Estimating remaining carbon budgets using emulators of CMIP6 models

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A remaining carbon budget (RCB) estimates how much CO_2 we can emit and still reach a specific temperature target. The RCB concept is attractive since it easily communicates to the public and policymakers, but RCBs are also subject to uncertainties. The expected warming levels for a given carbon budget has a wide uncertainty range, which we show here to increase with less ambitious targets, i.e., with higher CO_2 emissions and temperatures. We demonstrate that the leading cause of the revealed RCB uncertainty is the spread in the equilibrium climate sensitivity (ECS) among climate models. In the Coupled Model Intercomparison Project Phase 6 (CMIP6) ensemble, the models with the lower ECS predict an RCB that is twice as high as that of models with the higher ECS, for temperature targets between 1.5-3.0°C.

The concept of remaining carbon budgets (RCBs) is appealing and highly applicable to cli-

mate mitigation policy. It allows us to relate a specific climate target to the remaining greenhouse gases humans can release into the atmosphere and still comply with this target. However, like all simple ideas in climate science, it demonstrates ambiguities and uncertainties. Ambiguities arise as the number of specific definitions of temperature targets and RCBs increase during efforts to make concepts and procedures precise. Uncertainties follow from these ambiguities and, more importantly, from the large spread in the projections of state-of-the-art climate and Earth system models (ESMs). Notably, the spread across different models and the corresponding uncertainties in both their equilibrium climate sensitivity (ECS) and RCBs do not seem to diminish with increasing model complexity. The state-of-the-art versions of ESMs included in the Coupled Model Intercomparison Project Phase 6 (CMIP6) show a span in ECS of 1.6–5.6 K with 10 models out of 27 exceeding 4.5 K[1]. The increase in ECS is primarily linked to a stronger positive cloud feedback in some of the models, although this is still under investigation. The appealing simplicity tends to be lost in a plethora of specialized papers, and recent reviews[2,3] hardly resolve this.

The present paper is based on the general observation and insight that the dominating uncertainty of the RCB is the large spread in the projections by the ESMs. This uncertainty is much more critical than the ambiguities that arise from the varying definitions of climate targets and estimations of RCBs. We employ definitions based on generally accepted results from the climate modeling literature, while keeping them operational and straightforward.

It has been revealed that there is an approximate scenario independence in the relationship between the cumulative emissions and the global mean surface temperature (GMST) over a consid-

erable range of realistic mitigation scenarios[2–4]. More precisely, there is an approximately linear relationship between the cumulative emissions and the peak temperature. The increase in peak temperature per unit of emitted CO_2 is called the effective transient climate response to cumulative emissions of carbon (TCRE). By estimating the TCRE, one can obtain the RCBs for different climate targets. For instance, suppose that we run a climate model for ambitious scenarios where the annual emissions decay to zero (Fig. 1a). As we will argue below, the maximum GMST in each scenario will occur close to when the emissions have dropped to zero. We can plot this maximum GMST versus the cumulative emissions after 2018 up to that time, as shown in Fig. 1b. Here we have used 86 emission scenarios from the Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis (IIASA)[5] evaluated by the intermediate complexity model MAGICC (Model for the Assessment of Greenhouse-gas-Induced Climate Change)[6]. The slope of a straight line regressed to this plot serves as an estimate of TCRE based on this single climate model. We define a climate target as a particular GMST-value, e.g., 2.0 °C above the pre-industrial baseline, and the corresponding RCB for this particular climate model as the corresponding cumulative emissions obtained from this regression line (Fig. 1b).

The transient climate response obtained by this procedure is the so-called *effective* TCRE, since the emission scenarios applied to obtain the points in Fig. 1b contain other anthropogenic emissions than CO_2. The effective TCRE accounts for warming from other greenhouse gases than CO_2, most importantly methane, and for cooling effects due to atmospheric aerosols. In contrast, the CO_2-only TCRE is defined as the warming attributable to CO_2 forcing alone. One can estimate the CO_2-only TCRE from ESM experiments, driven by atmospheric CO_2 concentration

increases of 1% per year. The CO_2 emissions can be derived from the specified atmospheric CO_2 concentrations and the atmosphere-ocean and atmosphere-land CO_2-fluxes, and hence the CO_2-only TCRE can be computed by dividing the GMST increase by the cumulative emissions. Using 15 CMIP5 models, Gillett et al.[7] find CO_2-only TCRE in the range $0.22-0.65$°C per 1000 Gt CO_2, with a mean of 0.44°C per 1000 Gt CO_2. With the current GMST at 1.1°C above the pre-industrial baseline, this estimate corresponds to a remaining CO_2-only budget (from present) of 1080 Gt CO_2 for the 1.5°C target, 2430 Gt CO_2 for the 2.0°C target, and 5140 Gt CO_2 for a 3.0°C target.

The basis of these estimates are scenarios where atmospheric CO_2 concentration increases by 1% per year, and not scenarios where we reduce emissions to mitigate climate change. One may argue that these estimates of TCRE do not take into account the effect of ”warming in the pipeline“ due to a large thermal inertia of the oceans, and therefore a slow temperature response to a forcing. However, this warming is the increase of surface temperature we would experience if the atmospheric CO_2 concentration stabilizes at a given level, not if emissions are rapidly reduced to zero. In the latter case, ESM experiments indicate that as emissions are strongly reduced, the historic emission-driven imbalance in the carbon cycle would lead to a reduction of atmospheric CO_2 due to uptake in the oceans. This will fast offset the radiative imbalance at the top of the atmosphere implying no further warming[8].

Hence, the net result is that in scenarios where emissions are brought to zero at a given time and then kept constant, GMST will remain approximately constant for centuries after this time. More generally, in all realistic scenarios and at any point in time, the instantaneous GMST is pro-

portional to the cumulative emissions up to that time. Future temperature change is approximately independent of the history of past emissions, it is dependent only on their total amount[8]. Hence, scenarios with 1% annual CO_2-concentration increase are relevant: When the GMST exceeds a given temperature target in such a scenario, we can envisage that the emissions drop abruptly to zero, and the GMST will hereafter slowly decrease. Moreover the cumulative emissions for a given temperature target is independent of scenario. For instance, the cumulative emissions in the 1% scenario corresponding to a given temperature target will match the cumulative emissions up to the time when annual emissions have dropped to zero in *any* scenario for which the GMST stabilizes at this target. Since the GMST stops increasing once the emissions have dropped to zero, the above claim also holds if there are negative emissions after the GMST-maximum is reached[8].

There are several ways of adjusting CO_2-only TCREs and RCBs to obtain their effective counterparts. One method is to estimate the fraction of the total radiative forcing attributable to anthropogenic CO_2-emissions. In the CMIP5 ensemble, the multi-model mean ratio of CO_2 forcing to total anthropogenic forcing has been estimated to be 0.86[8,9], which yields a multi-model mean effective TCRE of 0.51°C per 1000 Gt CO_2 based on the CO_2-only estimate[7] of 0.44°C per 1000 Gt CO_2.

Another approach[8] is to estimate the effective TCRE by dividing the observed 1861-2015 GMST increase of 0.99°C by the 1870-2015 cumulative CO_2 emissions of 2035 Gt CO_2 to obtain TCRE $= 0.49$°C per 1000 Gt CO_2. However, in ambitious yet realistic future mitigation scenarios, where emissions are brought rapidly to zero in this century, the ratio of CO_2 forcing to total

anthropogenic forcing may deviate from the historical estimates. In this case, it is necessary to make assumptions regarding the time evolution of this ratio. The method applied in this paper is to analyze scenarios constructed using integrated assessment models (IAMs)[5] (Fig. 1a). Hence, here the total CO_2 and methane emissions are known, and we make assumptions only on the evolution of aerosol emissions as greenhouse gas emissions are reduced to zero.

From the emission scenarios, we can obtain corresponding temperatures from an Earth model of intermediate complexity (EMIC) model such as MAGICC[6]. However, using a single climate model does not consider the large spread in climate model projections. To assess the uncertainties in RCBs, one should ideally explore an ensemble of realistic mitigation scenarios using the full set of ESMs in the CMIP6 ensemble, which is not feasible due to the computational costs. In this study, we construct emulators of ESMs in the CMIP6 ensemble based on $4\times CO_2$-runs of the models. We use impulse-response models to approximate how the atmospheric CO_2 concentrations depend on greenhouse gas emissions. From the emulators, we can analyze the relationship between cumulative emissions and peak temperatures, and estimate TRCE and RCBs. Our simple modeling set-up is described in the Methods section.

Results

Our ESM emulators show that the linear relationship between total emissions and maximum GMST is an excellent approximation for each climate model, but that the TCRE varies considerably over the model ensemble (Fig. 2a). Using the carbon impulse response fitted to the multi-

model mean in the ensemble of Joos *et al.*[10] we find mean TCRE for peak warming of 0.58°C per 1000 Gt CO2, with a 66% likely range of 0.46-0.73°C per 1000 Gt CO2 (See the histogram and the solid black curve in Fig. 2b). Using the upper and lower ranges of CO_2 concentrations in the ensemble of CO_2-pulse simulations[10], i.e. plus/minus one standard deviation, we find mean TCREs for peak warming of 0.53°C and 0.63°C per 1000 Gt CO2, respectively. The 66% likely ranges are 0.49-0.78°C per 1000 Gt CO2 and 0.42-0.66 °C per 1000 Gt CO2 (see the dashed and dotted curves in Fig. 2b). The probability density functions (PDFs) for the TCRE can be translated into PDFs for the 1.5, 2.0, 2.5, and 3.0°C climate targets (Fig. 3) and allow us to compute confidence ranges for the RCB for each target. We can also compute these PDFs for each target, and the RCB gives a 50% (or 66%) chance to meet the target (Table 1).

The estimated TCRE for peak warming correlates strongly with the estimated ECS of the ESMs (Fig. 3a). The correlation coefficient is $\rho = 0.94$, and the statistical significance is $p = 10^{-19}$. The estimated relationship is

$$\text{TCRE} = A + B\,\text{ECS}\,,$$

with $A = 0.2$ °C per 1000 Gt CO2 and $B = 0.1$ °C per K per 1000 Gt CO2. The ECS ranges from 1.8 to 5.6 K in the CMIP6 ensemble, corresponding to a range of 0.4 to 0.8°C per 1000 Gt CO2 in TCRE. Assuming a linear relationship between cumulative positive emissions and peak temperature, the RCB for a given peak temperature target varies by a factor of two over the model ensemble.

For the climate models with ECS > 4.0 K, the mean TCRE for peak warming is 0.71°C per

1000 Gt CO2, with a 66% likely range of 0.66-0.77°C per 1000 Gt CO2. For the climate models with ECS < 4.0 K, the mean TCRE for peak warming is 0.51°C per 1000 Gt CO2, with a 66% likely range of 0.44-0.59°C per 1000 Gt CO2. The corresponding difference in RCB grows linearly with the temperature target (Fig. 4b and Supplementary Fig. 1).

Over the ensemble of scenarios, the multi-model mean GMST response of the CMIP6 emulators align closely with the estimates from the MAGICC model (Supplementary Fig. 4). This agreement provides evidence that our results are consistent with previous results in terms of averages. At the same time, our approach has the advantage that we can quantify the uncertainties based on the spread over the different CMIP6 models.

Discussion

Our analyses show that estimates of RCBs are associated with considerable uncertainty, which is mainly due to the uncertainty in the global temperature response to radiative forcing, quantified for example as the spread over different members of the CMIP6 model ensemble. We further show that model estimates of TCRE correlate strongly with ECS. The estimated uncertainty in TCRE corresponds directly to the uncertainty in RCB, which we find to grow linearly with the GMST target. Hence, the less ambitious the temperature target, the higher the uncertainty in the corresponding RCB. There is an additional source of uncertainties that are not accounted for, induced by positive feedbacks in the dynamics of the Earth system. For example, permafrost thawing in response to rising surface temperatures leads to the release of greenhouse gases that

had been stored in high-latitude soils for centuries to millennia, thereby extracted from the carbon cycle. The release of these additional greenhouse gases will in turn accelerate global warming.

The Amazon rainforest gives a second example of such a positive feedback. It has been argued and observed in climate model projections that the Amazon ecosystem might transition from its current rainforest state to a state dominated by grassland and savanna vegetation[11–14] which would be accompanied by the release of large amounts of CO_2 to the atmosphere: Carbon-cycle feedbacks have an overall accelerating effect on global warming[15], and the situation seems particularly evident for the Amazon. Increasing tree mortality during a transition from rainforest to Savanna will cause the rainforest to turn from a global carbon sink to a global source of carbon[16], as has already happened temporarily during the severe droughts of 2005 and 2010[17]. Climate-change-induced dieback of the Amazon would lead to the release of additional greenhouse gases, which would further accelerate global temperature rise.

The Amazon rainforest also provides an example of how anthropogenic forcing other than greenhouse gas release can affect the climate system: Modelling evidence suggests that only partial deforestation of the Amazon rainforest might – through intricate couplings between evapotranspiration, condensational latent heating, and the South American low-level circulation system – lead to a collapse of the South American monsoon system and thus, ultimately, of the Amazon rainforest[18].

As a third example, the ice-albedo feedback implies rising temperatures, e.g., in the Arctic, leading to accelerating sea ice retreat, lowering albedo, and effectively increasing mean surface

temperatures regionally. This positive feedback contributes to the so-called Arctic amplification, i.e., the observation that Arctic temperatures have been rising much faster than the global average.

The uncertainty introduced by these kinds of positive feedbacks is – due to their nonlinearity – also likely to increase with higher temperature targets. In the Arctic, for example, where the sensitivity of temperature to global emissions is stronger than globally, the uncertainty in TCRE translates to even more considerable uncertainty in the amount of greenhouse gas emissions we can allow to still limit peak temperature to specified targets. These three examples of positive Earth system feedbacks are all – in some form – implemented in state-of-the-art models such as the ones from the CMIP6 suite, and systematic searches have revealed many abrupt transitions related to such positive feedbacks in model projections[19]. Nevertheless, such feedbacks are most likely associated with the largest uncertainties in model projections, and it is still assumed that state-of-the-art models remain too stable[20]. The presence of positive feedbacks and potential tipping points within the Earth system adds a layer of uncertainty on RCBs that is extremely difficult to quantify.

Methods

We use a simple modeling set-up where atmospheric CO_2 concentrations are computed from emissions through an impulse response function that describes the ratio of emitted CO_2 absorbed by land and ocean, the ratio that remains in the atmosphere, and the characteristic time scales of absorption. The form of the response function is derived from CO_2 pulse experiments in a carbon model intercomparison project[10]. We make crude assumptions about how methane and aerosol emissions depend on CO_2 emissions, determine resulting concentrations as linear responses to CO_2

emissions, and then compute the global radiative forcing using standard relations. The GMST is eventually computed from the radiative forcing using linear response models (essentially equivalent to three-box energy balance models[21]) with parameters fitted to $4\times CO_2$ experiments in ESMs (See Supplementary Fig. 2). These box models work as emulators of the ESMs for GSMT.

We model the concentrations of CO_2 and methane as linear responses of scenario data for emissions, $E_{\mathrm{CO_2}}(t)$ and $E_{\mathrm{CH_4}}(s)$:

$$[\mathrm{CO_2}] = 280\,\mathrm{ppm} + \int_{t_0}^{t} G_{\mathrm{CO_2}}(t-s)E_{\mathrm{CO_2}}(s),\, ds$$

and

$$[\mathrm{CH_4}] = 700\,\mathrm{ppb} + \int_{t_0}^{t} G_{\mathrm{CH_4}}(t-s)E_{\mathrm{CH_4}}(s)\, ds\,.$$

The time t_0 refers to the year 1750, and the concentrations 280 ppm and 700 ppb are the preindustrial concentrations of CO_2 and methane, respectively. The impulse response function for CO_2 is of the form

$$G_{\mathrm{CO_2}}(t) = c_0 + \sum_{i=1}^{4} c_i e^{-t/\tau_i}\,.$$

We use the results for the CO_2 fraction remaining in the atmosphere from 1 to 1000 years after a 100 GtC pulse from the CO_2 impulse experiments[10] to calibrate this response function. Parameters for the impulse response functions are obtained by fitting to the multi-model mean and the curves for the mean plus/minus one standard deviation. Estimated parameters are given in the Supplementary information for this paper.

Methane concentration is modeled using a response function $G_{\mathrm{CH_4}}(t) = c\,e^{-t/\tau}$ with $c = 0.34$ ppb/(Mt CH_4 per yr) and $\tau = 12.3$ yrs. The factor c is chosen to yield the observed atmospheric

methane concentration in 2019 of 1880 ppb and based on the emissions since 1750. We model methane emissions to be proportional to CO_2 emissions before 2018: $E_{\mathrm{CH_4}}(t) = aE_{\mathrm{CO_2}}(t)$ with $a = 11.9$ (ppb CH_4)/(ppm CO_2). After 2018 we assume a quadratic relationship fitted to the empirical relationship between CO_2 and methane emissions in the scenario data base[5]. (See Supplementary Fig. 4). The quadratic relationship ensures that methane emissions remain positive even if CO_2 emissions become negative.

Forcing is computed from emissions using the approach of Myhre *et al.*[22]: The radiative forcing associated with atmospheric CO_2 is

$$F_{\mathrm{CO_2}} = \frac{F_{2\times\mathrm{CO_2}}}{\log 2} \log\left(1 + \frac{[\mathrm{CO_2}] - 280\,\mathrm{ppm}}{280\,\mathrm{ppm}}\right),$$

where $F_{2\times\mathrm{CO_2}}$ is the forcing associated with a CO_2-doubling. This number is model-dependent and obtained from the Gregory plots for the abrupt $4\times$$CO_2$ experiments in the CMIP6 ensemble[23]. The radiative forcing associated with atmospheric methane is modelled as

$$F_{\mathrm{CH_4}} = p\Big(\sqrt{\frac{[\mathrm{CH_4}]}{\mu}} - \sqrt{\frac{700\,\mathrm{ppm}}{\mu}}\Big),$$

where $\mu = 1\,\mathrm{ppm}$ and $p = 0.036\,\mathrm{W/m^2}$ describes the potential of methane as a greenhouse gas. Aerosol forcing is assumed to be negative with magnitude proportional to CO_2 emissions but assumed not to go below $-0.4\,\mathrm{W/m^2}$ as emissions are reduced:

$$F_{\mathrm{aero}} = \begin{cases} bE_{\mathrm{CO_2}} & \text{if } E_{\mathrm{CO_2}} > 20 \text{ Gt CO}_2 \text{ per yr} \\ -0.4\ \mathrm{W/m^2} & \text{otherwise} \end{cases},$$

with $b = -0.02$ W/m^2 per Gt CO_2 obtained from the ratio between CO_2 forcing and aerosol forcing since the preindustrial period[24]. Our analyses show that the overall conclusions of this study

are not sensitive to the assumed aerosol forcing of -0.4 W/m^2 after reaching net-zero emissions.

Our model for GMST is

$$T(t) = \int_{t_0}^{t} G_T(t-s) F_{\text{tot}}(s) ds \,,$$

with $F_{\text{tot}} = F_{\text{CO}_2} + F_{\text{CH}_4} + F_{\text{aero}}$ and

$$G_T(t) = \sum_{i=1}^{3} d_i e^{-t/\tau_i} \,.$$

The time scales τ_i are chosen to be 1, 10, and 100 yrs, and the factors d_i are estimated from the first 150 yrs in $4\times\text{CO}_2$ experiments in CMIP6 using linear regression (Supplementary Fig. 2). The results are not sensitive to the choice of time scales[21].

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Data and code availability Emission scenarios are openly available[5] and model output from CMIP6 from is available from `https://esgf-node.llnl.gov/projects/cmip6/`. The code for carrying out the analyses presented in this paper is available from `https://site.uit.no/cosmo/`

Author contributions MR, AJ, AM, EM, NB, and KR designed the study with input from all authors. KE and HF processed the CMIP6 data and estimated ECS values. MR, AJ, AM, and EM carried out the analyses. MR, NB, RG, and KR wrote the manuscript with input from all authors.

Target (°C)	50%-chance RCB (Gt CO_2)	66%-chance RCB (Gt CO_2)
1.5	421	330
2.0	1274	1119
2.5	2168	1920
3.0	3064	2721

Table 1 Estimated RCBs based on the emulators of ESMs in the CMIP6 ensemble.

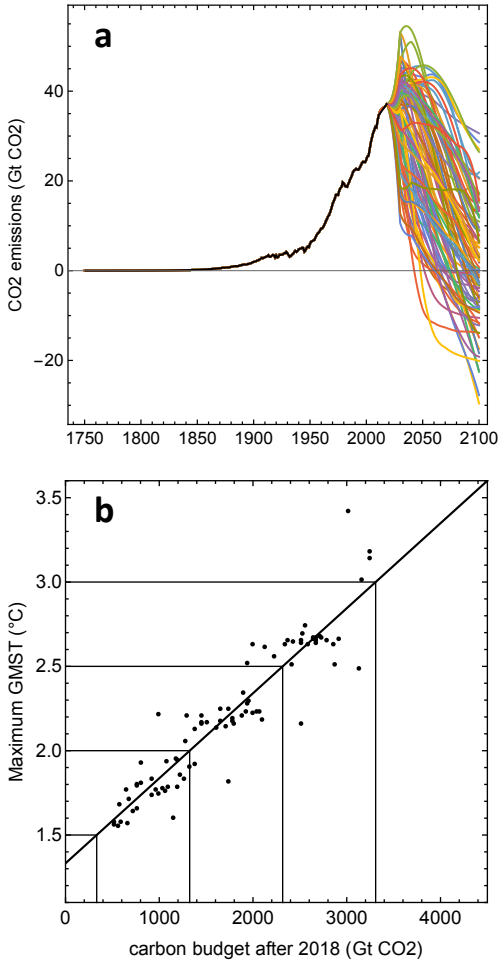

Fig. 1 Emission scenarios and RCB estimates from the MAGICC model. **a** The 86 emission scenarios analyzed in this paper. They are collected from the Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis (IIASA)[5]. **b** The plot shows peak GMST versus cumulative positive emissions after 2018 evaluated by the MAGICC model. The lines explicitly show the RCBs for this particular model, for the GMST targets 1.5, 2, 2.5, and 3°C.

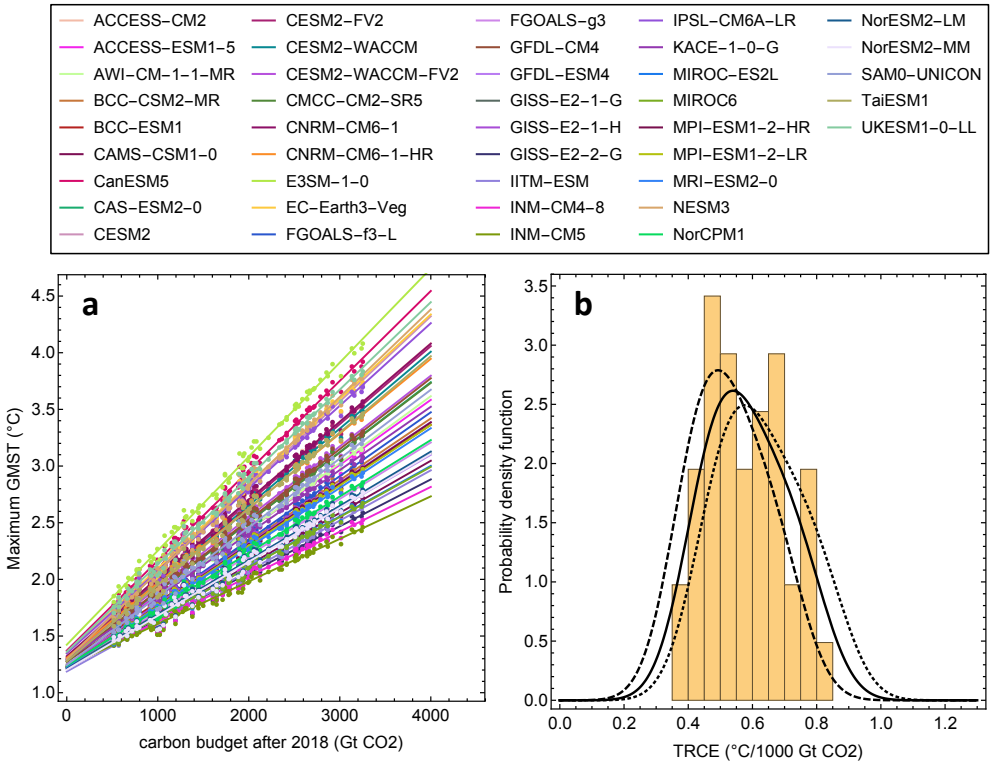

Fig. 2 Estimates of TRCE from CMIP6 emulators. **a** Shows the approximately linear relationship between total positive CO_2 emissions between 2018 and 2100 and the maximum GMST for 86 emission scenarios and evaluated with emulators of 41 different climate models in the CMIP6 ensemble. Each color represents a climate model and each point an emission scenario. The lines are fitted for each model using linear regression. **b** The histogram shows the distribution of the TCRE obtained from the slopes of the linear fits in Fig. 2a for the 41 different climate model emulators. The solid curve is a smooth kernel estimate of the probability density. The dotted and dashed curves are the estimated probability densities for the TCRE when we use the upper- and lower ranges (model mean plus/minus one standard deviation) of the impulse-response carbon model.)

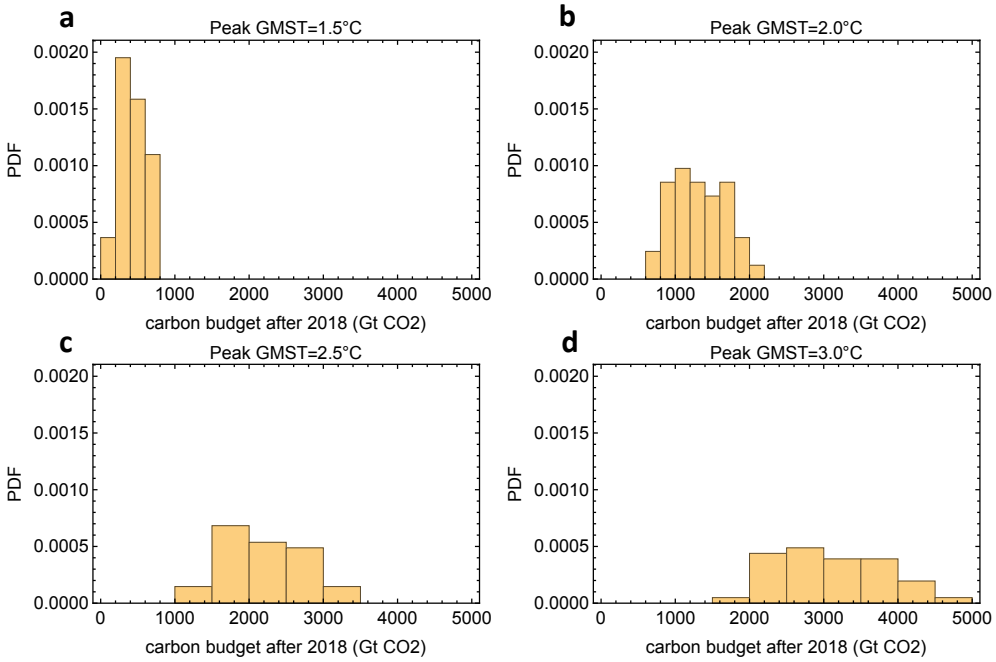

Fig. 3 Estimates of RCB for different temperature targets. a,**b**,**c**, and **d** show the results for the 1.5, 2.0, 2.5, and 3.0 °C-targets, respectively.

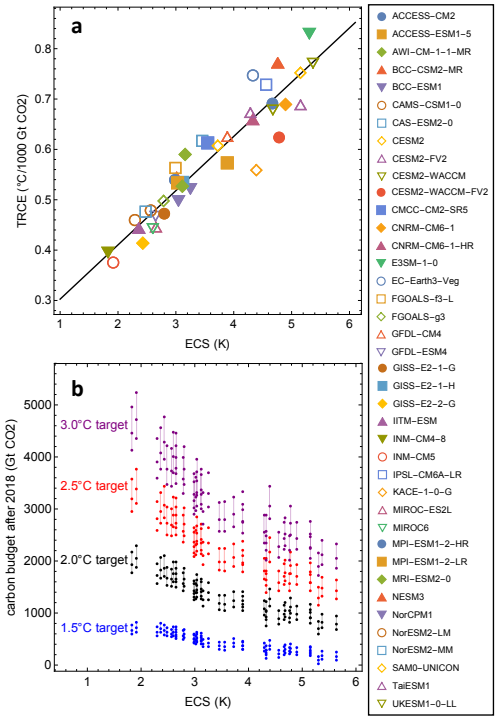

Fig. 4 The relationship between RCBs and ECS in the CMIP6 ESM emulators. **a** Shows the approximately linear relationship between the TCRE of the ESM emulators and the ECS estimated from Gregory-plots for 41 models in CMIP6. **b** Shows the RCBs for different maximum GMST targets as against the ECS of the climate model. The points are obtained using the multi-model mean impulse-response carbon model and the upper- and lower ranges (multi-model mean plus/minus one standard deviation).