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► **To cite this version:**

Norman Loeb, Hailan Wang, Richard Allan, Timothy Andrews, Kyle C Armour, et al.. New Generation of Climate Models Track Recent Unprecedented Changes in Earth's Radiation Budget Observed by CERES. *Geophysical Research Letters*, 2020, 47 (5), 10.1029/2019GL086705 . hal-02530975

HAL Id: hal-02530975

<https://hal.science/hal-02530975>

Submitted on 7 May 2020

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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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37

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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 21st 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 21st 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 CO₂
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 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°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.

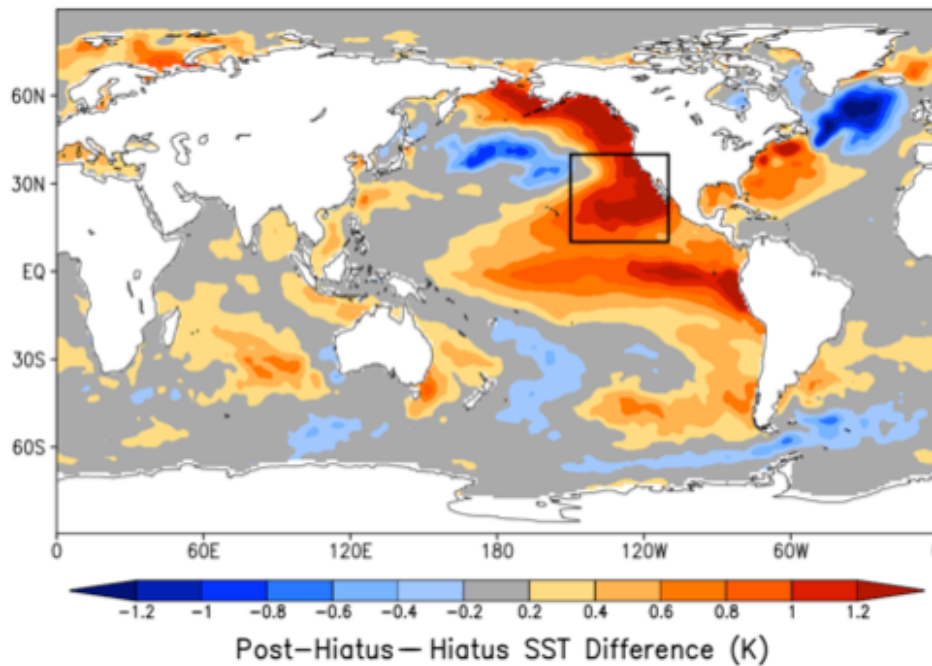
163 Table 1 List of CMIP6 models considered in this study.

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

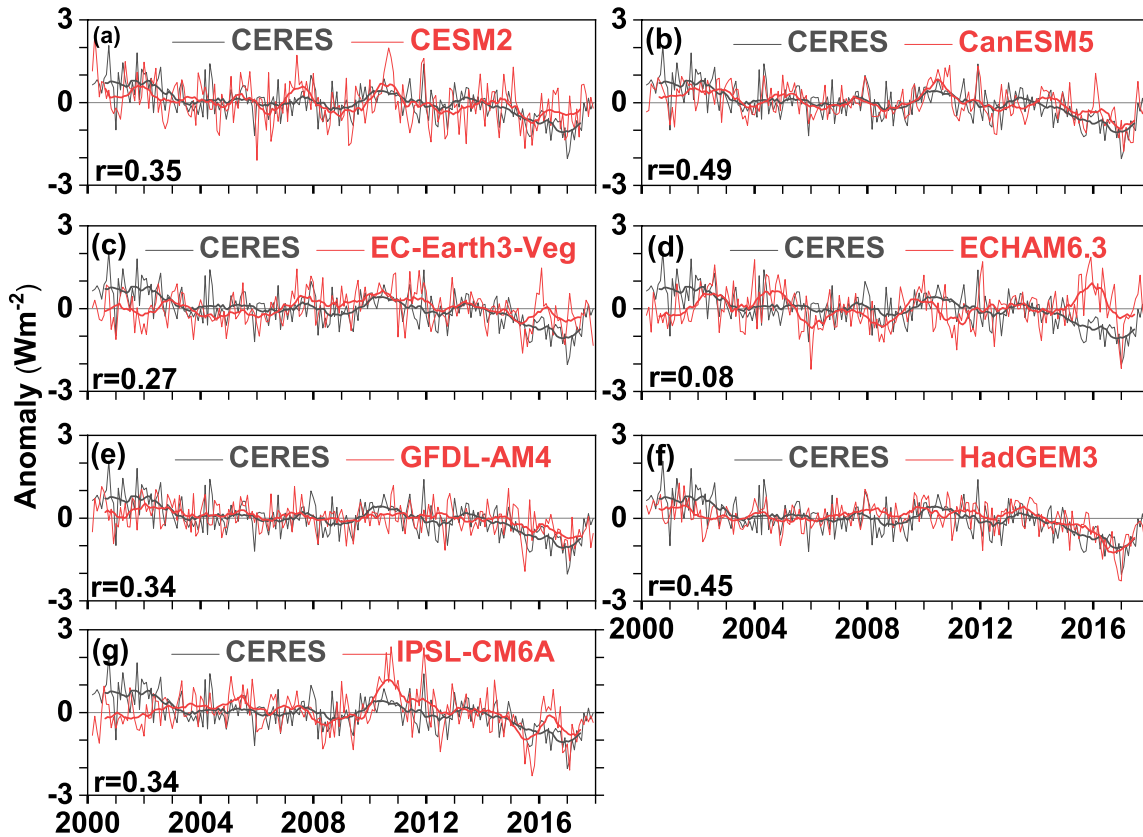
177 3. Results

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 ± 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

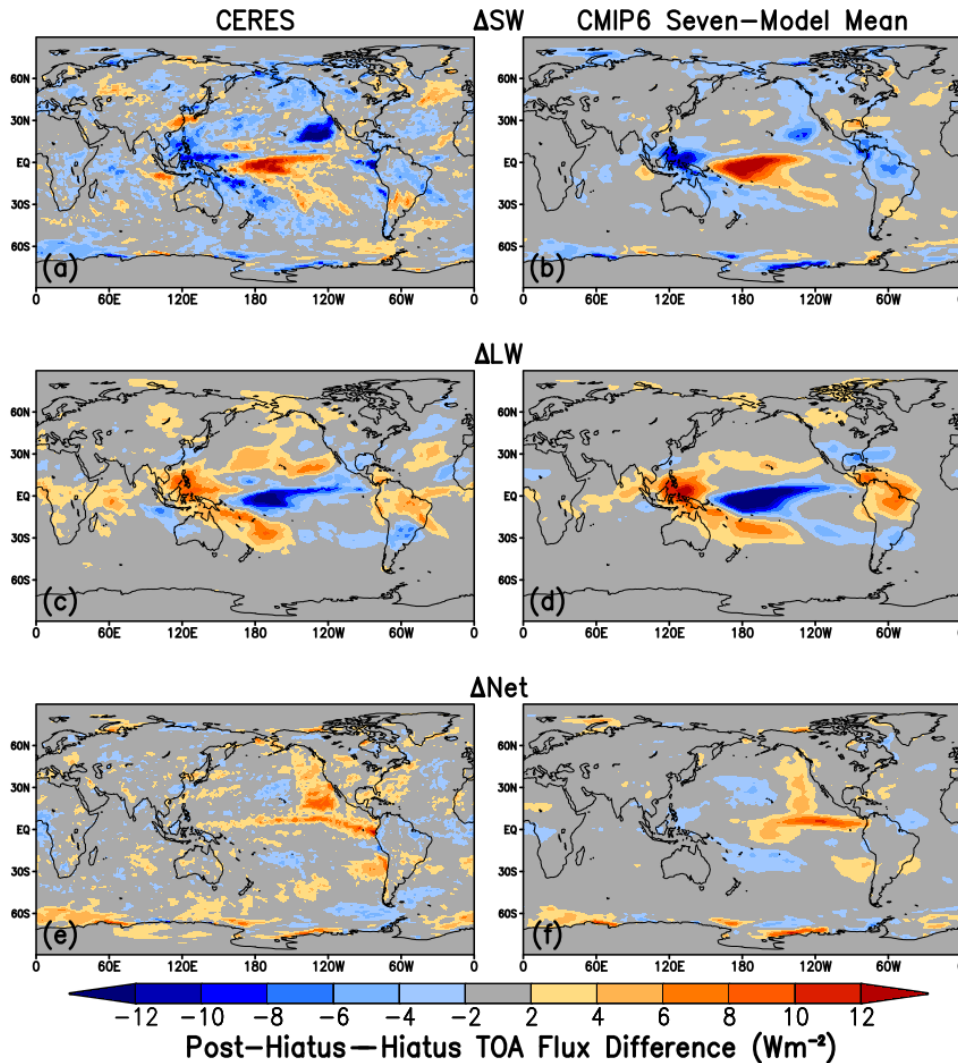
209 We find encouraging similarities between regional patterns of post-hiatus—hiatus
 210 flux difference for CERES and the mean of the seven CMIP6 models (Figure 3a-f). The
 211 CERES observations show a marked SW decrease during the post-hiatus period off the
 212 west coast of North America (Figure 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 Wm^{-2} and 0.15 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 Wm^{-2})
266 yet its bias in the post-hiatus—hiatus difference is only 1 Wm^{-2} . In contrast, EC-Earth3-
267 Veg shows a climatological mean bias of 2 Wm^{-2} and a post-hiatus—hiatus difference of
268 4 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.

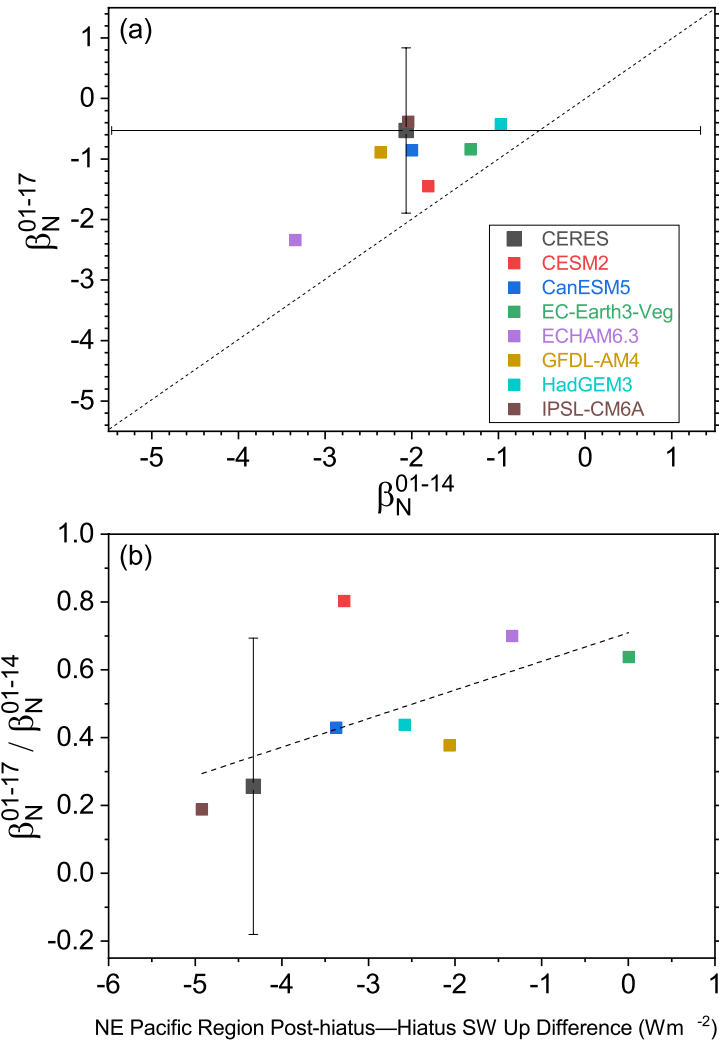
274 3.3 Pattern Effect

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 (λ_N) for the historical record (1871-2010) and long-
279 term CO₂ forcing. We refer to a radiative restoring coefficient (Lutsko and Takahashi,
280 2018) for the CERES period (β_N) instead of λ_N in order to emphasize that β_N is primarily
281 a response to internal variability in the climate system whereas λ_N is primarily a response
282 to external radiative forcing. We define β_N as $\beta_N = (\delta N - \delta F)/\delta T_s$, where δN is net flux
283 anomaly, δF is the effective radiative forcing anomaly and δT_s is the surface temperature
284 anomaly. Here, δ 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 β_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 δT_s using a standard ordinary least
289 squares fit. To calculate δF , 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, β_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 β_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 β_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 β_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 β_N compared to CERES for 2001-2014
302 by $0.3 \text{ Wm}^{-2} \text{ K}^{-1}$ and a more stabilizing β_N by approximately the same magnitude for 2001-
303 2017.

304 We quantify the pattern effect during the CERES period as the ratio of β_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 β_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.

337 **Acknowledgements**

338 N.G.L. and H.W. were supported by the NASA CERES project. R.P.A. was supported by
339 the UK National Environment Research Council (NERC) SMURPHS project
340 (NE/N006054/1). TA was supported by the Met Office Hadley Centre Climate
341 Programme funded by BEIS and Defra. A.G. was supported by The National Center for
342 Atmospheric Research, which is sponsored by the U.S. National Science Foundation.
343 T.M. acknowledges funding from the European Research Council grant #770765 and
344 European Union Horizon 2020 project #820829. This is IPRC publication X and SOEST
345 contribution Y. EBAF Ed4.1 data was downloaded online from:
346 <https://ceres.larc.nasa.gov/products-info.php?product=EBAF>. ERA5 data from the
347 European Centre for Medium-range Weather Forecast (ECMWF) was downloaded online
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Supporting Information for

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

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Figure S1-S12

Table S1

1. Global TOA Flux Anomalies

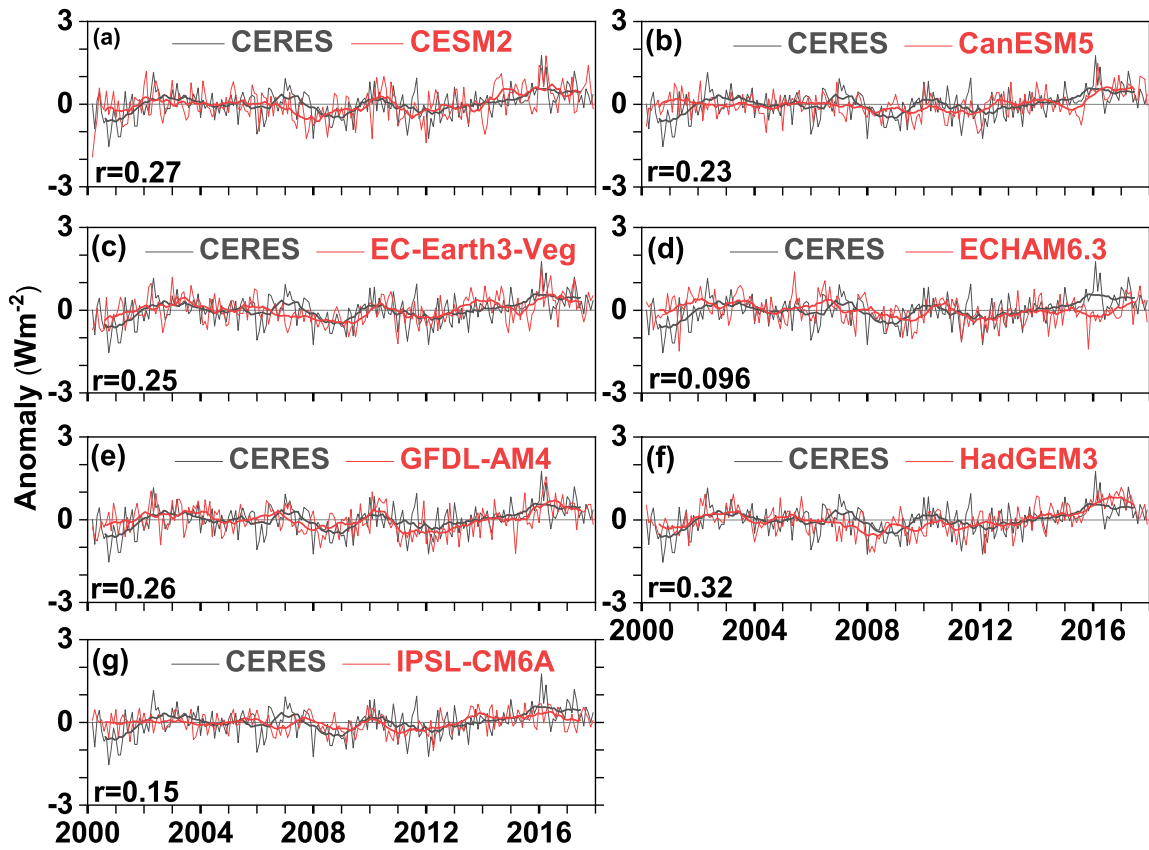


Figure S1. Same as Figure 2 but for TOA LW upward flux.

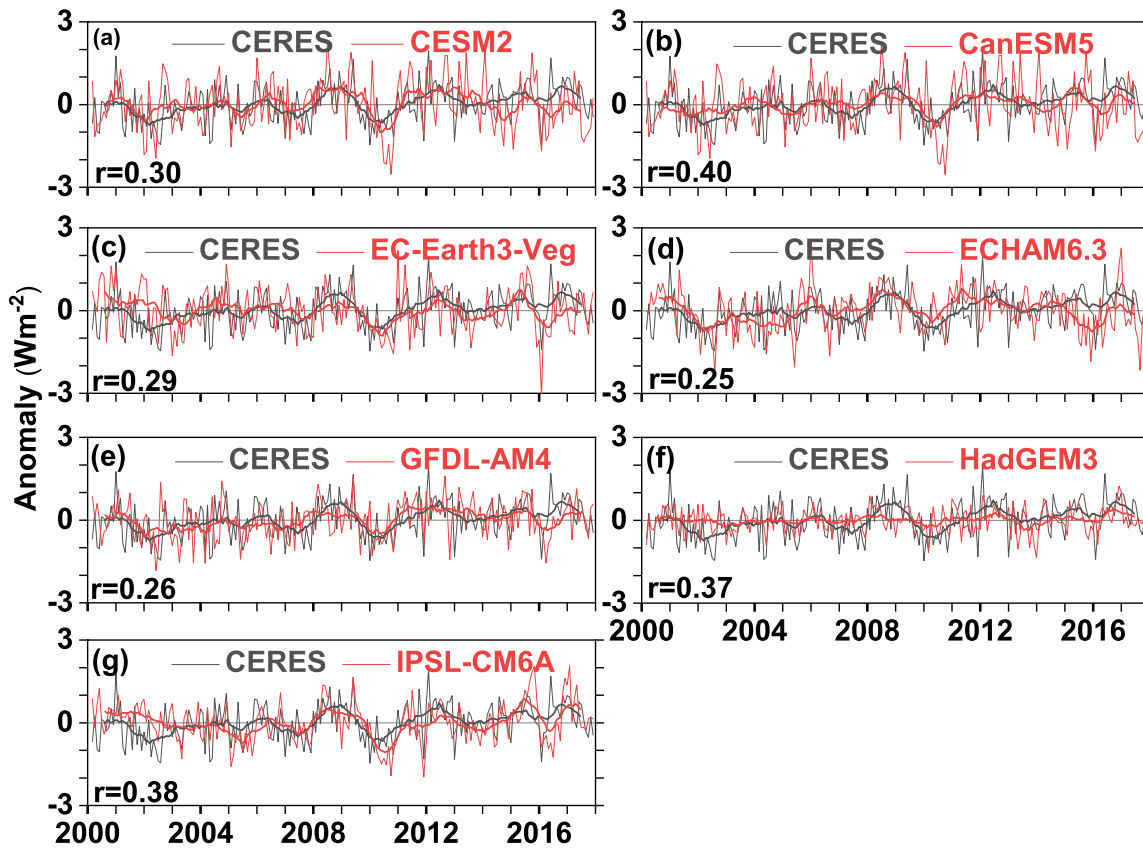


Figure S2. Same as Figure 2 but for TOA net downward flux.

2. Post-Hiatus—Hiatus Differences

2.1 Regional

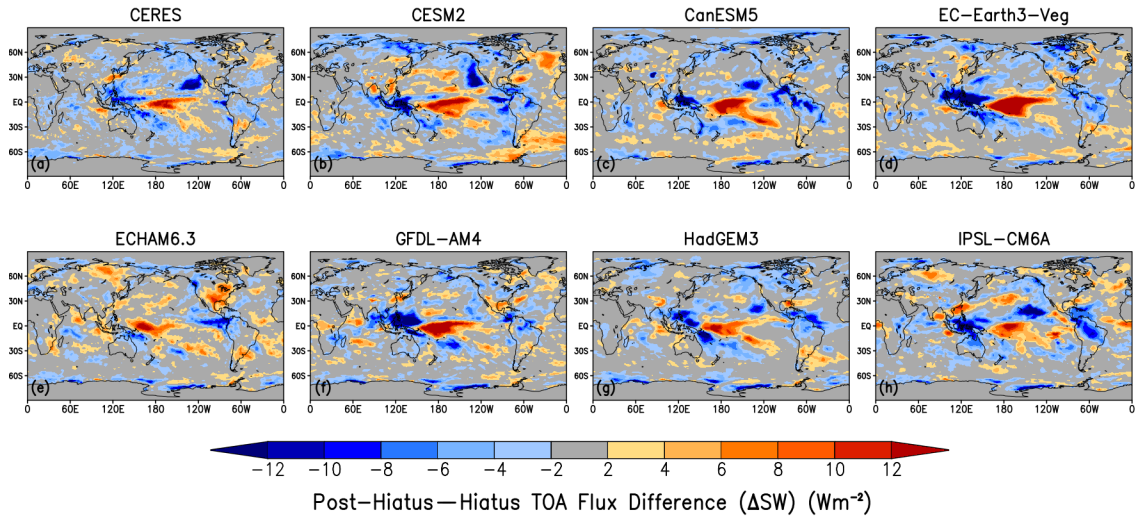


Figure S3. Post-hiatus—hiatus difference in SW TOA upward flux for (a) CERES, (b) CESM2, (c) CanESM5, (d) EC-Earth3-Veg, (e) ECHAM6.3, (f) GFDL-AM4, (g) HadGEM3, (h) IPSL-CM6A.

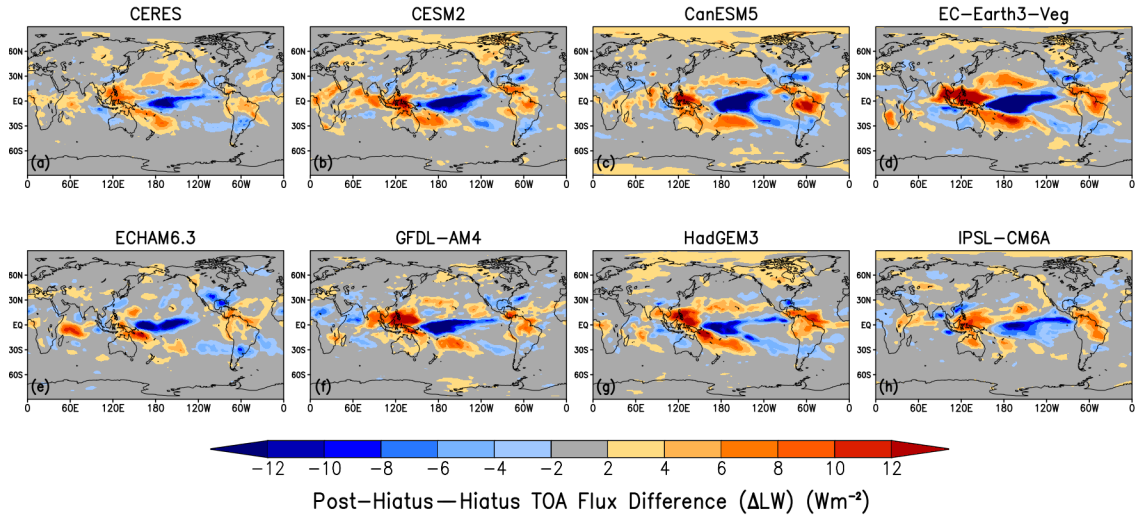


Figure S4. Same as Figure S3 but for TOA LW upward flux.

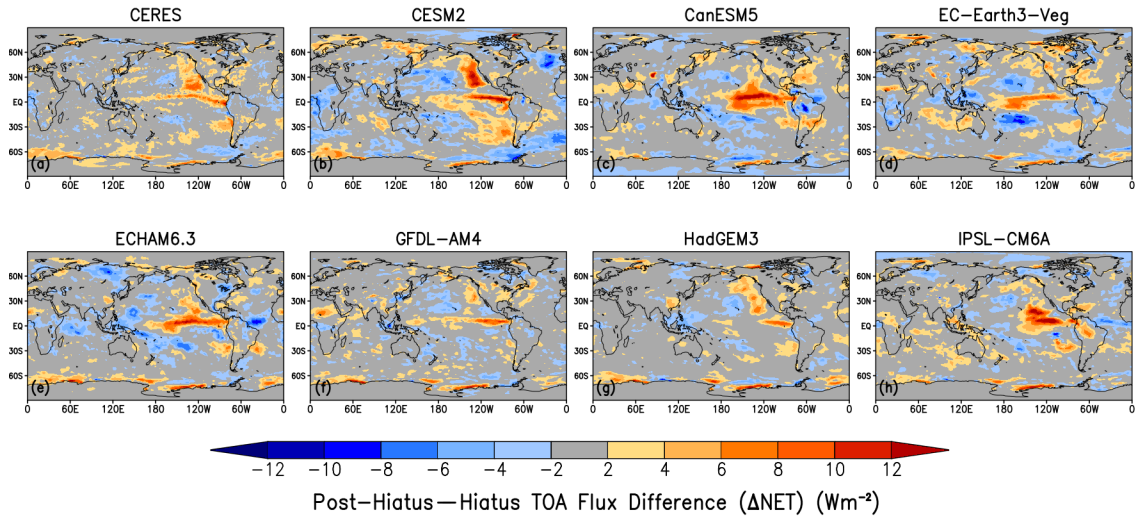


Figure S5. Same as Figure S3 but for TOA Net flux.

2.2 Global

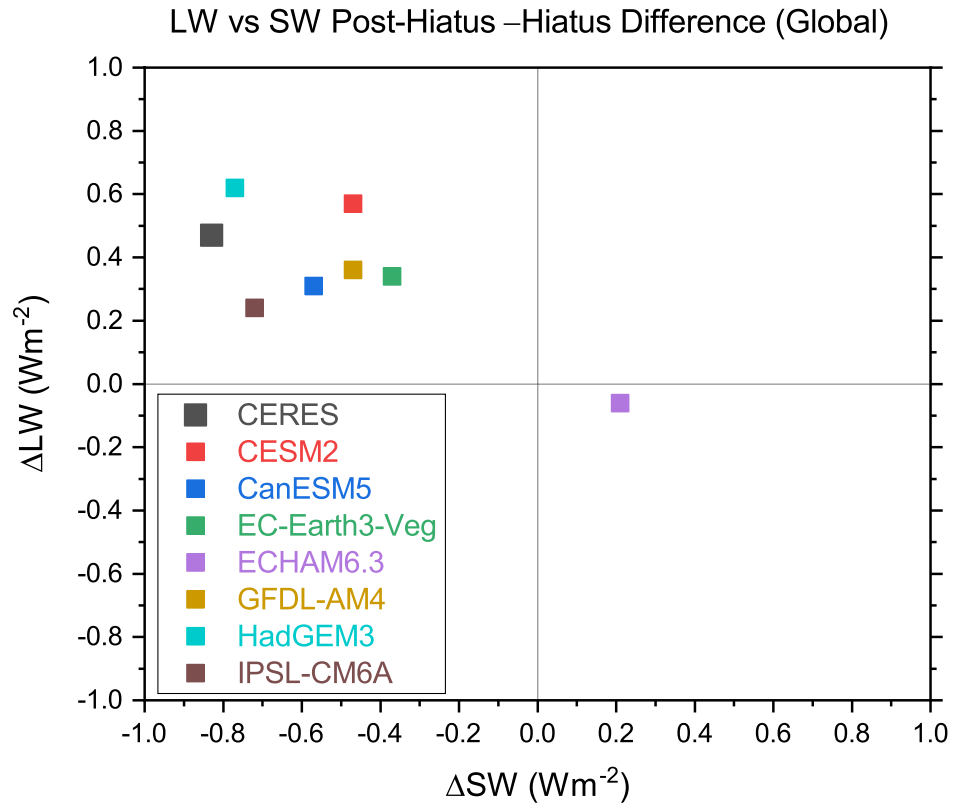


Figure S6. Global mean post-hiatus—hiatus difference in LW and SW TOA upward flux for CERES and the seven CMIP6 model simulations.

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 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°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 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.

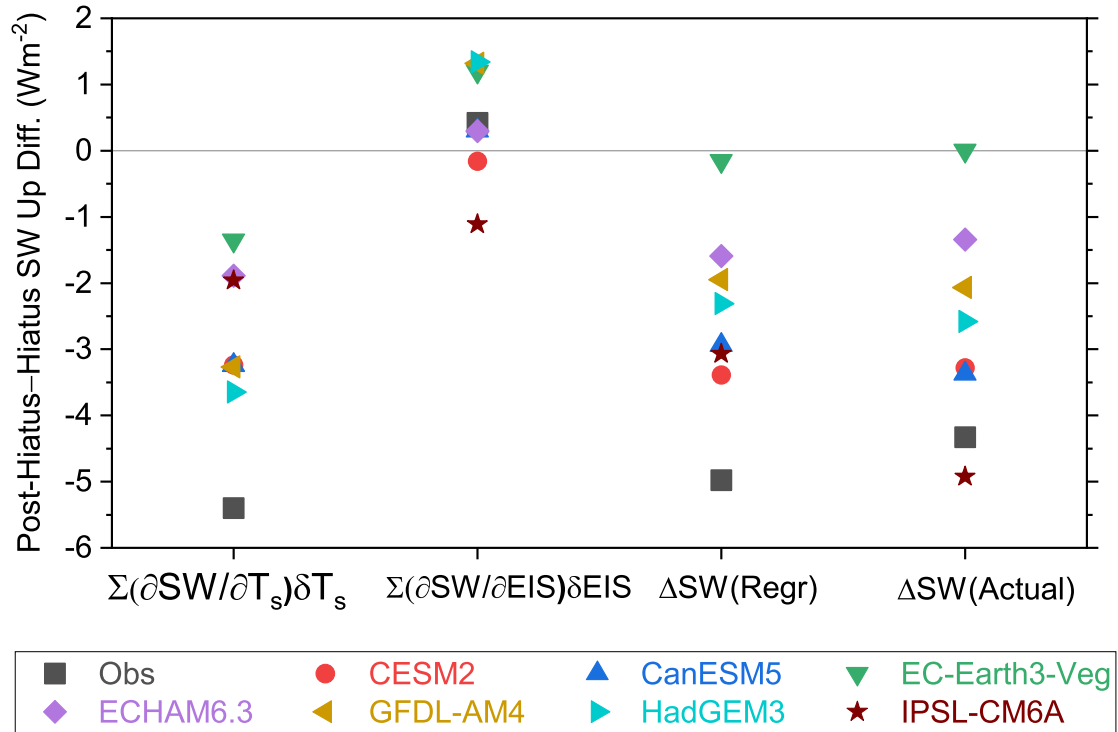


Figure S7. Post-hiatus—hiatus SW up difference due to surface temperature ($\Sigma(\partial SW/\partial T_s)\delta T_s$) and EIS ($\Sigma(\partial SW/\partial EIS)\delta EIS$) contributions, their sum ($\Delta SW(\text{Regr})$) and the actual observed difference ($\Delta SW(\text{Actual})$) for the EP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

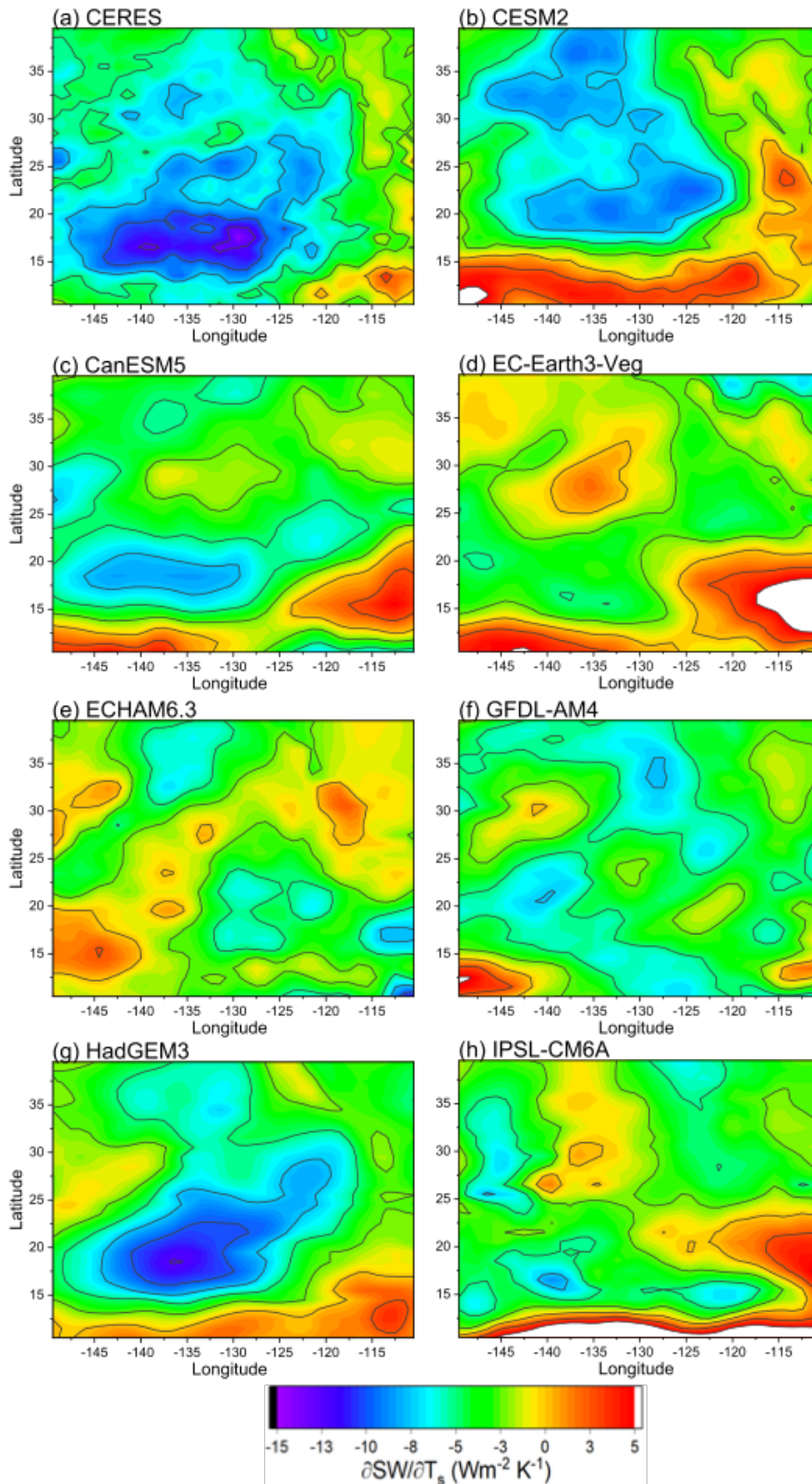


Figure S8. Sensitivity in SW upwards flux to surface temperature.

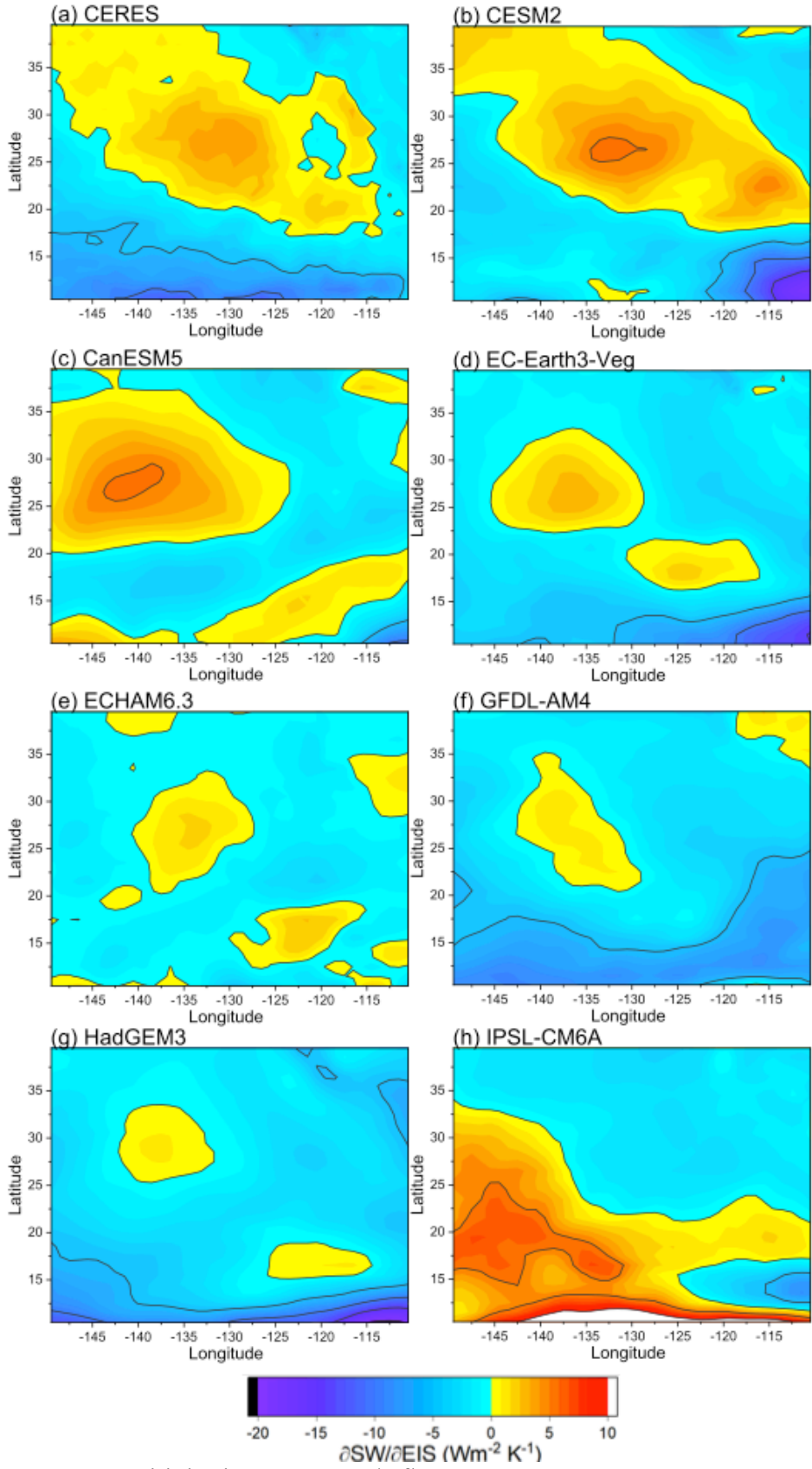


Figure S9. Sensitivity in SW upwards flux to EIS.

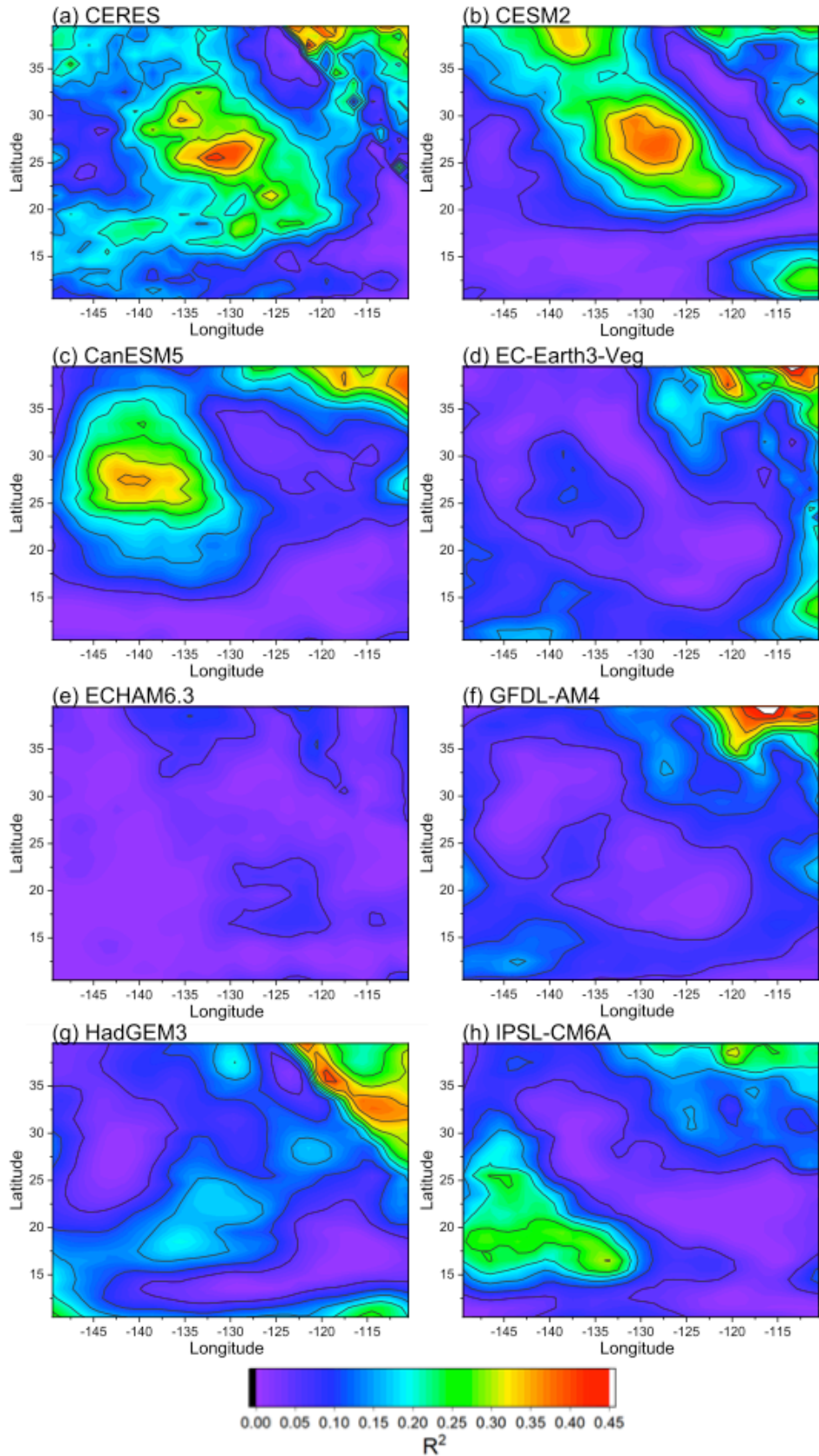


Figure S10. Multiple linear regression coefficient of determination (R^2).

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

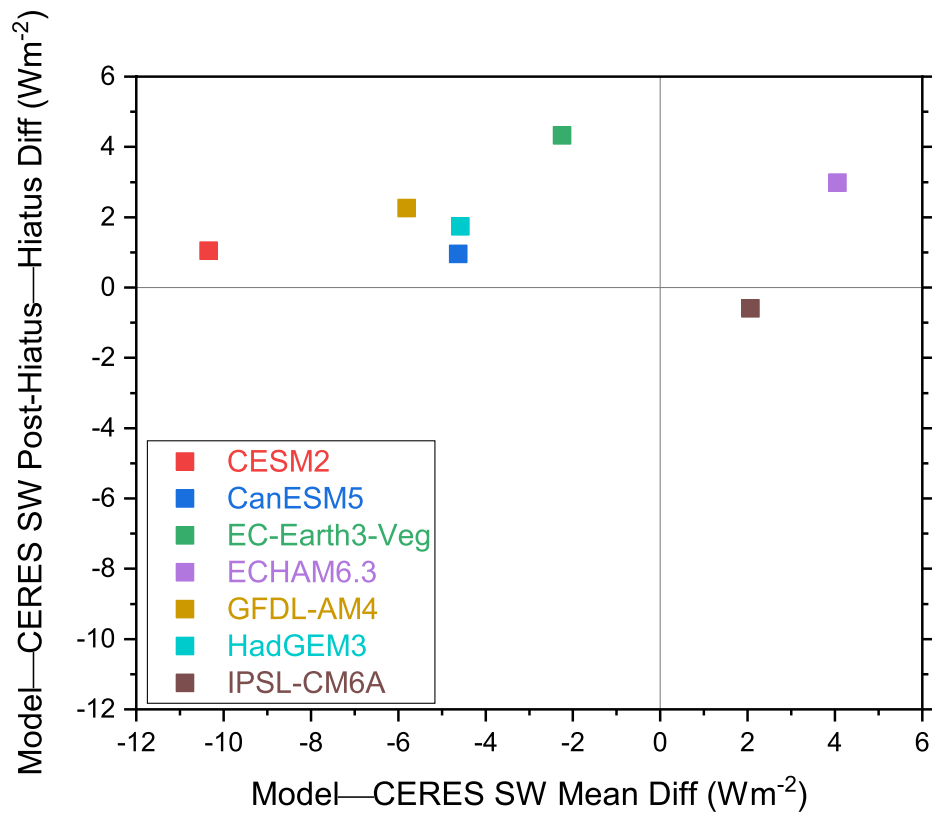


Figure S11. Bias in SW TOA flux post-hiatus—hiatus difference against bias in SW TOA flux climatological mean for the EP region for July 2000-June 2017.

3. Radiative Restoring Coefficient

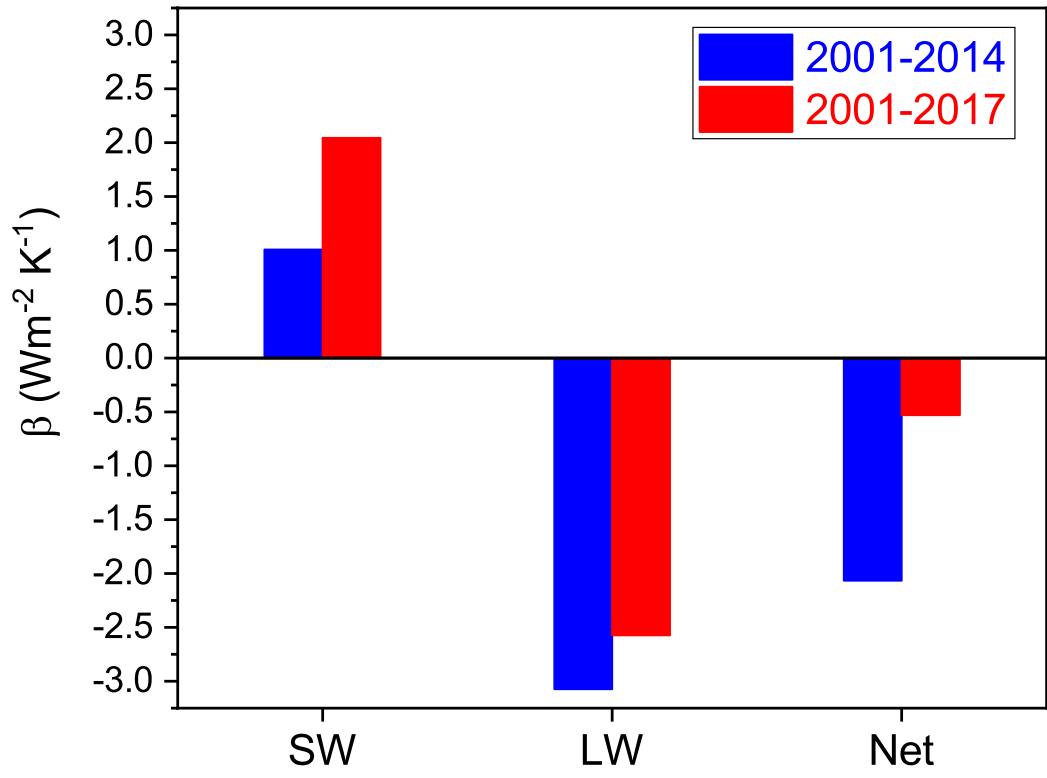


Figure S12. Observed SW, LW and Net radiative restoring coefficients (β) for 2001-2014 and 2001-2017.

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 ⁻²)	r	Stdev (Wm ⁻²)	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 ⁻²)	r	Stdev (Wm ⁻²)	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 ⁻²)	r	Stdev (Wm ⁻²)	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