Equilibrium- and Transient-State Dependencies of Climate Sensitivity: Are They Important for Climate Projections?

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ABSTRACT

The effective equilibrium climate sensitivity is generally assumed to be constant in climate change studies, whereas it may vary due to different mechanisms. This study assesses the importance of the different types of state dependencies of the radiative feedbacks for constraining climate projections from the historical record. In transition, the radiative feedbacks may vary with the changes in the warming pattern due to inhomogeneous ocean heat uptake. They may also vary in equilibrium due to their dependence on both temperature and CO₂ concentration. A two-layer energy balance model (EBM) that accounts for these effects is shown to improve the representation of any CO₂ pathway for the CMIP5 ensemble. Neglecting the nonlinear effects in constraint studies of climate projections from the historical record may induce errors in the estimated future warming. The EBM framework is used to study these errors for three characteristic CO₂ pathways. The results show that the pattern effect of ocean heat uptake is not of major importance by inducing a median error of roughly -2% for a high-emission scenario. In contrast, assuming a log-linear CO₂–ERF relationship and neglecting the equilibrium-state dependencies induce a larger median error of roughly -10% . This median error is likely due to the non-log-linear dependency of the instantaneous (nonadjusted) forcing, suggesting that the equilibrium-state dependencies do not induce any systematic error. However, they contribute to increasing uncertainties in future warming estimation.

1. Introduction

The linear forcing–feedback framework has been proven successful in representing the joint evolution of the radiative imbalance and that of the global temperature change under an externally imposed radiative perturbation. It is widely used to constrain projections of future climate change. This framework assumes that the radiative response of the climate system scales instantaneously with the global-mean surface air temperature response through a constant parameter when considering only fast radiative feedbacks (Wetherald and Manabe 1988). However, the strength of the feedbacks has been shown to depend on the background climate state (e.g., Senior and Mitchell 2000).

The stratosphere–troposphere-adjusted radiative forcing or effective radiative forcing (ERF) is often assumed to be log linear dependent on the CO₂ concentration (e.g., Myhre et al. 1998). However, the ERF may increase more than logarithmically with the CO₂ concentration (Shi 1992; WMO 1999; Hansen et al. 2005; Colman and McAvaney 2009; Jonko et al. 2013; Block and Mauritsen 2013). Modern estimates of line-by-line radiative transfer models show such a nonlinear dependence of both the instantaneous (nonadjusted) forcing (Byrne and Goldblatt 2014, hereafter BG14) and stratosphere-adjusted radiative forcing (Etminan et al. 2016). Such non-log-linear CO₂–ERF relationships have been used in recent studies to describe the ERF evolution (e.g., Caldeira and Myhrvold 2013; Lewis and Curry 2018; Smith et al. 2018).

The strength of the feedbacks may be nonconstant due to different processes. The albedo feedback can decrease due to the disappearance of sea ice (Manabe and Bryan 1985; Colman and McAvaney 2009; Jonko et al. 2013). Delayed sea ice melting due to bounding land in the Northern Hemisphere may lead to the opposite effect at small perturbations (Meraner et al. 2013).

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Other radiative feedbacks may also increase as the climate is warmer (Colman et al. 1997; Jonko et al. 2013; Meraner et al. 2013), but the opposite is also found (Colman and McAvaney 2009). These nonlinear effects can be interpreted as nonlinear dependencies on the surface temperature change or on the CO₂ concentration change (e.g., Colman et al. 1997; Bloch-Johnson et al. 2015). They act in both transition and equilibrium and are referred to as equilibrium-state dependencies.

The ocean heat uptake has been suggested to modulate the strength of the feedbacks during a climate transition. Equilibrium and transient surface warming patterns differ, as shown by atmosphere–ocean coupled general circulation models. In transition, warming is particularly slowed down in regions of large ocean heat uptake (Manabe et al. 1991). Because of the evolving surface temperature pattern during a climate transition, the strength of climate feedbacks may vary with a tendency of the feedback to increase with the degree of equilibration (Winton et al. 2010). Remote effects have been shown to play the most important role, primarily by acting on the temperature lapse rate and the cloud feedbacks (Ceppi and Gregory 2017). This dependency of the radiative feedbacks on the surface warming pattern is generally referred to as the pattern effect (Stevens et al. 2016).

The linear forcing–feedback framework can be combined with a suitable parameterization of the ocean heat uptake to represent the time evolution of the response of the climate system to an external radiative perturbation (Gregory 2000; Held et al. 2010; Geoffroy et al. 2013a). The pattern effect can be represented through an efficacy factor of deep-ocean heat uptake (Winton et al. 2010; Held et al. 2010; Geoffroy et al. 2013b). Whether or not the pattern effect is taken into account, the two-layer energy balance model (EBM) combined with a log-linear CO₂–ERF formulation shows quasi-systematic biases in its ability to represent both responses in abrupt-4×CO₂ and 1pctCO₂ simulations (Geoffroy et al. 2013a,b, hereafter G13a and G13b, respectively). The inconstancy of the radiative properties have been suggested to explain most of this difference (Gregory et al. 2015).

Energy balance models or similar models such as impulse response functions (e.g., Good et al. 2012) have been widely used to constrain climate sensitivity from the observed present warming (e.g., Gregory et al. 2002; Otto et al. 2013). These constraints generally lead to sensitivity estimates lower than those projected by climate models (e.g., Stevens et al. 2016). It has been suggested that limitations in the linear forcing–feedback framework, such as the dependency of the feedbacks on the warming pattern, play an important role in this

mismatch (Armour 2017; Proistosescu and Huybers 2017). Accounting for nonlinear effects can lead to different estimations of the ECS. For example, a fit of years 1–150 and a fit of years 21–150 of a step-forcing experiment can lead to different ECS estimations. The diverse ways of estimating the ECS may lead to misleading interpretation of the results when comparing ECS estimated using different methods.

The objectives of this study are 1) to represent the main state dependencies in a two-layer EBM for all CMIP5 climate models and 2) to use this EBM to assess the importance of these dependencies of constraining climate projection. Studying nonlinearity may necessitate additional experiments that are not included in the CMIP5 database. Hence, a majority of studies are limited to the analysis of one single model (e.g., Block and Mauritsen 2013; Meraner et al. 2013; Rohrschneider et al. 2019). The nonlinMIP project will provide coupled experiments useful to analyze these effects in CMIP6 models (Good et al. 2016). Here the effects are analyzed for the full CMIP5 ensemble from the abrupt-4×CO₂ and the 1pctCO₂ simulations. Sections 2 and 3 present the linear forcing–feedback framework, the CO₂–forcing relationship and discuss implications of their combination. Sections 4 and 5 summarize the different types of transient- and equilibrium-state dependencies and discuss their representation in an EBM. Section 6 investigates their importance in terms of constraining climate projections from the historical record.

2. The linear forcing–feedback framework

The linear forcing–feedback framework assumes that the radiative imbalance at the top of the atmosphere ΔN is a linear function of the global-mean surface air temperature response ΔT . In response to a change in the CO₂ concentration, the evolution of ΔN follows the equation (Wetherald and Manabe 1988; Gregory et al. 2004)

$$\Delta N(t) = F[n_c(t)] - \lambda \Delta T(t), \quad (1)$$

where $n_c(t)$ is the normalized CO₂ concentration relative to the preindustrial one, $n_c(t) = [\text{CO}_2](t)/[\text{CO}_2]_0$; F is the ERF (Gregory and Webb 2008; Sherwood et al. 2015); and λ is the radiative response parameter (also referred to as feedback parameter). Whatever the history of the CO₂ concentration evolution, $[\Delta T(t), \Delta N(t)]$ lies on a line with a slope λ and an intercept $F[n_c(t)]$. If the CO₂ concentration is held fixed at this value, $[\Delta T(t), \Delta N(t)]$ will then follow this line until equilibrium (Fig. 1). At equilibrium, $\Delta N = 0$ and the temperature response is equal to $\Delta T_{\text{eq}}(n_c) = F(n_c)/\lambda$, with

FIG. 1. Schematic illustrating the relationship between transient and equilibrium climate states under the linear-log(CO_2)-feedback framework: location in a (T, N) space (Gregory plot) of an abrupt- $2\times\text{CO}_2$ experiment (global annual means, black dots), a 1pct CO_2 experiment (global annual means, blue dots; decadal values only, blue circles), and a rescaled 1pct CO_2 experiment with rescaling factor of $1/\log_2[n_c(t)]$ (decadal values only, red circles). Whatever the history of the CO_2 concentration evolution, $[\Delta T(t), \Delta N(t)]$ lies on a line with a slope $-\lambda$, intercept $F[n_c(t)]$, and intersection with the $\Delta N = 0$ line of the equilibrium temperature response $\Delta T_{\text{eq}}(n_c)$. Once rescaled, $\{\Delta T(t)/\log_2[n_c(t)], \Delta N(t)/\log_2[n_c(t)]\}$ lies on the abrupt- $2\times\text{CO}_2$ line, with radiative response parameter λ , with forcing F_2 , and with temperature response at equilibrium ECS.

$$\lambda = \frac{F[n_c(t)] - \Delta N(t)}{\Delta T(t)}. \quad (2)$$

This equation for λ is often used to define the effective feedback parameter (Murphy 1995; Andronova et al. 2007). Within the linear forcing–feedback framework, λ is invariant and can be calculated at any time from $(\Delta T, \Delta N)$ once the ERF is known.

3. The effective radiative forcing ERF

a. Log-linear CO_2 dependency of the ERF

An additional equation is often added to extend the framework. To first order, the ERF can be expressed as linear function of the logarithm of the CO_2 concentration (Myhre et al. 1998):

$$F[n_c(t)] = F_r \log_r[n_c(t)], \quad (3)$$

where F_r is a reference forcing parameter at normalized CO_2 concentration r : $F_r = F(r)$. It is generally taken as the $2\times\text{CO}_2$ radiative forcing F_2 ($r = 2$) or the $4\times\text{CO}_2$ radiative forcing F_4 ($r = 4$).

For any given scenario $t \mapsto n_c(t)$, the values of $[\Delta T(t), \Delta N(t)]$ multiplied by the scaling factor $\alpha_r(t) = 1/\log_r[n_c(t)]$ are on the line with slope $-\lambda$ and intercept F_r :

$$\alpha_r(t) \Delta N(t) = F_r - \lambda \alpha_r(t) \Delta T(t). \quad (4)$$

The equilibrium climate sensitivity (ECS) is the equilibrium temperature response to a doubling of CO_2 . Within this linear log(CO_2)-feedback framework, it is equal to any rescaled equilibrium temperature response for $r = 2$:

$$\widehat{\text{ECS}} = \frac{\Delta T_{\text{eq}}(n_c)}{\log_2(n_c)}. \quad (5)$$

This formulation is used when the ECS is estimated by dividing by two the equilibrium temperature change derived from an abrupt- $4\times\text{CO}_2$ simulation (e.g., Flato et al. 2013). The rescaling method is schematically illustrated by Fig. 1 for a 1pct CO_2 experiment. Any deviation of the line described by Eq. (4) shows a limitation of the linear log(CO_2)-feedback framework (i.e., F_r or λ nonconstant).

TABLE 1. Summary of the EBMs.

EBM	CO ₂ -ERF relationship, $F(n_c) = F(4)\{(1-f)\log_4(n_c) + f[\log_4(n_c)]^2\}$	Transient radiative response parameter	Equilibrium radiative response parameter λ
EBM- f_0	$f = 0$	λ	Constant
EBM- f_{bg}	$f = f_{bg}$	λ	Constant
EBM- f	f	λ	Constant
EBM- $f_{bg}-\lambda_c$	$f = f_{bg}$	λ	$\lambda_4^c[(1-g_c) + g_c \log_4(n_c)]$
EBM- $f_{bg}-\lambda_T$	$f = f_{bg}$	λ	$\lambda_0^T \left[(1-g_T) + g_T \frac{\Delta T}{ECS_0} \right]$
EBM- $f_0-\varepsilon$	$f = 0$	$\lambda + (\varepsilon - 1)H/\Delta T$	Constant
EBM- $f_{bg}-\varepsilon$	$f = f_{bg}$	$\lambda + (\varepsilon - 1)H/\Delta T$	Constant
EBM- $f-\varepsilon$	f	$\lambda + (\varepsilon - 1)H/\Delta T$	constant
EBM- $f_{bg}-\lambda_c-\varepsilon$	$f = f_{bg}$	$\lambda + (\varepsilon - 1)H/\Delta T$	$\lambda_4^c[(1-g_c) + g_c \log_4(n_c)]$
EBM- $f_{bg}-\lambda_T-\varepsilon$	$f = f_{bg}$	$\lambda + (\varepsilon - 1)H/\Delta T$	$\lambda_0^T \left[(1-g_T) + g_T \frac{\Delta T}{ECS_0} \right]$

b. Non-log-linear CO₂ dependency of the ERF

The ERF can be more precisely expressed as a quadratic function of $\ln(n_c)$ (BG14; Gregory et al. 2015):

$$F(n_c) = F_r \{(1-f)\log_r(n_c) + f[\log_r(n_c)]^2\}, \quad (6)$$

where f represents the fraction of non-log-linearity of the ERF. Note that f depends on the normalized CO₂ concentration r . This formulation includes the CO₂-stratosphere-adjusted forcing relationship and any non-log-linear dependence of the tropospheric adjustments on the CO₂ perturbation. The particular case $f = 0$ corresponds to the log-linear relationship given by Eq. (3).

Line-by-line radiative transfer models show that both the instantaneous and the stratosphere-adjusted radiative forcings are adequately represented by such a relationship (BG14; Etminan et al. 2016). By assuming that tropospheric adjustments are proportional to the instantaneous forcing with a constant scaling parameter, the BG14 formulation can be applied to the ERF. By rescaling their non-troposphere-adjusted forcing such that it equates the 4×CO₂ ERF for $n_c = 4$, the ERF reads

$$F_{bg}(n_c) = F_4 \{(1-f_{bg})\log_4(n_c) + f_{bg}[\log_4(n_c)]^2\} \quad (7)$$

with

$$f_{bg} = \frac{0.39[\ln(4)]^2}{5.32 \ln(4) + 0.39[\ln(4)]^2} \approx 0.09. \quad (8)$$

The reference forcing F_r is chosen at 4×CO₂ ($r = 4$) because this ERF can be directly estimated from CMIP abrupt-4×CO₂ experiments. The rescaling of a given CO₂ scenario illustrated in Fig. 1 can be performed by using this more precise formulation of the CO₂ forcing. In this case, the scaling factor α_4^{bg} is

$$\alpha_4^{bg}(t) = \frac{1}{(1-f_{bg})\log_4[n_c(t)] + f_{bg}[\log_4[n_c(t)]]^2}. \quad (9)$$

The rescaling of a given scenario in the (T, N) space allows a simple graphical representation of the validity of this framework.

4. State dependencies of the radiative feedbacks in a two-layer EBM

a. The two-layer energy balance model framework

The two-layer EBM (Gregory and Mitchell 1997; Gregory 2000; Held et al. 2010; G13a) reads

$$C \frac{dT}{dt} = F - R - H, \quad (10)$$

$$C_d \frac{dT_d}{dt} = H, \quad (11)$$

with $\Delta N = F - R$ and $H = \gamma(\Delta T - \Delta T_d)$, T_d is a characteristic temperature of the deep ocean, R is the radiative response of the climate system, and H is the deep-ocean heat uptake. The parameter γ is a heat exchange coefficient between the near-surface ocean and the deep ocean, also referred to as ocean heat uptake efficiency. The parameters C and C_d are specific heat capacities of near-surface ocean and deep ocean, respectively. Note that C and C_d cannot be directly computed from the upper and deep-ocean total mass because they also depend on the spatial distribution of the temperature change in the ocean.

When combined with the linear forcing-feedback framework [Eq. (1)] and with a log-linear forcing [Eq. (3)], the two-layer EBM is referred to as EBM- f_0 (see Table 1). When the ERF is assumed to follow the relationship derived from BG14 [Eq. (7)], the EBM is referred to as EBM- f_{bg} . For a model-dependent parameter f in the

TABLE 2. For the CMIP5 climate models and CNRM-CM6-1, parameters of the linear EBM without pattern effect and, in parentheses, parameters of the EBM- ε . The parameter in the right column, $\rho_{\Delta T_{eq}}$, is the ratio of the $4\times\text{CO}_2$ equilibrium temperature response of the linear EBM without pattern effect over that of the EBM- ε .

Model	C ($\text{W yr m}^{-2} \text{K}^{-1}$)	C_d ($\text{W yr m}^{-2} \text{K}^{-1}$)	γ ($\text{W m}^{-2} \text{K}^{-1}$)	F_4 (W m^{-2})	λ ($\text{W m}^{-2} \text{K}^{-1}$)	ε	$\Delta T_{eq}(n_c = 4)$ (K)	$\rho_{\Delta T_{eq}}$
CNRM-CM6.1	7.3 (7.5)	111 (115)	0.57 (0.56)	7.2 (7.4)	0.73 (0.73)	1 (1.09)	9.8 (10.1)	1.03
ACCESS1.0	7.1 (8.9)	77 (83)	0.82 (0.71)	5.8 (7.2)	0.75 (0.81)	1 (1.55)	7.8 (8.9)	1.14
ACCESS1.3	8.2 (10.1)	99 (114)	0.83 (0.72)	5.8 (7.0)	0.82 (0.81)	1 (1.62)	7.1 (8.7)	1.23
BCC-CSM1.1	7.9 (8.8)	54 (57)	0.66 (0.58)	6.8 (7.4)	1.21 (1.27)	1 (1.28)	5.6 (5.9)	1.04
BCC-CSM1.1m	8.4 (9.3)	50 (53)	0.56 (0.49)	7.4 (8.1)	1.31 (1.37)	1 (1.32)	5.7 (5.9)	1.04
BNU-ESM	7.2 (7.2)	88 (87)	0.52 (0.53)	7.4 (7.4)	0.93 (0.93)	1 (0.98)	8.0 (8.0)	0.99
CanESM2	7.6 (8.3)	71 (77)	0.59 (0.54)	7.6 (8.2)	1.03 (1.05)	1 (1.28)	7.4 (7.8)	1.06
CCSM4	6.2 (7.8)	69 (72)	0.93 (0.81)	7.2 (8.4)	1.24 (1.40)	1 (1.36)	5.8 (6.1)	1.05
CNRM-CM5	8.8 (8.7)	100 (96)	0.50 (0.51)	7.3 (7.1)	1.11 (1.12)	1 (0.92)	6.5 (6.4)	0.98
CSIRO-Mk3.6.0	6.7 (9.3)	70 (77)	0.88 (0.71)	5.0 (6.8)	0.61 (0.66)	1 (1.80)	8.3 (10.3)	1.24
FGOALS-s2	6.8 (7.3)	124 (136)	0.74 (0.70)	7.5 (8.0)	0.88 (0.87)	1 (1.23)	8.5 (9.3)	1.09
GFDL CM3	8.5 (9.9)	71 (76)	0.80 (0.71)	5.9 (6.8)	0.75 (0.78)	1 (1.39)	7.8 (8.7)	1.11
GFDL-ESM2G	6.0 (6.5)	100 (104)	0.84 (0.80)	6.7 (7.1)	1.42 (1.48)	1 (1.17)	4.7 (4.8)	1.03
GFDL-ESM2M	8.1 (8.9)	106 (113)	0.93 (0.86)	6.5 (7.1)	1.34 (1.38)	1 (1.23)	4.9 (5.1)	1.05
GISS-E2-H	9.6 (10.5)	81 (86)	0.78 (0.70)	7.4 (8.1)	1.57 (1.64)	1 (1.27)	4.7 (4.9)	1.04
GISS-E2-R	4.6 (6.1)	126 (135)	1.16 (1.07)	7.3 (9.2)	1.70 (2.03)	1 (1.44)	4.3 (4.5)	1.05
HadGEM2-ES	7.2 (8.3)	82 (99)	0.56 (0.49)	5.9 (6.7)	0.66 (0.60)	1 (1.57)	9.0 (11.2)	1.24
INM-CM4	9.3 (9.1)	327 (277)	0.66 (0.69)	6.1 (6.0)	1.50 (1.57)	1 (0.82)	4.1 (3.8)	0.94
IPSL-CM5A-LR	8.3 (8.6)	95 (100)	0.59 (0.57)	6.4 (6.6)	0.79 (0.79)	1 (1.14)	8.1 (8.4)	1.04
IPSL-CM5A-MR	8.8 (9.4)	98 (108)	0.60 (0.56)	6.6 (7.0)	0.81 (0.79)	1 (1.24)	8.2 (8.9)	1.09
IPSL-CM5B-LR	8.3 (9.7)	63 (68)	0.73 (0.63)	5.2 (6.0)	1.00 (1.07)	1 (1.43)	5.2 (5.6)	1.08
MIROC5	9.3 (9.7)	149 (163)	0.77 (0.74)	8.5 (8.9)	1.58 (1.57)	1 (1.20)	5.4 (5.7)	1.05
MIROC-ESM	9.5 (10.2)	128 (146)	0.70 (0.65)	8.5 (9.1)	0.91 (0.87)	1 (1.32)	9.3 (10.5)	1.13
MPI-ESM-LR	7.9 (9.2)	71 (78)	0.71 (0.62)	8.2 (9.4)	1.14 (1.20)	1 (1.43)	7.2 (7.8)	1.08
MPI-ESM-MR	7.7 (8.9)	72 (79)	0.69 (0.60)	8.2 (9.3)	1.18 (1.24)	1 (1.43)	6.9 (7.5)	1.08
MPI-ESM-P	7.4 (8.7)	71 (79)	0.72 (0.61)	8.6 (10.0)	1.25 (1.34)	1 (1.49)	6.9 (7.5)	1.08
MRI-CGCM3	9.4 (10.1)	66 (70)	0.66 (0.60)	6.5 (7.0)	1.26 (1.30)	1 (1.25)	5.2 (5.4)	1.04
NorESM1-M	8.1 (9.9)	106 (122)	0.87 (0.76)	6.2 (7.4)	1.11 (1.15)	1 (1.57)	5.6 (6.5)	1.15
CMIP5 median	8.1 (8.9)	82 (87)	0.72 (0.65)	6.8 (7.4)	1.11 (1.15)	1 (1.32)	6.9 (7.5)	1.06

quadratic ERF formulation [Eq. (6)], the EBM is referred to as EBM- f . The calibration method of this EBM is provided in the appendix.

b. Transient-state dependency due to the pattern effect

The pattern effect due to the deep-ocean heat uptake can be represented in the two-layer EBM through the use of an efficacy factor of ocean heat uptake (Winton et al. 2010; Held et al. 2010; G13b). Under this framework, the radiative response in Eq. (10) reads

$$R = \lambda \Delta T + (\varepsilon - 1)H, \quad (12)$$

where λ denotes the radiative response parameter in equilibrium ($R = F$ and $H = 0$). This model, referred to as EBM- ε in the following, has been shown to effectively represent the nonlinear variation of ΔN against ΔT observed in climate model abrupt- $4\times\text{CO}_2$ experiments at the centennial scale (G13b). When combined with the log-linear forcing relationship, the BG14 relationship and a quadratic relationship with a model-dependent f ,

the EBM- ε is referred to as EBM- f_0 - ε , EBM- f_{bg} - ε , and EBM- f - ε , respectively (Table 1).

The parameters of the EBM- ε are computed by G13b for a limited set of CMIP5 climate models. These parameters are summarized in Table 2 for all CMIP5 models and for the CNRM-CM6.1 climate model (Voldoire et al. 2019). Parameters are computed following the method detailed in G13b. Note that the radiative parameters can be equivalently computed simply by performing two linear regressions of ΔN against ΔT in the step-forcing experiment. A regression of the first years (e.g., years 1–10) allows us to compute the ERF, and one of the last years (e.g., years 21–150) allows us to compute λ/ε (as the slope of the fit) and the ECS (G13b). Then λ can be deduced from the ECS and from F_r .

Because the radiative feedbacks tend to amplify more the warming in equilibrium than in transition, the nonlinear equilibrium climate sensitivity (ECS_e) computed by using the EBM- ε is generally larger than the linear one (ECS_l) computed from the method of Gregory et al. (2004). For each model, the ratio $\text{ECS}_e/\text{ECS}_l$ is indicated

in Table 2. It varies from 0.94 to 1.24 with a median value of 1.06.

c. Equilibrium-state dependencies

The equilibrium-state dependencies of the radiative feedbacks include the surface temperature dependency and the CO₂ dependency of the radiative feedbacks. The T dependency is the nonlinear evolution of the feedback strength with the magnitude of the mean global warming (Colman and McAvaney 1997; Block and Mauritsen 2013; Meraner et al. 2013; Bloch-Johnson et al. 2015; Rohrschneider et al. 2019). This is a possible explanation for the inconstancy of the transient radiative feedbacks observed in an abrupt-4×CO₂ experiment. Even if they also act in transition, they are referred to as equilibrium-state dependencies (e.g., Block and Mauritsen 2013), in contrast with the pattern effect that is a transient phenomenon only.

1) CO₂ DEPENDENCY OF THE RADIATIVE RESPONSE

A CO₂ dependency of the radiative response parameter can be written as

$$\lambda(n_c) = \lambda_4^c [(1 - g_c) + g_c \log_4(n_c)], \quad (13)$$

where g_c is the fraction of nonlinearity of the radiative response parameter due to CO₂ dependency. The reference feedback parameter λ_4^c is chosen at 4×CO₂ because it can be directly estimated from CMIP abrupt-4×CO₂ experiments. Such a dependence of λ on CO₂ would take into account any dependence of the forcing adjustment on the mean climate state.

In the following, a two-layer EBM that includes this effect is referred to as EBM- $f_{bg}-\lambda_c$ when combined with a BG14 forcing (Table 1). For the sake of simplicity, when combined with an EBM- ε , the CO₂ dependency is applied to the equilibrium radiative response parameter λ [cf. Eq. (12)] and the ocean heat uptake efficacy is assumed to remain constant. This model is referred to as EBM- $f_{bg}-\lambda_c-\varepsilon$. The calibration method of g_λ for both EBM- $f_{bg}-\lambda_c$ and EBM- $f_{bg}-\lambda_c-\varepsilon$ is provided in the appendix.

2) T DEPENDENCY OF THE RADIATIVE RESPONSE

The temperature dependency of the radiative feedbacks can be simply expressed through a second-order Taylor expansion of the radiative imbalance as a function of temperature (Colman et al. 1997; Bloch-Johnson et al. 2015). Then the radiative response parameter λ reads

$$\lambda = \lambda_0^T \left[(1 - g_T) + g_T \frac{\Delta T}{ECS_0} \right], \quad (14)$$

with $ECS_0 = F_4/\lambda_0^T$ and g_T represents the fraction of nonlinearity of the radiative response parameter due to

temperature dependency. As previously, an EBM including this formulation of λ and a BG14 forcing is referred to as EBM- $f_{bg}-\lambda_T$ (Table 1). This EBM can be combined with the pattern effect in EBM- $f_{bg}-\lambda_T-\varepsilon$. The calibration method of both EBM- $f_{bg}-\lambda_T$ and EBM- $f_{bg}-\lambda_T-\varepsilon$ is provided in the appendix.

5. Nonlinear effects in CMIP5 models

a. Limitations of the linear EBMs

Once calibrated with an abrupt-4×CO₂ simulation, the EBM- $f_0-\varepsilon$ correctly reproduces the TCR4× (the warming at the time of CO₂ quadrupling in the 1pctCO₂, i.e., 140 years) (Fig. 2, first row). However, it shows a quasi-systematic overestimation of the transient climate response (TCR; the warming at the time of CO₂ doubling in the 1pctCO₂, i.e., 70 years) (Table S1 in the online supplemental material; Geoffroy et al. 2012; Gregory and Andrews 2016; G13b).

Both the representation of the radiative imbalance and that of the heat uptake can play a role in this overestimation of the TCR. The first can be interpreted as the need for a more adequate CO₂ concentration–ERF relationship and/or additional state dependencies of the strength of the radiative response (Gregory et al. 2015). The second is related to the limited number of time scales (two) of the EBM and can be simply formulated with a varying γ . The surrogate EBM- $f_0-\varepsilon$ of the CNRM-CM6-1 climate model exhibits the strongest overestimation of the TCR with a relative error of 27%. When the EBM is instead calibrated with an abrupt-2×CO₂ experiment, the TCR is better predicted with a relative error of 5%. Beyond, the EBM underestimates the TCR4× with a relative error of –11% (not shown). The thermal inertia parameters appear to explain roughly 45% of this difference against roughly 55% for the radiative parameters (not shown).

To highlight the importance of the radiative parameters for all CMIP5 climate models and CNRM-CM6-1, the 1pctCO₂ experiments are rescaled in a (T , N) space to match a 4×CO₂ step forcing by multiplying both ΔN and ΔT by $\alpha_4(t)$ [cf. Eq. (4)]. For each climate model, Fig. 3a shows the multimodel mean of the annual-mean values of the rescaled 1pctCO₂ (pink dots). The 10-yr means are also shown (red dots). Figures 3c and 3d and Fig. S1 show the results for each model. The first quarter of each simulation (35 years) has been removed because of their small signal-to-noise ratio.

The linear log(CO₂)-feedback framework predicts that both the abrupt-4×CO₂ and the rescaled 1pctCO₂ simulations end up on the same line [cf. Eq. (4)]. An EBM- $f_0-\varepsilon$ also predicts that both simulations are almost

FIG. 2. (left) Time evolution of the multimodel mean of the global-mean surface air temperature response in the 1pctCO₂ experiment of climate models (black line) and that of their surrogate EBMs (blue line). (center) Scatterplot between the temperature response in the 1pctCO₂ at 70 years (TCR, red dots) and at 140 years (TCR4 $\times$, blue dots) of each climate models and the corresponding temperature change in their surrogate EBM (y axis). The TCR is calculated as the average of 11 years centered over the year 70 and the TCR4 $\times$ as the average of the last 10 years of the 1pctCO₂. (right) Relative error of the TCR (red dots) and the TCR4 $\times$ (blue dots) between the climate models and their surrogate EBM as a function of the TCR and the TCR4 $\times$ of each climate model, respectively. The EBM is (top) the EBM- $f_0-\varepsilon$ and (bottom) the EBM- $f_{bg}-\varepsilon$.

identical. For some models, the rescaled 1pctCO₂ strongly deviates from the abrupt experiment at small temperature changes (e.g., CNRM-CM6-1 and HadGEM2-ES as shown in Figs. 3c,d). The surrogate EBM- f_0 of the climate models with the largest difference between the abrupt-4 $\times$ CO₂ and the rescaled 1pctCO₂ (e.g., CNRM-CM6.1, MIROC5 and MIROC-ESM, GFDL-ESM2G) also exhibit the strongest relative error in TCR (not shown).

By using the quadratic ERF formulation derived from BG14 [Eq. (7)] rather than the log-linear relationship, the mean TCR overestimation is largely reduced (Fig. 2, second row). Figure 3b and Fig. S1 show the rescaled 1pctCO₂ in the (T, N) space with the scaling factor $\alpha_4^{bg}(t)$ [Eq. (9)] rather than $\alpha_4(t)$. The multimodel-mean rescaled 1pctCO₂ perfectly matches the abrupt-4 $\times$ CO₂ after few years of simulations. This suggests that such a formulation is more suitable to represent the climate models ensemble.

Taken individually, some climate models strongly deviate from this line (Figs. 3c,d, Fig. S1). These

differences reflect the effect of any difference between the climate model CO₂-ERF relationship and that given by Eq. (7) and/or of the effect of the equilibrium state dependencies. Finally, this representation illustrates the need of non-log-linear dependency of the radiative forcing on the CO₂ concentration and/or the need of equilibrium-state dependencies of radiative feedbacks for a precise representation of the radiative imbalance evolution, in agreement with the conclusion of Gregory et al. (2015).

b. Non-log-linear CO₂ forcing and equilibrium-state dependencies

The nonlinear behavior of the effective climate sensitivity observed in the T - N space can be due to a different representation of the CO₂-ERF relationship in the climate model from that derived from BG14. It can also be due to the equilibrium-state dependencies of the radiative feedbacks. By using only the abrupt-4 $\times$ CO₂ and the 1pctCO₂ simulations, the

FIG. 3. (a) Representation in a (T, N) space of the multimodel mean of the abrupt-4 $\times$ CO₂ experiments (annual means, black dots) and of the multimodel mean of the rescaled 1pctCO₂ experiments with rescaling factor $1/\log_4(n_c)$ (annual means, light blue dots; 10-yr means, blue dots). Also shown is the multimodel mean of the abrupt-4 $\times$ CO₂ simulated by the EBM- ϵ (black line). (b) As in (a), but the 1pctCO₂ experiments are rescaled with the factor α_4^{bg} [see Eq. (9)] (annual means, pink dots; 10-yr means, red dots). (c), (d) As in (a) and (b), but for CNRM-CM6-1 and HadGEM2-ES climate models, respectively. Both rescaled 1pctCO₂ with rescaling factors $1/\log_4(n_c)$ (blue) and α_4^{bg} (red) are shown ($t > 35$ years only). Changes are relative to the piControl simulation.

different effects are hardly dissociable. Each effect is considered individually in the corresponding EBM by assuming it fully explains the full nonlinear behavior.

The results presented in the following of the paper are unchanged when taking into account the pattern effect or not. Hence the simplest versions of the EBMs without pattern effect (EBM- f , EBM- $f_{\text{bg}}-\lambda_c$, and EBM- $f_{\text{bg}}-\lambda_T$) are considered in the rest of the study. The results of

the EBMs that represent the pattern effect (EBM- $f-\epsilon$, EBM- $f_{\text{bg}}-\lambda_c-\epsilon$, and EBM- $f_{\text{bg}}-\lambda_T-\epsilon$) are shown in the supplemental material (Figs. S2 and S3).

The EBM- f is calibrated for each CMIP5 climate model. The parameters are given in Table 3. The inter-model spread and the mean overestimation of the TCR are strongly reduced with the calibrated quadratic ERF (Fig. 4, first row). For most models, there is still a small overestimation of the TCR. The calibrated EBM- $f_{\text{bg}}-\lambda_c$

TABLE 3. Additional parameter of the EBM- f and that of the EBM- $f_{bg-\lambda_c}$ and, in parentheses, additional parameter of the EBM- $f_{0-\varepsilon}$ and that of the EBM- $f_{bg-\lambda_c-\varepsilon}$.

Model	f	g_c
CNRM-CM6.1	0.25 (0.24)	-0.37 (-0.38)
ACCESS1.0	0.02 (0.00)	0.16 (0.22)
ACCESS1.3	0.12 (0.09)	-0.06 (-0.03)
BCC-CSM1.1	0.11 (0.09)	-0.02 (-0.01)
BCC-CSM1.1m	-0.10 (-0.12)	0.24 (0.27)
BNU-ESM	-0.04 (-0.04)	0.21 (0.21)
CanESM2	0.05 (0.04)	0.07 (0.09)
CCSM4	0.13 (0.11)	-0.06 (-0.04)
CNRM-CM5	0.10 (0.11)	-0.02 (-0.02)
CSIRO-Mk3.6.0	0.18 (0.16)	-0.28 (-0.33)
FGOALS-s2	0.08 (0.07)	0.02 (0.03)
GFDL CM3	0.05 (0.04)	0.09 (0.12)
GFDL-ESM2G	0.30 (0.29)	-0.40 (-0.41)
GFDL-ESM2M	0.10 (0.09)	0.00 (0.02)
GISS-E2-H	-0.16 (-0.17)	0.36 (0.39)
GISS-E2-R	-0.15 (-0.15)	0.37 (0.39)
HadGEM2-ES	-0.06 (-0.08)	0.30 (0.43)
INM-CM4	0.01 (0.02)	0.13 (0.11)
IPSL-CM5A-LR	0.10 (0.10)	-0.03 (-0.02)
IPSL-CM5A-MR	0.18 (0.16)	-0.19 (-0.18)
IPSL-CM5B-LR	0.17 (0.16)	-0.19 (-0.19)
MIROC5	0.34 (0.32)	-0.52 (-0.54)
MIROC-ESM	0.27 (0.25)	-0.44 (-0.47)
MPI-ESM-LR	0.19 (0.17)	-0.18 (-0.17)
MPI-ESM-MR	0.15 (0.13)	-0.10 (-0.08)
MPI-ESM-P	0.20 (0.19)	-0.21 (-0.21)
MRI-CGCM3	0.13 (0.12)	-0.07 (-0.06)
NorESM1-M	0.21 (0.19)	-0.24 (-0.26)
CMIP5 median	0.11 (0.10)	-0.03 (-0.02)

gives very close behavior to that of the EBM- f in its representation of the temperature response (Fig. 4, second row). When rescaled in the (T, N) space, the EBM- f and the EBM- $f_{bg-\lambda_c}$ significantly differ only at small ΔT due to differences in the ERF when the CO_2 concentration tends to the preindustrial concentration (Fig. S1, red and purple lines, and Fig. S2 for the versions with ε). In line with the same rationale for using forcing efficacies (Hansen et al. 2005), this good correspondence between the two EBMs shows that a quadratic forcing can be used to represent not only the CO_2 -ERF relationship but also the dependency of the radiative response on the CO_2 concentration.

Then, the temperature dependency of the radiative feedbacks is examined. When the EBM- $f_{bg-\lambda_T}$ is calibrated with the abrupt- $4\times\text{CO}_2$ experiment only, the mean overestimation of the TCR is reduced in comparison with that of the EBM- f_{bg} but the bias increases for the TCR $4\times$ and the intermodel spread largely increases for both TCR and TCR $4\times$ (not shown). When the EBM- $f_{bg-\lambda_T}$ is calibrated with both abrupt- $4\times\text{CO}_2$ and 1pctCO2 (parameters given in Table 4) the TCR representation is similar to that

obtained with the EBM- f and the EBM- $f_{bg-\lambda_c}$ (Fig. 4, third row, and Fig. S1). However, the representation of the abrupt- $4\times\text{CO}_2$ is degraded for some models. Finally, the nonlinear dependency of ΔN on ΔT cannot be fully explained by a temperature dependency of the radiative feedbacks for a large number of climate models.

These similar results obtained with the different EBMs do not allow us to dissociate each effect. All the EBMs presented here provide a similar reduction of the TCR overestimation. This suggests that the remaining small bias is due to limitations in the ocean heat uptake formulation, as shown with the CNRM-CM6-1 climate model (section 5a). For the CNRM-CM6-1 climate model, Fig. S4 shows the time series of the temperature change for three members of the 1pctCO2, for a $2\times\text{CO}_2$ stabilization, for a ramp-down experiment, and their representation by each EBM. All three EBMs—EBM- f , EBM- $f_{bg-\lambda_c}$, and EBM- $f_{bg-\lambda_T}$ —give similar results and provide a better representation than the EBM- $f_{0-\varepsilon}$ and the EBM- $f_{bg-\varepsilon}$ of the temperature change for these scenarios. In next section, the EBMs are used to represent these three types of scenarios.

6. Importance of the state dependencies for constraining climate projections

a. General method

Most constraint studies of climate projections based on the historical period assume that the effective climate sensitivity is invariant over the course of a perturbed scenario. Moreover, the radiative properties of the climate system are estimated from a small amount of realized warming. This may induce errors in the estimated projected warming.

In this section, these errors are evaluated by using the two-layer EBM as a perfect model. Each nonlinear effect is examined separately. First a reference simulation is performed with the EBM incorporating the considered nonlinear effect. Then the simulation is repeated with the nonlinear effect removed by holding fixed the corresponding radiative variable to its present-day estimation. The difference between both EBM simulations allows us to quantify the error induced by the nonlinear effect. For example, the dependency of the radiative feedbacks on the transient pattern can be tested by setting the radiative response variable at its present-day value and setting $\varepsilon = 1$. This procedure is repeated for each set of parameters derived from the CMIP5 climate models.

The present-day value is defined as that obtained at $t = 40$ years in the 1pctCO2 experiment. At this time, the multimodel warming is roughly 1 K (Fig. 4), which roughly corresponds to the present-day global warming. Results are also shown in the supplementary

FIG. 4. As in Fig. 2, but for (top) EBM- f , (middle) EBM- $f_{bg}-\lambda_c$, and (bottom) EBM- $f_{bg}-\lambda_T$.

material by setting the radiative response variable at its value in the limit of t toward zero in the 1pctCO₂ experiment rather than at its 40-yr value (Fig. S5). This assumes that the realized warming is infinitely small. Hence, it provides an upper boundary of the considered nonlinear effect.

The errors are evaluated at year 140 of three types of CO₂ concentration pathways: a 1pctCO₂ increase, a stabilization after the time of CO₂ doubling and a ramp-down experiment, that is, a decreasing 1pctCO₂ after the time of CO₂ doubling. The latter can be considered as representative of all types of possible greenhouse gas emission scenarios. The 1pctCO₂ scenario is similar to a high-emission scenario such as RCP8.5

(Taylor et al. 2012) or ssp585 (O'Neill et al. 2016). The stabilization can be considered as representative of RCP scenarios with mitigation and the ramp-down experiment may be viewed as a geoengineering scenario. The focus of year 140 in the idealized scenario is representative of focusing on year 2100 in a particular climate change scenario.

b. Pattern effect

The importance of the pattern effect for constraining climate projections is investigated by using an EBM- $f_0-\epsilon$. At time $t = 40$ yr, the radiative response parameter is expressed as the following (G13b):

TABLE 4. Parameters of the EBM- f_{bg} - λ_T and, in parentheses, parameters of the EBM- f_{bg} - λ_T - ε . Both are calibrated with the abrupt- $4\times\text{CO}_2$ and the 1pctCO2.

Model	γ ($\text{W m}^{-2} \text{K}^{-1}$)	F_4 (W m^{-2})	λ_0^T ($\text{W m}^{-2} \text{K}^{-1}$)	ε	g_T	$\Delta T_{eq}(n_c = 4)$ (K)
CNRM-CM6.1	0.57 (0.57)	8.6 (8.3)	1.27 (1.29)	1 (0.88)	-0.04 (-0.05)	— (—)
ACCESS1.0	0.85 (0.72)	5.8 (7.0)	0.69 (0.58)	1 (1.67)	0.03 (0.26)	7.5 (8.2)
ACCESS1.3	0.83 (0.71)	6.0 (6.7)	0.92 (0.79)	1 (1.51)	-0.02 (0.15)	7.4 (8.4)
BCC-CSM1.1	0.65 (0.58)	6.8 (7.2)	1.24 (1.24)	1 (1.21)	-0.00 (0.00)	5.7 (5.8)
BCC-CSM1.1m	0.54 (0.45)	5.8 (6.6)	0.74 (0.70)	1 (1.59)	0.13 (0.23)	5.6 (5.9)
BNU-ESM	0.53 (0.53)	6.9 (7.1)	0.70 (0.69)	1 (1.08)	0.06 (0.09)	7.7 (7.8)
CanESM2	0.59 (0.54)	7.6 (8.1)	0.98 (0.96)	1 (1.29)	0.01 (0.04)	7.3 (7.6)
CCSM4	0.88 (0.79)	7.4 (8.2)	1.36 (1.42)	1 (1.28)	-0.01 (-0.04)	5.9 (6.1)
CNRM-CM5	0.50 (0.51)	7.3 (7.2)	1.14 (1.15)	1 (0.92)	-0.00 (-0.02)	6.5 (6.4)
CSIRO-Mk3.6.0	0.86 (0.69)	5.3 (6.2)	0.77 (0.65)	1 (1.59)	-0.05 (0.13)	11.6 (11.4)
FGOALS-s2	0.72 (0.68)	7.3 (7.6)	0.83 (0.82)	1 (1.14)	0.01 (0.03)	8.5 (8.8)
GFDL CM3	0.83 (0.72)	6.0 (6.6)	0.75 (0.69)	1 (1.35)	0.01 (0.11)	7.7 (8.1)
GFDL-ESM2G	0.82 (0.79)	7.8 (7.6)	2.28 (2.27)	1 (0.92)	-0.03 (-0.03)	5.7 (5.5)
GFDL-ESM2M	0.92 (0.85)	7.4 (7.8)	1.69 (1.69)	1 (1.19)	-0.01 (-0.01)	4.8 (4.9)
GISS-E2-H	0.82 (0.72)	6.1 (7.0)	0.85 (0.80)	1 (1.47)	0.19 (0.34)	4.6 (4.8)
GISS-E2-R	1.19 (1.08)	5.8 (7.5)	0.85 (0.92)	1 (1.50)	0.26 (0.25)	4.1 (4.3)
HadGEM2-ES	0.56 (0.48)	5.6 (6.3)	0.49 (0.36)	1 (1.65)	0.12 (0.51)	8.3 (9.4)
INM-CM4	0.68 (0.70)	5.6 (5.6)	1.17 (1.19)	1 (0.96)	0.05 (0.03)	4.0 (4.0)
IPSL-CM5A-LR	0.59 (0.57)	6.2 (6.5)	0.76 (0.72)	1 (1.18)	0.00 (0.06)	8.2 (8.6)
IPSL-CM5A-MR	0.59 (0.56)	7.0 (7.2)	0.99 (0.95)	1 (1.15)	-0.03 (0.01)	9.1 (9.8)
IPSL-CM5B-LR	0.72 (0.62)	5.1 (5.5)	1.05 (1.02)	1 (1.28)	-0.02 (0.01)	5.5 (5.8)
MIROC5	0.78 (0.75)	8.3 (8.2)	1.95 (1.96)	1 (0.95)	-0.03 (-0.04)	— (—)
MIROC-ESM	0.69 (0.64)	9.0 (9.2)	1.31 (1.27)	1 (1.11)	-0.03 (0.00)	— (—)
MPI-ESM-LR	0.71 (0.62)	8.8 (9.4)	1.43 (1.42)	1 (1.24)	-0.02 (-0.01)	7.6 (8.0)
MPI-ESM-MR	0.68 (0.59)	8.5 (9.3)	1.35 (1.35)	1 (1.34)	-0.01 (0.00)	7.1 (7.5)
MPI-ESM-P	0.70 (0.61)	9.1 (9.7)	1.55 (1.56)	1 (1.23)	-0.02 (-0.02)	7.3 (7.6)
MRI-CGCM3	0.67 (0.61)	6.6 (6.8)	1.32 (1.31)	1 (1.15)	-0.01 (0.00)	5.3 (5.5)
NorESM1-M	0.88 (0.77)	7.1 (7.7)	1.63 (1.62)	1 (1.32)	-0.03 (-0.02)	6.4 (7.3)
CMIP5 median	0.71 (0.64)	6.9 (7.2)	1.05 (1.02)	1 (1.24)	-0.01 (0.01)	7.1 (7.3)

$$\lambda_{t40} = \lambda + (\varepsilon - 1) \frac{H(t = 40)}{\Delta T(t = 40)}. \quad (15)$$

The reference simulations are performed with the EBM- f_0 - ε for each set of parameters. A second set of simulations is performed by fixing $\varepsilon = 1$ and $\lambda = \lambda_{t40}$. All other parameters are unchanged.

The top-left panel of Fig. 5 shows the temperature evolution of the multimodel ensemble mean of the reference EBM- f_0 - ε simulations (black lines) and the simulations with the pattern effect removed for the 1pctCO2, the stabilization and the ramp-down scenarios (colored lines). The top-center and top-right panels of Fig. 5 focus on the absolute and relative differences between the temperature at 140 years in the reference and that of the sensitivity experiments for the three scenarios. Absolute and relative differences are shown for each CMIP5 set of parameters, separately. A set of simulations with λ fixed at its $t \rightarrow 0$ value $\lambda_{t \rightarrow 0} = \lambda + (\varepsilon - 1)\gamma$ is also shown in Fig. S2.

Because the pattern effect induces an increase in effective climate sensitivity for most climate models ($\varepsilon > 1$), the mean warming is underestimated when the pattern effect is

removed. On average, the difference in TCR40 is small. The relative error varies from -8% to less than 1% with a median of -2%. In a 1pctCO2 or a RCP8.5, the surface warming pattern remains relatively constant, hence the pattern effect is small. As the climate system approaches equilibrium, the relative error increases. It theoretically increases more if the radiative imbalance and the deep-ocean heat uptake becomes negative as is the case in a ramp-down experiment. As a result, relative errors are larger for the stabilization (from -12% to 1% with a median of -3%) and even larger for the ramp-down experiment (from -38% to 9% with a median of -16%).

However, the simulations with the largest relative impact are those that experience the smallest warming. The absolute differences are small with a median error of -0.07 K for the ramp-down experiment, -0.09 K for the stabilization, and -0.10 K in the high-emission scenario. When setting the effective climate sensitivity at its $t \rightarrow 0$ value, the absolute errors remain small (with respective median errors of -0.08, -0.12, and -0.16 K) (Fig. S2). These results show that the pattern effect associated with ocean heat uptake is not a major effect to take into account for constraining climate projections from the historical warming.

FIG. 5. (left) Time evolution of the multimodel mean of the global-mean surface air temperature response of the EBM with a nonlinear effect (black lines) and that of the EBM with the effect removed (colored lines), for the 1pctCO₂ experiment (purple), the 2xCO₂ stabilization experiment (red), and the ramp-down experiment (orange). For each climate model's surrogate EBM and for each scenario, (center) absolute difference and (right) relative difference between the temperature change at $t = 140$

c. *CO₂–ERF relationship, CO₂, and T dependencies of λ*

This section investigates the importance of the CO₂–ERF relationship, CO₂, and *T* dependencies of the radiative feedbacks. These effects cannot be dissociated. One single effect at a time is assumed to fully explain the nonlinear behavior observed in the (*T*, *N*) space.

1) ASSUMPTION OF A LOG-LINEAR FORCING

First, the impact of the CO₂–ERF relationship is examined by replacing the CO₂–ERF relationship of the EBM-*f* by a log-linear relationship. At *t* = 40, the 4×CO₂ reference forcing in Eq. (6) reads

$$F_{4,t40} = F_4 \{ (1 - f) + f \log_4 [n_c(t = 40)] \}. \quad (16)$$

The second set of simulations is performed with this value of the 4×CO₂ ERF and with *f* = 0 in Eq. (6). The results are displayed in Fig. 5 (second row). Fixing the reference forcing in an EBM-*f*- ϵ gives the same results (not shown). Due to the high CO₂ level, the TCR4× relative errors are the largest with values varying from −25% to 7% with a median of −10%. This corresponds to an absolute error of −0.42 K. These errors can be due not only due to limitations in the representation of the CO₂–ERF relationship but also to the equilibrium state dependencies.

2) ASSUMPTION OF A BG14 FORCING

In a second step, the ERF is assumed to follow the relationship derived from line-by-line radiative transfer models [Eq. (7)]. By assuming no equilibrium-state dependency, the errors estimated here are those caused by the difference between the ERF predicted by the climate models and that predicted by line-by-line radiation codes. At *t* = 40, the 4×CO₂ reference forcing in Eq. (7) reads

$$F_{4,t40} = \frac{F_4 \{ (1 - f) + f \log_4 [n_c(t = 40)] \}}{\{ (1 - f_{bg}) + f_{bg} \log_4 [n_c(t = 40)] \}}. \quad (17)$$

The second set of simulations is performed with this value of the 4×CO₂ ERF and with *f* = *f*_{bg} in Eq. (6). The median relative error in the constrained warming is close to 0% for the three idealized scenarios (Fig. 5, third

row). However, the intermodel spread remains large with values ranging from −17% to 17%. When fixing the reference forcing to its *t* → 0 value $F_{4,t \rightarrow 0} = F_4(1 - f)/(1 - f_{bg})$, errors are larger by varying from −26% to 25% (Fig. S5, third row). If the climate model ensemble correctly represents the CO₂–ERF relationship, then the use of an adequate forcing would not induce any systematic error for constraining climate projections. Assuming a log-linear forcing would lead to a median underestimation of the projected warming of roughly 10% for a high-emission scenario.

3) CO₂ DEPENDENCY REMOVED IN AN EBM-*F*_{BG}- λ_c

It is now assumed that any deviation from the EBM-*f*_{bg} is due to the dependence of the radiative feedbacks on CO₂. In an EBM-*f*_{bg}- λ_c , at *t* = 40, the radiative response parameter reads

$$\lambda_{t40} = \lambda_4^c \{ (1 - g_c) + g_c \log_4 [n_c(t = 40)] \}. \quad (18)$$

The second set of simulations is performed by fixing λ to this value. The errors are roughly identical to those obtained by fixing the forcing to the BG14 relationship in an EBM-*f* (Fig. 5 and Fig. S5, fourth rows).

4) *T* DEPENDENCY REMOVED IN AN EBM-*F*_{BG}- λ_T

Finally, the *T* dependency is investigated with the help of the EBM-*f*_{bg}- λ_T . At *t* = 40, the radiative response parameter reads

$$\lambda_{t40} = \lambda_0^T \left[(1 - g_T) + g_T \frac{\Delta T(t = 40)}{ECS_0} \right]. \quad (19)$$

For the ramp-down experiment, the effect is larger with a *T* dependency than with a CO₂ dependency (Fig. 5 and Fig. S5, fourth and fifth rows). Indeed, the effective climate sensitivity at 140 years is that of the first years with a CO₂ dependency, whereas it is larger with a *T* dependency because warming is not zero at 140 years. The errors are similar to those found with the EBM-*f*_{bg}- λ_c , ranging from −15% to 25% with a median of −3% for the TCR4× (Fig. 5, fifth row). They range from −18% to 38% when fixing the feedback parameter at its *t* → 0 value $\lambda_{t \rightarrow 0} = \lambda_0^T (1 - g_T)$ (Fig. S5, fifth row).

←

years of the EBM with nonlinear effect and that of the EBM with the effect removed as a function of the temperature change of the EBM with nonlinear effect. The crosses indicate the median values of each scenario ensemble. (top) The pattern effect is removed in an EBM-*f*₀- ϵ , (second row) the forcing is assumed log linear in an EBM-*f*, (third row) the forcing is assumed to follow the BG14 relationship in an EBM-*f*, (fourth row) the dependency of λ on CO₂ is removed in an EBM-*f*_{bg}- λ_c , and (fifth row) the dependency of λ on *T* is removed in an EBM-*f*_{bg}- λ_T . Each effect is removed by fixing the corresponding variable to its 40-yr value in the 1pctCO₂.

Finally, whatever the equilibrium-state dependencies of the feedbacks at play and under the assumption that the CO₂ nonadjusted radiative forcing simulated by climate models follows the relationship predicted by line-by-line radiative models, neglecting the equilibrium state dependencies does not lead to any systematic error for constraining future warming but the spread of the errors may be significant.

7. Conclusions

In climate change studies the radiative response parameter is often assumed constant. However, it may vary due to the equilibrium-state dependencies that include the dependence of the strength of the radiative feedbacks on the temperature and on the CO₂ concentration. The radiative feedbacks can also vary with the strength of the ocean heat uptake due to its modulation of the surface warming pattern during a climate transition. In addition, the forcing is often assumed to be log-linear dependent on the CO₂ concentration, whereas this relationship is not purely logarithmic.

Once calibrated with an abrupt-4×CO₂ experiment, the linear two-layer EBM shows an overestimation of the TCR for most CMIP5 climate models. As shown by Gregory et al. (2015), limitations in the log-linear CO₂–ERF relationship and/or the inconstancy of the radiative response parameter can explain this mismatch. This can be highlighted by rescaling the 1pctCO₂ experiments to a CO₂ quadrupling in a (T , N) space. By using a quadratic formulation of the instantaneous forcing derived from line-by-line radiative transfer models rather than a linear one, the multimodel-mean TCR bias is strongly reduced.

However, a large spread remains. Much of this spread can be attributed to a deviation from the CO₂–ERF relationship derived from line-by-line radiative transfer models and/or to the equilibrium-state dependencies of the radiative feedbacks. These effects are hardly dissociable. Combined all together they significantly reduce the spread in TCR. The remaining bias may be due to limitations in the formulation of heat uptake. These results quantitatively confirm the importance of non-log forcing and/or equilibrium-state dependence of the radiative feedbacks to represent the full evolution of the warming as shown by Gregory et al. (2015).

The importance of these nonlinear effects for constraining climate projection from the historical record is investigated. The two-layer EBM calibrated with the CMIP5 ensemble is used as a perfect model. The errors induced when not taking into account these effects are evaluated for three 140-yr academic scenarios: a 1pctCO₂, a 2×CO₂ stabilization, and a ramp down. The temperature change at the end of these simulations are

used as metrics representative of global warming in 2100. Because the method of calibration of the EBM may induce overfitting, nonlinear effects may be overestimated in the EBM. These estimates must be considered as an upper bound of the errors induced by these dependencies.

For the high-emission scenario, neglecting the pattern effect does not induce an important error on the warming at the centennial scale, with a median underestimation of roughly –2% and a small spread. The pattern effect is slightly more important for mitigating scenarios that are closest to equilibrium. However, the absolute errors remain small, on the order of a few tenths of a degree or less. These results show that the pattern effect is not of major importance for constraining climate projections.

Assuming that the ERF follows a log-linear relationship may lead to underestimation of future warming of roughly 10%. By assuming that the ERF follows the same dependence as the instantaneous forcing calculated with line-by-line radiation codes (BG14), the equilibrium-state dependencies and any deviation of the ERF from this relationship do not induce any error for the multimodel ensemble median. If the multimodel ensemble is realistic, equilibrium-state dependencies can be neglected once the forcing is well represented.

However, there is some spread in the errors when considering climate models individually. Accounting for these effects in constraint studies would increase the uncertainties in climate model projections. This spread can result from a large diversity in the representation of the equilibrium-state dependencies by climate models. In addition, it is unclear how much their representation of the CO₂–ERF relationship differs from the CO₂–forcing relationship estimated by line-by-line radiative transfer models. These results highlight the importance of better understanding the CO₂–forcing relationship and the equilibrium-state dependence of the radiative feedbacks in each climate model.

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modeling groups for producing and making available their model outputs. with

$$x(t) = \log_4[n_c(t)] - 1, \quad (\text{A3})$$

APPENDIX

Calibration Methods of EBM-f

a. Calibration of the EBM-f

Except for f , the parameters of the EBM- f are those of the linear two-layer EBM. These parameters are calibrated from the abrupt-4×CO₂ experiment following (G13a). Note that the first 10 years of the simulation are used to compute the fast time scale except for GISS-E2-R and GFDL-ESM2G. Only 5 years are used for these models to avoid log of negative values.

From Eq. (6) the parameters f follows

$$\frac{1}{\log_4(n_c)} \frac{F[n_c(t)]}{F(4)} - 1 = f[\log_4(n_c) - 1]. \quad (\text{A1})$$

The parameter f is calculated as the linear regression of $y(t)$ over $x(t)$:

$$f = \frac{\sum_t x(t)y(t)}{\sum_t x(t)^2}, \quad t > 35 \text{ years}, \quad (\text{A2})$$

$$y(t) = \frac{1}{\log_4[n_c(t)]} \frac{\Delta N_{\text{GCM}}(t) + \lambda \Delta T_{\text{GCM}}(t)}{F(4)} - 1, \quad (\text{A4})$$

where $\Delta N_{\text{GCM}}(t)$ and $\Delta T_{\text{GCM}}(t)$ are the annual-mean values of the top-of-the-atmosphere radiative imbalance and surface air temperature response in the 1pctCO₂ of the climate model. The first 35 years of the 1pctCO₂ simulation are excluded because of their small signal-to-noise ratio.

b. Calibration of the EBM- $f_{bg}-\lambda_c$

As previously, except for g_c , the parameters of the EBM- $f_{bg}-\lambda_c$ are those of the linear two-layer EBM. From Eq. (13) the parameters g_c reads

$$\frac{\lambda[n_c(t)]}{\lambda(4)} - 1 = g_c[\log_4(n_c) - 1]. \quad (\text{A5})$$

It is calculated as the linear regression of $y(t)$ over $x(t)$ [Eq. (A2)] with $x(t)$ given by Eq. (A3) and

$$y(t) = \frac{1}{\lambda(4)} \frac{F_4((1 - f_{bg}) \log_4[n_c(t)] + f_{bg} \{\log_4[n_c(t)]\}^2) - \Delta N_{\text{GCM}}}{\Delta T_{\text{GCM}}} - 1. \quad (\text{A6})$$

As previously, the first 35 years of the 1pctCO₂ simulation are excluded.

c. Calibration of the EBM- $f-\varepsilon$

Except for f , the parameters of the EBM- $f-\varepsilon$ are those of the EBM- ε . They are calibrated from the abrupt-4×CO₂ experiment following (G13b). The parameter f_F is calculated from Eq. (A2), $x(t)$ is given by Eq. (A3), and $y(t)$ reads

$$y(t) = \frac{1}{\log_4[n_c(t)]} \frac{\Delta N_{\text{GCM}}(t) + \lambda \Delta T_{\text{GCM}}(t) + (\varepsilon - 1)H(t)}{F(4)} - 1. \quad (\text{A7})$$

The calculation of $y(t)$ requires knowing $(\varepsilon - 1)H(t)$ for the 1pctCO₂. It is calculated by iteration. In the first iteration, H is assumed to be zero. In the following iterations, $H(t)$ is given by the two-layer EBM- $f-\varepsilon$.

d. Calibration of the EBM- $f_{bg}-\lambda_c-\varepsilon$

The procedure is similar to that of the EBM- $f-\varepsilon$ except that the variable $y(t)$ in Eq. (A2) reads

$$y(t) = \frac{1}{\lambda(4)} \frac{F_4((1 - f_{bg}) \log_4[n_c(t)] + f_{bg} \{\log_4[n_c(t)]\}^2) - \Delta N_{\text{GCM}} - (\varepsilon - 1)H(t)}{\Delta T_{\text{GCM}}} - 1. \quad (\text{A8})$$

As previously, the parameter g_c is calculated by iteration by assuming $H(t) = 0$ in the first iteration and by taking the EBM values in the following iterations.

e. Calibration of the EBM- f_{bg} - λ_T

The parameters λ_0 and g_T in Eq. (14) can be determined from a bilinear regression of the radiative imbalance against the surface air temperature change and the square of the surface air temperature change. The intercept is the forcing and the two coefficients allow us to compute λ_0 and g_T by solving a quadratic equation. When calibrating the coefficients with both the abrupt- $4\times\text{CO}_2$ and the 1pctCO2 experiment, the first 35 years of the 1pctCO2 experiment are not used.

f. Calibration of the EBM- f_{bg} - λ_T - ε

The EBM- f_{bg} - λ_T - ε is calibrated by iteration from both the abrupt- $4\times\text{CO}_2$ and the 1pctCO2 (years 35–140) experiments. In the first iteration, parameters are taken as equal to the EBM- ε parameters. For the sake of simplicity, the parameters C and C_d are kept equal to those of the EBM- ε . The reference radiative forcing F_4 and the parameters λ_0 , g_T , and ε are calibrated from a multiple regression of the radiative imbalance against the surface air temperature change, the square of the surface air temperature change (both taken from the climate model) and the deep-ocean heat uptake H (taken from the EBM). The parameters γ is computed such that it minimizes the root-mean-square error between the EBM and the climate model for years 30–150 of the abrupt- $4\times\text{CO}_2$ simulation.

REFERENCES

- Andronova, N., M. E. Schlesinger, S. Dessai, M. Hulme, and B. Li, 2007: The concept of climate sensitivity: History and development. *Human-Induced Climate Change*, M. E. Schlesinger et al., Eds., Cambridge University Press, 5–17, <https://doi.org/10.1017/CBO9780511619472.003>.
- Armour, K. C., 2017: Energy budget constraints on climate sensitivity in light of inconstant climate feedbacks. *Nat. Climate Change*, **7**, 331–335, <https://doi.org/10.1038/nclimate3278>.
- Bloch-Johnson, J., R. T. Pierrehumbert, and D. S. Abbot, 2015: Feedback temperature dependence determines the risk of high warming. *Geophys. Res. Lett.*, **42**, 4973–4980, <https://doi.org/10.1002/2015GL064240>.
- Block, K., and T. Mauritsen, 2013: Forcing and feedback in the MPI-ESM-LR coupled model under abruptly quadrupled CO_2 . *J. Adv. Model. Earth Syst.*, **5**, 676–691, <https://doi.org/10.1002/jame.20041>.
- Byrne, B., and C. Goldblatt, 2014: Radiative forcing at high concentrations of well-mixed greenhouse gases. *Geophys. Res. Lett.*, **41**, 152–160, <https://doi.org/10.1002/2013GL058456>.
- Caldeira, K., and N. P. Myhrvold, 2013: Projections of the pace of warming following an abrupt increase in atmospheric carbon dioxide concentration. *Environ. Res. Lett.*, **8**, 034039, <https://doi.org/10.1088/1748-9326/8/3/034039>.
- Ceppi, P., and J. M. Gregory, 2017: Relationship of tropospheric stability to climate sensitivity and Earth's observed radiation budget. *Proc. Natl. Acad. Sci. USA*, **114**, 13 126–13 131, <https://doi.org/10.1073/pnas.1714308114>.
- Colman, R. A., and B. J. McAvaney, 1997: A study of general circulation model climate feedbacks determined from perturbed sea surface temperature experiments. *J. Geophys. Res.*, **102**, 19 383–19 402, <https://doi.org/10.1029/97JD00206>.
- , and —, 2009: Climate feedbacks under a very broad range of forcing. *Geophys. Res. Lett.*, **36**, L01702, <https://doi.org/10.1029/2008GL036268>.
- , S. B. Power, and B. J. McAvaney, 1997: Non-linear climate feedback analysis in an atmospheric general circulation model. *Climate Dyn.*, **13**, 717–731, <https://doi.org/10.1007/s003820050193>.
- Etminan, M., G. Myhre, E. J. Highwood, and K. P. Shine, 2016: Radiative forcing of carbon dioxide, methane, and nitrous oxide: A significant revision of the methane radiative forcing. *Geophys. Res. Lett.*, **43**, 12 614–12 623, <https://doi.org/10.1002/2016GL071930>.
- Flato, G., and Coauthors, 2013: Evaluation of climate models. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 741–866.
- Geoffroy, O., D. Saint-Martin, and A. Ribes, 2012: Quantifying the sources of spread in climate change experiments. *Geophys. Res. Lett.*, **39**, L24703, <https://doi.org/10.1029/2012GL054172>.
- , —, D. J. L. Oliv, A. Voldoire, G. Bellon, and S. Tytca, 2013a: Transient climate response in a two-layer energy-balance model. Part I: Analytical solution and parameter calibration using CMIP5 AOGCM experiments. *J. Climate*, **26**, 1841–1857, <https://doi.org/10.1175/JCLI-D-12-00195.1>.
- , —, G. Bellon, A. Voldoire, D. J. L. Oliv, and S. Tytca, 2013b: Transient climate response in a two-layer energy-balance model. Part II: Representation of the efficacy of deep-ocean heat uptake and validation for CMIP5 AOGCMs. *J. Climate*, **26**, 1859–1876, <https://doi.org/10.1175/JCLI-D-12-00196.1>.
- Good, P., W. Ingram, F. H. Lambert, J. A. Lowe, J. M. Gregory, M. J. Webb, M. A. Ringer, and P. Wu, 2012: A step-response approach for predicting and understanding non-linear precipitation changes. *Climate Dyn.*, **39**, 2789–2803, <https://doi.org/10.1007/s00382-012-1571-1>.
- , T. Andrews, R. Chadwick, J.-L. Dufresne, J. M. Gregory, J. A. Lowe, N. Schaller, and H. Shiogama, 2016: nonlinMIP contribution to CMIP6: Model intercomparison project for non-linear mechanisms: Physical basis, experimental design and analysis principles (v1.0). *Geosci. Model Dev.*, **9**, 4019–4028, <https://doi.org/10.5194/gmd-9-4019-2016>.
- Gregory, J. M., 2000: Vertical heat transports in the ocean and their effect on time-dependent climate change. *Climate Dyn.*, **16**, 501–515, <https://doi.org/10.1007/s003820000059>.
- , and J. F. B. Mitchell, 1997: The climate response to CO_2 of the Hadley Centre coupled AOGCM with and without flux adjustment. *Geophys. Res. Lett.*, **24**, 1943–1946, <https://doi.org/10.1029/97GL01930>.
- , and M. Webb, 2008: Tropospheric adjustment induces a cloud component in CO_2 forcing. *J. Climate*, **21**, 58–71, <https://doi.org/10.1175/2007JCLI1834.1>.
- , and T. Andrews, 2016: Variation in climate sensitivity and feedback parameters during the historical period. *Geophys. Res. Lett.*, **43**, 3911–3920, <https://doi.org/10.1002/2016GL068406>.
- , R. J. Stouffer, S. C. B. Raper, P. A. Stott, and N. A. Rayner, 2002: An observationally based estimate of the climate sensitivity.

- J. Climate*, **15**, 3117–3121, [https://doi.org/10.1175/1520-0442\(2002\)015<3117:AOBEOT>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<3117:AOBEOT>2.0.CO;2).
- , and Coauthors, 2004: A new method for diagnosing radiative forcing and climate sensitivity. *Geophys. Res. Lett.*, **31**, L03205, <https://doi.org/10.1029/2003GL018747>.
- , T. Andrews, and P. Good, 2015: The inconstancy of the transient climate response parameter under increasing CO₂. *Philos. Trans. Roy. Soc.*, **373A**, 20140417, <https://doi.org/10.1098/rsta.2014.0417>.
- Hansen, J., and Coauthors, 2005: Efficacy of climate forcings. *J. Geophys. Res.*, **110**, D18104, <https://doi.org/10.1029/2005JD005776>.
- Held, I. M., M. Winton, K. Takahashi, T. Delworth, F. Zeng, and G. K. Vallis, 2010: Probing the fast and slow components of global warming by returning abruptly to preindustrial forcing. *J. Climate*, **23**, 2418–2427, <https://doi.org/10.1175/2009JCLI3466.1>.
- Jonko, A. K., K. M. Shell, B. M. Sanderson, and G. Danabasoglu, 2013: Climate feedbacks in CCSM3 under changing CO₂ forcing. Part II: Variation of climate feedbacks and sensitivity with forcing. *J. Climate*, **26**, 2784–2795, <https://doi.org/10.1175/JCLI-D-12-00479.1>.
- Lewis, N., and J. Curry, 2018: The impact of recent forcing and ocean heat uptake data on estimates of climate sensitivity. *J. Climate*, **31**, 6051–6071, <https://doi.org/10.1175/JCLI-D-17-0667.1>.
- Manabe, S., and K. Bryan, 1985: CO₂-induced change in a coupled ocean-atmosphere model and its paleoclimatic implications. *J. Geophys. Res.*, **90**, 11 689–11 707, <https://doi.org/10.1029/JC090iC06p11689>.
- , R. J. Stouffer, M. J. Spelman, and K. Bryan, 1991: Transient responses of a coupled ocean-atmosphere model to gradual changes of atmospheric CO₂. Part I. Annual mean response. *J. Climate*, **4**, 785–818, [https://doi.org/10.1175/1520-0442\(1991\)004<0785:TROACO>2.0.CO;2](https://doi.org/10.1175/1520-0442(1991)004<0785:TROACO>2.0.CO;2).
- Meraner, K., T. Mauritsen, and A. Voigt, 2013: Robust increase in equilibrium climate sensitivity under global warming. *Geophys. Res. Lett.*, **40**, 5944–5948, <https://doi.org/10.1002/2013GL058118>.
- Murphy, J. M., 1995: Transient response of the Hadley Centre coupled ocean-atmosphere model to increasing carbon dioxide. Part III: Analysis of global-mean response using simple models. *J. Climate*, **8**, 496–514, [https://doi.org/10.1175/1520-0442\(1995\)008<0496:TROTHC>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<0496:TROTHC>2.0.CO;2).
- Myhre, G., E. J. Highwood, K. P. Shine, and F. Stordal, 1998: New estimates of radiative forcing due to well mixed greenhouse gases. *Geophys. Res. Lett.*, **25**, 2715–2718, <https://doi.org/10.1029/98GL01908>.
- O'Neill, B. C., and Coauthors, 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.*, **9**, 3461–3482, <https://doi.org/10.5194/gmd-9-3461-2016>.
- Otto, A., and Coauthors, 2013: Energy budget constraints on climate response. *Nat. Geosci.*, **6**, 415–416, <https://doi.org/10.1038/ngeo1836>.
- Proistosescu, C., and P. J. Huybers, 2017: Slow climate mode reconciles historical and model-based estimates of climate sensitivity. *Sci. Adv.*, **3**, e1602821, <https://doi.org/10.1126/sciadv.1602821>.
- Rohrschneider, T., B. Stevens, and T. Mauritsen, 2019: On simple representations of the climate response to external radiative forcing. *Climate Dyn.*, **53**, 3131–3145, <https://doi.org/10.1007/s00382-019-04686-4>.
- Senior, C. A., and J. F. B. Mitchell, 2000: The time-dependence of climate sensitivity. *Geophys. Res. Lett.*, **27**, 2685–2688, <https://doi.org/10.1029/2000GL011373>.
- Sherwood, S. C., S. Bony, O. Boucher, C. Bretherton, P. M. Forster, J. M. Gregory, and B. Stevens, 2015: Adjustments in the forcing-feedback framework for understanding climate change. *Bull. Amer. Meteor. Soc.*, **96**, 217–228, <https://doi.org/10.1175/BAMS-D-13-00167.1>.
- Shi, G., 1992: Radiative forcing and greenhouse effect due to the atmospheric trace gases. *Sci. China*, **35B**, 217–219.
- Smith, C. J., P. M. Forster, M. Allen, N. Leach, R. J. Millar, G. A. Passerello, and L. A. Regayre, 2018: FAIR v1.3: A simple emissions-based impulse response and carbon cycle model. *Geosci. Model Dev.*, **11**, 2273–2297, <https://doi.org/10.5194/gmd-11-2273-2018>.
- Stevens, B., S. C. Sherwood, S. Bony, and M. J. Webb, 2016: Prospects for narrowing bounds on Earth's equilibrium climate sensitivity. *Earth's Future*, **4**, 512–522, <https://doi.org/10.1002/2016EF000376>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Voltaire, A., and Coauthors, 2019: Evaluation of CMIP6 DECK experiments with CNRM-CM6-1. *J. Adv. Model. Earth Syst.*, **11**, 2177–2213, <https://doi.org/10.1029/2019MS001683>.
- Wetherald, R. T., and S. Manabe, 1988: Cloud feedback processes in a general circulation model. *J. Atmos. Sci.*, **45**, 1397–1416, [https://doi.org/10.1175/1520-0469\(1988\)045<1397:CFPIAG>2.0.CO;2](https://doi.org/10.1175/1520-0469(1988)045<1397:CFPIAG>2.0.CO;2).
- Winton, M., K. Takahashi, and I. M. Held, 2010: Importance of ocean heat uptake efficacy to transient climate change. *J. Climate*, **23**, 2333–2344, <https://doi.org/10.1175/2009JCLI3139.1>.
- WMO, 1999: Scientific assessment of ozone depletion: 1998. Global Ozone Research and Monitoring Project, WMO Rep. 44, 558 pp., https://library.wmo.int/doc_num.php?explnum_id=7304.