



# Expected and Actual Forecast Errors by a Non-normal Model of El Niño

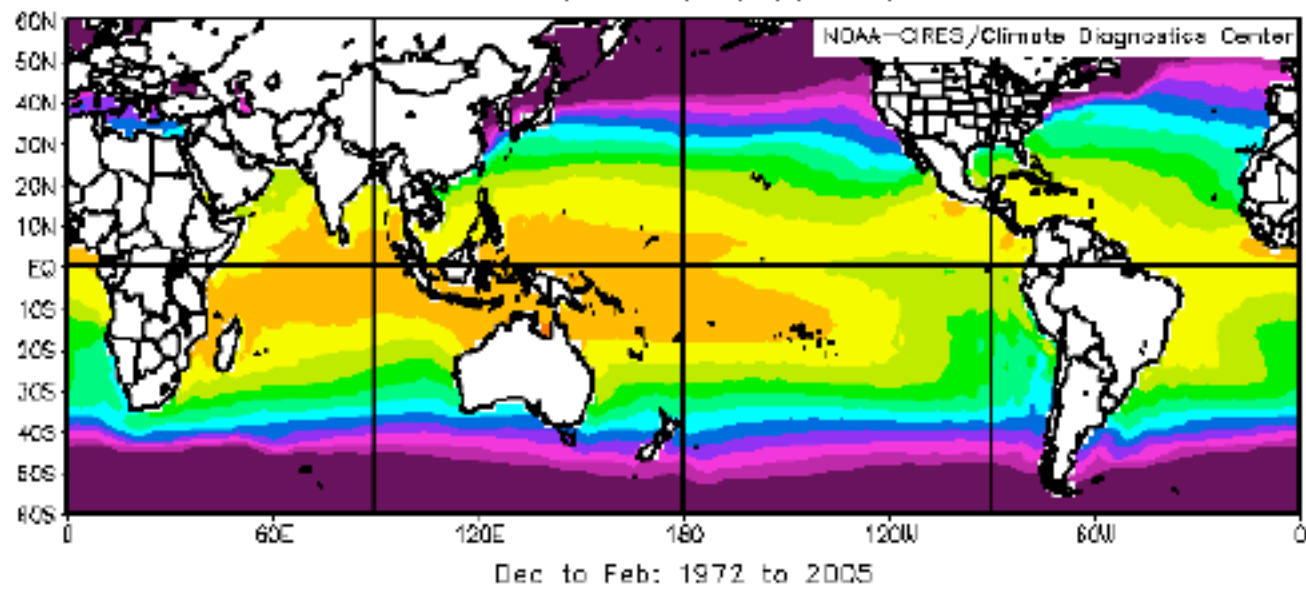
Cécile Penland

*NOAA/ESRL/Physical Sciences Division*

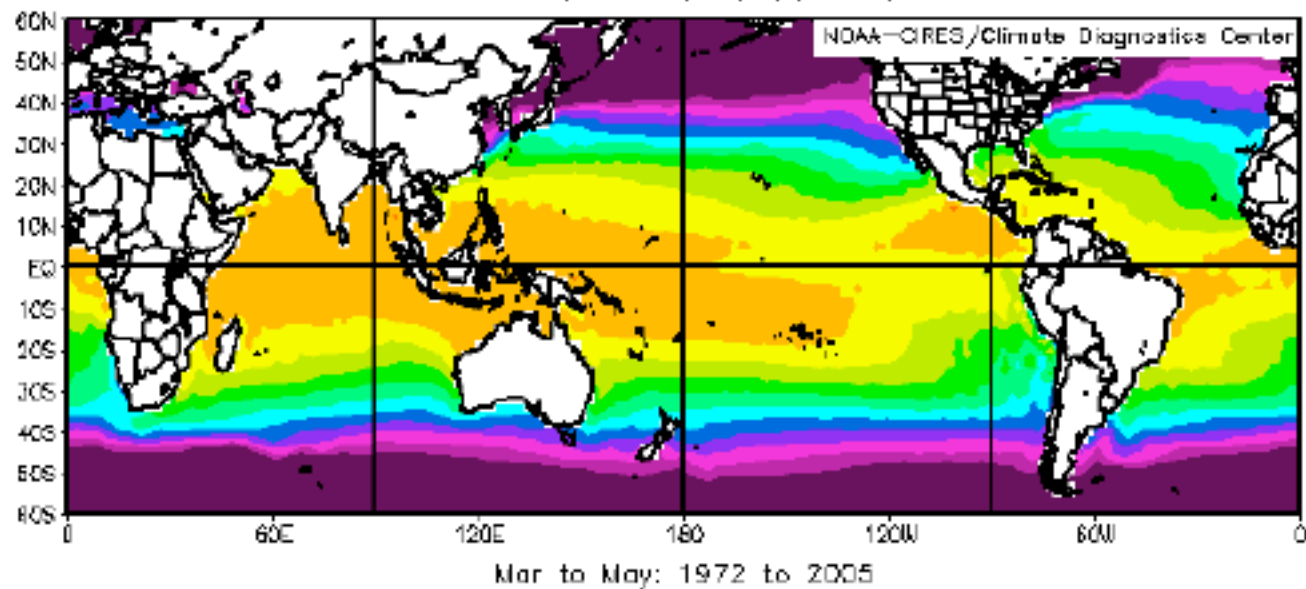
# *Outline*

- Some phenomenology: What is El Niño
  - The Annual Cycle
  - Deviations from it, especially El Niño
- An empirical-dynamical model
- Uncertainty and errors

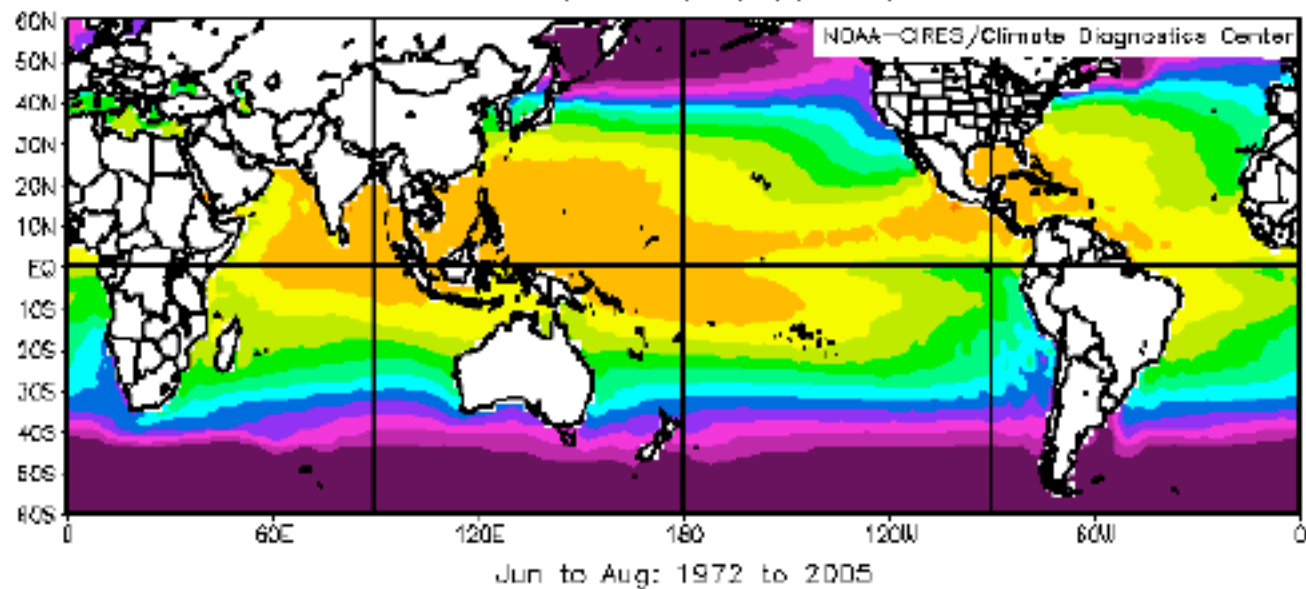
NCEP/NCAR Reanalysis  
Surface Skin Temperature(SST) (C) Composite Mean



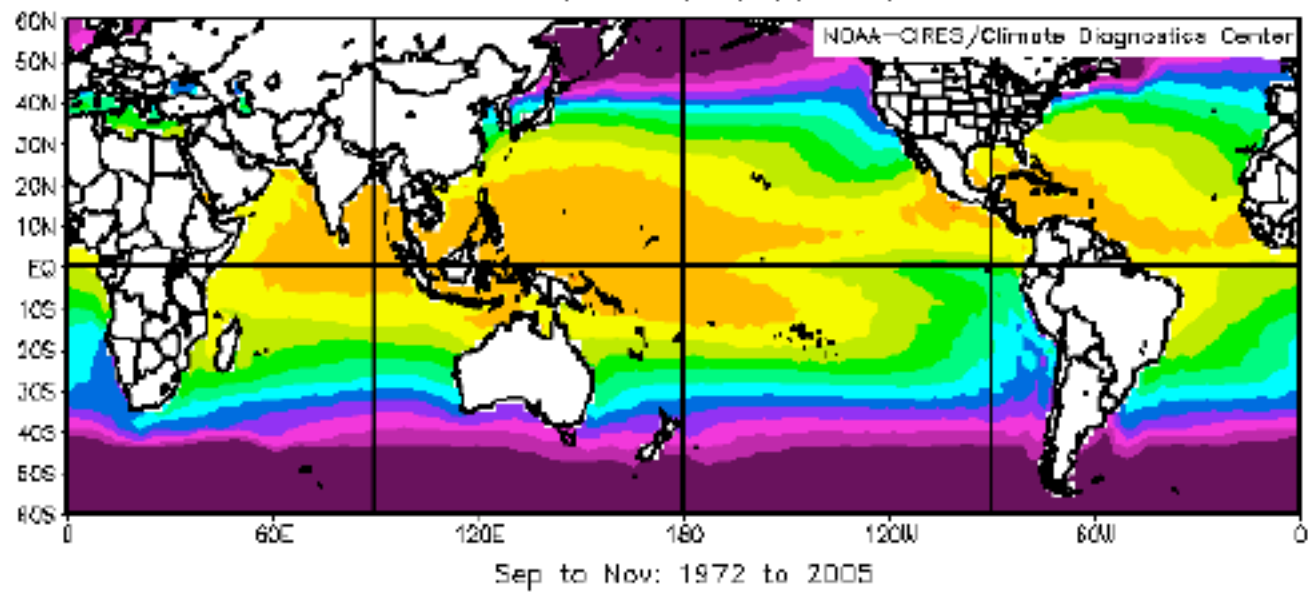
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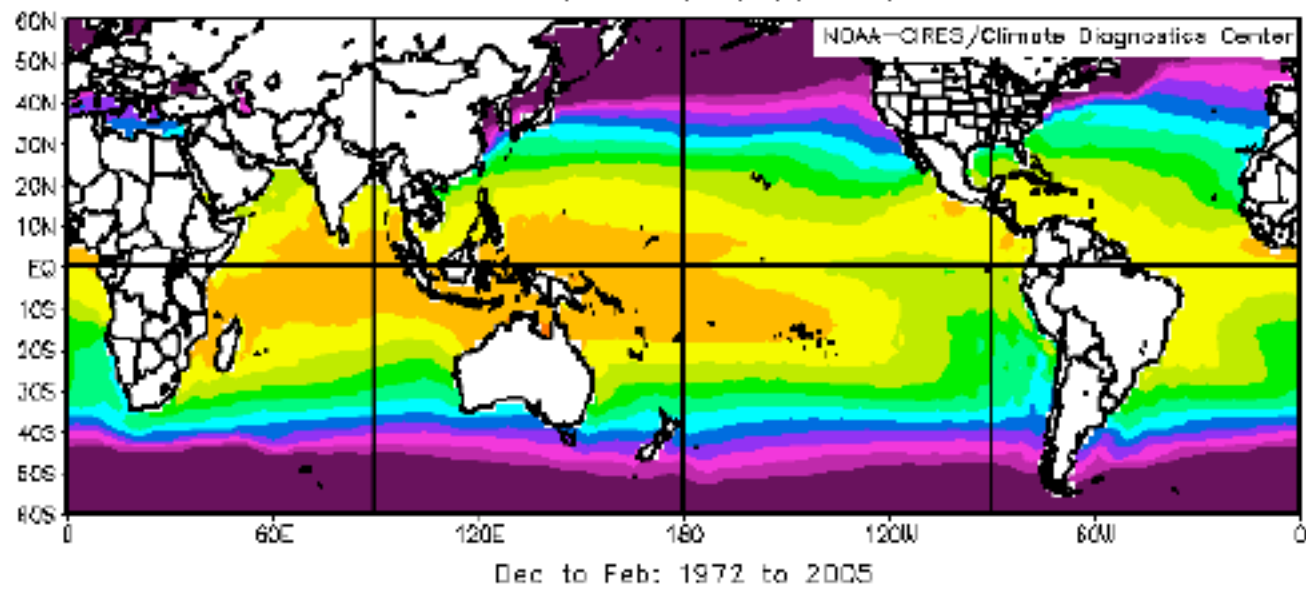
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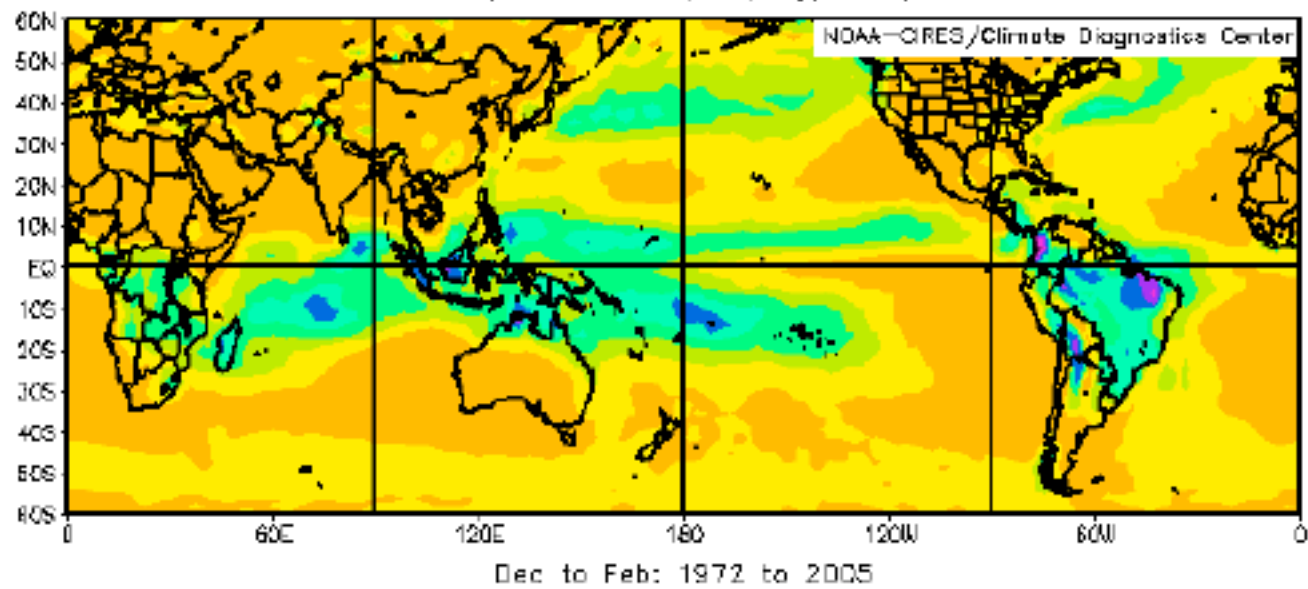
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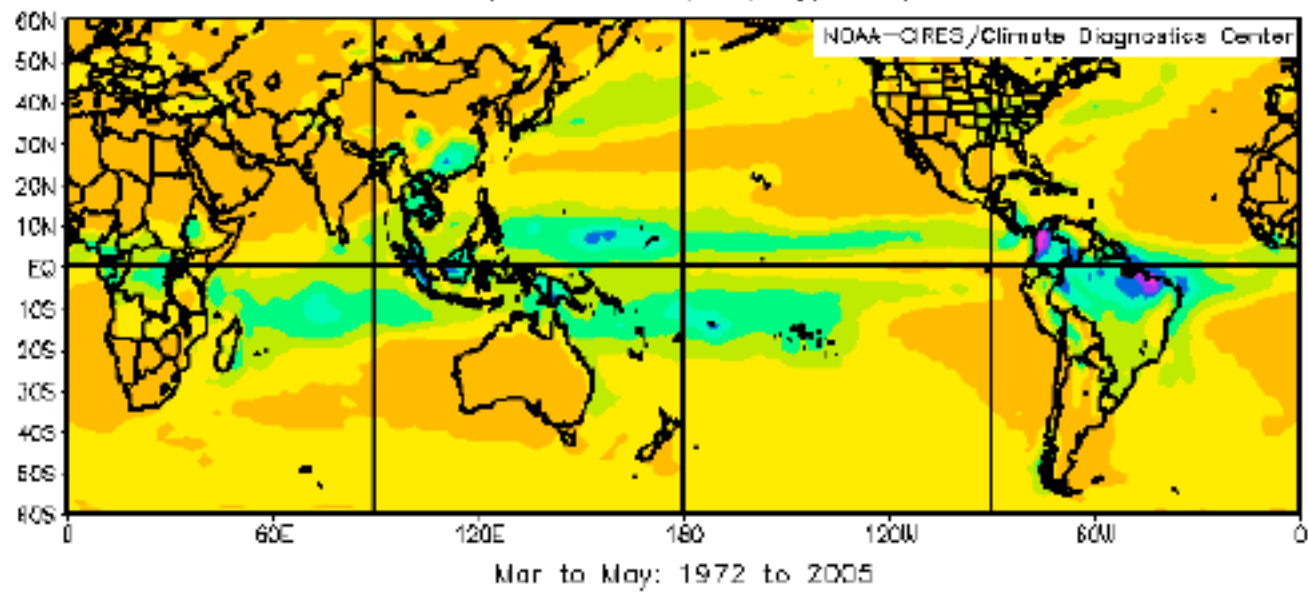


NCEP/NCAR Reanalysis  
Surface Precipitation Rate (mm/day) Composite Mean

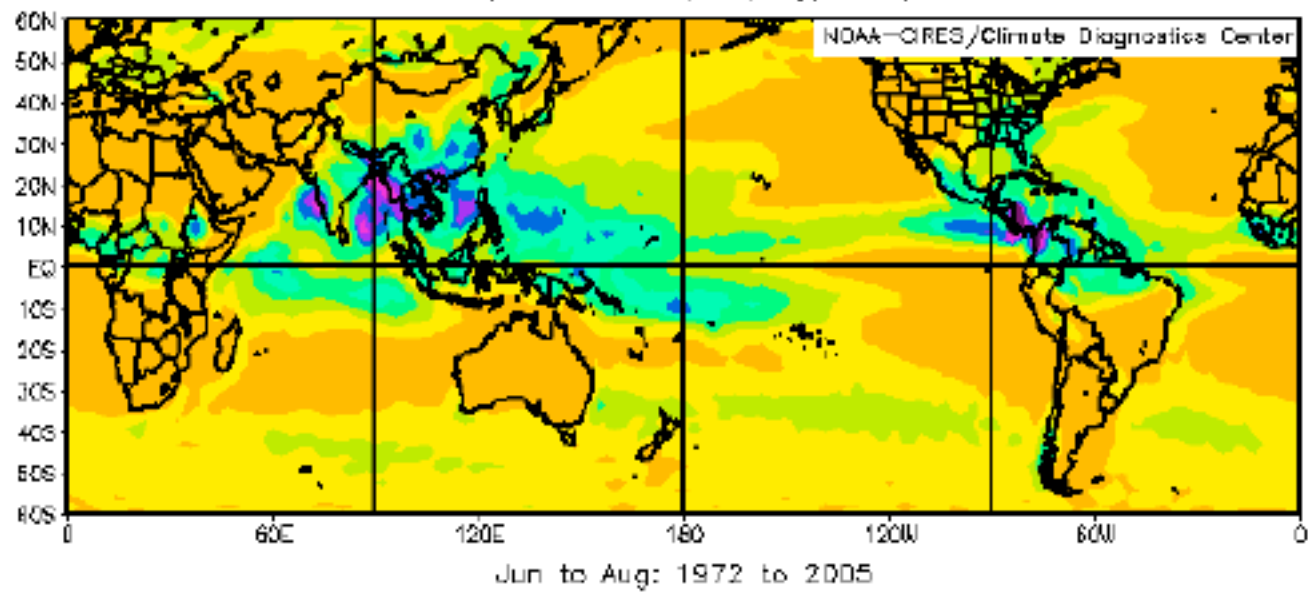




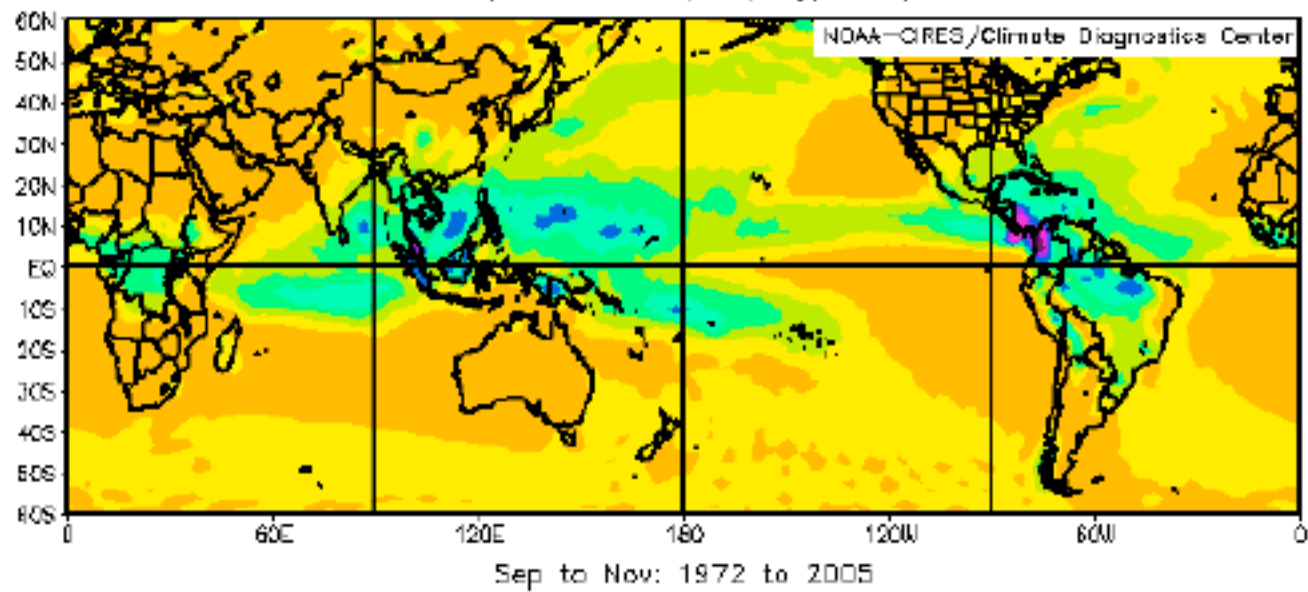
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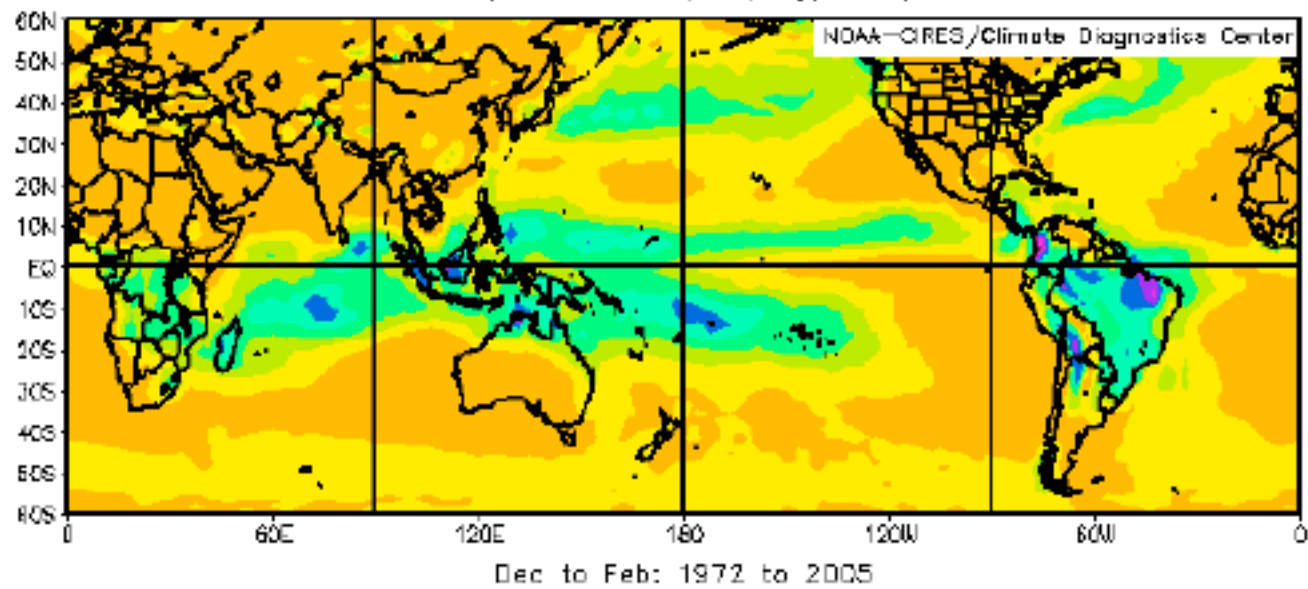
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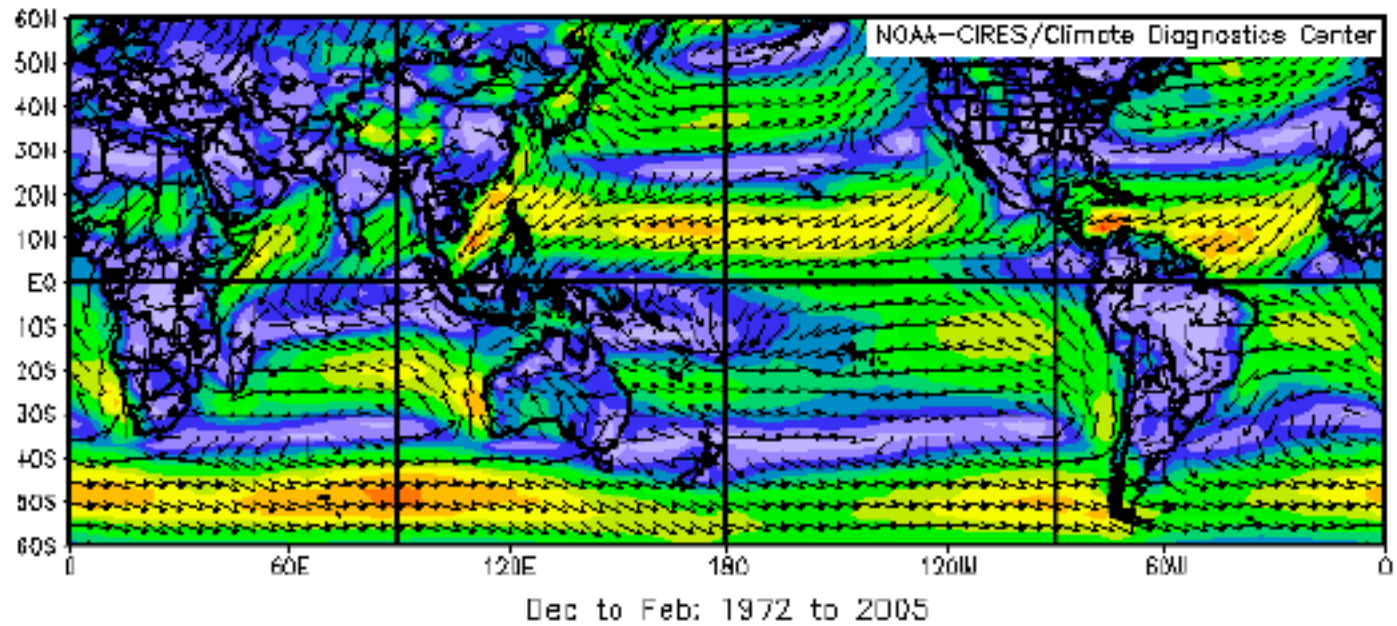
NCEP/NCAR Reanalysis  
Surface Precipitation Rate (mm/day) Composite Mean



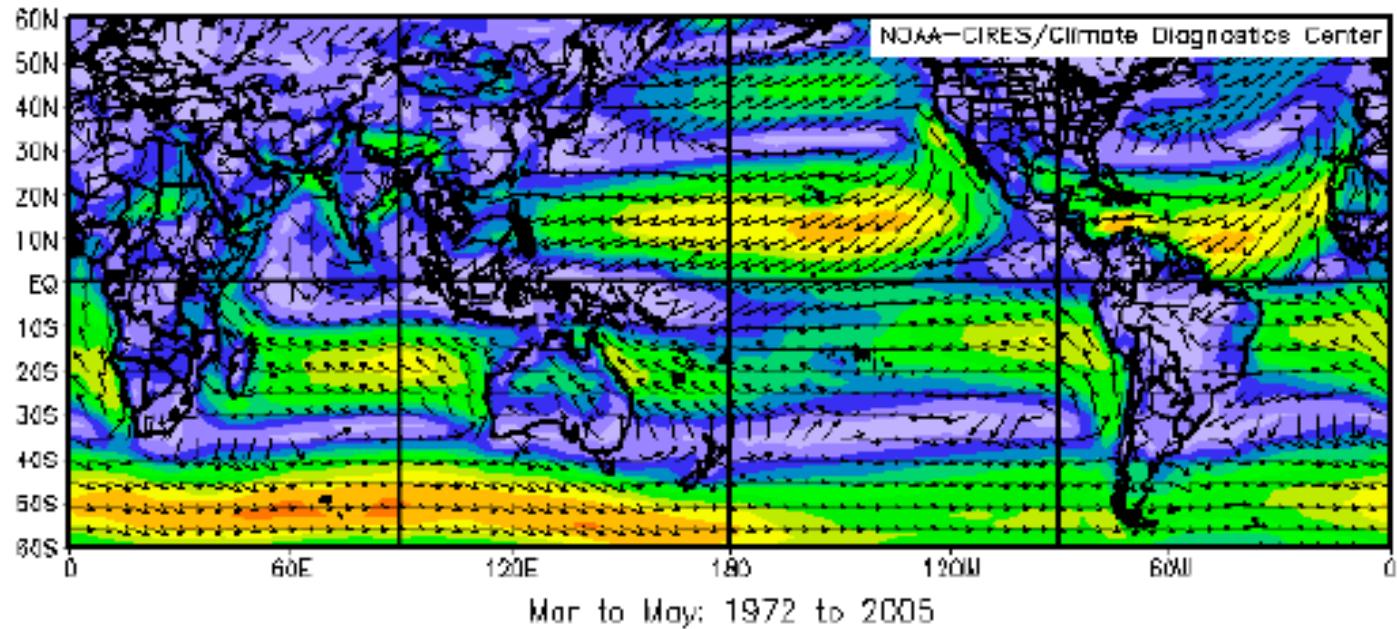
NCEP/NCAR Reanalysis  
Surface Precipitation Rate (mm/day) Composite Mean



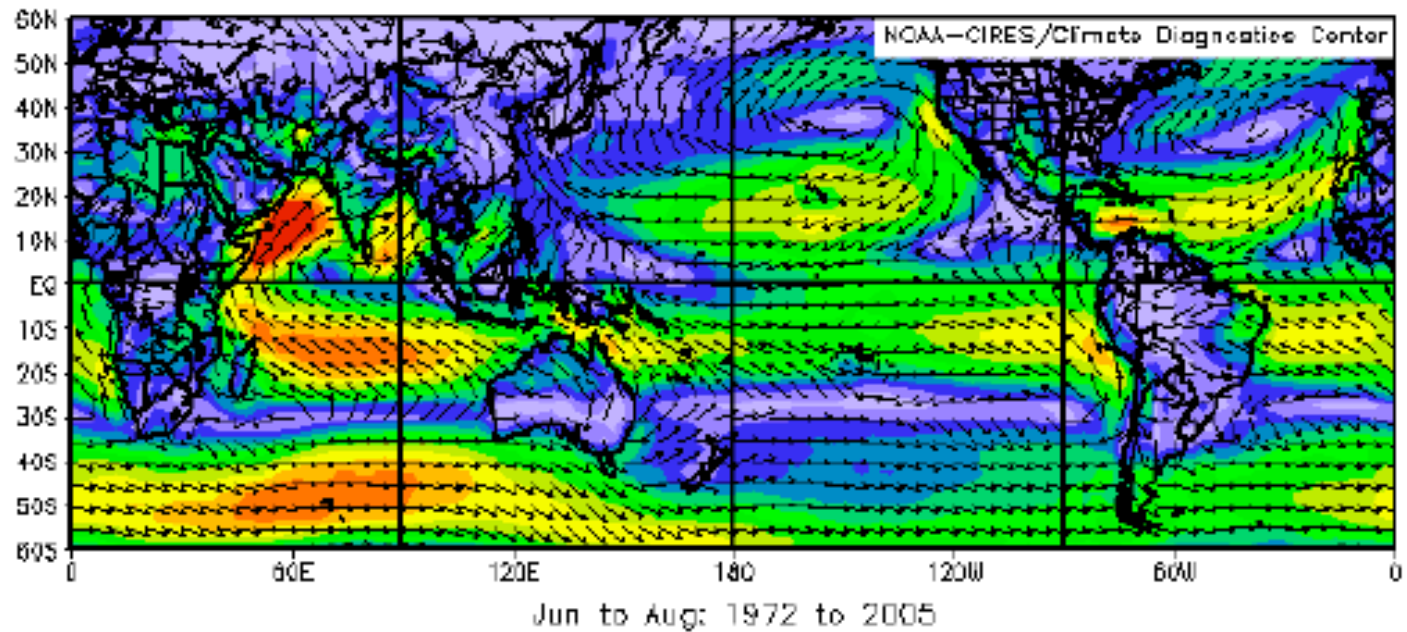
NCEP/NCAR Reanalysis  
Surface Vector Wind (m/s) Composite Mean



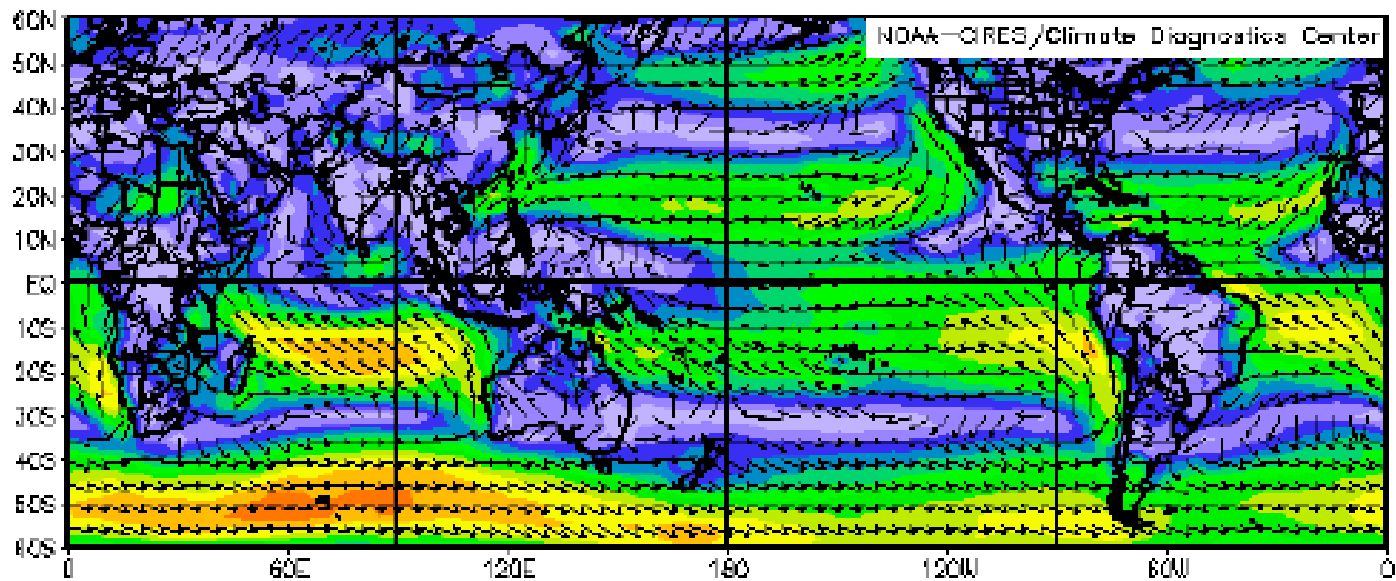
NCEP/NCAR Reanalysis  
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NCEP/NCAR Reanalysis  
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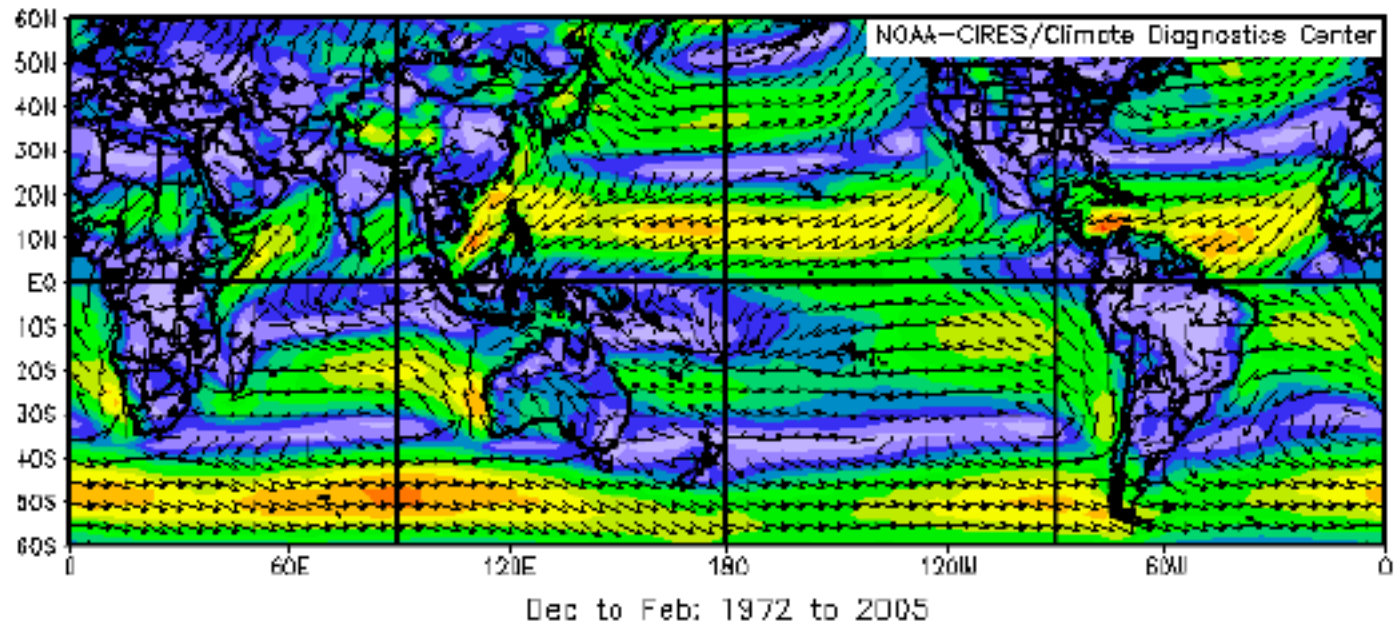


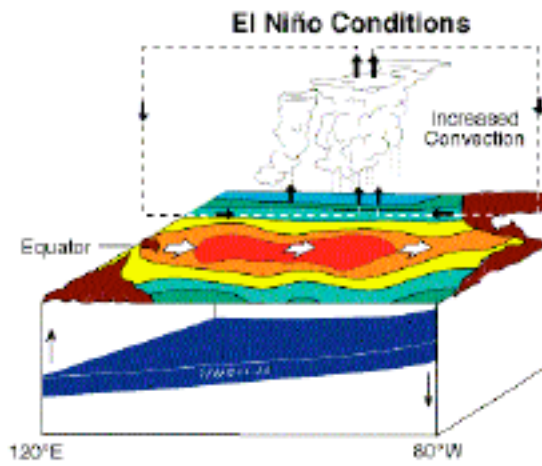
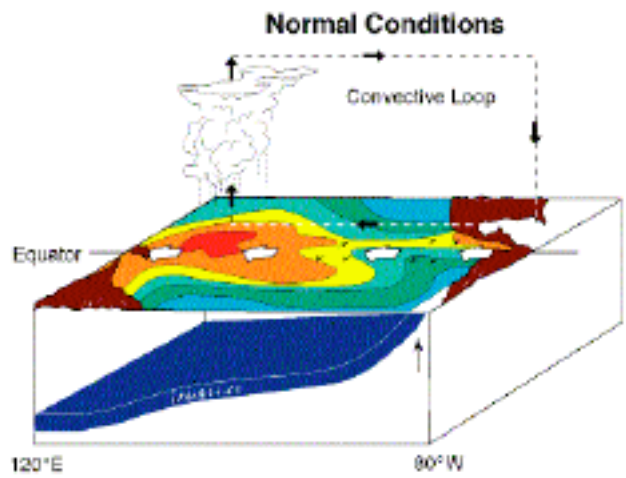
Sep to Nov: 1972 to 2005



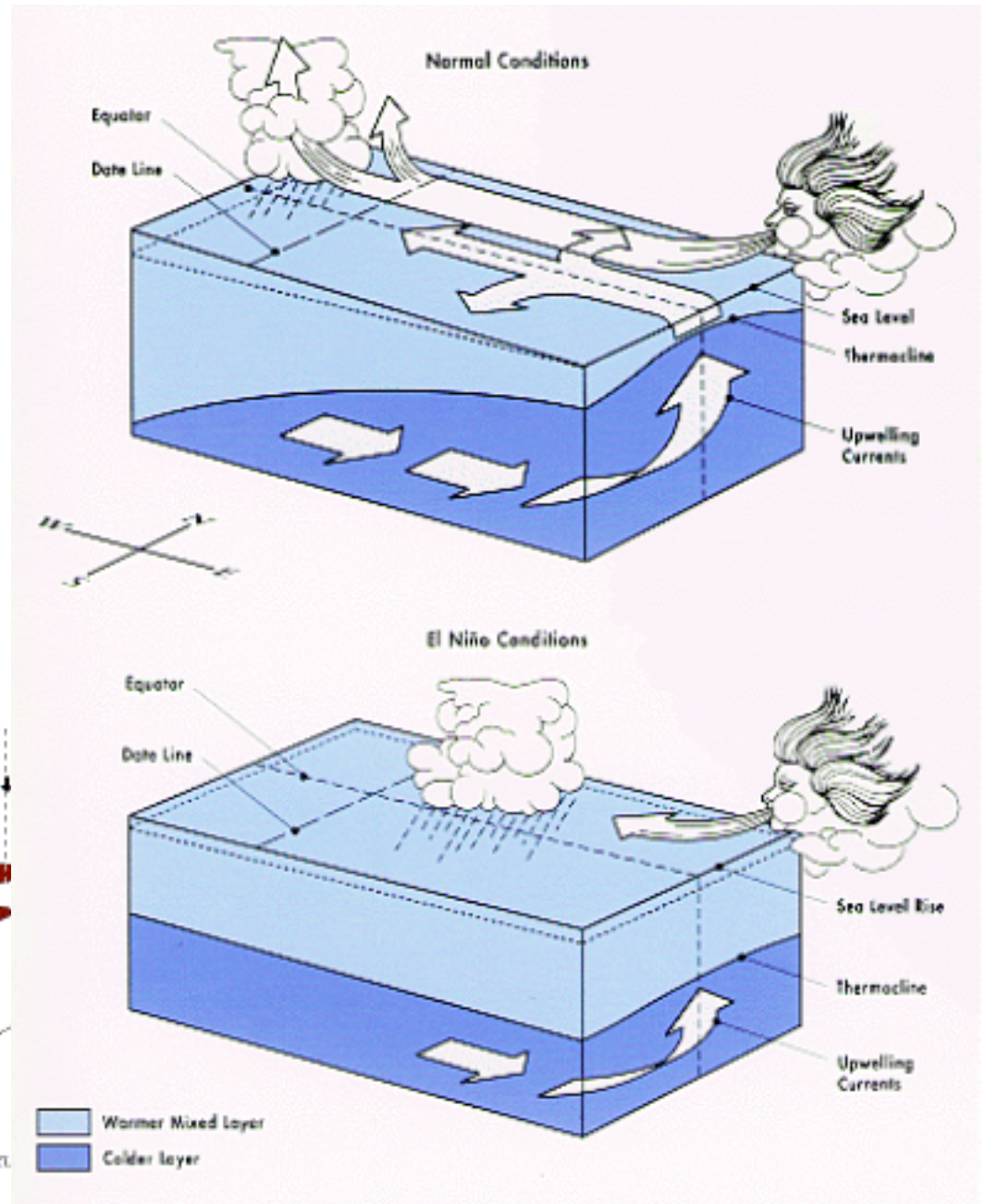


NCEP/NCAR Reanalysis  
Surface Vector Wind (m/s) Composite Mean

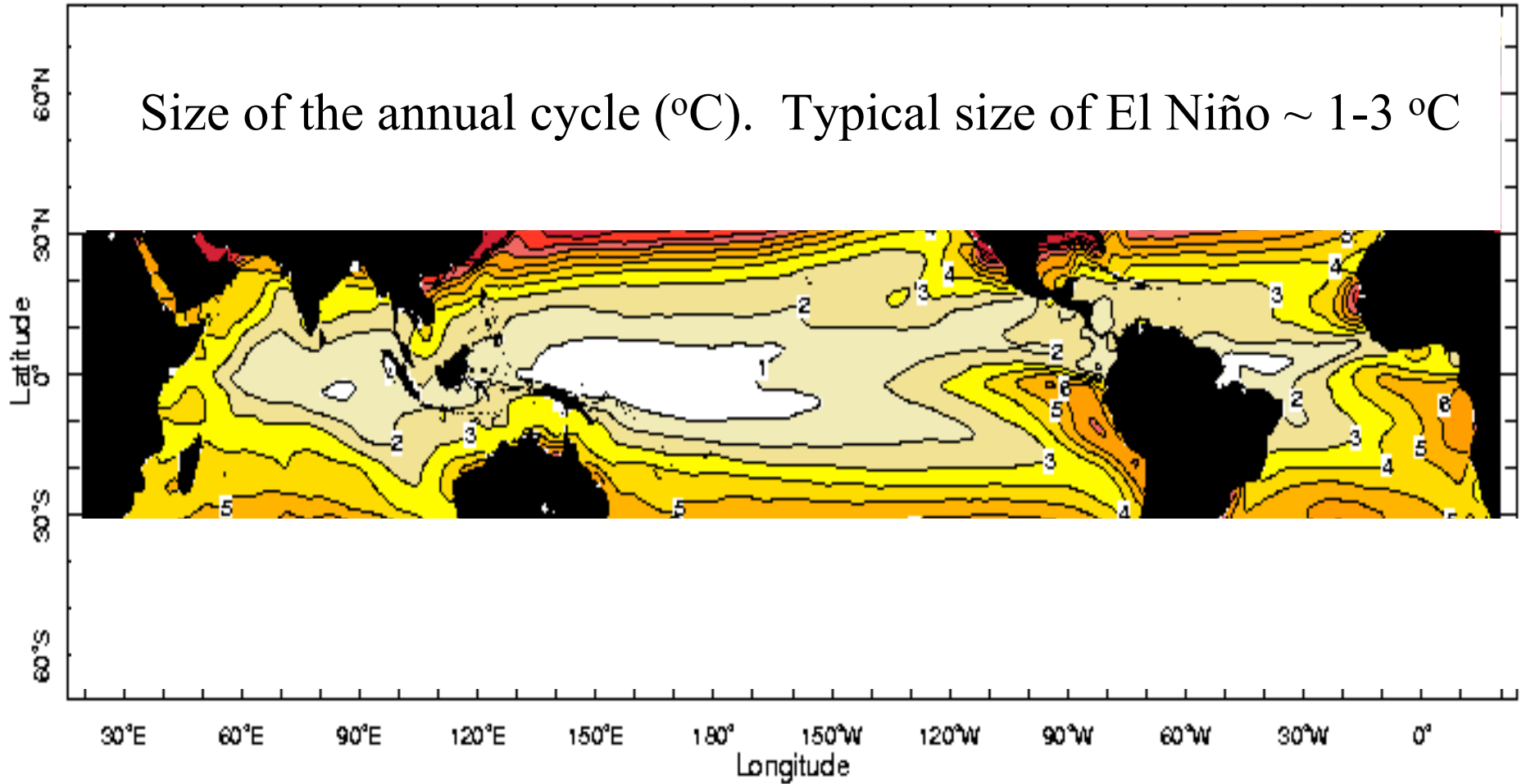




NOAA/PWEL



Size of the annual cycle ( $^{\circ}\text{C}$ ). Typical size of El Niño  $\sim 1\text{-}3\text{ }^{\circ}\text{C}$



# Linear Inverse Modeling

*Assume* linear dynamics (dropping the primes):

$$d\mathbf{T}/dt = \mathbf{B}\mathbf{T} + \boldsymbol{\xi}, \text{ with } \langle \boldsymbol{\xi}(t+\tau) \boldsymbol{\xi}^T(t) \rangle = \mathbf{Q}(t)\delta(\tau)$$

For now, we'll assume additive noise, although that assumption is false.  $\mathbf{Q}(t)$  is periodic.

Corresponding FPE:

$$\frac{\partial p(\mathbf{T}, t)}{\partial t} = -\sum_{ij} \frac{\partial}{\partial T_i} [B_{ij} T_j p(\mathbf{T}, t)] + \frac{1}{2} \sum_{ij} \frac{\partial^2}{\partial T_i \partial T_j} [Q_{ij}(t) p(\mathbf{T}, t)]$$

From the FPE.

$p(\mathbf{T}, t + \tau | \mathbf{T}_o, t)$  is Gaussian, centered on  $\mathbf{G}(\tau) \mathbf{T}_o$

where  $\mathbf{G}(\tau) = \exp(\mathbf{B} \tau) = \langle \mathbf{T}(t + \tau) \mathbf{T}^T(t) \rangle \langle \mathbf{T}(t) \mathbf{T}^T(t) \rangle^{-1}$ .

The covariance matrix of the predictions:

$$\Sigma(t, \tau) = \langle \mathbf{T}(t + \tau) \mathbf{T}^T(t + \tau) \rangle - \mathbf{G}(\tau) \langle \mathbf{T}(t) \mathbf{T}^T(t) \rangle \mathbf{G}^T(\tau).$$

Further,

$$\frac{\partial}{\partial t} \langle \mathbf{T}(t) \mathbf{T}^T(t) \rangle = \mathbf{B} \langle \mathbf{T}(t) \mathbf{T}^T(t) \rangle + \langle \mathbf{T}(t) \mathbf{T}^T(t) \rangle \mathbf{B}^T + \mathbf{Q}(t)$$

Digression : *The disturbing assumption of additive noise.*

Instead of  $d\mathbf{T}/dt = \mathbf{B}\mathbf{T} + \boldsymbol{\xi}$ , the system is actually of the form

$$d\mathbf{T}/dt = \mathbf{B}\mathbf{T} + (\mathbf{A}\mathbf{T} + \mathbf{C})\xi_1 + \mathbf{D}\xi_2.$$

All of the LIM formalism follows through, with the identification

$$\mathbf{B} \rightarrow \mathbf{B} + \mathbf{A}^2/2; \quad \mathbf{Q} \rightarrow \langle (\mathbf{A}\mathbf{T} + \mathbf{C}) (\mathbf{A}\mathbf{T} + \mathbf{C})^T \rangle + \mathbf{D}\mathbf{D}^T$$

$$\mathbf{G}(\tau) \rightarrow \exp \{ (\mathbf{B} + \mathbf{A}^2/2) \tau \}$$

Note:  $p(\mathbf{T}, t + \tau | \mathbf{T}_o, t)$  is no longer Gaussian, but  $\mathbf{G}(\tau) \mathbf{T}_o$  is still the best prediction in the mean square sense.

Eigenvectors of  $\mathbf{G}(\tau)$  are the “*normal*” modes  $\{\mathbf{u}_i\}$ .

Eigenvectors of  $\mathbf{G}^T(\tau)$  are the “*adjoints*”  $\{\mathbf{v}_i\}$ ,

$$\text{(Recall: } \mathbf{G}(\tau) = \langle \mathbf{T}(t+\tau)\mathbf{T}^T(t) \rangle \langle \mathbf{T}(t)\mathbf{T}^T(t) \rangle^{-1})$$

and  $\mathbf{u}\mathbf{v}^T = \mathbf{u}^T\mathbf{v} = 1$ .

Most probable prediction:  $\mathbf{T}(t+\tau) = \mathbf{G}(\tau) \mathbf{T}_o(t)$

The neat thing:  $\mathbf{G}(\tau) = \{\mathbf{G}(\tau_o)\}^{\tau/\tau_o}$ .

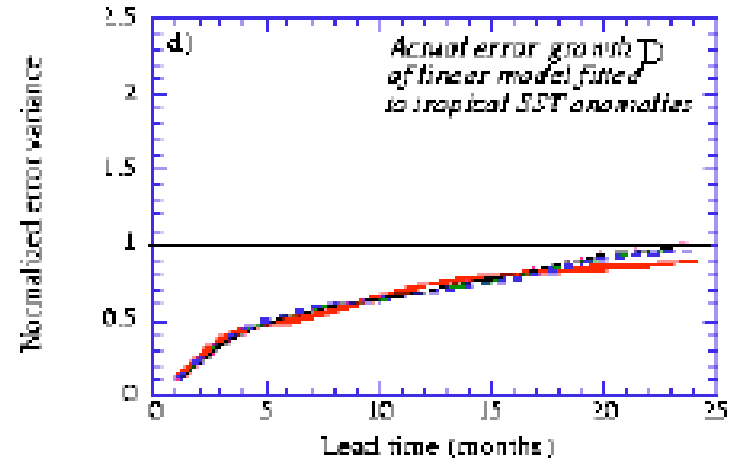
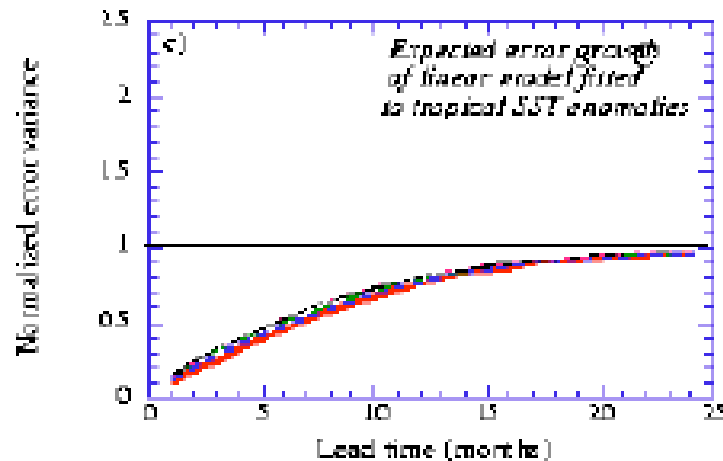
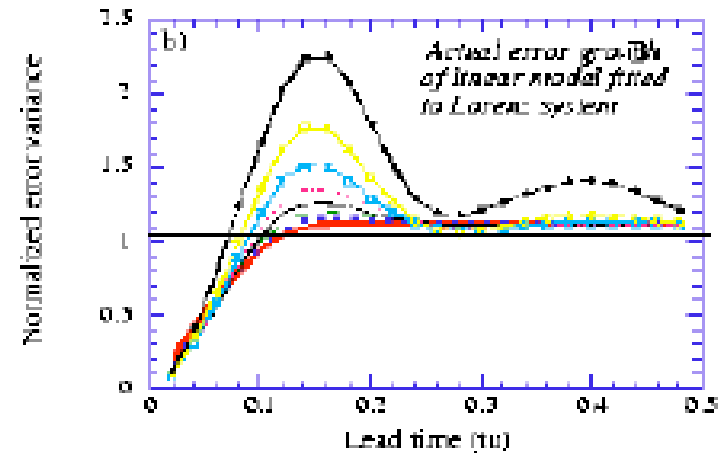
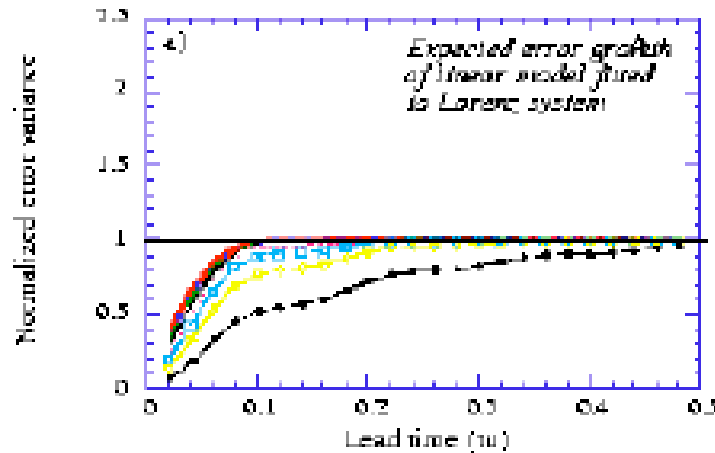
If LIM’s assumptions are valid, the prediction error  $\boldsymbol{\varepsilon} = \mathbf{T}(t+\tau) - \mathbf{G}(\tau) \mathbf{T}_o$  does not depend on the lag at which the covariance matrices are evaluated. This is true for El Niño; it is *not* true for the chaotic Lorenz system.

## SST Data used:

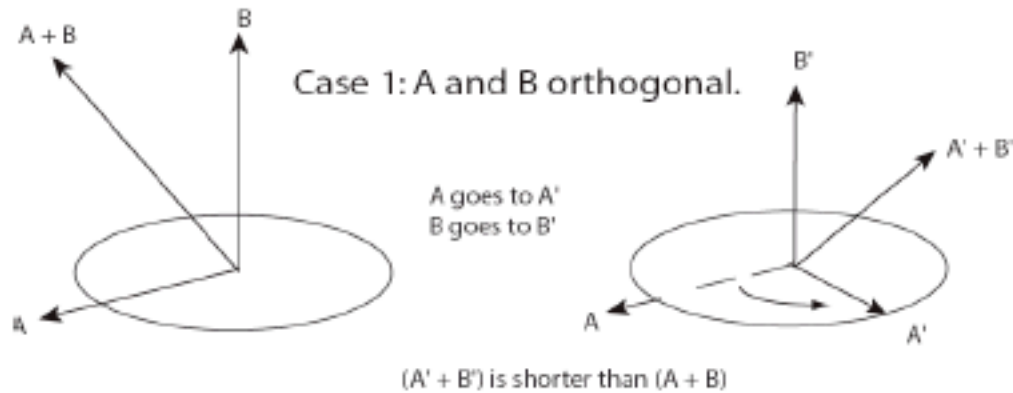
- COADS (1950-2000) SSTs in 30E-70W, 30N – 30S, or in the global tropical strip, consolidated onto a 4x10-degree grid.
- Subjected to 3-month running mean.
- Projected data onto an orthogonal basis to reduce dimensionality.



Below, different colors correspond to different lags used to identify the parameters. What is plotted:  $Tr(\epsilon)$  vs lead.

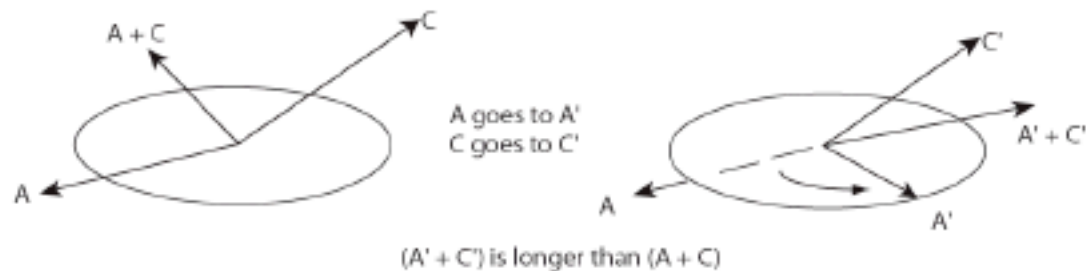


When a system is linear, we can completely identify it from data (**Linear Inverse Modeling**). When it is multi-dimensional, its size can temporarily *grow*, even though all of its components are *decaying*. This happens if the components are almost never orthogonal.

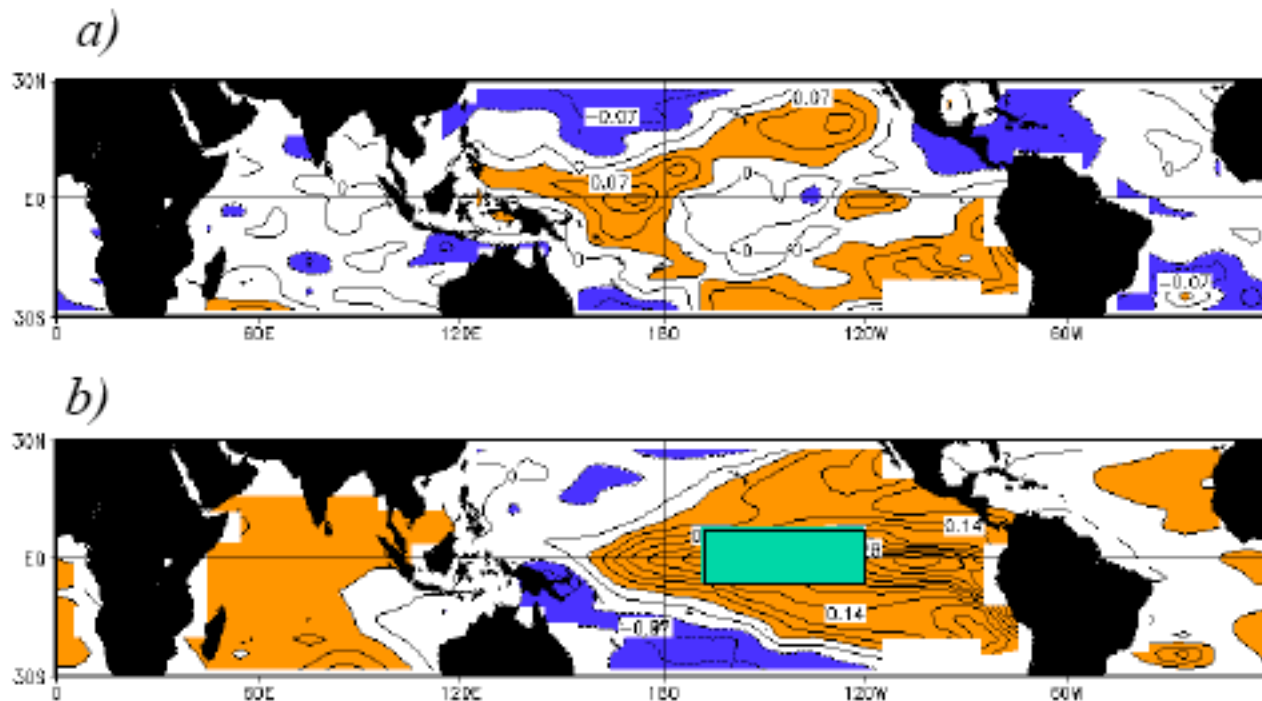


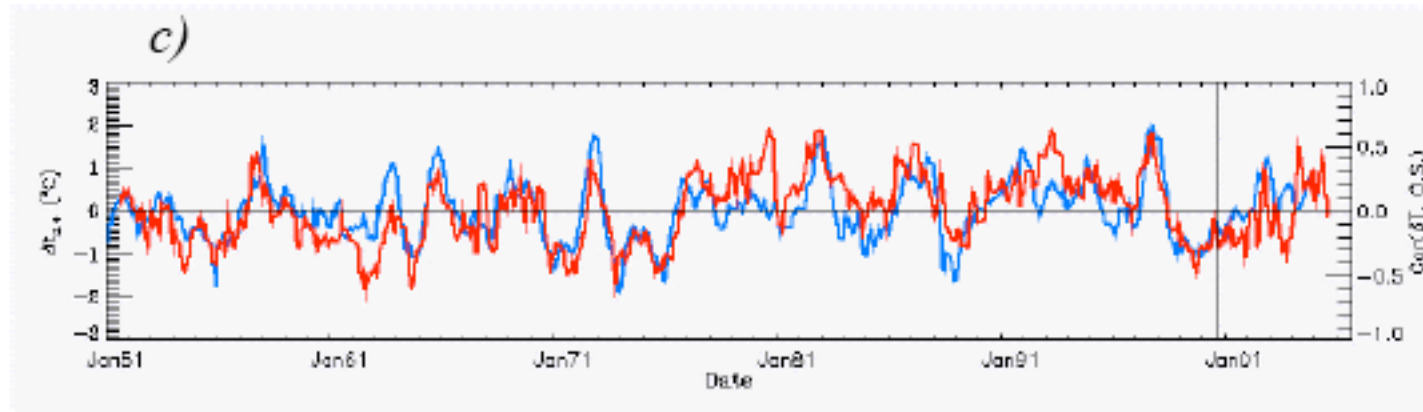
B and C are the same length.  
 $B'$  and  $C'$  are the same length.

Case 2: A and C non-orthogonal.

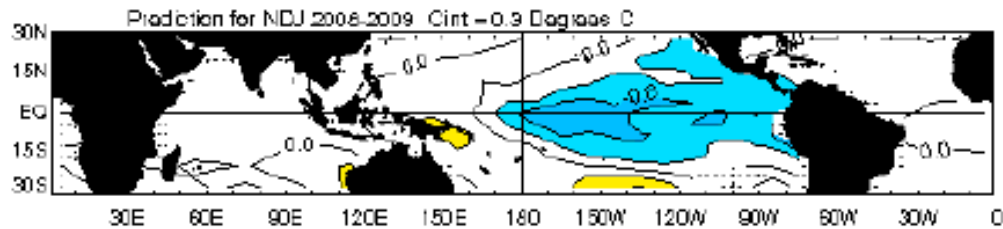
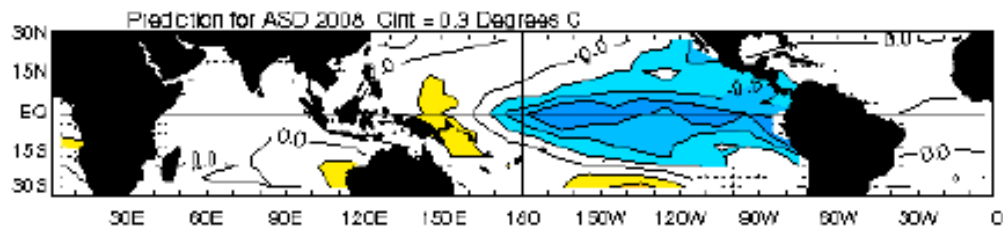
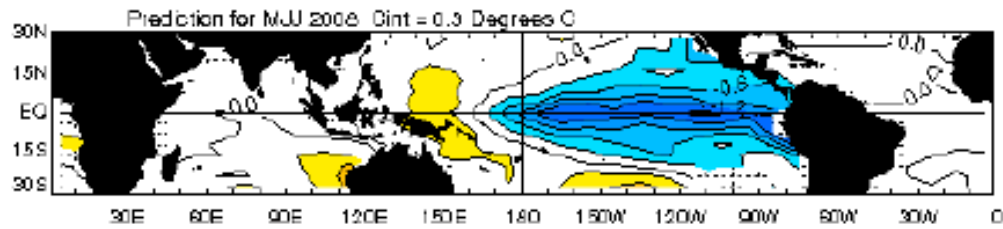
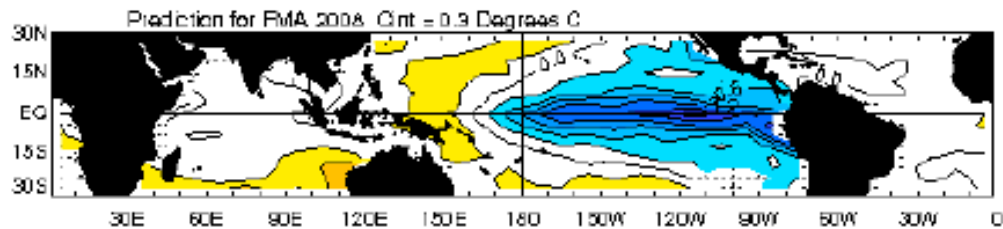
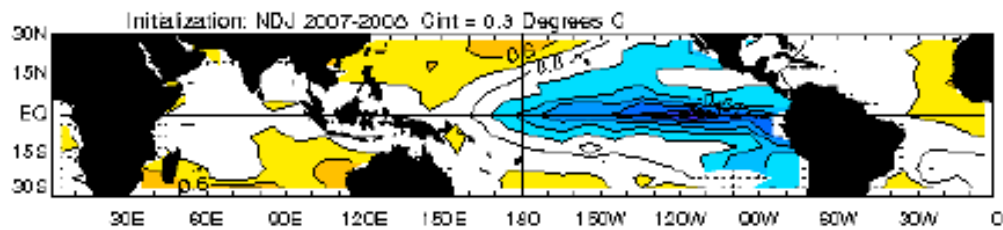


The transient growth possible in a multidimensional linear system occurs when an El Niño develops. *LIM* predicts that an *optimal pattern* (a) precedes a mature El Niño pattern (b) by about 8 months





Does it? Judge for yourself! The red line is the time series of pattern correlations between pattern (*a*) and the sea surface temperature pattern 8 months earlier. The blue line is a time series index of how strong pattern (*b*) is at the date shown; the blue line is an index of El Niño when it is positive and of La Niña when it is negative.



Degrees C

NOAA/ESRL PSD and CIRES/CDC Experimental Forecast

## *Several sources of expected error and uncertainty:*

- Stochastic forcing:

$$\Sigma(t, \tau) = \langle \mathbf{T}(t+\tau)\mathbf{T}^T(t+\tau) \rangle - \mathbf{G}(\tau) \langle \mathbf{T}(t)\mathbf{T}^T(t) \rangle \mathbf{G}^T(\tau)$$

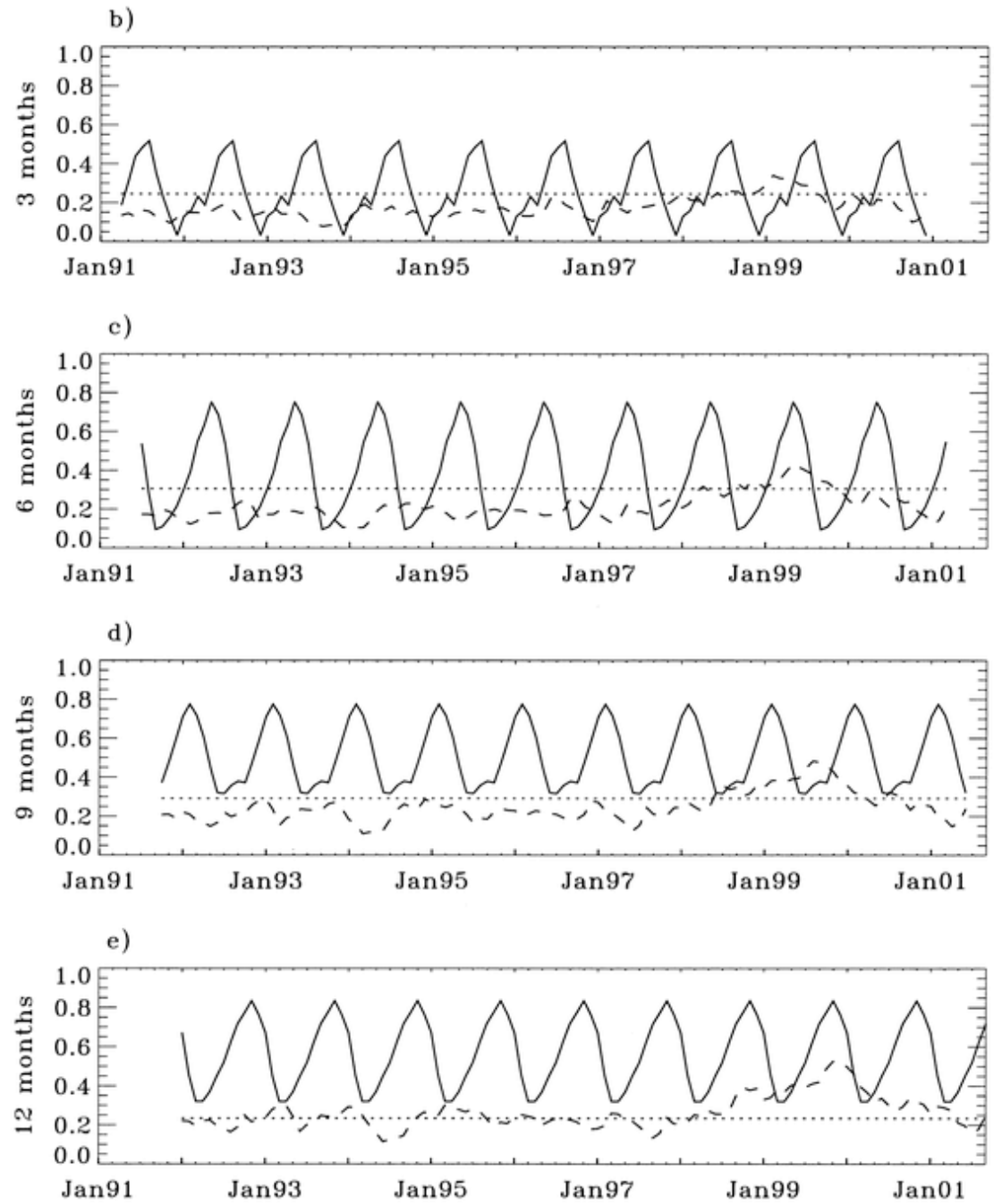
- Uncertain initial conditions:

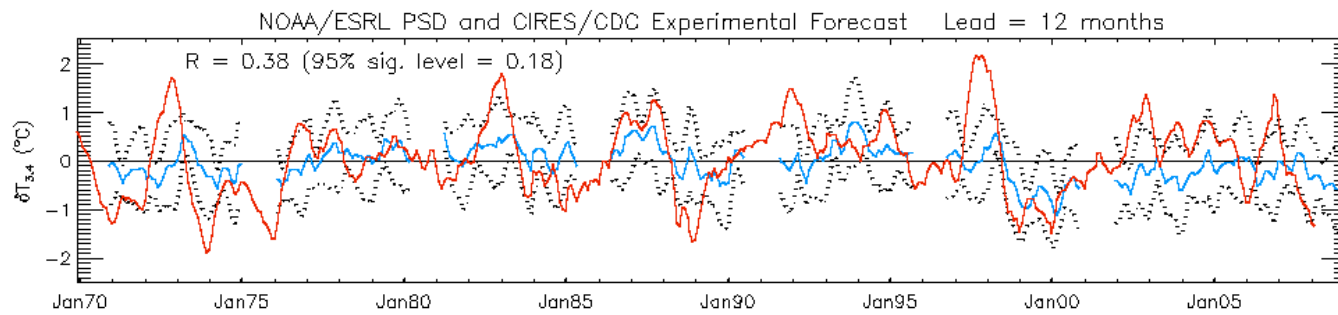
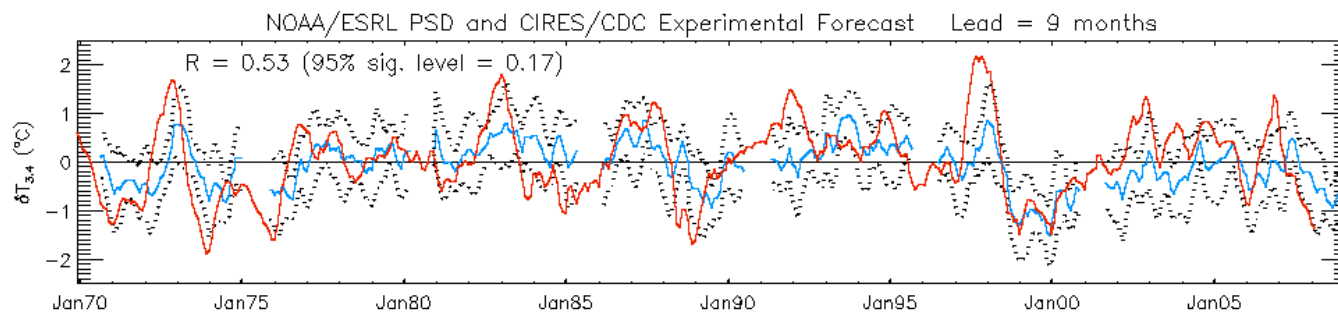
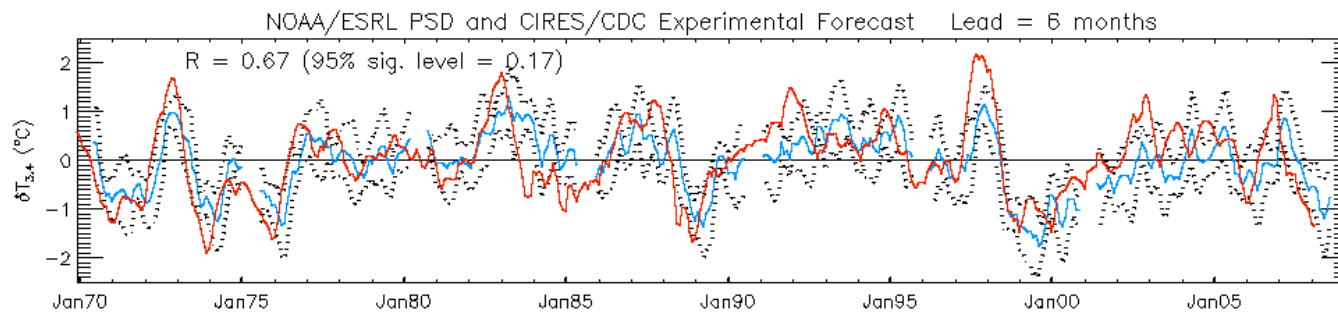
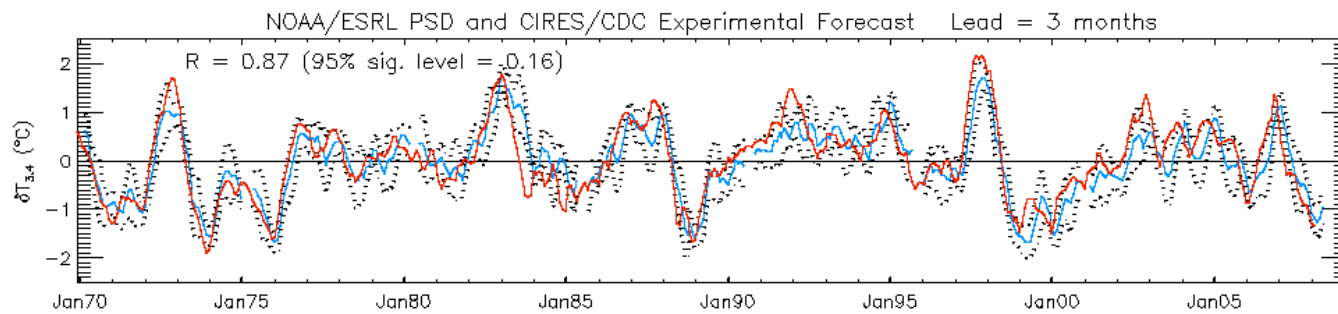
$$\langle \delta\mathbf{T}(t+\tau)\delta\mathbf{T}^T(t+\tau) \rangle_{i.c.} = \mathbf{G}(\tau) \langle \delta\mathbf{T}(t)\delta\mathbf{T}^T(t) \rangle \mathbf{G}^T(\tau)$$

- Sampling errors when estimating  $\mathbf{G}(\tau)$  :

$$\langle \delta\mathbf{T}(t+\tau)\delta\mathbf{T}^T(t+\tau) | \mathbf{T}(t) \rangle_{ij, Samp} = \sum_{km} \langle \delta G_{ik} \delta G_{jm} \rangle T_k(t) T_m(t)$$

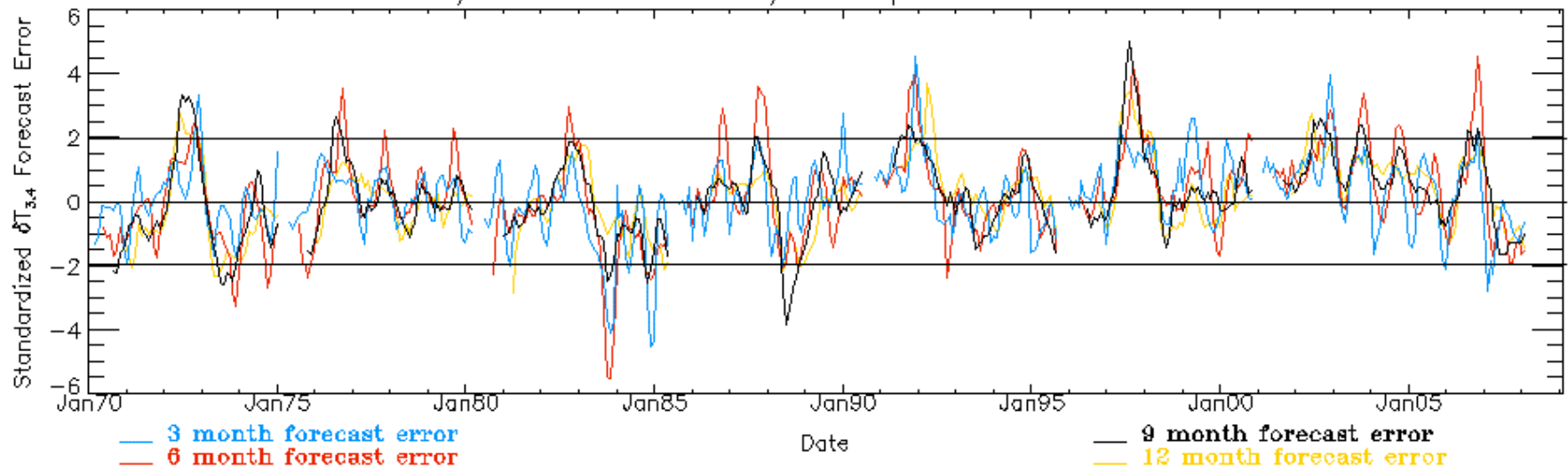
# Expected error in Niño 3.4 anomaly forecast







NOAA/ESRL PSD and CIRES/CDC Experimental Forecast Errors



## *Conclusions*

- Expected and actual errors can be a useful diagnostic tool
- El Niño is mainly a linear process maintained by additive and multiplicative cyclostationary stochastic forcing
- Initial condition errors grow and then decay