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Global-scale multidecadal variability missing in state-of-the-art climate models

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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 attention. Such decadal mismatches between model-simulated and observed climate trends are common throughout the twentieth century, and their causes are still poorly understood. Here we show that the discrepancies between the observed and simulated climate variability on decadal and longer timescale 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 25–35 years. While climate models exhibit various levels of decadal climate variability and some regional similarities to observations, none of the model 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.

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INTRODUCTION

Climate research involves a combination of approaches based on instrumental observations, palaeo-climate records and computer modelling of the climate system. Decadal climate variability (DCV)^{1–4}—which modulates long-term global warming trends—presents a unique set of challenges to scientific community. On the one hand, observational analyses of DCV are hampered by shortness of instrumental climate record and/or general scarcity of climate data before the middle of the twentieth century.⁵ On the other hand, climate system is an inherently multi-scale system, which makes global climate models highly susceptible to errors associated with their necessarily imperfect representation of small-scale processes that could provide essential feedbacks in DCV.^{6–12}

The resulting model uncertainties can be estimated by considering simulations of multiple climate models (with distinct physical parameterisations) conducted in the framework of the Coupled Model Intercomparison Project, Phase 5 (CMIP5).¹³ CMIP5 protocol consists of several types of simulations, including historical simulations of the twentieth-century climate subject to variable natural (solar activity and volcanic activity) and anthropogenic (greenhouse-gas and aerosol emissions) external forcing, as well as long control simulations with constant external forcing fixed at pre-industrial levels. The climate variability simulated in these control runs is referred to as internal climate variability. By contrast, historical simulations’ output is a mixture of internal and forced climate variability. Multiple historical simulations with a single model started from a set of statistically independent initial conditions (usually taken from its pre-industrial control run) provide means to isolate this model’s simulated forced signal (defined here as the system’s response to variable external

forcing) by averaging among all available simulations, since independent realisations of internal variability in different runs tend to cancel in the ensemble mean. Indeed, in contrast to the forced signal, which is common in all model simulations, the internal variability samples in different runs are uncorrelated; hence, the ensemble averaging over increasing number of realisations tends to leave only the response to external forcing. Multi-model ensemble mean of historical simulations arguably constitutes the best available estimate of the forced climate change in observations,¹⁴ with individual-model ensemble means providing a requisite estimate of the model uncertainty.¹⁵ Complementary methods/strategies for isolating forced and internal climate variability in observations rely on utilising additional information from model control runs.^{16–19}

Irrespective of exact methodology used to infer the internal component of the observed DCV, it appears that climate model simulations tend to underestimate its magnitude and fall short of faithfully replicating its spatial patterns.^{15,16,18,20–23} These deficiencies may have substantially contributed to climate models’ apparent lack of skill in reproducing recent decadal slowdown, or “hiatus” in the near-surface global warming of the Earth, although multiple factors could be at play.^{22–27} Similar decadal discrepancies between modelled and observed decadal climate trends are ubiquitous throughout the twentieth century.^{14–20} In this paper, we use an objective filtering method to succinctly characterise such observed-vs.-modelled decadal and longer time scale climate differences over the entirety of the twentieth century and show that these differences are dominated by a pronounced global multidecadal signal with a distinctive spatiotemporal structure absent from any of the model simulations considered.

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Fig. 1 Analysis of CESM LENS simulations. **a** Ensemble-mean global warming pattern ($^{\circ}\text{C}$) obtained by regressing the secular SAT signals onto centred and normalised time series of their Northern Hemisphere mean [black line in **b**]. **b** Normalised time series of the Northern Hemisphere mean SAT. Individual simulations, thin grey curves; ensemble mean, red curve; ensemble mean of secular signals, solid black curve; standard uncertainty of the secular signals (over 40 estimates), dashed black curves. **c**, **d** Spatial pattern ($^{\circ}\text{C}$) and normalised time series of the leading mode of the difference between the estimated secular SAT signal and the CESM's ensemble-mean SAT ('true' forced signal)

Optimal data-adaptive space–time filters developed here are designed to isolate secular, low-frequency variability (long-term trends and multidecadal fluctuations; hereafter, secular signals) in spatially extended surface atmospheric temperature (SAT) time series by discriminating against stationary noise. This was achieved by using a combination of Multichannel Singular Spectrum Analysis (M-SSA)^{28,29} and classical optimal (Wiener) filtering, with noise contributions to the M-SSA spectrum estimated via linear inverse modelling (Supplementary Section 1; Supplementary Fig. 1). Our new filtering methodology permits a more robust identification of non-stationary climate trends in short observational records, due to its making use of intrinsic space–time dependencies within the secular signal distinct from those characterising internal climate fluctuations. However, we note here—and will further demonstrate below—that our main results with regards to the differences between observations and climate model simulations are insensitive to the filter details and can be qualitatively replicated using traditional, and more straightforward, non-data-adaptive low-pass filtering methods, such as simple running-mean boxcar averaging.

RESULTS

Forced vs. internal secular variability in climate models

We first applied our filtering methodology to SAT from 40 historical simulations within the Community Earth System Model (CESM) Large Ensemble Project (LENS)³⁰; these simulations reflect a common forced signal summed with independent realisations of internal climate variability. The intention behind and utility of the LENS ensemble is in its relatively large number of independent historical climate realisations, which allows one to accurately identify forced and internal components of climate variability in the individual-model simulations. We thus compared the resulting secular signals from each of the 40 simulations with the CESM's

'true' forced signal defined via ensemble averaging of SAT over all simulations, at each grid point.

Figure 1b illustrates the results for the Northern Hemisphere mean SAT, and shows the ensemble-mean secular signal, as well as its standard deviation (standard uncertainty and standard spread) computed over the 40 estimates of the secular signal based on different CESM LENS realisations. It also shows the true forced response in the Northern Hemisphere SAT, which consists of non-uniform long-term warming trend punctuated with episodic interannual cooling events associated with volcanic eruptions. The secular signal in each simulation closely resembles the former, low-frequency component of the true forced response of the CESM model (as documented by a narrow standard spread of the secular SAT signal in Fig. 1b) and exhibits a pattern of polar-intensified global warming (Fig. 1a). The secular climate signal in LENS simulations is, therefore, predominantly forced, whereas their multidecadal internal variability is relatively small (with standard deviation of internal multidecadal SAT variability close to the standard spread of the secular SAT signal in Fig. 1b), consistent with a recent study.³¹

While successfully isolating forced multidecadal climate trends in CESM LENS, our filtering procedure fails to capture episodic interannual cooling events resulting from volcanic eruptions (Fig. 1b), which dominate the differences between the true forced signal and our M-SSA signal reconstruction (Fig. 1c, d). This is due to the fact that spatial patterns and time development of the simulated climate response to volcanic forcing in CESM model turn out to be similar to those of the CESM's stationary high-frequency internal variability, which results in the low signal-to-noise ratio and the resulting inability of the Wiener filter to differentiate between the two. Note, however, that this deficiency is immaterial to our purposes, since we focus here on climatic timescales much longer than those associated with climate response to volcanic eruptions.

Analogous results were obtained for the sub-ensemble of 17 CMIP5 models with four or more historical realisations (and the total of 111 simulations) (Supplementary Table 1). Although the number of realisations in these models is much smaller than in the CESM LENS ensemble, it is still sufficient to evaluate contributions from forced signal and internal climate fluctuations to these models' secular variability.^{15,20} Here again, the M-SSA reconstructed secular signals in individual simulations of each model are generally close to this model's ensemble mean, with the differences between them being dominated by the short-term response to volcanic events (Supplementary Fig. 2c, d). The spread of the estimated secular signals across the entire multi-model CMIP5 ensemble considered (Supplementary Fig. 2b) is larger than that in the CESM LENS simulations (Fig. 1b). This is primarily due to model uncertainty, that is, due to the differences between the forced responses of individual models. Indeed, the spread of secular signals among different simulations of a given model (not shown) is small and consistent in magnitude, for most models, with the spread of secular signals among different CESM LENS simulations in Fig. 1b. Furthermore, the standard spread among the ensemble-mean secular signals of different models (not

shown) is close to the standard spread over the entirety of estimated secular signals shown in supplementary Fig. 2b, implying that the model uncertainty does dominate the latter spread.

Note that deviations of secular signal in an individual simulation of a given model from this model's ensemble-mean secular signal represent an estimate of the internal secular variability in this simulation. The main result of this section is, therefore, that the secular signals in individual simulations of climate models are dominated by a non-uniform forced climate trend, whereas multidecadal internal climate anomalies relative to this trend are much smaller.

Observed secular variability and estimation of its internal component

Finally, we analysed SAT time series from the twentieth century reanalysis (20CR) project,³² which provides gapless, in space and time, objective reconstruction of atmospheric fields by assimilating surface pressure observations into a state-of-the-art global atmospheric model forced, in part, by the observed sea-surface temperature and sea-ice distributions. There currently exist two

Fig. 2 Observed and CMIP5-simulated secular variability in select climate indices. **a** Atlantic Multidecadal Oscillation (AMO) index [mean Atlantic SST 0–60°N]. **b** Pacific Multidecadal Oscillation (PMO) index [mean Pacific SST 0–60°N]. **c** Northern Hemisphere Multidecadal Oscillation (NMO) index [Northern Hemisphere mean SAT]. **d** Global Multidecadal Oscillation (GMO) index [global-mean SAT]. Raw data based on 20CRv2, thin red curves; M-SSA estimated secular signal based on 20CRv2: ensemble mean, heavy black curve; standard uncertainty (over 56 estimates), dashed black curves; CMIP5 secular signals: ensemble mean, heavy blue curves; standard uncertainty (over 111 estimates), dashed blue curves

versions of the 20CR reanalysis: 20CRv2 and 20CRv2c, which differ, among other things, by their sea-surface temperature and sea-ice boundary conditions. Each reanalysis data set consists of the output from 56 ensemble integrations of the model; the ensemble mean over these simulations represents the best estimate of the evolution of a given climatic variable, while the ensemble spread allows one to estimate the reanalysis uncertainty. We will first analyse the 20CRv2 data set (sections Observed secular variability and estimation of its internal component and Global stadium wave), and present comparisons between the two reanalyses later on in the paper (section Global stadium wave).

The observed ensemble-mean secular signal (Supplementary Fig. 3) has a richer structure compared to model-simulated signals

Fig. 3 M-SSA analysis of observed and model-simulated internal secular variability. **a** M-SSA spectra showing the levels of variability associated with dominant space-time M-SSA patterns underlying the data. Results for differences between the observed and CMIP5-simulated secular signals (observed internal variability): ensemble-mean spectrum and standard uncertainty (over the 111 estimates), black curves and error bars, respectively; analogous results for deviations of individual-model secular signals from each model's ensemble mean (simulated internal variability), blue curves and error bars; 99th percentile of simulated spectra, blue dashed curve; the 99.99th percentile of variances obtained by projecting the simulated internal variability onto the M-SSA patterns of observed internal variability, red curve. **b** Locations of regional SAT indices. **c** Reconstructed time series associated with the leading M-SSA pair of observed-model-simulated data differences (observed internal variability) in select regional indices: NA North Atlantic, NP North Pacific, SWP Southwest Pacific, AA Antarctica, SA South Atlantic, A Arctic; Global Multidecadal Oscillation (GMO) time series represents the reconstruction of the global-mean temperature. All of the time series are normalised to unit standard deviation; the actual standard deviations of A and AA indices are around 0.6 °C; that of all others—0.1 °C

both in terms of being comprised of a larger number of significant M-SSA modes (Supplementary Fig. 1b) and in terms of exhibiting a more pronounced multidecadal variability (Supplementary Fig. 3b); its global warming pattern (Supplementary Fig. 3a) is also more complex than the model-simulated patterns (Fig. 1a, Supplementary Fig. 2a), while the effects of volcanic eruptions are much less pronounced than in the models (Supplementary Fig. 3b), without any indication of dramatic surface temperature cooling episodes apparent in the model-simulated SAT time series (Fig. 1b, Supplementary Fig. 2b); these results are consistent with recent work.³³

Note that the standard uncertainty of the 20CRv2 secular-signal estimates (that is, standard deviation, for each time, of the 56 available estimates of the observed secular signal), given by the spread between black dashed curves in the supplementary Fig. 3b, is small compared to the spread of the secular signals in the CMIP5 model ensemble (Supplementary Fig. 2b). Since each of the 56 versions of the 20CRv2 reanalysis secular signal are very close to the ensemble-mean secular signal, we will use, in section Global stadium wave below, the latter ensemble-mean signal to characterise the differences between the CMIP5-simulated and reanalysis-estimated secular trends.

To compare the observed and model-simulated secular signals, we first rescaled the latter signals (at each grid point throughout the globe) via linear regression to best match the observed signal.^{14,15,20} This procedure is standard and designed to correct for biases in the models' transient climate response; note that it minimises, by construction, the differences between models and observations. These differences, however, still turn out to be large enough to be able to modify and reverse regional, as well as global climate trends on multidecadal timescales of 30–50 years (Fig. 2). Since secular signals based on CMIP5 simulations are dominated by the forced response (section Forced vs. internal secular variability in climate models), their (scaled) subtraction from the observed secular temperature signal represents an estimate of the internal secular variability in the observed climate, with the total of 111 such estimates obtained using different historical CMIP5 simulations considered. We also computed 111 estimates of the internal secular variability in the models by forming the difference between secular signal of each simulation and the ensemble-mean secular signal of the corresponding model.

Fig. 4 The 1921–1963 segment of the global stadium wave. Shown are reconstructed ensemble-mean SAT anomalies (in °C) raised to the power of 1/7, which alleviates differences between SAT anomalies over ocean and over land to better visualise the propagation of anomalies across the globe. Colour axis is from -1.5 (saturated blue) to 1.5 (saturated yellow). Stippling identifies areas of anomalies that are statistically significant at the 5% level (that is, $<5\%$ out of the 111 available GMO estimates exhibit anomalies of the opposite sign in these areas)

Global stadium wave

The M-SSA analysis of each of 111 available observed–model-simulated secular SAT differences (representing, as stated above, 111 estimates of internal secular variability in observations) identifies a pronounced pair of M-SSA modes, which stands out of the rest of the spectrum and is altogether absent from the

model-simulated internal secular variability (Fig. 3a, Supplementary Figs. 4, 5, Supplementary Table 2) (ref.³⁴). The model-simulated spectra (Fig. 3a, blue curve) are characterised by a much smaller variance compared to the observed spectra (black curve), reflecting a weaker internal secular variability around the forced climate trends in models, and, most importantly, by

Fig. 5 M-SSA spectra of observed and model-simulated internal secular variability defined using different filtering methods or different reanalyses. **a** The same as in Fig. 3a (Wiener filtering, 20CRv2). **b** Results based on the 30-year boxcar running-mean filtered data (20CRv2). **c** Results based on the 20CRv2c data and Wiener filtering. **d** Results based on the ERA-20CR reanalysis and Wiener filtering. Same symbols and conventions as in Fig. 3a

completely different space–time patterns associated with the leading M-SSA eigenmodes. This is seen from the fact that the projections of the simulated secular signals onto the space–time patterns of the observed M-SSA modes have negligible variance (red curve in Fig. 3a). Most of the M-SSA spectra based on model simulations are also less peaked, in relative sense, than the observed spectrum and decay monotonically, without statistically significant separation between their leading mode(s) and trailing M-SSA modes. The pairs of M-SSA eigenmodes with similar magnitudes and timescales, as seen in the observed spectra, may indicate the presence of a quasi-oscillatory mode²⁹ in the data; in the context of the secular signals, which have timescales comparable to the length of the data record, the periodicity of such a signal cannot be verified, but the propagation of the anomalies in space in the course of the oscillation can still be established with statistical significance.³⁵ Indeed, the reconstruction of this pair of modes for regional climate indices (Fig. 3b, c) manifests as a multidecadal signal propagating across the climate index network (with certain time delays between different indices)—a so-called stadium wave (refs. ^{20,35–37})—which we will refer to as the global stadium wave (GSW) or, when referring to the global-mean temperature, Global Multidecadal Oscillation (GMO), although, once again, the oscillatory character of this phenomenon is impossible to establish due to shortness of the data record. The phasing of indices in the GSW is consistent with earlier

work (ref. ²⁰), which analysed a limited subset of the Northern Hemisphere climate indices (Supplementary Fig. 6). The global-mean temperature trends associated with GSW are as large as 0.3 °C per 40 years, and so are capable of doubling, nullifying or even reversing the forced global warming trends on that timescale.

The order of indices in the sequence of Fig. 3c (except for the GMO index) is chosen based on the visual analysis of the SAT anomaly propagation over the time period between 1921 and 1963, which roughly spans half of the oscillation period (Fig. 4); see Supplementary Videos 1, 2 for the GSW animation over the entire twentieth century. In year 1921, the oscillation is in its cold phase, with the exception of four major positive SAT anomaly spots: west of Weddell Sea, in the eastern equatorial Pacific, as well as over central United States and Greenland. The GSW development starts with emergence of the positive SAT anomaly in the North Atlantic (1921–1930), which subsequently expands and grows along with SAT anomalies in the North and South-western Pacific (1933–1942), then Southern Ocean and Antarctica (1941–1957) and, finally, over Arctic (1960–1963), at which point the oscillation arrives at its positive (warm) phase throughout the world (less four major negative SAT anomaly regions, roughly at the same locations as their positive analogues 40 years ago). We thus identify the North Atlantic Ocean as the major centre of action that initiates the global GSW sequence (refs. ^{28,36}).

Fig. 6 Reconstructions of the global stadium wave in select regional indices using different reanalyses products. The indices represent reconstructed component (RC) time series associated with the leading M-SSA pair of the observed-minus-simulated secular SAT signals area-averaged over the regions defined in Fig. 3b: NA North Atlantic, NP North Pacific, NWA Northwest Africa, SA South Atlantic, SWP Southwest Pacific, IO Indian Ocean. Ensemble-mean indices, solid curves; standard uncertainty, error bars; both quantities are computed over 111 available estimates of the observational-model data differences. Reconstructions based on the 20CRv2, 20CRv2c and ERA-20CR are shown in blue, red and black, respectively

GSW sensitivity to methodological details

We first repeated the above analyses of observed-modelled data differences using, instead of the M-SSA based Wiener filtering, a more straightforward 30-year running-mean boxcar filter to define

secular signals in both models and 20CRv2 observations. Figure 5b, which is completely analogous to Fig. 3a (or Fig. 5a) (except for using 30-year low-pass filtered input data), demonstrates that our main conclusions—the existence of a pronounced GSW in

observational data and its absence in the CMIP5 model simulations—are robust with respect to the low-pass filtering methodology used. In fact, the leading M-SSA pair of observed internal variability is even more pronounced in the 30-year low-pass filtered data (and accounts for a larger fraction of total variance) (Fig. 5b) compared to the leading M-SSA pair of Wiener-filter-based secular signals (Fig. 3a, Fig. 5a); none of the models are able, once again, to match its magnitude and spatiotemporal structure. Furthermore, the M-SSA reconstruction of the GSW based on the 30-year low-pass filtered secular signals (Supplementary Fig. S7) is nearly identical to the reconstruction shown in Fig. 3c. Hence, while our Wiener filtering methodology applied in M-SSA-based space–time phase space provides an inherently more accurate identification of secular signals and explicitly deals with the issues associated with observational uncertainties in sparsely sampled regions of the globe (by employing space–time covariance-based signal detection), the key differences between observed and model-simulated climates on multidecadal timescales are so pronounced that can be easily detected using traditional time-filtering methods.

Next, we applied our methodology to the two alternative reanalysis data sets spanning the twentieth century: 20CRv2c reanalysis and a more recent ERA-20C reanalysis.^{38,39} The 20CRv2c reanalysis uses different oceanic reanalysis products, compared to the 20CRv2 version, to define variable sea-surface temperature and sea-ice boundary conditions, but essentially the same assimilation scheme. By contrast, the boundary conditions used in ERA-20C reanalysis are fairly close to those in 20CRv2, but the assimilated variables, methodologies and the atmospheric model itself are different (see Supplementary Information for further details). The M-SSA analysis of the observed-minus-simulated secular SAT differences using both of the alternative reanalyses (Fig. 5c, d) reproduces all of the key features identified using 20CRv2 data: the existence of a pronounced leading pair in the M-SSA spectrum of the observed internal variability; general lack of the multidecadal variance in climate models; and the absence of the observed space–time patterns in the CMIP5-simulated SAT time series. Note, however, that the differences between models and observations are somewhat alleviated in the 20CRv2c-based M-SSA spectra and become even more pronounced in the M-SSA spectra associated with ERA-20C data (when compared with the results for the 20CRv2 data set).

The GSW reconstructions using different reanalyses show consistent behaviour over most of the low- and mid-latitude World Ocean (Fig. 6). The GSW variability over land is consistent between 20CRv2 and 20CRv2c reanalyses but is entirely different in the ERA-20C reanalysis (Supplementary Fig. 8). Finally, the details of the GSW in the coastal Southern Ocean and Arctic region are also reanalysis-dependent (Supplementary Fig. 9). Overall, the GSW space–time development exhibits consistency between the two versions of the 20CR reanalysis (Supplementary Fig. 1,0; Supplementary videos 3 and 4), except for the behaviour over the narrow strip in the coastal Southern Ocean and a decadal shift in the Arctic component of the GSW. The 20CR and ERA-20C reanalyses are generally consistent over low-to-middle latitude oceans but exhibit much larger differences over land and in polar regions. All three reanalyses thus identify the GSW emanating from the North Atlantic region and spreading over the globe via a combination of oceanic and atmospheric teleconnections, but the response over land is entirely different in ERA-20C.

Large differences between the 20CR and ERA-20C reanalyses on regional scale were noted before.³⁹ Our analysis provides, among other things, a global-scale view of these differences. For example, the GSW exhibits almost out-of-phase behaviour between 20CR- and ERA-20C-based reconstructions over Antarctica (Supplementary Fig. 8), with the former (20CR) reanalysis indicating trends in 1950–2005 consistent with earlier work:⁴⁰ a warming trend in 1950–1980 period and a cooling trend afterwards. This example

suggests that 20CR reanalysis outperforms ERA-20C reanalysis over Antarctica (as far as decadal-scale regional trends are concerned). The detailed analysis and intercomparison of the two reanalyses are, however, beyond the scope of the present study and are left for future work.

DISCUSSION

Multidecadal signals originating in the North Atlantic Ocean and exerting some influence on the Northern Hemisphere climate have been observed and simulated before.^{41,42} They are thought to be rooted in the variability of the Atlantic Meridional Overturning Circulation (ref. 43). Recent observational^{5,40,44,45} and modelling studies^{46,47} 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 synchronisation of decadal climate modes.^{48–50}

Controlled coupled climate model experiments nudged to replicate the observed surface temperatures in the Atlantic or Pacific sector are able to simulate observed global teleconnections associated with DCV.^{33,51–57} However, free runs of these models are much less skilful in reproducing these teleconnections and exhibit spontaneous ultra-low-frequency variations in their inter-basin connectivity.^{18,21,58} Although some of the climate models are able to simulate certain qualitative features of the observed DCV,^{18,59} our results summarise and rigorously document pronounced quantitative discrepancies between models and observations, which should help guide further DCV research.⁴

METHODS

Methods and any associated references are available in the Supplementary Information.

DATA AVAILABILITY

All raw data, MATLAB code and results from our analysis are available at the website listed in the Supplementary Information.

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AUTHOR CONTRIBUTIONS

S.K. designed the study and wrote the paper, S.K. and C.G. performed the analyses, S.G. advised on technical aspects of the analysis.

ADDITIONAL INFORMATION

Supplementary information accompanies the paper on the *npj Climate and Atmospheric Science* website (<https://doi.org/10.1038/s41612-018-0044-6>).

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