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Quantifying the probability distribution function of the transient climate response to cumulative CO₂ emissions

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Abstract

The Transient Climate Response to Cumulative CO₂ Emissions (TCRE) is the proportionality between global temperature change and cumulative CO₂ emissions. The TCRE implies a finite quantity of CO₂ emissions, or carbon budget, consistent with a given temperature change limit. The uncertainty of the TCRE is often assumed to be normally distributed, but this assumption has yet to be validated. We calculated the TCRE using a zero-dimensional ocean diffusive model and a Monte-Carlo error propagation (n = 10,000,000) randomly drawing from probability density functions of the climate feedback parameter, the land-borne fraction of carbon, radiative forcing from an e-fold increase in CO₂ concentration, effective ocean diffusivity, and the ratio of sea to global surface temperature change. The calculated TCRE has a positively skewed distribution, ranging from 1.1 to 2.9 K EgC⁻¹ (5–95% confidence), with a mean and median value of 1.9 and 1.8 K EgC⁻¹. The calculated distribution of the TCRE is well described by a log-normal distribution. The CO₂-only carbon budget compatible with 2 °C warming is 1100 PgC, ranging from 700 to 1800 PgC (5–95% confidence) estimated using a simplified model of ocean dynamics. Climate sensitivity is the most influential Earth System parameter on the TCRE, followed by the land-borne fraction of carbon, radiative forcing from an e-fold increase in CO₂, effective ocean diffusivity, and the ratio of sea to global surface temperature change. While the uncertainty of the TCRE is considerable, the use of a log-normal distribution may improve estimations of the TCRE and associated carbon budgets.

1. Introduction

To avoid the most severe impacts of climate change the Paris Agreement aims to limit global warming to well below 2 °C relative to pre-industrial temperatures, and to pursue efforts to limit the warming to 1.5 °C [1–4]. Carbon dioxide is the principal driver of anthropogenic climate change due to its longevity [5–7] and the quantity of anthropogenic emissions of this gas [2, 8–13]. Due to the saturation effect the radiative forcing per unit change in atmospheric CO₂ concentration decreases with increased atmospheric CO₂ concentrations. Simultaneously the heat and carbon uptake efficiency of the ocean decreases with increased radiative imbalance and atmospheric CO₂ concentrations. The combined effect of these complex nonlinear processes is a near linear increase in global surface air temperature with increased cumulative CO₂ emissions, known as the as the Transient Climate Response to Cumulative CO₂ Emissions (TCRE) [2, 3, 6, 10, 14–16]. The finding of a linear relationship between CO₂ emissions and global mean temperature change has climate policy significance, suggesting that any given warming target is associated with a cumulative quantity of CO₂ emissions, regardless of the emission scenario followed [10, 11, 14, 16–19]. The TCRE allows the development of a ‘carbon-budget’, which conveys the total allowable quantity of CO₂ emissions consistent with not exceeding a certain temperature change limit [2, 4, 6, 11, 19–22].
Carbon budgets are effective climate policy tools [1, 6, 10, 20, 22–24], yet their application is challenged by scientific uncertainty in the TCRE, translating into an extensive breadth of estimated allowable CO2 emissions compatible with a given temperature target [2, 8, 12, 19, 24–27]. While total carbon budgets reflect the amount of CO2 emissions that can be released from the preindustrial period on, including past, present, and future CO2 emissions, remaining carbon budgets are estimates of the amount of CO2 emissions that can be released in the future without surpassing a given global warming temperature change limit [19]. The remaining carbon budget must also account for non-CO2 forcing, which reduces allowable CO2 emissions, and thus makes the policy relevance of the metric more complex [24]. CO2-only total carbon budgets can be estimated by dividing a warming target by the TCRE, and remaining CO2-only carbon budgets can be estimated by either dividing the remaining allowable warming with the TCRE or computing the total CO2-only carbon budget and subtracting emissions to date [19, 24]. However remaining carbon budgets estimated this way assume a normality in the TCRE which may not fully hold under constant, declining, or zero emissions [2, 28].

The Intergovernmental Panel on Climate Change (IPCC) Special Report on the impacts of global warming of 1.5 °C (SR1.5) suggested a median 2 °C carbon budget from 2018 onwards of about 410 PgC (rounded to the nearest 5 PgC) corresponding to the 50th percentile of the TCRE distribution. The 67th to 33rd TCRE percentile range by the SR1.5 corresponds to a 2 °C remaining carbon budget range of 320–550 PgC [24], equivalent to about 37, and 29–50 years of emissions at current emission rates of 11 PgC yr−1, respectively. While CO2-only budgets constructed from TCRE inversion assume CO2 is the sole climate forcing agent, in reality non-CO2 greenhouse gases and aerosols influence temperature change [11, 14, 15, 19, 24, 29]. The IPCC SR1.5 report indicates uncertainty due to non-CO2 forcing may reduce the remaining median carbon budget for 1.5°C warming by 177 PgC or increase the budget by 123 PgC, due largely to the asymmetric influence associated with future declining sulfate aerosol emissions and uncertainty due to non-CO2 scenario variation [24]. With this caveat in mind, the TCRE can still be useful in prescribing allowable cumulative CO2 emissions.

The probability density function (PDF) of the TCRE is often assumed to be a normal distribution [7, 14, 16, 30]. However, there is little evidence to support the assumption of a normally distributed TCRE [19], and this assumption may have been an artefact inherited from the ensemble of opportunity within CMIP5 models. The Fifth Assessment Report of the IPCC (AR5) did not assess the PDF shape compatible with the proposed likelihood range for the TCRE, though the SR1.5 acknowledged the TCRE may have a normal or log-normal PDF, while not suggesting one as more likely than the other.

The SR1.5 chose to represent the influence of imprecise TCRE distribution uncertainty as +27 to +54 PgC for the 1.5 °C remaining carbon budget [24] showing the influence of an assumed log-normal rather than normal distribution. Previous studies show that climate sensitivity has a strong influence on estimates of the TCRE [31, 32]. MacDougall et al [31] observed a small positive skew in a histogram of TCRE values produced through 150 perturbed physics ensemble simulations conducted with an Earth System Model (ESM) of intermediate complexity, and suggested the positive skew of the TCRE is due to the long tail of the climate sensitivity PDF. Climate sensitivity is generally represented with a positively skewed distribution [8, 33–35], which may translate into the TCRE distribution [19, 30]. Puyo [35] provide arguments for the assumption of a log-normal PDF for prior distributions of the climate sensitivity parameter, their arguments also apply to the TCRE.

The uncertainty in the TCRE is the result of primarily uncertainty in climate sensitivity [17, 33] followed by uncertainty in the carbon cycle response to CO2 emissions [2, 10]. The transient climate response (TCR), represents the transient warming response to a doubled atmospheric CO2 concentration relative to pre-industrial levels [33]. Equilibrium climate sensitivity (ECS) is defined as the warming response to a doubled atmospheric CO2 concentration relative to pre-industrial levels after the climate has fully equilibrated [33]. While the timescale of transient rather than equilibrium climate response is of more relevance to the TCRE, the uncertainty associated with climate sensitivity is primarily inferred from ECS, as the transient climate response is a less applicable model metric highly dependent upon emission pathway. The IPCC AR5 evaluated the ECS lies between 1.5 °C and 4.5 °C (66% confidence) [17, 33, 36]. ECS is typically represented with a positively skewed distribution due to the nonlinear relationship between forcings and feedbacks [13, 33]. While ECS is an effective model intercomparison tool, it does not encompass the uncertainty arising from how CO2 emissions influence atmospheric CO2 concentrations [10, 33], and therefore cannot be used to directly quantify the warming from CO2 emissions.

How the carbon cycle responds to CO2 emissions constitutes another major source of uncertainty for TCRE and carbon budget calculations after climate sensitivity [2, 19]. Atmospheric CO2 concentrations evolve from the combined influence of CO2 emissions from land use change, and fossil fuel combustion, as well as CO2 uptake by the ocean and terrestrial biosphere [37]. The rate of ocean carbon uptake is predicted to decline initially in response to emissions due to the limited ocean alkalinity shifting the dissolved inorganic carbon equilibrium towards CO2, the reduced solubility of dissolved CO2 with increased
ocean temperature [13, 21, 38], and increased stratification [39]. Processes contributing to an increased land carbon uptake include CO₂ fertilization, nitrogen deposition, deforestation, and a lengthening growing season, while conversely drought, deforestation, enhanced decomposition, nitrogen and phosphorus limitations reduce land carbon uptake, and these carbon losses are predicted to dominate future carbon-climate feedbacks [13, 15, 21, 40–43].

Rather than separately conceptualizing the uncertainty of two nonlinear, emission rate-dependent processes, the TCRE encompasses uncertainty from both climate sensitivity and carbon cycle feedbacks into a single metric largely robust to varying emission rates [2, 4, 10, 11, 17, 18, 20, 44, 45]. Several approaches have been explored to estimate the TCRE, which can be classified as observational or simulation based, with the comprehensive IPCC AR5 best estimate ranging from 0.8 to 2.5 K EgC⁻¹ [10, 30].

Allen et al [20] employed observationally and comprehensively constrained simulations to estimate the TCRE at 2 K EgC⁻¹, with a 5%–95% confidence interval of 1.3–3.9 K EgC⁻¹. Gillett et al [14] used a detection and attribution analysis based on 150 years of observations, proposing a lower range of TCRE values from 0.7 to 2.0 K EgC⁻¹ at 5%–95% confidence, with a best-estimate of 1.35 K EgC⁻¹. Recently, using a standard detection and attribution technique, Millar and Friedlingstein [26] estimated the TCRE to be 0.88–2.60 K EgC⁻¹ (5%–95% confidence), with a best estimate of 1.31 K EgC⁻¹. Observational estimations of the TCRE have varied over the past decade, with no clear trend in mean or median values and confidence interval limits.

ESMs of simple [18, 32, 46], intermediate [21, 38, 44, 47], and full-complexity [14, 28, 45, 48] have been used to study the TCRE and to establish a physical basis for the path-independence of the TCRE [16, 18, 21, 49]. Williams et al [38] used a set of full-complexity CMIP5 ESMs to diagnose the relative importance of thermal and carbon responses to CO₂ emissions, as well as the importance of non-CO₂ forcing. The full-complexity ESMs used in IPCC AR5 produced TCRE estimates of 0.8–2.4 K EgC⁻¹, with a median value of 1.6 K EgC⁻¹ [30]. Using the temperature outputs from 23 models of the CMIP5, and a perturbed physics approach within the University of Victoria Earth System Climate Model, MacDougall et al [31] found a mean TCRE of 1.72 K EgC⁻¹, and a 5%–95% confidence interval of 0.88–2.52 K EgC⁻¹, consistent with the CMIP5 range of 0.8–2.5 K EgC⁻¹. Generally, the estimated TCRE ranges from simulation-based approaches are more broad than those of observational based approaches [2, 26].

Here we calculate the TCRE based upon current understandings of the interactions between climate and carbon processes, examine the uncertainty distribution of the TCRE using a Monte-Carlo error propagation, explore the sensitivity of the TCRE to various Earth system parameters, and compute the CO₂-only carbon budget consistent with 2 °C warming.

2. Methods

2.1. Calculating the TCRE

To calculate the TCRE, we used the Zero Dimensional Diffusive Ocean heat and carbon uptake Model (ZD2OM) derived by MacDougall [18]. The analytical model is based upon the mathematical definition of the TCRE by Matthews et al [16], the forcing response equation developed by Wigley and Schlesinger [50] and a relationship for cumulative CO₂ emissions, summarized as follows:

\[
\Lambda = R \left( 1 - I \right) \frac{\ln \left( \frac{C_a}{C_{AO}} \right)}{\lambda + \frac{f_o \rho_c \sigma_c B}{\mu \lambda \ln \left( \frac{C_a}{C_{AO}} \right)}} \times \left( \frac{1}{C_a - C_{AO} + \frac{2 B \rho_c \sigma_c B}{3 \mu \lambda \ln \left( \frac{C_a}{C_{AO}} \right)}} \right) \quad (1)
\]

where \( \Lambda \) is the TCRE, \( R \) is radiative forcing from an e-fold increase in atmospheric CO₂, \( I \) is the land-borne fraction of carbon, \( \lambda \) is the climate feedback parameter, \( C_a \) is the size of the atmospheric carbon pool, \( C_{AO} \) is the original size of the atmospheric carbon pool, \( f_o \) is the fraction of the Earth covered by ocean, \( \rho_c \) is the specific heat capacity of water, \( \tau \) is a unit conversion for heat in units of \( s \cdot a \cdot m^2 \cdot Pg \cdot mol^{-1} \), \( \epsilon \) is the ratio of sea surface temperature change to global temperature change, \( \mu \) is effective ocean diffusivity, \( \beta \) is the change rate of atmospheric CO₂, \( B_0 \) is the unit conversion constant for carbon in \( m^2 \cdotPg\cdotmol^{-1} \), \( \Gamma \) is the ocean surface dissolved inorganic carbon change from e-fold change in atmospheric CO₂. We assumed a present-day CO₂ concentration of 400 ppm, corresponding to a \( C_a \) of 852 PgC. We assumed \( C_{AO} \) to be constant at 596.4 PgC. For the complete derivation of equation (1), see MacDougall [18].

2.2. Monte-carlo simulation

To examine the PDF for the TCRE, we calculated the TCRE using a Monte-Carlo error propagation (\( n = 10 \ 000 \ 000 \) drawing parameter values from PDFs of the climate feedback parameter \( \lambda \) (W m⁻²°C⁻¹), radiative forcing from an e-fold increase in atmospheric CO₂ \( R \) (W m⁻²), effective ocean diffusivity \( \mu \) (m² s⁻¹), the land-borne fraction of carbon \( I \), and the ratio between sea surface and global temperature change \( \epsilon \) (figure 1). To explore the sensitivity of the TCRE to these parameters and their distributions, we
conducted a sensitivity analysis assuming normal distributions, and another assuming uniform distributions between the minimum and maximum plausible values for each input parameter PDF (see figure S1, S2, and table S1 of supplementary material available online at stacks.iop.org/ERL/15/034044/mmedia). These sensitivity tests explore the important influence of prior distribution assumptions in computing uncertain parameters such as the TCRE \[35\]. The correlation between the TCRE and each parameter value for each iteration were also computed to understand the portion of variation in the TCRE explained by each parameter.

2.3. Parameter distributions

To develop the PDF for \( \lambda \) (climate feedback), we first computed the PDF for climate sensitivity, from the combination of two normal inverse gaussian distributions following Olson \textit{et al.} \[34\]. We designated the median value of the climate sensitivity PDF as 3.0 °C W m\(^{-2}\), to reflect the combined likely PDF suggested by Knutti \textit{et al.} \[33\] developed from historical warming, climatological constraints on full complexity models, and paleoclimate data, including Rohling \textit{et al.} \[51\]. To convert climate sensitivity values to \( \lambda \) values, we divided 3.71 W m\(^{-2}\), the radiative forcing for a doubling of CO\(_2\) \[33, 52\], by the climate sensitivity PDF values. We conducted a sensitivity analysis to examine the effect of varying or holding constant the climate forcing associated with a doubling of CO\(_2\), in constructing the \( \lambda \) PDF and subsequently calculating the TCRE, shown in figure S5 of the supplementary material. The median and mean values of the \( \lambda \) PDF were 1.24 and 1.32 W m\(^{-2}\) °C\(^{-1}\), corresponding to equilibrium climate sensitivity values of 3.0 and 2.8 °C W m\(^{-2}\).

To develop the PDF for \( R \) (radiative forcing from an e-fold increase in atmospheric CO\(_2\)), we assumed a normal distribution around a mean value of 5.35 W m\(^{-2}\), calculated from the radiative forcing corresponding to a doubling of CO\(_2\), 3.71 W m\(^{-2}\) \[31, 33, 52\] with a standard deviation of 0.4 W m\(^{-2}\) based upon the mean variability of three methods of CO\(_2\) radiative forcing estimation \[31, 53–55\]. While there is an inverse correlative structure between \( R \) and \( \lambda \) \[56\], we chose to vary these parameters independently to assess the influence of each parameter on the TCRE. The \( R \) parameter is relatively well constrained,
though the $\lambda$ is less well constrained, and could vary independently of radiative forcing from CO$_2$ due to the influence of forcing from aerosol and non-CO$_2$ greenhouse gas emissions, as well as unforced climate variability [33, 57, 58]. However to explore the influence of the correlative structure between $R$ and $\lambda$ we conducted an additional Monte Carlo simulation to calculate the PDF of the TCRE while varying these parameters with dependent probabilities (see figure S3 of supplementary material).

We generated the PDF for $\mu$ (effective ocean diffusivity) using the relationship for ocean heat removal velocity ($V_q$) in a diffusive half-space, which is inversely proportional to the root of the product of $\mu$ and time [18]:

$$V_q = \frac{1}{\sqrt{\mu t}}, \quad (2)$$

where $t$ is time. We used $t$ values selected from a uniform distribution ranging from 75 to 100 years, corresponding to a stability in the fit between ocean heat removal velocity values and diffusive approximations within the ZD$^2$OM [18]. We obtained $V_q$ from ocean heat uptake as follows [18]:

$$V_q = \frac{N}{\rho C_p T_0}, \quad (3)$$

where $T_0$ is the change in sea surface temperature and $N$ is the ocean heat uptake. We represented the uncertainty in $N$ using a normal distribution centered on 0.71 W m$^{-2}$ with a standard deviation of 0.11 W m$^{-2}$ corresponding to the 2005.5–2015.5 period by Johnson et al [59], with a corresponding change in sea surface temperature since the preindustrial era (1850) until the midpoint of the 2005.5–2015.5 period (2011) of 0.63 °C [60]. We then generated the PDF for $\mu$ from $V_q$, in units of m$^2$ a$^{-1}$. The PDF for $\mu$ had a mean value of $1.69 \times 10^{-4}$ m$^2$ a$^{-1}$ and a median value of $1.57 \times 10^{-4}$ m$^2$ a$^{-1}$. In representing the ocean in a diffusive manner, we are approximating in a simplified way the advection dominated ocean ventilation processes which control ocean heat and carbon uptake in the natural ocean. On annual to centennial timescales, ocean heat and carbon removal at the global scale in ESMs have been shown to mimic that of a diffusive process [18]. Thus our approximation, though simple, is consistent with processes simulated in complex models, for our timeframe of interest. However this simplification of ocean ventilation processes may negatively bias the TCRE, as it omits the surface warming effect of reduced ocean heat uptake with weakened overturning circulation which occurs in the natural ocean.

We generated the PDF for $\epsilon$ (ratio between sea surface and global temperature change) using a normal distribution constructed from the ratio of decadal mean sea to global surface temperature anomalies from 1950 to 2010, relative to the 1880–1910 normal [18, 60], with a mean ratio of 0.83 and standard deviation of 0.02.

We generated the PDF for $l$ (land-borne fraction of carbon) based upon land-borne CO$_2$ emissions and net CO$_2$ emissions from 1750 to 2011 estimated by the IPCC AR5 [30]. We generated two normal distributions, one for land-borne CO$_2$ emissions and one for net CO$_2$ emissions, with mean values of 160 and 550 PgC and standard deviations of 55 and 52 PgC. We then generated the PDF for $l$ by calculating the ratio of land-borne CO$_2$ emissions PDF values to the net CO$_2$ emissions PDF values using 10 000 000 randomly chosen values from each PDF. The PDF for $l$ had a mean value of 0.29 and standard deviation of 0.10.
Table 1. The interval, best estimate, and median values of the TCRE estimated by this study and previous studies.

| TCRE interval (K EgC$^{-1}$) | Range | Best estimate (K EgC$^{-1}$) | Median (K EgC$^{-1}$) | References |
|-----------------------------|-------|-----------------------------|----------------------|------------|
| 1.0–2.7                     | 5%–95% Confidence | 1.9                     | 1.8                   | This study |
| 1.14–1.26                   | Inter-simulation range | —                     | —                     | Katavouta et al [46] |
| 2.08–2.37                   | Inter-simulation range | 2.2                     | —                     | Tachiiri et al [28] |
| 1.1–2.4                     | 5%–95% Confidence | 1.8                     | 1.7                   | Katavouta et al [63] |
| 0.88–2.60                   | 5%–95% Confidence | 1.3                     | —                     | Millar and Friedlingstein [26] |
| 0.96–2.23                   | 5%–95% Confidence | —                     | 1.4                   | Smith et al [61] |
| ~0.9 to 2.1                 | 5%–95% Confidence | ~1.6                    | —                     | Wang et al [72] |
| 1.1–2.1                     | Inter-model range | —                     | —                     | Ehler et al [70] |
| 0.88–2.52                   | 5%–95% Confidence | 1.72                    | —                     | MacDougall et al [31] |
| 1.0–2.4                     | 5%–95% Confidence | 1.5                     | —                     | Millar et al [68] |
| 0.65–2.28                   | 17%–83% Confidence | —                     | 1.29                  | Millar et al [7] |
| 1.63–1.73                   | Seasonal range | 1.68                    | —                     | Partanen et al [65] |
| 1.39–2.21                   | 2 standard deviations | 1.8                   | —                     | Williams et al [88] |
| 1.25–1.54                   | Inter-simulation range | —                     | —                     | Hansen et al [73] |
| 1.3–2.1                     | 2 standard deviations | 1.7                    | —                     | Leduc et al [74] |
| 1.93–1.98                   | Inter-simulation range | 1.95                   | —                     | Liddicoat et al [75] |
|                            | —                     | —                     | 1.72                  | Simmons and Matthews [76] |
| 1.3–2.7                     | 17%–83% Confidence | 1.9                     | —                     | Steinacher and Joos [66] |
| 1.28–1.9                    | Inter-model range | 1.64                    | —                     | Tokarska et al [65] |
| 2.31–2.67                   | Inter-simulation range | 1.69                   | —                     | Williams et al [38] |
| 1.21–1.80                   | Inter-simulation range | —                     | —                     | Zickfeld et al [77] |
| 1.1–2                       | 2 standard deviations | 1.4                    | —                     | Fröhlicher and Paynter [62] |
| 0.6–1.6                     | 5%–95% Confidence | 1.1                     | —                     | Goodwin et al [64] |
| 1.61–1.71                   | Inter-scenario range | 1.66                    | —                     | Leduc et al [78] |
|                            | —                     | —                     | 2.2                   | MacDougall and Friedlingstein [15] |
| 1.57–1.79                   | Inter-simulation range | —                     | —                     | MacDougall et al [1] |
| 1.8–2.4                     | Inter-simulation range | 2.2                    | —                     | Nohara et al [79] |
| 1.4–3.1                     | Inter-simulation range | —                     | —                     | Randerson et al [13] |
| 1.3–1.7                     | 5%–95% Confidence | —                     | —                     | Tachiiri et al [80] |
| 1.6–2.3                     | 2 standard deviations | 1.95                   | —                     | Cherubini et al [64] |
| 1.9–2.4                     | 5%–95% Confidence | —                     | 2.1                   | Friedlingstein et al [37] |
| 1.7–1.9                     | Inter-scenario range | 1.8                    | —                     | Herrington and Zickfeld [21] |
| 0.76–1.04                   | Inter-scenario range | —                     | —                     | Kramst et al [17] |
| 1.07–2.12                   | Inter-model range | 1.57                    | —                     | Eby et al [47] |
| 0.8–2.5                     | 66% Confidence | —                     | —                     | IPCC AR5 [30] and SRT1.5 [24] |
| 0.7–2.0                     | 5%–95% Confidence | 1.3                     | —                     | Gillett et al [14] |
| 1.4–2.5                     | 5%–95% Confidence | 1.9                     | —                     | Zickfeld et al [67] |
| 1–2.5                       | 5%–95% Confidence | 1.8                     | —                     | Matthews et al [81] |
| 1                            | 5%–95% Confidence | —                     | —                     | Rogelj et al [82] |
| 0.8–1.9                     | Inter-simulation range | —                     | —                     | Williams et al [83] |
| 1.3–1.52                    | 5%–95% Confidence | 1.4                     | —                     | Zickfeld et al [22] |
| 1.0–4.0                     | Inter-model range | —                     | —                     | Johns et al [49] |
|                            | —                     | —                     | 2                     | Raupach et al [32] |
| 1.4–2.5                     | 5%–95% Confidence | 1.9                     | —                     | Allen et al [20] |
| 1.0–2.0                     | 5%–95% Confidence | 1.6                     | —                     | Matthews et al [16] |
| 1.1–2.7                     | 5%–95% Confidence | —                     | —                     | Meinshausen et al [84] |
|                            | —                     | —                     | 1.5                   | Zickfeld et al [85] |

3. Results and discussions

3.1. TCRE distribution

Figure 2 shows the PDF for the TCRE as calculated using our method. The TCRE has a positively skewed PDF ranging from 1.1 to 2.9 K EgC$^{-1}$ (5%–95% confidence), with mean and median values of 1.9 K EgC$^{-1}$ and 1.8 K EgC$^{-1}$, respectively. This is comparable to previous estimates (table 1), though with a positively shifted range of values relative to the IPCC AR5 expert judgement range of 0.8–2.5 K EgC$^{-1}$ [30]. While our lower limit of the 5%–95% confidence interval is slightly greater than previous estimates [26, 31, 61], our upper limit is considerably higher than previously reported upper limits [2, 14, 21, 31, 44, 62, 63]. Our mean and median values are similar to previous estimates [15, 20, 21, 28, 62–67]. The agreement we observed between our TCRE estimates and previous estimates in terms of lower limits, mean, and median values, in contrast to the relatively high upper limit we found suggests that the TCRE may
exhibit a more positively skewed distribution than previously thought, though this observation may be sensitive to assumed prior distributions. Allen et al. [20] and Matthews et al. [2] also reported asymmetry in the range of Cumulative Warming Commitment or TCRE values observed from simple, intermediate, or full complexity ESMs. The Cumulative Warming Commitment is the peak warming associated with a quantity of cumulative CO₂ emissions, and therefore equivalent to the TCRE assuming a negligible zero-emissions commitment, or the amount of unavoidable warming following cessation of CO₂ emissions. However Allen et al. [20] suggested the asymmetry in the distribution of the Cumulative Warming Commitment is due to the possibility of a substantial zero-emissions commitment. The results of our sensitivity analyses revealed that the form of the TCRE we observed is robust to the distribution of the underlying parameters, when all parameters are assigned normal distributions, the TCRE still is best approximated with a log-normal distribution PDF (see figures S1 and S2), therefore it can be concluded that the positive skew of the TCRE is likely not inherited directly from the skewed distribution of the climate feedback parameter, though it may similarly be the result of mathematically combining two varying uncertain parameters to calculate the TCRE.

The transient climate response, the warming expected at the time of atmospheric CO₂ concentration doubling relative to the pre-industrial period under an idealized 1% yr⁻¹ CO₂ increase experiment, also follows a positively-skewed PDF [33, 68]. The commonality of the application of physical climate parameters for the equation of the TCRE with that of the transient climate response may provide another explanation for the shape of the TCRE PDF we observed. The transient climate response is determined by the ratio of observed warming to radiative forcing under a doubled atmospheric CO₂ concentration, and has a positively skewed distribution due to the assumption of non-stationary feedbacks within the climate system in response to radiative forcing. Therefore the form of the TCRE we observed may be the result of the assumption of non-stationary feedbacks.

Given the difference between the median and mean value we observed was small, <0.1 K EgC⁻¹, the implications of this asymmetry for allowable carbon budgets may be negligible assuming the true value of the TCRE lies near the centre of this PDF. However, if the true value of the TCRE is actually within either tail of the PDF, though unlikely, assuming a normally distributed TCRE PDF rather than a log-normally distributed PDF may overestimate allowable carbon budgets. While the use of median values rather than mean values in describing the central tendency of an uncertain parameter is more robust to outliers [69], it may be important to consider the implications of the difference between the median and mean value for a log-normally distributed variable such as the TCRE. We recommend where possible for future studies of the TCRE to report both a mean and median value, and that the mean value is used for the basis of carbon budgets to avoid overestimation of allowable carbon budgets.

3.2. Relative parameter influence

Figure 3 shows the correlations between input parameters and TCRE values for each iteration. The most important parameter to the TCRE is the climate feedback parameter, followed by the land-borne fraction of carbon, radiative forcing, effective ocean diffusivity, and lastly the ratio of sea to global surface temperature change.

Our observed hierarchy in importance is similar to that observed by MacDougall et al. [31], who found a $r = 0.86$ between climate sensitivity and the TCRE, $−0.39$ with ocean heat uptake, and $0.17$ with radiative forcing for a doubling of CO₂. As climate sensitivity is inversely proportional to climate feedback, ocean heat
uptake is inversely proportional to effective ocean diffusivity, and radiative forcing for a doubling of CO₂ is directly proportional to radiative forcing for an e-fold increase in CO₂, our results for the relative importance of climate feedback, effective ocean diffusivity, and radiative forcing are in agreement with MacDougall et al. \[31\].

The ocean plays a predominant role in the global uptake of excess energy at the surface, and an important role in modulating the airborne fraction of CO₂ emissions, and thus modulates the TCRE \[38, 44, 46, 48, 63, 70\]. Heat and CO₂ are taken up by the mixed layer of the ocean and transported through depth primarily via advective meridional circulation \[46\]. This mechanism is expected to vary substantially with a changing temperature stratification regime within the ocean \[38, 48\], though a recent study, Ehlert et al. \[70\] suggests the processes of ocean heat and carbon flux scale linearly with changes in vertical mixing. We have chosen to represent ocean heat and CO₂ uptake using a diffusive approximation for simplicity, and as at a global scale ocean uptake of heat and CO₂ mimics that of a diffusive process, as previously shown in intermediate and full-complexity ESMs \[18\]. This simplifying assumption may over-estimate heat uptake by the ocean, by omitting the important influence of a changing ocean ventilation in response to isopycnal heave associated with increased stratification weakening ocean meridional circulation \[71\]. Katavouta et al \[63\], Ehlert et al. \[70\], Williams et al \[38\], and Goodwin et al \[44\] suggest processes of ocean heat and carbon compense one another in affecting the linearity between surface warming and cumulative CO₂ emissions. Williams et al \[38\] further advise that the warming effect of decreased ocean heat uptake may exceed the cooling effect by ocean uptake of CO₂, and Goodwin et al \[44\] show that a predicted drift in the Atlantic meridional overturning uptake alters thermal uptake more than carbon uptake, while Ehlert et al \[70\] show that variations in vertical ocean mixing have a greater influence on the TCRE than changes in mixing along isopycnals. Thus caution is warranted when extending our results beyond decadal to centennial time-scales at which the diffusive approximation works well \[18\].

3.3. The consequences of a non-normal TCRE distribution

To examine how our calculated TCRE differs from a normally distributed TCRE PDF, we generated a normally distributed TCRE PDF with an identical mean and standard deviation to that of our calculated TCRE PDF, as well as a log-normally distributed PDF, shown in figure 4. Note that a PDF generated this way can have non-physical values corresponding to continuous prescribed probabilities rather than sampled TCRE estimates. A normally distributed TCRE has a negatively shifted 5%–95% confidence range relative to the calculated TCRE, 1.0–2.8 K EgC⁻¹ and 1.1–2.9 K EgC⁻¹, respectively. Previous studies which construct a PDF for the TCRE assuming a normal distribution using standard deviation and mean TCRE estimates may negatively bias confidence intervals for the TCRE, even if reported mean values and standard deviations are representative.

To limit global warming to 2 °C relative to pre-industrial temperatures, the CO₂-only cumulative carbon budget is between 700 and 1800 PgC (5%–95% confidence), with a best estimate value of 1100 PgC (rounded to the nearest 100 PgC). Figure 5 shows the consequences of a calculated TCRE PDF relative to a normally distributed TCRE PDF with regards to a CO₂-only carbon budget. A calculated TCRE reduces
the upper confidence limit of the CO₂-only carbon budget. While both share a mean projected carbon budget of 1100 PgC, a normally distributed TCRE produces a greater upper limit of emissions allowance than the calculated TCRE, 2100 and 1800 PgC, respectively. At annual emissions of 11 PgC yr⁻¹, the difference between these upper limits is equivalent to about 27 years of emissions.

While the TCRE and proposed CO₂-only carbon budgets relate the primary driver of anthropogenic climate change, CO₂ emissions, to global warming, these do not take into account the influence of non-CO₂ greenhouse gas and aerosol emissions [15]. Caution is warranted in the interpretation and application of CO₂-only carbon budgets associated with the TCRE, as these overestimate emissions compatible with a given temperature target by not encompassing non-CO₂ forcing [24].

4. Conclusion

Here we have examined the uncertainty distribution of the Transient Climate Response to Cumulative Emissions (TCRE) using a Monte-Carlo error propagation, and found the TCRE to have a positively skewed PDF best approximated as a log-normal distribution rather than a normal distribution as is commonly assumed [24, 30]. The TCRE ranges from 1.1 to 2.9 K EgC⁻¹ at 5%–95% confidence, with a mean and median value of 1.9 and 1.8 K EgC⁻¹. While our lower limit and mean estimate of the TCRE is consistent with previous estimates, our upper limit is greater than previous estimates. We explored the relative influence of sources of uncertainty for the TCRE and found that climate feedback is the most influential parameter, followed by the land-borne fraction of carbon, radiative forcing, effective ocean diffusivity, and lastly the ratio of sea to global surface temperature change. A positively skewed TCRE reduces the upper limit on CO₂-only carbon budgets, producing a CO₂-only carbon budget for 2°C warming of 700–1800 PgC at 5%–95% confidence, while a normally distributed TCRE produces a budget of 700–2100 PgC at 5%–95% confidence. The difference in the upper limit estimates on carbon budgets corresponds to about 27 years of emissions at 11 PgC yr⁻¹. The uncertainty in the TCRE and associated carbon budgets is substantial. However the representation of the TCRE as a log-normal PDF improves estimations of the TCRE and associated carbon budgets. Given the large roles of climate sensitivity and the land-borne fraction of carbon, improved estimates of these variables may contribute to reducing uncertainty in the TCRE and carbon budgets.

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Data availability

Any data that support the findings of this study are included within the article. The code we used to perform the Monte-Carlo simulation can be accessed at https://doi.org/10.25412/10.11450286.v1.

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