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Beyond equilibrium climate sensitivity

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Equilibrium climate sensitivity characterizes the Earth's long-term global temperature response to increased atmospheric CO_2 concentration. It has reached almost iconic status as the single number that describes how severe climate change will be. The consensus on the 'likely' range for climate sensitivity of 1.5 °C to 4.5 °C today is the same as given by Jule Charney in 1979, but now it is based on quantitative evidence from across the climate system and throughout climate history. The quest to constrain climate sensitivity has revealed important insights into the timescales of the climate system response, natural variability and limitations in observations and climate models, but also concerns about the simple concepts underlying climate sensitivity and radiative forcing, which opens avenues to better understand and constrain the climate response to forcing. Estimates of the transient climate response are better constrained by observed warming and are more relevant for predicting warming over the next decades. Newer metrics relating global warming directly to the total emitted CO_2 show that in order to keep warming to within 2 °C, future CO_2 emissions have to remain strongly limited, irrespective of climate sensitivity being at the high or low end.

If we increase the amount of CO_2 in the Earth's atmosphere and wait for the climate to respond, how much warmer would surface temperatures eventually get? What seems like a simple but important question to ask given current and projected human-induced CO_2 emissions is one that scientists have struggled with since the first rough estimates were made more than a century ago[1,2]. To answer that question, starting in the 1960s scientists have used energy-balance arguments combined with observed changes in the global energy budget, evaluated comprehensive climate models against observations, and analysed the relationship between external forcing and climate change over different climate states in the past (see Methods for a list of early publications). The idea of using those different lines of evidence has not changed, but progress in simulating climate, a longer and more accurate observed record of past warming, and better constrained palaeoclimate reconstructions now offer more possibilities to evaluate and constrain models. However, recent research has pointed out previously unknown limitations in some of the concepts and assumptions underlying a single constant climate sensitivity[3]. Although publications using various methods have appeared, arguably the most important recent conceptual insight is that feedbacks change with equilibration time, an insight that is based on studies in comprehensive climate models. Other recent insights show that the treatment of observations is important[4].

Knowing to the first order how the global climate will warm in response to increased CO_2 is critical: for unabated emissions, it is the difference between a hot and extremely hot future. The value of halving the uncertainty in that projection may be in the trillions of dollars[5]. Here we update an earlier Review[6] and report recent progress in this area. We discuss limitations, highlight the implications for climate science and policy, discuss new metrics that relate the climate response directly to emissions and propose avenues for future research.

The climate system response to changes in the Earth's radiative balance depends fundamentally on the timescale considered. The initial transient response over several decades is characterized by the transient climate response (TCR), defined as the global mean surface warming at the time of doubling of CO_2 in an idealized 1% yr^{-1} CO_2 increase experiment, but is more generally quantifying warming in response to a changing forcing prior to the deep ocean being in equilibrium with the forcing (see Methods). Based on state-of-the-art climate models, and instrumentally recorded warming in response to CO_2 and other anthropogenic and natural forcings, the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5) assessed that the transient climate response is 'likely' (>66% probability) to be in the range of 1 °C to 2.5 °C (Fig. 1)[7]. By contrast, the equilibrium climate sensitivity (ECS) is defined as the warming response to doubling CO_2 in the atmosphere relative to pre-industrial climate, after the climate reached its new equilibrium, taking into account changes in water vapour, lapse rate, clouds and surface albedo. It takes thousands of years for the ocean to reach a new equilibrium. By that time, long-term Earth system feedbacks — such as changes in ice sheets and vegetation, and the feedbacks between climate and biogeochemical cycles[3,6,8] — will further affect climate, but such feedbacks are not included in ECS because they are fixed in these model simulations. Despite not directly predicting actual warming, ECS has become an almost iconic number to quantify the seriousness of anthropogenic warming. This is a consequence of its historical legacy, the simplicity of its definition, its apparently convenient relation to radiative forcing, and because many impacts to first order scale with global mean surface temperature. The estimated range of ECS has not changed much despite massive research efforts. The IPCC assessed[7] that it is 'likely' to be in the range of 1.5 °C to 4.5 °C (Figs 2 and 3), which is the same range given by Charney in 1979. The question is legitimate: have we made no progress on estimating climate sensitivity?

Constraints from the instrumental record and variability

ECS and TCR cannot be measured directly, but in principle they can be estimated from: (i) quantifying feedbacks, ECS, and TCR in comprehensive climate models; (ii) potentially constraining models by their representation of present-day mean climate and variability; (iii) analysis of the post-industrial observed warming of the ocean and atmosphere in response to forcing; (iv) the short-term climate response to forcing (such as volcanic eruptions) or interannual temperature variations; and (v) palaeoclimate records (for example, the cooling at the Last Glacial Maximum or the warming during earlier warm periods). A summary of estimates are shown in Figs 1, 2 and 3.

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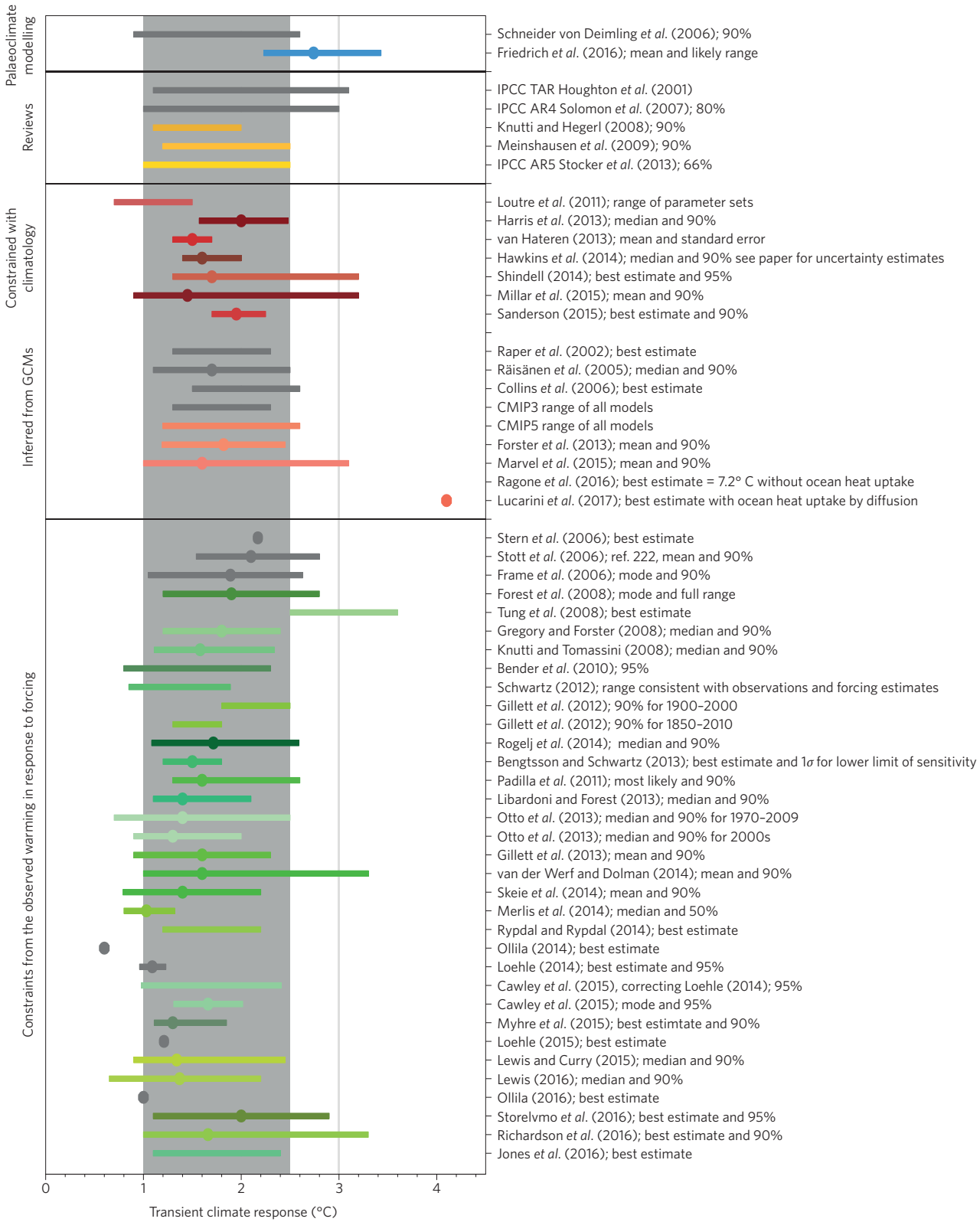

Figure 1 | Overview of published best estimates and ranges for the transient climate response constrained by different lines of evidence. Different colours represent different studies. Dots mark means, medians or best estimates; lines mark different percentile ranges. The grey shaded range marks the 1 °C to 2.5 °C range within which the TCR is 'likely' to lie (probability >66%) as assessed by the IPCC, the grey vertical line indicates a value of 3 °C above which TCR is 'extremely unlikely' (<5%). Details and assumptions are given in the text, the Methods section and Supplementary Table 1.

The use of the recent warming as a constraint is attractive, as greenhouse gases have 'likely' caused 0.5 °C to 1.3 °C of warming (>66% probability) over the period 1951–2010, whereas there is also 'very likely' a human contribution to upper-ocean warming[7]. However, estimating ECS and TCR from the instrumental record requires a conceptual or physical model[10]. In the simplest form, the

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difference between the radiative forcing (F) today and the subsequent change in radiation (λT) resulting from the surface warming (T) needs to be equal to the net energy uptake (Q) of the system: $Q = F - \lambda T$ (see refs 3,6 for details). Over 90% of the excess energy, Q, is taken up by the ocean, so Q is usually taken equal to the global ocean heat uptake. The inverse of the climate feedback parameter, λ, is the estimated climate sensitivity parameter in °C per W m^{-2}, which is converted to ECS by multiplying it with the forcing for 2 × CO_2 (about 3.7 W m^{-2}). The ratio of T/F estimates TCR[11]. In principle, observations of T and Q combined with a model-based estimate of F therefore determine ECS and TCR. Other approaches evaluate which values of ECS or TCR in models best reproduce observed patterns in space and time of surface and ocean warming. Related detection and attribution approaches separate the response to greenhouse gases from that to other drivers and variability to estimate TCR and ECS (see Methods for details and references). In all of these methods, uncertainties in forcing (particularly from aerosols) are a key driver of the overall uncertainty: energy budget estimates use the overall magnitude of F directly, whereas in pattern-based methods the uncertainty in the space–time patterns of forcing limits confidence in separating the response to greenhouse gases from that to aerosols.

Many recent estimates of ECS based on historic warming yield a reduced probability for large ECS, reduced lower bounds, and most likely values near 2 °C. This is reflected in the shift of the IPCC assessed lower limit of the 'likely' range from 2 °C in AR4 to 1.5 °C in AR5 (Fig. 2), and supports the statement that it is 'very unlikely' that ECS is greater than 6 °C. A tightened range of ECS from historical climate change can be attributed to longer records measured at (nominally or actually) higher precision and with better coverage particularly in the ocean, such that the forced signal emerges more clearly from variability[12,13], and a larger estimate of total radiative forcing (as a result of increasing GHG concentrations and a smaller, less negative aerosol forcing[7,14]). Warming rates have been somewhat lower between about 1998 and 2013 compared to decades before[15], which tightens some estimates[16] but not others[17]. Following some criticism[18,19] recent estimates generally use multiple prior assumptions in order to evaluate to what extent results hinge on those assumptions[20]; some use 'objective Bayesian methods'[18]. Results illustrate that prior assumptions particularly matter for the likelihood of high ECS.

Uncertainty ranges in individual studies are affected by the often-simple models used (see section 'Limitations and future research avenues'), and by assumptions made, including those about forcing and internally generated variability[21]. Recently it has also been recognized that results that compare model surface air temperature with observed sea surface temperature over ocean — together with biases due to uncaptured warming in some regions — may underestimate equilibrium and transient warming[4,22]. Often labelled as 'observational', these methods do rely on models: both to provide forcing estimates, such as aerosol forcing, and to link forcing to climate response through energy balance models. Hence, observational estimates are complementary to methods using comprehensive models, but have their own uncertainties.

Since TCR is determined by the ratio of observed warming to forcing, the observed warming constrains TCR better than ECS, as evident by the closer agreement of ranges arising from TCR estimates between each other and with those from climate models (Fig. 1).

Constraints from climatology, feedbacks and models

The values of ECS and TCR from comprehensive fully coupled climate models — which embed our best understanding of the relevant feedbacks — are one line of evidence and provide a plausible range that is consistent with a variety of observations. With the advance of perturbed physics ensembles (that is, one climate model run with multiple parameter sets exploring uncertainty more systematically) and the Coupled Model Intercomparison Project (CMIP) multi-model ensembles[23], studies on 'emergent constraints' became another prominent and complementary line of argument. The idea is to downweigh models with large biases, or to find well-understood relationships between an observable quantity in the present day and future projections, and thus use observations to constrain the range of models. In many cases, correlations of observable quantities to TCR and ECS are weak, but some studies find relationships between atmospheric mixing, humidity or radiative fluxes and ECS (see Methods). Open issues are the choices of metrics for emergent constraints or weighting, and the fact that many models share code or parameterization concepts and are therefore not independent. There is strong evidence, however, that a credible representation of the mean climate and variability is difficult to achieve in current models with equilibrium climate sensitivities below 2 °C, and current GCMs favour sensitivities near 3 °C or above (see Methods). This is consistent with the argument that water vapour and lapse rate combined would almost double the black-body response to near 2 °C, and with the surface albedo feedback being positive, a substantially negative cloud feedback (or a large part of the recent warming being of natural origin) would be needed to explain a low sensitivity[24,25], which is not supported by observations and attribution studies[7]. Recent progress in estimating cloud feedbacks therefore leads to a null hypothesis for ECS above 3 °C based on the robustly quantified feedbacks[26–29]. Few studies have used climatological mean constraints[30] or decadal prediction bias tendencies to constrain TCR[31]. Overall, the raw range of ECS values in CMIP5 as well as emergent constraints from selected observations and CMIP5, and analysis of feedbacks favour the upper half of the IPCC ECS range (Fig. 3).

Constraints based on palaeoclimate

Constraints on ECS also arise from palaeoclimate studies, which relate long-term temperature responses to changes in the planet's energy balance and have made significant progress in recent years (see Methods, also reflected in several studies shown in Figs 1 & 3). Estimates derived from the palaeoclimate record are based on a response that is often close to equilibrium, but are affected by uncertainty in reconstructed past climate and forcing, both of which are inferred from indirect evidence that may not be spatially representative or may be responding to multiple factors, uncertainties that are difficult to quantify. The majority of estimates arise from the Last Glacial Maximum (LGM) or the last few glacial cycles. Most of that period was substantially colder than present, driven by the albedo effect of large ice sheets, reduced greenhouse gases, dust forcing, changed vegetation cover and different orbital forcing. If climate models include these changes, reconstructed cooler sea surface temperatures in the tropics, and colder global temperatures are reproduced reasonably well, although with spatial uncertainty. Most but not all estimates of ECS that are based on model-data fit of these reconstructed ranges for models with different values of ECS support the range of 1.5 °C to 4.5 °C and yield ECS higher than 5 °C to 6 °C as unlikely (see Fig. 3, refs 7,8 and Methods). Uncertainties in reconstructed temperatures and forcing become larger when moving into the more distant past.

Palaeoclimate evidence and modelling suggest that Earth system feedbacks, such as the growth of ice sheets in response to cooling during the LGM, enhance the response to a long-term change in CO_2, acting as further long-term feedback, as do vegetation changes and changes in dust. In the studies shown in Fig. 3, these feedbacks are generally treated as a forcing and not part of ECS. However, when considering predictions into the far future, Earth system feedbacks will come into play and will probably enhance warming anticipated from ECS on timescales of centuries to millennia.

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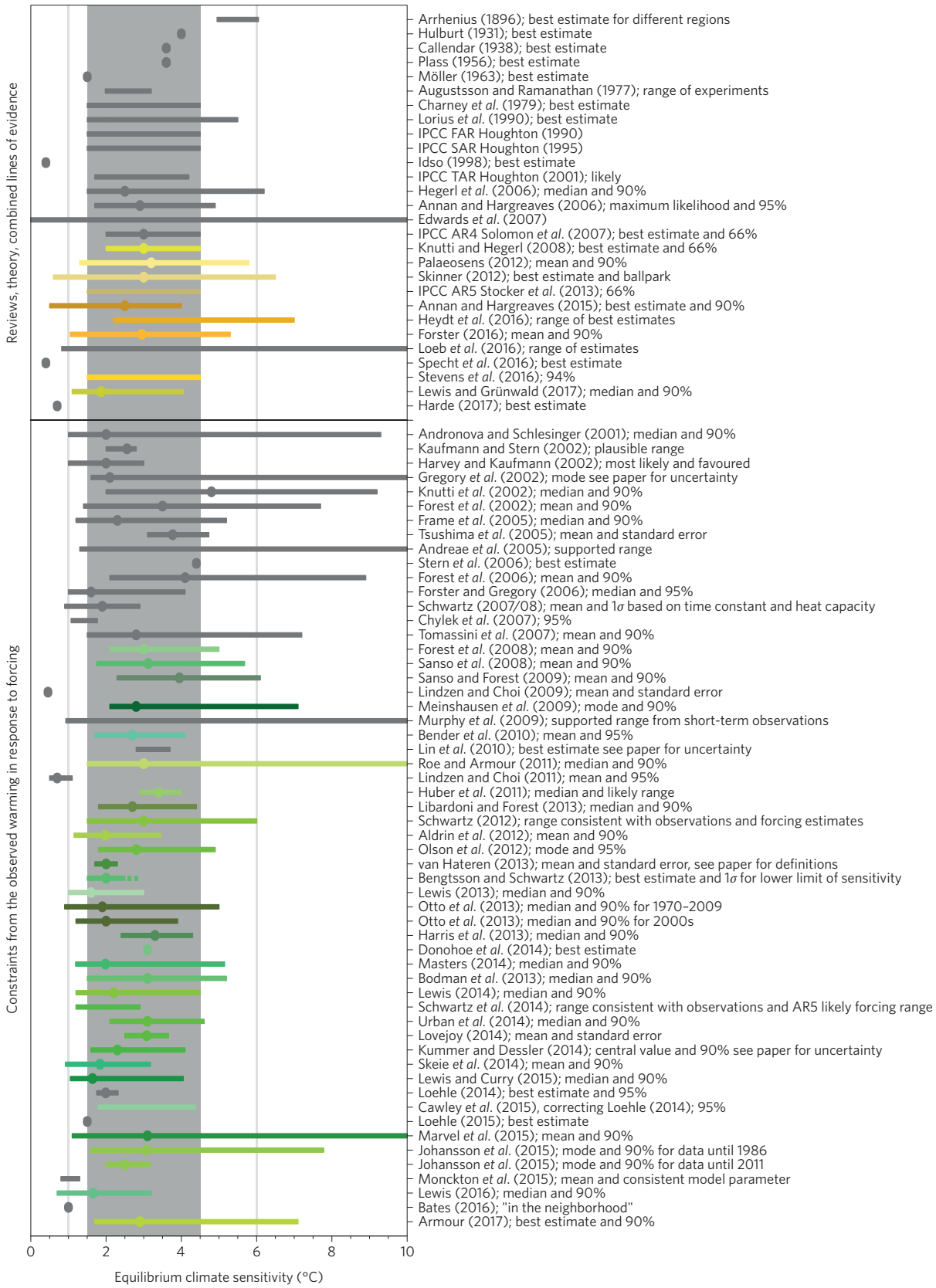

Figure 2 | Overview of published best estimates and ranges for equilibrium climate sensitivity constrained by different lines of evidence. As with Fig. 1, but the grey shaded range marks the 1.5 °C to 4.5 °C range within which the IPCC have assessed that ECS is 'likely' to lie (probability >66%), the grey vertical lines indicate a value of 1 °C below which ECS is 'extremely unlikely' (<5%), and a value of 6 °C above which ECS is 'very unlikely' (<10%). Details and assumptions are given in the text, Methods section and the Supplementary Table. Supplementary Figure 1 provides a combination of Figs 2 and 3.

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Discrepancy and lack of progress?

A striking feature of Figs 2 and 3 is that evidence from climate modelling favours values of ECS in the upper part of the 'likely' range, whereas many recent studies based on instrumentally recorded warming — and some from palaeoclimate — favour values in the lower part of the range. Since each line of evidence is affected by different uncertainties, their uncertainty ranges should encompass the 'true value' but the ranges do not need to be identical. It is, however, important to understand the differences, as discussed in the following sections. In principle, the consistency of information across the partially independent lines of evidence should further reduce uncertainty in ECS, as illustrated in Fig. 2 for a few published attempts using combined constraints.

As a result of some recent low ECS estimates, the central 'likely' range assessed by the IPCC[7] was wider than the 2 °C to 4.5 °C range in the previous report, and no best estimate was given. However, the outer boundaries were better constrained than before, rendering it 'extremely unlikely' (<5%) that ECS is less than 1 °C (high confidence), and 'very unlikely' (<10%) that it is greater than 6 °C (medium confidence), based on the combined evidence.

The IPCC[7] assessed that TCR is 'likely' be in the range of 1 °C to 2.5 °C (close to the estimated 5% to 95% range of the CMIP5: 1.2 °C to 2.4 °C) and 'extremely unlikely' (<5%) to be greater than 3 °C. For TCR, a few climate models with the largest TCR are outside of the 5% to 95% range estimates derived from the instrumentally recorded warming, but some of this may be affected by the treatment of observations (see below and Methods) and variability. In general, the GCM ranges and those from the observed warming are more consistent for TCR than ECS.

Limitations and future research avenues

For comprehensive climate models, the biggest concern is that they share some limitations (for example, finite resolution, parameterized convection and so on) and are evaluated against the same imperfect observations, so they may be biased in a similar way. Clouds have long been (and still are) the largest uncertain feedback[7,32,33], in particular in the stratocumulus subsidence regions over tropical oceans. It will take decades before clouds can actually be resolved in climate change simulations using global models because of the required resolution, even if computing capacity continues to increase as it has. Climatological fields and warming over the twentieth century are taken as a constraint for model evaluation explicitly in many institutions, but models are not tuned to specific values of ECS. Whether there is a tendency for model developers to keep ECS in an 'acceptable' range is unclear. Given the skewedness of ECS from feedback theory, and the fact that it is challenging to produce a substantially negative cloud feedback, it is much easier to produce a model with good performance on mean climate and a climate sensitivity above the IPCC range than one below. Despite all limitations in models, the range of ECS across 'best-effort' models has been stable at around 2 °C to 5 °C for decades, and fundamental understanding of feedbacks and climatological mean constraints are very difficult to reconcile with a very low ECS (see Methods).

Evidence from observed climate change is also uncertain. Observational uncertainty remains, even for the most recent decades, and like-with-like comparison of data is important[4,22]. Also, natural variability superimposes on the forced trend and causes uncertainty even for multidecadal trends[12,13]. This is usually addressed by using internal variability estimates, although in some cases quite simple ones, or by including modes of variability as explanatory variables or covariates. However, it is not always clear to what extent such modes partly reflect the response to forcing — the Atlantic Multidecadal Oscillation (AMO), for example, may partly be a response to volcanic and aerosol forcing. Furthermore, forcing is a key uncertainty: although some studies argue for a smaller (less negative) aerosol forcing[14], others argue for a larger aerosol radiative forcing uncertainty than used by the IPCC[34], both of which would affect ECS estimates. The magnitude of the pre-industrial aerosol baseline is also important but hard to constrain[35].

The most pressing issue, however, is the growing concern that assuming a single constant λ is unrealistic. Doing so would imply that the equilibrium climate sensitivity for CO_2 doubling in a fully coupled model is the same as the effective climate sensitivity extrapolated from a transient simulation[36], yet many simple models interpreting the observed record are just assuming such a constant feedback. It also neglects differences in the temperature response to forcing that are not captured by a forcing efficacy. Feedbacks, however, are spatially heterogeneous. They are not necessarily linear with increasing temperature[37], and the total response depends strongly on the spatial pattern of warming[38–42], which changes over time. Despite characterizing equilibrium, ECS therefore — just like TCR[43,44] — strongly depends on the ocean heat uptake and circulation response, which modifies the pattern of atmospheric warming. It was pointed out long ago that the transient feedback may be a poor estimate of ECS[36,45,46], but recent studies provide stronger evidence for substantial state and time dependence of the global feedback: for CO_2 forcing exclusively, and for the historical period[3,38,41,47–62]. As one example, Fig. 4a shows the estimated temperature response and radiative imbalance from the National Center for Atmospheric Research (NCAR) community Earth system model (CESM) resulting from a step increase to $4 \times CO_2$. The initial years are simulated many times for different initial conditions to get a precise estimate of the forced response. The evolution in CESM clearly deviates from a straight line implied by a constant feedback. The slope of the regression λ is also not constant for most other CMIP5 models due to both short-term atmospheric and oceanic adjustments, and due to feedbacks and warming patterns changing over time.

Other concerns are that feedbacks may not be additive, and the climate response depends on the type and magnitude of the forcing[37,61,63–80]. Additional difficulties arise in separating forcings and feedbacks[27,80,81], and defining appropriate forcings that account for short-term atmospheric and oceanic adjustments[82–91]. The slope of the regression as a measure of the feedback may further depend on the climate base state, and the particular observed realization of natural variability in the real world. Most of these effects sketched in Fig. 4b that potentially affect the total feedback cannot be quantified robustly at this point. Current understanding, however, indicates that estimates of ECS based on the instrumental warming and a constant λ model are biased low, as indicated by the curvatures in Fig. 4a. The delayed Eastern tropical Pacific and Southern Ocean warming in the observed historical period — combined with feedbacks changing as the warming pattern changes, plus the composition of the historical forcing and an underestimation of the observed warming (see Methods) — imply that ECS estimates assuming constant λ are probably underestimated[3,4,54,59–62]. In principle, climate models can be used to study how feedbacks vary, but different models show different changes in λ, so the bias in the ECS estimated from historical data when assuming constant λ may be anywhere from near zero to about a factor of two[54,59,60,65,68,92]. Accounting for changes in feedbacks and the observation issues largely resolve the apparent discrepancies between the estimates from the observed warming and those from comprehensive models.

Testing if simple methods work by estimating known ECS and TCR from complex models[93] may help improve energy-balance models[50,51]. Now that the observations are longer and less uncertain, and the warming signal becomes stronger relative to variability, the observations provide much stronger constraints even on ECS. This is why limitations in the model structure become more important, and these can potentially be understood when such methods are evaluated in perfect model tests.

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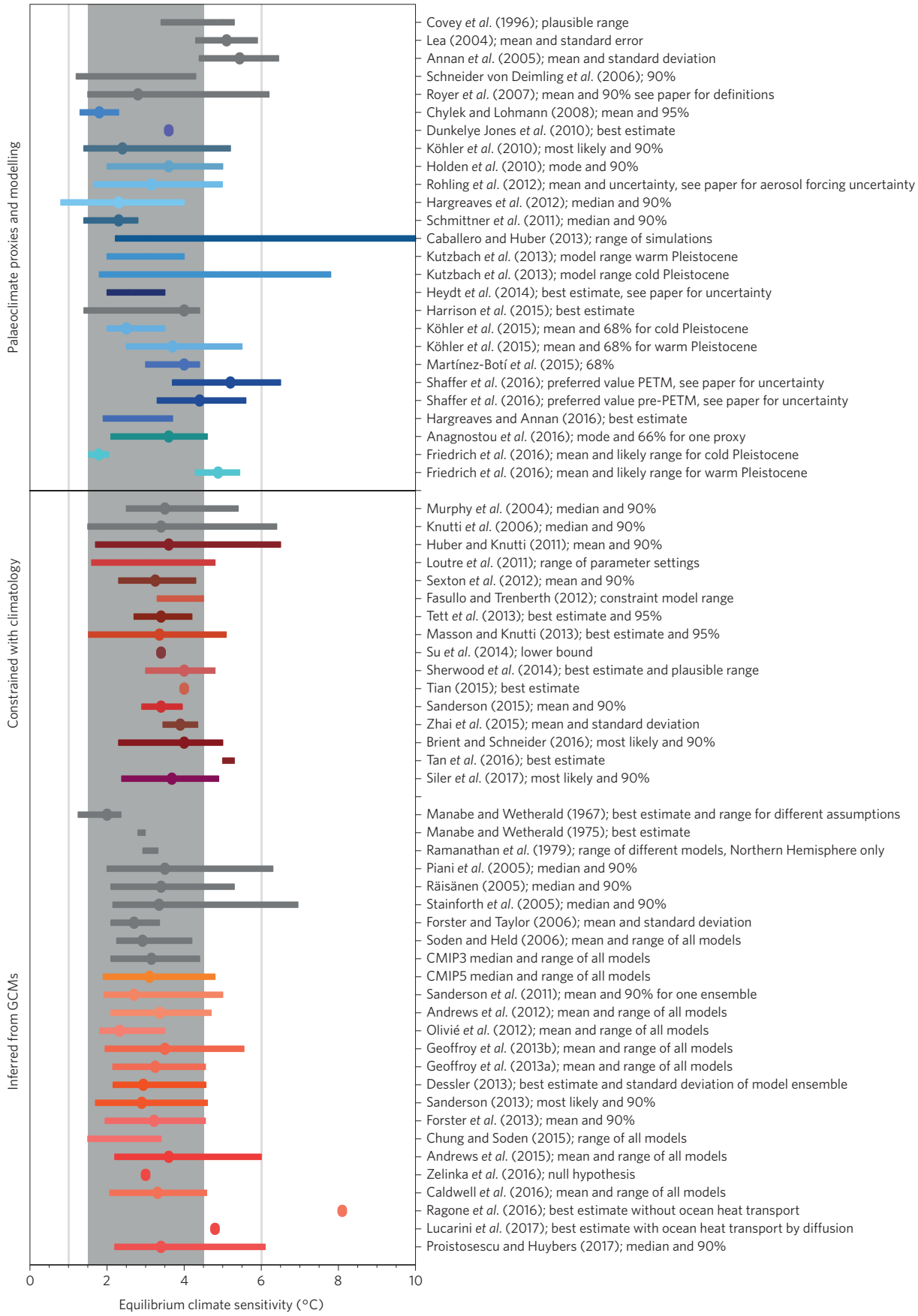

Figure 3 | Overview of published best estimates and ranges for equilibrium climate sensitivity constrained by different lines of evidence. Continued from Fig. 2. Supplementary Figure 1 provides a version where Figs 2 and 3 are combined.

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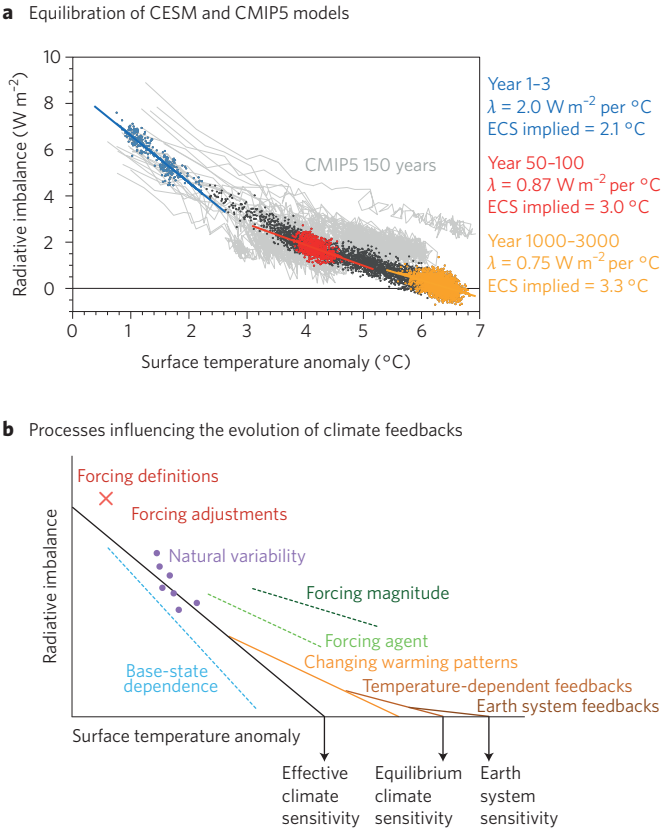

Figure 4 | Illustration of feedbacks changing in result to various boundary conditions. a, Top-of-atmosphere radiative imbalance as a function of global mean surface temperature (annual mean values) for CESM (dark grey and different timescales highlighted in colours) and CMIP5 models (light grey), illustrating the change in the global feedback over different time periods and the implications on equilibrium climate sensitivity. **b**, Conceptual illustration of the different processes, boundary conditions and forcings that can cause such changes in the global feedback parameter and climate sensitivity (slope and intercept of the line, respectively).

Conclusions and implications for research and policy

The goal of this Review is not to come up with a single number or range for ECS based on a rigorous mathematical framework. Indeed that is very challenging given the various methods, assumptions, datasets and models used in all of the studies. Our overall assessment of ECS and TCR is broadly consistent with the IPCC's[7], but concerns arise about estimates of ECS from the historical period that assume constant feedbacks, raising serious questions to what extent ECS values less than 2 °C are consistent with current physical understanding of climate feedbacks. A value of around 3 °C is most likely given the combined evidence and the recognition that feedbacks change over time. A rough sketch of the three main constraints as probability density functions (PDFs) is given in Fig. 5a (see Methods for details). For uniform priors and independent constraints, the PDFs could simply be multiplied[94,95]. However, combining multiple lines of evidence in a formal statistical way is difficult: independence is difficult to establish, joint PDFs would need to be combined, and uncertainties that are poorly quantified or neglected will eventually render the result unreliable[6]. The product here results in a combined constraint that is very narrow and probably overconfident. When the individual PDFs of GCMs and palaeoclimate are, just for illustration (Fig. 5b), inflated in their lower and upper bounds to account for potential structural problems, state-dependent feedbacks and dependency across the lines of evidence, and in addition the mismatch between the historically inferred and future sensitivity[4,59,60] is accounted for by extending the historical PDF upward (see Methods), the combined evidence from the three PDFs would still yield a rather narrow range, constraining ECS to 2 °C to 4 °C with a most likely value near 3 °C. However, this toy model does not replace a full assessment. Indeed the single biggest future challenge (and opportunity at the same time) is to combine the different lines of evidence, taking into account the dependence between them and avoid overconfidence due to missing uncertainty in individual lines of evidence[32].

The IPCC-assessed ranges of ECS and TCR are supported by multiple lines of evidence, each based on many published studies that account for uncertainty to varying extents, and are combined by an expert assessment accounting for overall uncertainty. This is in sharp contrast to Charney in 1979[9], who quoted the same ECS range, but whose argument was based on physical intuition and results from only two early climate models, which by any standards today would be considered inadequate.

Uncertainties in projections may not decrease quickly in the future[96], but there are promising avenues for future research. The greenhouse gas induced warming will continue to strengthen the constraint on TCR and ECS as warming continues[97,98], but accounting for variations in feedbacks over time and variations in feedbacks across forcings remains a major challenge. Model-based estimates of ECS and TCR now more fully account for model uncertainty, and much hope lies in the use of more detailed process understanding — combined with better observations and higher computational capacity — to better quantify individual feedbacks. Emergent constraints provide another avenue to further reduce uncertainty[99]. Super-parameterizations and large-eddy simulations offer new opportunities to better represent clouds[100,101]. Using GCM ensembles for palaeoclimate studies and for the historical period allow to better use spatial information, to estimate how past warming or cooling relates to future warming as feedbacks vary over time[102]. The challenge then, is that climate model information (and potential biases) are part of each line of evidence, making them less independent.

When a PDF of ECS or TCR is required for impact studies or economic models, we recommend selecting carefully among the published estimates, using those that include recent data when the constraints become stronger, and add further structural uncertainty that often is not considered in individual estimates. There is no reason to give all published PDFs equal weight. A preferable option is to use an overall range based on an assessment combining the evidence[32]. Cost–benefit studies are particularly sensitive to assumptions about the tails of ECS and TCR PDFs[103].

A pressing issue is to eliminate the confusion between different concepts of climate sensitivity and to agree on a target quantity that most meaningfully quantifies the climate response to CO_2, and to investigate whether thinking about it as a universal, constant, climate system property is meaningful at all. Almost all GCMs, and studies based on the instrumental period actually estimate an effective sensitivity (the measure of the feedbacks over some past or near future period, extrapolated to equilibrium assuming in most cases constant feedbacks) rather than a true equilibrium. Palaeoclimate estimates are near equilibrium but have to account for Earth system feedbacks. Given the huge computational costs and large differences in model behaviour when approaching the equilibrium, we need to rethink the timescale for which climate sensitivity is defined in the most helpful way. We also need to better quantify how the different quantities — TCR, effective climate sensitivity, near-equilibrium sensitivity (for example, after 300 years of stable forcing, or within 0.5 W m^{-2} global imbalance) and true ECS — are related[59], and which of these many quantities is most relevant for which question.

Knowing a fully equilibrated response is of limited value for near-term projections and mitigation decisions[104], and the social

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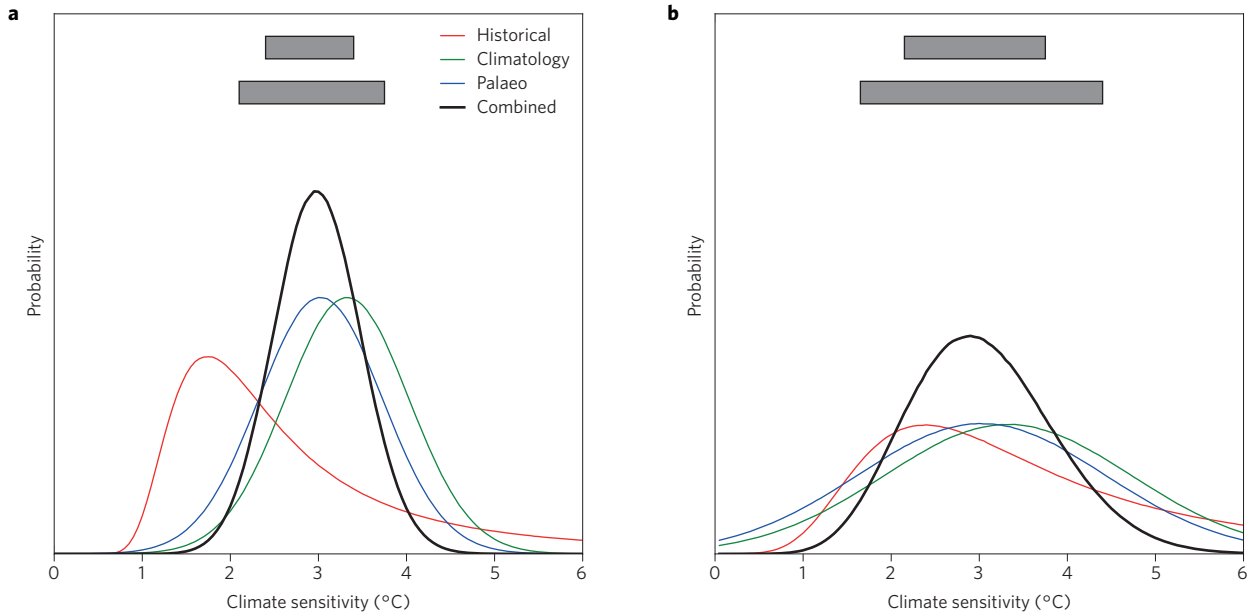

Figure 5 | Illustrative example of combining multiple constraints for climate sensitivity. Overall PDFs are the products of three PDFs based on the historical warming, climatological constraints on mostly GCMs, and palaeoclimate. Grey ranges at the top indicate a 'likely' (66%) and 'very likely' (90%) combined range. **a**,**b**, Constraint based on an optimistic interpretation of uncertainty ranges and assuming full independence (**a**) and on inflated ranges (**b**) to account for structural uncertainties, and with historical estimates inflated and scaled up to account for observation biases, and feedbacks varying from historical to future and across forcings. See Methods for details.

anchoring on ECS[105] detracts from what science can in fact say about future warming. The TCR is more relevant for predicting climate change over the next century, relates more clearly to the social cost of carbon[106], is better constrained by instrumentally recorded climate change, and the emerging warming signal (combined with the well-known CO_2 forcing becoming increasingly dominant over the declining aerosol forcing) is likely to constrain it further and faster[98,107]. Some earlier studies indicate that the CMIP5 long-term temperature projections may be slightly biased towards a high temperature[108,109], whereas others suggest the opposite[110,111]. But given the most recent data, knowledge of coverage issues and the difficulties of calibrating TCR based on past trends (see above), we argue that there is no evidence that the CMIP5 projections are biased. The overall assessed-temperature range by the IPCC is broader than the CMIP model range[7,112]. In terms of policy, and from a risk perspective, it is important to know the upper bound on TCR and ECS when limiting warming to 2 °C or 1.5 °C with high probability[113].

The arguably most powerful recent new insight for mitigation decision is that transient warming is nearly proportional to the total emitted carbon. This concept is captured in a parameter called the transient climate response to cumulative carbon emissions (TCRE), and is another central emerging climate system property. It is defined as the global temperature change for 1,000 GtC of carbon emissions. The IPCC estimated that the TCRE is 'likely' (>66% probability) to be in the range of 0.8 °C to 2.5 °C per 1,000 GtC (1 GtC = 10^{15} grams of carbon = 3.67 $GtCO_2$) for emissions up to about 2,000 GtC and until temperatures peak (see Methods). Even though the limits of the TCRE concept remain to be fully understood, TRCE relates climate targets more directly to emission reductions needed than ECS[114]: any temperature target implies a limit on the cumulative emission budget. To 'likely' remain below 2 °C, about two-thirds of the total 'permitted' emissions have been emitted already[7,115]. The remaining budget at current emissions would last only about 30 years, and less for a 1.5 °C target or if a more realistic pre-industrial temperature baseline is chosen[116,117]. If TCR and ECS were lower than currently assessed (for which there is little evidence), that would allow for only slightly less aggressive mitigation, but not eliminate the need for decarbonization of society. Mitigating non-CO_2 forcings also offers little flexibility in achieving the 2 °C goal[118]. Reducing the uncertainty range of the allowable cumulative carbon budget is more important for mitigation decisions than knowing ECS. But even more pressing are the debates about fair contributions for each country in reducing emissions, helping others to do so, and adapt[119–121], and the lack of willingness to step up and lead the pack[122]. Current and proposed mitigation efforts are inconsistent with what would be required for the 1.5 °C or 2 °C target[114,123], and even these are politically difficult. Better quantifying climate feedbacks and climate sensitivity is not necessary for eliminating those roadblocks.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available in the online version of this paper.

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Author contributions

All authors wrote the Review. M.A.A.R. produced Figs 1–4. R.K. produced Fig. 5.

Additional information

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Methods

After some early estimates with varying definitions of ECS[1,2,124–126], scientists in the 1960s started to use energy-balance arguments combined with observed changes in the global energy budget since the beginning of the industrialization[127–132], to use more-or-less comprehensive climate models to study feedback processes and evaluate them against observations[133–139] and to study different climate states in the past[140–142], all in the hope to constrain future climate change. The following sections provide definitions; details about the methods used in most common categories; references; and discuss selected results and limitations of more recent studies. The discussion is focused on ECS but many studies also provide estimated TCR based on the same or similar methods. Some studies are reviews, a combination of methods, or otherwise do not easily fit into any of the categories below[6,143–147].

Definitions and timescales. Radiative forcing is defined as the changes in the radiation balance at the tropopause as a result of external drivers such as greenhouse gases and aerosols before the surface responds, but different definitions exist for different purposes[7,86,87,91] and the forcing is not easily separable from the response in the real world and even the models. The warming following a step change in radiative forcing is characterized by multiple timescales, which are related to the climate model feedbacks[3,60,93,148–160]: a large fraction of the response occurs within years to a few decades (40–50% after a decade, 60–70% after a century). The transient climate response (TCR) — defined as the global mean surface warming at a doubling of CO_2 in an idealized 1% yr^{-1} CO_2 increase experiment of a climate models — characterizes the temperature response on timescales of decades to a century. It agrees well with the transient climate sensitivity concept and hence captures the warming in response to forcing before the deep ocean has equilibrated[161]. For predictions over the next several decades TCR is therefore the most relevant predictor[48,112,162–164]. The ocean–atmosphere system only approaches equilibrium with a radiative forcing (about 90% after 1,000 years) when the deep ocean is close to equilibrium as well. The timescales of equilibration (and therefore the ratio of TCR to ECS) depend on ocean mixing and ECS[3,6,11,128,130,136,148,150,162,165–172]. Equilibrium climate sensitivity (ECS) is defined as the equilibrium warming after doubling CO_2 in the atmosphere, but disregarding Earth system feedbacks. The radiative forcing for a doubling of CO_2 is about 3.7 W m^{-2} (ref. 173). When estimating an effective climate sensitivity through linear regression[36], CMIP5 models suggest that 3.4 W m^{-2} is a more representative value (ref. 7, Table 9.5). But because of atmospheric and oceanic adjustment processes on various timescales and changing feedbacks there is no consensus on what value to use for radiative forcing in simple models, and by which method to estimate it for different applications[7,84,86,91,174]. Further difficulties arise in defining forcing for species other than CO_2. In state-of-the-art climate models, the warming to equilibrium beyond present day, but based on present day atmospheric concentrations, ranges between about 0.6 °C and 2.5 °C (refs 7,93).

Constraints from feedback analysis. IPCC AR5 estimated that the combined lapse rate and water feedback is 'extremely likely' (>95%) positive, and cloud and albedo feedbacks are 'likely' positive. Together, this leads to 'very high confidence' that these feedbacks amplify the warming of about 1.1 °C that would occur without feedbacks. Recent studies based on individual feedback analysis suggest that ECS should be near or above 3 °C based on well quantified feedbacks, with additional uncertain cloud feedbacks either increasing or decreasing that value[26–28]. Inferring the uncertainty in ECS, the inverse of the total feedback, is challenging in particular when the total feedbacks are strong, and results in a poorly constrained upper bound[146,175–179]. Non-constant feedbacks (see section 'Limitations and future research avenues' in the main text) are another strong argument that constraining feedbacks might be more helpful than constraining ECS[180]. A caveat on analysing individual feedbacks is that there are covariances between feedbacks.

Constraints from the observed transient warming. A variety of mostly energy balance models and statistical methods have estimated ECS and TCR based on some form of the energy balance concept $Q = F - \lambda T$, where F is the calculated total radiative forcing, Q is the observed planetary heat uptake, λ is the climate feedback parameter and T is the observed total surface warming from all forcings. These methods either infer ECS or TCR from a present-day warming in response to forcing relative to an earlier baseline period, or fit simple models to the observations while varying sensitivity, ocean heat uptake and scan forcing uncertainty in order to determine what values of these parameters combined yield consistent simulations of the historical record[11,12,16,18,21,44,169,181–213], or fitting other statistical models to the observed warming[214–216]. Results from these methods are affected by assumptions such as a constant feedback parameter, and also need a realistic model for internal climate variability. A few more complex models have also been constrained with both past trends and climatology[217,218].

Detection and attribution methods are based on the physical mechanisms of greenhouse gas forcing causing a characteristic space–time pattern of warming, for example, more warming over land than ocean, delays in the response to radiative forcing driven by the thermal inertia of the ocean, cooling from aerosols being concentrated in certain regions, as well as a vertical pattern of warming in the troposphere and cooling in the stratosphere. They relate only the greenhouse gas attributable warming to the greenhouse gas forcing to estimate mostly TCR (or equivalently near term warming in a scenario)[17,108,109,163,219–224]. Thereby they circumvent the large uncertainty in the total radiative forcing due to the aerosols, but are affected by uncertainty in the model-simulated fingerprints that are matched to observations, and in the assumption that forced responses approximately superimpose linearly. A detailed discussion of each study is beyond the scope of this Review, but previous reviews and assessments[6,7,225] discuss most individual studies and find an overall 'likely' (>66% probability) range of about 1 °C to 5 °C. The aerosol forcing in theory can also be estimated from changes in the water cycle, but observations are insufficient and model errors too large to successfully do it at this point[226].

Most of the above results depend on the sources of uncertainties considered (for example: whether all forcing components or just the aerosol is assumed to be uncertain); on the structure of the model[227]; the length and type of data and its uncertainties that are used[12,16]; and on assumptions for priors and likelihoods[18–20,185,193], more so for the earlier studies where the anthropogenic signal was weaker and observational uncertainties were larger than for the newer ones. Many studies are affected by the limitations of assuming constant feedbacks for all climate states and forcings in energy balance models, as discussed in the main text. This limitation, along with incomplete coverage and the blending of sea surface with land air temperature data[4,22,228], probably biases results of many such studies low.

These energy balance and attribution results are consistent with estimates explicitly using the energy budget and radiative forcing estimates[229], using understanding of feedbacks and processes as evident from observations and models[3,230], and with observed and simulated changes in the global energy budget[150,231–241]. Observed trends in clouds are also detectable and some are consistent with models[242].

Estimates of TCR are generally better constrained by the recent warming, but TCR depends on the state of the ocean when initialized[43,243–245] and, as with ECS, measures the response to CO_2 forcing only. Another important open question is the relation of inconstant feedbacks and TCR: the more feedbacks change through time the less representative TCR will be of the overall model behavior.

Results from both energy balance methods and detection and attribution can directly be used to generate future warming estimates for scenarios that are constrained by past warming[108,112,181,182,185,192,209,219–222,246–250]. Some results indicate that the observed warming is now powerful enough to reduce the range of predictions provided by models, for example, by ruling out models with the strongest response as less likely[108,221], but more recent studies indicate that some of these might have underestimated observed changes by comparing with model surface air tempreature rather than sea surface temperature over oceans[4]. The dependence on the model and assumptions in the method[251] also question the robustness of those results.

A number of other statistical methods have been used to infer ECS from various historical and palaeo time-series[252–255]. Inferring the long term response from short term variability, for example, through a flux dissipation theorem, has been tried since the 1970s[256–264]. However, short-term climate variations have long been known to provide a poor and unreliable constraint on the long term response[132,169]. Short-term variations in the energy budget can be informative to compare feedbacks in models and observation, and relate them to long-term feedbacks in the form of an emergent constraint[24,225,265–268], but feedbacks depend on the timescale and are different for variability[231,269,270]. The results in such studies also hinge on assumptions on the response timescales, and are affected by limitations of simple models fitted. Many estimates based on those methods have therefore been criticized; we generally have low confidence in relying on them in this assessment, but provide further references to studies and critical comments here for completeness[7,24,56,93,225,231,259,269,271–301]. Similarly, the response to volcanic eruptions provides a test for models[302] but in our view the implications for ECS are unclear since the timescale and type of forcing is very different, the feedbacks arising are different, and the response is difficult to separate from El Niño variability[185,303–311]. It has also been attempted to estimate TCR from the observed temperature response to the sunspot cycle[312]. The resulting estimate is higher than those based on other approaches and may be affected by different feedbacks for solar forcing and possibly aliasing of other forcings.

Constraints from climatology. The raw distribution or range of ECS and TCR simulated by models has been used in some studies[313–315], but the interpretation of that range is unclear as the model space is not sampled systematically and the degree of tuning of models is unknown[316,317]. But comprehensive models are routinely evaluated against climatological fields, including interannual variability and trends, and specific feedbacks are quantified[318–320]. Such evaluations of major feedbacks in a process based climate model can also be used to determine ECS by correlating observable quantities to ECS or TCR. In most cases correlations of general climatological mean patterns and variability to ECS or TCR are weak or model-dependent[23,321–326]. Despite the fact that newer models agree better with observations[7,96,327,328], their spread in the climate response has not decreased[96,112], possibly because most observations have already been used to evaluate models[329]. Yet there have been studies that have constrained individual relevant feedbacks like the sea ice, snow albedo or cloud feedbacks[180,265,330] and their implication on projections[331,332].

Robust evidence based on many studies using Peturbed Physics Ensembles (PPEs) and CMIP show that a credible representation of the mean climate and variability is difficult to achieve with ECS below 2 °C, good agreement with observations favours values in the 2 °C to 4.5 °C range, and most likely ECS values are close to or above the CMIP mean of about 3.2 °C once emergent constraints are

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included[99,110,180,324,333–356], consistent with studies constraining individual feedbacks suggesting that the net feedbacks are not small[26–28,357–360]. Questions remain about shared model biases and tuning techniques[361–363], the robustness of emergent constraints in ensembles of opportunity[364,365] and whether those ensembles sample the full range of ECS and TCR consistent with observations, in particular on the low end[109,227]. Although high ECS values (in rare cases above 10 °C) were found in some PPE simulations, these are found to be much less likely based on model's climatology than values in the range of 2 °C to 4.5°C[326,333–335,366–368]. The largest source of model spread continues to be related to low level clouds and convection[27,32,33,318,319,369–379].

Results based on emergent constraints depend on the metrics used[110,324,380–390]. A further issue is that the number of truly independent climate models in the overall ensemble is limited, and results may be biased towards near duplicate models[23,110,328,383,388,391–396]. As a result of the underlying small sample size, screening for predictors may lead to apparent relationships that are unphysical or unreliable[324,337,365,397,398]. As a result, weighted ensembles may be overconfident if the number of models is small or variability is large[399].

Palaeoclimate. Palaeoclimate is a useful testbed for simple and complex climate models[400–405] and numerous studies have estimated climate sensitivity from past periods, in particular the Last Glacial Maximum or the last few glacial cycles, but also the Holocene and warm periods millions of years back[95,102,400,406–426]. Uncertainties in some individual studies are small but the range across studies is similar to the range derived from other methods. Many studies find that climate sensitivity in the present and future differs from that inferred from past colder (glacial) or warmer states[407,414,427–432], whereas others find little state dependence[433,434]. Including vegetation and ice-sheet feedbacks can cause negative feedbacks[435,436], but the overall Earth system sensitivity resulting from all feedbacks is consistently estimated to be higher than ECS[8,420,437–445]. This implies that ECS based on atmosphere–ocean climate models will underestimate warming on millennial timescales. If Earth system feedbacks are treated as additional forcings, as they generally are for example in ECS estimates from the Last Glacial Maximum, then the overall assessed palaeoclimate constraints[7,8,446] also support the consensus range of ECS, including its upper bound, but do not constrain it further.

Expert elicitations. A number of studies have summarized expert elicitations on ECS and TCR[447–449]. These largely agree with the conclusions here, but are obviously assessing the same studies. There is a desire for more formalized elicitations but this has not been done for ECS and TCR[450]. Sometimes such elicitations are used as prior information when estimating ECS[183]. However, the information used by the experts is not independent from that used to provide a posterior distribution.

The transient climate response to cumulative carbon emissions. There is strong and robust evidence from a variety of models that the transient warming, largely due to the long residence time of CO_2 in the atmosphere, is approximately proportional to the total CO_2 emitted[115,120,192,223,451–463], even though towards stabilization that proportionality does not hold in all models when emissions cease[464–469]. The proportionality arises from an approximate cancellation of multiple nonlinear effects, including the decrease in additional radiative forcing per unit CO_2 at higher concentrations, the change in carbon sinks and therefore increase in the airborne fraction with emission rates and warming, and the unrealized warming in the system (TCR being lower than ECS).

Illustrative combined constraint. In Fig. 5a, the PDF for ECS estimated from the historical period is based on $Q = F–\lambda T$ (see main text) using Gaussian distributions for $Q = 0.8 \pm 0.3$ W m^{-2}, $F = 2.0 \pm 0.6$ W m^{-2}, $T = 0.8 \pm 0.1$ °C. The values are chosen to be approximately consistent with recent published estimates and to produce a PDF that reflects the range in recent studies[11]. The radiative forcing for $2 \times CO_2$ is assumed to be the standard value of 3.7 W m^{-2} used in most studies. For the PDF of CMIP we assume a Gaussian distribution with 3.3 ± 0.7 °C for ECS centered on the CMIP5 mean, for palaeoclimate a Gaussian distribution with 3.0 ± 0.7 °C. Values indicate ±1 standard deviation. The combined constraint as the product of the three PDFs[94] is shown in black along with 'likely' (66%) and 'very likely' (90%) ranges. For a revised combined constraint (Fig. 5b) we scale up the observed warming by 20 ± 15% (ref. 4), use a forcing of 3.4 W m^{-2} for $2 \times CO_2$ that may be more appropriate for such regressions (see above), and scale up the sensitivity inferred from the twentieth century by 30 ± 30% to account for changes in feedbacks (see above, and ref. 59). The width of the CMIP and palaeoclimate PDFs is doubled to account for biases and uncertainties not otherwise accounted for (for example, feedbacks changing from cold to warm states, structural model biases), and for dependencies between estimates. We emphasize that such a toy model is insufficient for an assessment, and that other, defensible decisions would lead to slightly different overall ranges. However, it illustrates the value, and the challenges, of combining all the lines of evidence.

Notes on figures. Figures 1, 2 and 3 show published ranges of ECS and TCR over a wide range of studies with different assumptions and definitions of climate sensitivity. Some studies provide PDFs, others just ranges, with our without proper statistical descriptions of what those are. Some studies provide multiple ranges, in which case subjective judgement was used to select the most relevant or representative one. More details are given in the supplementary online table. Some studies show quite different ranges compared to other lines of evidence. However, many of these have not held up to tests estimating a model's known sensitivity, robustness tests or evaluation of their assumptions. These studies, those estimating somewhat different quantities, those arguing that there is no reliable constraint, and all those before 2008 (approximately predating the IPCC AR4 in 2007 and our earlier Review) are marked in grey to indicate that those might not be the most reliable estimates, although we recognize that this is a judgement call and others might come to slightly different decisions on grey versus coloured lines. The overall aim of the figures is to show the wide range of research on this topic, realizing that a like-with-like comparison of different estimates is difficult. The categorization, discussion and assessment of the many studies is solely the view of the authors of this review, but the overall conclusions do not depend on these choices.

Figure 4 includes simulations of 4 x CO_2 forcing scenarios with the following CMIP5 models as grey lines (each 150 years long): ACCESS1-0, ACCESS1-3, bcc-csm1-1-m, bcc-csm1-1, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3-6-0, FGOALS-g2, GFDL-CM3, GFDL-ESM2M, GFDL-ESM2G, inmcm4, IPSL-CM5A-LR, IPSL-CM5B-LR, MIROC5, MIROC-ESM, MPI-ESM-LR, MPI-ESM-MR, MPI-ESM-P, MRI-CGCM3, NorESM1-M. For CESM 3,675 years of a simulation with a step change to 4 x CO_2 are shown, based on data from ref. 3. The implied ECS numbers are the extrapolation of the blue, red and orange lines to zero imbalance, divided by two to obtain the values for CO_2 doubling instead of quadrupling.

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