Circulation Regimes and Regime Transition Probabilities in the COLA C20C Integrations: Dependence on The Slowly Varying Climate State and SST Forcing

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Circulation Regimes: An Introduction

- **Hypothesis that the large scale intra-seasonal and seasonal variability of the extra-tropical atmosphere can be described by preferred circulation, patterns, called "regimes"**
  - **Amplitude and phase of planetary waves are dynamically equilibrated with variations in heating, and with feedbacks from synoptic-scale eddies**

- **Preferred patterns identified as "clumping" of low-frequency states in an appropriate state space- try to identify subtle maxima in the pdf**

- **Early work on QG – channel models** (Reinhold and Pierrehumbert 1982; Vautard and Legras, 1988)

- **Global QG models –** (Marshall and Molteni, 1993; D'Andrea and Vautard 2001)

- **PE GCMs – (**Haines and Hannachi 1995; Monahan et al 2000)

Circulation Regimes in Observations

- ***Rigorous* Identification of large-scale hemispheric or regional circulation regimes in observations is a very difficult statistical problem** (Straus, Corti and Molteni, 2007; Stephenson et al 2004; Molteni et al. 2005)

- **There are simply not enough circulation data !**

- **We may have to give up on the notion of rigorously defined, unique regimes, and settle for approximations.**

Relationship to Forcing

- **By analogy with low-order chaotic systems, it has been argued that moderate changes in forcing (boundary conditions) would not lead to changes in circulation regimes, but only in their frequency of occurrence** (Palmer, 1993, 1999; Molteni et al. 1993)

- **Observed inter-decadal variability in NH regime frequency may be one aspect of atmospheric response to increased greenhouse forcing** (Corti et al, 1999, Shindel et al., 1999, Hsu and Zwiers, 2001)

- **However, recent studies have shown that large variations in the forcing (diabatic heating due to major changes in tropical Pacific SST) lead to more substantial changes in regime properties- (both patterns and number of regimes)** (Molteni and Corti 1998; Straus and Molteni, 2004)

The Need for GCMs

- **The (possible) change in extra-tropical regime properties with tropical SST seriously compounds the already difficult problem of rigorous identification of regimes in observations.**

- **We only have very few (observed) realizations of winter seasons for a given tropical Pacific SST configuration.**

- **We really do need very large ensembles of realistic global GCMs to estimate the sampling properties of circulation regimes – that is, to estimate the effects of internal vs. external variability on regime properties.**

- **But very little work has been done on this!**

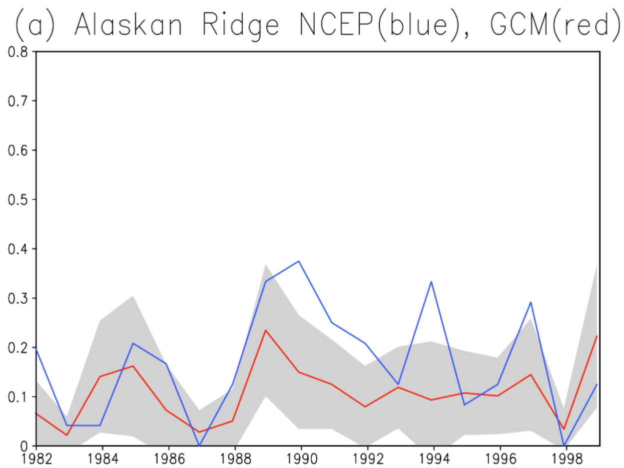
Is frequency of occurrence of regimes related to SST?

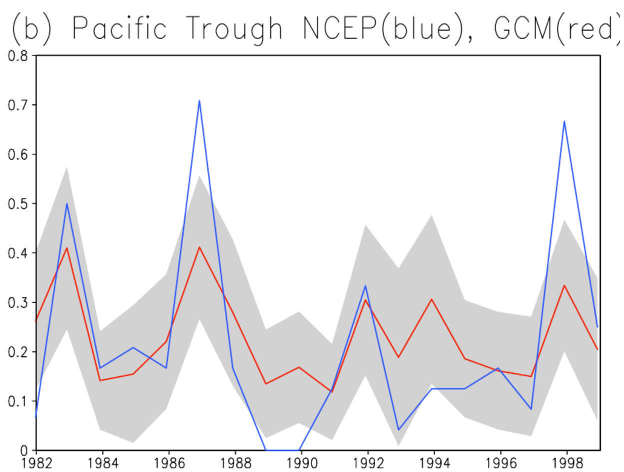
Case Study of 18-year period: 1982 - 1998 (winter only)

Red line: GCM

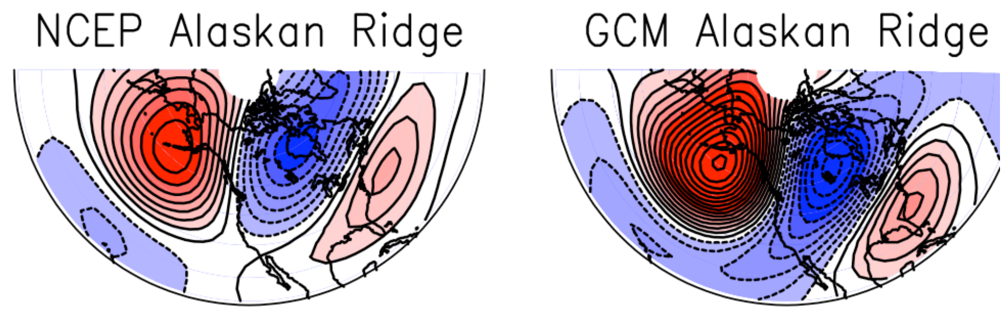
Blue line: NCEP

Gray: intra-ensemble σ in GCM

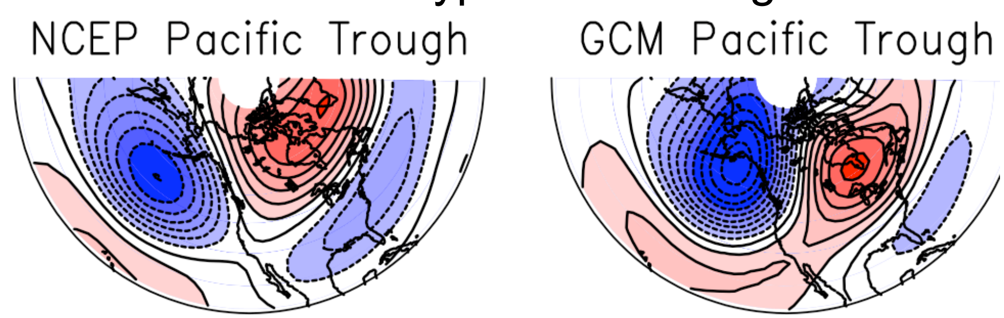




GCM 55 winter seasonal simulations with obs SST for each winter



ENSO-type Pacific Ridge



Is the frequency of occurrence of Alaskan Ridge and Pacific Trough even partly predictable on the basis of SST? - Look at frequency of occurrence year by year for the recent 18-winter period - *results are encouraging!*

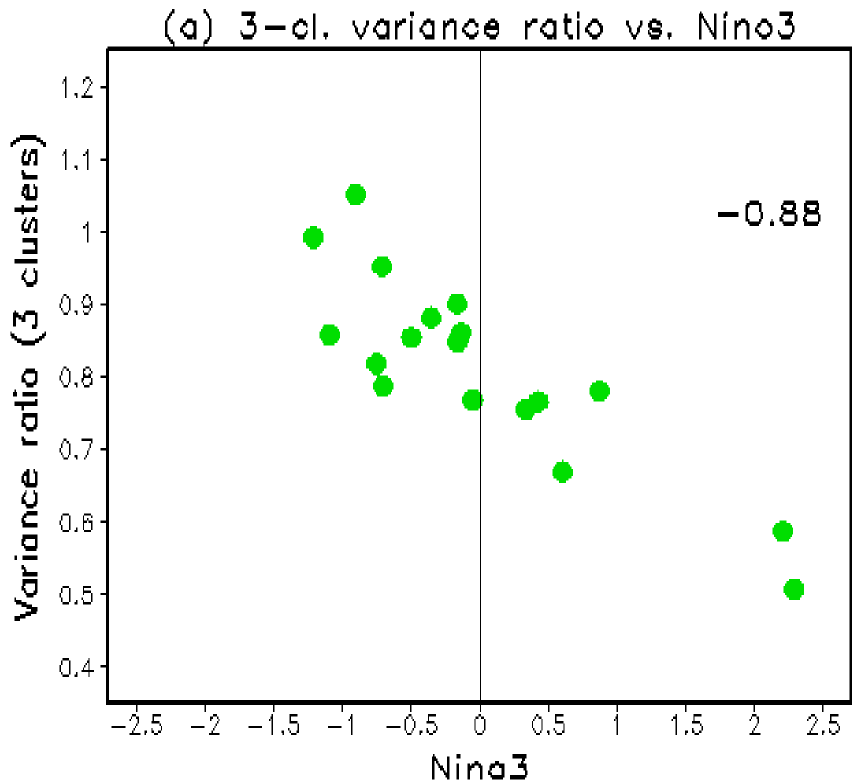
Palmer's hypothesis and inter-annual variability

Relationship to Boundary Forcing - Tropical SST

Examine "super-ensembles" of seasonal AGCM simulations made **with observed SST** for each of 18 recent winters. (Ensemble size = 55).

Cluster analysis on each winter (55 realizations) **separately** --> set of 18 independent analyses.

Results show significant clustering for each winter **except the warm ENSO winters** (El-Ninos): 1982/83, 1986/87 and 1997/98.



Straus and Molteni, 2004: Circulation Regimes and SST Forcing: Results from Large GCM Ensembles. *J. Climate*, **17,** 1641-1656.

Tropical SST Forcing influences degree to which preferred states are seen

Is ENSO the whole story?

A more systematic approach

- **Identify the very slowly varying (inter-annual and decadal) component of the atmospheric circulation itself - the component due to slowly varying SST forcing and very slow internal dynamical modes.**

- **Explore the dependence of regimes on this slowly varying state**

- **To accomplish this, we must separate out the interannual variability that is due to the residual of the regimes (intra-seasonal variabiliy) themselves**

- **A systematic method has been proposed by Zheng and Frederiksen (2004)**

Zheng and Frederiksen method applied to C20C

-COLA AGCM (T63) 10 runs from Nov 1949 - Nov 1998

- Use 49 x 10 winters ("DJF") monthly and seasonal means

- Compute the covariance matrix due to slowly varying (forced + slow internal) atmospheric "potentially predictable" states

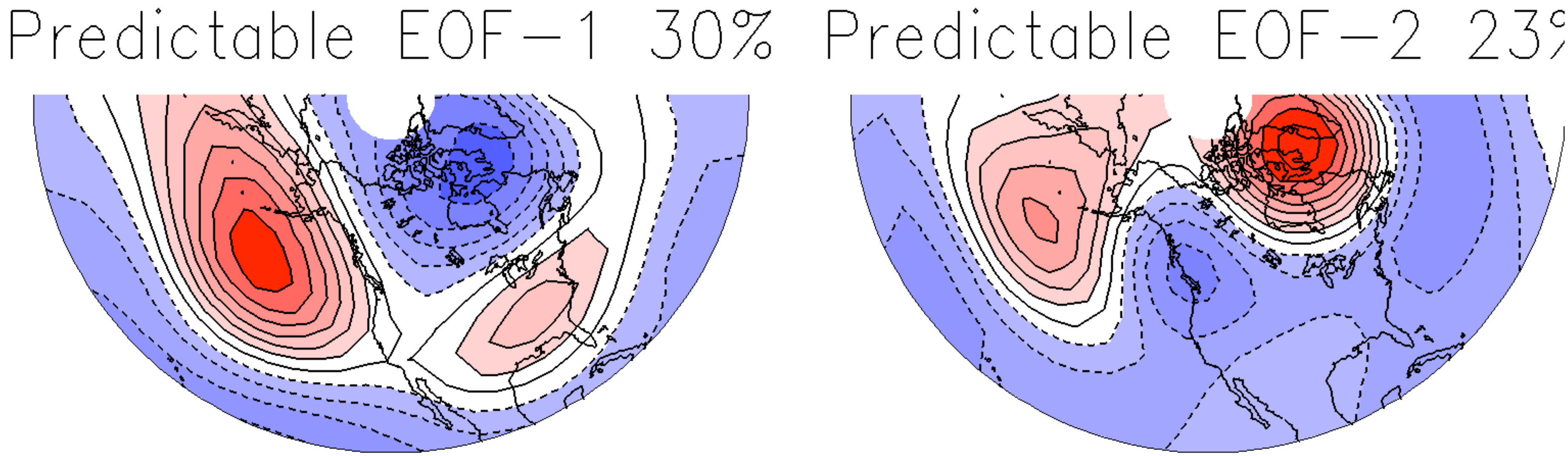
- Compute EOFs and PCs.

- From the leading PCs, identify two classes of winters that have very different configurations of the "potentially predictable" slow states.

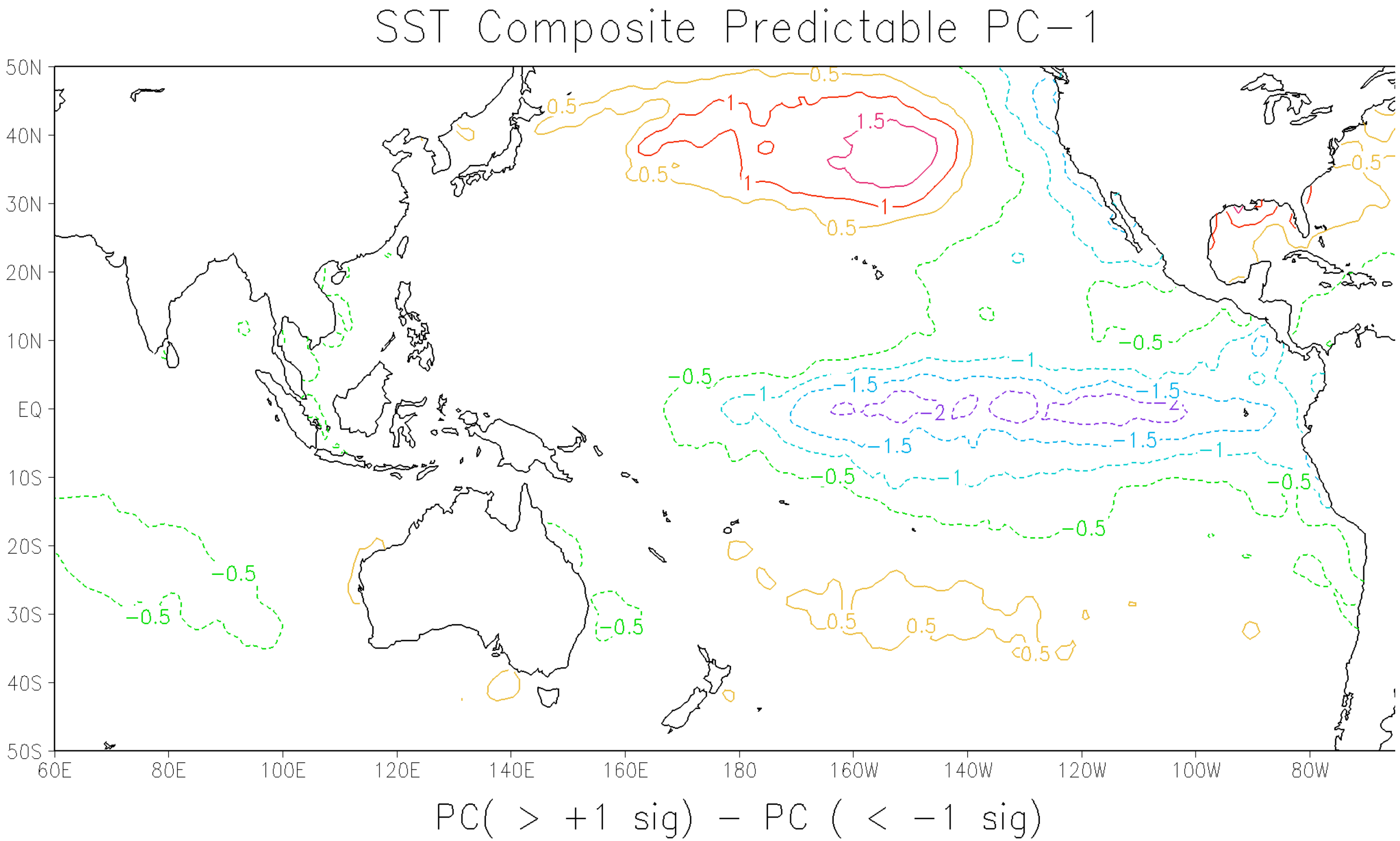
Are the regimes in intra-seasonal flow more readily seen in one class than another?

Predictable Component Leading EOFs from COLA C20C

Seasonal Mean 200 hPa height - DJF average



Relationship of PC-1 to SST: La-Nina in the Pacific + mid-latitude anomalies



DJF SST mean difference between winters: (PC-1 > 1 std) - (PC-1 < -1 std)

Units: Degrees C

Cluster Analysis of Winter States

Data Sets

- Reanalysis
- C20C GCM: ensemble of continuous runs forced by obs SST
  (ensemble size = 10) for 49 years
- DSP GCM: ensemble of seasonal runs with obs ICs and obs SST
  (ensemble size = 55 or 10) for 18 winters

Fields and Processing

- Z 200 daily
- Remove only "grand mean" annual cycle"
- Low-Pass filter (retain periods of only 10 days of longer)
- Retain only leading N = 4-6 EOFs (~ 2/3 variance retained)
- Keep only quasi-stationary states (not too rapid movement
  in state space of PCs)

Partitioning Method (k-means algorithm)

- Applied to the set of points in the N-dimensional PC space
- Fix number of clusters (regimes) sought (k)
- Find the division of state space into k partitions that

  maximizes the variance ratio =

  variance between cluster centers /

  intra-cluster variance

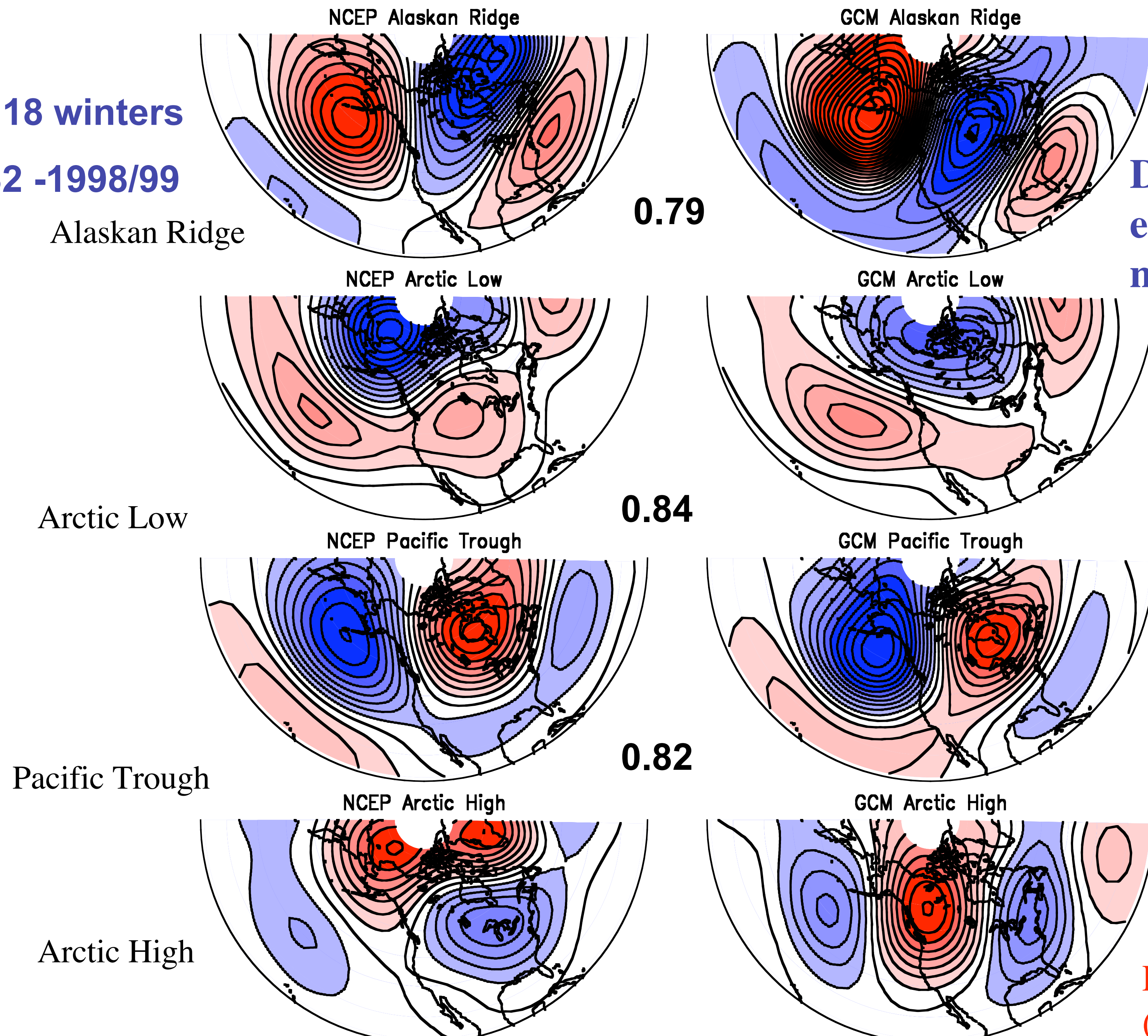
- Test the "significance" of the partition vis-à-vis a multi-normal (multi-variate Gaussian) null hypothesis by Monte Carlo testing. (True data must have higher variance ratio than ~90% of multi-normal samples).
- Test the reproducibility of the results on a large number of randomly-chosen half-length data sets*
- Can take into account skewness of PCs in Monte-Carlo tests

* (Due to SST-dependence, each half-length data set should be compared on another half-length data set ONLY in the same year)

NCEP 18 winters

1981/82 -1998/99

DSP: 55 ensemble members

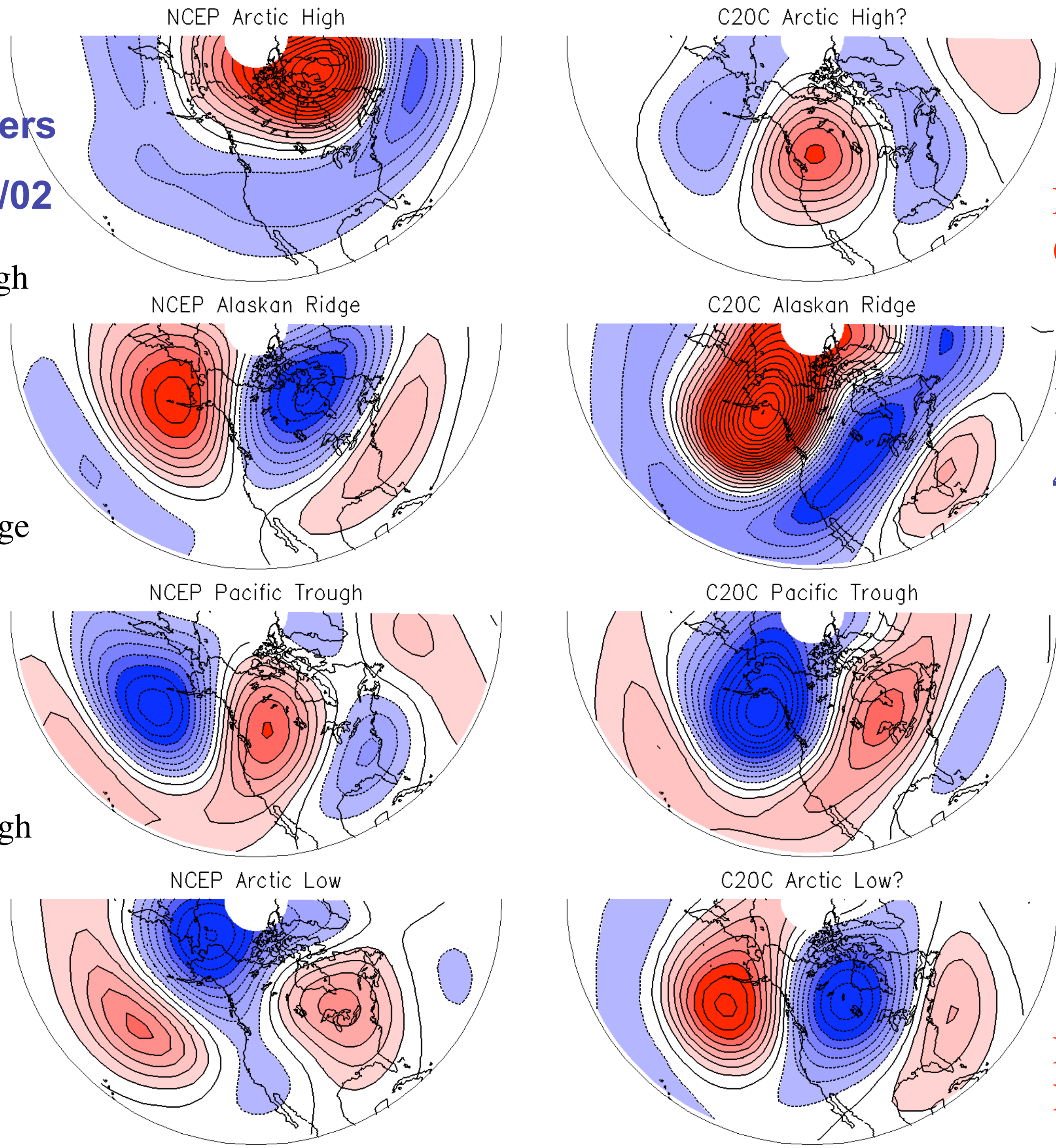


Ridge (PNA)?

200 hPa Z CI:20 m blue (negative) red (positive)

NCEP 54 winters

1948/49 -2001/02



Arctic High

Ridge (PNA)?

C20C

10 members

49 winters

Alaskan Ridge

Pacific Trough

Arctic Low

Pacific Ridge

	C20C PC > 1	C20C PC > 1	C20C PC < -1	C20C PC < -1	DSP 18 (10)	DSP 18 (10)
k	**Signif.**	**V Ratio**	**Signif.**	**V Ratio**	**Signif.**	**V Ratio**
2	97%	0.621	24%	0.408	94%	0.570
3	100%	0.983	40%	0.652	99%	0.912
4	95%	1.232	54%	0.899	99%	1.247
5	97%	1.520	29%	1.090	100%	1.370
6	97%	1.745	41%	1.278	100%	1.596

Diffusiveness of flow in a very coarse-grained view of state space from an Atmospheric General Circulation Model

Coarse-Grained Markov Chain approach
(Crommelin, 2004, Journal of the Atmospheric Sciences)

Start with Markov chain description:

$$p_i(t + \Delta t) = \sum_j M_{ij}\, p_j(t)$$

(In principle exact if probability p includes all variables and is a point pdf)
Here p is the probability that the system is in coarse-grained partition i of the state space.

M is a matrix which describes the probability of transitions

Major assumption that transition probability does not depend on past history.

References:

Crommelin, D. T., 2004: Observed Nondiffusive Dynamics in Large-Scale Atmospheric Flow. *J. Atmos. Sci.,* **61**, 2384-2396

Egger, J. 2001: Master Equations for Climatic Parameter Sets. *Climate Dyn.,* **18,** 169-177.

Pasmanter, R. A., and A. Timmermann, 2003: Cyclic Markov Chains with an Application to an Intermediate ENSO Model. *Nonlinear Processes in Geophysics*, **10**, 197-210.

Basic Ideas:

Non-Diffusive Flow:

Regular cycles through parts of phase space are considered to be “conservative” or “non-diffusive”, and are associated with no information loss (entropy production)

(Interesting limit: Very fine discretization of state space - these cycles converge to unstable periodic orbits)

Diffusive Flow:

If occupation in partition i of state space is followed by occupation of all partitions at the next time step with equal probability - the system is “diffusive” and the flow has large information loss (entropy production)

Measure of Information Loss μ

μ ranges from 1 (totally diffusive) to 0 (totally conservative)

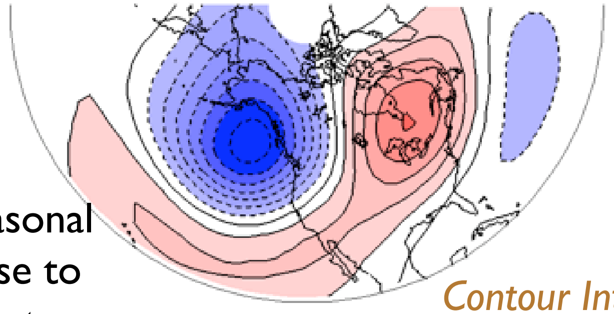
Significance of Transitions

The significance of individual transitions (individual matrix elements of M) can be assessed in a straightforward manner IF the coarse-grained partitions of the finite data set are arranged to have an equal number of states (equipartition).

How to Divide State Space into a Few (equally populated) regions in a Dynamically Meaningful Way ?

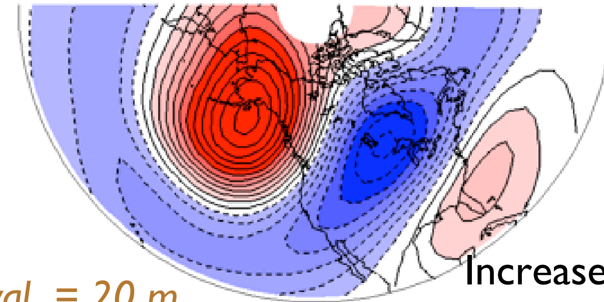
Start with cluster analysis of C20C winter time states
NO Quasi-stationary filtering applied!

(1) Pacifc Trough PT



Related to seasonal mean response to El-Nino events

(2) Alaska Ridge AR

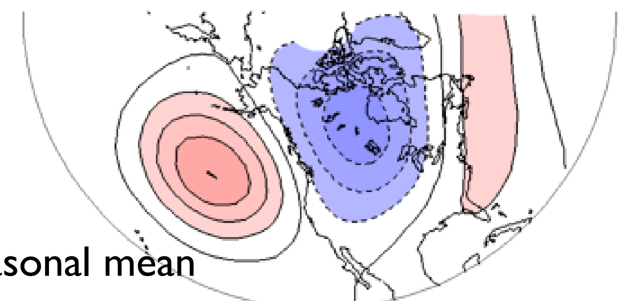


Increased incidence of Alaskan Blocking

Contour Interval = 20 m

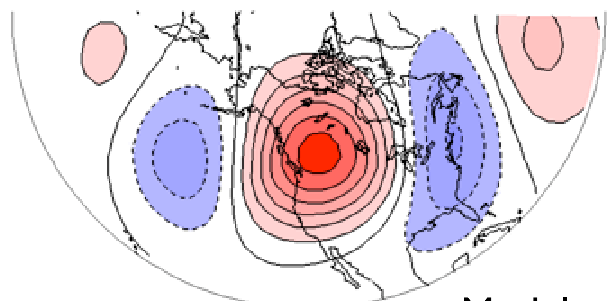
Geopotential states corresponding to centers of 4 partitions (clusters based on geopotential states)

(3) Arctic Low? / La-Nina ?

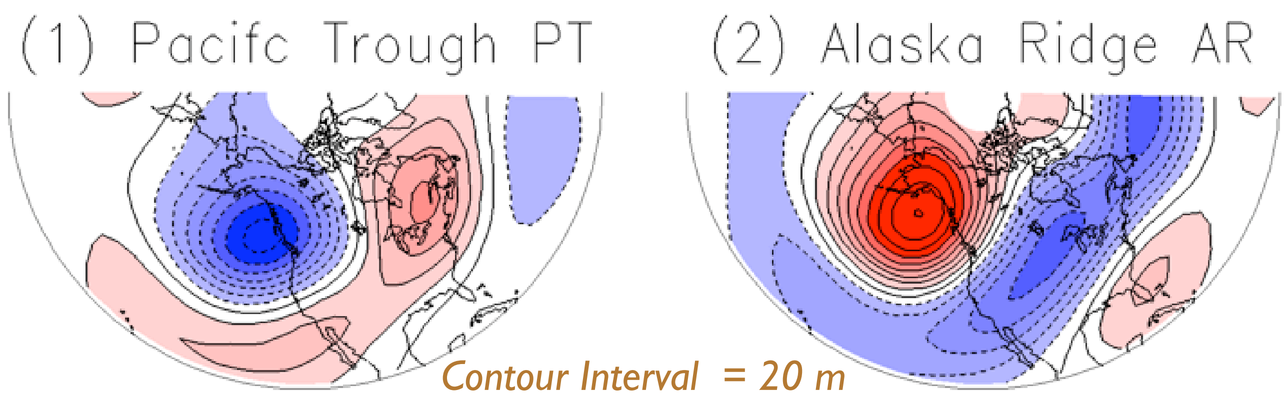


Related to seasonal mean response to La-Nina events

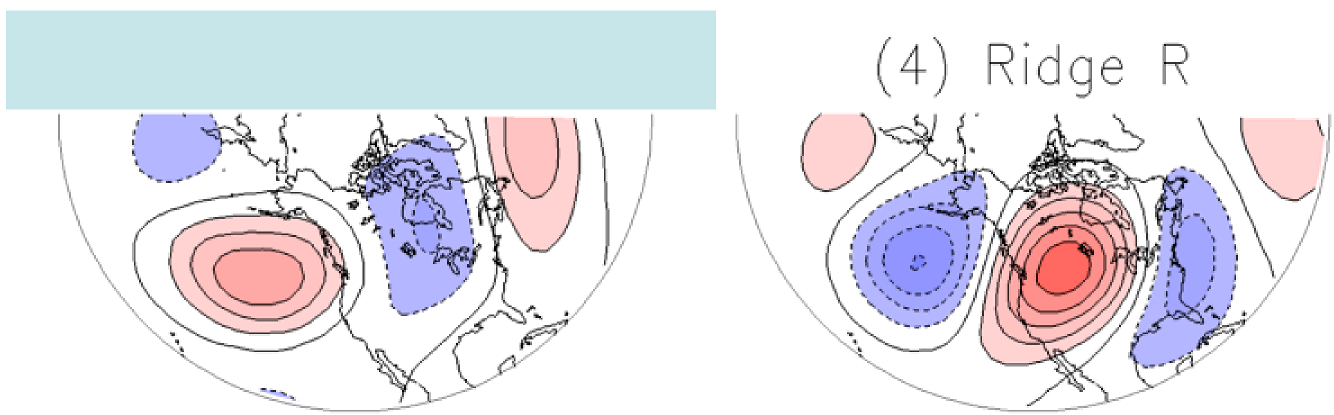
(4) Ridge R



Model version of "PNA"



Geopotential states corresponding to centers of 4 partitions
(clusters based on precipitation states)



Percent occurrence of different clusters

	geopotential clusters	precipitation clusters
PT	32%	28%
AR	16%	18%
AL	25%	29%
R	27%	25%

Equipartition Not Achieved: Adjustment of states necessary!

Adjustment: Take states from "overpopulated" clusters and assign them "underpopulated" clusters based on minimum distance in state space to cluster center.

(*Results sensitive to this ad hoc adjustment ???*)

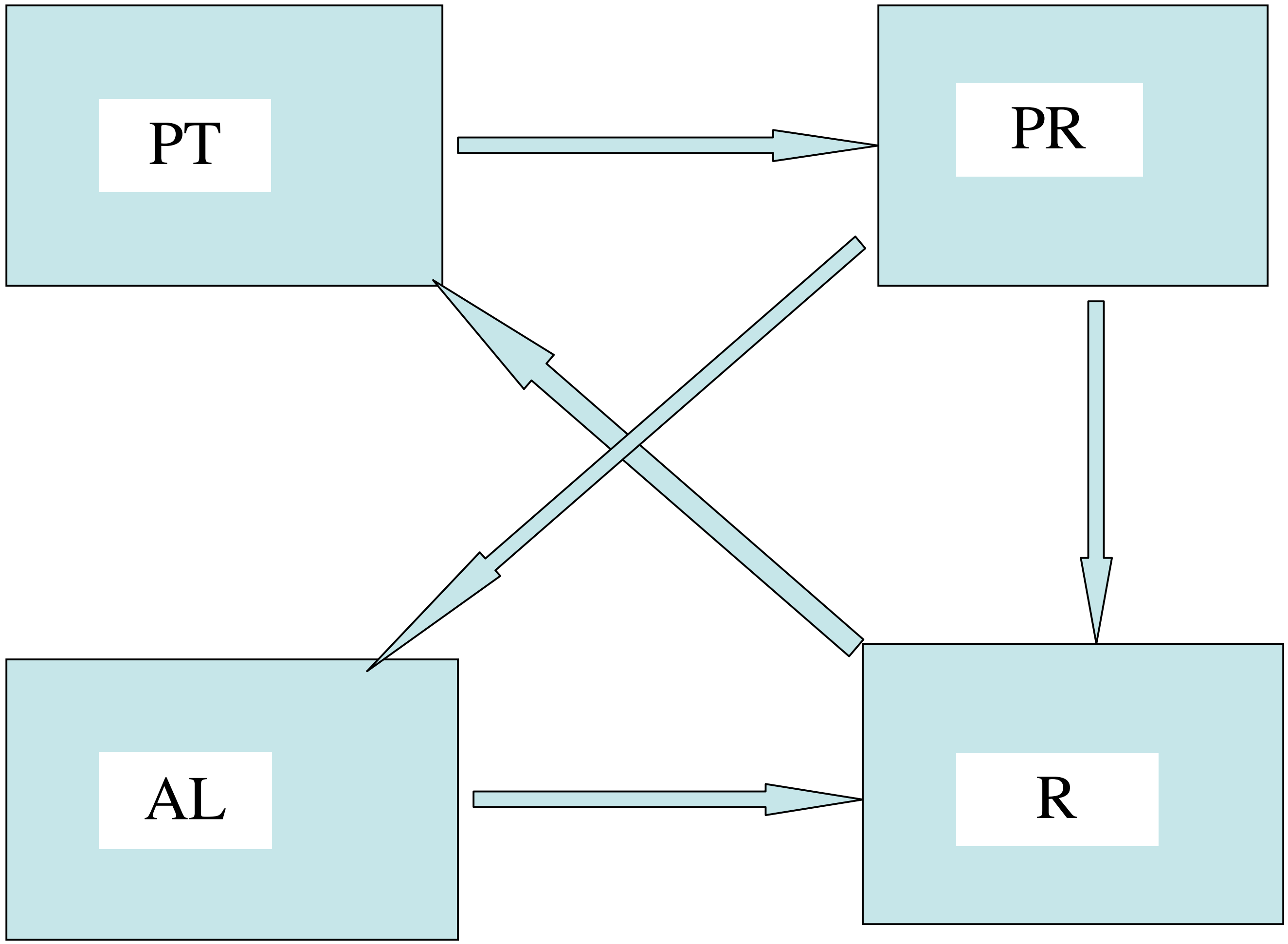
Inter-Cluster Transitions are Highly Diffusive (μ = 0.9887)

Yet some transitions are still significantly different from random:

x: self-transitions always most likely (τ ~8-10 days)

Transitions for one "time step" = 4 days

	From PT	From AR	From AL	From R
To PT	x			S
To AR		x	S	
To AL	S		x	
To R		S	S	x


PT
PR
AL
R

Limitations of this analysis:

Do pairs of individual transitions occur in sequence often enough
for a statistically significant cycle to be identified?
(future work)

Transitions identified not sensitive to ad hoc population adjustment:

An episode analysis based solely on the cluster partitions themselves identifies the same transitions as being most likely - even after episodes of longer than 4 days.

Stability properties of states conditioned on cluster of initial state

Approach:
The venerable identical twin experiments!

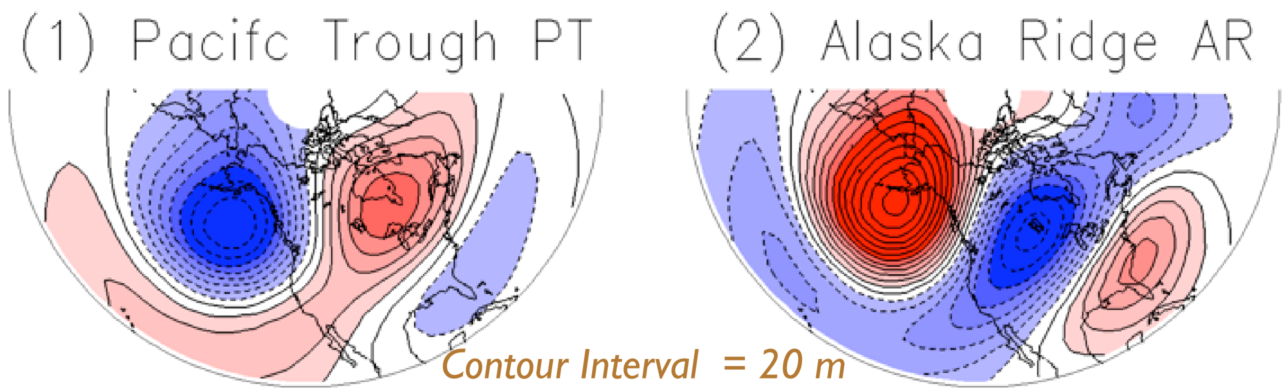
Model: Same AGCM as used in C20C experiments

160 Control Integrations:
10 winter simulations: Late November - end of March for each of 16 winters 1981/82 - 1996/97
Initial conditions: Reanalysis states for 10 days in late Nov. of each year
Boundary conditions: SST sea-ice for each winter specified from observations

160 Perturbation Integrations:
Identical to Control Integrations, but with all variables initially perturbed by ~0.1 %

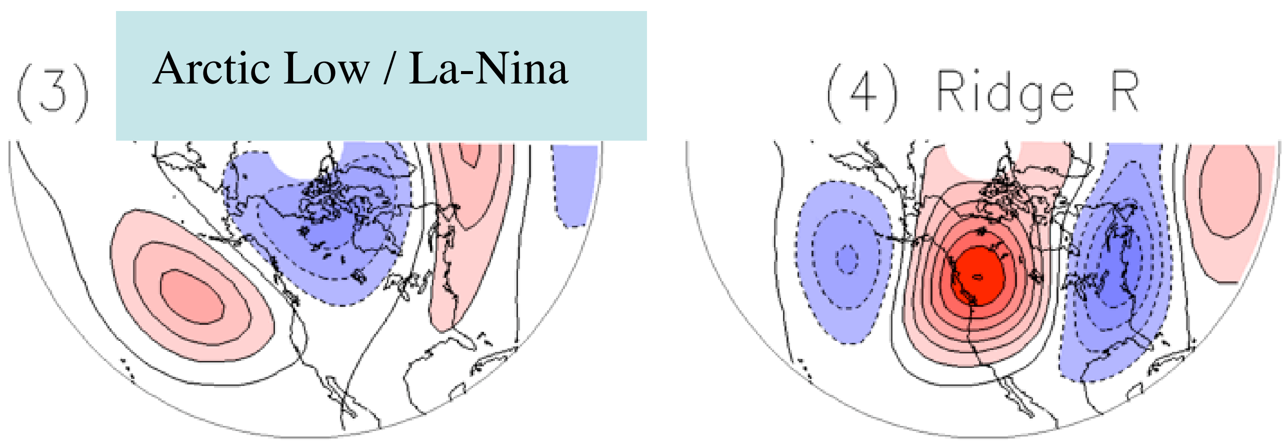
Error is defined as difference between Perturbation and Control

(Acknowledgment to Dan Paolino, COLA)

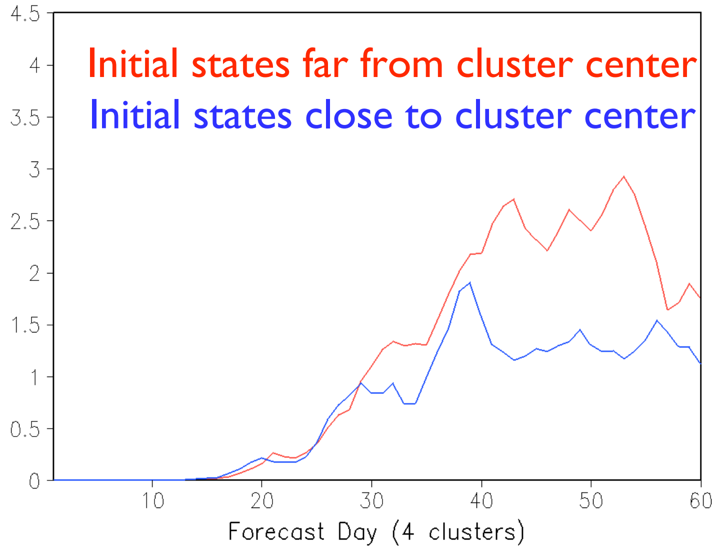


Control+Perturbation Run Clusters

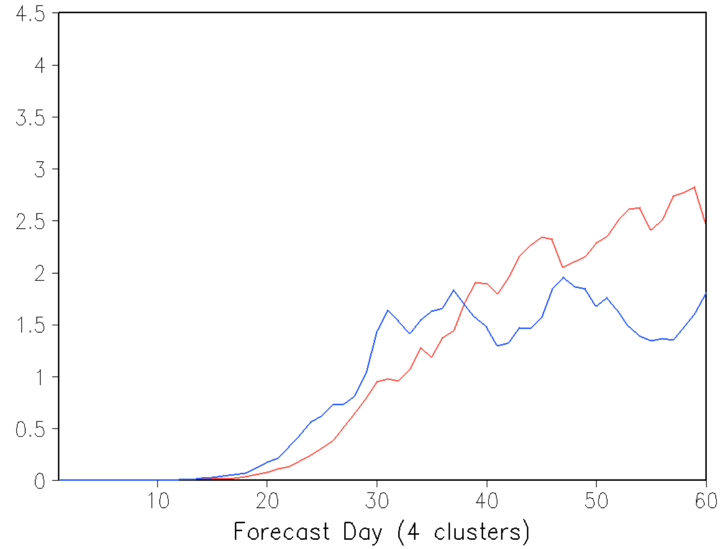
Geopotential states corresponding to centers of 4 partitions
(clusters based on geopotential states)



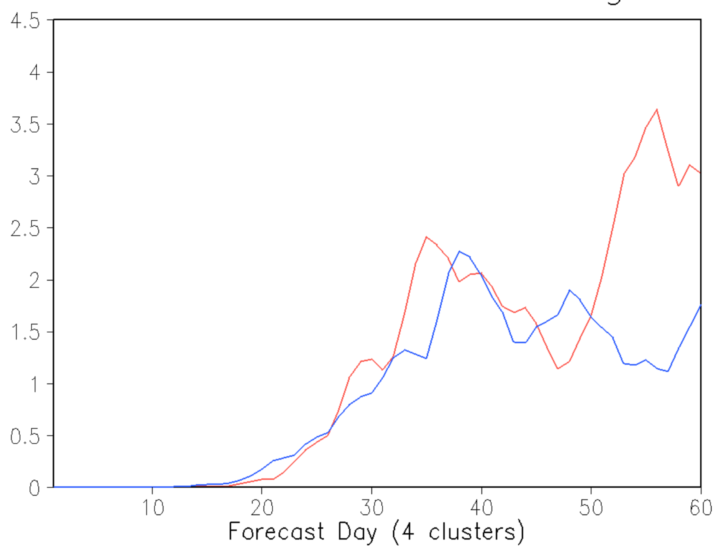
Cond Error Growth PT



Cond Error Growth AR



Cond Error Growth Ridge



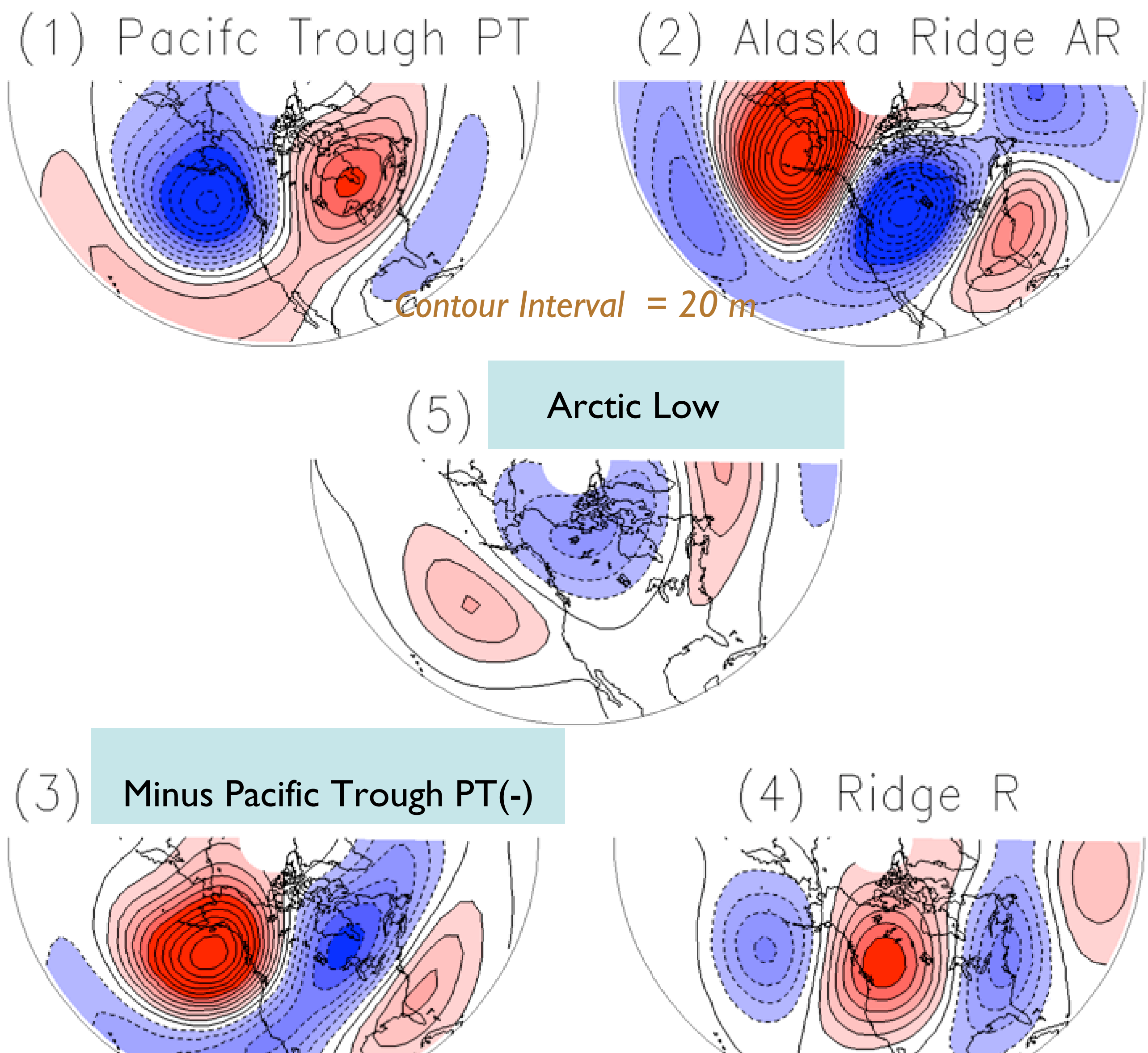
Error growth of states initially in a cluster:

(1) Project instantaneous daily states of control and perturbation runs on low-frequency PCs

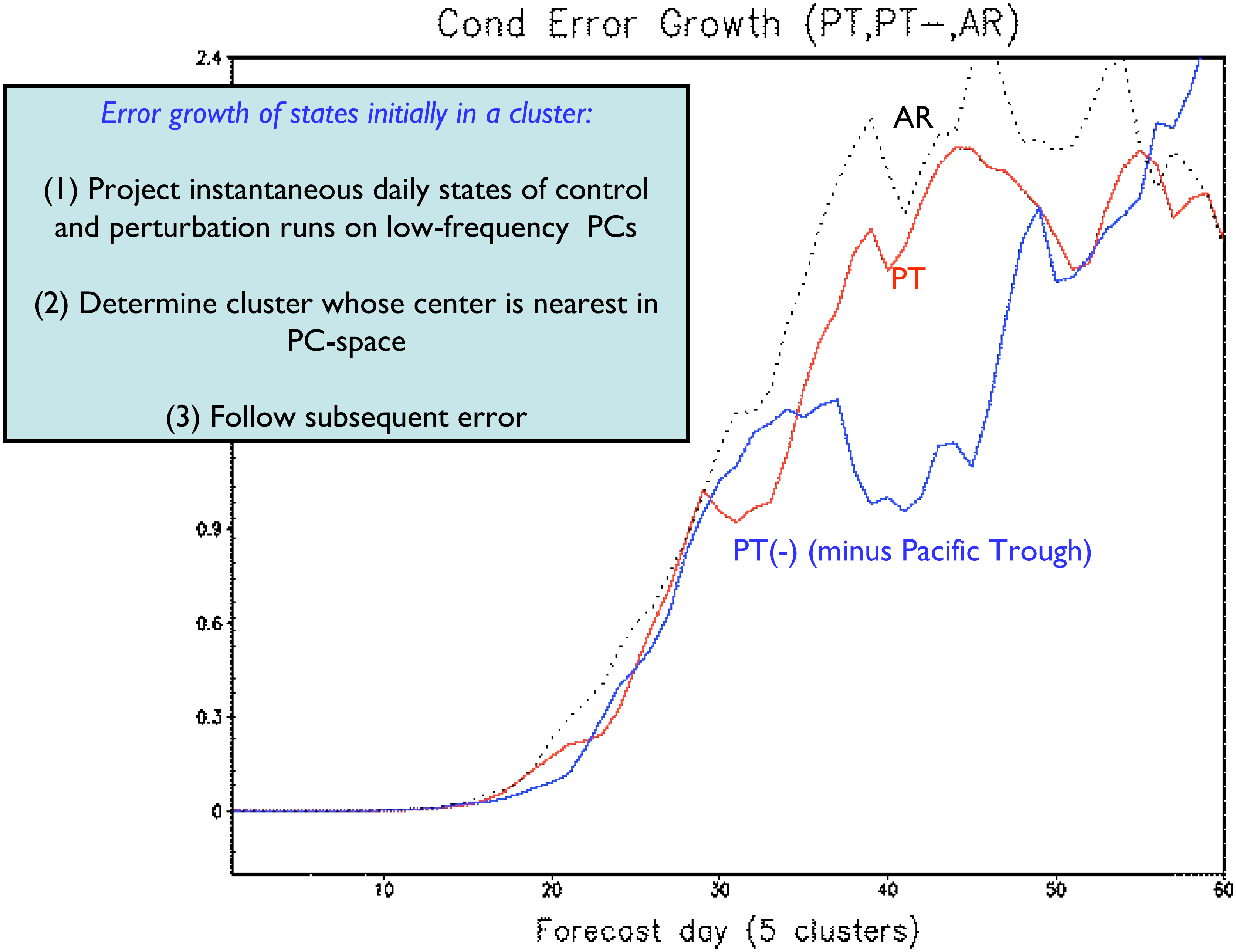
est

(2) Determine cluster whose center is nearest in PC-space

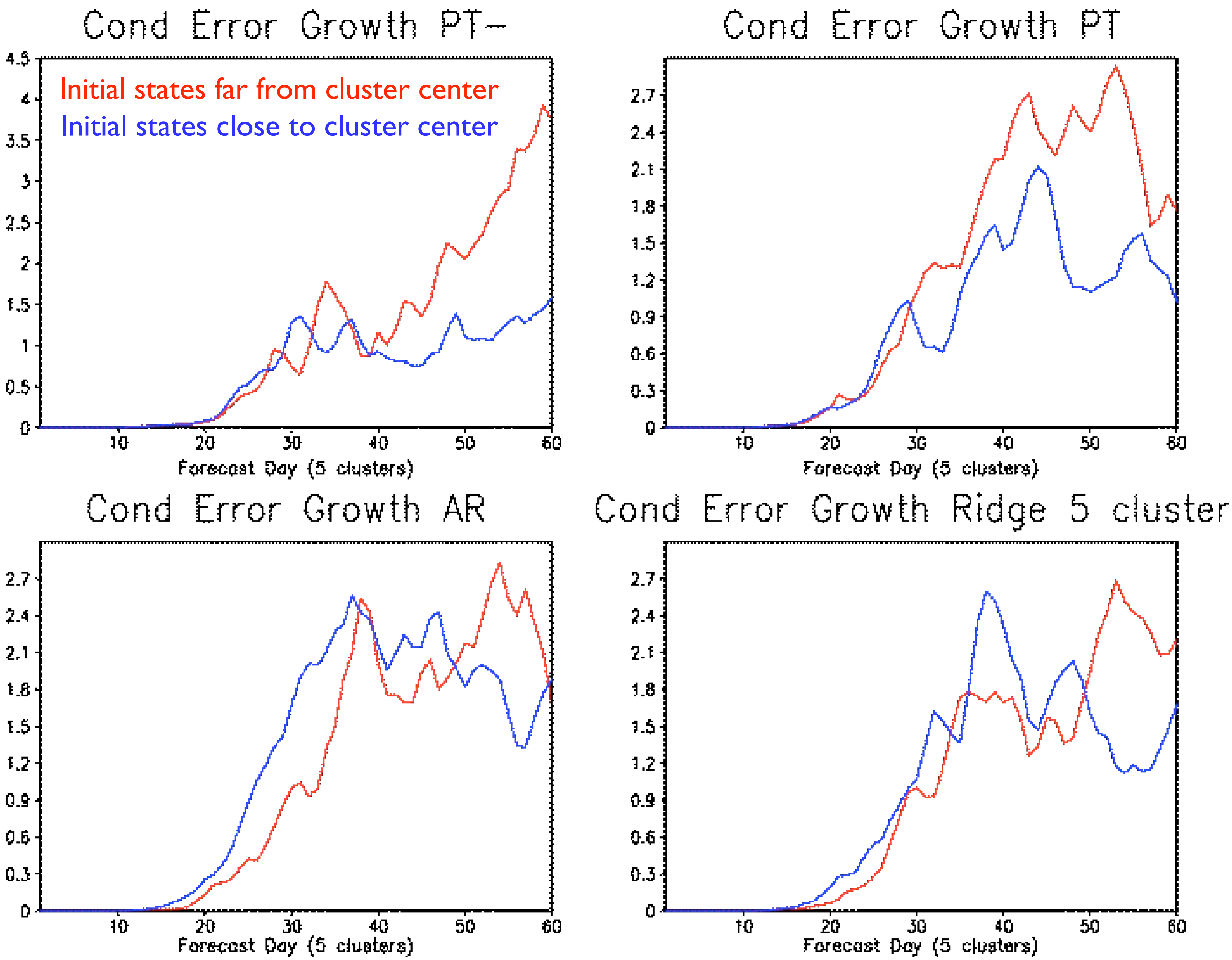
(3) Follow subsequent error



Geopotential states corresponding to centers of 5 partitions
(clusters based on geopotential states)



Cond Error Growth (PT,PT–,AR)
Error growth of states initially in a cluster:
(1) Project instantaneous daily states of control and perturbation runs on low-frequency PCs
(2) Determine cluster whose center is nearest in PC-space
(3) Follow subsequent error
AR
PT
PT(-) (minus Pacific Trough)
2.4
0.9
0.6
0.3
0
10
20
30
40
50
60
Forecast day (5 clusters)



Cond Error Growth PT-
Initial states far from cluster center
Initial states close to cluster center
Forecast Day (5 clusters)
Cond Error Growth PT
Forecast Day (5 clusters)
Cond Error Growth AR
Forecast Day (5 clusters)
Cond Error Growth Ridge 5 cluster
Forecast Day (5 clusters)

Some comments about error growth results:

(1) Relatively slower error growth of PT and PT(-) states nearer the cluster center indicates these preferred states are relatively stable

(2) Error growth asymmetry between PT and PT(-) has strong predictability implications for medium range forecasts

(3) Alaskan Ridge has relatively large error growth compared to other clusters - and the states that are closest to the cluster center are the most unstable! (Is there a link to under-prediction of blocking in this AGCM and others?)

(4) The big difference in stability properties of the Pacific Ridge (stable) and Alaskan Ridge (unstable) remains to be explained.

(5) More diagnosis and numerical experiments are needed