The Abdus Salam International Centre for Theoretical Physics

United Nations Educational, Scientific and Cultural Organization

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2050-5

Targeted Training Activity: Predictability of Weather and Climate: Theory and Applications to Intraseasonal Variability

27 July - 7 August, 2009

Seasonal Mean Predictability over the Pacific - North American Region

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International Centre for Theoretical Physics

Targeted Training Activity:

Predictability of Weather and Climate

David M. Straus

(1) The Global Atmospheric Circulation: Observations

(2) Modeling the Weather and Climate

(3) Errors in Forecasts: Roles of Initial States, Model Errors, and Chaos

(4) Climate Predictability on Seasonal Time Scale: Role of Boundary Forcing

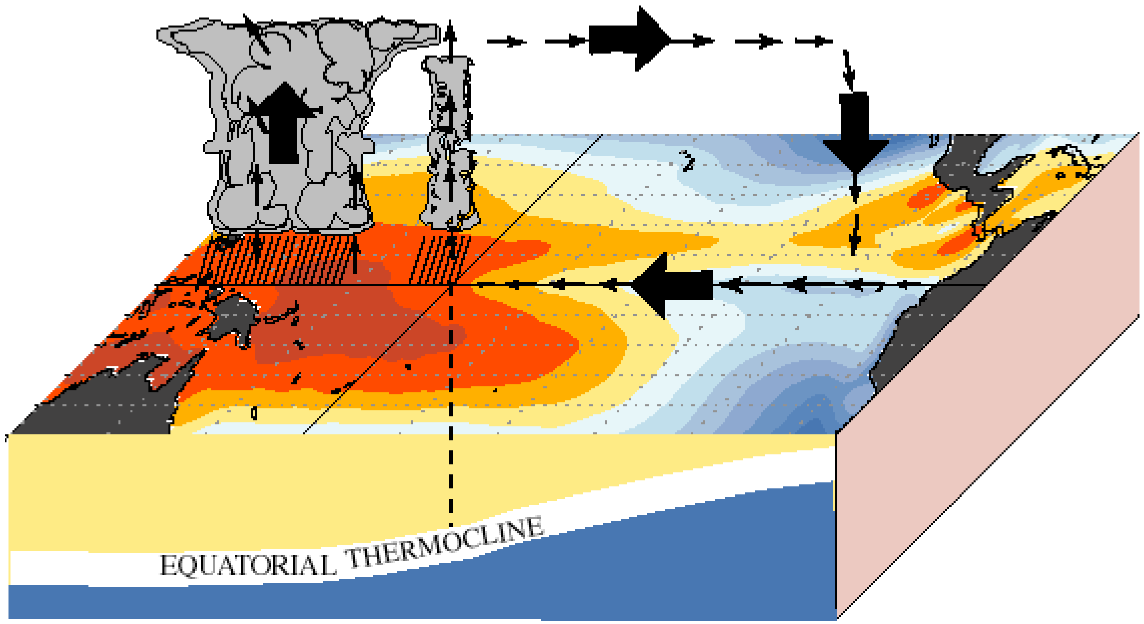
(5) Seasonal Mean Predictability over the Pacific - North American Region

Normal Winter Conditions, Equatorial Pacific

“Walker Circulation” driven by sea surface temperature gradient

Rainy west

in West, “warm pool” of surface water



Dry east

in East, “cold tongue” of water upwells from below

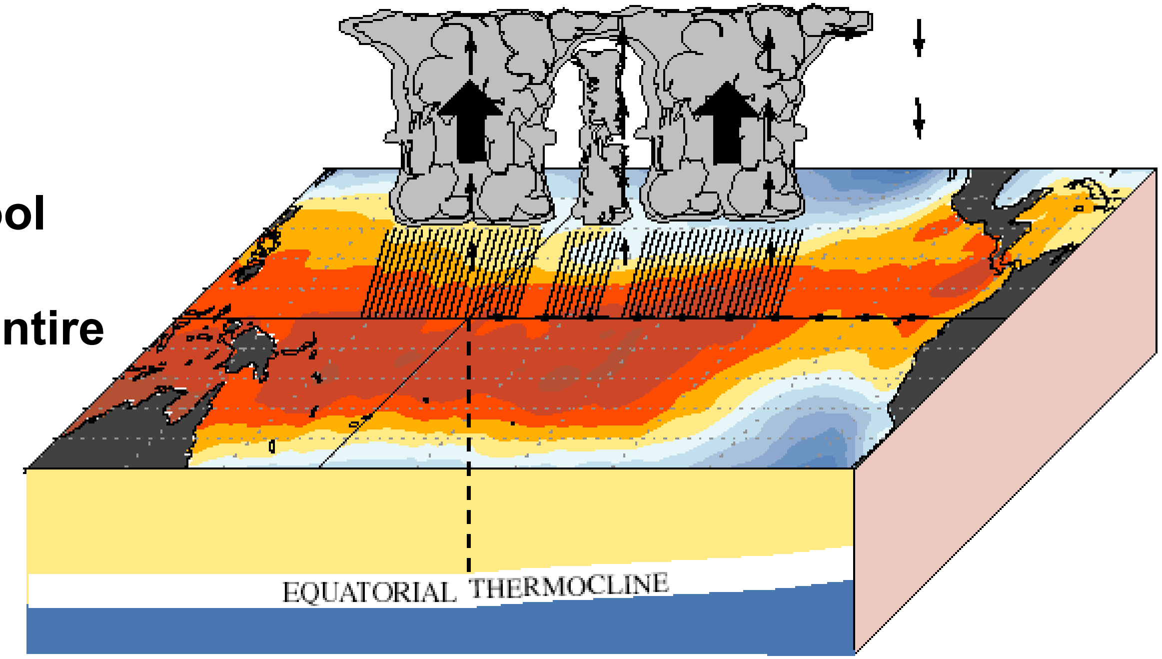
Thermocline tilt/upwelling driven by westward wind stress

www.cpc.ncep.noaa.gov/products/analysis_monitoring/impacts/warm_impacts.html

El Nino Winter Conditions, Equatorial Pacific

Warm SSTs in the Eastern Pacific -->Increased evaporation in the Eastern Tropical Pacific, increased deep convection and rainfall, increased rising motion, and finally increased tropical divergence near the top of the troposphere

warm pool extends across entire Pacific

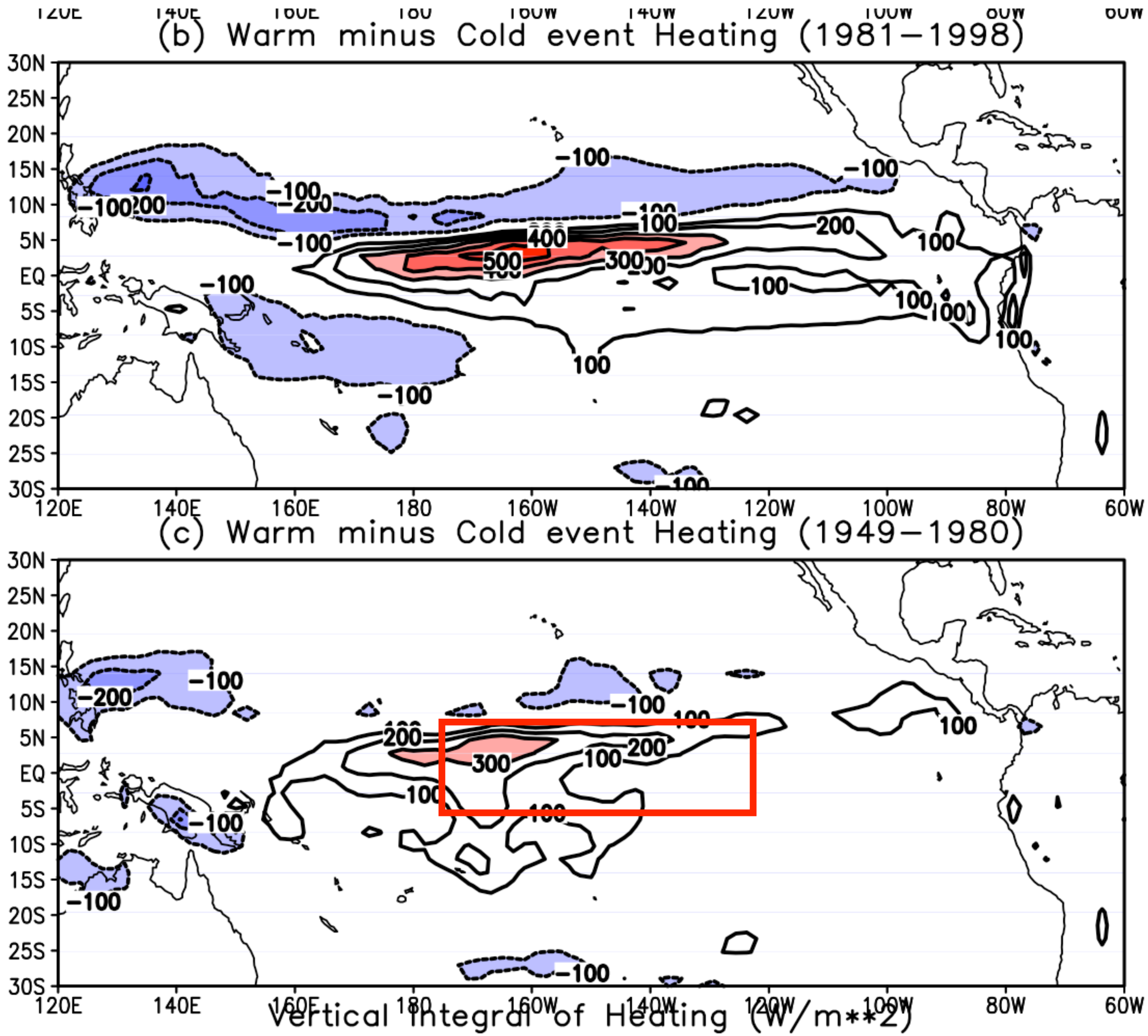


cold tongue disappears

weakening of westerlies allows flattens thermocline, weakens upwelling

www.cpc.ncep.noaa.gov/products/analysis_monitoring/impacts/warm_impacts.html

C20C simulations with COLA AGCM



Warm and Cold events identified by value of SST averaged over box (Nino3.4 index)

ENSO SST variability is caused by coupled atmosphere-ocean interaction

BUT

The *effects* of these SST variations can be studied by atmospheric models (AGCMS) forced by given SST variability.

Why?

In the central and eastern Pacific, although the atmosphere and ocean interact strongly on inter-annual time scales, the ocean forces the atmosphere fairly strongly on seasonal and sub-seasonal time scales.

There are many regions where the atmosphere forces the ocean on seasonal and intra-seasonal time scales:

- The Indian Ocean - where once the summer Monsoon winds have been set up, they can lead to increased evaporation from the Indian Ocean, which leads to cooling of the ocean

- The North Pacific, where atmospheric wind stress is an important forcing of the ocean

The path for ENSO SSTs to affect mid-latitudes

Step 1: During El-Nino, the (anomalous) latent heating due to deep convection in the mid-Pacific is balanced by upward vertical motion.

To see this we examine the thermodynamic equation: $T\frac{ds}{dt} = Q$ or

$$\frac{\partial\theta}{\partial t} + u\frac{1}{a\cos(\phi)}\frac{\partial\theta}{\partial\lambda} + v\frac{1}{a}\frac{\partial\theta}{\partial\phi} + \boxed{\omega\frac{\partial\theta}{\partial p} = \frac{Q}{c_p}}$$

where θ is potential temperature, s is entropy per unit mass, $s = c_p \log(\theta)$

ω= dp/dt (the vertical velocity in pressure coordinates), Q is the rate of latent heating, and we also have:

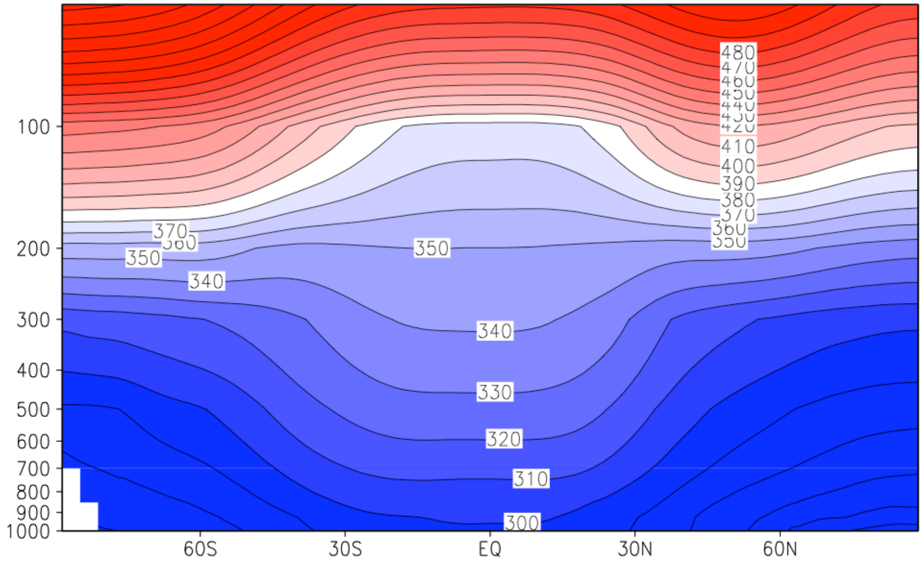
$$\theta = \left(\frac{p_0}{p}\right)^{\kappa} T \quad \kappa = R/c_p$$

where R is the gas constant and c_p = 7/2 R the specific heat at constant pressure of an ideal gas.

The dominant balance is given in the blue box (for the tropics). Since $\frac{\partial\theta}{\partial p} < 0$

we have that $\omega < 0$, which corresponds to *upward motion*.

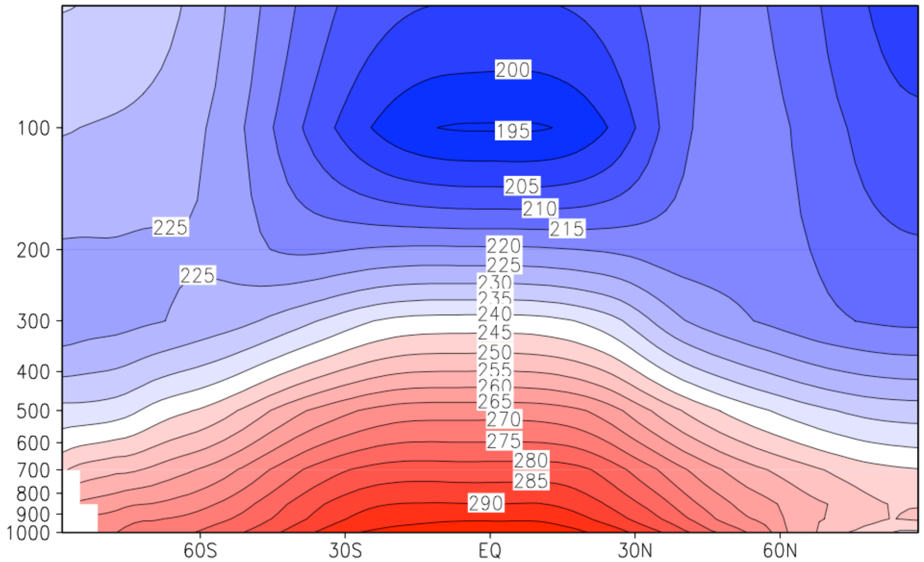
$$[\theta] = [T]\left(\frac{p_0}{p}\right)^{\kappa}$$



Both θ and T decrease towards the poles - but while T decreases with altitude,

θ increases with altitude - hence θ decreases with pressure

$$[T]$$

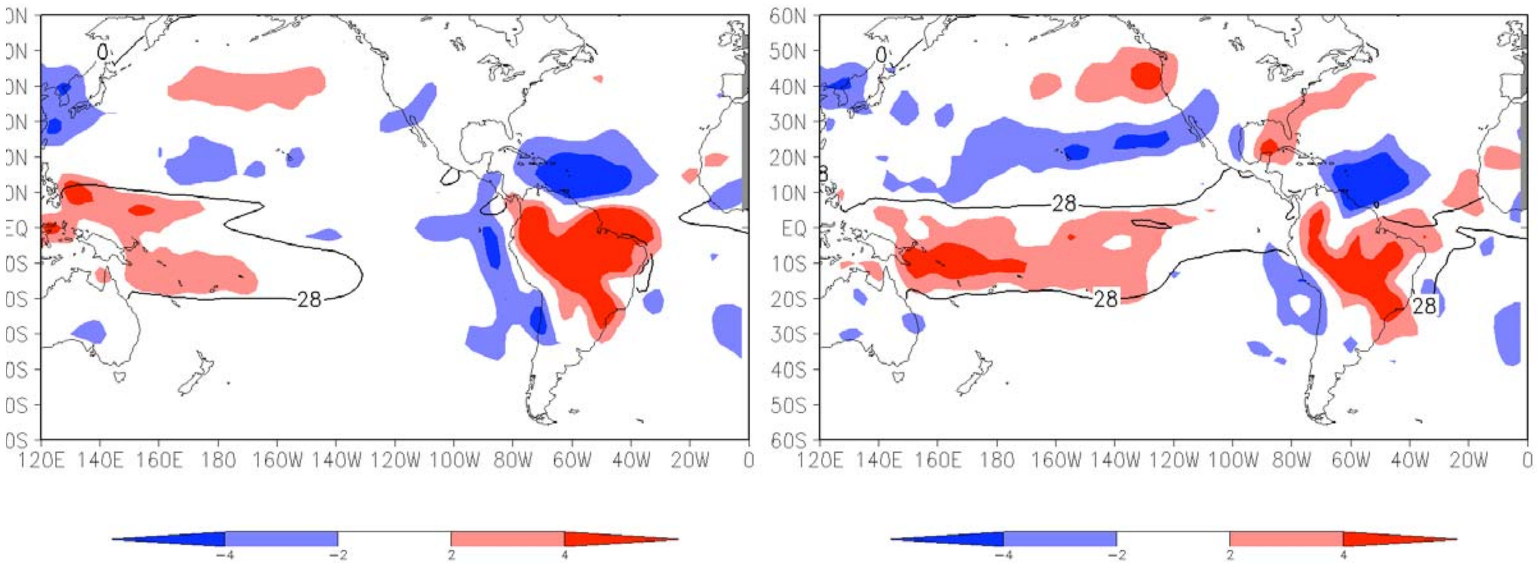


- vertical coordinate is log (p)
- zonal means are computed at constant pressure.

The path for ENSO SSTs to affect midlatitudes: Step 1 - continued

Increased Rising Motion in the Tropical Eastern Pacific Leads to increased upper-level (200 hPa) divergence of flow.

JFM seasonal mean 1982-2002 | Mean of JFM 1983 and 1998
Normal Conditions *for winter* | **Warm Event (avg. of obs)**



Shading: Winter Mean upper level divergence (CI=2.0 x 10^{-6} 1/s)

SST Isotherm of 28 C is shown (warmer water allows convection)

Step 2 of the path:

How do we understand the response to deep heating / upper level divergence anomalies?

In nature, we refer to the “stationary response” as the seasonal mean of a time-varying response.

In idealized “stationary wave” models, we look for the true steady state (time-independent) response. (In these models baroclinic instability is eliminated by using large damping / dissipation.

Another approach:

Turn on the heating at t=0 in a full primitive equation model where the initial conditions correspond to the observed time mean circulation, and *measure the the mid-latitude response to the heating after 1 - 2 weeks* (before baroclinic instability has grown too strong).

The Direct Response to Tropical Heating in a Baroclinic Atmosphere by Feifei Jin and Brian J. Hoskins, *Journal of the Atmospheric Sciences* Volume 52, Issue 3 (February 1995) pp. 307–319

An example of stationary Rossby waves at upper levels

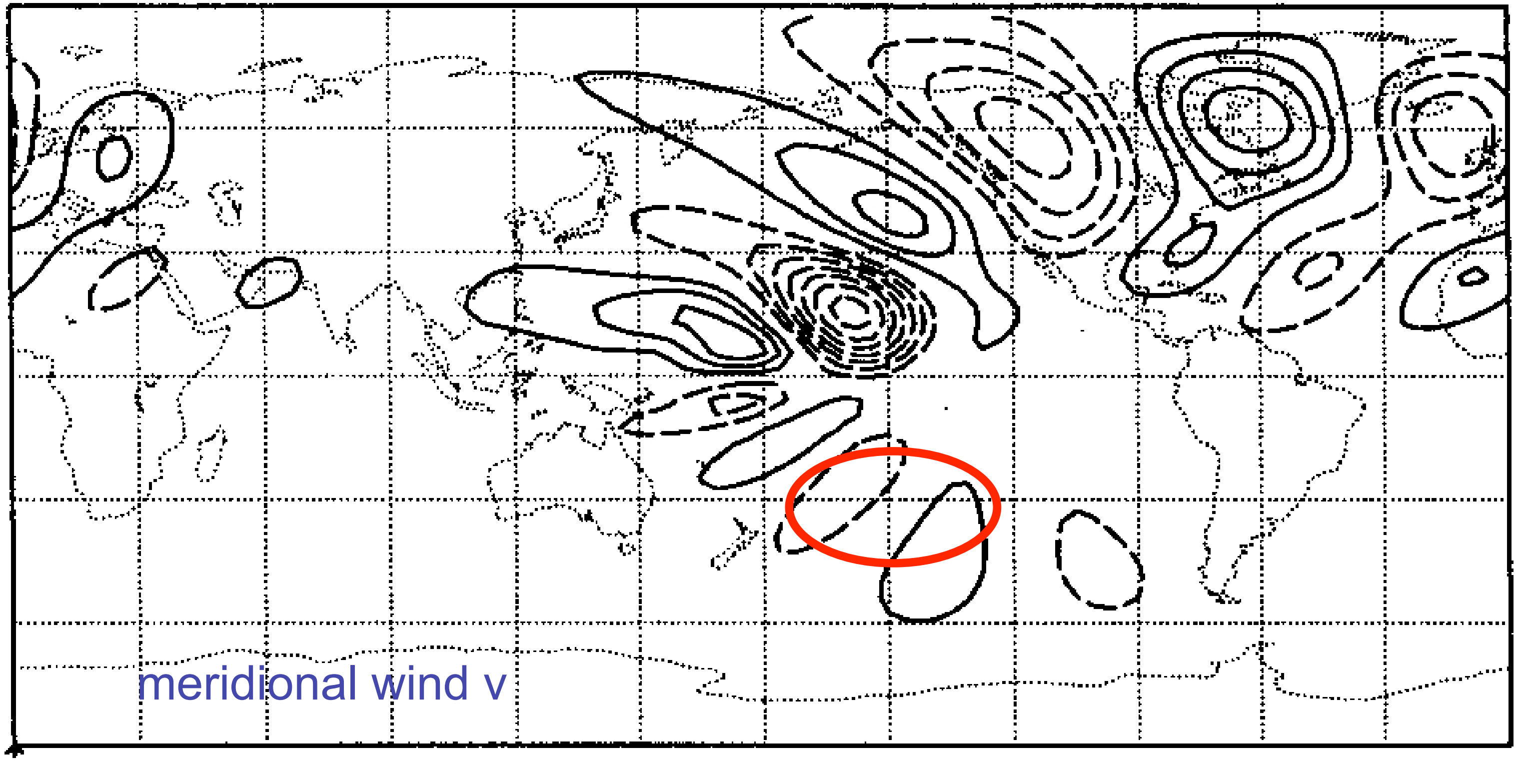


FIG. 8. Longitude–latitude picture of the day 15 $\sigma \approx 0.24$, meridional wind perturbation for the heating on a Dec–Feb zonal flow. The contour interval is 0.5 m s^{-1}. The zero contour is not shown, and the negative contours are dashed.

$$
\begin{aligned}
v &= \frac{1}{a\cos(\phi)}\frac{\partial\psi}{\partial\lambda} \\
\psi &= \sum_m (A_m\cos(m\lambda) + B_m\sin(m\lambda)) \\
v &= \sum_m \frac{m}{a\cos(\phi)}(A_m\cos(m\lambda) + B_m\sin(m\lambda))
\end{aligned}
$$

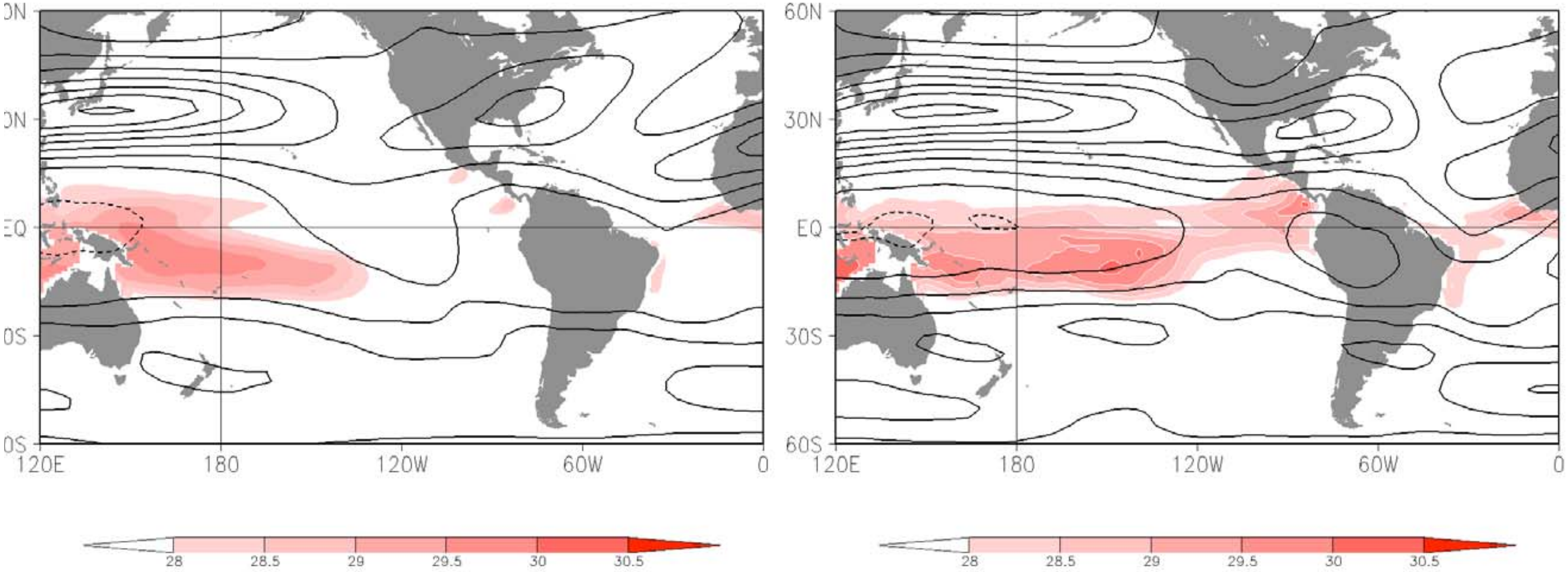
The meridional wind v emphasizes the smaller scale features compared to the streamfunction (or height) field. (Sum above is weighted by wavenumber m)

Part of interest in ENSO warm event is what it does to midlatitudes:

Extension of Pacific Jet

Normal Conditions: JFM seasonal mean 1982-2002

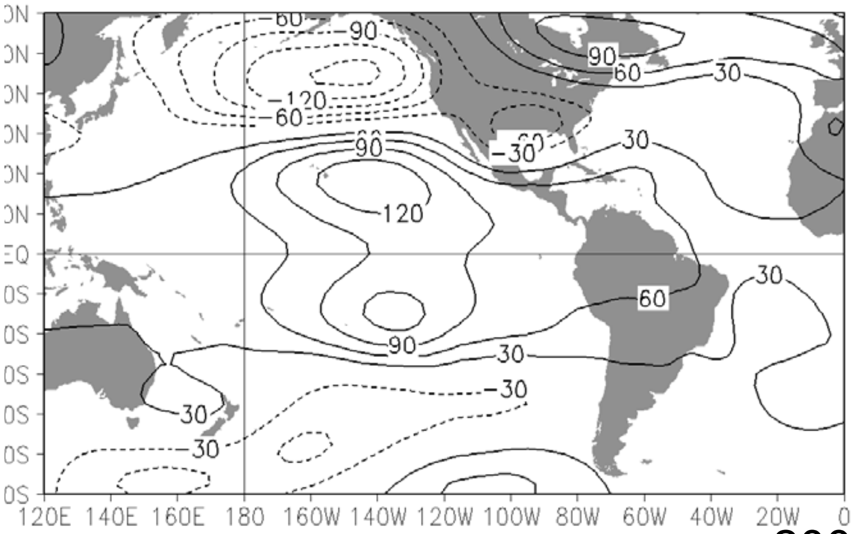
ENSO Warm event (avg of obs) Mean of JFM 1983 and 1998

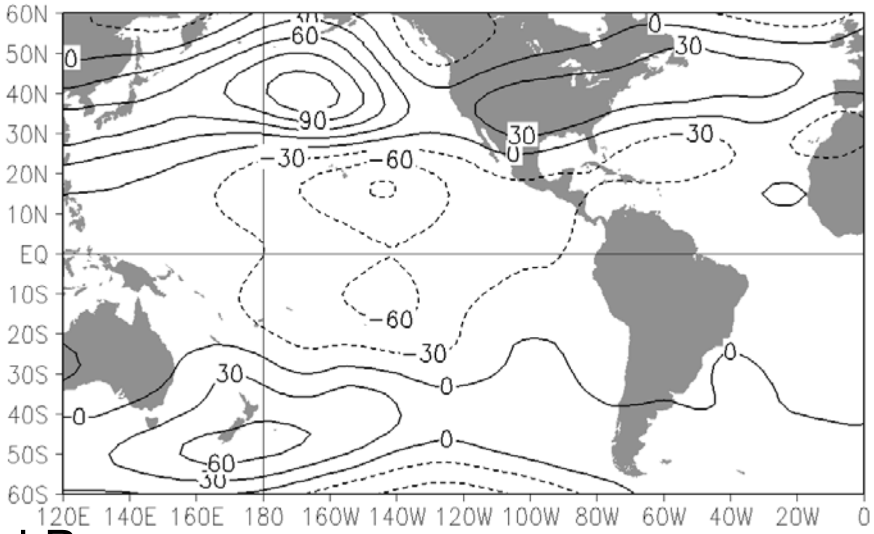


Contours are jets: Winter mean 200 hPa zonal wind (CI=10 m/s)

Shading is SST in degrees C

Height anomalies = departure of JFM seasonal mean Z from long-term mean





200 hPa

El-Nino (warm SST) events

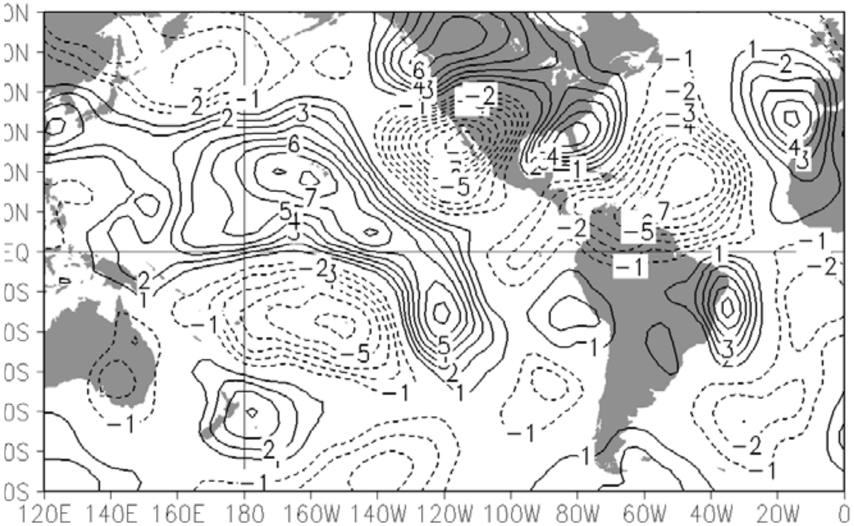
(avg of 1983, 1998)

La-Nina (cold SST) events

(avg of 1989, 1999)

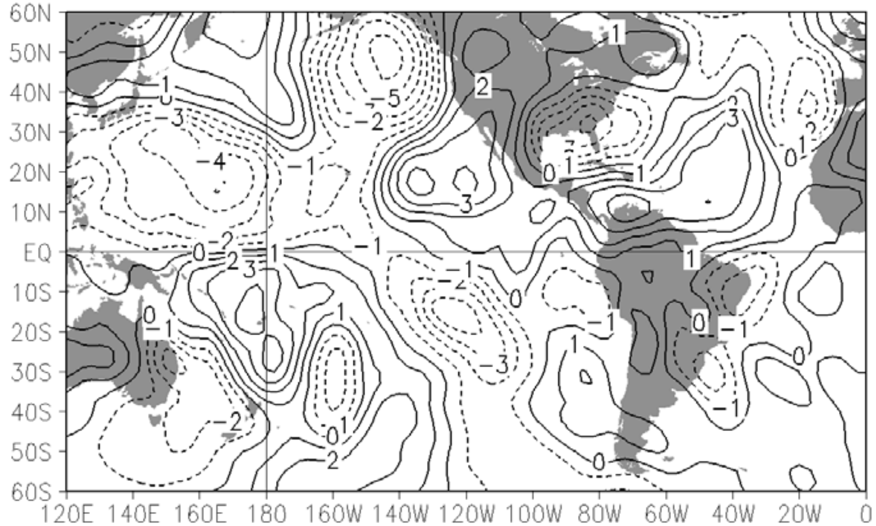
El-Nino (warm SST) events

(avg of 1983, 1998)



La-Nina (cold SST) events

(avg of 1989, 1999)



Meridional wind v
Anomalies (JFM)

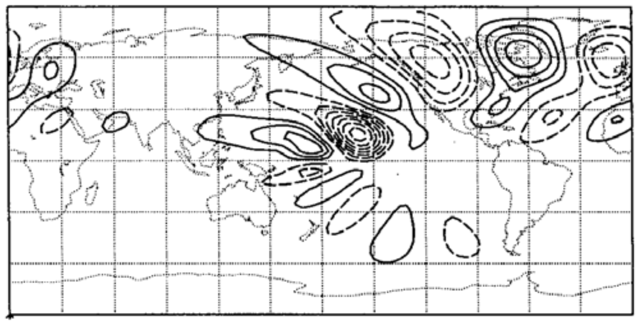


FIG. 8. Longitude–latitude picture of the day 15 $\sigma \approx 0.24$, meridional wind perturbation for the heating on a Dec–Feb zonal flow. The contour interval is 0.5 m s^{-1}. The zero contour is not shown, and the negative contours are dashed.

Careful theoretical and numerical attempts to explain the mid-latitude height and wind anomalies in terms of a direct effect of tropical heating anomalies (the forced Rossby wave theory) have failed!

To explain the observed anomalies we *must* take into account the changes in the baroclinic wave transport of heat, momentum and moisture by the baroclinic eddies:

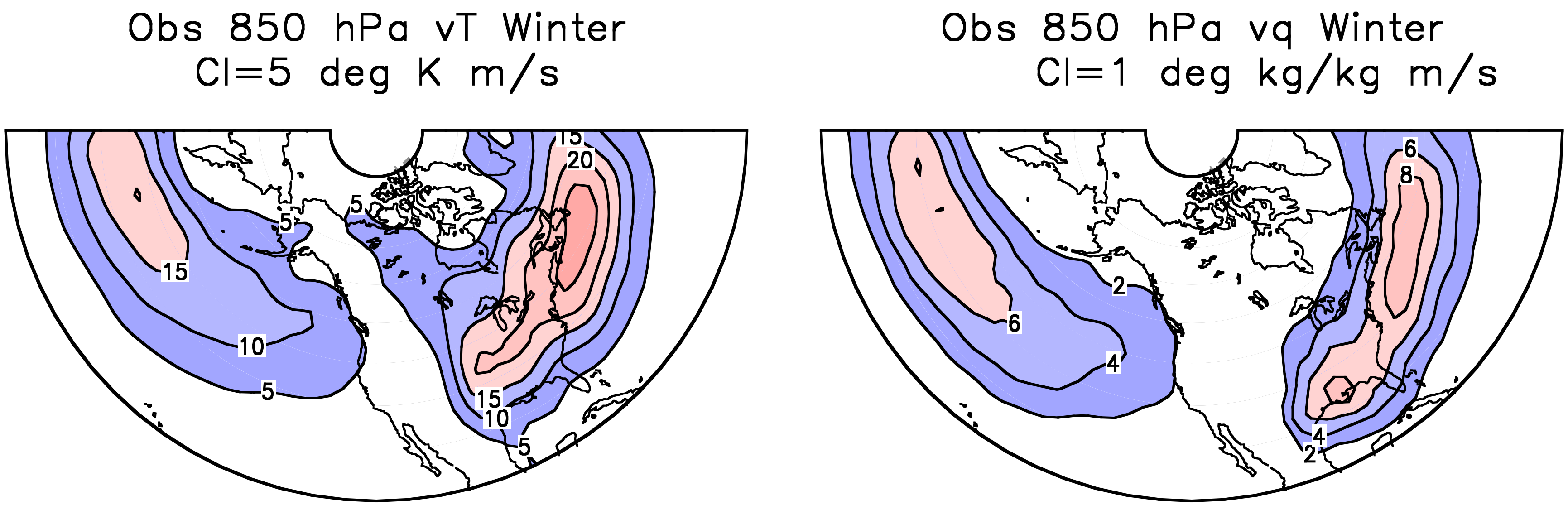
$$\overline{v'T'}\,,\overline{u'v'}\,,\overline{v'q'}$$

These baroclinic transports in general change the basic flow itself.

So when the transports change (as during El Nino and La Nina), their effect on the mean flow also changes. This additional change in the mean flow (beyond that given by the direct effect of the heating) are necessary to explain the observed anomalies!

Change in jets means a change in storm - tracks.

One very good measure of storms and storm tracks is given by the poleward transport of heat and moisture by motions with time scales of 2-10 days

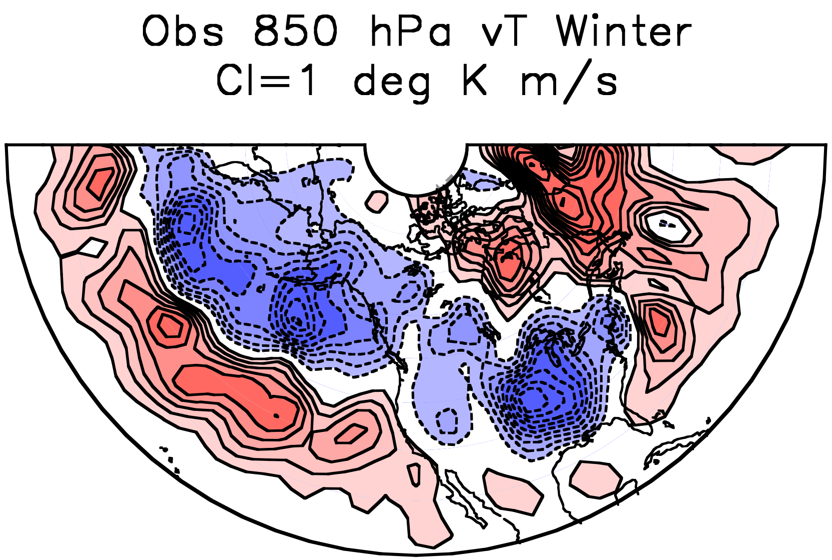


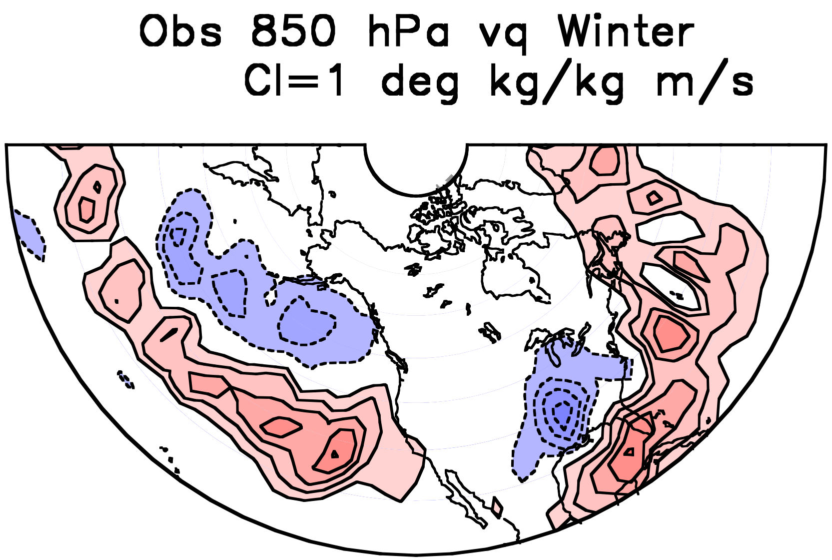
Heat Transport BP (2–10 days) **Moisture Transport**

climate

Normal Conditions (1948-2001 winter)

The equatorward and eastward extension of the jets during El-Nino pulls the storm tracks along!





Change in heat transport from normal to warm event (El Nino Anomalies)

BP (2–10 days)

Warm Composite

Change in moisture transport from normal to warm event (El Nino Anomalies)

But chaos does cause problems here too!

Even in the presence of a strong boundary forcing (SST), predicting the seasonal mean from an initial value problem can be very difficult due to non-linearity

Essentially, many atmospheric simulations using the same SST forcing, but slightly different initial conditions may have very different seasonal means!

So how can we trust one forecast for the seasonal mean, even in we know the SST conditions?

$$X_{n+1} = aX_n - X_n^2$$

The problem of deducing the climate from the governing equations

By EDWARD N. LORENZ, *Massachusetts Institute of Technology*[1]

(Manuscript received January 22, 1964)

ABSTRACT

The climate of a system is identified with the set of long-term statistical properties. Methods of deducing the climate from the equations which govern the system are enumerated. These methods are illustrated by choosing a first-order quadratic difference equation in one variable as a governing equation. The equation contains a single parameter. Particular attention is given to the climatic mean of the single variable.

Analytic methods yield the climate in some cases where the system varies periodically, but generally fail when the system varies nonperiodically. Numerical integration yields a value of the climatic mean for any individual value of the parameter. Additional analytic reasoning is needed to determine the nature of the climatic mean as a function of the parameter.

The progression from steady-state to periodic to nonperiodic behavior, as the parameter increases, is compared to the progression from steady-state to periodic to irregular flow in the rotating-basin experiments, as the rate of rotation increases.

$$X_{n+1} = aX_n - X_n^2$$

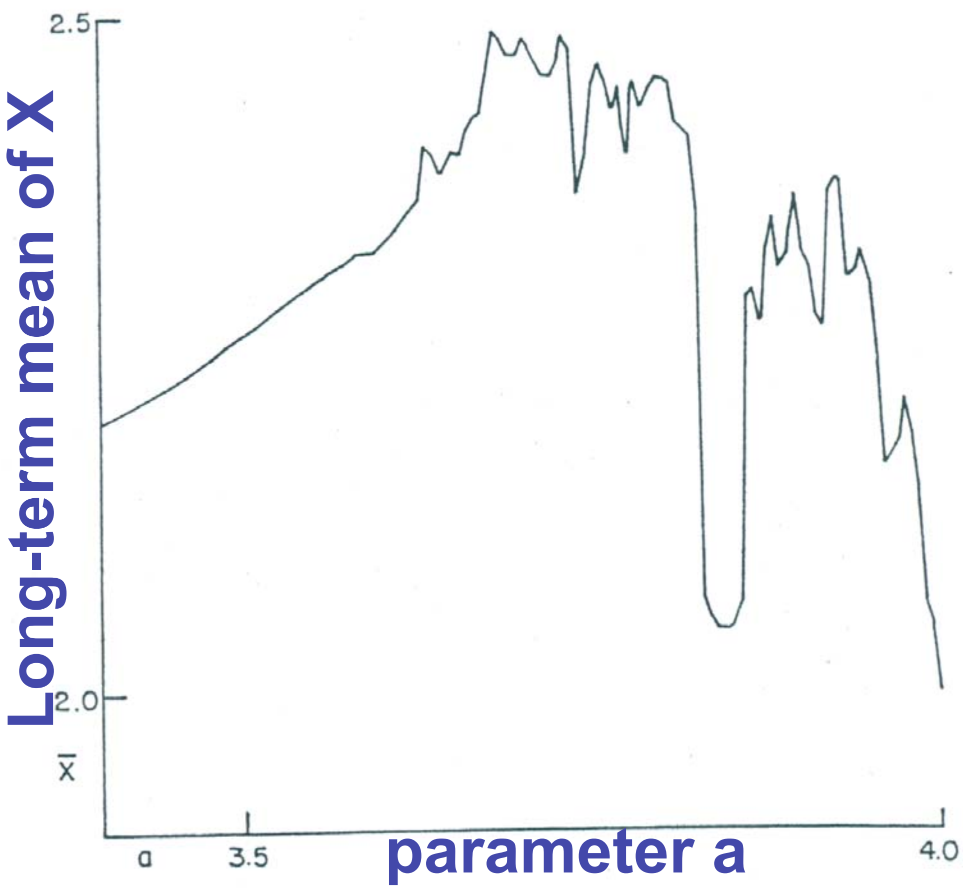
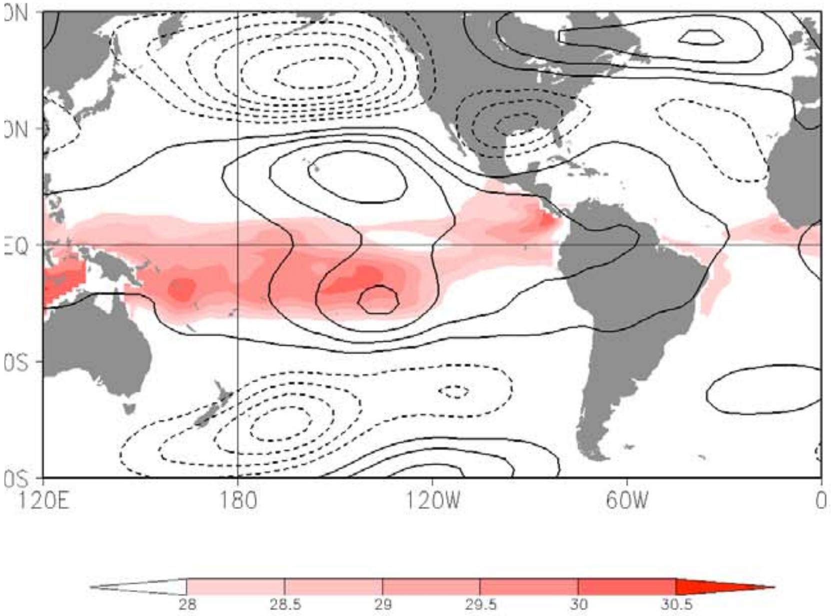


FIG. 3. Graph of $\bar{X}$ as a function of a, as estimated for the interval $3.4 \leqslant a \leqslant 4$.

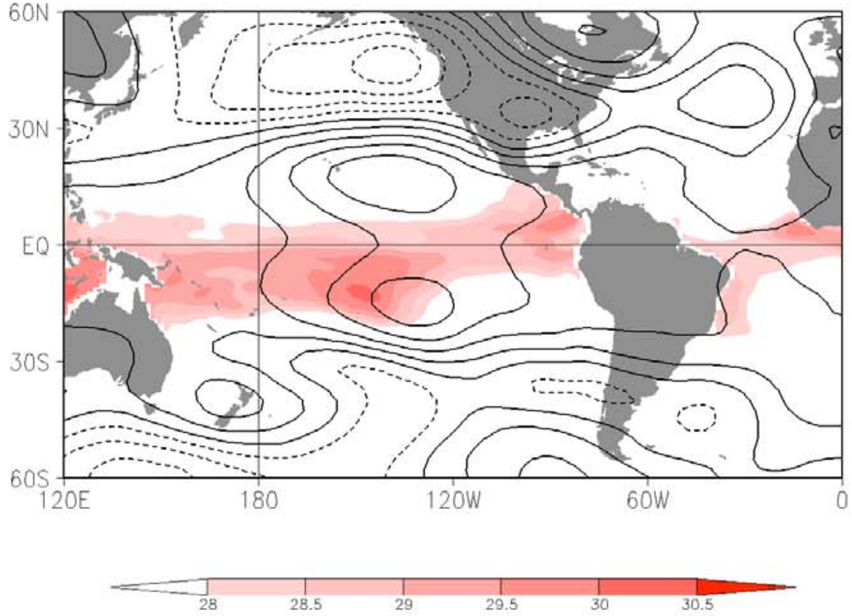
Climate depends sensitively on the value of a

Different observed warm event SSTs have lead to different observed responses

Response to 1982/83 Warm Event



Response to 1997/98 Warm Event



Contours give the 200 hPa height response (CI = 30 m)

Shading gives the SST in degrees C

-What part of the difference between two observed events is due to the (modest) difference in SSTs during the two winters?

- What part is due to chaos?

The Ensemble Approach.

For each winter, the ensemble consists of a number of simulations made *with the same SST* but slightly different atmospheric initial conditions

The assumption is that the average seasonal mean of all simulations run for the same winter (same SST) gives a reasonable approximation to the true “forced” response of the atmosphere to that SST

(Note that we cannot observe this theoretical forced response)

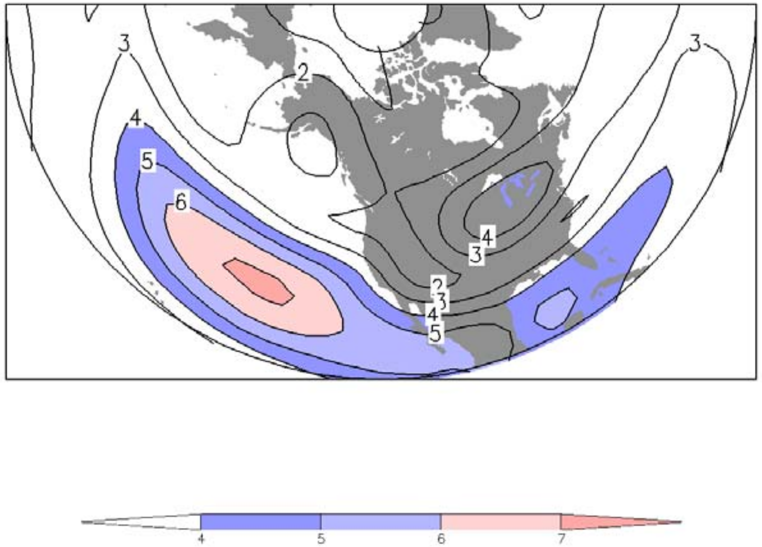
Signal variance:

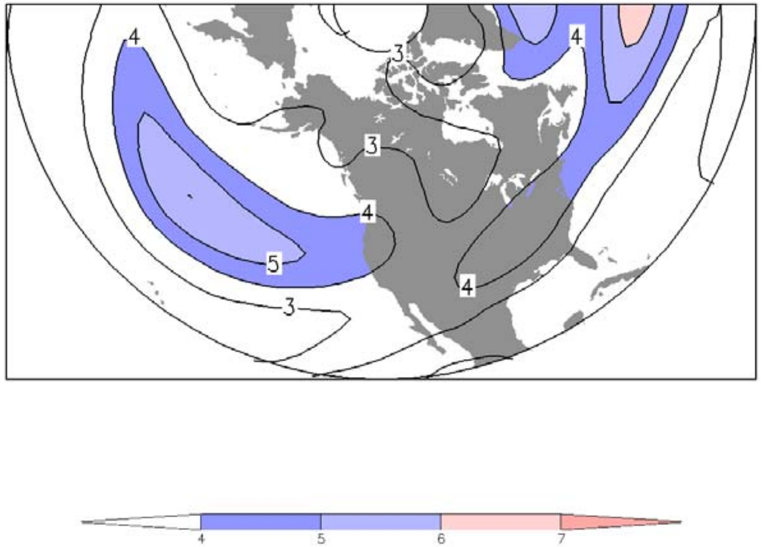
Variance of 18 winter time series of ensemble mean

Noise variance:

Variance of each ensemble member about the ensemble mean

200 hPa Seasonal Mean Zonal Wind (jet) variance (units of m^2/s^2)





Signal Variance

Noise Variance

Analysis of Ensemble Simulations

Isolating a few critical patterns in mid-latitudes forced by tropical SST.

The idea is to expand a sequence of (seasonal mean winter) fields using a set of orthogonal patterns. Mathematically this is simply a change of coordinate systems, in which our new coordinates are the coefficients of the patterns. But if the patterns are chosen well, the first few leading patterns (variables) will give us a lot of useful information.

Method A: Principal Component Analysis (EOF analysis)

Here we first take the ensemble mean of (seasonal mean) fields for each year, that is we average over all simulations made with the same SST. If we remove the N-year mean from this sequence of fields, and call the ensemble mean anomaly for grid point i and time t $Z_{i,t}$, the expansion we seek is:

$$Z_{i,t} = \sum_{\alpha} p_t^{(\alpha)} E_i^{(\alpha)}$$

where α is the mode, or pattern index. Note that all the time information is in the components p_t, which are our new coordinates.

In order for the patterns E_i to form an orthogonal set (in the usual vector sense, we must have:

$$\sum_i E_i^{(\alpha)} E_i^{(\beta)} = \delta_{\alpha,\beta}$$

where $\delta_{\alpha,\beta}$ = 1 if $\alpha = \beta$ and 0 otherwise.

The new coordinates p_t are also orthogonal in time:

$$\frac{1}{N} \sum_t p_t^{(\alpha)} p_t^{(\beta)} = \delta_{\alpha,\beta} \lambda^{(\alpha)}$$

where λ is an eigenvalue of the covariance matrix $C_{i,j} = \frac{1}{N} \sum_t Z_{i,t} Z_{j,t}$

The corresponding eigenvector is E_i, also known as an Empirical Orthogonal Function.

$$\sum_j C_{i,j} E_j^{(\alpha)} = \lambda^{(\alpha)} E_i^{(\alpha)}$$

The coordinates p_t are called the principal components (PCs).

What makes this expansion very efficient in representing patterns is the property that each mode (α) "explains" a fraction of the total variance V:

$$V = \sum_i \left(\frac{1}{N} \sum_t Z_{i,t}^2 \right) = \sum_\alpha \lambda^{(\alpha)}$$

If the (positive definite) eigenvalues λ are arranged in descending order, then the leading mode explains the largest percentage of the variance, the second mode the largest percentage of the variance of any mode orthogonal to the first, and so on. Another way of putting this is that if you synthesize the field with only a few leading modes (say = 1-3 only), the fraction of the

$$Z_{i,t} = \sum_{\alpha=1}^{3} p_t^{(\alpha)} E_i^{(\alpha)}$$

the total variance V explained by only these three modes is: $\dfrac{\lambda^{(1)} + \lambda^{(2)} + \lambda^{(3)}}{\sum_{(\alpha)} \lambda^{(\alpha)}}$

Thus if a few eigenvalues dominate, then only a few modes are needed to explain most of the variance V.

Method B. Optimal Signal-to-Noise Patterns

This approach tries to use *all* the ensemble members (labelled by m) for each winter (again labelled by i) to determine an SST forced signal and the internal dynamics generated noise.

We proceed by first subtracting the climate mean, as before, and expand each seasonal mean field in terms of a set of patterns again:

$$Z_{i,t,m} = \sum_{\alpha} p_{t,m}^{(\alpha)} E_i^{(\alpha)}$$

Note that all seasonal means have been used, and that the ensemble information is carried in the coefficients. We also form the ensemble mean coefficients:

$$\hat{p}_t^{(\alpha)} = \frac{1}{M} \sum_m p_t^{(\alpha)}$$

where M is the ensemble size. Then the signal S and noise N are defined *for each individual mode α* as follows:

$$
\begin{aligned}
S &= \frac{1}{N}\sum_t \left(\hat{p}_t^{(\alpha)}\right)^2 \\
N &= \frac{1}{N}\sum_t \left(\frac{1}{M}\sum_m \left(p_{t,m}^{(\alpha)} - \hat{p}_t^{(\alpha)}\right)^2\right)
\end{aligned}
$$

The patterns E_i and coefficients $p_{t,m}$ are determined (via a generalized eigenvalue problem by the requirement that:

-The leading mode maximizes the signal-to-noise ratio S/N

- The second leading mode maximizes S/N subject to the constraint that the associated pattern $E_i^{(2)}$ is orthogonal to $E_i^{(1)}$.

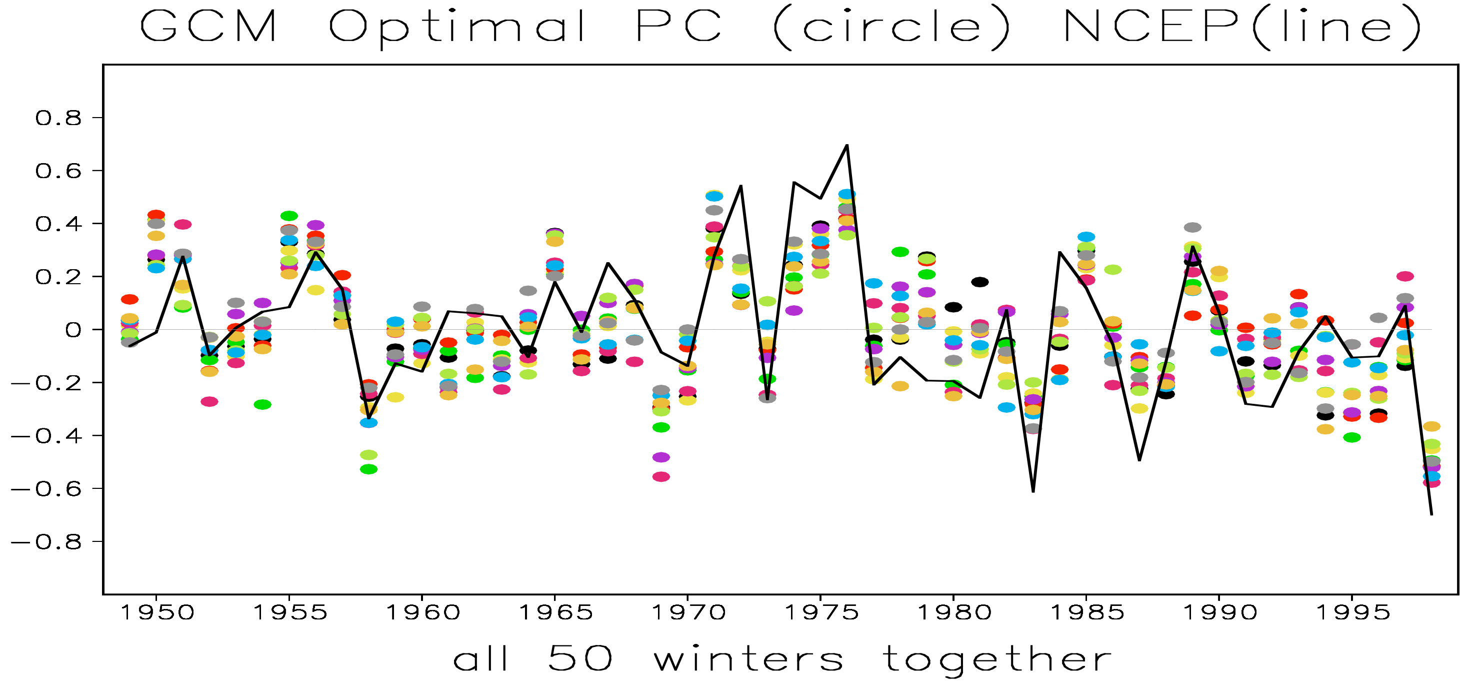
-…

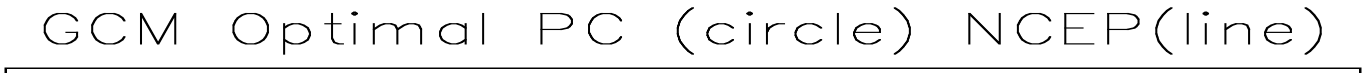
The patterns in Principal Component Analysis are orthogonal, while those in the Optimal Signal-to-Noise expansion are bi-orthogonal. **In both cases they form a complete set that can be used to expand any set of fields.**

Application to C20C Experiments with COLA AGCM
10 member ensembles, 50 winters used

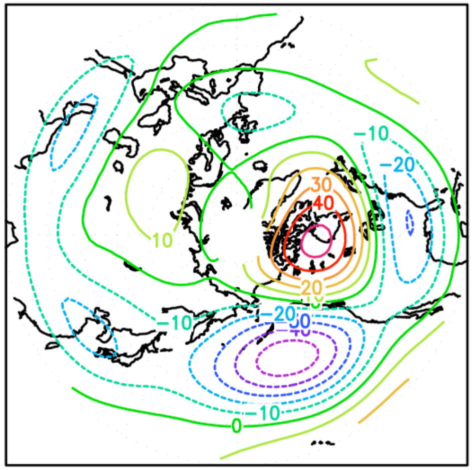
Each colored dot represents one of the coefficients $p_{t,m}$ for the leading Optimal mode.

The solid line is the (single) NCEP reanalysis winter seasonal mean projected onto the pattern of the leading mode



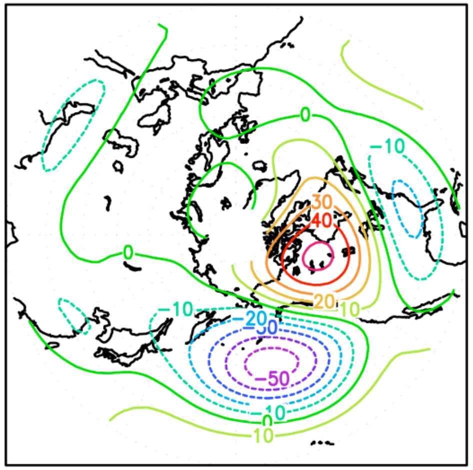


1981–1998 EEOF–1



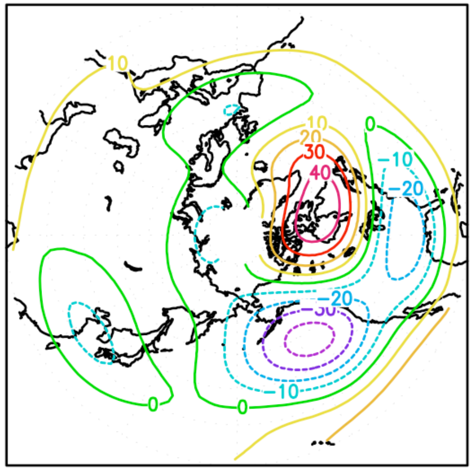
38% variance explained

1949–1980 EEOF–1



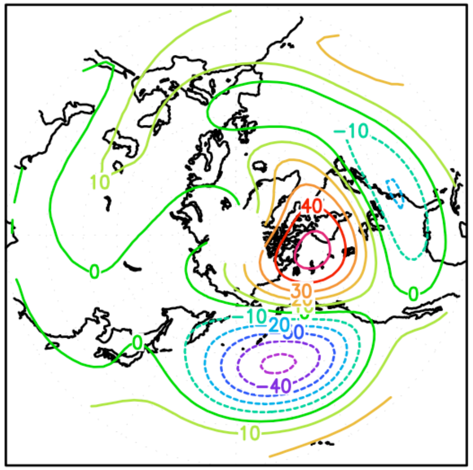
42% variance explained

1981–1998 OPT–1



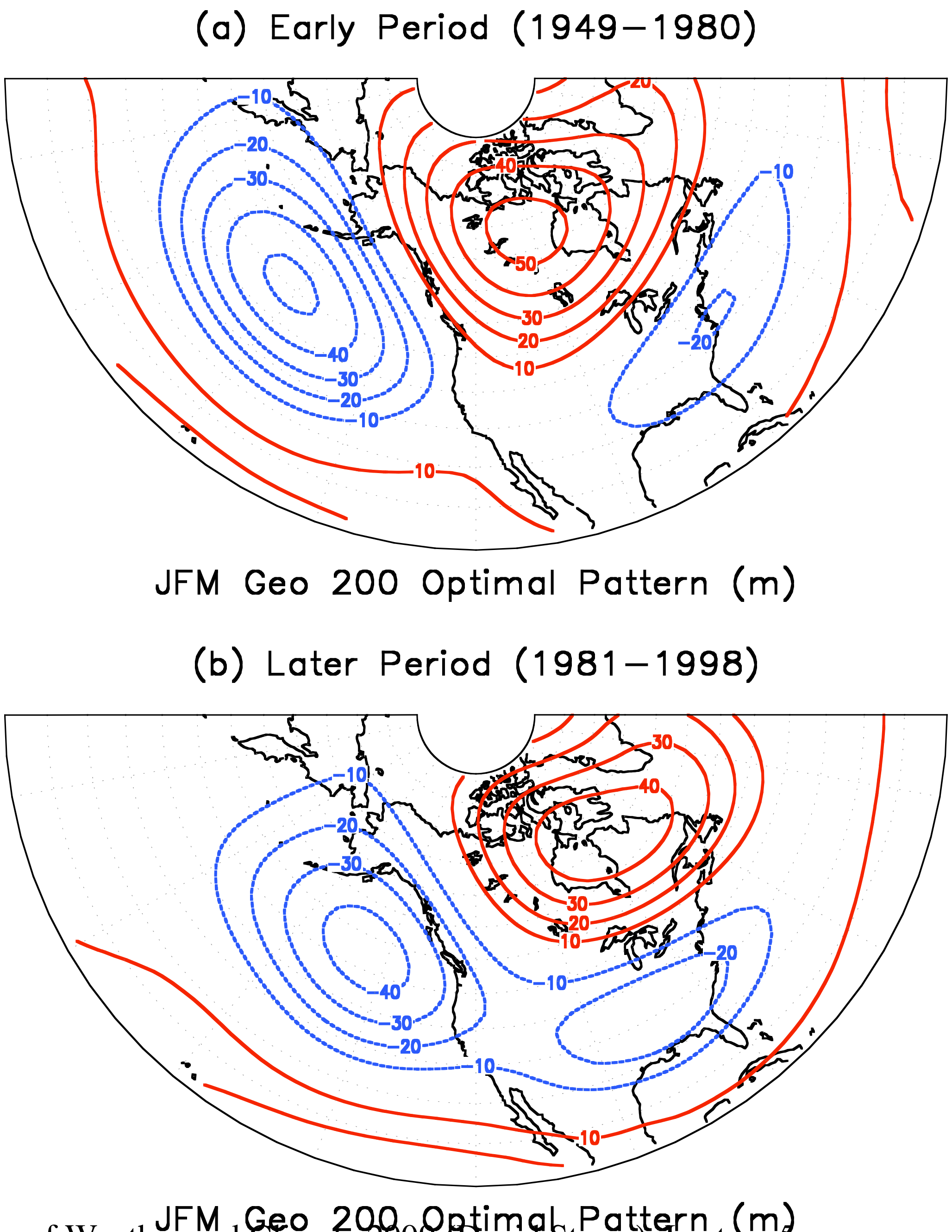
Ratio = 8.2

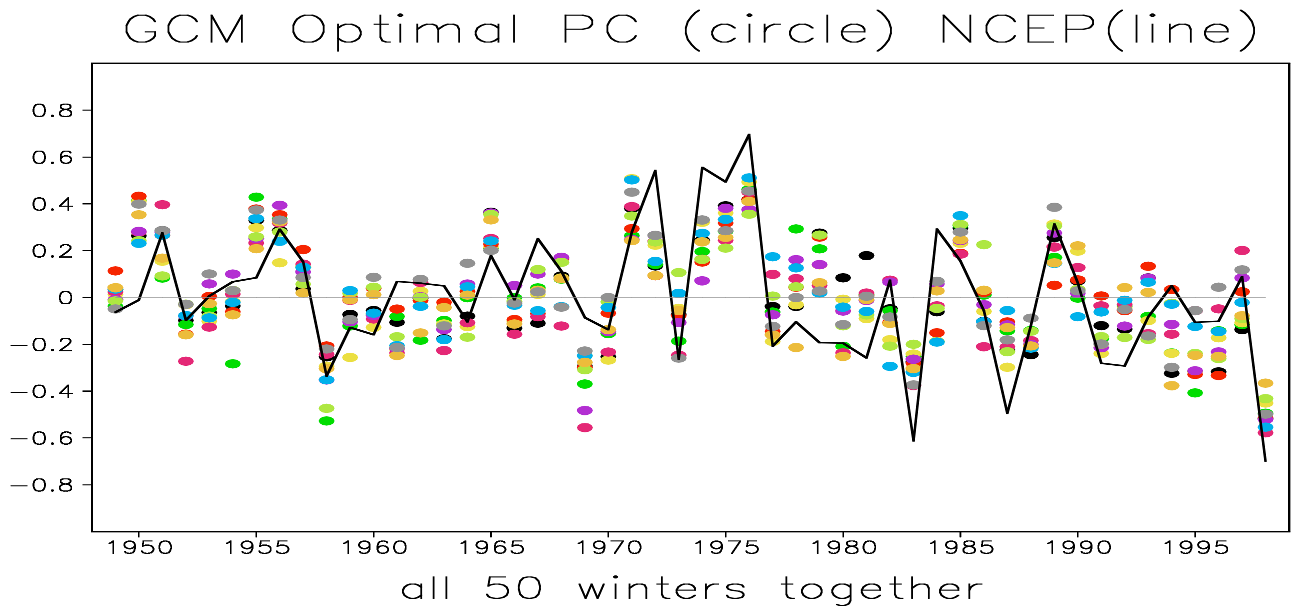
1949–1980 OPT–1

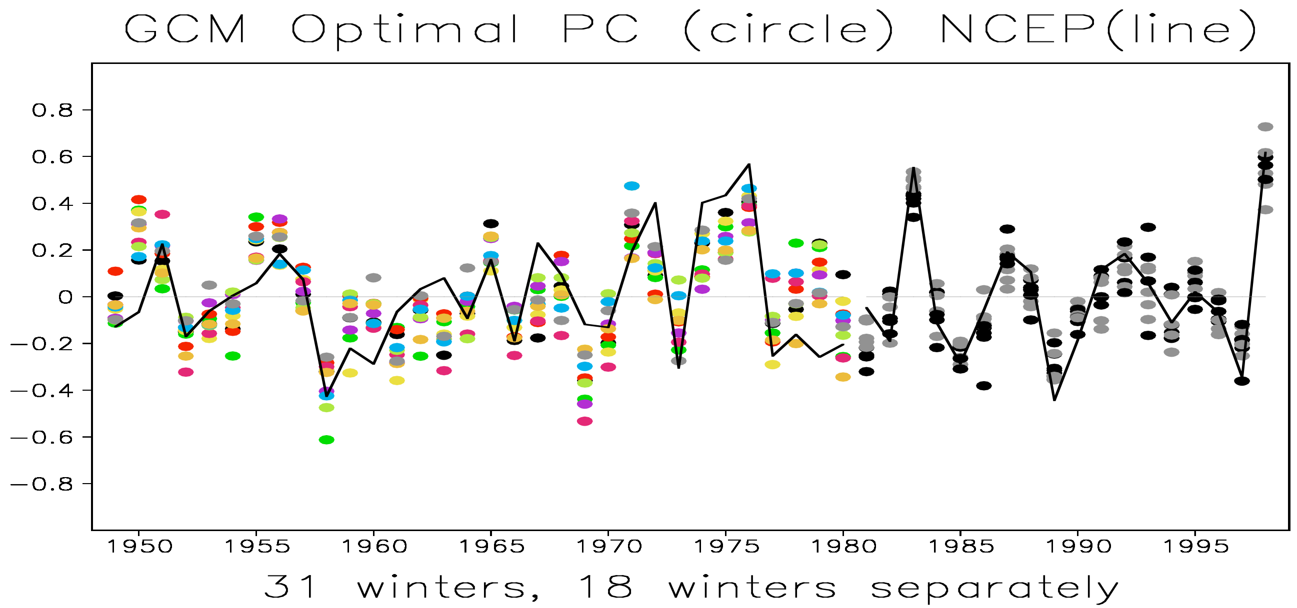


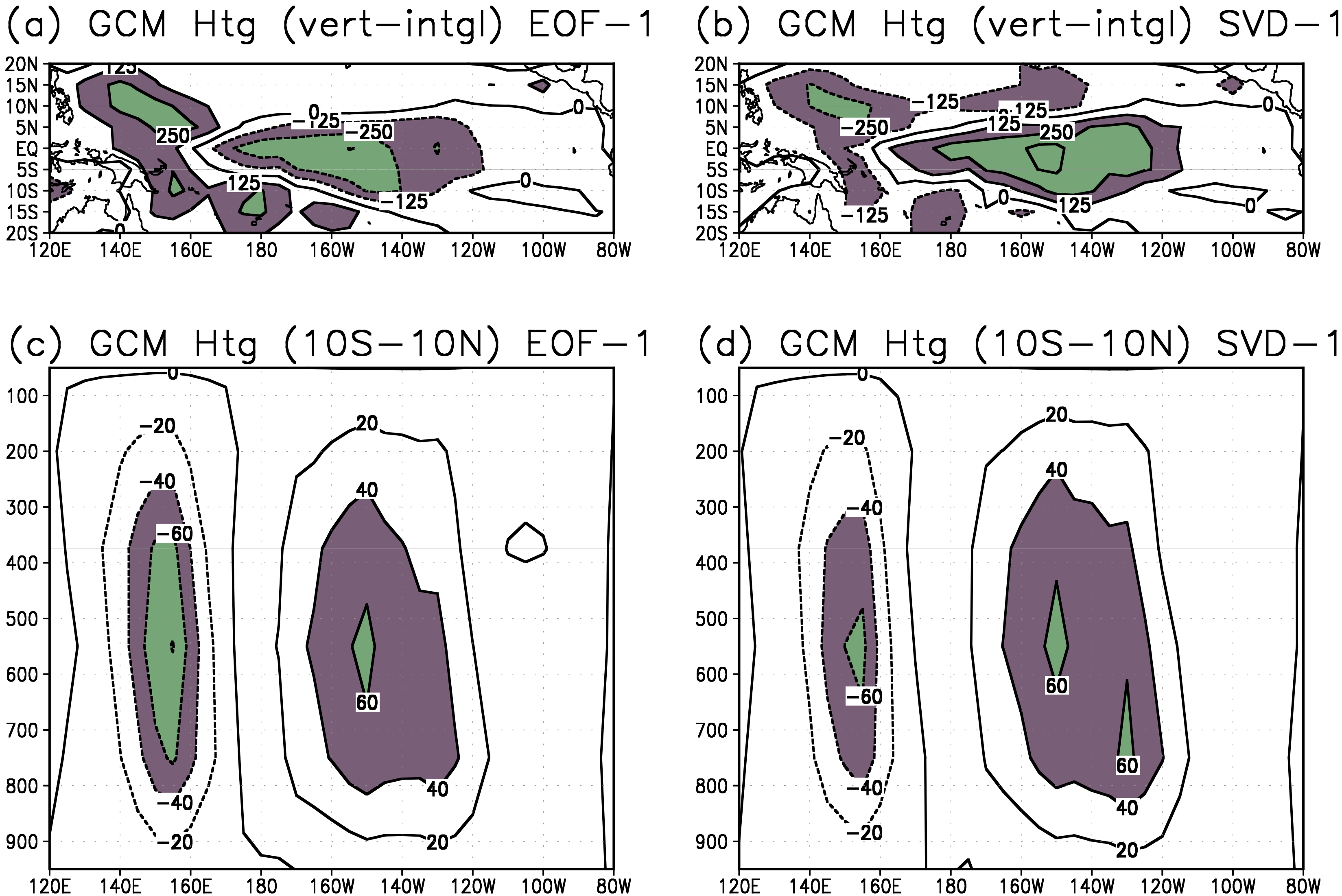
Ratio = 5.7

Pattern that optimizes the signal-to-noise ratio for seasonal mean 200 hPa height for winter, from observations.




GCM Optimal PC (circle) NCEP(line)
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
all 50 winters together


GCM Optimal PC (circle) NCEP(line)
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
31 winters, 18 winters separately


(a) GCM Htg (vert−intgl) EOF−1
(b) GCM Htg (vert−intgl) SVD−1
(c) GCM Htg (10S−10N) EOF−1
(d) GCM Htg (10S−10N) SVD−1
20N 15N 10N 5N EQ 5S 10S 15S 20S
120E 140E 160E 180 160W 140W 120W 100W 80W
100 200 300 400 500 600 700 800 900