Spatial Patterns and Frequency of Unforced Decadal-Scale Changes in Global Mean Surface Temperature in Climate Models

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ABSTRACT

The causes of decadal time-scale variations in global mean temperature are currently under debate. Proposed mechanisms include both processes internal to the climate system as well as external forcing. Here, the robustness of spatial and time scale characteristics of unforced (internal) decadal variability among phase 5 of the Coupled Model Intercomparison Project (CMIP5) preindustrial control runs is examined. It is found that almost all CMIP5 models produce an interdecadal Pacific oscillation–like pattern associated with decadal variability, but the frequency of decadal-scale change is model dependent. To assess the roles of atmosphere and ocean dynamics in producing decadal variability, two preindustrial control Community Climate System model (version 4) configurations are compared: one with an atmosphere coupled to a slab ocean and the other fully coupled to a dynamical ocean. Interactive ocean dynamics are not necessary to produce an IPO-like pattern but affect the magnitude and frequency of the decadal changes primarily by impacting the strength of El Niño–Southern Oscillation. However, low-frequency El Niño–Southern Oscillation variability and skewness explains up to only 54% of the spread in frequency of decadal swings in global mean temperature among CMIP5 models; there may be other internal mechanisms that can produce such diversity. The spatial pattern of decadal changes in surface temperature are robust and can be explained by atmospheric processes interacting with the upper ocean, while the frequency of these changes is not well constrained by models.

1. Introduction

Models agree on the spatial pattern associated with internal, decadal-scale temperature variability, but models do not agree on the magnitude, time scale, and most importantly, the driving mechanism of variability. The purpose of this study is twofold: 1) to assess the robustness of unforced decadal swings in surface temperature across models from phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al. 2012) and 2) to investigate the role of the deep ocean in producing

decadal swings in surface temperature. The observed spatial pattern in surface temperature from around 2000 to 2014 bears a striking resemblance to the negative phase of the interdecadal Pacific oscillation (IPO) pattern, a dominant mode of unforced decadal-scale variability (Trenberth and Fasullo 2013). This suggests that unforced decadal-scale variability is superimposed on the temperature response to external forcing. In fact, a decadal swing in global mean temperature (GMT) has the potential to offset the GMT rise associated with global warming. This phenomenon occurred recently and was dubbed “the global warming hiatus” (Easterling and Wehner 2009; Trenberth and Fasullo 2013; Watanabe et al. 2014). Understanding the onset and mechanism of such variability is crucial.

Decadal surface temperature cooling events, like the global warming hiatus, occur in all CMIP5 models, but only two studies have considered the inconsistency in how frequently these events occur (Maher et al. 2014; Roberts et al. 2015) across models. By investigating how different models simulate unforced decadal-scale variability, we attempt to identify processes that influence

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decadal-scale variability. The frequency of decadal cooling events has been associated with the amount of volcanic or anthropogenic forcing (Maher et al. 2014), but not analyzed within the context of constant radiative forcing to isolate the effect of internal variability. Roberts et al. (2015) noted that, during decadal cooling events, CMIP5 models consistently show an increase in deep ocean energy content, a decrease in energy content in the upper ocean and a decrease in downward top-of-the-atmosphere radiation fluxes, but with a range of magnitudes. This analysis chose models based to their ability to simulate El Niño–Southern Oscillation (ENSO), thus restricting the possible internal processes contributing to decadal variability.

El Niño–Southern Oscillation is often considered the source of unforced decadal variability based on the fact that ENSO explains a large portion of the GMT variance (Pan and Oort 1983; Graham 1994; Risbey et al. 2014). We investigate how much of the spread in decadal variability across CMIP5 models can be attributed to ENSO. One consistent modeling result is that, with or without changes in external forcing, the IPO-like pattern seen in observations is recognizable in decadal swings in temperature across CMIP5 models (Maher et al. 2014; Roberts et al. 2015). Indeed, along with being “IPO like,” the spatial pattern associated with internal decadal-scale variability is also deemed “ENSO like,” because of the signal in the Pacific cold tongue (Zhang et al. 1997; Chen and Wallace 2015). More frequent La Niña events coincide with the global warming hiatus in observations (Trenberth and Fasullo 2013; Watanabe et al. 2014), which suggests a role for ENSO. ENSO’s involvement in producing decadal swings in surface temperature was further substantiated by a study that could reproduce the hiatus with high confidence by prescribing sea surface temperatures only in the eastern tropical Pacific (Kosaka and Xie 2013). Choosing models based on their ability to recreate ENSO allows the hiatus to be reproduced to a degree, but not completely (Risbey et al. 2014; Huber and Knutti 2014; Roberts et al. 2015). The fact that El Niño–Southern Oscillation is not the perfect predictor for decadal swings in temperature implies that other processes of internal variability may play a role.

The strong, low-frequency temperature variability of the North Atlantic may also contribute to GMT variability, and the way it contributes may clarify on the mechanism for decadal swings in GMT. Observational and modeling studies show that changes in North Atlantic SST (Keenlyside et al. 2008; Wu et al. 2011) and associated changes in the Atlantic meridional overturning circulation (AMOC; DelSole et al. 2011; Chylek

et al. 2014) contribute significantly to multidecadal variability of GMT. A modeling study using an atmospheric global climate model (AGCM) coupled to a slab ocean with no ocean dynamics could produce an IPO-like pattern on decadal time scales by prescribing sea surface temperatures in the Atlantic Ocean and leaving other surface temperatures free to interact with the atmosphere (McGregor et al. 2014). This suggests influence from the Atlantic through atmospheric dynamics. On the other hand, through observational (Chen and Tung 2014) and modeling studies (Meehl et al. 2013), the global warming hiatus has been associated, in part, with a slowdown of the AMOC, resulting in increased deep-ocean heat content. Precisely how internal variability in the Atlantic or any other ocean basin contributes to decadal swings in GMT—whether through ocean dynamics, atmospheric dynamics, or a combination of both—remains an open question.

Many modeling and observational studies attribute deep-ocean heat uptake to offsetting heat trapped by greenhouse gas forcing, resulting in a decrease in surface temperatures (i.e., the “hiatus”) (Balmaseda et al. 2013; Chen and Tung 2014; Meehl et al. 2011, 2013; Watanabe et al. 2013; Trenberth et al. 2014; Trenberth and Fasullo 2013; Palmer et al. 2011; Lee et al. 2015). Deep-ocean heat uptake is associated with a decadal-scale internal response of the climate system, but this association cannot be justified by observations because of the short record of deep-ocean data. Here, we offer an alternative hypothesis for the production of decadal swings in surface temperature.

Low-frequency variability can be produced in climate models through thermal coupling of the ocean and atmosphere (Barsugli and Battisti 1998; Frankignoul and Hasselmann 1977; Dommenget and Latif 2008; Clement et al. 2011; Okumura 2013; Chen and Wallace 2015; Xie et al. 2016), which becomes more enhanced with more ocean dynamics included (Barnett et al. 1999a,b; Deser et al. 2003; Okumura 2013). The role of thermal coupling in driving the current hiatus is not known. Cooler eastern tropical Pacific surface temperatures associated with the global warming hiatus can be initiated by stronger trade winds (England et al. 2014; Watanabe et al. 2014), possibly through thermal coupling (McGregor et al. 2014). These results are likely to be model dependent, since both the simulation of internal variability and the sensitivity to external forcing vary from model to model (Clement and DiNezio 2014). The effect of thermal coupling on surface temperature is also influenced by radiative feedbacks, though the simulation of radiative feedbacks varies considerably among models (Soden and Held 2006). Short-wave feedbacks have been identified as a large source of intermodel spread in climate

sensitivity (Sherwood et al. 2014); they are also strongly tied to unforced decadal changes in surface temperature in both fully coupled simulations (Brown et al. 2014; Xie et al. 2016) and an AGCM coupled to slab-ocean models (Xie et al. 2016). Thus, the fact that atmospheric processes contribute significantly to decadal-scale variations in GMT should not be overlooked.

In this study, we assess the robustness of spatial patterns and the frequency of substantial cooling and warming decades (SCDs and SWDs, respectively). We examine the spread in GMT tendency statistics of said decades across CMIP5 preindustrial control runs and test the hypothesis that ENSO might be playing a role. We investigate the contribution of ocean dynamics to unforced decadal variability further by comparing decadal variability in an AGCM model coupled to a slab ocean to another fully coupled to a dynamical ocean. The slab-ocean model is only thermodynamically coupled to the atmosphere, and heat cannot be stored in the ocean of this model configuration aside from the heat capacity of a ~ 50 -m mixed layer.

2. Methods

To isolate processes during times of exceptional decadal-scale global cooling or warming, 10-yr trends periods are considered. Only 10-yr trend periods are analyzed for simplicity, but a brief consideration of other trend lengths is presented in figures in the supplemental material (see also Table 1). The decadal trends in surface temperature are found at every year of the run and are identified by their starting year. The spread is calculated on the resulting decadal trends. To identify decades of substantial cooling or warming, the decadal trends are filtered for those that exceed predetermined thresholds. These thresholds are chosen based on the standard deviation of the decadal global mean temperature trends in GISTEMP observations (Hansen et al. 2010) with changes in external forcing removed. Forcing is removed from GISTEMP by, first, interpolating the CMIP5 multimodel mean of historical runs to the same as GISTEMP; then, subtracting the multimodel mean at every grid point; and, last, creating a time series through a weighted area average. Thus, these thresholds determined by observations quantify the distribution of unforced decadal variability.

In model runs with fixed radiative forcing (including solar and volcanic forcing), that is, preindustrial control runs, decades with surface air temperature trends below $-0.13 \text{ K decade}^{-1}$ are considered “substantial cooling decades” (SCDs) in the sense that, if they were to occur in the late twentieth century, they would offset

the overall global warming trend. Decades with trends exceeding $0.13 \text{ K decade}^{-1}$ are considered “substantial warming decades” (SWDs). Next, the largest-magnitude trends among the decadal trends that overlap are selected. This is to ensure there is not inappropriate weighting when finding the average SCD or SWD spatial pattern of surface temperature trends. Note that there is no overlap among SCDs or among SWDs, but that an SCD decade may overlap an SWD. Along with finding the average spatial pattern among SCDs, the frequency of nonoverlapping SCDs and SWDs is considered to be a measure of how often one might expect a decadal swing in surface temperature. Generally, the frequency increases with the variance of GMT at decadal time scales (Fig. 2 in the supplemental material).

The trend analysis is performed on surface temperature in a similar manner to a few other studies regarding the global warming hiatus, where decades are selected based on their linear trends exceeding some threshold. This is similar to the analysis of previous studies that selected decadal periods according to their trend thresholds but with different objectives (Meehl et al. 2013; Maher et al. 2014; Roberts et al. 2015). For example, Meehl et al. (2013) utilized this methodology in a single model (CCSM4) with RCP4.5 forcing, and, here, we extend our analysis to all CMIP5 models and with preindustrial control forcing. Maher et al. (2014) analyzed warming and cooling decades in a suite of CMIP5 models but with various external forcing changes. That study also compared IPO patterns among CMIP5 preindustrial control runs (see the corresponding supplemental material), which we revisit, including more CMIP5 models. Finally, Roberts et al. (2015) selected 5-, 10-, and 20-yr periods based on trend thresholds in CMIP5 preindustrial control runs, though these authors predicted the likelihood of future decadal variability from certain models based on their ability to accurately produce ENSO. Here, our analysis focuses on how much ENSO can explain the spread of decadal variability in climate models.

First, we analyze trends in preindustrial control runs in 38 CMIP5 models to estimate the robustness of unforced decadal variability among IPCC models. All of the preindustrial control runs in this study are unforced control runs with perpetual 1850 greenhouse gas concentrations. The temporal resolution of each model run is monthly and ranges in length from 200 to 1156 yr. Each run is detrended prior to decadal analysis. Next, decadal trends in two Community Atmosphere Model, version 4 (CAM4), runs are analyzed using the same methods to quantify the roles of atmospheric and oceanic processes. These runs include 450 yr of CAM4 coupled to a slab-ocean model with preindustrial

TABLE 1. Statistics of decadal trends in CMIP5 models. The $\pm$ values after the frequency of SCDs or SWDs indicate the standard deviation of frequencies across 40 subsets of 100-yr periods within each model run.

Model name	Length of run (yr)	Frequency of SCDs (periods century ⁻¹)	Frequency of SWDs (periods century ⁻¹)	SCD pattern correlation with multimodel mean (only listed for >95% significance)	SWD pattern correlation with multimodel mean (only listed for >95% significance)
ACCESS1.0	500	4.200 $\pm$ 0.93	3.400 $\pm$ 0.66	0.771	0.741
ACCESS1.3	500	4.200 $\pm$ 0.80	4.200 $\pm$ 0.77	0.810	0.801
BCC_CSM1.1(m)	400	3.500 $\pm$ 0.66	4.000 $\pm$ 1.07	0.783	0.744
BCC_CSM1.1	500	3.600 $\pm$ 0.90	4.000 $\pm$ 0.85	0.498	0.699
CanESM2	996	5.623 $\pm$ 1.24	5.221 $\pm$ 0.78	0.856	0.830
CCSM4	1051	5.043 $\pm$ 1.22	5.043 $\pm$ 0.89	0.853	0.838
CESM1-Biogeochemistry (CESM1-BGC)	500	5.000 $\pm$ 1.29	5.600 $\pm$ 1.39	0.815	0.830
CESM1(CAM5)	319	3.762 $\pm$ 0.93	4.702 $\pm$ 1.26	0.654	0.778
CESM1(FASTCHEM)	222	4.505 $\pm$ 1.36	4.505 $\pm$ 0.74	0.800	0.818
CESM1(WACCM)	200	5.000 $\pm$ 0.66	5.000 $\pm$ 0.46	0.749	0.775
CMCC-CESM	277	6.498 $\pm$ 0.69	5.776 $\pm$ 0.65	0.803	0.823
CMCC-CM	330	3.333 $\pm$ 0.74	3.939 $\pm$ 0.67	0.523	0.480
CMCC-CMS	500	5.400 $\pm$ 0.71	5.200 $\pm$ 0.92	0.747	0.836
CNRM-CM5.2	490	4.490 $\pm$ 0.98	4.898 $\pm$ 0.83	0.643	0.597
CNRM-CM5	850	4.118 $\pm$ 0.86	3.765 $\pm$ 1.09	0.640	0.651
CSIRO Mk3.6.0	500	5.200 $\pm$ 1.06	5.000 $\pm$ 0.85	0.686	0.709
FGOALS-g2	700	3.143 $\pm$ 1.24	2.714 $\pm$ 0.86	0.714	0.599
FGOALS-s2	501	5.190 $\pm$ 0.73	5.389 $\pm$ 1.32	0.709	0.710
GFDL CM3	500	4.400 $\pm$ 1.11	4.600 $\pm$ 1.27	0.704	0.775
GFDL-ESM2G	500	4.400 $\pm$ 0.86	4.200 $\pm$ 1.27	0.763	0.664
GFDL-ESM2M	500	5.400 $\pm$ 0.69	5.600 $\pm$ 0.84	0.802	0.789
GISS-E2-H-CC	251	3.187 $\pm$ 0.63	2.789 $\pm$ 1.19	0.502	0.512
GISS-E2-H	780	2.180 $\pm$ 1.26	1.795 $\pm$ 1.34	0.577	0.561
GISS-E2-R-CC	251	2.789 $\pm$ 0.82	3.586 $\pm$ 0.88	0.545	0.529
GISS-E2-R	850	2.588 $\pm$ 1.13	2.471 $\pm$ 0.96	Not significant	0.461
INM-CM4.0	500	2.600 $\pm$ 0.63	1.600 $\pm$ 0.78	0.496	0.597
IPSL-CM5A-LR	1000	5.300 $\pm$ 1.14	5.200 $\pm$ 0.84	0.838	0.836
IPSL-CM5A-MR	300	4.333 $\pm$ 0.85	5.000 $\pm$ 0.53	0.839	0.799
IPSL-CM5B-LR	300	4.667 $\pm$ 0.93	4.000 $\pm$ 0.65	Not significant	0.474
MIROC-ESM-CHEM	255	5.098 $\pm$ 0.55	4.314 $\pm$ 0.47	0.714	0.724
MIROC-ESM	630	4.603 $\pm$ 0.95	4.603 $\pm$ 0.88	0.766	0.764
MIROC5	670	4.925 $\pm$ 1.37	5.373 $\pm$ 0.75	0.796	0.809
MPI-ESM-LR	1000	5.300 $\pm$ 1.18	5.700 $\pm$ 0.88	0.773	0.798
MPI-ESM-MR	1000	5.200 $\pm$ 1.00	5.000 $\pm$ 0.73	0.825	0.855
MPI-ESM-P	1156	5.709 $\pm$ 0.98	5.277 $\pm$ 0.70	0.839	0.782
MRI-CGCM3	500	4.600 $\pm$ 1.48	4.400 $\pm$ 1.43	0.626	0.688
NorESM1-M	501	4.990 $\pm$ 0.79	3.393 $\pm$ 0.85	0.848	0.807
NorESM1-ME	252	4.365 $\pm$ 0.73	5.556 $\pm$ 0.51	0.752	0.786
Multimodel mean	553.47	4.414 $\pm$ 0.95	4.385 $\pm$ 0.89	0.724	0.718

forcing (“cam4som”) and 1051 yr of fully coupled CCSM4 with preindustrial forcing (“ccsm4”). The same analysis was performed on smaller subsets of the 1051-yr-long fully coupled run, and the results did not change. The forcing of these two runs is identical to those of the CMIP5 models, and the temporal resolution is monthly as well.

The AGCM-slab model, cam4som, does not include interactive ocean dynamics. The ocean has a spatially varying depth of around ~ 50 m, corresponding to the average mixed layer depth, and does not vary with time. This means that the amount of heat stored in this ocean

is limited to the heat capacity of the slab layer. The SST produced in cam4som is a result of thermodynamic coupling only; the heat transport due to ocean dynamics is prescribed. To represent the effect of ocean dynamics in establishing the models climatology, a seasonally varying q -flux term is added to the surface energy budget, which is computed from a previous CAM4 control simulation with prescribed SSTs (Bitz et al. 2012). We perform a surface energy budget analysis to decompose the contributions of various thermal fluxes to decadal trends in surface temperature.

FIG. 1. GISTEMP instrumental analysis data from 1880 to 2006 with forcing removed. (top) SCDs and (bottom) SWDs are highlighted in blue and red for SCDs and SWDs, respectively. Methods of removing forcing and finding said decades are described in the text.

3. Results and discussion

a. Frequency of substantial cooling and warming decades in observations

We start with an analysis of the substantial cooling and warming decades (SCDs and SWDs, respectively) found in GISTEMP surface temperature analysis from 1880 to 2014 (available online at data.giss.nasa.gov/gistemp/; see also Hansen et al. 2010) with forcing removed, using the predefined threshold of $\pm 0.13^{\circ}\text{C decade}^{-1}$ (Fig. 1). Nonoverlapping SCDs occur five times [$3.37 \text{ times } (100 \text{ yr})^{-1}$], while substantial warming decades occur seven times [$5.22 \text{ times } (100 \text{ yr})^{-1}$]. Note that when external forcing changes are removed from GISTEMP through methods described in the previous section, the most recent hiatus is captured. When the decades are selected using the same thresholds on GISTEMP with external forcing changes included, the most recent hiatus is not captured, and the frequency of the SCDs and SWDs decreases from $3.37 \text{ times century}^{-1}$ to $2.2 \text{ times century}^{-1}$ (see Fig. 1 in the supplemental material). This reflects the reduced likelihood of a substantial

cooling decade with increased anthropogenic global warming (Maher et al. 2014; Roberts et al. 2015) but also that the magnitude of unforced variability we are considering does not overwhelm the forced response.

b. Robustness of unforced decadal variability in CMIP5 models

The frequency of nonoverlapping SCDs and SWDs is shown in Table 1. The frequency is calculated as the number of SCDs or SWDs and reported in frequency per 100 yr. We also compute the standard deviation of frequencies of SCDs and SWDs during 40 different 100-yr periods within each model run as a measure of the stability of that frequency over the course of the simulations. Averaged over all models, SCDs occur about 4.41 ± 0.95 times every 100 yr, with a range of $2.18 \pm 1.26 \text{ SCDs century}^{-1}$ in GISS-E2-H to $6.50 \pm 0.69 \text{ SCDs century}^{-1}$ in CMCC-CESM.

The spatial composite of SCDs (Fig. 2b; SWDs, Fig. 2c) among all the models resembles the negative (positive) phase of an IPO-like pattern (Fig. 2a; see the individual models' IPO patterns in Fig. 3 of the

FIG. 2. Multimodel mean of spatial patterns associated with (a) the IPO, calculated as the first EOF of 13-yr low-pass-filtered surface temperature data; (b),(c) decadal trends in surface temperature during SCDs and SWDs, respectively. Runs from 38 CMIP5 models with preindustrial controls were considered. The color bar refers to values in (b) and (c). Values in (a) are on the order of 20% of the values in the color bar. Stippling indicates that 75% of models agree in sign at that point. See Table 1 for individual models' spatial correlations with the multimodel mean, and see Table 2 in the supplemental material for individual models' spatial correlation of SCD and SWD patterns with each model's IPO pattern.

supplemental material), as found in previous analyses of preindustrial control CMIP5 models with similar methodology (Maher et al. 2014; Roberts et al. 2015). To measure the robustness of this pattern across the CMIP5 models, the spatial pattern of each CMIP5 model run

was correlated with the CMIP5 multimodel mean spatial pattern (pattern correlation values are listed in Table 1). Thirty-six out of 38 models shared a significant pattern correlation with the multimodel mean at the 95% level for SCDs by a Student's two-sided t test (method of finding degrees of freedom is described in the appendix). All models had a significant pattern correlation with the multimodel mean spatial pattern for SWDs. The average across cooling decades is also almost the exact mirror image of the average across warming decades, consistent with results from Meehl et al.'s (2013) analysis of CCSM4-RCP4.5 runs.

We also note that the frequency of 3.37 SCDs century⁻¹ in GISTEMP with forcing removed is within the range simulated in preindustrial simulations with CMIP5 models (2.31–6.86 SCDs century⁻¹). This suggests that the observed behavior is consistent with unforced variability within climate models, though the contribution of natural forcing such as volcanoes or aerosols for particular time periods cannot be ruled out (Maher et al. 2014). It is worth noting that while the observed frequency is on the low end of the simulated range, the 5.22 SWDs century⁻¹ observed is on the high end of what CMIP5 models simulate. This leaves open the possibilities that 1) models are not consistently simulating enough decadal variability (Laepple and Huybers 2014), possibly through inaccurate representation of the response to volcanoes and aerosols (Maher et al. 2014), and 2) that the response to anthropogenic forcing (not present in the preindustrial control runs) was not removed entirely and may be playing some role in producing the SCDs and SWDs apparent in Fig. 1.

c. CCSM4 with and without interactive ocean dynamics

Using the same analysis techniques for CCSM4 models with (ccsm4) and without an interactive ocean (cam4som), we isolate the contribution of ocean dynamics to decadal variability. Table 2 shows the length of each run, the frequency of SCDs and SWDs, and the standard deviation and skewness of all possible 10-yr trends. Nonoverlapping SCDs in the fully coupled preindustrial control run occur 5.33 ± 1.22 times century⁻¹, more frequently than the CMIP5 multimodel mean. In the atmosphere-slab model (cam4som) SCDs occur 3.11 ± 1.62 times century⁻¹, well within the range of the CMIP5 model frequencies. The standard deviation of all 10-yr trends increases from $+0.095^{\circ}\text{C decade}^{-1}$ in cam4som to $+0.120^{\circ}\text{C decade}^{-1}$ in the fully coupled version. This suggests that while the heat capacity of the mixed layer ocean can produce significant decadal time-scale variability (more than half of the variance of 10-yr trends), interactive ocean circulation increases this variance in this model. This is not surprising

TABLE 2. Statistics of decadal trends in two CCSM4 configurations. MMM refers to the CMIP5 multimodel mean spatial patterns.

Model name	Length of run (yr)	Frequency of SCDs	Frequency of SWDs	Std dev of trends	Skewness of trends	Std dev of 10-yr LPF GMT ($^{\circ}\text{C}$)	Pattern correlation with CMIP5 MMM SCD
cam4som	450	3.11 ± 1.62	3.78 ± 1.53	0.0951	0.0513	0.0492	0.586
ccsm4	1051	5.33 ± 1.22	5.14 ± 0.89	0.1204	-0.0300	0.0529	0.853
CMIP5 preindustrial control multimodel mean	553.47	4.43 ± 0.95	4.39 ± 0.89	0.1390	0.0589	0.0751	0.724

given that CCSM4 produces significant decadal-time-scale variability in ENSO (Deser et al. 2012) that is not present in the slab version of the model (Clement et al. 2011; Okumura 2013; Xie et al. 2016).

The spatial pattern of decadal trends is strikingly similar between a model with interactive ocean dynamics and without interactive ocean dynamics. In both the atmosphere-slab version (cam4som) and the fully coupled version (ccsm4), the IPO-like pattern is clear, consistent with results from Okumura (2013) and Xie et al. (2016). In cam4som, the midlatitudes and extratropics appear to play a relatively larger role in determining SCDs or SWDs than do the tropics (Figs. 3a,d). The largest differences between cam4som and ccsm4 occur over Eurasia, the western boundary regions, the southern extratropical Pacific, and the ENSO region (Figs. 3c,f). In particular, including ocean dynamics produces a clear ENSO signal, and the trends become larger in the Pacific Ocean (Fig. 3b,c,e,f). This suggests that ENSO plays a role in producing unforced decadal variability in this model.

d. *El Niño–Southern Oscillation and SCDs and SWDs*

The role of ENSO in decadal-and-longer variability has long been debated because of the ENSO-like spatial pattern seen across lower-frequency time scales. Many previous studies regarding the global warming hiatus depended on the idea that tropical Pacific variability is responsible for decadal GMT variability (Risbey et al. 2014; Huber and Knutti 2014; Roberts et al. 2015).

If ENSO is playing a role in determining the phase of decadal swings in temperature, then the spread in low-frequency ENSO variability should explain the spread in frequencies of SCDs or SWDs. One would expect that, if ENSO explains a relatively large portion of GMT (Pan and Oort 1983; Graham 1994), especially on decadal time scales (Risbey et al. 2014), then this would be correlated with how frequently a swing in decadal temperature occurs. To test whether a spread in ENSO magnitude is the cause of multimodel spread (Table 2), we plot the standard deviation of the 10-yr low-pass-filtered ENSO

indices against the frequency of substantial cooling and warming GMT trends in the preindustrial control CMIP model runs (Fig. 4). Figure 4 shows that the magnitude of each Niño index explains about half of the spread of the frequency of SCDs (R^2 values of 47%–54%, all significant at the 95% level by a Student's two-sided t test). The third moment, or ENSO asymmetry, has also been identified as a source of decadal variability (Rogers et al. 2004; Knutson and Manabe 1998; An and Wang 2000; Sun and Yu 2009; Yu and Kim 2011). Figure 8 in the supplemental material to this paper shows the relationship between the skewness of 10-yr low-pass-filtered El Niño indices versus the frequency of SCDs and SWDs, and illustrates that there is no significant relationship between the two.

Additional analysis of various ENSO measures and their relationship to the frequency of SCDs and SWDs can be found in the supplemental material (see Figs. 5–10 and 13), but the largest portion of the spread in frequencies is explained by the magnitude of the 10-yr low-pass-filtered ENSO indices. This suggests that ENSO explains only a portion of the decadal variability, and that other processes may be controlling the phase of the decadal–interdecadal swings in surface temperature.

What else might explain the spread across models in the frequency of cooling and warming decades? In an analysis of cooling decades (those with less than $-0.2\text{ K decade}^{-1}$) in preindustrial control CMIP5 models, Roberts et al. (2015) noted considerable intermodel spread in measures previously used to identify hiatus periods; specifically, there is large spread among the relative importance of ocean heat uptake and TOA radiation fluxes in producing decades of GMT cooling in CMIP5 models. Other studies have suggested that cooling associated with the recent hiatus, and thus, internal decadal-scale variability, may be tied to ocean basins outside of the Pacific. As mentioned previously, unforced decadal GMT variability may be caused by Atlantic Ocean circulation (Meehl et al. 2013; Chen and Tung 2014) or surface temperature variability (McGregor et al. 2014; Keenlyside et al. 2008; Wu et al. 2011; Chylek et al. 2014). Our analysis of decadal surface temperature variability, though, does not show large signals in the North Atlantic in most of the models

FIG. 3. Spatial patterns of decadal trends in different CCSM4 model setups. The decadal trend spatial pattern in CAM4 coupled to a slab-ocean model averaged across (a) SCTs and (d) SWDs. To the right of each spatial plot is the zonal average of the decadal trend spatial patterns during each individual SCD or SWD. (b),(e) As in (a),(d), but for the fully coupled CCSM4 run. (c),(f) The differences between the results.

analyzed here (Fig. 2 and Fig. 4 in the supplemental material), except for in cam4som (Fig. 3). This may be due to the fact that low-frequency North Atlantic signals leads Northern Hemisphere temperatures by 15–20 yr (Li et al. 2013), so our decadal analysis may not capture this connection accurately. Other studies have suggested that strengthening subtropical ocean cells for increased subsurface heat uptake in the Pacific Ocean may be one driver of decadal-time-scale cooling (Meehl et al. 2013; England et al. 2014), and this has been suggested as a mechanism for the 1976/77 climate shift (McPhaden and Zhang 2002; Rogers et al. 2004). Our results do not raise issues with any of the studies listed above, though it remains to be seen how these ocean processes would give rise to the characteristic pattern of SCTs and SWDs in the Pacific Ocean.

e. Surface energy budget during SCTs and SWDs in CCSM4

As a first step to understanding the pattern shared by the cam4som and ccsm4 in Fig. 3, we look at the surface

energy budget during SCTs, SWDs, and all other decades. We expect the surface energy budget in ccsm4 to be different than that of cam4som if atmospheric processes are playing a different role in decadal changes in surface temperature in the presence of ocean circulation. Sea surface temperatures in the cam4som are determined solely from the surface heat flux and the heat capacity of the slab mixed layer, which is constant in time. This means that decadal variability in this model configuration is determined by thermal damping of stochastic atmospheric noise by the ocean's mixed layer—a theory for climate variability introduced by Frankignoul and Hasselmann (1977). Surface temperature in cam4som is determined by the following equation:

$$C_p \frac{dT}{dt} = Q_{SW} - Q_{LW} - Q_{SH} - Q_{LH}. \quad (1)$$

Here, Q_{SW} is the net shortwave flux (positive down), Q_{LW} is the net longwave flux (positive up), Q_{SH} is the net sensible heat flux (positive up), and Q_{LH} is the net latent heat flux at the surface (positive up). In addition,

FIG. 4. Frequencies of (left) SCDs and (right) SWDs vs the magnitude of 10-yr low-pass-filtered ENSO indices: (top) Niño-3, (middle) Niño-3.4, and (bottom) Niño-4 in preindustrial control CMIP5 models (different colors and symbols). Results from the GISTEMP analysis are indicated by the black circle and the CMIP5 multimodel mean is shown by the black $\times$ symbol.

C_p is the heat capacity of the surface below—either land or the mixed layer slab ocean. One caveat to this type of analysis is that as the analysis time scale increases, $C_p dT/dt$ goes to zero, so determining causal relationships is problematic. We can, at least, see if the contributions from atmospheric components to decadal trends in temperature differ with and without the ocean circulation's influence, that is, if the pattern in cam4som is happening for the same reasons that we see it in ccsm4.

We take the average of the surface fluxes over the course of each decade to look for a robust contribution to decadal temperature changes. Figure 5 shows the globally averaged heat flux anomalies for each component averaged over the course of the SCDs, SWDs, and all other decades for cam4som (top panel) and ccsm4 (bottom panel). As predicted by Eq. (1), the average decadal surface temperature trend during SCDs and SWDs is the same sign as the integrated net surface flux over the course of a decade. Further, the cooling is

FIG. 5. Global average surface flux anomalies averaged during SCDs, SWDs, and all other decades. The average decadal surface temperature trend across SCDs (light blue), SWDs (red), and all other decades (dark blue) is also included. Sensible, latent heat, and longwave fluxes have been multiplied by -1 in Eq. (1) so that they are positive down. Standard deviations are indicated by the vertical dotted lines.

associated with reduced SW absorbed and increased latent heat flux (shown in Fig. 5 as a cooling) in both model configurations. However, the error bars for the fluxes are large, which indicates that while the components of the net surface heat flux are contributing on average in a consistent way between the two models, their contributions to each realization of an SCD or SWD within the model simulations may not be the same.

The role of latent heat flux is consistent with results from previous studies that showed that decadal changes in trade winds coincide with Pacific decadal variability (England et al. 2014). Additionally, the contribution from shortwave radiation is in line with studies highlighting the effect of shortwave radiation on decadal

surface temperatures. For example, stratocumulus cloud cover influences low-frequency surface temperature in the northeast Pacific Ocean in climate models through positive shortwave feedback (Bellomo et al. 2014) and is corroborated with observations (Clement et al. 2009). A more recent study analyzing the same model configurations as in the present study showed that the net TOA shortwave radiation leads decadal changes in net TOA radiative balance and decadal changes in GMT (Xie et al. 2016). The current analysis does not determine that winds and cloud feedbacks cause decadal swings in surface temperature, but shows that the contributions from the atmosphere are the same in both cam4som and ccsm4. The results presented here support that radiative feedbacks internal to the climate

system should not be ignored when considering contributions to internal low-frequency variability in surface temperature.

4. Conclusions

In this study, we have analyzed substantial cooling and warming decades in CMIP5 models and two different CCSM4 configurations in order to characterize low-frequency internal variability as simulated by climate models. We have found that an “IPO like” signal is a robust, unforced pattern associated with decadal-scale warming and cooling in almost all CMIP5 models, which is consistent with previous results (Maher et al. 2014; Roberts et al. 2015; Brown et al. 2015). Additionally, the same decadal-scale IPO-like pattern is produced in a model without interactive ocean dynamics. This highlights that interactive ocean dynamics are not required to explain the spatial pattern of the recent hiatus decade, and that SCDs and SWDs can occur with just a 50-m mixed layer ocean. This raises questions about the prominent role of the deep ocean, as suggested in previous studies (Balmaseda et al. 2013; Chen and Tung 2014; Meehl et al. 2011, 2013; Watanabe et al. 2013; Trenberth et al. 2014; Trenberth and Fasullo 2013; Palmer et al. 2011; Lee et al. 2015).

While the spatial pattern associated with SCDs and SWDs is consistent among all models, the frequency of substantial decadal-scale cooling or warming events varies considerably across the models. The presence of an ENSO-like signal in almost all CMIP5 models’ spatial patterns suggests that tropical Pacific decadal variability may influence decadal variability and may explain the spread in frequency of SCDs across models. When comparing the spread and skewness of ENSO indices against the frequency of cooling or warming decades, there is a significant but not a strong relationship. This suggests that other processes aside from ENSO alone are playing a role in generating internal decadal variability. In a surface energy budget analysis, we find that latent heat and shortwave flux are the largest contributors to decadal swings in surface temperature in both an AGCM coupled to a slab ocean and in a fully coupled model. Our results suggest that stochastic atmospheric noise can cause decadal-time-scale variability without ocean dynamics.

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APPENDIX

Statistical Significance of Pattern Correlations

We use pattern correlation to measure the robustness of the spatial pattern associated with substantial cooling and warming decades across the CMIP5 models (individual SCD patterns may be found in the supplemental material; see also Fig. 4). We do this by correlating the average spatial pattern across substantial cooling (and warming) decades for each individual model with the multimodel mean spatial pattern. The spread of correlation among models quantifies the variation of spatial patterns among CMIP5 models. We also use pattern correlation to quantify how much this decadal trend spatial pattern is similar to the interdecadal Pacific oscillation pattern.

The pattern correlation is calculated by the Pearson’s product moment coefficient of the linear correlation across grid points, weighted by latitude. The statistical significance of each model’s correlation coefficient is determined by a Student’s two-sided t test and is dependent on the degrees of freedom, which changes with each model. The degrees of freedom are determined by $\text{DOF} = m/\tau$, where m is number of meridional grid points and τ is the average decorrelation length scale in the zonal direction for every run’s mean SCD or SWD pattern. Spatial patterns are more coherent in the zonal direction, so we expect the degrees of freedom to be lower and, thus, a more rigorous significance test. We exclude the polar regions because of the large coherence; statistical significance is never reached if the poles are included. The decorrelation length scale is represented at every latitude between -70°S and 70°N by the number of zonal grid points required for the autocorrelation of decadal trends to fall below $1/e$. The model’s resulting degrees of freedom are the average of zonal decorrelation length scales with cosine weights.

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