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## New Generation of Climate Models Track Recent Unprecedented Changes in Earth's Radiation Budget Observed by CERES

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28

### 29 **Key Points**

- 30 • There is good agreement between radiation budget variations observed by CERES and  
31 simulated by seven state-of-the-art climate models
- 32 • The relationship between global mean net TOA radiation and surface temperature is  
33 sensitive to changes in regions dominated by low clouds
- 34 • Most models underestimate shortwave flux changes in response to SST changes over  
35 the east Pacific, suggesting too weak a “pattern effect”

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38

### **Abstract**

39 We compare top-of-atmosphere (TOA) radiative fluxes observed by the Clouds and the  
40 Earth's Radiant Energy System (CERES) and simulated by seven general circulation  
41 models forced with observed sea-surface temperature (SST) and sea-ice boundary  
42 conditions. In response to increased SSTs along the equator and over the eastern Pacific  
43 (EP) following the so-called global warming "hiatus" of the early 21<sup>st</sup> century, simulated  
44 TOA flux changes are remarkably similar to CERES. Both show outgoing shortwave and  
45 longwave TOA flux changes that largely cancel over the west and central tropical Pacific,  
46 and large reductions in shortwave flux for EP low-cloud regions. A model's ability to  
47 represent changes in the relationship between global mean net TOA flux and surface  
48 temperature depends upon how well it represents shortwave flux changes in low-cloud  
49 regions, with most showing too little sensitivity to EP SST changes, suggesting a "pattern  
50 effect" that may be too weak compared to observations.

51

### **Plain Language Summary**

52 Earth's radiation budget describes the balance between radiation from the sun intercepted  
53 by Earth and radiation returned back to space through reflection of solar radiation and  
54 emission of terrestrial thermal infrared radiation. This balance is a fundamental property  
55 of Earth's climate system as it describes how Earth gains and sheds heat. Here we use  
56 observations from the Clouds and the Earth's Radiant Energy System (CERES) to evaluate  
57 how seven state-of-the-art climate models represent changes in Earth's radiation budget  
58 during and following the so-called global warming "hiatus" of the early 21<sup>st</sup> century. The  
59 models were provided observed sea-surface temperature and sea-ice boundary conditions  
60 as well as natural and anthropogenic forcings. We find remarkable agreement between

61 observed and simulated differences in reflected solar and emitted thermal infrared radiation  
62 between the post-hiatus and hiatus periods. Furthermore, a model's ability to correctly  
63 relate Earth's radiation budget and surface temperature is found to depend upon how well  
64 it represents reflected solar radiation changes in regions dominated by low clouds,  
65 particularly those over the eastern Pacific ocean.

66

67

## 68 **1. Introduction**

69 A key measure of radiative feedback in the climate system, and therefore climate  
70 sensitivity, is the relationship between net top-of-the-atmosphere (TOA) radiation and  
71 global mean surface air temperature change. From climate model simulations in which CO<sub>2</sub>  
72 is quadrupled instantaneously, the climate feedback parameter can be determined from the  
73 slope of a linear regression fit between net flux and surface temperature change, with the  
74 intercept yielding the imposed forcing (Gregory et al., 2004). This linear framework  
75 assumes that the climate feedback parameter is constant in time, so that variations in net  
76 flux and surface temperature are related by a constant of proportionality. However,  
77 numerous modeling studies have shown that for transient warming, global radiative  
78 feedback is time-varying (Murphy 1995; Senior and Mitchell 2000; Winton et al. 2010;  
79 Armour et al. 2013; Andrews et al. 2015; Paynter et al. 2015; Gregory & Andrews, 2016;  
80 Zhou et al., 2016; Armour, 2017; Proistosescu & Huybers, 2017; Marvel et al., 2018;  
81 Silvers et al., 2018). This is primarily due to temporal changes in surface warming patterns,  
82 which induce changes in global radiation that differ from those associated with global  
83 warming (Armour et al., 2013; Rose et al., 2014; Andrews et al., 2015; Zhou et al., 2016,  
84 2017; Ceppi & Gregory, 2017; Haugstad et al., 2017; Andrews & Webb, 2018; Silvers et  
85 al., 2018; Andrews et al. 2018; Dong et al. 2019). These “pattern effects” (Stevens et al.,  
86 2016) can be a result of both internal variability and climate forcing (Mauritsen, 2016).

87 The “pattern effect” is the reason why general circulation models (GCMs) driven  
88 with historical patterns of sea-surface temperature (SST) and sea-ice concentrations (SIC)  
89 yield climate feedback parameters that are more stabilizing—implying a lower climate  
90 sensitivity—compared to simulations that are forced with projected long-term increases in

91 greenhouse gas concentrations (Zhou et al., 2016; Andrews et al., 2018; Marvel et al.,  
92 2018). While global mean surface temperatures have been continuing to increase in recent  
93 decades, there has been relatively less warming (or even cooling) over the eastern tropical  
94 Pacific (e.g., McGregor et al., 2014) and Southern Oceans (e.g., Armour et al., 2016). These  
95 regional patterns have been shown to produce greater low-level cloud cover and reflection  
96 to space, explaining why there was a more stabilizing climate feedback parameter observed  
97 during the past forty years compared to that of future warming (Zhou et al., 2016, 2017;  
98 Andrews et al., 2018; Dong et al. 2019). Zhou et al. (2016) further argue that SST pattern-  
99 induced low-cloud cover anomalies may have also contributed to reduced warming  
100 between 1998 and 2013, a period that has come to be known as the global warming “hiatus”  
101 (e.g., McGregor et al., 2014). More recently, Fueglistaler (2019) demonstrated the  
102 influence of SST pattern changes on observed tropical mean SW cloud radiative effect  
103 using data from the Clouds and the Earth’s Radiant Energy System (CERES).

104         In this study, we use CERES observations to evaluate how state-of-the-art climate  
105 models represent changes in Earth’s radiation budget following a large change in SST  
106 patterns. The CERES data reveal a  $0.83 \text{ Wm}^{-2}$  reduction in global mean reflected  
107 shortwave (SW) flux during the three years following the hiatus, resulting in an increase in  
108 net energy into the climate system (Loeb et al., 2018a). Furthermore, decreases in low-  
109 cloud cover are found to be the primary driver of the decrease in SW flux. The low-cloud  
110 cover decreases are associated with increases in SST reaching  $2^{\circ}\text{C}$  on average in some  
111 locations over the eastern Pacific Ocean following a change in the sign of the Pacific  
112 Decadal Oscillation from negative to positive phase.

113 In light of these dramatic changes, we ask the question: can climate models  
114 reproduce the changes observed by CERES if they are provided observed SSTs and SIC?  
115 Such a comparison serves as a “reality check” on the models used to study the pattern  
116 effect, low-cloud feedbacks and changes in total climate feedback during the historical  
117 period. We caution that there is no attempt here to provide an “emergent constraint” on  
118 future climate (Klein and Hall, 2015) that can be used to constrain long-term climate  
119 feedback and climate sensitivity. Rather, the goal is to determine whether or not current  
120 atmospheric models are capable of reproducing the TOA radiative response to a large-scale  
121 and well-observed event that arguably involves processes relevant to the representation of  
122 both current and future climate.

## 123 **2. Data and Methods**

### 124 **2.1 Observations**

125 We use observational data from the CERES EBAF Ed4.1 product (Loeb et al.,  
126 2018b, 2019) for March 2000–December 2017. EBAF provides monthly mean TOA and  
127 surface SW and longwave (LW) radiative fluxes on a  $1^\circ \times 1^\circ$  grid. Here, only the TOA  
128 fluxes are considered. TOA radiative fluxes in EBAF are derived from CERES SW and  
129 LW radiance measurements.

130 Also considered are atmospheric and surface data from the European Centre for  
131 Medium-Range Weather Forecasts ERA5 reanalysis product (Hersbach et al., 2018). We  
132 use near-surface air temperature ( $T_s$ ), surface pressure, 700 hPa air temperature and SST.  
133 The first three parameters are used to calculate the estimated inversion strength (EIS)  
134 (Wood and Bretherton, 2006).



## 135 **2.2 CMIP6 AMIP Simulations**

136 TOA radiative fluxes,  $T_s$  and EIS from seven models participating in the Coupled  
137 Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016) are considered (Table  
138 1). The simulations are forced with monthly time-varying observationally derived fields of  
139 SST and SIC using the Atmospheric Model Intercomparison Project (AMIP) boundary  
140 conditions (Gates et al., 1999; Hurrell et al., 2008; Taylor et al., 2000). Between the start  
141 of the CERES record in 2000 and the official end-date of CMIP6 AMIP in 2014, all  
142 simulations have time-varying natural and anthropogenic forcings. We have run AMIP  
143 simulations three more years, through the end of 2017. In those simulations, radiative  
144 forcings are held fixed at 2014 levels between 2015-2017 for all models except EC-Earth3-  
145 Veg, which used the Shared Socioeconomic Pathways (SSP2-4.5) radiative forcings (Riahi  
146 et al., 2016). The time dependent forcings beyond 2014 have small perturbations that are  
147 not expected to influence the results. The main influence on TOA flux variability is from  
148 SST, which is time dependent through 2017 in all models. Monthly time-varying observed  
149 fields of SST and SIC are either from merged Reynolds/HADISST (Hurrell et al., 2008) or  
150 HadISST1 (Rayner et al., 2003) (Table 1). All AMIP simulation output are spatially  
151 interpolated onto a  $1^\circ \times 1^\circ$  grid.

152 Since AMIP simulations use observed SSTs and SIC boundary conditions, the  
153 model atmosphere responds to SSTs but there is no equivalent ocean surface response to  
154 atmospheric changes. This is in contrast to observations, which include two-way  
155 atmosphere-ocean interactions. A reasonable question to ask, therefore, is whether it is  
156 reasonable to evaluate models by comparing AMIP simulations and observations. This has  
157 been addressed in several studies with different models (Andrews et al., 2015; He and

158 Soden, 2016; Haugstad et al., 2017; Mauritsen and Stevens, 2015). The studies find that  
 159 time-varying net feedback parameters simulated by atmosphere-ocean GCMs (AOGCMs)  
 160 and AMIP-style simulations for the same models forced using the AOGCM SST and SIC  
 161 boundary conditions are consistent, suggesting that AMIP-style simulations and  
 162 observations should also show consistent results.

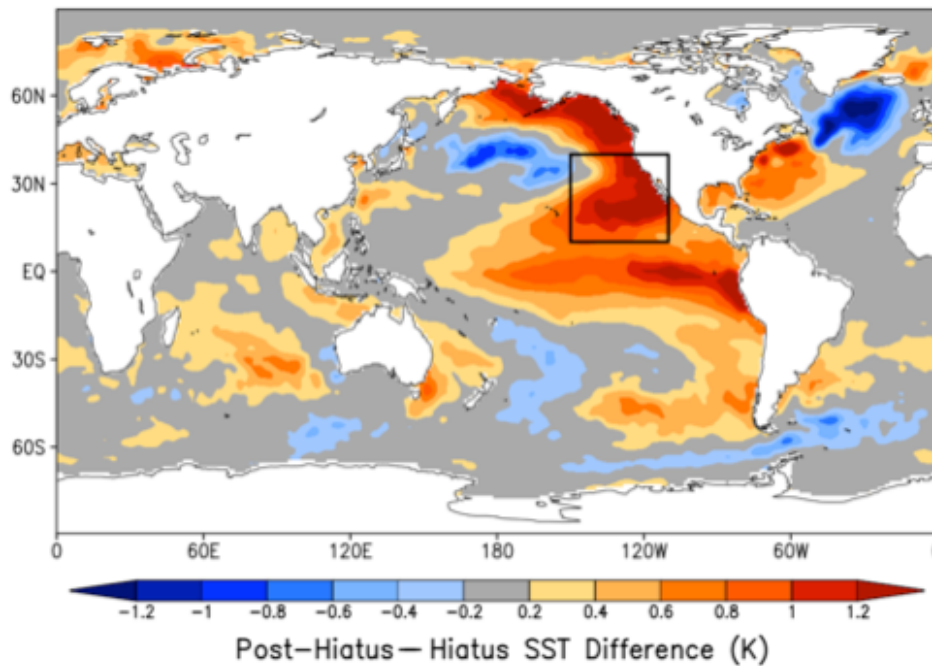
163 Table 1 List of CMIP6 models considered in this study.

Model (Short Name)	Model (Long Name)	Country	Resolution (°) (lonxlat)	SST/SIC Dataset	Reference
CESM2	CESM2 AMIP	USA	1.25x0.94	Merged Reynolds/HADISST	Gettelman et al. (2019)
CanESM5	CanESM5 AMIP	Canada	2.8x2.8	Merged Reynolds/HADISST	Swart et al. (2019)
EC-Earth3-Veg	EC-Earth3-Veg AMIP	Europe/EC	0.7x0.7	Merged Reynolds/HADISST	Davini et al. (2017)
ECHAM6.3	echam6.3.05-LR AMIP	Germany	1.875x1.86	HadISST1	Mauritsen et al. (2019)
GFDL-AM4	GFDL-AM4 AMIP	USA	1.25x1.0	HadISST1	Zhao et al. (2018)
HadGEM3	HadGEM3-GC31-LL AMIP	UK	1.875x1.25	HadISST1	Williams et al. (2018)
IPSL-CM6A	IPSL-CM6A-LR AMIP	France	2.5x1.27	Merged Reynolds/HADISST	Hourdin et al. (2013)

164 **2.3 Methods**

165 Deseasonalized monthly anomalies are determined by differencing the average in  
 166 a given month from the average of all years of the same month. We consider TOA flux  
 167 differences between means for the post-hiatus and hiatus periods, where the hiatus period  
 168 is defined as July 2000–June 2014 and the post-hiatus period is July 2014–June 2017. The

169 corresponding SST difference pattern (Figure 1) shows marked SST increases during the  
170 post-hiatus period along the entire coast of North America, central Pacific Ocean, and to a  
171 lesser extent, along the coast of South America. In addition to examining global results, we  
172 also investigate how the models capture flux changes in a domain dominated primarily by  
173 low clouds over the eastern Pacific (EP) (see box in Figure 1).



174 **Figure 1.** Post-hiatus—hiatus difference in sea-surface temperature. The black box shows  
175 the EP domain defined by 10°N-40°N and 150°W-110°W.  
176

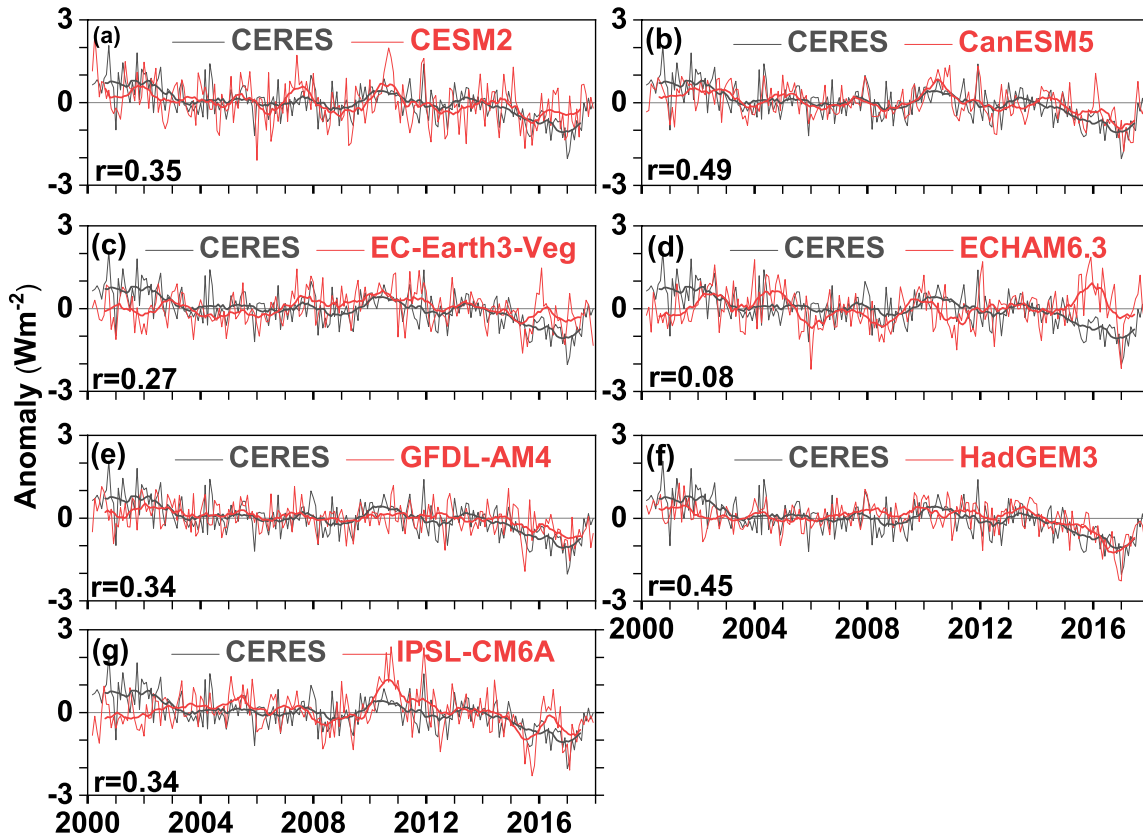
### 177 3. Results

#### 178 3.1 Global TOA Flux Anomalies

179 A comparison between SW flux anomalies from CERES and the seven CMIP6  
180 models is provided in Figures 2a-g, with positive numbers indicating anomalous upward  
181 radiation at the TOA. The corresponding comparisons for LW upward and net downward  
182 fluxes are shown in Figures S1 and S2. The CERES observations show appreciable positive  
183 SW and negative LW anomalies at the beginning of the CERES record, following a period  
184 of prolonged La Niña conditions that started in mid-1998 and ended in mid-2001.

185 Anomalies remain fairly weak between 2002 and 2013. Starting in 2014, a marked trend  
186 toward negative SW anomalies occurs that reaches a minimum value in January 2017, one  
187 year after the peak of the 2015/2016 El Niño event (one of the largest on record). SW  
188 anomalies return to near-normal levels at the end of 2017.

189 The CanESM5 and HadGEM3 models track the observed SW anomalies  
190 remarkably well during the entire period. All models except ECHAM6.3 capture the large  
191 negative SW flux anomalies during the post-hiatus period, but three models fail to  
192 reproduce the large positive anomalies at the beginning of the CERES record. While the  
193 overall mean correlation coefficient between model and observed monthly SW anomalies  
194 is only  $0.33 \pm 0.098$ , the standard deviation in CMIP6 SW monthly anomalies is consistent  
195 with CERES (Table S1). For LW and net, most of the models closely track the CERES 12-  
196 month running average, but they are less successful at capturing monthly variations. When  
197 annual anomalies are considered, model-observed correlation coefficients increase by a  
198 factor of 2 (Table S1). This is likely because more of the variability at annual time-scales  
199 is driven by interannual variability in the SST boundary conditions, whereas significant  
200 sub-annual variability is due to atmospheric stochastic variability, which is poorly  
201 correlated between models and observations (Proistosescu et al., 2018).



202

203 **Figure 2.** Deseasonalized anomalies in global mean TOA SW upward flux for CERES  
 204 and each of the seven CMIP6 models considered in Table 1. Thin lines correspond to  
 205 monthly anomalies; thick lines are 12-month running averages. Correlation  
 206 coefficients ( $r$ ) between model and observed monthly anomalies are also shown.  
 207

### 208 3.2 Post-Hiatus—Hiatus Differences

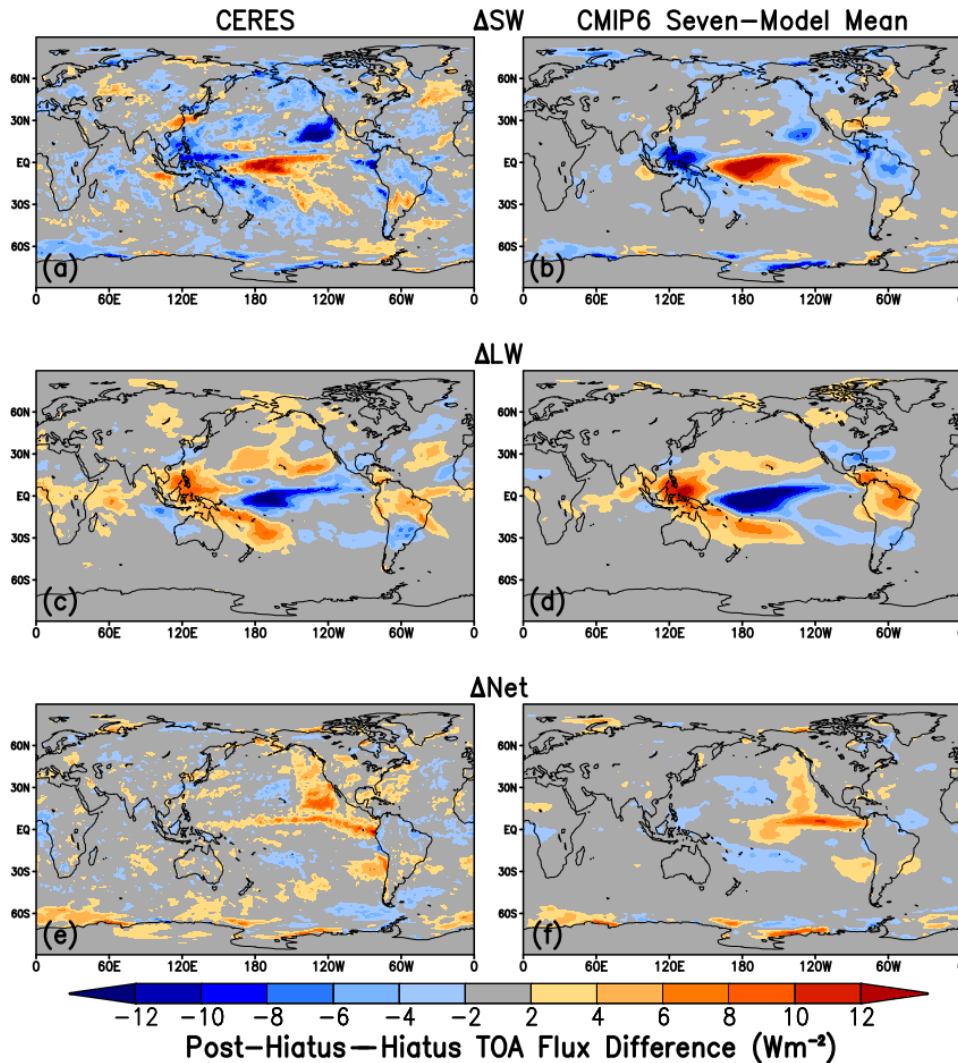
209 We find encouraging similarities between regional patterns of post-hiatus—hiatus  
 210 flux difference for CERES and the mean of the seven CMIP6 models (Figure 3a-f). The  
 211 CERES observations show a marked SW decrease during the post-hiatus period off the  
 212 west coast of North America (Figure 3a), a region characterized by persistent marine  
 213 stratocumulus. Surface warming in the East Pacific reduces the vertical stratification,  
 214 which reduces low-cloud cover (Klein and Hartmann 1993) and reflected solar radiation.  
 215 Large decreases in low-cloud cover in this region are thought to have played a significant  
 216 role in causing record-breaking warm SST anomalies after 2014 (Johnson and Birnbaum,

217 2016; Myers et al., 2018). In the tropics, CERES shows positive SW and negative LW  
218 differences in the central Pacific, and differences of the opposite sign in the western Pacific  
219 (Figures 3a and 3c). These patterns are consistent with an eastward shift in the location of  
220 tropical convection during the 2015/2016 El Niño event. The marked SW and LW tropical  
221 differences largely cancel, however, and are thus less prominent in the regional distribution  
222 of net flux differences (Figure 3e). Large positive net flux differences appear off the west  
223 coasts of the Americas since cancellation between SW and LW is weaker there.

224 The flux difference pattern for the mean of the seven CMIP6 models is similar to  
225 CERES (Figures 3b, 3d and 3f). Like CERES, the CMIP6 mean SW flux decreases in the  
226 region of large SST increase off the west coast of North America (Figure 3b). However,  
227 the magnitude of the decrease is weaker than CERES. Results for the individual models  
228 show that CanESM5 and HadGEM3 produce SW flux decreases that are larger than the 7-  
229 model mean and occur in the same location as CERES (Figure S3). Large decreases also  
230 occur for IPSL-CM6A and CESM2, but the locations differ from CERES. The SW flux  
231 decrease with SST off the west coast of North America is qualitatively consistent with  
232 other satellite studies that found a negative correlation between low-cloud cover and SST  
233 from passive (Myers and Norris, 2015; Qu et al., 2015; McCoy et al., 2017; Yuan et al.,  
234 2018) and active sensors (Myers and Norris, 2015; Cesana et al., 2019).

235 In the tropics, the locations of negative SW and positive LW anomalies in the South  
236 Pacific Convergence Zone (SPCZ) and Maritime Continent, and positive SW and negative  
237 LW anomalies in the central Pacific coincide with CERES (Figures 3a-d). However, the  
238 magnitudes of the CMIP6 model anomalies are larger than CERES both for the seven-  
239 model mean (Figures 3a-b) and most of the models individually (Figures S3-S4). The

240 CMIP6 model mean reproduces the large positive net downward flux anomalies off the  
 241 west coast of North America and along the equator seen in CERES (Figure 3e-f, Figure  
 242 S5).



243  
 244 **Figure 3.** Post-hiatus—hiatus difference in (a, b) SW upward, (c, d) LW upward and (e,  
 245 f) net downward TOA flux for CERES (left column) and average of seven CMIP6  
 246 model simulations (right column).

247 When averaged globally, all CMIP6 models except ECHAM6.3 show negative SW  
 248 and positive LW upward flux differences between the post-hiatus and hiatus periods,  
 249 consistent with CERES (Figure S6). The ECHAM6.3 model underestimates the magnitude  
 250 of negative SW differences associated with decreases in low clouds off the west coast of

251 North America and convection over the western tropical Pacific yet shows strong positive  
252 SW (and negative LW) differences in the central tropical Pacific and over North America,  
253 resembling a slight geographical shift of tropical convection in the zonal direction (Figures  
254 S3e, S4e). Excluding ECHAM6.3, the root-mean-square difference of the other six CMIP6  
255 models relative to CERES is  $0.3 \text{ Wm}^{-2}$  and  $0.15 \text{ Wm}^{-2}$  for SW and LW, respectively. The  
256 model most consistent with CERES is HadGEM3, which in addition to producing very  
257 similar global mean post-hiatus—hiatus differences, reproduces observed regional patterns  
258 rather well.

259 In the EP domain, the post-hiatus—hiatus difference in reflected SW flux is almost  
260 entirely associated with changes in  $T_s$ , based upon a multivariate regression analysis of SW  
261 against  $T_s$  and EIS (see Supporting Information). All of the models have a  $T_s$  contribution  
262 to the SW flux difference that is too weak compared to the observations (Figure S7). We  
263 also find little correlation between how well a model represents the SW flux post-hiatus—  
264 hiatus difference in the EP domain and the corresponding climatological mean value  
265 (Figure S11). The CESM2 model shows the greatest climatological mean bias ( $-10 \text{ Wm}^{-2}$ )  
266 yet its bias in the post-hiatus—hiatus difference is only  $1 \text{ Wm}^{-2}$ . In contrast, EC-Earth3-  
267 Veg shows a climatological mean bias of  $2 \text{ Wm}^{-2}$  and a post-hiatus—hiatus difference of  
268  $4 \text{ Wm}^{-2}$ . Notably, all of the models but two (ECHAM6.3 and IPSL-CM6A) have negative  
269 biases in the climatological mean SW flux. This is consistent with earlier studies that have  
270 shown models having a tendency to underestimate low-cloud cover in the subtropical  
271 stratocumulus regions off the west coasts of North and South America and Africa (Zhao et  
272 al., 2018). These results imply that good agreement between observed and model  
273 climatology does not necessarily imply good agreement in climate variability.



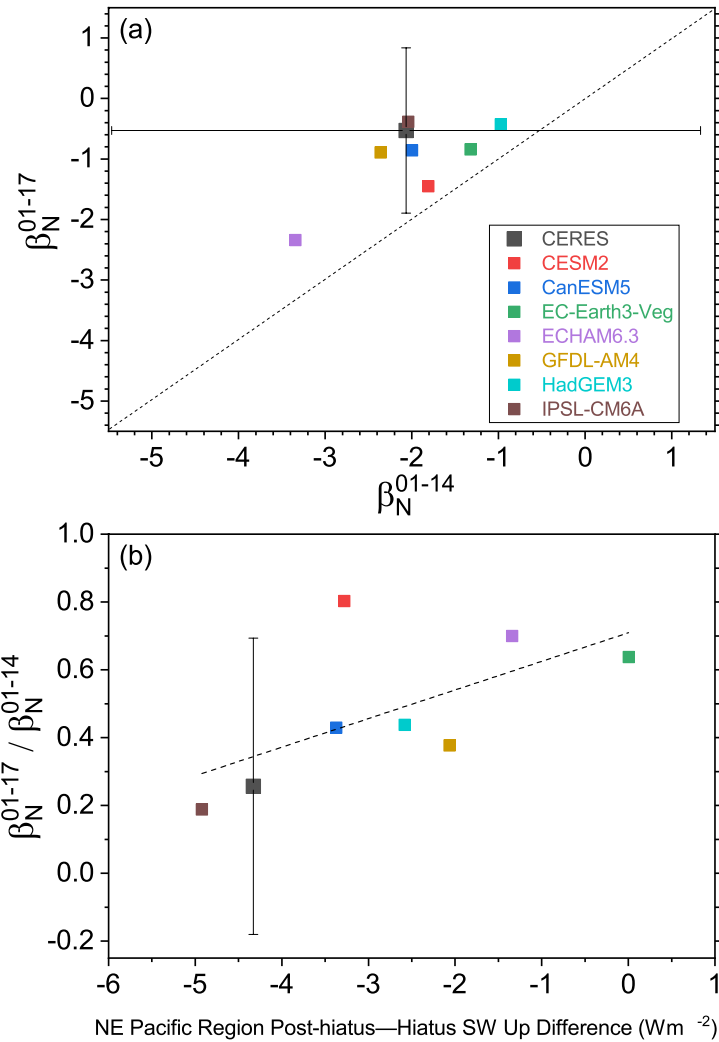
### 274 3.3 Pattern Effect

275 To examine the influence of the SST pattern change during the CERES period  
276 (Figure 1) on the relationship between net flux and surface temperature, we use an approach  
277 similar to Andrews et al (2018), who demonstrated the influence of the pattern effect on  
278 the net climate feedback parameter ( $\lambda_N$ ) for the historical record (1871-2010) and long-  
279 term CO<sub>2</sub> forcing. We refer to a radiative restoring coefficient (Lutsko and Takahashi,  
280 2018) for the CERES period ( $\beta_N$ ) instead of  $\lambda_N$  in order to emphasize that  $\beta_N$  is primarily  
281 a response to internal variability in the climate system whereas  $\lambda_N$  is primarily a response  
282 to external radiative forcing. We define  $\beta_N$  as  $\beta_N = (\delta N - \delta F)/\delta T_s$ , where  $\delta N$  is net flux  
283 anomaly,  $\delta F$  is the effective radiative forcing anomaly and  $\delta T_s$  is the surface temperature  
284 anomaly. Here,  $\delta$  are annual anomalies over the CERES period.  $F$  is obtained from the  
285 Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5)  
286 forcing time series updated and extended following Dessler and Forster (2018). We  
287 determine  $\beta_N$  for 2001-2017 and 2001-2014 from CERES and each of the seven CMIP6  
288 models by calculating the slope of  $\delta N - \delta F$  against  $\delta T_s$  using a standard ordinary least  
289 squares fit. To calculate  $\delta F$ , the same time-varying  $F$  is assumed for CERES and each  
290 CMIP6 model through 2014. For 2015-2017,  $F$  is held fixed at the 2014 value for the  
291 CMIP6 models but is time-varying for CERES. The uncertainty in the regression slope is  
292 represented by its 95% confidence interval.

293 For CERES,  $\beta_N$  becomes dramatically less stabilizing when the three post-hiatus  
294 years are included (Figure 4a), changing from  $-2.1 \text{ Wm}^{-2} \text{ K}^{-1}$  ( $-5.5$  to  $1.3 \text{ Wm}^{-2} \text{ K}^{-1}$ ) for  
295 2001-2014 to  $-0.53 \text{ Wm}^{-2} \text{ K}^{-1}$  ( $-1.9$  to  $0.83 \text{ Wm}^{-2} \text{ K}^{-1}$ ) for 2001-2017. The change in  $\beta_N$  is  
296 mainly due to a strong positive SW feedback (Figure S12) associated with the large

297 decrease in global mean reflected SW flux during the post-hiatus period. We note that the  
298 95% confidence intervals in  $\beta_N$  for these short periods are large owing to the short record  
299 of CERES. With the exception of ECHAM6.3, all of the model  $\beta_N$  values for 2001-2017  
300 fall within the 95% confidence interval of the observations. Excluding ECHAM6.3, the  
301 mean of the other six models have a less stabilizing  $\beta_N$  compared to CERES for 2001-2014  
302 by  $0.3 \text{ Wm}^{-2} \text{ K}^{-1}$  and a more stabilizing  $\beta_N$  by approximately the same magnitude for 2001-  
303 2017.

304 We quantify the pattern effect during the CERES period as the ratio of  $\beta_N$  for 2001-  
305 2017 to that for 2001-2014. This ratio is plotted against the post-hiatus—hiatus difference  
306 in SW upward flux for the EP domain in Figure 4b. The IPSL-CM6A model shows  
307 remarkable agreement with CERES, whereas the other models have both a  $\beta_N$  ratio that is  
308 too large, indicating too weak a pattern effect, corresponding to too weak a SW response  
309 in the EP domain. The positive correlation in Figure 4b suggests that at least for these  
310 periods, a model’s ability to represent changes in the relationship between global mean net  
311 flux and surface temperature (and therefore the pattern effect) depends critically upon how  
312 well it represents SW flux changes in low-cloud regions.



313

314 **Figure 4.** (a) Global net climate feedback parameter for 2001-2017 against that for 2001-  
 315 2014. (b) Ratio of 2001-2017 and 2001-2014 global net climate feedback parameters  
 316 against NE Pacific region post-hiatus—hiatus SW up difference. Dashed lines  
 317 correspond to one-to-one line in (a) and linear regression fit to all points in (b).

318 **4. Conclusions**

319

320 The general agreement between TOA radiation changes simulated by the seven  
 321 CMIP6 AGCMs considered in this study and CERES is encouraging as it suggests that the  
 322 models' atmospheric response to large-scale SST pattern changes resulting from a  
 323 combination of internal and forced variations is realistic. We find that a model's ability to

324 represent changes in the relationship between global mean flux and surface temperature  
325 depends critically upon how well it represents SW flux changes in regions dominated by  
326 low clouds, such as the EP domain considered here. Part of the reason is because there is  
327 less cancellation between SW and LW flux changes in these regions compared to the west  
328 and central Pacific, where marked SW and LW differences are quite similar in magnitude  
329 but opposite in sign. Over longer timescales, coupled climate model simulations also  
330 suggest an important role for low clouds in determining the future climate state. However,  
331 model biases could play a critical role (McGregor et al. 2018) in explaining why coupled  
332 models are not able to simulate the observed SST pattern during the hiatus (McGregor et  
333 al. 2014, Coats and Karnauskas, 2017). We thus caution that consistency between AGCM  
334 simulations and observations at interannual timescales is not a guarantee of success in  
335 projecting future climate, as other processes operating at longer timescales likely also  
336 matter.

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347 European Centre for Medium-range Weather Forecast (ECMWF) was downloaded online  
348 from: <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>. The EC-  
349 Earth3-Veg simulations were performed on resources provided by the Swedish National  
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351 [https://ceres.larc.nasa.gov/amip\\_data.php](https://ceres.larc.nasa.gov/amip_data.php).

352 **References**

353

354 Andrews, T., Gregory, J. M., Paynter, D., Silvers, L. G., Zhou, C., Mauritsen, T., et al.  
355 (2018). Accounting for changing temperature patterns increases historical estimates  
356 of climate sensitivity. *Geophysical Research Letters*, 45, 8490–8499.  
357 <https://doi.org/10.1029/2018GL078887>.

358

359 Andrews, T., Gregory, J. M., & Webb, M. J. (2015). The dependence of radiative forcing  
360 and feedback on evolving patterns of surface temperature change in climate models.  
361 *Journal of Climate*, 28(4), 1630–1648. <https://doi.org/10.1175/jcli-d-14-00545.1>.

362

363 Andrews, T., & Webb, M. J. (2018). The dependence of global cloud and lapse rate  
364 feedbacks on the spatial structure of tropical Pacific warming. *Journal of Climate*,  
365 31(2), 641–654. <https://doi.org/10.1175/JCLI-D-17-0087>.

366

367 Armour, K. C., Bitz, C. M., & Roe, G. H. (2013). Time-varying climate sensitivity from  
368 regional feedbacks. *Journal of Climate*, 26(13), 4518–4534.  
369 <https://doi.org/10.1175/JCLI-D-12-00544.1>.

370

371 Armour, K. C., J. Marshall, J. R. Scott, A. Donohoe, and E. R. Newsom (2016), Southern  
372 Ocean warming delayed by circumpolar upwelling and equatorward transport, *Nature*  
373 *Geoscience*, 9, 549–554, doi: [10.1038/ngeo2731](https://doi.org/10.1038/ngeo2731)

374

375 Armour, K. C. (2017). Energy budget constraints on climate sensitivity in light of  
376 inconstant climate feedbacks. *Nature Climate Change*, 7(5), 331–335.  
377 <https://doi.org/10.1038/nclimate3278>.

378

379 Ceppi, P., & Gregory, J. M. (2017). Relationship of tropospheric stability to climate  
380 sensitivity and Earth's observed radiation budget. *Proceedings of the National*  
381 *Academy of Sciences of the United States of America*, 114(50), 13,126–13,131.  
382 <https://doi.org/10.1073/pnas.1714308114>

383

384 Cesana, G., and D. E. Waliser (2016), Characterizing and understanding systematic  
385 biases in the vertical structure of clouds in CMIP5/CFMIP2 models, *Geophys.*  
386 *Res. Lett.*, 43, 10,538–10,546, doi:10.1002/2016GL070515.

387

388 Cesana, G., A. D. Del Genio, A. S. Ackerman, M. Kelley, G. Elsaesser, A. M. Fridlind, Y.  
389 Cheng, and M.-S. Yao (2019), Evaluating models' response of tropical low clouds  
390 to SST forcings using CALIPSO observations. *Atmos. Chem. Phys.*, 19, 2813–2832.  
391 <https://doi.org/10.5194/acp-19-2813-2019>.

392

393 Coats, S., & Karnauskas, K. B. (2017). Are simulated and observed twentieth century  
394 tropical Pacific sea surface temperature trends significant relative to internal  
395 variability? *Geophysical Research Letters*, 44, 9928–9937.  
396 <https://doi.org/10.1002/2017GL074622>

397

398  
399 Dessler, A. E., and Forster, P. M. (2018). An estimate of equilibrium climate  
400 sensitivity from interannual variability. *J. Geophys. Res. Atmos.*  
401 doi:10.1029/2018JD028481.  
402  
403 Davini, P., and Coauthors, 2017: Climate SPHINX: evaluating the impact of resolution  
404 and stochastic physics parameterisations in the EC-Earth global climate model.  
405 *Geosci Model Dev.* 10(3):1383.  
406  
407 Dong, Y., Proistosescu, C., Armour, K. C. & Battisti, D. S. (2019): Attributing historical  
408 and future evolution of radiative feedbacks to regional warming patterns using a  
409 green's function approach: The preeminence of the Western Pacific. *Journal of*  
410 *Climate*, 32, 5471-5491. doi: 10.1175/JCLI-D-18-0843.1.  
411  
412 Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K.  
413 E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6  
414 (CMIP6) experimental design and organization, *Geosci. Model Dev.*, 9, 1937-  
415 1958, <https://doi.org/10.5194/gmd-9-1937-2016>  
416  
417 Fueglistaler, S. (2019). Observational evidence for two modes of coupling between sea  
418 surface temperatures, tropospheric temperature profile, and shortwave cloud radiative  
419 effect in the tropics. *Geophysical Research Letters*, 46.  
420 <https://doi.org/10.1029/2019GL083990>  
421  
422 Gates, W. L., Boyle, J. S., Covey, C., Dease, C. G., Doutriaux, C. M., Drach, R. S., et al.  
423 (1999). An overview of the results of the Atmospheric Model Intercomparison Project  
424 (AMIP I). *Bulletin of the American Meteorological Society*, 80(1), 29–55.  
425 [https://doi.org/10.1175/1520-0477\(1999\)080<0029:AOOTRO>2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080<0029:AOOTRO>2.0.CO;2)  
426  
427 Gettelman, A., Hannay, C., Bacmeister, J. T., Neale, R. B., Pendergrass, A. G.,  
428 Danabasoglu, G., et al. (2019). High Climate Sensitivity in the Community Earth  
429 System Model Version 2 (CESM2). *Geophys. Res. Lett.* 46, 8329–8337.  
430 doi:10.1029/2019gl083978  
431  
432 Gregory, J. M., & Andrews, T. (2016). Variation in climate sensitivity and feedback  
433 parameters during the historical period. *Geophysical Research Letters*, 43, 3911–  
434 3920. <https://doi.org/10.1002/2016GL068406>.  
435  
436 Haugstad, A. D., Armour, K. C., Battisti, D. S., & Rose, B. E. J. (2017). Relative roles of  
437 surface temperature and climate forcing patterns in the inconstancy of radiative  
438 feedbacks. *Geophysical Research Letters*, 44, 7455–7463.  
439 <https://doi.org/10.1002/2017GL074372>  
440  
441 He, J., & Soden, B. J. (2016). Does the lack of coupling in SST-forced atmosphere-only  
442 models limit their usefulness for climate change studies? *Journal of Climate*, 29,  
443 4317-4325. <http://dx.doi.org/10.1175/JCLI-D-14-00597.s1>

444  
445 Hersbach, H., et al., 2018: Operational global reanalysis: progress, future directions and  
446 synergies with NWP. ERA Report Series. European Centre for Medium Range  
447 Weather Forecasts. Reading, UK. [Available from:  
448 <https://www.ecmwf.int/file/276463/download?token=q6uGbnPD>]  
449

450 Hourdin H, et al. (2013): LMDZ5B: The atmospheric component of the IPSL climate  
451 model with revisited parameterizations for clouds and convection. *Climate Dynamics*,  
452 40, 2193-2222. <https://doi.org/10.1007/s00382-012-1343-y>.  
453

454 Hurrell, J., Hack, J., Shea, D., Caron, J., & Rosinski, J. (2008). A new sea surface  
455 temperature and sea ice boundary dataset for the community atmosphere model.  
456 *Journal of Climate*, 21(19), 5145–5153. <https://doi.org/10.1175/2008JCLI2292.1>.  
457

458 Johnson, G. C., and A. N. Birnbaum (2017), As El Niño builds, Pacific Warm Pool  
459 expands, ocean gains more heat, *Geophys. Res. Lett.*, 44, 438–445,  
460 doi:10.1002/2016GL071767.  
461

462 Klein, S. A., Hall, A. (2015). Emergent constraints for cloud feedbacks. *Curr. Clim.*  
463 *Change Rep.*, 1:276–287. <https://doi.org/10.1007/s40641-015-0027-1>  
464

465 Klein, S. A., & Hartmann, D. L. (1993). The seasonal cycle of low stratiform clouds.  
466 *Journal of Climate*, 6, 1587-1606.  
467

468 Loeb, N. G., Thorsen, T. J., Norris, J. R., Wang, H., & Su, W. (2018a). Changes in  
469 earth’s energy budget during and after the “Pause” in Global Warming: An  
470 observational perspective. *MDPI Climate*, 6, 62; doi:10.3390/cli6030062.  
471

472 Loeb, N. G., D. R. Doelling, H. Wang, W. Su, C. Nguyen, J. G. Corbett, L. Liang, C.  
473 Mitrescu, F. G. Rose, and S. Kato, 2018b: Clouds and the Earth’s Radiant Energy  
474 System (CERES) Energy Balanced and Filled (EBAF) Top-of-Atmosphere (TOA)  
475 Edition 4.0 data product, *J. Climate*, 31, 895-918. doi:10.1175/JCLI-D-17-0208.1.  
476

477 Loeb, N.G., F.G. Rose, S. Kato, D.A. Rutan, W. Su, H. Wang, D.R. Doelling, W.L.  
478 Smith, Jr., and A. Gettelman, 2019: Towards a consistent definition between satellite  
479 and model clear-sky radiative fluxes. *J. Climate*, 33, 61-75. doi: 10.1175/JCLI-D-19-  
480 0381.1.  
481

482 Lutsko, N. J., & Takahashi, K. (2018). What can the internal variability of CMIP5  
483 models tell us about their climate sensitivity? *Journal of Climate*, 31, 5051-5069.  
484 doi:10.1175/JCLI-D-17-0736.1  
485

486 Marvel, K., Pincus, R., Schmidt, G. A., & Miller, R. L. (2018). Internal variability and  
487 disequilibrium confound estimates of climate sensitivity from observations.  
488 *Geophysical Research Letters*, 45, 1595–1601.  
489 <https://doi.org/10.1002/2017GL076468>.

490  
491 Mauritsen, T., (2016). Clouds cooled the Earth. *Nature Geoscience*, 9, 865-867.  
492  
493 Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., et al. (2019).  
494 Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and its  
495 response to increasing CO<sub>2</sub>. *Journal of Advances in Modeling Earth Systems*, 11,  
496 998–1038. <https://doi.org/10.1029/2018MS001400>.  
497  
498 Mauritsen, T., & Stevens, B. (2015). Missing iris effect as a possible cause of muted  
499 hydrological change and high climate sensitivity in models. *Nature Geoscience*, 8,  
500 346-351. doi:10.1038/NGEO2414  
501  
502 McCoy, D. T., Eastman, R., Hartmann, D. L., and Wood, R.: The Change in Low Cloud  
503 Cover in a Warmed Climate Inferred from AIRS, MODIS, and ERA-Interim, *J.*  
504 *Climate*, 30, 3609–3620, <https://doi.org/10.1175/JCLI-D-15-0734.1>, 2017.  
505  
506 McGregor, S., A. Timmermann, M. F. Stuecker, M. H. England, M. Merrifield, F.-F. Jin,  
507 and Y. Chikamoto (2014), Recent Walker circulation strengthening and Pacific  
508 cooling amplified by Atlantic warming, *Nature Climate Change*, 4, 888–892,  
509 doi:10.1038/nclimate2330.  
510  
511 McGregor, S., M. F. Stuecker, J. B. Kajtar, M. H. England, & M. Collins (2018): Model  
512 Tropical Atlantic biases underpin diminished Pacific decadal variability, *Nature*  
513 *Climate Change*, 8, 493–498, doi:10.1038/s41558-018-0163-4.  
514  
515 Murphy, J. M. (1995): Transient response of the Hadley Centre Coupled Ocean-  
516 Atmosphere Model to increasing carbon dioxide. Part 1: Control climate and flux  
517 adjustment. *Journal of Climate*, 8, 36-56. doi:10.1175/1520-  
518 0442(1995)008<0036:TROTHC>2.0.CO;2  
519  
520 Myers, T. A., Mechoso, C. R., Cesana, G. V., DeFlorio, M. J., & Waliser, D. E. (2018).  
521 Cloud feedback key to marine heatwave off Baja California. *Geophysical Research*  
522 *Letters*, 45, 4345–4352. <https://doi.org/10.1029/2018GL078242>.  
523  
524 Myers, T. A., and J. R. Norris (2016), Reducing the uncertainty in subtropical cloud  
525 feedback, *Geophys. Res. Lett.*, 43,2144–2148, doi:10.1002/2015GL067416.  
526  
527 Myers, T. A., and J. R. Norris (2015), On the relationships between subtropical clouds  
528 and meteorology in observations and CMIP3 and CMIP5 models, *J. Clim.*, 28, 2945–  
529 2967.  
530  
531 Paynter, D., and T. L. Frölicher (2015), Sensitivity of radiative forcing, ocean heat  
532 uptake, and climate feedback to changes in anthropogenic greenhouse gases and  
533 aerosols, *J. Geophys. Res. Atmos.*, 120, 9837–9854, doi:10.1002/2015JD023364.  
534



535 Proistosescu, C., & Huybers, P. J. (2017). Slow climate mode reconciles historical and  
536 model-based estimates of climate sensitivity. *Science Advances*, 3(7), e1602821.  
537 <https://doi.org/10.1126/sciadv.1602821>.  
538

539 Proistosescu, C., Donohoe, A., Armour, K. C., Roe, G. H., Stuecker, M. F., & Bitz, C. M.  
540 (2018). Radiative feedbacks from stochastic variability in surface temperature and  
541 radiative imbalance. *Geophysical Research Letters*, 45, 5082–5094.  
542 <https://doi.org/10.1029/2018GL077678>  
543

544 Qu, X., A. Hall, S. A. Klein, and A. M. DeAngelis (2015), Positive tropical marine low-  
545 cloud cover feedback inferred from cloud controlling factors, *Geophys. Res. Lett.*, 42,  
546 7767–7775, doi:10.1002/2015GL065627.  
547

548 Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D.  
549 P., Kent, E. C., and Kaplan, A. (2003) Global analyses of sea surface temperature, sea  
550 ice, and night marine air temperature since the late nineteenth century, *J. Geophys.*  
551 *Res.*, 108(D14), 4407, doi: 10.1029/2002JD002670  
552

553 Riahi, K., et al. (2017): The Shared Socioeconomic Pathways and their energy, land use,  
554 and greenhouse gas emissions implications: An overview. *Global Environmental*  
555 *Change*, 42, 153-168.  
556

557 Rose, B. E. J., Armour, K. C., Battisti, D. S., Feldl, N., & Koll, D. D. B. (2014). The  
558 dependence of transient climate sensitivity and radiative feedbacks on the spatial  
559 pattern of ocean heat uptake. *Geophysical Research Letters*, 41, 1071–1078.  
560 <https://doi.org/10.1002/2013GL058955>.  
561

562 Senior, C. A., & Mitchell, J. F. B. (2000): The time-dependency of climate sensitivity.  
563 *Geophys. Res. Lett.*, 27, 2685-2688. <https://doi.org/10.1029/2000GL011373>.  
564

565 Silvers, L. G., Paynter, D., & Zhao, M. (2018). The diversity of cloud responses to  
566 twentieth century sea surface temperatures. *Geophysical Research Letters*, 45, 391–  
567 400. <https://doi.org/10.1002/2017GL075583>.  
568

569 Stevens, B., Sherwood, S. C., Bony, S., & Webb, M. J. (2016). Prospects for narrowing  
570 bounds on Earth’s equilibrium climate sensitivity. *Earth’s Future*, 4(11), 512–522.  
571 <https://doi.org/10.1002/2016EF000376>.  
572

573 Swart, N. C. and co-authors. (2019). The Canadian Earth System Model version 5  
574 (CanESM5.0.3). *Geosci. Model. Dev.*, <https://doi.org/10.5194/gmd-2019-177>.  
575

576 Taylor, K. E., Williamson, D., & Zwiers, F. (2000). The sea surface temperature and sea-  
577 ice concentration boundary conditions for AMIP II simulations, PCMDI Report No.  
578 60, Program for Climate Model Diagnosis and Intercomparison, Lawrence Livermore  
579 National Laboratory.  
580

581 Williams, K. D., and Coauthors, 2018: The met office global coupled model 3.0 and 3.1  
582 (GC3.0 & GC3.1) configurations. *J. Adv. Model Earth Syst.*, 10(2):357–380.  
583

584 Winton, M., Takahashi, K. & Held, I. M. (2010): Importance of ocean heat uptake  
585 efficacy to transient climate change. *Journal of Climate*, 23, 2333-23444.  
586 doi.org/10.1175/2009JCLI3139.1  
587

588 Wood, R., and C. S. Bretherton, 2006: On the relationship between stratiform low cloud  
589 cover and lower-tropospheric stability. *J. Climate*, 19, 6425–6432.  
590

591 Yuan, T., Oreopoulos, L., Platnick, S. E., & Meyer, K. (2018). Observations of local  
592 positive low cloud feedback patterns and their role in internal variability and climate  
593 sensitivity. *Geophysical Research Letters*, 45, 4438–4445.  
594 <https://doi.org/10.1029/2018GL077904>.  
595

596 Zhao, M., Golaz, J.-C., Held, I. M., Guo, H., Balaji, V., Benson, R., et al. (2018). The  
597 GFDL global atmosphere and land model AM4.0/LM4.0: 1. Simulation  
598 characteristics with prescribed SSTs. *Journal of Advances in Modeling Earth  
599 Systems*, 10, 691–734. <https://doi.org/10.1002/2017MS001208>.  
600

601 Zhou, C., Zelinka, M. D., & Klein, S. A. (2016). Impact of decadal cloud variations on  
602 the Earth’s energy budget. *Nature Geoscience*, 9(12), 871–874.  
603 <https://doi.org/10.1038/ngeo2828>.  
604

605 Zhou, C., Zelinka, M. D., & Klein, S. A. (2017). Analyzing the dependence of global  
606 cloud feedback on the spatial pattern of sea surface temperature change with a  
607 Green’s function approach. *Journal of Advances in Modeling Earth Systems*, 9,  
608 2174–2189. <https://doi.org/10.1002/2017MS001096>.

Supporting Information for

**New Generation of Climate Models Track Recent Unprecedented Changes in Earth's Radiation Budget Observed by CERES**

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Contents of this file

Figure S1-S12

Table S1

## 1. Global TOA Flux Anomalies

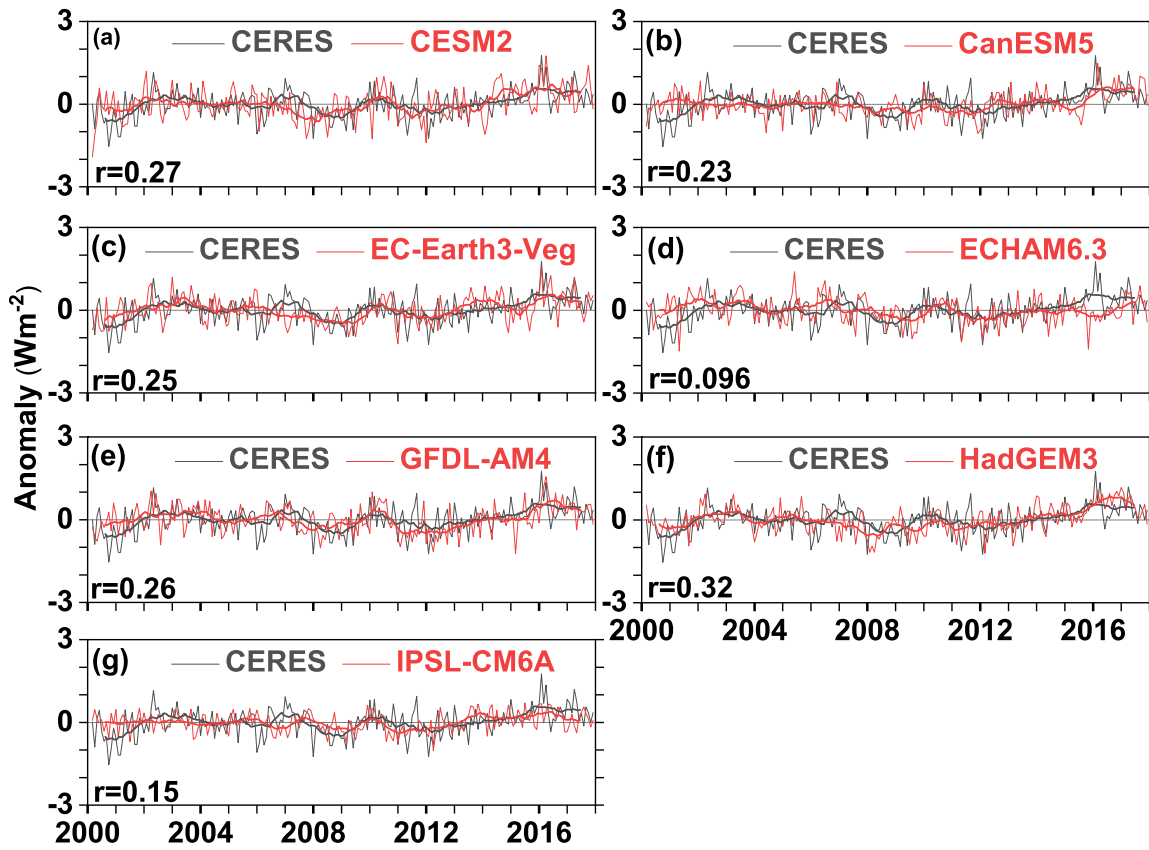


Figure S1. Same as Figure 2 but for TOA LW upward flux.

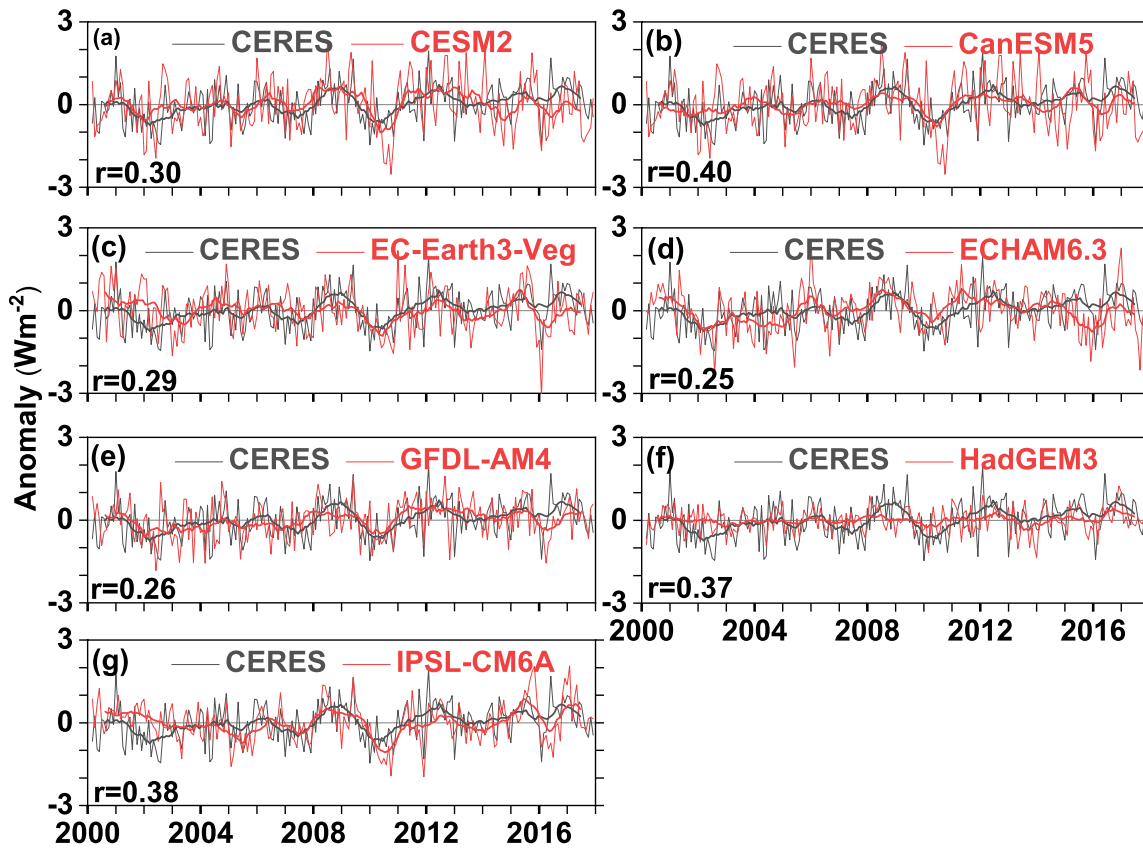
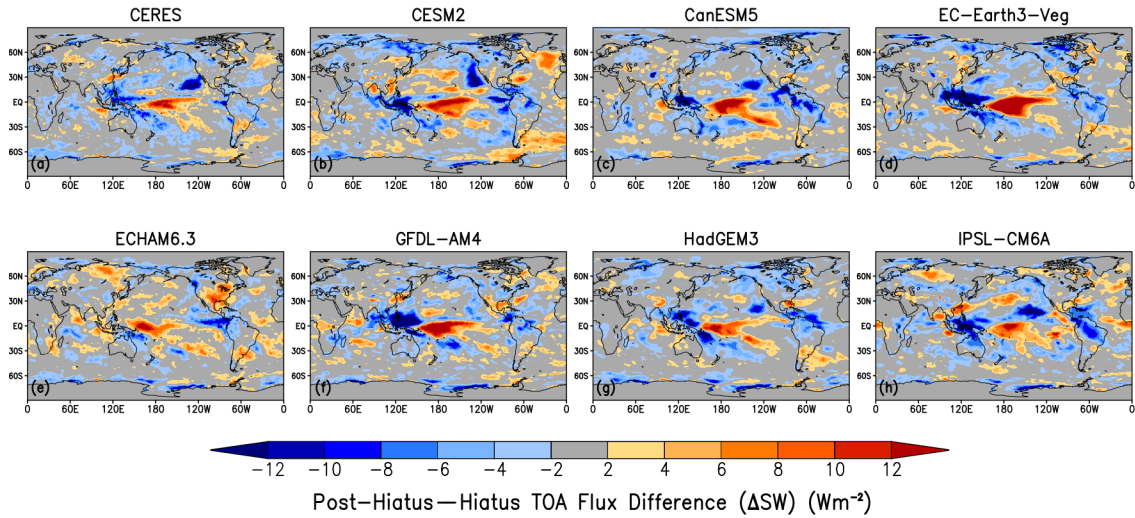


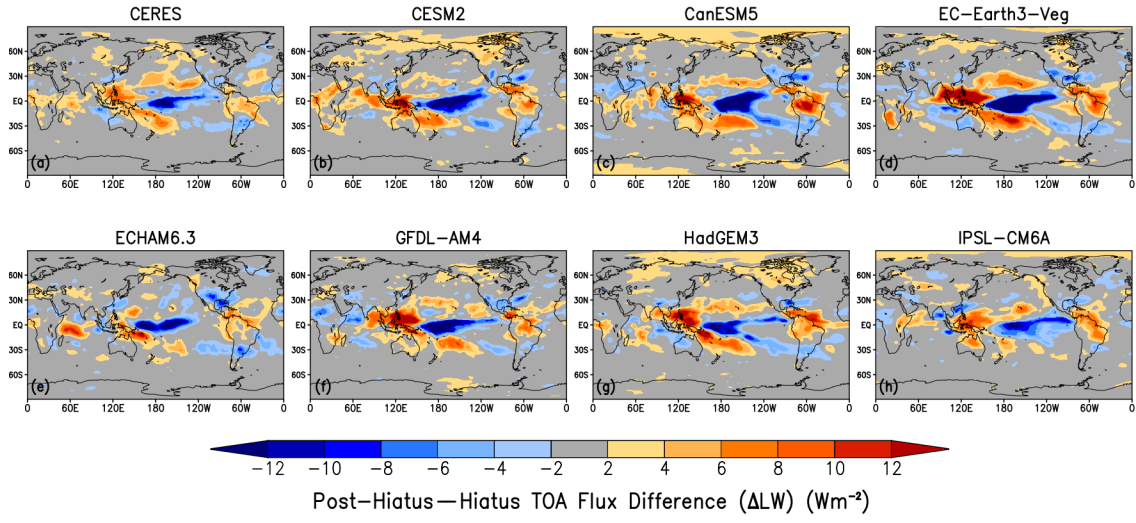
Figure S2. Same as Figure 2 but for TOA net downward flux.

## 2. Post-Hiatus—Hiatus Differences

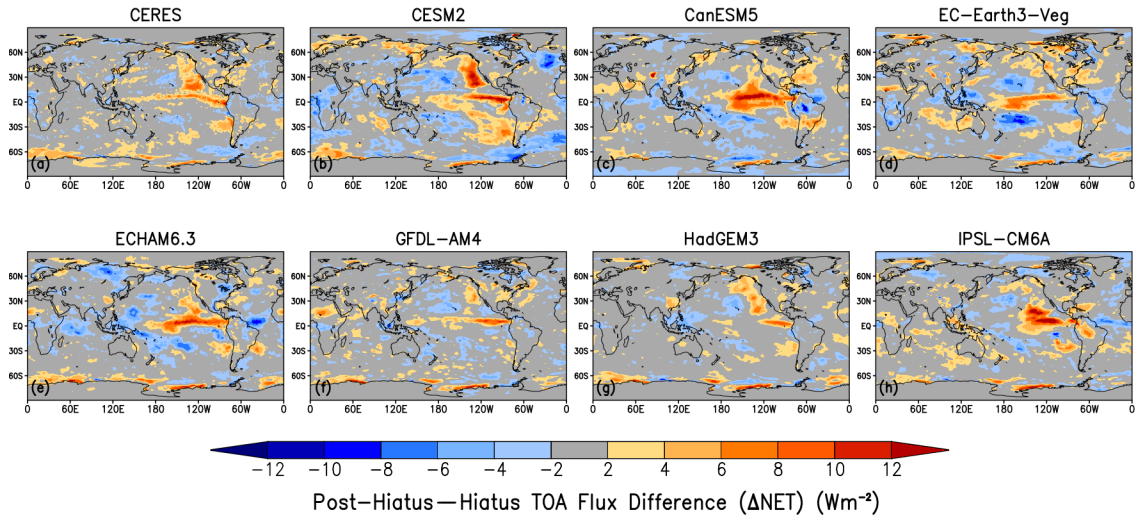
### 2.1 Regional



**Figure S3.** Post-hiatus—hiatus difference in SW TOA upward flux for (a) CERES, (b) CESM2, (c) CanESM5, (d) EC-Earth3-Veg, (e) ECHAM6.3, (f) GFDL-AM4, (g) HadGEM3, (h) IPSL-CM6A.



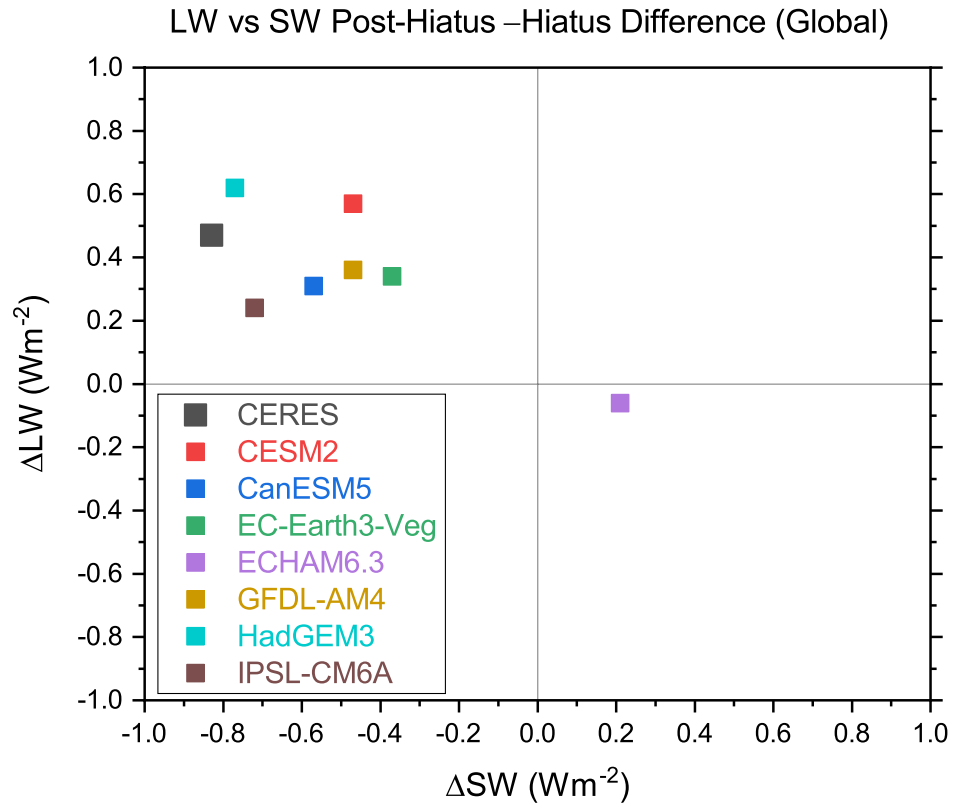
**Figure S4.** Same as Figure S3 but for TOA LW upward flux.



**Figure S5.** Same as Figure S3 but for TOA Net flux.



## 2.2 Global

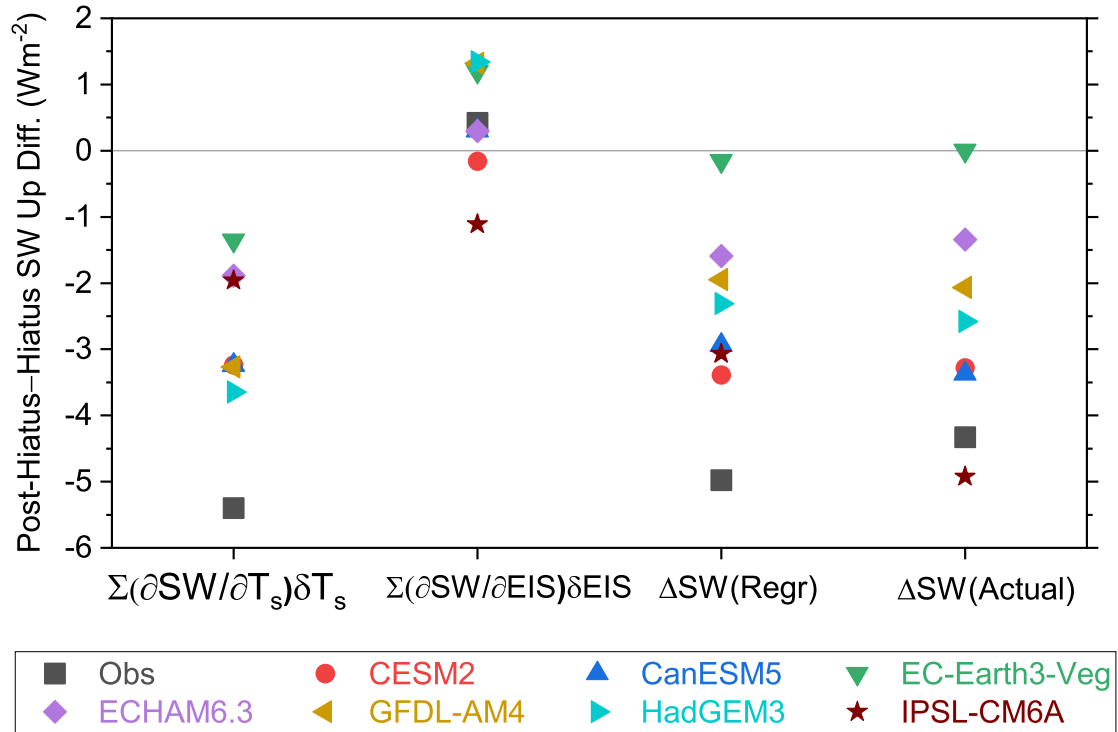


**Figure S6.** Global mean post-hiatus—hiatus difference in LW and SW TOA upward flux for CERES and the seven CMIP6 model simulations.

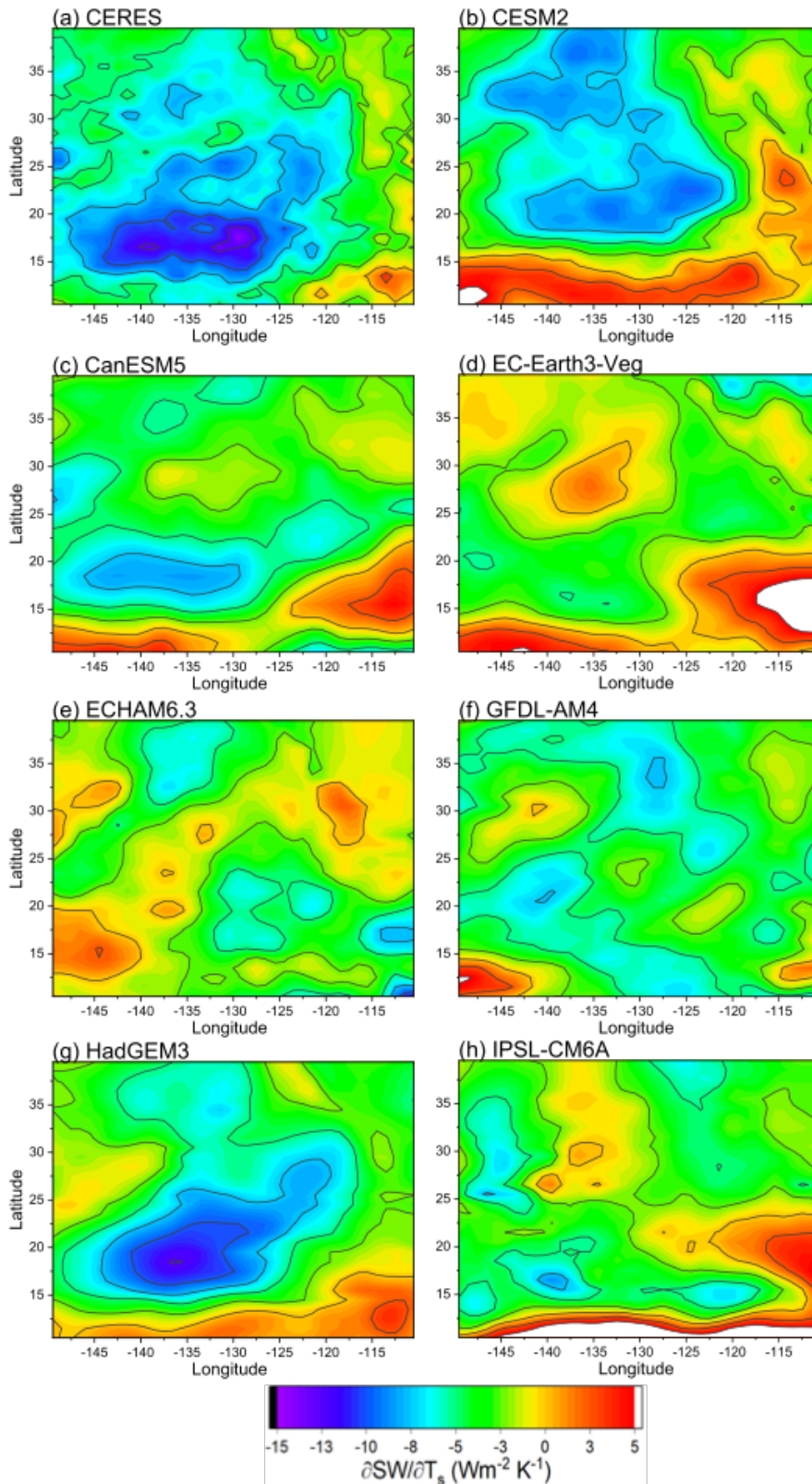
### 2.3 Multivariate Regression Analysis

We examine the dependence of the post-hiatus—hiatus SW flux difference on  $T_s$  and EIS for the EP domain by performing a multiple regression analysis. Anomalies in SW flux for each  $1^\circ \times 1^\circ$  gridbox are regressed against local anomalies in  $T_s$  and EIS. The domain average  $T_s$  and EIS contributions to the post-hiatus—hiatus SW flux difference are determined from the area-weighted product of the regression coefficients ( $\partial SW/\partial T_s$  or  $\partial SW/\partial EIS$ ) and the  $T_s$  or EIS post-hiatus—hiatus difference. We recognize that other meteorological variables can also explain some TOA radiation variability in low-cloud regions (Myers and Norris, 2016), but given the unprecedented changes in SST (and therefore,  $T_s$ ) observed in the EP domain, we only consider  $T_s$  and EIS, the two most dominant meteorological factors found to impact SW cloud feedback (Myers and Norris, 2016).

In the EP domain, the post-hiatus—hiatus difference in reflected SW flux is almost entirely associated with changes in  $T_s$ , based upon a multivariate regression analysis of SW against  $T_s$  and EIS (Figure S7). All of the models have a  $T_s$  contribution to the SW flux difference that is too weak by at least  $2 \text{ Wm}^{-2}$  compared to the observations. The regional pattern of observed SW sensitivity to  $T_s$  ( $\partial SW/\partial T_s$ ), given by the regression coefficient of each  $1^\circ \times 1^\circ$  gridbox in the EP domain (Figure S8), shows negative values throughout, except for a small area in the southeast portion of the domain. Most of the CMIP6 models show weaker SW sensitivity to  $T_s$  with a pattern that differs markedly from the observations. The two models that place the peak negative  $\partial SW/\partial T_s$  values in approximately the correct location (e.g., CESM2 and HadGEM3) show weaker peak values compared to the observations and have large positive values south of  $15^\circ\text{N}$ . As a result, all of the models produce a weaker  $T_s$  contribution to the SW flux difference in Figure S7. The EIS contribution to the SW flux difference (Figure S7) is less than  $0.5 \text{ Wm}^{-2}$  in magnitude in the observations and three of the models (CESM2, CanESM5, and ECHAM6.3), and is closer to  $\pm 1 \text{ Wm}^{-2}$  for the other models. The regional pattern of observed SW sensitivity to EIS ( $\partial SW/\partial EIS$ ) shows an area of positive values along the northwest to southeast diagonal in Figure S9a. The CESM2 model shows a remarkably similar  $\partial SW/\partial EIS$  pattern to the observations whereas the other model results differ markedly. The regional distribution of the coefficient of determination of the regression in  $T_s$  and EIS on monthly timescales (Figure S10a) peaks at 0.42 in the center of the domain and has a pattern that resembles the  $\partial SW/\partial EIS$  pattern in Figure S9a.



**Figure S7.** Post-hiatus—hiatus SW up difference due to surface temperature ( $\Sigma(\partial SW/\partial T_s)\delta T_s$ ) and EIS ( $\Sigma(\partial SW/\partial EIS)\delta EIS$ ) contributions, their sum ( $\Delta SW(\text{Regr})$ ) and the actual observed difference ( $\Delta SW(\text{Actual})$ ) for the EP region (10°N-40°N; 150°W-110°W).



**Figure S8.** Sensitivity in SW upwards flux to surface temperature.

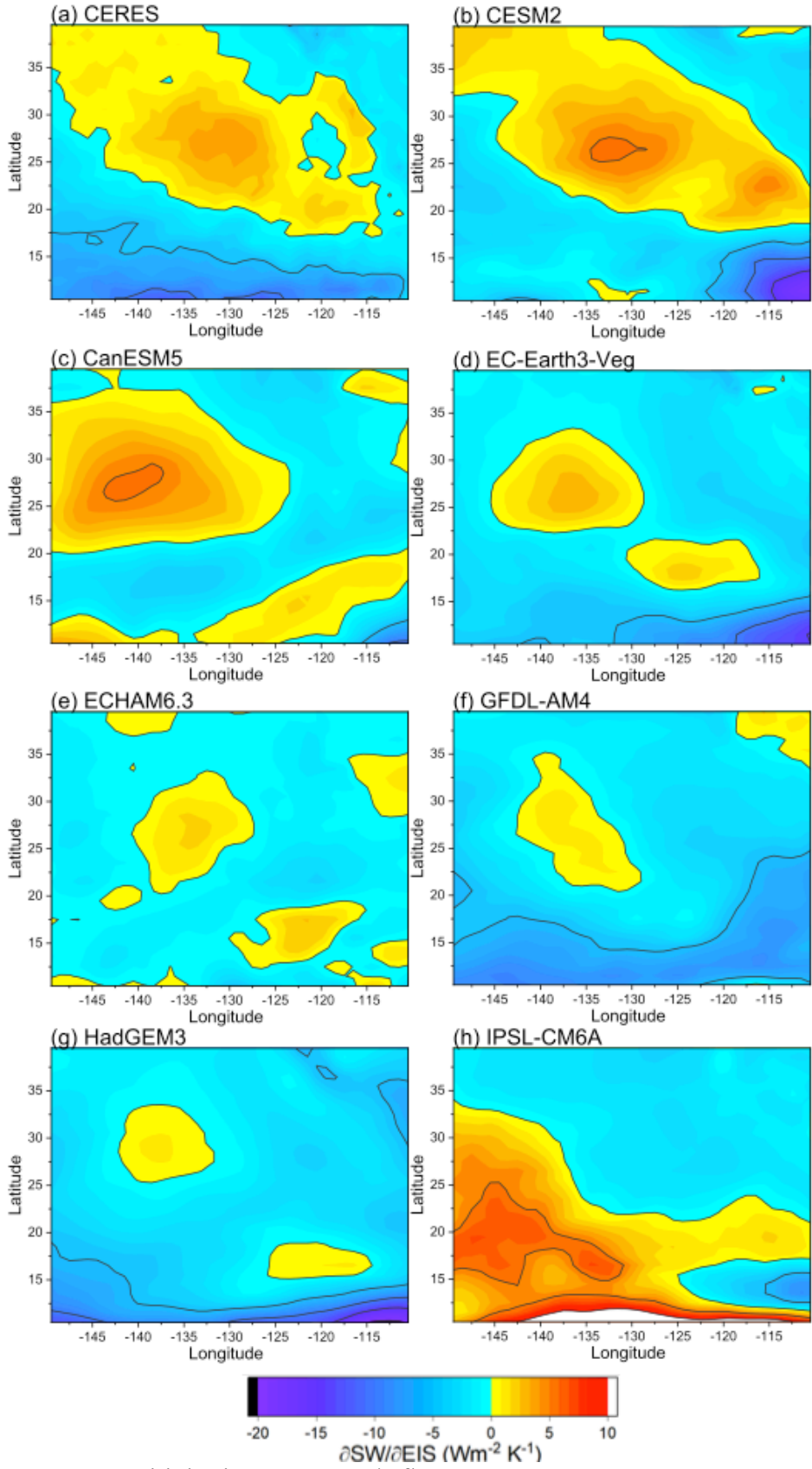
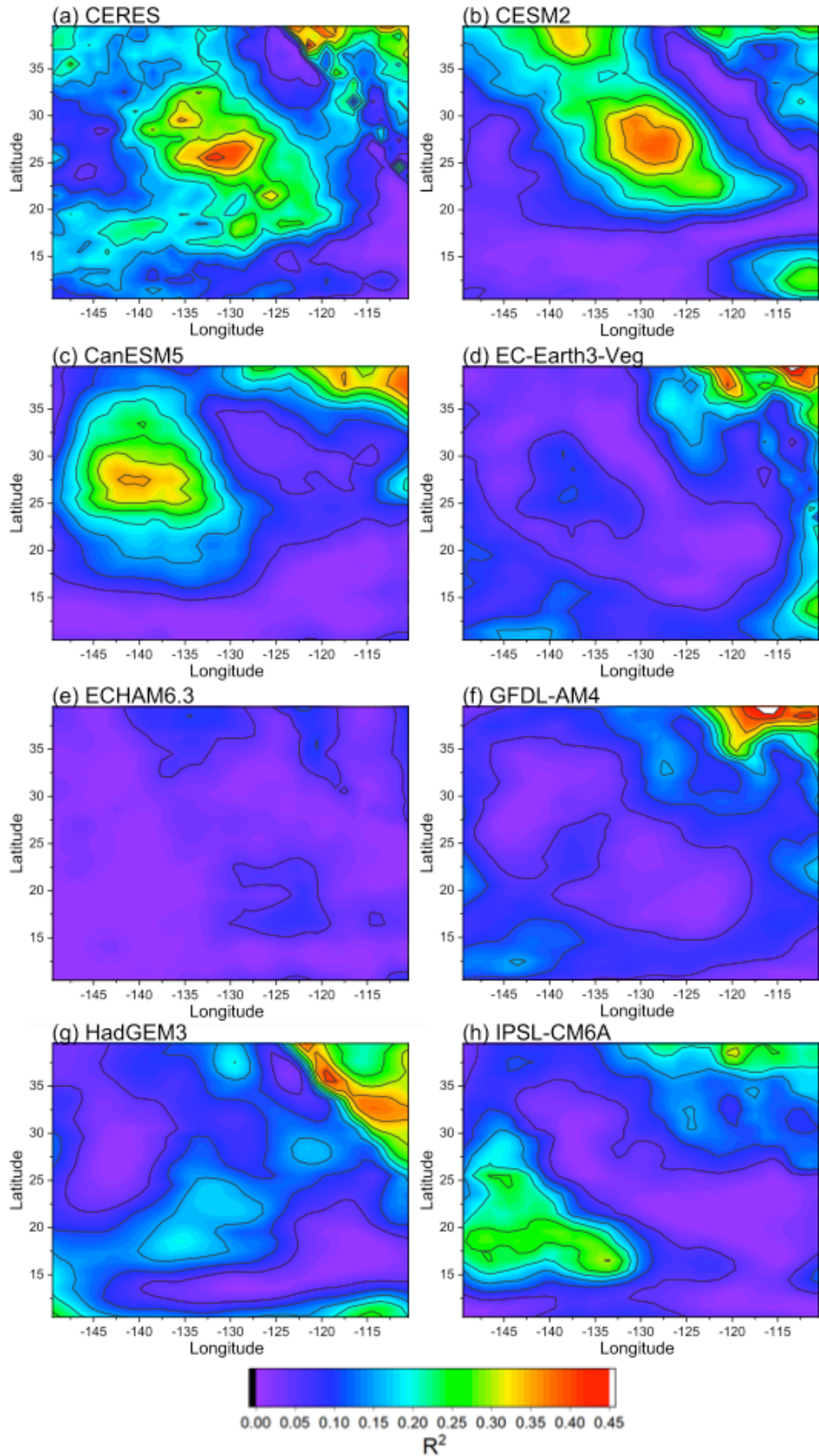
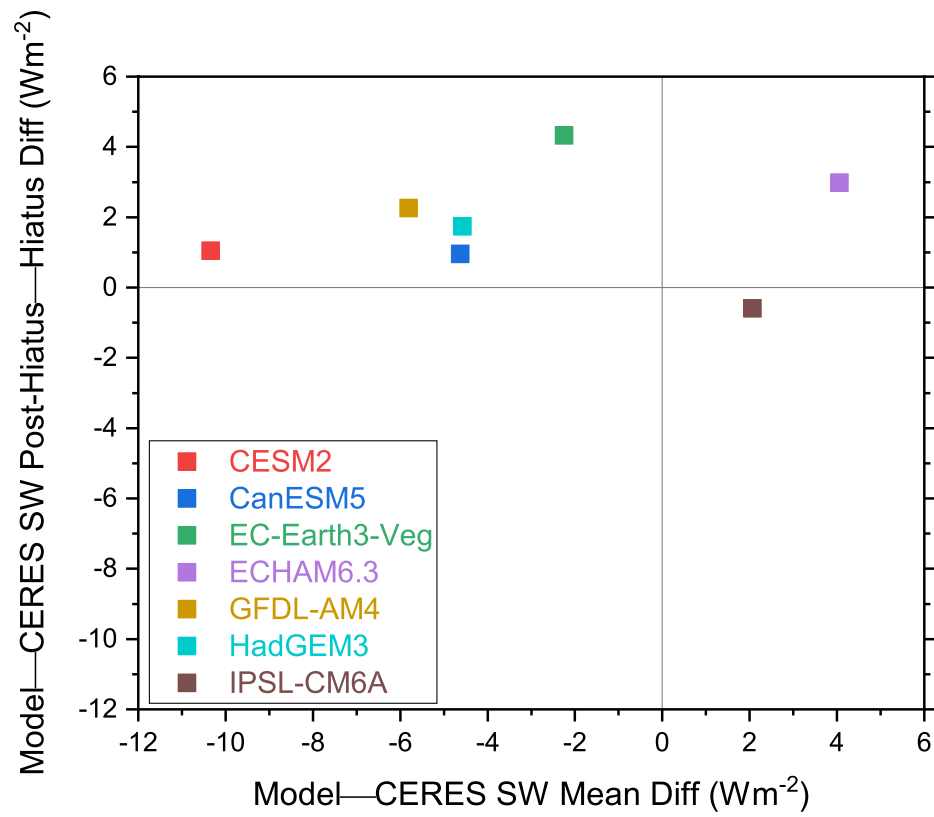


Figure S9. Sensitivity in SW upwards flux to EIS.



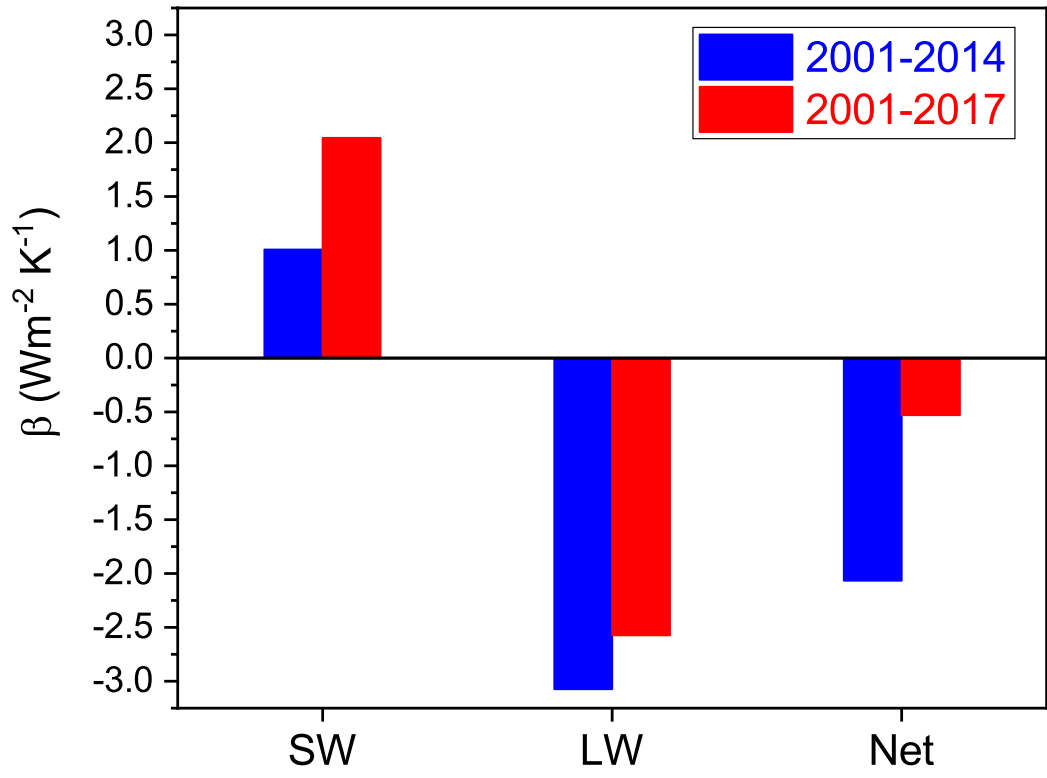
**Figure S10.** Multiple linear regression coefficient of determination ( $R^2$ ).

## 2.4 Relationship Between Biases in Climatological Mean and Post-Hiatus—Hiatus Difference for EP Region



**Figure S11.** Bias in SW TOA flux post-hiatus—hiatus difference against bias in SW TOA flux climatological mean for the EP region for July 2000-June 2017.

### 3. Radiative Restoring Coefficient



**Figure S12.** Observed SW, LW and Net radiative restoring coefficients ( $\beta$ ) for 2001-2014 and 2001-2017.



## Tables

**Table S1.** Standard deviation (Stdev) of monthly and annual anomalies in global mean SW, LW and Net TOA flux and correlation coefficient (r) between CERES and each CMIP6 simulation. Last row provides mean CMIP6 Stdev and r with 90% confidence interval. Annual anomalies are calculated from July to June means between 2001-2017.

	SW Anomalies			
	Monthly		Annual	
Name	Stdev (Wm <sup>-2</sup> )	r	Stdev (Wm <sup>-2</sup> )	r
CERES	0.64	1.00	0.44	1.00
CESM2	0.77	0.35	0.33	0.81
CanESM5	0.58	0.49	0.35	0.87
EC-Earth3-Veg	0.59	0.27	0.28	0.44
ECHAM6.3	0.69	0.080	0.38	-0.07
GFDL-AM4	0.54	0.34	0.25	0.90
HadGEM3	0.57	0.45	0.37	0.83
IPSL-CM6A	0.72	0.34	0.40	0.60
Mean (90% CI)	0.64±0.065	0.33±0.098	0.34±0.041	0.62±0.26
	LW Anomalies			
	Monthly		Annual	
Name	Stdev (Wm <sup>-2</sup> )	r	Stdev (Wm <sup>-2</sup> )	r
CERES	0.51	1.00	0.30	1.00
CESM2	0.57	0.27	0.27	0.66
CanESM5	0.43	0.23	0.21	0.40
EC-Earth3-Veg	0.48	0.25	0.24	0.70
ECHAM6.3	0.47	0.096	0.19	0.21
GFDL-AM4	0.49	0.26	0.27	0.68
HadGEM3	0.48	0.32	0.32	0.69
IPSL-CM6A	0.34	0.15	0.19	0.45
Mean (90% CI)	0.47±0.051	0.23±0.055	0.24±0.037	0.54±0.14
	Net Anomalies			
	Monthly		Annual	
Name	Stdev (Wm <sup>-2</sup> )	r	Stdev (Wm <sup>-2</sup> )	r
CERES	0.69	1.00	0.34	1.00
CESM2	0.90	0.30	0.33	0.57
CanESM5	0.61	0.40	0.23	0.66
EC-Earth3-Veg	0.79	0.29	0.27	0.37
ECHAM6.3	0.77	0.25	0.40	0.45
GFDL-AM4	0.68	0.26	0.27	0.71
HadGEM3	0.45	0.37	0.13	0.60
IPSL-CM6A	0.71	0.38	0.32	0.52
Mean (90% CI)	0.70±0.11	0.32±0.044	0.28±0.063	0.55±0.087