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Global-scale Multidecadal Variability Missing in State-of-the-Art Climate Models

Sergey Kravtsov

University of Wisconsin-Milwaukee, USA
P. P. Shirshov Institute of Oceanology, Russia

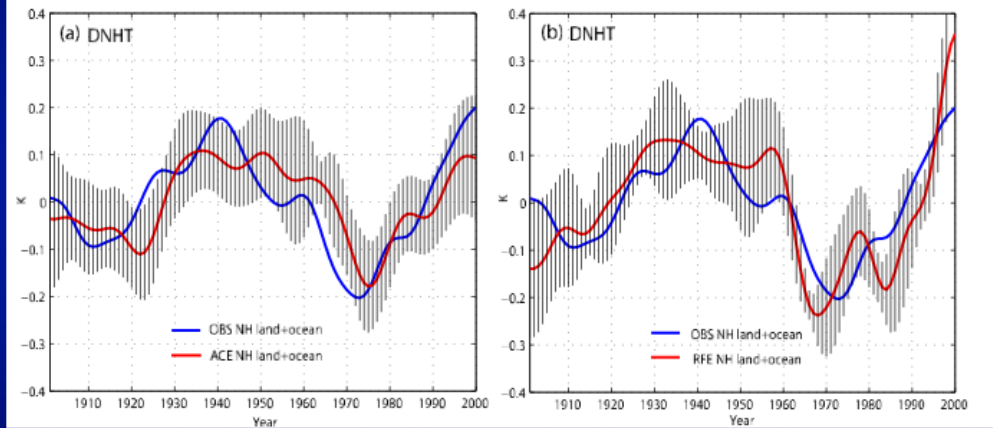
Collaborators: Christian Grimm, Shijie Gu (UWM)

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<https://people.uwm.edu/kravtsov/>

Establishing causes of multidecadal variability is tricky...

ZHANG ET AL.: NORTHERN HEMISPHERE MEAN TEMPERATURE



Slab-ocean mixed layer in the North Atlantic with time-dependent Q-flux, constant RF

Radiatively forced (RF) GFDL CM2.1 ensemble

...since the internally generated SST anomalies (e.g. due to variations in AMOC) and non-uniform (in time) radiative forcing may both be responsible for the observed non-uniformities in the NH warming! Other pacemaker experiments (e.g., SSTs prescribed in the Pacific, Indian Ocean) show analogous results.

...so, multidecadal deviations of NH surface temperature from linear trend may well be rationalized as being either due to the climate's response to the ocean-driven heat-flux forcing from the North Atlantic SSTs, or due to the response to non-linear trends in the radiative forcing

Notes:

- in both setups, the climate response is forced
- the ensemble spreads (due to internal variability) are similar too, and are fairly narrow: this suggests that in the coupled setting, GFDL2.1's internally generated decadal-scale SST anomalies in the North Atlantic have a smaller magnitude than the observed SST anomalies

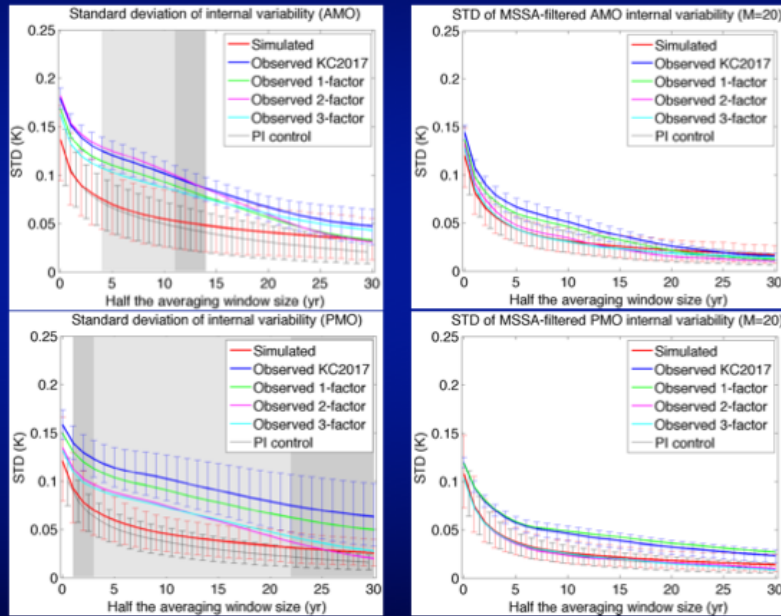
This (underestimating the magnitude of internal variability) turns out to be a common problem for many CMIP5 models. Not only that, but also — timescales and patterns of multidecadal climate variability turn out to be different!

Kravtsov (2017) GRL

- Estimate forced signal and its uncertainty from CMIP5 multi-model ensemble, for several climate indices: AMO, PMO, NMO, NAO, ALPI
- Combine these forced-signal estimates with individual model simulations as well as observations to obtain estimates of internal climate variability
- Compare characteristics of the simulated and “observed” (semi-empirical) internal variability

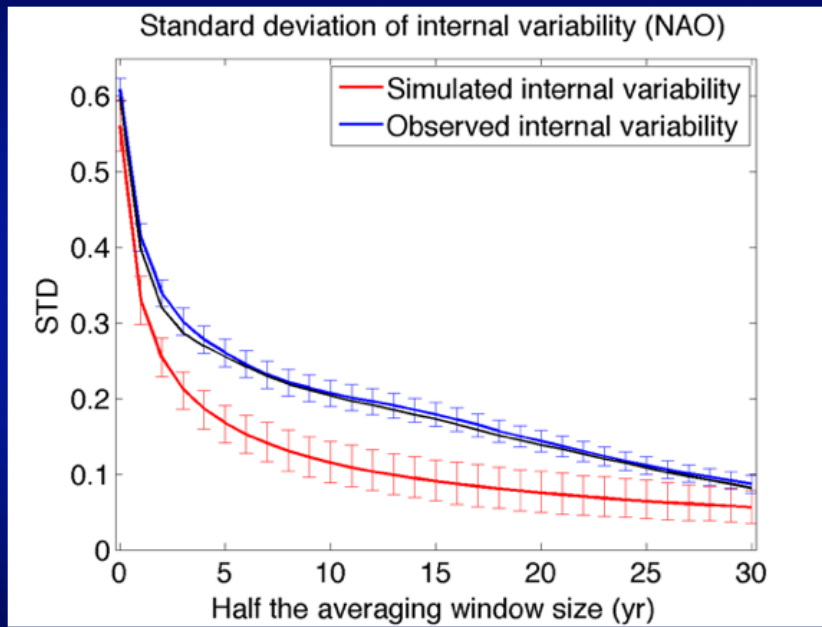
AMO – SST averaged over North Atlantic, PMO – SST averaged over North Pacific, NMO – surface air temperature averaged over the entire Northern Hemisphere (ocean+land), NAO – leading EOF of SLP over North Atlantic, ALPI – leading EOF of SLP over North Pacific.

Comparing the “observed” and simulated internal variability

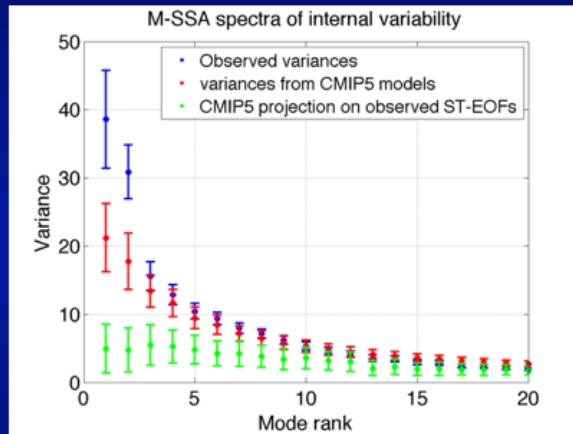


Inflation factors have been developed and applied to account for a small number of realizations and insufficient averaging of internal variability in the ensemble averaged “forced” signal. Even inflated internal variability in CMIP5 simulations is significantly smaller than observed estimates!

Same story for NAO and ALPI



M-SSA of internal variability network (AMO, PMO, NMO, NAO, ALPI)

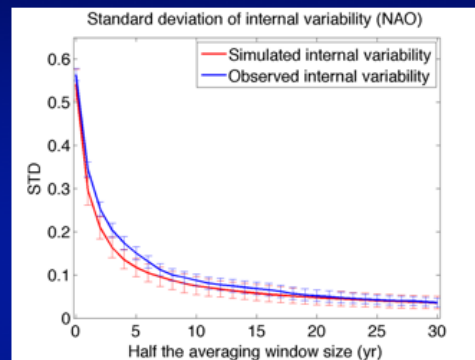
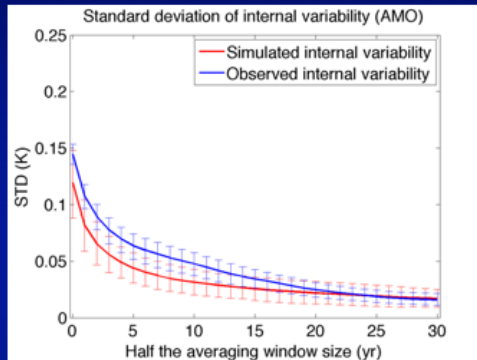


- Dominant leading pair in observations
- Monotonic decay of variance in models
- Leading pair dominates the difference btw models and observations

- Different spatiotemporal structure of the observed and simulated variability

Blue – observed, red – simulated, green – variance of projections of the simulated trajectory matrices onto the observed T-EOFs. Dominant leading pair in observation, with the variance much larger than that of the dominant pair in models. Model's projections onto observed T-EOFs are tiny: different spatiotemporal structure of the simulated variability compared to the observed.

Subtract leading M-SSA pair...



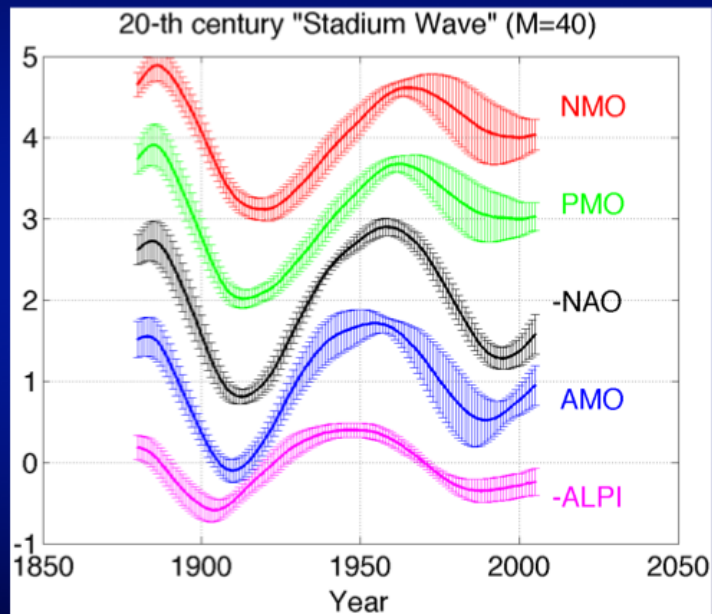
... the difference in the variance between the “observed” and simulated internal variability is greatly reduced!

So comparing semi-empirical internal variability in models and observation recovers the results based on comparing the deviations from the linear trends in observations and model simulations: lack of multidecadal variance and different spatiotemporal structure of variability in the models relative to observations.

Summary (Kravtsov 2017)

- We **estimated forced signals** from multi-model ensemble of CMIP5 historical simulations
- These forced signals were subtracted from individual model runs and, after rescaling, from observed time series to **derive the internally generated component of the observed and simulated climate variability**
- Internal climate variability in models has **a smaller amplitude and different spatiotemporal structure** wrt the observed variability
- The differences between models and observations are dominated by **a low-dimensional multidecadal mode of the observed climate variability**, which has a hemispheric character and is apparently absent from models

Observed "Stadium Wave" (cf. Wyatt et al.)



Here is how this observed mode of variability — absent from the models — looks like, in the five indices considered.

Now **generalize** this result in the gridded surface atmospheric temperature data

Models:

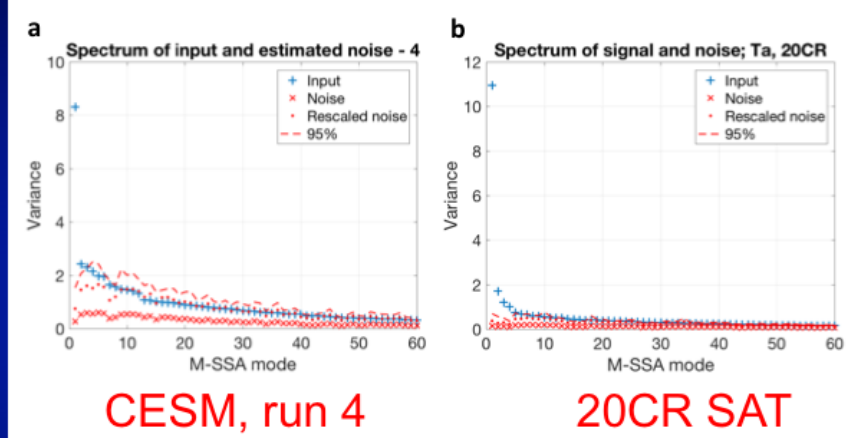
- CESM large ensemble (LENS) project: 40 historical simulations, 1920–2012 [Kay et al. 2015]
- CMIP5 historical simulations. 17 models with 4 or more 20th century realizations, 111 individual simulations [Taylor et al. 2012]

Observations:

- 20th century reanalysis (20CR) [Compo et al. 2011]

Since the emphasis is on the large-scale low-frequency variability, simply applying the above analysis at the level of individual grid points (where the noise is much larger than in the regional averages) won't work: we need to filter the data to focus on the appropriate time and spatial scales.

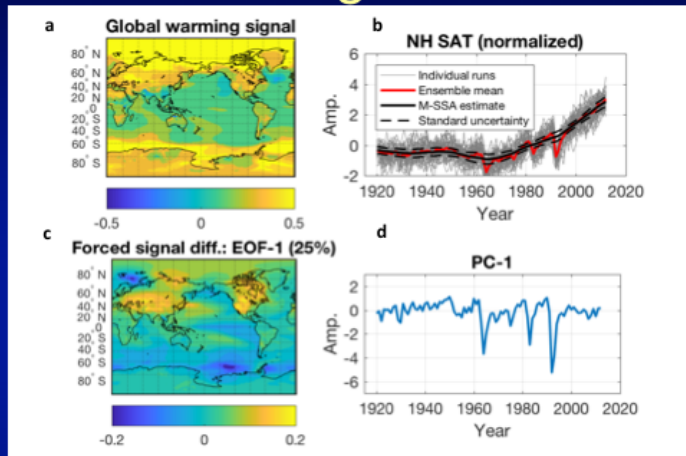
Wiener filtering in M-SSA basis



- Idea: Isolate **secular variability** using data-adaptive M-SSA based space–time filters which **discriminate against stationary noise** (as simulated by multi-scale empirical LIM models).

(a) Input/noise spectra for one of the simulations of the CESM model; (b) The same for 20CR SAT data. Statistically significant M-SSA modes are multiplied by signal-to-input variance ratio and their sum is reconstructed in physical space. Inflation factors (based on comparing filtered and raw time series) are needed, since both signal and noise tend to get attenuated in Wiener filtering.

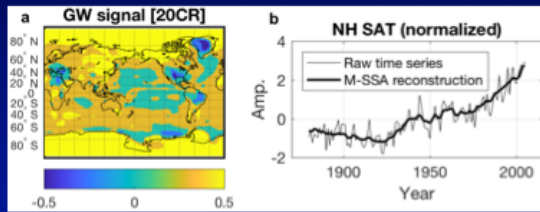
Secular Signals in LENS



- **Secular variability** is dominated by **low-frequency component of the forced signal**. Multidecadal internal variability is small (cf. Bellomo et al. 2018).
- Interannual dips due to **volcanic eruptions** are not captured
- Essentially **the same results for CMIP5**, a bit more spread mainly due to **model uncertainty**

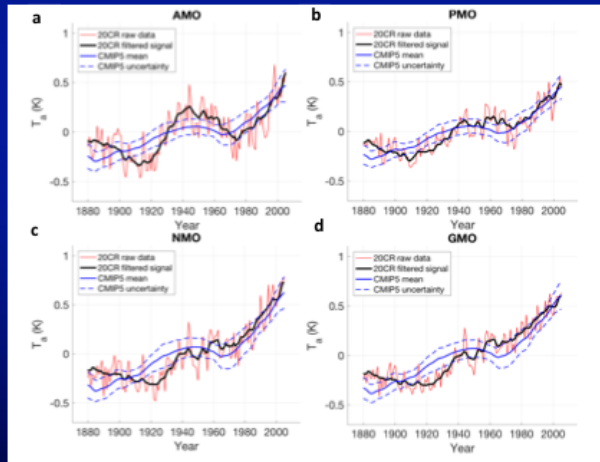
Note narrow uncertainty range of the secular signal in NH SAT, meaning that essentially the same (forced) signal is isolated in each individual CESM run. In CMIP5, the spread is a bit more (model uncertainty) - see backup slides.

Secular Signals in 20CR/CMIP5



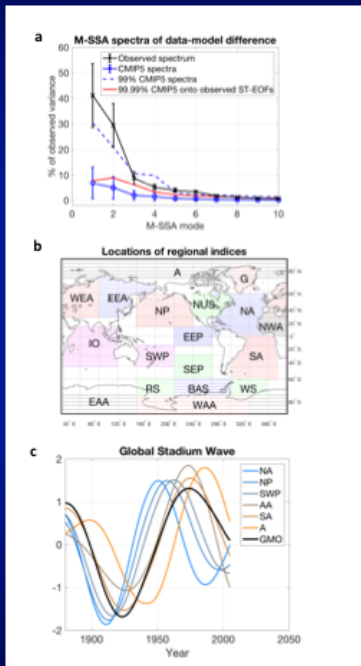
- volcanic eruptions are not as pronounced (compared to models)

- again, substantial differences between observed and model simulated secular signals!



Now take the difference (at each grid point) between secular signals in observations and each (scaled) model simulation, and do M-SSA analysis to isolate dominant data-model differences. Since secular signals in models are dominated by forced variability, the data-model difference can be thought of as an estimate of internal climate variability in observations. We also analyze the differences between secular signals in individual simulations and this model's ensemble-mean secular signal. This would be an estimate of the internal secular variability in models.

Data-model differences



- The M-SSA results are completely analogous to Kravtsov (2017) work, which considered a few climate indices: **dominant M-SSA pair in observations**, flatter spectrum and lack of observed ST-EOFs in the models
- **Regional reconstructions indicate global "stadium wave"** (Wyatt et al. 2012), which originates in the North Atlantic (cf. Moron et al. 1998) and then "propagates" to North and South Pacific, South Atlantic and Southern Ocean/Antarctica, and, finally, the Arctic ([see animation](#))

Reconstructions are consistent with Kravtsov (2017). In reconstructions, the ocean indices are scaled by 0.1K and land indices – by 0.6K. This is why the animation shows stretched signals to better visualize the sequence of anomaly propagation. [Movie here.](#)

Summary

Reliability of future global warming projections depends on how well climate models reproduce the observed climate change over the twentieth century. In this regard, deviations of the model simulated climate change from observations, such as a recent “pause” in global warming, have received considerable attention¹⁻³. Such decadal mismatches between model simulated and observed climate trends present a systemic problem throughout the twentieth century, and their causes are still poorly understood⁴⁻¹⁰. Here we use a new objective filtering method to show that the discrepancies between the observed and simulated climate variability on decadal and longer time scale have a coherent structure suggestive of a pronounced global multidecadal oscillation. Surface temperature anomalies associated with this variability originate in the North Atlantic and spread out to the Pacific and Southern oceans and Antarctica, with Arctic following suit in about 40 years. While climate models exhibit various levels of decadal climate variability and some regional similarities to observations, neither of the simulations considered match the observed signal in terms of its magnitude, spatial patterns and their sequential time development. These results highlight a substantial degree of uncertainty in our interpretation of the observed climate change using current generation of climate models.

Discussion

Multidecadal signals originating in the North Atlantic Ocean and exerting some influence on the Northern Hemisphere climate have been observed and simulated before^{35,36}. They are thought to be rooted in the variability of the Atlantic Meridional Overturning Circulation (AMOC) (ref. 37). Recent observational^{15,38-40} and modelling studies^{41,42} highlighted global character of such DCV, especially its connections to the Southern Ocean, which is also consistent with our findings. These global DCV modes are likely to be due to a combination of multiple slow, regional-to-basin-scale oceanic processes defining dynamical memory of the climate system in the presence of fast, large-scale atmospheric processes. The latter fast processes can both supply energy for DCV and provide means for intra- and inter-basin communication and synchronization of decadal climate modes⁴³⁻⁴⁵.

Although some of the climate models are able to simulate certain qualitative features of the observed DCV^{8,54}, our results summarize and rigorously document pronounced quantitative discrepancies between models and observations, which should help guide further DCV research¹⁴.

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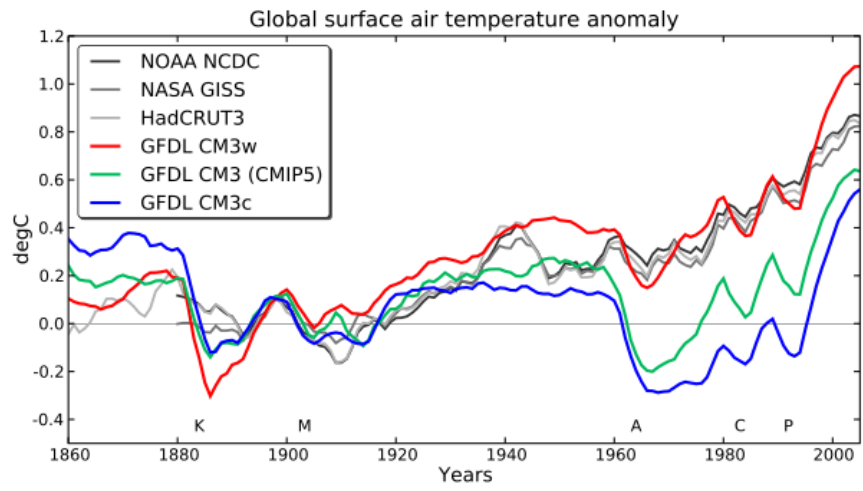
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Back-up slides

For further info:

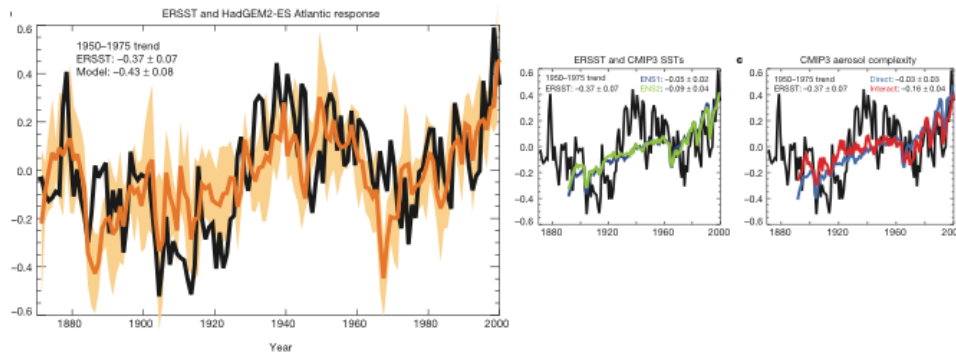
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- Kravtsov, S., 2018: Paper submitted to npj Climate and Atmospheric Science

GOLAZ ET AL.: CLOUD TUNING AND 20TH CENTURY WARMING



Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability

Ben B. Booth¹, Nick J. Dunstone^{1*}, Paul R. Halloran^{1*}, Timothy Andrews¹ & Nicolas Bellouin¹



- Lack of multidecadal SST variability in the North Atlantic was suggested to be due to underestimation of aerosol indirect effects in coupled climate models
- In this interpretation, multidecadal variations of the North Atlantic SSTs are forced (cf. Zhang et al. 2007)

Aerosols?

Have Aerosols Caused the Observed Atlantic Multidecadal Variability?

RONG ZHANG,* THOMAS L. DELWORTH,* ROWAN SUTTON,[†] DANIEL L. R. HODSON,[†] KEITH W. DIXON,*
ISAAC M. HELD,* YOCHANAN KUSHNIR,[#] JOHN MARSHALL,[@] YI MING,* RYM MSADEK,* JON ROBSON,[†]
ANTHONY J. ROSATI,* MINGFANG TING,[#] AND GABRIEL A. VECCHI*

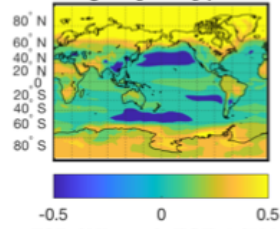
- major discrepancies between HadGEM2-ES simulations and observations in terms of the 3-D structure of multidecadal upper-ocean temperature and salinity in the North Atlantic, as well as in various fields outside of North Atlantic
- Still, if observed multidecadal deviations of North Atlantic SSTs from linear trend are internally generated, why is their magnitude so much larger than that in CMIP5 coupled runs?

Well, maybe not, but what would then be the explanation for the insufficient simulated amplitude of multidecadal variability?...

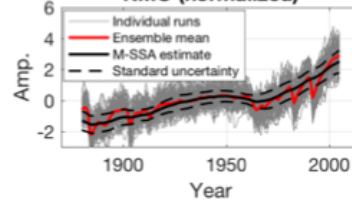
Model #	Model acronym	# of runs
1	CanESM2	5
2	CCSM4	6
3	CNRM-CM5	10
4	CSIRO-MK3-6-0	10
5	GFDL-CM2.1	10
6	GFDL-CM3	5
7	GISS-E2-Hp1	6
8	GISS-E2-Hp2	6
9	GISS-E2-Hp3	6
10	GISS-E2-Rp1	6
11	GISS-E2-Rp2	6
12	GISS-E2-Rp3	6
13	HadCM3	10
14	HadGEM2-ES	5
15	IPSL-CM5A-LR	6
16	MIROC5	5
17	MRI-CGCM3	3
Total:	17 models	111 simulations

Wiener Filtering in CMIP5

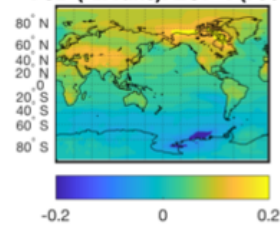
a GW signal [NMO] (All runs)



b NMO (normalized)



c FSD (All runs): EOF-1 (78%)



d PC-1

