Key messages:

- Both CO2 and non-CO2 greenhouse gas emissions must be decreased as quickly as possible to maintain a chance of not exceeding the global temperature limits in the Paris Agreement.
- Using historical warming to constrain future climate projections, we narrow down the uncertainty in climate sensitivity and projected warming by 30-50%.
- We provide a framework to estimate the remaining carbon budget that enables taking into account uncertainties in climate sensitivity and other feedbacks.
- The median estimate for the remaining carbon budget given a 1.5°C limit was 440 GtCO2 from 2020 onwards, which will be surpassed in 2032 at the current levels of emissions.
- Some climate models of the latest generation (CMIP6) have projected very strong warming, however these models represent unlikely futures as they simulate implausibly strong reductions in shallow cloud coverage and are difficult to reconcile with historical data.
- Due to decadal changes in the spatial pattern of warming (the “pattern effect”), climate sensitivity as derived from historical data is probably underestimated. Once this effect is accounted for, “observed” climate sensitivity is in better agreement with other lines of evidence.

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Knowledge Gains: Summary and Implication Report

Climate sensitivity, TCRE, and its role in projections
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Context
What is climate sensitivity?

Climate sensitivity indicates how strongly and how quickly the Earth’s temperature responds to rising greenhouse gas concentrations. If the Earth’s climate sensitivity is high, it means a lot of warming will occur for a given increase of the atmospheric CO\textsubscript{2} concentration. Obtaining an accurate estimate of climate sensitivity is thus central to calculating reliable projections of future climate change.

There are many ways of estimating climate sensitivity and different estimates can diverge. This report will provide a synthesis of recent advances that have helped better understand and reconcile these different estimates. As several metrics have been employed to look at specific aspects of climate sensitivity, we briefly define in this introduction the metrics most relevant to this report.

Two of the most frequently used metrics that characterize future warming are the Transient Climate Response (TCR) and the Equilibrium Climate Sensitivity (ECS, Figure 1). TCR is estimated as the amount of warming that occurs when atmospheric CO\textsubscript{2} concentration has doubled, in an idealized experiment where the concentration is increased by 1% every year. It indicates how strongly but also how quickly the Earth’s climate responds to increasing CO\textsubscript{2} concentrations. In contrast, ECS indicates the total amount of warming after CO\textsubscript{2} concentrations stabilize, usually long after

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{climate_sensitivity_diagram.png}
\caption{Illustration of two of the most frequently used metrics for climate sensitivity: the Transient Climate Response (TCR) and the Equilibrium Climate Sensitivity (ECS).}
\end{figure}
the initial increase. While TCR and ECS are closely related, they mainly differ because some components of the Earth system have a high inertia (like ocean heat capacity) and may take several thousands of years to adjust until the Earth’s climate reaches a new equilibrium.

TCR and ECS are both expressed as a function of the atmospheric CO$_2$ concentration. However, policy-makers may be more interested to know the total amount of CO$_2$ that can be emitted until a certain temperature level is reached (say, 2°C of warming). In that case, one also has to take into account the fact that not all CO$_2$ emissions stay forever in the atmosphere. In fact, about half of the CO$_2$ emitted into the atmosphere is absorbed by the ocean and by land ecosystems (Figure 2). This is why ocean and land are referred to as important carbon sinks, and their future capacity to act as sinks is taken into account when calculating how quickly CO$_2$ emissions should be limited to avoid dangerous global warming. The Transient Climate Response to cumulative carbon Emissions (TCRE) is a metric that takes these carbon feedbacks into account and directly relates cumulative CO$_2$ emissions to global temperature change. Thus, unlike TCR or ECS, TCRE is also additionally affected by uncertainties in our understanding of carbon feedbacks and how they will be affected by future climatic changes.

**Summary of Knowledge Gains**

Why do climate models disagree on climate sensitivity?

One of the approaches to estimating climate sensitivity is to use numerical simulations from climate models (or Earth system models). As these models represent the most essential physical processes driving atmospheric and ocean circulation, they can be used to describe the Earth’s climate and determine its sensitivity to greenhouse gas emissions. Earth system models provide a full, three-dimensional representation of energy and mass fluxes in the ocean, atmosphere, and land and can thus also be evaluated and verified against an extremely large number of in situ, airborne, and satellite observations.

In the most recent phase of the Coupled Climate Model Intercomparison Project (CMIP6), the current generation of climate models is producing estimates of ECS (and TCR) that are, on average, substantially higher and also in larger disagreement with each other compared to previous generations (CMIP5 and CMIP3) (Forster et al. 2020, Meehl et al. 2020). This higher climate sensitivity would mean that climate change will be even worse than what we had expected so far. Thus, it is crucial to understand why models disagree with each other and determine whether the models with a high sensitivity are trustworthy.

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Because climate sensitivity is the net result of many different processes and feedbacks within the climate system, it is not something that Earth system models can just prescribe in advance. Instead climate sensitivity is an emergent property of each model, making it hard to identify what processes exactly are causing disagreement between the models and should be improved in future versions. Recent contributions and collaborations by CONSTRAIN-funded scientists have focused on improving our understanding of the reasons behind inter-model differences in climate sensitivity.

**Clouds and radiative feedbacks**

Cloud radiative feedbacks are known to represent a key uncertainty in climate models, with the potential to strongly influence climate sensitivity. Flynn and Mauritsen (2020) showed that it is changes in cloud shortwave radiative feedbacks that caused the overall shift towards higher ECS between CMIP5 and CMIP6, together with changes in the representation of Antarctic sea ice. Other studies have also shown that models with a high ECS tend to have stronger reductions in shallow cloud coverage (Zelinka et al. 2020, Forster et al. 2021). Shallow clouds over subtropical oceans typically cool the planet by reflecting incoming solar radiation. Using new field observations, Vogel et al. (2022) found evidence that the mechanisms leading to strong reductions in shallow cloud coverage are exaggerated in climate models with high ECS. Their observations suggest that decreases in cloud cover due to desiccation of the lower cloud layer are inhibited by an increase in mesoscale motions, a compensating mechanism that appears too weak in most climate models, and especially high ECS models. Their results thus indicate a lower plausibility for the CMIP6 models with highest ECS (i.e. the warmest models).

In another study, Olonscheck and Rugenstein (in review) evaluate how CMIP5 and CMIP6 models simulate the response of top-of-atmosphere outgoing radiation to surface warming against satellite observations. They found that most models tend to have a too weak local coupling between surface warming and top-of-atmosphere radiation, and that better performing models correspond to those with a relatively low ECS, again indicating a lower plausibility for models with very high ECS (Figure 3).

![Figure 3](image.png)

**Figure 3.** Models with a smaller bias in TOA response to surface warming tend to have a lower effective climate sensitivity (EffCS is closely related to ECS). Figure from Olonscheck and Rugenstein (in review).

Their results also suggest that about half of these biases persist even in atmosphere-only simulations where observed historical sea surface temperatures are used as boundary conditions. This confirms issues related to atmospheric physics and radiative feedbacks, in addition to the well-documented (but poorly understood) tendency of fully coupled CMIP models to only rarely reproduce recent historical sea surface warming patterns (Olonscheck et al. 2020).
Dependence of climate models

In terms of their conception, the Earth system models developed and used within the climate research community may have more or less similarities. For instance, they may represent certain processes or numerically solve certain equations in a similar way. As a result, and even though they may have a different name, some climate models are in fact sharing the same algorithms and thus may end up producing similar results. If a few families of models sharing the same code become over-represented in an analysis, this may give a false impression that the consensus among models has shifted, whereas in fact we just have many more simulations coming from a few model families.

In recent work, Merrifield et al. (in review) showed that the over-representation of certain families of models in CMIP6 partly explains why the ECS distribution shifted towards higher values and became more uncertain in CMIP6 (compared to CMIP5). Their results show that a substantial fraction of the discrepancy in climate sensitivity distributions is eliminated when correcting for the uneven representation of model families (Figure 4). This is done by adjusting the composition of the multi-model ensemble such that each model family is represented by only one of its members. The results showed that while model family over-representation also affected CMIP5 (though to a lesser extent), it had practically no impact for climate sensitivity at that time, which was only a coincidence. Altogether, these results indicate a lower probability for particularly high values of ECS (e.g. ECS > 4.5°C) in CMIP6, both because high values of ECS are less plausible (as suggested by the model evaluation efforts discussed in the section Clouds and radiative feedbacks) and because they are over-represented within the ensemble.

Figure 4. Distribution of ECS as simulated by Earth system models in CMIP5 and CMIP6. The boxplots indicate the following percentiles: 5-25-50-75-95. When considering all available models, the median ECS appears to have increased substantially from CMIP5 to CMIP6, but when model families are equally represented, this increase is much more modest. Data from Merrifield et al. (in review).

Observational estimates of climate sensitivity and the pattern effect

Climate sensitivity from historical records

In principle, plausible estimates of climate sensitivity may also be obtained directly from historical observations of global temperature, and the Earth’s energy budget. However, two main obstacles, in addition to observational uncertainties and the presence of unforced (natural) variability, make such an assessment particularly challenging. First, historical observations are affected not only by increasing CO$_2$ concentrations, but also by important changes in other forcing agents like aerosols (Smith et al. 2020). This means that any estimation of climate sensitivity that is based on historical observations has to be able to disentangle (or be robust against) these other historical contributions.
The second obstacle occurs because various fast and slow climate feedbacks can cause the ‘apparent’ climate sensitivity to vary over time, mainly as a result of changes in the global sea surface temperature (SST) pattern (Gregory and Andrews, 2016). This difference between the true climate sensitivity and the one estimated over the relatively short historical record has been coined the ‘pattern effect’. If the pattern effect is large, estimates of climate sensitivity based on historical observations may even appear to be significantly lower than other estimates, coming for example from Earth system models. This is in fact what has happened recently (Forster et al. 2016), and significant work within the CONSTRAIN project has been dedicated to better understanding the magnitude of the pattern effect and its influence on observational estimates of climate sensitivity.

**Magnitude of the pattern effect**

In recent work, Dong et al. (2021) analyzed coupled ocean-atmosphere CMIP6 simulations and showed that the ‘pattern effect’ causes estimates of ECS and TCR to be slightly biased low when derived from (simulated) historical periods. In addition, they showed that a much lower ECS and TCR is inferred from models when these are forced with the historically observed SST patterns, in line with previous findings. It is still unclear why the pattern effect is so large when using the historical SSTs compared to what can be expected from coupled CMIP6 simulations. Lewis and Mauritsen (2021) showed that it seems unlikely that natural variability alone can explain such a large difference, and instead that much of the pattern effect is forced, especially when considering the whole century.

Because observations themselves carry uncertainties, it could also be that some errors in the historical SST datasets lead to an overestimation of the pattern effect. Here, recent work by Modak and Mauritsen (in review) suggests that the magnitude of the historical pattern effect depends substantially on which SST dataset is being used to force the atmosphere-only simulations. They find that the AMIPII SST dataset produced by far the strongest estimate, appearing as an outlier among the seven tested different SST products. Thus, the large magnitude of the historical pattern effect as diagnosed from AMIPII-forced simulations, which are the most common, has likely been overestimated to some extent. This was also shown in Andrews et al. (2022) who found that the estimated pattern effect over 1870-2010 is about 30% lower when using SSTs from HadISST1 compared to using AMIPII. Yet, even when accounting for these differences, all datasets agree that the pattern effect significantly increased during the recent period (1980-2010), with a magnitude that remains hard to reconcile with coupled ocean-atmosphere simulations, while still being in excellent agreement with satellite-based observations of the Earth’s energy budget. The explanation is usually traced to the fact that coupled climate models struggle to capture the particular pattern of SST warming since the 1980s, suggesting either that this period was affected by a rare mode of variability, or that models systematically fail to capture some of the forced response over that period.

**Implications**

**Improved estimates of climate sensitivity**

*From the observational record*

Due to the pattern effect, it is not trivial to estimate climate sensitivity from historical observations alone. To overcome this problem, one possibility is to include estimates of the pattern effect when inferring ECS from the historical record. Here, Modak and Mauritsen (in review) show that once an estimate of the pattern effect is included in the assessment of historical ECS, the median ECS estimate...
substantially increases, as well as the uncertainty range (Figure 5, change from black to yellow line). However, once uncertainty about the pattern effect itself is included by incorporating pattern effect estimates derived from various SST datasets, the median ECS value as well as its uncertainty are reduced back to 2.9°C (1.7 to 6.7°C) (red line), in broad agreement, though with a higher upper bound, compared to a previous estimate (Jiménez-de-la-Cuesta and Mauritsen, 2019) that was contingent on the pattern effects simulated by the models instead of inferred from historical SSTs. These results suggest that once the historical pattern effect is included in the estimation of historical ECS, the agreement with other lines of evidence is substantially improved.

Combining several lines of evidence

In addition to evidence based on historical observations, other estimates of climate sensitivity can be obtained from theoretical understanding as well as paleo-climate records. Using a statistical framework to synthesize these various lines of evidence (and their respective uncertainties), Sherwood et al. (2020) assessed that the likely ECS range is 2.3-4.5°C (66% confidence interval). They could also show that an ECS lower than 2°C is extremely unlikely, thus raising the lower end of the likely ECS range compared to previous assessments. This means we are now extremely confident that a doubling of CO₂ concentration would lead to a long-term warming of at least (and very likely more than) 2°C. Sherwood et al. (2020) also showed that while the Last Glacial Maximum provides strong evidence against ECS values greater than 4.5K, such values cannot be entirely ruled out.

Figure 5. Probability distributions for ECS constrained based on the instrumental record of historical warming as per IPCC AR6 and updated with pattern effect estimates as indicated by the legend. AR6 without pattern effect estimate is the baseline for all the other estimates.
out either, a statement that remains supported by the additional material summarized in this report.

**Less uncertain climate projections**

While some of the work within CONSTRAIN focused on improving our understanding of the underlying physical processes and reasons explaining the unexpectedly high distribution of ECS in CMIP6 (section *Knowledge Gains*), other work has also focused on using available observations of historical warming to directly narrow down the uncertainty in model-based projections of future warming.

When a relationship exists between historical warming and climate sensitivity, it is possible to reduce the uncertainty in future warming by discarding those climate models which do not agree well with historical warming. For instance, Tokarska et al. (2020) evaluated the ability of CMIP6 models to reproduce historical warming over the recent period (1981-2017), where the warming trend can be expected to be mostly affected by greenhouse-gas induced warming while aerosol effects are relatively stable. Taking into account the uncertainty in estimates of historical warming, they derived a constrained range for TCR, the transient climate response, as well as constrained ranges for future climate projections. For example, they could reduce the 90% range in projected end-of-century warming for the SSP3-7.0 scenario from 2.20-4.83°C to 1.84-3.69°C, which represents a 30% reduction of the overall uncertainty (Figure 6).

Using a linear inverse method (kriging), Ribes et al. (2021) combined CMIP6 simulations and observations of historical warming since 1850 to produce constrained projections. Their results also substantially reduce (by up to 50%) the range of projected future warming (Figure 6) and are in relatively good agreement with the results of Tokarska et al. (2020). In addition, their results show that the shift in observationally constrained TCR and ECS between CMIP5 and CMIP6 is relatively minor, with ECS being shifted upwards by about 0.2°C, a much more modest increase

![Figure 6. Unconstrained (left) and constrained (right) warming ranges as reported in Chapter 4 of the Sixth Assessment Report of the IPCC (Lee et al. 2021). This figure is directly reproduced after figure 4.11 of the report and depicts the 90% confidence ranges.](image-url)
compared to what would be inferred from raw unconstrained ensembles (e.g. Figure 4), and consistent with other model weighting methods developed in earlier H2020 projects (Brunner et al. 2020).

Results from these two papers (together with many other studies) have contributed to the assessed future warming ranges provided by the 6th Assessment Report of the Intergovernmental Panel on Climate Change (Lee et al. 2021, Figure 6). This means that assessed ranges within the IPCC report already correct for the fact that some climate models with high sensitivity are over-represented in CMIP6. Assessed future warming ranges in Chapter 4 of the IPCC report thus represent an estimate that also incorporates information about historical warming, paleoclimates and process understanding and provides the best available information on future warming for the different scenarios.

However, it is also worth noting that many climate impact studies based on CMIP6 are not based on a set of models that is necessarily compatible with observationally constrained temperature projections. Current work within CONSTRAIN aims to develop a universal and flexible approach for generating CMIP6 model subsets that are as consistent as possible with constrained projected warming ranges. This will make it easier to transfer knowledge gains on climate sensitivity directly to other areas of research, including impact assessments.

Another new line of research involves providing similar projections constrained by observations at the regional or local scale. Recent work done within CONSTRAIN suggests that observational constraints can reduce uncertainty at this scale (Qasmi and Ribes, 2022), and that, over some particular regions, models with high sensitivity can be more consistent with observations than others (Ribes et al., 2022).

TCRE and the remaining carbon budget

As mentioned in the introduction, TCRE is a climate sensitivity metric that directly relates cumulative CO₂ emissions to the associated global warming. This is different from TCR and ECS that are describing the response to fixed concentrations of CO₂. TCRE can thus be used to determine the remaining carbon budget for given specified levels of warming, such as those mentioned in the Paris agreement. Here additional sources of uncertainty, in addition to climate sensitivity, must be considered, such as the fraction of non-CO₂ forcing that also contributes to warming, or the uncertainty in the response of natural carbon sinks to future warming. With the objective to provide guidance and recommendations on how to estimate remaining carbon budgets, Matthews et al (2020) provide a framework that enables incorporating these various sources of uncertainty in a transparent and traceable way (Figure 7). To a large extent TCRE is linearly related to TCR, and thus observational constraints discussed above and applied to TCR (e.g. Tokarska et al. 2020, Ribes et al. 2021) can similarly be used to derive a constrained TCRE estimate. Other prominent sources of geophysical uncertainty include the response of the carbon cycle to global warming (e.g. Figure 2), and the effect of changes in non-CO₂ forcing agents such as aerosols, all of which may potentially be further constrained with observations.

In order to individually combine such constrained estimates of the different geophysical quantities controlling the remaining carbon budget, Matthews et al. (2021) proposed an integrated probabilistic approach. With this approach, remaining carbon budget estimates, along with their uncertainties can be calculated in a consistent way. This approach also allows for non-symmetrical shapes in the distribution of the underlying metrics (e.g. as in Figure 5). Considering only geophysical uncertainties,
the median estimate for the remaining carbon budget compatible with a 1.5°C target was 440 GtCO₂ from 2020 onwards, which is roughly equivalent to 12 years of anthropogenic emissions at the current rate, and thus will be surpassed in year 2032.

It is important to note that the uncertainty related to the geophysical parameters remains substantial, with a likely range of 230-670 GtCO₂. The uncertainty related to socioeconomic choices affecting non-CO₂ emissions is about as large, further increasing the range by -200 to +100 GtCO₂ (IPCC, 2023). Thus, there is an uncertainty in remaining carbon budgets (relative to the total size) and it may remain so because these factors are inherently hard to constrain on a decadal time scale. It will be helpful to provide regular updates of the remaining carbon budget as better constrained estimates of TCRE and other geophysical parameters become available (Dickau et al. 2022). Most recently, Lamboll et al. (in review) provide an updated median estimate of 300 GtCO₂ as from 2022 onwards for a 1.5°C target, with an uncertainty of 110-530 GtCO₂ (for a 33% and 66% chance of exceeding the target, respectively).

![Figure 7](image_url)

*Figure 7. (a) Idealized representation of the TCRE, effective TCRE and related total and remaining carbon budgets. (b) Simulated climate response to CO₂ emissions only (purple) and all anthropogenic drivers (red) for scenarios from the SR1.5 scenario database, estimated with the climate emulator MAGGIC7. Reproduced from Matthews et al. (2020).*
References

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About this Knowledge Gains: Summary and Implication Report
CONSTRAIN's Knowledge Gains: Summary and Implication Reports outline CONSTRAIN’s contributions to the peer reviewed literature (knowledge gains), and summarise the implications for both the scientific community and broader society. This report and other CONSTRAIN publications are available at http://constrain-eu.org.

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About CONSTRAIN

The 2015 Paris Agreement sets out a global action plan to avoid dangerous climate change by limiting global warming to well below 2°C, whilst pursuing efforts to limit warming to 1.5°C. However, predicting how the climate will change over the next 20-50 years, as well as defining the emissions pathways that will set and keep the world on track, requires a better understanding of how several human and natural factors will affect the climate in coming decades. These include how atmospheric aerosols affect the Earth's radiation budget, and the roles of clouds and oceans in driving climate change.

The EU-funded CONSTRAIN project, a consortium of 14 European partners, is developing a better understanding of these variables, feeding them into climate models to reduce uncertainties, and creating improved climate projections for the next 20-50 years on regional as well as global scales. In doing so, CONSTRAIN will take full advantage of existing knowledge from the Sixth Phase of the Coupled Model Intercomparison Project (CMIP6) as well as other Horizon 2020 and European Research Council projects.

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