Emergent constraints on Earth's transient and equilibrium response to doubled CO₂ from post-1970s global warming

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Future global warming is determined by both greenhouse gas emission pathways and Earth's transient and equilibrium climate response to doubled atmospheric CO₂. Energy-balance inference from the instrumental record typically yields central estimates for the transient response of around 1.3 K and the equilibrium response of 1.5–2.0 K, which is at the lower end of those from contemporary climate models. Uncertainty arises primarily from poorly known aerosol-induced cooling since the early industrialization era and a temporary cooling induced by evolving sea surface temperature patterns. Here we present an emergent constraint on post-1970s warming, taking advantage of the weakly varying aerosol cooling during this period. We derive a relationship between the transient response and the post-1970s warming in Coupled Model Intercomparison Project Phase 5 (CMIP5) models. We thereby constrain, with the observations, the transient response to 1.67 K (1.17–2.16 K, 5–95th percentiles). This is a 20% increase relative to energy-balance inference stemming from previously neglected upper-ocean energy storage. For the equilibrium climate sensitivity we obtain a best estimate of 2.83 K (1.72–4.12 K) contingent on the temporary pattern effects exhibited by climate models. If the real world's surface temperature pattern effects are substantially stronger, then the upper-bound equilibrium sensitivity may be higher than found here.

The combination of greenhouse gas emission trajectories, Earth's transient climate response (TCR) and equilibrium climate sensitivity (ECS)^{1,2} determines future climate change. ECS is the Earth's long-term sensitivity to a doubling of atmospheric CO₂ over pre-industrial levels, and can be estimated from periods that span typically thousands of years in which the system can attain statistical stationarity. Some palaeoclimates qualify for this purpose³. Estimation of the Earth's transient response to increasing forcing (TCR), however, requires a highly resolved period of gradual warming. This requirement restricts us to the instrumental record of warming as the primary source of information. Unfortunately, anthropogenic forcing since the pre-industrial period is poorly known^{4–7} and the energy imbalance of the Earth, which mostly consists of the flow of energy into the deep oceans, is only well observed in the twenty-first century⁸. On top of these uncertainties, inhomogeneous sea surface temperature (SST) patterns, hereafter referred to as pattern effects, can temporarily dampen the transient warming^{9,10}, for example by inducing more low-level clouds¹¹ and, thereby, permitting a larger true ECS than that inferred from the historical warming with the help of a simple energy-balance framework^{12,13}. Thus, the disequilibrium of the Earth climate system during the instrumental record of warming poses several major challenges in the determination of climate sensitivity. This study presents a method to overcome several of these challenges and identifies upper-ocean heat content as an essential factor low-biasing past estimates of TCR from the instrumental record.

A substantial limitation of the studies that infer Earth's climate sensitivity from twentieth-century warming is the poorly known anthropogenic radiative forcing^{4–7}. Whereas the forcing from increasing greenhouse gas concentrations is sufficiently certain, anthropogenic aerosol-induced cooling is highly uncertain. This uncertainty leaves considerable room for interpretation of the

instrumental record: if the aerosol cooling was strong, such that the total anthropogenic forcing is weak, Earth's climate sensitivity has to be large, or vice versa¹⁴. The aerosol cooling, nevertheless, exhibited a rapid increase up until around 1970. Hereafter, air quality restrictions on pollutants resulted in an only slowly changing global aerosol cooling^{15–17}. Thus, focusing on this shorter period, although it offers less of a warming signal than the full record, could offer a period with stronger total anthropogenic forcing and potentially overcome the aerosol uncertainty problem^{5,18,19}.

Constraining TCR

We find a tight linear relationship between climate models' warming over the post-1970s period and their TCR, with a near-zero offset (Fig. 1a, Supplementary Table 4). We evaluate the statistical significance of the relationship with a leave-one-out method, which indicates that the slopes and offsets obtained do not depend strongly on specific models (Methods). The statistical relationship is in line with the theoretical expectation that the historical warming is proportional to the TCR (Methods). In contrast, no such proportionality of the centennial warming to the TCR is found, presumably due to inter-model spread in aerosol cooling on this timescale²⁰. We use the identified relationship as an emergent constraint to infer the TCR from the well-known post-1970s temperature record, whereby the observed warming (ΔT) is projected on TCR via the emergent constraint slope (s) and the small offset (e) such that $\text{TCR} = s\Delta T + e$. Uncertainty in the three terms is propagated to a combined uncertainty in the TCR using Monte Carlo sampling (Methods).

This straightforward technique gives us a median TCR of 1.67 K (Fig. 2, Supplementary Table 5). This median is roughly 20% higher than the energy-balance inferred values for the post-1970s warming period (1.41 K), the later period 1970–1989 to 2005–2015 (1.54 K) and the centennial warming (1.42 K). Moreover, the emergent

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Fig. 1 | Emergent constraints based on the 1970–2005 warming.

a, Emergent constraints on the TCR. **b**, Emergent constraints on the ECS. Thin lines show inference using energy-balance and two-layer model frameworks, whereas the thick line shows the relationship found in the CMIP5 ensemble (Supplementary Table 2) fitted using orthogonal distance regression (Methods). Each dot is an ensemble mean over all available realizations of the historical experiment. The MPI-ESM1.2-highECS and GFDL-ESM2G models were not used in the regression. The dashed lines enclose the 5–95% statistical prediction band for the regression. The probability distribution on the x axis is based on the average of five datasets and an estimate of systematic error plus natural variability found in a large model ensemble. The observational distribution is mapped via the fitted relationship to obtain the probability of the TCR and ECS, respectively, shown on the y axes. The estimated values in the top left corners are the median and 5–95th percentiles.

constraint places considerably less likelihood on lower TCRs than any of the energy-balance estimates (Fig. 2); for example, the probability of the TCR being below 1 K decreases from 2.2–9.6% to a merely 1.5% (Supplementary Table 5). The centennial warming inference gives a 5.6% probability that the TCR exceeds 2.5 K, whereas both the emergent constraint and energy-balance inference based on post-1970s warming place near-zero probability on such a large TCR: this is chiefly a consequence of the tighter constraint on aerosol cooling for the post-1970s period. If we vary (within a reasonable range) the assumed natural temperature variability on the post-1970s warming, the uncertainty in the TCR estimate varies little, and it is instead dominated by the relationship coefficients.

The larger median TCR found with the emergent constraint could either be caused by a stronger aerosol cooling increase in models during the post-1970s period or by the underlying assumptions of energy-balance inference. It turns out that aerosol forcing is an unlikely candidate. For instance, the MPI-ESM1.1 model shows larger TCR/ ΔT ratios than assumed in energy-balance inference,

Fig. 2 | Probability distributions of the TCR. The derived emergent constraint is shown in black and energy-balance estimates based on observations in blue. Horizontal lines show the median and the 5–95th percentile range.

despite the fact that it has a weaker increase in aerosol cooling²¹. This behaviour is consistent with aerosol forcing uncertainty not being a dominant source of uncertainty on post-1970s warming. And furthermore, since a majority of models have a weaker TCR to post-1970s warming than MPI-ESM1.1, a strong aerosol cooling in CMIP5 models in general is not a viable explanation for the higher TCR obtained using the emergent constraint compared with energy balance.

Instead, we find a plausible physical explanation for the larger median TCR. Energy-balance inference of the TCR relies on the zero-layer assumption, wherein the heat capacity of the upper ocean is neglected (Methods). This assumption is only valid if the forcing increases gradually over multiple decades and the increase is slow enough that the upper ocean, atmosphere and land are approximately in equilibrium. Until equilibrium between these components is attained, the system warms less than expected from the zero-layer approximation as part of the energy is stored in the upper ocean²². This happens when the forcing rapidly changes, for example in the cooling arising from explosive volcanic eruptions²³. In the historical record, the bulk of the warming occurred over just a few decades since the 1970s and, therefore, the validity of the zero-layer assumption is questionable. If we relax this assumption and use the two-layer model instead (see Methods) we obtain a slope indistinguishable from that obtained with the emergent constraint based on complex climate models. Thus, it is plausible that the zero-layer assumption has low-biased previous inferences^{5–7} of the TCR from the instrumental record.

Low-frequency natural variability in global mean temperature can introduce a non-forced signal into the instrumental record. The non-forced signal is typically handled by the selection of two periods with similar states of natural variability, for instance, related to El Niño and the Atlantic Multidecadal Oscillation (AMO)⁶. A challenge posed by the post-1970s period is that the AMO index shifted from negative to positive, leading to a possible contribution of natural variability to global warming. We find, however, model-based evidence that the shift is forced: across most models the positive shift in the AMO occurs in the historical simulations, even when subtracting the contribution from global warming, which can be done on large ensembles (Methods, Supplementary Fig. 4). Hence, we do not compensate for AMO change in this study, but remark that a blind compensation for an assumed unforced AMO would lead to both a reduction of the observed ΔT and a change in the emergent constraint (Supplementary Table 7), which means a mere 10% reduction of the median TCR (Supplementary Figs. 3a, 5 and Supplementary Table 8).

Out-of-range TCR would be possible if post-1970s aerosol cooling change deviates considerably from the best estimate of -0.15 W m^{-2} from Assessment Report Five (AR5) of the Intergovernmental Panel on Climate Change (IPCC)²⁴ (Supplementary Table 3).

Fig. 3 | Comparison of the MPI-ESM1.2-highECS model with observations.

The curves show the instrumental temperature record and model runs with the different aerosol cooling strengths noted in the figure. The model was run four times with each aerosol setting and the ensemble mean is displayed.

Even though the precursor emissions stagnated¹⁵, one argument for a weakly strengthening aerosol cooling is the geographical shift in the emissions from the North Atlantic towards East Asia and other tropical regions. As the relationship between aerosol concentrations and reflected sunlight is logarithmic, the geographical shift distributes the same amount of aerosols in a larger and more sunny region, leading to a strengthened aerosol cooling. The described behaviour is in line with a majority of models²⁵. Thus, a constant or weakening aerosol cooling change would allow a lower TCR to match post-1970s warming, as some models show^{26,27}. If the best estimate of aerosol cooling is zero, the energy-balance-inferred median TCR reduces by 12%.

We now challenge the upper bound on the TCR by constructing a version of the MPI-ESM1.2 model with strong positive cloud feedbacks, resulting in a high-end TCR of 2.3 K and an ECS of 4.8 K (Fig. 1, Methods). A new feature of the MPI-ESM1.2 model over the predecessor MPI-ESM1.1 is the representation of aerosol–cloud interactions as a parameterized Twomey effect^{17,21}. With an unaltered total aerosol forcing of around -0.6 W m^{-2} relative to the pre-industrial, the model clearly warms more than observed from 1960 onwards (Fig. 3). With an enhanced total aerosol cooling of -1.2 W m^{-2} , both centennial and post-1970s warming agree with observations (Figs. 1 and 3). However, for a long period between 1940 and 2000, the model is on average colder than observed. Further enhancement of the aerosol cooling leads to a negative total forcing starting in the 1960s, leading to an inconsistency with observed warming during that period. Thus, a larger TCR than indicated by the emergent constraint, paired with stronger aerosol cooling, yields an implausible historical temperature evolution.

Constraining ECS

We now explore whether post-1970s warming can constrain the ECS. To constrain the ECS from non-equilibrium states, we need information on deep-ocean heat uptake²⁸ and pattern effects. Energy-balance inference of the ECS does not usually consider the pattern effects that can temporarily dampen the warming^{12,13}. We assume that the form of the relationship between warming and ECS is $\text{ECS} = \Delta T / (s' - e' \Delta T)$, where the parameter s' is related to post-1970s forcing and e' represents the combined damping by deep-ocean heat uptake and pattern effects (Methods, Supplementary Table 4). Using the same methods as with the TCR case, we find a median ECS of 2.83 K, which is 20–30% above the energy-balance-inferred value (Figs. 1 and 4, Supplementary Table 6). Whereas the probability of ECS exceeding 4.5 K is similar to energy-balance estimates, the likelihood of an ECS below 1.5 K is reduced from 4–23%

Fig. 4 | Probability distributions of the ECS. The derived emergent constraint is shown in black and energy-balance estimates based on observations in blue. Horizontal lines show the median and the 5–95th percentile range.

to only 2.4% (Supplementary Table 6). An earlier study¹² used idealized runs with CMIP5 models to correct the energy-balance-inferred ECS from centennial warming and obtained an ECS of 2.9 K (5–95th percentile range: 1.7–7.1 K). Our estimate is consistent with this result and our considerably smaller upper bound can be ascribed to a less-uncertain aerosol cooling change during the post-1970s era.

The higher median ECS arises primarily from the pattern effects that temporarily buffer the warming¹². Pattern effects are represented in the two-layer framework as the deep-ocean heat uptake efficacy ϵ . From climate models²⁹, ϵ is 1.28 (range: 0.83–1.82) and the deep-ocean heat uptake coefficient γ is $0.73 \text{ W m}^{-2} \text{ K}^{-1}$ (0.5 – $1.16 \text{ W m}^{-2} \text{ K}^{-1}$). The product $\epsilon\gamma$ ($0.93 \text{ W m}^{-2} \text{ K}^{-1}$) controls the relationship between transient and equilibrium warming, as can be shown by running the two-layer model. Operating the two-layer model with the model mean value of $\epsilon\gamma$ delivers a striking similarity to the emergent constraint relationship (Fig. 1). If we introduce the uncertainty on $\epsilon\gamma$, the resulting relationships encompass almost all CMIP5 models (Fig. 5b) and potentially explain much of the intermodel spread. The reader should note that $\epsilon\gamma$ has no impact on the emergent constraint of the TCR (Fig. 5a) because both transient historical warming and the TCR are affected in equal proportion by $\epsilon\gamma$. This independence of the TCR from pattern effects further corroborates our main finding: the difference between the TCR from the emergent constraint and energy-balance inference is primarily due to upper-ocean warming.

Taking into account the disequilibrium of the Earth system—including that of the upper ocean—is crucial to inferring climate sensitivities from the instrumental record. The oceans buffer anthropogenic warming for centuries by both sequestering most of the trapped energy in the deep ocean and through a pattern of SST that enables the atmosphere to radiate more efficiently to space. If pattern effects of the Earth are stronger than those indicated by models, as suggested in a recent study¹³, then a higher ECS than that found by our emergent constraint cannot be ruled out. Hence, low ECS values would be even less likely than found here and in ref.¹². Finally, the insight gained here that the often-neglected upper ocean dampens transient warming and, consequently, impacts inferred TCR, has particular value since the instrumental record is practically the only period with sufficient temporal resolution to estimate Earth's TCR, and thus justifies an upward revision of the central estimate and the tightening range of uncertainty.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of code and data availability and associated accession codes are available at <https://doi.org/10.1038/s41561-019-0463-y>.

Fig. 5 | The impact of pattern effects. **a,b**, Exploration of the impact of pattern effects, as represented by ϵ_T (see Methods), on the relationship between post-1970s warming and the TCR (**a**) and ECS (**b**). A range of values for pattern effects are shown, shaded from magenta to green. Note that these curves mostly overlap for the TCR (**a**).

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Author contributions

D.J.-d.-l.-C. and T.M. developed the methodology and wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

Observational data, model output and radiative forcing. We use observations of global mean surface temperature (GMST) from five different datasets: HadCRUT4.6³⁰, NOAA GlobalTemp³¹ (known before as MLOST, gridded version obtained from the NOAA/OAR/ESRL PSD website), GISTEMP³² (gridded version obtained from the NOAA/OAR/ESRL PSD website), Berkeley³³ and the Cowtan and Way 2.0 dataset³⁴. Some of these datasets take different approaches to extrapolating to unobserved regions, where regional warming may have been faster than global warming. However, there is not much difference between their post-1970s warming (Supplementary Table 1), and in fact the dataset with strongest warming (HadCRUT4.6) does not apply extrapolation so observational coverage is probably a minor issue over this period. Although the datasets agree closely, we choose to average and use the spread as an estimate of structural uncertainty. Uncertainty from natural variability is determined from a 100-member ensemble of historical climate model simulations using the MPI-ESM1.1 model, and this dominates over structural uncertainty. In practice, we generate five Gaussians centred on the mean values from the temperature datasets, and randomly sample these distributions to construct a joint distribution that integrates not only the differences in the datasets, but also the internal variability estimate.

Climate model output from CMIP5 models listed in Supplementary Table 2 was obtained through the Earth System Grid Federation nodes. Here control experiments with constant pre-industrial boundary conditions (piControl), historical boundary conditions for 1850–2005 (historical), gradually increasing CO₂ at a rate of 1% yr⁻¹ (1pctCO2) and with abruptly quadrupled CO₂ (abrupt4xCO2) were downloaded in as many realizations as were available. The results were averaged when multiple realizations were available (see Supplementary Table 2).

We use surface temperature instead of surface air temperature to compare models and observations. This is because the oceans cover 70% of the Earth's surface, meaning that most of the observations used to estimate global temperature change are actually surface temperatures, not surface air temperatures (as is observed on land). Furthermore, surface air temperature in models is a diagnosed quantity and, unlike surface temperature, does not influence radiative response. Models indicate that the difference in the global mean change between these values is approximately 6%, and thus if the ECS and TCR in terms of surface air temperature is sought then the results found here should be adjusted slightly upwards. Since about 30% of the observed temperatures are already surface air temperatures, the upward adjustment should be about 4%.

We calculate TCR and ECS from anomalies of the surface temperature in the 1pctCO2 and abrupt4xCO2 simulations by first subtracting the long-term mean from piControl. TCR is the mean temperature in a 20-year period around year 70 of the 1pctCO2 experiment when CO₂ is doubled. ECS is calculated using the de facto standard method of a linear regression of planetary imbalance over surface temperature change of the first 150 years of the abrupt4xCO2 experiment³⁵. The temperature change in the post-1970s period is taken as the difference between the mean surface temperature anomaly in 1970–1989 to the mean temperature anomaly in 1994–2005. We chose to have the 5-year gap to reduce the influence of the Mt Pinatubo volcanic eruption.

We must remark that the aforementioned definition of the ECS is only an approximation. Only the steady state of a abrupt2xCO2 would provide the true value of the ECS. The approximation underestimates the true ECS, because the pattern effect tends to enhance the warming at the end of the abrupt forcing runs. On the other hand, as the forcing does not precisely scale in a logarithmic fashion and the water vapour feedback is stronger in a warmer climate, our estimate of the ECS is larger than the one derived from the abrupt2xCO2 experiments. In summary, the pattern effect and the larger response work in opposite directions and, thus, reduce the error in the approximation.

The GFDL-ESM2G model was excluded from the calculation of the regressions, since it was well outside the 5–95th percentile prediction band: The GFDL-ESM2G model's historical simulation shows a large post-1970s warming, even though its TCR is the lowest found among models. Given that we have only one realization for this model (Supplementary Table 2), that the closely related GFDL-ESM2M model (which differs only in its ocean component) is in line with the behaviour of other models and that the aerosol forcing cannot explain the result (M. Zhao, personal communication), we consider that this outlying behaviour is due to the models internal variability expressing itself in this single realization. The evolution of the historical run depends on the state of the pre-industrial control used as the initial condition. There are fluctuations in this base state (unforced variability) that may change the warming in the period. As the model had only one run, which can be affected by the initial conditions, and the warming was more substantial than suggested by the climate responses, we excluded the model. In support of this last point, GFDL-ESM2G shows a warming of 0.60 K with a TCR of 1.07 K and an ECS of 2.13 K. For instance, CANESM2 (with five ensemble members) shows a warming of 0.61 K with a TCR of 2.29 K and an ECS of 3.65 K, which are higher climate responses for the same warming. Moreover, GFDL-ESM2M with one realization has a warming of 0.41 K with a TCR of 1.21 K and an ECS of 2.23 K; FGOALS-G2 also has lower warming of 0.37 K with a TCR of 1.34 K and an ECS of 3.29 K (See Supplementary Table 2).

Whereas the emergent constraint relies only on the global mean surface temperature change, the interpretive energy-balance framework and the two-layer model integration also require radiative forcing (as will be described below). We take the forcing from greenhouse gases, aerosols, ozone, stratospheric water vapour, land use, contrails, solar variability and black carbon on snow from Annex II of the IPCC AR5³⁶. The forcing from a doubling of atmospheric CO₂, $F_{2\times}$, is set to 3.71 W m⁻², which is consistent with the tabulated forcing. The uncertainty in each component, except post-1970s aerosol forcing and greenhouse gas forcing, is taken from ref. 7, which is based on the IPCC Assessment Report. The uncertainty in post-1970s aerosol forcing is assessed to be small and is modelled as a Gaussian with a standard deviation of 0.1 W m⁻², allowing a 7% probability of a weakening post-1970s aerosol cooling. The uncertainties in the well-mixed greenhouse gas forcings are assumed relative to the forcing strength and are therefore reduced for the post-1970s periods. Forcing changes and assumed uncertainties are tabulated in Supplementary Table 3 for the three different periods.

Two-layer model and energy-balance inference with pattern effect. The energy-balance framework for inferring the TCR from historical warming builds on an approximation, sometimes referred to as the zero-layer assumption, to a prognostic linearized two-layer model. Here we expand on previous work in this regard by including a representation of the pattern effect and by evaluating the bias introduced by making the zero-layer approximation. As a starting point, we take the widely used prognostic linearized diffusive two-layer model, which provides a surprisingly close approximation of the temporal evolution of much more complex climate models^{7,9,10,12,21,29}:

$$\begin{aligned} C \frac{dT}{dt} &= F + \lambda T - \epsilon \gamma (T - T_d) \text{ (upper layer)} \\ C_d \frac{dT_d}{dt} &= \gamma (T - T_d) \text{ (deep layer)} \end{aligned} \quad (1)$$

where T is representative of the upper ocean plus the troposphere and land global mean temperature, T_d is the deep-ocean temperature, C and C_d their respective heat capacities, F a radiative forcing, λ the feedback parameter, ϵ the heat uptake efficacy (pattern effect) and γ the deep-ocean heat uptake coefficient; all of the temperatures in these equations are anomalies from a mean state at stationarity. The planetary imbalance, N , can be diagnosed as the rate of change of energy in the system: $N = C dT/dt + C_d dT_d/dt = F + \lambda T - (\epsilon - 1)\gamma(T - T_d)$, whereby we note that the pattern effect is non-zero whenever $\epsilon \neq 1$ and scales with the imbalance. The prognostic two-layer model can be readily integrated in time using F , for example, from the best estimate of historical forcing from AR5³⁶. The ECS with respect to $F_{2\times}$ is then:

$$ECS = -\frac{F_{2\times}}{\lambda} \quad (2)$$

In the zero-layer approximation we consider a gradually changing forcing that occurs on a timescale long enough that the upper ocean is in approximate equilibrium, such that $C dT/dt \approx 0$ and short enough that the deep-ocean temperature has not yet responded substantially, such that $T_d \approx 0$. Timescales at which this approximation is reasonable are longer than a decade and shorter than a century. In this limit, we obtain a set of diagnostic equations that we refer to as the zero-layer model:

$$\begin{aligned} 0 &= F + (\lambda - \epsilon \gamma) T \\ N &= \gamma T \end{aligned} \quad (3)$$

and by considering the TCR in an experiment with gradually increasing CO₂ at the time of doubling, we readily obtain:

$$TCR = -\frac{F_{2\times}}{\lambda - \epsilon \gamma} \quad (4)$$

We can now use the diagnostic zero-layer model to eliminate λ and γ from the expressions for the ECS and TCR, whereby we further calculate the change between two periods as indicated by the Δ s:

$$TCR = \frac{F_{2\times} \Delta T}{\Delta F} \quad (5)$$

$$ECS = \frac{F_{2\times} \Delta T}{\Delta F - \epsilon \Delta N} \quad (6)$$

Equations (5) and (6) are the energy-balance-inference method of estimating the TCR and ECS in terms of observed warming and forcing modified to explicitly account for a pattern effect. Standard energy-balance-inference studies implicitly assume no pattern effect by effectively having $\epsilon = 1$.

The heat capacities for the layers (C and C_d) were calculated considering properties of tropospheric dry air and its moisture content, the land and an ocean covering 70% of the surface with an average depth of 4 km and a mixed-layer of 75 m. Thereby, the upper-ocean layer is approximately equivalent to a 55 m water layer covering the entire surface of the Earth and the deep-ocean layer is approximately equivalent to a 2,768 m water layer.

Emergent constraint regression model. The regression model used in the emergent constraint on post-1970s global warming is derived from the energy-balance framework. To do so, we notice that we can substitute back $\Delta N = \gamma \Delta T$ and perform a coordinate transformation such that expressions purely in terms of the temperature evolution are obtained:

$$\text{TCR} = s\Delta T + e \quad (7)$$

$$\text{ECS} = \frac{\Delta T}{s' - e'\Delta T} \quad (8)$$

where $s = F_{2\kappa}/\Delta F$, $s' = \Delta F/F_{2\kappa}$ and $e' = \epsilon\gamma/F_{2\kappa}$. We also introduce an offset in equation (7) that should be indistinguishable from zero and can be considered a test of whether sufficient information is contained in the CMIP5 model ensemble.

We apply orthogonal distance regression (ODR), which considers uncertainty in the independent variable³⁷ to fit the theoretically derived models that link post-1970s warming to the TCR and ECS, equations (7) and (8). Equal weighting of each model is applied. Models that supply only one or a few ensemble members will induce uncertainty in the regression that is due to natural variability, which inflates the estimates of uncertainty in TCR and ECS as we also account for natural variability in the distribution of observed post-1970s warming. Nevertheless, we deem this a minor effect, as most models supply multiple ensemble members (Supplementary Table 2). We perform the regression on the set of model ensemble means.

We take a Monte Carlo approach to estimating uncertainty in the TCR and ECS from the emergent constraints. With the results of the regression algorithm, we generate a joint distribution of the parameters and the error in the estimation, taking into account the covariance of the parameters. We draw random samples of parameters from this distribution to generate the distribution of the prediction uncertainty, which is the 5–95th percentile range around regression curves as shown in Fig. 1. We generate a joint distribution of parameters, error in estimation and the observed temperature change in the post-1970s, draw random samples and calculate with them the corresponding TCR and ECS values. These sets of TCR and ECS values form the predicted distributions for the TCR and ECS and from them we obtain the 5th, 50th (median) and 95th percentiles (Supplementary Tables 5 and 6).

Statistical measure of the robustness. We use one metric that can show the statistical goodness-of-fit: a jackknife. It consists of the calculation of a set of regressions for which we leave out one of the data points. For both the TCR and ECS, the results for the jackknife (Supplementary Fig. 1) show that all the jackknife regressions are close to the respective regressions based on all models. Thus, we show that the derived relationships are statistically robust and support the physical significance of the results, which are the actual finding. Moreover, for both the TCR and ECS, in Supplementary Fig. 2 we show that the distributions derived from the jackknife regressions are not appreciably broader than the distributions derived from the regressions based on all models. The median values are also not far from the median from the full regressions.

Experiments with MPI-ESM1.2-highECS. To explore the upper bound of the constrained ECS and TCR we modified the Max Planck Institut MPI-ESM1.2 coupled model to have stronger positive cloud feedbacks. The modifications alter the mixing rate between the lower and middle troposphere, a feature that can explain half of the variance of the ECS in the CMIP5 ensemble^{38,39}. The shallow mixing dries the lower troposphere by exporting the moisture out of the boundary layer. The mixing rate increases with warming, and the way it increases depends on the initial mixing rate. Thus, as the Earth warms, a higher initial mixing ratio dries the boundary layer and promotes a decrease in the shallow clouds, resulting in a positive cloud feedback. To do so, we increased the shallow mixing by reducing the lateral entrainment rate in the shallow convective parameterization. To enhance shallow clouds in the base state, such that they can contribute to cloud feedback, the critical relative humidity profile was altered. Furthermore, the negative mixed-phase cloud feedback dominant at mid- to high latitudes was weakened by enhancing a cloud-ice concentration threshold for the fast conversion from cloud liquid to cloud ice. Finally, to explore the influence of uncertainty in aerosol cooling, we modify the parameterization of aerosol-cloud-induced forcing. The aerosol forcing in MPI-ESM1.2 is parameterized using a Twomey effect that is sensitive to the assumed concentration of background cloud condensation nuclei^{17,40}. To obtain a stronger aerosol cooling, we reduce the assumed background concentration by a factor of ten to a hundred. The stronger cooling is considered a surrogate for non-Twomey aerosol–cloud interactions not represented by the model.

Internal variability and the AMO–IPO correction. We calculate SST indices for the major modes of variability, the AMO, Niño 3.4 and the Interdecadal Pacific Oscillation (IPO), for each of the experiments of the CMIP5 models. We obtain the monthly and the corresponding yearly time series. Using the results from piControl

experiments, we find an empirical linear relationship between the SST index and GMST in an equilibrium state for each model. We select one of the Pacific Ocean modes and the AMO and regress GMST over them using the model

$$T_{\text{piControl}} = \beta_0 + \beta_1 \text{AMO}_{\text{piControl}} + \beta_2 \text{SPI}_{\text{piControl}}$$

where SST Pacific Index (SPI) is either Niño 3.4 or IPO. With the coefficients β_i obtained from the regressions, in principle, we can correct the other experiments (1pctCO2, abrupt4xCO2 and historical) for the influence of these internal variability patterns using indices values for each experiment

$$T_{\text{corr}} = T - \beta_0 - \beta_1 \text{AMO} - \beta_2 \text{SPI} \quad (9)$$

To obtain a standard for the corrections, instead of using each model's coefficients, we compute the correction with the coefficients obtained for the MPI-ESM1.1 100-member ensemble. In fact, most of the coefficients for the other models are similar in magnitude to those of MPI-ESM1.1 (Supplementary Table 11). Because the index of the IPO includes northern, southern and equatorial zones of the Pacific basin, we consider SPI = IPO, although the coefficients with Niño 3.4 are similar. Supplementary Table 10 is analogous to Supplementary Table 2, but using the corrections. When a comparison between tables is undertaken, it is evident that the TCR and ECS differences are small, but ΔT differences are large. This suggests that historical forcing has an influence on these modes of variability and, therefore, are partly forced.

From gridded datasets of the observations, we can also calculate the indices and apply the correction to obtain corrected time series of the GMST. Corrected temperature datasets now can be used to repeat the analyses. A summary of the corrections for the observations are given in Supplementary Table 1.

Data availability

CMIP5 data can be accessed through ESGF nodes. HadCRUT4 data are provided by the UK Met Office Hadley Centre. The NOAA/OAR/ESRL PSD dataset website provided the NOAA GlobalTemp dataset as well as the GISTEMP dataset. BEST was downloaded from the Berkeley Earth website. The Cowtan and Way 2.0 dataset is available from the author's website (<https://www-users.york.ac.uk/~kdc3/papers/coverage2013/series.html>). Forcing data comes from the IPCC AR5 WG1 report²⁴.

Code availability

An archive with scripts to conduct the data download, preprocess the data, analyse them and obtain the figures supporting this study is archived by the Max Planck Institute for Meteorology and can be obtained by contacting either the corresponding author or publications@mpimet.mpg.de.

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