Model Fidelity and Model Predictability

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Outline

- Introduction
- Model Fidelity and Sensitivity to Global Warming
- Model Fidelity and Skill of Dynamical Seasonal Prediction
- Model Deficiencies in Simulating the Present Climate
- Tropical Heating and ENSO Forced Response
- Suggestions for the Future

Climate Model Fidelity and Projections of Climate Change

1.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.

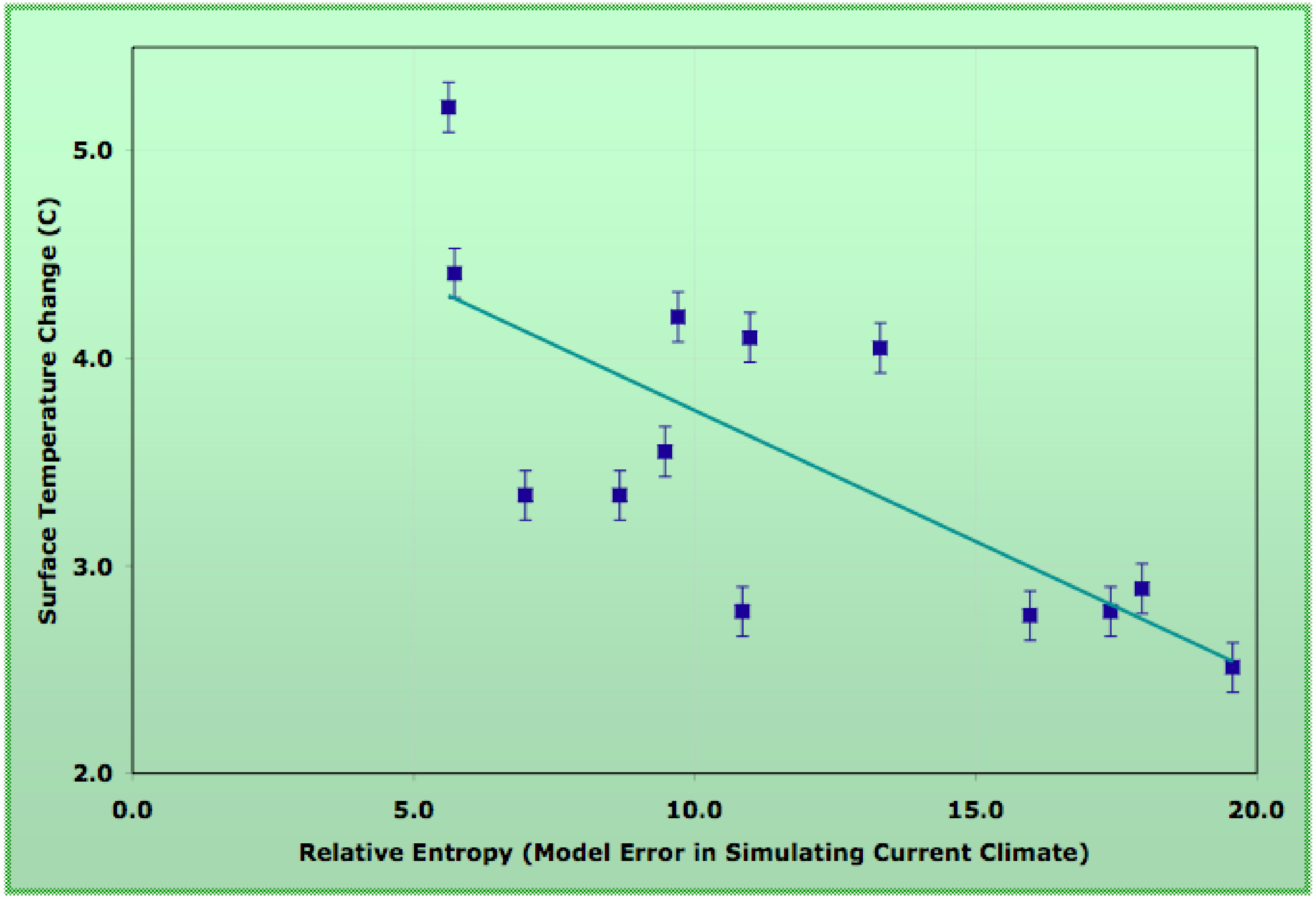
IPCC AR4 Models

Originating Group(s)	Country	CMIP3 I.D.
National Center for Atmospheric Research	USA	CCSM3
Météo-France / Centre National de Recherches Météorologiques	France	CNRM-CM3
Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM
US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.1
NASA / Goddard Institute for Space Studies	USA	GISS-AOM
NASA / Goddard Institute for Space Studies	USA	GISS-EH
NASA / Goddard Institute for Space Studies	USA	GISS-ER
Institut Pierre Simon Laplace	France	IPSL-CM4
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	MIROC3.2(hires)
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	MIROC3.2(medres)
Meteorological Research Institute	Japan	MRI-CGCM2.3.2
National Center for Atmospheric Research	USA	PCM
Hadley Centre for Climate Prediction and Research / Met Office	UK	UKMO-HadCM3

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.

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

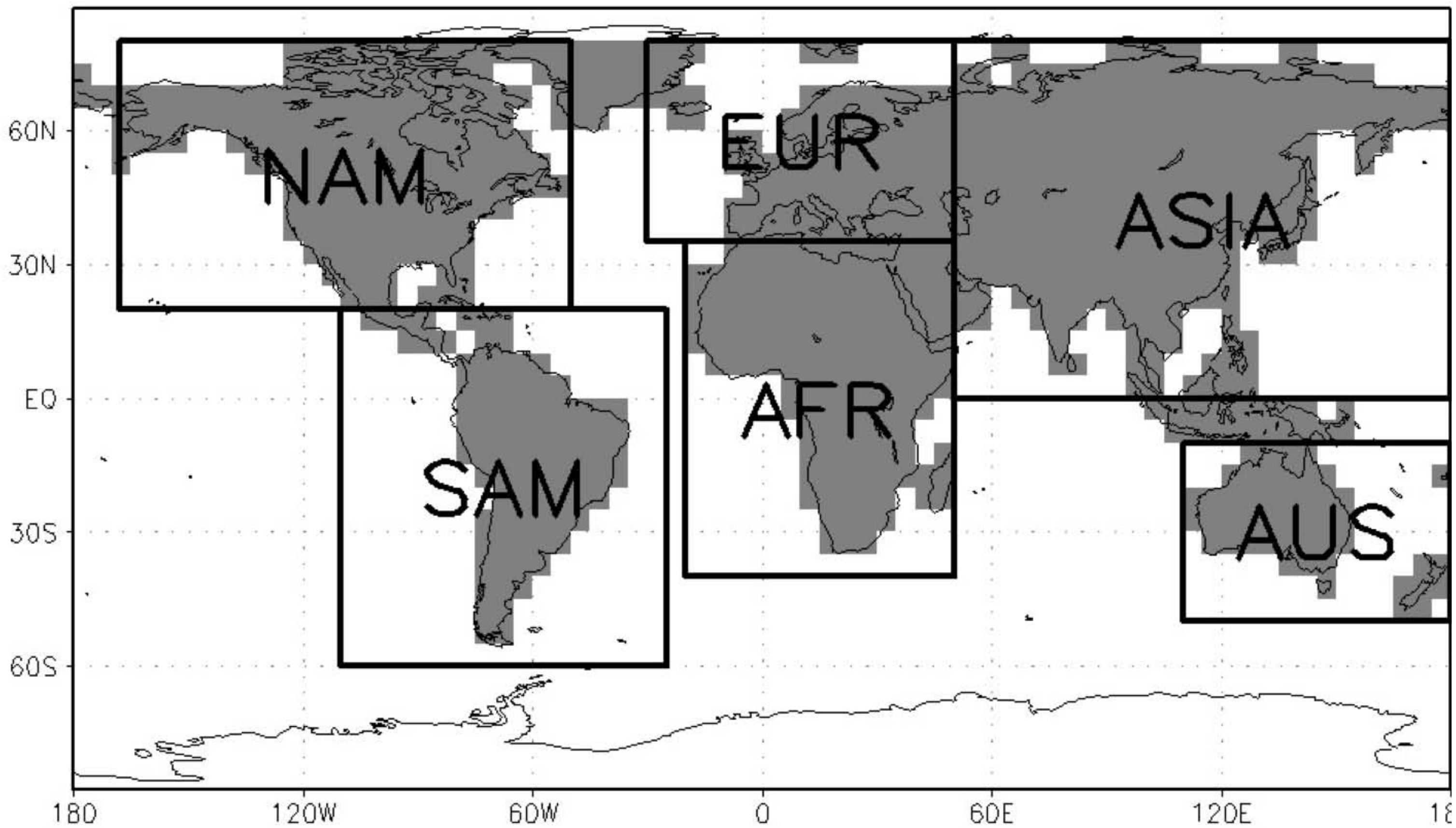
- Demeter hindcasts downloaded from ECMWF[1]
- 7 models (CER, ECM, ING, LOD, MET, MPI, UKM)
- 9 ensemble members
- Initial conditions: February 1, May 1, August 1, November 1
- 6-month lead time
- 22 Years: 1980-2001
- 2m temperature over land
- Consider only 3-month means (JFM, FMA, . . ., OND)

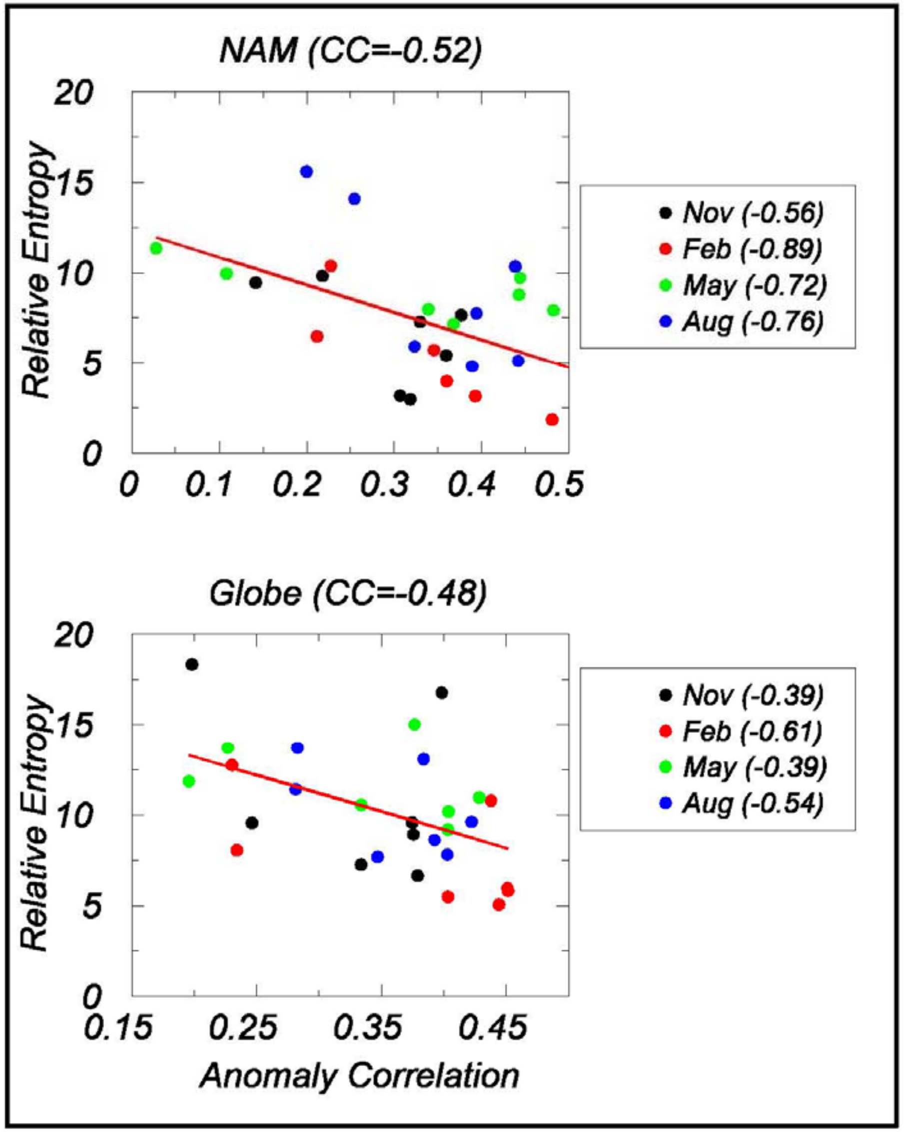
Thanks to Emilia Jin for providing the DEMETER data.

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

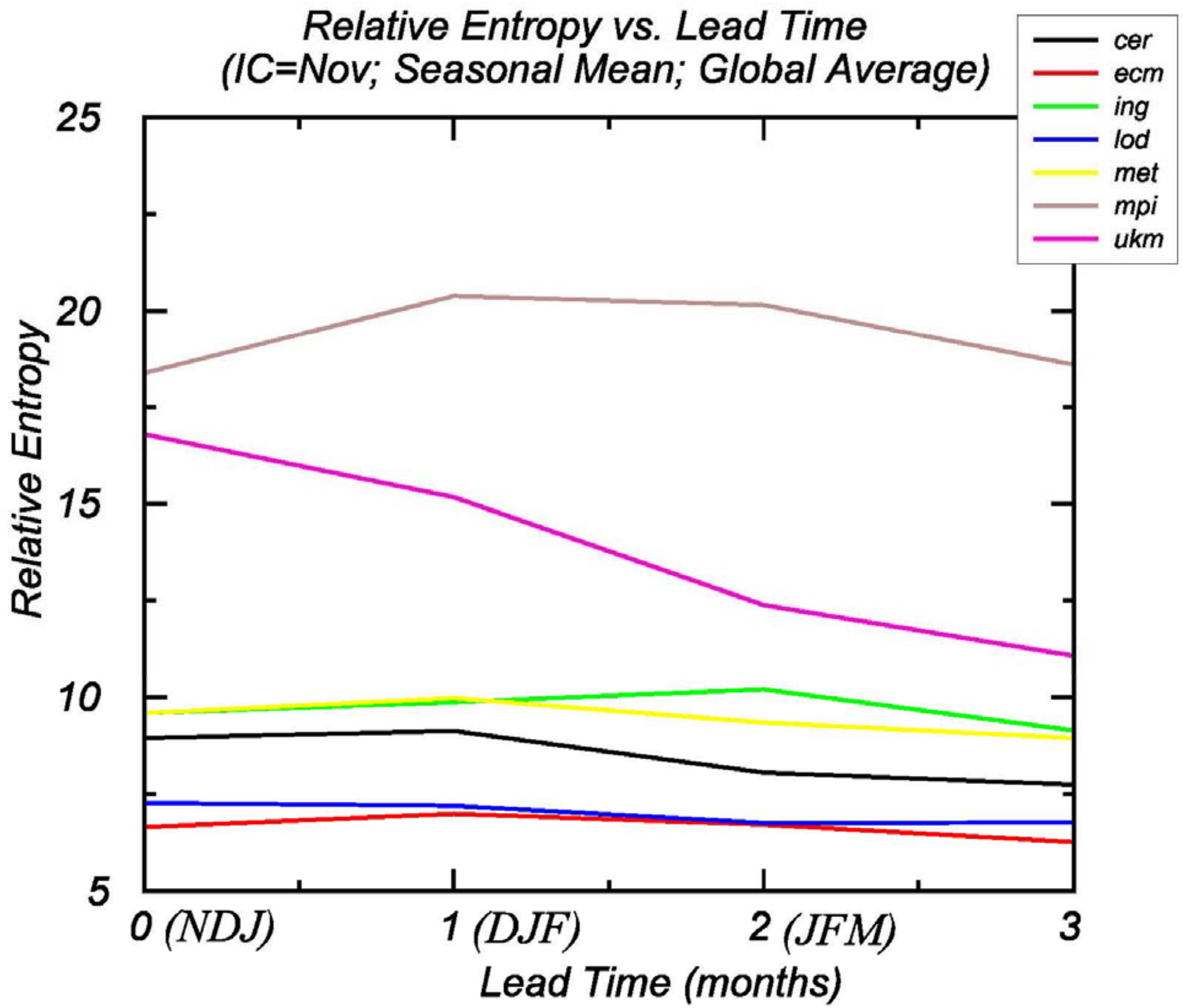
Lead Time = 0 months

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)

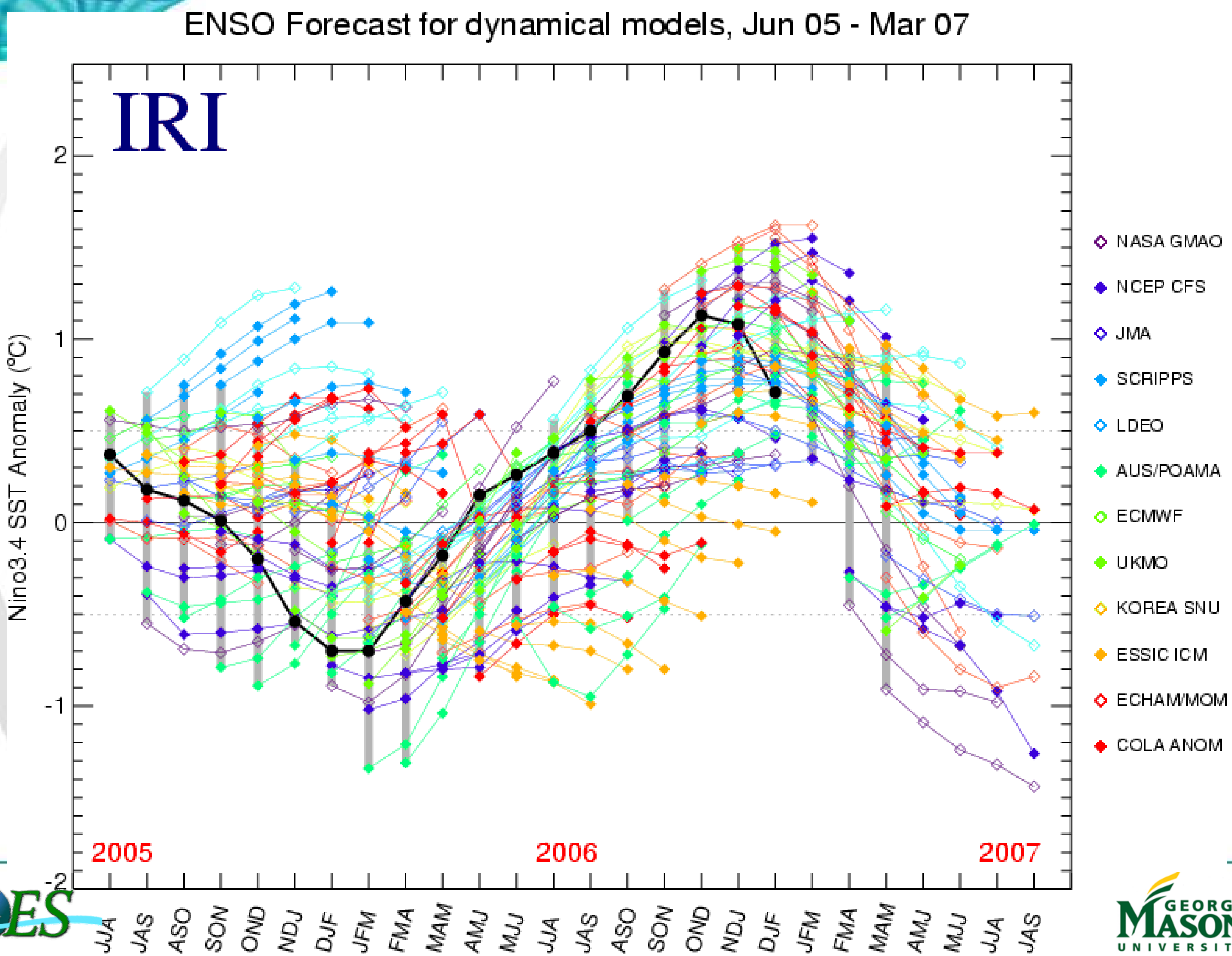


Note: Model errors saturate within the first season

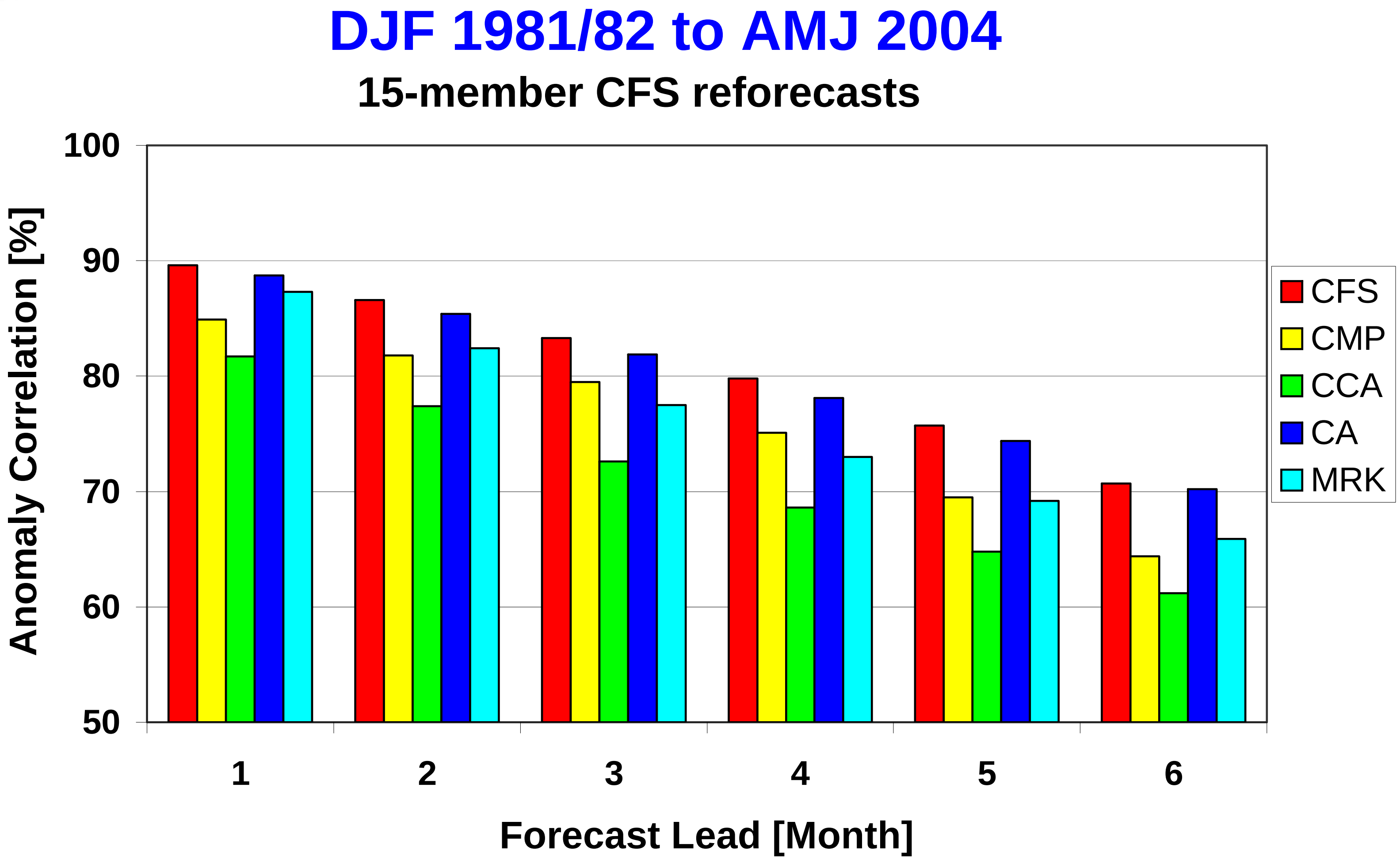
DelSole 2007 (research in progress)

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.

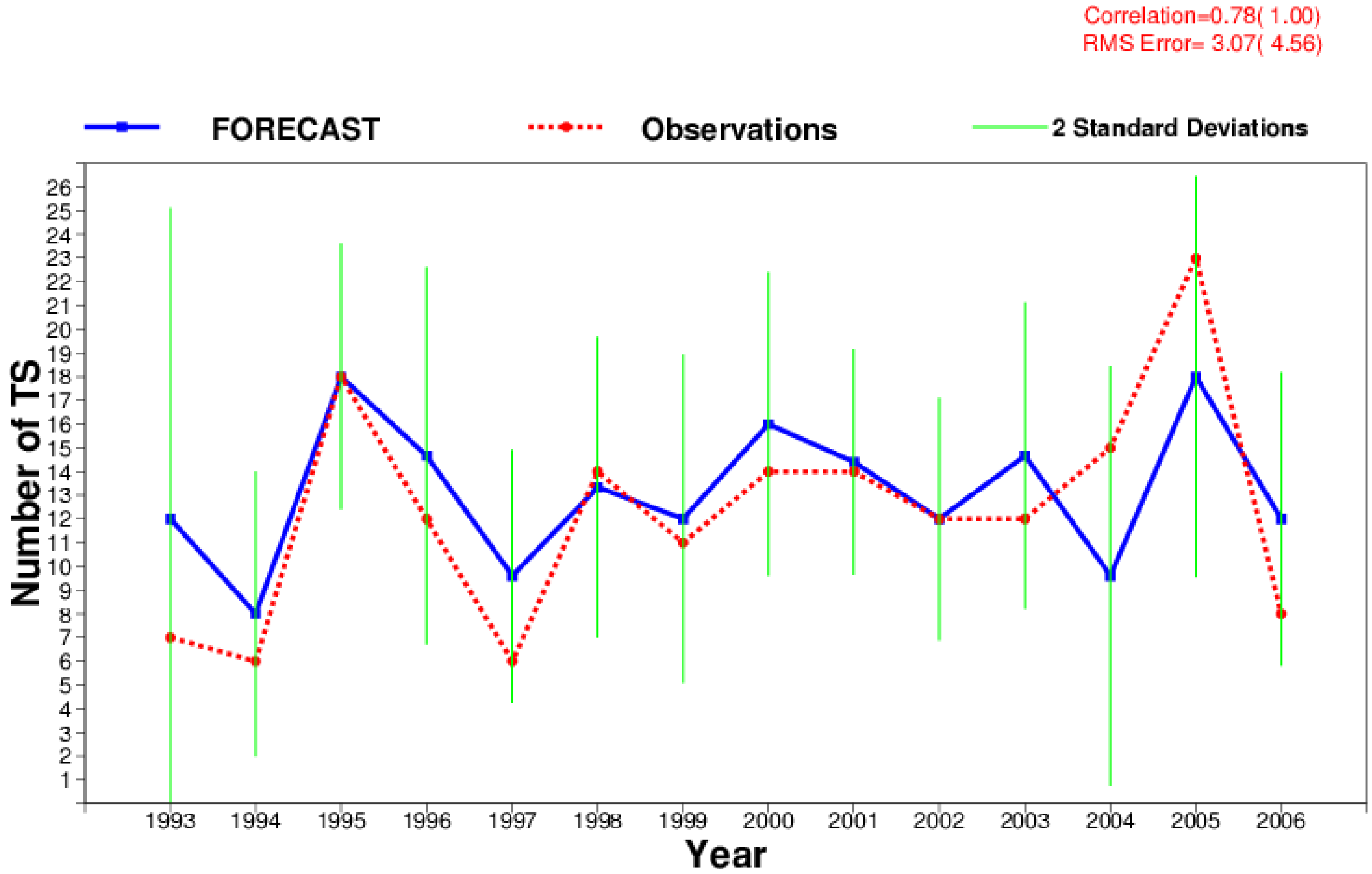

ENSO Forecast for dynamical models, Jun 05 - Mar 07
IRI
Nino3.4 SST Anomaly (°C)
2
1
0
-1
-2
2005
2006
2007
JJA
JAS
ASO
SON
OND
NDJ
DJF
JFM
FMA
MAM
AMJ
MJJ
JJA
JAS
ASO
SON
OND
NDJ
DJF
JFM
FMA
MAM
AMJ
MJJ
JJA
JAS
NASA GMAO
NCEP CFS
JMA
SCRIPPS
LDEO
AUS/POAMA
ECMWF
UKMO
KOREA SNU
ESSIC ICM
ECHAM/MOM
COLA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

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.**

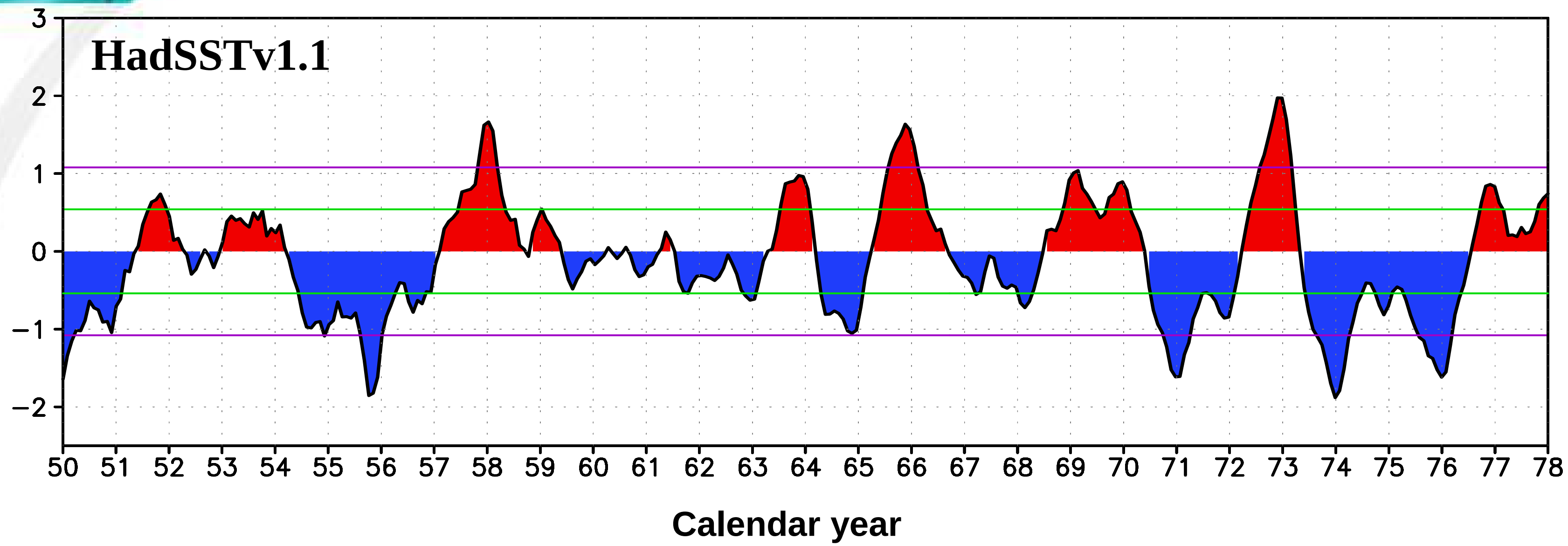
Current Status of Dynamical Seasonal Prediction

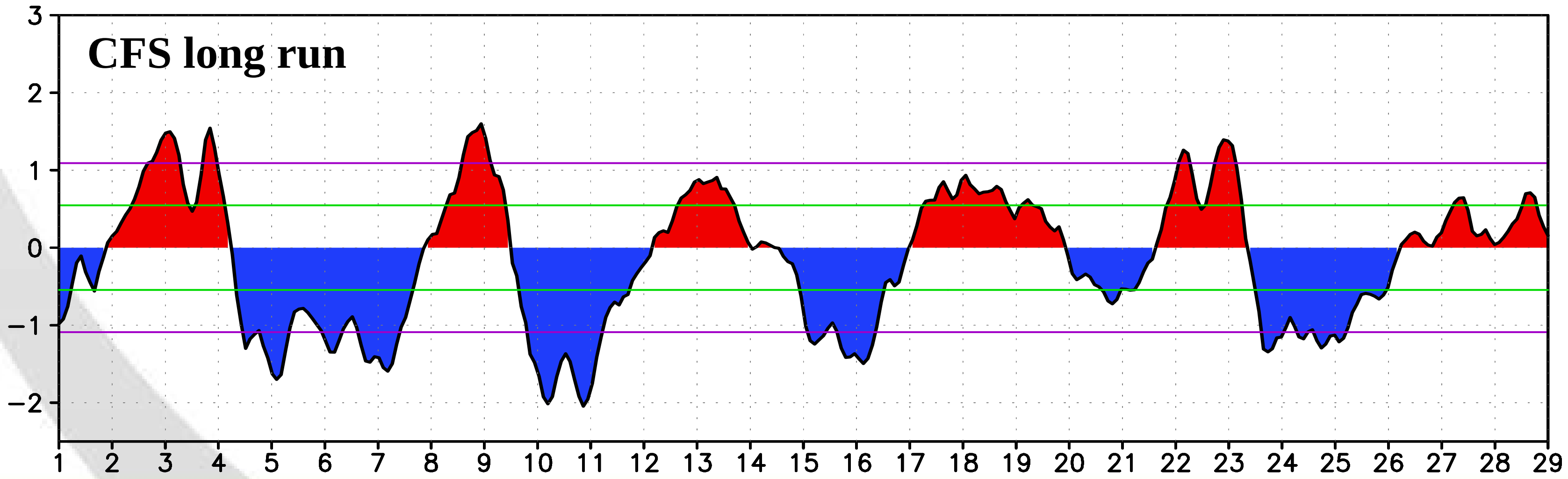
1. Coupled O-A models (both complex GCMs and intermediate complexity models) are frequently making skillful prediction of tropical Pacific SSTA (NINO 3, NINO 3.4, etc) and the corresponding tropical circulation up to six months. However, the skill is highly variable depending on IC, year (ENSO events), 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.

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.**

NINO 3.4 Index (Observed and CFS)





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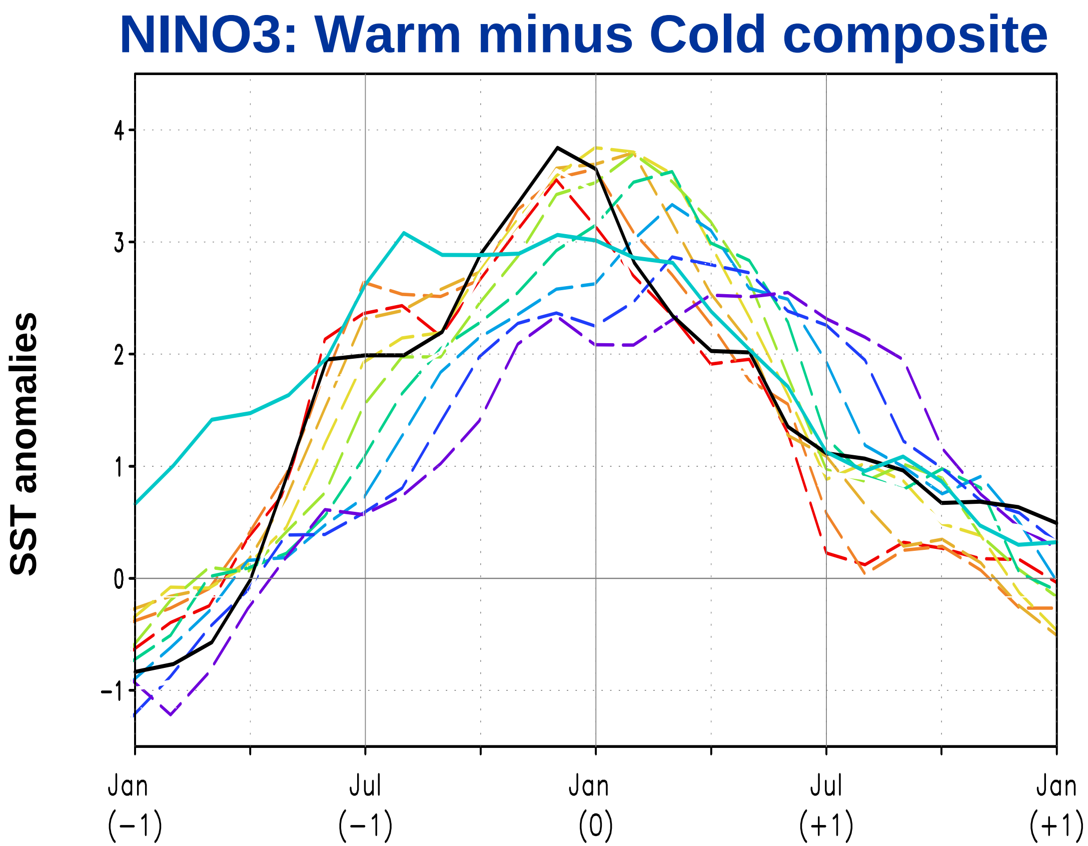
Influence of Systematic Error on CFS Forecast Skill



- 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

Commentary

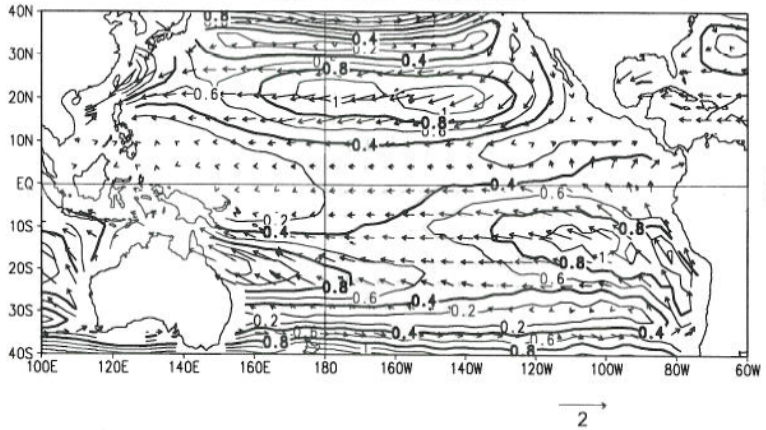
- Models with high deficiencies in simulating tropical heating produce highly deficient extratropical response to ENSO
- Examples: ECMWF, NCEP, GFDL, COLA

Thanks to Arun Kumar (CPC/NCEP)

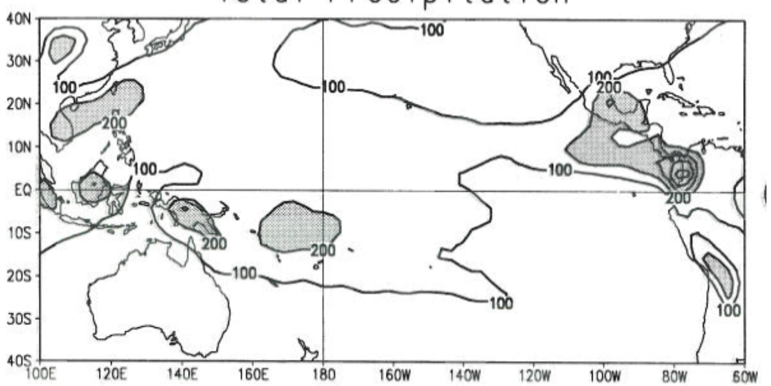
MRF8

SEP–NOV Climatology (AMIP)

Surface Stress



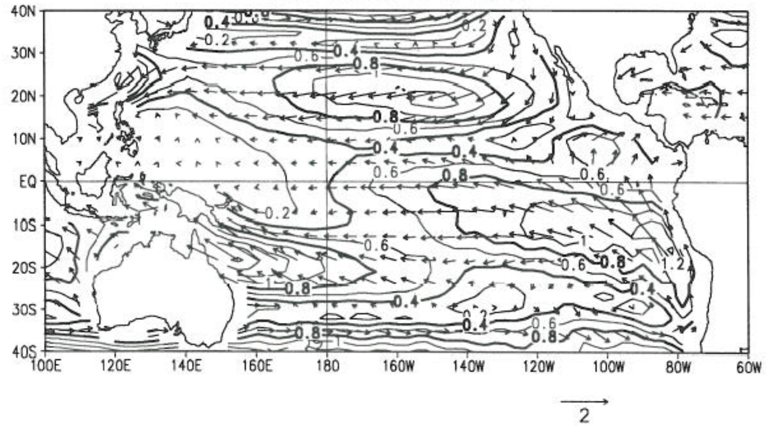
Total Precipitation



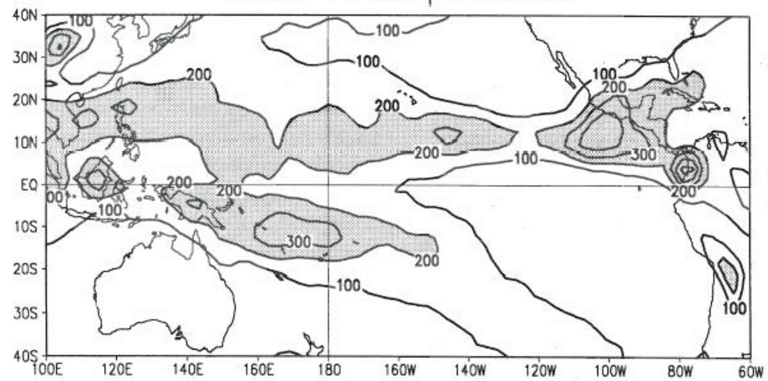
MRF9

SEP–NOV Climatology (CMP)

Surface Stress



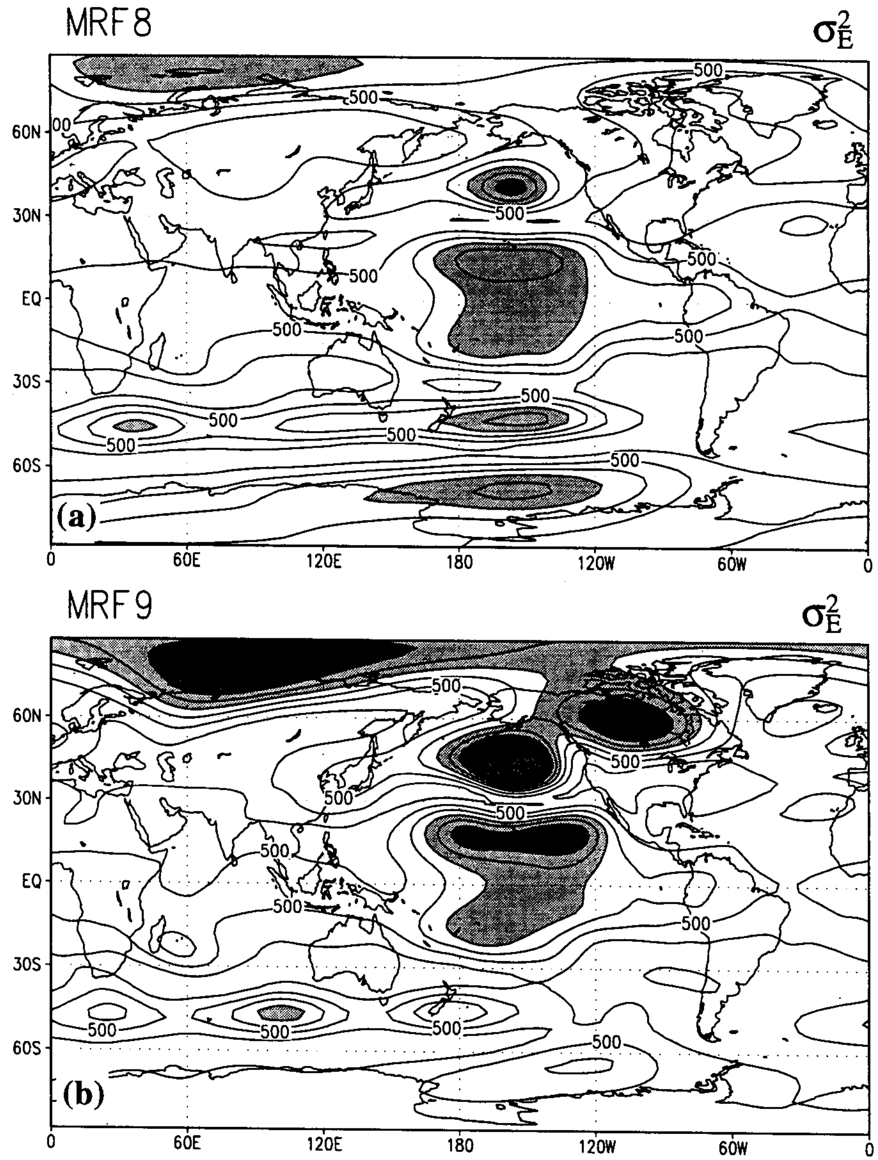
Total Precipitation

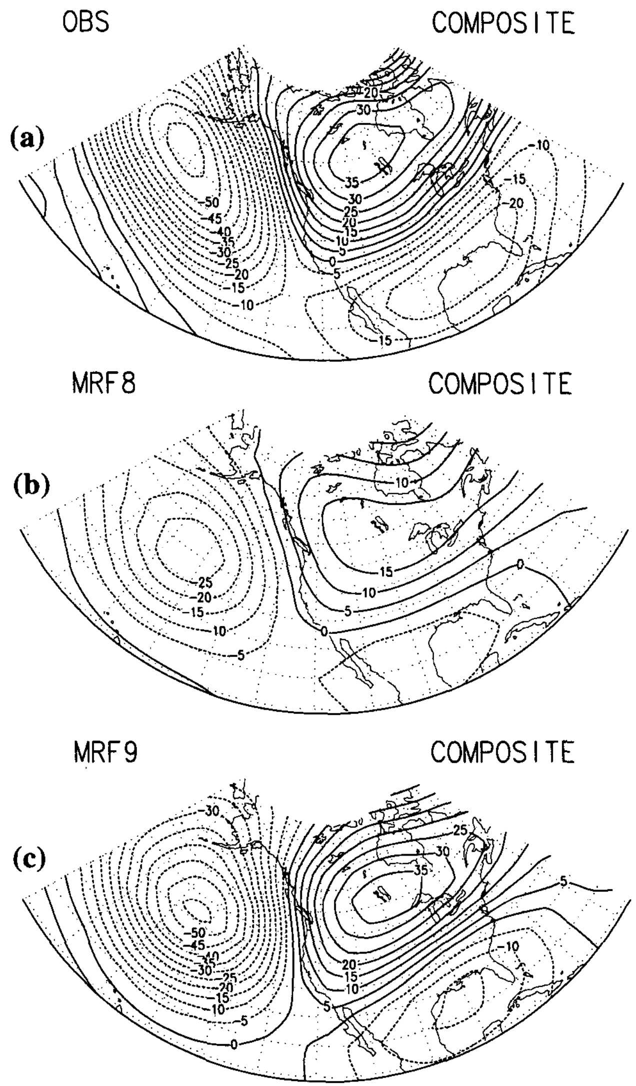


MRF8: high, middle, low clouds allowed to exist

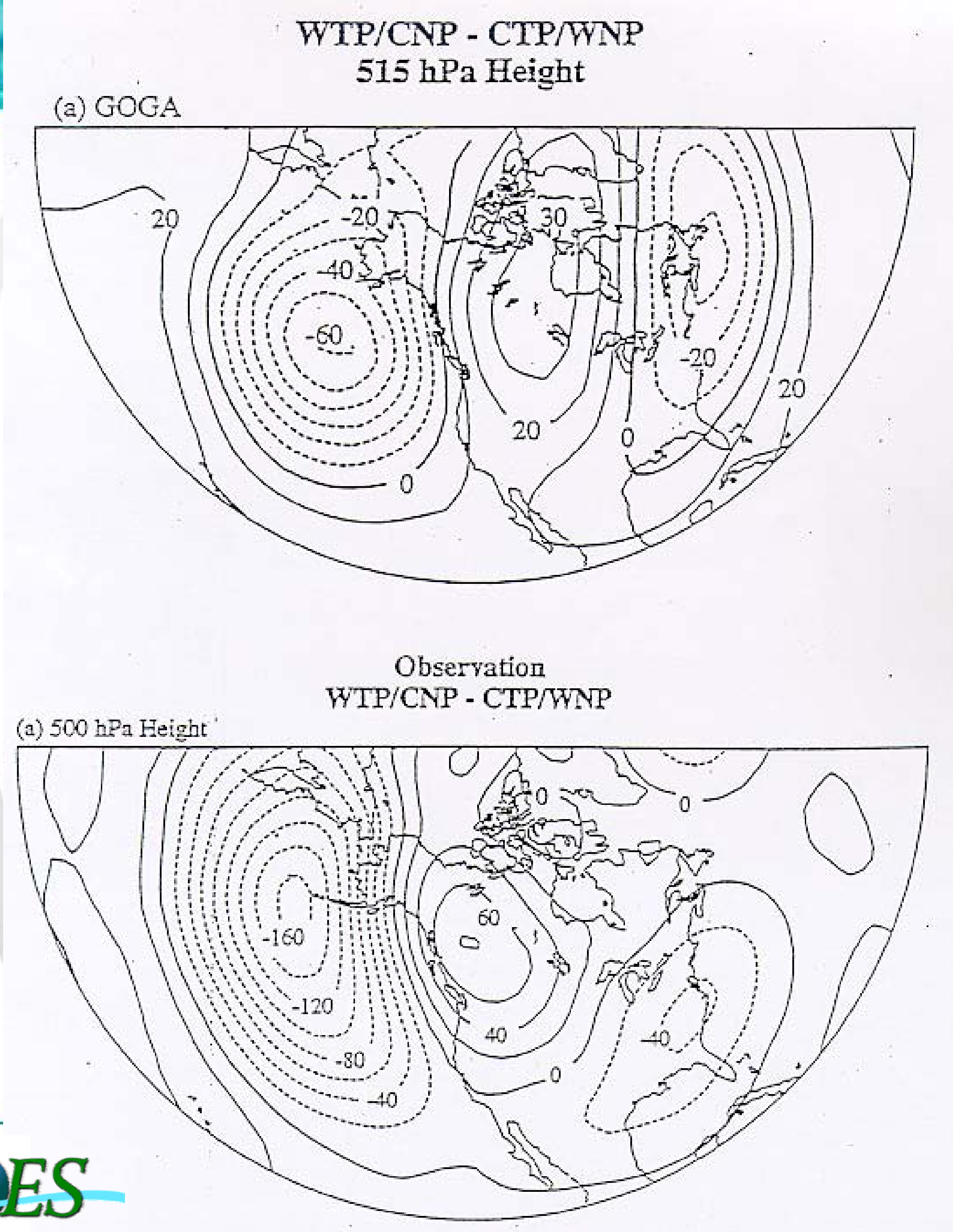
MRF9: Only high cloud allowed to exist over regions of tropical deep convection

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



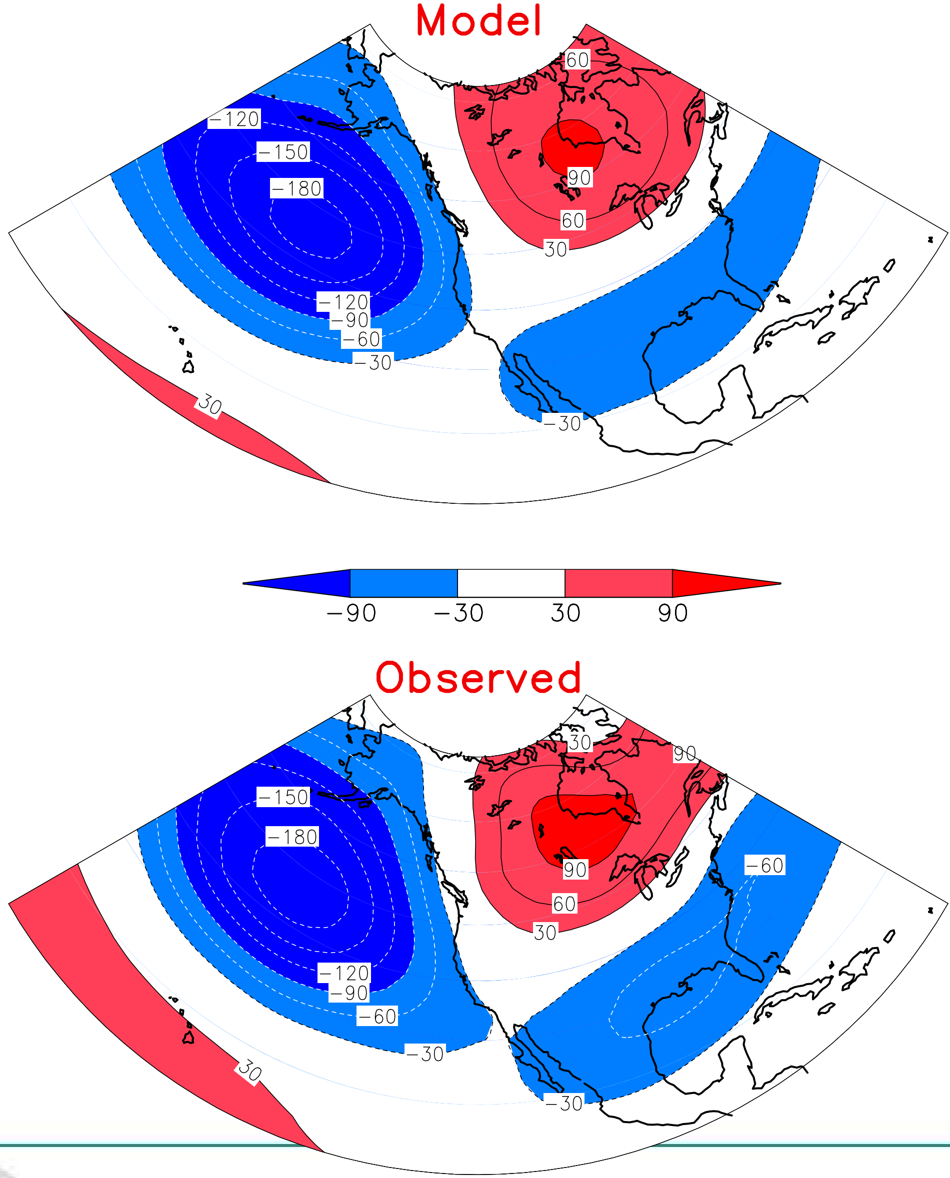
Note: amplitude of model response quite weak; structure is PNA rather than ENSO forced

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)

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EFFECTS OF SST ANOMALY

$\delta T(x,y)$ → $\delta Q(x,y,z)$ → δV

SST anomaly — heating anomaly — circulation anomaly

~ 5-7 days

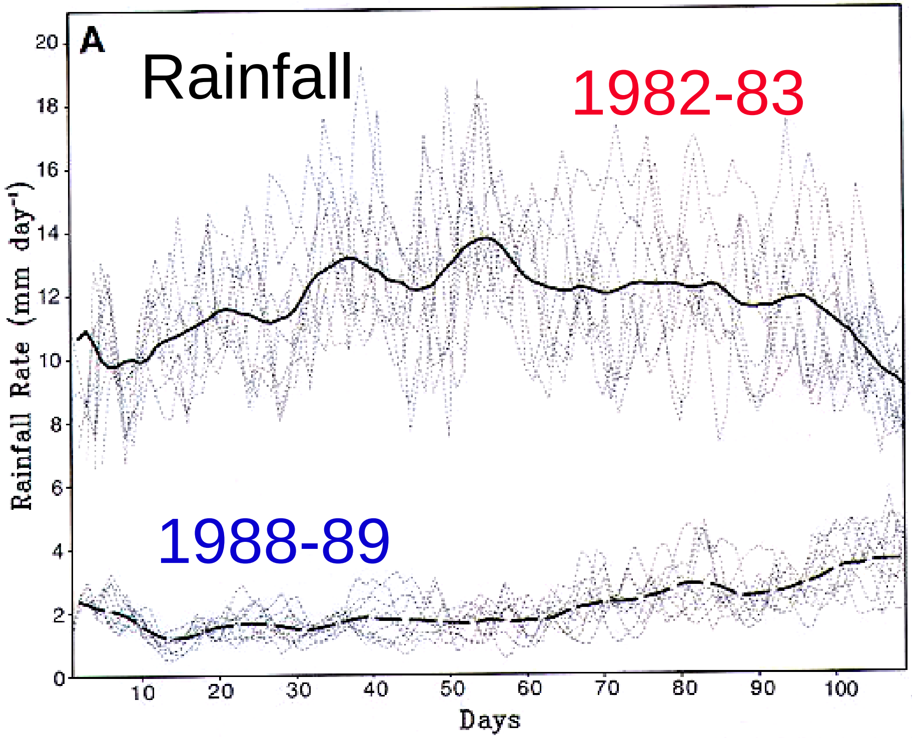
- δT (magnitude, structure)
- T (magnitude, structure)
- V (x,y,z): large scale flow
- δ (conv., div.):
  latitude regime (f)
- instability

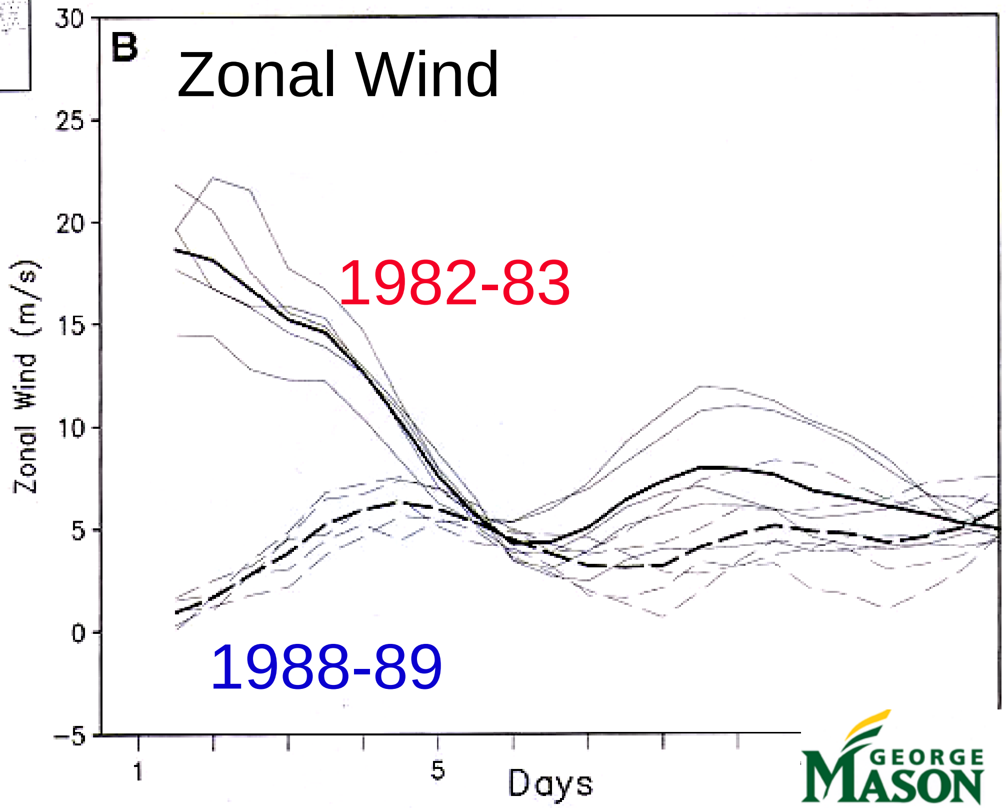
~ 10-30 days

- 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
  ($\delta Q \Leftrightarrow \delta U$)

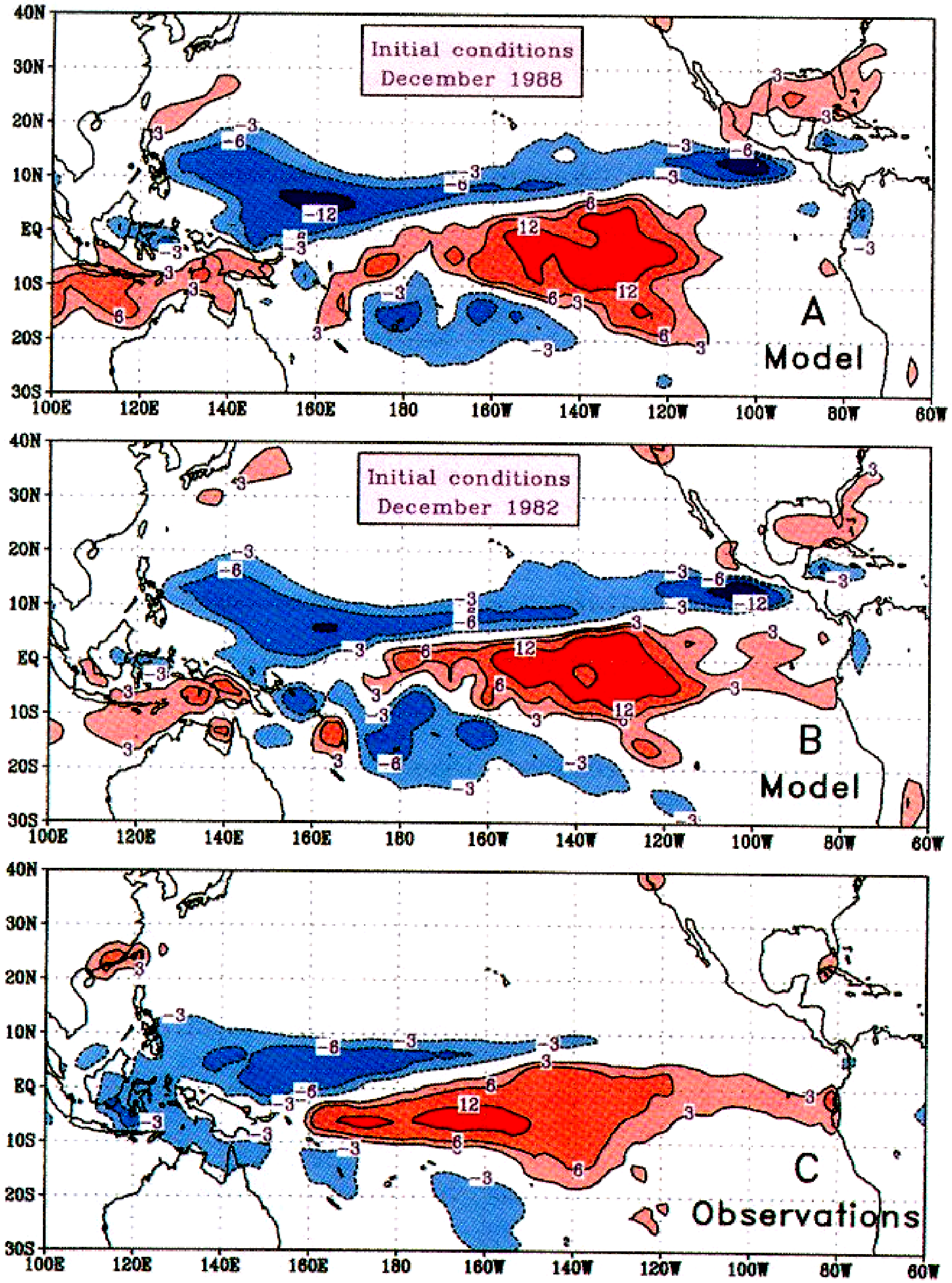
1. $\delta Q \Rightarrow \delta$(Hadley) $\Rightarrow \delta U \Rightarrow \delta$ (extratrop. stat. waves)
2. Forced Rossby waves
3. Normal modes

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).



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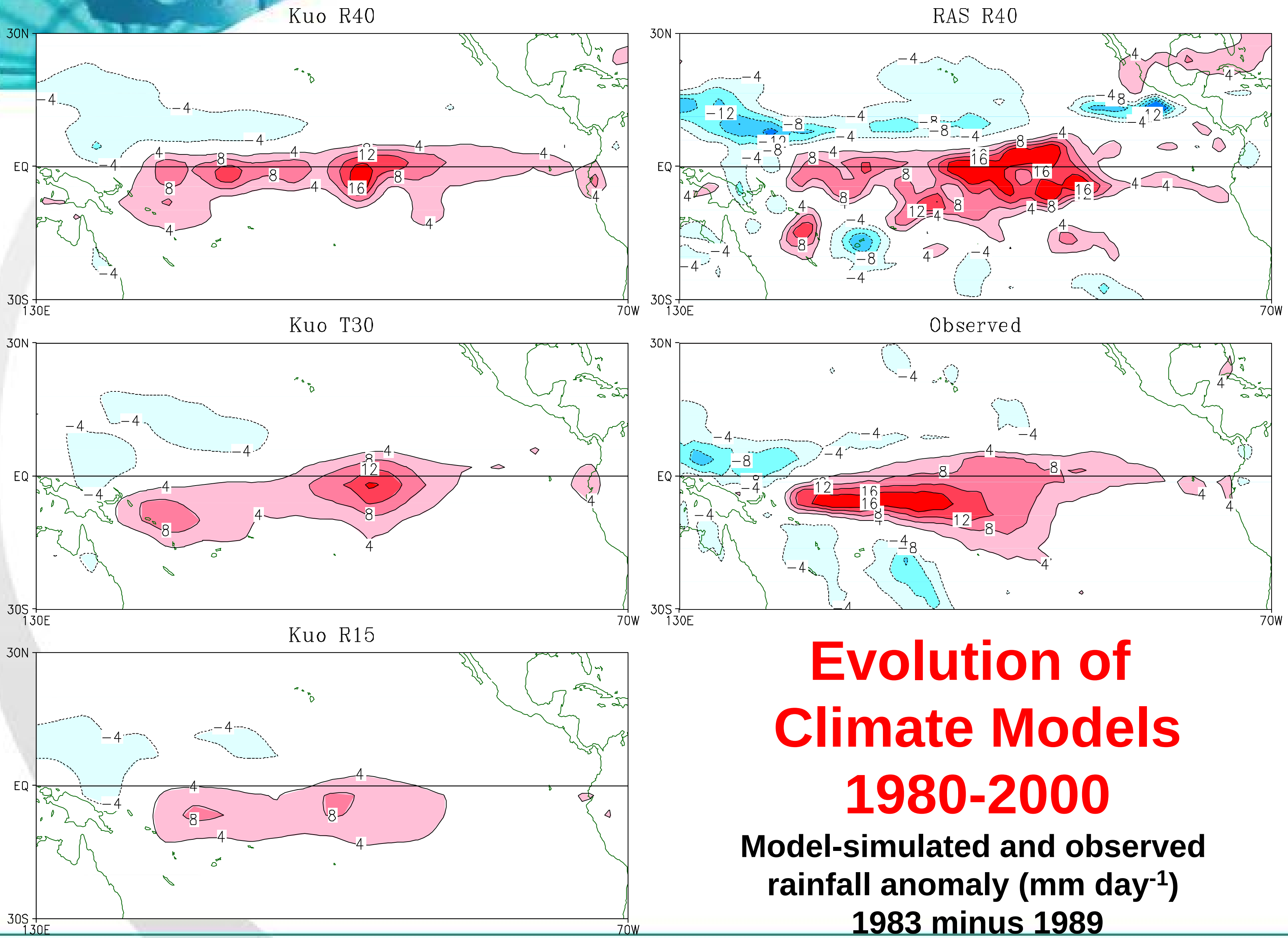
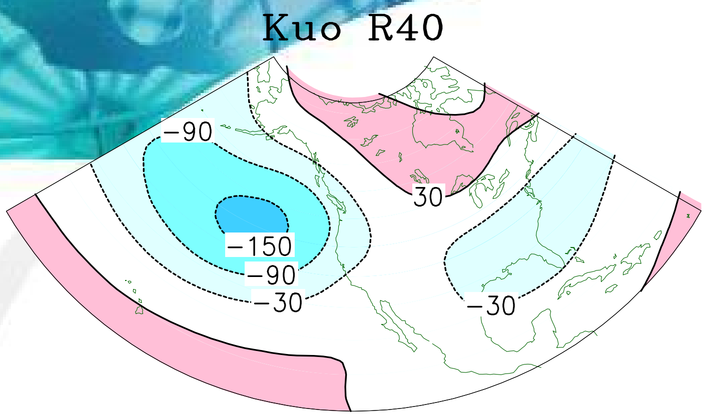
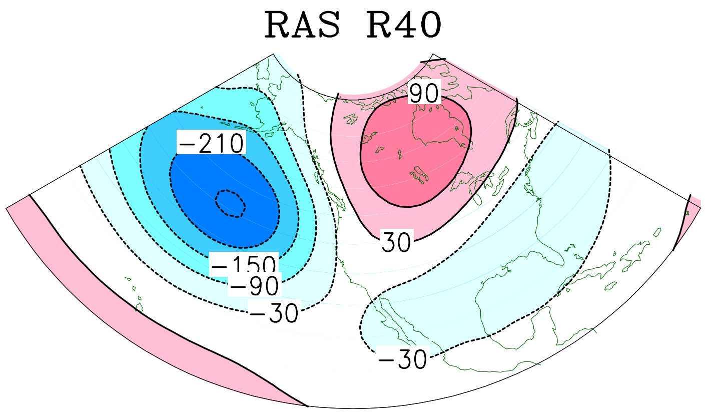


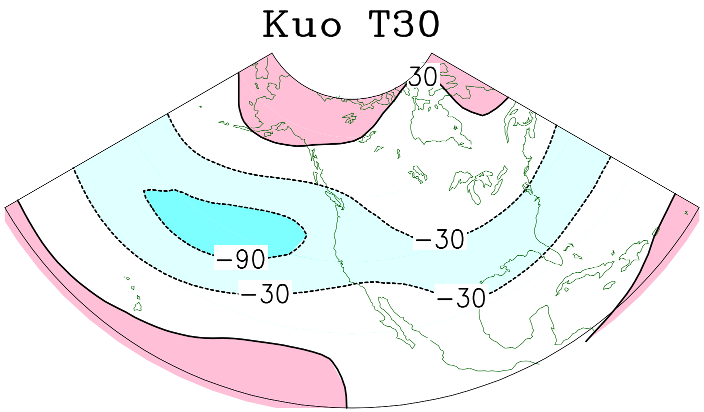
Evolution of Climate Models 1980-2000

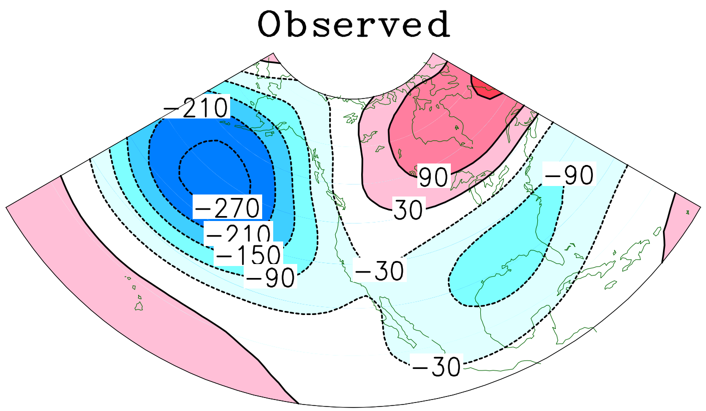
Model-simulated and observed rainfall anomaly (mm day^{-1})
1983 minus 1989

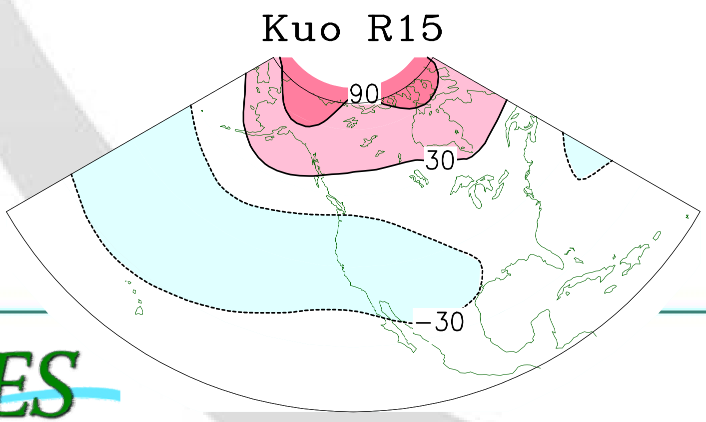
Center of Ocean-Land-Atmosphere studies











Evolution of Climate Models 1980-2000

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

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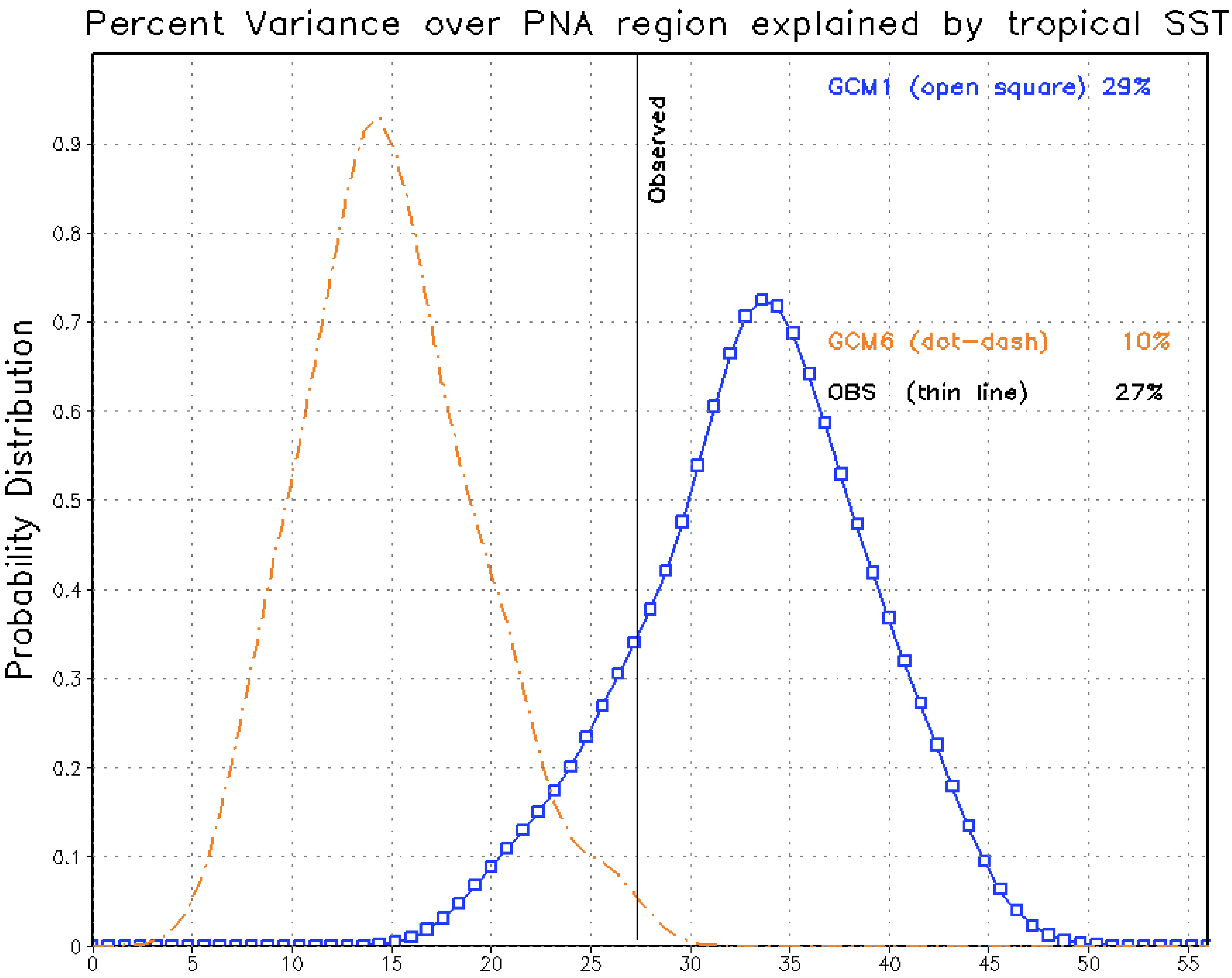
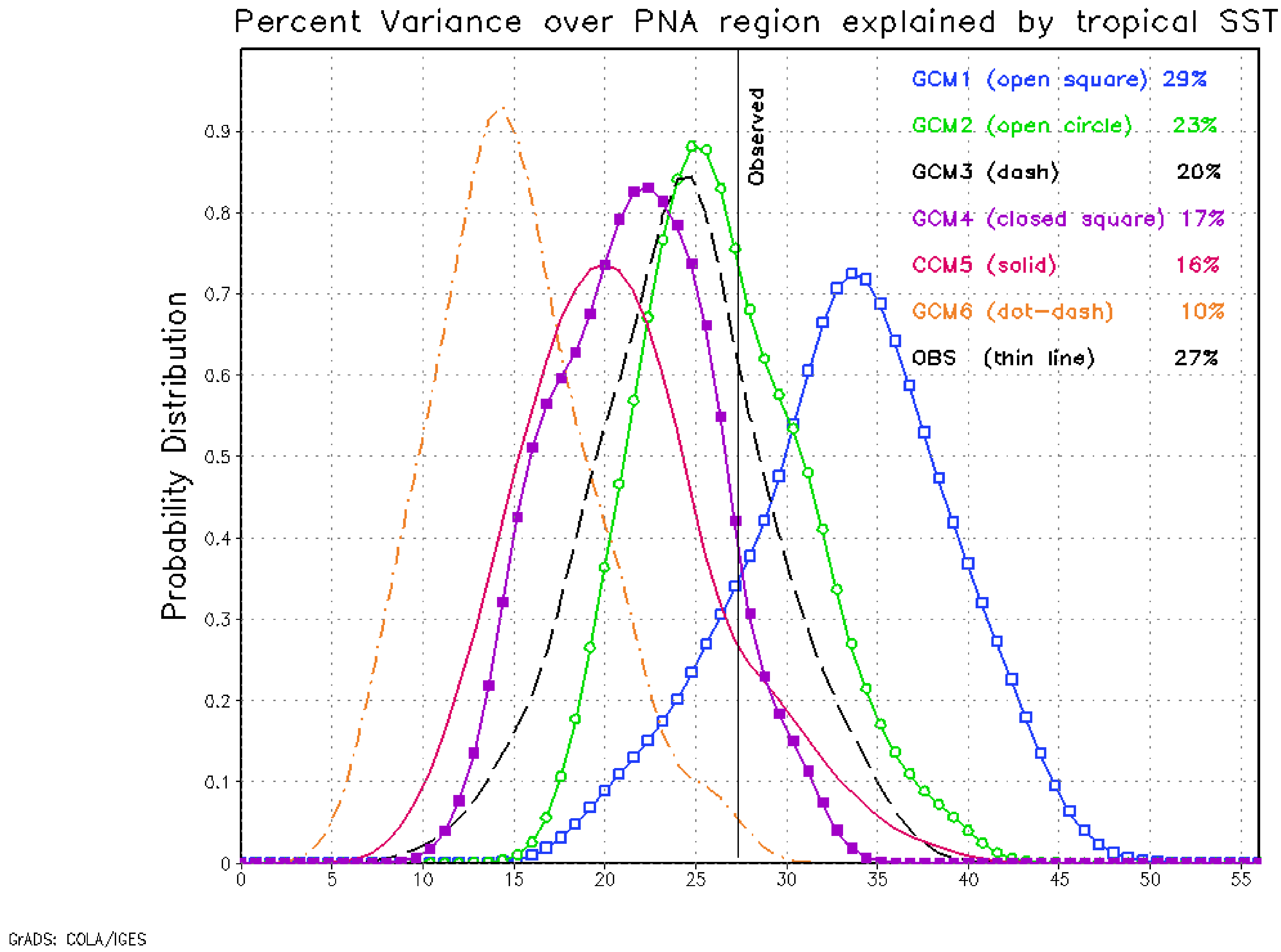
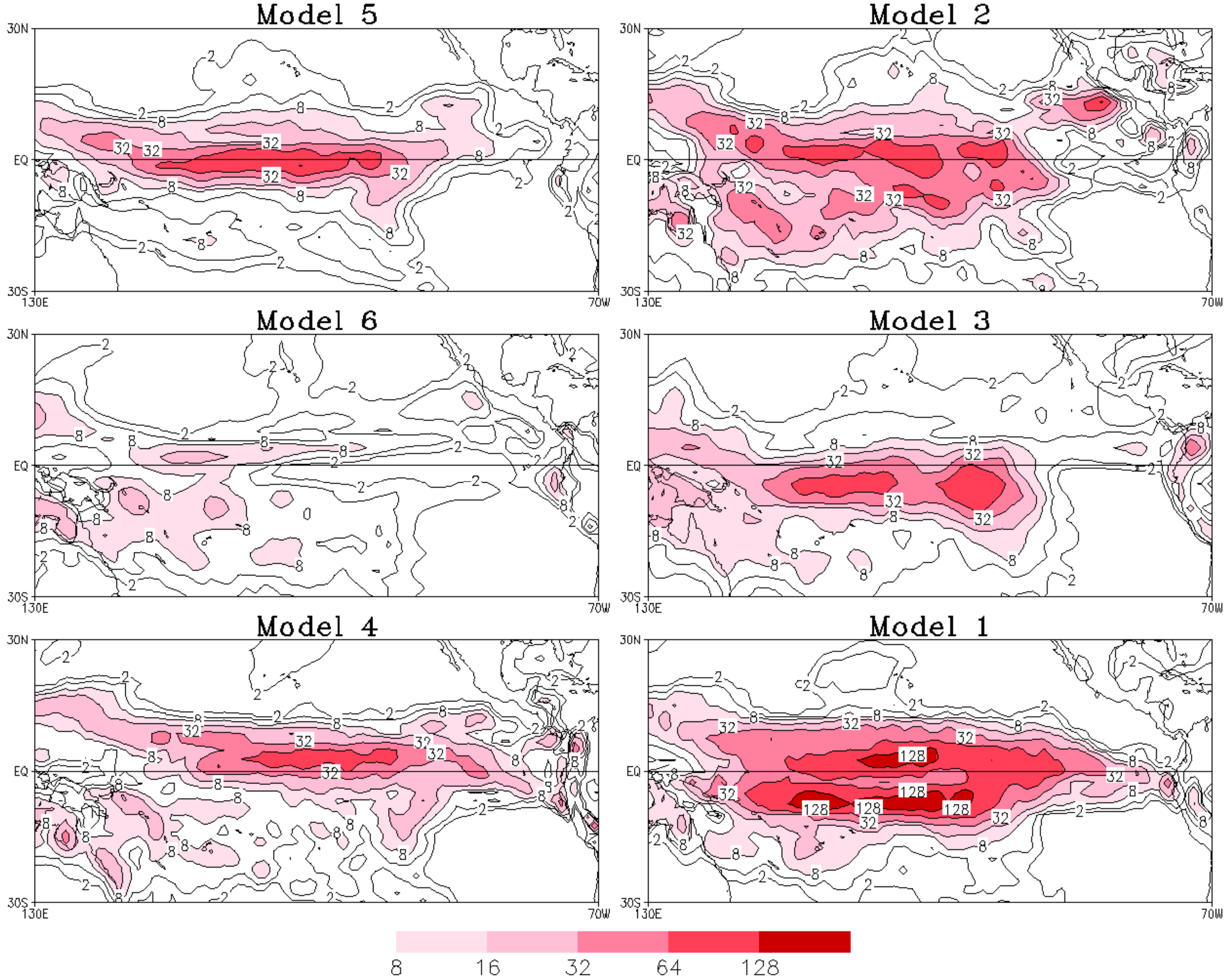


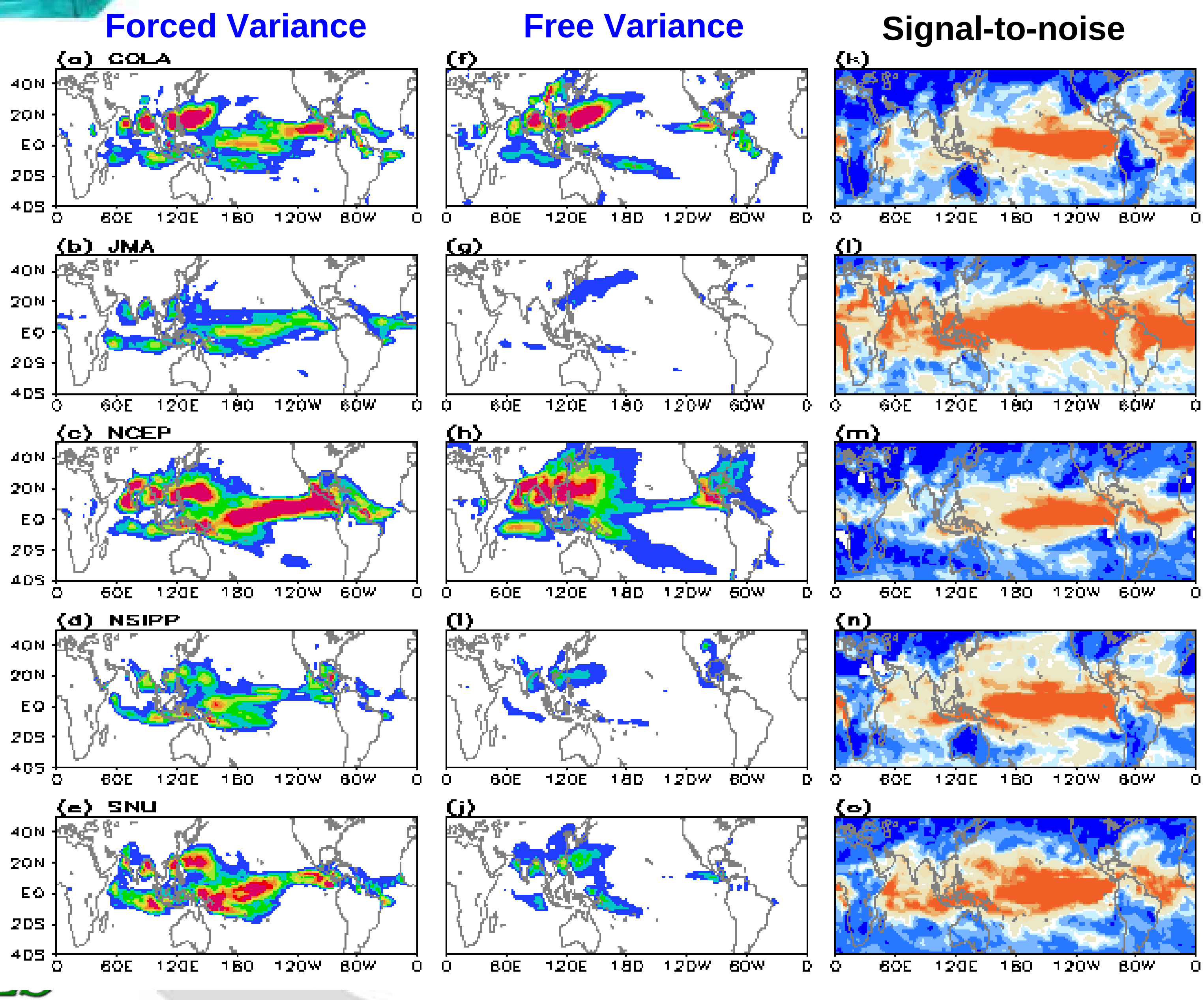
Percent Variance over PNA region explained by tropical SST
Probability Distribution
Observed
GCM1 (open square) 29%
GCM6 (dot-dash) 10%
OBS (thin line) 27%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
5
10
15
20
25
30
35
40
45
50
55


Percent Variance over PNA region explained by tropical SST
Probability Distribution
Observed
GCM1 (open square) 29%
GCM2 (open circle) 23%
GCM3 (dash) 20%
GCM4 (closed square) 17%
CCM5 (solid) 16%
GCM6 (dot-dash) 10%
OBS (thin line) 27%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
5
10
15
20
25
30
35
40
45
50
55
GrADS: COLA/IGES

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



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



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, Shingo, 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.

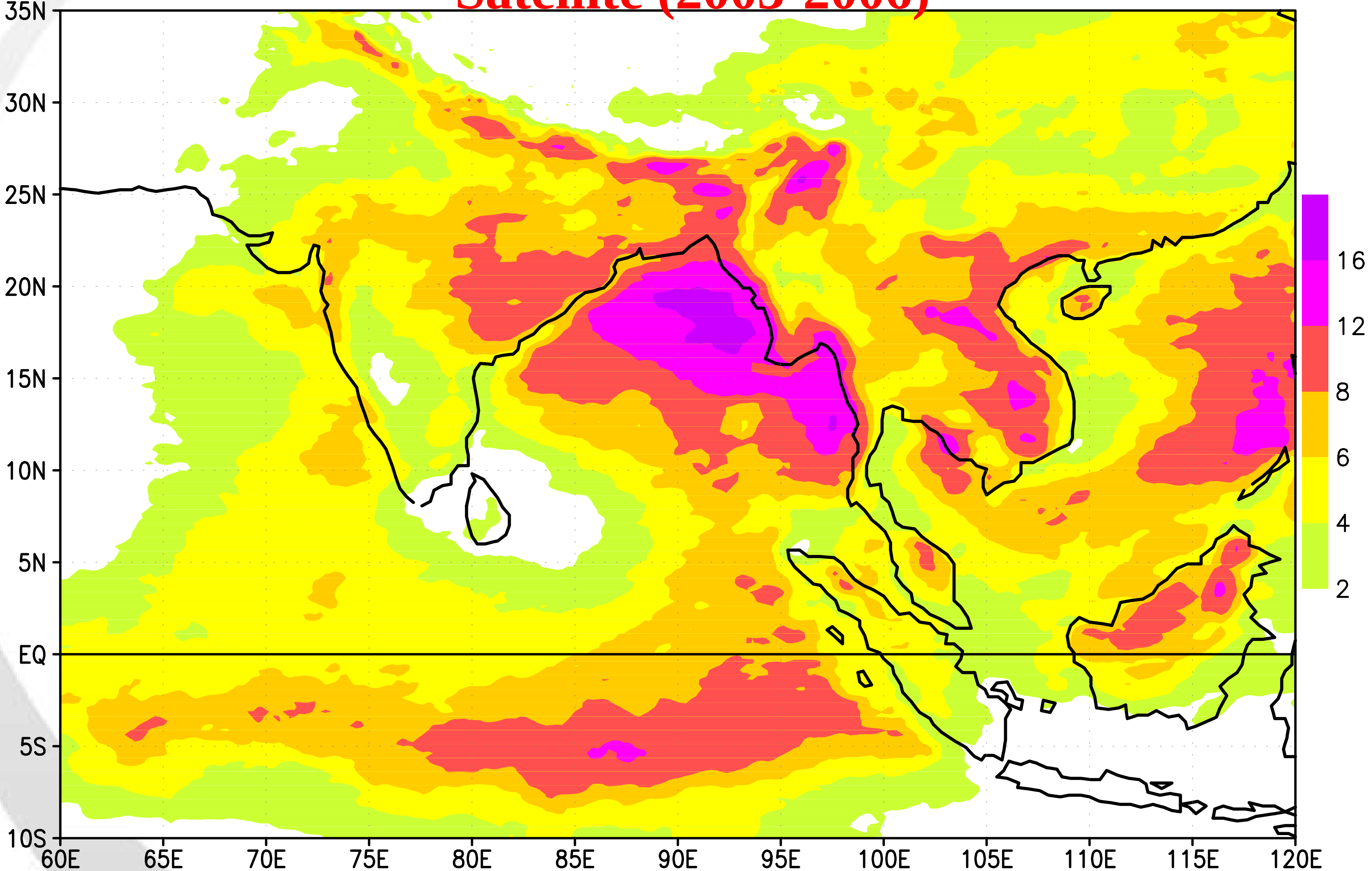
From Cyclone Resolving Global Models
to
Cloud System Resolving Global Models

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

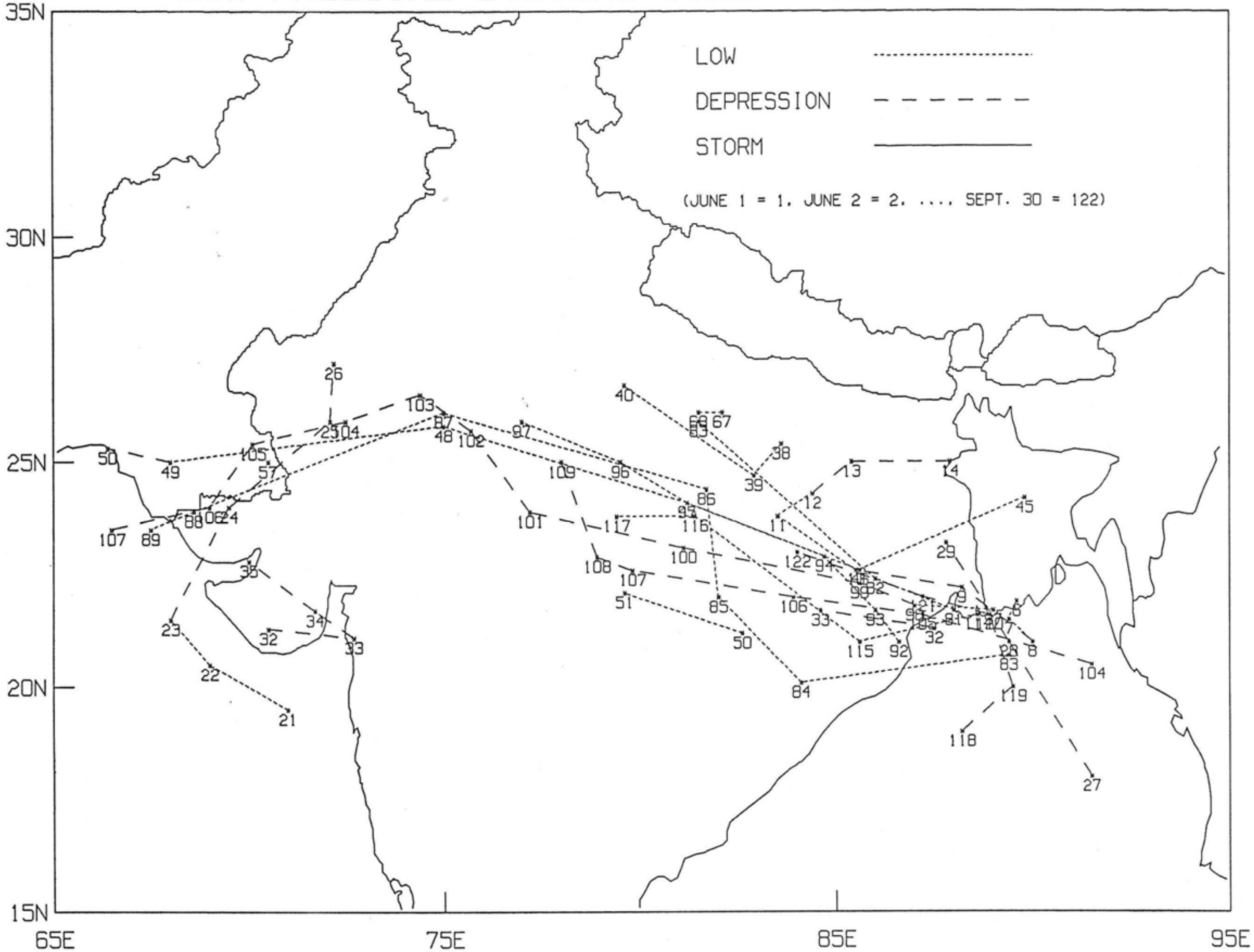
Organized Convection → Cloud System → Mesoscale System → Synoptic Scale → Planetary Scale

Convective Heating → MJO → ENSO → Climate Change

Observed Summer (JJAS) Precipitation (mm/day) from Satellite (2003-2006)



LOW PRESSURE SYSTEMS JUNE - SEPT. 1961



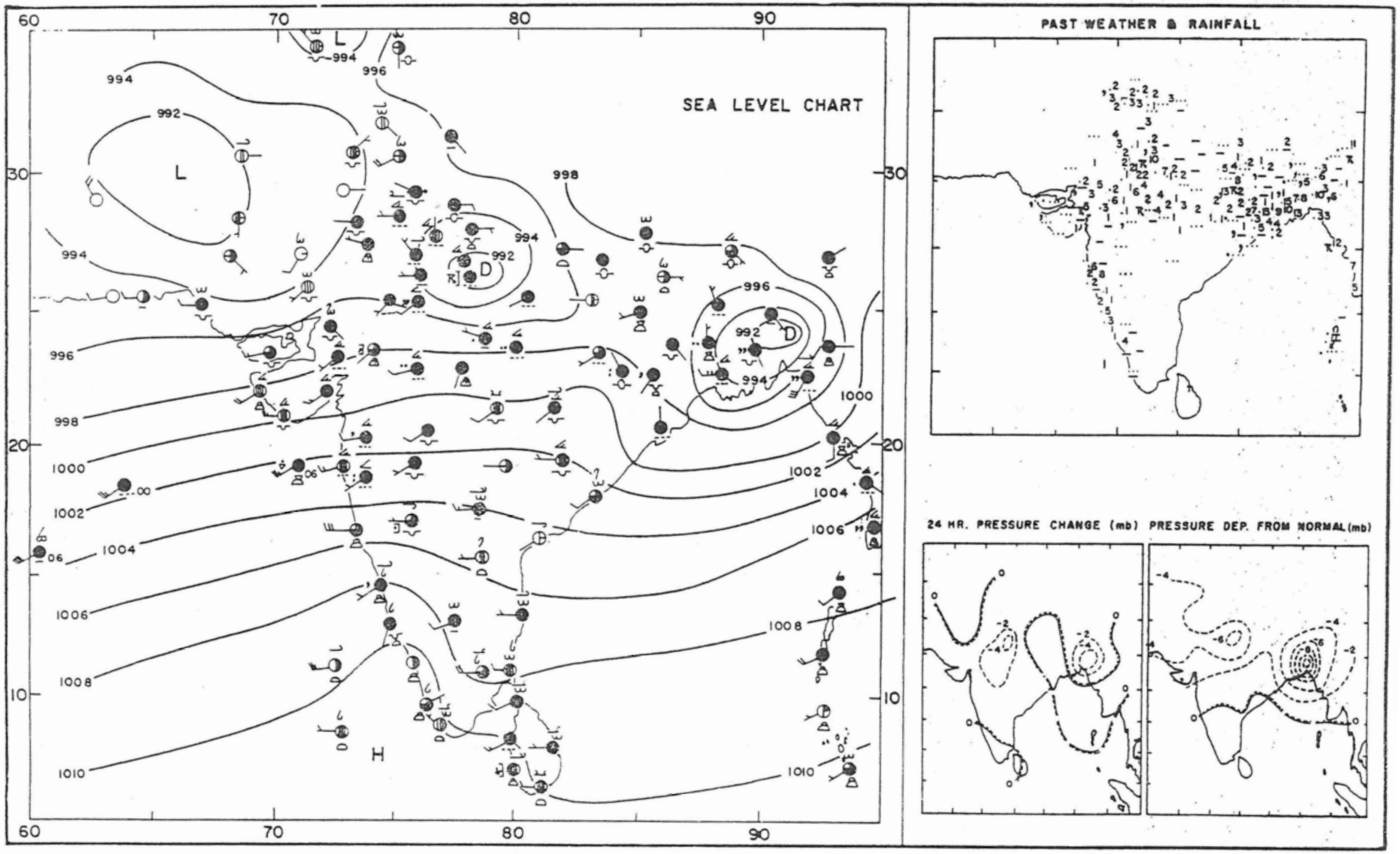
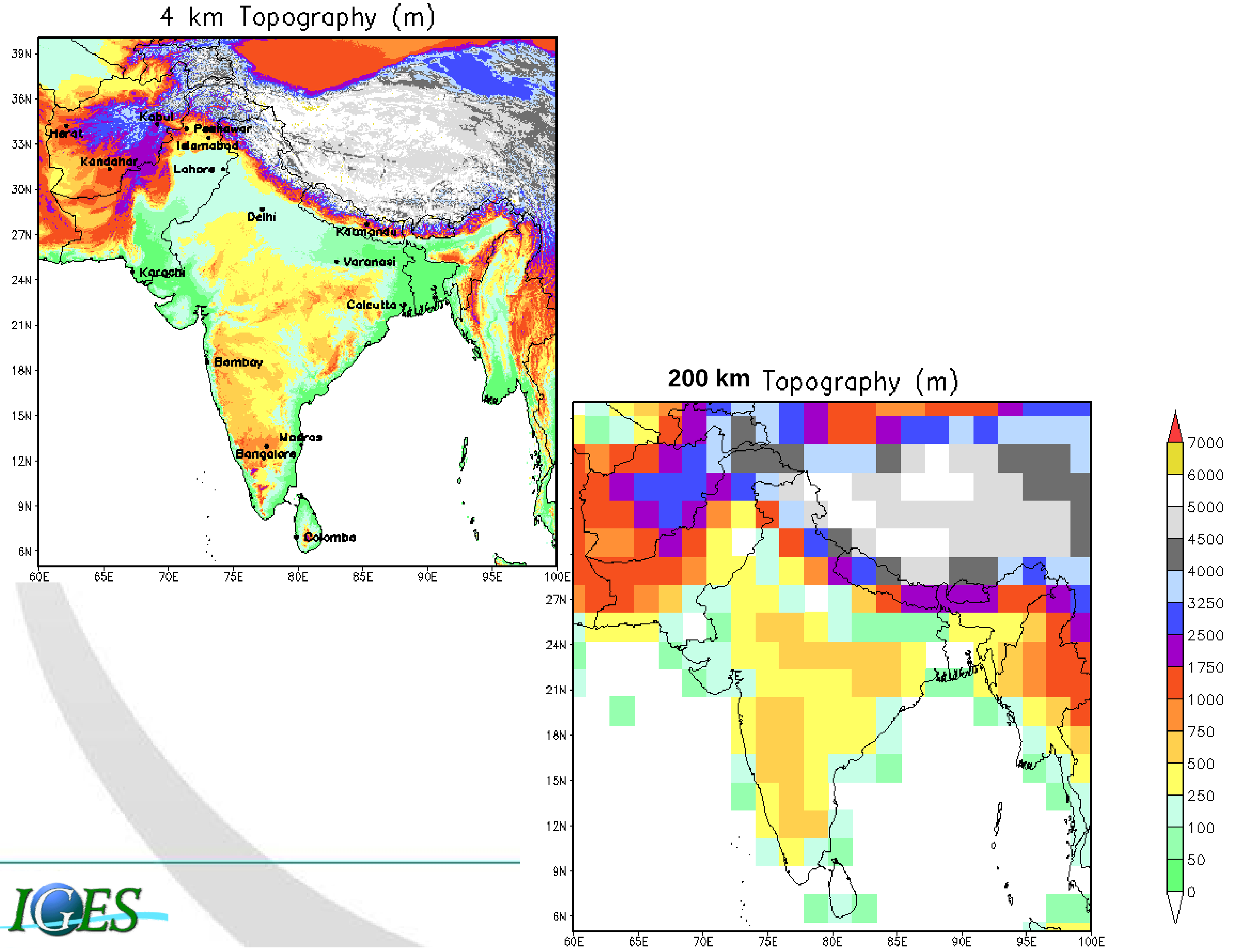


Fig.9.7(h) Synoptic charts 0300 GMT 10 July 1968.



4 km Topography (m)
Kabul
Herat
Peshawar
Islamabad
Kandahar
Lahore
Delhi
Katmandu
Varanasi
Karachi
Calcutta
Bombay
Madras
Bangalore
Colombo
200 km Topography (m)
7000
6000
5000
4500
4000
3250
2500
1750
1000
750
500
250
100
50
0

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**

THANK YOU!

ANY QUESTIONS?

2. Observations: We compare the models and observations in a state space defined by the leading 15 principal components of the observed seasonal mean surface temperature anomaly field derived from HADCRUT2 (the 5x5 gridded surface air temperature analysis of *Jones and Moberg* [2003]). This truncation for the PCs captures at least 65% of the variance of the seasonal means.

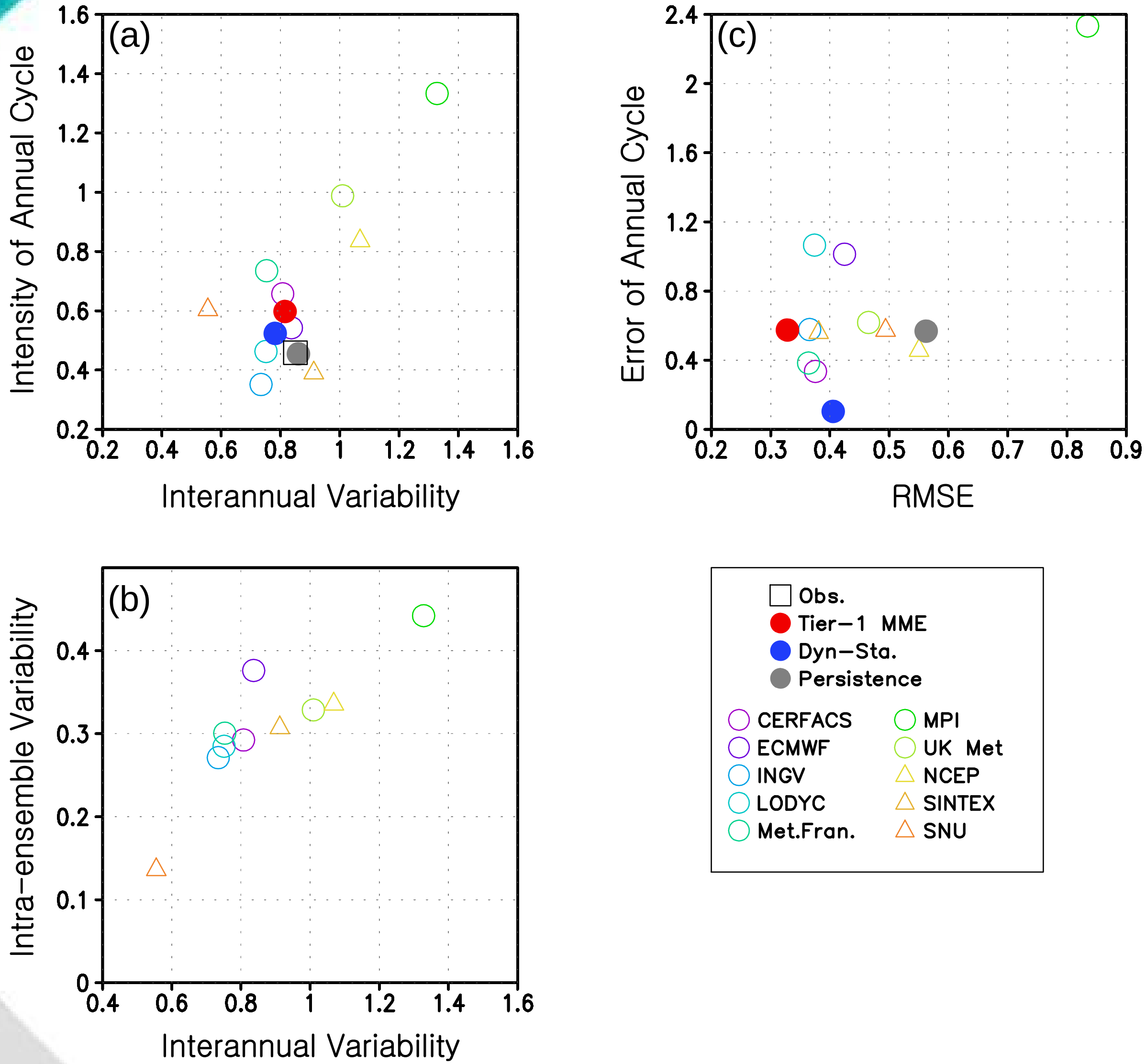
The principal components of observations were computed by first projecting all model fields onto the 5° x 5° observational grid and masking out regions of missing data, then multiplying the value at each grid point by the square root of the cosine of latitude so that the square of the value is weighted by area. The masking procedure eliminates all but 301 grid points. The resulting defined points cover most of North America, Europe, and India, and certain coastal regions of East Asia, South America, and Australia.

Climate Model Fidelity and Projections of Climate Change

3. Models: The 13 models (listed alphabetically: CNRM-CM3, GFDL-CM2.1, GISS-AOM, GISS-EH, GISS-ER, IPSL-CM4, MIROC3.2(hires), MIROC3.2(medres), MPI-ECHAM5, MRI-CGCM2.3.2, NCAR-CCSM3, NCAR-PCM, UKMO-HadCM3 were chosen for this study based on data availability at the time of the analysis.

The model sensitivity is defined as the area-weighted model global average of the change in surface air temperature between the 720 ppm stabilization experiment (A1B; years 71-100 average) and the twentieth century (20C3M) integration (years 1971-2000). The scenario A1B includes a 1% per year increase in CO_2 concentration, until year 70, after which the concentration is held constant at a value of 720 ppm.

4. Conclusion: If we conjecture that models that better simulate the present climate should be considered more credible in projecting the future climate change, then this relationship suggests that the actual changes in global warming will be closer to the highest projected estimates among the current generation of models used in IPCC AR4.



Jin et al. (2007)