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LETTER

Quantifying process-level uncertainty contributions to TCRE and carbon budgets for meeting Paris Agreement climate targets

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Abstract

To achieve the goals of the Paris Agreement requires deep and rapid reductions in anthropogenic CO_2 emissions, but uncertainty surrounds the magnitude and depth of reductions. Earth system models provide a means to quantify the link from emissions to global climate change. Using the concept of TCRE—the transient climate response to cumulative carbon emissions—we can estimate the remaining carbon budget to achieve 1.5 or 2 °C. But the uncertainty is large, and this hinders the usefulness of the concept. Uncertainty in carbon budgets associated with a given global temperature rise is determined by the physical Earth system, and therefore Earth system modelling has a clear and high priority remit to address and reduce this uncertainty. Here we explore multi-model carbon cycle simulations across three generations of Earth system models to quantitatively assess the sources of uncertainty which propagate through to TCRE. Our analysis brings new insights which will allow us to determine how we can better direct our research priorities in order to reduce this uncertainty. We emphasise that uses of carbon budget estimates must bear in mind the uncertainty stemming from the biogeophysical Earth system, and we recommend specific areas where the carbon cycle research community needs to re-focus activity in order to try to reduce this uncertainty. We conclude that we should revise focus from the climate feedback on the carbon cycle to place more emphasis on CO_2 as the main driver of carbon sinks and their long-term behaviour. Our proposed framework will enable multiple constraints on components of the carbon cycle to propagate to constraints on remaining carbon budgets.

1. Introduction

Perhaps the most common question required for mitigation policy is 'by how much do we need to reduce our carbon emissions?'. It is well accepted that deep and rapid emissions cuts are required in order to achieve the UN's Framework Convention on Climate Change goal of avoiding dangerous climate change, but in order to develop quantitative and measurable policy targets we must quantify the emissions compatible with any climate goal. Since the global community has adopted the Paris Agreement, which entered into force in November 2016, the requirement to quantify carbon budgets for low climate targets has grown.

1.1. The transient climate response to cumulative carbon emissions

A body of literature from 2009 found consistently that warming was much more closely related to the cumulative CO_2 emissions than the time profile or particular pathway (Allen *et al* 2009, Matthews *et al* 2009, Meinshausen *et al* 2009). This relationship between warming and cumulative emissions was one of the new and innovative outcomes of the IPCC's Fifth Assessment Report (AR5) report (IPCC 2013). AR5's Figure SPM.10 showed this relationship—known as TCRE: the Transient Climate Response to cumulative carbon Emissions.

The physical basis of TCRE was first hinted at by (Caldeira and Kasting 1993) who noted that saturation of the radiative effect of CO_2 in the atmosphere could be balanced by saturation of uptake by ocean carbon leading to insensitivity of the warming to the pathway of CO_2 emissions. Literature since then has put this on a firm footing with numerous authors showing that trajectories of ocean heat and carbon uptake have similar effects on global temperature due to the diminishing radiative forcing from CO_2 in the atmosphere and the diminishing efficiency of ocean heat uptake (Goodwin *et al* 2015, Macdougall 2016, Ehlert *et al* 2017). Although as noted by (Macdougall 2017) that terrestrial carbon uptake is equally important for the magnitude of TCRE—in fact we will show here that land and ocean contribute equally to the magnitude of TCRE and that land dominates over the ocean in terms of model spread.

1.2. Application of TCRE to quantify carbon budgets

IPCC AR5 assessed a total carbon budget of 790 PgC to likely (66% chance) remain below 2 °C above pre-industrial, of which about 630 PgC has been emitted over the 1870–2018 period (Friedlingstein *et al* 2019). However, the spread of models means that the uncertainty in the remaining carbon budget to achieve 1.5 °C or 2 °C is very large—in fact possibly larger than the remaining budget itself. This large uncertainty hinders the potential usefulness of this simplifying concept to policy makers. All studies and reports which present estimates of the remaining carbon budget (e.g. The IPCC's Fifth Assessment Report, its Special Report on Global Warming of 1.5 °C, or the UNEP Gap Report) have to make an assumption on how to deal with and present this uncertainty. Some explicitly describe the chosen assumptions (such as 50% or 66% probability of meeting targets) or tabulate multiple options, but all are hindered in some way by the precision with which carbon budgets are known.

The AR5 Synthesis Report quoted a value of 400 $GtCO_2$ (110 GtC) remaining budget from 2011 for a 66% chance to keep warming below 1.5 °C. It is now clear that this was an underestimate as this would mean a remaining budget of about 20 GtC from 2020. Since AR5 there has been extensive literature on the application of the TCRE concept and its limitations including the choice of temperature metric and baseline period and issues of biases in Earth system models (ESMs). Some studies accounted for climate model biases by relating warming from present day onwards to the remaining carbon budget (e.g. Millar *et al* 2017, Tokarska and Gillett 2018). Other studies have used the historical record to constrain TCRE and the remaining budget using simple models (Goodwin *et al* 2018) or attribution techniques (Millar and Friedlingstein 2018). Both these approaches find a substantial increase in the remaining carbon budget for 1.5 °C compared to the IPCC AR5 SPM approach. Further studies have tried to additionally account for non-CO_2 warming. (Matthews *et al* 2017) show CO_2-only TCRE budgets are a robust upper limit but taking account of non-CO_2 forcing results in lower allowable emissions. (Smith *et al* 2012 and Allen *et al* 2018) have proposed techniques for combining emissions rates of short-lived climate pollutants with long-term CO_2 cumulative emission budgets. In light of these advances, the IPCC Special Report on Global Warming of 1.5 °C (SR15, Rogelj *et al* 2018) quotes a value of 420 $GtCO_2$ remaining carbon budget for a 66% chance to keep warming below 1.5 °C—a value very similar to the AR5 value from 5 years earlier.

There is also a lot of focus on how to achieve such carbon budgets and the increasing realisation of the need for carbon dioxide removal and research into the feasibility and implications of negative emissions technology. The discussion around carbon dioxide removal (CDR) requires more detailed assessment of the magnitude and timing of any requirement for negative emissions technology and hence more precise estimates of remaining carbon budgets (Fuss *et al* 2016). While Peters (2018) argues that large uncertainty in budget estimates may be used to 'justify further political inaction', (Sutton 2018) argues for careful consideration of the full range of climate projections, including 'physical plausible high impact' outcomes in the tails of the likelihood distribution. The same argument applies to TCRE and carbon budgets: we need information on best estimates but also possible extremes however unlikely. For example, (Kriegler *et al* 2018) show that the feasibility of achieving 1.5 °C without net negative emissions depends on the remaining budget being at the high end of current estimates. Knowing the likelihood of the range as well as central estimate is required to inform the debate on requirements for negative emissions.

SR15 and (Rogelj *et al* 2019) present a framework to breakdown individual contributions to uncertainty in carbon budgets. They separately assess: (i) the historical human induced warming to date; (ii) the likely range of TCRE, (iii) the potential additional warming after emissions reached zero (zero-emissions commitment, ZEC); (iv) the warming from non-CO_2 forcing agents (such as other greenhouse gases and aerosols); (v) carbon emissions from Earth system feedbacks not yet represented in ESMs (such as carbon release from thawing of permafrost). While there are multiple ways of decomposing this issue, an unavoidable conclusion is that our imperfect ability to model the climate-carbon cycle system plays a dominant role in uncertainty surrounding assessment of the remaining carbon budget.

Of the five components described above, three are directly linked to coupled climate-carbon cycle modelling: TCRE, ZEC and missing feedbacks. These are being addressed. For example, a new initiative—ZECMIP (Jones *et al* 2019)—was launched to address uncertainty in the zero-emission commitment and initial results (MacDougall *et al* 2020) suggest that SR15 assumptions of no significant further warming after CO_2 emissions cease is consistent with the multi-model mean. Similarly, CMIP6 and ever increasingly sophisticated ESMs (e.g. Sellar *et al* 2019, Séférian *et al* 2019) begin to include additional Earth system feedbacks into models—e.g. coupled terrestrial nitrogen cycle is now expected in approximately half of CMIP6 ESMs and some also begin to include permafrost carbon (Arora *et al* 2019). However, the elephant in the room is that past generations of models has not seen a decreased spread in TCRE (Friedlingstein *et al* 2006, Arora *et al* 2013, 2019) and rarely does adding complexity reduce this. Much longer experience on assessment of the climate sensitivity to increasing CO_2 (ECS, equilibrium climate sensitivity; Flato *et al* 2013) suggests little GCM convergence with a persistent large range of about 3 °C (from about 1.5 to about 4.5 °C) since the Charney report (1979).

It is therefore required to understand at a process level where the uncertainty in TCRE comes from in order to target observational constraints and prioritise model development and associated evaluation.

Here we perform a new analysis of three generations of Earth System Model results, spanning over a decade, to examine whether or not existing simulations and analyses are well placed to answer the increasing requirements of policy makers on the carbon cycle research community. In section 2 we present a new analytical framework which allows us to quantify sources of uncertainty in carbon budgets to land or ocean response to CO_2 or climate. Analysis of results in section 3 shows that it is the carbon cycle response to CO_2, rather than its response to climate, which dominates the uncertainty in TCRE and hence carbon budgets. We conclude with recommendations for the carbon cycle research community.

2. Framework for uncertainty propagation

At a very broad level the global carbon cycle can be characterised by two strong and opposing responses: how it responds to rising CO_2 concentration and how it responds to a changing climate. Firstly, as atmospheric CO_2 increases, natural carbon reservoirs act to take up carbon from the atmosphere, inducing carbon sinks. Secondly, as the world warms, this climate change also affects these carbon sinks, for example through changes in vegetation growth or ocean stratification. This paradigm has become a widely-used framework for carbon cycle analyses with the former (carbon cycle response to CO_2) often referred to as 'concentration-carbon feedback' and denoted β, while the latter is often termed 'climate-carbon feedback' and denoted by γ (Friedlingstein *et al* 2006, Gregory *et al* 2009, Arora *et al* 2013).

There are some clear and obvious similarities between feedbacks in the physical climate system and the carbon cycle system, which have aided derivation of this carbon cycle feedback framework but may also have mis-directed carbon cycle research attention. A radiative imbalance which warms the planet in turn increases the amount of outgoing energy radiated by the Earth and so represents a very strong negative (stabilising) feedback. On top of this stabilising response there are many feedbacks within the climate system caused by physical components responding to the change in global temperature. The response of clouds is commonly acknowledged to be the largest source of model spread but others include ice and snow-albedo feedbacks, water vapour or atmospheric lapse rate (Bony *et al* 2006, Soden *et al* 2008).

However, in the case of climate feedbacks, the stabilising negative response (Planck response) is extremely well known and almost all of the uncertainty in the overall climate sensitivity comes from the multitude of additional physical feedbacks within the climate system (see Gregory *et al* 2009, figure 2), whereas in the carbon cycle case the stabilising negative response—carbon sinks induced by elevated CO_2—is not quantitatively well known. (Gregory *et al* 2009) showed that in fact it is both *stronger* and *more uncertain* than the carbon cycle response to climate.

These similarities between carbon cycle and climate feedback formalisms led early analyses to focus on the positive feedbacks in the system. These were analogies to the climate feedbacks and were often seen as the largest source of uncertainty (Matthews *et al* 2005, Raddatz *et al* 2007). Even before the first generation of C4MIP modelling results, (Friedlingstein *et al* 2003) derived an uncertainty analysis to show that the carbon cycle response to climate ('γ') contributes the majority of the differences between the first Hadley Centre and IPSL carbon cycle feedback experiments (Cox *et al* 2000, Friedlingstein *et al* 2001). While this remains true: γ contributes most of the uncertainty in the climate carbon cycle gain, it neglects the underlying uncertainty in the unmodified sinks themselves.

Here we derive analytical expressions to substantially extend the analysis of (Friedlingstein *et al* 2003) and allow us to quantify the contribution of uncertainty in carbon cycle components to different quantities of interest. We show that TCRE and the airborne fraction (AF, the ratio of atmospheric CO_2 increase to anthropogenic CO_2 emissions) can be derived from process-level feedback metrics and that although the derivation assumes linearity (as per Friedlingstein *et al* 2003, 2006) our framework can accurately reproduce TCRE and AF of two generations of ESMs and therefore can be used to identify sources of uncertainty in these quantities.

The linearized feedback framework adopted by C4MIP in (Friedlingstein *et al* 2006) was first derived by (Friedlingstein *et al* 2003). They defined α, β, γ such that:

$$\Delta T = \alpha \Delta C_a, \tag{1}$$

$$\Delta C = \beta \Delta C_a + \gamma \Delta T, \tag{2}$$

where T, C and C_a are global mean temperature, land plus ocean carbon stock and atmospheric CO_2 concentration, respectively. The carbon store, and β and γ terms can be split into land and ocean components often denoted by 'L' and 'O' suffices respectively (e.g. C_L or β_O) but here we combine into a single term for clarity.

They also showed that the carbon cycle feedback gain, *g*, could be expressed in terms of these quantities:

$$g = -\frac{\alpha\gamma}{1+\beta}. \tag{3}$$

This applies to quantities expressed in common units, such as PgC, PgC/K, PgC/PgC. More commonly, land and ocean carbon stores are expressed in PgC while atmospheric CO_2 is in ppm, and sensitivities to it in ppm^{-1}. Hence the expression for g requires an additional constant, k, to account for unit conversion: $k = 2.12$ PgC ppm^{-1}, giving:

$$g = -\frac{\alpha\gamma}{k+\beta}. \tag{4}$$

Further manipulation of these metrics (see Methods) allows us to express other quantities in terms of individual feedbacks. Cumulative airborne fraction, AF, defined as the increase in atmospheric CO_2 per unit emission (both in units of mass of carbon) is given by:

$$AF = \frac{k}{k+\beta+\alpha\gamma}. \tag{5}$$

Finally, TCRE, defined as the warming per unit emission of mass of carbon, is simply related to the airborne fraction by the climate sensitivity parameter:

$$TCRE = \frac{\alpha}{k+\beta+\alpha\gamma}. \tag{6}$$

Crucially, our framework can be extended to also quantify propagation of uncertainty in component feedback parameters to gain, AF and TCRE. Identification of sources of uncertainty is important if we are to target model development and evaluation on aspects of performance which most affect the outcomes we care about. For derivation see Methods, but we show that the variance in gain, AF and TCRE can be given by:

$$dg^2 = g^2\left(\frac{1}{\alpha^2}d\alpha^2 + \frac{1}{\gamma^2}d\gamma^2 + \frac{1}{(k+\beta)^2}d\beta^2\right), \tag{7}$$

$$dAF^2 = \frac{AF^4}{k^2}\left(\gamma^2 d\alpha^2 + d\beta^2 + \alpha^2 d\gamma^2\right), \tag{8}$$

$$d(TCRE)^2 = \frac{AF^4}{k^4}\left((k+\beta)^2 d\alpha^2 + \alpha^2 d\beta^2 + \alpha^4 d\gamma^2\right). \tag{9}$$

If required, these equations can be broken down further into land and ocean components of β and γ.

3. Results

3.1. Synthesis across multiple C4MIP generations

In order to develop and test the framework we assemble feedback metrics and related quantities from the three generations to date of coupled climate-carbon cycle models: 'C4MIP' (first generation C4MIP simulations, from circa 2006; documented in Friedlingstein *et al* 2006), 'CMIP5' (carbon cycle ESMs from CMIP5, documented in Arora *et al* 2013) and 'CMIP6' (simulations and results documented in Jones *et al* 2016a; Arora *et al* 2019 respectively). Individual values from the models contributing to those studies and the values we use in this analysis are shown in supplementary information (stacks.iop.org/ERL/15/074019/mmedia), table SI.1. There are multiple choices of CMIP5 feedback metrics that we could use. In the supplementary information we discuss the implications of these and explain our choice of using feedback metrics derived from CMIP5 models at a level of 2 × CO_2, rather than 4 × CO_2.

Figure 1 summarizes these numbers graphically to help visualize changes in feedback metrics over the three model generations. Although the original C4MIP analysis made use of a different scenario of CO_2 (SRES A2) and simulations were emissions-driven instead of concentration-driven, the comparison is useful to see, but we note especially for ocean β and γ the reduced spread is more likely due to experimental design differences than due to model changes. Since the adoption of the 1% p.a. simulation results are much more directly comparable between CMIP5 and CMIP6 generations.

Comparing specifically between CMIP5 and CMIP6 we find that α has the same mean value but a larger spread (table 1), β has similar mean value but smaller spread. γ values have decreased slightly between CMIP5 and CMIP6. (Arora *et al* 2019) discuss reasons for the changes, especially on land, where the introduction of a terrestrial nitrogen cycle in approximately half the models has reduced values of both β and γ in those models.

3.2. Reconstructing gain, AF and TCRE

Figure 2(a) shows the successful reconstruction of gain across C4MIP and CMIP5 generations of models with R^2 of 0.89 for the correlation of actual and reconstructed values of *g* (no gain values are available for CMIP6). Figures 2(b) and (c) show similar success of our framework to reconstruct AF and TCRE from all three multi-model ensembles (R^2 = 0.85,

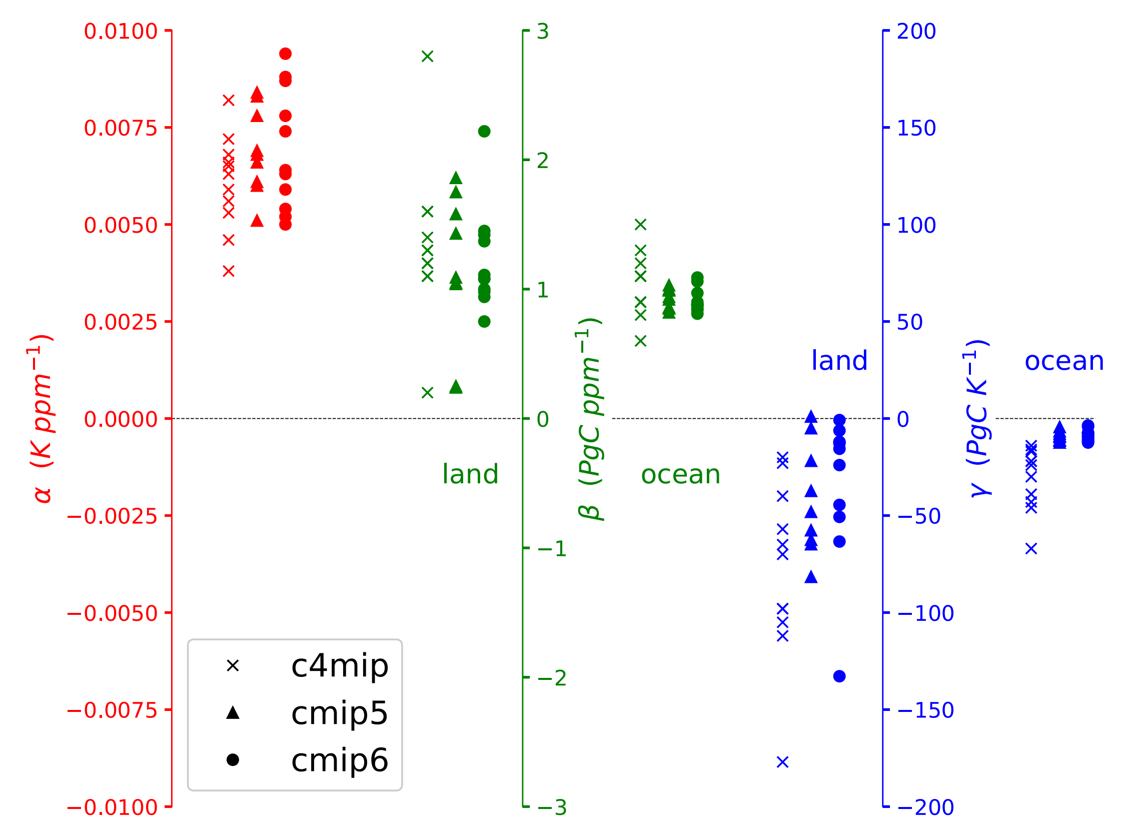

Figure 1. Comparison of ESM carbon cycle feedback metrics by generation (C4MIP, CMIP5, CMIP6). Metrics shown are: response of climate to elevated CO_2 (α: red axis); response of carbon sinks to CO_2 (β: green axis) split into land (left hand side of axis) and ocean (right hand side); response of carbon sinks to climate (γ: blue axis) split into land (left hand side of axis) and ocean (right hand side).

Table 1. Compiled mean and standard deviation of feedback metrics for the 3 generations of model ensembles and across all models.

	α (K ppm^{-1})	β land (PgC ppm^{-1})	β ocean (PgC ppm^{-1})	γ land (PgC K^{-1})	γ ocean (PgC K^{-1})
C4MIP	0.0061 ± 0.0012	1.34 ± 0.58	1.04 ± 0.24	-78.6 ± 43.7	-30.9 ± 15.5
CMIP5	0.0069 ± 0.0010	1.14 ± 0.56	0.93 ± 0.07	-42.0 ± 26.7	-9.2 ± 2.5
CMIP6	0.0069 ± 0.0015	1.22 ± 0.38	0.91 ± 0.09	-34.1 ± 36.6	-8.6 ± 2.8
All models	0.0066 ± 0.0013	1.24 ± 0.52	0.96 ± 0.17	-52.2 ± 41.9	-16.7 ± 14.2

0.89, respectively). For the same reasons (see supplementary information) that using feedback metrics diagnosed at 2 × CO_2 gave a better fit to AF and TCRE, it also means we get a worse fit to gain, g, which was diagnosed for CMIP5 at 4 × CO_2.

The agreement of our reconstruction is strong—each component is accurately reproduced not only in its mean but also its spread (shown here as standard deviation) (table 2). This gives us confidence not only that we can reconstruct the global behavior of these models from their component sensitivities, but also that we can reconstruct and understand their variance and hence reliably test the dependence of these aggregate quantities on their components.

As with the individual feedback metrics, it is illustrative to look at changes in gain, AF and TCRE over the generations of coupled climate carbon cycle modelling (figure 3). As before, the different experimental design and scenario make precise comparison impossible back to the original C4MIP but possible between CMIP5 and CMIP6. We see that AF has decreased slightly in magnitude and markedly in spread between the two most recent generations. This change in mean and variance is captured by our reconstruction allowing us to probe the underlying reasons, as discussed below. Conversely, TCRE has not changed systematically between the two generations either in magnitude or spread. We note here that AF is defined and calculated when CO_2 reaches 2× pre-industrial levels in the 1% p.a. simulation and as such has different values from, and should not be compared to, observational airborne fraction of approximately 45% derived over the recent historical record (Friedlingstein *et al* 2019).

3.3. Quantified sources of uncertainty

In order to quantify sources of uncertainty in g, AF and TCRE, we apply our framework to this

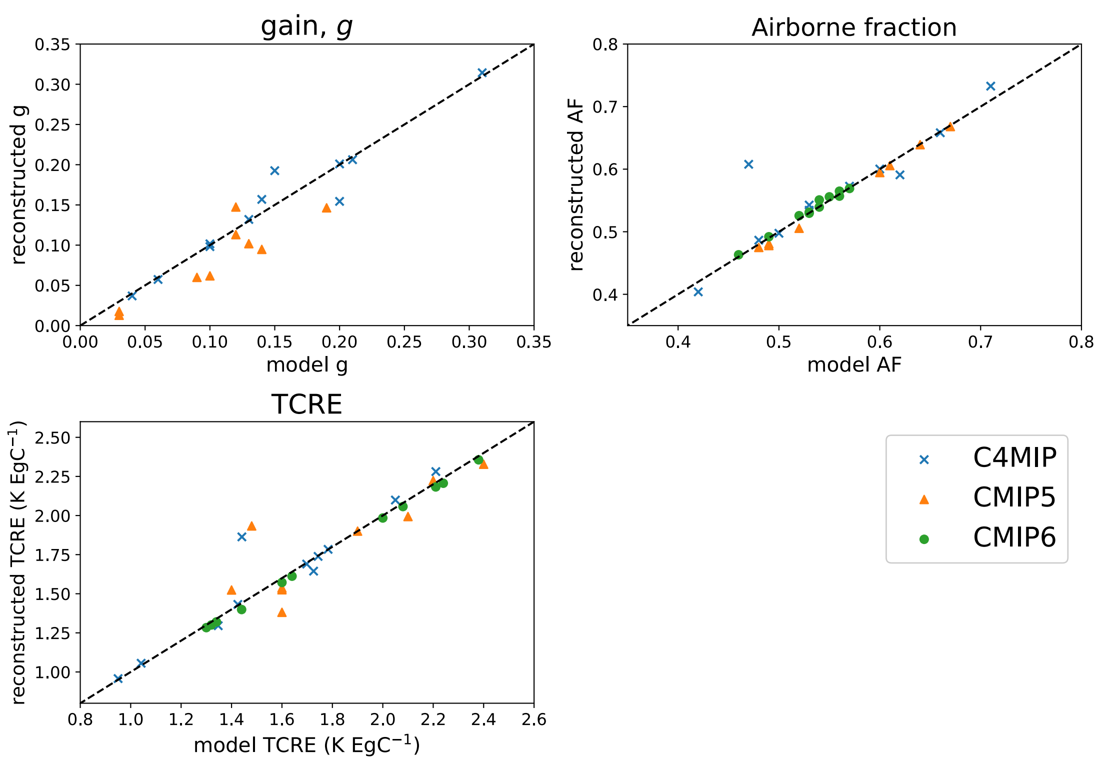

Figure 2. Actual and reconstructed values of (a) gain; (b) Airborne fraction, AF; (c) TCRE using ensemble output from C4MIP (2006) CMIP5 (2013) and CMIP6 (2019) listed in supplementary information, table SI.1. The black dashed line is the one-to-one line for illustration.

Table 2. Actual and reconstructed values of gain, AF and TCRE and also their uncertainty. Shown here as mean and standard deviation across the available models. Gain and AF are expressed without units, TCRE is in units of K per Exagram of carbon (1 EgC = 10^{15} gC).

		Gain (g)	Airborne fraction	TCRE (K EgC^{-1})
C4MIP	Actual	0.149 ± 0.073	0.554 ± 0.084	1.58 ± 0.37
	Reconstructed	0.150 ± 0.075	0.566 ± 0.085	1.62 ± 0.39
CMIP5	Actual	0.106 ± 0.048	0.563 ± 0.071	1.81 ± 0.33
	Reconstructed	0.084 ± 0.047	0.556 ± 0.074	1.82 ± 0.32
CMIP6	Actual	—	0.532 ± 0.031	1.78 ± 0.39
	Reconstructed	—	0.534 ± 0.031	1.75 ± 0.39
All models	Actual	0.130 ± 0.067	0.548 ± 0.067	1.72 ± 0.38
	Reconstructed	0.099 ± 0.068	0.552 ± 0.068	1.72 ± 0.38

3-generation multi-model ensemble. When we use calculated variances of α, β and γ from the ensembles we can quantify the uncertainty in each of gain, AF and TCRE due to each feedback term. Figure 4 shows the contribution to variance in these terms which arises from model spread in α, β and γ. We find, as expected, that the carbon cycle response to climate (γ: blue bars) is indeed the primary driver of uncertainty in the climate carbon cycle gain, *g*. However, this is not the case for the more policy relevant quantities of cumulative airborne fraction (AF) and TCRE. We find that the response to CO_2 (β: green bars) is a much greater source of uncertainty in the other quantities, being the dominant uncertainty controlling AF and jointly dominating TCRE with the climate response to CO_2 (α: red bars). Model spread of γ plays very little role in the ultimate spread of TCRE.

For both β and γ we show that spread in terrestrial ecosystem response is much greater than the ocean response and therefore contributes much more to resultant uncertainty in AF and TCRE. However, we stress that this refers only to the contribution of components to *uncertainty* (or more strictly, model *spread*) in g, AF and TCRE from the given sets of models available here. But of course oceans, as well as land, are still vitally important in determining the overall magnitude of the feedback responses: the ocean contributes almost exactly the same as land to β and a significant fraction to γ (figure 5). Only in the uncertainty terms does land dominates.

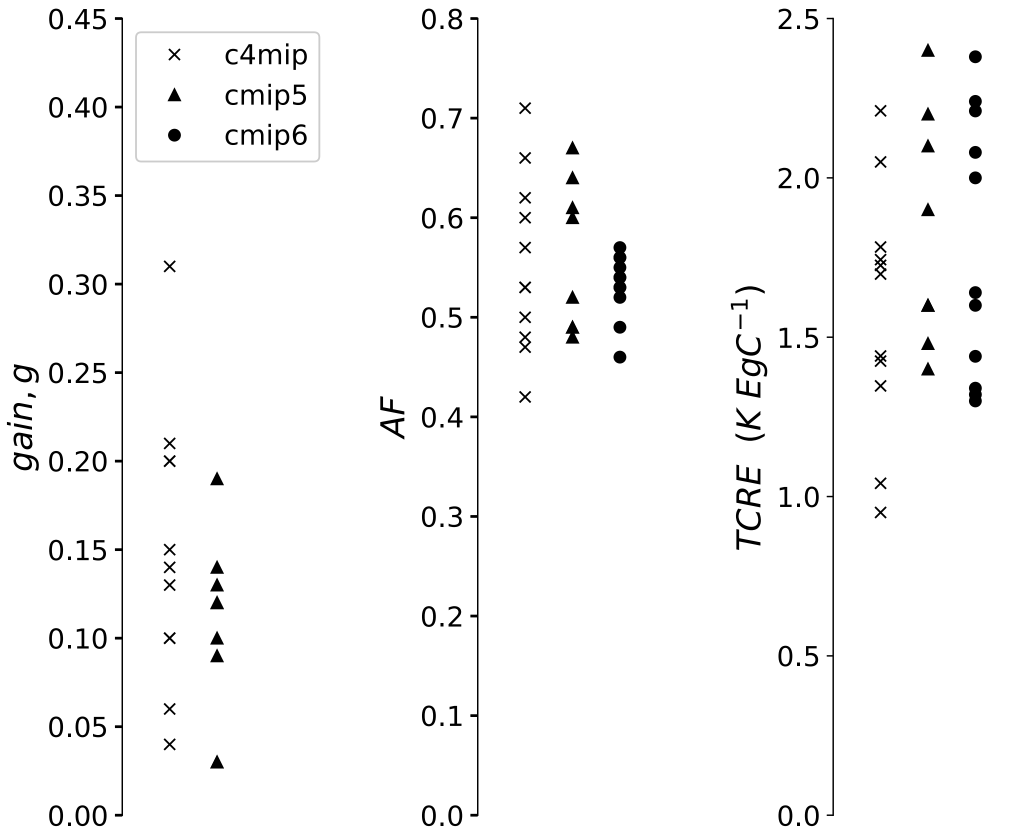

Figure 3. Comparison of ESM sensitivities by generation (C4MIP, CMIP5, CMIP6). Metrics shown are carbon cycle feedback gain, g (left hand axis), airborne fraction, AF (middle axis) and TCRE (right hand axis).

4. Discussion

We discussed earlier that initial analysis of C4MIP results focussed on the climate feedback, γ, as the largest source of uncertainty. While both carbon cycle terms (β and γ) exhibit substantial spread across models, on land and in the oceans, our results show that the most important component to constrain depends on which measure we look at. If we want to know the climate carbon cycle feedback gain, g, then the biggest source of uncertainty is indeed γ. But, to constrain the cumulative airborne fraction, we need to constrain β, and to constrain TCRE we need to constrain both α and β. Our results demonstrate that a change in emphasis is required in order to target carbon cycle research more directly at issues associated with meeting the goals of the Paris Agreement. Specifically, we argue that there is a need to re-focus analysis and model evaluation on CO_2 response and drivers of sinks. It is this response to CO_2 that drives a greater amount of the future behaviour of carbon sinks under low CO_2 pathways where climate change is limited.

What does this analysis mean for projections for the 21st century? To date almost all climate-carbon cycle modelling and feedback analysis has focussed on high, monotonic CO_2 scenarios: from IS92a (Cox *et al* 2000) to SRES-A2 (Friedlingstein *et al* 2006) to the RCP8.5 and 1% idealised experiments of CMIP5. These scenarios see rapid and continuous increase in CO_2 reaching between 700 and 1100 ppm by 2100 (figure 6). In contrast, however, strong mitigation scenarios aimed at achieving the climate targets of the Paris Agreement stabilise or peak and decline at much lower levels: e.g. RCP2.6 peaks CO_2 at 443 ppm by 2050, just 30 ppm above 2020 levels. How do we know, therefore, that our feedback analysis remains valid under the very difference scenario characteristics?

Analysis of CMIP5 simulations (Jones *et al* 2013) showed that in future, land, ocean and airborne fractions of emissions were quite different under RCP2.6 than the other scenarios. This is not unexpected—(Raupach 2013) showed that the near-constancy of historical airborne fraction was a direct result of the near-exponential increase in emissions. Deviation from exponential increase would therefore lead to deviation from a constant airborne fraction. Other recent work has shown path-dependence of carbon cycle response and TCRE. For example, (MacDougall *et al* 2015) demonstrate carbon budgets after overshoot may be smaller than without overshoot due to non-linearities in the ocean thermal and carbon response and permafrost carbon feedbacks. (Tokarska

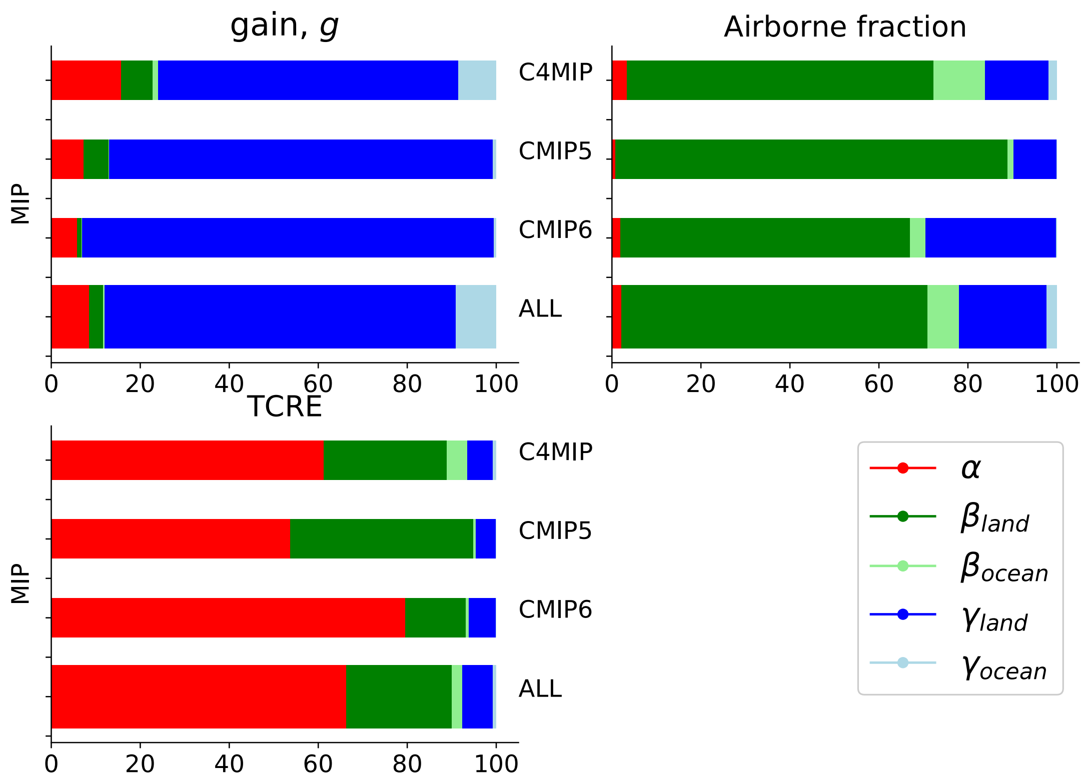

Figure 4. Contributions to variance in g, AF and TCRE, respectively, from α (red), β (green) and γ (blue). Β and γ are further split into land (dark) and ocean (light) components.

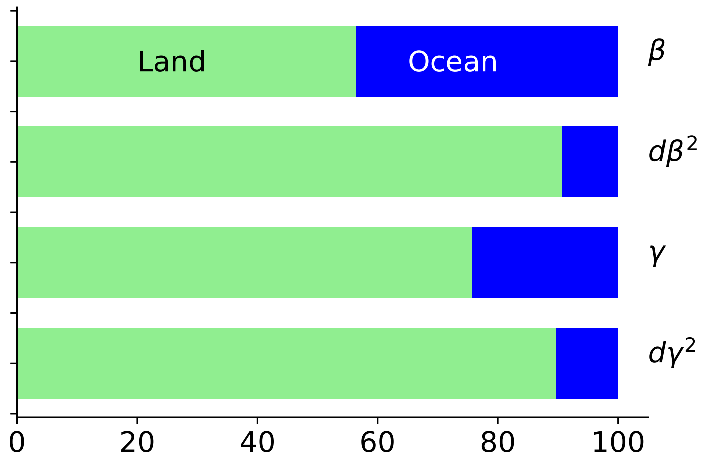

Figure 5. Contributions to the absolute values of β and γ, and their variances, $d\beta^2$, $d\gamma^2$, from land (green) and ocean (blue) carbon cycle, respectively.

et al 2019) showed path dependence of the land versus ocean division of net carbon uptake leading also to path dependence of impacts on terrestrial and marine ecosystems, although for limited overshoot cases, carbon budgets were similar with and without overshoot. (Zickfeld *et al* 2016) explicitly showed non-linearity of global temperature decrease during rampdown of CO_2 and therefore a smaller TCRE to negative emissions, due to the time lag in response to 1% increase in CO_2.

As the policy focus moves towards low targets, it seems therefore likely that future emissions will deviate strongly from continued exponential increase and therefore that the future airborne fraction will depart from its historical value of approximately 50%. Although we know that TCRE and individual elements of the carbon cycle may behave differently under low scenarios such as RCP2.6, very little specific feedback analysis has been conducted on low stabilisation or peak-and-decline scenarios. Under

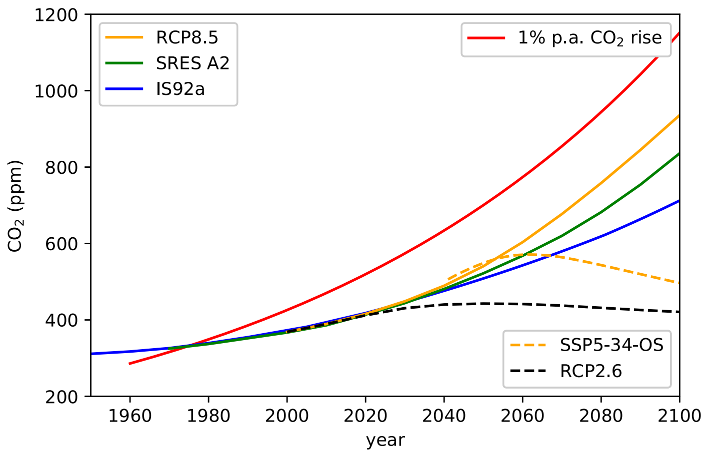

Figure 6. CO_2 concentration scenarios commonly used—previous analysis has focussed on rapid/monotonic increase. For example (Cox *et al* 2000) used IS92a (blue line), the first C4MIP (Friedlingstein et al 2006) used SRES A2 (green line) and CMIP5 and CMIP6 simulations drew on both 1% per annum increase (red line: Arora et al 2013, 2019, Ciais et al 2013) and RCP8.5 (yellow line: Collins et al 2013; Friedlingstein et al 2014). Note 1% per annum increase nominally begins in 1850 but plotted here relative to 1960 for ease of comparison on this schematic figure. Policy relevant mitigation scenarios that aim to achieve global climate targets typically show overshoot of CO_2 concentration—e.g. RCP2.6 and SSP5-3.4-OS (dashed lines).

such scenarios which limit global climate change, focus on the drivers of natural carbon sinks and their persistence becomes even more important—for example, (Schwinger and Tjiputra 2018) showed non-reversibility of components of the ocean carbon store in response to CO_2 reversal. Specifically, for CMIP6 the ScenarioMIP and C4MIP pair of simulations based around SSP5-3.4OS will bring valuable insights into how feedback metrics change in time.

The framework we have developed here serves multiple purposes. Firstly, it allows us to construct the behaviour of key parts of the Earth system such as airborne fraction and TCRE from process-level carbon feedback components. Secondly it allows us to attribute uncertainty in these properties to uncertainty in components and therefore focus research priorities onto the carbon cycle response to CO_2 ('β'). Thirdly, in addition to these, it opens up possibilities of applying and combining constraints on feedbacks. For example, if we know α we can calculate how the value and range of AF, TCRE is constrained. The β and γ quantities are formed linearly from the contribution at each gridbox (e.g. Roy *et al* 2011, Ciais *et al* 2013) and so we could further allocate uncertainty more regionally such as to ocean basins or on land in latitude bands. Currently we have no way of perfectly constraining these components, but our feedback framework would allow partial constraints to be combined into a stronger one. Literature is emerging that demonstrates emergent constraints on regional aspects of carbon feedbacks such as interannual variability in the tropics (Cox *et al* 2013) or seasonal cycle in mid-latitudes (Wenzel *et al* 2016) as well as on TCR (Nijsse *et al* 2020). Further work will apply these constraints to reduce spread in AF and TCRE.

5. Conclusions

The concept of TCRE has been successful in combining the full Earth system response into a single, simplifying number which can be used to calculate remaining carbon budgets to help achieve global climate targets. But in order to understand it and constrain its sources of uncertainty we need to break it apart again. It can be easily split into 'climate' and 'carbon cycle' terms (although these are not independent as they interact) e.g. (Gillett *et al* 2013). Williams *et al* (2017, 2020) focus on the climate aspect and split TCR into terms of individual feedbacks and ocean heat uptake. Here we focus on the carbon cycle aspect and explore within AF the contribution from carbon-cycle feedback components. The two approaches are complimentary and find similar results—that both climate and carbon responses are similarly responsible for TCRE, with the balance of uncertainty varying in time within a simulation (Williams *et al* 2017) and between generations of models (this study). The comparison between generations of models, however, should be interpreted with caution due to the small sample of models. Ringer (2020) shows how even across 30–40 models in CMIP generations, changes in the distribution of feedbacks may happen by chance. Our samples here of the order <10 models per generation are not enough to draw robust conclusions that changes in uncertainty follow a systematic change. Therefore, we conclude that both climate and carbon cycle must remain vital avenues of research to reduce uncertainty TCRE.

Based on our analysis we make some recommendations for the climate-carbon cycle research community. These recommendations feed into the WCRP number-1 question 'where does the carbon go?' (Marotzke *et al* 2017) and also address the 3 priority questions of the WCRP Grand Challenge on carbon cycle feedbacks—what processes drive land and ocean carbon sinks? how will climate-carbon feedbacks amplify climate change? and how will it affect vulnerable carbon stores?

Our primary recommendation is to re-focus research effort onto understanding and better simulating carbon cycle response, both land and marine, to CO_2. This represents the primary driver of natural carbon sinks, the largest source of uncertainty in future airborne fraction and contributes much more than γ to uncertainty in TCRE. If we are to reduce uncertainty in future carbon budgets this must be our primary focus. While land contributes most to model spread, ocean sinks contribute equally to the carbon sink and have substantial uncertainty at regional level (Hewitt *et al* 2016) and become increasingly important on timescales beyond 2100 (Randerson *et al* 2015, Jones *et al* 2016b).

Secondly, we have shown that reconstruction of the airborne fraction of CO_2 emissions and TCRE, are achieved more precisely using feedback metrics derived at a level of 2 $\times$ CO_2 in the 1% simulation than at the end (at 4 $\times$ CO_2). Therefore we recommend that future feedback analyses quote values at both of these levels as has been done in (Arora *et al* 2019).

Thirdly, research is lacking into the behaviour of carbon cycle feedbacks in low stabilisation and overshoot scenarios. The airborne fraction and sink efficiency are not uniform under different scenarios or rates of change. We know that TCRE and other components of the Earth system can exhibit path dependence, so research must also focus on low stabilisation or overshoot scenarios. For such low scenarios, both fully coupled and biogeochemically coupled simulations are required.

Fourthly, we recommend that more effort is put into understanding the full range of uncertainty within and across models. We have demonstrated marked differences in the ensemble spread between CMIP5 and CMIP6 but we do not know how robust this finding is, nor its full implication, due to the small set of models available. Perturbed parameter approaches (e.g. Booth *et al* 2012, MacDougall *et al* 2016) offer a way to more systematically explore the uncertainty range of feedback metrics and their implications for AF and TCRE, and we recommend that more ESM models should consider such approaches.

Finally, we stress the vital role of evaluation. As ESMs have developed in complexity, they bring unprecedented opportunity to simulate these quantities such as AF and TCRE which inform global negotiations on carbon budgets, but they also require increasing levels of evaluation to ensure process realism (Jones 2020). CMIP6 sees a marked difference over CMIP5 regarding inclusion of terrestrial nitrogen cycle in many models: a key systematic omission in previous generations. But whether CMIP6 models will systematically evaluate better than CMIP5 is not yet known. Comparison of models against the growing wealth of ecosystem observations and manipulation experiments (e.g. Medlyn *et al* 2015, Walker *et al* 2015) is crucial. Posterior constraints on projections can also be very powerful. Our framework offers an exciting opportunity to combine existing and new constraints and make real progress towards reduced uncertainty in assessing remaining carbon budgets.

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Data availability

No new data were created or analysed in this study. Data analysed has been assembled from previously published work. Data sources are listed in the caption for table SI.1 in the supplementary information.

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