather than an intrinsic limit of predictability.

WCC3 White Paper on Seasonal to Interannual Prediction

- Forecast systems are still a long way from reaching their potential;
- Model error is still a critical problem… A key lesson from seasonal prediction is that model error is a big contributor to forecast error;
- Regional models …are not a solution to the problem of errors in global models

Recent Papers (Decadal Variability)

"A significant Component of Unforced Multidecadal Variability in Twentieth Century Global Warming"
Timothy DelSole, Michael K. Tippett, Jagadish Shukla
(To Appear: Journal of Climate)

"The Impact of North Atlantic-Arctic Multidecadal Variability on Northern Hemisphere Surface Air Temperature"
Vladimir A. Semenov, Mojib Latif, Dietmar Dommenget, Noel S. Keenlyside, Alexander Strehz, Thomas Martin, Wonsun Park
(To Appear: Journal of Climate)

"On the Trend of the Global Mean Surface Temperature"
Norden E. Huang, Zhaohua Wu, John M. Wallace, Xianyao Chen, Brian Smoliak, Compton J. Tucker
(Under Review)

How to Define Patterns of Multidecadal variability/predictabi

EOF? Optimizes variance, not time scale.

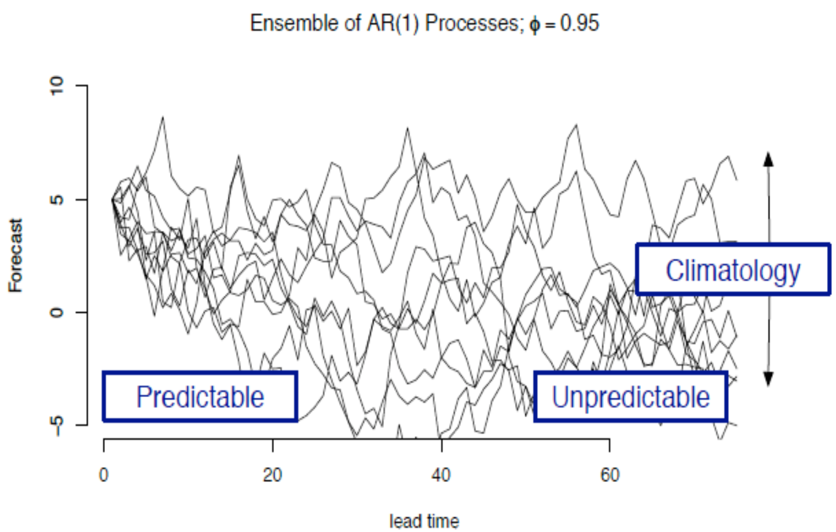
EMD? Ignores spatial correlations, hence is suboptimal.

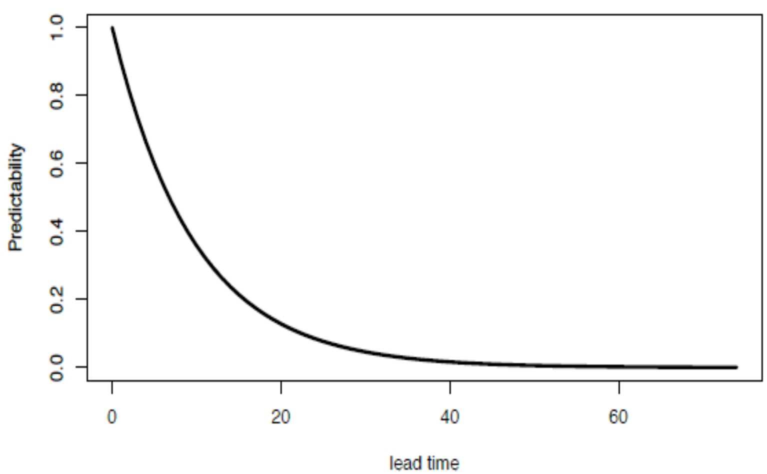
SSA? Ignores spatial correlations, hence is suboptimal.

EEOF? Not specifically optimized for multidecadal predictability.

New approach: Average Predictability Time (APT)

Definition of Predictability





Measure of Predictability

$$P = \frac{\sigma^2_{clim} - \sigma^2_{forecast}}{\sigma^2_{clim}}$$

$\sigma^2_{forecast}$: Variance of forecast.
σ^2_{clim}: Variance of climatology.

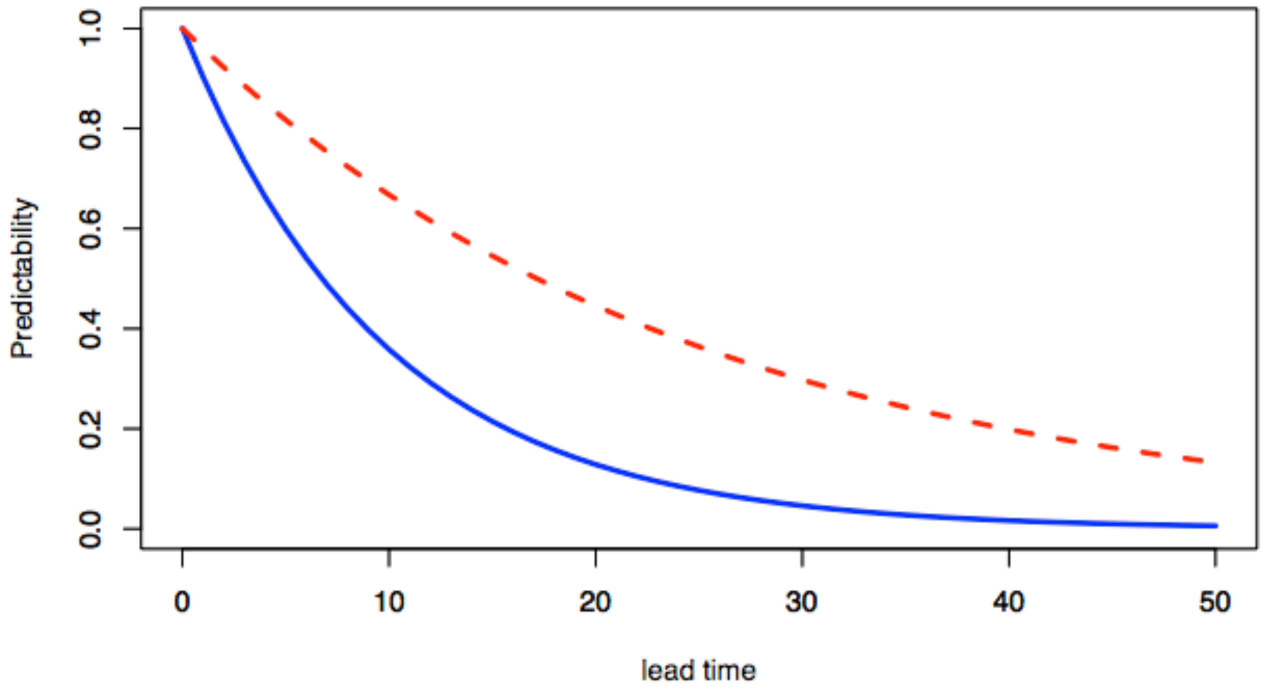
Identifying Internal Multidecadal Patterns (IMP)

Find a pattern that maximizes "persistence" (unlike EOF which maximizes variance).

Average Predictability Time (APT)

Average predictability can be characterized in a way that is independent of lead time by integrating the predictability metric, which always decreases with time. For example, the rate of decay is much slower and enhance the integral is much higher for decadal variation than seasonal variation.

Average Predictability Time (APT)



APT = integral of 2P over all lead times

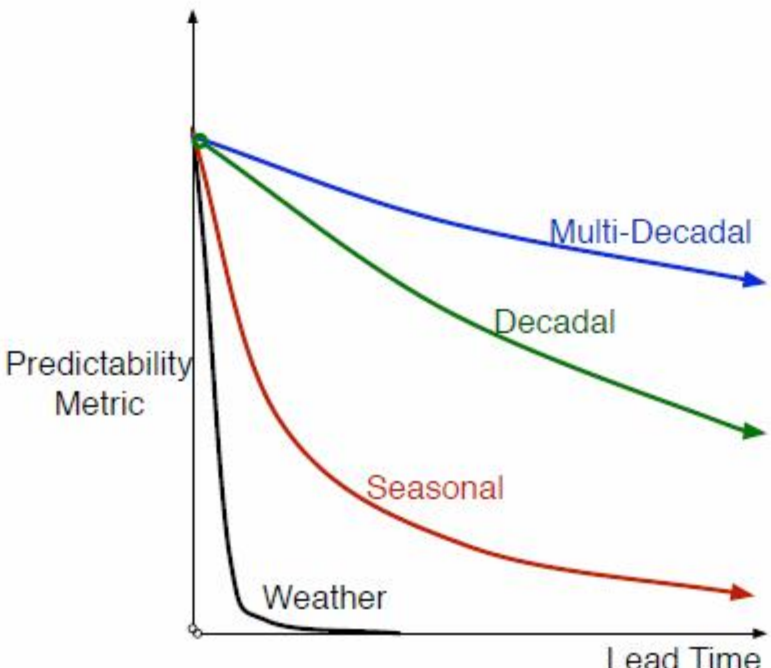
$$APT = 2\int_0^\infty \left(\frac{\sigma_c^2 - \sigma_f^2}{\sigma_c^2}\right) d\tau$$

Decomposing Predictability

Characterize predictability independent of lead time by integrating over lead time:

$$APT = 2\int_0^\infty \left(\frac{\sigma^2_{clim} - \sigma^2_{forecast}(\tau)}{\sigma^2_{clim}}\right) d\tau$$

Find component that maximizes APT (DelSole and Tippett 2009).



Optimize APT in Control Runs

- Use IPCC AR4 data set (also called CMIP3).
- Last 300 years of PICNTRL are used.
- Model grids interpolated onto HadSST2 grid.
- Only "well-observed" grid points in the model are analyzed.
- Annual averaged sea surface temperature.
- Each model's climatology subtracted out.
- All runs pooled to compute "total EOF" and "total APT."
- The "outliers" IAP, GISS-EH, GISS-ER were omitted.
- 14 models, effective time series length = 4200 years.
- 40 EOF truncation, 20-year maximum lag for APT.
- No Detrending
- Null hypothesis: white noise when sampled every 2 years.

Challenges in Separating Forced and Un-Forced Patterns

- **Forcing may project strongly on un-forced patterns.**
  - **Time series of IMP in different ensemble members are uncorrelated in most (but not all) models.**
- **Model estimates of forced pattern may be wrong.**
  - **Results are the same if observed trend pattern is used for the “forced pattern” (no model is used to estimate forced pattern).**
- **Forced response may not be captured by one pattern.**
  - **Including second SN-EOF does not change the results.**
  - **Second signal-to-noise EOF is statistically insignificant.**

Signal-to-Noise EOFs: Response Pattern to Forcings

(Anthropogenic and Natural (Solar, Volcanic)

Find components that maximize the ratio of variances:

- **Discriminant analysis (Fisher 1938)**
- **Seasonal Predictability (Straus et al. 2003)**
- **Decadal Predictability (Venzke et al. 1999)**
- **Climate Change (Ting et al. 2009) (No IPCC Control Runs)**

Response pattern to climate forcing estimated by finding the pattern that maximizes the ratio

$$\frac{\text{variance in twentieth century runs}}{\text{variance in pre-industrial control runs}} = \frac{\sigma^2_{20c3m}}{\sigma^2_{picntrl}}$$

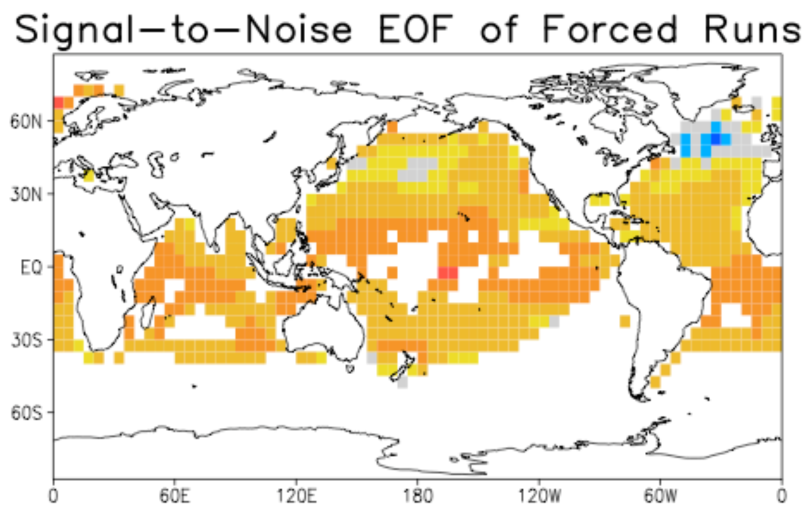
If forced response is additive, $\sigma^2_{20c3m} = \sigma^2_{picntrl} + \sigma^2_{\text{forced response}}$

Trend Patterns:

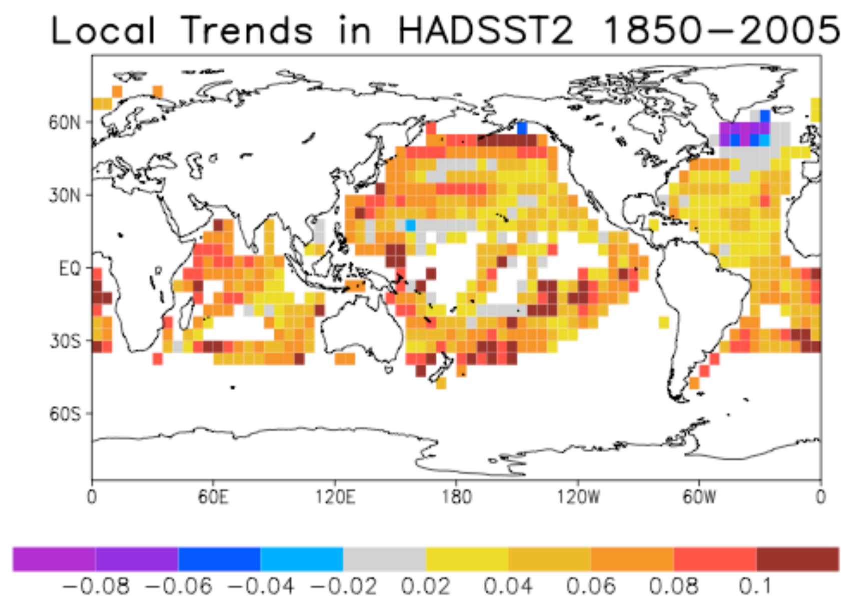
To be interpreted as Response Pattern to Forcings

Fit linear trend between 1850-2005, plot the slope expressed as degrees per decade.

Estimated Response to Anthropogenic and Natural Forcings



Signal to Noise EOF



Local Trend Pattern

IGES

COLA

Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

Fingerprinting Method

Fit observed annual average SST to

$$\underbrace{T_{obs}(x,y,t)}_{\textit{Observed}} = \underbrace{a_{for}(t)\,T_{for}(x,y)}_{\textit{Forced Response}} + \underbrace{a_{imp}(t)\,T_{imp}(x,y)}_{\textit{Internal Pattern}} + \underbrace{w(x,y,t)}_{\textit{Random Noise}}$$

- Define spatial response to external forcing $T_{for}(x,y)$.
- Define spatial structure of IMP $T_{imp}(x,y)$.
- Define statistics of internal variability (from 'control runs').
- Fit equation using generalized least squares:

Detection: Test hypothesis $a_{for}(t) = 0$.

Attribution: Test hypothesis $a_{for}(t) =$ predicted amplitude.

How to Define the Response to Climate Forcing?

Pattern should characterize response to natural and anthropogenic forcing, but also filter out as much internal variability as possible.

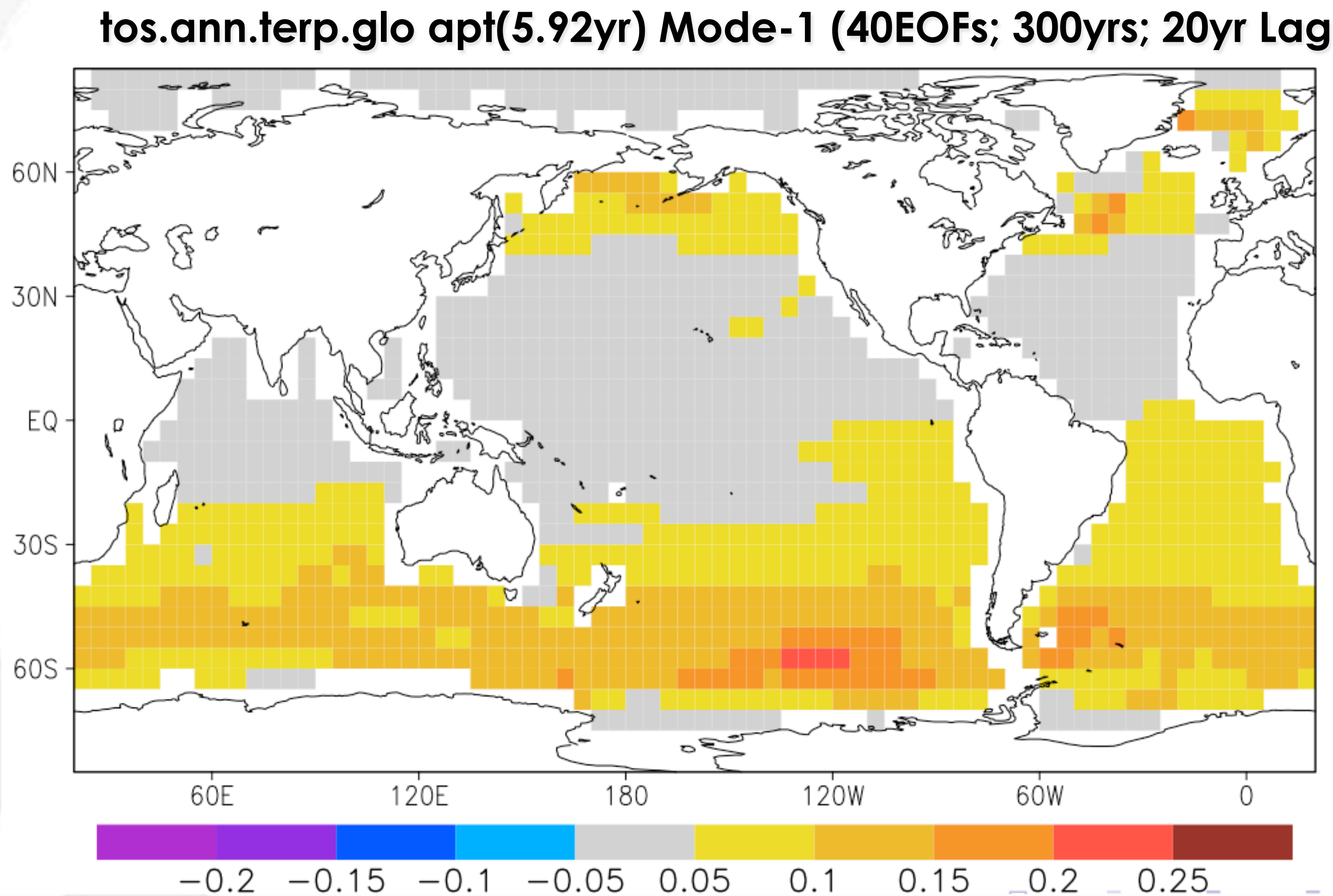
Hypothesis:

$$\begin{array}{ccccc} \text{Total} & = & \text{Forced Response} & + & \text{Internal Variability} \\ & & \textit{Signal} & & \textit{Noise} \end{array}$$

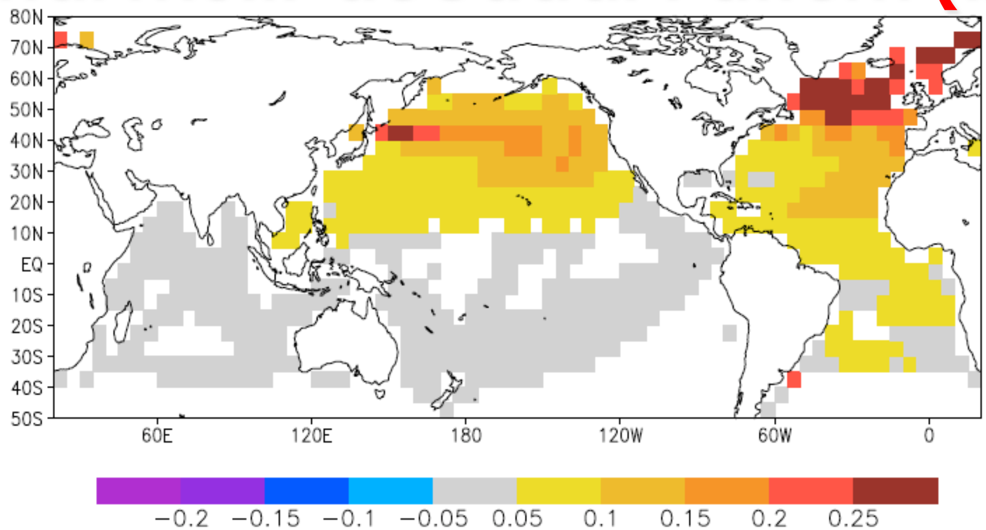
Find projection vector that maximizes the ratio of the variance in the forced run to variance in the control run:

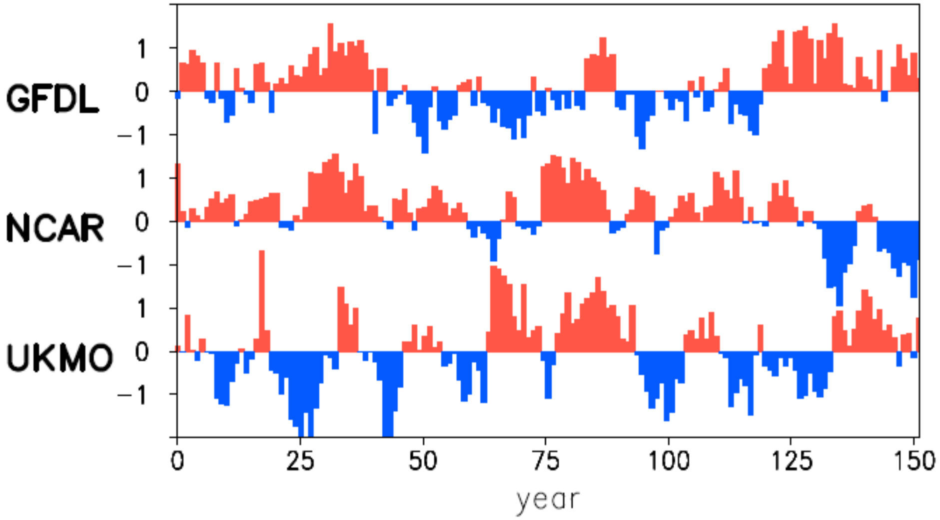
$$\frac{\sigma^2_{forced}}{\sigma^2_{control}} = \frac{\sigma^2_S + \sigma^2_N}{\sigma^2_N} = \frac{\sigma^2_S}{\sigma^2_N} + 1$$

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



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





IGES

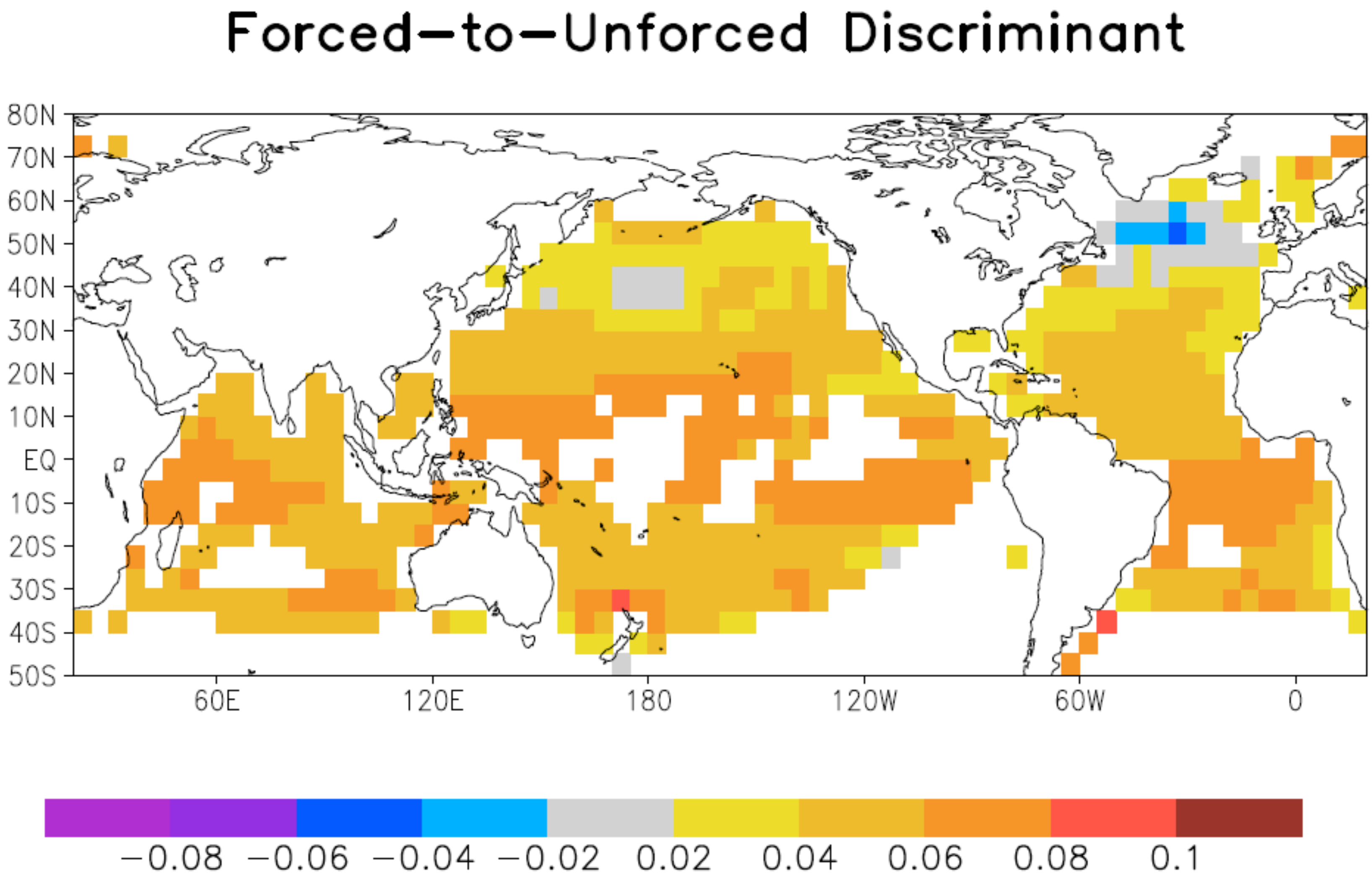
Center of Ocean-Land-Atmosphere studies

COLA

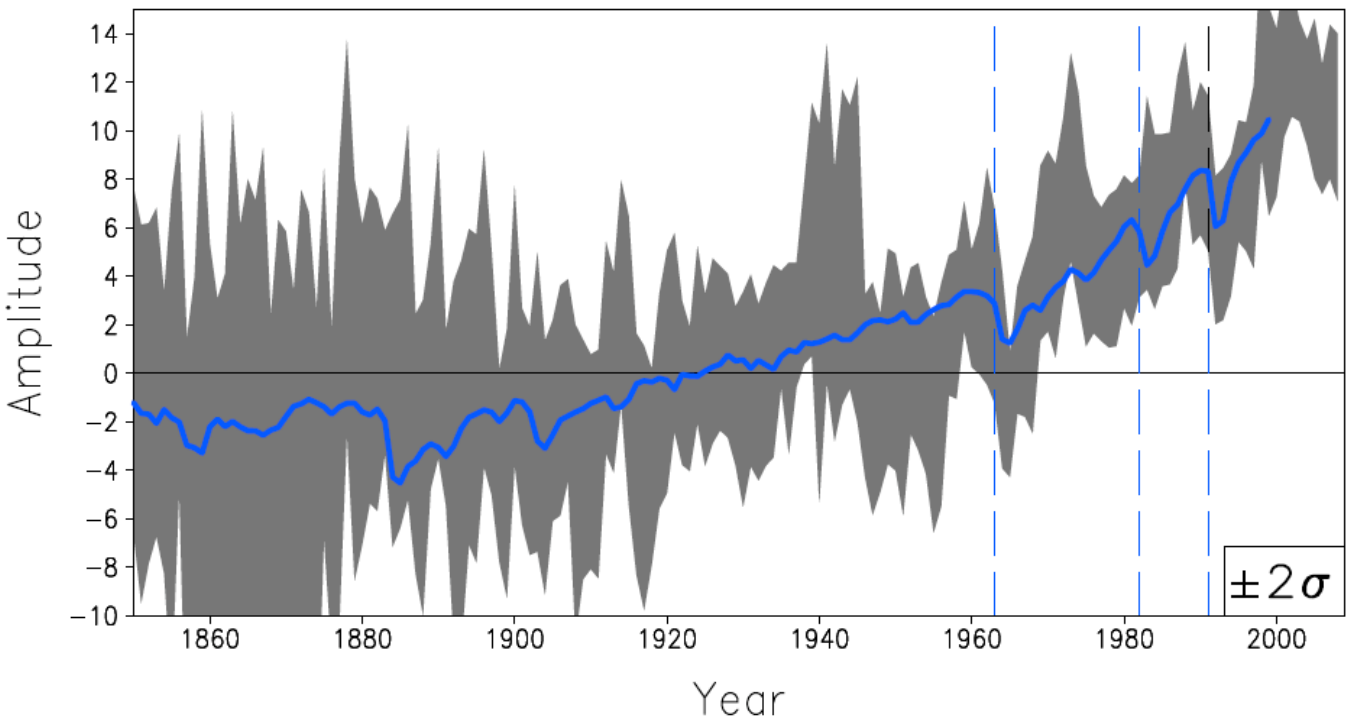
CREW
Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

Forced-to-Unforced Discriminant from Control Runs



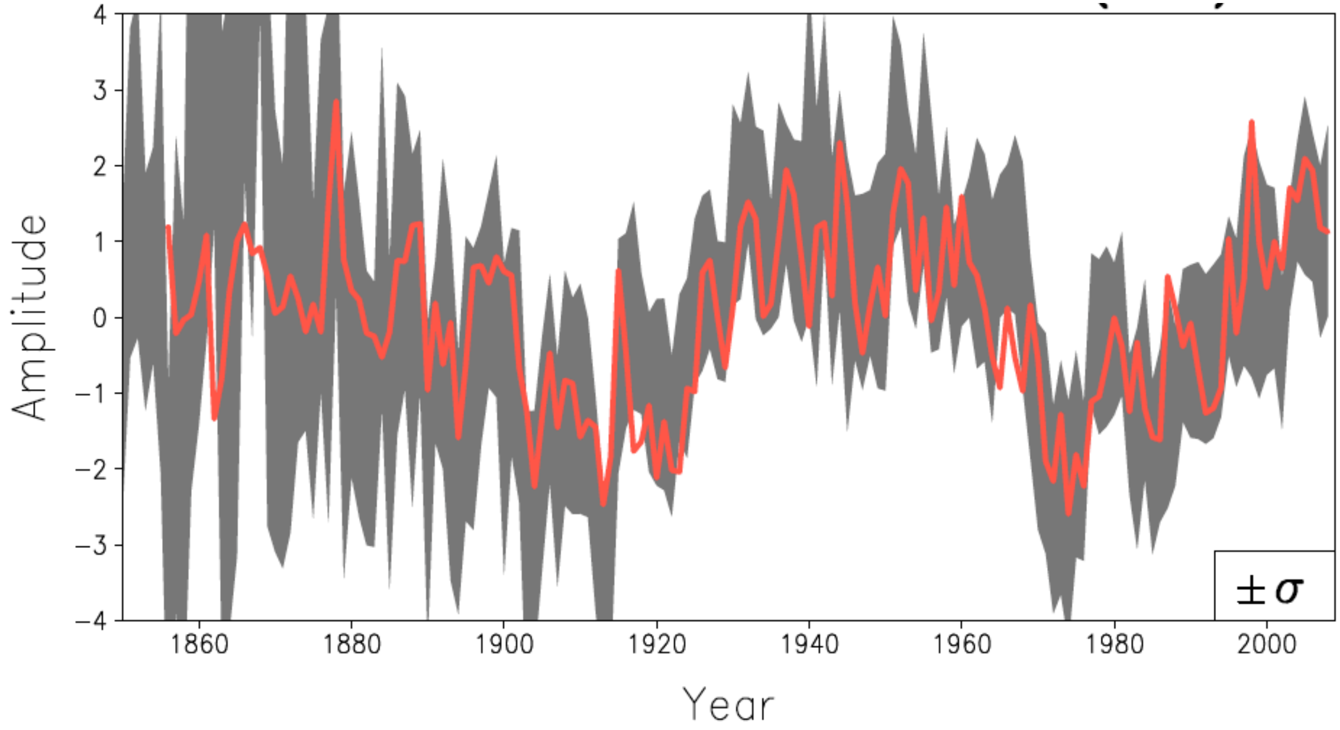
Forced Pattern



shaded area: 95% confidence interval of forced pattern in observations.

blue line: Ensemble mean amplitude of forced pattern in models

Internal Multi-decadal Pattern (IMP)



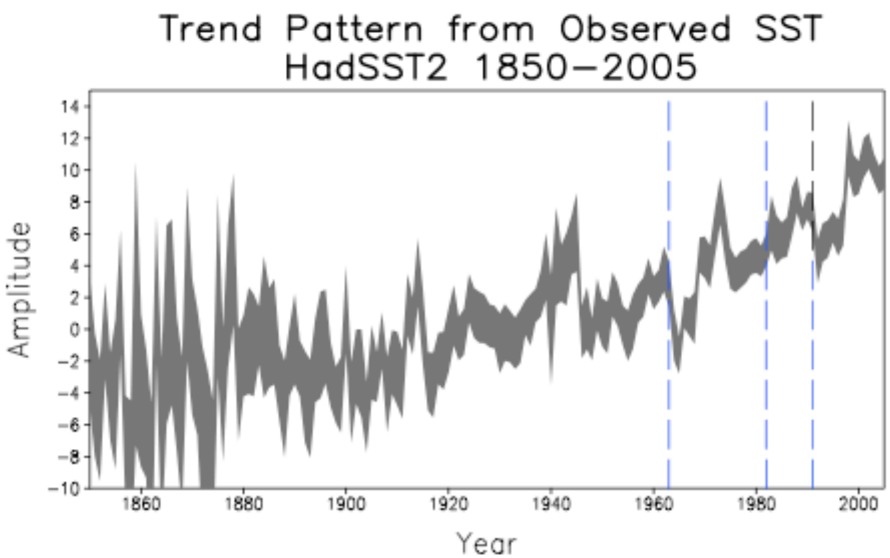
shaded area: 66% confidence interval of IMP in observations.

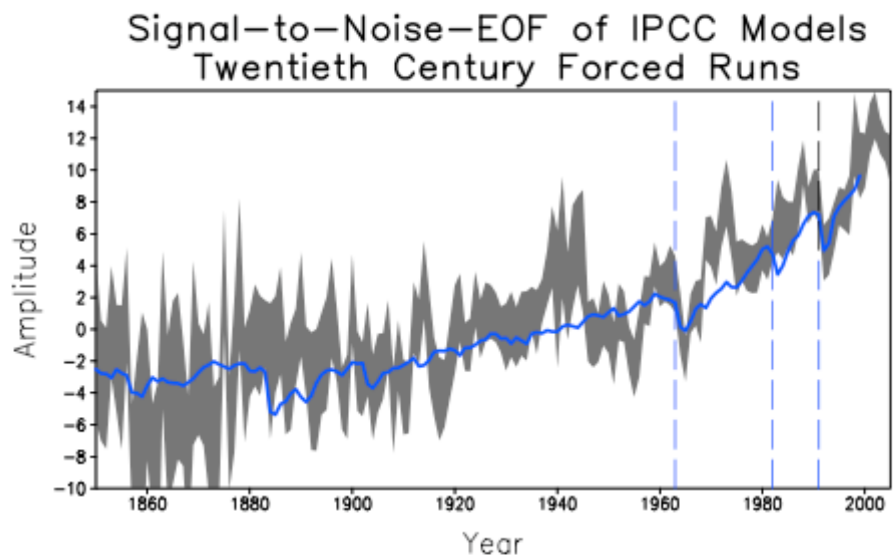
red line: Observed Atlantic Multidecadal Oscillation (AMO) index.

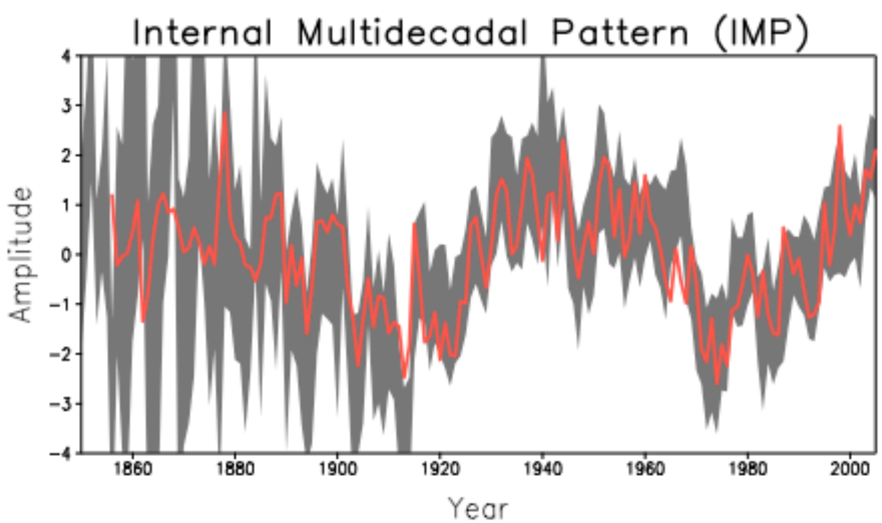
Amplitude of Forced Patterns and Unforced Patterns

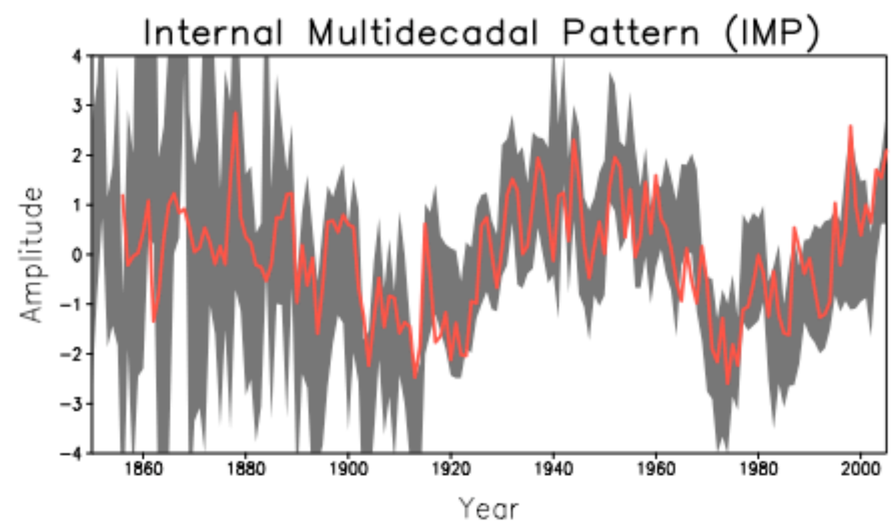
Trend

Signal-to-Noise

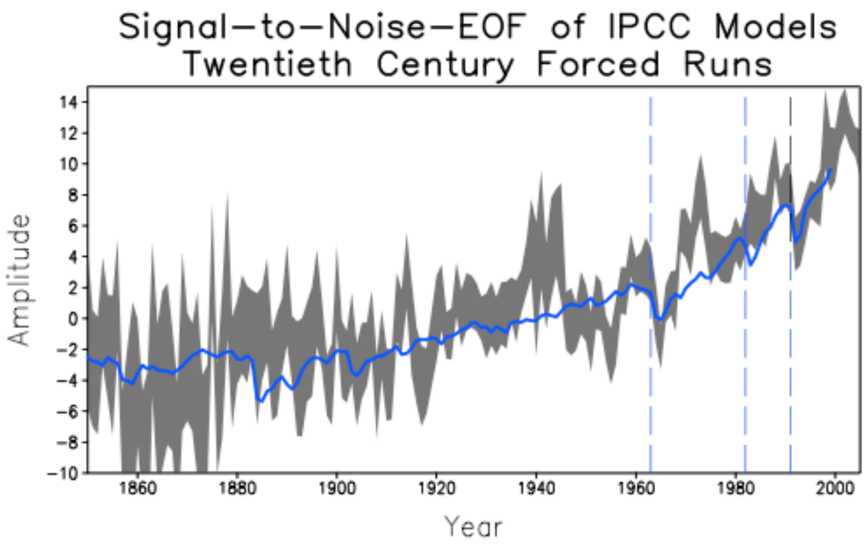








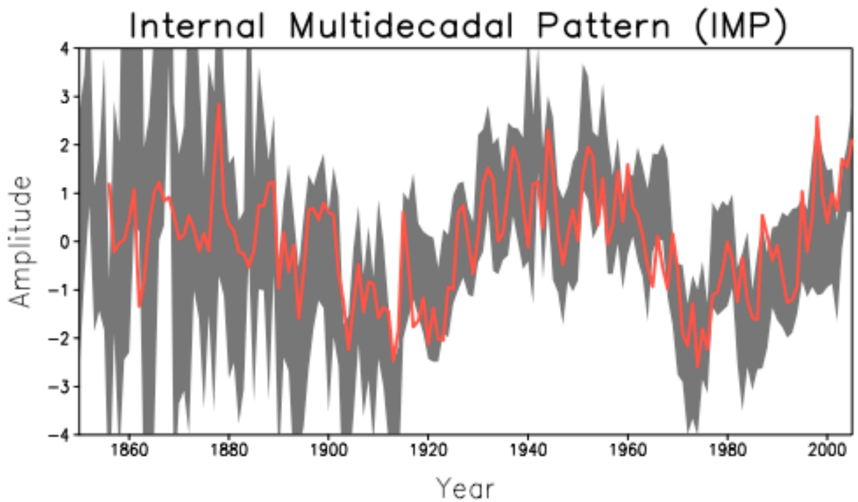
Amplitude of Forced and Unforced Patterns



Shading: $\pm\sigma$ Fingerprint Amplitude

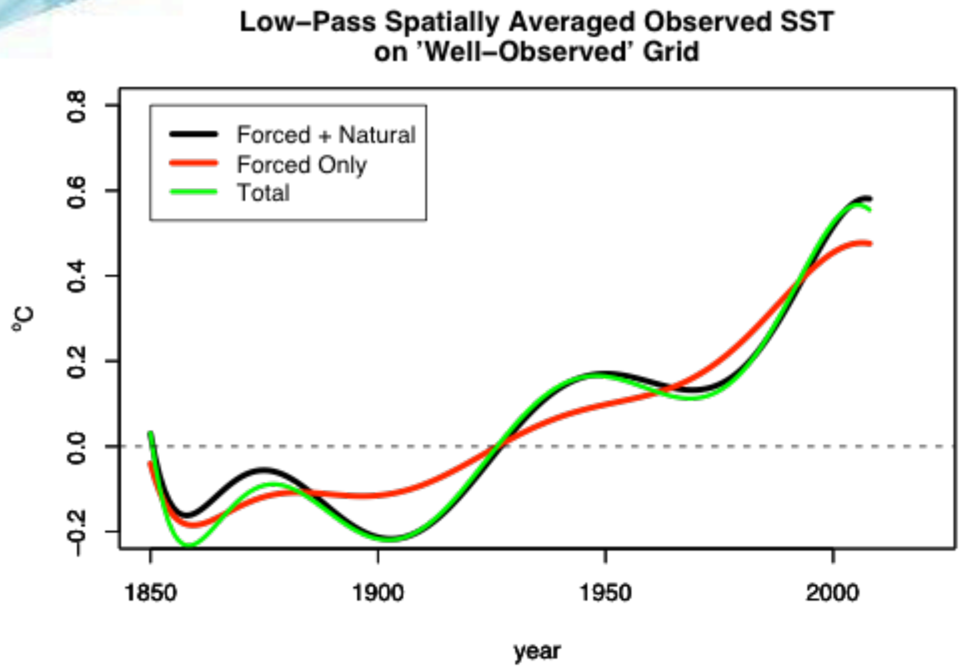
Blue Solid Line: Signal-to-noise PC

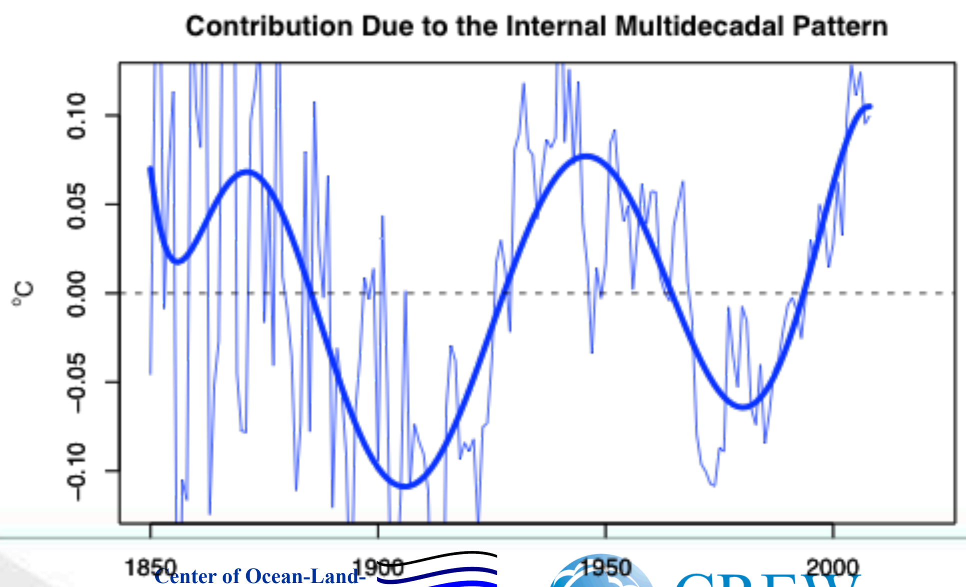
Blue Dashed Line: Major Volcanic eruptions



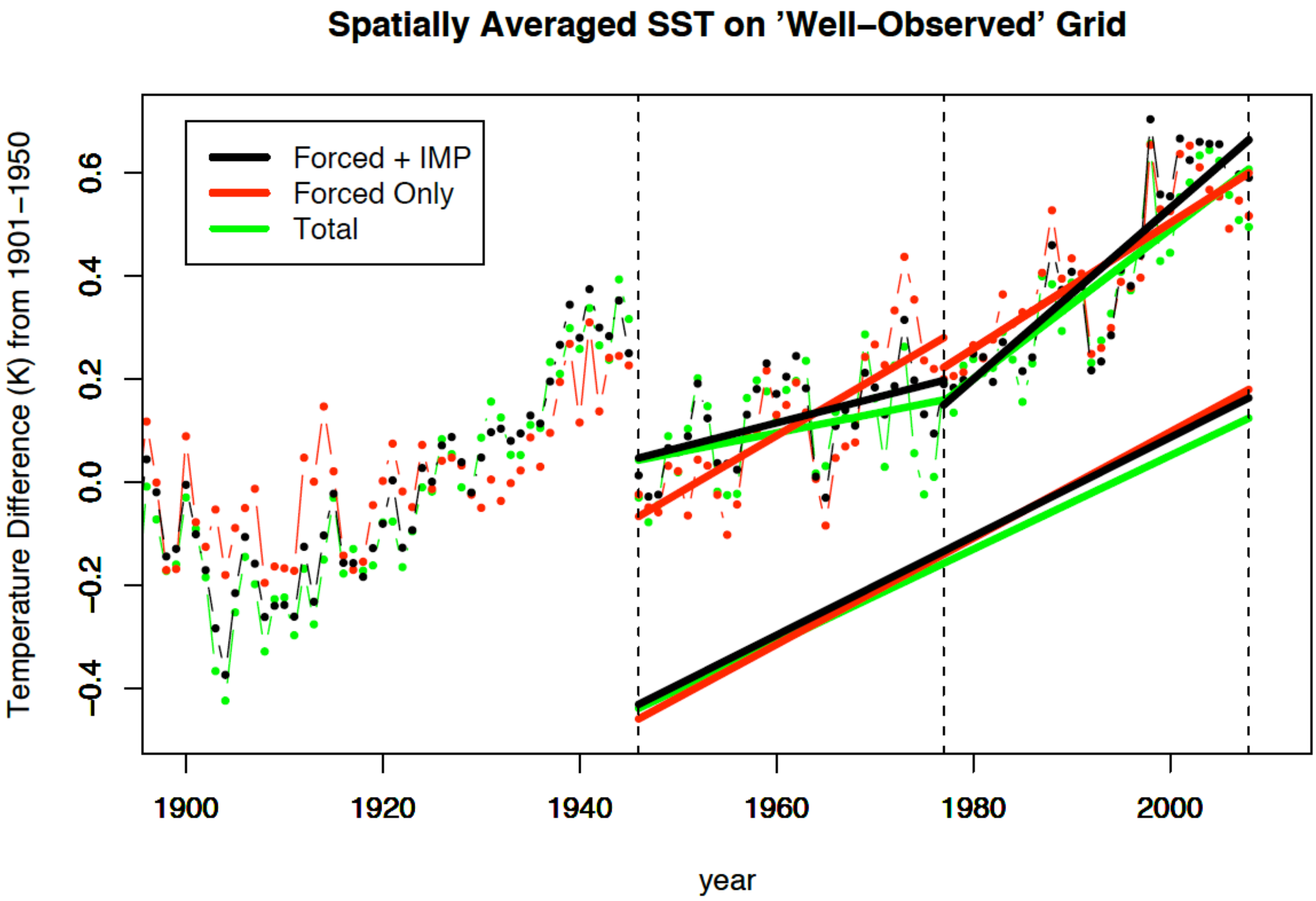
Shading: $\pm\sigma$ Fingerprint Amplitude

Blue Solid Line: AMO Index

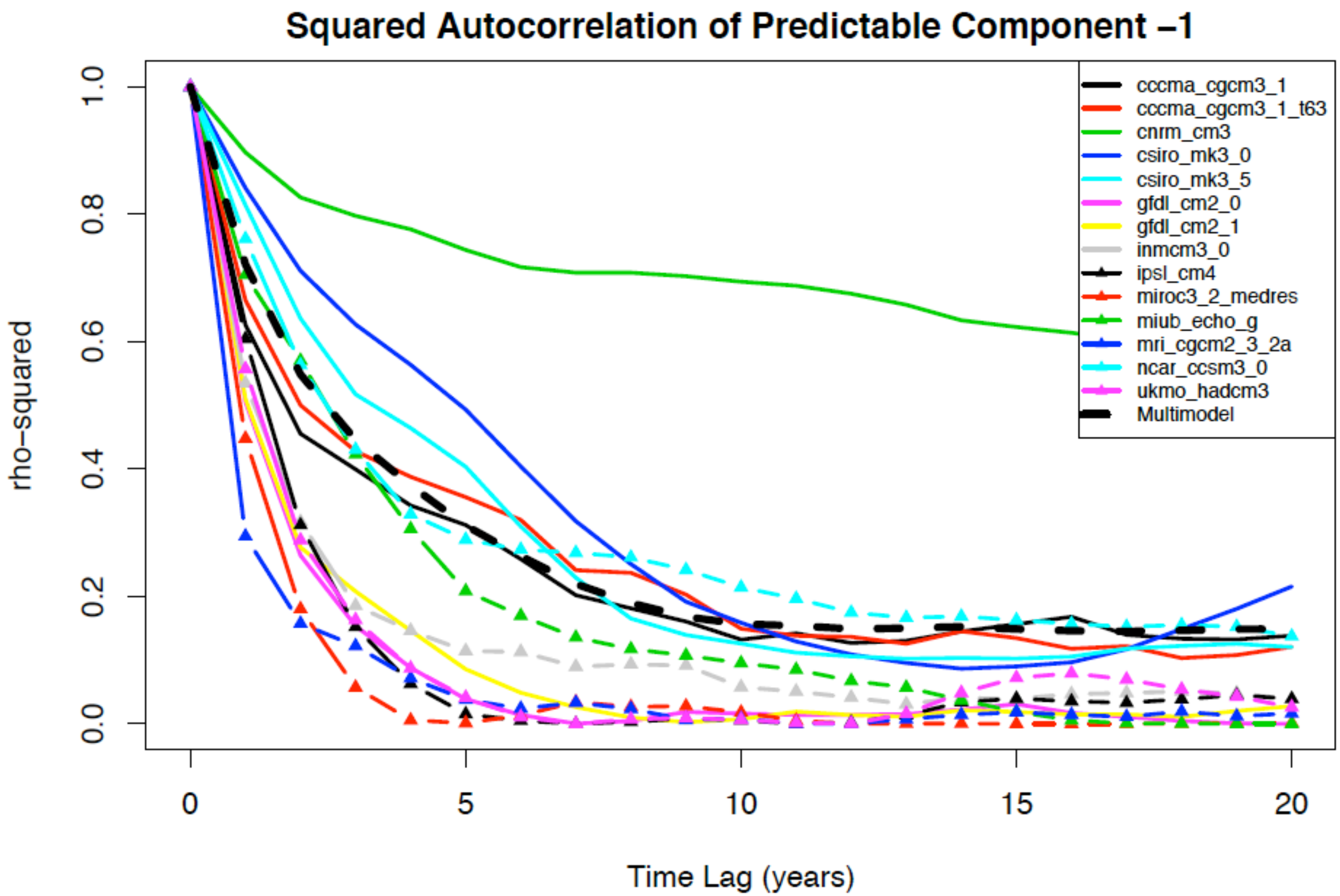

Low–Pass Spatially Averaged Observed SST
on 'Well–Observed' Grid
Forced + Natural
Forced Only
Total
°C
0.8
0.6
0.4
0.2
0.0
−0.2
1850
1900
1950
2000
year


Contribution Due to the Internal Multidecadal Pattern
°C
0.10
0.05
0.00
−0.05
−0.10
1850
1900
1950
2000
year

Global Mean SST



Scientific Basis for Decadal Predictability



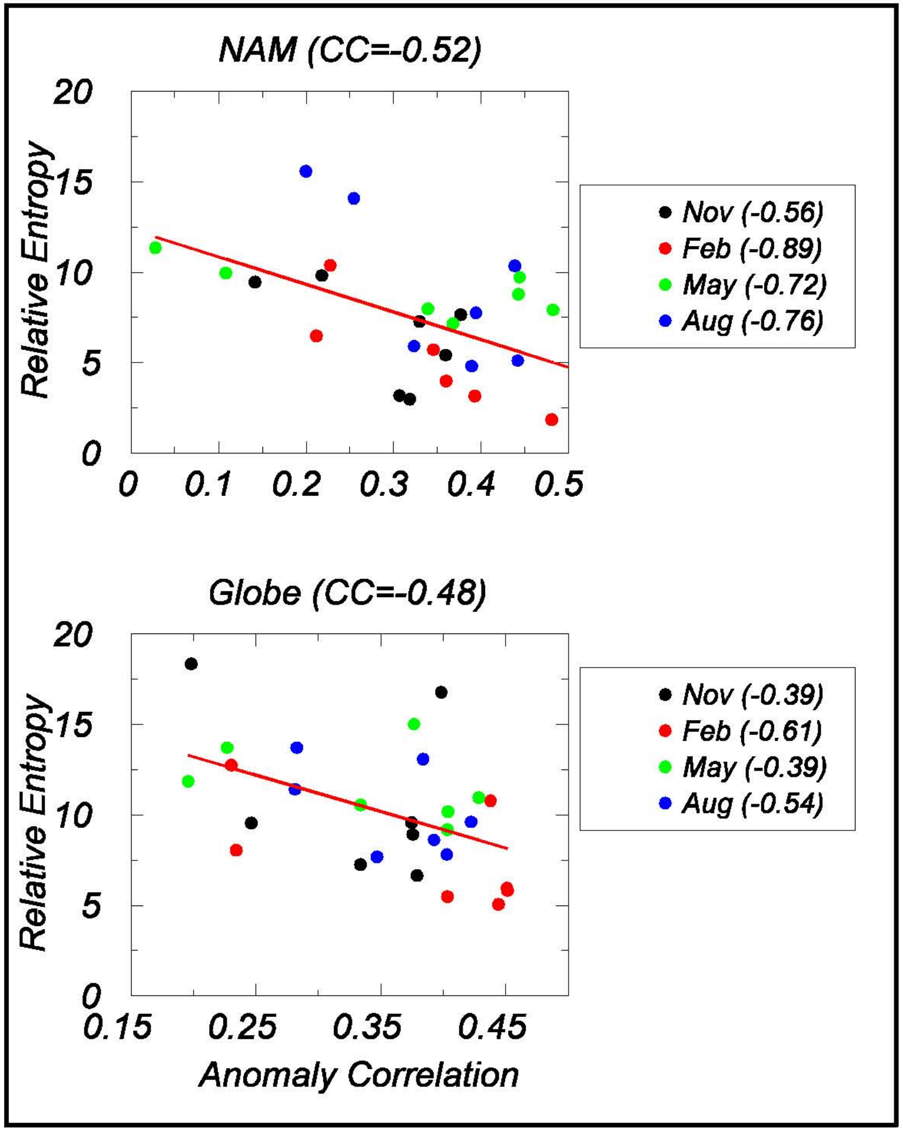
Dynamical Prediction Experience
(~30 years)

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

Dynamical Prediction Experience

Model predictability depends on model fidelity

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.

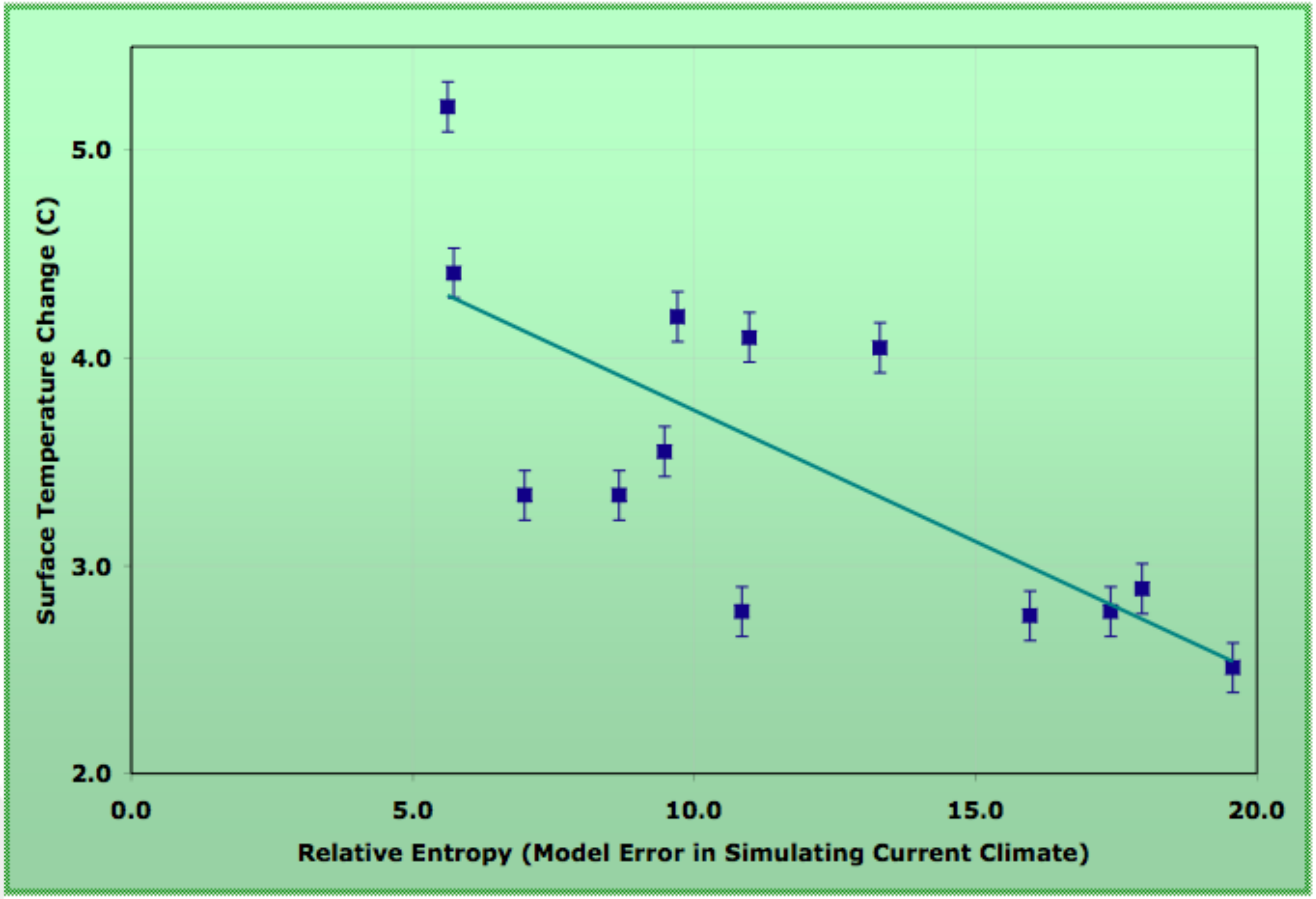
Models with better climatology tend to have better skill.

Courtesy of Tim DelSole

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.

Uncertainty in Global Warming Projected by IPCC Models (Fixed Forcing)

"…models still show significant errors. Although these are generally greater at smaller scales, important large-scale problems also remain. ……**The ultimate source of most such errors is that many important small-scale processes cannot be represented explicitly in models**, and so must be included in approximate form as they interact with larger-scale features……consequently models continue to display a substantial range of global temperature change in response to specified greenhouse gas forcing."

Chapter 8; IPCC (2007)

WCRP Modeling Panel (WMP) Report

Meeting: Oct 23-24 2006, NCAR, Boulder, CO; Approved by JSC 3 July 2007

1. Insufficient comprehensive model development globally.
2. Low resolution climate models have serious limitations in simulating the current climate.
3. Use of regional models to downscale regional climate change is questionable.
4. Modeling community does not have sufficient computing power.
5. It is difficult to realize the maximum possible value from space measurements.
6. WCRP/IGBP/WMO establish appropriate computing and data facilities.

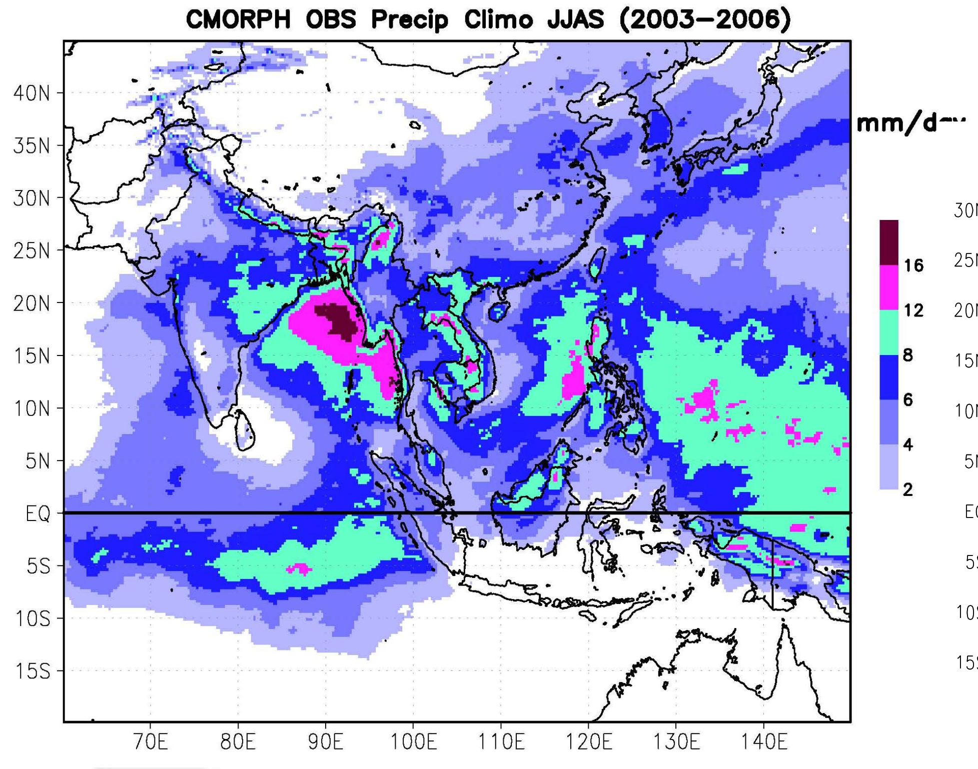
Dynamical Prediction Experience

Examples of global climate model deficiencies

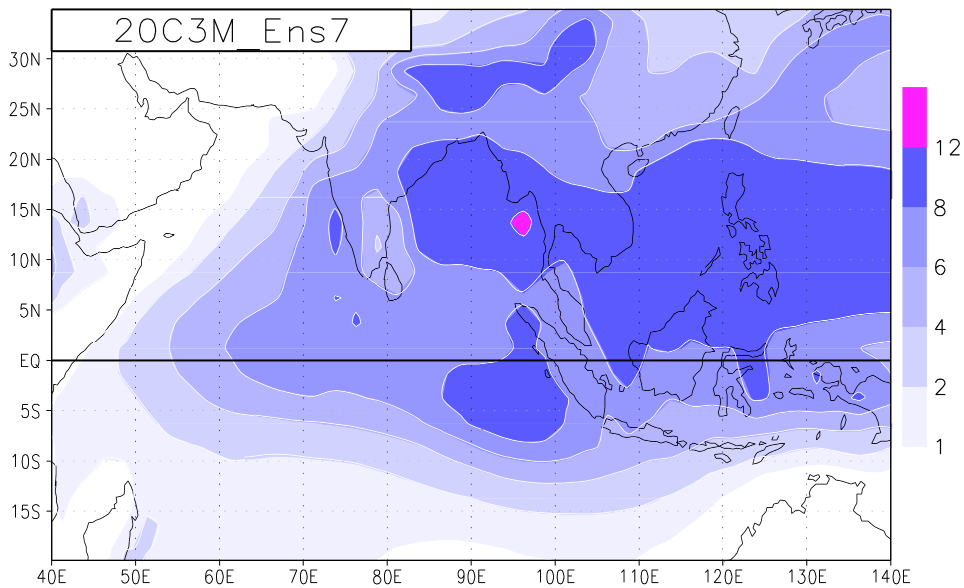
(Regional downscaling is not the answer)

JJAS Precipitation

Observed TRMM



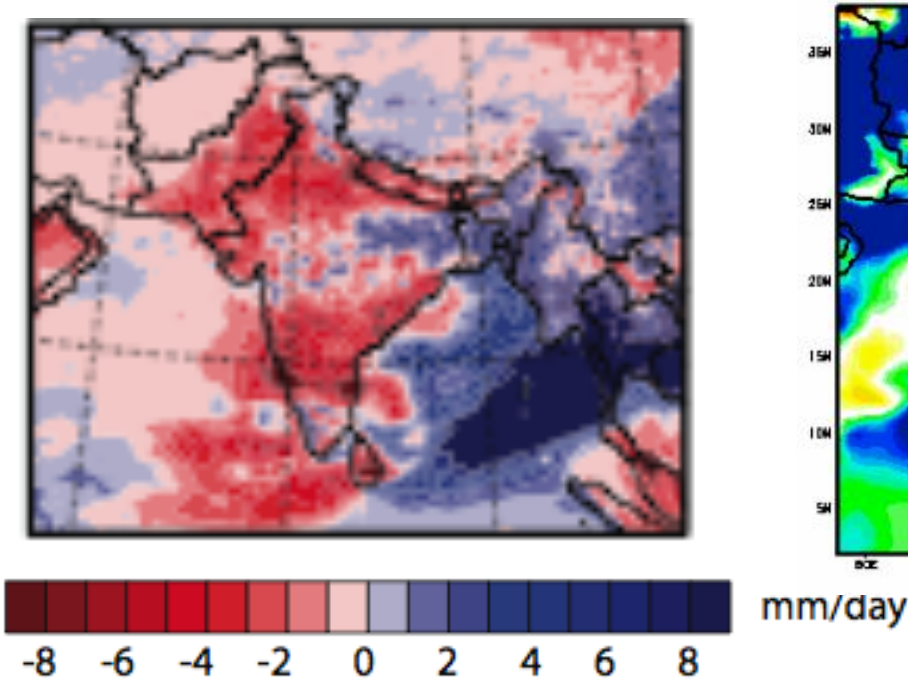
IPCC Model: 20C3M
1979-1998



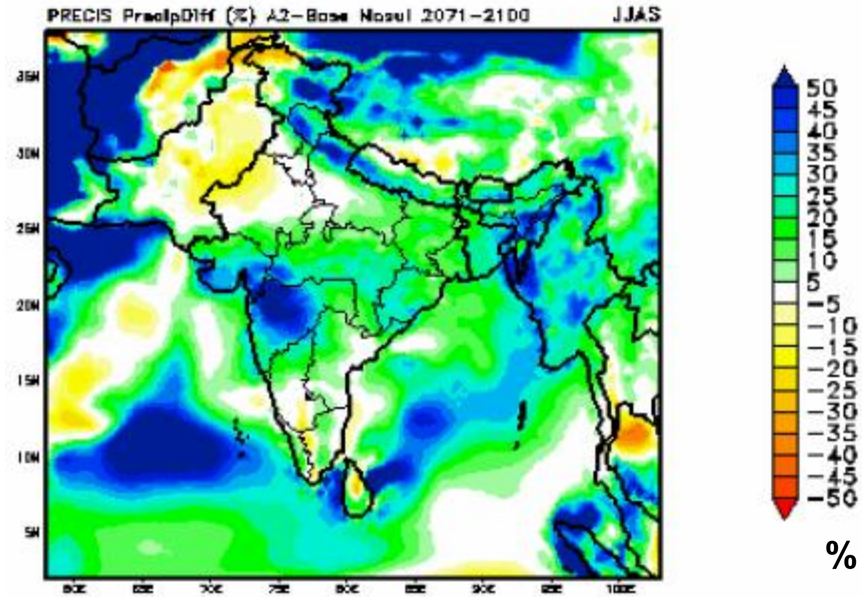
IPCC Models are unable to simulate mean monsoon rainfall.

Changes in (A2 minus Reference) in precipitation (mm/day) due to global warming as simulated by regional models

July



JJAS

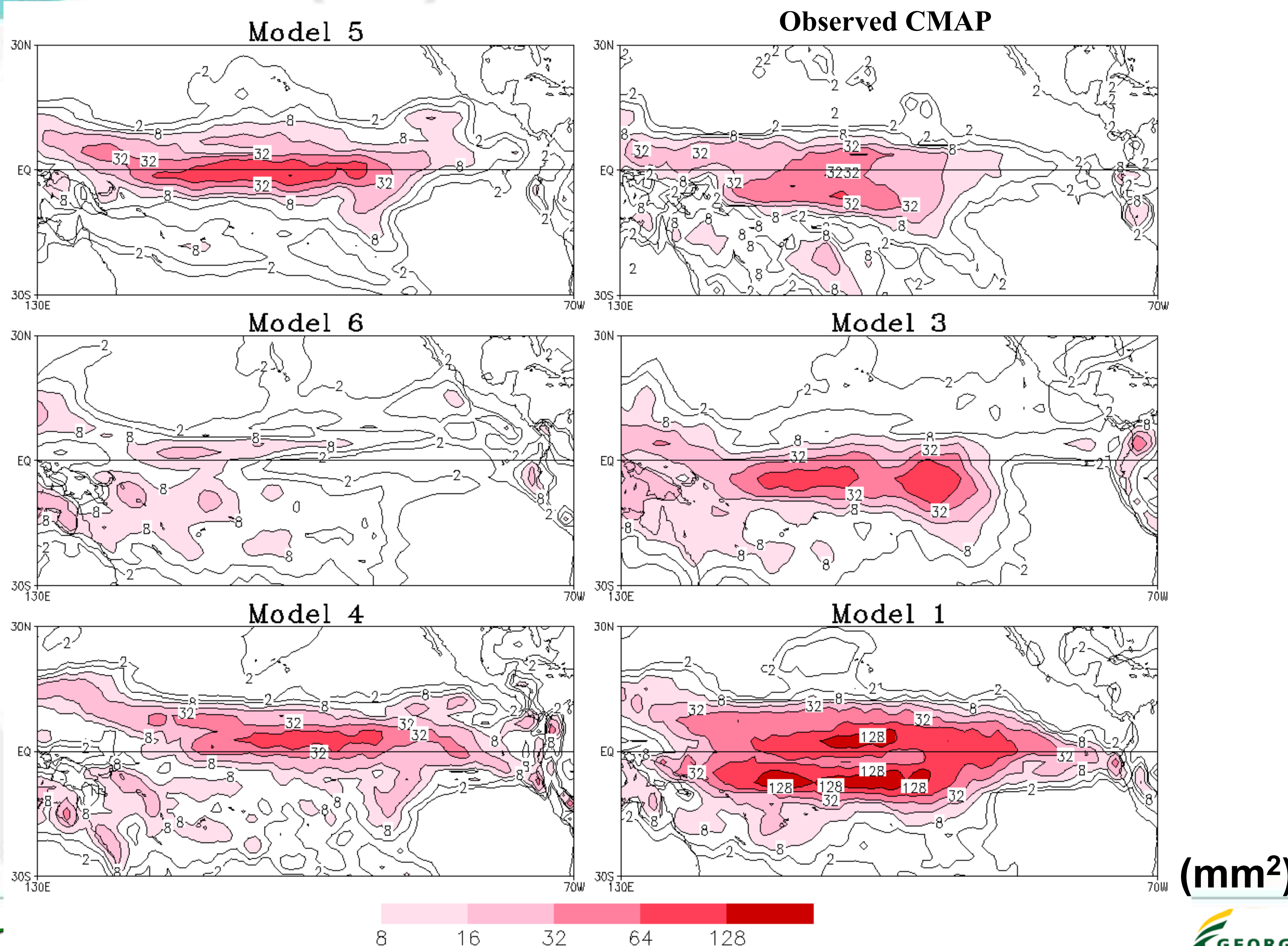


HadCM3/NASA FVGCM/RegCM3
(Ashfaq *et al*., 2009, GRL)

HadCM3/PRECIS
(Rupa Kumar *et al*., 2006, Current Science)

(RegCM3 produces weaker monsoon; PRECIS produces stronger monsoon due to global warming)

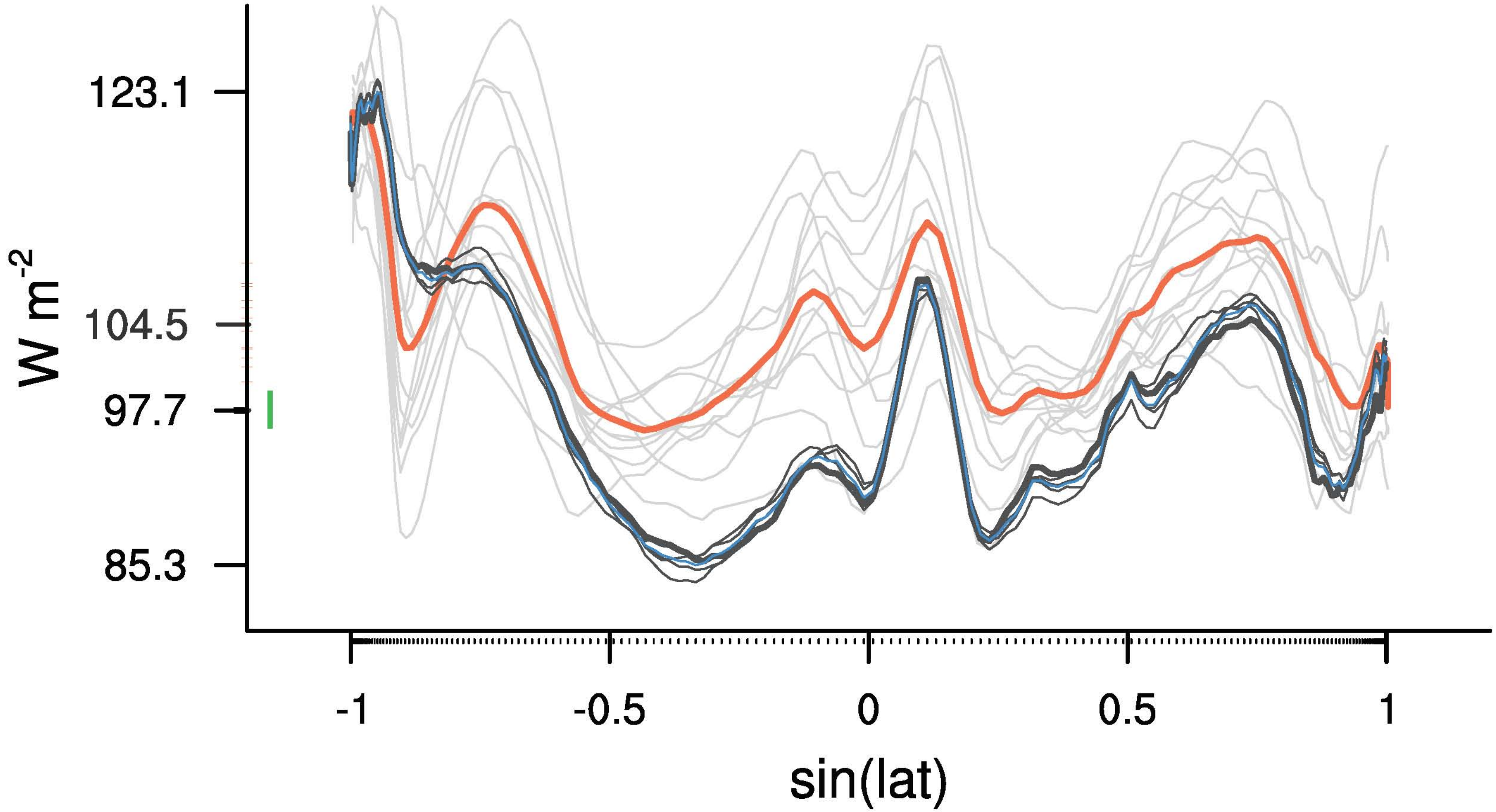
Boreal Winter (DJF) Rainfall Variance in AGCMs



Fundamental barriers to advancing weather and climate diagnosis and prediction on timescales from days to years are (partly) (almost entirely?) attributable to gaps in knowledge and the limited capability of contemporary operational and research numerical prediction systems to represent precipitating convection and its multi-scale organization, particularly in the tropics.

(Moncrieff, Shapiro, Slingo, Molteni, 2007)

Annually & Zonally Averaged SW Radiation (AR4)



- 101-106 W/m2 (Wild et al., survey)
- 107 W/m2 (Trenberth and Kiehl (ERBE)
- 101 W/m2 (CERES)

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

WMS takes place at ECMWF (6-9 May 2008). Nearly 150 participants from all modelling centers of the world.

They say they want a revolution

Climate scientists call for major new modelling facility.

Climatologists have called for massive investment in computer and research resources to help revolutionize modelling capabilities. The eventual aim is to provid predictions that are as weather forecasts.

At the end of a four-day at the European Centr Weather Forecasts in Rea made the case for a clim on the scale of the Hum key component of this cost something up to, lars, would be a world cl research facility with co

— to speeds in the hundreds of petaflops — would allow modellers to study simulations at the kilometre scale, enabling better predictions

Article in Nature, May 2008

Researchers from around the world gathered in Reading, UK, for the summit.

IGES

Center of Ocean-Land-Atmosphere studies

COLA

CREW Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

From Cyclone Resolving Global Models to Cloud System Resolving Global Models

1. Planetary Scale Resolving Models (1970~): Δx~500Km
2. Cyclone Resolving Models (1980~): Δx~100-300Km
3. Mesoscale Resolving Models (1990~): Δx~10-30Km
4. Cloud System Resolving Models (2000 ~): Δx~3-5Km♪

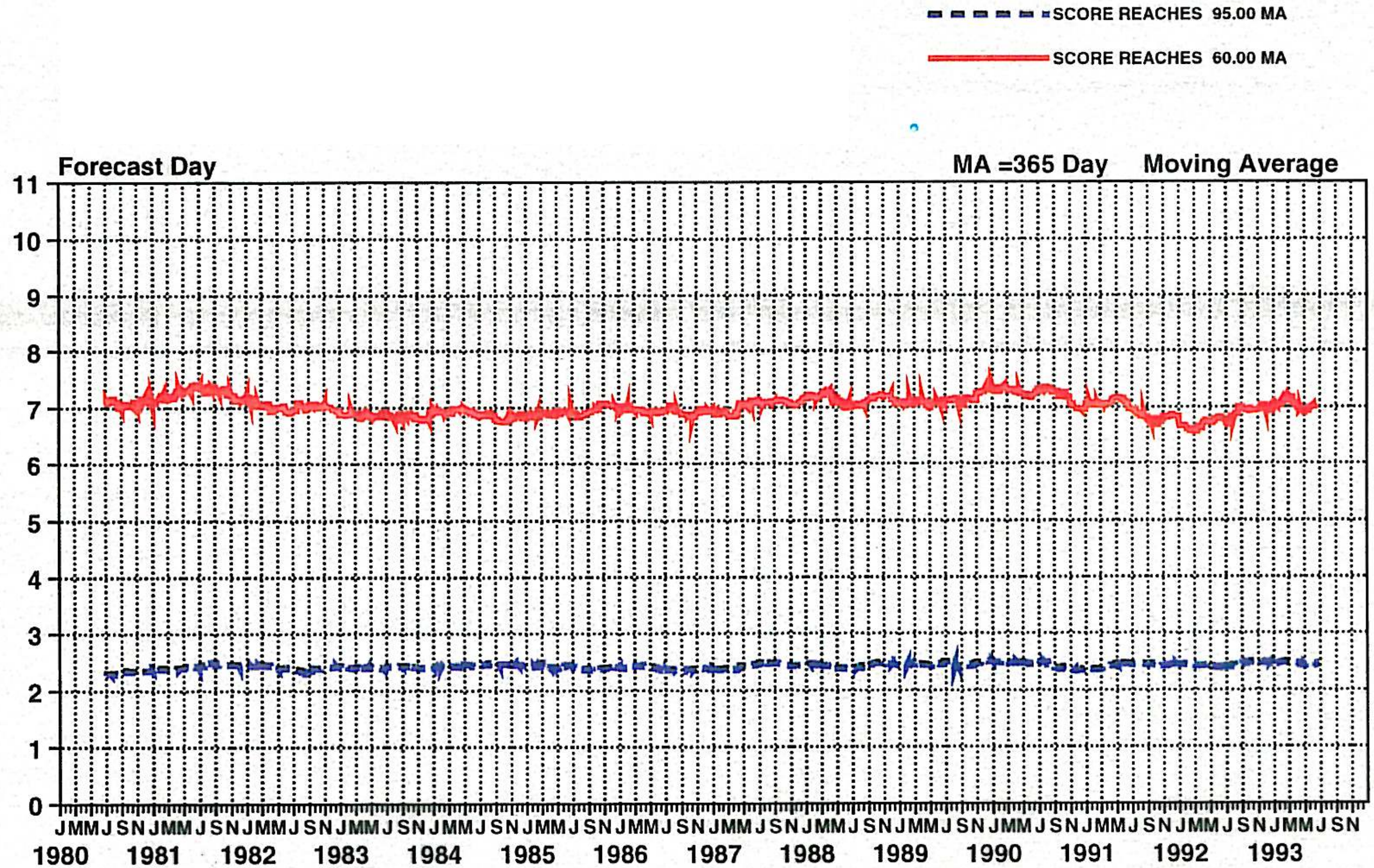
Organized Convection → Cloud System → Mesoscale System → Synoptic Scale → Planetary Scale

Convective Heating → MJO → ENSO → Climate Change

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

ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N



Blocking Frequency

Black: Reanalysis (ERA); Red: T 159; Blue: T 1279 (ECMWF)

(Higher Resolution Model Improves Simulation of Blocking Frequency)

40

Reanalysis
T159 (IBM)
T159 (XT4)
T1279 (XT4)

30

Blocking Frequency (%)

20

10

0

-180 -120 -60 0 60 120 180

Longitude

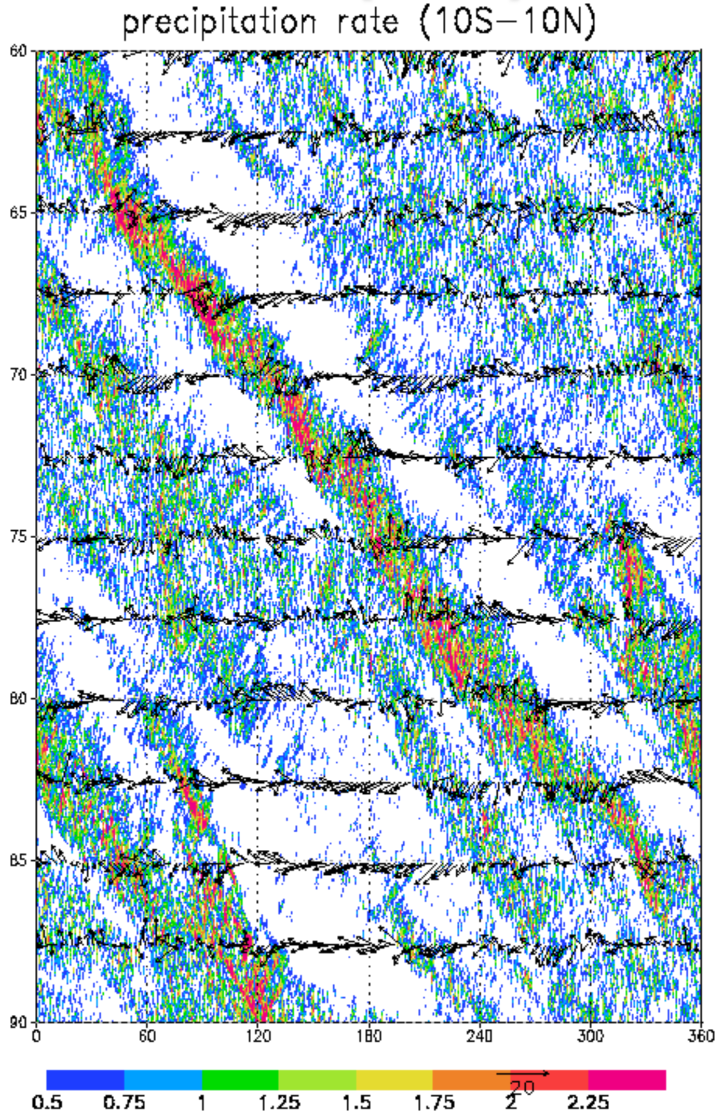
Center of Ocean-Land-Atmosphere studies

COLA

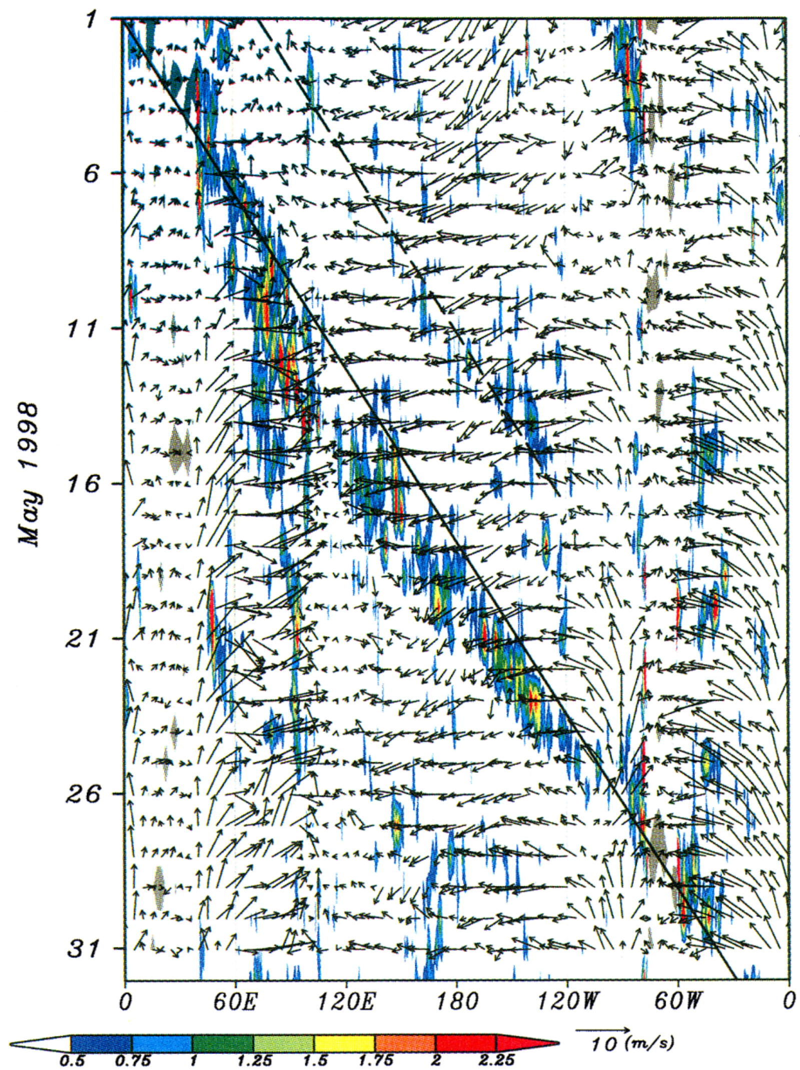
CREW Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

NICAM (7-km)

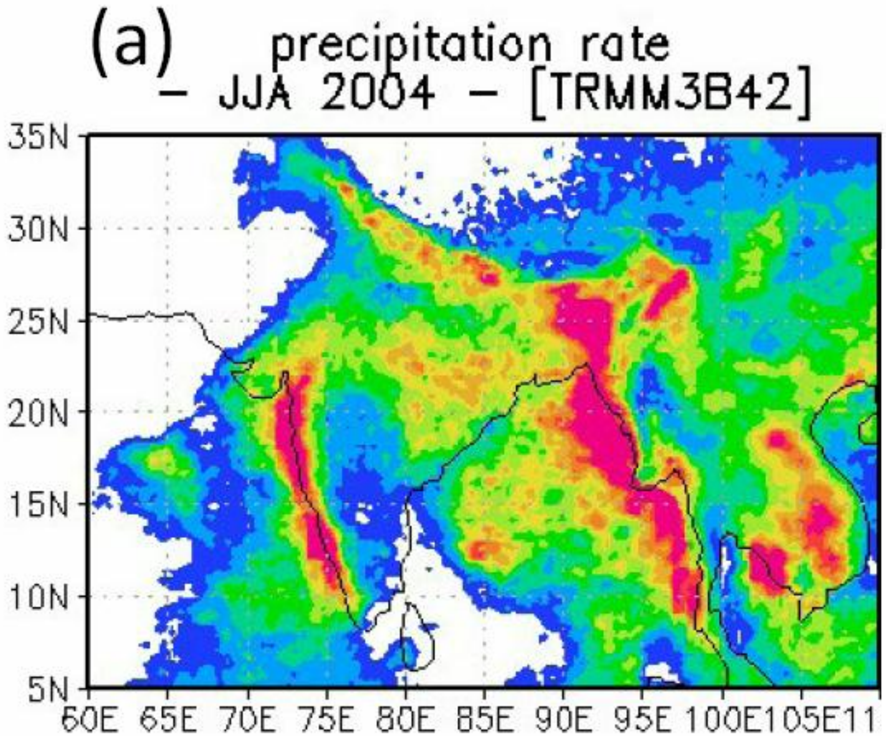


Obs. (Takayabu et al. 1999)

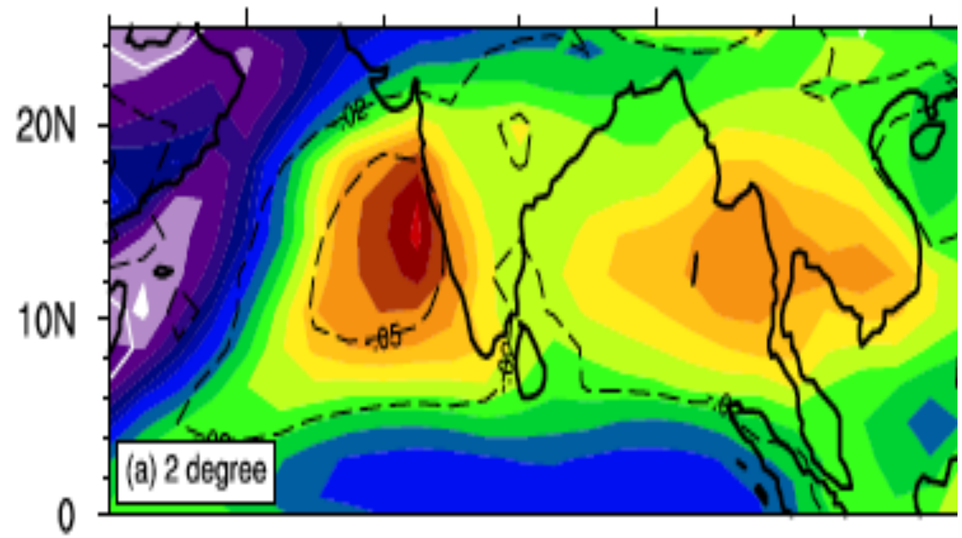


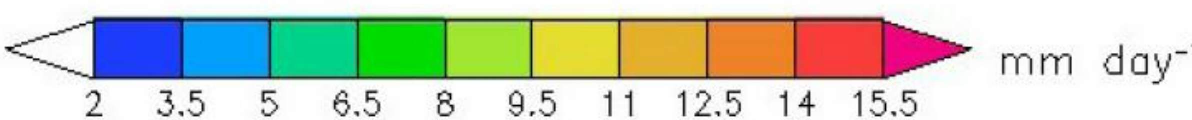
Matsuno (AMS, 2007)

Monsoon Rainfall in Low Resolution Model

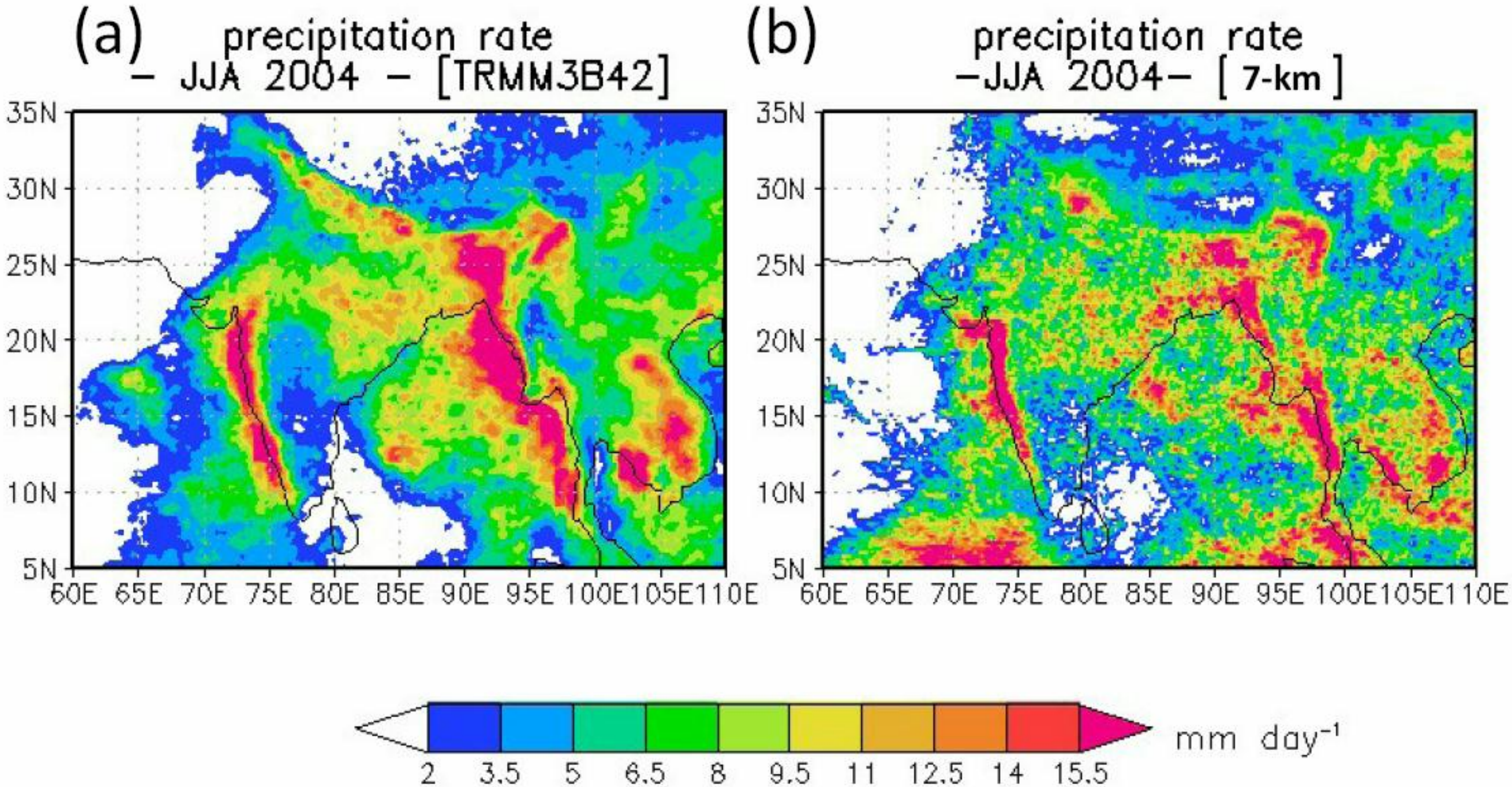


(b) Coupled model (2 degree)
- Climatology -





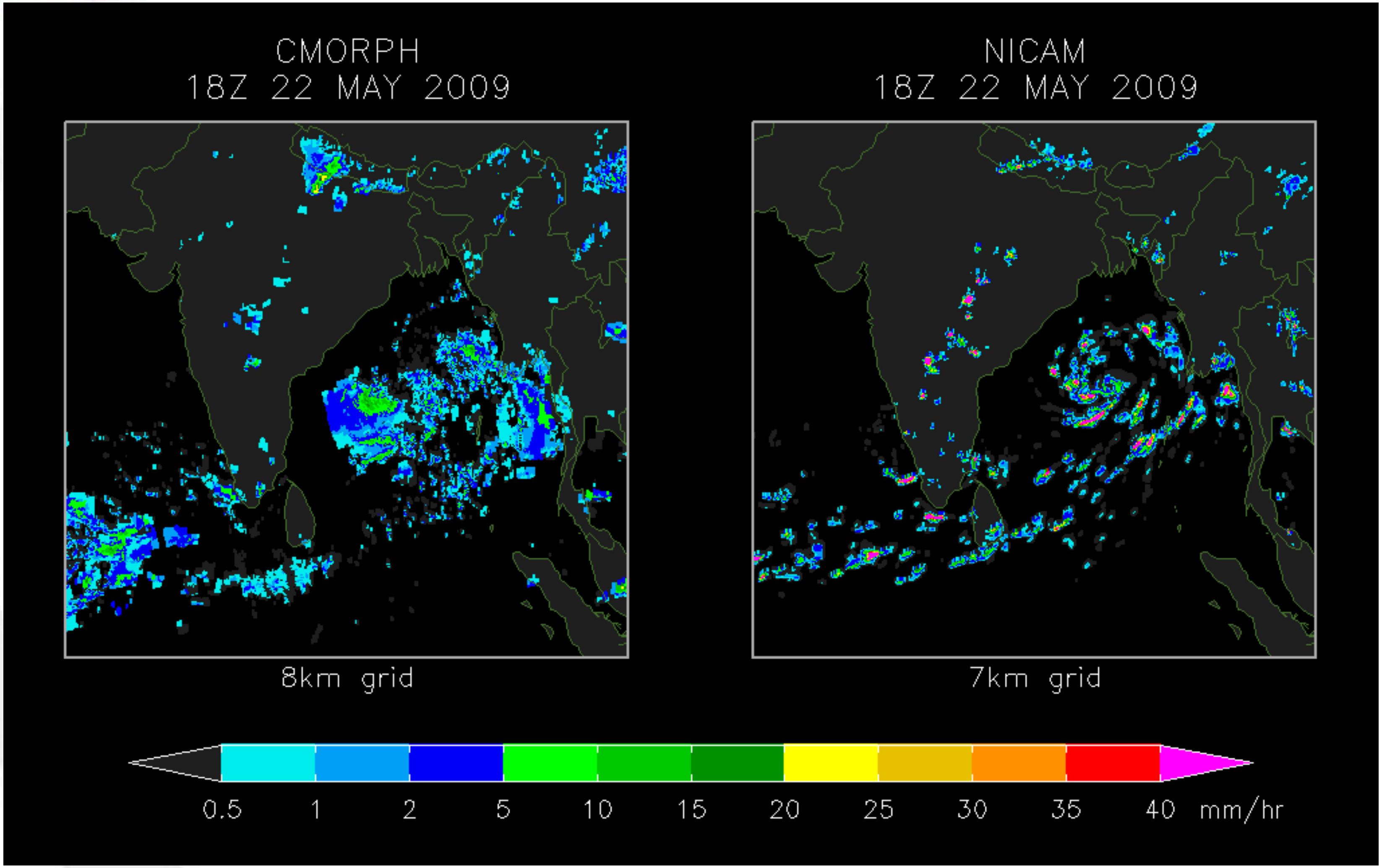
Monsoon Rainfall in High Resolution Model



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.**

NICAM 7km Run

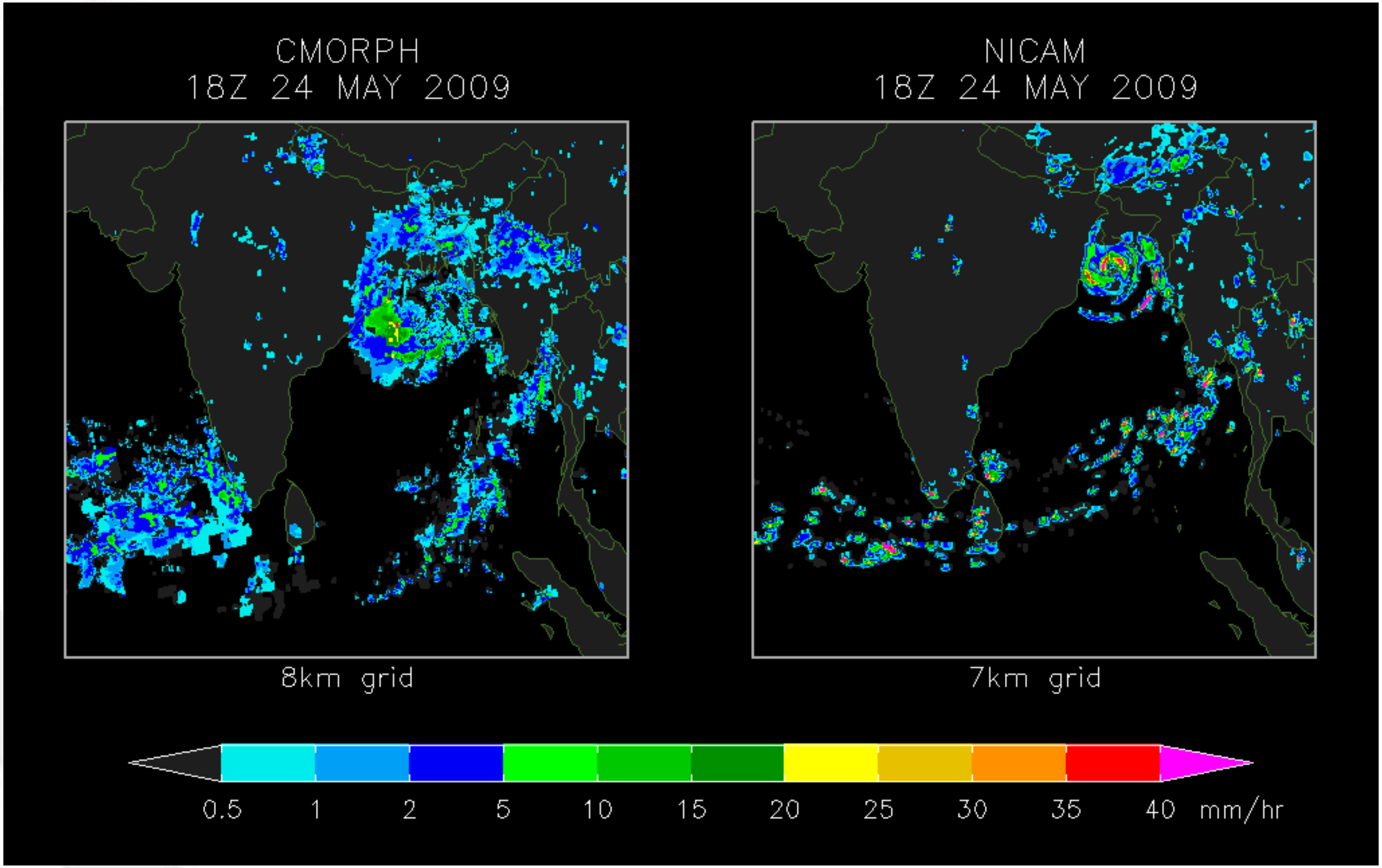
Obs. **Model (Initial:00Z 21May)**



COLA, JAMSTEC/Univ. of Tokyo, NICS

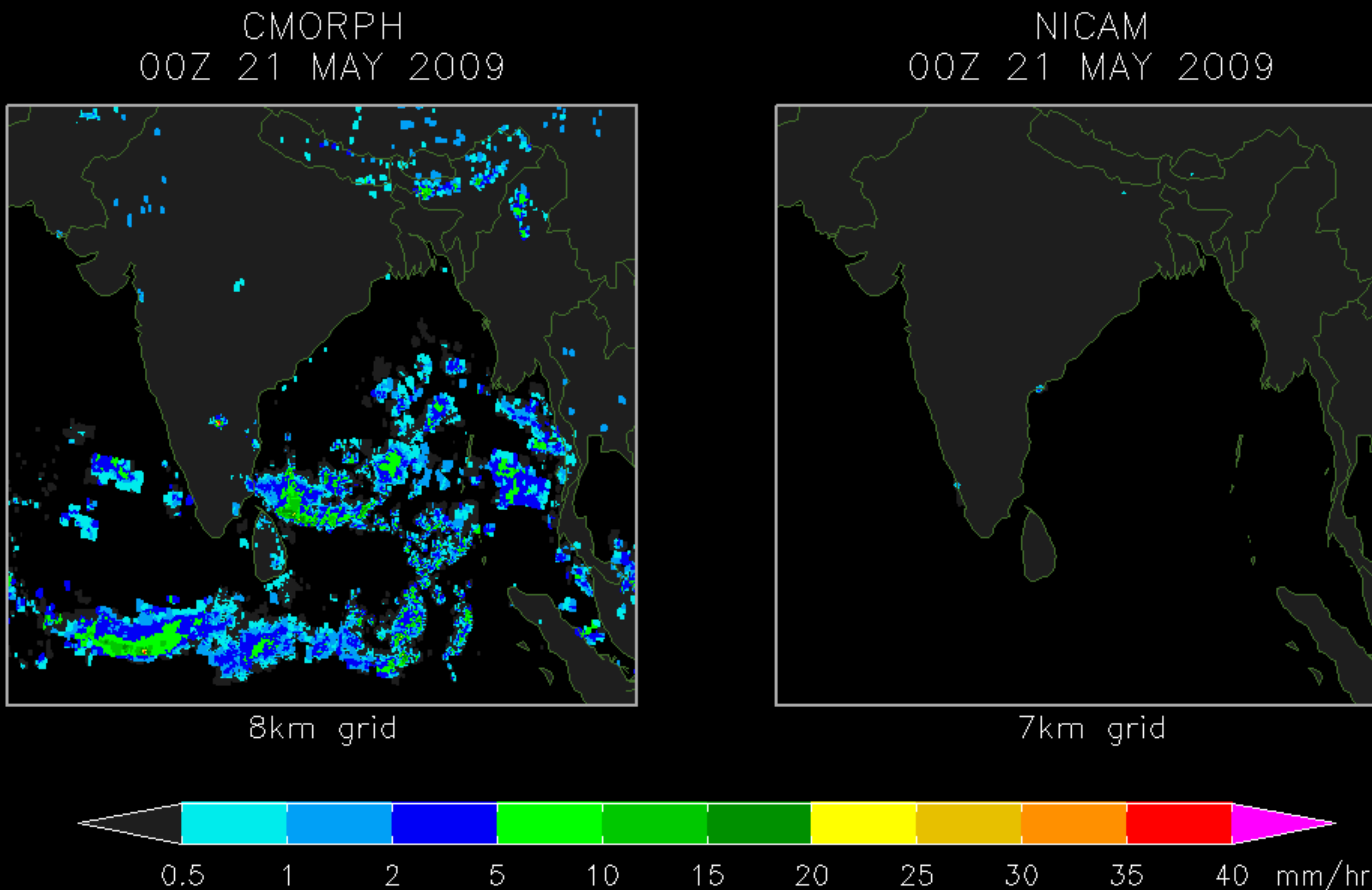
NICAM 7km Run

Obs. **Model (Initial:00Z 21May)**



COLA, JAMSTEC/Univ. of Tokyo, NICS

NICAM 7km Run



COLA, JAMSTEC/Univ. of Tokyo, NICS

A Proposal to Revolutionize Climate Prediction

Shukla, J., T.N. Palmer, R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, and J. Slingo, 2010: Towards a New Generation of World Climate Research and Computing Facilities. *BAMS, Vol.91, 1407-1412*

World Modelling Summit for Climate Prediction, Reading, UK, 6-9 May 2008, Workshop Report (January 2009). *WMO/TD-No. 1468.*

From Cyclone Resolving Global Models to Cloud System Resolving Global Models

1. Planetary Scale Resolving Models (1970~): Δx~500Km
2. Cyclone Resolving Models (1980~): Δx~100-300Km
3. Mesoscale Resolving Models (1990~): Δx~10-30Km
4. Cloud System Resolving Models (2000 ~): Δx~3-5Km♪

Organized Convection → Cloud System → Mesoscale System → Synoptic Scale → Planetary Scale

Convective Heating → MJO → ENSO → Climate Change

Revolution in Climate Prediction is Possible and Necessary

Coupled Ocean-Land-Atmosphere Model ~2015

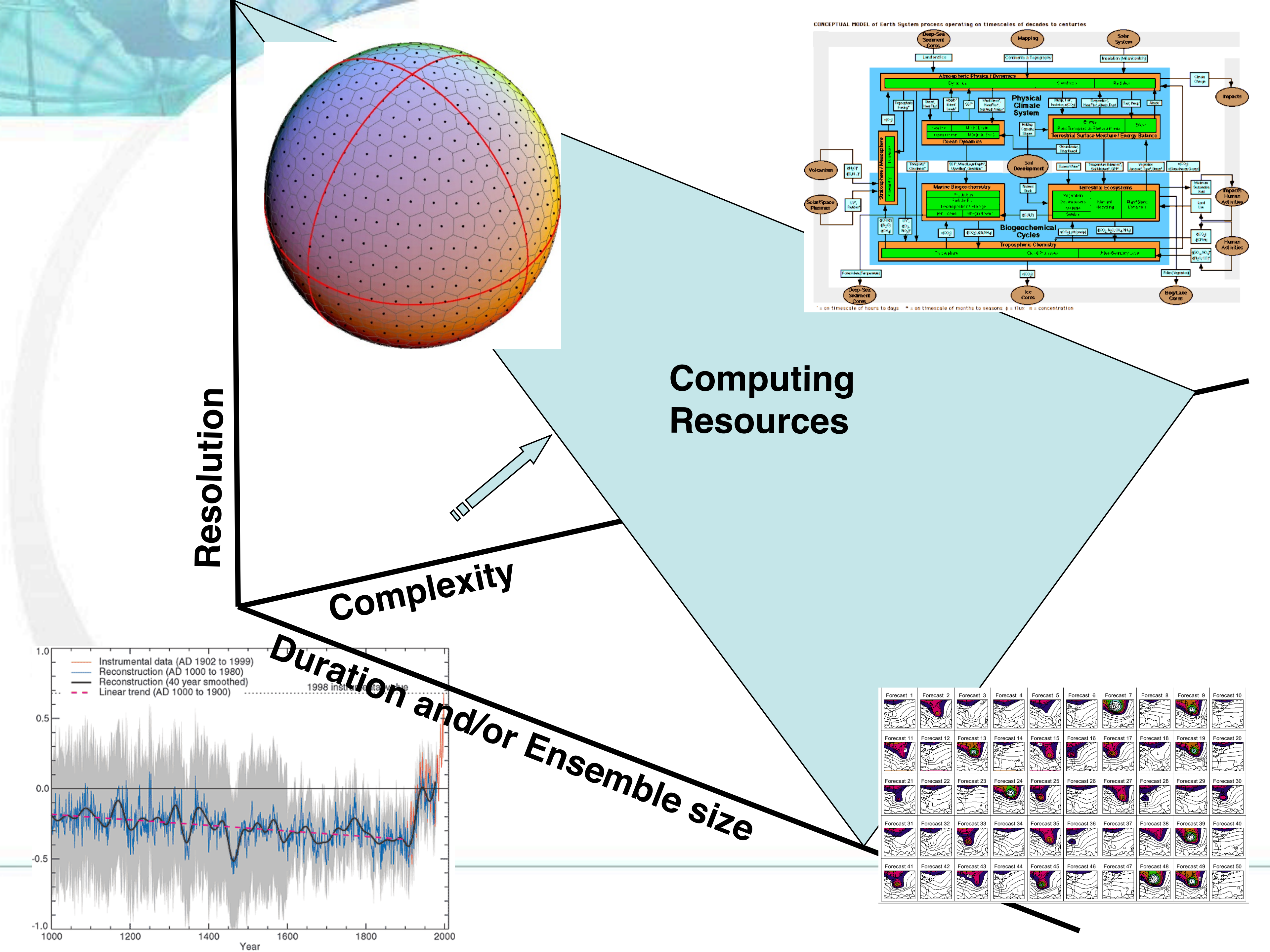
Assumption:
Computing power enhancement by a factor of 10^6

~1 km x ~1 km (cloud-resolving)
100 levels
(Unstructured, adaptive grids)

~100 m
10 levels
Landscape-resolving

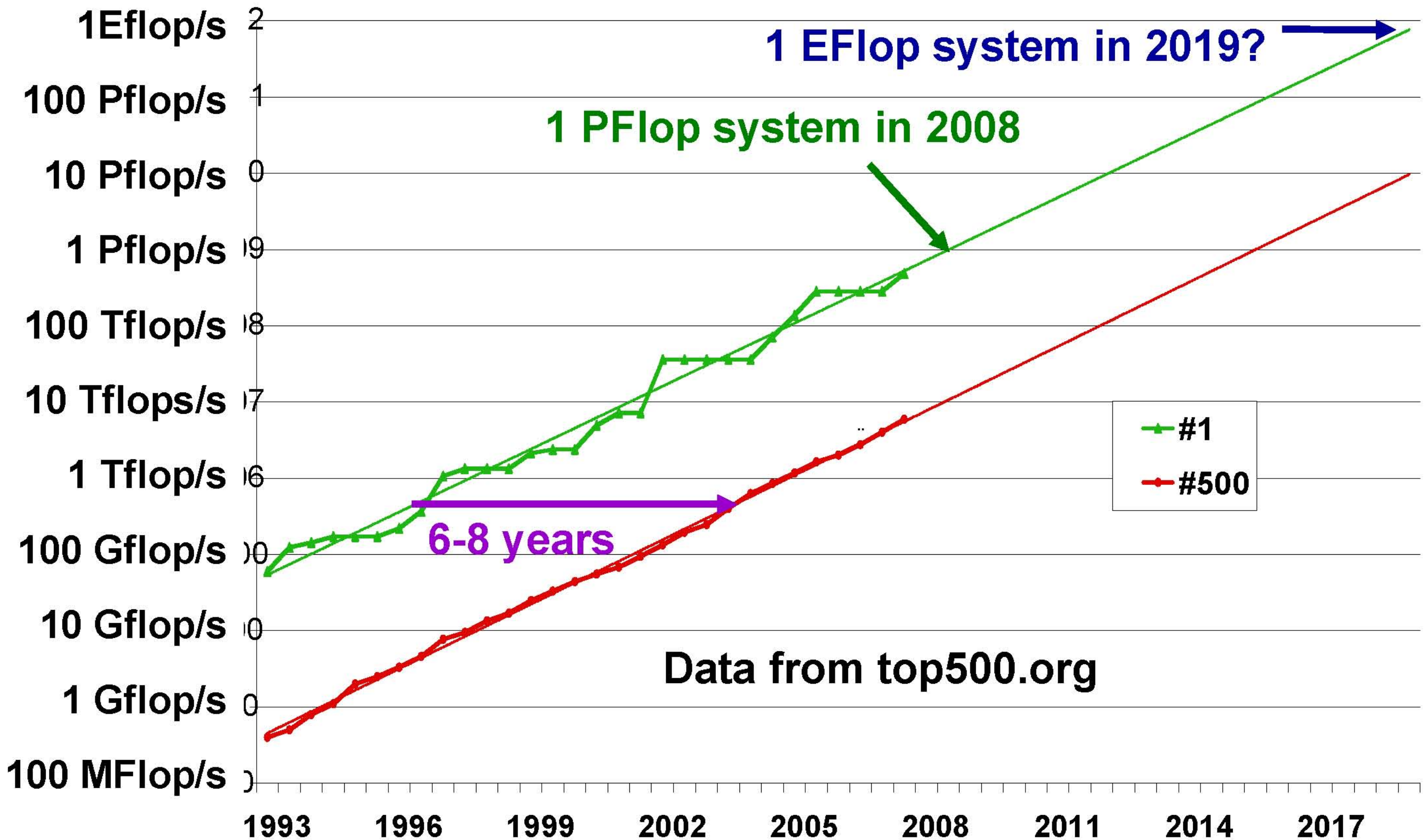
~10 km x ~10 km (eddy-resolving)
100 levels
(Unstructured, adaptive grids)

- **Improved understanding of the coupled O-A-B-C-S interactions**
- **Data assimilation & initialization of coupled O-A-B-C-S system**



Computing Resources
Resolution
Complexity
Duration and/or Ensemble size
CONCEPTUAL MODEL of Earth System process operating on timescales of decades to centuries
Physical Climate System
Biogeochemical Cycles
Instrumental data (AD 1902 to 1999)
Reconstruction (AD 1000 to 1980)
Reconstruction (40 year smoothed)
Linear trend (AD 1000 to 1900)
Year

Petaflop with ~1M Cores by 2008



Slide source Horst Simon, LBNL

Computing Capability & Model Grid Size (~km)

Peak Rate:	10 TFLOPS	100 TFLOPS	1 PFLOPS	10 PFLOPS	100 PFLOPS
Cores	1,400 (2006)	12,000 (2008)	80-100,000 (2009)	300-800,000 (2011)	6,000,000? (20xx?)
Global NWP[0]: 5-10 days/hr	18 - 29	9 - 14	4 - 6	2 - 3	1 - 2
Seasonal[1]: 50-100 days/day	17 - 28	8 - 13	4 - 6	2 - 3	1 - 2
Decadal[1]: 5-10 yrs/day	57 - 91	27 - 42	12 - 20	6 - 9	3 - 4
Climate Change[2]: 20-50 yrs/day	120 - 200	57 - 91	27 - 42	12 - 20	6 - 9

Range: Assumed efficiency of 10-40%
0 - Atmospheric General Circulation Model (AGCM; 100 levels)
1 - Coupled Ocean-Atmosphere-Land Model (CGCM; ~ 2X AGCM computation with 100-level OGCM)
2 - Earth System Model (with biogeochemical cycles) (ESM; ~ 2X CGCM computation)

*** Core counts above $O(10^4)$ are unprecedented for weather or climate codes, so the last 3 columns require getting 3 orders of magnitude in scalable parallelization (scalar processors assumed; vector processors would have lower processor counts)**

Thanks to Jim Abeles (IBM)

How to Implement a Seamless Prediction System in the midst of Several Pre-existing Separate, Independent National Centers for Weather, Climate, and Earth System Science?

Impediments to Progress in Earth System Prediction

1. The science community uses low-resolution inadequate climate models for prediction, not only because of a lack of knowledge of science, but also because of the lack of appropriate Earth System Modeling infrastructure with sufficient computational capacity and critical mass of qualified scientists.

2. Major national modeling centers (NCAR, GFDL) use one set of models, and national prediction centers (NCEP, FNMOC) use another set of models (insufficient or no interaction).

3. Operational centers have been less successful than research centers in attracting young talented scientists.

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.

International Thermonuclear Experimental Reactor
(Gadarache, France)

Particle Accelerators for High Energy Physics Research

1939: Ernest Lawrence (Radiation lab at Berkeley) received the Nobel Prize in Physics for building Cyclotron.

1940s – 1950s: (Competitive) construction of high energy particle accelerators in USA and Europe.

It was recognized that no single institution could afford to construct or staff the new machines, consortiums were formed to build them.

A group of universities in the eastern US joined forces in 1947 to construct an accelerator on Long Island – Brookhaven National Laboratory's Cosmotron.

Europe's major nations banded together in 1954 to found CERN, the European Organization for Nuclear Research (in French: *Conseil Européenne pour la Recherche Nucléaire*).

Particle Accelerators for High Energy Physics Research

FermiLab
Batavia, IL, USA
Tevatron 980 GeV

SLAC
Menlo Park, CA, USA
50 GeV

DESY
Hamburg, Germany
HERA, 920 GeV

Brookhaven
Upton, NY USA
RHIC, 100-250 GeV

CERN Policies for Collaboration

John Ellis,
CERN

Particle Accelerators for High Energy Physics Research

CERN
Geneva, Switzerland
LHC, 7 TeV

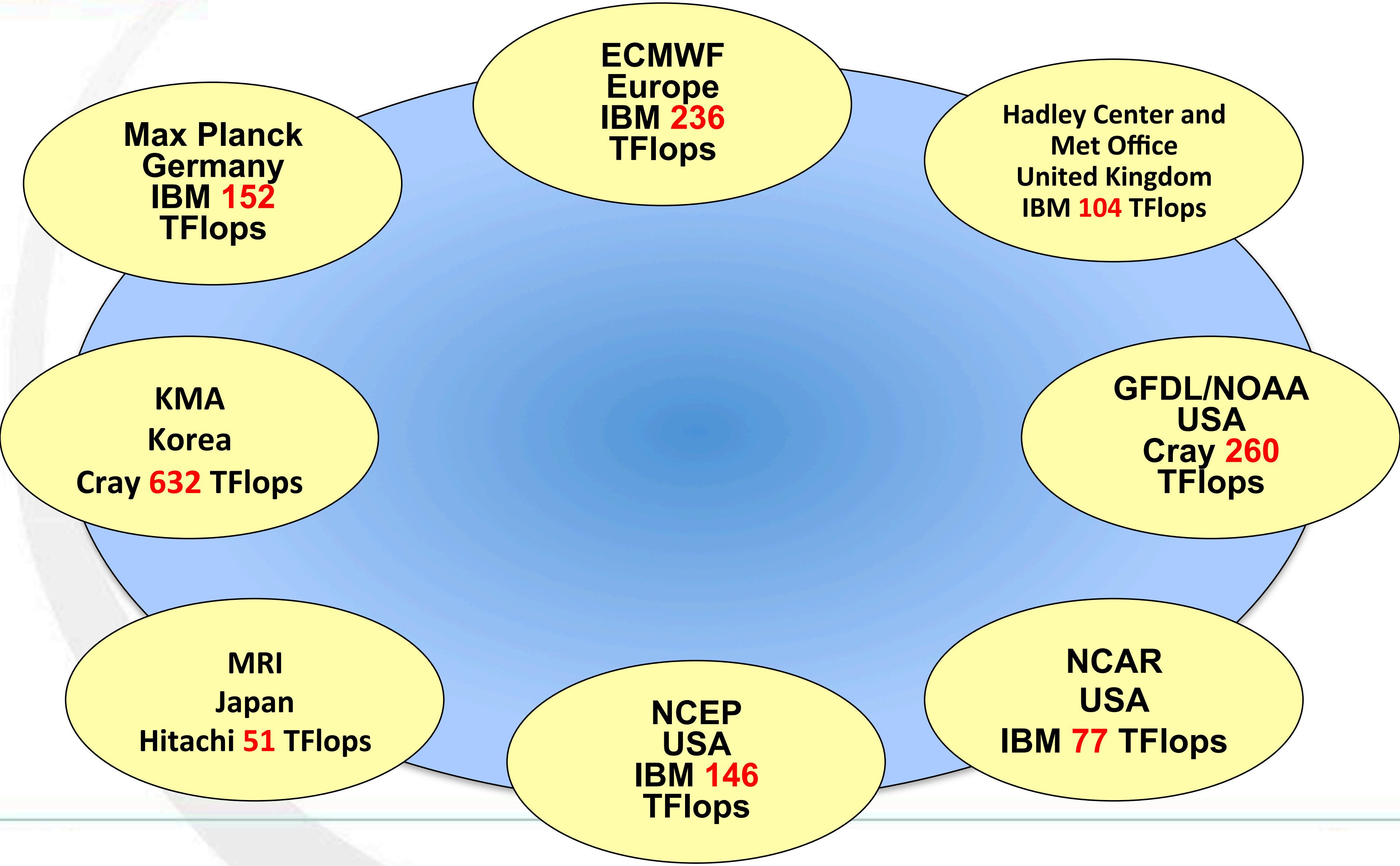
FermiLab
Batavia, IL, USA
Tevatron 980 GeV

SLAC
Menlo Park, CA, USA
50 GeV

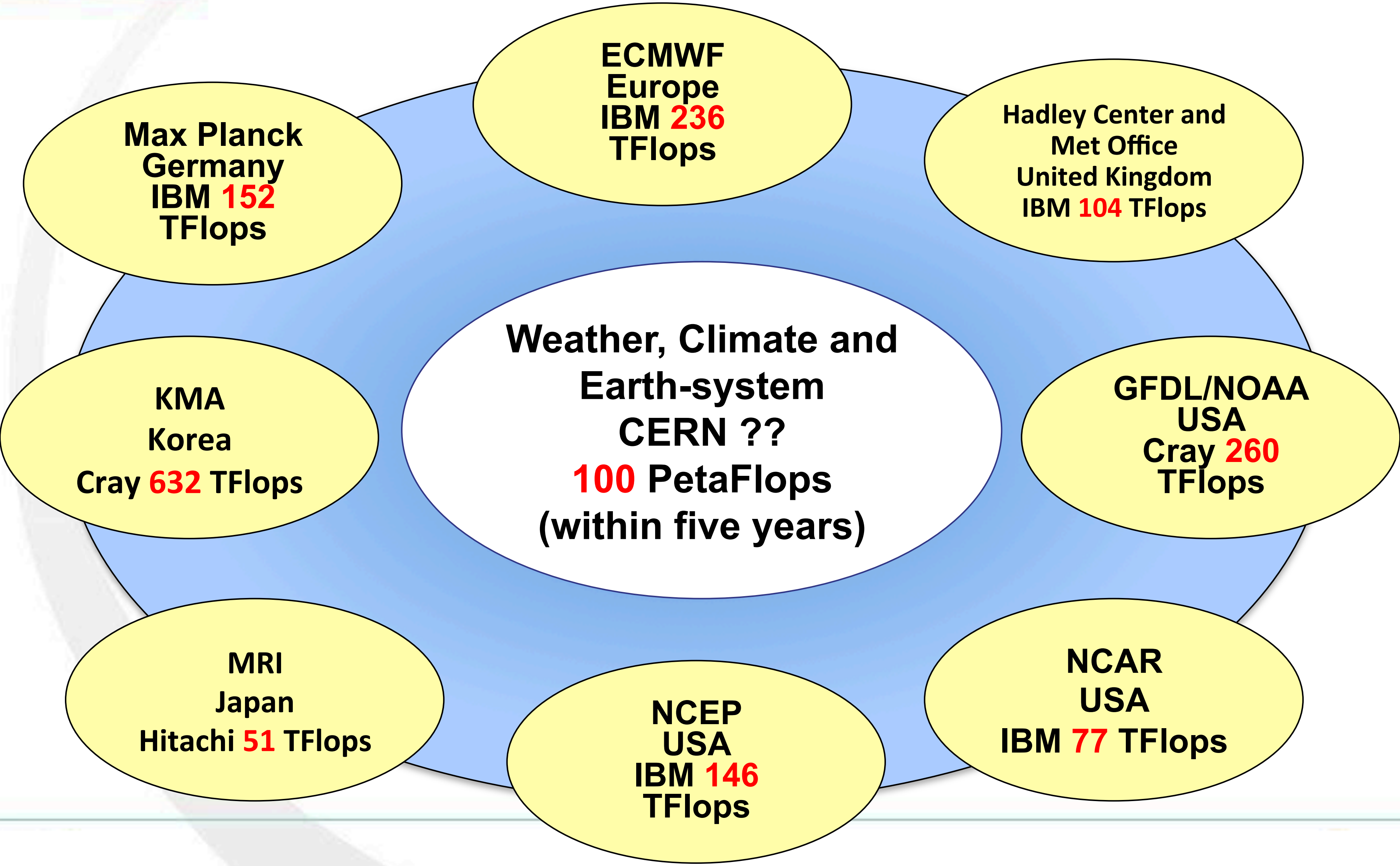
DESY
Hamburg, Germany
HERA, 920 GeV

Brookhaven
Upton, NY USA
RHIC, 100-250 GeV

Supercomputers for Weather, Climate and Earth-System Research



Supercomputers for Weather, Climate and Earth-System Research



International Research and Computational Facility to Revolutionize Climate Prediction

1. Computational Requirement:

- Sustained Capability of 2 Petaflops by 2011
- Sustained Capability of 10 Petaflops by 2015

Earth Simulator (sustained 7.5 Teraflops) takes 6 hours for 1 day forecast using 3.5 km global atmosphere model; ECMWF (sustained 2 Teraflops) takes 20 minutes for 10 day forecast using 24 km global model

2. Scientific Staff Requirement:

- Team of 200 scientists to develop next generation climate model
- Distributed team of 500 scientists (diagnostics, experiments)

A computing capability of sustained 2 Petaflops will enable 100 years of integration of coupled ocean-atmosphere model of 5 km resolution in 1 month of real time

Summary

- The most dominant obstacle in realizing the potential predictability of intraseasonal and seasonal variations is inaccurate models, rather than an intrinsic limit of predictability.

- Our inability to improve climate simulations using ultra-high resolution models is not primarily limited by lack of knowledge of science, but lack of powerful computers and a critical mass of scientific staff.

THANK YOU!

ANY QUESTIONS?

Particle Accelerators for High Energy Physics Research

Max Planck
Germany
IBM 152 TFlops

Hadley Center
United Kingdom
IBM 100 TFlops

KMA
Korea
Cray 319 TFlops

GFDL/NOAA
USA
Cray 260 TFlops

MRI
Japan
IBM 152 TFlops

NCAR
USA
IBM 77 TFlops

Particle Accelerators for High Energy Physics Research

Max Planck
Germany
IBM 152 TFlops

Hadley Center
United Kingdom
IBM 100 TFlops

KMA
Korea
Cray 319 TFlops

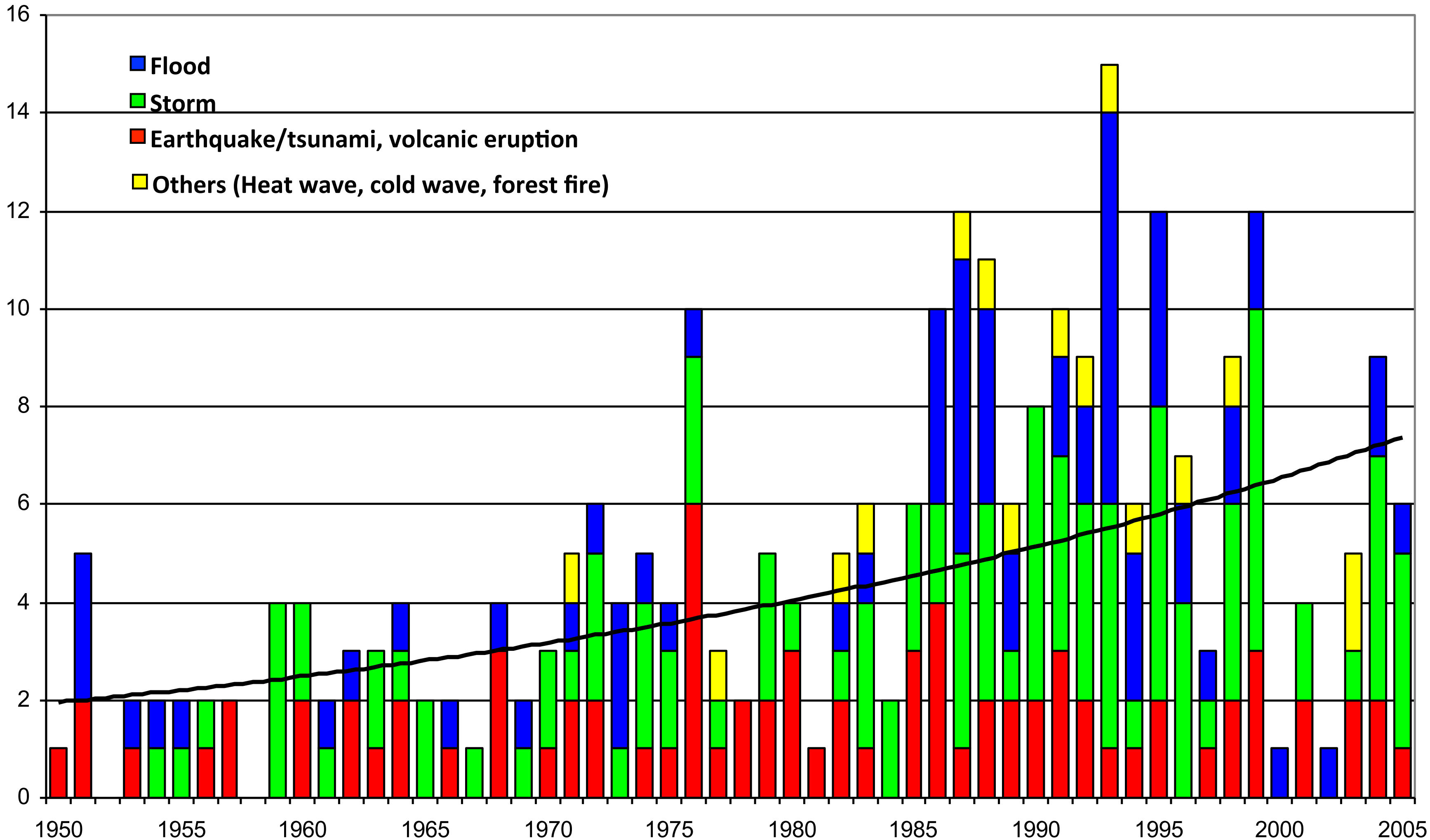
Climate
CERN ??
100 PetaFlops

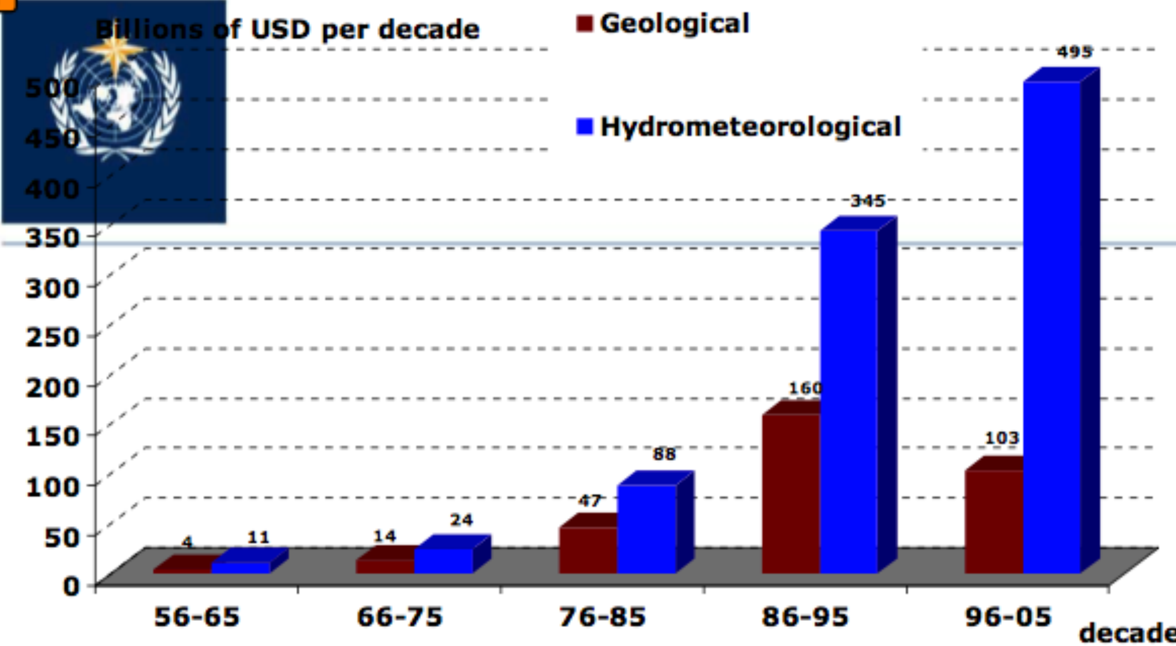
GFDL/NOAA
USA
Cray 260 TFlops

MRI
Japan
IBM 152 TFlops

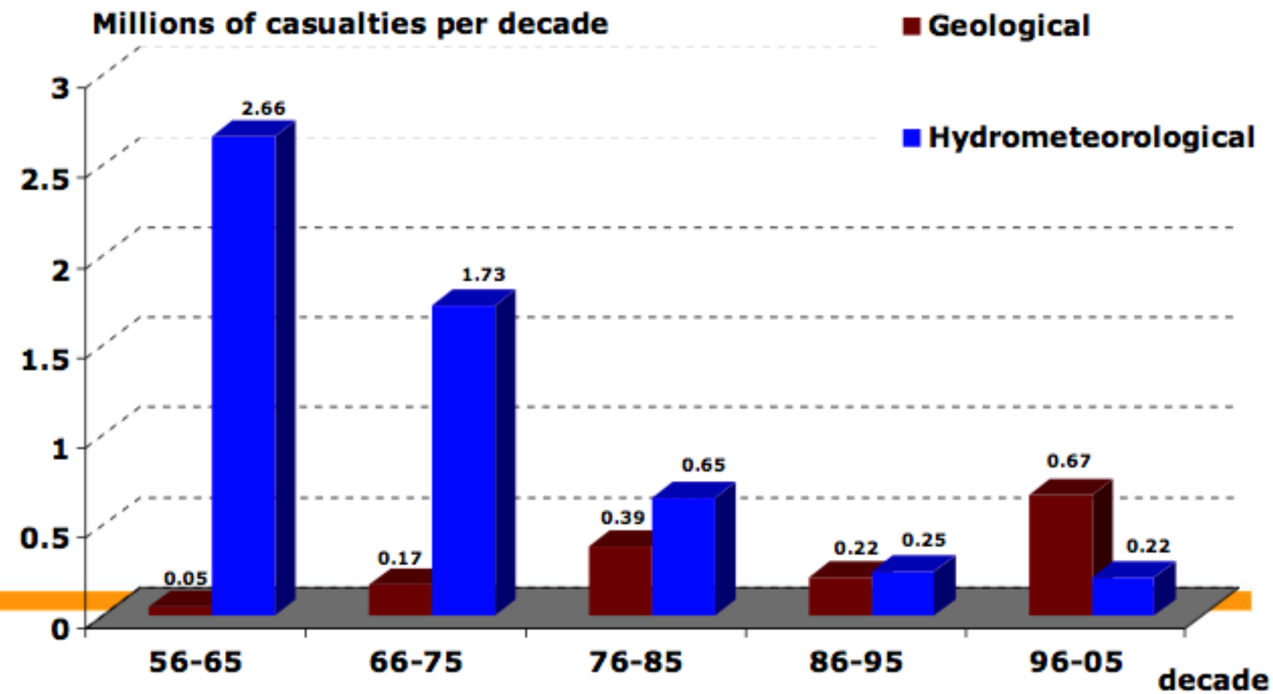
NCAR
USA
IBM 77 TFlops

Great Natural Disasters
1950 – 2005
Number of events



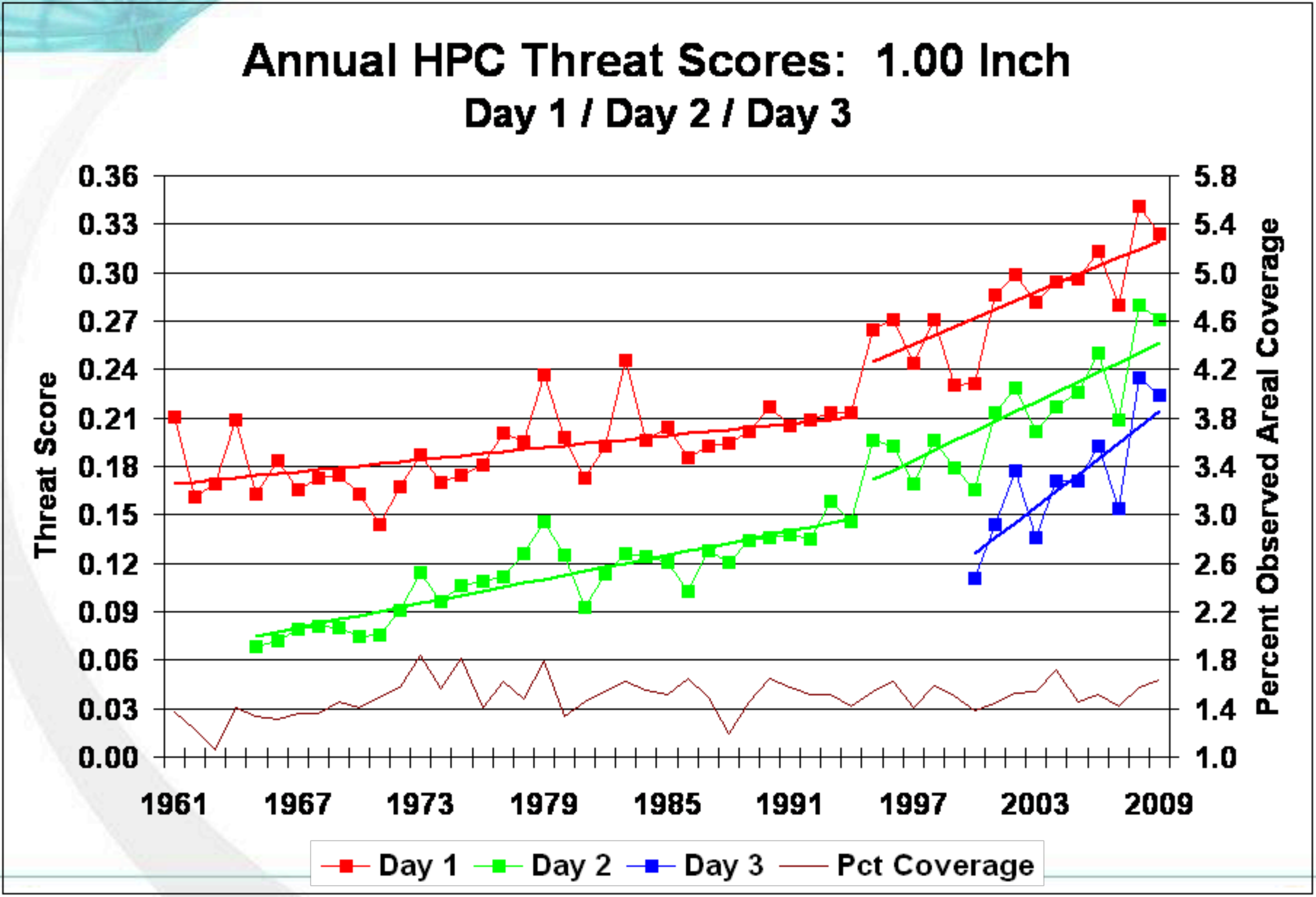


Economic losses related to disasters are on the way up…



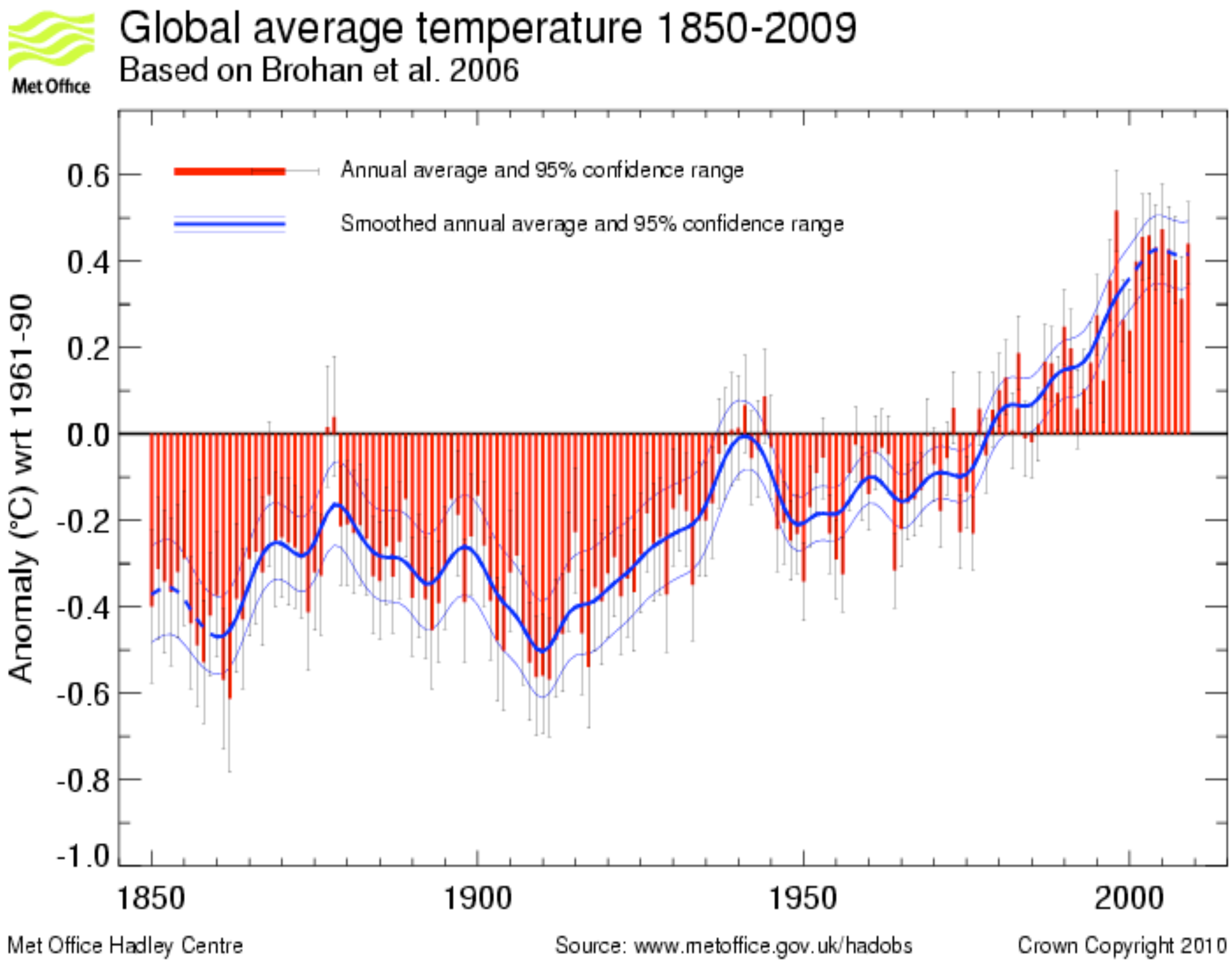
While casualties related to hydro-meteorological disasters are decreasing

Source: EM-DAT: The OFDA/CRED International Disaster Database



Annual HPC Threat Scores: 1.00 Inch
Day 1 / Day 2 / Day 3
Threat Score
Percent Observed Areal Coverage
0.36
0.33
0.30
0.27
0.24
0.21
0.18
0.15
0.12
0.09
0.06
0.03
0.00
5.8
5.4
5.0
4.6
4.2
3.8
3.4
3.0
2.6
2.2
1.8
1.4
1.0
1961
1967
1973
1979
1985
1991
1997
2003
2009
Day 1
Day 2
Day 3
Pct Coverage

Combined Land-surface, Air and Sea Surface Temperature anomaly

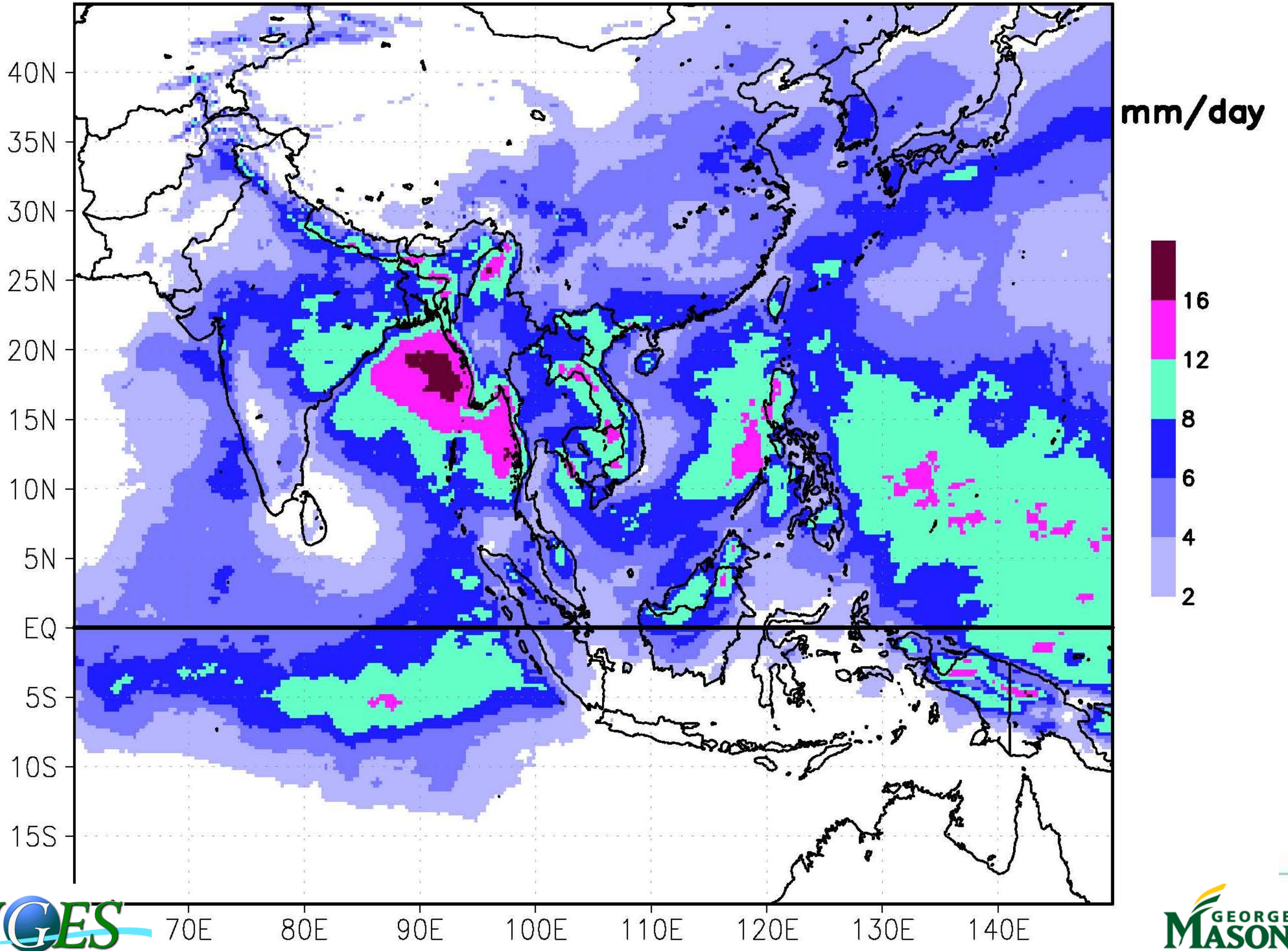


Examples of Weather and Climate Variability

- Annual Cycle
- Daily Weather
- Seasonal Climate
- Interannual (ENSO)
- Decadal
- Centennial (Climate Change)

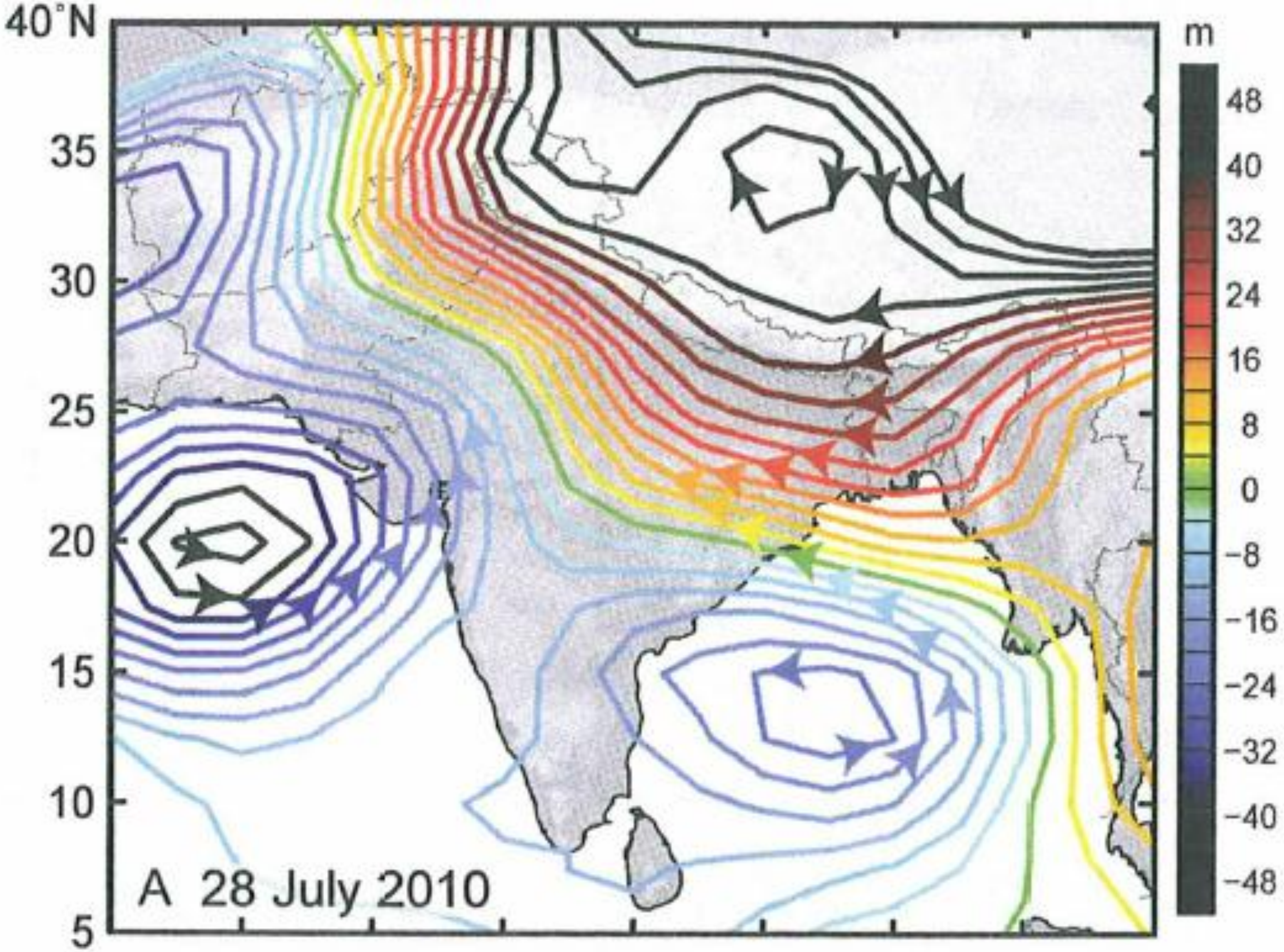
Accurate and reliable prediction of regional climate change requires realistic simulation of daily-seasonal-decadal variations.

CMORPH OBS Precip Climo JJAS (2003–2006)



IGES

GEORGE MASON UNIVERSITY



Anomalous atmospheric structure of 500 hPa at time of heavy rains in Pakistan on 28 July 2010.

Fingerprinting Method

Fit observed annual average SST to

$$\underbrace{T_{obs}(x,y,t)}_{\text{Observed}} = \underbrace{a_{for}(t)\,T_{for}(x,y)}_{\text{Forced Response}} + \underbrace{a_{imp}(t)\,T_{imp}(x,y)}_{\text{Internal Pattern}} + \underbrace{w(x,y,t)}_{\text{Random Noise}}$$

- Define spatial response to external forcing $T_{for}(x,y)$.
- Define spatial structure of IMP $T_{imp}(x,y)$.
- Define statistics of internal variability (from 'control runs').
- Fit equation using generalized least squares:

Detection: Test hypothesis $a_{for}(t) = 0$.

Attribution: Test hypothesis $a_{for}(t) =$ predicted amplitude.

How to Define the Response to Climate Forcing?

Pattern should characterize response to natural and anthropogenic forcing, but also filter out as much internal variability as possible.

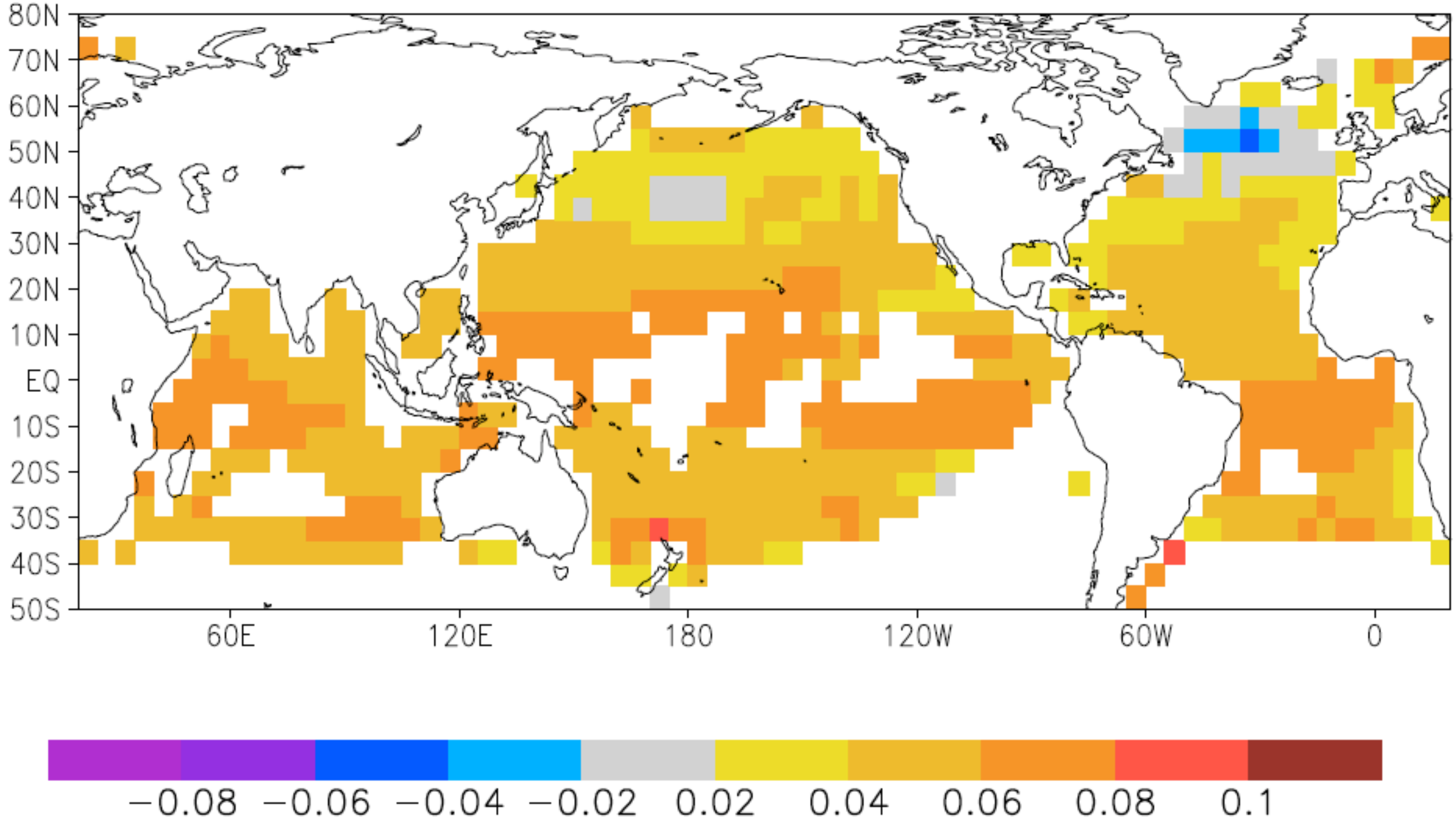
Hypothesis:

$$\text{Total} = \underset{\textit{Signal}}{\text{Forced Response}} + \underset{\textit{Noise}}{\text{Internal Variability}}$$

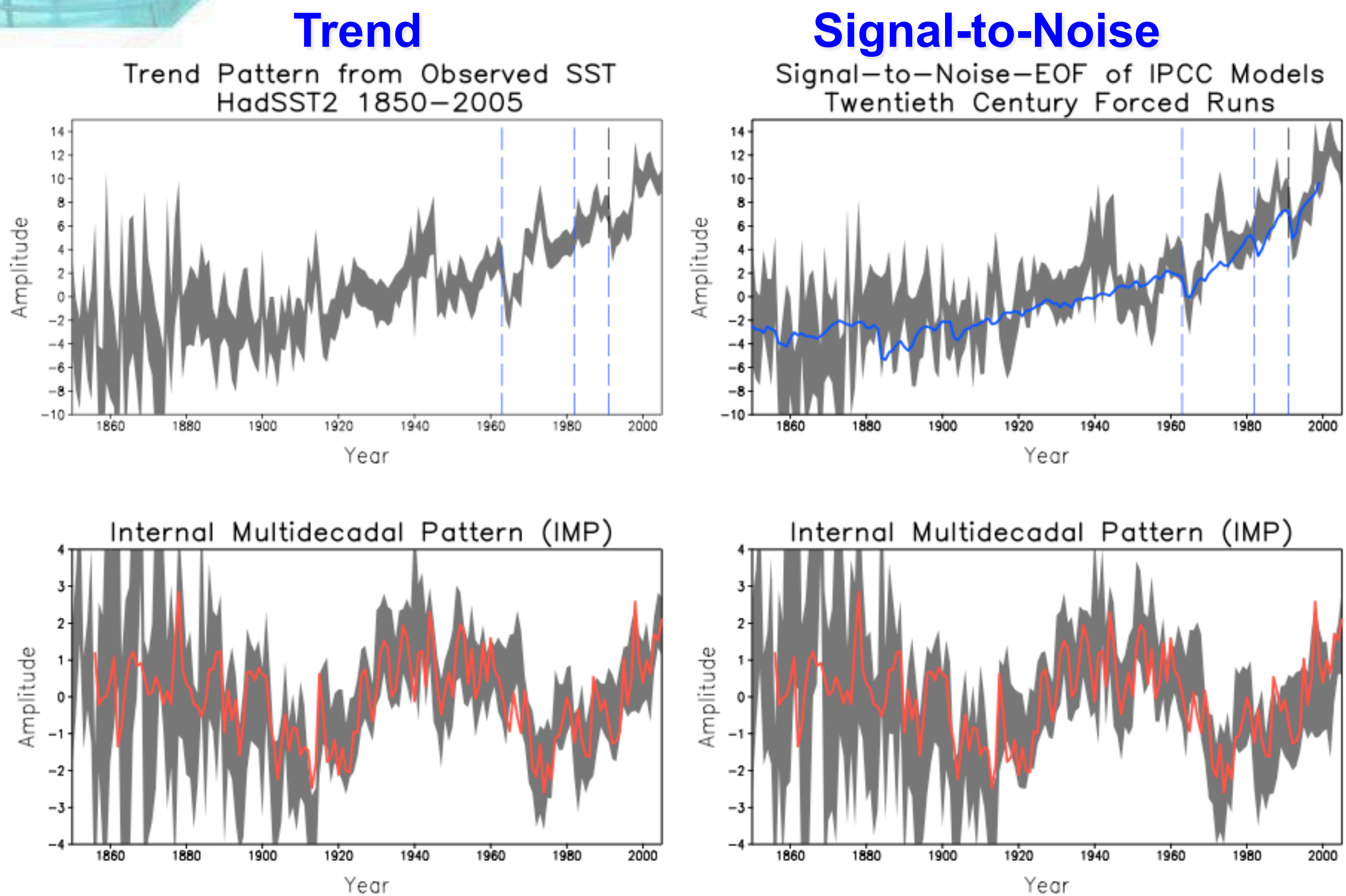
Find projection vector that maximizes the ratio of the variance in the forced run to variance in the control run:

$$\frac{\sigma^2_{forced}}{\sigma^2_{control}} = \frac{\sigma^2_S + \sigma^2_N}{\sigma^2_N} = \frac{\sigma^2_S}{\sigma^2_N} + 1$$

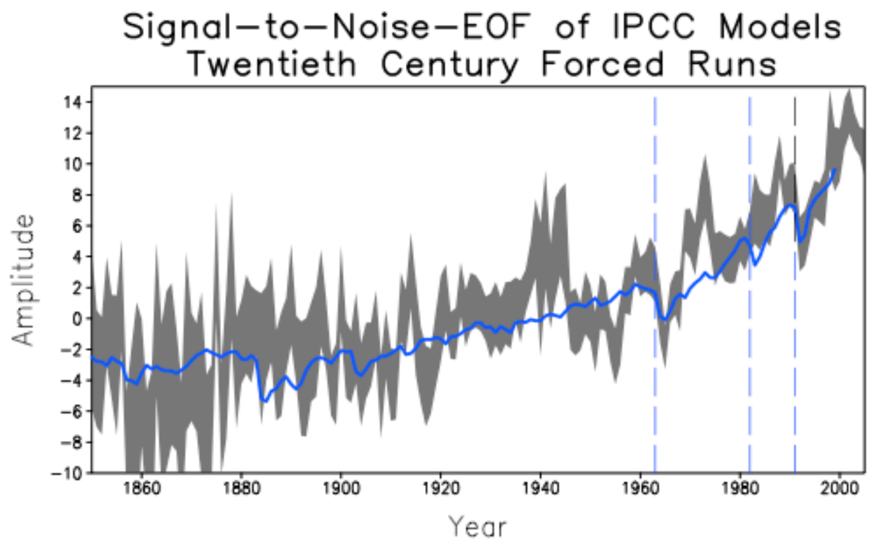
Forced-to-Unforced Discriminant from Control Runs



Amplitude of Forced Patterns and Unforced Patterns



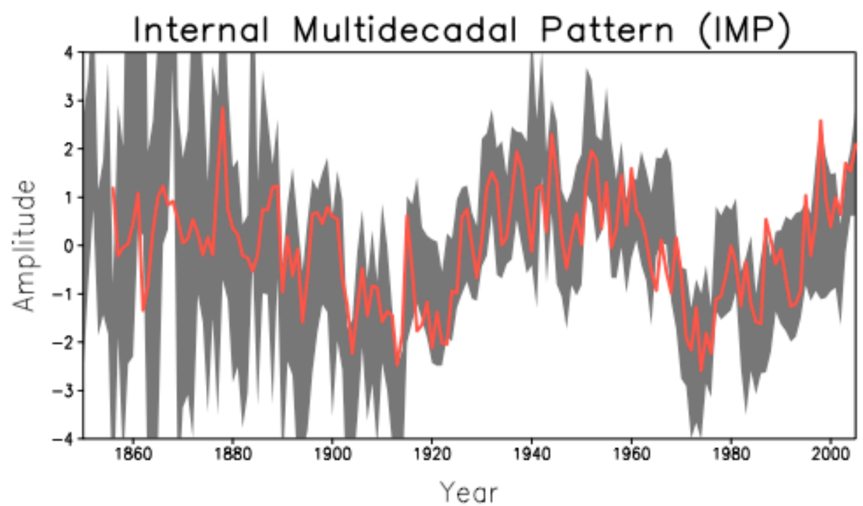
Amplitude of Forced and Unforced Patterns



Shading: $\pm\sigma$ Fingerprint Amplitude

Blue Solid Line: Signal-to-noise PC

Blue Dashed Line: Major Volcanic eruptions



Shading: $\pm\sigma$ Fingerprint Amplitude

Blue Solid Line: AMO Index

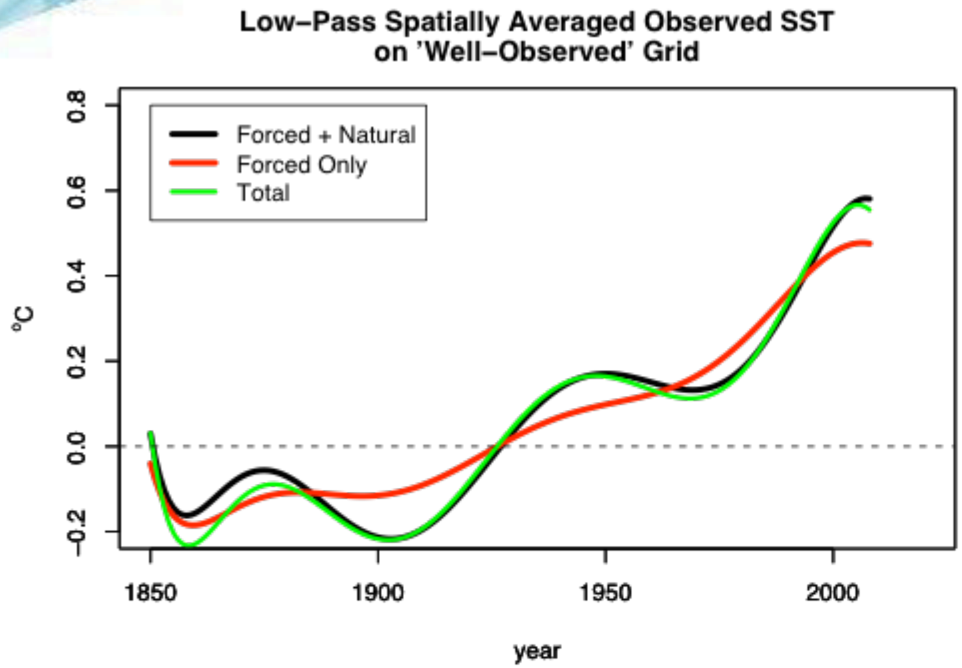
Center of Ocean-Land-Atmosphere studies

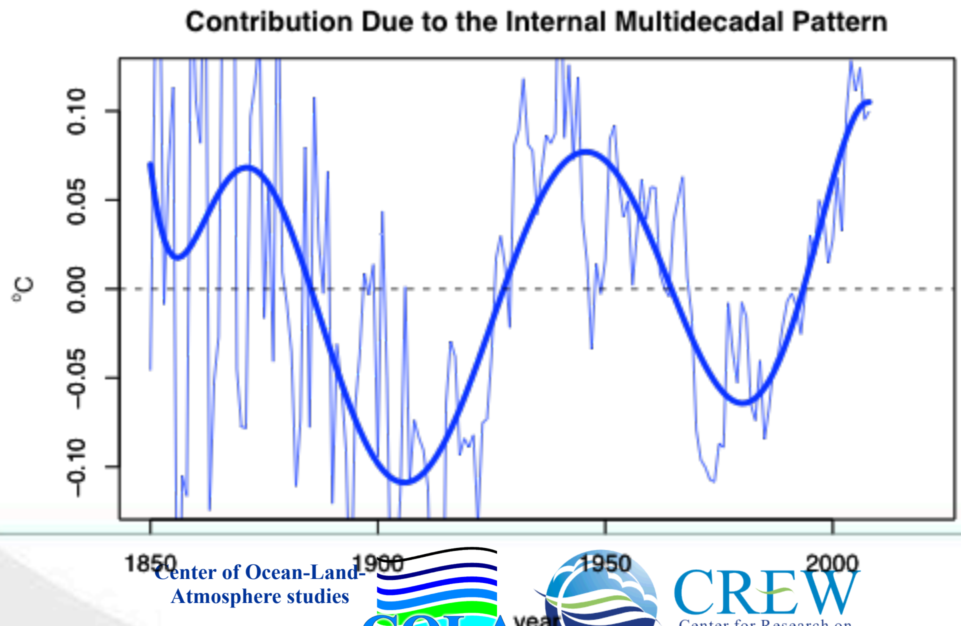
COLA

CREW
Center for Research on Environment and Water

IGES

GEORGE MASON UNIVERSITY





Center of Ocean-Land-Atmosphere studies

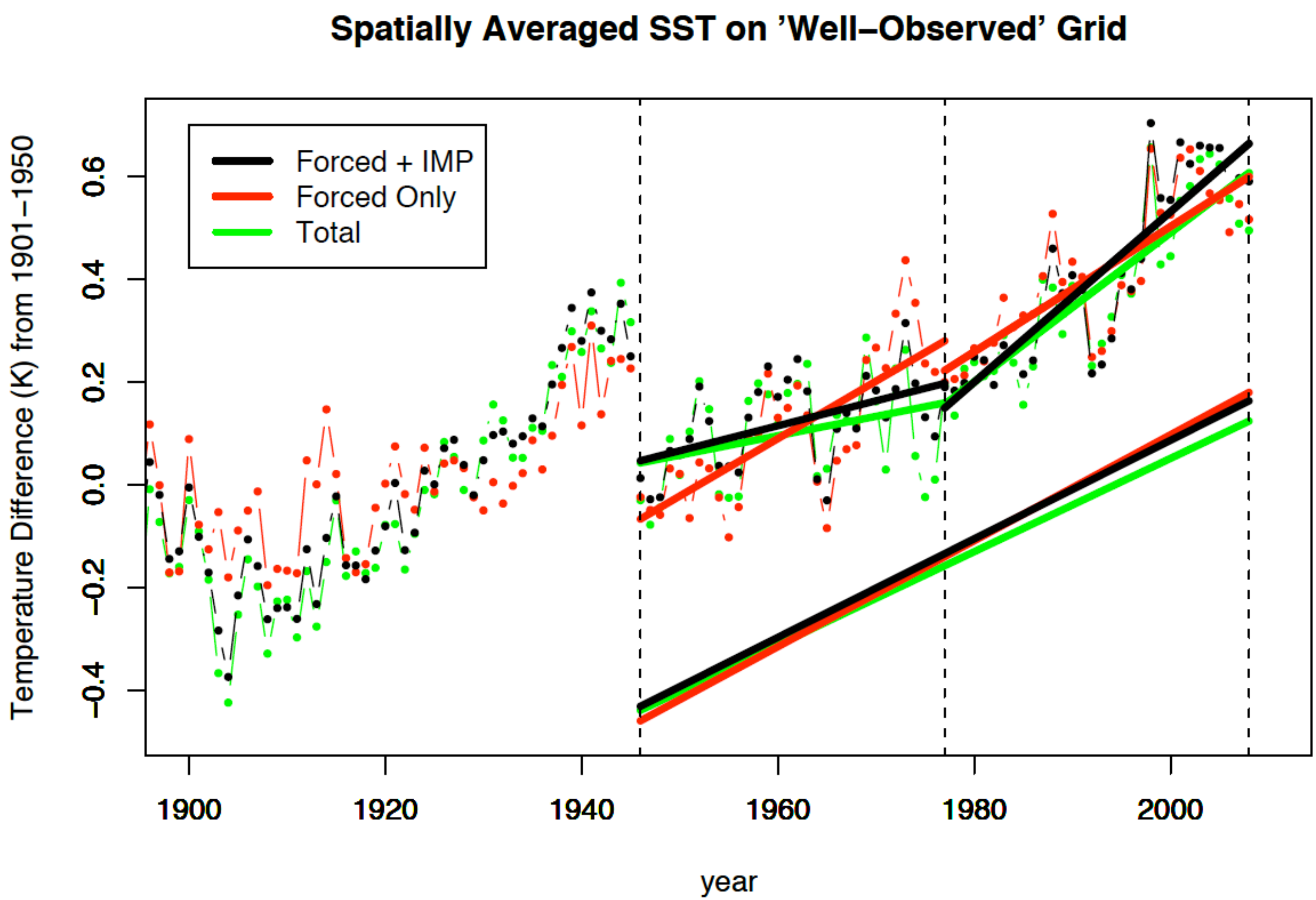
COLA

IGES

CREW Center for Research on Environment and Water

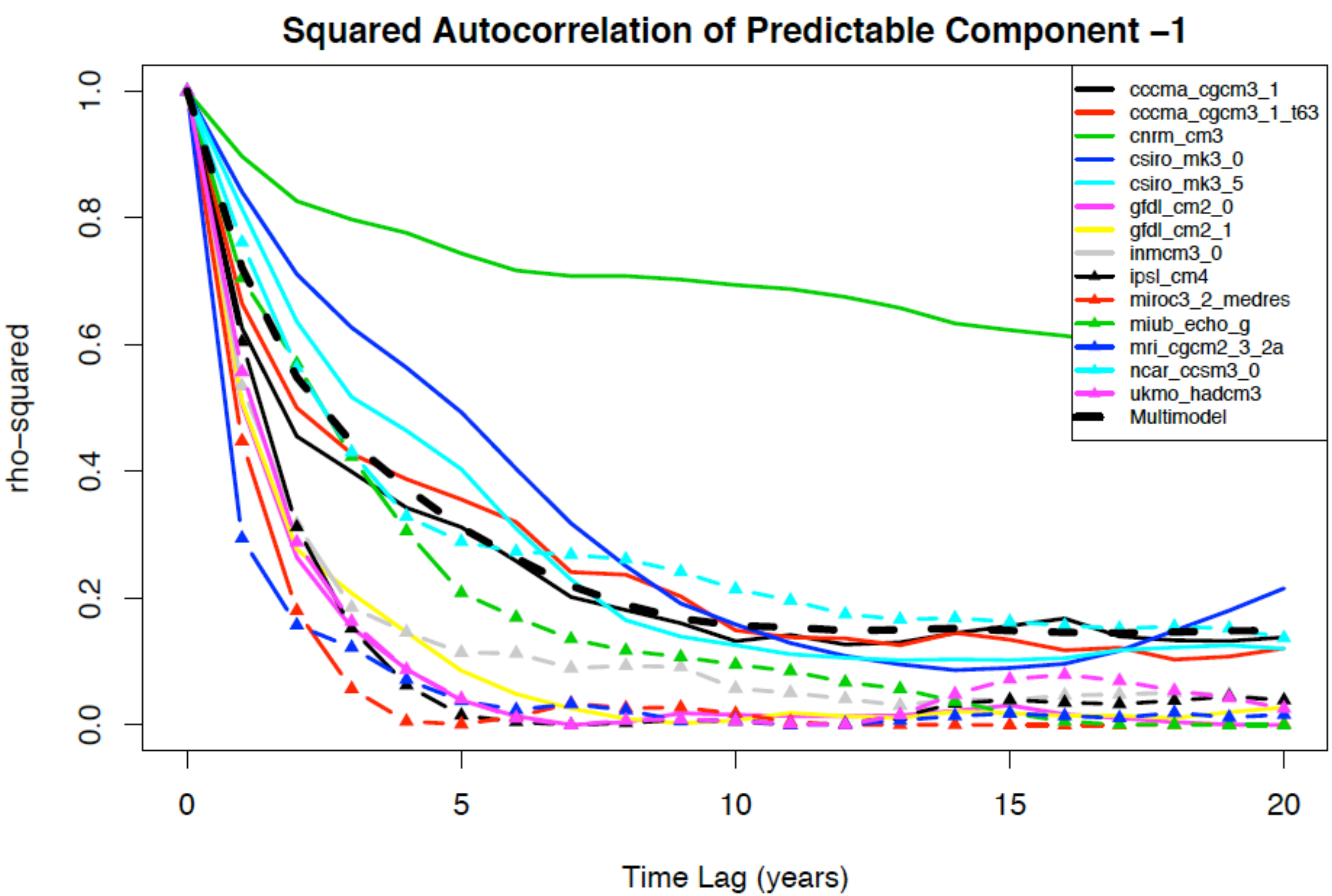
GEORGE MASON UNIVERSITY

Global Mean Sea Surface Temperature



Atmosphere Studies
COLA
Center for Research on Environment and Water
George Mason University

Scientific Basis for Decadal Predictability



Summary (1)

1. An unforced, multidecadal SST pattern is identified in simulations using IPCC pre-industrial control runs and observations by a new statistical method.

2. Maximizing the ratio of forced to internal variability indicates only one forced pattern in SST. Pattern has cooling in N. Atlantic.

3. Both the forced and unforced patterns are estimated by optimal spatial filtering techniques.

4. Forced component contributes uniform 0.1K/decade of warming.

Summary (2)

5. An Internal Multi-decadal Pattern (IMP) is identified that explains about 0.1C fluctuations in low-pass, global average SST.

6. Amplitude of this pattern helps explain major multi-decadal fluctuations in global mean temperature in the 20th century.

7. Amplitude of IMP matches AMO and is sufficient amplitude to explain acceleration in warming between 1946-1977 and 1977-2008.

8. Forced response projects only weakly on IMP, if at all.

9. Cooling trend over 10-year periods not statistically significant.

Summary of Summit Declaration

1. Most important requirement: Prediction of changes in the statistics of regional weather variations.

2. Models have serious problems and cannot provide information with accuracy required by society

3. "A revolution in climate prediction is necessary and possible." (one of the most important declarations of the summit)

4. Proposal to establish a Climate Prediction Project

5. Enhance national centers

6. Establish a small number of climate research facilities for decadal prediction.

Summary of Summit Declaration

7. Dedicated high-end computing facilities are required (at least a thousand times more powerful than the currently available computers)

8. More computing power will help to enhance resolution and include complexity (e.g. biogeochemical cycles).

9. Global observations and assimilations are needed for prediction project.

10. Better estimates of uncertainties in climate prediction.

11. Collaboration between weather and climate prediction research communities (Seamless prediction).

12. Encourage the participation of young generation of climate modelers

Recent Papers

Brunet, G., et al, 2010: Collaboration of the Weather and Climate Communities to Advance Sub-Seasonal to Seasonal Prediction. *BAMS, Vol. 91, 1397-1406*

Shapiro, M., J. Shukla, et al, 2010: An Earth-System Prediction Initiative for the 21st Century. *BAMS, Vol.91, 1377-1388*

Shukla, J., T.N. Palmer, R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, and J. Slingo, 2010: Towards a New Generation of World Climate Research and Computing Facilities. *BAMS, Vol.91, 1407-1412*

Shukla, J., R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, T.N. Palmer, and J. Slingo, 2009: Revolution in climate Prediction is Both Necessary and Possible: A Declaration at the World Modelling Summit for Climate Prediction. *BAMS*, *Vol.90*, 16-19

World Modelling Summit for Climate Prediction, Reading, UK, 6-9 May 2008, Workshop Report (January 2009). *WMO/TD-No. 1468.*