Multidecadal Climate Variability

Signal Propagation across the Northern Hemisphere

2012
Marcia Glaze Wyatt

Outline presentation:

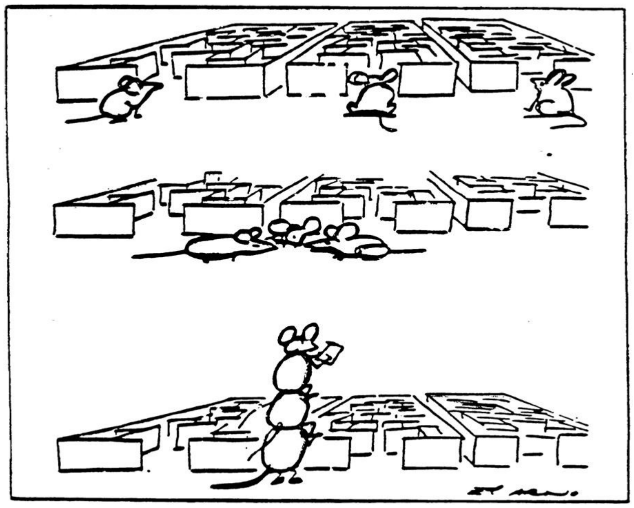
There are three major goals I wish to accomplish with this talk:

1). To explain the approach/view of climate.

2.) To detail the strategy to test the hypothesis: methods, and data sets.

3.) To present the results and offer insights gained from them.

How Something is Viewed Determines What Can be Seen!



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My first goal in this presentation is to tamper a bit with convention. Traditionally, in science, the reductionist approach often is undertaken, with scrutiny of individual processes, particular geographical regions, or specific variables. In short, we often study the "parts" of a system, especially in complex systems such as climate.

Observation of natural systems reveals to us on an elementary level that understanding component parts is less instructive than recognizing interaction of component parts. An orchestra of crickets and the choreography of birds in flight provide examples. Counterintuitive as this may appear, simplifying has its strengths.

Offer general approach taken with this study, briefly introducing a few concepts that frame how climate variability was studied. (will introduce networks, self-sustained oscillators and their ability to be synchronized, synchronization within a network with local coupling within the architecture, allowing for propagating signal.)

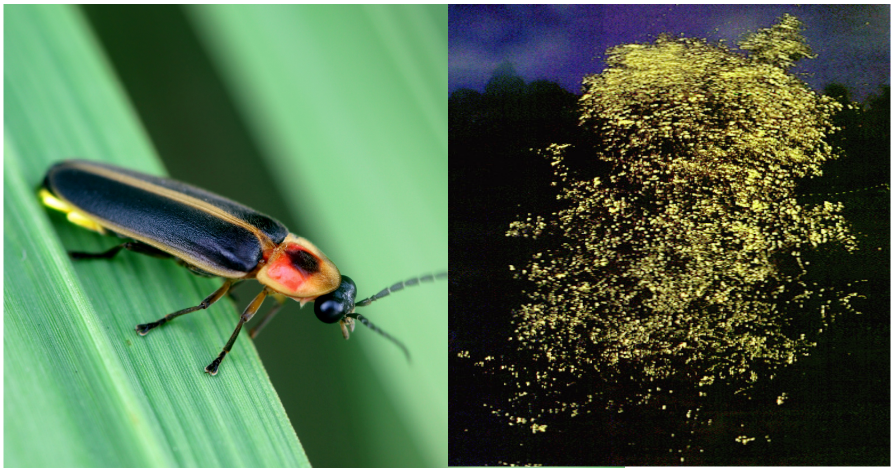
<u>Reductionism</u>: A scientific approach that focuses on the study of component parts. Masks true dynamics of earth systems.

Caveat: Processes in nature interact, generating complex systems. Such systems and are far more than the sum of their individual parts.

<u>Collective View</u>: A scientific approach that considers the <u>interactions</u> between and among component parts. Understanding details of phenomenology of a system is compromised slightly at the expense of gaining greater insight into interactive behavior, which is not equivalent to the sum of parts.

How well can we understand a system by “viewing” only its parts?

A network’s ultimate expression is not merely a sum total of its parts.



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It is the interaction of individual parts that gives a sense of organization to a system.

Sum of Parts not equal to the Whole! The whole is far greater. <u>Interaction</u> of parts explains observation.

Simplifying has its strengths when evaluating complexity of systems.

Complexity theory: organized behavior of large systems. Global coupling to local coupling, the latter, in chains and lattices, for examples.

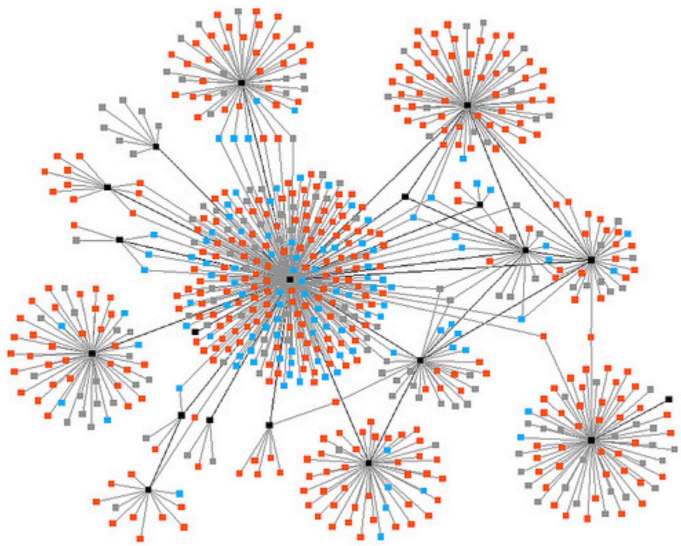
Beyond pure synchrony: *waves* of activity can propagate steadily from one oscillator to the next. Ex: intestine “squeeze” sequence or heart. Good analogy for stadium-wave propagation.

<u>Notes to self</u>: Discuss general approach taken with this study, briefly introduce a few concepts that frame how climate variability was studied. (introduce networks, self-sustained oscillators and their ability to be synchronized, synchronization within a network with local coupling within the architecture, which allows for propagating signal.)

Reductionism: study of component parts

Collective View: considers the interaction of component parts. The phenomenology is compromised slightly at the expense of gaining greater insight into interactive behavior, which is not equivalent to the sum of parts.

Viewing Climate as a Network



Network = a collection of interacting "parts"

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Complexity: defined by configurations of parts, rather than the nature of the parts themselves.

Focus on interactions of component parts and the macroscopic properties that result. An example of a system that spontaneously emerges due to feedback = the wave. Cascading behavior.

***Scale-free graph**, grown by attaching new nodes at random to previously existing nodes. The probability of attachment is proportional to the degree of the target node; thus richly connected nodes tend to get richer, leading to the formation of hubs and a skewed degree distribution with a heavy tail. Architecture of interaction. Quest for spontaneous order, self-organization.

***scale-free networks and power distribution** of links. Number of links between nodes in relationship to the number of nodes follows a power law that is *scale-free.

Can find power laws in fractals; they also arise at phase transitions. Such power laws suggest **self-organization**. At brink of phase transitions. Natural consequence of network growth. Symptom that reveals a process. Three tendencies: short chains, high clustering, scale-free link distributions. Are inherently resistant to random failures; yet vulnerable to attack against their hubs.

One way to define links in a network is by correlation coefficients. **Scale-free** networks are characterized by supernodes.

Connectivity. Structure always affects function. For example: clustered local connections and haphazard global ones. Think of crickets. When nonlinear elements are hooked together in gigantic webs, the "wiring" matters! The layout of the structure affects its dynamics. Duncan Watts (1998) student of Strogatz. Neither regular or random networks seemed applicable. Ex: web = pattern and a maze. Realm b/n order and randomness.

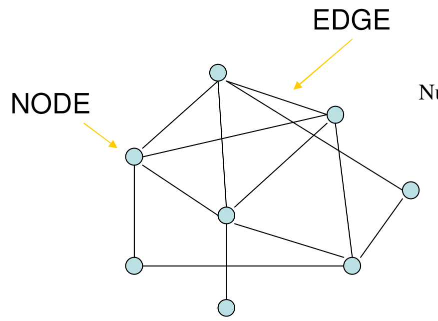
Clustering: probability that 2 nodes connected to a common node will be linked to each other.

Discuss **small-world and its power in communicating** so that far-away nodes can become connected. Mark Granovetter came up w/ idea of weak ties (the strength of).

* Scale-free meaning that this distribution of links in a network is not dominated by any single representative scale.

NETWORKS:

Communication
Stability



Number of edges = Node-degree

In its simplest form, a network is a collection of nodes joined by edges

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Earth's climate will be presented here as a network.

In simplest form, network = collection of nodes joined by lines or edges.

Studied since at least the 18th century, networks have taken on a new practical role in recent years as a primary tool in the study of complex systems – real-world systems of interacting components for which networks provide a simple but tremendously useful representation.

Statistical properties of networks studied; revealed observation that although a pattern of connections is not a regular one, it is not completely random.

Each Node = Self-Sustained "Oscillator"

Self-sustained Oscillators Can be Synchronized

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In the CLIMATE NETWORK, each node is a self-sustained oscillator.

An autonomous, or self-sustained oscillator, in isolation = system's natural oscillation (dynamics w/o explicit time dependence).

Cyclic frequency convenient way to characterize: #oscillations/unit time.

Angular frequency 2pi/T or 2pi*frequency.

Autonomous systems oscillate b/c of an internal energy source that is transformed into oscillation (think of person standing on swing, pumping energy into system by timing the stand and squat positions according to phase). Oscillation continues until energy source expires.

Source of energy for regional oscillatory systems on Earth maybe = winds, and those result from feedback of T gradients. ??? Solar is ultimate source. Earth's rotation plays role, as well. Planetary-scale ocean waves and their interactions influence oscillatory behavior, as well.

Outstanding feature common to all autonomous oscillators = ability to be synchronized. Reason lies in free phase. If perturbed, restores to new position. Remembers initial state. For a self-sustained oscillator, if perturbed, its phase point falls back to original limit cycle and original rhythm is restored. (but can move to a different place if adjusting to rhythm of another oscillator (refer to synchronization, next slide).

In contrast to self-sustained oscillation, in the case of a forced movement, a system whose fluctuation is driven by external force (resonance) might be perturbed. If so, when restored, phase falls back to exact phase of driving force. Resonance is not same as synchronization!

Both forced and self-sustained oscillators are represented by closed curves in phase space, but phase on limit cycle (autonomous system) is free.

Terms: phase = quantity that increases 2pi w/ one oscillation cycle. Determines state of oscillator. Limit cycle represents periodic process of oscillator. Phase space coordinates plotted. Evolution in time describes the behavior (periodic). Ex. For a sinusoidal oscillation, the trajectory (circle) of the limit cycle is represented by the sine curve on a plot of x (vertical) against time. X(t) = peridodic process= Asin(ώt + initial phase) [A=amplitude = intensity of oscillation and w = angular frequency (2pi*freq). Perturbation of amplitude decays; perturbation of phase does not. All trajectories tend toward the limit cycle in autonomous system; the limit cycle is therefore considered to be a simple attractor (and strange if chaotic oscillator). Convergence w/ time follows direction described by Lyapunov exponents.

For self-sustained oscillator, phase difference = phase 1 – phase 2, where original phase + angle of that difference as represented on closed curve in space, and that angle = phase shift.

SYNCHRONIZATION

Synchronization involves adjustment of tempos and matching of rhythms. With synchronization of phase, amplitude not necessarily synchronized.

Note, if noisy forcing, can cause phase diffusion or random walks. The phase perturbations accumulate, some cancelling out over time. They never grow or decay. (ex: circadian rhythm and cloudy vs sunny days and relationship to phase shift b/n circadian and external daylight forcing).

Phase locking = phase difference bounded.

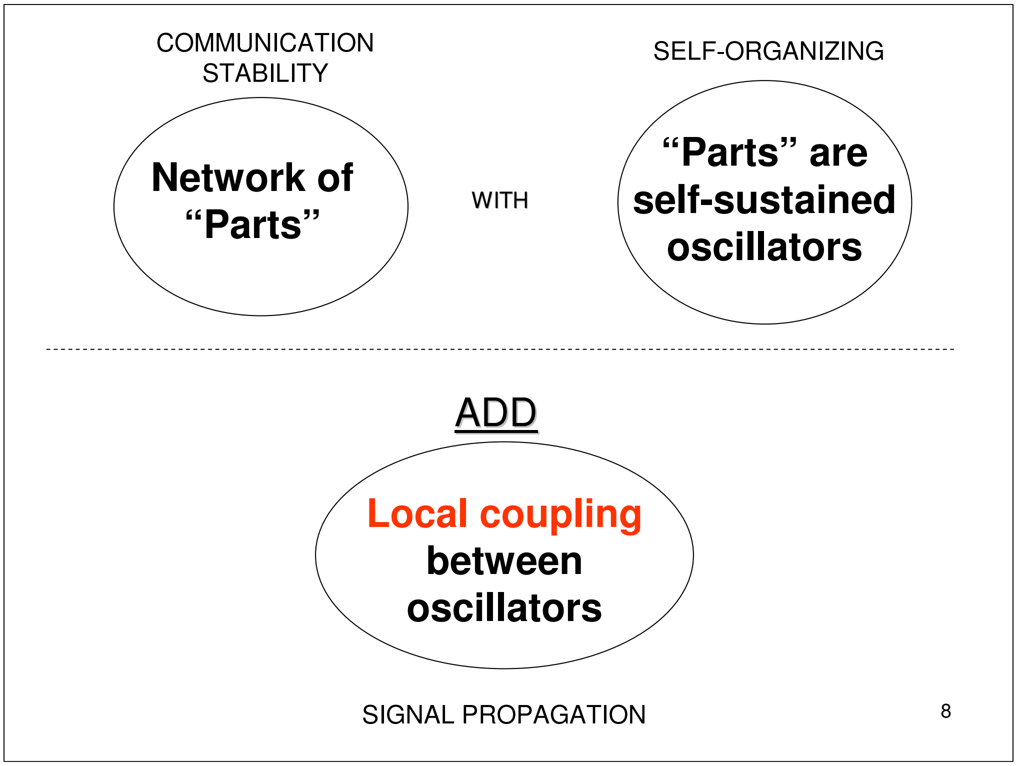
Synchronization = will result in onset of constant phase difference among synchronized oscillators. Also frequency locking among the synchronized oscillators.

Typical synchronization involves one system more powerful than other, more influence on resulting shared tempo.

Synchronization depends on frequency detuning and coupling strength. Frequencies of self-sustained oscillators must be similar and the coupling strength b/n them not too strong. A fine balance leads to a collection of self-sustained oscillators adjusting their intrinsic tempo to match a universal one that all "march" to. When coupling among oscillators breaks down, the oscillators resume their internal rhythms.

Phase shift (or difference) depends on initial frequency mismatch (detuning) and the parameters of coupling.

Arnold tongue = region of synchronization where these factors are "just right".



For the CLIMATE NETWORK, we have: a network of nodes, or parts (provides **communication stability**). Each node (part) is a self-sustained oscillator (prone to **self-organization** when collective behavior ensues). A variety of network architectures. Some are globally coupled. Many are locally coupled. Such coupling is ubiquitous in nature, and hypothesized as underpinning signal-**propagation** through the stadium-wave climate network.

Beyond Synchrony

"**Stadium-Wave Signal**"

Local Coupling →Signal Propagation 9

Synchronization requires the participating systems be self-sustained oscillators.

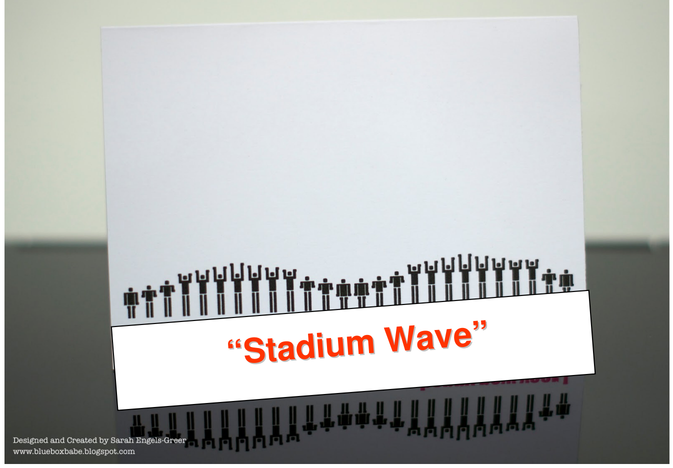
If the oscillators have different intrinsic rhythms, there will always be a phase lag between systems. Most phase lags between the oscillators are imperceptibly small, as most systems studied have very short periodicities relative to those of climate; regardless of length of phase-lag, the synchronized systems are phase-locked: a fixed relationship of phase (angle 0 to 2pi) is locked in.

Local coupling provides means of signal propagation.

Chaotic oscillators can synchronize. Result is similar to periodic oscillators in presence of noise.

Hypothesis

Climate as a Stadium Wave:



Propagation of a low-frequency climate-signal through a network of atmospheric, Ice, and oceanic self-sustained oscillating indices

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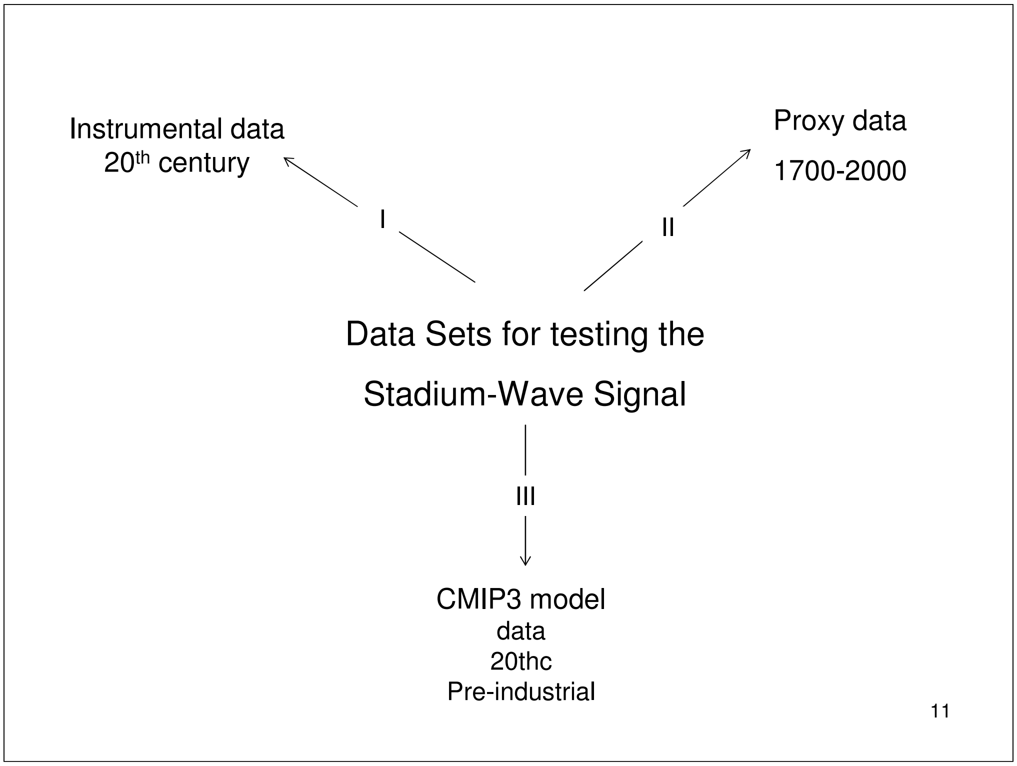
As opposed to the global coupling that Kuramoto and others had studied, oscillators can be arranged in a **one-dimensional chain or ring**. This network architecture is described as "beyond synchrony"! Waves of activity can propagate steadily from oscillator to oscillator. Waves turn out to be more common than sync (in the sense of synchronous (occurring together) fluctuations). In other words, waves can be described as a lead-lag relationship among locally coupled oscillators. Most real oscillators are, indeed, coupled locally, not globally – hence, propagate a signal through the network. **Ex**: intestine is effectively a one-dimensional chain of oscillators. Spiral waves propagate endlessly. Around and around. (Belousov).



Three different data sets for three different goals: document/probe mechanism; history; model reproduction.

Step One:

Goal:

- **A.)** Test existence of signal 20th century
- **B.)** Document its Character
- **C.)** Explore mechanisms

Data Sets:

20th Century Instrumental

Step Two:

Goal:

Test History with Proxy Data

- **A.)** 1900-2000
- **B.)** 1850-2000
- **C.)** 1700-2000

Data Sets:

- **A.)** Proxy Data

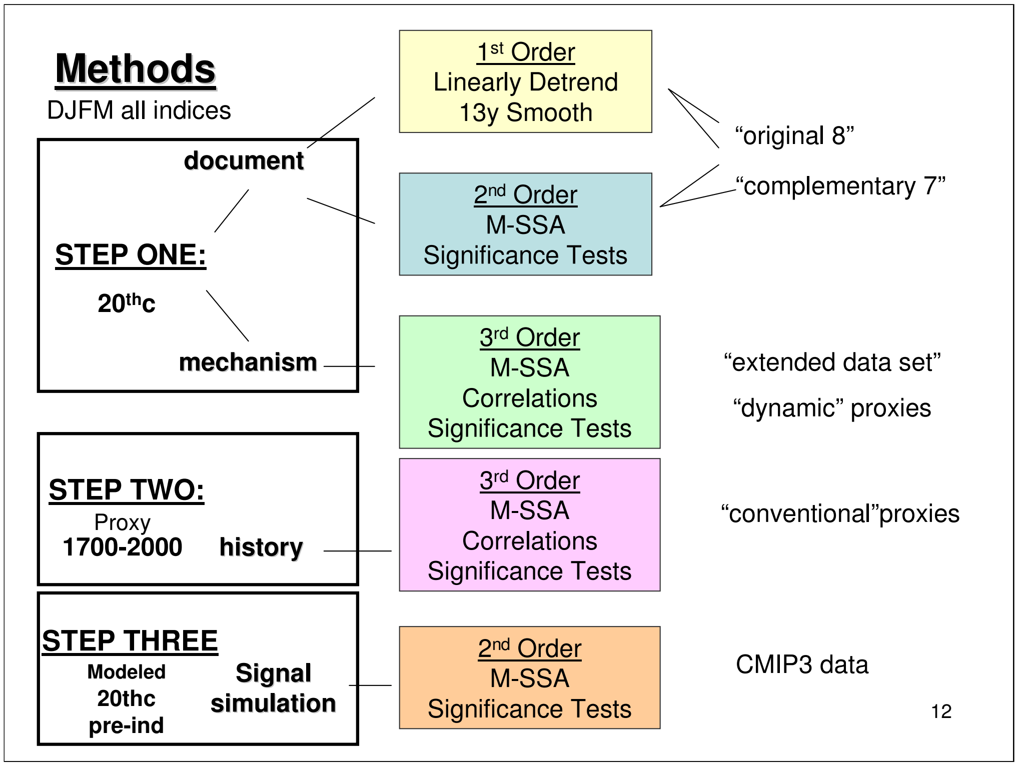
Step Three:

Goal:

Determine if model-generated data can reproduce signal

Data Sets:

- **A.)** 20th century CMIP3 data
- **B.)** Pre-industrial CMIP 3data



A series of methodologies was followed in testing the stadium wave.

The first step was rudimentary, using raw observational data, linearly detrending each index to highlight any inherent multi-decadal signal, and applying to each index a 13-year filter to remove the seasonal, annual, interannual, and decadal-scale fluctuations.

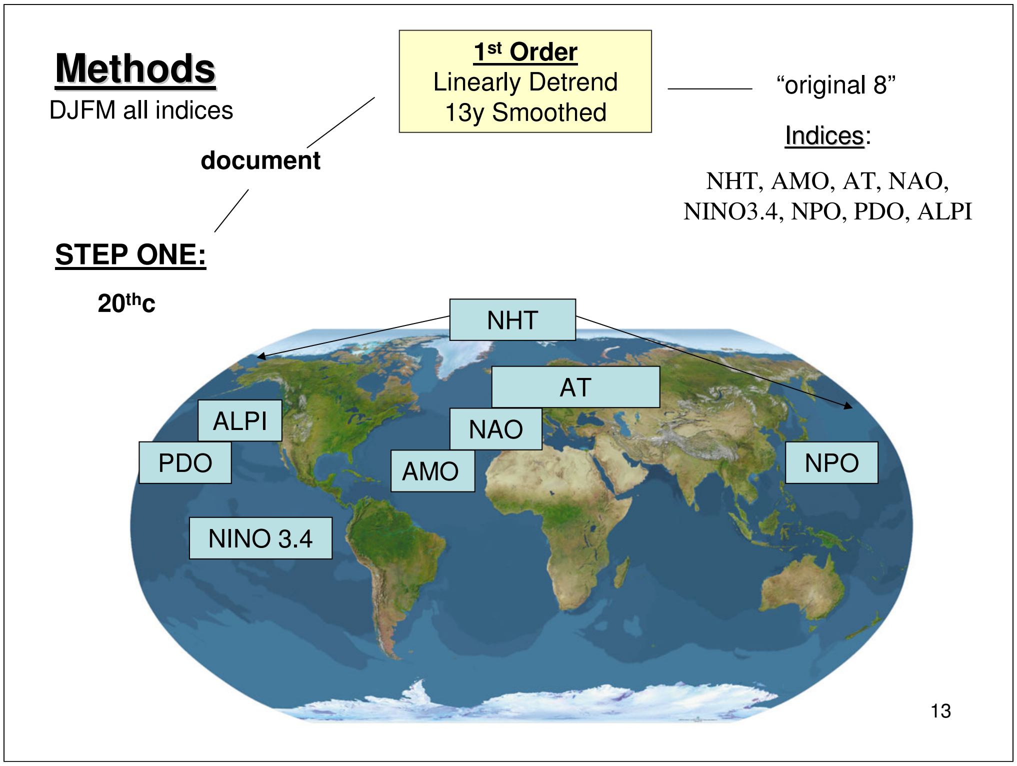
Emphasis on winter months (DJFM) when ocean-atmosphere interaction most active:

Raw data analysis suggested: Similar multi-decadal timed variability among all indices, with lead-lag relationships that could be supported by various local and regional mechanisms.

Employed next step: multi-variate statistical analysis that focuses on lead-lag relationships and adept at identifying shared timescales of variability. Used Multiple Channel Singular Spectrum Analysis (M-SSA). Used M-SSA to document relationships among collection of indices and to establish statistical robustness of signal propagation. Used different data sets of observational data to do this, each representing spatial range across entire Northern Hemisphere.

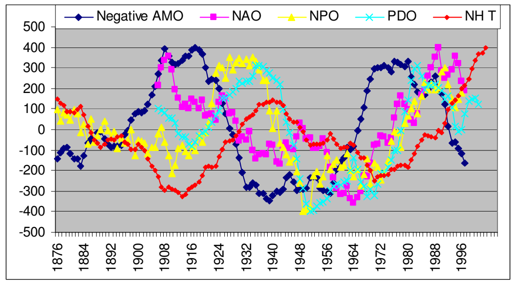
The second step involved proxy data, first for the 20th century. The proxies were chosen specifically based on their relationship to the observed indices. Results supported the observational data. More proxy data were used to extend the time line into the 19th and then the 18th centuries. Signal propagation between 1850 to 2000 was similar; between 1800 and 1850, slight differences emerged in amplitude and frequency. From 1800 back to 1700, amplitudes were considerably smaller and frequencies higher. Proxy data contain considerable noise and carry numerous messages within their records, making evaluation difficult.

The third step involved reconstructing the stadium-wave indices from raw data simulated by computer models from the CMIP3 project. M-SSA was applied to these simulated indices in the same manner as was done with the observational data. In scores of runs, no stadium waves were detected. We suggest that this is likely due to absent or poor representation, of multi-decadal interactive dynamics in the computer models employed. Subsequent studies by the stadium-wave team (2014, 2015, and 2017) support this interpretation.



First Step: Evaluating observed raw data (linearly detrended, 13-year smoothed) of eight climate indices representing various geographical regions and diverse dynamical foundation.

“Real Time” timeseries:
-NHT, -AMO, NAO, NPO, PDO



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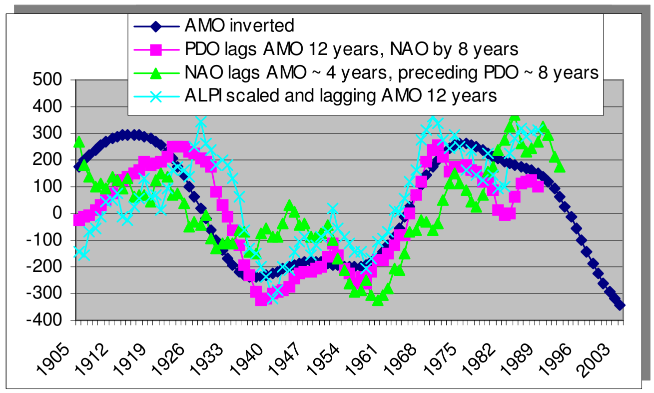
Even with just five indices shown here (raw indices linearly detrended, 13-year smoothed, winter months), one can see, it’s a mess… But something is there…

Random Red-Noise? or Coherent Signal?

-AMO (4y) +NAO (8y) +PDO (4y) +ALPI



•Lagged correlations of multidecadal signal in various indices

•Conclude possibility of signal

•Need tool that detects lagged relationships

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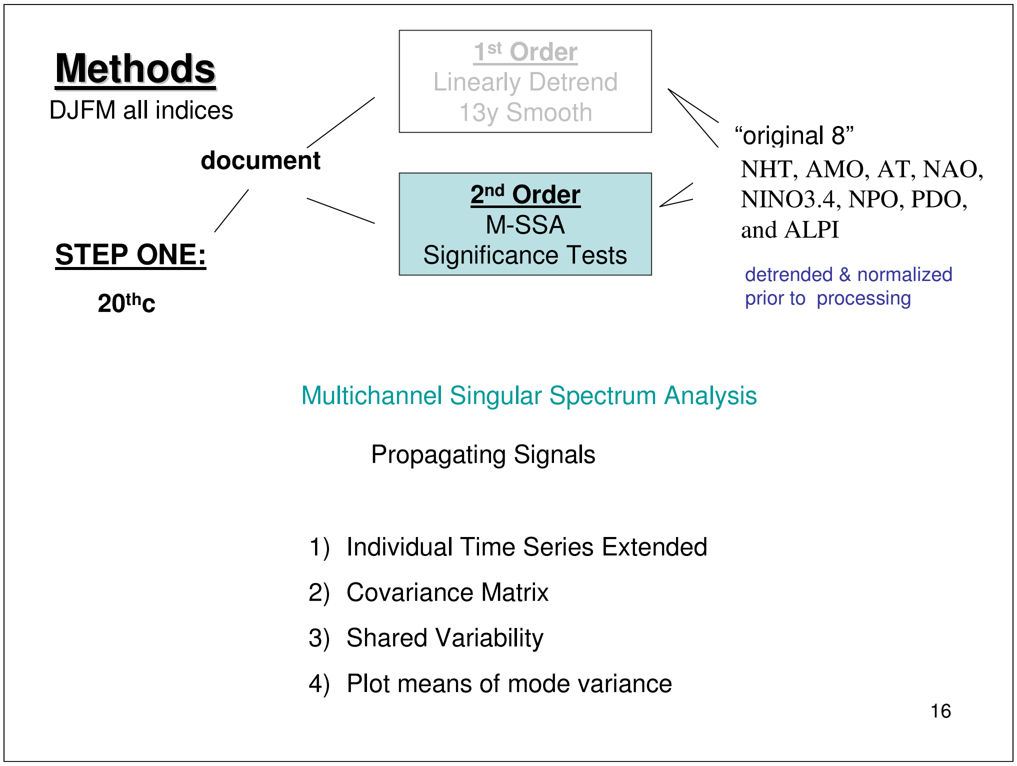
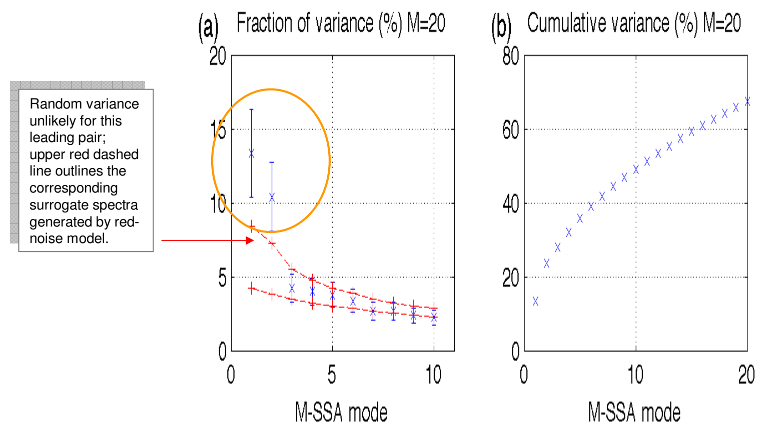
Here are plotted four of the eight indices (raw data linearly detrended, 13-year smoothed, winter months). The Atlantic Multidecadal Oscillation (AMO) is plotted in negative polarity. Lags highlight apparent order. Suggest higher-order method needs to capture lagged signals.

Need Tool that Detects Lagged Relationships



M-SSA is a multivariate statistical tool adept at finding relationships among a collection of variables. See page 12 for brief description of usage; see page 17 for further details.

M-SSA Plots



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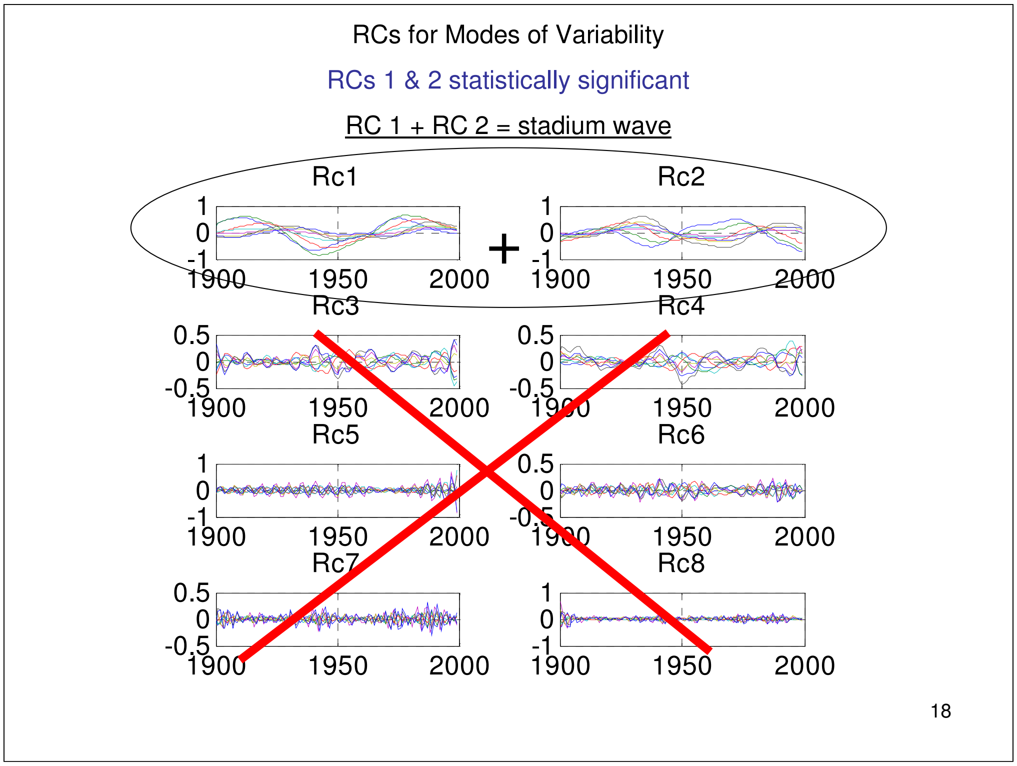
M-SSA spectrum of eight climate indices. Real data in lagged covariance matrix. M-SSA “disentangles” the lagged covariance matrix. It is a generalized form of EOF analysis; it is EOF analysis applied to an extended time series. Excels in its ability to detect lagged relationships characteristic of propagating signals. Where EOF detects zero-lag relationships, M-SSA detects non-zero-lagged ones.

M = window = number of lagged (or shifted on matrix) copies of time series of given index. Do this to all the indices. All in the covariance matrix. So looking for repeating patterns and propagating signals.

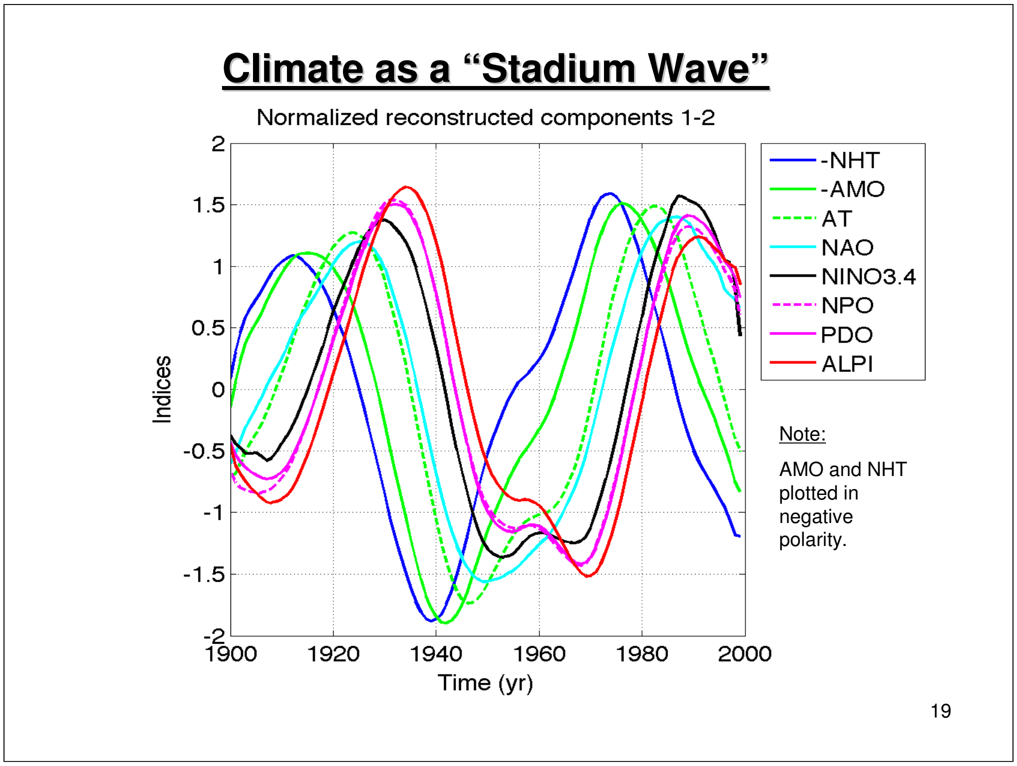
Detected shared (at a lag) patterns of variability are described by an eigenfunction. The eigenfunction that best describes this co-variability among all indices = mode 1. The next best eigenfunction = mode 2, etc. The mean of the variance of each time series of this eigenfunction is calculated for each mode. These individual mean variances (mean of mode) plotted in (a). Modes (patterns of shared variability at a lag). The variances of each mode represent the temporal variability shared by all the indices. But significantly, b/c the indices sharing this pattern of variability represent geographically diverse regions, a spatial component is added to the temporal character. Thus, the modes in our analysis will be used as spatio-temporal filters. A total of 20 modes were extracted; ten are given in this spectrum. To test the significance of the occurrence of these modes, in other words, to test the likelihood or non-likelihood that these modes are simply a product of random measurements, a red-noise model is fitted to the raw data of the indices. Red-noise is a low-frequency signal resulting from random fluctuations. It is common in geophysical indices where “memory” or inertia in the systems carry a signal from one year to the next. For example, slowly varying factors like snow cover, polar ice, SST, and soil moisture will contribute persistence to a time series (memory). The spatial pattern of this red-noise would differ from the spatial pattern of a coherent signal. This allows us to test for the randomness of our identified modes. Using red-noise modelbased on linear regression based on x to the nth power and random numbers selected from a normal distribution with zero mean and unit variance. Parameters a and σ of equation (x^n+1 = ax^n + σw) are determined by linear regression. The surrogate time series are analyzed using autocorrelation max lag-1 which can extract a repeating pattern (if there is one) from the noise of the data set. This procedure was similarly done to the original “real” data. From this red-noise test, we get two “checks” on randomness. One is the red-noise envelope. This envelope represents 2 standard deviations of an assumed Gaussian distributed sample population of red-noise surrogate modes of variance. We plot the boundaries of this 95% distribution of surrogate-based modes (red dashed lines). The means of the modes extracted from real data are plotted also. Modes of real data that fall within the red-noise envelope are assumed to be random fluctuations. They cannot be considered significant. On the other hand, modes that fall outside this envelope may be non-random. We attach to these mode means error bars. These indicate the 95% confidence level (standard uncertainty) of the mean. How closely do these mean values reflect true values? The standard error is the standard deviation of the mean. The std/(N*)^1/2 is the formula. N* = the degrees of freedom (in our case, we use a formula (Bretherton) where N* is based on the maximum correlation of the lag-1 autocorrelation of indices and the decorrelation time results from this. N* = N(1-r^2)/(1+r^2), where r=0.65 here and N=100 (for # original time series). N* = 40 and decorrelation time = 100/40 (N/N*) = 2.5. This is an estimate of how many years it takes for an observation to be independent of another observation. These error bars are computed from the red-noise model described previously. Attached to the real-data mode-means is plus and minus one std dev (total=2std). Thus, if these mean variances AND their attached error bars fall outside this envelope, they are 5% or less likely to be non-random (the null hypothesis of randomness has only a 5% chance of being “right”). The next step in assessing significance is a pair of modes. Their mean value must be statistically indistinguishable. This is assessed by an overlap of error bars.

Red-noise model based on x to the nth power and random numbers selected from a normal distribution with zero mean and unit variance. Parameters a and σ of equation (x^n+1 = ax^n + σw) are determined by linear regression. The surrogate time series are analyzed using autocorrelation max lag-1 which can extract a repeating pattern (if there is one) from the noise of the data set. This procedure was similarly done to the original “real” data.



If the a pair of modes has been identified from the real data, whose error bars overlap (and therefore = an oscillatory pair), and their significance at the 5% level is determined, we then look to see if this pair is truly a candidate for being oscillatory. We generate a time series for each index. This new time series is derived from each mode. The variance time series of each mode is a temporal filter. In short, where the shared signal fluctuates up and down, this “filter” (boxcar) detects where this occurs in each index. A new time series of each index is thus generated. This new “M-SSA-filtered” time series of an index is called a reconstructed component (RC). Plotted are the index RCs for each mode, one through 8. We are considering only statistically significant modes. The only significant ones are one and two. Note: M-SSA with a window of 20 (20 lagged copies) is designed to resolve periodicities of 20y or less. None of statistical significance were detected as a shared signal among the indices of our chosen network. The only ones detected were larger than a 20-year periodicity. Such cannot be resolved as true periods. The time series length is too short. We describe the variability as secular-scale or secular variation, meaning one or fewer cycles per century. We find a secular variability in each of the leading two modes ~ 64 years (visual inspection).

If both leading modes have similar periodicity, then one last “check” is that their phasings are in-quadrature. Phasing refers to where the peaks and troughs are. In-quadrature means a quarter of a cycle offset. In the case here, with an approximate 64-y “quasi-period” in the 20th century, in-quadrature would indicate an approximate 15-y offset between RCs in mode one and RCs in mode 2. Now we can say we have a true oscillatory pair. We next combine them. This hybrid of modes becomes our “climate signal”. We use the resulting RC combination as our filter, which we apply to all indices of the network in order to visualize the climate signal as it propagates through them.



Hemispheric Signal Propagation
via
a synchronized sequence of
atmospheric and lagged oceanic teleconnections
Note each index has been normalized by dividing by the std dev of the index

While an exact multidecadal variability cannot be assigned with any statistical rigor, what is significant is that this same secularly varying signature is shared by many indices from diverse regions and that this signal is found in one index and followed by the same phase in another index within a year or so, followed predictably by the same phase in the next index, etc.

We can consider this "signal" a spatio-temporal filter. Index acronyms in sequence, ordered according to signal propagation. Years b/n indices = lag times b/n. Bootstrap method applied to estimate mean lag times b/n each pair of indices. The resulting total "period" assessed by MESA (maximum-entropy spectral analysis) and by totaling the individual lags assessed by bootstrap-based cross-correlations.

Statistical Results

Climate signal (propagation) documented

Significance 95%

Speculation

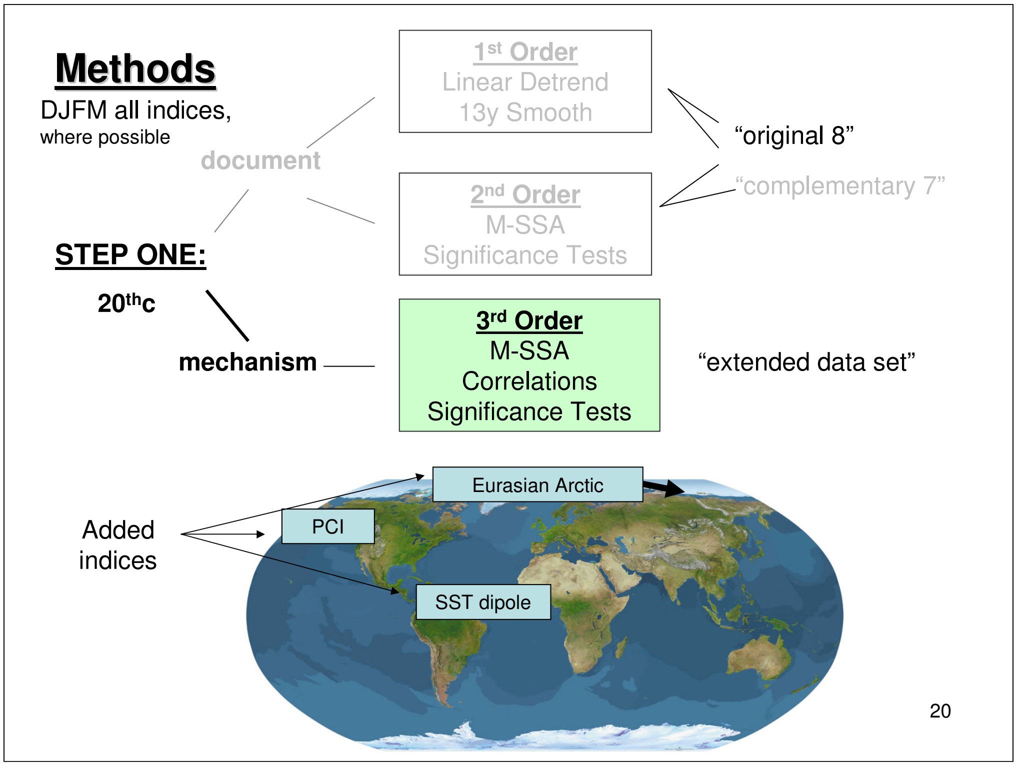
Tempo (cannot test for statistical significance of periodic behavior, as time series too short)

Feedback

Cautionary Note

Next Step:

Explore Mechanism



Running Conclusion
(Step One: 2nd order analysis)

Statistical Results

Climate signal (propagation) documented

Significance 95%

Speculation

Tempo

Feedback

Cautionary Note

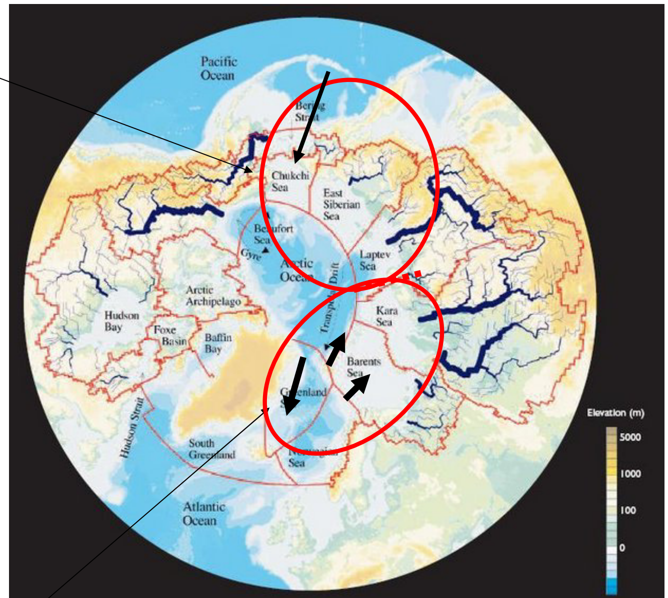
Next Step:

Explore Mechanism

Eurasian Arctic Shelf Seas

“East Ice”

“Total Ice”



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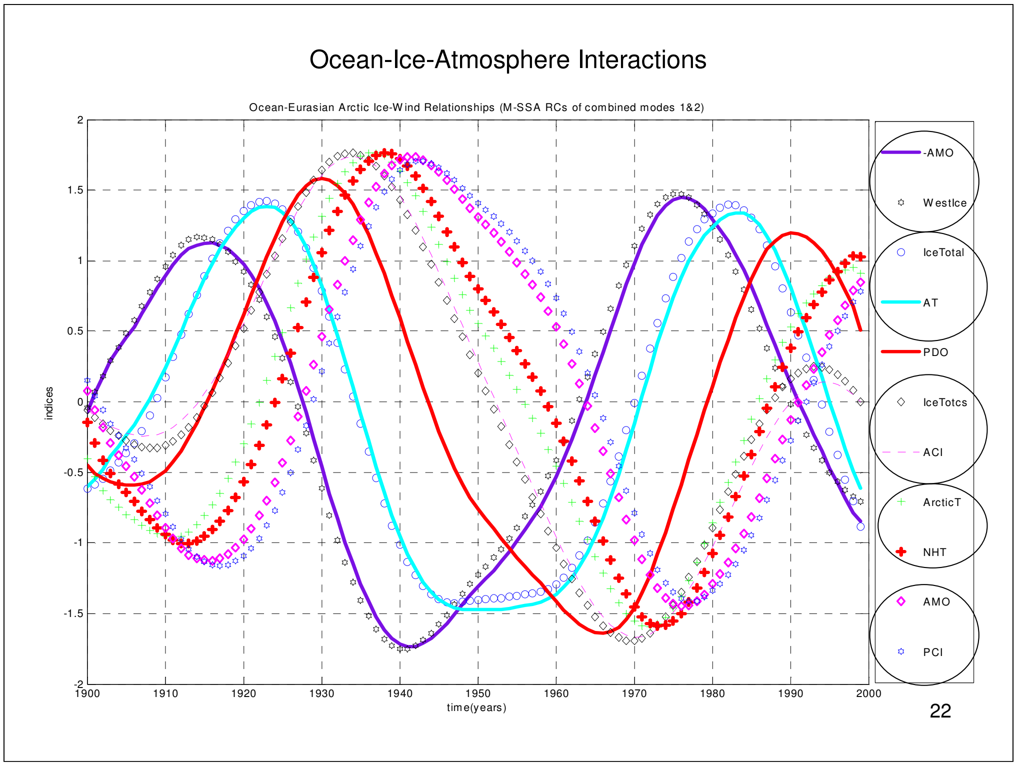
“West Ice”

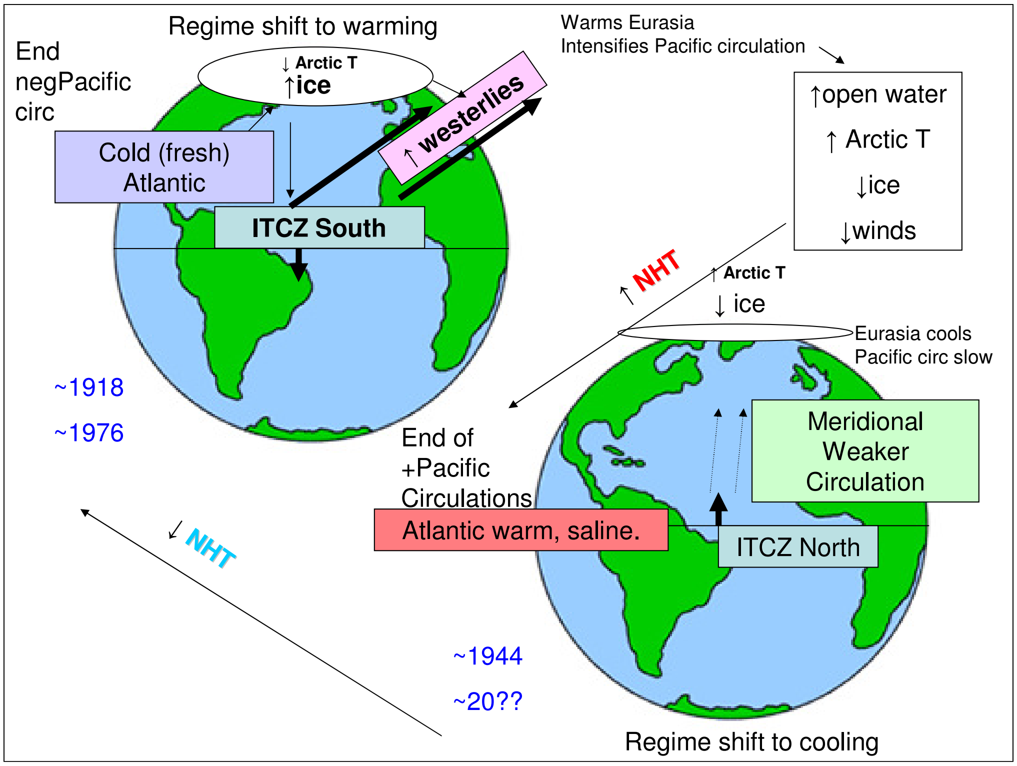
In addition to dissertation (Wyatt), see Wyatt and Curry 2014 for paper (Role for Eurasian Arctic shelf sea ice in a secularly varying hemispheric climate signal during the 20th century) on involvement in stadium-wave propagation.



-NHT, -AMO, AT, NAO, NINO, NPO, PDO, ALPI, GB, JS, NPGO, SSN, -LOD, Arctic T, TIE = 15 indices (Plotted are the reconstructed versions of these indices (RCs), generated from the combination of RC1 and RC2, as products of M-SSA, meaning that the two leading modes of multidecadal variability <u>shared</u> among all these indices are represented by these plotted curves).

Note relationships: WIE & negativeAMO; Ice Total & AT; cumulative sum of Ice Total and ACI (anomaly trends); Arctic T and NHT; AMO & PCI (anomaly trend of Pacific circulations)

Propagation signal among the indices passed all significance tests



<u>Refer to Wyatt and Curry 2014:</u> *Role for Eurasian Arctic shelf sea ice in a secularly varying hemispheric climate signal during the 20th century* for mechanistic details.

<u>Eurasian Arctic Sea Ice</u>

Relationship with Atlantic

Relationship with Winds

<u>ITCZ Migrations</u>

Max NHT, Min Sea Ice, North ITCZ

Min NHT, Max Sea Ice, South ITCZ

<u>Pacific feedback to Atlantic</u>

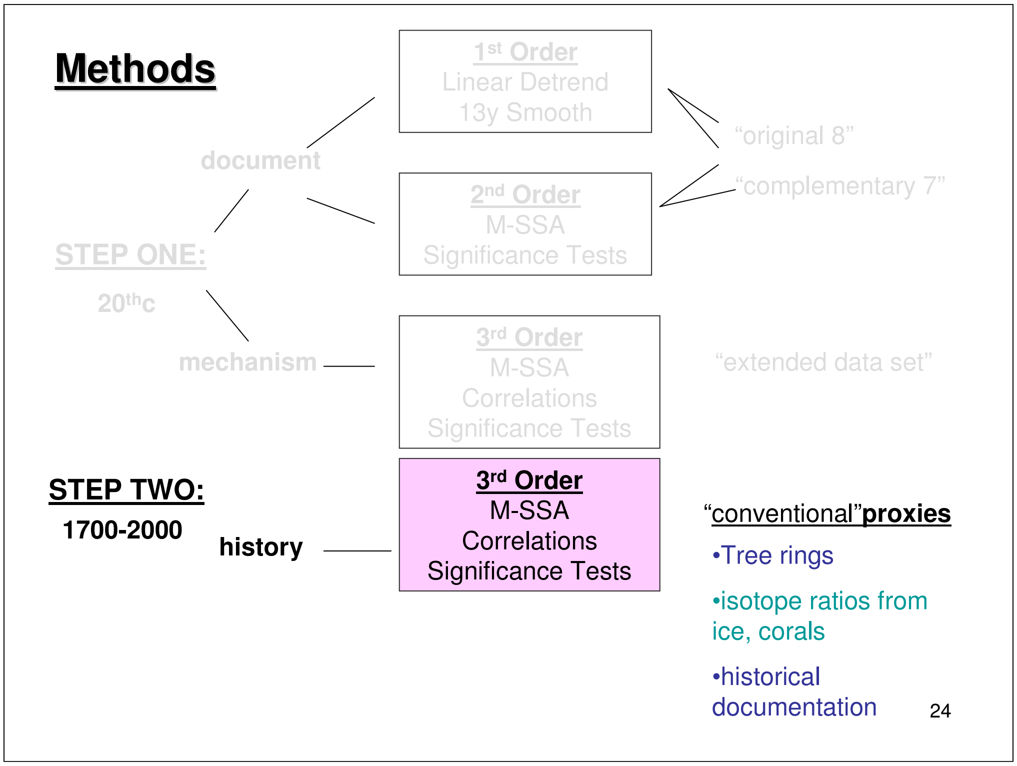
Pacific Anomaly Trend and AMO

<u>Next Step:</u>

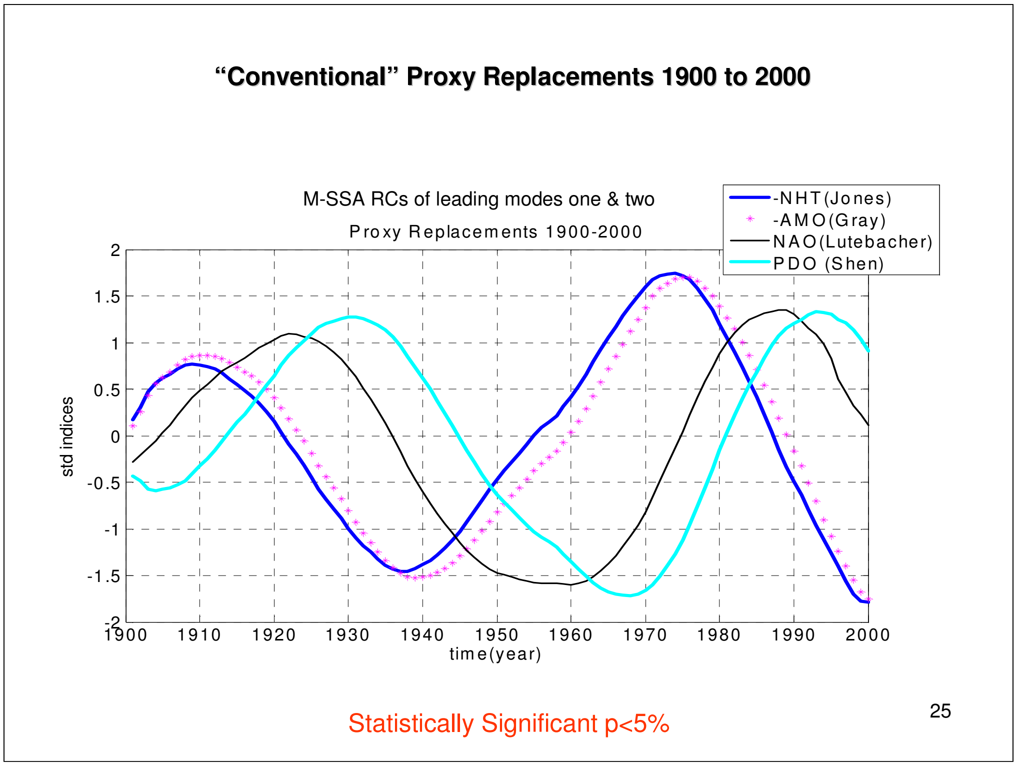
Probe History

Example: ~1918 min NHT, AMO = regime shift to warming trend
Then in ~ 1940, NHT and AMO at max = regime shift to cooling trend
Later in 1976, NHT and AMO min again, shift to warming.
Early 2000s (???) shift to cooling trend???

Note: shifts in index trends are not the same as shifts in anomaly polarity. This can be confusing when "regime shifts" are discussed. **<u>Ex</u>**. AMO begins warming <u>trend</u> from its minimum value ~1918 and continues to its maximum, about 1942, when it then reverses to a decreasing trend. Yet, if described in terms of <u>polarity of anomalies</u>, warm AMO anomalies begin ~1930 and continue in that polarity until ~ 1962, then switching to negative polarity until ! 1990, etc. [Refer to page/slide 19.]

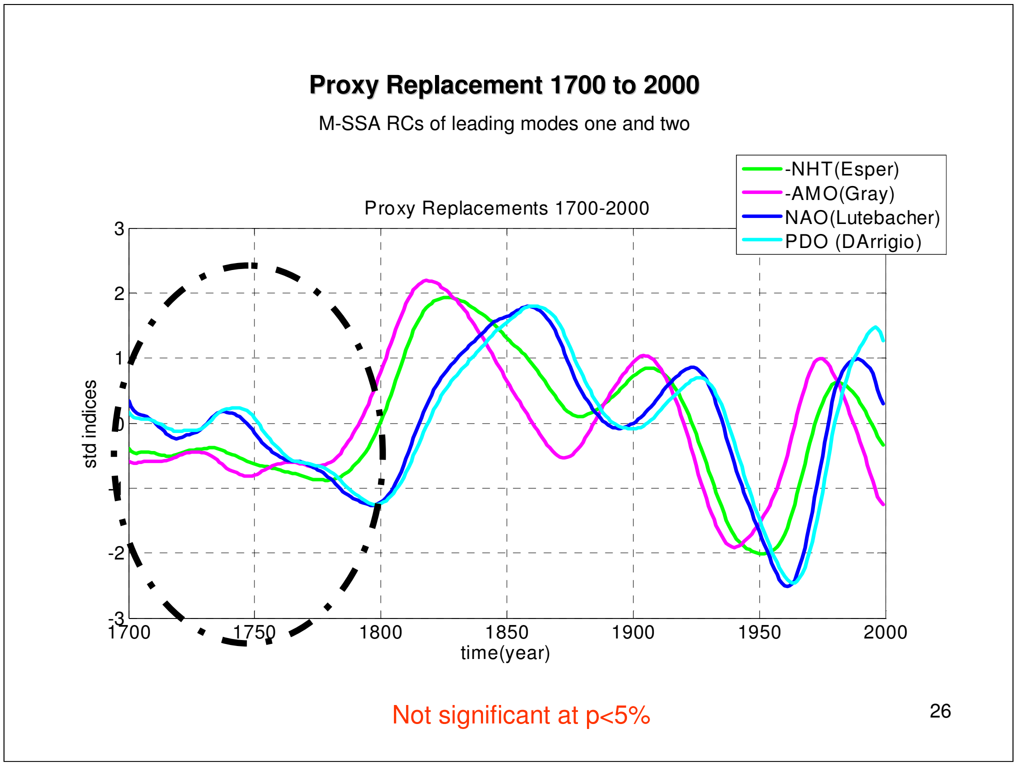


Proxy data used with same methodology as used on observational data.



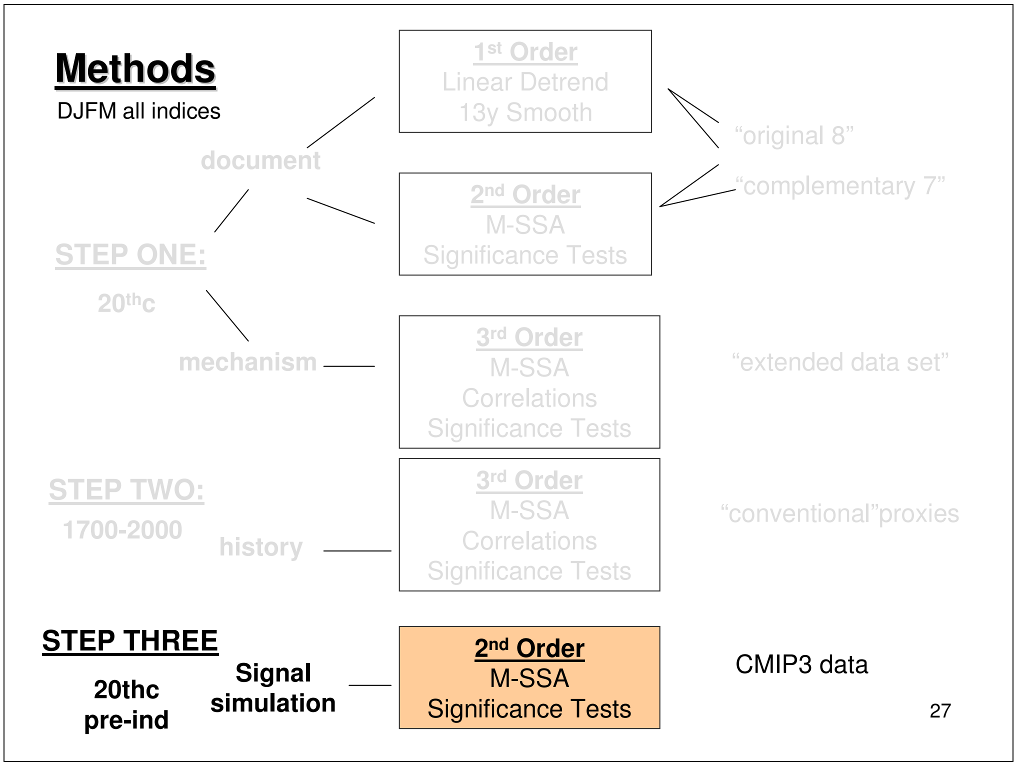
From ProxyCompilation20c_w_Replacements.m for 20c

Need to use proxies. Assess if proxies show similar behavior for 20th c. Statistical significance excellent on all measures for this collection for 20thc. Now test further back in time.



No significance. Proxy quality? Noisy? Or No signal?

From ProxyCompilation_1700_2000_revised_infill



Running Conclusion
(Step Two: 3rd order analysis)

20thc stadium wave

All proxies

1850-2000

Significant (not shown)

Prior to 1850

"Signal", yet amplitude, frequency modifications

Significance not identified

No signal? Or diminished quality of proxy data? Or other?

Next Step:

Model-Data Simulations

CMIP3 data base of raw variables

Reconstructed indices: All indices linearly detrended and normalized prior to analysis

NHT, AMO, NAO, NINO3.4, PDO, NPO, ALPI

20th century

Pre-industrial

RC Number	Group	Periodicity	Model	Experiment	Run	Significant with Annual Sampling	Significant with Sampling @ 5y Running Mean	Comments Related to Signal Propagation or Other Behavior
1	single	~70y	CCCMA_cgcm3	20c	1	yes	no	
1,2	pair	bi-annual	CNRM_cm3	20c	1	yes	no	
3	single	~25y	CNRM_cm3	20c	1	yes	no	
3	single	subdecadal	CSIRO_mk3	20c	1	yes	no	
5	single	subdecadal	CSIRO_mk3	20c	1	yes	no	
6,7	pair	bi-annual	CSIRO_mk3	20c	1	yes	no	
1	single	~70y	CSIRO_mk3	20c	1	no	yes	
1,2	pair	~35y	*GFDL_2_0	20c	1	marginal	yes	no propagation
1,2	pair	~35	GFDL_2_1	20c	3	no	marginal	no propagation
1	single	100y	IAP_fgoals_1_0_g	20c3m	1	yes	yes	
2,3	pair	biannual	IAP_fgoals_1_0_g	20c3m	1	yes	no	non-stationary behavior
1	single	interannual	MIUB_echo_g	20c	2	yes		
1	single	~60y	MIUB_echo_g	20c	2		yes	
2	single	~60y	MIUB_echo_g	20c	2	yes	no	
3	single	~25y	MIUB_echo_g	20c	2	yes	no	
3	single	~55y	UKMO_hadcm3	20c	1	marginal	no	
1	single	~50y	CNRM_cm3	control	1	no	marginal	
2	single	~25y	CSIRO_mk3	control	1	no	yes	
1	single	~55 to 75y	GFDL_2_0	control	1	n/a	yes	
2	single	~25y	GFDL_2_0	control	1	n/a	yes	

No "Stadium Wave" Signal Detected in CMIP

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Summary

- **Hypothesis**: Low-frequency climate signal propagates across NH
- **Tested** : M-SSA cornerstone of analysis techniques
  - 20th century Instrumental Data
    - Documentation of Signal
    - Explore Mechanism
  - Proxy Data: 1700-2000
    - Probe History
  - CMIP3 Model-Generated Data: 20thc and pre-industrial
    - Model Reproduction?
- **Results**:
  - A statistically significant low-frequency climate signal propagates through network of indices 20thc
    - Ocean-ice-atmospheric coupling
  - Proxies show signal: 1850 (significant) and to 1700 (with statistical uncertainty)
  - Models do not reproduce signal

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Running Conclusion
(Step Three: 2nd order analysis)

No stadium wave signal in Model-Simulated Data

Speculation on reason

Signal could be random

Models could have deficiencies in representing features vital to behavior on multi-decadal time scale

Sea-ice

COAs

Western-boundary currents and interaction with atmosphere

Interpretation/Thoughts

- Step One 20th Century Instrumental Data
  - Statistics can not “prove”.
  - Need mechanism.
  - Literature support for “links”
    - Highlight deep, interactive ocean
    - COA position, migration
    - Western-boundary currents/extensions
- Step Two: 1700-200 Proxy Data
  - Not statistically significant prior to 1850:
    - Could mean no signal
    - Could mean proxy data too noisy
- Step Three: model-generated Data
  - No signal with statistical significance, frequency, or propagation characteristics of stadium-wave signal
    - Critical links not well-modeled:
      - COAs
      - Sea-ice, especially motion and export
      - Western-boundary currents

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Outstanding Questions:

- What explains the signal's absence of statistical significance in proxy data prior to1850?
- Does sea ice influence the climate signal's sensitivity?
- Why do models not simulate the signal?

Signal Propagation & Synchronized Networks

THE END

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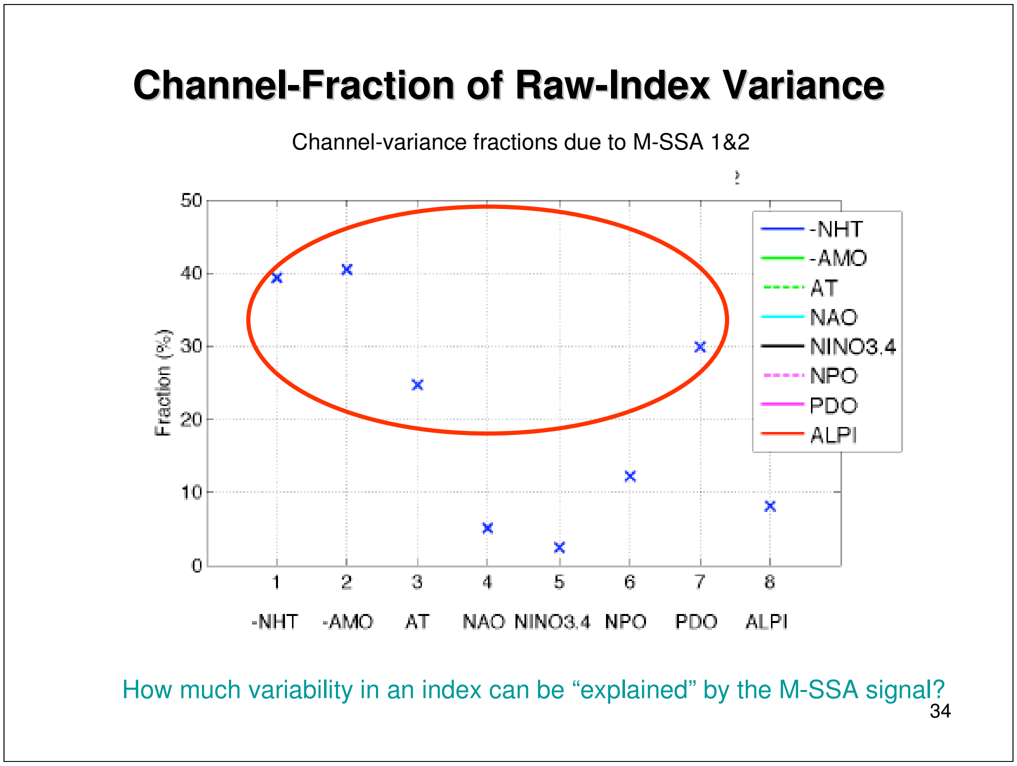
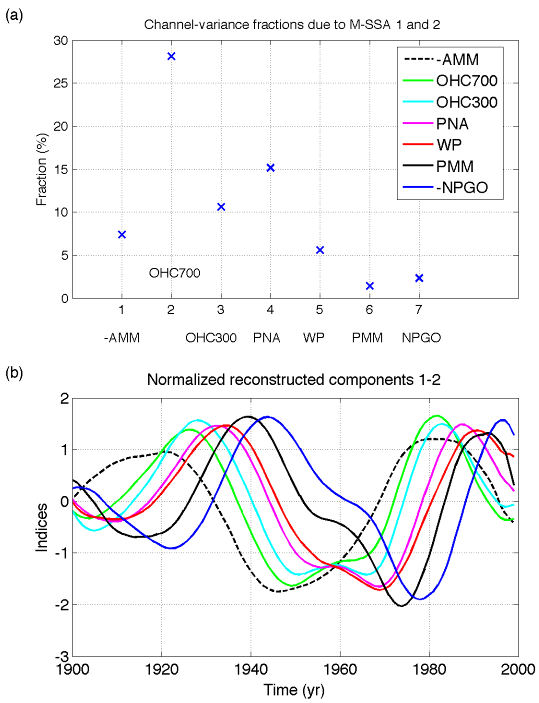
Miscellaneous
Extras follow



Bootstrap procedure done initially to ensure signal was not only in one or two indices. All indices indicated an expression of this signal. Some indices reflect the signal more than others. Those indices that are dominated by higher-frequency behavior tend to have less of their total variability “explained” by the signal than those indices with more “memory”, and therefore low-frequency behavior.



<u>Note</u>: Atlantic Meridional Mode (AMM) is plotted below in negative polarity.

7 Indices added to Index Network

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Missing data infilled. Same results of significance. Signal found in all, with fractional variances differing among indices. In particular, OHC700 in Pacific strong presence (Coincides w/ AT). OHC300 more closely affiliated with NAO. PNA traces same path as PDO, no surprise.

Running Conclusion

(Step One: 2nd order analysis)

- **Statistical Results**
  - Climate signal documented
  - Significance 95%
- **Speculation**
  - Tempo
  - Feedback
- **Cautionary Note**
- **Next Step:**
  - **Explore Mechanism**

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Secular-scale variability 20thc
Propagates through atmospheric-oceanic indices
Warm Atlantic → Cool hemispheric T ~ 32y later
Cool Atlantic → Warm hemispheric T ~ 32y later

Important: while cannot claim a statistically significant periodicity was identified, what is significant is the fact that the mode of variability was found in each index. The indices represent geographically diverse regions. The expression of the signal occurs in one, followed by another, and then another – suggestive of conveying predictive capacity.

Need Further Analysis/More Data Sets

Atlantic (tempo and atmospheric response):AMOC sets AMO tempo: (interdecadal to multidecadal results: closest to observation of ocean tempo and winter atmospheric circulation deep or interactive ocean (Knight et al. 2005; Msadek et al. 2010b).

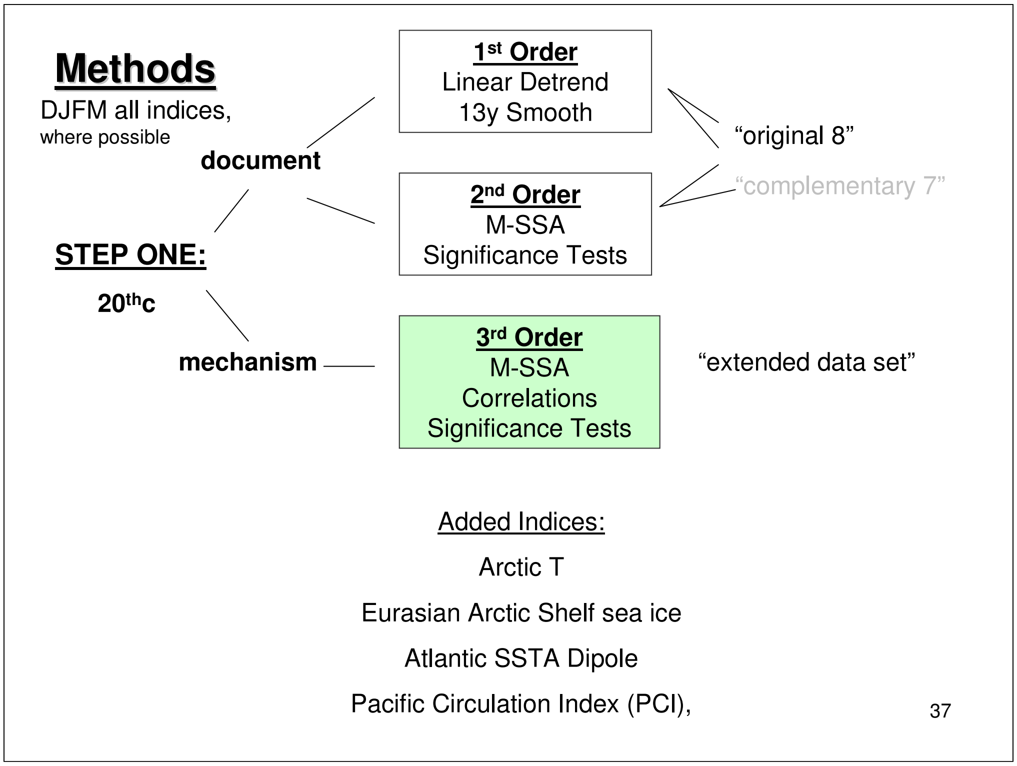
Bjerknes compensation (Bjerknes 1964) long-term TOA radiative balance fairly constant, and so is total polar heat transport accomplished by ocean and atmosphere. When one vehicle weakens, the other strengthens. Model studies: Shaffrey and Sutton (2006) and Van der Swaluw et al. (2007) support w/ max expression 60-80N on decadal timescales and longer.

Signal ocean to atmosphere: response of atmosphere to heat source in wbc (Kelly and Dong 2004; Dong and Kelly 2004; Kelly 2004). Positive reinforcing feedback on SSTA through ocean modification via atmospheric circulation overhead (Palmer and Sun 1985; Latif and Barnett 1994, 1996; Rodwell et al. 1999; Latif et al. 2000; for examples). Details of response sensitive to location of heat source w/ respect to mid-latitude storm track (Peng et al. 1997; Peng and Whittaker 1999; Peng and Robinson 2001; Czaja and Marshall 2001; Peng et al. 2002; Nakamura et al. 2004; Xie et al. 2004; Minobe et al. 2008). Model results are inconsistent (Msadek et al. 2010b).

Signal Atlantic to Pacific: Numerous models; inconsistent results. Longitudinal and latitudinal migrations of COAs (atmospheric) govern circumpolar communication of regionally generated climate signals (Kirov and Georgieva 2002; Polonshky et al. 2004; Grosfeld et al. 2006; Dima and Lohmann 2007; Msadek et al. 2010b). Interbasin connectivity (Wang et al. 2007), where Pacific ALPI dominated by ENSO during global cool regimes and is not dominated by it during warm, when mid-latitude circulation more influential. Enhanced PNA and eastwardly extended jet due to AL shift to south and east. PNA intensification and area coverage connects up and down stream.

Lat/lon shifts strongly influence NPO/WP (Sugimoto and Hanawa 2009; Frankignoul et al. 2011) and have been shown to influence interdecadal-scale migrations of wbc extensions (oceanic gyre frontal boundaries), w/ impact on ocean dynamics and ocean-atmospheric interaction (Kwon et al. 2010 and Frankignoul et al. 2011) Latitudinal shifts in ITCZ involved in Atlantic to Pacific communication at low latitudes, as proposed by Vellinga and Wood 2002; Vellinga and Wu 2004; Vimont and Kossin 2007). Multidecadal changes in tropical Pacific may further modify. Atlantic response to Pacific, for example (Latif et al. 2006 (atmospheric bridge)). Schmittner et al. 2000 and Niebauer 1998 both discuss Pacific remote influence on freshwater balance in Atlantic, and therefore influence on thermohaline circulation. Arctic/Atlantic freshwater exchange related to position of COAs (Dima and Lohmann 2007; Frankcombe and Dijkstra 2011). Kwok et al. 2011 discusses COA placement of Arctic High and effect on sea-ice extent.

Observation of NPO and NAO co-varying as proposed result of NAM (Chao and Au (2001?) (personal communication and paper)). Hurrel and van Loon 1997; Thompson et al. 2000 have observed. Van Loon has discussed (Greece presentation).



Running Conclusion
(Step One: 2nd order analysis)

Statistical Results

Climate signal documented

Significance 95%

Speculation

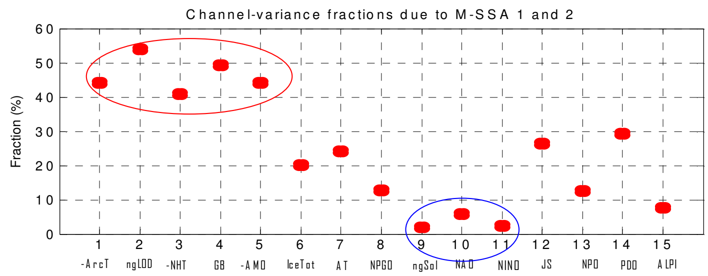
Tempo

Feedback

Cautionary Note

Next Step:

Explore Mechanism



Channel-Fraction Variance of Select
Indices from Original plus Arctic
Variables and Dynamic Proxies

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Running Conclusion:
(Step One: 3rd order analysis)

- **Eurasian Arctic Sea Ice**
  - Relationship with Atlantic
  - Relationship with Winds
- **ITCZ Migrations**
  - Max NHT, Min Sea Ice, North ITCZ
  - Min NHT, Max Sea Ice, South ITCZ
- **Pacific feedback to Atlantic**
  - Pacific Anomaly Trend and AMO
- **Next Step:**
  - Probe History

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Atlantic Ocean strong influence on sea ice

Sea ice affects meridional temperature gradient (MTG)

MTG triggers atmospheric response

Atmospheric response plays back on ice/ocean Atlantic variability and PCI

Cumulative impact of Pacific circulations

Remote influence of Pacific circulations on Atlantic
Sequence:ocean-**ice**-atmospheric indices

Cool Atlantic coincides with Eurasian Arctic shelf-sea ice (landfast ice included), especially the Western Eurasian Arctic Ice (Greenland, Barents, and particularly Kara. 30W to 110E). Most significant control on sea-ice growth = low salinity (and cool); affects far more than overlying T. (Frolov et al. 2009 and references w/n; Zakharov and Malinin (2000) p 5,6.

Increase in Arctic ice decreases Arctic T and increases MTG, leads to atmospheric heat flux low to high latitudes NH. Forms planetary air flow west to east. (Frolov). In turn, atmospheric flow influences ice-motion dynamics = convergence, ridging, leading to open water, which then allows considerable flux to atmosphere. This reduces the MTG and with it, the atmospheric and heat transport associated with it. The freshwater export related to COA placement as a result of changed atmospheric circulation generates multidecadal Rossby salinity cycle in Arctic, influencing salinity balance of North Atlantic high latitudes. In addition, there is feedback on Atlantic from Pacific.

Pacific circulations

Running Conclusion

(Step Two: 3rd order analysis)

- 20thc stadium wave
  - All proxies
- 1850-2000
  - Significant (not shown)
- Prior to 1850
  - “Signal”, yet amplitude, frequency modifications
  - Significance not identified
    - No signal? Or diminished quality of proxy data? Or other?
- Next Step:
  - Model-Data Simulations

Running Conclusion

(Step Three: 2nd order analysis)

- No stadium wave signal in Model Data
- Speculation on reason
  - Signal could be random
  - Models could have deficiencies
    - Sea-ice
    - COAs
    - Western-boundary currents

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Van de Berge supermodel (variables exchange information). Better results than model-ensemble averages and much better than any individual models.