Fidelity and Predictability of Models for Weather and Climate Prediction

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Institute of Global Environment and Society (IGES)

"Revolution in Climate Prediction is Both Necessary and Possible"

Shukla, Hagedorn, Hoskins, Kinter, Marotzke, Miller, Palmer, and Slingo, BAMS, Feb. 2009, pp 175-178

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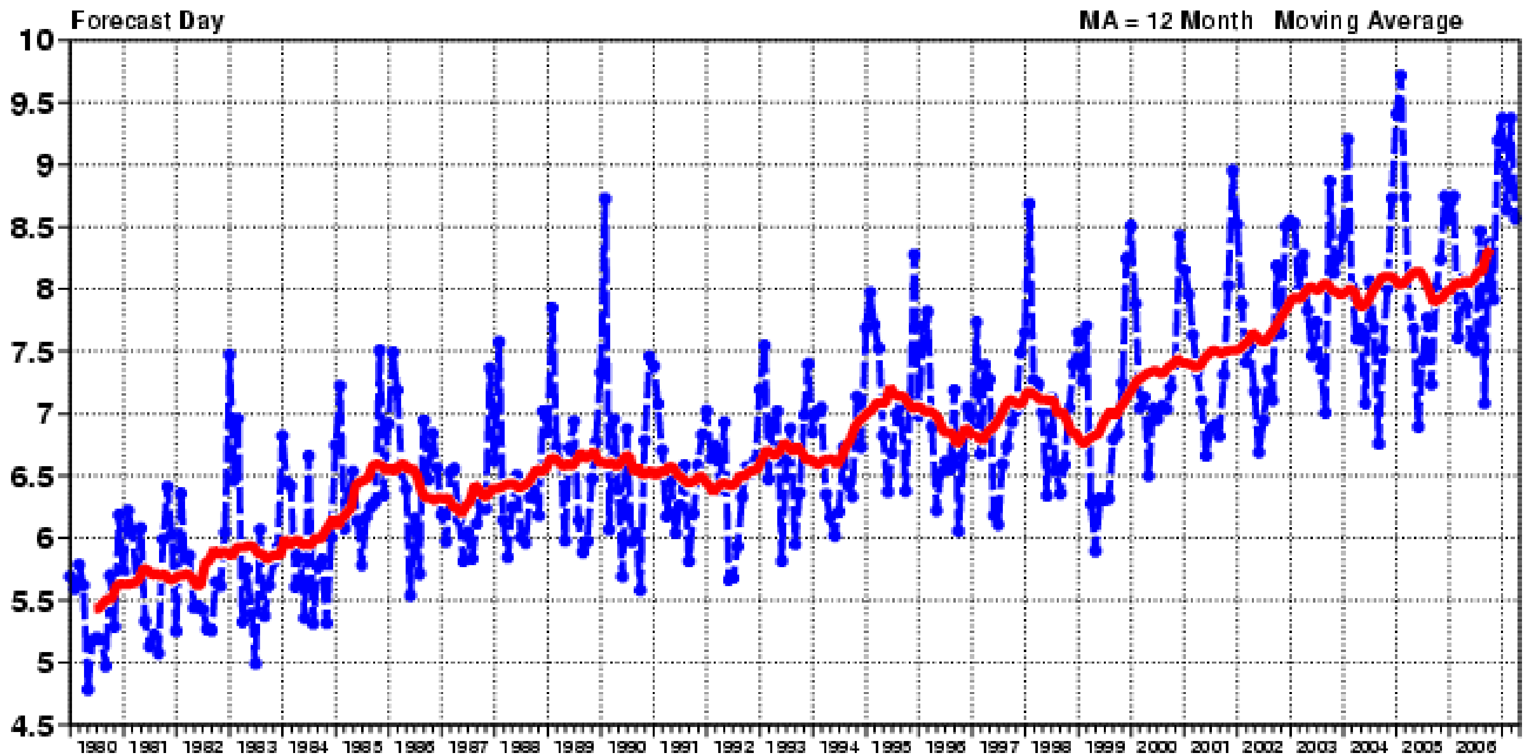
ERA Forecast Verification

Anomaly Correlation of 500 hPa GPH, 20-90N

SCORE REACHES 60.00

SCORE REACHES 60.00 MA

1980-2006



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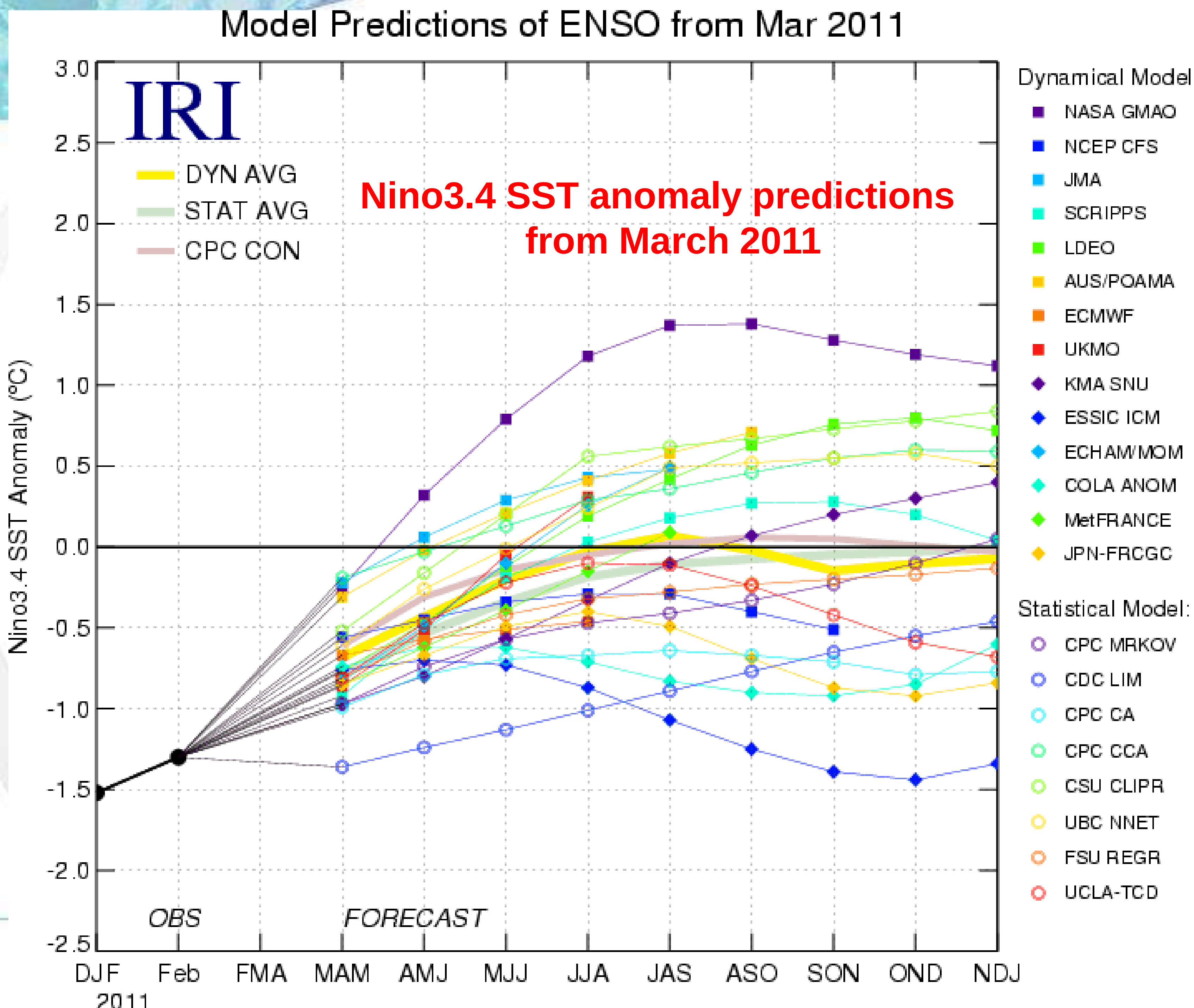
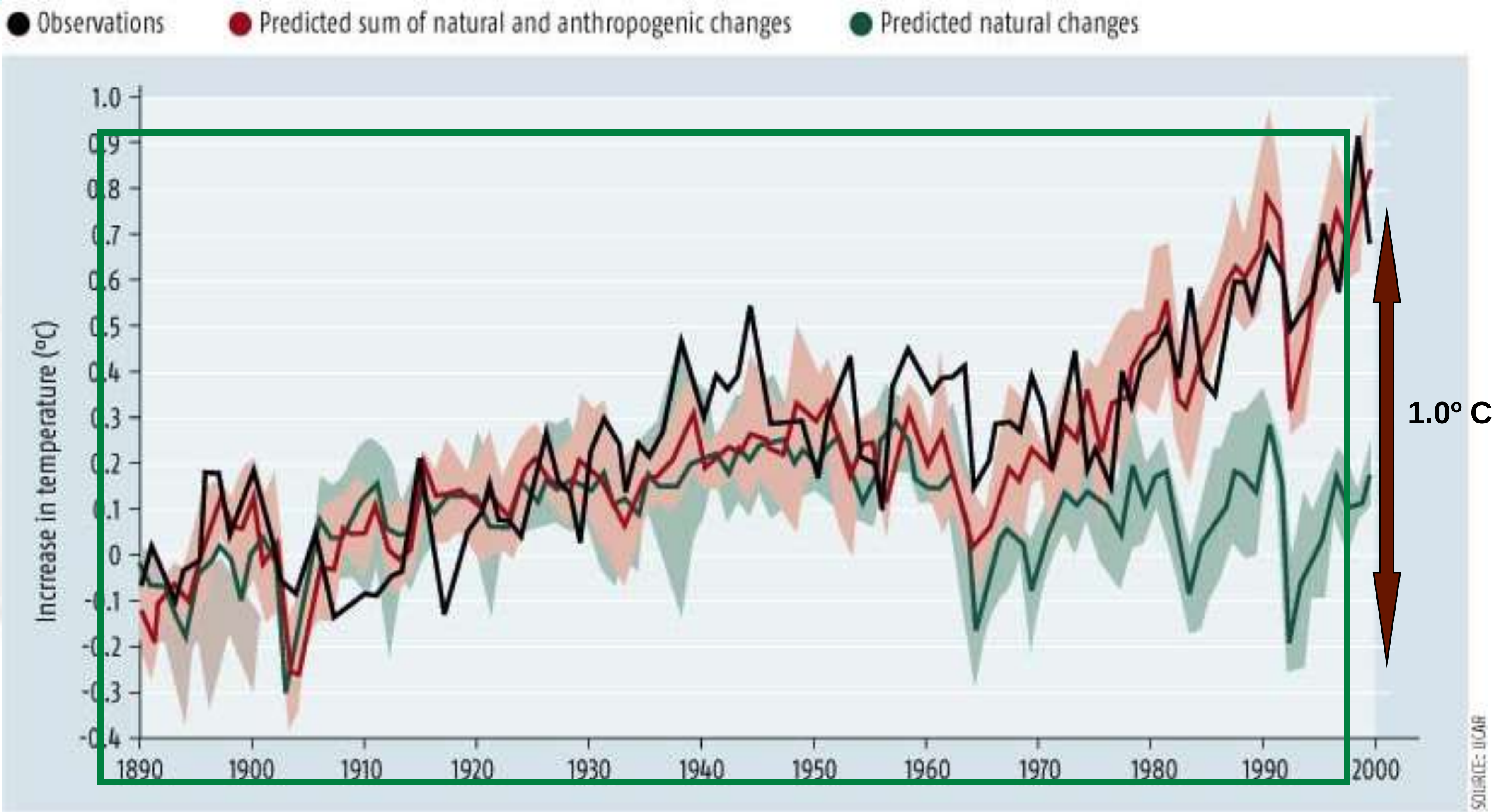
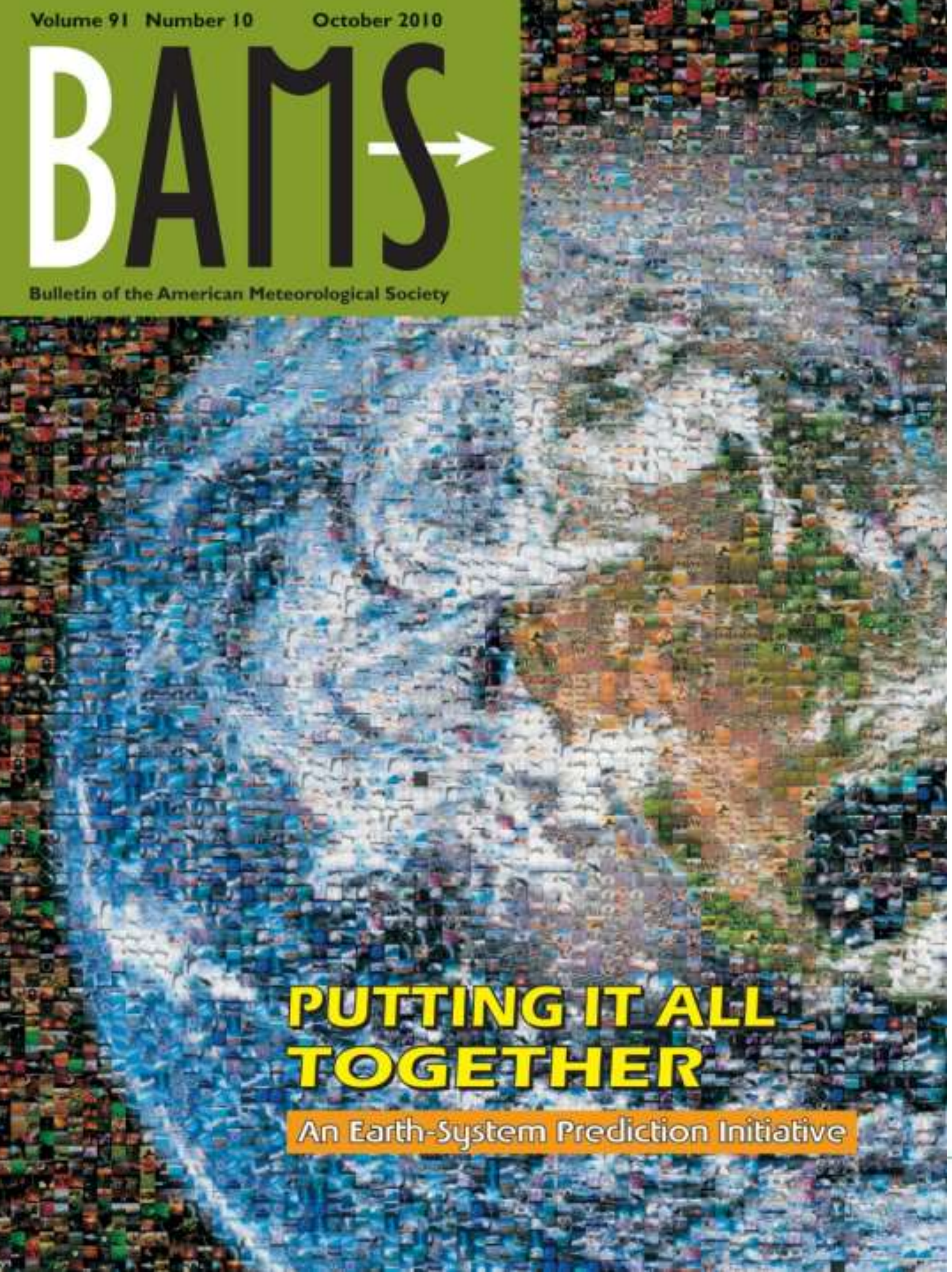


Model Predictions of ENSO from Mar 2011
IRI
DYN AVG
STAT AVG
CPC CON
Nino3.4 SST anomaly predictions
from March 2011
Nino3.4 SST Anomaly (°C)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
OBS
FORECAST
DJF
2011
Feb
FMA
MAM
AMJ
MJJ
JJA
JAS
ASO
SON
OND
NDJ
Dynamical Model:
NASA GMAO
NCEP CFS
JMA
SCRIPPS
LDEO
AUS/POAMA
ECMWF
UKMO
KMA SNU
ESSIC ICM
ECHAM/MOM
COLA ANOM
MetFRANCE
JPN-FRCGC
Statistical Model:
CPC MRKOV
CDC LIM
CPC CA
CPC CCA
CSU CLIPR
UBC NNET
FSU REGR
UCLA-TCD



Courtesy of UCAR



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 21^{st} 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*

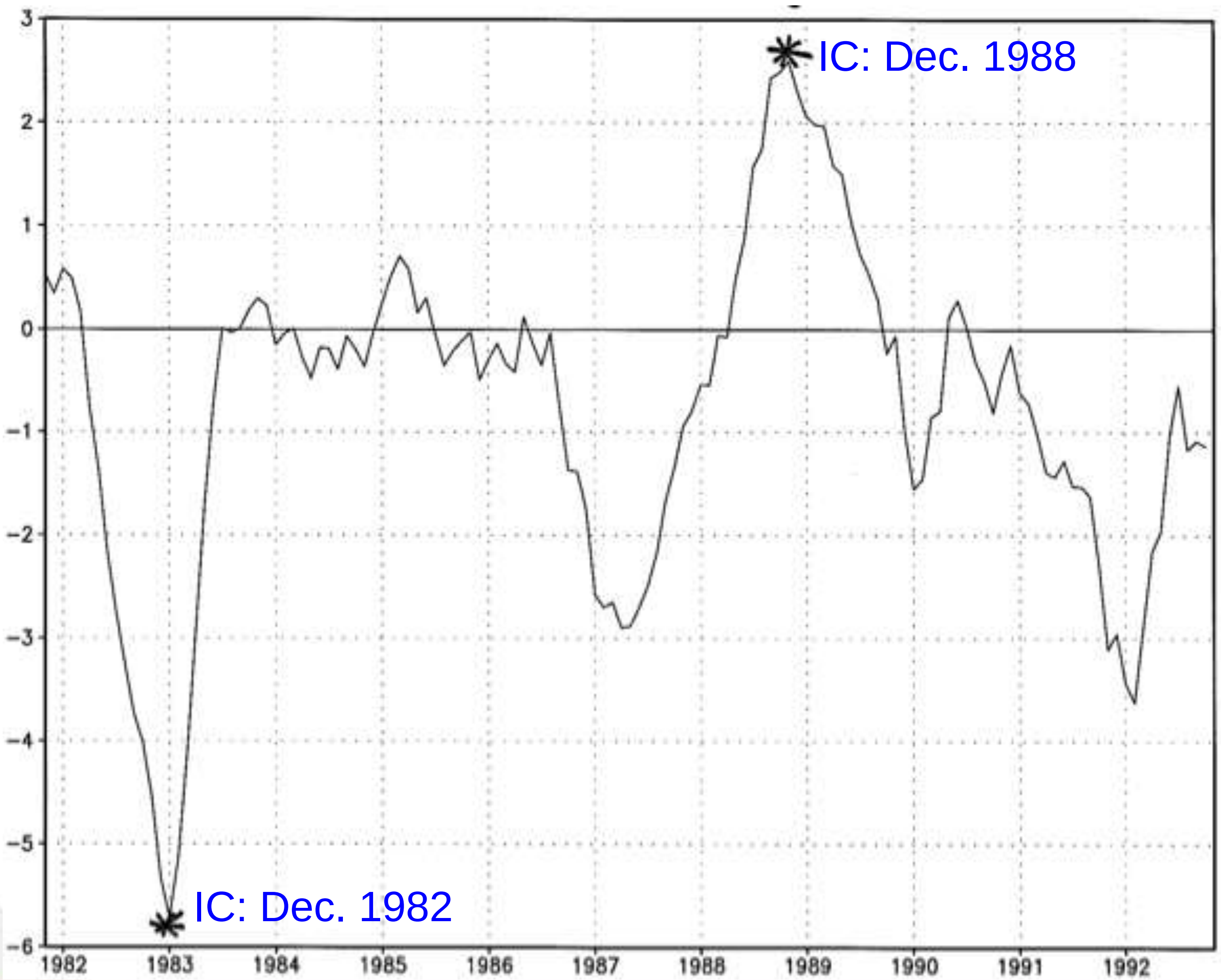
Shukla, J., R. Hagedorn, B. Hoskins, J. Kinter, J. Marotzke, M. Miller, T.N. Palmer, and J. Slingo, 2009: Revolution in climate Prediction is Both Necessary and Possible: A Declaration at the World Modelling Summit for Climate Prediction. *BAMS*, *Vol.90*, 16-19

An Earth system Prediction Initiative

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

"Predictability in the midst of chaos"

Observed 5-month running mean SOI



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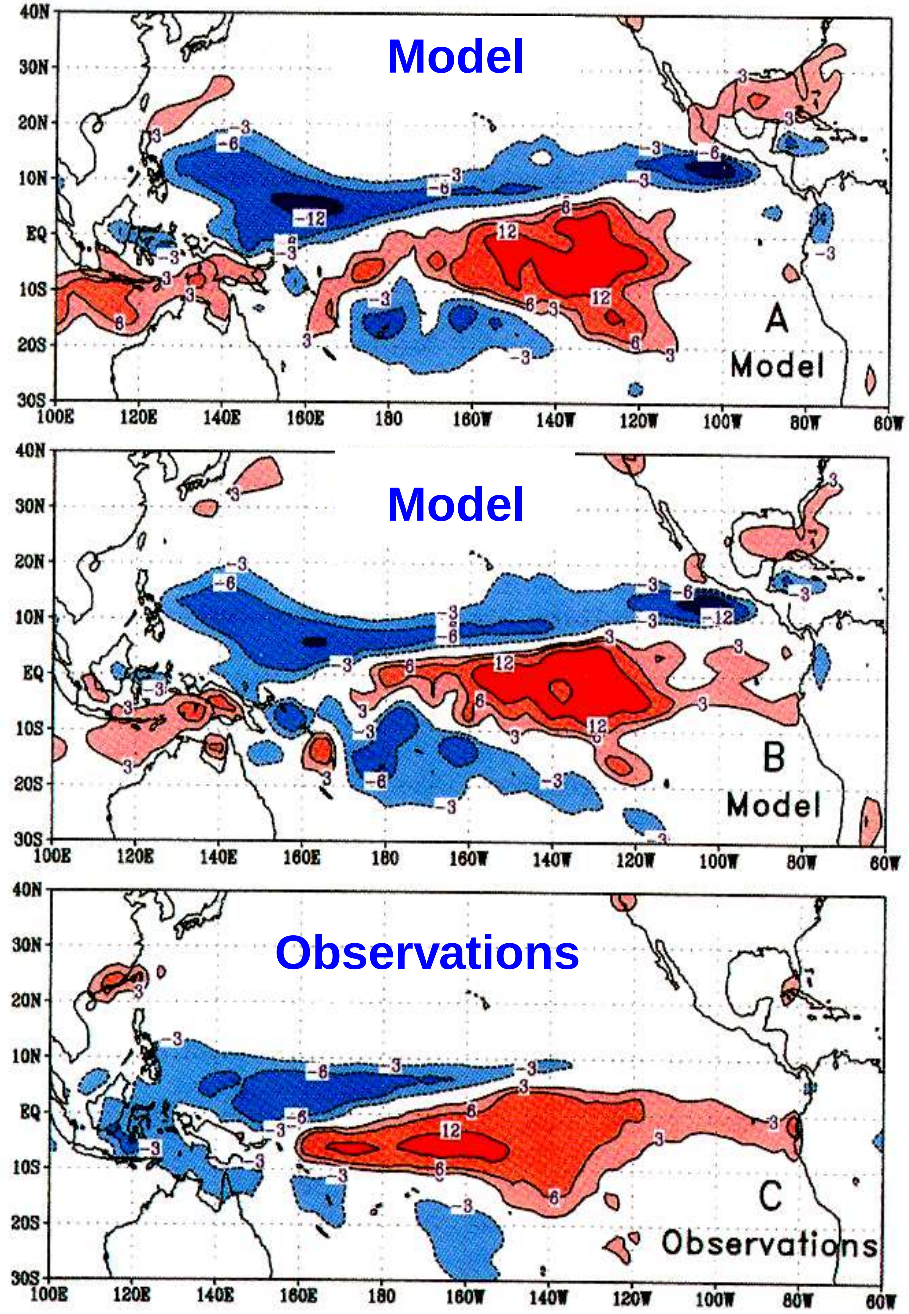
JFM Mean Rainfall Anomalies

"Predictability in the Midst Of Chaos"

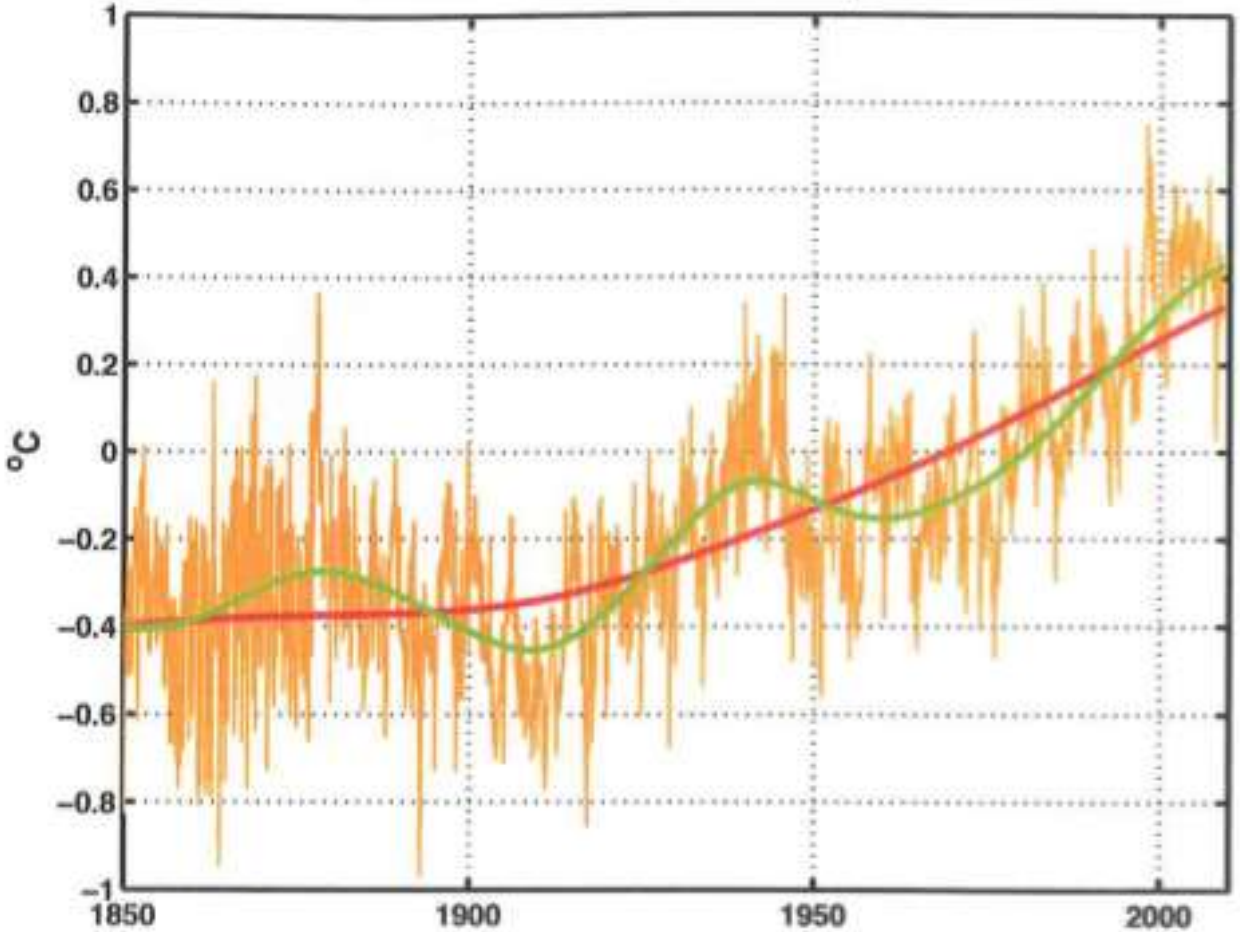
IC: Dec. 1988

IC: Dec. 1982



B.C.(SST): 1982 -83

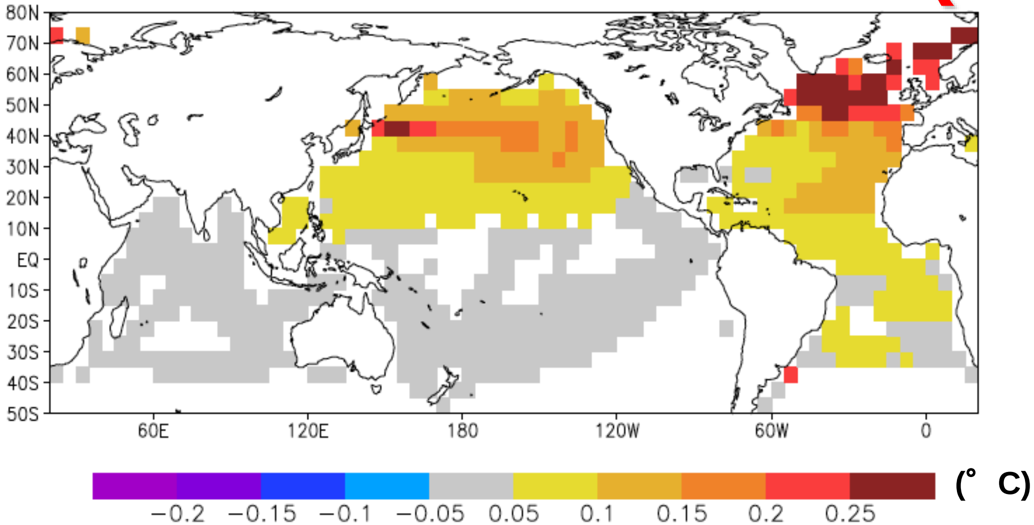
Global-mean Surface Temperature

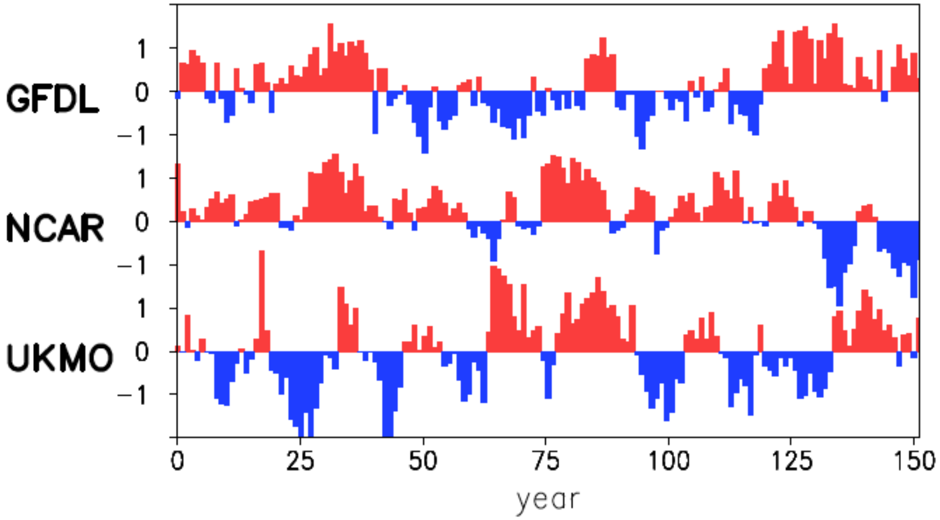


On the Time-Varying Trend in Global-Mean Surface Temperature
by Huang, Wu, Wallace, Smoliak, Chen, Tucker
EEMD: Ensemble Empirical Mode Decomposition; MDV: Multi Decadal Variability

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)





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Dynamical Prediction Experience

Model predictability depends on model fidelity

Hypothesis

Models that simulate climatology "better" make better predictions.

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

Testing the Hypothesis: Data

DEMETER Data

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

Climate Model Fidelity and Predictability

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

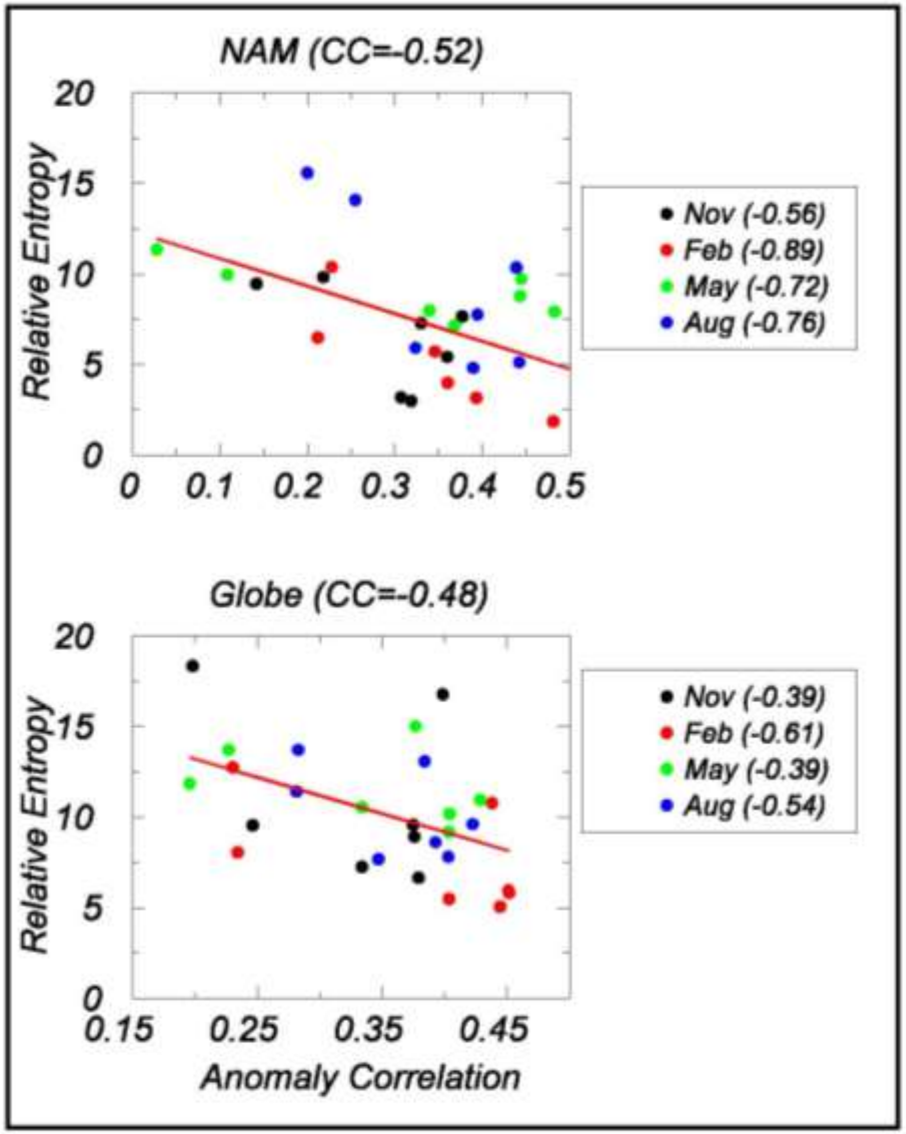
$$R(p_1, p_2) = \int_{R^M} p_1 \log\left(\frac{p_1}{p_2}\right) dx \qquad (1)$$

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

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

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

Fidelity vs. Skill



Fidelity vs. Skill
DEMETER 1980-2001
Seasonal Forecasts

7 models, 4 initial conditions

Lead Time = 0 months

Fidelity and Skill are related.

Models with poor climatology tend to have poor skill.

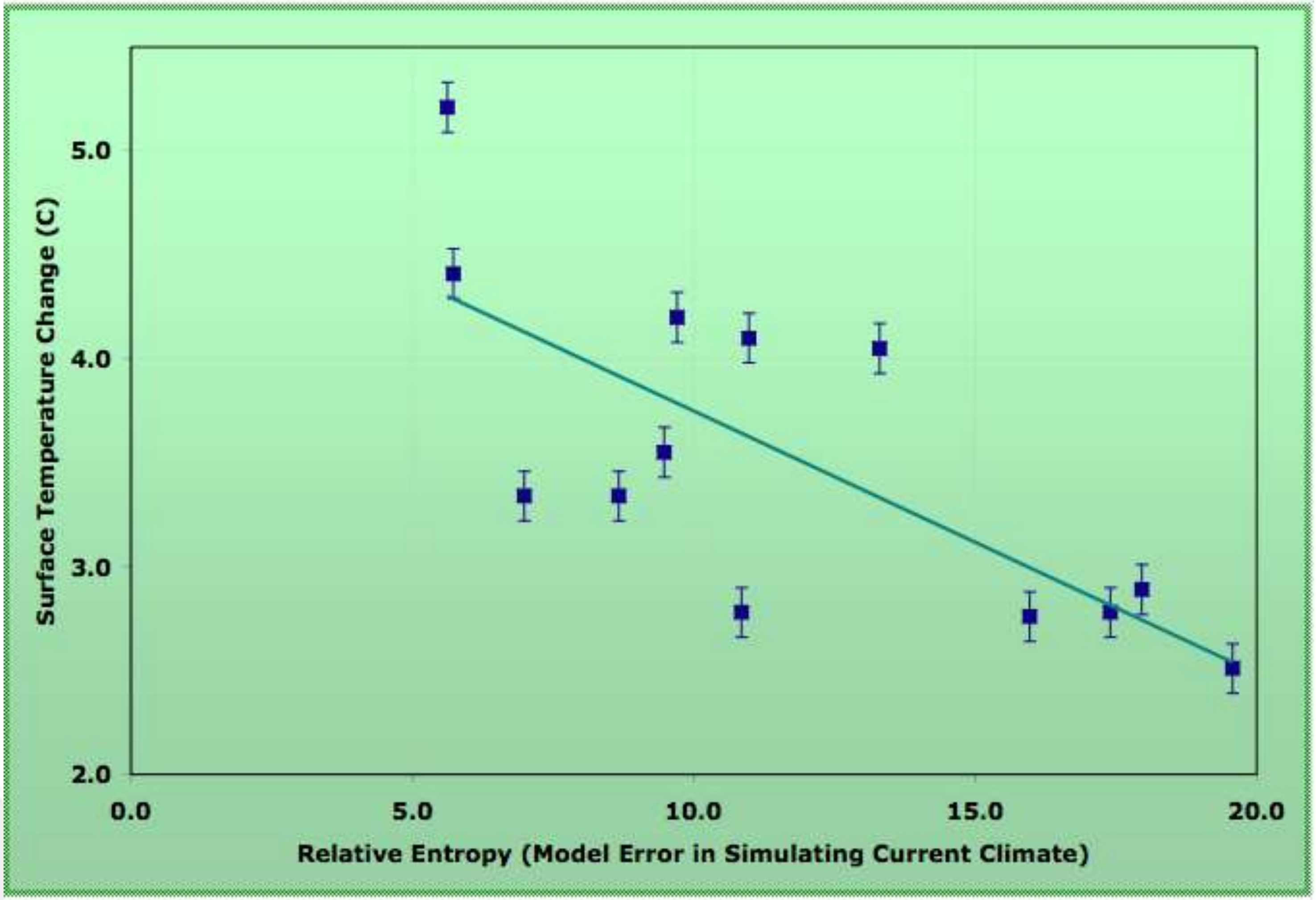
Models with better climatology tend to have better skill.

Courtesy of Tim DelSole

Climate Model Fidelity and Projections of Climate Change

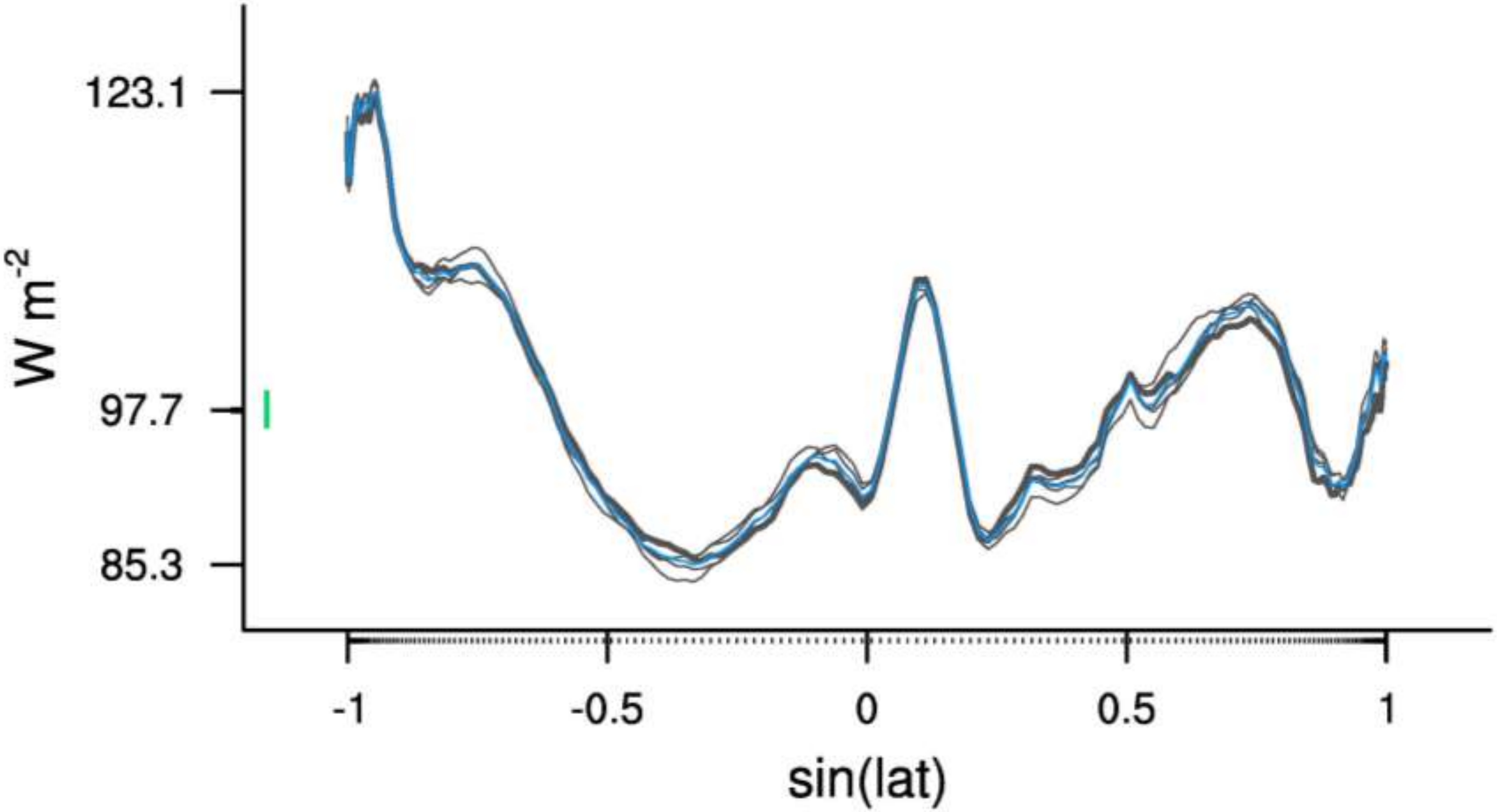
J. Shukla, T. DelSole, M. Fennessy, J. Kinter and D. Paolino

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



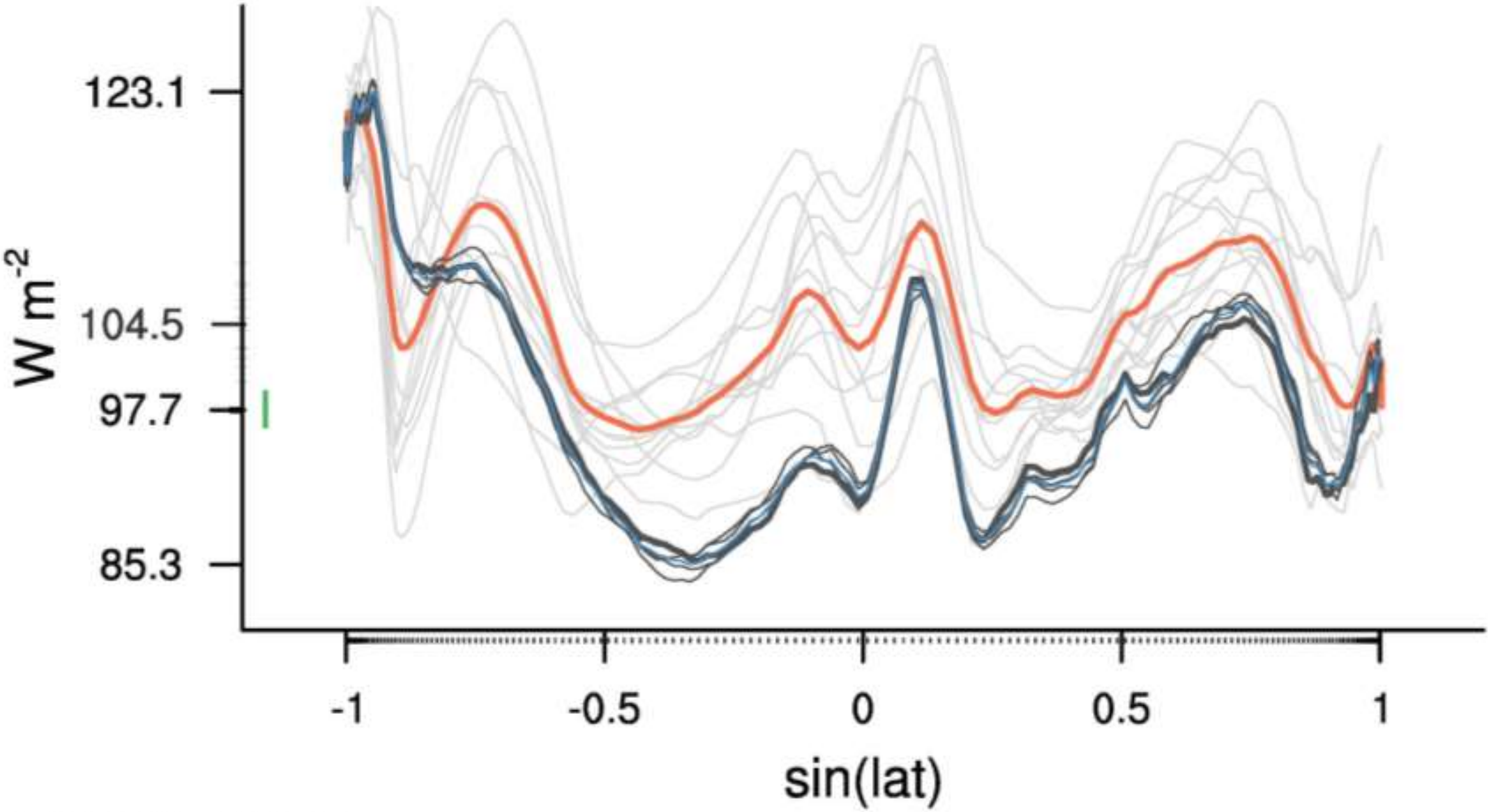
Model sensitivity versus model relative entropy for 13 IPCC AR4 models. Sensitivity is defined as the surface air temperature change over land at the time of doubling of CO_2. Relative entropy is proportional to the model error in simulating current climate. Estimates of the uncertainty in the sensitivity (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.

Annually & Zonally Averaged Reflected SW Radiation



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

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)

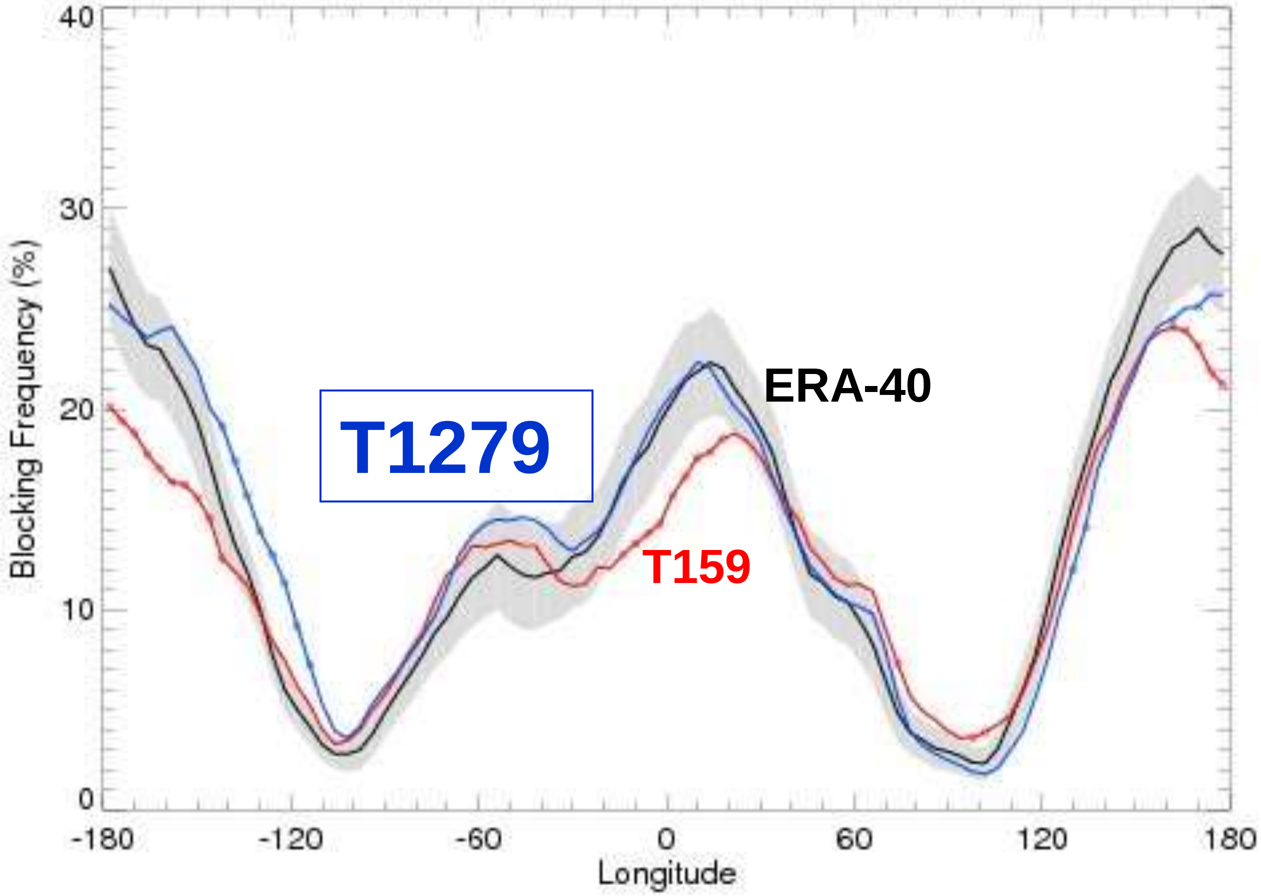
Bjorn Stevens, UCLA
World Modelling Summit, ECMWF, May 2008

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

Blocking Frequency

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

(Higher Resolution Model Improves Simulation of Blocking Frequency)



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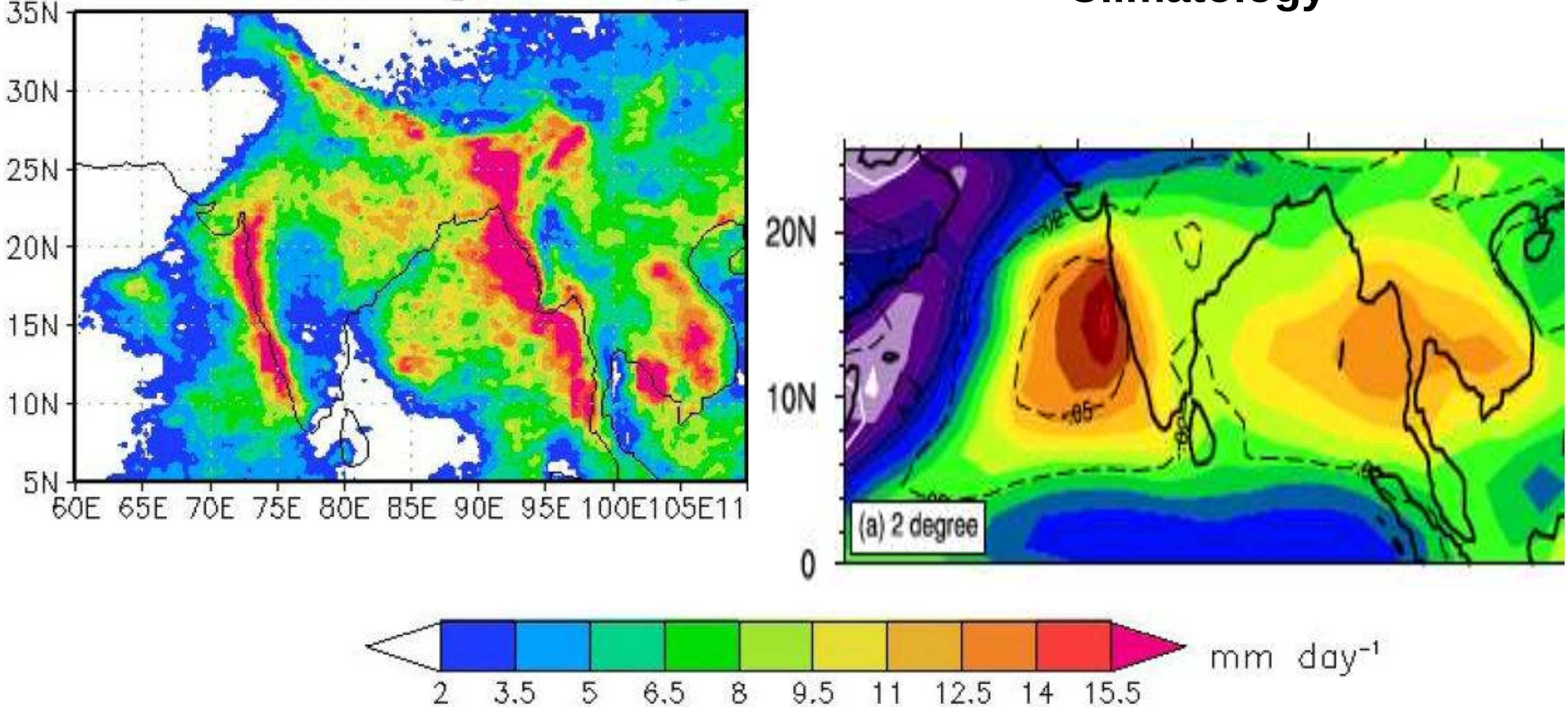
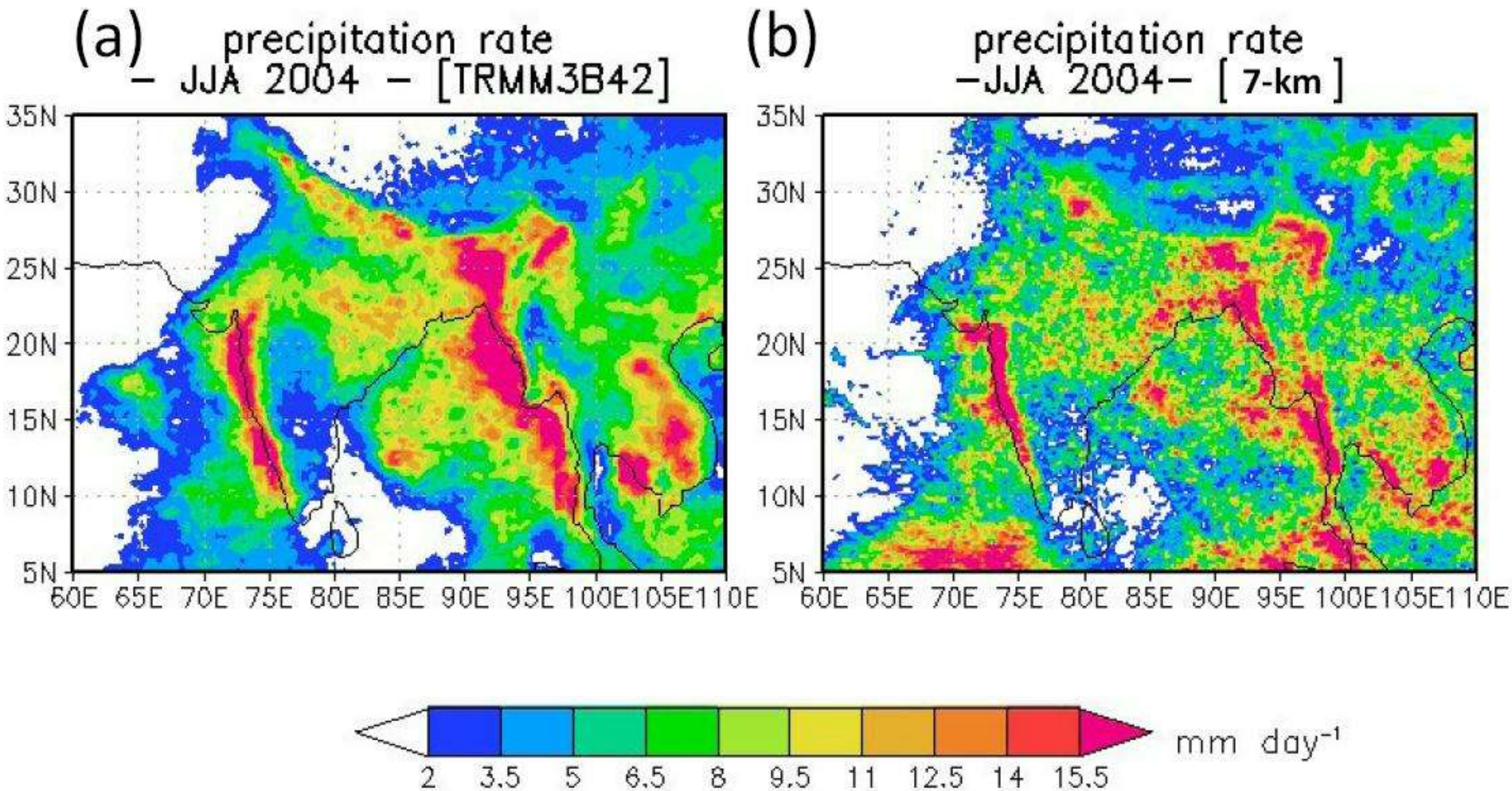
Monsoon Rainfall in Low Resolution Model

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

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



Monsoon Rainfall in High Resolution Model

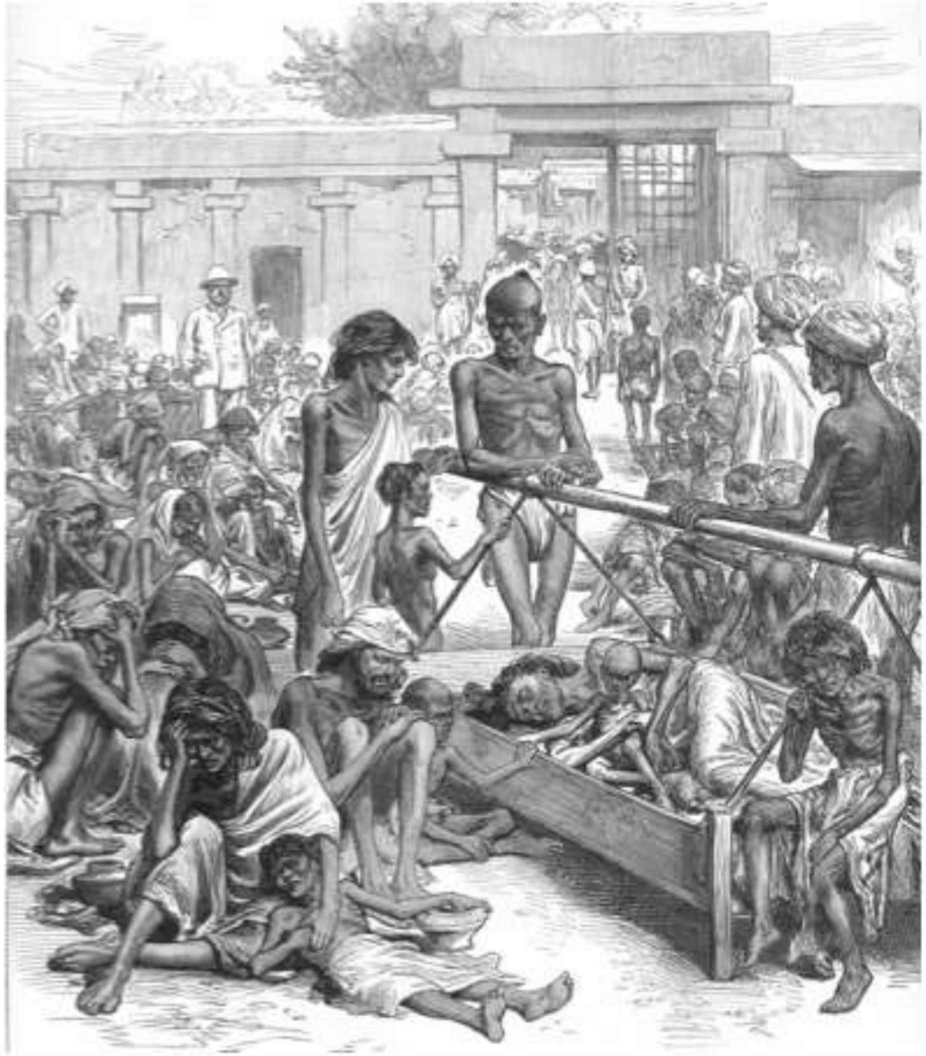


***Oouchi et al. 2009*: (a) Observed and (b) simulated precipitation rate over the Indo-China monsoon region as June-July-August average (in units of mm day -1). The observed precipitation is from TRMM_3B42, and the simulation is for 7km-mesh run.**

Dynamical Seasonal Prediction of Summer Monsoon Rainfall

After 50 years of climate modeling,
the current climate models can now produce
skillful prediction
of summer monsoon rainfall.

Great Famine of 1876-78 (India)



Great Famine of 1876-78 (India)

All India Monsoon Rainfall: -29%

Drought Area: 670,000 km^2

Estimated Deaths (Wikipedia): 5.5 – 8.2 million

Governance:

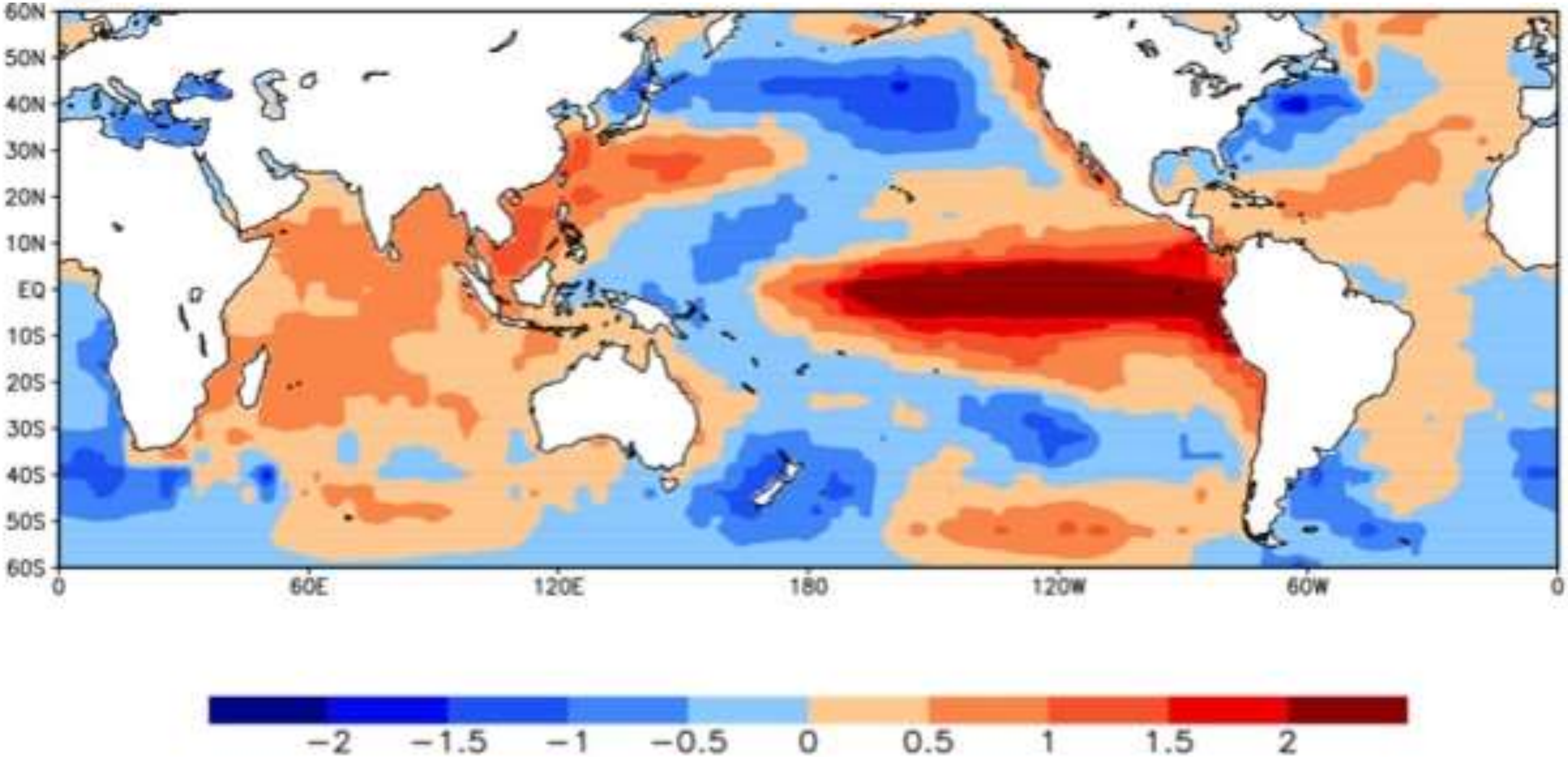
British Rule

(Lord Lytton exported food from India to England)

About 13 million people died in China

Late Victorian Holocausts **(2001)**
by Mike Davis
El Nino Famines and the Making of the Third World

SST Anomaly (˚C) for DJF 1877



Courtesy of Lakshmi Krishnamurti

Dynamical Seasonal Prediction (DSP)

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

DSP = NWP + IC of Ocean, Land, Atmosphere

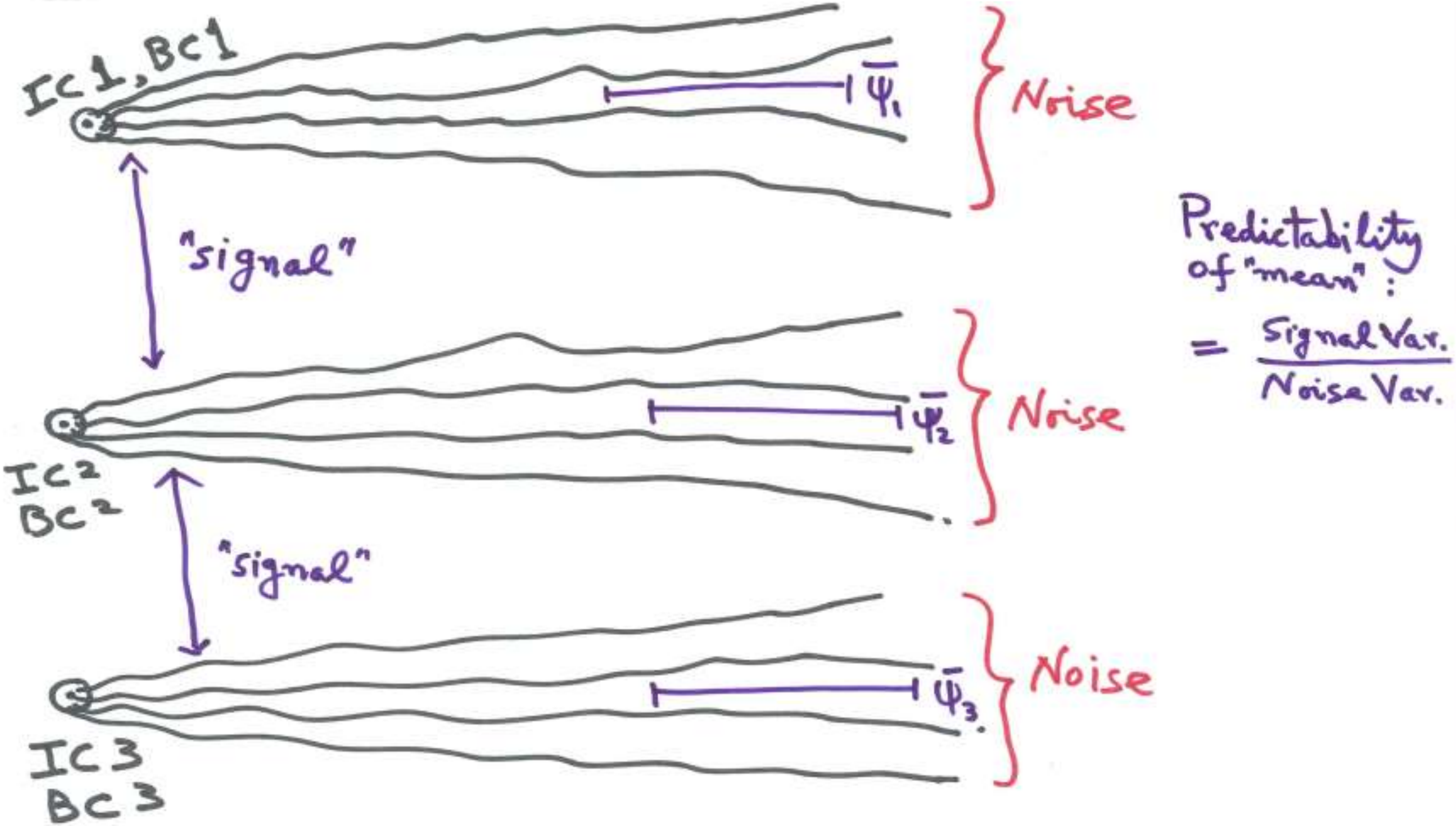
- *dynamically coupled and consistent IC*
- *Global ocean (especially upper ocean); sea ice (volume)*
- *Global Atmos. including stratosphere (IC)*
- *Global GHG (especially CO_2, O_3)*
- *Global land (soil moisture, vegetation, snow depth) IC*

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

Tier 2: Predict Boundary Forcing separately; use AGCM

- **(NWP=Atmos. IC + SST IC)**

Predictability of Time (Seasonal) Mean



Analysis of Variance: F as a measure of predictability
5 CGCMs, 46 years, 9 ensembles

Measure of predictability is

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

where

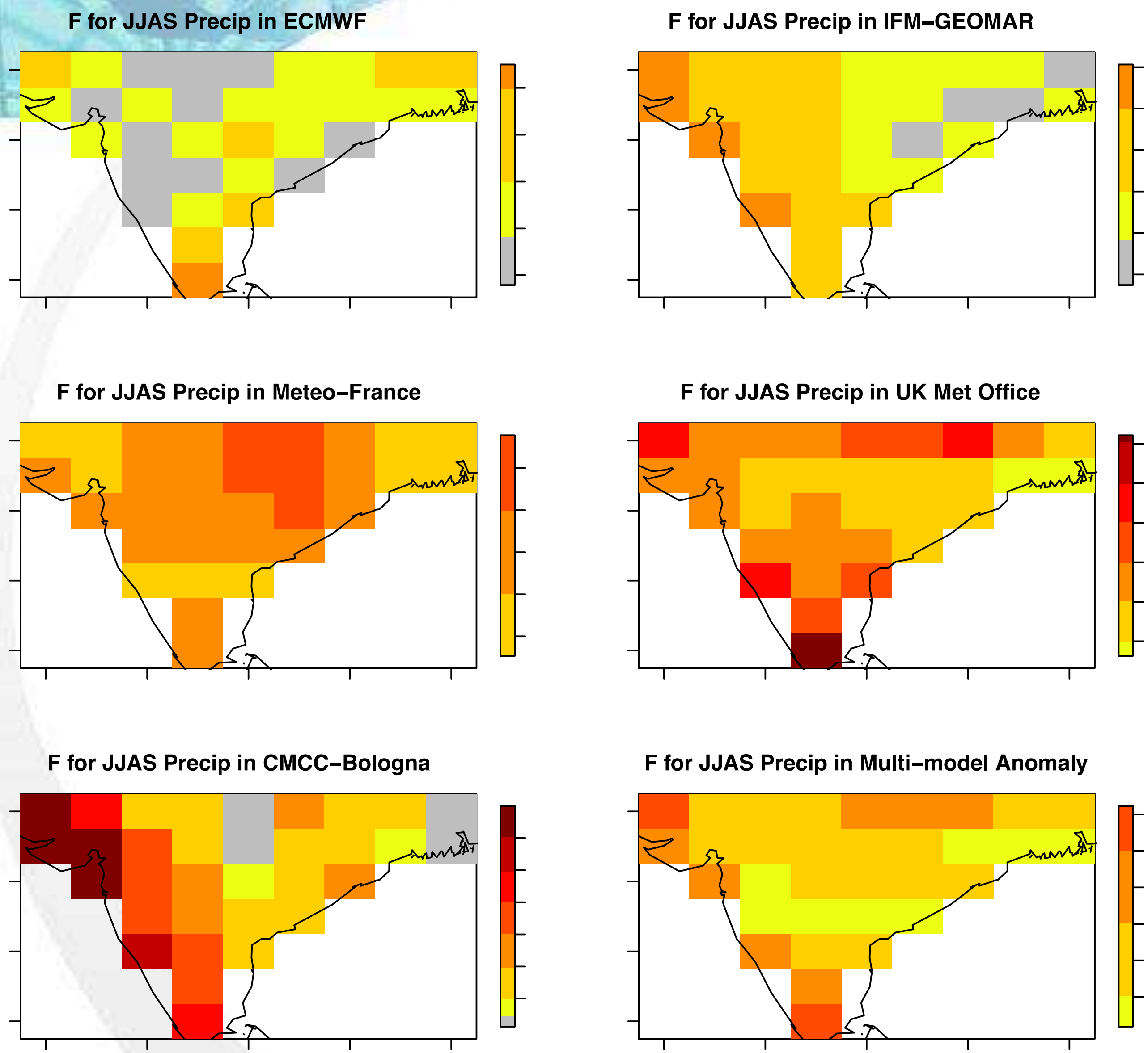
$$\hat{\sigma}_S^2 = \frac{1}{Y-1}\sum_{y=1}^{Y}\left(P_{y,e} - \overline{\overline{P}}\right)^2$$

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

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

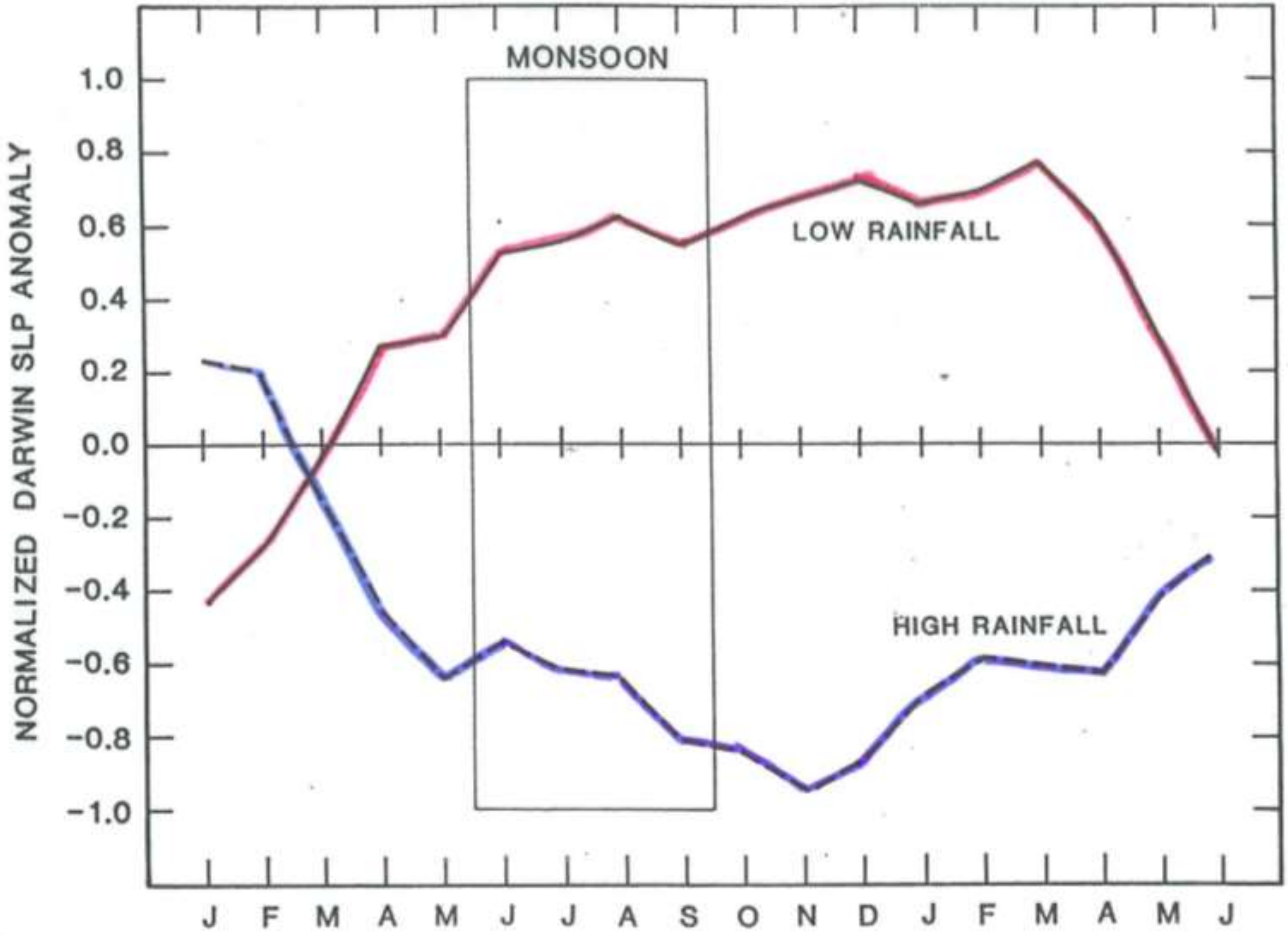
$$\overline{\overline{P}} = \frac{1}{Y}\sum_{y=1}^{Y} \overline{P}_y$$

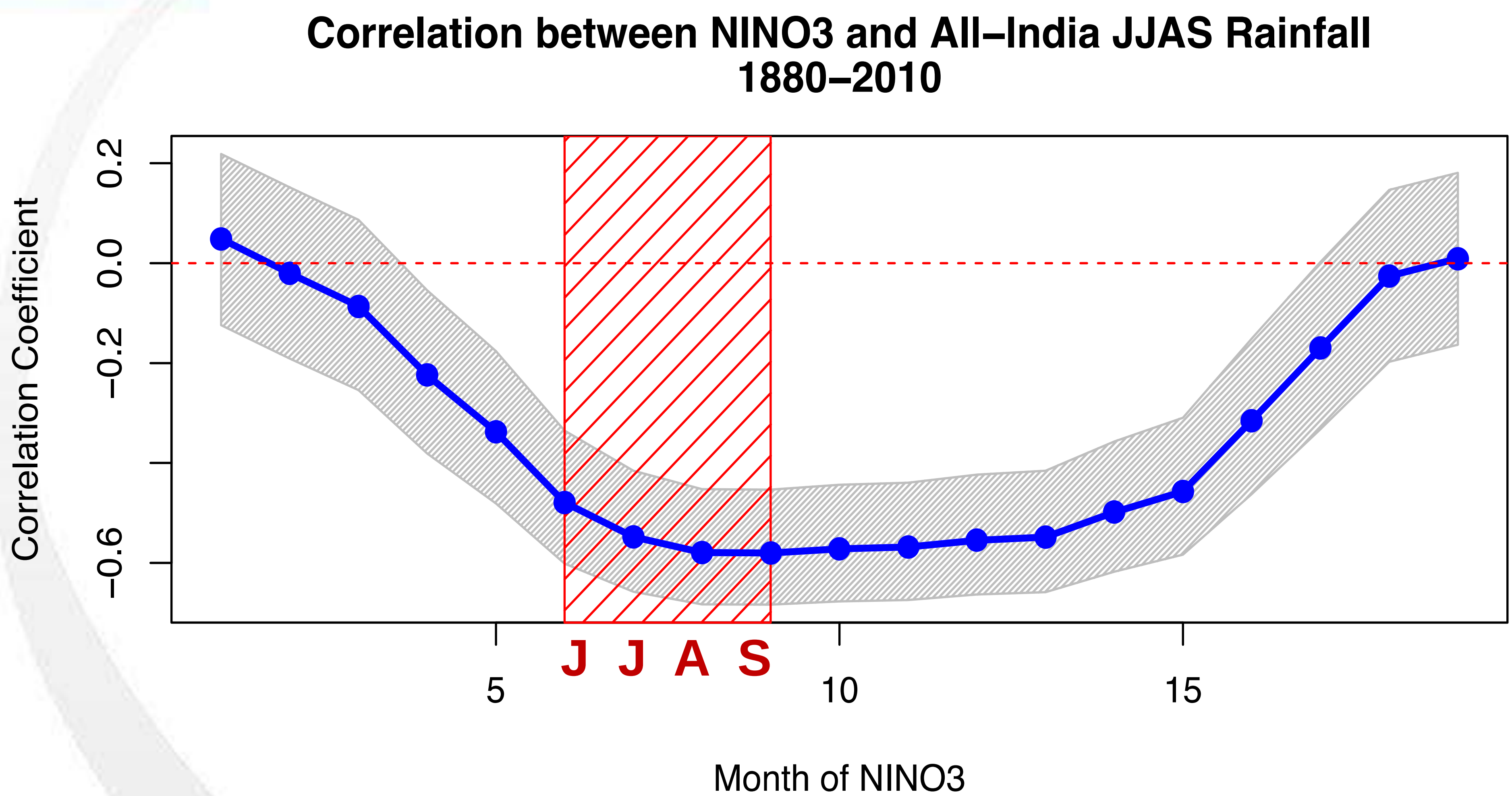
For samples drawn independently from the same normal distribution, and for $Y = 46$ and $E = 9$, the 5% significance threshold of F is 1.40



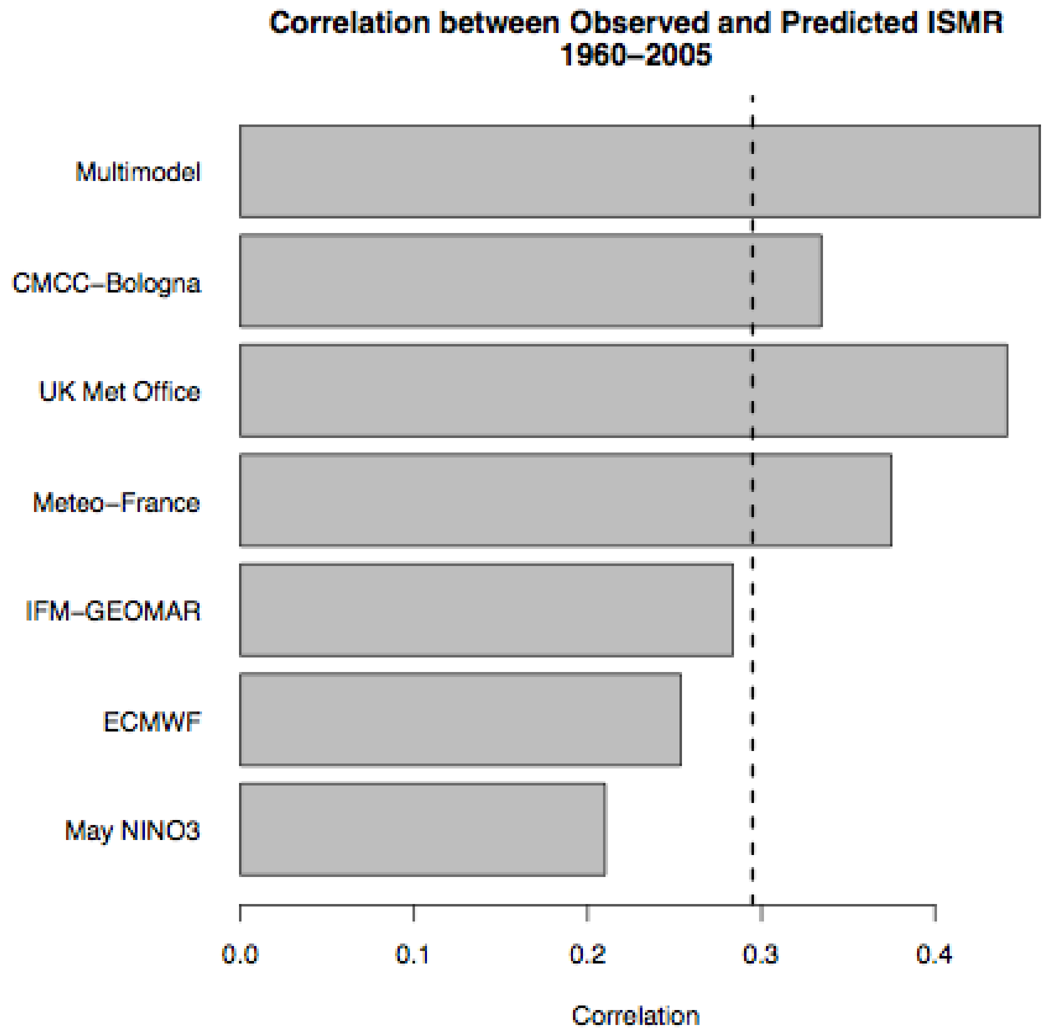
F-values for JJAS precip. For 46-years and 9 ensemble members the 5% significance is F=1.4. Gray color indicates not statistically significant at 95% confidence interval.

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





Correlation between NINO3 and All–India JJAS Rainfall
1880–2010
Correlation Coefficient
0.2
0.0
–0.2
–0.6
J J A S
5
10
15
Month of NINO3



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

For 1960-2005 Obs,

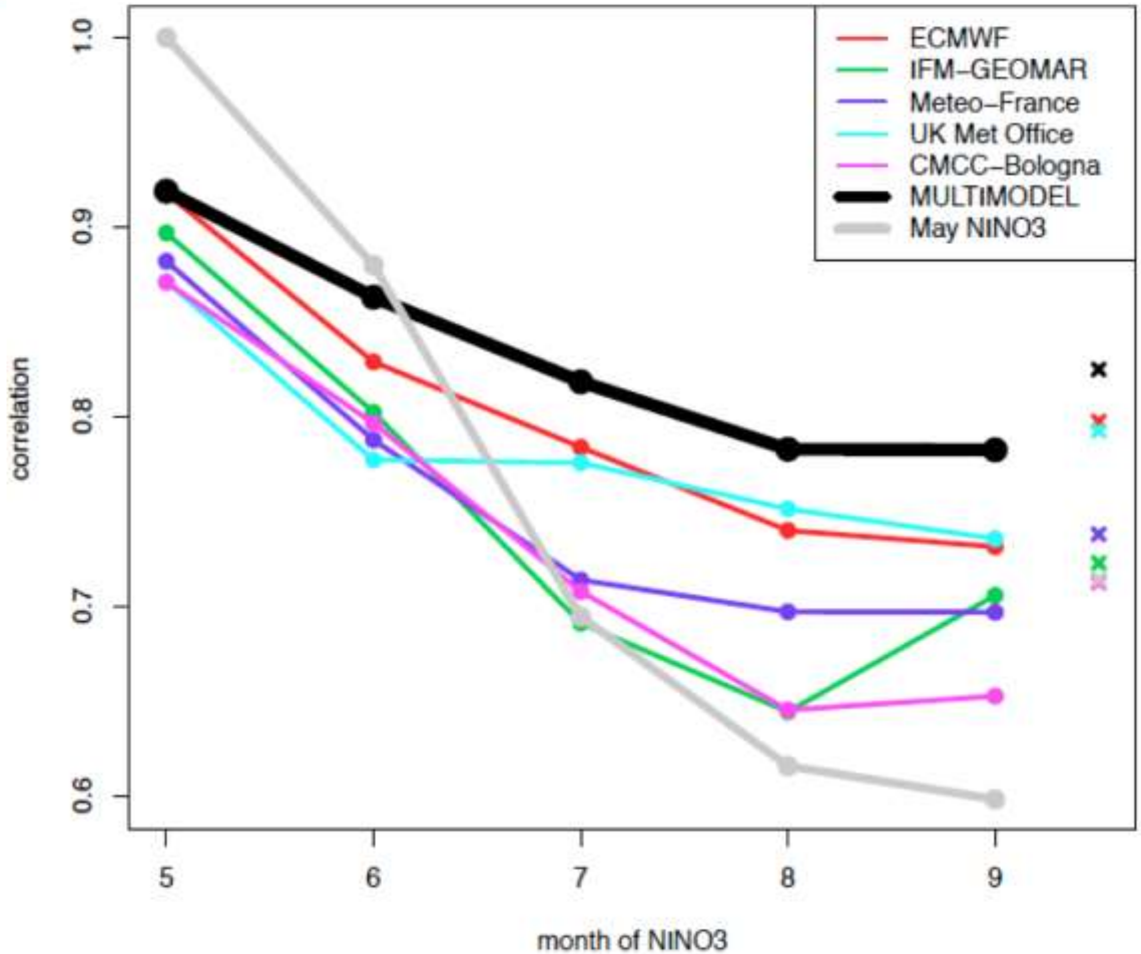
CC (April Nino3, ISMR): −0.1

CC (May Nino3, ISMR): −0.21

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

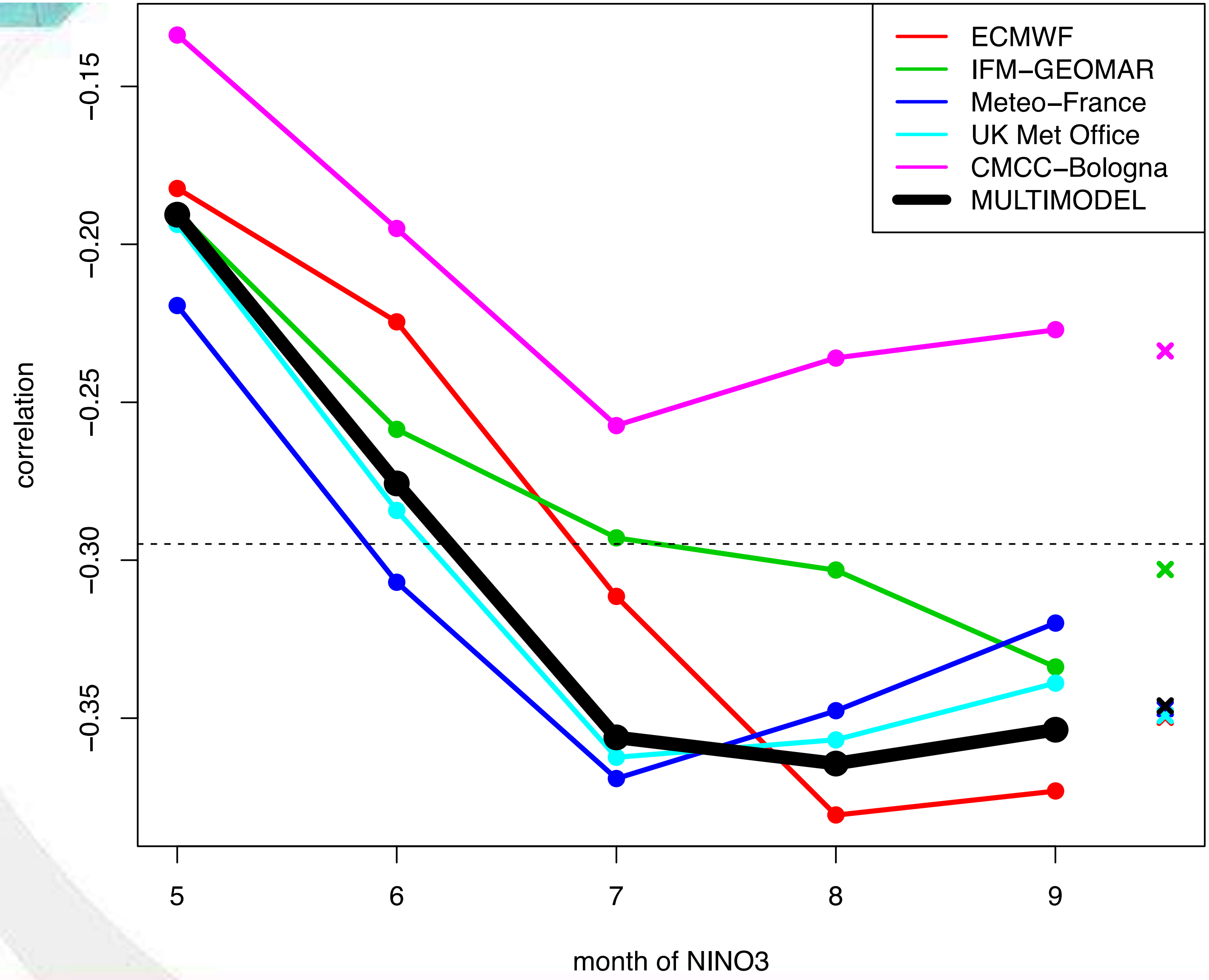
Last row shows empirical prediction using observed May NINO3.

Correlation between Observed and Predicted NINO3



Correlation between observed NINO3, and ensemble mean NINO3 predicted by the ENSEMBLES models, for hindcasts in the period 1960-2005, as a function of calendar month. Also shown is the correlation between observed NINO3 and the least squares prediction of NINO3 based on the observed May NINO3 value (thick grey). The 'x'-symbols on the far right give the correlations between the observed and predicted JJAS NINO3 index.

Correlation between Observed JJAS all India rainfall and Model NINO3



Summary (monsoon prediction)

•Model's ability to simulate SST and Q in West Pacific and Indian Ocean are critical for accurate monsoon prediction.

•Predictability (Analysis of Variance, F test) calculation for 5 coupled model ("ENSEMBLES" Project) seasonal predictions for 46 years, 9 member ensembles:

(ISMR is predictable at 95% significance)

•Skill of coupled O-A models for predicting ISMR for 1960-2005 is significant at 95%.

(Coupled O-A models for monsoon prediction is the future.)

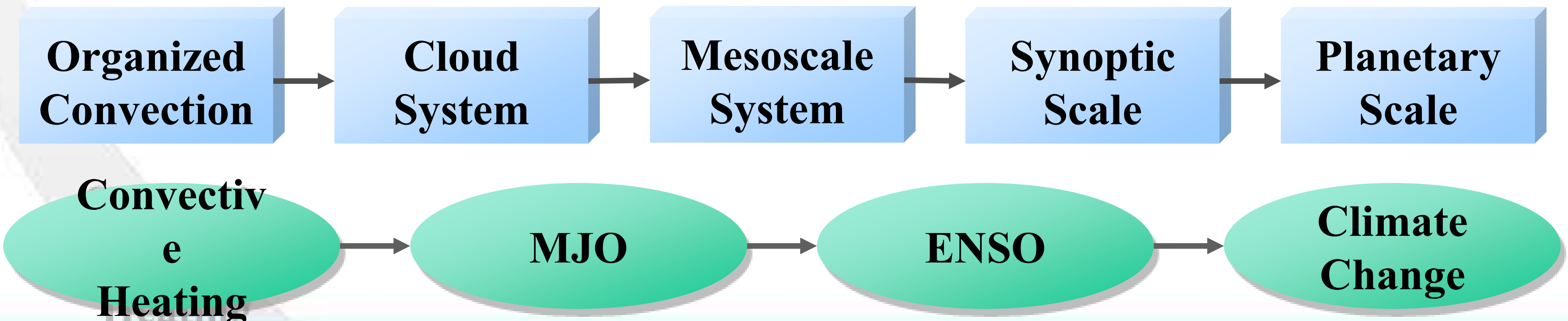
Towards a Hypothetical “Perfect” Model

- Replicate the statistical properties of the past observed climate
  - Means, variances, covariances, and patterns of covariability
- Utilize this model to estimate the limits of predicting the sequential evolution of climate variability
- Better model → Better prediction (??)

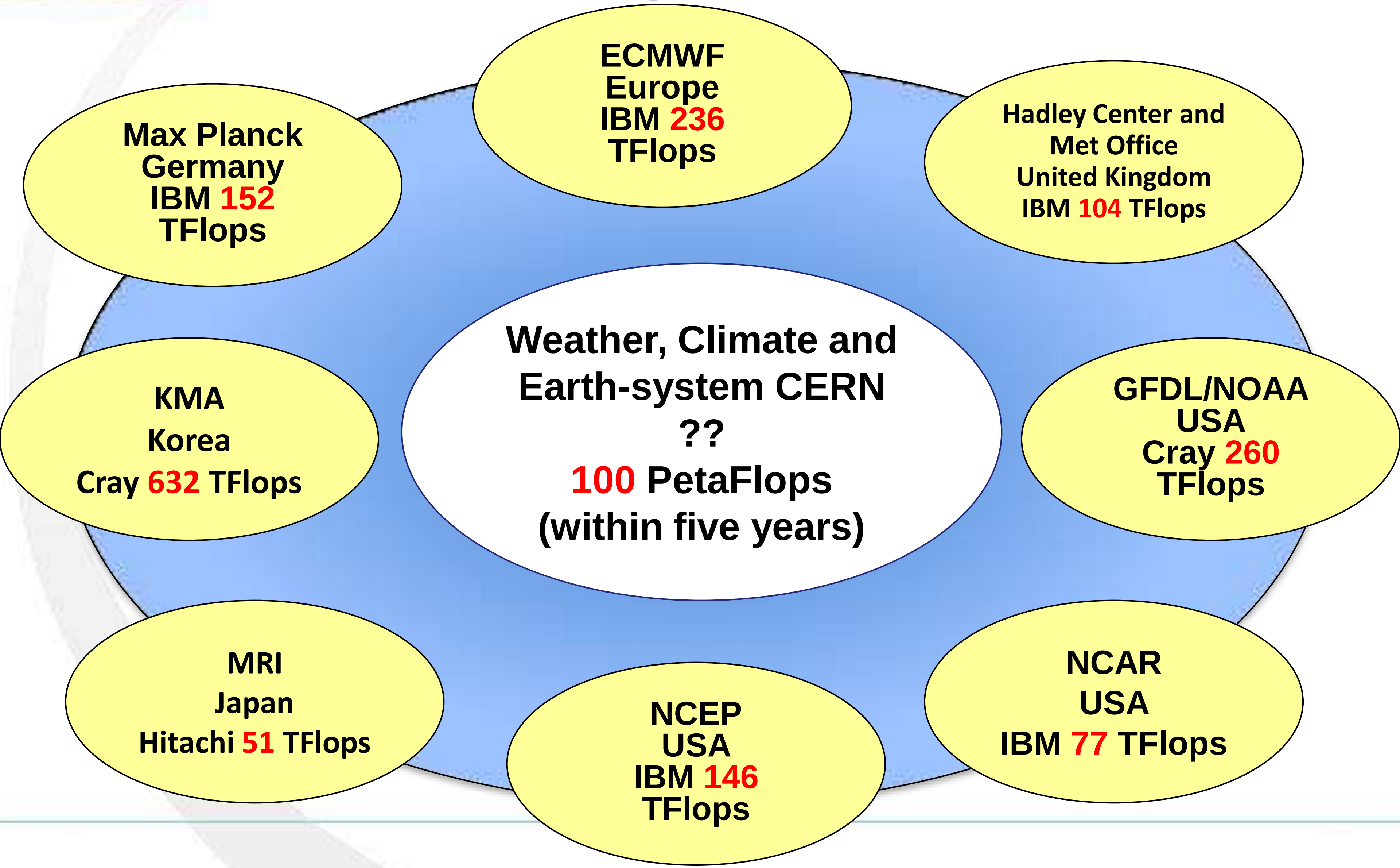
Seamless Prediction of Weather and Climate

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



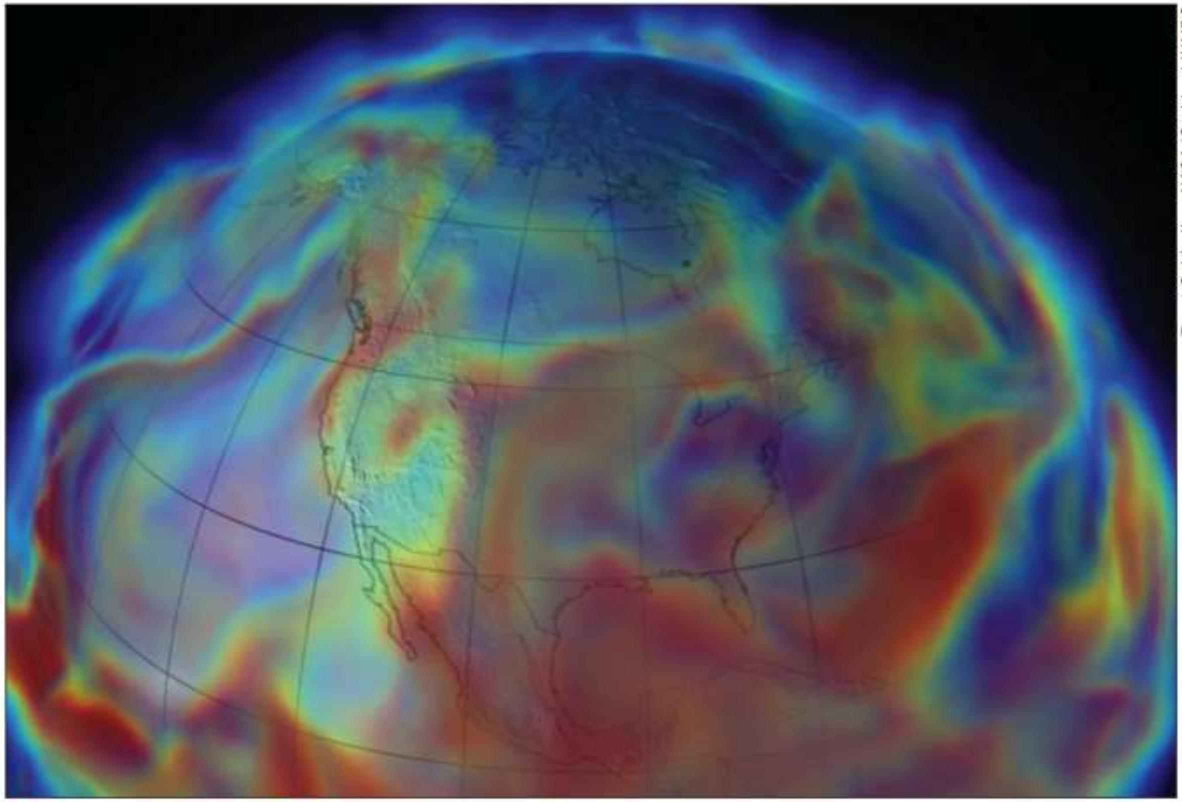
Supercomputers for Weather, Climate and Earth-System Research



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 Osbourne, 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.



Trent Schindler, NASA/Goddard/UMBC

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

In Physics World by Tim Palmer

THANK YOU!

ANY QUESTIONS?