Dynamical Seasonal Prediction:
Prospects, promises, and challenges

Jagadish Shukla

University Professor, George Mason University (GMU)

President, Institute of Global Environment and Society (IGES)

with contributions from:

Tim Delsole, Emilia Jin, Ben Kirtman

WCRP Seasonal Prediction Workshop, Barcelona, 4-7 June 2007

IGES

Center of Ocean-Land-Atmosphere studies

COLA

CREW
Center for Research on Environment and Water

GEORGE MASON UNIVERSITY

Outline

- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
    - ✓ Data Assimilation and Initialization
    - ✓ Biosphere, Cryosphere, Stratosphere Effects
    - ✓ Seasonal Prediction in a Changing Climate
    - ✓ Seamless Prediction of Weather and Climate
    - ✓ Computational Power
- Suggestions for the Future

Laplacian Determinism

We may regard the present state of the universe as the effect of its past and the cause of its future. An intellect which at a certain moment would know all forces that set nature in motion, and all positions of all items of which nature is composed, if this intellect were also vast enough to submit these data to analysis, it would embrace in a single formula the movements of the greatest bodies of the universe and those of the tiniest atom; for such an intellect nothing would be uncertain and the future just like the past would be present before its eyes.

Laplace

Essai philosophique sur les probabilités

Historical Views of Predictability (1)

1.The Austrian School ~ 1893

The meteorologist of Austrian School considered forecasting to be unscientific.

Evoking the attitude of some members of this school: forecasting is immoral, a danger to the character of a meteorologist, and an affair for romantics.

(BAMS, 2006, Vol.87, pp1662-1667)

Historical Views of Predictability (2)

2. The Norwegian School (V. Bjerknes) ~1904

- Presented a set of equations that should be solved to calculate the future weather, as an application of Laplacian determinism.
- Considered weather to be predictable in principle.

3. The Chicago School ~ 1950s

- Optimistic followers of the Laplacian determinism (V. Bjerknes)
- Considered the limit of predictability of the weather restricted only by the imperfections of observations of the initial conditions and the imperfections in the models.

(BAMS, 2006, Vol.87, pp1662-1667)

Historical Views of Predictability (3)

4. Lorenz (Deterministic Chaos, Predictability) ~ 1960s

- **An irrefutable theory of the predictability of weather, nonlinear dynamical systems.**
- **Showed that for some physical systems, while Laplacian determinism holds, the prediction of future behavior will necessarily be imperfect.**

(BAMS, 2006, Vol.87, pp1662-1667)

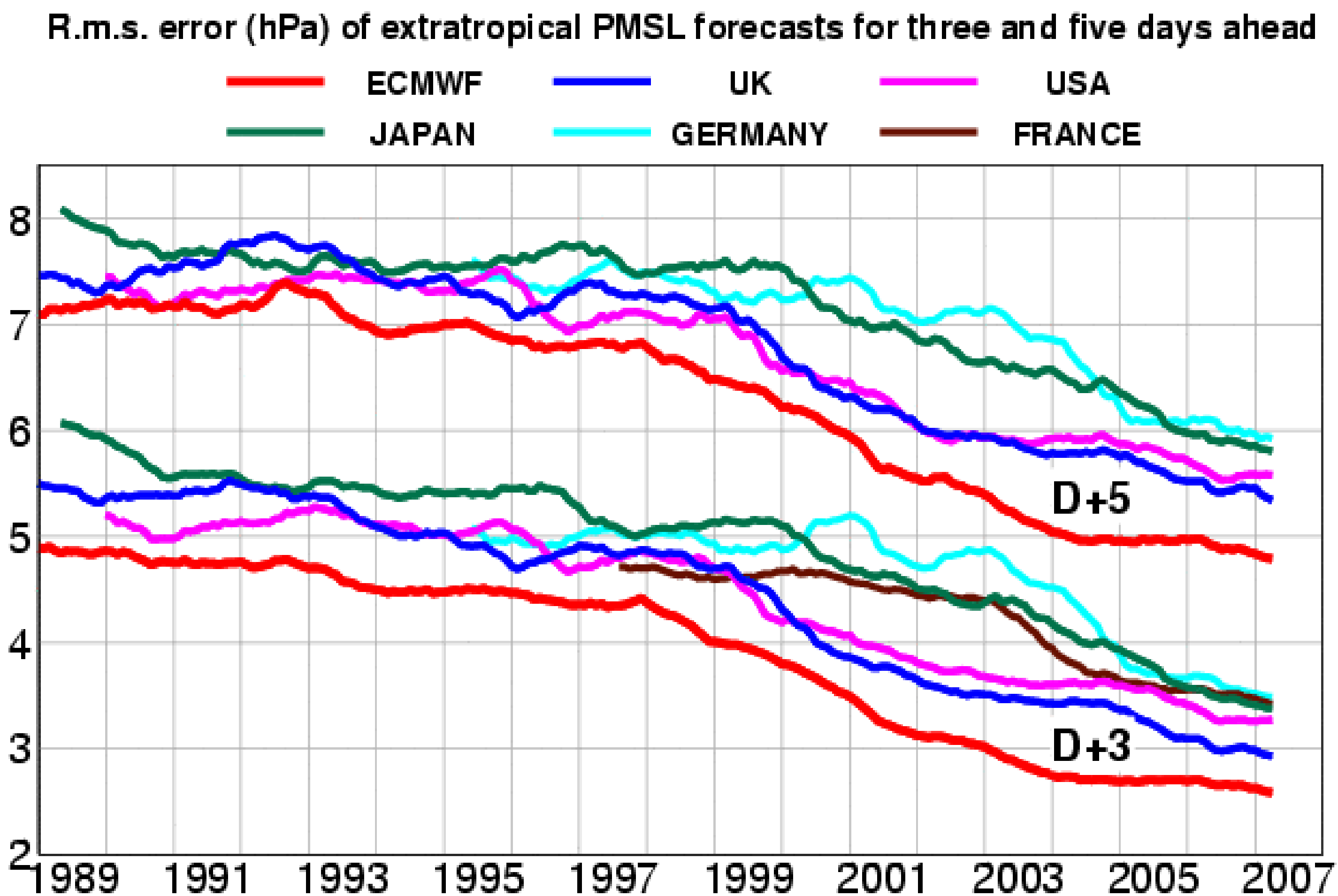
Historical Views of Predictability (4)

5. Predictability in the midst of Chaos ~ 1980s

- **Atmosphere-ocean interactions and atmosphere-land interactions enhance predictability of the coupled system far beyond the limits of predictability of weather.**
- **Forced response of the tropical atmosphere is so strongly determined by the underlying ocean, and the forced response of the tropical ocean is so strongly determined by the overlying atmosphere, that there is no sensitive dependence on the initial conditions.**
- **Coupled ocean-land-atmosphere system is predictable.**

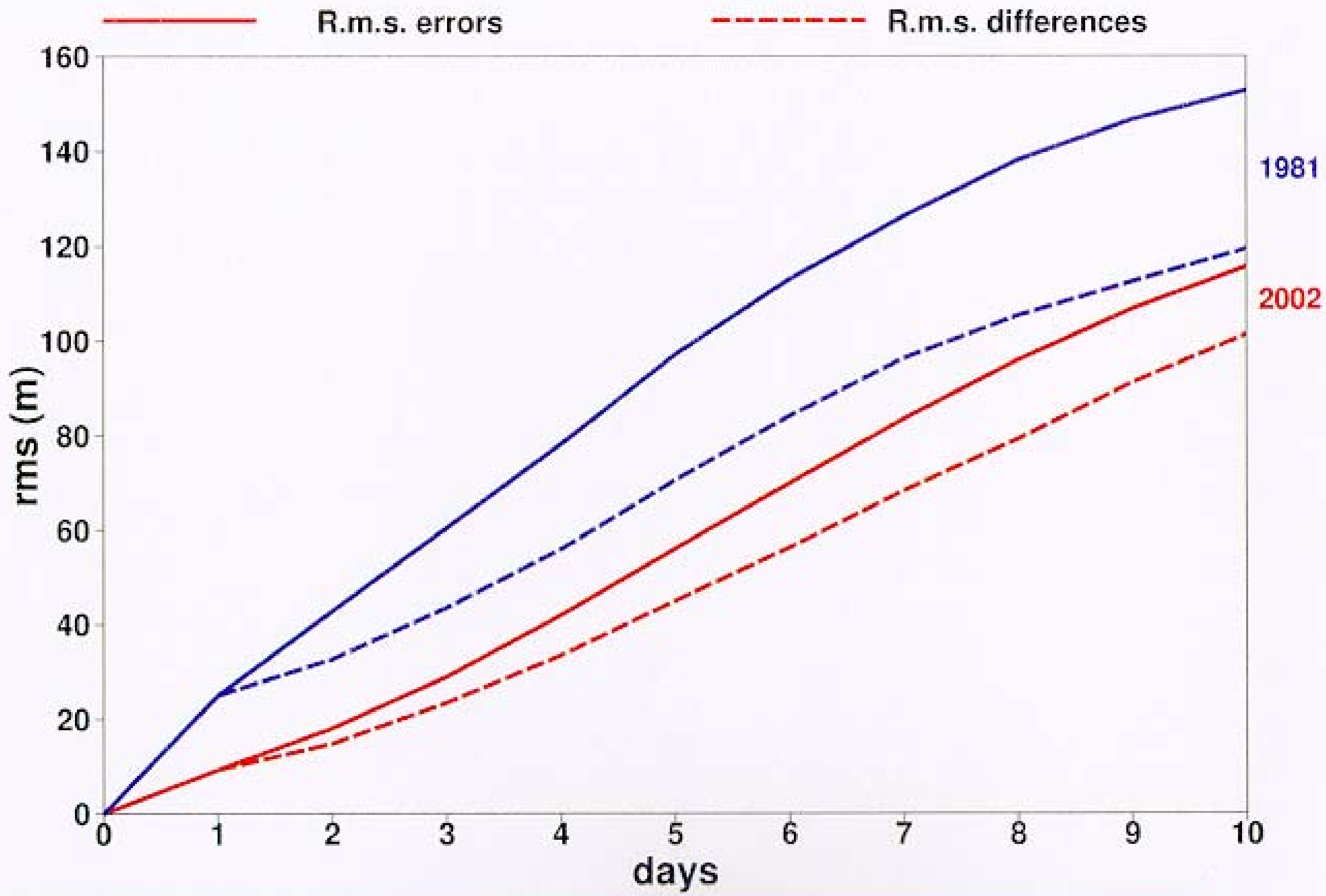
Outline

- Historical Overview
- **Success of NWP during the past 30 years**
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future



(Thanks to ECMWF!)

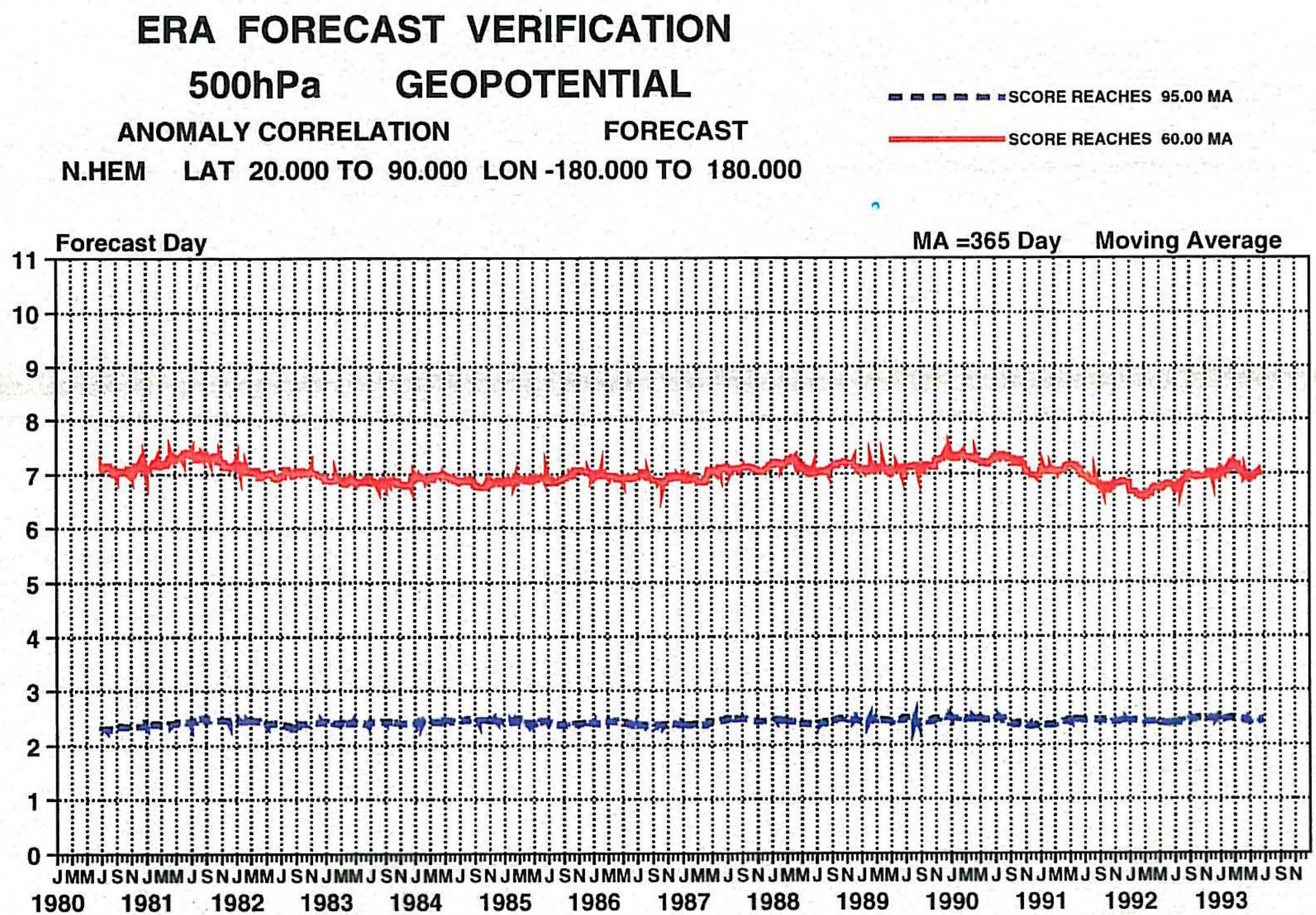
R.m.s. errors and differences between successive forecasts
Northern hemisphere 500hPa height Winter



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
500hPa GEOPOTENTIAL
ANOMALY CORRELATION FORECAST
N.HEM LAT 20.000 TO 90.000 LON -180.000 TO 180.000
SCORE REACHES 95.00 MA
SCORE REACHES 60.00 MA
Forecast Day
MA =365 Day Moving Average
11
10
9
8
7
6
5
4
3
2
1
0
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993

Commentary

- Several NWP Models have comparable skill.
- Initial error growth has steadily increased, yet skill of five day forecast has also increased.
- NWP progress in past 30 years: Improved one day forecast.
- No scientific breakthrough (except ensemble forecasting).
- No enhancement of observations.
- Hard work, improve models, improved assimilation and initialization.
- Possible lesson for Dynamical Seasonal Prediction.

Outline

- Historical Overview
- Success of NWP during the past 30 years
- **From Weather Prediction to Dynamical Seasonal Prediction**
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

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

- Operational Short-Range NWP: was already in place
- 15-day & 30-day Mean Forecasts: demonstrated by Miyakoda (basis for creating ECMWF-10 days)
- Dynamical Predictability of Monthly Means: demonstrated by analysis of variance
- Boundary Forcing: predictability of monthly & seasonal means (Charney & Shukla)
- AGCM Experiments: prescribed SST, soil wetness, & snow to explain observed atmospheric circulation anomalies
- 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

Simulation of (Uncoupled) Boundary-Forced Response: Ocean, Land and Atmosphere

INFLUENCE OF OCEAN ON ATMOSPHERE

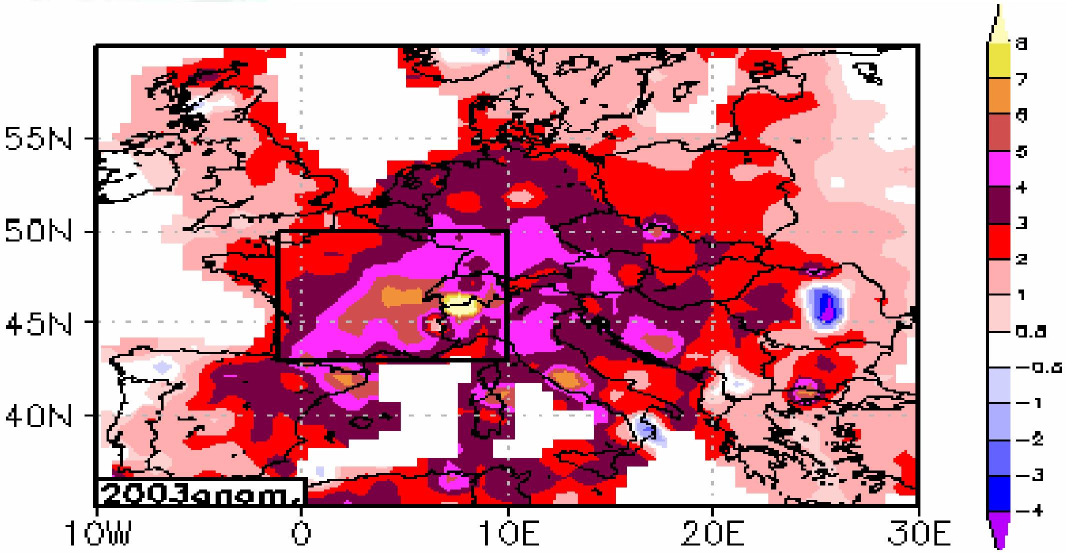
- Tropical Pacific SST
- Arabian Sea SST
- North Pacific SST
- Tropical Atlantic SST
- North Atlantic SST
- Sea Ice
- Global SST (MIPs)

INFLUENCE OF LAND ON ATMOSPHERE

- Mountain / No-Mountain
- Forest / No-Forest (Deforestation)
- Surface Albedo (Desertification)
- Soil Wetness
- Surface Roughness
- Vegetation
- Snow Cover

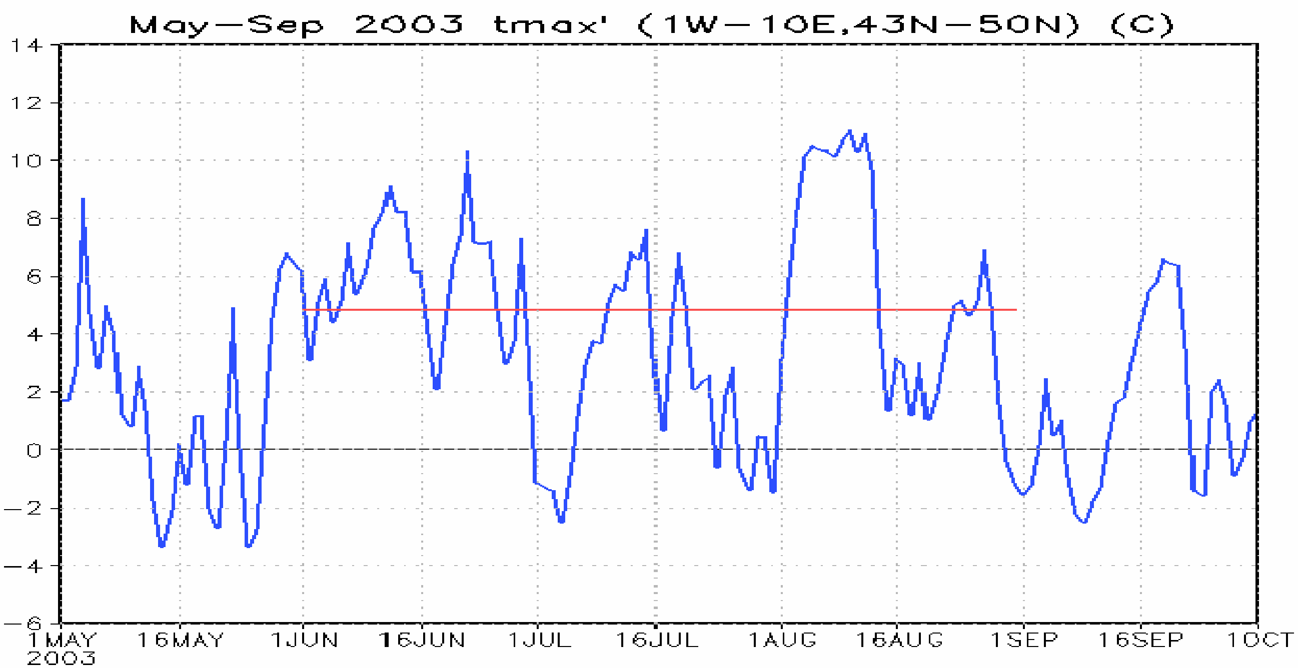
(Thanks to COLA!)

European Heat Wave of summer 2003



Tcmx JJA 2003

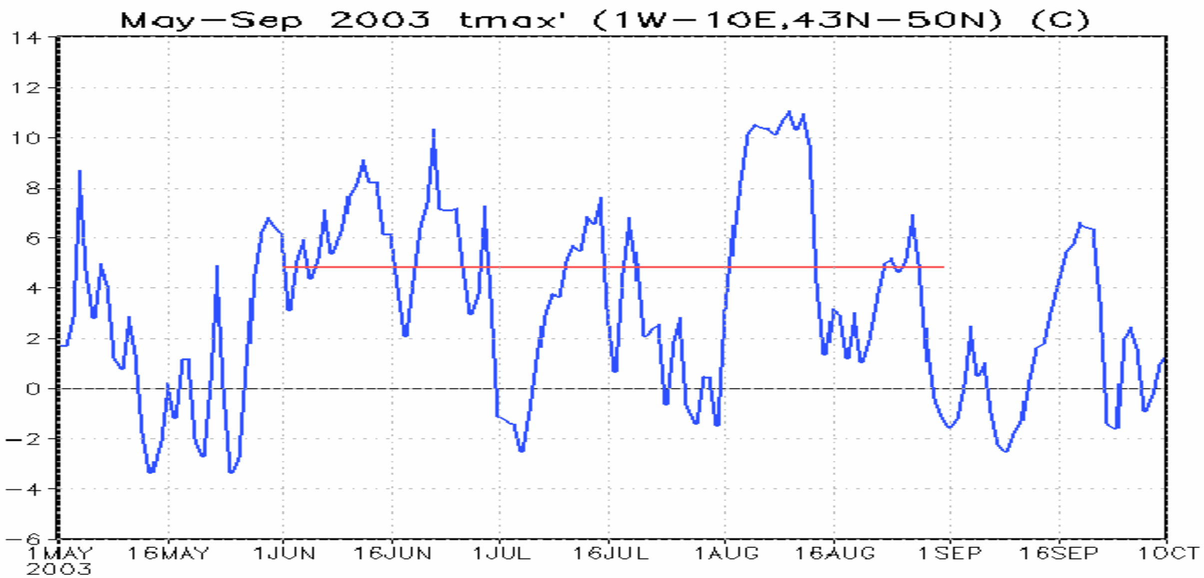
(Xie Pingping data)



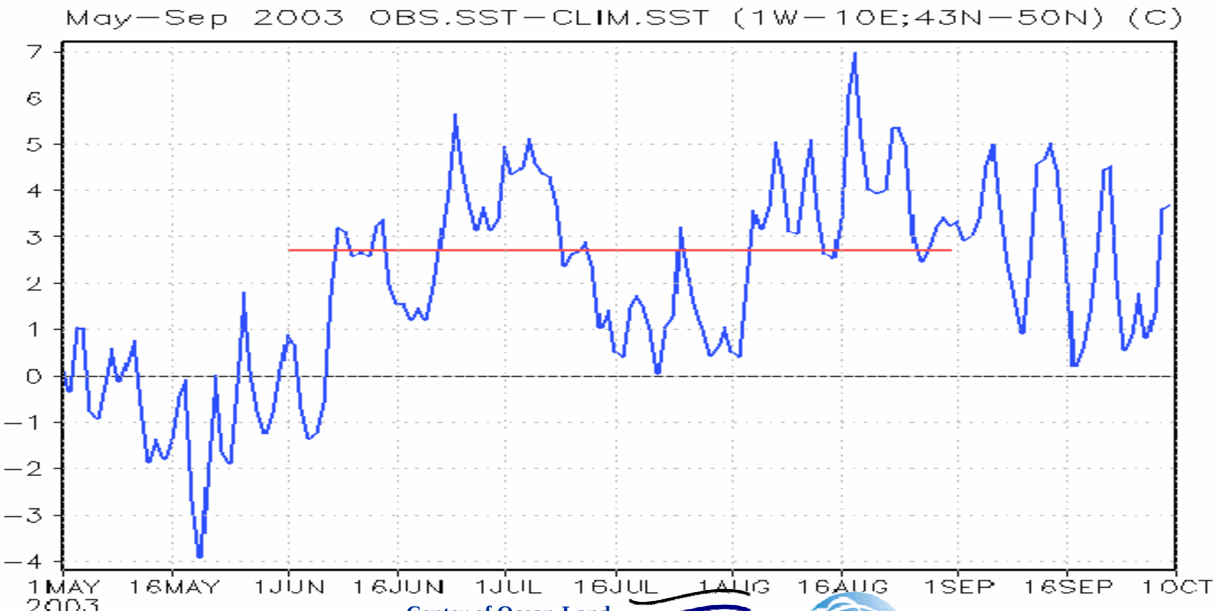
Anomaly of maximum surface temperature

Feudale (Ph.D. GMU)

OBSERVATIONS

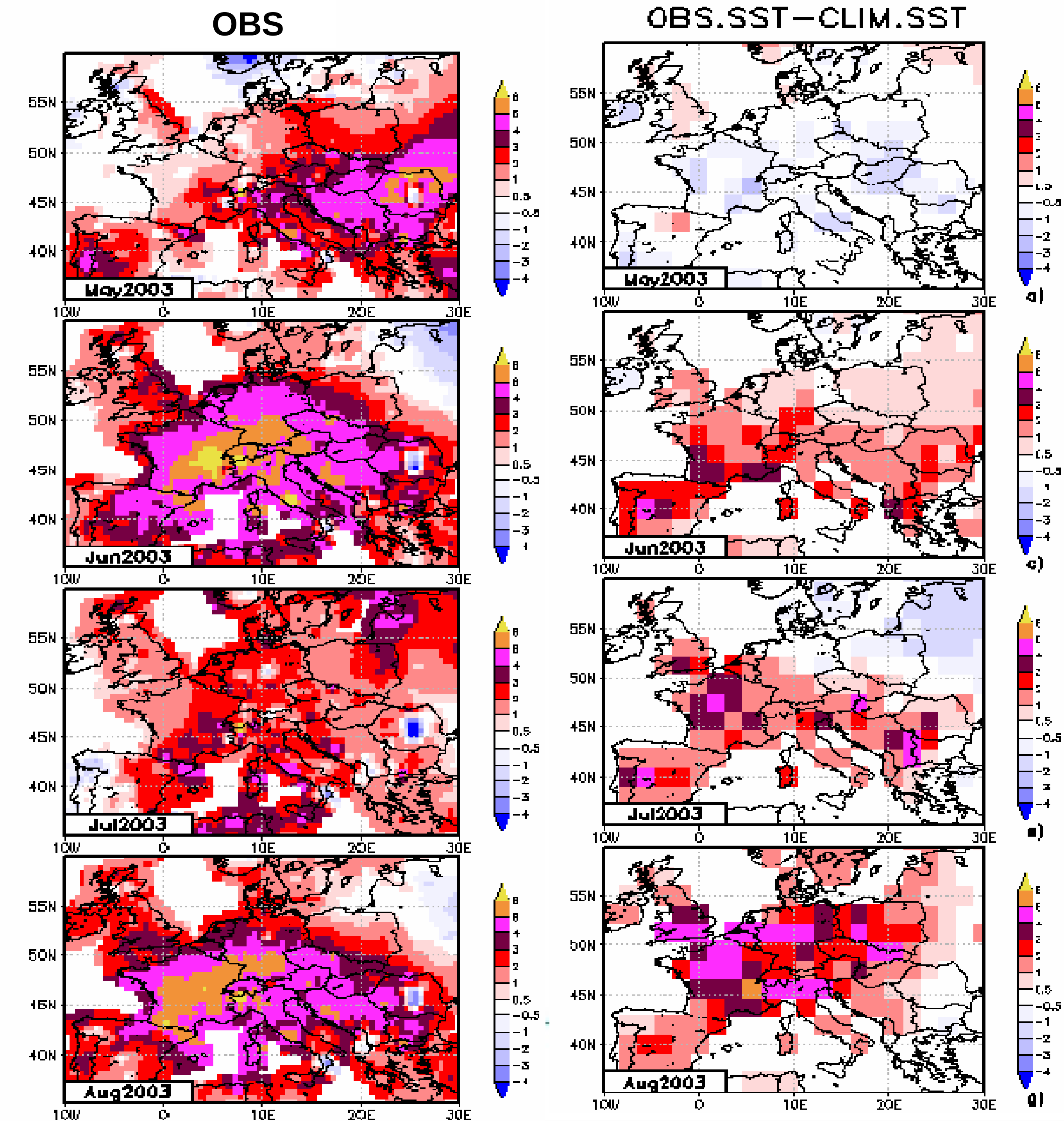


OBS.SST-CLIM.SST
- Global SST effect -



Anomaly of maximum surface temperature on (1W-10E;43N-50N)

Feudale (Ph.D. GMU)



T_{MAX} anomaly:

comparison between ***observations*** *and*

global SST run

Feudale (Ph.D. GMU)

EFFECTS OF SST ANOMALY

$\delta T(x,y) \longrightarrow \delta Q(x,y,z) \longrightarrow \delta V$

SST anomaly — heating anomaly — circulation anomaly

~ 5-7 days

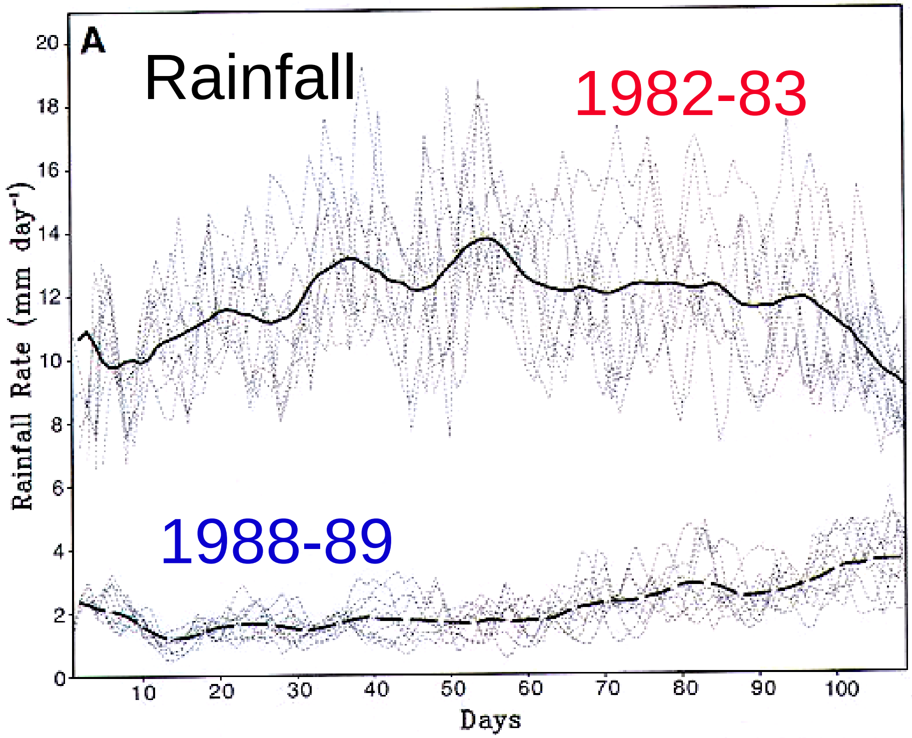
- δT (magnitude, structure)
- T (magnitude, structure)
- V (x,y,z): large scale flow
- δ (conv., div.):
  latitude regime (f)
- instability

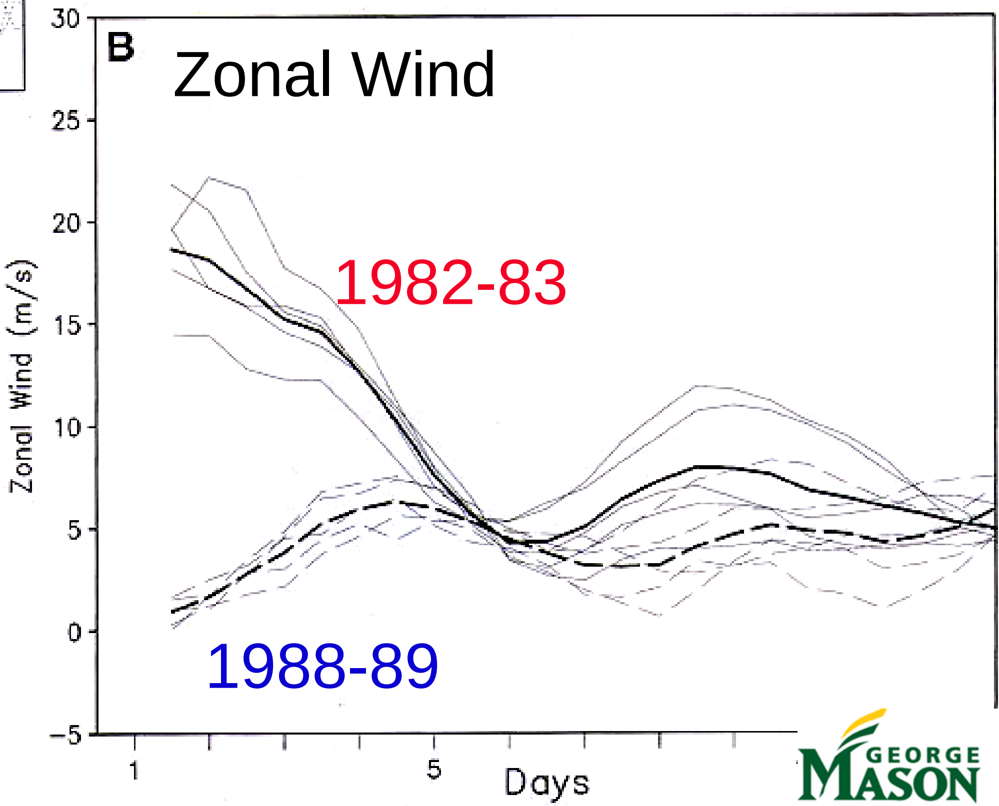
~ 10-30 days

- δQ (magnitude, structure)
- location of δQ w.r.t. V
  - tropics: Hadley, Walker, monsoon
  - extratropics: quasi-stationary waves, forcings and instability
- U(y,z): resonance, propagation
  ($\delta Q \Leftrightarrow \delta U$)

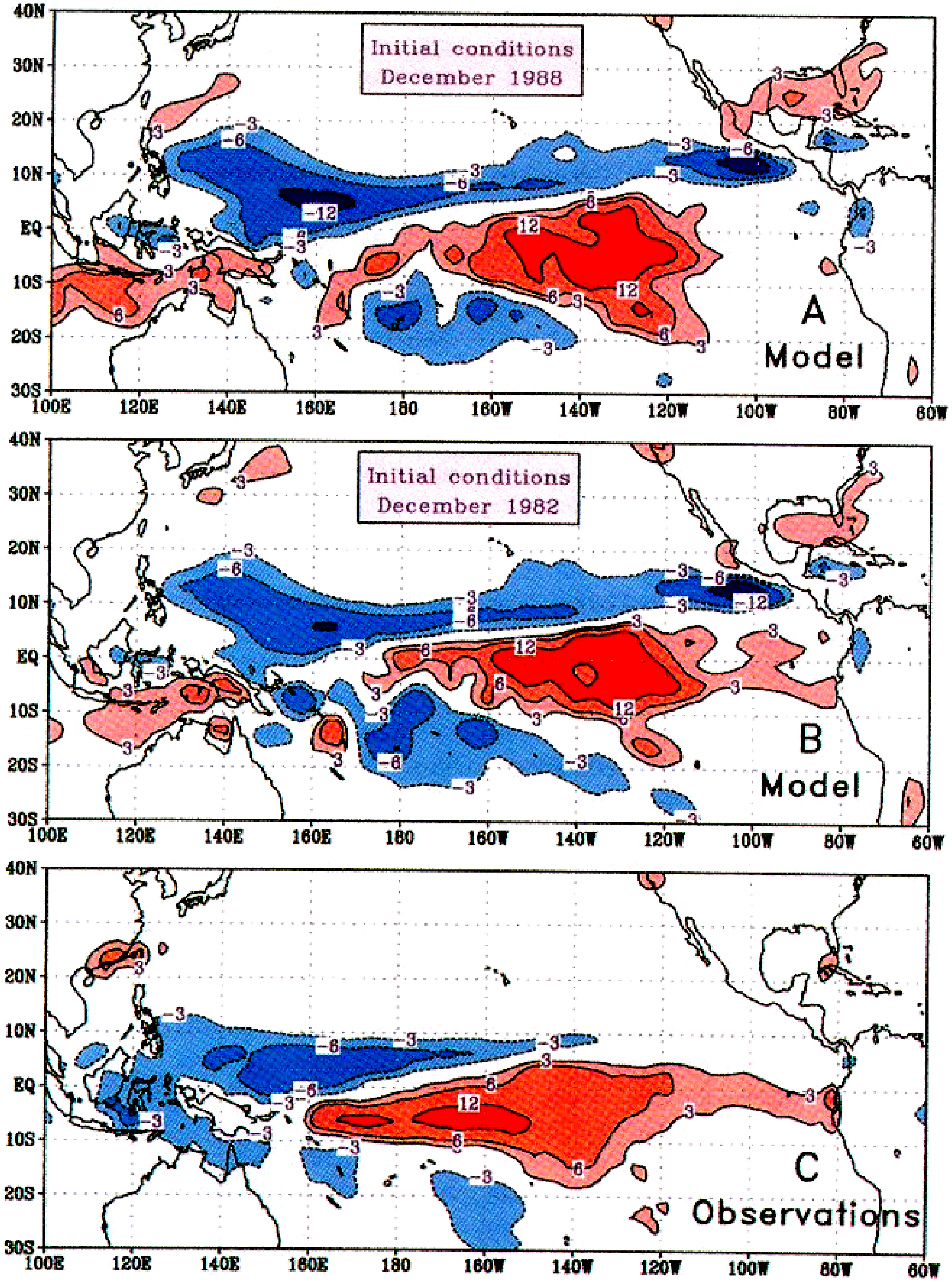
1. $\delta Q \Rightarrow \delta$(Hadley) $\Rightarrow \delta U \Rightarrow \delta$ (extratrop. stat. waves)
2. Forced Rossby waves
3. Normal modes

Shukla and Kinter 2006





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).


Initial conditions
December 1988
A
Model
Initial conditions
December 1982
B
Model
C
Observations
40N
30N
20N
10N
EQ
10S
20S
30S
100E
120E
140E
160E
180
160W
140W
120W
100W
80W
60W

Outline

- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- **Current Status of Dynamical Seasonal Prediction**
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

Questions:

Have "We" Kept the Promises We Made?

What are the Stumbling Blocks?

What are the Prospects for the Future?

Model Description and Experimental Design

APCC CLIPAS

6 CGCMs

- 1980 – 2004
- 4 case of initial time (Feb, May, Aug, Nov)
- 3-15 member
- 5-9 months duration

	Lead month	run	Period	AGCM	OGCM
COLA	12	6	80-99	COLA	MOM
FRCGC SINTEX-F	6	9	82-04	ECHAM 4 T106 L19	OPA 8.2 2x2 L31
NASA	5	3	80-04	NSIPP 1 2x2.5 L34	Poseidon V4 1/3x1 L40
SNU	6	6	60-01	SNU T42 L21	MOM 2.2 1/3x1 L32
UH	6	10	83-03	ECHAM 4 T31 L19	UH Ocean 1x2 L2
NCEP CFS	9	15	81-03	GFS T62 L64	MOM 3 1/3x5/8 L27

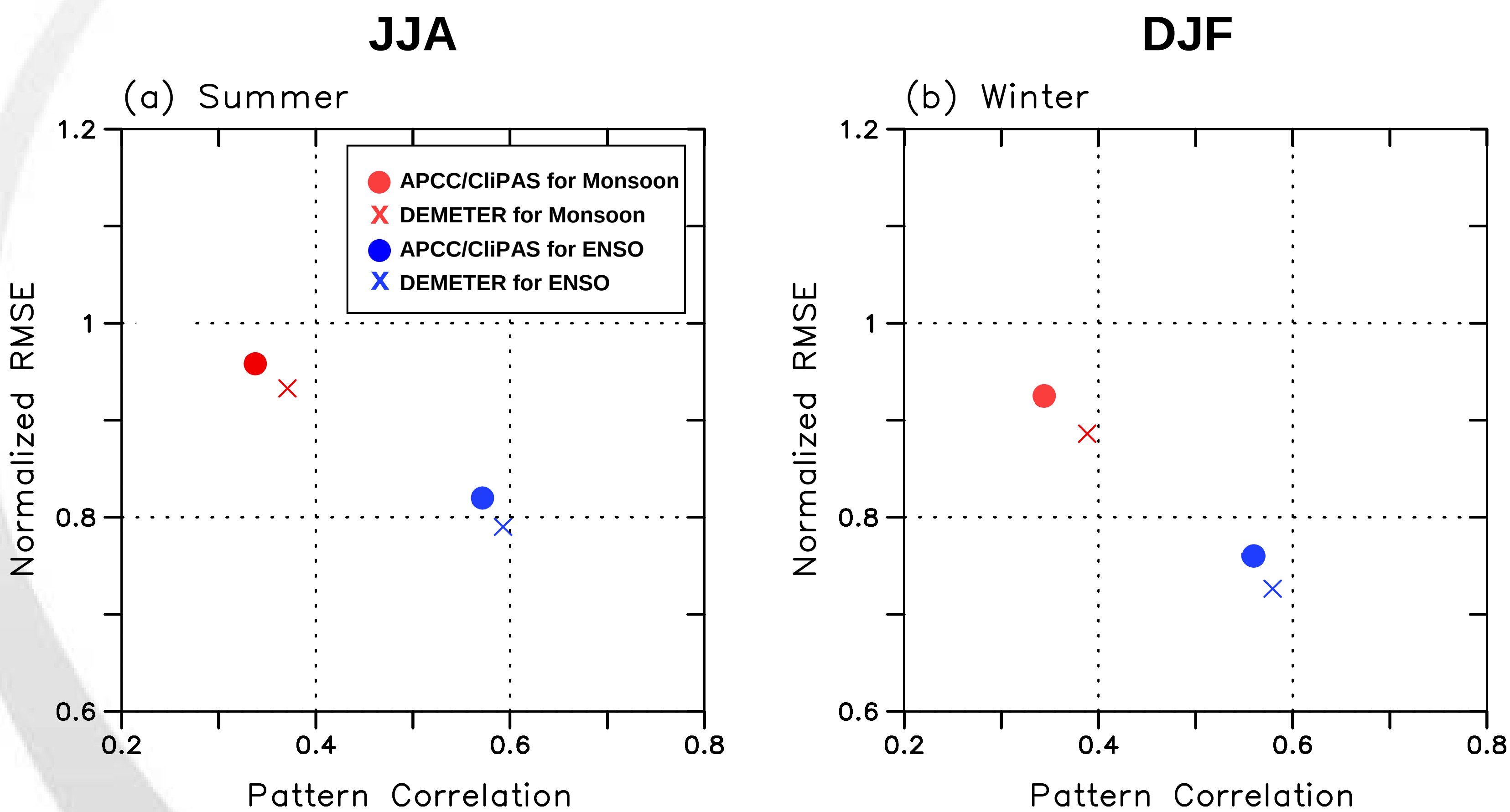
DEMETER

7 CGCMs

- 1980 – 2001
- 4 case of initial time (Feb, May, Aug, Nov)
- 9 ensemble member
- 6 months duration

	AGCM	OGCM
CERFACS	ARPEGE T63 L31	OPA 8.2 2.0x2.0 L31
ECMWF	IFS T95 L40	HOPE-E 1.4x0.3-1.429 L29
INGV	ECHAM 4 T42 L19	OPA 8.1 2.0x0.5-1.5 L31
LODYC	IFS T95 L40	OPA 8.2 2.0x2.0 L31
Meteo-France	ARPEGE T63 L31	OPA 8.0 192-152, L31
MPI	ECHAM-5 T42 L19	MPI-IM1 2.5x0.5-2.5 L23
UK Met Office	HadAM3 2.5x3.75 L19	GloSea OGCM 1.25x0.3-125 L40

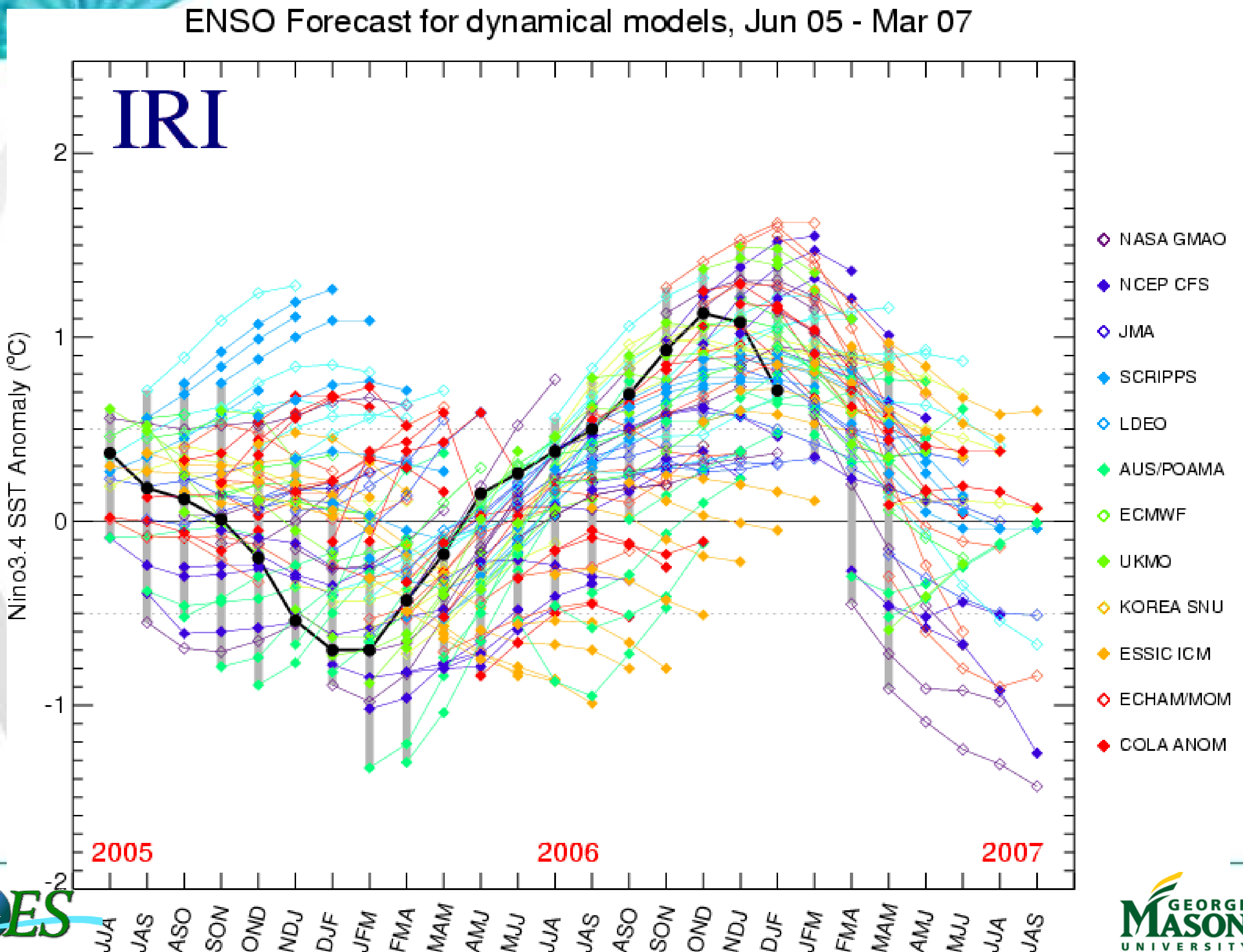
Skill of APCC/CliPAS and DEMETER Ensembles

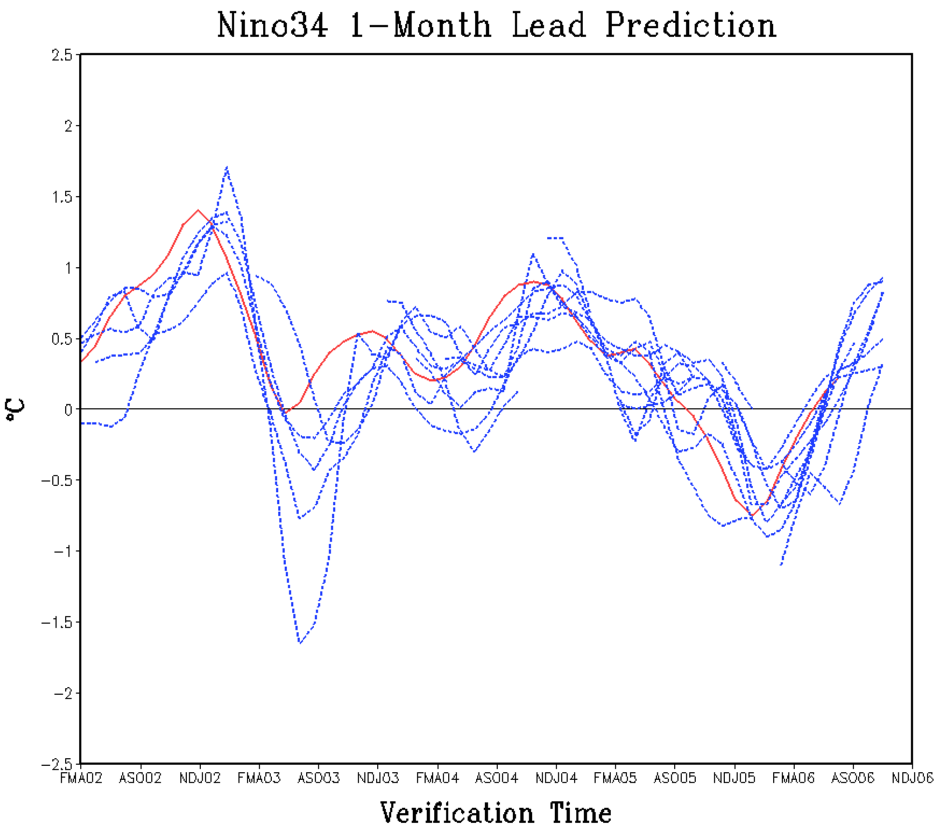


Asian-Australian Monsoon region: 40-160E, 30S-30N

ENSO region: 160-280E, 30S-30N

Wang et al. 2007

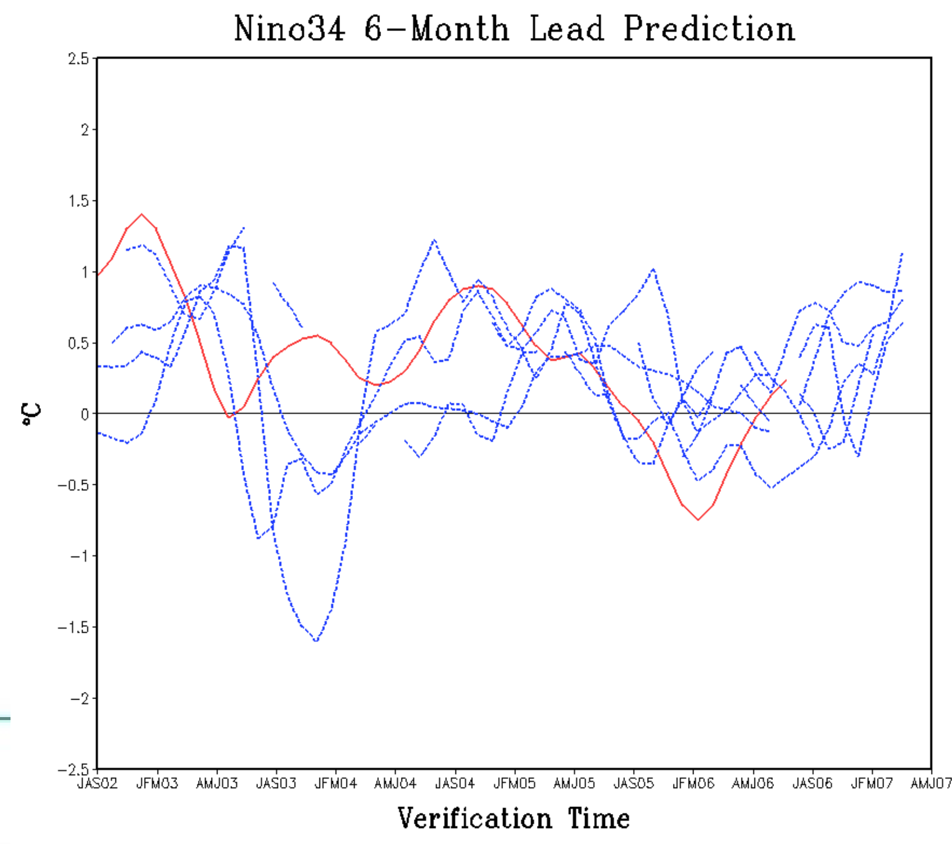

ENSO Forecast for dynamical models, Jun 05 - Mar 07
IRI
Nino3.4 SST Anomaly (°C)
2
1
0
-1
-2
2005
2006
2007
JJA
JAS
ASO
SON
OND
NDJ
DJF
JFM
FMA
MAM
AMJ
MJJ
JJA
JAS
ASO
SON
OND
NDJ
DJF
JFM
FMA
MAM
AMJ
MJJ
JJA
JAS
NASA GMAO
NCEP CFS
JMA
SCRIPPS
LDEO
AUS/POAMA
ECMWF
UKMO
KOREA SNU
ESSIC ICM
ECHAM/MOM
COLA ANOM



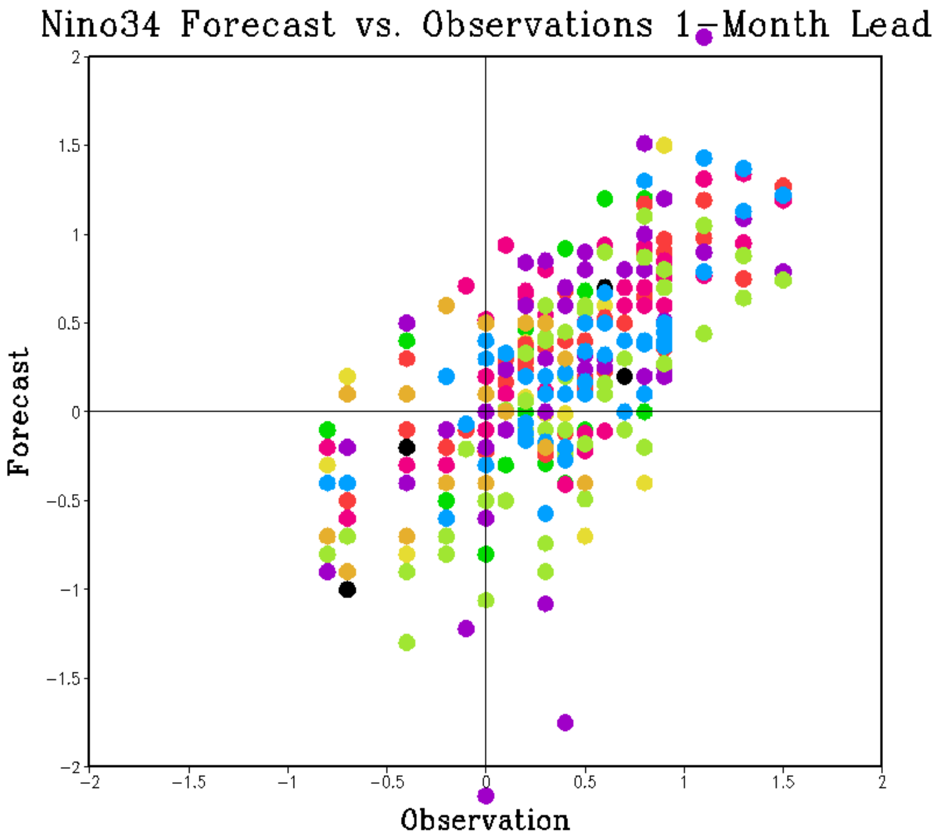
Dynamic CGCMs Only

IRI Nino34 Forecast Archive
February 2002-September 2006

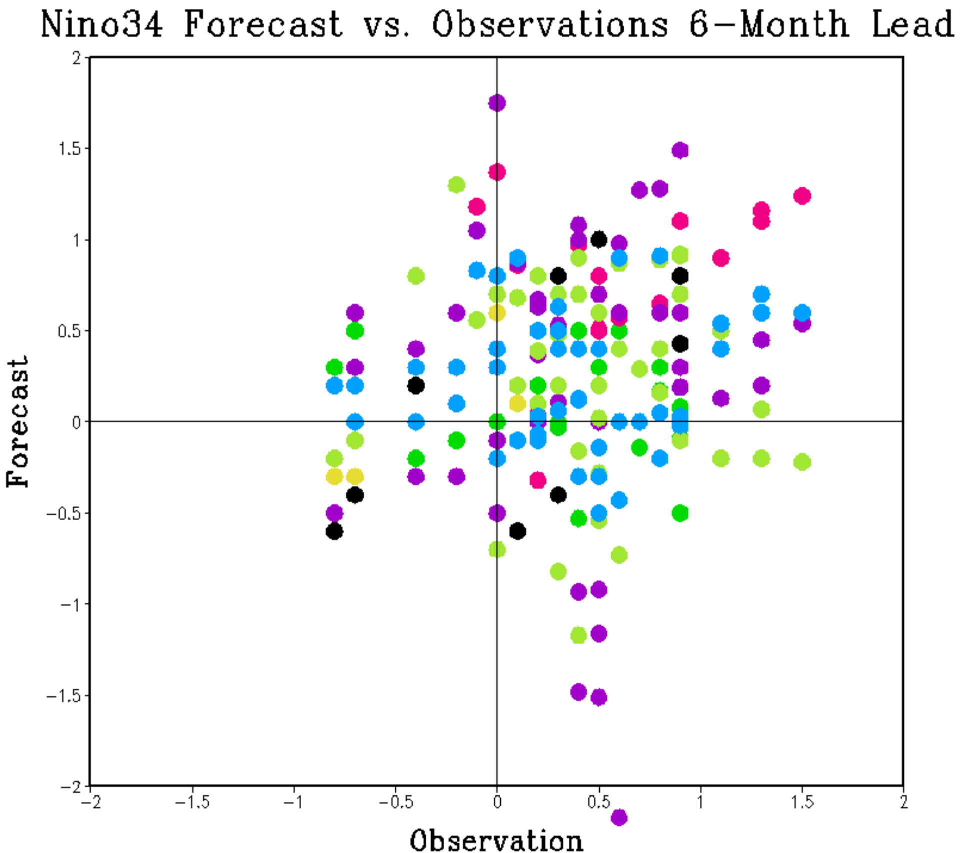
Running Seasonal Means



IGES



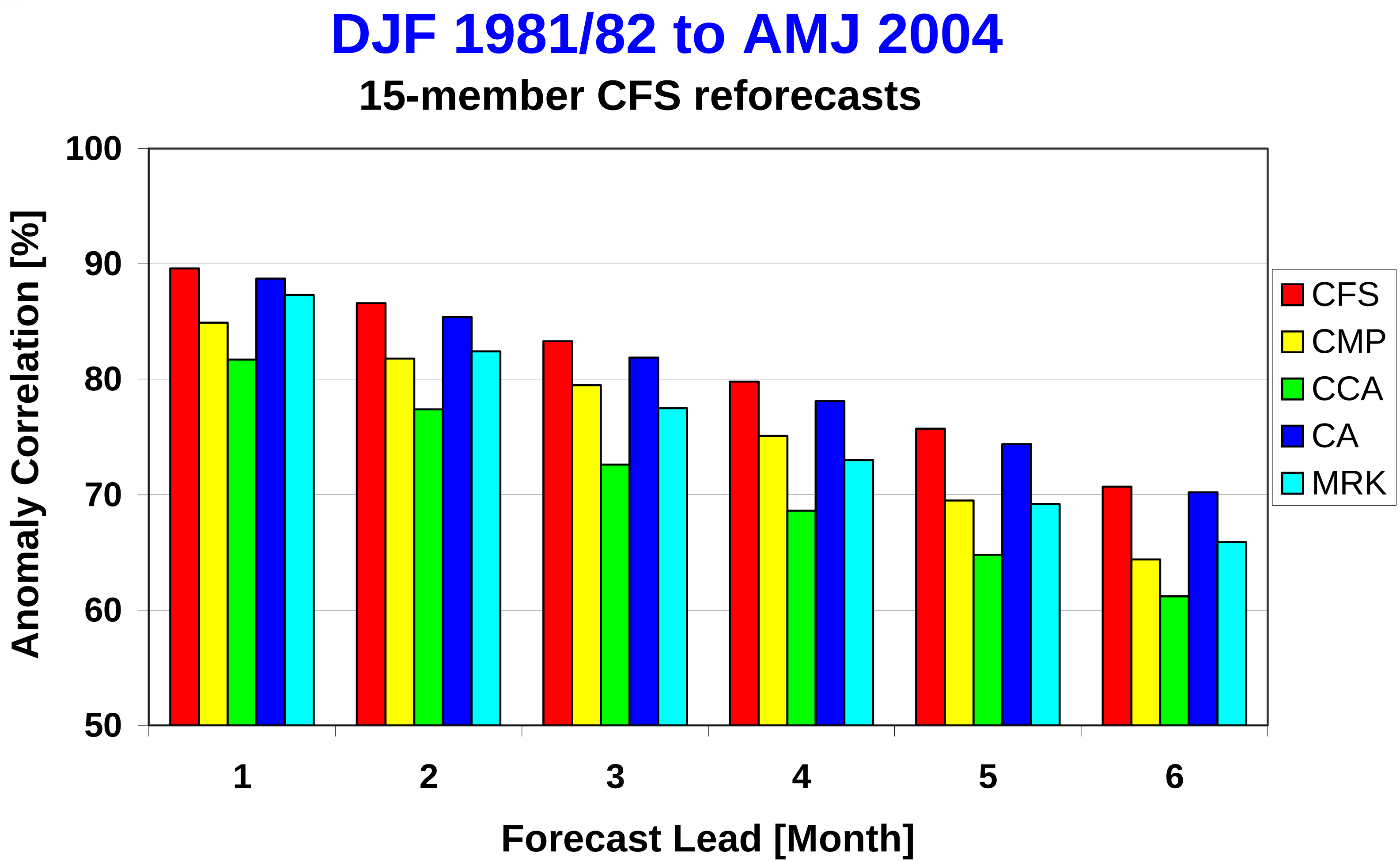
Dynamic CGCMs Only



IRI Nino34 Forecast Archive
February 2002-September 2006

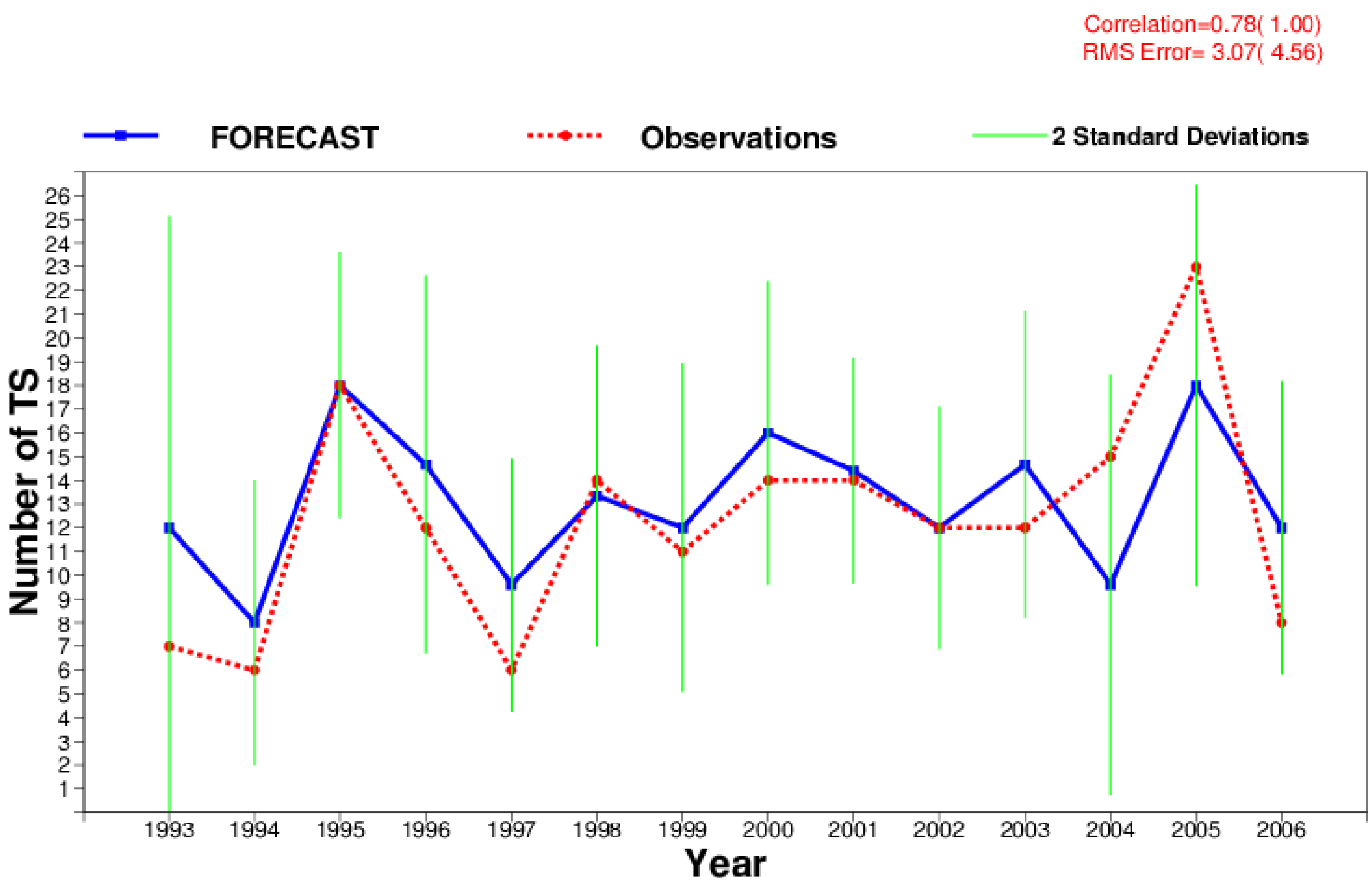
Running Seasonal Means

Skill in SST Anomaly Prediction for Nino3.4



EUROSIP Atlantic Seasonal Forecasts

July to Nov



Commentary

- 25 years ago, a dynamical seasonal climate prediction was not conceivable.
- In the past 20 years, 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 anomalies at the Earth’s surface. Dynamical seasonal predictions for one month lead are not yet superior to statistical forecasts.
- There is significant unrealized seasonal predictability. Progress in dynamical seasonal prediction in the future depends critically on improvement of coupled ocean-atmosphere-land models, improved observations, and the ability to assimilate those observations.

Current Status of Dynamical Seasonal Prediction

1. Coupled O-A models (both complex GCMs and intermediate complexity models) are frequently making skillful prediction of tropical Pacific SSTA (NINO 3, NINO 3.4, etc) and the corresponding tropical circulation up to six months. However, the skill is highly variable depending on IC, year (ENSO events), model, ensemble size etc. Multi Model ensembles are most skillful.
2. Even the prediction of ENSO is limited to a selective preconditioning of wind stress, SST, and subsurface temperature anomalies in the equatorial Pacific.
3. There is no robust evidence of skill in seasonal prediction of SSTA in the Indian Ocean, the tropical Atlantic, or the extratropical oceans; or any other planetary scale modes of atmospheric circulation (monsoons, NAO etc.)
4. There is no robust evidence that dynamical seasonal prediction of surface temperature and precipitation over North America is more skillful than statistical models.

Outline

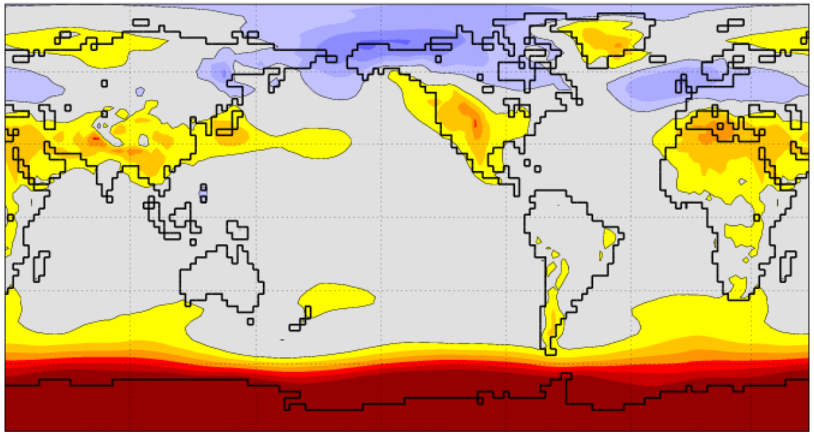
- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- **Model Deficiencies in Simulating the Present Climate**
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

Commentary

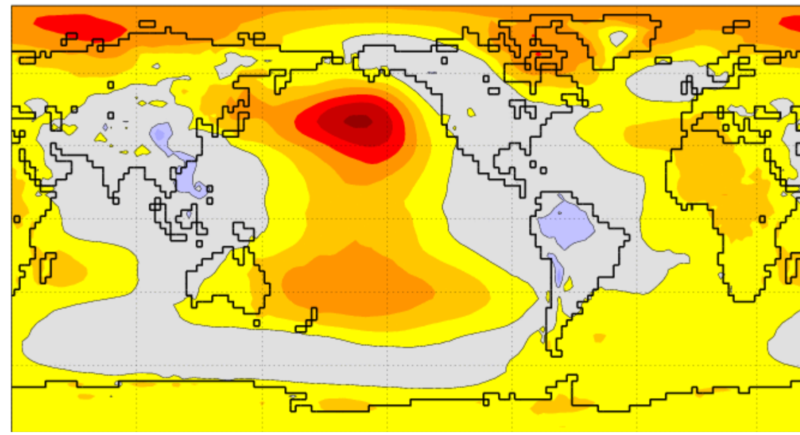
- The most dominant obstacle in realizing the potential predictability of intraseasonal and seasonal variations is inaccurate models, rather than an intrinsic limit of predictability.

Systematic Error: MSLP (NDJ)

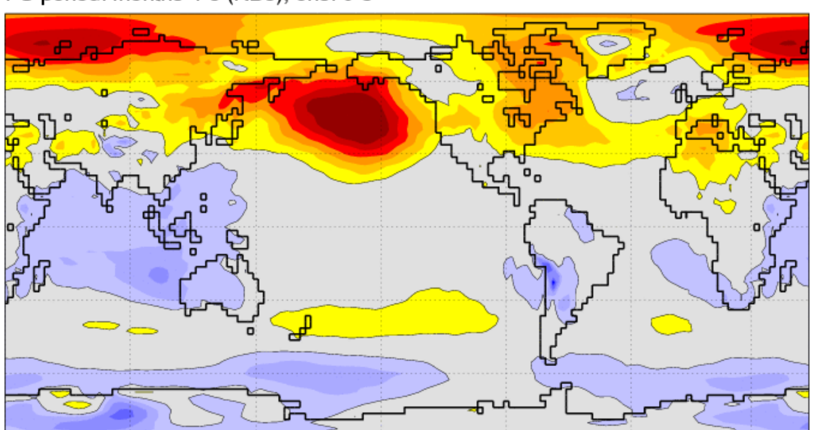
Mean Sea Level Pressure [hPa]
Bias: EXP(CNRM) regarding ERA-40 reanalysis
Forecast start month and years: August / 1958-2001
FC period: months 4-6 (NDJ), ens: 0-8

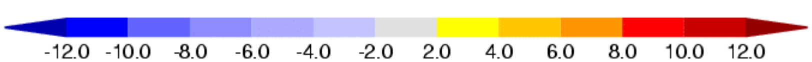


Mean Sea Level Pressure [hPa]
Bias: EXP(ECMWF_ctrl) regarding ERA-40 reanalysis
Forecast start month and years: August / 1958-2001
FC period: months 4-6 (NDJ), ens: 0-8

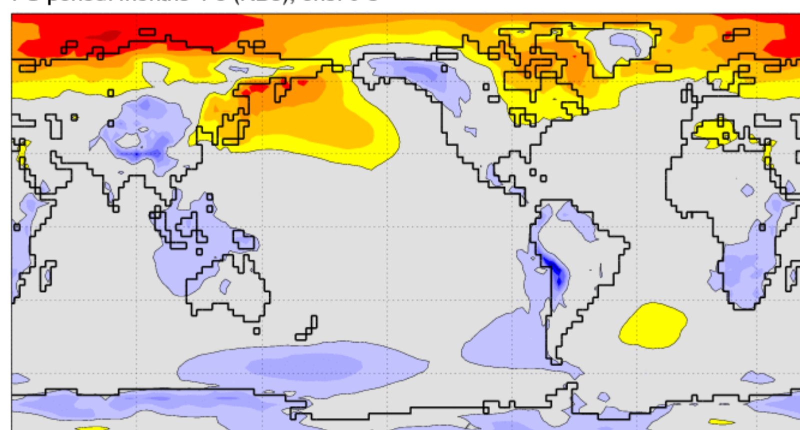


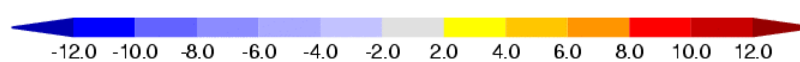
Mean Sea Level Pressure [hPa]
Bias: EXP(MPI) regarding ERA-40 reanalysis
Forecast start month and years: August / 1969-2001
FC period: months 4-6 (NDJ), ens: 0-8



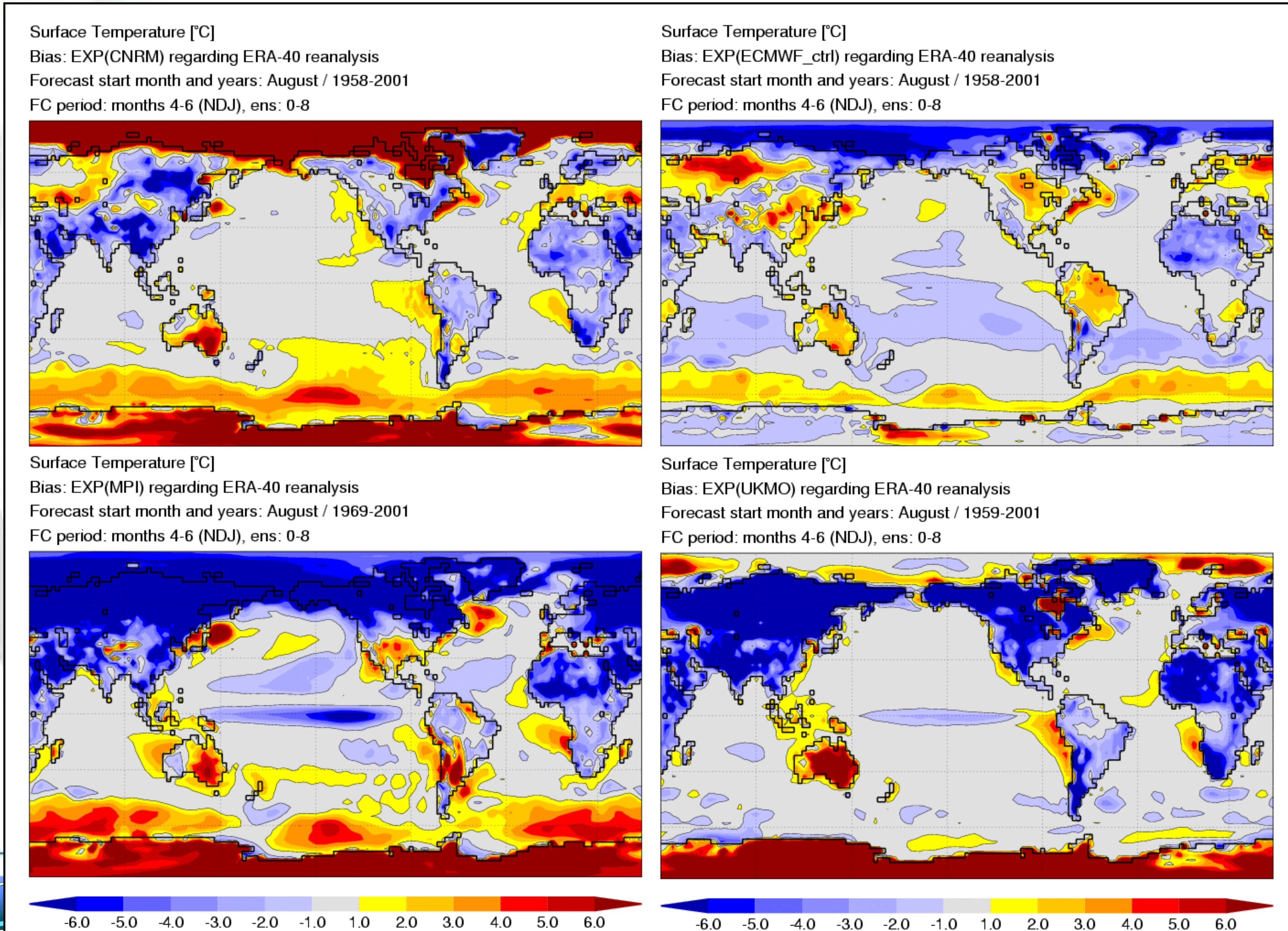


Mean Sea Level Pressure [hPa]
Bias: EXP(UKMO) regarding ERA-40 reanalysis
Forecast start month and years: August / 1959-2001
FC period: months 4-6 (NDJ), ens: 0-8

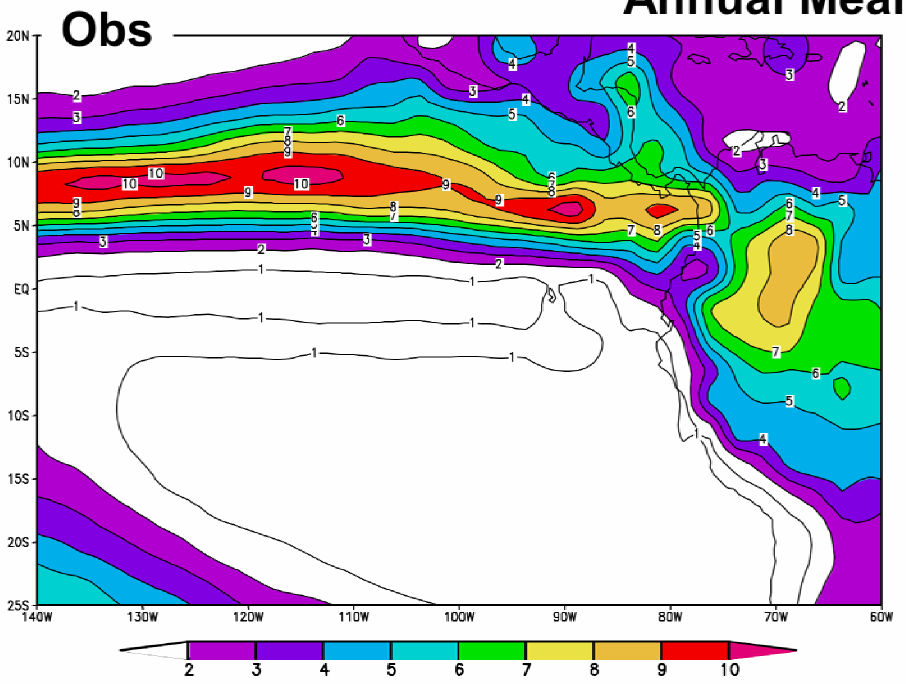


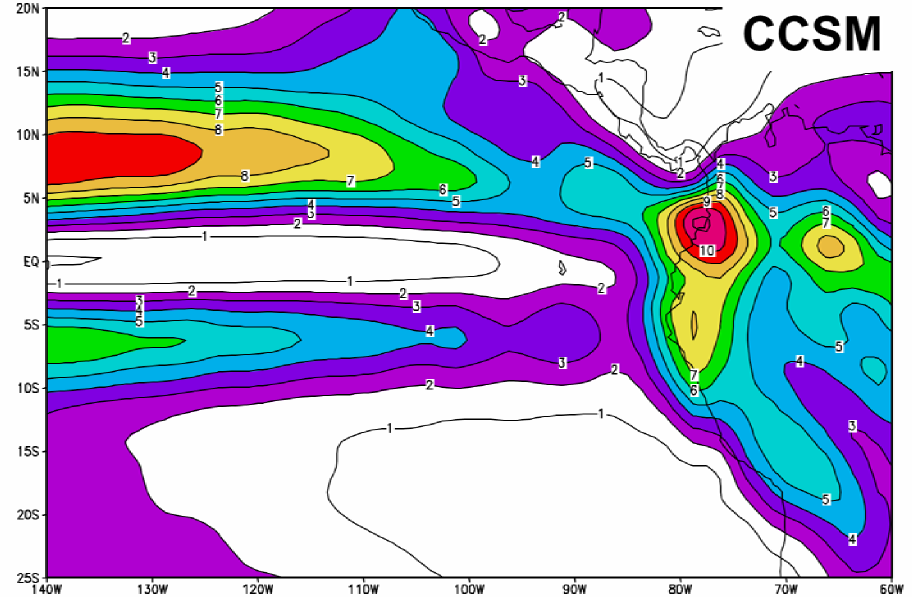


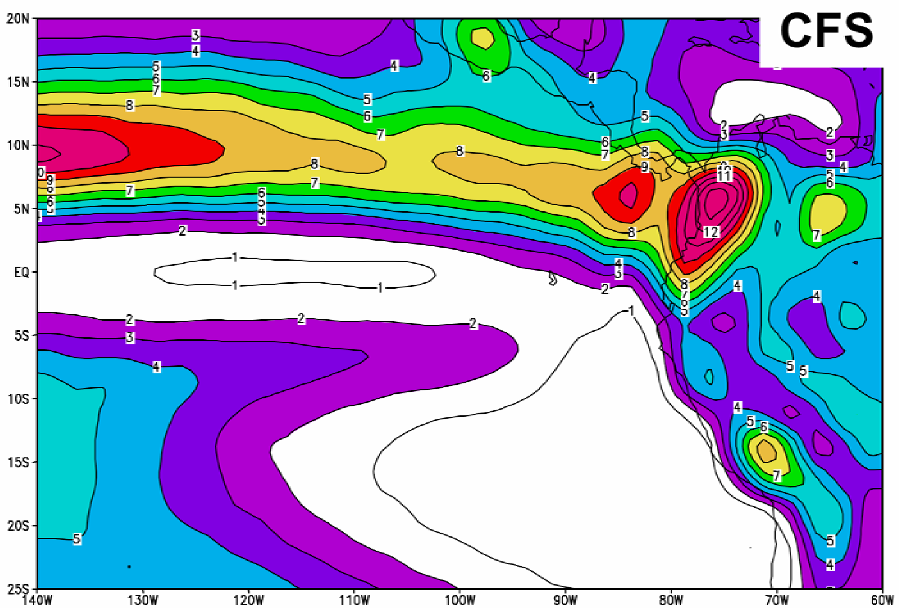
Systematic Error: Surface Temp. (NDJ)



Annual Mean Precipitation



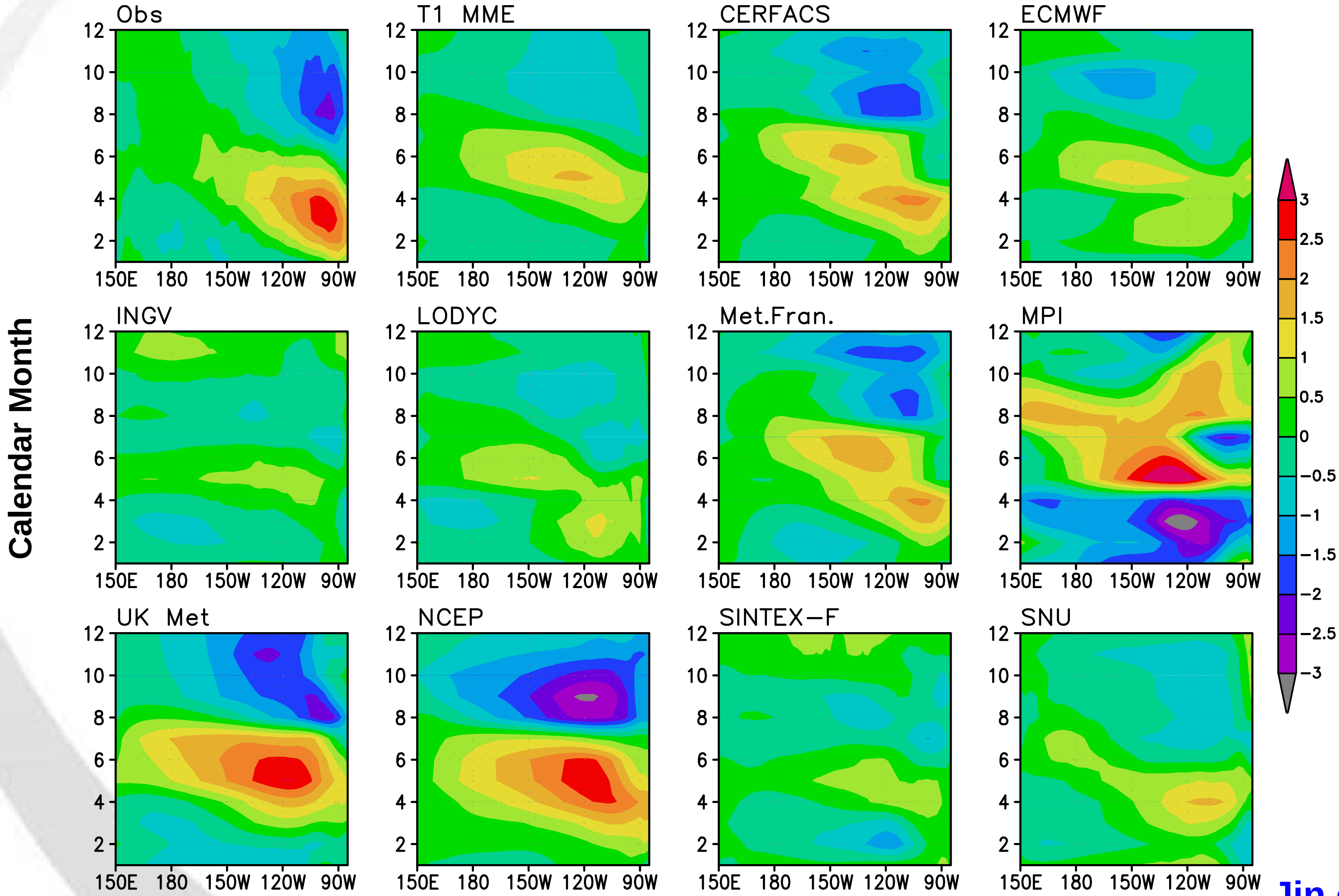




Infamous Double ITCZ Problem

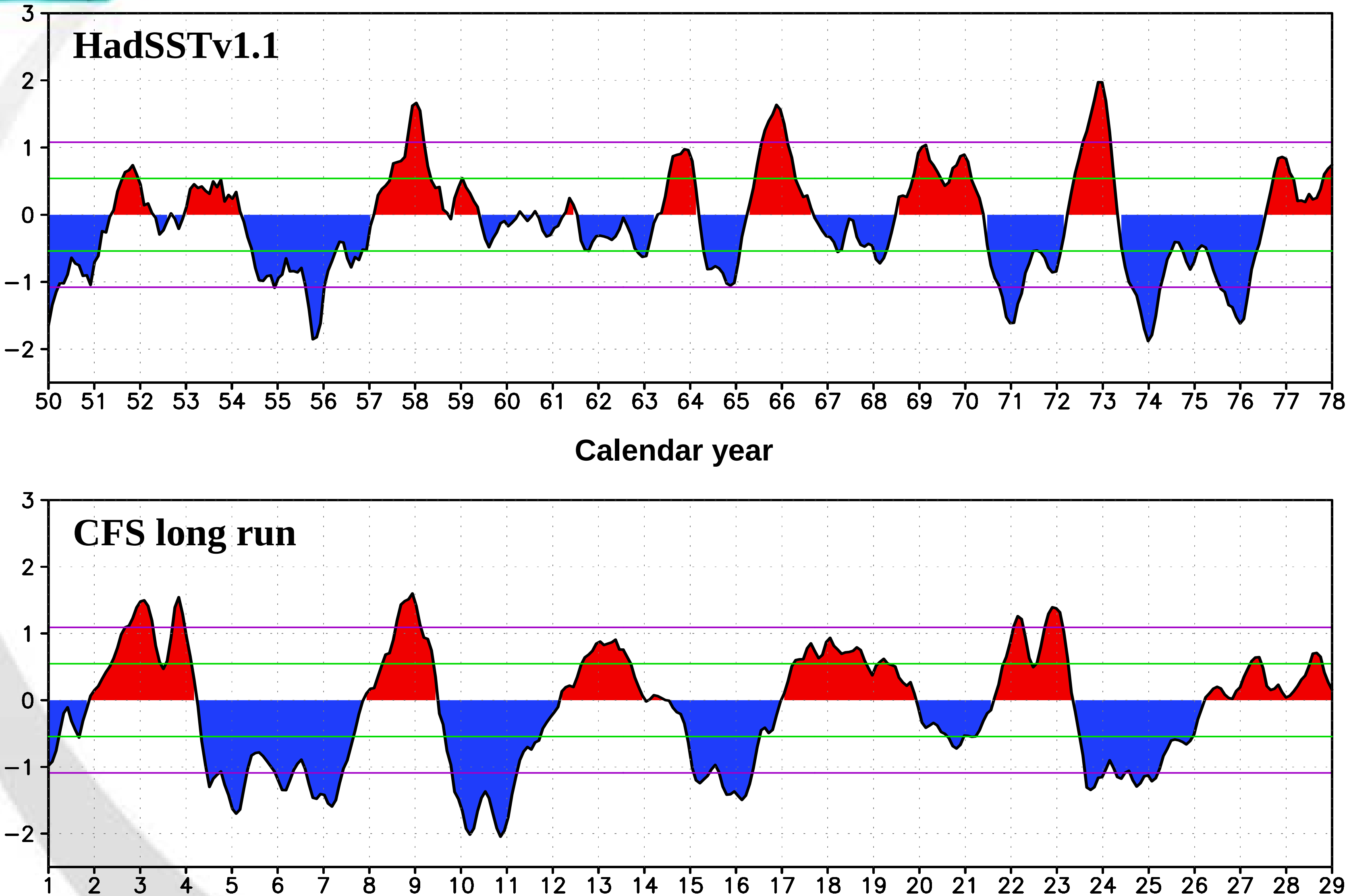
Annual Cycle of SST Climatology

4-6 month forecast, APCC/CliPAS & DEMETER CGCMs

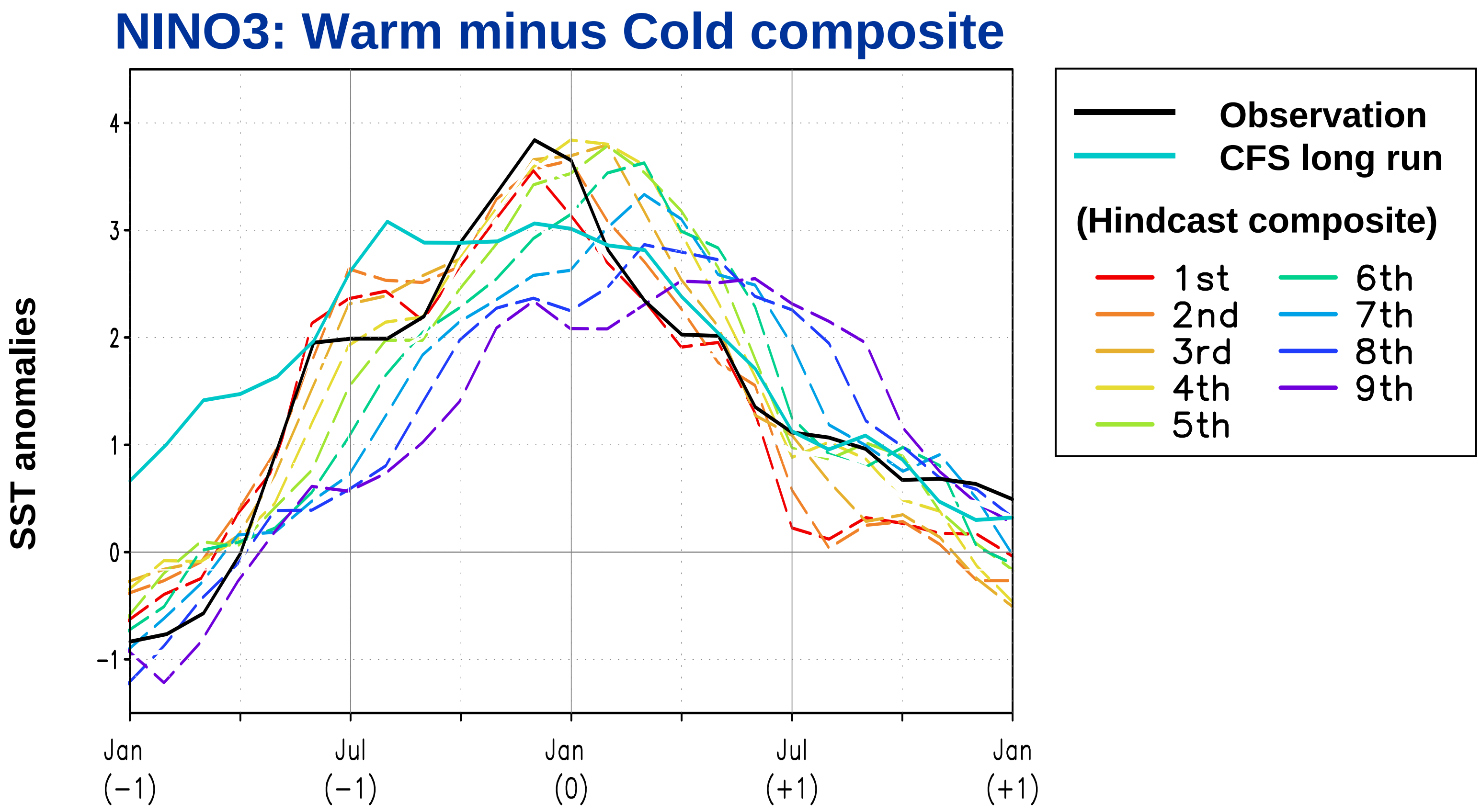


Jin et al. 2007

NINO 3.4 Index (Observed and CFS)



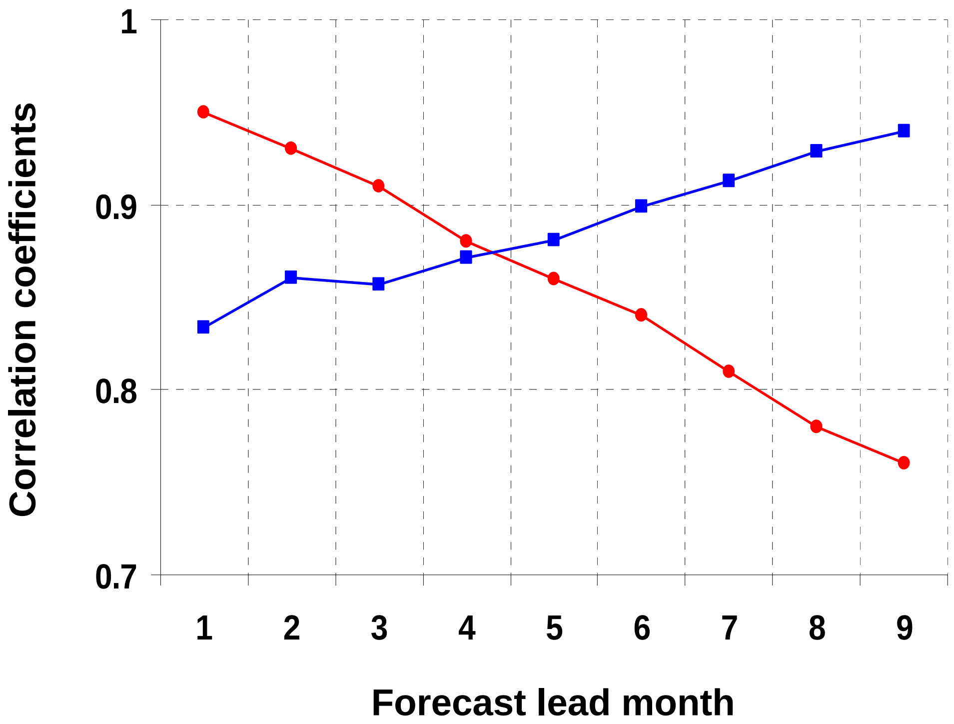
Influence of Systematic Error on CFS Forecast Skill



- Warm composite (82/83, 86/87, 91/92, 97/98) - Cold composite (84/85, 88/89, 98/99, 99/00)
- Dashed lines denote composite for Hindcasts at different lead times

Jin and Kinter, 2007

Influence of Systematic Error on CFS Forecast Skill



Correlation between 1st PCs based on observations and hindcasts at different lead times

Correlation between 1st PCs based on long run and hindcasts at different lead times

Jin and Kinter, 2007

Outline

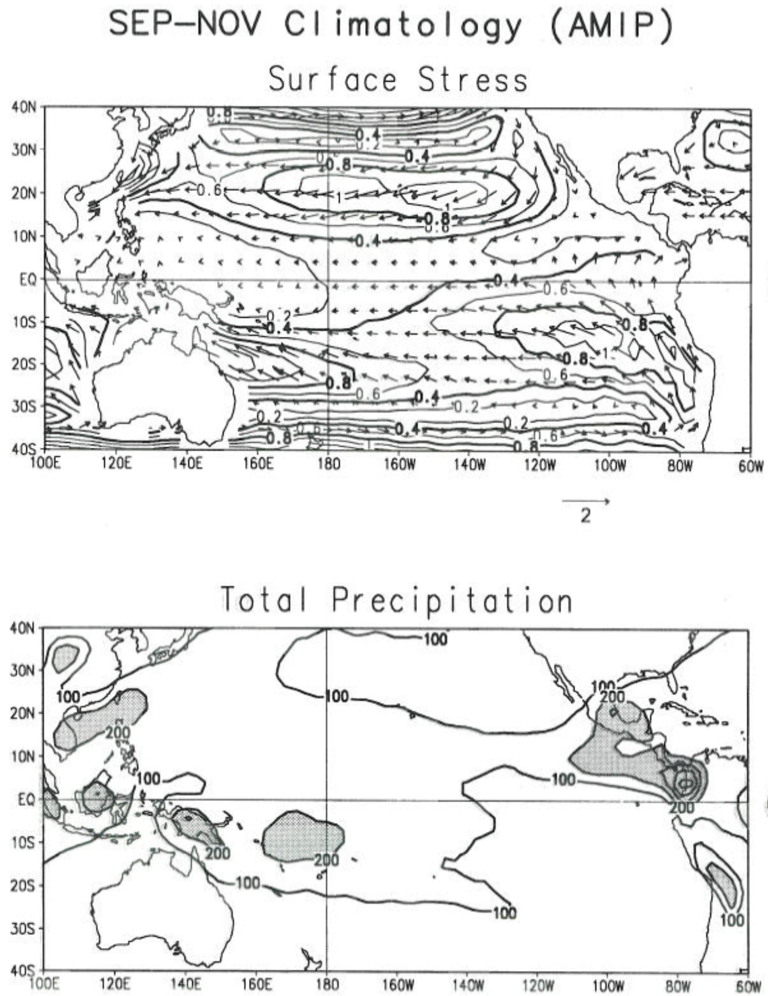
- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- **Tropical Heating and ENSO Forced Response**
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

Commentary

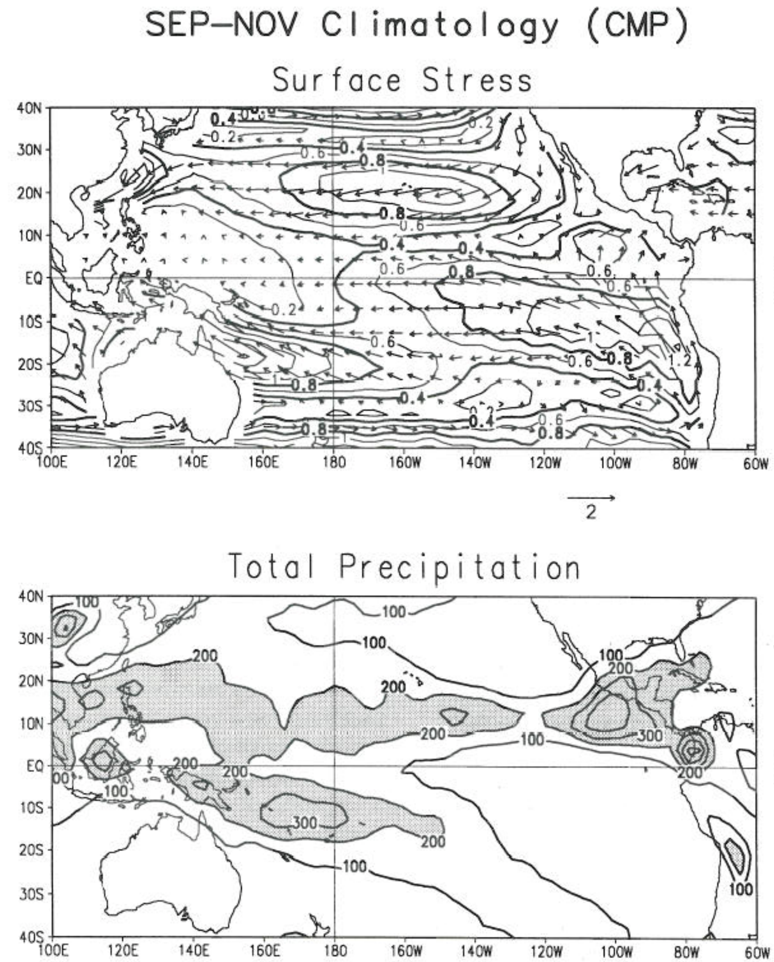
- Models with high deficiencies in simulating tropical heating produce highly deficient extratropical response to ENSO
- Examples: ECMWF, NCEP, GFDL, COLA

Thanks to Arun Kumar (CPC/NCEP)

MRF8



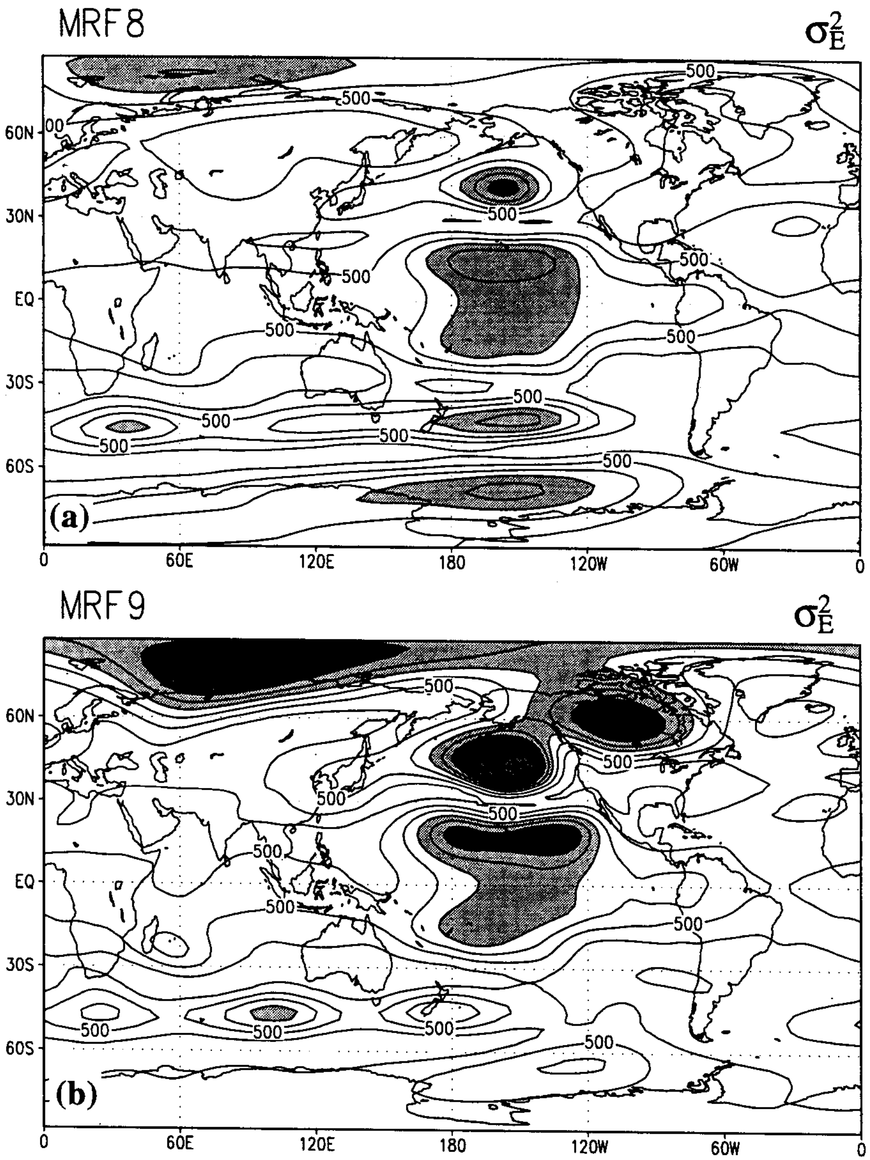
MRF9

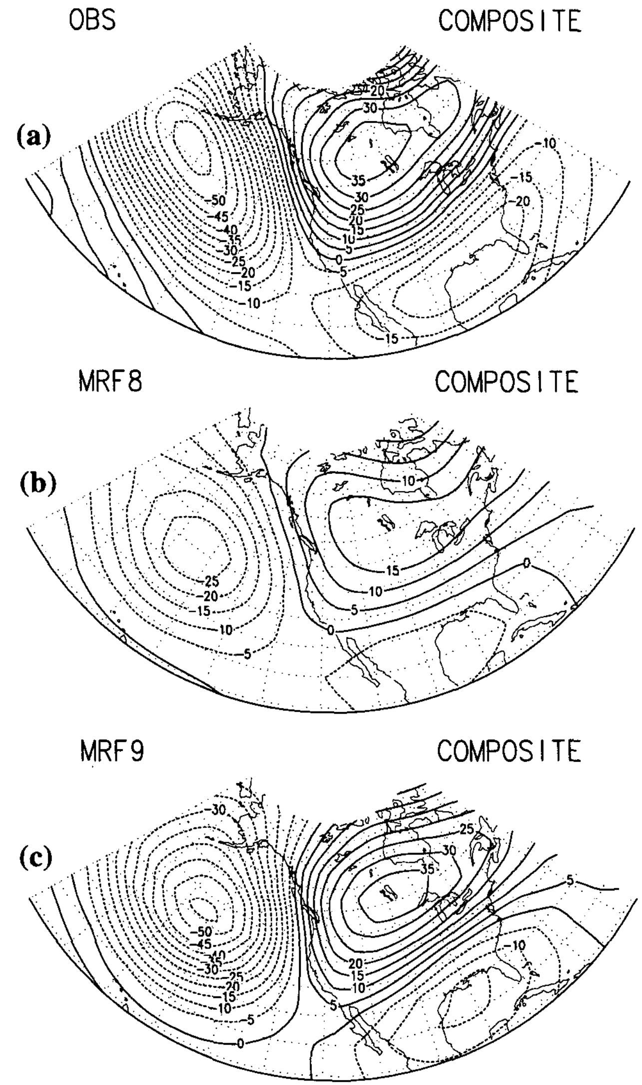


MRF8: high, middle, low clouds allowed to exist

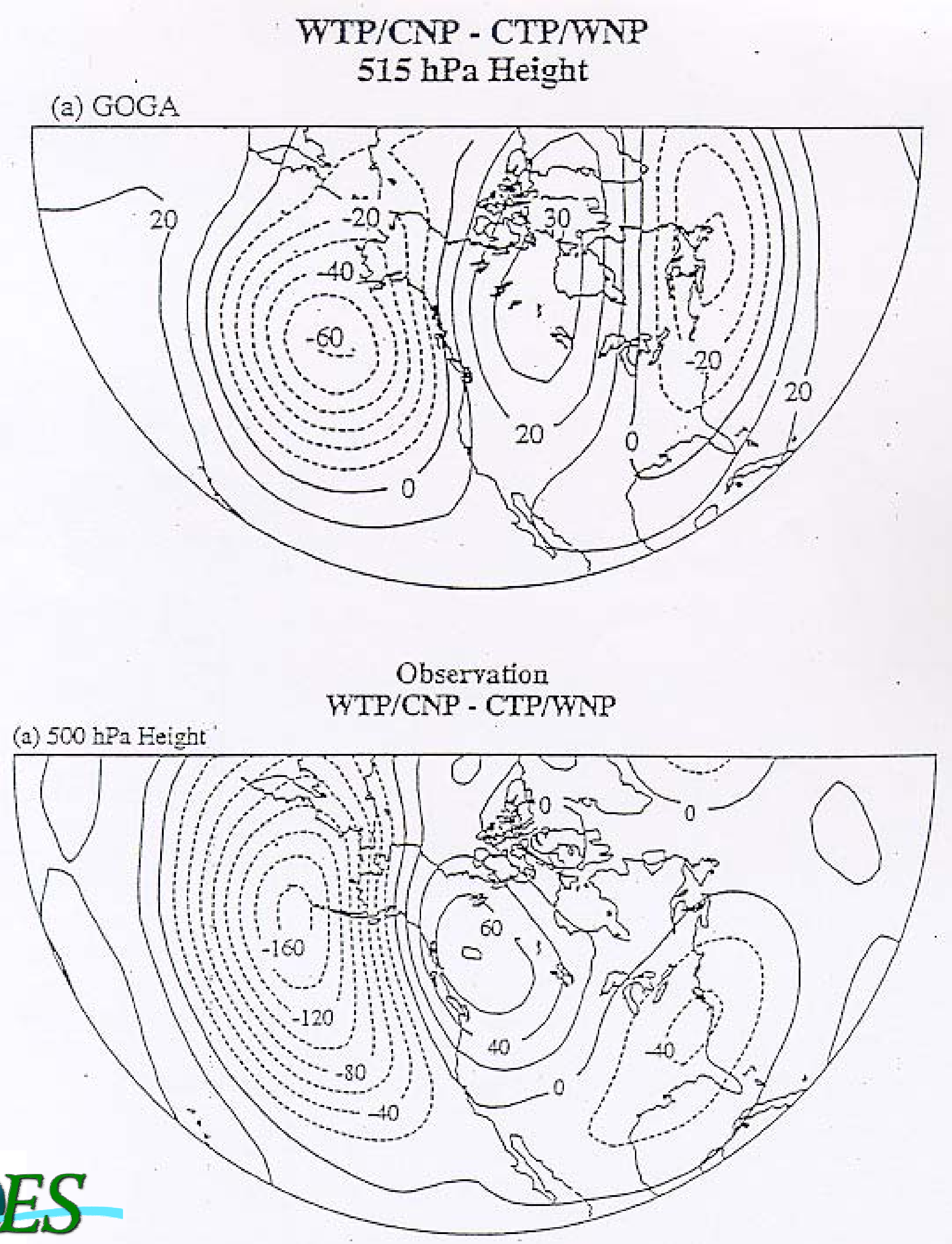
MRF9: Only high cloud allowed to exist over regions of tropical deep convection

Thanks to Arun Kumar (CPC/NCEP)





MRF8: high, middle, low clouds allowed to exist
MRF9: Only high cloud allowed to exist over regions of tropical deep convection



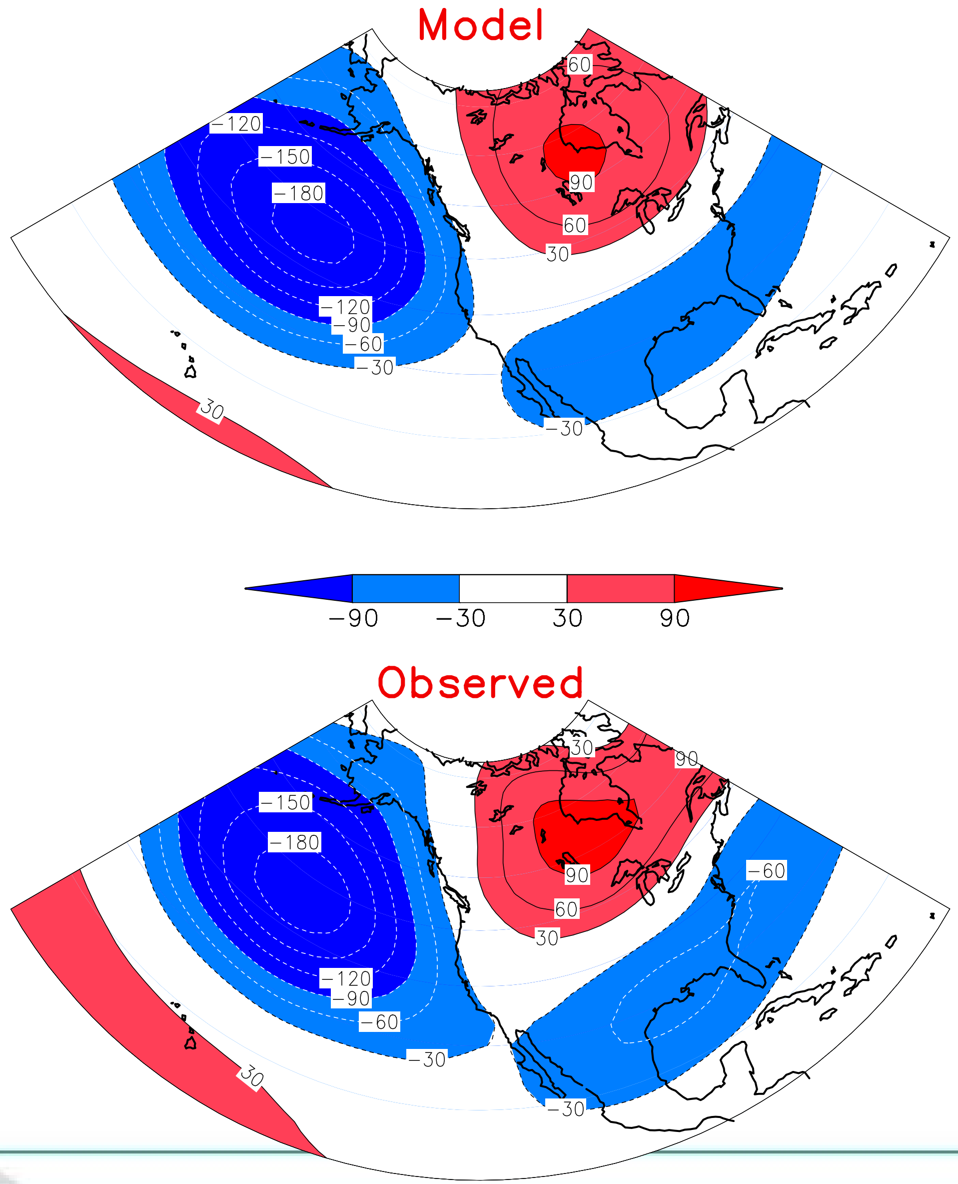
Note: amplitude of model response quite weak; structure is PNA rather than ENSO forced

Vintage 1980 AGCM (Lau, 1997, BAMS)

Model Simulation of ENSO Effects

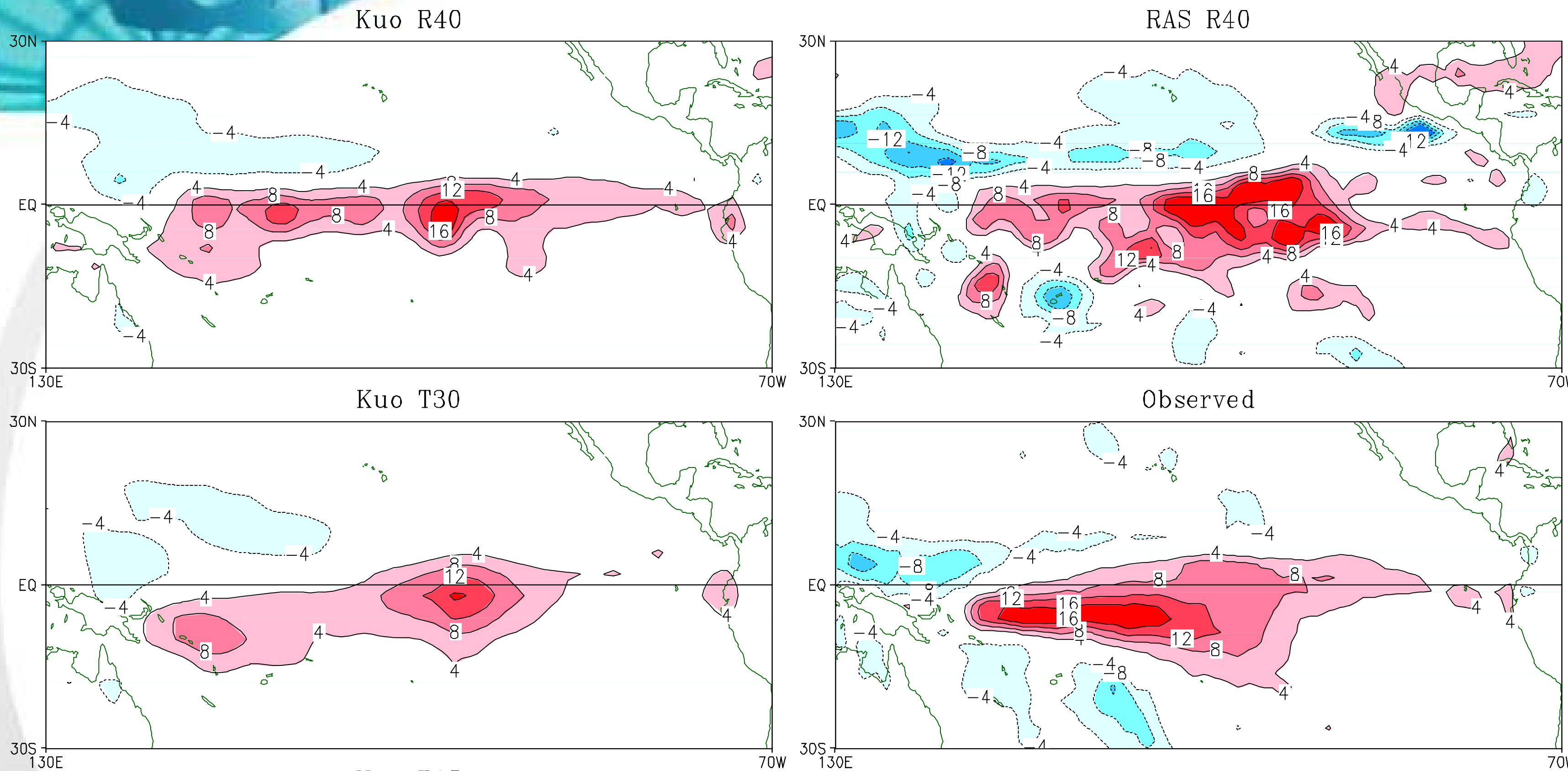
500 hPa height (meters) anomalies

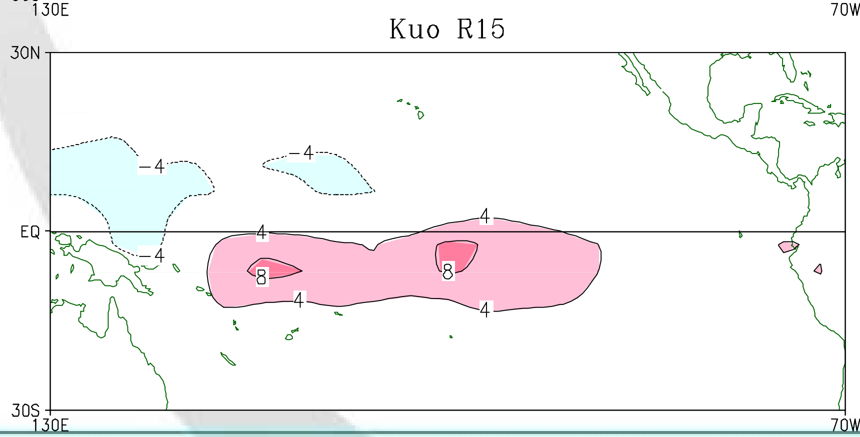
ACC = 0.98



Vintage 2000
AGCM

NINO3 Warm(83,87,92) − Cold(85,89)

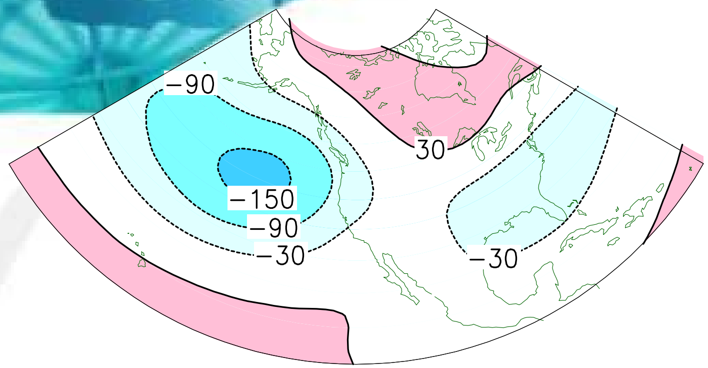




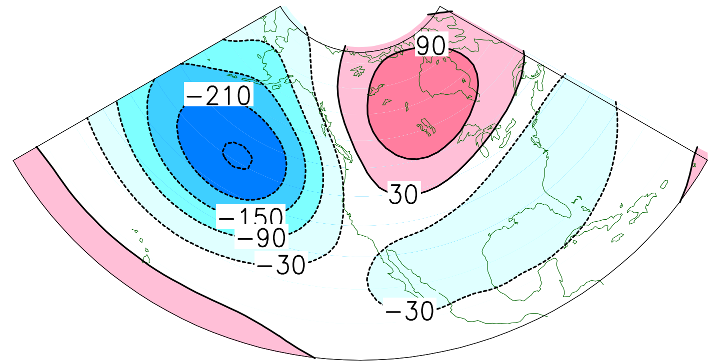
Evolution of Climate Models 1980-2000

Model-simulated and observed rainfall anomaly (mm day^{-1}) 1983 minus 1989

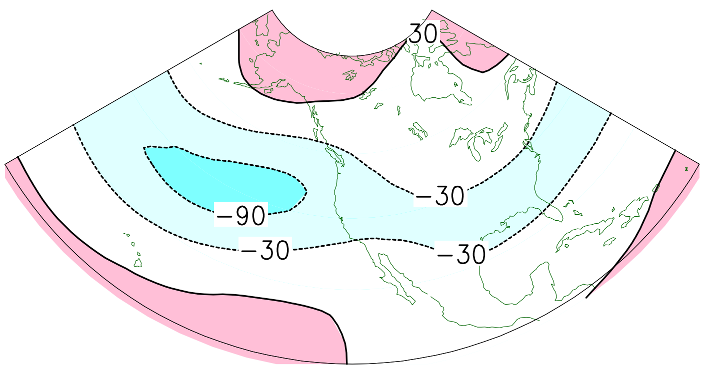
Kuo R40



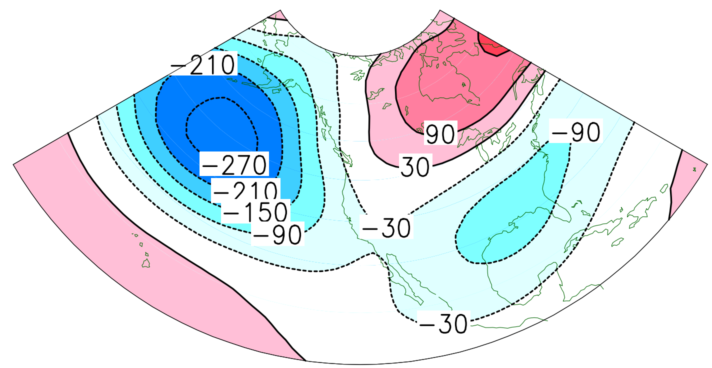
RAS R40



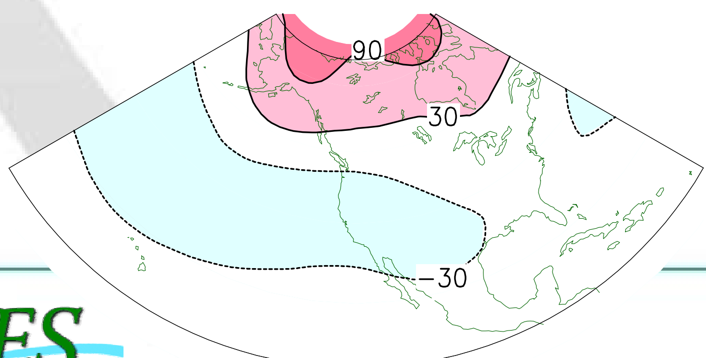
Kuo T30



Observed



Kuo R15



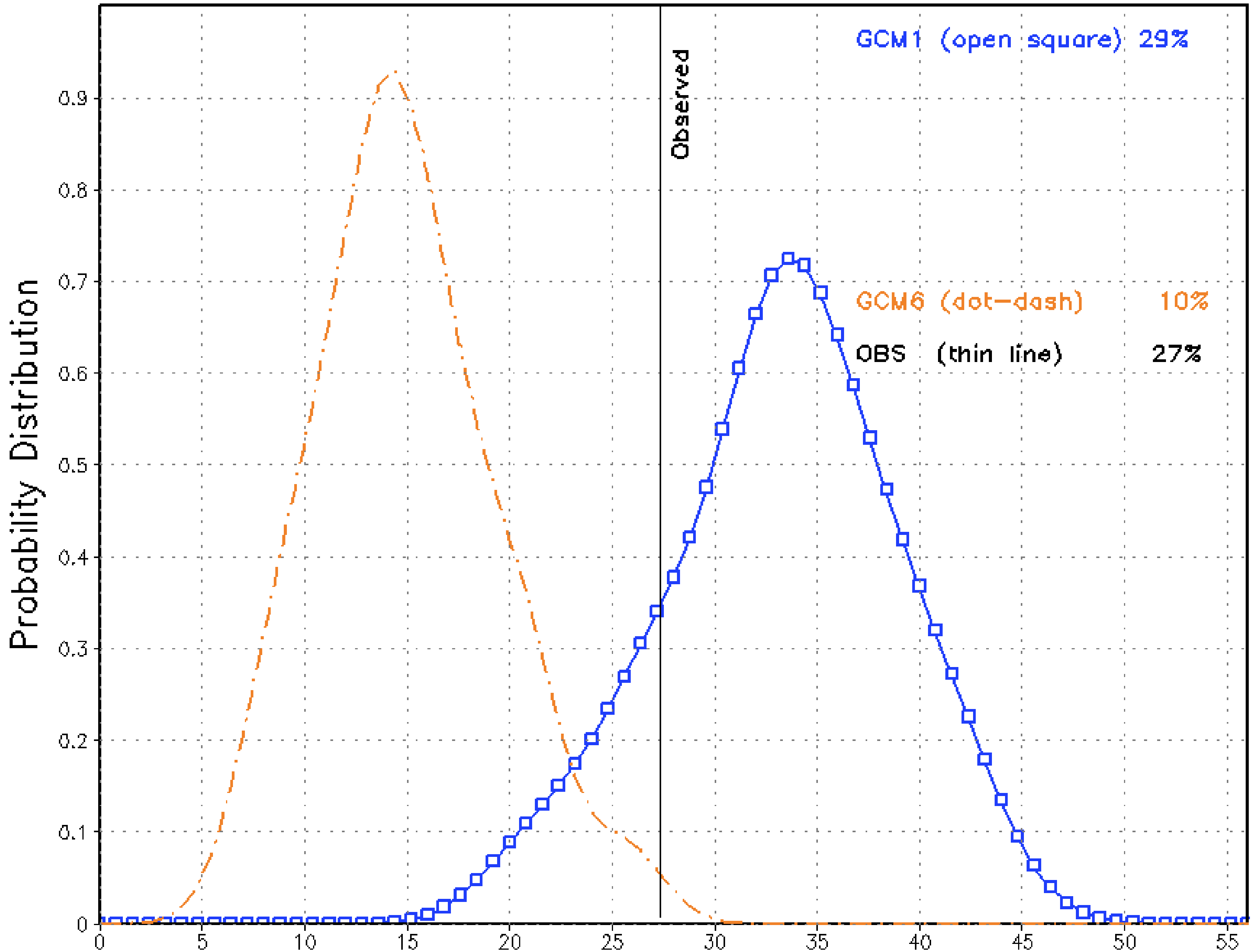
Evolution of Climate Models 1980-2000

Model-simulated and observed 500 hPa height anomaly (m) 1983 minus 1989

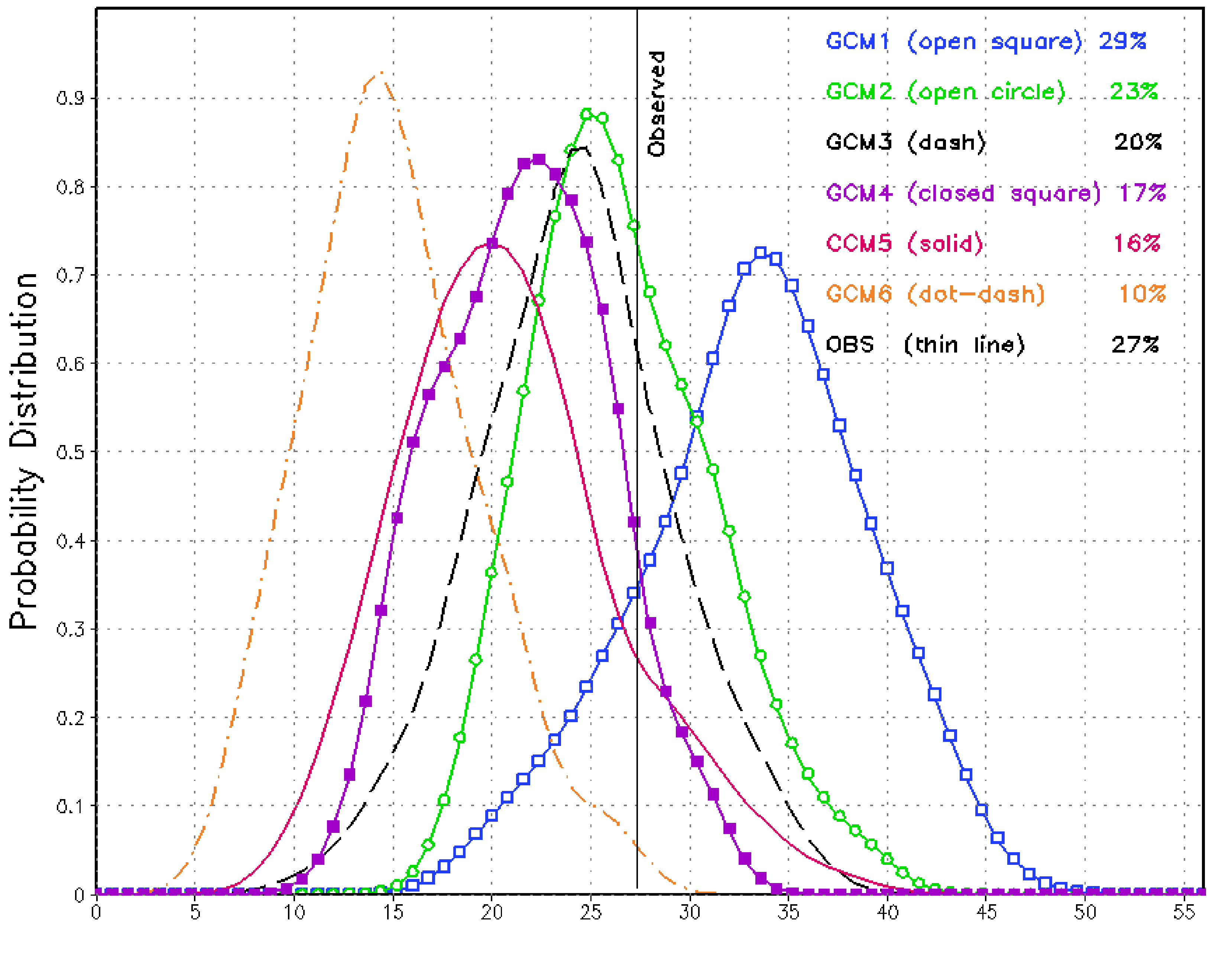
IGES

GEORGE MASON UNIVERSITY

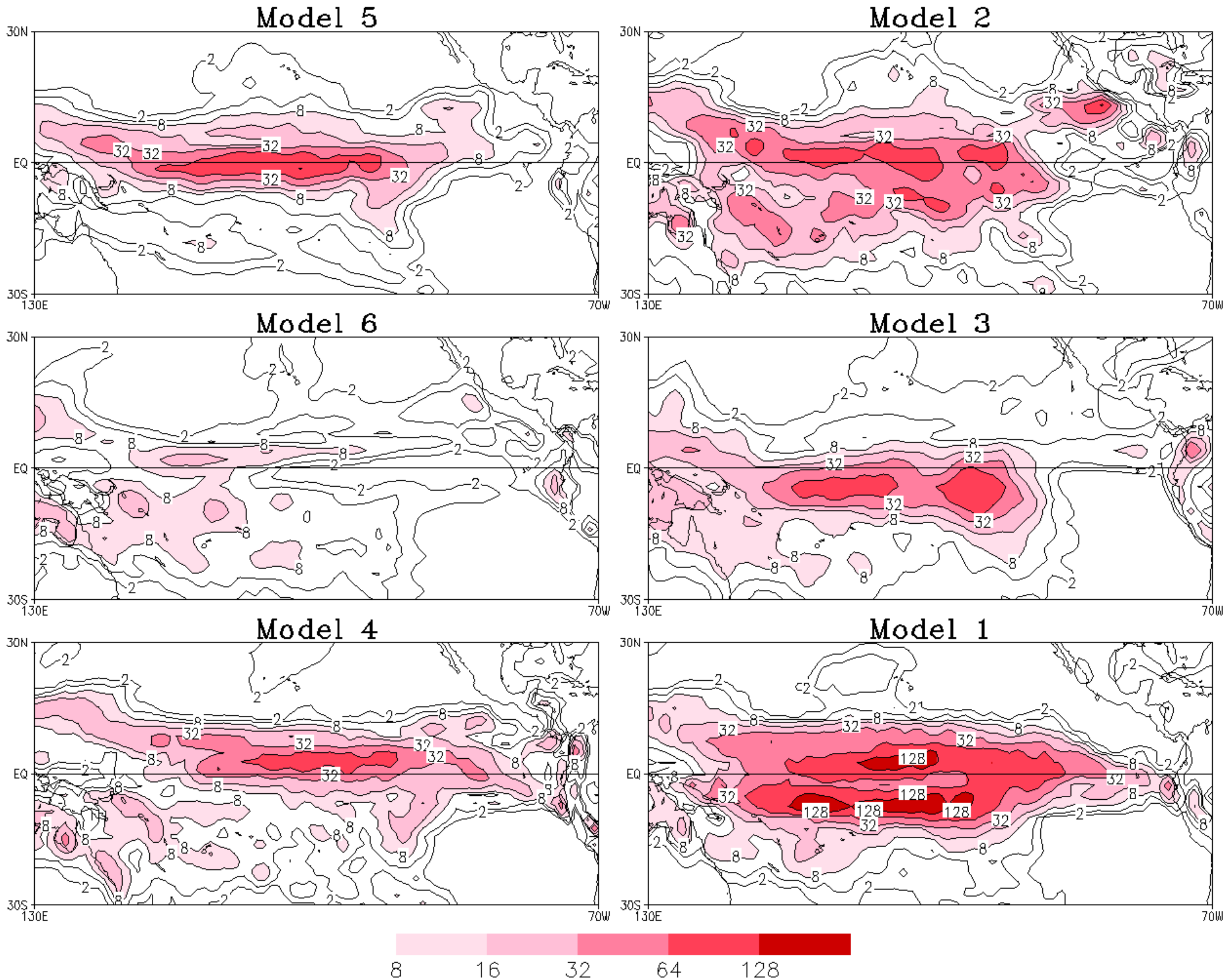
Percent Variance over PNA region explained by tropical SST



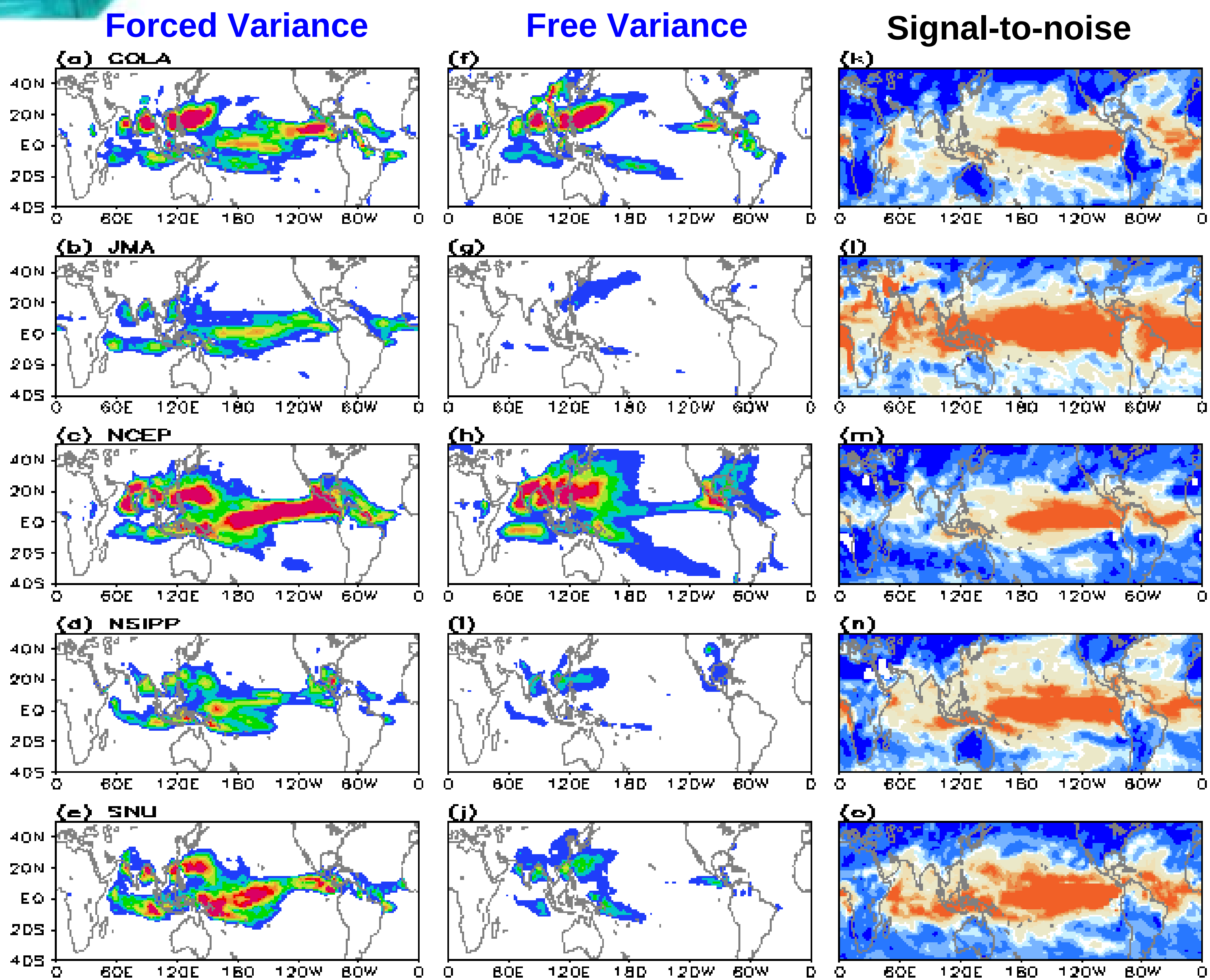
Percent Variance over PNA region explained by tropical SST



Boreal Winter (JFM) Rainfall Variance in Models [mm^2]



Boreal Summer (JJA) Rainfall Variance in AGCMs [mm^2]



Outline

- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- **Model Fidelity and Prediction Skill**
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

Hypothesis

Models with low fidelity in simulating climate statistics have low skill in predicting climate anomalies.

DelSole 2007 (research in progress)

Measure of Fidelity: Relative Entropy

(Kleeman 2001; DelSole and Tippett, 2007)

- Measure of the "distance" between two pdfs

$$R = \int a(x) \log \frac{a(x)}{f(x)} \, dx$$

- f = climatology of model forecasts at fixed lead time, fixed initial time
-
- a = climatology of analyses ("observations") (distribution of variable in JFM, FMA, etc.)

- For 1D normal distributions with mean μ and variance σ^2

$$R = \log \frac{\sigma_a^2}{\sigma_f^2} + \frac{\sigma_f^2}{\sigma_a^2} - 1 + \frac{(\mu_f - \mu_a)^2}{\sigma_a^2}$$

Measure of Fidelity: Anomaly Correlation

ACC = correlation between forecast and verification at each grid point

$$ACC = \frac{cov(F, A)}{\sigma_f \, \sigma_a}$$

Notes:

- ACC is calculated from seasonal means for 1981-2001.
- ACC measures joint variability (i.e. skill), relative entropy does not. Relative entropy measures fidelity of climatological distribution.
- ACC is not a spatial correlation, but a temporal correlation at each grid point.

DEMETER

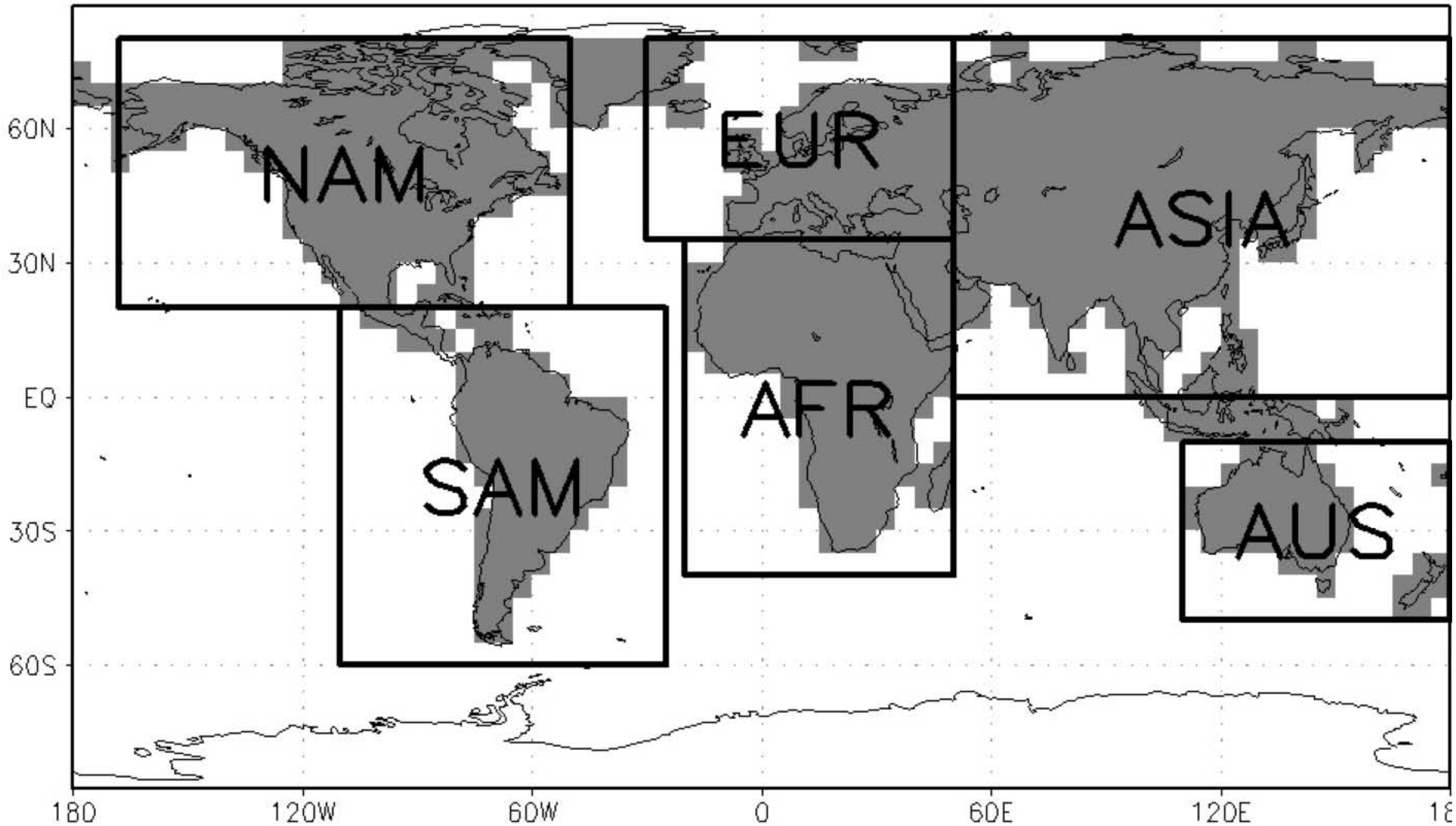
- Demeter hindcasts downloaded from ECMWF[1]
- 7 models (CER, ECM, ING, LOD, MET, MPI, UKM)
- 9 ensemble members
- Initial conditions: February 1, May 1, August 1, November 1
- 6-month lead time
- 22 Years: 1980-2001
- 2m temperature over land
- Consider only 3-month means (JFM, FMA, . . ., OND)

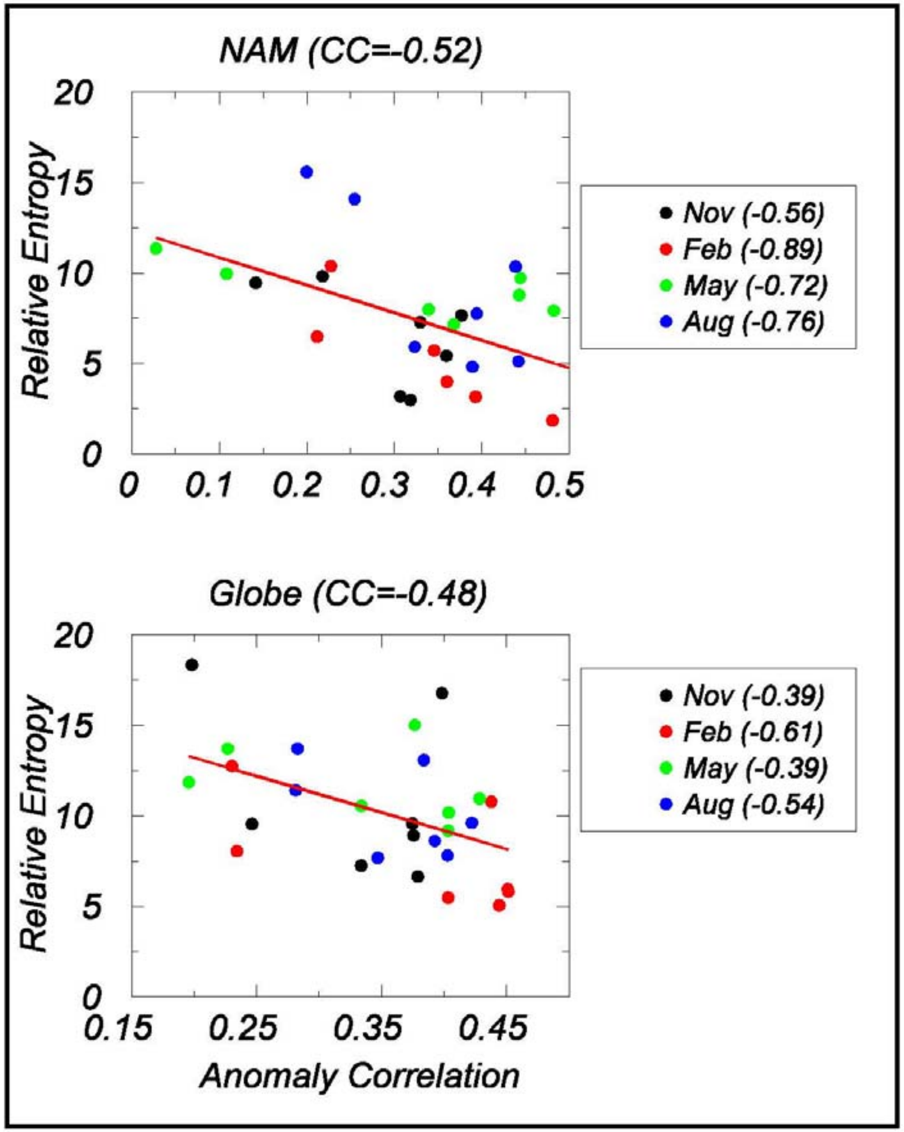
Thanks to Emilia Jin for providing the DEMETER data.

Calculation Details

- Verification data: HADCRUT2 from CRU (Jones & Moberg)
- All data interpolated onto HADCRUT2 observation grid
- Relative entropy and anomaly correlation computed at each grid point separately for 1980-2001.
- Grid point values of R and ACC averaged over selected regions.

Regions Investigated





Fidelity vs. Skill
DEMETER 1980-2001
Seasonal Forecasts

7 models, 4 initial conditions

Lead Time = 0 months

Fidelity and Skill are related.

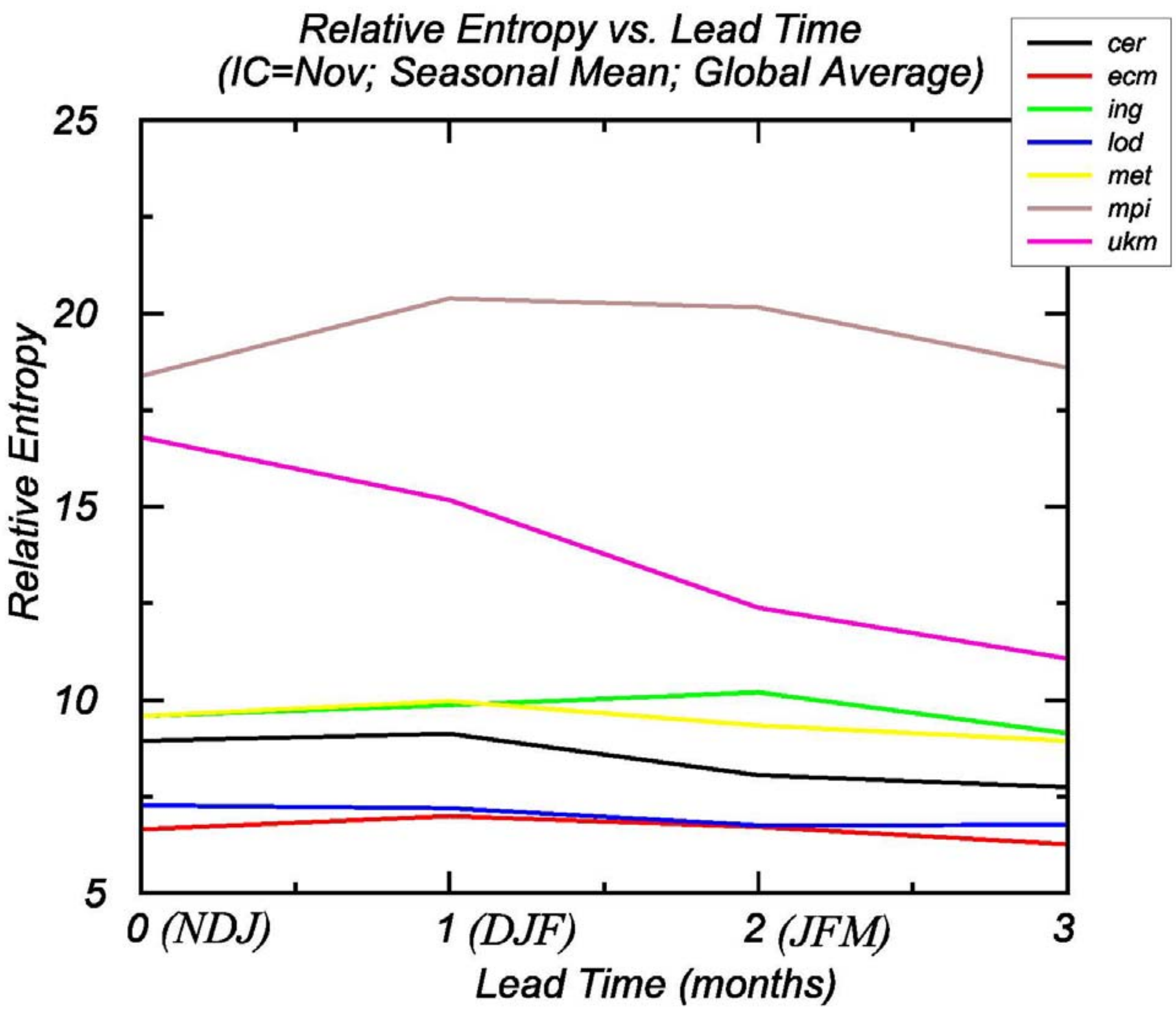
Models with poor climatology tend to have poor skill.

Models with better climatology tend to have better skill.

DelSole 2007 (research in progress)

Center of Ocean-Land-Atmosphere studies

CREW Center for Research on Environment and Water



Note: Model errors saturate within the first season

DelSole 2007 (research in progress)

Systematic errors of climate models can be substantially reduced by empirical corrections (e.g. flux correction, anomaly coupling, nudging based on tendency error, etc.)

However, empirical corrections do not consistently improve forecast skill.

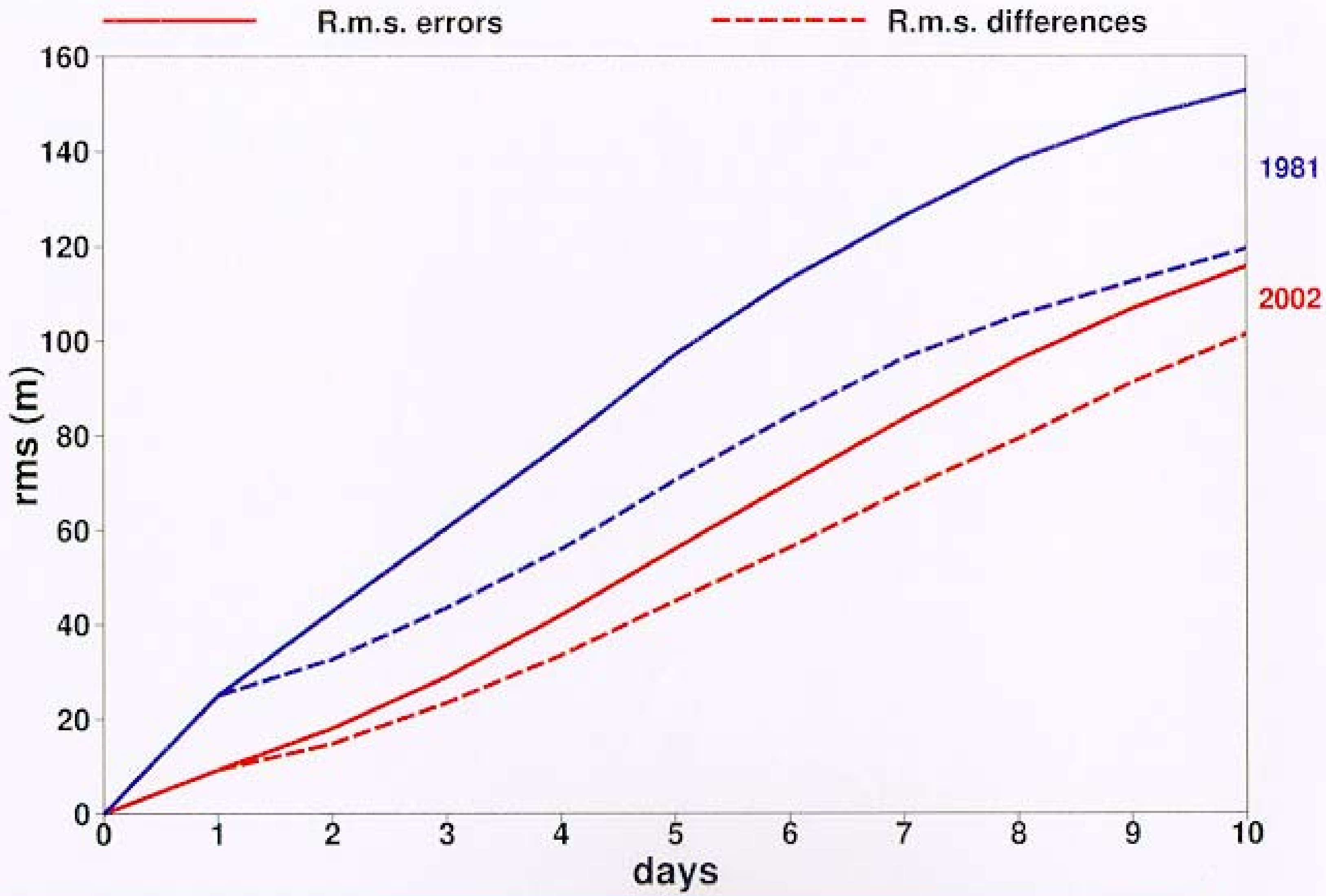
Outline

- Historical Overview
- Success of NWP during the past 30 years
- From Weather Prediction to Dynamical Seasonal Prediction
- Current Status of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Model Fidelity and Prediction Skill
- Factors Limiting Predictability: Future Challenges
  - ✓ Data Assimilation and Initialization
  - ✓ Biosphere, Cryosphere, Stratosphere Effects
  - ✓ Seasonal Prediction in a Changing Climate
  - ✓ Seamless Prediction of Weather and Climate
  - ✓ Computational Power
- Suggestions for the Future

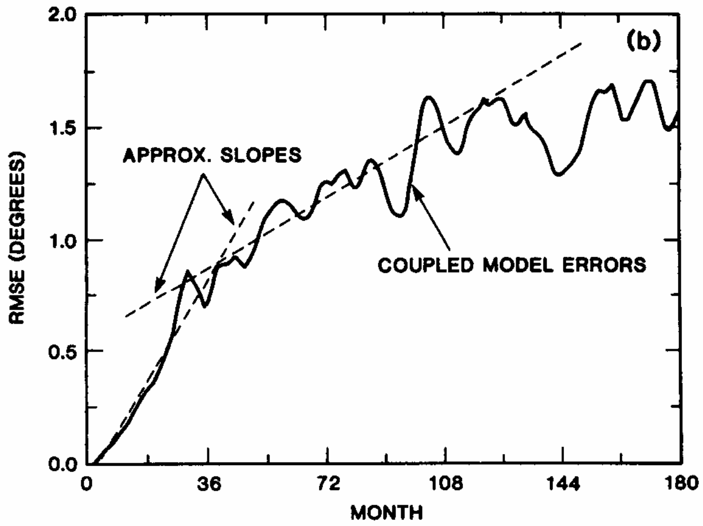
Understanding Variations in Forecast Skill

- **What is the Overall Limit of Predictability?**
- **What Limits Predictability?**
  - **<u>Uncertainty in Initial Conditions:</u> Chaos within Non-Linear Dynamics of the Coupled System**
  - **<u>Uncertainty as the System Evolves:</u> External Stochastic Effects**
- **Model Dependence?**
  - **Model Error**

R.m.s. errors and differences between successive forecasts
Northern hemisphere 500hPa height Winter



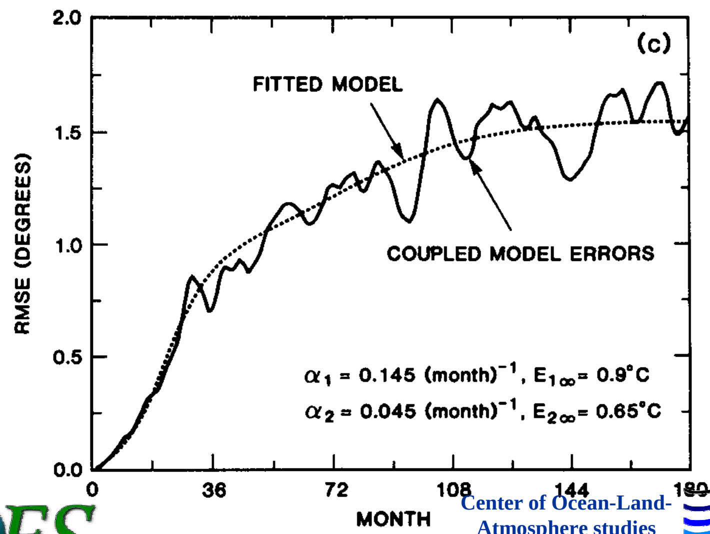
Predictability Limited Due to Initial Condition Uncertainty: Two Time Scales in the Error Growth?



$$E(t) = E_1(t) + E_2(t)$$

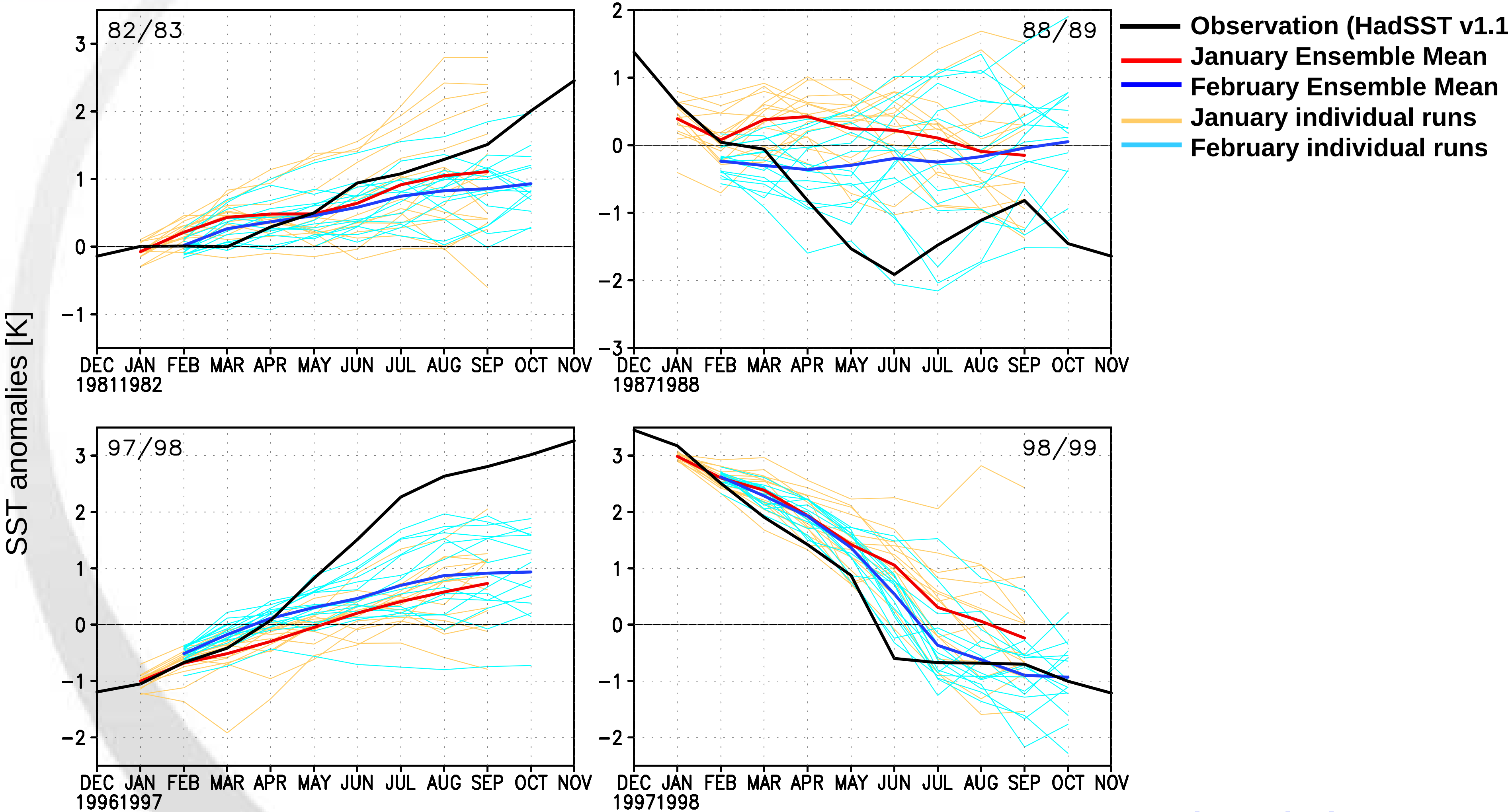
$$\frac{dE_1}{dt} = \alpha_1 E_1 - \alpha_1 E_1^2 \big/ E_{1\infty}$$

$$\frac{dE_2}{dt} = \alpha_2 E_2 - \alpha_2 E_2^2 \big/ E_{2\infty}$$



Goswami and Shukla 1991

Examples: 4 ENSO cases of NINO3 index in CFS

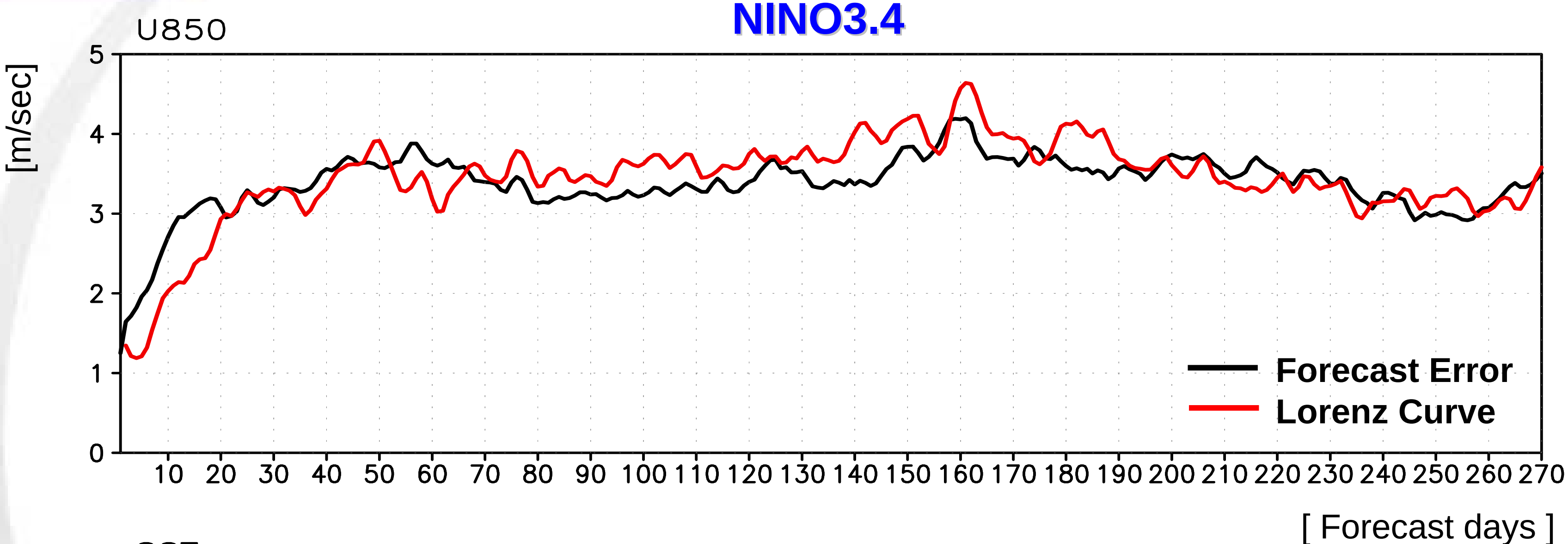


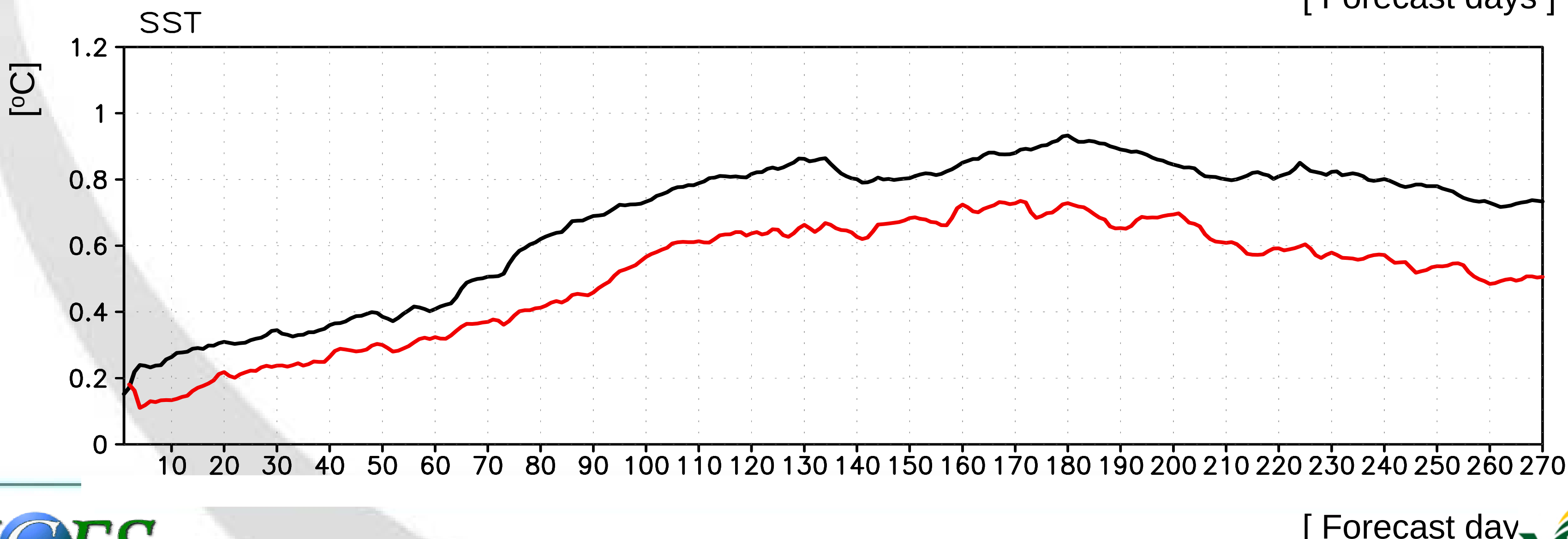
Jin and Kinter, 2007

Forecast Error and Lorenz Curve

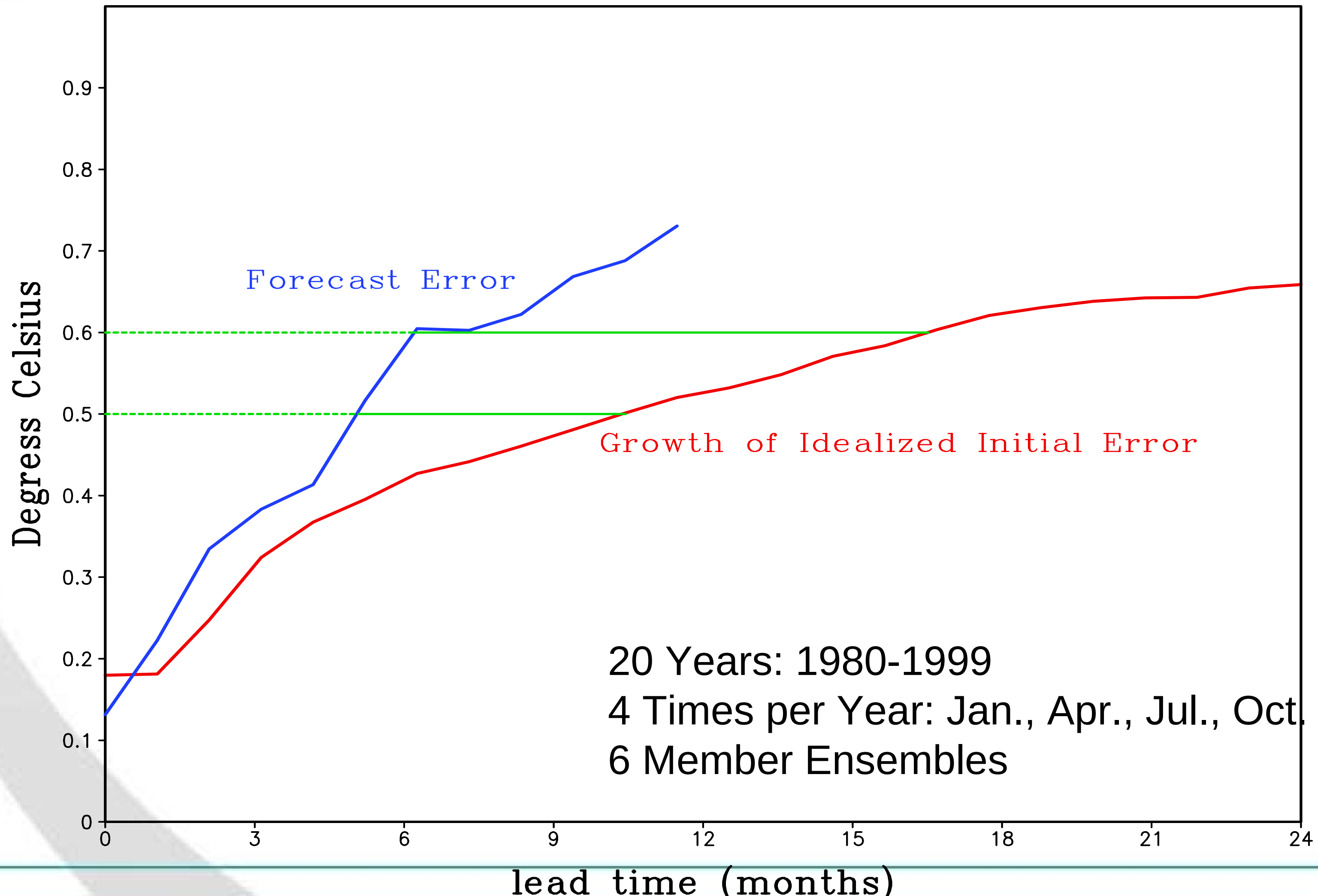
NCEP CFS daily forecast start from 9Apr to 3May (15 members)

NINO3.4



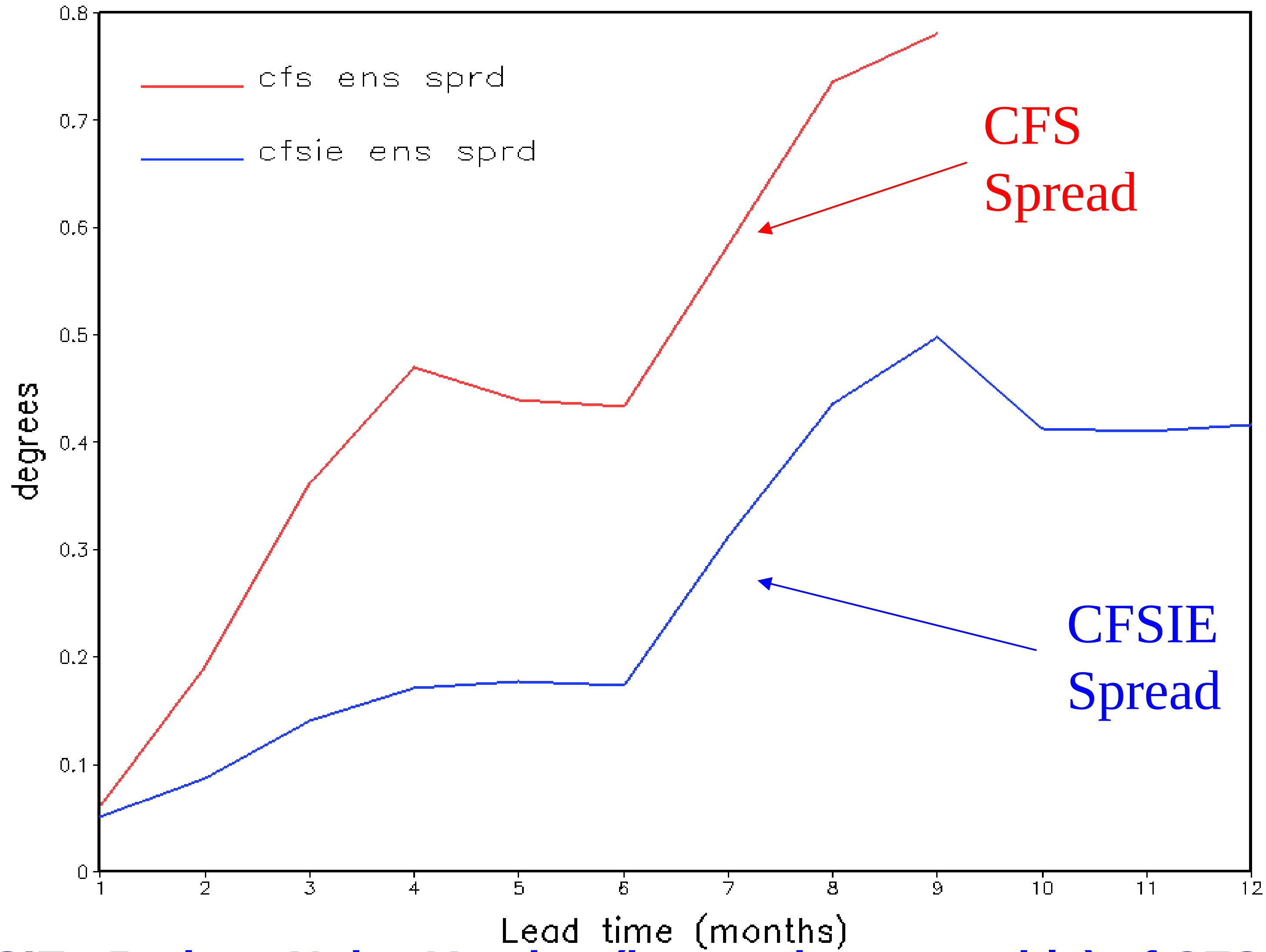


Current Limit of Predictability of ENSO (Nino3.4)
Potential Limit of Predictability of ENSO

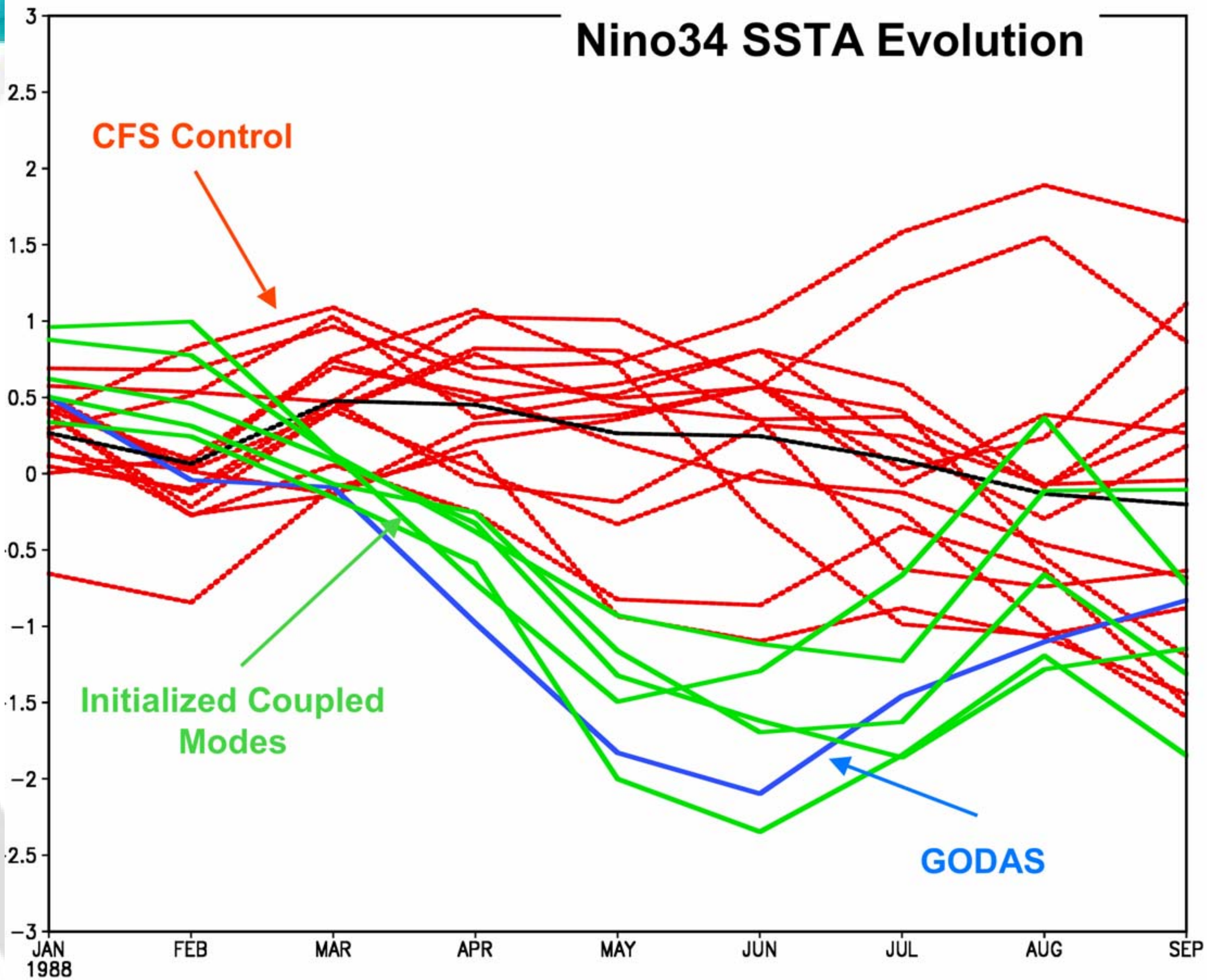


Kirtman, 2003

Nino3.4 Index

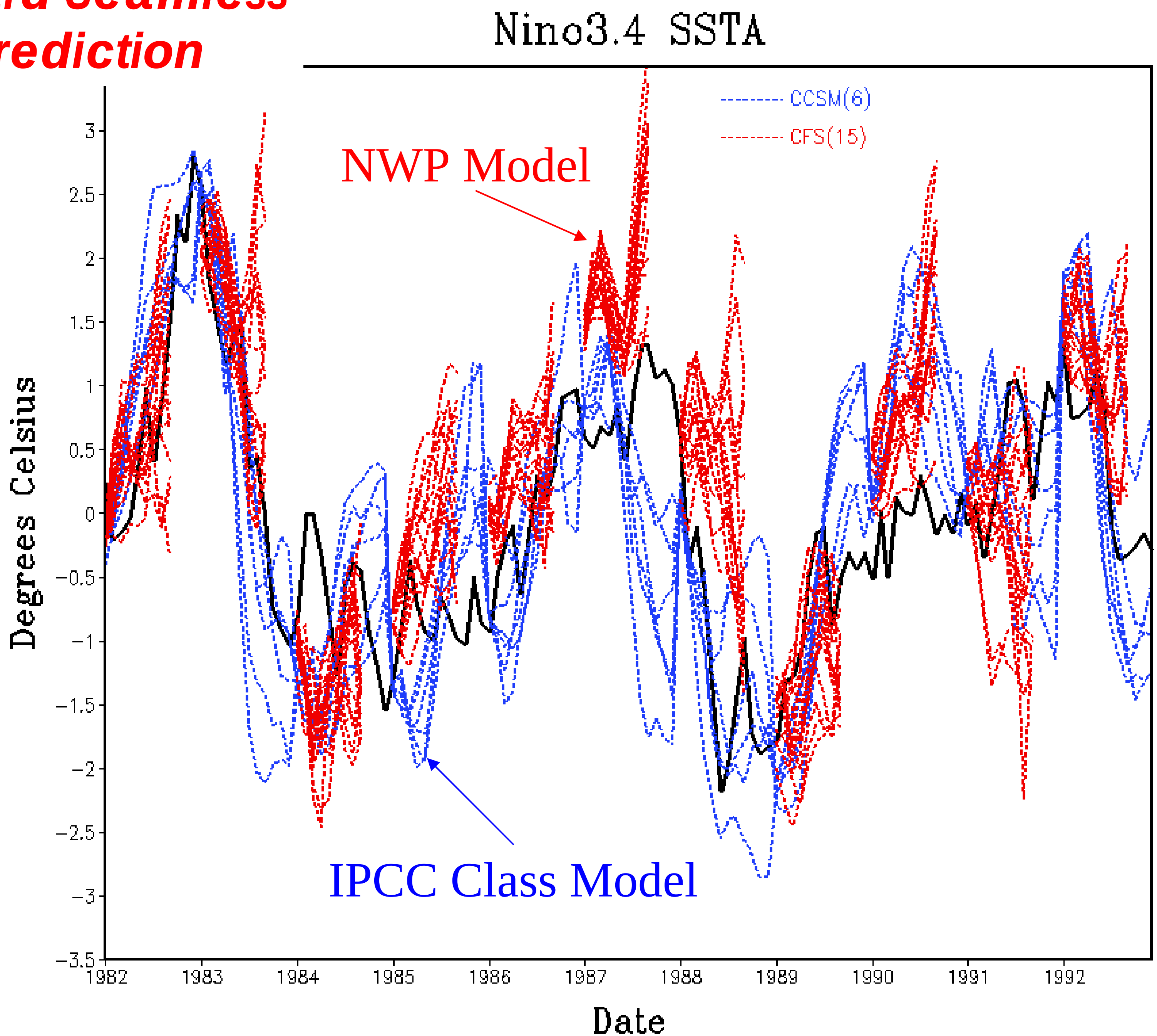


CFSIE - Reduce Noise Version (interactive ensemble) of CFS



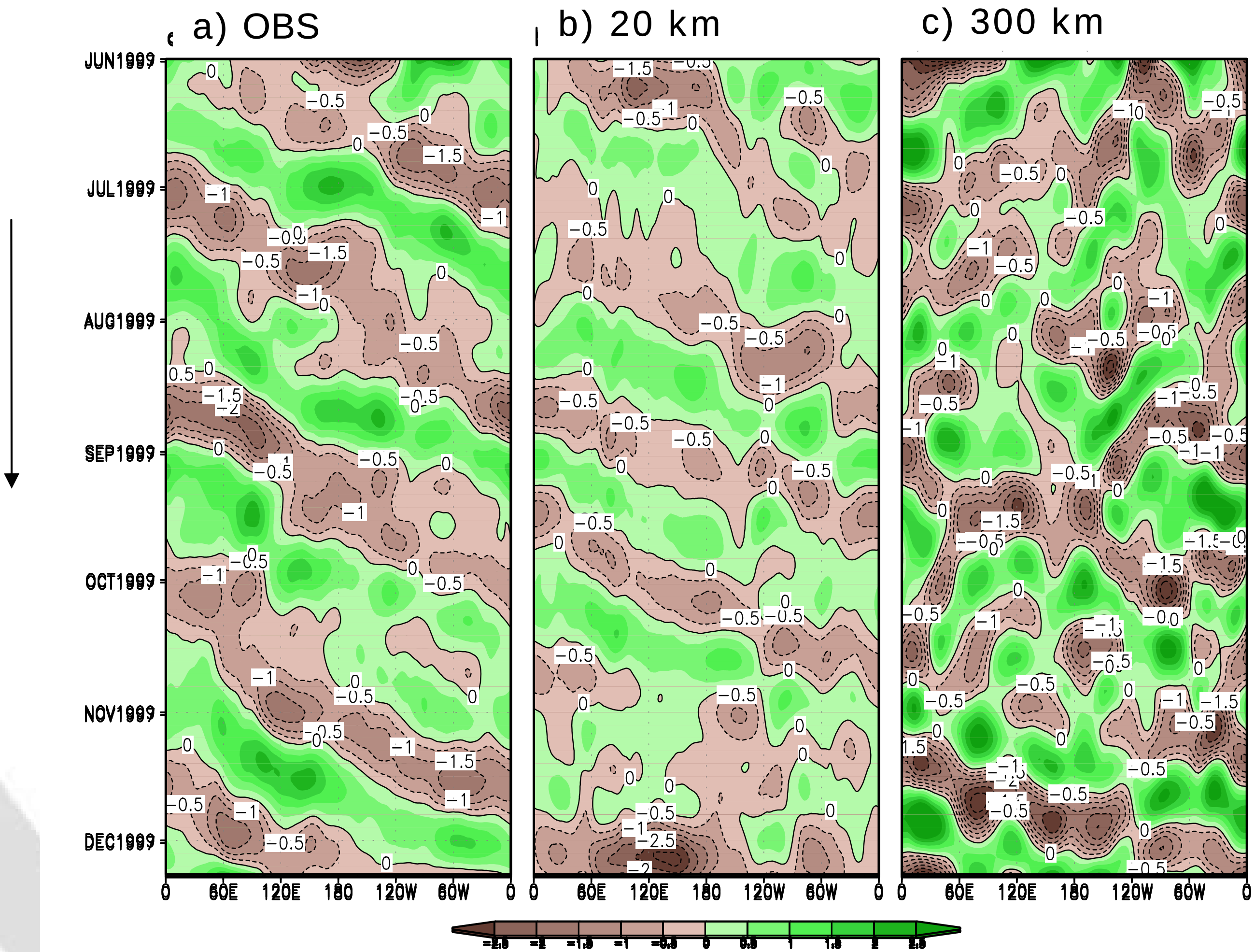
Nino34 SSTA Evolution
CFS Control
Initialized Coupled Modes
GODAS
3
2.5
2
1.5
1
0.5
0
-0.5
−1
-1.5
−2
-2.5
−3
JAN 1988
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP

Toward Seamless Prediction



MJO Propagation

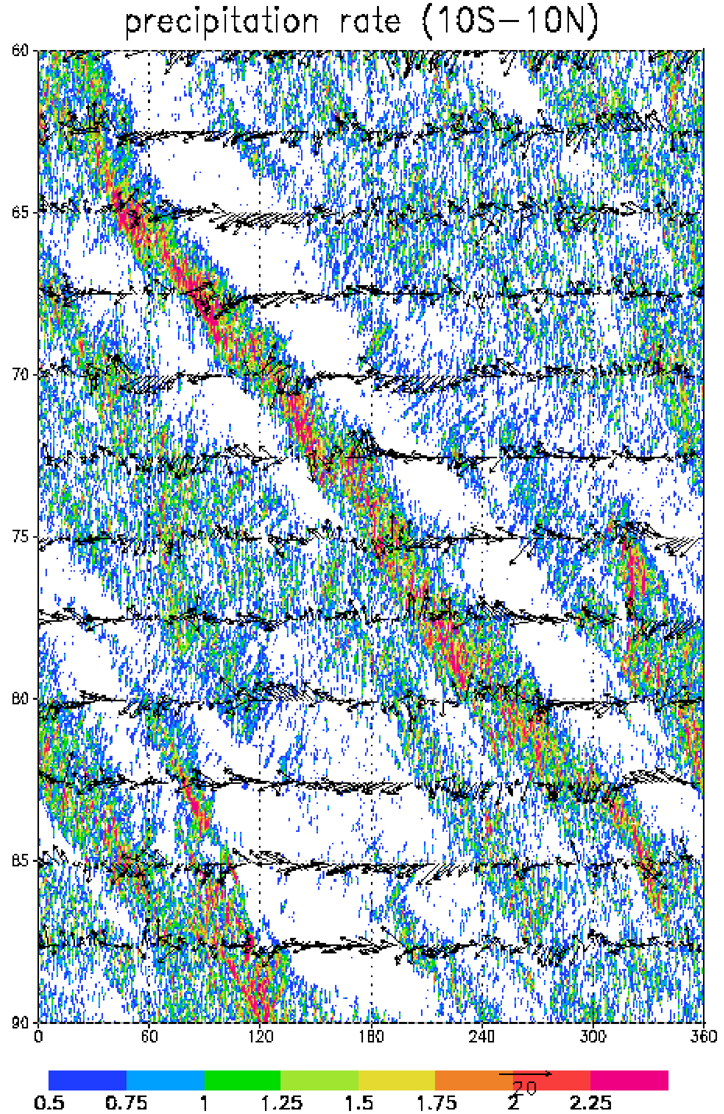
- 200hPa velocity potential : 1999yr



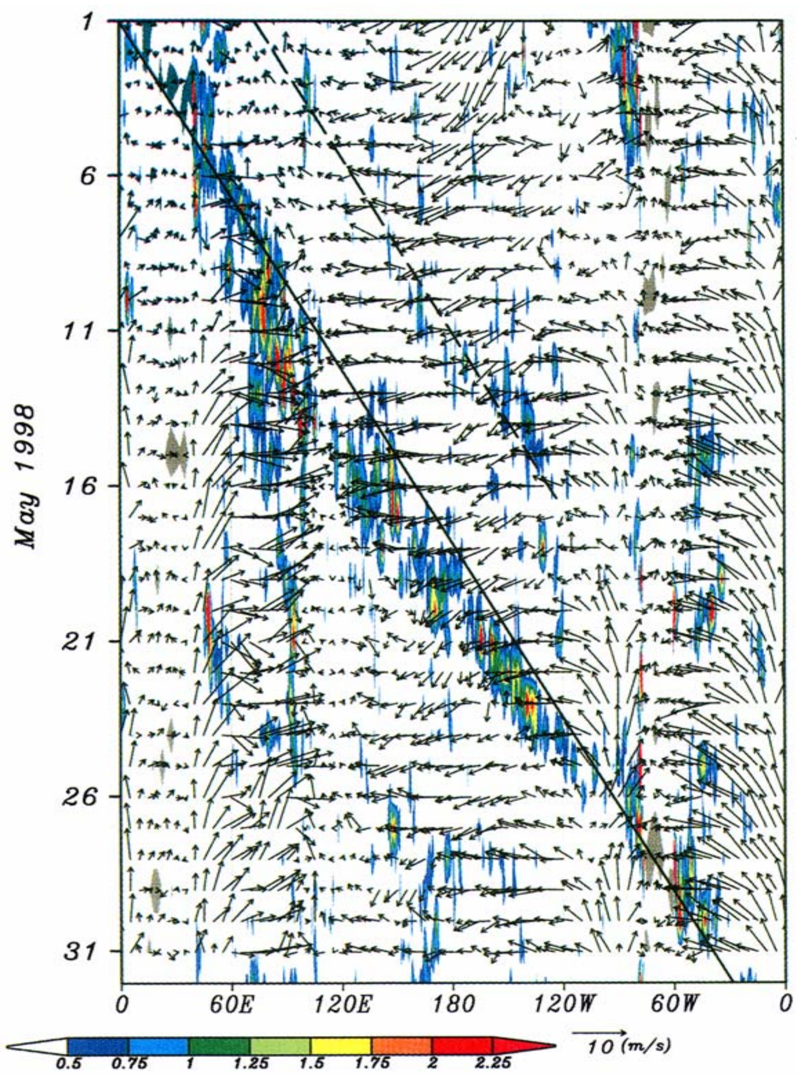
• **High resolution shows more clear eastward propagation MJO in 1999yr**

Kang (2007)

NICAM (7-km)



Obs. (Takayabu et al. 1999)



Matsuno (AMS, 2007)

Factors Limiting Predictability: Future Challenges

"Fundamental barriers to advancing weather and climate diagnosis and prediction on timescales from days to years are partly 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)

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)

Seamless Prediction

Since climate in a region is an ensemble of weather events, understanding and prediction of regional climate variability and climate change, including changes in extreme events, will require a unified initial value approach that encompasses weather, blocking, intraseasonal oscillations, MJO, PNA, NAO, ENSO, PDO, THC, etc. and climate change, in a seamless framework.

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

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

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

~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

THANK YOU!

ANY QUESTIONS?