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Key Points:

- Pattern effect and feedback temperature dependence lead to a proliferation of feedback definitions
- We contrast equilibrium, effective, and differential feedbacks and their physical interpretation
- Extending CMIP step-forcing simulations to 400 years would allow estimating equilibrium climate sensitivity more precisely

Supporting Information:

Supporting Information may be found in the online version of this article.

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Three Flavors of Radiative Feedbacks and Their Implications for Estimating Equilibrium Climate Sensitivity

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Abstract The realization that atmospheric radiative feedbacks depend on the underlying patterns of surface warming and global temperature, and thus, change over time has lead to a proliferation of feedback definitions and methods to estimate equilibrium climate sensitivity (ECS). We contrast three flavors of radiative feedbacks – equilibrium, effective, and differential feedback – and discuss their physical interpretations and applications. We show that their values at any given time can differ more than 1 $\mathrm{Wm^{-2}K^{-1}}$ and their implied equilibrium or effective climate sensitivity can differ several degrees. With ten (quasi) equilibrated climate models, we show that 400 years might be enough to estimate the true ECS within a 5% error using a simple regression method utilizing the differential feedback parameter. We argue that a community-wide agreement on the interpretation of the different feedback definitions would advance the quest to narrow the estimate of climate sensitivity.

Plain Language Summary Global radiative feedbacks and their extrapolation to an equilibrium state (effective climate sensitivity) are not constant, as long assumed. This leads to the use of various methods and definitions for feedbacks and climate sensitivity. We contrast the equilibrium, effective, and differential feedback parameter definitions and discuss their implications for estimating climate sensitivity. We suggest using the differential feedback parameter, which notably does not satisfy the standard model of global energy balance, to estimate equilibrium climate sensitivity. To do so with minimum information, the climate model intercomparison protocol of simulating 150 years would need to be extended to 400 years. We further argue that a community-wide agreement on the interpretation of the feedback definitions would advance the quest to narrow the estimate of climate sensitivity and understand how feedbacks change through time.

1. Motivation

Following a radiative forcing (F) applied to the climate system, the degree of imbalance in the global top-of-atmosphere (TOA) radiation budget (N) is given by the sum of F and the radiative response (R) induced by a global surface temperature change (ΔT):

$$N = F + R. \tag{1}$$

In equilibrium, the absorbed and reflected solar shortwave and outgoing terrestrial longwave radiation must once again balance ($N = 0$) such that $R = -F$. In turn, R can be described in terms of a Taylor series expansion about a climate state (e.g., Roe, 2009):

$$R = \underbrace{\frac{\partial R}{\partial T}}_{\tilde{\lambda}} \Delta T + \mathcal{O}(\Delta T^2), \tag{2}$$

where $\tilde{\lambda} = \partial R \,/\, \partial T$ (units of $\mathrm{Wm^{-2}\,K^{-1}}$) is the radiative feedback parameter, which traditionally includes radiation anomalies associated with the Planck response and changes in lapse rate, water vapor, clouds, and surface albedo ("Charney" or fast feedbacks; Charney et al., 1979). Additional climate processes that affect R – such as changes in dust, atmospheric methane, and vegetation – are increasingly well understood and might act on similar timescales as the Charney feedbacks (e.g., Thornhill et al., 2020). The term $\mathcal{O}(\Delta T^2)$

represents the sum of all higher-order terms of the Taylor series expansion in ΔT including nonlinearities of individual processes and interactions between different feedbacks.

Two approximations are commonly applied to Equation 2: (a) that ΔT is sufficiently small that $\mathcal{O}(\Delta T^2)$ is negligible; and (b) that $\tilde{\lambda}$ is constant. Under these assumptions, and setting $\tilde{\lambda} = \lambda$, Equations 1 and 2 provide what can be considered the "Standard Model" of global climate response to forcing (popularized by Gregory et al., 2002):

$$N = F + \lambda \Delta T, \tag{3}$$

where λ must be negative for a stable climate. Using this equation, the warming at equilibrium ($N = 0$) can be readily expressed as $\Delta T = -F / \lambda_{\mathrm{eq}}$, where λ_{eq} denotes the value of the net feedback that brings the system into the new equilibrium. The special case of the equilibrium response to CO_2 doubling above pre-industrial levels defines the equilibrium climate sensitivity: ECS = $-F_{2\times} / \lambda_{\mathrm{eq}}$. Note that some studies choose an opposite sign convention for λ (sometimes referred to as α), but in either case ΔT and ECS are expressed as positive for warming.

Equation 3 has afforded substantial advances in understanding of climate change. For instance, estimates of ΔT, F, and N over the instrumental record or from proxy reconstructions of past climates provide constraints on the value of λ which, in turn, permit estimates of ECS (e.g., Sherwood et al., 2020). However, the traditional assumptions that underpin Equation 3 may not hold to the level needed to make accurate estimates of ECS. First, the $\mathcal{O}(\Delta T^2)$ term is important to account for when considering climates that are colder or warmer than the modern (e.g., Bloch-Johnson et al., 2020). Second, $\tilde{\lambda}$ (Equation 2) is in general not a constant value, and can vary with the spatial pattern of surface temperature change. This "pattern effect" (Gregory & Andrews, 2016) reflects that warming in some regions – such as the western equatorial Pacific Ocean – produce a relatively large TOA radiation response (strong negative feedback), while warming in other regions – such as the eastern tropical Pacific Ocean and Southern Ocean–produce a relatively small TOA radiation response (weak negative or positive feedback; e.g., Andrews & Webb, 2018; Ceppi & Gregory, 2017; Dong et al., 2019; Zhou et al., 2016). Furthermore, the spatial pattern of warming evolves over time owing to the different timescales of ocean adjustment in different regions, with a tendency for faster warming in more-negative feedback regions and slower warming in less-negative feedback regions leading to a trend toward less-negative values of $\tilde{\lambda}$ as climate equilibrates with an applied radiative forcing (e.g., Andrews et al., 2015; Armour et al., 2013; Dong et al., 2020; Marshall et al., 2015; Proistosescu & Huybers, 2017; Rugenstein, Caldeira, & Knutti, 2016; Senior & Mitchell, 2000; Williams et al., 2008). The pattern effect arises from changing surface warming patterns, whether those changes are caused by CO_2, aerosol, or volcanic forcing or induced by internal variability (e.g., Dessler, 2020; Gregory et al., 2020; Loeb et al., 2018; Olonscheck et al., 2020; Paynter & Frölicher, 2015).

In light of the limitations of Equation 3, it is understandable that there has been a proliferation of feedback definitions. Several reasonable choices of feedback definition can be made, including a local tangent of the radiative response defined by regressing R against T values ($\tilde{\lambda} = \partial R / \partial T$) or the use of a finite climate change of one period relative to a reference period ($\lambda = \Delta R / \Delta T$). That feedbacks can vary over time means that λ and $\tilde{\lambda}$ are not the same as λ_{eq} and that their values depend on the time period used and method by which a feedback is calculated (e.g., Barnes & Barnes, 2015; Gregory et al., 2020).

In this study, we provide physical interpretations of three different feedback definitions, discuss how they relate to each other (Section 2), and illustrate using climate model simulations when each of their applications is most appropriate (Section 3). We review proposed methods to estimate ECS from climate models and suggest how many years of a transient simulation are necessary to estimate ECS with high precision (Section 4). We argue that the quests to understand the pattern effect and to narrow the uncertainty in ECS should be accompanied by a community-wide agreement on the interpretation and calculation of feedback definitions (Section 5).

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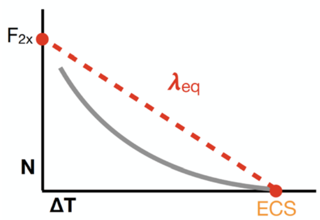
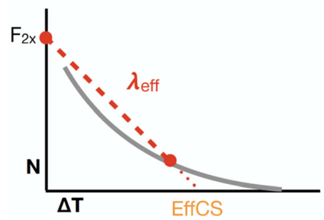
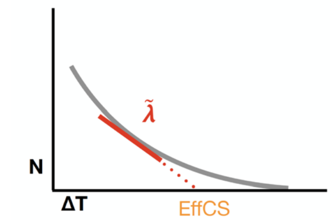
Table 1
Properties of Feedback Definitions and Their Corresponding Climate Sensitivity Interpretations

Equilibrium feedback parameter	Effective feedback parameter	Differential feedback parameter
$\lambda_{eq} = -F_{2\times}/\text{ECS}$ Difference between two equilibrated states	$\lambda_{eff} = \Delta R/\Delta T$, with $R = F - N$ Change w.r.t. a steady state	$\widetilde{\lambda} = \delta R/\delta T$ or $\widetilde{\lambda} = \delta N/\delta T$ Covariance of R (or N) and T w.r.t. a selected state
		
Dependent on the two endpoint states	**Dependent on two states (starting and current)**	**Dependent on warming within the concerned period**
• Satisfies $N = F + \lambda_{eff}\,\Delta T$ at $N = 0$, thus $\text{ECS} = -F_{2\times}/\lambda_{eq}$ • Time-invariant; not impacted by internal variability → Studying $\mathcal{O}(\Delta T^2)$, i.e. nonlinearities → Comparing equilibrated models and paleo-proxies	• Satisfies $N = F + \lambda_{eff}\,\Delta T$, $\text{EffCS} = -F_{2\times}/\lambda_{eff} \neq \text{ECS}$ • Can be impacted by internal variability and pattern effect, depending on period → Estimate EffCS from the historical period, the paleo record, and non-equilibrated climate model simulations	• $N \neq F + \widetilde{\lambda}\Delta T$; $\text{ECS} \neq -F_{2\times}/\widetilde{\lambda}$ • Can be dominated by internal variability if δR or δT small → Understanding causes of temporal changes in λ → Estimate EffCS from satellite or other short observations

Equilibrium climate sensitivity (ECS)	Effective climate sensitivity (EffCS)
Equilibrated temperature to doubled CO_2 above pre-ind. levels	Extrapolation of (linear) fit to time-evolving ΔT and R (or N)
+ Clear and concise definition – Conceptually blurs into Earth System Sensitivity with slow, non-Charney feedbacks – Requires long simulations or paleo-proxies equilibrated w.r.t. Charney feedbacks and ocean heat uptake	+ Correlates with a model's effective and differential feedback magnitude + Used widely for short simulations and historical observations – Not well defined – Measures various degrees of equilibration, depending on input – Difficult to compare to ECS and EffCS computed with other definitions of time-frames due to missing standards on timescales, fitting methods, quantification of internal variability and F

Note. For simplicity, all values and notation in the table refer to a doubling of CO_2, and thus, $F_{2\times}$ and ECS. "Gregory plots" illustrate a step-forcing response of a climate model in gray, the feedback parameter in red, and the climate sensitivity in orange. Noteworthy properties of the definitions are denoted with bullet points, common applications with arrows, advantages with a plus, and disadvantages with a minus.

2. Three Flavors of Radiative Feedbacks

Table 1 contrasts possible feedback definitions with illustrative sketches of the evolution of N with ΔT following an abrupt CO_2 increase – often referred to as a "Gregory plot" (Gregory et al., 2004). The intersect at $\Delta T = 0$ defines the effective radiative forcing, which contains tropospheric and stratospheric adjustments to the increased CO_2 concentrations before surface temperatures increase (e.g., Boucher et al., 2013) and is used as F in Equations 1 and 3. The intersect at $N = 0$ defines ΔT_{eq}, or specifically ECS in the case of a doubling of CO_2. If the $N = 0$ intersect is estimated by extrapolation of a regression, it is often referred to as effective climate sensitivity (EffCS). We use the expression "true ECS" and "true ΔT_{eq4x}" for doubling and quadrupling CO_2 concentrations, respectively, to indicate the actual – not estimated – equilibrium temperature value. The curvature of the gray line illustrates that climates models (here understood as general circulation models including a dynamic atmosphere and ocean; GCMs) tend to reduce the magnitude of λ with warming.

The *equilibrium feedback parameter* ($\lambda_{eq} = \Delta R_{eq} / \Delta T_{eq}$) is defined as the global radiative response per degree of surface warming calculated based on anomalies between two equilibrated climate states, notably not obtained by a regression. It can be thought of as integrating all processes which brought the climate system into the new equilibrium, which is a hypothetical state the real world will probably never experience. Providing long-enough averaging periods are used, λ_{eq} and ΔT_{eq} are constant values.

The *effective feedback parameter* ($\lambda_{eff} = \Delta R / \Delta T$) is defined as the global radiative response per degree of surface warming calculated based on anomalies between two climate states; most commonly between an initial equilibrated climate and a transient perturbation of that climate. It can be thought of as integrating all processes which brought the climate system into the new state; its extrapolation to a new equilibrium results in a measure of EffCS. This EffCS is sometimes called the "inferred" or "instantaneous" climate sensitivity, usually when calculated using observed global energy budget constraints (e.g., Armour, 2017; Lewis & Curry, 2015; Otto et al., 2013; Proistosescu & Huybers, 2017). λ_{eff} and EffCS are time-dependent as long as N, F, and ΔT change, and only become equal to the values of ΔT_{eq} and λ_{eq} as the equilibrium is approached. This results in an inherent problem: There are no commonly agreed or best-practice methods of computing values of λ_{eff} and EffCS, so care must be taken when comparing values between studies that use different periods for analysis.

Finally, and fundamentally different, is the *differential feedback parameter*, ($\tilde{\lambda} = \delta R / \delta T$), calculated based on R–ΔT regression (or N–ΔT regression in the case the forcing is constant). In a step-forcing GCM experiment, δR and δT can be a few Wm^{-2} and K, respectively, representing a forced response or a radiative feedback in the traditional sense (Andrews et al., 2015; Ceppi & Gregory, 2019; Knutti & Rugenstein, 2015). In observations and simulations with continuously changing or constant forcing, δR and δT might cover only a few tenth of Wm^{-2} and K, respectively and referred to as radiative restoration strength (e.g., Colman & Hanson, 2017; Donohoe et al., 2014; Lutsko & Takahashi, 2018; Murphy, 2010; Proistosescu et al., 2018).

$\tilde{\lambda}$ represents all the processes causing δR to change with δT for the period over which the calculation is performed, as opposed to λ_{eq} and λ_{eff} representing the integrated nature of ΔR per ΔT between two states. For example, under transient warming, $\tilde{\lambda}$ quantifies changes in R per δT associated with the regions which are warming during that time (Andrews et al., 2015; Armour et al., 2013; Rugenstein, Caldeira, et al., 2016).

Importantly, $\tilde{\lambda}$ does not satisfy the equation $N = F + \lambda \Delta T$, unless a radical re-definition of the forcing term is used such as a "virtual forcing" (Rugenstein, Gregory, et al., 2016; Williams et al., 2008). Thus, while a value $-F_{2\times} / \tilde{\lambda}$ can be readily calculated it should not be interpreted as ECS. However, the regression $\delta R / \delta T$ extrapolated to $N = 0$ does result in an EffCS – the use of which we will demonstrate below. Thus, when the terminology EffCS is used, care must be taken to determine whether the calculation was performed using the *effective* or *differential* feedback definition.

Importantly, the different feedback definitions and resulting climate sensitivities can be only meaningfully compared if their differences are understood and accounted for. First attempts of developing relations between climate sensitivity estimates or radiative feedbacks driven by different surface warming patterns ("transfer functions") have been made (Armour, 2017; Andrews et al., 2018; Sherwood et al., 2020). Refined transfer functions require an improved process understanding, especially on the influence of large spatial warming patterns on TOA fluxes in the observed record, climate models, and the paleo record.

3. Radiative Feedbacks and Their Implications for Estimating ECS in GCMs

The time evolution of the effective and differential feedbacks differs substantially in simulations with an idealized step-forcing and simulations with slowly or realistically increases of CO_2 concentrations. For illustrative purposes, we use simulations of one model, CESM 1.0.4, forced with a step-forcing of quadrupling

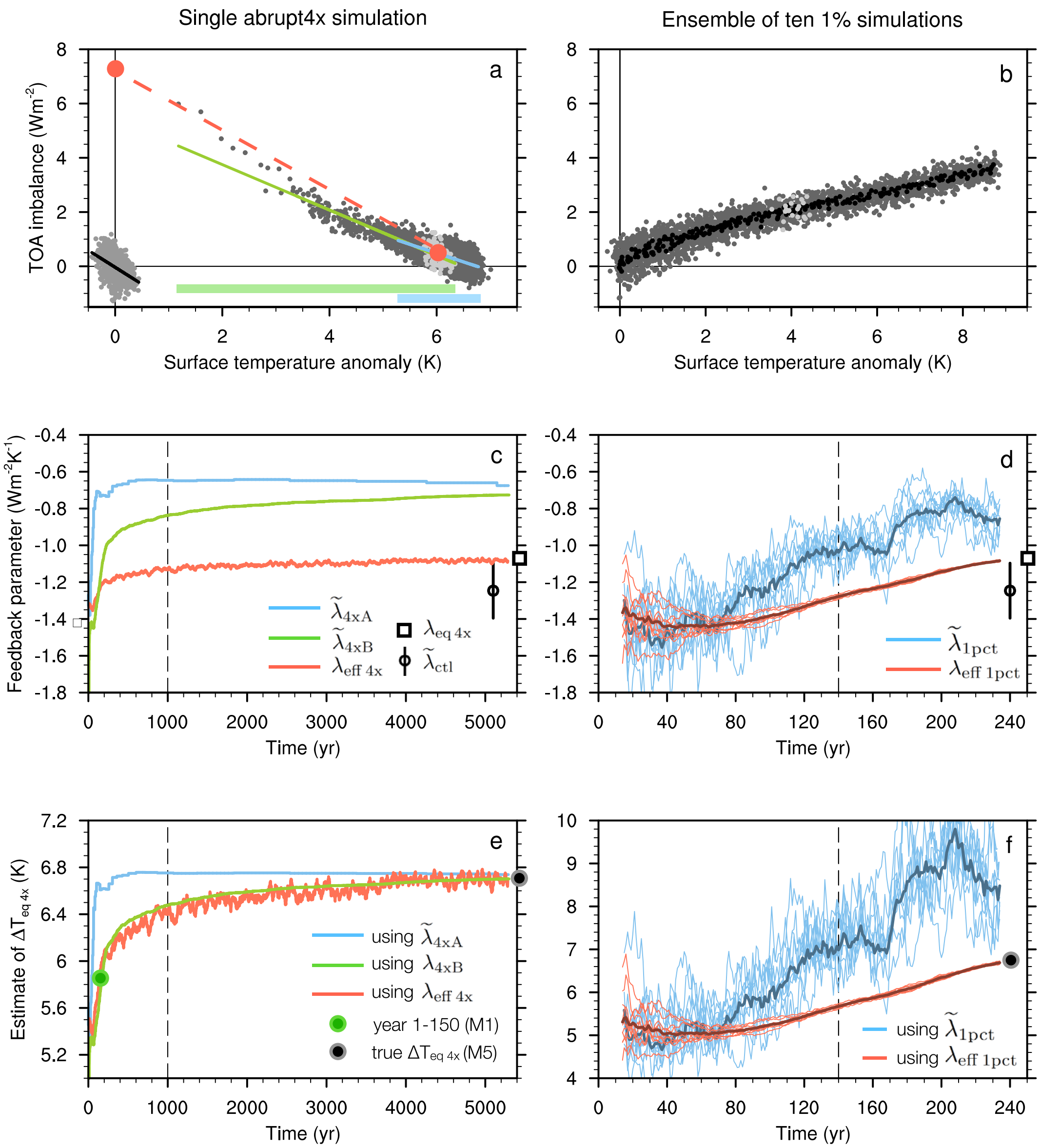


Figure 1. Flavors of feedback parameters in the model CESM 1.0.4: Gregory plots for a CO_2 step-forcing simulation (a) and an ensemble of 10 simulations with slowly increasing CO_2 concentrations (b), their evolution of effective and differential feedback parameters (c and d), and the implied estimate of the equilibrium temperature ΔT_{eq4x} (e and f). In panel (a), the gray dots around (0,0) indicate annual means of the 1000-year long control simulation; the colored lines indicate, for illustrative purposes, the regressions that determine the feedback parameters shown in panel c around year 1,000. Years 900–1,100 are indicated in lighter gray and the temperature ranges for the regressions of the differential feedback parameters in green and blue. In panel (b), black dots indicate the ensemble average and light gray dots year 130–150 values to highlight the time of CO_2 quadrupling. The feedback parameters shown in panel d are calculated according to the equations in the text (in time and not temperature space) and thus not indicated in panel b. In panel d and f, each ensemble member is depicted as thin and the ensemble average as darker thick line. In panel c and d the uncertainty bars for $\tilde{\lambda}_{ctl}$ (also shown in panel a) indicate the 2.5%–97.5% confidence interval. M values in brackets refer to methods in Table 2.

CO_2 concentrations ("*abrupt4x*") and with an annually increasing CO_2 concentration of 1% ("*1pct*"). Here and later, N and ΔT are the global and annual mean anomalies of these simulations relative to a stable control simulation averaged over 1,000 years. In a step-forcing simulation (Figure 1a), the *equilibrium feedback parameter* is calculated as $\lambda_{eq4x} = -F_{fixedSST4x} / \Delta T_{eq4x}$, where $F_{fixedSST4x}$ is obtained from a dedicated simulation of quadrupling CO_2 concentrations while holding the sea surface temperatures and sea ice (but not the land temperatures) fixed at pre-industrial values (7.25 Wm^{-2}). ΔT_{eq} is the average temperature over several centuries at the end of the 5,300 years long simulation. The *effective feedback parameter* is calculated as $\lambda_{eff4x} = -(F_{fixedSST4x} - N(t)) / \Delta T(t)$, where $N(t)$ and $\Delta T(t)$ are the 30-year moving averages of the respective terms. λ_{eff4x} changes most initially and then slowly approaches λ_{eq4x}. We calculate two *differential feedback parameters*: $\tilde{\lambda}_{4x\,A}$ is the regression of all N on ΔT values within a temperature bin of 1.5 K which is slid through the entire ΔT range of 1–6.8 K covered by the simulation. $\tilde{\lambda}_{4x\,B}$ is the slope of the regression of all N and ΔT values prior to each time step, e.g., at year 100 regressing years 1–100, at year 101 regressing years 1–101, etc.. It changes more slowly than $\tilde{\lambda}_{4x\,A}$ over the course of several thousand years (Figure 1c). Finally, $\tilde{\lambda}_{ctl}$ is the radiative restoration strength of an unperturbed, 1,000 years long control climate (Figure 1a), obtained by regressing annual deviations (spanning 2.5 Wm^{-2}) of the mean N onto the deviations (spanning 0.87 K), and is influenced by correlated noise (Gregory et al., 2020; Proistosescu et al., 2018).

In a simulation with slowly increasing forcing (Figure 1b), the *effective feedback parameter*, $\lambda_{eff1pct}$ is calculated as $(F_{1pct}(t) - N(t)) / \Delta T(t)$, with $N(t)$ and $\Delta T(t)$ being the 30-year moving averages of the respective time series. $F_{1pct}(t) = F_{fixedSST4x}\, t / 140$, with t referring to time in years, is the radiative forcing assuming linearity with the logarithm of CO_2 concentration. The *differential feedback parameter* ($\tilde{\lambda}_{1pct}$) is calculated as the linear regression of $F_{1pct}(t) - N(t)$ onto $\Delta T(t)$ for 30-year bins slid through the time series (as opposed to using bins defined in temperature space as for the *abrupt4x* simulation). With stronger forcing and more warming, internal variability – illustrated by 10 ensemble members branched-off different years of the control simulations – becomes negligible after 120 years for $\lambda_{eff1pct}$, but not for $\tilde{\lambda}_{1pct}$ (Figure 1d).

The choices of feedback definitions imply different estimates of ΔT_{eq4x} (Figure 1e and 1f): In a step forcing simulation, on the one hand, $\Delta T_{eq4x} = -F_{fixedSST4x} / \lambda_{eff\,4x}(t)$ or extrapolating the regression used to define $\tilde{\lambda}_{4xB}(t)$ to $N = 0$ results in a similar time-evolving ΔT_{eq4x} estimate which approaches the true ΔT_{eq4x} within several millennia. On the other hand, extrapolating the regression used to define $\tilde{\lambda}_{4xA}(t)$ to $N = 0$ results in a close estimate of ΔT_{eq4x} within 200 years. In the simulations with slower changing forcing, using $\Delta T_{eq4x} = -F_{fixedSST4x} / \lambda_{eff1pct}(t)$ or $\Delta T_{eq4x} = -F_{fixedSST4x} / \tilde{\lambda}_{1pct}(t)$ leads to arbitrary, unreasonable estimates of ΔT_{eq4x}. $\lambda_{eff1pct}(t)$ underestimates ΔT_{eq4x} when it passes the equivalent forcing value around year 140, and hits the correct ΔT_{eq4x} value coincidentally after 240 years at a forcing of ≈12 Wm^{-2}. $\tilde{\lambda}_{1pct}(t)$ is influenced by internal variability throughout the simulation but passes $\Delta T_{eq4x} = 6.8$K at the correct forcing values around year 140 (see discussion in Gregory et al., 2015). The values of $\lambda_{eff1pct}$ and $\tilde{\lambda}_{1pct}$ strongly depend on the formulation of $F_{1pct}(t)$ for high forcing levels (e.g., Bloch-Johnson et al., 2020; Byrne & Goldblatt, 2014; Gregory et al., 2015).

4. Estimating Climate Sensitivities From Climate Models

Since the wide recognition of the inconstancy of radiative feedbacks many methods have been proposed to estimate the true ECS (labeled M1 to M11 in Table 2). Recently, a large number of GCMs were integrated to near or full equilibrium (1,000–6,000 years simulation time; LongRunMIP, Rugenstein et al., 2019) which is computationally expensive, and thus not frequently done. Rugenstein et al. (2020) showed that across 14 models the most commonly used extrapolation methods (M1, M2, and M7) underestimate the true ΔT_{eq4x} or true ECS (or where not available, the estimate using M5) by 5%–20%. Dunne et al. (2020) showed that M10 underestimates a "long ECS" (defined by a variation of M6) by 6% ± 7% in 13 models and suggested another variation of M6 – regressing 5-year averages between year 50 and 150 – to most closely estimate "long ECS." The general underestimation of the true ECS has been also shown for single models and estimation methods (e.g., Danabasoglu & Gent, 2009; Li et al., 2013; Paynter et al., 2018; Saint-Martin et al., 2019; Senior & Mitchell, 2000; Winton et al., 2020).

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Table 2
ECS Estimation Methods, all are Variants of Effective Climate Sensitivity

Method #	Explanation	Example references
M1*	linearly regressing year 1–150 of N against ΔT	Andrews et al. (2012); Gregory et al. (2004); Sherwood et al. (2020)
M2*	linearly regressing year 20 or 21–150 of N against ΔT	Armour (2017); Andrews et al. (2015); Forster (2016)
M3*	local tangent, $\delta N / \delta \Delta T$, to the $N - \Delta T$ point cloud using a sliding window of ΔT large enough to capture the warming response	Ceppi and Gregory (2019); Knutti and Rugenstein (2015); Rugenstein, Gregory, et al. (2016)
M4	differencing either $(F - N(t)) / \Delta T(t)$ for an increasing number of years or $(N_2 - N_1) / (\Delta T_2 - \Delta T_1)$ for two time periods	Dong et al. (2019); Rugenstein et al. (2020); Senior and Mitchell (2000)
M5*	linearly regression all years of N against ΔT within the last 15% of warming of a simulation which is at least 1,000 years long	Rugenstein et al. (2020) and this section; For equilibrated simulations this is equivalent to averaging the temperature over the final decades.
M6*	linearly regressing five, ten, ..., 50-year averages of N against ΔT	Dunne et al. (2020); Gregory et al. (2004); Winton et al. (2020)
M7	fitting an energy balance model including ocean heat uptake efficacy, EBM-ϵ, to a number of years in N against ΔT	Dai et al. (2020); Geoffroy et al. (2013); Held et al. (2010); Rohrschneider et al. (2019)
M8*	eigenmode decomposition, fitting exponential functions through time series of ΔT (and N) with conditions about their common timescales or axes intersects	Caldeira and Myhrvold (2013); Mauritsen et al. (2018); Proistosescu and Huybers (2017); Sanderson (2019)
M9	Cess-sensitivity: differencing two equilibrated atmospheric states forced with different SST ($\Delta N / \Delta T$), F assumptions come from other simulations	Becker and Wing (2020); Cess and Potter (1988); Gettelman et al. (2012); Ringer et al. (2014)
M10	slab ocean simulations, which prescribe a spatially varying ocean mixed layer depth and heat uptake distribution	Danabasoglu and Gent (2009); Dunne et al. (2020)
M11	a series of specific, short, coupled GCM simulations with different forcing levels	Saint-Martin et al. (2019)

Note. In the first column, methods implying a differential versus an effective feedback parameter definition are indicated with versus without an asterisk. Abbreviations: GCM, general circulation model; SST, sea surface temperature.

Figure 2 summarizes and expands these analyses in that it compares estimates of ΔT_{eq4x} using (variations of) methods M1–M8. The computation of M1–M5 follows the description in Table 2. For M6, we show two versions of linearly regressing N against ΔT: of the averages of years 50–100, 101–150, 151–200, 201–250, and 251–300 (Winton et al., 2020) and of the 5-year averages of year 50–150 (Dunne et al., 2020). For M7, the energy balance model formulation of Geoffroy et al. (2013) is fitted to ΔT and N of years 1–150 and years 1–1,000. Likewise, for M8 the Bayesian framework of Proistosescu and Huybers (2017) is used to fit exponential functions with three exponents to years 1–150 and years 1–1,000 of the ΔT and N timeseries. Using 1,000 years for method M7 and M8 somewhat defeats the purpose of estimating ΔT_{eq4x} as the simulation is close to the new equilibrium then. We cannot evaluate M9–M11 because these methods require dedicated climate model simulations not done routinely and not available in the LongRunMIP archive.

Figure 2 shows that different methods to estimate ΔT_{eq4x} or ECS qualitatively measure the overall sensitivity of a model in that more sensitive models appear more sensitive and less sensitive models appear less sensitive, independent on the exact method. However, the relative rank of the models does not stay the same for different methods, especially if the overall sensitivity is similar or the sensitivity is very high. Furthermore – in our set of models – more sensitive models have a higher spread in sensitivity measures than less sensitive

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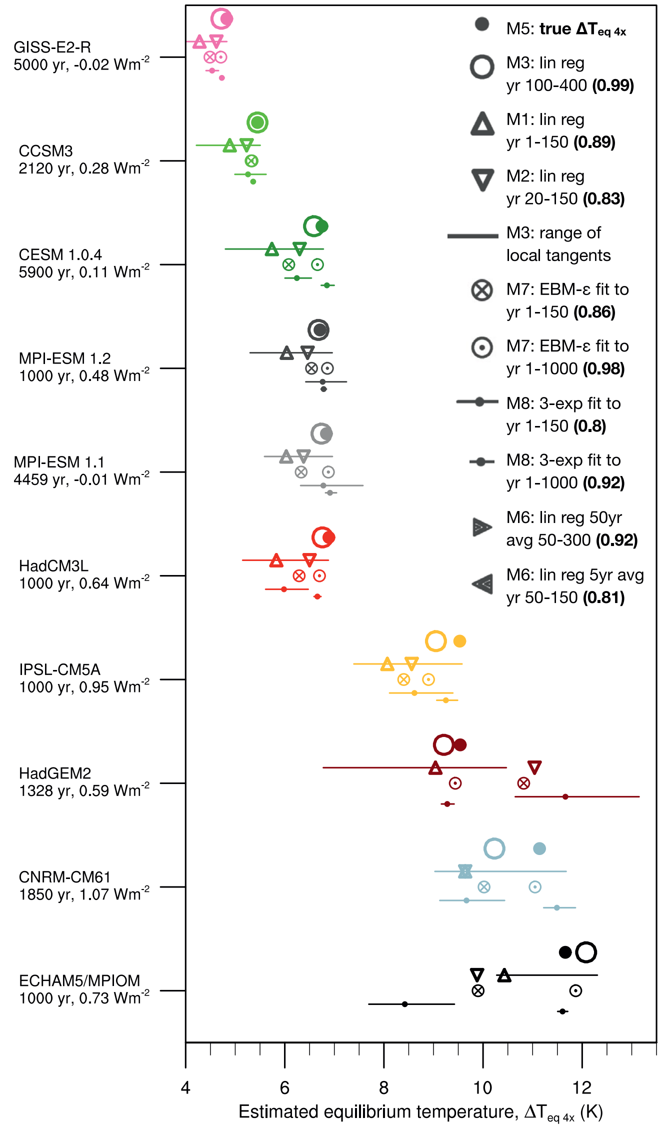

Figure 2. Values of ΔT_{eq4x} estimates using variations of method M1–M8 for 10 general circulation models (GCMs) *abrupt4x* simulations. The correlation coefficient between each method and the true ΔT_{eq4x} quantified by M5 is indicated as a bold number in brackets in the legend. The simulation length and N averaged over the last 50 years are mentioned beneath the model's name. "Range of local tangents" span the minimum to maximum estimates of ΔT_{eq4x} based on the differential feedback parameter calculated by regressing N onto ΔT values.

models. Feedback temperature dependence would increase that tendency. Finally, the different methods explain the evolution of the surface temperature across models differently well through time (Figure S1).

We quantify how many years of a transient simulation are necessary to predict the true ΔT_{eq4x} correctly using the differential feedback definition and extrapolating the linear regression to equilibrium (M1–M5). Figure 3 shows the model-mean fraction of ΔT_{eq4x} depending on first and last year of a linear regression of N on ΔT and reveals three insights: (a) Solely increasing the number of years in the linear regression (M4) requires many years to approach the true ΔT_{eq4x} (zoom-in panel). Thus, skipping several decades in the beginning of the simulation (as in M2, M3, M6) is necessary to gain predictive skill. (b) Regressing too few years too far into the simulation will mostly sample internal variability and randomly predict ΔT_{eq4x} values more than 20% too high or too low. (c) The standard deviation between the 10 models is large and only reduces on the centennial timescale. We suggest to linearly regress years 100–400 to estimate ΔT_{eq4x}

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within a 5% error (see also Figure 2). For single models, regressing fewer years results in the same accuracy, however, for generally more sensitive models even more years might be necessary, which is likely also true for other CMIP6 models (e.g., Forster et al., 2019; Tokarska et al., 2020; Zelinka et al., 2020). Supporting Information S1 and Figures S2 and S3 discuss the equilibration pace for the subset of five models for which *abrupt2x* and *abrupt4x* simulations are available.

5. Conclusions

We have shown that the equilibrium, effective, and differential feedback parameter definitions are physically meaningful (Table 1), however, they represent different properties of the climate system, are not easily translatable, and differ in value and implications for estimating ECS (Figure 1). The realization that feedbacks change in response to surface warming patterns and global mean temperature has led to a development of many methods to estimate ECS (Table 2), relying on different feedback definitions. All methods capture the overall sensitivity of the models but can result in ECS or ΔT_{eq4x} estimates that differ more than 1 K and do not necessarily record the equilibrated state (Figure 2).

If the goal is to predict ECS or ΔT_{eq4x} from a transient simulation as quickly and precisely as possible, the first couple of decades must be discarded when applying regression methods (Figure 3; Dai et al., 2020; Dunne et al., 2020; Rugenstein et al., 2020; Winton et al., 2020). Using the differential feedback definition and extrapolating the linear regression of annual averages of N against ΔT of years 100–400 of an *abrupt4x* simulation results in a ΔT_{eq4x} estimate with less than 5% error across the 10 climate models for which true equilibrium values are available. Thus, we suggest an extension of the CMIP6 step-forcing simulations of *abrupt4x* and/or *abrupt2x* in the CMIP6 protocols of DECK and nonlinMIP (Eyring et al., 2016; Good et al., 2016) from their typical length of 150 years to a length of 400 years.

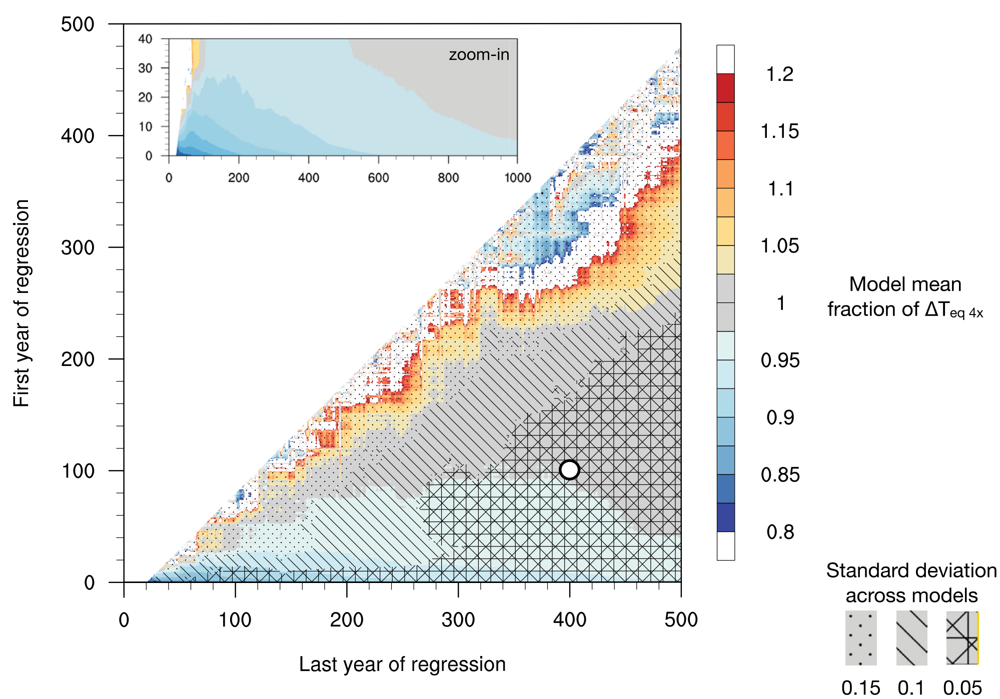

Figure 3. Model-mean fraction of ΔT_{eq4x} quantified by M5 depending on first and last year of a linear regression of N on ΔT (color shading) for the same ten *abrupt4x* simulations as in Figure 2. The standard deviation across the simulations is shown in hashed patterns; for example, a regression of years 100–220 results in a 5% error for the model mean (gray shading), but the standard deviation across the 10 models is still 10% (line hashing). The white dot indicates the suggested method of regressing years 100–400. The axes of the inset are first and last year of the regression as in the larger plot.

While the use of ECS has some distinct advantages over effective or inferred climate sensitivities because no adjustment for the degree of equilibration or the surface warming patterns is necessary, characterizing instead feedbacks and their uncertainty for a specific climate state might be methodologically preferred (Dunne et al., 2020; Klein et al., 2017; Roe, 2009). The most pressing open questions are (a) how to relate feedback estimates from different states of surface warming patterns or global mean temperatures, thus, developing feedback transfer functions based on physical processes; (b) how to apply the global energy balance framework to short observations and short and limited-domain very high resolution model simulations which are dominated by internal variability or representing one specific state which may or may not relate to anticipated future warming; (c) how to re-phrase the global energy balance model to include the pattern effect; (d) how to treat non-Charney feedbacks present in Earth System Models and the real world on decadal to millennial timescales in the energy balance perspective.

We conclude that the quests to understand the pattern effect, to estimate ECS from observations, and to narrow the overall uncertainty in ECS with process studies and paleo climate estimates should be accompanied by a community-wide agreement on the interpretation of the different feedback definitions and the methods to compute them.

Data Availability Statement

All data behind Figures 1–3 are available under: http://dx.doi.org/10.25675/10217/232176.

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Erratum

A typographical error was corrected. This version may be considered the authoritative version of record.