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New Potential to Reduce Uncertainty in Regional Climate Projections by Combining Physical and Socio-Economic Constraints

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Key Points:

- There has been progress on constraining socio-economic projections and the climate system's response to emissions
- Combining these constraints reduces regional climate projection uncertainty, more than either constraint individually
- It is time to explore and communicate these combined constraints more widely in climate change impact assessments

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Combining new constraints on future socio-economic trajectories and the climate system's response to emissions can substantially reduce the projection uncertainty currently clouding regional climate adaptation decisions—more than either constraint individually.

Plain Language Summary Projections of future climate change tend to have large uncertainties because we do not exactly know what humans will do and how the climate system will react to it. Here, we argue that we now know more about both of these things and that combining results from these different science disciplines can reduce uncertainties around future climate change. This will hopefully make it easier to plan adaptation to ongoing and future climate change.

1. Main

With ongoing climate change and the certainty of additional near-term warming, adaptation to climate change is now a necessity for many regions. But despite the importance of adaptation decisions to manage present and future climate risks, the large range of future projections can be paralyzing for stakeholders. From a climate system perspective, this uncertainty originates from three sources: scenario uncertainty, response uncertainty, and internal variability (Hawkins & Sutton, 2009). While internal variability is largely unpredictable and thus irreducible on decadal time scales and beyond (Deser et al., 2012), scenario and response uncertainty originate from our limited understanding of socio-economic and climate dynamics and are, in principle, reducible.

Over the last two decades, neither the magnitude of scenario nor response uncertainty have changed much. In fact, estimates of each increased slightly from the 5th to 6th IPCC Assessment Reports (IPCC, 2021). AR6 uses a larger number and wider range of socio-economic scenarios to reflect the full potential for new technology and policy to affect future emissions (Moss et al., 2010), constituting a more robust testbed for science (Tebaldi & Arblaster, 2014). Response uncertainty, on the other hand, reflects our imperfect understanding of the climate system and ability to represent it numerically in climate models; the global temperature range spanned by such models increased with the latest generation (the 6th Coupled Model Intercomparison Project, or CMIP6), mostly due to stronger positive cloud feedbacks in some models (Zelinka et al., 2020).

Both of these sources of uncertainty have received scrutiny in recent years. Experts argue that high emissions scenarios are less probable given that, among other reasons, the expansion rate of renewables is outpacing projections from a decade ago when these emissions scenarios were developed (Hausfather & Peters, 2020). The high sensitivity climate models that have increased estimates of response uncertainty from CMIP6 are likely inconsistent with observed warming (Tokarska et al., 2020) and paleoclimate evidence (Tierney et al., 2020). The latter concern was addressed in the IPCC AR6, where constrained *global* temperature projections with a narrower "assessed" range were presented in addition to the unconstrained model projections. Thus, it is timely to take stock of current climate projection uncertainty, especially for mid-century and at regional scales, which are important for adaptation decisions.

Two new research avenues that build on these discussions enable us to take the next step in constraining climate projections. First, there is increasing evidence that the set of emissions scenarios can be probabilistically

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constrained within the range of scenarios used for climate modeling that do not have probabilities associated with them (Representative Concentration Pathways, RCPs, and Shared Socioeconomic Pathways, SSPs). These limits are emerging both from the developing policy, institutional, technical, and economic landscape, as well as work to structurally model the coupled climate-social-political system in order to probabilistically project these trends forward (Beckage et al., 2018, 2022; Moore et al., 2022; Otto et al., 2020). Moore et al. (2022) developed a model in which climate policy emerges endogenously within the coupled climate-social system, partially constraining this using historical trends in public opinion and climate policy ambition and find a more constrained range of plausible temperature outcomes than based on the full range of RCP-SSP scenarios. Second, there are new physically based constraints on global and regional climate response uncertainty (Brunner, McSweeney, et al., 2020; Lehner et al., 2019; Lorenz et al., 2018; Qasmi & Ribes, 2022). For example, drawing on the often strong relationship between changes in global and local temperature and existing constraints on global temperature, Qasmi and Ribes (2022) developed constrained grid-cell level temperature projections using CMIP6 models.

Here we combine these two recent advances in understanding of socio-economic dynamics and climate system response to create constrained global and regional projections of temperature with the goal of illustrating the current potential to better inform climate adaptation decisions at mid-century and beyond. Specifically, we scale existing scenario uncertainty based on CMIP6 multi-model means (as calculated in Lehner et al. (2020)) to span a range of 1.4°C–3.6°C global warming at 2100, following Moore et al. (2022) for constraints on the upper bound of the scenario uncertainty. This is equivalent to strongly down-weighting the probability of the high emissions scenarios SSP3-7.0 and SSP5-8.5, in line with other recent assessments of the probability of those emissions scenarios (Hausfather & Moore, 2022; Meinshausen et al., 2022; Srikrishnan, Guan, et al., 2022). Notably, currently implemented mitigation policies are projected to lead to a warming range of 2.2°C–3.5°C by 2100 (IPCC, 2022), that is, a lower upper bound than used here. We then combine the constrained scenario uncertainty with the constrained gridded temperature projections from Qasmi and Ribes (2022), which themselves reduce both the absolute warming (by about 15% for global temperature under SSP5-8.5) as well as the *range* of warming (by about 40%–50%). There is a small additional reduction of the range of warming due to the interaction of the constrained scenario uncertainty with the constrained response uncertainty (Yip et al., 2011). Projection uncertainty for global temperature is reduced substantially when combining these different constraints (Table 1). For example, the 5%–95% range of decadal mean global temperature in 2050 shrinks from 1.3–3.4°C to 1.4–2.5°C, with even stronger constraints later this century.

As shown by Qasmi and Ribes (2022), the constraints on global temperature response are substantial enough to warrant carrying them through to the regional scale, where response uncertainty is known to often be important (Hawkins & Sutton, 2009, 2011; Lehner et al., 2020). Further combining regional constraints with the reduced scenario uncertainty can yield significant decreases in projection uncertainty through lowering the upper bound and raising the lower bound of the range (Figures 1a and 1b). For example, total uncertainty in temperature projections over Central Europe for 2050 is reduced by ~50%, with the relative importance of response uncertainty decreasing from 44% to 30% and scenario uncertainty decreasing from 46% to 39% (Figures 1a and 1b). Consequently, internal variability becomes relatively more important, increasing from 10% to 31%, providing renewed motivation for decadal prediction efforts that aim to reduce uncertainty from internal variability on regional scales (Mahmood et al., 2022). Overall, this uncertainty reduction is roughly equivalent to waiting another ~15 years, that is, moving the reference period to 2016–2035 (from 2001 to 2020) for the unconstrained CMIP6 ensemble.

Due to the dependence of other variables on decadal mean annual temperature, secondary constraints are possible. For example, changes in summer (June–August) temperatures over Central Europe are strongly correlated with changes in the annual mean, such that their plausible range in 2050 can also be reduced substantially by projecting the constrained annual temperature, the predictor, onto summer temperature, the predictand (Figure 1c). We use York regression (York et al., 2004) to account for internal variability correlation between predictor and predictand, using each model's preindustrial control simulation to establish the correlation. The regression coefficients, their uncertainty, and the constrained range of annual temperature are then sampled 1,000 times to predict a constrained distribution of summer temperature change. With both scenario and response uncertainty constrained, it is very likely that the Central Europe decadal mean summer warming will stay below ~2.5°C compared to 2001–2020 (~4°C compared to preindustrial). However, the average summer in the decade centered on 2050 is still projected to be about as warm as the observed 2022 summer, Central Europe's hottest summer on record, which saw increased human mortality and damaging effects on agriculture (https://www.worldweather-

Table 1
Very Likely (5%–95%) Range of Decadal Global Mean Temperature Change Around 2050 and 2095, Based on Unconstrained and Constrained CMIP6 Simulations, Relative to the 1850–1900 Mean

Global mean surface temperature change	Mid-term 2046–2055 5%–95% range (°C)	Long-term 2090–2099 5%–95% range (°C)
Unconstrained	1.3–3.4	1.1–7.1
Scenario uncertainty constrained	1.3–3.1	1.1–4.8
Response uncertainty constrained	1.4–2.8	1.2–5.8
Scenario and response uncertainty constrained	1.4–2.5	1.2–4.0

attribution.org/wp-content/uploads/WCE-NH-drought-scientific-report.pdf (accessed 20th June 2023)).

The general prospect for uncertainty reduction depends on the variable and spatial scales considered (Hawkins & Sutton, 2009, 2011). There are other regions and variables with strong links to global and local temperature and thus the potential for constrained projection uncertainty, for example,: mean, extreme, and variability of precipitation in regions where the change signal is dominated by thermodynamics, such as at high latitudes (Pendergrass et al., 2017); changes in temperature extremes (Seneviratne et al., 2016), and in Arctic sea ice area (Bonan et al., 2021). Caution is certainly warranted when developing such regional constraints, as their robustness can be difficult to establish (Caldwell et al., 2014), model interdependency can jeopardize statistical inference (Sanderson et al., 2015), and scenario composition can lead to departures from linear temperature scaling, for example, due to aerosols (Deser et al., 2020; Lehner & Coats, 2021; Pendergrass et al., 2019). The latter point is of particular concern, since the current portfolio of emissions scenarios does not sample spatially heterogenous aerosol trajectories in a systematic way (Persad et al., 2022; Rogelj et al., 2014). Based on existing studies, we estimate that regional projection uncertainty as presented here could be enlarged by 10%–20% via aerosol storylines not covered by the SSP scenarios (Persad & Caldeira, 2018; Westervelt et al., 2020); a new Model Intercomparison Project will help to better quantify this uncertainty, especially for the hydrologic cycle (Wilcox et al., 2022). There are also remaining uncertainties in the climate carbon cycle feedback that could lead to high forcing without high anthropogenic emissions (Arora et al., 2020). Equally, geopolitical changes remain difficult to predict and could slow or speed up momentum toward Net Zero (Sanderson & Knutti, 2017). Various international

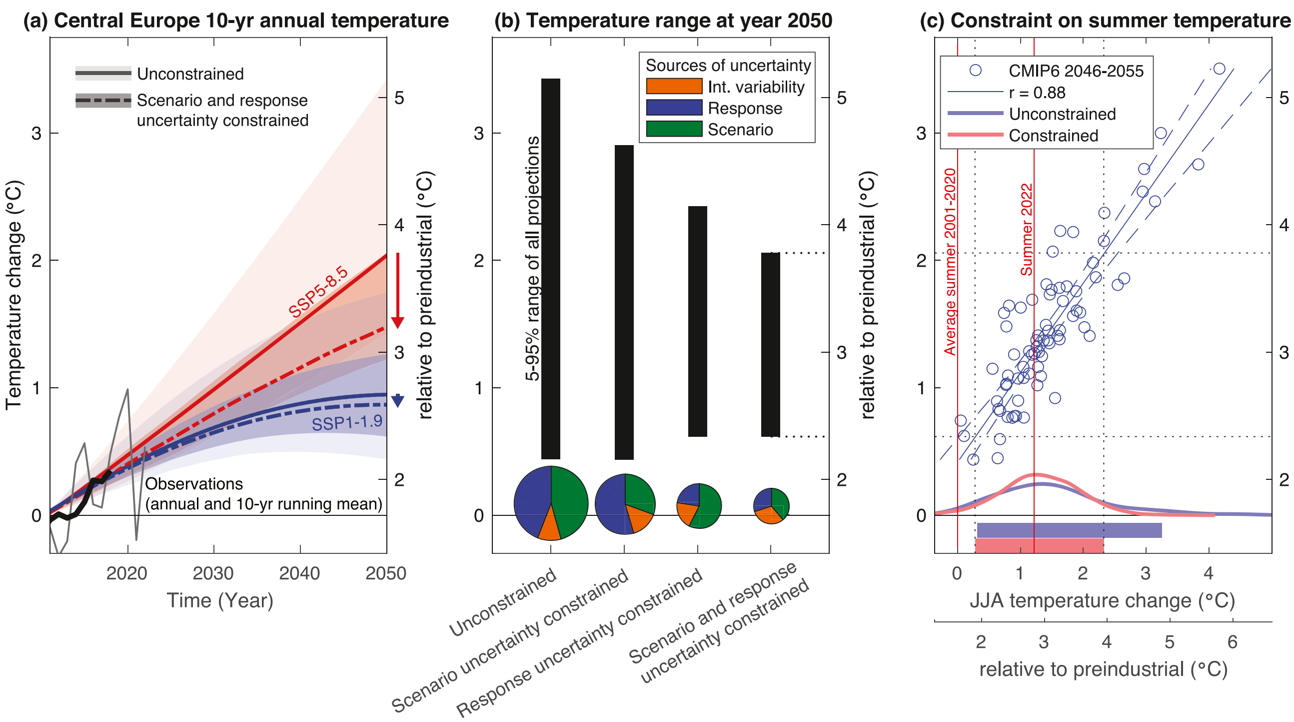

Figure 1. Reduced uncertainty in regional climate projections. (a) Decadal mean annual temperature over Central Europe from the unconstrained CMIP6 multi-model mean (15 models) under SSP5-8.5 and SSP1-1.9. Constrained versions of those scenarios are given in dotted-dashed lines. The 5%–95% range for the unconstrained (constrained) projections is given in light (dark) shading. Observations from Berkeley Earth (Rohde et al., 2013) are given as annual values and a 10-year running mean. Data is relative to (left *y*-axis) 2001–2020 and (right *y*-axis) 1850–1900. (b) Temperature ranges for the decade of 2046–2055 from unconstrained, partly constrained, and fully constrained projections. Pie charts give the relative importance of different sources of uncertainty relative to 2001–2020. (c) Decadal mean annual versus summer temperature from individual models and scenarios. Normalized PDFs for unconstrained and constrained summer temperatures are given together with 5%–95% range horizontal bars.

bodies continue to highlight the gaps between climate ambitions and existing and promised policies on emission reductions (UNEP, 2022). Thus, to more robustly assess projection uncertainty, there is a need to develop computationally nimble climate model emulators and climate-social models that are however able to simulate complex non-linear interactions resulting from spatio-temporally heterogenous forcing scenarios (Beusch et al., 2022; Srikrishnan, Lafferty, et al., 2022). This includes refined uncertainty estimates not just of climate forcing and response, but also feedbacks between climate change impacts and economic activity (e.g., Dall'Erba et al., 2021).

Notwithstanding the above caveats, we believe that the current progress in constraining CMIP6-based climate projection uncertainty is worth exploring, communicating, and deploying more widely in context of impact assessments and adaptation. Climate information at decision-relevant time and spatial scales is urgently needed by those tasked with managing climate risks in the public and private sector (Condon, 2023; Fiedler et al., 2021; Sobel, 2021). These needs will best be served by integrating available information on both scenario and response uncertainty as they evolve. This need not lead to overconfidence, as perfect model tests (Brunner, Pendergrass, et al., 2020) and emergent constraint protocols (Hall et al., 2019) can help guard against that. We also encourage continued use of high impact-low likelihood scenarios (such as SSP5-8.5) in risk assessments that do seek to explore those (Lawrence et al., 2020) or that already apply algorithms of robust decision making to develop adaptation strategies for a wide range of plausible but perhaps unlikely futures (Lempert, 2019; Smith et al., 2022). In fact, physical climate scientists will continue to be interested in running climate models with high emissions scenarios, as they provide a large signal-to-noise ratio, which aids process understanding and provides training grounds for emulators. Rather, constrained climate projections demonstrate real progress in the understanding of likely futures that can support climate adaptation planning in cases where large uncertainty has previously hindered progress.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All climate model data is available from https://esgf-node.llnl.gov/search/cmip6/. Observational temperature data is available from https://berkeleyearth.org/data/. Code to reproduce the analysis is available from https://github.com/flehner/lehner23aguadv (https://doi.org/10.5281/zenodo.8061577).

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