DATA GUIDED DISCOVERY OF DYNAMIC CLIMATE DIPOLES

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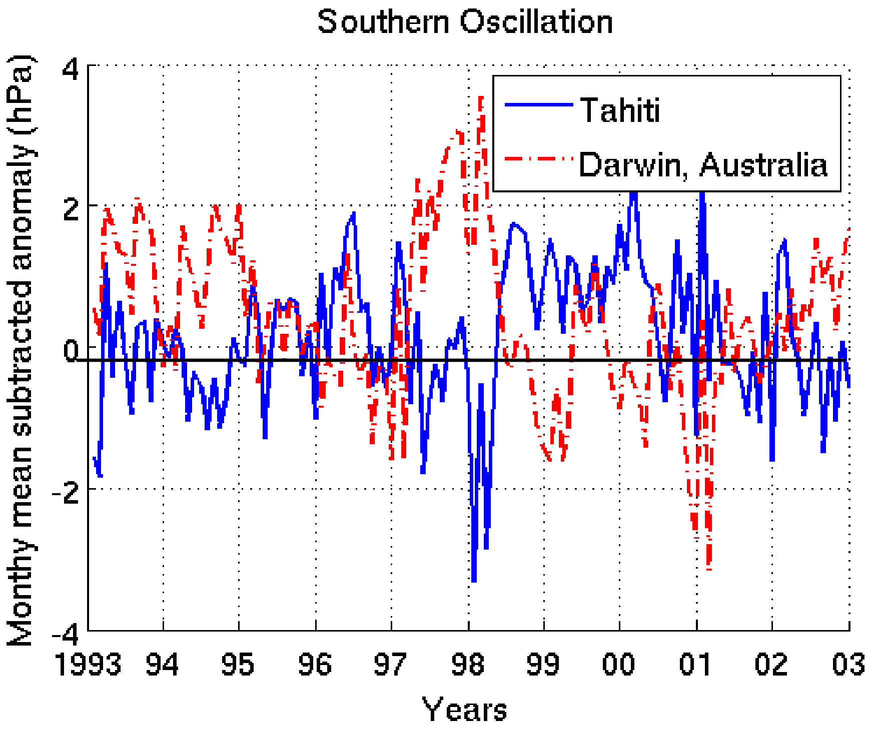
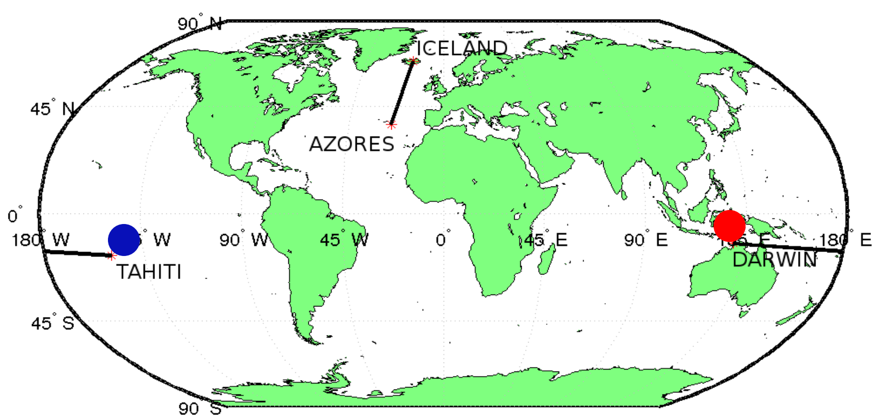
Overview

- Introduction to Dipoles.
- Motivation for Automatic Dipole Discovery.
- Our approach - Shared Reciprocal Nearest Neighbors.
- Benefits of Automatic Dipole discovery.
- Application of Dipole Discovery in analysis of GCMs.

Dipoles

Dipoles represent a class of teleconnections characterized by anomalies of opposite polarity at two locations at the same time.





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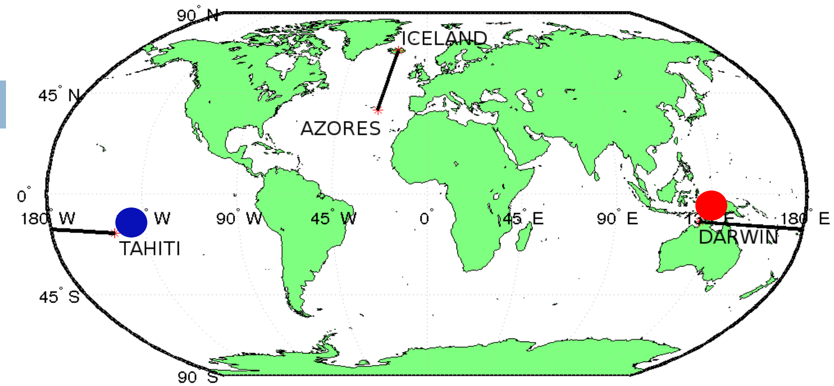

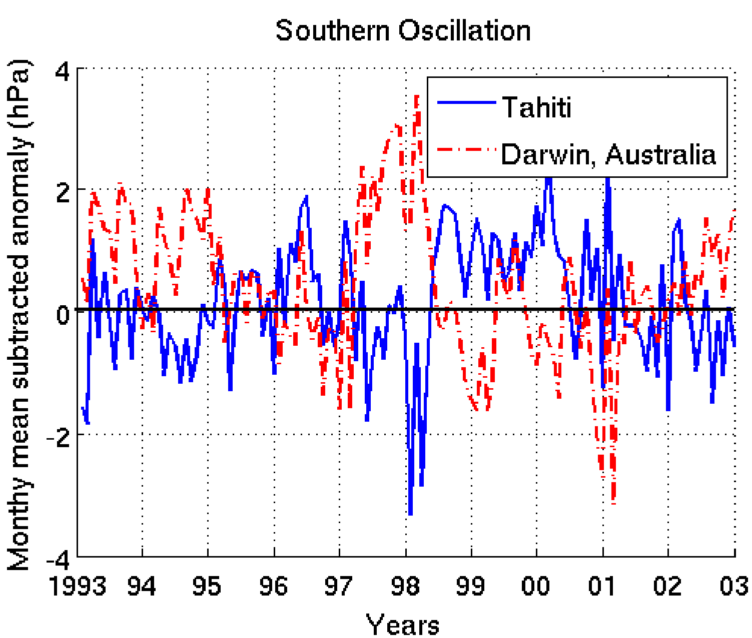

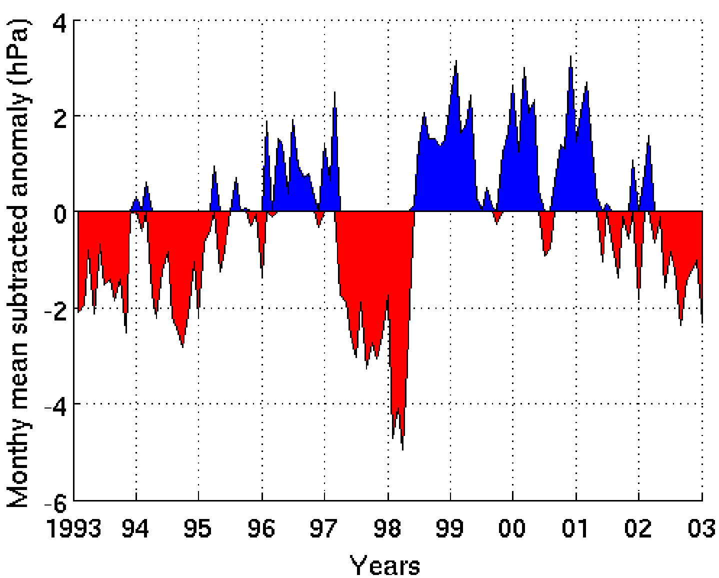

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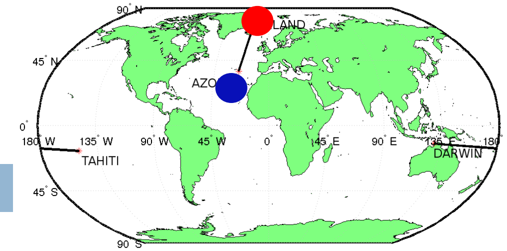
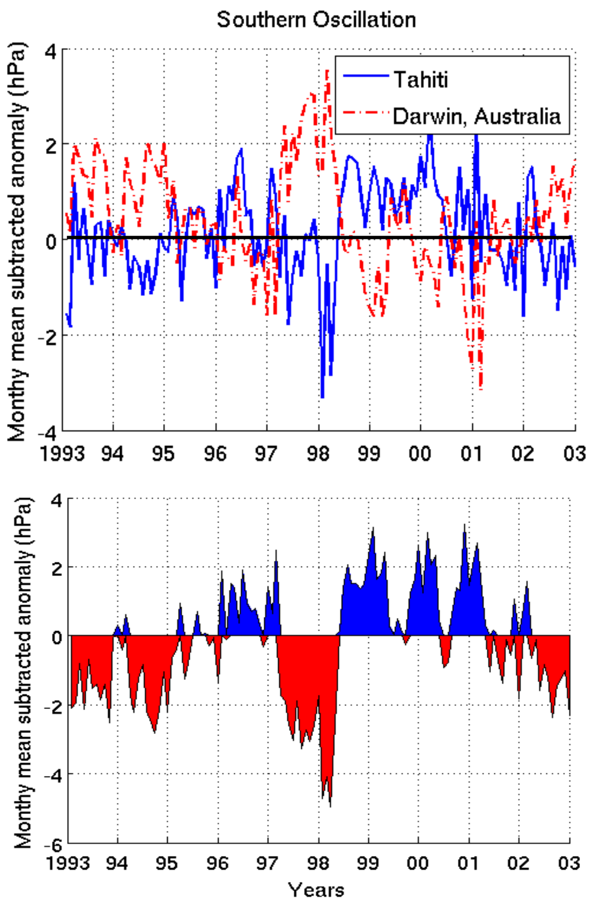
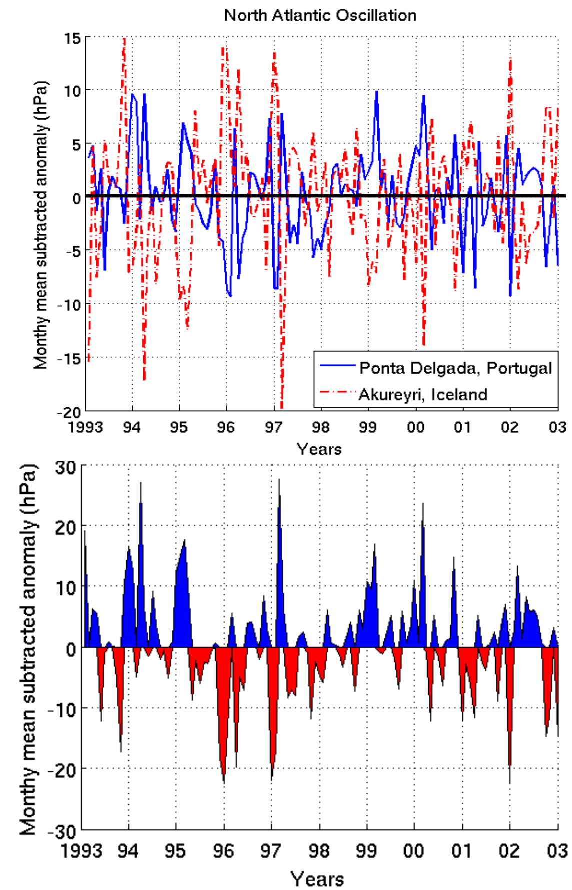


North Atlantic Oscillation: Iceland and Azores



Southern Oscillation: Tahiti and Darwin



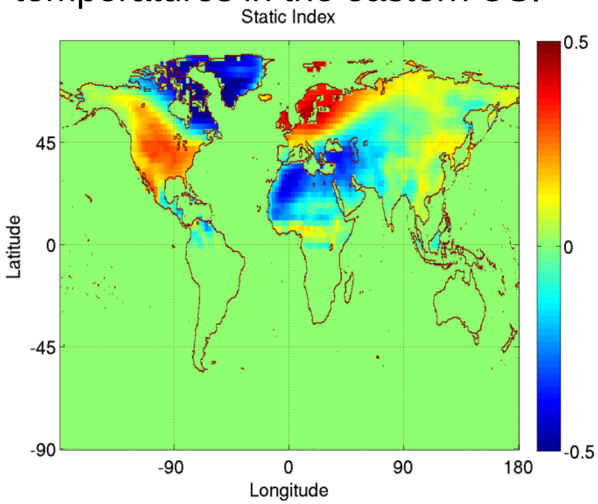
North Atlantic Oscillation: Iceland and Azores

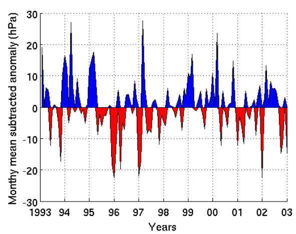
Importance of Dipoles

Crucial for understanding the climate system and are known to cause precipitation and temperature anomalies throughout the globe.

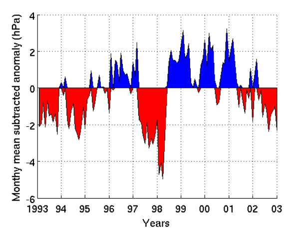
NAO influences sea level pressure (SLP) over most of the Northern Hemisphere. Strong positive NAO phase (strong Islandic Low and strong Azores High) are associated with above-average temperatures in the eastern US.

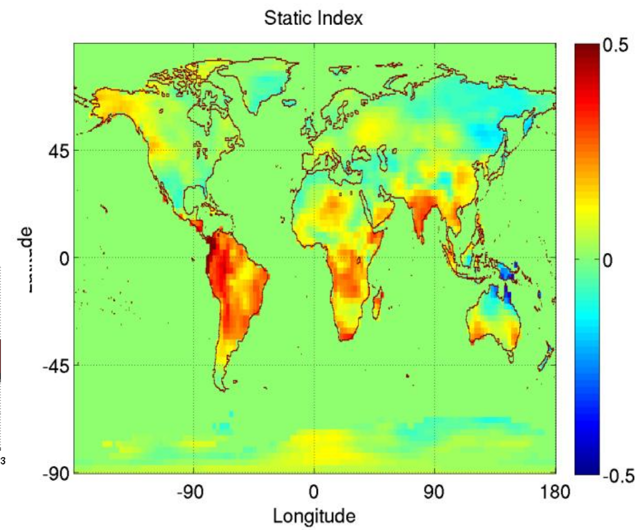
SOI dominates tropical climate with floodings over East Asia and Australia, and droughts over America. Also has influence on global climate.





Correlation of Land temperature anomalies with NAO





Correlation of Land temperature anomalies with SOI

List of Major Dipole Oscillations

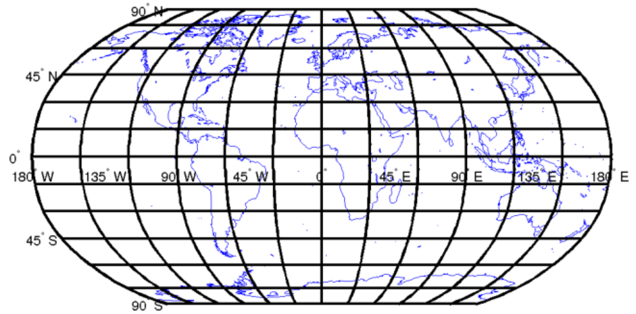
Index	Description
SOI	**Southern Oscillation Index:** Measures the SLP anomalies between Darwin and Tahiti. It has a period averaging 2.33 years and is analysed as a part of an ENSO event.
NAO	**North Atlantic Oscillation:** Normalized SLP differences between Ponta Delgada, Azores and Stykkisholmur, Iceland
AO	**Arctic Oscillation:** Defined as the first principal component of SLP northward of 20° N
WP	**Western Pacific:** Represents a low-frequency temporal function of the ‘zonal dipole' SLP spatial pattern involving the Kamchatka Peninsula, southeastern Asia and far western tropical and subtropical North Pacific
PNA	**Pacific North American:** SLP Anomalies over the North Pacific Ocean and the North America
AAO	**Antarctic Oscillation:** Defined as the first principal component of SLP southward of 20° S

Related Work to find Dipoles

- Discovered earlier by human observation.
  - NAO observed in 1770-1778[1]
  - SOI observed by Sir Gilbert Walker as a sea-saw like oscillation of sea level pressure in the Pacific Ocean in 1924[2]
- EOF analysis used to identify individual dipoles for the Arctic Oscillation (AO) and Antarctic Oscillation (AAO)[3]
  - Similar to PCA, decomposes the time series into orthogonal basis functions.

AO: EOF Analysis of 20N-90N Latitude

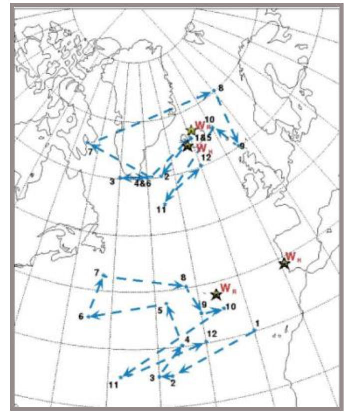
AAO: EOF Analysis of 20S-90S Latitude



1. H. van Loon and J. C. Rogers. The seesaw in winter temperatures between greenland and northern europe. Part i: General description. Monthly Weather Review, 106(3):296{310, 1978}
2. G. Walker. Correlation in seasonal variations of weather, a preliminary study of world weather. Memoirs of the India Meteorological Department, 24(4):75{131, 1923}
3. H. Von Storch and F. Zwiers. Statistical analysis in climate research. Cambridge Univ Pr, 2002
4. Portis, D. H., Walsh, J. E., El Hamly, Mostafa and Lamb, Peter J., Seasonality of the North Atlantic Oscillation, Journal of Climate, vol. 14, pg. 2069- 2078, 2001

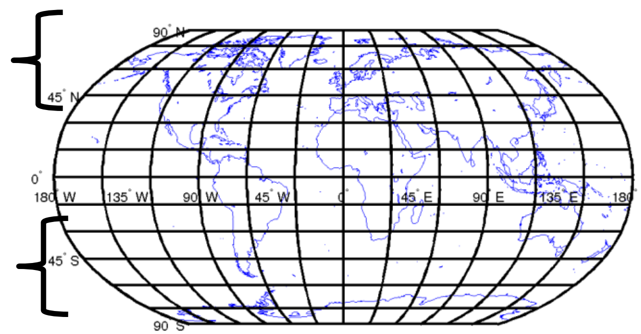
Motivation for Automatic Discovery of Dipoles

- The known dipoles are defined by static locations but the underlying phenomenon is dynamic
- Manual discovery can miss many dipoles
- EOF and other types of eigenvector analysis finds the strongest signals and the physical interpretation of those can be difficult.
- Enables analysis of the various GCMs



Dynamic behavior of the high and low pressure fields corresponding to NOA climate index (Portis et al, 2001)

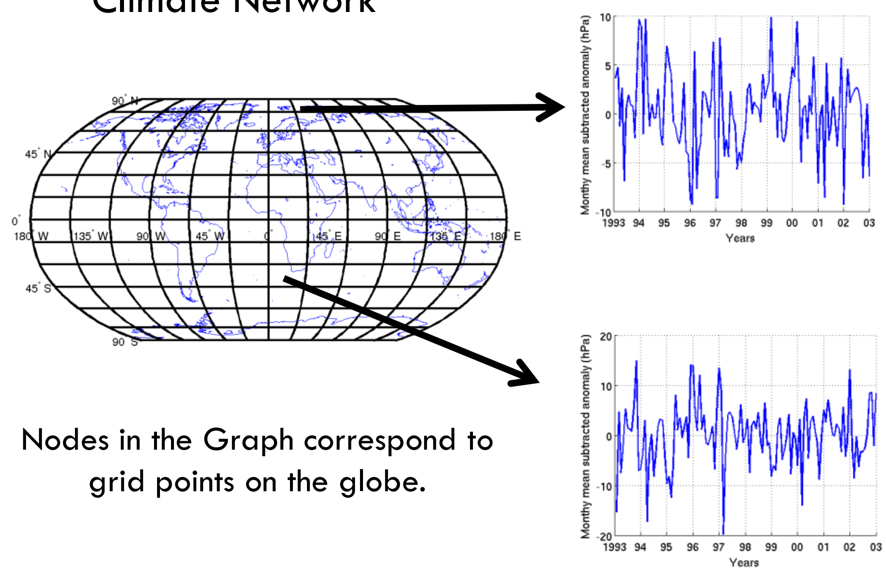
AO: EOF Analysis of 20N-90N Latitude



AAO: EOF Analysis of 20S-90S Latitude

Shared Nearest Neighbor

Climate Network*



Nodes in the Graph correspond to grid points on the globe.

Edge weight corresponds to correlation between the two anomaly timeseries

*Tsonis, et al. 2003, Donges et al. 2008, Steinhaeuser et al. 2009

Steinbach et al., KDD 03

- Construct climate network.
- Consider top K neighbors.
- Re-assigns edge weights between two nodes to reflect the number of shared nearest neighbors.
- However the focus was only on positive correlations and dipoles are a result of negative interactions were not found as accurately

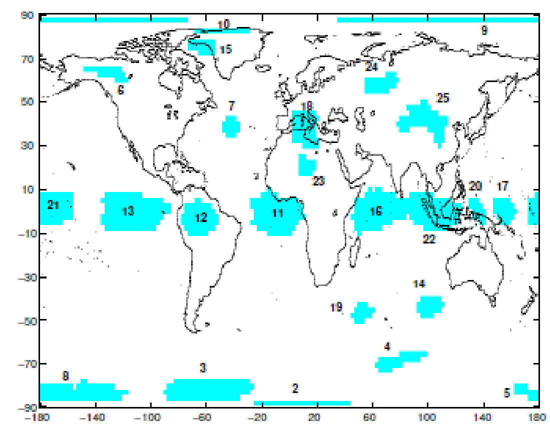


Figure 16: 25 SLP clusters.

Shared Reciprocal Nearest Neighbors

- Reciprocity: Two nodes A and B are reciprocal if they lie on each other's nearest neighbor list.
- Helps in noise reduction. (asymptotic reduction is θ(N/K).
- Removes noise such as weakly correlated regions and anomalous connections.

A	C	B	E	D	B	A	F	E	D

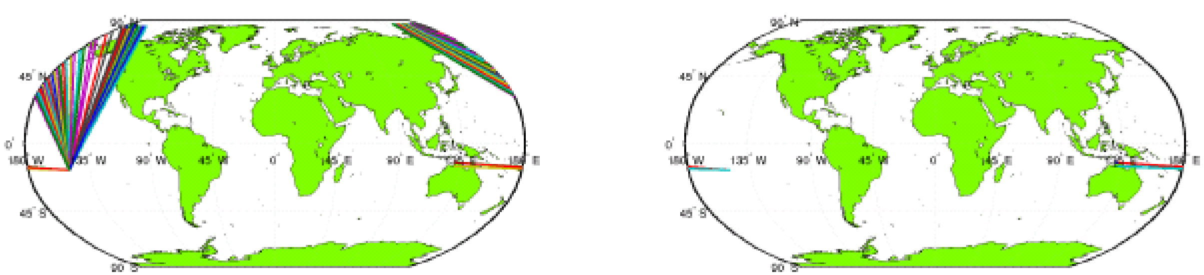
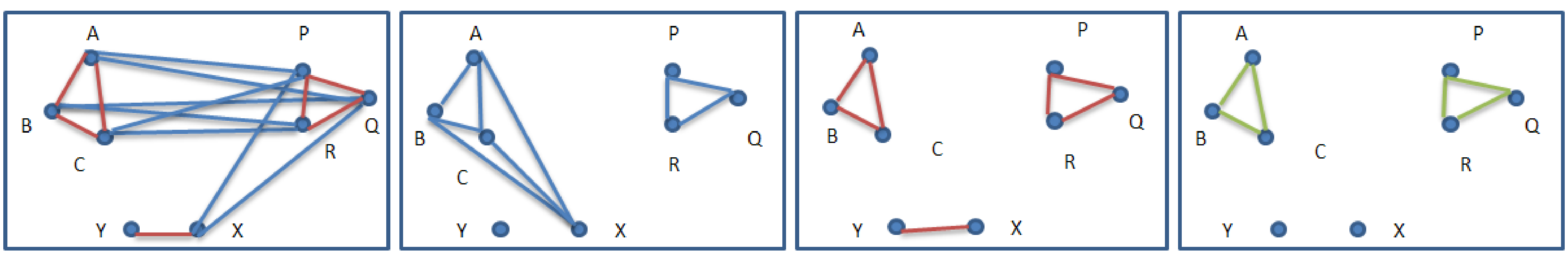


FIGURE 2. All KNN^- and only reciprocal edges from Tahiti using K=50

Basic Steps in the Algorithm

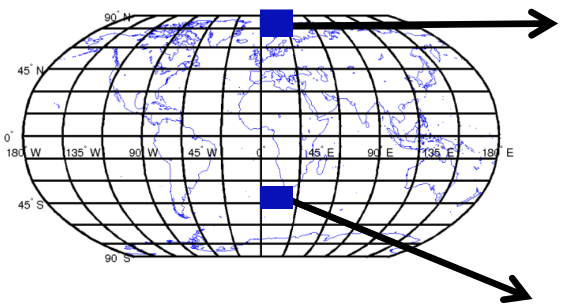
- Step 1: Find the KNN Positive and Negative Neighbors
- Step 2: Consider only *reciprocal* neighbors.
- Step 3: Construct the *shared reciprocal nearest neighbor* graph. $(G^{SNN_-} \text{ and } G^{SNN_+})$
- Step 4: Merge $(G^{SNN_-} \text{ and } G^{SNN_+})$ $\quad E_{i,j}^{SRNN} = E_{i,j}^{SNN_-} * E_{i,j}^{SNN_+}$
- Step 5: Find clusters in the SRNN graph (local attractor)

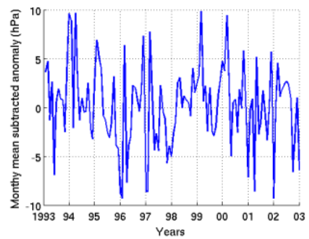
Original Graph **Step1: S^{-}_{SNN}** **Step2: S^{+}_{SNN}** **Overall SRNN**

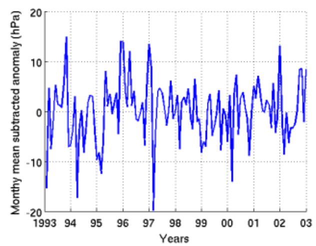


Overall Algorithm: Discovering Climate Teleconnections using SRNN

Climate Network*







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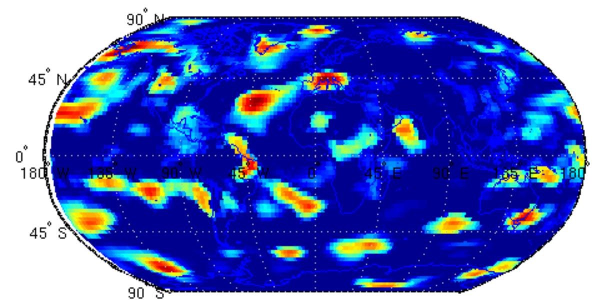
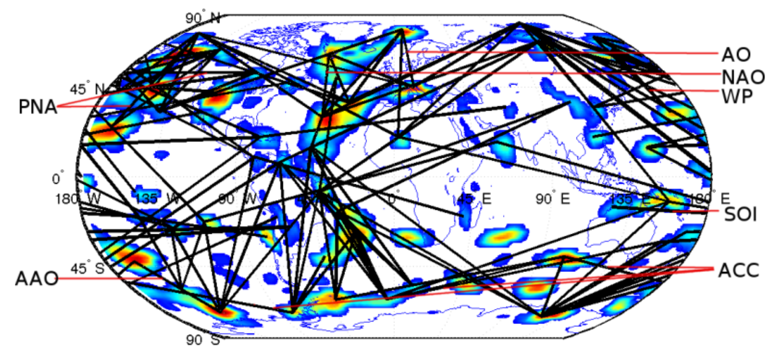
Edge weight corresponds to correlation between the two anomaly timeseries

Shared Reciprocal Nearest Neighbors (SRNN) Density



NCEP

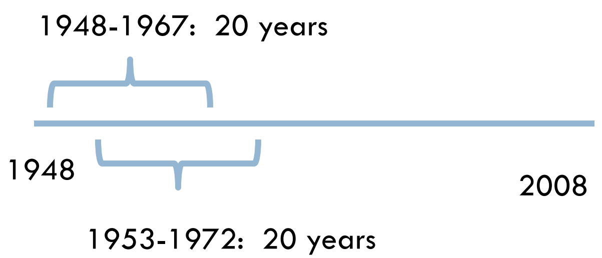


Dipoles from SRNN density

*Tsonis, et al., Donges et al., Steinhaeuser et al.

Data guided approach to find dipoles in NCEP data

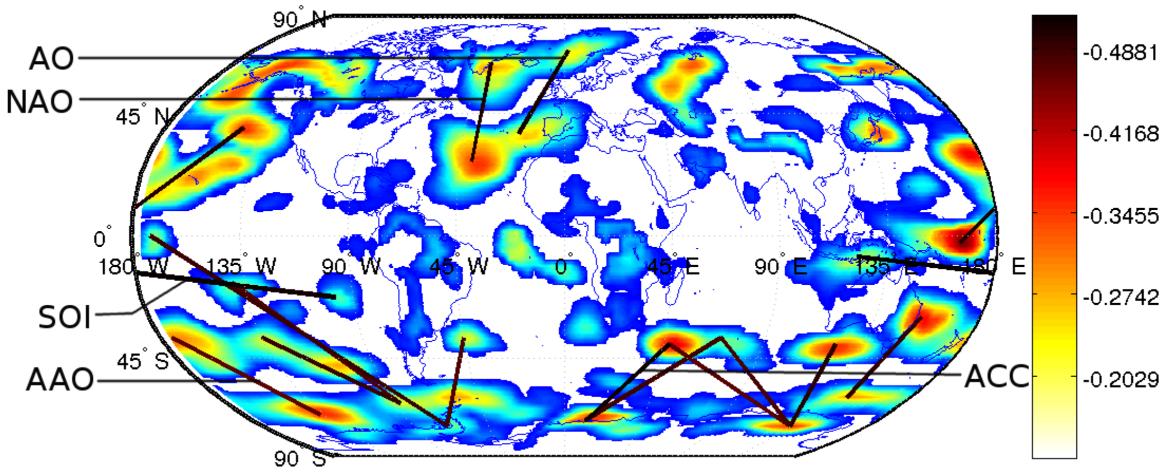
- Dataset: NCEP/NCAR's Reanalysis project.
  - Gridded data created by physical interpolation of observations to grid space.
  - Pressure data used to find the dipoles as most of the climate indices are based on it.



- Overall 60 years of data. Dipole detection done for 20 years of data with a sliding window of 5 years. Hence there were 9 such network periods.

Benefits: Detection of Global Dipole Structure

NCEP (National Centers for Environmental Prediction) Reanalysis Data



- Most known dipoles discovered
- Location based definition possible for some known indices that are defined using EOF analysis.
- New dipoles may represent previously unknown phenomenon.

Benefits: Detection of Global Dipole Structure

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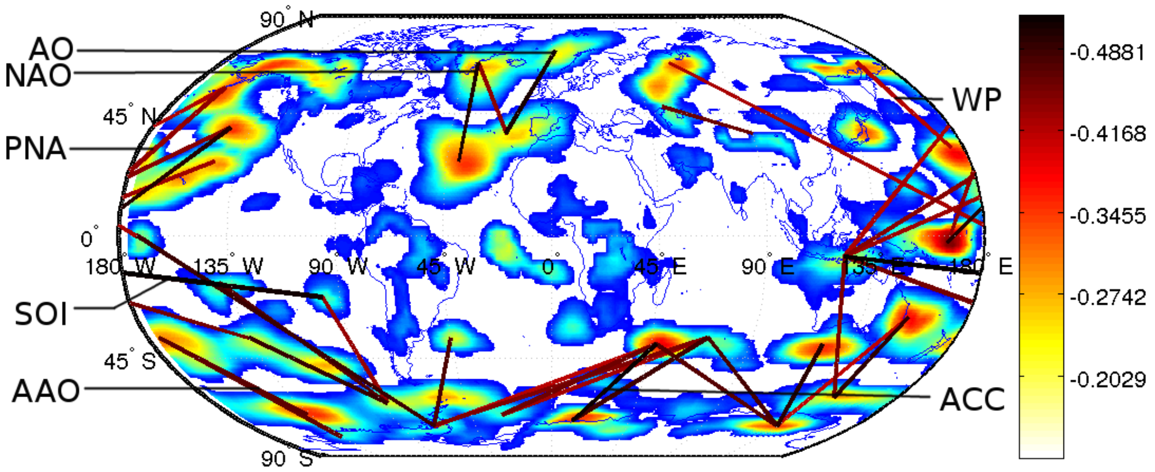

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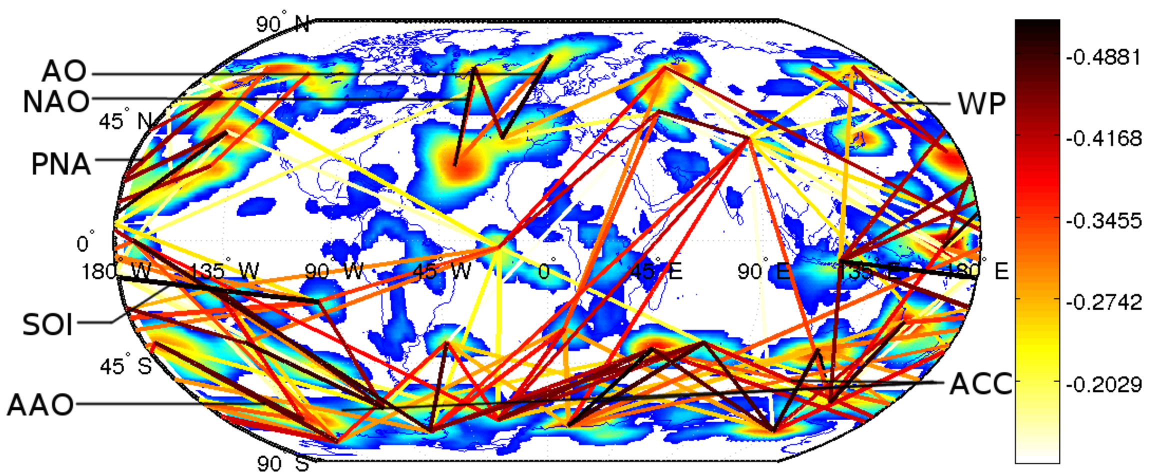

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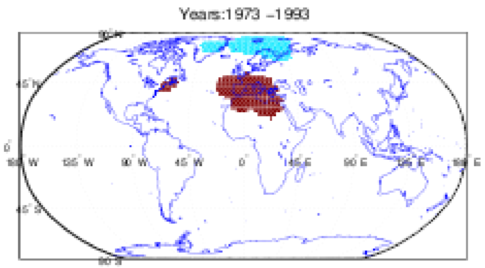
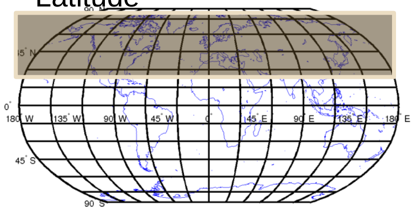
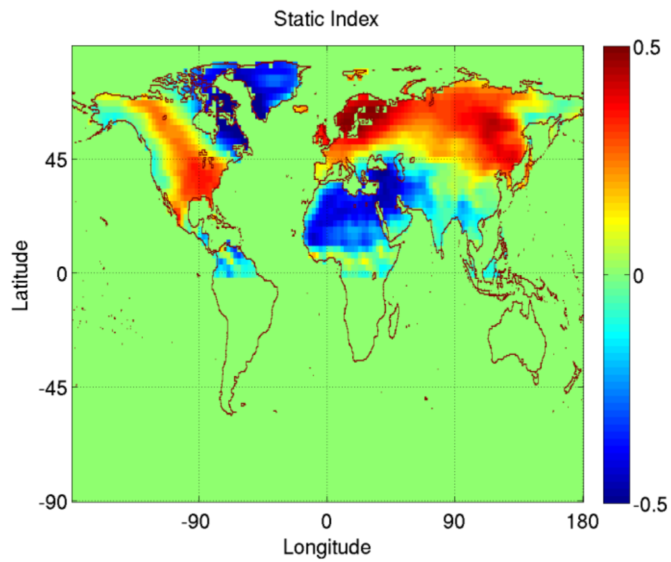
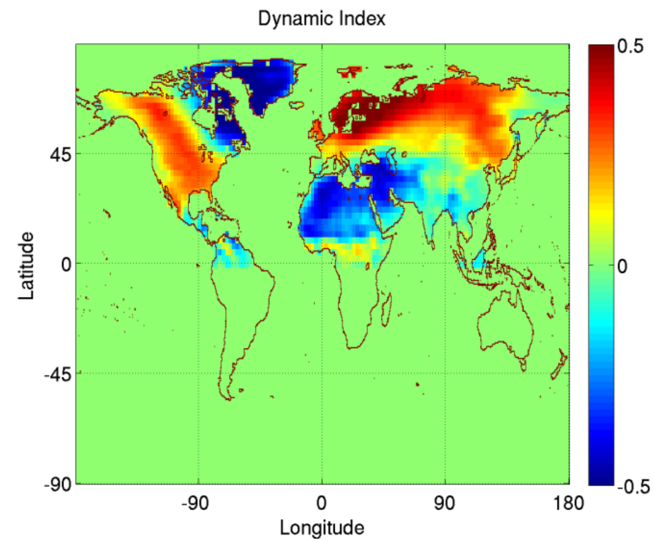
Benefits: Location Based definition AO



Static AO: EOF Analysis of 20N-90N Latitude



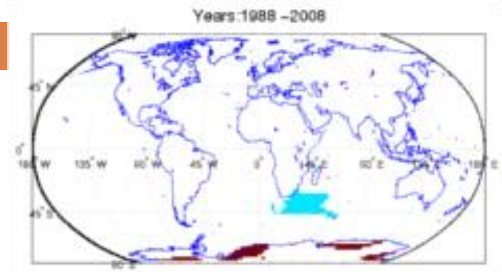




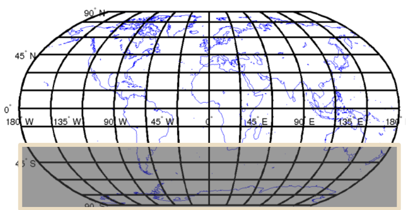
Impact on Land temperature Anomalies using Static and Dynamic AO

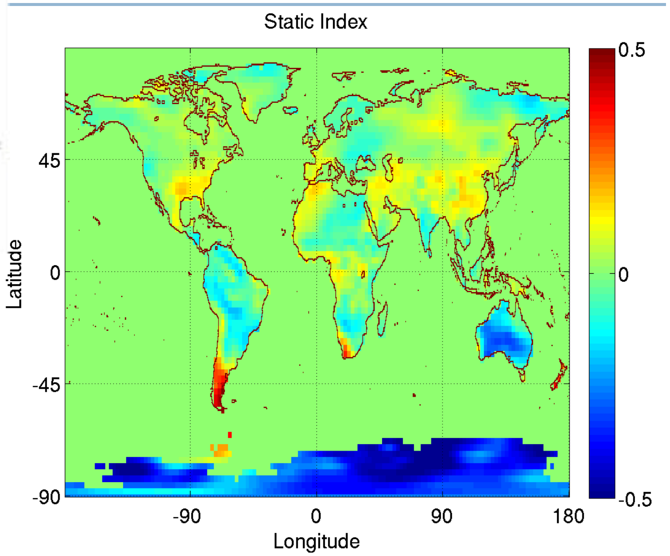
- Mean Correlation between static and dynamic index: 0.84
- Impact on land temperature anomalies comparatively same using static and dynamic index

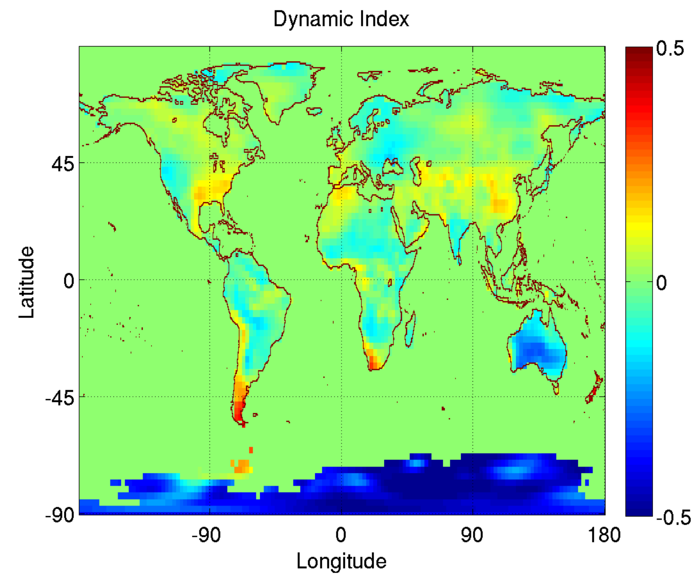
Benefits: Location Based definition AAO



Static AAO: EOF Analysis of 20S-90S Latitude



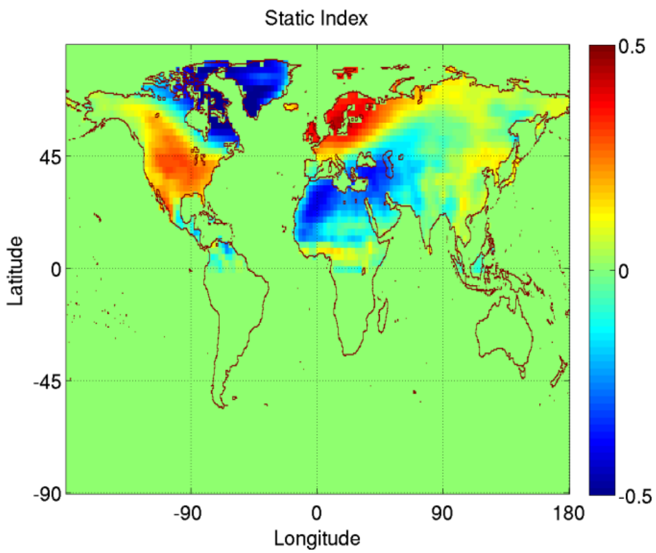


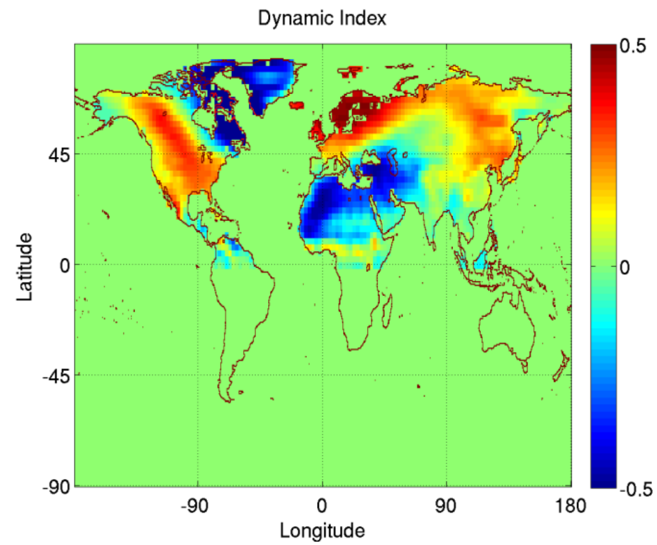


Impact on Land temperature Anomalies using Static and Dynamic AAO

- Mean Correlation between Static and Dynamic index = 0.88
- Impact on land temperature anomalies comparatively same using static and dynamic index

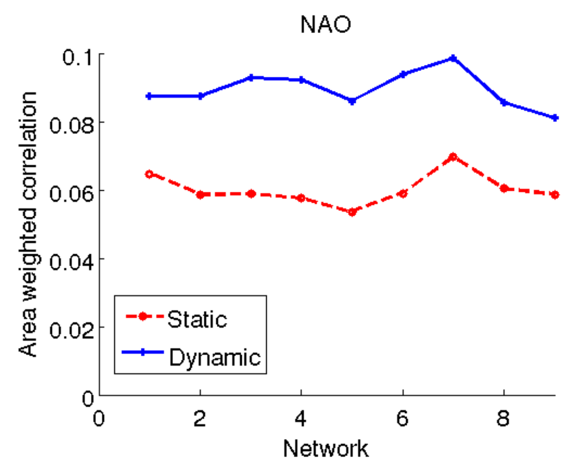
Benefits: Static vs Dynamic NAO Index - Impact on land temperature



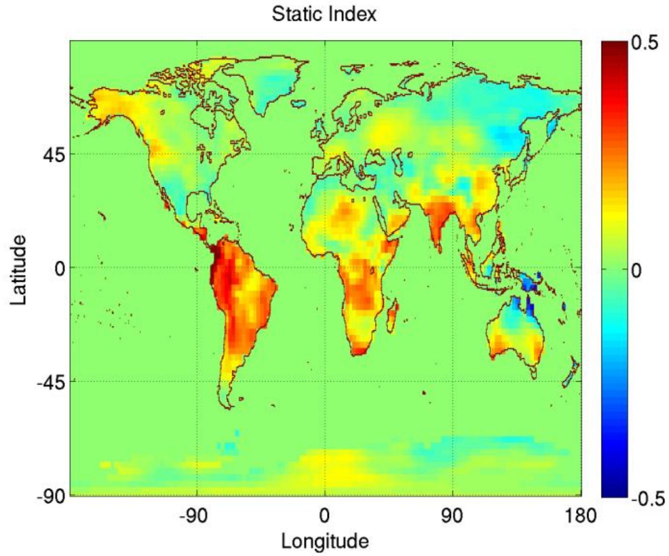


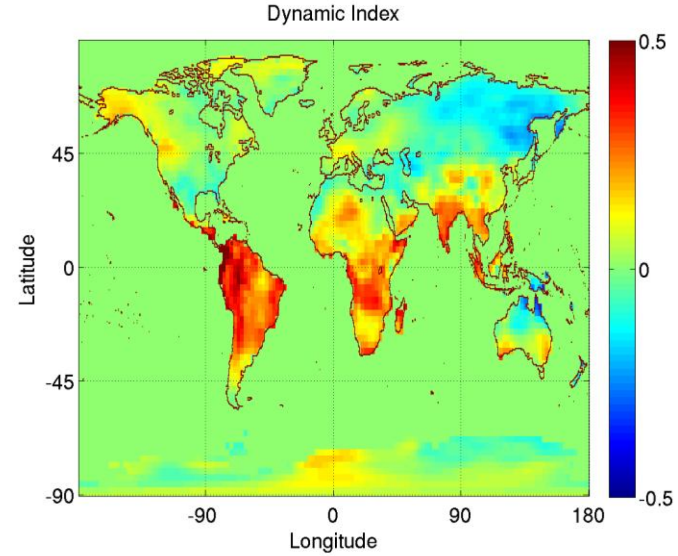
The dynamic index generates a stronger impact on land temperature anomalies as compared to the static index.

Figure to the right shows the aggregate area weighted correlation for networks computed for different 20 year periods during 1948-2008.



Benefits: Static vs Dynamic SO Index - Impact on land temperature





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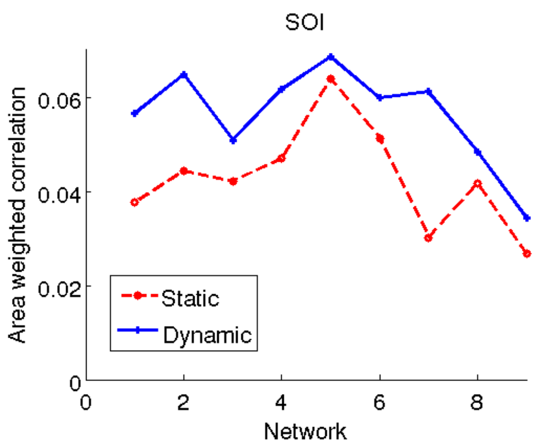


Comparison of Climate Models using Dipole Structure

- Examined the dipole structure in 6 models –

Model	Institute	Grid Size
CCCMA CGCM 3.1	Canadian Centre for Climate Modelling and Analysis (CCCMA)	96x48
GISS Model E-H	NASA Goddard Institute for Space Studies (GISS)	72x46
CSIRO 3.0	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	192x96
GFDL 2.1	Geophysical Fluid Dynamics Laboratory (GFDL)	144x90
BCCR BCM2.0	Bjerknes Centre for Climate Research (BCCR)	128x64
UKMO HadCM3	Hadley Centre for Climate Prediction and Research	96x73

- Hindcast data: Generally cover the period of 1850-2000. We use data from 1948-2008.

- Forecast data/Projections: Data available for several warming scenarios from 2000-2100. We use the A1B scenario which incorporates IPCC's moderate case.

Comparison of Climate Models using Dipole Structure in Hindcast data

Strength of NAO dipole in the 6 different models

Network	Start year	CCCMA	GISS	CSIRO	GFDL	BCM2.0	HadCM3
1	1948	-0.484	-0.4676	-0.4744	-0.4251	-0.55	-0.474
2	1953	-0.4962	-0.4667	-0.4605	-0.4274	-0.5719	-0.4817
3	1958	-0.5187	-0.4193	-0.4441	-0.4472	-0.5465	-0.5149
4	1963	-0.5304	-0.4244	-0.3962	-0.294	-0.5642	-0.4785
5	1968	-0.5191	-0.4263	-0.4056	-0.4263	-0.5296	-0.4558
6	1973	-0.4887	-0.4135	-0.2551	-0.4524	-0.4697	-0.4335
7	1978	-0.4456	-0.447	-0.2621	-0.5301	-0.5193	-0.4593

NAO found with reasonable strength in **all** the models.

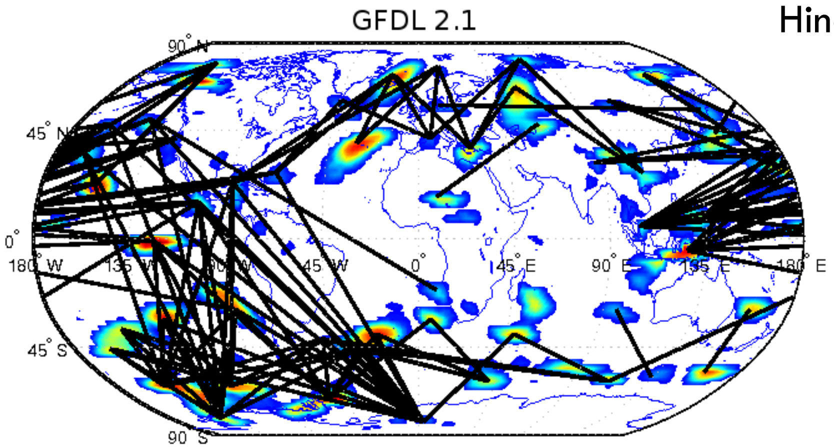
Strength of SOI dipole in the 6 different models

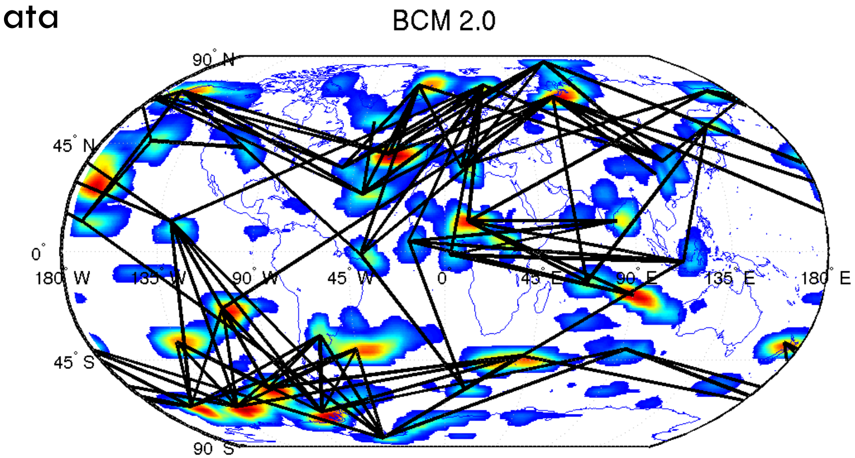
Net	Year	CSIRO	GFDL	HadCM3
1	1948	-0.5421	-0.443	-0.2651
2	1953	-0.5122	-0.4603	-0.2835
3	1958	-0.6208	-0.5091	-0.3055
4	1963	-0.568	-0.5132	-0.3172
5	1968	-0.3826	-0.5482	-0.4233
6	1973	-0.3296	-0.5021	-0.4671
7	1978	-0.3638	-0.5186	-0.3187

SOI Missed in **half** of models – GISS, CCCMA and BCM 2.0!

Comparison of Climate Models using Dipole Structure

Hindcast data





- Differences in dipole structure can offer valuable insights to climate scientists on model performance

- Strength of the dipoles varies in different climate models
    - SOI is only simulated by GFDL 2.1 and not by BCM 2.0.

Comparison of Climate Models using Dipole Structure in Projection data

Strength of NAO dipole in the 6 different models

Network	Start year	CCCMA	GISS	CSIRO	GFDL	BCM2.0	HadCM3
1	2000	-0.4525	-0.405	-0.3529	-0.2753	-0.5141	-0.3844
2	2020	-0.4603	-0.4152	-0.4253	-0.5108	-0.5444	-0.4557
3	2040	-0.5308	-0.4611	-0.348	-0.4883	-0.5614	-0.4874
4	2060	-0.4542	-0.461	-0.3913	-0.443	-0.4493	-0.538
5	2080	-0.4921	-0.4	-0.4195	-0.3488	-0.5332	-0.4047

NAO found with reasonable strength in **all** the models.

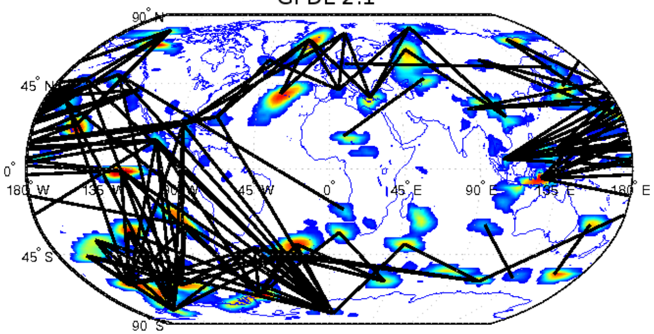
Strength of SOI dipole in the 6 different models

Net	Year	CSIRO	GFDL	HadCM3
1	2000	-0.3401	-0.5856	-0.302
2	2020	-0.3559	-0.5412	-0.3278
3	2040	-0.3181	-0.3303	-0.4237
4	2060	-0.3338	-0.4015	-0.3598
5	2080	-0.2856	-0.3563	-0.385

SOI Missed in **half** of the models – GISS, CCCMA and BCM 2.0!

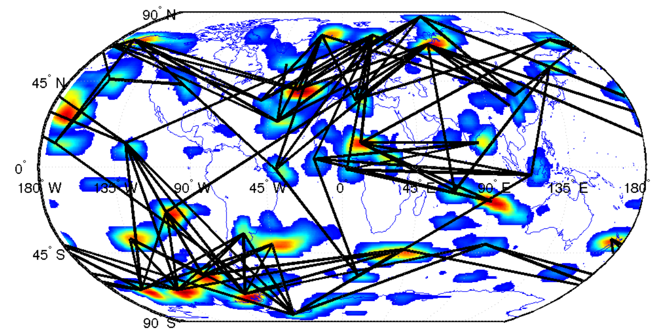
Comparison of Climate Models using Dipole Structure

GFDL 2.1

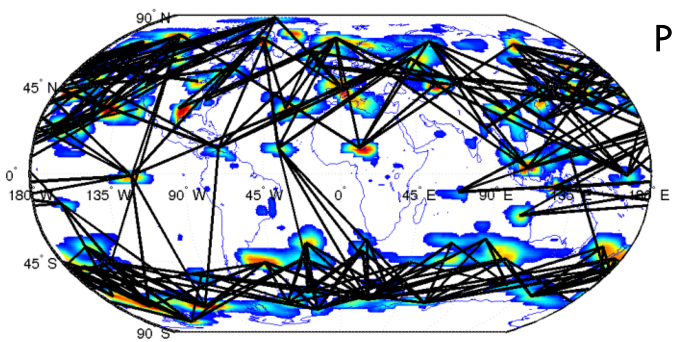


Hindcast data

BCM 2.0

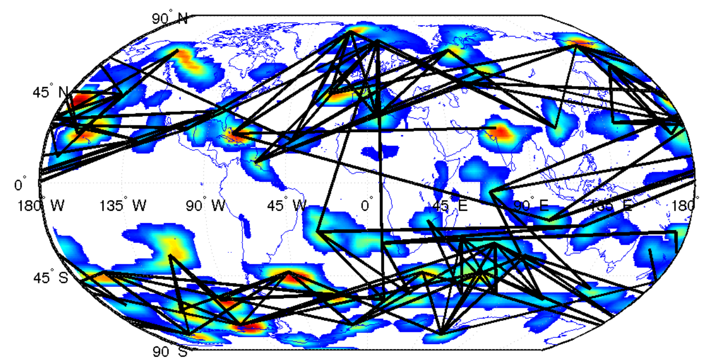


GFDL 2.1



Projection data

BCM 2.0



• Dipole connections in forecast data provide insights about dipole activity in future.

• For e.g. both forecasts for 2080-2100 show continuing dipole activity in the extratropics but decreased activity in the tropics. SOI activity is reduced in GFDL2.1 and activity over Africa is reduced in BCM 2.0. This is consistent with archaeological data from 3 mil. years ago, when climate was 2-3°C warmer (Shukla, et. al).

Conclusion

- We present a graph based approach to find dipoles in climate data.
- We show the utility of data guided approaches to find dipoles in comparison to static indices used by climate scientists.
- We use data guided approaches to evaluate the various GCMs.

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Thanks