

# **MODES OF VARIABILITY OF THE COUPLED ATMOSPHERE-OCEAN SYSTEM**



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# Research Objectives

- Research is part of theme 1.2.2
  - Exploratory studies on joint assimilation into coupled models
  - Model background and observation errors for coupled system:  $\varepsilon_b$  and  $\varepsilon_o$
  - Solve for B and R covariance matrices
- Identify global covariance structures of coupled system
- Locate regions of possible interest
- Explore new statistical techniques

# The Data Variable Fields

- Global Atmosphere - Ocean Variables:
  - Sea Surface Temperature (**SST**)
  - Sea Level Pressures (**SLP**)
- CCCma (CGCM3) model output fields
  - atmosphere resolution:  $\sim 3.75^\circ$  longitude by  $3.71^\circ$  latitude (96 by 48 grid points).
  - ocean variables  $\sim$  double that of the atmospheric
- NCEP reanalysis data
  - SST grid:  $2^\circ$  by  $2^\circ$ , SLP grid:  $2.5^\circ$  by  $2.5^\circ$
  - Data range: January 1st 1948 to 2007

# Principal Component Analysis

- Search for uncorrelated linear combinations of  $X$  whose variances are as large as possible
- Let  $\Sigma$  be the covariance matrix associated with the random vector  $X' = [X_1, X_2 \dots X_n]$  with eigenvalue-eigenvector pairs  $(\lambda, e)$ .
- Then the  $i$ th principal component is given by the expression:  $Y_i = e_i' X$
- Explained variance of  $i$ th component is:  $\frac{\lambda_i}{\sum_k \lambda_k}$

# Processing the Data Matrix: X

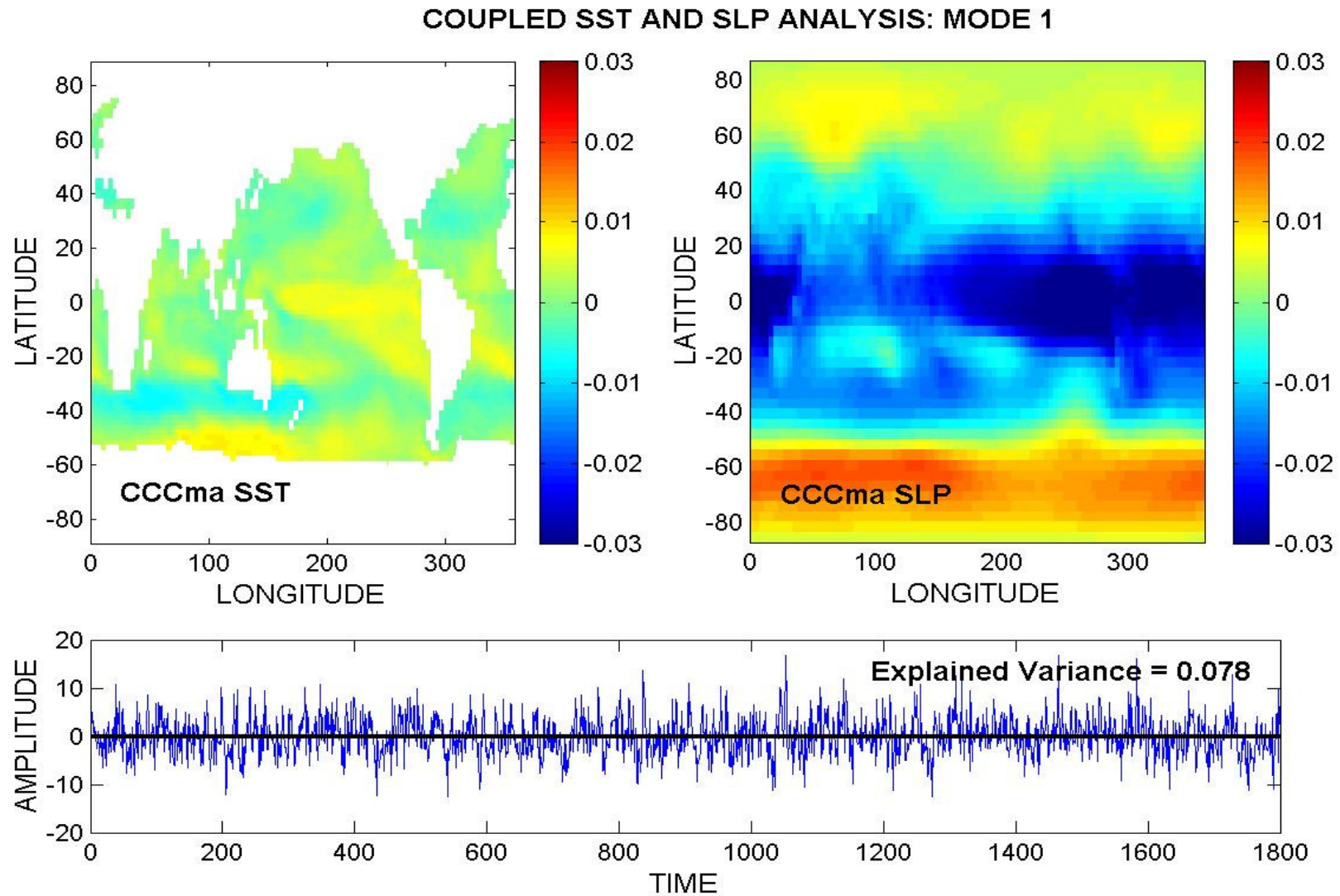
- Remove Ice cover points from data
- Detrend the data
- Remove Seasonal component from data
- Standardize data
- Area weight the data by factor  $\sqrt{\cos \lambda}$
- Grid point weight data
- Combine SST and SLP fields => X matrix

$$X = \begin{pmatrix} \text{SST}_1 & \text{SLP}_1 \\ \text{SST}_2 & \text{SLP}_2 \\ \bullet & \bullet \\ \bullet & \bullet \\ \text{SST}_p & \text{SLP}_p \end{pmatrix}$$

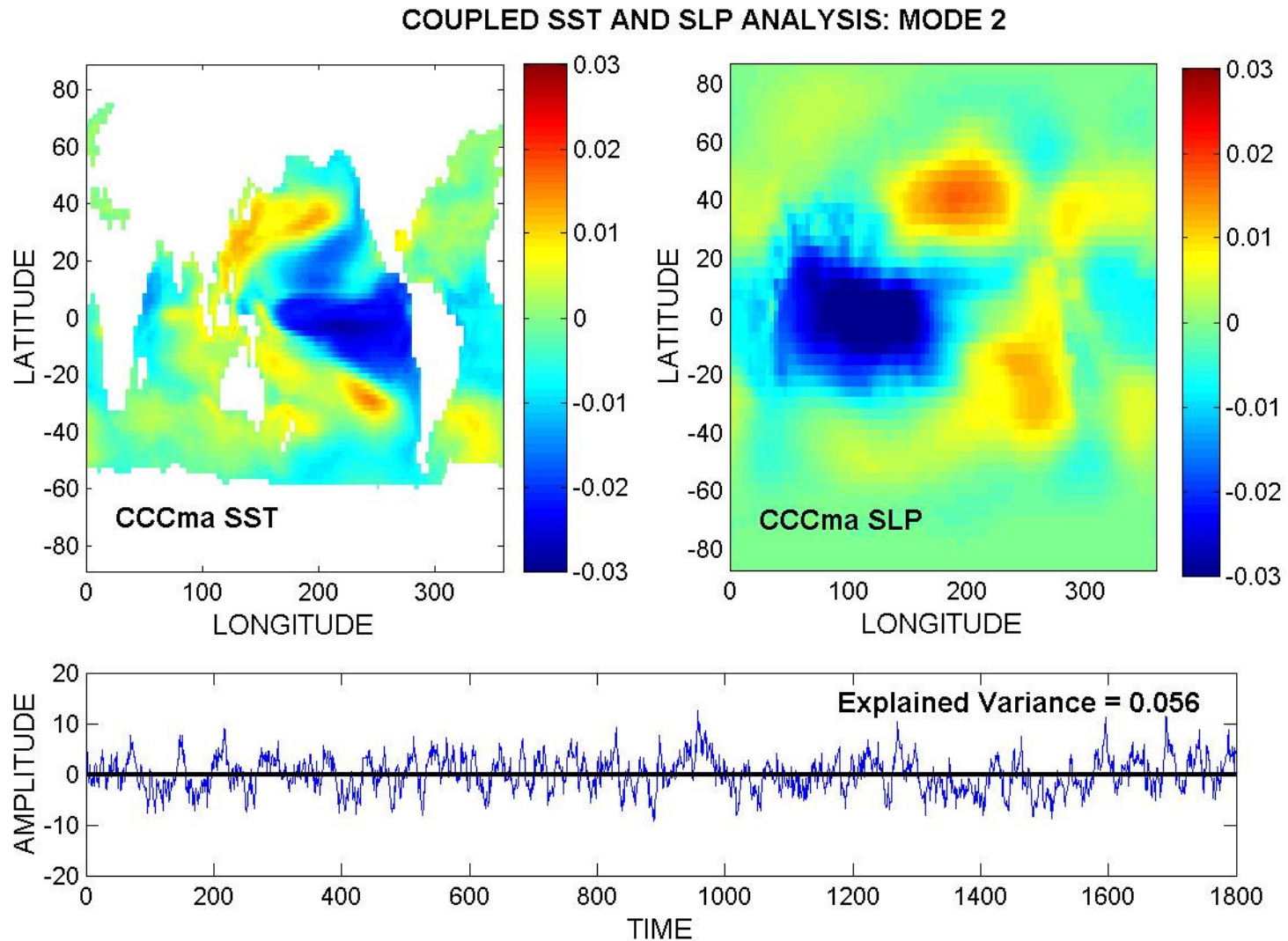
## Data Matrix Dimensions

- CCCma and NCEP Data fields
  - Space dimensions: exceeding 10,000!!
  - Time dimensions: less than 2000!!
- Set up  $X$  matrix such that each row contains the “spatial” SST and SLP data at time  $t_i$
- the Covariance matrix  $X*X'$  is a matrix of less than 2000 x 2000 grid points
- Saves considerable computation time

# CCCma Mode 1: Southern Annular Mode (SAM)?

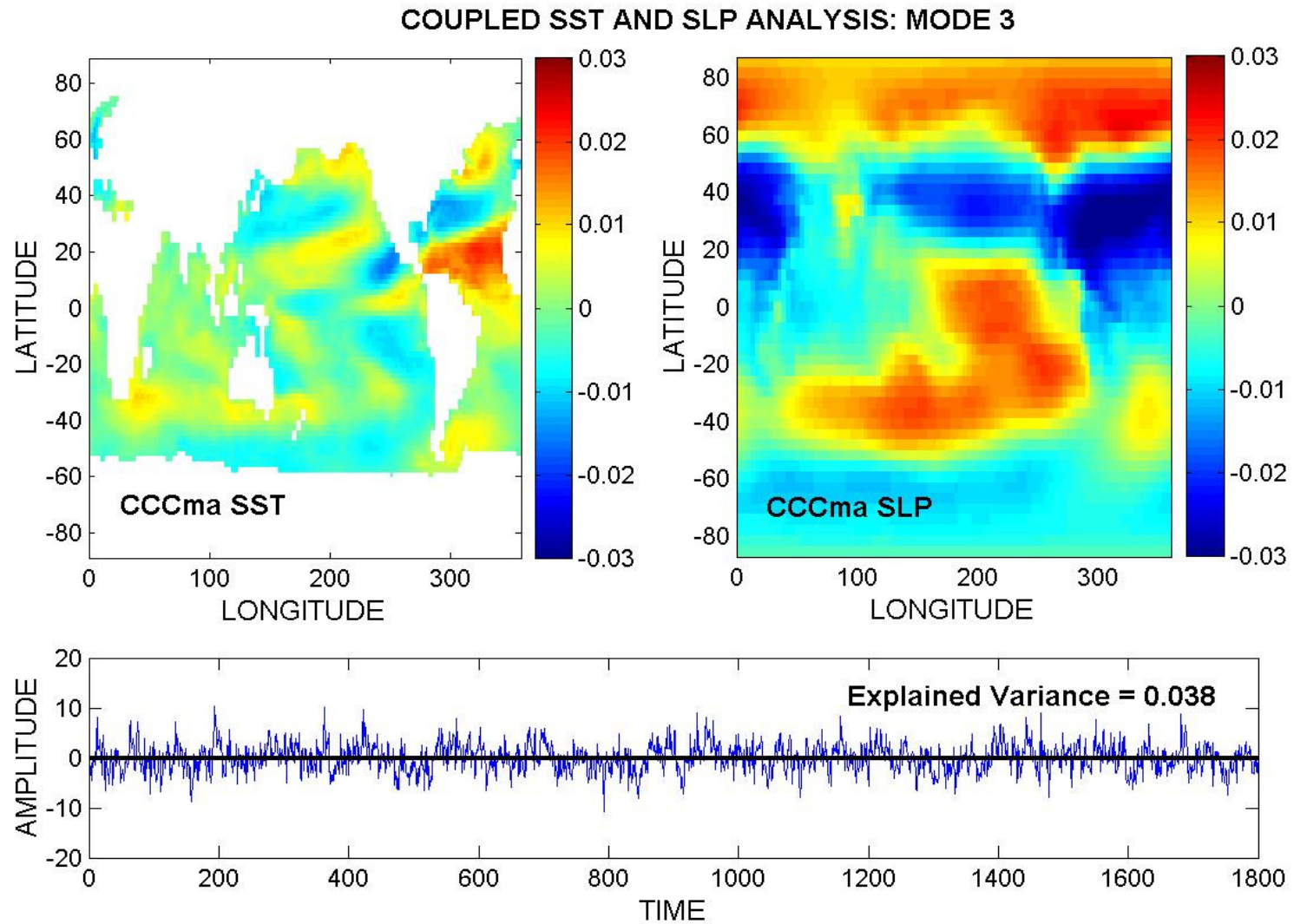


# CCCma Mode 2: El Niño pattern

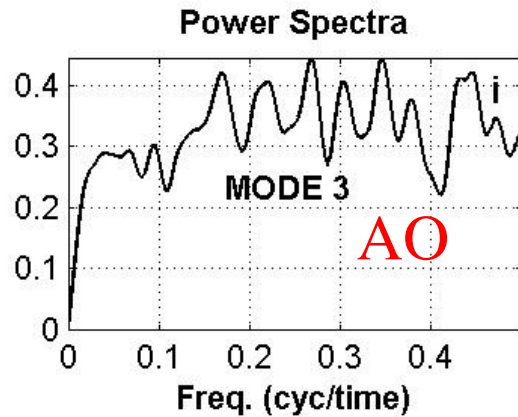
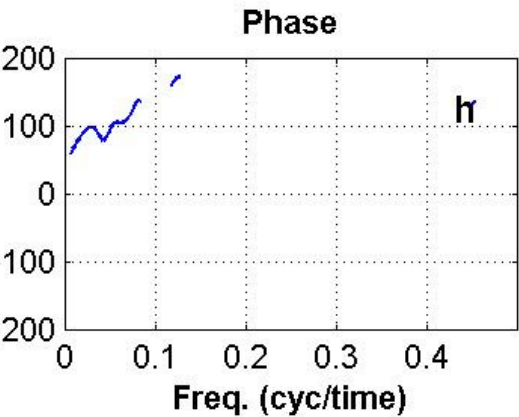
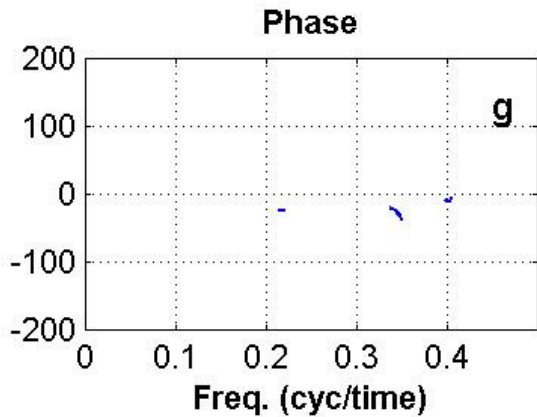
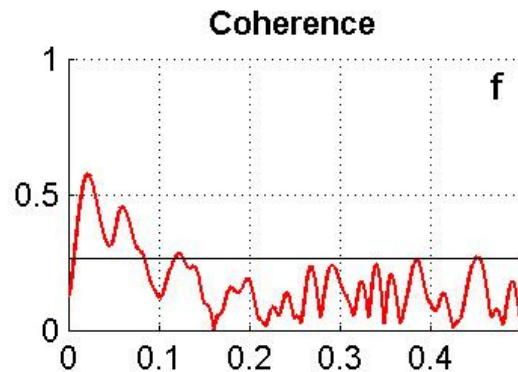
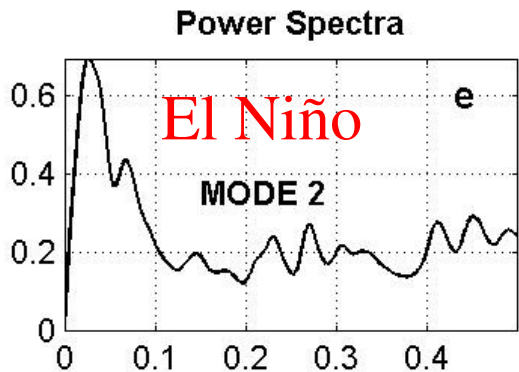
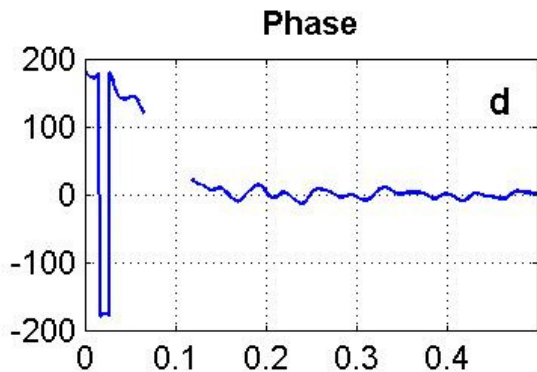
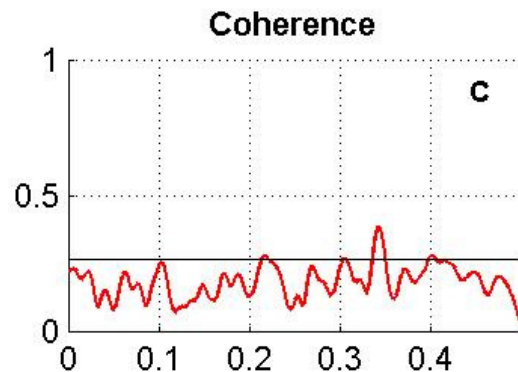
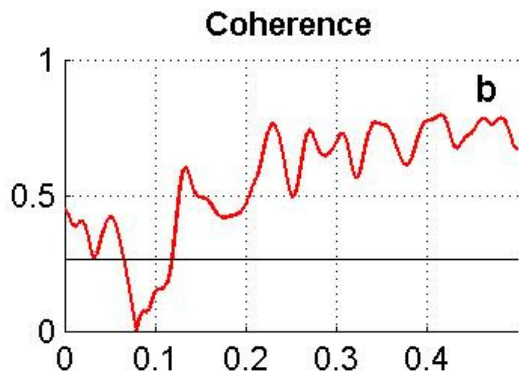
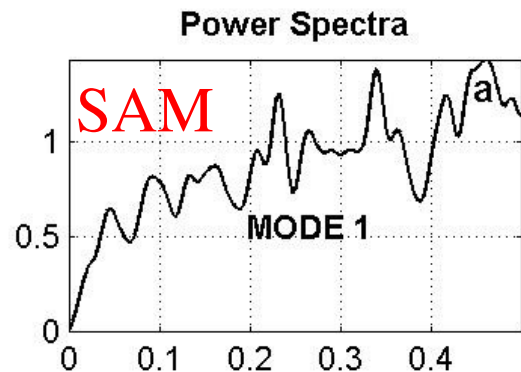




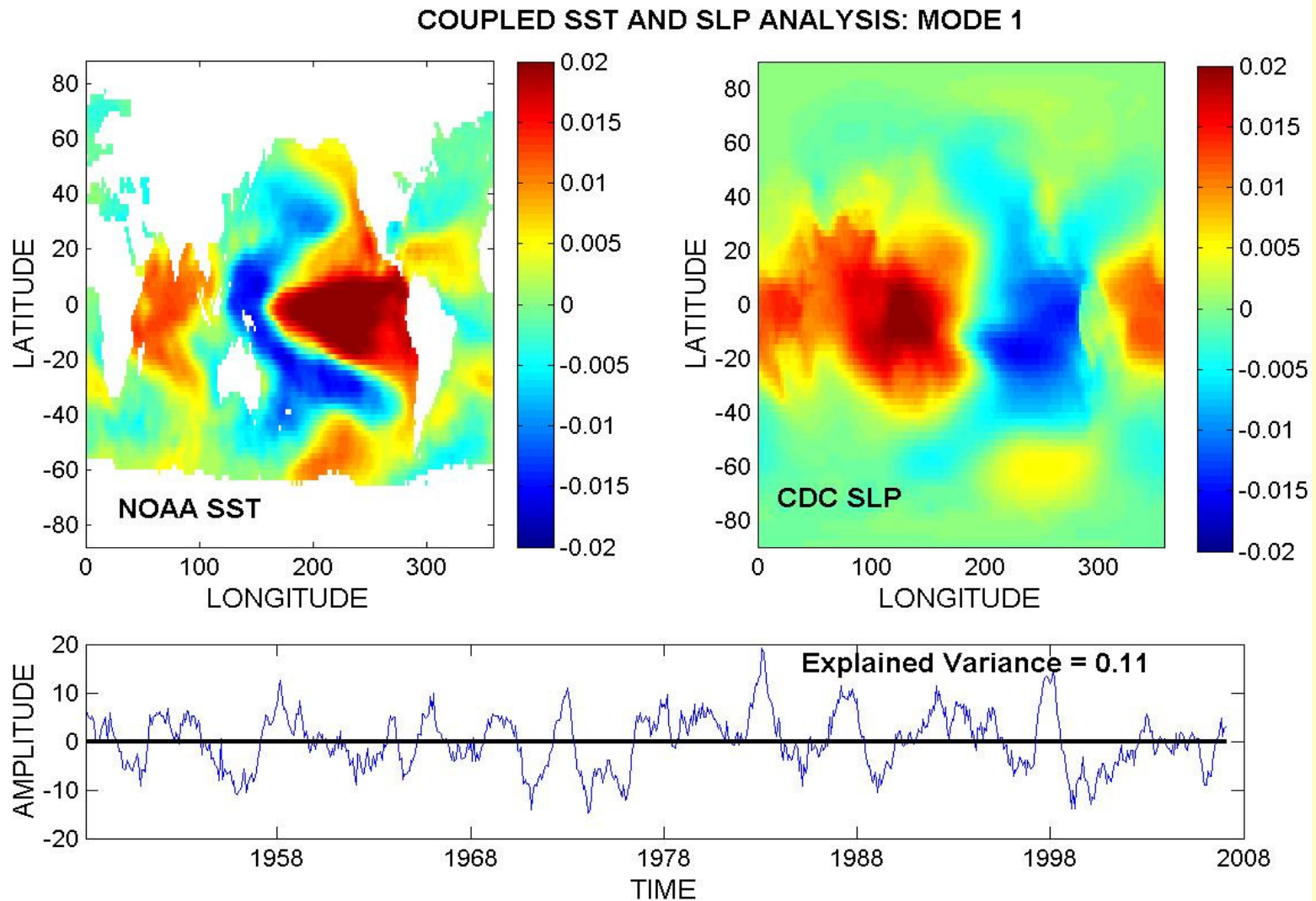
# CCCma Mode 3: Arctic Oscillation (AO)?



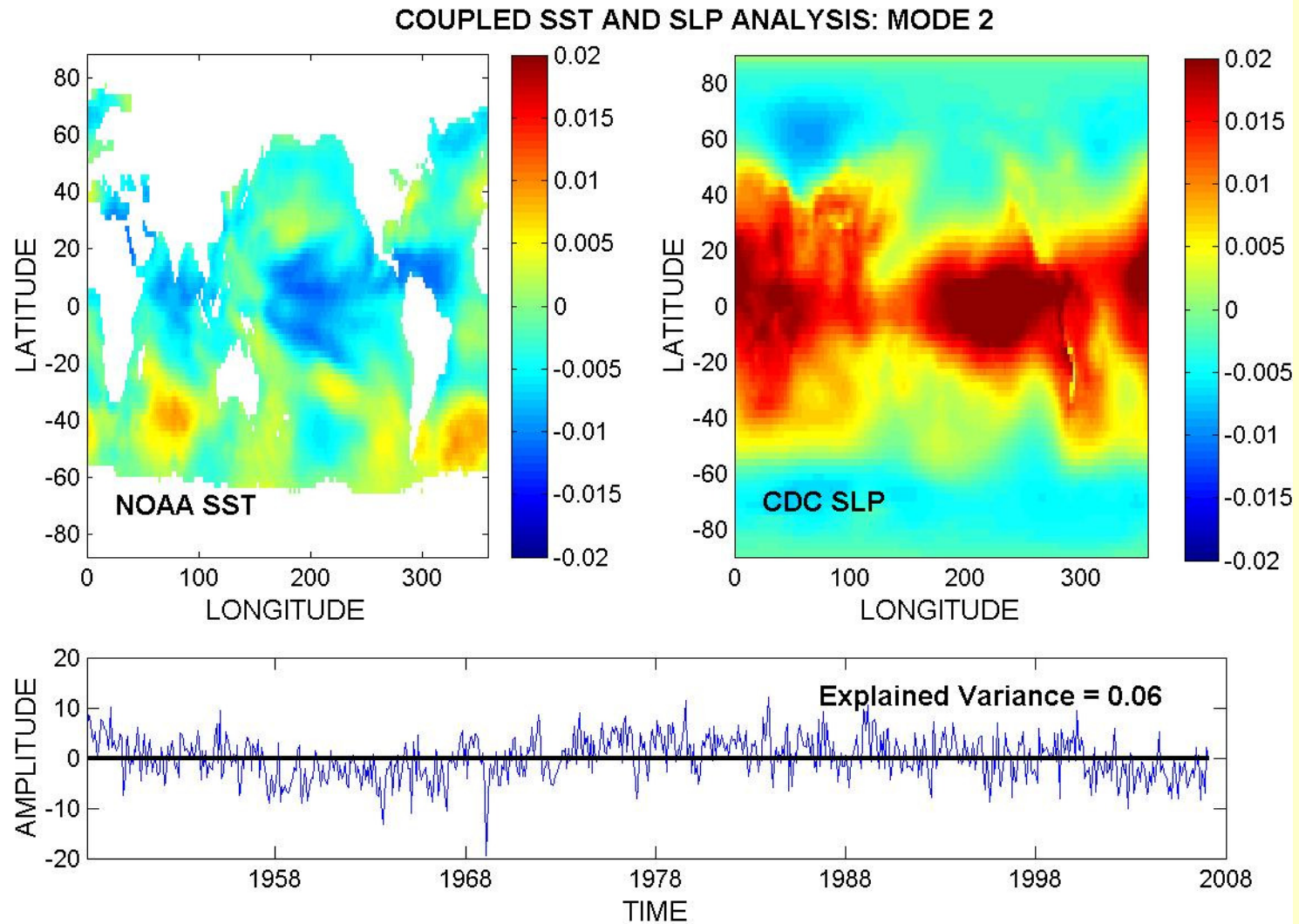
# CCCma Model Output



# NCEP Mode 1: EL Niño pattern

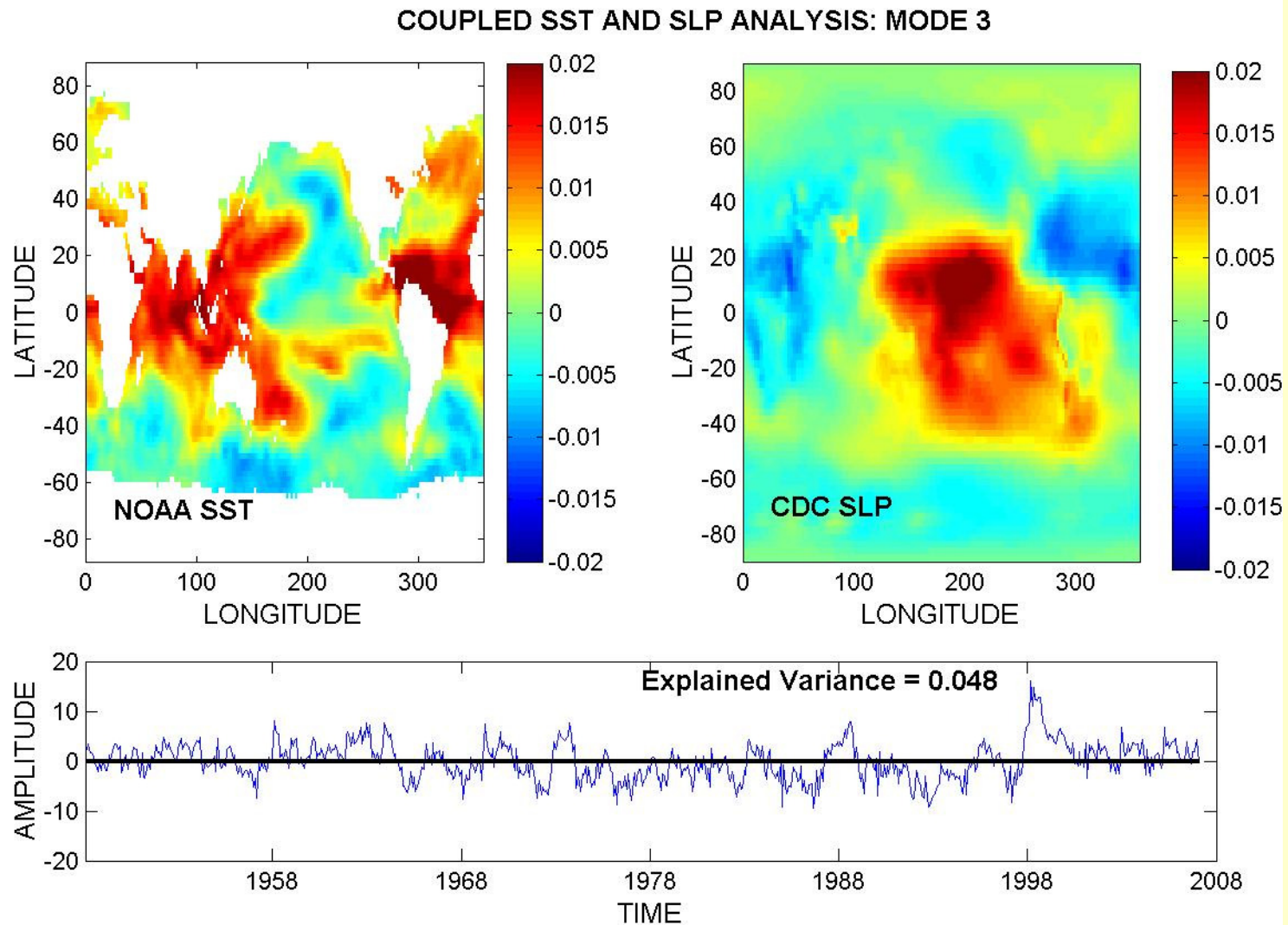


# NCEP Mode 2: Equatorial High Pressure

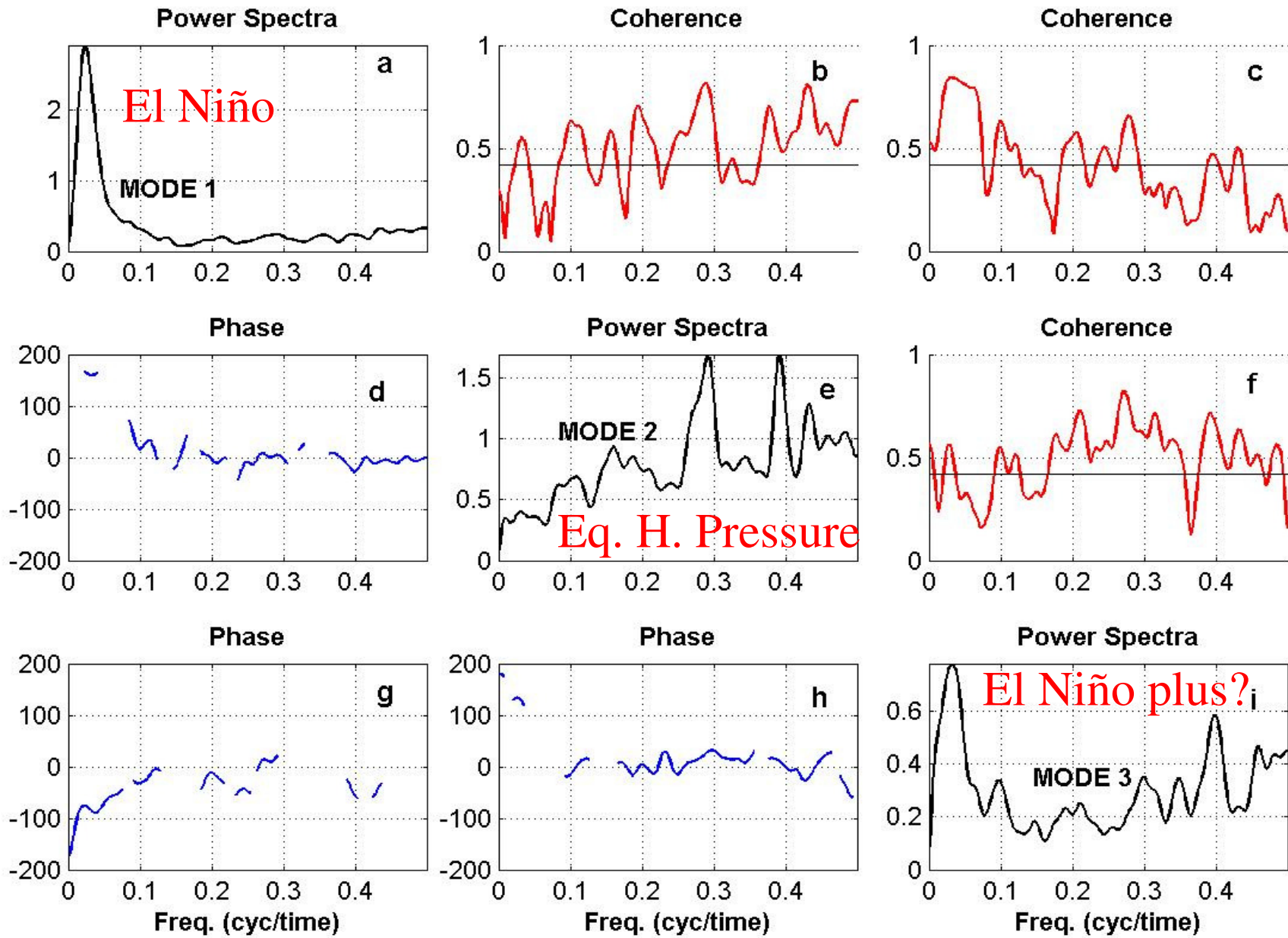




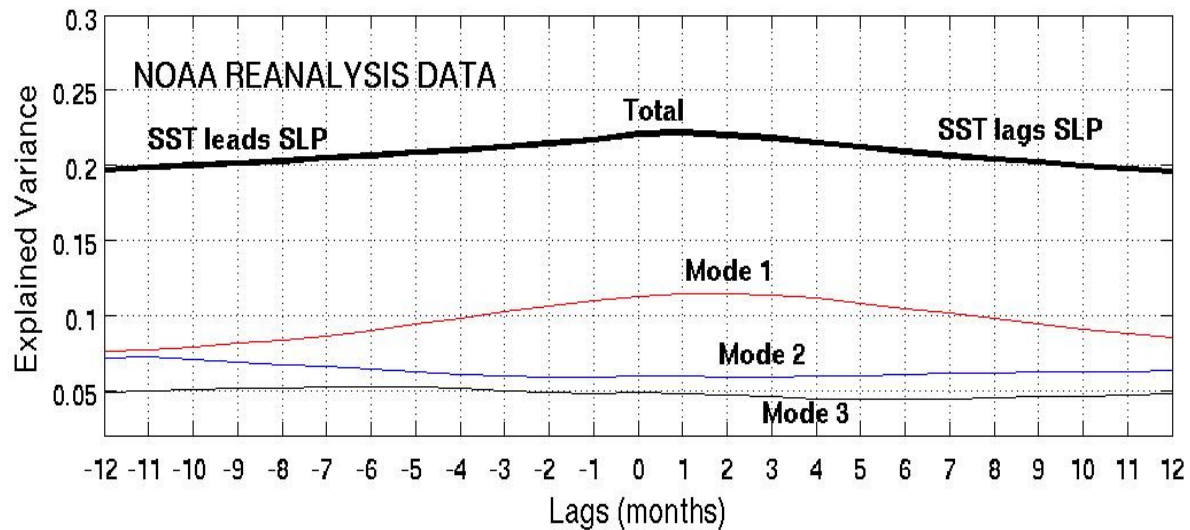
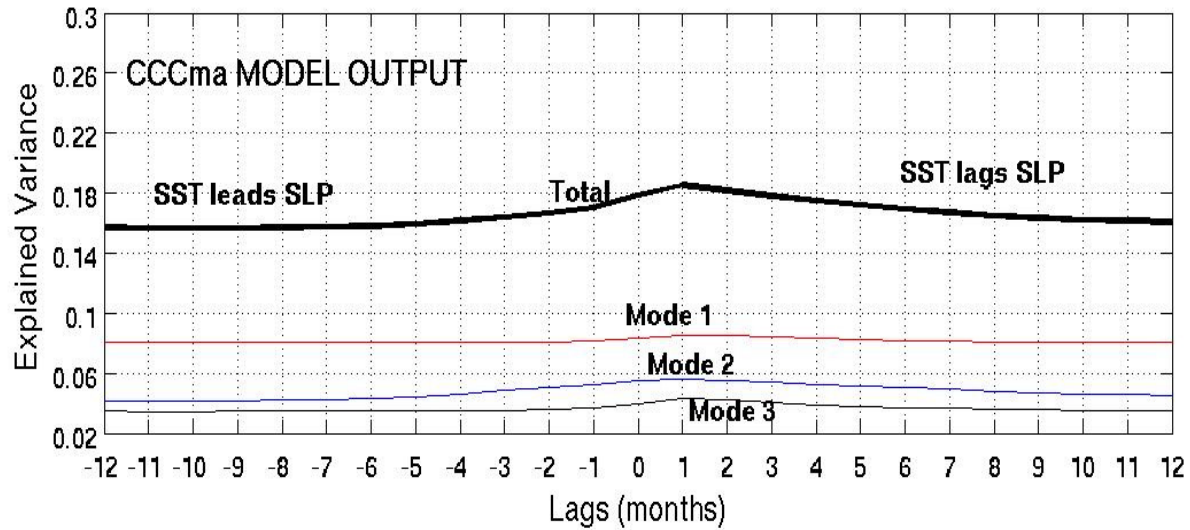
# NCEP Mode 3: Propagating El Niño Signal?



# NOAA reanalysis data



# Time-Lagged Explained Variances



# Principle Component Analysis Summary

- Similarities between CCCma and NCEP:
  - detection of El Niño signal in Pacific ocean
  - propagating feature of El Niño from Pacific to Atlantic => propagation time ~ 2 to 3 months!
  - Greatest variance explained when Global SLP leads SST by 1 month!!



# Principle Component Analysis Summary

- Differences between NCEP and CCCma:
  - El Niño under-represented in CCCma (8% variability) compared to NCEP (11% variability)
  - detection of SAM and AO modes in CCCma
  - detection of high pressure anomaly in equatorial region in NCEP
  - somewhat conflicting SLP patterns associated with propagating El Niño signature

# Motivation for Redundancy Analysis

- Limitation of PCA analysis
  - Identified patterns that maximized variance in SST and SLP fields ... no cause or effect implied
- Address “cause - effect” relations
  - Set up a regression equation:  $SST = a b^T SLP$
  - Find pattern in SLP that best explains the variance in SST
  - Find resultant SST pattern
- Redundancy analysis  $\Rightarrow$  “cause - effect”

# Redundancy Analysis

- Assume a data matrix  $X$  and a separate data matrix  $Y$  related by a regression equation:

$$Y = a b^T X + \varepsilon$$

- Reduces to two Eigenvector equations:

$$\Sigma_{yx} \Sigma_{xx}^{-1} \Sigma_{xy} a = a \lambda$$

$$\Sigma_{xx}^{-1} \Sigma_{xy} \Sigma_{yx} b = b \lambda$$

- $b$ -pattern: pattern in  $X$  data that maximizes variance in  $Y$  data field
- $a$ -pattern: resultant pattern in  $Y$  data field

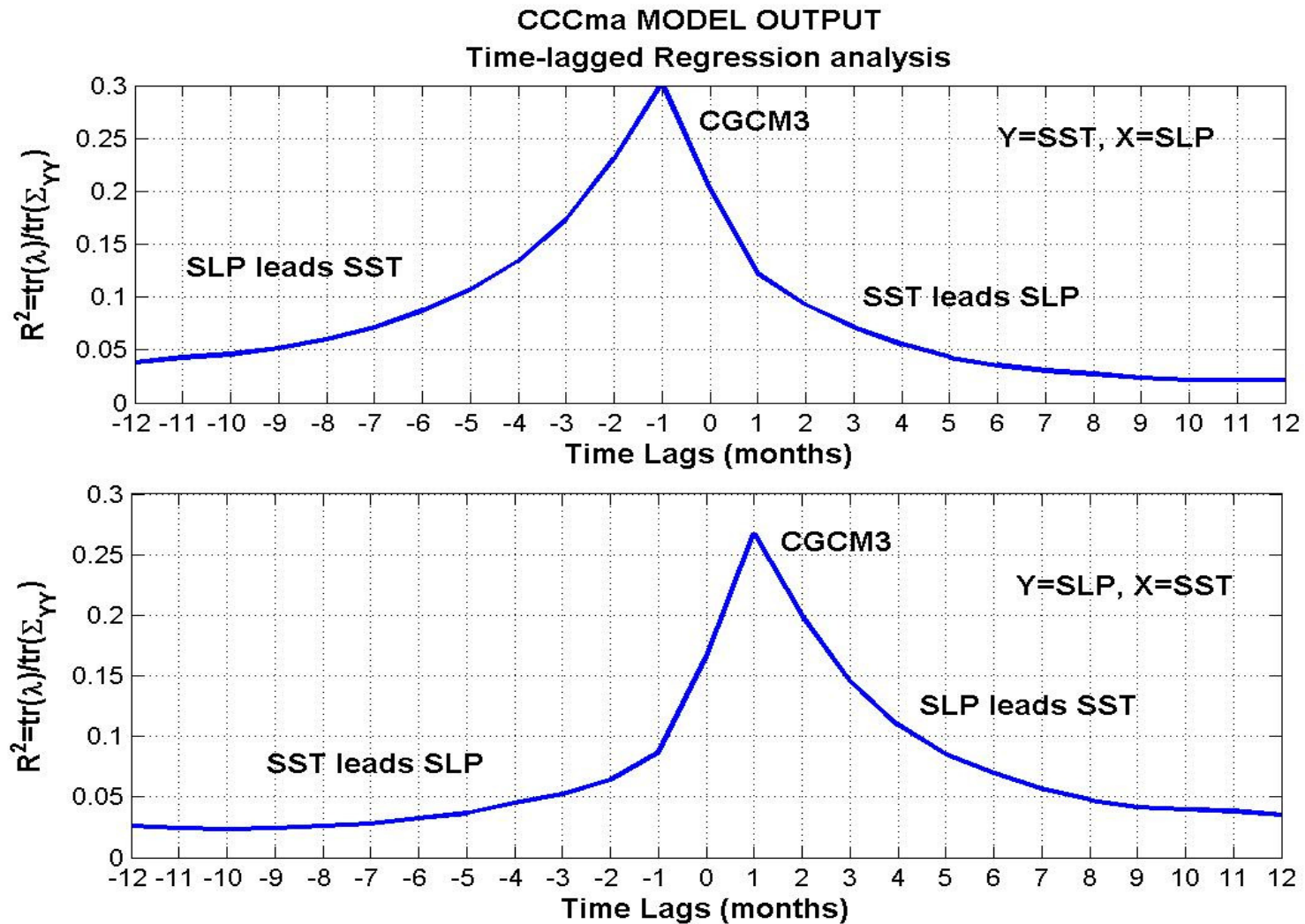
## Redundancy Index

- A measure of how much variance in Y data field is expressed by the modeled  $\hat{Y} = a b^T X$  field (or basically how redundant information in Y is provided information in X):

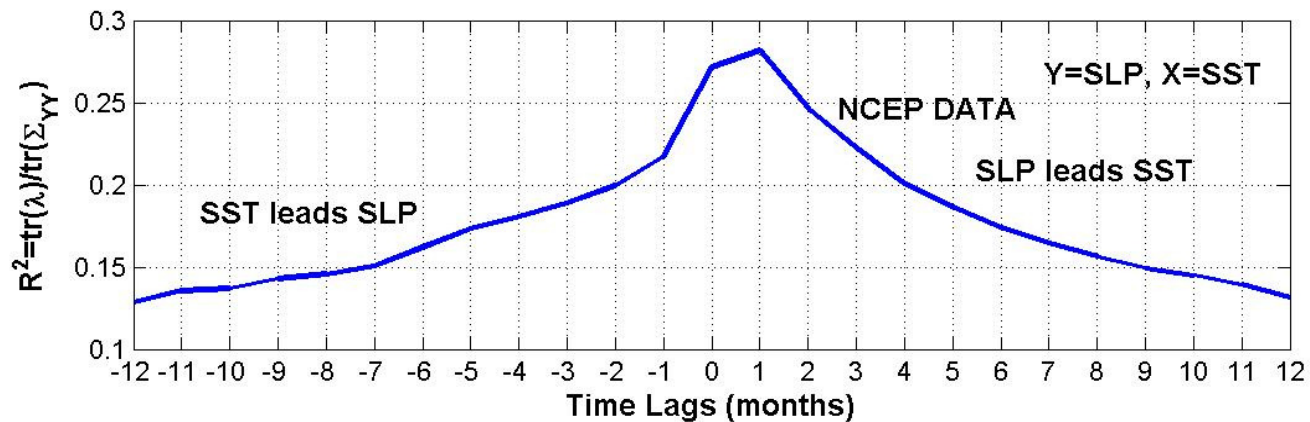
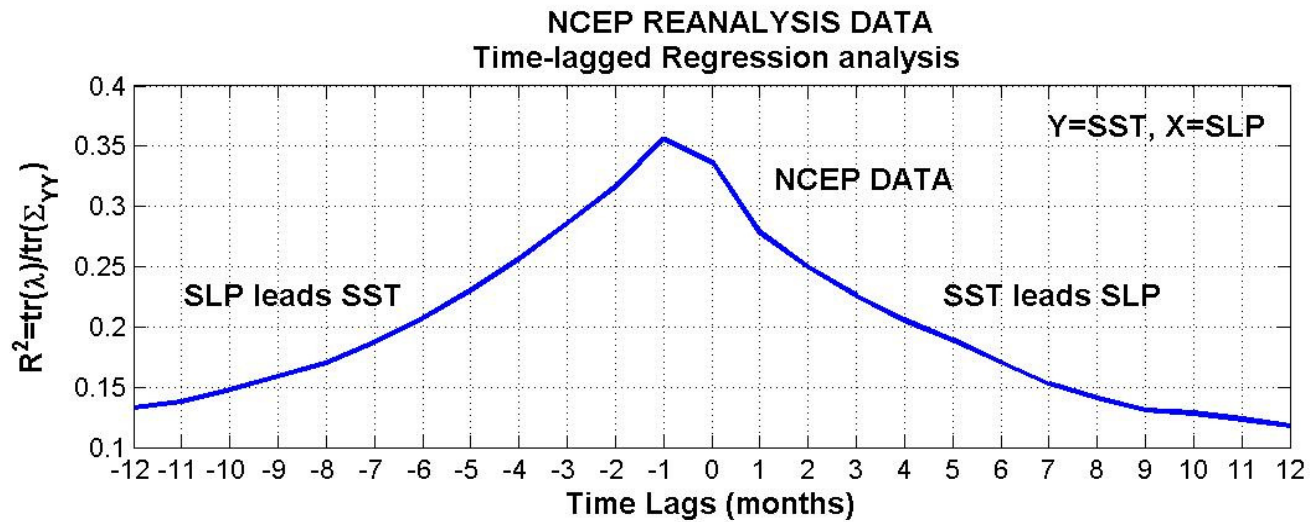
$$R^2(Y : \hat{Y}) = \frac{\sum_{j=1}^k \lambda_j}{\text{tr}(\Sigma_{YY})}$$

- Time-Lagged Redundancy Index as an indicator of cause-effect relation

# CCCma Global Redundancy Index: SLP leads SST

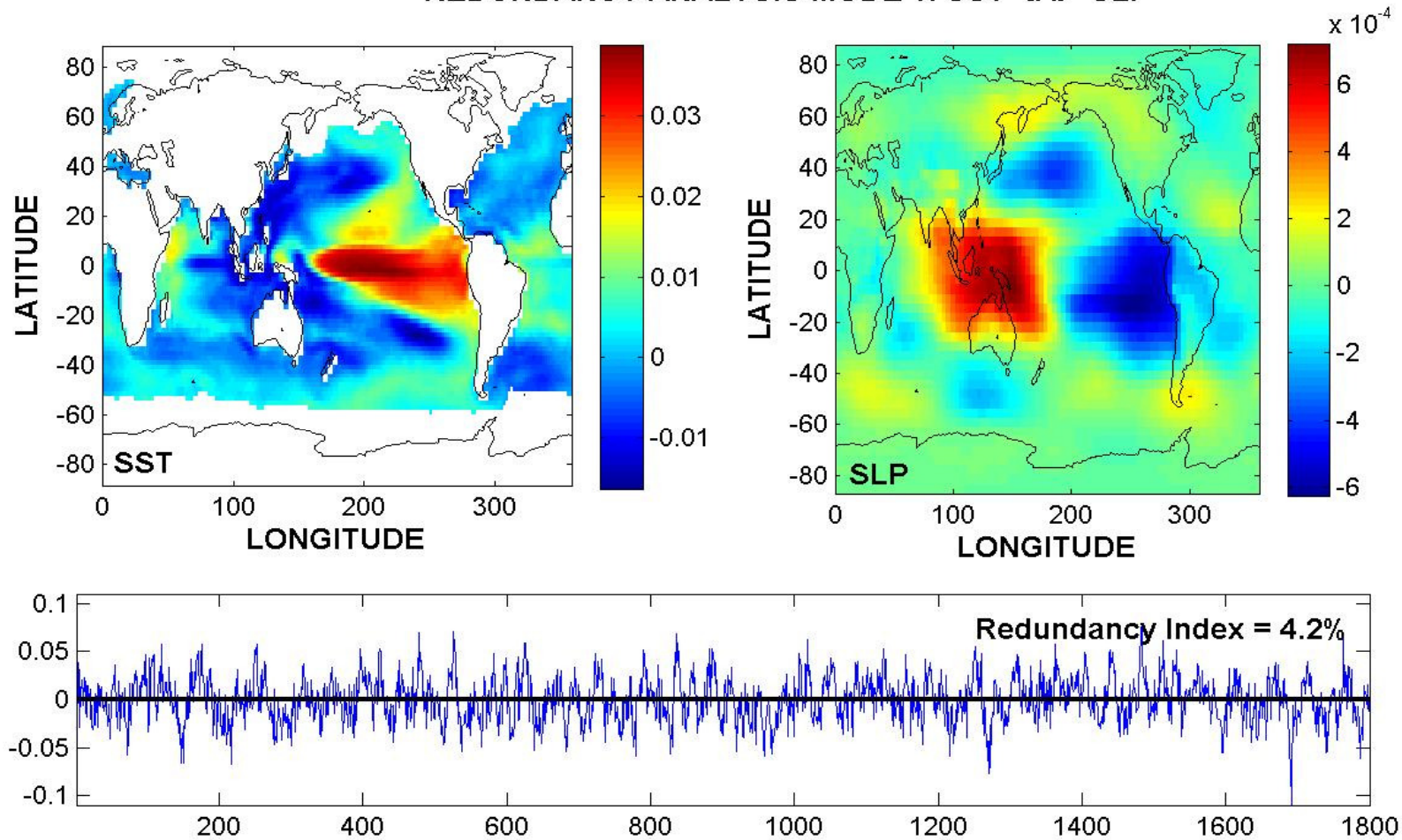


# NCEP Redundancy Index: SLP leads SST



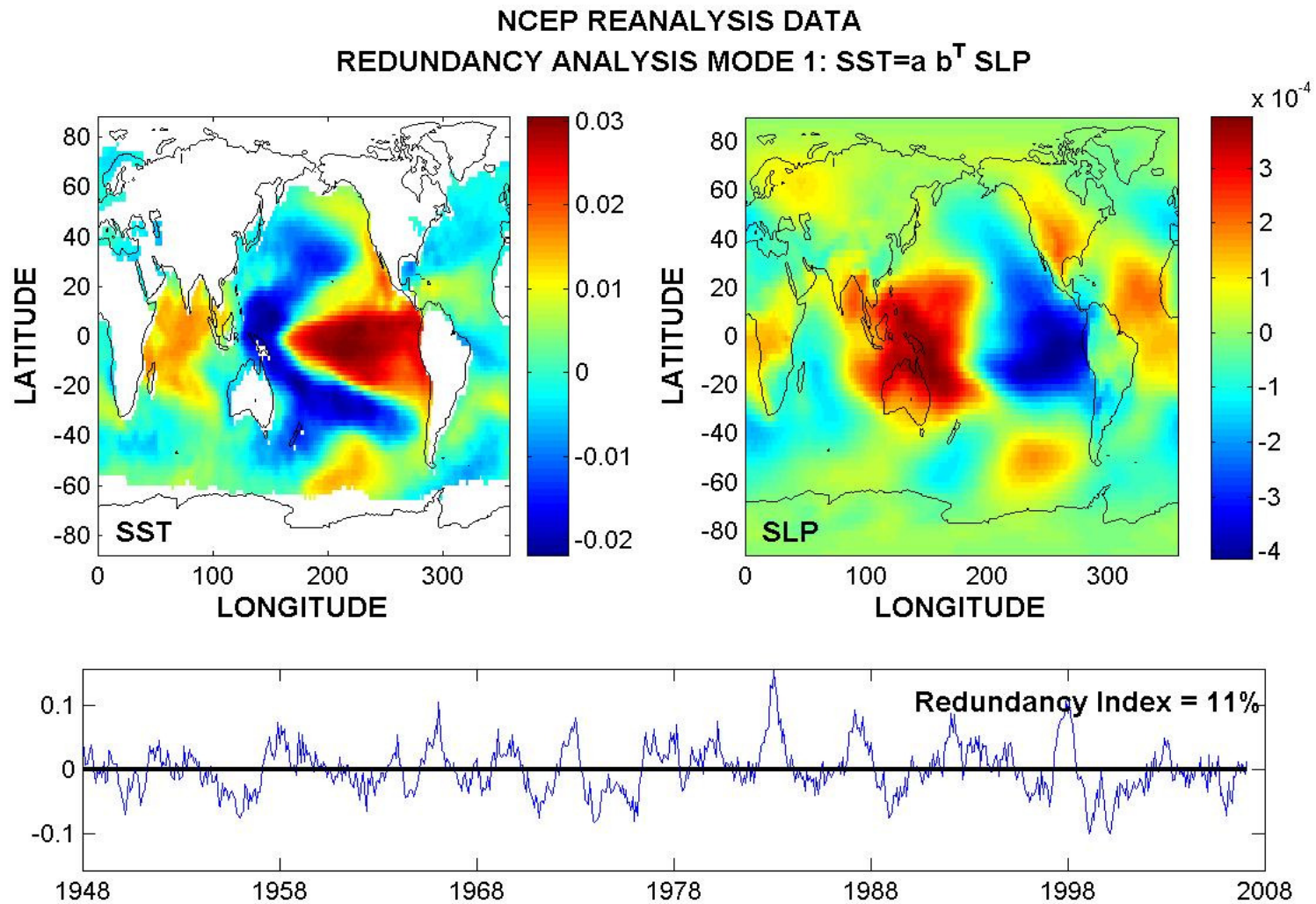
# CCCma Redundancy Analysis: Mode 1

CCCma MODEL OUTPUT  
REDUNDANCY ANALYSIS MODE 1: SST=a b<sup>T</sup> SLP





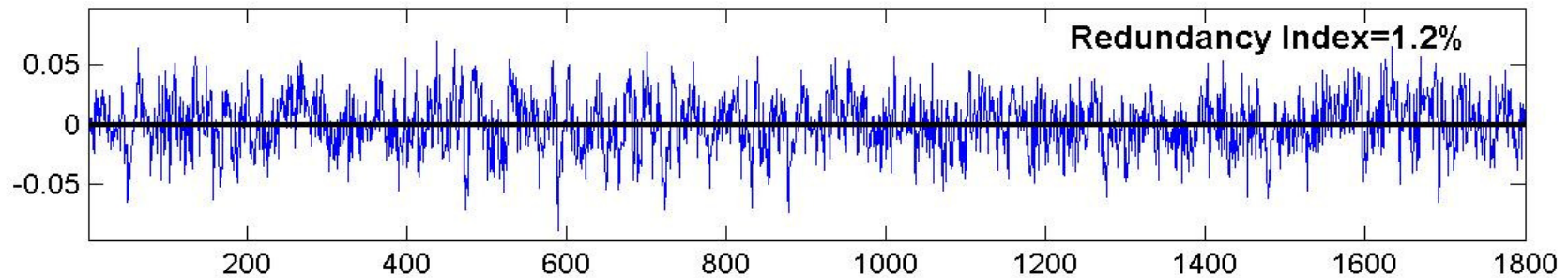
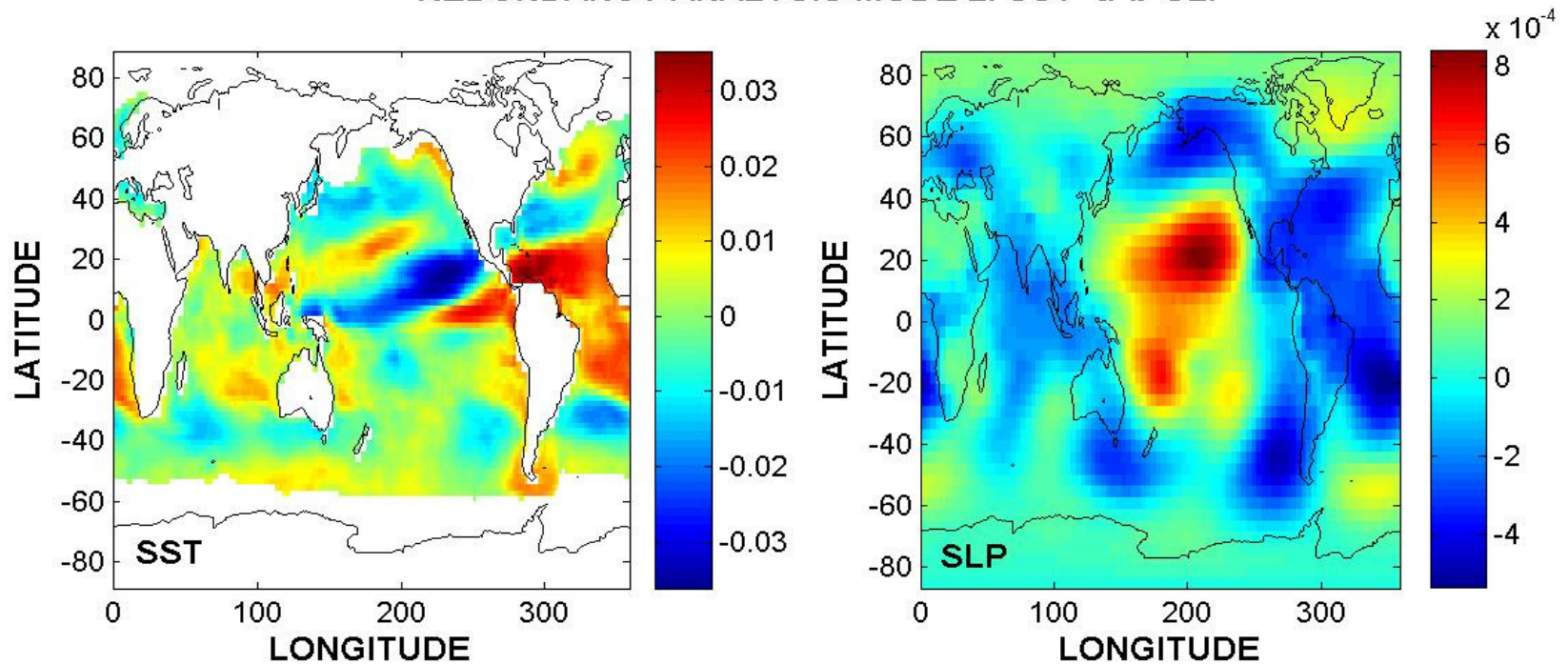
# NCEP Redundancy Analysis: Mode 1



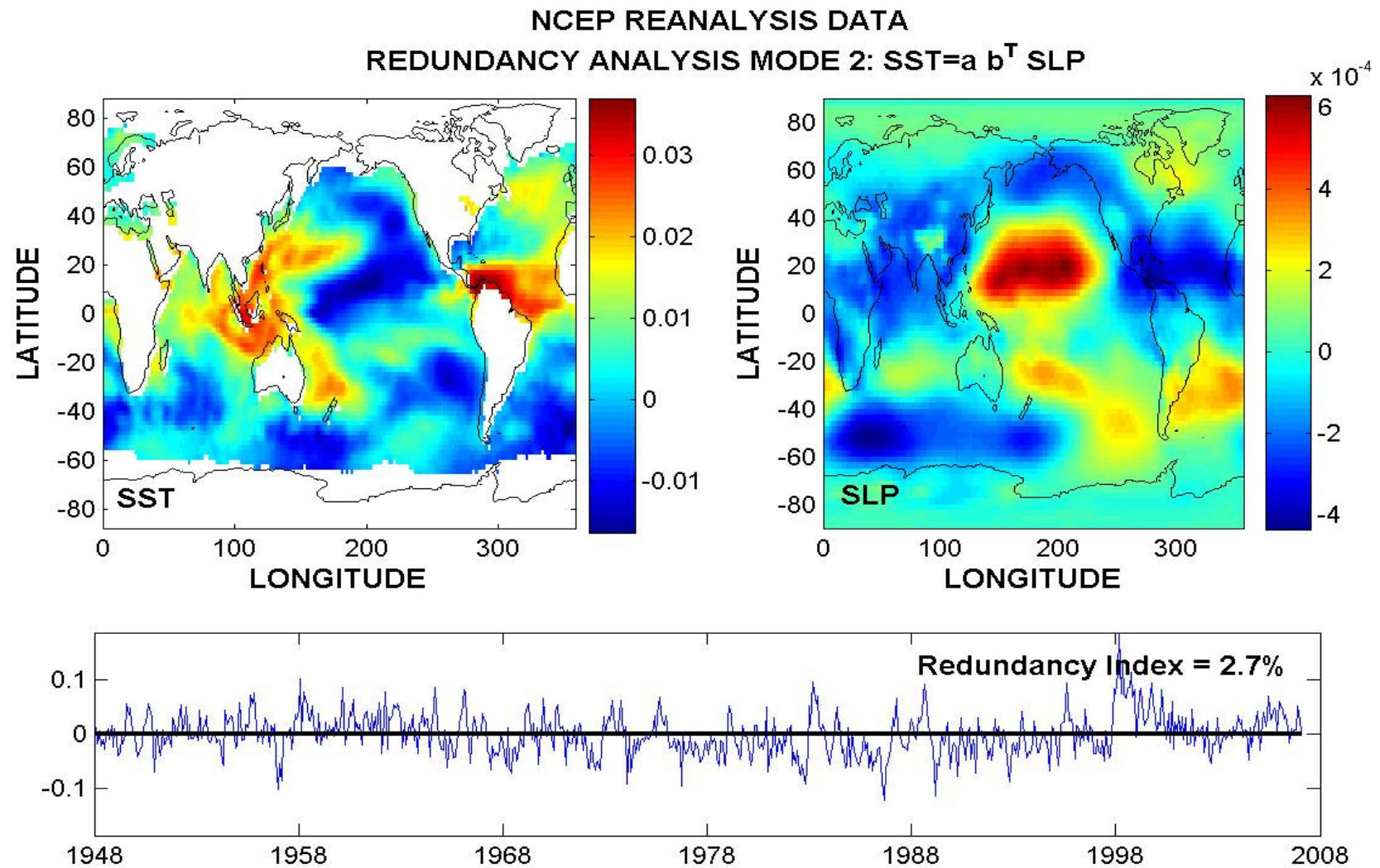


# CCCma Redundancy Analysis: Mode 2

CCCma MODEL OUTPUT  
REDUNDANCY ANALYSIS MODE 2:  $SST = a \cdot b \cdot SLP$



# NCEP Redundancy Analysis: Mode 2



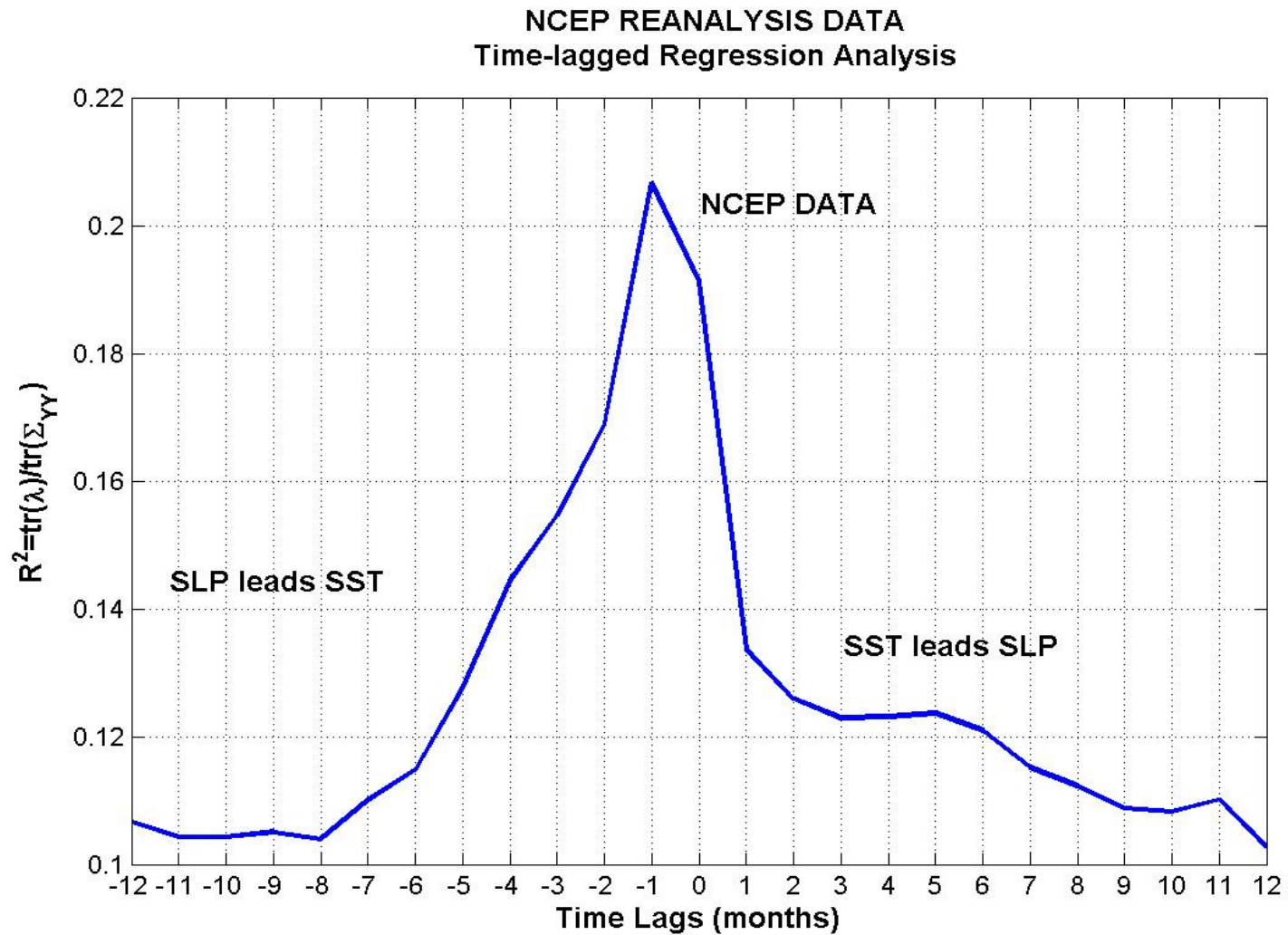
## Redundancy Analysis Summary

- $R^2$  is maximum when global SLP leads global SST by 1 month
- Redundancy index is asymmetric:  
 $R^2(x \rightarrow y) \neq R^2(y \rightarrow x)$
- Both Modes 1 and 2 of NCEP and CCCma patterns agree to first order
- El Niño pattern “driven” by low-high SLP centers over Equatorial Pacific ocean
- Propagating El Niño feature “driven” by high SLP center over mid-pacific ocean

# A Geographic Focus: North Atlantic Region

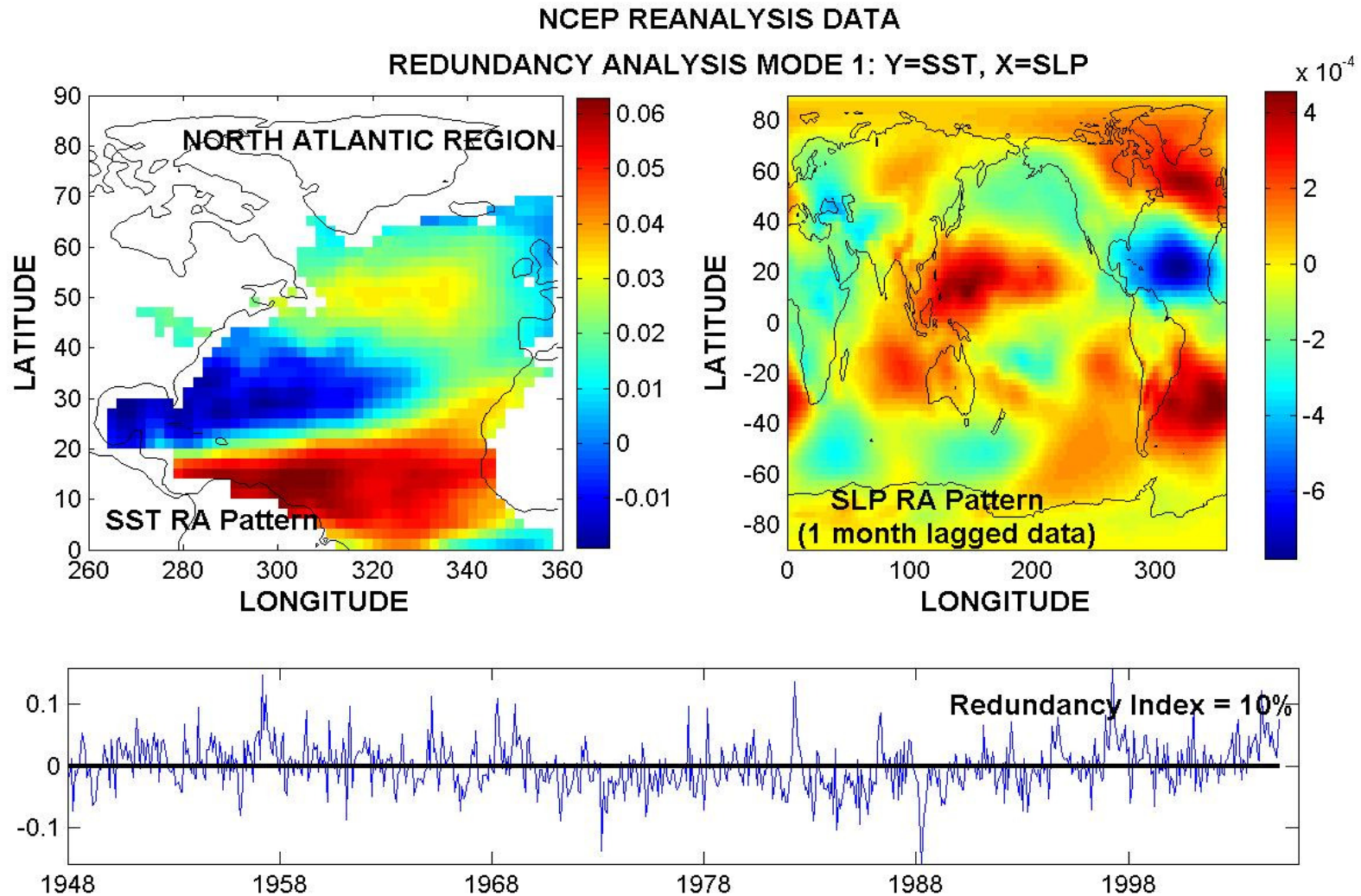
- Let us consider the patterns that emerge when global fields are mixed with localized fields
  - Do global SLP control local SST? Or do local SST dominate global SLP?
  - What variable should one choose as the predictand or predictor?
  - What patterns emerge in the fields when considering global and local fields?

# $R^2 (Y_{\text{Global SLP}}: X_{\text{N. Atlantic SST}})$

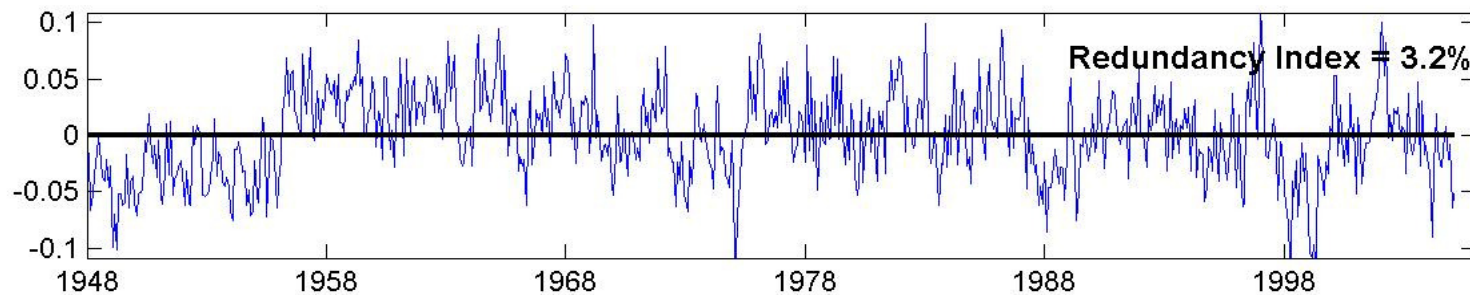
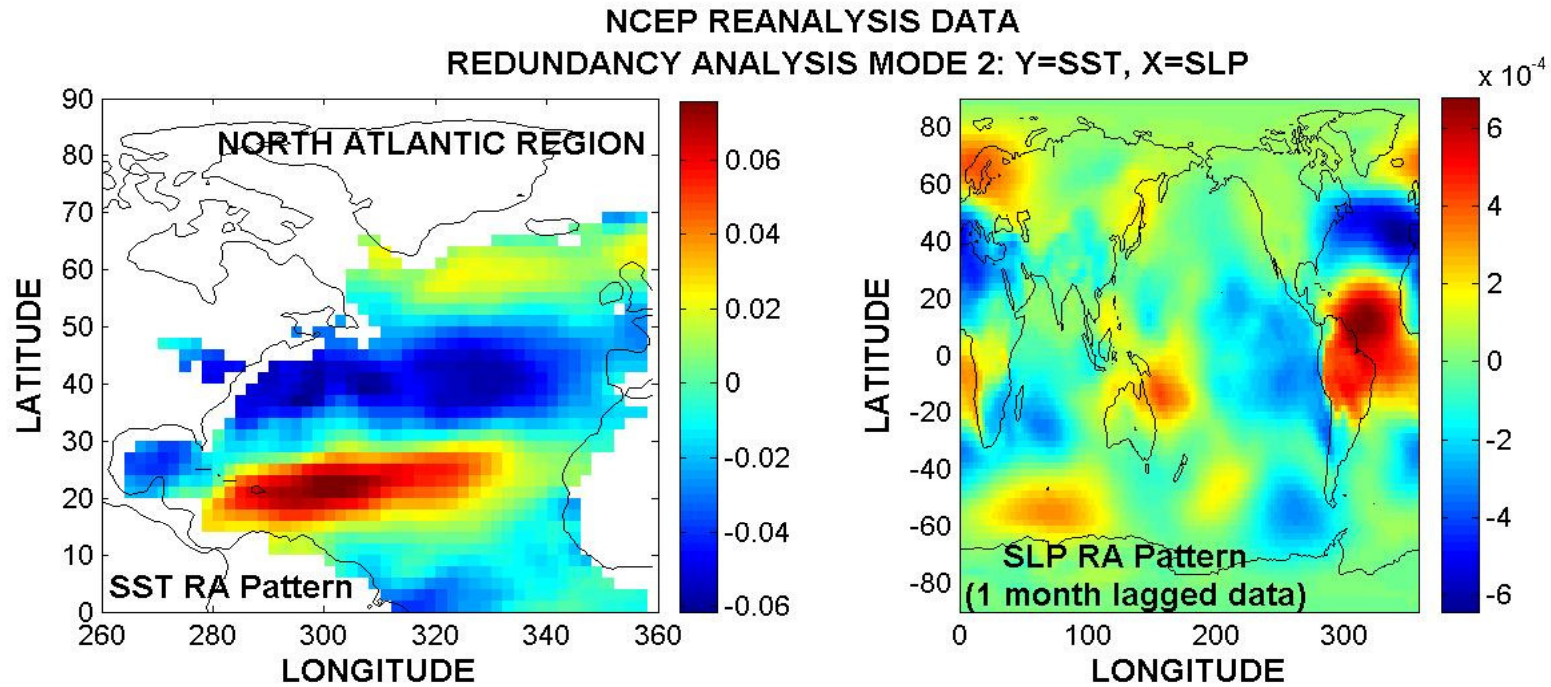




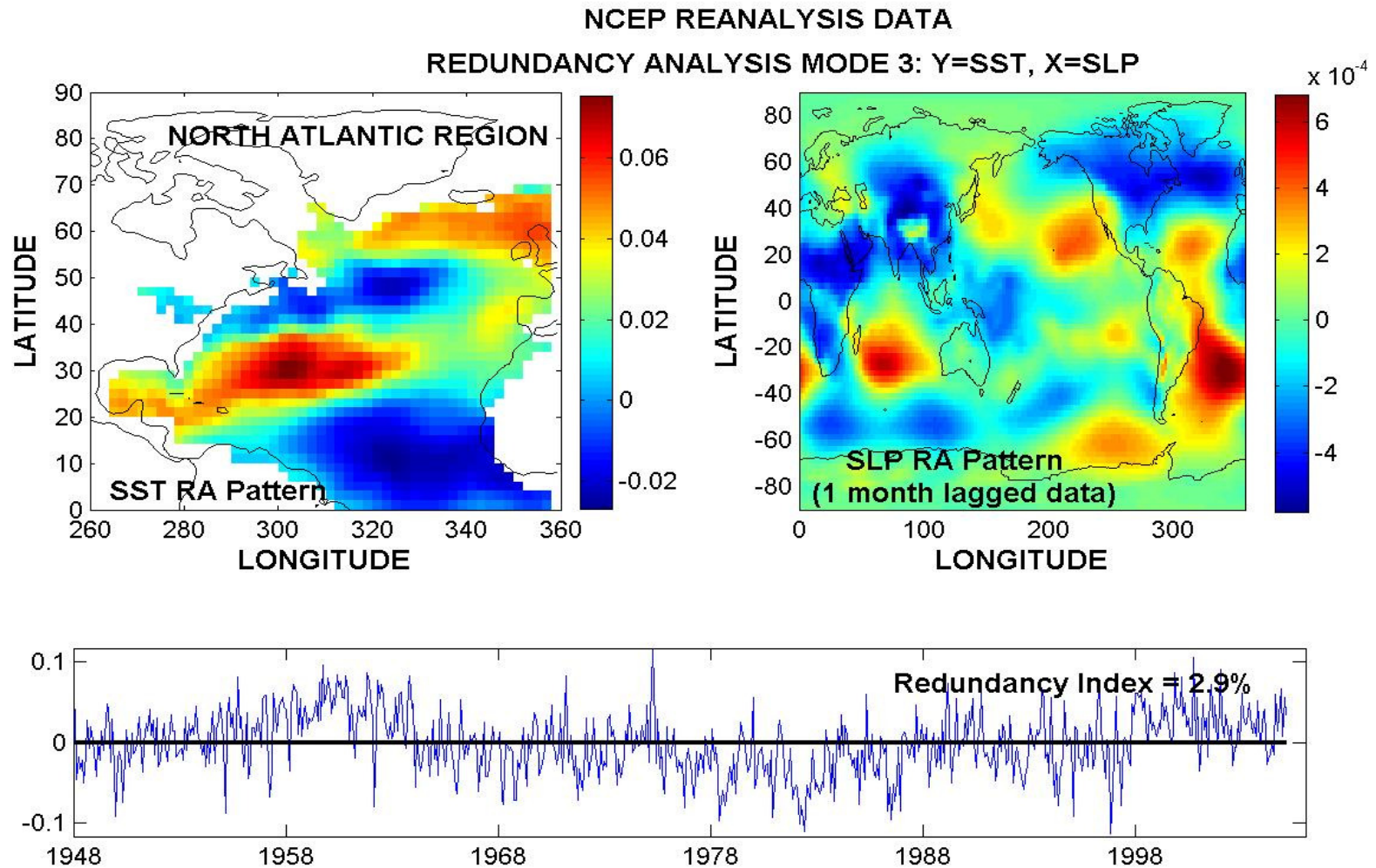
# Mode 1: North Atlantic Region



# Mode 2: North Atlantic Region



# Mode 3: North Atlantic Region





## North Atlantic Region Summary

- Variations in Azores High and Icelandic Low Pressure drives Tripole SST anomaly in mid-North Atlantic Latitudes
- Variations in Azores and Icelandic Pressure systems linked to South Atlantic Pressure system (negative correlation)

# References

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