1	Two contrasting views of multidecadal climate variability in the 20 <sup>th</sup> century
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3	
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6	
7	Key points:
8	• An objective filtering method identifies a global mode of climate variability
9	• Space-time structure of climate in historic simulations reflects forced signal
10	• Modeled multidecadal climate variations are too weak, especially in atmosphere
11	

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**Abstract:** The bulk of our knowledge about causes of 20<sup>th</sup> century climate change comes 2 3 from simulations using numerical models. In particular, these models seemingly 4 reproduce the observed nonuniform global warming, with periods of faster warming in 5 1910–1940 and 1970–2000, and a pause in between. However, closer inspection reveals 6 some differences between the observations and model simulations. Here we show that 7 observed multidecadal variations of surface climate exhibited a coherent global-scale 8 signal characterized by a pair of patterns, one of which evolved in sync with multidecadal 9 swings of the global temperature, and the other in quadrature with them. In contrast, 10 model simulations are dominated by the stationary — single pattern — forced signal 11 somewhat reminiscent of the observed "in-sync" pattern most pronounced in the Pacific. 12 While simulating well the amplitude of the largest-scale — Pacific and hemispheric — 13 multidecadal variability in surface temperature, the model underestimates variability in 14 the North Atlantic and atmospheric indices.

15 **1. Introduction** 

Multidecadal variations in the rate of global warming over the course of 20<sup>th</sup> century 16 17 may reflect a combination of nonlinear changes in external forcing [Nagashima et al., 2006; Meehl et al., 2007; Booth et al., 2012; Evan, 2012] with a global expression of 18 19 intrinsic climate variability superimposed on forced warming trends [Folland et al., 1984; 20 Ghil and Vautard, 1991; Schlesinger and Ramankutti, 1994; Delworth and Mann, 2000]. 21 Relative contributions from the forced and intrinsic components are still being debated. 22 In particular, evidence from climate models implies a limited role for intrinsic variability 23 [Knight et al., 2005; Delworth et al., 2007; Booth et al., 2012; Evan, 2012]. On the other hand, observational studies indicate a more ubiquitous hemispheric signature of
 multidecadal climate variations, implying a more complex climate evolution [*Minobe*,
 1997, 1999; *Enfield et al.*, 2001; *Wyatt et al.*, 2012].

4 Coupled models do produce synthetic climates that exhibit intrinsic (unforced) 5 multidecadal variability in the North Atlantic region. However, the hemispheric and 6 global expressions of this variability were generally too weak to rationalize the observed 7 nonuniformity of the global warming rate [Knight et al., 2005; Delworth et al., 2007]. A 8 natural conclusion was that other factors must have contributed to the 20-30-yr-long mid-9 century pause in global warming, with the most likely candidate being a forced climate 10 cooling by the tropospheric aerosols [Nagashima et al., 2006]. Some recent studies suggested that aerosol forcing dominates multidecadal climate signal in the 20<sup>th</sup> century 11 12 not only globally, but also regionally over the North Atlantic Ocean [Booth et al., 2012; 13 *Evan*, 2012], while others emphasized large uncertainties associated with both natural 14 and anthropogenic aerosol forcing on climate [Carslaw et al., 2012; Stevens, 2013].

15 Following Tsonis et al. [2007], Wyatt et al. [2012] considered a network of climate 16 indices associated, geographically and dynamically, with different climatic subsystems, 17 and used an objective filtering method to isolate secular multidecadal variability within this network during the 20<sup>th</sup> century. On top of a uniform linear trend, they identified an 18 19 oscillatory-looking wiggle with a common multidecadal time scale, but with different 20 phases across the different indices of the climate network, thus manifesting a signal that 21 propagates in the space of climate indices. The authors termed this propagating signal the 22 "stadium wave," reflecting a speculation that it dynamically originates in the North 23 Atlantic and spreads over the remainder of the Northern Hemisphere via a hypothesized sequence of delayed dynamical feedbacks. However, search for the stadium wave in a
 suite of simulations by multiple global climate models only returned stationary, in-phase
 signals [*Wyatt and Peters*, 2012], in sharp contrast with the observational analysis of
 *Wyatt et al.* [2012].

5 There are two possible explanations for this documented inconsistency between 6 climate model simulations and observations. The first one is that the propagation detected 7 by Wyatt et al. [2012] is an artifact of their statistical analysis and the lagged phasing of 8 various climate indices is entirely due to sampling [Mann et al., 2014]. An alternative 9 explanation is that a coherent propagating multidecadal climate signal in the Northern 10 Hemisphere is real, in which case one needs to look further into the inability of climate 11 models to simulate this signal. The goals of this letter are to: (i) establish robustness of the observed 20<sup>th</sup>-century stadium-wave signal and refute the Mann et al. (2014) 12 13 conjecture; and (ii) document and analyze the differences between the observed secular 14 climate variability and the one simulated by a state-of-the-art climate model.

15

- 16 **2.** Data and methods
- 17 **2.1 Data sources**

We analyzed two-dimensional global monthly sea-surface temperature (SST) and sea-level pressure (SLP) time series based on the Extended Reconstructed Sea-Surface Temperature (ERSST.v3b) data set [*Smith et al.*, 2008] and the 20<sup>th</sup> century reanalysis (NCEP-20) data set [*Compo et al.*, 2011]. In addition, we considered five available historical 20<sup>th</sup> century simulations by Geophysical Fluid Dynamics Laboratory Coupled Physical Model, CM3 [*Donner et al.*, 2011], hereafter GFDL CM3. For each of these
 data sets, we computed their associated climate index networks. We also used an original
 network of climate indices from *Wyatt et al.* [2012], which is based on alternative data
 sources (see Table 1).

5

6

2.2 Methodology

Following *Wyatt et al.* [2012], we defined the 20<sup>th</sup>-century secular climate variability 7 8 in the climate-index networks considered as the sum of a linear trend and a dominant 9 multidecadal signal. This signal was objectively identified via multi-channel version of 10 the Singular Spectrum Analysis [SSA: Broomhead and King, 1986; Elsner and Tsonis, 1996] called M-SSA [Moron et al., 1998; Ghil et al., 2002]. M-SSA is an extended 11 variant of a widely used Empirical Orthogonal Function (EOF) analysis technique 12 13 [Monahan et al., 2009], which looks for the space-time patterns that maximize lagged 14 covariance for a given multivariate time series within a range of M lags. The original raw 15 time series can be fully recovered as the sum, over all modes, of the so-called 16 reconstructed components (RCs) associated with each M-SSA mode. The secular 17 multidecadal signal for the time series considered here is well represented by the sum of 18 two leading RCs, which we will hereafter refer to as the stadium-wave signal. While the 19 secular variability has, by definition, timescales exceeding the M-SSA window M, the M-20 SSA can identify time delays of up to *M* time units between different indices (channels) 21 comprising the climate network. In the analysis below, we used annual data and M=30.

Note that our method for decomposing the climate variability into linear trend, multidecadal stadium-wave signal and the residual components is purely statistical and cannot be used for signal attribution. It is likely, however, that the trend is forced and the residual variability — which is predominantly interannual — is intrinsic, while the stadium wave may be a combination of the intrinsic and forced signals.

6

7 **3. Results** 

#### 8

## 3.1 Observed multidecadal climate variability in the 20<sup>th</sup> century

9 The stadium wave (Fig. 1, left panel) for the set of annual indices in Table 1 10 exhibits a common multidecadal signal, with widespread phase shifts between the 11 individual-index RCs defining a striking propagation across the space of climate indices 12 emphasized by Wyatt et al. [2012]. Mann et al. [2014] correctly pointed out that the 13 phases of the stadium-wave components are subject to uncertainty. We devised the 14 following Monte-Carlo procedure to estimate this uncertainty. This procedure is 15 analogous in spirit to the one used by Mann et al. (2014) to demonstrate artificial 16 propagation in a synthetic climate network, but does not require the *a priori* knowledge 17 of the forced signal. Upon computing the decomposition of our climate-index network 18 into the linear trend, multidecadal secular signal and the residual time series, we 19 produced surrogate realizations of the residual using a linear stochastic model constructed 20 to statistically reproduce the observed residual's lag-0 and lag-1 covariance structure. 21 Adding the surrogate residual time series to the actual linear trend and stadium-wave 22 signal resulted in surrogate versions of the original climate network. These surrogate

1 networks were then subjected to the same decomposition procedure as the original 2 network: that is, subtraction of a new linear trend, and identification of a new leading M-3 SSA based stadium-wave signal, which can indeed be phase shifted with respect to the 4 original signal due to sampling variations (see Fig. 1, right panel). However, repeating 5 surrogate stadium wave identification 1000 times to compute phase uncertainties 6 demonstrated that these variations are insufficient to explain the observed phase spread 7 among individual stadium-wave components (Table 2), thus suggesting that the observed 8 stadium-wave propagation is real. Our procedure thus presents evidence to refute the 9 Mann et al. (2014) conjecture about artificial propagation of the observed stadium wave. 10 The same results were obtained for the climate index network based on an alternative 11 ERSST/NCEP-20 data set (see Supporting Information).

12

# 3.2 Multidecadal climate variability in the GFDL CM3 model's 20<sup>th</sup> century runs

15 Unlike the observed stadium wave, the stadium waves identified in the *individual* GFDL CM3 20<sup>th</sup> century simulations exhibit a common shape which is characterized by 16 17 in-phase signal dominated by the SST-based indices (see Supporting Information). The 18 ensemble-mean over these five individual "stadium waves" is shown in the left panel of Fig. 2. The common shape and phasing of these individual "stadium waves" across 19 different realizations of the GFDL CM3 simulated 20<sup>th</sup> century climate indicates that this 20 21 signal describes the forced climate response. This forced signal in fact dominates the *total* 22 multidecadal variability in the GFDL model, while the residual intrinsic variability in the individual GFDL runs has interannual-to-decadal timescales (not shown). The in-phase,
stationary character of the forced stadium wave in the GFDL model means that it can be
well described by a single time series, which we objectively computed as the leading
EOF of the set of stadium-wave reconstructions for each individual GFDL run. Indeed,
such EOFs account for a major fraction of the reconstructed variance in each run, and
well approximate the shape of the forced signal (Fig. 2, right panel).

7

#### 3.3 Patterns, magnitudes and time scales of hemispheric teleconnections

8 The results of the above analysis show that the observed and simulated 9 multidecadal climate variations are fundamentally different: the observations involve 10 contributions from at least two spatial patterns to rationalize the stadium-wave 11 propagation, while the model simulations can be well described by the stationary stadium 12 wave characterized by a single pattern. We defined these patterns by regressing the 13 observed and simulated SST fields onto the normalized sine and cosine predictors, with 14 the period of 75 yr and the zero phase at year 1920. The sine predictor is thus aligned 15 with the multidecadal undulations of the global temperature time series, in particular, 16 with its downswing between 1940 and 1970. It also roughly corresponds to the shape of 17 the GFDL CM3's "stadium wave" (Fig. 2). While the GFDL CM3 based linear trend and 18 sine patterns are reasonably consistent with their observational analogues, the cosine 19 pattern, which is quite pronounced in observations, is essentially absent from model 20 simulations (Fig. 3), indeed in line with our earlier stadium-wave diagnosis (see 21 Supporting Information for SLP analysis and animations of the observed and simulated 22 multidecadal variability).

1 Note that the simulated patterns shown in Fig. 3 are based on the ensemble averages of the GFDL CM3 20<sup>th</sup> century runs. This is justified by the fact that the 2 simulated secular forced signal (trend + multidecadal stadium wave) - which is 3 4 essentially the same in all of the individual GFDL runs — completely dominates the 5 secular variability in these runs, whereas the residual intrinsic variability in all model 6 simulations has interannual-to-decadal time scales at most (not shown). Thus, the 7 intrinsic multidecadal variability doesn't contribute much to the GFDL CM3's dominant 8 stadium wave (see Fig. 2).

9 Furthermore, comparing the spectra of the observed and simulated climate-10 network indices (Fig. 4) shows that the total variance levels of the secular climate 11 variability in observations and models are also very different for some of the indices 12 considered. We must note first that the GFDL model does a very good job in reproducing 13 observed variances of the indices representing secular climate signal on the largest spatial 14 scale, namely, the PDO and NHT indices and, by this measure, provides a skillful 15 simulation of the observed large-scale climate variability. This suggests that the 16 combination of forced and intrinsic decadal variability of Pacific SSTs dominates the 17 NHT's decadal variability, consistent with the results of Kosaka and Xie [2013]. However, while the variances of all raw climate indices are comparable between the 18 19 observed and GFDL CM3 based climate networks, the simulated atmospheric indices, as 20 well as the SST indices representing the relatively smaller but important Atlantic sector, 21 namely the AMO and DP indices, have variances in the decadal-to-multidecadal range 22 that are strikingly smaller than the observed variances by up to an order of magnitude. In 23 summary, the bulk of the evidence suggests that the GFDL CM3's simulated leading

1 multidecadal variations in the 20<sup>th</sup> century are due to the forced signal dominated by the
2 Pacific sector and synchronized with the Northern Hemisphere's temperatures, while the
3 multidecadal variance in the Atlantic SSTs and the atmosphere is much weaker than the
4 observed variance.

- 5
- 6

#### 4. Summary and discussion

7 Our analysis demonstrates that, within the constraints imposed by a limited 8 observational record, the spatiotemporal structure of multidecadal variability in the GFDL CM3 model exhibits noticeable differences from the observed 20<sup>th</sup>-century climate. 9 10 In particular, while capturing the secular signal in the Pacific and hemispherically 11 averaged surface temperatures very well, the simulated climate fails to exhibit 12 multidecadal atmospheric (SLP) variations comparable in magnitude with the observed 13 SLP variations; the simulated multidecadal SST variability in the Atlantic sector is also 14 underestimated. Furthermore, the model is missing the lagged spatial coherence between 15 different regional climatic fields characteristic of the observed multidecadal climate 16 variability. Consequently, irrespective of the cause of the observed variability — natural, 17 forced or combined — there could be some physical processes, probably operating in the 18 Atlantic sector of the climate system, that are not well represented in the GFDL model. 19 Possible candidates include lack of atmospheric sensitivity to ocean induced SST 20 anomalies [Kushnir et al., 2002], inaccurate parameterization of the mesoscale ocean 21 eddies [Kravtsov et al., 2011], or distortion of sea-ice effects on the high-latitude air-sea

interaction [*Wyatt and Curry*, 2014]. Examining these issues is a worthwhile subject for
 future studies.

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13	

## 2 Table captions

4	Table 1: Climate index definitions and abbreviations. The same indices were used by
5	Wyatt et al. [2012] except for the DP index based here on the ERSST data. The
6	acronyms SST and SLP stand for "sea-surface temperature" and "sea-level
7	pressure," respectively.
8	Table 2: Stadium-wave phase uncertainties for the climate index set defined in Table 1
9	(see also Fig. 1, left panel). The stadium wave cycle length for this data set is
10	68±4.3 yr, with the 98% uncertainty range of 64–81 yr. The phase of each index
11	here was defined as the location of the first maximum of its stadium-wave
12	reconstruction. All uncertainties were computed using the Monte-Carlo procedure
13	outlined in text. Comment: The spread of the phases among different indices
14	(irrespective of the sign) is larger than the phase uncertainty, thus suggesting real
15	stadium-wave propagation in the phase space of climate indices.
16	

## **Figure captions**

4	Figure 1: The observed stadium wave defined as the sum of two leading M-SSA modes
5	for the 7-member set of annual climatic indices (see Table 1). Left panel:
6	normalized stadium-wave reconstructions of each index. Right panel: actual
7	(blue) and synthetic (red) time series for the AMO index; light lines show raw
8	time series, while heavy lines — the sum of linear trend and the leading M-SSA
9	pair reconstruction. See text for details on the generation of synthetic time series.
10	We removed linear trends from each index and normalized each residual time
11	series by its standard deviation prior to applying M-SSA with window size $M=30$
12	yr. <u>Comments</u> : (i) The M-SSA filtered indices share a common timescale, but
13	exhibit a range of phases, which defines the stadium wave "propagation." (ii) The
14	phases of the stadium wave are subject to uncertainty.
15	Figure 2: The "stadium wave" in the 20 <sup>th</sup> century simulations of the GFDL CM3 model;
16	we looked at the same climate-index subspace as in Fig. 1 except for the AT index,
17	which was not included. Left panel: ensemble-mean of stadium-wave
18	reconstructions for each index over 5 available GFDL simulations. Right panel:
19	the leading principal component (PC) of the M-SSA stadium-wave reconstruction
20	for individual runs (see legend, which also shows the percentage of the
21	reconstructed variance accounted for by this leading PC). We removed linear
22	trends from each index and normalized each residual time series by its standard
23	deviation prior to applying M-SSA with window size <i>M</i> =30 yr. <u>Comments</u> : (i)
24	The M-SSA filtered indices share a common in-phase signal for all runs,

suggesting it to represent a forced climate response. (ii) The phases of this forced
 signal vary slightly from simulation to simulation, reflecting uncertainties of our
 identification procedure.

4 Figure 3: Regression (map units: °C) of the observed (ERSST: left) and simulated (ensemble average of the five GFDL's 20<sup>th</sup> century runs: right) SST time series 5 6 (1900–1999) onto linear trend (top), as well as onto 75-yr-periodic sine (middle) 7 and cosine (bottom) predictors; zero phase for these harmonic predictors was 8 chosen to correspond to year 1920. All three predictors were normalized to unit variance, with the resulting ranges over the 20<sup>th</sup> century of 3.4 units for the trend 9 10 and 2.9 units for the sine and cosine predictors. We smoothed each SST time 11 series by the 20-yr boxcar running-mean filter prior to computing regressions. 12 Comment: Multidecadal climate variability in GFDL CM3 is characterized by a 13 reasonable trend, underestimated sine pattern in the Atlantic and essentially non-14 existent cosine pattern.

Figure 4: Spectra of the observed and GFDL simulated climate indices. The spectra are 15 16 defined here as the variance of the boxcar-running-mean averaged time series for 17 different window sizes. The abscissa on all plots shows half the window size in units of years, with 0 corresponding to no averaging (raw annual data), 1 --- to 3-18 yr boxcar averages, 2 — to 5-yr boxcar averages and so on. The blue line shows 19 the observed spectra based on the ERSST/20<sup>th</sup>-century reanalysis indices, and the 20 21 red dashed lines show the range of spectral estimates over those for 5 individual 20<sup>th</sup> century runs. Index names are listed in the caption of each panel. <u>Comments</u>: 22 23 (i) *The GFDL CM3 model matches well the observed variance of raw (unfiltered)* 

1	data for all indices, and that throughout the whole spectral range for the NHT
2	and PDO indices. (ii) However, the GFDL-based variance of low-frequency
3	(multidecadal) behavior for other indices (DP, AMO, NAO, and ALPI) is smaller
4	than the observed variance by a factor of $5-10$ .

#### **Table 1:** Climate index definitions and abbreviations<sup>\*</sup>

Index/Acronym	Reference/source	Description
Atlantic Dipole/DP	ERSST data set Smith et al. [2008]	Difference in SST area averages between the (60°– 10°W, 40°–60°N) and (50°– 0°W, 60°–40°S)
NH surface temperature/NHT	HadCRUT3 data set <i>Brohan et al.</i> [2006]	Average land-surface temperatures and SSTs of Northern Hemisphere
Atlantic Multidecadal Oscillation/AMO	<i>Kaplan et al</i> . [1998] SST data set	North Atlantic SST averaged across 0–60°N, 75–7.5°W
Atmospheric Mass Transfer/AT	[Vangenheim, 1940; Girs, 1971]	Prevailing air transfer direction 30°–80°N; 45– 75°E
North Atlantic Oscillation/NAO	Hurrell [1995]	Normalized SLP difference between Azores and Iceland, wintertime values (DJFM) were used
Pacific Decadal Oscillation/PDO	[Mantua et al., 1997; Minobe, 1997, 1999]	Leading principal component of monthly SST north of 20°N in the North Pacific, with century-scale globally averaged SST signal removed
Aleutian Low Pressure/ALPI	Beamish et al. [1997]	Mean area of the North Pacific region with monthly SLP < 1005 mb during winter (DJFM)

\*The same indices were used by *Wyatt et al.* [2012] except for the DP index based here on the ERSST data. The acronyms SST and SLP stand for "sea-surface temperature" and 

"sea-level pressure," respectively. 

1

Index	–DP	-NHT	-AMO	AT	NAO	PDO	ALPI
name							
Phase/	1908±2.9	1907±3	1912±2.7	1919±3.2	1921±6.5	1929±3.3	1932±5
STD							
Phase	1903 –	1901 -	1907 –	1914 –	1911 –	1924 –	1924 –
90%	1913	1911	1915	1924	1932	1934	1940
range							

2 **Table 2:** Stadium-wave phase uncertainties for the climate index set defined in Table 1<sup>\*</sup>

4 <sup>\*</sup>(See also Fig. 1, left panel.) The stadium wave cycle length for this data set is 68±4.3 yr,

5 with the 98% uncertainty range of 64–81 yr. The phase of each index here was defined as

6 the location of the first maximum of its stadium-wave reconstruction. All uncertainties

7 were computed using the Monte-Carlo procedure outlined in text. Comment: *The spread* 

8 of the phases among different indices (irrespective of the sign) is larger than the phase

9 uncertainty, thus suggesting real stadium-wave propagation in the phase space of climate

10 *indices*.





2 Figure 1: The observed stadium wave defined as the sum of two leading M-SSA modes 3 for the 7-member set of annual climatic indices (see Table 1). Left panel: 4 normalized stadium-wave reconstructions of each index. Right panel: actual 5 (blue) and synthetic (red) time series for the AMO index; light lines show raw time series, while heavy lines — the sum of linear trend and the leading M-SSA 6 7 pair reconstruction. See text for details on the generation of synthetic time series. 8 We removed linear trends from each index and normalized each residual time 9 series by its standard deviation prior to applying M-SSA with window size M=3010 yr. Comments: (i) The M-SSA filtered indices share a common timescale, but 11 exhibit a range of phases, which defines the stadium wave "propagation." (ii) The 12 phases of the stadium wave are subject to uncertainty.



**Figure 2:** The "stadium wave" in the 20<sup>th</sup> century simulations of the GFDL CM3 model; 2 3 we looked at the same climate-index subspace as in Fig. 1 except for the AT index, 4 which was not included. Left panel: ensemble-mean of stadium-wave 5 reconstructions for each index over 5 available GFDL simulations. Right panel: 6 the leading principal component (PC) of the M-SSA stadium-wave reconstruction 7 for individual runs (see legend, which also shows the percentage of the 8 reconstructed variance accounted for by this leading PC). We removed linear 9 trends from each index and normalized each residual time series by its standard 10 deviation prior to applying M-SSA with window size M=30 yr. Comments: (i) 11 *The M-SSA filtered indices share a common in-phase signal for all runs.* 12 suggesting it to represent a forced climate response. (ii) The phases of this forced 13 signal vary slightly from simulation to simulation, reflecting uncertainties of our 14 identification procedure.



Figure 3: Regression (map units: °C) of the observed (ERSST: left) and simulated 1 (ensemble average of the five GFDL's 20<sup>th</sup> century runs: right) SST time series 2 3 (1900–1999) onto linear trend (top), as well as onto 75-yr-periodic sine (middle) 4 and cosine (bottom) predictors; zero phase for these harmonic predictors was chosen to correspond to year 1920. All three predictors were normalized to unit 5 variance, with the resulting ranges over the 20<sup>th</sup> century of 3.4 units for the trend 6 and 2.9 units for the sine and cosine predictors. We smoothed each SST time 7 8 series by the 20-yr boxcar running-mean filter prior to computing regressions. 9 Comment: Multidecadal climate variability in GFDL CM3 is characterized by a 10 reasonable trend, underestimated sine pattern in the Atlantic and essentially non-11 existent cosine pattern.



2 Figure 4: Spectra of the observed and GFDL simulated climate indices. The spectra are 3 defined here as the variance of the boxcar-running-mean averaged time series for 4 different window sizes. The abscissa on all plots shows half the window size in 5 units of years, with 0 corresponding to no averaging (raw annual data), 1 — to 3yr boxcar averages, 2 — to 5-yr boxcar averages and so on. The blue line shows 6 the observed spectra based on the ERSST/20<sup>th</sup>-century reanalysis indices, and the 7 8 red dashed lines show the range of spectral estimates over those for 5 individual 9 20<sup>th</sup> century runs. Index names are listed in the caption of each panel. Comments: (i) The GFDL CM3 model matches well the observed variance of raw (unfiltered) 10 11 data for all indices, and that throughout the whole spectral range for the NHT 12 and PDO indices. (ii) However, the GFDL-based variance of low-frequency 13 (multidecadal) behavior for other indices (DP, AMO, NAO, and ALPI) is smaller 14 than the observed variance by a factor of 5–10.