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Model structure in observational constraints on transient climate response [*]

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Abstract

The transient climate response (TCR) is a highly policy-relevant quantity in climate science. We show that recent revisions to TCR in the IPCC 5th Assessment Report have more impact on projections over the next century than revisions to the equilibrium climate sensitivity (ECS). While it is well known that upper bounds on ECS are dependent on model structure, here we show that the same applies to TCR. Our results use observations of the planetary energy budget, updated radiative forcing estimates and a number of simple climate models. We also investigate the ratio TCR:ECS, or realised warming fraction (RWF), a highly policy-relevant quantity. We show that global climate models (GCMs) don't sample a region of low TCR and high RWF consistent with observed climate change under all simple models considered. Whether the additional constraints from GCMs are sufficient to rule out these low climate responses is a matter for further research.

1 Introduction

The steady-state global mean surface temperature (GMST) response of the climate system to a doubling of atmospheric CO_2 concentrations, the "equilibrium" climate sensitivity (ECS), is the standard metric of the response of our climate to external forcing. Typically, general circulation model (GCM) simulations take many centuries to fully realise this new climate equilibrium, due to long response timescales associated with the thermal inertia of the deep ocean, but estimates of the effective ECS (evaluated from a regression of top-of-atmosphere radiative flux against GMST change) can be made from much shorter integrations (Gregory et al., 2004). ECS is highly relevant to concentration stabilisation scenarios, which remain the stated goal of the UNFCCC process. However, over the next few decades, and in scenarios where the radiative forcing continues to increase, or peaks and declines (Frame et al., 2006; Allen et al., 2009),

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the long timescales and potential nonlinear feedbacks (Andrews et al., 2012) associated with ECS do not make ECS the most relevant measure of the climate response for the next century. It has often been argued that the transient climate response (TCR) is more policy-relevant for contemporary climate change (Frame et al., 2006; Hegerl et al., 2007). The TCR is defined as the GMST warming when atmospheric CO_2 concentrations double after 70 years when increased by 1% per year from pre-industrial values. The TCR describes warming for a climate system in disequilibrium and can be better constrained by observations of the disequilibrium climate and radiative forcing of the 20th century and the near future.

Various methods have been used to try and constrain the uncertainty on ECS and TCR. One class of such methods is to use a simple model to constrain the joint distribution of TCR and ECS from observations of the planetary energy budget. Recent studies estimating TCR and ECS via these methods have received substantial attention (Otto et al., 2013; Huntingford, 2013; Schmidt et al., 2014), especially as they have suggested TCR uncertainty intervals that include lower values than sampled by existing GCMs. These methods, which incorporate direct observations of the climate system and do not use GCMs, are often referred to as observational estimates of TCR and ECS, which incorrectly implies they are model-independent. It is well-established that inferences about ECS using such methods depend on the structure of the simple model used as shown by Knutti et al. (2008) in response to Schwartz (2007). However, it is often assumed that estimates of TCR are more-or-less independent of the specifics of the simple climate model.

2   Uncertainty in recent estimates of TCR and ECS

The TCR and ECS are inherently related, both being measures of the climate response to external radiative forcing, but on different time-scales. In GCMs ECS is approximately linearly related to TCR over low to mid range realisations of ECS (Knutti et al., 2005; Forster et al., 2013). Figure 1 shows this relationship in both the CMIP5 multi-model ensemble (MME) and a large perturbed-physics ensemble (PPE) of the HadCM3 GCM selected based on their emulated ability to reproduce global radiation balance in their control climate (Yamazaki et al., 2013).

Figure 1 includes the IPCC *likely* uncertainty ranges (a 2 in 3 chance of finding the value within this range) for ECS and TCR from the 4th (AR4 - green) and 5th (AR5 - red) Working Group 1 Assessment Reports (IPCC, 2007, 2013). In AR4, there was no *likely* range for TCR given, with TCR uncertainty assessed as *very likely* greater than 1.0K and *very unlikely* less than 3.0 K (Solomon et al., 2007), where *very likely* denotes a 9 in 10 probability and *very unlikely* a 1 in 10 probability. The only TCR *likely* range that can be inferred from AR4 without further assumptions is to set it equal to this interval. This is the most conservative estimate possible and avoids over-interpreting the result from AR4 whilst allowing comparison with the *likely* range from AR5. This means the lower limits of the *likely* ranges of TCR (1.0K) are taken as equal between AR4 and AR5 and likewise, the upper ECS *likely* range limit (4.5K) is taken as equal between AR4 and AR5.

Currently, IPCC estimates for TCR and ECS are given independently without reflection of the correlations shown in figure 1. These independent ranges do not explicitly rule out regions in TCR-ECS space that have TCR>ECS. Taking this additional constraint (the $TCR = ECS$ line is represented by the dashed grey line in figure 1) would rule out parts of region A and B in figure 1 as physically implausible.

Figure 2 shows an alternative way to visualise the information shown in figure 1. The TCR:ECS ratio used as the y-axis in figure 2 is a measure of the fraction of committed warming already realised after a steady increase in radiative forcing, a clearly policy-relevant quantity. We call this quantity the *realised warming fraction* (RWF) hereafter. The lower correlation between the RWF and the TCR demonstrates that these two quantities are more statistically independent of each other in contemporary GCMs than TCR and ECS (correlation coefficients of 0.12 and 0.86 respectively for the CMIP5 models). Whilst the RWF and TCR are mathematically linked (via ECS), this approximate statistical independence in state
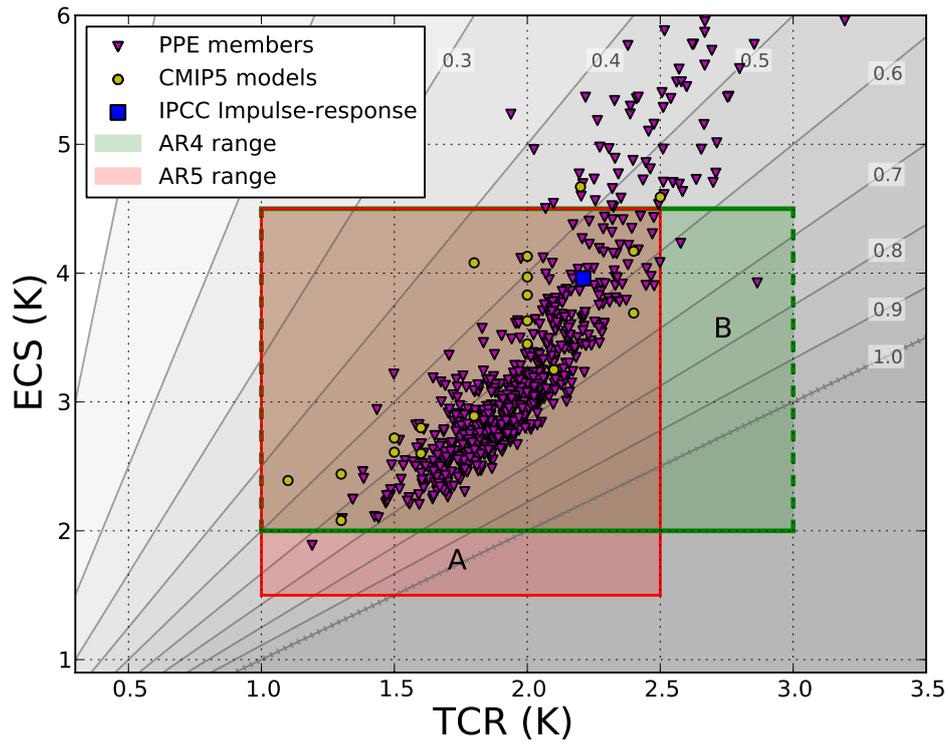
Figure 1: The TCR and the ECS for the CMIP5 MME (yellow circles) and for a PPE of the HadCM3 GCM (purple triangles). The *likely* ranges from the IPCC AR5 (red) and the inferred AR4 (green) *likely* ranges (the inferred limits are marked as dashed lines) are shown along with grey lines of constant RWF (TCR:ECS ratio). The implicit sensitivity of the impulse-response model used for metric calculations in AR5 is marked as "IPCC Impulse-response". Regions not common to both AR4 and AR5 *likely* estimates are marked A and B.

Figure 2: As figure 1 but the y-axis is the RWF (TCR:ECS ratio) and now lines of constant ECS are marked and shaded in grey.

of the art climate models makes characterising the climate response in terms of these quantities more informative than in terms of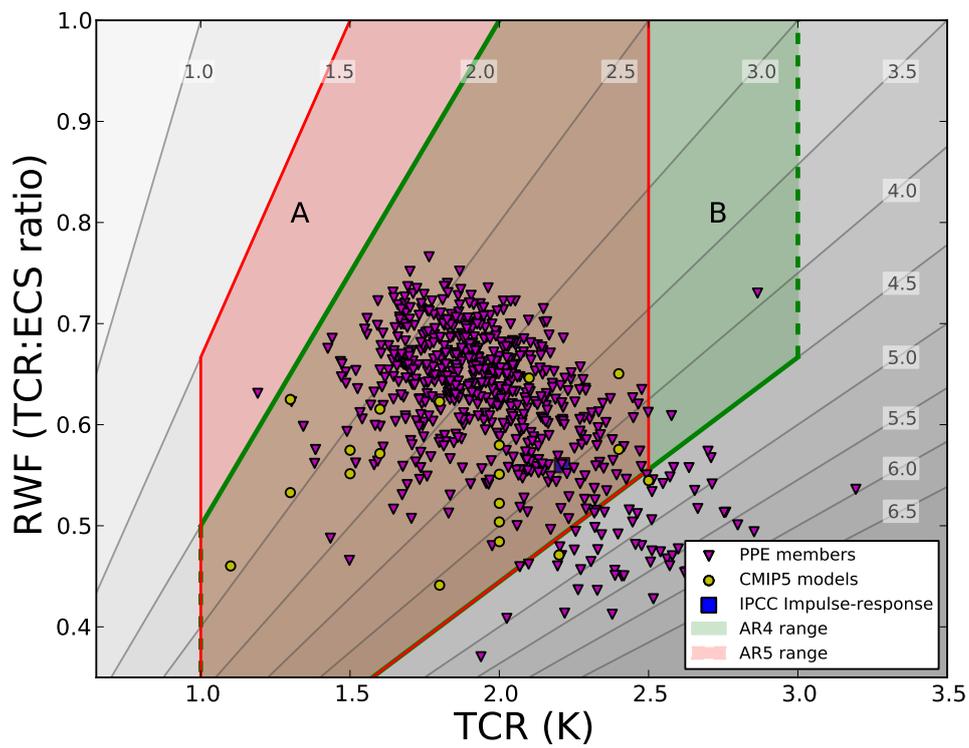 the more correlated TCR and ECS. There is evidence of negative correlation between RWF and TCR in the PPE (particularly at high TCR). This is consistent with the frequently noted deviation of the TCR vs. ECS relationship from linearity at high climate sensitivities (Knutti et al., 2005), which are sampled more densely in the PPE than the MME.

In terms of understanding future climate response it may be easier to understand the implications for climate projections if studies focus on estimating these two near-independent quantities, which can both be estimated from observations (RWF can be estimated from observations via a simple model, e.g. equation 4), although estimates of any two are of course sufficient to determine the third. It could be more useful to policy-makers for a body such as the IPCC to report uncertainty ranges in these two more independent quantities rather than independent ranges for the correlated TCR and ECS. A choice of more independent parameters would communicate more information about the climate response. Andrews and Allen (2008) discusses how independent metrics of climate response are preferable for understanding climate response within a simple model framework. The use of RWF and TCR as independent metrics of climate response fulfils this criteria and is equally applicable to simple models and GCMs.

Neither the HadCM3 perturbed physics ensemble nor the CMIP5 ensemble give an indication of a decrease in RWF for low TCR. Similarly, recent observational estimates of TCR and ECS using simple climate models are also consistent with a high RWF at low TCR (e.g. (Otto et al., 2013)). As such, the AR5 *likely* region, which includes region A in figure 2 whilst excluding region B, represents a region more consistent with our overall understanding of TCR and ECS uncertainties based on published evidence from multiple methods.

3   The constant climate resistance approximation

Several recent investigations have attempted to constrain TCR and ECS using recent observations of the planetary energy budget (Padilla et al., 2011; Schwartz, 2012; Otto et al., 2013; Lewis, 2013). In order to relate such observations to measures of climate response, such as TCR and ECS, a simple climate model structure must be assumed.

A common method to estimate TCR from observations of the planetary energy budget relies on approximating the net heat uptake by the climate system ("energetic disequilibrium of the climate") as a heat sink proportional to the change in GMST, as seen approximately in GCMs with steadily increasing forcing (Gregory and Forster, 2008). The energy balance of the climate can be represented in a global-mean formulation as,

$$\Delta Q = \Delta F - \lambda \Delta T, \tag{1}$$

where ΔQ is the heat uptake of the climate system (dominated by the ocean heat uptake on climatological timescales), ΔF is the tropopause radiative forcing of the climate system, λ the climate feedback parameter and ΔT the GMST change due to the forcing. Making the assumption $\Delta Q = \kappa \Delta T$ (known from here on as the "constant climate resistance" approximation) is equivalent to assuming that the deep ocean acts as an infinite heat sink. This allows equation (1) to be rewritten as $\Delta F = (\kappa + \lambda)\Delta T$ (Gregory and Forster, 2008). If we assume that the sum of κ and λ is constant over time, this model contains no response timescales and implies that GMST change is directly proportional to the radiative forcing change. Then the TCR can be estimated from observations as:

$$\widehat{TCR} = F_{2\times} \frac{\Delta T(t)}{\Delta F(t)}. \tag{2}$$

$F_{2\times}$ is the radiative forcing from doubling atmospheric CO_2 concentrations relative to pre-industrial, $\Delta T(t)$ and $\Delta F(t)$ are respectively the GMST warming and change in radiative forcing at any point in

time, t, relative to a reference period, and $\hat{x}$ is used to denote an observational-estimate for a property of the system, x. $\widehat{TCR}$, might be called an effective TCR (as it is estimated from observed climate change), but in many ways this would be misleading as, unlike the climate sensitivity parameter, for which there is evidence of genuine time dependence in GCMs (Senior and Mitchell, 2000), the TCR itself is a time-independent quantity. Incorporating observations of changes in planetary heat uptake, ΔQ, an observational quantity that has a large uncertainty and a short observational timeseries (Levitus et al., 2012), allows the ECS to be estimated within the same framework:

$$\widehat{ECS} = \frac{F_{2\times}\Delta T(t)}{\Delta F(t) - \Delta Q(t)}. \tag{3}$$

Under the "constant climate resistance" approximation, the RWF becomes,

$$RWF = \frac{\widehat{TCR}}{\widehat{ECS}} = 1 - \frac{\kappa}{F_{2\times}}\widehat{TCR} = 1 - \frac{\Delta Q}{\Delta F}. \tag{4}$$

For GCMs to lie along a straight line in figure 2 the ratio $\kappa : F_{2\times}$ would need to be constant between models. For a given TCR, the RWF (or ECS) would be determined by the ratio $\kappa : F_{2\times}$. It may be productive for future studies to examine whether this absence of GCMs with ECS significantly below 2K is physically-based via this ratio of more statistically independent climate parameters.

4   The impact of AR5 TCR and ECS uncertainty ranges on future climate projections

A simple energy balance model that incorporates response timescales of the climate system is a two-box impulse-response model (Boucher and Reddy, 2008). The use of two constraints allows the parameters of the impulse-response model consistent with a particular TCR and ECS combination to be formulated assuming fixed response timescales (see Supplementary Information). We can use the impulse-response model to examine the impact of changes in the IPCC uncertainty ranges for TCR and ECS between AR4 and AR5 on future projections of climate change (Rogelj et al., 2014).

For specific values of TCR and ECS, the impulse-response function can be integrated with the observed historical radiative forcing and future scenarios. However, to assess the consistency of different TCR and ECS impulse-response models with observations of historical climate change, uncertainty in historical radiative forcing must also be considered.

We follow Padilla et al. (2011) in assigning all the uncertainty in the historical radiative forcing time series to anthropogenic aerosols, as the IPCC assigns the greatest radiative forcing uncertainty to this component. This is expressed via the use of an aerosol forcing scaling factor,

$$F(t) = F_{other}(t) + xF_{aero}(t), \tag{5}$$

with F_{aero} the best estimate of the component of radiative forcing due to anthropogenic aerosols, F_{other} all other components of the radiative forcing, and x the non-dimensional scaling factor. As the model response is linear in its forcing inputs, this scaling factor propagates into a scaling factor in the temperature response,

$$T(t) = T_{other}(t) + xT_{aero}(t). \tag{6}$$

By constraining temperature change over a certain period to agree with observations, we can calculate the aerosol forcing scaling factor required to make a climate response function of specified ECS and TCR consistent with observed climate change whilst ensuring that total forcing is consistent with AR5
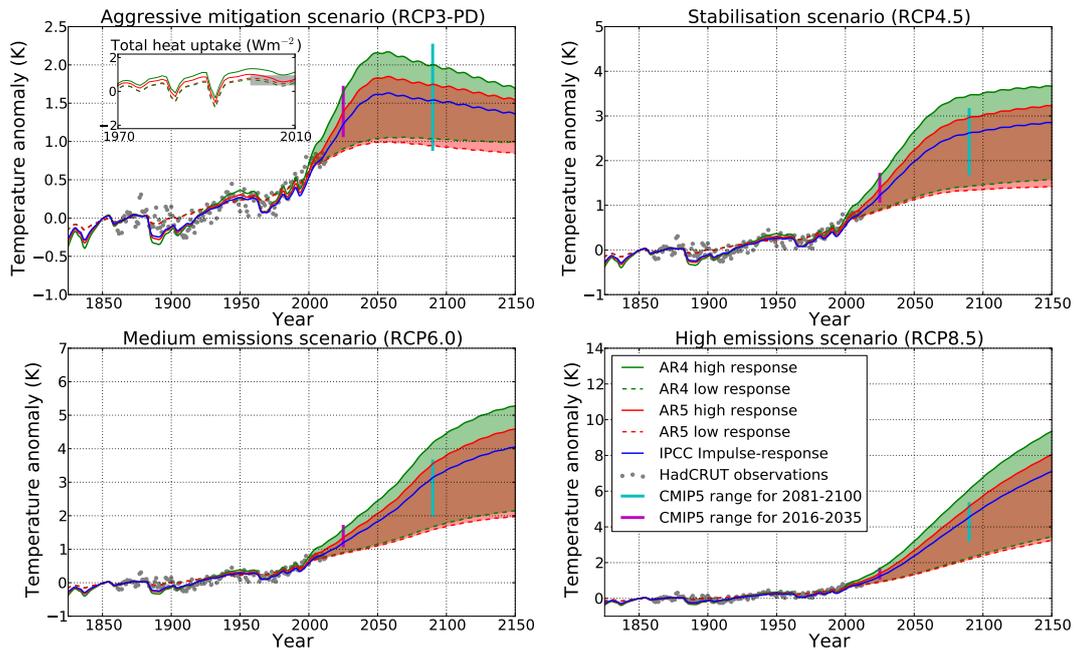
Figure 3: GMST projections for the four RCP scenarios derived using the impulse-response simple climate model (described in the Supplementary Information). Note that the y-axis scales are not identical. The red shading shows the projection envelope consistent with AR5 ECS and TCR *likely* ranges and scaled forcings. The green shading shows the same for the AR4 *likely* ranges. All temperature changes are given relative to the 1860-1880 average. The range of the CMIP5 models for the near-term and long-term GMST projections from AR5 are included. The blue line shows scenario projections under the impulse-response model used for metric calculations in AR5 Ch 8 (Myhre et al., 2013b). The inset panel shows system heat uptake for the limits of the *likely* ranges with the grey shaded bar marking the standard deviation around the 2000-2009 average.

estimates. We integrate the upper/lower limits of the AR5 *likely* TCR and ECS ranges with the anthropogenic aerosol timeseries scaled to give lower/upper *likely* estimates of 2011 total radiative forcing in AR5.

The panels showing the projections for RCP6.0 and RCP8.5 in figure 3 show that the reduction of the lower ECS *likely* bound (the lower limits of the projection envelopes, in which the only difference between the AR4 and AR5 case is the lower ECS limit in AR5) in AR5-based projections has a barely discernible effect relative to the AR4-based projections out until around 2150, where the longer timescale climatic response, mainly associated with ECS, starts to emerge. The main effect of the AR5 TCR and ECS uncertainty updates is to reduce the likelihood of the high end of AR4-based projections, corresponding to the downgrading of the upper limit of the TCR estimate. Therefore, for policy-relevant projections, the revision of TCR range is much more important than revisions to the ECS range.

RCP2.6 shows a faster cooling after the temperature peak in the AR4 high-sensitivity case than the AR5 high-sensitivity case, despite a greater peak temperature change being achieved mid-century under the AR4 high-sensitivity integration. This is consistent with the higher TCR in the AR4 high-sensitivity limit causing a faster decrease of temperatures in response to the net negative emissions technologies incorporated in the RCP2.6 scenario. However, we should be cautious about giving too much weight

to the projections of a simple climate model beyond the peak of any forcing timeseries (Schaller et al., 2014).

It is clear that models that fit the observational record can still simulate a large variety of climate futures. Unlike the long-term CMIP5 projections, the near-term CMIP5 projections span a range that extends above the projection envelope indicated by the AR5 TCR, ECS and forcing uncertainties. In all scenarios (except for RCP2.6 where the radiative forcing peaks and declines) the long-term GMST projections are either completely contained within the AR5 uncertainty envelope or extend beyond it by a lower percentage than in the near-term projections. This analysis supports the scaling down of the raw CMIP5 model projections for the near-term warming (2016-2035) but an unadjusted long-term warming (2081-2100) when forming the *likely* projection ranges quoted in AR5 in order to be consistent with the sensitivity and forcing uncertainties quoted elsewhere in the report (IPCC, 2013). In the RCP scenarios with fast growing radiative forcing (RCP6.0 and RCP8.5), the long-term CMIP5 projection ranges lie over the warmer part of the simple model AR5 uncertainty envelope. This would be consistent with increases in the climate sensitivity parameter at higher GMST in the GCMs associated with potential additional feedbacks that are not captured in the fixed sensitivity simple model (Gregory and Forster, 2008; Winton et al., 2010).

In this section, we have considered the literal interpretation of independent ECS and TCR ranges in AR4 and AR5 for future temperatures under standard emission scenarios. In allowing the TCR to change and ECS to be held constant (varying RWF) between the high sensitivity limits of the AR4 and AR5 cases (and vice versa for the low sensitivity limits) we offer only a literal interpretation of which of these assumed independent parameters make the most difference for future temperature projections. As shown clearly in figure 1, ECS and TCR are correlated, and assuming they can vary independently does not reflect the representaions of climate response in current GCMs. This offers further evidence for the value of summarising future GMST response using the more independent quantities RWF and TCR.

5   Estimating TCR and ECS from observations and simple models

Constraining climate response from observations always requires a model to relate the observations to the climate response. This section contrasts the use of the two-timescale impulse-response model with the previously used "constant climate resistance" approximation in order to show the impact of simple model structure on inferences about the transient climate response. In this section we choose to focus on uncertainties in TCR estimates rather than in ECS estimates. This is both because dependence of uncertainties in observationally-based estimates of ECS are already well-established (Knutti et al., 2008), and because the varying radiative forcing in the TCR definition is more relevant to policy decisions that have to be taken over the next few decades in which the radiative forcing is likely to still be increasing and the climate system is substantially out of equilibrium due to heat uptake by the oceans. Indeed, the analysis in section 4 shows that when TCR and ECS are considered independent the TCR is more important for climate projections out until around 2150. TCR is a more relevant metric of climate response to future projections as it better predicts the transient response to cumulative emissions (TCRE) (Gillett et al., 2013) and is also relevant to any scenario in which concentrations peak and decline (Frame et al., 2006).

The "constant climate resistance" approximation, where the temperatures respond instantaneously to the forcing, is the limiting case of the impulse-response model in which the short time-constant tends to zero and the long time-constant tends to infinity. This makes the approximation for TCR in (2) exact. Under a linear forcing ramp in which CO_2 concentrations are increased by 1% each year for 70 years, the "constant climate resistance" approximation underestimates the GCM-calibrated impulse-response model's actual TCR due to the inclusion of thermal delay in the impulse-response model.

We use a likelihood-maximising method to sample uncertainties in the last decade of observations
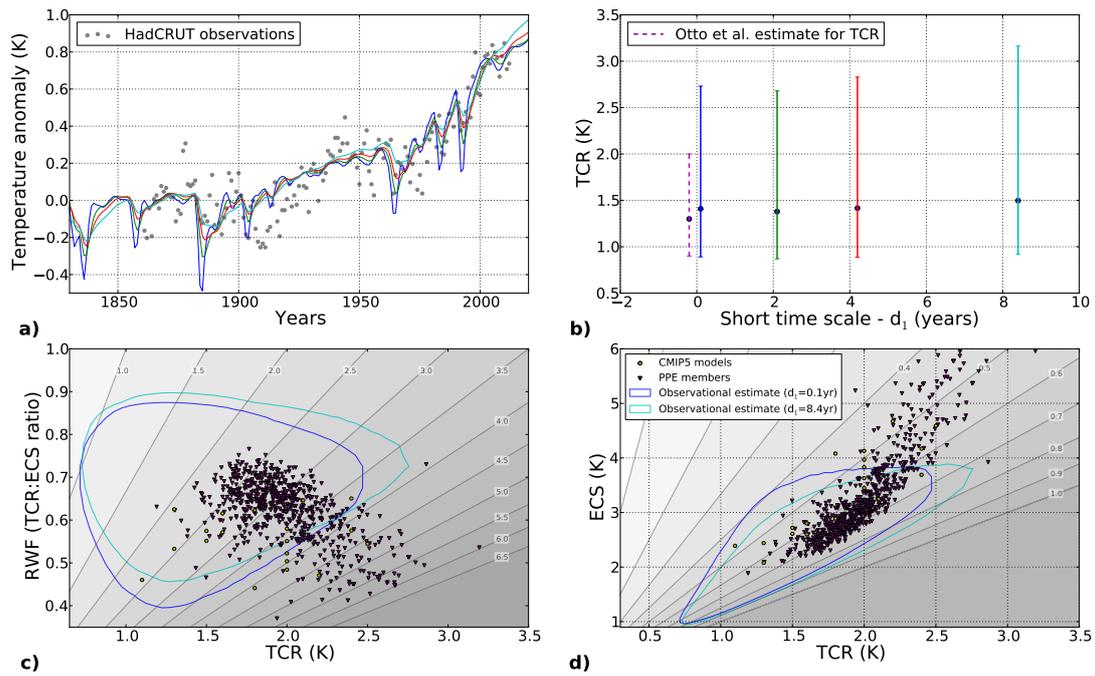
Figure 4: a) The best fit model to observations with a variety of values for d_1, the short timescale in the impulse-response model. b) The best estimate and 5 - 95% confidence intervals for TCR for different values of d_1. The dashed purple bar shows the estimate derived in Otto et al. (2013). Its position on the x-axis is arbitrary. c) The 90% maximum likelihood regions for the GCM-tuned impulse-response model (light blue) and "constant climate resistance" approximation (royal blue) on the same axes as in figure 2. d) The same information transformed onto the axes of figure 1.

of the planetary energy budget and then infer joint distributions of TCR and ECS consistent with these observational uncertainties using the simple climate models. An ensemble of effective radiative forcing is derived by splitting the total radiative forcing into the 11 components of the timeseries of historical radiative forcing given by Myhre et al. (2013a) and randomly sampling each component based on the 5-95% confidence intervals and best estimates of each forcing component given in AR5 (Myhre et al., 2013b). We exactly follow Otto et al. (2013) in sampling the observed GMST anomaly uncertainty and the uncertainty in ocean heat uptake observations. All changes are expressed as the difference of the 2000-2009 average from a reference period of 1860-1879 over which ocean heat uptake is assumed small.

From these observational Gaussians for temperature change and ocean heat uptake we again sample a large number of realisations of the data. From these independent realisations of the GMST change, planetary heat uptake anomaly and radiative forcing we use our simple model to infer the values of the c_1 and c_2 parameters that are consistent with each realisation of the observational data, assuming given response timescales, d_1 and d_2. Realisations that produce model parameters that obviously correspond to non-physical representations of the climate (negative climate sensitivities) are excluded from the calculated distributions. We then follow the method of Allen et al. (2009) (Supplementary Information) to draw our likelihood region contours.

The panels in figure 4 show inferences about TCR and its uncertainty from the observational data as a function of the short timescale of the climate response used in the impulse-response function, d_1. As the short response timescale is the dominant mode over the observed historical period, inferences about TCR are largely insensitive to the long response timescale (not shown).

The observational GMST data can be fit well for a variety of impulse-response models (figure 4a). The main difference of fit between the models occurs where they are responding to strongly negative but short-lived forcing such as from volcanic eruptions. These appear (assuming all forcing efficacies to be unity) to allow us to exclude the shortest timescale version of the impulse-response (equivalent to the "constant climate resistance" model) but do not distinguish the other models. Using volcanoes to constrain response timescales is also complicated by dynamical features of the volcanic response not captured by an energy-balance model.

Figure 4b shows that the choice of short timescale leads to considerable difference in upper bound of the TCR confidence interval. We here focus on frequentist confidence intervals to make our approach more transparent and avoid issues over prior distributions. We show distributions for multiple values of the short response timescale solely in order to demonstrate structural uncertainty in this method. As we are not attempting to construct a Bayesian posterior representing a degree of belief in the exact TCR of the real climate system, we do not comment on the relative likelihoods of different short response timescales and our discussion here serves merely to highlight the sensitivity of the results to this parameter. While the best estimate TCR and lower confidence interval bound are relatively insensitive to d_1, the upper confidence interval bound shows a nonlinear dependence on d_1, demonstrating the choice of simple climate model is important. The dashed purple bar shows the TCR confidence interval from Otto et al. (2013). That study used the "constant climate resistance" approximation, with the deviation from the blue bar (our "constant climate resistance" model) arising from the updated radiative forcing uncertainties used here. The increased radiative forcing uncertainty again primarily impacts the upper bound of the TCR confidence interval.

Figure 4c and d show the 90% likelihood regions for the GCM-calibrated impulse-response model and the "constant climate resistance" approximation in the two-dimensional space shown in figure 2 and figure 1 respectively. The dependence of our inferences about the climate response on simple-model structure is again shown via the difference between the two contours. However, a common feature of the inferences from observations using the simple models considered here is a region of high RWF at low TCR that is consistent with these observationally-based methods but is not sampled by the GCMs. The HadCM3 perturbed-physics ensemble samples higher RWFs than the CMIP5 ensemble (although not at the same time reaching the low TCR values necessary to match the contours from the simple models). However,

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these models have had no tuning or validation beyond their ability to reproduce top-of-atmosphere fluxes in a control climate.

Comparing GCM sensitivities from CO_2-only integrations with sensitivities derived from the historical observational period, in which multiple forcing agents have been forcing the climate system with inhomogeneous spatial coverage and different efficacies (the relative efficiency of a unit of radiative forcing from a gas in driving GMST change relative to a unit of CO_2 radiative forcing), are potential explanations of this low sensitivity discrepancy between the two methods (Shindell, 2014; Kummer and Dessler, 2014). Additional caveats are the limitations of the simple climate model used to analyse the observational data. The simple model used contains no representation of internal variability in GMST, which may conflate decadal scale variability with forced response which has knock-on effects for estimates of climate sensitivity (Huber and Knutti, 2014). A particularly important limitations of these energy balance models is that the climate feedback parameter is assumed to be constant in time, which is seemingly contradicted in the CMIP ensemble (Winton et al., 2010). Accounting for these simplifications in the simple model, may be partly responsible for the RWF discrepancy between the observational and simple model RWF ranges and the CMIP5 ensemble. However, as no systematic attempts have been made to explore the regions of GCM climate response space consistent with a low TCR and a high RWF, it is unclear whether GCMs cannot simulate this region of climate response space that is consistent with observational and simple model estimates, let alone whether this inability is physically-based. The physical plausibility of a GCM ocean with a very high RWF should be a matter for future research.

6   Summary and wider implications

To understand 21st century climate change, an understanding of the sensitivity of the climate to steadily increasing radiative forcing is important as this will be the dominant mode of climate change experienced on policy-relevant time-scales, unless significant mitigation actions are taken soon. We have analysed the implications of the latest IPCC uncertainty ranges for TCR and ECS. We suggest that the more statistically independent quantities, RWF (the TCR:ECS ratio) and TCR (both of which can be estimated from observations), might be more policy-useful than the highly correlated ECS and TCR.

When estimating TCR or ECS from observations a model is always needed to relate the observations to the fundamental climate response parameters of the system. We have discussed two different simple models of GMST response. We have shown that, like ECS, inferences about the upper bound of the confidence interval for TCR are dependent on the structure of the simple model. Therefore, a truly 'model independent' estimate of TCR is not possible. Inferences about the upper bound on the TCR confidence interval are important for economic analysis of climate policy because much of the risk associated with future climate change typically comes from the upper end of the projection distribution.

Recent work using the "constant climate resistance" approximation has downplayed the role of structural uncertainty in simple energy balance estimates of TCR (Lewis and Curry, 2014). Whilst the lower bound of the confidence interval and best estimates of the TCR using simple models with multiple response timescales are captured well by the "constant climate resistance" approximation, this work has shown that this is not true for the upper bound of the TCR confidence interval.

Revisions of uncertainty assessments of the TCR and ECS in the AR5 have a limited impact on climate projections until around the middle of next century. The downgrading of the upper TCR *likely* bound is more important than revisions to the lower *likely* bound of ECS in terms of projections over policy-relevant timescales.

Simple energy balance methods using observations and simple climate models indicate a region of low TCR and low ECS that is common to the simple models considered here but not sampled by GCMs. Although issues of data masking, different forcing efficacies and inhomogeneous forcing distributions may account for some of this discrepancy, it is not clear that there are as of yet sufficient constraints

from GCMs to assuredly rule out this region of response space. This may be a interesting issue for future research.

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