Sea-surface temperature pattern effects have slowed recent global warming and biased emergent constraints on climate sensitivity

Kyle C. Armour[a,b,1,2], **Cristian Proistosescu**[c,1], **Yue Dong**[d], **Lily C. Hahn**[a], **Edward Blanchard-Wrigglesworth**[a], **Andrew G. Pauling**[a], **Robert C. Jnglin Wills**[a,e], **Timothy Andrews**[f], **Malte F. Stuecker**[g], **Stephen Po-Chedley**[h], **Ivan Mitevski**[i], **Piers M. Forster**[j], **and Jonathan M. Gregory**[f,k]

[a]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA; [b]School of Oceanography, University of Washington, Seattle, WA, USA; [c]Department of Atmospheric Sciences and Department of Geology, University of Illinois Urbana-Champaign, Champaign, IL, USA; [d]Lamont-Doherty Earth Observatory, Palisades, NY, USA; [e]Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland; [f]Met Office Hadley Centre, Exeter, UK; [g]Department of Oceanography and International Pacific Research Center, School of Ocean and Earth Science and Technology, University of Hawai'i at Mānoa, HI, USA; [h]Program for Climate Model Diagnosis and Intercomparison, Lawrence Livermore National Laboratory, Livermore, CA, USA; [i]Department of Applied Physics and Applied Mathematics, Columbia University, New York, NY, USA; [j]Priestley International Centre for Climate, University of Leeds, Leeds, UK; [k]National Centre for Atmospheric Science, University of Reading, Reading, UK

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The rate of recent global warming has been proposed as an "emergent constraint" on equilibrium climate sensitivity (ECS) and transient climate response (TCR) – key metrics of the global climate response to greenhouse-gas forcing. Using CMIP5/6 models, we show that the inter-model relationship between warming and these climate sensitivity metrics (the basis for the emergent constraint) arises from a similarity in transient and equilibrium warming patterns within the models, producing an effective climate sensitivity (EffCS) governing recent warming that is comparable to the value of ECS governing long-term warming under CO_2 forcing. However, CMIP5/6 historical simulations do not reproduce observed warming patterns. When driven by observed patterns, even high ECS models produce low EffCS values consistent with the observed global warming rate. The inability of CMIP5/6 models to reproduce observed warming patterns thus results in a bias in the modeled relationship between recent global warming and climate sensitivity. Correcting for this bias means that observed warming does not exclude high values of ECS and TCR. These findings are corroborated by energy balance model simulations and coupled model (CESM1-CAM5) simulations that better replicate observed patterns via tropospheric wind nudging or Antarctic meltwater fluxes. Because CMIP5/6 models fail to simulate observed warming patterns, proposed emergent constraints on ECS, TCR, and projected global warming are biased low. The results reinforce recent findings that the unique pattern of observed warming has slowed global-mean warming over recent decades, and how the pattern will evolve in the future represents a major source of uncertainty in climate projections.

climate sensitivity | global warming | climate dynamics

Equilibrium climate sensitivity (ECS) and transient climate response (TCR) are key metrics of the global-mean surface temperature response to increasing greenhouse-gas concentrations. They represent the warming under a doubling of atmospheric carbon dioxide (CO_2) at equilibrium and at the time of CO_2 doubling, respectively. Model values of ECS and TCR are strongly correlated with projections of 21st century warming (1, 2). The recent IPCC Sixth Assessment Report (AR6) assessed the ranges of ECS and TCR to be substantially more narrow than in previous Reports (2) following advances in scientific understanding of several independent lines of observational evidence (e.g., 3). Narrower ranges of ECS and TCR in turn translate to better-constrained projections of 21st century warming compared to projections based on global climate models (GCMs), which span wider ECS and TCR ranges (4).

One major update in IPCC AR6 was a reinterpretation of historical energy budget constraints on climate sensitivity based on observed warming since the 1800s. While the historical energy budget was once thought to place strong constraints on ECS (5–7), in IPCC AR6 it was assessed to provide relatively weak constraints, particularly at the high end of the climate sensitivity range. This assessment was based on (i) stubbornly-large uncertainty in the radiative forcing that drove historical warming, owing primarily to uncertainty in aerosol forcing, and (ii) work since AR5 showing that differences between historical and future (centennial timescale) sea-surface temperature (SST) trend patterns result in estimates of ECS that are biased low (2, 3, 8–19). This SST *pattern effect* occurs because the feedbacks governing Earth's global radiative response per degree of global warming depend on the spatial pattern of that warming. In particular, warming

Significance Statement

Global climate models show a tight relationship between post-1970s global warming and climate sensitivity. The latest IPCC Assessment Report (AR6) used observations of the warming rate together with model-derived estimates of the warming-sensitivity relationship as a key piece of evidence constraining Earth's climate sensitivity and warming projections. However, climate models do not reproduce the observed spatial pattern of warming, introducing a bias in the modeled warming-sensitivity relationship that results in overly-confident constraints on climate sensitivity. The findings suggest that high values of climate sensitivity cannot be excluded based on observed warming over recent decades. How the spatial pattern of warming will evolve will influence the rate of future global warming, introducing a major uncertainty in climate projections.

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[1]K.C.A. contributed equally to this work with C.P.

[2]To whom correspondence should be addressed. E-mail: karmour@uw.edu

since the 1800s has been relatively slow within key regions of positive (destabilizing) radiative feedbacks including the eastern tropical Pacific Ocean and Southern Ocean; in the long term, however, these regions are expected to warm more than the global mean, leading to a less-negative global feedback and thus an increase in the climate's sensitivity to greenhouse-gas forcing (8, 9, 19–27). Thus, the value of the *effective* climate sensitivity (EffCS) governing historical warming is thought to be lower than the value of ECS governing equilibrium warming under CO_2 forcing (2, 3).

Another major advance in recent years has been the development of "emergent constraint" methods, wherein coupled GCMs are used to find a correlation between an observable quantity and something we wish to predict, and then the model-based relationship is combined with observations of that quantity to derive constrained predictions (28–31). Strong emergent constraints on ECS and TCR have been derived using the post-1970s rate of global-mean warming (18, 32–34): because GCMs with higher ECS and TCR values tend to overestimate the observed rate of warming, the implication is that high values of climate sensitivity are less likely. This emergent constraint was proposed to avoid the issues plaguing energy budget constraints based on warming since the 1800s (32): because global aerosol radiative forcing changes have been relatively small since the 1970s, the use of this period substantially reduces the impact of uncertainty in radiative forcing; and SST pattern effects are implicitly accounted for in the use of GCMs to derive the correlation between recent warming and ECS (or TCR).

As summarized in Forster et al. (2), studies using post-1970s global warming as an emergent constraint produce narrow bounds on ECS (with best estimates of 2.6-2.8°C and 5-95% ranges within 1.5-4.1°C) and TCR (with best estimates of 1.6-1.7°C and 5-95% ranges within 1.0-2.3°C). Collectively, these studies provided the strongest constraints on ECS and TCR of any of the main lines of evidence assessed in IPCC AR6, and were a primary justification for assessing the upper bounds on the ECS *likely* (2.5-4°C) and *very likely* (2-5°C) ranges to be lower than in previous Reports. These narrower ranges also suggest that GCMs with ECS values higher than about 5°C, of which there are many (35) in the Coupled Model Intercomparison Project phase 6 (CMIP6, ref. 36), may be less valid for projecting future warming (e.g., 2, 37).

For an emergent constraint to be robust, it must exhibit two key properties. First, because many spurious correlations between observable and predicted quantities of interest can be found by chance within GCMs (38), any correlation that is used as the basis for an emergent constraint must rest on sound physical principles (28, 29, 31, 39). Second, the GCMs used as the basis for an emergent constraint must not share a common bias, relative to nature, in their representation of this correlation (e.g., 28, 40).

For emergent constraints on ECS and TCR based on post-1970s global warming, there is a strong physical basis for the modeled correlation: higher ECS and TCR correspond to a less-efficient radiative response per degree of global warming which, all else being equal, should lead to a faster rate of global warming under greenhouse-gas forcing. And the emergent constraints have been shown to produce similar results whether using CMIP5 or CMIP6 models (18, 32–34), providing confidence in their robustness.

However, recent work has found that historical simulations of CMIP5/6 models generally fail to simulate the observed spatial pattern of post-1970s SST trends (16, 17, 41, 42). In particular, the models produce relatively weak spatial gradients in SST trends, with somewhat enhanced warming in the eastern tropical Pacific Ocean and at high latitudes, while observations show strong spatial gradients in SST trends, with cooling in the eastern Pacific and Southern Oceans.

These model-versus-observed discrepancies in SST trend patterns influence the radiative feedbacks that govern climate sensitivity: when atmosphere GCMs are forced with the observed post-1970s SST trends, they generally produce global radiative feedbacks that are substantially more negative (lower EffCS) than feedbacks produced over this period by historical simulations of the same coupled GCMs (16, 17). This suggests that there *is* in fact a common bias across CMIP5/6 GCMs that could affect the modeled relationship between post-1970s warming and climate sensitivity metrics. It is possible, for instance, that GCMs overestimate recent warming in part due to their biases in simulated warming patterns, with relatively too much warming in key positive feedback regions, rather than simply having too-high values of ECS or TCR (as is assumed by the emergent constraint). IPCC AR6 noted this possibility, finding it *more likely than not* that emergent constraints on ECS and TCR based on post-1970s global warming are biased low (2); but without studies quantifying the magnitude of this bias, no corrections could be made.

Here we evaluate the potential for SST pattern effects to bias emergent constraints on ECS and TCR via their influence on the CMIP5/6-based relationship between post-1970s global warming and these climate sensitivity metrics. We first reproduce emergent constraints on ECS and TCR based on recent warming and find similar results to the published literature. We then analyze a subset of CMIP5/6 models that provide the output necessary to accurately calculate radiative feedbacks (and corresponding EffCS) over the historical period. We find that CMIP5/6 models warm too much over recent decades in large part due to their failure to replicate the observed post-1970s SST trend patterns, and thus even high values of climate sensitivity cannot be excluded based on observed warming. We conclude that the proposed emergent constraints on ECS and TCR based on the recent global warming rate are biased low. We evaluate the robustness of our findings using energy-balance model simulations and coupled-model (CESM1-CAM5) simulations that better replicate observed patterns via tropospheric wind nudging or Antarctic meltwater fluxes. Finally, we discuss implications of these results for 21st century warming.

The relationship between post-1970s warming and climate sensitivity

While several different time periods have been used to place emergent constraints on climate sensitivity (32, 33), here we focus on 1981-2014 following Tokarska et al. (34). We show relationships between the rate of global-mean surface warming over this period and ECS (Fig. 1a) for all GCMs that provide the necessary output on the CMIP5/6 archives (21 CMIP5 models and 38 CMIP6 models; see Supplementary Information for a list). While we focus on ECS in the main text, the full analysis using TCR produces similar results (Supplementary Information). We calculate warming rates by averaging over

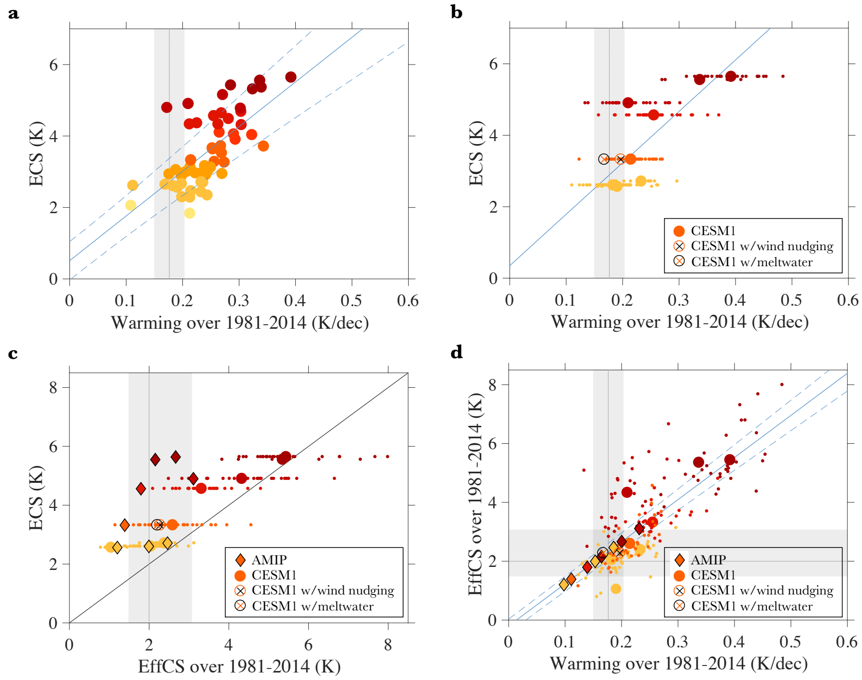

Fig. 1. Relationships between equilibrium climate sensitivity (ECS), effective climate sensitivity (EffCS), and the 1981-2014 warming rate in CMIP5/6 models. a, CMIP5/6 ECS versus warming rate using averages of all available ensemble members for each model (correlation $r = 0.68$); colors correspond to values of ECS. **b,** Eight-model subset ECS versus warming rate with ensemble means shown as larger circles and ensemble members shown as smaller dots. **c,** Eight-model subset ECS versus EffCS over 1981-2014 with ensemble means shown as larger circles and ensemble members shown as smaller dots; diamonds show EffCS values from AGCM simulations forced by observed SST and SIC trend patterns. **d,** Eight-model subset EffCS over 1981-2014 versus warming rate with ensemble means shown as larger circles and ensemble members shown as smaller dots; diamonds show warming rates estimated based on EffCS values from AGCM simulations using the regression between EffCS and warming rate calculated from the eight-model subset (blue line). In **b-d**, open circles show CESM1-CAM5 simulations with wind nudging or meltwater fluxes as described in the text. Blue lines show fits calculated using ordinary least squares regression, with dashed blue lines showing 5-95% ranges of fit parameters (Methods). Gray shading shows observational estimates (5-95% range) of observed warming rate (HadCRUT5, ref. 45) and EffCS (19). See Supplementary Information for a list of models used.

all available ensemble members of each model's *historical* simulation (extended using RCP4.5 over years 2006-2014 for CMIP5 models), where each ensemble member is forced by identical historical greenhouse-gas, aerosol, volcanic, and solar forcings, and differ only in their phasing of internal variability. CMIP5/6 model values of ECS have been estimated using the standard approach of extrapolating to equilibrium the regression between global top-of-atmosphere energy imbalance and global temperature change over 150 years of abrupt CO_2 quadrupling simulations, scaled by a factor of a half to account for CO_2 doubling (35, 43, 44).

We find a strong correlation between the 1981-2014 global warming rate and ECS (Fig. 1a) or TCR (Fig. S1a). Using this regression (Methods), the observed warming rate of 0.18°C dec^{-1} (0.15-0.21°C dec^{-1}, 5-95% range) calculated from HadCRUT5 (45) gives ECS = 2.7°C (1.5-3.9°C) and TCR = 1.6°C (1.1-2.1°C), in good agreement with previous studies (18, 32–34).

To better understand the modeled relationship between global warming and climate sensitivity, we consider a subset of eight CMIP5/6 models representing all those that provide at least three *historical* ensemble members and the output necessary to accurately calculate radiative feedbacks over the historical period: CanESM5, CNRM-CM6-1, GISS-E2-1-G, HadGEM3-GC31-LL, IPSL-CM6A-LR, MIROC6, NorESM2-LM, and CESM1-CAM5. The relationships between 1981-2014 global warming rate and ECS are similar for this eight-model subset (Fig. 1b) to those found in the full CMIP5/6 ensemble (Fig. 1a). For each model, there is substantial spread in warming rates across ensemble members due to internal climate variability (Fig. 1b), raising two key questions: (i) What factors control the variability in warming rates across model ensemble members? And, (ii) do CMIP5/6 models accurately represent how those factors were expressed in observations over the period 1981-2014?

Each of the eight models in our subset has a corresponding CMIP6 *piClim-histall* simulation wherein the same atmosphere GCM (AGCM) was run with fixed pre-industrial SSTs and sea-ice concentrations (SICs) while all radiative forcing agents were varied as in the corresponding CMIP6 *historical* simulations. The *piClim-histall* simulations were performed as part of the Radiative Forcing Model Intercomparison Project (RFMIP, ref. 46) for CMIP6, while we perform our own *piClim-histall*-style simulation for CESM1-CAM5 following the same protocol. From these simulations, the historical effective radiative forcing (ERF) can be diagnosed from top-of-atmosphere radiation anomalies relative to pre-industrial conditions (17, 47), with a small correction for land warming (2, 48) (Methods). Using the standard model of global energy balance,

$$N = \lambda T + \mathrm{ERF}, \qquad [1]$$

where N is the global top-of-atmosphere radiation anomaly and T is the global near-surface air temperature anomaly (both relative to pre-industrial), we diagnose the global *effective* radiative feedback λ (< 0 for a stable climate) from linear regression of $N - \mathrm{ERF}$ against T over the period 1981-2014 for each ensemble member (Methods). From this, we calculate EffCS for the period 1981-2014 as,

$$\mathrm{EffCS} = -\frac{\mathrm{ERF}_{2\times}}{\lambda}, \qquad [2]$$

where $\mathrm{ERF}_{2\times}$ is the effective radiative forcing from CO_2 doubling (35, 44) (Methods). EffCS is largely set by the value of λ both because it is in the denominator in equation (2) and because λ varies fractionally more than does $\mathrm{ERF}_{2\times}$ across models (35). EffCS can be interpreted as the equilibrium warming that would occur in response to CO_2 doubling if the value of λ calculated over the period 1981-2014 applied to that equilibrium state.

We find that there is a large spread in EffCS for the period 1981-2014 across ensemble members of each GCM (small dots in Fig. 1c). Moreover, differences in EffCS explain a large fraction of the variance ($r^2 = 0.61$) in the 1981-2014 warming rate across all ensemble members of our eight-model subset; those with EffCS values near 2°C tend to produce warming rates in line with observations, while those with higher values of EffCS warm too much (Fig. 1d).

The high correlation between EffCS and the global warming rate can be understood by making the approximation $N = \kappa T$ in equation (1), where κ is the ocean heat uptake efficiency representing all processes setting the amount of global ocean heat uptake per degree of global warming (e.g., 49–51); a larger value of κ corresponds to a more efficient uptake of heat by the deep ocean and thus less surface warming. Then, the rate of warming can be approximated as (e.g., 52),

$$\frac{dT}{dt} = \frac{d(\mathrm{ERF})/dt}{\kappa - \lambda}. \quad [3]$$

Calculating κ from regression of N against T over 1981-2014, and given $d(\mathrm{ERF})/dt$ and λ as calculated above, equation (3) explains 83% of the variance in the 1981-2014 warming rate across all ensemble members of our CMIP5/6 model subset. Most of the explanatory power comes from variations in λ: holding κ and $d(\mathrm{ERF})/dt$ fixed at ensemble-mean values, equation (3) still explains 58% of the variance across ensemble members. That is, variations in λ (and thus EffCS) largely govern the global warming rate, with variations in κ playing a secondary role. There is little correlation between λ and κ on the timescales considered here (Methods), so we treat them as independent for our purposes.

Using the regression between EffCS and the 1981-2014 warming rate derived from the eight-model subset (Fig. 1d), the observed warming rate of 0.18 (0.15-0.21) °C dec^{-1} implies EffCS = 2.3 (1.9–2.7)°C. While on the low end of the CMIP5/6 models (Fig. 1d), this implied value of EffCS is in good agreement with a recent observational estimate (19) of EffCS = 2.0 (1.5–3.1)°C based on global energy imbalance calculated from a merged satellite dataset (53) in combination with ERF estimates from IPCC AR6 (2) and HadCRUT5 temperature observations over 1985-2014. The CMIP5/6-based relationship between EffCS and warming rate thus compares well with observations.

Importantly, EffCS may be different from ECS, which is given by

$$\mathrm{ECS} = -\frac{\mathrm{ERF}_{2\times}}{\lambda_{2\times}}, \quad [4]$$

owing to the fact that the radiative feedback λ governing recent warming may be different from the radiative feedback $\lambda_{2\times}$ governing the equilibrium response to CO_2 doubling if warming patterns differ between the two timescales. Given that ECS is a measure of the *equilibrium* climate response to CO_2 forcing, it is worth considering why it is highly correlated with the rate of *transient* warming over 1981-2014 in CMIP5/6 models (Figs. 1a,b). The reason appears to be that values of ECS and ensemble-mean EffCS are nearly identical for each of the CMIP5/6 models (Fig. 1c); EffCS is similar to but slightly smaller than ECS for most of the GCMs, with a high correlation between them ($r^2 = 0.70$).

These findings are consistent with the fact that the spatial patterns of historical warming (setting EffCS over 1981-2014) and equilibrium warming under abrupt CO_2 forcing (setting ECS) are similar in CMIP5/6 models (Figs. 2a,b) (17); both are characterized by relatively weak spatial gradients in SST trends. That is, the relationship between ECS and the 1981-2014 warming rate, which forms the basis for the emergent constraint, reflects similar patterns of transient and equilibrium warming within the coupled CMIP5/6 models, corresponding to a relatively small pattern effect (i.e., values of EffCS governing recent warming are comparable to values of ECS governing long-term warming).

As noted in the introduction, the observed SST trend pattern over 1981-2014 (Fig. 2c) is distinct from patterns simulated by the coupled CMIP5/6 models (17, 41, 42). With strong warming in the western tropical Pacific Ocean (a region of negative feedbacks) and cooling in the eastern Pacific and Southern Oceans (regions of positive feedbacks), the observed pattern should favor a low value of EffCS (8, 9, 14, 16, 17, 19–27) and thus a reduced global warming rate (equation (3)). This observed pattern of warming is also distinct from the long-term warming pattern we expect under CO_2 forcing (2), suggesting that the relationship between EffCS (governing recent warming) and ECS (governing long-term warming) in nature may be different from that simulated by CMIP5/6 models. In the next section, we consider how model SST trend biases may, in turn, bias the warming-sensitivity relationship which forms the basis for the emergent constraint.

Impact of model SST trend biases on the warming-sensitivity relationship

To quantify the impact of the SST trend pattern on global warming rate, we make use of *amip* simulations wherein the same subset of eight AGCMs are run with prescribed time-evolving observed SSTs and SICs while all radiative forcing agents are varied as in the corresponding *historical* simulations. The *amip* simulations refer to the Atmospheric Model Intercomparison Project (AMIP II) DECK experiments performed as part of CMIP6 (36); we perform our own *amip*-style simulation for CESM1-CAM5. In combination with the RFMIP simulations, these simulations allow us to calculate λ and EffCS using regression over the period 1981-2014 as described above (see also refs. 14, 17, 19).

Across the eight AGCMs, the observed 1981-2014 SST trend pattern produces an average value of EffCS = 2.1°C (range 1.3-3.2°C) – in good agreement with EffCS derived from observed energy budget constraints (19) and implied by the observed global warming rate (Figs. 1c,d). This EffCS value is lower than the average EffCS simulated by the same coupled GCMs over 1981-2014. With identical atmospheric physics in AGCM and coupled GCM versions of each model, EffCS differences are due only to differences in observed and simulated SST and SIC trend patterns (14, 17, 19).

For the coupled GCMs with low values of ECS (GISS-E2-1-G, MIROC6, NorESM2-LM), 1981-2014 EffCS values are similar for AGCM and coupled GCM simulations (Fig. 1c). However, for all other GCMs in our subset (CanESM5, CNRM-CM6-1, HadGEM3-GC31-LL, IPSL-CM6A-LR, CESM1-CAM5), 1981-2014 EffCS values in AGCMs are substantially lower than they are in the same coupled GCMs, with AGCM values being at the edge of or even below the range of EffCS values generated by internal variability in the coupled model historical simulations. This suggests that the observed SST trend pattern (Fig. 2c) reflects either (i) an extreme phase of internal variability and/or (ii) a forced response not captured by the coupled GCMs (17, 42).

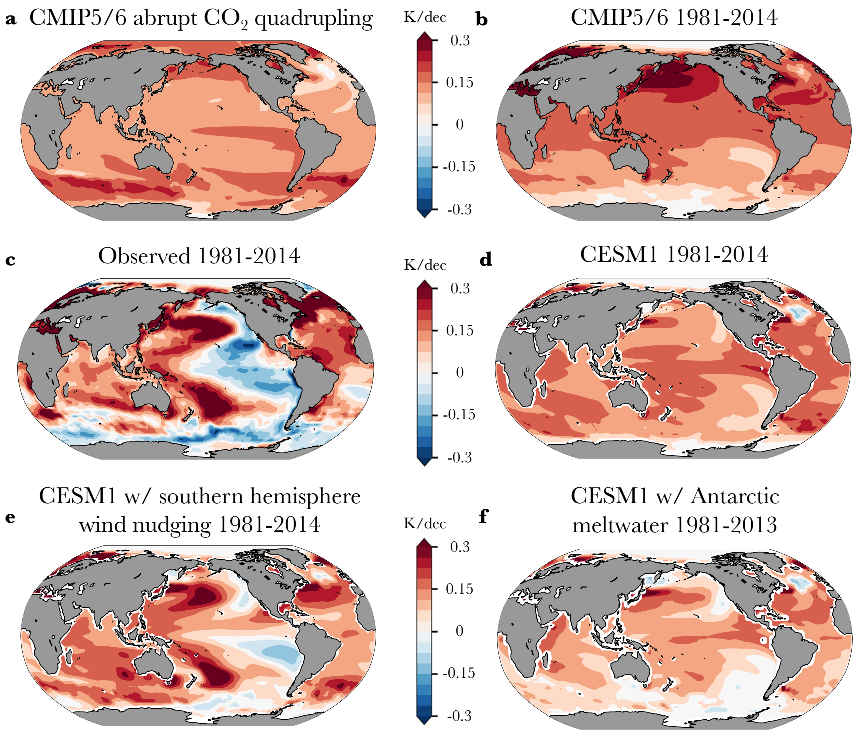

Fig. 2. Sea-surface temperature (SST) trends in CMIP5/6 models and observations. SST trend patterns for **a,** CMIP5/6 models over years 1-150 following abrupt CO_2 quadrupling (CMIP5/6 *abrupt-4xCO2* simulation from which ECS is calculated). **b,** CMIP5/6 models over 1981-2014 (CMIP5/6 *historical* from which EffCS is calculated). **c,** Observations over 1981-2014 (from *amip*). **d,** CESM1-CAM5 over 1981-2014. **e,** CESM1-CAM5 over 1981-2014 with Southern Hemisphere high latitude wind nudging. **f,** CESM1-CAM5 over 1981-2013 with Antarctic meltwater fluxes.

A possible reason for the larger differences between AGCM and coupled GCM values of EffCS in high-ECS models is that ECS differences across models stem largely from model differences in cloud feedbacks in the eastern tropical Pacific and Southern Oceans (35). Thus, observed cooling in these regions over 1981-2014 reduces the value of EffCS more for models with higher ECS, while leaving the value of EffCS relatively unchanged for models with lower ECS. Further examination of CESM1-CAM5 shows that the regression of local SST trends onto either the global warming trend or EffCS over 1981-2014 across ensemble members highlights the eastern tropical Pacific and Southern Oceans as key regions governing the warming rate and EffCS (Fig. S2).

The larger values of EffCS in the coupled GCMs relative to AGCMs suggests that at least a portion of the reason the coupled GCMs overestimate warming over 1981-2014 is that they fail to simulate the observed SST trend patterns – rather than simply having too-high values of ECS (or TCR). Moreover, it suggests that if the coupled GCMs were able to correctly simulate the observed warming patterns, they would produce lower values of EffCS (as shown by their AGCM simulations) and thus reduced 1981-2014 warming rates. In other words, CMIP5/6 models share a common bias in their ability to simulate the observed SST trend pattern which increases their values of EffCS and thus their rate of warming over recent decades – directly biasing their simulated relationship between warming rate and ECS on which emergent constraints are based.

Correcting for SST trend pattern biases in emergent constraints

We next estimate the global-mean warming each GCM would produce if it correctly simulated the observed 1981-2014 SST trend pattern. To do so, we multiply the value of EffCS derived from the AGCM simulations by the regression coefficient between the EffCS and the 1981-2014 warming rate derived from all ensemble members in the eight-GCM subset (diamonds in Fig. 1d; Methods). The results suggest that each of the eight CMIP5/6 models would have produced warming near the observed warming rate had it simulated the observed SST trend pattern. Thus, once biases in SST trend patterns are accounted for, there is little correlation between the 1981-2014 warming rate and ECS (Fig. 3a). The average warming rate correction across the eight GCMs is $-0.09°\text{C dec}^{-1}$, with larger reductions in warming rates (and EffCS) for models with higher ECS (Figs. 1c and 3a).

We conclude that observed warming does not exclude high values of ECS, and that by failing to account for biases in coupled GCM SST trend patterns, the proposed emergent constraint biases estimates of ECS toward low values. Similar results hold if we instead use the regression between 1981-2014 EffCS and warming rate derived from each GCM separately to estimate the warming rate consistent with AGCM EffCS values, but uncertainties are larger owing to larger uncertainty in the regression, particularly for models with few ensemble members (Figs. S3-4).

As another method to estimate warming rates in the eight GCMs when correcting for biases in SST trend patterns, we use equation (3) with values of λ derived from each model's AGCM simulation (Methods). Once again, the results suggest that each of the eight CMIP5/6 models would have produced warming near the observed warming rate had they simulated the observed SST trend pattern, leaving little correlation between the 1981-2014 warming rate and ECS (Fig. 3b). The average warming rate correction across the eight GCMs is $-0.05°\text{C dec}^{-1}$ with a larger impact for models with higher ECS, once again. This supports our conclusion that observed warming does not exclude high values of ECS, and that the

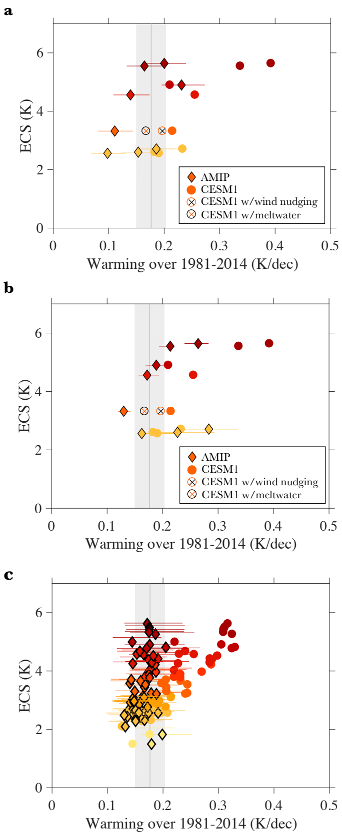

Fig. 3. Relationships between equilibrium climate sensitivity (ECS) and the 1981-2014 warming rate with (diamonds) and without (circles) accounting for observed warming patterns. ECS vs warming rate for **a,** CMIP5/6 eight-model subset, with circles showing uncorrected warming rates (from Fig. 1b) and diamonds showing corrected warming rates estimated using AGCM values of EffCS and the relationship between EffCS and warming (Fig. 1d); horizontal lines show 5-95% confidence ranges from uncertainty in the fit. **b,** CMIP5/6 eight-model subset, with circles showing uncorrected warming rates (from Fig. 1b) and diamonds showing corrected warming rates estimated using AGCM values of λ and equation (3), with horizontal lines showing uncertainty ranges reflecting the spread in κ across ensemble members. **c,** Relationship between ECS and warming rate in two-layer EBM simulations with circles showing uncorrected warming rates and diamonds showing corrected warming rates using observed values of EffCS (19) (Fig. S6), with a median of 2°C and horizontal lines showing 5-95% confidence ranges illustrating 1.5-3.1°C. Gray shading shows observational estimates (5-95% range) of observed warming rate (HadCRUT5, ref. 45).

proposed emergent constraint biases estimates of ECS toward low values; similar results hold for constraints on TCR (Figs. S1,4). It also suggests that observed global warming has been slowed by the unique SST trend pattern over recent decades (Fig. 2c) and that warming would have been more rapid had the pattern been more similar to that simulated by CMIP5/6 models (Fig. 2b).

Simulations with a two-layer energy balance model (EBM). The results presented so far rely on diagnostic interpretation of CMIP5/6 output and on inferences of GCM warming rates had they correctly simulated the observed 1981-2014 SST trend pattern and associated EffCS. Here we evaluate the robustness of this interpretation within the context of a widely-used energy balance model (EBM, refs. 54–56) which represents the Earth as two interacting layers – one representing all surface components of the climate system, including the near-surface atmosphere, ocean mixed layer, and land; and one representing the ocean below the mixed layer. The EBM predicts the surface temperature response to ERF through a representation of the efficiency of radiative response (governed by λ), the efficiency of ocean heat uptake, and the efficacy of ocean heat uptake which allows feedbacks to change over time as in coupled GCMs (Methods). This EBM was used extensively in IPCC AR6, including for constraining global temperature projections (see climate model "emulators" in refs. 2, 4). We fit the two-layer EBM parameters to the CMIP5/6 *abrupt4xCO2* simulations of all models used in the analysis above (Methods; Supplementary Information).

For each CMIP5/6 model parameter set, we run the EBM over the period 1850-2014 using the timeseries of historical ERF calculated as an average over the eight-model subset as described above, and we calculate EffCS over 1981-2014 using equations (1) and (2). We also run the EBM under an abrupt increase in ERF representing CO_2 quadrupling (to calculate EBM values of ECS using regression over 150 years, as in the CMIP5/6 models).

The EBM produces features similar to the CMIP5/6 analysis seen in Fig. 1. There is a strong correlation between the 1981-2014 warming rate and ECS, with lower ECS values being more consistent with observations (Figs. 3c and S5). This correlation is explained by the fact that 1981-2014 EffCS values, governing warming over that period, are similar to ECS values (Fig. S5); EffCS tends to be slightly smaller than ECS owing to the ocean heat uptake efficacy parameter being larger than one for most CMIP5/6 models (Supplementary Information), allowing feedbacks under transient warming to be slightly more negative than at equilibrium. Differences in EffCS explain a large fraction of the variance in the 1981-2014 warming rate ($r^2 = 0.88$); values of EffCS near 2°C tend to produce warming rates in line with observations, while higher values of EffCS produce too much warming (Fig. S5). The remaining variations in EBM warming rates come from differences in ocean model parameters (Methods), but differences in forcing do not contribute here because we have used the same historical ERF for all parameter sets. The regression between EffCS and the 1981-2014 warming rate also nearly matches that found from the eight-model subset, and agrees well with the relationship between EffCS and the 1981-2014 warming rate derived from observational constraints (Fig. S5).

We next consider how EBM simulations of the 1981-2014 warming rate change when we introduce a linear trend in λ (Methods), representing an idealization of trends in λ over recent decades as simulated by AGCMs forced by observed warming patterns (8, 14, 17, 19, 25), such that EffCS over 1981-2014 becomes equal to the value EffCS = 2.0°C (with bounds of 1.5 to 3.1°C also tested) estimated from global energy budget constraints (19). This produces a substantial decrease in EffCS for high ECS models, but little change in EffCS for low ECS models (diamonds in Fig. S5), similar to differences seen in coupled GCM and AGCM versions of CMIP5/6 models (Fig. 1c). The result is that the EBM produces warming near the observed rate for all CMIP5/6 model parameter sets, in line with expectations based on the regression between EffCS and warming rate (Figs. 3c and S5). The average warming rate correction across the subset of eight models is -0.06°C dec^{-1}, with larger reductions in warming rates (and EffCS) for models with higher ECS, similar to our analysis using

CMIP5/6 models above.

The relationship between ECS and the warming rate when imposing observed EffCS within the EBM is shown in Fig. 3c. Each CMIP5/6 model parameter set produces warming near the observed 1981-2014 warming rate, with little correlation between warming rate and ECS. These results show that the low value of EffCS produced by the observed 1981-2014 SST trend pattern implies warming in line with the observed global warming rate, regardless of the value of ECS. This supports our interpretation that observed warming does not exclude high values of ECS once accounting for the observed SST trend pattern and its associated low EffCS. Similar results hold for comparisons of warming rates and TCR (Fig. S5).

Simulations with a coupled GCM nudged toward observed warming patterns. Finally, we evaluate the robustness of our results using two sets of CESM1-CAM5 simulations wherein the coupled model is nudged toward the observed 1981-2014 SST trend pattern in physically-plausible ways. The first set of simulations, performed by Dong et al. (57) based on methods developed in Blanchard-Wrigglesworth et al. (58), involves nudging Southern Hemisphere tropospheric winds (above the boundary layer) poleward of 40°S to match the ERA-Interim Reanalysis over the period 1981-2014; five ensemble members were run, which we average together for comparison to the CESM1-CAM5 ensemble mean response. The second set of simulations, performed by Dong et al. (52) and Pauling et al. (59), involves adding meltwater to the Southern Ocean subsurface to represent discharge due to mass imbalance of the Antarctic ice sheet over 1981-2013 (an effect not represented in CMIP5/6 *historical* simulations); nine ensemble members were run, which we average together for comparison to the CESM1-CAM5 ensemble mean response. In both sets of simulations, the SST trend pattern more closely matches observations, with some cooling in the Southern Ocean and eastern tropical Pacific Ocean and with warming in the western Pacific Ocean becoming relatively larger (Figs. 2e,f); see ref. (57) for a discussion of the atmospheric teleconnection pathways by which these southern high latitude forcings influence tropical SST patterns.

Using equations (1) and (2) as before, we find that both sets of simulations produce smaller values of EffCS than the ensemble mean of CESM1-CAM5 *historical* simulations (Fig. 1c), bringing EffCS nearer to that estimated from observed global energy budget constraints (19). In turn, both sets of simulations show reduced global warming rates (Fig. 1d) that are more in line with observations. The relationship between EffCS and warming rate in these simulations also approximately follows expectations based on the regression between EffCS and warming rate derived from either the eight-model subset (Fig. 1d) or CESM1-CAM5 (Fig. S3). However, despite similar changes to EffCS, Antarctic meltwater forcing produces a larger reduction in global warming rate than Southern Hemisphere wind forcing in this model owing to an increase in ocean heat uptake efficiency (κ) that works together with feedback (λ) changes to slow the warming (52). Similar results hold for comparisons of warming rates and TCR (Figs. S1,4). These findings support the interpretation above that EffCS (rather than ECS or TCR) governs the global warming rate over 1981-2014, and that when coupled GCMs more accurately replicate observed SST trend patterns, they produce lower EffCS and thus slower global warming, in line with observations.

Discussion and conclusions

The results presented here suggest that high-sensitivity CMIP5/6 models produce too much post-1970s warming in part due to their failure to simulate observed SST trend patterns, which in turn leads to model values of EffCS that are too high compared to the observed EffCS of around 2°C over this period. Because GCMs with high values of ECS and TCR are able to produce values of EffCS near 2°C when forced by observed SSTs over 1981-2014 (Figs. 1c, S1c), we estimate that even those high-sensitivity GCMs could produce global warming rates in line with observations if they were able to better simulate observed SST trend patterns (Figs. 1d, 3a,b). This is a bias in the GCM-based relationship between post-1970s warming and climate sensitivity metrics which causes the proposed emergent constraints to be biased toward low values of climate sensitivity. Published constraints (18, 32–34) may still reflect useful lower bounds on ECS and TCR, but should not be used to exclude high ECS and TCR values. While not a focus here, model biases in historical radiative forcing (e.g., 60) could also impart biases in the modeled warming-sensitivity relationship on which the emergent constraint is based.

Important questions remain, including: (i) why do CMIP5/6 models fail to replicate observed warming patterns over recent decades, and how can this model bias be corrected? And, (ii) for how long will the observed pattern of warming over recent decades continue into the 21st century? Model-observation discrepancies may be due to model deficiencies in simulating internal variability and/or historical forced responses. Paleoclimate proxy and instrumental data suggest that tropical Pacific multidecadal variability may be substantially larger than that produced by coupled GCMs (e.g., 61–63), which seems consistent with the observed 1981-2014 SST trend pattern resembling an extreme phase of the Interdecadal Pacific Oscillation mode of variability (e.g., 41, 42, 63). Alternatively, several other model deficiencies have been proposed to contribute to the SST trend pattern over recent decades including: model biases in trends in the Southern Annular Mode, potentially due to a misrepresentation of ozone depletion (e.g., 57, 64, 65); missing Antarctic meltwater fluxes (e.g., 52, 57, 59, 66); a misrepresentation of tropospheric aerosol forcing, which can affect Pacific trade winds (e.g., 67); model biases in Atlantic Ocean SSTs that limit the ability of the Atlantic basin to affect Pacific trade winds (68); and model biases in the transient response of the tropical Pacific to CO_2 forcing (e.g., 69, 70) or volcanic forcing (16). The results presented here do not depend on the source of the discrepancy between CMIP5/6-simulated and observed warming patterns because radiative feedbacks and EffCS depend only on SST and SIC patterns, regardless of how those patterns arise (e.g., 71).

The results presented here suggest that changes in EffCS have the capacity to substantially affect the global warming rate and that a low value of EffCS driven by a unique SST trend pattern has slowed global-mean warming over recent decades, relative to what it would have been had the pattern been more spatially uniform. However, more work is needed to determine whether CMIP5/6 models with high ECS (above ~ 4°C) are capable of producing the observed SST trend pattern and associated low EffCS needed to bring their simulated global warming rates in line with observations over recent decades. It would be valuable to perform similar wind nudging and/or Antarctic meltwater flux simulations, shown here for CESM1-

CAM5, using high ECS models.

These results reinforce previous findings that global warming will depend on how the SST trend pattern evolves in the future (e.g., 52, 72, 73). Our findings suggest that if the observed 1981-2014 pattern continues over the 21^{st} century, then the value of EffCS governing future warming will remain near 2°C. This would produce 21^{st} century global warming near the lower end of IPCC AR6 projections (Fig. S6), which assume a *very likely* range of ECS of 2-5°C (2). However, if enhanced warming of the eastern tropical Pacific and Southern Oceans were to emerge in the future – a pattern projected by GCM simulations of the 21^{st} century and supported by paleoclimate proxy evidence (e.g., 2, 74) – then EffCS would increase, resulting in an increase in the rate of global warming (Fig. S6). The degree to which EffCS could increase depends on the magnitude of the warming in the the eastern tropical Pacific and Southern Oceans, and on the magnitude of the radiative feedbacks in those regions. Because observed post-1970s warming has a unique spatial pattern that does not appear to be representative of the long-term response to greenhouse-gas forcing, it does not preclude the possibility that high values of EffCS are possible for the future, potentially leading to future warming near or even above the upper end of IPCC AR6 projections if ECS turns out to be on the high end. How the pattern of warming will evolve in the future thus represents a major source of uncertainty in climate projections.

Developing improved understanding of the causes of the observed SST trend pattern over recent decades and better constraints on how those patterns will evolve in the future is a major challenge for climate science with direct implications for how we interpret the historical warming record and project 21^{st} century warming. We could, for instance, see an increase in the climate's sensitivity to greenhouse-gas forcing if SST trend patterns evolve to become more similar to those projected by models. For now, climate model biases in historical SST trend patterns suggest that caution is needed in the use of models to derive emergent constraints on climate sensitivity or future warming based on the observed rate of global warming over recent decades.

Materials and Methods

Linear regression methods. We use ordinary least squares (OLS) regression to calculate 1981-2014 warming rates and the regression of climate sensitivity metrics (ECS, TCR) against 1981-2014 warming rates using ensemble-mean values (Figs. 1a,b and S1a,b). To estimate ECS and TCR from the warming-sensitivity relationships (Figs. 1a, S1a), we calculate a linear fit of ECS (or TCR) versus 1981-2014 warming rate and use the parameters of that fit to estimate ECS (or TCR) given the observed warming rate (HadCRUT5, ref. 45) over 1981-2014. Uncertainties in ECS and TCR reflect 5-95% confidence ranges of fit parameter values.

For the calculation of the effective feedback λ from the regression of $N - \mathrm{ERF}$ against T (equation (1)), the presence of error in the predictor variable biases OLS regression toward zero (regression dilution). To correct for this, we use Deming regression, a total least squares regression method, to calculate λ. We estimate the ratio of error variances (variance of global average top-of-atmosphere radiation and variance in global average surface temperature) to be approximately 10 $\mathrm{W^2m^{-4}K^{-2}}$ based on AGCM simulations using sea-surface temperatures fixed at pre-industrial conditions. We use OLS regression for all regressions based on the two-layer EBM, which does not represent internal variability. Within CESM1-CAM5, high correlations between EffCS and warming rate over 1981-2014 are found when using the CAM5 Green's function (22) combined with SST trend patterns to estimate radiative feedback and EffCS (Fig. S2).

Effective radiative forcing. Historical effective radiative forcing (ERF) is calculated for each of the eight models in our subset using RFMIP (46) simulations. The historical ERF is diagnosed as the global top-of-atmosphere radiation anomaly in *piClim-histall* simulations (wherein SSTs and SICs are fixed to pre-industrial values while all radiative forcing agents are varied as in the corresponding CMIP6 *historical* simulations) relative to *piClim-control* simulations (wherein SSTs, SICs, and all radiative forcing agents are fixed to pre-industrial values). A small correction (2, 48) is made to remove the radiative response to global near-surface air temperature change T (mostly land warming) by subtracting $\lambda_{2\times}T$, where $\lambda_{2\times}$ is estimated from *abrupt4xCO2* simulations (35). For all RFMIP simulations, the ensemble mean is used when more than one member of the simulation exist. CMIP5/6 model values of effective radiative forcing for CO_2 doubling ($\mathrm{ERF}_{2\times}$) have been estimated using the standard approach of extrapolating to zero global temperature change the regression between global top-of-atmosphere energy imbalance and global temperature change over 150 years of abrupt CO_2 quadrupling simulations, scaled by a factor of a half to account for CO_2 doubling (35, 44).

Correcting for SST trend pattern biases. For the first method of estimating the warming each GCM would produce if it correctly simulated the observed 1981-2014 SST trend pattern (Fig. 3a), we first calculate a linear fit (OLS regression) of EffCS versus 1981-2014 warming rate from all ensemble members of the eight-GCM subset (Fig. 1d). We then use that fit to estimate the warming rate given EffCS derived from each AGCM simulation (diamonds in Figs. 1d, 3a). Uncertainties (horizontal lines in Fig. 3a) reflect 5-95% confidence ranges of fit parameter values.

For the second method of estimating the warming each GCM would produce if it correctly simulated the observed 1981-2014 SST trend pattern (Fig. 3b), we use equation (3) with values of λ derived from each model's AGCM simulation. In the eight-model ensemble considered here, the average correlation between λ and κ across historical ensemble members is small (average $r^2 = 0.25$), and models disagree on the sign of the correlation. Without a deeper understanding of how variations in λ and κ are related, we assume they can be varied independently and use ensemble-mean values of κ for each model in this estimate. To evaluate the degree to which variations in κ could affect the results, uncertainties (horizontal lines in Fig. 3b) are generated by using the highest and lowest values of κ from the ensemble members of each model in this calculation.

Two-layer energy balance model. The two-layer energy balance model (EBM, refs. 54–56) evolves surface temperature according to the following equations:

$$\begin{aligned} C\frac{dT}{dt} &= \lambda T + \mathrm{ERF} - \varepsilon\gamma(T - T_0), \\ C_0\frac{dT_0}{dt} &= \gamma(T - T_0), \end{aligned} \qquad [5]$$

where T is the temperature anomaly of the upper layer, representing the global surface temperature anomaly; T_0 is the temperature anomaly of the lower layer; ERF is the effective radiative forcing, as above; C is the effective heat capacity of the upper layer (representing the ocean mixed layer, land, and atmosphere); C_0 is the effective heat capacity of the lower layer (representing the ocean below the mixed layer); γ represents the efficiency of vertical heat transport between upper and lower layers; and ε is the efficacy of ocean heat uptake, which allow effective radiative feedbacks to change over time as represented by coupled GCMs. Note that in the limit of $C_0 \gg C$, such that deep ocean temperature T_0 does not change much, these equations reduce to equation (3) with $\kappa = \varepsilon\gamma$.

We fit the two-layer EBM parameters to the *abrupt4xCO2* simulations of all CMIP5/6 models used in the analysis above using the fitting scheme developed by Lutsko and Popp (75), which was based on Geoffroy et al. (56) (see Supplementary Information for parameter values). To simulate historical warming consistent with observational constraints on EffCS, we run the model using a wide range of linear trends in λ over the period 1981-2014 (starting from initial values of λ as fit to CMIP5/6 models and changing linearly with time) and calculate EffCS over this period (using equation (1)) for each. We then select the simulations that correspond to EffCS values of 2.0°C, 1.5°C, and 3.1°C (50%, 5%, and 95% intervals of the observationally constrained EffCS from ref. (19). See Supplementary Information for details regarding the 21$^{\text{st}}$ century EBM simulations under different assumptions about how EffCS will evolve in the future.

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Supplementary Information for

Sea-surface temperature pattern effects have slowed recent global warming and biased emergent constraints on climate sensitivity

Kyle C. Armour, Cristian Proistosescu, Yue Dong, Lily C. Hahn, Edward Blanchard-Wrigglesworth, Andrew G. Pauling, Robert C. Jnglin Wills, Timothy Andrews, Malte F. Stuecker, Stephen Po-Chedley, Ivan Mitevski, Piers M. Forster, and Jonathan M. Gregory

Kyle Armour
E-mail: karmour@uw.edu

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Supplementary text
Figs. S1 to S6
Tables S1 to S2

Supporting Information Text

Tables S1 and S2

Tables S1 and S2 show relevant parameters for CMIP5 and CMIP6 models, respectively. This includes the number of *historical* ensemble used in the analysis in the main text; equilibrium climate sensitivity (ECS); transient climate response (TCR); and two-layer energy balance model (EBM) parameter values. Also noted are which models are included in our eight-model subset.

The relationship between post-1970s warming rate and transient climate response

Fig. S1 shows the equivalent of Fig. 1 in the main text, but for the relationship between TCR and the 1981-2014 warming rate or effective climate sensitivity (EffCS). TCR values are calculated from the global temperature change near year 70 (time of CO_2 doubling) of CMIP5/6 1%/yr CO_2 ramping simulations (*1pctCO2*). See Fig. S4 for the relationships between TCR and the 1981-2014 warming rate when accounting for observed sea-surface temperature (SST) trend patterns.

The relationship between SST trend patterns, EffCS, and global warming rate in the CESM1-CAM5 large ensemble

Fig. S2 shows regressions between local SST trend patterns and either global warming rates or EffCS over 1981-2014. Also shown is the relationship between EffCS and warming rate over 1981-2014 when using the CAM5 Green's function of Zhou et al. (22) combined with SST trend patterns to estimate radiative feedback and EffCS (Fig. S2c), rather than regression methods as in Fig. 1d of the main text.

Correcting for warming rates using model-specific relationships between EffCS and warming rates over 1981-2014

Figs. S3 and S4c,d show the equivalent of Figs. 1d and 3a in the main text, but using model-specific relationships between EffCS and warming rates over 1981-2014 in the estimate of the warming rate in each model had it simulated the observed SST trend pattern.

Two-layer energy balance model (EBM) simulations

Figure S5 shows the equivalent of Fig. 1 in the main text, but for the EBM response to historical and RCP8.5 (to 2014) ERF as described in the Methods. Figure S6 shows the EBM response to historical and RCP8.5 ERF over 1850-2100 using parameters fit to CMIP5/6 models (see Methods, and Tables S1-2). We also run the EBM under a linear increase in ERF representing 1%/yr CO_2 ramping simulations (to calculate EBM values of TCR, as in the CMIP5/6 models).

To evaluate the impact of changing EffCS on projected warming, we introduce a linear trend in the radiative feedback λ such that EffCS $\approx 2°$C over the period 1981-2020 for each CMIP5/6 parameter set, with this value of EffCS chosen to match observed energy budget constraints and *amip* simulations (see main text).

We also perform several simulations with different evolutions of λ over the period 2021-2100. Figure S6b shows the EBM response when λ remains constant over the period 2021-2100, thus maintaining EffCS $\approx 2°$C. Figure S6c shows the EBM response when λ is linearly returned to CMIP5/6 model values by 2060 (reversing the linear λ trend applied over 1981-2020 in the same number of years). Figure S6d shows the EBM response when λ is linearly returned to CMIP5/6 model values by 2060 (more slowly reversing the linear λ trend applied over 1981-2020).

Table S1. CMIP5 model ECS, TCR, and two-layer energy balance model (EBM) parameter values. Number of *historical* ensemble members used in the analysis listed in parentheses. Models included in the eight-model subset in the main text denoted by *.

			Two-layer EBM parameters fit to *abrupt4xCO2* simulations					
Model	ECS (K)	TCR (K)	C (W yr m^{-2}K^{-1})	C_0 (W yr m^{-2}K^{-1})	λ (Wm^{-2}K^{-1})	γ (Wm^{-2}K^{-1})	ε	ERF$_{2\times}$ (Wm^{-2})
ACCESS1-0 (1)	3.90	1.77	8.9	83	-0.81	0.71	1.55	3.6
ACCESS1-3 (1)	3.63	1.60	10.1	114	-0.81	0.72	1.62	3.5
bcc-csm1-1 (1)	2.91	1.76	8.8	57	-1.28	0.58	1.27	3.6
CCSM4 (6)	2.94	1.80	7.8	72	-1.40	0.81	1.36	4.2
CESM1-CAM5* (40)	3.32	2.07	8.7	144	-1.22	0.60	1.19	4.3
CNRM-CM5 (1)	3.28	1.97	8.7	96	-1.12	0.51	0.92	3.5
CSIRO-Mk3-6-0 (10)	4.36	1.69	9.3	77	-0.66	0.71	1.80	3.4
CanESM2 (5)	3.71	2.30	8.3	77	-1.05	0.54	1.28	4.1
GFDL-CM3 (3)	4.03	1.76	9.9	76	-0.78	0.71	1.39	3.4
GFDL-ESM2G (1)	2.34	1.21	6.5	104	-1.48	0.80	1.17	3.5
GFDL-ESM2M (1)	2.46	1.37	8.9	113	-1.38	0.86	1.23	3.6
GISS-E2-H (5)	2.43	1.78	10.5	86	-1.64	0.70	1.27	4.1
GISS-E2-R (6)	2.28	1.48	6.1	135	-2.03	1.07	1.44	4.6
HadGEM2-ES (4)	4.64	2.43	8.3	99	-0.60	0.49	1.57	3.4
inmcm4 (1)	2.05	1.29	9.1	277	-1.57	0.69	1.82	3.0
IPSL-CM5A-LR (4)	4.05	1.97	8.6	100	-0.79	0.57	1.14	3.3
IPSL-CM5B-LR (1)	2.64	1.44	9.7	68	-1.07	0.63	1.43	3.0
MIROC5 (5)	2.70	1.47	9.7	163	-1.58	0.74	1.20	4.4
MPI-ESM-LR (3)	3.66	2.01	9.2	78	-1.20	0.62	1.43	4.7
MRI-CGCM3 (1)	2.61	1.52	10.1	70	-1.30	0.60	1.25	3.5
NorESM1-M (1)	2.93	1.39	9.9	122	-1.15	0.76	1.57	3.6

Table S2. CMIP6 model ECS, TCR, and two-layer energy balance model (EBM) parameter values. Number of *historical* ensemble members used in the analysis listed in parentheses. Models included in the eight-model subset in the main text denoted by *.

			Two-layer EBM parameters fit to *abrupt4xCO2* simulations					
Model	ECS (K)	TCR (K)	C (W yr m^{-2}K^{-1})	C_0 (W yr m^{-2}K^{-1})	λ (Wm^{-2}K^{-1})	γ (Wm^{-2}K^{-1})	ε	ERF$_{2\times}$ (Wm^{-2})
ACCESS-CM2 (3)	4.72	2.10	9.0	93	-0.71	0.53	1.55	4.0
ACCESS-ESM1-5 (20)	3.87	1.95	9.0	97	-0.72	0.60	1.73	3.5
AWI-CM-1-1-MR (5)	3.16	2.06	8.3	57	-1.22	0.46	1.49	4.1
BCC-CSM2-MR (3)	3.02	1.72	6.5	64	-1.20	0.84	1.37	3.8
BCC-ESM1 (3)	3.26	1.77	8.9	98	-0.91	0.52	1.39	3.3
CAMS-CSM1-0 (7)	2.29	1.73	10.2	61	-1.87	0.47	1.29	4.4
CanESM5* (25)	5.64	2.74	8.0	80	-0.65	0.52	1.07	3.8
CESM2 (11)	5.15	2.06	8.7	75	-0.69	0.66	1.89	4.5
CESM2-WACCM (3)	4.68	1.98	8.5	89	-0.74	0.69	1.57	4.1
CMCC-CM2-SR5 (1)	3.52	2.09	8.9	79	-1.06	0.41	1.27	4.0
CNRM-CM6-1* (30)	4.90	2.14	7.6	147	-0.74	0.50	1.00	3.6
CNRM-CM6-1-HR (1)	4.33	2.48	8.2	95	-0.92	0.55	0.72	3.7
CNRM-ESM2-1 (10)	4.79	1.86	7.5	100	-0.63	0.59	0.91	2.9
E3SM-1-0 (3)	5.31	2.99	8.6	44	-0.63	0.35	1.50	3.7
EC-Earth3 (73)	4.10	2.30	8.1	37	-0.81	0.42	1.42	3.7
EC-Earth3-Veg (8)	4.33	2.62	8.4	40	-0.82	0.40	1.42	3.8
FGOALS-f3-L (3)	2.98	1.94	9.3	88	-1.41	0.53	1.58	4.7
FGOALS-g3 (5)	2.88	1.54	7.8	98	-1.30	0.69	1.30	4.0
GISS-E2-1-G* (12)	2.71	1.80	6.7	144	-1.47	0.84	1.10	4.1
GISS-E2-1-H (25)	3.12	1.93	8.9	86	-1.15	0.61	1.20	3.7
HadGEM3-GC31-LL* (5)	5.55	2.55	8.0	77	-0.63	0.51	1.22	3.7
HadGEM3-GC31-MM (4)	5.42	2.58	8.3	73	-0.66	0.58	1.03	3.6
INM-CM4-8 (1)	1.83	1.33	6.4	26	-1.68	0.78	1.31	3.1
IPSL-CM6A-LR* (32)	4.56	2.32	8.2	63	-0.75	0.41	1.33	3.7
KACE-1-0-G (3)	4.48	1.41	9.0	120	-0.71	0.74	1.31	3.8
MIROC-ES2L (11)	2.66	1.55	10.6	185	-1.56	0.67	0.93	4.1
MIROC6* (50)	2.60	1.55	8.9	175	-1.38	0.65	1.32	3.9
MPI-ESM-1-2-HAM (3)	2.96	1.80	9.5	113	-1.44	0.64	1.34	4.5
MPI-ESM1-2-HR (8)	2.98	1.66	8.9	84	-1.33	0.66	1.50	4.3
MPI-ESM1-2-LR (10)	3.00	1.84	9.5	114	-1.40	0.59	1.23	4.4
MRI-ESM2-0 (6)	3.13	1.64	8.7	96	-1.21	0.85	1.43	4.1
NESM3 (5)	4.77	2.72	5.6	105	-0.78	0.46	0.97	3.7
NorCPM1 (29)	3.05	1.56	9.9	108	-1.18	0.78	1.55	4.0
NorESM2-LM* (3)	2.56	1.48	5.6	119	-1.71	0.86	1.99	5.0
NorESM2-MM (3)	2.50	1.33	6.0	114	-1.74	0.79	1.66	4.8
SAM0-UNICON (1)	3.72	2.27	7.3	100	-1.09	0.79	1.24	4.3
TaiESM1 (1)	4.31	2.34	8.8	97	-0.93	0.63	1.34	4.4
UKESM1-0-LL (18)	5.36	2.79	8.0	80	-0.67	0.52	1.12	3.7

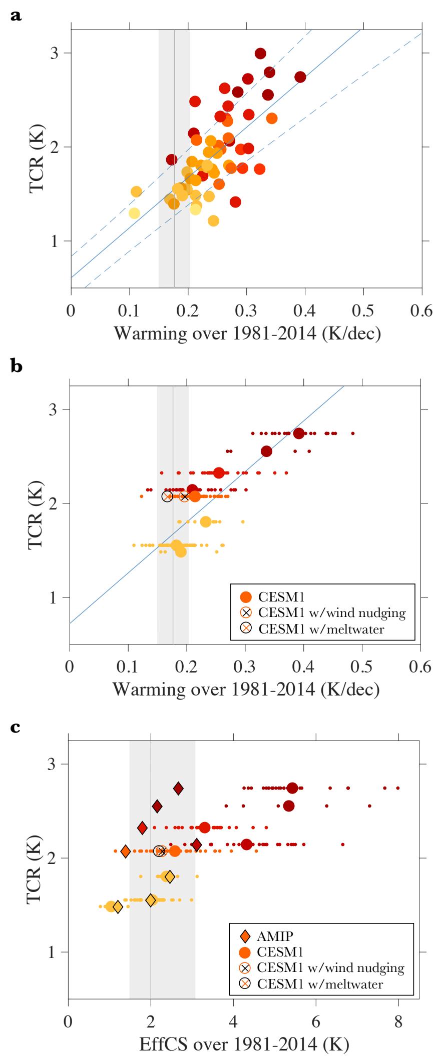

Fig. S1. Relationships between transient climate response (TCR), effective climate sensitivity (EffCS), and the 1981-2014 warming rate in CMIP5/6 models. a, CMIP5/6 TCR versus warming rate using averages of all available ensemble members for each model (correlation $r = 0.68$); colors correspond to values of ECS. **b,** Eight-model subset TCR versus warming rate with ensemble means shown as larger circles and ensemble members shown as smaller dots. **c,** Eight-model subset TCR versus EffCS over 1981-2014 with ensemble means shown as larger circles and ensemble members shown as smaller dots; diamonds show EffCS values from AGCM simulations forced by observed SST trend patterns. In **b,c**, open circles show CESM1-CAM5 simulations with wind nudging or meltwater forcing as described in the main text. Blue lines show fits calculated using ordinary least squares regression, with dashed blue lines showing 5-95% ranges of fit parameters. Gray shading shows observational estimates (5-95% range) of observed warming rate and EffCS as described in the main text.

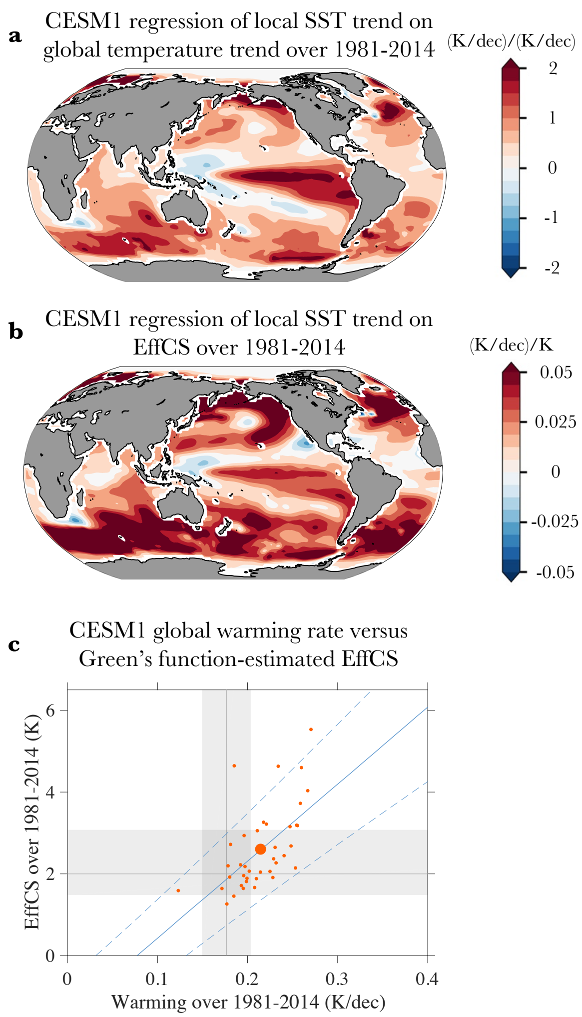

Fig. S2. The relationship between SST trend patterns, EffCS, and 1981-2014 warming rate in the CESM1 large ensemble. a, Regression between local SST trends and global warming rates across ensemble members. **b,** Regression between local SST trends and EffCS values (calculated as described in main text) across ensemble members. **c,** Green's function-estimated EffCS (calculated using the CAM5 Green's function of Zhou et al. (22) convolved with SST trend pattern of each ensemble member) versus warming rate over 1981-2014, with ensemble mean shown as larger circles and ensemble members shown as smaller dots (correlation $r = 0.6$). Blue lines show fit calculated using ordinary least squares regression, with dashed blue lines showing 5-95% ranges of fit parameters. Gray shading shows observational estimates (5-95% range) of observed warming rate and EffCS as described in the main text.

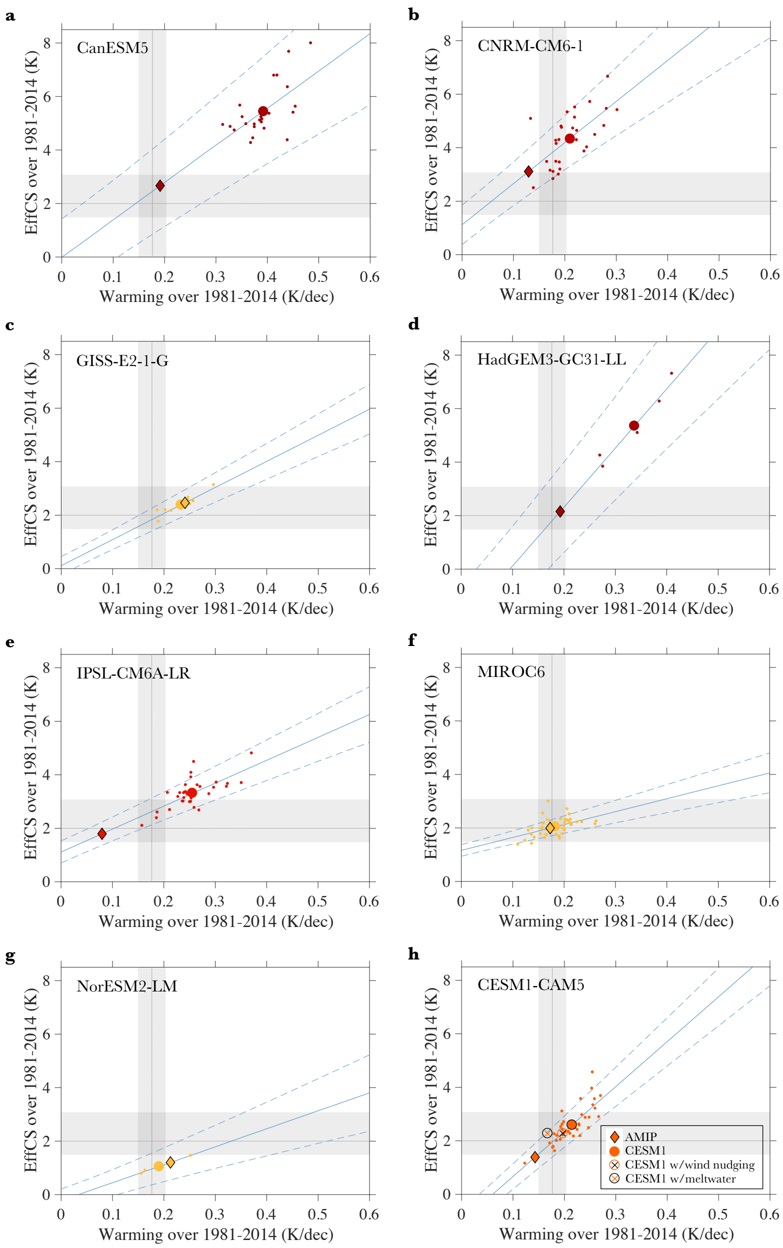

Fig. S3. Relationships between effective climates sensitivity (EffCS) over 1981-2014 and 1981-2014 warming rate in individual CMIP5/6 models. a, CanESM5. **b,** CNRM-CM6-1. **c,** GISS-E2-1-G. **d,** HadGEM3-CG3-LL. **e,** IPSL-CM6A-LR. **f,** MIROC6. **g,** NorESM2-LM. **h,** CESM1-CAM5. Ensemble means shown as larger circles and ensemble members shown as smaller dots. Also shown are EffCS and warming rates in CESM1-CAM5 simulations with wind nudging or meltwater forcing (see main text). Blue lines show fits calculated using ordinary least squares regression, with dashed blue lines showing 5-95% ranges of fit parameters. Gray shading shows observational estimates (5-95% range) of observed warming rate (HadCRUT5) and EffCS (see main text). Diamonds show EffCS values from AGCM simulations forced by observed warming patterns, with the corresponding warming rates estimated from the regression between EffCS over 1981-2014 and warming rate for each model (blue line).

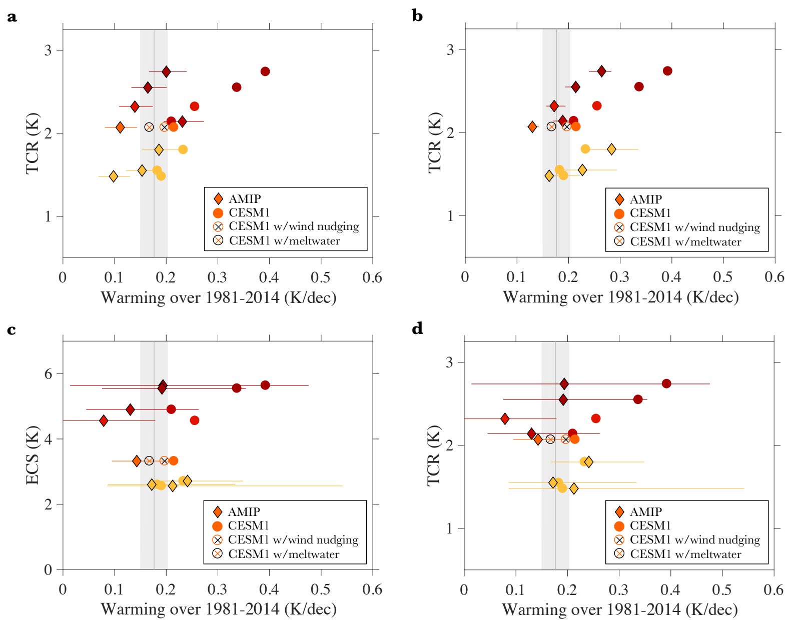

Fig. S4. Relationships between climate sensitivity metrics and the 1981-2014 warming rate with (diamonds) and without (circles) accounting for observed warming patterns. TCR vs warming rate for **a,** CMIP5/6 eight-model subset, with circles showing uncorrected warming rates (from Fig. 1b) and diamonds showing corrected warming rates estimated using AGCM values of EffCS and the relationship between EffCS and warming (Fig. 1d); horizontal lines show 5-95% confidence ranges from uncertainty in the fit. **b,** CMIP5/6 eight-model subset, with with circles showing uncorrected warming rates (Fig. S1b) and diamonds showing corrected warming rates estimated using AGCM values of λ and equation (3), with horizontal lines showing uncertainty ranges reflecting the spread in κ across ensemble members. **c,** CMIP5/6 ECS vs warming rate, with corrected warming rates (diamonds) estimated using AGCM values of EffCS and the relationship between EffCS and warming in the individual CMIP5/6 models (Fig. S3), with horizontal lines showing 5-95% confidence ranges from uncertainty in the fit; circles show uncorrected values as in Fig. 1b. **d,** CMIP5/6 TCR vs warming rate, with corrected warming rates (diamonds) estimated using AGCM values of EffCS and the relationship between EffCS and warming in the individual CMIP5/6 models (Fig. S2), with horizontal lines showing 5-95% confidence ranges from uncertainty in the fit; circles show uncorrected values as in Fig. S1b. Gray shading shows observational estimates (5-95% range) of observed warming rate as described in the main text.

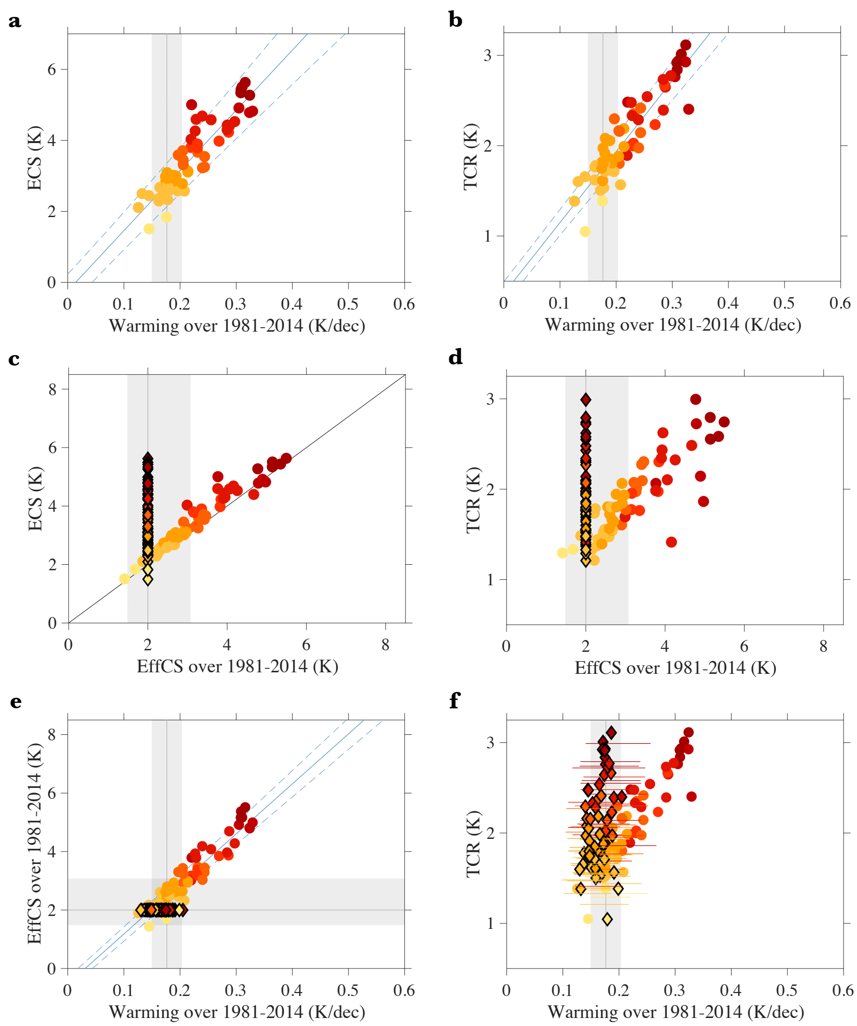

Fig. S5. Relationships between equilibrium climate sensitivity (ECS), transient climate response (TCR), effective climate sensitivity (EffCS), and the 1981-2014 warming rate in the two-layer energy balance model (EBM). a, ECS versus warming rate; colors correspond to values of ECS. **b,** TCR versus warming rate. **c,** ECS versus EffCS over 1981-2014; diamonds show an EffCS value corresponding to an observational estimate of 2°C. **d,** TCR versus EffCS over 1981-2014; diamonds show an EffCS value corresponding to an observational estimate of 2°C. **e,** EffCS over 1981-2014 versus warming rate; diamonds show warming rates simulated by the EBM when using an EffCS value corresponding to an observational estimate of 2°C over 1981-2014, which are in good agreement with the regression slope (blue line with dashed blue lines showing 5-95% ranges of fit parameters). **f,** Relationship between TCR and warming rate with circles showing uncorrected warming rates and diamonds showing corrected warming rates using observed values of EffCS as described in main text, with a median of 2°C and horizontal lines showing 5-95% confidence ranges showing 1.5-3.1°C. Gray shading shows observational estimates (5-95% range) of observed warming rate and EffCS as described in the main text.

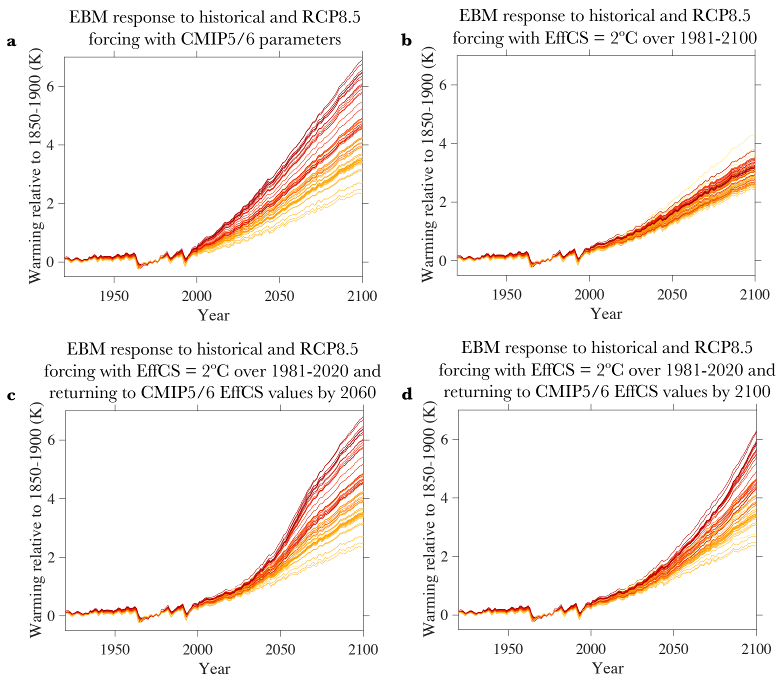

Fig. S6. Two-layer energy balance model (EBM) response to historical and RCP8.5 radiative forcing, either with CMIP5/6 model parameters or with changes in EffCS. a, EBM response using CMIP5/6 parameters; colors correspond to values of ECS. **b,** EBM response using CMIP5/6 parameters but with EffCS = 2°C over 1981-2100. **c,** EBM response using CMIP5/6 parameters but with EffCS = 2°C over 1981-2020 and EffCS returning to CMIP5/6 values by 2060. **d,** EBM response using CMIP5/6 parameters but with EffCS = 2°C over 1981-2020 and EffCS returning to CMIP5/6 values by 2100.