

# Quantifying the Agreement Between Observed and Simulated Extratropical Modes of Interannual Variability

**Jiwoo Lee**

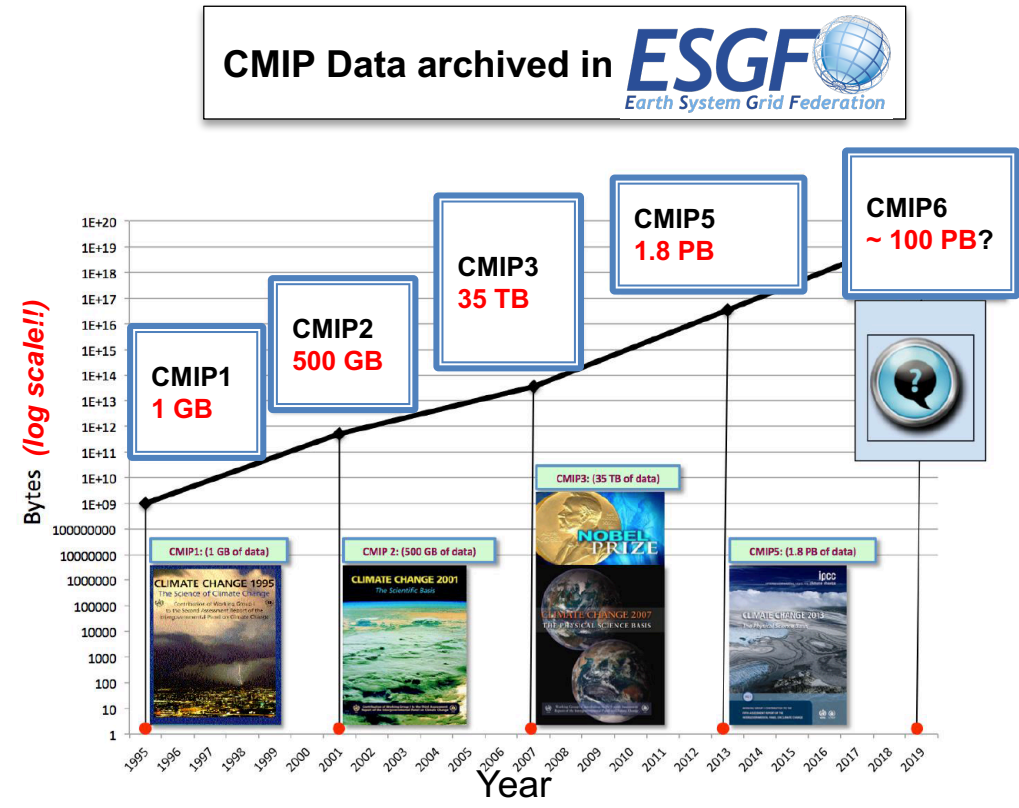
***with* Kenneth Sperber, Peter Gleckler, Celine Bonfils, and Karl Taylor**

*PCMDI/LLNL, California, USA*



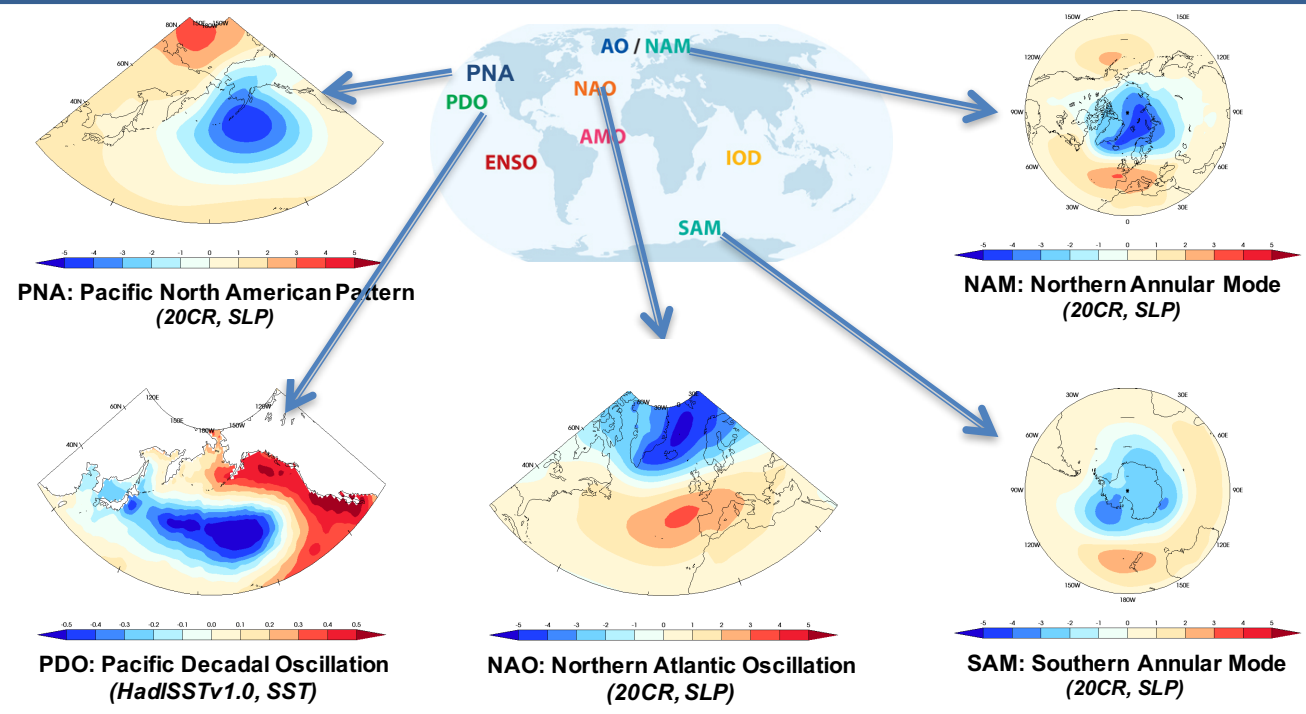
# Objective: Routine Evaluation of Models

- **CMIP** has collected a massive volume of climate model output
- To have a better understanding of model *uncertainties and performance*, it is important to *evaluate models routinely in a systematic and collective way*
- PCMDI/LLNL is developing a metrics package (the PMP) to more directly contribute to model development (via quick feedback)



(Williams et al. 2015, BAMS)

# Background (1): Modes of Variability



- Generally defined by the leading EOF mode in observations
- Represent long-term large-scale variance
- Important test for diagnosing model behavior, and detection & attribution

# Background (2): Previous studies

- The majority of previous studies have focused on one or two modes of variability
- A few studies have conducted systematic evaluation for a variety of modes, e.g.:
  - *Stoner et al. (2009)* focused on the CMIP3 simulations
  - *Phillips et al. (2014)* has developed diagnostic package (NCAR CVDP) and released a repository for evaluating simulated modes in CMIP5
- We expand these studies to develop metrics with an emphasis on how to:
  - Objectively compare the models with observations, including seasonality
  - Test the skill sensitivity to:
    - 1) multiple realizations from individual models
    - 2) choice of observations
    - 3) methodological consideration
  - Ascertain the role of pattern error versus amplitude error in assessing the fidelity of the simulations using *skill metrics*



# Datasets

## ■ CMIP5 Models

- Models: **180 historical simulations (45 models with their realizations)**
- Time window: 1900-2005 (except SAM: 1956-2005)
- Variables:
  - 1) **Sea level pressure (SLP)**: Seasonal anomalies
  - 2) **Sea surface temperature (SST)**: Monthly anomalies (for PDO)
- Area-weighted average over EOF domain was removed at each time step



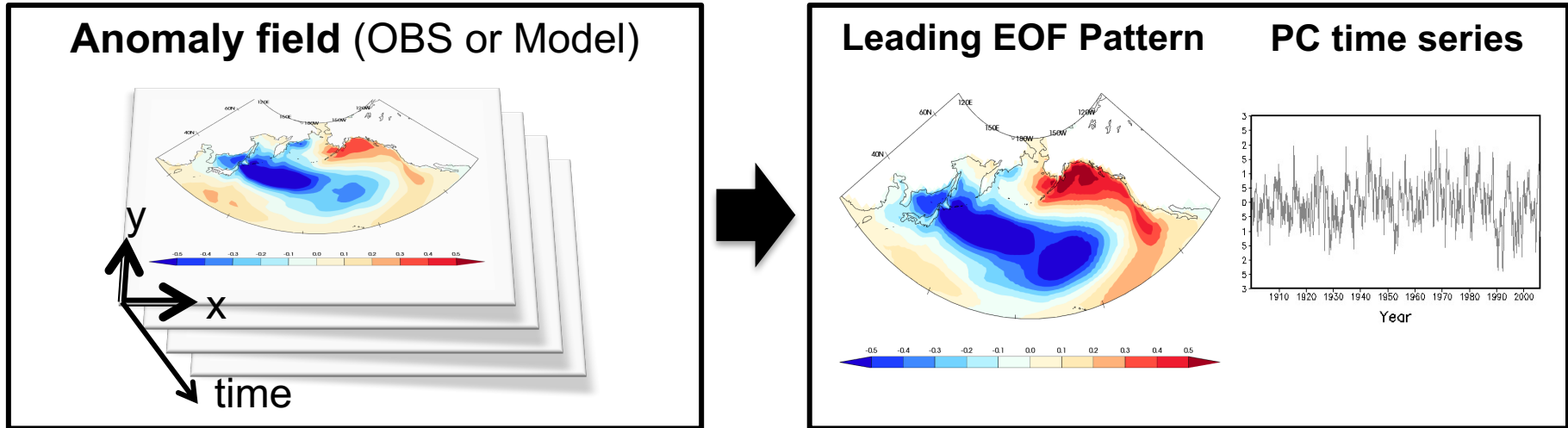
## ■ Observation based reference datasets

	SLP	SST
<b>OBS 1 (default)</b>	NOAA CIRES 20CR	HadISST v1.1
<b>OBS 2</b>	ERA 20C	HadISST v2.1
<b>OBS 3</b>	HadSLP	ERSST v3.0

## ■ Tools

- **PCMDI Metrics Package (PMP)**: Python based open-source tool (*Gleckler et al. 2016, EOS*)
- **UV-CDAT**: Python based large-scale data analysis and visualization tool (*Williams 2014, EOS*)
- **eofs**: Python library for EOF analysis (*Dawson 2016*)

# Conventional EOF Approach

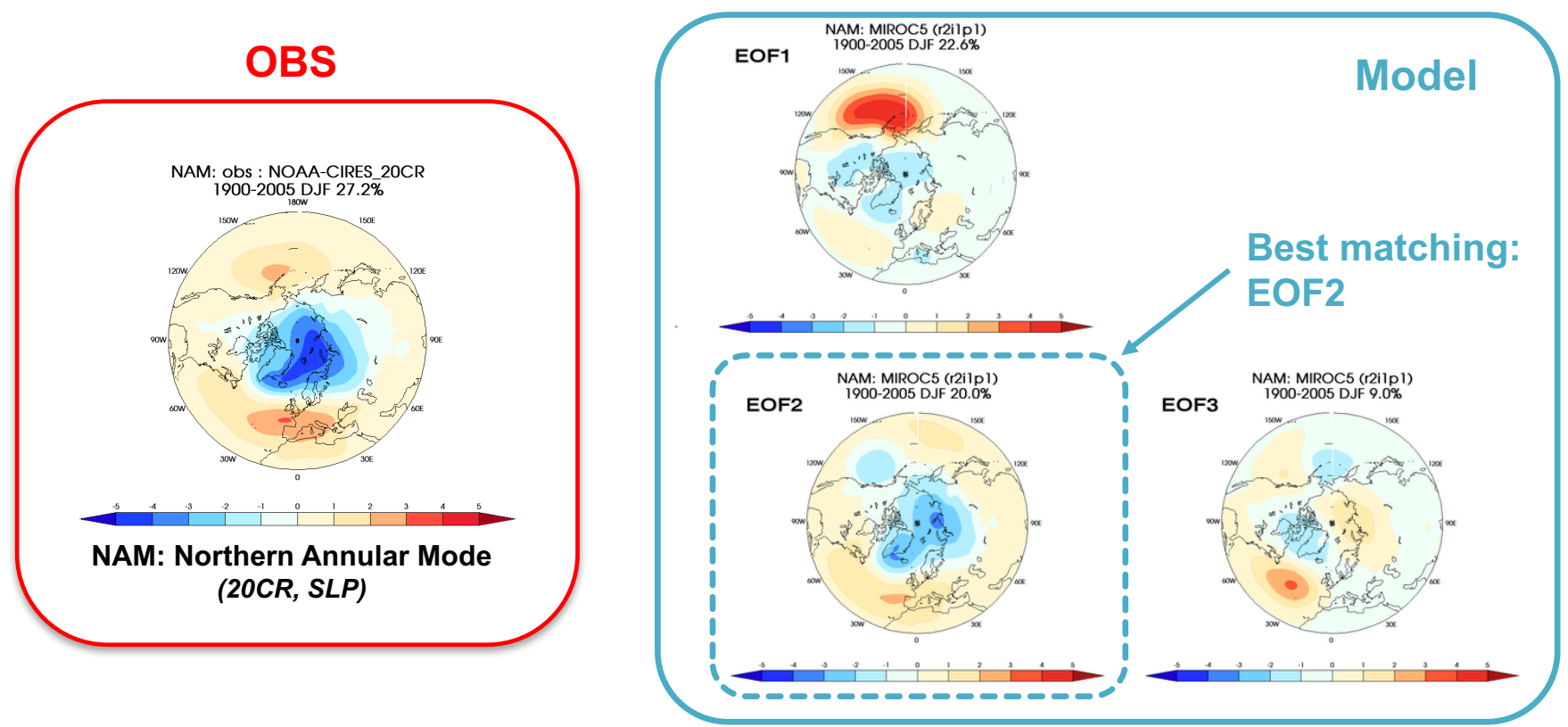


## Limitations:

1. **Sign ambiguity:** EOF sign is arbitrary, sometimes it needs to be flipped
2. **EOF mode swapping:** Cases in which leading OBS EOF better corresponds to 2<sup>nd</sup> or 3<sup>rd</sup> mode of model

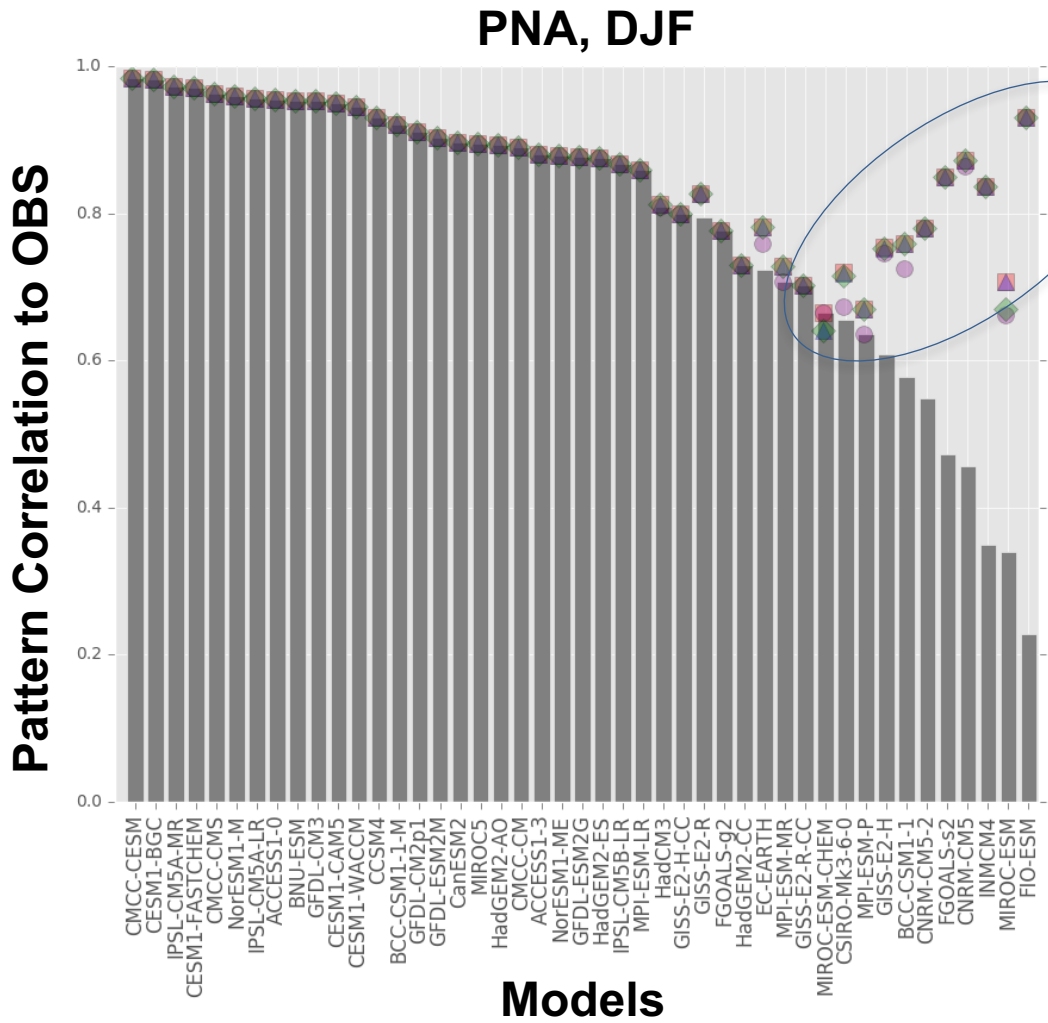
# EOF mode swapping (1): Example

- NAM (DJF) simulated by MIROC5 (r2i1p1)

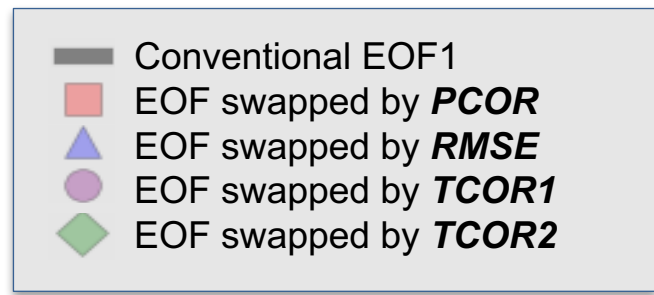


The leading OBS EOF corresponds best to model's 2<sup>nd</sup> EOF mode

# EOF mode swapping (2): Is it significant?



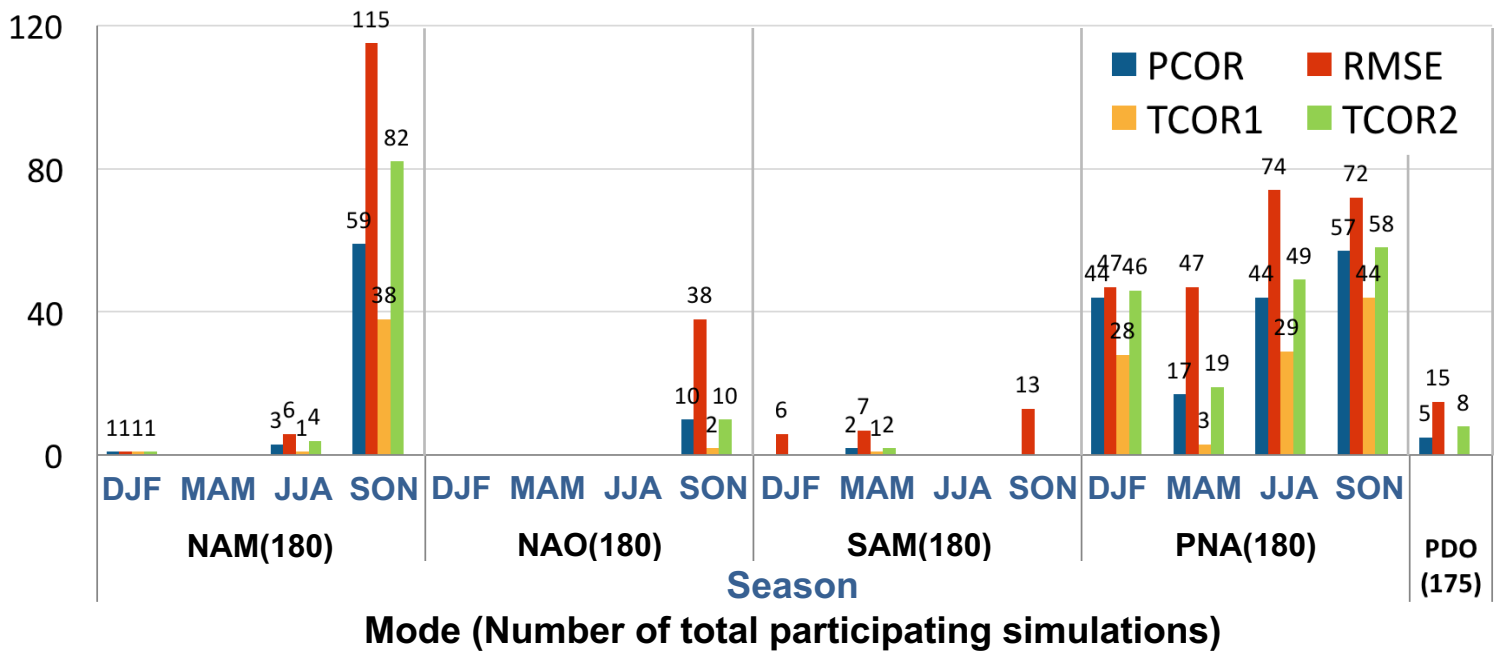
- Yes, it could be!
- Accounting for EOF swapping gives more fair comparison





# EOF mode swapping (3): How often it happen?

Number of EOF swapping cases identified



Applied criteria to decide best matching EOF:

**Spatial:**

- **PCOR:** Pattern correlation
- **RMSE:** Root mean square error

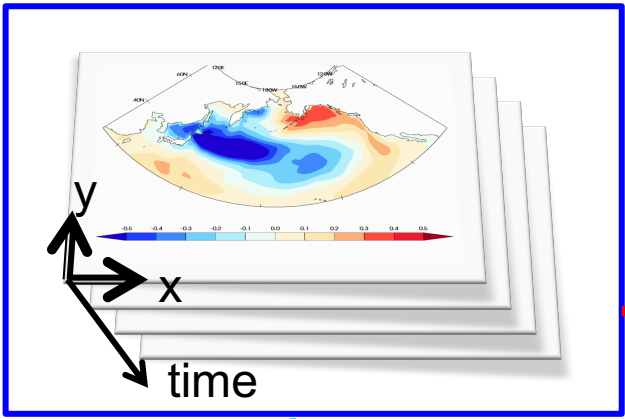
**Temporal:**

- **TCOR1:** CBF PC vs EOF PCs
- **TCOR2:** OBS PC vs tweaked CBF PCs

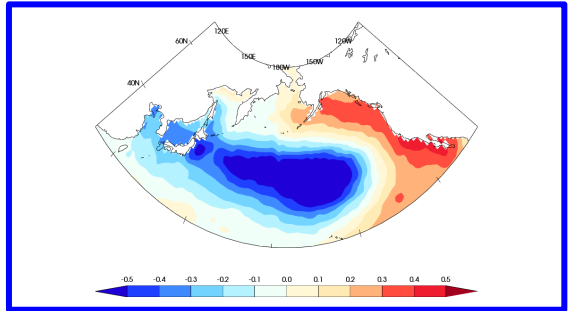
- Significant number of EOF swapping cases are identified
- There is no single best criteria

# Common Basis Function (CBF) Approach

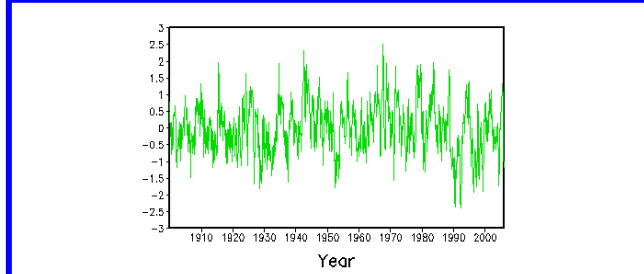
### Model's anomaly field



### OBS leading EOF pattern



### Model's CBF PC time series

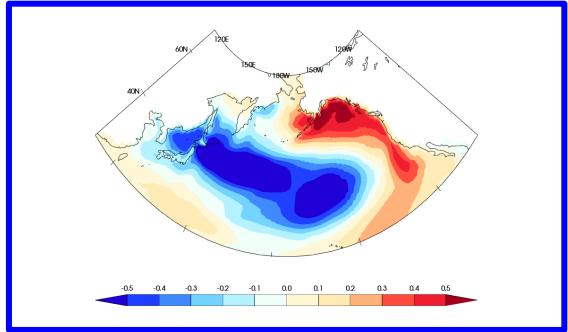


Get PC time series by projecting OBS pattern into model's anomaly space

(1) Projection

(2) Linear Regression

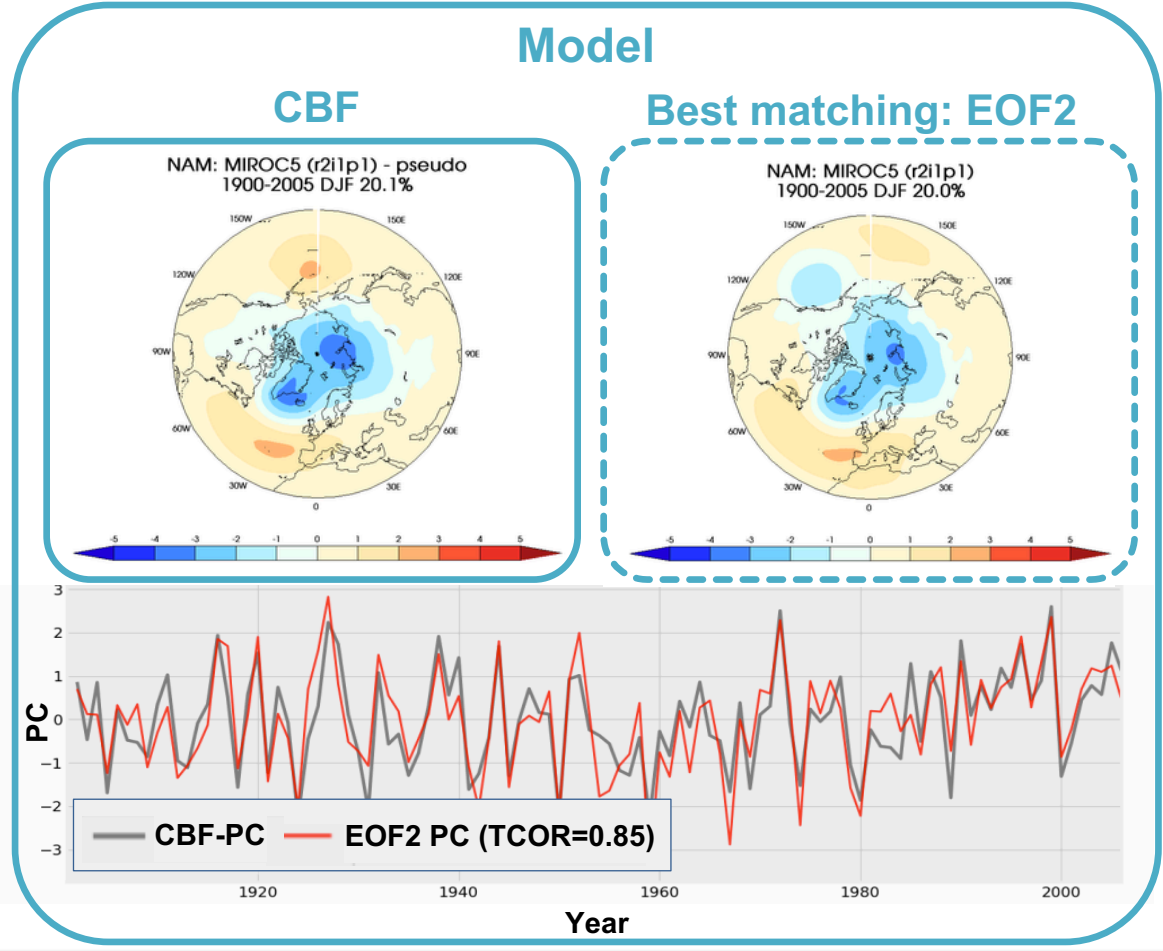
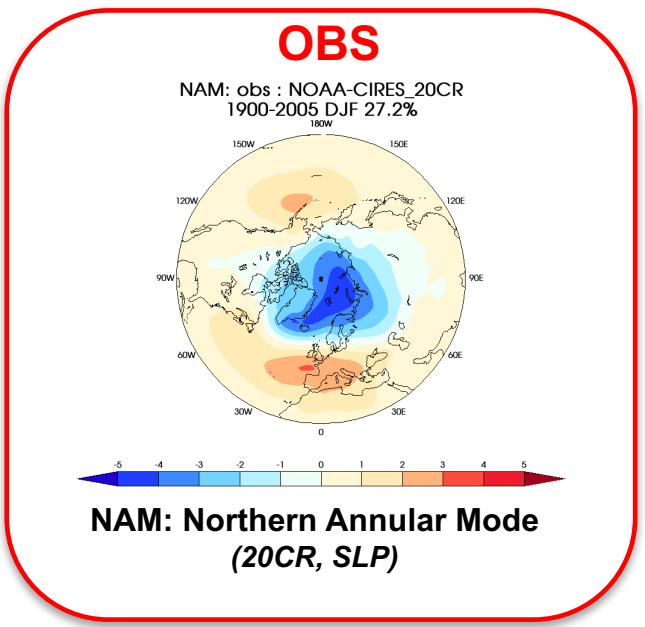
### Model's CBF Pattern



Reconstruct Pattern by linear regression between CBF PC & model field

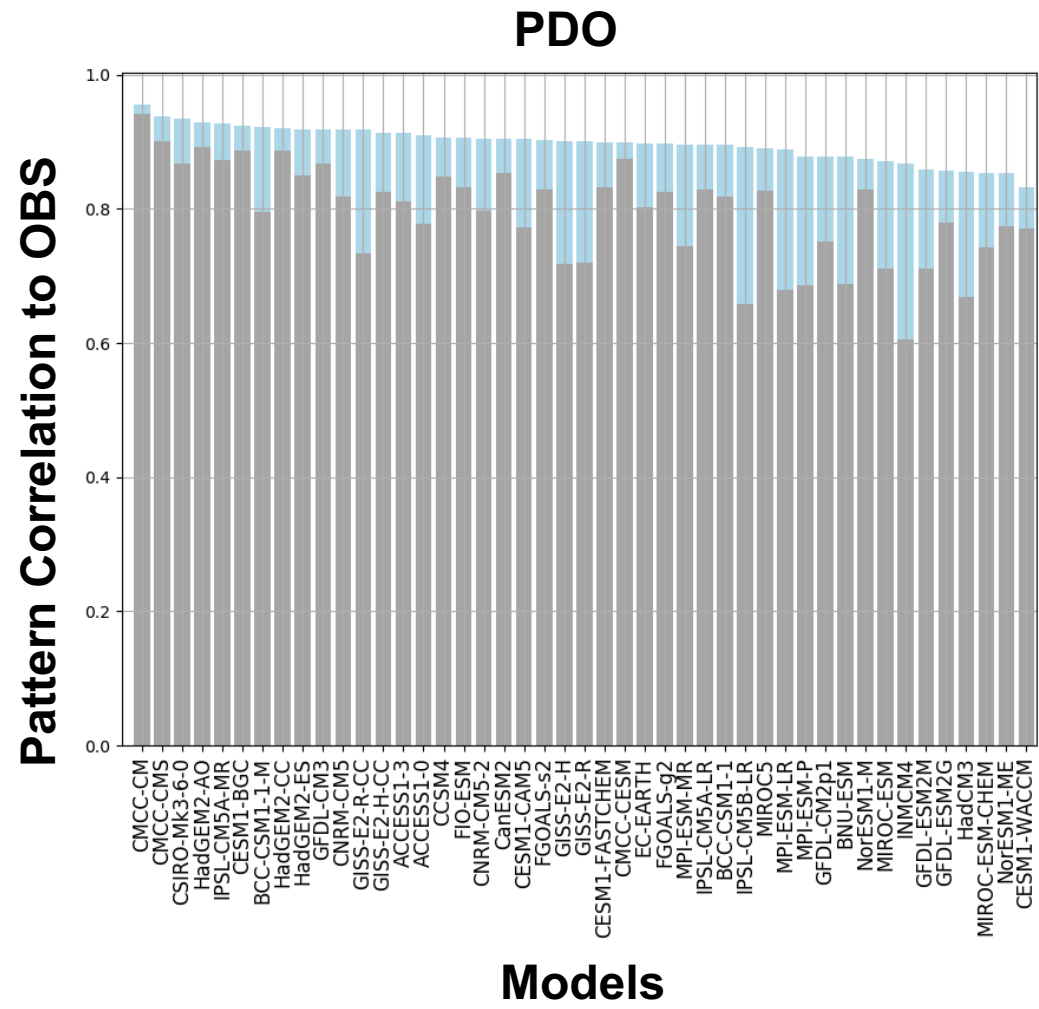
# CBF Result: Example

- NAM (DJF) simulated by MIROC5 (r2i1p1)



- CBF pattern better corresponds to OBS than the best-matching EOF mode
- CBF PC corresponds to PC of best-matching EOF mode

# CBF vs. EOF swapping

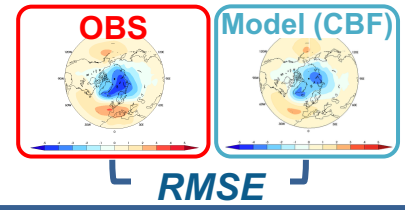


■ CBF  
■ EOF swapped  
 Averaged across realizations

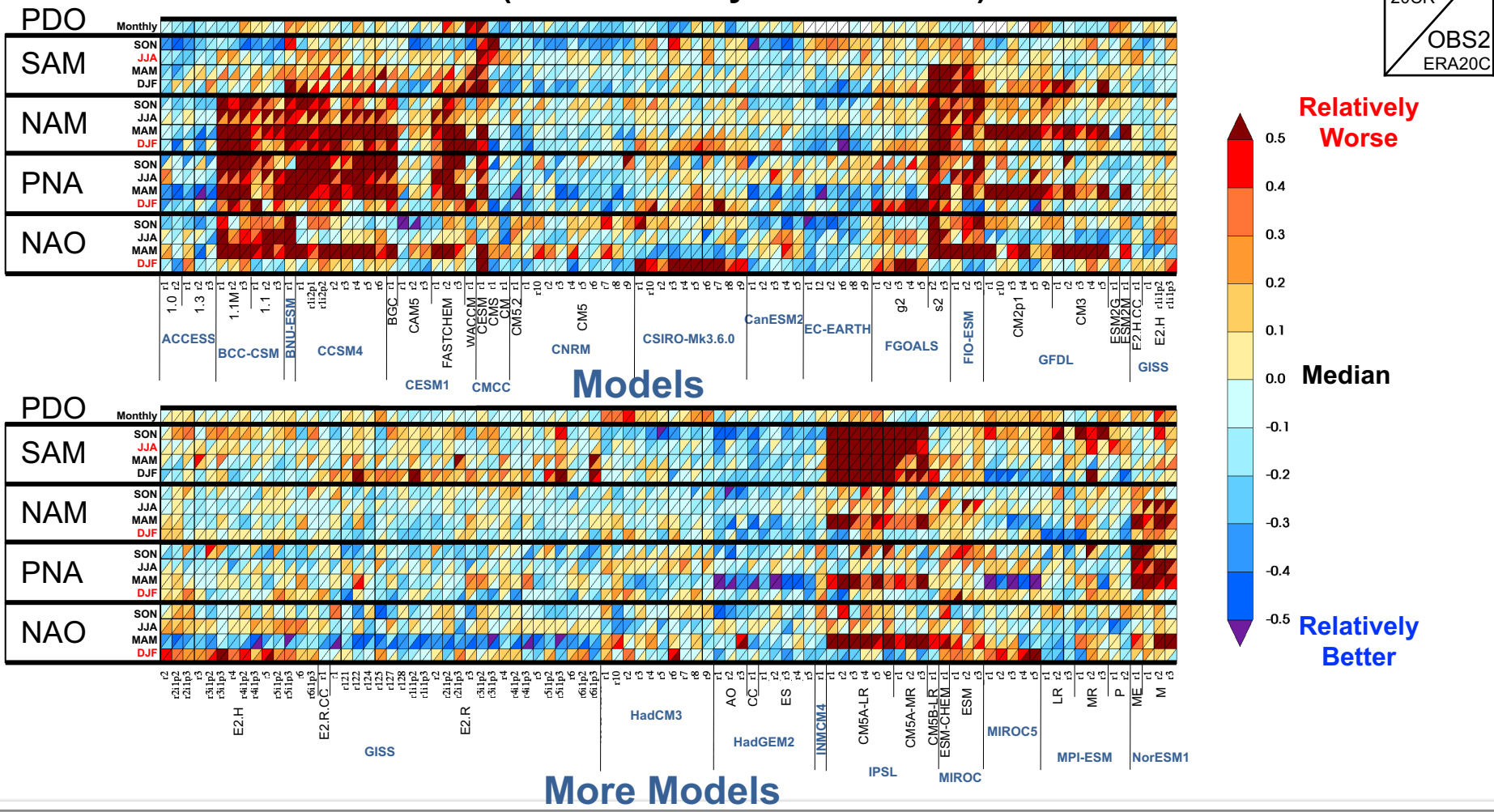
- The CBF provides a **more fair comparison with observations** than the conventional EOF
- The CBF reveals that **model skill is better** than indicated by conventional EOF analysis



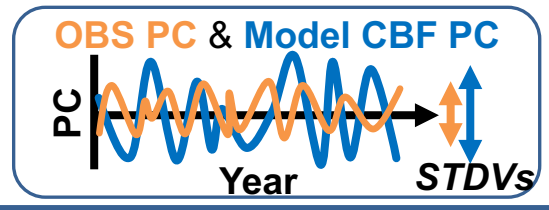
# Performance Diagnostics (1): Pattern + Amplitude



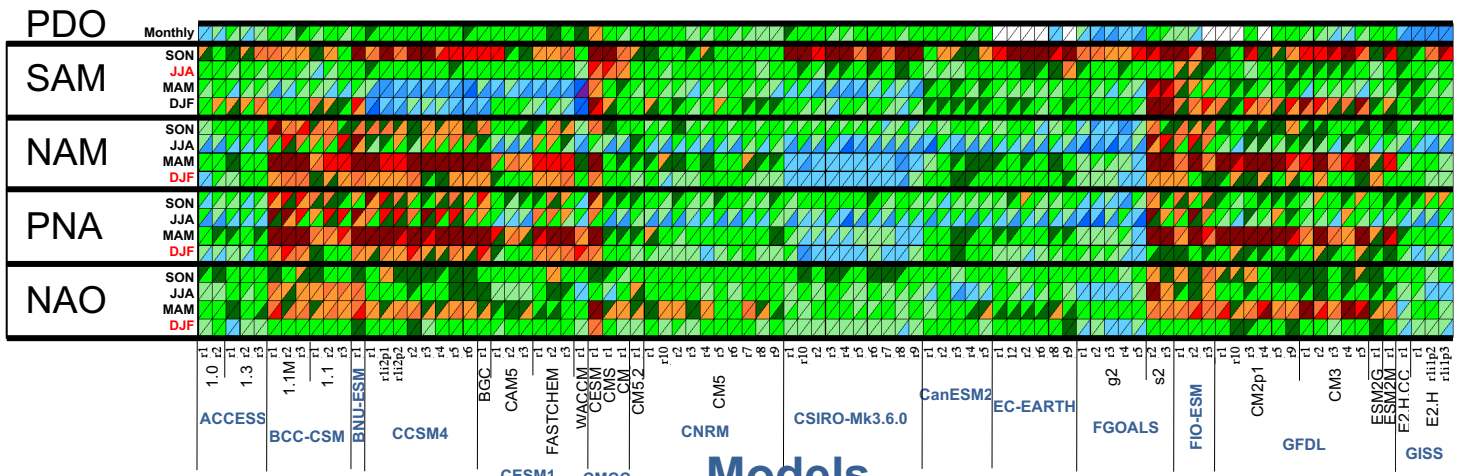
## RMSE (Normalized by median value)



# Performance Diagnostics (2): Amplitude

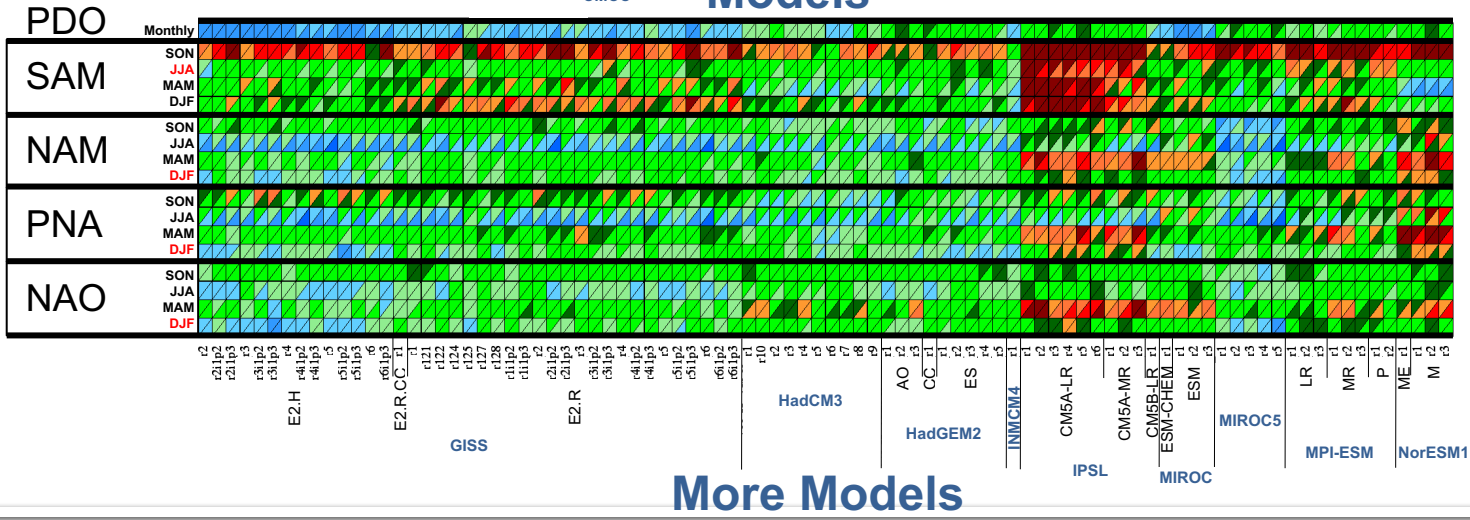
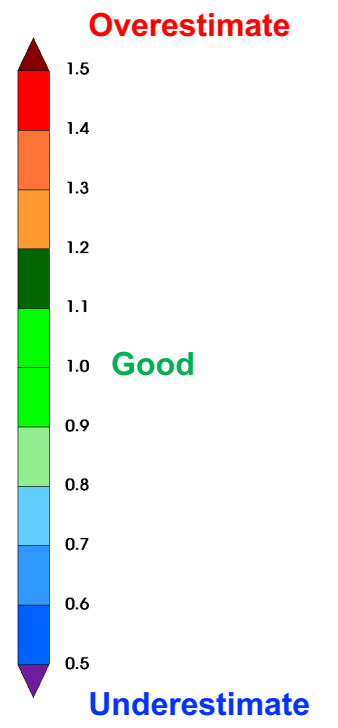


## Ratio of PC STDVs: Model/OBS

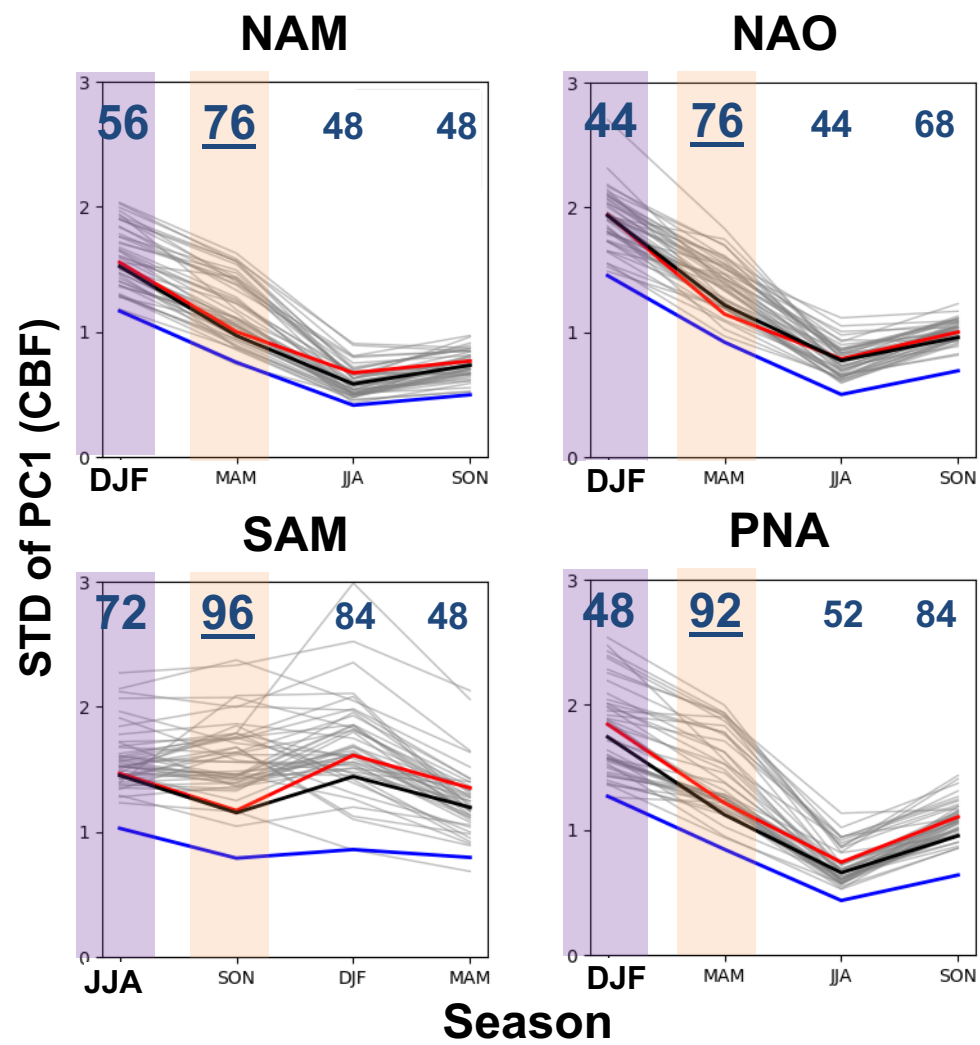


OBS1  
20CR

OBS2  
ERA20C



# Seasonal Variation



**Dominant Season (Winter)**

**Post-dominant Season (Spring)**

— **OBS1** (20CR)

— **OBS2** (ERA20C)

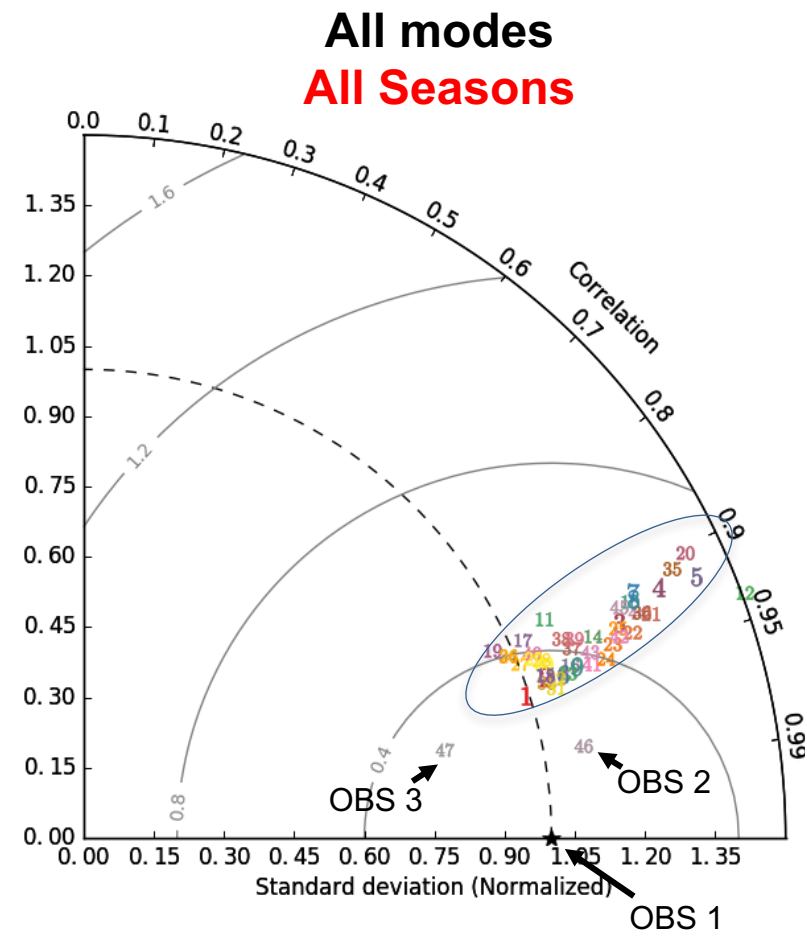
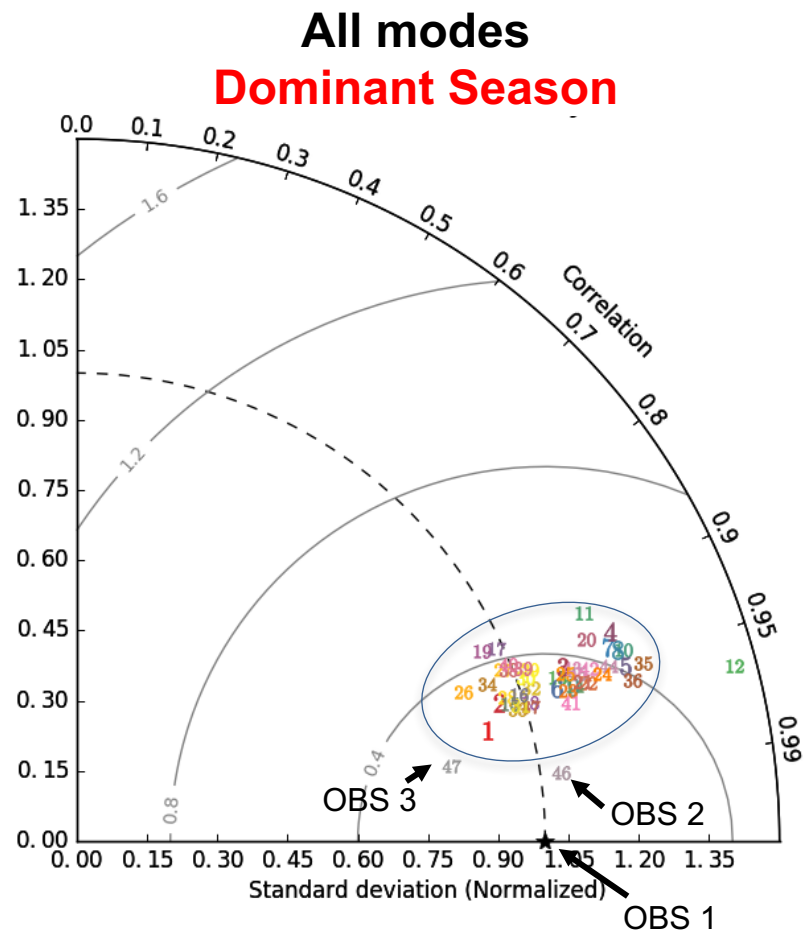
— **OBS3** (HadSLP2)

— **Models** (averaged across realizations)

Percentage [%] of overestimating models

- Some models dramatically overestimate variability immediately following dominant season
- More attention is needed for evaluating the *seasonality* of these modes, not just the dominant season

# Taylor Diagrams



- ★ **OBS 1**
- 1 ACCESS1-0
- 2 ACCESS1-3
- 3 BCC-CSM1-1
- 4 BCC-CSM1-1-M
- 5 BNU-ESM
- 6 CanESM2
- 7 CCSM4
- 8 CESM1-BGC
- 9 CESM1-CAM5
- 10 CESM1-FASTCHEM
- 11 CESM1-WACCM
- 12 CMCC-CESM
- 13 CMCC-CM
- 14 CMCC-CMS
- 15 CNRM-CM5
- 16 CNRM-CM5-2
- 17 CSIRO-Mk3-6-0
- 18 EC-EARTH
- 19 FGOALS-g2
- 20 FGOALS-s2
- 21 FIO-ESM
- 22 GFDL-CM2p1
- 23 GFDL-CM3
- 24 GFDL-ESM2G
- 25 GFDL-ESM2M
- 26 GISS-E2-H
- 27 GISS-E2-H-CC
- 28 GISS-E2-R
- 29 GISS-E2-R-CC
- 30 HadCM3
- 31 HadGEM2-AO
- 32 HadGEM2-CC
- 33 HadGEM2-ES
- 34 INMCM4
- 35 IPSL-CM5A-LR
- 36 IPSL-CM5A-MR
- 37 IPSL-CM5B-LR
- 38 MIROC-ESM
- 39 MIROC-ESM-CHEM
- 40 MIROC5
- 41 MPI-ESM-LR
- 42 MPI-ESM-MR
- 43 MPI-ESM-P
- 44 NorESM1-M
- 45 NorESM1-ME
- 46 **OBS 2**
- 47 **OBS 3**

Post-dominant season (Spring) is the major contributor to the overestimation



# Summary

Further detail:

J. Lee, K. R. Sperber, P. J. Gleckler, C. W. Bonfils, and K. E. Taylor (2017)  
Quantifying the Agreement Between Observed and Simulated Extratropical Modes of Interannual Variability. *Climate Dynamics* (in review)

- We have developed **evaluation metrics** for extra-tropical **modes of variability** using **CBF approach** – *projecting model anomalies onto the observational leading EOF*
- The CBF method leads to a more **consistent** approach for evaluation, overcoming limitations of conventional EOF
- The CBF reveals that **model skill** is better than indicated by conventional EOF analysis, even with swapping
- Our results are relatively **insensitive to sampling, observations, and processing choices**
- The **amplitude error** is the dominant contributor to systematic error in many models
- Models generally agree **better in the dominant season** of each mode, while many models systematically **overestimate** the variability in **post-dominant season**  
→ *More attention needs to be devoted to evaluating the seasonality of modes*



**Lawrence Livermore  
National Laboratory**

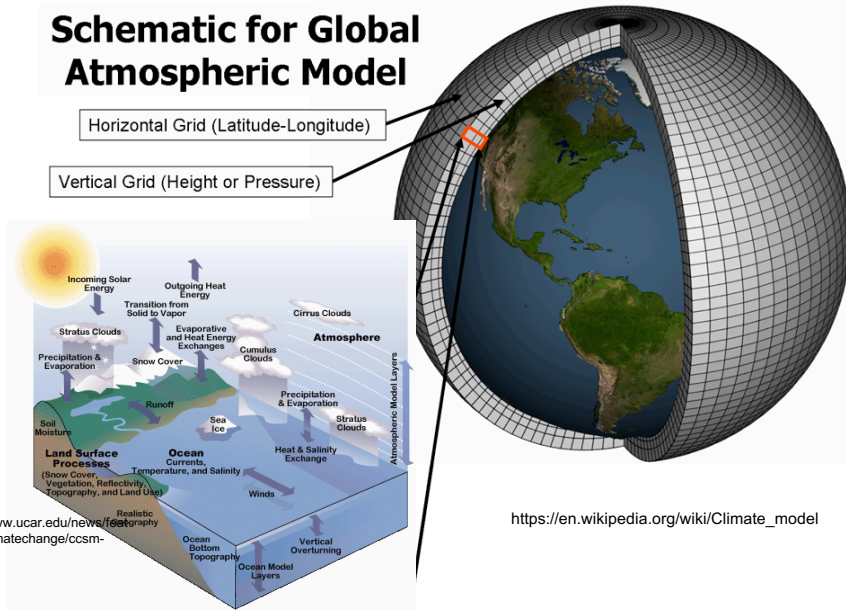
---

# Extra Back-up Slides

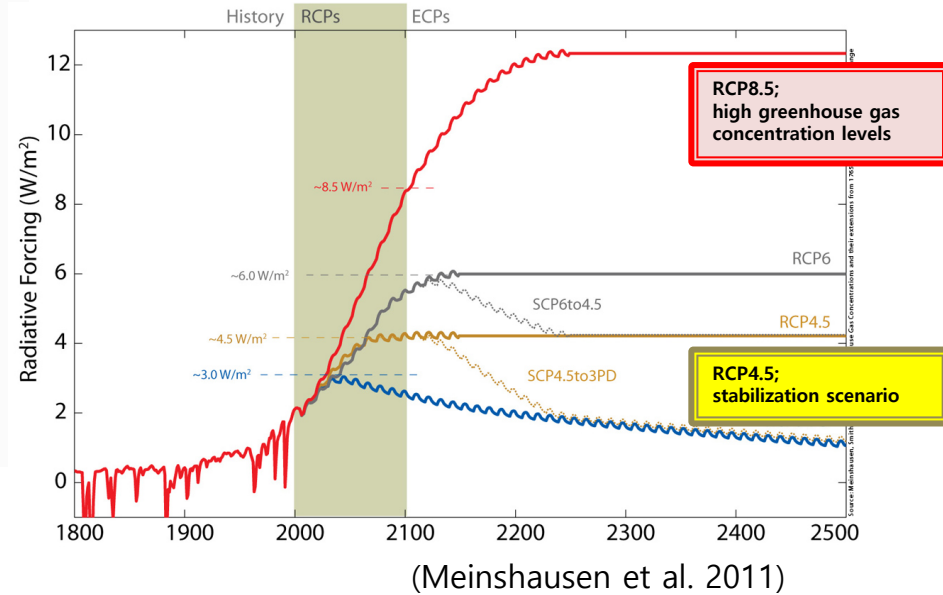


# Modeling Climate Under Future Possible Change Scenarios

## Schematic for Global Atmospheric Model



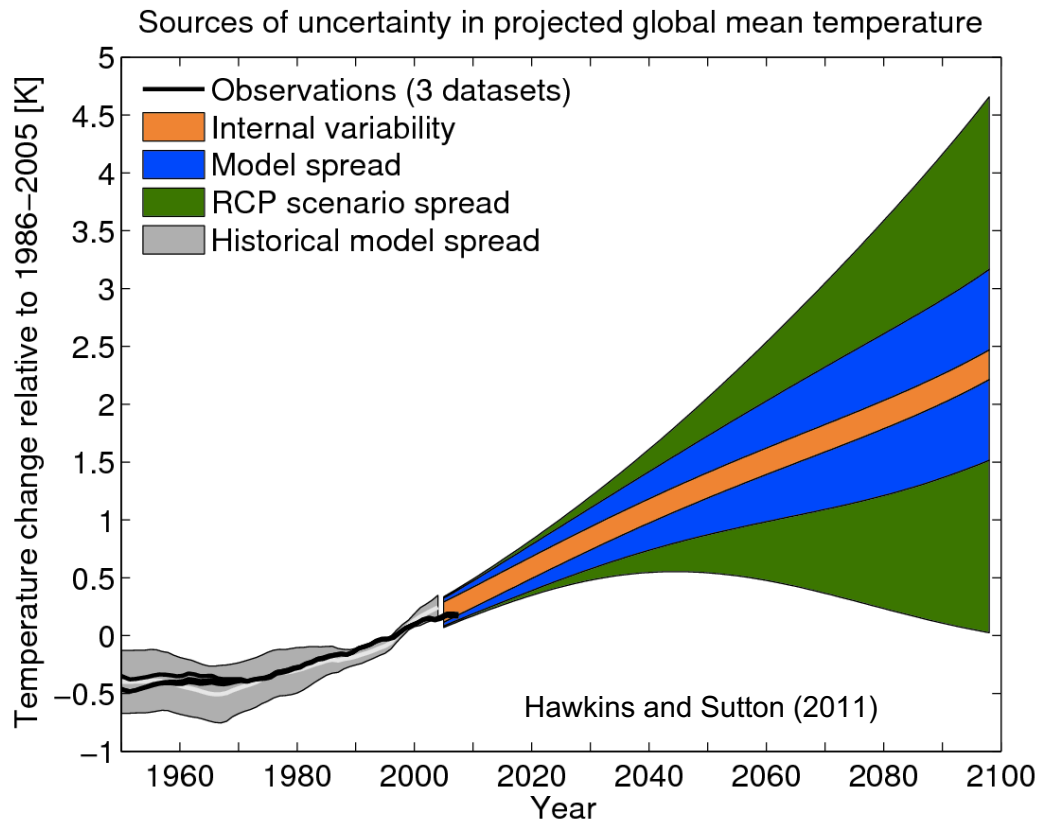
[https://en.wikipedia.org/wiki/Climate\\_model](https://en.wikipedia.org/wiki/Climate_model)



<http://www.ucar.edu/news/features/climatechange/ccsm-text.jsp>

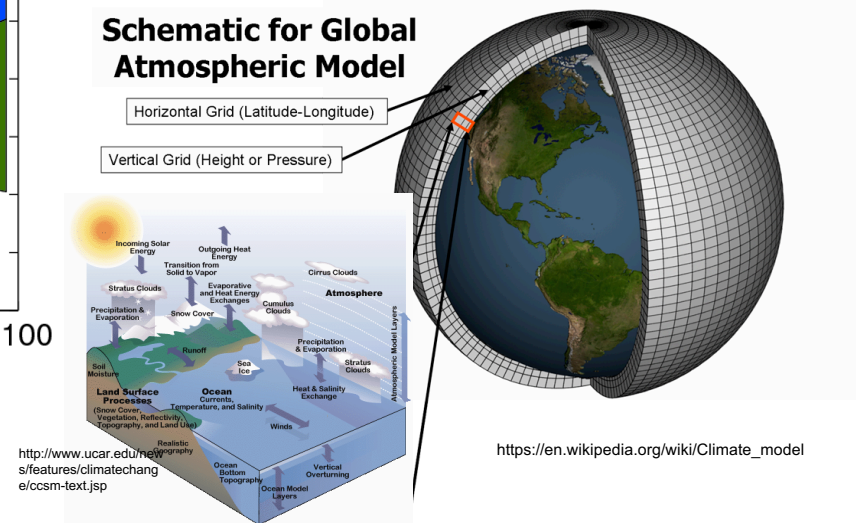


# Climate Model Inter-comparison



- Coupled Model Intercomparison Project Phase 5 (CMIP5)

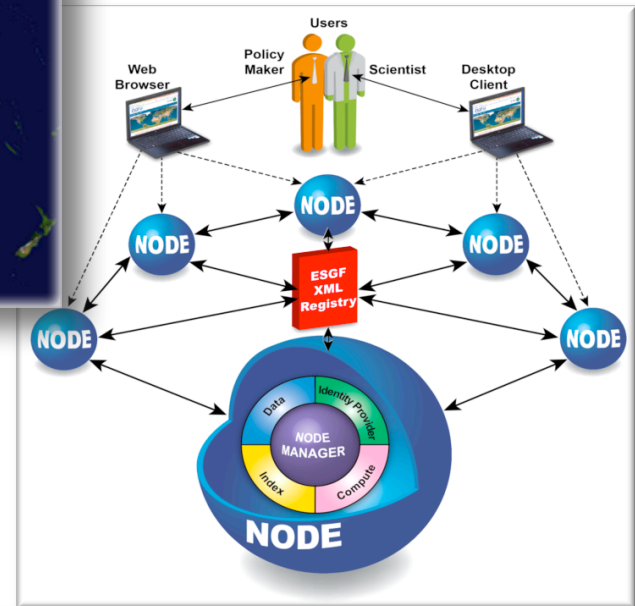
## Schematic for Global Atmospheric Model



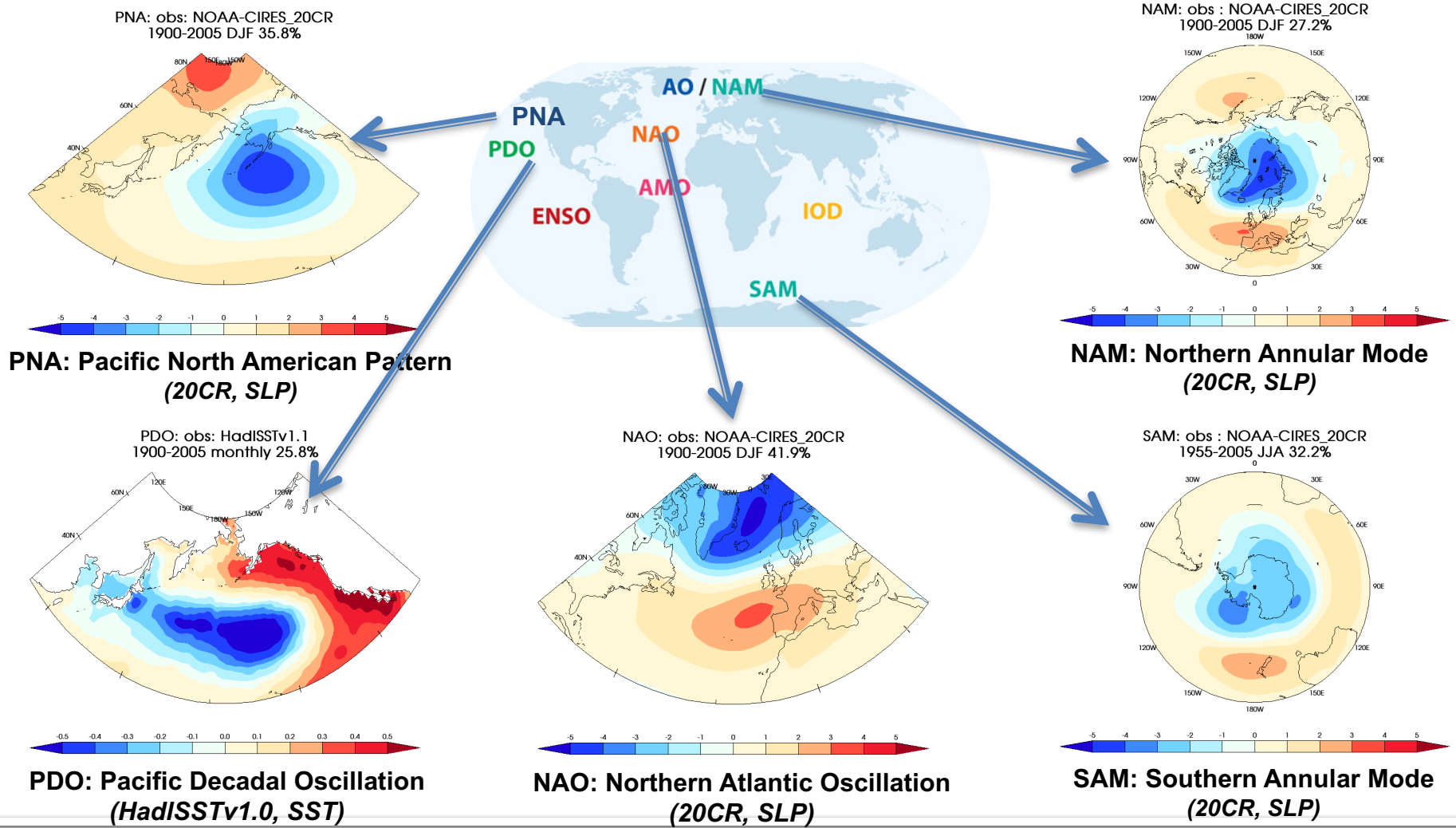
# World-wide Climate Data Archive



+ Data standardization,  
which open door to  
***Climate Model Inter-comparison***



# Modes of variability (1)



# Modes of variability (2): NAO

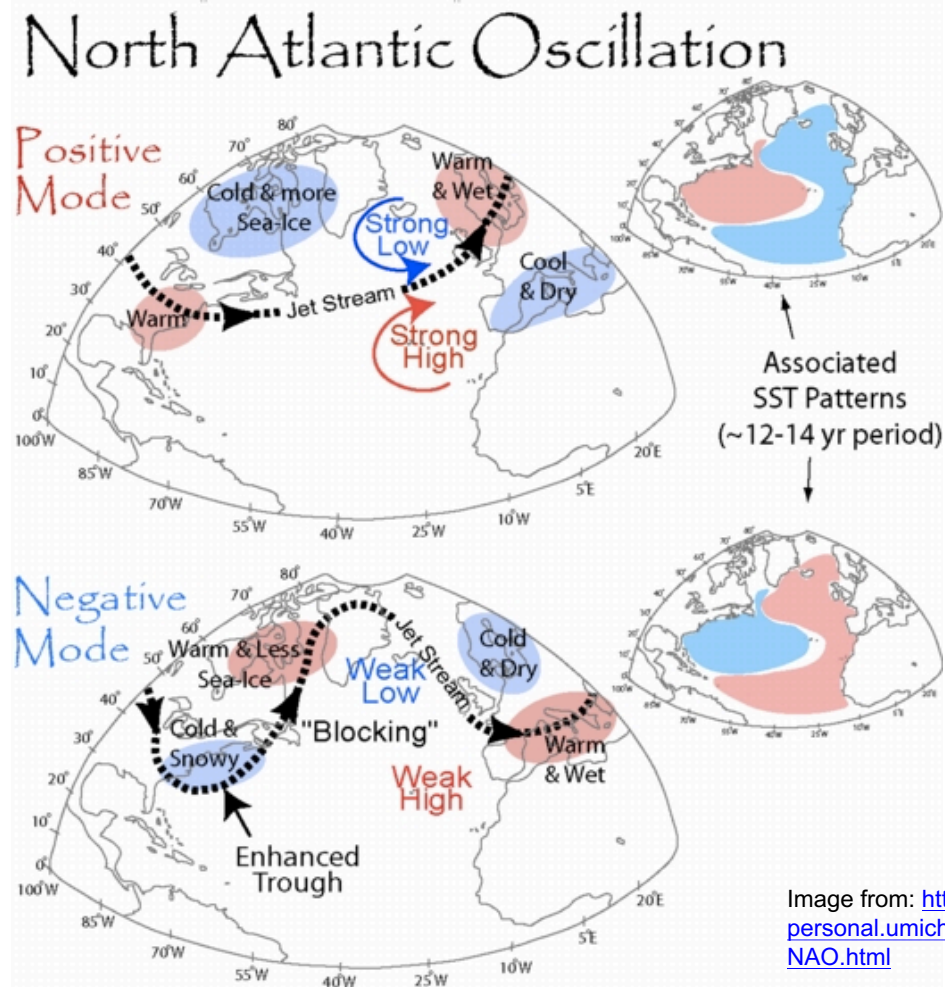
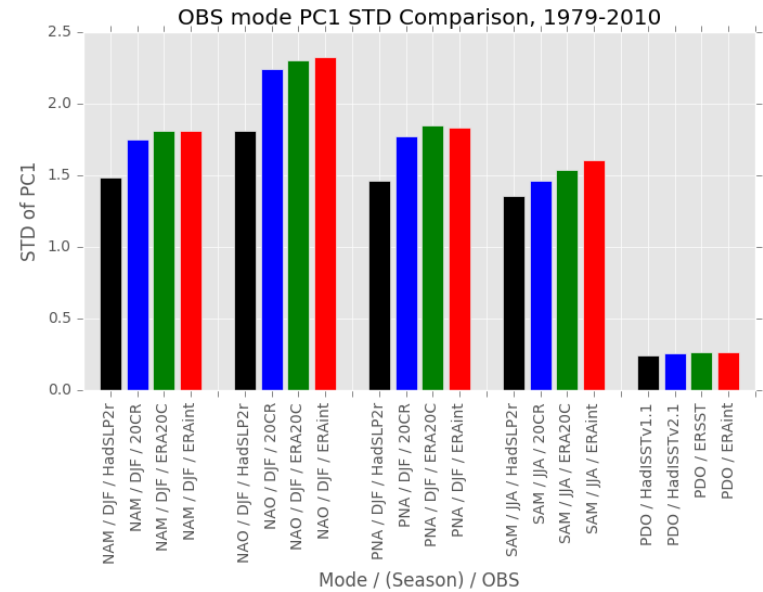
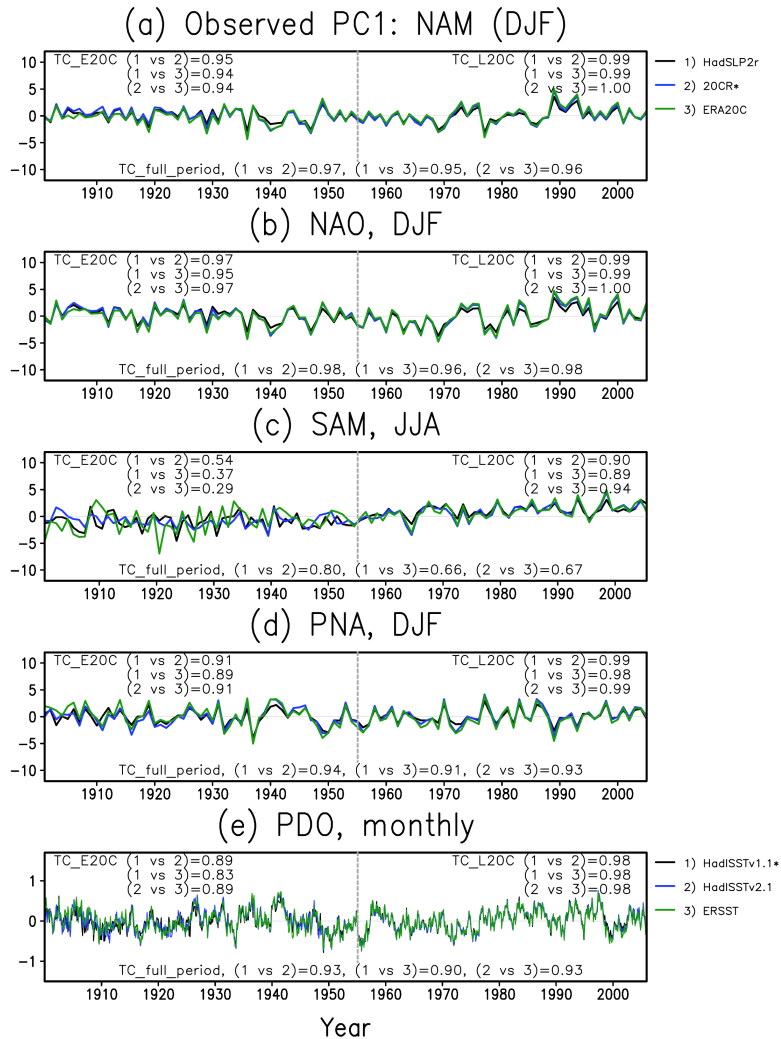


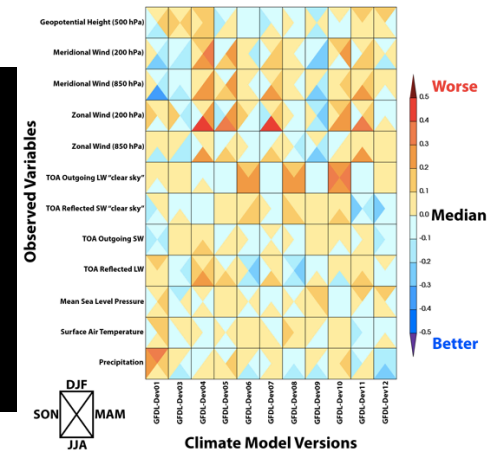
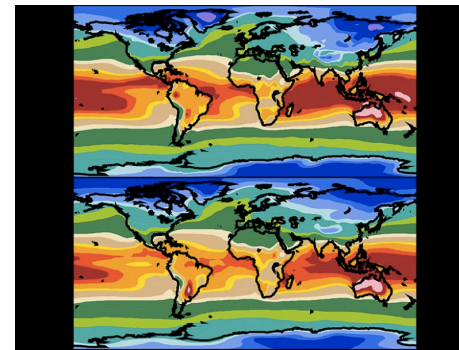
Image from: <http://www-personal.umich.edu/~auraell/precipitation/pages/NAO.html>

# Observation



# Software Development

- **Python** (free of H/W System dependency)
- **Built over:**
  - PCMDI Metrics Package (PMP)
  - UV-CDAT
  - EOFs (Dawson 2016)
- **Open source (Github)**
- **Reusable code**
  - user friendly designed
  - self-describing documentation

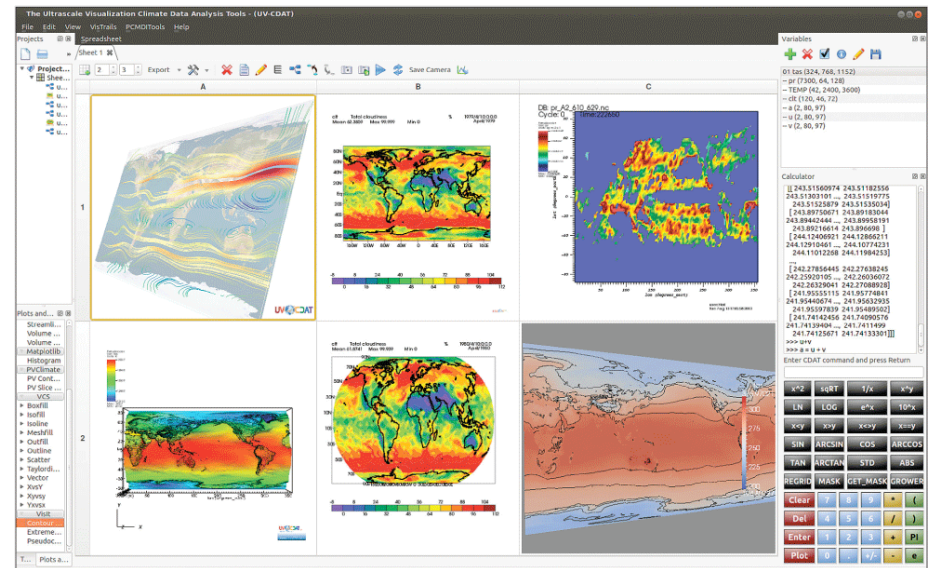
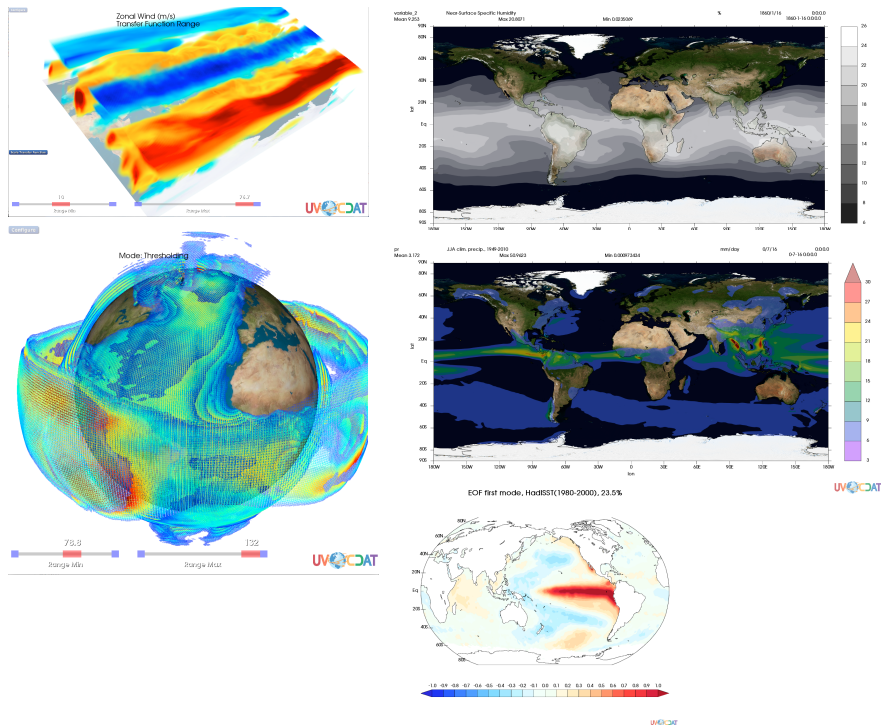


Gleckler, P. J., C. Doutriaux, P. J. Durack, K. E. Taylor, Y. Zhang, D. N. Williams, E. Mason, and J. Servonnat (2016), A more powerful reality test for climate models, *Eos*, 97, doi:10.1029/2016EO051663. Published on 3 May 2016.



# Ultra-scale Visualization Climate Data Analysis Tools (UV-CDAT)

- CDMS (Climate Data Management System)
  - Handle multi-dimensional climate variables
- VCS Graphics Module



# Python EOFs Library

- High-level interface for computing empirical orthogonal functions (EOFs) and related quantities

Dawson, A., (2016). eofs: A Library for EOF Analysis of Meteorological, Oceanographic, and Climate Data. Journal of Open Research Software. 4(1), p.e14. DOI: <http://doi.org/10.5334/jors.122>

Journal of Open Research Software

Dawson, A 2016 eofs: A Library for EOF Analysis of Meteorological, Oceanographic, and Climate Data. Journal of Open Research Software, 4, e14, DOI: <http://doi.org/10.5334/jors.122>

SOFTWARE METAPAPER

## eofs: A Library for EOF Analysis of Meteorological, Oceanographic, and Climate Data

Andrew Dawson<sup>1</sup>  
<sup>1</sup>Atmospheric, Oceanic & Planetary Physics, Department of Physics, University of Oxford, [andrew.dawson@physics.ox.ac.uk](mailto:andrew.dawson@physics.ox.ac.uk)

The eofs library provides a high-level Python interface for computing EOFs and related quantities, with a focus on correctness and ease of use. The library is designed to be modular and hierarchical, allowing computations using plain Python or through a convenient package for users wanting to integrate with popular libraries from atmospheric and climate science.

**Keywords:** EOF analysis; Meteorology; Oceanography; Climate; Python

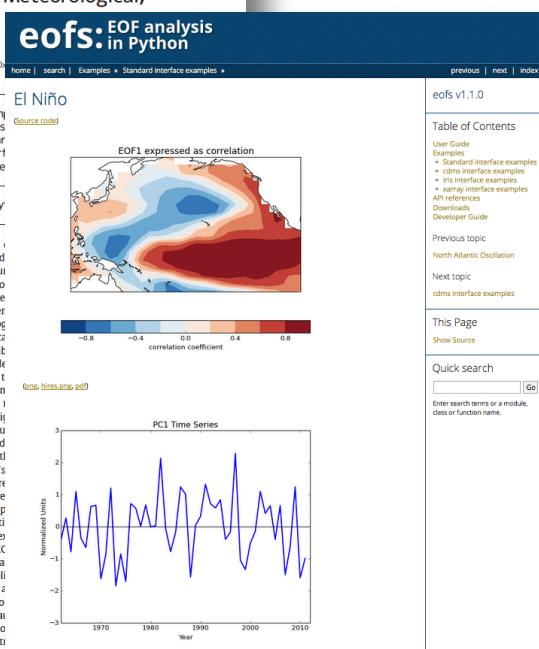
### (1) Overview

**Introduction**

Data sets in meteorology, oceanography, and climate are typically very large, containing data covering large spatial areas, observed or modelled over long periods of time. Studying variability in these data sets can be challenging, with coherent modes of large-scale spatial and temporal variability in the atmosphere-ocean system hidden amongst the noise of smaller scale physical processes. An often used technique for examining large-scale patterns of variability in such data sets is the analysis of empirical orthogonal functions (EOFs) [1]. Decomposing a complex data set varying in time and space into a set of EOFs and associated principal component time series (PCs) can allow insight into the most dominant modes of spatial variability, for example El Niño, one of the leading modes of climate variability, is often characterised by the first EOF and PC of sea surface temperature in the tropical Pacific [2].

The EOFs and PCs of a data set describe a new basis, where instead of a series of spatial observations varying in time, the data set is represented as a set of fixed spatial patterns or modes, which represent a given amount of the total variance in the data set, and a set of time series describing how each pattern changes with time. In typical applications the first few EOFs account for a large portion of the total variance, allowing the study of one or two modes to give insight into the variability present in the data set. The method of analysis is purely mathematical and does not depend on any physical properties of the quantity being analysed.

The process of computing and analysing EOFs and related structures is non-trivial, and highly error prone. For example, consider the computation of EOFs from a time-series longitude grid data to account cells due to coordinate system and care taken of an oceanographic matrix as the (possibly) associated with the EOFs. Inserting any weights, and weight also in other dimensions associated with the EOFs. The procedure and great care of these patterns of each quantity. There are several computing EOF type of data using an unpublic EOF analysis procedure to that cannot be kept in the analysis of the major eofs was to re-object-oriented.



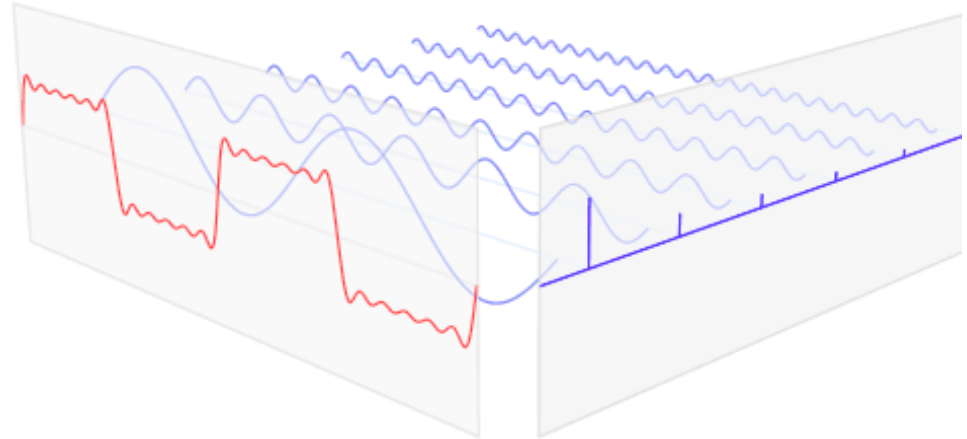
The screenshot shows the website for the eofs library. It features a navigation bar with links for home, search, examples, and standard interface examples. The main content area displays the title 'eofs: EOF analysis in Python' and a section for 'El Niño' with a 'Course code' link. Below this is a map titled 'EOF1 expressed as correlation' showing a spatial pattern of sea surface temperature anomalies in the tropical Pacific, with a color scale from -0.8 to 0.8. A 'PC1 Time Series' plot shows the time series of the first principal component from 1970 to 2010, with normalized units ranging from -3 to 3. A 'Quick search' box is visible on the right side of the page.

```
from eofs.standard import EOF
from eofs.variables import example_data_path

# Read SST anomalies using the netCDF module. The file contains
# November-March coverage of SST anomalies in the central and western Pacific.
filename = example_data_path('el_nino_sst_anom.nc')
pc1 = Dataset(filename)['pc1']
```

# Empirical Orthogonal Function (EOF) analysis

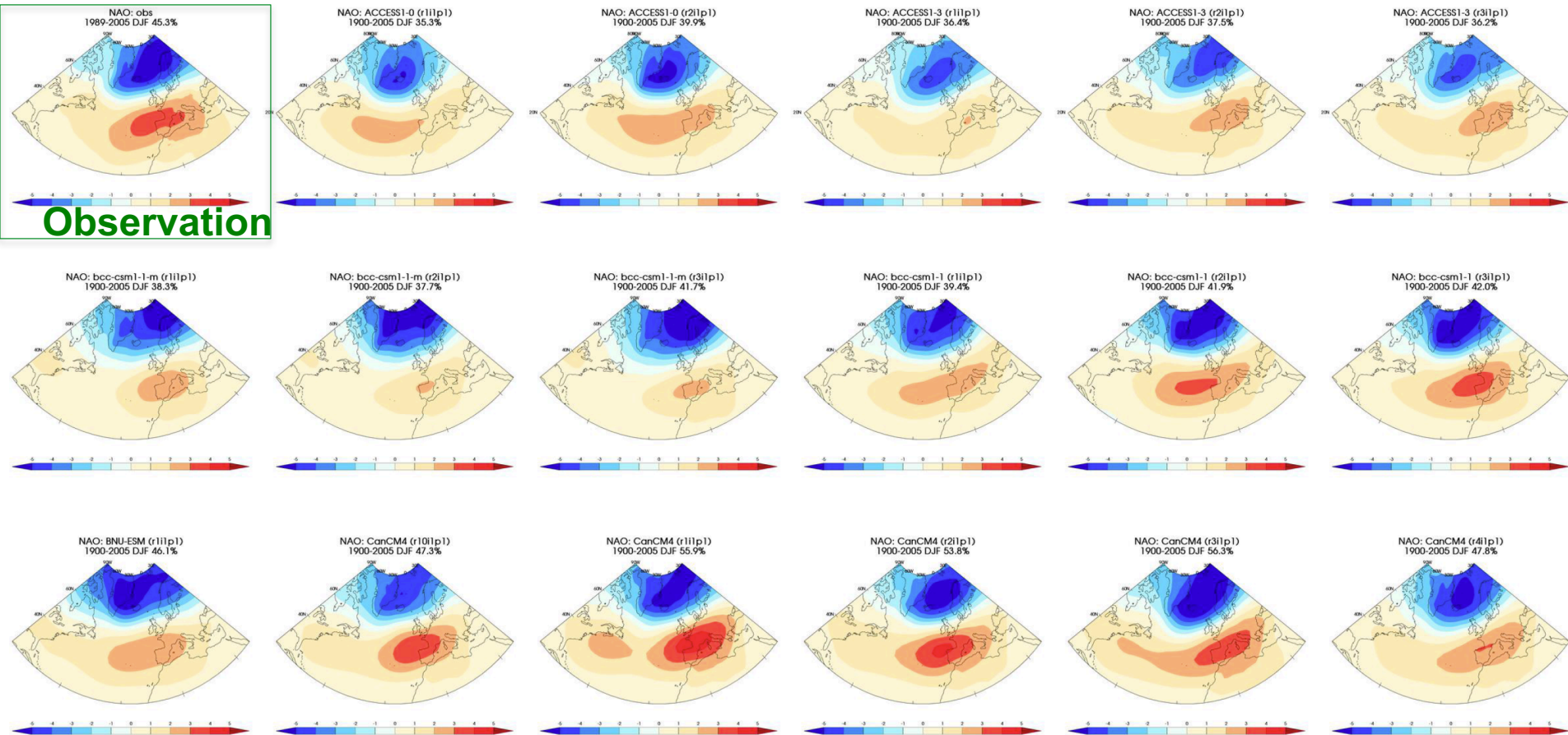
- **Fourier Transform:**



<http://tex.stackexchange.com/questions/127375/replicate-the-fourier-transform-time-frequency-domains-correspondence-illustrati>

- **EOF:**
  - **Similar concept to FT, but separates modes based on orthogonality**
  - **It is more useful when time series has “jumps” in it**

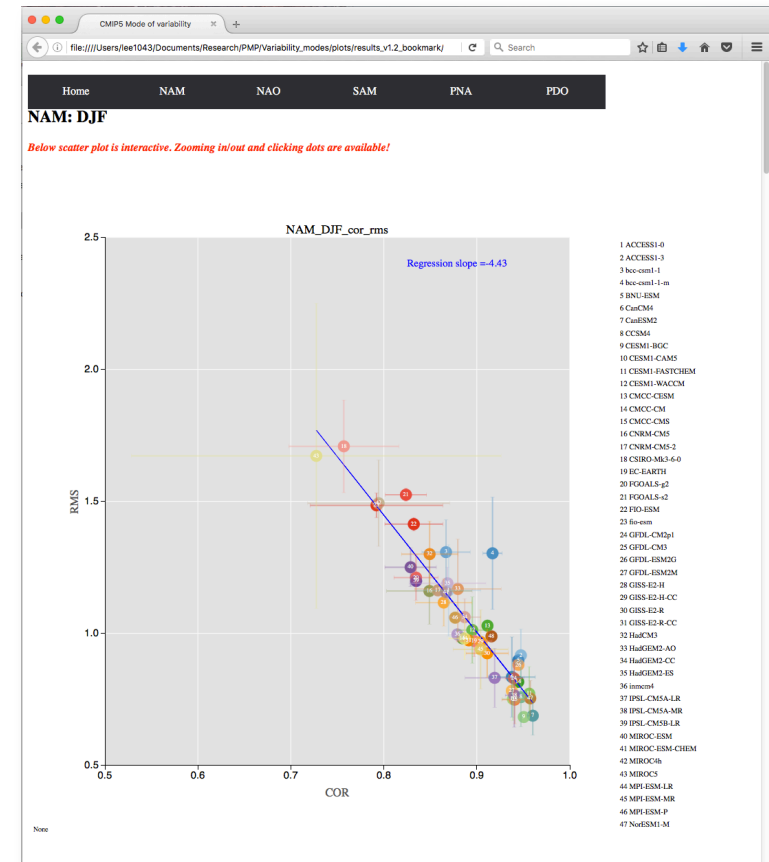
# Loop through all CMIP5 simulations.. (e.g. NAO)



5 modes, 4 seasons, about 45 models with all available realizations (1~25 per model), various type of plots;  
≈ 13,000 images at the end...

# Database Construction

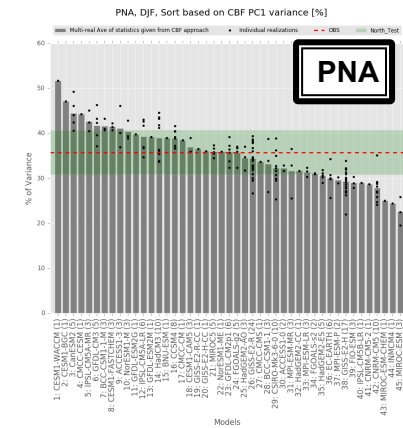
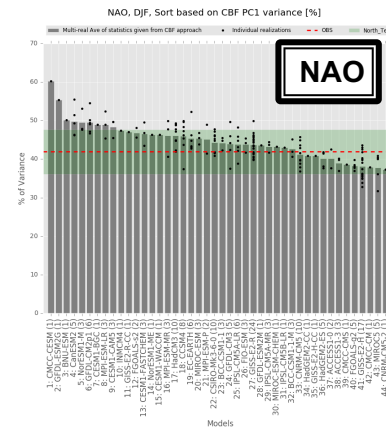
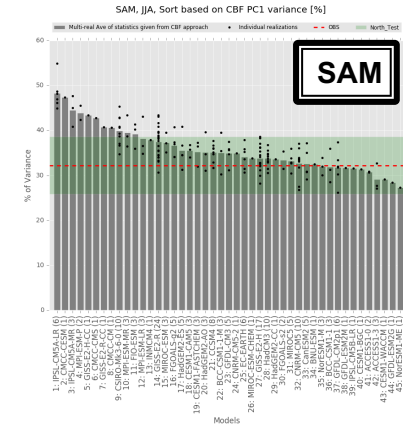
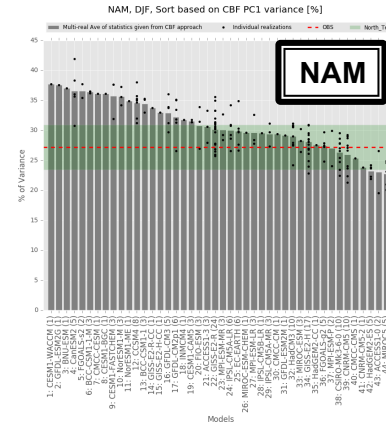
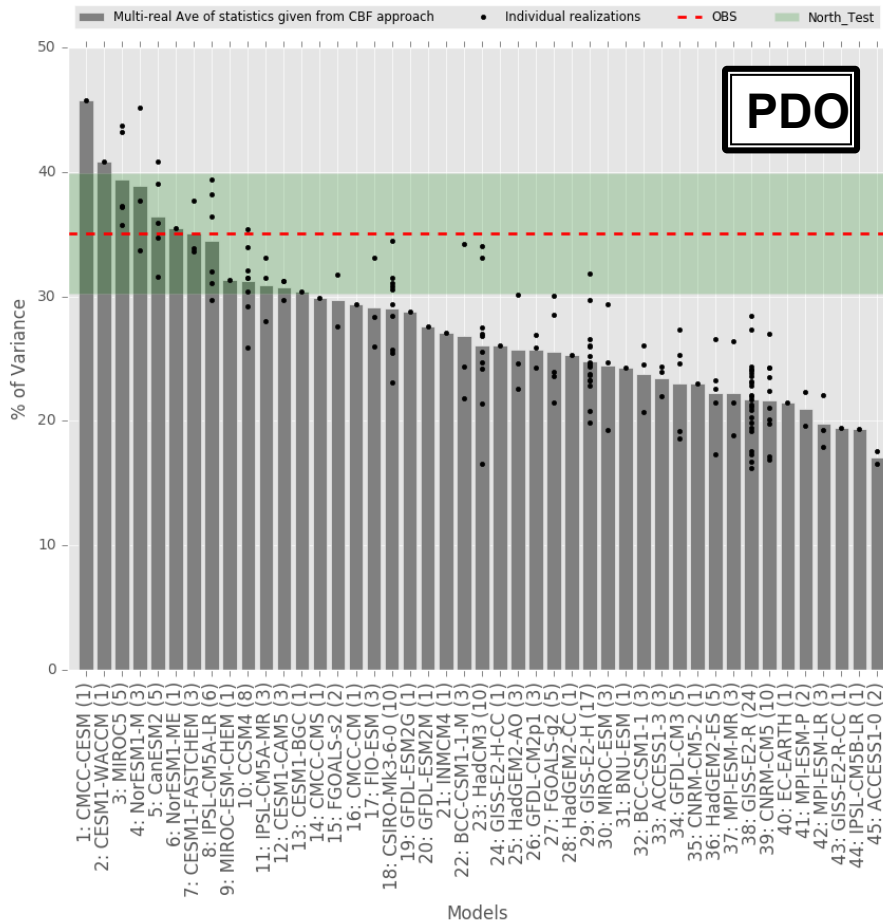
- Browsing available web-like navigation
- Statistics based **Interactive plots** ( **mpld3** Library)
- Starting version for **PCMDI web service**





# PDO and others - Variance in time

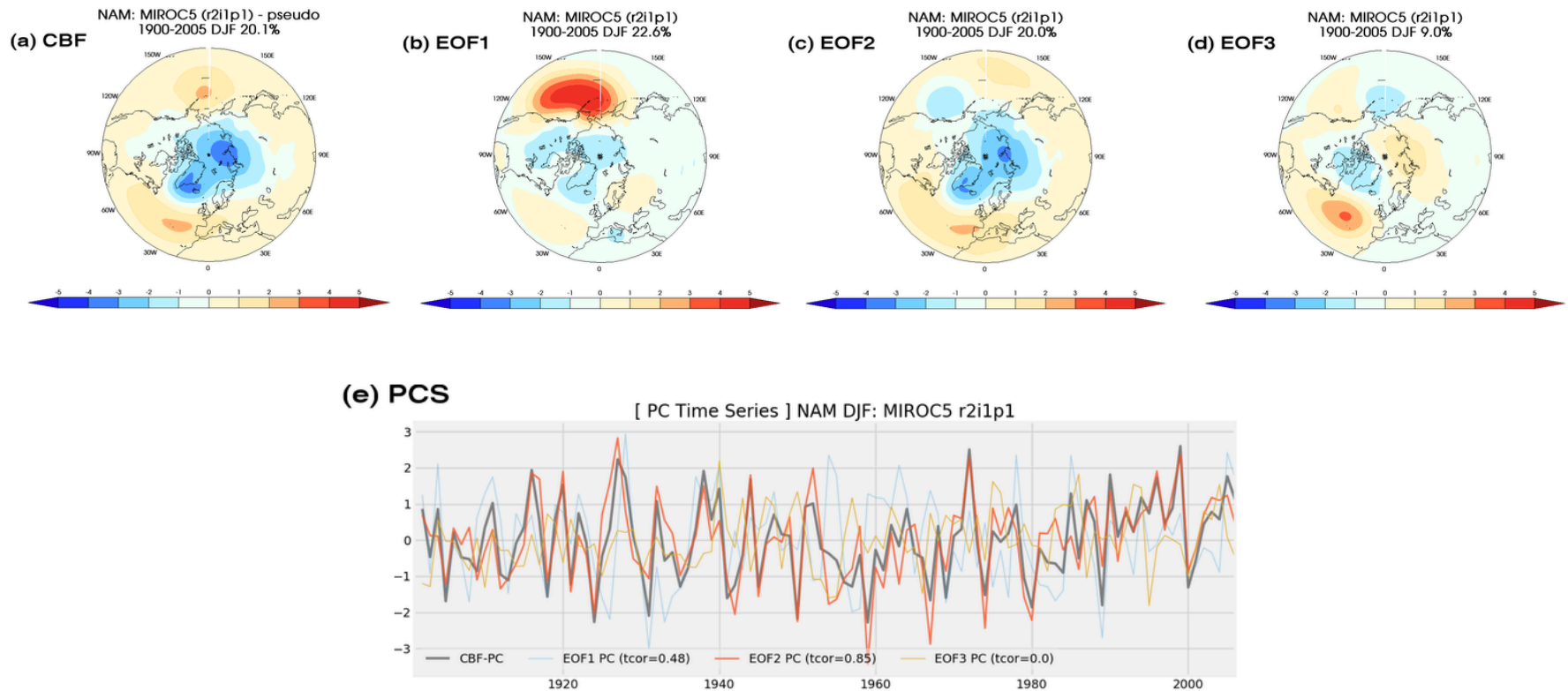
PDO, yearly, Sort based on CBF PC1 variance [%]





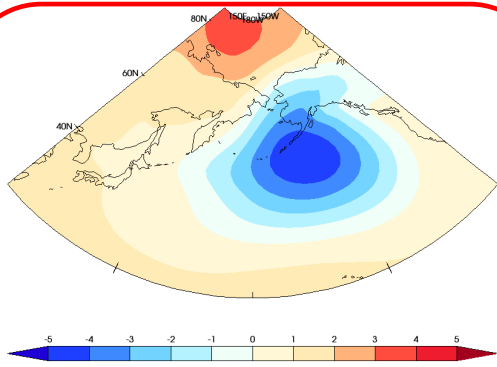
# EOF mode swapping: NAM, DJF

- NAM in MIROC5 (r2i1p1)



# EOF mode swapping and CBF: PNA Example

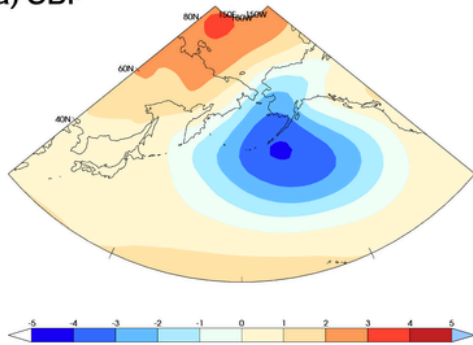
**OBS**



**PNA: Pacific North American Pattern (20CR, SLP)**

**(a) CBF**

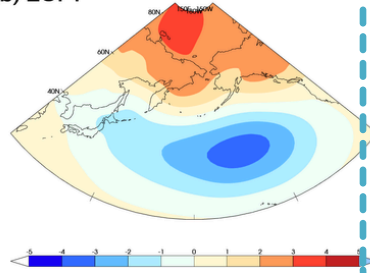
PNA: CNRM-CM5 (r1i1p1) - CBF  
1900-2005 DJF 28.9%



**Model**

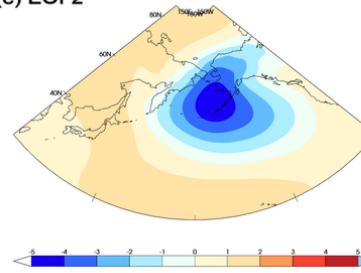
**(b) EOF1**

PNA: CNRM-CM5 (r1i1p1)  
1900-2005 DJF 32.4%



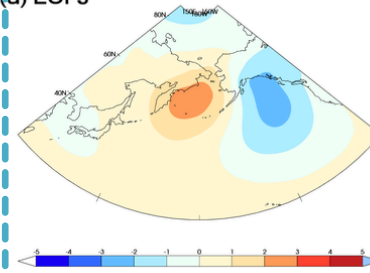
**(c) EOF2**

PNA: CNRM-CM5 (r1i1p1)  
1900-2005 DJF 28.3%



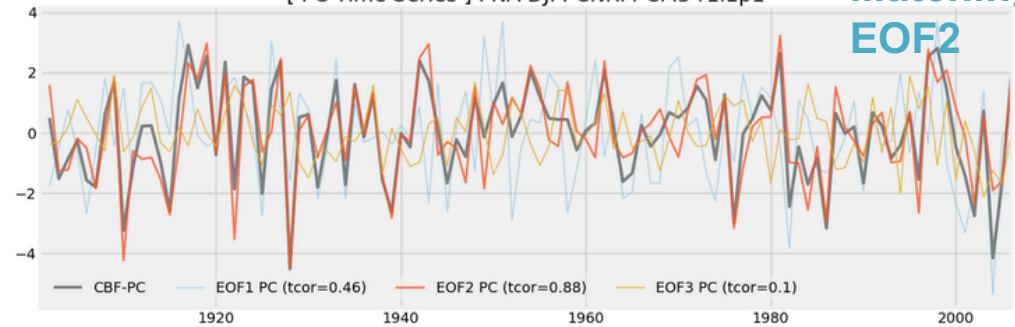
**(d) EOF3**

PNA: CNRM-CM5 (r1i1p1)  
1900-2005 DJF 9.9%



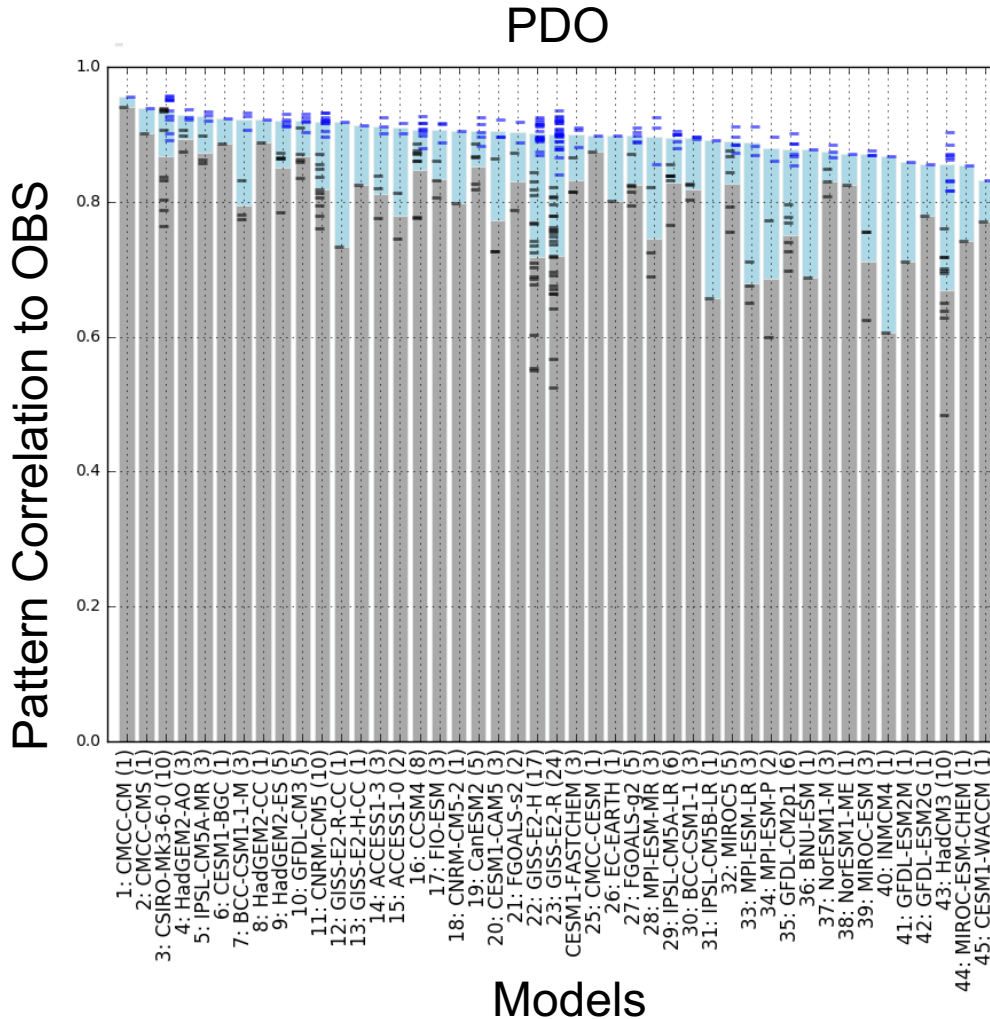
**(e) PCS**

[ PC Time Series ] PNA DJF: CNRM-CM5 r1i1p1



**Best Matching:  
EOF2**

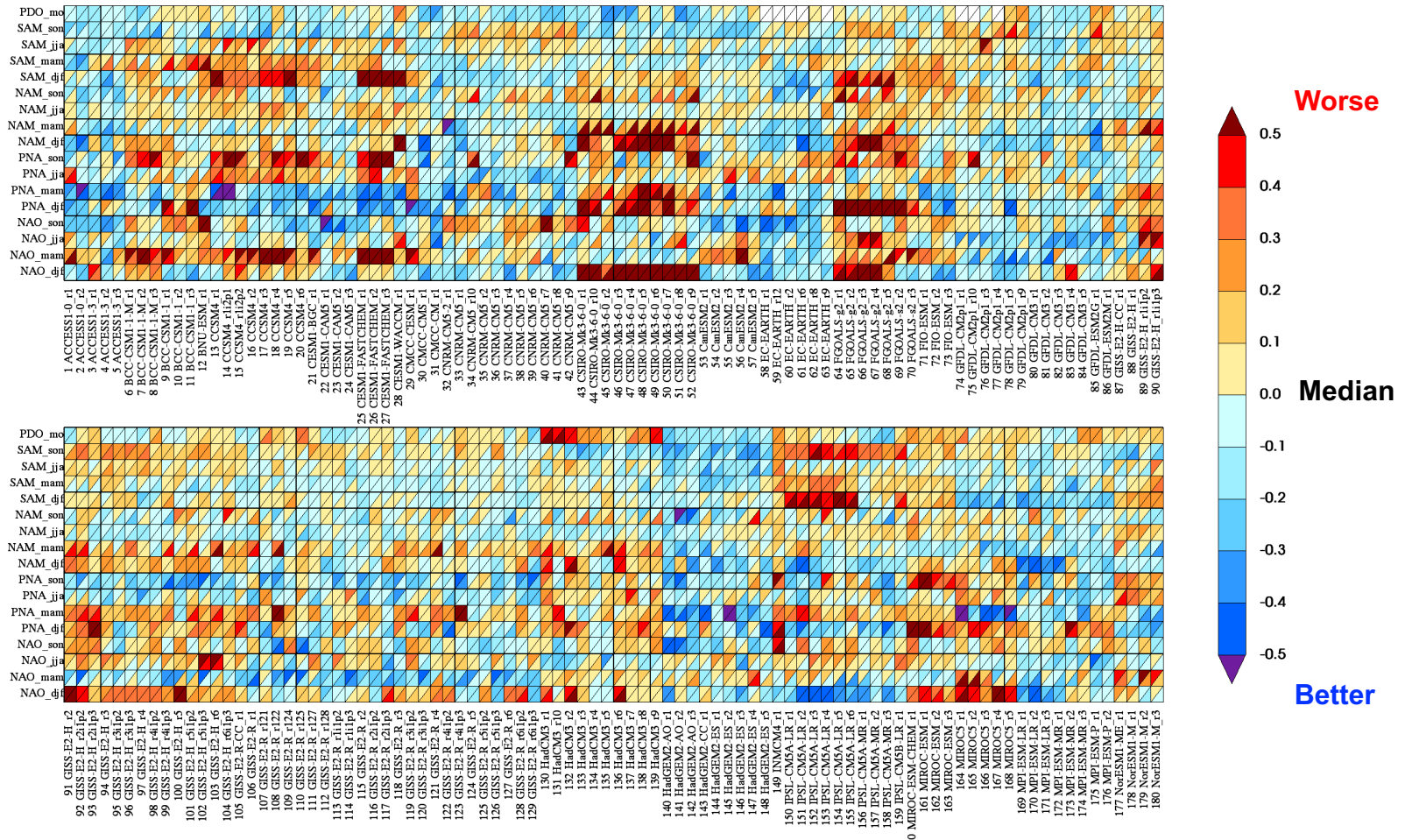
# CBF vs. EOF swapping



- CBF has better performance than EOF swapping
- CBF brings models to space of more fair comparison

# Performance Diagnostics: Pattern (RMSE) – Unit variance map

RMS using CBF approach with 20CR vs ERA20C 1900-2005 (Unit Variance Map)



# Amplitude comparison for CBF

Markers: Average of all seasons and realizations per model

