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Pronounced differences between the observed and CMIP5 simulated climate variability in the twentieth century

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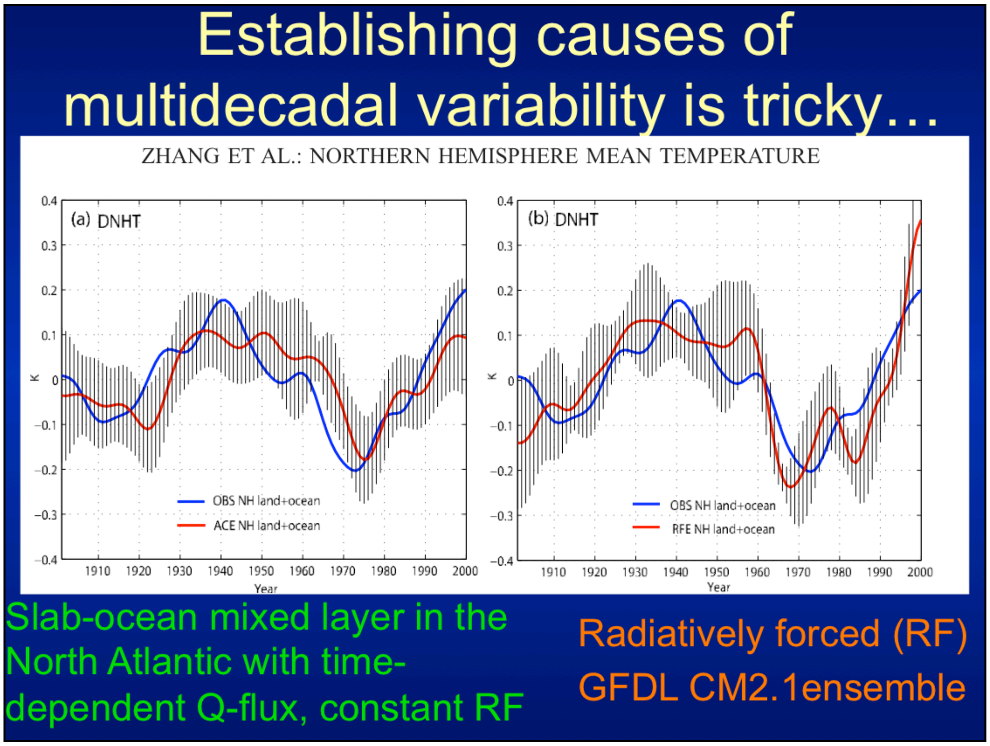
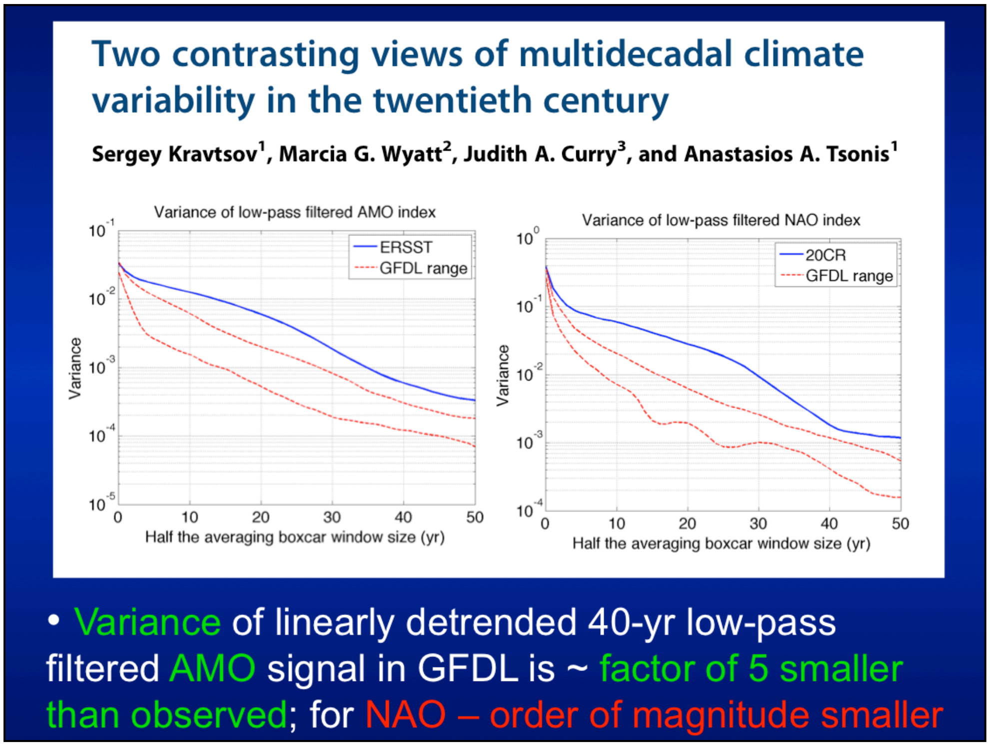


…since the internally generated SST anomalies (e.g. due to variations in AMOC) and non-uniform (in time) radiative forcing may both be responsible for the observed non-uniformities in the NH warming!

…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:

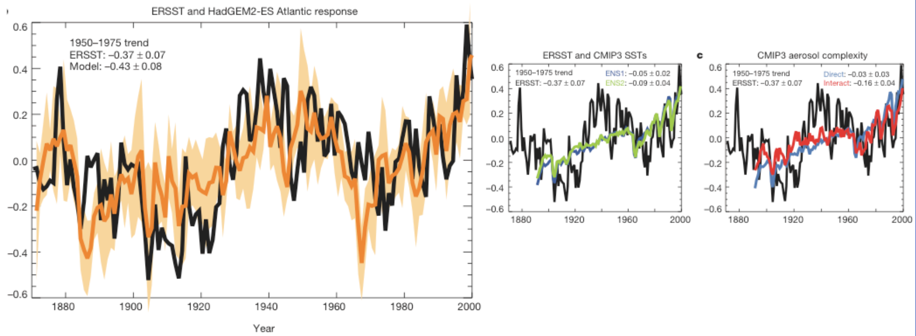
- in both setups, the climate response is forced
- the ensemble spreads (due to internal variability) are similar too, and are fairly narrow: this suggests that in the coupled setting, GFDL2.1's internally generated decadal-scale SST anomalies in the North Atlantic have a smaller magnitude than the observed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



The multidecadal deviations from the linear trend in GFDL2.1 simulated North Atlantic SSTs are indeed much smaller than observed, but this is even more so for NAO (which, incidentally, has essentially no forced component in the CMIP5 model simulations). Note that the linearly detrended NHT variance is similar to the observed, consistent with Zhang et al. (2007).

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

Ben B. B. Booth[1], Nick J. Dunstone[1]*, Paul R. Halloran[1]*, Timothy Andrews[1] & Nicolas Bellouin[1]



- 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?

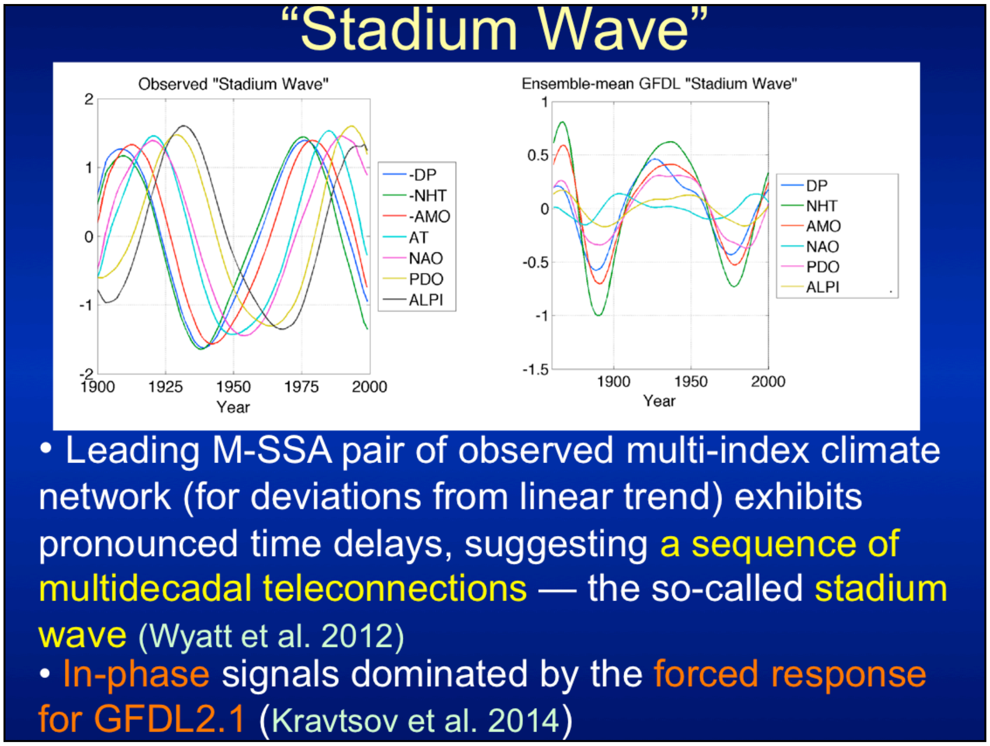
Have Aerosols Caused the Observed Atlantic Multidecadal Variability?

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?...



The spatiotemporal structures of dominant multidecadal climate variability over a multi-index climate network in observations and GFDL2.1 model are also very different. This multidecadal signal in GFDL is predominantly *forced*. The run-to-run uncertainties in the simulated phases of the stadium-wave components corresponding to different indices (not shown) are small compared to the phase shifts between the observed components of the stadium wave. So the observed and GFDL2.1 simulated multidecadal variability in the 20th century (in deviations from the linear trend, which trend is, btw, similar in GFDL model and observations) differ in magnitude and spatiotemporal structure.

Forced climate model runs can be used to estimate the response of the climate system to forcing

- Linear detrending is not meant to isolate forced and internal components of variability (as opposed to claims in, e.g., Mann et al. 2014)
- One can use ensemble simulations using single (SM) or multiple (MM) climate models to estimate the climate's forced response over the 20th century (Kravtsov and Spannagle 2008; Knight 2009; Terray 2012, Steinman et al. 2015a)
- SMEM (ensemble mean) time series of a given climatic quantity would approximate an individual model's forced response. MMEM would characterize the average forced response of the MM ensemble

We aim to:

- 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.

Methodology: Models

- Analyze CMIP5 historical runs for models with four or more realizations (18 models, 116 simulations, table slide)
- Use 5-yr low-pass filtered SMEM as an initial estimate of each model's forced signal, compute 'internal' residuals
- Fit low-order ARMA models to these residuals and produce multiple synthetic versions of internal variability for each model
- Add synthetic residuals to estimated forced signals to produce synthetic CMIP5 "ensembles"
- Use the synthetic ensembles to correct for the biases in the initial estimates of the forced signals and internal variability; these biases can be computed since the true forced signals in the synthetic samples are known by construction

This gives us 116 bias corrected time series of the internal variability as simulated by CMIP5 models

Model runs used (20th century)

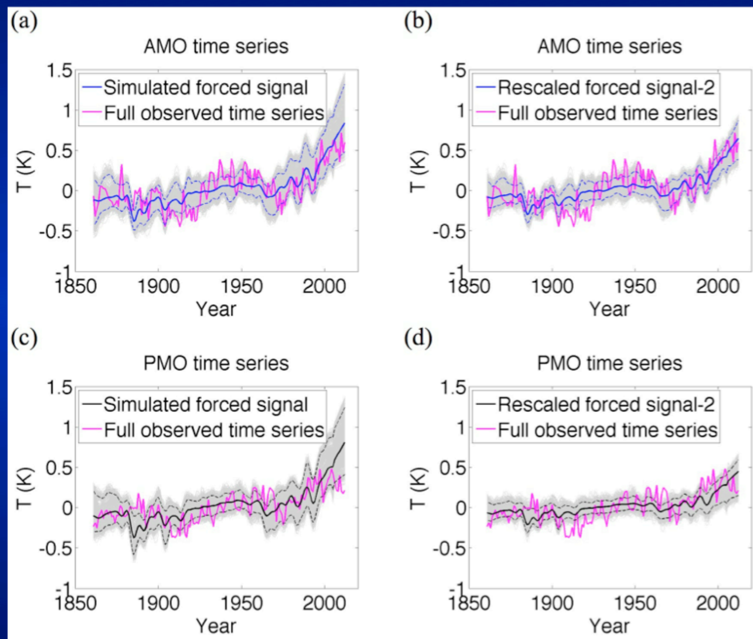
Model #	Model acronym	Number of realizations	Scaling wrt observations		
			AMO (0.8)	PMO (0.57)	NMO (1.02)
1.	*CCSM4*	*6*	*0.68*	*0.47*	*0.78*
2.	*CNRM-CM5*	*10*	*1.15*	*0.76*	*1.22*
3.	**CSIRO-Mk3-6-0***	**10**	**1.10**	**0.57**	**1.21**
4.	*CanESM2*	*5*	*0.81*	*0.53*	*0.95*
5.	GFDL-CM2p1	10	0.61	0.48	0.78
6.	GFDL-CM3*	5	0.80	0.21	0.91
7.	GISS-E2-Hp1	6	0.82	0.70	1.04
8.	*GISS-E2-Hp2*	*5*	*1.03*	*0.72*	*1.21*
9.	GISS-E2-Hp3	6	0.72	0.61	0.92
10.	GISS-E2-Rp1	6	0.8	0.70	1.11
11.	GISS-E2-Rp2	6	1.1	0.71	1.30
12.	GISS-E2-Rp3	6	0.48	0.64	0.93
13.	GISS-E2-Rp4	6	0.56	0.50	0.71
14.	*HadCM3*	*10*	*0.83*	*0.57*	*1.11*
15.	**HadGEM2-ES***	**5**	**0.84**	**0.33**	**1.21**
16.	**IPSL-CM5A-LR**	**6**	**0.48**	**0.42**	**0.72**
17.	**MIROC5***	**4**	**0.93**	**0.64**	**1.13**
18.	MRI-CGCM3*	4	0.77	0.70	1.20

We analyzed model 20th century CMIP5 runs for models with 4 or more realizations available, and several climate indices: AMO, PMO, NMO of Steinman et al. (2015a), as well as SLP based indices not shown here (NAO, ALPI).

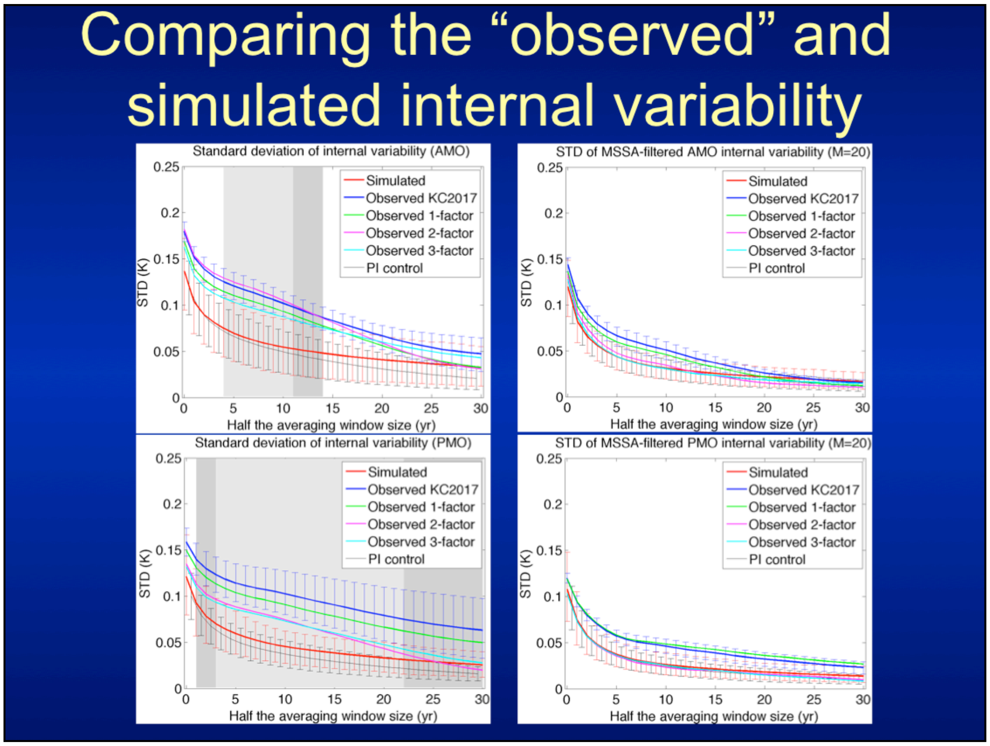
Methodology: Observations

- In synthetic CMIP5 ensembles, rescale the estimates of the forced signal in individual models (5-yr LPF SMEM) to best fit the observed time series considered. This is meant to correct for different climate sensitivities of different models.
- Estimate the forced signal uncertainty by computing 100 versions of SMEMs in the 100 synthetic CMIP5 ensembles (the total of 18x100=1800 estimates of the forced signal). These are now our estimates of the forced signal in observations (due to prior rescaling!)
- Subtracting the estimated forced signals from the observed time series gives us 1800 estimates of internal variability in observations

Estimates of the forced signal

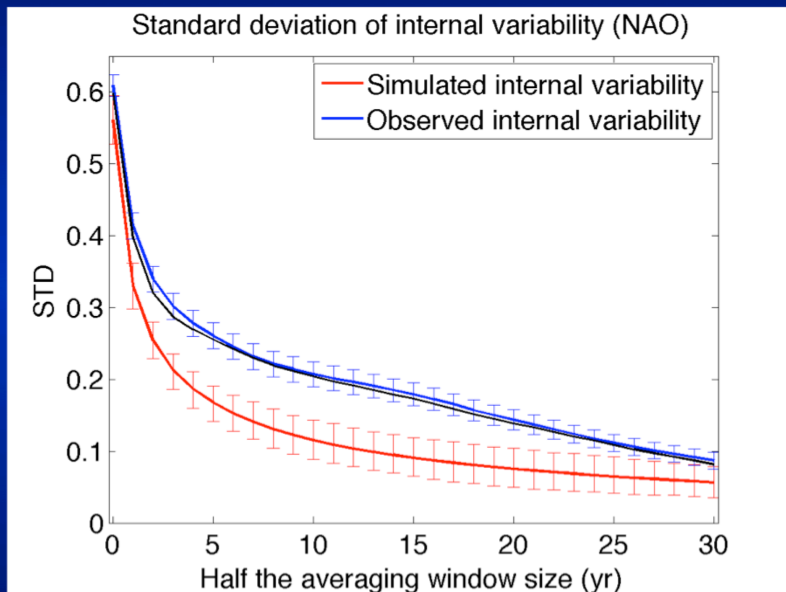


Left – no rescaling; right – rescaled signals. Linear growth of uncertainty at the end of the record is due to linear extrapolation of model time series from 2005 through 2012. NMO requires essentially no rescaling (not shown). Forced signal is near zero for NAO and ALPI (not shown).

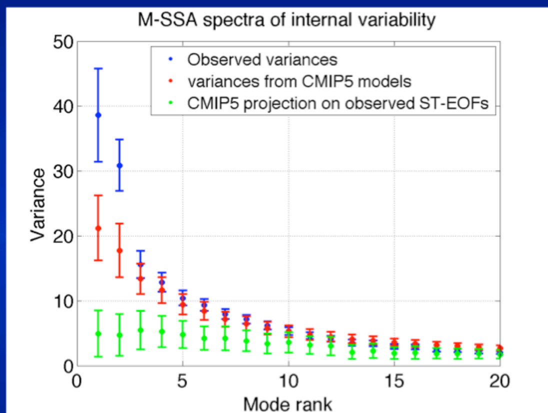


Even inflated internal variability in CMIP5 simulations is significantly smaller than observed estimates!

Same story for NAO and ALPI

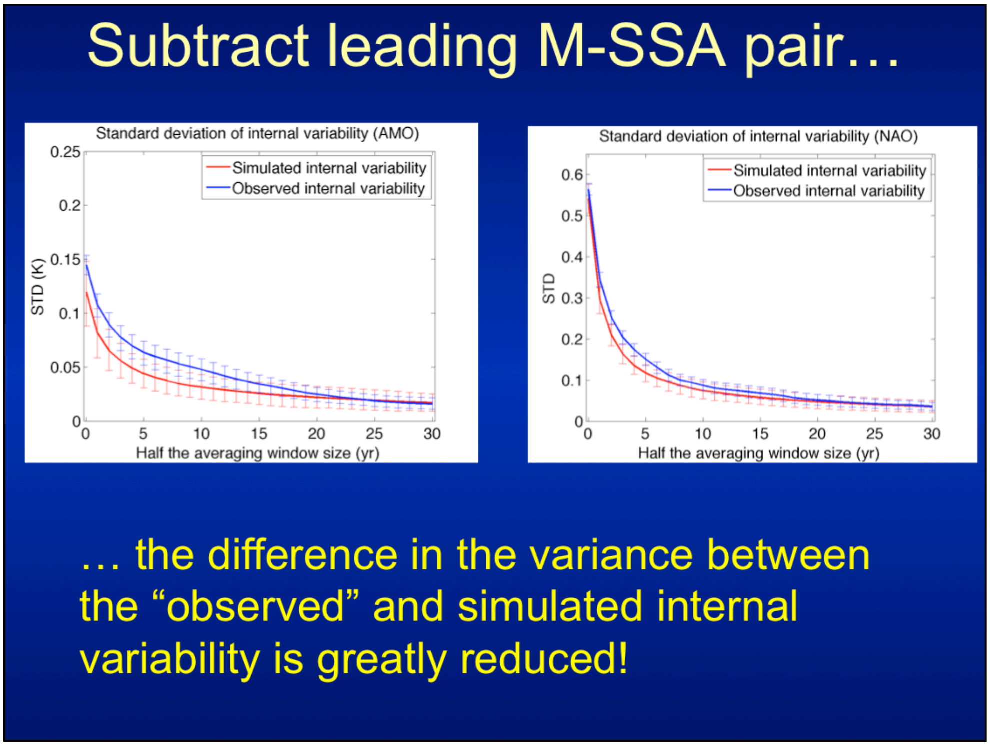


M-SSA of internal variability network (AMO, PMO, NMO, NAO, ALPI)



- 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

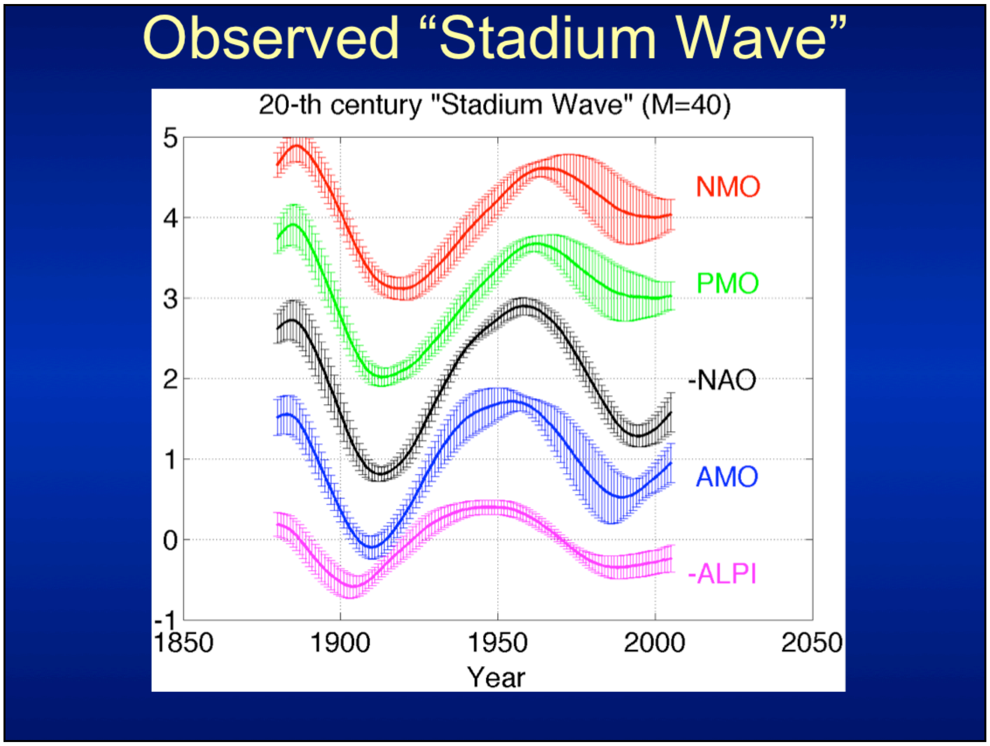
Blue – observed, red – simulated, green – variance of projections of the simulated trajectory matrices onto observed T-EOFs. Dominant leading pair in observation, with the variance much larger than that of the dominant pair in models. Model's projections onto observed T-EOFs are tiny: different spatiotemporal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



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

- 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

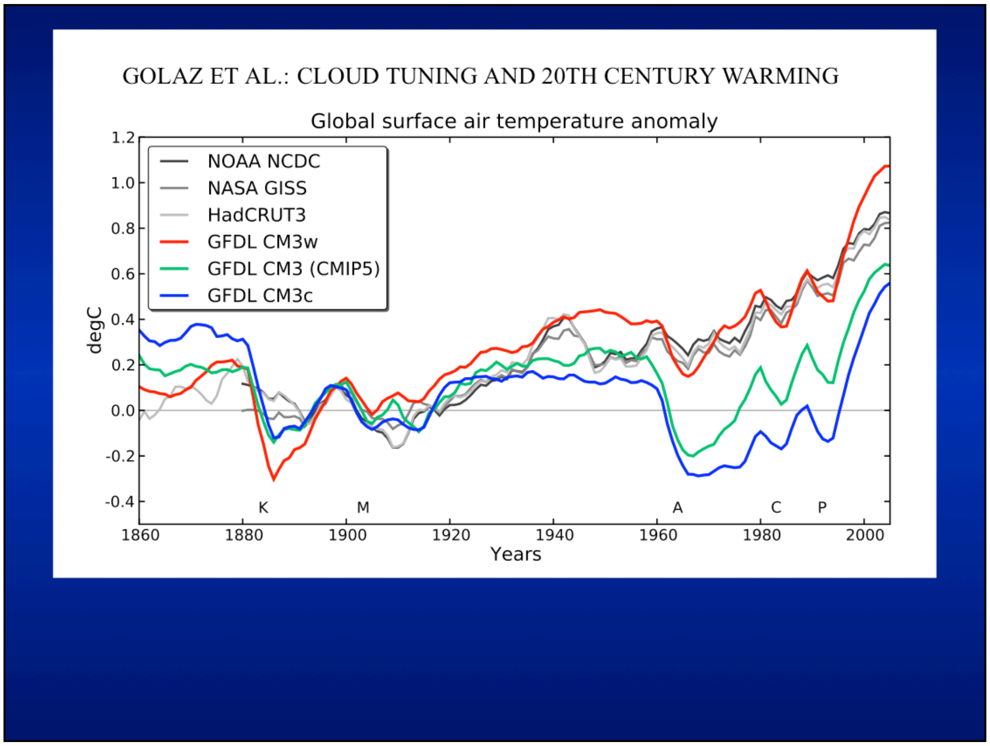


Here is how this observed mode of variability — absent from the models — looks like.

For further info:

- Kravtsov, S., 2017: Pronounced differences between observed and CMIP5 simulated multidecadal climate variability in the twentieth century. *Geophys. Res. Lett.*, DOI: 10.1002/2017GL074016.
- Kravtsov, S., and D. Callicutt, 2017: On semi-empirical decomposition of multidecadal climate variability into forced and internally generated components. *International J. Climatol.,* DOI: 10.1002/joc.5096.

Back-up slides



GOLAZ ET AL.: CLOUD TUNING AND 20TH CENTURY WARMING
Global surface air temperature anomaly
NOAA NCDC
NASA GISS
HadCRUT3
GFDL CM3w
GFDL CM3 (CMIP5)
GFDL CM3c
degC
1.2
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
K
M
A
C
P
1860
1880
1900
1920
1940
1960
1980
2000
Years

Causes of GW hiatus

- Steinman et al.: “internal” AMO flat, PMO drops strongly, NMO in between, hence PMO drives the NMO’s internal downswing, which counteracts forced warming
- Our results: the NMO’s “internal” drop is steeper than PMO’s, hence NMO decrease cannot be solely due to PMO decrease, and hemispheric-scale dynamics must be in play to cause the hiatus

Caveat: it all depends on rescaling!

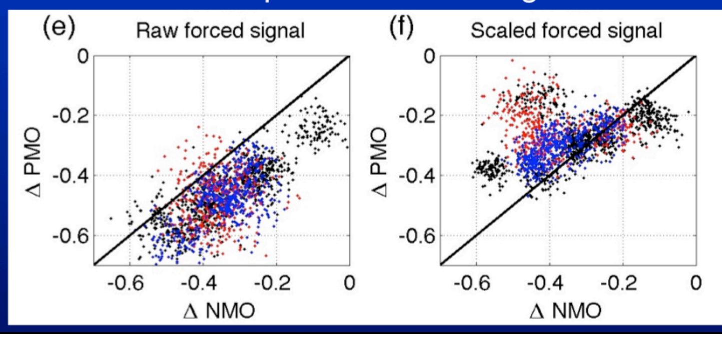
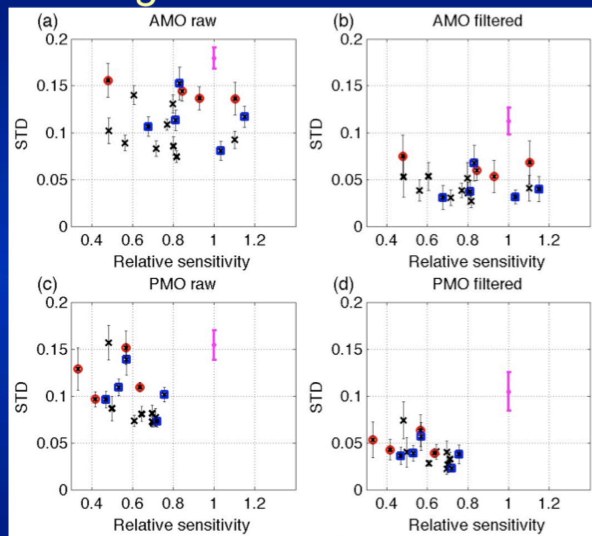


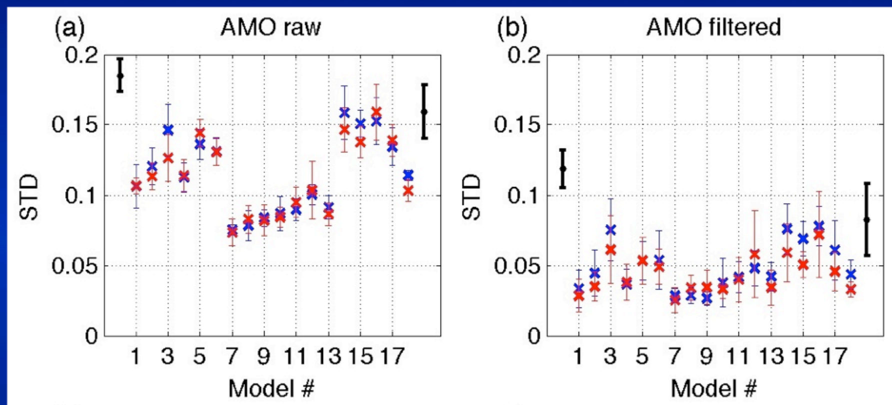
Fig.: In the models, Pacific warms faster than NH; if we rescale to match observations, NMO drop doesn’t change much, but PMO forced warming gets scaled down a lot, leading to the I”nternal” NMO drop being larger than PMO drop.

Any connection btw model climate sensitivity and magnitude of internal variability?



… Doesn't look like it: forced response processes and feedbacks seem to be different from those for internal variability

Any evidence of suppression of internal variability in the second half of the century?



Nope! There is no evidence of forced suppression of internal variability in models.

- Both of these properties justify our treatment of forced signal and internal variability as being independent of each other